CHAPTER ONE

Foundations for an Applied Science of Data Visualization

In his book *The End of Science*, science writer John Horgan (1997) argued that science is finished except for the mopping up of details. He made a good case where physics is concerned. In that discipline, the remaining deep problems may involve generating so much energy as to require the harnessing of entire stars. Similarly, biology has its foundations in DNA and genetics and is now faced with the infinite but often tedious complexity of mapping genes into proteins through intricate pathways. What Horgan failed to recognize is that cognitive science has fundamental problems that are still to be solved. In particular, the mechanisms of the construction and storage of knowledge remain open questions. He implicitly adopted the physics-centric view of science, which holds that physics is the queen of sciences and in descending order come chemistry, then biology, with psychology barely acknowledged as a science at all. In this pantheon, sociology is regarded as somewhere on a par with astrology. This attitude is shortsighted. Chemistry builds on physics, enabling our understanding of materials; biology builds on chemistry, enabling us to understand the much greater complexity of living organisms; and psychology builds on neurophysiology, enabling us to understand the processes of cognition. At each level is a separate discipline greater in complexity and level of difficulty than those beneath. It is difficult to conceive of a value scale for which the mechanisms of thought are not of fundamentally greater interest and importance than the interaction of subatomic particles. Those who dismiss psychology as a pseudo-science have not been paying attention. Over the past few decades, enormous strides have been made in identifying the brain structures and cognitive mechanisms that have enabled humans to create the huge body of knowledge that now exists. But we need to go one step further and recognize that a person

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working with the aid of thinking tools is much more cognitively powerful than that person alone with his or her thoughts. This has been true for a long time. Artifacts such as paper and pens, as well as techniques such as writing and drawing, have been cognitive tools for centuries.

As Hutchins (1995) so effectively pointed out, thinking is not something that goes on entirely, or even mostly, inside people's heads. Little intellectual work is accomplished with our eyes and ears closed. Most cognition is done as a kind of interaction with cognitive tools, pencils and paper, calculators, and, increasingly, computer-based intellectual supports and information systems. Neither is cognition mostly accomplished alone with a computer. It occurs as a process in systems containing many people and many cognitive tools. Since the beginning of science, diagrams, mathematical notations, and writing have been essential tools of the scientist. Now we have powerful interactive analytic tools, such as MATLAB, Maple, Mathematica, and S-PLUS, together with databases. The entire fields of genomics and proteomics are built on computer storage and analytic tools. The social apparatus of the school system, the university, the academic journal, and the conference are obviously designed to support cognitive activity.

Cognition in engineering, banking, business, and the arts is similarly carried out through distributed cognitive systems. In each case, "thinking" occurs through interaction between individuals, using cognitive tools and operating within social networks. Hence, cognitive systems theory is a much broader discipline than psychology. This is emerging as the most interesting, difficult, and complex, yet fundamentally the most important, of sciences.

Visualizations are an increasingly important part of cognitive systems. Visual displays provide the highest bandwidth channel from the computer to the human. Indeed, we acquire more information through vision than through all of the other senses combined. The 20 billion or so neurons of the brain devoted to analyzing visual information provide a pattern-finding mechanism that is a fundamental component in much of our cognitive activity. Improving cognitive systems often means optimizing the search for data and making it easier to see important patterns. An individual working with a computer-based visual thinking tool is a cognitive system where the critical components are, on one side, the human visual system, a flexible pattern finder coupled with an adaptive decision-making mechanism, and, on the other side, the computational power and vast information resources of a computer coupled to the World Wide Web. Interactive visualization is the interface between the two sides. Improving this interface can substantially improve the performance of the entire system.

Until recently, the term *visualization* meant constructing a visual image in the mind (Little et al., 1972). It has now come to mean something more like a graphical representation of data or concepts. Thus, from being an internal construct of the mind, a visualization has become an external artifact supporting decision making. The way visualizations can function as cognitive tools is the subject of this book.

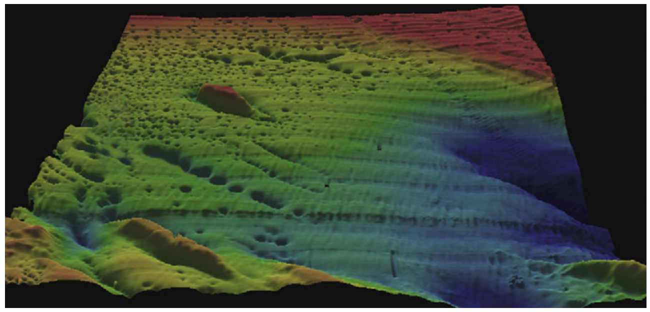


Figure 1.1 Passamoquoddy Bay visualization. (*Data courtesy of the Canadian Hydrographic Service*.)

One of the greatest benefits of data visualization is the sheer quantity of information that can be rapidly interpreted if it is presented well. Figure 1.1 shows a visualization derived from a multibeam echo sounder scanning part of Passamoquoddy Bay, between Maine in the United States, and New Brunswick in Canada, where the tides are the highest in the world. Approximately one million measurements were made. Traditionally, this kind of data is presented in the form of a nautical chart with contours and spot soundings; however, when the data is converted to a height field and displayed using standard computer graphics techniques, many things become visible that were previously invisible on the chart. A pattern of features called *pockmarks* can immediately be seen, and it is easy to see how they form lines. Also visible are various problems with the data. The linear ripples (not aligned with the pockmarks) are errors in the data because the roll of the ship that took the measurements was not properly taken into account.

The Passamoquoddy Bay image highlights a number of the advantages of visualization:

- Visualization provides an ability to comprehend huge amounts of data. The important information from more than a million measurements is immediately available.
- Visualization allows the perception of emergent properties that were not anticipated. In this visualization, the fact that the pockmarks appear in lines is immediately evident. The perception of a pattern can often be the basis of a new insight. In this case, the pockmarks align with the direction of geological faults, suggesting a cause. They may be due to the release of gas.
- Visualization often enables problems with the data to become immediately apparent. A visualization commonly reveals things not only about the data itself but also about the way it is collected. With an appropriate visualization, errors and artifacts in the data often jump out at you. For this reason, visualizations can be invaluable in quality control.

- Visualization facilitates understanding of both large-scale and small-scale features of the data. It can be especially valuable in allowing the perception of patterns linking local features.
- Visualization facilitates hypothesis formation. For example, the visualization in Figure 1.1 led to questions about the how the pockmarks might have formed and motivated a research paper concerning the geological significance of the features (Gray et al., 1997).

Visualization Stages

The process of data visualization includes four basic stages, combined in a number of feedback loops. These are illustrated in Figure 1.2. The four stages consist of:

- The collection and storage of data.
- A preprocessing stage designed to transform the data into something that is easier to manipulate. Usually there is some form of data reduction to reveal selected aspects. Data exploration is the process of changing the subset that is currently being viewed.
- Mapping from the selected data to a visual representation, which is accomplished through computer algorithms that produce an image on the screen. User input can transform the mappings, highlight subsets, or transform the view. Generally this is done on the user's own computer.
- The human perceptual and cognitive system (the perceiver).

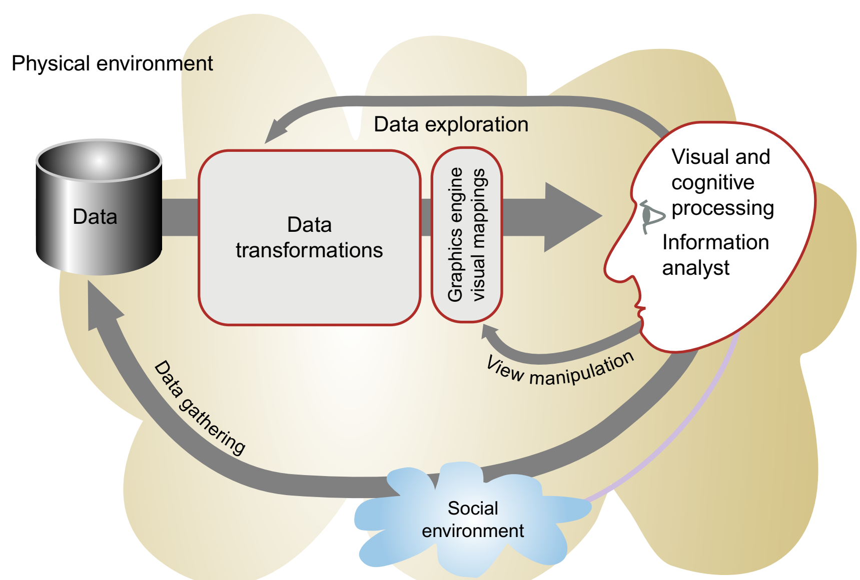


Figure 1.2 The visualization process.

The longest feedback loop involves gathering data. A data seeker, such as a scientist or a stock-market analyst, may choose to gather more data to follow up on an interesting lead. Another loop controls the computational preprocessing that takes place prior to visualization. The analyst may feel that if the data is subjected to a certain transformation prior to visualization, it can be persuaded to give up its meaning. Sometimes the process is a search through a very large volume of data to find an important nugget. Finally, the visualization process itself may be highly interactive; for example, in three-dimensional (3D) data visualization, the scientist may "fly" to a different vantage point to better understand the emerging structures. Alternatively, a computer mouse may be used interactively to select the parameter ranges that are most interesting.

Both the physical environment and the social environment are involved in the data-gathering loop. The physical environment is a source of data, while the social environment determines in subtle and complex ways what is collected and how it is interpreted. In this book, the emphasis is on data, perception, and the various tasks to which visualization may be applied. In general, algorithms are discussed only insofar as they are related to perception. The computer is treated, with some reservations, as a universal tool for producing interactive graphics. This means that once we figure out the best way to visualize data for a particular task, we assume that we can construct algorithms to create the appropriate images.

The critical question is how best to transform the data into something that people can understand for optimal decision making. Before plunging into a detailed analysis of human perception and how it applies in practice, however, we must establish the conceptual basis for the endeavor. The purpose of this discussion is to stake out a theoretical framework wherein claims about visualizations being "visually efficient" or "natural" can be pinned down in the form of testable predictions.

Experimental Semiotics Based on Perception

This book is about the applied science of visualization. It is based on the idea that the value of a good visualization is that it lets us see patterns in data and therefore the science of pattern perception can provide a basis for design decisions, but the claim that visualization can be based on science may be disputed. Let's look at the alternative view. Some scholars argue that visualization is best understood as a kind of learned language and not as a science at all. In essence, their argument is the following. Visualization is about diagrams and how they can convey meaning. Diagrams are made up of symbols, and symbols are based on social interaction. The meaning of a symbol is normally understood to be created by convention, which is established in the course of person-to-person communication. Diagrams are arbitrary and are effective in much the same way as the written words on this page are effective—we must learn the conventions of the language, and the better we learn them the clearer that language will be. Thus, one diagram may ultimately be as good as another; it is just a matter of learning the code, and the laws of perception are largely irrelevant.

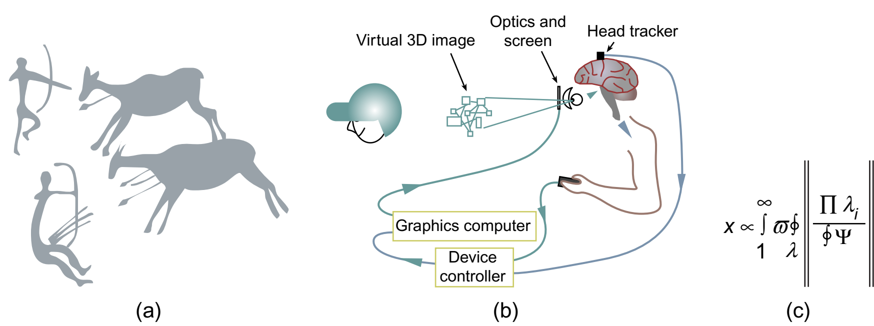
This view has strong philosophical proponents from the classical field of semiotics. Although it is not the position adopted here, the debate can help us define where vision research can assist us in designing better visualizations and where we would be wise to consult a graphic designer trained in an art college.

Semiotics of Graphics

The study of symbols and how they convey meaning is called *semiotics*. This discipline was originated in the United States by C. S. Peirce and later developed in Europe by the French philosopher and linguist Ferdinand de Saussure (1959). Semiotics has been dominated mostly by philosophers and by those who construct arguments based on example rather than on formal experiment. In his great masterwork, *Semiology of Graphics*, Jacques Bertin (1983) attempted to classify all graphic marks in terms of how they could express data. For the most part, this work is based on his own judgment, although it is a highly trained and sensitive judgment. There are few references to theories of perception or scientific studies.

It is often claimed that visual languages are easy to learn and use, but what do we mean by the term *visual language*? Clearly not the writing on this page. Reading and writing take years of education to master, and it can take almost as long to master some diagrams. Figure 1.3 shows three examples of languages that have some claim to being visual. The first example of visual language is based on a cave painting. We can readily interpret human figures and infer that the people are using bows and arrows to hunt deer. The second example is a schematic diagram showing the interaction between a person and a computer in a virtual environment system; the brain in the diagram is a simplified picture, but it is a part of the anatomy that few have directly perceived. The arrows show data flows and are arbitrary conventions, as are the printed words.

The third example is the expression of a mathematical equation that is utterly obscure to all but the initiated. These examples clearly show that some visual languages are easier to "read" than others. But why? Perhaps it is simply that we have more experience with the kind of pictorial image shown in the cave painting and less with the



$$x \propto \int_{1}^{\infty} \varpi \oint_{\lambda} \left\| \frac{\prod \lambda_i}{\oint \Psi} \right\|$$

Figure 1.3 Three graphics. Each could be said to be a visualization.

mathematical notation. Perhaps the concepts expressed in the cave painting are more familiar than those in the equation.

The most profound threat to the idea that there can be a scientific basis for visualization design originates with Saussure. He defined a principle of arbitrariness as applying to the relationship between the symbol and the thing that is signified. Saussure was also a founding member of a group of structuralist philosophers and anthropologists who, although they disagreed on many fundamental issues, were unified in their general insistence that truth is relative to its social context. Meaning in one culture may be nonsense in another. A trash can as a visual symbol for deletion is meaningful only to those who know how trash cans are used. Thinkers such as Levi-Strauss, Barthes, and Lacan have condemned the cultural imperialism and intellectual arrogance implicit in applying our intellects to characterizing other cultures as "primitive." As a result, they have developed the theory that all meaning is relative to the culture. Indeed, meaning is created by society. They claim that we can interpret another culture only in the context of our own culture and using the tools of our own language. Languages are conventional means of communication in which the meanings of symbols are established through custom. Their point is that no one representation is "better" than another. All representations have value. All are meaningful to those who understand them and agree to their meanings. Because it seems entirely reasonable to consider visualizations as communications, their arguments strike at the root of the idea that there can be an applied science of visualization with the goal of establishing specific guidelines for better representations. We reject this view and instead argue that it is possible to have a new semiotics based not on philosophical claims for symbols being arbitrary, but instead on scientific evidence.

Are Pictures Arbitrary?

The question of whether pictures and diagrams are purely conventional or are perceptual symbols with special properties has been the subject of considerable scientific investigation. A good place to begin reviewing the evidence is the perception of pictures. There has been a debate over the past century between those who claim that pictures are every bit as arbitrary as words and those who believe that there may be a measure of similarity between pictures and the things that they represent. This debate is crucial to the theory presented here; if even "realistic" pictures do not embody a sensory language, it will be impossible to make claims that certain diagrams and other visualizations are better designed perceptually.

The nominalist philosopher, Nelson Goodman (1968), has delivered some of the more forceful attacks on the notion of similarity in pictures:

> *Realistic representation, in brief, depends not upon imitation or illusion or information but upon inculcation. Almost any picture may represent almost anything; that is, given picture and object there is usually a system of representation—a plan of correlation—under which the picture represents the object.*

For Goodman, realistic representation is a matter of convention; it "depends on how stereotyped the model of representation is, how commonplace the labels and their uses have become." Bieusheuvel (1947) expressed the same opinion: "The picture, particularly one printed on paper, is a highly conventional symbol, which the child reared in Western culture has learned to interpret." These statements, taken at face value, invalidate any meaningful basis for saying that a certain visualization is fundamentally better or more natural than another, for if even a realistic picture must be learned this would mean that all languages are equally valid in that all must be learned. If we accept this position, the best approach to designing visual languages would be to establish graphical conventions early and stick to them. It would not matter what the conventions were, only that we adhered to them in order to reduce the labor of learning new conventions.

In support of the nominalist argument, a number of anthropologists have reported expressions of puzzlement from people who encounter pictures for the first time. "A Bush Negro woman turned a photograph this way and that, in attempting to make sense out of the shadings of gray on the piece of paper she held" (Herskovits, 1948). The evidence related to whether or not we must learn to see pictures has been carefully reviewed and analyzed by Kennedy (1974). He rejected the strong position that pictures and other visual representations are entirely arbitrary. In the case of the reported puzzlement of people who are seeing pictures for the first time, Kennedy argued that these people are amazed by the technology rather than unable to interpret the picture. After all, a photograph is a remarkable artifact. What curious person would not turn it over to see if, perhaps, the reverse side contains some additional interesting information?

Here are two of the many studies that contradict the nominalist position and suggest that people can interpret pictures without training. Deregowski (1968) reported studies of adults and children in a remote area of Zambia who had very little graphic art. Despite this, these people could easily match photographs of toy animals with the actual toys. In an extraordinary but very different kind of experiment, Hochberg and Brooks (1962) raised their daughter nearly to the age of two in a house with no pictures. She was never read to from a picture book, and there were no pictures on the walls in the house. Although her parents could not completely block the child's exposure to pictures on trips outside the house, they were careful never to indicate a picture and tell the child that it was a representation of something. Thus, she had no social input telling her that pictures had any kind of meaning. When the child was finally tested she had a reasonably large vocabulary, and she was asked to identify objects in line drawings and in black-and-white photographs. Despite her lack of instruction in the interpretation of pictures, she was almost always correct in her answers, indicating that a basic understanding of pictures is not a learned skill.

Nevertheless, the issue of how pictures, especially line drawings, are able to unambiguously represent things is still not fully understood. Clearly, a portrait is a pattern

Figure 1.4 Two graphical methods for showing the same set of relationships between entities.

of marks on a page; in a physical sense, it is utterly unlike the flesh-and-blood person it depicts. The most probable explanation is that, at some stage in visual processing, the pictorial outline of an object and the object itself excite similar neural processes (Pearson et al., 1990). This view is made plausible by the ample evidence that one of the most important products of early visual processing is the extraction of linear features in the visual array. These may be either the visual boundaries of objects or the lines in a line drawing. The nature of these mechanisms is discussed further in Chapter 6.

When we turn to diagrams and non-pictorial visualizations, it is clear that convention must play a greater role. Figure 1.3(b) is not remotely "like" any scene in the real world under any system of measurement. Nevertheless, we can argue that many elements in it are constructed in ways that for perceptual reasons make the diagram easy to interpret. The lines that connect the various components, for example, are a notation that is easy to read, because the visual cortex of the brain contains mechanisms specifically designed to seek out continuous contours. Other possible graphical notations for showing connectivity would be far less effective. Figure 1.4 shows two different conventions for demonstrating relationships between entities. The connecting lines on the left are much more effective than the symbols on the right.

Sensory versus Arbitrary Symbols

In this book, the word *sensory* is used to refer to symbols and aspects of visualizations that derive their expressive power from their ability to use the perceptual processing power of the brain without learning. The word *arbitrary* is used to define aspects of representation that must be learned, because the representations have no perceptual basis. For example, the written word *dog* bears no perceptual relationship to any actual animal. Probably very few graphical languages consist of entirely arbitrary conventions, and probably none is entirely sensory; however, the sensory-versus-arbitrary distinction is important. If well designed, sensory representations are effective because they are well matched to the first stages of neural processing. They tend to be stable across individuals, cultures, and time. A circle represents a bounded region for everyone. Conversely, arbitrary conventions derive their power from culture and are therefore dependent on the particular cultural milieu of an individual.

The theory that a visual representation can be good or poor depending on how well it fits with visual processing is ultimately based on the idea that the human visual system has evolved as a specialized instrument to perceive the physical world. It rejects the idea that the visual system can adapt to any universe. It was once widely held that the brain at birth was an undifferentiated neural net, capable of configuring itself to perceive in any world, no matter how strange. According to this theory, if a newborn human infant were to be born into a world with entirely different rules for the propagation of light, that infant would nevertheless learn to see. Partly, this view came from the fact that all cortical brain tissue looks more or less the same, a uniform pinkish gray, so it was thought to be functionally undifferentiated. This *tabula rasa* view has been overthrown as neurologists have come to understand that the brain has a great many specialized regions. Figure 1.5 shows the major neural pathways between different parts of the brain involved in visual processing (Distler et al., 1993). Although

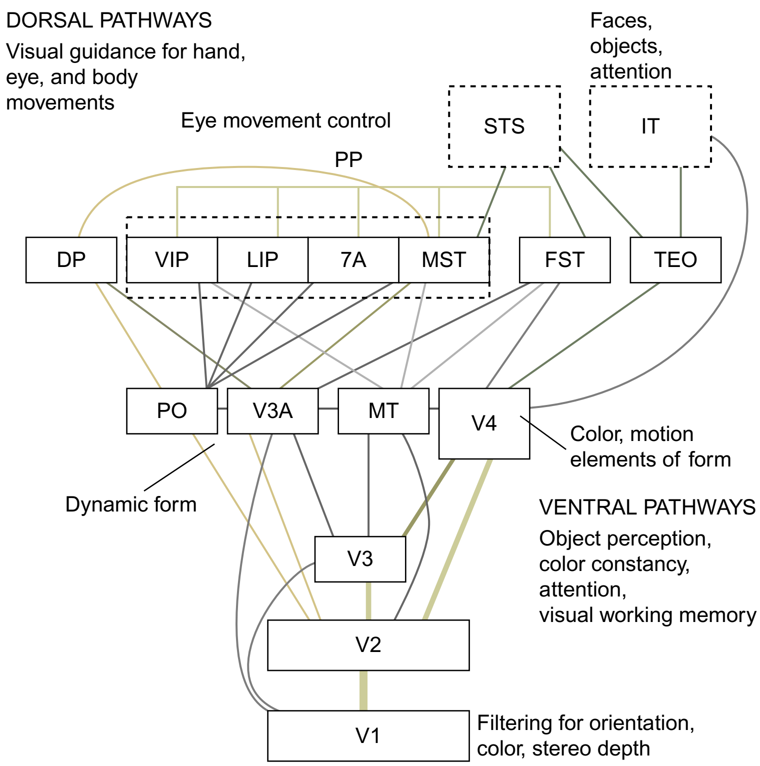


Figure 1.5 The major visual pathways of the Macaque monkey. This diagram is included to illustrate the structural complexity of the visual system and because a number of these areas are referenced in different sections of this book. V1 to V4, visual areas 1 to 4; PO, parietooccipital area; MT, middle temporal area; IT, inferotemporal cortex. (*Redrawn from Distler et al. (1993)*.)

much of the functionality remains unclear, this diagram represents an amazing achievement and summarizes the work of dozens of researchers. These structures are present in both higher primates and humans. The brain is clearly not an undifferentiated mass; it is more like a collection of highly specialized parallel processing machines with high-bandwidth interconnections. The entire system is designed to extract information from the world in which we live, not from some other environment with entirely different physical properties.

Certain basic elements are necessary for the visual system to develop normally; for example, cats reared in a world consisting only of vertical stripes develop distorted visual cortices, with an unusual preponderance of vertical-edge detectors. Nevertheless, the basic elements for the development of normal vision are present in all but the most abnormal circumstances. The interaction of the growing nervous system with everyday reality leads to a more or less standard visual system. This should not surprise us; the everyday world has ubiquitous properties that are common to all environments. All earthly environments consist of objects with well-defined surfaces, surface textures, surface colors, and a variety of shapes. Objects exhibit temporal persistence—they do not randomly appear and vanish, except when there are specific causes. At a more fundamental level, light travels in straight lines and reflects off surfaces in certain ways. The law of gravity continues to operate. Given these ubiquitous properties of the everyday world, the evidence suggests that we all develop essentially the same visual systems, irrespective of cultural milieu.

Monkeys and even cats have visual structures very similar to those of humans; for example, although Figure 1.5 is based on the visual pathways of the Macaque monkey, a number of lines of evidence show that the same structures exist in humans. First, the same areas can be identified anatomically in humans and animals. Second, specific patterns of blindness occur that point to the same areas having the same functions in humans and animals; for example, if the brain is injured in area V4, patients suffer from achromatopsia (Zeki, 1992; Milner & Goodale, 1995). These patients perceive only shades of gray, and they cannot recall colors from times before the lesion was formed. Color processing occurs in the same region of the monkey cortex. Third, new research imaging technologies, such as positron emission tomography (PET) and functional magnetic resonance imaging (fMRI), show that in response to colored or moving patterns the same areas are active in people as in the Macaque monkey (Zeki, 1992; Beardsley, 1997). The key implication of this is that, because we all have the same visual system, it is likely that we all see in the same way, at least as a first approximation. Hence, the same visual designs will be effective for all of us.

Sensory aspects of visualizations derive their expressive power from being well designed to stimulate the visual sensory system. In contrast, arbitrary, conventional aspects of visualizations derive their power from how well they are learned. Sensory and arbitrary representations differ radically in the ways they should be studied. In the former case, we can apply the full rigor of the experimental techniques developed by sensory neuroscience, while in the latter case visualizations and visual symbols can best be studied with the very different interpretive methodology, derived from the structuralist social sciences. With sensory representations, we can also make claims that transcend cultural and racial boundaries. Claims based on a generalized perceptual processing system will apply to all humans, with obvious exceptions such as color blindness.

This distinction between the sensory and social aspects of the symbols used in visualization also has practical consequences for research methodology. It is not worth expending a huge effort carrying out intricate and highly focused experiments to study something that is only this year's fashion; however, if we can develop generalizations that apply to large classes of visual representations, and for a long time, the effort is worthwhile. If we accept the distinction between sensory and arbitrary codes, we nevertheless must recognize that most visualizations are hybrids. In the obvious case, they contain both pictures and words, but in many cases the sensory and arbitrary aspects of a representation are much more difficult to tease apart. There is an intricate interweaving of learned conventions and hardwired processing. The distinction is not as clean as we would like, but there are ways of distinguishing the different kinds of codes.

Properties of Sensory Representation

The following paragraphs summarize some of the important properties of sensory representations:

> ***Understanding without training.*** A sensory code is one for which the meaning is perceived without additional training. Usually, all that is necessary is for the audience to understand that some communication is intended. For example, it is immediately clear that the image in Figure 1.6 has an unusual spiral structure. Even though this visually represents a physical process that cannot actually be seen, the detailed shape can be understood because it has been expressed using an artificial shading technique to make it look like a 3D solid object. Our visual systems are built to perceive the shapes of 3D surfaces.

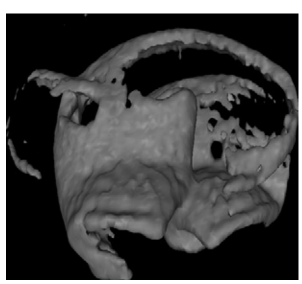


Figure 1.6 The expanding wavefront of a chemical reaction is visualized (Cross et al., 1997). Even though this process is alien to most of us, the shape of the structure is readily perceived.

Resistance to alternative denotation. Many sensory phenomena, such as the illusions shown in Figure 1.7, persist despite the knowledge that they are illusory. We can tell someone that the lines are the same length, but they will still seem to that person as different. When such illusions occur in diagrams, they are likely to be misleading. What is important to the present argument, though, is that some aspects of perception will be taken as facts that we contradict at our peril; for example, using connecting lines to denote that two objects are *not* (conceptually) connected would be a very bad idea, as it would contradict a deep perceptual metaphor.

Sensory immediacy. The processing of certain kinds of sensory information is hardwired and fast. We can represent information in certain ways that are neurally processed in parallel. This point is illustrated in Figure 1.8, which shows five different textured regions. The two regions on the left are very difficult to separate; the upright Ts and inverted Ts appear to be a single patch. The region of oblique Ts is easy to differentiate from the neighboring region of inverted Ts. The circles are the easiest to distinguish (Beck, 1966). The way in which the visual system divides the visual world into regions is called *segmentation*. The evidence suggests that this is a function of early rapid-processing systems. (Chapter 5 presents a theory of texture discrimination.)

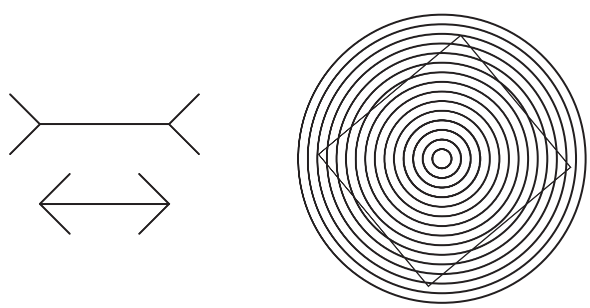


Figure 1.7 In the Muller–Lyer illusion on the left, the horizontal line in the upper figure appears longer than the one below. On the right, the rectangle appears distorted into a pincushion shape.

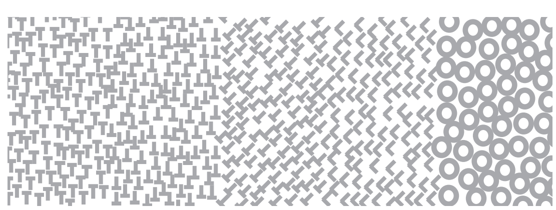


Figure 1.8 Five regions of texture. Some areas are easier to distinguish from others. (*Adapted from Beck (1966)*.)

Cross-cultural validity. A sensory code will, in general, be understood across cultural boundaries. These may be national boundaries or the boundaries between different user groups. Instances in which a sensory code is misunderstood occur when some group has dictated that a sensory code be used arbitrarily in contradiction to the natural interpretation. In this case, the natural response to a particular pattern will, in fact, be wrong.

The foregoing analysis leads us to our first guideline.

> **[G1.1]** Design graphic representations of data by taking into account human sensory capabilities in such a way that important data elements and data patterns can be quickly perceived.

Exactly how this can be done is the subject of this book, but we will begin with two fundamental principles.

> **[G1.2]** Important data should be represented by graphical elements that are more visually distinct than those representing less important information.

Important information should be easy to find. The neural basis for visual search is now quite well understood, and as we shall see this allows us to determine with some precision which items are more findable than others.

> **[G1.3]** Greater numerical quantities should be represented by more distinct graphical elements.

This can be accomplished, for example, by making those elements, larger, more vividly colored, or more strongly textured. The basis for this claim is that even nonvisual thought as embodied in spoken and written language is grounded in sensory metaphors (Pinker, 2007).

Notice that guidelines G1.2 and G1.3 propose using the same kind of coding (visual distinctness) for different purposes, and this can lead to design conflicts. Also, sometimes a large quantity of something may not be especially important. Indeed, if we are running out of a critical asset (such as petroleum in the gas tank), we will want whatever represents this small quantity to be visually distinct. Ultimately, deciding how to use visual coding principles is a design issue. In any complex design problem, the optimal perceptually based coding solution may not be possible for each individual piece of information because some graphic resource (e.g., a bright color) may have already been used. It is only possible to provide perceptually based design guidelines for relatively simple situations. Where requirements are complex, it is the designer's task to make the right choices and use graphic resources wisely.

The solution in the gas tank problem, for example, can be something additional and very visually salient—a blinking light—to indicate the shortage of gas.

Testing Claims about Sensory Representations

Entirely different methodologies are appropriate to the study of representations of the sensory and arbitrary types. In general, the study of sensory representations can employ the scientific methods of vision researchers and biologists. The study of arbitrary conventional representations is best done using the techniques of the social sciences, such as sociology and anthropology; philosophers and cultural critics have much to contribute. Appendix C provides a brief summary of the research methodologies that apply to the study of sensory representations. All are based on the concept of the controlled experiment. For more detailed information on techniques used in vision research and human-factors engineering, see Palmer (1999) and Wickens (1992).

Representations That Are Arbitrary

One way of looking at the sensory-versus-arbitrary distinction is in terms of the time the two modes have taken to develop. Sensory codes are the products of the millions of years it has taken for our visual systems to evolve. The development of arbitrary conventional representations (such as number systems) occurred over the past thousands of years, but many more have had only a few decades of development. High-performance interactive computer graphics have greatly enhanced our capability to create new codes. We can now control motion and color with flexibility and precision. For this reason, we are currently witnessing an explosive growth in the invention of new graphic codes.

Arbitrary codes are by definition socially constructed. The word *dog* is meaningful because we all agree on its meaning and we teach our children the meaning. The word *carrot* would do just as well, except we have already agreed on a different meaning for that word. In this sense, words are arbitrary; they could be swapped and it would make no difference, as long as they are used consistently from the first time we encounter them. Arbitrary visual codes are often adopted when groups of scientists and engineers construct diagramming conventions for new problems that arise. Examples include circuit diagrams used in electronics, diagrams used to represent molecules in chemistry, and the unified modeling language used in software engineering. Of course, many designers will intuitively use perceptually valid forms in the codes, but many aspects of these diagrams are entirely conventional. Arbitrary codes have the following characteristics:

> **Hard to learn.** It takes a child hundreds of hours to learn to read and write, even if the child has already acquired spoken language. The graphic codes of the alphabet and their rules of combination must be laboriously learned. The Chinese character set is reputed to be even harder to work with than the Roman.

Easy to forget. Arbitrary conventional information that is not overlearned can easily be forgotten. It is also the case that arbitrary codes can interfere with each other. In contrast, sensory codes cannot be forgotten.

Embedded in culture and applications. Different cultures have created their own distinctive symbol sets. An Asian student in my laboratory was working on an application to visualize changes in computer software. She chose to represent deleted entities with the color green and new entities with red. I suggested to her that red is normally used for a warning, while green symbolizes renewal, so perhaps the reverse coding would be more appropriate. She protested, explaining that green symbolizes death in China, while red symbolizes luck and good fortune.

Many graphical symbols are transient and tied to a local culture or application. Think of the graffiti of street culture or the hundreds of new graphical icons that are being created on the Internet. These tend to convey meaning with little or no syntax to bind the symbols into a formal structure. On the other hand, in some cases, arbitrary representations can be almost universal and have elaborate grammars associated with their use. The Arabic numerals shown in Figure 1.9 are used widely throughout the world. Even if a more perceptually valid code could be constructed, the effort would be wasted. The designer of a new symbology for Air Force or Navy charts must live within the confines of existing symbols because of the huge amount of effort invested in the standards. We have many standardized visualization techniques that work well and are solidly embedded in work practices, and attempts to change them would be foolish. In many applications, good design is standardized design.

Conventional symbol systems persist because they have become embedded in ways in which we think about problems. For many geologists, the topographic contour map is the ideal way to understand relevant features of the Earth's surface. They often resist shaded computer graphics representations, even though these appear to be much more intuitively understandable to most people. Contour maps are embedded in cartographic culture and training.

Formally powerful. Arbitrary graphical notations can be constructed that embody formally defined, powerful languages. Mathematicians have created hundreds of graphical languages to express and communicate their concepts. The expressive power of mathematics to convey abstract concepts in a formal, rigorous way is unparalleled; however, the languages of mathematics are extremely difficult to learn (at least for most people). Clearly, the fact that something is expressed in a visual code does not mean that it is easy to understand.

Figure 1.9 Two methods for representing the first five digits. The code given below is easier to learn but is not easily extended.

The foregoing analysis leads to our fourth guideline.

> **[G1.4]** Graphical symbol systems should be standardized within and across applications.

It is important, however, that they first be designed to be perceptually efficient.

The Study of Arbitrary Conventional Symbols

The appropriate methodology for studying arbitrary symbols is very different from that used to study sensory symbols. The tightly focused, narrow questions addressed by psychophysics are wholly inappropriate to investigating visualization in a cultural context. A more appropriate methodology for the researcher of arbitrary symbols may derive from the work of anthropologists such as Clifford Geertz (1973), who advocated "thick description." This approach is based on careful observation, immersion in culture, and an effort to keep "the analysis of social forms closely tied … to concrete social events and occasions." Also borrowing from the social sciences, Carroll and co-workers developed an approach to understanding complex user interfaces that they call *artifact analysis* (Carroll, 1989). In this approach, user interfaces (and presumably visualization techniques) are best viewed as artifacts and studied much as an anthropologist studies cultural artifacts of a religious or practical nature. Formal experiments are out of the question in such circumstances, and if they were actually carried out, they would undoubtedly change the very symbols being studied. Unfortunately for researchers, sensory and arbitrary aspects of symbols are closely intertwined in many representations, and although they have been presented here as distinct categories the boundary between them is very fuzzy. There is no doubt that culture influences cognition; it is also true that the more we know, the more we perceive. Pure instances of sensory or arbitrary coding may not exist, but this does not mean that the analysis is invalid. It simply means that for any given example we must be careful to determine which aspects of the visual coding belong in each category.

In general, our scientific understanding of how visualizations work is still in its infancy. There is much about visualization and visual communication that is more craft than science. For the visualization designer, training in art and design is at least as useful as training in perceptual psychology. For those who wish to do good design, the study of design by example is generally most appropriate, but the science of perception can provide a scientific basis for design rules, and it can suggest entirely new design ideas and methods for displaying data that have not been tried before.

Gibson's Affordance Theory

The great perception theorist J. J. Gibson brought about radical changes in how we think about perception with his theories of ecological optics, affordances, and direct perception. Aspects of each of these theoretical concepts are discussed throughout this book. We begin with affordance theory (Gibson, 1979).

Gibson argued that we perceive in order to operate on the environment. Perception is designed for action. Gibson called the perceivable possibilities for action *affordances*, and a cornerstone of his theory is that affordances are perceived in a *direct* and immediate way. They are not *inferred* from sensory clues. This theory is clearly attractive from the perspective of visualization, because the goal of most visualization is decision making. Thinking about perception in terms of action is likely to be much more useful than thinking about how two adjacent spots of light influence each other's appearance (which is the typical approach of classical psychophysicists). Much of Gibson's work was in direct opposition to the approach of theorists who reasoned that we must deal with perception from the bottom up, as with geometry. The pre-Gibsonian theorists tended to have an atomistic view of the world. They thought we should first understand how single points of light were perceived, and then we could work on understanding how pairs of lights interacted and gradually build up to understanding the vibrant, dynamic visual world in which we live. Gibson took a radically different, top-down approach. He claimed that we do not perceive points of light; rather, we perceive possibilities for action. We perceive surfaces for walking, handles for pulling, space for navigating, tools for manipulating, and so on.

In general, our whole evolution has been geared toward perceiving useful possibilities for action. In an experiment that supports this view, Warren (1984) showed that subjects were capable of accurate judgments of the "climbability" of staircases. These judgments depended on their own leg lengths. Gibson's affordance theory is tied to a theory of direct perception. He claimed that we perceive affordances of the environment directly and immediately, not indirectly by piecing together evidence from our senses.

Translating the affordance concept into the interface domain, we might construct the following principle: A good interface has affordances that make the user's task easy; for example, if we have a task of moving an object in 3D space, it should have clear handles to use in rotating and lifting the object. Figure 1.10 shows a design for

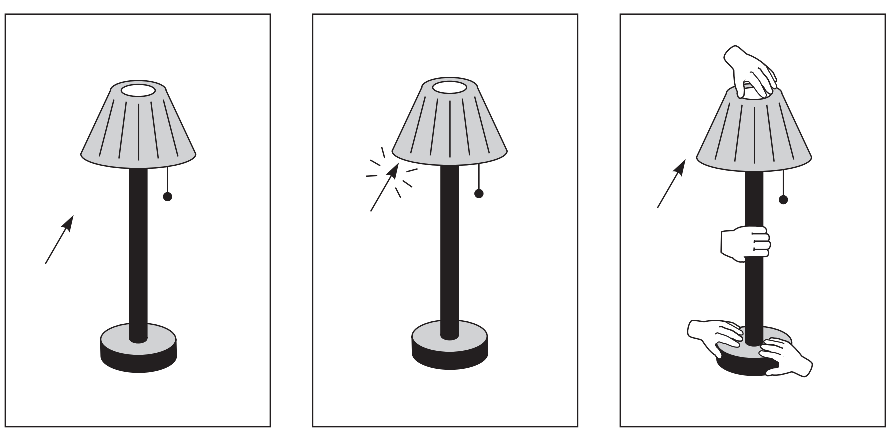


Figure 1.10 Cartoon cues are used to illustrate what interactions are possible. (*From Houde (1992). Reproduced with permission*.)

a 3D object manipulation interface from Houde (1992). When an object is selected, "handles" appear that allow the object to be lifted or rotated. The function of these handles is made more explicit by illustrations of gripping hands that show the affordances.

Gibson's theory, however, presents problems if it is taken literally. According to Gibson, affordances are physical properties of the environment that we directly perceive. Many theorists, unlike Gibson, think of perception as a very active process: The brain deduces certain things about the environment based on the available sensory evidence. Gibson rejected this view in favor of the idea that our visual system is tuned to perceiving the visual world and that we perceive it accurately except under extraordinary circumstances. He preferred to concentrate on the visual system as a whole and not to break perceptual processing down into components and operations. He used the term *resonating* to describe the way the visual system responds to properties of the environment. This view has been remarkably influential and has radically changed the way vision researchers think about perception; nevertheless, few would accept it today in its pure form.

There are three problems with Gibson's direct perception approach in developing theories of how visualizations work. The first problem is that even if perception of the environment is direct, it is clear that visualization of data through computer graphics is very indirect. Typically, there are many layers of processing between the data and its representation. In some cases, the source of the data may be microscopic or otherwise invisible. The source of the data may be quite abstract, such as company statistics in a stock-market database. Direct perception is not a meaningful concept in these cases.

Second, there are no clear physical affordances in any graphical user interface. To say that a screen button "affords" pressing in the same way as a flat surface affords walking is to stretch the theory beyond reasonable limits. In the first place, it is not even clear that a real-world button affords pressing. In another culture, these little bumps might be perceived as rather dull architectural decorations. Clearly, the use of buttons is arbitrary; we must learn that buttons, when pressed, do interesting things in the real world. Perception and action are linked in even more indirect ways when we use a computer; for instance, we must learn that a picture of a button can be "pressed" using a mouse, a cursor, or yet another button. This is far from being direct interaction with the physical world.

Third, Gibson's rejection of visual mechanisms is a problem. To take but one example, much that we know about color is based on years of experimentation, analysis, and modeling of the perceptual mechanisms. Color television and many other display technologies are based on an understanding of these mechanisms. To reject the importance of understanding visual mechanisms would be to reject most of vision research as irrelevant. This entire book is based on the premise that an understanding of perceptual mechanisms is basic to providing visualization designers with sound design principles.

Despite these reservations, Gibson's theories influence much of this book. The concept of affordances, loosely construed, can be extremely useful from a design perspective. The idea suggests that we build interfaces that beg to be operated in appropriate and useful ways. We should make virtual handles for turning, virtual buttons for pressing. If components are designed to work together, this should be made perceptually evident, perhaps by creating shaped sockets that afford the attachment of one object to another. This is the kind of design approach advocated by Norman in his famous book, *The Psychology of Everyday Things* (1988). Nevertheless, on-screen widgets present affordances only in an indirect sense. They borrow their power from our ability to represent pictorially, or otherwise, the affordances of the everyday world. Therefore, we can be inspired by affordance theory to produce good designs, but we cannot expect much help from that theory in building an applied science of visualization.

A Model of Perceptual Processing

In this section, we introduce a simplified information processing model of human visual perception. As Figure 1.5 shows, there are many subsystems in vision, and we should always be wary of overgeneralization. Still, an overall conceptual framework is useful in providing a starting point for more detailed analysis. Figure 1.11 gives a broad schematic overview of a three-stage model of perception. In Stage 1, information is processed in parallel to extract basic features of the environment.

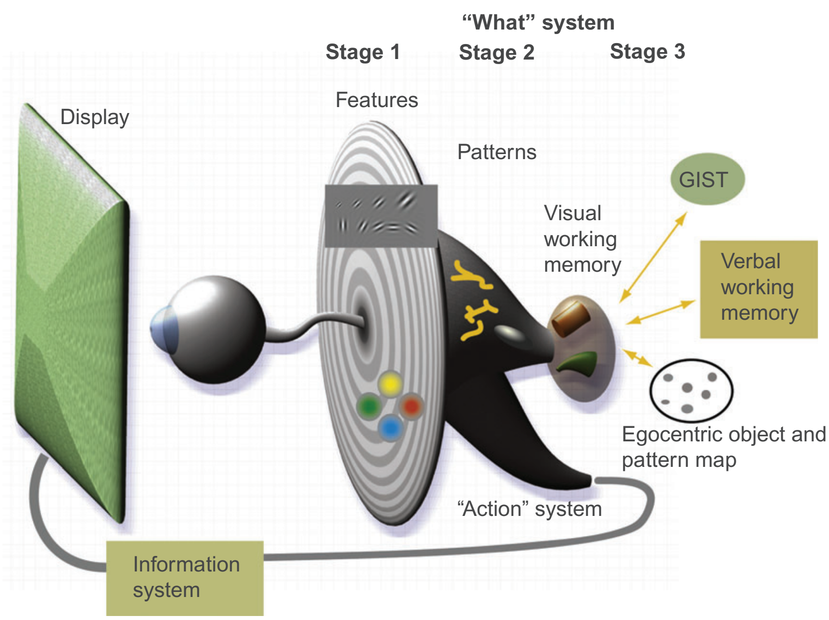


Figure 1.11 A three-stage model of visual information processing.

In Stage 2, active processes of pattern perception pull out structures and segment the visual scene into regions of different color, texture, and motion patterns. In Stage 3, the information is reduced to only a few objects held in visual working memory by active mechanisms of attention to form the basis of visual thinking.

Stage 1. Parallel Processing to Extract Low-Level Properties of the Visual Scene

Visual information is first processed by large arrays of neurons in the eye and in the primary visual cortex at the back of the brain. Individual neurons are selectively tuned to certain kinds of information, such as the orientation of edges or the color of a patch of light. In Stage 1 processing, billions of neurons work in parallel, extracting features from every part of the visual field simultaneously. Treisman (1985) described the result as a set of feature maps. This parallel processing proceeds whether we like it or not and is largely independent of what we choose to attend to (although not where we look). It is also rapid. If we want people to understand information quickly, we should present it in such a way that it can be easily detected by these large, fast computational systems in the brain. Important characteristics of Stage 1 processing include:

- Rapid parallel processing
- Extraction of features, orientation, color, texture, and movement patterns
- Transitory nature of information, which is briefly held in an iconic store
- Bottom-up, data-driven model of processing
- Serving as the basis for understanding the visual salience of elements in displays

Stage 2. Pattern Perception

At the second stage of visual analysis, rapid active processes divide the visual field into regions and simple patterns, such as continuous contours, regions of the same color, and regions of the same texture. Patterns of motion are also very important, although the use of motion as an information code is relatively neglected in visualization. The pattern-finding stage of visual processing is extremely flexible, influenced both by the massive amount of information available from Stage 1 parallel processing and by the top-down action of attention driven by visual queries. Marr (1982) called this stage of processing the *2-1/2D sketch*. Rensink (2002) called it a *proto-object flux* to emphasize its dynamic nature. Important characteristics of Stage 2 processing include:

- Slower serial processing
- Top-down attention being critical to the formation of objects and patterns pulled out from the feature maps

- A small number (one to three) patterns becoming "bound" and held for a second or two under top-down attentional processes
- Different pathways for object recognition and visually guided hand motion (the perception and action channels)

There is a major fork in the pattern-processing pathway, with one branch leading to object perception and the other branch leading to parts of the brain involved in the control of actions. This is the basis for the two-visual-system theory: one system for locomotion and action, called the *action system*, and another for object identification, called the *what system*. A detailed and convincing account of it can be found in Milner and Goodale (1995).

Stage 3. Visual Working Memory

At the highest level of perception are the objects held in visual working memory by the demands of active attention. In order to use an external visualization, we construct a sequence of visual queries that are answered through visual search strategies. At this level, only a few objects can be held at a time; they are constructed from the available patterns that may provide answers to the visual query and from information stored in long-term memory related to the task. For example, if we use a road map to look for a route, the visual query will trigger a search for connected red contours (representing major highways) between two visual symbols (representing cities).

Attention

Describing the visual system as a set of processing stages implies that visual information flows only from Stage 1 through Stage 2 to Stage 3. When a *new* image flashes on the screen in front of our eyes, or we make an eye movement to a part of the world we have not seen before, this is the only way information can flow. But, immediately following the upflow of information there is a top-down signal that consolidates and enhances what is happening at earlier stages. The entire system is being constantly tuned from top to bottom based on our expectations and on what will be most useful to us.

The generic name for this is *attention*. Attention is a multifaceted pervasive set of processes involving the entire visual system. Even the Stage 1 feature maps are subject to attention being tuned to be more sensitive to what we need to find. The Stage 2 patterns are the very essence of attention, and where our brains direct our eyes to move determines what will become the focus of our attention in the next instant. Eye movements are literally acts of reallocation of attention.

One of the more radical ideas in this book is that the effects of attention can be propagated outside of the brain into the world through cleverly designed interactive visualizations that cause information we are interested in to be highlighted on the screen.

Beyond the visual processing stages shown in Figure 1.11 are interfaces to other subsystems. The visual object identification process interfaces with the verbal linguistic subsystems of the brain so that words can be connected to images. The action system interfaces with the motor systems that control muscle movements.

The three-stage model of perception is the basis for the organization of the first seven chapters of this book. We work our way up from early to late stages of processing. Later chapters are more concerned with the system as a whole and the way visual thinking occurs as a process. The later chapters also discuss the interfaces between perceptual and other cognitive processes, such as those involved in language and decision making.

Costs and Benefits of Visualization

The ultimate goal of interactive visualization design is to optimize applications so that they help us perform cognitive work more efficiently. Optimizing a system requires that we have at least some conception of value. We use visualizations because they help us solve problems faster or better, or they let us learn something new, and these activities usually have monetary value. The following analysis is based in part on an economic model of the value of visualizations carried out by Jarke van Wijk (2006), but it differs in some important respects. Where van Wijk took *knowledge gain* to be the value of visualization we shall use the broader concept of *cognitive work*, as visualization can help us with many routine tasks: Executing trades on the stock market, cooking with a recipe, and working a cash register all involve cognitive work, part of which may be achieved through a form of visual thinking. The cash register in a fast-food restaurant has many specialized buttons relating to distinct combinations of fried potatoes, drinks, and different types of sandwiches. With the right layout and graphic design, a worker will process orders more rapidly with less training. At the other end of the spectrum is a major scientific discovery arising through the use of a visualization tool. In either case, the cognitive work has monetary value. This is not to deny that sometimes we pursue knowledge for its own sake and that it can be extremely difficult to place a value on a particular insight. But, if we are to compare the costs of producing a visual thinking tool with the value of using it, then we must use the same units on both sides of the equation and money is the obvious token of value. Because it is so difficult to quantify the value of knowledge, a highly detailed analysis is pointless—why add variables that we cannot quantify? Nevertheless, there are useful insights to be gained from first-order approximations.

A visualization can be viewed from two important perspectives: the perspective of the developer and the perspective of the user. We begin with the user. In the following, the * symbol is used to denote multiplication.

The basic user costs are

$$(\textit{The time to learn to use the visualization} * \textit{the value of the user's time}) + (\textit{the time spent carrying out the work} * \textit{the value of the user's time})$$

The user benefits are

$$\textit{The cognitive work done} * \textit{the value of the work}$$

There are some straightforward implications of this.

> **[G1.5]** Where two or more tools can perform the same task, choose the one that allows for the most valuable work to be done per unit time.

This rather obvious guideline is the basis for much of the content of this book, because in many cases we will be considering alternative visual representations of the same data for the same purpose. Efficient visualizations allow people to find important patterns faster and thereby perform work in less time.

> **[G1.6]** Consider adopting novel design solutions only when the estimated payoff is substantially greater than the cost of learning to use them.

Learning to interpret a novel data representation or a novel mode of interaction can require a significant effort. It is often not worth learning a new tool, especially if the number of times it will be used is uncertain.

People use a variety of different thinking tools that are inconsistent with one another in the sense that operations must be carried out with different commands and the same data types are represented using different visual symbols. There is a cognitive cost to this, both in learning and continuous use. Perhaps different symbols are used to represent the same piece of information.

> **[G1.7]** Unless the benefit of novelty outweighs the cost of inconsistency, adopt tools that are consistent with other commonly used tools.

This guideline can be extremely frustrating for the designer of innovative solutions. It often means that something that seems to be clearly and measurably superior when viewed in isolation is in fact not useful overall.

Now look at the developer side of the ledger.

The basic developer costs are

$$\begin{aligned}&\textit{The cost to design and implement a cognitive tool} + \textit{the cost to market} +\\&\quad \textit{the cost to manufacture} + \textit{the cost to service}\end{aligned}$$

The developer benefits are

$$\begin{aligned}&(\textit{The number of units sold} * \textit{the price per unit}) +\\&\qquad \textit{the revenue from maintenance contracts}\end{aligned}$$

With computer software, manufacturing costs are essentially zero and the cost to service is typically covered by maintenance. Profit can be approximated as follows:

$$\textit{Profit} = (\textit{Units sold} * \textit{price}) - (\textit{cost to create} + \textit{cost to market})$$

Significant revenue can come by selling a lot of cheap things or selling a few expensive ones. Examples of high-volume visualizations are the weather maps used by millions of people every day. Examples of customized, high-value visualizations are the tools used to control spacecraft. Because tool developers are interested in profiting from their efforts, the amount of design effort should be related to the anticipated payoff.

> **[G1.8]** Effort spent on developing tools should be in proportion to the profits they are expected to generate. This means that small-market custom solutions should be developed only for high-value cognitive work.

It must be recognized that this simple profit model often does not apply because many people who generate visualizations are academics not motivated by profit or even by the goal of increasing the efficiency of cognitive work. To the academic, for the most part, value is not based on monetary return; instead, it is based on published ideas. Published academic papers result in job tenure, increased recognition, and ultimately greater salary. Although this suggests an ultimate financial motive, novelty and a certain level of sophistication are more important requirements for getting a paper published, as opposed to whether a method is actually superior. The academic approach often results in methods that are not valuable, but sometimes it results in inventions that a more commercial approach would never discover.

Types of Data

If the goal of visualization research is to transform data into a perceptually efficient visual format, and if we are to make statements with some generality, we must be able to say something about the types of data that can exist for us to visualize. It is useful, but less than satisfying, to be able to say that color coding is good for stock-market symbols but texture coding is good for geological maps. It is far more useful to be able to define broader categories of information, such as continuous quantity maps (scalar fields), continuous flow fields (vector maps), and category data, and then to make general statements such as "Color coding is good for category information" and "Motion coding is good for highlighting selected data." If we can give perceptual reasons for these generalities, we have an applied science of visualization.

Unfortunately, the classification of data is a big issue. It is closely related to the classification of knowledge, and it is with great trepidation that we approach the subject. What follows is an informal classification of data classes using a number of concepts that we will find helpful in later chapters. We make no claims that this classification is especially profound or all encompassing.

Bertin (1977) suggested that there are two fundamental forms of data: data values and data structures. A similar idea is to divide data into entities and relationships (often called *relations*). Entities are the objects we wish to visualize; relations define the structures and patterns that relate entities to one another. Sometimes the relationships are provided explicitly; sometimes discovering relationships is the very purpose of visualization. We can also talk about the attributes of an entity or a relationship; for example, an apple can have color as one of its attributes. The concepts of entity, relationship, and attribute have a long history in database design and have been adopted more recently in systems modeling; however, we shall extend these concepts beyond the kinds of data that are traditionally stored in a relational database. In visualization, it is necessary to deal with entities that are more complex, and we are also interested in seeing complex structured relationships—data structures—not captured by the entity relationship model.

Entities

Entities are generally the objects of interest. People can be entities; hurricanes can be entities. Both fish and fishponds can be entities. A group of things can be considered a single entity if it is convenient—for example, a school of fish.

Relationships

Relationships form the structures that relate entities. There can be many kinds of relationships. A wheel has a "part-of" relationship to a car. One employee of a firm may have a supervisory relationship to another employee. Relationships can be structural and physical, as in defining the way a house is made of its many component parts, or they can be conceptual, as in defining the relationship between a store and its customers. Relationships can be causal, as when one event causes another, and they can be purely temporal, defining an interval between two events.

Attributes of Entities or Relationships

Both entities and relationships can have attributes. In general, something should be called an attribute (as opposed to an entity itself) when it is a property of some entity and cannot be thought of independently. Thus, the color of an apple is an attribute of the apple. The temperature of water is an attribute of the water. Duration is an attribute of a journey. Defining what should be an entity and what should be an attribute is not always straightforward. The salary of an employee, for example, could be thought of as an attribute of the employee, but we can also think of an amount of money as an entity unto itself, in which case we would have to define a relationship between the employee entity and the sum-of-money entity.

Data Dimensions: 1D, 2D, 3D, …

An attribute of an entity can have multiple dimensions. We can have a single scalar quantity, such as the weight of a person. We can have a vector quantity, such as the direction in which that person is traveling. Tensors are higher-order quantities that describe both direction and shear forces, such as occur in materials that are being stressed. We can have a field of scalars, vectors, or tensors. The gravitational field of the Earth is a three-dimensional attribute of the Earth. In fact, it is a three-dimensional vector field attribute. If we are interested only in the strength of gravity at the Earth's surface, it is a two-dimensional scalar attribute. Often, the term *map* is used to describe this kind of field; thus, we talk about a gravity map or a temperature map.

Types of Numbers

It is often desirable to describe data visualization methods in light of the quality of attributes they are capable of conveying. A useful way to consider the quality of data is the taxonomy of number scales defined by the statistician Stevens (1946). According to Stevens, there are four levels of measurement: nominal, ordinal, interval, and ratio scales:

Nominal. This is the labeling function. Fruit can be classified into apples, oranges, bananas, and so on. There is no sense in which the fruit can be placed in an ordered sequence. Sometimes numbers are used in this way; for example, the number on the front of a bus generally has a purely nominal value. It identifies the route on which the bus travels.

Ordinal. The ordinal category encompasses numbers used for ordering things in a sequence. It is possible to say that a certain item comes before or after another item. The position of an item in a queue or list is an ordinal quality. When we ask people to rank some group of things (films, political candidates, computers) in order of preference, we are requiring them to create an ordinal scale.

Interval. When we have an interval scale of measurement, it becomes possible to derive the gap between data values. The time of departure and the time of arrival of an aircraft are defined on an interval scale.

Ratio. With a ratio scale, we have the full expressive power of a real number. We can make statements such as "Object A is twice as large as object B." The mass of an object is defined on a ratio scale. Money is defined on a ratio scale. The use of a ratio scale implies a zero value used as a reference.

In practice, only three of Stevens's levels of measurement are widely used, and these in somewhat different form. The typical basic data classes most often considered in visualization have been greatly influenced by the demands of computer programming. They are the following:

Category data. This is like Stevens's nominal class.

Integer data. This is like his ordinal class in that it is discrete and ordered.

Real-number data. This combines the properties of interval and ratio scales.

Uncertainty

In science and engineering it is common to attach an uncertainty attribute either to raw data or to derived data. Estimating uncertainty is a major part of engineering practice, and showing uncertainty in a visualization is important, although difficult to achieve. The problem is that once data is represented as a visual object, it attains a kind of literal concrete quality that makes the viewer think it is accurate.

Operations Considered as Data

An entity relationship model can be used to describe most kinds of data; however, it does not capture the operations that may be performed on entities and relationships. We tend to think of operations as somehow different from the data itself, neither entities nor relationships nor attributes. The following are a few common operations:

- Mathematical operations on numbers—multiplication, division, and so on
- Merging two lists to create a longer list
- Inverting a value to create its opposite
- Bringing an entity or relationship into existence (such as the mean of a set of numbers)
- Deleting an entity or relationship (a marriage breaks up)
- Transforming an entity in some way (the chrysalis turns into a butterfly)
- Forming a new object out of other objects (a pie is baked from apples and pastry)
- Splitting a single entity into its component parts (a machine is disassembled)

In some cases, these operations can themselves form a kind of data that we may wish to capture. Chemistry contains a huge catalog of the compounds that result when certain operations are applied to combinations of other compounds. These operations may form part of the data that is stored. Certain operations are easy to visualize; for example, the merging of two entities can easily be represented by showing two visual objects that combine (visually merge) into a single entity. Other operations are not at all easy to represent in any visualization; for example, the detailed logical structure of a computer program may be better represented using a written code that has its basis in natural language than using any kind of diagram. What should and should not be visualized is a major topic in Chapter 9.

Operations and procedures often present a particularly difficult challenge for visualization. It is difficult to express operations effectively in a static diagram, and this is especially a problem in the creation of visual languages. On the other hand, the use of animation opens up the possibility of expressing at least certain operations in an immediately accessible visual manner. We shall deal with the issue of animation and visual languages in Chapter 9.

Metadata

Metadata is data about data—who collected it, what transformations it has been subjected to, what is its uncertainty. When we are striving to understand data, certain products are sure to emerge as we proceed. We may discover correlations between variables or clusters of data values. We may postulate certain underlying mechanisms that are not immediately visible. The result is that theoretical entities come into being. Atoms, photons, black holes, and all the basic constructs of physics are like this. As more evidence accumulates, the theoretical entities seem more and more real, but they are nonetheless only observable in the most indirect ways. Metadata can be of any kind. It can consist of new entities, such as identified classes of objects, or new relationships, such as postulated interactions between different entities, or new rules. We may impose complex structural relationships on the data, such as tree structures or directed acyclic graphs, or we may find that they already exist in the data.

The visualization of metadata presents the same kinds of challenges as the visualization of non-metadata, as metadata consists ultimately of entities and relationships and of different kinds of numbers from nominal to real, and metadata may have a complex structure. Graphically representing metadata can be very challenging because it inevitably adds complexity, but the problems of representation are essentially the same. For this reason, metadata visualization is not discussed as a separate topic in this book.

Conclusion

Visualization applies vision research to practical problems of data analysis in much the same way as engineering applies physics to practical problems of building factories. Just as engineering has influenced physicists to become more concerned with areas such as semiconductor technology, so we may hope that the development of an applied science of data visualization can encourage vision researchers to intensify their efforts in addressing such problems as 3D space and task-oriented perception. There is considerable practical benefit in understanding these things. As the importance of visualization grows, so do the benefits of a scientific approach, but there is no time left to lose. New symbol systems are being developed constantly to meet the needs of a society increasingly dependent on data. Once developed, they may stay with us for a very long time, so we should try to get them right.

We have introduced a key distinction between the ideas of sensory and arbitrary conventional symbols. This is a difficult and sometimes artificial distinction. Nonetheless, the distinction is essential. Were there no basic model of visual processing to support the idea of a good data representation, all visual representations would be arbitrary, and ultimately the problem of visualization would come down to establishing consistent notations.

In opposition to the view that consistency is the only important criterion, this book takes the view that all humans have more or less the same visual system. This visual system has evolved over tens of millions of years to enable creatures to perceive and act within the natural environment. Although very flexible, the visual system is tuned to receiving data presented in certain ways, but not in others. If we can understand how the mechanism works, we can produce better displays and better thinking tools.