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DECISION SUPPORT SYSTEMS

Summary of Lectures

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Reviewer – Professor, Doctor of Economics, Head of Management and Business Department *T. Lepeyko*.

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The main theoretic and methodological approaches to decision theory, decision-making process and means of decision support by various information systems, i.e. decision support systems are presented.

It is recommended for the students of the preparatory direction 6.030601 "Management".

Наведено теоретичні та методичні підходи до теорії прийняття рішень, процесу прийняття рішень і засоби підтримки рішень інформаційними системами, тобто системами підтримки прийняття рішень.

Рекомендовано для студентів напряму підготовки 6.030601 "Менеджмент".

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Introduction

Profound changes in Ukrainian as well as global economy are evidently the sources of new business needs in quick sound decisions, which should be based on grounded analysis and forecast. Agile, real time adoption of these decisions becomes a crucial competence of every manager. Sophisticated managers don't rely only on their experience, intuition and judgment. All these elements are highly important in making decisions concerning complex systems, but they are not enough for predicting reaction on the external influences of any complex system with many variables. In such a situation prediction of the total outcome often strains human cognitive capabilities and may be daunting.

The 'Decision Support Systems' course is a professionally-oriented optional discipline for students of preparatory direction 6.030601 'Management'. It is held for the forth-year students during the seventh semester. It is a methodic and methodological base for the choice of models and methods of effective and efficient decision-making with the help of decision support systems of various kinds. This book will be helpful in organization and support of various decisions at enterprises of any scale. It is also useful for students of specialities 'Administrative Management' and 'Management of Innovation' in their educational activity.

The subject of 'Decision Support Systems' course is theoretic basis and methods of complex managerial problems solution with the help of decision support systems.

The aim of the course is theoretic knowledge system and practical skills formation in methods and techniques of decision-making. It forms the following competencies: knowledge of approaches in decision theory, methods and techniques of decision-making processes mathematical support, skills in grounded choice of methods and decision support systems types according to specific demands of business tasks and situations, etc.

Module 1. Main decision support theory terms.

The notion of decision support systems

Theme 1. Decision-making as a part of management activity

1.1. The role of DSS in a manager's knowledge system. Expedience of learning the course.

1.2. Main terms and their definitions.

1.3. Key actors of decision-making process.

1.4. Decision-making stages.

1.5. Decision types. Their classification.

References: [1; 3; 6; 12; 16; 28; 33; 54; 59].

1.1. The role of DSS in a manager's knowledge system. Expedience of learning the course

Profound changes in Ukrainian as well as global economy are evidently the sources of new business needs in quick sound decisions, which should be based on grounded analysis and forecast. Agile, real time adoption of these decisions becomes a crucial competence of every manager. Sophisticated managers don't rely only on their experience, intuition and judgment. All these elements are highly important in making decisions concerning complex systems, but they are not enough for predicting reaction on the external influences of any complex system with many variables. In such a situation prediction of the total outcome often strains human cognitive capabilities and may be daunting.

Scientific research and many empirical experiments prove that human intuitive judgments (taken individually or in groups) are frequently far from optimal, and they become much worse under the influence of stress and complex subtle interdependences. Due to great importance of decisions' quality, the tasks of efficient aiding human decision-making process has become of a major focus in many scientific areas. In order to indicate these areas and the decision-making domain itself special research was conducted by S. B. Eom [3, pp. 141–159]. According to his findings, the main reference disciplines of Decision Support Systems (DSSs) are Systems Science, Organizational Science, Cognitive Science, Artificial Intelligence, Multiple-Criteria Decision-Making, Communication Science, and Psychology.

Organization science has enriched DSS with organizational decision-making models and organizational information requirements, which became a basis of DSS design methodologies, helped to adapt systems to organizational environment, objectives and to provide uses with correct and sufficient information of suitable richness. Also ideas of alternative group decision-making methods and of psychologically attuned tools were implemented. Multiple-criteria decision-making enriched DSS with interactive procedures for multiple-criteria optimization and such techniques as ordinal comparisons, pairwise alternative comparisons, implicit utility functions, goal programming, analytical hierarchical process and others. All of them resulted in multiple-criteria decision model-embedded DSS emergence. Also the following business disciplines contributed to decision support theory: economics, management science, strategic management and accounting. Their influence is traced in improvement of consistency of judgments through investigation of the effects of heuristics on the accuracy of judgments and development of different expert systems in order to estimate probabilities of different economic events breaking. Theory of ingroup interactions and game theory have become the basis for group decision support systems. Forecasting and statistical models, simulation, integer and linear programming, network models and other economic methods have been incorporated in DSS and in some tools for their creation. Economic sciences also formed theoretic ground for some DSS, which analyze external environment, likelihood of crises, support strategic planning and new product development, and so forth [3].

Due to systems science cognitive styles and behavioral variables were taken into account within DSS design of presentation formats. Achievements in limitations of the human information processing research gave a new direction in descriptive decision theory improvement and implementations. Artificial intelligence, computer science, communication theory, knowledge management and psychology contributed to DSS greatly to model base construction, representation and processing, machine learning algorithms incorporation, group software design, etc [3].

All mentioned reference disciplines contributed greatly to decision theory formation and development, which was implemented in various DSS. DSS broadly might be defined as a kind of software which aims to aid user(s) in judgment and choice activities. It is a kind of interactive computer-based information system which uses hardware, software, data, model base and

manager's work in order to support all decision stages (of ill-structured and unstructured problems). The concept of DSS would be proved later.

It is difficult to overestimate the importance of various DSS in managerial activities which are widely used in all industries and business domains. They are exceptionally valuable in financial audit, risk assessment, investment choices and marketing. DSS supports choice in complex situations by eliminating human cognitive deficiencies using formal techniques and heuristic methods.

Proper usage of DSS brings not only confidence to a decision-maker, but also leads to efficiency in business [54].

1.2. Main terms and their definitions

The main term we may face in decision theory is a decision. In general, a decision is understood as a choice from multiple alternatives (options). This choice is taken by a decision-maker due to professional or vital importance. In this context decision is overlooked as an act which depicts the will of an individual, his/her possibility to take any choice and influence the current situation. Making no decision is also a kind of choice, because it is a possible option which is taken by the individual. In this case the decision is a characteristic of individual's will which lacks the result. In general, any decision is associated with a result or an outcome. So, in human perception any decision is naturally combined with choice as a will and choice as a result of some thinking procedure. In Slovan mentality decisions are also associated with a choice as a process of decision-making, it has definite linguistic ground.

The necessity of decision-making is defined by inconvenience of present situation which is called a problem. Problem is a kind of situation that force an individual to change it for the better because of inconvenience or threat under current conditions. The will to change it raises an idea or an image why or how exactly it should be changed, i. e. some objective. Any objective might be characterized as a desirable situation which is wished to be achieved by the decision-maker (individual or a group). By nature, objective might be of different levels and be named as an aim, a perspective or a goal. Bottom line: the main driver of the decision-making process is a gap between current situation (a problem) and a desirable situation (an objective) which stimulates the decision-maker to certain actions.

A set of actions aimed at solving existing problem and helping to achieve the planned objective are called alternatives [16, p. 24]. Alternatives mean options which except each other. The alternatives may represent different possible actions aimed at achieving the given objective, different hypotheses about the character of the future, different classifications and so on. The number of alternatives may range from two to infinite. In order to make a good choice between them a set of criteria is used.

A criterion is the basis of choice, a kind of preference. Criteria are used to measure a role or extent of attractiveness of each alternative from the point of view of the objective. By nature, criteria might be qualitative and quantitative. In real business situations both types of criteria are used in order to choose the best alternative. Generally, criteria influence the choice of alternatives by way of exclusion or evaluation. Some alternatives are excluded from the set of possible options if our criterion has a characteristic of constraint (or so called limiting factor). In this case a criterion serves to limit the alternatives under consideration or to express the characteristic that the decision set must possess. Criteria which might be considered as factors evaluate alternatives by the range of their attractiveness in achieving an objective, they show the suitability of a specific alternative [54].

The procedure by which criteria are selected and combined to arrive at a particular evaluation, and by which evaluations are compared and acted upon, is known as a decision rule [54]. Decision rules typically contain procedures for combining criteria into a single composite index and a statement of how alternatives are to be compared using this index.

Criteria are the measurements of effectiveness of the various alternatives and correspond to different kinds of system performance. Besides economic criteria, which tend to prevail in the decision-making process within companies, it is however possible to identify other factors influencing rational choice. They are [16, p. 25]: economic, technical, legal, ethical, procedural, political. Economic factors are the most influential in decision-making processes, and are often aimed at the minimization of costs or the maximization of profits. Options that are not technically feasible must be discarded. Legal rationality implies that before adopting any choice the decision-makers should verify whether it is compatible with the legislation and with ethical principles and social rules of the company. A decision may be considered ideal from an economic, legal and social standpoint, but it may be unworkable due to cultural limitations of the organization in terms of

prevailing procedures and common practice. The decision-maker must also assess the political consequences of a specific decision among individuals, departments and organizations.

Identifying decision outcomes has been a particularly difficult challenge for decision-makers as well as for decision researchers. Decision outcomes are frequently multifaceted and often difficult to fully grasp and quantitatively measure.

1.3. Key actors of decision-making process

The main actor of the decision-making process is definitely a decision-maker. A decision-maker is an individual or a group of people, who is/are making a choice, because of being uncontented with the present situation (or its perspective), having wish and authority to change it. Langley et al [1, p. 654] identified the following aspects of a decision-maker: a decision-maker as a creator (he or she reaches results through the creative notion of insights and intuition or creative synthesis); a decision-maker as an actor (he or she not only needs to make a choice, but has to be committed to action and execute it with feedback. This requires inspiration, inspiring of one self and others involved); a decision-maker as a carrier (he or she carries 'memories, experiences and training, the cumulative impact of the work around' this carrier) [1, p. 654].

The selection of appropriate decision support methods aiding various phases of the decision-making process may be based on the roles and motivations of the participants. Vari A. and Vecsenyi J. identified the following.

1. Decision-makers (these are people who have the executive power to determine the use of outputs of the decision-making process).
2. Proposers (proposers make recommendations to decision-makers).
3. Experts (they provide input and knowledge to model and structure the problem).
4. Those concerned with implementation (they participate in the execution of the selected and approved solution).
5. Clients (in case decision support is sought, they are the ones who have asked for such help).
6. Decision analysts or consultants (consultants help with methodology and modelling choices as well as with decision-making procedures, or may facilitate the collaboration among all participants).

In some DSS literature, one might also encounter references to such players as facilitators, developers, users, project champions, and supporters, and the list goes on. Their roles are the following. The decision owner is the one who leads the decision from start to finish either because he or she is the project leader or has been assigned supervision of the decision. Decision-maker is the person who can alter the activities and may commit to resource allocation. Facilitator is usually a consultant or analyst who provides a framework for the iterative development of a coherent representation of the problem and supports group work. In most cases problem owner is the one affected by the issues to be solved or indicates those who would benefit from the solution. Stakeholder: it is any group or individual who is affected by or can affect the achievement of an organization's objectives. A stakeholder usually has a stake in the business, therefore, their needs and issues may affect outcomes [1, p. 660]. So, the decision-maker is an individual (or group) who has to be committed to action. He or she has the power to allocate the resources of the organization or, in other words, has the executive power to determine the use of outputs of the decision-making process. It is often used in an abstract sense as the one who needs to make a choice.

1.4. Decision-making stages

H. A. Simon is considered the pioneer in the development of human decision-making models, who established the foundation for human decision-making models. His basic model depicts human decision-making as a three-stage process. These stages are: intelligence, design, choice. Intelligence is in the identification of a problem (or opportunity) that requires decision and collection of information relevant to the decision. Design is in creating, developing, and analyzing alternative courses of action. Choice is in selecting a course of action from those available [1, p. 218].

Intelligence. In the intelligence phase the task of the decision-maker is to identify, circumscribe and explicitly define the problem that emerges in the system under study. The analysis of the context and all the available information may allow decision-makers to quickly grasp the signals and symptoms pointing to a corrective action to improve system performance. During the intelligence stage it is obligatory to observe the reality, gain problem understanding and acquire needed information.

Design. In the design phase actions aimed at solving the identified problem should be developed and planned. At this level, the experience and creativity of the decision-makers play a critical role, as they are asked to devise viable solutions that ultimately allow the intended purpose to be achieved. Where the number of available actions is small, decision-makers can make an explicit enumeration of the alternatives to identify the best solution. If, on the other hand, the number of alternatives is very large, or even unlimited, their identification occurs in an implicit way, usually through description of the rules that feasible actions should satisfy [16, p. 27]. During this stage decision criteria and alternatives are developed, uncontrollable events are identified.

Choice. Once the alternative actions have been identified, it is necessary to evaluate them on the basis of the performance criteria deemed significant. Mathematical models and corresponding solution methods usually play a valuable role during the choice phase. For example, optimization models and methods allow the best solution to be found in very complex situations involving countless or even infinite feasible solutions. On the other hand, decision trees can be used to handle decision-making processes influenced by stochastic events [16, p. 27].

Commonly the last stages are implementation and control. When the best alternative has been selected by the decision-maker, it is transformed into actions by means of an implementation plan. This involves assigning responsibilities and roles to all those involved into the action plan. Once the action has been implemented, it is finally necessary to verify and check that the original expectations have been satisfied and the effects of the action match the original intentions.

During the intelligence phase, the decision-maker observes the reality, gains fundamental understanding of the existing problems or new opportunities, and acquires general quantitative and qualitative information needed to address the problems or opportunities. In the design phase, the decision-maker develops a specific and precise model that can be used to systematically examine the discovered problem or opportunity. This model will consist of decision alternatives, uncontrollable events, criteria, and the symbolic or numerical relationships between these variables. Usage of the explicit models to logically evaluate the specified alternatives and to generate recommended actions constitutes the ensuing choice phase. During the subsequent implementation phase, the decision-maker ponders the analyses

and recommendations, weighs the consequences, gains sufficient confidence in the decision, develops an implementation plan, secures needed financial, human and material resources, and puts the plan into action [54].

After the final choice is implemented, the decision-maker should observe the new reality and, where appropriate, follow through with intelligence, design, choice, and implementation. Moreover, phase analyses may suggest the need for revisions at the preceding phases. For example, analyses at the choice phase may necessitate adjustments in the previous design. Such continuous monitoring and adjustment is similar to Simon's review phase [54].

No decision process is this clear-cut in an ill-structured situation. Typically, the phases overlap and blend together, and there will be a return to earlier stages, as more is learned about the problem, or solutions do not work out, and so forth [54]. Conceptually, the decision-making process applies in the same manner to individual or group decision-making.

1.5. Decision types. Their classification

Simon described decision problems as existing on a continuum from programmed (routine, repetitive, well-structured, easily solved) to non-programmed (new, novel, ill-structured, difficult to solve) [54]. Gorry and Scott described decision problems as structured, unstructured, and semi-structured, rather than programmed and non-programmed. It is obligatory to take into account that it is the decision context that is unstructured, not the DSS itself.

Since it is likely that decision-making processes with similar characteristics may be supported by the same set of methodologies. Decisions can be classified in terms of two main dimensions, according to their nature and scope [16, p. 29]. According to their nature, decisions can be classified as structured, unstructured or semi-structured.

Structured decisions. A decision is structured if it is based on a well-defined and recurring decision-making procedure. In most cases structured decisions can be traced back to an algorithm, which may be more or less explicit for decision-makers, and are therefore better suited for automation. More specifically, we have a structured decision if input flows, output flows and the transformations performed by the system can be clearly described in the three phases of intelligence, design and choice [16, p. 29].

Unstructured decisions. A decision is said to be unstructured if the three phases of intelligence, design and choice are also unstructured. This means that for each phase there is at least one element in the system (input flows, output flows and the transformation processes) that cannot be described in detail and reduced to a predefined sequence of steps. Business intelligence systems may provide support to decision-makers through timely and versatile access to information [16, p. 30].

Semi-structured decisions. A decision is semi-structured when some phases are structured and others are not. Most decisions faced by knowledge workers in managing public or private enterprises or organizations are semi-structured. Hence, they can take advantage of DSSs and a business intelligence environment primarily in two ways. For the unstructured phases of the decision-making process, business intelligence tools may offer a passive type of support which translates into timely and versatile access to information. For the structured phases it is possible to provide an active form of support through mathematical models and algorithms that allow significant parts of the decision-making process to be automated [16, p. 30].

Depending on their scope, decisions can be classified as strategic, tactical and operational. Decisions are strategic when they affect the entire organization or at least a substantial part of it for a long period of time. Strategic decisions strongly influence general objectives and policies of an enterprise. As a consequence, strategic decisions are taken at a higher organizational level, usually by the company top management. Tactical decisions affect only parts of an enterprise and are usually restricted to a single department. The time span is limited to a medium-term horizon, typically up to a year. Tactical decisions place themselves within the context determined by strategic decisions. In a company hierarchy, tactical decisions are made by middle managers, such as the heads of the company departments. Operational decisions refer to specific activities carried out within an organization and have a modest impact on the future. Operational decisions are framed within the elements and conditions determined by strategic and tactical decisions. Therefore, they are usually made at a lower organizational level, by knowledge workers responsible for a single activity or task.

The characteristics of the information required in the decision-making process will change depending on the scope of the decisions to be

supported, and consequently also the orientation of a DSS will vary accordingly [16, p. 32].

Questions

1. What is a decision?
2. What kinds of decisions do you know?
3. Who are the main actors of the decision-making process?
4. What decision stages do you know?
5. Why is it important to differentiate semi-structured and unstructured problems? How does this differentiation influence the decision-making process?

Theme 2. Visualization techniques usage during decision-making

- 2.1. Visualization techniques usage according to decision-making stages.
- 2.2. Main components of visualization techniques.
- 2.3. Visualization techniques usage at intelligence stage.
- 2.4. Visualization techniques usage at design and implementation stages.
- 2.5. Data types and their representation.

References: [1; 12; 13; 32; 40; 43].

2.1. Visualization techniques usage according to decision-making stages

Visualization, well done, harnesses the perceptual capabilities of humans to provide visual insight into data. Early statistical methods provided reasonable visual support for data explorers. Similarly, modern graphical techniques help provide visual comprehension of various computational approaches. The primary goal of data visualization is to find a view or projection of the data, which reduces complexity while capturing important information [32]. The goal is to reduce complexity while losing the least amount of information.

At the intelligence stage different visualization techniques help understand the problem and different relations between all interacting

elements. It is obvious, that visual means able to convey the complexities of an unstructured situation more effectively than prose, so can various diagrammatic representations help in clarifying both structure and process for many systems. The effective human explorer now needs to understand both the structure of the data and the subtleties of the exploration process that lead to these structures.

At design stage it is vital to build a robust model of the process and calculate the outcomes of the alternatives. Visualization is not a substitute for quantitative analysis. However, it is a qualitative means for focusing analytic approaches and helping users select the most appropriate parameters for quantitative techniques.

Different packages integrate statistical tools with visualizations to allow users [32]:

1) to interactively formulate a model to describe the data being analyzed;

2) to combine data mining operations (such as association rule generators, clustering, and decision tree classifiers) with visualizations;

3) to guide the visualization and analysis processes.

At implementation and control stage visualization is used to trace deviations. Successful managers are skillful at spotting exceptional events, identifying emerging fashions, and noticing what is missing.

2.2. Main components of visualization techniques

Basic visualization terminology, that everyone should know is the following [32]:

1. Visualization (the graphical (as opposed to textual or verbal) communication of information (e.g., data, documents, structure)).

2. Interaction (a fundamental component of visualization that permits user-specified modifications to visualization parameters).

3. Data model (a representation of data that may include structure, attributes, relationships, behavior, and semantics, as well as a repository for data values themselves).

4. Graphical attributes (user-controllable aspects of the image generation process, including position, size, color, shape, orientation, speed, texture, and transparency of graphical entities).

5. Mapping (an association of data values and attributes to graphical entities and attributes).
6. Rendering (creating and displaying an image).
7. Field (a grid of data points that may be uniform or nonuniform).
8. Scalar (a single numeric data value).
9. Vector (a 1D list of values associated with a single datum).
10. Tensor (a 2D array of values associated with a single datum).
11. Isosurface (contours or boundaries in a field with a common value, usually dependent on interpolating between values in the field).
12. Glyph (a shape or image generated by mapping data components to graphical attributes (also called an icon)).
13. Relation (it is simply a property specifying some dependency between fields (attributes) over a subset of the data).

Visualizations can be used to explore data, to confirm a hypothesis, or to manipulate a viewer such as in a marketing brochure. In exploratory visualizations, the user does not necessarily know what he is looking for. This creates a dynamic scenario in which interaction is critical. The user is searching for structure or trends and is attempting to arrive at some hypothesis. In a confirmatory visualization, the user has a hypothesis that needs to be tested. This scenario is more stable and predictable. In production visualizations, the user has a validated hypothesis and, thus, knows exactly what is to be presented and focuses on refining the visualization to optimize that presentation (think of a marketing campaign).

A visualization can be stationary, animated, or interactive (respectively, for example, a set of images, a simulation of a finite element analysis over time, or a real-time representation of wind flow across an automobile) [32]. The processing of the data in the visualization system can be batch or interactive (batch for the analysis of a set of images; interactive for pre-surgery analysis). Not all techniques fall precisely into one of the foregoing classifications. The lines of separation are not precise, and many displays are hybrids of various techniques.

There is an interesting asymmetry between data presented in a tabular format and data presented in a graphical format [32]. Although one can always transform the tabular format into the graphical format, the reverse is not always true without losing some precision. This, then, is the trade-off when one balances the graphical or tabular formats: one wins on understanding, but loses on precision. When both are important, most users

tend to prefer receiving both formats rather than one or the other. So, let's consider different types of charts and diagrams, keeping in mind this critical characteristic.

A dot scale, which plots each value as a dot on the scale of the variable. This gives us an insight in the distribution of the individual data values on the entire range of values. The dot scale starts to lose its value when you have a large number of data points and the distribution of values along the axis becomes blurry. In that case one can resort to plotting statistical aggregation measures.

The box plot (Tukey plot contains) aggregated measures [32]. The box starts at the first quartile and ends at the third quartile. This range in the box is the interquartile range (half of the values). The line inside the box represents the median value. The lines outside the box, called the whiskers, branch out to the lowest value (the minimum) and the highest value (the maximum).

Frequency tables are special kinds of summary tables, in which they provide aggregate measures for one variable. The type of chart one chooses for the visualization of these frequency tables depends on the measurement scale of your variable. If one has a frequency table for an ordinal, interval, or ratio-scaled variable, it is better to use a histogram. A histogram has two axes, a horizontal axis representing the bins, and a vertical axis representing the frequency. Visualizing a nominal-scaled variable, one should use a bar chart to represent your frequency table. A bar chart is like a histogram but the nominal values do not represent any order. To avoid confusion with the histogram, the bar chart is often depicted horizontally.

If we are more interested in relative frequency, rather than absolute frequency, we can visualize a variable with a pie chart or a stacked bar chart [32]. You would use these charts to emphasize the percentages, not the absolute data values. You can see that the stacked bar chart is simply a 'stretched out' version of the pie chart.

The typical way to visualize cross-tabulations is to use the side-by-side variants of the univariate charts. When using a side-by-side variant of a chart, you will need to use different colours or patterns to identify different categories. You, therefore, need to include a legend, to show which colour or pattern you have assigned to which value. Side-by-side variants of univariate charts should be contrasted to bivariate charts, which aim to visualize a relationship between one variable and another. The technical name for what

we are visualizing is co-variation because we are attempting to detect whether the variables change ‘together’, or in other words, whether a change in one variable is accompanied by a change in another. If that is the case, we would say that the variables ‘co-vary’.

When constructing bivariate charts it is often possible to declare one variable as the independent variable, and the other attribute as the dependent variable. The independent variable is the variable that represents the cause. The dependent variable is the variable that represents the effect. Doing so defines the direction of co-variation. Declaring a dependency has important implications for the chart because the independent variable should go on the horizontal axis, and the dependent variable should go on the vertical axis.

The scatter plot is the bivariate extension of the dot scale, with each dot representing two values, one on the X-axis, and the other on the Y-axis [32]. Note that charting a scatter plot does not imply that the variables co-vary, or that they share a dependency relationship. It is rather the purpose of drawing a scatter plot to explore the two variables, to see whether a covariation can be suspected.

When two variables co-vary, the dependency relationship can be presented, but there are three other possibilities [32]:

- 1) dependency may be suggested but non-existent, when a change in one variable does not actually lead to a change in another, but is rather the result of pure coincidence;
- 2) the direction of the dependency may be the other way around;
- 3) (often overlooked) the variables may change together as a result of a change in a third variable, the spurious variable. The spurious variable is perhaps not even modelled, and it may be difficult to locate it.

In sum, if you are studying the relationships between two variables, do not assign dependency relationship lightly. Think carefully about the other three options, and if you are unsure, be careful not to assign one. If you are in doubt, the measurement scale of the variables might be of help.

The line chart is a special kind of scatter plot, where a line is then drawn between the points. The line suggests a trend, and it suggests that the values on the line can be inferred. A special kind of line chart is the time series chart, which uses a time series variable to be displayed on its X-axis and some other variable (often one that is ordinal and up) to be displayed on its Y-axis.

When we need to visualize three variables at the same time, we have a number of options [32]. First, we can use a three-dimensional (3D) scatter plot or 3D line chart, using an X-axis, a Y-axis, and a Z-axis. We can then plot our values in a three-dimensional space. This may cause problems though, because the exact data values on the X, Y, and Z axes are often ambiguous.

A better alternative, that only works with three variables, is to create a bubble chart. A bubble chart is like a bivariate scatter plot, but the values on the third dimension are represented by the width of the dot (effectively turning the dot into a bubble).

Looking at patterns in bubble charts, we need to look for co-variation again. Larger-sized bubbles (higher values of Var3) would seem to be associated with higher values of Var1 and higher values of Var2. It would, thus, seem that there is a positive co-variation between all three variables. One other option for three-dimensional data, frequently used, is to simplify the visualization by plotting out all possible two-dimensional relationships in a scatter plot matrix.

Multi-dimensional data with five or more dimensions are even harder to visualize, and few techniques are available to do so effectively. The most common way is to use a parallel coordination plot [32]. With such a plot, you put the axes parallel to each other (one for each variable), and for each instance you draw a line to connect the individual values on each of the axes.

Sometimes the axes are not put in parallel but rather in circular format, resulting in something that is called a radar chart or star plot. These plots are also not without serious problems [32]:

- 1) parallel coordination plots are often confused with line charts;
- 2) the plot becomes very cluttered quickly with more than four or five instances;

3) a further limitation of these plots is that they only really work well with variables that are measured on exactly the same scale. It is perhaps tempting to put axes next to each other that are from different scales (e.g. ordinal or even nominal), but in that case the choice of axes and the choice of the position of the values can seriously distort the overall picture.

Sometimes in order to compress multidimensional data into data with fewer dimensions we may use statistical techniques. Factor analysis can reduce dimensions by creating a so-called factor score: one value that represents the values on all four or more dimensions. Cluster analysis reduces the instances by creating clusters of instances: one instance that

represents instances with similar values in their dimensions. The aggregate values that cluster and factor analyses produce can help us to visualize the data more effectively, particularly when we enter four or more dimensions.

Dynamic charts are charts that change in appearance after a user interaction. They are a powerful way of visualizing trends, and they can also save screen space as they can replace a series of static charts. By definition, dynamic charts can only be implemented in computerized information systems, and they cannot be used in traditional management reports.

Precedence charts indicating the sequence in which certain activities have to be performed.

2.3. Visualization techniques usage at intelligence stage

During intelligence stage the most useful types of diagrams are influence diagrams and maps of different kinds.

The idea of 'cognitive mapping' is to develop a simple two-dimensional representation of the concepts that people express and to show their links as expressed by the person or group involved. The term 'cognitive mapping' has a number of meanings. In the literature it usually denotes attempts to depict a person's mental image of physical space. They are to be developed by a mapper who tries to capture the ideas of the interviewee or group, using the words used by the participants [13, pp. 139–140].

The maps are preferable to verbal accounts because they enable the links between the concepts used by the person to be shown on the map in an unambiguous way. Verbal accounts of many linked concepts tend to be ambiguous. A number of mapping approaches have been devised for use within organizations, especially to help senior managers with their strategic thinking. Different approaches are based on a range of assumptions, which stem from personal construct theory in cognitive psychology. Personal construct psychology is 'an attempt to understand the way in which each of us experiences the world, to understand our 'behaviour' in terms of what it is designed to signify and to explore how we negotiate reality with one another. It can be used to help people understand and interpret other people's views of reality. Eden developed the cognitive mapping technique with this in mind, intending its use to be simple, transparent and flexible' [13, pp. 139–140].

An influence diagram is another type of diagram particularly useful for depicting detailed steps of the decision-making process, involving open-loop

as well as feedback control mechanisms, of quantitative as well as qualitative nature. Influence diagrams are particularly insightful for bringing out the transformation process of the system in terms of structural and causal relationships between systems' components. Influence diagrams share some similarities with the cause-and-effect diagrams used in systems dynamics (to study the dynamic behavior of complex systems with lagged feedback and feed forward loops).

An influence diagram depicts influence relationships [32]:

- 1) between the inputs into a system and its components,
- 2) between the components of the system, and
- 3) between the components and the outputs of the system, including system performance measures. In some projects, these influence relationships can usually be measured in quantitative terms.

However, influence diagrams are equally effective for depicting non-quantitative relationships. If the system's processes lead themselves to being captured quantitatively, a system's component is usually represented by its corresponding state variable(s) or other numerical measures in the form of time integrated averages or the cumulative sum of state variable values over time. Rather than being a simple average of observed values, for a time integrated average each observed value is weighted by the relative length of time when the system holds that value. A system variable is always affected by inputs, controls, or/and other system variables.

The arrows indicate the direction of the influence relationships. However, they do not show the strength of the relationships. But the diagram is not intended to tell us by how much, i.e., it does not indicate the exact quantitative relationship between variables. Influence diagrams can easily depict feedback loops in the transformation process, which are part of the dynamic aspects present in the system. Influence diagrams are not intended to show the flow of material or information between various components of a system, or the various steps of a decision process, nor are they precedence charts indicating the sequence in which certain activities have to be performed, unless these features naturally coincide with the influence chain. They only depict in detail what affects the chain of impacts from controllable and uncontrollable inputs via state variables to system output and performance measures.

Although drawing an influence diagram is a helpful first step for building a mathematical model, influence diagrams are also a useful diagrammatic aid

for depicting qualitative relationships. Furthermore, influence diagrams facilitate and clarify the communication process between decision actors. However, there are situations where an influence diagram may not be a suitable vehicle for bringing out the structure of a decision problem. Other diagrammatic aid, such as material flow diagrams, decision flow diagrams, precedence charts, or a simple schedule of the time sequence of events may be able to shed more light on the problem and its structure.

2.4. Visualization techniques usage at design and implementation stages

Influence diagrams, which have their foundation in mathematical graph theory, are a form of acyclic digraph. A digraph is a visual representation of a set of nodes, and a set of ordered pairs of those nodes – represented by visually by arrows linking the nodes. Influence diagrams are used in systems dynamics, knowledge-based systems, decision support systems, and management science. Relatively new systems of automated reasoning, fuzzy cognitive maps, and probabilistic expert systems also rely on modelling techniques that are based upon influence diagrams. However, the most important application of influence diagrams has been in the area of decision analysis [1, p. 475].

Decision analysis is a structured approach to analyzing a decision situation and making a decision. The most commonly used tool in decision analysis to graphically describe a decision situation is a decision tree. Decision trees depict all the possible combinations of decision outcomes to be described [1, p. 475]. A decision tree allows the explicit representation of two variable types: variables that represent decisions and variables that represent different states of nature.

Decision trees are especially useful for determining the best strategy to adopt in decision situations. Expected value calculations, based on the structure of a decision tree, allow the decision-makers to determine the strategy that will lead to the best-expected result [1, p. 476].

There are many problems associated with the use of decision trees. The most significant of these is that a decision tree grows exponentially with the number of variables. This combinatorial growth makes decision trees for even simple decision situations very large and difficult to modify and maintain. It is difficult to obtain information from decision tree other than expected values [1, p. 476]. A decision tree contains much redundant

information. They can only be deduced after careful examination of the probabilities assigned to each branch of the tree. Decision trees have also been criticized for imposing a structure on the decision-maker's view of the world. One often-confusing aspect of the decision structure strongly implied by a decision tree is a left to right chronological ordering of the subdecisions and variables of the decision situation [1, p. 476–477].

A recent trend in the application of decision analysis is to use influence diagrams rather than decision trees. In decision analysis, an influence diagram is defined as a singly connected acyclic digraph. Influence diagrams can be used, as can decision trees, to calculate expected values of alternatives and, hence, to determine the best decision alternative to choose [1, p. 477].

In general, influence diagrams are much easier to draw, understand, and use than decision trees. An important advantage that influence diagrams have over decision trees is that their size grows linearly rather than combinatorially, as variables are added. There exist software tools that support creation of influence diagrams; many of these are able to convert an influence diagram into a decision tree and vice versa [1, p. 477].

Among the growing family of visual analytic tools, treemaps are flourishing in organizations that require daily monitoring of complex activities with thousands of products, projects, or salespeople. Tabular reports, bar charts, line graphs and scattergrams are important tools, but for complex activities where there are numerous sales regions, manufacturing plants, or product lines the hierarchical structures provided by treemaps can be helpful. While tabular displays and spreadsheets can show 30 – 60 rows at a time on typical displays, the colorful presentations in treemaps can accommodate hundreds or thousands of items in a meaningfully organized display that allows patterns and exceptions to be spotted in seconds.

Treemaps are a space-filling approach to showing hierarchies in which the rectangular screen space is divided into regions, and then each region is divided again for each level in the hierarchy. The original motivation for treemaps was to visualize the contents of hard disks with tens of thousands of files in 5 – 15 levels of directories.

2.5. Data types and their representation

Data are specific to a particular domain or application. A datum has one or more components (scalar, vector, tensor), possibly with geometric and structural attributes such as location and connectivity. Each component may

be nominal or ordinal, and discrete or continuous. Each component may be ordered, may have a distance relationship, or may have an absolute zero (mathematicians call this scale) [32]. The location attribute is relevant only for data from a physical domain, and may be on a regular or irregular grid. The connectivity of data specifies the neighborhood relationship among data points, and is most often used for resampling or interpolation.

In any managerial situation we can assume that there is some understanding of what it is that needs to be managed: employees, budgets, customers, production processes, and so on. We would say that these are the entities of our particular management domain. When we design information systems to support the management of these entities, we must at first seek to obtain a more precise understanding of them. We model the structures of data using conceptual diagrams. A complete set of diagrams describing the entities from our managerial domain represents our data model. The data model can be drawn using a variety of diagramming techniques.

Thus far we have not really said anything in detail about the attributes themselves. Yet it is clear that it is good practice to specify precisely what the allowable range of data values is going to be. We do so by specifying the attribute type. Synonyms sometimes encountered for attribute type are the value range or data type. A list of attribute types is provided below [32].

1. Number (any numeric value).

2. Text (free text, not predefined. In a more technical environment, this is usually called a string, or varchar (for 'variable characters')).

3. Category (predefined, non-numeric values. Ranking of the values is sometimes possible, sometimes not. I need to issue an immediate warning here. Take a note if you encounter an attribute that you believe is of Category type. At a later stage in the structuring process, you will get rid of the Category attribute by converting the category into an entity and introducing a so-called one-to-many relationship).

4. True/False (an attribute that is modelled as a True/False question. The response is either True or False or Yes or No).

5. Time stamp (a combination of Date and Time. A special attribute type is the time stamp, which is a date or time that a specific event occurs. The event is the attribute and the time stamp is the value).

Questions

1. Mention all the visualization techniques you know.
2. What is the difference between a histogram and a bar chart?

3. What classification of visualization techniques do you know?
4. How do decision stages influence the choice of visualization techniques?
5. How does the data type influence the choice of visualization technique?

Theme 3. Computer decision support systems

- 3.1. Definition and core attributes of DSS.
- 3.2. Structure and functions of DSS.
- 3.3. Types of information systems. DSS emergence prerequisites.
- 3.4. Types of DSS.

References: [7; 10; 22; 23; 46; 48; 57; 58].

3.1. Definition and core attributes of DSS

Let's define decision support system as a kind of interactive computer-based information system, which uses hardware, software, data, model base and manager's work in order to support all decision's stages (of ill-structured and unstructured problems). This definition is not the only one, but rather common. Other forgoing definitions are not so common or compete, but they show up different attributes and facets of DSS.

DSS is 'an interactive computer-based system that aids users in judgment and choice activities'. According to Scott-Morton, DSS is 'an interacting computer-based system that helps the decision-maker in the use of data and models in the solution of unstructured problems'. Little defines DSS as 'a model-based set of procedures for processing data and judgments to assist a manager in his/her decision'.

DSS couple the intellectual resources of individuals with the capabilities of the computer to improve the quality of decisions. It's a computer-based support for management decision-makers who deal with semi-structured problems (Keen and Scott-Morton). DSS is a system that is extendable, capable of supporting ad hoc analysis and decision modelling, oriented towards future planning, and of being used at irregular, unplanned intervals (Moore and Chang). DSS enables managers to use data and models related to an entity (object) of interest to solve semi-structured and unstructured problems with which they are faced (Beulens and Van Nunen).

The main feature of DSS relies in the model component. Formal quantitative models such as statistical, simulation, logic and optimization models are used to represent the decision model, and their solutions are alternative solutions (Emery, Bell). DSSs are systems for extracting, summarizing and displaying data (McNurlin, Sprague). As a generic term DSS is referring to a computerized program, which gathers various data from different resources at the enterprise level, in order to assist the decision-maker in decision-making activity, by presenting a set of indicators results from aggregating collected data [23]. DSS should be defined as a broad category of information systems for informing and supporting decision-makers [58].

Suitable DSSs prove to have the following features [46, p. 302]. They:

- 1) reduce costs in long-term perspective;
- 2) provide managers at different levels with precise information or grounded recommendations;
- 3) allow decisions made by an individual or group;
- 4) are able to make both sequential and interdependent decisions;
- 5) provide a variety of decision-making styles;
- 6) are user-friendly;
- 7) don't need users to be programmers;
- 8) facilitate the formulation of the problem by the end user; and
- 9) allow analysis of the results.

DSS is intended to improve the efficiency of the decision-making process, provide better administrative control and facilitate communication. It allows for the analysis of existing alternatives, optimizing alternatives and other combinations of decision alternatives.

3.2. Structure and functions of DSS

Drawing on various definitions that have been suggested, a DSS can be described as a computer-based interactive human – computer decision-making system that:

- 1) supports decision-makers rather than replaces them;
- 2) utilizes data and models;
- 3) solves problems with varying degrees of structure;
- 4) focuses on effectiveness rather than efficiency in decision processes (facilitating decision processes).

Main DSS features are:

- 1) DSSs support all decision-making stages (intelligence, design, choice, implementation);
- 2) DSSs are targeted at ill-structured and unstructured problems;
- 3) managers are used to choose a model for data processing and often form (or reform) inflowing data as far as DSS has the model base;
- 4) DSSs are interactive (they are not oriented on predefined process).

So, the user should know, what information is needed as well as how to get it.

The DSS has a three-tier architecture, where the components are disposed as follows:

- 1) database, with internal and external sources, containing information which will be processed by upper layers to contribute to decision-making process support;
- 2) model, containing a set of procedures and rules transposed in algorithms which use the data from the database to assist the decision-making process;
- 3) user interface, having interactive help and a navigation screen, used to acquiring the decision-maker's needs and to display the selected decision or suggestion for a specific problem.

The first step of the decision-making process begins with the creation of a decision support model, using an integrated DSS program (DSS generator). A model is an image of an object (process or event), which is simplified in order to be well processed. The user interface sub-system (or dialogue generation and management systems) is the gateway to both database management systems (DBMS) and model-based management systems (MBMS).

DBMS are a set of computer programs that create and manage the database, as well as control access to the data stored within it. The DBMS can be either an independent program or embedded within a DSS generator to allow users to create a database file that is to be used as input to the DSS.

Database management systems are computer programs which are primarily concerned with managing a large amount of data in a physical storage such as hard disks and creating, updating and querying databases in an optimal way. Data management in DSS is a necessary function primarily useful at the intelligence stage of the decision-making process, but not sufficient to support design and choice stages of decision-making processes.

In performing these essential tasks, DSS utilizes many types of management science/operations research (MS/OR) models. They include

linear programming, integer programming, network models, goal programming, simulation and statistical models and spreadsheet modelling. All these models are stored in the model base.

MBMS is a set of computer programs embedded within a DSS generator that allows users to create, edit, update, and/or delete a model. Users create models and associated database files to make specific decisions. The created models and databases are stored in the model base and database in the direct access storage devices such as hard disks.

From a user's viewpoint, the user interface subsystem is the only part of DSS components with which they have to deal.

The interface allows users to access to: 1) the data sub-system: (a) database (b) database management software; and 2) the model sub-system: (a) model base (b) model base management software.

The functions of the user interface (dialogue generation and management) sub-system are to:

1) allow the user to create, update, delete database files and decision models via database management systems and model-based management systems;

2) provide a variety of input and output formats;

3) provide different styles of dialogues (such as graphical user interfaces, menus, direct command languages, form interaction, natural language interaction, and questions and answers).

Main DSS functions are to:

1) expand the decision-maker's memory (DSS provides quick and associative (content addressable) access to problem domain and its parts);

2) store and activate decision-maker's and expert's experience (DSS stores knowledge of previous decisions and their results);

3) activate intuition and creativity of the decision-maker (it supports goal generating and non-standard decisions);

4) support mathematic models usage.

3.3. Types of information systems. DSS emergence prerequisites

As far as DSS is an information system, therefore, its definition is the following: 'Information systems are systems, which provide problem-domain's data storage and processing'. The term 'information system' is often used for information processing computer-based systems, which are grounded on hardware and software usage.

Historically transaction processing systems (TPS) first appeared in the 1950s. These are information systems, that automatize pre-defined, routine business operations. Often they are real-time information systems, which embody OLTP-technology (Online Transaction Processing): it means, that every record (row) in such a system is an image (or trace) of definite operation. The main effect from TPS is an ability to calculate different past business indicators and compute future perspectives.

Transaction processing systems are those systems that provide support to the operations of the organization. Data such as sales orders, production orders, and accounting data are input into these systems on a daily basis. The data is then used to provide information to other employees working in the organization.

Information management system (MIS) appeared in the 1960s, it is an information system, which provides collection of full data-set about enterprise activity, organizes and summarizes them in a form of pre-defined (regimented) reports, which are convenient to managers. Management information systems provide support for tactical and strategic decisions. The information that these systems provide will not affect operations in the short term, but will form the basis for longer-term decisions, with broader and wider implications for operations. The focus in these systems is thus on summarizing and analyzing transaction data, for the benefit of effective managerial decision-making.

Usually, managers have two core questions: 1) what exactly is going on? and 2) what should be done with it? TPS and MIS answer only the first question, DSSs answer the last question or both.

DSSs have been produced since the 1970s – 1980s.

The first one among DSSs was the executive information system. It is a system, that secures top management in providing instantaneous access to key factors, that influence enterprise goals achievement. Such systems' reports are demonstrative, interactive, with the broadest data access. So it gives not only the aggregated results of analysis, but provides a comparison with enterprise goals and some recommendations.

Expert systems are information systems that provide decision on the basis of knowledge (from knowledge-bases) in situations, where human experts were employed before. The main distinction of the system is an opportunity to make new knowledge on the basis of existing knowledge. They are designed to identify a situation, to make a diagnosis, to set recommendations/guidelines in some domain. They provide what-if analysis.

The next one was the artificial neural networks, a program or technical imitation of the biological neural network. Artificial neural networks are assembly of uniform processor elements, which are simplified functional models of neurons. Due to their ability of self-learning, they are used for voice and image patterns recognition (image and speech discernment), financial situation forecasting, etc.

Intelligent DSSs are DSSs that include elements of expert systems and other artificial intelligence technologies.

3.4. Types of DSS

Every DSS could be categorized by the user interaction degree:

- 1) passive, where the DSS aids the decision-maker without giving explicit solution to a specified problem;
- 2) active, DSS offering an unique solution for a given problem;
- 3) cooperative, where the solutions offered by DSS are modified, refined or completed by the decision-maker and sent back to the system for validation.

Also, having in mind the criterion of the mode of assistance, DSS could be differentiated in: document-driven, communication-driven, model-driven, data-driven, knowledge-driven.

In document-driven DSSs unstructured information in various formats is managed and manipulated. A new type of DSS, a document-driven DSS is evolving to help managers retrieve and manage unstructured documents and web pages. A document-driven DSS integrates a variety of storage and processing technologies to provide complete document retrieval and analysis. Examples of documents that would be accessed by a document-based DSS are policies and procedures, product specifications, catalogues, and corporate historical documents, including minutes of meetings, corporate records, and important correspondence. A search engine is a powerful decision-aiding tool associated with a document-driven DSS.

In communication-driven DSS the support is used for multiple users that share the same task or for a single user performing a specific part in a shared project. Group DSS and single user DSS have distinguishable purposes. To support a set of decision-makers working together as a group, group DSSs have special technological requirements of hardware, software, people and procedures. Group DSS software also needs special functional capabilities, in addition to the capabilities of single user DSS software, such as anonymous

input of the user's ideas, listing group members' ideas, voting and ranking decision alternatives.

Group decision support systems (GDSS) came first, but now a broader category of communications-driven DSS or groupware can be identified. This type of DSS includes communication, collaboration and decision support technologies. A group DSS is a hybrid DSS that emphasizes both the use of communications and decision models; it is an interactive computer-based system intended to facilitate solution of problems by decision-makers working together as a group. Groupware supports electronic communication, scheduling, document sharing, and other group productivity and decision support enhancing activities.

Model-driven DSS uses data provided by the user to assist the decision-maker. It is based on access and manipulation of an optimization, simulation or other type of analyzing algorithm. Model-driven DSS emphasizes access to and manipulation of a model. Simple statistical and analytical tools provide the most elementary level of functionality. Some OLAP systems that allow complex analysis of data may be classified as hybrid DSS systems providing modelling, data retrieval and data summarization functionality. Model-driven DSS uses data and parameters provided by decision-makers to aid them in analyzing a situation, but they are not usually data intensive. Very large databases are usually not needed for model-driven DSSs.

In data-driven DSS time series of various internal or external indicators are accessed, aggregated and manipulated to support the decision-making process. Data-driven DSS includes file drawer and management reporting systems, data warehousing and analysis systems, executive information systems (EIS) and spatial decision support systems, business intelligence systems. Data-driven DSS emphasizes access to and manipulation of large databases of structured data and especially a time-series of internal company data and sometimes external data. Simple file systems accessed by query and retrieval tools provide the most elementary level of functionality. Data warehouse systems that allow the manipulation of data by computerized tools tailored to a specific task and setting or by more general tools and operators provide additional functionality. Data-Driven DSS with Online Analytical Processing (OLAP) provides the highest level of functionality and decision support that is linked to analysis of large collections of historical data.

In knowledge – driven DSS sets of procedures, rules and facts are stored and used to solve specialized problems. Knowledge-based decision support systems (KBDSS) are hybrid systems of DSS and ES that help solve a broad range of organizational problems. Expert support systems (ESS) are to replace human expertise with machine expertise, while ISS are to amplify the memory and intelligence of humans and groups. A broad range of real-world managerial problems can be solved in a better way by using analysis of both quantitative and qualitative data. A bottleneck in the development of knowledge-based systems such as ESS is knowledge acquisition, which is a part of knowledge engineering.

DSSs may also be divided to inter-organizational or intra-organizational DSSs. A relatively new targeted user group for DSS, which was made possible by new technologies and the rapid growth of the Internet, includes customers and suppliers. We can call DSS targeted at external users an inter-organizational DSS. Companies can make a data-driven DSS available to suppliers or a model-driven DSS available to customers to design a product or choose a product. Most DSSs are intra-organizational DSSs that are designed for use by individuals in a company as a 'standalone DSS' or for use by a group of managers in a company as a group or enterprise-wide DSS.

There are function-specific or general purpose DSSs. Many DSSs are designed to support specific business functions or types of businesses and industries, which are called function-specific or industry-specific DSSs. A function-specific DSS like a budgeting system may be purchased from a vendor or customized in-house using a more general-purpose development package. Function or task-specific DSS can be further classified and understood in terms of the dominant DSS component, that is as a model-driven, data-driven or suggestion DSS. A function or task-specific DSS holds and derives knowledge relevant for a decision about some function that an organization performs (e.g., a marketing function or a production function). This type of DSS is categorized by purpose; function-specific DSSs help a person or group accomplish a specific decision task. General-purpose DSS software helps support broad tasks like project management, decision analysis, or business planning. The most general purpose DSSs are sometimes called DSS generators because they can be used to develop or 'generate' more specific DSS.

Questions

1. What is a DSS? How does it differ from other types of information systems?
2. What functions of DSSs do follow from their definitions?
3. What is a common structure of DSS?
4. Why did DSSs emerge? What kind of problems do they face?
5. What types of DSSs do you know? How do they differ?

Theme 4. Normative decision theory. Decision support models

- 4.1. Decision theory.
- 4.2. Normative decision theory.
- 4.3. Decision support models.
- 4.4. Uncertainty, its definition and types.
- 4.5. Decision support models under uncertainty.
- 4.6. Multi-criteria decision support models.

References: [17; 39; 46; 59].

4.1. Decision theory

Decision theory is a scientific discipline, which deals with two main tasks:

- 1) to study/explore how people are making decisions;
- 2) to develop methods for decision-making, which help to justify selection of the best alternative from a feasible alternative set.

As it is seen from the definition, decision theory deals with two classes of problems. According to them, descriptive and normative theory might be distinguished.

Descriptive theory component describes the actual behavior and thinking of people in decision-making (so called psychological theory). Descriptive component is psychological, because it is based on a study of the human psychology.

Normative component, by contrast, tells people how they should make decisions. Normative theory is a system of techniques that support decision-making. Such methods are 'organizing' human thinking and prescribe to individuals how to behave in the decision-making process.

The normative component is mathematical, because it is based on rigorous mathematical models and calculations.

Usually decision-making models fall into one of the following categories [46, p. 206]:

1. *Normative models* discuss and present mathematical or algorithmic aspects of the decision-making process, taking into consideration the formal aspects (theoretical or 'ideal') about 'what should be done' in a decision-making situation. Because they usually consider quantitative values, decision-making problems at the operational and tactical levels are mostly analyzed.

2. *Descriptive models* show discussions and cases involving practical aspects of what is usually done' in decision-making without distinguishing among the operational, tactical, or strategic decision levels.

3. *Prescriptive models* seek to answer the question 'what can be done most realistically' to improve the decision-making process, including analysis and resolution of problems with multiple criteria, conflicting objectives, and fuzzy variables.

4. *Decision support* systems and business intelligence using data mining techniques present a general analysis of the models, structure of data and mathematical algorithms utilized to form a guide to orient the use of DSSs and data mining techniques.

4.2. Normative decision theory

Normative theory is a mathematical theory of decision-making, which is based on the assumption that any problematic situation can be described as a mathematical model that supports selection of the best alternative on the basis of some criteria.

Normative theory is grounded on the following premises:

1) first of all, the mathematical model of any situation might be build and it would generate a set of alternatives;

2) secondly, the objective model (goal model) might be build, which would allow to estimate the measure of concordance/adequacy of each alternative to the goal.

Initially, the basis for normative decision theory lays in the classical concept of maximizing the expected utility. According to this concept, an individual is always trying to make the best decision, which corresponds to

the maximum expected utility/gain. It is assumed that the decision-maker has enough information about the environment, alternatives and their consequences of his/her choices.

The main elements, which are used in the process of selecting the best alternative from the set of alternatives are formalized in the form of a 'decision-making task'.

The task of decision-making is a pair $\langle A, P \rangle$, where: A is a set of alternatives, P is the principle of optimality, which defines the best alternative (that is a model of an objective).

A solution of the task $\langle A, P \rangle$ is a subset $A_{opt} \in A$, which supervenes from the principle of optimality.

If the principle of optimality (P) is a set of contradictory criteria, then there is a multi-criteria task.

4.3. Decision support models

The main practical result of research conducted under the normative decision theory are different mathematical models aimed to find the solution of $\langle A, P \rangle$.

A model is an image of (similar to) the original object, which reflects its significant attributes/properties and which is used in the research process (replacing the original object).

A mathematical model of an economic object (process, event) is a description, made by mathematical means, such as expression equations, inequalities and logical relations.

Examples of mathematical economic models can be:

- 1) mathematical economics (production functions and industries' balances);
- 2) models of mathematical programming;
- 3) game theory models;
- 4) statistics, probability and simulation models.

A normative (pragmatic) decision model means the right representation of the decision-making process and its outcome. These models show how to make a decision.

Models have developed normative theory of decision-making, particularly demanded in those situations when a man lacks information for accurate selection from the set of alternatives – this situation is a situation of

uncertainty. Therefore, before turning to the specific normative decision-making model, let's consider the notion of uncertainty.

The most common model used for decision-multi-criteria problems, is the model based on the total efficiency criteria: all the alternatives' payoffs are multiplied on their weight (according to criteria values).

4.4. Uncertainty, its definition and types

A decision-making task lies in the choice of the best way of acting from the set of possible variants of actions.

It means that there a set of possible variants of actions exist. The choice of one of the variants (choice of one alternative) leads to some outcome. So the task is to choose the best (in some sense) variant of actions, which leads to the best outcome. It describes an assumption, that there is a casualty connection between an alternative and outcome. Here it is also important to follow some decision rules (certain optimality criterion – a way of of each alternative or outcome estimation quality). For the right choice it is important to know, whether it is a single choice or a repeatable one.

One of the most important moments is to define the type of connection between alternatives and outcomes. If the choice of every alternative leads to definite outcome, then it is a deterministic task.

When the type of connection between alternative and outcome has probabilistic character, then it is called task under risk. Probability itself tells us that the probability values are known, the probability of coming of every outcome is known (and there is some kind of gamble). The sum of all the probabilities is 1. When the type of connection has probabilistic character, though we don't know the values of probability – that is a task under uncertainty. We may include decisions under risk which are taken just once (when choice is not repeatable) to the latter class of tasks.

There also exists a special case of connection between alternatives and outcomes which is called decision under conflict. It means that the decision is made by two or more actors, who have different interests. These interests might not be opposite but they coincide. Game theory deals with such decisions.

Uncertainty is some incompleteness and inaccuracy of information about conditions of realization of the decision. There are different kinds of uncertainty:

1) uncertainty of incoming information or data (uncertainty of its elements, connections between elements and complex uncertainty of both). In application to decision task there is uncertainty of the elements of the problem: alternative value, its connection with outcome, etc.;

2) goal uncertainty is an inaccurate understanding of objectives by decision-maker (target uncertainty is often associated with the presence of several conflicting criteria for evaluated alternatives);

3) the uncertainty of the environment; the unknown consequences of alternatives are associated with the impossibility of accurate environment estimation (for example, it is unknown what will be the proceeds from the sale of businesses that work with different types of products, thus not known in advance of the competitors).

Depending on the presence or absence (or level) of uncertainty decisions are divided into following groups:

1) certainty of the situation, characterized by complete information;

2) risk situations in which the probability of environment states occurrence is known;

3) uncertainty in which the probability of environment certain states occurrence can't be determined.

Other sources of uncertainty are:

1) elements of the problem;

2) type of connection between alternatives and outcomes;

3) unknown set of alternatives or their values (we are not sure about the importance of the alternative);

4) uncertain decision rule (how the multi-criteria optimality should be reached);

5) conflicts of objectives;

6) lack of mathematic description (structured, semi-structured, unstructured problem).

4.5. Decision support models under uncertainty

Thus, if the decision-maker optimistically believes that the nature will always be 'on his/her side' regardless of the decision he/she makes, he or she should choose the alternative which leads to the largest possible payoff. This type of reasoning is reflected in the maximax decision rule, which determines the maximum payoff for each alternative and then selects the

alternative associated with the largest payoff [32]. A payoff matrix is a table that summarizes the final outcome (or payoff) for each decision alternative under each possible state of nature. To construct a payoff matrix, we need to identify each decision alternative and each possible state of nature.

The decision-making model based on the criterion of extreme optimism is as follows. This entry means that as the best alternative is proposed to choose the best result which will be relatively higher than the best results of other alternatives.

To answer the question about what model should be applied in each case, experts offer the following series of rules: the criterion of extreme optimism should be used when the price of risk is relatively low compared with the existing stock of resources.

A more conservative approach to decision-making is given by the maximin decision rule, which pessimistically assumes that nature will always be 'against us' regardless of the decision we make. This decision rule can be used to hedge against the worst possible outcome of the decision. To apply the maximin decision rule, we first determine the minimum possible payoff for each alternative and then select the alternative with the largest minimum payoff (or the maximum of the minimum payoffs – hence the term 'maximin').

The decision-making model based on the criterion of pessimism is the follows. The alternative to be chosen as the best alternative is characterized by the best result in the worst situation, it means that the worst outcome of which will be relatively better than the worst results of other alternatives.

The criterion of pessimism should be used when necessary to show extreme caution. This criterion allows you to choose a solution that will deliver guaranteed results.

Another way to approach decision-making problems involves the concept of regret, or opportunity loss.

To use the minimax regret decision rule, we must at first convert our payoff matrix into a regret matrix that summarizes the possible opportunity losses that could result from each decision alternative under each state of nature [32].

Each entry in the regret matrix shows the difference between the maximum payoff that can occur under a given state of nature and the payoff that would be realized from each alternative under the same state of nature.

The last column summarizes the maximum regret that could be experienced with each decision alternative. The minimax regret decision corresponds to the alternative with the smallest (or minimum) maximum regret.

4.6. Multi-criteria decision support models

Present-day management systems have become complex and are seldom evaluated in terms of quantitative linear components. Multi-criteria problems arise in the design, modelling, and planning of many complex systems in the areas of industrial production, urban transportation, energy production and distribution, health delivery, etc [46, pp. 256–261]. These problems can be formulated and optimized using the quantitative approach to linear or nonlinear mathematical programming, but real-life decision problems involve many conflicting goals expressed by quantitative and/or qualitative criteria.

The fact that strategic decisions typically involve consideration of multiple strategic objectives, suggests adoption of multi-criteria decision analysis (MCDA) as the evaluation tool for strategic choices [17, pp. 33–35]. In strategic management other MCDA methods can also be employed, such as goal programming, scenario planning, outranking methods.

One important change that organizations may experience, when using MCDA for strategic decisions, is the use of a value-focused framework to guide the decision-making process. For example, the key aspect in supporting strategic decisions using value-focused thinking is, therefore, the need to define and structure these strategic objectives. There are several tools that can be used for the structuring of objectives, such as means-ends networks, causal/cognitive maps, post-it workshops with the CAUSE framework, affinity diagrams and soft-systems methodology.

Multicriteria thinking demonstrates that in order to make the best choice in a decision, discussion and cause-effect reasoning are inadequate to learn what the best overall outcome is. The Analytic Hierarchy Process (AHP) and its generalization to dependence and feedback, the Analytic Network Process (ANP), provide a comprehensive structure and mathematics to incorporate measurements for tangible criteria and derive priorities for intangible criteria to enable one to choose the best alternative for a decision. It overcomes so-called bounded rationality that is based on the assumption of transitivity by including in its structures and calculations, the sensitivity and depth of feelings associated with understanding and the imagination and awareness needed to address to all the concerns [17, p. 91]. The AHP can cope with the inherent subjectivity in all decision-making, and make it explicit to the stakeholders through relative quantitative priorities. It also provides the

means to validate outcomes when measurements are available to show that it does not do number crunching without meaningful justification. It can deal with benefits, opportunities, costs and risks separately and bring them together to determine the best overall outcome. One can also perform dynamic sensitivity analysis of changes in judgements to ensure that the best outcome is stable.

The AHP is a method of choosing the best decision alternative considering multiple criteria and goals expressed by qualitative or quantitative values. This method created by Saaty (1980) has been used in the decision-making process to establish: priority definition, cost and profits assessment, resource deployment, benchmarking, market survey, strategic decisions, conflict negotiation and resolution, social or political decisions, and forecasts [46, pp. 256–261].

The AHP is based on parity matrices to express subjective assessment values attributed to variable pairs of each factor or criterion involved in the problem. AHP is a single-step decision process, which does not consider risk or uncertainty. Since manual calculation is difficult for decision problems with a large number of factors or alternatives (usually more than five criteria and five alternatives), an AHP software should be used.

The AHP consists of the following four basic steps the aim of which are to:

- 1) develop the decision hierarchy of levels of decisions elements;
- 2) collect preference data for each decision element by performing pairwise comparisons;
- 3) determine relative priority or weight of each decision element using the eigenvalue method or alternative approximation method;
- 4) aggregate the relative priorities of the final decision alternatives relative to the overall goal.

The quality of the final decision is dependent upon the consistency of the judgment throughout the pairwise comparison process. A measure of consistency called consistency ratio is used to determine the decision-maker's consistency after the development of each pairwise comparison matrix. If the consistency ratio is large, the decision-maker should revise the pairwise comparison matrix. The decision-maker can also revise the subjective judgement giving more preference to one of the criteria or one of the objectives. This revision procedure may introduce changes in the final priority.

AHP is one of the most used methods for making decisions with multiple criteria involving complexity and subjectivity. One of the difficulties

pointed out for the AHP is the amount of required parity comparisons, which increase rapidly with the number of criteria depending on the complexity of the decision tree. The reversal effect of the priority order, which occurs when the dominant alternatives are altered due to the inclusion or exclusion of irrelevant alternatives, is another problem pointed to by AHP critics [46, pp. 256–261]. The order reversal effect is attributed by researchers as a ‘side effect’ of the calculus used to normalize the priority vector. In response to this problem, Saaty created the ‘ideal mode’ calculation, indicated for the cases when only the best alternative is desired.

Questions

1. What is the decision theory?
2. What is the normative decision theory? What premises does it use?
3. What is the decision support model? What is a decision task?
4. What kinds of uncertainty do you know? What role does it play in the decision-making process?
5. What is the essence of multicriteria decision support model?

Theme 5. Decision-making under risk, uncertainty and conflict

- 5.1. Main decision-maker mistakes in risky, uncertain and conflict situations. Recommendations on psychological pressure reduction.
- 5.2. Methods and techniques of uncertainty reduction.
- 5.3. Decision-making under risk, risk assessment methods.
- 5.4. Conflict types. Decision-making under conflict. Guidelines for avoiding complications in conflicts.

References: [26; 34; 35; 36; 38; 46; 49].

5.1. Main decision-maker mistakes in risky, uncertain and conflict situations. Recommendations on psychological pressure reduction

Since risk is a mental construct there is a wide variety of construction principles for conceptualizing it. Different disciplines within the natural and social sciences have formed their own concepts of risk; stakeholder groups, driven by interest and experience, have developed specific perspectives on risk; and, last but not least, representatives of civil society as well as the general public are responding to risks according to their own risk constructs

and images. These images are called 'perceptions' in the psychological and social sciences and they have been intensely researched in relation to risk – as have their underlying factors [49, pp. 31–33].

First of all it is highly important to know that human behaviour is primarily driven by perception and not by facts or by what is understood as facts by risk analysts and scientists. Most cognitive psychologists believe that perceptions are formed by common-sense reasoning, personal experience, social communication and cultural traditions [49, pp. 31–33]. In relation to risk it has been shown that humans link certain expectations, ideas, hopes, fears and emotions with activities or events that have uncertain consequences. People do not, however, use completely irrational strategies to assess information: most of the time they follow relatively consistent patterns of creating images of risks and evaluating them. These patterns are related to certain evolutionary bases of coping with dangerous situations. Faced with an imminent threat, humans react with four basic strategies: flight, fight, play dead and, if appropriate, experimentation (on the basis of trial and error).

In the course of cultural evolution the basic patterns of perception were increasingly enriched with cultural patterns. These cultural patterns can be described by so-called qualitative evaluation characteristics. They describe properties of risks or risky situations going beyond the two classical factors of risk assessment on the basis of which risk is usually judged (level of probability and degree of possible harm).

Considered together qualitative evaluation characteristics can be subdivided into a limited number of consistent risk perception classes (semantic risk patterns) [49, pp. 33–34]:

- 1) immediate threats, such as risk associated with nuclear energy or large dams;
- 2) risks dealt with as a blow of fate, such as natural disasters;
- 3) risks presenting a challenge to one's own strength, such as sports activities;
- 4) risk as a gamble, such as lotteries, stock exchanges or insurance;
- 5) risks as an early indication of insidious danger, such as food additives, ionizing radiation or viruses.

These patterns have functions similar to drawers in a filing cabinet. When faced with a new risk or when obtaining new information about a risk, most people try to file this new information into one of the existing drawers. In addition to cognitive processing of risk characteristics and risk situations,

studies have shown that people tend to stigmatize risk sources that are associated with specific dreadful associations [49, pp. 33–34]. Stigmatization leads to a cycle of public outrage and regulatory responses, feeding into a process that has been described as social amplification of risk.

Based on the distinction between complexity, uncertainty and ambiguity it is possible to design generic strategies of risk management to be applied to classes of risks. Four classes one can distinguish [49, pp. 49–55]:

1. Simple risk problems. This class of risk problems requires hardly any deviation from traditional decision-making. Data are provided by statistical analysis, goals are determined by law or statutory requirements, and the role of risk management is to ensure that all risk reduction measures are implemented and enforced. Traditional risk-to-risk comparisons (or risk-to-risk trade-offs), risk-to-benefit analysis and cost-effectiveness studies are the instruments of choice to find the most appropriate risk reduction measures. Additionally, risk managers can rely on best practice and, in cases of low impact, on trial and error. It should be noted, however, that simple risks should not be equated with small or negligible risks. The major issues here are that the potential negative consequences are obvious, the values that are applied are non-controversial and the remaining uncertainties are low.

2. Complex risk problems. For this risk class major input for risk management is provided by the scientific characterization of the risk. Complex risk problems are often associated with major scientific dissent about complex dose-effect relationships or the alleged effectiveness of measures to decrease vulnerabilities. The objective for resolving complexity is to receive a complete and balanced set of risk and concern assessment results that fall within the legitimate range of plural truth claims. In a situation where there are no complete data the major challenge is to define the factual basis for making risk management or risk regulatory decisions.

3. Risk problems due to high unresolved uncertainty. If there is a high degree of remaining uncertainties, risk management needs to incorporate hazard criteria (which are comparatively easy to determine), including aspects such as reversibility, persistence and ubiquity, and select management options empowering society to deal even with worst-case scenarios (such as containment of hazardous activities, close monitoring of risk-bearing activities or securing reversibility of decisions in case risks turn out to be higher than expected). Management of risks characterized by multiple and high uncertainties should be guided by the precautionary approach.

4. Risk problems due to interpretative and normative ambiguity. If risk information is interpreted differently by different stakeholders in the society – in other words there are different viewpoints about the relevance, meaning and implications of factual explanations and predictions for deciding about the tolerability of a risk as well as management actions – and if the values and priorities of what should be protected or reduced are subject to intense controversy, risk management needs to address to the causes for these conflicting views.

Managing interdependencies. In an interdependent world, the risks faced by any individual, company, region or country depend not only on their own choices but also on those of others. Nor do these entities face one risk at a time: they need to find strategies to deal with a series of interrelated risks that are often ill-defined or outside their control.

The more interdependencies there are within a particular setting and the more that setting's entities are, the less incentive each potentially affected participant will have to invest in protection. At the same time, however, each participant would have been better off, had all the other participants invested in risk-reducing measures. In other words, weak links may lead to suboptimal behavior by everyone.

5.2. Methods and techniques of uncertainty reduction

One of the primary difficulties in decision-making is that we usually do not know which state of nature will occur [32]. As we have seen, estimates of probability of each state of nature can be used to calculate the EMV (expected monetary value) for various decision alternatives. However, probabilities do not tell us which state of nature will occur – they only indicate the likelihood of various states of nature.

Suppose that we could hire a consultant who could tell us in advance and with 100 % accuracy which state of nature will occur. Thus, with advance perfect information about the states of nature decision-making is much easier. So, how much should a decision-maker be willing to pay a consultant for such information?

The expected value of perfect information (EVPI) is the expected value obtained with perfect information minus the expected value obtained without perfect information (which is given by the maximum EMV).

The expected value of perfect information (EVPI) is equivalent to the minimum expected opportunity loss (EOL).

5.3. Decision-making under risk, risk assessment methods

It is clear that financial 'decision-making' cannot avoid periodic financial collapses without clearly defining and measuring risk. Risk certainly is related to the probabilities of gain and loss with respect to specified target levels [17, pp. 256–262].

Probabilistic decision rules can be used if the states of nature in a decision problem can be assigned probabilities that represent their likelihood of occurrence. For decision problems that occur more than once, it is often possible to estimate these probabilities basing on historical data. However, many decision problems represent one-time decisions for which historical data for estimating probabilities are unlikely to exist. In these cases, probabilities are often assigned subjectively based on interviews with one or more domain experts [32].

Since probabilities are known, one may use Bayes criterion. The expected monetary value decision rule (Bayes criterion) selects the decision alternative with the largest expected monetary value (EMV) [32]. The probabilities for each state of nature are multiplied on payoffs from each alternative respectively. Using these probabilities, the EMV for each decision alternative is calculated. The largest EMV is associated with the decision to choose.

The purpose of risk assessment is the generation of knowledge linking specific risk agents with uncertain but possible consequences. The final product of risk assessment is the estimation of risk in terms of a probability distribution of the modelled consequences (drawing on either discrete events or continuous loss functions). There is agreement on basically three core components of risk assessment [49, pp. 24–31]:

- 1) identification and, if possible, estimation of hazard;
- 2) assessment of exposure and/or vulnerability; and
- 3) estimation of risk, combining the likelihood and the severity of the targeted consequences, based on the identified hazardous characteristics and the exposure/vulnerability assessment.

The estimation of risk depends on an exposure and/or vulnerability assessment. Exposure refers to the contact of the hazardous agent with the target; vulnerability describes various degrees to which the target experiences harm or damage as a result of the exposure.

The basis of risk assessment is the systematic use of analytical – largely probability-based – methods. Probabilistic risk assessments for large technological systems, for instance, include tools such as fault and event trees, scenario techniques, distribution models based on geographic information systems, transportation modelling and empirically driven human – machine interface simulations. The processing of data is often guided by inferential statistics and organized in line with decision analytic procedures. Risk assessments specify what is at stake, calculate the probabilities for wanted or unwanted consequences, and aggregate both components into a single dimension. In general there are five methods for calculating probabilities [49, pp. 24–31]:

1. Collection of statistical data relating to performance of a risk source in the past (actuarial extrapolation).

2. Collection of statistical data relating to components of a hazardous agent or technology. This method requires a synthesis of probability judgments from component failure to system performance – probabilistic risk assessments.

3. Epidemiological or experimental studies which are aimed at finding statistically significant correlations between an exposure to a hazardous agent and an adverse effect in a defined population sample (probabilistic modelling).

4. Experts' or decision-makers' best estimates of probabilities, in particular for events where only insufficient statistical data are available (normally employing Bayesian statistical tools).

5. Scenario techniques by which different plausible pathways from release of a harmful agent to the final loss are modelled on the basis of worst and best cases or estimated likelihood of each consequence at each knot.

All these methods are based either on the past performance of the same or a similar risk source or an experimental intervention. However, the possibility that the circumstances of the risk situation may vary over time in an unforeseeable way and that people will thus make decisions in relation to changing hazards – sometimes they may even change in an unsystematic, unpredictable manner – leads to unresolved or remaining uncertainty (second order uncertainty).

One of the main challenges of risk assessment is the systematic characterization of these remaining uncertainties. They can partly be modelled by using inferential statistics (confidence interval) or other

simulation methods (such as Monte Carlo), but often they can only be described in qualitative terms. Risk analysts consequently distinguish between aleatory and epistemic uncertainty: epistemic uncertainty can be reduced by more scientific research, while aleatory uncertainty will remain fuzzy regardless of how much research is invested in the subject [49, pp. 24–31].

Risk assessment is confronted with three major challenges that can be best described using the terms 'complexity', 'uncertainty' and 'ambiguity'. These three challenges are not related to the intrinsic characteristics of hazards or risks themselves but to the state and quality of knowledge available about both hazards and risks. Since risks are mental constructs, the quality of their explanatory power depends on the accuracy and validity of their (real) predictions.

Compared with other scientific constructs, validating the results of risk assessments is particularly difficult because, in theory, one would need to wait indefinitely to prove that the probabilities assigned to a specific outcome were correctly assessed. If the number of predicted events is frequent and the causal chain is obvious, validation is relatively simple and straightforward. If, however, the assessment focuses on risks where cause–effect relationships are difficult to discern, effects are rare and difficult to interpret, and variations in both causes and effects obscure the results, the validation of the assessment results becomes a major problem. In such instances, assessment procedures are needed to characterize the existing knowledge with respect to complexity, remaining uncertainties and ambiguities [49, pp. 24–31].

Complexity refers to the difficulty of identifying and quantifying causal links between a multitude of potential causal agents and specific observed effects.

The nature of this difficulty may be traced back to interactive effects among these agents (synergism and antagonisms), long delay periods between cause and effect, interindividual variation, intervening variables or other factors. Risk assessors have to make judgements about the level of complexity that they are able to process and about how to treat intervening variables (such as lifestyle, other environmental factors and psychosomatic impacts). Complexity is particularly pertinent at the phase of estimation with respect to hazards as well as risks.

Uncertainty is different from complexity but often results from an incomplete or inadequate reduction of complexity in modelling cause – effect chains.

Human knowledge is always incomplete and selective and thus contingent on uncertain assumptions, assertions and predictions. It is obvious that the modelled probability distributions within a numerical relational system can only represent an approximation of the empirical relational system with which to understand and predict uncertain events. It therefore seems prudent to include other, additional, aspects of uncertainty. The key components of uncertainty [49, pp. 24–31]:

- 1) target variability (based on different vulnerability of targets);
- 2) systematic and random error in modelling (based on extrapolations, statistical inferential applications, etc);
- 3) indeterminacy or genuine stochastic effects (variation of effects due to random events, in special cases congruent with statistical handling of random errors);
- 4) system boundaries (uncertainties stemming from restricted models and the need for focusing on a limited number of variables and parameters);
- 5) ignorance or non-knowledge (uncertainties derived from lack of knowledge).

The first two components of uncertainty qualify as epistemic uncertainty and therefore can be reduced by improving the existing knowledge and by advancing the present modelling tools. The last three components are genuine uncertainty components of an aleatory nature and thus can be characterized to some extent using scientific approaches but cannot be further resolved. If uncertainty, in particular the aleatory components, plays a large role then the estimation of risk becomes fuzzy. The validity of the end results is then questionable and, for risk management purposes, additional information is needed such as a subjective confidence level in the risk estimates, potential alternative pathways of cause – effect relationships, ranges of reasonable estimates, loss scenarios and so forth.

Whereas uncertainty refers to a lack of clarity over the scientific or technical basis for decision-making, ambiguity is a result of divergent or contested perspectives on the justification, severity or wider ‘meanings’ associated with a given threat. In relation to risk governance it is understood as ‘giving rise to several meaningful and legitimate interpretations of accepted risk assessments results’. It can be divided into interpretative

ambiguity (different interpretations of an identical assessment result, for example as an adverse or non-adverse effect) and normative ambiguity (different concepts of what can be regarded as tolerable referring, for example, to ethics, quality of life parameters, distribution of risks and benefits).

A condition of ambiguity emerges where the problem lies in agreeing on the appropriate values, priorities, assumptions or boundaries to be applied to the definition of possible outcomes. High complexity and uncertainty favour the emergence of ambiguity, but there are also quite a few simple and highly probable risks that can cause controversy and thus ambiguity.

Risk assessment techniques. There are a wide range of risk assessment techniques available. Techniques for risk assessment are [35, pp. 123–126]:

1. Questionnaires and checklists (use of structured questionnaires and checklists to collect information that will assist with the recognition of the significant risks).

2. Workshops and brainstorming (collection and sharing of ideas at workshops to discuss the events that could impact the objectives, core processes or key dependencies).

3. Inspections and audits (physical inspections of premises and activities, and audits of compliance with established systems and procedures).

4. Flowcharts and dependency analysis (analysis of the processes and operations within the organization to identify critical components that are key to success).

5. HAZOP and FMEA approaches (hazard and operability studies and failure modes effects analysis are quantitative technical failure analysis techniques).

6. SWOT and PESTLE analysis (strengths, weaknesses, opportunities, threats (SWOT) and political, economic, social, technological, legal, environmental (PESTLE) analyses offer structured approaches to risk identification).

Checklists and questionnaires have the advantage that they are usually simple to complete and are less time-consuming than other risk assessment techniques. However, this approach suffers from the disadvantage that any risk not referenced by appropriate questions may not be recognized as significant.

Given that risks can be attached to other aspects of an organization as well as or instead of objectives, a convenient and simple way of analyzing risks is to identify the key dependencies faced by the organization. Most people within an organization will be able to identify the aspects of the business that are fundamentally important to its future success. Identifying the factors that are required for success will give rise to a list of the key dependencies for the organization.

Key dependencies can then be further analyzed by asking what could impact each of them. If a hazard analysis is being undertaken then the question is: 'What could undermine each of these key dependencies?' If control risks are being identified, then the question can be asked: 'What would cause uncertainty about these key dependencies?' For an opportunity risk analysis, the question would be: 'What events or circumstances would enhance the status of each of the key dependencies?'

For many organizations, quantification of risk exposure is essential and the risk assessment technique that is chosen must be capable of delivering the required quantification.

Risk workshops are probably the most common of the risk assessment techniques. Brainstorming during workshops enables opinions regarding the significant risks faced by the organization to be shared. A common view and understanding of each risk is achieved. However, the disadvantage can be that the more senior people in the room may dominate the conversation, and contradicting their opinions may be difficult and unwelcome.

When a risk has been recognized as significant, the organization needs to rate that risk, so that the priority significant risks can be identified. Techniques for ranking risks are well established, but there is also a need to decide what scope exists for further improving control. Consideration of the scope for further cost-effective improvement is an additional consideration that assists the clear identification of the priority significant risks. The most common form of a risk matrix is one that demonstrates the relationship between the likelihood of the risk materializing and the impact of the event should the risk materialize.

During a risk ranking it is necessary to decide [35, pp. 123–126]:

- 1) the magnitude of the event should the risk materialize;
- 2) the size of the impact that the event would have on the organization;
- 3) the likelihood of the risk materializing at or above the benchmark;
- 4) the scope for further improvement in control.

This will lead to the clear identification of the significant risks priority.

The classification of risks into short, medium and long-term helps to identify risks as being related (primarily) to operations, tactics and strategy, respectively. This distinction is not clear-cut, but it can assist with further classification of risks. In fact, there will be some short-term risks to strategic core processes and there may be some medium-term and long-term risks that could impact core operational processes [35, pp. 131–139].

A short-term risk has the ability to impact the objectives, key dependencies and core processes, with the impact being immediate. These risks can cause disruption to operations immediately at the time the event occurs. These risks are normally associated with unplanned disruptive events, but may also be associated with cost control in the organization. Short-term risks usually impact the ability of the organization to maintain efficient core processes that are concerned with the continuity and monitoring of routine operations.

A medium-term risk has the ability to impact the organization following a (short) delay after the event occurs. Typically, the impact of a medium-term risk would not be apparent immediately, but would be apparent within months, or at most a year after the event. Medium-term risks usually impact the ability of the organization to maintain effective core processes that are concerned with management of tactics, projects and other change programs. These medium-term risks are often associated with projects, tactics, enhancements, developments, product launch and the like.

A long-term risk has the ability to impact the organization some time after the event occurs. Typically, the impact could occur between one and five years (or more) after the event. Long-term risks usually impact the ability of the organization to maintain the core processes that are concerned with efficacious strategy development and delivery. These risks are related to strategy, but they should not be treated as being exclusively associated with opportunity management. Risks that have the potential to undermine strategy and the successful implementation of strategy can destroy more value than risks to operations and tactics.

In order to identify all of the risks an organization faces, a structure for risk identification is required. Formalized risk classification systems enable the organization to identify where similar risks exist within the organization.

The main risk classification systems are the COSO, IRM standard, BS31100, FIRM risk scorecard and PESTLE. There are similarities in most of

these systems, although PESTLE takes a slightly different approach. It should be noted that identifying risks as: 1) hazard, control or opportunity; 2) high, medium or low; and 3) short-term, medium-term and long-term should not be considered to be formal risk classification systems.

There are similarities in the way that risks are classified by different risk classification systems. COSO takes a narrow view of financial risk, with particular emphasis on reporting. It includes such types as strategic, operations, reporting and compliance types of risks. British Standard BS 31100 helps to define the scope of risk management in the organization, providing a structure and framework for risk identification, and giving the opportunity to aggregate similar kinds of risks across the whole organization. It includes the following types of risk: strategic, program, project, financial and operational. The British Standard states that the number and type of risk categories employed should be selected to suit the size, purpose, nature, complexity and context of the organization. The categories should also reflect the maturity of risk management within the organization [35, pp. 131–139].

The four headings of the FIRM risk scorecard offer a classification system for the risks to the key dependencies in the organization. The classification system also reflects the idea that 'every organization should be concerned with its finances, infrastructure, reputation and commercial success'. In order to give a broader scope to commercial success, the headings of the FIRM risk scorecard are as follows: financial; infrastructure; reputational; marketplace [35, pp. 131–139].

PESTLE risk classification system is an acronym that stands for political, economic, sociological, technological, legal and environmental risks.

In some versions of the approach, the final E is used to indicate ethical considerations (including environmental). This risk classification system is most applicable to the analysis of hazard risks and is less easy to apply to financial, infrastructure and reputational risks.

These risk classification systems are most easily applied to the analysis of hazard risks, except that the IRM Standard (includes financial, strategic, operational, hazard types of risk) and the COSO framework offer strategic risk as a separate risk category [35, pp. 131–139]. As with other core processes in an organization, classification of risks facing projects is essential, so that the appropriate response to each risk can be identified.

In order to identify and reduce influence of different risks there exist so called soft and hard methods [36, pp. 57–69].

The following soft methods are widespread:

- 1) brainstorming;
- 2) mind mapping;
- 3) strengths, weaknesses, opportunities and threats (SWOT);
- 4) critical systems heuristics;
- 5) soft systems methodology;
- 6) stakeholder analysis;
- 7) futures workshop.

The first three methods are well-known and practiced in a number of more or less formal versions. Brainstorming may range from 'free-and-open' discussion to a version based on rules, where a facilitator conducts the session that will typically contain a sequence of questions; mind mapping is also relatively well-known, where ideas and especially how they interrelate are brought forward successively as the process goes on and ends up presenting the team involved with what is sometimes called rich pictures. Especially wider concerns and diversity issues can be shed light on using brainstorming and mind mapping in combination [36, pp. 57–69].

A more structured way of thinking about a complex, strategic problem can be obtained by a SWOT analysis, where internal and external factors are approached by imagination and consideration of respective strengths versus weaknesses and opportunities versus threats leading to a SWOT-matrix that can facilitate further process of scoping the alternatives.

What constitutes the differences between the methods is their balance between being unstructured and thereby allowing open discussions and being more structured and thereby securing a relevant result (in some respect) to come out of the efforts [36, pp. 57–69].

Methods more demanding in time but with a capability to 'dig out' knowledge about the decision problem in hand and have a critical influence on the outcome of the process are critical systems heuristics, soft systems methodology, stakeholder analysis and futures workshop. An alternative way of making use of critical systems heuristics is to concentrate on the questions that seem to be most relevant and productive with regard to obtaining new insights concerning the particular problem dealt with.

Soft systems methodology was developed by Peter Checkland [36, pp. 57–69]. It is set up as a learning cycle with a prescribed content of the process to be carried out. The structure of SSM is made up of seven interrelated activities. They are: (1) *problem situation: unstructured,*

(2) *problem situation: expressed*, (3) *root Definitions of relevant human activity system*, (4) *conceptual Models of the system concepts named in the Root Definitions*, (5) *comparison*, (6) *changes: desirable and feasible and* (7) *action*.

The principle of SSM can be understood by surveying the stages of the methodology. Stages 1 and 2 try to build as rich a picture of the problem situation as possible. The subsequent stage 3 concerns what Checkland calls Root Definitions. Their purpose is to define one or more relevant systems in a way that makes it possible to discuss their nature more openly. Such definitions constitute a survey of the problem situation and provide the base from which such a survey and its implications can be further developed. At stage 4, what Checkland calls Conceptual Models are formulated. Conceptual Models can be seen as structured sets of activities combined logically in accordance with their underlying Root Definitions. The aim of stage 6 is to make use of the comparison results obtained at stage 5 to discuss possible, relevant changes. These should be both desirable on the basis of the insights from Root Definitions and Conceptual Models and they should also be culturally feasible in the actual context. At stage 7, action should be taken on the basis of the outcome of stage 6, whereby the learning cycle is closed and a new situation is obtained [36, pp. 57–69].

Assessing consequences and risks become important when scoping has produced a set of strategic choice alternatives. With the core performance of the alternatives addressed at best in doing screening based on rough estimates in the scoping, it now becomes essential to take a closer look at each alternative by asking fundamentally whether it remains attractive with a view on both its core performance and its wider performance. Scrutinizing each alternative in turn will also lay the basis for a subsequent exploration of their relative attractiveness.

While scoping was conducted principally on the basis of soft methods, examination of the attractiveness, at least at the beginning of the assessment process, will be dominated by analytic methods referred to as belonging to the category of hard methods.

The following hard methods are [36, pp. 57–69]:

- 1) cost-benefit analysis;
- 2) analytic hierarchy process (AHP);
- 3) simple multi-attribute ranking technique (SMART);
- 4) scenario analysis;

- 5) preference analysis;
- 6) risk analysis based on Monte Carlo simulation;
- 7) composite methodology for assessment (COSIMA, SIMDEC).

Assessing of the consequences of alternatives will depend on the nature of the consequences identified. In our 'monetized' world the first issues addressed are often those where consequences are identified by being described in money terms such as expenses and gains, or in the language of economics as costs and benefits. This type of assessment is cost – benefit analysis (in the sphere of private firms it is also known as financial analysis).

The approach of CBA is quite simple: What does it cost? What comes out of it? The logic of the analysis consists of selecting the decision choice alternative that gives 'the most' for 'the least'. This should accordingly result in a favourable situation with a 'surplus' by implementing the identified best decision alternative.

Multi-criteria analysis is a fairly recent method of assessing and selecting projects exerting complex socio-economic effects. In this method, individual assessment elements are taken separately and measured in the appropriate dimensions. The criteria will have to be weighted among each other because they are not of equal relevance. Determining the weights requires much responsibility and expertise from the decision-maker as the weights have considerable influence on the results of the assessment.

Two main branches of multi-criteria analysis methods have been found particularly useful for assisting decision-making regarding complex strategic choices [36, pp. 57–69]. One concerns using multi-attribute utility theory and is represented with SMART (simple multi-attribute ranking technique). This type of method consists of scaling and weighing different attributes of the alternatives to define the one which scores the highest. The other branch proceeds by applying pairwise comparisons, which has been found useful in the way decision-makers can be involved in the assessment. This methodology is represented by AHP (analytic hierarchy process).

Typically these can inspire 'what-if'-questions of a wide range. In this respect scenario analysis (SA) is a well-known methodology, where critical assumptions are derived from scenarios representing what is perceived as possible, plausible and internally consistent images of the future. Preference analysis (PA) is a kind of hard version of the softer stakeholder analysis (STA). Typically analysts and modellers can identify certain parameters that they interpret as being sensitive with regard to different decision interests involved.

In scoping mainly the soft methods assist planners in their deliberations, while mainly the hard methods are applied in the assessment for the determination of the consequences and risks that relate to each of the choice alternatives. Scoping and assessment are necessarily interrelated activities. What matters in scoping is that an option or choice alternative is not excluded if later on in the assessment it could have come forward as a serious competitor to the alternative assessed as being the most attractive one. Therefore, scoping should be returned to and reconsidered on the basis of the assessment.

5.4. Conflict types. Decision-making under conflict. Guidelines for avoiding complications in conflicts

There exists a special case of connection between alternatives and outcomes which is called decision under conflict. It means that decision is taken by two or more actors, which have different interests. These interests might not be opposite but they coincide. Game theory deals with such decisions.

Behavioral theory, adopted by the social sciences, reminds us that competition which occurs in practice does not take into account only systematic and logical decisions about wins and losses. The behavioral perspective examines which attitude an administrator or a business assumes when faced with a given situation [46, pp. 323–326]. It is a way of explaining how the decision alternatives were selected to formulate the strategy. It also works to minimize the influence of the subjective determination of the qualitative and quantitative values for the parameters involved.

In general, strategic decision-making is a procedure for making decisions working against some competitor or against the state of nature. The states of nature or the scenarios that can occur involve risk or uncertainties with regard to market behavior, climatic influences, available capital, etc. A company should have knowledge about the possible scenarios and the risks built into these scenarios and choose a decision alternative.

A competitive situation, or one of conflict, occurs when the result of a decision is influenced by decisions made by other participants. Game theory, formulated by Von Neumann and Morgenstern, analyzes decisions made where conflict exists [46, pp. 323–326]. Game theory examines actions and reactions to the existing alternatives in order to analyze and plan a

competitive strategy. It allows the administrator to analyze the systematic mode of wins and losses resulting from a given action, as well as the possible wins and losses of the competitor.

Conflict occurs when two or more distinct alternatives, selected as the means for achieving stated objectives, are mutually exclusive. A conflict can be characterized as being induced by the mutual exclusivity of distinct alternatives selected by decision agents. A conflict is definitely not the absence of a prominent alternative. Such a prominent alternative is a tradeoffs-free solution (or as close to tradeoffs-free as possible).

Conflict situations appear in the choice of alternatives using contradictory criteria, objectives or decision-makers (decision-makers may have conflict points of view because of different criteria, objectives or values of objectives). Even though they have a common objective and there are no cognitive differences, no mistakes or insufficient communication, there might be a conflict [17, pp. 256–262].

Conflict situation implies boundary (rigid or ill-defined) that represents a region of compromise, a bargaining set. Observe that no compromise solution, including both extremes, removes or resolves the underlying conflict. Conflict resolution via compromise is only a temporary disguise of the absence of an alternative that fits all (decision agents or criteria). At any compromise located on the heavy boundary of the bargaining set there is at least one decision agent (or at least one objective) which remains unsatisfied in relation to what is actually achievable.

The only way to dissolve conflict is to consider, find or create an alternative that fits all ('ideal alternative'). The only way to reduce the intensity of conflict is to generate alternatives that are 'closer' to the 'ideal alternative'. If one cannot achieve the 'ideal alternative', one should at least attempt to move as close to it as possible, as in compromise programming. The unattainable ideal should not serve as an excuse for trying to achieve what is simply given. Ignoring the ideal and settling down to what is 'good enough', like in Simon's satisficing, does not remove the conflict and it is incompatible with good management. It is not good enough [17, pp. 256–262].

The original Compromise Programming (CP method) is designed to minimize distances of the criteria evaluation vectors of feasible alternatives from the ideal point. If one cannot have the best solution, one should aim for at least the second best [17, pp. 256–262]. CP first calculates a combined n-dimensional distance for each feasible alternative. The normalized

differences between every component of the ideal point and the evaluation of an alternative with respect to the criterion are calculated. Normalized difference means that the resulting value is in the range [0, 1]. The alternative with the smallest combined distance is the best proxy for the ideal one.

One can modify the CP method by maximizing the distance from the worst point (nadir). The structure of the CP remains the same, but instead of minimizing the distance from the zenith one maximizes the distance from the nadir. The pull towards the ideal is of course preferable to the push from the nadir because the zenith approach pulls towards tradeoffs-free alternative (worthy of making feasible) while the nadir approach pushes towards tradeoffs-based alternatives (feasible already) [17, pp. 256–262]. So we are moving to minimizing the maximum regret. In all such cases, inferior, tradeoffs-based solutions are computed and recommended in the end even though designing towards feasibility of tradeoffs-free options is always preferred by the customer.

As a result of the financial and economic crisis there will be significant paradigmatic changes in the way businesses are being run, value created and decisions made. The tradeoffs-based solution concepts of win-lose type will be replaced by the tradeoffs-free concepts of the win-win type. We cannot afford gaining only what somebody else has lost. Instead of choosing the 'best' among bad tradeoffs-based alternatives, we have to learn how to design the best systems in order to deliver the tradeoffs-free alternatives that consumers want and economies need [17, pp. 256–262]. Correspondingly, the field of conflict management and its multiobjective optimization have to shift from merely optimizing the given to designing the optimal.

Questions

1. What important human behavior features should be taken into account during the decision-making process?
2. How may uncertainty be reduced?
3. What is the risk? How does it influence the decision-making process?
4. What risk assessment methods do you know?
5. What impact does decision-making under conflict have on decision-making in general?

Theme 6. Group decision-making and group decision support systems

- 6.1. The term of group decision-making.
- 6.2. Group decision support methods.
- 6.3. Expert values processing.
- 6.4. Voting rules. Group deficiencies.
- 6.5. Group decision support systems.

References: [2; 8; 17; 27; 46; 51].

6.1. The term of group decision-making

In organisations many decisions are made by groups of people, not individuals. If handled in the right way, a decision made by a group can evoke greater commitment than one made by an individual because more people feel the sense of involvement in it. On the other hand, group decisions usually consume more time (and more money) than individual ones, so they need to justify extra costs. In fact it is not possible to generalise about whether individuals or groups are universally better. It depends on the abilities and training of the individuals and groups, and also on the kind of task being tackled. Main decision-making tasks that groups can face are [2, pp. 435–445]: generating plans; generating ideas; solving problems with correct answers; deciding issues with no identifiably correct answer at the time the decision is being made.

Psychologists have conducted a number of experiments comparing individual and group performance on problems with correct answers. For example, Vollrath found that groups recognised and recalled information better than individuals [2, pp. 435–445]. However, McGrath pointed out that the extent to which the correct answer can be shown to be correct varies. On the one hand, there are ‘Eureka’ tasks – when the correct answer is mentioned, everyone suddenly sees that it must be right. There are also problems where the answer can be proved correct with logic, even though its correctness is not necessarily obvious at the first sight. Then there are problems where the correct (or best) answer can only be defined by experts, whose wisdom may be challenged by a layperson.

Some early research dealing with problems of this kind produced several important findings [2, pp. 435–445]. Firstly, lower-status group members had less influence on the group decision than higher-status ones,

even when they (the lower-status people) were correct. Secondly, even where at least one person in the group knew the correct answer, the group decision was by no means always correct. Thirdly, group discussion made people more confident that their consensus decision was correct, but unfortunately the discussion did not in fact make the correct decision more likely! For solving problems with correct answers, groups are on average better than individuals, but inferior to the best individuals. For problems with demonstrably correct answers, groups are on average as good as their second-best member. However, groups can do better or worse than this average depending on their membership and process. Many decisions in organisations do not have a provable correct answer, or even an answer that experts can agree on. Also, even if groups typically do badly, they can be improved.

6.2. Group decision support methods

Involving lots of people in the decision-making process provides a greater basis of experience, knowledge, and creative insights. It is intuitively reasonable that the chances of overlooking possible events and possible courses of actions are diminished in group decision-making. The synergy of individuals may make the overall quality of the group decisions greater than the sum of parts [46, p. 327–331]. However, if the opinion and values of individuals differ, how should the differences be resolved? Difference of opinion may inhibit the expression of critical ideas, resulting in an incomplete survey of alternative action courses or choices. Techniques to enhance a group's creative potential and interaction such as Delphi, SODA (strategic options development and analysis), and even the brainstorming process are widely used.

The main difference of a group activity from an individual activity is the opportunity for interaction among the group members, which enriches the discussion and the analysis of the problem and provides a more objective choice of alternatives to resolve the problem. Some of the well-known group-decision methods are [46, p. 327–331]: brainstorming, Q-sort method, Delphi method, NGT – nominal group technique, SODA – strategic options development and analysis, and GDSS – electronic meetings via video conferencing and e-mail using work flow systems.

Brainstorming is a meeting held to extend the discussion of a given problem stimulating creativity and discovery of new solutions or new directions to the problem. The informal type of discussion helps greater participation of the group members but good control of the discussion as well as documentation of important facts and results are essential.

Q-SORT is a group decision process where each participant structures the decision problem, sorting a set of declarations according to his or her preference. Each participant receives a set of cards containing the declarations about the problem [46, p. 327–331]. A scaling measure is used to guide the sorting process of the declarations. The main advantage of this procedure is that it can be repeated many times using different sorting criteria for the problem.

Delphi is known as a methodology useful to generate, clarify, structure, and organize a set of ideas. The methodology collects and evaluates information or expert's opinion with respect to the main subject. It is not allowed for persons of the group to maintain communication among them. A supervisory team selects a group of 30 to 100 experts giving to each expert a questionnaire based on the most significant answers received, the supervisory team prepares a new questionnaire to be distributed among the same or a new group of experts [46, p. 327–331]. The process continues until the supervisory team evaluates that a significant and structured set of answers has been received to solve the problem. A final report must contain: the purpose of the decision, all the intermediate results, and the final decision based on individual votes aggregation. The final report should be discussed and approved by a representative committee formed by members of respondent groups. For purposes of feedback and closure, participants should be given a copy of the final report.

Nominal group technique is a technique similar to Delphi, used for more complex problems to be solved by a small group of persons through face-to-face contact. NGT can usually be done much quicker than Delphi. Steps to conduct this technique are the follows [46, p. 327–331]. The leader gives each participant (5 to 9 persons) a written copy of the question or problem being considered. Participants write their own idea or answers to the question or problem presented. The results of group thinking are recorded on a flip chart to avoid duplication. The leader may merge similar ideas forming a new idea, with the agreement of the group. Each idea written on the flip chart is sequentially presented and discussed. Preliminary vote of item importance is

requested. Individual judgements of each idea are expressed by a numerical ranking system and an average value of the group preference for each idea will be defined. This average value serves to express the mathematical evidence of the increase or decrease in the group's preference. New discussions and new voting are permitted. Then the final vote is conducted.

Strategic options development and analysis (SODA) is a methodology oriented to structure a complex problem with the support of a reduced number of persons [46, p. 327–331]. The basic tools used are: the cognitive map that helps to identify the objectives of the problem, the key ideas that direct the decision process, and the actions to be taken to solve the problem. An interactive software called COPE (cognitive policy evaluation) is used to give support to the decision process.

6.3. Expert values processing

In group decision-making there are two main issues in values processing. The first is how to aggregate individual judgements, and the second is how to construct the group choice from individual choices [46]. In reality group decisions should not go by consensus because not all people feel the same about things. The minority can have very strong commitments to a cause and can give rise to disruptions that the majority feels lukewarm about. There is no hiding from this issue in the real world. The reciprocal property plays an important role in combining the judgements of several individuals to obtain a judgement for the group. Judgements must be combined so that the reciprocal of the synthesized judgements must be equal to the syntheses of the reciprocals of these judgements.

It has been proved that the geometric mean is the unique way to do that. If the individuals are experts, they may not wish to combine their judgements but only their final outcome from a hierarchy. In that case one takes the geometric mean of the final outcomes. If the individuals have different priorities of importance their judgements (final outcomes) are raised to the power of their priorities and then the geometric mean is formed.

The construction of group choice from individual choices. Given a group of individuals, a set of alternatives (with cardinality greater than 2), and individual ordinal preferences for the alternatives, Arrow proved with his Impossibility Theorem that it is impossible to derive a rational group choice (construct a social choice function that aggregates individual preferences)

from ordinal preferences of the individuals that satisfy the following four conditions, i.e., at least one of them is violated [17, pp. 160–193]:

1. Decisiveness: the aggregation procedure must generally produce a group order.

2. Unanimity: if all individuals prefer alternative A to alternative B, then the aggregation procedure must produce a group order indicating that the group prefers A to B.

3. Independence of irrelevant alternatives: given two sets of alternatives which both include A and B, if all individuals prefer A to B in both sets, then the aggregation procedure must produce a group order indicating that the group, given any of the two sets of alternatives, prefers A to B.

4. No dictator: no single individual preferences determine the group order.

Using the absolute scale approach of the analytic hierarchical process, it can be shown that due to the fact that now the individual preferences are cardinal rather than ordinal, it is possible to derive a rational group choice satisfying the above four conditions. It is possible because: a) individual priority scales can always be derived from a set of pairwise cardinal preference judgements as long as they form at least a minimal spanning tree in the completely connected graph of the elements being compared; and b) the cardinal preference judgements associated with the group choice belong to an absolute scale that represents the relative intensity of group preferences.

6.4. Voting rules. Group deficiencies

Sequential pairwise voting and the paradox of voting. The Marquis de Condorcet proposed a method of election by making all pairwise choices between alternatives. Condorcet proposed that the alternative that obtains the majority against each other alternative by pairwise vote should be the social choice. The alternative (if any) that defeats all the other alternatives by pairwise voting is called the Condorcet winner [8].

Sequential pairwise voting is the procedure followed by many decision-making groups such as parliaments, senates, or faculty meetings. But Condorcet also presented several theorems on the possibility of agenda manipulation. An individual or subgroup that controls the meeting agenda may be able to achieve a favored decision by arranging the agenda so that

an alternative that could defeat the favored alternative will be defeated by some other alternative in an earlier pairwise vote.

Runoff elections. A runoff election has two stages. At the first stage each voter has one vote for any of three or more candidates. If a candidate has a majority of these votes, the candidate is elected. If no candidate has the majority, all candidates except the two receiving the highest number of votes are eliminated. A second runoff election is then conducted between the two candidates who received the most votes.

Rank order voting. Jean-Charles de Borda proposed a rival method of election [8]. Each voter rank orders each candidate from the most to least favored. For each voter the highest-ranked candidate (alternative) receives $n-1$ points, the second-highest $n-2$ points, the third-highest $n-3$ points, and so forth, to the lowest-ranked alternative, which receives 0 points. The points for each alternative are then summed across voters, and the alternative with the highest sum is the decision.

Approval voting. In contrast to majority/plurality voting systems that consider only voter-first preferences, the Borda count considers ranking of all alternatives. Approval voting is a more recent system that may also incorporate more than first preferences. In approval voting, each voter may give one vote to as many alternatives as desired. The alternative with the most votes is selected.

The median voter theorem. In a famous theorem Black proved that if the committee member preference orders can be ordered on one dimension on the horizontal axis (say, allocation of money) and are single-peaked (rising to a point and then falling), then the median notion (alternative) can defeat all other alternatives by pairwise votes [8]. Moreover, Black demonstrated that sequential pairwise voting between adjacent alternatives (1 vs. 2, 2 vs. 3, 3 vs. 4, and so on) rather than all pairwise votes will have the same effect. Black further considered majority voting if the collective preference order is not single-peaked, decisions under special (higher-order) majorities, and changing orders of majorities (for example, passage of legislation by a simple majority but overrule of a veto by a two-thirds majority).

Condorcet jury theorem. Although best remembered for pairwise voting between alternatives, Condorcet also attempted to develop a probabilistic theory of group decision-making. In this endeavor he proposed what Black later called the Condorcet jury theorem. It entails three assumptions [8]:

1. Voters are expressing their considered judgements on whether a claim is true or false (rather than simply voting for what is in their interests).
2. Each voter forms his or her judgement independently from the others.
3. Each voter is on the average right more often than wrong, even if only by a small margin.

In summary, Condorcet's method of voting by pairwise comparisons led to discovery of the 'paradox of voting', in which the order of pairwise decisions determine the outcome of decisions for nontransitive collective preference orders. Black both rediscovered Condorcet's forgotten work on the paradox of voting and considered other possibilities of agenda influence with sequential pairwise decisions. Experimental research on agenda effects supports Black's analysis by demonstrating that the composition and order of successive group decisions may determine the outcome of the decision.

A logical extension of the Condorcet jury theorem is the effect of successive majorities in a hierarchical structure, where successive majority decisions, with the majority winner going on to the next level, will exaggerate original preference distribution.

Group deficiencies and overcoming them. Some social scientists identified the context within which groups can perform well and pointed out necessities such as having group members who are knowledgeable about the problem faced, having a clearly defined and inspiring goal, having group members who are committed to solving the problem optimally, and support and recognition from important people outside the group [2, pp. 435–445].

Social psychologists have noted many features of the group decision-making process that can impair decision quality. Hoffman and Maier noted a tendency to adopt 'minimally acceptable solutions', especially where the decision task is complex. Instead of seeking the best possible solution, group members often settle on the first suggested solution that everyone considers 'good enough'. In certain circumstances this might be an advantage, but on most occasions it is probably not a good idea. Hackman pointed out that groups rarely discuss what strategy they should adopt in tackling a decision-making task (i.e. how they should go about it), but that when they do, they tend to perform better.

Motivational losses in groups can also be a problem. Experimental research has repeatedly shown that as the number of people increases, the effort and/or performance of each one often decreases – the so-called social loafing effect (e.g. Latane). On the other hand, this motivational loss can be

avoided if individuals in the group feel that their contribution can be identified, and that their contribution makes a significant difference to the group's performance (Williams, Kerr, Bruun) [2, pp. 435–445]. Hence the group leader would be well advised to ensure that each group member can see the connection between individual efforts and group performance both for themselves and other group members.

Interestingly, there is some evidence that social loafing does not occur in collectivist societies. In collective societies, one's sense of responsibility shared with others (in contrast with individualistic Western cultures) is perhaps the source of this difference. More than that, Erez and Somech found that subcultural differences in individualism-collectivism even within one country made a difference to the social loafing effect. But even then, groups in an individualistic subculture showed social loafing only when they lacked specific goals. As Erez and Somech pointed out, most groups in the workplace have members who know each other, who communicate, have team goals that matter to them, and whose individual performance can be identified. So social loafing may be the exception, not the rule, in the real world, even in individualistic cultures.

Group members tend to reduce their efforts as group size increases, at least in individualistic cultures. This problem can, however, be overcome. It seems that groups may be even more likely than individuals to escalate their commitment to a decision even if it does not seem to be working out well. This can occur even if the majority of group members start off with the opinion that they will not invest any further resources in the decision [2, pp. 435–445]. The essentially risky decision of the group may be even more marked if it is framed in terms of avoiding losses rather than achieving gains. As most people are more inclined to accept the risk of a big loss in the hope of avoiding a moderate loss than they are to risk losing a moderate profit in pursuit of a big profit.

Groupthink. Janis arrived at some disturbing conclusions about how some real-life policy-making groups can make extremely poor decisions that have serious repercussions around the world. He suggested that in fiascos, various group processes could be seen, which he collectively called groupthink. According to Janis, groupthink occurs when group members' motivation for unanimity and agreement over-rides their motivation to evaluate carefully the risks and benefits of alternative decisions [2, pp. 435–445]. This usually occurs in 'cohesive' groups – i.e. those where

group members are friendly with each other, and respect each other's opinions. In some groups of this kind disagreement is construed (usually unconsciously) as a withdrawal of friendship and respect. When this is combined with a group leader known (or believed) to have a position on the issues under discussion, absence of clear group procedures, a difficult set of circumstances, and certain other factors, the group members tend to seek agreement. This leads to the symptoms of groupthink, which can be summarised as follows [2, pp. 435–445]:

1. Overestimation of the group's power and morality (after all, group members have positive opinions of each other).

2. Closed-mindedness (including efforts to downplay warnings and stereotype other groups as inferior).

3. Pressures towards uniformity (including suppression of private doubts, leading to the illusion of unanimity and 'mindguards' to shield group members (especially the leader) from uncomfortable information).

Groupthink is a set of group malfunctions that occurs when group members are more concerned (although they may not realise it) to achieve unanimity and agreement than to find the best available solution to a problem or situation.

Janis argued that certain measures could be taken to avoid groupthink. These include [2, pp. 435–445]:

- 1) impartial leadership (so that group members are not tempted simply to 'follow the leader');

- 2) each person in the group should be told to give high priority to airing doubts and objections;

- 3) experts should be in attendance to raise doubts;

- 4) 'second chance' meetings should be held where members express their doubts about a previously made but not yet implemented decision.

One might add the necessity of fostering a group norm that disagreeing with another group member does not signal disrespect or unfriendliness towards him or her. It is possible for groups to use formal procedures to combat groupthink, even though these may be tiresome and time-consuming.

Some research has found that group cohesiveness actually helps open discussion of ideas, rather than inhibiting it [2, pp. 435–445]. In fact, the relationship between group cohesiveness and group performance is that cohesiveness was on average a significant (though not large) aid to performance, especially when groups were small. They also found that

successful group performance tended to foster cohesiveness more than cohesiveness fostered performance. This is not surprising. If we think of cohesiveness as a combination of interpersonal attraction, commitment to the task and group pride, we would expect all of these to increase when the group succeeds in its tasks.

Schulz-Hardt found that groups of managers who had similar points of view even before they met, tended to seek yet more information that supported their existing view. Genuine disagreement in initial points of view led to a much more balanced information search [2, pp. 435–445]. The presence of people instructed to be a ‘devil's advocate’ (i.e. to argue the opposite view of the group's preference whatever their own private opinion) also had some limited effect in reducing a group preference for information agreeing with their initial opinions. These findings support ideas that groups where the members agree are prone to restricting their information search and that appointing a ‘devil's advocate’ may go some way towards correcting that. All of the criticisms of groupthink have some force, the groupthink model appears not to be entirely accurate, but it includes many ideas that have had a big impact on research on groups and teams.

Group polarisation. One often-voiced criticism of groups is that they arrive at compromise decisions. But in fact this is often not so. Instead, it seems that groups tend to make more extreme decisions than the initial preferences of group members. This has most often been demonstrated with respect to risk. If the initial tendency of the majority of group members is to adopt a moderately risky decision, the eventual group decision is usually more risky than that. Conversely, somewhat cautious initial preferences of group members translate to even more cautious eventual group decisions.

The social comparison explanation is that we like to present ourselves in a socially desirable way, so we try to be like other group members, only more so. The persuasive argumentation explanation is that information consistent with the views held by the majority will dominate the discussion, and (as long as that information is correct and novel) have persuasive effects [2, pp. 435–445]. Both explanations are valid, though the latter seems to be stronger. While polarisation is not in itself inherently good or bad, group members clearly need to ensure that they air all relevant information and ideas so that arguments rejecting the initially favoured point of view are heard. They also need to avoid social conformity, using a quantitative decision aid can reduce the impact of overly biased persuasive arguments on group members, albeit only slightly.

Contrary to popular opinion, groups often produce more extreme decisions, and fewer compromises, than individuals.

Minority influence. Minorities within groups only rarely convert the majority to their point of view. But how can they maximise their chances? Many people say that they should gain acceptance of the majority by conforming wherever possible, and then stick out for their own point of view on a carefully chosen crucial issue. Moscovici and colleagues argued otherwise (Moscovici, Mugny) [2, pp. 435–445]. They found that, if it is to exert influence, a minority needs to disagree consistently with the majority, including on issues other than the one at stake. Minorities do not exert influence by being liked or being seen as reasonable, but by being perceived as consistent, independent and confident. Consistent with this, Van Hiel and Mervielde found that group members believe that being assertive and consistent is an effective strategy for minorities, while being agreeable is better for majorities than for minorities. This has connections with the previous section concerning group polarisation. A minority that demonstrates these characteristics will tend to express many arguments that oppose the majority point of view, thereby limiting the extent of group polarisation.

Much debate has centered on why and how minorities in groups exert influence. The predominant view is that minorities and majorities exert influence in different ways. Nemeth concluded from experimental data that: those exposed to minority viewpoints are more original, they use a greater variety of strategies, they detect novel solutions, and importantly, they detect correct solutions. Furthermore, this beneficial effect occurs even when the minority viewpoints are wrong [2, pp. 435–445]. This emphasises again that groups need to encourage different points of view, not suppress them. Minority views may be tiresome, but their expression typically leads to better group functioning, even if they are incorrect.

Wood found that minorities do indeed have some capacity to change the opinions of people who hear their message. This effect is stronger if recipients of the message are not required to publicly acknowledge their change of opinion to the minority. Opinion change is also much greater on issues indirectly related to the message than on those directly related to it. Indeed, although the opinion of the majority usually has more effect than that of the minority, this seems not to be the case on issues only indirectly related to the message. Ng and Van Dyne have found in an experimental study with students, that group members who (i) value collectivist beliefs (i.e. act

according to social norms and stressing interpersonal harmony) and (ii) do not value individualist beliefs (i.e. focus on personal goals and perspectives) are less influenced than others by minority views [2, pp. 435–445]. This tends to impair their decision-making. Ng and Van Dyne also found that when a one-person minority happens to be the leader of the group, he or she has more influence than when the one-person minority is not the leader.

6.5. Group decision support systems

Group decision support system (or GDSS) is a system whose design, structure, and utilization reflect the manner in which members of a group interact to choose an alternative of decision [46, p. 331–332]. The system should have technological support for communication, file sharing, modelling group activities, aggregating individual perspectives to form a group perspective, and other facilities that permit interaction within the group. The GDSS can encompass all the sectors of an organization or only certain activity sectors, with the possibility of expanding participation of individuals according to the functional level of the sectors involved. The GDSS is programmed to accept appropriate input data, to analyze the objectives (such as productivity, profitability, etc.) and to provide solutions to the selected problems, generating the appropriate reports.

GDSS may be concerned with the problem of communication media richness. Media richness is defined as the potential information-carrying capacity of a data-transmission medium. Different types of media, differing in their richness, may be appropriate for different types of tasks. For instance, face-to-face contact is the highest ranked medium in richness, followed by video conference, audio conference, real-time electronic chat, and finally, electronic mail. Electronic mail is ranked as the medium with lowest richness. The following three general types of GDSS have been distinguished [46, p. 331–332]:

1. Communication management system: provides communication flows by means of facilities to store and exchange messages. Common examples of this type of system are the electronic mail packages.

2. Content management systems: provide automatic routing of messages according to the contents in a standardized way.

3. Process management systems: provide important aid in both individual and group decision-making process controlling: the pattern,

contents, timing, and flow of the information exchange. Control of pattern and contents of the message can be made by forms represented by different types of documents. Control of timing and flow can be made by a script that defines the routing of the form. A Work Flow system, considered as 'intelligent electronic mail' is an example of this type of GDSS.

These different types of GDSS can be used to manage differences in opinion, focus on the goal of the strategic decision, control the time factor, lead to objective analysis and judgements.

Questions

1. What is group decision-making? How does it differ from individual decision-making?
2. What group decision support methods do you know?
3. What voting rules do you know?
4. What are group deficiencies? Mention them.
5. What is group DSS? Mention the main distinctions of group DSSs.

Theme 7. Decision support with spreadsheets

- 7.1. DSS components in spreadsheets.
- 7.2. Models of decision support subsystem.
- 7.3. 'What-if' analysis MS Excel toolkit: scenario, data tables, etc.
- 7.4. Data tables usage for sensitivity analysis.
- 7.5. Functional DSS creation with spreadsheets.
- 7.6. Optimization models usage in DSS.

References: [3; 4; 7; 32].

7.1. DSS components in spreadsheets

Spreadsheets are software applications that organize data into worksheets: free-format, table-like structures with rows and columns. The data are captured into intersections of rows and columns, known as cells. Not only can data be captured, but they can also be processed for further analysis. This is facilitated in that cells can be derivatives of other cells. For example, one cell can provide the total of a set of numbers in other cells. In further data processing of this kind, spreadsheets are incredibly versatile [32, p. 7].

One type of bounded DSS-generator is spreadsheet. As an example we will work with MS Excel. This application should have been studied already, so we will look through all its possible functions as a bounded DSS-generator and will stop only before difficult passages.

Usually, spreadsheets support the following types of analysis:

- 1) 'what-if' analysis;
- 2) sensitivity analysis;
- 3) optimization analysis;
- 4) 'how-can' analysis;
- 5) correlation-regression analysis;
- 6) time series forecasting.

The de-normalized tables are typically very large, and they contain a large number of columns and a large number of rows. In order to make sense of the data, we would typically reduce the table to something that is more meaningful to grasp. This is called table manipulation, and the ways that we manipulate these tables also have some terminology associated with them. The first manipulation on these tables is to select only a subset of rows. The term which is used for selecting a subset of rows in a multidimensional table is called slicing. We 'slice' the table by removing a number of rows that, for one reason or another, do not interest us. The second manipulation on these tables is to select only a subset of columns (dimensions). This is called dicing. We 'dice' the table by removing the columns that, for one reason or another, do not interest us [32, p. 65].

The third and fourth type of manipulation on these tables deal with the aggregation itself. We can 'collapse' a number of rows by replacing them with one row, and have appropriate aggregate values to 'represent' the underlying individual values [32, p. 66].

This process of collapsing data into aggregate values is known as rolling up data. The opposite of rolling up is drilling down. Here, you 'expand' an aggregated value into its underlying transactional values [32, p. 67].

7.2. Models of decision support subsystem

Several decision rules can be used to help a decision-maker choose the best alternative. None of these decision rules works best in all situations and each has some weaknesses. However, these rules help to enhance insight and sharpen intuition about decision problems so that one can make more informed decisions [32].

The decision rules can be divided into two categories: those that assume that probabilities of occurrence can be assigned to the states of nature in a decision problem (probabilistic methods), and those that do not (nonprobabilistic methods). Let's discuss the nonprobabilistic methods first.

Thus, if the decision-maker optimistically believes that nature will always be 'on its side' regardless of the decision it makes, he or she should choose an alternative which leads to the largest possible payoff. This type of reasoning is reflected in the maximax decision rule, which determines the maximum payoff for each alternative and then selects the alternative associated with the largest payoff [32].

A more conservative approach to decision-making is given by the maximin decision rule, which pessimistically assumes that nature will always be 'against us' regardless of the decision we make. This decision rule can be used to hedge against the worst possible outcome of a decision. To apply the maximin decision rule, we first determine the minimum possible payoff for each alternative and then select the alternative with the largest minimum payoff (or the maximum of the minimum payoffs – hence the term 'maximin').

Another way of approaching decision problems involves the concept of regret, or opportunity loss. To use the minimax regret decision rule, we first must convert our payoff matrix into a regret matrix that summarizes the possible opportunity losses that could result from each decision alternative under each state of nature [32]. The minimax regret decision corresponds to the alternative with the smallest (or minimum) maximum regret.

Probabilistic decision rules can be used if the states of nature in a decision problem can be assigned probabilities that represent their likelihood of occurrence. For decision problems that occur more than once, it is often possible to estimate these probabilities from historical data. However, many decision problems represent one-time decisions for which historical data for estimating probabilities are unlikely to exist. In these cases, probabilities are often assigned subjectively based on interviews with one or more domain experts [32]. Highly structured interviewing techniques exist to solicit probability estimates that are reasonably accurate and free of the unconscious biases that might affect an expert's opinion.

The expected monetary value decision rule (Bayes criterion) selects the decision alternative with the largest expected monetary value (EMV) [32]. The probabilities for each state of nature are multiplied by payoffs from each alternative respectively. Using these probabilities, the EMV for each decision

alternative is calculated. The largest EMV is associated with the decision to choose.

We can also use the probability of the states of nature to compute the expected regret, or expected opportunity loss (EOL), for each alternative in a decision problem. The calculations are identical to those used in computing the EMVs, but in this case we substitute regret values (or opportunity losses) for the payoffs. The decision with the smallest EOL will also have the largest EMV. Thus, the EMV and EOL decision rules always result in the selection of the same decision alternative.

7.3. 'What-if' analysis MS Excel toolkit: scenario, data tables, etc.

Stress testing is an approach to risk measurement that attempts to grapple with the difficulties of modelling returns statistically. It posits the size of shocks directly, or with a 'light' modelling apparatus. It is also sometimes called scenario analysis, since it asks the question, 'what happens to our firm (or portfolio) if the following asset price changes take place'. In spite – or because – of its light modelling infrastructure, scenario analysis has become a very widespread approach to risk measurement. While only indirectly related to internal risk management by banks, an important example was the supervisory scenario analysis procedure carried out in the United States in early 2009 and in Europe in mid-2010 [38, pp. 499–501]. The U.S. exercise, repeated and to be conducted regularly thereafter, helped authorities determine which banks would be obliged to raise additional equity capital or prevented from paying out dividends.

In a scenario analysis, we compute the losses resulting from sharp adverse price moves, or from an adverse macroeconomic scenario. The challenge of stress testing is to design scenarios that are extreme enough to constitute a fair test of severe potential loss, but are still plausible and could realistically take place. One can distinguish two schools of thought on scenario analysis by the extent to which macroeconomic design, as opposed to statistical analysis of risk-factor behavior, enters into scenario design.

Another purpose of scenario analysis is to examine scenarios in which market prices behave in a way unlikely in the classical normal-return model. To a large extent, increasing reliance on stress testing is a response to the many drawbacks of the market and credit risk modelling approaches [38, pp. 499–501]. One possible response to the drawbacks of the standard

statistical models is to develop better statistical models or techniques, and much valuable discussion has explored potential advantages of, say, extreme value theory (EVT) techniques, or the use of implied volatility data. However, these discussions have not led to a definitive and widely shared conclusion about a superior alternative to the standard model. Rather than relying entirely on the results of a model to obtain a 'likely worst case', stress testing skirts the modelling issues by placing the scenario itself, rather than the model, in the forefront.

Scenario analysis has also become more important over time because it is easier to communicate stress test results than model results to most audiences. Most investors and financial firm executives do not have specialized training in statistical modelling. It is remarkable that VaR, a fairly sophisticated risk measure involving quantiles and distributional hypotheses, as well as a good understanding of its limitations, has extended as far into mainstream financial discussion as they have [38, pp. 499–501]. Even if better statistical models could provide the solution to the limitations of the normal distribution, it is unlikely that the necessary fluency in the statistical issues would keep up. To be useful, and to have impact on decision-making, risk measures have to be understandable. It is, therefore, appropriate to develop risk measures that can be understood and acted on without extensive quantitative training. Stress testing does not need to stand in opposition to statistical modelling. As noted, some approaches to stress testing build on the results of return models.

Depending on one's view of the standard models, scenario analysis can be considered a supplement or a substitute for the joint normal distribution and other non-normal model-based approaches. We may use historical data, or human judgement, or both, to create likely worst-case scenarios.

There are different purposes of stress tests. On the one hand, stress tests are designed for ensuring a firm's capital adequacy and survival through a crisis [38, pp. 504–506]. Therefore, both risk appetite and economic analysis have important roles to play in determining stress scenarios. On the other hand, they are designed to take account of alternative return distribution and volatility models to the normal.

Scenario analysis must be formulated with a specific discrete time horizon, that is, the return scenario is posited to take place, say, over one day or one month. Unless the stress test horizon is extremely short, we need specific assumptions about what trading of positions and hedging, and at

what prices, will take place within the stress test horizon [38, pp. 504–506]. Some trading assumptions, such as ongoing delta hedging of option positions, are perhaps reasonable accommodations to dynamic strategies. Permitting other positions to change so as to protect against loss within a stress scenario raises the possibility that the stress test results will understate losses, since the point of a stress test is to explore potential losses given the current portfolio or book of business. More importantly, the deterioration of market and funding liquidity, and impairment of market functioning are also likely to limit the amount of trading that can be done in stress conditions. Stress scenarios should, therefore, take current positions for the most part as unalterable.

Stress tests have been classified into several types. Historical stress tests apply shocks that have actually been realized in a historical crisis to the portfolio. Several ambiguities need to be resolved in carrying out a historical stress test. The stress loss for a portfolio will be greater if the worst losses are bundled together as an instantaneous mark-to-market than if a particular historical interval is chosen [38, pp. 504–506]. Historical stress tests are important and valuable as a point of reference, but history never repeats itself. An alternative approach is based on possible future events though it may be informed by history. Most stress tests in practice are of this type. But if history is no longer a rigid guide, how do we design the scenarios? One important principle is to identify portfolio vulnerabilities and see to it that they are properly stressed. VaR analysis can be a useful complement to stress testing, as it has a capacity to identify subtle vulnerabilities in a complex portfolio that are not obvious when looking at line-item positions. Discussion with traders is also important in identifying potential stresses.

Other approaches to scenario analysis are less dependent on judgement and rely more on algorithms for evaluating the portfolio in different scenarios.

Such approaches capture both multiple risk factors interaction in generating losses, such as occurs in option positions, as well as the susceptibility of the specific portfolio to particular combinations of factor returns. In the factor-push approach, many combinations of risk factor returns are tested, and the stress loss is taken as the largest portfolio loss that occurs. The highest and lowest returns for each risk factor are set at some reasonably large potential range, resulting in a grid of shocks. The stress test result is the largest portfolio loss resulting from this grid of stresses. A class

of tools for limiting the range of risk factor combinations using distributional assumptions is called the maximum loss approach.

In many cases, we are interested in shocking only some risk factors in a portfolio [38, pp. 504–506]. This raises the issue of how to treat the remaining risk factors. One approach is to use their last-observed values, that is, set their returns to zero, in computing portfolio losses in the stress scenario. This may lead to unrealistic scenarios. Another approach, sometimes called predictive stress testing, is to use their conditional expected values. The expected values are conditioned on the values taken by the stressed risk factors, using the estimated correlation matrix of all the risk factors. This in turn raises a final issue in the treatment of the risk factor correlations; correlations between many risk factor returns are higher during periods of financial stress.

In spite of its difficulties, stress testing has taken on great importance relative to VaR in recent years. At one point, stress testing was discussed as a complement to VaR and in the context of VaR modelling, but the emphasis has now shifted, and the results of VaR analysis are now apt to be reported as a stress scenario among others. Stress testing should be carried out regularly, as a regular part of the risk reporting cycle. The scenario design should be varied as portfolio concentrations and market conditions evolve.

7.4. Data tables usage for sensitivity analysis

A sensitivity analysis simulates the changes that can occur in key performance indicators (KPI) if certain base data change. A KPI is often derived from base data [32, pp. 113–115]. To calculate a KPI thus requires a number of input values. If these input values change, then so does the KPI value. For example, aggregated sales revenue is dependent on the number of sales orders that sales organization manages to secure. A sensitivity analysis would display the effect of these changes on the value of the KPI. This type of sensitivity analysis is also commonly known as 'what-if' analysis.

It is common to think of the technique as 'tinkering' with input to examine the effect on output. But the analysis can also work the other way around: you can fix the value of the output and see what kind of input values you would need to arrive at that particular output. This type of analysis, where you manipulate the goal output to see how the input should change, is often called 'goal-seeking' analysis.

Sensitivity analysis is well-developed in the field of mathematical programming, which studies problems where an optimal decision is calculated given certain input parameters. Although researchers have put substantial effort into the mathematics of sensitivity analyses, research into the visualization of these analyses has not been as forthcoming. It appears to be difficult to convey a picture of sensitivity analysis [32, pp. 113–115]. The only chart that captures sensitivity analysis graphically is the so-called tornado chart.

The tornado chart represents sensitivity in the main value for input parameters. The horizontal axis represents the change in KPI if the value of each of these input parameters vary.

The sensitivity analysis for this tornado chart uses three values for every input parameter: a worst-case value, a best-case value, and a base-case value. The bar for each input parameter represents the difference in the KPI ranging from worst-case to best-case [32, pp. 113–115]. Sensitivity is measured as the length of the interval between the worst and the best cases of KPI. A tornado chart sorts the bars according to their sensitivity, that is, the ones that are the most sensitive come on top. The tornado chart overviews the impact of confidence on the eventual outcome of the result.

Tornado charts are not yet supported in the mainstream spreadsheet packages, which is unfortunate because there are very few techniques that visualize sensitivity in performance indicators. The other alternative is dynamic charts, in which one can vary an input parameter with (say) a slider bar, and one can immediately witness the effect on the performance indicator in (say) a bar chart [32, pp. 113–115]. Professional business intelligence packages use dynamic charts for very good effect, and it is worth the effort to spend time studying the options that are available if you have access to such tools.

7.5. Functional DSS creation with spreadsheets

A spreadsheet-based decision support system as a decision support system developed in a spreadsheet environment with the enhancement of a programming language and user interface developer. A decision support system gives its users access to a variety of data sources, modelling techniques, and stored domain knowledge via an easy-to-use GUI [3, pp. 277–297]. A DSS can refer to data residing in the spreadsheets, prepare

a mathematical model using these data, solve it or analyze it using problem-specific methodologies implemented via spreadsheet functions or a programming language, and assist the user in the decision-making process through a graphical user interface.

A decision support system (DSS) is a model- or knowledge-based system intended to support managerial decision-making in semistructured or unstructured situations. It uses data, provides a clear user interface, and can incorporate the decision-maker's own insights. A DSS application contains five components: database, model base, knowledge base, GUI, and user. The database stores data, the model and knowledge bases store collections of models and knowledge, respectively, and the GUI allows the user to interact with the database, model base and knowledge base. The database and knowledge base can be found in a basic information system. The knowledge base may contain simple search results for analyzing the data in database [3, pp. 277–297]. A decision support system is an intelligent information system due to addition of the model base. The model base includes models used to perform optimization, simulation, or other algorithms for advanced calculations and analyses. These models allow the decision support system not only to supply information to the user but aid the user in making a decision.

Spreadsheet software provides all of the components necessary for a DSS. In the database component, spreadsheets can easily store relatively large amounts of data in rows and columns on multiple worksheets. These data can be organized using sorting features or various formats. In the model base component, spreadsheet software can perform calculations using spreadsheet functions or a programming language [3, pp. 277–297]. In the knowledge base component, spreadsheets can again be used to store basic knowledge or a programming language can be used to perform more-advanced knowledge base analysis. In the GUI component, most spreadsheet software offer a variety of GUI options from basic formatting and drawing tools to more advanced GUI features such as user forms and control tools. Thus, a user is able to access and analyze data, perform problem solving, and interact with a GUI through a spreadsheet-based DSS.

Spreadsheets are an excellent option for developing many DSS applications since they are available for almost any operational system and have many features that are relatively easy to learn and can be implemented for a large variety of problems.

With the increasing demand for IT-based systems and quick decision-making, spreadsheet-based DSSs are an important and necessary tool for any industry. Thus, students and professionals should learn the basic process for developing a DSS. Spreadsheets are an attractive environment for developing a DSS as they can be easily found and quickly learned. Once the spreadsheet software and a programming language tools have been learnt, an efficient and user-friendly DSS application can be created for almost any situation.

7.6. Optimization models usage in DSS

Our world is filled with limited resources. Deciding how best to use the limited resources available for an individual or a business is a universal problem. In today's competitive business environment, it is increasingly important to make sure that a company's limited resources are used in the most efficient possible manner. Typically, this involves determining how to allocate resources in such a way as to maximize profits or minimize costs. Mathematical programming is a field of management science that finds the optimal, or most efficient, way of using limited resources to achieve the objectives of an individual or a business. For this reason, mathematical programming is often referred to as optimization [32, p. 17]. Let's consider several examples of decision-making situations in which mathematical programming techniques have been applied.

Determining the product mix. Most manufacturing companies can make a variety of products. However, each product usually requires different amounts of raw materials and labor. Similarly, the amount of profit generated by the products varies. The manager of such a company must decide what amount of each product to produce to maximize profits or to satisfy demand at minimum cost.

Manufacturing. Many operations of producing details are automatized or halfautomatized, so they need to be programmed in the most efficient way.

Routing and logistics. Many retail companies have warehouses around the country that are responsible for keeping stores supplied with merchandise to sell. The amount of merchandise available at the warehouses and the amount needed at each store tends to fluctuate, as does the cost of shipping or delivering merchandise from the warehouses to the retail locations. Large amounts of money can be saved by determining the least costly method of transferring merchandise from the warehouses to the stores.

Financial planning. There are various rules that must be followed to avoid paying penalty taxes on retirement withdrawals. Most individuals want to withdraw their money in a manner that minimizes the amount of taxes they must pay while still obeying the tax laws [32, pp. 17–18].

Optimization tasks consist of:

1. Goal/objective (or objective function). In many tasks it should be minimized or maximized, in some cases – it should reach some definite level.
2. In all the cases the goal function is described in such a way, that includes possible alternatives, so the question is which combinations of available resources should be used to get the optimal result.
3. Constraints or restrictions are a very important part of the case. They depict availability of resources and their amount needed in every possible solution.

So, the first point is to put the problem into the spreadsheet in the form available for computing, put all the needed formulas. Afterwards it is possible to use answer report. This report summarizes the solution to the problem, and is fairly self-explanatory. The first section of the report summarizes the original and final (optimal) value of the set cell. The next section summarizes the original and final (optimal) values of the adjustable (or changing) cells representing the decision variables.

The final section of this report provides information about the constraints. In particular, the Cell Value column shows the final (optimal) value assumed by each constraint cell. These values correspond to the final value assumed by the formula of each constraint. The Formula column indicates the upper or lower bounds that apply to each constraint cell. The Status column indicates which constraints are binding and which are nonbinding. A constraint is binding if it is satisfied as a strict equality in the optimal solution; otherwise, it is nonbinding [32].

Finally, the values in the Slack column indicate the difference between the proposed decision and the binding value of each constraint. By definition, binding constraints have zero slack and nonbinding constraints have some positive level of slack. The slack values for the nonnegativity conditions indicate the amounts by which the decision variables exceed their respective lower bounds of zero.

The Answer Report does not provide any information that could not be derived from the solution shown in the spreadsheet model [32, pp. 138–139].

The sensitivity report. This report summarizes information about the objective (or target cell), the variable (or adjustable) cells, and constraints for the model. This information is useful in evaluating how sensitive the optimal solution is to changes in various coefficients in the model.

To any linear programming there is a graphical solution. The slope of the original level curve is determined by the coefficients in the objective function of the model. So, if the objective function coefficients are at all uncertain, we might be interested in determining how much these values could change before the optimal solution would change. This information is provided in the Sensitivity Report. The original objective function coefficients associated with the variable cells are listed in the Objective Coefficient column. The next two columns show allowable increases and decreases in these values.

Questions

1. What are DSSs generators?
2. What models are generally used in spreadsheet DSSs?
3. What is scenario analysis?
4. What kind of mathematical models are supported by sensitivity analysis?
5. What spreadsheet techniques do implement optimization models?

Module 2. Management decision support systems and technologies

Theme 8. Expert and advisory decision support systems.

Consumer-oriented decision support systems

- 8.1. Expert systems assigning. Main types of expert systems.
- 8.2. Factors that influence human information processing.
- 8.3. DSS attributes according to the information perception type of the user.
- 8.4. Individual DSS.

References: [3; 4; 5; 25; 40; 44; 46].

8.1. Expert systems assigning. Main types of expert systems

The expert system is an information system (file or database managed by a computer program) which contains data or descriptive sentences about a given branch of activity such as medical diagnosis, weather forecast, financial forecasts, machine design, consultations on geography, archeology, tourism, language, etc. The information existing in the expert system was collected and organized under the supervision of a group of experts in the subject [46, p. 298–299]. The system can answer questions formulated by users, as if he or she were consulting an expert person in the area.

Information is stored in the form of sentences called production or decision rule of the following type: If { facts are true } then { execute algorithm A } else { execute algorithm B} forming a knowledge database. These sentences are chosen to resolve a problem, using software known as inference mechanism [46, p. 298–299].

In response to the organizational need in intelligent decision support, expert systems were developed by coupling artificial intelligence and knowledge management techniques. Expert systems are designed to encapsulate the knowledge of experts and to apply it in evaluating and determining solutions to well-structured problems [3, pp. 511–524].

Expert systems have applications in virtually every field of knowledge. They are most valuable to organizations that have a high level of knowledge and expertise that cannot be easily transferred to other members. They can be used to automate decision-making or as training facilities for non-experts. Expert systems were designed to deal with complex problems in narrow, well-defined problem domains. If a human expert can specify the steps and reasoning by which a problem may be solved, then an expert system can be created to solve the same problem.

Expert systems are generally designed very differently from traditional systems because the problems they are designed to solve have no algorithmic solution. Instead, expert systems utilize codified heuristics or decision-making rules of thumb which have been extracted from the domain expert(s), to make inferences and determine a satisfactory solution. The decision areas expert systems are typically applied to include configuration, diagnosis, interpretation, instruction, monitoring, planning, prognosis, remedy, and control [3, pp. 511–524]. Expert systems research and development encompass several domains, which include but are not limited to: medicine,

mathematics, engineering, geology, computer science, business, and education.

Many expert systems are based on the notion that the process of solving unstructured decisions consists of five sequential phases: 1) problem identification; 2) assimilating necessary information; 3) developing possible solutions; 4) solution evaluation; 5) solution selection [3, pp. 511–524]. These expert systems perform the last four decision-making steps for the user and have been applied successfully in a wide variety of highly specialized domains. Traditionally rule-based expert systems operate best in structured decision environments, since solutions to structured problems have a definable right answer, and the users can confirm correctness of the decision by evaluating the justification provided by the explanation facility. However, researchers have identified many limitations to current expert systems, which include [3, pp. 511–524]:

- 1) difficulty in capturing deep knowledge of the problem domain;
- 2) lack of robustness and flexibility;
- 3) inability to provide in-depth explanations of solution logic (instead, expert system explanations are generally restricted to a description of the steps taken in finding a solution);
- 4) difficulties in solution verification;
- 5) little learning from experience.

The inflexibility of traditional expert systems reduces their ability to handle unstructured and more loosely defined problems.

An artificial intelligence technique known as an expert system is recommended for solving complex problems from the real world, which takes into consideration inferences with qualitative as well as quantitative variables [46, p. 298–299].

Expert systems are used to solve problems in well-defined, narrowly focused problem domains, whereas advisory systems are designed to support decision-making in more unstructured situations which have no single correct answer. Advisory systems provide advice and help to solve problems that are normally solved by human experts; as such, advisory systems can be classified as a type of expert system [3, pp. 511–524]. Both advisory systems and expert systems are problem-solving packages that mimic a human expert in a specialized area. These systems are constructed by eliciting knowledge from human experts and coding it into a form that can be used by a computer in the evaluation of alternative solutions to problems within that domain of expertise.

While advisory systems and expert systems share a similar architectural design, they do differ in several significant ways. Expert systems are typically autonomous problem solving systems used in situations where there is a well-defined problem and expertise needs to be applied to find the appropriate solution. In contrast, advisory systems do not make decisions but rather help guide the decision-maker in the decision-making process, while leaving the final decision-making authority up to the human user. The human decision-maker works in collaboration with the advisory system to identify problems that need to be addressed, and to iteratively evaluate the possible solutions to unstructured decisions. The advisory system, for ethical reasons, only acts as a tool to aid in the decision-making process, it can't be accountable for the decision made [3, pp. 511–524]. Advisory systems are advice-giving systems as opposed to systems that present a solution to the decision-maker.

Advisory systems support decisions that can be classified as either intelligent or unstructured, and are characterized by novelty, complexity, and open-endedness [3, pp. 511–524]. In addition to these characteristics, contextual uncertainty is ubiquitous in unstructured decisions, which when combined exponentially increases the complexity of the decision-making process. Because of the novel antecedents and lack of definable solution, unstructured decisions require the use of knowledge and cognitive reasoning to evaluate alternative courses of action to find the one that has the highest probability of desirable outcome.

The decision-making process that occurs when users utilize advisory systems is similar to the judge-advisor model [3, pp. 511–524]. Under this model decision-makers are motivated to seek advice from others for decisions that are important, unstructured, and involve uncertainty. Similarly, advisory systems help to synthesize knowledge and expertise related to a specific problem situation for the user; however, the ultimate decision-making power and responsibility lie on the user – not the system. Advisory systems can also support problem identification in unstructured decision-making environments.

Although advisory and expert systems do share some commonalities in their shell structures, the major differences are the decisions they are each designed for (unstructured versus structured), the artificial intelligence methodologies that each uses (case-based versus rule-based), the role they each play in the decision-making process (decision support versus decision-

maker) [3, pp. 511–524]. In addition to these differences, advisory systems incorporate new advancements in the active monitoring functionality and are designed to further supplement human cognitive problem solving process by incorporating iterative interaction with the user.

8.2. Factors that influence human information processing

In the 1970s, decision theorists discovered that the phases within the decision process are executed iteratively until an acceptable decision is reached [3, pp. 511–524]. When a decision-maker gathers and assimilates information, he/she subconsciously begins to comparatively evaluate it with previously gathered information. This comparative evaluation of information, coupled with an understanding of the information's contextual relevancy, results in decisions sufficient for unstructured problems which have no definable right solution because of the existence of outcome uncertainty. One reason that the rule-based inference engines used in traditional expert systems have limited capacity to handle unstructured decisions is because they usually do not support the required iterative process of decision-making.

Decision models suppose that the decision-maker resolves a problem by choosing the best alternative in terms of gain or profit. In decision analysis theory and game theory this aspect is rigorously obeyed, even though in the majority of cases the formulated alternatives are simplified or condensed versions of the possible states of nature. In real-life problems, we also need to take into consideration the behavior of the individuals or organizations involved in decision-making [39, pp. 333–337]. One can classify decision problems according to the behavior of persons or organization as:

1. *Decision for the complete resolution of the problem.* A decision is made to choose one of the possible alternatives, which proposes to resolve the problem completely. All decision models from game theory and decision analysis pertain to this category.

2. *Decision by oversight.* In this case, the decision is made in a superficial or negligent way without any criteria for analyzing the problem.

3. *Decision by flight.* Encompasses problems approved (or abandoned) due to difficulty in appropriately appreciating and resolving them, since they involve conflicts of interest, lack of objectives, lack of interest, lack of time, etc.

These three types of situations can be represented by the garbage can model [39, pp. 333–337]. The garbage can model proposed by Cohen et al.

pictures the problem of decision-making as an enormous garbage can where problems to be resolved are put. Well-structured problems or those with a higher priority are resolved and taken out of the can. The other problems are taken out after a superficial examination or are taken out of the can because they are taking up space. Many neglected problems remain on the bottom of the garbage can, which requires periodic emptying.

The garbage can model is made up of the following elements:

1. Decision mechanism is a structure or instance for deciding a problem, spending a certain amount of energy, according to the difficulty or interest in resolving this problem.

2. Participants are people or organizations that are part of the decision-making mechanism and spend a certain amount of ENERGY (time, knowledge, money) to try to resolve a problem.

3. Problems are proposals presented to the decision mechanism.

4. Solution to the problem – decision alternatives chosen for each problem. The occurrence of oversight or flight-type decisions can be linked to the greater or lesser importance or priority attributed to a problem. These decisions may occur due to the existence of the phenomenon called organizational anarchy. According to Cohen et al., organizational anarchy may be the result of existence of many problems which are difficult to describe in a precise way [39, pp. 333–337].

8.3. DSS attributes according to the information perception type of user

In the behavioral model of decision-making, it is important to consider the behavior of each person or group of persons regarding the psychological preference of each person. The Swiss psychologist Carl Gustav Jung created and developed a theory of psychological types in an attempt to explain the apparent differences existing in people's behavior. Jung stated that he began to construct his theory when he perceived the differences of conception and behavior between him and his colleagues in analyzing the same problem, and also observing the behavior of patients and other people. Jung's theory is based on the supposition that differences among individuals are caused by different ways that people use their minds [39, pp. 333–337]. In using the mind, a person becomes involved with the following mental activities:

- 1) perception: contact with events or collecting information without concerning oneself with its organization or purpose, and

2) judgement: information is 'received' via a process of organizing, planning, and analysis to draw a conclusion.

For Jung, these two activities constitute the innate preferences of individuals who prefer one of the two activities.

The process of perception can be affected in two distinct and opposite ways:

1) sensing: when attention is directed to what can be observed or what is real, and

2) intuiting: perceiving the relationships among events, persons, or ideas, observing what is behind them.

The process of judging can take place in two distinct ways:

1) thinking: takes the pros and cons into consideration to try to come to a conclusion in a logical manner, but can neglect some existing relationships among persons, or

2) feeling: takes sentimental values into consideration and can neglect logical thinking.

Jung believed that these four processes of using the mind can be applied to events from the outside as well as the interior world, and thus added the following types [39, pp. 333–337]:

1) extroverts: individuals who direct their thinking and energy to events from the world outside, acting and reacting with it, or

2) introverts: those who receive information from the outside, as well as the interior world, through contemplation and reflection, keeping this information inside themselves.

Each of these psychological types affects a person's behavior in many areas, including decision-making.

The MBTI method (Myers-Briggs Type Inventory), developed by Briggs and Briggs-Myers determines the personality type based on combination of these eight basic personality types [39, pp. 333–337]. According to this approach extroverts prefer brainstorming in group evaluation scenarios or actions. Introverts prefer brainstorming privately. The sensing type of preceptors prefer sharing values and ideas taking into consideration many factors. Intuitives prefer deductive reasoning and use of images. The 'thinking' type decision-makers prefer to make task analysis using graphs, trees or networks. They like information to be classified and categorized. The 'feeling' type people listen to others values. The 'judging' type prefer using comparisons during evaluation. The 'perceiving' type prefer usage of different and contradictory statements.

8.4. Individual DSS

DSSs are computer-based information systems that are designed with the purpose of improving the process and outcome of decision-making. There are many approaches to using information technology to support managers and executives. In practice the current emphasis is on the large-scale systems of business intelligence and data warehouses [4, pp. 127–142].

The original approach to DSS was much narrower and therefore less complex. This approach can be termed personal decision support systems. Personal DSSs are relatively small-scale systems that are normally developed for one manager, or a small number of managers, for an important decision task. Despite the dominance of business intelligence and data warehouses in the management support component of information technology budgets in organizations, it may be the case that personal DSS remains the most used form of decision support, particularly in the form of spreadsheet-based models.

There are a number of fundamentally different approaches to DSS and each has had a period of popularity in both research and practice. Each of these DSS types represents a different philosophy in terms of support, system scale, level of investment, and potential organizational impact. They may use quite different technologies and support different managerial constituencies.

Another dimension in DSS evolution is improvement in technology, as the emergence of each of the DSS types has usually been associated with the deployment of new information technologies. Personal DSSs are the oldest form of decision support system. They effectively replaced management information systems (MISs) as the management approach support of choice in the 1970s and 1980s. In the 1960s and 1970s the emphasis was on empowering individuals and democratization of decision-making. Personal DSS followed this philosophy by supporting individual managers. The technology that enabled the development of personal DSS was the minicomputer and relatively user-friendly software applications, especially financial modelling and database software. In the mid-1980s the personal computer and spreadsheet software further drove down the cost of technology and dispersed personal DSS through all levels of management.

The classical view of personal DSS is that in a project a systems analyst supports one manager for a particular decision task. A more-

contemporary view is to focus on DSS engagement, a project that involves a contract or relationship between manager/users and developers to deliver decision support capabilities [4, pp. 127–142]. A particular engagement may focus on a major decision task but this could manifest in a number of smaller, discrete but interrelated tasks. Each of these smaller tasks can be supported by one or more information technology applications. As a result, modern personal DSS engagement can have multiple clients.

Personal DSSs were the foundation of the DSS discipline. From this origin the field has blossomed into a number of support approaches and technologies that are institutionalized in modern organizations. However, personal DSS remain an important part of most managers' working life.

While personal DSSs have a 30-year history in practice, contemporary PDSSs are in many ways different to their forebears. These differences have been driven by sustained improvements in information technology, particularly in processing power, data storage, and the Internet [4, pp. 127–142]. However, while improvement in information technology is fundamental in improvements in personal DSSs, two other factors have changed the PDSSs landscape. The first is that senior executives are now sophisticated users of information technology. The second factor is the mathematical ability of managers. Over the history of personal DSS, business schools have been emphasising quantitative skills and the early graduates of these schools are now ascending to executive ranks. The executives can integrate complex analytical models into their decision processes.

The increase in sophistication of information technology use and mathematical ability and improvements in IT mean that personal DSS developers face a demanding development environment. They require more sophisticated information technology and information systems knowledge, and skills than the original DSS developers and also require more detailed business domain knowledge [4, pp. 127–142]. The applications evolution speed within an engagement is also likely to be faster. While a demanding environment, contemporary personal DSS development can be a rewarding experience for both managers and analysts.

Future research. Improving user interaction with advisory systems requires additional understanding and research on the role of advice in decision-making, facilitating the iterative interaction between decision-makers and the system, and the impact of the advice given on the final decision that is made [3, pp. 511–524]. Specifically, there is a need to determine how

systems can best give advice which is adaptive and conducive to the cognitive decision-making process of the user(s). Research is also needed to examine how to enhance the iterative decision support functionality of advisory systems.

There is also a need for additional research in knowledge acquisition and representation. The process of eliciting tacit knowledge obtained by an expert and coding it into explicit knowledge that is congruent with the artificial intelligence technology in the inference engine is a very complicated process which spans across the following research disciplines: psychology, information systems, and computer science [3, pp. 511–524]. This process differs from that found in traditional expert systems because the tacit knowledge which is necessary for the system is much more difficult to define, codify, evaluate, and represent than rule-based explicit knowledge.

Questions

1. What is an expert system?
2. What is an advisory system?
3. What factors do influence human information processing?
4. What is your perception type?
5. How does individual DSS differ from other types of DSSs?

Theme 9. Descriptive decision theory

- 9.1. Descriptive decision theory.
- 9.2. Bounded rationality concept.
- 9.3. Regret theory.
- 9.4. Prospect theory.
- 9.5. Individual decision regularities.

References: [39; 41; 49; 53; 55; 56; 59].

9.1. Descriptive decision theory

Economics has always been concerned with the motivations and behavior of consumers. Rational behavior, in the broad meaning of sensible, planned, and consistent, is believed to govern most conduct in economic markets, because of self-interest and the tendency of markets to punish foolish behavior [53, pp. 2–4].

In Herb Simon's words, 'the rational man of economics is a maximizer, who will settle for nothing less than the best' [59]. While this model of consumer behavior dominates contemporary economic analysis, there is a long history among economists of questioning its behavioral validity and seeking alternatives.

What has come to be known as behavioral decision theory had its origins in the von Neumann and Morgenstern treatise on choice under uncertainty and game theory [53, pp. 2–4]. The rational consumer model is so deeply entwined in economic analysis, and in broad terms so plausible, that it is hard for many economists to imagine that failures of rationality could infect major economic decisions or survive market forces. Nevertheless, there is accumulating behavioral evidence against the rational model. Choice behavior can be characterized by a decision process, which is informed by perceptions and beliefs based on available information, and influenced by affect, attitudes, motives, and preferences. A few brief definitions are needed. Perceptions are the cognition of sensation. We will use 'perceptions' broadly to include beliefs, which are mental models of the world, particularly probability judgments. Affect refers to the emotional state of the decision-maker and its impact on cognition of the decision task. Attitudes are defined as stable psychological tendencies to evaluate particular entities (outcomes or activities) with favor or disfavor. Technically, attitudes are often defined as latent factors that explain the variation in a battery of indicators (most commonly semantic differentials). The domain of attitudes may be very broad, including for example comparative judgments, but an attitude itself is a unitary valuation [53, pp. 2–4]. Preferences are comparative judgments between entities. Under certain technical conditions, including completeness and transitivity, preferences can be represented by a numerical scale, or utility. Motives are drives directed toward perceived goals. The cognitive process for decision-making is the mental mechanism that defines the cognitive task and the role of perceptions, beliefs, attitudes, preferences, and motives in performing this task to produce a choice [53, pp. 2–4].

The way people can and do make decisions varies considerably. Much early research has focused on the way we are observed to make decisions and the way in which we should theoretically make decisions, and as a result, the range and diversity of theory is vast [53, p. 2].

It is, however, important that the distinction between descriptive and normative remains clear; the distinction acts as a useful reference point when

attempting to improve managerial decision-making processes. A prescriptive model is one which can and should be used by a real decision-maker and is tuned to both the specific situation and needs of the decision-maker. Prescriptive models are based on both the strong theoretical foundation of normative theory in combination with the observations of descriptive theory [53, p. 2]. A simple way of distinguishing between these modes of decision-making is:

1. Descriptive: What people actually do, or have done.
2. Prescriptive: What people should and can do.
3. Normative: What people should do (in theory) [53, p. 2].

Descriptive (behavioral/psychological) decision theory is a system of theories, which describe real-world people's behavior in choice situations and underlining psychological mechanisms.

Descriptive decision theory focuses primarily on:

- 1) common behavioral regularities in choice situations;
- 2) individual differences in the decision process.

Regularities found in human behavior are called phenomena or effects, they are forming the descriptive models of making decisions – these concepts allow to understand and to forecast human actions in choice situations.

9.2. Bounded rationality concept

One of the central themes of descriptive decision-making literature is the idea of Bounded Rationality, also known as Limited Rationality which was first proposed by Simon [59]. The basic tenet of Bounded Rationality is that all intendedly rational behaviour occurs within constraints, including cognitive ones [59]. Rational behaviour is typified by a decision-maker who has a 'well-organised and stable system of preferences and a skill in computation that enables him to calculate, for the alternative courses of action that are available to him, which of these will permit him to reach the highest attainable point on his preference scale' [59]. Simon first made mention of human 'physiological and psychological limitations' in his work on rational choice [59]. He states 'the maximum speed at which an organism can move establishes a boundary on the set of its available behaviour alternatives', which interprets simply to mean humans have limits which they cannot exceed.

Possibly the oldest descriptive theory is the Satisficing model, which emerged around the same time, and is linked to the idea of Bounded

Rationality. First reported by Simon [59], this theory posits that decision-makers choose an alternative that exceeds some criterion or standard. Behaviour of organisations in learning and choice situations falls far short of the idea of 'maximising' postulated in economic theory, '... organisations adapt well enough to satisfice, they do not, in general, optimise' [59]. Simon's argument is centered around the fact that decision-makers do not and cannot maximise in most situations [53, p. 3–4].

9.3. Regret theory

One of the key descriptive decision models is regret theory. Regret theory (made by Loomes, Bell, Sugden) makes use of a two-attribute utility function that incorporates two measures of satisfaction, namely (1) utility of outcomes, as in classical economic utility, and (2) quantity of regret. By regret is meant 'the painful sensation of recognising that 'what is' compares unfavourably with 'what might have been'.' The converse experience of a favourable comparison between the two has been called 'rejoicing' [55, pp. 46–47].

In the simplest form of regret theory, regret is measured as 'the difference in value between the assets actually received and the highest level of assets produced by other alternatives'. The utility function has the form $u(x,y)$, where x represents actually received assets and y stands for the difference just referred to. This function can reasonably be expected to be an increasing function of both x and y .

Regret theory can also explain how one and the same person may both gamble (risk prone behaviour) and purchase insurance (risk averse behaviour) [55, pp. 46–47].

9.4. Prospect theory

Prospect theory (made by Tversky, Kahneman) is a descriptive decision model, it describes decision behavior taken under risk. In this case the term 'prospect' means arbitrary choice situation with probabilistic actions. The main results of the theory are variety of psychological effects, which reflect regularities of human choice behavior taken under risk.

Prospect theory differs from most other theories of decision-making by being 'unabashedly descriptive' and making 'no normative claims'. Another

original feature is that it distinguishes between two stages in the decision process [55, pp. 47–48].

The first phase, the editing phase serves ‘to organize and reformulate the options so as to simplify subsequent evaluation and choice’. In the editing phase, gains and losses in different options are identified, and they are defined relative to some neutral reference point. Usually, this reference point corresponds to the current asset position, but it can be ‘affected by the formulation of the offered prospects, and by the expectations of the decision-maker’.

In the second phase, the evaluation phase, the options – as edited in the previous phase – are evaluated. According to prospect theory, evaluation takes place as if the decision-maker uses two scales. One of these replaces the monetary outcomes given in the problem, whereas the other replaces the objective probabilities given in the problem. Monetary outcomes (gains and losses) are replaced by a value function v , which reflects the subjective value of that outcome. In other words, the value function is a function from monetary gains and losses to a measure of subjective utility. The major difference between this value function and conventional subjective utility is that it is applied to changes – that is gains and losses – rather than to final states.

Objective probabilities are transformed in prospect theory by a function π that is called the decision weight [55, pp. 47–48].

Psychology has developed a variety of theories and techniques for studying the process of decision-making. The leading research paradigm has been the focus of Amos Tversky and Danny Kahneman on experimental study of cognitive anomalies: circumstances in which individuals exhibit surprising departures from rationality.

The experimental results from psychology have not been codified into a ‘standard model’ for behavioral decision theory; and many psychologists would argue it is not possible or useful to construct such a model. Nevertheless, it is possible to identify some of the major features of a psychological view of decision-making. The central element is the process by which the cognitive task is defined and elements such as perceptions and attitudes enter. Attitudes and affect are major factors in determining motivation and structuring of the cognitive task.

Attitudes and affect also influence perceptions. Finally, there may be feedbacks from process and choice to attitudes and perceptions, as the

decision-maker reconciles and rationalizes trial choices. Preferences may play a role in the psychological view, as may maximization, but they compete with other heuristics for defining and solving the cognitive task.

Psychologists make a sharp distinction between attitudes and preferences. In this view, attitudes are multi-dimensional, with no requirement of consistency across attitudes. Preferences are viewed as constructed from more stable attitudes by a context-dependent process that determines prominence given to various attitudes and tradeoffs between them [53, pp. 8, 10–11].

9.5. Individual decision regularities

Psychology has developed a variety of theories and techniques for studying the process of decision-making. The leading research paradigm has been the focus of Amos Tversky and Danny Kahneman on experimental study of cognitive anomalies: circumstances in which individuals exhibit surprising departures from rationality.

The problems associated with risk perception are compounded because of the difficulty individuals have in interpreting low probabilities when making their decisions (Kunreuther). In fact, there is evidence that people may not even want data on the likelihood of an event occurring. If people do not think probabilistically, then how do they make their choices? Psychological research has revealed the following patterns of drawing inferences about probabilities and risks [49, pp. 33–34]:

1. The easier and faster a risk is recognized, the more conscious individuals are of it and the greater is the chance of its probability being overestimated. If, for example, an individual knows someone who died after being struck by lightning, that individual will perceive the risk of being struck by lightning as being particularly large (availability bias).

2. The more a risk provokes associations with known events, the more likely its probability will be overestimated. This is why, for example, the use of the term ‘incinerating’ in waste-disposal facilities readily evokes an association with harmful chemicals, especially dioxines and furans, even if there is no way that they could be released into the environment by the facilities concerned (anchoring effect).

3. The more constant and similar the losses from risk sources, the more likely the impact of average losses will be underestimated. While road traffic

accidents are not deemed acceptable, they are more or less passively accepted. If the average annual number of road deaths in a given country were to occur at one point in time instead of being spread out over the year, then a considerably greater level of rejection could be expected. Thus, people are not indifferent as regards the distribution of risks over time: they prefer even loss distribution over individual disasters (Kahneman and Tversky).

4. The greater the uncertainty of loss expectation, the more likely the average loss assessment will be in the region of the median of all known loss expectations. In this way, loss expectations in objectively low risks are often overestimated while objectively high risks are often underestimated (assessment bias) (Tversky, Kahneman, Ross, Renn).

While important for actually evaluating and managing a risk, overestimation or underestimation of loss expectations is not, however, the most important aspect of risk perception. Instead the context-dependent nature of risk assessment is the deciding factor. This context includes qualitative risk evaluation characteristics, semantic images and stigma effects. More recently, psychologists have also discovered that affect and emotions play an important role in people's decision-making processes (Slovic, Loewenstein) [49, pp. 33–34]. These factors are particularly relevant when individuals face a decision that involves a difficult trade-off between attributes or where there is interpretative ambiguity as to what constitutes the 'right' answer. In these cases, people often appear to resolve problems by focusing on those cues that send the strongest affective signals (Hsee, Kunreuther).

As Kahneman and Tversky have pointed out, we tend to be less attracted than we should be to a highly likely (but not certain) pleasant outcome [2, pp. 431–434]. Similarly, we are likely to be more attracted than we should be to a highly unlikely but pleasant outcome. Hence we tend to be less inclined to take a small risk for a gain, and more inclined to bet on a long shot, than is indicated by objective probability. The popularity of lotteries in many countries is a good example of this. Monetary gambles are relatively simple contexts for the study of risk. Many other contexts are less simple, and then the meaning of risk is ambiguous.

As Kahneman and Tversky put it, the attractiveness of a possible gain is less than the aversiveness of a loss of the same amount. This leads to risk-averse decisions concerning gains and risk-seeking decisions concerning losses. This has some interesting implications. For example, an unpopular

government facing an election may be more inclined to risk a new policy initiative that could lose votes than a popular government in the same position. Firms in financial difficulties may take more risks (because they are trying to eliminate losses) than firms doing well (which are dealing with gains) (Fiegenbaum and Thomas) [2, pp. 431–434].

Framing effect. The same information can be presented in different ways. This can affect decisions made on the basis of that information. An often-used scenario in laboratory experiments concerns the choice of medical programs to combat a killer disease. The potential benefits of these programs are presented either in terms of the number of people who will be saved (equivalent to gains), or the number who will die (equivalent to losses). According to Kahneman and Tversky when the options are presented in terms of number of deaths, people tend to prefer a program that might succeed completely or fail completely (i.e. a risk) over one with a guaranteed moderate success level [2, pp. 431–434]. The reverse is true when the same figures are presented in terms of number of lives saved.

The role of emotion in decision-making has recently received increasing research attention. There is some evidence that people who are experiencing positive emotion are able to be more creative than those who are not, and more able to process information. On the other hand, it also seems that positive emotions can lead people to be unrealistically optimistic about future events and outcomes.

People also seem to consider their likely future emotions when making decisions. One emotion that has been studied a lot is regret. Kahneman argues that people regret actions (what they have done) more than inactions (what they failed to do, or decided not to do), probably because actions are more salient in our memory and their consequences are more tangible [2, pp. 431–434]. Consistent with this, Baron found that worries about future regrets tended to make people prefer inaction to action. This might suggest that, for example, people may tend to stay in jobs or occupations they do not like very much if the alternative is a step into the unknown.

Some approaches to commitment (Kiesler) emphasise that if a decision is made freely and explicitly, the person making it feels a need to justify it to him or herself and others [2, pp. 431–434]. The person is committed to it, and seeks retrospectively to find reasons why he or she 'did the right thing'. In laboratory simulations, people who are told that their own earlier financial investment decisions have so far been unsuccessful tend to allocate more

additional funds to that investment than if the earlier decisions were made by another member of their (imaginary) organisation.

They feel compelled to prove that ultimately their own wisdom will be demonstrated, but observers are more likely to think they are 'pouring good money after bad'. This 'escalation of commitment' phenomenon is now well established. The next question is, therefore, how it can be reduced or eliminated. In a laboratory study of a simulated marketing decision, Simonson and Staw asked decision-makers to specify in advance minimum outcome levels that would have to be achieved for the decision to be considered successful [2, pp. 431–434]. If their decisions did not achieve that level, they were less likely to invest further in it than decision-makers who did not specify a minimum outcome level. Simonson and Staw also found that further investment in a losing course of action was less likely if decision-makers were told that, owing to the artificiality of the task, their performance on this task did not reflect their managerial abilities – in other words, some of the threat to decision-makers' dignity was removed. Finally, escalation of commitment was also reduced if decision-makers were told that their performance would be evaluated on the quality of decision-making processes, not the outcomes (which in the real world depend partly on factors outside the decision-maker's control).

While the second strategy is rather laboratory-specific, the first and last strategies can and should be used by decision-makers and those who appraise their performance at work.

Heuristics are 'rules of thumb' that people use to simplify information processing and decision-making [2, pp. 431–434]. These can be social – for example, 'I will ignore everything person X tells me' – or abstract – such as, 'Never do anything without checking the production figures first'. In their early work, Tversky and Kahneman identified three particularly common heuristics. The representativeness heuristic is analogous to finding in a person's perception that we do not use base-rate information. We judge someone or something purely according to how representative it appears of a particular category, and we ignore the naturally occurring probability of belonging to that category in the first place. We are swayed by the person's appearance. The anchoring bias refers to our failure to change our views as much as we should in the light of new information. We seem 'anchored' by our starting point. This, too, finds expression in a person's perception, in the same sense that the first impressions can be hard to dislodge. Finally, the availability

heuristic concerns our tendency to consider an event more probable if it can easily be imagined than if it cannot.

Heuristics, or rules, can be especially useful when the impact of a course of action being considered only becomes clear in the long term and/or with repetition.

Questions

1. What is descriptive decision theory?
2. What is bounded rationality concept?
3. What is the influence of regret theory on individual and group choice?
4. What is the main idea of the prospect theory?
5. What is the impact of individual decision regularities on the decision-making process?

Theme 10. Heuristic methods in decision support systems

10.1. Heuristic domain term. Heuristic rules. Heuristic methods.

10.2. Heuristic module in DSS. Methods of controlling human mind processes and its computer aid.

10.3. Methods of guiding strategies and their computer aid.

10.4. Methods of generating alternatives and their computer aid.

10.5. Heuristic methods based on a systems approach.

References: [13; 14; 18; 24; 45].

10.1. Heuristic domain term. Heuristic rules. Heuristic methods

The semi-structured decision process consists of many difficult operations and leads, sometimes, to people's frustrations because of long term of mental overloading and unpredictable results.

As we know, in adopting decisions of semi-structured problems there might be used such methods as:

analytical;

sequential search;

heuristic search.

Analytical methods presuppose building of a model of a process, formulating objective function and all the constrains, choice and application of fitted analytical procedure, which may lead to optimal decision, if such one exists.

Before looking at the meta-heuristics it is worth asking why such approaches should be used if they cannot guarantee an optimal solution. (optimization methods). To use these approaches, the model must be formulated in such a way that it fits the optimization approach being used. Thus, in linear programming, the objective function and all of the constraints must be relatively simple linear functions.

Though all models are simplifications and approximations, for many applications such simplification may be an approximation too far [13, pp. 263–264]. The model may have to be so distorted that its solutions are far, far removed from the real world in which they need to be implemented. In such cases, it may make much more sense to use a heuristic approach even though there is no guarantee of optimality. A near-optimal solution to a good model may be much better than an optimum solution to a bad one.

The second reason relates to the computational demands made by many optimization algorithms. Many optimization algorithms, though guaranteeing an optimum solution, have a solution time that increases exponentially as the size of the problem increases. Thus, for many very large problems, even if the model is a good representation of the real system and even if very powerful computers are brought to bear, the solution times are simply too long to be of use. This is particularly true of situations in which frequent changes are made to the number and type of options being compared. In such situations, the only practicable way forward may be to use the approximate, that is, heuristic, approach [13, pp. 263–264].

In linear programming, the method guarantees that an optimum solution to a correctly formulated model will be found, if it exists. This does not guarantee that the optimum solution to the model will be the best solution in practice. This can only be the case if the model is a perfect fit to the system being modelled, which is unlikely [13, p. 260].

The idea of sequential searches through a decision space (which is close to the ideas proposed by Simon and Newell), – that is sometimes described as linear, or sequential, search. In essence it imagines that the task of a decision-maker is to start from the left-hand side of the figure and move toward the right-hand side, hoping to end up at a destination that is either optimal or satisfactory. To do so, the decision-maker is faced with a series of choices that constitutes the solution space of the problem [13, p. 261].

For semi-structured and unstructured decisions adoption special methods and rules, which are called heuristics are used. Particularity of their usage is studied by a special science – heuristic).

There are the following meanings of heuristic:

- 1) that is a science, which investigates productive creative thinking;
- 2) that is a method of learning with the help of leading questions (Socrates method);
- 3) that is theory and practice of elective choice in difficult intellectual tasks decision;
- 4) that is a pool of special methods and rules in discovering and investigations.

Heuristic task decision methods are the system of principles, rules and approaches, which stimulate creative thinking and new ideas generation, and, consequently rise in effectiveness of some theoretic tasks achievement.

Heuristic rules (heuristics, heuristic operators) are guidelines on choosing a possible action in the search for alternatives, formulated on the basis of practical expertise.

Heuristic search, like simulation methods, gives no guarantee that any proposed solution will be optimum and even in the context of the model, let alone in the context of the system being modelled. Though these search methods share this limitation with simulation approaches, there is also an important difference: a simulation approach is usually based on experiments guided by humans. By contrast, heuristic search methods provide ways of automatically generating solutions to problems that have been formulated in certain ways. They are approximate approaches as they aim to come as close as possible to some optimum, but they may fail to do so [13, p. 260].

The second reason is that they take management science to the edge of artificial intelligence methods. There are great benefits in being able to design human – machine systems that are able to cope with complicated circumstances [13, p. 261].

Heuristic rules and methods have the following specific properties:

1. They are widely used in solving problems, which do not have algorithms that guarantee finding the 'right decision'.
2. They leave wide latitude for the manifestation of creative activity of the man.
3. They do not guarantee 'positive' results, though it is generally possible to obtain better results than without their usage.

Examples of heuristic rules:

1. 'First, check the entire site, and only then proceed with the check of its components' (heuristics used in the troubleshooting process of a technical system).

2. 'Cheap parts should be checked at first, and more expensive afterwards' (another rule from the scope of repairs).

3. 'The units that have the same customers (competitors), and shared resources, should maintain a centralized competitive intelligence. However, if the degree of similarity is low, the centralized structure of competitive intelligence shouldn't be created' (heuristic rule to determine the appropriate competitive intelligence centralization degree in a diversified company).

4. 'If you want to remove the harmful effect of an object or process, look in favor of harm' (one of the rules in conflict resolution systems).

As you can see, heuristic rules to a large extent direct human activity, but do not bind restrictions. They are rather the recommendations made by a human expert based on his experience (or an information system that mimics the behavior of an expert). And on the application of heuristics solve person-to-user based on their experience and intuition.

Heuristics are divided into those, which restrict (bound) and guide. Restrictive heuristics may be absolute and relative.

Guide heuristics are heuristics, which show the way, where decisions should be searched primarily.

Restrictive (bounding) heuristics exclude some areas of search as blind-alleys.

Absolute heuristics exclude those areas of search, which definitely lack searched elements.

Relative heuristics exclude those areas of search, which lack searched elements with high level of probability.

Heuristic methods are the methods that aim to organize human creative thinking. The basic idea of heuristic methods is to combine organized mind process, which gives a guaranteed result, with the intuitive, spontaneous ideas, which give an unusual solution.

There exist the following heuristic methods:

methods of controlling human mind process;

methods of guiding strategies;

methods based on a systems approach;

methods of generating alternatives.

10.2. Heuristic module in DSS. Methods of controlling human mind processes and their computer aid

The main purpose of the methods within this group is the control and analysis of the decision-maker's thought. As an example, the methods of this group, consider the method of protocol analysis and the method of switching strategies.

The method of protocol analysis.

The method of protocol analysis (incentives to 'think aloud') is a technique which is based on the idea of recording the process of decision-making. Afterwards the protocol is analyzed to detect errors and inaccuracies made by the man.

The implementation of this method in the DSS includes:

1) organization of the dialogue between the DSS and the decision-maker in such a way as to encourage people to 'think aloud' – this can be achieved by including the script dialogue set of additional questions to the decision-maker, the answers to which are fixed by the system;

2) developing protocol of interactions between decision-maker and the DSS.

Analysis of the recorded protocol can be made by a decision-maker, and other specialists - experts and analysts. Another option is automatic protocol analysis system to support decision-making. Such analysis will help identify errors in the organization of decision-making process: a missing step in the procedure of choice, incorrect information, etc.

It should be noted that the method of protocol analysis is widely used not only to detect errors in the human thinking process, but also for knowledge extraction. In a fixed protocol of reasoning expert knowledge engineers are trying to find the concepts and procedures that have been used by the man in the process of solving the problem.

The method of switching strategies.

The method of switching strategies is a method aimed to remove a conflict between spontaneous and organized thinking of decision-makers. The method consists in stimulating the spontaneous judgments relating to the problem, but in a range of the chosen decision strategy. Such thoughts are recorded in a special database of spontaneous judgments for the purpose of further analysis and usage in solving the problem.

Implementation of the method to switch strategies include the following steps:

1. Search for solution in accordance with a selected strategy (basic strategy).
2. Fixing every spontaneous judgment.
3. Formation on the basis of spontaneous judgments of new possible strategies to solve problems and compare them with the basic strategy.
4. Adoption of procedural decisions on future strategies for addressing the problem: the decision-maker is either returned to the basic strategy, or moves to a new strategy provoking spontaneous judgments.
5. Steps are repeated until the final strategy is chosen, which generates the appropriate solution.

10.3. Methods of guiding strategies and their computer aid

The methods within this group are intended to guide heuristics with various decision-makers to encourage the efficient way of solving the problem. As an example, the methods within this group consider the method of checklists (test questions) and techniques of Theory of Inventive Problem Solving (TRIZ).

Method of checklists.

Method of checklists is the method of psychological activation of the creative process, which leads a person to problem solution by using leading questions.

The main tool of this method is checklists, which are formed corresponding to the domain experts and then act as a guide heuristics in problem-solving process.

Advantages: it is simple, versatile and effective (if the analysis is performed by professionals); there's no need to learn. Drawback: this method can take away from creative solutions, focusing on thinking of a similar situation.

Implementation of the method of test questions with the help of the DSS includes the following steps:

1. In the scenario dialogue lays the initial DSS checklists, formed by experts in the relevant subject area.
2. During a session the DSS provides decision-makers with questions as the guides of heuristics. The choice of classifier type of a problem situation sets a filter to select the list of issues.
3. The decision-maker answers questions. During questions responding the situation is clarified and tasks are solved.

4. In the future the decision-maker enriches DSS base of questions. Each question is provided with symbols relating it to one or another type of problem situations.

The technique facilitates idea generation by having one prepare a list of items related to a problem and checking the items against certain aspects of the problem. It can be used both as a problem delineation list and as a solution-finding list. The purpose of the former is to provide a direction for the idea search, to make sure that no ideas have been overlooked, and to evaluate the applicability of ideas borrowed from a previous problem. Checklists used for possible solutions are concerned with developing new ideas. The most common use of checklists involves identifying new product ideas by making alterations to existing products [14, p. 100].

This is the use of questions as spurs to ideation. The simplest checklist comes from the six basic questions [14, p. 98]:

1. Why is it necessary?
2. Where should it be done?
3. When should it be done?
4. Who should do it?
5. What should be done?
6. How should it be done?

Methods of the theory of inventive problem solution.

Theory of Inventive Problem Solution (TRIZ) is a methodology of finding solutions to problems by scientific and technical creativity, developed by Altshuller. Theoretical basis of TRIZ are the patterns of development of technical systems, identified as a result of processing large volumes of patent information. In TRIZ an inventive problem-solving process is seen as a sequence of operations to identify, clarify and overcome a set of contradictions. As a consequence, an important tool of creative activity (generated within the TRIZ) is a system of principles and techniques of conflict resolution. Similar principles are used as heuristics in guiding the process of semi-structured problems solution by creating and reframing various systems.

The technology of using TRIZ methods for conflict resolution through the DSS includes the following steps:

1. We formulate the problem.
2. DSS presents a set of techniques of TRIZ to the user.
3. The user scans these TRIZ techniques in order to generate options for solving the problem: each technique allows us to formulate one or more alternatives.

4. Among the variety of alternatives formulated one chooses the best.

Some techniques of TRIZ are:

1. 'Union' technique. It presumes the following actions in order to resolve identified problems:

- a) connection of similar or related objects;
- b) integration in time homogeneous or contiguous operations;
- c) placing one object inside another.

2. 'Segmentation' technique. This technique, among other things, involves the following steps:

- a) to divide an object into independent parts;
- b) to make an object sectional;
- c) to increase the degree of fragmentation of the object.

3. 'In advance' technique. The basis of this technique is the following heuristic rule: 'If you cannot take action with the object at the required time, then make the necessary action in advance'. It presupposes the following steps:

- a) to perform the requested action (in whole or in part) in advance;
- b) pre-arrange the objects in such a way that they can be immediately involved into the action, without preparatory costs.

4. 'Improving agility' technique. This technique involves the following solutions to the problems:

- a) to make the characteristics of the object change in response to changing environmental conditions;
- b) to divide the object into parts capable of change and to move relative to each other;
- c) if the object is immovable, make it mobile.

5. 'Zoom' technique. This technique involves the following steps:

- a) change the real scale of the system;
- b) change the scale of the nominal system.

6. 'On the contrary' technique. It offers the following:

- a) instead of the usual steps to make the inverse (opposite) effect;
- b) rotate the object 'upside down', turn it.

7. 'Copy' technique. The basis of this technique implies the following heuristic rule: 'If it is difficult or not possible to perform, the necessary actions with the object, it is advisable to use a copy of it', i.e.:

- a) to replace the inaccessible, complex, expensive object by its simplified and cheap copy;
- b) to replace the object by its optical copy image.

10.4. Methods of generating alternatives and their computer aid

The methods within this group are aimed at stimulating the creative activity of human in the process of generating alternative solutions to the problem. This group of methods includes the method of focal objects, as well as the method synectics.

Method of focal objects.

Method of focal objects presupposes transferral of random attributes on a pulled up object. This method is widely used in cases of some object improvement. The essence of this method is in transference to the improving object of some attributes of randomly chosen objects. So the creativity is stimulated.

Synectics.

Synectics is a method of enhancing creative human thinking, which implies special conditions that stimulate unexpected and non-stereotyped analogies and associations to the task.

The term 'synectics' is a neologism, meaning the union of disparate elements. In synectics brainstorming, and the methods of analogies and associations are used. Unlike conventional brainstorming in synectics the group is composed of experts from various professions. The basic principle of synectics is 'to make unfamiliar as familiar and vice versa'. This principle allows us to move beyond traditional ways of thinking, to abandon stereotypes and expand search for new ideas.

The main technique is analogy as a mean of shifting from one level to level of spontaneous conscious thought to another. Analogy is applied: a) at the stage of understanding the problem (in an unusual turn familiar, that is, to express the situation analyzed in familiar terms) and b) during solutions generation process. In synectics the following types of analogy are used: a direct analogy (search for similar processes in other fields); personal assimilation (identification of oneself with a test system or its element); symbolic analogy (use of poetic images and metaphors), fantastic analogy (the problem is solved mentally 'like a fairy tale', ignoring the fundamental laws of nature).

Computer support synectics method can be implemented by creation and application:

1. Computer database of analogies, allowing to express the situation analyzed in familiar terms.
2. The basic heuristic operators, enabling the decision-maker to go beyond the obvious solutions to the problem and use different types of analogies.

10.5. Heuristic methods based on a systems approach

As an example, the methods of this group include the method of morphological analysis.

The method of morphological analysis.

The method of morphological analysis is a method of exploring all possible combinations of values for the attributes (parameters) of the system.

This method is intended to identify a set of alternatives of a system. The method includes systematic study of all possible options arising from the laws of the structure (i.e. morphology) of analyzed object. The technology of morphological analysis involves three steps:

1. Formation of a list of the main parameters in the system (its components, functions, properties, etc.).
2. Creating a list of possible values for each parameter.
3. Compilation of all possible systems through a combination of the values of its parameters.

It is assumed that in such a systematic examination of the object in view of the researcher can get those of alternative options for the parameters that have not been addressed previously.

- 4) Next, measuring the effectiveness of the system consisting of options and selection of the preferred option.

Questions

1. What is heuristics?
2. What heuristic methods do you know?
3. What is the essence of switching strategies method?
4. What TRIZ rules do you know?
5. Show an example of synectics usage in management.

Theme 11. Data search and preparation for analytical processing

11.1. Economic data search in open sources. Economic data basis usage.

11.2. Technical requirements to data quality.

11.3. Core algorithms of data preparation and preprocessing.

References: [11; 15; 29; 37; 42].

11.1. Economic data search in open sources. Economic data basis usage

Economic data normally fall into three basic types: demographic, behavioral, and psychographic or attitudinal [15, pp. 26–31].

Demographic data generally describe personal or household characteristics. They include characteristics such as gender, age, marital status, income, home ownership, dwelling type, education level, ethnicity, and presence of children. They are very stable, which makes them appealing for use in predictive modelling. Characteristics like marital status, home ownership, education level, and dwelling type aren't subject to change as frequently as behavioral data such as bank balances or attitudinal characteristics like favorite political candidate. And demographic data is usually less expensive than attitudinal and behavioral data, especially when purchased on a group level. One of the weaknesses of demographic data is that it is difficult to get on the individual basis with a high degree of accuracy. Unless it is required in return for a product or service, many people resist sharing this type of information or supply false information.

Behavioral data is a measurement of an action or behavior. Behavioral data are typically the most predictive type of data. Depending on the industry, this type of data may include elements like sales amounts, types and dates of purchase, payment dates and amounts, customer service activities, insurance claims or bankruptcy behavior, and more. Web site activity is another type of behavioral data. Behavioral data usually does a better job of predicting future behavior than the other types of data. It is, however, generally the most difficult and expensive type of data to get from an outside source. This will be discussed in more detail in the next section.

Psychographic or attitudinal data are characterized by opinions, lifestyle characteristics, or personal values. Traditionally associated with market research, this type of data is mainly collected through surveys, opinion polls,

and focus groups. It can also be inferred through magazine and purchase behavior [15, pp. 26–31]. Due to increased competition, this type of data is being integrated into customer and prospect databases for improved target modelling and analysis. Psychographic data bring an added dimension to predictive modelling. For companies that have squeezed all the predictive power out of their demographic and behavioral data, psychographic data can offer some improvement. It is also useful for determining the life stage of a customer or prospect. This creates many opportunities for developing products and services around life events such as marriage, childbirth, college, and retirement. The biggest drawback to psychographic data is that it denotes intended behavior that may be highly, partly, or marginally correlated with actual behavior. Data may be collected through surveys or focus groups and then applied to a larger group of names using segmentation or another statistical technique. If data is applied using these methods, it is recommended that a test be constructed to validate the correlation.

Data for modelling can be generated from a number of sources. Those sources fall into one of two categories [15, pp. 36–37]: internal or external. Internal sources are those that are generated through company activity such as customer records, web site, mail tapes from mail or phone campaigns, or databases and/or data warehouses that are specifically designed to house company data. External sources of data include companies such as credit bureaus, list brokers and compilers, and corporations with large customer databases like publishers and catalogers.

Internal sources are data sources that are housed within a company or establishment. They are often the most predictive data for modelling because they represent information that is specific to the company's product or service. Some typical sources are the customer database, transaction database, offer history database, solicitation tapes, and data warehouses.

A customer database is typically designed with one record per customer. In some organizations, it may be the only database. If that is the case, it may contain all the sales and/or activity records for every customer. It is more common, though, that the customer database contains identifying information that can be linked to other databases such as a transaction database to obtain a current snapshot of a customer's performance. Usually it includes a unique numeric or alphanumeric code that identifies the customer throughout his or her entire lifecycle. It also includes customer name, address, phone number, some demographics (characteristics such as

gender, age, and income may be stored for profiling and modelling), products or services usage history, offer details (the date, type of offer, creative, source code, pricing, distribution channel and any other details of an offer), etc [15, pp. 36–37].

The transaction database contains records of customer activity. It is often the richest and most predictive information, but it can be the most difficult to utilize. In most cases, each record represents a single transaction, so there may be multiple records for each customer. The transaction database can take on various forms depending on the type of business. In order to use this data for modelling, it must be summarized and aggregated to a customer level. Number of records per customer can differ.

The offer history database contains details about offers made to prospects, customers, or both. The most useful format is a unique record for each customer or prospect. Variables created from this database are often the most predictive in response and activation targeting models. It seems logical that if you know someone has received your offer every month for six months, they are less likely to respond than someone who is seeing your offer for the first time.

A data warehouse is a structure that links information from two or more databases. Using the mentioned data sources, a data warehouse brings data into a central repository, performs some data integration, cleanup, and summarization, and distributes information data marts. Data marts are used to house subsets of the data from the central repository that has been selected and prepared for specific end users. (They are often called departmental data warehouses.) An analyst who wants to get data for a targeting model accesses the relevant data mart.

External sources consist mainly of list sellers and compilers. List sellers are companies that sell lists. Few companies, however, have the sale of lists as their sole business. Many companies have a main business like magazine sales or catalogue sales, with list sales as a secondary business. Depending on the type of business, they usually collect and sell names, addresses, and phone numbers, along with demographic, behavioral, and/or psychographic information. Sometimes they perform list ‘hygiene’ or cleanup to improve the value of the list. Many of them sell their lists through list compilers and/or list brokers [15, pp. 40–43]. List compilers are companies that sell a variety of single and compiled lists. Some companies begin with a base like the phone book. Then they purchase lists, merge them together, and impute missing

values. Many list compilers use survey research to enhance and validate their lists. There are many companies that sell lists of names along with contact information and personal characteristics. Some specialize in certain types of data. Credit bureaus are well-known for selling credit behavior data. They serve financial institutions by gathering and sharing credit behavior data among their members. There are literally hundreds of companies selling lists from very specific to nationwide coverage. But it ought to be noted, that the Ukrainian legislation system restricts these operations, therefore, they are done halflegally, in shadow.

Selecting the best data for targeting model development requires a thorough understanding of the market and the objective. Although the tools are important, the data serve as the frame or information base. The model is only as good and relevant as the underlying data.

While potential sources for raw data are almost endless, the most likely potential sources of raw data are divided into three basic categories [42, pp. 67–90]: government and non-profits; private sector; media.

Data sources within each category have important characteristics in common. It can be important to remember that where you get data is not necessarily the ultimate source of that data. This means that you may be able to access the data you want without having to contact the data's original source [42, pp. 67–90]. But, it also means that you must make sure you know whether the source of data actually produced the data, just transmitted them, or modified them in some way. Confusing the data producer with the data provider has important, sometimes damaging, consequences.

As a group, government and non-profit sources generally provide only indirect assistance. That is because the vast bulk of data that they access and release is highly aggregated, as with business census reports, or consists of data already collected by another provider, such as information taken from a commercial directory. Some, however, can be very specific, firm level or even facility level, such as filings made with a state, or local government by a target. Data in those channels tend to be very company- or subject-specific rather than aggregated. They tend to be relatively easily and inexpensively accessed whether online or through freedom of information/open records laws, although it may take a relatively long time to do so [42, pp. 67–90].

The consumer and other advocacy groups and the trade associations all collect and provide data for a reason – to advance what they each see as

their own best interests or the best interests of those that they represent. To put it bluntly, they all have an 'ax to grind'. In doing this, they may well spend significant time and funds to collect data, publish reports, bring lawsuits, or test products/services, all of which may be sources of raw data. However, some of them may limit their data to members.

Academics often seek funding support for research which they are interested in, or conduct consulting assignments. From these efforts, professors and their researchers may provide such useful input as publications, special detailed studies, and access to research centers for collecting important historical data.

Private sector sources. These include people and organizations whose business directly involves producing or selling the kinds of data you may be seeking. For some, providing data is their business. Others may come across data you need as a part of their own business.

Examples of common private sector data sources [42, pp. 67–90]:

- 1) primary competitor's employees (sales, market research, planning, engineering, purchasing, former employees of the target company);
- 2) primary competitor (internet home page, catalogues and price lists, in-house publications, press releases and speeches, presentations to analysts, advertisements and promotional materials, products, annual reports, regulatory filings, customers and suppliers, retailers, distributors, and agents, advertising and marketing agencies);
- 3) other competitors (business information services, dun and bradstreet, standard and poor's, proprietary research firms);
- 4) experts (consultants, expert witnesses, security (stock) analysts).

In dealing with these sources, you must avoid confusing the package with its contents. When comparing data from different sources they may appear identical. However, that is not necessarily correct. You see, the report's author could have purchased data on your competitor, so if they look the same as data from another business source, that may be because they are the same. That does not mean they are correct. This is just a false confirmation.

Experts include everyone from consultants to expert witnesses, and from clinical laboratories to security analysts. Their work reflects a common goal: to advance the individual's career, whether it is by obtaining assignments, helping an employer sell stock, or some other means. But each lies in providing data for a particular audience, which can color not only how they say things but what they say and do not say.

The media. All these varied sources collect, generate, and process data for a specific audience. To fully understand both the data you may find on your competitor and how to analyze them, you must first understand from whom the media collects these data, how, and why it releases them.

Examples of common media data sources [42, pp. 67–90]:

- 1) business newspapers and magazines (advertisements and want ads, articles, reporters);
- 2) wire services (articles, reporters);
- 3) specialized directories;
- 4) local and national newspapers;
- 5) advertisements and want ads (articles, reporters, obituaries);
- 6) technical journals (articles, authors);
- 7) trade papers and journals; financial periodicals (advertisements and want ads, articles, reporters, marketing studies and media kits, special issues, related publications);
- 8) security analysts' reports (company reports, industry profiles).

The media, in the broadest sense, can be one of the most productive resources for obtaining raw data. But always keep in mind that many publications exist to serve a particular industry or market. Thus they are positioned to help you locate some important data and develop leads for additional data, but may their own significant blind spots as well.

Secondary sources such as government press offices, commercial news organizations, NGO spokespersons, and other information providers can intentionally or unintentionally add, delete, modify, or otherwise filter the information they make available to the general public [42, pp. 67–90]. These sources may also convey different messages for different markets. All media are controlled. The issue for analysts is what factors and elements (elites, institutions, individuals) exercise control, how much relative power or weight does each factor or element possess, and which factors or elements are of interest to analysts and their customers.

11.2. Techniquial requirements to data quality

Data quality and data governance assessment clarifies how the information architecture is used to support compliance with defined information policies. It suggests that data quality and data standards management are part of a much larger picture with respect to oversight of enterprise information.

In the siloed environment, the responsibilities, and ultimately the accountability for ensuring that the data meet the quality expectations of the client applications lie within management of the corresponding line of business. This also implies that for MDM, the concept of data ownership must be aligned within the line of business so that ultimate accountability for the quality of data can be properly identified [37, pp. 72]. But looking at the organization's need for information oversight provides a conduit for reviewing dimensions of data quality associated with data elements, determining their criticality to the business operations, expressing data rules that impact compliance, defining quantitative measurements for conformance to information policies, and determining ways to integrate these all into a data governance framework.

Similar to the way that data quality expectations for operational or analytical data silos are specified, master data quality expectations are organized within defined data quality dimensions to simplify their specification and measurement/validation. This provides an underlying structure to support expression of data quality expectations that can be reflected as rules employed within a system for validation and monitoring [37, pp. 89–93]. By using data quality tools, data stewards can define minimum thresholds for meeting business expectations and use those thresholds to monitor data validity with respect to those expectations, which then feed into the analysis and ultimate elimination of root causes of data issues whenever feasible.

Data quality dimensions are aligned with the business processes to be measured, such as measuring the quality of data associated with data element values or presentation of master data objects. The dimensions associated with data values and data presentation lend themselves well to system automation, making them suitable for employing data rules within data quality tools used for data validation. These dimensions include (but are not limited to) the following [37, pp. 89–93]: uniqueness; accuracy; consistency; completeness; timeliness; currency.

Uniqueness refers to requirements that entities modelled within the master environment are captured, represented, and referenced uniquely within the relevant application architectures. Asserting uniqueness of the entities within a data set implies that no entity logically exists more than once within the MDM environment and that there is a key that can be used to uniquely access each entity (and only that specific entity) within the data set. The dimension of uniqueness can be monitored in two ways [37, pp. 89–93]. As a static assessment, it implies applying duplicate analysis to the data set

to determine if duplicate records exist, and as an ongoing monitoring process, it implies providing identity matching and resolution service inlined within the component services supporting record creation to locate exact or potential matching records.

Data accuracy refers to the degree with which data correctly represent the 'real-life' objects they are intended to model. In many cases, accuracy is measured by how the values agree with an identified source of correct information (such as reference data). Accuracy is actually quite challenging to monitor, not just because one requires a secondary source for corroboration, but because real-world information may change over time. If corroborative data are available as a reference data set, an automated process can be put in place to verify the accuracy, but if not, a manual process may be instituted to contact existing sources of truth to verify value accuracy. The amount of effort expended on manual verification is dependent on the degree of accuracy necessary to meet business expectations.

Consistency refers to data values in one data set being consistent with values in another data set. A strict definition of consistency specifies that two data values drawn from separate data sets must not conflict with each other [37, pp. 89–93]. Note that consistency does not necessarily imply correctness. The notion of consistency with a set of predefined constraints can be even more complicated. More formal consistency constraints can be encapsulated as a set of rules that specify consistency relationships between values of attributes, either across a record or message, or along all values of a single attribute. However, there are many ways that process errors may be replicated across different platforms, sometimes leading to data values that may be consistent even though they may not be correct.

The concept of completeness implies the existence of non-null values assigned to specific data elements. Completeness can be characterized in one of three ways. The first is asserting mandatory value assignment—the data element must have a value. The second expresses value optionally, essentially only forcing the data element to have (or not have) a value under specific conditions. The third is in terms of data element values that are inapplicable. Consistency contexts [37, pp. 89–93]: between one set of attribute values and another attribute set within the same record (record-level consistency); between one set of attribute values and another attribute set in different records (cross-record consistency); between one set of attribute values and the same attribute set within the same record at different points in

time (temporal consistency); across data values or data elements used in different lines of business or in different applications; consistency may also take into account the concept of 'reasonableness', in which some range of acceptability is imposed on the values of a set of attributes.

Timeliness refers to the time expectation for accessibility and availability of information. Timeliness can be measured as the time between when information is expected and when it is readily available for use. The success of business applications relying on master data depends on consistent and timely information. Therefore, service levels specifying how quickly the data must be propagated through the centralized repository should be defined so that compliance with those timeliness constraints can be measured.

Currency refers to the degree to which information is up-to-date with the world that it models and whether it is correct despite possible time-related changes. Currency may be measured as a function of the expected frequency rate at which the master data elements are expected to be updated, as well as verifying that the data are up-to-date, which potentially requires both automated and manual processes. Currency rules may be defined to assert the 'lifetime' of a data value before it needs to be checked and possibly refreshed.

Every modelled object has a set of rules bounding its representation, and conformance refers to whether data element values are stored, exchanged, and presented in a format that is consistent with the object's value domain, as well as consistent with similar attribute values. Each column has metadata associated with it: its data type, precision, format patterns, use of a predefined enumeration of values, domain ranges, underlying storage formats, and so on. Parsing and standardization tools can be used to validate data values against defined formats and patterns to monitor adherence to format specifications [37, pp. 89–93].

Assigning unique identifiers to those data entities that are ultimately managed as master data objects (such as customers or products, etc.) within the master environment simplifies data management. However, the need to index every item using a unique identifier introduces new expectations any time that identifier is used as a foreign key across different data applications. There is a need to verify that every assigned identifier is actually assigned to an entity existing within the environment. Conversely, for any 'localized' data entity that is assigned a master identifier, there must be assurance that the master entity matches that identifier. More formally, this is referred to as referential integrity. Rules associated with referential integrity are often

manifested as constraints against duplication (to ensure that each entity is represented once, and only once) and reference integrity rules, which assert that all values used for all keys actually refer back to an existing master record.

11.3. Core algorithms of data preparation and preprocessing

Data quality and data integration tools have evolved from simple standardization and pattern matching into suites of tools for complex automation of data analysis, standardization, matching, and aggregation. For example, data profiling has matured from a simplistic distribution analysis into a suite of complex automated analysis techniques that can be used to identify, isolate, monitor, audit, and help address anomalies that degrade the value of an enterprise information asset [37, pp. 93–94]. Early uses of data profiling for anomaly analysis have been superseded by more complex uses that are integrated into proactive information quality processes. When coupled with other data quality technologies, these processes provide a wide range of functional capabilities. In fact, there is a growing trend to employ data profiling for identification of master data objects in their various instantiations across the enterprise.

Most important is the ability to transparently aggregate data in preparation for presenting a uniquely identifiable representation via a central authority and to provide access for applications to interact with the central authority. Data integration products have evolved to the point where they can adapt to practically any data representation framework and can provide the means for transforming existing data into a form that can be materialized, presented, and manipulated via a master data system.

Over time, cleansing has become more sophisticated; now we rely on the master repository for cleanliness, but the methods necessary to integrate stewardship roles in making corrections as well as learning from decisions made need to be introduced into the automation processes. For example, early cleansing processes were performed in batch, without files provided to analysts for ‘postmortem’ review and decision-making [37, pp. 93–94]. Modifications to actual records were performed manually, with all the associated challenges of synchronization and propagation of changes to dependent data sets downstream. The automation process at the service layer must now be able to embed functionality supporting the data

stewardship part of the business process. Instead of batch processing for cleansing, services can now inline the identity resolution as part of data acquisition.

If the identity can be resolved directly, no interaction with the business client is needed. However, if there are potential match discrepancies, or if no exact matches are found, the application itself can employ the underlying service to prompt the business user for more information to help in the resolution process.

Enabling real-time decisions to be made helps in eliminating introduction of duplicate or erroneous data at the earliest point of the work stream. At an even higher level of sophistication, there are techniques for learning from the decisions made by users to augment the rule sets for matching, thereby improving precision of future matching and resolution.

Business processes are implemented within application services and components, which in turn are broken down into individual processing stages, with communication performed via data exchanges. Business processing stages expect that the data being exchanged are of high quality, and the assumption of data appropriateness is carried over to application development as well.

However, no system is immune to the potential for introduction of flawed data into the system, especially when the acquired data are being repurposed across the enterprise. Errors characterized as violations of expectations for completeness, accuracy, timeliness, consistency, and other dimensions of data quality often impede the ability of an automated task to effectively complete its specific role in the business process.

Data quality control initiatives are intended to assess the potential for the introduction of data flaws, determine the root causes, and eliminate the source of the introduction of flawed data if possible.

If it is not possible to eliminate the root cause, it may be necessary to use a data source that is known to have flaws. However, being aware of this possibility, notifying the downstream clients, and enabling the staff to mitigate any impacts associated with known flawed data helps to control any potential damage if that is the only source available for the needed data [37, pp. 97–100]. But the reality is that even the most sophisticated data quality management activities do not prevent all data flaws. Consider the concept of data accuracy. Although we can implement automated processes for validating that values conform to format specifications, belong to defined data

domains, or are consistent across columns within a single record, there is no way to automatically determine if the value is accurate.

The upshot is that despite your efforts to ensure data quality, there are always going to be data issues that require attention and remediation. The goal is to determine the protocols that need to be in place to determine data errors as early as possible in the processing stream(s), whom to notify to address the issue, and whether the issue can be resolved appropriately within a 'reasonable' amount of time. These protocols are composed of two aspects: controls, which are used to determine the issue, and service level agreements, which specify the reasonable expectations for response and remediation.

In practice, every processing stage has embedded controls, either of the 'data control' or 'process control' variety. The objective of the control process is to ensure that any issue that might incur a significant business impact late in the processing stream is identified early in the processing stream [37, pp. 97–100]. Data quality control differs from data validation in that validation is a process to review and measure data conformance with a set of defined business rules, but control is an ongoing process to reduce the number of errors to a reasonable and manageable level and to institute a mitigation or remediation of the root cause within an agreed-to-time frame. A data quality control mechanism is valuable for communicating data trustworthiness to enterprise stakeholders by demonstrating that any issue with a potential impact would have been caught early enough to have been addressed and corrected, thereby preventing the impact from occurring altogether.

Questions

1. What kinds of economic data do you know?
2. What common sources of economic data do you know?
3. Mention all the main technical requirements to data quality.
4. What are the consequences of data duplication?
5. Mention the main algorithms of data preparation and processing.

Theme 12. Principles of analytical data processing for decision support

- 12.1. Analytic information destination and usage.
- 12.2. On-line analytical data processing.

12.3. Knowledge discovery in databases. Data mining.

12.4. Analytical programs overlook.

References: [9; 11; 15; 20; 32; 43; 46].

12.1. Analytic information destination and usage

Statistical analysis has been around for a long time, but necessity may indeed be the mother of invention. During the past 60 years, business, industry, and society have accumulated a huge amount of data. It has been estimated that over 90 % of the total knowledge we have now has been learned since 1950 [11]. Faced with huge data sets, analysts could bring computers to their 'knees' with processing classical statistical analyses. A new form of learning was needed. A new approach to decision-making based on input data had to be created to work in this environment of huge data sets. Scientists in artificial intelligence (AI) disciplines proposed that we use an approach modelled on the human brain rather than on Fisher's parametric model. From early AI research, neural nets were developed as crude analogs to the human thought process, and decision trees (hierarchical systems of Yes/No answers to questions) were developed as a systematic approach to discovering 'truth' in the world around us.

Data mining approaches were also applied to relatively small data sets, with predictive accuracies equal to or better than statistical techniques. Some medical and pharmaceutical data sets have relatively few cases but many hundreds of thousands of data attributes (fields).

Another attitude known as exploration seeks to discover new occurrences or innovative actions for the organization, searching the organization's past database [46, pp. 309–313]. This process involves experiments in the search for new or hidden information inside the database. It can lead to inconsistent results, but occasionally leads to new courses and important discoveries. Statistical techniques such as regression and correlation analysis have been traditionally used to explore new facts or trends.

Business Intelligence, also known as KDD (knowledge data discovery), technology is applied to suitably related information from different databases to discover new facts, new relationships, or previously unknown trends. Data mining techniques are used to seek out and discover new relationships and tendencies [46, pp. 309–313]. While a DSS is a mean to refine the existing information and data search for refined or optimized results, a KDD is a

technology used to explore data files searching for new knowledge (new information or new relationships hidden inside the database).

This new type of tool to support decision-making is developed due to two main reasons: the pressure to increase the company's competitiveness and the desire to take advantage of the investments already made in information technology.

The search for these objectives is made by organizing data warehouses, which are new data deposits, suitably joined with the existing database to explore the benefits offered by the data mining technology.

Some terms and definitions used in a KDD environment according to [46, pp. 309–313] are the following. Business intelligence provides a route to obtain new knowledge needed to make important decision in the organization. Datawarehouse is a collection of integrated, dynamic, nonvolatile subject-oriented data to support managerial decision-making; or a warehouse of data, collected from several sources, inside and outside the organization, which is available to end users to be used in the context of the organization. Data mart is a smaller version of a datawarehouse, containing data related to a certain functional area of the company. Data mining is the process of extracting valid, unknown and wide ranging data from a data-warehouse, making it possible to organize new decision-making processes.

Data mining can be defined in several ways, which differ primarily in their focus on different aspects of data mining. One of the earliest definitions is the following. The non-trivial extraction of implicit, previously unknown, and potentially useful information from data [11]. As data mining developed as a professional activity, it was necessary to distinguish it from the previous activity of statistical modelling and the broader activity of knowledge discovery.

Knowledge discovery in databases is the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data. The definition focuses on the patterns in the data rather than just information in a generic sense. These patterns are faint and hard to distinguish, and they can only be sensed by analysis algorithms that can evaluate nonlinear relationships between predictor variables and their targets and themselves. This form of definition of data mining developed along with the rise of machine learning tools for use in data mining. Tools like decision trees and neural nets permit the analysis of nonlinear patterns in data easier than is possible in parametric statistical algorithms [11]. The reason is that machine learning algorithms learn the way humans do – by example, not by calculation of metrics based on averages and data distributions.

The modern KDD process combines mathematics used to discover interesting patterns in data with the entire process of extracting data and using resulting models to apply to other data sets to leverage the information for some purpose. This process blends business systems engineering, elegant statistical methods, and industrial-strength computing power to find structure (connections, patterns, associations, and basic functions) rather than statistical parameters (means, weights, thresholds, knots).

The evolutionary nature of the definition and focus of data mining occurred primarily as a matter of experience and necessity [11]. A major problem with this development was lack of a consistent body of theory, which could encompass all aspects of what information is, where it comes from, and how is it used. This logical concept is sometimes called model-theoretic. Model theory links logic with algebraic expressions of structure to describe a system or complex process with a body of terms with a consistent syntax and relationships between them (semantics). Most expressions of data mining activities include inconsistent terms (e.g., attribute and predictor), which may imply different logical semantic relations with the data elements employed.

Traditional statistical studies use past information to determine a future state of a system (often called prediction), whereas data mining studies use past information to construct patterns based not solely on the input data, but also on the logical consequences of those data [11]. This process is also called prediction, but it contains a vital element missing in statistical analysis: the ability to provide an orderly expression of what might be in the future, compared to what was in the past (based on the assumptions of the statistical method).

Compared to traditional statistical studies, which are often hindsight, the field of data mining finds patterns and classifications that look toward and even predict the future. In summary, data mining can (1) provide a more complete understanding of data by finding patterns previously not seen and (2) make models that predict, thus enabling people to make better decisions, take action, and, therefore, mold future events.

12.2. On-line analytical data processing

Major data mining activities include the following general operations [11]:

1. Exploratory data analysis. These data exploration activities include interactive and visual techniques that allow you to 'view' a data set in terms of

summary statistical parameters and graphical display to 'get a feel' for any patterns or trends that are in the data set.

2. Descriptive modelling. This activity forms higher-level 'views' of a data set, which can include the following:

a) determination of overall probability distributions of the data (sometimes called density estimations);

b) models describing the relationship between variables (sometimes called dependency modelling);

c) partitioning of the data into groups, either by cluster analysis or segmentation. Cluster analysis is a little different, as the clustering algorithms try to find 'natural groups' either with many 'clusters', or in one type of cluster analysis, the user can specify that all the cases 'must be' put into x number of clusters (say, for example, three cluster groups). For segmentation, the goal is to find homogeneous groups related to the variable to be modelled (e.g., customer segments like big-spenders).

3. Predictive modelling: classification and regression. The goal here is to build a model where the value of one variable can be predicted from the values of other variables. Classification is used for 'categorical' variables.

Regression is used for 'continuous' variables (e.g., variables where the values can be any number, with decimals, between one number and another; age of a person would be an example, or blood pressure, or number of cases of a product coming off an assembly line each day).

4. Discovering patterns and rules: This activity can involve anything from finding the combinations of items that occur frequently together in transaction databases (e.g., products that are usually purchased together, at the same time, by a customer at a convenience store, etc.) or things like finding groupings of stars, maybe new stars, in astronomy, to finding genetic patterns in DNA microarray assays. Analyses like these can be used to generate association rules; e.g., if a person goes to the store to buy milk, he will also buy orange juice. Development of association rules is supported by algorithms in many commercial data mining software products. An advanced association method is sequence, association, and link (SAL) analysis. SAL analysis develops not only the associations, but also the sequences of the associated items. From these sequenced associations, 'links' can be calculated, resulting in web link graphs or rule graphs.

5. Retrieval by content: This activity type begins with a known pattern of interest and follows the goal to find similar patterns in the new data set. This

approach to pattern recognition is most often used with text material (e.g., written documents, brought into analysis as Word docs, PDFs, or even text content of web pages) or image data sets.

To those unfamiliar with these data mining activities, their operations might appear magical or invoke images of the wizard.

Contrary to the image of data miners as magicians, their activities are very simple in principle. They perform their activities following a very crude analog to the way the human brain learns. Machine learning algorithms learn case by case, just the way we do. Data input to our senses are stored in our brains not in the form of individual inputs, but in the form of patterns. These patterns are composed of a set of neural signal strengths our brains have associated with known inputs in the past. In addition to their abilities to build and store patterns, our brains are very sophisticated pattern recognition engines. A machine learning algorithm builds the pattern it 'senses' in a data set. The pattern is saved in terms of mathematical weights, constants, or groupings. The mined pattern can be used to compare mathematical patterns in other data sets, to score their quality.

Granted, data miners have to perform many detailed numerical operations required by the limitations of our tools. But the principles behind these operations are very similar to the ways our brains work.

12.3. Knowledge discovery in databases. Data mining

The concept of data mining to a business data analyst includes not only finding relationships, but also the necessary preprocessing of data, interpretation of results, and provision of the mined information in a form useful in decision-making. In other words, a business data analyst includes classical definitions of data mining and knowledge discovery into one process [11]. While this approach is not very palatable for the academic, it serves the business analyst quite well.

The process of KDD starts with determining the KDD goals, and 'ends' with implementation of the discovered knowledge. As a result, changes would have to be made in the application domain (such as offering different features to mobile phone users in order to reduce churning). This closes the loop, and the effects are then measured on the new data repositories, and the KDD process is launched again. Here follows a brief description of the nine-step KDD process, starting with a managerial step [11].

1. *Developing an understanding of the application domain.* This is the initial preparatory step. It prepares the scene for understanding what should be done with many decisions (about transformation, algorithms, representation, etc.). The people who are in charge of a KDD project need to understand and define the goals of the end-user and the environment in which the knowledge discovery process will take place (including relevant prior knowledge). As the KDD process proceeds, there may be even a revision and tuning of this step. Having understood the KDD goals, preprocessing of data starts, as defined in the next three steps (note that some of the methods here are similar to data mining algorithms, but are used in the preprocessing context).

2. *Selecting and creating a data set on which discovery will be performed.* Having defined the goals, the data that will be used for the knowledge discovery should be determined. This includes finding out what data are available, obtaining additional necessary data, and then integrating all the data for knowledge discovery into one data set, including the attributes that will be considered for the process. This process is very important because data mining learns and discovers from the available data. This is the evidence base for constructing the models. If some important attributes are missing, then the entire study may fail. From success of the process it is good to consider as many attributes as possible at this stage. On the other hand, it is expensive to collect, organize and operate complex data repositories, and there is a tradeoff with the opportunity for best understanding the phenomena. This tradeoff represents an aspect where the interactive and iterative aspects of the KDD is taking place. It starts with the best available data set and later expands and observes the effect in terms of knowledge discovery and modelling [11].

3. *Preprocessing and cleansing.* At this stage, data reliability is enhanced. It includes data clearing, such as handling missing values and removal of noise or outliers. Several methods are explained in the handbook, from doing nothing to becoming the major part (in terms of time consumed) of a KDD process in certain projects. It may involve complex statistical methods, or using specific data mining algorithm in this context. For example, if one suspects that a certain attribute is not reliable enough or has too many missing data, then this attribute could become the goal of a data mining supervised algorithm. A prediction model for this attribute will be developed, and then missing data can be predicted. The extent to which one pays

attention to this level depends on many factors. In any case, studying these aspects is important and often revealing insight by itself, regarding enterprise information systems.

4. *Data transformation.* At this stage, generation of better data for the data mining is prepared and developed. Methods here include dimension reduction (such as feature selection and extraction, and record sampling), and attribute transformation (such as discretization of numerical attributes and functional transformation). This step is often crucial for the success of the entire KDD project, but it is usually very project-specific. However, even if we do not use the right transformation at the beginning, we may obtain a surprising effect that hints us about the transformation needed (in the next iteration). Thus the KDD process reflects upon itself and leads to an understanding of the transformation needed (like a concise knowledge of an expert in a certain field regarding key leading indicators). Having completed the above four steps, the following four steps are related to the data mining part, where the focus is on the algorithmic aspects employed for each project [11].

5. *Choosing the appropriate data mining task.* We are now ready to decide which type of data mining to use, for example, classification, regression, or clustering. This mostly depends on the KDD goals, as well as on the previous steps. There are two major goals in data mining: prediction and description. Prediction is often referred to as supervised data mining, while descriptive data mining includes the unsupervised and visualization aspects of data mining. Most data mining techniques are based on inductive learning, where a model is constructed explicitly or implicitly by generalizing from a sufficient number of training examples. The underlying assumption of the inductive approach is that the trained model is applicable to future cases. The strategy also takes into account the level of meta-learning for the particular set of available data.

6. *Choosing the data mining algorithm.* Having the strategy, we now decide on the tactics. This stage includes selecting the specific method to be used for searching patterns (including multiple inducers). For example, in considering precision versus understandability, the former is better with neural networks, while the latter is better with decision trees. For each strategy of meta-learning there are several possibilities of how it can be accomplished. Meta-learning focuses on explaining what causes a data mining algorithm to be successful or not in a particular problem. Thus, this approach attempts to understand the conditions under which a data mining

algorithm is most appropriate. Each algorithm has parameters and tactics of learning (such as ten-fold cross-validation or another division for training and testing).

7. *Employing the Data Mining algorithm.* Finally the implementation of the data mining algorithm is performed. At this step we might need to employ the algorithm several times until a satisfied result is obtained, for instance by tuning the algorithm's control parameters, such as the minimum number of instances in a single leaf of a decision tree.

8. *Evaluation.* At this stage we evaluate and interpret the mined patterns (rules, reliability etc.), with respect to the goals defined at the first step. Here we consider the preprocessing steps with respect to their effect on the data mining algorithm results (for example, adding features in step 4, and repeating from there). This step focuses on the comprehensibility and usefulness of the induced model. At this step the discovered knowledge is also documented for further usage. The last step is the usage and overall feedback on the patterns and discovery results obtained by the data mining [11].

9. *Using the discovered knowledge.* We are now ready to incorporate knowledge into another system for further action. The knowledge becomes active in the sense that we may make changes to the system and measure the effects. Actually the success of this step determines the effectiveness of the entire KDD process. There are many challenges at this step, such as losing the 'laboratory conditions' under which we have operated. For instance, the knowledge was discovered from a certain static snapshot (usually sample) of the data, but now the data become dynamic. Data structures may change (certain attributes become unavailable), and the data domain may be modified (such as, an attribute may have a value that was not assumed before).

It is useful to distinguish between two main types of data mining: verification-oriented (the system verifies the user's hypothesis) and discovery-oriented (the system finds new rules and patterns autonomously) [9].

Discovery methods are those that automatically identify patterns in the data. The discovery method branch consists of prediction methods versus description methods. Descriptive methods are oriented to data interpretation, which focuses on understanding (by visualization for example) the way the underlying data relate to their parts. Prediction-oriented methods aim to automatically build a behavioral model, which obtains new and unseen

samples and is able to predict values of one or more variables related to the sample. It also develops patterns, which form the discovered knowledge in a way which is understandable and easy to operate upon. Some prediction-oriented methods can also help provide understanding of the data [9].

Most of the discovery-oriented data mining techniques (quantitative in particular) are based on inductive learning, where a model is constructed, explicitly or implicitly, by generalizing from a sufficient number of training examples. The underlying assumption of the inductive approach is that the trained model is applicable to future unseen examples [9].

Verification methods, on the other hand, deal with the evaluation of a hypothesis proposed by an external source (like an expert etc.). These methods include the most common methods of traditional statistics, like goodness of fit test, tests of hypotheses (e.g., t-test of means), and analysis of variance (ANOVA). These methods are less associated with data mining than their discovery-oriented counterparts, because most data mining problems are concerned with discovering a hypothesis (out of a very large set of hypotheses), rather than testing a known one. Much of the focus of traditional statistical methods is on model estimation as opposed to one of the main objectives of data mining: model identification and construction, which is evidence-based (though overlap occurs).

Another common terminology, used by the machine-learning community, refers to the prediction methods as supervised learning, as opposed to unsupervised learning [9]. Unsupervised learning refers to modelling the distribution of instances in a typical, high-dimensional input space. Unsupervised learning refers mostly to techniques that group instances without a prespecified, dependent attribute. Supervised methods are methods that attempt to discover the relationship between input attributes (sometimes called independent variables) and a target attribute sometimes referred to as a dependent variable). The relationship discovered is represented in a structure referred to as a model. Usually models describe and explain phenomena, which are hidden in the data set and can be used for predicting the value of the target attribute knowing the values of the input attributes. The supervised methods can be implemented on a variety of domains, such as marketing, finance and manufacturing. It is useful to distinguish between two main supervised models: classification models and regression models. The latter map the input space into a real-valued domain. For instance, a regressor can predict the demand for a certain product given

its characteristics. On the other hand, classifiers map the input space into predefined classes. For example, classifiers can be used to classify mortgage consumers as good (full mortgage payback on time) and bad (delayed payback), or as many target classes as needed. There are many alternatives to represent classifiers. Typical examples include, support vector machines, decision trees, probabilistic summaries, or algebraic function.

12.4. Analytical programs overlook

Data mining technology can be applied anywhere a decision is made, based on some body of evidence. The diversity of applications in the past included the following [9; 46, p. 309–313]:

1) Sales forecasting. That is one of the earliest applications of data mining technology.

2) Marketing. Includes target marketing, cross selling, web usage analysis, market basket analysis (The term 'market basket analysis' used to designate the algorithm to find new association rules, has its origin in the problem classifying customers according to the contents of their market basket or cart).

3) Shelf management. It is a logical follow-on to sales forecasting.

4) Gaming and sports. A method of predicting which customers have the highest potential for spending. Although, it is a method of discovering which players/game situations have the highest potential for high scoring.

5) Customer relationship management (retention, cross-sell/up-sell propensity) and customer acquisition (a way to identify the prospects most likely to respond to a membership offer).

6) Risk analysis. It includes service fraud, Churn attrition analysis (Churn model predicts which customers are likely to leave in the near future).

7) Production management. It has various applications in this field according to high level of automotization, i.e. in inventory analysis, lay-out design, demand forecasting, business scorecard.

Questions

1. What on-line analytical data processing do you know?
2. What is knowledge discovery in databases?
3. What is data mining?

4. Show the sequence of common data-mining activities.
5. Describe KDD-process on any management example.

Theme 13. Decision support with the help of data mining algorithms

- 13.1. Data mining algorithms and results visualization.
- 13.2. Neural networks usage for economic decisions support.
- 13.3. Classification tasks resolution by tree mapping.
- 13.4. Decision support based on Kohonen maps.
- 13.5. Event analysis and regularities search with association rules.
- 13.6. Decision modelling with 'What-if' analysis.
- 13.7. Text mining algorithms and results visualization.

References: [15; 20; 29; 43].

13.1. Data mining algorithms and results visualization

Today, there are numerous tools for developing predictive and descriptive models like neural networks, genetic algorithms, classification trees, and regression trees.

Neural network processing is very different from regression in that it does not follow any statistical distribution. It is modelled after the function of the human brain. The process is one of pattern recognition and error minimization. You can think of it as obtaining information and learning from each experience.

Neural networks are made up of nodes that are arranged in layers. This construction varies depending on the type and complexity of the neural network [15, pp. 12–20]. Before the process begins, the data are split into training and testing data sets. (The third group is held out for final validation.) Then weights or 'inputs' are assigned to each of the nodes in the first layer. During each iteration, the inputs are processed through the system and compared to the actual value. The error is measured and fed back through the system to adjust the weights. In most cases, the weights get better at predicting the actual values. The process ends when a predetermined minimum error level is reached. One of the advantages of a neural network is its ability to pick up nonlinear relationships in the data. This can allow users to fit some types of data that would be difficult to fit using regression. One drawback, however, is its tendency to over-fit the data. This can cause the model to deteriorate more quickly when applied to new data. Another

disadvantage to consider is that the results of a neural network are often difficult to interpret.

Similar to neural networks, genetic algorithms do not have an underlying distribution. Their name stems from the fact that they follow the evolutionary process of 'survival of the fittest' [15, pp. 12–20]. Simply put, many models are compared and adjusted over a series of iterations to find the best model for the task. There is some variation among methods. In general, though, the models are altered in each step using mating, mutation, and cloning. As with all modelling methods, the first step is to determine the objective or goal of the model. Then a measure is selected to evaluate model fit. It creates a group of models that represent the 'first generation' of candidate models. Each model is tested for its ability to predict. The '% of Total' is treated like a weight that is then used to increase or decrease the model's chances to survive in the next generation of tests. In addition to the weights, the models are randomly subjected to other changes such as mating, mutation, and cloning. These involve randomly switching variables, signs, and functions. To control the process, it is necessary to establish rules for each process. After many iterations, or generations, a winning model will emerge. It does an excellent job of fitting a model. It, however, requires a lot of computer power. As computers continue to become more powerful, this method should gain popularity.

The goal of a classification tree is to sequentially partition the data to maximize differences in the dependent variable. It is often referred to as a decision tree. The true purpose of a classification tree is to classify data into distinct groups or branches that create the strongest separation in the values of the dependent variable [15, pp. 12–20].

Classification trees are very good at identifying segments with a desired behavior such as response or activation. It has an advantage over regression in its ability to detect nonlinear relationships. Classification trees are 'grown' through a series of steps and rules that offer great flexibility.

13.2. Neural networks usage for economic decisions support

Neural networks have been one of the most popular approaches in statistical learning and data mining. Neural networks are based on an 'artificial' representation of the human brain, through a directed acyclic graph with nodes (neurons) organized into layers [17, pp. 221–234]. In a typical

feed-forward architecture, there is a layer of input nodes, a layer of output nodes, and a series of intermediate layers. The input nodes correspond to the information that is available for every input vector (the attributes/independent variables), whereas the output nodes provide recommendations of the network.

The nodes in the intermediate (hidden) layers are parallel processing units that define the input-output relationship. Every neuron at a given layer receives as input the weighted average of the outputs of the neurons at the preceding layer and maps it to an output signal through a predefined transformation function. Depending on the topology of the network and the selection of the neurons' transformation functions, a neural network can model real functions of arbitrary complexity [17, pp. 221–234]. This flexibility has made neural networks a very popular modelling approach in addressing complex real-world problems in engineering and management.

Training a neural network involves optimization of the connections' weights. In a supervised learning context, the optimization is based on a training set, in accordance with the general framework of statistical learning. Unconstrained non-linear optimization algorithms are commonly used in this context. Evolutionary techniques have also been used recently.

The basic elements of a neural network construction are: the input (units), fed with information from the environment, the 'shadow' units within the network (hidden neurons), controlling the actions in the network, and the output (units), which synthesize(s) the network response[29, pp. 205–217]. All these neurons must be interconnected in order that the network becomes fully functional. The neural network architecture refers to the topological organization of neurons (their number, number of layers of neurons, layer structure, the signal direction and reciprocity). The operating mode refers to the nature of activities during the information processing (dynamic or static for each new input). Finally, the learning paradigm refers to the way the neural network acquires knowledge from the training dataset.

In this context, a basic issue is the so-called feedback (reverse connection) present or not in such systems. There is a feedback in a dynamical system when the output of an item belonging to the system has a certain influence on the input of that element, via the so-called feedback loop. A neural network has a feedforward type structure when the signal moves from input to output, passing through all the network's hidden units, so the outputs of neurons are connected to the next layer and not to previous ones.

These networks have the property that the outputs can be expressed as a deterministic function of inputs. A set of values entering the network is transmitted through the activation functions over the network to its output. Such a network has a stable operating mode.

Different from feedforward neural networks, there are networks with feedback loops, the so-called recurrent neural networks (RNN). Common examples of such RNNs are Elman and Jordan networks, also known as simple recurrent networks (SRN). Regarding the neural network architecture, three fundamental categories of such networks exist [29, pp. 205–217]:

1. Single-layer feedforward networks. In this case, the simplest one, there is an input layer of the source nodes, followed by the output layer of computing nodes. Note that the term single layer refers only to the output layer, because it is involved in the computation.

2. Multilayer feedforward networks. Unlike the previous network, in this case there are one or more hidden layers, (computing) elements of which are called hidden neurons, their role being to act between the input layer and the output layer, so that the network performance is improved. Schematically, by the input layer the information from the environment enters the network, representing the inputs of neurons in the second layer (i.e., the first hidden layer), then, being processed by them it will become the input of the next layer (i.e., the second hidden layer), and so on.

3. Recurrent networks. As we have already said, this network differs from those of the feedforward type by the existence of at least one feedback loop. Presence of such a feedback loop is very important both concerning the learning method and its performance.

The learning paradigm, viewed in the neural network context, is the process of the network adaptation to external environment (i.e., the adaptation/ tuning/ adjustment of its parameters) by a process of stimulation due to the environment. Schematically, the environment stimulates the network (neural network receives inputs from the environment), the system parameters receive certain values as reaction to these stimuli, and then the neural network responds to its external environment with its new configuration [29, pp. 205–217]. Since there are several ways of setting the network parameters, there will be several types of learning rules. Some of the best known learning rules of the type are:

- 1) error-correction learning is based on a control 'mechanism' of the difference between the actual response and the network response.

Technically, the network weights are adapted according to the error of the neurons output;

2) memory-based learning (instance-based learning) uses the explicit memorization of the training data;

3) hebbian learning is based on neurobiological considerations, named in honor of the neuropsychologist Hebb (Hebb's postulate of learning);

4) competitive learning is based on competition between neurons, i.e., only one neuron (winner neuron) from a given iteration in a given layer will fire at a time;

5) boltzmann learning is based on ideas borrowed from statistical mechanics, and is named in honor of the physicist Boltzmann.

There are two fundamental characteristics of the learning process:

1. Learning with a 'teacher'.

2. Learning without a 'teacher'. There are two categories of such learning, depending on the method by which parameter adaptation is performed: a) reinforcement learning, that is learning to map situations to actions, maximizing, thus, a numerical reward (reinforcement) signal. Basically, learning of an input-output mapping is performed by repeated interactions with the environment, in order to maximize the performance; b) self-organized (or unsupervised) learning with no external teacher, or referee, to monitor the learning process.

Neural network can be implemented both as usual software simulations, related to our main interest – the data mining field, and in the hardware area (software engineering), known as neurocomputers.

13.3. Classification tasks resolution by tree mapping

Rule-based and decision tree models are very popular within the machine learning research community. The symbolic nature of such models makes them easy to understand, which is usually a very important characteristic in decision aiding problems. This approach is widely used as preference modelling tools in multicriteria decision analysis and disaggregation analysis [17, pp. 221–234]. Within this framework there is a complete and well-axiomatized methodology for constructing decision rule preference models from decision examples, based on the rough sets theory. Rough sets have been initially introduced as a methodology to describe dependencies between attributes, to evaluate the significance of attributes

and to deal with inconsistent data in multicriteria decision problems. The main novelty of this approach concerns the possibility of handling criteria, i.e. attributes with preference-ordered domains, and preference ordered classes in the analysis of sorting examples and the induction of decision rules. Rough approximations of decision classes involve the dominance relation, instead of the indiscernibility relation considered in the basic rough sets approach. They are built of reference alternatives given in the decision examples. Decision rules derived from these approximations constitute a preference model. Each 'if ... then ...' decision rule is composed of a condition part specifying a partial profile on a subset of criteria to which an alternative is compared using the dominance relation, and a decision part suggesting an assignment of the alternative to 'at least' or 'at most' a given class.

The decision rule preference model has also been considered in terms of conjoint measurement and Bayesian decision theory. A representation theorem for multicriteria sorting states equivalence of simple cancellation property, a general discriminant (sorting) function and a specific outranking relation, on the one hand, and the decision rule model on the other hand [17, pp. 221–234]. The decision rule model resulting from the dominance-based rough set approach has an advantage over the usual functional and relational models because it permits handling inconsistent sorting examples. The inconsistency in sorting examples is not unusual due to instability of preference, incomplete determination of criteria and hesitation of the decision-maker.

An important feature of this methodology is that its applicability is not restricted to multicriteria classification problems, but is also extended to ranking and choice decision problems. It also provides the ability to work with missing data and to handle cases that involved both criteria and attributes.

One of the most popular classification techniques used in the data mining process is represented by the classification and decision trees. Because after accomplishing a classification process, a decision is naturally made, both labels are correctly inserted in its name, though they are usually used separately (i.e., classification trees or decision trees) [29, pp. 159–179]. The greatest benefit to use decision trees is provided by both their flexibility and understandability. In principle, decision trees are used to predict the membership of objects in different categories (classes), taking into account the values that correspond to their attributes (predictor variables). The flexibility of this technique makes it particularly attractive, especially because

it presents the advantage of a very suggestive visualization (a 'tree' which synthetically summarizes the classification). However, it should be stressed that this technique must necessarily be corroborated with other traditional techniques, especially when their working assumptions (e.g., assumptions about data distribution) are checked. Nevertheless, as an experimental exploratory technique, especially when traditional methods cannot be available, decision trees may successfully be used, being preferred to other classification models. The procedure to build (to 'grow') a decision tree represents an inductive process and, therefore, the established term is 'tree induction'.

The decision trees have three classical approaches [29, pp. 159–179]:

1) classification trees – the term used when the prediction result is the class membership of data;

2) regression trees, when the predicted result can be considered as a real number (e.g., oil price, value of a house, stock price, etc.);

3) CART (or CandRT), i.e., a classification and regression tree, when we take into consideration both above-mentioned cases.

The methodology concerning the induction of decision tree is the follows. A decision tree represents a tool to discriminate between classes, that recursively divides the training dataset until getting the (final) 'leaves', i.e., the terminal nodes that consist of either objects of the same category or objects belonging to a dominant (majority) category. In this respect, any node of the tree which is not a 'leaf' is a split (partition) point based on a test attribute that determines the way to divide that node. The idea underlying the optimal node splitting (partitioning) is similar to the 'greedy algorithm', i.e., a 'top-down' recursive construction, using the 'divide and conquer' strategy. We recall that the greedy algorithms are algorithms that use metaheuristics to solve problems by identifying local optima, and trying to find the global optimum, based on this approach. A classic example of such approach is represented by the famous 'ravelling salesman problem', in which, at each step, the nearest city that has not been travelled yet is visited . Regarding the concept 'divide and conquer' and consists in the recursive division of a problem in two or more similar sub-problems, until they reach the degree of simplicity that allows us to obtain their solutions; afterwards, starting from the solutions of these sub-problems, one tries to solve the original problem.

In principle, the methodology concerning the decision tree induction consists of two phases [29, pp. 159–179]:

1) building the initial tree, using the available training dataset until each 'leaf' becomes 'pure' (homogeneous) or almost 'pure';

2) 'pruning' the already 'grown tree' in order to improve the accuracy obtained on the testing dataset.

Regarding the split indices (criteria), seen as measures of node 'impurity' or 'goodness-of-fit measures', the most commonly used [29, pp. 159–179] are the GINI (impurity) index, used mainly in CART (CandRT) and SPRINT algorithms (represents a measure of how often a randomly chosen object from the training dataset could be incorrectly labelled if it were randomly labelled according to the distribution of labels in the dataset); the misclassification measure (based on classification error as its name suggests, is sometimes used to measure the node 'impurity'); Chi-square measure (which is similar to the standard Chi-square value computed for the expected and observed classifications); G-square measure (which is similar to the maximum-likelihood Chi-square).

All these measures are defined in terms of the class distributions of objects, considered both before and after splitting. Obviously, the purpose of building a decision tree is to obtain a precise, as good as possible, prediction for new entry data. Although it is extremely difficult, if not impossible, to define in an 'absolute' manner what the valence of the predictive accuracy is, in practical terms, some indicators of prediction process, known as prediction 'costs' [29, pp. 159–179]. Thus, an optimal prediction will, therefore, imply minimum erroneous classification costs. Essentially, the idea of prediction costs generalizes the fact that a better prediction would lead to a more reduced rate of wrong classification. From practice it resulted that, in most cases, it is not the classification rate only that is important, but also the consequences of an incorrect classification.

13.4. Decision support based on Kohonen maps

A form of neural network in which there are no known dependent variables was proposed by Kohonen for use in unsupervised clustering [11, p. 169]. The network is trained by assigning cluster centres to a radial layer by iteratively submitting training patterns to the network and adjusting the winning (nearest) radial unit centre and its neighbors toward the training pattern (Kohonen, Fausett, Haykin, Patterson). The resulting operation causes data points to 'self-organize' into clusters. A short-hand acronym for Kohonen networks is a self-organizing feature map (SOFM).

Kohonen self-organizing (feature) map represents an unsupervised neural network trained to obtain a transformation of an incoming signal pattern of arbitrary dimension (generally, large) into a one- or two-dimensional discrete map, performing this transformation adaptively in a topological order way [29, pp. 215–216]. This neural network has a feedforward structure, with one layer devoted to computation, consisting of neurons arranged in rows and columns (lattice of neurons). Each neuron is fully connected to all the source nodes in the input layer, and each (synaptic) weight vector of each neuron has the same dimension as the input space. The weights are first initialized by assigning them small random values. Once the network has been initialized, the process continues with the following three steps [29, pp. 215–216; 11, p. 169]:

1. Competition: for each input pattern, the neurons compute their values for a discriminant function, which provides the framework for competition between neurons. Thus, the particular neuron with the largest value will be declared as winning neuron. For each input pattern, the neurons compete with one another.

2. Cooperation: the winning neuron will determine the spatial location of a topological neighborhood of excited neurons, providing the basis for cooperation among the neighboring neurons. The winning neuron determines the spatial location of a topological neighborhood of excited neurons, thereby providing the basis for cooperation among the neurons.

3. Synaptic adaptation: the excited neurons are enabled to increase their individual values of the discriminant function in relation to the input patterns through suitable adjustments applied to their synaptic weights. In this way, the response of the winning neuron to a similar input pattern will be enhanced. The excited neurons adjust their synaptic weights to enhance their responsiveness to a similar input pattern.

To conclude, SOM is a computational method for the visualization and analysis of high-dimensional data, especially experimentally acquired information. In particular, we can mention: visualization of statistical data and document collections, process analysis, diagnostics, monitoring and control, medical diagnosis, data analysis in different fields, etc.

13.5. Event analysis and regularities search with association rules

Basically, association rule learning is a well-known method in data mining for discovering interesting relations between variables in large

databases [29, pp. 249–252]. An association rule can be seen as an implication of the form $X \rightarrow Y$, where X and Y are distinct items or item sets (collections of one or more items), X being the rule antecedent and Y being the rule consequent. In other words, a rule antecedent is the portion of a conditional rule that needs to be satisfied in order that the rule consequent is true. It is an unsupervised data mining technique looking for connections between items/records belonging to a large dataset. A typical and widely-used example of association rule mining is market basket analysis. Market basket analysis tries to identify customers, purchasing certain grouped items, providing insight into the combination of products within a customer's 'basket'. Based on association rule mining, managers could use the rules discovered in such a database for adjusting store layouts, for cross-selling, for promotions, for catalogue design, for identifying the customer segments based on their purchase pattern. It is also used by Amazon, when, looking, for instance, for a book on data mining, a list of potentially interesting books on neighboring subjects (e.g., data analysis, statistical analysis, statistical learning, etc.) is presented (list built based on a profile of what other 'similar' customers have ordered).

To select interesting rules from the set of all possible rules, we need some 'measures' assessing the effectiveness of the association rule process: support, confidence and lift [29, pp. 249–252]. Thus, the support represents the number of transactions that include all items in the antecedent and consequent parts of the rule (transactions that contain both X and Y), being sometimes expressed as a percentage. The confidence represents the ratio of the number of transactions that include all items in the consequent as well as the antecedent to the number of transactions that include all items in the antecedent. Finally, the lift represents the ratio of confidence of the rule and the expected confidence of the rule.

One can define the process of discovering association rules as follows: 'Given a set of transactions, discover all possible rules when both support and confidence are equal or greater than some predefined thresholds'. The way these rules are discovered depends on the chosen procedure, but the idea behind this methodology may be summarized in the following two steps [29, pp. 249–252]:

- 1) find those item sets occurrences of which exceed a predefined threshold in the database, item sets called frequent or large item sets;
- 2) generate association rules from those large item sets with the constraints of minimal confidence.

The first stage proceeds by generating all one-item sets with the given minimum coverage and then using this to generate the two-item sets (second column), three-item sets (third column), and so on. Each operation involves a pass through the dataset to count the items in each set, and after the pass the surviving item sets are stored in a hash table – a standard data structure that allows elements stored in it to be found very quickly. From the one-item sets, candidate two-item sets are generated, and then a pass is made through the dataset, counting the coverage of each two-item set; at the end the candidate sets with less than minimum coverage are removed from the table. The candidate two-item sets are simply all of the one-item sets taken in pairs, because a two-item set cannot have the minimum coverage unless both its constituent one-item sets have the minimum coverage, too. This applies in general [52, pp. 116–123]: a three-item set can only have the minimum coverage if all three of its two-item subsets have minimum coverage as well, and similarly for four-item sets.

The second stage of the procedure takes each item set and generates rules from it, checking that they have specified minimum accuracy. If only rules with a single test on the right side were sought, it would be simply the matter of considering each condition in turn as the consequent of the rule, deleting it from the item set, and dividing the coverage of the entire item set by the coverage of the resulting subset – obtained from the hash table – to yield accuracy of the corresponding rule [52, pp. 116–123]. Given that we are also interested in association rules with multiple tests in the consequent, it looks like we have to evaluate the effect of placing each subset of the item set on the right side, leaving the remainder of the set as the antecedent.

13.6. Decision modelling with ‘What-if’ analysis

Symbolic models expressed as decision trees and rule sets are quite popular among machine learning researchers and practitioners, mainly due to their interpretability. Typically, the nodes of a decision tree represent a series of (usually) binary splits defined on the independent variables, while the recommendations of the model are given at the terminal nodes of the tree. Decision tree models can also be expressed in a rule-based format of the form of ‘If ... then ...’ decision rules [17, pp. 221–234]. The first part of a given rule examines the necessary conditions required for the conclusion part to be valid. The conclusion provides recommendations (output) of the rule. Except

for the easy interpretation and use of such models by decision-makers and analysts, other advantages also include their ability to handle different types of data (quantitative or qualitative), handle of missing data, as well as their applications in discovering interesting relations between variables in large databases (e.g., through development of association rules).

When we study a particular real situation, the so-called prototype, one of the most important questions that can be asked is: ‘what happens if something changes in the prototype data, i.e., what is the influence of some changes on its ‘operation’?’ The problem here is that we cannot verify what happens using just the prototype, since it is either too complicated, or impossible, or we can even damage it [29, pp. 34–35]. To solve this problem, we could use a model on which we can practice different modifications to see what changes occur and thus to be able to extrapolate the knowledge obtained for the prototype. This is what is called a ‘What-if analysis’.

This kind of analysis may be represented by interactive trees. One can perform ‘what-if’ analyses to gain better insights into data by interactively deleting individual branches, growing other branches, and observing various results statistics for the different trees (tree models) [11, pp. 154–158].

13.7. Text mining algorithms and results visualization

Data mining is about looking for patterns in data. Likewise, text mining is about looking for patterns in a text. It is the process of analyzing a text to extract information that is useful for particular purposes [52, pp. 386–386]. Compared with the numeric kind of data, text is unstructured, amorphous, and difficult to deal with. Nevertheless, in modern Western culture, text is the most common vehicle for the formal exchange of information. The motivation for trying to extract information from it is compelling – even if success is only partial. The superficial similarity between text and data mining conceals real differences.

With text mining, however, the information to be extracted is clearly and explicitly stated in the text. It is not hidden at all – most authors go to great pains to make sure that they express themselves clearly and unambiguously. From a human point of view, the only sense in which it is ‘previously unknown’ is that time restrictions make it infeasible for people to read the text themselves. The problem, of course, is that the information is not couched in a manner that is amenable to automatic processing [52, pp. 386–386]. Text

mining strives to bring it out in a form that is suitable for consumption by computers or by people who do not have time to read the full text.

One important text mining problem is document classification, in which each instance represents a document and the instance class is the document topic. Documents are characterized by the words that appear in them. Presence or absence of each word can be treated as a Boolean attribute, or documents can be treated as bags of words, rather than sets, by taking word frequencies into account.

There is, of course, an immense number of different words, and most of them are not very useful for document classification. This presents a classic feature selection problem. Some words – for example function words, often called stopwords – can usually be eliminated a priori, but although these occur very frequently there are not all that many of them. Other words occur so rarely that they are unlikely to be useful for classification. Paradoxically, infrequent words are common – nearly half the words in a document or corpus of documents occur just once. Another issue is that the bag-of-words (or set-of-words) model neglects word order and contextual effects. There is a strong case for detecting common phrases and treating them as single units [52, pp. 386–386].

Another general class of text mining problems is metadata extraction. Metadata was mentioned earlier as data about data. In the realm of text the term generally refers to salient features of a work, such as author, title, subject classification, subject headings, and keywords. The idea of metadata is often expanded to encompass words or phrases that stand for objects or ‘entities’ in the world, leading to the notion of entity extraction.

Many short documents describe a particular kind of object or event, combining entities into a higher-level composite that represents the document's entire content. The task of identifying the composite structure, which can often be represented as a template with slots that are filled by individual pieces of structured information, is called information extraction. Once the entities have been found, the text is parsed to determine relationships among them. Typical extraction problems require finding the predicate structure of a small set of predetermined propositions [52, pp. 386–386]. These are usually simple enough to be captured by shallow parsing techniques such as small finite-state grammars, although matters may be complicated by ambiguous pronoun references and attached prepositional phrases and other modifiers. Machine learning has been

applied to information extraction by seeking rules that extract fillers for slots in the template. These rules may be couched in pattern-action form, the patterns expressing constraints on the slot-filler and words in its local context. These constraints may involve the words themselves, their part-of-speech tags, and their semantic classes.

Text mining is a burgeoning technology that is still, because of its newness and intrinsic difficulty, in a fluid state. There is no real consensus about what it covers: broadly interpreted, all natural language processing comes under the ambit of text mining. It is usually difficult to provide general and meaningful evaluations because the mining task is highly sensitive to the particular text under consideration. Automatic text mining techniques have a long way to go before they rival the ability of people, even without any special domain knowledge, to glean information from large document collections.

Questions

1. Mention the main data mining algorithms.
2. What are neural networks?
3. What management classification tasks may be resolved by tree mapping?
4. Where are association rules mostly used?
5. What is the essence of the text-mining algorithm?

Theme 14. Management decision support systems

- 14.1. DSS classification on the basis of implementation in management.
- 14.2. Peculiarities of DSS usage during investment portfolio making.
- 14.3. Marketing DSS.
- 14.4. Attributes of financial DSS.
- 14.5. Other DSS usage examples.

References: [3; 4; 26; 45; 54].

14.1. DSS classification on the basis of implementation in management

Usage of DSSs becomes every-day practice in management activity. They are widely used at Ukrainian and foreign enterprises of all sizes and in all industries. Applications of decision support systems may be classified as follows [54]:

1) accounting/auditing (auditing health insurance claims, estimating pencil manufacturing cost, stochastic cost-volume-profit analysis);

2) finance (asset-liability management, cash management and debt planning, capital budgeting, evaluating financial risks, financial analysis and diagnosis, funding strategic product development, locating banks, portfolio management, planning in mergers and acquisitions, selecting RandD project, structuring optimal lease, real estate appraisal and investment, setting interest rates for money market deposit accounts, small business financial planning);

3) human resources management (manpower planning, massive personnel assignment, resolving labor management dispute, tracking critical human resources information);

4) international business (allocating investment funds in MNCs, analyzing international investment options, planning global logistics, planning global marketing/production/distribution);

5) information systems (data communication, evaluating LAN topologies, designing a fiber optic WAN, DSS generators, application (domain)-independent system for supporting (group decision-making, massive data retrieval and extraction, MCDM problems, consensus reaching processes, generating and exploring alternatives, decision conferencing, multicultural/multilingual communication, small groups decision-making under uncertainties, modelling tasks, the Japanese style of group decision-making), systems analysis, design, development and evaluation, designing online retail banking systems, evaluating MIS effectiveness, joint application development, optimizing MIS project portfolio mix, systems analysis and planning, strategic planning of system development, information resources management, planning information systems security, supercomputer acquisition and capacity planning);

6) marketing (allocating retail space in retail outlets, competitive pricing and market share, designing freight networks and integrated distribution systems, distribution planning, logistics planning and vehicle scheduling, managing hazardous material shipments, media-planning for advertising agencies, measuring direct product profitability in retail merchandising, selecting telemarketing sites);

7) production and operations management:

a) planning for demand (designing sampling procedures for accurate estimation of electrical demand, forecasting rotatable aircraft parts demand);

b) master scheduling (production planning, production planning and control);

c) operations scheduling and control (manufacturing industry (designing electronics test facilities, managing manufacturing logistics and dispatch, operations scheduling, operations control, process planning, planning for offshore drilling, project scheduling and termination), service industry (airline arrival slot allocation system, integrated management of fleet, scheduling courier vehicle, flight, and day-off assignment for airlines cockpit crew, train dispatching));

d) operations design (evaluating personal and machine productivity, gasoline blending and planning refinery operations, managing quality-control process, product design, selecting machines in integrated process planning, TQM consultant);

e) capacity planning (factory automatisations, capacity planning, FMS configuration, FMS scheduling and control, just-in-time production, line-balancing, personnel assignment within FMS production cell, setup reduction investment, selecting robot);

f) inventory planning (inventory planning and control, material requirement planning);

g) resource management (designing materials for management processes, procurement in business volume discount environments, purchasing and material management of large projects, selecting suppliers);

8) strategic management (external environment and industry analysis, strategic analysis of mergers and acquisitions, multi-level (corporate, division, department) and multifunctional corporate planning, product/market position, grand strategy selection (managing a portfolio of new product development research projects, and terminating projects), strategy control and evaluation, decision conferencing for strategic planning, integrated strategic planning process support, managing organizational crisis);

9) multifunctional management (multi-refinery, multi-period capital investments, planning for expanding refining capacity, budgeting and manpower planning, strategic production and distribution planning, manpower and vehicle scheduling, integrated multifunctional systems for chemical production, supporting reciprocally interdependent decisions).

The Internet revolution enabled firms to operate across the globe and distribute decisions even further, spanning multiple countries. Advanced DSS tools (e.g., data warehouse, online analytical processing, data mining) and

web-based tools are used to reduce technological barriers. For example, data mining tools help analyze customer data, advanced operations research modelling (e.g., tabu-search, genetic algorithms, neural networks) support analysis, and intelligent agents help integrate information from distributed decision-makers in a global setting. However, decision-making processes have to cross regional and national boundaries and bridge cultural, social, and political differences. The systems have to synthesize organizational, personal, and technical perspectives associated with differing mental models and varying ethical and aesthetic factors. In other words, the decision-making process has become even more equivocal, and DSS research calls for the use of many rich artificial intelligence-based, Internet-enabled, collaborative technologies to support global decision-making.

14.2. Peculiarities of DSS usage during investment portfolio making

Market volatility and innovations in financial trading have made investment decision-making increasingly complicated and risky. However, the availability of reliable financial market data and powerful software tools has never been greater. In this environment, DSSs are playing more important roles and improving the quality of decisions made by both professional and individual investors.

For both individuals and professional fund managers, investment decisions are complex with catastrophic losses possible. Investors and portfolio managers today face daunting challenges in selecting the best investments from among an expanding range of alternatives. Investing though is well suited to computerized decision support.

Investing intelligently today requires computerized support [4, pp. 419–442]. Market uncertainty and price risk make decision-makers vulnerable to decision biases, and cognitive limitations can lead to poor-quality investment decisions. New instruments, derivatives, and hedging opportunities have expanded the choices in recent years. Yet, vast quantities of historic data, forecasts, and analytic models are available to investors to help guide their choices and determine the best portfolio given their requirements and tolerance for risk.

Decision support tools are available today to give investors – professionals and individuals alike – well-grounded methods to make disciplined portfolio choices. With computerized tools, investors can perform

better, even when confronted with the swelling number of investment alternatives, and overwhelming quantities of market data.

Financial analysis tools are implemented in DSSs to support individuals deciding how to invest their personal savings, or to aid more-sophisticated approaches used by investment institutions managing larger asset pools [4, pp. 419–442]. The challenge in design and development of DSS tools is to retain the investors' preferences and goals in a way that helps them overcome decision biases and cognitive limitations. The result is improved quality of investment decisions made by DSS-equipped investors, and greater profits with less risk.

Today, powerful DSSs for an individual investor can be created with a spreadsheet combined with the detailed, historical market data now available at, for example, Yahoo!-Finance. Yet, despite the promise of computer-based decision support, few investors take full advantage of the DSSs capabilities to guide their investment choices.

In financial markets, decision support technologies are essential to maintain good health of any investment portfolio. Greed, the hope of outsize profits from an investment, needs to be balanced against fear, the risk of a large loss from an ill-chosen investment. As importantly, investors need to diversify and avoid having all their eggs in one basket. Advances in financial theory, and an explosion of data sources, have enabled risk and diversification to be calculated and analyzed.

Portfolio management is one of the central problems in modern financial theory. It involves selection of a portfolio of securities (stocks, bonds, derivatives, etc.) that maximizes the investor's utility. The process of constructing such a portfolio consists of several steps [4, pp. 419–442]. At step one, the investor or portfolio manager has to determine the securities that are available as investment instruments. The vast number of available securities makes this step necessary, in order to focus the analysis on a limited number of the best investment choices. A decision-maker's investment policies and risk tolerance may narrow the field. For instance, some asset managers are only allowed to hold bonds that are rated investment grade by the major bond rating agencies (e.g., Moody's and Standard and Poor's). This investment policy restriction eliminates speculative grade securities from the available universe. Other funds avoid the so-called sin stocks of companies selling tobacco, firearms, or operating gambling venues.

On the basis of the screening stage, the decision-maker at step two accesses and evaluates relevant data for their screened securities universe. An optimization model is then used to select and assign weights (the percentage of total assets) to the far smaller number of securities that constitute the best investment portfolio in terms of risk and return. At the third step of the process, the decision-maker must determine the number of shares or bonds that should be purchased or sold based on the amount of the available capital that should be invested in each security. The portfolio decisions should be implemented by trading in ways that keep transaction costs low.

The decision-making flow of an investor or fund manager has four components, beginning with investment decisions, and flowing through to trading and back-office and accounting operations. Beyond portfolio recordkeeping, vendors and in-house systems groups have developed information technology to support all stages of the securities investment process from stock screening and portfolio risk modelling to trade order management systems.

Systematic approaches to portfolio management emerged from the work of Nobel laureate Harry Markowitz that underpins modern portfolio theory (MPT) [4, pp. 419–442]. Investors benefit by diversifying their investment portfolio by holding a range of securities. The value of diversification was quantified by Markowitz, who demonstrated that a diversified portfolio provides either a higher expected rate of return or a lower variance (risk) of return than an undiversified portfolio. Since the advent of MPT, investors have expanded their attention beyond selecting attractive individual investments to examining overall characteristics of their portfolio.

Research based on Markowitz showed that systematic and disciplined approaches to investing outperform intuitive and unaided investment decision-making. Yet, MPT does not provide a single prescription for all investors. It allows for variation in investment horizons and individual preferences toward risk. Moreover, its optimal portfolios are sensitive to assumptions such as estimates of volatility and correlations levels. This means that the set of investments will differ as assumptions diverge, and what is suitable to one investor may not be for another.

The use of a DSS can help ensure a consistent process that is based on MPT, and that is adhered to despite the ebbs, flows, and emotions of markets. Today's financial technology provides numerous alternatives for

successful investment decision-making. Sophisticated DSS tools are used for fundamental and technical analysis, back testing, and simulation, and can lead to improvements in performance. Even though individual interactions among the variables in a financial model may be well understood, predicting how the system will react to an external shock such as a volatility spike or interest rate shift is essential to enhancing decision-making.

Investment decisions can fall anywhere on the structured to unstructured continuum of problems. For example, portfolio theory offers a precise tool for constructing a portfolio, but its input parameters are subject to misestimation and individual judgment errors. Unstructured decisions for investors involve assessing data quality, understanding risk tolerance, and forecasting parameter values. These are particularly strong challenges that arise when investing in new and illiquid or emerging market securities, where historic data are limited. For each of the DSSs to be described, we will give an example of a problem that it can solve for someone making an investment decision but desiring the ability to explore the consequences of their estimation results and other less-structured choices.

14.3. Marketing DSS

Systems to support marketing decisions may be called marketing management support systems (MMSSs), marketing decision support systems (MDSSs) or intelligent MDSSs (IMDSSs). They can assist marketing management in a range of strategic planning, tactical, and decision-making activities [4, pp. 396–416].

In a survey of decision support applications from the academic literature between 1988 and 1994, Eom et al. [4, pp. 396–416] selected articles that included descriptions of 'a semi- or unstructured decision, a human-computer interface, the nature of the computer-based support for human decision-makers' intuitions and judgments, and a data-dialogue-model system'. Just over half of the resulting 271 applications were in regular use, and 72 % were in the corporate functional management area, split into production and operations management (41 %), MIS (19 %), marketing (13 %), finance (10 %), strategic management (6 %), human resources (4 %), and other areas. This reveals that, despite being in some ways a relatively nonquantitative area, marketing was not lagging behind in making use of such systems.

There are many different requirements for marketing managers and decision-makers. Some require a precise answer, such as quantity, price or place. In other cases managers need to explore a situation creatively, look for relationships, suggest alternative options and new ideas, and share these with others as part of an ongoing process.

For developing marketing strategies there might be used such types of computer-based systems as marketing information systems, decision support systems, executive information systems, expert systems, artificial neural networks (ANNs), and fuzzy logic. The proportion of marketing information systems software devoted to the categories of decision modelling, artificial intelligence modelling or system simulation are relatively low, suggesting little real decision support activity amongst marketing managers. They also assert that results of marketing resource allocation may be improved through use of a well-designed marketing DSS, and users may be willing to move to decisions further from the base case.

Appropriately designed and implemented DSSs can potentially improve strategic marketing planning by (a) aiding the use of marketing tools through visual displays, calculations, quick iteration and user guidance; and (b) facilitating group planning with better focused discussions, better mutual understanding, and greater consensus on strategic choices [4, pp. 396–416]. This would, however, only occur provided success factors are present, including a senior sponsor, a system that is intuitive and seen to be empowering rather than controlling, a team with breadth of experience and authority, and clear definitions of units under analysis.

There exist DSSs for marketing strategy making and its implementation tracing. They are based on various expert systems, artificial neural networks and analytical hierarchy processes. For customer segmentation different clustering and forecasting methods are used, because the main tasks are to group clients and prospects properly and express the potential benefits of relationships with these groups according to so called customer lifetime value. Generally for such purposes classification trees are used for clustering and association rules mining is applied to analyze clients's past transactions and forecast their future behavior. Especially useful for these purposes are self-organizing Kohonen maps (as one of association rules mining method).

To support pricing decisions on-line analytical processes are used. For eliciting customer requirements for a new product and for finding patterns in them a prototype system is formed. The customer requirements elicitation

uses the laddering process to derive a customer attributes hierarchy, and feeds this into a neural network to derive a series of output patterns for the company and its main competitor, segmented into appropriate customer groups.

Sales forecasting is a key element of marketing planning. The category management DSS with Bayesian vector error correction allows interaction to a marketing analyst, and category managers to input tactical marketing information. Test results on retail data show reduced forecast errors overall [4, pp. 396–416]. Market basket analysis became possible when increased computing power enabled detailed analysis of transaction-level data, with the association-rule mining introduced.

To target customers at direct mailing a DSS called Ensemble was used [4, pp. 396–416]. A genetic algorithm first greatly reduces the large initial set of consumer parameters, taking into account the percentage of customers to target. Using a reduced feature set, an artificial neural network then selects the customers with most profit potential. It leads to reduction of data collection and storage costs.

Software agents can play a major role in supporting decision-making in electronic trading and electronic commerce. A web-based electronic commerce system with multiple agents for customers and merchants incorporates an interactive multiple-criteria decision-making tool for a purchaser agent to compare a range of seller proposals. A three-layer framework for using intelligent agents to support electronic commerce allows different decision models to aid choice and facilitate transactions, according to the type of trade.

Systems to support marketing decisions are now in their fifth decade. Over that period of time the global market place has changed greatly, as have the requirements and expectations of marketers. At the same time both the availability and level of detail of data have mushroomed, and the capabilities of systems to store and analyze these data have increased exponentially. Many new management and marketing theories have emerged, and systems have been developed to take advantage of them.

14.4. Attributes of financial DSS

Financial DSSs can be defined as computer information systems that provide information in the specific problem domain of finance using analytical

decision models and techniques, as well as access to databases, in order to support an investor in making decisions effectively when their problems are complex and ill-structured. Financial DSS software should directly support modelling decision problems and identifying the best alternatives (Palma-dos-Reis, Zahedi) [4, pp. 419–442].

A financial DSS, therefore, formalizes domain knowledge about financial management and portfolio selection problems so that it is amenable to modelling and analytic reasoning.

The role of a financial DSS can be that of a normative system that leads to a clear solution – i.e., recommendations are based on established theoretical principles, or it can be a decision-analytic DSS that supports the process of decision-making but retains subjective elements and does not necessarily lead to a clear ranking and a unique best alternative [4, pp. 419–442].

The components of a financial DSS are the same as those of other DSSs: the database, the model base, and the user interface. A DSS will retrieve information from large databases, analyze it according to user selections and suitable models, then present the results in a format that users can readily understand and apply.

Financial planning proved to be readily implemented as DSS tools. Early financial planning DSSs were intended to provide end-user functions and accessibility that would allow executives to build models without data processing expertise and programmer intermediaries. Solving a number of problems in financial management turned out to be readily accomplished using early personal computer (PC)-based DSS tools.

The interactive financial planning system (IFPS) was a popular DSS tool for financial analysis, and was widely used from its 1978 launch as a mini-computer package until the early 1990s [4, pp. 419–442]. IFPS, in common with other DSS packages, implemented models in a transparent, natural language that separated the financial model from the data. Spreadsheets, with their universality and their ease of use, eventually overtook specialized tools such as IFPS in popularity and features. Unfortunately, separation of data and model in DSSs is lacking in spreadsheet DSSs. The standard DSS components can be found in a financial DSS). Context knowledge and experience, along with solution methods, are combined to develop the appropriate model for the problem. From there a decision model is implemented in a DSS, which provides the

analytic capabilities and outputs to enable the financial decision to be arrived at confidently.

In recent years value-at-risk (VaR) models have taken on greater importance, especially for risk-management purposes. Financial regulators are particularly eager to use VaR to set capital adequacy levels for banks and other financial institutions in a consistent way that reflects the risk of the positions held. That is a part of an international standard for measuring the adequacy of a bank's capital, and promotes greater consistency in the way banks and banking regulators approach risk management.

Value-at-risk modelling is an increasingly popular method for risk management. It has the advantage of allowing investors and financial institutions to make risk comparisons across asset classes (equities, bond, currencies, derivatives, etc.). DSS tools are increasingly used to carry out VaR assessments, and to find hedging and risk mitigating opportunities proactively. As with the portfolio optimization and arbitrage trade modelling examples, the greatest benefits from VaR come from using a DSS to empower the investment manager or decision-maker to explore and analyze the complete range of alternatives, and to make well-grounded financial decisions in the face of price risk and market uncertainty.

Within the context of corporate planning, specifically financial planning and budgeting, early decision support system research focused on integrating decisions made by the functional units, either explicitly through the integration of models developed by functional units or implicitly through decision parameters estimated by these units.

A firm can estimate the transaction values based on functional decisions (e.g., sales forecasts, production and financial plans) and use these estimates to project financial statements/ratios for goal setting. Alternately, a firm can first establish certain financial goals (e.g., return on sales or assets) and allow the functional units to use these as targets as they plan their decisions (e.g., cash and credit sales, and earnings after taxes).

The complexity of decision support in financial planning varies depending on the degree of dependency among functional decisions: pooled, sequentially interdependent, or reciprocally interdependent [4, pp. 241–308]. For example, in sequential interdependency, sales decisions can impact production and they can both, in turn, impact administration and finance. In reciprocal interdependency, sales projections can impact production and financial costs, and these costs can together influence the calculation of the

standard cost of each product sold, which in turn impacts the sales projections. Reciprocal interdependency is the most complex situation and calls for iterative decision-making between corporate and functional models and sensitivity analysis of these models for varying inputs calls for complex database management. Regardless of the dependency nature, the general assumption in all these planning decisions is that models can be developed and integrated, and input variables for these models can be estimated and tested to reduce uncertainty.

Interdependency in a distributed environment requires functional groups to communicate decision outcomes and transactions in order to assess their impacts on financial performance of a firm. This is done in two ways. An explicit approach may use knowledge-based technology to validate accounting identities (e.g., $\text{assets} = \text{current assets} + \text{fixed assets}$) and the input/output interdependencies of a functional model, by comparing them against repositories within model integration [4, pp. 241–308]. This allows functional units to uncover any missing information as well as correct the use of any organizational parameters (e.g., tax rates, interest rates).

An implicit approach calls for the use of a decision guidance system that makes model repositories available to functional units during their model construction. Such unobtrusive validation by the system lets a decision-maker compare his/her model against a library of similar models and identify gaps for additional analysis.

In financial planning firm-level strategy and the resulting network of interactions often dictate the nature of decision support. In arriving at such support, a firm needs to consider its differentiating strategy, the task it has to support (i. e., the level of interaction and its frequency), and the people involved in performing this task (i. e., their familiarity with such interactions, diversity of the firm: language, cultural background) [4, pp. 241–308]. These in turn should help the firm determine the mix of asynchronous and synchronous tools (rich, face-to-face communications) needed to reduce equivocality and the modelling tools (repository, communities of practice) needed to reduce uncertainty.

14.5. Other DSS usage examples

Many manufacturing companies, such as those operating in the consumer goods industry, have concentrated their efforts on the integrated

operations of the supply chain, even to the point of incorporating parts of the logistic chain that are outside the company, both upstream and downstream [16, pp. 361–363]. The major purpose of an integrated logistic process is to minimize the function expressing the total cost, which comprises processing costs, transportation costs for procurement and distribution, inventory costs and equipment costs. Note that optimization of the costs for each single phase does not generally imply that the minimum total cost of the entire logistic process has been achieved, so that a holistic perspective is required to attain a really optimized supply chain.

The need to optimize the logistic chain, and, therefore, to have models and computerized tools for medium-term planning and for capacity analysis, is particularly critical in the face of the high complexity of current logistic systems, which operate in a dynamic and truly competitive environment. We are referring here to manufacturing companies that produce a vast array of products and that usually rely on a multicentric logistic system, distributed over several plants and markets, characterized by large investments in highly automated technology, by an intensive usage of the available production capacity and by short-order processing cycles. The features of the logistic system reflect the profile of many enterprises operating in the consumer goods industry.

In the perspective, the aim of a medium-term planning process is, therefore, to devise an optimal logistic production plan, that is, a plan that is able to minimize the total cost, understood as the sum of procurement, processing, storage, distribution costs and the penalty costs associated with the failure to achieve the predefined service level [16, pp. 361–363]. However, to be implemented in practice, an optimal logistic production plan should also be feasible, that is, it should be able to meet the physical and logical constraints imposed by limits on the available production capacity, specific technological conditions, the structure of the bill of materials, the configuration of the logistic network, minimum production lots, as well as any other condition imposed by the decision-makers in charge of the planning process.

Optimization models represent a powerful and versatile conceptual paradigm for analyzing and solving problems arising within integrated supply chain planning, and for developing the necessary software. Due to the complex interactions occurring between different components of a logistic production system, other methods and tools intended to support the planning

activity seem today inadequate, such as electronic spreadsheets, simulation systems and planning modules at infinite capacity included in enterprise resource planning software [16, pp. 361–363]. Conversely, optimization models enable development of realistic mathematical representations for a logistic production system, able to describe with reasonable accuracy the complex relationships among critical components of the logistic system, such as capacity, resources, plans, inventory, batch sizes, lead times and logistic flows, taking into account various costs. Moreover, the evolution of information technologies and the latest developments in optimization algorithms mean that decision support systems based on optimization models for logistic planning can be efficiently implemented.

Questions

1. What are the main fields of DSSs application in management?
2. How may investment decisions be supported by DSSs?
3. What marketing tasks need to be supported by DSSs?
4. Describe DSS usage for financial decision-making.
5. How may DSSs support operations management and logistics?

Theme 15. Decision support systems development prospects

- 15.1. Current management tasks.
- 15.2. Fields of artificial intelligence usage.
- 15.3. Creative decisions support systems.
- 15.4. Other future directions of DSS development.

References: [1; 3; 4; 5; 10; 11; 12; 30; 31; 52].

15.1. Current management tasks

Decision-making support systems involve various creative, behavioral, and analytic foundations that draw on a variety of disciplines. These foundations give rise to various architectures that deliver the fundamental support concepts to individual and group users. A variety of public and private sector applications include scheduling of railway services, urban transportation policy formulation, health care management, decision-making in the pharmaceutical industry, banking management, and entertainment industry management [10, p. 399]. DSS applications draw on advanced

information technologies (IT) to physically deliver support to the decision-maker, they include intelligent agents, knowledge-based procedures, ripple down rules, narratives, and synthetic characters. Despite the technical progress, a key challenge persists – how to reduce DMSS implementation failures in organizations.

According to research [10, p. 399] the following achievements, challenges and opportunities were recognized as vital in the field: (a) providing quality data for decision support, (b) managing and creating large decision support databases, (c) model management and reuse, (d) building knowledge-driven DMSS, (e) improving communication technologies, (f) developing a uniform and comprehensive scheme, (g) developing an effective toolkit, (h) developing and evaluating a synergistic integrated DMSS, (i) collecting insights about the neurobiology of decision support for managers' less structured work, (j) application of agent and object-oriented methodologies and (k) developing DMSS through well-established methodologies. In summary, the opinions seem to focus on the deployment of new and advanced information technology (IT) to improve the quality of the overall DMSS design.

Process mining techniques are a rather new trend in DSSs. They can be used in a variety of application domains ranging from manufacturing and e-business to health care and auditing [3, pp. 637–655]. The main focus is on the analysis of the current situation rather than evaluating redesigns or proposing improvements. In order to use them one has to have a clear view of the real process. People tend to think in terms of highly simplified processes, and their views on these processes often contain an initial bias. Therefore, it is vital to have an objective understanding of reality. Moreover, it is often not sufficient to understand things at an aggregate level. One needs to take notice of causalities at a lower level, i. e., at the level of individual activities within specific cases rather than at the level of frequencies and averages. The goal of process mining is to provide a variety of views on the processes. This can be done by discovering models based on directly observing reality or by comparing reality with some a priori model. The outcome of process mining is better understanding of the process and accurate models that can safely be used for decision support because they reflect reality.

An important decision support system component is machine learning. Classical machine learning methods implicitly assume that attributes of

instances under classification do not change to acquire a positive classification. However, in many situations these instances represent people or organizations that can proactively seek to alter their characteristics to gain a positive classification. The learning mechanism should take this possible strategic learning into consideration during the induction process. [4, pp. 759–774] call this ‘strategic learning’. The strategic learning paradigm is new and many areas of research are possible. It opens the door to new ideas and approaches. Strategic learning adds agent utilities that are self-interested, utility maximizing, intelligent decision-making units. So far, the main concerns of utility-based learning (such as cost-sensitive learning and costs of data acquisition) have not been jointly investigated with the strategic learning issues.

It is possible to reverse the strategic learning problem and use these ideas to create a classifier (or a policy) that promotes certain actions (rather than avoids them) or use these ideas as a what-if tool to test the implications of certain policies. For example, a board of directors could develop executive compensation policies for different performance classes to promote long-term value generation by anticipating how the chief executive officers can play the system to their advantage (which usually causes short-term gains at the cost of long-term value).

All discussion so far has focused on using values as a classifier even though learning theory and rational expectations theory are independent from the implementation details. It would be very useful to determine validity of these results independent from implementation and introduce the strategic learning problem to other classifiers such as decision trees, nearest neighbor, neural networks, etc. Essentially, strategic learning is a general problem that will arise in any learning situation involving intelligent agents, so it should be applied to other learning algorithms [11, pp. 755–778].

Another key area of future research is the application of domain knowledge to strategic learning. Kernel methods accomplish this by using a nonlinear, higher-dimensional mapping of attributes of features to make the classes linearly separable. It may be possible to compute an appropriate kernel that can anticipate and cancel the effects of strategic behavior. Such a kernel could be developed using agents' utility functions and cost structures, which are a form of domain-specific knowledge.

Research on strategic learning mainly addresses only static situations [11, pp. 755–778]. However, it is possible that some exogenous

factors such as the environment or the parameters being used change over time. For example, it might be possible that, over time, new attributes may be added to the data set or conversely some may become obsolete. This type of dynamic situation may need to be modelled in a way to accommodate these possible changes to determine classifiers that will adapt efficiently.

An important area of research in strategic learning is to find better algorithmic methods to solve the strategic learning problem. While mixed integer formulations exist, solution methods currently do not scale up like their nonstrategic counterparts.

15.2. Fields of artificial intelligence usage

As the complexity of the real world problems increases, the capabilities of the quantitative models to analyze these problems in a systematic manner should also increase. The artificial neural network (ANN) has emerged (as a quantitative modelling tool) as a response to such complex and ever less-structured real-world problems [3, pp. 572–574]. The ANN is proven to consistently produce better prediction results as compared to more traditional statistical modelling techniques. Compared to the normative techniques, such as optimization with linear programming, ANN is a relatively more complex modelling technique that often leads to a non-optimal solution (because it is a heuristic modelling technique). Therefore, it should be chosen when the problem situation is rather complex and there is not an optimal solution option to the problem. As the complexity of the problem situation increases, the likelihood that the problem can be solved with normative techniques decreases, making the case for using ANN-type heuristic methods more convincing.

Development of an ANN is a rather complex process, especially for a novice user. There are a large number of parameters that need to be ‘optimized’ in order to get the best out of the ANN model. Since there is not a mathematical close form solution to what those parameter values are supposed to be, one can only rely upon one's knowledge and experiences. Even though most ANN software tools do a good job of setting those parameter values to reasonably justifiable values, the optimal configuration of the values still need experimentation [3, pp. 572–574]. In order to automate such experimentation process, some researchers suggest using genetic

algorithms or simulated annealing as the 'intelligent' search mechanism to optimize the parameter values.

From the standpoint of usability of an ANN as part of a DSS, one should be careful in making sure to hide the complexity of the model from the end user. Once trained, an ANN model is nothing more than a bunch of numerical values (a rather large number of values) that transforms the input vector (representing the values of the predictor variables) into an output vector (representing the desired prediction values) via a series of mathematical equations. The ANN models are a member of the machine learning techniques that learn from the past experiences either to explain the patterns in the data set or to predict the future values of certain decision variables. If the past repeats itself, then the future predictions of the ANN model will come out to be accurate. If a dramatic change occurs in the data overtime, then the model (which is based on the data prior to those changes in the environment) will not predict accurately [3, pp. 572–574]. The solution to this problem is to detect that the accuracy of the model is deteriorating over time, and retrain the model on new data. Another option is to gradually adapt the model to the new data as the data become available, and do this in an automated manner, so that the model does not become absolute. This second approach is an ongoing research area in the ANN world.

In the field of finance, most attention of ANN-enabled DSS is dedicated to predicting stock markets. Since such a prediction may lead to a rather quick and easy way to make money, many research efforts are reported in this area with variable levels of success [3, p. 566]. Some studied and reported on successful applications of neural network modelling in predicting the stock market movements, exchange rates, bankruptcy prediction, portfolio management etc.

15.3. Creative decisions support systems

Creativity support systems aid companies in finding ways to differentiate themselves by examining their current paradigm and improving or modifying the paradigm in a fundamentally new way. The four key factors involved in the execution of creative acts are the four Ps: person, process, press, and product [4, 745–754]. Each of these four factors plays an active role in how creativity support systems should be designed and utilized. The cognitive process of creativity starts in the mind of individuals to formulate the

problem and produce ideas. At the individual level, a creativity support system can be used to present a variety of stimuli to the individual in an effort to break cognitive inertia and to help stimulate dissimilar memory chunks or frames. Various creative processes and techniques can be supported and implemented in a creativity support system. The creative press or environment is the context in which creative ideas are produced and explored.

When a creativity support system is introduced to the creative process, it brings in its own internal environment comprising the technology spirit and its structural features. The creative product can be measured by the quality, novelty, degree of originality, feasibility, appropriateness, or usefulness of the idea. As organizations strive to produce creative products, CSS tools, with their potential to enhance or modify the creative output of an individual or group, become increasingly called upon to aid in this goal.

Creativity support system tools will have the potential to greatly enhance the creative output of an individual, group, or organization. When selecting or designing a creativity support system, we need to consider the press that is present within the system, as well as the external environment in which it will be used, the people or groups that will use the system, and the creative processes embedded in the system. Creativity support system brings to the table another dimension through which creativity can be enhanced.

Combining rich and restrictive languages in multi-media has been shown to have a strong impact on creative and innovative decision-making. The richness of the metaphors, labels, and platitudes that describe context in linguistic, visual, and other media can have a powerful impact on sharing of contextual understanding. This is not to say the volume of external knowledge is increased, rather than the construction and accessibility of contextual knowledge plateaus is improved within the rhizome [4, 741].

Creativity support systems imply the co-authoring, within the interaction context, of entirely new contextual knowledge, which may or may not be a synthesis of pre-existing contextual knowledge. The generation of this new contextual knowledge, and improvement of its accessibility, at the level of the group, becomes useful beyond the immediate moment in time. It becomes regenerated by itself as it moves through time, and is available for proceduralization as the decision-making context shifts.

15.4. Other future directions of DSS development

The diversity of data, data mining tasks, and data mining approaches poses many challenging research issues in data mining. The development of efficient and effective data mining methods, systems and services, and interactive and integrated data mining environments is a key area of study. The use of data mining techniques to solve large or sophisticated application problems is an important task for data mining researchers and data mining system and application developers [30, pp. 622–625].

Early data mining applications put a lot of effort into helping businesses gain a competitive edge. The exploration of data mining for businesses continues to expand as e-commerce and e-marketing have become mainstream in the retail industry. Data mining is increasingly used for the exploration of applications in other areas such as web and text analysis, financial analysis, industry, government, biomedicine, and science. Emerging application areas include data mining for counterterrorism and mobile (wireless) data mining. Because generic data mining systems may have limitations in dealing with application-specific problems, we may see a trend towards the development of more application-specific data mining systems and tools, as well as invisible data mining functions embedded in various kinds of services.

In contrast with traditional data analysis methods, data mining must be able to handle huge amounts of data efficiently and, if possible, interactively. Because the amount of data being collected continues to increase rapidly, scalable algorithms for individual and integrated data mining functions become essential. One important direction toward improving the overall efficiency of the mining process while increasing user interaction is constraint-based mining [30, pp. 622–625]. This provides users with added control by allowing specification and use of constraints to guide data mining systems in their search for interesting patterns and knowledge.

It is important to ensure that data mining serves as an essential data analysis component that can be smoothly integrated into such an information processing environment as search engines, database systems, data warehouse systems, and cloud computing systems. A data mining subsystem/service should be tightly coupled with such systems as a seamless, unified framework or as an invisible function. This will ensure data availability, data mining portability, scalability, high performance, and an

integrated information processing environment for multidimensional data analysis and exploration [30, pp. 622–625]. Mining social and information networks and link analysis are critical tasks because such networks are ubiquitous and complex. Development of scalable and effective knowledge discovery methods and applications for large numbers of network data is essential.

Mining such kinds of data as multimedia, text, and web data is a recent focus in data mining research. Great progress has been made, yet there are still many open issues to be solved. Visual and audio data mining is an effective way to integrate with humans' visual and audio systems and discover knowledge from huge amounts of data. Systematic development of such techniques will facilitate promotion of human participation for effective and efficient data analysis.

Advances in distributed data mining methods are also expected. Moreover, many applications involving stream data (e.g., e-commerce, web mining, stock analysis, intrusion detection, mobile data mining, and data mining for counterterrorism) require dynamic data mining models to be built in real time. Additional research is needed in this direction. An abundance of personal or confidential information available in electronic forms, coupled with increasingly powerful data mining tools, poses a threat to data privacy and security. Further development of privacy-preserving data mining methods is foreseen [30, pp. 622–625]. The collaboration of technologists, social scientists, law experts, governments, and companies is needed to produce a rigorous privacy and security protection mechanism for data publishing and data mining.

With confidence, we look forward to the next generation of data mining technology and the further benefits that it will bring.

Questions

1. What are the main trends in DSSs research?
2. What novel spheres of artificial neural networks application are appearing?
3. What are creative decision support systems?
4. What DSS techniques are the most perspective?
5. Where may dynamic data mining models be used?

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