Distribution of Information Processing While Performing Complex Cognitive Activities with Visualization Tools

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Abstract When using visualization tools to perform complex cognitive activities, such as sense-making, analytical reasoning, and learning, human users and visualization tools form a joint cognitive system. Through processing and transfer of information within and among the components of this system, complex problems are solved, complex decisions are made, and complex cognitive processes emerge—all in a manner that would not be easily performable by the human or the visualization tool alone. Although researchers have recognized this, no systematic treatment of how to best distribute the information-processing load during the performance of complex cognitive activities is available in the existing literature. While previous research has identified some relevant principles that shed light on this issue, the pertinent research findings are not integrated into coherent models and frameworks, and are scattered across many disciplines, such as cognitive psychology, educational psychology, information visualization, data analytics, and computer science. This chapter provides an initial examination of this issue by identifying and discussing some key concerns, integrating some fundamental concepts, and highlighting some current research gaps that require future study. The issues examined in this chapter are of importance to many domains, including visual analytics, data and information visualization, human-information interaction, educational and cognitive technologies, and human-computer interaction design. The approach taken in this chapter is human-centered, focusing on the distribution of information processing with the ultimate purpose of supporting the complex cognitive activities of human users of visualization tools.

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W. Huang (ed.), *Handbook of Human Centric Visualization*,
DOI 10.1007/978-1-4614-7485-2_28,

1 Introduction

The use of visualization tools (VTs) is on the rise in many spheres of human activity. Such tools are increasingly being used in the areas of insurance, education, science, finance, public health, emergency management, journalism, business, and others (see, e.g., [23, 32, 56, 57, 64]). In this chapter, a VT is an electronic computational tool that visually represents (i.e., encodes and visualizes) data and/or information at its visually perceptible interface to help human users[1] analyze data, solve problems, make decisions, and perform other such complex cognitive activities. Therefore, visualizations—whether simple or complex—that do not have an electronic, computational component that allows them to be interactive, and to potentially perform computational and analytic operations, are not considered VTs. Examples of visualizations that are not considered VTs are info-graphics and other static information representations. Furthermore, this chapter is concerned with VTs that support the performance of complex cognitive activities—activities that involve higher-order cognitive processes and occur under complex conditions. Examples of complex cognitive activities are problem solving, sense-making, learning, decision making, and analytical reasoning. VTs have been referred to in the literature by different names, including, but not limited to, cognitive activity support tools, decision support tools, knowledge discovery tools, visual analytics tools, educational tools, and cognitive tools and technologies. This chapter is concerned with all such tools, and does not confine itself to discussion of tools in only one domain. Therefore, any tool—whether used in the context of science, business, insurance, education, libraries, or journalism—that is electronic, computational, and encodes and displays data and/or information in visual forms at its visually perceptible interface is considered a VT.

When using VTs to support the performance of complex cognitive activities, users and VTs are coupled together to form a joint cognitive system [53, 55]. Because of this, information processing that is required to perform complex cognitive activities is distributed across the components of the human-VT system. Moreover, unlike static information-based tools, VTs can take on an active role in the processing of information. For example, VTs can perform data analysis and engage in data mining and knowledge discovery, and can store, manipulate, and encode data in numerous forms. However, as this is a relatively young research area, we still have very little understanding of how to best distribute the information-processing load during the performance of different complex cognitive activities. For example, consider an emergency manager performing time-critical risk and impact analysis of a pending natural disaster. Consider also a university student learning about subatomic particle interactions as part of an undergraduate course. In both cases, a VT could greatly benefit the performance of the activity; however, the ideal distribution of information-processing load in each case would almost

[1] In this chapter, the terms human and user are used interchangeably.

certainly be much different. In the latter case, the user would benefit from being required to take on much of the information processing—that is, being required to engage in deep and effortful mental processing of the information to develop sophisticated mental models of the phenomena. In the former case, however, the user would likely benefit most from having the VT shoulder much of the information-processing load, through data analysis and other computational processes, to simply communicate the result for quick decision making. This chapter will more fully explicate the underlying issue, describe some of the features that affect the ideal distribution of information processing, and provide some high-level suggestions as to how information-processing may be best distributed in different contexts.

As this handbook is concerned with human-centric visualization, this chapter assumes a human-centric perspective on information processing in complex cognitive activities. While computational agents may communicate and work together to analyze data, make decisions, and so on, we are interested in joint cognitive systems that have a human core. In such systems, although some information processing may not be taken on by the human, the human is an essential component of the system, and often has the majority of control in the performance of the activity. Moreover, the goal of using VTs is usually to ultimately alter the mental state of the human user. In other words, the performance of an activity results in some change in the user's knowledge, understanding, worldview, schemas, mental models, or other forms of internal, mental representation.

The structure of this chapter is as follows: Sect. 2 will discuss some necessary background concepts and terminology, including distributed cognition and interactive coupling, complex cognitive activities, information processing and human-information interaction, and types and functions of VTs. Section 3 will examine previous work that has categorized the human-VT system into five spaces—information, computing, representation, interaction, and mental space—and will discuss how information is processed in each of the spaces. Section 4 will identify some of the factors that contribute to the ideal distribution of information processing, including activities, information spaces, users, and VTs, and will include a discussion of how researchers and designers can think about the distribution of information processing according to each of these factors. Finally, Sect. 5 will summarize the ideas discussed in the chapter.

2 Background

This section will examine some necessary background concepts and terminology. Four main issues will be briefly examined: (1) distributed cognition and interactive coupling, (2) complex cognitive activities, (3) information processing and human-information interaction, and (4) types and functions of VTs.

2.1 Distributed Cognition and Interactive Coupling

Until recently, the unit of analysis for human cognition—i.e., that which was considered the necessary scope of study to understand human cognition—was typically limited to internal mental structures and processes. Recent research in the cognitive sciences, however, has led scholars to posit that the unit of analysis should be extended to include the body, the external environment, and interactions with objects (e.g., people, artifacts) within the external environment. Numerous subdomains and areas of interest have emerged from this consequential and far-reaching revision in our understanding of human cognition, each emphasizing different aspects of cognition and using slightly different terminology—e.g., suggesting that cognition is embodied, extended, embedded, distributed, and/or situated (see [4, 8, 21, 31, 48]). Whatever the preferred terminology, these recent perspectives all characterize human cognition as an emergent feature of interactions among the internal mental space, the rest of the body, and the external environment and its objects and processes.

One of the better-known theories to emerge from the shifting landscape in cognitive science research is known as the theory of distributed cognition. This theory proposes that cognitive processes are distributed across the internal mental space and the external environment. Hollan et al. [19] posit that this distribution occurs in three main ways: socially, temporally, and across internal (mental) representations and external representations of information. In order to perform complex cognitive activities, such as those performed with the support of VTs, one often combines and processes information from both internal and external representations, in an integrative and dynamic manner [68].

These new perspectives on cognition are not simply changes in terminology; rather, they effect changes in the methodology of cognitive science research and in the explanatory methods of human cognition [8]. Thus, there are vast implications for how we conceptualize the use of VTs for performing complex cognitive activities. Not only do VTs help with memory offloading and computation; they are also integral components of a joint cognitive system, and fundamentally shape and alter cognitive processes [33, 52, 53]. Kirsh [25] suggests that a key tenet of distributed cognition is that of coordination—that the user-VT relation is dynamic, involving reciprocal action and harmonious interaction. That is, the key interactive relation between the user and VT has to do with coordination rather than control. In other words, there is a partnership between a user and VT that results in reciprocal causal influence. This notion of computational technologies acting as partners in cognition has been around for some time now. For instance, based on the theory of distributed cognition, Salomon and colleagues [48, 50] emphasized the idea of thinking *with* computers two decades ago (see [49] for a more recent discussion of the issue). While such ideas have been discussed in the field of education and psychology for some time, visualization researchers have been slow to catch up.

When two entities reciprocally interact—i.e., changes in one cause changes in the other—and the state trajectory of one is dependent on the state trajectory of the other, the two entities are considered to be closely coupled [26]. In the context of a user-VT system, there is reciprocal interaction and mutual causal influence between the user and the VT. Furthermore, since cognitive processes are intrinsically temporal and dynamic, interactive VTs can create a harmony and a close temporal coupling with cognitive processes [4, 24, 25, 53]. This close and interactive coupling is significant, as the user and the VT each have a causal influence on one another (see [7, 52]). Due to their emergent nature, *the performance of any complex cognitive activity is fundamentally affected by the characteristics of both the user and the VT, as well as the strength of the coupling between them* (see [55] for a discussion of what contributes to the strength of this coupling). Therefore, to study the performance of complex cognitive activities with VTs, the unit of analysis must be the user-VT system.

While computers may communicate and work together to analyze data, make decisions, and so on, we are interested in joint cognitive systems that have a human core. In user-VT systems, although the user does not do all of the information processing, he or she is an essential component of the system. Moreover, the goal of using VTs is usually to alter the mental state of the user and to help carry out complex cognitive activities. This primary focus on mental state changes is a fundamental aspect of all human-centric informatics research (see Sect. 2.3).

2.2 Complex Cognitive Activities

Cognitive scientists make a distinction between complex cognition and simple cognition. Whereas simple cognition refers to elementary cognitive and perceptual processes, complex cognition refers to high-level, emergent cognitive processes, such as decision making and problem solving, that take place in complex environments and/or under complex conditions [30, 51, 63]. To emphasize the active aspect of such cognitive processes, and to emphasize their complex nature, they can be referred to as complex cognitive activities (see, e.g., [12]). Although there are numerous complex cognitive activities that can be performed, some of the more common ones are decision making, problem solving, planning, analyzing, forecasting, reasoning, learning, and sense-making [53]. Section 4.1 will elaborate on some of some of these.

2.3 Information Processing and Human-Information Interaction

Complex cognitive activities involve the engagement of human beings in goal-directed information processing [15, 30, 63]. What is meant by the term 'information processing', however, varies according to the context and domain in which it is used. Moreover, such a definition also depends on the definition of information itself, which also varies according to the domain and context. We adopt Bates' [1] definition of information as the pattern of organization of matter and energy. Information processing, then, has to do with changes in the organization of matter and energy. In the context of this chapter, however, the concern is more specific—information processing refers to any change in a mental or physical state (i.e., organization) of the user-VT system. Just as physical state changes provide the basis for classical information theory, it is the focus on mental state changes that characterizes human-centric informatics [35]. Thus, although information processing done by VTs can by analyzed through the lens of classical information theory, because the approach here is human-centric, and because VTs necessarily involve human users, information-processing that results in at least some mental-state changes in a human user is the focus of this chapter.

It should be noted that there is debate that crosses multiple disciplines including cognitive science, artificial intelligence, and philosophy of mind, regarding the information-processing theory of cognition. Much of the disagreement that exists seems to be with the way that 'information' and 'information processing' are defined (see [5]). In this chapter, however, we are not endorsing any particular take on this issue, nor are we concerned with technical definitions in these different fields. Regardless of the adopted theory and terminology, in accordance with the definitions given above, users and VTs share the load of the requisite information processing during the performance of complex cognitive activities.

2.4 Types and Functions of VTs

As mentioned previously, VTs have the following necessary characteristics: they are electronic, computational, and encode and display data and/or information in the form of visual representations (VRs) at their visually perceptible interface. As this characterization is general, there is a broad range of VTs, with varying functions and levels of sophistication, to which the ideas in this chapter are applicable. Some VTs have tremendous computing power (e.g., those that are connected to distributed computer networks), while others have comparatively little power (e.g., some tablet computers). This dictates their ability to perform complex computational analysis, and thus, also determines their potential functions. For instance, a tablet-based VT cannot (as of now) be used to sequence the human genome and display VRs to offer a visual data-mining component for further genome analysis. However, such a VT can support doctors in their decision making by performing simple analysis on patient data and displaying and inviting actions upon VRs. Depending on the context of use, some VTs do not need to perform much computational analysis, and simply need to display VRs and respond to actions from the user (see Sect. 4.4). In addition, VTs offer all kinds of different possibilities for interaction with the underlying information. Some invite the performance of only one or two interactions (e.g., selecting, filtering), whereas others offer many (see [53] for more discussion of this issue). Another consideration still is the types of interactions that are performed. These range from allowing the user to only access existing information, to annotate it (i.e., add a layer of personal meta-information), to modify properties of the existing information, to insert completely new information into the VT, or any combination thereof. Still another dimension in which VTs differ is the degree to which a VT takes a proactive role in information processing. VTs can simply wait for user input before responding, can engage in computational processing in the background, or can actively prompt the user with some information that the VT deems to be appropriate.

Aside from their processing power, storage, and other such characteristics, VTs are also used in a wide variety of domains. For instance, VTs can be used in educational, financial, scientific, journalistic, insurance, emergency response, healthcare, national defense, and many other settings. Thus, the necessary demands of each domain require VTs with different characteristics; however, this chapter is relevant across all domains in which VTs are used to support the performance of complex cognitive activities.

3 Structure of the Human-VT Cognitive System

In order to discuss the distribution of information processing in a human-VT system, there must be a clear division of the different components of the system. Although there is necessary overlap, each component must have a clear function. In previous work, the authors have categorized the human-VT system into five spaces: (1) information space, (2) computing space, (3) representation space, (4) interaction space, and (5) mental space. Information space refers to the body of information with which users interact while performing complex cognitive activities. Computing space is concerned with encoding and storing internal representations of items from an information space and performing operations upon them. Representation space is concerned with encoding and displaying VRs of information so as to be visually perceptible to the user. Interaction space is where actions are performed and consequent reactions occur. Finally, mental space refers to the space in which internal mental events and operations take place (e.g., apprehension, induction, deduction, memory encoding, memory storage, memory retrieval, judgment, classification, categorization). Readers are referred to [54] for a more detailed discussion of these different spaces. Figure 1 depicts this categorization of the human-VT cognitive system.

According to this categorization, the information processing that occurs in each space can be examined in relative isolation. The following three subsections will examine information processing in (1) mental space, (2) computing space, and (3) representation and interaction space. Because of the necessary dependence that exists between interaction and representation space (i.e., actions are performed on VRs, reactions are perceived from changes in VRs), we have chosen to examine them together. However, for other purposes, such as interaction design and represen-

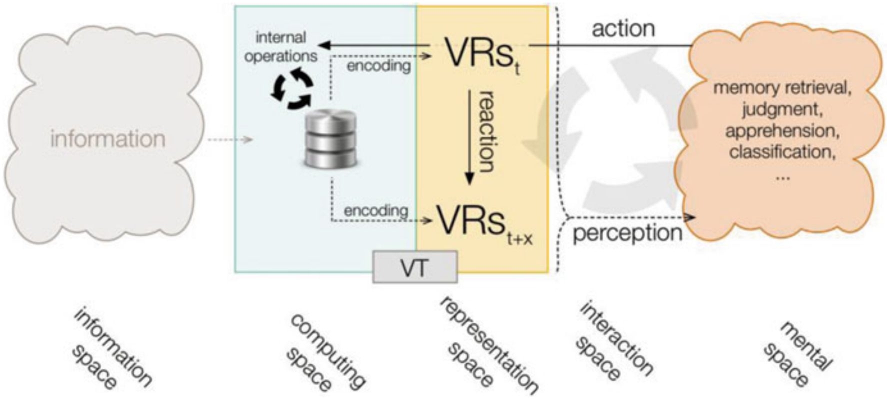

Fig. 1 Categorization of the human-VT cognitive system into five spaces

tation design, it can be important to examine these two spaces independently [53]. Although information processing occurs in all dynamic information spaces (e.g., genetic mutation, social interaction, and financial trading all involve information processing), it is not necessary to examine in light of the goals of this chapter—namely, to examine the distribution of information processing in a user-VT system. It should be noted that decomposing the user-VT system to examine information processing in each of these spaces is useful as an analytical, conceptual tool to facilitate systematic thinking about this issue. In practice, information processing often occurs simultaneously, and in an interdependent manner, in each of these different spaces. Therefore, analyzing the distribution of information processing in this manner serves primarily to assist researchers and designers with conceptualization, rather than to offer prescriptive design guidelines.

3.1 Information Processing in Mental Space

Information processing in mental space consists of changes in the mental state of a user. Changes in one's mental state can take place by working with only internal, mental representations, or by acting upon external representations—i.e., VRs—to co-ordinate and adjust internal mental representations (see [11, 14, 27, 53]). When information processing in mental space involves working with external representations, such as VRs, perception—i.e., awareness of and interpretation of external stimuli—becomes part of the information processing. This perceptual processing of information is a bridge between the internal mental space of the user and the external world. Therefore, the manner in which information is processed by the human perceptual system is an important consideration for research, design, and evaluation of any VT. Figure 2 depicts the different stages of information processing in mental space. The earliest stage of the process can be referred to

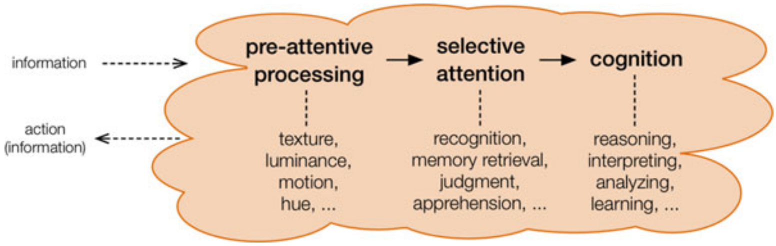

Fig. 2 Information processing in mental space

as pre-attentive processing (also called early vision by some scientists). Although there is considerable debate regarding the boundary of vision and cognition, and the degree to which pre-attentive processing is influenced by cognition (see [20, 43]), pre-attentive processing is typically considered to operate largely independent of conscious cognitive processing and prior knowledge. Therefore, some universal principles of pre-attentive processing can be identified. These are very important for the effective design of VTs—especially for the design of VRs—as some of the features of pre-attentive processing can be exploited with proper visualization design. For example, our visual systems pre-attentively process many features within our visual field in less than 250 milliseconds without requiring any conscious cognitive effort [17]. Such features include length, orientation, width, hue, curvature, and intersection, among others (see [17]). The second stage of information processing in mental space is the stage of selective attention, where attention is concentrated to a specific area in the visual field. This stage can generally be considered as the bridge between perception and cognition [44]. In the context of most visualization research, the first two stages are typically considered as being part of perception. Researchers have identified many principles and guidelines for VR design that are in accordance with the first two stages of processing (e.g., see [9, 34, 38, 65]).

The third stage involves conscious and deliberate information processing to adjust, add to, create, or remove mental representations, models, and/or schemas. In this stage, users consciously perform tasks such as generating hypotheses, comparing them to existing mental structures, constructing analogies, chaining items of information together through inference, categorizing information items, and many others. This is also where metacognitive awareness and regulation take place. That is, one plans cognitive tasks, monitors the performance of such tasks, and evaluates the outcomes of such tasks. Although many visualization researchers have suggested a need for deeper understanding of cognitive—rather than just perceptual—issues in VT use (see [13, 16, 33, 37, 64]), many visualization researchers still consider only the first two stages in their research (see [40] for more discussion). As a result, there is a lack of research in the visualization literature that deals with information processing in mental space in a comprehensive manner.

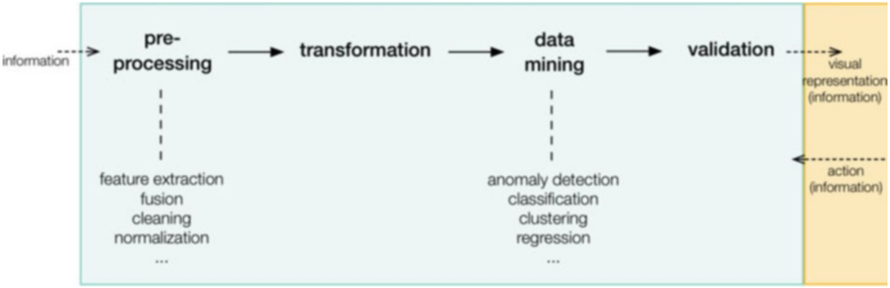

Fig. 3 Information processing in computing space

3.2 Information Processing in Computing Space

Information processing in computing space is concerned primarily with encoding data and other information items into data representations, performing operations upon such representations, and organizing and storing such representations.[2] The ability to computationally process information makes VTs much more powerful mediators of human thinking than static media. Indeed, the speed and precision of information processing in computing space allows VTs to perform all kinds of information processing tasks that would be difficult or impossible for a human user to perform. Figure 3 depicts the stages of information processing in computing space. Although there is no commonly agreed upon set or number of steps, and the labeling changes according to the domain and application of use, a number of potentially present stages can be identified. Depending on the VT, certain stages may not be present or may be skipped during some portion of an activity.

First, information comes from an information space and is input into the VT—this information can come from many sources: textual sources such as e-mails, web pages, and other documents; databases; images and videos; and sensors, such as gyroscopes, altimeters, particle detectors, barometers, and others. Incoming information must often first be pre-processed. Depending on the context, pre-processing can include sub-processes such as cleaning, filtering, fusion, integration, normalization, and others. In other words, this stage processes the information so that it is consistent; free from errors, missing values, and duplicates; and so that both the VT and the user can further process it in a meaningful way. Statistical and mathematical procedures, such as data transformations, also take place within computing space (the transformation stage is sometimes considered as part of the pre-processing stage and not as its own stage). In the most basic sense, data transformations are computational procedures that convert between data representations. These data transformations serve multiple functions. First,

[2]Representations in computing space (i.e., data representations) are not visually perceptible to users and should not be confused with visual representations in representation space.

data transformations can create new, derived information from the existing data. In this sense, data transformations create a new subspace of information that is derived from the information space. Second, data transformations can convert data into representational forms that are best suited for encoding in VRs. Third, data transformations can result in representations that are better suited to a user's tasks (for more discussion of data representations and transformations in the context of visualization see [22]). The third step of information processing in computing space involves processing information to discover meaningful patterns—also known as data mining. This stage often involves the performance of computational tasks such as classification, clustering, regression, and anomaly detection. Finally, if the data-mining stage does occur, it is often necessary to check whether the patterns discovered by the data mining algorithms are valid. If there are training samples to facilitate the data-mining step, for example, there may be over-fitting of the model.

Aside from the typical challenges of information processing in computing space, due to the influx of information in all domains, the increase in computing power, and the increasing demand for analytics, new challenges are emerging. For example, incoming information is often heterogeneous, presenting many challenges for existing relational database systems, computational algorithms, and other well-established architectures and techniques (see [23, 66, 67] for more discussion of these issues).

As computing space is only one component of the user-VT system, it receives from and transmits information to other spaces—namely, representation space and interaction space. An additional step of information processing, which bridges computing space and representation space, is the encoding of information in visually perceptible forms (i.e., VRs) for the user to perceive and act upon. This space also receives information from the user in the form of actions. Actions performed by the user can influence and/or be components of any of the stages of information processing in this space (e.g., as in interactive visual data mining).

3.3 Information Processing in Representation and Interaction Space

Because information stored in computing space is not directly accessible to users, and because the form in which information is represented in computing space is not meaningful to humans, VTs encode information from computing space into meaningful visual forms in representation space. These visual forms (i.e., VRs) are the primary means through which users access, work with, and interpret the underlying information. Examples of common VRs are geo-spatial maps, network diagrams, natural and formal languages, treemaps, glyphs, and Venn diagrams. Cognitive scientists have studied VRs for many years, and have discovered numerous benefits that VRs provide for our thinking and reasoning processes (see, e.g., [27]). Furthermore, because VTs inherently have interactive potential, VRs can be made malleable, providing numerous benefits to the user for performing complex cognitive activities [53]. The back-and-forth flow of information that occurs in these two spaces is critical to human-information discourse. Information processing occurs at the boundary of computing space and representation space, where information is encoded into VRs. This information is then perceptually detected by the user and further processed in mental space. Information processing in these spaces also occurs when users input information by performing actions, and VRs are removed, created, or modified in the representation space.

As was mentioned in Sect. 2.4, VTs vary in terms of how pro-active they are in their information processing. One underexplored area of research is to what degree VTs should shoulder the information-processing load in the context of a single interaction that is taking place. For instance, if the user wishes to perform an annotating action, the VT can be completely passive, requiring the user to perform all of the work, or can be active, making suggestions or performing automatic annotations based on the user's action history.

One of the challenges for researchers and designers of VTs is knowing what interactive possibilities can and should be made available to users, and how such interactions impact cognitive and perceptual processes during the performance of complex cognitive activities [64]. Sedig and Parsons [53] have recently developed a framework to address this challenge. The framework includes a comprehensive catalog of fundamental action patterns that users perform when engaged in complex cognitive activities. While each of these actions necessarily impacts information processing in different ways, another important factor to consider is the manner in which interactions are operationalized. Different ways of operationalizing the action and reaction component of an interaction have different cognitive effects, and ultimately influence information processing throughout the human-VT system in different ways. Another chapter of this book (see [55]) presents a framework dealing with macro- and micro-level interactivity considerations for visualization tools—where interactivity refers to the quality of interaction between a user and a VT. As part of the framework, 12 micro-level interactivity elements, which collectively give structure to an individual interaction, are identified and characterized. Each element has different operational forms, and each is identified and briefly discussed. As any individual interaction is composed of an action and a reaction component, some of the elements pertain to the action component and some pertain to the reaction component. The operationalization of each of these elements constitutes part of the information processing that occurs in these two spaces. For instance, one element that is present in both action and reaction is *flow*. Flow is concerned with how an action or reaction is parsed in time. Flow has two operational forms: discrete and continuous. If flow is discrete, the action or reaction occurs instantaneously and/or is punctuated. If flow is continuous, the action or reaction occurs over a span of time in a fluid manner. The manner in which flow is operationalized affects information processing in representation space and interaction space (see [55] for further detail), and has been shown to have a significant impact on the performance of complex cognitive activities (see Sect. 4.5 for some discussion of this issue). Figure 4 depicts some of these aforementioned aspects of information processing in interaction and representation space.

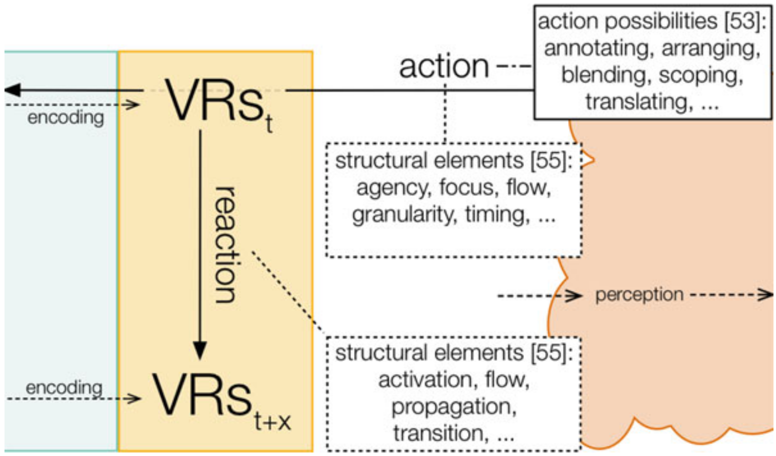

Fig. 4 Information processing in interaction and representation space

4 Factors Affecting the Ideal Distribution of Information Processing

No systematic treatment of how to best distribute the information-processing load during the performance of complex cognitive activities is available in the existing literature. Although some previous research has identified some relevant principles and guidelines, the relevant information is not integrated and is scattered across many disciplines, such as cognitive psychology, educational psychology, information visualization, data analytics, and computer science. Because of the highly variable nature of VTs and complex cognitive activities, any ideal prescription on this matter is very much activity-, user-, and VT-dependent. For example, an intelligence analyst making time-critical decisions, a scientist making sense of research collections over a long period of time, and a student learning about biological processes, would each benefit from different distributions of the requisite information-processing load. To get a sense of the factors that contribute to this ideal distribution, we examine four interrelated considerations on which the ideal distribution is dependent: (1) activities, (2) users, (3) information spaces, and (4) visualization tools. Following the examination of each of these considerations, we will discuss some of the implications for the distribution of information processing.

4.1 Activity-Dependent

Although there are overlaps among different complex cognitive activities, and activities are often embedded within one another during the performance of an overall activity, it is still beneficial to identify their individual characteristics (see also [53]). Depending on the activity that is being performed, information processing should be distributed differently. Having an idea of the characteristics of an activity can help with research and design decisions. Moreover, since activities are often embedded within one another as sub-activities, having a clear conceptualization of each sub-activity can allow the information processing to be best distributed for a particular stage of an overall activity. Although many different activities with distinguishing features can be identified, in what follows, we examine only three activities: sense-making, analytical reasoning, and learning. As this chapter is mostly a preliminary examination, future work is needed to more fully explicate different complex cognitive activities, particularly in the context of VTs.

4.1.1 Sense-Making

Sense-making is a term that has often been used in a somewhat nebulous manner. In an attempt to clarify its meaning, Klein et al. [28] briefly examine five common concepts through which sense-making can be primarily understood: creativity, curiosity, comprehension, mental modeling, and situation awareness. Although each of these can be considered as facets of sense-making, they suggest that modern researchers typically mean something more than just these. They then posit that the additional characteristics that are implicit in the modern use of the term sense-making are "*motivated*, *continuous effort* to *understand connections* ... in order to *anticipate their trajectories* and *act effectively*" (p. 71, italics added). In a companion paper [29], they attempt to explicate the process of sense-making, suggesting that it begins with some mental model—how-ever minimal—that involves tasks such as elaborating on the model by adding to it, questioning the model and its assumptions, rejecting the model and replacing it, and comparing different models. They posit that the sense-making process involves a closed-loop transition sequence between mental model formation and mental simulation. In response to Klein et al.'s approach to sense-making, Blandford et al. [2] suggest that not enough attention is given to the conceptual structures that people work with when making sense of an information space. They describe sense-making as an 'information journey' that typically starts with either identifying a need (a gap in knowledge) or encountering some information that addresses a latent need or interest. Whatever the particular theory or perspective on sense-making, there are a number of typically present characteristics that can be identified: motivated, continuous, active, inquisitive, open-ended, anticipatory, connective, constructive, and exploratory. Tasks that are typically performed during a sense-making activity include scanning the information space, assessing the relevance of items within the space, selecting items for further attention, examining them in more detail and integrating them into mental models, establishing questions to be asked, determining how to organize the answers, searching for pieces of information, filtering aspects of information, and categorizing items of information [45–47].

4.1.2 Analytical Reasoning

Analytical reasoning is a special type of reasoning, and is based on rational, logical analysis and evaluation of information [53]. Because of its intrinsic analytic nature, an analytical reasoning activity typically involves decomposing or deconstructing an information space to clearly identify its components and their relationships. Analytical reasoning is a core concern of visual analytics, and is an activity performed by analysts from numerous domains, including finance, insurance, national defense, intelligence, climate science, and others [18, 64]. Although some aspects of an analytical reasoning activity can be open-ended and exploratory, one feature that distinguishes it from other complex cognitive activities is its more focused, closed-ended nature that requires the performance of tasks that have a limited set of viable, definite solutions. For instance, an analyst is often presented with a claim and must examine the evidence to either confirm or contradict the claim [58]. Other typical tasks involved in an analytical reasoning activity include examining an information space to find alternative or conflicting evidence in order to challenge an assumption or claim, asserting and testing key assumptions, testing biases, assessing alternatives, comparing and contrasting different hypotheses with the goal of identifying the most plausible one, detecting causal relationships and determining the nature of the supporting evidence, determining which available resources to use, tracing and identifying cause-effect relationships, predicting future states of an information space, identifying the variables within an information space, supporting conclusions and statements with adequate data or evidence, and elaborating an argument and developing its implications [18, 42, 58, 64].

4.1.3 Learning

Learning refers to an activity in which one gains knowledge of an information space and develops skills and capabilities to function in the space [36]. During the process of learning, information is converted into knowledge and assimilated into pre-existing mental models, thereby creating new or revised knowledge structures [3]. Although the exact mechanisms by which one learns are not well understood, a number of mental-state changes that typically occur during a learning activity can be identified. Chi and Ohlsson [6] characterize such changes as potentially occurring along seven different dimensions: (1) growth in mental representation (e.g., mental model or schema) of the information space about which one is learning; (2) denser connectedness among knowledge elements that exist in mental space; (3) increased consistency between mental representations and the information space; (4) finer grain of mental representation of an information space along with appreciation of emergent features of the information space; (5) greater complexity of mental representations; (6) mentally re-representing information items at higher levels of abstraction; and (7) developing multiple perspectives of an information space in order to shift vantage points. In other words, during a learning activity, mental models or schemas change along multiple dimensions: size, connectedness, consistency, grain, complexity, abstraction, and perspective. Although these dimensions are separated for analytical purposes, Chi and Ohlsson suggest that when learning is a complex—rather than simple—cognitive activity, there are typically mental-state changes along multiple dimensions simultaneously.

Learning shares characteristics of both sense-making and analytical reasoning. For instance, some aspects of learning are exploratory, inquisitive, and open-ended, whereas others are focused, analytical, and closed-ended. Unlike other complex cognitive activities that may be time-sensitive (e.g., decision making in a disaster scenario), or may not require a deep understanding of the information space (e.g., browsing a dataset to identify outliers), complex learning requires effortful and reflective information processing with the ultimate goal of understanding. In other words, a distinguishing feature of learning as a complex cognitive activity is that the ultimate focus is on creating lasting and meaningful changes in mental space that give one new knowledge and/or skills.

4.2 User-Dependent

While there are obvious differences among users that must be considered for design and evaluation of any VT, such as age and physical or mental ability, there can be significant differences among users even within these typical categories. For example, users differ based on cognitive, thinking, and learning styles. Sternberg [62] identifies 13 prevalent thinking styles—that is, preferred ways of thinking and of using the abilities that one has, and posits that they fundamentally influence one's cognitive performance. Green and Fisher [16] note that individual user differences can have significant effects on problem solving behaviors, tasks such as categorization and information search, and rationality and reasoning (see also [39, 60, 61]). Not only do users have different personalities and cognitive and thinking styles, they also have different levels of knowledge and expertise that fundamentally influence courses of action in any given situation. That is, the extent of one's knowledge, and the sophistication of one's conceptual structures, *determine what action choices one has to draw from when performing a complex cognitive activity* [10]. Petre and Green [41] also emphasize the roles of training and experience in the interpretation of VRs. People see VRs differently—some people see abstract structure, while others see more concrete configurations and detect different features [59]. Users should thus be given different VRs to work with, and should be given multiple action possibilities to work with the given VRs [53]. Treatment of this issue in the visualization literature is sparse, making it difficult to suggest any concrete design guidelines for VTs at this point.

4.3 Information-Space-Dependent

Certain characteristics of an information space fundamentally influence the appropriate distribution of information processing. Such characteristics include the size of the information space, whether information is static or dynamic, homogeneous or heterogeneous, and structured or unstructured. If the information space consists solely of a relatively small dataset that does not require any pre-processing or data mining, for example, most of the information processing occurs in mental space, interaction space, and representation space. In such a case, the function of computing space is simply to encode information in VRs and respond to input from the user's actions (as is the case in many data and information visualization tools). Many of these concerns have been discussed previously in Sect. 3.2. Aside from such concerns, however, are the density, complexity, and other characteristics of an information space that can place a burden on a user's mental space while performing an activity. In other words, some information spaces are more difficult to understand, conceptualize, mentally navigate, and make sense of. For instance, an information space containing complex mathematical concepts and an information space containing simple sports statistics do not require the same amount of mental effort to understand. In the latter case, it may be desirable to place much of the information-processing load on mental space, since a typical activity would require only relatively simple operations (e.g., inferences, categorizations) to be made. In the former case, however, the required information-processing operations may be much more sophisticated, necessitating the transfer of information processing onto other spaces. Although in both cases the user and VT form a joint cognitive system, the former case requires more sophisticated coordination between the user and the VT. In such situations, the manner in which the transactions between the user and VT take place (i.e., via information processing in interaction and representation space) are of critical importance. The manner in which such transactions are operationalized can determine the strength of the coupling of the user-VT system and ultimately affect the quality of the activity being performed (see [55] for more on this issue). Although some recent work has been done in this area, we still do not have a principled understanding of how to best distribute the load of information processing according to the features of the information space.

4.4 VT-Dependent

The ideal distribution of information processing is naturally dependent on the VT that is mediating the human-information discourse. Numerous characteristics of the VT and its underlying technology must be considered. These include processing power, storage capacity, battery power, display resolution, and display size. Furthermore, the activity must be appropriate for the technology so that the necessary tasks can be carried out. If the underlying technology is a handheld device, for example, the possibilities for intense information processing in computing space are limited compared to those of a desktop computer. The underlying technology on which a VT is built also affects the interaction possibilities that can be offered, and the manner in which information can be processed in interaction and representation space. For instance, certain technologies may limit the possible operational forms that interaction elements can take (see Sect. 3.3).

4.5 Discussion

While more research in this area is required before precise descriptions or prescriptions can be given, some previously conducted studies can shed some light on this matter and provide an empirical basis for discussion. Two studies conducted by Sedig and colleagues (see [32, 52]), have not only confirmed that cognitive processes are distributed across users and VTs, that tools shape thinking and reasoning processes and canalize them in certain directions, and that the design of VTs fundamentally influences the performance of complex cognitive activities, but have also made some findings that go against conventional wisdom in the visualization literature. Such wisdom has often promoted ease of use and intuitiveness as hallmarks of well-designed VTs. In other words, the suggestion is often that the load of information processing in mental space should be minimized. However, these two studies have shown that subscribing to such wisdom while designing VTs can actually result in negative effects on the performance of complex cognitive activities. VTs designed according to such advice may unintentionally communicate to the user that he or she need not invest much mental effort to consciously process information and plan his or her actions with care.

Based on the results of the study reported in [52], the authors suggested that VTs should reduce the mental information-processing load while users perform tasks that are not directly focused on information that needs to be integrated into mental space. These include working with menus, buttons, and other interface elements that are not encodings of items within the information space. In contrast, it can be beneficial to increase the mental information-processing load for some tasks that are directly focused on the information space—e.g., tasks that require forming hypotheses about items within the space, comparing and assessing alternatives within the space, and drawing inferences about causal relationships. The second study [32] examined the cognitive effects of different operational forms of the element of *flow* (see Sect. 3.3) while using a VT to support a complex learning activity. The results of the study suggest that ease and intuitiveness of use are not necessarily conducive to deep thinking, and can cause the processing of information in mental space to be more automatic and shallow. Results of the study showed that *participants who used the most intuitive and easy to use version of the VT had significantly lower scores* on post-tests that assessed cognitive performance. Moreover, an extra finding of the study was that the manner in which flow was operationalized significantly affected the amount of time required to complete tasks. The groups using discrete actions—

the more difficult and less intuitive ones—were actually more efficient in completing the tasks. In contrast, *the group that had the most intuitive and easy to use version of the tool took significantly more time* than the other groups. The researchers concluded that this is likely due to the cost associated with performing interactions. When users could undo actions with ease, they were not forced to develop premeditated strategies and reflect carefully before performing an action. Therefore, although counterintuitive according to conventional wisdom in the visualization literature, not only did placing more information-processing load on mental space result in better cognitive performance, but it also resulted in faster completion of tasks.

While such issues are rarely discussed in the visualization literature, they have vast implications for all VTs that support the performance of complex cognitive activities. By understanding the distinction among different types of tasks as highlighted in [52], for instance, designers of VTs can deliberately alter the distribution of information processing according to the tasks that are being performed, and can free up mental resources for the most important information-processing tasks. For example, consider the design of a visual analytics tool for intelligence analysis. If designers are aware of the characteristics of analytical reasoning, as described in Sect. 4.1.2, they can then adjust the load of information processing according to the tasks an analyst is likely to perform. For instance, the information processing required to identify and categorize potential threats can be placed mostly on the computing space. The tasks of assessing a hypothesis to determine its validity and then comparing it to other hypotheses, however, requires very careful and effortful processing of information. As a human analyst has more expertise and better judgment skills than any VT, more of the information-processing load for such a task should be placed on the mental space. Moreover, by providing specific action possibilities (see [53]), and by constraining the operationalization of these action possibilities in particular ways (e.g., as in the study reported in [32]), the thinking processes of the analyst can be canalized in certain directions to result in more effective analysis of the information space. While visualization researchers are often focused on "building impressive tools" [13], discovering and studying the types of issues mentioned above are necessary if we are to develop highly coordinated, strongly coupled user-VT systems.

5 Summary

This chapter has examined the distribution of information processing that occurs when VTs are used to support the performance of complex cognitive activities. When engaged in the performance of such activities, information processing occurs simultaneously in multiple spaces in the joint user-VT cognitive system. Furthermore, the processing that occurs in these different spaces is often interdependent. In order to design and/or evaluate VTs in an effective manner, the issues identified in this chapter must be well understood. This chapter has drawn on research from multiple disciplines, including cognitive and perceptual psychology, computer science, information visualization, visual analytics, and educational technologies, to provide an initial examination of the aforementioned issue of information-processing distribution for complex cognitive activities. By identifying and discussing some key concerns, integrating some fundamental concepts, and highlighting some current research gaps that require future study, this chapter lays some groundwork for future research in this area. The issues examined in this chapter are of importance to many domains, including visual analytics, data and information visualization, human-information interaction, and educational and cognitive technologies.

As society's production of information increases, and the desire to analyze and make sense of this information also increases, the issues discussed in this chapter are becoming more pertinent to all areas of endeavor. Whether in insurance, finance, education, medicine, public health, journalism, science, or other information- and knowledge-based enterprises, humans need to work with VTs to perform their information-based activities. Having a principled understanding of how to best distribute the load of information-processing, according to the considerations identified in this chapter, will allow for the development of VTs that more effectively support the complex cognitive activities of their users.

Acknowledgements The authors would like to thank the Natural Sciences and Engineering Research Council of Canada for their financial support.

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