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Judgments Of and By Representativeness

Amos Tversky

Stanford University

Daniel Kahneman

University of British Columbia

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The concept of representativeness and the conditions in which it can be used to explain intuitive predictions and probability judgments are discussed. Four cases of representativeness are distinguished that refer to the relations between (1) a value and a variable; (2) an instance and a category; (3) a sample and a population; (4) an effect and a cause. The principles of representativeness differ significantly from the laws of probability. In particular, specificity can increase the representativeness of an event, even though it always reduces its probability. Several studies of judgment are reported in which naive and sophis-

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ticated respondents judge a conjunction to be more probable than one of its components. Violations of the conjunction rule, P(A&B) < P(B), are observed in both between-subjects and within-subjects comparisons, with both fictitious and real-world events. The theoretical and practical implications of the conjunction fallacy are explored.

Several years ago, we presented an analysis of judgment under uncertainty which related subjective probabilities and intuitive predictions to expectations and impressions about representativeness. Two distinct hypotheses incorporated this concept: (i) people expect samples to be highly similar to their parent population, and also to represent the randomness of the sampling process (Tversky & Kahneman, 1971, 1974); (ii) people often rely on representativeness as a heuristic for judgment and prediction (Kahneman & Tversky, 1972, 1973).

The first hypothesis was advanced to explain the common belief that chance processes are self-correcting, the exaggerated faith in the stability of results observed in small samples, the gambler's fallacy and related biases in judgments of randomness. We proposed that the lay conception of chance incorporates a belief in the law of small numbers, according to which even small samples are highly representative of their parent populations (Tversky & Kahneman, 1971). A similar hypothesis could also explain the common tendency to exaggerate the consistency and the predictive value of personality traits (Mischel, 1979) and to overestimate the correlations between similar variables (Jennings, Amabile and Ross, 1982) and behaviors (Shweder and D'Andrade, 1980). People appear to believe in a hologram-like model of personality in which any fragment of behavior represents the actor's true character (Kahneman & Tversky, 1973).

The hypothesis that people expect samples to be highly representative of their parent populations is conceptually independent of the second hypothesis, that people often use the representativeness heuristic to make predictions and judge probabilities. That is, people often evaluate the probability of an uncertain event or a sample "by the degree to which it is (i) similar in essential properties to its parent population and (ii) reflects the salient features of the process by which it is generated" (Kahneman & Tversky, 1972, p. 431). This hypothesis was studied in several contexts, including intuitive statistical judgments and the prediction of professional choice (Kahneman & Tversky, 1972, 1973).

The two representativeness hypotheses have been used to explain a variety of observations, such as the relative ineffectiveness of consensus information and the use of similarity in the interpretation of projective tests (Nisbett & Ross, 1980). These hypotheses have also provided direction to a well-rewarded search for significant violations of normative rules in intuitive judgments. Most of this research was been concerned with judgments <u>by</u> representativeness, that is, with the role of representativeness in prediction and inference. Relatively little work has been devoted to judgments <u>of</u> representativeness, that is, to the nature of this relation and its determinants, outside the context of random sampling (Bar-Hillel, 1980b). The first part of this chapter is concerned with the nature of the representativeness relation and also with the conditions in which the concept of representativeness is usefully invoked to explain intuitive predictions and judgments of probability. In the second part of the chapter we illustrate the contrast between the logic of representativeness and the logic of probability in judgments of the likelihood of compound events.

THE REPRESENTATIVENESS RELATION

Representativeness is a relation between a process or a model M and some instance or event X associated with that model. Representativeness, like similarity, can be assessed empirically, e.g., by asking people to judge which of two events X1 or X2 is more representative of some model M, or whether an event X is more representative of M1 or of M2. The model in question could be of a person, a fair coin or the world economy, and the respective outcomes might be a comment, a sequence of heads and tails, or the present price of gold.

Representativeness is a directional relation: we say that a sample is more or less representative of a particular population, and that an act is representative of a person. We do not normally say that the population is representative of the sample or that the person is representative of the act. In some problems, however, it is possible to reverse the roles of model and outcome. For example, one may evaluate whether a person is representative of the stereotype of librarians, or whether the occupation of librarian is representative of that person.

We distinguish four basic cases in which the concept of representativeness is commonly invoked.

(1) <u>M is a class and X is a value of a variable defined in this class</u>. It is in this sense that we speak of (more or less) representative values of the income of college professors, or of the age of marriage in a culture. Naturally, the most representative value will be close to the mean, median or mode of the distribution of the relevant variable in the class M. The relation of representativeness is mainly determined in this case by what the judge knows about the frequency distribution of the relevant variable.

(2) <u>M is a class and X is an instance of that class</u>. Most readers will probably agree that John Updike is a more representative American writer than Norman Mailer. Clearly, such a judgment does not have a frequentistic basis; it reflects the degree to which the styles, themes and ideas of these authors are central to contemporary American writ-

ings. Similar considerations determine the representativeness of instances that are themselves classes rather than individuals. For example, a robin is judged to be a more typical bird than a chicken, although it is less frequent (Rosch, 1978; Smith, Shoben & Rips, 1974). Thus, an instance is representative of a category if it has the essential features that are shared by members of that category, and does not have many distinctive features that are not shared by category members (Rosch, 1975; Tversky, 1977).

Contemporary work on concept formation (Rosch & Mervis, 1975; Mervis & Rosch, 1981), semantic memory (Bransford & Franks, 1971) and pattern recognition (Posner & Keele, 1968) has shown that the most representative, or prototypical, elements of a category are better learned, recalled and recognized than elements that are more frequent but less representative. Moreover, people often err by "recognizing" a prototypical stimulus that had never been shown. Representativeness, therefore, can bias recognition memory as well as judgments of frequency.

It should perhaps be noted that there are two ways in which an element can be highly representative of a class. The two senses of representativeness correspond closely to the relations of typicality and prototypicality. An element is highly representative of a category if it is typical or modal; it can also be representative if it is an ideal type that embodies the essence of the category. New York, for example, is the prototype of an American city, but Cincinnati is more likely to be selected as a typical city. Similarly, our notions of the prototypical and of the typical Frenchwomen may be quite different. The former is probably a young, elegant Parisian, while the latter is more likely to be a chubby middle aged woman from the provinces.

(3) M is a class and X is a subset of M. Most people will probably agree that the population of Florida is less representative of the U.S. population than is the population of Illinois, and that students of astronomy are less representative of the entire student body than are students of psychology. The criteria of representativeness are not the same for a subset and for a single instance, because an instance can only represent the central tendency of attributes, whereas a subset can also represent range and variability. A man whose height, weight, age and income match the average values for the U.S. population is, clearly, representative of that population. A group of 100 men with the same characteristics would fail to represent the variability of the attributes.

If the class M consists of distinct clusters such that the variability within each cluster is very small relative to the variability between the clusters, we tend to treat each cluster as an instance of the category rather than as a subset. Thus, it is natural to regard 'robin' as a kind of bird, or as an instance of the category 'bird', although the set of robins is a subset of the class of birds. More generally, (2) can be regarded as a special case of (3) where the subset X consists of a single member. Similarly, (1) can be regarded as a unidimensional version of (2). The three types of representativeness are distinguished by the complexity of X, where (1) is the single-element, single-attribute case, (2) is the single-element, multiattribute case, and (3) is the multiple element case -- with one or more attributes.

A particularly important example of the representativeness of a subset is the case in which X is a random sample from a specified population. A random sample is expected to represent the randomness of the selection process, not only the essential features of the population from which it is drawn. When 100 people are selected at random, for example, a sample of 53 men and 47 women may appear more representative than a sample of 50 men and 50 women, because the former represents the irregularity of random sampling while the latter does not (Kahneman and Tversky, 1972). The statistical concept of a representative sample is discussed by Kruskal and Mosteller (1979a, b).

(4) M is a (causal) system and X is a (possible) consequence. This case differs from the preceding ones in that M is no longer a class of objects or instances, but rather a system that produces various effects. For example, M can be the U.S. economy and X the rate of inflation, or M can be a person and X an act performed by M, e.g., divorce, suicide, professional choice. Here, X is representative of M either because it is frequently associated with M (e.g., high fever commonly accompanies pneumonia) or because people believe, correctly or incorrectly, that M causes X (e.g., capital punishment prevents kidnappings). Intrusions of causal schemas in judgments of conditional probabilities are illustrated and discussed in Tversky and Kahneman (1980).

In summary, a relation of representativeness can be defined for (1) a value and a distribution, (2) an instance and a category, (3) a sample and a population, (4) an effect and a cause. In all four cases, representativeness expresses the degree of correspondence between X and M, but its determinants are not the same in the four cases. In case (1), representativeness is dominated by perceived relative frequency or statistical association. In cases (2) and (3) representativeness is determined primarily by similarity, e.g., of an instance to other instances, or of sample statistics to the corresponding parameters of a population. Finally, in case (4) representativeness is controlled largely by (valid or invalid) causal beliefs.

Representativeness and Probability

The use of representativeness to explain probability judgments and intuitive predictions rests on the following assumptions:

(i) that the relation "X is (very, . . . , not at all) representative of M" can be meaningfully assessed by judges;

(ii) that these assessments should not be based on impressions of probability or frequency, which are to be explained by representativeness;

(iii) that the relation of representativeness has a logic of its own, which departs systematically from the logic of probability.

When these assumptions are satisfied, it is of interest to test whether judgments of probability are mediated by assessments of representativeness.

The evaluation of the probability of an uncertain event or the prediction of an unknown quantity is a complex process, which comprises an interpretation of the problem, a search for relevant information and the choice of an appropriate response. It can be compared to the operation of a flexible computer program which incorporates a variety of potentially useful subroutines. In the terms of this analogy, the representativeness heuristic is one of the procedures that may be used to retrieve, interpret and evaluate information. The use of this heuristic, of course, does not preclude the use of other procedures, much as the use of imagery as a heuristic for recall does not preclude the use of other strategies. However, the reliance on heuristics leads to characteristic biases. When imagery is used to recall the people who were present at a particular meeting, for example, participants who were clearly visible are expected to be remembered better than those who were not. Similarly, the use of representativeness to assess subjective probability produces overestimation of some probabilities and underestimation of others.

Early studies gave rise to the extreme hypothesis that some probability judgments are based exclusively on representativeness. For example, the observation that subjective sampling distributions are essentially independent of sample size (Kahneman & Tversky, 1972) suggested that people evaluate the probability of a sample by the similarity of its statistics to the corresponding parameters of the population. Most of the available data, however, support a more moderate hypothesis that intuitive predictions and probability judgments are highly sensitive to representativeness although they are not completely dominated by it. Thus, subjective probabilities are strongly influenced by (normatively) irrelevant factors that affect representativeness, and are relatively insensitive to (normatively) relevant variables that do not affect representativeness. The magnitude of representativeness biases and the impact of variables such as sample size, reliability and base rate depend on the nature of the problem, the characteristics of the design, the sophistication of the respondents and the presence of suggestive clues or other demand characteristics. The role of these factors in judgment research is discussed in Kahneman and Tversky (1981).

If the reliance on representativeness leads to systematic errors, why do people use this relation as a basis for prediction and judgment? The answer to this question has three parts. First, representativeness appears readily accessible and easy to evaluate. Modern research on categorization (Mervis & Rosch, 1981; Rosch, 1978) suggests that conceptual knowledge is often organized and processed in terms of prototypes or representative examples. Consequently, we find it easier to evaluate the representativeness of an instance to a class than to assess its conditional probability. Second, probable events are usually more representative than less probable events. For example, a sample that resembles the population is generally more likely than a highly atypical sample of the same size. Third, the belief that samples are generally representative of their parent populations leads people to overestimate the correlation between frequency and representativeness or between statistical association and connotative similarity. Thus, representativeness is used because (i) it is accessible, (ii) because it often correlates with probability, and (iii) because people overestimate this correlation. The reliance on representativeness, however, leads to predictable errors of judgment because representativeness has a logic of its own, which differs from the logic of probability.

The contrast between representativeness and probability is most pronounced (i) when the evidence is fallible, or (ii) when the target event is highly specific. In case (i), an outcome which is highly representative of our model may nevertheless be improbable -- if our mental model is based on evidence of limited validity. Consider, for example, the probability that a candidate who made an excellent impression during an interview will succeed in a very difficult task. Because impressions based on interviews are notoriously fallible, and success or failure on the job are controlled by numerous factors that are not predictable from a brief conversation, success may be very unlikely even when it is highly representative of our impression of the candidate.

In case (ii), a representative outcome may be very improbable because it is highly specific or detailed. In general, an event can be improbable either because it is atypical or because it is highly specific. A weight under 135 lbs. is atypical for a middle-aged man; a weight of 157.625 lbs. is typical but highly specific. Indeed, the latter is more representative for a middle-aged man, although the former is much more probable. As this example illustrates, an increase in specificity does not generally lead to diminished representativeness. Consequently, the comparison of events that differ in specificity often creates a conflict between representativeness and probability. For example, a random sample of four cards consisting of the king of hearts, ace of spades, nine of diamonds, and four of clubs, appears more representative than a sample consisting of four cards of the same suit, although the latter is far more probable. Thus, representativeness biases in probability judgments should be most pronounced in the assessment of events that are representative but highly specific. Such biases are demonstrated in studies of probability judgments of compound events described in the next section.

ON THE EVALUATION OF COMPOUND EVENTS

The sharpest contrast between probability and representativeness arises in the evaluation of compound events. Suppose that we are given some information about an individual (e.g., a personality sketch) and that we speculate about various attributes or combinations of attributes that this individual may possess, such as occupation, avocation or political affinity. One of the basic laws of probability is that specification reduces probability. Thus, the probability that a given person is both a Republican and an artist must be smaller than the probability that the person is an artist. This condition holds not only in the standard probability calculus but also in non-standard models (e.g., Shafer, 1976; Zadeh, 1978).

However, the requirement that $P(A\&B) < P(B)$, which may be called the conjunction rule, does not apply to similarity or representativeness. A blue square, for example, can be more similar to a blue circle than to a circle, and an individual may resemble our image of a Republican artist more than our image of a Republican. Because the similarity of an object to a target can be increased by adding to the target features that are shared by the object (see Tversky, 1977), similarity or representativeness can be increased by specification of the target. If probability judgments are mediated by representativeness or similarity it should be possible to construct problems where a conjunction of outcomes appears more representative, and hence more probable than one of its components.

The Conjunction Effect: Study 1

This prediction was first tested in an experiment conducted in Jerusalem in 1974. We presented 184 subjects with four personality sketches. Each sketch matched the stereotype of a particular occupation (e.g., a cab driver) and differed sharply from the stereotype of a particular political party (e.g., labor), or vice versa. Hence, each description (X) was representative of one target, denoted A, and unrepresentative of another target denoted B. Every sketch was followed by a list of five or six target events described by an occupation, a political affiliation or a conjunction, e.g., a cab driver who is a member of the labor party. For each description, half the subjects received a list including both target A and target B, while the other half received a list including the compound target A & B. The remaining four targets were identical in the two lists. Half the subjects were asked to rank the targets according to "the degree to which X is representative of that class", and the other half ranked them according to "the probability that X is a member of that class".

The design of the study permitted an indirect comparison of representativeness and probability for the event B and the compound A&B, in relation to the four constant alternatives. The results may be summarized as follows. First, all four descriptions were judged to be more representative of the compound target A & B than of target B alone. Second, the representativeness ordering and the likelihood ordering of each set of targets were almost identical in all cases; the average product moment correlation between mean ranks was .96. In particular, the compound target A & B was assigned a significantly higher mean rank in the probability ordering than the simple target B. Evidently, the reliance on the representativeness heuristic led the respondents to regard a conjunctive event as more probable than one of its components, contrary to the conjunction rule of probability theory. This pattern of judgements will be called the conjunction effect.

<u>Study 2: Bill and Linda</u>

Because the stimulus material used in the early study was highly specific to Israeli culture, we constructed an English version of the problems and replicated the study with several significant variations. First, we compared the results of a between-subject design, in which each respondent compared either the compound target A & B or the simple target B to the same set of alternatives, to a within-subject design in which each respondent compared the two critical targets directly. We hypothesized that the conjunction rule would fail in the former design, as in our previous study, but we expected that the frequency of violations would be greatly reduced in the latter design where the participants were asked, in effect, to compare P(A) with P(A&B). Second, we expected that even limited statistical sophistication would eliminate most violations of the conjunction rule, at least in a within-subject design.

To investigate these hypotheses, we conducted both a (direct) within-subject and an (indirect) between-subjects study, with the same stimulus material. The study was replicated in three groups of respondents that differed in statistical sophistication. The statistically naive group consisted of undergraduate students from the University of British Columbia and Stanford University, with no background in probability or statistics. The intermediate group consisted of graduate students in psychology and education, and of medical students from Stanford University who had taken several courses in statistics and were all familiar with the basic concepts of probability. The statistically sophisticated group consisted of graduate students in the decision science program of the Stanford Business School who had all taken several advanced courses in probability and statistics.

Two brief personality sketches were constructed. Each participant encountered one of these sketches in the within-subject treatment, and the other in a between-subjects treatment. In the former, the personality sketch was followed by eight possible outcomes, including a representative outcome, an unrepresentative outcome, and the conjunction of the two. In the between-subjects treatment the list of outcomes included either the two critical single outcomes or their conjunction. The within-subject forms of the two problems are shown below. The numbers in parentheses are the mean ranks assigned to the various outcomes by the subjects who received this form.

Bill is 34 years old. He is intelligent, but unimaginative, compulsive, and generally lifeless. In school, he was strong in mathematics, but weak in social studies and humanities.

Please rank order the following statements by their probability, using 1 for the most probable and 8 for the least probable.

(3.7) Bill is a physician who plays poker for a hobby.

(3.9) Bill is an architect.

(1.1) Bill is an accountant. (A)

(6.2) Bill plays jazz for a hobby. (J)

(6.6) Bill surfs for a hobby.

(5.7) Bill is a reporter.

(3.4) Bill is an accountant who plays jazz for a hobby. (A&J)

(6.1) Bill climbs mountains for a hobby.

Linda is 31 years old, single, outspoken and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.

Please rank the following statements by their probability, using 1 for the most probable and 8 for the least probable.

(4.1) Linda is a teacher in elementary school.

(3.5) Linda works in a bookstore and takes Yoga classes.

(1.5) Linda is active in the feminist movement. (F)

(2.1) Linda is a psychiatric social worker.

(5.6) Linda is a member of the League of Women Voters.

(7.2) Linda is a bank teller. (T)

(7.1) Linda is an insurance salesperson.

(4.7) Linda is a bank teller and is active in the feminist movement. (T&F)

As the reader has probably guessed, the description of Bill was constructed to be representative of an accountant (A) and unrepresentative of a person who plays jazz for a hobby (J). Similarly, the description of Linda was constructed to be representative of an active feminist (F) and unrepresentative of a bank teller (T). In accord with psychological principles of similarity (Tversky, 1977) we expected that the compound targets, an accountant who plays jazz for a hobby (A & J) and a bank teller who is active in the feminist movement (T & F), would fall between the respective simple targets. To test this prediction, we asked a group of 88 statistically naive subjects to rank the 8 targets "by the degree to which Bill (Linda) resembles the typical member of that class". The similarity rankings validated our hypotheses about the descriptions. The proportion of respondents who displayed the predicted order for Bill (A > A & J > J) was 87%; the percentage of subjects who displayed the predicted order for Linda (F > T & F > T) was 85%.

Insert Table 1 here

All participants received either the description of Bill or the description of Linda in the within-subject form and rank ordered the 8 targets according to their probabilities. These data are summarized in

Table 1

The Conjunction Effect

	Naive		Intermediate		Sophisticated	
Within-subject Design	Linda	Bill	Linda	Bill	Linda	Bill
Conjunction effect (%)	89%	92%	90%	86%	85%	83%
Mean Rank: A&B	4.2	3.4	3.9	3.5	4.0	3.4
Mean Rank: B	6.3	6.6	6.2	6.4	6.1	5.6
N	88	94	53	56	32	32
Between-subject Design						
Mean Rank: A&B	3.3	2.3	2.9	2.4	3.1	2.5
Mean Rank: B	4.4	4.5	3.9	4.2	4.3	4.6
N	86	88	55	56	32	32

the upper part of Table 1, where the row labeled 'conjunction effect (%)' presents the percentage of subjects in each group that ranked the compound target above the less representative simple target. The rows labeled 'A&B' and 'B' present, respectively, the mean ranks assigned to the compound and to the less representative simple target. The mean rank of similarity is plotted, for the naive subjects, against the mean rank of probability in Figure 1 for the two descriptions.

Insert Figure 1 here

In the between-subjects condition, two versions of each problem were constructed by deleting from the target list either the compound target or the two simple targets. The personality sketch, the instructions and the remaining five targets were the same as in the within-subject version. The results of the between-subjects design for all groups of respondents are presented in the lower part of Table 1.

The results summarized in Table 1 show that the compound target was ranked as more probable than the critical simple target in both within-subject and between-subjects designs. This result held for both descriptions and for all groups. Much to our surprise, statistical sophistication had a negligible effect on the conjunction effect, which was exhibited by more than 80% of the subjects in all three groups.

In the preceding studies, the critical targets were embedded in a larger set of possible outcomes, which could have masked the relation of inclusion between them. It is of interest, therefore, to investigate

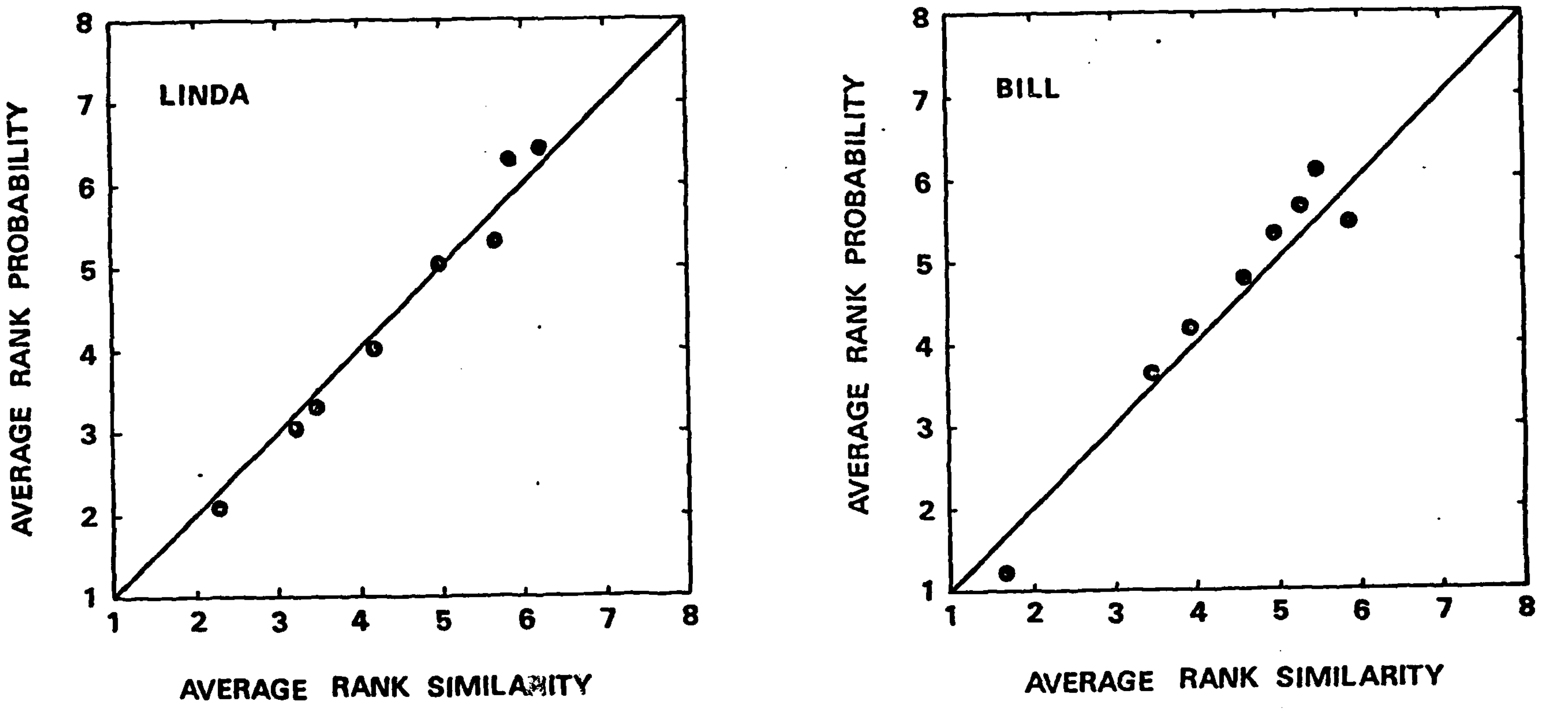

Figure 1: Plot of average ranks for eight outcomes, ranked by probability and by similarity for two descriptions.

whether people violate the conjunction rule even when the logical relation between the targets is highly transparent. To test this hypothesis, we presented a new group of (statistically naive) subjects with the descriptions of Bill and Linda. Each subject was presented with one of the two descriptions, and was asked which of the two critical targets (i.e., J and A & J, or T and T & F) was more probable. This procedure did not reduce the conjunction effect: the compound target was selected by 92% of the subjects (N=88) in the case of Bill, and by 87% of the subjects (N=86) in the case of Linda.

The massive failure of the conjunction rule raises intriguing questions concerning its normative appeal. To examine this question, we interviewed 36 graduate students, from the intermediate group, who had participated in the experiment. They were asked (1) how they had ordered the two critical categories, (2) why they had done so; and (3) they were asked to consider the argument "that the probability that Bill is both an accountant and a jazz player cannot exceed the probability that he is a jazz player, because every member of the former category is also a member of the latter." More than two thirds of the subjects (1) said that they had selected the compound target, (2) gave some version of a similarity or a typicality argument as a reason, and (3) agreed, after some reflection, that their answer was wrong since it was at variance with the conjunction rule. Only two of the subjects maintained that the probability order need not agree with class inclusion, and only one claimed that he had misinterpreted the question. Although the interview might have biased the respondents in favor of the conjunction rule, the results suggest that statistically informed subjects, at least, are willing to regard a violation of this rule as a regrettable error. For further discussion of this issue, see Kahneman and Tversky

(1981).

In interpreting the failure of the conjunction rule, it is important to consider whether the effect is attributable, in whole, or in part, to linguistic conventions or conversational rules. For example, in an early study we presented people with the following description, "John is 27 years old, with an outgoing personality. At college he was an outstanding athlete but did not show much ability or interest in intellectual matters". We found that John was judged to be more likely to be "a gym teacher" than merely "a teacher". Although every gym teacher is, in a sense, a teacher, it could be argued that the term teacher is understood here in a sense that excludes a gym teacher or a driving school instructor. This problem is avoided in the present design by defining the the critical outcome extensionally as an intersection of two sets, e.g., accountants and amateur jazz players.

Violations of the conjunction rule have also been observed in sequential problems where the target consists of a sequence of events. Slovic, Fischhoff and Lichtenstein (1976) presented subjects with a personality sketch of a person who resembled the stereotype of an engineer but not of a journalist. Their subjects assigned a lower probability to the event "Tom W. will select journalism as his college major" than to the event "Tom W. will select journalism as his college major but quickly become unhappy with his choice and switch to engineering". Strictly speaking, the former event includes the latter, and the above judgment violates the conjunction rule. This example, however, is open to the objection that, according to normal rules of conversation, the statement that Tom W. chose journalism as his college major implies that he also remained a journalism major. Otherwise, the statement would be misleading.

Similar objections can also be raised regarding the examples of Bill and Linda. Thus, it may be argued that subjects read, for example, the category "a bank teller" as " a bank teller who is not active in the feminist movement" in contrast to the given category "a bank teller who is active in the feminist movement". However, the presence of the conjunction effect in a between-subjects design, in which the critical targets are not compared directly, indicates that the effect cannot be adequately explained in terms of a reformulation of the target categories according to standard conversational implicatures. Rather, the observed judgments reveal a common tendency to evaluate the probabilities of the relevant events by the degree to which Linda is representative of the typical or the prototypical members of the respective categories.

Furthermore, we have observed the conjunction effect in several tasks that appear free of conversational implicatures. The following problems, for example, concern the prediction of future events where the interpretation of B as B & not-A seems implausible.

Study 3: Predictions for 1981

The problems described below were designed to test the conjunction rule in predictions of real-world events where subjects rely on their general knowledge. These problems were answered by a group of 93 statistically naive subjects. The following instructions were given:

> "In this questionnaire you are asked to evaluate the probability of various events that may occur during 1981. Each problem includes four possible events. Your task is to rank order these events by probability, using 1 for the most probable event, 2 for the second, 3 for the third and 4 for the least probable event."

The questionnaire included six questions. Two of the questions are shown below. The result for other questions were very similar. The numbers in paratheses are the average ranks for each event; we also show the percentage of subjects who ranked the compount target as more probable than the simple target.

Tennis 1981 (Conjunction effect: 72%)

Suppose Bjorn Borg reaches the Wimbledon finals in 1981. Please rank order the following outcomes from most to least likely.

(1.7) Borg will win the match.

(2.7) Borg will lose the first set.

(3.5) Borg will win the first set but lose the match.

(2.2) Borg will lose the first set but win the match.

U.S. Politics, 1981 (Conjunction effect: 68%)

Please rank order the following events by their probability of occurrence in 1981.

(1.5) Reagan will cut federal support to local government.

(3.3) Reagan will provide federal support for unwed mothers.

(2.7) Reagan will increase the defense budget by less than 5%.

(2.9) Reagan will provide federal support for unwed mothers and cut federal support to local governments.

As in the preceding studies, the compound category was judged more probable than one of its components. The result is compatible with a notion of representativeness, which refers in this case to the relation between a causal system and its outcomes rather than to the similarity of a description to a stereotype. In the second problem, for example, it appears unrepresentative for President Reagan to provide federal support for unwed mothers, and quite representative for him to cut federal support for local governments. The conjunction of these acts appears intermediate in representativeness, and the assessments of probability evidently follow the same pattern.

In the first problem, most respondents evaluated Borg's wining the title as the most probable event and regarded the possibility of Borg losing the first set as less likely. The conjunction of the two, namely Borg losing the first set but wining the match, was again judged as less likely than the first possibility but more likely than the second. Evidently, the subjects combined events according to principles of representativeness, or causal impact, rather than according to the laws of probability.

Discussion

The results reported in the preceeding studies provide direct support for the hypothesis that people evaluate the probability of events by the degree to which these events are representative of a relevant model or process. Because the representativeness of an event can be increased by specificity, a compound target can be judged more probable than one of its components. This prediction was supported by studies using both within-subject and between-subjects designs, in subject populations that cover a broad range of statistical sophistication.

Unlike other probabilistic rules, such as regression toward to mean, which naive subjects find difficult to understand and accept, the conjunction rule is both simple and compelling. The majority of the subjects were willing to endorse it in an abstract form, although almost all them violated it in practice, when it conflicted with the intuition of representativeness. The present results contrast with the findings of Johnson-Laird and Wason (1977) about the verification of "if-then" statements, see also Johnson-Laird, Legrenzi & Sonino-Legrenzi (1972). These investigators found that most subjects failed the verification task with abstract material, but not in a concrete example. Our respondents, on the other hand, endorsed the conjunction rule in an abstract form, but violated it in concrete examples, see Kahneman and Tversky (1981).

The finding that a conjunction often appears more likely than one of its components could have far-reaching implications. We find no good reason to believe that the judgments of political analyists, jurors, judges and physicians are free of the conjunction effect. This effect is likely to be particularly pernicious in the attempts to predict the future by evaluating the perceived likelihood of particular scenarios. As they stare into the crystal ball, politicians, futurologists and laypersons alike seek an image of the future that best represents their model of the dynamics of the present. This search leads to the construction of detailed scenarios, which are internally coherent and highly representative of our model of the world. Such scenarios often appear more likely than less detailed forecasts, which are in fact more probable. As the amount of detail in a scenario increases, its probability can only decrease steadily, but its representativeness and hence its apparent likelihood may increase. The reliance on representativeness, we believe, is a primary reason for the unwarranted appeal of detailed scenarios and the illusory sense of insight that such constructions often provide.

The confusion between considerations of probability and of similarity applies not only to the prediction of an uncertain future, but also to the reconstruction of an uncertain past, for example in history and criminal law. Here too, an account of past events is often incorporated into a representative scenario, which includes plausible guesses about unknown events. The inclusion of such guesses can only decrease the probability that the entire account is true, but it provides a sense of representativeness and coherence which may increase the perceived likelihood of the scenario. For example, the hypothesis that "the defendant left the scene of the crime" may appear less plausible than the hypothesis that "the defendant left the scene of the crime for fear of being accused of murder" although the latter account is less probable than the former. A good story is often less probable than a less satisfactory one.

Finally, it is important to realize that the conjunction effect is the symptom of a more fundamental problem. It merely reveals the inconsistency between the logic of probability and the logic of representativeness, which often governs people's beliefs about uncertain events. Since human judgment is indispensible for many problems of interest in our lives, the conflict between the intuitive concept of probability and the logical structure of this concept is troublesome. On the one hand, we cannot readily abandon the heuristics we use to assess uncertainty because much of our world-knowledge is tied to their operation. On the other hand, we cannot defy the laws of probability, because they capture important truths about the world. Like it or not, A cannot be less probable than A & B, and a belief to the contrary is fallacious. Our problem is to retain what is useful and valid in intuitive judgment while correcting the errors and biases to which it is prone.

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