Generalization and Tinbergen’s four whys

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Abstract: Shepard’s exponential law provides a functional explanation of generalization. The account complements the more common mechanistic models. The elegant and powerful analyses answer one of Tinbergen’s (1963) four whys of behavior: a benefit conferred on the animal by generalizing in this way. A complete account might address evolutionary and developmental questions in addition to mechanistic and functional ones.

In the classic paper “On aims and methods in Ethology,” Tinbergen (1963) identified four types of “why” questions to be addressed about any behavior. Mechanistic explanations concern the immediate conditions for a behavior, from stimulus conditions to brain structures. Developmental questions ask about the ontogenetic history of a behavior. The field of psychology addresses mostly these proximate questions of mechanism and development, with more on mechanism than on development. Far less frequently tackled are the ultimate questions of function (what Tinbergen called “survival value”) and evolution. Functional questions address the benefits conferred, at present, by a behavior, while evolutionary questions address the evolutionary history of a behavior. To fully understand a phenomenon in learning, perception, or cognition, answers to all four whys are needed.

Shepard’s article reprinted here takes the road less travelled and answers functional questions about learning, cognition, and perception. The aim is to look for abstract universal principles that animals “should” honor because the world they live in possesses representations (whether representations of points in space, of scripts, sentences, or whatever), by the complexity of the process of “distorting” each representation to the other. Specifically, the distance between two representations, A and B, is defined to be the sum of the lengths of the shortest computer program that maps from A to B and the length of the shortest computer program that maps from B to A. This is known as sum-distance (Li & Vitányi 1997). Sum-distance measure is attractive not only because it has some theoretical and empirical support as a measure of similarity (Chater & Hahn 1997; Hahn et al., submitted), but also because it connects with the theoretical notion of information distance, developed in the mathematical theory of Kolmogorov complexity (Li & Vitányi 1997). (See Chater 1999, for an informal introduction in the context of psychology.) The intuition behind this definition is that similar representations can be “distorted” into each other by simple processes, whereas highly dissimilar representations can only be distorted into each other by complex processes; the complexity of a process is then measured in terms of the shortest computer program that codes for that process.

Shepard uses a specific function, G(A, B), as a measure of the confusability between two items. It turns out that – using only the assumption that the mapping between the input stimuli and the identical responses is computable – it can be shown that G(A, B) is proportional to the negative exponential of the sum-distance between A and B. That is, if distance is measured in terms of the complexity of the mapping between the representations A and B, then Shepard’s universal law, when applied to confusability, follows automatically (Chater & Vitányi, submitted).

We have suggested that this result is attractive, because it applies in such a general setting – it does not presuppose that items correspond to points in an internal multidimensional psychological space. This observation suggests a further line of empirical research: to determine whether the Universal Law does indeed hold in these more general circumstances.
certain invariant properties. To put it bluntly, behaving in accord with these invariants should add survival value. The invariants are abstract and deep, and digging them out is hard work to my mind. The functional universals thus unearthed add a new dimension to understanding the phenomena, a dimension often missing in psychology.

In the rest of my commentary, I will limit consideration to the topic of generalization, the topic with which I am most familiar. Mechanistically, various models of spreading activation, going back to Shepard (1958), can produce generalization gradients (e.g., Cheng et al. 1997; Reid & Stadlon 1998). Others take a network approach (e.g., Ghirlanda & Enquist 1998; 1999; Gluck 1991; Saksida 1999). Choosing amongst them remains difficult, but we have plenty of recent thinking on the topic.

On the functional question, SHEPARD’s is the only account of generalization to date. It offers far more than speculation about the possible advantages of generalizing. The analysis tackles the form of gradients. It is SHEPARD’s style not to contrast how animals might differ in generalization, but to find universals. In the face of seeming diversity, SHEPARD tells us where and how to look for universality. The functional analysis came up with elegant reasons why animals should follow the exponential law, and the conditions and ideas required for finding it. It is thus helpful in offering not only reasons for generalizing, but some deep insights into the way it should happen. The law has found support in evidence in humans and pigeons (Shepard 1987b), and recently in honeybees (Cheng 2000).

The exponential law gives us a universal for generalization, and tells us why it benefits animals today. We may further ask how animals evolved to generalize in this way. Given that the law is found in diverse animals, convergent evolution is suggested. But it is hard to add much. The evolutionary question is difficult to answer for the lack of behavioral records. Generalization gradients are not imprinted on rocks. An answer will likely require a far broader and deeper comparative study of learning.

How do animals “come up with” SHEPARD’s law in the course of their lives? One possibility is that \( y = e^{-kx} \) is wired in the brain. To be more precise, the exponential law might be mostly a matter of maturation. The worker bee hatching out of her cell immediately starts generalizing in accord with SHEPARD’s law, in each and every task that she undertakes in her life. Thus, the initial state for generalization is an exponential gradient. Experience fills in the scaling parameter left free in the equation (k). But the initial state might not be of functional and it may be necessary to narrow the gradients down to the exponential shape.

In general, it is by no means clear how to give a good operational characterisation of the three dimensions of SHEPARD’s representational colour space in terms of lightness, hue, and saturation. The difficulty is very apparent in the ubiquitous ambiguity surrounding a lightness- or brightness-axis. The lightness-axis is, primarily, a black-white axis, based on contrast experiences; the brightness axis is based primarily on the luminosity of colour patches. Problems arise with the psychological difference between black/white, dark/light, and dull/bright. Furthermore, there are interdependencies between hue, brightness, and saturation, however defined, and the three of them fail to cover all aspects of “colour” appearance (for references see Saunders & van Brakel 1997, p. 175).

Third, it is not obvious how to characterise the dimensions of the representational colour space unambiguously. Traditionally, there are three dimensions, but this rests on rather vague introspective intuitions. Multi-dimensional scaling (MDS) techniques allow the ordering of colour comparisons in a spatial structure. However, these techniques yield a variety of results and are difficult to interpret. Moreover, how to choose samples that do not prejudice the outcome? Further, even if MDS techniques yield three dimensions, there is nothing to tell you how to define the axes and measure distances. Finally, it has been claimed that four, six, or seven dimensions are needed to adequately represent human colour vision (Chang & Carroll 1980; Sokolov 1997).

According to SHEPARD the colour appearances of surfaces correspond to relatively fixed points in a three-dimensional colour space (his emphasis). However, the distinction between phenomenal, perceptual, psychological, or internalised representational colour spaces and the various technological or (psycho)physical colour spaces is blurred. Examples of psychophysical colour spaces are the Munsell colour system, the CIE system, the CIECAM02 system, the CIECAM97s system, and the CIEDE2000 system. But there is insufficient evidence for Shepard’s stronger claim that the three-dimensionality of colour perception has resulted from natural selection, moulded by the particulars of the solar spectrum and its variations.

Abstract: Contra Shepard we argue, first, that his presentation of a three-dimensional representational (psychological or phenomenal) colour space is at odds with many results in colour science, and, second, that there is insufficient evidence for Shepard’s stronger claim that the three-dimensionality of colour perception has resulted from natural selection, moulded by the particulars of the solar spectrum and its variations.

Which colour space(s) is Shepard talking about?

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