The User Puzzle—Explaining the Interaction with Visual Analytics Systems

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Abstract—Visual analytics emphasizes the interplay between visualization, analytical procedures performed by computers and human perceptual and cognitive activities. Human reasoning is an important element in this context. There are several theories in psychology and HCI explaining open-ended and exploratory reasoning. Five of these theories (sensemaking theories, gestalt theories, distributed cognition, graph comprehension theories and skill-rule-knowledge models) are described in this paper. We discuss their relevance for visual analytics. In order to do this more systematically, we developed a schema of categories relevant for visual analytics research and evaluation. All these theories have strengths but also weaknesses in explaining interaction with visual analytics systems. A possibility to overcome the weaknesses would be to combine two or more of these theories.

Index Terms—Cognitive theory, visual knowledge discovery, interaction design, reasoning, problem solving.

INTRODUCTION

It has been argued by Green et al. [13] that interaction with information visualizations can be conceptualized as problem solving activity. This is especially relevant for the explanation of exploratory interaction with visual analytics tools. When users interact with such systems, they formulate hypotheses, look for patterns in the data, and adapt the specific appearance of the data on the screen to find information substantiating their assumptions and hypotheses [2]. All these are problem-solving activities. The definition of visual analytics (VA) by Thomas and Cook as "the science of analytical reasoning facilitated by interactive visual interfaces" ([58], p.10) emphasizes the reasoning aspect of the process of getting insights from massive amounts of data provided by modern information systems.

Keim et al. [21] argue that visual analytics combines humans and machines, exploiting their respective capabilities. It should be pointed out, however, that it is not the computer which engages in reasoning processes but the human user interacting with the visual interface. Consequently, visual analytics tools should be designed in a way to support human reasoning efficiently. While computers are able to process large amounts of information and search for specific items, humans have a great deal of knowledge about the context, which is not available to the computer. This enables humans to draw conclusions even in the absence of relevant pieces of information. We assume that a science of interaction [37] should take this interplay between humans and computers into account. According to Card et al., such questions have already been addressed in the early days of information visualization research [4]. However, these analytical processes are not fully understood. Progress in this area will improve visual analytic tools.

Similar questions are raised by existing research concerning analytic provenance [10], [20], [28]. This area of research tries to clarify the users' reasoning processes while they interact with visual analytic tools. The goal is, however, to support analysts in their work. Previous exploration processes are made available to reuse insights gained at an earlier stage and compare these insights to their current work. Nevertheless, there is some overlap, and research on analytic provenance can provide useful information on how reasoning processes work in practice.

The aim of this paper is to look more deeply into these human reasoning processes and how they relate to tool interaction, information interaction, and perceptual interaction. Several theoretical approaches from psychology and HCI might be relevant for a theoretical framework for this area of research. There are many theories explaining various aspects of human reasoning processes. Especially those theories targeted at explaining logical reasoning in a more narrow sense (see e.g. Evans [11]) can only clarify explorative interaction with VA systems to a limited extent. For our overview we have, therefore, chosen theories with a broader scope which can explain problem-solving activities in the real world and a more complex context. Many theories about human reasoning are based on empirical research using puzzles as problems to solve. Such puzzles (e.g. towers of Hanoi, missionaries and cannibals etc.) usually have a clear solution and a well-defined path to this solution. People can solve them by adopting generic strategies (e.g. means-ends analysis). It has to be pointed out that in realistic problem solving processes, in contrast, background knowledge plays a crucial role (Novick and Bassok [33]). In addition, problems in VA are seldom well-defined. Therefore, approaches based on research of puzzle-like problems only have a limited value for explaining interaction with VA systems. The theories described in this paper try to overcome these limitations. They also cover real-world and complex problem-solving activities. All these theories highlight specific aspects of human reasoning which might be relevant for the different kinds of interaction with VA systems. We concentrate on theories explaining open ended and/or exploratory activities. All these theories emphasize visual forms of reasoning to a greater extent than symbolical, abstract reasoning. We assume that such theories are better able to describe processes of interaction with visual analytics systems.

In this paper, we describe five theories (sensemaking theories, gestalt theories, distributed cognition theories, graph comprehension theories and skill-rule-knowledge theories) explaining human reasoning processes which seem to be relevant for explaining interaction with VA systems. In sections 1 to 5 we describe these theories. We also discuss how they might be applied in empirical research about VA systems. Then, we discuss their advantages and disadvantages in this context. The theories emphasize different aspects of the process of interaction with VA systems. We, therefore, developed a set of relevant categories to assess and compare these theories more systematically (see section 6). Based on this comparison, we suggest several possible ways in which these theories might be used to explain interaction with VA tools. The

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comparison highlights which aspects of the exploration process of VA systems (e.g. perception and visualization, interaction strategies, hypothesis formulation, etc.) are reflected in which theory. This overview helps researchers to identify which of the theories might be used as a foundation of their empirical research.

1 Starting Point: Sensemaking

Russel et al. [47] and others assume that interaction with information visualizations can be described as sensemaking. They argue that there are several stages of sensemaking: acquire information, make sense of it, create something new, and act on it. Making sense of information consists of at least two processes, namely extraction of information and fusion of information from different sources. During sensemaking, representations of the information have to be generated. These representations may be altered by conflicting information. All these processes have to be supported specifically by information visualizations.

1.1 Description of the Theory

There are two different approaches based on the concept of sensemaking which are relevant for VA. One is the sensemaking loop developed by Pirolli and Card [40]. This approach has been influenced by the theory on information foraging (Pirolli, [39]). The other approach was developed by Klein et al. [24][25]. The concept of sensemaking is, therefore, quite complex and allows some interesting insights into exploration processes in VA.

Pirolli and Card [40] developed a very influential model of sensemaking specifically shaped to reflect the work of intelligence analysts. They distinguish between a foraging loop aimed at searching for and filtering information and a sense-making loop which is supposed to interpret the found information and develop a consistent model out of it. Pirolli and Card point out that there are cost structures associated with this model (e.g. the trade off between wide exploration and detailed exploitation of the information). In this context, the process of abduction plays an important role. Abduction is a process which is adopted by humans to find explanations for perceived phenomena. From the observation of the circumstance b they infer that the antecedent a is given [3]. This process is essential for the generation of hypotheses which is central in the interaction with visual analytics tools.

Though Pirolli and Card's sensemaking model [40] did find quite some resonance in the information visualization literature [22], the model does not seem to be suitable to explain user interaction with information visualizations in detail due to (1) a restricted conceptualization of user interaction, (2) open questions how to test the model empirically, and (3) the model's high level focus.

First, the model mainly focuses on information interaction, that is, which information a user extracts, how (s)he enriches it with prior knowledge and which knowledge (s)he exploits. However, in the case of interactive information visualization and visual analytics tools, the user's tool interaction and perceptual interaction (making sense of information without physical interaction with the tool) are additionally relevant, but are not covered in Pirolli and Card's sensemaking model [40]. By using a tool's interactive features a user can actively determine which information is displayed and how. The design of these features is highly relevant for the success of information visualizations and, thus, findings on what drives tool interaction and how it connects to human problem solving. Also, a theoretical model on human reasoning with information visualizations should cover the user's perceptual interaction with the displayed information as well. Which information is perceived is not only controlled by top-down, user-driven processes (like searching for relevant information), but also by bottom-up, visualization-driven processes (like salience or Gestalt laws).

The sensemaking theory relies on a fairly rigid assumption of stages building on one another. In evaluation practice, it is probably very difficult to distinguish between the different initial stages of information foraging and the later stages of sense-making as these stages are very tightly intertwined. From our evaluation experience in business intelligence, users jump back and forth from raising hypotheses (level 13) to searching for supporting information (level 2) to building new schemata (level 10) or retrieving existing ones from memory. Therefore, it is difficult to distinguish clearly between these stages or to conceptualize them as one building on the one before (see Smuc et al. [57] for examples about the use of prior knowledge during the exploration process). Additionally, it remains unclear which processes are driven by the information provided and which are driven by the user's prior knowledge because from a cognitive perspective processes like 'schematize' or 'build case' have to be classified as top-down, knowledge-driven processes, but were classified as bottom-up processes in Pirolli and Card's model.

Following Green and Fisher, the model only reflects more abstract processes of reasoning [14], but omits highly relevant, more detailed aspects of reasoning (e.g. whether subjects adopt deductive strategies). "For while descriptive models like the sensemaking loop do much to frame the big picture, intuitive interfaces will require a more detailed working-order understanding of what lies inside the frame" ([14], p.43).

Klein et al. [24][25] propose another model of sensemaking. The authors assume that current psychological theories are not comprehensive enough to describe sensemaking in naturalistic settings. Their model is based on the concept of frames (which was inspired by work in Artificial Intelligence). Frames are developed when people want to make sense of the phenomena around them. Frames can either be elaborated or rejected. Elaboration means that additional detail is added to a frame. A frame can be rejected when it is not useful or accurate any more. Elaborating, questioning frames and reframing (substitution of one frame for a better one) are iterative processes which make up sensemaking. Klein et al. [25] argue that this model is able to represent real-world decision making in an appropriate way. Attfield et al. [3] used the approach of Klein et al. [24][25] as a conceptual basis to conduct their empirical research concerning fraud investigation.

1.2 Application in Visual Analytics

Sensemaking is a concept which is fairly influential in VA. It implies an iterative reasoning process which is driven by the continuous formulation of new hypotheses. This conforms to analytical processes undertaken by human users of VA systems. Sensemaking as a concept, therefore, seems to model such behavior quite well. Nevertheless, the model of the sensemaking loop developed by Pirolli and Card [40] has, to the best of our knowledge, not been applied in empirical investigations of reasoning processes in information visualization or VA. This might be due to the fact that this approach is specifically tailored to reflect the work process of intelligence analysts. The sensemaking approach of Klein et al. [24][25] has been used more often (see e.g. Attfield et al. [3]). This approach is more general and applies to any decision making processes of domain experts. It can, therefore, be used more easily to investigate exploration processes with VA.

1.2.1 Advantages

The concept of sensemaking seems to be very attractive to model the activities of users of VA systems. The theory can clarify complex problem-solving activities and exploration of data. Sensemaking also implies that different viewpoints of various users are taken into account. The approach of Klein et al. [24][25] also addresses the problem of cooperative sensemaking, that is, how groups of users can achieve a common interpretation of the data.

1.2.2 Disadvantages

Sensemaking models usually emphasize the representation and rearrangement of information in the user's mind. They are very well able to model these activities in detail. Other activities which are also highly relevant for the explanation of reasoning processes supported by VA tools are less well described by the theory such as perception and the interaction with VA systems. The sensemaking theory, therefore, contains no specific component explaining how visualizations should be designed to support human reasoning processes. Guidelines can only be derived from the general considerations of reasoning processes. This can make it difficult to model the specific character of interaction with VA tools.

2 Gestalt Psychology And Insights

2.1 Description of the Theory

Modern computers enable users to solve increasingly complex problems. As Mirel [32] pointed out, interfaces of computer programs have to be designed in a way to support such complex tasks. Many real-world problems which are addressed by computer software nowadays are ill-defined in nature. This implies that it is often not clear what exactly the problem is, how a solution might look like, and which methods might be used to reach a goal. There is usually no single right answer to the problem. Often several different ways to reach a solution exist, and users often change strategies and goals while dealing with such problems. Systems which typically support complex problem solving are interactive information visualization tools [32]. According to Andrienko and Andrienko [2] these systems support exploratory behavior of the users.

In this context, the psychology of problem solving distinguishes between routine and non-routine problems. For routine problems, people have preexisting procedures for solving them. Davidson [8] assumes that non-routine problems involve conceptual change and insight. The concept of insight was first discussed by Gestalt psychologists and is defined as a process during which a problem is solved through restructuring [62]. Problem solvers try to redefine the representation of the problem to find a solution. Insights are a result of creative thinking going beyond the given information. Pretz et al. ([43], p.18) describe insight "as a sudden understanding that results when the problem solver realizes how all parts of a problem fit together to form a coherent whole, or Gestalt". Mayer [30] discusses several assumptions of Gestalt psychology about problem solving. One central idea is that insight is a sudden reorganization of visual information. The problem solver looks at the given information in a completely new way. This does not imply, as is often assumed, that Gestalt psychology posits that solutions in problem solving processes occur immediately (the so-called "aha" experience). As suggested by Dominowski and Dallob, restructuring might sometimes take quite a lot of time and might be an iterative process [9].

Gestalt psychology emphasizes the representational aspect of problem solving. When the structure (or Gestalt) of a problem is made clear, a solution can be found fairly easily. Therefore, it is essential for problem solvers to understand the relations existing among the components of an entity [9]. Gestalt psychology has a highly dynamic view of problem solving. Problem representations are modified during the thought processes.

One of the most serious difficulties in problem solving identified by Gestalt psychologists is fixation, that is, the situation when individuals do not perceive the underlying structure of a problem. They are fixated on an inappropriate representation of this structure. To overcome this problem, the representation must be transformed radically. Interactive information visualizations can support this transformation process as they offer the opportunity to show the data in different arrangements on the screen, to filter the data or sometimes even to represent the data in a completely different visual form. If used appropriately, such features can help to overcome fixation.

In problem solving psychology, there is a renewed interest in the concept of insight. According to Novick and Bassok, this is related to a trend toward examining more complex, ill-structured problems [33]. Therefore, Gestalt psychology has gained in importance in problem solving research. It should be pointed out, however, that there is no common definition of insights, and it is still controversial whether gaining an insight is a specific process compared to other problem solving activities or not.

2.2 Application in Visual Analytics

There is some similarity between the insight definition of Gestalt psychology and the insight definition used in information visualization and visual analytics. Saraiya et al. [49] define insight "as an individual observation about the data by the participant, a unit of discovery". In this context, restructuring a problem plays an important role, and users may notice aspects of the presented information which were overlooked before. On the other hand, there are distinct differences between the concept of insight used in Gestalt psychology and visual analytics. Chang et al. [6] point out that in visual analytics insight is seen as a substance or product while cognitive psychology has a more process oriented view. North [34], for example, assumes that insights are complex, deep, qualitative, unexpected, and relevant. This view assumes that insights are the results of a problem solving process. Chang et al. [6] also argue that insight in cognitive psychology is seen as a subconscious process in which no predefined strategies or heuristics are used. Such processes are difficult to analyze. Yi et al. [64] also discuss that there is no common definition of the concept of insight in information visualization and visual analytics. Nevertheless, Lam et al. showed that there is some influential research aimed at the analysis of reasoning processes which yield insights [27]. Insight studies play some role in evaluating visualizations [41].

2.2.1 Advantages

Gestalt psychology is an appropriate framework for explaining problem solving in ill-structured domains. It takes into account that problem-solving is often not a straightforward process based on a well-defined strategy. Solutions reflect that the structure of a problem situation emerges as a consequence of creative thought processes. These processes encompass repeated reorganization of information in the human mind. The representations of the problem situation are changed in the course of the individual's examination of the problem situation. The continuous reformulation of representations can neutralize the effect of fixation. All these assumptions from Gestalt psychology describe the process of interacting with VA tools very well. VA systems with various interactive possibilities are especially appropriate to overcome fixation because they are able to represent the problem situation in many different ways.

2.2.2 Disadvantages

Basic concepts of Gestalt psychology are not very well defined. Older research from Gestalt psychologists did not follow strict rules of experimentation. Therefore, it is difficult to use Gestalt psychology as a theoretical framework for explaining the interaction with information visualizations. Newer research is oriented towards scientific experimentation, and there is already a significant body of empirical research concerning Gestalt psychology. Still, the concepts are very general and cannot be easily applied to the analysis of interaction with VA tools. In addition, Gestalt psychology is not very much concerned about the different steps or strategies problem solvers might adopt. It tends to conceptualize reasoning processes as intuitive and opaque. This makes it less useful for explaining the interaction with VA systems. Without detailed results concerning the specific interaction of the users with these systems, it is very difficult to conduct research with the goal to improve VA systems.

3 Distributed Cognition

3.1 Description of the Theory

Distributed cognition as a theoretical approach is relevant for visual analytics because it emphasizes the interaction between users and artefacts [17][18][36][48]. In contrast to most psychological theories, in the context of this theory cognitive processes are not only located in the human brain, but are conceptualized as distributed across the situation. Distributed cognition assumes that "knowledge" is distributed among users and artefact and that human knowledge is embodied in artefacts. Knowledge about measuring temperature, for example, is embodied in a thermometer or knowledge about computing in a computer. In many cases, people who use computer programs were never acquainted with the knowledge embodied in this program. Nevertheless, they are enabled to apply this knowledge in practice because of the availability of this program. In this sense, knowledge is distributed among users and computers. Therefore, O'Malley and Draper state that human users often have no coherent and comprehensive mental models of how things work [35]. Such mental models only emerge in the process of using a technology. Clark stated that artefacts act as scaffold [7]: We delegate knowledge to artefacts and thereby reduce the need to store information in memory and consequently the cognitive workload. Results achieved by using such cognitive tools emerge from the interaction between humans and artefacts and cannot be attributed to human activity alone.

The crucial factor in the relationship between humans and computers is how knowledge is distributed between these two components and how they interact with each other. This issue is especially relevant for visual analytics where a visualization is complemented by a component for analytical reasoning. In visual analytics systems, tasks should be distributed between users and systems according to the specific strengths and weaknesses of those two components. Humans possess the ability to infer information from visualizations very quickly through visual thinking. They are superior to computers in many reasoning tasks, especially when a huge amount of background information is needed [21]. Computers, on the other hand are very good at processing large amounts of information and doing more formal reasoning processes.

Liu et al. [29] point out that distributed cognition could form an appropriate theoretical framework for information visualization. They argue that the form of representation may evoke different solution strategies because of the different affordances of the systems. This phenomenon can be better explained by distributed cognition than by other theoretical approaches. They also posit that a science of interaction is at the core of an approach based on distributed cognition. Interaction mediates between the user and the artefact. These interaction processes are still not very well understood. A possible approach in this context is described in Pohl et al. [42]. We have little systematic knowledge of how people really work with visual analytics systems, and especially of which cognitive processes occur when they do this. We also do not know which cognitive processes are supported by what kind of visualization and analytical support. Therefore, designers of such systems are forced to use intuition to design appropriate systems.

Another aspect emphasized by distributed cognition is the fact that human activities usually not only depend on artefacts but also on other human beings. Cooperation is increasingly seen by Isenberg et al. as a constituting element of visual analytics [19]. Many analytical processes occur in collaboration with others. Again, systems have to be designed appropriately to accommodate such processes.

Methodologically, research within the distributed cognition tradition is ethnographically oriented (e.g., Hutchins [18]). Shneiderman and Plaisant point out that interaction with information visualizations is observed during everyday work and - combined with other research methodologies - provides valuable findings on how to re-design and improve those information visualizations [55].

3.2 Application in Visual Analytics

The fact that insights emerge from the interaction between human and artefact implies that users of VA systems usually do not develop elaborate strategies in their minds before they start working but react interactively to what is represented on the screen (situated cognition). They use the information visualization as a scaffold for the ir problem solving process. How successful the user is depends also on what kinds of interaction (s)he perceives as afforded in the interface.

Scaife and Rogers [50] described this process as external cognition. The question then is how to design systems to support these interaction processes. A specific challenge in this context is to clarify how the problem representations in the brain look like and whether they conform with, or are supported through the representation on the screen, as described by Mayr et al. [31]. A detailed, stepwise analysis of user interactions and their representations is needed.

3.2.1 Advantages

The theory of distributed cognition emphasizes the interaction between human and artefact. This makes it easier to conceptualize specific interaction processes between users and information visualizations. Studies conducted by Saraiya et al. using thinking aloud indicate that insight processes occur in close interaction of humans with machines [49]. The idea that insights emerge while users interact with the system corresponds to the assumption of visual Andrienko and Andrienko that insight generation is an explorative process [2]. Distributed cognition is also an appropriate framework to explain epistemic actions (see Kirsh and Maglio [23]). Epistemic actions are actions which help users to gain information about the problem at hand, in contrast to pragmatic actions which support users to get closer to achieve their goal.

3.2.2 Disadvantages

Distributed cognition is a fairly general and abstract theory. Researchers have described cases which demonstrate how distributed cogniton works. Nevertheless, there is no general concept of interaction, and this concept is not very well understood. It is especially challenging to develop systems exploiting the strengths of humans as well as that of visual analytics systems and to enable them to interact smoothly and efficiently. There are no general principles how the interaction between humans and artefacts might be supported by an appropriate design. In addition, distributed cognition does not specifically address issues of visualization. All this makes it difficult to derive concrete guidelines for the design of visual analytics systems from this approach.

4 Graph Comprehension

4.1 Description of the Theory

Graph comprehension theories deal with the "graph readers' abilities to derive meaning from graphs" (Friel et al. [12], p. 132). According to Tversky, graph comprehension is informed by theories of visuospatial reasoning [60]. Visuospatial thinking is a broad and interdisciplinary approach which tries to explain "how people represent and process visual information" (Shah and Miyake [52], p.xi). Such theories can, for example, explain how inferences can be drawn from simple diagrams, and they are typically based on perceptual principles and processes mostly focused on less complex graphs like line plots or bar charts. Past research has led to various cognitive models with distinct components that constitute a graph comprehension framework. Friel et al. [12] reviewed several graph comprehension models and concluded that they consist of three levels and cyclic structures, addressing the questions of how information gets extracted, which relationships in the data can be found and what can be done to make sense out of the data. Friel et al. differentiate between the levels of (1) reading the data (i.e. extracting data, locating), (2) reading between the data (i.e. finding relationships, integrating), and (3) reading beyond the data (i.e. extrapolating from the data and generating hypotheses).

One of these models is Kosslyn's graph comprehension model [26] with syntactic, semantic, and pragmatic levels of processing. Shah and Miyake [52] distinguish between two major classes of graph comprehension models. The first class of models provides comprehensive descriptions of how users interact with graphs. The second class tries to explain how people interpret graphs, but make less detailed predictions about graph comprehension activities. The integrative model developed by Carpenter and Shah [5], which tries to combine both approaches, focuses on pattern encoding, the translation of the resulting visual chunks and the relation of this information to referents. For the first level of processing, the visual chunking process, graph comprehension theories meet Gestalt theory when dealing with a graph on a very basic level. Following Pinker [38], the principles of proximity, similarity, and good continuity are used to form the first useful entities of information. Shah et al. extended this integrative model by adding graphical skills and content knowledge as influential factors [53]. This has led to the (mental) interactive model where both bottom-up and top-down processes like expectations and prior knowledge interact. In another approach, Trafton and Tricket [59] proposed different components of visual integration which get cognitively integrated in a process of multiple cycles. Later, Ratwani et al. [44] extended their model by elements like spatial transformations and the application of mental models in graph comprehension.

4.2 Application in Visual Analytics

4.2.1 Advantages

Graph comprehension theories are a well-tried instrument to reflect the micro-architectures of graphs in a very detailed manner and to get deeper insights about the cognitive structures involved when looking at (simple) charts or graphs like the ones often used with multiple view techniques. Therefore, they offer a rich basket of arguments and starting points on how to design and optimize graphs. Especially cognitive tasks like visual decoding, pattern recognition, the usage of referents, visual memory and spatial reasoning were examined to a huge extent in the last years and the results of this research should not be overlooked when designing visualizations.

In graph comprehension frameworks, a basic "language" of graphs [26] was developed by Kosslyn, allowing the description of transformations of one graph type into another graph type. Although transformations depending on data types and their attributes are sometimes tackled as side aspects by VA task taxonomies (e.g. [54]), using the existing syntax and grammar of graph comprehension theories could be a fruitful starting point for further investigation in VA research.

Another interesting aspect of graph comprehension research is the focus on graph reader characteristics which presumably originates in its educational research tradition, being one of its main research fields. The role of skills, expertise, experience and prior knowledge seems to play a secondary role in VA (for exceptions see [14][65]), since it is mainly focused on domain experts and expert skills have usually been treated without a shadow of doubt.

4.2.2 Disadvantages

Graph comprehension theories do not cope with tool interaction or dynamics in visual displays (except animation, see Tversky et al. [61]), visual displays are treated as fixed and completed. As pointed out earlier, graph comprehension theories have their strengths in explaining conventional (bar charts, line charts, pie charts, scatter plots etc.) and simple graph usage. However, in VA we deal with more complex visualizations and systems. Studies on novel visualizations and more complex graphs are often called for, but rarely conducted. One of these rare studies on complex graphs was conducted by Trafton and Trickett [59], who discussed the question whether graph comprehension theories could be easily scaled up from simple to complex graphs. In their view, spatial processing becomes more relevant for more complex data. Shah and Freedman [51] also noted other critical factors when dealing with complex graphs, like the decision making process on what to encode in the vast amount of data and the problem of multiple goals when interpreting graphs.

Another weakness of graph comprehension theories is the lack of integration of problem solving theories for highly abstract levels of processing, when reading beyond the data. This topic is also connected to sensemaking which is, in the view of graph comprehension, very often based on making sense of one visual display instead of the whole exploration process, as in VA sensemaking theories (see section 1).

5 Skill-Rule-Knowledge Models

5.1 Description of the Theory

These models could provide a possible medium level link between the rather atomistic graph comprehension theories (often near to perception) and more abstract models like Card's sense-making-loop. J. Reason developed a cognitive model of users to analyze their errors in working contexts [45]. The model is based on the research of some prominent theories about cognition, memory and learning which are often used in cognitive task and cognitive work analysis. Although the objective of this model is to generate an error taxonomy with specific, diverging errors, dependent on the cognitive level of processing (GEMS - Generic Error Modeling System), it is also adaptable to and beneficial for interactive explorations with the help of VA tools (see also Smuc [56]).

The core of Reason's model is a cyclic skill-rule-knowledge loop developed by Rasmussen and Goodstein [46], consisting of three hierarchical levels of cognitive processing: on the lowest level of processing, users act based on their learned skills, in a schematic and highly automatic manner. On the rule-based level, users make a diagnosis of the situation and try to minimize the mismatch of the situation and their internal representation by applying heuristics or previously learned rules. If the users do not find a satisfactory solution on this level, they have to switch to the cognitively most demanding level of processing, the knowledge based level. This is the level of classical reasoning and problem solving, i.e. the user applies his/her knowledge and mental models, undertakes abstract analysis or deploys analogies to interact with new situations.

To sum up, this model consists of a three-fold hierarchy of processing levels which allows clear and distinct descriptions of how an operator or user handles known and unknown situations, taking his/her skills, learned rule-sets and his/her prior knowledge into account. As stated earlier, Reason's model gained a lot of empirical evidence for the creation of error taxonomies, especially for supervisory control and maintenance of large, highly complex systems like atomic power plants. But how can these levels get linked to the cognitive processes needed in a visual data exploration process?

5.2 Application in Visual Analytics

Focusing exclusively on errors to analyze visual data exploration has some drawbacks, since making some errors now and then, condemning and reconsidering hypotheses and occasionally taking the wrong turn are always an essential part of a vibrant visual exploration process - as long as these misapprehensions are managed appropriately and do not bias the final results. Although an analysis of errors based on differentiated error-categories can offer a lot of insights into the strengths and weaknesses of a VA tool, it makes more sense to place some emphasis on success parameters (like insights into the data) in combination with explorers' failures during the exploration process. This shift of perspective does not harm the model's integrity when it is deployed for VA, since success parameters simply represent the other side of the same coin.

If we separate the two main aspects of VA tools, namely the visualization and the interaction part, we can find many similarities regarding the hierarchy of processing levels and some three-fold graph comprehension theories (see section 4) as well as tool interaction theories (see table 1).

Let us imagine a professional visualization explorer who is so skilled in graph perception and tool handling that many operations are usually automatic. In case of problems s/he knows the grammar of graphs and has a repertoire of helpful cognitive interaction scripts.

Table 1. Possible links of Reason's model to graph comprehension, interaction and cognitive factors.

	visualization	tool / handling	memory / response time
skills	syntax of graph perception	handling / automatic	short-term memory / fast
rules	how to read the properties	diagnosis / easy scripts	working memory / medium
knowledge	semantic content (domain) knowledge, (visual) problem solving	novel ways of tool exploration / (tool) problem solving	long term memory / slow

If all that fails s/he has to apply her/his semantic domain knowledge to make sense of the data or s/he has to find novel ways of tool exploration to get more out of the tool. In contrast to a novice in visual exploration, a professional will rarely have to move to the very demanding knowledge based processing level for simple, basic tasks.

5.2.1 Advantages

One of the advantages of this theory is that learning and users' efforts in understanding data become better traceable. The model can be seen as an instrument for differential diagnosis: users' skills, rule-sets and knowledge base are an integrative part of explorers' operations and become separable, since the hierarchy of levels allows analysis based on cognitive processes. The results of such a diagnosis can be integrated in design concepts about better visual analytics tools, for example by making some room for problem solving by shifting tasks from the knowledge level to the skill level, e.g. by finding another representation of the data which can more easily activate users' schemata.

5.2.2 Disadvantages

Since this model is designed for monitoring tasks and has not been applied to VA until now, the obstacles to adapt this model for a creative, open, and dynamic exploration process remain unknown.

From a methodological point of view, the operationalization and measurement of success parameters could be problematic. While rule- and knowledge based processing is inspectable through time-logs and verbal protocols to some extent, skill based processing may be only partly covered as spontaneous associations. Thus, analysis on the skill based level has to be supported by eyetracking studies and has to be reviewed by intricate experimental perception studies. Especially the integration of findings from graph comprehension studies should be taken into consideration.

6 Discussion

An overall assessment of the different theories described in this paper is a challenging task. In order to make such an assessment more systematic, we developed a set of relevant categories. These categories reflect, on the one hand, requirements of visual analytics systems and, on the other hand, specific characteristics of human information processing. We want to discuss whether the five different theories enable researchers to model processes like sensemaking, insight generation, hypothesis testing, interpretation, collaboration or other processes which have been identified by researchers in the area as important for interacting with visual analytics systems. On the other hand, the theories reflect the information processing model developed in cognitive psychology (see Anderson [1]) in various degrees. This process incorporates activities as, for example, perception (preattentive processing as described by Healy at al. [15], visual pattern detection), understanding (especially of the chosen mapping for the visualization), problem solving and decision making; these activities are also part of the categories used for the assessment of the five theories. The category "interaction strategies" addresses the question whether a theory is able to model specified interaction processes of the users in the sense of a theory of interaction [63]. Operationalizability reflects whether it is easy to test a theory empirically. "Errors" signify the extent to which a theory explains user errors in a more sophisticated manner.

The results of the categorization process are shown in figure 1. Intensity of the colors denotes to which extent a theory addresses a certain category.

What can be seen is that the sensemaking approach is the most focused one of the five theories. It has a strong emphasis on interpretation, hypothesis testing and sensemaking, but it does not cover perceptual aspects of using visual analytics tools. In contrast, distributed cognition, graph comprehension and skill-rule-knowledge cover most of the categories we used. Gestalt psychology, graph comprehension and skill-rule-knowledge all reflect perception processes to a high degree. Graph comprehension has a distinctive focus on the perception processes and does not account for problem solving or reasoning processes to a large degree. Distributed cognition is good at modelling exploration and problem solving. It is the only theory which allows to incorporate the users' interaction strategies and collaborative processes. Here, a distinctive difference to the other categories can be seen. Skill-rule-knowledge covers many aspects of the categorization scheme quite evenly, but shows disadvantages in its operationalizability and does not cover interaction strategies. Further, it has not been used for interactive visualizations until now. It has a strong emphasis on the treatment of errors, a topic which is often ignored in other theories.

It is our belief that, in addition to the description of the five different theories, the categorization scheme can show some strengths and weaknesses of the different theories in a more systematic way. The theories clearly have different focal points but also overlapping areas. Problem-solving and hypothesis generation/testing are covered quite well in all theories. On the other hand, we would like to point out that insight generation, a concept discussed to a great extent in information visualization and visual analytics, is not emphasized in most theories. A categorization scheme as the one in figure 1 makes it easier to detect such features of theories and might be of some practical interest when used as an aid to decide on analysis focus and analysis direction for the evaluation of visual analytics methods.

6.1 Future Research Agenda

In summary, the five theories described in this paper show that although a lot of research has been done in recent years, a comprehensive theory for human information processing in visual analytics is still missing. If we take figure 1 as starting point, three different paths to deal with this information deficit might be worth a second look:

6.1.1 Path 1 - "Merge theories to a coherent theoretical framework"

But which theories could or should be merged? For example, interaction theories, decision making processes and collaboration issues are only tackled in distributed cognition theories to a adequate extent. Depending on the research focus, either graph comprehensions theories, to add lower level processing, or sense making theories, to add higher level processing, could be interesting candidates for a merger with distributed cognition.

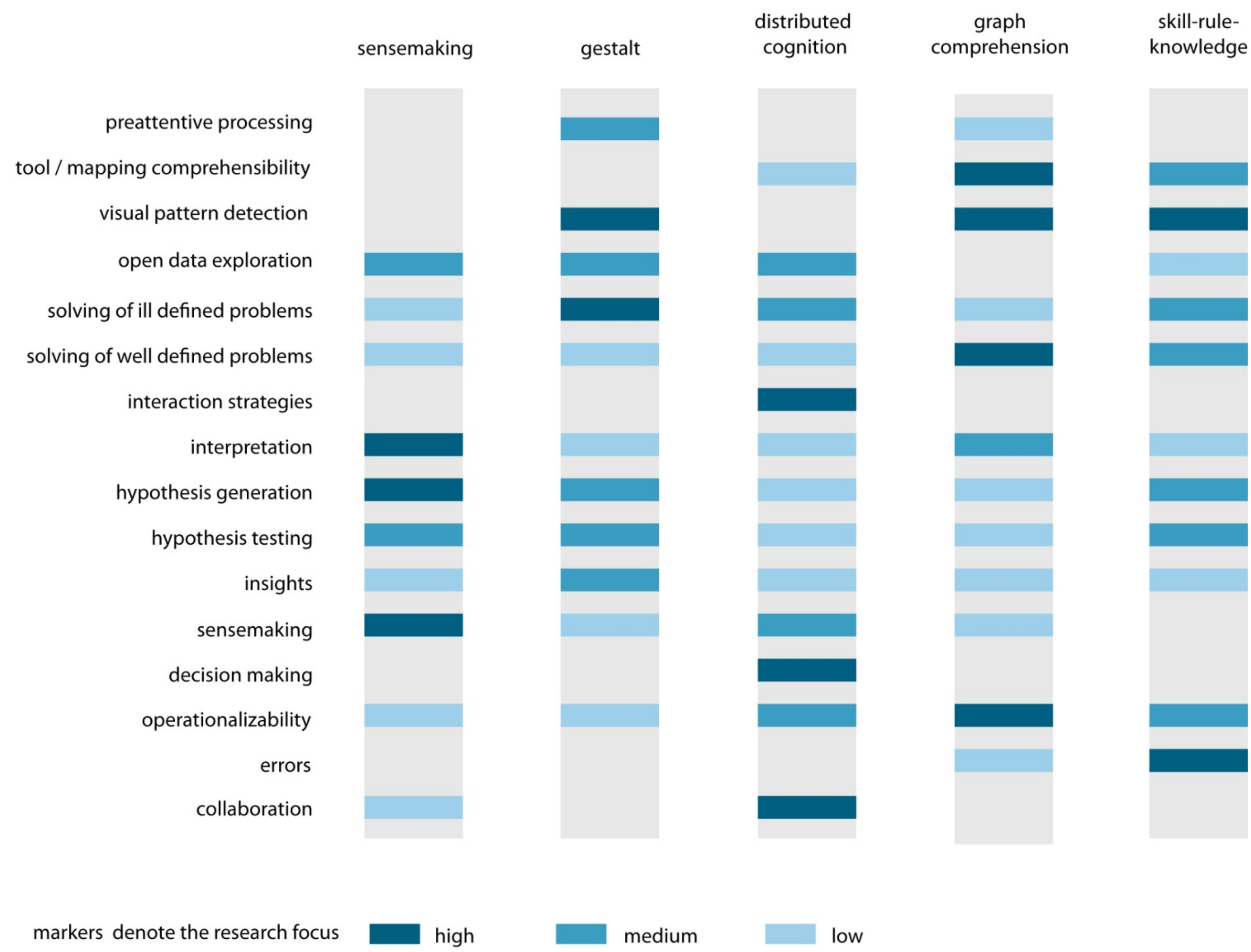

Fig. 1. Characterization of theories based on relevant categories for VA.

However, it has to be considered that some of the theories are not suitable for merging, for example the sensemaking theory according to Pirolli and Card [40], which makes fairly specific assumptions about the reasoning process, which are to some extent not consistent with other approaches.

6.1.2 Path 2 - "Extend or transfer theories"

The white spaces in existing theories could be filled by merging parts of the five discussed theories, but also by including or transferring other concepts (e.g. interaction concepts) from other research areas. For example, graph comprehension theories could be better applied to VA if decision making could be covered more systematically, since there is a vast amount of decision making theories in cognitive psychology. Regarding interaction, also Shneiderman's Visual Information-Seeking Mantra [54] or similar models of interaction might be candidates to extend one of the theories described above.

6.1.3 Path 3 - "Create novel theories"

Another possible path aside from merging and patching might be the creation of a novel theory from scratch. Taking into consideration that the creation of a new theory leads to considerable expenditures not only in the theoretical development alone, but also in providing empirical evidence for the theory, this path might be the most risky and time-consuming. However, the categorization scheme provided above (see figure 1) might be supportive of setting the main components and priorities for the creation of a new theory.

As a final remark, VA is sometimes seen as a "science for practitioners" by emphasizing the applicatory nature of this research field. This raises the question whether theories are needed in VA at all and what would be the benefits of more comprehensive theories. In our view, theories provide an explanation of the core part of VA, the understanding of analytical processes in the human mind. Without theories, designing and evaluating VA methods would be like fishing in muddy water. Theories allow to explicate users' behavior systematically, thus they can be used to make predictions, combine singular research results and enable the deduction of guidelines. Theories can put order into the "user puzzle". But current theories about analytical processes in VA are sorely lacking in comprehensiveness and completeness - and who wants to solve a puzzle with important pieces missing?

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