"It is not enough to have a good mind. The main thing is to use it well."

—Rene Descartes, *Discourse on Method*, 1637

2

The Science of Analytical Reasoning

When we create a mental picture, speak of the mind's eye, say "I see" to indicate understanding, or use many other vision-based metaphors, we are expressing the innate connection among vision, visualization, and our reasoning processes. This chapter describes the work needed to put this deep realization onto a useful scientific foundation backed by theory, predictive models, and evaluations.

This science of analytical reasoning provides the reasoning framework upon which one can build both strategic and tactical visual analytics technologies for threat analysis, prevention, and response. Analytical reasoning is central to the analyst's task of applying human judgments to reach conclusions from a combination of evidence and assumptions.

Visual analytics strives to facilitate the analytical reasoning process by creating software that maximizes human capacity to perceive, understand, and reason about complex and dynamic data and situations. It must build upon an understanding of the reasoning process, as well as an understanding of underlying cognitive and perceptual principles, to provide mission-appropriate interactions that allow analysts to have a true discourse with their information. The goal is to facilitate high-quality human judgment with a limited investment of the analysts' time.

In emergency management and border security contexts, analytical reasoning provides the foundation for the abstraction of data at multiple levels to convey the right information at the right time and place. It provides the principles for conveying context-appropriate information that can be cascaded to all levels of an organization to support rapid decision making.

Analytical reasoning must be a richly collaborative process and must adhere to principles and models for collaboration. Collaborative analysis provides both the human and computational scalability necessary to support reasoning, assessment, and action.

The science of analytical reasoning underpins the research areas described in the rest of this book. It provides a basis and a direction for the science of visual representations and interactions described in Chapter 3. It forms a foundation for the principles of depicting information in meaningful and novel visual representations.

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The integration of interaction at a basic level in perceptual and cognitive theory will explain and empower interactive visualizations, which are fundamentally different from static visualizations and are essential to visual analytics tools. The focus on analytic discourse and reasoning processes will make visual representations relevant, focused, and effective. The data representations and transformations described in Chapter 4 must be informed by the needs to support the creation of interactive visualizations from massive and complex data and to represent higher-level concepts, such as levels of abstraction. These representations and transformations must also support the capture of both intermediate and final products of the analytical process. Analytical reasoning principles must inform the research in production, presentation, and dissemination described in Chapter 5, so that the resulting communications can be clear and on point. As illustrated in Chapter 6, the science of analytical reasoning provides a practical basis for evaluation of visual analytics tools, as well as important insights about the training and user support necessary to facilitate adoption of these tools in analytical environments.

This chapter begins with an overview of the analysis process and its products, from the point of view of the practitioner. We then discuss the concept of analytic discourse, which is the interactive, computer-mediated process of applying human judgment to assess an issue. This discourse is at the core of the analytical process and is integral to threat analysis, emergency response, and borders and infrastructure protection. Analytic discourse represents an applied research approach to the analytic reasoning challenge. Next, we describe sense-making, which provides a more theoretical basis for understanding the reasoning process based on models of human information processing. Sense-making is both a working analysis approach and a possible framework for a broader theory of analytical reasoning and human-information discourse. Next, we discuss the foundational perceptual and cognitive theory and models that provide the grounding for visual analytics tools that support the analytical reasoning process. We conclude with a discussion of the theoretical basis for successful collaborative visual analytics. Such collaboration must extend the principles of visual analytics to environments where humans and machines reason together intimately regardless of whether or not they are separated by time or distance.

An Overview of Analysis

The goal of visual analytics is to create software systems that will support the analytical reasoning process. This section describes the process and language of the analysis process from the practitioner's perspective and describes the intermediate and final products of the analytical reasoning process.

The Analysis Process

Analysis is both an art and a science. The goal of analysis is to make judgments about an *issue*, or larger question. Analyses are often done on smaller questions relating to a larger issue. Analysts must often reach their judgments under significant time pressure and with limited and conflicting information. Their judgments necessarily reflect their best understanding of a situation, complete with assumptions, supporting evidence, and uncertainties. Analytical outcomes are documented in the form of a *product*, which is a tangible result of an analysis that can be shared with others.

Analysis is necessary to support identification of threats and vulnerabilities, protection of borders and critical infrastructure, and emergency preparation and response. Analysts may be asked to perform several different types of tasks, depending upon the requester's needs:

- ***Assess*** – Understand the current world around them and explain the past. The product of this type of analysis is an *assessment*.
- ***Forecast*** – Estimate future capabilities, threats, vulnerabilities, and opportunities.
- ***Develop Options*** – Establish different optional reactions to potential events and assess their effectiveness and implications. For homeland security issues in particular, analysts may develop options to defend against, avert, or disrupt threats. In emergency response situations, analysis is used to understand response options and their implications.

Regardless of the type of analysis, analysts make judgments from evidence and assumptions using reasoning. They seek and process a set of information, ideally from multiple sources; assert and test key assumptions; and build knowledge structures using estimation and inferential techniques to form chains of reasoning that *articulate and defend* judgments on the issue [Chen, 2003; Clark & Brennan, 1991].

The term *defend* suggests that the reasoning, evidence, level of certainty, key gaps, and alternatives are made clear. Defensible judgments enable effective collaboration, review, and communication. They also support the comparison of conclusions drawn from alternative techniques. The analysis practices used and standards for their application, including checks and balances to ensure thorough consideration of options, are collectively referred to as *tradecraft* [CIA, 1997].

Analysis is an iterative process. Not only is the process of reaching judgment about a single question often an iterative one, but obtaining that answer produces several more questions, leading to additional analyses about the larger issue.

Analysis is also a collaborative process. Information, including judgments and written products, are shared among analysts working on related problems. Research issues associated with supporting this collaboration are discussed later in this chapter. Collaboration must be conducted with full adherence to security and privacy laws and policies. Security and privacy issues are discussed in more depth in Chapter 6.

Steps in the Analytical Process

The analytical process is structured and disciplined. Depending on time availability and task complexity, it is often an iterative process. The analyst's solution process begins with planning. He or she must determine how to address the issue that has been posed, what resources to use, and how to allocate time to various parts of the process to meet deadlines. Next, the analyst must gather information containing the relevant evidence and become familiar with it, and incorporate it with the knowledge he or she already has. The analyst next generates multiple candidate explanations, often in the form of hypotheses. The analyst evaluates these alternative explanations in light of evidence and assumptions to reach a judgment about the most likely explanations or outcomes. Once conclusions have been reached, good analytical practice dictates that the analyst engage in processes to broaden his or her thinking to include other explanations that were not previously considered.

At the conclusion of the analysis, the analyst creates reports, presentations, or other products that summarize the analytical judgments. These products are reviewed extensively in a collaborative process. Then they are shared with the requesters of information and with other audiences as appropriate. These products summarize the judgments made and the supporting reasoning that was developed during the analytical process. The subject of production, presentation, and dissemination of results is addressed in more depth in Chapter 5.

A detailed discussion of the intelligence cycle, or knowledge management process within which the analytic endeavor exists, is beyond the scope of this chapter but can be found in Tenet [1999] and Waltz [2003].

This analysis process is important to a wide variety of homeland security needs. Desk analysts predominantly address the analysis of threats and vulnerabilities. Their careers focus on daily practice of these analytical techniques. Border and infrastructure protection requires analytic effort to understand and respond to evolving situations. Emergency management personnel, whether first responders or personnel coordinating the response, pursue similar goals in order to identify and take appropriate actions. In emergency response contexts, however, the time available for analysis is generally shorter, meaning that the analysis cannot be as thorough, and the results must be converted directly into action.

Regardless of the situation, executing sound analysis routinely is challenging. This is further complicated by the fact that the pool of experienced analysts is limited. As Richards Heuer illustrates in his key work, *Psychology of Intelligence Analysis* [1999], analytical processes can compensate for human limitations in managing complex and fluid problems.

Analytic Reasoning Artifacts

The analyst collects and organizes information as he or she progresses toward judgment about a question. Throughout the reasoning process, the analyst identifies or creates tangible pieces of information that contribute to reaching defensible judgments. We refer to these pieces of information here as *reasoning artifacts. Products* can be thought of as reasoning artifacts that are meant to be shared with others to convey the results of the analysis. A description of common analytical reasoning artifacts appears in Table 2.1.

***Table 2.1**. Common reasoning artifacts.*

Elemental artifacts: artifacts derived from isolated pieces of information	
Source Intelligence	An individual piece of intelligence (e.g., a document, photograph, signal, sensor reading) that has come to the analyst's attention through a collection or retrieval activity.
Relevant Information	Source intelligence that is believed to be relevant to the issue and usable for constructing arguments and judgments.
Assumption	An asserted fact, and its basis, that will be used for reasoning. Assumptions must be managed separately from evidence, as sound practice demands their critical inspection. An assumption may come from the analyst's prior knowledge, an earlier conclusion or product of an analysis, or a key, presently unknowable presumed fact that allows judgment to progress despite a gap in knowledge.
Evidence	The information or assumption takes on argument value when the analyst assesses its quality, accuracy, strength, certainty, and utility against higher-level knowledge artifacts such as hypotheses and scenarios. Assessing the utility can be as simple as judging if the evidence is consistent or inconsistent with a hypothesis or scenario or if the evidence argues for or against an inference.
Pattern artifacts: artifacts derived from collections of information	
Patterns and Structure	Relationships among many pieces of data to form evidence. Analysts often create tables, charts, and networks of data to detect and extract pattern or structure.
Temporal and Spatial Patterns	Temporal relationships and spatial patterns that may be revealed through timelines and maps. Changes in pattern, surprising events, coincidences, and anomalous timing may all lead to evidence recognition. The simple act of placing information on a timeline or a map can generate clarity and profound insight.
Higher-order knowledge constructs	
Arguments	Logical inferences linking evidence and other reasoning artifacts into defensible judgments of greater knowledge value. Extensive formal systems, such as predicate calculus, give a solid inferential basis.
Causality	Specialized inference about time, argument, and evidence that makes the argument that an event or action caused a second event or action. Causality is often critical to assessments. It is also a source of many biases and errors, and demands careful review.
Models of Estimation	A means of encoding a complex problem by understanding logic and applying it to evidence, resulting in a higher-level judgment that estimates the significance of available evidence to the issue at hand. Some important classes of models are utility models (which estimate the value of a potential action to an actor using multiple weighted criteria), indicator models (used to estimate if outcomes of interest may be in the process of development), behavioral models (of individual and group dynamics), economic models, and physical models. Specialized analytic activity may involve research using models, simulation, and gaming. A repertoire of basic problem modeling and structuring techniques is invaluable to the analyst.
Complex reasoning constructs	
Hypothesis	A conjectured explanation, assessment, or forecast that should be supported by the evidence.
Scenarios or Scenario Fragments	Sequences of information with "story" value in explaining or defending part of a judgment chain. For example, a threat scenario might address a target, method, actor, motive, means, and opportunity.

These artifacts range from the very simplest pieces of raw data to the highest-level constructs that represent large parts of the analytic solution. The most complex constructs, such as hypotheses and scenarios, are used primarily to help structure the available knowledge, facilitate its articulation and delivery in product, test the completeness of the knowledge, and identify if additional knowledge or explanatory paths may be required.

Hypotheses and scenarios are used to express and explain a large collection of evidence, so they are valuable both as reasoning aids and to support the process of conducting competing evaluations. For example, the technique of alternative competing hypothesis evaluation [Garfinkel, 1967] highlights the value of retaining competing hypotheses and seeking evidence that refutes hypotheses, or, even better, diagnostic evidence that supports one hypothesis but refutes another, to select the hypothesis that best explains the evidence.

Analytic Discourse

The analytical reasoning process described above forms the basis for the ongoing dialogue between analysts and their information. Enabling this discourse is at the heart of the visual analytics mission. This section describes the relationship of this discourse to the analysis process and recommends steps for advancing the state of the art in analytic discourse.

A Definition of Analytic Discourse

Analytic discourse is the technology-mediated dialogue between an analyst and his or her information to produce a judgment about an issue. This discourse is an iterative and evolutionary process by which a path is built from definition of the issue to the assembly of evidence and assumptions to the articulation of judgments.

The analyst's information includes:

- The issue being addressed. At the outset, the analyst refines his or her understanding of the question to be answered, sometimes broadening or adjusting the scope so as to respond to the question that was intended, rather than what was explicitly asked.
- Information that the analyst has gathered regarding the issue, which may or may not include relevant evidence. Through exploration and investigation, the analyst identifies and evaluates evidence within the available data and requests additional data as needed.
- The analyst's evolving knowledge about the issue, including assumptions, hypotheses, scenarios, models, or arguments.

In an analytic discourse, the strengths of both the computer system and the human are harnessed to improve the analysis process. The computer finds patterns in information and organizes the information in ways that are meant to be revealing to the analyst. The analyst supplies his or her knowledge in ways that help the computer refine and organize information more appropriately.

Analytic discourse should support the goal of creating a product that articulates a defensible judgment in problems of assessment, forecasting, and planning. Effective solutions will require a true dialogue, mediated by technology, among the user, information, issue, and evolving judgment.

Supporting Analysis Through Analytic Discourse

It should be the goal of visual analytics systems to support the analyst in *executing sound analytic technique routinely*, facilitating insight and sound judgment in time-pressured environments and compensating for inexperience wherever possible. An effective analytic discourse must accommodate the unique characteristics of the analysis process, some of which are described here.

Analysis is generally not a linear process. Analysts spend time engaged in *convergent thinking*, which involves assembling evidence to find an answer, and *divergent thinking*, which involves thinking creatively to ensure that plausible alternatives have not been overlooked. Many analysts engage in controlled broadening checks during their investigations, during which they consider the broader context of the issue and examine alternative explanations and data that do not fit with their current reasoning. Therefore, visual analytics systems must facilitate this iterative and nonlinear process through an active discourse.

People cannot reason effectively about hypotheses and scenarios that are unavailable to them [Garfinkel, 1967]. Key to good analytic discipline is early identification of competing explanations and chains of reasoning for the issue under study. Awareness of the competing ideas must be maintained actively, so that they are kept “alive” as analytic possibilities. Often the most plausible explanation will be researched extensively, but a thorough check is to always revisit the key alternative ideas and ask, “If I were wrong, how would I know?” Visual analytics tools must facilitate the analyst’s task of actively considering competing hypotheses.

Another important analytic technique is the enumeration and testing of assumptions. Explicit representation of these assumptions facilitates this process. Additional analytical techniques include consideration of biases that may have precluded consideration of important alternatives, sensitivity to potential deception in evidence, and in cases of high risk, devil’s advocacy processes that assume a differing interpretation of data and attempt to reason in that direction, exposing potential weaknesses in the product. These techniques are examples of structured ways to review the product and its supporting evidence and reasoning, and they can be greatly facilitated by a visual analytics system.

Analysis products are expected to clearly communicate the assessment or forecast, the evidence on which it is based, knowledge gaps or unknowns, the analyst’s degree of certainty in the judgment, and any significant alternatives and their indicators. Visual analytics systems must capture this information and facilitate its presentation in ways that meet the needs of the recipient of the information.

These tools and techniques also must allow analysts to look at their problem at multiple levels of abstraction and support reasoning about situations that change over time, sometimes very rapidly.

Supporting Analyst Operations on Reasoning Artifacts

Analytic discourse must support a full range of operations to derive, manipulate, and understand reasoning artifacts. For simple elemental and pattern artifacts, visual analytics tools must support data retrieval, navigation, and discovery operations to permit data collection or foraging. For higher-level knowledge artifacts such as arguments, causality, and estimative modeling, visual analytics tools must support construction or formulation operations.

Analytic discourse must permit the analyst to create abstractions of these artifacts. That is, it must be possible to obtain a simpler representation of the information that is more suitable for the product or collaboration.

Analysts often want to compare knowledge artifacts to find similarities and differences in evidence, arguments, or hypotheses. The analysis process often demands that an argument, hypothesis, or scenario be challenged or tested to find weaknesses and inconsistencies. During the collaborative creation of a product, it is often critical to frame the questions being addressed in terms of the evidence and reasoning rather then in terms of a conclusion.

Visual analytics systems must support all of these needs to enable true analytic discourse.

State of the Art

Much has been done to study and document simple and effective analysis techniques. References such as *The Thinker's Toolkit* [Jones, 1995], *Conceptual Blockbusting* [Adams, 2001], and *Psychology of Intelligence Analysis* [Heuer, 1999] describe representative approaches. The professional analyst is often armed with a broad repertoire of techniques, but these are not available to the research community as a whole.

Analysts must deal with data that are dynamic, incomplete, often deceptive, and evolving. The problem of coping with such diverse and changing information has been recognized for centuries. Descartes [1637] described a problem-solving method wherein data are analyzed, broken into their elements, and studied to reveal evidence, and solutions are synthesized by accumulating the evidence. For the researcher, the concept of allowing the breakdown of information and its assembly to solutions remains an interesting one. For example, a single piece of source information (e.g., document or photograph) may contribute many different pieces of evidence to understanding and may support or refute many differing and competing hypotheses.

Methods of evidence navigation and discovery from available information collections, even ones of a practical scale in the problem areas of homeland security, are rapidly maturing. Retrieval technology is very mature; Boolean retrieval is universally in practice; and more advanced forms of retrieval, such as natural language question answering for simple facts, are maturing. Extraction technology, to isolate entities and relationships within text, is maturing, with entity extraction commonly used.

There is an excellent body of science, some in service, to support the visualization and navigation of information spaces of up to one million documents or so. There are mature capabilities to support basic analytic discourse, but work needs to be done to expand the ability to respond to the analyst's more sophisticated problem-solving goals. Much work remains to be done to extend these techniques to accommodate the massive scale and dynamic nature of visual analytics tasks.

Many mathematical techniques exist for representing pattern and structure, as well as visualizing correlations, time patterns, metadata relationships, and networks of linked information. For simple patterns and structure they work well; for more complex reasoning tasks—particularly temporal reasoning and combined time and space reasoning—much work remains to be done. The existing techniques also fail when faced with the massive scale, rapidly changing data, and variety of information types we expect for visual analytics tasks.

Structured argumentation, which is the linking of evidence and assumptions through formal logic, has a large literature to draw on (see, for example, Schum [1994]). Some capabilities for structured argumentation are in limited practice, and a good basic body of research has been conducted. Kirschner [2003] summarizes current views of the relationship between visualization and argumentation. It is often speculated that structured argumentation could be the basis of visual analytics systems. More work is needed to explore this possibility. One concern is that formalized systems trend towards interaction that lacks the approachability, fluidity, and speed needed for effective application.

In hypothesis formulation and testing, and in models of inference, there is considerable science as well—some from the artificial intelligence and ontological modeling communities, and some from epistemology. Some promising science demonstration systems have been developed to generate and track hypotheses, but this research remains a longer-term goal for effective, tractable application.

Current techniques break down when composite reasoning processes—that is, the joining of many types of reasoning artifacts—are in use; when the problem demands harmonizing many different insights from differing artifacts; and when the ability to retain active competitive explanations, such as during suspected deception, is critical.

Current techniques also break down when applied to the massive and dynamic multi-type data common to the homeland security arena, as described in Chapter 1. Another area of weakness in existing science is that once an important piece of evidence is recognized or an inference is made, it is often exceedingly difficult to capture and record the progress directly, forcing reliance on memory, notes, or annotations. Likewise, a sudden recognition, question, or insight usually cannot be recorded without disrupting the ongoing analysis context. Visual analytics software can and should maintain records of progress for the analyst as an intrinsic byproduct of engaging in the discourse.

An integrated science for analytic discourse does not yet exist, but its creation will offer tremendous benefits to analysts and the homeland security missions.

Technology Needs

To develop an integrated science for analytic discourse, we recommend two initial actions.

Recommendation 2.1

Refine our understanding of reasoning artifacts and develop knowledge representations to capture, store, and reuse the knowledge generated throughout the entire analytic process.

These knowledge representations will primarily be used to support interoperation among software tools used to support analytic discourse. These knowledge representations must retain the reasoning artifacts that are produced throughout the analytical process, as well as retain the judgment chains and links to supporting information associated with each analytical product. It must provide the mapping between the reasoning artifact and the original data used to produce it, along with information about both data quality and method of derivation for the reasoning artifact.

Recommendation 2.2

Develop visually based methods to support the entire analytic reasoning process, including the analysis of data as well as structured reasoning techniques such as the construction of arguments, convergent-divergent investigation, and evaluation of alternatives. These methods must support not only the analytical process itself but also the progress tracking and analytical review processes.

The challenge of integrating the entire range of activity described here, in a manner that is usable, understandable, and time-efficient to the analyst, is substantial. We must enable not only the analytic processes that an individual follows to reach a judgment but also the communication processes that are necessary both to track the progress of the analytical process and to share the results of the analysis and supporting information to facilitate reviews.

Sense-Making Methods

While the concept of analytic discourse represents a more applied research perspective, research in sense-making provides a theoretical basis for understanding many of the analytical reasoning tasks that the analyst performs.

Many analytical reasoning tasks follow a process of

- Information gathering
- Re-representation of the information in a form that aids analysis
- Development of insight through the manipulation of this representation
- Creation of some knowledge product or direct action based on the knowledge insight.

As illustrated in Figure 2.1, these activities may be repeated and may come out of order, although there is the notion of an overall cycle. We call tasks that follow this sort of pattern *sense-making tasks* or sometimes *knowledge crystallization tasks*.

Examples abound in commerce, education, research, military activities, and intelligence. For example, consider the sense-making process involved in choosing which model of laptop computer to purchase. The shopper may *gather information* from magazines and the internet. The information collected may be *re-represented* by creating a table of computer models by attributes. This representation may be *manipulated*, deleting rows of attributes for serial and parallel ports, for example, and adding new rows for FireWire and graphics accelerators. The shopper gains insight into her choice by inspecting the matrix, possibly by rearranging the rows and columns, or highlighting cells. The *knowledge product* in this case is a rationalized purchase decision.

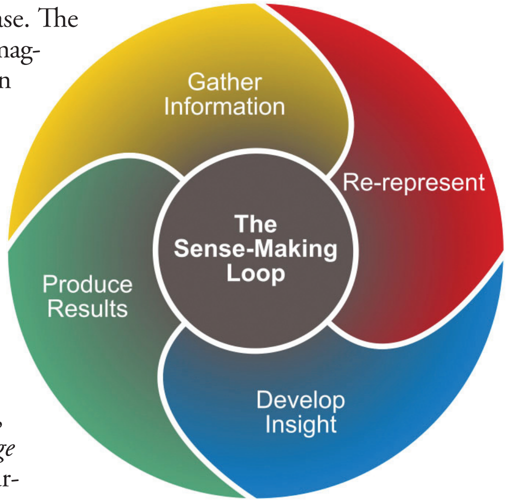

***Figure 2.1**. The analytical reasoning process.*

State of the Art

Some variant of this sense-making process is often encountered in the analysis of information-intensive tasks. For example, Lederberg [1989] describes the scientific process as a sort of sense-making cycle with multiple feedbacks. The CIA [1995], in a report on the need for visualization, discusses intelligence analysis essentially as a sense-making loop of collection tasking, data monitoring, interpretation and analysis, drafting/editing, and customer support. Card et al. [1999] frame information visualization using the concept of a sense-making loop. Recent work has suggested a similar sense-making loop cycle (Figure 2.2, adapted from Pirolli & Card, 2005) for some types of analysis work. Boxes in the diagram represent data and arrows represent processes. An analyst filters message traffic and actively searches for information, collecting it in an information store (called a *shoebox* in the diagram). Relevant snippets from this store are extracted from these documents into evidence files, which may be simply text files in a word processing program. Information from the evidence may be represented in some schema, or a conceptual form into which information is transformed for exploration and manipulation, and from which it is translated to produce briefings and other products. Schemas may take the form of representations such as timelines, or they may simply reflect the internalized mental representations of the expert. The evidence thus laid out may be cast into hypotheses or methods of structured reasoning. Finally, information is transformed into an output knowledge product, such as a briefing or a report. This is an expansion of the process we saw in the laptop example above: the information is gathered, mapped into some set of core representations that encapsulate the heart of the knowledge domain and where operators on the knowledge are enabled, then transformed into the knowledge product.

The process is not a straight progression but can have many loops. For example, construction of an evidence file can evoke the need to go back and collect new evidence. Among the many possible loops, there are two especially important ones: an information

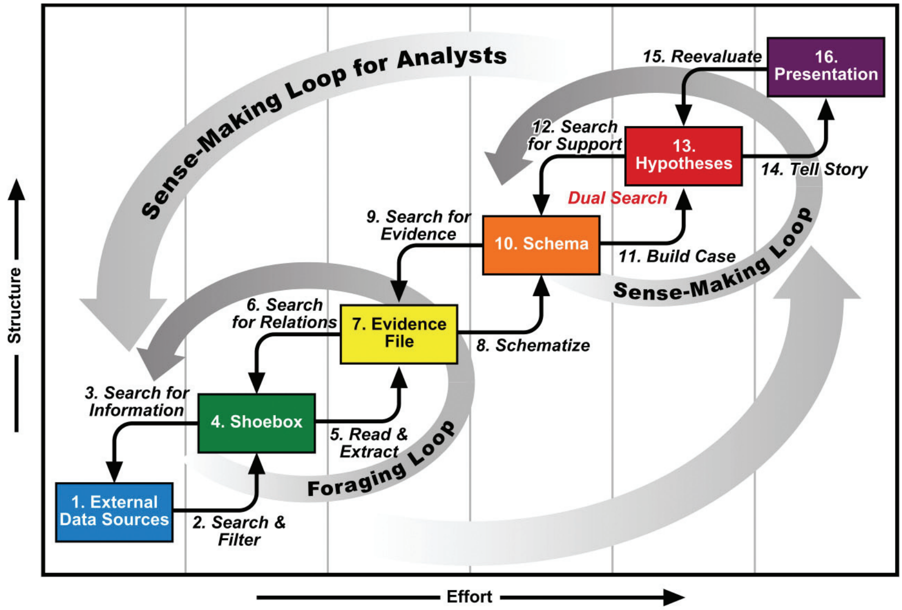

Figure 2.2. *Nominal sense-making loop for some types of intelligence analysts.*

foraging loop, which focuses on the gathering and processing of data to create schemas, and the sense-making loop, which includes the processes involved in moving from schemas to finished products.

Other researchers have come to a similar conclusion about the nature of sense-making for intelligence analysts and first responders. For example, Klein [2004] has a data/frame-based theory of sense-making, which plays a similar role to *schema* in Figure 2.2. For Klein, a frame is a mental structure that organizes the data and sense-making is the process of fitting information into that frame. Frames are a consequence of developed expertise. Bodnar [2003] describes a process similar to Figure 2.2 in his book on warning analysis for intelligence.

Effects of time scale on sense-making

Sense-making has been studied from more varied points of view than the intelligence analysis process described in Figure 2.2. Leedom [2001], for example, has reviewed this field with respect to its relevance to military decision making. The sense-making process is affected by the time scale for the process and whether the process involves individuals or organizations.

At the organizational level and operating on a time scale of months and years, Weick [1995] claims that the social dynamics of organizational processes are based on sense-making. A set of "mental minimal sensible structures" together with goals lead to the creation of situational understanding and direction for members of organizations.

In situations that require action within minutes or hours, Klein [1989, 1998] has developed a model of recognition-primed decision making, as part of a program on naturalistic decision making that has been used as the basis of military command and control. This model emphasizes the role of the knowledge structures built from expertise and experience in allowing a soldier or a firefighter to make sense of a situation and rapidly formulate an action. The lack of some expected features of a situation can also trigger sense-making and action.

In cases where action is required within seconds or minutes, Endsley [1995] and others have studied the notion of *situational awareness* for individuals, particularly in the context of advanced cockpit displays for combat air tasks. Situational awareness is the perception of the elements in the environment within a volume of space and time; comprehension of their meaning; the projection of their status into the near future; and the prediction of how various actions will affect the fulfillment of one's goals.

It thus contains a cycle of perception, comprehension, projection, and prediction. A related action-oriented cycle is Boyd's Observation-Orientation-Decision-Action loop [1987]. Although Boyd was a combat Air Force pilot and his ideas derive from the time pressure of combat, he generalized them to strategizing taking place over days and months by organizations.

Models of sense-making and its cost structure

Each of the processes of sense-making, from finding and extracting information to re-representing it for analysis, to creating an end product, has a cost. Costs could be thought of in terms of time investment, level of difficulty, or resources required, for example. The collective costs and gains of the individual sense-making processes are referred to as its *cost structure*. The cost structure may strongly shape the behavior of the user.

The cost structure of the lower end of the sense-making loop in Figure 2.2 has been addressed in work on information foraging theory [Pirolli & Card, 1999]. The cost structure is characterized in terms of information gain and costs (usually measured in time) for obtaining and consuming the information. A reasonable model is that the user will seek to adapt to the information environment to maximize information gains per unit cost. Predictions can be made about what sorts of information users will exploit and when users will decide to move from one patch of information to another.

Other models have been developed to represent user strategies for sense-making. Patterson et al. [2001] show how intelligence analysts in a simulated situation trade off between widening the search for documents ("explore"), narrowing it ("enrich"), and reading documents ("exploit") and how these relate to missed information (Figure 2.3). In general, they show that techniques for handling

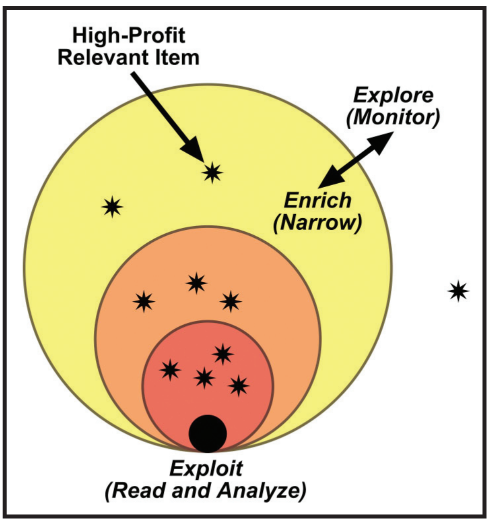

***Figure 2.3**. Circles show the space of documents being considered. Stars indicate relevant documents. Analysts adjust their activities among exploring, enriching, and exploiting documents.*

context are a key to coping with high information loads [Woods et al., 2002].

Russell et al. [1993] have described sense-making in terms of a "learning loop complex" (Figure 2.4). First is a search for a good representation (the generation loop). Then there is an attempt to encode information in the representation (the data coverage loop). The attempt at encoding information in the representation identifies items that do not fit ("residue"). This gives rise to an attempt to adjust the representation so that it has better coverage (the "representation shift loop"). The result is a more compact representation of the essence of the information relative to the intended task.

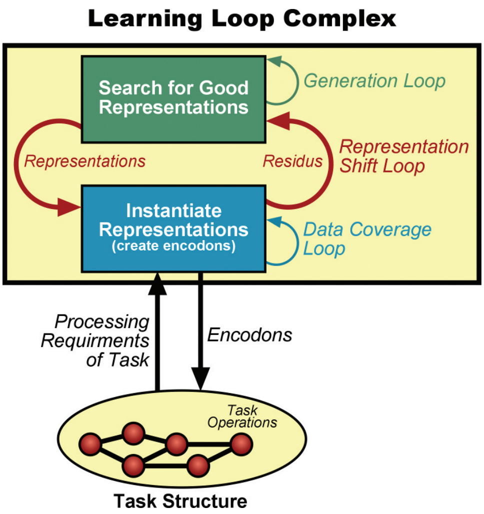

Figure 2.4. *Learning Loop Complex theory of sense-making.*

Another source of theory for the sense-making process comes from the study of scientific discovery [Shrager & Langley, 1990; Klahr, 2000]. An important theoretical concept is the Scientific Discovery through Dual Search (SDDS) model. This model emphasizes that sense-making or discovery in science often involves an alternating dual search both through a problem space of hypotheses and through a problem space of data. Sometimes it is easier to make progress by looking for explanations of data by generating hypotheses; other times it is easier to make progress by creating experiments to generate data to test hypotheses. The SDDS model was proposed as a general framework for behavior in any scientific reasoning task. The full set of possible activities is represented in Figure 2.5.

The Role of Visual Analytics in Sense-Making

Visual analytics seeks to marry techniques from information visualization with techniques from computational transformation and analysis of data. Information visualization itself forms part of the direct interface between user and machine. Information visualization amplifies human cognitive capabilities in six basic ways (Table 2.2) [Card et al., 1999]: 1) by *increasing cognitive resources*, such as by using a visual resource to expand human working memory, 2) by *reducing search*, such as by representing a large amount of data in a small space, 3) by *enhancing the recognition of patterns*, such as when information is organized in space by its time relationships, 4) by *supporting the easy perceptual inference of relationships* that are otherwise more difficult to induce, 5) by *perceptual monitoring* of a large number of potential events, and 6) by *providing a manipulable medium* that, unlike static diagrams, enables the exploration of a space of parameter values.

These capabilities of information visualization, combined with computational data analysis, can be applied to analytic reasoning to support the sense-making process.

Visual analytics could be used to facilitate any point along the sense-making cycle, such as accelerated search, accelerated reading, accelerated extracting and linking, schema visualization, hypothesis management and structured argumentation, or interactive presentation. Visual analytics can enhance the scale or effectiveness of the analyst's schemas, not only for expert analysts but also—and especially—for those below the expert tier.

Visual analytics can reduce this cost structure associated with sense-making in two primary ways: 1) by transforming information into forms that allow humans to offload cognition onto easier perceptual processes or to otherwise expand human cognitive capacities as detailed in Table 2.2, and 2) by allowing software agents to do some of the filtering, representation translation, interpretation, and even reasoning.

Visual analytics systems can be developed starting from a notion of sense-making and adding computer-enhanced capabilities of visualization and data analytics. The ultimate goal is to produce a broader science of analytical reasoning built on the foundation of sense-making.

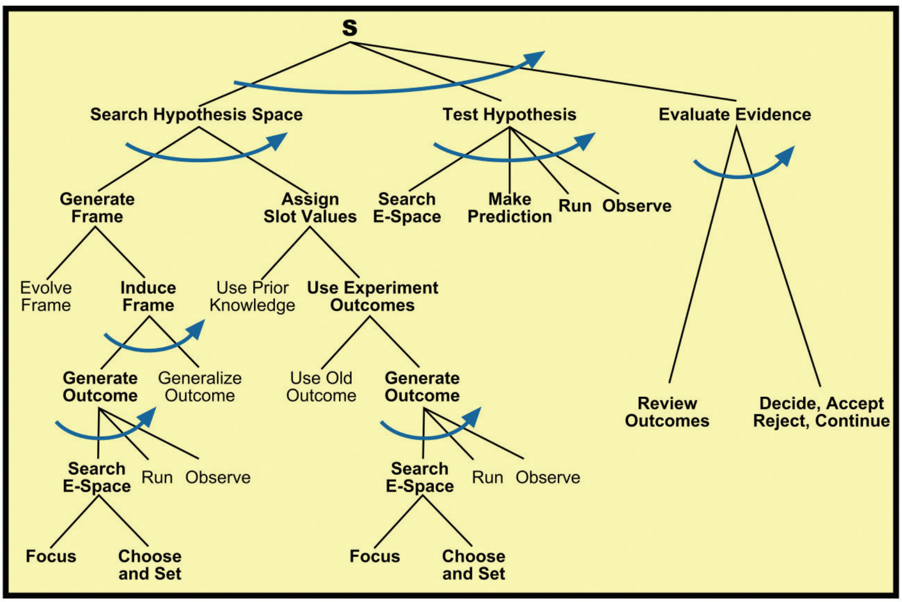

Figure 2.5. *Klahr's SDDS theory of scientific discovery. The dual search through hypothesis and experiment problem spaces is represented here as an "and/or graph" of operations. Arrow arcs indicate all of the sub-operations that must be performed. For sub-operations without an arrow arc, only one needs to be performed.*

***Table 2.2**. How information visualization amplifies cognition.*

1. Increased resources	
High-bandwidth hierarchical interaction	The human moving gaze system partitions limited channel capacity so that it combines high spatial resolution and wide aperture in sensing the visual environments [Resnikoff, 1989].
Parallel perceptual processing	Some attributes of visualizations can be processed in parallel compared to text, which is serial.
Offload work from cognitive to perceptual system	Some cognitive inferences done symbolically can be recoded into inferences done with simple perceptual operations [Larkin & Simon, 1987].
Expanded working memory	Visualizations can expand the working memory available for solving a problem [Norman, 1993].
Expanded storage of information	Visualizations can be used to store massive amounts of information in a quickly accessible form (e.g., maps).
2. Reduced search	
Locality of processing	Visualizations group information used together, reducing search [Larkin & Simon, 1987].
High data density	Visualizations can often represent a large amount of data in a small space [Tufte, 1983].
Spatially-indexed addressing	By grouping data about an object, visualizations can avoid symbolic labels [Larkin & Simon, 1987].
3. Enhanced recognition of patterns	
Recognition instead of recall	Recognizing information generated by a visualization is easier than recalling that information by the user.
Abstraction and aggregation	Visualizations simplify and organize information, supplying higher centers with aggregated forms of information through abstraction and selective omission [Card et al., 1991; Resnikoff, 1989].
Visual schemata for organization	Visually organizing data by structural relationships (e.g., by time) enhances patterns.
Value, relationship, trend	Visualizations can be constructed to enhance patterns at all three levels [Bauer et al., 1999].
4. Perceptual inference	
Visual representations make some problems obvious	Visualizations can support a large number of perceptual inferences that are extremely easy for humans [Larkin & Simon, 1987].
Graphical computations	Visualizations can enable complex, specialized graphical computations [Hutchins, 1996].
5. Perceptual monitoring	
	Visualizations can allow for the monitoring of a large number of potential events if the display is organized so that these stand out by appearance or motion.
6. Manipulable medium	
	Unlike static diagrams, visualizations can allow exploration of a space of parameter values and can amplify user operations.

Technology Needs

Sense-making provides a basis for analytic discourse, but research is necessary to expand this foundation to provide the necessary theoretical grounding for visual analytics.

Recommendation 2.3

Characterize the sense-making process as applied to analytic discourse in terms of the sense-making loop or other constructs and identify leverage points that are opportunities for intervention. Identify laboratory analogs of these tasks for development and evaluation.

We need to know more about the nature of the sense-making loop. We need integrated characterizations of sense-making problems, the systems used, and the users. Such characterizations would, of course, include descriptive studies. Visual analytics systems that do not adequately take into account the context of the data and their use will likely fail. But descriptive studies alone are not adequate for system design. Task analysis of user problems needs to reveal the underlying problem drivers, the forces shaping user behavior, the pain points, and the bottlenecks. We need models and theories of the situations at hand that shape the design space and predict a likely design result. We also need to develop problem analogs that can be used in the laboratory for development and testing. Andries Sanders [1984] advocated a "back-to-back" testing philosophy in which laboratory tests to obtain control were paired with field studies to assess content validity. The ability to evaluate problem analogs in the laboratory is especially important for applications such as analysis and emergency response, where access to analysts and large-scale emergency response scenarios may be limited.

Taxonomies of task types and data types must be developed. Studies must identify bottlenecks associated with different tasks and data characteristics. For example, looking for the answer to something you know, such as troop strength at a given point at a certain time in the context of abundant data, is different from looking for the same information with sparse data, which is different still from looking for anomalies that signal something you don't know.

Recommendation 2.4

Identify and focus on core conceptual schemas and create visually based components that support the analytical reasoning tasks associated with these schemas.

Because schemas are so central to the sense-making process, great benefit can be gained by identifying the core conceptual schemas for the intended domains and to create analytic visualizations to support these schemas. Certain core needs will arise repeatedly, such as analysis of timelines. By creating components that support the major analytic tasks associated with each of these conceptual schemas, we can address a wide range of common problems.

Several techniques have already been explored for how to map out scientific literatures [Small & Griffith, 1974; Chen, 2003], techniques that could be used for analysis.

Recommendation 2.5

Explore paradigms of human-machine interaction that treat visual analytic systems as mixed initiative supervisory control systems.

Visual analytics systems will have semi-automated analytic engines and user-driven interfaces. Some of these will be mixed initiative systems, in which either the system or the user can initiate action and have independent access to information and possibly to direct action. These systems need to be studied with insights derived from supervisory control systems. For example, if we consider which system can initiate action, which has to ask permission of the other before action can be executed, which can interrupt the other when, and which has to inform the other that it has taken action, we can define dozens of possible paradigms.

Perception and Cognition

Visual analytics combines analytical reasoning with interactive visualization, both of which are subject to the strengths and limitations of human perceptual and cognitive abilities. Effective tools must build on a deep understanding of how people sense, reason, and respond.

Many of the driving problems in Chapter 1 concern managing and understanding the enormous data stream intrinsic to visual analytics. An important aspect of the science of analytical reasoning is to create ways to represent data in forms that afford interaction and enable thought processes to translate from data to information, information to meaning, and meaning to understanding. As Herbert Simon [1996] said, “Solving a problem simply means representing it so that the solution is obvious.” There is a long history of work on interactive technologies for cognitive augmentation, a goal set by Vannevar Bush in his article “As We May Think” [1945] and first put into operation by Douglas Engelbart and colleagues at Stanford Research Institute [Spohrer & Englebart, 2004] and the Bootstrap Institute.

Other driving problems have to do with improving visual representation. Chapter 3 is devoted to the science of visual representation and includes a thorough discussion of the state of the art in that domain, including some of the underlying perceptual and cognitive principles that are applied today. These principles must be better understood and integrated with those principles supporting analysis and reasoning to create more complete models for visual analytics.

Human-information discourse is that state where the mechanics of accessing and manipulating the tools of visual analytics vanish into a seamless flow of problem solving. How to achieve this flow, and how to use it to produce the concrete products needed in all visual analytic domains, constitutes a major research challenge. The concept of *flow* has its roots in psychology; application of its principles to interactive systems has yet to be achieved.

A key problem for visual analytics arises from the limited abilities of human perception and cognition, e.g., limits on short-term memory. To get around these limits, we use external aids, as discussed in Norman’s *Things That Make Us Smart*. Heuer [1999] says, “Only by using such external memory aids am I able to cope with the volume and complexity of the information I want to use." Visual analytics is just such an external aid. To achieve the flow of analytic discourse, we need to better understand the interaction between perception and cognition and how they are affected when we work with a dynamic external aid. In other words, it is the process of perception and cognition and our resulting interactions that updates our understanding.

To achieve this understanding, which is crucial for meeting the challenges posed in this agenda, perception and cognition research will draw from work in multiple disciplines, such as perceptual and cognitive psychology, neuroscience, cartography and geographic information science, cognitive science, human-computer interaction, design, and computing. Visual analytics research must build on this work to forge a new and fundamental bond with interactive visualization.

State of the Art

The traditional model for human performance is a simple three-stage process, where some stimulus, such as a pattern of light, is processed first by the perceptual system to create a mental representation. In the second stage, cognitive processes evaluate that representation, accessing memory of other representations or schemas, for example, leading to some decision about the nature of the event and any response it requires. Finally, in stage 3, some motor action may be taken based on the decision reached in stage 2. Perceptual principles based on this process have been applied extensively to interactive visualization, as discussed further in Chapter 3. This common conceptual breakdown of mental processing forms the basis for the mass of experimental studies in perception, where each trial of an experiment presents a stimulus that is perceived and understood by the subject and the resulting motor response recorded as data for analysis of the nature of their perceptual and cognitive processes. While this is a useful conceptual breakdown for task performance (and as a window into the traditional literature in these fields), it is less useful as a model in situations such as analytic discourse where perception, cognition, and action iterate in a continuous flow.

Interaction must be a central concept in both perceptual and cognitive models. Interaction provides the mechanism of communication among users, visualizations, and visualization systems; it broadens the perceptual and cognitive processes by controlling how information is considered, taking second and subsequent looks at information, and taking different perspectives on the same information. These are key components in reasoning, problem solving, and knowledge building. Most visual perception research directed to understanding and using visual information displays has focused on static display. Much of the power of today's visual analytic methods, however, comes from their support for dynamic interaction. But the science of analytical reasoning must go beyond this. Just as it recognizes that interactive visualizations are fundamentally different from static visualizations, it must recognize that analytical reasoning coupled with interactive visualization is fundamentally different.

While scientists who conduct laboratory experiments take care to have all of their subjects use a consistent strategy, in practice our perceptual experience interacts with cognitive processes at all levels, enabling us to vary our strategies to fit a given problem situation. Whereas empirical studies typically avoid giving subjects feedback on their performance, in real-world tasks we are able to assess our performance by perceiving the results of our actions. This guides our further action. We perceive the repercussions of our actions, which also recalibrates perception, ensuring that vision, hearing, and touch maintain their agreement with each other. If we are to build richly interactive environments that aid cognitive processing, we must understand not only the levels of perception and cognition but also the framework that ties them together in a dynamic loop of enactive, or action-driven, cognition that is the cognitive architecture of human-information processing.

The literature on human abilities can be characterized roughly into three groups: higher-order embodied, enactive, and distributed models such as those proposed by Gibson [1986] and Varela et al. [1991] that describe conceptually the nature of processing in real-world environments; the large mass of laboratory-based psychology studies that establish the basic bottlenecks in human abilities to perceive, attend, and process information; and relatively applied work such as Bertin [1982], Norman [1993], Wickens and Hollands [2000], and Ware [2004] that seeks to adapt the laboratory and conceptual work to interaction tasks and situations of use.

Within specific domains, there are excellent examples of work that integrate perceptual, cognitive, and analytical models. For example, research to optimize the design of cockpit displays has created models that integrate perception, cognition, and decision making [Zhang, 1997] with an explicit goal of "decision support to provide the right information, in the right way, and at the right time" [Taylor et al., 2002]. There has been extensive work in the area of cartography and geographic information science to understand how maps and graphics do more than "make data visible" but are "active instruments in the users' thinking process" [MacEachren & Kraak, 2001]. MacEachren's *How Maps Work* [1995] combines an understanding of visual perception and cognition (along with other cognitive theory) with a semiotic approach to visual representation to create an integrated model of map-based visualization.

Researchers in fields other than the analysis domain also have looked at perceptual and cognitive support for decision making. The fields of law and medicine both have "evidence-based" approaches [Patel et al., 1994; 1997] analogous to those used for analytical reasoning in intelligence applications.

The perceptual aspects of interaction with information displays have been addressed occasionally (e.g., Rheingans [1992]; Jones [2000]) and research agendas have pointed to both perceptual and cognitive implications of interaction as research challenges (e.g., MacEachren and Kraak [2001]; National Research Council [2003]). Limited progress has been made so far; thus, understanding the relationships between visual perception and user interaction with visual analytic displays represents an important challenge at the core of visual analytic theory.

Work relating to the perceptual and cognitive underpinnings of visual analytics must often be assembled from a range of conferences and journals within isolated academic disciplines. However, there are a number of recent journals and conferences that attempt to integrate work from a number of disciplines. *ACM Transactions on Applied Perception* is just such a journal (http://www.acm.org/tap). The Symposium on Applied Perception in Graphics and Visualization (http://isg.cs.tcd.ie/gap/) alternates between a vision conference, such as the European Conference on Visual Perception, and SIGGRAPH, with papers that apply perceptual science to the design of visual interfaces. The Workshop on Smart Graphics (http://www.smartgraphics.org/) attempts to bring together researchers from Computer Graphics, Visualization, Art & Graphics Design, Cognitive Psychology, and Artificial Intelligence for multiple perspectives on computer-generated graphics. An increased number of applied papers are appearing at vision conferences, most notably the annual Vision Sciences conference (http://www.vision-sciences.org/). At the cognitive end of the spectrum, recent interest in augmented cognition (http://www.augmentedcognition.org) examines methods for supporting cognitive processing with interactive technologies.

The temptation here is to concentrate on applied work, which is most accessible to the design practitioner. It is important, however, to recognize that the complexity of the representations, tasks, and activities of analytic discourse will require us to delve further into the more abstract conceptualization of human performance as well as into research into bottlenecks in human abilities derived from laboratory studies. We are aided in this effort by recent work in the more global structure of human information processing, the cognitive architecture of task performance. Pylyshyn's *Seeing and Visualizing, It's Not What You Think* [2003] provides one example of this level of analysis.

Technology Needs

The science of visual analytics must be built on a deep understanding of how people sense, reason, and respond. This understanding is essential if we are to create tools, systems, and processes that complement the strengths and compensate for the weaknesses of the human beings involved.

Previous research towards applying perceptual and cognitive principles to the design of interactive systems has identified many of the fundamental perceptual and cognitive limits of the human mind. These limits are important, as they can help identify bottlenecks in the use of tools for interaction, visualization, and analytic reasoning. However, our goal must go beyond the identification of limits to the creation of predictive models, which inspire entirely new approaches to the problems of visual analytics. Such models permit the narrowing and focusing of the design space, and they make tenable the problems of efficient design that would otherwise be intractable. The foundation of a theory-based model is what gives power to the sense-making approach described previously.

Recommendation 2.6

Develop a supporting science for visual analytics, integrating research in analytical reasoning and sense-making as well as the principles of perception and cognition that underlie interactive visualization.

This science must be built on integrated perceptual and cognitive theories that embrace the dynamic interaction among cognition, perception, and action. It must provide insight on fundamental cognitive concepts such as attention and memory. It must build basic knowledge about the psychological foundations of concepts such as *meaning, flow, confidence,* and *abstraction*.

To be effective, the science of visual analytics must be developed within the context of the demands of visual analytics systems. This research will be different from and much more than task analysis. It will be an integration of basic research with a specific task domain to create robust and practical results that advance both visual analytics and efforts to understand the fundamental workings of the human mind.

The goal of a supporting science for visual analytics is large, but research must focus on particular components of the visual analytics domain to meet the homeland security challenge. Key components are analytic reasoning (discussed in this chapter) and interactive visualization (discussed in Chapter 3).

To achieve this objective, we must develop a supporting science for the analytical reasoning process itself. Heuer [1999] contributes an important summary of the aspects of perception, memory, and cognitive biases that affect analysis. He focuses on the fundamental limits that constrain the process of analysis and provides analytical methods for compensating for these limits. However, a fully developed science must include constructive theories and models as well as such guidelines.

With the ever-increasing complexity of the challenge, it is important to better understand abstraction and how people create, evaluate, and compare such "mental models" to first make sense and then take action based on these models. Understanding abstraction clearly supports not only the design of tools to create (or help users create) abstractions but also the ability to capture the reasoning process and its artifacts.

In visual analytics, the process of analytical reasoning, or deriving meaning from masses of data, is supported by interactive visualization. "Using pictures to think" is a primary component of visual analytics, but analysis is a process that must involve action, and thus interaction, at all its stages. Thus, the supporting science for visual analytics must also include the development of theories and principles for how interactive visualization works both perceptually and cognitively to support analytical reasoning. An integrated model of visualization, especially visualization as mediated by interaction, could be used in a constructive and evaluative form on a broad range of visualization tasks and data.

Recommendation 2.7

Research how visual analytic systems function at the micro levels of perception and cognition, especially in focusing user attention and facilitating cognitive shifts.

There is a great need to study visual analytic systems at the micro level. In visual analytic systems, visual form is given to conceptual abstractions. While in some cases automated reasoning techniques may be used within analytical tools as an aid to the analyst, in many cases visual analytics tools instead use well-chosen data representations and transformations that help the analyst to recognize and discover information. The success of an analytical tool can be strongly affected by low-level visual attention phenomena.

A detailed-level understanding of how visualizations work at the perceptual and cognitive level does not exist yet. This understanding is an important foundation that must be established to support the construction of visual analytics systems. We must better understand how to capture and focus attention and how to facilitate cognitive shifts, especially to avoid missing alternative hypotheses and solutions. An accurate model of attention would have a profound impact on analysis, but it would also have relevance to other issues ranging from the effectiveness of multimodal interfaces to general support for multi-tasking.

Collaborative Visual Analytics

As the scenarios in Chapter 1 illustrate, homeland security challenges are so complex and dynamic that they cannot be addressed by individuals working in isolation. Threat analysis, border protection, and emergency management and response efforts are of sufficiently large scale and importance that they must be addressed through the coordinated action of multiple groups of people, often with different backgrounds and working in disparate locations with differing information. Here, the issue of human scalability plays a critical role, as systems must support the communications needs of these groups of people working together across space and time, in high-stress and time-sensitive environments, to make critical decisions.

According to the *Intelligence Community Collaboration Baseline Study Report* [Hall, 1999], "Collaboration is broadly defined as the interaction among two or more individuals and can encompass a variety of behaviors, including communication, information sharing, coordination, cooperation, problem solving, and negotiation."

In relation to knowledge management in the context of intelligence, Waltz [2003] lists the following functions for collaboration:

- Coordinate tasking and workflow to meet shared goals.
- Share information, beliefs, and concepts.
- Perform cooperative problem-solving analysis and synthesis.
- Perform cooperative decision making.
- Author team reports of decisions and rationale.

Advances in collaborative visual analytics have the potential to enable each of these functions for teams of individuals as well as for organizations; they are central to the problem-solving analysis and synthesis function. Enabling joint work requires support for both *cooperative-competitive* dialogue (in which team members or different teams work toward the same goals but pose competitive explanations and solutions) and *collaborative* dialogue (in which team members share a problem conceptualization, share responsibilities, and coordinate). Both types of dialogue are typically needed within the same analytical reasoning task, as analysts cycle between focused attention and controlled broadening components of the analytic discourse and sense-making processes described earlier in this chapter.

In an emergency, collaboration among agencies and with the first responder communities is essential. Agencies, including neighboring state and local governments, collaborate to share available resources. They must maintain a clear shared understanding of the capabilities and status of available resources, whether they are fire trucks or hospital beds. In an emergency, decisions must be made quickly using the best available information. The role of visual analytics is to assist in sharing information with the best available minds so that informed decisions can be made. Information must be shared with experts to answer difficult and previously unanticipated questions, such as how to protect the public in the event of a chemical explosion.

State of the Art

Collaborative situations can be categorized with respect to space and time as shown in Figure 2.6 [Waltz, 2003]. This time and space matrix distinguishes between support of local and distributed (space) working contexts and between synchronous or asynchronous (time) work situations [Johansen, 1988]. There has been extensive research in Computer Supported Collaborative Work (CSCW) and other communities in all four quadrants of this diagram. However, attention to the role of visualization in cooperative work and to the process of cooperative-competitive (or collaborative) analytical reasoning has been limited. Below, we briefly highlight key aspects of the current state of the art and identify critical gaps in both knowledge and analytic methods relevant to development and application of collaborative visual analytics.

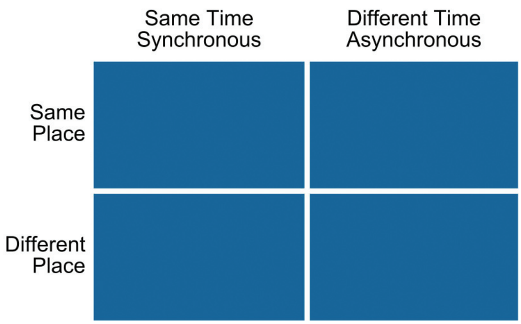

***Figure 2.6**. Typology of collaborative situations.*

Supporting same place, synchronous work

Same place, synchronous work involves groups of people meeting face to face. This has been extensively studied, both to improve the productivity of group interactions and to define a baseline for the other quadrants of collaborative situations. It is clear that people working together use speech, gesture, gaze, and nonverbal cues to attempt to communicate in the clearest possible fashion. In addition, real objects and interactions with the real world can also play an important role in face-to-face collaboration. Garfinkel [1967, 1970], Schegloff and Sacks [1973], and Mehan and Wood [1975] all report that people use the resources of the real world to establish shared understanding. In addition, Suchman [1988] reports that writing and drawing activities could be used to display understanding and facilitate turn taking in much the same way that other non-verbal conversational cues do. In collaborative teamwork, team members coordinate their actions around the artifacts and the spaces they occupy [Hollan, 1992].

To advance collaborative visual analytics, it is essential to understand and support group reasoning with a range of analytic reasoning artifacts. McNeese and colleagues [2000a, 2000b] have investigated the use of *perceptual anchors*, or externalized representations that map to mental models, in individual and team problem solving related to search and rescue. They have identified interactions between individual and team problem-solving strategies and studied the transfer of successful strategies to other problem contexts. They are working toward collaborative tools that alleviate problem-solving weaknesses for both individual and group problem solving.

Although technology can be used to enhance face-to-face collaboration, it can also negatively affect the communication cues transmitted between collaborators. The effect of mediating technology can be better understood through the use of communication models, such as Clark and Brennan's theory of "grounding" [1991]. In this case, conversational participants attempt to reach shared understanding using the available communication channels modified by the available technology. Olson and Olson [2001] provide a list of 10 key characteristics of face-to-face interaction that can be used as a guide for comparing the effect of technologies on collaboration.

Visually based analysis tools encourage problem solving and brainstorming in team environments, but research is required in order to take full advantage of the power that these tools can provide in a team setting.

Supporting different place, synchronous work

Another class of collaborative technologies supports distributed, synchronous work. The most common example is distributed meetings. Synchronized audio and shared presentations are now commonly used in business meetings. For example, NetMeeting, Placeware, and WebEx are applications that allow several participants to teleconference while simultaneously viewing a slide presentation or sharing a computer demonstration. Shared chat rooms are another example of a popular CSCW application. These applications are beginning to have a large impact on business practices.

Emergency response situations clearly demand support for distributed teams of people working together synchronously. Communication must take place among the responders in the field, the emergency operations centers involved, and the incident commander, who is the decision maker in the field. Information must be shared to the level necessary to support decision making, and information must be preserved to illustrate why decisions were made. This history becomes extremely important if an emergency grows in size and jurisdiction so that additional agencies become involved and control for the overall emergency response transfers from one organization to another.

Two-way communication must be supported. Responders in the field provide real-time sharing of information about what is happening at the scene, while operations centers provide direction and response. Communication in the field is primarily through tools such as cell phones and web-based applications for information sharing. Although the emphasis is on portable communication, these devices are vulnerable to disruptions in connectivity.

Each emergency is unique, so the team's focus must be on applying their training and experience to the new situation. The tools used to support emergency response must take into account the highly stressful nature of the situation. Tools must be extremely simple and clear to use, because user attention must be focused on the emergency rather than the mechanics of the software.

Visual analytic methods can be extended (or invented) to support distributed synchronous work such as emergency response. The challenges include:

- Developing effective interfaces to visual displays and visual analytics tools operating on multiple kinds and sizes of devices in varied circumstances (for example, mobile devices used in field operations)
- Supporting analysis of continually updating geospatially referenced information of heterogeneous form (for example, map-based field annotations, streaming video, photos and remote imagery, sensor networks)
- Supporting coordinated reasoning and command-control through the complex, multi-scale organizational structures of emergency response.

In general, CSCW research suggests that a remote communications space should have three elements: high-quality audio communication, visual representations of the users, and an underlying spatial model. These elements correspond to the three available communication channels: audio, visual, and environmental. The affordances of the communications technology used will modulate the cues carried by each of these channels [Gaver, 1992]. The unique stress and urgency of many analysis and emergency response situations may pose special demands on the remote, real-time collaborations. Research is needed to determine whether the general rules of thumb in typical collaborative situations hold true in high-pressure analysis and emergency response situations as well.

To understand the effect of technology on remote collaboration, many experiments have been conducted comparing face-to-face, audio-and-video, and audio-only communication. Not unexpectedly, when visual cues are removed, the communication behavior changes; however, performance in an audio-only condition may be unchanged. Even with no video delay, video-mediated conversation doesn't produce the same conversational style as face-to-face interaction. These results suggest that technology may not be able to replace the experience of shared presence and that research should focus on ways to provide experiences that go "beyond being there" [Hollan, 1992]. Examples include a tool that allows a remote expert to look through the eyes of a novice and place virtual annotations in his or her environment to improve performance on a real-world task [Bauer et al., 1999] or a tool that allows the novice to access a context-sensitive, expert-derived template for application of a visual analytic method.

Supporting different place, asynchronous work

In a distributed organization, work takes place at different places and at different times. In emergency preparedness activities, for example, distributed and asynchronous collaboration is feasible and valuable. Longer-term analytical efforts can also be supported through distributed and asynchronous collaboration.

Sharing information across place and time is one of the main reasons the internet is so popular. But the internet has spawned many technologies besides dynamic, linked documents. *Wikis* are collaborative documents that anyone may edit. They incorporate version control and simple editing and formatting protocols such as structured text so that a group of people can easily and safely edit a collection of web pages. Wikis are commonly used to organize complex projects. Web logs, or blogs, and remote syndication services, or RSS, are other examples of online technology that are rapidly spreading. Blogs provide simple interfaces for maintaining online diaries. RSS notifies interested parties when new content is available. Web-based collaboration technologies are among the fastest growing internet applications.

Over the past decade, scientific attention and resources have been directed to development of scientific collaboratories. This work can be leveraged to develop methods and tools that support collaborative visual analytics. The concept of national collaboratories to enable science was articulated in a 1993 National Research Council report [Cerf et al., 1993]. This report characterizes a collaboratory as a "... center without walls, in which the nation's researchers can perform research without regard to geographical location—interacting with colleagues, accessing instrumentation, sharing data and computational resources, and accessing information from digital libraries." Considerable progress has been made toward the report goals (e.g., Kouzes et al. [1996], Olson et al. [2001]), particularly for collaboratories that facilitate research in physical or medical sciences and on real-time data collection or control of experiments.

These efforts have shown that there are several requirements for supporting remote asynchronous work [Maher & Rutherford, 1997; Dufner et al., 1994], including:

- Support for a shared workspace, enabling easy distribution and access of data
- Access to an application domain with all the shared applications needed
- A data management system, ensuring data consistency and concurrency control
- Access to a reference area with links to relevant online material
- Tools/support structures for asynchronous messaging and communication
- A focus on data-centric (rather than connection-centric) collaboration
- Tools for recording collaboration history and data changes
- Security and privacy control.

Supporting same place, asynchronous work

Co-located, asynchronous collaboration is focused on place-based communication among members of an analytic or command and control team. Continuous operations in emergency operations centers represent a good example of co-located asynchronous communication. Individuals from an earlier work shift must preserve relevant information and decisions made for their colleagues who are working succeeding shifts. Although there is some overlapping time during the shift change process so that important information can be transferred in person, much of the communication still takes place asynchronously.

Collaborative work in this category often centers on large shared displays, or collections of such displays, sometimes called *interactive workspaces* [Johansen, 1988; Streitz et al., 1999]. The displays are used in such environments to replace flipcharts and whiteboards, as well as large computer screens visible to collaborative teams [Pedersen et al., 1993; Abowd et al., 1998]. By extending these technologies, the work process may be captured and annotated, making it possible to capture histories of collaborative analysis.

One example is the MERBoard, which has a large, shared display used as the portal into a repository of shared information and which can be accessed by different users at different times. MERBoard was designed at the Jet Propulsion Laboratory (JPL) in collaboration with International Business Machines Corporation (IBM) to support the planning, decision making, and execution of the Mars Exploration Rovers. Personnel at the National Aeronautics and Space Administration (NASA) use a large, interactive display to share and access mission data. Remote users can view and interact with the display using a shared desktop protocol such as Virtual Network Computing (VNC). The MERBoard is an outgrowth of the IBM BlueBoard, which was originally designed for walk-up meetings and collaborations. However, current research on this system is focused on interactive, shared visualizations, such as the status of IBM's 200+ servers, presented in a form easily accessible by systems administration staff. An overview of both systems is provided in Russell et al. [2004]. Unlike traditional command and control centers, systems such as MERBoard and BlueBoard are designed for easy, walk-up use.

The role of visual display for cooperative/competitive analytical reasoning

Dynamic visual analytics environments have at least three distinct roles in support of cooperative/competitive analytical reasoning:

1. As a representation of the features in the world that are the object of focus, thus as a model of the physical world (e.g., maps depict aspects of the world critical to situation assessment and planning of actions associated with emergency management) and as a mechanism to assemble a view into an information space populated by an array of information artifacts
2. As a support for analytic discourse among collaborators as they reason (individually, cooperatively, and competitively) about strategies for information analysis, situation assessment (and the strength of evidence that underlies the assessment), hypotheses about future developments, and plans for action
3. As a support for coordinated activity (e.g., helping to synchronize the actions of multiple participants in that activity). See MacEachren [1995].

Considerable attention has been directed to the role of external (usually visual) representations in enabling collaboration generally. This attention, however, is fragmented, appearing in a range of disciplines from CSCW through diagrammatic reasoning and argument visualization [Johansen, 1988], to multimodal interfaces for geospatial information [McGee et al., 2001]. For example, Suthers has implemented concepts from diagrammatic reasoning in an open-source toolkit for collaborative learning (http://sourceforge.net/projects/belvedere/) and has conducted several empirical studies of the impact of abstract visual representations on reasoning and hypothesis generation. In one study, Suthers et al. [2003] found that visually structured representations (graph, matrix) influenced representation and discussion of evidential relations, with a matrix increasing discussion but graphs producing more focused consideration of evidence. Complementary to these efforts to understand the role of particular kinds of visual representation on collaboration, progress has been made in understanding the general role of external (usually visual) representations and artifacts in the cognitive process of groups [Zhang, 2001].

Sharing information and perspective

In an effort to describe features of the world and manage associated knowledge, domains that range from computational sciences and artificial intelligence (e.g., Gaver [1992]) to the environmental and social sciences (e.g., Fonesca et al. [2002]) have developed knowledge representation languages and constructed ontologies that use them. This prior work, however, is missing a key element that is critical to supporting collaborative visual analytics in the intelligence analysis and emergency management domains: consideration of how knowledge is generated, revised, promulgated, shared, built upon, and retired. Formal representation of knowledge typically focuses on recording propositions and rules about a domain without attempting to situate knowledge in the context of its creation or use. As discussed for sense-making above, knowledge representation and management to support collaborative visual analytics requires that knowledge is situated in the context of its creation, use, sharing, and re-use.

Many have described human-computer interaction as a conversation or dialogue—with oneself, with one's current collaborators, with future actors, with a machine [Nake & Grabowski, 2001; Winograd & Flores, 1986; MacEachren, 2004]. We propose extending the notion of human-information dialogue, or analytic discourse, as the vehicle to help analysts uncover the lineage and basis of shared ideas as they move from one analyst to another, from one information source to another, from one geographic context to another, and from one time to another. This approach complements recent efforts in visualization of argumentation to support science work [Shum et al., 2003].

Supporting distributed cognition/common ground

In his study of shipboard navigation on Navy vessels, Edwin Hutchins [1996] illustrated that critical insights about coordinated team activity can be achieved by applying a distributed cognition perspective. From this perspective, teamwork is viewed as a process in which aspects of cognition are distributed across the collaborating agents, which in this case are individuals with different roles and tasks, and the artifacts through which the agents acquire, construct, and share knowledge. A distributed cognition perspective has been adopted as a framework for understanding group work in contexts that include complex team problem solving in shared information spaces, the development of team situation awareness for emergency operations and military action, and the process of collaborative urban design.

A successful distributed cognition process, whether distributed among individuals and artifacts that are co-located or geographically distributed, requires that participants establish common ground through a set of shared pertinent knowledge, beliefs, and assumptions [Klein et al., 2004]. Chuah & Roth [2003] contend that visualization tools can be used to help collaborators establish common ground and have developed an environment within their Command Post of the Future project for creating collaborative information analysis and decision-making applications. Common ground in this system is established through a combination of explicitly shared objects and events, representations of level of attention directed to objects, depiction of goals for analyzing objects and events, representation of interpretations and thoughts through annotations and sketches, and representation of object history.

Theory, Knowledge, and Technology Needs

Current visual analytic methods and tools are designed for use by individuals. However, the homeland security challenges facing the nation require concerted, cooperative, and coordinated efforts by teams and sets of teams that bring a range of expertise to the task. Our goals range from developing fundamental knowledge about the role of visual analytics in enabling team cognition to advancing the technology to facilitate coordinated, distributed analytical reasoning. Key goals include the following:

- Develop a better understanding of how interactive visualization is used for coordination, for collaborative analysis together across space and time, and for establishing and managing group dynamics.
- Take advantage of knowledge of perception and cognition and advances in display technology to apply the new display technology productively to support co-located and distributed work teams.
- Learn from, apply, and extend developments in collaborative visualization, group games and simulation models, and multi-criteria decision-support systems.
- Develop strategies for connecting visualization and semantic frameworks that underpin analytic discourse.
- Understand how the analytic sense-making, reasoning, and judgment process differs for teams—and develop methods and tools to meet the needs of teams and to enable analytic reasoning outcomes that are more than the sum of the parts, thus generating key insights through juxtaposition and/or integration of perspectives.
- Understand and support the role of team-enabled visual analytics in each stage of the sense-making processes in threat analysis and emergency response.
- Apply knowledge from addressing the above goals to developing visual analytics systems that enable analytic discourse and coordinated action within teams.

These goals lead to the following recommendation.

Recommendation 2.8

Develop a theory and approaches to characterize and enhance the ways visual analytics is used for coordination and collaboration, especially in situations of high stress and great urgency; more specifically, discover how analytic processes can be enabled by interactive visualization so that distributed expertise is better exploited and clear communication is enabled.

Visual analytics methods and tools must support the work of analyst/decision-maker teams, ranging from small work groups applying collective expertise to relatively narrow analytic problems to cross-organizational, distributed teams faced with complex information sifting and analysis tasks. In emergency situations, where information is ambiguous and collaboration is taking place with a wide range of people under extreme time pressure and at great consequence, collaboration is paramount.

Visual analytics tools must also support seamless interaction with information of heterogeneous forms, derived from heterogeneous sources, and having varied ontological structures. A key goal is to develop methods that support capture, encoding, and sharing of both explicit and tacit knowledge derived from integrated exploration of diverse sources and that support use of encoded knowledge from these diverse sources to generate and mediate among alternative interpretations of evidence and plans for action.

Summary

The goal of visual analytics is to facilitate the analytical reasoning process through the creation of software that maximizes human capacity to perceive, understand, and reason about complex and dynamic data and situations. It builds upon an understanding of the reasoning process, as well as an understanding of underlying cognitive and perceptual principles, to provide mission-appropriate interactions that allow analysts to have a true discourse with their information. This discourse is essential to facilitating informed judgment with a limited investment of the analysts' time.

Summary Recommendations

The following high-level recommendations summarize the detailed recommendations from this chapter. These actions are necessary to advance the science of analytical reasoning in support of visual analytics.

Recommendation:

Build upon theoretical foundations of reasoning, sense-making, cognition, and perception to create visually enabled tools to support collaborative analytic reasoning about complex and dynamic problems.

To support the analytical reasoning process, we must enable the analyst to focus on what is truly important. We must support the processes involved in making sense of information and developing and evaluating alternative explanations. Tools and techniques must support both convergent thinking and divergent thinking. These tools and techniques also must allow analysts to look at their problem at multiple levels of abstraction and support reasoning about situations that change over time, sometimes very rapidly. They must support collaboration and teamwork, often among people with very different backgrounds and levels of expertise. Accomplishing this will require the development of theory to describe how interactive visual discourse works, both perceptually and cognitively, in support of analytical reasoning.

Recommendation:

Conduct research to address the challenges and seize the opportunities posed by the scale of the analytic problem. The issues of scale are manifested in many ways, including the complexity and urgency of the analytical task, the massive volume of diverse and dynamic data involved in the analysis, and challenges of collaborating among groups of people involved in the analysis, prevention, and response efforts.

The sheer volume and scale of data involved in the analytical process offer as many opportunities as they do challenges for visual analytics. A science of scalable, visually based analytical reasoning, or visual analytic discourse, must take the issue of scale into consideration. Different types of analytic discourse will be appropriate to different analytical tasks, based on the level of complexity of the task, the speed with which a conclusion must be reached, the data volumes and types, and the level of collaboration involved.

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