THESIS ON INFORMATICS AND SYSTEM ENGINEERING C37

Concept Formation in Exploratory Data Analysis: Case Studies of Linguistic and Banking Data

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for any academic degree.

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INFORMAATIKA JA SÜSTEEMITEHNIKA C37

Mõistete moodustamine uurivas andmeanalüüsis: keele- ja pangandusandmete juhtumianalüüsid

TOOMAS KIRT

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Chapter 1

Introduction

To be successful in this world it is necessary to have some idea of the surrounding environment. In addition to perception by sensory organs, a human can gather information by using some artificial tools that widen tremendously one's ability to measure characteristics of several phenomena and to perceive the world. Artificial tools allow gathering a huge amount of data and by successful interpretation some knowledge can be acquired about the surrounding world. As the amount of data is increasing enormously, it is not possible to grasp the structure within the data by the naked eye, some tools for processing are needed. The easiest way would be to use just a pen and paper and use the approach of the exploratory data analysis (Tukey, 1977), where the data is illustrated by drawing the values of minimum and maximum, median, first and third quartile. As the dimensionality of the data increases the tools must be more complex.

Exploratory data analysis is said to be data driven and the methods used in the exploratory data analysis can be used as tools in knowledge discovery and data mining (Fayyad, 1996, and see discussion Kaski, 1997; Kaski & Kohonen, 1997). In a scientific jargon they indicate that "data speaks for itself". It can be argued that data does not speak for itself. To the scientists, reality amounts to data plus those theories, which make sense of the gathered data (Hoffmayer, 1996). Someone with a priori knowledge is needed to get some understanding of data. Without an interpreter data remains silent.

Methods used in exploratory data analysis do not need any supervision to reveal the hidden structure within the data and to discover so far unknown knowledge. Those methods project data so that new knowledge could be grasped easily. A method belonging to this group is the self-organizing map (SOM) (Kohonen, 1982; 2000) the main method used in this thesis. The SOM is a useful tool to visualize multidimensional data and is an effective and widely used method of the exploratory data analysis. This method is used to project multidimensional data into two-dimensional topological map and to reveal its clustered structure. As the classification is highly related to concept formation, and it is proposed by Gärdenfors (2000b) that SOM could reveal the conceptual structure of the data. Based on this presumption the SOM has also been used as a conceptual memory system of agents (Honkela & Winter, 2003). During the self-organizing process the points in high-dimensional space are mapped onto a two-dimensional output map that can be identified as a conceptual space. Formed local clusters on the SOM hold similar properties and can be explained by the same description as concepts. Such a conceptual structure is a basis for discovering new knowledge.

In the Western philosophy, knowledge is said to be a justified true belief (Moser, Mulder, & Trout, 1998). That is a traditional approach to epistemology. But how much justification is needed to believe that something is true and is also the knowledge. In the everyday life humans do not expect that the surrounding phenomena could be fully justified, otherwise they would not be able to live and make any decision. Human reasoning is rather based on the probability that certain events occur together or sequentially. Bishop and Trout (2005a; 2005b) have criticized the traditional epistemology and have proposed a naturalized approach to epistemology called strategic reliabilism. The strategic reliabilism is a collection of reasoning strategies to reason relatively well. The aim of the data analysis would be to offer relatively well justified theories about the world at a reasonable cost.

Acknowledgements. Once, when I started my master studies I was interested in how a human mind works and what is needed to build intelligent machines. Unfortunately, I was too shy to say it openly because I thought it to be a very respectable topic. So I started my studies in the field of machine learning that seemed to be one of the closest topics to my endeavours. To begin with, I would like to thank my first supervisor Jaak Tepandi for his support in my first steps in science.

When I met my current supervisor Leo Võhandu, he introduced the self-organizing maps to me. As the technique was said to be a type of neural networks, the decision was made and this topic has remained my companion until today.

I am very grateful to Leo Võhandu for his patience on this long way towards preparing my thesis and offering and guessing the ideas that I could be interested in.

So, I also would like to thank all the others who had to suffer with me. I enjoyed the study period itself because it gave me a new insight into how the world works and many friends whom I otherwise would not have met.

1.1 Outline of the Thesis

The first part of the thesis is concentrated on the study of concepts and knowledge. It is some background knowledge of how to understand what all the analysis is based on and why it signifies for us something. The second part introduces the self-organizing map and takes a look at the self-organizing phenomenon the method of SOM is based on. The third part is focused on the case studies and two types of data have been analyzed and the results are discussed. And finally, a general discussion of the concept formation and interpretation of the results are given.

1.2 Contribution of the Thesis

The thesis is an overview of publications published during my doctorate studies. The main topics of the publications are exploratory data analysis and use of the self-organizing map. Five publications form a part of the thesis and other articles are related to several topics covered in the thesis (see section Author's Publications). The thesis contains an overview of two case studies and provides a general framework and discussion of interpretation and conceptualisation of the results.

The thesis has grown out of two main case studies. The first one is a study and analysis of banking data. The topic is continuation of the work done in the master thesis (Kirt, 1999). Banking data is analyzed in three publications (covering chapters 3.3, 4.1 and 5.1). The first (Kirt, 2002) is a comparison of performance of the dimensionality reduction methods, in the second (Kirt & Võhandu, 2007) array algebra was used to speed up eigenvectors and PCA analysis of banking data was performed and the third publication (Kirt, Vainik, & Võhandu, 2007) includes a similarity measurement methodology to assess whether the SOMs created of original data and reduced data are similar.

The second case study is about the Estonian concepts of emotion and the topic is covered by eight publications (covering chapters 2.2, 3.3, 4.2 and 5.1). The first publications describe different aspects of data analysis by SOM (Kirt, Vainik 2004; Vainik & Kirt, 2005) and regard the SOM as an alternative method in the field of psycho-lexical studies where MDS has prevailed. The theory of conceptual spaces is used to interpret the results in publications (Kirt & Vainik, 2005; Vainik & Kirt, in press). Two articles (Kirt & Vainik, 2007; Kirt, Liiv, & Vainik, 2007) are concentrated on the comparison of different methods and analysis to find whether different methods allow us to improve interpretation rules and to interpret the results in a better way. The publication (Kirt, Vainik, & Võhandu, 2007) provides a methodology to compare similarity between the maps and a comparison of the two task of the survey. The final publication is an overview of the theories of concepts providing an evolutionary approach understanding the concepts (Vainik & Kirt, 2007). It is a logical continuation to the studies of concepts of emotion and the theory of conceptual spaces.

The third area of research is related to the phenomenon of self-organization and multi-agent systems. As the self-organization is the basis of the method of SOM and many processes surrounding humans are also based on self-organization (language, economy etc.) the topic is important. Publications in this field propose an alternative self-organizing approach to solve the scheduling problem in a ad hoc wireless networks (Kirt, 2006; Kirt & Võhandu, 2006a; Kirt & Võhandu, 2006b), to optimise energy consumption in wireless networks (Kirt & Anier, 2006), and to use an evolutionary multi-agent system to test some aspects of the emergence of meaning (Kirt; 2007). The publications are covering chapters 3.1 and 2.2.3.

The thesis also covers some philosophical issues of Popperian approach to the world, the theory of knowledge and includes a general discussion. Those topics were added to generate a better picture where to place this work and to serve as an introduction to further research. It is an emergent outcome of the thesis.

1.3 Abbreviations and Symbols

AP	– Ameliorative psychology
BMU	– Best matching unit
FCA	– Formal concept analysis
J	– Jaccard coefficient
KDD	– Knowledge discovery in databases
MDS	– Multidimensional scaling
MR	– Matrix reordering
PEEL33	– A data set consisting of 33 variables selected by peeling method
PEEL36	– A data set consisting of 36 variables selected by peeling method
PCA	– Principal component analysis
PCA50	– A data set consisting of 5 principal components
PCA95	– A data set consisting of 26 principal components
SMC	– Simple matching coefficient
SOM	– Self-organizing map

C	– correlation matrix
x, y	– sample vector
m	– number of samples
n	– number of variables
t	– time index
m_i	– map unit
n_{ij}	– element of neighbourhood matrix
e_i	– eigenvectors
λ_i	– eigenvalues

Chapter 2

Knowledge and Concepts

In this chapter a general framework is introduced that might be useful in interpreting the results of data analysis. The proposed conceptual framework examines how humans interact with the surrounding world and how they acquire knowledge from there. Knowledge is regarded as a justified true belief. But the world around us is not deterministic and our ability to perceive it is limited. Despite the fact we are able to survive in such conditions, because there are several regularities in the world that can be predicted. In everyday life humans still have some knowledge about the world although it does not correspond to the definition mentioned before. Here an alternative approach to the justification is considered that is based on heuristics and cost-effectiveness. A short overview of the theories of concepts, the basic elements of knowledge is given. There are several approaches how to explain the origin of concepts but no common theory has been presented yet. Despite the fact that it is not explained how concepts are formed in human mind, the classical theory of concepts has powerful explanatory resources in epistemic justification (Laurence & Margolis, 1999).

2.1 Knowledge

In everyday life humans interact with the surrounding world that contains several regularities within it and therefore it is possible to recognize them and use in planning and predicting future events. If there had not been any regularity, then it would be impossible to say anything on the moment t about the moment t +1 and all the possible future states would have equal probability (Forster, 1999). The acquired knowledge about the world is needed to be successful and to survive. Popper has proposed a model how a human interacts with the world (Popper & Eccles, 1977), also called Popperian cosmology (Figure 1) that brings out relations between the physical world, subjective experience and things created by a human. The worlds are called World 1, World 2 and World 3.

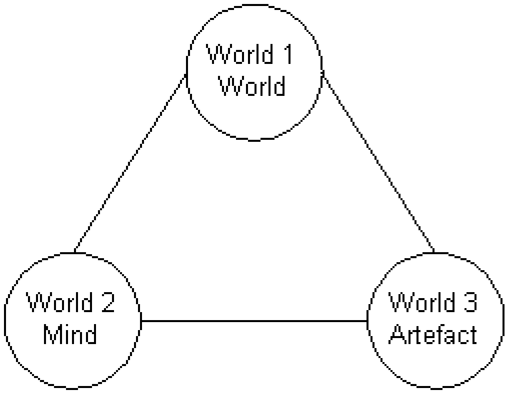


Figure 1. Popperian cosmology

World 1 – the physical world with its objects and events. Popper and Eccles (1977) discuss that an approach to the physical world is rather probabilistic. Elementary particles can be destroyed and transformed into other forms of energy like light. Causal explanation is replaced by probabilistic explanation and in some statements of classical physics about macroscopic objects the probability is close to 1 (Popper & Eccles, 1977). In a material universe something new can emerge when system components interact with each other. The emergence means the whole is more than the sum of its parts (Holland, 1998). For living organisms the surrounding world seems to have regularities to allow predicting. There are 'real' things – that are material things of ordinary size – things the existence of which a baby can control by putting them into his mouth (Popper & Eccles, 1977).

World 2 – the individual and unique mind of a human. It is a subjective and unique experience of the world – the beauty of being. The concept of quale introduced by Lewis (1929/1991) is connected with that individuality. The quale is regarded as a unique and subjective experience that an organism experiences, like the experience of colour red. Cognitive scientists present a critique that there cannot be a separate experience, because the perception is a whole, connected with previous experiences and it cannot be divided into parts (Edelman, 2006).

World 3 – all the artefacts created by a human, like art, machines and languages to communicate with other humans. World 3 is highly connected with the idea of meme, which was introduced by Dawkins (1976/2006), see detailed discussion in (Blackmore, 2000). World 3 contains language and science that are the results of human activity. Objects in World 3 cannot exist without subjective interpretation of World 2 and would be only physical objects of World 1, like a book as a thing. Even if the book would contain words with their explanations using other words it would not have any meaning alone, because they are not grounded (Harnad, 1990). To have some meaning, those words must interact with concepts formed in World 2.

Knowledge acquisition and the creation of a scientific theory are interaction between the three worlds. The Popper's view of developing a scientific theory is as follows (Popper & Eccles, 1977). The scientist starts from a problem and tries to understand it. It is an intellectual task – a World 2 attempt to grasp a World 3 object. It can be done by using books from World 1. A proved scientific theory becomes a World 3 object that can be as a memory in World 2 or a manuscript in World 1 and have impact on World 1. Popper argues that humans build up their knowledge and science using a trial-and-error search (Popper, 1991).

Philosopher Margenau has proposed a description of the structure of scientific theories (Margenau, 1950, and see Torgerson, 1958). He proposed that there exists an observable nature, some theories that are based on empirical data that measure some phenomenon in the nature and some other theories that generalize the theories that are based on empirical evidence (double lines). The idea is illustrated in Figure 2 where the cloud is a natural world, and on the left there are theoretical constructs (C) that are connected to each other by some formal, logical connections and by the nature there is connection between the theoretical construct and observable data.

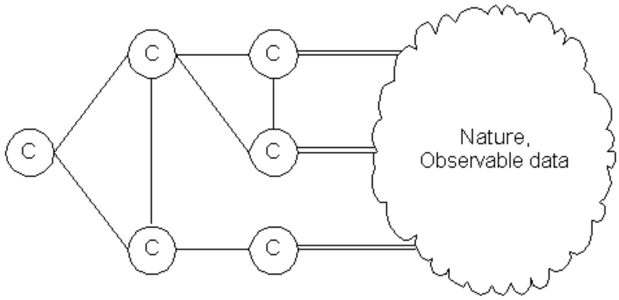


Figure 2. A diagram of Margenau's treatment of science (Margenau, 1950, p. 85)

So the description of the world covering its regularities and exceptions can be built. If there is enough evidence to believe the description to be true we can talk about having some knowledge. Possessing knowledge has some value, for example, knowing the future trends of a stock market, or just the way home. Especially valuable is true knowledge. Epistemology is the area of philosophy that tries to find an answer what knowledge is and how to distinguish true belief from a false one.

2.1.1 Theory of Knowledge

Knowledge is said to be in the Western philosophy as a justified true belief (Moser et al., 1998). Believing is logically a necessary condition for knowing but it is not sufficient for the knowledge because the belief can be false. The second condition for knowing is a truth and a belief is needed to be true to become knowledge. For a true belief to become knowledge it has to be justified and justification is the third condition for knowledge. Belief needs adequate support to confirm it to be true. Some knowledge can be acquired by sensing it (*a posteriori*) but some other is based on a concept what a thing is (*a priori*). That is the traditional approach to epistemology.

Some more naturalistic approach to epistemology is evolutionary epistemology (Bradie & Harms, 2004), which emphasizes the importance of natural selection. It has two main roles, first, to ensure fit between an organism and environment and second, trial and error learning as a way to acquire knowledge and to build scientific theories. As Popper (1991) noted, the method of learning by trial and error is learning from our mistakes and it seems to be practised by lower and higher animals. Trial and error learning requires a mechanism for variation, for selection (fitness) and for preserving and propagating the selected variations (Campbell, 1979). Even if there seems to be some shortcuts to avoid trial and error approach, such approach is still needed at some level.

Another naturalized approach to epistemology is based on psychology and human's natural way of reasoning. Bishop and Trout (2005a, 2005b) have argued that traditional epistemology uses very conservative principles for judgements and have proposed a naturalized approach to epistemology called strategic reliabilism. Strategic reliabilism is an epistemological theory under the ameliorative psychology (AP) and is a collection of reasoning strategies to reason relatively well (Bishop & Trout, 2005b).

In everyday life humans do not expect that the surrounding phenomena could be fully justified, because the human's ability to perceive the world is limited and there are many things that are not understood but used in everyday life and reasoning. Human's reasoning is rather based on the probability that certain events occur together or sequentially, otherwise it would not be difficult to live and make decisions. It is noted that the brain is exquisitely sensitive to the statistical structure of experience (Barselou, in press). AP identifies reasoning strategies based on their reliability. If the environment is unknown and resources are limited, then simple mechanisms are needed to make quick decisions. Several fast and frugal heuristics, like the recognition heuristics, elimination heuristics and satisfying heuristics, have been proposed (Gingerenzer & Todd, 1999; Todd, 1999). The goal of using a set of simple decision rules is to maximize the payoff (Forster, 1999).

Strategic reliabilism has the following starting-points. Three central features of epistemological framework guided by ameliorative psychology are the robust reliability, the cost benefit approach to reasoning and the importance of significance. A rule is robustly reliable when it makes accurate predictions and can be used in a wide range of problems. Strategic reliabilism takes into account the fact that resources are limited and choices must be made in a certain time range. Therefore the cost-benefit analysis is used to identify an optimal reasoning strategy. Using simple reasoning strategies leads to a decrease in the local reliability, at the same time an increase in the global reliability will take place. Reasoning should be more accurate about significant problems. It should also be taken into account that certain errors are more costly than others. The problem should be significant for some reason and a significant problem can take more resources because the cost of failure is higher.

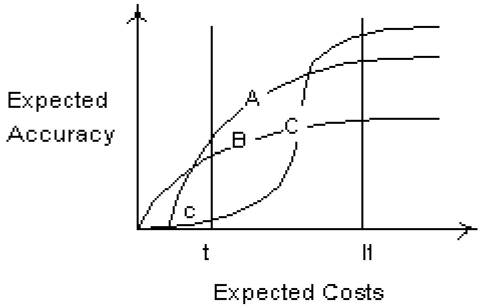


Figure 3. Cost benefit graph (Bishop & Trout, 2005a, pp. 61, 62, 67)

The simple reasoning strategy can bring some benefit by reducing the cost of the truth and enable one to get more truth in a shorter time period than by a sophisticated one. If there are three reasoning strategies A, B and C, their performance can be visualized on the cost-benefit graph (Figure 3). Strategy B performs worse and brings less benefit in a long term. Strategy C gives the most reliable results in a long term but if the costs are limited, strategies A or B are preferable. At the time step t it is not known what the additional cost of strategy C might be, whether it is reasonable to switch on it or not because at the time step t1 the accuracy might be lower than that of strategy A. At the same time, Strategy A has some start-up costs c. Strategy A performs better but it has some time lag before the advantage becomes visible. The start-up costs make reasoning conservative because it is not known beforehand whether the new strategy will perform as well as the strategy in use and people usually do not want to change their acquired method.

Both the evolutionary epistemology and strategic reliabilism use a cost-benefit model to assess the sufficiency of justification. They are additional and complementary tools for knowledge acquisition.

2.2 Concepts

Concepts are tools that help us to handle problems we are facing in this world. They allow us to classify, categorize and evaluate objects and events in the surrounding environment. The purpose is to identify proper behaviour in the situation. Concepts can be regarded as a subjective classification of things. It is argued that cognition is categorization and objects afford certain sensorimotor interaction with them (Harnad, 2005).

The purpose of the categorization system of an organism is to provide maximum information about the environment with the least cognitive effort (Rosch, 1978). Categorization must use features that maximize similarity between the samples in the cluster and at the same time separate different clusters as well as possible. An organism must not differentiate stimulus that is irrelevant to the purpose at hand.

As one tends to interchange the categorization and concepts, it is proposed that there exists clear distinction between the perceptual categories and concepts (Ashby & Maddox, 2005). Concepts are something more than categorization they are ideas or meaningful entities. But Barsalou (2003) argues that a conceptual system is knowledge of categories and it shares mechanisms with perception and action.

Most of the discussion of concepts is going around lexical concepts. Lexical concepts are concepts like BACHELOR, BIRD, and CHAIR – corresponding to lexical items in a natural language (Laurence & Margolis, 1999). The meaning of lexical concepts is explained by using some other words, that is, their symbolic representation. Based on this contradiction, Harnad (1990; 2003) raised a question how an arbitrary symbol system can be grounded in the other meaningless symbols and how words actually get their meaning and names this problem a symbol grounding problem. An overview of different approaches to solve the problem is given by Taddeo and Floridi (2005).

The relation between concepts and their meaning is another open question: some authors equate a concept and lexical meaning (Cruse, 2000) and talk about the meaning of a concept (Osgood, Suci, Tannenbaum, 1975). It is also an open question what a meaning is and whether a symbol system alone can have a meaning (see Searle's (1980) thought experiment called Chinese Room Argument). It is noted that for living organisms the surrounding environment has some meaning. Everything an organism senses signifies something to it: food, fight, reproduction (Hoffmeyer, 1996).

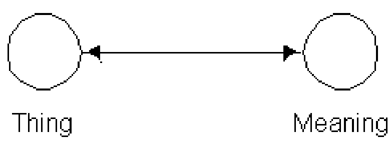


Figure 4. Meaning

Meaning can be regarded as a relation between an element in a set of things and an element in a set of meanings (Figure 4). A two-part model offered by Saussure consists of a 'signifier' - the form which the sign takes; and the 'signified' - the concept it represents. The sign is the whole that results from the association of the signifier with the signified (Saussure, 1916/1983; and see Chandler, 2002). A similar approach is encountered in semantics where a more complicated language is used to describe the meaning of words, e.g., a semantic lexicon system WordNet (Miller et al., 1990). The database consists of words and their mutual relations.

As the symbols need to be grounded on some object or referent in the world, it must be added to the model. Several triangular models of semantics have been proposed.

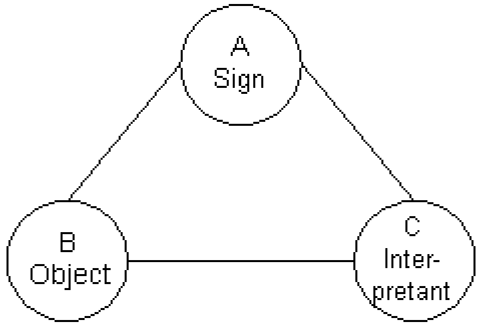


Figure 5. Semiotic Triangle

Peirce proposed a triangular model of signs called the semiotic triangle (Figure 5). The sign presents a relation between three factors: a) the sign; b) the object – to which the sign refers; and c) the interpretant – the one who constructs the relationship between the sign and the object (Peirce, 1931-58). A similar triangular structure was also proposed by Odgen and Richards (1923) and their model consists of a) symbol; b) referent; and c) thought or reference. Popper's three world model introduced before is also quite similar. For grounding the symbols an additional link between the a) symbol and the c) concept (interptretant) has been proposed – a method that constrains the use of the symbol for the objects which it is associated with (Steels, 2006).

As concepts are studied by different disciplines there are several controversies about defining what a concept is. Many reviews have been written about concepts (e.g., Laurence & Margolis, 1999; Murphy 2002; Smith & Medin, 1981), but there is no theory that could give a comprehensive understanding what concepts are. In the following sections, the main theories of concepts are briefly reviewed, the theory of conceptual spaces is introduced in more detail and in the final part the situated simulation theory and some supporting ideas of this theory are covered.

2.2.1 Theories of Concepts

The most dominating view of concepts is the classical theory of concepts. The classical theory holds that concepts are defined as a set of necessary and sufficient features. If a concept does not exhibit the necessary and sufficient features, then it does not belong to the class. An example of a classical concept is BACHELOR it can be composed as a set of features such as NOT MARRIED, MALE and ADULT. Those features specify a condition that must be met to be a bachelor. But the classical theory has problems, for example, whether a Pope is a bachelor (Laurence & Margolis, 1999). As many special cases are present and concepts tend to be rather fuzzy, it is difficult to offer plausible definitions.

During the 1970s, a new alternative theory to the classical theory of concepts emerged. Experimental data indicated that some samples are better members of a category. Whether a sample belongs to a category is decided by using its similarity with a prototype (Rosch, 1976; 1978). To measure similarity with the prototype, a set of features is needed. Some of the features have higher weight than others and the membership of the sample in a category is determined by measuring similarity between a sample and the category representation. The prototype theory is effective in categorization, but it has similar problems with highly atypical samples (Laurence & Margolis, 1999) and many concepts lack prototypes.

Similar to the prototype theory is the exemplar theory of concepts. In the exemplar theory, the similarity is measured with the closest exemplars and the sample belongs to the class of the closest exemplar (Smith & Medin, 1999). Category membership is decided using a probabilistic view where concepts are represented in terms of properties that are only characteristic or probable of class members (Medin & Smith, 1984). The exemplar approach looks like a statistical tool for classifying data.

To explain coherence between the concepts, Murphy and Medin (1999) have suggested a theory-based approach to concepts. Concepts are in relations in the same way as the terms of scientific theory and categorization resembles the process of scientific reasoning. The theory theory is facing difficulties to explain whether different people possess the same concept or for the same person to have the same concepts over time (Margolis & Laurence, 2006).

Several other theories have been proposed and continuous discussion is going on. One of the geometrical approaches of concept representation is introduced in a more detailed way in the next section.

2.2.2 Theory of Conceptual Spaces

Gärdenfors (2000a; 2000b) has proposed a geometrical model for the representations of concepts called Conceptual Spaces. In this model he distinguishes three levels of representations: the most abstract level is the symbolic level on which the observation is described by means of some language, the second level is the conceptual level on which observations are located as points in the conceptual space and the least abstract level is the subconceptual level on which the observations are characterized by inputs from sensory receptors which form the dimensions of the conceptual space. For example, the geometrical representation of colours – a colour space where a small subset of colours forming a smaller colour spindle is a space of possible colours of skin (Figure 6).

A conceptual space is described by a number of quality dimensions. Qualities are mostly measured by our sensory receptors, but they can be more abstract by nature as well. Quality dimensions describe the properties of an object and relations between the properties. Quality dimensions are divided into two groups: integral and separable. A value on an integral dimension is always co occurring with another value measurable on another dimension: for example, the hue and brightness of an object are inseparable, integral dimensions. Independent dimensions on the contrary are separable in principle, for example, the size and hue of an object are considered as independent dimensions. The function of the quality dimensions is to represent the “qualities” of the observations and to build up domains needed for representing concepts. Spatial dimensions belong to one domain, colour dimensions to another and so on. The notion of a cognitive domain can be defined as a set of integral dimensions that are separable from all the other dimensions.

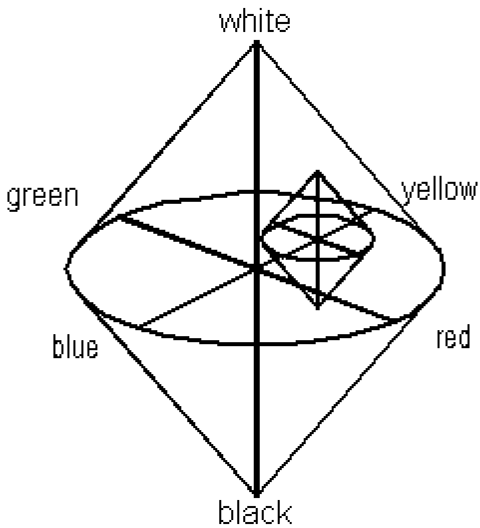


Figure 6. The subspace of skin colours as a part of a colour space (Gärdenfors, 2000, p. 121)

The quality dimensions are the main tools for measuring similarity of the concepts. If we assume that dimensions are metric, then we can talk about distances in the conceptual space. The smaller the distance between the representations of two objects, the more similar they are. In this way, the similarity of two objects can be defined as the distance between their representing points in the space.

A conceptual space can be defined as a collection of one or more domains. A point in the space may denote a concept. The properties of the object can be identified with its location in space. And a property can be represented as a region of the domain. The domains of a conceptual space should not be seen as totally independent entities, but they are correlated in various ways since the properties of the objects modelled in the space covary. On symbolic level we can say that “all A-s are B-s” and on conceptual level it means that there is a strong correlation between an object in conceptual space and a certain value of its property.

As Gärdenfors has suggested there is an analogy between the Conceptual Spaces and the Self-Organizing Maps. During the self-organizing process the points in high-dimensional space are mapped onto a two-dimensional output map that can be identified as a Conceptual Space. The self-organizing map is one way of modelling how the geometric structure within a domain can be created from the information on the subconceptual level.

In the theory of conceptual spaces (Gärdenfors, 1997) the properties of a concept are defined by a number of quality dimensions, which also represent semantic information and symbols are high level representation of concepts. But in this theory a value dimension is missing that might be an important factor to create meaning. Meaning is defined by the value of the relationship between an individual and his environment (Zlatev, 2001).

2.2.3 Grounding Concepts

Several aspects make understanding what a concept is rather difficult. On the one hand, there are features of the world perceived through sensory organs that are engaged in the process of classification of objects and events through distinguishing and combining class elements. On the other hand, there are words and their ambiguity. Between them remains a conceptual level where the perception is connected with its subjective importance (for example, if the legs are tired, then rather many objects seem to be like chairs, despite the fact that they do not resemble a classical chair) and with symbolic representation (which is also acquired through sensory organs). As all the levels are not overlapping (through perception chairs and stones can be distinguished, but a stone can be used as a chair, at the same time, a chair at school is anyhow connected with a stone). The result is a confusion regarding to defining a concept. According to Wittgenstein a sign gets its meaning through the use (Wittgenstein, 1958/2005, §432). So the continuous interaction with the surrounding world creates content and meaning for concepts and related symbols.

Such a process of interaction is regarded as grounding and Harnad (1990) proposes that symbols can be grounded by sensory-motor interactions with the surrounding world. Harnad's model consists of three kinds of representation: iconic representation – receiving sensory signals, categorical representation – recognition of a certain pattern and symbolic representation – assigning a symbol. The physical grounding hypothesis proposed by Brooks (1990) expects there is no need to use symbolic representation for grounding and the meaning is directly grounded in the environment. But such grounding externally has some difficulties to represent abstract concepts (Barsalou, in press). Knowledge acquired from introspection is central to the representation of abstract concepts (Barsalou & Wiemer-Hastings, 2005). Also a term 'embodied cognition' (e.g., Wilson, 2002) is used and it is expected that cognition is highly connected with bodily states, but grounding seems to have wider sense (Barsalou, in press).

Barsalou (2003) has proposed a so-called situated simulation theory to explain the essence of a concept and how human's conceptual system functions. The proposed approach does not expect that two separate systems exist for the sensory-motor and conceptual processing, a common representational system underlies both. To represent concepts – simulations are used that are reenactments of the sensory-motor states. For example, when the conceptual system represents an object's visual properties, it uses representations in a visual system. Those simulations are not identical to perception.

Conceptual representation is highly contextualized and dynamical. A concept is not an abstract representation of the category but instead a unique representation of needs in a current action. A simulator can produce an infinite number of simulations depending on the current goals and situation (Barsalou, 2003). As it is noted, no word ever has exactly the same meaning twice (Hayakawa & Hayakawa, 1990, p. 39).

Simulation is the re-enactment of perceptual, motor, and introspective states acquired and integrated during experience (Barsalou, in press). The experience is memorized as a set of neural cliques that encode different features ranging from the general to the specific (Lin, Osan, & Tsien, 2006). Most animals learn to associate pleasures and pains with the memorized experience which enables steering toward pleasure and away from pain before they actually experience either (Gilbert & Wilson, 2007). The perception of a relevant object or event triggers affordance (Gibson, 1979) what an object can afford and means for one organism something different than for the other. The meaning of an object or event depends on what it makes possible. Observation of the surrounding world is always selective (Popper, 1991) and it needs some point of view or a problem why a certain thing is important.

The triggering effect and the motivational system can be explained by a "control metaphor" proposed by Cisek (1999). He states that organisms behave so that they could get the right stimulus. Objects and events mean to the agent whether they support survival or not and whether they enable one to achieve a desirable or avoid an undesirable state. A basis of this process can be found in the beginning of life.

There are several theories how the first living pieces of matter came into existence, like 'autocatalytic sets' described by Kaufman (1993) that formed the self retaining metabolic cycles (Shapiro, 2007). The main property of the living system ensures that the conditions to continue their existence are met. The living systems should keep certain critical variables within an acceptable range and this mechanism is called "homeostasis". The variables are kept in the desired range by feedback loops forming a control cycle. If a certain variable is out of the desired range, a cascade of chemical reactions follows that brings the system back to the desired situation and the trigger of the reactions ceases.

The control cycles also help an organism to classify things or events as "good" or "bad" because of their possible impact on survival (Damasio, 2006). The internal and external signals are triggers of a certain response or behavioural pattern. Animals distinguish inherently some input; some of them are "desirable" and some "undesirable" (Cisek, 1999). The desirable situations are preferred, like a full stomach, and undesirable are avoidable, like danger. Such a distinction gives the meaning to the perception–whether the perceived object or event enables one to achieve a favourable situation or must be avoided. Control is gained by studying the regularities within the environment that define reliable rules of interaction. The perception is connected to the value category memory (Edelman, 2005) and it is evaluated what the surrounding environment can afford and what it means to an agent in terms of survival.

Hawkins has proposed that a human brain deals with predicting (Hawkins & Blakeslee, 2004) and so do all the other living organisms – they are predicting sequences and regularities in the surrounding world. The goal of such predicting is to select one of the actions made possible by the environment that has the best payoff (Cisek, 2005) or utility (Körding, 2007). Objects and events in the surrounding environment are means to achieve a desired state and every subject classifies them and builds up their meaning in accordance with their ability to achieve a desired state. It is the basis of simulation how perceptual, motor and introspective states can be connected to achieve a desired state. The described control or motivational system could explain the basis of the situated simulation theory of concepts (Barsalau, 2003) and why things could afford something for an agent (Gibson, 1979). The control process could explain why a force exists that turns an organism to behave in the world and how the objects and events in the surrounding environment get their meaning through the introspection of an agent.

Chapter 3

Self-Organizing Map

The self-organizing map (Kohonen, 2000) is a widely used method in knowledge discovery and data mining because of its relative simplicity and effectiveness. Data mining is defined as the analysis of observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner (Hand, Mannila, & Smyth, 2001). Methods of exploratory data analysis or methods of knowledge discovery and data mining are used to let the data speak for themselves.

SOM is a widely used application of the general principles of self-organization in the field of data analysis. Self-organization is a process characterized by an increase of the order in the system without any external control, i.e. it is only the components of the system itself and their interactions which are responsible for organizing it (Heylighen, 2001). As with any other reductional analysis, the purpose of SOM is to reduce the dimensionality of input data and to reveal its hidden structure. It performs two tasks: (i) clustering, that is, reducing the amount of data by grouping similar samples together, and (ii) projection, that is, reducing the dimensionality of the data by projecting the input data into a lower-dimensional space in such a way that the samples located close to each other in the multidimensional space will also appear close to each other on a two-dimensional map (Kaski, 1997). The method of the self-organizing map uses an unsupervised learning algorithm which is claimed to partly simulate the self-organizing processes which take place in the human brain (Kohonen, 2000, p. 104, Kohonen & Hari, 1999). The results of the analysis are presented on a topological map called the Unified Distance Matrix (U-matrix). SOM is also homologous with the theory of Conceptual Spaces (Gärdenfors, 2000b), a geometrical model of conceptual representations where the similarity of concepts is represented by their spatial closeness.

This chapter introduces the main aspects of the self-organizing phenomenon and the self-organizing map. Firstly, an overview of the self-organizing phenomenon and its main characteristics will be given. Secondly, the SOM algorithm will be described. Next, the visualization technique and interpretation rules will be introduced. Finally, the methodology to compare two different SOM is proposed.

3.1 Self-Organization and Emergence

In many natural systems it can be noticed that an order arises from local interactions between the system components without any external help. Just a few simple laws generate complex phenomena in nature (Bak, 1996). The process of generating order and moving the system towards a more orderly and stable state by local interactions between the system components is called self-organization. Using the definition proposed by Heylighen (2001) the self-organization is a spontaneous creation of a globally coherent pattern out of local interactions between initially independent components.

De Wolf and Hovolet (2005) have summarized the main characteristics that are commonly used in different definitions of self-organization. The most important characteristics are as follows: increase in the order or organization of the system; absence of any external control; adaptability in the presence of perturbations and change; and being a process. The self-organizing systems usually exhibit the phenomenon of emergence; it means that global behaviour created by system components is something more than just the sum of activities of these components.

Some additional characteristics of self-organizing systems are brought out by Heylighen (2001). As there is no external control the control of the system is distributed among the system components. Self-organizing systems are by nature non-linear. The non-linearity is caused by the positive and negative feedback loops. Positive feedback accelerates changes and negative feedback stabilizes the system. The self-organized systems form a hierarchy of levels and higher levels are characterized by emergent properties that are peculiar to the system as a whole and cannot be reduced to the properties of the elements. Self-organizing systems tend to move to a more orderly state or more stable configurations, called attractors. The decision points where the system decides which direction to move are called bifurcations. Complex self-organizing systems are far from equilibrium to keep up their organization. A flow of energy or resources keeps the system far from equilibrium and it helps the system to adapt to the changes in the environment.

Many examples of self-organizing systems could be identified around us. Magnetization is a very simple and expressive example of self-organization (Heylighen, 2001). Tiny magnets inside the potentially magnetic material that are randomly oriented in higher temperatures tend to become oriented in the same direction in lower temperatures. Biological systems are defined to exhibit the self-organizing phenomenon (Camazine et al., 2001) as well as processes in human brain (Kelso, 1995).

A good example of a self-organizing system with emergent properties is a flock of birds. There is no clear leader in the flock who tells others how to form a flock as all the birds follow three simple rules that make the flock behave in an organized way. The birds in a flock just keep the minimum distance from others birds, move closer to the centre point of the nearest neighbours and follow the average direction of the neighbours' movements. Out of those local interactions a global coherent pattern emerges (Reynolds, 1987). The birds following those three rules generate a behaviour that requires a new concept to describe it – a flock.

Self-organization can be found in many natural systems but there are also artificial systems based on the self-organizing principles. For example, the self-organizing approach can be used in the applications of the ad hoc wireless network (Kirt & Anier, 2006). An ad hoc wireless network can be considered as a self-organizing system. An ad hoc wireless network consists of nodes that are independent, work in a similar manner, and do not depend on a central station that manages connections between them or controls them. The nodes are connected directly only to their neighbours that are in a wireless transmission range and indirectly to others, relying on its neighbours to forward messages towards the destination (Feeney, 2004). An ad hoc network builds its structure autonomously and reacts to changes in the structure when a node joins, moves around or leaves. Only local information that a node owns itself or can acquire from its neighbouring nodes can be used in the applications of ad hoc networks.

The self-organizing approach can be used to agree on a schedule between the nodes (Kirt & Võhandu, 2006) and this approach is based on a stochastic and self-organizing solution to solve complex problems (Kanada & Hirokawa, 1994). A schedule is needed to prevent two neighbouring network nodes from performing the same operation at the same time. The scheduling problem is reducible to the well-known graph vertex colouring problem that belongs to the class of NP-hard problems (Garey, 2003). To solve the problem graph vertexes should be coloured so that the two vertexes having a common edge do not have the same colour. The network nodes share information locally only with their neighbours, but despite the fact the information spreads through the network rather rapidly. It is in accordance with the idea of the small-world network (Watts & Strogatz, 1998).

The method of the self-organizing map also shows self-organizing behaviour and only simple local interactions lead the system to a more orderly state. In the case studies banking and linguistic data are analyzed. Both the data describe processes that are parts of a self-organizing process as the economy and language. The system behaviour is created by local interactions between huge amounts of agents (people).

3.2 Self-Organizing Map

The self-organizing map SOM (Kohonen, 1982; 2000) is a neural network that uses an unsupervised learning algorithm. It means that there is no prior information presented to the algorithm on how input and output are connected. The SOM can be used for clustering and visualizing multidimensional data and for reducing the dimensionality of the data by plotting them in a two-dimensional output grid, also called a map. The SOM algorithm maps data from a high-dimensional space onto a plane so that the points that are near each other in the input space are plotted to nearby map units in the SOM. The SOM solves two tasks: first, clustering—reducing the amount of data by grouping similar samples together, and second, projection—reducing data dimensionality by projecting the data into a lower-dimensional space in such a way that certain structural properties of the data set are preserved as faithfully as possible.

The SOM analysis was performed by the SOM Toolbox for Matlab (Alhoniemi, Himberg, Parhankangas, & Vesanto, 2005).

3.2.1 SOM algorithm

To describe how the process to create the self-organizing map works let us assume that we have input data as a set of sample vectors x. The output of the self-organizing map is a grid of vectors m_i that has the same number of elements as the sample vector. The output vector is called a unit. The algorithm of the SOM has two main basic steps that are repeated a number of times. Before starting the learning stage, the vectors of the output grid are randomly initialized. In the first step, a random sample vector x is chosen and compared with all the output vectors m_i to find the closest unit c on the output grid that has a minimum distance $d(x, m_i)$ with a sample vector x.

$$c = c(x) = \arg \min_i \{d(x, m_i)\} .$$

Usually the Euclidean distance

$$\|x - m\| = \sqrt{\sum_{i=1}^{n} (x_i - m_i)^2}$$

is used as a measure of the distance between two vectors.

As a next step, this best matching or winning vector and its neighbourhood are changed closer (transformed) to the sample vector. The formula for the learning process is as follows:

$$m_i(t+1) = m_i(t) + \alpha(t) h_{ci}(t)(x(t) - m_i(t)) .$$

Here $\alpha(t)$ is the learning rate factor and $h_{ci}(t)$ – neighbourhood function value at the step t. During the learning process the learning rate $\alpha(t)$ and the neighbourhood function values $h_{ci}(t)$ are shrinking. The result of the learning process is that the output becomes ordered and all the output vectors are valued so that the total distance with the sample vectors will be minimized.

3.2.2 Visualization and Interpretation of SOM

For the visualization of the self-organizing map, a Unified distance matrix (U-matrix) is often used. The U-matrix represents the distances between each pair of map units by colour coding (Ultsch, 1993). A light colour corresponds to a small distance between two map units and a dark colour represents a bigger difference between the map units. The points on the output map that lie in the light area belong to the same group or cluster, while the dark area shows the borders between the clusters. The main idea for interpreting the results is to search the map for lighter areas and darker borders that separate them. A light area corresponds to a group of data that are similar and behave in the same way.

3.3 Methodology of Similarity Measurement

When different sources of data are used that describe the same phenomenon but are collected somehow differently or the number of variables is varying, then it is needed to assess whether the results of the two analyses are similar. To measure the similarity between self-organizing maps, a visual inspection is commonly used. Subjective factors, such as one's attentiveness to both general patterns and local details of a large number of presented data samples, might diminish the objective value of data analysis. Mandl and Eibl (2001) have proposed a more formal method to evaluate two- or three-dimensional visualizations and to measure distances between the two representations. They calculate Euclidian distances between all the items and find correlation between two representations. But it is easier to use topological representation and not to convert it once more into the Euclidian space and so a novel similarity measurement methodology is proposed.

As the SOM projects close units of the input space into nearby map units, the local neighbourhood should remain quite similar and the neighbourhood relations are expected to remain unchangeable even when the overall orientation of the map changes. While the SOM represents data on topological maps, the local topological relations between samples can be used to assess whether the maps have the same structure. Therefore the local neighbourhood is the basis of the proposed approach to measure similarity between the maps.

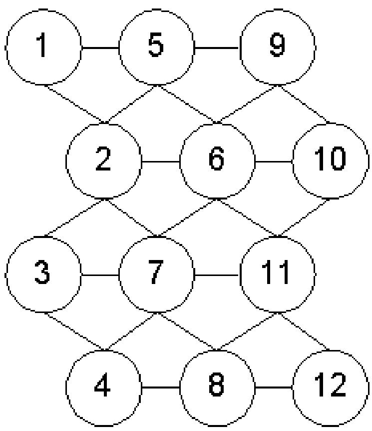


Figure 7. Neighbourhood relations on the SOM

The proposed methodology to measure similarity between the self-organizing maps consists of four main steps. Firstly, visual inspection and general organization of the maps is assessed, secondly, neighbourhood relations are defined and measured, thirdly, similarity measurements coefficients are calculated and different aspects of relations are analyzed, and finally, neighbourhood relations are compared and the maximum isomorphic subgraph is found.

To analyze general organization the resulting map is visually examined and clusters and their borders are identified and so are also the general orientation and locations of samples. Thereafter the matrix of neighbourhood relations is formed. Neighbourhood assessment is based on the location of the best matching units (BMU - a point on the map that is the closest to the sample data vector) on the self-organizing map. Two samples are neighbours if they are marked to locate on the same node or in the neighbouring nodes depending on the neighbourhood range. The neighbourhood on the hexagonal map is demonstrated in Figure 7. If we use hexagonal arrangements of nodes and the neighbourhood range is defined as 1, the neighbourhood of the node 6 is defined as nodes 2, 5, 6, 7, 9, 10, and 11. The neighbours of a sample are all the samples located at the same or at the neighbouring nodes, as defined before. The neighbourhood matrix is an n-by-n square symmetric matrix N where n is the number of samples and that matrix can also be regarded as a graph. If there is neighbourhood relation between the i-th and the j-th element, the value of the matrix element is marked 1 and remains 0 in other cases.

$$n_{ij} = \begin{cases} 1, ifneighbour \\ 0, otherwise \end{cases}$$

The next stage of similarity analysis is the calculation and assessment of similarity coefficients. Many similarity and dissimilarity measures have been proposed to identify the distance between binary variables (Tan, Steinbach, & Kumar, 2005). The coefficients have typically values between 0 and 1. Value 1 indicates that the two objects are completely similar and value 0 indicates that the objects are not similar at all. Three similarity coefficients - Simple Matching Coefficient (SMC), Jaccard Coefficient (J) and Cosine Similarity - have been used.

Let us have two sets of data X and Y consisting of vectors x_i and y_i described by n variables. Vectors x_i and y_i are binary. For comparison of two binary vectors we can use the following quantities

f00 = the number of variables where a is 0 and b is 0 – negative match.

f10 = the number of variables where a is 1 and b is 0 – not matching.

f01 = the number of variables where a is 0 and b is 1 – not matching.

f11 = the number of variables where a is 1 and b is 1 – positive match.

Each variable must belong into one of these four categories, meaning that f11 + f01 + f10 + f00 = n (the total number of variables).

Simple Matching Coefficient (SMC) is a commonly used coefficient which is defined as

$$\mathrm{SMC} = \frac{\text{number of matches}}{\text{total number of variables}} = \frac{(f11 + f00)}{(f01 + f10 + f11 + f00)}.$$

The SMC rates positive and negative similarity equally and can be used if positive and negative values have equal weight.

Jaccard Coefficient (J) is used if the negative and positive matches have different weights (are asymmetric).

$$J = \frac{\text{number of positive matches}}{\text{number of variables - negative matches}} = \frac{f11}{(f01 + f10 + f11)} .$$

Jaccard Coefficient ignores negative matches and can be used if the variables have many 0 values.

Cosine Similarity ignores also the 0-0 matches, but it can also be used if the variables are non-binary. If x and y are vectors, Cosine similarity between two vectors is defined as

$$\mathrm{Cos}(x, y) = \frac{x \cdot y}{\| x \| \| y \|} .$$

Here x • y is dot product of vectors x and y $\sum_{k=1}^{n} x_k y_k$ and ||x|| is the length of the vector x, $\| x \| = \sqrt{\sum_{k=1}^{n} x_k^2} = \sqrt{x \cdot x}$.

Cos(x, y) is the cosine of the angle between x and y. If the value of Cos is 1, the angle between vectors x and y is 0 degrees and if the value of Cos is 0, the angle is 90 degrees. As the Cosine Similarity value is normalized by the length of the vectors, the similarity does not depend on the magnitude of the two vectors.

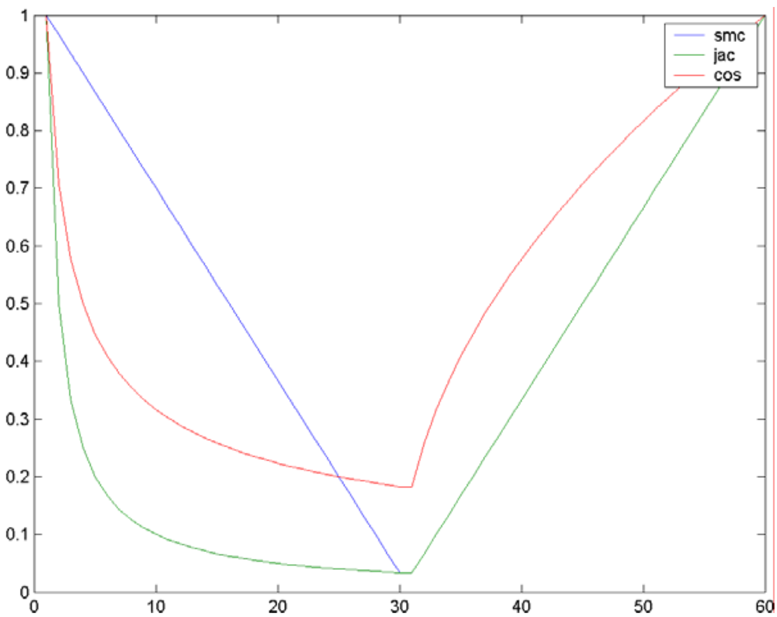


Figure 8. Similarity measurements coefficients

To visualize the behaviour of the similarity coefficients two binary vectors x and y with the length of 30 elements have been used. To avoid division by 0 the first element has constantly the value 1. The values of the coefficients were measured 60 times and at each step one element of a vector was changed to 1 (e.g., x_1 = [1, 0, 0, …], y_1 = [1, 0, 0, …]; x_{30} = [1, 1, 1, …], y_{30} = [1, 0, 0, …]; x_{60} = [1, 1, 1, …], y_{60} = [1, 1, 1, …]). The behaviour of the similarity coefficients is visualized in Figure 8. It could be seen that it is difficult to define the significance levels of the coefficients. Those coefficients are usually used to measure relative distance between the objects. If the value of the Jaccard coefficient is below 0.5 or the cosine similarity is below of 0.7, then the number of positive matches is less than half of the sum of positive and not matching units. The value of SMC is over 0.5 if the sum of positive and negative matches is more than half of the total number of variables.

The fourth part of the similarity measurement consists of finding whether the two neighbouring matrices are identical, that is, isomorphic. Usually the neighbourhood matrices are not identical and therefore we can only find a maximum isomorphic subset. The task is not as complicated as the general isomorphic graph problem because the order of the samples is known and to identify the maximum isomorphic subgraph we can use an AND operator. If n_{ij} & n_{ij} (elements of the neighbourhood matrices have both value 1), the neighbourhood relation is isomorphic. Here a new meta-level analysis can be performed and to see commonly shared information between the two maps, the isomorphic sub-graph can be reordered and visualized. For visualization the Graphviz software[1] has been used. Before visualization the elements of the matrix are rearranged using the method of the matrix reordering (MR). The method reorganizes the neighbourhood graph data vertices according to specific property–systems monotonicity (Võhandu, 1979; Võhandu, 1989). The main goal of such matrix analysis is to permutate (reorder) rows and columns to maximize the similarity of the neighbouring elements (Kirt, Liiv, Vainik, 2007).

[1] Graph Visualization Software available from http://www.graphviz.org/

Chapter 4

Case Studies

In this chapter two case studies are presented to illustrate the methodological part and the use of the self-organizing map. The first case study covers banking data and the second one concerns Estonian concepts of emotion.

The first set of data is time-series data of Estonian commercial banks. In this case study the purpose of the analysis is to detect whether and to what degree the dimensionality reduction methods applied to the data has preserved its structure.

The second set focuses on the concepts of emotion in Estonian language. The set of data is based on a survey. The survey consisted of two parts and as a result, two different data matrixes describe the same set of concepts of emotion. The aim of the analysis was to find out whether the two approaches to conceptual space give a similar structure and to test what might be the impact of different methods of analysis.

4.1 Analysis of Banking Data

The banking data set is used to illustrate the impact of dimensionality reduction on the SOM maps. The SOM performs mapping of multidimensional data onto a two-dimensional map while preserving proximity relationships as well as possible. The SOM projects multidimensional data into two-dimensional representation, thereby reducing dimensionality, but it would work faster if the dimensionality of the input data were reduced. There are several methods to reduce dimensionality of data and recently the methods that overcome the limitations of linear approaches and are only locally linear, such as locally linear embedding (LLE) (Roweis & Saul, 2000; Saul & Roweis, 2002) and Isomap (Tenenbaum, de Silva, & Langford, 2000) have become popular. In this work the principal component analysis (PCA) (Jolliffe, 2002) as a classical linear method and the peeling method (Võhandu & Krusberg, 1977) as an alternative are used. The principal component analysis transforms data so that the first principal components retain most of the variability within the data. The peeling method selects the most varying (influential) variables from the original data set. The performance of the PCA and the peeling method is compared in (Kirt, 2002).

In this section the dimensionality reduction methods are introduced and the SOM analysis is performed using original and reduced dimensionality data. To compare similarity between the results and to identify whether the reduction methods had retained enough variability within the data a similarity measurement methodology was applied.

There are several studies where the SOM has been used in the analysis of financial data (e.g., study about Russian banks, Shumsky & Yarovoy, 1998; analysis of emergent markets Deboeck 1998; bankruptcy analysis of companies, Kaski, Sinkkonen, & Peltonen, 2001). In this analysis the financial dataset is used to find out the impact of the dimensionality reduction techniques and to compare the results. The similarity measurement methodology is used to find out whether the structure remains the same in the case of dimensionality reduction. But at the same time, the analysis reveals the structure of Estonian commercial banks and classifies them according to their size, risk portfolio and ownership.

4.1.1 Principal Component Analysis

To reduce the dimensionality of the data, the principal component analysis (PCA) is rather often used. The main idea of the principal component analysis is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set (Jolliffe, 2002). The PCA makes a linear transform of the data and projects original data on a new set of variables that are called the principal components. The principal components are uncorrelated and ordered so that the first few components represent most of the variation of the original variables.

To find the principal components for the matrix X consisting of m samples and n variables, first, a n x n correlation or covariance matrix C is computed for the data set. Next, the eigenvalue problem $Ce = \lambda e$ is solved and the scalars λ_i called an eigenvalue and corresponding eigenvectors e_i are calculated. The eigenvalues are sorted in a decreasing order and the sum $\sum_{i=1}^{k} \lambda_i / n$ of the k first eigenvalues shows the variance described by the k first eigenvalues and the corresponding eigenvectors.

The k-th principal component z_k is found as follows

$$z_k = e_k' x$$

where e_k is an eigenvector corresponding to its k-th largest eigenvalue λ_k and x is a vector of the original matrix X. Calculating the $k < n$ first principal components we could reduce the dimensionality of the data retaining most of the variation of the original variables.

4.1.2 Peeling Method

The peeling method can be used to find the most important variables that are describing the main part of the variation of the data set (Võhandu & Krusberg, 1977).

The algorithm works as follows:

1. For every column of a correlation matrix C size of n × n a measure of influence S_j is calculated

$$S_j = \frac{\sum_{i=1}^{n} c_{ij}^2}{c_{jj}} .$$

2. The maximum of those measures S_j $S^{(k)} = \max S_j$ identifies the most important among them.

That is the number of the most important in average variable in the system. Superscript k shows the number of the running iteration (k = 1, …, n)

3. The correlation coefficients of the maximal variable will be divided by the square root of the diagonal element c_{jj} of the matrix C. The transformed column vector $b_1 = c_j \big/ \sqrt{c_{jj}}$ is the first vector of the new factor matrix B.

$\frac{1}{n} S^{(k)}$ gives the weight of the parameter k.

4. Find the residual matrix

$C^{(1)} = C - b_1 b_1^{'}$

5. Repeat the process r times, where r ≤ n is the rank of C.

According to the elimination order the first r most important variables are taken and used in the following activities.

4.1.3 Banking Data

The data set consists of banking data from the period of 1997 until 2000. It was an interesting period in the Estonian banking history because at the beginning of the period there was rapid growth and at the same time there was also a consolidation in the banking sector. In 1998 the so-called Russian crisis started that had strong impact on the part of Estonian economy which depended on the export to Russia and thereby consequently also on the banking sector. At the beginning of 1997 there were 14 banks in Estonia and in 2000 there were only 7 banks left. The minimum number of banks was in 1999 when there were only 6 banks.

The banking data that the analysis is based on have been downloaded from the web page of the Bank of Estonia (http://www.bankofestonia.info). 133 public quarterly reports including a balance sheet and an income statement prepared by individual banks have been used. The 50 most important variables (see Vensel, 1997) were selected to form a short financial statement of a bank. All the variables were normalized by the variable of total assets to make the reports comparable.

4.1.4 Results of Banking Data

For the analysis five data sets have been formed. All the sets describe 133 quarterly reports of the banks. The first set consists of all 50 original variables

(Original), the second set consists of 36 variables selected by the peeling method (PEEL36), the third set consists of 33 variables selected by the peeling method (PEEL33), for the fourth set 26 principal components describing 95% of the variation were selected (PCA95), and for the fifth set 5 principal components describing 50% of the variation are selected (PCA50). The number of variables of PEEL36 was selected to find the number of variables that allowed to draw the connected isomorphic sub-graph and to see the connections between different clusters. The PEEL33 has a variance representation similar to the set of PCA95. From those data sets, three self-organizing maps were created (Figure 9, Figure 10 and Figure 11). Our aim has been to measure how similar those maps are and whether similar banks are projected into nearby map units in all cases. From the maps, neighbourhood matrixes were generated, consisting of 133 rows and columns to represent the neighbourhood relations between the samples.

When the maps are analyzed visually, it can be seen that in general the maps have a similar structure. As the overall structure is more interesting, only the first BMUs are marked on the map. The labels refer to the number of the report. Comparing the SOMs, division into two main groups can be identified: one bigger light area and another group separated by a darker area. The smaller group is located at the bottom in the case of Original, PCA95 and PCA50 map and is located on top in the case of PEEL36 and PEEL33 maps. The original and the PCA50 map seem to be rather similar but in the case of the PCA95 left-right sides are interchanged. On the larger light area of the SOM the larger and main retail banks are located. On the smaller separated area, some smaller and niche banks are collected.

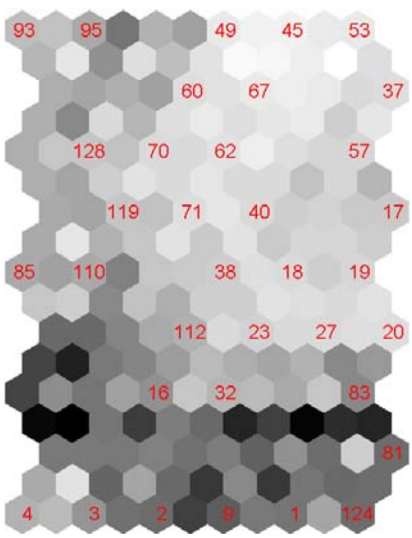
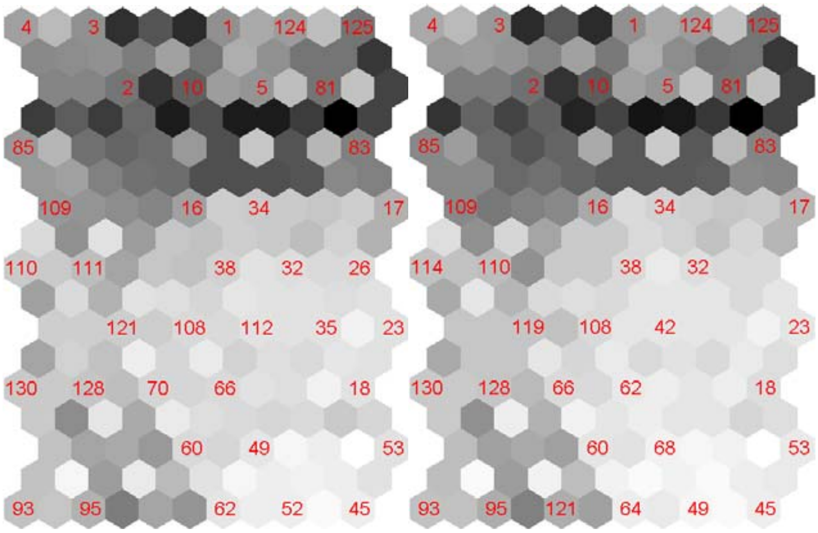
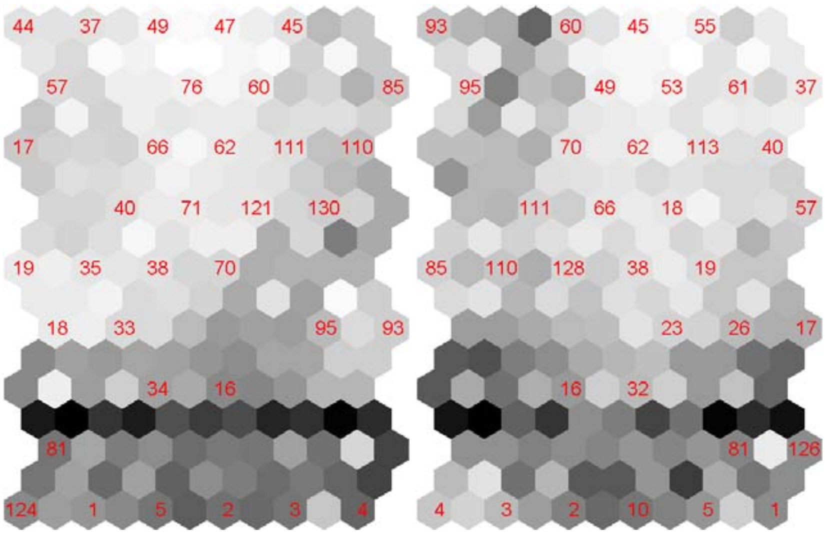


Figure 9. SOM of 50 original variables



a) b)

Figure 10. SOM of peeling method. a) 36 variables, b) 33 variables



a) b)

Figure 11. SOM of PCA. a) 26 principal components describing 95% of variation b) 5 principal components describing 50% of variation

Table 1 shows the similarity measurement coefficients of the banking data. The density of samples on the map is quite high and it is also visible in the number of neighbourhood relations. There is a slight difference in the number of neighbourhood relations between PCA95 and PCA50. It shows that the principal component analysis retains the internal structure of the samples.

Although the peeling method required more variables to describe the same amount of variance, the values of the coefficients are close to the values of the PCA results. The SMC value is very high in all cases, but is becoming lower as the neighbourhood range is widening. The Jaccard coefficient shows about 0.6 similarities between the different representations of the samples. The cosine similarity ranges from 0.74 to 0.78.

Table 1. Neighbourhood similarity of the SOM of banking data (PCA)

Experiment	Neigh. range	Orig neigh.	PCA neigh.	Pos. match	Total neigh.	SMC	Jaccard coef.	Cosine
Orig vs. PCA 95%	1	1876	1772	1426	2222	0.9550	0.6418	0.7821
Orig vs. PCA 50%	1	1876	2120	1480	2516	0.9414	0.5882	0.7421
Orig vs. PEEL36	1	1876	1896	1400	2372	0.9451	0.5902	0.7423
Orig vs. PEEL33	1	1876	1838	1400	2314	0.9483	0.60501	0.7539
Orig vs. PCA 95%	2	4078	3972	3122	4928	0.8979	0.6335	0.7757
Orig vs. PCA 50%	2	4078	4038	3046	5070	0.8856	0.6008	0.7506
Orig vs. PEEL36	2	4078	4120	3108	5090	0.8880	0.6106	0.7582
Orig vs. PEEL33	2	4078	4180	3206	5052	0.8956	0.6346	0.7765

As the banking data consisted of 133 samples, the neighbouring relations are rather strong. The neighbouring matrixes were found and compared. Figure 12 shows an isomorphic subgraph showing neighbourhood relations between the SOM of the original data and the SOM of the PCA95. The neighbourhood range is defined as 1. The graph illustrates quite well the structure within the data. The same grouping is visible on the graph representing only 50% of the variations. When the neighbourhood range is increased, the isomorphic sub-graph becomes connected but at the same time the neighbourhood relations become so dense that the structure is not clearly visible any more.

The graph showing the neighbourhood relations between the SOM of the original data and the SOM of the peeling method with 36 variables is presented in Figure 13. The neighbourhood range is defined as 1. The graph is connected except one separate group and it is possible to identify similarity relations between the banks. Neighbourhood relations with fewer variables are more fragmented and the structure is not so well identifiable.

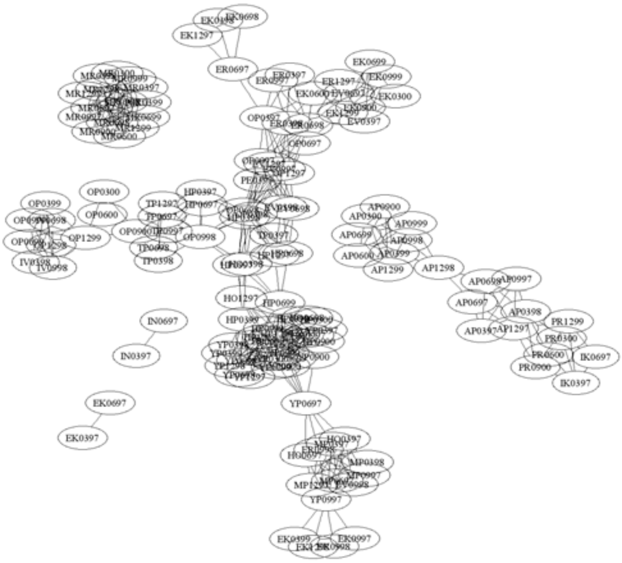


Figure 12. Reordered and visualized isomorphic subgraph of banking data (Original vs. PCA 95% variation). Neighbourhood range 1

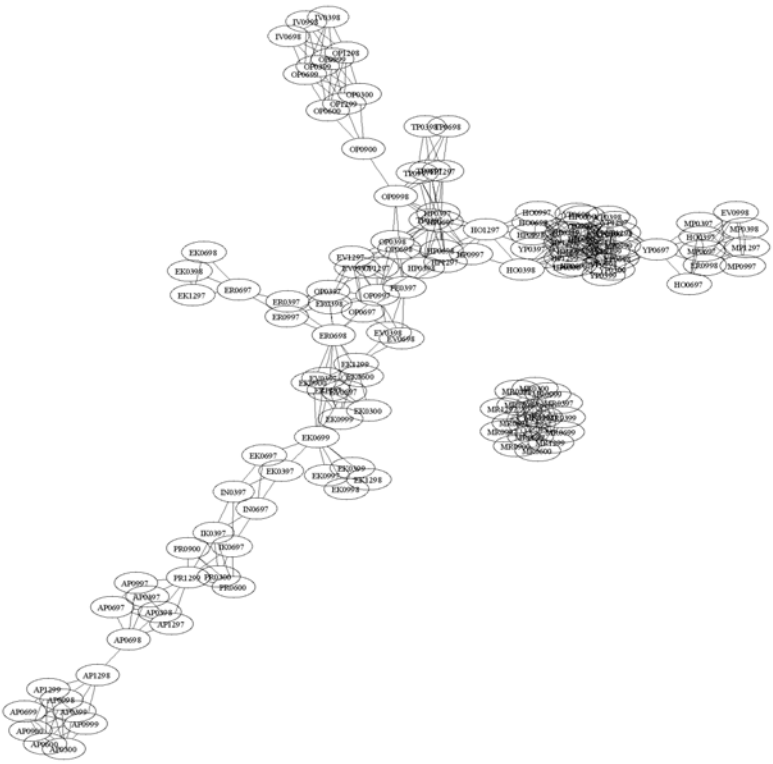


Figure 13. Reordered and visualized isomorphic subgraph of banking data (Original vs. Peeling 36 variables). Neighbourhood range 1

4.1.5 Discussion of Banking Data

As a result of the analysis targeted to the impact of dimensionality reduction it was confirmed that even the dramatic dimensionality reduction by the PCA method retains the most important internal relations in the data. The number of variables was reduced ten times – from 50 to 5, but even then the internal structure remained the same. The peeling method was not capable enough of reducing the number of variables, but was able to retain original variables that were important for further studies of the data. It was possible to find the most important variables and their impact on the results. The maps retained similar structure but only orientation was changed. To measure how much local neighbourhood relations remain the same, the similarity measurement methodology was applied. Local neighbourhood relations between the samples were found and the similarity of relations by coefficients was measured by finding an isomorphic subgraph.

Three similarity measurement coefficients are used: Jaccard Coefficient, SMC and Cosine Similarity. As the data was binary, the first two could give most of the information needed to measure similarity. The significance level for the coefficients could be the level when half of the measured elements are matching. If we look at the coefficients together we could get some additional information about the similarity. If the SMC value is high and at the same time the Jaccard coefficient and cosine similarity have a lower value, then it indicates the presence of a clustered structure. The bigger the difference the smaller are the clusters.

A maximum isomorphic subgraph has been expected to be as a measure for identifying the similarity between the SOMs. But the isomorphic subgraph has become a new meta-level tool to find a hidden structure and to reveal the grouping structure of the data. The main parameter in the similarity analysis is the range of neighbourhood. The number of neighbourhood relations increases if the number of samples or the range of the neighbourhood widens. The size of a map also has an impact on the density of samples on the map. If the neighbourhood range is increased from 1 to the maximum length of the map, then different connectivity levels could be seen. Depending on the density of the samples range 1 or 2 gives a good insight into the hidden structure or the so-called backbone within the data. The visualized isomorphic neighbourhood matrix gave us a new perspective on relations between the samples.

4.2 Analysis of Estonian Concepts of Emotion

Several data analysis techniques and methods are used to project multidimensional data into a lower two- or three-dimensional space and to visualize its structure. In this case study, the methods of self-organizing maps (SOM) and multidimensional scaling (MDS) were under discussion. One of the purposes of comparing those methods was to introduce the method of SOM as relatively unexploited in psychology and linguistics. In the field of psycho-lexical studies MDS has prevailed so far (e.g., the MDS based Geneva Emotion Wheel (Scherer, 2005)). It was intended to demonstrate the layout of data on both cases and to discuss their compatibility. The method of Self-Organizing Maps is a widely used in the general philosophy of self-organization in the field of data analysis. Although it is not a mainstream method in linguistics there are some applications of SOM in the field of semantics (e.g., Honkela, 1997a; 1997b; Lagus, Airola, & Creutz, 2002; Linden, 2004; Ritter & Kohonen, 1989; Wittenburg & Frauenfelder, 1992). However, no previous attempts to apply it to the conceptual structure of emotions were available.

Some of the researchers have compared the SOM and the MDS earlier and outlined both their similarities and dissimilarities (e.g., Duda, Hart, & Stork, 2001; Kaski, 1997). Kaski has emphasized that the two methods are quite similar in general in respect that both methods tend to reduce dimensionality of the observed data and reveal its hidden structure. The two methods differ in the strategy applied to the data. The SOM tries to preserve local neighbourhood relations and the MDS the interpoint distances between the samples.

A hypothesis for this case study could be formulated that the way the data are handled in an analytical tool might have an impact on the layout of the results. In order to test this hypothesis the data of the present case study–a study of the Estonian emotion terms–was analyzed by both the SOM and MDS.

The second purpose of the study was to apply the similarity measurement methodology to the SOM maps of the data collected from two different sources.

4.2.1 Multidimensional Scaling

The multidimensional scaling is a set of related statistical techniques often used in data visualization for exploring proximities in data. The goal of the method is to project data points as points in some lower-dimensional space so that the distances between the points correspond to the dissimilarities between the points in original space as closely as possible. Such representation is valuable to gain insight into the structure of data. The MDS can be used as a method to reduce the dimensionality of the data and reveal the dissimilarities between the samples.

The method of multidimensional scaling is said to be metrical if it is based on the measured proximities and nonmetrical when the proximities are based on judgement (Jobson, 1992). The original MDS method was metric (Torgerson, 1958). The current analysis is based on the nonmetrical data and therefore the nonmetrical MDS is used. The data were analyzed by the statistical software package SPSS. In this analysis the ALSCAL algorithm (Takane, Young, & de Leeuw, 1977) was used.

There are n sample vectors $x_1,...,x_n$ and the distance between original samples i and j is g_{ij}. The y_i is the lower-dimensional representation of x_i and the distance between the projected items i and j is d_{ij}. The aim of the MDS method was to find a configuration of image points $y_1,...,y_n$ in a lower dimensional space for which the distances d_{ij} between the samples are as close as possible to the corresponding original distances g_{ij} so that the dissimilarities between the sample vectors are retained as well as possible. Since it is impossible to find a configuration for which $d_{ij} = g_{ij}$ for all i and j, a certain criterion is needed whether the result is good enough to finish the approximation process.

4.2.2 Data of Estonian Concepts of Emotions

The purpose of the study was to discover the hidden structure of the Estonian emotion concepts and to test a hypothesis that the way the information about concepts is collected can influence its emergent structure. The survey was conducted by E. Vainik from the Institute of the Estonian Language. Two lexical tasks were carried out providing information about emotion concepts either through their relation to the episodes of emotional experience or through semantic interrelations of emotion terms (synonymy and antonymy) (see Vainik, 2004).

The inquiry was carried out in written form during the summer months of 2003 in Estonia. The number of respondents was 100 (50 men and 50 women), aged from 14 to 76, all native speakers of the Estonian language. There were 24 emotion concepts selected for the study that form a small but representative set of the category, sharing the prototypical features of emotion concepts to a various degree. The selection is based on the results of tests of free listings (Vainik, 2002) as well as on word frequencies in the corpora. The participants had to complete two tasks measuring the concepts by means of different levels of knowledge.

In the first task they had to evaluate the meaning of every single word against a set of seven bipolar scales, inspired by Osgood's method of semantic differentials (Osgood et al., 1975). The "semantic features" measured with polar scales drew qualitative (unpleasant vs. pleasant), quantitative (strong vs. weak emotion, long vs. short in duration), situational (increases vs. decreases action readiness, follows vs. precedes an event), and interpretative distinctions (felt in the mind vs. body, depends mostly on oneself vs. others). The original bipolar scales were transformed from having +/- values into positive scales of 7–1, starting from 7 as the maximum value of the dominant or default feature, over 4 pointing to the irrelevance of the scale, and down to 1 as the minimum value (corresponding to the maximum of the opposite feature).

In the second task the same participants had to elicit emotion terms similar to and opposite by meaning the same 24 stimulus words. This task relied on the speaker's intuitive knowledge about the similarities and dissimilarities of the concepts. The task eliciting similar concepts resulted in 4068 lexical items (on average 169.5 per word) and the task eliciting opposite concepts resulted in 3694 lexical items (153.9 per word). Before the analysis the information about the lexical relations was first quantified. Every single event of listing similar or opposite concepts was treated as a task of free listing (Corbett & Davies, 1997) and so an index of relative cognitive salience (Sutrop, 2001) was calculated for every relation mentioned by at least three persons. The indices of similarity S_s were transformed into those of theoretical closeness between the concepts 1 - S_s and the indices of oppositeness S_o were transformed into theoretical distances with polar values 0 - S_o.

The index which takes into account both the frequency and the mean position of a term was calculated for every word mentioned by at least three persons. Out of the total of 488 relations only 219 with indices greater than or equal to the average (Save = .07) were subsequently processed with SOM and MDS.

4.2.3 Results of Estonian Concepts of Emotion

In the first task the data pool of all answers to the 24 concepts on the 7 joint scales was processed. So a vector consisting of 700 answers represented each word. In the second task the words were described by the vector in the length of 219 representing values of the index of relative cognitive salience.

Figure 14 and Figure 15 present the structure of Estonian emotion concepts according to the results of the first task of the survey. Figure 14 presents the result of the SOM analysis and Figure 15 the MDS analysis. The translations and locations of words on the SOM are given in Table 2. The MDS was created using translations of the words. Both pictures present a clear distinction between the concepts.

The SOM of the first task appears as a bilaterally symmetrical representation. The positive emotion concepts tend to gather to the upper part of the graph and the words referring to negative emotions to the lower part of the graph. The main organizing dimension of the representations appears to be the negativeness and positiveness of the concepts that extends the shape of the SOM map in one direction (see also component planes in Figure 16). As the anticipatory states (*hirm* ‘fear’, *erutus* ‘excitement’, *mure* ‘concern’), gathered to the right edge of the graph, the scale follows vs. precedes an event seems to function as an additional dimension. There is a darker area in the middle clearly separating these two clusters. There is a concept *ärevus* ‘anxiety’ located outside these two clusters. Apparently it is identifiable neither as positive nor negative or having conflicting specifications in respect of affiliation. This kind of a structure is most in common with the results of Watson and Tellegen (1985) who have found that 50—75 % of the semantics of emotion vocabulary in multiple languages is accounted for two unipolar dimensions of Positive and Negative affect. The extendedness of the graph also speaks for the preference of focus on valence over arousal (Feldman Barrett, 1995).

Figure 14. The SOM of the first task

Table 2. Location of words on the SOM of the first task

enthusiasm	pleasure	passion
happiness	fun	
joy	love	
		excitement
		desire
surprise		
pride		
		anxiety
pity		
rage		concern
envy		
anger		
guilt	sadness	fear
disappointment	shame	
contempt	oppression	

The MDS represents concepts on the circle. By shape it resembles the circumplex model proposed by Russell (Russell, 1980; Russell, Lewicka, &

Niit, 1989). The MDS presents also a clear distinction between the positive and negative concepts on the horizontal scale – the more negative the concepts the more left they are situated and the positive concepts are situated on the right-hand side, accordingly. There is another dimension that distinguishes the concepts on the vertical scale: the states perceived as events preceding are situated on the upper part of the circle and the states perceived as following some event are situated in the bottom.

The results of the first task characterize how the conceptual organization of emotion emerged from subconceptual and experiential level of knowledge in Gärdenfors's model (2000). It can be seen that as the concepts are addressed through their relation to the individual perceptions of episodes of emotional experience, the two methods result in very similar layouts, except the orientation of the dimensions and the way of discriminating the groups.

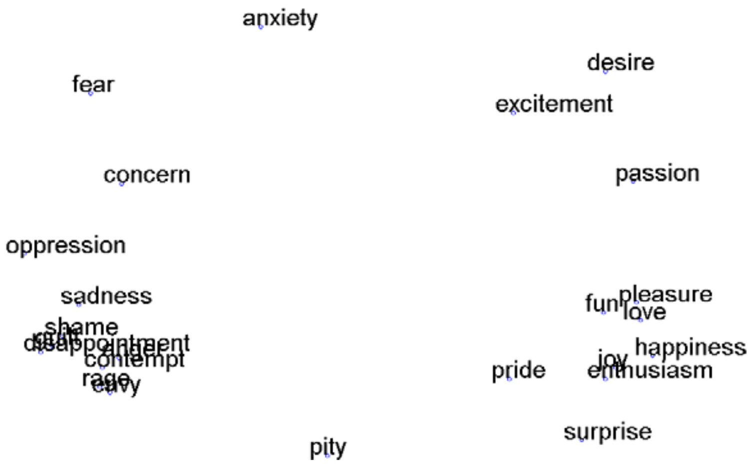


Figure 15. The MDS of the first task

Additionally the mean values of seven scales were computed and represented as component planes of the SOM (Figure 16). It gives insight into correlations between the scales. It seems that the scale strong vs. weak emotion is an additional measure whether the concept belongs to a group of positive or negative concepts. Additionally, correlations were calculated between the scales (Table 3). Correlations between the scales are rather low except for negative correlation between that increases action readiness and unpleasantness.

Table 3. Correlations of variables

ID	joint scale	1	2	3	4	5	6	7
1	strong (vs weak) emotion	—	-.041	-.028	.253	.032	.157	-.162
2	follows (vs precedes) an event		—	.239	-.008	-.060	-.079	.121
3	felt in the mind (vs body)			—	.093	.050	-.031	.122
4	long (vs short) in duration				—	.137	.034	-.045
5	depends mostly on oneself (vs others)					—	.002	-.017
6	increases (vs decreases) action readiness						—	-.720
7	unpleasant (vs pleasant)							—

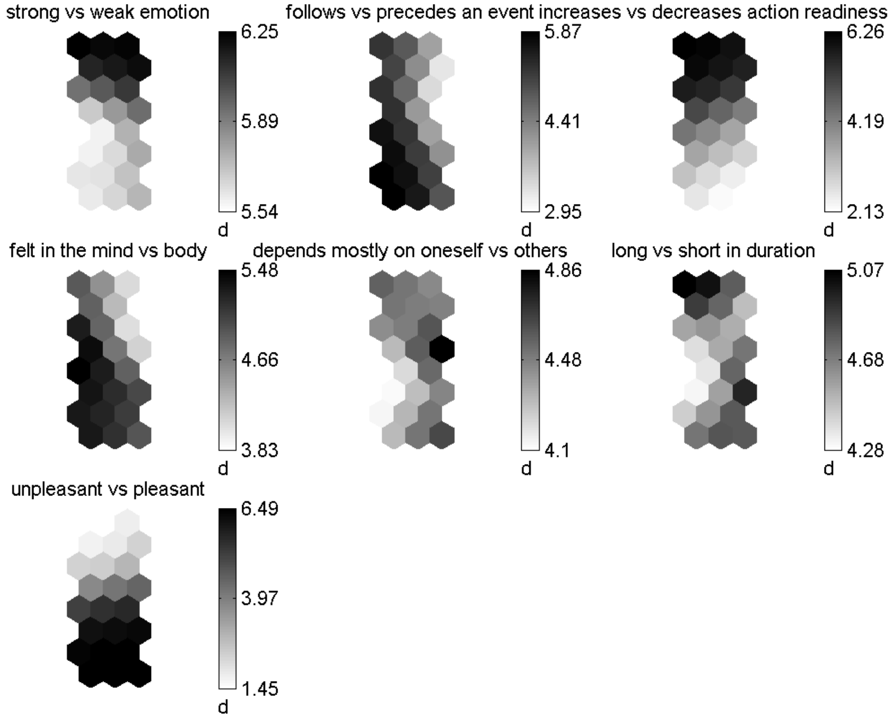


Figure 16. Mean values of seven scales on the component plane

Figure 17 and Figure 18 present the structure of Estonian concepts of emotion according to the results of the second task of the survey addressing the concepts through the semantic interrelations of emotion terms. This task addressed the most abstract and symbolic level of representation of emotion knowledge, according to the theory of conceptual spaces (Gärdenfors, 2000b), which was accessed through the semantic interrelations of emotion terms in the task. Figure 17 and Table 4 present the result of the SOM analysis and Figure 18 that of the MDS analysis.

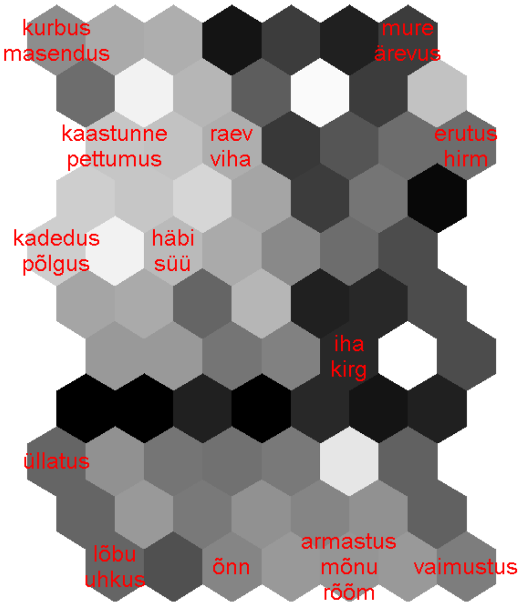


Figure 17. The SOM of the second task

Table 4. Location of words on the SOM of the second task

sadness oppression			concern anxiety
pity disappointment	rage anger		excitement fear
envy contempt	shame guilt		
		desire passion	
surprise			
fun pride	happiness	love pleasure joy	enthusiasm

On the SOM of the second task, general vertical alignment of positive (bottom) versus negative (top) concepts is observable. There is a remarkably darker row of nodes aligned horizontally, separating those two categories of unequal size. The concepts have self-distributed into three clusters, though, as in the upper part of the graph there is a diagonally located darker area excluding the bunch of concepts in the uppermost right corner. One node containing two concepts *iha* 'desire' and *kirg* 'passion' are standing outside the clusters not belonging to any of them. There is a cluster of closely related concepts of negative emotions in the uppermost left part of the graph. Inside the cluster the concepts have positioned in a way that the most similar concepts are collocated in the same node.

This SOM does not coincide with the SOM of Task 1. Instead of two here are three clearly distinguishable clusters. This allows us to conclude that the organization of emotion concepts is slightly different while accessed through the relations of similarity and oppositeness.

The MDS of the second task retains the circular structure and there might be seen the horizontal alignment of positive (right-hand side) versus negative (left-hand side) concepts on the graph, as well as the vertical alignment of event preceding states (the upper part) versus the event following states (the lower part of the graph).

At first glance the result of Task 2, as analyzed by MDS, is very similar to the result of Task 1 except that the locations of *kaastunne* ‘pity’ and *vaimustus* ‘enthusiasm’ do not fit. This result allows us to conclude either that the level of access to the concepts has almost no impact on the structure of the emotion concepts or that the method of MDS tends to generalize the results to fit a solution best described by two crossing dimensions. But with prior knowledge from the SOM analysis even on the circular arrangement there are visible actually three groups of concepts. On the bottom right are positive concepts, on the bottom left are negative concepts and on the top are concepts that might be described mostly by their quality as event preceding states. These three clusters are partly compatible with the three described on the SOM of task two (Figure 17).

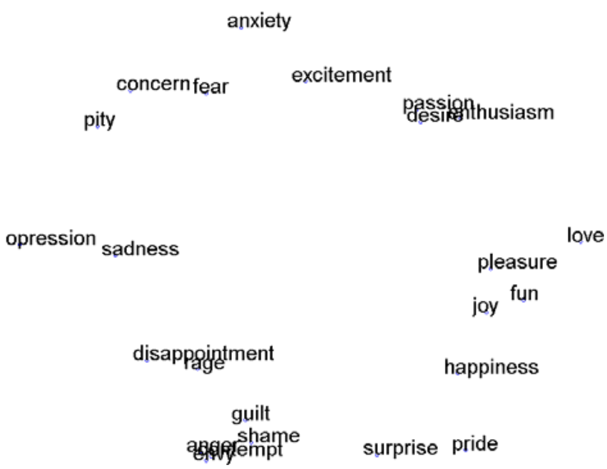


Figure 18. The MDS of the second task.

The aim of the meta-analysis of the SOM was first to compare systematically the neighbourhood relations of both maps. Two neighbourhood matrixes were compared by an AND operator and a matrix of common neighbours was found and visualized after reordering. The summary of the neighbourhood relations between the two tasks is given in Table 5. The number of relations was measured with a different range of neighbourhood, starting from 1 to 3. An increase in the neighbourhood range causes also an increase in the number of relevant neighbourhood relations. The SMC coefficient is decreasing if the neighbourhood is increasing because the growing range increases the possibility of relations between the words that actually do not belong to the same neighbourhood. The SMC could be used as an indicator of stability. The SMC coefficient can also be used if the samples are exclusive like in the case of lexical study. There are two exclusive groups of data – positive and negative emotion concepts – that had weak neighbourhood relations. Jaccard Coefficient and Cosine Similarity are increasing if the neighbourhood range is widening. Both of them characterize the positive matches and there is a tendency to have more positive matches if the number of neighbourhood relations increases.

Table 5. Neighbourhood similarity of the SOM of conceptual data

Neigh. range	Task 1 neigh.	Task 2 neigh.	Pos. match	Total neigh.	SMC	Jaccard coef.	Cosine similarity
1	96	100	52	144	0.8403	0.3611	0.5307
2	198	216	150	264	0.8021	0.5682	0.7253
3	276	346	230	392	0.7188	0.5867	0.7443

As far as the neighbourhood range remains open it is still difficult to decide whether the two SOMs of our two tasks were different enough to claim our hypothesis of the case study proven.

The second step of the meta-analysis is to find a maximum isomorphic sub-graph and to find a clue what the suitable range of neighbourhood could be.

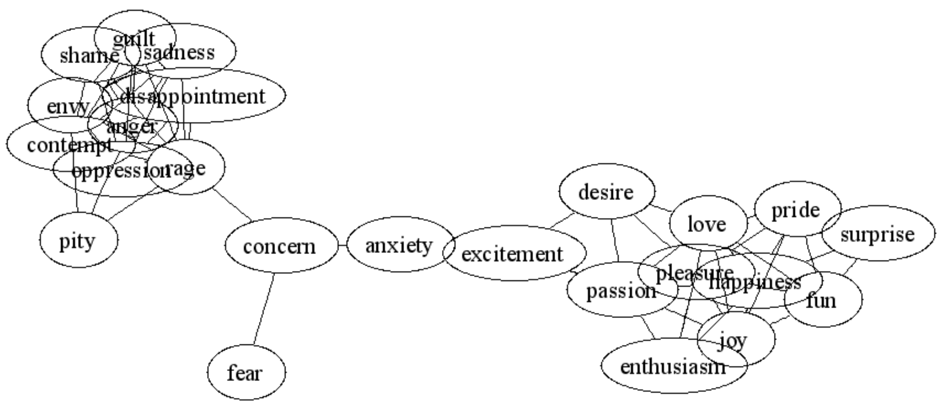


Figure 19. Reordered and visualized isomorphic subgraph of lexical data (Task 1 vs. Task 2). Neighbourhood range 2

In the case the neighbourhood range is provisionally set on 1, several separate fragments of conceptual networks are formed. The general structure of the data does not appear as a connected system. In the case the neighbourhood range is set on 2, the graph becomes connected. It can be speculated that it represents the common structure or a backbone of the conceptual data gathered from two tasks and therefore 2 as the range of neighbourhood can be preferred. The neighbourhood graph is shown in Figure 19.

A conclusion can be drawn that the match of the two structures based on our two tasks is partial and it is measurable in principle. The degree of measured structural isomorphism depends on the rigidity of the selected criteria of neighbourhood.

4.2.4 Discussion of Estonian Concepts of Emotion

In the previous section two methods and two tasks of differently accessed semantics (subconceptually and symbolically (via the relations of antonymy and synonymy) accessed knowledge) of Estonian concepts of emotion were compared. As a result, the two tasks and the two methods showed a similar structure but naturally the results are not identical. The data produced by the informants about one and the same set of stimulus words organized itself differently according to the level of abstractness, the conceptual knowledge about emotions was accessed at and also the methods bring forth specific details connected with the methods peculiarities. The SOM is good if local relations between the samples are important. The MDS is oriented to reveal the structure of metric distances between the samples and it reveals the overall picture of the dissimilarities.

Comparing the results of the analysis of linguistic data, the SOM formed clearly separable clusters and the MDS projected data on the circle. It might be that the MDS presented the overall distances between the samples and therefore the extremity of dominant positive negative scale became dominant and the overall look of the results is the same–circular. Or it can be caused by the well known “horseshoe effect” that is common to the multidimensional scaling (Buja & Swayne, 2002). At the same time, the SOM gives an overview of local relations between the concepts and forms local clusters, but even projection of local relationships between the samples gave an insight that there is division between the positive and negative concepts. The formation of two exclusive groups is well identifiable on the visualized isomorphic subgraph (Figure 19).

Thus, at first glance the results of the case study reveal that the structure of emotion concepts does not depend on how the information is gathered while the MDS is used and it does depend on how the data is gathered while the method of the SOM is used. Thus, the hypothesis of the study could be tested only partly.

In the case the data was gathered from the task relying on the procedure of the Osgood’s semantic differential or alike (Task 1), the two methods revealed very similar results. In the case the data was gathered by assessing similarity and oppositeness of a concept, the layouts of the MDS and the SOM seem somehow different. It is probably the point where the different strategies used in the analytical tools turn out as critical. The MDS uses a strategy to keep most dissimilar items as apart as possible (it preserves the distances) and the SOM uses the strategy to keep the most similar samples together (it preserves the neighbourhood relations). The data of Task 2 contain data about both assessed concept similarity (a tendency to interpret similar concepts as situated close to each other) and about oppositeness (a tendency to interpret most dissimilar samples as most apart in a hypothetical conceptual space (Gärdenfors, 2000b)). Thus, the construal of Task 2 might have made it sensitive to the procedures used in the analytical tool.

While analyzing linguistic data containing information about the similarities and dissimilarities of a concept, it might be useful not to be grounded in one analytical tool, because the MDS gave a similar circular structure as a result of both tasks. When some additional knowledge was acquired from the SOM analysis more complicated structure within the data was revealed. The interpretation of the results may depend on the interpreter – his or her thoroughness and in a more general context, what he or she wants or supposes to see.

The method of SOM is used as an independent analytical tool to study the concepts of emotion and as an analogy of the network model of human data processing. One should not forget, however, that any visually attractive representation of conceptual space or emotion qualia cannot be identified either with spatial dimensions or with distances between the nodes of a real "wet" neural network (Kirt & Vainik, 2005). Despite the fact that we could not construct an exact presentation of cognitive processes taking place in the brain at least we could get some insight into the space of concepts.

Chapter 5

Discussion and Conclusions

This chapter contains a general discussion about the results of the case studies. Here the results are fitted for a theoretical framework introduced in Chapter 2. The methods of exploratory data analysis and data mining transform the data into a new representation that reveals the internal structure of data that would be impossible to see by a naked eye. This thesis presents the self-organizing map as an example of the projection and clustering method. The self-organizing map is one of the methods that projects data into a new representation that is called a map. The map reveals the internal structure of the data. The formed clusters on the map can be regarded as concepts. An analysis can be performed to find out the main constituent features that determine the conceptual structure. Additional discussion is related to knowledge and the important role of subjective evaluation of the results. Finally, some conclusions are made.

5.1 Concepts Formation

The process by which specific experience is learned to sort into general rules or classes is called concept formation (Britannica, 2007). Concept formation describes how one learns to form classes and how he subjectively manipulates those classes. Concept formation in computer science is the way to process information for developing classification rules or for classifying samples.

Several data analysis and data mining methods are addressed to classifying data and to find subclasses with similar behaviour and a classified sample is interpreted as a concept (Witten & Frank, 2005). Formal concept analysis (FCA) is used to find conceptual clusters through connecting natural properties and natural objects (Ganter & Wille, 1998). Inspired of probabilistic concepts (Smith & Medin, 1981), a conceptual clustering system COBWEB has been developed (Fisher, 1987). According to Gärdenfors (2000b), there is an analogy between the conceptual spaces and the self-organizing map (see section 2.2.2). During the self-organizing process the points in a high-dimensional space are mapped onto a two-dimensional output map that can be identified as a conceptual space. Those different approaches are used to reveal the clustering structure within the data, thereby discovering the conceptual structure, but for acquiring some knowledge an interpreter is needed.

The results of the case studies revealed a clear structure within the data. Visualization of the isomorphic subgraph revealed how samples form a backbone of data. This structure can be regarded as a conceptual representation. In the case of banking data several groups were formed and members of those groups had specific characteristics. Some large retail banks formed a group, with a group of some problematic banks close to them. From the group of problematic banks three were bankrupted and two were taken over by other larger financial institutions. It is rather strong evidence that the method could reveal relations between the sample data through self-organizing and unsupervised ways without any a priori knowledge. As the reports were quarterly, dynamics was visible and depending on the financial state, the banks could move close to some other group or cluster of banks. Depending on the feature values, the classification information could change.

The SOM of the concepts of emotions revealed a clear division between the two clusters – positive and negative. The main organizing dimension of the representations appears to be the negativeness and positiveness of the concepts, which extends the shape of the SOM map in one direction. This is, however, a higher order dimension as compared to the dimensions of evaluated qualities (see Vainik 2004; Vainik & Kirt, 2005 for a closer discussion). As the anticipatory states, gathered to the right edge of the graph, the scale follows vs. precedes an event seems to function as an additional dimension of the conceptual space. This is a situational characteristic inherent in some of the selected emotion terms.

The SOM is a tool to reveal some knowledge about an empirically studied phenomenon. It is the first level tool to study the essence of nature (see the Margenau treatment of the science in section 2.1). The SOM is based on rather unpredictable process called self-organization and exhibits emergence (Ultsch, 1999). The process of self-organization tends to form hierarchies with emergent properties (Campabell, 1990). It is not enough to study separate components of the world, because the interactions between the system components might generate emergent properties that are not identifiable by studying components separately. If the evidence is quite fuzzy, then we cannot expect the absolute truth, but some probability of the truth. The question is how some knowledge can be acquired by such methods. The interpretation is based on the observation. As the SOM algorithm is rather popular and widely used, there is also a lot of evidence that it may reveal what is expected. It can be said that it is highly probable to believe that the knowledge is justified.

Knowledge acquisition seems to be rather a cost-benefit analysis. Living organisms have acquired knowledge about the surrounding environment through the evolutionary process and trial-and-error search that maximizes their probability to survive in a certain environment but does not guarantee it because it would be too costly. For users of data analysis it is also a question how much to spend on resources and what the acceptable outcome of the analysis is. Even the most expensive tool for an analysis does not guarantee the absolute truth because the data can be not trustworthy or the interpretation could be influenced by local factors or even time could change the understanding of a certain phenomenon (e.g, Goodman's (1983) concept of *grue*). The use of a certain method could influence the understanding of the world (e.g., use of MDS and a belief that emotions have circular structure as (Scherer, 2005)). It must be evaluated what the cost of the wrong prediction and what the possible benefit is.

The SOM algorithm is quite popular among the researchers in different fields. This is caused by its relative simplicity and also by the used visualization technique. As it was discussed in section 2.1.1, the initial costs to use the new method are quite low, and all the costs of using this method are low. But despite the fact that the initial costs of the method are low, there still are initial costs and that is the reason why in certain fields of science mainly some other methods are dominating. If some new method comes into use, then a lot of interpretation rules are to be generated to compare it with an older method already in use. It might be the reason why the research fields are so conservative with the methods already in use.

Someone who sees the output of the self-organizing map for the first time sees for sure this map in a way different from that of a more experienced user. At first all the people see it like a honeycomb covered with randomly distributed labels on it. The user lacks the interpretation rules. To interpret the picture he would miss the required concept system that is accumulated during the earlier research. All the people live and interpret the surrounding world differently, based on their previous experience and their conceptual system. The interpretation depends on what we would like to see. If the results afford proof for a theorem, then it would be easy too see the results of the analysis to afford a required proof. As the concepts can be seen dynamic and context based (see section 2.2.3) it is needed to synchronize conceptual system or active parts of concept features. Otherwise participants could not understand each other and they would use concepts in some other context.

Another question is how to convince a person, e.g. customer, who is not familiar with the interpretation rules that the output of the analysis is what it is said to be. How to make another person to believe the picture and its explanation is true and has enough justification to prove the phenomenon. Some mathematical formalization can be used. But even this requires that it should be somehow grounded. The customer would not have enough mathematical background to make him believe the result is true. He would not be able to build up justification chain that is needed to start from the ground to the final justification of the problem. It is like Margenau's structure of a well-developed science that is grounded on the empirical data gathered from observable nature (see Figure 2). All the science needs to be grounded like the meaning (see section 2.2.3) and without human interpretation the results would not have any signification. On the one hand, everything can be grounded on the surrounding world but on the other hand, some introspective view is needed what the new knowledge allows one to afford or why it is significant.

5.2 Conclusions

In this thesis a theoretical framework has been described for interpreting results of exploratory data analysis. The framework includes a general overview of the theories of concepts, the theory of knowledge and self-organization. Such framework could offer a somewhat broader view of data analysis and data mining methods. Those are quite fundamental issues that actually form the world we live and interact in. To link the theories, two case studies have been analyzed by the method of self-organizing map. The first case study is based on the financial data of Estonian commercial banks and in the second one linguistic data is used.

Two sets of data were used to illustrate the method of the SOM. The first data set is banking data and the purpose of the analysis of the data was to detect whether and to what degree the dimensionality reduction methods PCA and the peeling method applied to the data have preserved their inner structure.

The second case study is a research into the concepts of emotion in Estonian language. The study was based on the survey that consisted of two parts and as a result two different data matrixes describe the same set of concepts of emotion. In the meta-analysis an attempt was made to analyze whether and to what extent the results of the two tasks are comparable.

As a result, the self-organizing map has been found to be a useful method to identify the internal structure of the data. The proposed methodology to measure similarity between the self-organizing maps is successful if the maps are describing the same phenomenon but use different sources of data or the number of variables are different. The results of the two case studies have shown us that the suggested method to measure similarity between two self-organizing map is applicable and it gives new insights into the data.

The results of those analyses can be interpreted as concept formation and by using the method of the SOM the internal structure of the data can be revealed. The formed clusters have certain local properties that may be regarded as subconceptual dimensions according to the theory of conceptual spaces (Gärdenfors, 2000b).

Further work would be connected to multi agent systems. A goal of the work would be to study whether it is possible to create an effective conceptual framework for pattern classification and recognition by using the evolutionary approach.

Abstract

Humans have developed technologies that allow them to acquire information that would be impossible to gather by their own sensory organs. The complementary information gives additional possibilities to understand the surrounding world. At the same time, the amount of collected data increases rapidly and perception of such multidimensional data is rather difficult by naked eye. Therefore, some additional techniques and methods are needed to gain insight into them. One of such methods is the self-organizing map (SOM) that is used also in this thesis. The SOM is a type of neural networks that is widely used in several applications of exploratory data analysis. Data driven methods of exploratory data analysis can be used for knowledge discovery in databases.

In Western philosophical traditions knowledge is regarded as a justified true belief. Basic components of knowledge formation are well-defined concepts. One task that the SOM can be used is data classification and this process is regarded as a concept formation in machine learning. The results of the classification are very close to the concepts that are the fundamental constructs of human cognition. But they have a big difference because the results of concept formation need some subjective interpretation by humans but so-called 'wet' concepts seem to be meaningful entities by themselves.

This study focused on how the results of exploratory data analysis could be arranged into a conceptual framework. The thesis includes two case studies to illustrate the theoretical part. In the first case study banking financial data and in the second one the data of the empirical study into Estonian concepts of emotion are analyzed. In the thesis the basis of the theories of knowledge and concepts are reviewed. The two-dimensional topological representation of data on the self-organizing map makes it possible to interpret the formed clusters of data as concepts in a conceptual space. In the part of discussion it is proposed that a missing value dimension is the reason why the results need some human interpretation.

Keywords: concept, epistemology, data analysis, knowledge discovery, neural network.

Kokkuvõte

Inimese poolt välja mõeldud alternatiivsed infokogumise viisid võimaldavad oluliselt täiendada tajuorganitest saadavat infot. Täiendav informatsioon loob võimalusi paremaks toimetulekuks selles maailmas. Samas informatsiooni hulga kasvades muutub üha raskemaks selle läbitöötamine ning inimese poolt tajutavaks muutmine. Kasutusele on võetud mitmeid meetodeid ja tehnikaid projekteerimaks andmeid inimese poolt visuaalselt kergesti haaratavale kujule. Üheks selliseks meetodiks on iseorganiseeruvate kaartide meetod (SOM), mis on antud töös peamiselt rakendatav meetod. SOM on väga laialdaselt kasutatud uuriva andmeanalüüsi erinevates valdkondades. Andmetest juhinduvaid meetodeid uurivas andmeanalüüsis nimetatakse ka teadmiste avastamiseks andmebaasides.

Läänemaailmas on defineeritud teadmine kui põhjendatud tõene uskumus. Teadmiste omandamisel on esmasteks ehituskivideks hästi defineeritud mõisted. Üheks ülesandeks, milleks SOMi saab kasutada, on andmete klassifitseerimine ning seda protsessi vaadatakse kui mõistemoodustamist masinõppes. Need klassifitseerimise tulemused on tõlgendatavad sarnaselt inimese kognitiivse toimimise põhialusteks olevate mõistega. Aga on üks oluline vahe, mille poolest andmeanalüüsi poolt loodud mõisteline struktuur erineb inimvaimu mõistelisest struktuurist, et andmeanalüüsi tulemused vajavad subjektiivset tõlgendamist inimese poolt. Inimese mõisteline struktuur on tähenduslik.

Selles töös on analüüsitud uuriva andmeanalüüsi tulemuste paigutamist mõistelisse raamistikku kahe juhtumianalüüsi põhjal. Esimesel juhul uurides pangandusandmeid ja teisel juhul emotsioonisõnavara semantika empiirilise uuringu tulemusi. Töös on tutvustatud teadmise ja mõiste teooria lähtekohti. Iseorganiseeruvate kaartide meetodi poolt loodav kahemõõtmeline andmete topoloogiline esitus loob võimalused sellel tekkinud andmete klastrite interpreteerimiseks mõistetena mõisteruumis. Kuid erinevalt inimese mõisteruumist puudub sellel esitusel väärtuskategooria, mistõttu on tulemuste tõlgendamisel vaja inimese subjektiivset hinnangut.

Töös toodu on lähtealuseks edasisele uurimistööle ning edasisteks suundadeks oleks hinnata võimalust siduda kontseptuaalne raamistik väärtuskategooriatega ning luua läbi evolutsioonilise protsessi efektiivne klassifitseerimisülesannete lahendamise vahend.

Võtmesõnad: mõiste, epistemoloogia, andmete analüüs, neurovõrk.

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WHERE DO CONCEPTUAL SPACES COME FROM? AN EXAMPLE OF THE ESTONIAN EMOTION CONCEPTS

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Abstract

The key question in cognitive science is how to represent concepts. In this paper, we present results of our study of the Estonian emotions concepts in the light of the theory of conceptual spaces. The purpose of our study is to find out if there is an underlying universal structure of emotion knowledge that is independent of the nature of the source data and analytical tools. In the empirical study we report the results of 100 Estonian subjects. As an analytical tool we used the self-organizing maps (SOM) that is a useful method to classify and visualise multidimensional data. Another benefit of the self-organising maps is that it simulates partly the self-organizing processes that take place in the human brain. It converts the nonlinear statistical relationships between high-dimensional data into simple geometric relationships of their image points on a regular two-dimensional grid of nodes. The SOM is useful tool for identifying quality dimensions that the conceptual space is based on.

Keywords: self-organizing maps, neural networks, semantics, linguistics, conceptual spaces

1. Introduction

The idea, that human conceptual representation of the world – or the mental lexicon (Aitchison 2003) – is structured and organized by nature, not an arbitrary mess of words is widespread throughout the cognitive linguistics (e. g. Langacker 1987, Viberg 1994 & Cruse 2000 among others). This presupposition should hold in all cognitive domains, including the culturally shared knowledge about mental life – e.g. emotions. On the other hand, the statistical studies carried out in the field of psychology relying on the results of different lexical tasks tend to end up with controversial solutions as regards to the structure of the emotion lexicon (see Russell 1980, Watson & Tellegen 1985 for example). The organizing “dimensions” of some semantic field spoken intuitively about in the cognitive linguistics seem not to match with the results of factor analysis or multidimensional scaling applied on the empirical data of that particular field, nor do the last match each other.

The purpose of present study is to find out if there is an underlying universal structure of emotion knowledge that is independent of the nature of the source data and analytical tools (see Vainik 2004 for a more details). As a theoretical framework for this paper we chose the P. Gärdenfors’s theory of conceptual spaces (2000a & 2000b) that is compatible with the idea of neural networks and self-organization as the two general principles used in both computational and human data processing. In the following paper we use the empirical data of the Estonian emption terms to illustrate the process of self-organization and to discuss where do the conceptual spaces (or the inner structure of a semantic field) come from.

2. The Main Ideas of the Theory of Conceptual Spaces

Gärdenfors (2000) proposed a geometrical model for representations of concepts called Conceptual Spaces. In this model he distinguishes three levels of representations: the most abstract level is the symbolic level on which the observation is described by means of some language, the second level is the conceptual level on which observations are located as points in the conceptual space and the least abstract level is the subconceptual level on which the observations are characterized by inputs from sensory receptors which form the dimensions of the conceptual space.

A conceptual space is described by a number of quality dimensions. Qualities are mostly measured by our sensory receptors, but they can be more abstract by nature as well. Quality dimensions describe the properties of an object and relations between the properties. Quality dimensions are divided into two groups: integral and separable. A value on an integral dimension is always co occurring with another value measurable on another dimension: for example the hue and brightness of an object are inseparable, integral dimensions. Independent dimensions on the contrary are separable in principle, for example the size and hue of an object are considered as independent dimensions. The function of the quality dimensions is to represent the “qualities” of the observations and to build up domains needed for representing concepts. Spatial dimensions belong to one domain, colour dimensions to another and so on. The notion of a cognitive domain can be defined as a set of integral dimensions that are separable from all the other dimensions.

The quality dimensions are the main tool for measuring similarity of the concepts. If we assume that dimensions are metric then we can talk about distances in the conceptual space. The smaller the distance is between the representations of two objects, the more similar they are. In this way, the similarity of two objects can be defined as the distance between their representing points in the space.

A conceptual space can be defined as a collection of one or more domains. A point in the space may denote a concept. The properties of the object can be identified with its location in space. And a property can be represented as a region of the domain. The domains of a conceptual space should not be seen as totally independent entities, but they are correlated in various ways since the properties of the objects modelled in the space covary. In symbolic level we can say that “all A-s are B-s” and in conceptual level it means that there is a strong correlation between an object in conceptual space and a certain value of its property.

As Gärdenfors has proposed there is an analogy between the Conceptual Spaces and the Self-Organizing Maps. During the self-organizing process the points in high-dimensional space are mapped onto a two-dimensional output map that can be identified as a Conceptual Space. The self-organizing map is one way of modelling how the geometric structure within a domain can be created from the information on the subconceptual level.

3. Method: The Self-Organizing Maps

The self-organising map is a feedforward neural network that uses an unsupervised training algorithm (Kohonen 2000, Deboeck & Kohonen 1998). The algorithm provides a topology- preserving mapping from high-dimensional space to map units. Map units, or neurones, usually form a two-dimensional space grid and thus the mapping is a mapping from a high-dimensional space onto a plain. The property of topology preserving means that the SOM groups data vectors of similar input on neurons: the points that are near each other in the input space are mapped to nearby map units in the SOM. The SOM can thus serve as a clustering tool as well as a tool for visualising high-dimensional data. The process of creating a self-organising map requires two layers of processing units.

The learning process goes on as follows. At first the output grid will be initialised with initial values that could be random values from the input space. One sample will be taken from the input variables and presented to the output grid of the map. All the neurons in the output layer compete with each other to become a winner. The winner will be the output node that is the closest to the sample vector. The distance between two vectors is measured by Euclidean distance. The weights of the winner neuron will be changed closer to the sample vector, moved in the direction of the input sample. The weights of the neurons in the neighbourhood of the winner unit will also be changed. During the process of learning the learning rate becomes smaller and the rate of change declines around the neighbourhood of the winning neuron. At the end of the training only the winning unit is adjusted. As a result of the self- organising process the data vectors of similar input are mapped to nearby map units in the SOM.

4. Used Data: The Two Lexical Tasks on Emotion Concepts

In our study we have used the data based on a survey that was carried out in written form during the summer months of 2003 in Estonia. The number of respondents was 100 (50 men and 50 women), aged from 14 to 76, all native speakers of the Estonian language. There were 24 emotion concepts selected for the study that form a small but representative set of the category, sharing the prototypical features of emotion concepts to various degree. The selection is based on the results of tests of free listings (Vainik 2002) as well as on word frequencies in the corpora. The participants had to complete two tasks measuring the concepts by means of different levels of knowledge.

In the first task they had to evaluate the meaning of every single word against a set of seven bipolar scales, inspired by Osgood's method of semantic differentials (Osgood, Suci, Tannenbaum 1975). The "semantic features" measured with polar scales drew qualitative (unpleasant vs. pleasant), quantitative (strong vs. weak emotion, long vs. short in duration), situational (increases vs. decreases action readiness, follows vs. precedes an event), and interpretative distinctions (felt in the mind vs. body, depends mostly on oneself vs. others). According to the theory of conceptual spaces this task addressed itself to the emotion concepts at the least abstract or subconceptual level of representations, where concepts get their value and structure via organizing the data of perceptual input according to their measurable qualities.

In the second task the same participants had to elicit emotion terms similar and opposite by meaning to the same 24 stimulus words. This task addressed itself to the emotion concepts via the most abstract or symbolic level of representations in the Gärdenfors's model. This task relayed on the speaker's intuitive knowledge about the similarities and dissimilarities of the concepts.

As the quality dimensions are claimed to be the main tool of similarity judgements, the underlying structure of conceptual space of emotion terms should not depend on the nature of the task the data are gathered in. From whatever direction to approach, the inherent and universal structure of the conceptual space should stay intact and to show up brilliantly. This was the assumption before applying the process of self-organization of SOM program[1] to our data.

5. The Self-Organizing Maps of the Emotion Concepts

Figure 1 pictures the conceptual space of emotions in Estonian according to the results of the first task, and Figure 2 according to the second task. From the very first glimpse it is clear, that the structure of concept organization approached via different levels of knowledge is not identical, though.

The SOM of the first task appears as a bilaterally symmetrical representation where the differences of judgments accumulate in the middle of the chart as a dark area. The darker is the colour on the graph, the bigger are the differences in the semantic profiles of the emotion terms. The positive emotion concepts tend to gather to the upper part of the graph and the words referring to negative emotions to the lower part of the graph.

The concepts are situated on the edges of the graph only, what means, that the similarity of the neighbouring nodes is big enough and the discrepancies from the nodes situated on the opposite side of the graph are big and systematic enough, too. The main organizing dimension of the representations appears to be the negativeness and positiveness of the concepts, that extends the shape of the SOM map in one direction. This is, however, a higher order dimension as compared to the dimensions of evaluated qualities (see Vainik 2004 for a closer discussion). As the anticipatory states (*fear, excitement, concern*), gathered to the right edge of the graph, the scale *follows* vs *precedes an event* seems to function as an additional dimension of the conceptual space. This is a situational characteristic inherent in some of the selected emotion terms.

The inter-correlations of the variables are presented in Table 1. There is a quite notable negative correlation between the scales *increases* (vs. *decreases*) *action readiness* and *unpleasant* (vs. *pleasant*). A distinction between positive and negative emotions (Figure 1) and high correlation with action readiness gives us the main idea of the functional quality dimension of giving two-valenced feedback among the emotion concepts. We conclude that the dimensions of hedonistic (*pleasantness-unpleasantness* and motivational (*increase-decrease action readiness*) evaluations appear as inseparable, integral dimensions co-occurring in the meanings of Estonian emotion terms and consisting the main structure of the conceptual space.

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[1] The SOM Toolbox made by researchers at Helsinki University of Technology (HUT).

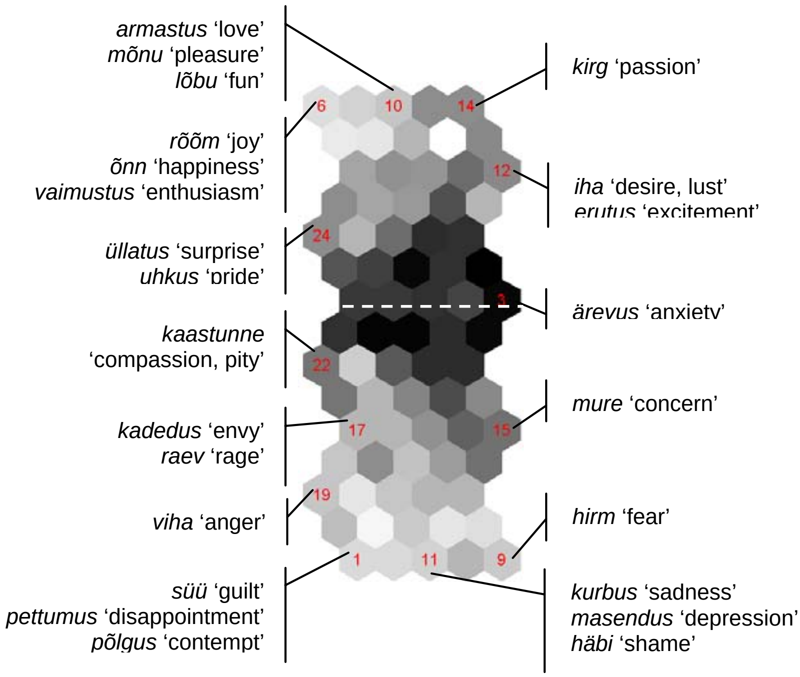

Figure 1. The locations of 24 concepts of emotion in the Estonian language on the self-organising map according to the evaluations on seven scales.

Table 1. Correlations of variables

ID Joint scale	1.	2.	3.	4.	5.	6.	7.
1. strong (vs. weak) emotion	—	-.041	-.028	**.253**	.032	.157	-.162
2. follows (vs. precedes) an event		—	**.239**	-.008	-.060	-.079	.121
3. felt in the mind (vs. body)			—	.093	.050	-.031	.122
4. long (vs. short) in duration				—	**.137**	.034	-.045
5. depends mostly on oneself (vs. others)					—	.002	-.017
6. increases (vs. decreases) action readiness						—	**-.720**
7. unpleasant (vs. pleasant)							—

The SOM of the second task (Figure 2) presents the structure of the same set 24 concepts together with the 71 most frequently elicited "similar" and "opposite" terms. Instead of bilateral symmetry and differences accumulating in the middle (Figure 1) we can see here the similarities to accumulate in the middle (the bright area) and instead of gathering to the edges, the concepts are situated throughout the whole graph. Closer look at the data reveals that the central part of the graph consists of the "opposite" concepts, missing some prototypical emotional quality (see Vainik 2004 for a closer information).

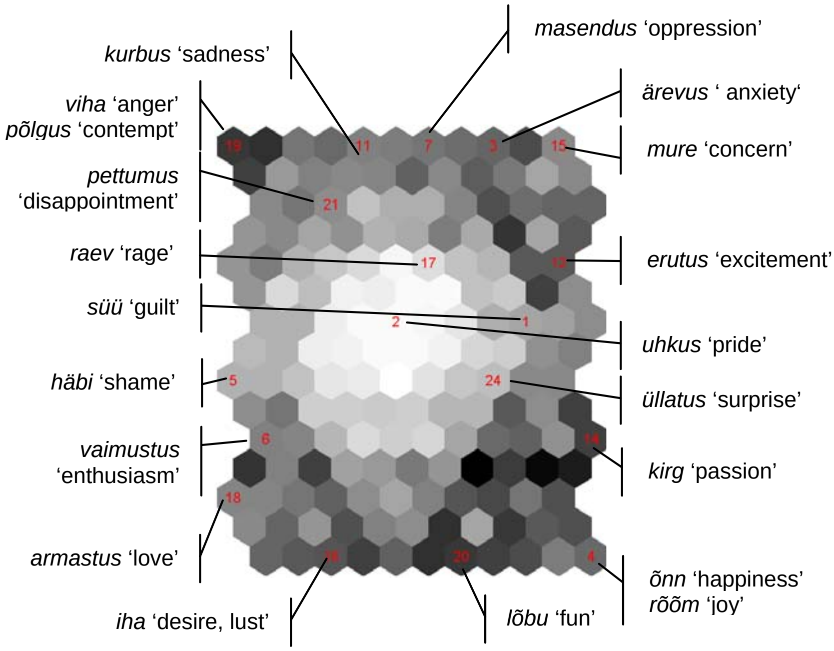

Figure 2. A self-organizing map of emotion concepts based on the relations of similarity and oppositeness.

The overall organization of the graph is radially symmetrical. There are complementarily matching (positive vs. negative) counterparts of affective states sitting in the opposite corners of the graph: positive reactional states match negative reactional states; positive proactional states match negative ones. Symmetrical are also the edges of the graph between the corners of high activation. So a positive hedonistic state matches antihedonistic states, and states of positive social feedback match the states of getting negative feedback from social interaction, all of a relatively low activation.

The most important dimension in the results of the second task seems to be the level of activation. The division of concepts into positive and negative ones is related to feedback functions and is therefore many-folded and holds for specific types and aspects of the emotional situation in which the feedback takes place.

6. A conclusion: where do the conceptual spaces come from?

The Self-organizing maps (Figures 1 and 2) as the main results of differently accessed semantics of Estonian emotion terms do not look identical. The data produced by the informants about one and the same set of stimulus words organized itself differently according to the level of abstractness the conceptual knowledge about emotions was accessed at.

The subconecptually accessed knowledge self-organized itself as a bilaterally symmetrical conceptual space with one dominating higher order dimension (positivity-negativity). The symbolically (via the relations of antonymy and synonymy) accessed knowledge self-organized itself as a radially symmetrical conceptual space, where the level emotional activation seemed to be the main hidden organizing dimension. In the second task of our model the concepts of emotions didn’t have enough information to share. It means the concepts were presented only by relations between them but there was no information in the subconceptual level. As a result we could see on the graph (Figure 2) that the specific quality dimensions, that could describe the emotions, are missing.

There seems to be no such thing as one independent conceptual space of emotions in the form of fixed network of interrelated emotion concepts determined by a fixed number of dimensions holding for most speakers of Estonians nor are the experimentally self-organized conceptual spaces independent of the nature of source data (numerical self-ratings vs. lexical production) and the level of access. All there is shared is a rather general division of the emotion terms into positive and negative ones and the flexibility to apply these concepts to ones experiences of positive and negative feedback in the course of intra- and interpersonal communication.

Gärdenfors (2000a: 228) noted that humans have powerful abilities to detect multiple correlations among different domains. In theory of conceptual spaces, this kind of inductive process corresponds to determining mappings between the different domains of a space. Using such mapping, one can then determine correlations between the regions of different domains.

The method of SOM was used as an independent analytical tool and as an analogy of the network model of human data processing. One should not forget, however, that any visually attractive representation of conceptual space or emotion *qualia* cannot be identified either with spatial dimensions or with distances between the nodes of a real “wet” neural network. Despite the fact that we couldn’t construct an exact presentation of cognitive processes taking place in the brain at least we could get some insight into the space of concepts.

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II

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Graph Coloring by Self-Organizing Algorithm

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Abstract: A self-organizing method to solve complex optimization problems as a graph vertex coloring is proposed in this paper. The self-organizing approach is needed in the environment of ad hoc networks because there is no central management and the network nodes can use only local information. The solution can be found only by local interaction between the system components without any help from outside. The proposed method is inspired by the chemical casting model but it is extended and more generalized. The method's accuracy is tested with instance graphs.

Keywords: self-organization, graph vertex coloring, ad-hoc network.

1. Introduction

In many natural systems it can be noticed that order arises from local interactions between the system components and without any external help. Just a few simple laws generate complex phenomena in nature [1]. The process of generating order by local interactions between the system components is called self-organization [6]. The self-organizing approach is needed to solve some new engineering tasks where the system and relations between the system components become more complex and the components are distributed. For example, an ad hoc wireless network has no central management and decisions are made locally by network nodes.

To avoid that two neighboring network nodes do perform the same operation at the same time in the environment of ad hoc networks a schedule should be agreed between the nodes. This problem is reducible to the well-known graph vertex coloring problem. It is not possible to use any traditional graph coloring methods in ad hoc networks because those methods use global approach and global information i.e., information about all the vertexes. In ad hoc networks only local information can be used and the solution can be found by using local interactions between the network nodes. The aim of this paper is to propose a graph coloring method that satisfies the locality restrictions.

The best method compatible with previously defined requirements is the chemical casting model proposed by the Japanese researcher Kanada [8]. The only disadvantage of his method is that it uses a predefined maximum number of colors. In this paper an extended method is introduced that can be used in the environment of ad hoc networks. The extended chemical casting model allows to find the number of needed colors and also has some improvements in the fitness condition to get more stable results. In this paper the extended method's ability to work in a distributed environment is analyzed, some instance graphs are used to measure the method's adequacy and some comparisons are made with the original method.

The paper is divided into three parts. Firstly, the environment will be introduced and some background information will be given. Secondly, a self-organizing method for graph coloring will be described in more detail. Finally, the results of the tests with some instance graphs will be shown.

2. Self-Organization and Environment of Ad Hoc Networks

Self-organization can be found in many natural systems where the system moves towards a more ordered and stable state without external help. Self-organization is defined in many ways but in this paper the definition proposed by Heylighen is used – self-organization is a spontaneous creation of a globally coherent pattern out of local interactions between initially independent components [6]. Wolf and Hovolet [11] have summarized the main characteristics that are commonly used in different definitions of self-organization. The most important characteristic are as follows: increase in order or organization of the system; absence of external control; adaptability in the presence of perturbations and change; and being a process. The self-organizing systems usually exhibit the phenomenon of emergence, it means that global behavior created by system components is something more than the sum of activities of these components.

A good example of a self-organizing system with emergent properties is a flock of birds. Reynolds proposed a model that only consist of three rules to form a flocking behavior [9]. The birds following those three rules generate behavior that requires a new concept to describe it – a flock. The flock of birds is an elegant example how simple local rules can lead the system into a more structured state.

An ad hoc wireless network can also be considered as a self-organizing system. An ad hoc wireless network consists of nodes that are independent, work in a similar manner, and do not depend on a central station that manages connections between them or controls them. The nodes are connected directly only to their neighbors that are in wireless transmission range and indirectly to others, relying on its neighbors to forward messages towards the destination [4]. An ad hoc network builds its structure autonomously and reacts to changes in the structure when a node joins, moves or leaves. Only local information that a node owns itself or can acquire from its neighboring nodes can be used in the applications of ad hoc networks. An ad hoc wireless network is like a graph, where the network nodes are vertexes and if the two nodes are connected then the connection can be regarded as an edge, see Fig. 1. In the figure the dashed line marks transmission range and the solid line connections between the network nodes.

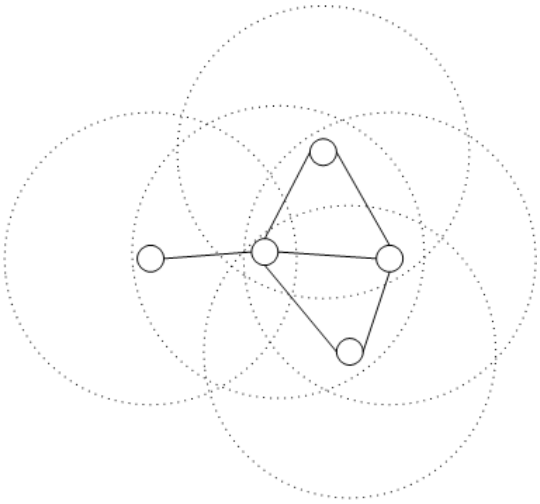


Fig. 1. An example of an ad hoc wireless network.

3. Self-Organizing Method for Graph Coloring

The graph vertex coloring problem is also called the graph coloring problem. To solve the problem graph vertexes should be colored so that two vertexes having a common edge do not have the same color (Fig. 2). The graph coloring problem belongs to the class of NP-hard problems [5] and usually approximation methods are used to find a near-optimal solution. There are many algorithms to solve the graph coloring problem, but usually those methods use a global approach and global information and therefore are not applicable in ad hoc networks.

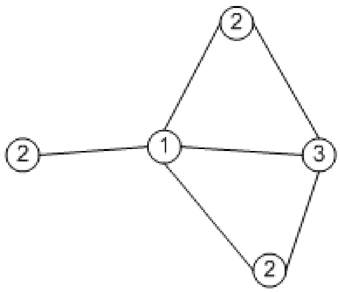


Fig. 2. Optimal coloring of the graph. The number indicates color of a vertex.

The graph coloring is a complicated task where only local information can be used and decisions are made locally by a network node. A node does not have overview of the coloring process in a global level and it solves the coloring problem locally. On the one hand locality sets some restrictions on solving the problem but on the other hand it is an advantage because a node solves a local problem and it could be expected to reduce the complexity of the global problem.

To solve the graph coloring problem in the environment of ad hoc networks a solution should be found that covers three main components of the algorithm. Firstly, the rule for changing the color of a node has to be defined. Secondly, the fitness function to measure the optimality of a new color has to be defined. Thirdly, the maximum number of colors has to be increased and the new number has to be spread across the network. Despite the fact that there is no central point for sharing global information every node still needs to know the maximum number of colors to color the graph. A solution can be found that is connected to the small-world phenomena, or more exactly to the idea of the small-world network [10]. It is shown that actually in such networks the information spreads rapidly if the locally known information is sent to all neighboring nodes. In current case if the maximum number of colors is changed in a network node then the node immediately sends a message about it to all of its neighbors.

The restrictions caused by the environment of ad hoc networks are satisfied by self-organizing approach. There are some methods, for example, the genetic algorithms [3], and the extremal optimization [2] that are defined as self-organizing but the fitness is compared all over the population to select a new configuration. A method that only uses local information is the chemical casting model [8].

3.1 Chemical Casting Model

The Chemical Casting Model (CCM) for solving large scale constraint satisfaction problems has been proposed by Kanada [7], [8]. The method follows the idea how chemical reactions take place between the molecules. This process takes place only in a local manner and only neighboring molecules can react when the required conditions are satisfied. The CCM method minimizes the number of constraint violations through optimization of local evaluation functions. The function has a higher value when the constraint is satisfied and a lower value when the constraint is violated.

Another important term is the reaction rule, which defines how one component of the system reacts with its neighbor. The reaction rule for the graph coloring problem is used to choose randomly a new color for a vertex from all the available colors between 1 and the maximum number of colors.

The evaluation function o between two vertexes v1 and v2 is defined in case of the coloring problem – the value is 1 if the constraint between v1 and v2 is satisfied and otherwise it is 0 and formally as follows:

$$o(v1, v2) = \begin{cases} 1 & \text{if not connected}(v1, v2) \text{ or } v1.color \neq v2.color \\ 0 & \text{otherwise} \end{cases}$$

Reaction takes place between two connected vertexes v1 and v2 if the following fitness condition is satisfied:

$$o(v1, v2) \leq o(v1', v2). \quad (1)$$

The v1' denotes the vertex with the new number of color after the reaction.

If a vertex has more than one neighboring vertex then the values of the evaluation functions are summarized and evaluated together. For example, the reaction takes place if the condition is satisfied

$$o(v1, v2) + o(v1, v3) \leq o(v1', v2) + o(v1', v3). \quad (2)$$

The sum of the evaluation functions is represented by O and the new value after the reaction by O'. The Eq. (2) equals to:

$$O \leq O'. \quad (3)$$

If there has not been any reaction for a long time and all the constraints are not satisfied i.e., the system is in a local optimum, then it is necessary to push the system out of equilibrium. The frustration accumulation method is used to avoid a local optimum and reaction occurs when following condition is satisfied:

$$O - v1.frustration \leq O' - v1.frustration'. \quad (4)$$

If a reaction takes place or all the constraints are satisfied then the value of frustration function f is initialized by initial value f0. If there is no reaction then the function is increased to f' = f c, where c is a constant. If the value of the frustration function is high enough then the reaction occurs and the system escapes from the local optimum.

3.2 Extended CCM

Here the extended CCM method is proposed for using in the environment of ad hoc networks. The original CCM method expected that the maximum number of colors is predefined, but extended method also finds the optimal maximum number of colors. The reaction rule remained the same and a new color is chosen randomly, because a node does not have any global overview of the state of coloring and therefore all the choices are equal. For example, if the maximum number of colors G is 3 the algorithm has three equal choices to choose a new color C, see in Fig. 3.

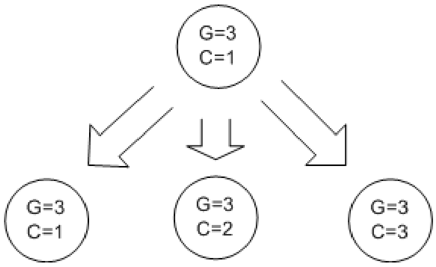


Fig. 3. The reaction rule.

The evaluation function gets the value 1 if two connected vertexes have different color and 0 otherwise. Here the fitness condition O < O' is used instead of the original fitness condition O ≤ O' proposed by Kanada, because the latter one did not allow the frustration function to increase. An example of choosing a new color is given in Fig. 4. The value of the evaluation function O before the reaction is in Fig. 4a. If the new color is 2 the fitness condition is not satisfied and there is no reaction, see in Fig. 4b. If the new color is 1 the fitness condition is satisfied and the reaction occurs, see in Fig. 4c. The goal was also to minimize the maximum number of colors and therefore the values of colors that were closer to the smallest value are preferred. The fitness condition is defined as follows:

$$O < O' \text{ or } (O = O' \text{ and } v1'.color < v1.color). \quad (5)$$

When the algorithm starts the maximum number of colors is equal to 1. The maximum number of colors should increase fast when a vertex has many neighboring vertexes with the same color and increase slowly when the maximum number of colors is high and most of the neighbors have a different color. To find the maximum number of colors a frustration function f and a coefficient c are used.

The frustration function f gets the initial value f0 if the algorithm starts, or the maximum number of colors is increased, or the reaction takes place. The initial value of f0 used in experiments is 0.06. At each step the value of the frustration function f is multiplied by the coefficient c.

$$f' = f\,c. \quad (6)$$

Before the reaction the value of the coefficient c is 1 and if there is no reaction then the c gets a new value as follows:

$$c = n / O, \quad (7)$$

where n is the number of neighbors of the vertex. The maximum number of colors is increased if the value of the frustration function f is higher than 1.

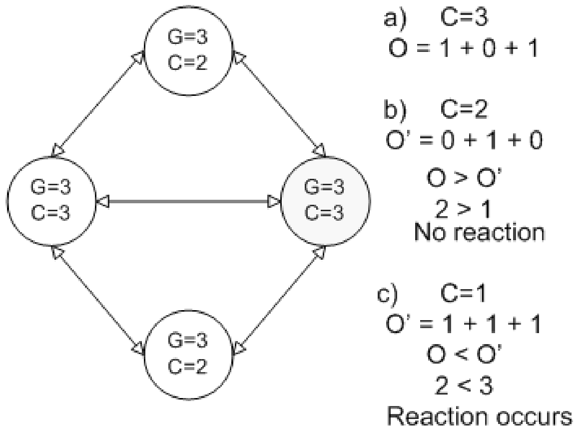


Fig. 4. The fitness condition.

When all the neighboring vertexes have the same value as the current vertex, it means that the sum of the evaluation function O is zero then the number 1 is used instead of the sum of the evaluation function values to avoid division by zero. If one vertex has many neighbors and all the values of colors are the same then the frustration function grows rapidly and a new color is added soon. If most of the neighbors have different color then the algorithm has more time to find optimum coloring before increasing the maximum number of colors.

The original method did not have finishing condition and it worked continuously. The extended algorithm can also be used continuously but in the following experiments it finishes if all the vertexes have different color than their neighbors.

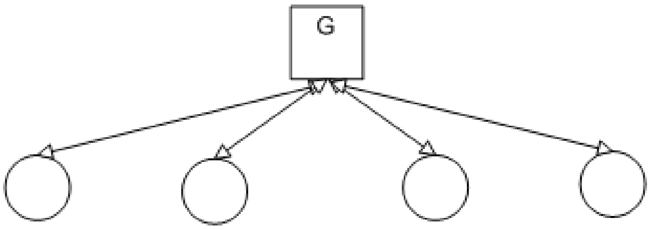
4. Results

To evaluate the method's accuracy the algorithm is implemented in the Matlab and tested with instance graphs. The used graphs are similar to geometric graphs and vertexes are connected if they are close enough in the geometric space. Five instance graphs are used that have the same number of vertexes 128 but the distance defining neighborhood is different and it determines the number of connections between vertexes. The properties of the graphs are given in Table 1. Two types of experiments are performed with the algorithm. Firstly, different aspects of the algorithm are analyzed and secondly, the performance of the algorithm is measured with instance graphs having different density and the results are compared with those of the original CCM.

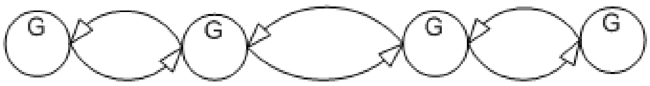
Table 1. The properties of the graphs.

Graph	No of vertexes	No of edges	Optimal colouring
miles250.col	128	387	8
miles500.col	128	1170	20
miles750.col	128	2113	31
miles1000.col	128	3216	42
miles1500.col	128	5198	73

In the first group of experiments the performance of the algorithm is measured with two different strategies to share the value of a global variable i.e., the maximum number of colors. The question is whether there is difference when one global variable is used or a value of global variable is spread across the network using a self-organizing approach. Two approaches are illustrated in Fig. 5.



a) The nodes use one global variable.



b) The nodes share the value of a global variable with the neighboring nodes.

Fig. 5. Two strategies to share a global variable G.

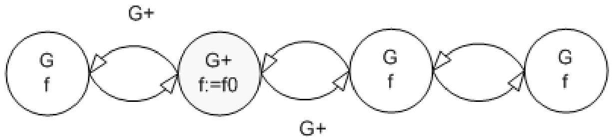
Two strategies are used to initialize the frustration function. Firstly, the frustration function gets the initial value whenever the maximum number of colors changes, see in Fig. 6b. Secondly, the frustration function gets the initial value only if the node itself increases the maximum number of colors, see in Fig. 6c. The second strategy should be much faster because the nodes can increase the maximum number of colors in a shorter time period and the frustration function is not initialized too often. The aim is to assess the difference and to show how different strategies influence the result.

Table 2. Results of the experiments. Different strategies for sharing the variable and initializing the frustration function.

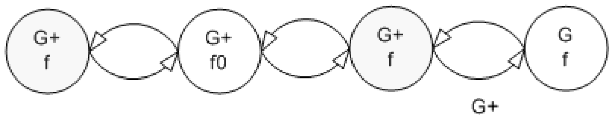
Exp.	No of colours			No of steps			Time		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
“A”	20	21.0	22	782	898.5	1007	15.6	20.6	31.4
“B”	20	20.7	22	763	908.9	1013	20.7	24.7	29.8
“C”	20	21.5	23	103	170.6	226	3.4	5.1	6.5

The results of the first group of experiments are given in Table 2. The instance graph miles500.col is used and 15 tests are performed with each configuration. In Table 2 the experiment “A” is the experiment with one global variable for the maximum number of colors and the frustration function is initialized whenever the number changes. The experiment “B” is the experiment when sharing strategy is used to share the maximum number of colors and the frustration function is initialized whenever the number changes. The experiment“C” is the experiment when the same global value sharing strategy is used as in the experiment “B” but the frustration function f gets the initial value only in the node where the value of global variable is first increased.

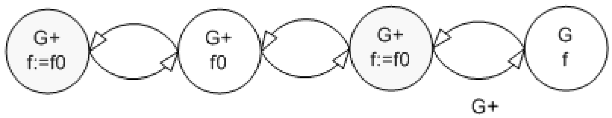
Two strategies to share the global variable give almost the same result, see in Table 2 the experiments “A” and “B”. Both strategies give a similar average number of colors and it takes almost the same number of steps to find the solution. There is a slight difference in time because sharing a global variable with the neighbors needs some additional handling and that increases the working time of the algorithm. It can be said that actually there is no need to use one global variable and avoid self-organizing approach, because two strategies showed almost similar performance. The algorithm can use only local information and is applicable in the environment of ad hoc networks.



a) A node increases the maximum number of colors (because the frustration function f > 1) and sends the new value to its neighbors. The node initializes the frustration function.



b) The neighboring nodes increase the maximum number of colors and send the new value to their neighbors. The nodes initialize the frustration function.



c) The neighboring nodes increase the maximum number of colors and send the new value to their neighbors. The nodes do not initialize the frustration function.

Fig. 6. Two strategies to initialize the frustration function when the maximum number of colors is increased.

When two strategies to initialize the frustration function f are compared then there is a big difference in results. The comparison of the results of the experiments “B” and “C” (Table 2) gives approximately six times difference in performance. If the frustration function is initialized only in the node where the global variable is changed then the algorithm finds a solution much faster but at the same time the result is farther from the optimum. The results of the experiments are also more volatile and there is a big difference between the minimum and maximum value of performance indicators. If a probability to get an optimum solution is smaller but faster in time is acceptable then the strategy to initialize the frustration function only by a node increasing the maximum number of colors can be used.

The second task is to measure how the algorithm works if the number of connections between the vertexes and the maximum number of optimal coloring increases. 20 tests with each instance graph are performed. A self-organizing approach is used to spread the maximum number of colors and the frustration function is initialized whenever the global variable is changed. The results are given in Table 3. The algorithm performed quite well and found usually optimal or near-optimal solution. There were some smaller deviations with the graph 'miles750' where the algorithm did not find the optimal solution, but on the other hand the algorithm found almost every time the optimal solution with the graph 'miles1500'. The accuracy of solution does not depend on the size of the problem.

Table 3. Results of the experiments with the graphs of different density.

Graph	No of colours			No of steps Mean	Time Mean
	Min	Mean	Max		
miles250	8	8.72	10	135.56	2.356
miles500	20	21.16	23	921.40	17.411
miles750	32	32.80	35	2135.04	40.312
miles1000	42	43.80	45	3869.00	72.621
miles1500	73	73.08	74	10676.36	211.162

The same experiments of the second task are performed with the original CCM method and the mean number of steps to color the graph is as follows: 55.3, 53.2, 372.5, 2343.6, and 720.2. The original CCM method expected the maximum number of colors to be predefined, therefore the results are not fully comparable, but the original CCM is faster by average but at the same time more unpredictable and for example, the number of steps required to color the graph 'miles1000' is 114 to 16531 steps. The difference between the minimum and maximum is 145 times.

The extended method satisfies the locality restriction but currently the main weakness of the method is that it does not decrease the maximum number of colors. Further work is needed to find a solution to decrease the maximum number of colors, because nodes can leave from the system and the configuration of the network can change. The following rule can probably solve the problem but it needs testing. When a node is colored by maximum color and finds a smaller value of color then it sends a special message to its neighbors that the maximum number of colors is reduced.

5. Conclusions

The proposed self-organizing graph coloring method satisfies the criteria that are used in definitions of self-organization and also the locality restrictions caused by the nature of ad hoc networks. The outcome of the process is a colored graph and an ordered state. There is no central management and the decisions to find a new color are made locally. The maximum number of colors is spread across the network by sharing the value with neighboring nodes. The coloring is a continuous process and if a node joins or leaves the system, the system reacts to the change and retains its ordered state.

Acknowledgments

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III

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Comparison of the Methods of Self-Organizing Maps and Multidimensional Scaling in Analysis of Estonian Emotion Concepts

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Abstract

Self-organizing map (SOM) and multidimensional scaling (MDS) are the methods of data analysis that reduce dimensionality of the input data and visualize the structure of multidimensional data by means of projection. Both methods are widely used in different research areas. In the studies of emotion vocabulary and other psycho-lexical surveys the MDS has been prevalent. In this paper both of the methods are introduced and as an illustration they are applied to a case study of Estonian emotion concepts. There is a need to introduce some new methods to the field because exploiting only one analytical tool may tend to reveal only specific properties of data and thus have an unwanted impact on the results.

1 Introduction

Human's ability to perceive the structure of multidimensional data is limited and some methods are needed to reduce the dimensionality of data and to reveal its structure. Several methods and techniques of data analysis are used to project multidimensional data into a lower two- or three-dimensional space and to visualize the structure of it. In this paper the methods of self-organizing map (SOM) and multidimensional scaling (MDS) are under discussion.

Some of the researchers have compared the methods of SOM and MDS earlier and outlined both their similarities and dissimilarities (e.g., Kaski, 1997; Duda et al., 2001). Kaski has emphasized their general similarity in respect that both methods tend to reduce dimensionality of observed data and reveal its hidden structure. The two methods differ in the strategy applied to the data. The SOM tries to preserve local neighborhood relations and MDS the interpoint distances between samples.

A hypothesis could be formulated that the way the data are handled in an analytical tool might have an impact on the layout of the results. In order to test this hypothesis the data of present case study – a study of the Estonian concepts of emotion – was analyzed by both SOM and MDS. In the following we will demonstrate the layout of data on both cases and discuss their compatibility.

One of the purposes of the comparison of the two methods is to introduce the method of SOM as relatively unexploited in psycho-lexical studies. Although there are some examples of applying SOM to linguistic data (e.g., Honkela, 1997; Lagus et al., 2002) there are no references to other studies of emotion concepts by the self-organizing maps, yet. In the field of psycho-lexical studies MDS has prevailed so far (e.g., the MDS based Geneva Emotion Wheel (Scherer, 2005)), despite SOM's great popularity in several areas of data analysis (Kohonen, 2000).

In the first part of the paper the two methods are introduced. In the second part of the paper the survey of Estonian emotion concepts is used as an example to demonstrate the similarities and differences the methods.

2 The Self-Organizing Map

The self-organizing map (Kohonen, 1982; 2000) is a tool for the visualization of high-dimensional data. It projects nonlinear relationships between high-dimensional input data into a two-dimensional output grid, named also a map. The self-organizing map is an artificial neural network that uses an unsupervised learning algorithm – it means there is no prior knowledge how input and output are connected.

To describe how the process for creating the self-organizing map works let assume, that we have input data as a set of sample vectors x. It is also called an input space. The output of the self-organizing map is a grid of vectors m_i that have the same number of elements as the sample vector x. Initially all the vectors of the output grid are initialized randomly.

The algorithm of SOM has two main basic steps that are repeated a number of times. First a random sample vector x(t) is chosen and compared with all the output vectors m_i to find closest unit c on the output grid that has a minimum distance $d(x - m_i)$ with a sample vector x. Secondly this best matching or winning vector and its neighborhood are changed closer to the sample vector. The formula for learning process is as follows:

$m_i(t+1) = m_i(t) + a(t)\, h_{ci}(t)(x(t) - m_i(t))$.

Where a(t) is learning rate factor and $h_{ci}(t)$ – neighborhood function at the time step t. During the learning process the learning rate and the neighborhood function are shrinking. The learning process results in an ordered output where similar sample vectors are projected as closely located units on the map.

For visualization of the self-organizing map an Unified distance matrix (U-matrix) is used (Ultsch, 1993). The U-matrix presents the distances between each map unit by color coding. The light color corresponds to a small distance between two map units and the dark color presents a bigger difference between the map units. The points on the output map that are on the light area belong to the same group or cluster and the dark area shows the borders between the clusters.

To illustrate the behavior of the SOM the matrix of distances between Estonian cities is used. The input data consists of distances between 59 Estonian cities. The initial distance matrix is downloaded from the web page of the Estonian Road Administration[1]. From the distance matrix the relative coordinates are calculated. The coordinate matrix is two-dimensional and therefore it is useful to see, how a method transforms the original data. The analysis is performed by the SOM toolbox ver 2.0 for Matlab[2].

The output of the SOM is presented in Figure 1. The map retains Estonian original topological structure in general terms, despite the fact that the eastern side of Estonia is projected on the top of the map. The cities that are close to each other in the real map are projected on the close map units. The color coding also gives some insight into distances between the cities and it is possible to identify regions where the density of population is higher. The local neighborhood is retained, but it is difficult to fully identify the map with the real map of Estonia.

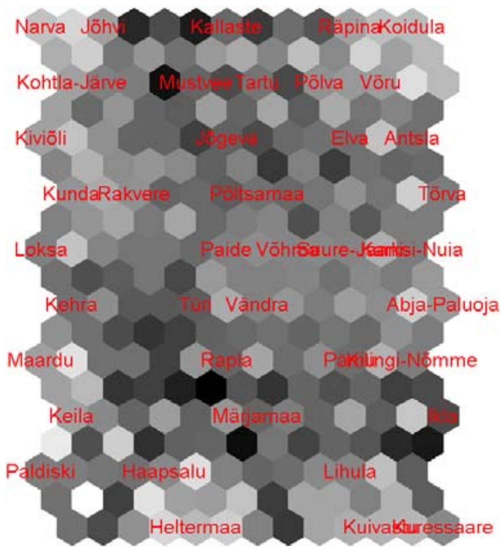

Figure 1. The SOM of Estonian Cities.

3 Multidimensional Scaling

The method of multidimensional scaling (MDS) is a set of related statistical techniques often used in data visualization for exploring proximities in data. The goal of the method is to project data points as points in some lower-dimensional space so that the

[1] Downloaded from http://www.mnt.ee/
[2] Downloaded from http://www.cis.hut.fi/projects/somtoolbox/

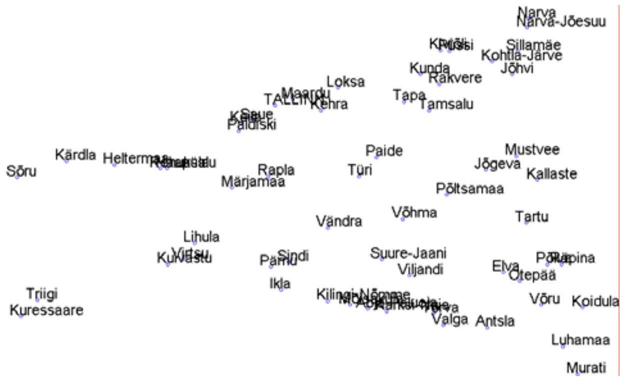

Figure 2. The MDS of Estonian Cities.

distances between the points correspond to the dissimilarities between the points in the original space as closely as possible. Such representation is valuable for gaining insight into the structure of data. MDS can be used as a method of reducing the dimensionality of the data and revealing the dissimilarity between the samples.

MDS is said to be metrical if it based on measured proximities and nonmetrical when the proximities are based on judgment (Jobson, 1992). The original method of MDS was metric (Torgerson, 1958). In current paper the analysis is based on nonmetrical data and therefore the nonmetric MDS is used. The data is analyzed by the statistical software package SPSS and the ALSCAL algorithm created by Takane et al. (1977).

There are n sample vectors $x_1,...,x_n$ and the distance between original samples i and j is g_{ij}. The y_i is the lower-dimensional representation of x_i and the distance between projected samples i and j is d_{ij}. The aim of the MDS method is to find a configuration of image points $y_1,...,y_n$ in a lower dimensional space for which the distances d_{ij} between the samples are as close as possible to the corresponding original distances g_{ij} so that the dissimilarities between the samples are retained as well as possible. Because it is impossible to find a configuration for which $d_{ij} = g_{ij}$ for all i and j, certain criteria are needed whether the result is good enough.

The interdistance matrix of Estonian cities is used again to illustrate the method of MDS (Figure 2). As it can be noticed the result resembles Estonian map despite the fact that some cities in the Northwest and Southwest are projected closer than they are in the real map. It can be caused by the well known "horseshoe effect" that is common to the multidimensional scaling (Buja and Swayne, 2002).

As we can see from the initial example (Figures 1 and 2) the two methods have their preferences. The SOM is good, if the data is represented as coordinates and local relations between the samples are important. The MDS is oriented to reveal the structure of metric distances between the samples and it reveals the overall picture of the data.

4 Study of Estonian Emotion Concepts

The purpose of the case study was to discover the hidden structure of the Estonian emotion concepts and whether it depended on how the information about concepts was gathered. According to the theory of conceptual spaces (Gärdenfors, 2000), the level of conceptual representations of emotions is assumed to be intermediate in abstractness between the levels of purely linguistic (symbolic) and subconceptual representation which is related to emotional experience. In the experiment these two levels of emotion knowledge (lexical and experiential) were used to approach the intermediate level of concepts. Two lexical tasks were designed that provided information about emotion concepts either through their relation to the episodes of emotional experience or through semantic interrelations of emotion terms (synonymy and antonymy).

4.1 Subjects and Procedures

The inquiry was carried out in written form in, 2003, in Estonia. The number of respondents was 100 (50 men and 50 women), aged from 14 to 76 (M = 40.2, SD = 18.61), all native speakers of Estonian. The selection of concepts to be included in the study (N=24) was based on the results of tests of free listings (Vainik, 2002), word frequencies in the corpora, and a comparison with word lists used by some earlier studies of Estonian emotion terms. We believe that the selected lexical items form a small but representative set of the core of the emotion category of Estonian lexicon, sufficient for comparing the structures of emotion concepts, which emerge from the two different lexical tasks.

In the first task the participants had to evaluate the meaning of every single word against a set of seven bipolar scales, inspired by Osgood's method of semantic differentials (Osgood et al., 1975). The "semantic features" measured with polar scales drew qualitative (unpleasant vs. pleasant), quantitative (strong vs. weak emotion, long vs. short in duration), situational (increases vs. decreases action readiness, follows vs. precedes an event), and interpretative distinctions (felt in the mind vs. body, depends mostly on oneself vs. others). The original bipolar scales were transformed from having +/- values into positive scales of 7–1, starting from 7 as the maximum value of the dominant or default feature, over 4 pointing to the irrelevance of the scale, and up to 1 as the minimum value (corresponding to the maximum of the opposite feature).

The second task was a free listing task (Corbett and Davies, 1997). Participants were provided with a blank space to write down as many synonyms and antonyms as came to mind for every presented item. The task eliciting similar concepts resulted in 4068 lexical items and the task eliciting opposite concepts resulted in 3694 lexical items. Before the analysis with SOM and MDS the information was first quantified. The words listed as similar or opposite were characterized by their indices of relative cognitive salience (Sutrop, 2001). The index which takes into account both frequency and mean position of a term was calculated for every word mentioned by at least three persons. Out of total 488 relations only 219 with indices greater than or equal to the average (S_{ave} = .07), were subsequently processed with SOM and MDS

4.2 Results of Task 1 and Task 2

In the first task the data pool of all answers to the 24 concepts on the 7 joint scales was processed. So a vector consisting of 700 answers represented each word. In the second task the words were described by a vector in length of 219 representing values of the index of relative cognitive salience.

Figure 3 and 4 present the structure of Estonian emotion concepts according to the results of the first task. The translations and locations of words on the SOM are given in the following Table 1. The MDS was created with translations only.

The SOM of the first task appears as a bilaterally symmetrical representation. The positive emotion concepts tend to gather to the upper part of the graph and the words referring to negative emotions to the lower part of the graph. Thus, the main organizing dimension of the representation, which extends the shape of the SOM map in one direction, appears to be negativeness and positiveness of the concepts. There is a darker area in the middle, which clearly separates these two clusters. One concept, *ärevus* 'anxiety', is located outside of these two clusters. Apparently it is identifiable neither as positive nor negative or having conflicting specifications in respect of affiliation. As the anticipatory states (*hirm* 'fear', *erutus* 'excitement', *mure* 'concern') are gathered to the right edge of the graph, the scale follows vs. precedes an event seems to function as an additional less important dimension. There is, however, no darker area on the SOM separating the extremes of this dimension.

The MDS represents concepts on the circle. By shape it resembles the circumplex model proposed by Russell (Russell, 1980; Russell et al., 1989). The MDS presents also a clear distinction between the positive and negative concepts on the horizontal scale – the more negative the concepts the more left they are situated and the positive concepts are situated on the right-hand side, accordingly. In MDS, too, the concept of *ärevus* 'anxiety' occurs as ambivalent between positive and negative concepts, and so does *kaastunne* 'pity, compassion'.

Figure 3. The SOM of the First Task.

Table 1. Location of Words on the SOM of the First Task.

enthusiasm happiness joy	pleasure fun love	passion
		excitement desire
surprise pride		
		anxiety
pity		
rage envy		concern
anger		
guilt disappointment contempt	sadness shame oppression	fear

There is another dimension that distinguishes the concepts on vertical scale: the states perceived as event preceding are situated on the upper part of the circle and the states perceived as following some event are situated in the bottom. According to the MDS presentation the concept *masendus* ‘oppression’ can be regarded as not clearly preceding nor following its eliciting event.

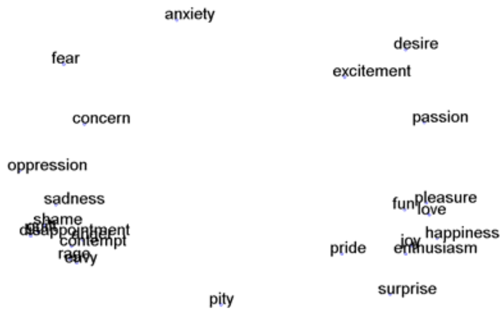

Figure 4. The MDS of the First Task.

The results of the first task characterize how the conceptual organization of emotion emerged from subconceptual and experiential level of knowledge in Gärdenfors’s model (2000). It can be seen, that the two methods resulted in very similar layouts, except the orientation of the dimensions and the way of discriminating the groups.

Figures 5 and 6 (and Table 2) present the structure of the Estonian emotion concepts according to the results of the second task of the survey. This task addressed the most abstract and symbolic level of representation of emotion knowledge, according to the Theory of conceptual spaces (Gärdenfors, 2000), which was accessed through the semantic interrelations of emotion terms in our task.

On the SOM of the second task also a general vertical alignment of positive (bottom) versus negative (top) concepts is observable. There is a remarkably darker row of nodes aligned horizontally, separating those two categories of unequal size. The concepts have self-distributed into three clusters, though, as in the upper part of the graph there is a diagonally located darker area excluding the cluster of concepts in the uppermost right corner. One node containing two concepts *iha* ‘desire’ and *kirg* ‘passion’ are standing outside the clusters not belonging to any of them.

This SOM does not coincide with the SOM of the Task 1. Instead of two we have three clearly distinguishable clusters here. This lets us to conclude that the organization of emotion concepts is slightly different while emerging from the data about the relations of similarity and oppositeness. The SOM layouts thus occur to support the hypothesis of the case study about the plausibility of differences in conceptual organization due to the way the data about concepts is gathered.

Figure 5. The SOM of the Second Task.

Table 2. Location of Words on the SOM of the Second Task.

sadness oppression			concern anxiety
pity disappointment	rage anger		excitement fear
envy contempt	shame guilt		
		desire passion	
surprise			
fun pride	happiness	love pleasure joy	enthusiasm

The MDS of the second task, on the other hand, retained the circular structure and there might be seen the horizontal alignment of positive (right-hand side) versus negative (left-hand side) concepts on the graph, as well as the vertical alignment of event preceding states (the upper part) versus the event following states (the lower part of the graph).

At the first glance the result of Task 2 as analyzed by MDS is very similar to the result of Task 1 except that the locations of *kaastunne* ‘pity’ and *vaimustus* ‘enthusiasm’ do not fit. This result leads us to two possible conclusions. First, we can conclude that the way the information about emotion concepts was gathered had no or only nonsignificant impact on their emergent structure, which proves the invalidity of our hypothesis of the case study. On the other hand, we can conclude that the method of MDS tends to generalize the results to fit a circular solution best presented by two crossing dimensions.

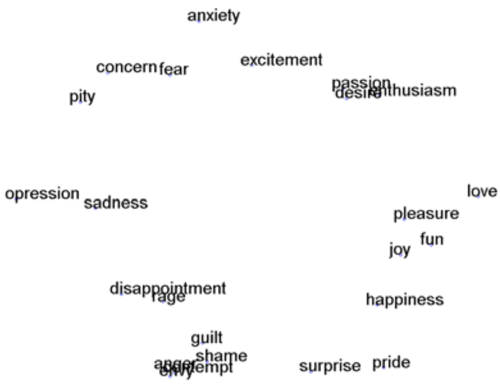

Figure 6. The MDS of the Second Task.

However, even on the circular arrangement there are actually three groups of concepts visible, especially with the prior knowledge from the SOM analysis. On the bottom right there is a cluster of positive concepts, the cluster of negative ones is situated on the bottom left and on the top there are concepts that might be described mostly by their quality as event preceding states. These three clusters are partly compatible with these three described on the SOM of the Task 2 (Figure 5).

5 Discussion

In previous section two tasks of differently accessed semantics of the Estonian emotion terms were compared and two methods of data analysis were applied. As a result, both methods gave us a general understanding what are the main dimensions that distinguish emotion concepts and revealed that there is clear distinction between positive and negative concepts. In the first task both methods distinguished two groups of concepts and in the second task one additional cluster emerged. The level of abstractness at which emotion knowledge was accessed in the tasks (subconceptual and experience-related vs. symbolic and lexicon-related) turned out as critical while SOM was used and nonsignificant while MDS was used. The hypothesis of the case study was thus proven only in the case of using SOM. With this conflicting result, however, is proven the main hypothesis of our present study. Namely, the way the data was handled in an analytical tool turned out to have an impact on the layout of the results.

Comparing the results of analysis of linguistic data SOM formed clearly separable clusters and MDS projected data on the circle. Supposedly, MDS presented the overall distances between the samples and therefore the extremity of dominant positive negative scale became dominant in both cases and the overall layout of the results occurred as the same - circular. At the same time the SOM gives an overview of local relations between concepts and forms local clusters. However, even the projection of local relationships between the samples gave us the insight that there is the division between the positive and negative concepts.

In the case the data was gathered from the task relying on the procedure of the Osgood's semantic differential or alike, the two methods revealed very similar results. In the case the data was gathered by assessing concept similarity and oppositeness the layouts of MDS and SOM seem somehow differently. It is probably the point where the different strategies used in the analytical tools turn out as critical. MDS uses a strategy to keep most dissimilar samples as apart as possible (it preserves the distances) and SOM uses the strategy to keep the most similar samples together (it preserves the neighborhood relations). The data of the Task 2 contained data about both assessed concept similarity (a tendency to interpret similar concepts as situated close to each other) and about oppositeness (a tendency to interpret most dissimilar samples as most apart in a hypothetical conceptual space (Gärdenfors, 2000)). Thus the construal of the Task 2 might have made it sensitive to the procedures used in the analytical tool.

While analyzing linguistic data containing information about concept similarities and dissimilarities it might be useful not to be grounded in just one analytical tool, because MDS gave similar circular structure as a result of both tasks. When some additional knowledge was acquired from the SOM analysis, a more complicated structure within the data was revealed. The interpretation of the results may depend on the interpreter – his or her thoroughness and in more general what he or she wants or supposes to see.

6 Conclusions

In the present paper the results of analysis of Estonian emotion concepts by two methods—the self-organizing maps and multidimensional scaling—were compared. Both methods gave us a general understanding what are the main dimensions distinguishing emotional concepts and revealed a clear distinction between positive and negative ones. Both methods also demonstrated their peculiarities due to the different strategies used in their procedures of data handling. Although both methods reveal the dominant dimensions describing the data, SOM stresses more on the local similarities and distinguishes clearly groups within the data. MDS reveals global dissimilarities between the samples and some background information is needed to distinguish groups. Our conclusion would be that exploiting only one analytical tool may tend to reveal only specific properties of data and thus have an unwanted impact on the results.

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IV

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An Agent Based Simulation for Testing the Emergence of Meaning

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Abstract: To understand the essence of meaning is a crucial point to build intelligent systems. It is proposed that meaning emerges if an agent starts to distinguish objects or events that have positive or negative impact on survival and to prefer desirable and avoid undesirable states. In this paper a simulation is proposed to evaluate whether it is possible that from a random initial configuration with the help of an evolutionary process an evaluation system emerges that helps an agent to distinguish and gather energy rich resources and to avoid dangerous matter.
Keywords: Meaning, agents, artificial life, evolutionary computation.

1. Introduction

For humans and other living organisms the surrounding environment has some meaning. Everything an organism senses signifies something to it: food, fight, reproduction [15]. The understanding of the essence of meaning seems to be a fundamental question to build artificial intelligent systems that would be able to communicate with humans using a language. A language consists of symbols and rules for manipulating these symbols. Meaning is associated with the symbols that stand for entities in the world. Symbols are arbitrary and there is no relation between the shape of the symbol and the object or event the symbol refers to. In semantics some more complex languages are used to describe the meaning of symbols.

Harnad raised a question how an arbitrary symbol system can be grounded in the other meaningless symbols and how words actually get their meaning [12] and names this problem a symbol grounding problem. To solve the problem an overview of different approaches is given by Taddeo and Floridi [21]. All the approaches ground the symbols through sensorimotor capacities of an agent. But the non-representational approach expects there is no need to use symbolic representation for grounding and the meaning is grounded in the environment, e.g., the physical grounding hypothesis proposed by Brooks [2].

The relationship between the symbol and the object or the event in the world does not explain why such a phenomenon as meaning arises. An approach to explain the meaning is the control metaphor proposed by Cisek and it based on the idea that organisms behave so that they could get the right stimulus [5]. Objects and events mean to the agent whether they support survival or not and whether they enable to achieve desirable or avoid undesirable state (simply by making a distinction between good and bad). In this paper the results of the simulation are presented that test whether from a random initial configuration and with the help of an evolutionary process such a control loop, making a distinction between good and bad, can emerge.

In this paper some basic introduction to the study of meaning is given. Thereafter an experiment is composed and executed to test the hypothesis that meaning can arise through an evolutionary process. Finally, the results of the simulations are discussed.

2. Study of Meaning

The meaning has been a philosophical issue but has now turned more to be as a scientific issue without having some mythical background. According to the classical approach, the meaning is a relationship between the things (signs) and their meaning (what they intend, express or signify). In semantics a more complicated language is used to describe the meaning, e.g., a semantic lexicon system WordNet [17]. The database consists of words and their mutual relations.

To solve the symbol grounding problem Harnad expects that the symbols and their meaning can be grounded if reference between objects or events and symbols is built up [12] [13]. Harnad's model consists of three kinds of representation: iconic representation – receiving sensory signals, categorical representation – recognition of a certain pattern and symbolic representation – assigning a symbol.

Cisek [5] is critical of the Harnad's solutions and turns back to the beginning of life. There are several theories how the first living pieces of matter came into existence, like 'autocatalytic sets' escribed by Kaufman [16]. The self retaining cycle is the basis of life. It corresponds to a definition called the NASA definition of life: life is a self-sustained chemical system capable of undergoing Darwinian evolution [19]. The main property of the living system ensures that the conditions to continue their existence are met. The living systems should keep certain critical variables within an acceptable range and this mechanism is called "homeostasis". The variables are kept in the desired range by feedback loops forming a control cycle. If a certain variable is out of the desired range a cascade of chemical reactions follows that brings the system back to the desired situation and the trigger of the reactions ceases. It is also a trigger for a motivational system and enables to make decisions.

For example, several hours after eating the blood sugar level drops and it activates certain neuronal activity. Activation of the pertinent innate pattern makes the brain alter the body state so that the probability for correction can be increased [7]. You feel hungry and that makes you take steps to get some food. After eating the blood sugar level increases and the feeling of satiety follows.

The control cycles also help an organism to classify things or events as “good” or “bad” because of their possible impact on survival [7]. And the things are categorized as good or bad and the process of defining new good and bad things grows exponentially. The internal and external signals are triggers of a certain response or behavioral pattern. Animals distinguish inherently some input; some of them are “desirable” and some “undesirable” [5]. The desirable situations are preferred, like a full stomach, and undesirable are avoidable, like danger. Such a distinction gives the meaning to the perception–whether the perceived object or event enables to achieve a favorable situation or must be avoided. Control is gained by studying the regularities within the environment that define reliable rules of interaction.

Cisek states that in the living systems the meaning comes long before symbols because organisms have interacted with their living environment long before they started using symbols. An object or event in the surrounding environment affords something for an organism [10] and means for one organism something different than for the other. The meaning of an object or event depends on what it makes possible.

3. Experiment Design

Previously described solution to the origin of meaning needs some testing whether it is possible that such cycles arise which distinguish good from bad and motivate organisms to move towards good things that give them resources and energy. The test is inspired by the idea that cycles can arise from a random configuration of non-living matter which prefer moving towards some energy sources and avoid dangerous matter. For testing aspects from artificial life and evolutionary computing are combined.

Sun has proposed a solution that uses an evolutionary approach to solve the symbol grounding problem that uses a two-level learning [20]. The first level is like evolutionary learning using a trial-and-error approach and the second stage is fine tuning to produce the best possible behavior. This approach is based on the reinforcement learning principle where a good choice is rewarded and a bad choice is punished. Taddeo and Floridi [21] have criticized the evolutionary approach to solve the symbol grounding problem. They argue that a programmer generates the goal of the evolutionary system and therefore the “natural” selection process follows the programmer’s intentions. As life is a self-organizing system and develops following the laws of evolution and natural selection the evolutionary approach might offer the most promising solution to the symbol grounding problem. To avoid the critics of intentionality the simulation must be based on natural laws.

Biological systems are defined to exhibit the self-organizing phenomenon [4]. The self-organizing systems can be regarded as open systems, it means the energy and matter is flowing through them [18]. A fundamental starting point to design the experiment is that organisms or agents need some energy to function. Consumption of energy is an important factor because it is needed to keep an entropy level of a living organism low. Without continuous flow of additional energy and resources the process will reach equilibrium when all the stored resources are used. If an organism is successful to find new energy sources, he will survive and otherwise he dies out.

The simulation is based on the idea that energy-driven networks of small molecules were the initiators of life. Shapiro supports the theory of metabolism first and argues that life began as a combination of simple organic molecules that stored information for duplication and passing it to their descendants [19]. Multiplication took place through catalyzed reaction cycles and some external source of energy was needed. Based on the Shapiro's assumptions the simulation was constructed as a very simple one and agents have only simple drives to gather external sources of energy and to replicate.

Based on those presumptions an agent based simulation has been built. The aim of the simulation is to test whether it is possible that first, a random configuration occurs which allows to recognize energy sources, and second, a system starting from a random configuration is able to reconfigure and to adapt the surrounding environment and generate rules to distinguish good things from bad ones. It is a test to assess whether it is possible that control cycles supporting an organism’s ability to distinguish good from bad can arise.

3.1 Simulation Environment

The simulation consists of a world where initially a number of agents and resources are distributed randomly. The agents have an ability to move, distinguish things in the surrounding environment and reproduce. There is a rule in the world that an agent needs some energy to live and to reproduce and without energy an agent dies. An agent can consume both good things and bad things. A good thing gives him n units additional energy and a bad thing speeds up energy consumption. The value of internal energy decreases at each step of simulation. When an agent reproduces half of the good and bad resources are given to his offspring.

The simulation presupposes that agents have an ability to perceive resources occupying the neighboring area. An agent has weighted values to determine which resources and moving directions to prefer. The set of weights determining behavior of an agent is called a configuration. Initially all the weights have a random value and it is presupposed that agents can prefer an arbitrary resource which is the trial-and-error approach. During the simulations the weights are changed. If the value of internal energy of an agent is increased, the weight related to the consumed resource is increased and at the same time the weights of the other resources are decreased. It is the other way round when the energy decreases. The simulation uses a gradual learning because it is presupposed that even the trial-and-error approach can lead the system to the desired state but it takes more time.

Time in the simulation is discrete. At each step an agent evaluates the surrounding environment, makes decisions which direction to move and consumes resources. To make a decision the weight value of the resource and half of the weight value of the direction are summed up and the direction with the highest value is selected. At the end of each step the used resources are restored and replaced randomly on the world.

4. Experiments

To test the hypothesis several experiments were performed. All the experiments were made in the world with the size of 20 x 15 units (Fig. 1). The initial number of agents was 10. With each world 10 tests were performed. The simulation ended when it had performed 300 steps or all the agents had become dead.

Fig. 1. A simulation. (Legend: ■ - agent, ■ - good, ■ - bad).

The results of the tests are given in Table 1, which defines the number of good and bad things, the energetic value of good and bad things and the results of the experiments.

Table 1. The results of the tests.

Number of good	Number of bad	Good energetic value	Bad energetic value	No of successful experiments	Average number of steps
20	20	4	-1	1	42.8
20	20	6	-6	0	30.9
20	20	8	-8	0	15.9
30	30	4	-1	4	132.5
30	30	6	-6	7	214.3
30	30	8	-8	3	101.6
30	10	4	-1	7	215.5
30	10	6	-6	7	231.9
30	10	8	-8	5	172.1

Next several observations and generalizations of the performed simulations will be given. The world needed certain energetic density to keep the agents living. It can be calculated by the probability to find a new energy source within a certain time limit. As a result the configuration preferring energy rich resources appeared quite frequently. The probability of survival of such a configuration was higher when the energetic density of the world was high. The natural selection was pitiless and all the configurations preferring something else than energy rich resources usually died out.

The population of agents was successful when the whole population acquired a similar behavior and started to move in the same direction as a wave. The population growth seems to be connected to the Bak-Sneppen model [1]. A certain small change in a configuration was needed to make the number of agents grow very rapidly until it reached the equilibrium with the available resources (Fig. 2).

From the initial population only a few species remained and usually they acquired similar behavior. If several sub-populations acquired different behavioral pattern, they started to compete for the energy sources and the size of the population remained cyclic.

Usually the use of negative energy sources ceased during the simulation because all the organisms that preferred to consume bad things died out and only agents preferring good things survived. If the energetic value of the world was high, quite often the use of bad things did not cease because the agents had enough energy available to compensate the additional expense.

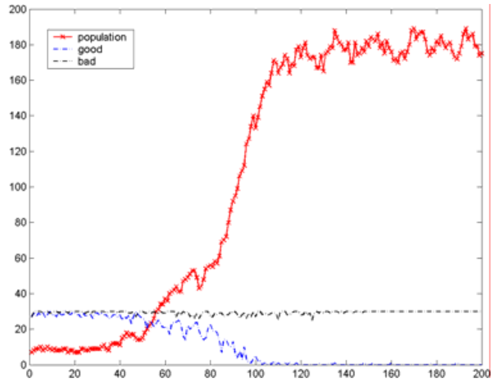

Fig. 2. A typical graph of the simulation of a successful population.

5. Conclusions and Discussion

The results of the simulations indicated firstly that it is possible that a random initial configuration determining an agent's behavior may have an ability to recognize energy rich resources and secondly that a configuration recognizing and distinguishing good resources from bad ones can emerge through an evolutionary process. It might give some indication of starting a process that is the precursor of the meaning.

The experiment was very simple but proved that a configuration distinguishing good from bad can possibly emerge. As Brooks noticed there is no need for the world model [2] and the best world model is the world itself. There are several regularities in the world and an agent must remember what those regularities may result in and whether their outcome is desirable or undesirable. An object or event in the world means to an agent a certain possibility to satisfy his needs. Why was the first stone axe created – because it increased the possibility that an animal had been caught and it meant more food and less hunger. The tool was sharpened and improved to increase the probability that the desired state was achieved. Again, things can afford something in a sense of the theory of affordances [10]. An agent selects an action that allows the most probable way to achieve the desired state. The weights defining probabilistic relations between the action and the achieved state are changed through the interactions with the surrounding environment and the meaning can be regarded as a process. Events or objects can be recognized and classified and thereby conceptualized. Agents use a conceptual instead of symbolic representation.

The symbol grounding problem becomes easier if a concept approach is used [8]. In the theory of conceptual spaces [11] the properties of a concept are defined by a number of quality dimensions, which also represent a semantic information, and symbols are high level representation of concepts. But in this theory a value dimension is missing that might be an important factor to create meaning. Meaning is defined by the value of the relationship between an individual and his environment [22].

An object or event in the surrounding environment may be connected to several concepts and have different meaning depending on the situation, e.g., a daily use of a cup – it can be used to drink coffee, but also to keep flowers or to use for some other purposes. An agent usually, routinely, reflexively uses an object in its everyday life as it can be used [20]. When the context changes, also the meaning changes, e.g., when a human is thirsty, a cup means a tool for helping drinking and reducing thirst, when one has some flowers a cup enables to use it as a vase. The cup remains the same but its meaning changes. When the concept is analyzed, the values or feelings associated with it are changed like the Damasio's waterbed metaphor [7]. The process of meaning may work so that the relationship between a desired state, a conceptual representation of the environment and possible actions is continuously formed and evaluated.

The performed simulations gave some indication that from a random initial state a configuration can emerge that is able to survive and reproduce. To have a successful configuration a variety of initial states are needed but the nature had enough time to test different initial conditions. Once a successful configuration was found it turned out to be unstoppable when there was a continuous flow of additional energy and resources. Changes in the configuration could help an agent to adapt with the changing environment. Despite the different origin the agents exhibited similar behavior and it can be said that life is the same everywhere, it's only the faces that are different. Actually life can be taken as a whole and organisms are only components of it. Different organisms are different representations of the same life. Life tends to keep itself existing therefore it tries to invade different areas and has a wide variation.

Brooks argues that living systems are composed of non-living atoms and there is an unknown gap between the living and non-living matter [3]. Here the solution has been tested that might help to cross the gap. The solution may be in the new control approach where the system tries to achieve the desired state. From a random configuration the control cycles arise that keep the parameters of a system in a desired range. It also offers an explanation for the basis of the motivational system of a living organism. Hawkins has proposed that a human brain deals with predicting [14] and so do all the other living organisms – they predicting sequences and regularities in the surrounding world. The goal of such predicting is to select one of the actions made possible by the environment that has the best payoff [6]. Edelman argues that a living organism becomes conscious of the surrounding environment if the perception is connected to the value category memory [9]. The value system and the memorized previous experience generate a probabilistic view whether and how a certain desired state can be achieved. There seems to be three components that a living system might have – the motivational, evaluative, and predictive component. The motivational component explains why a system continuously acts in the changing surrounding environment and why it is motivated to act. A steady analysis whether the situation is desirable or not and whether it needs some correction to ensure the agent's existence is the basis of motivation. The evaluative component evaluates what the surrounding environment can afford and what it means to an agent in the terms of survival. The predictive component gives the best probable solutions how to reach desirable situations based on the previous experience of the regularities in the world stored in the memory system. Through continuous evolution or learning the parameters are changed to increase the probability of survival. The more adaptive and successful an agent is the more intelligent it seems to be.

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A Method for Comparing Self-Organizing Maps: Case Studies of Banking and Linguistic Data

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Abstract. The self-organizing map (SOM) is a method of exploratory data analysis used for clustering and projecting multi-dimensional data into a lower-dimensional space to reveal hidden structure of the data. The algorithm used retains local similarity and neighborhood relations between the data items. In some cases we have to compare the structure of data items visualized on two or more self-organizing maps (i.e. the information about the same set of data is gathered in different tasks, from different respondents or using time intervals). In this paper we introduce a method for systematic comparison of SOMs in the form of similarity measurement. Based on the idea that the SOM retains local similarity relations of data items those maps can be compared in terms of corresponding neighborhood relations. We give two examples of case studies and discuss the method and its applicability as an additional and more precise measure of similarity of SOMs.

Keywords: Neural networks, data mining, knowledge discovery, semantics.

1 Introduction

The self-organizing map (SOM) is a method to visualize multidimensional data. The SOM performs mapping of multidimensional data onto a two-dimensional map while preserving proximity relationships as well as possible. The results of the SOM analysis are usually assessed visually. Interpretation of the SOM and discovered knowledge depends mostly on an interpreter. Subjective factors such as one's attentiveness to both general patterns and local details of a large number of presented data items might diminish the objective value of data analysis.

When we use different sources of data that describe the same phenomenon but are collected somehow differently or the number of variables is varying then we have to assess whether the results of the two analyses are similar. As the SOM projects close units of the input space into nearby map units the local neighborhood should remain quite similar. In this paper we propose a simple method to compare the results of different self-organizing maps. The methodology is based on the measurement of similarities of the local neighborhood.

In the first part of the paper the used methods and techniques including similarity measurement methodology are introduced. In the second part of the paper two data sets as case studies are used to illustrate the similarity measurement methodology. Finally there is a discussion to analyze the results and the accuracy of the methodology.

2 Self-Organizing Map

The self-organizing map [2] is a powerful tool to visualize high-dimensional data. It projects nonlinear relationships between high-dimensional input data into a two-dimensional output grid (map). The SOM is an artificial neural network that uses an unsupervised learning algorithm without prior knowledge how systems input and output are connected. For visualization of the self-organizing map a Unified distance matrix (U-matrix) is used. The analysis has been performed by the SOM toolbox [4].

3 Dimensionality Reduction

To reduce dimensionality of the data we use the principal component analysis (PCA). The main idea of PCA is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set [1]. The PCA transforms the data linearly and projects original data on a new set of variables that are called the principal components. Those are uncorrelated and ordered so that the first few components represent most of the variation of the original variables.

4 Matrix Reordering

The matrix reordering is a structuring method for graphs (and general data tables). The method reorganizes the neighborhood graph data vertices according to specific property – systems monotonicity [8], [9]. For example, we start with a simpleminded graph input variant. Then we calculate the Hamming similarity matrix S for the given graph. To reorder the graph for an easy visibility we will find the row sums of H. Then we take the weakest object in the system (one with the minimal row sum) and subtract that chosen object's similarities from the sum vector. We repeat that elimination step n times whereby z is the evolving list of graph nodes in the elimination order. And as the last step we print our graph g in the new order z. The examples of such reordering can be seen in our case studies (Fig.3, Fig.5).

5 Methodology of Similarity Measurement

While the SOM represents data on two-dimensional topological maps the local topological relations between data items can be used to assess whether the maps have similar structure. The local neighborhood is the basis of our approach to measure the similarity between maps and we expect the neighborhood relations to remain stable even when the overall orientation of the map changes.

The proposed methodology to measure similarity between the self-organizing maps consists of four main steps.

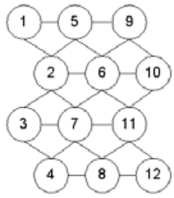

Fig. 1. Neighborhood relations on the SOM.

Firstly, to analyze general organization the resulting map is visually examined and clusters and their borders are identified, also the general orientation and locations of data items are identified. Thereafter the matrix of neighborhood relations is formed. Neighborhood assessment is based on the location of the best matching units (BMU - a point on the map that is the closest to the input data vector) on the self-organizing map. Two data items are neighbors if they are marked to locate on the same node or in the neighboring nodes depending on the neighborhood range. The neighborhood on the hexagonal map is demonstrated on Fig. 1. The neighborhood matrix is an n-by-n square symmetric matrix N where n is the number of data items and the matrix can also be regarded as a graph. If there is neighborhood relation between i*th* and j*th* element then the value of the matrix element is marked 1 and 0 otherwise.

$$n_{ij} = \begin{cases} 1, ifneighbor \\ 0, otherwise \end{cases}$$

Next stage of similarity analysis is the calculation and assessment of similarity coefficients [6]. The coefficients have typically values between 0 and 1. A value 1 indicates that the two objects are completely similar and a value 0 indicates that the objects are not at all similar. We have used two coefficients, such as the Simple Matching Coefficient (SMC) and Jaccard coefficient (J).

$$\mathrm{SMC} = \frac{\text{number of matches}}{\text{total number of variables}}. \qquad \textbf{(1)}$$

The SMC rates positive and negative similarity equally and can be used if positive and negative values have equal weight.

Jaccard Coefficient (J) is used if the negative and positive matches have different weights (are asymmetric).

$$J = \frac{\text{number of positive matches}}{\text{number of variables - negative matches}} . \quad (2)$$

Jaccard Coefficient ignores negative matches and can be used if the variables have many 0 values.

If the value of the Jaccard coefficient and SMC is below 0.5 then the number of positive matches is less than half of the total matches.

Fourth part of the similarity measurement consists of finding how much the two neighboring matrixes are identical what is a maximum isomorphic subset. The task is not as complicated as the general isomorphic graph problem, because the order of the data items is known and to identify the maximum isomorphic subgraph we can use an AND operator. If a_{ij} & b_{ij} (elements of the neighborhood matrixes have both value 1), then the neighborhood relation is isomorphic. Here we can perform a new meta-level analysis and reorder and visualize the isomorphic sub-graph to see commonly shared information between two maps. For output the Graphviz[1] software has been used.

6 Case Studies

We use two sets of data to illustrate the method of similarity measurement. The first is a research into the concepts of emotion in Estonian language. The survey consisted of two parts and as a result two different data matrixes describe the same set of emotion concepts. In our meta-analysis we attempt to analyze whether and to what extent the results of two tasks are comparable. The second data set is banking data. In this case the purpose of our meta-analysis is to detect whether and to what degree the dimensionality reduction method (PCA) applied to the data has preserved its structure. Those two data sets reveal different aspects of the comparison methodology.

6.1 Study of Estonian Concepts of Emotion

The purpose of the study was to discover the hidden structure of the Estonian emotion concepts and test a hypothesis that the way the information about concepts is collected can influence its emergent structure. Two lexical tasks were carried out providing information about emotion concepts either through their relation to the episodes of emotional experience or through semantic interrelations of emotion terms (synonymy and antonymy).

Subjects and Procedures

The inquiry was carried out in written form during the summer months of 2003 in Estonia. There were 24 emotion concepts selected for the study based on the results of tests of free listings [7] and also on word frequencies in the corpora. The participants

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[1] Graph Visualization Software available from http://www.graphviz.org/

had to complete two tasks measuring the concepts by means of different levels of knowledge (see [10]). In the first task they had to evaluate the meaning of every single word against a set of seven bipolar scales, inspired by the Osgood's method of semantic differentials [5]. In the second task the same participants had to elicit emotion terms similar and opposite by meaning to the same 24 stimulus words.

Analysis by SOM and Meta-Analysis of Neighborhood Relations

The data of both tasks was analyzed by SOM (Fig. 2). In a visual comparison of the two maps we could see completely different structures, but there is a clear distinction of concepts of positive vs. negative emotions observable on both maps. The locations of these clusters are reversed, however. In addition, the upper part of Fig. 2b is divided into two subclusters as there is a group of concepts located in the uppermost right edge of the graph. It is hard to decide whether the obtained structures are different enough to claim the hypothesis that the way of approach (in form of our two tasks) can influence the emerging conceptual structure, proved.

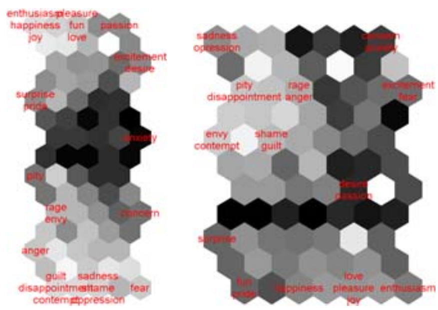


Fig. 2. a) Results of the Task 1 (24 concepts evaluated on the seven bipolar scales), b) Results of the Task 2 (24 concepts arranged according to relations of synonymy and antonymy)

Table 1. Neighbourhood similarity of the SOM of conceptual data

Neig. range	Task 1 neig.	Task 2 neig.	Similar neig.	Total neig.	SMC	Jaccard coef.
1	96	100	52	144	0.8403	0.3611
2	198	216	150	264	0.8021	0.5682
3	276	346	230	392	0.7188	0.5867

The summary of the neighborhood relations between two tasks is given in Table 2. The number of relations is measured with different range of neighborhood, starting from 1 to 3. Increase in neighborhood range causes also increase in the number of relevant neighborhood relations. The SMC coefficient is decreasing if the neighborhood is increasing because of possible connections between the words that actually do not belong to the same neighborhood. We could use the SMC as an indicator of stability. Jaccard coefficient is increasing if the neighborhood range is widening and there is tendency to have more positive matches if the number of neighborhood relations increases.

As far as the neighborhood range remains open it is still difficult to decide, whether the two SOMs of our two tasks were different enough to claim our hypothesis of the case study proven.

The second step of meta-analysis is to find a maximum isomorphic sub-graph and to find a clue what the suitable range of the neighborhood could be. In the case the neighborhood range was provisionally set on 1, several separate fragments of conceptual networks were formed. The general structure of the data did not appear as a connected system. With the neighborhood range 2, the graph became connected. One can speculate that it represents the communal structure or a backbone of the conceptual data gathered from two tasks. The reordered data matrix and its graph are visible on Fig. 3. The lighter part of the reordered matrix is isomorphic part of the matrix.

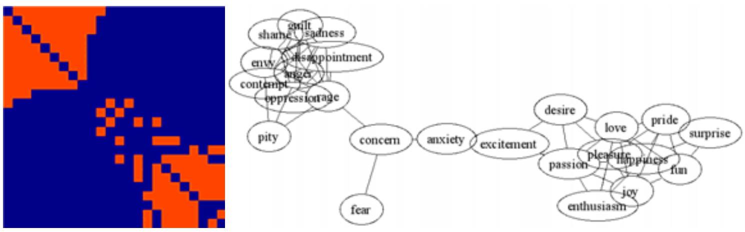


Fig. 3. Reordered and visualized isomorphic subgraph of lexical data (Task 1 vs. Task 2). Neighborhood range 2.

A conclusion can be drawn, that the match of the two structures based on our two tasks is partial, and it is measurable in principle. The degree of measured structural isomorphism depends on the rigidity of the selected criteria of neighborhood.

6.2 Study of Banking Data

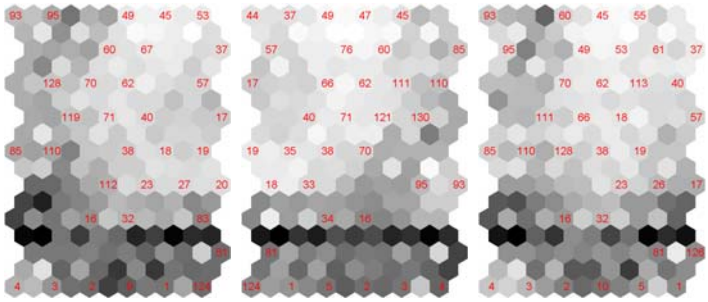
The second data set is used to illustrate the impact of dimensionality reduction by PCA on the SOM maps. The aim of the study is to measure the similarity between the results of SOM mapping of original data and reduced data.

The Banking Data

The second data set consists of banking data (1997—2000; http://www.bankofestonia.info). We have used 133 public quarterly reports by individual banks as a balance sheet and profit / loss statement (income statement). The 50 most important variables have been selected to form a short financial statement of a bank. All the variables are normalized by the variable of total assets to make the reports comparable.

Analysis by SOM and Meta-Analysis of Neighborhood Relations

We formed three sets of the banking data. The first set consisted of all 50 original variables (Original), for the second set 26 principal components describing 95% of variation were selected (PCA95) and for the third set 5 principal components describing 50% of variation were selected (PCA50). From those data sets three self-organizing maps were created (Fig. 4). Our aim has been to measure how similar those maps are and whether similar banks are projected into nearby map units in all cases.



a) b) c)

Fig. 4. a) SOM of 50 original variables, b) SOM of 26 principal components describing 95% of variation, c) of 5 principal components describing 50% of variation

Analyzing the maps visually we can see that in general the maps have a similar structure. As we are interested in overall structure we marked only the first BMUs on the map. The labels are referring to the number of a report. Comparing the SOMs we could identify one bigger group on top, another on bottom and a darker area between them. The original and PCA50 map seem to be rather similar but in case of the PCA95 left-right sides are interchanged. On the bigger light area on top of the SOM there are located the bigger and main retail banks. At the bottom some smaller and niche banks are gathered.

Table 2. Neighbourhood similarity of the SOM of banking data

Experiment	Neig. range	Orig neig.	PCA neig.	Similar neig.	Total neig.	SMC	Jaccard coef.
Orig vs. PCA 95%	1	1876	1772	1426	2222	0.9550	0.6418
Orig vs. PCA 50%	1	1876	2120	1480	2516	0.9414	0.5882
Orig vs. PCA 95%	2	4078	3972	3122	4928	0.8979	0.6335
Orig vs. PCA 50%	2	4078	4038	3046	5070	0.8856	0.6008

In Table 2 the similarity measurement coefficients of the banking data are given. The density of data items on the map is quite high and it is also visible in the number of neighborhood relations. There is a slight difference in the number of neighborhood relations between PCA95 and PCA50. It shows that the PCA retains the internal structure of the data items. The SMC value is very high in all cases, but is becoming lower if the neighborhood range is widening. The Jaccard coefficient shows about 0.6 similarities between the different representations of the data items.

As the banking data consisted of 133 data items the neighboring relations were much stronger than in case of linguistic data. In Fig. 5 there is given an isomorphic subgraph showing neighborhood relations between the SOM of original data and the SOM of PCA95. The neighborhood range is defined as 1. The graph illustrates quite well the structure within the data. The same grouping was visible on the graph representing only 50% of variations. When the neighborhood range was increased the isomorphic sub-graph became connected but at the same time the neighborhood relations became so dense that the structure was not clearly visible any more.

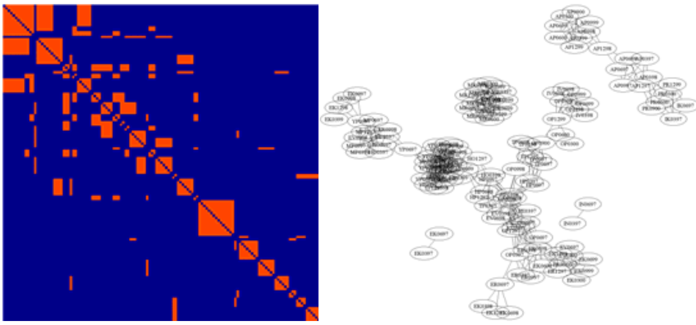


Fig. 5. Reordered and visualized isomorphic subgraph of banking data (Original vs. PCA 95% variation). Neighborhood range 1.

The analysis what is the impact of dimensionality reduction on the results gave us confirmation that even the dramatic dimensionality reduction by the PCA method retains the most important internal relations in the data.

7 Discussion and Conclusions

The case studies give an overview of possibilities to measure similarity between self-organizing maps that is based on the topology and neighborhood relations. We find local neighborhood relations between the data items and measure the similarity of relations by coefficients and by finding an isomorphic subgraph. There has been proposed another method to evaluate two- or three-dimensional visualizations and to measure distances between the two representations by Mandl and Eibl [3]. They calculate Euclidian distances between all the items and find correlation between two representations. We prefer to use local topological representation and not to convert it once more into the Euclidian space.

The similarity measurement coefficients together could give some additional information about the similarity. If the SMC value is high and at the same time the Jaccard coefficient has lower value then it indicates the presence of clustered structure. The bigger the difference is the smaller are the clusters. We can also use the SMC coefficient if the data items are exclusive like in the case of lexical study. There were two exclusive groups of data – positive and negative emotion concepts – that had weak neighborhood relations.

We expected to use the maximum isomorphic subgraph as a measure to identify the similarity between the SOMs, but it became a new meta-level tool to find hidden structure and to reveal the grouping structure of the data. The main parameter in similarity analysis is the range of neighborhood. The number of neighborhood relations increases if the number of data items or the range of the neighborhood widens. The size of a map has also an impact on the density of data items on the map. Depending on the density of the data items range 1 or 2 gives good insight into the hidden structure or the so-called backbone within the data. In both case studies the visualized isomorphic neighborhood matrix gave us a new perspective on relations between the data items.

In this paper, we have proposed a methodology to measure similarity between the self-organizing maps if the maps are describing the same phenomenon but use different sources of data or the number of variables are different. We illustrated the methodology by two sets of data. The results of the two case studies have shown us that the suggested method to measure similarity between two self-organizing map is applicable and it gives new insights into the data.

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French	Basic
Russian	Basic

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9. Theses Accomplished and Defended

B. Sc. in Information Processing (1995). Thesis: Analysis and design of an information system.
M. Sc. in Information Processing (1999). Thesis: Self Organising Maps of Estonian Banks

10. Research Interests

Neural networks, data analysis, pattern recognition, (artificial)intelligence, self-organization

11. Other Research Projects

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Signature: Date: