Metaphor Graphics & Visual Analogy For Medical Data

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Where is the wisdom we have lost in knowledge?
Where is the knowledge we have lost in information?
— T.S. Eliot, Chorus of The Rock

Where is the information we have lost in data? Medical information is the topic of this conference, but how well do we understand that word: information? Information is certainly not the same thing as data. A given piece of data may or may not be information, depending on whether that data helps answer some question we have or helps resolve some uncertainty about our actions. Medical data is what we have stored in great quantity, stored in our filing cabinets, our patient charts, our computer databases. But how informative is all this data? Often, data must become information via the judgment and understanding of a human. Medical informatics must therefore consider the nature of human understanding, human information processing, human wisdom. A medical informatics based only on the study of medicine and the study of computers will be a barren discipline. We must also consider a third thing: cognition.

A preview of my argument. There are five main points I wish to make.

<table>
<thead>
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<th>I. People are imperfect processors of information. They do not reason via formal logic but rather solve problems using mental models and pattern recognition.</th>
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<td>II. Digital representation of the analog world can be surprisingly unhelpful. Simply making data available is not helpful if that data cannot be brought to bear on the problem at hand.</td>
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<td>III. Graphic representation can help bring data to bear.</td>
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<td>IV. Standard graphics, such as line graphs, histograms, and pie charts, are limited in their usefulness.</td>
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<td>V. An alternative type of graphic exists: metaphor graphics. By creating a visual metaphor we recontextualize data, and thus create a picture of the problem.</td>
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I. How Do People Think While Solving Problems?

There are three distinct views as to the nature of human reasoning. Some see reasoning as a mental version of formal logic. Others see reasoning as a process of

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1This document was first created to supplement a tutorial on medical information science delivered by the author at the annual Symposium on Computer Applications in Medical Care, October, 1987, in Washington, D.C. It was further developed in conjunction with an invited address to the University of Utah's InfoFair, March, 1988 in Salt Lake City. This research is supported in part by New Investigator Research Award R23LM04517 to the author from the National Library of Medicine. Copyright, 1988, by the author. All rights reserved.
building mental models. Still others say reasoning is a kind of pattern recognition. What is the difference between these three views and what are their implications?

**Reasoning by logic.**

The notion that reasoning is a kind of logic is an old view, with powerful implications for the agenda of artificial intelligence (AI). If human reasoning is just a mental version of formal logic, then we should be able to build human-like reasoning into our computers simply by discovering the logical rules that people follow as they successfully complete the tasks they are good at. There are many problems with this view, however. Among them are the following.

First, if human reasoning is logic, we have to ask "Which logic?" There is no single formal logical system generally viewed as correct. On the contrary, many logics have been worked out over the years, and a new one could be invented tomorrow. Claiming to understand human reasoning by saying it is just a variation on logic would only beg the question of exactly which logic you have in mind.

Second, if we look at how people actually think, it seems clear that they do not reason by a process of formal logic. Give them a couple of premises and ask what conclusions can be drawn and they will tell you one or two conclusions, but will generally not go on to generate all the conclusions a formal logic will draw. Furthermore, if we give them a problem to solve with one set of window dressing, they may utterly fail to find a solution, yet if we change the scenario, change the objects mentioned in the problem while leaving the underlying formal problem unchanged, people will suddenly discover a solution. When we are faced with a logical problem, our ability to deal with the problem seems to depend on whether we are told the problem has to do with numbers on the backs of index cards, or stamps on the fronts of envelopes, or trains arriving at different stations. We do not perform very well as logical engines.

**Reasoning by mental models.**

The objections just mentioned have been raised by Phillip Johnson-Laird in his 1984 book *Mental Models*. Johnson-Laird and others have suggested the notion of mental models as an alternative to the reasoning-as-logic view of human thinking. The mental models approach pictures reasoning as a process of creating a model in the mind, a representation of the problem at hand that bears the same relation to the problem as a set of billiard balls does to the solar system. That is, the mental elements are like billiard balls that can be manipulated on a table in a way that mimics how we think planets move in space. By moving balls in various ways, we can test our understanding of planetary orbits, trying one way and then another until we find some billiard ball model that seems to fit with what we observe about the planets. Similarly, we may solve logical puzzles by making up imaginary elements that we then mentally rearrange over and over, trying to see if there is an arrangement that both fits what we know about the real world and also yields a way of solving the problem posed.

Models, both mental and physical, are abstractions, simplifications of the real world. Elements in the model stand for elements in the real world but do not attempt to capture all the attributes of the real world things. A model 747 airplane, for example, does not need teeny bathrooms. People, according to this theory, solve
problems by creating mental models and then running simulations, like moving the billiard balls around, to see if the model matches what they know about the real world situation.

There are many implications of such a view for medical informatics. If we reason by models rather than by logic, then the kind of conclusions we draw will depend both on our choice of a mental analogy (What if we started with a sink full of jello with embedded mini-marshmallows as our model of the solar system? How would this lead us to think about planetary motion?) and on the details of our mental simulation (What if we create a model with a dozen key elements and find that we keep forgetting the last known state of some of those elements when the time comes to cycle through the simulation one more time?). Most importantly, if people like to reason via mental models, we need to start building computer tools that aid this sort of reasoning, computer programs that do not try to simulate, to replace human reasoning but rather act as a companion to it. This is the essence of a notion that can be called cooperative computation.

Reasoning by pattern recognition.

A third point of view is that human reasoning often is based on pattern recognition. Dreyfus and Dreyfus (1985) distinguish pattern recognition from what they call information processing, on the following basis. If you approach a problem by collecting a set of key parameters and then try to combine these parameters by some algorithm or model, you are doing information processing. If, on the other hand, the problem reminds you of a similar problem experienced previously and you solve this problem by a variation of your earlier solution, you are doing pattern recognition. (It should be noted that there are many other definitions of these two phrases, information processing and pattern recognition and that for the moment we are only talking about them in the narrow sense in which they are here defined.)

A physician could use either kind of thinking to reason from presence of a symptom to the probability that disease is present. The information processing approach might go like this. "Here are three key symptoms", the physician thinks, "three symptoms that are 85% likely to be present in this disease and only 5% likely to be present in other diseases or in health. If my prior probability of disease were 10% and I now discover these three symptoms, I should probably update that probability of disease to 80% or better."

Another physician, however, might not go through all this mental machination at all. He might look at the same patient and say "Good grief! This guy looks exactly like a classic case of ankylosing spondelitis! Of all the people I've seen in my life with that appearance, every one has turned out to have a case of spondelitis. I bet that's what this case is, too."

What is the difference between these two physicians? The first physician computed the answer, reasoning computationally, in the way Dreyfus and Dreyfus call information processing. The second physician simply consulted memory. He recognized the pattern before him, correctly or incorrectly, as an example of a category of things he is familiar with. The first physician computed a posterior probability of disease based on a prior probability and knowledge of the diagnosticity of the symptoms. The second physician already had stored in memory a posterior probability, given these symptoms. The difference is a little like the difference between
figuring out how much three times six is versus just recalling the memorized fact that three times six is eighteen. Both ways may lead to the same answer, but the mental machinery underlying them is very different. What Dreyfus and Dreyfus call pattern recognition is similar to what others call case based reasoning.

I will argue two things here. First, that we are excellent at pattern recognition, better at this than at any sort of computation or logic. Second, that when we do not recognize a pattern, when we cannot solve a problem by appeal to memory, we reason by heuristics and mental models, falling back on formal logic only in rare and special cases. If I am right then we need to rethink how we are trying to use computers to aid problem solving, in medicine, industry, science, and education. We need to build systems that aid mental models and that permit us to use pattern recognition. We need to build systems for cooperative computation.

II. Digital Representation Of The Analog World
Can Be Surprisingly Unhelpful

Used to be, a physician dealt pretty directly with a patient. The physician looked at the patient, layed hands on the patient, placed a stethoscope on the chest and back, and just generally sniffed around. The physician also asked the patient a few questions and maybe looked up some information in the patient’s chart. In this process a great deal of information was acquired by the physician, along a broad range of input channels, as in Figure 1, below. Visual, auditory, tactile and olfactory cues came pouring in with great abundance. They interacted, supporting, reinforcing and commenting on each other. All of this process of encoding and interpreting the analog world led to a state of knowledge in the physician. Having noted the sound of his patient’s lungs, having felt for lumps under the skin, having looked carefully down the throat and into the eyes, the physician had an integrated picture of what sort of patient he was dealing with.

**Analog vs. digital inputs.** Actually, the physician in this example has used two quite different classes of data in his examination. On the one hand, there were all those sensory inputs, the sights, the sounds, the feels and smells. These inputs are sometimes collectively called analog stimuli, because they enter the human information processing system not as discrete, digital, hard edged symbols, but as continuous, graded, hard-to-pin-a-name-on signs. On the other hand, there were some inputs that were linguistic and numeric, digital inputs rather than analogic. Numbers came from taking a temperature with a thermometer, from laboratory test results, from entries in the patient chart. Words came from the patient’s description of his condition, from the patient chart, perhaps from consultation of this physician with a colleague.
Figure 1. Cognitive capacities of the human information processing system. Rich analog inputs are contrasted with the digital input of the numero-linguistic pipeline. After knowledge is attained, notes and records may be created through a recoding of the initial analog experience into a digital abstract.

Analog information is elaborate, redundant and interactive. Each of the analog channels carries vast quantities of data every moment of our waking life. The digital channel, however, appears to function more as a narrow pipeline, giving very sophisticated processing to just a few items at any given moment. (Short term memory for verbal items is typically limited to seven items, plus or minus two.) Analog inputs also tend to interact with and reinforce each other. Natural stimuli, such as a duck, give off many redundant stimuli simultaneously. A duck has a shape, a color, a gait, a whole set of characteristic sounds, and a smell. Coming across a duck in the natural world, our analog senses soak all this up and provide quite a bit of cross-reference. In the digital world, however, we seldom have this same redundancy and cross-reference available. As you read or hear these words, for example, the background sounds around you are irrelevant to my meaning, the smells you smell just don’t matter, and whatever you are currently tasting is entirely beside the point.

The analog world and the physician’s cognitive capacities are well matched. He can, for example, take great advantage of the redundancy that exists in the natural world. An object encountered in the natural world tends to leave a very complex, multisensory impression. We may not absolutely need to see something walk like a duck, hear it quack like a duck, then take it home and cook it for dinner and have it taste like a duck before we conclude that it is a duck. But when aboriginal man had duck for dinner, this was the nature of the experience. This is the experience for which we are designed.

Digital information is precise and compact. Although digital information is less rich than analog information (at least when it first arrives) it nonetheless has two very
important qualities: it is more precise and often more compact. When I want to keep a record of the ducks I have seen in my birdwatching career, I will probably not try to draw each one in detail. Nor will I attempt to take little samples of its feathers to get the colors exactly right, nor try to preserve the singular odor of each particular wild duck. I will, more likely, make a digital note somewhere that I have today seen my first hooded merganser, at dawn, in a marshland adjoining San Francisco Bay. I will have used digital representation to create an abstract of my analog experience. This process is included in Figure 1, above, as a step of recoding that every physician does constantly. Precise, compact records are wonderful guides. Although a picture is undoubtedly worth a thousand words, often the problem at hand is to decide which thousand words, or even which one word. Hanging a categorical label on a patient is immensely important in guiding our subsequent actions.

This notion of recoding analog experience into a compact, precise, digital abstract is the key to all that follows. It is this step that permits us to use computers to store data and retrieve it later on. By creating digital, symbolic representations of the analog world, we can write programs that try to help us make decisions, solve problems, to think.

Figure 2. Analog mind meets digital world. Is this data informative?

The information problem. All this abstracting worked fine as long as individual physicians were making their own abstracts, their own notes, were doing their own recoding. But then computers came along and suddenly we had devices that could acquire and store remarkable amounts of data. Take, as an example, mechanical ventilation.
Our physician has a patient lying unconscious following general anaesthesia. A large machine is handling the task of pumping fresh air in and out of the lungs. Since this is a digital and electronic machine, it can monitor and store stupifying amounts of data about the state of the patient and the state of the machine. Data is the result, massive amounts of it. But is the physician better informed? Where is the information? Where is the knowledge? Where is the wisdom?

Why did it work when the doctor stored an abstract digitally but it didn't work when the mechanical ventilator tried to do the same thing? There are at least two differences. One is the sheer mass of data that can be accumulated once we automate the process. The other difference is that when the doctor stored his own notes, these were reminders, cues to help recall a lush and complex memory. The ventilator data, however, was not initially acquired by the doctor’s own senses. These are raw data, not previously digested. They call up no complex, multisensory memory trace, but instead must be processed as new stimuli, new data. And how are they to get into the doctor’s mind? Via that limited capacity, digital, numero-linguistic pipeline. The data are just not in the right form for easy acquisition, easy encoding, easy interpretation. I believe it is this second problem (wrong representation) that is the key to information overload, not the first one (too much data).

The problem is not too much data. It would be easy to conclude, looking at Figure 2, that we are very limited in our capacity to process information. There are, in fact, years of research in cognitive psychology showing just how hard it is to hold more than seven items in short term memory, and how hard it is to get a few of those items over into long term memory. Looking at Figure 2, we might well conclude that it is a hopeless situation. We must either walk around dazed by all the information in our medical setting or else ignore 99 percent of it, as a kind of cognitive defense mechanism. Nothing could be further from the truth.

There are two answers to the assertion that the problem lies in too much data. First, it is easy enough to overload the cognitive apparatus with only three numbers if those numbers cannot be represented on a common mental ground. And second, when data is represented in the correct way, we can handle vast amounts of it every second with no sense of strain. Let's take the first answer first. Consider these three numbers and then tell me the answer to the problem. You have observed a positive test result in a patient. The test is 95% likely to detect disease when disease is present. It is 90% likely to be negative when disease is absent. In the general population from which this patient comes about one person out of a thousand has this disease. Your task is simply to tell me roughly how likely it is that this person with the positive test does in fact also have the disease. Think for at least 30 seconds, and use pencil and paper if you wish, but write an estimate like “between 50 and 60 percent likely” on this page. The answer will be found in a footnote below.2 Failure to solve this kind of problem easily and correctly is due at least in part to failure to find some way to

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2 Most people agree that this patient almost certainly has the disease. Estimates range from a low of seventy five percent up through the most common estimates of ninety to ninety five percent, to a few estimates of one hundred percent. In fact, the patient is less than one percent likely to have the disease. This “Bayesian” reasoning is very difficult for most people. Graphic representation of Bayesian reasoning is possible and seems to make problems such as this one much clearer.
mentally represent those three parameters in such a way that they can interact with one another effectively.

The data is in the wrong representation. All those years of research in cognitive psychology were focusing on digital information: numbers, letters, words. When psychologists began to investigate memory for photographs of the natural world they discovered that we have a remarkable ability to quickly acquire and retain visual information. In one landmark study, Standing, Conezio, and Haber (1970) showed 2,560 photographic slides to their subjects, then tested memory using a two-alternative forced choice procedure ("Did you previously see the slide on the right or the slide on the left?"). Even though each slide had initially been presented for only 10 seconds and even though the entire presentation sequence required 7 hours to sit through, average performance on the recognition test was 90 percent correct.

Actually, there is no need to even consult the psychological literature to answer this claim that there is just too much information in the array of Figure 2. Just take a look out your window and dwell for a moment on how much data you are seeing, and how effortlessly you grasp it all. Go out and stand on the top of a hill and soak up the sights, the sounds, the smells, the changing temperature as a breeze blows by, the feel of the grass between your toes, the kinesthetic sense you have of your bodily position and the vestibular sense you have of your relation to the gravitational field, and – continuing to process all this data in the background – dwell on how little cognitive strain you are experiencing. Then consider that paltry array of Figure 2 and decide for yourself if it contains more data than the average person can process.

I would argue that this is the core of the information problem in medicine (and in other fields) today. We have succeeded in creating digital devices that acquire, store, and make available to us prodigious quantities of data. But we have a great deal of difficulty in making use of that data, bringing that data to bear on a question or problem, being informed by the data. And the reason is that we have not yet grasped the importance of finding representational forms that are best for people rather than best for computers.

III. Graphic Representation Of Digital Data

"Representational Isomorphism". A Dark Chapter In The History of Cognitive Science. Does representational form really matter? There are those who would argue that the precise form that data takes is irrelevant. What matters is the content of the data. Back in the 1970s, for example, there was a great controversy in cognitive psychology over whether the knowledge we have stored in our minds is stored as a network of interrelated concepts or as a collection of individual, unconnected concepts with characteristic and defining features. Much of the steam went out of this controversy when James Hollan wrote a paper in 1975 pointing out that the content of any network model can be rewritten in the notation of the feature framework.

Isomorphism. He argued that the two frameworks differed in form but were representationally isomorphic, since any element in one representation could be mapped onto a distinct element in the other representation. "There's no difference between the two systems", Hollan argued, "because we can take any property or relational link in a network model and make it into a feature in a feature model." A similar argument was advanced by John Anderson with regards to the distinction
between propositional and pictorial representation. "Anything you build into a model
based on pictures in the head", Anderson argued, "I can also build into a propositional,
linguistic model that mimics your model and you cannot design any critical
experiment that will tell us whether your pictures or my propositions are the real stuff
of mind. So we should settle for propositional models, because hypothesizing one
form of representation is more parsimonious than two."

**Formal equivalence = functional equivalence.** This kind of argument is
greatly beloved among formalists and aficionados of artificial intelligence.
*Formally equivalent* representations are functionally equivalent. Pictures
don't matter because the content of pictures can be expressed in propositions, in
words, in numbers if need be, and linguists and computer scientists can more
easily deal with propositions, words, and numbers. Data is data and why bother
representing the data pictorially? We've already got propositions. Why not
just create propositional representations, since our computers and linguistic
theories can handle them easily?

![Figure 3. A data set that is first uninformative then very informative.](image)

**Formal equivalence = functional equivalence.** Take a look at the picture shown
here. If you've never seen it before, you will see a lot of data but no information. You
will see black blobs on a white ground and very little else. Keep looking, though, and
you'll eventually see something clearly recognizable. An animal, domestic. When
you finally do see it you will find it hard to look at these black blobs as mere blobs ever
again. It is a dog, facing left, walking rapidly with its nose to the ground. Whenever
you see this picture you will see the picture, not the blobs. It is a dalmation, walking
rapidly across a leaf strewn plaza. Can you see it yet? What happened? What changed?

Did the data change? It did not. Surely the data present before you figured out the picture is the same as the data after you figured it out. Surely these two data sets are isomorphic, since they are in fact identical. Why then is one data set (before insight) so uninformative and the second set (after insight) so very informative?

Data = information. Figure 3 illustrates the first step of a complex argument. The point of that figure is that data is not automatically information. Data must be apprehended, grasped, understood, before it can be informative. The second step in this argument will be illustrated below.

Details of display matter. The way data is displayed can greatly influence how it is grasped. Two "isomorphic" data sets with different displays may have vastly different information value. We all have within us some remarkable pattern recognition abilities. When they can kick in and perform their function, we find ourselves able to see an easily interpreted world where in fact there is an overwhelming set of data. But our ability to recognize patterns developed over thousands of years, in a certain kind of environment. For our pattern recognition abilities to work well, the data must be displayed just right. It matters a very great deal indeed how the data are displayed.

Here's an example. Consider the photo in Figure 4 and let's see if two "isomorphic data sets", in this case a rotated and an unrotated picture, are equivalent to you. First, can you recognize who the person is? Begin to slowly rotate the page, trying to recognize the person pictured. Somewhere during your rotation you will suddenly -aha!— realize who you have been looking at all along and when you restore the picture to its upside down position you may still be able to see who it is. Again, what changed? It is essentially the same data rotated or unrotated, isn't it? Well, formally we might say that one bit, or some other such unit of information, has been changed. But certainly the two data sets (rotated and unrotated) are isomorphic. Every point in the unrotated data set can be mapped onto one and only one point in the rotated set.

Figure 4. A data set that is vastly more informative in one orientation than another.

So, if representational isomorphism is the same as equivalence, why do the two data sets differ so much in their informativeness? The answer is that formal isomorphism is not equivalence, not by a long shot. There are two elements in this equation: representation and processing. Two things that are representationally isomorphic may be processed in completely different ways.

We are constructed in a very particular way, built up by millennia of evolution to have certain well developed capacities. Among these is the capacity to recognize
patterns, especially the sort of patterns that exist in the natural world, such as human faces. The two data sets (rotated vs. unrotated picture) are not equivalent at all. They are unequally informative because our cognitive system doesn't give a fig for the formalist notion of isomorphism. We see and understand certain kinds of patterns so quickly and effortlessly that we treat the process as trivial. The same data, rotated a little bit, suddenly loses some ineradicable coherence that our pattern recognition abilities requires, and the simple becomes the impossible.

Let's repeat the experiment looking at a second face. Here are two photos. Are they the same? Which one has been tampered with? Would you say the two pictures are very different or fairly similar? Most people find the two pictures to be similar, with only a little difference around the eyes and mouth. Well, let's see. Again, rotate the page very slowly and see what there is to be seen.

![Figure 5. Two data sets that seem quite similar in one orientation, quite different in another.](image)

Rotated and unrotated it's the same data. But look at what happens to the informational impact when you change the orientation! We are built a certain way. We see some things very well, but other things that are representationally isomorphic, formally equivalent to what we see well, these things we cannot see at all. We are masters at pattern recognition, far superior to any computer ever constructed, but we need to receive our data in a certain way before our pattern recognition abilities can kick in.

1.8 pounds of brain in your skull. How much is specialized for pattern recognition? You have visual pattern recognition as a powerful mental capacity. There's a lot of evidence to suggest that you even have a good chunk of your brain tissue set aside largely for this ability. People who sustain damage bilaterally to the two occipital poles (the back of the head) sometimes lose certain brain regions. When this happens, they end up with a disorder called prosopagnosia, and they find themselves in a curious world. If you were to meet a prosopagnostic you might not notice anything at all was wrong.
I once met a gentleman who had sustained exactly this sort of injury and he was intelligent, urbane, well spoken and charming. An entertaining companion, in fact. Problem was, he could not make sense out of certain types of visual patterns. He would look at a photo of an Irish Setter and believe it to be a photo of the woman who was holding it. He could only recognize his wife at a party if he carefully noted what color dress she put on at home. His profession? He was an architect of some eminence, although no longer able to create new drawings or make much sense out of old ones he had drawn. Oliver Sachs has recently written a book about his years as a neurologist, including a story about a prosopagnosic patient he once knew, "The Man Who Mistook His Wife For A Hat". You and I walk around every day performing remarkable feats of pattern recognition, yet we experience no sense of effort, strain, wonder, or awe. This is our evolutionary heritage, and we have a large chunk of brain to thank for it.

Why ignore this remarkable capacity? Why, then, would we ever want to design computer systems that convey information solely along our limited capacity numerological pipeline? Why would we ever approach the problem of using a computer to aid us in a complex environment by having our computer spit out vast quantities of numbers, letters, and words? Why would we ignore our remarkable ability to function in an analog world, and try to use our pitiful 7-slot numerological short term memory to shuffle through hundreds of lines of text and numbers, trying to make sense of it all? Why would we hide the patterns of our world in columns of letters, leaving us unable to see the whole, discover the similarities, find the Dalmation in the sea of dots?

This is an especially important point when you consider that it is exactly these things that computers do worst. These have been the rocks on which the AI enterprise has foundered. Perhaps the best use of computers is not as a simulation or replacement for human cognition, but rather to act as cognitive companions, doing what they do best while helping us do what we do best. This is the core of the notion of human-computer cooperative computation.

#### FIRST SUMMARY STATEMENT

**HUMANS ARE GREAT AT:** COMPUTERS ARE TERRIBLE AT:

1. **Recognizing Meaningful Configurations**
2. **Interpreting a Feature in Context**
3. **Noticing and Understanding Similarities**

### IV. The Limitations Of Standard Graphics

If we are especially good at visual pattern recognition, perhaps we should represent our data graphically. And if we like to reason via mental models, maybe graphic representation will help us run our mental simulations. The promise of graphic representation is a heady one, but I will argue that standard statistical graphics have an extremely limited usefulness and that the time has come to go beyond standard graphics.
Let's continue using mechanical ventilation as an example. This table shows an unrealistically simple ventilation problem. 11 minutes of data are shown as 11 rows.

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<thead>
<tr>
<th>Minute #</th>
<th>Ventilator</th>
<th>Patient</th>
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<td>Set Rate</td>
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<td>12</td>
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Table 1. A simple mechanical ventilation situation. Eleven minutes of data, with four parameters varying. Both the ventilator and the patient can contribute to air exchange. Each does so by breathing at a certain rate and by exchanging "tides" of a certain volume.

In each row there are four numbers, the first two coming from the ventilator settings (set rate and volume), the second two coming from whatever breathing the patient is contributing spontaneously (spontaneous rate and volume). Rate refers to how many times in a minute a "tide" of air goes in and out of the lungs. Volume refers to just how much air there is in any one of these tides, measured in liters. In minute one of this scenario (see row one of the table), the ventilator pumped 12 such tides, with the tides averaging 0.50 liters of air. The patient spontaneously generated zero tides and, of course, the average volume of a tide was zero. That sums up the key events of minute one.

Can you look at this extremely simplified problem in mechanical ventilation and sum up what happens over all 11 minutes? Probably not very easily. If you can figure this table out, then congratulations. We will now move you up to a more realistic situation in which you try to quickly make sense not of four variables over 11 minutes, but of a dozen variables over a 48-hour period, as though you were a physician stopping by the intensive care unit to check on a patient you haven't seen in a couple of days.

But for the moment, let's stick with the simple example. Is the problem inherently difficult? Or is the data just represented in a way we do not deal cleverly with? Let's try graphic representation of the data. Here is a standard sort of graphic, called a line graph, in which those same numbers are shown as lines that rise and fall over 11 minutes, spread along the X axis. Does this make the problem clear to you? It doesn't do much for me, although it seems to be some improvement over the table of numbers.
Figure 6. A line graph representation of the data in Table 1. This is an arbitrary or universal graphic. It arbitrarily maps any kind of data onto a line that rises and falls across the x axis. It is therefore universally applicable. Universal graphics, however, do not always make the underlying situation much clearer than the tables they replace.

V. Metaphor Graphics And Visual Analogy

Figure 7. A metaphor graphic. "Volume rectangle" representation of the data in Table 1 and Figure 6. 11 minutes are represented by 11 frames. In each minute-frame two rectangles can appear: one for the ventilator, one for the patient. Each rectangle shows breath volume as the depth of the rectangle and breath rate as the width. Such rectangles encourage representation of critical ventilation parameters such as the distinction between "dead space" and alveolar space, and oxygen or other gas concentrations, shown by a degree of shading.
Universal Graphics vs. Metaphor Graphics. The line graph in Figure 6 is an example of what I call a universal or arbitrary graphic. It is universal in that it can represent most any numerical quantity that varies along some dimension, such as time. It achieves this universality, however, by being arbitrary. All physical world variables receive the same graphic world treatment. Consider the rate at which you breathe and the volume of any given breath. Very different variables in the physical world, but the line graph treats them exactly the same. As the rate of breathing gets faster, a line climb higher. As the volume of breaths increase, another line climbs higher. Compare this line graph with the metaphor graphic of Figure 7, in which the same set of numbers is given a very different graphic treatment.

Volume Rectangles. These volume rectangles also depict 11 minutes of data, as 11 frames on a blank background. The key to understanding them is in three parts. First, within each frame there is room for two rectangles, a ventilator rectangle and a patient rectangle. Second, within any frame, the ventilator and the patient each have two key parameters that can be represented by the two sides of their respective rectangles: how many tides of air were exchanged, and the volume of each tide (tidal volume). These are represented by the two sides of a rectangle, such that as a parameter increases, the corresponding side gets longer. Finally, it is easy to represent the distinction between "dead space" and alveolar space in such a graphic. A breath with shallow volume only gets as far as the mouth and trachea, accomplishing nothing. Only a breath larger than a certain critical volume actually gets down to the alveolae of the lungs and contributes to physiologic gas exchange.

Metaphoric Mapping. The sides of the rectangle are not assigned arbitrarily. Rather, a metaphoric mapping, an analogue is created. When you breathe deeply, your diaphragm moves downward and your whole torso gets deeper, so we represent a deeper tide as a deeper rectangle. Then, the more of these tides that come in a given minute, the wider the total rectangle gets as we stack each "slice" alongside the others, yielding a very wide rectangle if there are very many tides and a relatively narrow rectangle if there are relatively few tides. Faster rate = wider rectangles. Deeper breaths = deeper rectangles. (If this metaphor seems reversed to you, you can simply reverse the mapping when you run our computer program. It doesn't matter which mapping is used as long as the mapping seems natural to the user.)

Beyond Rate And Volume. Emergent properties begin to pop out. First of all, a vital thing to know in ventilation is the product of rate times tidal volume. This is the total "minute volume" for that minute and it is easily seen as total area within the rectangle. Second, it becomes very easy to show the key distinction between shallow breathing that only penetrates the mouth and trachea (and not contributing to real air exchange in the lungs) versus deeper breathing in which gas exchange occurs down in the alveolae of the lungs. A horizontal line is drawn, showing what, for this patient, is the depth of breath necessary to get down into alveolar space. Finally, the alveolar space is shaded, both to distinguish it from dead space, and also to provide a way of encoding gas information. Want to know what concentration of oxygen we are pumping into Mr. Jones? We can represent that by varying the shading of the alveolar region. Would you rather know what Mr. Jones's blood concentration of CO2 is? We can have the shading reflect this parameter instead.

Grasping 11 Minutes Of Data. Let's look at the 11 minutes worth of data now and see if it makes any sense. In frame 1, there is only one rectangle. If you had been working with this representation for any length of time you would immediately
recognize that this is the ventilator rectangle alone. The patient is contributing nothing spontaneously. In frame 2 (minute 2), we see nothing has changed. Same with frame 3. In frame 4, however, the patient kicks in with some spontaneous breathing. What kind? Fast or slow? Shallow or deep? Recall the metaphor: deep breathing means deep rectangles, and that's what we have here. Fast breathing means many breaths per minute, many individual rectangles stacked next to each other to make one wide rectangle. But here we have a very narrow total patient rectangle, so we probably had only one or two breaths.

In frame 5, things have gotten better, with depth of patient tides holding nicely steady and with rate picking up. But at frame 6 everything goes haywire as the patient breathes very rapidly but with such shallowness that there is no significance, no alveolar exchange. In frame 7 we see good rate and improved depth. In frame 8, even better depth. In frame 9 we see the patient breathing with good rate and good depth, so much so that the ventilator is being cut back. In frame 10 this continues, and by frame 11 we have a patient who has taken over his own breathing again, with only minor assistance from the ventilator. Review the big picture again. You can now just glance at that graphic and see the general course of events very quickly. You need not translate between numbers and their real world implications. The metaphoric graphic does that for you. You can look at the graphics as though you were viewing the world, because the graphic was carefully designed to act as a visual analogue.

Costs And Benefits Of Metaphoric Graphics. This is not a universal graphic, since it is not an arbitrary graphic. You could not use our computer program to display other kinds of data. Because the representational system is metaphoric, different types of real world variables must receive distinctly different graphic treatments. This can be a significant cost to developing such a system. On the other hand, there appear to be some benefits.

1. You can learn this representational system very quickly. Nobody so far has needed more than five minutes to learn it.

2. You will retain this learning for the rest of your life. I can show you a page of ventilator volume rectangles a year from now and you will be able to immediately make sense of them.

3. A great deal of data can be summarized in a small amount of space, limited only by the resolution of your display device. We can put 16 hours worth of data on a small Macintosh computer screen, by creating one frame for every 10 minutes.

4. You can quickly see interactions among parameters; you can trace synergistic effects rather than just focusing on how one parameter varies then focusing on how another one varies.

5. You can ignore the uninteresting parts of the data and home in on the place where the action is. This is something our visual system loves to do. Ordinarily, we give crude processing to most of our visual field and extremely sophisticated processing to the central portion of that field. This is efficient and natural and is a nice thing to have as part of any display system.
6. You can probably make sense out of this display even when you are distracted, are tired or have a memory load. You don’t need to talk to yourself to make sense out of volume rectangles, so if your numero-linguistic pipeline is busy rehearsing a phone number or is operating poorly due to fatigue or distraction you can still at least check to see if the general picture is changing, is stable, is getting better or worse.

Cognitive Science Research. All of these apparent benefits are one focus of our UCSF Medical Information Science research program, and over the next couple of years I hope to continue providing hard data to either support or refute the claims made here.

A Picture of a Database

Monitoring is only one area in which data is a problem. Consider the problem of a clinical database. UCSF has one of the best melanoma databases in the world. We also have some exceptionally competent melanoma physicians and some very bright computer scientists. How informative is our database? Well, why don’t you try to make sense out of a little piece of it? My colleague Mark Tuttle extracted some 800 cases from the database, the 800 most interesting patients. These are patients that are neither so ill that it is clear what to do with them nor so well that it is clear that we should do nothing at all. These are the 800 patients that keep our physicians awake at night, wondering what to do. What are the key variables? What contributes to a good vs. a bad outcome? You decide.

Here Are 400 Patients. You Be The Medical Researcher. For sake of space I will show you only the 400 "older than median" patients. Each patient is one row in the following table, and on each patient we have seven key binary, boolean attributes.

<table>
<thead>
<tr>
<th>Seven Attributes For Each Patient</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. The patient is either male or female.</td>
</tr>
<tr>
<td>2. The patient’s primary tumor is either in the extremity (e.g. arm) or is axial (e.g. on the chest).</td>
</tr>
<tr>
<td>3. The primary tumor is either thick or thin.</td>
</tr>
<tr>
<td>4. It is either shallow or deep (Clark’s level III or level IV).</td>
</tr>
<tr>
<td>5. It is either the only manifestation of melanoma (local disease) or is accompanied by known metastases (regional disease) indicating the disease is spreading.</td>
</tr>
<tr>
<td>6. The patient’s lymph nodes are either all intact or else some have been surgically removed.</td>
</tr>
<tr>
<td>7. Finally, the last we heard, the patient is either alive or dead.</td>
</tr>
</tbody>
</table>

Table 2. The seven key attributes we have coded for each of our 400 example patients.
Table 3. 400 patients, older than median, from the UCSF melanoma database. Each patient has 6 binary attributes that may be critical for predicting survival. The seventh attribute (current stage) is whether the patient is still alive.

Suppose we find it difficult to discover patterns in this data. How might we go about graphically representing a database of melanoma? There are two fundamental classes of representation possible: network models and feature models.
Network representation. Figure 8 illustrates what a network of our database would look like. Actually, it only shows the leftmost one eighth of the network. Trying to display the entire net would be awkward, because of the sheer number of nodes in the net. At each branch coming down the tree from the top to the bottom, the number of branches increases by a factor of two. There are thus $2^7$ or 128 branches in this network, 128 terminal nodes in the bottom row alone. Hard to display and perhaps hard to interpret.

Figure 3. A sketch of a network representation of the 400 patients. Only the leftmost branch is developed, due to space limitations. If the network were fully displayed, there would be 128 nodes in the bottom row alone. Displaying the full net would thus require a large area.
A network representation would include numbers attached to the nodes, showing how our 400 total patients are distributed in this two dimensional space. There are, for example, 188 males in the 400 patients. Of these 188, 147 have axial tumors and 41 have extremity tumors. The bottom row of nodes, with the letters A and D attached, shows who is currently alive and who is dead. Searching this graphic space for interesting main effects or interactions may or may not be feasible. Certainly some questions can be easily answered from this net. For instance, are there more male patients with axial or with extremity primaries? Other questions are more difficult to answer. What factors tend to be associated with an A in the bottom row, that is, with being alive? The advantages and disadvantages of network representation are not obvious. It is interesting that although "network" is the first thing that most people propose when you ask them about a picture of a database, there has been no research on how people can use a network representation of a database to make decisions or think about problems.

There is one clear thing to be said for network representation, however, even without conducting any experiments in statistical graphics perception. Networks, like line graphs and pie charts, are arbitrary, universal graphics. Any data that can be classified can be displayed as a network. This is, as always, a strength and a weakness.

**Feature representation.** An alternative to network representation is feature representation, where each element in the database is represented as a free standing element, with attributes that somehow correspond to real world attributes. Table 3 meets these criteria and is, in fact, a linguistic feature model of the electronic database. Each patient is represented as a row and each row has several columns containing a linguistic code that represents either an attribute of the patient or an attribute of the electronic database, depending on how you want to look at it. Features need not be represented as words, however. It is possible to create a visual language, metaphoric, whereby patient attributes appear as visual attributes. Consider, for example, the following scheme.

**Visual, metaphoric features.** Each patient can be represented as an individual icon, a little box. Every patient in our database has a primary tumor, and every icon in this picture has a corresponding horizontal line in the box. If the primary occurs in the extremities (e.g., arm or leg), the line is far over to the right side of the box; an axial tumor (e.g., on the chest) is represented by a line more central. If the tumor is thick, the line is thick. If the tumor is deep, the line is deep in the box. If there is regional disease, three little dots appear in the box, suggesting metastases. If the patient’s nodes have been removed, the box is missing a chunk out of the lower left corner. And finally, the key dependent variable. Is this patient still alive? If not, a diagonal line passes from upper right to lower left across the icon. Figure 9 shows all 400 patients in one compact display. Sex has been coded as a grouping attribute rather than as an attribute of individual icons.
<table>
<thead>
<tr>
<th>Each patient = one icon.</th>
<th>Every patient has at least a primary tumor.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Some primaries are axial.</td>
<td>Some patients only have a primary tumor (Local disease).</td>
</tr>
<tr>
<td>Some are in the extremity.</td>
<td>Some patients also have metastases (Regional).</td>
</tr>
<tr>
<td>Some primaries are thin.</td>
<td>Some patients have all lymph nodes intact.</td>
</tr>
<tr>
<td>Some are thick.</td>
<td>Some patients have had some nodes electively removed.</td>
</tr>
<tr>
<td>Some primaries are shallow.</td>
<td>Some patients are currently alive.</td>
</tr>
<tr>
<td>Some are deep.</td>
<td>Some have died.</td>
</tr>
</tbody>
</table>

**Male**

**Female**

Figure 9. 400 melanoma patients in an iconic feature representation.
Now try to answer a few questions. Overall, who survives better, men or women? If a patient has regional disease, how likely is it that nodes have been removed? Does regional disease tend to be associated with axial tumors? Is there a sex difference in propensity toward regional disease? If we wanted to ask a statistical question about the relationship between three variables—regional disease correlated with thickness of tumors, looking only at males—do we have enough patients to make a comparison worthwhile? What do the patients who have died seem to have in common? I have a patient who is male, has only local disease, but has a thick shallow tumor in the extremity. What is our experience with patients like this one?

There are many types of question that can be asked of a database, ranging from rifle shot questions such as, "Exactly how many of our patients have nodes removed, local disease, and shallow, thin primaries?" to scattergun questions such as, "Given that you have a thick primary, what other constellations of factors seem to put you most at risk?" Rifle shot questions can be handled well by database management systems. Rifle shot questions that only involve a single variable ("How many males do we have?") can even be answered by consulting a table listing all the patients. But the more a question involves configurations, constellations of effects, interactions among the factors, the harder it is to grasp what the data means.

It may be that iconic feature representation of a database helps answer some kinds of questions. It may be that these icons also help you form new questions, new hypotheses. The necessary research simply has not been done yet. At this stage these icons are nothing more than an interesting, perhaps even tantalizing new approach to interacting with a database. We have developed our computer programs to the point that the user can bring up large chunks of the database, as in Figure 9, then selectively display certain classes of patient in inverse video (white on black), erase a subclass of those patients, then grey out yet another subclass. These sorts of manipulations can make certain interesting subgroups pop out, and explicitly contrast one subgroup with another (e.g. via normal vs. inverse video). Grouping procedures (place all the men with local disease on the left and all the men with regional disease on the right) are currently being implemented. Animation procedures also have been created. For example, it is possible to quickly review the flow of patients into our clinic, through stages of disease, and observe their outcome over time, by watching a "melanoma movie" in which the characters are icons and the action involves moving from one part of the screen to another. Cognitive psychology experiments will be necessary to determine just how metaphor graphics influence database decision, judgment, & problem solving.

There is a great deal to say about representation of a database, but this is not the place to say it. The point to the pictures shown here is that metaphor graphics can be created for databases, just as they can be created for monitoring. In fact, metaphor graphics can be created in any number of areas, wherever there appears to be a great deal of data that is poorly understood.
SUMMARY

Five points have been made here. First, people do not solve problems by a mental version of formal logic but rather tend to use pattern recognition and mental models. Second, people have powerful facilities for dealing with the analog world. Representing data in digital form for people to process can lead to cognitive strain. Third, graphic representation holds a promise of help. Fourth, standard statistical graphics are universal but arbitrary and thus do not paint the kind of picture we understand best. Standard graphics are useful, but limited. Fifth, metaphoric graphics may be useful adjuncts to other representations, recontextualizing the digital data, placing it back into a context where it fits with our cognitive strengths.

The concept of a metaphor graphic is rooted in cognitive science issues of representation and processing. It is argued that two representations that are representationally isomorphic may have very different usefulness, very different informational value, because they are processed differently. Details of display can powerfully influence the kind of processing that we can use on any data set, and thus the informational impact of that data.

Metaphor graphics seem intuitively to have many useful properties, such as ease of learning, long retention, and usefulness even under conditions of stress, fatigue, or divided attention. Cognitive psychology experiments are in progress to evaluate these apparent benefits. No matter what the benefits, metaphor graphics have one clear cost. They require a careful consideration of the mapping between real-world and graphic world variables. Metaphor graphs are custom, not universal, graphs and their creation requires careful consideration of the cost of custom design. Computer tools could be created to reduce this cost.

This enterprise is an example of human-computer cooperative computation. Cooperative computation describes a situation in which multiple agents share data in a way such that their combined effort is superior to the effort either could produce in isolation. Human-computer cooperative computation will work best if we allow computers to do what they do best and humans to do what they do best. So far, it looks like computers are terrible at recognizing meaningful configurations in a complex world, at interpreting the meaning of a feature within context, and at noticing and understanding similarities. Humans are terrific at these tasks, but find it difficult to store and manipulate large arrays of digital data. Creating computer utilities that augment and supplement our natural strengths, filling in for us where we are at our weakest, will result in the creation of cognitive companions, computer systems that do not try to simulate our thinking or replace our judgment, but rather act to support us and strengthen our efforts, much as a lever increases our effectiveness in moving a stone blocking our path.