Believing Is Seeing: Troland Winner Peers Into Perceptual and Conceptual Learning

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Human concept learning clearly depends upon perception. Our concept of “gerbil” is built out of perceptual features such as “furry,” “small,” and “four-legged.” However, recent research has found that the dependency works both ways. Perception not only influences, but is influenced by, the concepts that we learn. Our laboratory has been exploring the psychological mechanisms by which concepts and perception mutually influence one another, and building computational models to show that the circle of influences is benign rather than vicious.

An initial suggestion that concept learning influences perception comes from a consideration of the differences between novices and experts. Experts in many domains, including radiologists, wine tasters, and Olympic judges, develop specialized perceptual tools for analyzing the objects in their domain of expertise. In trying to study novice/expert differences under controlled laboratory conditions, we have found that the process of learning new concepts alters perceptual judgments. In one set of experiments (Goldstone, 1994), participants first were trained to categorize simple squares into two groups, based on either their size or brightness. After this training, they made same/different judgments (“Are these two squares physically identical?”) involving dimensions that were either relevant or irrelevant during categorization training. Categorizations that the participants learned in the first phase of the experiment affected their ability to make strictly physical judgments in the second phase. First, participants greatly increased their perceptual sensitivity to the dimension that was relevant during categorization, and slightly decreased their sensitivity to the irrelevant dimension. Second, the increase in sensitivity was particularly pronounced right at the boundary between the learned categories.

TWO OPPOSING MECHANISMS OF PERCEPTUAL CHANGE

In subsequent work, we have explored two additional mechanisms of perceptual change during concept learning that are, at first sight, contradictory. The first of these mechanisms, unitization, creates perceptual units that combine object components that frequently co-occur. Components that were once perceived separately become psychologically fused together. For example, we (Goldstone, 2000) gave participants extended practice learning to place a complex concatenation of doodles into Category 1, while all of the “near misses” to this pattern belonged in Category 2. All of the pieces of the Category 1 pattern must be attended to accurately categorize it, because each piece is also present in several Category 2 patterns. After 20 hours of practice with these stimuli, participants eventually can categorize the Category 1 doodle very accurately, and more quickly than would be predicted if they were explicitly combining separate pieces of information from the doodle together. Consistent with other work on perceptual unitization (Gauthier et al., 1998; Shiffrin & Lightfoot, 1997), we argue that one way of creating new perceptual building blocks is to create something like a photographic mental image for highly familiar, complex configurations. Following this analogy, just as your local camera store does not charge more money for developing photographs of crowds than pictures of a single person, once a complex mental image has been formed, it does not require any more effort to process the unit than the components from which it was built.

Figure 1 – Arbitrary dimensions can be constructed by morphing between two faces. Each of the faces in the 4 x 4 array is comprised of a value along Dimension A ranging from Face 1 to Face 2, and a value along Dimension B from Face 3 to Face 4.

The second mechanism, dimension differentiation, involves learning to isolate perceptual dimensions that were originally psychologically fused together. For example, saturation and brightness are fused aspects of color for most people, in the same way that "heat" and "temperature" are fused together in most people's minds before they take a course in physics. However, if only one of these fused dimensions is relevant for a categorization, people can become selectively sensitized to that one dimension (Goldstone, 1994). Furthermore, Goldstone and Steyvers (2001) have argued that genuinely arbitrary dimensions can become isolated from each other. Their subjects first learned to group the 16 faces shown in Figure 1 into categories that either split the faces horizontally or vertically into two groups with eight faces each. The faces varied along arbitrary dimensions that were created by morphing between randomly paired faces. Dimension A was formed by gradually blending from Face 1 to Face 2, while Dimension B was formed by gradually blending from Face 3 to Face 4. Each of the remaining faces is defined half by its value on Dimension A and half by its value on Dimension B. Results showed that 1) people could easily learn either horizontal or vertical categorization rules; 2) once a categorization was learned, participants could effectively and automatically ignore variation along the irrelevant dimension; 3) the category-relevant dimension became especially sensitized when participants were given a transfer same/different perceptual judgment task; and 4) there was positive transfer between categorization rules that presumed the same organization of faces into perceptual dimensions and negative transfer between rules that required cross-cutting, incompatible organizations. Together, these results strongly suggest that there is more to category learning than learning to selectively attend to existing dimensions. Perceptual learning also involves creating new dimensions that can then be selectively attended once created.

A COMPUTATIONAL RECONCILIATION

Unitization involves the construction of a single functional unit out of component parts. Dimension differentiation divides wholes into separate component dimensions. There is an apparent contradiction between experience creating larger "chunks" via unitization and dividing an object into more clearly delineated components via differentiation. This incongruity can be transformed into a commonality at a more abstract level. Both mechanisms depend on the requirements established by tasks and stimuli. Objects will tend to be decomposed into their parts if the parts reflect independent sources of variation, or if the parts differ in their relevancy. Parts will tend to be unitized if they co-occur frequently, with all parts indicating a similar response. Thus, unitization and differentiation are both processes that build appropriately sized representations for the tasks at hand.

We have developed computational models to show how the concept learning can lead to learning new perceptual organizations via unitization and differentiation (Goldstone et al., 2000; Goldstone, 2003). We have been drawn to neural networks that possess units that intervene between inputs and outputs and are capable of creating internal representations. For the current purposes, these intervening units can be interpreted as learned feature detectors, and represent an organism's acquired perceptual vocabulary. Just as we perceive the world through the filter of our perceptual system, so the neural network does not have direct access to the input patterns, but rather only has access to the detectors that it develops.

Figure 2 – A sample output from the CPLUS model. After being exposed to the input pictures and their categorizations, the neural network creates detectors that can be assembled, like building blocks, to recreate the inputs. The detectors are learned at the same time that they are associated to categories. (Solid lines represent excitatory connections; dashed lines represent inhibitory connections.)

The Conceptual and Perceptual Learning by Unitization and Segmentation model, or CPLUS, is given a set of pictures as inputs, and produces as output a categorization of each picture. Along the way to this categorization, the model comes up with a description of how the picture is segmented into pieces. The segmentation that CPLUS creates will tend to involve parts that 1) obey the Gestalt laws of perceptual organization by connecting object parts that have similar locations and orientations, 2) occur frequently in the set of presented pictures, and 3) are diagnostic for the categorization. For example, if the five input pictures of Figure 2 are presented to the network and labeled as belonging to Category A or Category B, then originally random detectors typically become differentiated as shown. This adaptation of the detectors reveals three important behavioral tendencies. First, detectors are created for parts that recur across the five objects, such as the lower square and upper rectangular antenna. Thus, the first input picture on the left will be represented by combining responses of the square and rectangular antenna detectors. Second, single, holistic detectors are created for objects like the rightmost input picture that do not share any large pieces with other inputs. In this way, the model can explain how the same learning process unitizes complex configurations and differentiates other inputs into pieces. Third, the detectors act as filters that lie between the actual inputs and the categories. The learned connections between the acquired detectors and the categories are shown by thick solid lines for positive connections and dashed lines for negative connections. The network learns to decompose the leftmost input picture into a square and rectangular antenna, but also learns that only the rectangular antenna is diagnostic for categorization, predicting that Category A is present and that Category B is not. Interestingly, the network builds detectors at the same time that it builds connections between the detectors and categories. The psychological implication is that our perceptual systems do not have to be set in place before we start to use them. The concepts we need can and should influence the perceptual units we create.

Figure 3 – An illustration of the creation and subsequent use of perceptual building blocks. In the first panel, a man learned about a chicken. In the second panel, the man interprets the rest of the world in terms of the chicken he has learned. [Conceived by Robert Goldstone. Illustrated by Joe Lee]

UNITING CONCEPTS AND PERCEPTION

One of the most powerful ideas in cognitive science has been the notion that flexible cognition works by assembling a fixed set of building blocks into novel arrangements. Our work corroborates the productivity and efficiency of using building blocks to create novel arrangements, but we are also claiming that the building blocks themselves may be flexibly adaptive rather than fixed. The concepts we learn can reach down and influence the very perceptual descriptions that ground the concepts. This interactive cycle is figuratively shown in Figure 3. A person creates perceptual building blocks from their experiences in the world. Then, the person's subsequent experience of this same world is influenced by these learned building blocks.

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