Psychological Review
1989, Vol. 96, No. 1, 125–144

A Model of Perceptual Classification in Children and Adults

Linda B. Smith
Indiana University

The developmental trend from overall-similarity to dimensional-identity classifications is explained by a quantitative model. I begin with the assumption that objects are represented in terms of constituent dimensions and that the representation of objects changes little with development. Given this assumption, the model has three major parts. First, the similarity between objects is a function of the combination of the constituent dimensional differences. I propose developmental change in the likelihood that dimensions are differentially weighted in the calculation of similarity. Second, the perceived similarities between objects are valued for the purpose of constructing classifications. I propose that similarities are valued more dichotomously with age, such that identity becomes increasingly special. Third, the valued similarities are used to choose the best classification of those possible. The model provides good qualitative fits to the extant data. Three experiments examining classifications in 2- to 8-year-olds and in adults support specific new claims of the model. The data and the model provide new insights about development, classification, and similarity.

A classic controversy in the perception of multidimensional objects concerns the relation of the whole object to its constituent parts. When we perceive an object, say a cup, we perceive it both as a whole and as composed of constituent attributes—as being a unitary entity that is a particular color, size, and shape. By one classic view, it is the whole as a unit that is perceptually primary and the constituent attributes are only secondarily derived. By an alternative view, the attributes and parts are primary and the whole is built from them. Both characterizations can be argued to be right. The empirical evidence suggests that the primacy of the whole or parts depends on the particular level of processing, the particular task, and the particular stimulus parts (see, e.g., Kemler–Nelson, in press; Navon, 1977; Pomerantz, in press; Treisman, 1987). The primacy of wholes and parts also depends on the developmental level of the perceiver (see, e.g., E. J. Gibson, 1969; Werner, 1957). The traditional view is that objects are perceived as undifferentiated wholes early in development and are perceived as conjunctions of attributes, features, or dimensions later in development. The implications of this developmental trend for a theory of the perception of objects and their constituent attributes is unclear because exactly what changes with development and underlies the trend has not been specified. In this article, I propose a quantitative model that makes specific claims about what is and is not changing with development.

This research was supported by National Science Foundation Grant BNS 81-09888, National Institutes of Health Research Grant HD-19499, and National Institutes of Health Research Career Development Award HD-00589.

I thank Melanie Lockyear, Carol McCord, and Jennifer Staab for their assistance in data collection, Paul Evans for his contributions to my early thinking about the model, Robert Nosofsky for his many valuable discussions and comments on an earlier version of this article, and the Heatherwood Day Care Center and the Bloomington Developmental Learning Center.

Correspondence concerning this article should be addressed to Linda B. Smith, Department of Psychology, Indiana University, Bloomington, Indiana 47405.

From Overall Similarity to Dimensional Identity

I concentrate on children's classifications of multidimensional stimuli. The basic result, and one that has a long history in developmental psychology, is that older children spontaneously and easily classify objects by their sameness and difference on *single* dimensions, whereas children under the age of 6 or so do not (Denney, 1972; Inhelder & Piaget, 1964; Kofsky, 1966; Vygotsky, 1962). Given objects that vary, for example, in color, size, and shape, older children form such groups as red versus blue, big versus little, or square versus round. Young children, in contrast, do not classify by identity on single dimensions. Instead, young children spontaneously organize objects into groups by overall similarity (e.g., Kemler, 1983; Shepp, 1983; L. B. Smith & Kemler, 1977; Ward, 1980).

The specific classification task used to diagnose overall-similarity and dimensional-identity classifications was originally used by Handel and Imai (1972). This classification task is also one of the four converging operations defined by Garner (1974) to distinguish separable and integral dimensions. Separable dimensions (e.g., color–size) are dimensions that retain their perceptual independence when combined. Integral dimensions (e.g., saturation and brightness) form a single perceptual whole (color). Developmentalists (e.g., Shepp & Swartz, 1976; L. B. Smith & Kemler, 1977) borrowed this task specifically to test the hypothesis that young children's so-called *holistic* perceptions were like adult's perception of integral variation. Figure 1 illustrates schematically the structure of the stimulus sets. The three objects in the set may be described in two ways: First, by the dimensional description, Objects A and B are identical on Dimension x and different on Dimension y and both Objects A and B differ from Object C on both dimensions. Second, by the overall-similarity description, Objects B and C are very much alike (close to each other) and very different from Object A (far from Object C).

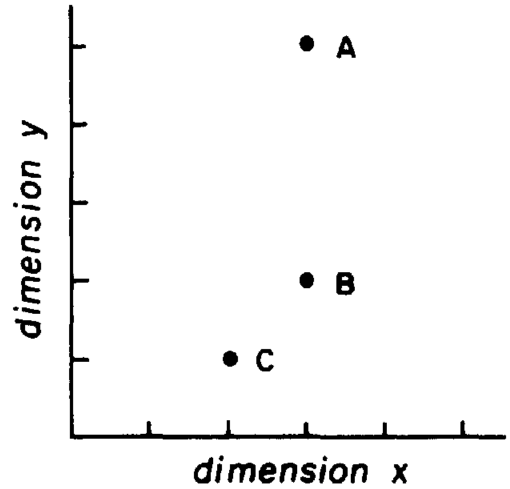

Figure 1. Schematic illustration of the structure of a triad used to diagnose overall-similarity (BC vs. A) and dimensional-identity (AB vs. C) classifications. (Individual Objects A, B, and C are represented in terms of their coordinates on two varying dimensions.)

In general, when adults are given objects that vary on separable dimensions such as color and size, they classify in accord with the dimensional description; they group together the objects (A and B) that are identical on a dimension. When adults are given objects that vary on integral dimensions, such as saturation and brightness, they classify in accord with the overall-similarity description, and they group together the objects (B and C) that are closest in the multidimensional space (see, e.g., Garner, 1974). When young children are given objects that vary on adult separable dimensions, they classify by overall similarity the same way that adults classify objects varying on integral dimensions (e.g., L. B. Smith & Kemler, 1977). It is specifically this trend from overall-similarity to dimensional-identity classifications that is addressed in this article.

The idea that young children's perceptions are "integral-like" (see Kemler-Nelson, in press) is also supported by performances in speeded classification tasks. In such reaction-time tasks, young children's performances with adult separable dimensions pattern like adult performances with integral dimensions: Speeded judgments of one dimension are interfered with by orthogonal variation on the second dimension but are benefited by redundant variation. In contrast, adult's and older children's speeded judgments with separable dimensions show no (measurable) interference effect or redundancy gain (see, Garner, 1974; Kemler & Smith, 1978; Shepp & Swartz, 1976; L. B. Smith, 1980). If we take the free and speeded classification results at face value, they seem to suggest a qualitative shift from integral-like to separable-like perception (see, Kemler, 1983; Shepp, Burns, & McDonough, 1980), from holistic dimensionless percepts structured by overall-similarity relations to differentiated percepts structured by relations on dimensions.

I question this proposed qualitative shift in perception. First, older preschool children can, under certain task conditions, classify objects by their identity on a single dimension (Caron, 1969; Odom, 1978; L. B. Smith, 1983, 1984; L. B. Smith & Kemler, 1978; Wilkening & Lange, 1987). Dimensional-identity classifications occur when there are no time limits on performance, the task and stimuli are simple, and the task requirement of selective attention is clear (see L. B. Smith, in press). Second, adults sometimes produce overall-similarity classifications when the varying dimensions are separable. They do so when the objects to be classified are relatively complex or when there are time constraints (J. D. Smith & Kemler-Nelson, 1984; L. B. Smith, 1981; Ward, 1983). Thus, both young children and adults sometimes classify by overall similarity and sometimes by identity on a single dimension. For both children and adults, time and task complexity appear to be critical determiners of which relation is used. The developmental difference is that young children are more likely to classify by overall similarity and adults are more likely to classify by dimensional identity. The difference is thus quantitative, not qualitative.

The goal of the present work is to construct a unified model that accounts for the developmental trend from overall-similarity to dimensional-identity classifications with the least amount of developmental change. In this effort, I concentrate on children's and adults' nonspeeded classifications of stimuli varying on (adult) separable dimensions.

I propose that what develops is (a) increased selective attention to single dimensions when comparing objects and (b) the treatment of identity as a special kind of similarity. These two areas of growth are suggested by the classification task. Given a stimulus set structured as depicted in Figure 1, the overall-similarity classification and the dimensional-identity classification differ, objectively, in two ways. One difference involves the number of dimensions contributing to similarity. In the overall-similarity classification, the objects grouped together are similar on both varying dimensions. In the dimensional-identity classification, the objects grouped together are similar on only one dimension. The second difference between the overall-similarity classification and the dimensional-identity classification involves the kind of similarity. In the overall-similarity classification, the objects grouped together are just similar. In the dimensional-identity classification, the objects are not just similar; rather, they are identical on one dimension. The two factors—numbers of dimensions attended and kind of similarity (similarity vs. identity)—are othogonal, as depicted in Figure 2. One can attend to both dimensions and classify by similarity (overall similarity) or by identity (absolute identity). Or one can attend selectively to a single dimension and classify by similarity (dimensional similarity) or by identity (dimensional identity).

Both factors may be intimately involved in the developmental trend. Much evidence, including reaction-time studies, documents an increased ability to attend to single dimensions of variation while ignoring others (see, e.g., Kemler & Smith, 1978; Shepp & Swartz, 1976). The specialness of identity relations in category formation is also suggested by a growing number of studies (Evans & Smith, 1988; Keil & Batterman, 1984). The present proposal is that selective attention and the specialness of identity are all that develop in perceptual classification. I will show that quantitative changes in selective attention to single dimensions and in the differentiation of identity as a special degree of similarity are sufficient to account for the developmental trend from overall-similarity to dimensional-identity classifications.

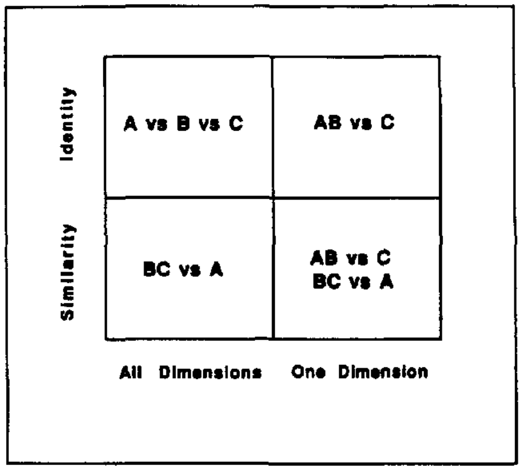

Figure 2. A 2 × 2 characterization of possible classifications of the triad illustrated in Figure 1.

The Weighted-Dimensions Plus Identity Model

The model consists of four major parts. First is an assumption about representation. Second is the calculation of similarity between represented objects. Third is the valuing of degrees of similarity and the differentiation of identity from similarity. Fourth is a rule for choosing the best classification given the valued similarities between objects.

An Assumption About Representation

I assume that represented objects are built in a bottom-up fashion from a feature level of processing, and I assume that objects are represented in terms of features and attributes. These assumptions stem directly from extant work on object perception (see Treisman, 1987, for a review) and are illustrated in Figure 3. However, I also assume that the represented object is a cohesive unit and is experienced as a unit. Represented objects as wholes are given to conscious experience as unitary entities, so that one cannot get to the represented parts (i.e., inside the parentheses in Figure 3) without some work. Moreover, I assume that objects are represented in terms of constituent parts but are given to conscious experience as wholes throughout development.

Calculating the Perceived Similarities

The whole is primary at the level of immediate experience because the whole object is the unit of comparison. One cannot compare one disembodied size to another; rather, one compares the size of one perceptually unitary object to the size of another perceptually unitary object. Attributes are never, at the level of experience, disembodied from the represented object.

These ideas are captured in the model's treatment of similarity. Similarity is a unitary measure of likeness between whole objects and is always calculated across all dimensions. Similarity does not therefore, in and of itself, provide information about single dimensions. However, as formalized by Nosofsky (1984, 1986), dimensions can be differentially weighted. And similarity can provide information about sameness on a single dimension if that dimension is weighted to the exclusion of all others. Within the model, the extreme differential weighting of dimensions is the only means through which the subject can experience separate dimensions of similarity. I propose further that the extreme differential weighting of dimensions requires attention. Thus, dimensionally nonspecific percepts of similarity that combine the similarities across many dimensions are cognitively less demanding than percepts of separate similarities on separate dimensions.

Following Nosofsky (1984) and Shepard (1987), similarity is calculated via an exponential decay function of the distance between stimuli in psychological space. The similarity between two objects O_i and O_j, then, is

$$S_{ij} = e^{-d_{ij}}. \quad (1)$$

The present concern is only with separable stimuli; thus, a city-block metric is used and distance is defined as the sum of the weighted dimensional differences

$$d_{ij} = \sum_{k=1}^{N} W_k |O_{ik} - O_{jk}| , \quad (2)$$

where $O_{ik} - O_{jk}$ is the difference between Objects i and j on Dimension k, N is the number of dimensions, W_k is the weight given dimension k, and $0 \leq w_k \leq 1.00$ and $\sum_{k=1}^{N} w_k = 1.00$.

The critical claims are that similarity is calculated across all dimensions and that the (extreme) differential weighting of one dimension to the exclusion of others requires attention. The cognitively simplest or default comparison given no intervention is one in which all varying dimensions enter (more or less) equally in the calculation of similarity. More overall-similarity classifications by young children than adults are thus expected. Young children are less able and less likely to differentially weight dimensions because differential weighting requires capacity. Furthermore, even when young children have the available resources and sufficient time to differentially weight specific dimensions when comparing objects, they may fail to do so because they do not appreciate the usefulness of such a strategy.

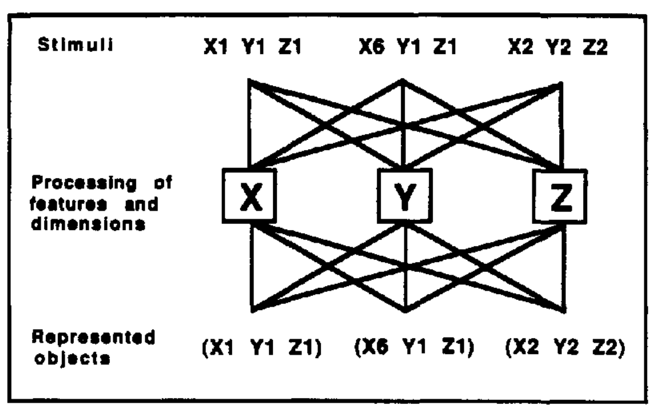

Figure 3. The building of represented whole objects from the prior processing of separate dimensions.

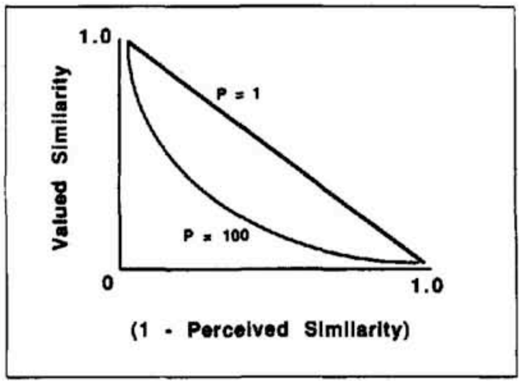

Figure 4. Valued similarity as a function of perceived difference for two levels of *P*.

The Valuation of Perceived Similarity

In classification tasks, the perceived similarities are used to form classifications. I suggest that younger classifiers take similarity just as it is—as a matter of degree. Objects are more and less similar to each other, and good classifications are ones in which highly similar objects are grouped together. I suggest, in contrast, that mature classifiers treat similarity dichotomously. Objects are the *same* and worthy of being classified together if their calculated similarity is close to 1 (i.e., identity); objects are *different* and not worthy of being grouped together otherwise. I suggest that older classifiers bother to selectively attend to single dimensions when classifying because they seek a particular degree of similarity—identity. Identity is rarely found on all dimensions at once. Thus, older classifiers selectively attend in order to find part identities; they differentially weight dimensions in order to maximize the value of the perceived similarity (see Estes, 1986; Nosofsky, 1984, 1986, for similar suggestions).

These claims are modeled by the calculation of *valued similarity.* The notion is that the perceived similarities are valued by the subject for the purpose of classifying. Specifically, the valued similarity of O_i and O_j is a power function of their perceived similarity, that is

$$V_{ij} = S_{ij}^{P}, \qquad (3)$$

where $o < p < \infty$. Figure 4 shows valued similarity as a function of perceived similarity for $P = 1$ and $P = 100$. When $P = 1$, the valued similarity is just the perceived similarity. I suggest that this function best describes young children's use of similarity in classification tasks. When P is high, the perceived similarities are sharply demarcated into two categories, so that only similarities at or close to 1 are highly valued. I suggest that this function describes mature classifiers' use of similarity. The use of a power function implies continuous, rather than all-or-none, growth in the valuing of similarity. This treatment and the implication of a continuous increase with development in the valuation of degree of similarity was suggested by empirical evidence.

The Goodness of a Classification

The valued similarities are used to form classifications. It is expected that subjects try to produce a "good" classification. Most models of classification use some sort of ratio rule to determine how good a classification is (e.g., Lockhead, in press; Medin & Schaffer, 1978; Nosofsky, 1986). In such approaches, an absolute level of similarity is not required to form a group; instead, the most similar objects of those present are grouped together. I suspect, as illustrated in Figure 5, that the absolute magnitude of similarity does matter. Set 1 shows three objects that are readily classifiable (AB vs. C). Sets 2 and 3 seem not so readily divisible. In Set 2, the objects seem too similar to partition into separate groups. In Set 3, the similarities between any pair of objects seem too low to form a group. These examples suggest that the absolute level of similarity matters. In making predictions, the absolute level of similarity is taken into account by considering a classifications' goodness relative to all possible classifications, including the grouping of all objects together in one group and the grouping of each object singly.

More precisely, the goodness of a classification is defined as equal to the product of the valued similarities of the objects classified together, and the reciprocal of the valued similarities of the objects classified apart. As shown in Table 1, G(AB, C), the goodness of the classification AB versus C, is equal to the product of valued similarity of AB, the objects grouped together, and the valued *dis*similarity (i.e., 1 minus the valued similarity) of AC and BC, the objects grouped apart. That is,

$$G(AB \text{ vs } C) = V_{AB} \times (1 - V_{AC}) \times (1 - V_{BC}). \qquad (4)$$

The equations for the goodnesses of all other possible classifications of the triad, including the case of classifying all three objects together and the case of classifying all three objects apart are also given in Table 1. The sum of the goodnesses is 1.0. This measure of goodness picks the best classification of a set and includes as a possible best classification the cases of all objects being too similar to separate into groups and the case of all objects being too dissimilar to group any of them together. The particular set of formulas for calculating goodness given in Table 1 are used heuristically. By this procedure, groups of more than two objects (i.e., ABC) are formed by single links between objects (or chaining) and not complete links. However, no claims are being made, at present, about the processes that un-

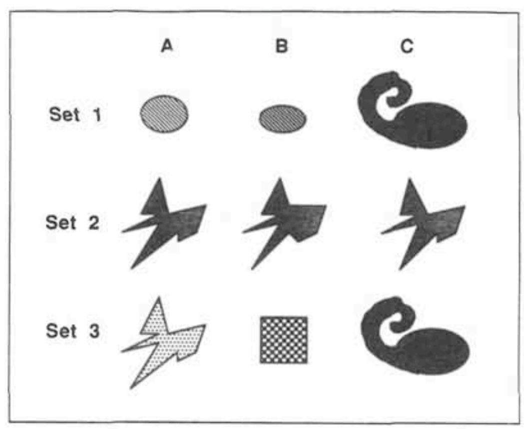

Figure 5. Three sets of objects (1, 2, and 3) that differ in how easily they can be divided into a group of two versus a group of one.

Table 1
Equations for Computing the Goodnesses of all Classifications of a Set of Three Objects

Equation
(1) $G(AB \text{ vs. } C) = V_{AB} \times (1 - V_{BC}) \times (1 - V_{AC})$
(2) $G(BC \text{ vs. } A) = V_{BC} \times (1 - V_{AB}) \times (1 - V_{AC})$
(3) $G(AC \text{ vs. } B) = V_{AC} \times (1 - V_{AB}) \times (1 - V_{BC})$
(4) $G(A \text{ vs. } B \text{ vs. } C) = (1 - V_{AB}) \times (1 - V_{BC}) \times (1 - V_{AC})$
(5) $G(ABC) = [V_{AB} \times V_{BC} \times (1 - V_{AC})] + [V_{AB} \times V_{AC} \times (1 - V_{AC})] + [V_{AC} \times V_{BC} \times (1 - V_{AB})] + [V_{AB} \times V_{AC} \times V_{BC}]$

Note. V_{AB} is the Valued similarity of objects A and B.

derlie the formation of classes. The distinction between single link and complete links does not matter for the small stimulus sets that are the present concern.[1]

The Input to the Model

The final component to the quantitative model concerns the description of stimulus objects. Given some set of objects to be classified, say, various sized circles of several shades of blue, structured as shown in Figure 1, what is input to the model as a description of the stimulus objects and their relations to each other? The usual solution to this problem is to obtain similarity judgments and use multidimensional scaling techniques to obtain direct estimates of the psychological distances as descriptors of stimulus sets. There are considerable difficulties in using this method in developmental work. The most critical problem is the possibility of developmental differences in the task (e.g., similarity ratings, memory confusions) used to measure similarity. Such tasks are unlikely to be immune to developmental differences in the differential weighting of dimensions (see Nosofsky, 1984, 1986; Shepard, 1964) and, perhaps, in the valuing of identity relations. In other words, the present model might well be required to explain developmental differences in multidimensional scaling solutions.

In light of these reservations, no attempt is made to precisely specify the distances in a stimulus set. Instead, predictions are made given the relative similarities in a set across absolute magnitudes of difference that vary from not discriminable to vastly different. More precisely, given a triad of objects to be classified such as those shown in Figure 1, the input to the model is a specification of which objects share a value on which dimensions and a set of ratios of the distances between pairs of objects. All of the predictions reported in this article are based on a 2:1 ratio of the distances (given equal dimensional weights) of the AB (dimensional identity) to BC (overall similarity) pairs. Predictions do not vary greatly with changes in the ratio used (from 4:1 to 1.5:1) as long as the BC distance is smaller than the AB distance (see Figure 1).[2] Given a specification of the ratio of distances between pairs of objects and a specification of which objects share values on the specific dimensions, all distances are set at zero and then increased incrementally until the perceived similarity, given equal weighting of all dimensions, is close to zero. The effects of various dimensional weights and valuing powers on the goodness of the possible classifications are examined over this range of distances.

The output of the model is therefore a set of curves of the goodness of various classifications over a range of magnitudes of stimulus difference. Because one cannot know precisely where any stimulus triad falls on these curves, the predictions concern the goodnesses of various classifications relative to each other (i.e., AB vs. C, as compared with AC vs. B) and changes in the relative goodness of particular classifications with changes in the magnitudes of stimulus difference. The goodness of a classification should not be interpreted as its expected frequency. I assume only that goodness is directly and monotonically related to frequency. Precise predictions of frequency require an objective measure of stimulus distance that is unaffected by possible developmental differences in the weighting of dimensions and the valuing of identity. Furthermore, a number of biases may intervene between goodness and the actual selection of a classification. For example, if the goodness of an ABC (all together) classification and an AB versus C classification were equivalent, would subjects be equally likely to form both kinds of groups? The evidence suggests that adults would not (Imai, 1966; Imai & Garner, 1968). Without estimates of such biases across developmental levels, quantitative fits are not possible. Accordingly, the critical predictions are about qualitative patterns of classification across different classification sets.

Summary

There are four conceptual claims embodied in the model. First, at all developmental levels, objects are represented and compared in terms of their constituent separable dimensions. Second, there is a developmental increase in the tendency and ability to differentially weight the constituent dimensions when comparing objects. Third, there is a developmental change in the valuation of degree of similarity so that identity becomes an increasingly special kind of similarity. Fourth, and a direct implication of the third claim, classifications have particular goodnesses; in classifying, it is not simply a matter of which objects are most similar, their absolute similarity also matters.

Predictions From the Model

The Developmental Trend

I propose two developing tendencies: increased differential weighting of dimensions and increased valuing of similarities at or close to identity. If we dichotomize each of these proposed

[1] The distinction between single-link and complete-link classification is critical for modeling the classification of large sets. With large sets, a requirement for complete links leads to many small (two and three object) rather than large categories, whereas a single-link requirement leads to very few groups, or to one group, with many members. I suspect that neither process alone adequately characterizes mature classifications of large sets. A more complicated metric may be required that evaluates number of links.

[2] As would be expected, higher ratios result in relatively more BC to AB pairings, but the shapes of the curves and the relations between them as a function of stimulus difference do not vary qualitatively.

developmental trends into (a) equal weighting of all dimensions versus selective attention to one dimension and (b) no valuing of identity versus a high valuing of identity, we may form the 2×2 table of Figure 2. In this section, the predictions from the model are considered for these four cases, which represent the two developmentally varying parameters, the dimension weights (w_i), and the power (P) of the valuing function at their limits. Intermediate cases are considered later.

Figure 6 shows the predicted goodnesses for the possible classifications of the triad depicted in Figure 1 for the cases of (a) equal weighting ($w_x = .50$), nonvaluing of identity ($P = 1$); (b) equal weighting ($w_x = .50$), valuing of identity ($P = 100$); (c) selective attention ($w_x = .001$ and $w_x = .999$), nonvaluing of identity ($P = 1$); and (d) selective attention ($w_x = .001$ and $w_x = .999$), valuing of identity ($P = 100$). What is illustrated in each panel is the predicted goodnesses as a function of the magnitude of stimulus differences from not discriminable to very different. Thus, in each panel, the classification in which all objects are grouped together (ABC) is expected to be good at the lowest levels of stimulus difference and there is some tendency, depending on the combination of weighting and valuing power, for the classification in which all objects are grouped singly (A vs. B vs. C) to be good at the extreme of differences. Because any particular classification of the items described in Figure 1 could result from any combination of weights and valuing power, I will describe individual classifications in terms of the grouping of reference objects in Figure 1 (e.g., AB vs. C, BC vs. A) and not in terms of their usual interpreted description (e.g., the overall-similarity classification or the dimensional-identity classification). The label *overall-similarity classification* is reserved for a BC versus A classification that results from distributed weighting and a nonvaluing of identity. The label *dimensional-identity classification* is reserved for an AB versus C classification that results from selective attention and a valuing of identity.

I will begin with Cases 1 and 4 as shown in Figure 6, because by hypothesis these correspond to the cases of the young child and the adult.

The young child: $w_x = .50$, $P = 1$. By my view, Panel 1 of Figure 6 describes the young child: equal weighting of the varying dimensions and no special treatment of similarities close to identity. If this description of the young child and the model are correct, then young children should produce the BC versus A classification across the midrange of stimulus differences and these overall-similarity classifications should always be more frequent than AB versus C or AC versus B classifications. Furthermore, there should be some tendency on the part of young children to classify all objects together at low magnitudes of difference and to classify all objects apart when they are, overall, extremely different. The BC versus A or overall-similarity classification is good only in the midranges of stimulus variation. Thus, BC versus A classifications ought to exhibit some fragility under expansions and shrinkings of the differences within the classification set.[3]

The adult: $w_x = .999$, $P = 100$. Panel 4 of Figure 6 illustrates the case descriptive of mature classifiers who both selectively attend to single dimensions and value identity. I assume that in constructing a classification, older classifiers first attend to one dimension, then the other, and then classify by the dimension that yields the classification with the highest goodness. Accordingly, two sets of curves are shown: the expected goodnesses given selective attention to Dimension x ($w_x = .999$) and the expected goodnesses given selective attention to Dimension y ($w_x = .001$). Given the triad depicted in Figure 1, adults should selectively attend to Dimension x and produce the AB versus C or dimensional-identity classification across a wide range of magnitudes of difference. As shown in Figure 6, however, the AB versus C classification may give way to classifying each object singly at extreme magnitudes of stimulus difference. This decline at extreme differences is expected only if selective attention is not perfect. If selective attention is perfect (i.e., $w_x = 1.00$) then the AB versus C or dimensional-identity classification is expected across the entire range. I discuss more fully the implications of imperfect selective attention in a subsequent section.

Selective attention without the valuing of identity ($w_i = .999$, $P = 1$). Panel 3 of Figure 6 illustrates the possibility of classifying by a single dimension but without any special valuing of identity. These are classifications by one-dimensional similarity. In this case, the best classification sometimes results from selective attention to Dimension x and sometimes from selective attention to Dimension y. In other words, subjects should sometimes produce what look like classifications by dimensional identity and what sometimes look like classifications by overall similarity, although in both cases, subjects are classifying by similarity on a single dimension. According to the model, which dimension is attended to and which classification, AB versus C or BC versus A, has the higher goodness depends on the magnitude of stimulus difference. At low levels of stimulus difference, selective attention to Dimension y yields the best classification and the BC versus A classification should predominate. At higher magnitudes of stimulus difference, selective attention to Dimension x yields the best classification and the AB versus C classifications should predominate.

This case of selective attention without the valuing of identity does not clearly fit any set of extant data. Nonetheless, it is an important possibility. First, although magnitude of stimulus difference has not been systematically considered in theorizing about the categorization of multidimensional stimuli (see Shepard, 1986), there are hints in the literature that it matters. Specifically, young children (and adults) are more likely to produce AB versus C (or what look like dimensional-identity) classifications when the stimulus differences are large (Kemler & Smith, 1978; L. B. Smith, 1979, 1983), just as would be expected if they attend selectively to single dimensions but do not value identity.

A second reason for the importance of selective attention without the special valuing of identity concerns Aschkenasy and Odom's (1982) criticism of the hypothesized trend from holistic overall similarity classifications to analytic dimensional classifications. They suggest that both older and younger children selectively attend to single dimensions, but that young children consistently attend to Dimension y, the dimension of largest

[3] These predictions about the effects of magnitude of difference are all tempered by the measurement uncertainties. We do not know precisely how wide an area of the x-axis corresponds to any particular range of stimulus differences.

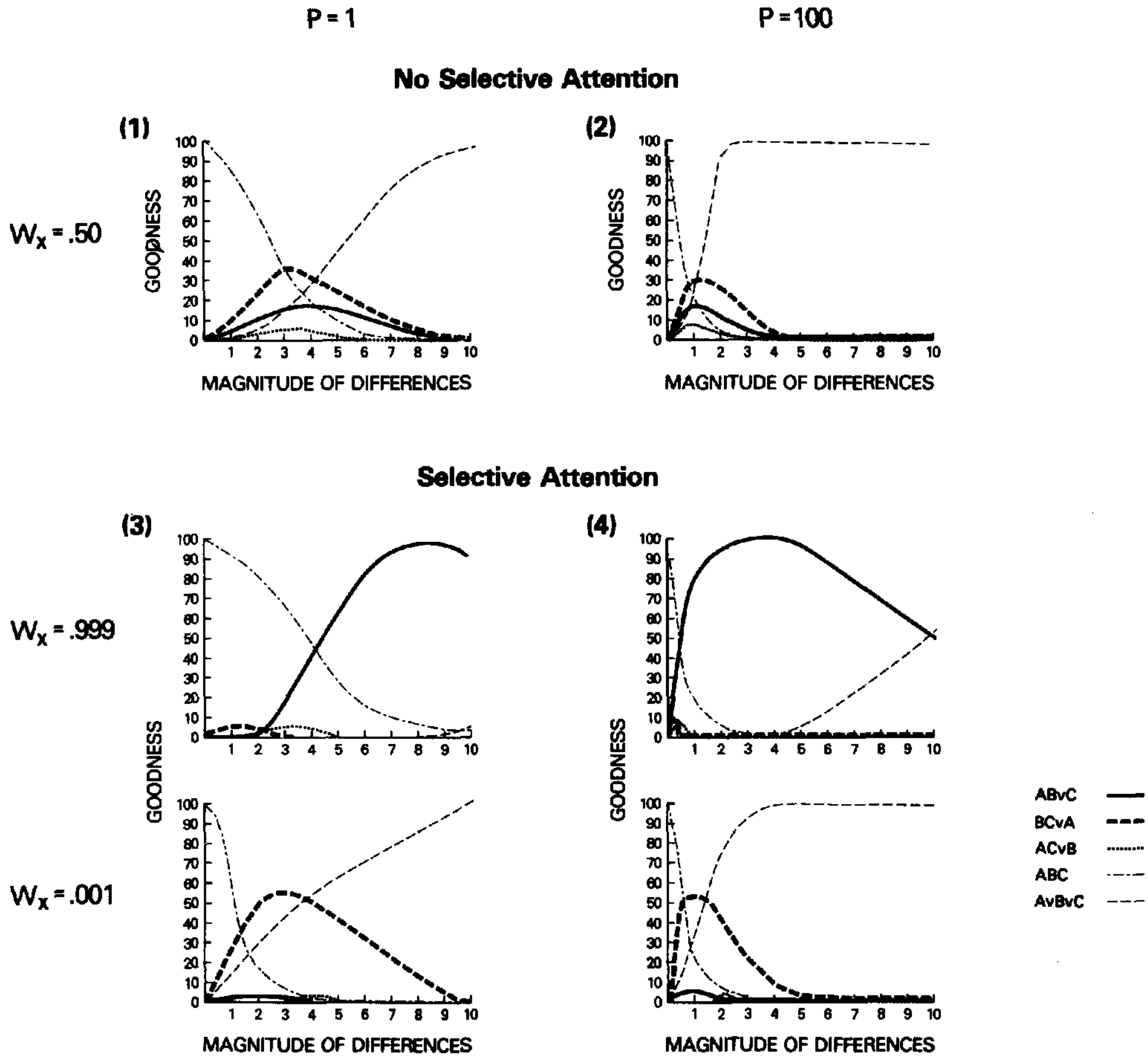

Figure 6. Predicted goodnesses of classification for four cases resulting from various combinations of dimensional weights (w_x) and powers (P) of the valuing function.

difference. The developmental trend, thus, may be from one kind of dimensional classification to another—from dimensional similarity to dimensional identity. This possibility of selective attention without the valuing of identity highlights the need to make precise claims about the developmental trend. Virtually all studies to date have used classification sets structured as in Figure 1 without systematic variation in the magnitudes of stimulus difference.

Nonselective attention and the valuing of identity. Panel 2 of Figure 6 illustrates the futility of the final combination of factors—nonselective attention but a high valuing of identity relations. Given the standard classification set as illustrated in Figure 1, in which the only identity relations are part identities, there is no classification of the items possible except grouping each object singly. This combination of factors, nonselective attention, and the valuing of identity would lead to groups of objects if the classification set contained objects that were absolutely identical to each other.

Interrelations Between the Three Parameters

As Figure 6 makes clear, the best classification depends on the two developmentally varying parameters, the distribution of dimension weights and the valuing power, and a third stimulus parameter, the magnitude of stimulus differences. This third stimulus parameter interacts importantly with the two psychological ones in determining the goodness of a classification. Before considering empirical evidence, I briefly consider interrelations between the parameters.

Magnitude of stimulus difference and the valuing of identity. The principal effect of a high valuing of identity is a magnification of stimulus differences. When identity is highly valued,

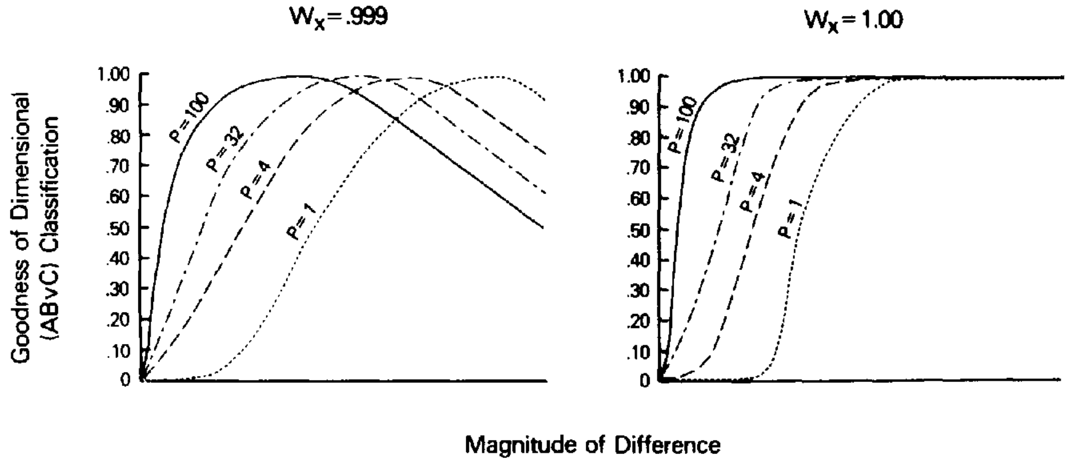

Figure 7. Predicted goodnesses of the AB versus C classification as the power (P) of the valuing function increases for near-perfect ($w_x = .999$) and perfect ($w_x = 1.00$) selective attention to Dimension x.

even small stimulus differences count a great deal in the determination of classification goodness. Figure 7 shows this magnifying effect: Increasing P squishes the curves leftward. Thus, within the model, an increased valuing of identity mimics an increase in the magnitude of stimulus differences at stimulus differences that are not close to zero.

Magnitude of stimulus difference and imperfect selective attention. Figure 8 shows the goodness of the dimensional-identity classification without and with a high valuing of identity at varying degrees of selective attention to Dimension x, the dimension affording the dimensional-identity classification. As is evident in Figure 8, the dimensional-identity classification requires virtually perfect selective attention to the appropriate dimension. The reason for this is that there is a similarity advantage of the AB pair over the BC pair only if the considerable difference between A and B on Dimension y makes no contribution to the calculated similarity. Thus, if subjects do not value identity, they should produce the AB versus C classification only at large stimulus differences and only then if they weight Dimension x to the virtual exclusion of Dimension y. If subjects place a high value on identity, they should produce the AB versus C classification across the full range of stimulus dimensions if they selectively attend perfectly to one dimension. If selective attention is merely near perfect (e.g., $W_x = .999$), then dimensional-identity classifications should decline at extreme magnitudes of stimulus difference.

If selective attention is imperfect (e.g., $w_x = .70$) rather than near perfect, the classification with the highest goodness depends on the degree to which identity is valued. If identity is highly valued, then classifying each object in a group by itself is the best grouping. Given imperfect selective attention and the criterion of identity, all three objects are simply different. If identity is not valued, then the BC versus A classification should dominate. This fact is illustrated in Figure 9, which shows the goodness of the AB versus C (dimensional-identity) and BC versus A (overall-similarity) classifications, given a weighting differential of .70/.30 for the two dimensions and $P = 1$. The advantage of the BC versus A over the AB versus C classification stems from there being two weighting routes to the BC versus A classification and only one for the AB versus C classification. If one imperfectly attends to Dimension x, $w_x = .70$, the AB versus C classification is only slightly better than the BC versus A classification across a range of stimulus differences. If one imperfectly attends to Dimension y, $w_x = .30$, which might be expected half of the time, the BC versus A classification is the only good classification.

The fact in the model that the BC versus A or ostensive overall-similarity classification is expected, given imperfect selective attention and the nonvaluing of identity, is important. Young children's so-called overall-similarity classifications need not mean that young children attend to all dimensions equally. Children may well attempt to compare objects on one dimension at a time but be unable to do so perfectly. Individual dimensions may differ in their intrinsic salience (Odom, 1978) but not to such a degree that one dimension is weighted to the exclusion of all others. Overall-similarity classifications or more technically, BC versus A classifications, then, ought not to be taken as indicating equal attention to both dimensions, but rather as indicating some attention to both dimensions. *Some attention to both dimensions* will be what I mean by nonselective attention and will be the most I infer from overall-similarity classifications through the remainder of this article.

Three Experiments

Experiment 1: Magnitude of Stimulus Difference

As Figure 6 makes clear, the best classification depends on the distribution of dimension weights, the value placed on identity, and the absolute magnitudes of difference between the objects to be classified. It is the pattern of performance across a range of stimulus differences that allows one to distinguish between particular combinations of dimension weights and valuing of identity. However, there is no evidence in the literature on classification performance across a range of stimulus differences. Accordingly, I report here a free classification experiment in which children from 2 to 8 years of age and adults classified sets that varied widely in the magnitudes of stimulus differences within the sets.

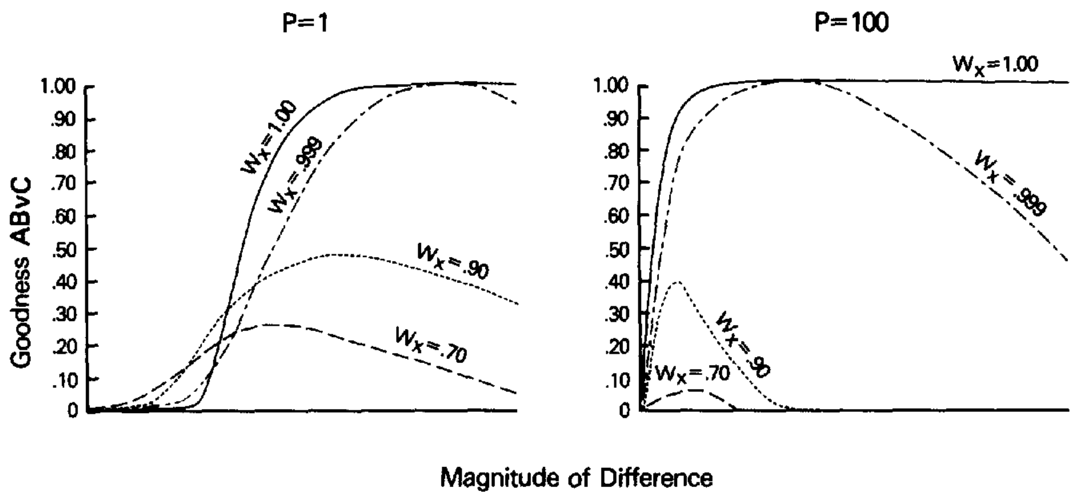

Figure 8. Goodness of the AB versus C classification at P = 1 and P = 100 at varying degrees of selective attention.

Method

Subjects. A total of 10 children at each of five age levels participated: 2-year-olds (*M* age = 2 years 7 months; range = 2 years 3 months to 2 years 10 months), 3-year-olds (*M* age = 3 years 6 months; range = 3 years 1 month to 3 years 10 months), 4-year-olds (*M* age = 4 years 7 months; range = 4 years 1 month to 4 years 10 months), 5-year-olds (*M* age = 5 years 5 months; range = 5 years 1 month to 5 years 10 months), and 8-year-olds (*M* age = 8 years 1 month; range = 7 years 6 months to 9 years 1 month). A total of 10 undergraduates also participated. Equal numbers of males and females participated in each group. The children were tested individually at their day-care or after-school programs. The undergraduates were tested individually in the laboratory and received course credit for their participation.

Stimuli. The stimulus objects were circles varying in color and size and mounted on 13-cm × 20-cm (5 in. × 8 in.) cards. These objects were organized into triads. There were six triads of each of the three types, as shown in Figure 10. For each type, Dimension *x* was color for half of the triads.

The triads were constructed by first selecting values for the standard triads shown in the middle panel. The values on the two dimensions used for these triads are identical to values used in other free classification experiments (L. B. Smith, 1983), and the magnitudes of difference are typical of those used in the literature. More specifically, the color and size values were chosen from magnitude estimations of difference of single-dimensional differences given by four undergraduates, so that all one-step, single-dimensional differences were comparable, and so that the sum of the differences on the two dimensions for Objects A and B was more than for Objects B and C. Furthermore, all one-dimensional, one-step differences were highly discriminable to children, as measured in an oddity task (AAX) in which 7 preschoolers (ages: 2 years 6 months, 2 years 8 months, 2 years 10 months, 3 years 0 months, 3 years 6 months, 3 years 7 months, and 4 years 0 months) participated. In this oddity task, each of the eight possible one-step differences (four on each dimension) was detected at least six out of eight times by each subject. The specific colors and sizes selected in this way were shades of green that varied from a pale green to a deep forest green. Coloraid notation was (a) YG-T_4, (b) YG-T_2, (c) GYG-T_1, (d) GYG-H, and (e) G-S_3. The diameters of the circles were (a) 3.25 cm, (b) 4.00 cm, (c) 4.75 cm, (d) 5.75 cm, and (e) 6.75 cm.

The six discriminable triads were constructed by adding new values that fell between the standard values 1 and 2 and between the values 4 and 5. These were (value 1.5) YG-T_3 and (value 4.5) G-H and for size (value 1.5) 3.5 cm and (value 4.5) 6.25 cm. The discriminable triad was

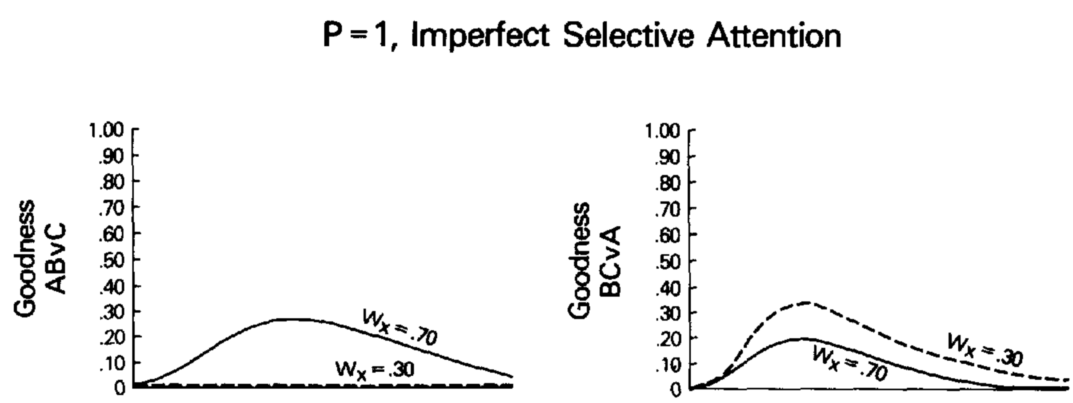

Figure 9. Goodness of the AB versus C and BC versus A classifications when one dimension is weighted more heavily than the other.

structured as shown in Figure 10, such that the AB difference was two steps on one dimension and the BC difference was a half step on each dimension. These half-step differences on each dimension alone were just discriminable to the 7 preschoolers who participated in the oddity task. The proportion of successful detection of the odd object when it differed by a half step on one dimension ranged from .54 to .64 for individual pairs and individual children (chance = .33).

The extreme set was constructed by adding a new value on each dimension that differed greatly from the values of the standard set. The new color was pink (RVR-T_4), and the new size was 9 cm. All triads of the extreme type were structured as shown in Figure 10 so that Objects A and B differed maximally on size or color (i.e., values YG-T_4 vs. RVR-T_4, or values 3.25 cm vs. 9 cm) and so that Objects B and C differed by four steps on each dimension. Note that the overall-similarity pair (BC) differs by more in the extreme set than does the dimensional-identity pair (AB) in the standard set. There are only four unique extreme triads possible (two with Dimension x equal to color; two with Dimension x equal to size). The four unique triads plus the replication of two of them (one with Dimension x equal to size) composed the six sets of this type.

The 18 experimental triads, 6 of each type, were arranged into one of two random orders for presentation to subjects. Three additional triads of stimuli were constructed in order to instruct subjects as to the task. These instruction sets consisted of pictures of objects mounted on 10-cm × 15-cm (4 in. × 6 in.) cards, and were structured as follows: (a) three identical red kites, (b) two identical yellow butterflies and one blue house, and (c) a red kite, a yellow butterfly, and blue house. The purpose of these sets was to convey to subjects the aim of grouping like objects and the acceptability of all possible kinds of groupings—three objects all together, two versus one, or each object singly.

Procedure. Subjects were told that they would be shown pictures and that they were to group together the "ones that go together." They were then given the instruction sets, one at a time, to classify. The three objects within a set were haphazardly laid out on the table, and the subject was again told to "make groups, put together the ones that go together." If a subject did not produce the absolute identity sort of any instruction set, that subject was shown the correct classification. Classification of the instruction sets was repeated until all sets were classified correctly. This was accomplished in three passes, save for two 2-year-olds who did not participate in the study and were replaced. After classification of the instruction sets, the 18 experimental sets were classified one at a time.

Results and Discussion

Figure 11 shows the proportions of BC versus A, AB versus C, one-group classifications (ABC), and classifications of each object singly (A vs. B vs. C). The kind of classification depended critically on the age of the subject and the magnitude of stimulus difference within the triad. Two separate analyses of variance (ANOVAS), one on the number of BC versus A classifications and one on the number of AB versus C classifications, revealed reliable main effects of age with the BC versus A classification decreasing with age, $F(5, 54) = 46.91$, $p < .001$, and the AB versus C classification increasing with age, $F(5, 54) = 55.99$, $p < .001$. Both also revealed reliable Age × Classification Set interactions: BC versus A, $F(10, 108) = 4.89$, $p < .001$, and AB versus C, $F(10, 108) = 3.50$, $p < .001$. All further differences cited are reliable at the .05 level, as indicated by Tukey's B (honestly significant difference, in proportion, .28 for the overall-similarity classifications and .25 for the dimensional-identity classifications). The critical question in interpreting the data is whether the patterns of classifications fit those predicted by the model and illustrated in Figure 6.

The 2- and 3-year-old patterns fit that predicted by the model, given distributed attention and the nonvaluing of identity (see Figure 6). The BC versus A (overall-similarity) classification reliably rises and then falls with increases in stimulus difference and is never exceeded by the AB versus C classification. Furthermore, for these youngest children there is a considerable tendency to group all objects together when the differences are small, and each object singly when the differences are great. This is precisely the pattern illustrated in Panel 1 of Figure 6. The youngest children, then, appear to produce true overall-similarity classifications on the basis of nonselective attention and a nonvaluing of identity.

The performances of the 4- and 5-year-olds fit that predicted by the model under the assumptions of perfect or nearly perfect selective attention to a single dimension but no (or little) valuing of identity. The 4- and 5-year-olds' classifications as a function of stimulus difference, shift from BC versus A to AB versus C classifications. This shift is expected if subjects selectively attend to one dimension, then the other, and pick the best classification. As illustrated in Panel 3 of Figure 6, which dimension and thus whether a BC versus A or AB versus C classification is better shifts with the magnitude of stimulus differences. The 4- and 5-year-olds thus classify by similarity on one dimension.

The performances of the 8-year-olds and adults also suggest (near-) perfect selective attention but differing valuing functions. Near-perfect selective attention is suggested by the lack of a downward trend in dimensional-identity classifications with increasing stimulus difference. A developmental increase in the valuing of identity is strongly suggested by the relation between the patterns of the 4- and 5-year-olds, the 8-year-olds, and the adults. There appears to be a leftward shift in the curves with age, with the 8-year-olds' curves falling between those of the 5-year-olds and the adults. Increasing the power of the valuing function has the effect of pushing the goodness curves leftward. The principal developmental change in the age range from 5 years to adulthood, then, would seem to be in the special treatment of identity in classification tasks. The fact that the 8-year-olds' data falls between those of the 4- and 5-year-olds and the adults suggests that the valuing function changes continuously and not in an all-or-none manner (see L. B. Smith & Evans, in press).

The results from Experiment 1 provide considerable support

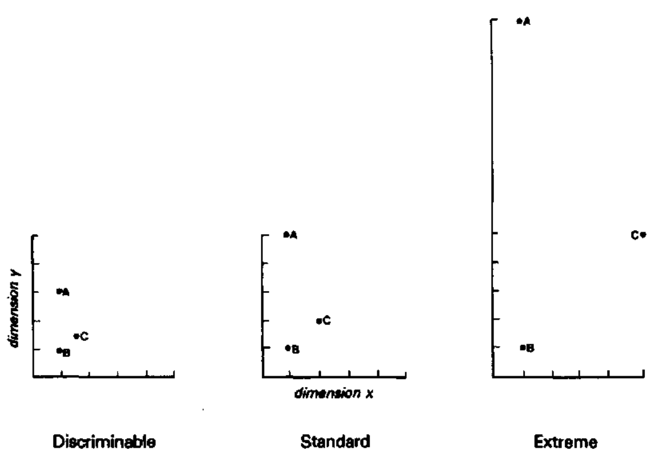

Figure 10. Experimental triads for Experiment 1.

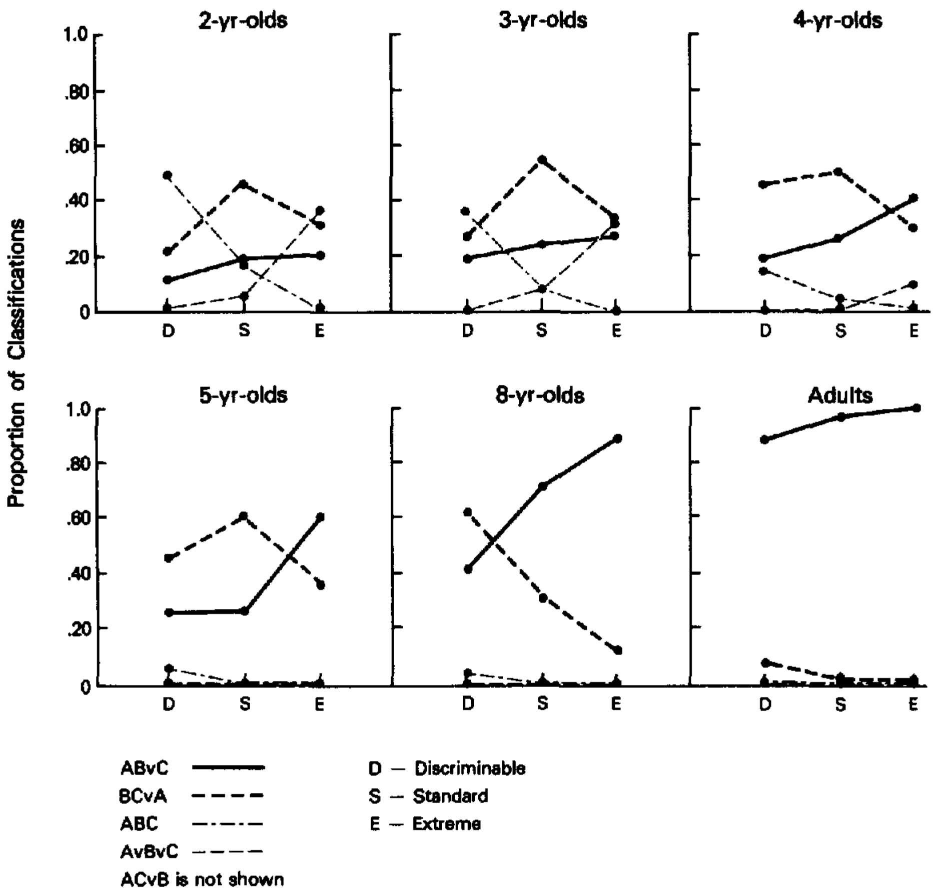

Figure 11. Mean proportions of the various classifications of the triads depicted in Figure 11 by children and adults.

for the model. Classification performance varies in the specific ways predicted by the model with increases in stimulus difference. Note that if only triads differing by the standard amount had been used, the standard result would have been obtained. Children under the age of 6 or so construct the BC versus A or overall-similarity classification, whereas older subjects construct the AB versus C or dimensional-identity classification. In contrast to this usual characterization of the developmental trend, the present results show that the classifications of 2- and 3-year-olds and 4- and 5-year-olds differ. Young preschoolers classify by overall similarity; older preschoolers classify by similarity on one dimension. The 4- and 5-year-olds, 8-year-olds, and adults differ not so much in attention to single dimensions but rather in whether they dichotomize similarity into *identical* and *different*. The results thus support two distinct components to the developmental trend: 2-year-olds differ from 5-year-olds in the number of dimensions attended. The 5-year-olds differ from the 8-year-olds and adults in the value accorded to particular degrees of similarity.

Experiment 2: Overall Similarity or Dimensional Similarity

The model discriminates between true overall-similarity classifications and dimensional-similarity ones by predicted changes in the frequency of AB versus C and BC versus A classifications with changes in the magnitude of differences within a triad (see Figure 6). However, overall-similarity and one-dimensional-similarity classifications can also be discriminated by using specially structured classification sets. I know of only two cases in the literature using such classification sets (L. B. Smith, 1979, 1981). Both studies indicate that true overall-similarity categories are sometimes constructed. In Experiment 2, classification sets much like those in L. B. Smith (1981) were used to corroborate the apparent trend from overall-similarity to dimensional-similarity to dimensional-identity classifications.

The top portion of Figure 12 shows the structure of the classification sets and the three possible classifications that are most informative. Shown first is the overall-similarity classification; the six objects are partitioned into three sets of two by similarity on both dimensions. This is a true overall-similarity classification; the objects should be grouped as illustrated only if both dimensions are attended. Shown second is one of two possible one-dimensional-similarity classifications. The one illustrated is by similarity on Dimension x; the objects are partitioned in a group of two and a group of four objects by value on Dimension x, with small differences on that dimension ignored. There is an analogous one-dimension-similarity classification by Dimension y. Shown last is one of two possible dimensional-identity classifications. In Figure 12, the six objects are partitioned into three groups of two by identity on Dimension x. There is an analogous identity classification by Dimension y. The question was whether 4- and 5-year-old children show a greater tendency to produce the one-dimensional-similarity classification than do younger and older subjects.

The one-dimensional-similarity classification requires a two versus four split of the objects, whereas the others consist of forming three groups of two objects each. Thus, a possible confound is developmental shifts in biases for different size categories. Two control sets were included as measures of such biases. One control set should be partitioned into two groups of three, and the other control set into a group of two and a group of four, regardless of equal weighting or selective attention. The structure of these control sets is illustrated at the bottom of Figure 12.

Method

Subjects. Ten 3-year-olds (M age = 3 years 7 months; range = 3 years 2 months to 3 years 10 months), ten 4-year-olds (M age = 4 years 6 months; range = 4 years 1 month to 4 years 11 months), and ten 5-year-olds (M age = 5 years 7 months; range = 5 years 3 months to 5 years 11 months), attending the same day-care centers as the children participating in Experiment 1, and 10 undergraduates participated. There was an equal number of males and females at each age level.

Stimuli and procedure. The classification sets were organized from the green circles that served as the stimulus objects for the standard triad of Experiment 1. There were 8 test sets, two replications of each of 4 unique test sets and 8 control sets: 4 unique 2 versus 2 versus 2 sets and 4 unique 2 versus 4 sets. These 16 sets were assembled into one of two random orders for presentation to the children. The procedure was identical to that used in Experiment 1, except that the two instruction sets consisted of (a) two identical red kites, two identical yellow butterflies, and two identical blue houses and (b) two identical red kites and four identical yellow butterflies.

Results and Discussion

Figure 13 shows the frequency of classifications of the various types. Consider, first, performance in the control sets shown at the bottom of Figure 13. There is a reliable increase with age in systematic classifications by the children, $F(2, 27) = 4.91, p < .02$, but no reliable difference in the construction of 2 versus 2 versus 2 partitions or 2 versus 4 partitions, $F(1, 27) = 1.04$, nor does age interact with control set, $F(2, 27) < 1.00$. The youngest children's difficulties with these sets (and the test sets; note the large proportion of other classifications) appears to stem from their taking of two objects that happen to be near each other on the table (but not highly similar) and then being unable to complete the classification or start over. These difficulties on the part of the youngest children in constructing classifications are well documented in the literature (Inhelder & Piaget 1964; Kofsky, 1966; L. B. Smith, 1983). The critical point for present purposes is that there does not seem to be any strong tendency to prefer 2 versus 2 versus 2 or 2 versus 4 partitions.

The top of Figure 13 shows the mean proportions of the three critical kinds of classifications of the test set. The results replicate the general trends of a decline in overall-similarity classifications from early childhood to adulthood and a dramatic increase in one-dimensional-identity classifications from early childhood to adulthood. The results also show that one-dimensional-similarity classifications are produced with some frequency by the older preschoolers. Separate ANOVAS on the children's proportions of overall-similarity and one-dimensional-similarity classifications provide statistical documentation for these trends. Whereas overall-similarity classifications decline only marginally from 3 to 5 years of age, $F(2, 27) = 2.51, p < .098$, one-dimensional-similarity classifications increase more markedly in this age range, $F(2, 27) = 5.99, p < .01$. Apparently, there is a point in development when children sometimes construct classifications by single dimensions but allow for some variation on that dimension within a category.

These results provide developmental support for the separateness of the two processes of differential weighting and of valuing similarity. The principal difference between 3-year-olds and 5-year-olds is in the increase in one-dimensional-similarity classifications. This increase presumably reflects growth in the differential weighting of dimensions. The difference between the performance of 5-year-olds and adults seems to lie in the increase in one-dimensional-identity classifications and to stem from an increased valuation of identity. The two developmentally varying parameters—w_i and P—in the quantitative model, thus, have developmentally separate time courses and appear to reflect real components of the developmental trend.

Experiment 3: The Specialness of Absolute Identity

What is the relation between growth in classifying by single dimensions and classifying by identity? The finding that older preschoolers selectively attend but do not value identity might seem to suggest that the comparison of objects on one dimension at a time emerges prior to a special emphasis on identities. However, such a developmental sequence—first selective attention, then the valuing of identity—may not be strictly correct. Evans and L. B. Smith (1988) found that 5-year-olds were much more likely than younger children to produce absolute identity classifications. In a situation in which selective attention was not required, there was an increase from overall-similarity to overall-identity classifications. It may be that the early valuing of identity requires the presence of absolute identities in the classification set. Quite early in development, identity may be accorded a special status when selective attention is not required and when the presence of the relation suggests it. This notion was pursued in Experiment 3.

Figure 14 shows the structure of four unique objects that make up the parent sets from which classification sets were drawn. In one kind of classification set, the *standard set,* children were given one of each of four unique objects (A, B, C, D). These four objects are divisible into two groups of two by overall similarity (AB vs. CD) or by identity on a single dimension. The second kind of set is labeled *identity-similar.* An example of this set is one composed of two replications of Object A and two of Object B. The expected absolute-identity classification of this set is AA versus BB. The third kind of classification set is labeled *identity-extreme.* An example of this set is one composed of two replications of Object A and two of Object D. The expected absolute identity classification of this set is AA versus DD. The critical predictions concern the standard set and the identity-similar set. The identity-extreme set serves as a base-

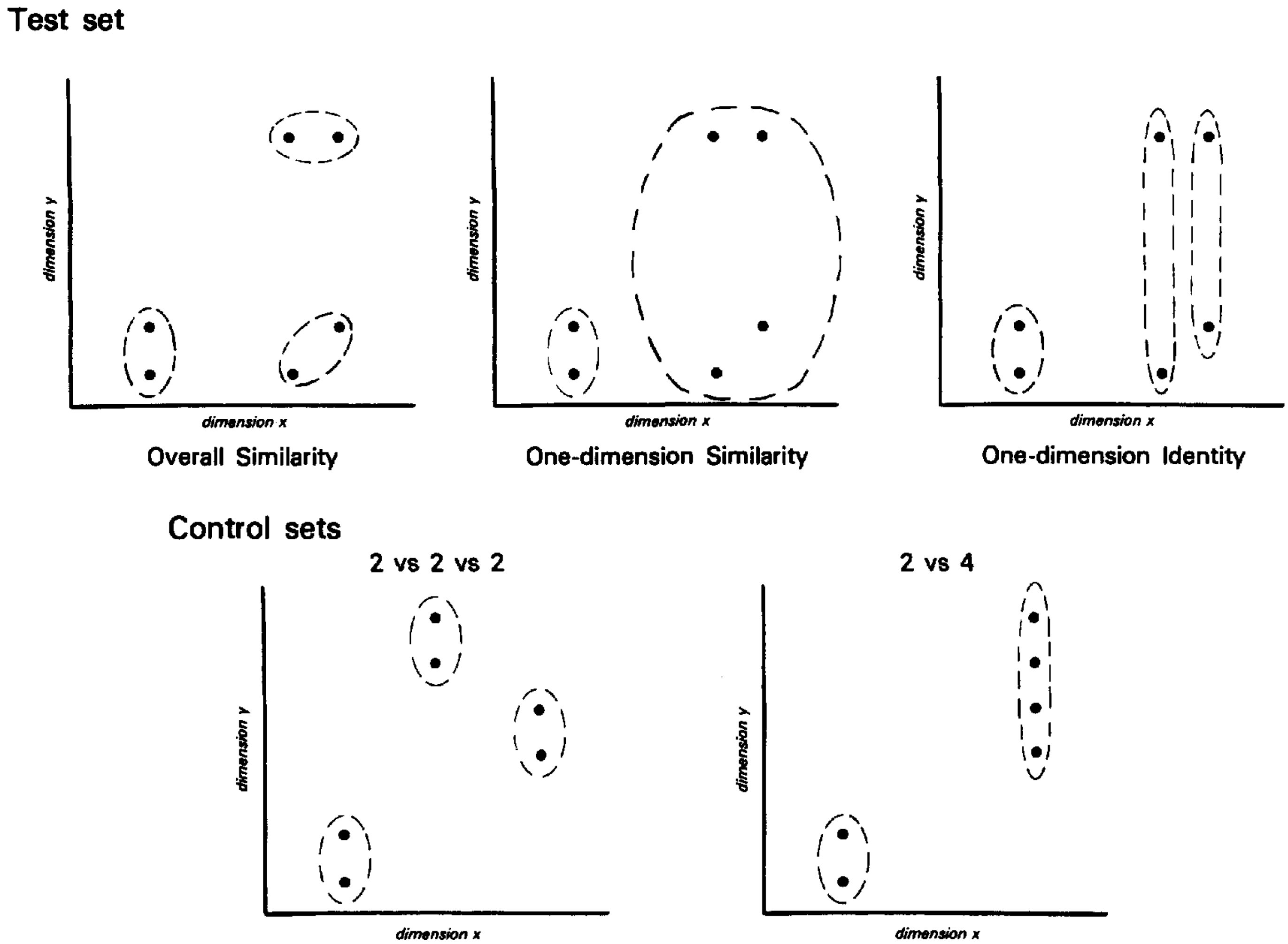

Figure 12. The classification set and the two control sets used in Experiment 2.

line for developmental comparisons because under all combinations of selective attention and valued identity, the AA versus DD classification is extremely good.

The goodnesses of the critical classifications if identity is not highly valued are shown in Figure 15. The crucial prediction is that if children produce the similarity classification (AB vs. CD) of the standard set, which the literature suggests they will, then they ought not to produce the AA versus BB classification of the identity-similar set. More precisely, given the nonvaluing of identity, the AB versus CD classification of the standard set is expected at middle ranges of stimulus difference, given attention to both dimensions or selective attention to Dimension *y*. However, at the specific magnitude of difference that the AB versus CD classification of the standard set is good, the AA versus BB classification of the identity-similar set is bad. If the valued similarity of A and B is such that they form a good group, then their similarity is such that they are not happily grouped apart. A pattern of results showing that children produce the similarity classification of the standard set (AB vs. CD) and the identity classification of the identity-extreme set (AA vs. DD), but group all four items of the AABB set together, implicates a nonvaluing of identity, including absolute identity.

The expected goodnesses of these various classifications if identity is highly valued are not illustrated because they are straightforward. If subjects value identity and selectively attend to single dimensions, they should produce the AC versus BD classification of the standard set and the identity classifications of both identity sets (AA vs. DD and AA vs. BB) at all discriminable stimulus differences. If subjects do not selectively attend but highly value identity, they should group each object in the standard set alone but produce both identity classifications (AA vs. DD and AA vs. BB) at all discriminable differences.

Notice that the one pattern not predicted is the AB versus CD or similarity classification of the standard set and the AA versus BB classification of the identity-similar set. Within the model, such a result would suggest a shift from the nonvaluing of identity, given objects ABCD, to the higher valuing of identity, given objects AABB.

Methods

Subjects. A total of 10 children, 5 boys and 5 girls, at each of the four age levels, participated: 2-year-olds (*M* age = 2 years 6 months; range = 2 years 1 month to 2 years 10 months), 3-year-olds (*M* age = 3 years 6

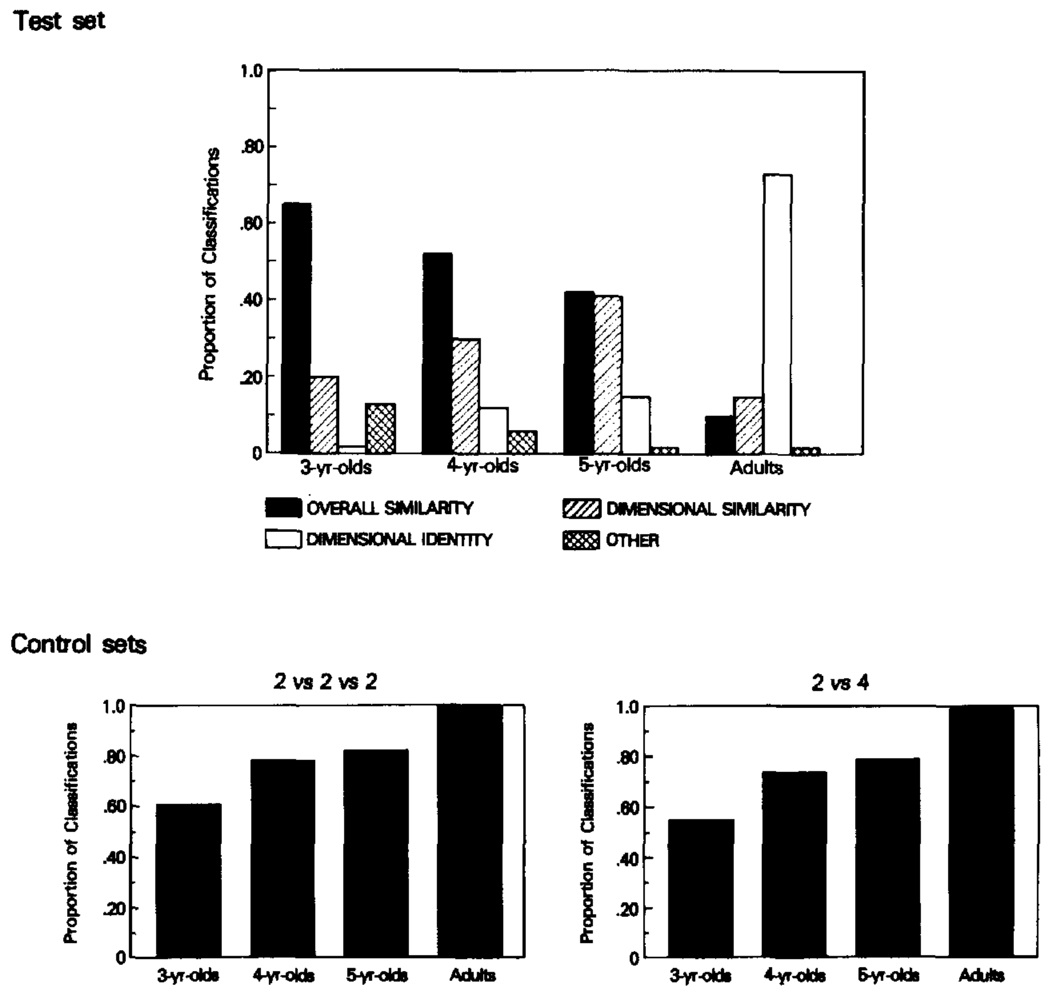

Figure 13. Mean proportion of classifications by children and adults of classification sets structured, as shown in Figure 12.

months; range = 3 years 1 month to 3 years 10 months), 4-year-olds (*M* age = 4 years 6 months; range = 4 years 0 months to 4 years 11 months), and 5-year-olds (*M* age = 5 years 4 months; range = 5 years 0 months to 5 years 9 months).

Stimuli and procedure. Three unique standard sets, three unique identity-similar sets, and three unique identity-extreme sets were constructed from the same color and size values that composed the standard set in Experiment 1. The procedure was identical to that used in Experiment 1, except that the two instruction sets consisted of (a) two identical red kites and two identical yellow butterflies and (b) two identical blue houses and two green boats. The children were given each of the nine unique sets twice, for a total of 18 trials, in one of two randomly determined orders.

Results and Discussion

Table 2 shows the proportions of the critical classifications of the three sets. Children at all ages produced the AB versus CD (similarity) classification of the standard set and the identity classification of the identity-extreme set. However, as is apparent in Table 2, there is a dramatic increase with age in the identity classification of the identity-similar set. The 2-year-olds hardly ever formed the AA versus BB classification of this last set. Instead, they often (57% of the time) classified all four objects together just as the model predicts they should at magnitudes of difference at which the AB versus CD classification is produced. The 3-year-olds also frequently (25% of the time) grouped all four objects in the identity-similar set together. The remaining classifications of the identity-similar set by 2- and 3-year-olds consisted of grouping two objects together and then stopping. Such incomplete classifications are characteristic at this age level (L. B. Smith, 1983). The structure of 2-year-olds' incomplete classifications suggests no special status of identity. The proportion of these incomplete classifications, in which the one pair formed was an identity pair (e.g., AA), was only slightly greater (.59) than the proportion (.41) consisting of a similarity pair (i.e., AB). The lack of identity classifications by 2-year-olds would not seem to reflect an inability to discriminate. Recall that the smallest one-dimensional differences that combine to form the AB difference are discriminable for 2-year-olds (see procedure for the standard set in Experiment 1). Rather, absolute identity appears to have no special classificatory status over overall similarity for the youngest children.

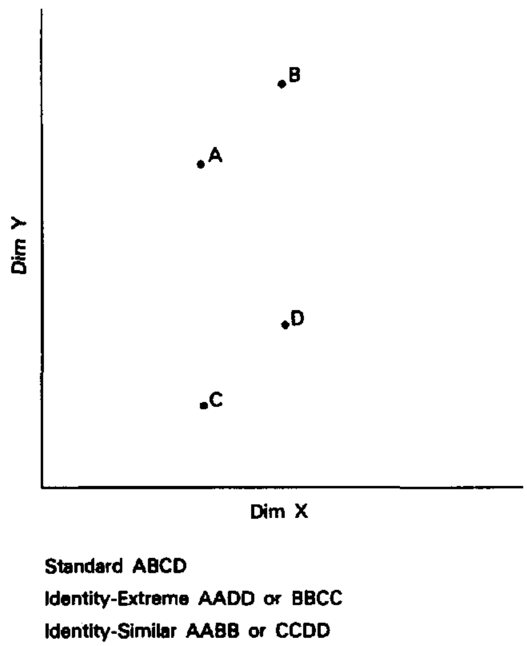

Figure 14. Parent set and the possible classification sets used in Experiment 3.

Table 2
Mean Proportion of Critical Classifications of the Sets Illustrated in Figure 14

Age in years	Standard (AB vs. CD)	Identity-extreme (AA vs. DD)	Identity-similar (AA vs. BB)
2			
M	.65	.88	.26
SD	.17	.20	.25
3			
M	.70	.93	.67
SD	.16	.17	.21
4			
M	.72	.97	.90
SD	.17	.08	.09
5			
M	.70	1.00	.92
SD	.21	.00	.09

Absolute identity, however, is a sufficient basis for classification for older preschoolers. These older children classify the standard set by similarity, AB versus CD, but the identity-similar set by identity, AA versus BB—a result that suggests a shift in the valuation of identity between classification sets. There are two possible explanations for the developmental trend. First, the presence of an absolute identity may elicit an increased valuation of identity in all but the youngest children. Second, older preschoolers' valuing of absolute identity may interact with their biases for 2 versus 2 classifications. Evidence from adults (L. B. Smith & Evans, in press), favors the first interpretation. Given red, red-orange, and blue color chips, adults group the red and red-orange together. If a second red chip, identical to the first, is added, adults form two reds versus red-orange versus blue. Thus, the value of identity may depend on its presence.

At any rate, the present results suggest that 3-, 4-, and 5-year-olds value absolute identity—at least in certain task contexts. At the same time, Experiment 2 suggests that the older pre-

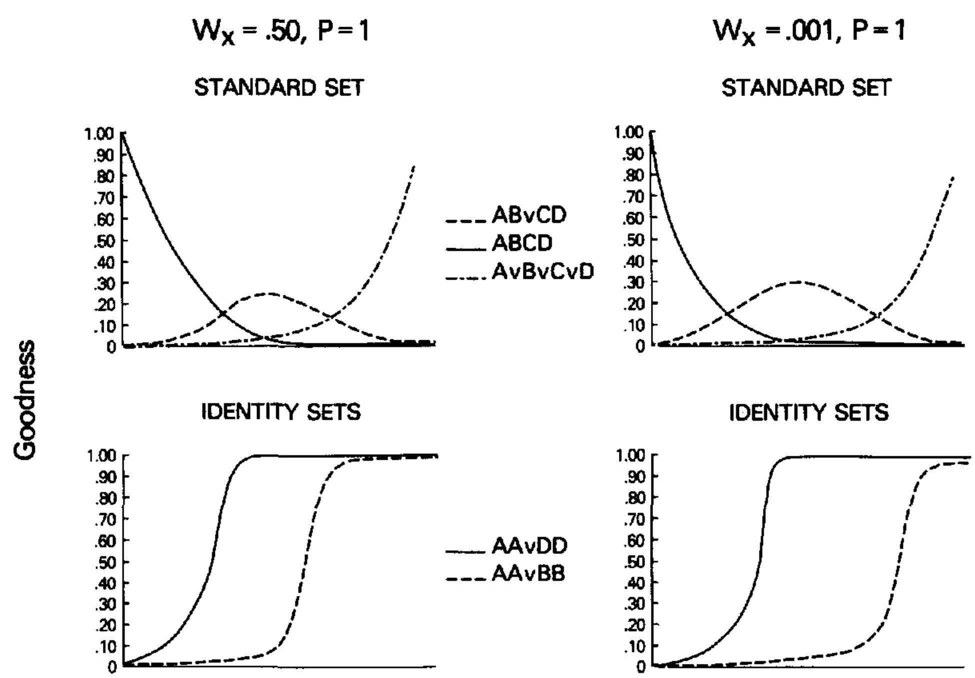

Figure 15. Predicted goodnesses of the critical classifications in Experiment 3.

schoolers selectively attend without valuing part identities. Thus, it would seem that the valuing of absolute identity emerges at about the same time (or perhaps even before) one-dimensional-similarity classifications. Given the results of Experiments 1 and 2, it seems likely that many of the 5-year-olds' similarity classifications of the standard set in Experiment 3 were one-dimensional-similarity classifications and not overall similarity classifications. Apparently, older preschoolers do calculate similarity on one dimension at a time, and they do dichotomously value similarities into identity and difference, but they do not do both at the same time.

Summary

The major claims of the model are as follows: (a) Represented whole objects operate as units and cannot be pulled apart. Objects are compared one whole with another; perceived similarity is calculated across all constituents at once. (b) The perceived similarity between one represented whole to another varies with changes in the weights assigned to individual dimensions. The likelihood of differential weighting (i.e., of selective attention) increases with age. (c) The value of perceived similarities also varies with development, so that early in development perceived similarities are treated more continuously and later in development similarity is dichotomized into the categories of identity and different.

I have shown that these three claims are sufficient to account for the developmental trend from so-called overall-similarity to dimensional-identity classifications. The evidence clearly supports the claim of two developmentally distinct areas of growth: selective attention to dimensions when comparing objects and the special emphasis on identities when classifying. The evidence also provides strong support for the model. The three theoretically motivated parameters provide a good qualitative fit to the development data. The frequencies of particular classifications vary in the way the model predicts with stimulus differences and subject maturity.

The value of the quantitative model is clear. By proposing a specific detailed model, I was able to show that both overall-similarity and dimensional-identity classifications are explainable by the same mechanisms. By proposing a specific quantitative model, I have also clarified the kinds of data than can and cannot usefully distinguish so-called holistic and analytic perception. First, ostensive overall-similarity classifications may be based on quite unequal weightings of the dimensions. Selective attention without a high valuing of identity may lead to apparent overall-similarity classifications at certain magnitudes of stimulus difference. Second, magnitude of stimulus difference matters. It is insufficient to show simply more overall-similarity or more dimensional-identity classifications. If one wants to conclude something about how holistic perception is from classification performance, then the structure of classifications must either be examined across a range of stimulus differences or the psychological magnitude of differences must somehow be specified.

Given this empirical support for the model, I now consider more broadly its implications for the nature of development.

What Develops and What Does Not

Aslin and Smith (1988) proposed three different structural levels that may develop in perception: (a) sensory primitives, (b) perceptual representations, and (c) higher order representations (i.e., relations between represented objects). These levels are clarified by the schematic illustration in Figure 3. The present model clearly places the source of the trend from overall-similarity to dimensional-identity classifications at higher order representations—in what happens after objects are perceptually represented. The developmental changes are in the operations of differential weighting and in the valuing of similarity, and thus are operations on represented objects. These developing operations may be applied to object representations that are relatively constant across development. This suggestion is supported by considering, first, the nature of what develops, and subsequently, the nature of what does not.

The Differential Weighting of Dimensions: Selective Attention

Within the model, only perfect selective attention dramatically alters the relative goodnesses of a classification. Although the differential weighting of dimensions varies continuously, there are only two classificatory outcomes. Either one selectively attends with near perfection and produces one-dimensional classifications or one does not and produces overall-similarity classifications. It is not unreasonable to suppose that such near-perfect selective attention—the setting of a dimensional weight at or close to 1.00—requires attention. Mature subjects presumably expend such attention regularly (maybe even obligatorily if there is available attention) because (near-) perfect selective attention yields information about the specific dimensions of sameness and difference. Imperfect selective attention does not yield information about dimensions. A bit more attention to one dimension or the other will alter the perceived similarities (Nosofsky, 1986), but such an intermediate weighting scheme cannot provide specific information about specific dimensions. Accordingly, I suggest that what develops is near-perfect selective attention—the ability (and tendency) to set (and hold) a dimensional weight at (or close to) 1.00. Young children may well differentially weight dimensions most of the time, but if they cannot do so almost perfectly, then they do not have separate information about separate dimensions and cannot, then, strategically classify by one dimension.

Having knowledge about separate dimensions yields better classifications. As is evident in Figure 6, selective attention to one dimension generally yields classifications with higher goodnesses than does distributed attention. This is necessarily so if a good classification is one in which highly similar objects are grouped together. Selective attention to one dimension removes a source of within-group dissimilarity. The fact that selective attention removes sources of within-category variation may be part of the reason that the scientist in all of us prefers categories structured by a few necessary and sufficient properties (see, e.g., Brooks, 1978; Keil & Batterman, 1984; Medin, Wattenmaker, & Hampson, 1987; L. B. Smith, 1979). This is not to say that the world readily yields such categories or, as I discuss subsequently, that natural categories are structured that way.

My proposal is that what develops in perceptual classification is (near-) perfect selective attention to single dimensions and the resulting knowledge of the specific dimensions of similarity. This proposal makes sense of the direction of the developmental trend—from distributed attention to all dimensions to focused attention on one dimension. There is no reason to attend to just one dimension unless doing so provides some gain. The advantage of selectively attending to single dimensions is that doing so reveals the constituent relations between objects and results in better classifications.

Valued Similarity: Identity as Special

I view the P parameter as a shiftable criterion as to what degree of perceived similarity is required to form a "good" classification (see Estes, 1986, for a similar argument that similarity can be cognitively adjusted). In terms of Aslin and Smith's (1988) tripartite view of perceptual development, the function that values similarity is postobject representation and, indeed, an operation on a higher level representation (the perceived similarity between two represented objects). This cognitive interpretation of P is consistent with its context-dependent nature. In Experiment 3, 5-year-olds valued identity only when absolute identities were present. Evans and Smith (1988; see also L. B. Smith & Evans, in press) have shown that adults' valuing of identity also shifts with changes in the stimulus relations present. Adults shift their criterion from identity to similarity when absolute and part identities are removed from the classification task.

This interpretation of the P parameter as reflecting a cognitive criterion for forming groups is not the only one possible. The P parameter is formally identical to the C parameter in Nosofsky's (1986) model of category learning. Nosofsky interprets his C parameter as reflecting discriminability and as being influenced by such factors as perceptual learning. Increased discriminability and perceptual learning are likely factors in perceptual development (see, e.g., J. J. Gibson & Gibson, 1955; Mednick & Lehtinen, 1957). It is quite possible that the psychological distance between stimuli expand with development. However, developmental changes in discriminability alone may not be able to account for the developmental trend in classification, especially given the high discriminability of the stimulus values at all age levels in standard classification tasks. I suspect that developmental changes in both discriminability (especially at early ages) and in classification criteria underlie the emergence of identity as a special kind of similarity.

This suggestion that identity is perceptually and conceptually unique and not merely high similarity is important. It is fundamental to perception for an object to be classed as itself. Identities as distinct from similarities across various orientations and environments may be critical to this process. Identity is also fundamental in reasoning. Identity is an equivalence relation—symmetric, transitive, and reflexive—and thus affords powerful inferences. Indeed, older classifiers may explicitly structure classifications by identity in order to form equivalence classes. The developmental trend, then, may be characterized as a shift toward more consciously organized and logical classifications. This is the traditional characterization of the developmental trend in classification (e.g., Inhelder & Piaget, 1964; Vygotsky, 1962) and one that fits with the fact that one-dimensional-identity classifications are intimately linked to schooling (see Cole & Scribner, 1974) and amount of knowledge in a given domain (Keil, 1984).

What Does Not Develop

The trend from overall-similarity to dimensional-identity classifications has sometimes been interpreted in terms of a qualitative shift in the structure of perceptual representations with the young child's holistic perceptions likened to the adult's perceptions of stimuli varying on integral dimensions (Kemler, 1981, 1983; Kemler–Nelson, in press; Shepp, 1983). Integral dimensions are often thought of as nonrepresented dimensions (Kemler–Nelson, in press). If this is so, then integral dimensions are an inappropriate model of the general character of immature perception. I am not suggesting that there are never developmental changes in the dimensions and features along which objects are represented. The human perceptual system is highly flexible and sensitive to the effects of experience (see, e.g., J. J. Gibson & Gibson, 1955). And one possible source of perceptual learning is the formation of new units at the level of perceptual representation, perhaps through a process of extracting task-relevant correlations between sensory primitives. Something of the sort seems to be the case in speech perception (see Aslin & Smith, 1988; L. B. Smith & Evans, in press).

However, changes in what features are represented is an unlikely source of developmental differences in classification. Except in perhaps very special cases (such as language learning or experience in some new perceptual domain; e.g., discriminating monkeys), it seems likely that infants beyond 1 year, children, and adults all perceive most objects in mostly the same way (see Aslin & Smith, 1988). It certainly seems unlikely that there are major shifts in the perceptual representation of shape, size, and color in childhood, and it is with these adult separable dimensions that the developmental trend is obtained. The model shows that one need not posit changes in how objects are perceptually represented to account for a shift from overall-similarity to single-dimension comparisons of objects.

Perceptual Similarity

The model and data have implications beyond development—in particular, implications for how we think about perceptual similarity. Similarity is a much maligned concept: It is characterized as, at best, a badly behaved relation (e.g., Goodman, 1951; Tversky, 1977; see also J. D. Smith, in press). The source of similarity's problems would seem to be in its inherent noninvariance. How similar two objects are appears to depend on the context within which the objects are compared. For example, the similarity of a 1-cm line and a 2-cm line changes when a 1.25-cm line is added (Lockhead, in press). Yet, the present model and data suggest that absolute magnitudes of similarity matter. Young children do not produce the best partition of a given set. It matters just how good the best is. Moreover, the function that values similarities operates on absolute magnitudes of similarity, and adults prefer, for classifying, a certain degree of similarity (i.e., identity). The model provides a means for reconciling these different characterizations of similarity.

Within the model, perceived similarity is not invariant because it varies with the particular dimension weights. Judged similarity will also vary with the power of the valuing function. The idea that the apparent relativity of similarity stems from shifts in selective attention is not a new one (Nosofsky, 1986; Shepard, 1964), yet its importance seems not to be widely recognized. Given a constant weighting scheme and valuing function, similarity may be a well-behaved relation.

Classification and Category Learning

Classification, what was modeled here, and category acquisition are related but they are not the same. In classification, the subject imposes order on a set of objects. In category learning, the subject's task is to acquire the category structure that is given. A good classification is one that maximizes within-group similarity and minimizes between-group similarity. Good category learning consists of acquiring the category as given—even if the structure as given is not aesthetically pleasing. Thus, in classification, near-perfect selective attention and the valuing of identity yields better classifications—logically powerful equivalence classes. However, in category learning, near-perfect selective attention and the valuing of identity will yield better category acquisition only if the categories to be acquired are so structured. The overwhelming evidence is that natural categories such as *boot* and *dog* are not so well structured (see, for review, E. E. Smith & Medin, 1981).

Nonetheless, the processes—dimension weights and valuation of similarity—that compose the present model are likely fundamental components of category learning. The differentiation of identity as a distinct kind of similarity has received no attention in the category-learning literature. But changes in dimension weights with learning are the central part of several models (see Gluck & Bower, 1988; Medin & Schaeffer, 1978; Nosofsky, 1986). In category-learning models, the changes in dimension weights are not extreme; instead, category learning appears to consist of subtle shifts in the distributions of dimension weights (see, especially, Nosofsky, 1986). The present model could easily be extended to include nonextreme changes in weights with learning. The resulting category-learning model would share much with Nosofsky's extension of Medin and Schaeffer's context model because it uses the same rule for determining similarity.[4] The issue is whether there are developmental changes in category learning.

I suspect that there are developmental changes in category learning of the sort predicted by the model, that is, increasing differential weightings of dimensions and emphasis on identity. Of course, these developmental differences will matter only to the degree that shifts in dimension weights and emphasis on identity matter in the categories to be learned. I think they do matter in early natural category acquisition. A brief consideration of two recent series of experiments (Jones, Smith, & Landau, 1988; Landau, Smith, & Jones, 1988) makes the point. These studies showed that 3-year-olds, but not 2-year-olds, shifted their dimension weights as a function of kind of category. The task was the generalization of nonsense syllable names of novel objects to new instances. Depending on whether the objects were represented as a certain kind of artifact or natural kind, 3-year-olds shifted their attention between the dimensions of size, shape, and texture, and moreover they often required an identity match (not mere similarity) on the attended dimension. For example, 3-year-olds seem to possess a rule for naming artifacts of the sort "same shape, same name." The 2-year-olds' naming patterns were largely determined by overall similarity. These results indicate early growth in how very young children extend names to objects of just the sort predicted by the model. The model with its emphasis on perceptual similarity may be most relevant at the earliest stages of natural category acquisition as knowledge about nonperceptual properties and relations play increasing roles in later development (Carey, 1985; Gelman & Markman, 1986).

Even in later development, the ability to selectively attend and seek out identities is crucial to cognition and reasoning about objects. We may know one object to be a table and another to be a boot, but nonetheless we perceive and think about their similarities and differences on single dimensions. The empirical evidence suggests that one has to go to great lengths to stop adults from selectively attending to single dimensions in classification tasks (Medin, Wattenmaker, & Hampson, 1987). This makes sense in the context of the present model. Near-perfect selective attention to single dimensions is prerequisite to a conscious understanding of the individual dimensions on which objects are the same and different. Selective attention to single dimensions is thus prerequisite to the apprehension of interrelations between dimensions. Near-perfect selective attention, the setting of individual weights at (or close to) 1.00, is prerequisite because the experience of individual dimensions as individuals results only from the setting of dimension weights at their limits.

Conclusion

My purpose in this article was to specify in detail what might be developing in perceptual-classification tasks. The building of a detailed model brought new insights. I discovered the critical importance of the absolute magnitude of stimulus difference; I discovered that apparent overall-similarity classifications need not be based on overall similarity at all, but rather may be based on single-dimension similarity. I discovered that there are two developing abilities—the differential weighting of dimensions and the differentiation of identity as a special kind of similarity; and I learned that the apparent *qualitative* differences in the structure of overall-similarity and dimensional-identity classifications may stem from solely *quantitative* differences in higher level operations on developmentally constant perceptual representations.

References

Aschkenasay, J. R., & Odom, R. D. (1982). Classification and perceptual development: Exploring issues about integrality and differential sensitivity. *Journal of Experimental Child Psychology, 34,* 435–488.

Aslin, R. N., & Smith, L. B. (1988). Perceptual development. In M. R.

[4] The model clearly could be extended in alternative ways as well—for example, as a prototype model rather than an exemplar learning model.

Rosenzweig & L. W. Porter (Eds.), *Annual review of psychology* (Vol. 39, pp. 435–473). Palo Alto, CA: Annual Reviews.

Brooks, L. (1978). Nonanalytic concept formation and memory for instances. In E. Rosch & B. B. Lloyd (Eds.), *Cognition and categorization* (pp. 169–211). Hillsdale, NJ: Erlbaum.

Carey, S. (1985). *Conceptual change in childhood.* Cambridge, MA: MIT Press, Bradford Books.

Caron, A. J. (1969). Discrimination shifts in three-year-olds as a function of dimensional salience. *Developmental Psychology, 1,* 333–339.

Cole, M., & Scribner, S. (1974). *Culture and thought: A psychological introduction.* New York: Wiley.

Denney, N. W. (1972). A developmental study of free classification in children. *Child Development, 43,* 221–232.

Estes, W. K. (1986). Array models for category learning. *Cognitive Psychology, 18,* 500–549.

Evans, P. M., & Smith, L. B. (1988). The development of identity as a privileged relation in classification: When very similar is just not similar enough. *Cognitive Development, 3,* 265–284.

Garner, W. R. (1974). *The processing of information and structure.* Potomac, MD: Erlbaum.

Gelman, S. A., & Markman, E. M. (1986). Categories and induction in young children. *Cognition, 23,* 183–208.

Gibson, E. J. (1969). *Principles of perceptual learning and development.* New York: Appleton-Century-Crofts.

Gibson, J. J., & Gibson, E. J. (1955). Perceptual learning: Differentiation of enrichment? *Psychological Review, 62,* 32–41.

Gluck, M. A., & Bower, G. H. (1988). From conditioning to category learning: An adaptive network model. *Journal of Experimental Psychology: General, 117,* 227–247.

Goodman, N. (1951). *The structure of appearance.* Cambridge, MA: Harvard University Press.

Handel, S., & Imai, S. (1972). The free classification of analyzable and unanalyzable stimuli. *Perception and Psychophysics, 12,* 108–116.

Imai, S. (1966). Classification of sets of stimuli with different stimulus characteristics and numerical properties. *Perception and Psychophysics, 1,* 48–54.

Imai, S., & Garner, W. R. (1968). Structure in perceptual classification. *Psychonomic Monograph Supplements, 2,* 153–172.

Inhelder, B., & Piaget, J. (1964). *The early growth of logic in the child.* New York: Norton.

Jones, S. S., Smith, L. B., & Landau, B. (1988, April). *The effects of verbal labels on concept formation strategies: Natural kinds and artifacts.* Paper presented at the meeting of the Midwestern Psychological Association, Chicago.

Keil, F. C. (1984). Mechanisms of cognitive development and the structure of knowledge. In R. J. Sternberg (Ed.), *Mechanisms of cognitive development* (pp. 81–99). New York: Freeman.

Keil, F. C., & Batterman, N. (1984). A characteristic-to-defining shift in the development of word meaning. *Journal of Verbal Learning and Verbal Behavior, 23,* 221–236.

Kemler, D. G. (1981). New issues in the study of infant categorization: A reply to Husaim and Cohen. *Merrill-Palmer Quarterly, 27,* 457–463.

Kemler, D. G. (1983). Exploring and reexploring issues of integrality, perceptual sensitivity, and dimensional salience. *Journal of Experimental Child Psychology, 36,* 365–379.

Kemler, D. G., & Smith, L. B. (1978). Is there a developmental trend from integrality to separability in perception? *Journal of Experimental Child Psychology, 26,* 498–507.

Kemler-Nelson, D. G. (in press). The nature and occurrence of holistic processing. In B. E. Shepp & S. Ballesteros (Eds.), *Object perception: Structure and process.* Hillsdale, NJ: Erlbaum.

Kofsky, E. (1966). A scalogram study of classifactory development. *Child Development, 37,* 191–204.

Landau, B., Smith, L. B., & Jones, S. S. (1988). The importance of shape in early lexical learning. *Cognitive Development, 3,* 299–321.

Lockhead, G. R. (in press). Concerning the formation of natural categories. In B. E. Shepp & S. Ballesteros (Eds.), *Object perception: Structure and process.* Hillsdale, NJ: Erlbaum.

Medin, D. L., & Schaffer, M. M. (1978). Context theory of classification learning. *Psychological Review, 85,* 207–238.

Medin, D. L., Wattenmaker, W. D., & Hampson, S. E. (1987). Family resemblance, conceptual cohesiveness, and category construction. *Cognitive Psychology, 19,* 242–279.

Mednick, S. A., & Lehtinen, L. E. (1957). Stimulus generalization as a function of age in children. *Journal of Experimental Psychology, 33,* 180–183.

Navon, D. (1977). Forest before trees: The precedence of global features in visual perception. *Cognitive Psychology, 9,* 353–363.

Nosofsky, R. M. (1984). Choice, similarity, and the context theory of classification. *Journal of Experimental Psychology: Learning, Memory and Cognition, 10,* 104–114.

Nosofsky, R. M. (1986). Attention, similarity, and the identification–categorization relationship. *Journal of Experimental Psychology: General, 115,* 39–57.

Odom, R. D. (1978). A perceptual-salience account of decalage relations and developmental change. In L. S. Siegal, & C. J. Brainerd (Eds.), *Alternatives to Piaget* (pp. 111–130). New York: Academic Press.

Pomerantz, J. R. (in press). Attention and object perception. In B. E. Shepp & S. Ballesteros (Eds.), *Perception of objects: Structure and process.* Hillsdale, NJ: Erlbaum.

Shepard, R. N. (1964). Attention and the metric structure of the stimulus space. *Journal of Mathematical Psychology, 1,* 54–87.

Shepard, R. N. (1986). Discrimination and generalization in identification and classification: Comment on Nosofsky. *Journal of Experimental Psychology: General, 115,* 58–61.

Shepard, R. N. (1987). Toward a universal law of generalization for psychological science. *Science, 237,* 1317–1323.

Shepp, B. E. (1983). The analyzability of multi-dimensional objects: Some constraints on perceived structure, the development of perceived structure, and attention. In T. J. Tighe & B. E. Shepp (Eds.), *Perception, cognition, and development* (pp. 39–73). Hillsdale, NJ: Erlbaum.

Shepp, B. E., Burns, B., & McDonough, D. (1980). The relation of stimulus structure to perceptual and cognitive development: Further tests of a separability hypothesis. In J. Becker & F. Wilkening (Eds.), *The integration of information by children* (pp. 113–145). Hillsdale, NJ: Erlbaum.

Shepp, B. E., & Swartz, K. B. (1976). Selective attention and the processing of integral and nonintegral dimensions: A developmental study. *Journal of Experimental Child Psychology, 22,* 73–85.

Smith, E. E., & Medin, D. L. (1981). *Categories and concepts.* Cambridge, MA: Harvard University Press.

Smith, J. D. (in press). On implicit metacognition. In B. E. Shepp & S. Ballesteros (Eds.), *Object perception: Structure and process.* Hillsdale, NJ: Erlbaum.

Smith, J. D., & Kemler-Nelson, D. G. (1984). Overall similarity in adults' classification: The child in all of us. *Journal of Experimental Psychology: General, 113,* 137–159.

Smith, L. B. (1979). Perceptual development and category generalization. *Child Development, 50,* 705–715.

Smith, L. B. (1980). Development and the continuum of separability. *Perception and Psychophysics, 28,* 164–172.

Smith, L. B. (1981). The importance of the overall similarity of objects for adults' and children's classifications. *Journal of Experimental Psychology: Human Perception and Performance, 1,* 811–824.

Smith, L. B. (1983). Development of classification: The use of similarity and dimensional relations. *Journal of Experimental Child Psychology, 36,* 150–178.

Smith, L. B. (1984). Young children's understanding of attributes and dimensions: A comparison of conceptual and linguistic measures. *Child Development, 55,* 363–380.

Smith, L. B. (in press). From global similarity to kinds of similarity: The construction of dimensions in development. In S. Vosniadou & A. Ortony (Eds.), *Similarity and analogy.* Cambridge, England: Cambridge University Press.

Smith, L. B., & Evans, P. M. (in press). Similarity, identity, and dimensions: Perceptual classification in children and adults. In B. E. Shepp & S. Ballesteros (Eds.), *Object perception: Structure and process.* Hillsdale, NJ: Erlbaum.

Smith, L. B., & Kemler, D. G. (1977). Developmental trends in free classification: Evidence for a new conceptualization of perceptual development. *Journal of Experimental Child Psychology, 24,* 279–298.

Smith, L. B., & Kemler, D. G. (1978). Levels of experienced dimensionality in children and adults. *Cognitive Psychology, 10,* 502–532.

Treisman, A. (1987). Properties, parts and objects. In K. Boff, L. Kaufman, & J. Thomas (Eds.), *Handbook of perception and performance* (pp. 159–198). New York: Wiley.

Tversky, A. (1977). Features of similarity. *Psychological Review, 84,* 327–352.

Vygotsky, L. S. (1962). *Thought and language.* Cambridge, MA: MIT Press.

Ward, T. B. (1980). Separable and integral responding by children and adults to the dimensions of length and density. *Child Development, 51,* 676–684.

Ward, T. B. (1983). Response tempo and separable–integral responding: Evidence for an integral-to-separable processing sequencing in visual perception. *Journal of Experimental Psychology: Human Perception and Performance, 9,* 103–112.

Werner, H. (1957). The concept of development from a comparative and organismic point of view. In D. B. Harris (Ed.), *The concept of development: An issue in the study of human behavior* (pp. 125–148). Minneapolis: University of Minnesota Press.

Wilkening, F., & Lange, K. (1987). When is children's perception holistic? Goals and styles in processing multidimensional stimuli. In T. Globerson & T. Zelniker (Eds.), *Cognitive style and cognitive development* (pp. 231–257). Norwood, NJ: Ablex.

Received December 11, 1987
Revision received May 18, 1988
Accepted May 25, 1988 ■

Squire Appointed Editor of *Behavioral Neuroscience,* 1990–1995

The Publications and Communications Board of the American Psychological Association announces the appointment of Larry R. Squire, Veterans Administration Medical Center and University of California, San Diego, as editor of *Behavioral Neuroscience* for a 6-year term beginning in 1990. As of January 1, 1989, manuscripts should be directed to

Larry R. Squire
Veterans Administration Medical Center (116 A)
3350 La Jolla Village Drive
San Diego, California 92161