3 THINKING WITH OUR EYES

I cherish all five of my senses. They connect me to the world and allow me to experience beauty in inexhaustible and diverse ways. But of all our senses, vision stands out as the primary and most powerful channel of input from the world around us. Approximately 70% of the body's sense receptors reside in our eyes.

Vision is not only the fastest and most nuanced sensory portal to the world, it is also the one most intimately connected with cognition. Seeing and thinking collaborate closely to make sense of the world. It's no accident that so many words used to describe understanding are metaphors for sight, such as "insight," "illumination," and the familiar expression "I see." The title of this book, *Now You See It*, uses this metaphor to tie quantitative sense-making to the most effective means available: information visualization.

Colin Ware of the University of New Hampshire is perhaps the world's top expert in harnessing the power of visual perception to explore, make sense of, and present information. Ware makes a convincing case for the importance of visualization:

> *Why should we be interested in visualization? Because the human visual system is a pattern seeker of enormous power and subtlety. The eye and the visual cortex of the brain form a massively parallel processor that provides the highest-bandwidth channel into human cognitive centers. At higher levels of processing, perception and cognition are closely interrelated, which is the reason why the words 'understanding' and 'seeing' are synonymous. However, the visual system has its own rules. We can easily see patterns presented in certain ways, but if they are presented in other ways, they become invisible. . . . The more general point is that when data is presented in certain ways, the patterns can be readily perceived. If we can understand how perception works, our knowledge can be translated into rules for displaying information. Following perception-based rules, we can present our data in such a way that the important and informative patterns stand out. If we disobey the rules, our data will be incomprehensible or misleading.*[1]

To use visualization effectively, we must do more than simply display data graphically. We must understand how visual perception works and then present data visually in ways that follow the rules.

1. *Information Visualization: Perception for Design*, Second Edition, Colin Ware, Morgan Kaufmann Publishers, San Francisco CA, 2004, p. xxi.

The Power of Visual Perception

Traditional methods of statistics and the less sophisticated methods that are traditionally supported by business intelligence software display information in a predominantly text-based manner, usually arranged in a table. According to Edward Tufte:

> *Modern data graphics can do much more than simply substitute for small statistical tables. At their best, graphics are instruments for reasoning about quantitative information. Often the most effective way to describe, explore, and summarize a set of numbers—even a very large set—is to look at pictures of those numbers. Furthermore, of all methods for analyzing and communicating statistical information, well-designed data graphics are usually the simplest and at the same time the most powerful.*[2]

2. *The Visual Display of Quantitative Information*, Edward R. Tufte, Graphics Press: Cheshire, CT 1983, Introduction.

The table below works well if we need precise values or an easy means to look up individual values.

2007 Sales Revenue
(U.S. dollars in thousands)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Domestic	1,983	2,343	2,593	2,283	2,574	2,838	2,382	2,634	2,938	2,739	2,983	3,493
International	574	636	673	593	644	679	593	139	599	583	602	690
	$2,557	$2,979	$3,266	$2,876	$3,218	$3,517	$2,975	$2,773	$3,537	$3,322	$3,585	$4,183

Figure 3.1

However, sense-making involves operations that go beyond looking up specific values in a table like the one above. For example, in this case, to understand trends in sales revenue, we need to compare revenue to other variables that might help us find relationships and patterns, which in turn would allow us to make decisions about changes in our business operation. During the process of sense-making, we only occasionally need precise values that must be expressed as text.

Most data analysis involves searching for and making sense of relationships among values and making comparisons that involve more than just two values at a time. To perform these operations and see relationships among data, which exhibit themselves as patterns, trends, and exceptions, we need a picture of the data. When information is presented visually, it is given form, which allows us to easily glean insights that would be difficult or impossible to piece together from the same data presented textually. The graph on the following page instantly brings to light several facts that weren't obvious in the table of the same data above.

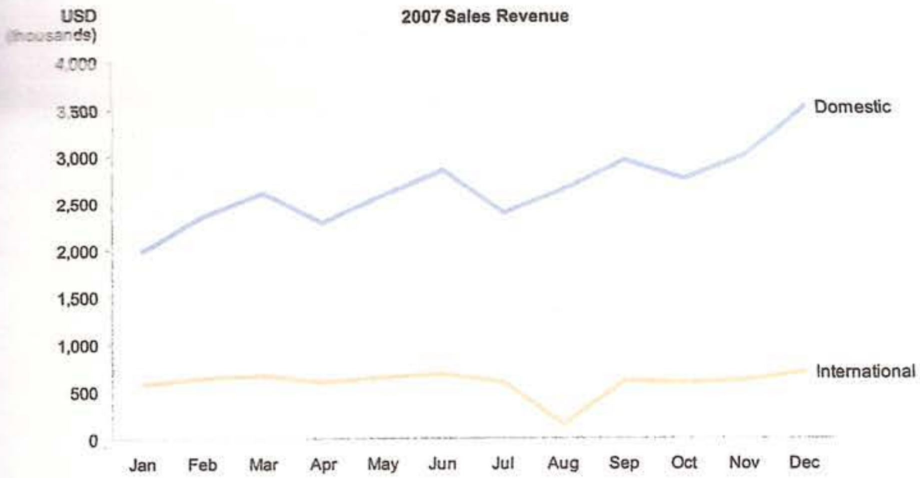


Figure 3.2

Notice aspects of the domestic versus international sales story that were not obvious in the table but pop out in the graph.

Here are a few facts that the graph makes visible:

- Domestic sales were much higher than international sales throughout the year.
- Domestic sales trended upward during the course of the year as a whole while international sales remained relatively flat.
- The month of August was an exception to otherwise relatively consistent sales in the international market. (Perhaps most of this company's international customers are Europeans who were on vacation in August.)
- Domestic sales exhibited a monthly pattern of up, up, down, which repeated itself quarterly, with the highest sales in the last month and the lowest sales in the first month of each quarter. (This is a common pattern in sales—sometimes called the "hockey stick" pattern because of its shape—which results from sales people being paid bonuses for meeting and exceeding quarterly sales quotas so that they intensify efforts to increase their bonuses as the quarter's end draws near.)

Patterns and relationships such as these are what we strive to find and understand when we analyze data.

How Visual Perception Works

We certainly don't need to be experts in visual perception to create effective information visualization, but here are a few basic facts we should know about how visual perception works:

- Our eyes sense light that enters them after reflecting off the surfaces of objects in the world.
- What we perceive as an object is built up in our brains as a composite of several visual properties, which are the building blocks of vision.
- Even though we perceive this composite of properties as a whole object, we can still distinguish the properties that compose it.
- These individual properties, which vision is specifically tuned to sense, include two-dimensional (2-D) location, length, width, area, shape, color, and orientation, to name a few.

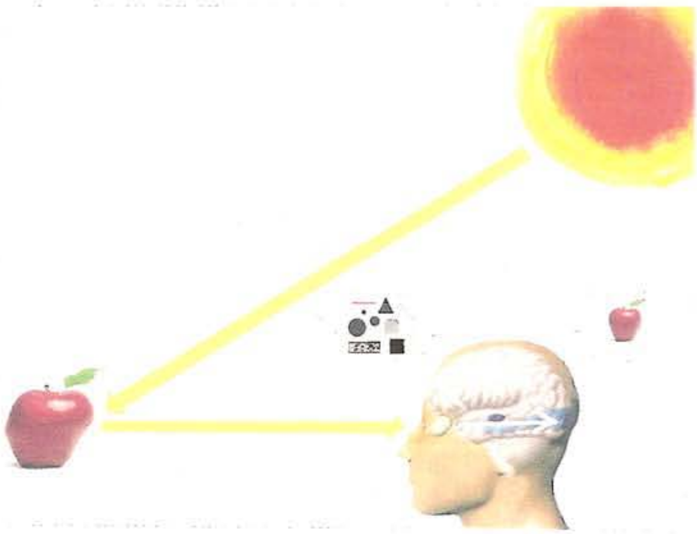


Figure 3.3

If we can use these basic and easily perceived attributes to represent data visually, we can direct much of the work that is required to view and make sense of data to simple and efficient perceptual processes in the brain. Rather than reading individual values one at a time, which is how we perceive tables of text, we can, thanks to a graph, see and potentially understand many values at once. This is because visual displays combine values into patterns that we can perceive as wholes, such as the patterns formed by lines in a line graph.

Figure 3.4

Using Knowledge of Perception to Create Effective Visualizations

We should keep a few facts in mind about how we collect and process visual information if we want to create effective information visualizations.

> Fact #1: We do not attend to everything that we see. Visual perception is selective, as it must be, for awareness of everything would overwhelm us. Our attention is often drawn to contrasts to the norm.

For this reason, to successfully see meaning in visual displays, we must encode data in ways that allow what's interesting and potentially meaningful to stand out from what's not. What stands out to you as you look at the image below?

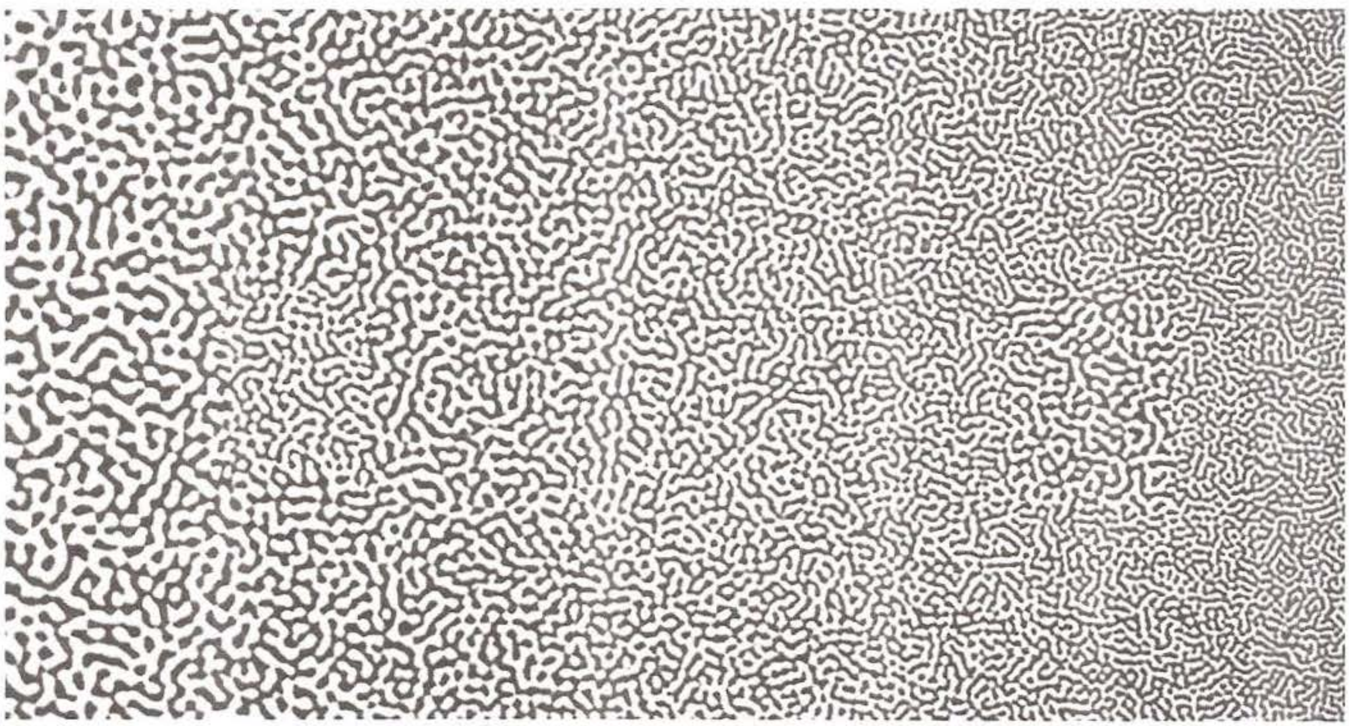


Figure 3.5. This image appears in *Information Visualization: Perception for Design,* Second Edition, Colin Ware, Morgan Kaufmann Publishers, San Francisco CA, 2004, p. 171.

Among the things you notice are probably two roughly oval-shaped areas of texture embedded within the pattern that stand out from the rest: one is in the left half and one in the right half of the image. They stand out because they differ from what surrounds them. What's not obvious is that these two regions that catch our attention are exactly the same. The area that stands out on the left is made up of lines that are less thick than those that surround them. By contrast, the area on the right is surrounded by lines that are thicker than the surrounding lines. Because the two areas that stand out are embedded in contexts that differ, our perception of them is affected so that it is difficult to see that they are made up of lines of the same thickness.

We learn from this fact that information visualizations should cause what's potentially meaningful to stand out in contrast to what's not worth our attention.

Fact #2: Our eyes are drawn to familiar patterns. We see what we know and expect.

When we look at the image below, our eyes see the familiar shape of the rose and our minds quickly categorize it as fitting a recognizable pattern that we know: a rose. However, another distinct image has been worked into the familiar image of the rose, which isn't noticeable unless we know to look for it. Take a few seconds right now to see if you can spot the image that's embedded in the rose.

Figure 3.6. This image was found at www.coolbubble.com.

Did you spot the dolphin? Once we have been primed with the image of the dolphin (turn to page 36 to see it), we can easily spot it in the rose. This second fact teaches us that visualizations work best when they display information as patterns that are both familiar and easy to spot.

In addition to visual perception, information visualization must also be rooted in an understanding of how people think. Only then can visualizations support the cognitive operations that make sense of information.

Fact #3: Memory plays an important role in human cognition, but working memory is extremely limited.

The two photographs on the next page illustrate one of the limitations of working memory. We only remember the elements to which we attend. Imagine that you haven't seen these two photos of the sphinx side by side and hadn't noticed that the stand of trees that appears to the left of the sphinx's head on the left is missing from the photo on the right. If these two versions of the photo were rapidly alternated on a screen with an instant of blank screen in between, you wouldn't notice this rather significant difference between the two unless you specifically attended to that section of the photo just before a swap occurred.

I've used an animated version of these two images in many classes and presentations, and only a few people notice the difference even after viewing the two images swapping back and forth for a full 30 seconds.

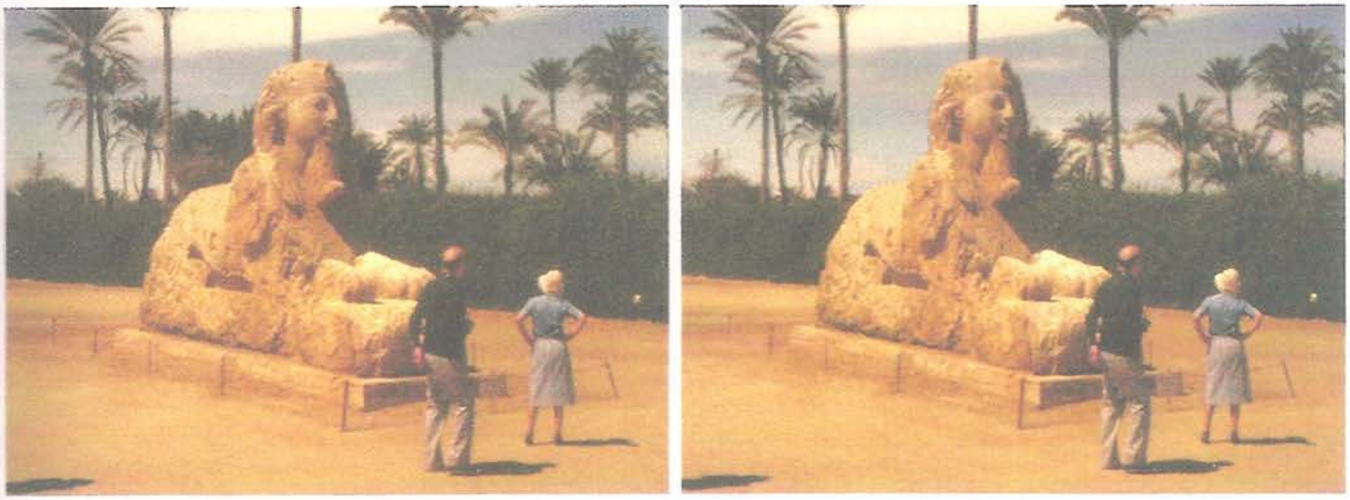


Figure 3.7. This demonstration of "change blindness" was prepared by Ronald A. Rensink, Associate Professor of Psychology and Computer Science at the University of British Columbia. Additional examples can be found at www.psych.ubc.ca/~rensink/flicker/download/.

Stated differently, unless the specific part of the photo containing the trees was stored in working memory just before the swap, you would no longer remember it when you viewed the next photo and therefore wouldn't notice the difference. In addition to not remembering anything other than the few things that we attend to, we also don't clearly see anything that we don't focus on directly. To see something clearly, we must look at it directly because only a small area of receptors in the retina of each eye called the fovea are designed for high-resolution vision. Light that hits the retina outside of this relatively small area is perceived much less clearly. This third fact makes it clear that information visualization must serve as an external aid to augment working memory.

The gist of the three facts above is that, for information visualization to be effective, just any old display won't do. According to Stuart Card:

> *Over history, visual abstractions have been developed to aid thinking... What information visualization is really about is external cognition, that is, how resources outside the mind can be used to boost the cognitive capabilities of the mind.*[3]

Software can only support information visualization effectively if the software operates on principles that respect how visual perception and cognition work.

3. Written by Stuart Card in the foreword to *Information Visualization: Perception for Design*, Second Edition, Colin Ware, Morgan Kaufmann Publishers, San Francisco CA, 2004, p. xvii.

Making Abstract Data Visible

We'll begin this section with an illustration. Something is wrong with the following graph. Take a moment to see if you can find a problem.

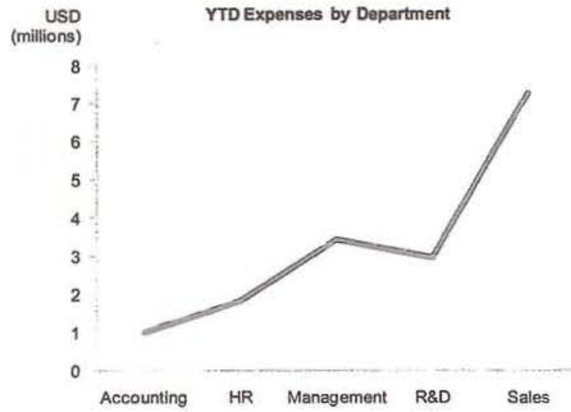
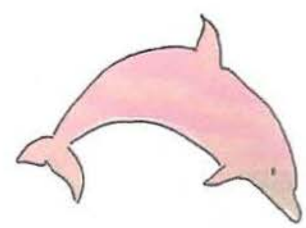


Figure 3.8

Does anything about this graph bother you? Does any aspect of its design undermine its ability to represent data appropriately? This is a case where it doesn't make sense to encode the values as a line. The line connects values for a series of categorical items—departments in this case—that are completely independent from one another. These are discrete items in the category called "departments," which have no particular order and no close connection to one another. To connect these values with a line visually suggests a relationship that doesn't exist in the data. We are used to interpreting a line like this as indicating an increase or decrease in some variable, in this case, expenses on the vertical axis, in relation to some variable on the horizontal axis that might reasonably be expected to affect or have a comprehensible relationship to expenses, such as time. The up and down slopes of the line and the pattern formed by them are meaningless.



This picture of a dolphin can be found embedded in the rose in Figure 3.6.

Lines work well for connecting values through time, such as months in a year, but are inappropriate for connecting categorical items such as departments. In the following graph, separate bars accurately encode and visually reinforce the independent nature of these departments and their expenses.

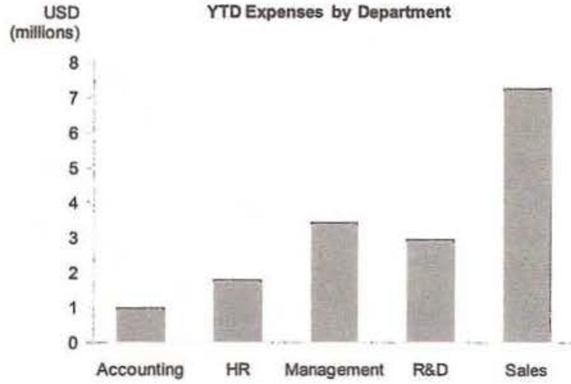


Figure 3.9

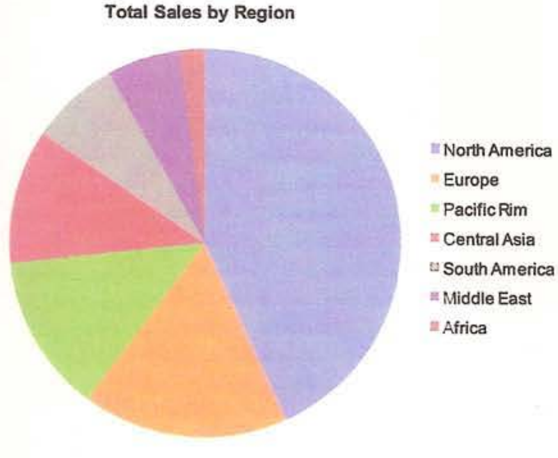
Listing departments along one of a graph's axes is an example of using a *nominal* scale. In a nominal scale, items have no particular order or close connection between one another. If we sorted these departments in order of expenses from greatest to least, this would change the scale from nominal to *ordinal* (department with the highest expenses, department with the second highest expenses, and so on), but the departments would still lack a close connection to one another. Units of time, such as years, quarters, months, or days, on the other hand, are not only ordered by their nature, they are also intimately connected one to the next. Time is an example of an *interval* scale.

An interval scale consists of a continuous range of quantitative values, divided into equal intervals. For example, if we want to count and compare sales orders of various dollar sizes, and the smallest order is 50¢ and the largest is $100, we could break order sizes into intervals of $10 each: $0.00-9.99, $10.00-19.99, and so on. This would be an interval scale. A range of time beginning at one point and ending at some later point is a quantitative range of values. Breaking time into intervals, such as years, also results in an interval scale. Because interval scales consist of ordered and intimately connected items, such as the years 2004, 2005, 2006, and 2007, it is appropriate to display values across those years using a line to connect them. It is natural and effective. Our eyes can easily trace how a set of values change through time when these values are displayed as a line, and our minds are able to easily understand the nature of this change.

Although it is true that years vary in length because of leap years and months have different numbers of days, for most analytical purposes we consider these intervals equal in size.

The point that I'm trying to make is that there are ways to visually display data that are effective because they correspond naturally to the workings of vision and cognition, and there are ways that break the rules and consequently don't work. If we wish to display information in a way that will enable us and others to make sense of it, we must understand and follow the rules.

I'll show another example to drive this truth home. If we wish to rank and compare the sales performance of the 10 products that are displayed in each of the two graphs below, which supports this task most effectively?



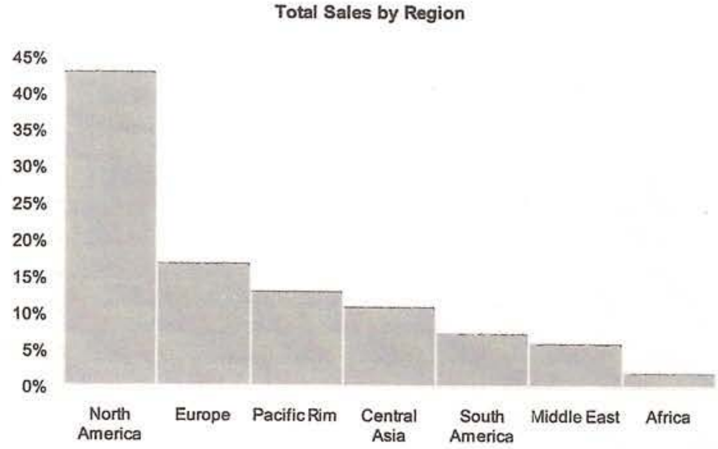


Figure 3.10

The pie chart doesn't work nearly as well as the bar graph because, to decode it, we must compare the 2-D areas or the angles formed by the slices, but visual perception doesn't accurately support either of these tasks. The graph on the right, however, superbly supports the task because we can easily compare the lengths of bars.

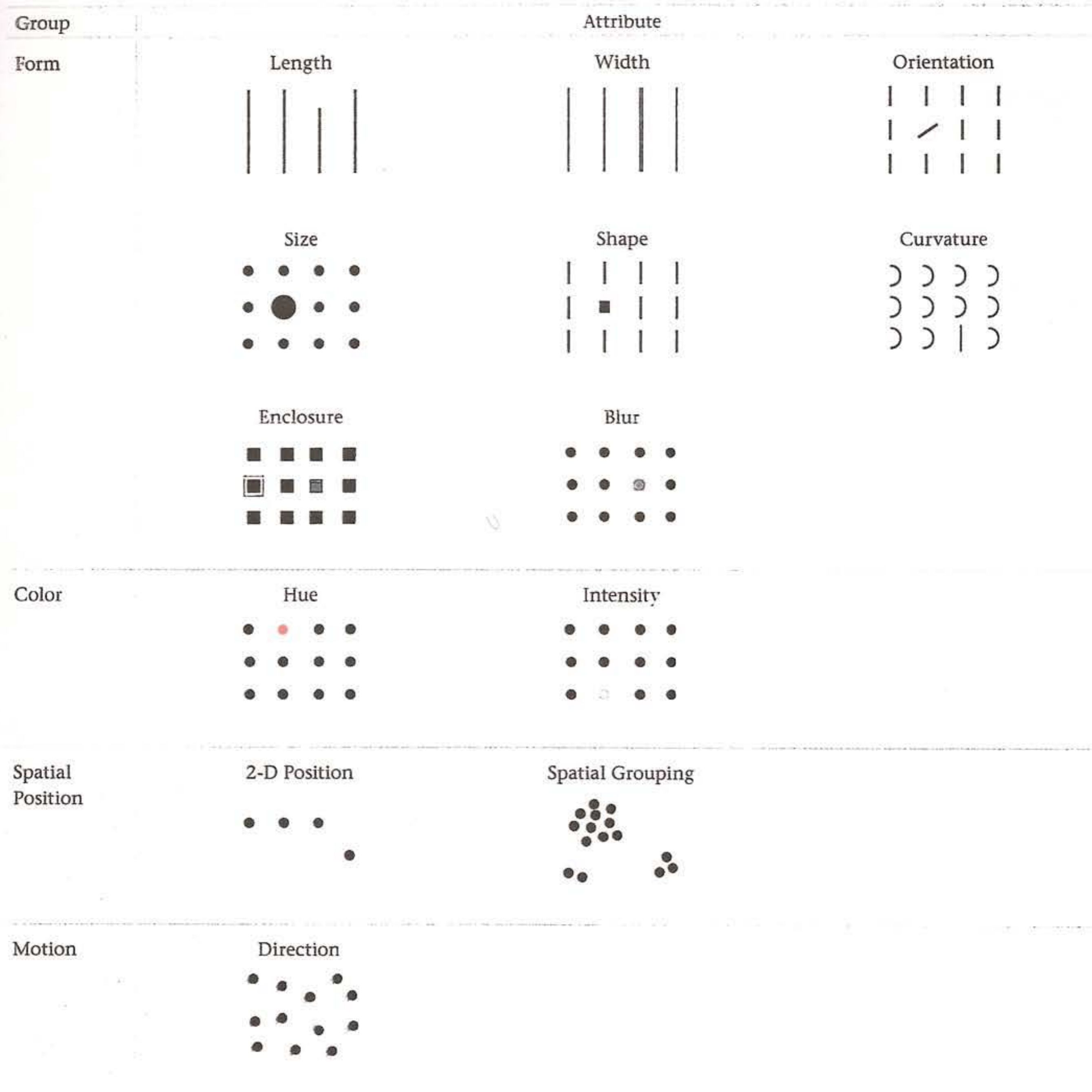
In 1967, with the publication of his seminal and brilliant work, *Semiologie graphique* (previously mentioned in Chapter 1) Jacques Bertin was the first person to recognize and describe the basic vocabulary of vision, that is, the attributes of visual perception that we can use to display abstract data. He teased out the basic rules of how visual perception works, which we can follow to clearly, accurately, efficiently, and intuitively represent abstract data. For any given set of information, there are effective ways to visually encode the meanings that reside within it, as well as ways to represent them poorly and perhaps even misrepresent them entirely. All those who have, since Bertin, worked to map visual properties to the meanings of abstract data have relied heavily on his work; I am among the many who owe him a debt of gratitude.

Much of Bertin's work is based on an understanding of the fundamental building blocks of visual perception. We perceive several basic attributes of visual images pre-attentively, that is, prior to and without the need for conscious awareness. For this reason, these are called *pre-attentive attributes* of visual perception. Colin Ware makes a convincing case for the importance of these pre-attentive attributes when we are creating visual representations of abstract information:

> *We can do certain things to symbols to make it much more likely that they will be visually identified even after very brief exposure. Certain simple shapes or colors 'pop out' from their surroundings. The theoretical mechanism underlying pop-out is called pre-attentive processing because logically it must occur prior to conscious attention. In essence, pre-attentive processing determines what visual objects are offered up to our attention. An understanding of what is processed pre-attentively is probably the most important contribution that vision science can make to data visualization.*[4]

4. *Information Visualization: Perception for Design*, Second Edition, Colin Ware, Morgan Kaufmann Publishers, San Francisco CA, 2004, p. 163.

Let's look at pre-attentive attributes more closely. Ware has provided a convenient list of them, organized into four groups: form, color, spatial position, and motion. The examples of each that I believe apply most directly and usefully to information visualization are:



Each of these pre-attentive attributes comes in handy for one or more information visualization purposes. From time to time throughout the book, I'll point out how they can be used. A few uses, however, are so important that they deserve to be mentioned and explained before we proceed.

Some of these pre-attentive attributes are especially useful for making objects in a visualization look distinct from one another. These attributes enable us to assign various subsets of visual objects (for example, data points in a scatterplot) to categorical groups (for example, to regions, departments, products, and so on). For instance, in a scatterplot that displays the number of ads that have run for products and the resulting number of products that were sold, we might want to distinguish newspaper, television, and radio ads. The best two pre-attentive attributes for doing this are hue and shape.

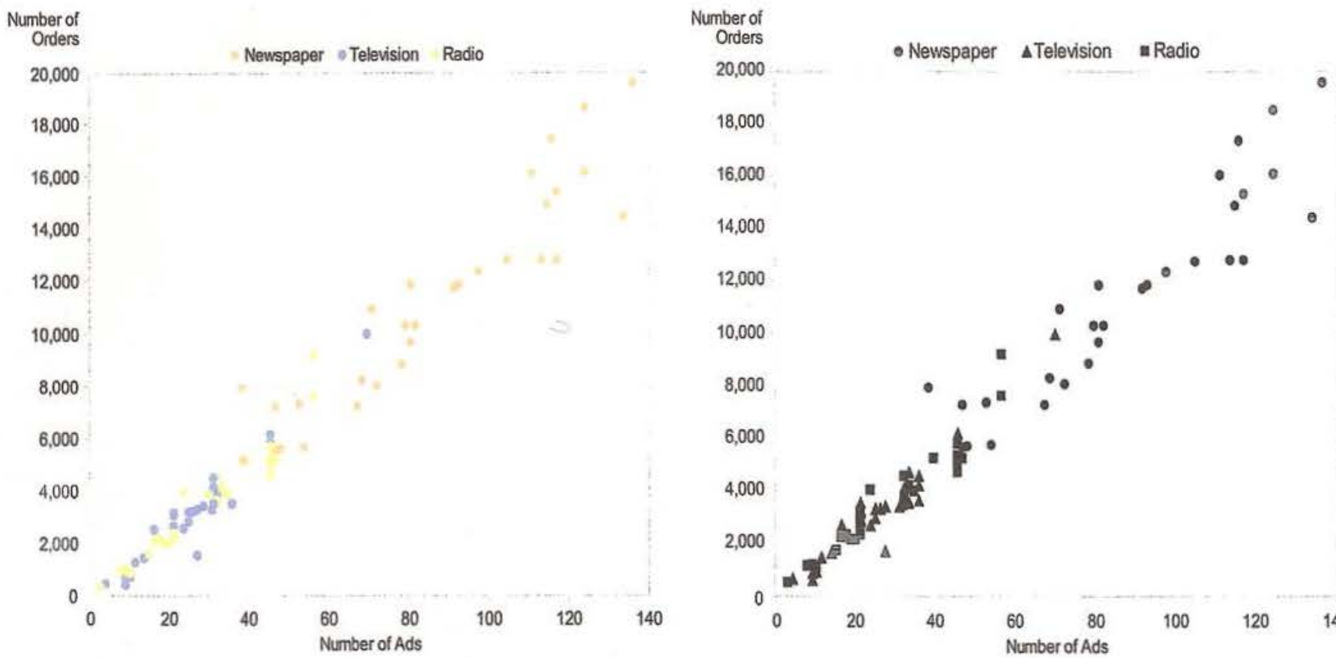


Figure 3.11

Assuming that none of us are color blind or that, if some are, we're careful to avoid using combinations of hues that we can't tell apart (for instance, red and green, which most people with color blindness have difficulty distinguishing), hues are usually a little easier to interpret than shapes (circles, squares, X's, triangles, and so on) for this purpose. Other types of graphs besides scatterplots, such as bar and line graphs, can also rely on hues to associate objects (bars or lines) with particular categories.

We can also use pre-attentive attributes to represent quantitative values. Although some attributes lend themselves to making things look different from one another (that is, to making categorical distinctions), a few naturally lend themselves to making things look greater or lesser than one another. Take a moment to examine each pre-attentive attribute in the following list to determine which ones we are able to intuitively perceive in a quantitative manner, that is, it's easy to recognize that some representations of the attribute appear greater than others:

- Length
- Width
- Orientation
- Size
- Shape
- Curvature
- Enclosure
- Spatial grouping
- Blur
- Hue
- Color intensity
- 2-D position
- Direction of motion

Here's the list of the pre-attentive attributes that are quantitatively perceived in and of themselves, without having values arbitrarily assigned to them:

Precision of Quantitative Perception	Attribute	Example	Description
Very precise	Length		Longer = greater
	2-D Position		Higher or farther to the right = greater
Not very precise	Width		Wider = greater
	Size		Bigger = greater
	Intensity		Darker = greater
	Blur		Clearer = greater

If you included "orientation" in your list, you probably did so because of your familiarity with clocks, which use different orientations to quantify hours and minutes around the dial. In this case, the quantitative meanings that we associate with various orientations of the hands (5 o'clock, 6 o'clock, and so on) have been learned and are therefore only meaningful through convention, not because we naturally think of particular orientations as representing greater or lesser values.

Only two pre-attentive attributes are perceived quantitatively with a high degree of precision: length and 2-D position. It isn't accidental that the most common ways to encode values in graphs rely on these attributes. Each of the popular graphs below uses one or both of these attributes to encode quantitative values, enabling us to compare those values with relative ease and accuracy.

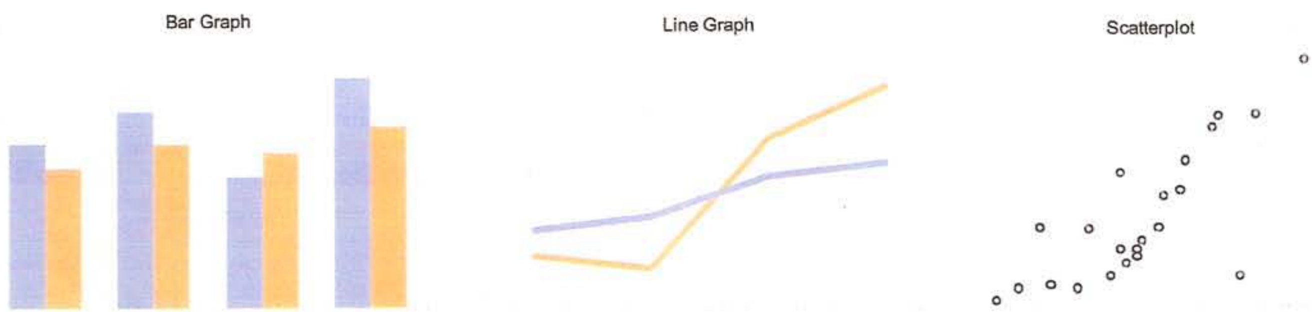


Figure 3.12

Even though information visualization relies on a broad assortment of graphs, only a few work well for typical quantitative analyses. Almost all effective *quantitative* graphs are of the 2-D, X-Y axis type.

Sometimes it's appropriate to encode quantities using one of the attributes that we can't perceive precisely, but we should usually do this only when neither length nor 2-D position is an option. For instance, each data point in the following scatterplot encodes two quantitative values: marketing expenses and sales revenues for particular products:

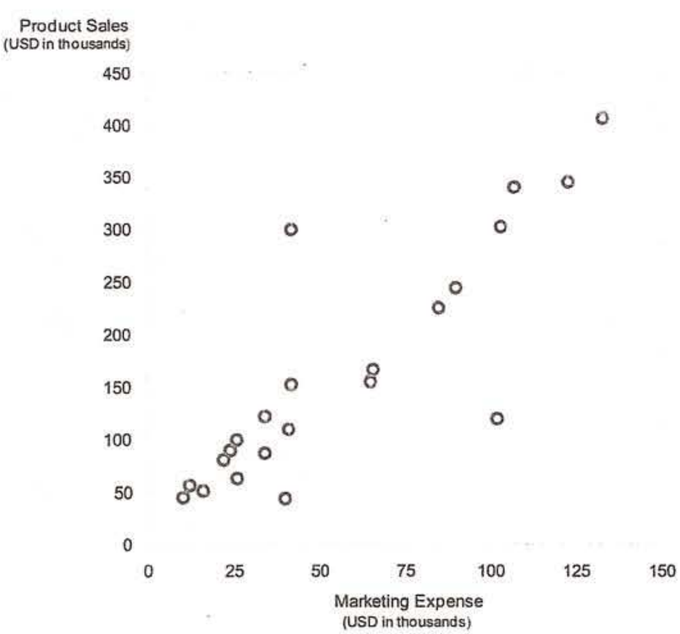


Figure 3.13

What if we needed to see the relationship of profits to both sales revenues and marketing expenses? We can't encode profits using 2-D position because we've already used the two dimensions available: horizontal position along the X-axis to encode expenses and vertical position along the Y-axis to encode revenues. What pre-attentive visual attribute could we assign to each data point to encode profit? One solution is to vary the size of each data point, with the biggest for the product with the greatest profit and the smallest for the one with the least, as illustrated below:

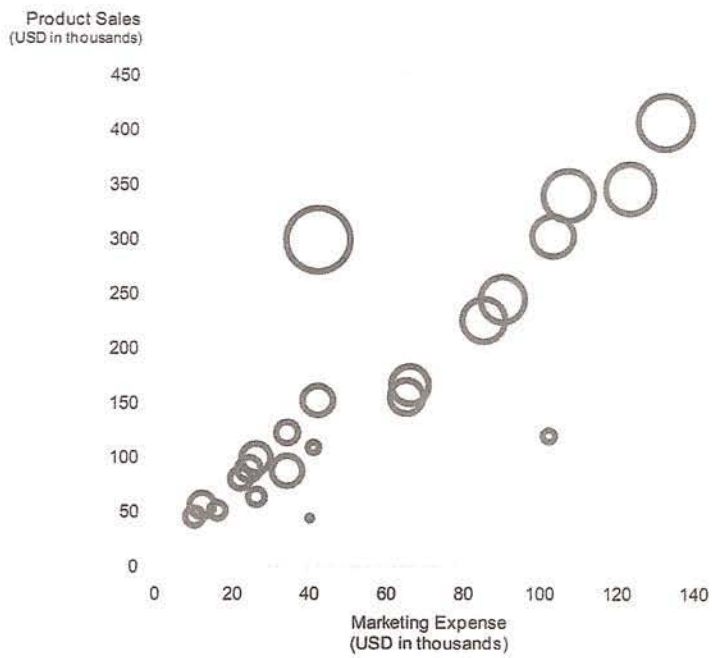


Figure 3.14

We can't compare the varying sizes of these data points precisely, but if all we need is a rough sense of how profits compare, this does the job. What if we're examining sales revenues by region, ranked from highest to lowest, using the bar graph below, but want to compare this to profits in those regions as well?

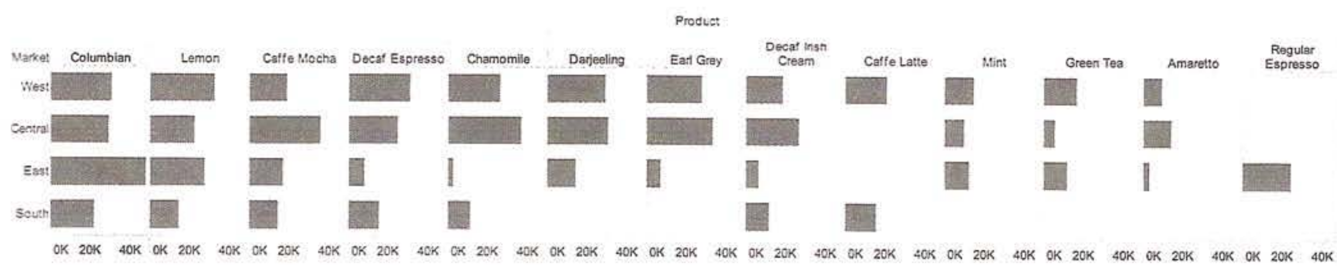


Figure 3.15. Created using Tableau Software

In this case, we could use variations in color intensity to add profits to the display, as illustrated below.

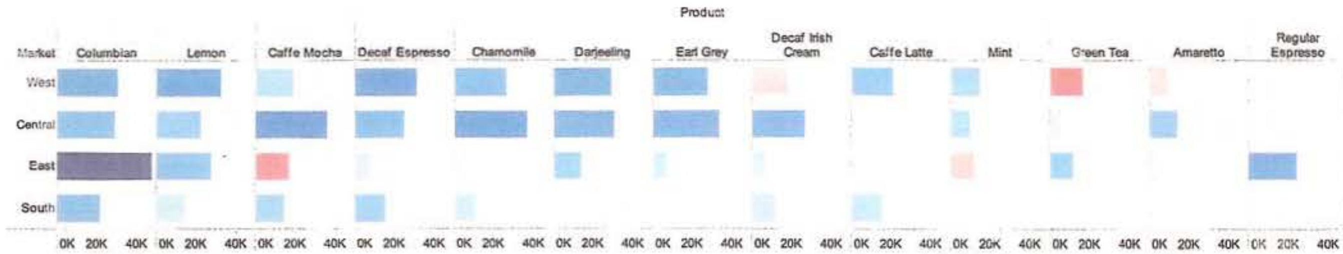


Figure 3.16. Created using Tableau Software

We would need a key indicating which colors signified what degree of profit, and, once again, we can't compare profits precisely when they are encoded as color intensity, but sometimes these approximate indications are all we need to make an analytical judgment.

Any time color is used the encode quantitative values, we have what's called a *heatmap*. The most familiar example of a heatmap is one that encodes values on an actual geographical map, such as a weather map where colors are used to represent variations in temperature or rainfall, as in the following example:

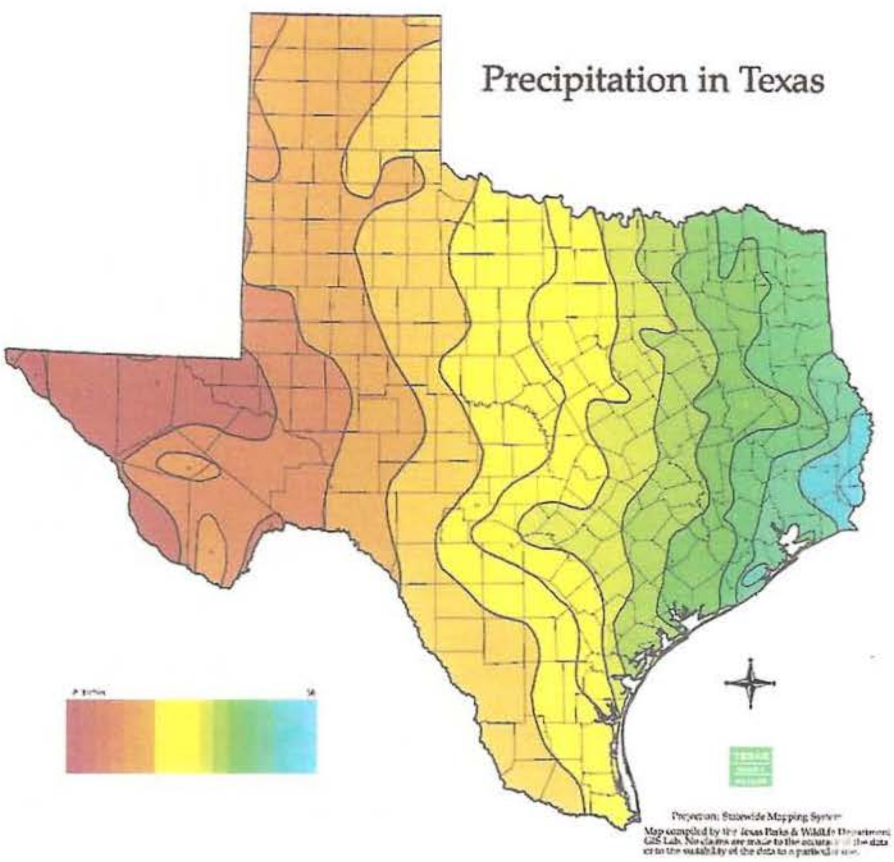


Figure 3.17. Rainfall map from the Texas Parks and Wildlife website (www.tpwd.state.tx.us/)

Heatmaps don't have to be associated with a geographical map. Another common heatmap is composed of cells (square or rectangular areas) arranged as a tabular matrix with each cell color-coded to display a quantitative value, as in the following example, which shows variations in gas mileage (miles per gallon, MPG), horsepower, and weight for several cars in the year 1982.

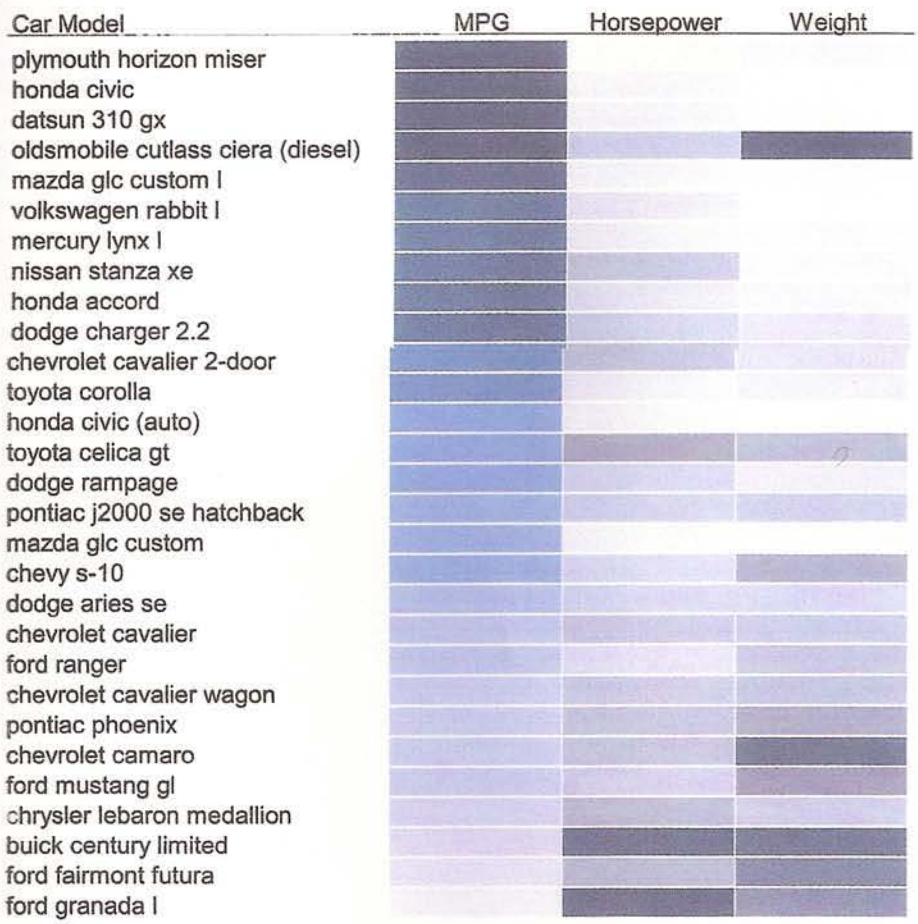


Figure 3.18

One special type of information visualization that is similar to a heatmap, called a *treemap*, uses both size and color to encode quantitative values. Treemaps were originally developed by Ben Shneiderman of the University of Maryland as a way to simultaneously display two quantitative variables for a large number of items, arranged hierarchically.

Here is an example of a treemap:

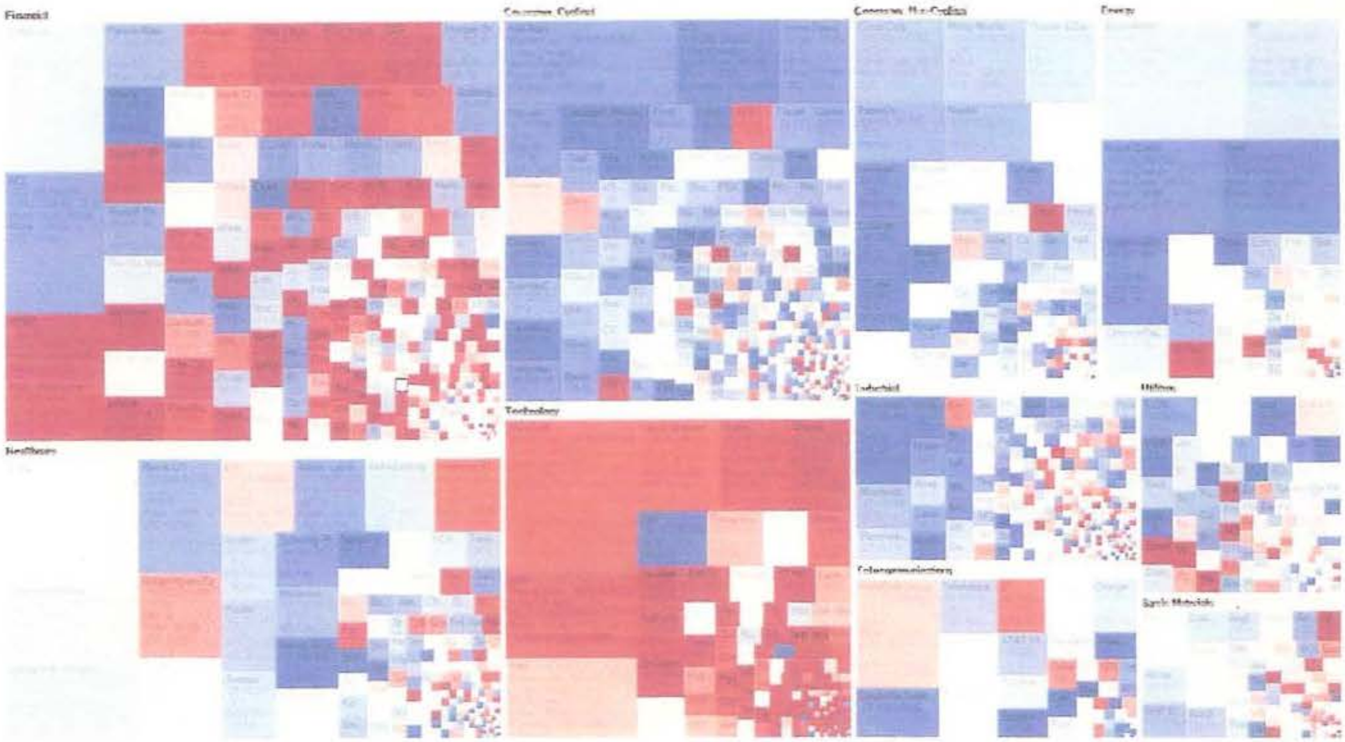


Figure 3.19. This treemap, produced using Panopticon Explorer, displays stock market cap values as variations in the size of each rectangle and the percentage of one-day change in their values as variations in color (increases in blue and decreases in red).

When conventional graphs, such as bar graphs, cannot be used because there are too many items to represent as bars in a single graph or even a series of graphs on a single screen, treemaps solve the problem by making optimal use of screen space. Because they rely on pre-attentive attributes to encode values (area and color) that we can't compare precisely, we reserve such methods for circumstances when other more precise visualizations cannot be used, or precision isn't necessary. We'll learn more about treemaps in *Chapter 4: Analytical Interaction and Navigation*.

Despite the usefulness of visualizations such as treemaps, most quantitative data analysis can be performed quite well with graphs that encode values using only four types of objects:

- *Points*, which use the 2-D positions of simple objects (dots, squares, triangles, and so on) to encode values
- *Lines*, which use the 2-D positions of points connected into a line to give shape to a series of values
- *Bars*, which use the heights (vertical bars) or lengths (horizontal bars) of rectangles to encode values, as well as the 2-D position of the bar's end
- *Boxes*, which are similar to bars and use lengths to encode values, but, unlike bars, are used to display the distribution of an entire set of values from lowest to highest along with meaningful points in between, such as the median (middle value)

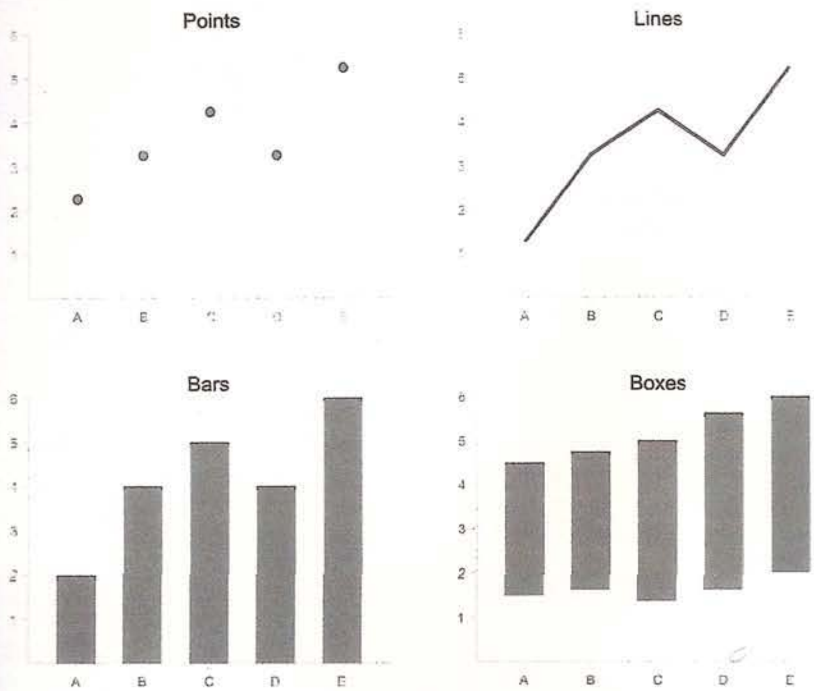


Figure 3.20

Most of us are probably familiar and comfortable with each of these ways to encode values in graphs, except perhaps for boxes, which we'll examine in detail in *Chapter 10: Distribution Analysis*. All of these methods are quite simple to decode and powerful for data analysis.

Despite similarities, visual perception does not work exactly like a camera. A camera measures the actual amount of light that comes in through the lens and shines on film or digital sensors; visual perception does not measure absolute values but instead registers differences between values. I'll illustrate what I mean. Below, you see a small rectangle colored a medium shade of gray.

Figure 3.21

Next, we have a large rectangle that is filled with a gradient of gray-scale color, ranging in luminance from fully white on the left to fully black on the right.

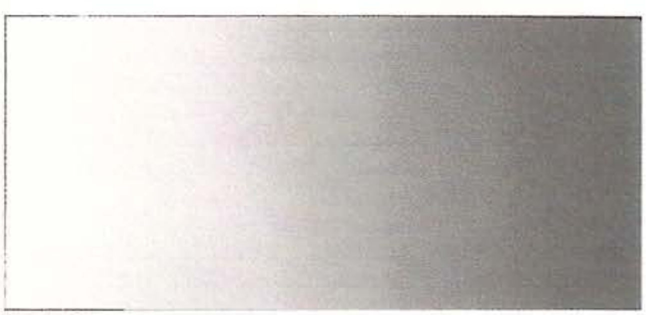


Figure 3.22

Now, I have placed the small gray rectangle we saw above, without altering its color, at various locations within the large rectangle. Notice how different the five small rectangles look from one another even though they are all the same color.

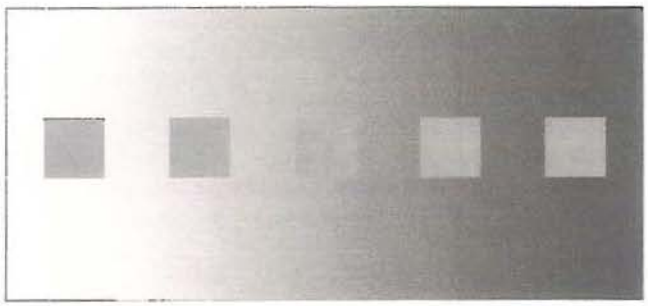


Figure 3.23

The reason for the apparent difference is that we perceive color not in absolute terms but as the difference between the color that we are focusing on and the color that surrounds it. In other words, we see color in the context of what surrounds it, and our perception is heavily influenced by that context. In fact, we perceive all visual attributes in this manner. Consider the lines below. The pair of lines on the left seem more different in length than the two lines on the right, but both sets differ by precisely the same amount. The difference on the left appears greater because we perceive differences as ratios (percentages) rather than as absolute values. The ratio of the lengths of the two lines on the left is 2 to 1, a difference of 100%, whereas the ratio of those on the right is 100 to 99, only a 1% difference.

Figure 3.24

Because visual perception works this way, when we want to use different expressions of a pre-attentive attribute, such as hue, to separate objects into different groups, we should select expressions of that attribute that vary significantly from one another. For example, the colors on the top row below are easier to discriminate than those on the bottom.

Figure 3.25

Another important fact about pre-attentive attributes that we ought to keep in mind is that our ability to perceive expressions of an attribute as distinct decreases to the extent that distractions clutter our field of vision. Ware warns:

Pre-attentive symbols become less distinct as the variety of distracters increases. It is easy to spot a single hawk in a sky full of pigeons, but if the sky contains a greater variety of birds, the hawk will be more difficult to see. A number of studies have shown that the immediacy of any pre-attentive cue declines as the variety of alternative patterns increases, even if all the distracting patterns are individually distinct from the target.[5]

5. *Information Visualization: Perception for Design*, Second Edition, Colin Ware, Morgan Kaufmann Publishers, San Francisco CA, 2004, p. 167.

As you can see in the following examples, it is much easier to focus exclusively on the red dots in a scatterplot when the only other hue is gray than when there are five other hues that are competing for our attention. Visual complexity is distracting and should therefore never be employed to a degree that exceeds the actual complexity in the data.

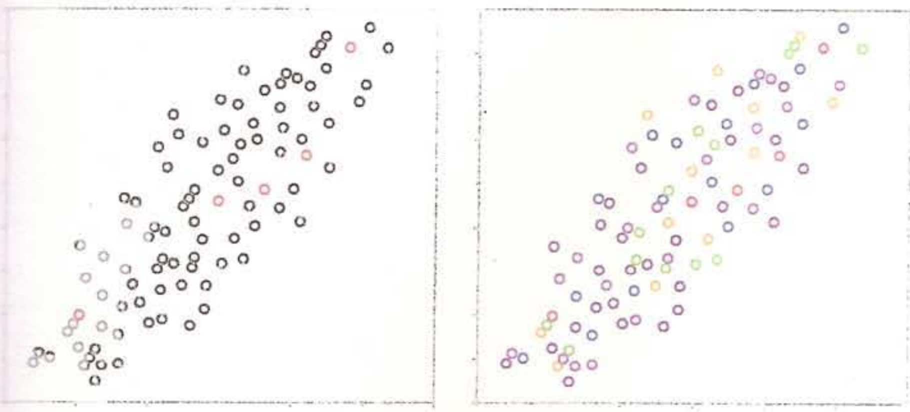


Figure 3.26

Overcoming the Limits of Memory

Memory is divided into two fundamental types: working memory and long-term memory. Long-term memory is where information is stored permanently (that is, until related brain cells die off), available for recall whenever it's needed. Long-term memory functions a bit like a computer's hard disk drive. By contrast, working memory stores information only briefly. Again using the analogy of a computer, working memory is a bit like random access memory (RAM) where information is temporarily stored while it is being processed. Information enters working memory from one of three sources: through our senses, from our imagination, or from long-term memory where it was previously stored. Working memory is where information resides while we're thinking about it; information only stays in working memory for a few seconds unless we keep it alive by continuing to think about it. If we think about it enough, it ends up being stored in long-term memory (if it wasn't already there). If we don't store it in long-term memory, it simply goes away once we cease thinking about it.

Technically, working memory consists of different sets of memory storage for different types of information. For instance, verbal information (something we've heard) and visual information (something we've seen) occupy separate repositories in working memory. Visual working memory, which is what we use when working with an information visualization, is very limited. You might think that the RAM in your computer is limited compared to the hard disk drive, but it's enormous compared to visual working memory in our brains. Research has found that visual working memory can only handle about three *chunks* (that is, storage units) of information at a time. It is hard to believe that our brains can function so powerfully with such limited capacity in working memory. If all three memory slots are already being used, the only way for a new item to get in is for one that's already there to be thrown out.

So how much is a chunk of visual information? The answer depends on the nature of the image and our expertise in handling the information that we're examining. In the following table of numbers, which we've seen before, most of us would need to store each number as a separate chunk in working memory. For instance, at any one moment, we might only be able to hold onto the three highlighted numbers.

2007 Call Volume (in thousands)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
United States	1,983	2,343	2,593	2,283	2,574	2,838	2,382	2,634	2,938	2,739	2,983	3,493
Europe	574	636	673	593	644	679	593	139	599	583	602	690

Figure 3.27

If this same information is displayed in a line graph, however, each line could be stored as a single chunk of visual memory, one for U.S. and one for European call volumes. The pattern formed by an entire line could constitute a single chunk.

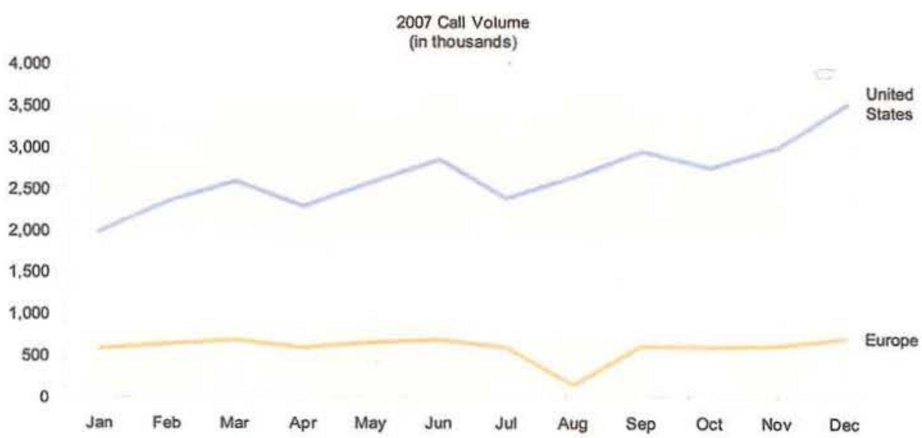


Figure 3.28

This is one of the great advantages of visualization for exploring and analyzing data. When quantitative values are displayed as visual images that exhibit meaningful patterns, more information is chunked together in these images, so we can think about a great deal more information simultaneously than if we were relying on tables of numbers alone. This greatly multiplies the number and complexity of insights that can emerge.

Getting back to the question of how much information constitutes a chunk, the amount varies depending on our expertise. Ware explains:

> *The process of grouping simple concepts into more complex ones is called chunking. A chunk can be almost anything: a mental representation of an object, a plan, a group of objects, or a method for achieving some goal. The process of becoming an expert in a particular domain is largely one of creating effective high-level concepts or chunks.*[6]

As our expertise in analyzing particular types of data increases, so will our ability to handle bigger and bigger visual chunks of that information and to recognize characteristics of that information as meaningful.

Even when we increase the capacity of working memory by expressing data as images, the limits are still considerable, so we need additional augmentation. This brings us to another way that visualizations help us work around the limits of working memory: by providing "external storage."

Because working memory can handle so little information, data that we are exploring and analyzing should be made readily accessible through an external medium. The oldest and most common external aid to working memory is a piece of paper or other writing surface. By writing information down and keeping it on the desk in front of us, we can rapidly access that information and move it into working memory for processing as needed because it is never more than a glance away. Today, computers, especially those with reasonably high-resolution displays, can serve the same purpose. By placing as much of the information we need as possible on the screen at once, we can make the process of comparing and thinking about data a fluid experience despite our working memory's limits.

We should avoid fragmenting information that we're examining by placing it on separate screens or in locations that we can't see without scrolling. For instance, if we see a pattern in a graph and then try to compare it to a pattern in another graph that is on another screen, we will no longer remember much of what we were looking at previously once we bring up the new screen. We'll end up bouncing back and forth between separate displays, wasting time, interrupting the flow of thought, and becoming frustrated in the process.

It's difficult if not impossible while using most data analysis software to combine the information we're examining onto a single screen without the need for scrolling. In the example on the next page, however, four months of expenses for 15 separate departments are displayed together in a way that supports both easy comparisons and formulation of the big picture about expenses. This display is a powerful external aid to working memory. If we had to examine each of these departmental graphs one at a time, neither of these analytical goals could be accomplished.

6. *Information Visualization: Perception for Design*, Second Edition, Colin Ware, Morgan Kaufmann Publishers, San Francisco CA, 2004, pp. 368 and 369.

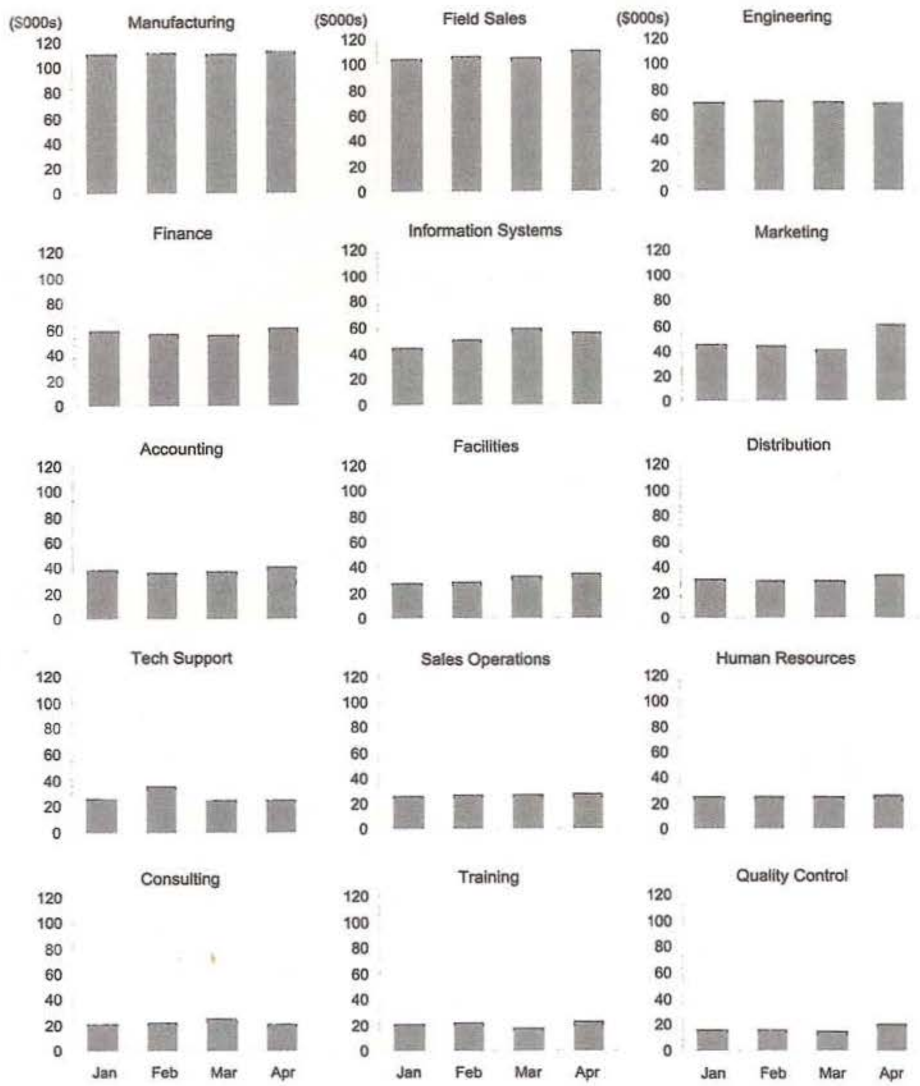


Figure 3.29

Once again, Ware states the case clearly:

> *The power of a visualization comes from the fact that it is possible to have a far more complex concept structure represented externally in a visual display than can be held in visual and verbal working memories. People with cognitive tools are far more effective thinkers than people without cognitive tools and computer-based tools with visual interfaces may be the most powerful and flexible cognitive systems. Combining a computer-based information system with flexible human cognitive capabilities, such as pattern finding, and using a visualization as the interface between the two is far more powerful than an unaided human cognitive process.*[7]

In several later chapters that examine useful visualizations and techniques for specific types of analysis, we'll look at examples of how visualizations can be designed to augment working memory.

7. *Knowledge and Information Visualization*, Sigmar-Olaf Tergan and Tanja Keller, Editors, "Visual Queries: The Foundation of Visual Thinking," Colin Ware, Springer-Verlag, Berlin Heidelberg, 2005, p. 29.

The Building Blocks of Information Visualization

To summarize the points made in this chapter, I'll describe the building blocks of quantitative information visualization. Effective information visualization is built on an understanding of how we see and think. Software that is built on this understanding can present data in ways that allow us to see what's meaningful, and it can augment our cognitive abilities in ways that allow us to make sense of what we see.

Perceptual building blocks consist of objects and the properties (such as pre-attentive attributes) that can visually represent quantitative data. It's essential that we use only objects and properties that map well to visual perception. The reasoning process that we engage in while viewing and interacting with a visualization consists of making comparisons and examining quantitative relationships (time-series, distributions, correlations, and so on). A visualization displays these relationships as visual patterns, trends, and exceptions. The goal of analyzing a visualization is to understand what these relationships mean, so we can make good decisions.

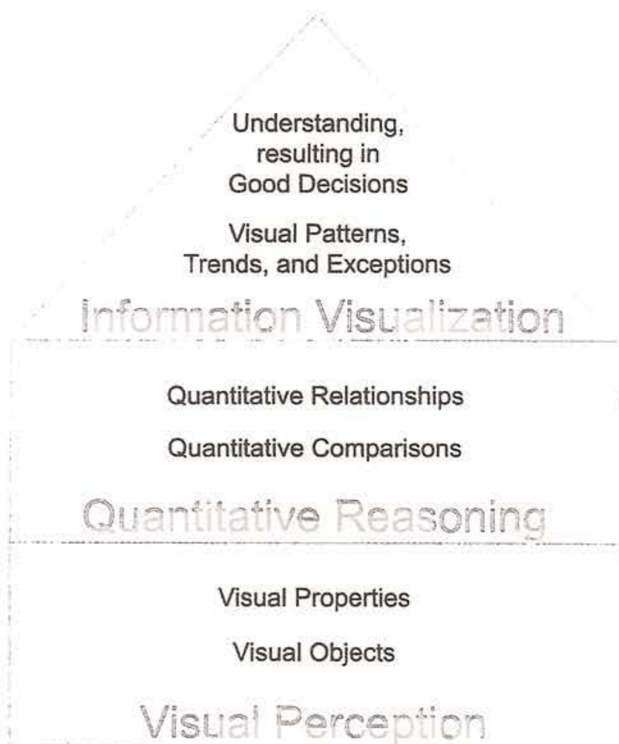


Figure 3.30

We should never forget that a picture of data is not the goal; it's only the means. Information visualization is all about gaining understanding so we can make good decisions.