Similarity and Choice

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This article examined choices between alternatives when the options confronting the decision maker have similar levels on an attribute. In these situations, 2 empirical phenomena often occur. First, differences on other attributes are enhanced. Similarity along 1 attribute magnifies differences on others. Second, violations of strong stochastic transitivity often occur. A contrast-weighting theory of choice is presented that can account for these puzzling phenomena. Binary choices are represented as a monotonic function of the difference between the utilities of the options. Furthermore, the utilities of any given attribute are weighted according to the similarity of the levels along the other attribute. Small contrasts along 1 dimension result in greater weight for the other dimension. This contrast-weighting theory is consistent with empirical results in several domains, including psychophysics, social judgment, and risky decision making.

Most of our decisions reflect trade-offs. Choices about which job to take, which vacation plans to pursue, or which mutual fund to select are often made by balancing one attribute against another. After narrowing down the options, we may find that the remaining pair has similar levels on one attribute and different levels on another. Two jobs might have similar salaries but different responsibilities. Two vacations might cost the same but differ in location. Two mutual funds might have similar annual returns but different degrees of risk. In these cases, two empirical phenomena often occur: similarity effects and violations of strong transitivity.

Similarity Effects

Almost 3 decades ago, Krantz (1967) noted that choices could not be described as simply the difference between the utilities of the options. Krantz hypothesized that choices depended on the comparability of options. Tversky and Russo (1969) investigated this claim and found that similarity along one attribute enhanced differences on other attributes. They presented subjects with pairs of geometric figures (a standard and a variable figure that differed in area or shape, or both) and asked subjects to judge which figure had the largest area.

Selected results from Tversky and Russo (1969) are shown in Figure 1. Frequencies (rather than probabilities) of choosing the variable figure as larger than the standard is tall and narrow, and in panel B, the standard is short and wide. If area discrimination had been perfect, all four curves would have appeared as step functions. That is, when the relative area of the variable figure was smaller than the standard (91% or 96% of the standard), the frequency of choosing the variable figure as larger would have been zero, and when the variable figure was larger than the standard (106% or 109%), frequencies would have been at the maximum.

Figure 1 shows that area discrimination was not perfect. Furthermore, area discrimination was influenced by shape as well as area. When the shapes of the figures were similar, area discrimination was better than when the shapes of the figures differed. Similarity along one dimension intensified differences along the other dimension, a result we refer to as the similarity effect.

Similarity effects are not limited to psychophysics. Mellers (1982) found similarity effects in a social judgment task in which subjects were asked to compare faculty members, given information about their annual salaries and overall merit ratings. The task was to rate the extent to which one faculty member, x, was unfairly treated relative to another, y. Figure 2 presents selected data from Mellers (1982). In panel A, mean unfairness judgments are plotted against salaries for person x, with separate curves for person x’s merit. In all cases, person y had a salary of $40,000 and a merit rating of 2.5 (on a scale from 0 to 4). When faculty members have similar merits, the slope of the curve is steeper than when merits are dissimilar. This pattern suggests that salary differences have a greater impact on unfairness judgments when merit ratings are similar than when they are dissimilar. Any given salary difference between faculty members with the same merit ratings is judged more unfair than the same salary difference between faculty members with different merit ratings. In sum, similarity effects can occur in both social and psychophysical judgments.

Panel B shows similarity effects in merit ratings for a given salary difference. Unfairness judgments are plotted against per-
When salaries are similar or when differences between faculty members are enhanced, discrimination is better. Data from Tversky and Russo (1969).

Violations of Strong Stochastic Transitivity

Most theories of choice imply some form of stochastic transitivity: weak, moderate, or strong (Coombs, 1983; Tversky, 1972). Suppose that \( p(a, b) \), the choice proportion for selecting option \( a \) over option \( b \), is greater than or equal to 0.5 and \( p(b, c) \) is greater than or equal to 0.5. Weak stochastic transitivity says that \( p(a, c) \) should be greater than or equal to 0.5. That is, if option \( a \) is usually chosen over option \( b \), and option \( b \) is usually chosen over option \( c \), then option \( a \) should usually be chosen over option \( c \). Moderate stochastic transitivity says that if the first two conditions hold, \( p(a, c) \) should be greater than or equal to the smaller of the two choice proportions. Strong stochastic transitivity says that if the first two conditions hold, \( p(a, c) \) should be greater than or equal to the larger of the two choice proportions.

Tversky and Russo (1969) proved that strong stochastic transitivity was equivalent to independence. Independence implies that for any set of options, \( a, b, c, \) and \( d \), \( p(a, b) > p(c, d) \) if and only if \( p(a, d) > p(c, d) \). That is, if two options \( (a \) and \( c \) are ordered relative to some option, \( b \), that order should hold for all other options (i.e., \( d \)). This equivalence is discussed later.

Results from a number of studies show that choice propor-
tions usually satisfy weak and moderate stochastic transitivity, but strong stochastic transitivity is often violated (Becker, DeGroot, & Marschak, 1963; Busemeyer, 1985; Krantz, 1967; Mellers, Chang, Birnbaum, & Ordoñez, 1992; Rumelhart & Greeno, 1971; Sjöberg, 1975, 1977; Sjöberg & Capozza, 1975). Furthermore, violations of strong stochastic transitivity often depend on the similarity of options within the choice set. To illustrate, Debreu (1960) constructed a classic thought experiment. Suppose you are given a choice between a vacation in Rome plus $1 (R + 1) or a vacation in Rome (R). This choice is easy; you pick Rome plus $1 over Rome, \( p(R + 1, R) = 1.0 \). Now you are faced with a choice between a vacation in Rome or a vacation in Paris (P). Suppose you are indifferent, \( p(R, P) = 0.5 \). Strong stochastic transitivity implies that when given a third choice between Rome plus $1 and Paris, you will always choose Rome plus $1 over Paris, \( p(R + 1, P) = 1.0 \). However, it seems unlikely that the dollar will alter the previous feeling of indifference between Rome and Paris; the probability of choosing Rome plus $1 over Paris seems more like 0.5.

In this example, utility differences between the three option pairs are probably small, but the pairs differ in their similarity or comparability. In the choice between Rome plus $1 and Rome, similarity of vacation sites may enhance the difference in petty cash. However, the other pairs seem less similar because they differ in vacation sites. Whenever a triplet contains one pair (or two pairs) with similar levels on an attribute and two other pairs (or a pair) that are dissimilar on all attributes, violations of strong stochastic transitivity are more likely to occur than when the triplet contains three pairs, each with dissimilar levels on all attributes.

As mentioned earlier, the subtractive model (Equation 1) can, in principle, account for similarity effects but not violations of strong stochastic transitivity. The next section presents a theory that relies on contrast weighting to account for both of these effects. According to this theory, choices depend on the difference in the utilities of the options as well as the similarity or comparability of options. Similarity of options is captured in the weighting of the attributes. This theory is examined with choice proportions, and in some cases, strength of preference judgments, from Rumelhart and Greeno (1971), Tversky (1969), and Mellers and Biagini (1993).

Contrast Weighting

Mellers et al. (1992) proposed a contrast-weighting theory to describe preference reversals in risky decision making. When subjects consider their preferences for pairs of risky options, attributes with similar levels receive less weight than attributes with dissimilar levels. For example, when options have similar probabilities of winning, probability receives less weight than when options have dissimilar probabilities. Likewise, when options have similar payoffs, payoff receives less weight than when options have dissimilar payoffs. We present their theory and show that a slightly different version may better capture the intuition that similarity along one dimension enhances differences on another dimension.

Consider two risky options. Gamble \( a \) has some probability, \( p_a \), of winning an amount, \( x_a \), otherwise nothing, and gamble \( b \) has the same structure. The judged strength of preference for gamble \( a \) over \( b \) is as follows:

\[
S(a, b) = J[u(x_a)^{\alpha(p_a)}s(p_a)^{\beta(p_a)}] - u(x_b)^{\alpha(p_b)}s(p_b)^{\beta(p_b)},
\]

where \( J \) is a monotonic judgment function; \( u(x_a) \) and \( u(x_b) \) are the utilities associated with the amounts to win; \( s(p_a) \) and \( s(p_b) \) are the subjective probabilities of winning; \( \alpha(x) \) is a contrast weight for utilities that depends on the payoff contrast (i.e., the absolute difference between \( x_a \) and \( x_b \)), and \( \beta(p) \) is a contrast weight for probabilities that depends on the probability contrast (the absolute difference between \( p_a \) and \( p_b \)). One simple representation of the contrast weights used by Mellers et al. (1992) allows two weights for each dimension: one when contrasts are small (i.e., levels are similar) and another when contrasts are large (i.e., levels are dissimilar). A more general representation would allow weights that are a continuous function of the absolute difference along a dimension.

In this article we examine another form of contrast weighting in which the similarity of levels along one dimension enhances the weight of the other dimension. This contrast-weighting theory asserts that the judged strength of preference for gamble \( a \) over \( b \) is as follows:

\[
S(a, b) = J[u(x_a)^{\alpha(p_a)}s(p_a)^{\beta(p_a)}] - u(x_b)^{\alpha(p_b)}s(p_b)^{\beta(p_b)}.
\]

Here, utilities, \( u(x_a) \) and \( u(x_b) \), are weighted by \( \alpha(p) \) rather than \( \alpha(x) \). That is, the weight of the utilities depends on the probability contrast rather than the payoff contrast. Moreover, subjective probabilities, \( s(p_a) \) and \( s(p_b) \), are weighted by \( \beta(x) \) rather than \( \beta(p) \). The weight of probability depends on the payoff contrast rather than the probability contrast. Although both versions of the contrast-weighting theory can account for similarity effects and violations of strong stochastic transitivity, Equation 3 seems to better capture the intuition of similarity weighting.

The next four sections of this article apply the contrast-weighting theory to different data sets in which subjects make choices between multi-attribute options. We examine the extent to which the theory can account for two of the most robust phenomena in the choice literature: similarity effects and violations of strong stochastic transitivity.

Conversations With Celebrities

Rumelhart and Greeno (1971) presented subjects with pairs of celebrities and asked them to select the person with whom they would prefer to spend an hour of conversation. Celebrities included three politicians (p,), three athletes (a,), and three movie stars (m,).

Similarity Effects

Figure 3 presents selected results from Rumelhart and Greeno (1971). Choice proportions for celebrity \( x \) over celebrity

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1 When this version of the contrast-weighting theory was fit to the data of Mellers et al. (1992), predictions could have described both violations of strong stochastic transitivity and preference reversals.
are plotted as a function of \( x \), where \( x \) refers to different individuals within an occupation. Levels of \( x \) refer to politicians, athletes, and movie stars in panels A, B, and C, respectively. Curves representing levels of \( y \) show a politician, \( p \), an athlete, \( a \), and a movie star, \( m \). When celebrities have the same occupation, curves are steeper than when the celebrities have different occupations. Predictions of the contrast-weighting model are plotted as dashed lines. Data from Rumelhart and Greeno (1971).

}\begin{figure}[h]
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\includegraphics[width=\textwidth]{figure3.png}
\caption{Choice proportions for celebrity \( x \) over celebrity \( y \), plotted as a function of individual personalities (within an occupation) for \( x \) with a separate curve for different occupations of \( y \): Levels of \( x \) refer to politicians, athletes, and movie stars in panels A, B, and C, respectively. Curves representing levels of \( y \) show a politician, \( p \), an athlete, \( a \), and a movie star, \( m \). When celebrities have the same occupation, curves are steeper than when celebrities have different occupations. In panel A, the curve \( p \) represents choices between politicians. The curve is steeper than the other two curves, representing celebrities with different occupations. In panel B, the curve is steepest when both celebrities are athletes \( (a) \), and in panel C, the curve is steepest when both celebrities are movie stars \( (m) \). A given difference in celebrity personalities has a greater effect on choice proportions when celebrities have the same occupation than when celebrities have different occupations. Similarity in occupations heightens differences in personalities.

\section*{Violations of Strong Transitivity}

The 36 choice proportions in Rumelhart and Greeno's (1971) experiment produced 84 triplets, for example, \( p(a, b) \), \( p(b, c) \), and \( p(a, c) \), that could be used to examine violations of weak, moderate, and strong stochastic transitivity. Weak and moderate stochastic transitivity were satisfied in every case, but 46% of the triplets violated strong stochastic transitivity.

\section*{Contrast Weighting}

The contrast-weighting theory was represented as follows:

\[ p(x, y) = J[c_x^{ao} - c_y^{ao}] \]

where \( p(x, y) \) is the proportion of subjects who choose celebrity \( x \) over \( y \); \( c_x \) and \( c_y \) are the scale values for each celebrity; and \( J \) is a cumulative logistic function. Contrast weights, \( a(o) \), were allowed to have two levels: one when celebrities had similar occupations and another when celebrities had different occupations. Because occupations were confounded with individual personalities, only one contrast weight was estimated.

This theory was fit to the 36 choice proportions by means of a FORTRAN program that used Chandler's (1969) STEPII subroutine to obtain least squares parameter estimates. In the program, the theory is represented as a prediction equation (Equation 4) with a set of unknown parameters. The program iteratively adjusts these parameters from some specified starting values, with the objective of minimizing the sum of the squared errors between observed and predicted choice proportions.

Parameters to be estimated included seven scale values (the two most extreme scales were arbitrarily fixed to their starting values), one contrast weight for dissimilar occupations (the contrast weight for similar occupations was fixed to 1.0), and one slope parameter for the \( J \) function, which was assumed to be a cumulative logistic function. Thus, there were nine estimated parameters to describe the 36 free choice proportions. Output from the program included predictions, a lack-of-fit index, and a set of parameters that best described the data.

The contrast-weighting theory accounted for all but 3% of the variance in the choice proportions. Estimated scale values for the celebrities ranged from 1.0 to 3.5. When celebrities had similar occupations, the contrast weight was 1.0. When celebrities had dissimilar occupations, the estimated contrast weight was 0.67. Thus, when celebrities had similar occupations, a given difference in personalities was predicted to have a greater effect on choice proportions than when celebrities had dissimilar occupations.

Predictions of the contrast-weighting theory are shown as dashed lines in Figure 3. There are clearly some deviations between data and predictions. However, in all three panels, predicted slopes of the curves for celebrities with similar occupations are steeper than those with dissimilar occupations, consistent with the observed similarity effects.

The contrast-weighting theory also approximated the general pattern of observed transitivity violations. There were 0%, 0%, and 46% observed violations of weak, moderate, and strong stochastic transitivity, respectively. The contrast-weighting theory predicted 0%, 0%, and 13% violations. Thus, the theory successfully predicted that weak and moderate transitivity were satisfied, although it underestimated the percentage of strong transitivity violations. In the sum, the contrast-weighting theory successfully described similarity effects and at least some violations of strong transitivity in the data of Rumelhart and Greeno (1971). To determine whether the contrast-weighting theory can describe violations of weak stochastic transitivity, we now turn to a classic data set of Tversky (1969).

\section*{Intransitive Preferences}

Tversky (1969) investigated a pattern of intransitive preferences in risky and riskless choices between options with two

\footnote{Presumably, less restrictive assumptions about the contrast weights would produce more predicted violations of strong transitivity.}
attributes. He presented subjects with pairs of gambles, each having some probability, \( p \), of winning an amount, \( x \), otherwise nothing. Gambles were constructed such that payoffs and probabilities were correlated: Larger probabilities of winning were associated with smaller amounts to win (see Table 1).

**Transitivity Violations**

The 10 choice proportions for each subject produced 10 triplets with which to examine properties of transitivity. Table 2 displays observed violations of weak, moderate, and strong stochastic transitivity for each of the 8 subjects. This data set is well known for its violations of weak stochastic transitivity. Seven of the 8 subjects violated weak and moderate stochastic transitivity in at least one triplet. All 8 subjects violated strong stochastic transitivity in at least three triplets. Median percentages of weak, moderate, and strong transitivity violations were 30%, 75%, and 80%, respectively.

Tversky (1969) hypothesized that when two gambles were similar (adjacent levels of probabilities and payoffs), subjects would choose the gamble with the higher payoff because the probability display (fractions) made fine discriminations difficult. When gambles were dissimilar (nonadjacent levels of probabilities and payoffs), subjects would select the gamble with the larger probability of winning. This pattern of preferences implies violations of weak stochastic transitivity. Therefore, not only did Tversky hypothesize intransitive preferences but he also predicted a pattern of intransitivities based on the similarity and dissimilarity of gamble pairs.

Figure 4 shows selected choice proportions for each of the 8 subjects from Tversky (1969). Choice proportions for Gamble 1 over Gamble 2 are shown as a function of gamble pairs. Data are black bars, and predictions of the contrast-weighting theory are grey bars. To highlight violations of weak stochastic transitivity, a dashed line is drawn across all panels for choice proportions of 0.5. A series of bars with heights above 0.5 followed by a bar below 0.5 represents a violation of weak stochastic transitivity. Subject 1, for example, prefers \( a \) to \( b \), \( b \) to \( c \), \( c \) to \( d \), and \( d \) to \( e \). For each pair of similar gambles, this subject prefers the larger amount to win. Weak stochastic transitivity implies that \( a \) should be preferred over \( e \), but \( e \) is preferred to \( a \), that is, \( p(a, e) \) is less than 0.5. For dissimilar gambles, Subject 1 prefers the larger probability of winning over the larger amount to win. Subjects 2 through 6 show similar patterns.

Tversky (1969) proposed that when making choices, subjects use a lexicographic semiorder, as follows: If the difference between the alternatives on Dimension I is greater than some threshold, choose the alternative that has the higher value on Dimension I. If the difference between the alternatives on Dimension I is smaller than the threshold, choose the alternative with the higher value on Dimension II. Subjects chose the gamble with the larger payoff when the probability difference was small. Otherwise, subjects chose the gamble with the larger probability.

Tversky (1969) formalized this rule as an additive difference model. According to this model, subjects consider the difference between the subjective values of the alternatives along a dimension \( \delta_i = t_i - \hat{t}_i \). To each quantity, a difference function, \( \phi \), is applied, and values of \( \phi(\delta_i) \) are summed over dimensions.

**Contrast Weighing**

An alternative explanation for this pattern of preferences is contrast weighting: When gambles have similar levels along one attribute, differences along the other attribute are enhanced. The contrast-weighting theory differs from the additive difference model in two important respects. First, contrast weighting assumes that subjects consider the difference between overall gamble utilities, rather than differences along dimensions, as in the additive difference model. Second, in the contrast-weighting theory, weights assigned to dimensions depend on the size of the contrast. In other words, different power functions are applied to the scale values, depending on the magnitude of the difference. In the additive difference model, the same function, \( \phi \), is applied to all values of \( \delta_i \).

To examine whether contrast weighting could describe the patterns of weak, moderate, and strong transitivity violations, we fit the theory to each subject’s choice proportions. The contrast-weighting theory was represented as follows:

\[
p(i, j) = J[u(g_i)^{\phi} - u(g_j)^{\phi}],
\]

where \( p(i, j) \) is the proportion of times a subject selected gamble

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<th>Expected value</th>
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Note. Obs = observed violations; Pred = predicted violations. All values are expressed as percentages and are based on 10 triplets for each of the 8 subjects. Predictions refer to the contrast-weighting theory (Equation 3 in the text).
Figure 4. Choice proportions for the first gamble over the second (gambles are defined in Table 1), plotted as a function of gamble pairs for 8 subjects in Tversky's (1969) experiment. Data are black bars, and predictions of the contrast-weighting theory are grey bars. A series of bars with heights above 0.5 followed by a bar below 0.5 represents a violation of weak stochastic transitivity. The contrast-weighting can account for the weak transitivity violations (Subjects 1–5) and the absence of such violations (Subjects 7–8). Data from Tversky (1969).

\[ i \] over gamble \( j \), and \( u(g_i) \) and \( u(g_j) \) represent the utilities of gambles \( i \) and \( j \), respectively; \( \alpha(g) \) is the contrast weight. Because probabilities of winning and amounts to win were confounded, only one set of contrast weights was estimated. Contrast weights, \( \alpha(g) \), were allowed to have three levels, depending on the degree of contrast between the two gambles—similar (adjacent), dissimilar (nonadjacent and one level apart), and very dissimilar (nonadjacent and more than one level apart). The weight for similar levels was fixed to 1.0. Weights for dissimilar and very dissimilar levels were estimated. For each subject, the theory required six estimated parameters to describe the 10 free choice proportions.

The percentage of residual variance for each of the 8 subjects ranged from 3% to 31%, with a median value of 14%. Although the percentage of residual variance is much larger than that obtained for the Rumelhart and Greeno (1971) study, each choice proportion is based on a small number of observations from the same subject rather than many independent observations from several subjects, and the data are not nearly as smooth. For all but 2 of the subjects (Subjects 7 and 8), contrast weights were largest for similar levels, followed by dissimilar levels, and smallest for very dissimilar levels. In other words, estimated contrast weights were consistent with the notion that similarity along one dimension amplifies differences on the other dimension, and the amplification grows with the size of the contrast. Subjects 7 and 8, whose choices did not show as many violations of weak stochastic transitivity, had weights that were similar for all three levels. For these subjects, contrast weighting was negligible.

The contrast-weighting theory successfully predicted the rates of weak, moderate, and strong stochastic transitivity violations in the data of Tversky (1969). Table 2 shows predicted percentages of violations. To examine the overlap in observed and predicted violations of weak stochastic transitivity violations, correlations were computed for each subject. The median correlation was 0.61. The contrast-weighting theory also predicted the intransitive choice patterns shown in Figure 4. Predictions (grey bars) follow the patterns in the data (black bars). The theory predicted intransitive preferences for Subjects 1 through 5, but no such patterns for Subjects 6, 7, and 8.

In sum, reanalyses of data from the experiments of Rumelhart and Greeno (1971) and Tversky (1969) lend support for contrast weighting. However, in these studies, levels of one attribute...
but were confounded with those of the other attribute. Furthermore, these studies are not optimal for testing the contrast-weighting theory; the experimental designs require a large number of estimated parameters relative to degrees of freedom. A stronger test of the theory is one with independent attributes and many more degrees of freedom. The next two experiments examine choices in risky and riskless choices, where the dimensions are unconfounded and subjects make a large number of judgments.

Gambles

In an experiment by Mellers and Biagini (1993), 60 subjects were presented with pairs of gambles, each having some probability of winning an amount, otherwise zero. Gambles were constructed from a factorial design of gamble \( a \) (Probability \( \times \) Payoff) by gamble \( b \) (Probability \( \times \) Payoff).

This experimental design created nondominated pairs, dominated pairs, and stochastically dominated pairs.\(^4\) Choice proportions for dominated and stochastically dominated choice pairs are obviously 0.1 and 0.0. However, strength of preference judgments could vary. Consider the strength of your preference for a vacation in Rome plus $1 versus a vacation in Rome. Now consider the strength of your preference for Rome plus $100,000 versus Rome. If the latter seems larger than the former, then perhaps you will agree that strength of preference judgments for dominated pairs might vary, although choice proportions would probably remain constant. Therefore, because strength of preference judgments might provide more continuous measures of preference, we examine both strength of preference judgments and the more familiar choice proportions in the analyses that follow.

On each trial, subjects selected the gamble they preferred, then indicated the strength of their preference for one gamble over the other. Subjects were told to use "0" for identical gambles and "100" to represent the strength of their preference for the best gamble (90% chance of $91, otherwise nothing) over the worst gamble (10% chance of $13, otherwise nothing). All other strength of preference judgments were made relative to these endpoints. All other pairs were judged relative to this one. Results are discussed for both strength of preference judgments and choice proportions.

Gamble pairs were constructed from a \( 25 \times 9 \) (Gamble \( a \times \) Gamble \( b \)) factorial design. Levels of gamble \( a \) were based on a \( 5 \times 5 \) (Payoff \( \times \) Probability) design, with payoffs of $13, $17, $51, $81, and $91, and probabilities of 0.1, 0.2, 0.5, 0.8, and 0.9. Levels of gamble \( b \) were a \( 3 \times 3 \) subset of those from gamble \( a \), with payoffs of $13, $51, and $91, and probabilities of 0.1, 0.5, and 0.9.

Violations of Strong Transitivity

Mellers et al. (1992) pointed out that violations of transitivity can be investigated in strength of preference judgments as well as choice proportions. Suppose that a judgment of zero represents indifference, and \( S(a, b) > 0 \) represents a judged preference for \( a \) over \( b \). Furthermore, suppose that \( S(a, b) > 0 \) and \( S(b, c) > 0 \). Weak transitivity states that if the two initial conditions hold, then \( S(a, c) > 0 \). Moderate transitivity says that \( S(a, c) > \min[S(a, b), S(b, c)] \), and strong transitivity requires that \( S(a, c) > \max[S(a, b), S(b, c)] \).

There were 660 triplets that could be used to examine properties of transitivity. Table 3 shows the observed percentages of weak, moderate, and strong transitivity violations. Weak and moderate transitivity were satisfied, but 30% of the triplets violated strong transitivity in the mean strength of preference judgments. Individual subject judgments resembled the aggregate data; median percentages of individual subject violations were 0%, 8%, and 37%, respectively. Choice proportions had fewer violations of strong stochastic transitivity because of the large number of tied responses at 0.0 and 1.0.

There was a systematic pattern in the strong transitivity violations. Violations of strong transitivity were more likely to occur with triplets that included one or two similar pairs and at least one dissimilar pair than with triplets consisting of three dissimilar pairs. Similar levels were assumed to be adjacent levels that differed by no more than an amount difference of $6 or a probability difference of 0.1. Therefore, similar payoffs were ($13, $17) and ($85, $91); similar probabilities were (0.1, 0.2) and (0.8, 0.9). All other pairs were assumed to be dissimilar. The correlation between strong transitivity violations and triplets with one or two similar pairs was statistically significant in both strength of preference judgments and choice proportions, \( \chi^2(1, N = 660) = 36.89 \), and \( \chi^2(1, N = 660) = 18.37 \), respectively.

Similarity Effects

Figure 5 presents similarity effects in the strength of preference judgments for gamble \( a \) over gamble \( b \). Mean strength of

\(^4\) Nondominated gamble pairs are those for which one gamble has a larger probability of winning and the other has a greater amount to win. Dominated pairs are those for which probabilities are the same, but one gamble has a larger payoff. Stochastically dominated pairs are those for which payoffs are the same, but one gamble has a larger probability of winning.
Figure 5. Mean strength of preference judgments for gamble $a$ over gamble $b$, plotted as a function of gamble $a$'s payoffs, with a separate curve for each level of gamble $a$'s probability. Gamble $b$ is held constant within a panel. Panels A, B, and C correspond to $b$s of ($51, 0.1; 0\$), ($51, 0.5; 0\$), and ($51, 0.9; 0\$), respectively. When gambles have the same probabilities, curves are steeper than when gambles have different probabilities across all three panels.

Preference judgments are plotted as a function of gamble $a$'s payoff, with separate curves for gamble $a$'s probability of winning. Within a panel, gamble $b$ was held constant. In panels A, B, and C, gamble $b$ had a .1, .5, and .9 probability of winning $51$, respectively.

In panel A, the steepest curve is the one for which gambles $a$ and $b$ have identical probabilities of winning (.1,.1). The next steepest curve is the one for which gambles $a$ and $b$ have similar probabilities of winning (.2,.1). Curves flatten out as probability differences increase. Thus, payoff differences have a greater effect on strength of preference judgments when probabilities of winning are either identical or similar. The effect of payoff differences diminishes as probability differences increase. This pattern appears in all three panels. Once again, similarity of probabilities enhances differences in payoffs. Results are similar with choice proportions, although the functions are not as smooth.

As mentioned earlier, Tversky and Russo (1969) showed that strong stochastic transitivity was equivalent to independence. With strength of preference judgments, independence implies that for any set of options, $a$, $b$, $c$, and $d$, $S(a, b) > S(c, d)$ if and only if $S(a, d) > S(c, b)$. Figure 5 presents selected curves from Figure 5 to illustrate violations of independence. Solid curves are data, and dashed lines are predictions of the contrast-weighting theory. Consider the two solid points in panel A labeled $S(a_1, b_1)$ and $S(a_2, b_2)$. $S(a_1, b_1)$ is the judged strength of preference for $a_1$ over $b_1$. $S(a_2, b_1)$ is the strength of preference for $a_2$ over $b_1$. Notice that gamble $a_2$ is preferred to $a_1$, relative to $b_1$, $S(a_2, b_1) > S(a_1, b_1)$. Independence implies that this ordering of $a_2$ and $a_1$ should hold for all levels of $b$. The same order is found in panel C, that is, $S(a_2, b_3) > S(a_1, b_3)$. However, in panel A, $a_1$ is preferred to $a_2$, relative to $b_2$, that is, $S(a_2, b_2) < S(a_1, b_2)$. This change in order is a violation of independence. These violations also occur in choice proportions: $p(a_2, b_1) = .99 > p(a_1, b_1) = .92$, $p(a_2, b_2) = .08 < p(a_1, b_2) = .47$, and $p(a_2, b_3) = .03 > p(a_1, b_3) = .00$.

Figure 6 shows that violations of independence are related to similarity effects. In panel B, both gamble pairs are dissimilar, and $S(a_2, b_2) < S(a_1, b_2)$. However, in panel A, gambles $a_2$ and $b_1$ have identical probabilities. Identical probabilities may enhance payoff differences between $a_2$ and $b_1$, such that $S(a_2, b_1) > S(a_1, b_1)$. In a similar manner, in panel C, $a_1$ and $b_3$ have identical probabilities, and $S(a_2, b_3) > S(a_1, b_3)$.

To test the significance of the rank order changes from panel A to panel B, individual strength of preference judgments were classified into groups with inconsistent, consistent, or tied rank orders. Forty-one percent of the subjects had the inconsistent rank order shown in panels A and B, and only 8% had the opposite inconsistent order. These proportions were significantly different, $\chi^2(1, N = 60) = 11.56$. The test was repeated to compare rank order change from panel B to panel C. Fifty-seven percent of the subjects had the inconsistent order shown in panels B and C, and only 2% had the opposite inconsistent order. Differences between these proportions were also statistically significant, $\chi^2(1, N = 60) = 26.1$. In sum, the independence assumption was violated in the means and the individual subject data. When subjects had inconsistent rankings, the inconsistency was clearly systematic.
Figure 6. Selected curves from Figure 5 replotted to highlight violations of independence. Data are solid lines and predictions of the contrast-weighting theory are dashed lines. In panel A, the point labeled $S(a_1, b_1)$ is below the point labeled $S(a_2, b_1)$. Independence implies that these points should have the same order across all three panels. Panel C has the same order, $S(a_1, b_2) < S(a_2, b_1)$, but panel B has the opposite order, $S(a_1, b_3) > S(a_2, b_3)$. The contrast-weighting theory can describe this violation of independence. Dashed lines show similar changes in rank order.

**Contrast Weighting**

The contrast-weighting theory (Equation 3) was fit to the mean strength of preference judgments. Five utilities and five subjective probabilities were estimated (with the smallest utility and the two most extreme probabilities fixed to their physical values). Three contrast weights were allowed for each dimension (identical, similar, and dissimilar). Similar payoffs were ($13, $17) and ($85, $91); similar probabilities were (.1, .2) and (.8, .9). All other differing pairs were assumed to be dissimilar. Contrast weights for identical levels were fixed to 1.0 and those for similar and dissimilar levels were estimated. The $J$ function was assumed to be a cumulative logistic function, and one slope parameter was estimated. Thus, there were 12 estimated parameters to account for the 180 free strength of preference judgments.

The theory described all but 1.8% of the variance in the mean strength of preference judgments. When the theory was fit without contrast weights, the residual variance was over 2.5 times as great; contrast weighting was a critical component of the theory. When payoffs were identical, similar, and dissimilar, contrast weights for probabilities were 1.00, .83, and .70, respectively. When probabilities were identical, similar, and dissimilar, contrast weights for utilities were 1.00, .47, and .34. Thus, estimated contrast weights were in the predicted direction; smaller contrasts along one dimension produced greater weights on the other dimension.

The contrast-weighting theory also gave a good account of the choice proportions. The residual variance was only 1.3%. When amounts were identical, similar, and dissimilar, contrast weights for probabilities were 1.00, .83, and .57, respectively. When probabilities were identical, similar, and dissimilar, contrast weights for amounts were 1.00, .45, and .32, respectively. Once again, estimated contrast weights were in the predicted direction.

Figure 6 shows that the contrast-weighting theory can describe similarity effects, violations of independence, and violations of strong transitivity. Predicted similarity effects are evident in Figure 6: When probability levels are identical, the effect of payoff is predicted to be greater than when probabilities differ. Predicted violations of independence are also shown in Figure 6: in panel A, $\bar{S}(a_1, b_1) > \bar{S}(a_2, b_1)$; in panel B, $\bar{S}(a_2, b_2) < \bar{S}(a_1, b_2)$; and in panel C, $\bar{S}(a_1, b_3) > \bar{S}(a_2, b_3)$, as found in the data. Finally, the theory captures the observed pattern of transitivity violations. Observed violation rates were 0%, 0%, and 30% for weak, moderate, and strong transitivity. Predicted violation rates were 0%, 4%, and 42%, respectively. Moreover, observed and predicted violations of strong transitivity were significantly correlated, $\chi^2(1, N = 660) = 28.8$. To summarize, the contrast-weighting theory could describe similarity effects, violations of independence, and strong transitivity violations in both strength of preference judgments and choice proportions.

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The 25 X 9 design had only 180 free strength of preference judgments because symmetry was assumed in 45 of the cells. That is, the strength of preference for $b$ over $a$ was assumed to be the same as the strength of preference for $a$ over $b$, with a change in sign.
portions. To test the generality of contrast-weighting, the theory is now applied to a riskless choice domain.

**Summer Jobs**

Mellers and Biagini (1993) presented 69 subjects with pairs of summer jobs, each described by hourly wage and one-way commute time. On each trial, subjects were asked to select the job they preferred and to state the strength of their preference for one job over the other. Subjects were told to use “0” for identical jobs and “100” to represent the strength of their preference for the best job ($12 per hr, 0-min commute time) over the worst job ($4 per hr, 60-min commute time). On all other trials, subjects judged strength of preference for one job over another relative to these endpoints.

Job pairs were constructed from a $25 \times 9$ (Job $a \times$ Job $b$) design similar to that used with the gambles experiment. Job $a$ levels were based on a $5 \times 5$ set of hourly wages and commute times, with hourly wages of $4, 5, 8, 11,$ and $12,$ and commute times of $0, 10, 30, 50,$ and $60$ min. Job $b$ levels were a subset of job $a$ levels, constructed from a $3 \times 3$ design of wages ($4, \$8,$ and $12$ per hr) by commute times ($0, 30,$ and $60$ min).

**Violations of Strong Transitivity**

Six hundred and sixty triplets were used to test properties of transitivity, and Table 4 shows the observed violations. In the mean strength of preference judgments, there were $0\%$, $0\%$, and $23\%$ violations of weak, moderate, and strong transitivity, respectively. Median individual subject violation rates were $0\%$, $6\%$, and $33\%$, respectively. Violation rates in the choice proportions were lower, presumably because of the large percentage of tied responses at 0.0 and 1.0.

There was a systematic pattern in the strong transitivity violations, related to the similarity of job pairs. A similar job pair was one for which wages differed by no more than $\$1$ or commute times differed by no more than 10 min, or both. Thus, similar wages were ($4, \$5$) and ($11, \$12$); similar commute times were ($10, 20$ min) and ($50, 60$ min). All other pairs were assumed to be dissimilar. Violations of strong transitivity were more likely to occur with triplets that included one or two similar or identical pairs and at least one dissimilar pair than with triplets consisting of three dissimilar pairs in both strength of preference judgments and choice proportions, $\chi^2(1, N = 660) = 12.6,$ and $\chi^2(1, N = 660) = 5.9$, respectively.

**Similarity Effects**

Figure 7 shows mean strength of preference judgments for job $a$ over job $b$, plotted as a function of job $a$ commute times with a separate curve for each hourly wage for job $a$. Within a panel, job $b$ is always held constant. In panels A, B, and C, job $b$ has a 30-min commute time and hourly wages of $4, \$8,$ and $12$, respectively. When hourly wages for the two jobs are identical, differences in commute times have a greater effect than when hourly wages differ. In panels A, B, and C, the steepest curve represents jobs with identical wages of $4, \$8,$ and $12$ per hr, respectively. Flatter curves correspond to jobs with different hourly wages. Differences in commute times have a greater effect when hourly wages are alike. Results are similar with choice proportions.

Systematic violations of independence are also found with summer jobs and are shown in Figure 8. Data are presented as solid lines, and predictions are dashed lines. In panel A of Figure 8, $S(a_2, b_1) > S(a_1, b_1)$, and in panel C, $S(a_2, b_1) > S(a_1, b_1)$, but in panel B, $S(a_2, b_2) < S(a_1, b_2)$. Thirty-six percent of the subjects had the rank order change shown in panels A and B, and only 6% had the opposite inconsistent order. These proportions were significantly different, $\chi^2(1, N = 69) = 11.56$. Thirty-seven percent of the subjects had the pattern of judgments shown in panels B and C, and only 5% had the opposite inconsistent ordering. Differences between these proportions were also significant, $\chi^2(1, N = 69) = 13.5$. Violations of independence were systematic at the individual subject level.

**Contrast Weighting**

To examine the contrast-weighting theory for riskless choices, it was necessary to specify a rule to represent the utility of a job described by hourly wage and commute time. Both additive and multiplicative combination rules were examined. Because the multiplicative rule gave a better account of the data, it is presented here. This version of the contrast-weighting theory can be expressed as follows:

$$S(a, b) = J[w(x_a)^{w(m_a)}(m_b)\gamma(x)] - w(x_a)^{w(m_a)}(m_b)\gamma(x),$$

where $w(x_a)$ and $w(x_b)$ are the subjective values of the hourly wages for jobs $a$ and $b$; and $t(m_a)$ and $t(m_b)$ are the subjective commute times (in minutes) for jobs $a$ and $b$. All other terms are as defined in earlier equations. Five hourly wages and five commute times were estimated (with the two most extreme wages and the 60-min commute time arbitrarily fixed). Three contrast weights were allowed for each dimension (identical, similar, and dissimilar). There was a total of 12 estimated parameters for 180 free strength of preference judgments. The contrast-weighting theory described all but 1.2% of the variance in the observed violations of independence.
in the strength of preference judgments. When wages were identical, similar, and dissimilar, contrast weights for commute times were 1.00, .87, and .72, respectively. When commute times were identical, similar, and dissimilar, contrast weights for amount were 1.00, .97, and .86, respectively.

The contrast-weighting theory was also fit to choice proportions, and the residual variance was less than 1%. When wages were identical, similar, and dissimilar, contrast weights for probabilities were 1.00, .70, and .47, respectively. When commute times were identical, similar, and dissimilar, contrast weights for wages were 1.00, .65, and .44, respectively.

Predictions of theory for strength of preference judgments are shown in Figure 8. The theory predicted the similarity effects: When levels of one attribute were identical or similar, differences along the other attribute were predicted to have a greater effect. The contrast-weighting theory also predicted the violations of independence. In panel A, $S(a_1, b_1) > S(a_2, b_2)$; in panel B, $S(a_2, b_1) < S(a_1, b_2)$; and in panel C, $S(a_2, b_3) > S(a_1, b_3)$, as found in the data. The theory also captured these violations of independence in the choice proportions. Finally, the theory could predict the violations of strong transitivity. Observed violation rates were 0%, 0%, and 23%, and predicted rates were 0%, 0%, and 28%. Furthermore, observed and predicted violations of strong transitivity were significantly correlated, $\chi^2(1, N = 660) = 46.89$.

In summary, contrast weighting was able to describe the similarity effects, most violations of independence, and violations of strong transitivity in strength of preference judgments and choice proportions when the two attributes were unconfounded. This more rigorous test of contrast weighting in both risky and riskless domains lends even greater support to the theory.

**General Discussion**

How well do existing theories of risky and riskless choice describe similarity effects and violations of strong stochastic transitivity? In the domain of risky choice, many theories, including the popular rank- and sign-dependent theories (Luce & Fishburn, 1991; Quiggin, 1982; Tversky & Kahneman, 1992), are deterministic rather than probabilistic. A few theories of risky choice permit violations of weak transitivity, including regret theory (Bell, 1982; Loomes & Sugden, 1982), the advantage model (Shafrir, Osherson, & Smith, 1989), and skew-symmetric bilinear utility theory (Fishburn, 1988). However, these theories do not address stochastic concerns.

In the domain of riskless choice, several probabilistic theories have been proposed. One of the most well-known theories is Thurstone's (1927) law of comparative judgment with correlated utilities. According to this theory, each option is represented as a normal distribution on a utility continuum, and on any given trial, the utilities of the two options may be correlated. Correlations provide the link between choice proportions and similarity; more similar options are more highly correlated. The theory, though elegant, permits violations of strong stochastic transitivity but does not allow violations of moderate or weak stochastic transitivity. Furthermore, Thurstone's theory typically requires a large number of parameters when fit to data.
Restle (1961) and Tversky (1972) developed set-theoretic choice theories that also relax the assumption of strong stochastic transitivity. Options are assumed to be sets of features, and choices between option pairs only depend on features that are unique to each option. A disadvantage of these models is that they require knowledge of the similarity structure of the options. It is necessary to specify which features describe the alternatives and how those features overlap. Though clearly important, this information may not be available in any real-life situation.

Carroll and his colleagues (Carroll & De Soete, 1991; De Soete & Carroll, 1992) developed several probabilistic choice theories to describe individual differences in choice. Wandering ideal point models place individuals and options in the same multidimensional space and represent individuals as distributions rather than points. Wandering vector models project stimulus values on individual vectors that are allowed to vary systematically within the psychological space. Stochastic tree unfolding models assume a hierarchical system of features and assert that choice is based on a probabilistic selection of these features. The most general versions of these models cannot be identified, but simpler cases can be fit to data. However, even the simpler cases require many parameters and sometimes knowledge of the similarity structure of the options.

Although violations of weak stochastic transitivity may not be common, Tversky (1969) has shown that they occur reliably and are related to the similarity of options. He proposed an additive difference model, described earlier. This model allows violations of weak stochastic transitivity. Though impressively general, the model does not directly address similarity effects. It is not immediately obvious how the difference functions capture the pattern of intransitive preferences found in the data because the same difference function is applied to all contrast magnitudes.

The contrast-weighting theory can account for similarity effects and violations of strong stochastic transitivity in psychophysics, social judgments, and risky decision-making experiments. In addition to its predictive power, the contrast-weighting theory has the following advantages: (a) It can address both risky and riskless choice domains within the same theory; (b) it requires relative few parameters; (c) it presupposes a fairly simple similarity structure for the options; (d) it directly models similarity effects; and (e) it can, in principle, predict violations of weak, moderate, and strong stochastic transitivity.

What are the disadvantages? First, the theory requires some knowledge of similarity to specify which alternatives are similar and which are dissimilar. However, fits of the theory show that even quite simple proxies for similarity (adjacent levels) and dissimilarity (nonadjacent levels) work reasonably well. Furthermore, it is probably easier in most situations to make simple assumptions about small and large contrasts than assumptions about the hierarchical organization of features. Second, the contrast-weighting theory is limited to a fairly narrow set of choice problems. In its present form, contrast weighting addresses only binary choices in which options are characterized by two attributes. Future work is under way to address these issues. Finally, the contrast-weighting theory does not fall neatly out of an axiomatic structure and, therefore, may seem somewhat ad hoc.
Despite these disadvantages, the theory has intuitive appeal. It seems reasonable that similarity of levels along one attribute would intensify differences on other attributes. But why? Weights may represent attentional focus, and the discounting of dimensions may be the consequence of a desire to focus attention primarily on attributes that differ.\(^6\) Focusing attention on these attributes may simplify the task and minimize effort (Payne, 1976; Payne, Bettman, & Johnson, 1992). However, this seemingly reasonable strategy can, at least in some cases, lead to violations of strong, moderate, and even weak stochastic transitivity.

Knowledge that subjects engage in contrast weighting may be useful in marketing contexts. If similarity along one dimension enhances differences on other dimensions, firms that introduce a new product can take advantage of this fact. Suppose the most popular brand of a product is known for its quality but costs considerably more than its competitor’s product. A firm might consider two strategies for a new product. The firm could slightly improve on both attributes (i.e., increase quality and lower price) or greatly improve on one attribute and hold the other constant (i.e., match the new brand and the popular brand on price and greatly improve quality or match the two brands on quality and substantially lower price). According to the contrast-weighting theory, the firm can get additional benefit from matching on one attribute and improving on the other. Perceived differences on the favored attribute will appear greater if products are similar on the other attribute.

Conclusions

Decision makers facing choices between jobs, vacation plans, or mutual funds may often find that when options are similar on one attribute, differences along the other attribute seem psychologically greater. Differences in job responsibilities may have a greater effect on preferences when salaries are similar, or differences between vacation plans may seem larger when both plans cost the same. Furthermore, faculty members evaluating the fairness of their salaries may perceive any given salary difference as larger if they compare themselves with others with similar merit. This article argues that these phenomena can be described by contrast weighting. Subjects consider the difference between the overall utilities of options and weight levels of an attribute according to the similarity of levels on the other attribute. Smaller contrasts along one dimension result in larger weights along the other dimension. This simple representation predicts both similarity effects and violations of strong transitivity in both choices and strength of preference judgments.

\(^6\) Because the contrast-weighting theory does not permit the estimation of weights that are separate from scales, an alternative interpretation for contrast weighting is that the utilities of the attributes vary as a function of the similarity of attribute levels. When attributes are similar on a dimension, utility differences on the other dimension are increased.

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