Title
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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 20(0)

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Publication Date
1998

Peer reviewed

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Abstract

Two experiments investigate the conjunction fallacy (judging that conjunctive probabilities are higher than the probabilities of the constituents). The conjunction fallacy was much less for P(E|C) tasks than for P(C|E) tasks. The results are explained in terms of the way people interpret the conditional probabilities. We argue that people prefer to reason from cause to effect (cause-to-effect reasoning heuristic), and for that reason, the instructions given for P(C|E) tasks were misinterpreted, resulting in apparent fallacy. In addition, we provide evidence showing that likelihood judgments are higher with more evidence (more-is-better heuristic).

Introduction

There has been a recent surge of interest in causal reasoning both in Psychology (e.g., Ahn, Kalish, Medin, & Gelman, 1996; Cheng, 1997; Shanks, Holyoak, & Medin, 1996) and in Computer Science (e.g., Pearl, 1988; 1995). Of many issues studied in this field, the rationality of human causal judgments has received a great deal of attention. The purpose of the current study is to investigate one apparently irrational phenomenon in causal judgments, namely conjunction fallacy.

Conjunction Fallacy

It is irrational if the probability of an event is judged to be less likely than the probability of the event along with some other event. Tversky and Kahneman (1983) first demonstrated that when laypeople were asked to judge the probability of occurrence of conjunctive events and their constituents, their judgments could violate such normative rules, committing the so-called Conjunction Fallacy. For instance, given a description of Linda who resembles a typical feminist, participants judged that the likelihood that Linda is a feminist and a bank teller is higher than the likelihood that Linda is a bank teller.

Leddo, Abelson, and Gross (1984) expanded this phenomenon to causal reasoning. For instance, participants received a story about John's decision to attend Dartmouth and rated the likelihood of various possible causal explanations. Some of these explanations were "single" explanations (e.g., "John wanted to attend a prestigious college," "Dartmouth offered a good course of study for John's major") and some were conjunctive (e.g., "John wanted to attend a prestigious college and Dartmouth offered a good course of study for John's major"). Normatively speaking, the likelihood of two causes' occurrence given an effect, $P(C_1\&C_2|E)$, can never exceed the likelihood of one cause's occurrence given an effect, $P(C_1|E)$ or $P(C_2|E)$. Unlike the normative predictions, participants' ratings on conjunctive explanations were greater than that on single explanations.

Leddo et al. (1984) discussed that one possible reason for the conjunction fallacy is that people misinterpret the inverse probabilities. That is, instead of judging $P(C_1\&C_2|E)$, participants might have judged $P(E|C_1\&C_2)$. (see Fisk, 1996; Wolford, Taylor, & Beck, 1990 for a similar debate on the Linda the bank teller problem.) Note that in this case, participants' responses are not necessarily non-normative because $P(E|C_1\&C_2)$ can be greater than $P(E|C_1)$ or $P(E|C_2)$. Leddo et al. (1984) dismissed this account by referring to their data. The argument was that if participants were working backwards, then conjunctions should always be rated higher than the single reasons because additional reasons should make the event more compelling. However, the conjoint explanations were rated less likely than at least one of the single explanations (i.e., atypical explanations) and they took this as evidence against the backward reasoning hypothesis.

However, it should be noted that there can be many other factors that could contribute to the conjunction fallacy in causal reasoning. Of most relevant to this point is Ahn and Bailenson (1996) who showed that the conjunction effect in causal explanations depends on the coherency of the two explanations; the more coherent story one can construct from the conjunctive explanations, the greater the conjunction effect was. If the two reasons do not make a coherent story, then even when the questions were described as $P(E|C_1\&C_2)$, people did not necessarily judge the two causes as better than one cause and, in some cases, the conjunctive likelihood was even lower than the single likelihood. Therefore, even if participants had actually reversed the conditional probabilities in Leddo et al.'s studies, the conjunctive explanations could have been rated less likely than one of the single explanations because the conjunctive explanations were not coherent enough. Thus, explaining the conjunction fallacy in causal reasoning in terms of misinterpretation of conditional probabilities has not yet been convincingly dismissed.

Misinterpreting conditional probabilities

In the area of judgments and decision making, a number of studies have shown that laypeople and experts confuse conditional probabilities by equating diagnostic probabilities, P(disease|symptom), with predictive ones, P(symptom|disease) (e.g., Dawes, Mirels, Gold, & Donahue, 1993; Eddy, 1982; Meehl & Rosen, 1955). Eddy (1982), for instance, told physicians that the probability of the patient has a positive X-ray report from mammography given that the patient has cancer is 0.792. Then, the physicians were asked to estimate the probability that a patient with the positive X-ray report would have a breast cancer. According to the Bayes' formula, the correct probability is 0.077 because the base rate of breast cancer is only 1%. However, 95 out of 100 physicians interviewed by Eddy misinterpreted the statements and estimated the probability to be about 75%.

In the area of causal reasoning, there has not yet been a systematic study testing whether the two conditional probabilities, P(C|E) or P(E|C), are confused. Matute, Arcediano, and Miller (1996) have utilized measures that somewhat analogously map onto these two probabilities ("Is C the cause of E?" and "Is E the effect of C?") and found no difference in the participants' estimates. In this study there was no normative criterion that the two estimates should be different (e.g., Bayesian theorem). Therefore, it is difficult to assess whether the answers were the same because the participants confused the two questions or because the answers to both questions can be actually the same.

Current causal reasoning models up to date have not yet made a clear distinction between these two probability estimates. For instance, Rescorla-Wagner model measures associative strength between two cues which are bi-directional (Rescorla & Wagner, 1972). Cheng's causal power in the Power PC theory (1996) seems to measure cause-to-effect strength but it does not indicate how effect-to-cause strength should be derived from it. The Bayesian network (Pearl, 1988) certainly makes a distinction between these two conditional probabilities but it has not yet been proposed as a psychological model (but see a more recent attempt in Glymour & Cheng, in press; Waldmann & Martingnon, in preparation).

In developing a causal reasoning model for predictive and diagnostic assessments, it is important to understand exactly in what way people confuse the two probabilities under what situations. For instance, if people equate predictive and diagnostic probabilities, which one do they use as a basis for both conditional probabilities? That is, do they use predictive probabilities to estimate diagnostic ones, or do they use diagnostic probabilities to estimate predictive ones?

A more-is-better heuristic and a cause-to-effect reasoning heuristic as an account for the conjunction fallacy

As discussed so far, judging conditional probabilities seems to pose a difficult and challenging task to laypeople and experts. Things can get only worse when conditional probabilities involve multiple events. We propose two heuristics that people use when reasoning with conditional probabilities involving multiple causes or multiple effects. We propose that these heuristics serve as bases for explaining the conjunction fallacy in causal judgments as will be explained later.

(1) A more-is-better heuristic; The more pieces of evidence are given to be true, the higher the likelihood judgment is. That is, $P(X|Y\&Z) > P(X|Y)$ or $P(X|Z)$.

In most situations, the more-is-better heuristic seems work well. When asked to predict whether John was going to choose Dartmouth for college, we would certainly ascribe a higher likelihood to this outcome if we knew that John wanted to attend a prestigious college and that Dartmouth had the major he was interested in, than we would if we only knew one of these pieces of information. This seems to be a reasonable heuristic to use for a simple reason that two causes tend to be more powerful than one cause. Thus, when there are two causes serving as evidence for a possible common outcome, this effect would be judged to be more likely to occur than only one of the causes is present. That is, in the *predictive* situation, the more-is-better heuristic would produce $P(E|C_1\&C_2) > P(E|C_1), P(E|C_2)$.

Likewise, the more-is-better heuristic seems to work well in diagnosis where one is to estimate the likelihood of causes given effects as evidence. For instance, if someone received a bad grade on a test and we were trying to determine the cause of the bad grade, we would be likely to ascribe a higher probability that the test was very hard if we learn that five or six other people got a bad grade. That is, if we have multiple pieces of evidence for the same cause, our estimation for the likelihood of that cause would be higher than if we have only one piece of evidence. Again, this is a reasonable heuristic to use in diagnosing causes of events; the more evidence for the common cause, the more likely the occurrence of the cause, or $P(C|E_1\&E_2) > P(C|E_1), P(C|E_2)$.

So far, we illustrated how the more-is-better heuristic can be used in both predictive and diagnostic situations. This heuristic concerns the likelihood estimates of a single event when two events are given to be true. Sometimes, however, one is to judge the likelihood of multiple events given one piece of evidence. For instance, one may judge two conjunctive causes (or effects) given that one effect (or cause) is given to be true; $P(C_1\&C_2|E)$ or $P(E_1\&E_2|C)$. Since we do not yet know whether or not the conjunctive events are true, these events cannot serve as evidence. Hence, the more-is-better heuristic cannot apply to this situation. We propose that under this situation, people use another heuristic to deal with the difficulty of judging the likelihood of conjunctive events.

(2) A cause-to-effect reasoning heuristic: In judging likelihood of complex events involving causal relations, people mentally simulate the events from cause to effect direction and provide the plausibility of the simulation as the estimate.

As discussed by Einhorn and Hogarth (1986), judging P(C|E) can be confusing because it contradicts the temporal sequence of events in the world. Cause always precedes effect in the world but one has to assume that an effect occurred and then estimate the likelihood of a candidate cause. It seems much easier to reason from cause to effect by estimating the likelihood of the target effect assuming that the candidate cause had occurred. Tversky and Kahneman (1982) made a similar argument. They presented their participants a number of cases where P(C|E) is equated with P(E|C), as in the case of P(mother's eye color|daughter's eye color) and P(daughter's eye color|mother's eye color). The results showed that people tend to judge P(E|C) to be higher than P(C|E). Tversky and Kahneman argued that this is because cause-to-effect reasoning is more natural to us, so P(E|C) tasks led to higher estimates than P(C|E) tasks.

People seem more prone to the cause-to-effect reasoning heuristic when judging complex events. For instance, judging $P(C_1\&C_2|E)$, the task used in studies demonstrating the conjunction fallacy, can be quite complex because the judgment is opposite to the temporal sequence in the world. Furthermore, one needs to estimate conjunctive probabilities. Given this overload, people might adopt the cause-to-effect reasoning heuristic and convert $P(C_1\&C_2|E)$ into $P(E|C_1\&C_2)$. Then, applying the more-is-better heuristic, the estimation can be quite high. Thus, this use of the cause-to-effect reasoning heuristic along with the more-is-better heuristic can result in the overestimation and hence the conjunction fallacy.

Interestingly, our account for the conjunction fallacy generates a novel prediction about the condition under which the conjunction fallacy would be greatly reduced. Consider the case where participants are asked to judge $P(E_1\&E_2|C)$, $P(E_1|C)$, and $P(E_2|C)$. In this case, the direction of the conditional probabilities are consistent with the direction of the cause-to-effect reasoning heuristic. Therefore, people do not need to inverse the probabilities. Furthermore, the more-is-better heuristic cannot be applied to this situation because the number of evidence is the same in all three judgments. Because neither heuristics apply, we predict that the conjunction fallacy would be greatly reduced under this condition.

Overview of Experiments

In order to test the hypothesis about the use of the two heuristics as a basis for the conjunction fallacy, the current experiments used the following 2X2 factorial design shown in Table 1. In two of the conditions, participants learned that there is a common effect for two causes (Common-Effect condition). In the other two conditions, participants learned that there is a common cause for two effects (Common-cause condition). In order to equate the correlation between the conjunctive events, identical events were used to construct the two causes in the common-effect condition and the two effects in the common-cause condition. The following are example scenarios:

Common Effect

In a study of 100 families, psychologist Alan Gregor found that distant and unloving parents can cause a child to cry more often. Another study by Michelle Birnbaum found, among other things, that ill health can cause babies to cry more than average.

Common Cause

In a study of 100 families, psychologist Alan Gregor found that children who cry often cause parents to become more distant and unloving than average. Another study by Michelle Birnbaum found, among other things, that excessive crying will cause ill health effects.

Table 1. Design and predictions of Experiments 1 and 2.

Causal Structure	Predictive Questions: P(E|C)	Diagnostic Questions :P(C|E)
Common Effect (CE) $C_1 \rightarrow E$, $C_2 \rightarrow E$	Strong Conj. Effect: $P(E\|C_1\&C_2)$ $> P(E\|C_1), P(E\|C_2)$ because of the more-is-better heuristic.	Moderate Conj. Effect: $P(C_1\&C_2\|E)$ $> P(C_1\|E),P(C_2\|E)$ if the cause-to-effect heuristic is applied. $P(C_1\&C_2\|E)$ $< P(C_1\|E),P(C_2\|E)$ if the cause-to-effect heuristic is not applied.
Common Cause (CC) $C \rightarrow E_1$, $C \rightarrow E_2$	Small Conj. Effect: $P(E_1\&E_2\|C)$ $< P(E_1\|C), P(E_2\|C)$ because no heuristic applies.	Moderate Conj. Effect: $P(C\|E_1\&E_2)$ $> P(C\|E_1), P(C\|E_2)$ because of the more-is-better heuristic. $P(C\|E_1\&E_2)$ $< P(C\|E_1), P(C\|E_2)$ if the cause-to-effect heuristic is applied.

Half of the tasks were predictive, P(E|C), and the other half were diagnostic, P(C|E). (See Table 2 for sample questions for both the common-cause and the common-effect conditions.) For both predictive and diagnostic conditions, three probability estimates were asked; two estimates involving single events and one estimate involving conjunctive events. Table 1 presents the actual conditional probabilities for each condition along with the predictions generated by the use of the two heuristics. Henceforth, each of the four conditions will be referred by combining the two variables (e.g., the predictive common-effect condition).

To reiterate the predictions based on the use of the two heuristics, the more-is-better heuristic is applicable to the predictive common-effect and the diagnostic common-cause conditions. We predicted that likelihood estimates would be higher when two pieces of evidence are given to be true than when only one piece is given, resulting in the conjunction effect[1]. In the diagnostic common-cause condition, it is possible that people might apply the cause-to-effect heuristic by inverting the probabilities, in which case the conjunction effect can be somewhat reduced.

[1] Since this is not a violation of probability theories, we will call this a conjunction effect rather than a conjunction fallacy.

Table 2. Sample predictive and diagnostic questions for single and conjunctive events used in the common-cause and the common-effect conditions of Studies 1 and 2.

Causal Structure	Predictive Questions	Diagnostic Questions
Common Effect	Single events, $P(E\|C_1)$ or $P(E\|C_2)$; *Suppose infant Amy's parents are distant and unloving. How likely is it that this will cause Amy to cry more than average?* *Suppose infant, Amy, is of ill health. How likely is it that this will cause Amy to cry more than average?* Conjunctive events, $P(E\|C_1\&C_2)$; *Suppose infant Amy's parents are distant and unloving and that she (Amy) is of ill health. How likely is it that this will cause Amy to cry more than average?*	Single events, $P(C_1\|E)$,$P(C_2\|E)$ *Suppose infant, Amy, cries more than average. How likely is it that this occurred because Amy's parents are distant and unloving?* *Suppose infant, Amy, cries more than average. How likely is it that this occurred because Amy is of ill health?* Conjunctive events, $P(C_1\&C_2\|E)$ *Suppose infant, Amy, cries more than average. How likely is it that this occurred because Amy's parents are distant and unloving and that she (Amy) is of ill health?*
Common Cause	Single events, $P(E_1\|C)$, $P(E_2\|C)$ *Suppose infant, Amy, cries more than average. How likely is it that this will cause Amy's parents to be distant and unloving?* *Suppose infant, Amy, cries more than average. How likely is it that this will cause Amy to be of ill health?* Conjunctive events, $P(E_1\&E_2\|C)$ *Suppose infant, Amy, cries more than average. How likely is it that this will cause both Amy's parents to be distant and unloving and ill health for Amy?*	Single events, $P(C\|E_1)$, $P(C\|E_2)$ *Suppose infant Amy's parents are distant and unloving. How likely is it that this occurred because Amy cries more than average?* *Suppose infant, Amy, is of ill health. How likely is it that this occurred because Amy cries more than average?* Conjunctive events, $P(C\|E_1\&E_2)$ *Suppose infant Amy's parents are distant and unloving and that she (Amy) is of ill health. How likely is it that this occurred because Amy cries more than average?*

Of particular interest are the diagnostic common-effect and the predictive common-cause conditions. As explained before, the diagnostic common-effect condition is expected to lead to the conjunction effect as in the previous studies. People would apply the cause-to-effect heuristic and judge $P(E|C_1\&C_2)$ rather than $P(C_1\&C_2|E)$. Once the questions are misrepresented, we predicted that two causes would be judged to be more likely to lead to an effect than one cause would, resulting in the conjunction fallacy. To the extent that participants in the diagnostic common-effect condition misinterpret the questions, their estimates would be similar to the responses from the predictive common-effect condition where participants were explicitly asked to reason from cause to effect. If participants in the diagnostic common-effect condition accurately interpret the task, they would not violate the normative probability theory. Hence, it is predicted that although the diagnostic common-effect condition would lead to the conjunction effect, the amount of the conjunction effect cannot exceed that in the predictive common-effect condition.

Finally, few instances of the conjunction effect was predicted from the predictive common-cause condition. In this condition, the cause-to-effect reasoning heuristic does not cause any misrepresentation of the problems because the problems are already presented as cause-to-effect questions. Furthermore, the more-is-better heuristic does not apply because the number of evidence is the same across the single and conjunctive judgments.

To summarize, the most crucial comparison is between the diagnostic common-effect condition and the predictive common-cause condition. As can be seen in the above two example scenarios, we used identical events and simply changed the causal status of the events. That is, C_1 and C_2 in the common-effect condition are identical to E_1 and E_2 in the common-cause condition except for the causal role the events play. If we indicate the three events as X, Y, and Z ignoring the causal status, the questions they answered were identical; $P(X\&Y|Z)$, $P(X|Z)$, and $P(Y|Z)$. Despite this identical content of the events and questions, the common-effect condition is expected to lead to the conjunction effect but the common-cause condition is not.

Study 1

Method

Study 1 had a 2 X 2 factorial design crossing Type of Questions (diagnostic, $P(C|E)$, or predictive questions, $P(E|C)$) and Causal Structure (common cause or common effect) as shown in Table 1.

Eight scenarios were created that could be used in all four conditions. Scenarios were designed so that the causal nature of the elements was reversible. That is, if A caused B in the common cause condition, then in the common effect condition B was the cause of A. Direction of causality was imbedded into the background or questions in each scenario as shown in the two example scenarios in the introduction.

Participants estimated the probability of three events for each scenario. Two of the events illustrated a one cause-one effect relationship (single events). The third event were either a two cause-one effect in the common effect condition or a one cause-two effect in the common cause condition (conjunctive events). For both single and conjunctive events, predictive and diagnostic questions were developed. The sample questions for the above example scenarios are provided in Table 2. Each probability estimation was rated on a 1 to 9 scale. A rating of one indicated "definitely no" and a rating of nine indicated "definitely yes".

Each subject completed all eight scenarios, but no subject received the same scenario more than once. All participants completed two scenarios for each of the four cell conditions. Scenarios were randomly assigned using a Latin-Squares design. For each scenario, three questions were presented, two about single events and one about conjunctive events. The order of the three questions was randomized across the eight scenarios and participants received the eight scenarios in a completely randomized order. Participants performed the task at their own pace. Fifty-six undergraduate students from an introductory psychology course at Yale University participated for partial course credit.

Results and Discussion

The mean ratings for the conjunctive events and the minimal of single events are presented in Table 3 along with the predictions described in Table 1. In addition, Table 3 lists the percentage of participants who showed the conjunction effect (i.e., judging that the conjunctive event is more likely than the less likely single event).

Table 3. Results of Study 1

Causal Structure	Predictive Questions: P(E|C)	Diagnostic Questions: P(C|E)
Common Effect $C_1 \rightarrow E \leftarrow C_2$	Strong Conj. Effect P(E|C); 4.8 $P(E\|C_1\&C_2)$; 6.4 Difference: 1.6 % of Conjunction Effect: 86.6%	Moderate Conj. Effect P(C|E): 4.5 $P(C_1\&C_2\|E)$: 5.5 Difference: 1.0 % of Conjunction Effect: 73.3%
Common Cause $E_1 \leftarrow C \rightarrow E_2$	No Conj. Effect P(E|C); 5.2 $P(E_1\&E_2\|C)$: 5.4 Difference: 0.2 % of Conjunction Effect: 43.3%	Moderate Conj. Effect P(C|E); 4.4 $P(C\|E_1\&E_2)$: 5.6 Difference: 1.3 % of Conjunction Effect: 75.0%

Consistent with previous research on the conjunction fallacies in causal reasoning, the diagnostic common-effect condition led to a strong conjunction fallacy as indicated by 73.3% of the participants committing the fallacy. However, when the same events are phrased as two effects for the same condition (the predictive common-effect condition), only less than half the people (43.3%) committed the fallacy. We also examined the amount of the conjunction effect defined as the difference between the likelihood of conjunctive events and the smaller of the likelihood ratings of the two single events. In the diagnostic common-effect condition, this amount was 1.0, but in the predictive common-cause condition, it dropped to 0.2. A repeated-measures ANOVA was conducted to test this comparison with the number of events (Conjunction or Single) and the Causal Structure (common-cause or common-effect) as two factors. As predicted, there was a very strong interaction effect, $F(1, 56) = 15.45$, $p < .001$. In addition, there was a reliable main effect of the number of events, $F(1, 56) = 23.75$, $p < .001$, because the conjunctive events were generally estimated to be higher than single events. There was no main effect of the Causal Structure. In addition, the predictive common-effect and the diagnostic common-cause conditions resulted in strong conjunction effects, providing evidence for the more-is-better heuristic.

Study 2

One concern from Study 1 is that there still was 43.3% of the participants who committed the conjunction fallacy in the predictive common-cause condition. We speculated that this occurred probably because both manipulations of Study 1 were within-subject variables. If participants attempted to make consistent responses for similar questions, the responses made on the questions in the diagnostic common-effect condition can influence their responses made on the predictive common-cause condition. Hence, in Study 2, we assigned different subjects to these conditions by making the Causal structure a between-subject variable.

Methods

The design, materials, and procedure were all identical to Study 1 except that the Causal structure was a between-subject variable. There were a total of 46 participants, of which 22 were assigned to the common cause condition and 24 were assigned to the common effect condition.

Table 4. Results of Study 2

Causal Structure	Predictive Questions: P(E|C)	Diagnostic Question: P(C|E)
Common Effect $C_1 \rightarrow E \leftarrow C_2$	P(E|C); 4.8 $P(E\|C_1\&C_2)$; 6.2 Difference: 1.7 % of Conjunction Effect: 95.8%	P(C|E): 4.8 $P(C_1\&C_2\|E)$: 6.4 Difference: 1.5 % of Conjunction Effect: 91.7%
Common Cause $E_1 \leftarrow C \rightarrow E_2$	P(E|C); 5.7 $P(E_1\&E_2\|C)$: 5.5 Difference: -0.2 % of Conjunction Effect: 31.8%	P(C|E); 4.7 $P(C\|E_1\&E_2)$: 5.7 Difference: 1.1 % of Conjunction Effect: 91.9%

Results and Discussion

The results are presented in Table 4. With the between-subject manipulation, the number of participants who committed the conjunction fallacy was reduced only to one third in the predictive common-cause condition. Furthermore, the amount of the conjunction effect in this condition was negative (-0.2). Still, the between-subject manipulation did not reduce the amount of the conjunction effect in any other conditions.

One might argue that there still are 31% of participants in the predictive common-cause condition committing the fallacy. We speculate that these participants might be overgeneralizing the more-is-better heuristic to the judgment of events. It also could be the case that presenting both predictive and diagnostic questions to the same participants might have made them misinterpret the predictive questions as diagnostic ones and vice versa. We are currently conducting a study to address this issue by manipulating both factors as between-subject variables.

General Discussion

The two experiments provided an account for the conjunction fallacy when judging the likelihood of conjunctive or single causes given an effect. We argue that this fallacy occurs because people use the cause-to-effect reasoning heuristic as well as the more-is-better heuristic. By employing a condition where neither heuristic applies, we could successfully eliminate the conjunction fallacy. In addition, the results from the predictive common-effect condition and the diagnostic common-cause condition provide evidence supporting the use of the more-is-better heuristic.

What are the implications of these results for the normative theory of causal judgments? Given limited computational capacity, it is obvious that people cannot be perfectly normative as prescribed by the probability theories when reasoning with complex causal relations involving multiple factors and conditional probabilities. If so, instead of asking whether people are rational, a more useful question would be what heuristics people use under what conditions. The current study demonstrated and justified the use of the two heuristics. Furthermore, when these two heuristics do not apply, people's responses did not violate the normative theory.

Acknowledgments

This project was supported by a National Science Foundation Grant (NSF-SBR 9515085) to Woo-kyoung Ahn. We thank Helen Sullivan for collecting data presented in this paper.

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