Developing an Information Space for Enhancing the Exploration of an Unfamiliar Collection of Scientific Literature

Diploma Thesis

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Universität Bremen
December 2006

Declaration

I have written this thesis independently, solely based on the literature and tools mentioned in the chapters and the appendix. I hereby certify that the work reported in this thesis is my own and that work performed by others is appropriately cited.

Bremen, December 2006

Eidesstattliche Erklärung

Hiermit erkläre ich, dass ich die vorliegende Diplomarbeit selbständig verfasst und noch nicht anderweitig zu Prüfungszwecken vorgelegt habe. Ich habe keine anderen als die angegebenen Quellen und Hilfsmittel benutzt. Wörtliche oder sinngemäße Zitate sind als solche gekennzeichnet.

Bremen, Dezember 2006

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Abstract

In this thesis I try to answer the question of how information spaces can be designed so that they support humans in the exploration of a large set of scientific literature items.

I will argue that the degree of support increases if the spatial representation assembles the mental representation of a certain spectator. In this regard, I will illustrate how humans build such mental representations and reason why it is necessary to include an idiosyncratic hierarchy for each spectator.

Starting from these theoretical fundamentals, I will present an approach of how mental structures and processes can be represented in the computational domain. This approach is realized in an application for exploring a collection of scientific literature. The resulting application is then evaluated by testing whether it maps the information from a hierarchy to a visual display.

Contents

Chapter 1

Introduction

1.1 Motivation

Browsing large archives of scientific literature on the Internet is often a great challenge. This results from the structure of online libraries: getting an overview can often only be done by searching through the collection. Searching through the collection means using queries whose results are represented as single items in a list. Therefore, the result forfeit their context and it is not possible to judge a piece of literature by its relationsship to others.

In their preface, Stuckenschmidt and van Harmelen point out that the problems on production, storage and transport of information are nearly solved but that there are two most urgent problems left which result from solving the first ones: Information finding and Information integration. They continue that information is only meaningful in the context of other information, but that most mechanisms that are available for publishing, locating and retrieving information deal with single, isolated instances of information and do not help recipients at all in integrating this information into what they already know. [Stuckenschmidt and van Hermelen, 2005]

Also Shneiderman stresses that *"exploring information collections becomes increasingly difficult as the volume and diversity grows. A page of information is easy to explore, but when the source of information is the size of a book, or a library, or even larger, it may be difficult [...] to browse to gain an overview."* [Shneiderman and Plaisant, 2005, p.560]

Today, there are several arguments for the necessity of information visualization. Ware argues that *"the power of visualization comes from the fact that it is possible to have far more complex concept structures represented externally in a visual display than can be held in visual and verbal working memories. People with cognitive tools are far more effective thinkers than people without cognitive tools and computer-based tools with visual interfaces may be the most powerful and flexible cognitive system."* [Ware, 2005, p.29]

Card et al. refer to information visualization as *"the use of computer-supported, interactive, visual representations of abstract data to amplify cognition."* [Card et al., 1999, p.7]

Keller states that "*there is a need for cognitive tools aiming at supporting cognitive processing in generating, representing, structuring and restructuring, retrieving, sharing, and using knowledge. Therefore, there is a need for visualization techniques for making structures of information in large repositories apparent[· · ·].*" [Keller and Tergan, 2005, p.2]

So, it is necessary to design an information visualization application in a way that it can be applicable as a cognitive tool. As cognitive tools are "*are computationally based tools that complement and extend the mind*" [Jonassen, 1994] designers must know some basics about human cognition, in detail about perception, information processing, and mental representation and reasoning. According to that, [Ware, 2000] focus on the facets of human perception in information visualization.

1.2 Goals

The goal of this thesis is to develop an interface which visualizes a set of bibliographic data in spatialized way. The key idea is that this representation follows the approach of external cognition which means that the visualization resembles the mental representation of humans.

At first sight, this idea seems to have only implications for the spatial representation. In fact, there are also implications for its creation. For example, for matching abstract data to the spatial domain it is necessary to map data to points in space. Following the view of external cognition, this mapping should follow processes which humans use to structure their knowledge mentally.

In addition to that, a cognitively adequate visualization should take into account that each human being has an idiosyncratic hierarchy of literature topics which has to be incorporated by the visualization.

For this reason, there has to be a process by which this knowledge is connected to this individual hierarchy and mapped to the spatial domain. Afterwards, it is possible to display the data in a spatialized way.

To sum it up, two processes are necessary to build a spatialized visualization: a process of **spatialization** where space is connected to the data and a **visualization** process in which this data is displayed.

1.3 Argumentation Structure

In the following, I will show how an application can support humans by exploring a large collection of literature items. Therefore, I will present how humans structure things in their environment mentally and how they build corresponding hierarchies. Afterwards, I will figure out how an application can become a so-called *cognitive tool* which can complement and extent the mind. On this account, I will first give an overview of information visualization and relate it with the term *information space*. Finally, I will explain why information spaces can be viewed as cognitive tools.

In the second part of this thesis, I will illustrate the cognitive processes of humans which are involved in exploring an information space. In addition, I will present which kind of information humans use when they explore a spatial representation and what kind of information is important for them during this process.

On the basis of the information given in the first two parts, I will present an approach which tries to meet the requirements for serving as a cognitive tool.

Part I

State of the Art

Chapter 2

Concepts in Human Cognition

When humans explore an unfamiliar collection they do not examine an item apart from the others but try to extract its relationship to other items and to things they already know. There is evidence that this is done by the use of concepts in the human mind. In the following, I will illustrate what concepts are, and present different theories about how they are mentally represented.

2.1 An Introduction

In general, concepts are ideas or principles connected to things or objects in the world. When cognitive scientists speak about concepts they think of mental representations of classes of things.

Concepts are an essential part of human being's cognition. Murphy points up that "*concepts are the glue that holds our mental world together*" [Murphy, 2002, p.1]. They are needed in order to be able to cope with the changing environment in everyday life. "*A concept is a mental representation that is used for a variety of cognitive functions, including memory, reasoning, and using and understanding language [Solomon et al., 1999]*" [Goldstein, 2005, p. 266].

Using concepts to cope with situations or cases one has never seen before is one of the fundamental functions of concepts in human cognition. As concepts comprise general knowledge about things an object which is connected to a concept is immediately related to general knowledge. Therefore, once human beings mentally relate an object to a specific category they know many general features about it and can focus on specifying the attributes of this particular object. [Solomon et al., 1999]

As concepts consequently enable human beings to identify things or objects by providing general knowledge, Yamauchi and Markman call them "*pointers to systematic knowledge structures*" [Yamauchi and Markman, 2000, p.793].

Medin and Coley define a concept as "*a mental representation of a category serving multiple functions of which is to allow for the determination of whether or not something belongs* *to the class*". They define a category as "*the set of entities picked out by the concept.*" [Medin and Coley, 1998, p.404] Murphy states that for each concept there exists "*a category of things that would be described by it.*" [Murphy, 2002, p.5]

Following these views, I will use the term *category* as a synonym for the set of entities belonging to a certain concept.

There are different approaches of how categories are created in human concepts. There is a lively discussion whether the membership of an object can be described by a definition which determines the corresponding members or whether there are other representations. Another controversial subject is if items of categories are distinguished by their similarity to other members or if each category is connected to a kind of explanation which determines its members properties.

In the following, I will present both the similarity-based and the explanation-based approach to categorization. Afterwards, I will illustrate the organization of categories in human mind.

2.2 Similarity-Based Approaches

Similarity-based approaches can be referred to as bottom-up approaches of categorization: their emphasize lies on extracting the features from the members of a category. An item must have certain features which are necessary to belong to a certain category. By comparing the similarity of an item to category members the membership is determined. As there are different ways to define similarity there are different ways to decide whether an item fits a certain category or not. In the following, I will present three approaches of how similarity can be determined.

2.2.1 The Classical View

For a long time, philosophers found it appropriate to characterize word meaning and category membership by using definitions. The origins of this view can be traced back to Aristotle [Apostle, 1980]. As there is no different approach until 1970, early scientists assume this definitional approach in their experiments about how people learn concepts.

Clark Hull stated that an object is a member of a certain category if it contains a certain characteristic which (i) is shared with all members of the category and (ii) may not be found in definitions of other categories [Hull, 1920].

Murphy summarizes this as the two aspects of a definition: *necessity* and *sufficiency*. The parts of the definition must be found in each item of the category and each item must have all attributes determined by the definition. [Murphy, 2002]

As Hull used patterns during his experiments where only a single characteristic was decisive he was criticized by other scientist, e.g. by Kenneth Ludwig Smoke who did the next major study of concept learning in 1932.

Smoke criticized Hull's definition of concepts as he could not believe that a concept can be determined by a single characteristic. He said "*As one learns more and more about dog, [one's] concept of 'dog' becomes increasingly rich, not a closer approximation to some 'bare' element*" [Smoke, 1932, p.5]. Therefore, Smoke's approach differs from Hull's mainly in the complexity of the definitions.

As the idea of definitions was very pervasive this approach was termed the *classical view* of categories. To sum the three main claims of this view Murphy summarizes: "*First, concepts are mentally represented as definitions. A definition provides characteristics that are a) necessary and b) jointly sufficient for membership in the category. Second, the classical view argues that every object is either in or not in the category, with no in-between cases. [· · ·] Third, the classical view does not make any distinction between category members. Anything that meets the definition is just as good a category member as anything else.*" [Murphy, 2002, p.15]

Criticism of the Classical View

According to the definitional approach of categorization the membership of an object can be determined by checking whether it meets the definition or not. This works well for e.g geometrical objects as they follow special rules and structures. In everyday life, human beings are confronted with man-made objects like e.g. tables and natural objects like plants or animals. Categories containing such objects have the property that not all members have the same characteristics.

The philosopher Wittgenstein questioned this and offered a different theory which is presented in the following section.

2.2.2 The Prototype View

Wittgenstein put forward a new idea of dealing with the problem that definitions often do not include all items of a category: the idea of *family resemblance*. He illustrates it with the concept of games. "*Consider for example the proceedings we call 'games'. I mean board-games, card-games, ball-games, Olympic games, and so on. [...] For if you look at them you will not see something that is common to them all, but similarities, relationships, and a whole series of them at that. [...] I can think of no better expression to characterize these similarities than 'family resemblances'*" [Wittgenstein, 1953, p.66f]

The theory of family resemblances takes advantage of the fact that all members of a category are similar in some way.

In contrast to this, there can be items in the category which are much better examples than others. Therefore, Eleanor Rosch incorporated the the theory of family resemblances into the *prototype approach* to categorization. [Rosch, 1973]

According to Rosch, a prototype is formed by averaging the present members of a category. The result is not a certain item of the category "*but is an 'average' representation* *of the category*"[1] [Murphy, 2002, p.270].

As members of a category may differ in their similarity to the prototype, Rosch argues that this fact represents differences in *prototypicality*: members which bear high resemblance to the prototype are *high-prototypical* whereas the member with little resemblance are *low-prototypical*.

Criticism of the Prototype View

In 1981, Mervis and Rosch show that people's representation of categories has to be much more complex than it is implied by the prototype approach. During their experiments, it turned out that categorical knowledge extends beyond the simple average representation. [Mervis and Rosch, 1981]

In addition to that, Roth and Shoben show that categorical knowledge is sensitive to context. As prototypical representation can not capture this property there has to be another way of representation. [Roth and Shoben, 1983]

2.2.3 The Exemplar View

Following the exemplar approach categories are represented by remembered exemplars. According to that, there is no single representation which is modified over time.

There are several opinions of the exemplar view. E.g. Brooks proposes that there are only exemplars in our categories and no possibility to generalize from an exemplar. [Brooks, 1987]

In contrast to that, Ross and Spalding argue that there are some exemplars which are used as general ones and can be applied for the categorization of other exemplars. Therefore, humans categorize by inferring from general exemplars to new ones. [Medin and Shafer, 1978, Spalding and Ross, 1994]

Criticism of the Exemplar View

Experiments show that people are able to recognize exemplars that they had never seen before. Therefore, there is a great evidence that humans use abstracted representations. [Posner et al., 1967, Robinson-Riegler and Robinson-Riegler, 2004]

In addition, some scientists argue that it is not clear which kind of exemplars are stored or if, in worst case, all encouters of an object are stored. It appears that the prototype and the exemplar view have no clear boundary and that people may classify based on either exemplars or prototypes. [Malt, 1989]

[1] In her later work, Rosch often denied that the prototype view was her proposal. She stressed that her work should demonstrate that there must be a kind of typicality instead of determining how this is represented. [Rosch and Mervis, 1975]

2.2.4 Evidence Against Similarity-Based Approaches

The results of experiments by Spalding and Ross lead to the conclusion that humans rather use explanations of categories than judging them by comparing features. It turns out that subjects assign a shark and a dolphin to different categories although these animals look very similar. So Spalding and Ross assume that subjects know that sharks and dolphins differ in their class of vertebrates and therefore associate them with different categories. [Spalding and Ross, 1994]

In addition, experiments done by Rips indicate that the judgment of similarity and of category membership are not of the same kind. [Rips, 1973]

Therefore, there is much evidence that categories are connected with a kind of upper knowledge which is not represented by visible features of category members but by explanations or a kind of theory. As a result, explanation-based approaches arise.

2.3 Explanation-Based Approaches

In contrast to similarity-based approaches explanation-based one might be termed as top-down approaches: categorization is based on a general idea or theory one has about the essence of a category.

There are several scientists who argue that categorization depends on knowledge about a category's essential properties. These properties depend on beliefs one has about a certain concept and are therefore different for each human.

These beliefs and understandings can be termed as *implicit theories*.

The approach of implicit theories is used to explain the ability of humans to understand complex concepts. Such concepts can hardly be explained isolated from other knowledge and other concepts; there exists a kind of network of interrelations. So humans create a kind of model by using this network and utilize this model understand a certain term. Such model is surely less sophisticated and less accurate than a scientific model would be. [Reisberg, 2001]

2.4 Organization of Concepts

As presented, humans use many different concepts to judge things and their environment. The question arises of how these are organized in human mind.

Murphy argues that concepts and categories respectively have a hierarchical structure: "*a sequence of progressively larger categories in which each category includes all the previous ones.*" [Murphy, 2002, p.199]. According to him, people tend to use categories which are organized in a hierarchical way. Berlin's remarks support this view. [Berlin, 1992]

Hierarchies are a special kind of network. As every network, it has nodes (here: categories) which are connected to each other by relations. The special thing is that the only relation allowed is the *set inclusion* relation. Collins and Quillian referred to this relation as *IS-A* relation because each subnode has the relation *is a* and only this single one to its parent node. [Collins and Quillian, 1969] Another important property of this relation is that it is asymmetric. That means that all subnodes can also be items of their parent node but not vice versa.

For the reason that the structure of concepts differs between people it is safe to say that also the hierarchy is different. Humans do have a subjective hierarchy of concepts represented in mind, a so-called *idiosyncratic hierarchy*. [Barkowsky, 2002]

2.4.1 Mental Representation

Although researchers agree that humans do structure concepts in a hierarchy it is not clear how this hierarchy is mentally represented. There are two possibilities which are not mutually exclusive: either hierarchies are completely stored in memory or they result from a kind of reasoning process.

Storing the Hierarchy

In the first case, humans' concepts are hierarchically structured in memory. In addition to IS-A-links there are properties associated to each concept. Following that, hierarchies are used to represent concepts and their relationships; judgment about category membership is done by inferring from concept's relations and properties. [Murphy, 2002]

In this case, the hierarchy's representation corresponds to a set of connections in memory. This view matches many models of memory where scientists argue that items in memory are linked in large networks (cf. 3.2.1 on page 14).

Reasoning about the Hierarchy

In the second case, the hierarchy of concepts is not explicitly stored in memory but a result from a kind of reasonsing process. Following this approach, humans are able to infer category inclusion and draw the appropriate conclusions through a reasoning process.

To be able to do so, humans must have some information in mind which they can use to compute the hierarchy. Rips, Soben and Smith suggest that this computation is done based on the properties that are known of a category. So, there would be a weighted list of properties for each category on which humans base their inferences. Therefore, Rips et al. argue that items are represent in human memory by the use of feature lists (cf. 3.2.2 on page 15). [Rips et al., 1973]

As presented, there are several approaches about how concepts are created and organized in human memory. In the next chapter, I will illustrate how these different approaches influence the assumptions about the structure of human memory.

Chapter 3

Representation of Concepts in Memory

Knowledge which is used to judge objects or situations is assumed to be represented in the long-term memory (LTM) in human memory. Therefore, I will first give a brief overview of LTM. Afterwards, I will illustrate what kind of distinctions of the underlying structure in LTM are implied by the different approaches of concepts.

3.1 Long-Term Memory

LTM is a basic part of human memory. It is used to store many different types of knowledge, e.g knowledge about experiences and events occurring during one 's life, learned facts and also knowledge about motor skills and other procedures.

It is widely considered that there a several types of memory which are mapped onto distinct anatomical areas in the brain. Although there have been proposed various taxonomic frameworks for different types of memory most of them share a common generic form: LTM consists of different parts of memory. It is not thought to be a unitary entity but to be partitioned in specialized modules: *explicit* or declarative *memory* and *implicit* or nondeclarative *memory*. [Tulving, 1983,Squire et al., 2004]

3.1.1 Explicit Memory

Explicit or declarative memory is used to store knowledge about both episodes and facts. As episodes refer to time and place whereas facts do not need such contextual elements a distinction between these two types of explicit memory seems necessary: episodic memory and semantic memory. *Episodic memory* is connected to memory for personally experienced incidences which include contextual elements like time and place for the incident's occurrence e.g. the last rock concert one attended to. *Semantic memory* is connected to knowledge which does not include contextual elements e.g. the Spanish vocabulary one learned in school. [Tulving, 1983]

3.1.2 Implicit Memory

In addition to knowledge about facts and episodes in life humans need to store knowledge of motor skills or perceptual abilities. This is termed as implicit memory.

The special characteristic of implicit memory is that humans are not able to recall it consciously. E.g. many humans are very well able to go by bike but they cannot verbalize what they are actually doing.

According to many researchers, there is no further partitioning of implicit memory. It is only used to store knowledge about skills and procedures. Therefore, it can be also termed as *procedural memory*. [Squire, 1993]

In contrast, some other scientists argue that implicit memory cannot only be referred to as procedural knowledge. As people can easily determine what kind of object they are looking at in a moment, but are not able to verbalize which features (edges or color) they considered to come to a conclusion there must be another type of implicit memory: *perceptual memory*. [Massaro and Loftus, 1996]

3.2 Representation of Categorical Knowledge in LTM

As concepts and categories respectively represent general knowledge about things in human's everyday life these can be termed as semantic knowledge. Hence, this kind of knowledge is thought to be represented in the semantic memory in LTM.[1]

Many scientists have investigated how semantic knowledge is represented in long-term memory and how it can be retrieved. As there are different approaches of how concepts are organized there are several approaches about how these are represented in LTM. In addition, some scientists developing a new approach for representing concepts compose a corresponding theory for long-term memory. In the following, I will present three models: hierarchical network model, features comparison model, and spreading activation model.

3.2.1 Hierarchical Network Model

The first idea propose that categories are according to their hierarchical structure (cf. section 2.4 on page 11) represented in a hierarchical network: concepts are organized hierarchically, specific concepts are nested within more general ones. Each *concept's node* is connected to a so-called *feature node* which represents all particular features of the concept.

[1] In studies, researchers are trying to find out if humans also use concepts in connection to implicit memory. This approach explains why humans judge other people by their first impression. Therefore, there are suggestions to divide long-term memory into another part: *conceptual memory* (cf. [Reisberg, 2001, pp.186 et seqq.])

Retrieval of knowledge

If a category membership query is presented this is answered by the use of activation spread in the network:

- Each node in the network has a certain *response threshold*. Hence, a node will only respond to an activation if the value reaches this threshold. Responding means that activation is again spread to connected neighbors. As this process spends energy the spread of activation decreases over time.
- If the level of activation does not reach a node's response threshold (a so-called *subthreshold activation*) the node keeps this energy for a certain time. By-and-by, the energy decreases until there is any left. If during this process, the node is again activated both values of activation are summed. The same is true for recently activated nodes. They also keep their energy for a certain amount of time. Therefore, nodes who have been activated recently can be brought to threshold by even a weak input.
- A categorization process is started by creating a kind of hypothesis about the concept membership of an object e.g., "A chair is piece of a furniture". The node corresponding to the concept "chair" is activated. From there, a spread of activation moves to linked concepts and features in the network. This is done as long as there is enough activation energy. If the corresponding concept "furniture" is activated during this time, this leads to an affirmative response. [Collins and Quillian, 1969]

Problems of the Hierarchical Network Model

The main problem of the hierarchical view is that psychological experiments do not support this view of representation. Assuming that the network is hierarchically structured categorization processes where traversing the hierarchy id needed should take longer than others where only neighbor nodes are involved. It turns out that there is no correspondence between the length of a path in a hierarchy and the response time. In some cases the response time even decreases while the path's length is supposed to increase. Therefore, other models for representation in long-term memory were developed. [Reisberg, 2001, Robinson-Riegler and Robinson-Riegler, 2004]

3.2.2 Feature Comparison Model

The feature comparison model was proposed by Smith, Shoben, and Rips as the representational framework for their approach of feature lists in human categories. (cf. section 2.4.1 on page 12)

Instead of being represented by nodes in a network conceptual knowledge consists of a set of descriptions where each feature is weighted. The features of each category

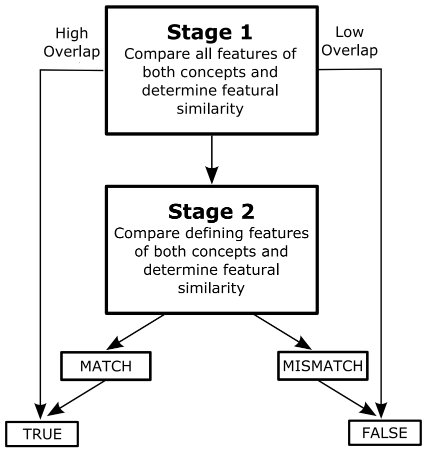

Figure 3.1: Steps involved in category/ feature verification, following the feature comparison model [Rips et al., 1973]

are divided into characteristic and defining features. Characteristic features might be a certain color of some category members whereas defining features are those which apply for all category members.

Retrieval of knowledge

The answering of a categorization query is either a one- or two-stage process (cf. figure 3.1).

Stage 1 When the query is presented the feature lists of the involved concepts are retrieved and overall compared. If this rough comparison of features yield either a significant or a marginal overlap this will provoke a quick true or false response respectively. So, this one-stage rough comparison of features yields enough evidence for a judgment.

Stage 2 If there was not enough evidence for a judgment on the first stage another comparison must be done on the second one. Here only the defining features of the concepts are compared. If there is a match between defining features a positive response is elicited, otherwise a negative one.

Problems of the Feature Comparison Model

As well as in case of the hierarchical network model results of experiments do not support the feature comparison model. It turned out that response time in categorization verification tasks do not correlate with the structure of the model. Following the model, determining the membership of a certain object to a category is supposed to take longer if a category is larger and has therefore more features which must be compared. In contrast to that, results show that response time decrease the larger a category is. [Murphy, 2002]

A second problem is that it is not clear how defining and characteristic feature are build. Smith, Shoben, and Rips "*do propose that this variable is a continuum rather than a dichotomy*" [Robinson-Riegler and Robinson-Riegler, 2004, p.344] so there is not yet a clear distinction between characteristic and defining features.

To sum up, both the hierarchical network model and the feature comparison model cannot represent all results of experiments. But in contrast to the feature comparison model the architecture proposed by the hierarchical network model has become a significant fundamental of knowledge representation and cognitive processes in general.

3.2.3 Spreading Activation Model

As a reaction to the difficulties encountered with the hierarchical network model Collins and Loftus create an extensive revision: *the spreading activation model*. In contrast to the model from 1969 by Collins and Quillian associations between concept nodes are not strictly hierarchical. In addition, nodes can be linked by several relations which represent a wide variety of relationships and are not restricted to *Is-A* relations: they can represent category membership, concepts relations or more subtle relationship as e.g. similarity or interrelation between concepts. [Collins and Loftus, 1975]

Similar to the hierarchical network model (cf. 3.2.1 on page 14), Collins and Loftus proposed the idea of activation spread over the network to activate involved nodes. As the network structure allows shortcuts between nodes of different concepts, the problems of the hierarchical network model are solved.

Evaluation of the Spreading Activation Model

In order to determine if the spreading activation model is a suitable representation of semantic memory in LTM it is tested if it can account for all phenomena of human memory. As already shown, it compensates the structural weakness of the hierarchical network model. The same is true for the weakness of the feature comparison model.

So, the spreading activation model in an network seems to be an adequate model for the structure of semantic memory. To strengthen this position, researchers tested if the model can explain another phenomenon of human memory: the phenomenon of *priming* in lexical decision tasks. [Robinson-Riegler and Robinson-Riegler, 2004]

Excursus: Priming In general, priming means a benefit in performance from an activation just before carrying out a specific task. In the context of semantic memory this means, that response time decreases if before a certain task a closely related concept has been activated.

> In a lexical decision task subjects are shown combinations of letters; some of them form words some of them do not. Participants then have to determine if they are presented words or not. The time of this process is measured. It turned out that response time decreases e.g. if subjects were shown the concept "butter" just before the concept "bread".

This result can be easily explained by the spreading activation model. Therefore, scientists consider it as a possible model of semantic memory in long-term memory.

3.3 Computational Approach

As presented, concepts seem to be represented in a network-based structure in LTM. For representing such structures in an applicationusing ontologies is proposed. In the following, I will give a brief introduction to ontologies and to how they can be represented within an application.

3.3.1 Ontologies: a Brief Survey

Originally, the notion of ontology comes from the philosophical domain but using ontologies for the explicit representation of knowledge has become very common in computer science. In the following, these two approaches are presented.

The Philosophical Approach

In philosophy, ontologies are used to described all things which physically exist in the world. This description is independent of any human mind that perceives it. From this fact follows the so-called *ontological realism*: all things which are represented in the ontology are also existing in the world. Therefore, ontologies in the philosophical sense supply an "*a priori distinction*" (i) "*among the entities of the world (physical objects, events, regions, quantities of matter)*" and (ii) "*among the meta-level categories used to model the world (concepts, properties, qualities, states, roles, parts).*" [Guarino, 1995, p.5] To sum it up, ontologies in a philosophical sense are used to model conceptions of reality.

The Cognitive Approach in Computer Science

In contrast to that, ontologies are also used to represent concepts conceived by humans. An ontology does not describe what really exists in the world, but rather what is thought to exist in some domain. Therefore, an ontology is "*an explicit specification*" of a "*conceptualization*". "*Conceptualization*" is the "*set of objects, concepts, and other entities that are assumed to exist*" [Gruber, 1995] in a certain domain.

This approach is referred to as the *cognitive approach*: the realism of the world is not necessarily followed but the main ideas of what is real and important are used to model some domain. This is why the term ontology connected to this approach is often used synonymously with the term *domain modelling*. [Farrar and Bateman, 2004]

Elements of an Ontology

No matter which approach is used, ontologies have to describe the most important entities in their domain. This is done by qualifying a domain's classes, its individuals and the corresponding attributes and relations:

Classes Classes represent concepts or categories found in the domain which has to be modelled by the ontology. A class can be subsumed by another class, e.g. the class of DOG is subsumed by the class of MAMMALS which is again subsumed by the class of ANIMALS.

Individuals Individuals represent concrete examples for objects in the world. E.g. if there is a class DOG then the individual SNOOPY is an individual for this class. Individuals are not mandatory within an ontology.

Instances Equal to individuals, instances are examples for a certain class, e.g. SNOOPY is an instance of the class DOG. Therefore, an instance is an example for a certain class.[2]

Attributes Every object in the ontology (no matter if class or individual) can be specified by assigning properties to it. Each of these properties and attributes respectively has at least a name and a value. So, e.g. an object SNOOPY has the attribute COLOR OF COAT with the value WHITE WITH BLACK EARS.

An ontology which has only relationships between classes and no other attributes is termed as *taxonomy*.

Relations Relations are used to describe the relationsships between objects in the ontology. Typically, a relation is an attribute whose value is another object (class or individual) of the ontology. The set of relations describe the semantics of the domain modelled by the ontology.

Domain and Upper Ontologies

Domain ontologies are used to model a specific part of the world. Such an ontology represents the specific meaning of terms in that particular domain. Consider the term *head* which can be used in different domains. In an ontology modelling the domain *human body* the term will be described differently as it would be in a domain *harddisk*.

[2] In addition to that, [Farrar and Bateman, 2004] reason that one has to distinguish between instances and individuals as instances can also be classes which are instances of other classes.

In contrast, upper ontologies are representations of common objects which are applicable across a wide range of domain ontologies. They comprise the core glossary which makes it possible to describe objects in a set of domains.

3.3.2 Representation of Ontologies

Mostly, ontologies are developed to model a domain and to use this knowledge in different systems or projects. Therefore, an ontology must be represented in a way that it can be easily used and distributed. So, the representation of an ontology must follow some conventions which allows others to understand it. [Gruber, 1995] Hence, ontologies are represented in some logical formalism, a so-called *modelling language*.

Chapter 4

Visualization of Information in General

As Shneiderman and Plaisant pose "*a picture is often said to be worth a thousand words, and, for some task, a visual presentation [· · ·] is dramatically easier to use or comprehend than is a textual description or spoken report*" [Shneiderman and Plaisant, 2005, p. 580]. They also stress that designers use information spaces to represent large amounts of data in information-exploration systems. [Wise et al., 1995], [Fekete and Plaisant, 2002] and the visualization toolkit [Laboratory, 2005] are good examples for this.

Sebrechts emphasizes that the creation of visual information spaces enables recipients to use resources that "*would need to be allocated for data assimilation can be used for analysis and problem solving*" [Sebrechts, 2005, p.139]. In addition to that, he stresses that implicit structures can be made explicit easily by the use of visual representations that "*otherwise may take a very substantial cognitive resource to extract*" [Sebrechts, 2005, p.139] for humans.

Below, I give a brief definition of information and argue why visual representations are useable for recipients. In addition to that, I will explain how an information space is characterized and why using it for representing large amounts of data is applicable for humans.

4.1 Definition of Information

In scientific literature, there are several definitions of what information is and how it can be represented respectively. These definitions try to define information in context of different disciplines, from physics to epistemology. Therefore, it is necessary to find and to compare only definitions which are suitable in the discipline of information visualization.

According to Ackoff endowing meaning to data by way of relational connection leads to information [Ackoff, 1989]. Davenport describes information as "*data endowed with relevance and purpose*" [Davenport, 2002, p.10]. Loose argues that "*one of the most common ways to define information is to describe it as one or more statements or facts that are received by* *a human and that have some form of worth to the recipient*" [Loose, 1997, p.256].

Both relevance and purpose and having some form of worth to the recipient can be put down to specific relational connections within the data. Hence, information can be characterized as data which is associated with relational connections. In the following, I will refer to this definition of information.

4.2 Visual Representation of Information

The analysis of visual representations of information and their effectiveness is a diverse field encompassing many different perspectives for the investigation.

An early result of research in the field of information representation has been the distinction of the two main classes of representations: the analogical and the propositional one [Kulpa, 1994]. Below, I will give a short overview about them. Afterwards, I will argue why visual representations are seldom pure analogical representations and reason how visual representations become effective ones.

4.2.1 Analogical Representations

Sloman characterizes an analogical representation in the following way:

"*If R is an analogical representation of T, [· · ·] then it must be possible to specify some sort of correspondence, possibly context-dependent, between properties or relations of parts of T.*" [Sloman, 1975, p.165]

Kulpa subscribes to this view and details the properties of such relations. According to him, an analogical presentation R must have some attributes which represent the corresponding attributes of T but these do not have to be implicitly named in R. For example, if two cities are represented in a map and one city is south of the other the relation *south of* does not have to be an object in the map. It is sufficient that it appears as an implicit fact. He summarizes his definition to;

"*An analogical representation is a structure whose syntax [· · ·] models, to a significantextend, the semantics of the problem domain.*" [Kulpa, 1994, p.80]

All in all, analogical representations permit explicit illustration and direct retrieval of information that can only be represented implicitly in propositional representations. Hence, analogical representations are more useful for e.g. the visualization of structural spatial relations.

4.2.2 Propositional Representations

Language-like representations are propositional ones. In contrast to analogical representations, propositional representations do not present the semantics of a problem domain.

As Kulpa states a phrase like *The city 250 km south of Warsaw* does not represent the relation between *Warsaw* and the city (which is *Cracow*). The only relation one can extract is that *Warsaw* follows after *south of* in the phrase, but this does not lead to some information about Cracow. Therefore, Kulpa concludes that propositional representations are by the reason of their lack of semantics much less effective. [Kulpa, 1994]

4.2.3 Visual Representations as a Combination of Both

Kulpa also argues that it seems to be appropriate to use mixed representation schemes. He poses that it might not be practical to use clear analogical representations. This view is shared by several scientists, by e.g. Barwise and Etchemendy. [Kulpa, 1994, Barwise and Etchemendy, 1991]

In addition to that, Cheng et al. reason that analogical and propositional representations are not clearly distinguishable from each other. They claim that "*the main characteristics of diagrams is their use of space and spatial properties [· · ·], but this is not exclusive to diagrams, because propositions also use "diagrammatic" properties to encode information*" [Cheng et al., 2001, p.84]. As an example, they assert the visual representation of a formula like 'A=B+C'. As it matters where the term '+C' is put, the propositional representation use visual properties to encode information.

Chen et al. go on that visual representations are not purely analogical ones because they often contain propositions like legends or labels and that "*strong claims about the difference between diagrams and other representations should be treated with caution*" [Cheng et al., 2001, p.84].

Considering visual representations of information, such a combination is essential. As it is described in section 4.1 on page 21 information can only be useful if it is connected to a certain context. Therefore, visual representations have to illustrate their context. This can be done e.g. by captions, labels or legends. Hence, a visual representation which displays a certain context must be a combination of analogical and propositional representation.

In the following, I will illustrate why such representations are effective tools for encoding information.

4.3 Effectiveness of Visual Representations

Visual representations have several characteristics which make a difference concerning their effectiveness.

Larkin and Simon argue that visual representations which are more effective than others tend to visualize information in a special way: information which is needed for the same inference can be found in adjacent regions. Therefore, the internal representations during diagram use must be taken into account in designing visual representations. [Larkin and Simon, 1987]

This view was advanced by additionally considering the role of external displays in cognitive problem-solving. Larkin considers how the use of external displays can reduce working memory load. Normam describes cognition as *knowledge in the world* and *knowledge in the head*. He argues that humans increase memory, thought and reasoning by the invention of external aids which make humans smart. Chabris and Kosslyn reason that displays can seem like extensions of the human mind if they are well designed. [Larkin, 1989, Norman, 1993, Chabris and Kosslyn, 2005]

Another argument is hold by Cheng et al. They state that the effectiveness of a visualization is mostly affected by the knowledge a viewer already has about the visualization's subject and the method of depiction. As a visualization can be highly specialized concerning its depiction of the subject the ability to use such a visual representation has to be learned and seems to be extremely domain-specific. [Cheng et al., 2001]

The argumentation by Chen et al. is confirmed by some experiments with novices and experts in the meteorological field and their usage of meteorological diagrams. It turned out that novices could only rely on visuospatial information as they were not able to invoke some domain-specific knowledge and therefore drew wrong conclusions. In contrast, experts were able to add some special knowledge and interpreted the diagrams the right way [Lowe, 1996]. In addition, Koedinger and Anderson did some experiments with novices and experts concerning geometry problem solving. These experiments demonstrate that there exists a difference in problem-solving [Koedinger and Anderson, 1990].

Similar to that, Chabris defines the *Representational Correspondence Principle* which states that diagrams to be effective "*should depict information in the same way that our internal mental representations do.*" [Chabris and Kosslyn, 2005, p.54] Therefore, the key factor of effective visualization is the cognitive processing of the viewer.

This conclusion is what Scaife and Rogers argued: "*What is needed, therefore, is a more systematic approach for evaluating the merits of different kinds of graphical representations, one that is theoretically-driven and which accounts for the cognitive processing when people interact with them.*" [Scaife and Rogers, 1996, p.186]

This argumentation is a new perspective of visual representation which is called *external cognition*. The focus lies in the interaction between the viewer and the representation itself. Important aspects are a) the cognitive processing which is involved during this interaction, b) the features of internal and external structures, and c) the cognitive benefits of different visual representations. In brief, external cognition is the interaction between the internal and external representation of a problem. [Card et al., 1999]

So, in order to create effective visualization the interaction between internal and external representation must be optimized. As optimizing the interaction means reducing the amount of cognitive effort in solving a problem visual representations must be designed that they match up with their viewers problem solving processes during a specific task.

Chapter 5

Information Spaces for the Exploration of Data

Information visualization for exploring large amounts of data is often done by building information spaces. Such visualizations rely on the use of spatial metaphors for illustrating the data's characteristics. Because of this, there is a consensus that information spaces are a possibility to represent data in a cognitively plausible way. Cognitive plausibility means that the representation matches human's internal visualizations well and supports the recipients in reasoning. [Hegarty, 2002, Fabrikant and Skupin, 2005]

In the following, I will illustrate why using spatial metaphors is an appropriate way for visualizations which support humans in exploring data sets. First, I will give an overview about metaphors in human cognition. Afterwards, I will argue why spatial metaphors are suitable for data exploration visualizations.

5.1 Metaphors in Human Cognition

In general, a metaphor is a description of a subject as being equal to a second subject in a certain way. That means, the first subject is specified by implicit or explicit attributes the second subject has. Therefore, metaphors are often termed as metaphorical expressions.

Most people think of them as a phenomenon in poetic arts but Lakoff and Johnson argue that metaphors are a significant part in everyday life and in human mind. Therefore, they introduce the idea of *conceptual metaphors*[1]. [Lakoff, 1993]

Conceptual metaphors differ from metaphorical expressions in that they do not only describe a certain subject but rather serve as a structure. That means that a conceptual metaphor provides a basis for the use of some kind of metaphorical expression. Considering e.g. the argument TIME IS MONEY as a conceptual metaphor leads to several metaphorical expressions (cf. [Lakoff and Johnson, 1980]):

[1] Lakoff and Johnson used the term *Metaphorical Concepts* [Lakoff and Johnson, 1980, p.6]

- To *waste* one's time
- To be *worth one's while*
- To *use* time *profitably*

By the use of conceptual metaphors generalizations are facilitated which would otherwise not be possible. This results from the idea that the human mind is metaphorically grounded: "*Our ordinary conceptual system, in which we both think and act, is fundamentally metaphorical in nature.*" [Lakoff and Johnson, 1980, p.3]

Metaphors always serve as a mapping between a target domain and a source domain. They connect two (distinct) conceptual domains. Their main property is their explanatory role which enables humans to capture an abstract domain or theoretical construct by "*conceptualizing them along the line of metaphorical projection.*" [Kertész, 2004, p.49]

The TIME IS MONEY mapping is a set of ontological correspondences that characterize epistemic correspondences by mapping knowledge about money onto knowledge about time. Such correspondences permit humans to reason about time using their knowledge they use to reason about money. [Lakoff, 1993]

5.2 Spatial Metaphors for Enhancing Exploration

As we have seen in Chapter 2 humans use categories to classify new things or information. Therefore, exploring a large amount of data means classifying its items by extracting their properties and internal relationships and assigning them to a certain category.

Supporting humans during this task would mean to visualize the data's characteristics by making their categorical structure visible. In this way, humans can gain an overview of the structure and easily distinguish between the items.

5.2.1 Metaphorical Space

The use of categories is metaphorically grounded: they are thought to be bounded regions. Items can therefore be *in* or *out of* a category. In addition, items can be *put into* or *removed from* a category. Therefore, the conceptual metaphor is CATEGORIES ARE CONTAINERS.

Because of this mapping categories inherit the logical properties of containers. As containers have specific topological properties these are also mapped to categories. Therefore, categories do also have topological properties. [Lakoff, 1993]

As presented, there is no problem to visualize categories by using of spatial metaphors.

So far, it would only be possible to visualize a pure hierarchical structure of categories where items are members of a certain category or not. What is missing is the representation of the internal relationships between certain concepts. This would mean that categories are represented in a specific way and spectators infer on them.

According to Lakoff "*all abstract inferences are actually metaphorical versions of spatial inferences*" [Lakoff, 1993, p.216] the exploration of relationships would be done by the help of spatial inference strategies. Therefore, a cognitively adequate representation should support the user in this inference and visualize the data in a spatialized view.

5.2.2 Cognitive Space

Freksa claims that spatial metaphors can be used for representing non-spatial knowledge: "*The spatial domain can be used particularly well as the source domain for metaphors with a non-perceivable or abstract domain. In this way, the properties of physical space can be used as a vehicle for conveying non-spatial concepts, provided there exists a mapping from the non-spatial to the spatial domain.*" [Freksa, 1991, p.362]

Therefore, a suitable representation has to use a kind of metaphor which maps information from the source domain to the spatial domain. This mapping must assure that the properties of space are retained.

As there are several definitions of space and the concept of space is used in many different contexts, Freksa and Habel describe four kinds of space which are particularly relevant in cognitive science [Freksa and Habel, 1990]:

Mathematical Space is represented by an abstract mathematical model. That means that there exists an axiom which specifies the properties of each point in this space.

Physical Space is the real space which humans encounter every day.

Psychological Space is the space which results from human perception. It is determined by both the properties of perception and the characteristics of physical space.

Metaphorical Space is created by transferring spatial concepts to non-spatial domains.

Following this, Hernández introduces the *cognitive space* which comprises these four types of space. A cognitive representation must provide a model of physical space which overall matches the way it is perceived and described by humans. In addition, it must be possible to formalize this space by using abstract mathematical structures. Finally, it must be possible to match the representation to non-spatial domains in a metaphorical sense. [Hernández, 1994]

5.3 Techniques for Creating Information Spaces

Information spaces are characterized by their property of being two- or three-dimensional. So, if some high-dimensional data is to be represented in an information space there must be a process which assures that this data can be represented in a two- or three-dimensional way: a *spatialization process*. Spatialization of high-dimensionality data is characterized by reducing the data's dimensionality to 2D or 3D. "*The problem is to find coordinates of* *points representing these multidimensional objects in a low-dimensional target space in such a way that the low-dimensional interpoint distances would correspond to the similarities of the original objects.*" [Duch and Naud, 1996, p.3]

In the following I will present two techniques which are used in reducing dimensionality to create information spaces: a statistical approach which is termed as theory of *multidimensional scaling* and a neural-network approach which is termed as theory of *self-organizing maps*.

5.3.1 Multidimensional Scaling (MDS)

Multidimensional scaling was first introduced by Torgerson. His idea was to find a low-dimensional representation of data so that the distances between the resulting points are good approximations of the original similarities and dissimilarities. [Torgerson, 1958]

Input Data

Multidimensional scaling needs some special information about the data in order to be able to calculate the similarities. In MDS, a symmetric matrix of similarities or dissimilarities between data items is taken as input.

Consider a data set with n items. The corresponding similarity matrix consists of n rows and n columns. For each item the metric distance to all other items is stored; the distance to itsself is 0. So, the dissimilarity d is defined by euclidean distance. The value is calculated by summing up all distances which are estimated for each feature dimension.

$$d_{ij} = \sqrt{\sum_a (x_{ia} - x_{ja})^2}$$

where x_{ia} equals the position of point i on dimension a.

The resulting values are then represented in the similarity matrix:

$$\mathbf{X} = \begin{pmatrix} 0 & d_{12} & \dots & d_{1n} \\ d_{21} & 0 & \dots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \dots & 0 \end{pmatrix}$$

After the matrix of proximity measures is created the MDS can be used to map data to space.

The Mapping Process

In order to map data to space, MDS uses a function f which defines the output distance between data items. The relationsship between f and the input data can be described as:

$$\text{Output Distance: } distOut_{ij} = f(d_{ij})$$

That means that the distances between objects of the data source should be preserved during the mapping to space. Depending on the data source, such a linear mapping can be impossible. Therefore, several authors suggest that a mapping function between original distance and distance afterwards should only be as close as possible. The degree of distance closeness is then estimate by a *stress coefficient* $S(distOut_{ij}, d_{i,j})$ [Kruskal, 1964], an *alienation coefficient* $A(distOut_{ij}, d_{i,j})$ [Duch and Naud, 1996] or an *error function* $E(distOut_{ij}, d_{i,j})$ [Sammon, 1969]:

$$S = \sqrt{\frac{\sum_{i>j}(distOut_{ij}-d_{ij})^2}{\sum_{i>j} distOut_{ij}^2}}; A = \sqrt{\frac{1-\sum_{i>j}(distOut_{ij} \cdot d_{ij})^2}{\sum d_{ij}^2}}; E = \sum_{i<j} \frac{(distOut_{ij}-d_{ij})^2}{distOut_{ij}} / \sum_{i<j} distOut_{ij}$$

5.3.2 Self-Organizing Maps (SOM)

The self-organizing map (SOM) method is a widely used form of artificial neural networks. They are most suitable for the conversion to metric space as they convert statistical relationships within the data into simple geometric relationships. Therefore, they produce a "*similarity graph of input data*" [Kohonen, 2001, p.106].

A SOM consists of a single layer which is represented by a network of neurons. These neurons are arranged as a two dimensional lattice, following a configuration similar to raster data models.

Each neuron is connected to its neighbors; neighborhood is defined either in a square or in a hexagonal way, depending on the map topology. Each neuron is associated with a reference vector which has the same dimensionality as the input data. [Kohonen, 2001]

Input Data

SOMs need a special form of input data in order to be able to structure data. This form is a n-dimensional vector which is called a *model* or *reference vector*: $m_i = [\mu_1, \mu_2, \cdots, \mu_n]$; n equals the number of dimensions of the input data. Therefore, there must be a kind of preprocessing which transforms the data into a model that can be used by the SOM. [Kohonen, 2001]

In such a preprocessing step, each item in data set is associated with a certain vector which represents an item's value in each dimension. The vector's dimension is equal to the dimension of the model vector:

$$v = [\xi_1, \xi_2, \cdots, \xi_n]$$

After this is done, the data can be presented to the SOM in order to be mapped.

The Mapping Process

Before a mapping process can be started, all m_i (model vectors) are initialized with random numbers. In addition, a certain *learning rate* is connected to the process. The value of this rate determines how strong the SOM adapts to a single input vector during the processing. After that the main process which is characterized as a recursive one can be started:

- **Choosing an input vector**
  An item is randomly chosen from the set of data; its input vector v is presented to the som.

- **Calculating the distance to each model vector**
  For the current input vector the distance to each model vector in the map is calculated:

$$dist(v, m_i)$$

- **Determining the model vector with the minimum distance**
  The model vector m_c with the minimum distance to the input vector v is determined:

$$c = argmindist(v, m_i)$$

  The neuron which is connected with the model vector m_c is termed the *winning neuron*.

- **Adapting model vector of winning neuron**
  The corresponding model vector is adapted to the input vector. The degree of adaption is determined by the learning rate: If it equals zero the model vector is not changed, if it equals one the model vector is changed so that it equals the input vector. Values between zero and one determine how strong the adaption is regarding to the input vector.

- **Adapting model vector of neighbors**
  Each SOM uses a *neighborhood function* which determines the neighbors of a certain neuron. This function acts as "*a smoothing kernel defined over the lattice points of the map*" [Kohonen, 2001, p.111]. Following this function, the resulting neighbors are also adapted to the input vector. Again, the degree of adaption is determined by the learning rate.

After all input vectors are assigned to a neuron, a single *training step* is complete. In order to get a better result and therefore a better topographical representation this step can be repeated several times.

As it is possible to assign more than only one input vector to a single neuron data items which are very similar (and whose input vector are therefore very similar) may be assigned to the same neuron.

The degree of this properties depends on the SOM's structure in relation to the number of items. If there are only a few more neurons than items in the set, more than one data item would be assigned to a certain neuron. If the SOM contains many more neurons than there are items in the set, it is likely that the item are assigned to different neurons. [Skupin, 2002]

Part II

Exploring Information Spaces: a Cognitive View

Chapter 6

The Route into Memory: Perception

Exploring an information space means to examine it in order to acquire knowledge about its content. There are several cognitive processes involved into this acquisition of knowledge:

1. Perceiving the visual representation
   As there are several strategies in human perception it is important to know how humans perceive visual representation and how they recognize contained objects. As the main focus of this thesis is not enhancing perception but external cognition I will not go into detail here but give a brief introduction about visual perception.

2. Creating a mental representation in memory
   After having perceived a visual representation this information must be "processed" in order to be able to acquire knowledge from it. Therefore, there must be mental representation which is used to store this information.

3. Enriching information through the implications one already knows
   After the information is represented in memory it must be enriched by the use of knowledge one already has. So, new information must be related to already acquired knowledge.

4. Interpreting the information
   Finally, there is a process which enables humans to extract knowledge from the enriched information: the process of reasoning.

It is very important to mention that these processes are done in a kind of cycle. That means that the mental representation is constantly changed by the information which is perceived. According to this, the mental representation changes and there is new information which must be enriched by already learned things. (cf. [Anderson, 2000, Reisberg, 2001, Robinson-Riegler and Robinson-Riegler, 2004])

In the following I will give a brief overview about human perception. Afterwards, I will present how the perceived information is represented in memory and enriched with

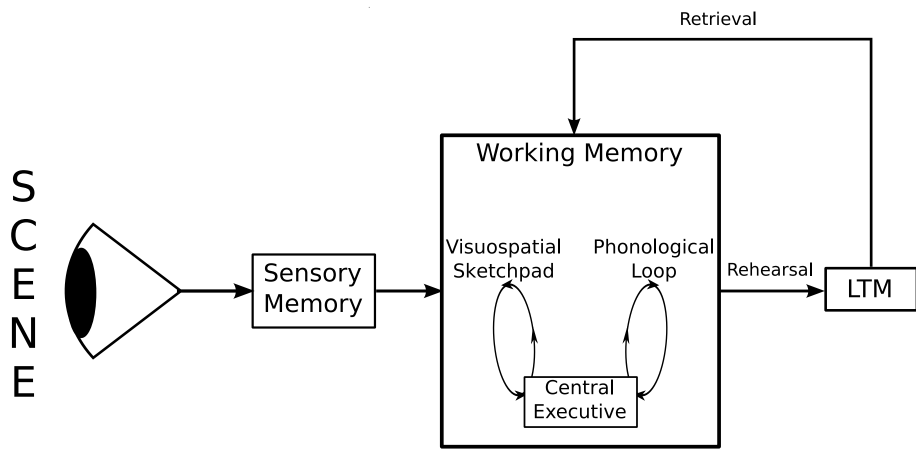

Figure 6.1: The route into memory

already stored knowledge. Finally, I will show how humans do reasoning on information spaces and which kind of information they use during this process.

6.1 Visual Perception

In general, perception is the process in which humans acquire, interpret, select, and organize sensory input. During visual perception, information from visual light is interpreted to build a mental representation of the surrounding world.

The visual light passes the eye's lens and is focused on the retina. The retina consists of three layers; each layer contains different cells which have different tasks in perceiving light: photoreceptors, bipolar cells and ganglion cells.

The layer of photoreceptors contains two types of cells: light-sensitive rods and color sensitive cones which are suitable to detect luminance or color respectively. Depending on the input, the receptor cells activate bipolar cells which are directly attached via synapses to the photoreceptors.

The bipolar cells are in turn directly connected to the ganglion cells. As each ganglion cell encodes information of a certain region on the retina a certain set of bipolar cells is attached to each of them. Such a set of cells is called receptive field. The ganglion cells' axons go directly to the visual cortex and build the visual nerve. According to the ganglion cells' activation, neurons of the visual cortex are activated or inhibited. So, the energy of the incoming light is converted to neural activity. [Anderson, 2000]

6.1.1 Object Perception

In order to be able to recognize objects, more information is needed than only knowledge about color and light. There have to be some processes that distinguish which information can be interpreted as a region and may belong to an object.

Gestalt Principles of Visual Organization

Humans tend to organize a set of objects in a certain way. The principles for this organization were first proposed by Gestalt psychologists such as [Wertheimer, 1912] and are therefore termed *Gestalt principles of visual organization*.

There are six principles which are suggested by Gestalt psychologists:

Proximity Humans tend to group features which are located in a certain proximity. Features that are close to each other are more likely associated than those which are farther apart.

Similarity Features that look similar are viewed to be members of the same group. Similarity is determined by characteristics like form, color, size, and brightness.

Continuity Humans tend to continue a pattern: that is why lines based on smooth continuity are preferred to be in a group over abrupt changes of direction.

Closure Patterns that look like broken objects are completed to a figure: e.g. a circle's boundary which lacks some parts is completed to a full boundary.

Smallness Smaller patterns in a scene are viewed as figures against a larger background.

Symmetry Symmetrical regions tend to be organized as figures against the asymmetrical background.

By using these principles, humans are able to construct elements out of perceived stimuli although they have never seen both these elemenst and their corresponding stimuli before.

It is important to notice that this process of grouping is no basic process of the visual system. It is rather a process which is done by the human memory system. How the visual information attains to human memory and how it is processed there is presented in the next section.

6.2 Information Processing

There are several theories about how humans process information and acquire knowledge. In this thesis, I will focus on the route into memory which is represented in 6.1 on the preceding page. In this case, human memory consists of three parts: sensory memory, working memory and long-term memory. As the main properties of long-term memory are already presented in 3.1 on page 13 I will not cover it here but focus on sensory and working memory.

6.2.1 Sensory Memory

Sensory memory is used to store the stimuli which are detected by the sensory receptors and which are stored for an instant of time in sensory registers. This kind of limited storage enables humans to decide whether or not it is worthwhile to perform further processing on the stimuli information. These stimuli are relatively unprocessed and they do only have a duration of ca. 500 milliseconds. [Matlin, 1998]

So, visual patterns attain sensory memory and are stored there for only a small period of time. If humans want to use the information (e.g. for creating a mental representation of their environment) these patterns have to be processed further. This is done by shifting the pattern to a more persistent memory: the working memory.

6.2.2 Working Memory

In working memory, the perceived stimuli which comes from sensory memory are used to build a mental representation of the surrounding environment. In order to explain this process, I will first give an overview about the working memory's structure.

The notion of working memory is a further development of the traditional concept of short-term memory. It was developed since theories of short-term memory had some limitations in explaining human memory effects.

According to Baddeley and Hitch working memory is comprised of three components: the Central Executive, the Phonological Loop, and the Visuo-Spatial Sketch Pad. [Baddeley and Hitch, 1974]

Central Executive The central executive constitutes the main part of the working memory. This component controls the interaction between all parts of working memory and other parts such as the sensory- and long-term memory. Therefore, the central executive decides whether or not information is forwarded from the sensory memory to working memory. In addition, the central executive determines if representation in the long-term memory ought to be activated or not. Therefore, the central executive determines if there has to be a retrieval from LTM or not.

The second task of the central executive is to coordinate the two subsystems of the working memory (visuo-spatial sketch pad and phonological loop). The central executive forwards the current information which comes from sensory memory to the corresponding subsystem. The subsystems are then used to deal with this information over a short period of time. As information may be visual or phonological in nature, there is a subsystem for each of it.

Phonological Loop The phonological loop is used to process and store phonological information. It consists of two parts: an active and a passive one. Whereas the passive part (the phonological store) is used to store information for a short period of time (ca. 1-2 sec) (it fades over time), the active one (the rehearsal process) is used to refresh this fading information in the store.

The parts of phonological loop can be easily explained by the processes which are involved in mentally repeating a telephone number one has just looked up in the telephone book. The phonological store represents this information for a short period of time. While the information fades the rehearsal process is used to refresh the information.

Visuospatial Sketchpad The visuo-spatial sketchpad is used to store visual and spatial information. It is also divided into an active and a passive part. The active one (the inner scribe) deals with spatial information like locations and movements whereas the passive one (the visual cache) deals with pure visual information like objects and their visible features (e.g. shape, color, and texture).

Limitations of the Working Memory

Working memory is generally considered to be limited in capacity. That means that it is only possible to hold a certain amount of information in memory. If the amount of information coming from sensory memory increases other information which is already in working-memory will get lost.

Before Baddeley's and Hitch's notion of working memory, [Miller, 1956] proposed a capacity of short-term memory as the "magical number seven" which was based on experiments with young adults. During these experiments it turned out that the adults were able to memorize about seven elements of information, so-called chunks, regardless if these elements were letters, words, or digits.

Baddeley and Hitch argue that the limitation of capacity comes from the fact that the sub-systems of the working memory are only able to store information for a short period of time. So, there must be a rehearsal process which allows to store the information again. Doing this, information can be held in memory for a certain period of time. With an increasing amount of information, it is not possible to reactivate information within the limited time span. Hence, this knowledge fades and is not stored in the subsystems any more. [Baddeley and Hitch, 1974]

Although there are several opinions with regard to the causes of limitation in working memory capacity a consensus has been reached in the research community about the existence of that limitation.

Interaction with long-term memory

As already presented, the central executive interacts with LTM in a way that it adds representations to LTM and activates representations in LTM respectively. It is important to notice, that this does not mean that working memory is only an actually activated piece of LTM. In contrast, the three components are independent from the LTM and only interact with it.

So, depending on the central executive parts of LTM are activated. The corresponding information is extracted and transmitted to the subsystems whose pieces of information are enriched with already known facts.

This process is very important for building effective representations in the subsystems, e.g. building a mental representation of spatial information is done in the visuo-spatial sketchpad. In the following, I will present how these presentations are build and how they are used to reason over space.

Chapter 7

Mental Representation and Reasoning

As already presented in section 5.2.1 on page 26 information spaces use spatial metaphors to illustrate non-spatial knowledge. Because of the metaphorical nature of the human conceptual system they may be explored as if they represent spatial information. [Fabrikant and Skupin, 2005] Therefore, the process of reasoning can be seen as a spatial one.

Reasoning on spatial representations means extracting the underlying spatial relations. Examples of such relations are "*is left of*" or "*is right of*". Such relations have certain characteristics which allow humans to extract information which is not explicitly given. For example, if an object A is left of an object B and an object C is left of object B one can infer that object C lies also left of A.[1]

These inferences have some underlying mental processes. In the following, I will present the main theories which attempt to explain these processes. Afterwards, I will give a brief overview of spatial relations.

7.1 Theory of Mental Proof

Researchers following this view claim that the human mind contains a kind of mental logic which consists of formal inference rules. A given problem is represented by some premises. Inference tasks are then solved by applying rules to the premises. This application of rules is analogous to applications in elementary logic. E.g. Rips argues that "*the sequence of applied rules forms a mental proof or derivation of the conclusion from the premises, where these implicit proofs are analogous to the explicit proofs of elementary logic.*" [Rips, 1994, p.40] Therefore, this theory is termed as *theory of mental proof*.

The main idea is that a set of inference rules is represented in long-term memory. Inferences are drawn by transferring these rules into working-memory and applying

[1]This inference can be drawn as the *is left of*-relation is transitive.

them there to the given premises. Hence, the given premises and the inference rules are kept separate in working-memory. There is no conjoint representation of premises and learned rules. [Knauff et al., 1998]

In contrast to that, there is a second theory of how inferences are drawn in human mind in which it is assumed that there must be a mutual representation in human mind: the *theory of mental models* in reasoning. In the following, I will present this theory in the context of the spatial domain but it should be mentioned that the theory is not restricted to this type of reasoning.

7.2 Mental Model Theory

The key idea of this theory is that humans transform the external situation they perceive into a mental representation of objects and relations that constitutes a model of the premises given in a reasoning task. This representation which is kept in working memory and which is used to solve given inference tasks is termed as *mental model*.

According to this view, spatial reasoning is not done by applying rules to given premises but rather by creating and manipulating mental models. During the reasoning process mental models are checked for their validity of a certain conclusion. This process can be divided into three phases: *construction*, *inspection* and *variation phase*. [Johnson-Laird, 1983, Knauff et al., 1998]

1. **Construction of Mental Model**
   In the first phase, humans use their general knowledge about semantics of spatial expressions to create an internal model of the situation which is perceived and its connected premises. These premises are integrated into a unified mental model. Therefore, only the model is held in memory, the premises are forgotten.

2. **Inspection of Model**
   During the next phase, the model is inspected with respect to information which is not explicitly given. That means that relations are extracted which are implicitly represented: a conclusion is drawn.

3. **Variation of Model**
   In the last phase, alternative models are created in order to test the conclusion. If there is no model which contradicts the conclusion, the latter must be valid. Otherwise (the conclusion contradicts with the model), the process starts from scratch. A new model is created and processed in the same way.

A main characteristic of mental models is that they are qualitative in nature. This results from the fact that knowledge about perceived information that is retrieved from memory is qualitative. Therefore, the perceived scene can only be reconstructed in parts: a mental model simply consists of certain qualitative relations among objects in the scene

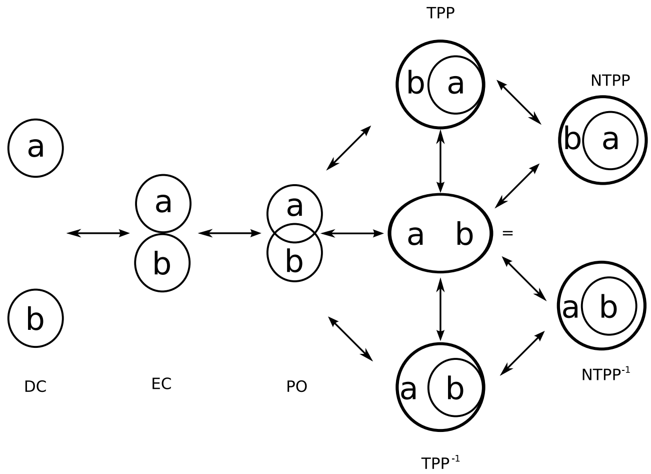

Figure 7.1: Topological Relations according to [Randell et al., 1992]

and information retrieved from memory (which is also qualitative in nature). [Freksa, 1991]

7.3 Concepts of Space

As space can be described by several concepts it is necessary to present how humans use different concept to extract spatial information. In the following, I will present three concepts of space.

7.3.1 Topology

Topology is used to describe features of mathematical spaces without using angles or distances. This is done by characterizing objects with respect to each other: whether there is a connection between them, whether one object is included by another, or whether or not the objects overlap.

There are several theories about topological relations which can be found in the literature. One is the **region connection calculus** by [Randell et al., 1992] in which eight binary relations (RCC-8) between two regions are described (cf. figure 7.1). Barkowsky enhanced this approach by adding relations between points and regions and between points among each other which leads to 16 different relations. [Barkowsky, 2002]

Empirical examinations support the view that humans use the notion of topology within qualitative spatial reasoning. [Knauff et al., 1997, Renz et al., 2000]

Topology can be thought of as the most essential form of qualitative spatial description. It turns out that topological relations as they are proposed by Randell are most important in human spatial cognition: "*Even those subjects who also took direction or size into account only did this to further refine the RCC-8 relations but never used orientation or shape independently* *of the topological relations.*" [Renz et al., 2000, p.194] In addition, topological relationships between objects are preserved in mental representations. [Barkowsky, 2002]

7.3.2 Distance

For the largest part of everyday life human spatial reasoning is driven by qualitative abstractions rather than by complete quantitative knowledge. As presented, mental representations are qualitative in nature as well. This follows from the limited resolution and capacity of human's cognitive mechanisms (c.f chapter 6 on page 35). Therefore, distances do not have to be represented by pure Euclidean ones but may be describes by categories like *at*, *near*, and *far*.

Such categories are characterized as being *ill defined*. For example, the interpretation of the feature *A is near B* cannot be easily determined. The meaning of *near* does not only depend on the positions of the objects involved but also on their relative sizes and shapes, the position of other objects in the spatial situation, and on the perspective from which the spatial situation is observed: the so-called *frame of reference* (cf. section 7.3.3). [Hernández, 1994, Mark, 1999]

7.3.3 Orientation

Orientational relations describe where objects are placed in relation to each another. Therefore, three elements need to be involved: a primary object, a reference object, and the frame of reference.

In general, a frame of reference specifies the perspective from which a situation is experienced. Depending on this, the interpretation can vary.

In case of orientational relations, the notion of reference frame can be divided into three types: *intrinsic*, *deictic*, and *extrinsic* reference frames [Barkowsky, 2002]:

- Establishing instrinsic reference frames is done by using inherent properties of reference objects used: e.g. the front side of an object: "the car is in front of the garage“.
- A deictic reference frame is determined by an observer's perspective on the reference object: e.g. "the car is left of the house“ where *left of* depends on the observer's point of view.
- Extrinsic reference systems are given by external factors: e.g. the georeferenced system, the reference object's accessibility, or the earth gravitation: "the lake is to the west of the house".

According to Mark, humans tend to specify directions qualitatively in everyday speech, typically in either four or eight directions. In addition, Frank reasons that eight directions are adequate for human spatial reasoning. [Frank and Mark, 1991, Frank, 1992, Mark, 1999]

Part III

Design Approach

Chapter 8

Starting Points

8.1 Necessity of Including an Idiosyncratic Hierarchy

As presented in chapter 6 the way humans explore information spaces depends significantly on what they already know. In addition, I illustrated in chapter 4 that a visualization becomes more useful if it matches human mental representations and agrees to human capabilities.

As each human being has its own concepts of the world and things in the world (cf. chapter 2) there is no general mental representation which fits all humans, especially in context of scientific literature.

Consider e.g. a scientist whose research interests are cognitive systems and knowledge representations. This person might have detailed knowledge about cognitive processes and mental representation but a broaden knowledge about other topics. Therefore, his idiosyncratic hierarchy differs from the hierarchy of a scientist whose main research focus lies e.g. in machine learning and artificial intelligence.

If these two explore the same set of scientific literature each of them structures it differently: whereas the first scientist might sub-divide the field of cognitive science into more specific topics like spatial cognition, mental representations, problem solving, et cetera, the second one might use only a broaden definition of cognitive science without any subdivisions.

Therefore, the idea of enabling a user to include an own hierarchy of topics and their relationships arises. The question which comes up is how to add that kind of additional information to an information space.

In the following I will present how such an information space can be created and illustrate how this additional information can be integrated.

8.2 Developing an Information Space

The development of an information space can be divided into three phases:

1. In the first phase the data has to be investigated to determine the internal relationships so that they can be represented later.

2. In the second phase there must happen a kind of mapping process which maps the data and its internal and external relationships to a spatial representation. It is important that this process does not falsify this information.

3. In the third phase the resulting spatial representation must be displayed.

As the first and the second phase allow to map abstract data to a spatial context they can be comprised to the process of *spatialization*. The third phase is termed the process of *visualization*.

In the third phase, the data is not changed but directly mapped to a certain type of visualization. Therefore, the idiosyncratic hierarchy must be included during the process of spatialization.

In the following chapter I will illustrate these two processes.

Chapter 9

Spatialization

Spatialization means extracting information from data and adding spatial properties to it in a way that it can be presented on a visual display. For this, it is often necessary to reduce dimensionality of data to map it to 2D (especially when dealing with highdimensional data). Doing this, the implicit information and relations between all data sets have to be kept.

Chen and Sebrechts describe this *"as requiring 'structural modeling' that captures the underlying relationships before the "graphical representation" that transforms those structures into visualizable representations. The representation is only as useful as the underlying structures and relationships that are displayed."* [Sebrechts, 2005, p.139] [Chen, 1999]

From this follows that those underlying structures are very important for the success of a representation. Its form determines if a visualization will work or not.

In context of visualizations which follow the theory of external cognition and whose underlying structures and relationships should assemble mental structures and relationships it results from this argument that including the information about a personal hierarchy is very important for the quality of a representation. Hence, the necessity for using an idiosyncratic hierarchy during the spatialization process is very suitable.

9.1 Adding the Idiosyncratic Hierarchy

As already presented such a hierarchy is a set of concepts and their corresponding relationships (cf. chapter 2 on page 7) which does not follow a pure hierarchical structure (cf. chapter 3 on page 13) and can be represented by the conception of ontologies (cf. section 3.3 on page 18).

Hence, the resulting system must be able to (i) include the ontology's structure and to (ii) extract the information inclosed by an ontology.

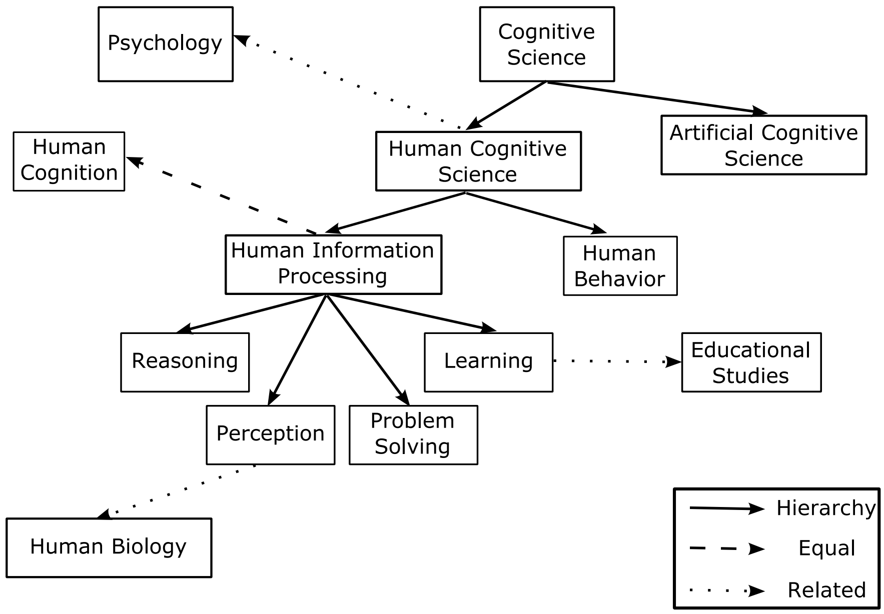

Figure 9.1: A hypothetical idiosyncratic hierarchy of a user

9.1.1 Representation of the Ontology

As the resulting visualization system is supposed to be used by several users each user must be able to add his/her own ontological structure of topics. Therefore, the ontology is included into the system by extracting its structure from a file.

The Ontology's Structure

In figure 9.1 a hypothetical idiosyncratic hierarchy of topics of a user is illustrated. Its structure is not a pure hierarchical one as e.g. in terms of scientific literature and its topic respectively there can be situations where the closeness of content or synonymical usage have to be modelled.

The structure of an ontology is determined by its elements like classes, relations, attributes, etc. (cf. section 3.3.1 on page 19). In the following section I will present the elements of the ontology which will be used in the resulting application.

Classes

The ontology is supposed to represent an idiosyncratic hierarchy of topics in scientific literature. Therefore, each class represents a certain topic. Due to the fact that each class is characterized by the topic it covers, there are no attributes assigned to each class. Hence, the ontology can be termed as **taxonomy of topics**(cf. section 3.3.1 on page 19).

Relations

The ontology contains three types of relations:

- **Hierarchical relation**
  Hierarchical relations are necessary to represent that a certain topic is a subfield of another topic: e.g. "HUMAN INFORMATION PROCESSING *is a subfield of* HUMAN COGNITIVE SCIENCE."

- **Relatedness relation**
  Relatedness relations are used to represent connections where topics have a significant overlap of contents.: e.g. "The field of HUMAN COGNITIVE science *is related to* the field of PSYCHOLOGY"

- **Equality relation**
  Equality relations are necessary to represent that one topic can be used as a synonym of the other: e.g. "HUMAN COGNITION *is equal to* HUMAN INFORMATION PROCESSING".

These three relations are not only chosen because they seem to make sense in the context of categorizing scientific literature: In further processing, an algorithm is used to detect semantic similarity between items in the data set which uses these three relations during the detection (cf. section 9.1.3 on page 57).

Individuals and Instances

It is very important to notice that there are no individuals or instances represented in this ontology. For simplification, it is assumed that a user is completely unfamiliar with the literature collection and that he/she does not know any literature item which overlaps with the idiosyncratic hierarchy.

Thus, instances are later added by sorting the data items into the ontology. Before this can be done, there must be a computational representation of the ontology's structure which can be used within the application.

As presented in section 3.3.2 on page 20 there are several possibilities how an ontology can be represented. In the following I will present which type of representation is used in the system and reason why this representation is chosen.

The Ontology's Representation

For representing the ontology in a computational form, the **extensible markup language** is selected.[1]

[1] The extensible markup language (abbr. XML). is a standard for creating documents which are readable by both humans and machines. XML has been especially developed to structure, store and send information. As XML is intended to model any information, the detailed structure of information for a new application must also be designed. [Turner, 2002]

There is a multiplicity of representations and languages for dealing with ontologies. As each language has its assets and drawbacks the decision has to be reached deliberately. In addition, the choice of representation and language has some crucial implications for the rest of the application. In contrast to that, using an XML structure does not constrict the following design process.

In addition there is no collection of existing ontologies for representing the structure of topics in scientific literature which could have influenced the decision. Quite the contrary, there are only structures which come from the field of categorization in libraries, e.g. the structure of *dewey decimal classification*[2] or the *library of congress classification*[3] of topics. As these approaches are often developed because of specific needs in a library, such categorizations are not suitable for being used as examples for an idiosyncratic hierarchy. In addition, such classification schemes lack a taxonomical structure. Therefore, it is necessary to modify existing ontologies so that they can model a hypothetical idiosyncratic hierarchy.

As XML structures allows an easy ddevelopmentof such ontologies without restricting the further design process of the application an XML structure is used for representing the ontology.

Designed XML-Structure

XML representations have to fulfill some conditions. To enable an automatic extraction of elements each element has to be enclosed by a certain symbol (a so-called *tag*) which determines its type.

The ontology's structure (its classes and its relations) is represented by the following symbols:

- Classes in the ontology are represented by the tag `Class`
- The hierarchical relation is represented by the tag `subClassOf`
- The relatedness relation is determined by the tags `isSimilarTo`
- The equality relation is represented by the tag `isEqualTo`

In figure 9.2 on the next page a part of the hypothetical idiosyncratic hierarchy is presented. This structure is represented in the following way:

[2]The dewey decimal classification (DDC) is a system for library classification which was founded by Melvil Dewey in 1876. In this structure the set of literature is divided into ten main classes. Each class is again divided into ten divisions. Each division is also divided into ten parts which are termed classes. So, in DCC the whole set of scientific literature is divided into ten main classes, 100 divisions, and 1000 sections. [Batley, 2005]

[3]The library of congress classification (LCC) was founded 1897 by Herbert Putman. The set of literature is divided into 12 subgroups. These subgroups are also divided into subparts; the number of parts is not static but determined by the necessity of another subdivision. Most classification decisions are driven by the practical needs of a library and not by epistemological reasons. [Batley, 2005]

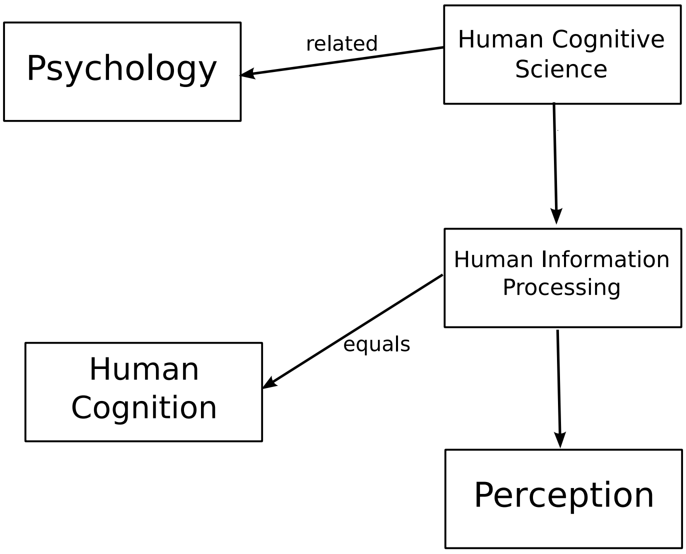

Figure 9.2: A part of the hypothetical idiosyncratic hierarchy to illustrate how its information is represented in XML

```
<Class id ="perception">
    <subClassOf>
      <Class id="human information processing"/>
    </subClassOf>
</Class>
<Class id ="human cognition">
    <isEqualTo>
      <Class id="human information processing"/>
    </isEqualTo>
</Class>
<Class id ="human information processing">
    <subClassOf>
      <Class id="human cognitive science"/>
    </subClassOf>
</Class>
Class id ="human cognitive science">
    <isRelatedTo>
      <Class id="psychology"/>
    </isRelatedTo>
</Class>
```

This kind of structuring facilitates including the ontology's structure and its information respectively.

9.1.2 Including the Ontology's Information

In order to be able to use the information within the application it must be represented in a way that algorithms can perform operations on it. For this reason, a network representation is created: a so-called *ontology graph*. This approach which proposed by [Maguitman et al., 2005] provides the opportunity to determine the semantic similarity of items in the data set in context of the information presented in the ontology. Before the similarity measurement can be done the graph-based representation of the ontology has to be created.

Graph-Based Representation

The ontology is represented by a directed graph G which consist of a set of vertices V and edges E: $G = (V, E)$, where:

- V is a set of vertices where each node corresponds to a certain set of topics. During further processing within the application, each node will contain documents which fit to its topic.
- E is a set of edges between vertices in V. E is divided into three parts H, R, and S :
  - H corresponds to the set of edges which determine the hierarchical relations between vertices.
  - R corresponds to the set of edges which determine the relatedness relations between vertices.
  - S[4] corresponds to the set of edges which determine the equality (or sameness) relations between vertices.

Figure 9.3 on the facing page shows the ontology graph G of the ontology represented in figure 9.2 on the previous page. G is defined by the set $V = \{v_1, v_2, v_3, v_4, v_5\}$, $H = \{(v_1, v_2), (v_2, v_3)\}$, $R = \{(v_1, v_4)\}$, and $S = \{(v_2, v_5)\}$.

Up to here, the ontology graph does only comprise topics. Therefore, there is not yet a connection between the ontology and the data set. In order to be able to measure similarities between items within the set of literature each item must be related to information about topics in the ontology.

Correlating Topics and Literature Items

Items are related to a certain topic by assigning them to the corresponding vertex. From this follows that for each vertex v_i there is a set of associated objects $|v_i|$.

As this means that items of the set are assigned to a certain class this process can be viewed as adding instances to an ontology.

[4] The symbol S is chosen to avoid ambiguity with the main set of edges E.

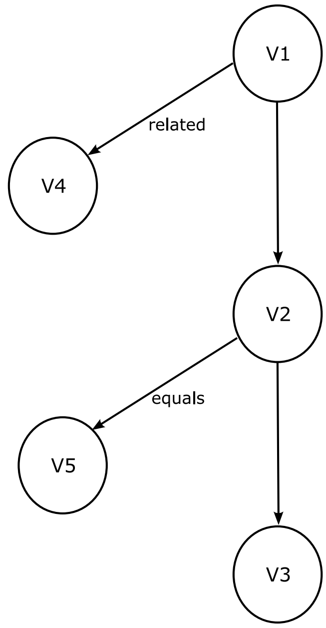

Figure 9.3: Graph-based representation of the ontology represented in figure 9.2 on page 55

After the connection between the information and the items in the set of data is created the semantics between items can be extracted.

9.1.3 Extracting Semantics

After adding instances to the classes the ontology comprises all information about how classes and their instances respectively are related. The semantics can be extracted by determining the relations between one class (and its instances respectively) and all other classes in the ontology.

This can be done by calculating the distance of an instance of a certain class to all other classes in the graph. So, for each item a list can be created whose number of entries equals the number of classes in the ontology.

Due to the fact that in an exploration task only the relationships between items in the data set are significant only the classes which are connected to a set of instances are used. The result is a list with n entries for each item, where n corresponds to the number of topics covered by the collection of literature.

After this, each item in the data set can be related to a kind of list which determines the relationship to other topics. These lists have many entries which impedes the direct representation on a visual display. There has to be a kind of mapping process which enables a visualization of the items.

9.2 Mapping Semantics to Space

The resulting data which is extracted from the ontology can be regarded as a set of high-dimensional data. To be able to represent this on a visual display it has to be spatialized. Spatializing data means to reduce its dimensionality in a way that it can be represented in space. As space can be represented both in 2D and in 3D, a decision must be made whether 2D or 3D representations should be created.

As the goal is to develop an information space for enhancing the exploration the set of literature should be represented regarding to its connections to certain topics. Due to the fact that such a relation can easily be represented by using topological properties like distance and orientation (cf. chapter 10 on page 61) a 2D representation is the goal of the system. Therefore, it is necessary to map these high-dimensional data to only two dimensions.

In section 5.3 on page 27 two methods for spatializing data are presented. In the following I will reason which method is most suitable.

9.2.1 MDS vs. SOM

As presented in section 5.3.1 on page 28 MDS determines similarity of items by calculating the distance between features. Therefore, each feature of each item is factored into the spatialization process. In addition, each item has to be compared with every other item in the set. This leads to high computational costs. [Rossi, 2006]

In contrast to that, a SOM determines the similarity between items by sorting them into a map according to their overall similarity. Only items which have a certain degree of similarity are compared in order to determine where a certain item fits best. As this leads to lower computational cost SOMs are suitable for the spatialization of large data sets. [Skupin and Fabrikant, 2003, Rossi, 2006]

Due to the fact that collections of literature contain many items using a SOM seems most suitable. Furthermore, SOMs have more advantages which are presented in the following.

- **SOMs create a Graph**
  Self-organizing maps are most suitable for the conversion to space as they convert statistical relationships within the data into simple geometric relationships: They produce a "*similarity graph of input data*" [Kohonen, 2001, p.106].

  In addition, a SOM "*is [...] focused on retaining topological relationships.*" [Skupin and Fabrikant, 2003, p.105] As presented in section 7.3 on page 43, topological properties of spatial representations are important for their interpretation. Therefore, the preservation of topology is an advantage.

- **SOMs as Memory Model**
  A SOM consists of several neurons which are able to adapt to inputs and which

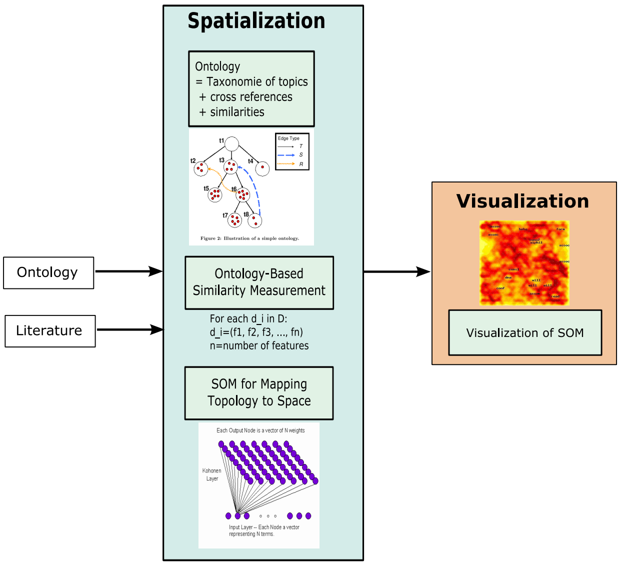

Figure 9.4: The process of the resulting application

are connected in an associative way. Therefore, SOMs are dynamic and associative networks whose elements can also be called adaptive prototypes. The mapping result is very much influenced by information which is already stored in the map.

Comparing the methods of SOMs to the model of representing and storing categories in LTM (cf. chapter 3.2) it turns out that there are many similarities:

– Categories are considered to be better represented by similarities or by feature list than being stored directly. The SOMs follow this approach: input vectors are not directly stored but added to a certain neuron by adapting its properties.
– In the spreading activation models it is assumed that LTM is a network which is structured in an associative way. This is true for the SOM: it consist of a network with an associative structure.
– The SOM also corresponds to the idea of spreading activation. This stems from the fact that an input is also active in the neighborhood of the winner neuron.

Therefore, the SOM can also be considered as a memory model. [Honkela et al., 2000]

As an advantage follows that SOMs are very suitable to be used in the context of external cognition: as their structure assembles famous memory models SOMs can be seen as an externalization of human memory.

Due to these reasons, a SOM is used for mapping the semantics to space. The process of the resulting application is presented in figure 9.4.

In the following chapter, I will present how this space can be visualized afterwards.

Chapter 10

Visualization

As presented in part II using spatial metaphors is an appropriate way for supporting humans in exploring large data sets. As humans use spatial knowledge for extracting information in different ways the effectiveness of such visualizations depends on the use of spatial relations and their corresponding visual cues.

In the following, I will present how the result of the spatialization process is visualized, which spatial relations are used, and which visual cues are given.

10.1 Representation of the SOMs result

The main task of the visualization is representing implicit and explicit information about the set of literature for allowing users to gain an overview of the data. Therefore, items must be displayed in a way that makes it possible to judge them by their similarity to each other, their togetherness with other items, and their belonging to a certain topic.

After the spatialization process there exists a similarity graph of the data in which these three relations are displayed:

- Similarity is represented by the SOM's spatial structure. Items which are assigned to a certain neuron are therefore very similar. In addition, items of neighboring neurons do also have a certain similarity. With decreasing proximity the similarity between items also decreases.

- Togetherness is represented by the partitioning of items by assigning them to different neurons. From this follows that each neuron represents a kind of cluster which comprises items that have much in common. So, if items are assigned to the same neuron this means that there is a strong togetherness between them.

- As each neuron is connected with a certain set of items it covers a certain set of topics. So, the topic of a neuron is determined by the most frequently contained keywords. So, if an item is assigned to a certain neuron it is also related to a certain topic.

This information about items and their relations has to be mapped to a spatial representation. As spatial concepts vary in their semantic it has to be assured that proper concepts are chosen to represent the respective information.

10.1.1 Representation of Similarity

As presented in section 7.3 on page 43 the concept of distance allows the representation of similarity: a small distance between two objects leads to the view that these objects are very similar and vice versa.

As SOMs assign very similar items to the same neuron items of a single neuron will be presented at close quarters when possible. Due to the fact that the position of a neuron in the SOM also implies information about similarity the distance between neurons has to be mapped to the visualization.

By doing this, relations between the neuron of the SOM are also mapped to space and represented by spatial relations. The items of a neuron are presented in proximity which leads to the interpretation that there is a kind of grouping (cf chapter 6 and section 10.1.2). Therefore, humans can use topological relation in combination with both orientation and distance for reasoning. As topological information is very important for human cognition this supports humans in reasoning over the spatial representation.

As humans' spatial reasoning is qualitative in its nature (cf. section 7 on page 41) there is no need for a metric function which allows to map similarity to distance. It is sufficient to use the rough positions which are determined by the neurons position in the SOM.

10.1.2 Representation of Togetherness

As presented, togetherness is determined by the partition of items to the same neuron. Therefore, all items of a neuron have to be visualized in a way that the togetherness can be noticed.

As presented in section 6.1 on page 36 humans tend to group items which are displayed in a certain proximity and whose presentation is very similar. Therefore, the information about togetherness can be easily represented by using spatial concepts which encode this information.

Therefore, items which are assigned to a certain neuron are visualized as a set of items in a small proximity so that they are grouped during perception.

In addition, the symbols which represent these items have to be very similar. This amplifies the grouping of items.

10.1.3 Representation of Topic Membership

The partitioning of items into clusters which are assigned to a certain combination of topics contains more information than the topic membership of a single neuron. Also the position of the neuron in the map is important. Due to the characteristics of SOMs dissimilar topics are assigned to neurons in a certain distance. Therefore, this information has also to be presented in the visualization.

As the partitioning of topics does not include a strict classification but a smooth distribution it does not make sense to visualize the topic partitioning by regions with strict boundaries. In contrast, this is done by mapping the center of a neuron to the central point of a neurons representation in the visualization. To this center, an item is assigned which fits the topics of the neuron and a label is added which shows the topic's name.

By doing this, similarities and dissimilarities between topics are visualized without restricting a topic to a certain region.

10.2 General Visualization Requests

There are additional requests on the visualization which result from humans' cognitive requirements (cf. section 7.3 on page 43):

- Distance between items must correspond to their similarity. It may not happen that items are positioned in a certain distance to another item by accident. This would lead to false conclusions by a viewer.
- The arrangement of items is also very important for the mental model one constructs. As items which are grouped together are viewed as being closely related accidentally positioned items would result in ambiguous mental models.
- A two-dimensional representation is preferred to a three-dimensional one as the latter would complicate the representation of topology [Trott and Greasley, 1999]. In addition, representations in which points are used to discriminate between items are most effective in 2D. Experiments also show that three-dimensional visualizations rather distract humans during a task. [Fabrikant, 2000]

Chapter 11

Implementation of the Application BibVis

The resulting program is supposed to provide the opportunity to load both an own bibliography and an own ontology of topics. Therefore, there must be a sufficient data structure which can handle all this information. In addition, the application's structure must be adapted to this data model to enable an effective process.

The application is written in Java (by using the Java^{TM}Development Kit 1.5.0_07) in order to allow using the system on many different operating systems. Also the object-oriented programming concept of Java is necessary in the present application. In addition, some important libraries exist for the development Java applications which are used in this thesis. Apart from that graphical user interfaces (GUIs) can be easily developed in Java.

In the following, I will present the data model for storing the most important information. Afterwards, I will illustrate how the application is structured and how all modules are connected to each other.

11.1 Main Data Model: Class `BibEntry`

The main challenge in developing the application structure is to assure that information about each item in the data set can be accessed at any time. Therefore, the class `BibEntry` was developed which is able to represent all information that is related to a certain entry in the data set.

11.1.1 Internal Structure

The member variables found in the `BibEntry` class can be divided into three parts where each part is storing important information for distinct further processing steps.

- Part `BibData`

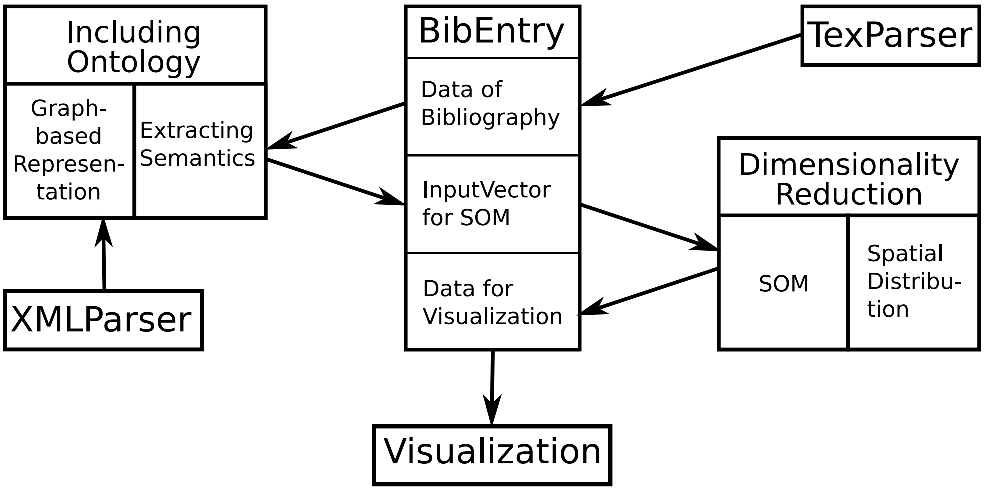

Figure 11.1: The system's structure

The variables associated with this part are used for storing all values of the bibliographic information, like author names, title, or keywords of a certain entry. In addition, each entry is equipped with a unique ID so that it can be easily distinguished from other entries in the bibliography.

- Part `InputVector`
  In this part, the information which is essential in order to sort the respective entry into a SOM is represented: the corresponding input vector of the entry.
- Part `VisualizationData`
  In the last part, all information which is necessary for mapping an entry into space is stored. Each entry is associated with a certain coordinate which is determined during the spatialization process.

Due to the system's application flow the data associated with these parts is compiled sequentially while the application is used. In the following, I will present what the structure is like and how the data model `BibEntry` is used.

11.2 System's Structure

The system can be partitioned into four modules where three of them (`ontology`, `som`, and `visualization`) cover specific tasks for extracting and generating the necessary information and the remaining module (`util`) comprises all utilities for interacting with files during the process.

In figure 11.1 a simplified model of the interaction between the modules is presented. It is important to mention that for each entry in the data set an object of `BibEntry` is

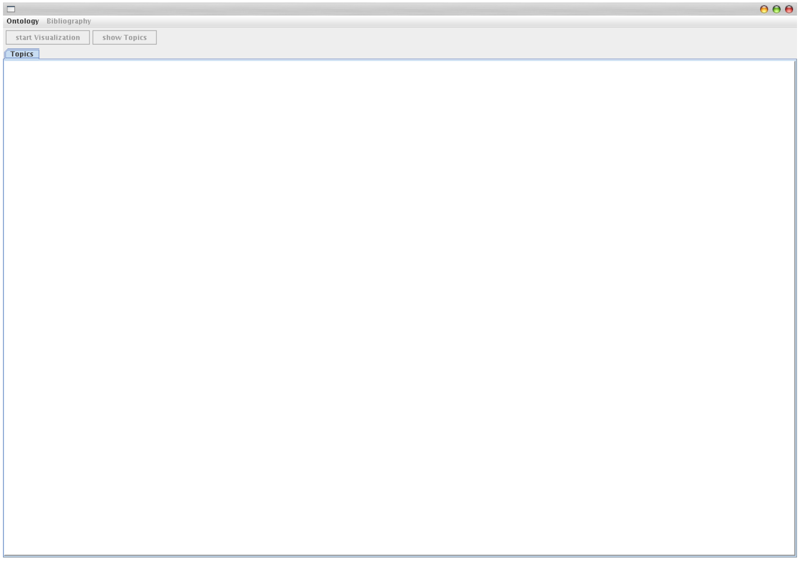

Figure 11.2: The applications GUI

created whose fields are sequentially filled with values.

At the beginning both the XML file containing the ontology and the bibtex file have to be presented to the program. After that the information is extracted from the file which contains the bibliography. For each entry in the bibliography an object `BibEntry` is created and the variables of the bibliographic part are filled. Then, the bibliographic data is connected with the information which is stored in the ontology. How this is done in detail is presented in section 11.4 on the next page. As a result of this process a vector of values is compiled which can be used afterwards as an input vector for the SOM (cf. section 11.5 on page 69).

By using the SOM, for each `BibEntry` a rough position is determined. Therefore, certain methods are implemented which determine the exact position in space. This coordinate is also stored in `BibEntry` and can be used by the `visualization` module which visualizes the data. By doing this, `BibEntry` can serve as an interface for including different types of visualization methods.

11.3 Class `BibVisGUI`

This class implements the GUI which is used to visualize the result of the spatialization process. The main purpose is first to provide the opportunity to load both the XML file of the ontology and the bibtex file of the bibliography and second to ensure that a spatialization/visualization process can only be initiated once both files are present. In figure 11.2 the application main window after starting the application is presented.

11.4 Module ontology

This module is responsible for all tasks which are related to the ontology. Therefore, within this module the file access to the ontology is realized as well as the extraction of semantics from the ontology.

11.4.1 Accessing the Ontology

As already mentioned the ontology is stored in an XML file. To integrate the ontology's information into the application there must be a possibility to encode its information. This is done by using the `XMLHandler` which is presented in section 11.7 on page 71.

11.4.2 Class OntoGraph

The encoded information is then transformed into a graph-based representation by using the JGraphT library[1].

This graph-theory based representation allows easy transformation and calculation. It is created by an `OntoGraph` object which comprises besides the graph-based representation all necessary methods for creating and accessing the graph.

The resulting graph is directed and weighted. This means that each edge has a certain associated weight (or cost) and a direction in which it can be traversed. The weights are assigned corresponding to the type of the edge: e.g. an edge which is supposed to represent a hierarchical relation has a different weight than an edge which represents equality or similarity between topics.

11.4.3 Extracting Semantics

Semantics between entries in the sample bibliography are then extracted by determining the relative similarities between an entry and all other topics. For this, a vector is created which contains as much entries as there are different topics covered by the bibliographic data. The similarity values are calculated by assigning each item to the corresponding node in the graph. Starting from this node, each distance to the topics covered by the vector is determined. The distance is calculated by summing the weights of an edge. If the similarity to all topics is calculated the vector is added to a new `InputVector` (cf. section 11.5 on the next page) object which stores all information that is necessary for the SOM. Afterwards, the `InputVector` object is assigned to the corresponding `BibEntry` object.

[1]JGraphT is a free Java graph library which provides mathematical graph-theory objects and algorithms. http://jgrapht.sourceforge.net

An Example

To illustrate this process the graph-based representation in figure 9.3 on page 57 is taken as an example. In this case, a sample bibliography id considered whose keywords only cover the topics of the vertices v_1, v_3, v_4, and v_5.

If an entry's input vector is created this vector consists of 4 value, each value representing the distance to a certain topic in the set; the order of values is equal for all entries in the sample bibliography:

$$ip_{v_i} = \{dist(v_i, v_1), dist(v_i, v_3), dist(v_i, v_4), dist(v_i, v_5)\}.$$

If an entry is assigned to the topic vertex v_3 it results for the input vector:

$$ip_{v_3} = \{\sum_w[v_3, v_2, v_1], \sum_w[v_3, v_3], \sum_w[v_3, v_2, v_1, v_4], \sum_w[v_3, v_2, v_5]\}.$$

It results:

$$ip_{v_3} = \{w_h + w_h, 0, w_h + w_h + w_r, w_h + w_s\}.$$

So, the distance between two vertices is calculated by summing up the weights of the shortest path between them. THis is done for all entries in the sample set. It results a set of input vectors which can be used by the SOM in the next step.

11.5 Module `som`

This module comprises all classes which are necessary for mapping the semantics which are extracted by using the ontology to space. The information which is needed by the SOM is stored in objects of the type `InputVector`.

11.5.1 Class `InputVector`

This class stores both the similarity values of an item and additional information which is needed by the SOM. For instance the SOM also needs the information about the overall number of entries in the set and the numbers of topics which are covered by the vector. In addition, this class provides all methods for creating and accessing an `InputVector` object.

11.5.2 Class `SOM`

The `SOM` class is neccessary to realize the interaction with a self-organizing map and to provide all methods for creating a spatial representation of the data set.

An object `SelfOrganizingMap` is created by using the MajorSpot AI SDK[2]. Afterwards, the respective `InputVector` of bibliographic entries are presented to the map. As a result

[2]MajorSpot AI SDK is an Java artificial intelligence platform which comprises common AI tools like neural networks, genetic algorithms, wavelets, etc. http://sourceforge.net/projects/majorspot

a spatial distribution of the items is obtained. Depending on the items, it can happen that several items are assigned to a certain neuron. Therefore, in the general case it is not possible to create a non-ambiguous spatial representation of all entries by performing only an immediate mapping of the map neurons to space. Thus further detailed methods for distributing all entries of a certain neuron to space.

11.5.3 Methods for Determining Positions in Space

The methods `placeAroundPoint` and `placeNearRelatedTopic` have been implemented in order to determine unique exact positions in space for each `BibEntry`.

If an neuron only comprises a singly entry of the sample this items can be directly mapped to the position on the map which corresponds to the center of the neuron. If the neuron contains more than one items it must be determined if it completely fits with the neuron's topic or not.

The topic of a neuron is determined by the topics comprised by its items. The topics of an neuron is then determined by calculating the topics which are most occuring in all of its items. If there are more than one topics which are present to the same amount the set of these topics is used as the central topic of a the neuron.

All entries whose keywords display the topics covered by a neuron are distributed around the central point in space within an area which corresponds to the area covered by the neuron. This is done by the `placeAroundPoint` method.

If an entry's keywords do not completely display the topics this entry is both placed next to the center of the neuron's area and depending on its neighborhood by using the method `placeNearRelatedTopic`. That means if there are neurons in the neighborhood which cover a topic which contained in an entry's keyword the entry is placed depending on the position of the topic in the neighborhood by using the method `getDependency`.

By doing this, it might happen that entries are assigned to positions which would be off the area covered by the visual representaion. Therefore, a bilinear interpolation is implemented to assure that all entries are mapped to the visual space.

The calculated position is stored to each entry so that any visualization method can be used to visualize the items.

11.6 Module `visualization`

This module enables the representation of all entries of the sample bibliography on a visual display. Due to the fact that the positions in space of all entries are assigned to their corresponding BibEntry object there are no additional calculation but only the direct mapping to the visual display.

The mapping is done by extracting each position from the set of BibEntries and adding a symbol at this position on the visual display. As the similarity is significant for

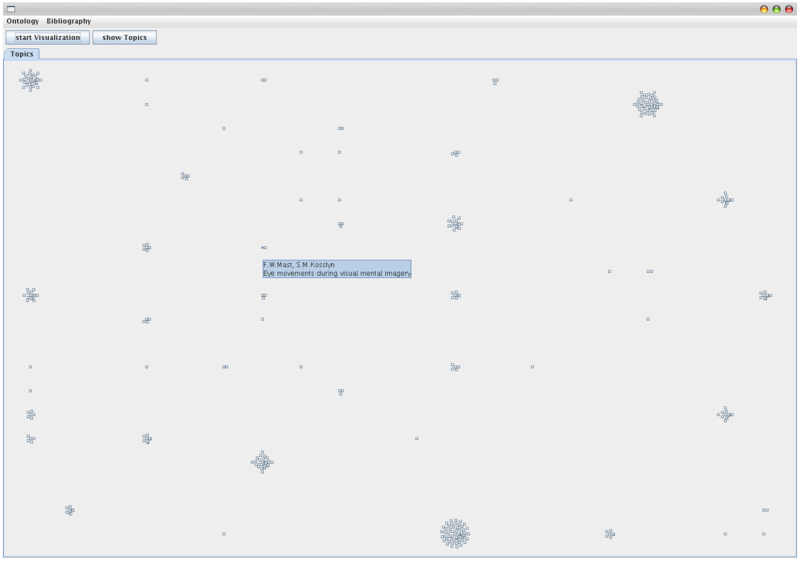

Figure 11.3: Visualization with additional information of an entry

the mental grouping, each item is represented by the same symbol.

For offering detailed information, a rollover effect is added. Such an effect enbles the visualization of a textbox if an item is touched by the mouse's cursor. In this textbox, information about the author(s) and the title of an entry is visualized (cf. 11.3).

It is important to stress that space is described by the concepts of distance, orientation and topology. There is no additional visual metaphor (like visual concepts from GIS or carthography) used in the visualization. This comes from that the fact that using a GIS toolkit often needs additional implementational work to enable the interaction with the information space.

As the implementation is only realized as a prove of concepts the restriction of visualization is accepted to save time for the theoretical rationale.

In addition to that, it is also possible to visualize the central topic(s) of all neurons. This information is represented by also using textboxes which can be faded in if needed.

11.7 Module `util`

This module comprises all classes which are necessary for including information of the files into the application. As the application uses both XML and bibtex files there is a corresponding parser for each file type.

11.7.1 Class `XMLHandler`

The `XMLHandler` is used to extract the information of the XML file which represents the ontology.

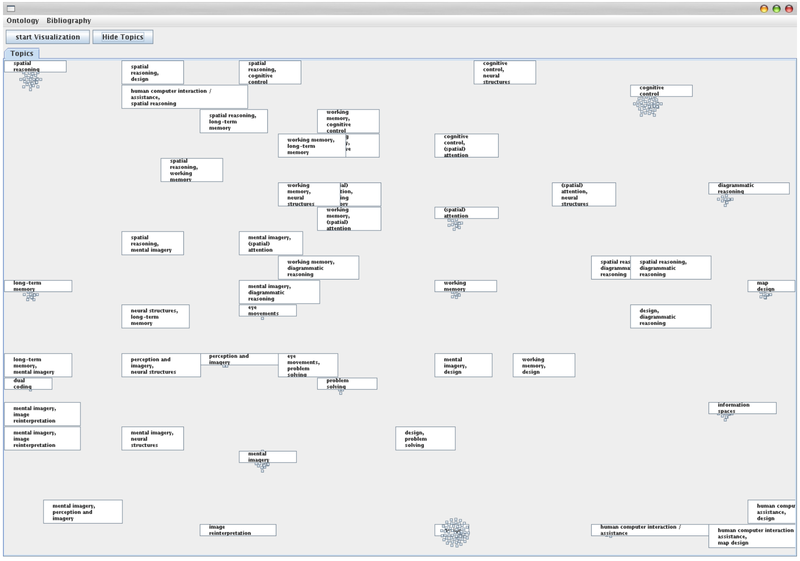

Figure 11.4: Visualization with additional labels of all groups of entries

The XML file is included by using a so-called DOM (Document Object Model) Parser[3]. Such a parser transforms the data of the XML file into a DOM tree. By doing this, each element in the file is connected to its particular tag (cf. section 9.1.1 on page 54) and added as a node to the tree. So the tree can be traversed by extracting the respective information which is connected to a certain tag.

11.7.2 BibtexParser

For including the information of the bibliography javaBib[4] is used. The mode of operation of this parser bears similarities to that of the aforementioned DOM parser. A tree is created which contains all information of the file in connection with its element type. The tree is also traversed by extracting the respective information which is connected to a certain tag. In this case the tags are given by a well-formed bibtex file.

[3]The DOM document is a part of the Java API for XML Parsing 1.1.1 http://java.sun.com/webservices/jaxp
[4]JavaBib is a bibtex parser written in Java http://www-plan.cs.colorado.edu/henkel/stuff/javabib

Chapter 12

Evaluation of the BibVis application

12.1 Evaluation of the Ontology

The main problem in evaluating the current application is to find a suitable ontology which can be used.

Due to that fact that I want to test the application with a bibliography which covers the field of cognitive science I have to use a corresponding ontology. As that there is no existing one, I use the ontology of information science [Techapanichgul and Syn, 2005] which is visualized in figure 13.1 on page 93 and extended it by adding several topics and relations. The result is represented in figure 12.1 on the following page.

This ontology has only been developed to serve as a data source for testing the design approach. So, it is important to stress that this ontology cannot meet the claim to represent the conceptual structure of a certain human. To do so, additional work with subjects has to be done. But as this was not the focus of this thesis I preferred to use this exemplary ontology.

12.2 Evaluation of the Bibliography

The second problem is to find a bibliography where as many entries as possible are connected with a set of keywords. It turned out that there are many bibliographies but most of them lack the usage of keywords.

So, I only used the R1 bibliography which covers the field of cognitive science. This bibliography contains 329 items which are connected to a set of keywords. As there are only one to three keywords assigned to each entry every item can be assigned relatively easy to a certain neuron. In addition, there are not many different combinations of keywords.

To sum it up, in order to evaluate the application in a better way the set of data has to be enhanced in a way: it has to comprise more keywords and each entry has to be related to a lot of keywords.

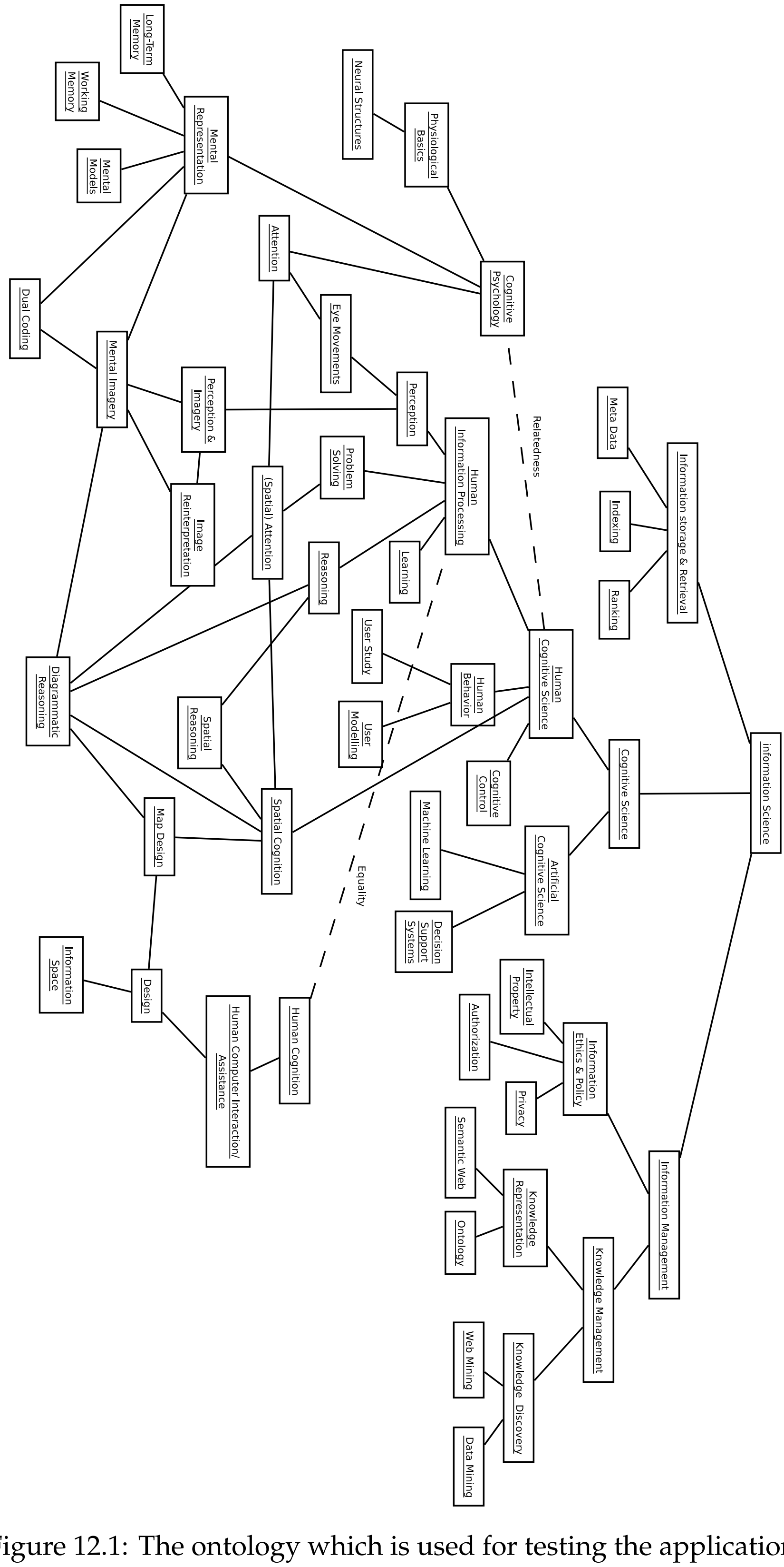

Figure 12.1: The ontology which is used for testing the application.

12.3 Evaluation of Visualization

To evaluate the application, first the original data set (`r1.bib`) was used. Afterwards, the set of data (`r1.bib`) was modified to test several scenarios.

12.3.1 Evaluation with `r1.bib`

In the first test the original set of data was presented to the application. It results in a visualization as presented in figure 13.2 on page 94.

Obviously, several groups of entries are extracted and represented on the visual space. When the corresponding labels are faded in (see figure 11.4 on page 72) the distribution of topics becomes visible. Apparently, topics which have a certain proximity in the ontology are also presented in a certain neighborhood on the map. Therefore, the distribution of topics in connection with an ontology seems to work. In order to test if thgis assumptions is valid additional test are done.

12.3.2 Evaluation with `r1_CogPsy.bib`

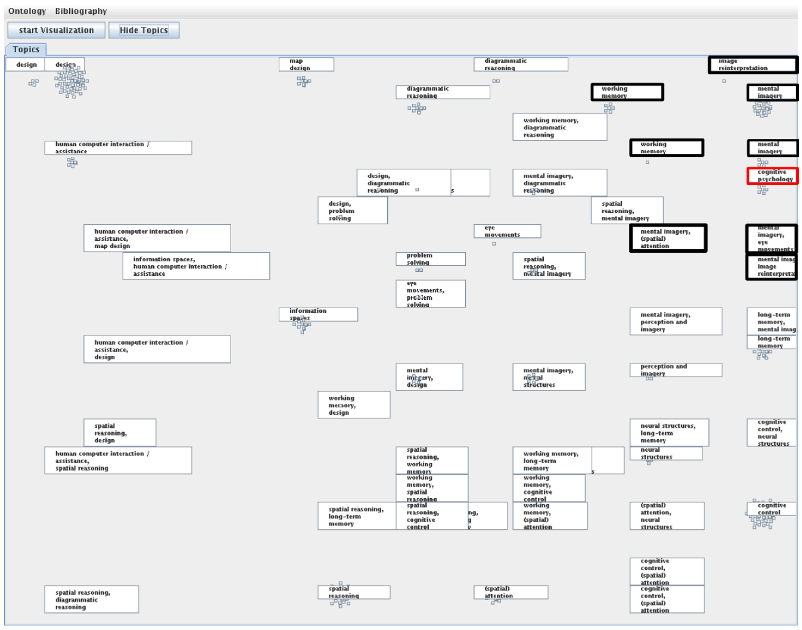

Figure 12.2: Visualization with topic labels of `r1_CogPsy.bib`. Important features are highlighted.

In order to test if the assumption is correct the set of data is enhanced by five entries. These entries comprise the keywords *cognitive psychology*. This enhanced bibliography is used by the application; the result can be seen in figure 13.3 on page 94.

It results that all of the manually added entries are assigned to the same neuron. In addition, the neighbors of this neuron cover topics which are also neighboring topics in the ontology (cf. figure 12.2 on the preceding page). To illustrate this fact the topic *cognitive psychology* and its neighborhood are both highlighted: obviously, the topics in the neighborhod correspond to neighbor topic in the ontology (cf. fig:onto). So, there is evidence that the distribution works for entries with a single keywords.

The question which comes up is if the spatialization also works if there is more than one keyword assigned to an entry. Therefore, the data set was again extended.

12.3.3 Evaluation with `r1_CogPsyDesign.bib`

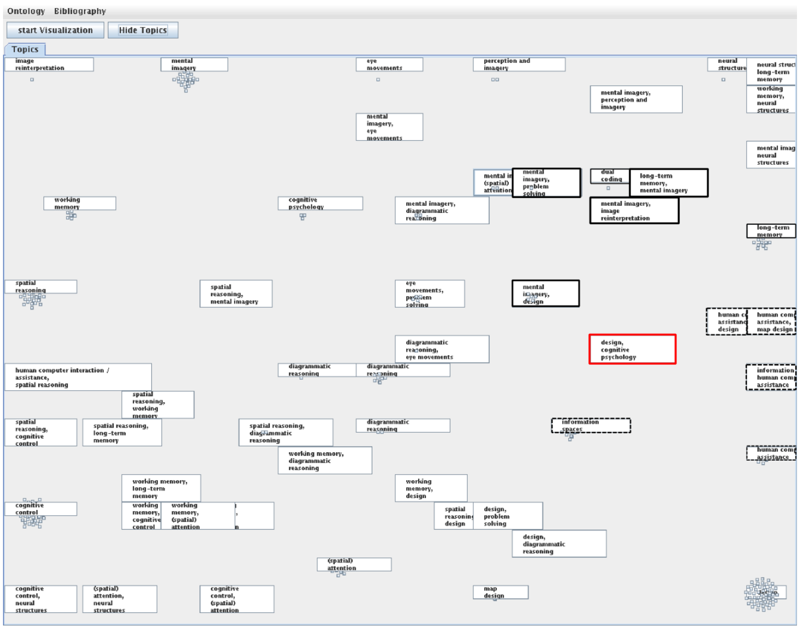

Figure 12.3: Visualization with topic labels of `r1_CogPsyDesign.bib`. Important features are highlighted.

In this case, the data set which was used in the preceding test was modified by changing the keywords of three of the new entries. Instead of *cognitive psychology* these entries were connected to the keywords *cognitive psychology* and *design*. This was done as these two topics are not in proximity in the ontology. The resulting visualization is presented in figure 13.4 on page 95.

Again, the group of entries which represent the modified entries is placed in proximity to both items of topics in proximity to *design* and to items of topics in proximity to *cognitive psychology*. This is presented in figure 12.3.

12.3.4 Evaluation with `r1_long.bib`

The last test is performed to show that the application can also handle data sets which contain more than 1000 entries. Due to the fact that it is not easy to find a suitable set

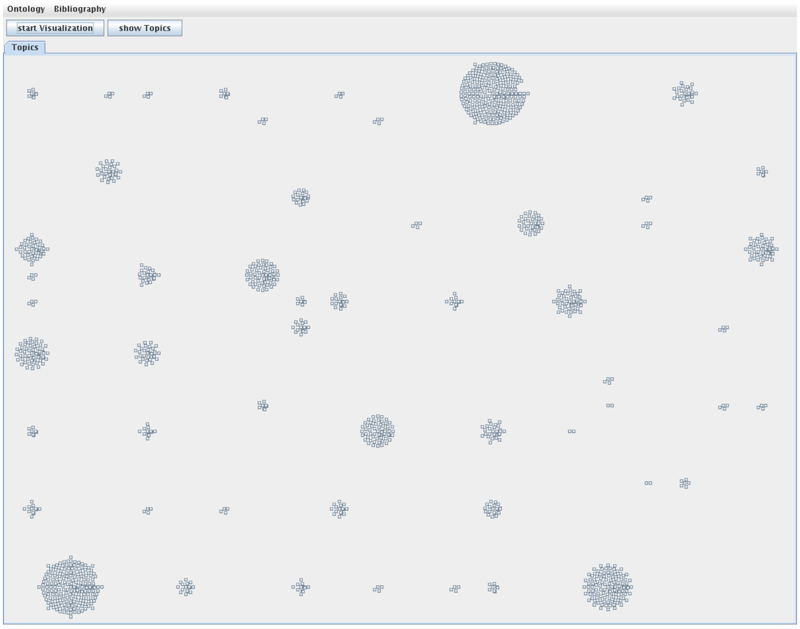

Figure 12.4: Visualization with topic labels of `r1_long.bib`.

of data the data set R1.BIB was concatenated to itself three time so that it results a set of 1316 entries. Because of the amount of data the calculation time increases. The result is presented in figure 12.4.

Obviously, the number of entries which are assigned to a single neuron increases. This comes from the fact that the sample R1.BIB was only copied three times and therefore, the amount of data which is assigned to a certain neuron is thrice as large as in the test in section 12.3.1 on page 75.

In addition, this is done with a data set which contains more than 6500 entries. It turns out that the calculation of both the graph-based representation and the self-organizing map takes a lot of time but that the application is able to handle such large data sets. The visualization result of the application is presented in figure 13.5 on page 95.

12.3.5 Conclusion

To sum it up, the application is able to distribute items in space according to their combination of keywords and the additional information from the ontology. So, the relations between topics are added to the entries of the data set and are mapped to space. Due to the limited data samples (where the number of assigned keywords is limited) this conclusion has to be tested with a set of data which contains a diversity of keywords.

It turns out that the application is able to deal with data sets which contain more than 5000 entries although it takes much time to import the data set and to create the information space. As the application is only a prototype which is used to illustrate that the approach is suitable this restriction can be accepted. Additionally the performed calculations are not meant to happen online but only the first time the application is used with a certain data set. From then on this preprocessed data should be used.

The main problem is that it is not clearly distinguishable if the resulting visualization is similar to the mental representation of a certain user. As humans tend to categorize items not only because of their keywords but with additional knowledge about entries it may happen that items are mentally assigned to a certain topic although their keywords do not directly lead to this topic. In order to model such additional knowledge the ontology has to be extended by assigning attributes to each topic which comprise additional knowledge about the topic members. In addition, it should be possible to add certain individuals to topics in the ontology which serve as examples for topic members. By doing this, the representation of the idiosyncratic hierarchy would assemble the mental representation to a higher degree.

Chapter 13

Conclusions

In this thesis I tried to answer the question of how information spaces can be designed so that they support humans in the exploration of large data set.

I argued that the degree of support increases if the spatial representation assembles the mental representation of a certain spectator. In this regard, I illustrated how humans build such mental representations and reason why it is necessary to include an idiosyncratic hierarchy for each spectator.

Starting from this, I presented an approach of how mental structures and processes can be represented in the computational domain and designed an application in which this approach is realized.

Finally, I showed that this approach is suitable to map information from an ontology to a set of literature data and reason that the relations are mapped to space for certain sets of data.

What is missing is the psychological evaluation of the present approach. So it is not clear if such a spatial representation of data really assembles the mental sructures of a spectator. In addition, there are a lot of starting points for enhancing the resulting application to stress the implementation of mental structures and processes.

13.1 Future Work

13.1.1 Ontology Language for Handling Ontology

The module `ontology` can be enhanced by changing the way an ontology is handled. Instead of using XML files for including an ontology and creating a graph-based representation the ontology could be modelled using a certain ontology language. Following this, the ontology's file structure has to correspond to the chosen language.

Using an ontology language for representing the ontology has two advantages: (i) there exist standard representation languages for ontologies which can also be used in other systems and (ii) a reasoner can be used for extracting the semantics between instances automatically. Therefore, it would not be necessary to implement methods which determine the similarity between items.

13.1.2 Enhancing Data Source

The data which is used to evaluate the program is in parts not very suitable for this application as it is restricted in generality and granularity.

As there is no existing idiosyncratic hierarchy any was created according to existing taxonomies. In addition, the used bibliography is not very detailed concerning the keywords which are assigned to each item. So, there is an opportunity to improve the quality of both the ontology and the bibliographic data.

Enhance Ontology

The ontology can be enhanced by providing the opportunity to create an own network by using a GUI.

At the moment, it is only possible to include an own ontology by encoding it into the supported XML structure. The main problem is that this structure becomes very confusing with increasing size. Therefore, an ontology editor which enables the user to create his/her own ontology by e.g. dragging and dropping elements on the screen would be appropriate.

In addition, such an editor would provide the opportunity to assign own weights to links between nodes. By doing this, specific relations could be expressed within the ontology. In this context, it seems to be appropriate to mention again the qualitative nature of human mental representations. Due to this fact, I suggest that weights are not be presented by numbers between 0 to 1 but rather as linguistic expressions which describe the degree of an relation, e.g. *Topic A is very similar to topic B* or *Topic C is not so similar to Topic B*.

Enhancing the Set of Literature Data

The bibliography data can be enhanced by increasing the number of keywords which are assigned to each entry. There are several approaches which are used to classify texts and automatically assign keywords to them (cf. [Scott and Matwin, 1998, Wermter and Hung, 2002]) among which WordNet®[1] is used for representing the language domain.

13.1.3 Enhancing Visualization

The visualization can be enhanced by amplifying the impression of the spatial representation. That means that e.g. the visualization can be advanced by using techniques

[1]WordNet®is a large lexical database for the English language which is developed by the Cognitive Science Laboratory of Princeton University. http://wordnet.princeton.edu

for creating cartographic or geographic representations (c.f [Ancona et al., 2002, Skupin, 2002]). As such visualizations increase the possibility to use strategies for exploring (geographic) maps the visualization result would then also support the exploration to a high degree.

For exaple, the tooplkit GeoTools[2] could be used for visualizing the items of the set.

Items are visualized by creating a layer on which they are mapped according to a certain style specification: a so-called styled Layer Description (SLD).

The main feature of GeoTools is that it implements the specification of the Open Geospatial Consortium (OGC). In addition, SLD is also specified by the OGC. Therefore, all interfaces are determined by the OGC which leads to easy portability and mutability of the visualization.

13.1.4 Enhancing Usability

The present visualization does only allow to gain an overview over all items in the set. So, it is not possible to view a certain region or item in detail.

According to Shneiderman and Plaisant there are seven tasks in visualization which have to be completed by an application: [Shneiderman and Plaisant, 2005, p.585]

1. Users have to be able to gain an overview of the whole collection. (Overview task)
2. It must be possible to zoom in on specific items. (Zoom task)
3. It must be possible to filter out uninteresting items. (Filter task)
4. There must be a possibility to select items or groups in order to get detailed information when needed. (Details-on-demand task)
5. Relationships among items have to be displayed. (Relate task)
6. There must be a history of actions which supports undo, redo and progressive refinement. (History task)
7. It must be possible to extract subcollections and the query parameters. (Extract task)

In the current application it is only possible to gain an overview of the whole collection (task 1) and to get additional information about items and groups (task 4). So, there has to be additional work to implement all other tasks in order to improve usability.

[2]GeoTools is an open source (LGPL) Java code library which provides standard compliant methods for the manipulation of geospatial data. http://geotools.codehaus.org/

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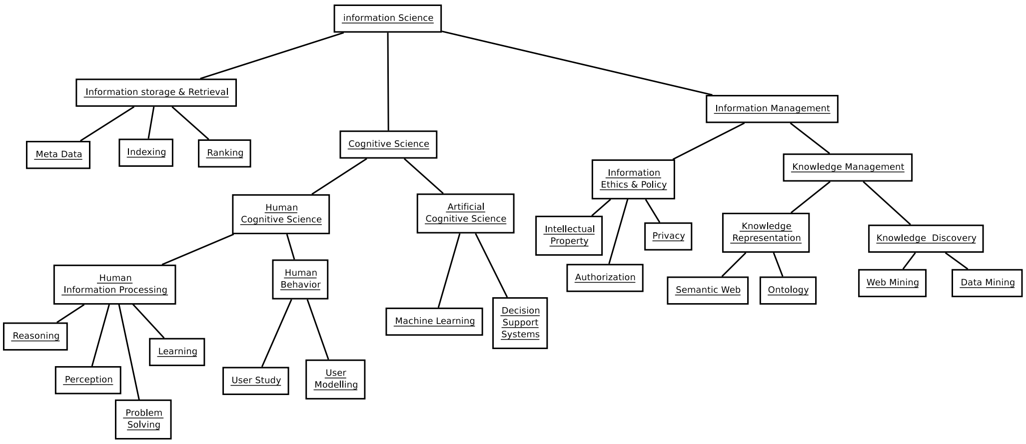

Figure 13.1: The ontology of information science [Techapanichgul and Syn, 2005]

Figure 13.2: Visualization of `r1.bib`.

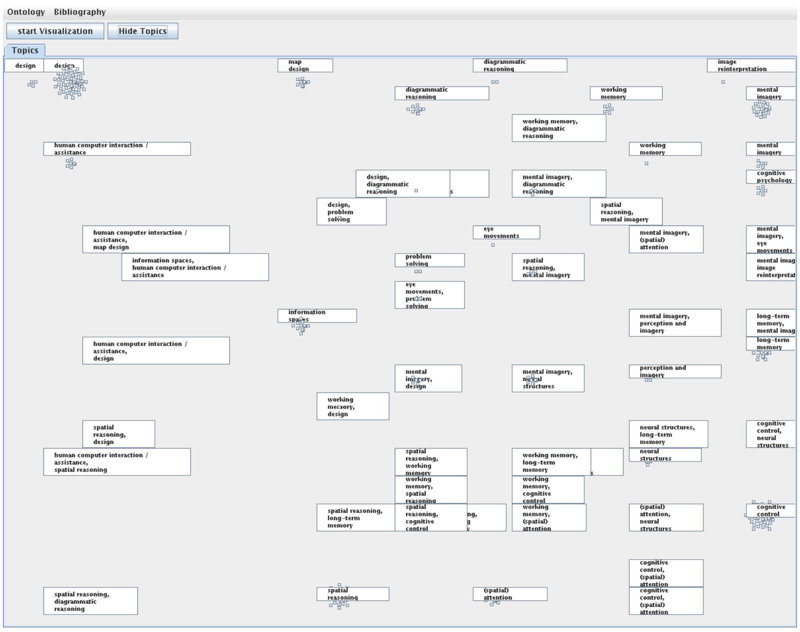

Figure 13.3: Visualization with topic labels of `r1_CogPsy.bib`.

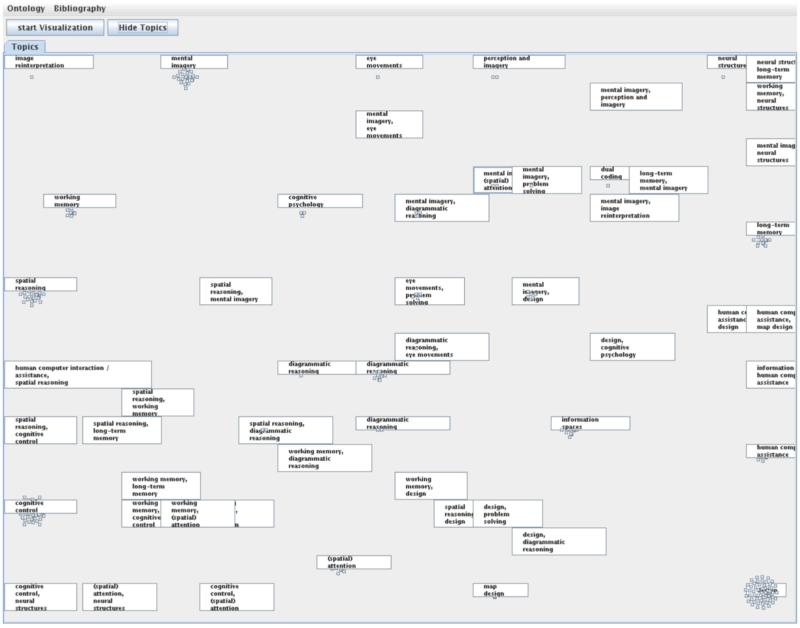

Figure 13.4: Visualization with topic labels of `r1_CogPsyDesign.bib`.

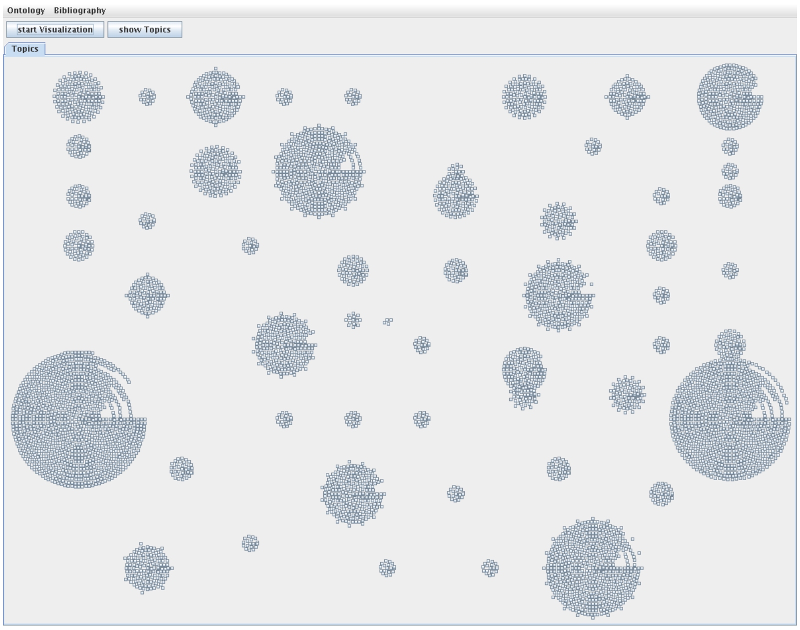

Figure 13.5: The visualization result of a bibliography with more than 6500 entries.

Contents of CD

The following directories and files can be found on the attached CD:

- Directory `app` contains the JAR file of the application with all libraries which are necessary to execute the programm (`app/lib`). The application can be started by typing `java -jar BibVis.jar`[3]
- Directory`data` contains all sample data which is used during the evaluation.
- Directory `doc` contains the present thesis in PDF format.
- Directory `src` contains the source code of the *BibVis* application

  application

[3]If this does not work because the heap size is to small try `java -jar -Xms64m -Xmx256m BibVis.jar`.