Towards a Characterization of Interactivity in Visual Analytics

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ABSTRACT: *Designing effective visual analytics systems is challenging. Not only must each component be well understood and effectively designed on its own, but each must also operate in harmony with the rest. To a large extent, the quality of the relationships among components determines how well visual analytic activities are supported. In this paper, we define the quality of interaction among the components of visual analytics systems as interactivity. This paper draws on research from the areas of cognitive and perceptual psychology, human-information interaction, visualization sciences, and interaction design to examine some of the current challenges faced in discussing and characterizing interactivity. In doing so, this paper attempts to contribute to a characterization of interactivity in visual analytics.*

Keywords: Analytical Reasoning, Human-Information Interaction, Interaction Design, Interactivity, Visual Analytics

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1. Introduction

Visual Analytics (VA) has experienced remarkable growth in recent years. Interest in VA systems was initially focused on public safety and security [14], but has quickly spread to finance, insurance, climate science, and many other areas. The discipline of VA arose in response to increasing amounts of data and a general lack of appropriate mechanisms for dealing with and supporting the analysis of such data. The massive influx of data has created a need for systems that support and enhance high–level cognitive activities such as analytical reasoning, knowledge discovery, sense making, forecasting, and decision making.

Because of the broad scope of VA, the large number of interaction and representation techniques, and the complexity of visual analytic activity, much of the focus of VA research has been on "*building impressive tools*" and, as a result, has neglected the cognitive and perceptual issues related to how analysts solve problems, make decisions, and how VA systems can best support complex cognitive activities [12]. To design systems that effectively support visual analytic activity, it is crucial to consider the cognitive and perceptual capacities and needs of analysts [1, 9, 41, 12, 18].[1]

For effective support of visual analytic activities there must be a strong coupling and harmonious functioning among all of the components of VA systems [31]. Computational methods, databases, software infrastructures, input and output devices, interactive

[1] In this paper the terms user and analyst are used interchangeably.

representations, and users are all examples of such components. In this paper, we define interactivity as the quality of interaction among the various components of a VA system. One of the current problems in discussing *interactivity* is that the terms interaction and interactivity are often used loosely and interchangeably [1, 36]. Broadly speaking, interaction refers to reciprocal action—that is, action and reaction. The suffix "*ity*" is used to form nouns that denote the quality or condition of something. Therefore, interactivity refers to the quality or condition of interaction. By defining *interaction* and *interactivity* in this manner, a clear distinction is made between them, and each can be analyzed and developed in relative independence. The distinction between interaction and interactivity is important—there may be interaction between components of a VA system, but if the quality of the interaction is not good, the system will not effectively support analytical reasoning activities. As VA is an inherently interdisciplinary science, this paper accordingly draws on research from the areas of cognitive and perceptual psychology, human-information interaction, visualization sciences, and interaction design, in an attempt to provide a preliminary characterization of interactivity in VA.

The structure of this paper is as follows. Before discussing interactivity in detail, section 2 examines the major structural divisions of VA. Section 3 characterizes some factors of interactivity by examining the quality of interaction among these structural divisions. Section 4 applies the identified interactivity factors to a brief scenario. Finally, section 5 provides a summary and some future research directions.

2. Visual Analytics Structure

To broadly conceptualize the structure of VA, we propose a rough division into 5 different spaces:

- Information space
- Computing space
- Representation space
- Interaction space
- Mental space

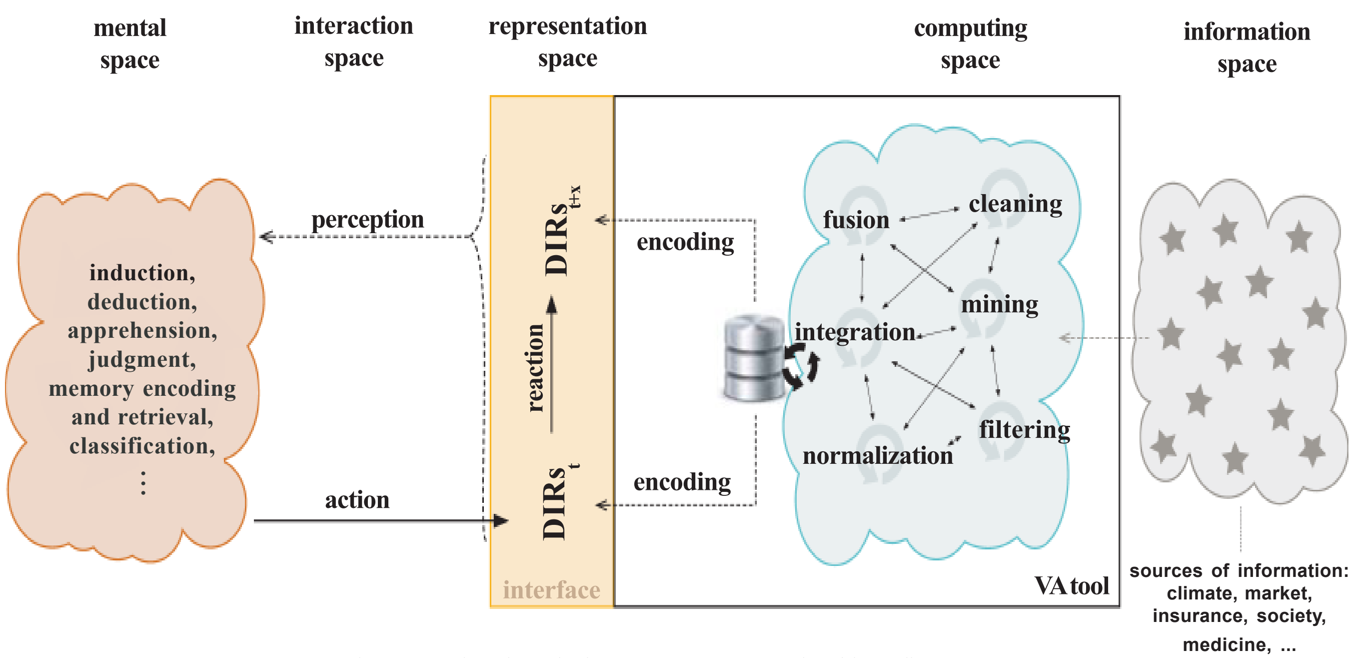

Figure 1. Visual analytics structure categorized into five spaces

All of the components of VA systems can be categorized according to these spaces. Categorizing VA in this manner can help researchers to examine each space in relative isolation, while still keeping in mind their necessary relationships. As this categorization is at a high level, numerous sub–spaces may be identified at different levels of granularity. This level of categorization, however, allows for discussion of the features of VA using a common language that is at a high enough level so as to be compatible with terminology that has been established at lower levels. Additionally, and what is most important in this paper, such a categorization facilitates a discussion of the interactivity of VA systems. Figure 1 depicts the proposed categorization and the relationships among each of these spaces. Each will be discussed in more detail in the following sections.

2.1 Information Space

The most basic function of VA systems is to enable human–information discourse [41].While research has recently been focusing on the human side of this discourse, not much attention has been paid to conceptualizing the information side. Many researchers in visualization sciences refer to the body of information with which users engage in discourse as 'information space' (e.g., [41, 18, 28, 29, 47]). However, aside from sporadic contributions (e.g., [30]), not much effort has been placed on the development of general models, theories, or characterizations of information space within the visualization literature. Moreover, researchers in multiple disciplines, such as information science [50], visualization science [10], and human–information interaction [25], have noted in recent years a lack of clarity surrounding the relationships among data, information, and knowledge. For many decades, researchers in various informatics disciplines have been working towards defining such concepts, and we propose that building upon some of this work can contribute to a conceptualization of information space for the VA community. According to Bates [4] and Marchionini [25], data and information can be characterized as increasingly ordered and complex forms of energy. Data originate in discernible differences in states of an information space—that is, states describable in terms of space, time, and energy [6]. These discernible differences are perceived by some sensory apparatus (e.g., by humans, computers, robots, sensors). Data manifest in many forms depending on how they are detected and measured. For example, a sensor may detect discernable differences in an information space such as an ocean. Depending on the amount of energy and on the sensors that are used, some differences are discerned by the sensor. It may detect differences in the water pressure and temperature, or in wave height, for example. Such discernible differences are then systematically mapped to some code, usually in the form of symbolic representation (e.g., numbers or letters), and then stored. The result of this process, stored symbolic representations, is typically what is meant when the term '*data*' is used in the visualization literature. In other words, data are disconnected symbolic representations of discernable differences within an information space. Significant regularities that reside in data are referred to as information [6]. Such regularities imply relations and, as knowledge is largely concerned with understanding relations, it is information that has the potential to lead to knowledge—by *informing* analysts about regularities within an information space.

Although basic and abstract, this conceptualization is useful for at least two reasons: 1) The scope of VA is quite broad, and all kinds of particular information spaces—whether abstract, concrete, large, small, static, or dynamic, as well as their temporal and spatial characteristics—must be accounted for. Such a definition accounts for all possible information spaces. 2) Conceptualizing information in this manner allows for more fine–grained elaboration of particular information spaces, while maintaining a common conceptual foundation. Building from a basic but broad definition allows for further characterization without risking complete fragmentation. Researchers can discuss, compare, and contrast particular information spaces with a common terminology and conceptual foundation.

Viewing bodies of information as *spaces* provides many benefits for conceptualizing the information side of the human–information discourse. This approach can assist especially with the conceptualization of abstract information spaces that have no natural geometric characteristics. Entities within such an information space, such as concepts and ideas, may be described according to their locations, relative distances, direction of motion, and so on. This conceptualization is compelling as it is naturally in agreement with the basic mechanisms of human thought. Indeed, research in cognitive science has demonstrated that spatial metaphors form a foundation upon which all conceptual structures are built (see [20]). Viewing information in geometrical terms can facilitate not only the conceptualization of information space, but can also help designers to think systematically about the encoding of information into visually-perceptible forms (see section 2.3).

In the context of VA, information may derive from abstract spaces (e.g., financial markets) or concrete spaces (e.g., oceans). Unlike other visualization sciences (e.g., information and scientific visualization), a conceptualization of information space for VA must account for both the abstract and the concrete. Visual analytic activity often necessitates access to both simultaneously. An insurance analyst, for instance, may need to investigate an information space that contains concrete entities such as hailstones and cars, and simultaneously investigate abstract entities such as probabilities and damage estimates. For ease of conceptualization and discussion, we refer to all components within information space as *information items* (e.g., data, conceptual entities, causal relationships, properties, temporal processes, structures). Information items may be static or dynamic. In Figure 1 these are depicted as stars within the information space.

One of the current research challenges in VA is dealing with heterogeneous data. The characterization given here is not meant to trivialize such a challenge; rather, it is an attempt to simplify and clarify the conceptualization of the information component of human-information discourse in VA. As Thomas and Cook [41] note "*we must eliminate the artificial analytical constraints imposed by data type so that we can aid the analyst in reaching deeper analytical insight.*" Characterizing information space at this level of abstraction accounts for all human-information discourse, and allows designers to direct attention to higher–level considerations that are consistent across many different analytic applications. As a result, designers can focus on creating a seamless visual analytic experience for the user.

2.2 Computing Space

Computing space is concerned with encoding and storing internal representations of items from an information space and performing operations upon such representations.[2] Data cleaning, filtering, fusion, integration, normalization, and other pre-processing procedures take place within computing space. Data mining and mathematical procedures, such as data transformations, also take place within computing space. Therefore, computing space is concerned with pre-processing, storing, and preparing data in order to be visually displayed to analysts to enable visual analytic activity.[3] When VA systems are designed effectively, users do not need to be aware of or concerned with any of the technological workings of computing space. Consideration and proper design of computing space is essential, however, as it provides the underlying operations that allow users to engage in effective information discourse. Data representation and transformation techniques that have been developed in the statistics, machine learning, and pattern recognition research communities are essential to the effective development of computing space. Although much valuable research has been done in this area, further research is required to address many standing issues [18]. This paper does not go into detail about these issues, and readers are referred to other research that deals with this space in more detail (e.g., [18, 19, 45, 46]).

2.3 Representation Space

In the context of VA, information items are encoded and stored internally (e.g., as magnetic patterns on a hard disk platter) and are not directly accessible to users. The only access that users have to this information is through digital information representations (DIRs)[4] at the visually-perceptible interface of a tool.[5] Therefore, the design of representation space fundamentally influences how users perceive information space.

As mentioned in section 2.1, a spatial conceptualization of the VA structure provides many benefits. One such benefit is that when information items are described in geometric terms, the process of encoding information items in representation space can be more natural to think about, since representation space has inherent geometric characteristics. Two information items (e.g., concepts) of different degrees of importance may be considered to have a certain distance from one another. A designer may then decide to encode their relative importance with the size of a DIR and their conceptual distance with the length or width of a DIR. If information items are conceptualized as growing, moving, having direction, and so on, such characteristics can be effectively encoded within DIRs in representation space (see [26, 39, 43] for more information about encoding techniques).

When we use information representations to assist with cognitive activities our external cognition is engaged [32]. The partnership that is formed between internal mental processes and external representations provides a number of benefits for performing analytic activities. In addition, representations may take on many forms—numbers, natural language, images, diagrams, and so

[2] Representations in computing space are invisible to users and are not the same as those in representation space.

[3] This is from a user—centered perspective and is not to suggest computing space is not important.

[4] Scatterplots, treemaps, glyphs, parallel coordinate plots, tables, and cartograms are all examples of DIRs. DIR is an umbrella term referring to all visual representations of digital, electronic information that have the potential to be dynamic and/or interactive.

[5] There may be many layers of organization of information between the user and an information space (e.g., hard disk—memory—relational database—graphics encoding algorithms—DIRs). The point here is that users do not have access to any information unless through some representational form.

on. Much research in cognitive science has demonstrated that these different forms have fundamentally different effects on cognitive processes and on how users understand information spaces [48]. During visual analytic activity, high–level cognitive activities take place over a span of time, where internal mental processes (e.g., categorizations, abstractions, deductions) are dynamic and involve constant assimilation and reorganization of information. When external cognition is engaged, external representations (e.g., DIRs) share in this temporal information and cognitive processing. As DIRs are interactive, users can operate on and adjust their features such that DIRs become dynamic components of external cognition. If a VA system has a high degree of interactivity, a strong coupling can be formed between mental space and representation space that provides better support for performing cognitive activities (see section 3).

Although DIRs give perceptual access to information space, most information spaces with which VA is concerned are too large and complex to be entirely encoded within representation space at any given time. For example, consider the occurrence of a natural disaster. In such a case, the information space with which an analyst is concerned may contain a large amount of complex information regarding financial, human, and environmental damage and losses; population resilience and vulnerability statistics; mathematical probability models and forecasting algorithms; accumulation risk statistics; and so on. As both representation space and human perceptual and cognitive processing capabilities are limited, it is not possible or desirable to encode the entirety of such an information space. In addition, as visual analytic activities are not simple linear processes [41], it is not possible to provide a single DIR that sufficiently meets the needs and goals of all analysts. Although proper representation design is critical for effective VA systems, it is through interaction that users adjust representation space to suit their contextual and cognitive needs. Therefore, the conceptualization and design of interaction space requires careful consideration.

2.4 Interaction Space

Interaction space is where actions are performed and consequent reactions occur.[6] This back–and–forth flow of information is a crucial component of the analytic discourse. By performing actions upon DIRs that effect reactions within representation space, users direct the analytic activity to meet their own goals and needs. In general, interaction space in the VA literature lacks a high degree of conceptual clarity. As Aigner [1] notes, although interaction is a fundamental component of VA, "*...there is hardly ever an explanation of what these benefits [of interaction] actually are as well as how and why they work*."

Numerous researchers have suggested that one way to address this problem is through the creation of interaction taxonomies. For instance, Thomas and Cook have claimed that "*the grand challenge*" of interaction is to develop a taxonomy to describe and clarify the interaction design space [41]. Other VA researchers (e.g., [17, 33]) have suggested that not only do we require knowledge of what actions are available, but we also require knowledge of how interactions facilitate activities such as problem solving and decision making. The development of such taxonomies must be motivated by a strong understanding of underlying cognitive and perceptual principles, so that designers may provide mission-appropriate interactions that facilitate meaningful discourse with information [41].

Numerous taxonomies have been devised in recent years that help give some structure to interaction space (e.g., [2, 13, 24, 38, 47]). While these taxonomies have been important contributions for the research community, there is still further work to be done along at least three different yet related paths. First, none of the taxonomies capture all possible interactions that may be performed, and the development of a comprehensive taxonomy would be beneficial. Second, a comprehensive taxonomy should include an explication of the cognitive and perceptual impacts of each individual interaction. Third, existing taxonomies often identify interactions at different levels of human–information discourse and combine them without making any categorical distinctions according to their granularity (see section 3 for a discussion about such levels). Sedig and Parsons [35] have recently devised a taxonomy that is a step towards addressing such existing research challenges. The taxonomy identifies and characterizes over 30 patterns of human–information interaction at the level of individual actions and reactions, and also discusses cognitive and perceptual effects of each pattern. The taxonomy is a component of a larger research plan to develop a comprehensive framework called EDIFICE (Epistemology and Design of human–InFormation Interaction in Cognitive activitiEs). As a component of this framework, the taxonomy in [35] is labeled EDIFICE–AP, where AP stands for Action Patterns. The patterns identified in this taxonomy are abstractions from interaction instances, and are concerned with how a user acts upon DIRs and the resulting utility for performing cognitive activities. As such, numerous interaction techniques are captured under each pattern. Table 1 provides a list and brief description of some of the patterns from EDIFICE-AP. Such a taxonomy can help

[6] Interaction space and representation space necessarily overlap. However, separating them helps with conceptualization and design.

bring structure and consistency to the landscape of ideas relevant to interaction-space conceptualization and design.

While necessary to inform and clarify the design landscape, interaction taxonomies on their own are not sufficient to ensure seamless visual analytic activity. The quality of discourse with information, at multiple levels of granularity, must be also be taken into consideration. Interactivity factors such as the operationalization of individual interactions (see section 3.1.1) and the manner in which interactions are combined and linked together to perform higher-level tasks and activities (see section 3.1.2) are also necessary considerations.

Interaction	Description (acting upon DIRs to:)
annotating	augment them with meta-information
arranging	change their ordering and organization
drilling	bring out information items that are not encoded
filtering	display only a subset of information
linking	connect or establish a relationship between them
scoping	adjust the amount of growth of an information space that is encoded
searching	seek out the existence of or locate information items
selecting	focus on or choose them

Table 1. Some human-information interaction patterns from the taxonomy of [35]

2.5 Mental Space

Mental space refers to the space in which internal mental events and operations (e.g., apprehension, induction, deduction, memory encoding, memory storage, memory retrieval, judgment, classification, categorization) take place. Often times in VA research, terms that refer to operations in mental space are used in a nebulous manner. For instance, while it is often suggested that '*insight*' is the goal of VA, Chang et al. [9] point out that the term insight is used ambiguously in the VA community, and that there is a need for clarification. They also note that researchers often conflate insight with knowledge, and that "*switching the word 'insight' with 'knowledge' doesn't effectively alter its meaning*". In a similar manner, VA researchers often substitute analytical reasoning with other high–level activities such as problem solving, sense–making, decision–making, knowledge discovery, and forecasting. While such activities share many similarities, distinguishing them can help bring more clarity to the VA landscape. If we are to characterize interactivity in a comprehensive manner, future research in VA must integrate research from cognitive science that explicates the structures and processes within mental space more fully. Some researchers have been working at this, and readers are directed to [3, 9, 35, 36] for more information.

When engaged in an analytical reasoning process, one can work with and transform internal representations of information (e.g., concepts and schemas within mental space) or can operate upon and work with external representations of information (e.g., DIRs within representation space). In the latter case, internal representations work in conjunction and partnership with external representations [48]. Such a partnership results in a cognitive system in which the distribution of cognitive processing is shared by elements external to the analyst's mental space.

2.6 Distribution of Cognitive Activity Across Spaces

The theory of distributed cognition proposes that cognition is distributed across mental space and the external environment [15]. That is, internal mental structures and processes and elements within the environment form a cognitive system that has greater processing abilities than the mental space alone. These elements range from simple things, such as a pen and paper [11], to complex things, such as information visualization tools and visual analytics systems [18, 23]. Within distributed cognitive systems, distribution occurs at many levels, from a distribution among members of social systems to distribution between a single individual and an artifact. Many researchers in the VA community point to distributed cognition theory to support a conceptualization of various aspects of VA (e.g., [1, 41, 18]). Viewing VA through the lens of distributed cognition can help designers to make decisions about distributing the information-processing load across these spaces. When users interact with VA systems, some of the processing takes place internally in the mental space, some is offloaded onto DIRs and computational processes, and some takes place through interactions with DIRs. In other words, a distributed cognitive system is formed in which the load of information processing is spread across the different spaces. The design of the VA system determines how much processing load is placed on each space, and the ideal distribution is user–and context–dependent. For example, some situations may require the user to make rapid decisions based on dynamic, '*real-time*' information. In such cases, not much processing load should be placed on the mental space, and the computing and representation spaces may take on the bulk of the processing load. Consequently, the user would not likely gain a deep understanding of the information space, but would be able to effectively make quick decisions. Other situations, however, may require the user to engage in deep and effortful mental processing of the information, such as in many sense–making activities. In such cases, more of the information processing load should be placed on the mental and interaction spaces, so that the user can build rich mental models of the information space through deep and prolonged discourse with the information. In any situation, the degree to which the components in these spaces interact and function in harmony—that is, their degree of interactivity—determines how well visual analytic activities are supported.

3. Characterizing Interactivity in Visual Analytics

As mentioned earlier, interactivity in VA refers to the quality of interaction among the components that comprise a VA system. One current problem surrounding the discussion of interactivity is that researchers are not in agreement as to whether the locus of interactivity lies with the user or with the technology (see [7]). This issue is important with VA systems, as the quality of interaction among the internal components as well as among the user and the system are essential. To address this issue we propose that interactivity in VA systems be categorized into two high–level components: external and internal interactivity. External interactivity refers to the quality of interaction among mental space, representation space, and interaction space. Internal interactivity refers to the quality of interaction among representation space, computing space, and information space. There are, of course, areas that overlap both categories. Making this categorization simply helps to conceptualize and deal with the complexities of designing VA systems. These two components are discussed in sections 3.1 and 3.2 below. Figure 2 applies this categorization to the spaces of VA described in section 2. Although both of these components of interactivity are critically important, this paper focuses mainly on external interactivity, and a detailed treatment of internal interactivity is left open for future development and integration.

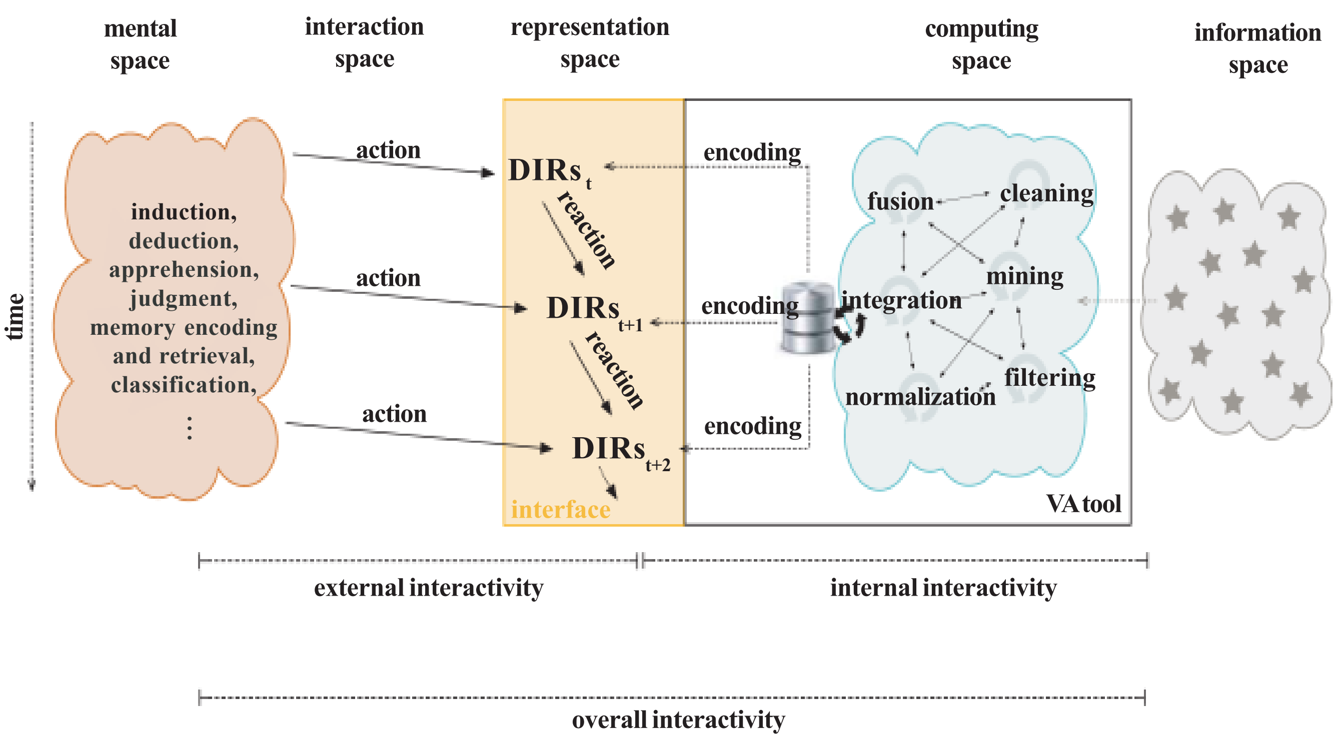

Figure 2. Categorization of interactivity into two broad sub-components

3.1 External Interactivity

External interactivity is concerned with the quality of interaction that takes place among the mental, interaction, and representation spaces. One of the challenges in conceptualizing external interactivity is that it is a complex construct that must account for and incorporate the visual analytic activity of users. VA researchers generally suggest that the overall activity occurring during human–information discourse is analytical reasoning. Within the VA community, however, there is no agreed upon characterization of the analytical reasoning process. This lack of clarity has been recognized by researchers such as Meyer et al. [27], who have recently suggested that what is missing from a science of interaction is "*research that focuses on cognition, the reasoning and argument process itself*...". Thomas and Cook [41] have also stressed the importance of developing a supporting science for the analytical reasoning process.

One of the difficulties in understanding the analytical reasoning processes is that it is a high-level cognitive activity that involves numerous sub–activities, such as problem solving, sense making, knowledge discovery, planning, forecasting, and decision making [27, 41, 18]. Researchers are often not clear about distinguishing between these activities and, as a result, such terms are often used interchangeably. Although support for problem solving and other activities is crucial for visual analytic activity, no existing research characterizes analytical reasoning in detail in the context of VA [12].

Research in the areas of activity theory, human–computer interaction, human-information interaction, and visualization sciences can shed light on the nature of visual analytic activity (e.g., [2, 13, 16, 22, 29]. In order to clearly discuss various dimensions of high–level cognitive activities, such researchers have proposed that activities be analyzed at multiple levels of granularity. Following this, we propose that visual analytic activity can be analyzed at four levels: activities, tasks, interactions, and events. Activities occur at a high level and are often complex and open-ended (e.g., problem solving, decision making, and forecasting); tasks are goal–oriented behaviors that occur at a lower level during the performance of activities (e.g., browsing, identifying, and ranking); interactions occur at an even lower level and involve actions that are performed upon DIRs (e.g., selecting, drilling, and filtering) and their consequent reactions; events occur at the lowest level and are the building blocks of interactions (e.g., mouse clicks, keyboard presses, and finger swipes). Visual analytic activity can be viewed, then, as hierarchical, embedded, and emergent. That is, each level of the visual analytic hierarchy is embedded within the level above and each level has emergent characteristics that result from the relationships occurring within the levels below.

As an example, consider the use of a VA system to support the analysis of a large information space regarding a national security threat. One necessary activity to perform may be sense making, in which a user needs to develop a mental model of the structure and features of the information space. To perform this sense making activity, an analyst must perform a number of tasks, such as *categorizing* phone records according to subject matter, *identifying* individuals of interest, ranking information sources according to reliability, and *browsing* through a collection of photographs. Each task would likely involve the performance of any number of interactions. For instance, to achieve the goal of categorizing phone records, the analyst may need to *filter* the records according to a particular date range, *drill* into a particular record to access more information, *rearrange* a list of records, or *search* for a particular record. To complete any one of these actions, a number of micro–level events such as mouse clicks, finger swipes, or keystrokes may be required. The performance of events leads to emergence of interactions; the performance of interactions leads to emergence of the categorization task; and, the performance of categorization and other tasks leads to emergence of sense–making—all of which are embedded within the overall visual analytic activity. Figure 3 depicts the hierarchical, embedded, and emergent nature of visual analytic activity.

As this overall discourse can be analyzed at many levels, external interactivity can also be analyzed at many levels. At this stage of the research on interactivity we discuss only two main levels: a micro and a macro level. Interactivity at the micro level is concerned with the structural elements of individual interactions that affect cognitive processes. As individual interactions have both an action and a reaction component, the manner in which the action and reaction components of an interaction are operationalized affects the quality of the interaction. The degree of interactivity at this level emerges from the structural elements that affect individual interactions. Interactivity at the macro level is concerned with the ways in which interactions are combined and chained together to accomplish and perform higher–level tasks and activities. The degree of interactivity at this level emerges from the aggregation of individual interactions. Although a comprehensive characterization of external interactivity is an ongoing research endeavor and is far from complete, some recent work has identified and characterized a number of micro– and macro-level interactivity considerations for general visualization tools (see [36]). This work is another component of the EDIFICE framework described in section 2.4, and is labeled EDIFICE-IVT, where IVT stands for Interactivity in Visualization Tools. EDIFICE-IVT identifies and characterizes twelve micro–level elements and five macro–level factors that affect interactivity of visualization tools in general. Some of these will be discussed in the more particular context of VA in sections 3.1.1 and 3.1.2, and section 4 will examine some of them in the context of a VA scenario, each of which suggest how such considerations help to think about interactivity for VA. Only a few of the identified interactivity considerations will be mentioned, however, and they will not be characterized or discussed in much detail. Readers are referred to [36] for a more complete and detailed discussion.

Figure 3. Visual analytic activity as hierarchal, embedded, and emergent

3.1.1 Micro-level External Interactivity

Interactivity at the micro level is concerned with the structural elements of individual interactions. As an interaction has both an action and a reaction component, the manner in which these components are operationalized affects the performance of an analytical reasoning activity. Studies have confirmed that elements of interaction at this level affect the cognitive processes of users (e.g., see [21]). Figure 4 depicts the structure of an individual interaction and some action and reaction elements that affect interactivity. Each of the action elements are orthogonal, as are each of the reaction elements. One of the structural elements that has been identified and studied empirically is *flow*. Flow is concerned with the duration of an interaction and with a user's perception of the relationship between cause and effect. Therefore, flow is concerned with both action and reaction. Because both action and reaction occur within time, flow can happen in one of two ways: continuous or discrete. Continuous flow refers to action and/or reaction occurring over a span of time in an uninterrupted, fluid manner. Discrete flow refers to action and/or reaction occurring at an instance in time. The element of flow creates 4 possibilities for operationalizing any interaction: continuous action–continuous reaction; continuous action–discrete reaction; discrete action-continuous reaction; and, discrete action–discrete reaction. As an example, if an analyst wishes to rotate a DIR of the earth while exploring climate change patterns, the action may be continuous (e.g., by dragging a slider in a fluid manner) or discrete (e.g., by clicking on numbers representing degrees of rotation). The reaction may also be continuous (e.g., a continuous and fluid rotation) or discrete (e.g., immediate change from initial state to desired degree of rotation). Results of a study that investigated flow provide evidence that each of the four forms of flow have distinct effects on the cognitive processes of users (see [21]).

Other action elements that affect interactivity include *agency* and *focus*. Agency is concerned with the metaphoric way in which an action is expressed. Some of the main forms that this element can assume include: verbal, manual, pedal, and aerial. These are based on root metaphors derived from how we act upon the physical world—that is, mouth/talking, hands/handling, feet/walking, and wings/flying. One relevant study, conducted by Svendsen [40], examined the effects of manual agency and verbal agency on a problem solving activity. The results suggested that verbal agency was more conducive to reflective thinking while problem solving, and thus manual agency, while typically preferred by users, is not always best. For instance, participants in the verbal agency group made fewer mistakes during the problem solving activity. This study, although old and not in the context of today's visualization sciences, suggests that the operational form of agency can affect the user's cognitive processes. However, more up–to–date research is required to determine the effects of different operational forms of agency in the context of VA. The element of focus is concerned with the locus of attention of a user while acting upon a DIR. Focus can be either direct or indirect. If the focus of action is direct, a user acts upon a DIR directly. On the other hand, if the focus of action is indirect, a user acts upon intermediary DIRs to affect the DIR of interest. Similar to the other elements, not much research has focused on this element, particularly in the context of VA. The results of one relevant study suggest that focus of action has significant effects on how well concepts from an information space are understood, especially when an activity involves the comprehension and manipulation of conceptual abstractions (see [34]).

Other reaction elements that affect interactivity include *spread* and *transition*. Spread is concerned with how an action performed upon a DIR affects other DIRs within representation space. There are two main forms of spread: self-contained and propagated. If spread is self–contained, only the DIR that is acted upon is affected by the action. If spread is propagated, the effect of the action propagates to other DIRs in representation space. This is often an important concern for complex interfaces in which many DIRs exist simultaneously. Designers must consider how interactions with a DIR affect the other DIRs. For instance, do some interactions affect only one DIR while others affect multiple DIRs? Little research has hitherto focused on this element, and thus prescriptive guidelines can be given only in an *ad hoc* fashion. The element of transition is concerned with how visual changes that occur as a result of an action are presented. As interactive DIRs are a spatio–temporal entities, changes can be presented by distorting either their temporal or spatial dimensions. Two main forms of transition may therefore be identified: stacked and distributed. If transition is stacked, changes are sequentially stacked on top of one another so that only the current frame of the changing DIR is visible. If transition is distributed, a number of distinct DIRs capture and preserve instances of the changing DIR and present them spatially—in other words, the temporal dimension of the changing DIR is distorted and is presented as parallel instances distributed in space (see [39, 42]; see also [37] for a study that investigates this factor.)

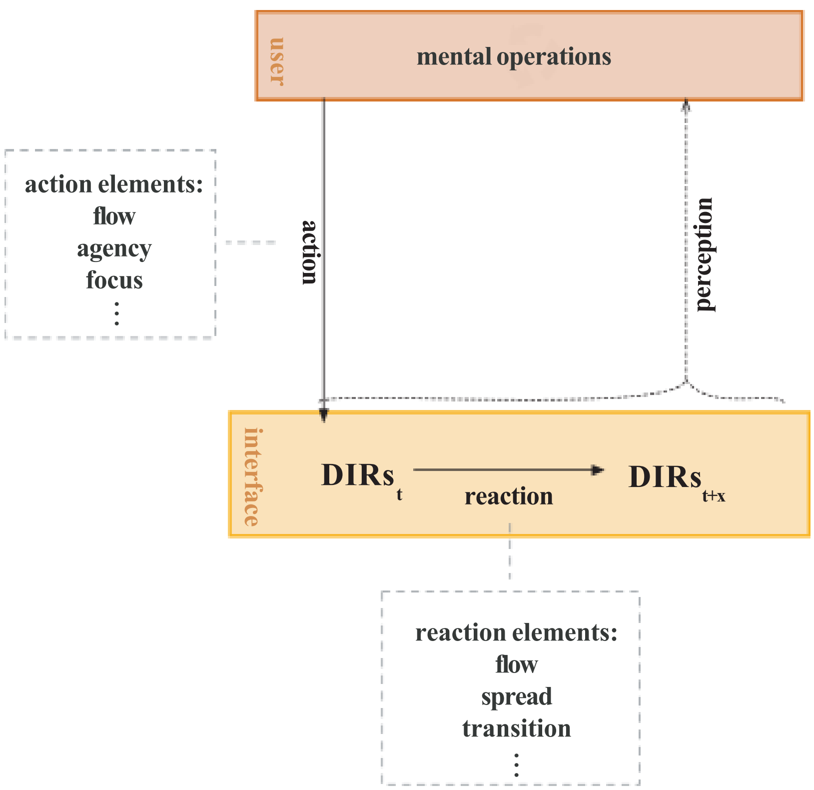

Figure 4. Some structural elements of an individual interaction that affect micro-level interactivity

Although these elements require further elaboration in future research, there is evidence to suggest that they do affect the cognitive processes of users. Future studies may investigate these in more detail. However, identifying these factors and discussing their features will help move towards a more comprehensive characterization of micro–level interactivity factors.

3.1.2 Macro-level External Interactivity

Although the structure of individual interactions affects interactivity, users of VA systems do not perform single interactions in isolation. When engaged in visual analytic activity, users combine and chain together numerous interactions to accomplish tasks and to perform activities (see section 3.1). Macro–level external interactivity is concerned with the quality of interaction at this level of human–information discourse. This level of discourse, in which interactions should merge into a seamless flow of visual analytic activity, is one of the least well understood aspects of interaction in VA [41].

Interactivity at this level has hitherto not received much attention and, as a result, there is not a large body of research from which a detailed characterization may be developed. However, a number of preliminary considerations can be identified to help move towards such a characterization. To design with this level of interactivity in mind designers first require an understanding of which interactions exist. Taxonomies such as those discussed in section 2.4 can address this need. Even with the provision of such taxonomies, however, designers must have a sense of how interactions are best put together to achieve goal–oriented tasks and perform high–level activities.

While the visual analytics mantra "*analyze first, show the important, zoom, filter and analyze further, details on demand*" [19] is a useful high–level guide for design of VA systems, we propose that it can be enhanced by a more fine–grained characterization of visual analytic activity that includes a consideration of these macro-level interactivity factors. Consider Figure 5, which depicts the process of human–information discourse of an analyst. While engaged in such a discourse, users repeatedly perform actions upon DIRs and perceive the reaction that occurs in representation space. Through such a process, users indirectly '*reach into*' information space to perform operations on information items, encode new information items, filter others from view, and so on. There are a number of factors that can be identified which affect the quality of discourse at this level.

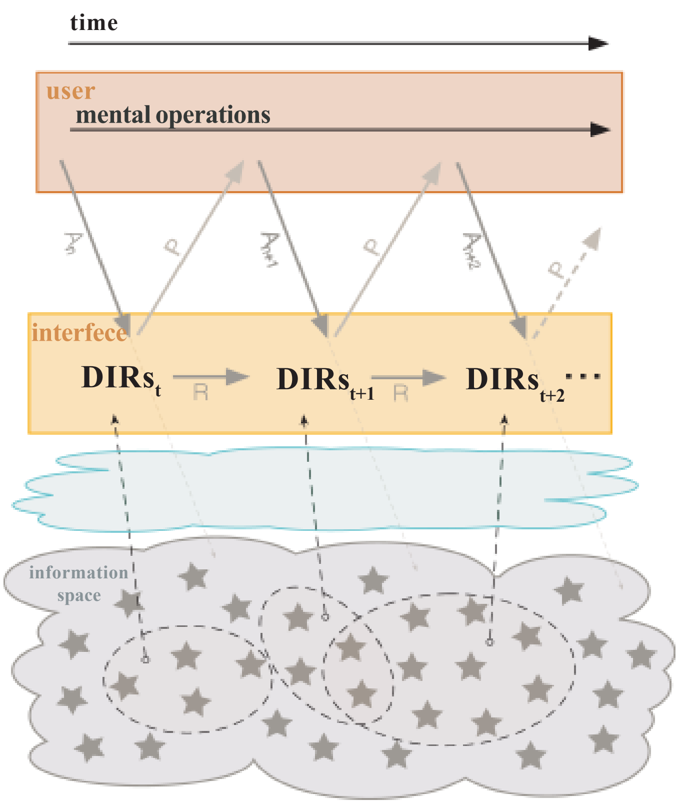

Figure 5. Human-information discourse at the macro level

To exemplify, consider again the example of the analyst given in section 3.1. Figure 5 can model the human–information discourse and can assist in thinking about macro–level interactivity factors during the performance of the categorization task, for instance. One interactivity factor to consider at the macro level is whether any of the available interactions can be performed at any time, or whether the performance of certain interactions '*unlocks*' the potential for performing other interactions. For instance, should the analyst be required to first filter (A_n), then drill (A_{n+1}), then arrange(A_{n+2})? Is there any benefit to the performance of tasks to have such constraints put in place? If so, should this be dependent on the tasks being performed or on the experience and skill level of the user? Designers must also consider whether the goal of a task may be achieved with different interactions and, if so, whether it is worthwhile or is a hindrance to provide analysts with such diversity. For instance, the analyst could achieve the goal of ranking sources by repeatedly performing the same one or two interactions (e.g., selecting and arranging), or by performing a number of distinct interactions (e.g., selecting, filtering, drilling, searching, arranging, and comparing). Other issues at the macro level include: how different interactions complement one another in the context of performing particular tasks; how interactions correspond to users' conceptual models of how such interactions should function; the degree to which the potential benefits of interactions outweigh the cost and effort associated with learning how to use them; and, the degree of control that users are given in terms of changing the many parameters of interaction with a VA tool. These must be elaborated upon in future research if we are to characterize interactivity in a comprehensive manner.

Categorizing external interactivity into two levels and discussing the features of each helps to conceptualize the emergent nature of interactivity. VA researchers can think about the factors from which the micro– and macro–level interactivity of a system emerges, and how external interactivity emerges from the interrelationships among micro– and macro–level factors. As a more comprehensive body of research regarding interactivity is developed, a number of new and more fine-grained considerations can become part of the design landscape. This will enable designers of VA tools to approach interactivity in a more systematic fashion, accounting for clearly-stated factors that affect visual analytic activity at different levels of analysis. Figure 6 provides an example of some questions that designers can consider while thinking about the external interactivity of a VA system.

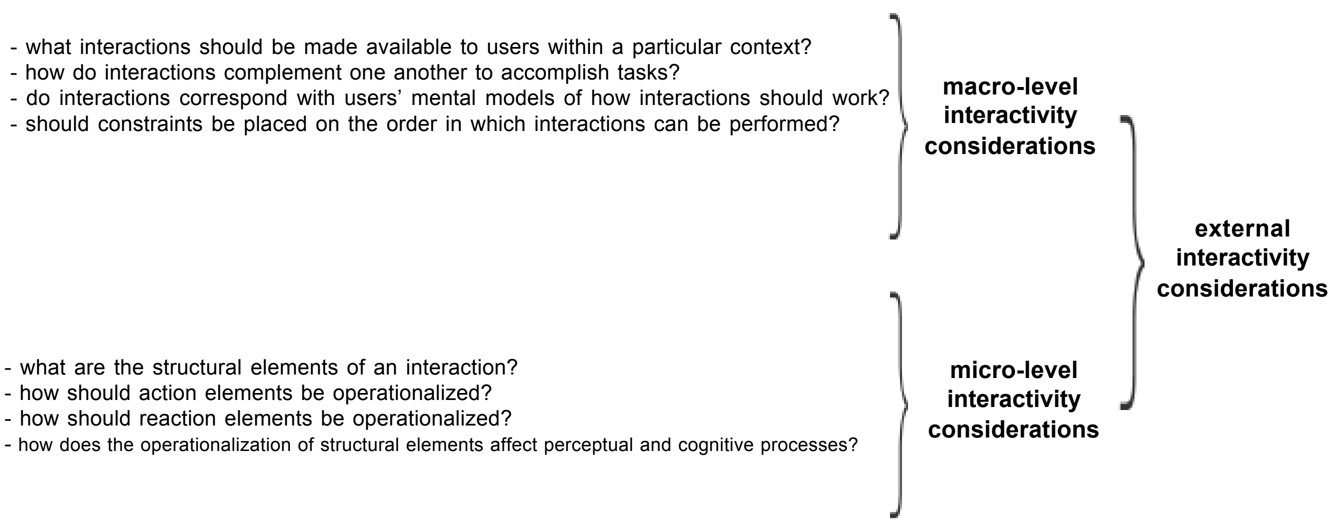

Figure 6. External interactivity considerations

3.2 Internal interactivity

Any effective VA system requires a strong coupling among many internal (i.e., not directly accessible by the user) components. For instance, Keim et al. [18] note that an integration between data mining and visual analytics is required, and that we need to reduce the gap that exists between them. Many VA tools operate with large amounts of data coming from multiple sources. Data entering the VA system first undergoes pre-processing, cleaning, and transformation. The data is often complex, ambiguous, and in many cases is incomplete and/or conflicting. Data transformations themselves generate additional uncertainties. Moreover, the exact data to be processed might not be known. The quality of interaction among raw data collection processes and automated data processing is of critical importance [44].

Information items are encoded, stored, organized, and manipulated in computing space. Information items may also be altered or refined through input from analysts. In this regard, internal interactivity refers to expressive ease and query complexity [8]. Also, the degree of internal interactivity depends on data accuracy, completeness, currency, timeliness, volatility, and consistency [5].

Internal interactivity is also concerned with graphics processing algorithms that encode the stored information within representation space. Further concerns include speed (e.g., interface response time, data loading, data update cycles) and efficacy of the chosen encoding (e.g., proximity, similarity, enclosure, continuity) [49]. See also section 2.2 for a brief discussion of some of these issues.

4. Scenario

This section demonstrates, through a brief scenario, how a characterization of interactivity can assist designers of VA systems. Consider the case of an epidemiologist needing to analyze the rapid spread of a new disease. First, a high–level approach to the design problem may be taken by categorizing different issues according to the VA spaces:

• **Information space:** Information is derived from numerous sources, and such an information space is extremely large and complex. The items within this space have geospatial, categorical, ordinal, and temporal characteristics. The major items within such a space can be identified. For example, locations of high importance such as hospitals and public spaces.

• **Computing space:** The manner in which various information items are encoded must be considered. For example, how are major structures and temporal processes stored within a relational database? Pre-processing, data mining, and storage must all be considered.

• **Representation space:** Based on the characteristics of the information space, designers must decide on appropriate DIRs. Established encoding techniques may emphasize particular aspects of the information space. Representation techniques may be considered to assist with analysis of different characteristics (e.g., temporal, spatial) of the information space.

• **Interaction space:** With such a complex information space, a single representation, no matter how appropriate or well designed, cannot be sufficient for the visual analytic activity. Designers must consider the landscape of possible interactions and how each may facilitate tasks and contribute to the overall activity.

• **Mental space:** Designers must consider the types of mental operations and events that take place during the analytic activity. For instance, will the analyst be engaged in inductive reasoning (e.g., observing particular disease cases and generating propositions about the spread of the disease)? Will the analyst be engaged in deductive reasoning (e.g., knowing that all people with particular immune deficiencies will contract the disease, and then deducing that particular groups of people and/or geospatial locations may require immediate consideration)?

Next, a team of designers may consider the general characteristics of the overall analytic activity. Some may consider the internal interactivity while others consider external interactivity. The designers examining external interactivity may initially require a sense of which activities may be involved in the analysis process. The following are examples of activities that may be performed by an epidemiological analyst:

• **Decision making:** the analyst may be presented with several options of where to send medical experts and must choose and recommend one.

• **Sense making:** the analyst may need to develop an accurate mental model of the major structure and features (e.g., important locations, speed of transmission, direction of transmission) of the information space.

• **Planning:** the analyst may need to construct a sequence of one or more courses of action to decide how to proceed with further analysis.

• . . .

The design of the VA system may then be approached at the level of tasks that an analyst may wish to accomplish to perform such activities. For example, consider the activity of deciding where to send medical experts. Such an activity may involve the following lower–level, goal–oriented tasks:

• categorizing cases of infection

• assessing disease determinants

• triaging geographical areas within a country that require attention

• identifying areas of critical importance

• locating the origin of the outbreak
• determining the speed and direction of the spread
• ranking potential risk factors
• organizing medical experts according to specialty
• . . .

As a design team begins to conceptualize the structure of the visual analytic activity, lower levels of the activity may be characterized. The goal-directed task of triaging, for example, arises when the analyst must rapidly assimilate and evaluate information and does not have enough time to deal with each information item in depth. VA systems must provide analysts with appropriate interactions to achieve this goal. At a macro level, designers must consider all of the factors that affect the quality of performing such a task. Designers first require access to interaction taxonomies and must have an idea of which interactions facilitate the triaging task. For instance, future research may determine that annotating, filtering, drilling, and arranging are particularly complementary for triaging. Future research may also determine that drilling into geographical areas to get infection statistics, then filtering them according to population density, then arranging them according to their perceived importance, may be the most effective sequence of interactions for achieving the triaging task. The designer may also decide that certain interactions are not beneficial and their availability may confuse the analyst.

At this point, the designers have taken into consideration the factors that influence the human-information discourse at a macro level. A set of interactions has been chosen, along with the constraints or stipulations for their use, and so on. Next, the designer can consider how to operationalize such interactions according to the micro-level interactivity elements. For example, consider the element of *flow* described in section 3.1.1. Let us assume that the analyst will use a filtering interaction to assist with the triaging task. If the representation space is densely populated with DIRs of disease cases, for example, the analyst may need to quickly filter out cities with populations under a particular population size or density. Designers can consider whether the action and reaction components should be operationalized in a fluid manner. If the reaction happens instantaneously (i.e., in a discrete manner), perhaps there will be a mental gap and the analyst will not be able to accurately integrate the effect into his mental space. Designers may also consider how the transition should be operationalized—should the result of the filtering action (i.e., the filtered DIR) replace the original DIR in the representation space, or should the original DIR and the resulting DIR be distributed in the representation space so that the analyst can perform visual comparisons between them? It is probable that all of these issues play a role in the cognitive processing of the analysts. Therefore, the performance of visual analytic activities could be enhanced if designers systematically consider these issues in the design of VA systems. The designers can then collaborate with others who have been analyzing the internal interactivity and take an integrated approach to the design of the overall system.

This section has briefly demonstrated how considering interactivity factors can assist with the conceptualization and design of VA systems. The design considerations in the brief scenario presented are only loosely prescriptive and are far from exhaustive. Future research may develop prescriptive frameworks to help guide designers in this process.

5. Summary and Future Work

As a relatively young area of research, VA still faces many challenges. One of the major challenges lies in integrating the components of VA systems in a harmonious manner. If the quality of interaction among the components of VA systems is not high, the quality of overall visual analytic activity is decreased. This paper has examined some aspects of the interactivity of VA systems, where interactivity refers to the quality of interaction among its components. Interactivity here has been categorized into two high-level components: internal interactivity and external interactivity.

External interactivity refers to the quality of interaction between an analyst and a system. Internal interactivity refers to the quality of interaction among all of the components internal to the system. Most of the emphasis of this paper has been on external interactivity, and internal interactivity has been left open for future characterization and integration. A characterization of interactivity can help researchers discuss important factors affecting the human-information discourse at multiple levels of granularity with a common conceptualization and terminology.

The ideas presented in this paper are preliminary and are an attempt to contribute towards a characterization of interactivity in

VA. As a result, a number of future lines of research are left open for consideration. For example, the nature of visual analytic activity can be characterized further. Research can be done to determine the manner in which tasks are performed within the context of particular activities. Tasks and activities themselves can be further explicated. Another line of research is in developing comprehensive taxonomies of interactions and of tasks that describe their cognitive and perceptual impacts. Also, more research is required to identify a comprehensive set of interactivity factors and to describe their features. A further line of research can be in conducting studies to determine how these factors influence the overall quality of the human-information discourse. Finally, as interactivity is further characterized, prescriptive frameworks and guidelines may be developed to assist in the design of VA systems.

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References

[1] Aigner, Wolfgang (2011). Understanding the role and value of interaction: First steps. *In*: Proceedings of the International Workshop on Visual Analytics (EuroVA 2011), p. 17–20.

[2] Amar, Robert., Eagan, James., Stasko,John . (2005). Low-level components of analytic activity in information visualization. *In*: Proceedings of the 2005 IEEE Symposium on Information Visualization (INFOVIS '05), p. 111–117. IEEE Computer Society.

[3] Arias-Hernandez, Richard., Green, Tera M., Fisher, Brian. (2012). From cognitive amplifiers to cognitive prostheses: Understandings of the material basis of cognition in visual analytics. *Interdisciplinary Science Reviews*, 37, 4–18.

[4] Marcia J. Bates. (2005). Information and knowledge: An evolutionary framework for information science. *Information Research*, 10 (4).

[5] Carlo Batini, Monica Scannapieco. (2006). Data Quality: Concepts, Methodologies and Techniques. Data-Centric Systems and Applications. Springer.

[6] Max H. Boisot, Agusti Canals. (2007). Data, Information, and Knowledge: Have We Got It Right? In Max H. Boisot, Ian C. MacMillan, and Kyeong Seok Han, editors, Explorations in Information Space: Knowledge, Agents, and Organization, chapter 1, p. 15–47. Oxford University Press.

[7] Erik P. Bucy. (2004). Interactivity in society: Locating an elusive concept. *The Information Society*, 20 (5) 373–383.

[8] Chan, Hock Chuan., Tan, Bernard C. Y., Wei,Kwok Kee . (1999). Three important determinants of user performance for database retrieval, *International Journal of Human-Computer Studies,* 51 (5) 895–918.

[9] Chang, Remco., Ziemkiewicz, Caroline., Green, Tera Marie., Ribarsky,William (2009). Defining insight for visual analytics. *IEEE Computer Graphics and Applications*, 29 (2) 14–17.

[10] Chen, Min., Ebert, David., Hagen, Hans., Laramee, Robert S., Liere, Robert van., Ma, Ksan-Liu., Ribarsky, William., Gerik, Scheuermann., Deborah Silver. Data, information, and knowledge in visualization. *IEEE Computer Graphics and Applications*, 29, 12–19.

[11] Clark, Andy. (1991). Microcognition: Philosophy, Cognitive Science, and Parallel Distributed Processing. MIT Press.

[12] Fabrikant, Sara Irina (2011). Persistent problems in geographic visualization: Evidence of geovis(ual analytics) utility and usefulness. ICA Geovis Commission ICC2011 Workshop, Paris, France.

[13] Gotz, David., Zhou,Michelle X.. (2009). Characterizing users' visual analytic activity for insight provenance. *Information Visualization*, 8 (1) 42–55.

[14] Greitzer, Frank L., Noonan, Christine F., Franklin,Lyndsey R.. (2011). Cognitive foundations for visual analytics. Technical report, Pacific Northwest National Laboratory (PNNL), Richland,WA.

[15] Hollan, James D., Hutchins, Edwin., Kirsh, David. (2000). Distributed cognition: Toward a new foundation for human-computer interaction research. ACM Transactions on Computer-Human Interaction, 7 (2) 174–196, 2000.

[16] Kaptelinin, Victor., Nardi,Bonnie A (2009). Acting With Technology: Activity Theory and Interaction Design. MIT Press.

[17] Keim, Daniel A., Andrienko, Gennady., Fekete, Jean-Daniel., Gorg, Carsten., Kohlhammer, Jorn., Melancon, Guy (2008). Visual analytics: Definition, process, and challenges, *In*: Andreas Kerren, John T. Stasko, Jean-Daniel Fekete, Chris North, editors, Information Visualization, V. 4950 of LNCS, p. 154–175. Springer-Verlag.

[18] Keim, Daniel A., Kohlhammer, Jörn., Ellis, Geoffrey., Mansmann, Florian (2010). Mastering the Information Age–Solving Problems with Visual Analytics. Eurographics Association.

[19]Keim, Daniel A., Mansmann, Florian., Schneidewind, Jörn., Ziegler, Hartmut (2006). Challenges in visual data analysis. *In*: Proceedings of the Tenth International Conference on Information Visualization (IV 2006), p. 9–16.

[20] Lakoff, George., Johnson, Mark (1996). Metaphors We Live By. University of Chicago Press.

[21] Hai-Ning Liang, Paul C. Parsons, Hsien-Chi Wu, Kamran Sedig. (2010). An exploratory study of interactivity in visualization tools: "*flow*" of interaction. *Journal of Interactive Learning Research*, 21 (1) 5–45.

[22] Liang, Hai-Ning., Sedig, Kamran (2010). Role of interaction in enhancing the epistemic utility of 3d mathematical visualizations.*International Journal of Computers for Mathematical Learning*, 15, 191–224.

[23] Liu, Zhicheng., Nersessian, Nancy J., Stasko, John T. (2008). Distributed cognition as a theoretical framework for information visualization. *IEEE Transactions on Visualization and Computer Graphics*, 14 (6) 1173–1180.

[24] Liu, Zhicheng., Stasko, John T. (2010). Mental models, visual reasoning and interaction in information visualization: A topdown perspective, *IEEE Transactions on Visualization and Computer Graphics,* 16 (6) 999–1008.

[25] Marchionini, Gary (2010). Information Concepts: From Books to Cyberspace Identities. Synthesis Lectures on Information Concepts, Retrieval, and Services. *Morgan and Claypool*.

[26] Mazza, Riccardo (2009). Introduction to Information Visualization. Springer.

[27] Meyer, Joerg., Thomas, James J., Diehl, Stephan., Fisher, Brian D. (2010). From visualization to visually enabled reasoning. *In*:Hans Hagen, editor, Scientific Visualization: Advanced Concepts, chapter 15, 227–245. Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik.

[28] Pike, William A., Stasko, John., Chang, Remco., O'Connell, Theresa A.. (2009). The science of interaction. *Information Visualization*, 8 (4) 263–274.

[29] Peter Pirolli, Stuart K. Card. (2005). The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis. *In*: International Conference on Intelligence Analysis, p. 1–6.

[30] Purchase, Helen C., Andrienko, Natalia., Jankun-Kelly, T. J., Ward, Mattew. Theoretical foundations of information visualization.*In*: Andreas Kerren, John T. Stasko, Jean-Daniel Fekete, Chris North, editors, *Information Visualization*, 4950 of LNCS, p. 46–64. Springer-Verlag.

[31] Ribarsky, William., Fisher, Brian D., Pottenger, William M. (2009). Science of analytical reasoning. *Information Visualization*, 8 (4) 254–262.

[32] Michael Scaife, Yvonne Rogers. (1996). External cognition: how do graphical representations work? *International Journal of Human-Computer Studies*, 45 (2) 185–213.

[33] Scholtz, Jean (2006). Beyond usability: Evaluation aspects of visual analytic environments. *In*: IEEE Symposium on Visual Analytics Science and Technology, p. 145–150.

[34] Sedig, Kamran., Klawe, Maria., Westrom, Marv. (2001). Role of interface manipulation style and scaffolding on cognition and concept learning in learnware, *ACM Transactions on Computer-Human Interaction* (TOCHI), p. 34–59.

[35] Sedig, Kamran., Parsons, Paul. Forthcoming. Interaction design for cognitive activity support tools: A pattern-based taxonomy. AIS Transactions on Human-Computer Interaction.

[36] Sedig, Kamran., Parsons, Paul., Ditter, Mark., Haworth, Robert. (2012). Human-centered interactivity of visualization tools: Micro- and macro-level considerations. *In*: Tony Huang, editor, Human-centric Visualization: Theories, Methodologies and Case Studies, chapter 22. Springer.

[37] Sedig, Kamran., Rowhani, Sonja., Liang, Hai-Ning. (2005). Designing interfaces that support formation of cognitive maps of transitional processes: An empirical study. *Interacting with Computers*, 17 (4) 419–452.

[38] Sedig, Kamran., Sumner, Mark (2006). Characterizing interaction with visual mathematical representations. *International Journal of Computers for Mathematical Learning*, 11, 1–55.

[39] Spence, Robert. (2007). *Information Visualization: Design for Interaction*. Pearson, 2nd edition.

[40] Svendsen, Gunnvald B.. (1991). The influence of interface style on problem solving, *International Journal of Man-Machine Studies*, 35, 379–397.

[41] Thomas, James. J., Cook, Kristen A.. (2005). Illuminating the Path: The Research and Development Agenda for Visual Analytics. National Visualization and Analytics Center (NVAC), Pacific Northwest National Laboratory (PNNL).

[42] Tufte, Edward. (1990). Envisioning Information. Graphics Press.

[43] Ware, Colin. (2008). Visual Thinking for Design. Morgan Kaufmann Series in Interactive Technologies. Morgan Kaufmann.

[44] Wen, Zhen., Zhou, Michelle X (2008). Evaluating the use of data transformation for information visualization, *IEEE Transactions on Visualization and Computer Graphics,* 14 (6) 1309–1316.

[45] Westphal, Christopher. (2009). Data Mining for Intelligence, Fraud, & Criminal Detection: Advanced Analytics & Information Sharing Technologies. CRC Press.

[46] Witten, Ian H., Frank, Eibe., Hall, Mark A.. (2011). Data Mining: Practical Machine Learning Tools and Techniques. The Morgan Kaufmann Series in Data Management Systems. Elsevier Science.

[47] Yi, Ji Soo., Kang, Youn ah., Stasko, John T., Jacko, Julie A.. (2007). Toward a deeper understanding of the role of interaction in information visualization, *IEEE Transactions on Visualization and Computer Graphics*, 13 (6) 1224– 1231.

[48] Zhang, Jiajie., Norman, Donald A.. (1994). Representations in distributed cognitive tasks. *Cognitive Science: A Multidisciplinary Journal*, 18 (1) 87–122.

[49] Zhibin, Xie., Lei, Shi. (2010). Research for humanity technology and physiology influence factors in product styling design. *In*: 29th Chinese Control Conference (CCC'10), p. 5496 –5499.

[50] Zins, Chaim (2007). Conceptual approaches for defining data, information, and knowledge. *Journal of the American Society for Information Science and Technology*, 58, 479–493.