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Why are some dimensions integral? Testing two hypotheses through causal learning experiments

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ABSTRACT

Compound generalization and dimensional generalization are traditionally studied independently by different groups of researchers, who have proposed separate theories to explain results from each area. A recent extension of Shepard's rational theory of dimensional generalization allows an explanation of data from both areas within a single framework. However, the conceptualization of dimensional integrality in this theory (the direction hypothesis) is different from that favored by Shepard in his original theory (the correlation hypothesis). Here, we report two experiments that test differential predictions of these two notions of integrality. Each experiment takes a design from compound generalization and translates it into a design for dimensional generalization by replacing discrete stimulus components with dimensional values. Experiment 1 showed that an effect analogous to summation is found in dimensional generalization with separable dimensions, but the opposite effect is found with integral dimensions. Experiment 2 showed that the analogue of a biconditional discrimination is solved faster when stimuli vary in integral dimensions than when stimuli vary in separable dimensions. These results, which are analogous to more "non-linear" processing with integral than with separable dimensions, were predicted by the direction hypothesis, but not by the correlation hypothesis. This confirms the assumptions of the unified rational theory of stimulus generalization and reveals interesting links between compound and dimensional generalization phenomena.

1. Introduction

An important aspect of all forms of learning is generalization; that is, once we have learned something about the environment, to what extent do we generalize this knowledge to new situations, similar but not identical to the original learning events?

All fields in psychology dealing with learning and inference have explored one or more aspects of this problem. For example, *dimensional generalization*, or how learning about a stimulus is transferred to new stimuli that differ from the original along continuous dimensions, has been studied in animal instrumental conditioning (e.g., Blough, 1975; Guttman & Kalish, 1956; Soto & Wasserman, 2010; for a review of unidimensional generalization, see Ghirlanda & Enquist, 2003) and human identification and categorization (for reviews, see Nosofsky, 1992; Shepard, 1991). On the other hand, *compound generalization*, or how learning about one stimulus is transferred to new compounds comprising that stimulus, has been studied in Pavlovian conditioning (e.g., Myers, Vogel, Shin, & Wagner, 2001; Rescorla, 1997; Whitlow & Wagner, 1972) and human causal and contingency learning (e.g., Collins & Shanks, 2006; Glautier, 2004; Soto, Vogel, Castillo, & Wagner, 2009).

Unfortunately, these two lines of research have been pursued largely independently and researchers have shown little interest in developing a unified theoretical framework to understand both forms of generalization. Recently, Soto, Gershman, and Niv (2014) provided such unified framework by extending the rational theory of dimensional generalization (Shepard, 1987; Tenenbaum & Griffiths, 2001) to the explanation of compound generalization phenomena. In the following two sections, we briefly review this theory, some of the relevant data that it attempts to explain and the open issues addressed by the present work. We then describe two experiments that aim to answer two of those open questions:

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Why are some dimensions integral and others separable? Are the assumptions about integrality that are necessary to explain compound generalization also important to explain dimensional generalization?

1.1. Dimensional generalization and Shepard's rational theory

The most common basic result of a dimensional generalization experiment is that the response controlled by a stimulus orderly decreases as the value of the stimulus in one or more continuous dimensions is changed. An important insight in the study of dimensional generalization was the idea that re-scaling of stimulus dimensions to reveal "psychological dimensions" could lead to the discovery of fundamental principles of generalization and to stimulus representations that are useful for the study of other cognitive processes (for a review, see Nosofsky, 1992).

Indeed, two fundamental results about dimensional generalization have been found after such re-scaling. First, response probability decays as an exponential function of the psychological distance between a test stimulus and the original training stimulus (Shepard, 1965, 1987). Second, when stimuli are varied in two dimensions, the shape of the multidimensional generalization gradient varies depending on the exact dimensions under study (Cross, 1965; Shepard, 1987, 1991; Soto & Wasserman, 2010). Here the distinction between *separable* and *integral* dimensions becomes important (Garner, 1974; Shepard, 1991). Two dimensions are separable if it is possible to perceive or attend to only one dimension without attending to the other (e.g., size and orientation of a line). These dimensions produce diamond-shaped generalization gradients (see Fig. 1a), in which there is more generalization in the direction of the dimensions than in other directions of space. Diamond-shape gradients are equivalent to using a city-block metric to compute distances from coordinates in a spatial representation of the generalization data, such as that obtained from multidimensional scaling (MDS; Shepard, 1991). Two dimensions are integral if it is *not* possible to perceive or attend to only one dimension without attending to the other (e.g., saturation and brightness). These dimensions produce circular generalization gradients (see Fig. 1b), in which there is more or less the same generalization in any direction in the stimulus space. Circular gradients are equivalent to using an Euclidean metric to compute distances from coordinates in a spatial representation of the generalization data (Shepard, 1991).

Note that the fact that different sets of dimensions produce multidimensional generalization gradients with different shapes – or, equivalently, different metrics in a MDS representation – is an empirical result. The usual mechanistic explanation for this result is that different sets of dimensions interact differently during perception. Separable dimensions, but not integral dimensions, are processed independently and can be attended selectively (Garner, 1974).

A full account of generalization requires answering not only questions about mechanism, but also questions about function, such as: Why is the shape of unidimensional generalization gradients exponential instead of some other shape? Why do some dimensions seem to be processed separately and others integrally? Rational theories of cognition (Anderson, 1990) provide answers to such questions about function (Griffiths, Chater, Norris, & Pouget, 2012). Rational explanations propose hypotheses about what aspects of the task of generalization could have led, through adaptation, to the observable features of generalization behavior.

Shepard (1987) proposed a rational theory in which the properties of dimensional generalization are explained as resulting from probabilistic inference. The theory proposes that when an observer encounters a stimulus S1 followed by some significant

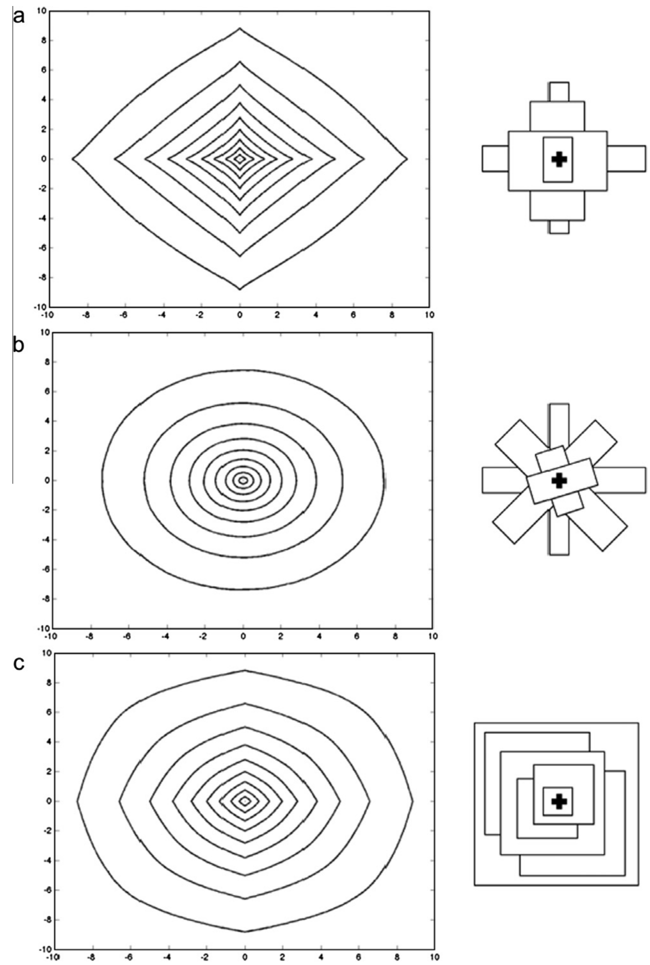

Fig. 1. Contour plots of multidimensional generalization gradients predicted by the consequential regions theory. The stimulus controlling a specific response is represented by the coordinates (0,0) and the scale in each axis represents distance from that stimulus along a specific perceptual dimension. Each line in a gradient represents the set of all points in the bidimensional space that have the same probability of generalization. These points of equal generalization probability assume the shape of a diamond for separable dimensions (a), and the shape of circles for integral dimensions using the direction hypothesis (b) and for integral dimensions using the correlation hypothesis (c). To the left of each gradient several examples of regions considered to evaluate the gradients are shown.

consequence, S1 is represented as a point in a psychological space.[1] The stimulus is assumed to be a member of a natural class associated with the consequence. This class occupies a region in the observer's psychological space, called a *consequential region*. The only information that the observer has about this consequential region is that it overlaps with S1 in psychological space. After observing a new stimulus, S2, the inferential problem is to determine the probability that S2 belongs to the same natural kind as S1—the same consequential region—thus leading to the same consequence. This probability can be obtained by "hypothesis averaging," by taking all possible

[1] There are two important points to clarify about Shepard's theory. First, when Shepard's first paper was published, Anderson's "rational" level (Anderson, 1990) had not yet been proposed. However, the most common interpretation of the theory is as a rational analysis of generalization (e.g., Soto et al., 2014; Tenenbaum & Griffiths, 2001). Second, despite being a rational analysis, the theory still makes representational assumptions that should be clearly separated from its assumptions about the generalization task (Fernbach & Sloman, 2011). The most important of these assumptions is that the observer represents stimuli as points in a psychological space. Importantly, explanations of generalization phenomena are a direct consequence of how the theory formalizes the inferential task of generalization, with the representational assumptions playing a minor role in such explanations.