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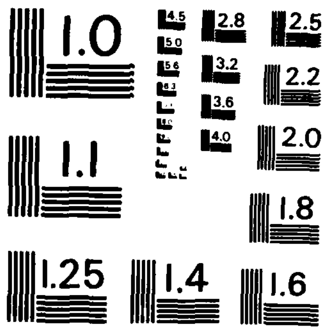

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A MODEL OF THE CONJUNCTION FALLACY

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June 1985

Sponsored by:
Engineering Psychology Programs
Office of Naval Research
Contract Number N00014-84-C-0018
Work Unit Number NR 197-080

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE

AD-A160 876

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION Unclassified	1b. RESTRICTIVE MARKINGS
2a. SECURITY CLASSIFICATION AUTHORITY	3. DISTRIBUTION/AVAILABILITY OF REPORT Approved for public release; distribution unlimited.
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE	
4. PERFORMING ORGANIZATION REPORT NUMBER(S) 15	5. MONITORING ORGANIZATION REPORT NUMBER(S)
6a. NAME OF PERFORMING ORGANIZATION Center for Decision Research Graduate School of Business University of Chicago 6b. OFFICE SYMBOL (If applicable)	7a. NAME OF MONITORING ORGANIZATION Engineering Psychology Programs Office of Naval Research
6c. ADDRESS (City, State, and ZIP Code) 1101 East 58th Street Chicago, IL 60637	7b. ADDRESS (City, State, and ZIP Code) Code #442 EP Arlington, VA 22217
8a. NAME OF FUNDING/SPONSORING ORGANIZATION Office of Naval Research 8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER N00014-84-C-0018
8c. ADDRESS (City, State, and ZIP Code) Department of the Navy Arlington, VA 22217	10. SOURCE OF FUNDING NUMBERS PROGRAM ELEMENT NO. | PROJECT NO. | TASK NO. | WORK UNIT ACCESSION NO. NR-197-080

11. TITLE (Include Security Classification)

A Model of the Conjunction Fallacy

12. PERSONAL AUTHOR(S)
Hillel J. Einhorn

13a. TYPE OF REPORT	13b. TIME COVERED	14. DATE OF REPORT (Year, Month, Day)	15. PAGE COUNT
Technical Report	FROM ______ TO ______	June 1985	25

16. SUPPLEMENTARY NOTATION

17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB-GROUP	Conjunctive probabilities; inference fallacies; model of inference.

19. ABSTRACT (Continue on reverse if necessary and identify by block number)

The conjunction fallacy occurs when the judged probability of a conjunctive event is larger than the probability of one (or more) of its constituents. A model of this phenomenon is proposed in which the judged conjunctive probability is a weighted geometric average of the component probabilities, where the weights reflect the representativeness of the components. The model generalizes to the case where the events involve a causal or correlational link, and, to the use of conjunctive explanations of an event. In all three situations, the model specifies the conditions under which different degrees of the fallacy will or will not occur.

20. DISTRIBUTION/AVAILABILITY OF ABSTRACT ☐ UNCLASSIFIED/UNLIMITED ☒ SAME AS RPT. ☐ DTIC USERS	21. ABSTRACT SECURITY CLASSIFICATION Unclassified
22a NAME OF RESPONSIBLE INDIVIDUAL	22b. TELEPHONE (Include Area Code) | 22c. OFFICE SYMBOL

DD FORM 1473, 84 MAR — 83 APR edition may be used until exhausted. All other editions are obsolete.

SECURITY CLASSIFICATION OF THIS PAGE

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A MODEL OF THE CONJUNCTION FALLACY

In a recent article, Tversky & Kahneman (1983) present convincing evidence that people often violate the conjunction rule of probability theory when assessing the joint probability of two events. This rule says that,

$$p(A \& B) \leq \min[\, p(A), p(B)] \qquad (1)$$

Tversky & Kahneman show that both sophisticated and naive people, in many different substantive problems, often judge the conjunction of events to be larger than one of its components (hereafter called a "single violation"). Furthermore, for some problems, people judge the conjunction as larger than both of its components (a "double violation").

The purpose of this ~~note~~ document is to propose a quantitative model of how people judge the probability of conjunctive events. The advantage of the model is that it makes specific predictions as to when conjunction fallacies of different types will or will not occur. Moreover, the model is naturally extended to deal with conjunctive explanations for events (Leddo, Abelson, & Gross, 1984; Locksley & Stangor, 1984). See #2-3

To begin, Tversky & Kahneman (1983) distinguish between two paradigms in discussing conjunction fallacies. I consider each in turn. The first is concerned with the case in which one has some causal model (M) of the situation, a basic target event B, which is unrepresentative of M, and an added event A, which is highly representative of M. For example, consider the personality sketch of Linda, who is described as very bright, majoring in philosophy, and is an activist in various social issues. When considering the probability that Linda is a bank teller (B), the job of bank teller is unrepresentative of her personality. On the other hand, in judging whether she is a feminist (A), that event seems highly representative. When subjects are asked to order the probabilities that Linda is a feminist, a bank teller, or a feminist bank teller, the conjunction is seen as more likely than bank teller although less likely than feminist.

To analyze problems of this type, the following notation is introduced: let,

A = the judged probability of event A given model M;

B = the judged probability of event B given model M;

J = the judged probability of the conjunction of A and B given model M.

The modeling task consists of meeting three criteria. The first is to find a rule that will allow for: (1) $J \leq \min(A, B)$; (2) $B < J < A$; and, (3) $B < A < J$. Second, the model should have some plausible psychological rationale. Third, the model should lead to specific predictions as to the conditions that will lead to (1), (2), or (3). As Tversky and Kahneman point out, the first criterion is not met by several rules commonly used in modeling judgment. For example, consider a weighted averaging rule with weights applied to A and B Such a rule will not be able to handle conditions (1) and (3) since a weighted average must fall at or between the two components. Similarly, an additive rule cannot yield conditions (1) and (2); a product rule cannot give (2) and (3), and so on.

The model I propose is consistent with a weighted averaging process of a special type. In particular, consider a weighted geometric average, which has been found to provide a good account of judgments in a variety of tasks (e.g., Helson, 1964). In terms of the judged conjunction and its components, the weighted geometric mean is given by,

$$J = A^a B^b \qquad (a, b \geq 0) \qquad (2)$$

Note that equation (2) is quite flexible and can, with the appropriate choice of values for a and b, give results consistent with conditions (1), (2), and (3). However, there are two other reasons for considering such a model seriously. First, equation (2) is the model proposed by Einhorn (1970) to approximate a conjunctive rule for combining multiattribute information. Note that (2) implies the following: if either of the components is judged to be impossible, the conjunction is impossible; if the two components are certain, the conjunction is certain; if the two components are unlikley, the conjunction is very unlikely; if there is a discrepancy between the probabilities of the components, the more likely component is "hurt" more in the conjunction. Second, note that equation (2) is similar to the product rule for independent probabilities; i.e., $p(A\&B) = p(A)\,p(B)$. Thus, if people anchored on the product of A and B and adjusted for perceived dependence, equation (2) would provide a reasonable account of their responses. Although the above reasons make (2) a suitable candidate model, it suffers from being too general; i.e., it can accomodate almost any result after the fact, but it does not lead to specific predictions.

To make (2) predictive, some theory is needed to specify what affects the weights, a and b. In accord with the explanation of the conjunction fallacy given by Tversky and Kahneman (1983), assume that the weights reflect the representativeness of the events vis-a-vis the model M. It is important to note that although A and B are themselves influenced by representativeness, they are also affected by other factors. Indeed, Tversky and Kahneman (1982, p.89) have stated that, "...probability judgments are highly sensitive to representativeness although they are not completely dominated by it." Furthermore, since probable events are usually more representative than less probable events (Tversky & Kahneman, 1982), the weights should be related to A and B In particular, if an increase in probability generally results in an increase in representativeness, more probable components should receive larger weights (reflecting greater representativeness). Since the weights enter equation (2) exponentially, a and b must decrease with increases in A and B To capture this, the weights can be written as,

$$a = 1 - A;\ \text{and},\ b = 1 - B \qquad (3)$$

The full model can be obtained by substituting (3) into (2):

$$J = A^{(1-A)}\ B^{(1-B)} \qquad (4)$$

Equation (4) has no free parameters and is meant to capture the most general aspects of the conjunction fallacy. Nevertheless, it has several interesting implications. In order to see these more clearly, consider Table 1, which shows J as a function of A and B (where $A \geq B$) for values of 0 to 1 in intervals of .1.

Insert Table 1 about here

Examination of Table 1 shows the following: (1) 61% of the entries in the table show violations of the conjunction rule (40/66). Of these, 11% are double violations and the remainder are single violations. Hence, if subjects make judgments of A and B that are uniformly distributed over the interval 0 to 1, and combine these judgments according to equation (4), 60% of the responses would violate the conjunction rule. Moreover, single violations would be much more likely than double violations; (2) In the type of problem considered above (denoted the M-A paradigm by Tversky and Kahneman, 1983), A is high and B is low to moderate. In this situation, single violations are very likely but double violations are not. However, as one of the components becomes very unrepresentative (i.e., B decreases), the violations decrease. Indeed, Tversky and Kahneman report that conjunction errors do not occur when the constituents are highly incompatible. In our terms, this means that A is high and B is very low (e.g., how likely is Linda a feminist and a Republican ?). Note that in the extreme case when B is judged to be impossible, the conjunction is always impossible regardless of the value of A; (3) When both of the constituents are unlikely, the model predicts no conjunction errors of either type (e.g. how likely is Linda a bank teller and a Republican ?); (4) Double violations are most likely when both components are highly probable and of comparable strength (e.g., how likely is Linda a feminist and a Democrat ?).

It is important to stress that the above results should not be generalized to all situations in which conjunctive events are judged. In particular, Tversky and

Table 1

Conjunctive Probability as a Function of Its Components

						A					
B	0	.1	.2	.3	.4	.5	.6	.7	.8	.9	1
0	0	0	0	0	0	0	0	0	0	0	0
.1	-	.02	.03	.05	.07	.09	.10	.11	.12	.12	.13
.2	-	-	.08	.12	.16	.20	.22	.25	.26	.27	.28
.3	-	-	-	.19	.25	.30	.35	.39	.41	.43	.43
.4	-	-	-	-	.33	.41	.47	.52	.55	.57	.58
.5	-	-	-	-	-	.50	.58	.64	.68	.70	.71
.6	-	-	-	-	-	-	$\boxed{.66}$	$\boxed{.73}$	.78	.81	.82
.7	-	-	-	-	-	-	-	$\boxed{.81}$	$\boxed{.86}$	.89	.90
.8	-	-	-	-	-	-	-	-	$\boxed{.91}$	$\boxed{.95}$	.96
.9	-	-	-	-	-	-	-	-	-	$\boxed{.98}$	.99
1	-	-	-	-	-	-	-	-	-	-	1

Note: ◯ represents a single violation

□ represents a double violation

Kahneman (1983) discuss a second structure (denoted the A - B paradigm) in which two events are seen to be directly related in a causal or correlated way, without direct reference to some underlying model M. For example, in a health survey of adult males, Mr. F is chosen at random; how likely has he had one or more heart attacks, versus how likely has he had one or more heart attack and he is over 55 years old (Tversky & Kahneman, 1983). Problems of this type characterize many important situations involving planning, forecasting, and the like.

To examine the A-B paradigm, let,

A = the judged probability of a potential cause or contributing factor;

B = the judged probability of some presumed effect/event;

J = the judged probability of events A and B.

In the interests of parsimony, I assume the same combining rule as before; i.e., equation (4). However, the weighting of A and B is assumed to reflect the degree to which event A is judged to be predictive of effect B. Since predictive judgments are strongly influenced by the representativeness heuristic (e.g., Kahneman & Tversky, 1973), the weighting process follows the same logic used to develop equation (2). However, if events A and B are weighted by the strength of the relation between them, a single weight applied to both components should suffice. Hence, the judged probability of the conjunction of A and B can be written as,

$$J = (A \cdot B)^{a} \qquad (a \geq 0) \qquad (5)$$

As before, the size of a should decrease as the judged strength of the relation between events A and B increases. To capture this, let,

Z = the judged probability of effect B given cause A; i.e., the predictability of the effect from the presumed cause.

The weight a can now be defined as,

$$a = 1 - Z \qquad (6)$$

The full model can then be written as,

$$J = (A \cdot B)^{1-Z} \qquad (7)$$

The implications of (7) are best seen in reference to Table 2, which shows J as a function of A·B and Z for values of 0 to 1 in increments of .1.

Insert Table 2 about here

First, note that the conjunctive probability increases with both A·B and Z. However, when either event is impossible (i.e., A·B = 0), the conjunction is always zero; when Z = 0, the conjunction is equal to its product, which implies that A and B are independent. Second, when the product is seen as certain, the conjunction is certain for all values of Z. Third, to show when the conjunction rule will be violated, it is necessary to examine the individual components of the product and compare them to the values in Table 2. This can be done most simply by first imagining that A = B. For example, consider the row in which A·B = .4 and thus, A = .63 and B = .63. Note that when Z = .5, the conjunctive probability is .63. When Z > .5, the conjunctive probability is greater than either of the components and hence, double violations should occur in these cases. On the other hand, when Z < .5, the conjunctive probabilities are less than either component and hence, no violations should occur. This example illustrates the following general result: when A = B, double violations will occur when Z > .5, and no violations when Z ≤ .5. Now consider the situation when A and B are discrepant; e.g., A= .8 and B = .5. We can see from Table 2 that the conjunctive probability will result in single violations when Z is approximately between .3 and .8. When Z is at or greater than .8, double violations are expected;

Table 2

Conjunctive Probability as a Function of A·B and Z

A·B \ Z	0	.1	.2	.3	.4	.5	.6	.7	.8	.9	1
0	0	0	0	0	0	0	0	0	0	0	0
.1	.1	.13	.16	.20	.25	.32	.40	.50	.63	.79	1
.2	.2	.23	.28	.32	.38	.45	.53	.62	.72	.85	1
.3	.3	.34	.38	.43	.49	.55	.62	.70	.79	.89	1
.4	.4	.44	.48	.53	.58	.63	.69	.76	.83	.91	1
.5	.5	.54	.57	.62	.66	.71	.76	.81	.87	.93	1
.6	.6	.63	.66	.70	.74	.77	.82	.86	.90	.95	1
.7	.7	.73	.75	.78	.81	.84	.87	.90	.93	.96	1
.8	.8	.82	.84	.86	.87	.89	.91	.94	.96	.98	1
.9	.9	.91	.92	.93	.94	.95	.96	.97	.98	.99	1
1	1	1	1	1	1	1	1	1	1	1	1

when Z is less than .3, no violations are predicted. As A and B get further apart (e.g., A = 1, B = .4), double violations disappear but single violations increase. The general principle to be gleaned from this is the following: as A and B become more discrepant, it takes a larger Z to get double violations. However, it takes a smaller Z to get single violations. Indeed, if one component is 1, single violations are guaranteed if Z > 0. The above also implies that adherence to the conjunction rule is most likely when Z is small and A and B are equal.

The above results contrast with those found in the M-A paradigm discussed earlier. For example, in that paradigm, low *A* and *B* lead to few single violations and no double violations; in the A-B paradigm, double violations are much more frequent. Furthermore, they can occur when both components are either likely or unlikely. Indeed, evidence for double violations when both events are seen as either likely or unlikely is reported by Yates and Carlson (1985). Hence, from a practical viewpoint, the A-B paradigm is of special concern since its structure results in particularly large errors, and, such errors are likely to occur in significant judgmental activities such as diagnosis, forecasting, and planning.

Extensions: Conjunctive Explanations

The model shown in equation (5) can be naturally extended to situations in which conjunctive explanations are used to explain the occurrence (or non- occurrence) of some event B. This case has been recently studied by Leddo, Abelson, and Gross (1984). They found both single and double violations as well as a triple violation, i.e., the conjunction of three explanations was judged higher than all three components. However, they also found that adding explanations did not always lead to increases in the conjunctive probability. Thus, it is necessary to present a model which delineates the conditions under which more explanations are judged to be better, equal to, or worse than, fewer explanations.

To discuss the above formally, let B be the event to be explained and denote E1 and E2 as two *explanations*. Let,

E1 = the judged probability of E1 given B;

E2 = the judged probability of E2 given B.

J12 = the judged probability that E1 and E2 are among the factors that caused B.

Following equation (5), **J12** can be writtten as,

$$J12 = (E1 \cdot E2)^{\alpha} \tag{8}$$

As before, some way of defining α is needed. Consider that the α parameter reflects the degree to which E1 and E2 are judged to be predictive or representative of B. Let J(B| E1 & E2) denote this judgment. The weight for the conjunctive event can then be defined as,

$$\alpha = 1 - J(B|\, E1 \,\&\, E2) \tag{9}$$

Note that greater predictability or representativeness of B due to E1 and E2 results in a smaller value of α and hence a greater weight for the E1 E2 product.

The implications of (8) and (9) can be seen by referring back to Table 2. In this case, let J stand for J12 and Z for J(B| E1 & E2). Since the conjunctive probability (J12) increases with Z (holding the product constant), the addition of an explanation that increases the predictability of B also increases the likelihood of single and double violations. Other results regarding the effect of discrepancies between E1 and E2 are the same as those discussed in connection with the A-B paradigm. However, a crucial issue specific to the explanation paradigm remains. In particular, when does the addition of further explanations increase, decrease, or leave unchanged, the probability of the original explanation (or conjunction of explanations) ?

To answer this question, consider the following example: imagine that E1 is .7 and a weak explanation, say E2 = .2, is added. The product is now .14. Clearly, the issue of whether the conjunctive explanation is larger or smaller than its components depends on J(B| E1 & E2). If the addition of E2 increases J(B| E1 & E2) over J(B| E1), i.e., it makes B more representative of both explanations, the conjunctive probability will violate the conjunction rule. However, if E2 adds little or decreases the predictability/representativeness of B, the reduction of E1 by E2 (due to multiplication), can lead to conjunctive probabilities that conform to the conjunction rule. Hence, the adding of explanations results in a basic conflict (cf. Coombs & Avrunin, 1977). On the one hand, more explanations weaken the product and lower the conjunction; on the other hand, more reasons generally lead to greater predictability/representativeness of B, thereby increasing the weight for the conjunction. A similar argument, in terms of covariation, is given by Einhorn & Hogarth (in press). They argue that while the sufficiency of an explanation is increased by adding more reasons, its necessity decreases. Thus, if sufficiency and necessity affect judgments of the plausibility of an explanation, adding reasons induces a conflict. In the present approach, if several explanations are virtually sufficient for Y, the addition of further explanations would have the effect of lowering the product (and possibly lowering representativeness as well), thereby decreasing the conjunctive probability (see, Leddo, et al., 1984). The implication is that double, triple, quadruple, etc., violations will occur if additional explanations increase J(B| E1 & E2 & ....) at a faster rate than the product decreases. However, at some point, the product will be so low that an increase in J(B| E1 & E2 & ...) will result in no change in the conjunction. Beyond this point, more reasons will be seen as worse than less.

Base Rate Effects

Locksley and Stangor (1984) have shown that conjunction fallacies occur more often when the event to be explained has a low rather than a high base rate. For example, consider an explanation of why someone committed suicide. Since this is a rare event, it could be argued that many reasons are needed to explain its occurrence; that is, a "sufficient" explanation for rare events generally requires multiple reasons. On the other hand, a highly probable event requires a less complex explanation since any one of a number of reasons can produce the event. In order to account for the effects of base rates on the judged probability of conjunctive explanations, the rates of change in $E1 \cdot E2$ and α must depend of the size of the base rate. In particular, for rare events, the adding of reasons increases $J(B|\ E1\ \&\ E2)$ at a faster rate than the reduction of the product $E1 \cdot E2$. This not only results in more violations of the conjunction rule, it also implies that a complex explanation for a rare event will generally be judged as more likely than a simpler one, up to a point. Indeed, the conjunctive probability is single-peaked with the number of reasons but the peak occurs for larger numbers of reasons. For more probable events, $J(B|\ E1\ \&\ E2)$ increases at a slower rate than for rare events, while $E1 \cdot E2$ decreases at a faster rate. Thus, for probable events, there will be fewer conjunction errors and, it will take fewer reasons for a complex explanation to be judged as less likely than a simpler one.

CONCLUSION

A simple quantitative model of the conjunction fallacy has been presented that specifies the conditions under which violations of the conjunction rule will or will not occur. The model captures the general effects found in the empirical work presented by Tversky & Kahneman (1983); and, it is consistent with an interpretation of the fallacy as resulting from the use of the representativeness heuristic.

Furthermore, an extension of the model delimits the conditions under which conjunctive explanations are more, less, or equally likely than their constituents. Since the model is simple, general, and predictive, the conjunction of these attributes makes it a (highly ?) plausible model of the phenomenon.

Acknowledgement

This work was supported by a contract from the Office of Naval Research.

I wish to thank John Hand, Robin Hogarth and Joshua Klayman for coments on an earlier draft of this paper.

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