Representations

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Cognitive science is all about representations. The mind/brain constructs mental models (Johnson-Laird 1983) of the external world, representing some aspects of the environment, while leaving other features out. Many other issues in cognitive science (e.g. analog versus digital computation) hinge on explicit or implicit differences in proposals or assumptions about representations. So, then, what are representations? One way to understand a concept is to trivialize it, and I propose to do just that with “representation”.

Thermostats

Most everyone is familiar with a home thermostat, even if they aren’t aware of how one works. Here is a (fuzzy) picture of the one on the wall of my living room:

Figure 1: A mechanical thermostat
There isn’t much to it, a slider to set the desired temperature, and a readout of the current temperature in the living room (i.e. a thermometer). Internally, the thermostat has a spiral loop made out of two metals with different coefficients of thermal expansion so that as the temperature rises, the metals expand at different rates. Simplifying somewhat, then, as the temperature rises, the position of the coil changes (due to the “curl” induced from the differing expansions of the metals) and when the temperature reaches the desired level it engages a switch which turns the furnace off.

The thermostat represents (Dretske 1988, p. 86) the ambient temperature in the state of the bimetal coil, that is, information about the ambient temperature is contained in its internal model of its world. It represents and remembers the desired temperature through the position of the contact switch. It does stuff (turns the furnace off or on) based on the interaction of the representation of the ambient temperature and the representation of the desired temperature. Fancier thermostats (like that in my air conditioner, Figure 2) solve the same problem with small embedded microprocessor controllers.

Figure 2: An electronic thermostat

Is the thermostat “intelligent”? Despite what advertising literature might imply, no it isn’t. The thermostat is too much of a one-trick pony—it can’t learn any new behaviors, couldn’t pass the Turing test, and certainly isn’t the least bit self-aware. But it does illustrate the concept of representation, and one of the building blocks of cognition.
MAPs

It is certainly useful, enlightening and even amusing to contemplate what it would be like to be a brain in a vat (Putnam 1981) or a bat (Nagel 1974), but here we will take a ruthlessly pragmatic approach to the issue. We will take the mind/brain to be a cooperating collection of information-processing, problem-solving devices (Marr 1982, Young 1989). As such, the brain solves many problems through *Memory-Action-Perception* (MAP) loops. Now some may object that they would like such processes to start external to the mind/brain and so Perception should start off the loop. We will arbitrarily dismiss this objection, simply to note that PMA doesn’t make for a good or useful acronym (at least in English).

The thermostat has such a loop: it *perceives* the ambient temperature, compares its perception with the *memory* of the desired temperature, and (perhaps) performs an *action* (turns on or off the furnace). Let us take one more over-simplified example to further illustrate the basic idea. Consider the everyday task of repeating a word. Sound-pressure waves are *perceived* by being transduced (mapped) by the ear into electrical nervous impulses, representing the external sound; this representation is further processed and eventually matched against our dictionary (containing representations of words we know), stored in long-term *memory*; we then retrieve the correct representations (hopefully!) and formulate a speech-motor plan of *action* for our lips, tongue and the other speech articulators. MAP loops thus depend on representations for perception, memory and action.

Marr’s levels

Marr 1982 is one of the most vigorous proponents of the information-processing, problem-solving approach to cognition. In this context he defines a representation as “a formal system for making explicit certain entities or types of information, together with a specification of how the system does this.” (p. 20). Furthermore, he distinguishes three levels of analysis of an information-processing, problem-solving device:

<table>
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<th>Computational theory</th>
<th>Representation and algorithm</th>
<th>Hardware implementation</th>
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<td>What is the goal of the computation, why is it appropriate, and what is the logic of the strategy by which it can be carried out?</td>
<td>How can the computational theory be implemented? In particular, what is the representation for the input and output, and what is the algorithm for the transformation?</td>
<td>How can the representation and algorithm be realized physically?</td>
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Table 1: Marr’s three levels (Marr 1982, p. 25)

The idea behind Marr’s analysis is straightforward Artificial Intelligence: the brain is not the only conceivable intelligent machine (Turing 1950) and we should be able to solve the same problem using different hardware. We can simultaneously understand
a problem to be solved in terms of (1) the problem statement itself (the computational level), (2) a set of data structures and algorithms, like a computer program (the algorithmic level), and (3) the (compiled) machine code executed on a particular piece of hardware (the implementational level). Marr's particular innovation is the algorithmic level; the function and neural instantiations of ecological behaviors have long been recognized in ethology (Lettvin et al 1959, Young 1989). Marr's view encourages us to view the mind/brain as a set of interacting modules, and to define data structures and interfaces between the modules so that we can tinker with internal implementations while keeping the public interfaces consistent (now basic practice in object-oriented programming, e.g. Goldberg and Robson 1989, Stroustrup 2000). This is also the basic belief behind neuro-prosthetics such as cochlear implants, whereby we can substitute electronic devices for existing biological systems provided that they provide equivalent functions at the algorithmic level and interface with existing biology at the implementational level. Although Marr's views have been enormously influential it remains an open question whether there are special aspects of the brain (perhaps in its evolution and development) that cannot be replicated in other hardware (for a recent articulation of this position see Mareschal et al 2007).

**There's more than one way to echo-locate a cat**

Consider the problem of identifying where an object is using sounds (Grothe 2003), either emitted by the object or reflected off it. This is a common problem to be solved by both predator and prey with obvious consequences for their evolutionary fitness. This problem (auditory localization of objects) is the task to be solved; the computational-level statement of the problem. If the animal has two ears located sufficiently far apart, then one way of determining the direction of the object is to compare the arrival times of the sound to each ear (the interaural time difference, ITD). The mapping between ITDs and locations is a geometrical statement (and algorithm) for solving the auditory localization problem (comparable to a parallax viewfinder for a camera); this is the algorithmic statement of the problem. One way to neurally instantiate and represent the ITD and therefore azimuthal direction is with an array of neurons tuned to different arrival time differences using delay lines and phase comparison between the incoming signals from the ears (a neural place code, Jeffress 1948). And indeed, this is how birds solve this problem, but it is **not** how mammals do. Instead, mammals encode the amount of azimuthal direction in the firing rate of a collection of neurons (a neural rate code). As Grothe remarks, “recent evidence strongly indicates that birds and mammals have their own, profoundly different solutions for the same problem of how to localize sounds by using ITDs.” (2003, p. 550). At the algorithmic level we require an encoding of the amount of the angular offset to the object, but we aren’t concerned with the details as to how this information is encoded. But at the implementational level we must pick our poison: place code or rate code (or something else again). Thus, we now have very strong reasons to accept the utility of Marr's three levels as we have at least one compelling example where the same problem is solved by different (indeed incompatible) neural implementations.
Layers of representations

Let us now briefly consider another seemingly simple problem (naming a color) that, when unpacked, reveals that the cognitive systems involved must contain a multiplicity of representations (for excellent summaries see the chapters in Hardin and Maffi 1997). Thanks to the pioneering work of such giants as Goethe, Young, Hering, Helmholtz and many others we have an excellent understanding of the biology and neuro-physiology of color vision (Gegenfurtner 2003). The big debate between Hering and Helmholtz was about the neuro-cognitive representation of color, is it like a color-wheel (Hering’s opponent process model) or is it three-dimensional (with red, green and blue intensities, RGB, Helmholtz)? It turns out that it’s both. Helmholtz was right about the “low level” visual system, there are three types of cone-receptors; but Hering was right about “higher level” organization of colors, which seem to be preferentially organized into a color wheel with red-green and yellow-blue opposing pairs, even in blind and color-blind individuals (Marmor 1974, Shepard and Cooper 1992). Beyond this, different languages encode the color space into color names differently (Berlin and Kay 1969). (And one might add to this the different types of software tools such as those provided by the Apple Color Picker Manager: RGB sliders, color wheels, and virtual crayon boxes.) Thus, there is no one cognitive representation of color, but rather a multiplicity of representations, arranged in a hierarchical, layered fashion. For some problems colors are represented in the RGB system, for others they are coded on a color wheel, for still others they are encoded linguistically. And, it might be added, none of these representations are faithful to the physical instantiation of color, in which red and violet stand at opposite ends of the spectrum (but which are adjacent on the color wheel for example). The human color system is not at all unusual, it is likely that many (perhaps even most) cognitive problems are solved using a cascaded set of representations. This suggests a methodological moral for us as well: beware of questions or answers suggesting that a proposal is the representation for a problem in cognition. If we push further, we’re likely to find that more than one representation of the problem is employed.

A long-standing issue: Local versus distributed representations

Is information generally represented locally, as a single symbol, in a single neuron (Lettvin’s fabulous grandmother cell, Barlow 1995) or is information generally contained in patterns of activation across many neurons (e.g. Parallel Distributed Processing, Rummelhart and McClelland 1986)? This classic debate continues, and will continue into the foreseeable future. As the ITD example shows, this isn’t a simple question, and brains are quite capable of using both methods. With a place code a single neuron best represents a particular angle (say 15 degrees), and so at most just a couple of adjacent neurons will fire to a stimulus with any particular azimuth. With a rate code, a gang of neurons fire together and the overall rate out of the gang encodes the magnitude of the azimuth (the farther off-center the stimulus, the greater the aggregate firing rate) so that no one neuron can be said to encode
anything, it is only the aggregate response that is invested with “meaning”. The individual neuron firings by themselves are not sensible. The morals are again very useful, though: most questions have more subtle answers than we expect, and it takes hard, time-consuming empirical investigation to uncover the precise nature of mental representations.
Useful online resources

Cogprints: http://cogprints.org/

References


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