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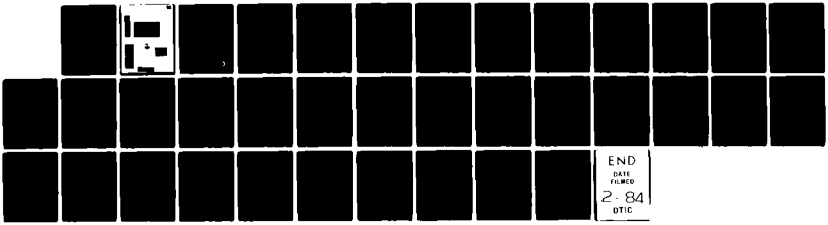

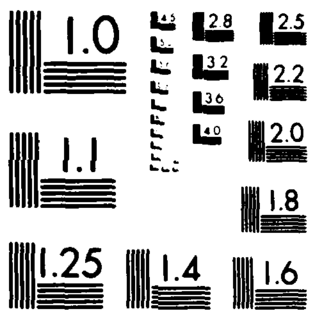

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A THEORY OF DIAGNOSTIC INFERENCE: CONTRACT FINAL REPORT

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This report summarizes research aimed at developing a theory of diagnostic inference carried out during the 30-month contract period of April 1, 1981 through September 30, 1983. The essential aspects of diagnostic inference are that they are causal rather than correlational, — pauce

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backward rather than forward (one goes from effects to prior causes), concerned with a specific rather than the general case, and constructive (one can synthesize, enlarge, or otherwise develop new hypotheses). We have developed and tested models of two aspects of diagnostic infer- inference: (1) judgments of the causal strength of a hypothesis/ explanation, and (2) how probabilistic assessments concerning the occurrence of a past event are made on the basis of (often conflicting) evidence received from less than perfectly reliable sources. The psychological rationales, quantitative formulations, and implications of these models are presented in this report together with a description of various experiments designed to test the models. We also discuss several commonalities between the two lines of research: the use of cognitive anchoring-and-adjustment strategies to cope with complex inference tasks; the constructive nature of diagnosis; the importance of surprise in inference; and the relation of the present work to normative standards of judgment and choice.

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Introduction

This report summarizes our work on developing a theory of diagnostic inference for the period April 1, 1981 through September 30, 1983. By diagnosis, we mean the following: Given the occurrence of a set of outcomes/results/symptoms, people infer what causal process could have produced the observed effects. The essential aspects of such inferences are that they are causal rather than correlational, backward rather than forward (one goes from effects to prior causes), concerned with a specific rather than the general case, and constructive (one can synthesize, enlarge, or otherwise develop new hypotheses). The importance of diagnosis goes beyond its obvious role in making sense of experience; it is crucial for predictive judgment as well as for defining what variables are "relevant." Moreover, since the evidence typically available for making diagnoses is fallible and/or conflicting, the process takes place under uncertainty.

The development of our theory has followed two complementary paths: (1) The formulation and testing of a theory of how causal judgments are made; and (2) the creation of a theory of evidence that concerns how judgments are made in ambiguous situations. We consider each of these topics in turn. Subsequently, we discuss some commonalities between the two lines of research.

Judgments of Causality

We have developed, and experimentally tested, a model of how people judge the causal strength of a hypothesis/explanation. As a specific illustration, imagine that a watch face has been struck sharply by a hammer and the glass breaks. You are then asked to assess how likely the breakage was caused by the force of the hammer. We argue that answers to this question will be mediated by three types of information: (1) The number and strength of specific alternative explanations. Part of the reason that the force of the hammer is a strong causal candidate is due to the fact that it is difficult to imagine specific alternatives that could reduce one's belief in that explanation; (2) The assumed causal background against which the judgment is made. For example, reconsider your response to the above question if the context was changed to a watch factory where a hammer strikes watch faces as part of a testing procedure. In this context, it is more likely that a defect in the glass will be judged to be the cause; (3) The judged causal strength of the explanation. We maintain that people use certain cues-to-causality in assessing the plausibility of an explanation; namely, temporal order, contiguity, covariation, and similarity of cause and effect. In our example, note that the glass broke immediately after being struck by the hammer; there is a high correlation between the breaking (or not) of glass with the force of solid objects; and there is similarity between the length and strength of cause and effect.

The role of alternatives

Causal judgments are complex. We therefore propose that people handle this task sequentially by a cognitive anchoring-and-adjustment strategy. This can be illustrated by considering how people adjust causal beliefs by the number and plausibility of specific alternative explanations. Consider an outcome Y, an initial explanation X, and alternative explanation Z_1. Furthermore, denote the "gross strength" of an explanation as being its plausibility or strength before competing alternatives are considered. Thus, the gross strengths of X and Z_1 refer to their plausibility when each is considered the sole explanation of Y. We propose that people anchor on the gross strength of the initial explanation X, and then adjust downward for the gross strength of Z_1. Moreover, the amount of the adjustment will depend on the strength of the anchor as well as the strength of the alternative. In particular, we assume that alternatives of equal strength discount strong explanations more than weaker ones. For example, imagine that one anchors on a weak hypothesis and is then confronted with a strong alternative. Since the anchor is already low, the size of the adjustment cannot be too large (indeed, if the anchor were worthless, there would be no adjustment). On the other hand, if the anchor was strong, we argue that the same alternative would discount the anchor substantially. Therefore, the basic idea is that the stronger the anchor, the larger the adjustment (holding the strength of alternatives equal). We call the strength of an explanation after it is reduced by an alternative, its "net strength."

The above process can be formally represented as follows:

$$S_1(Y,X|B) = s_o(Y,X|B) - w_o\, s(Y,Z_1|B) \qquad (1)$$

where,

$S_1(Y,X|B)$ = net strength of the causal link of Y with X, conditional on background B, after adjusting for Z_1

$s_o(Y,X|B)$ = gross strength of the causal link of Y with X, conditional on background B

$s(Y,Z_1|B)$ = gross strength of the causal link of Y with Z_1, conditional on background B

w_o = adjustment weight applied to the gross strength of Z_1 $(0 < w < 1)$

In equation (1) we adopt the convention that capital "S" stands for net strength and small "s" denotes gross strength. Of course, before any alternative is considered, $S_o = s_o$. Note that the adjustment weight, w, has the same subscript as the anchor since it is a function of the latter. Now consider what happens when a second alternative, Z_2, is introduced. We assume that the anchor-and-adjust strategy proceeds sequentially so that the net strength of X becomes the new anchor for the next adjustment. Thus,

$$S_2(Y,X|B) = S_1(Y,X|B) - w_1\ s(Y,Z_2|B) \tag{2}$$

Equation (2) can be be generalized to account for the net strength of X after the kth alternative (k = 1,2, ..., K); thus,

$$S_k(Y,X|B) = S_{k-1}(Y,X|B) - w_{k-1}\ s(Y,Z_k|B) \tag{3}$$

Furthermore, since $S_k(Y,X|B)$ is a judged likelihood, it is bounded between 0 and 1.

Now consider the functional relation between the strength of the anchor and the adjustment weight, w (called the "adjustment weight function"). It was assumed above that stronger anchors have larger adjustments. This implies that the adjustment weight is a monotonically increasing function of the strength of the anchor. To see this, consider equation (3) when the gross strength of Z_k is constant and the anchor varies in strength. It is clear that as $S_{k-1}(Y,X|B)$ increases, w_{k-1} must also increase to give larger adjustments. To model this monotonic relation, we posit a simple and convenient form, although others might serve as well; thus,

$$w_{k-1} = [S_{k-1}(Y,X|B)]^{\alpha} \quad (\alpha > 0) \tag{4}$$

Equation (4) is illustrated in Figure 1. Note that α affects the amount by

Insert Figure 1 about here

which explanations are discounted and can thus be thought of as varying as a function of task and/or individual characteristics. For example, $\alpha > 1$ implies that the adjustment weights are less than the anchor and corresponds to underweighting the impact of disconfirming evidence; $\alpha = 1$ implies that adjustment weights equal the anchor; $0 \leq \alpha < 1$ implies that adjustment weights are larger than the anchor. The importance of this for the final net strength of X can be seen by first substituting (4) into (3). This yields:

$$S_k(Y,X|B) = S_{k-1}(Y,X|B) - [S_{k-1}(Y,X|B)]^{\alpha} \, s(Y,Z_k|B) \qquad (5)$$

which can be thought of as the computational form of the anchor-and-adjust model. Indeed, as we have demonstrated empirically (see below), when α is estimated from data, equation (5) can be used to predict how people revise their causal judgments.

To illustrate how the model specified in (3) and (5) captures important aspects of the causal judgment process, consider the model in its non-sequential form;

$$S_K(Y,X|B) = s_o(Y,X|B) - \sum_{k=1}^{K} w_{k-1} \, s(Y,Z_k|B) \qquad (6)$$

That is, the net strength of an explanation is equal to its gross strength minus the sum of the adjusted alternative explanations. In other words, we posit that net strength follows a difference model as opposed to a ratio model such as probability theory. This means that net strength can be low when there are no alternatives if the gross strength of X is itself low.

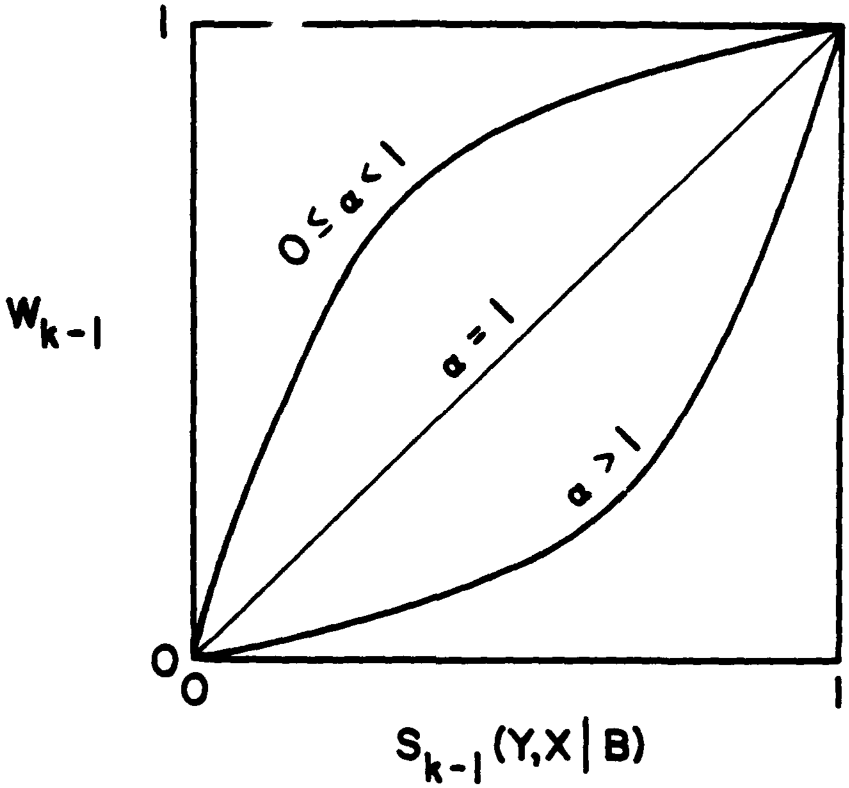

Figure 1. The Adjustment Weight Function

Moreover, net strength can also be low when gross strength is high if there are many strong alternatives. Indeed, net strength can only be high if gross strength is high and the strength of specific alternatives is low. For example, reconsider the initial watch-hammer scenario and contrast the net strength of the "force of the hammer" explanation with the net strength of any single explanation for the following questions:

1. Why are the outer rings of Saturn braided?
2. Why was Ronald Reagan elected President in 1980?

For the first question, it is difficult to generate a single explanation, thus suggesting its gross strength is low However, although there are no competing explanations, net strength remains low in accord with equation (6). For the second question, there are many strong explanations (e.g., the situation of the economy; the rise of the moral majority; the unresolved Iranian hostage problem; etc.). Therefore, while the gross strength of these are high, the net strength for any single one is low precisely because the others are plausible alternatives. On the other hand, the watch-hammer question leads to high net strength since the explanation is strong and there are few plausible alternatives. In short, it is argued that like good patterns, good explanations have few alternatives; or, to be more precise, whereas good explanations imply few alternatives, the lack of alternatives does not imply good explanations.

The causal background

Above, we have been careful to condition all terms on the causal background, B. We do this because diagnostic inference is typically invoked to make sense of deviations via causal explanation. However, the meaning of a deviation is itself crucially dependent on some assumed background or field. Specifically, we argue that causal relevance is generally related to the degree that a variable is a difference-in-a-background. By this is meant that factors that are part of some presumed background are judged to be of little or no causal relevance. For example, does birth cause death? While the former is both necessary and sufficient for the latter (and thus covaries perfectly with it), it seems odd to consider one the cause of the other. The reason is that death presumes that one has been born. Therefore, "birth" is part of the background and its causal relevance is low.

Cues-to-causality

In our model, the judged plausibility of a hypothesis/alternative (i.e., gross strength) is based on cues-to-causality. These are postulated to be imperfect indicators of causal relations that combine and trade-off in judgments of gross strength. Specifically, we define gross strength to be the following function of the cues-to-causality;

$$s(Y,X|B) = Q_1\gamma(\lambda_2 Q_2 + \lambda_3 Q_3 + \lambda_4 Q_4) \tag{7}$$

where,

Q_1 = temporal order = (0,1)

Q_2 = contiguity

Q_3 = covariation

Q_4 = similarity

$$\gamma = \begin{cases} 0 \text{ if } Q_4 < \text{threshold} \\ 1 \text{ if otherwise} \end{cases}$$

λ_i = importance weight for the ith cue (i = 1, ..., 4)

Note that if either temporal order is inappropriate or similarity is below threshold, gross strength is zero. Otherwise, the cues of contiguity, covariation, and similarity will trade-off.

Experimental evidence

Three types of experiment have been performed to test (1) the role of alternatives via the sequential anchor-and-adjust model, (2) the use of the cues-to-causality, and (3) the causal field concept.

(1) Equation (5) was estimated and tested on data where subjects were first asked to judge the gross strength of a hypothesis, and then assess its net strength after sequential presentation of two specific alternatives. In fact, the initial gross strength judgment and first assessment of net strength were used to estimate the α parameter, and the second net strength judgment was predicted on this basis. Across different permutations of hypotheses and alternatives in two scenarios, the mean absolute deviation was a mere .02 for judgments made on a 0 to 1 scale.

(2) A second series of experiments tested the role of the cues-to-causality as operationalized in equation (7). Three cues, contiguity, covariation, and similarity were varied factorially across 8 scenarios. Results showed predicted main effects for covariation and similarity but not contiguity. Furthermore, the data revealed interesting interactions between the cues and the scenarios thereby emphasizing the notion that the cues are perceived conditionally on the context or causal field in which they are embedded. In a second experiment, when the contiguity cue was manipulated to be more salient in the scenarios, significant main effects of the predicted sign were observed. In these experiments subjects not only judged a causal candidate, but made subsequent judgments after being informed of the presence of specific alternatives. This permitted two further tests of our model: (a) predictions using equation (5); and (b) a test of the similarity threshold hypothesis implicit in equation (7). In both cases, our hypotheses were supported by the data.

(3) Recall the example given above of the hammer hitting the face of a watch when no explicit context is provided and when the scene is supposed to take place in a watch factory. The effect of this shift in the causal background, with its corresponding change in the strength of causal candidates (the force of the hammer vs. a defect in the glass) was tested experimentally in both a between- and within-subjects design. The results provided strong support for the notion that shifts in the background can have dramatic effects on attributions of causality.

To summarize, the three components of our model (role of alternatives, cues-to-causality, and background) were tested and found to support our conceptualization. Whereas we clearly do not claim that our model provides a complete picture of the myriad issues involved in causal judgment, it does provide a solid, and parsimonious foundation on which to build. Furthermore, our model can be shown to subsume, and even quantify, earlier attempts to conceptualize causal judgment, e.g., various attribution theories

Evaluating Evidence under Ambiguity

An important input to diagnostic inference is the evaluation of evidence. Moreover, this usually takes place under conditions of uncertainty thereby invoking probabilistic reasoning. However, in an important paper Daniel Ellsberg demonstrated that subjective probabilities inferred from choices amongst gambles do not necessarily conform to the axioms of probability theory. Specifically, Ellsberg showed that such violations are likely to occur in ambiguous conditions where lack of knowledge about the process generating outcomes induces uncertainty about one's own degree of uncertainty. Contrast, for example, the nature of the uncertainty one faces in choosing between heads or tails on the flip of a fair coin as opposed to the uncertainties involved in deciding between two candidates for President.

<u>Task description</u>

The task we have explored requires subjects to assess the likelihood that a particular event happened given f reports favoring its occurrence and c reports favoring an alternative. The reports are deemed to emanate from a single source (e.g., witnesses) and to carry equal weight. A model of the task is depicted in Figure 2. That is, (1) an event occurs, (2) it is sensed by a source that can, in principle, be characterized by levels of sensitivity

Insert Figure 2 about here

and bias, (3) the source decides what to report (this can be thought of as analogous to a signal detection task), (4) several reports are obtained, and (5) the judge combines the reports with expectations based on the content of the scenario to come up with a likelihood judgment, S(f:c). It is important to note that in our task no explicit information is given to the subjects about the reliability (sensitivity, bias) of the reporting source. Rather, *this must be inferred* from the content of the scenarios. Thus, expectations held by the subjects (5) are inferred from ambiguous stimuli.

The importance of ambiguity in our task can be emphasized by contrasting it with more commonly studied probabilistic paradigms: (a) whereas we are dealing with inference from unreliable sources, this is not the standard cascaded inference task in that the judge does not know the precise level of the source's reliability; (b) we cannot apply the theory of signal detection since too many parameters are unknown (e.g., the source's hit-rate and false-alarm rate). We have, instead, a case of several observers reporting on one event (trial) as opposed to multiple trials of the same observer; and (c) the standard Bayesian paradigm cannot be applied *since no values are given either* for the prior probabilities of events or source reliability. However, since precise probabilities are not available in many important real-world problems,

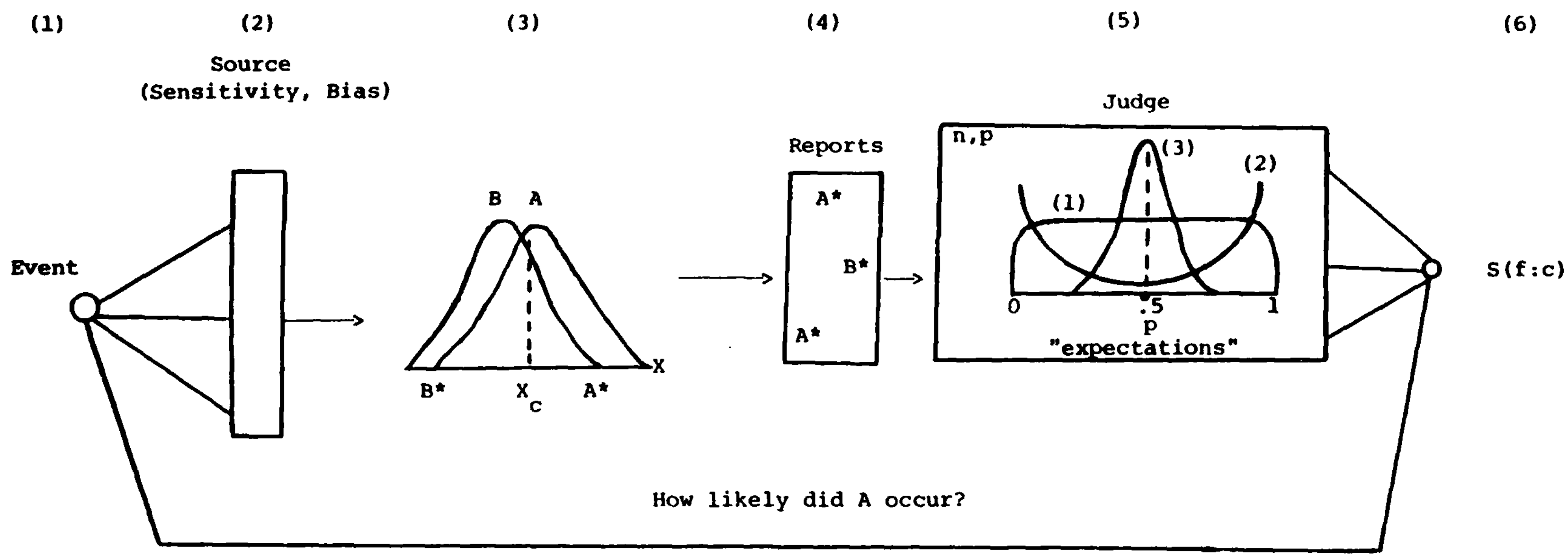

Figure 2. Structure of the ambiguous inference task

we believe that the ambiguity inherent in our task is both realistic and important.

A model for ambiguous inferences

Our model of how people handle the above task involves anchoring on the evidence presented ("what is") and adjusting for outcomes that one could imagine occurring ("what might have been"). That is;

$$S(f:c) = p + k \tag{8}$$

where $p = f/n$, the proportion of reports favoring the hypothesis, and k captures the net effect of imagining (i.e., mentally simulating) alternative outcomes greater and smaller than p. Specifically, we postulate that k will be affected by four variables: (1) the level of p since if $p = 1$, $k < 0$; but if $p = 0$, $k > 0$; (2) n, the number of reports; (3) a parameter θ that reflects the perceived lack of credibility of the source and dissimilarity of the signals $(0 < \theta < n)$; and (4) the effect of differentially weighting imagined outcomes greater and smaller than p. This is captured by a parameter β. The full model is;

$$S(f:c) = p + \frac{\theta}{n}(1 - p - p^{\beta}) \tag{9}$$

and is illustrated in Figure 3. Note that the absolute size of the adjustment

Insert Figure 3 about here

from p increases in θ but decreases in n. Note further that $S(f:c)$ is regressive with respect to p. Moreover, the parameter β implies a unique value of p, denoted p_c, for which $k = 0$ and thus where $S(f:c) = p$. We interpret β as the individual's "attitude toward ambiguity in the circumstances." In summary, note that when $(f/n) = p < p_c$, $k > 0$ so that $S(f:c) > p$; however, when $(f/n) = p > p_c$, $k < 0$ so that $S(f:c) < p$.

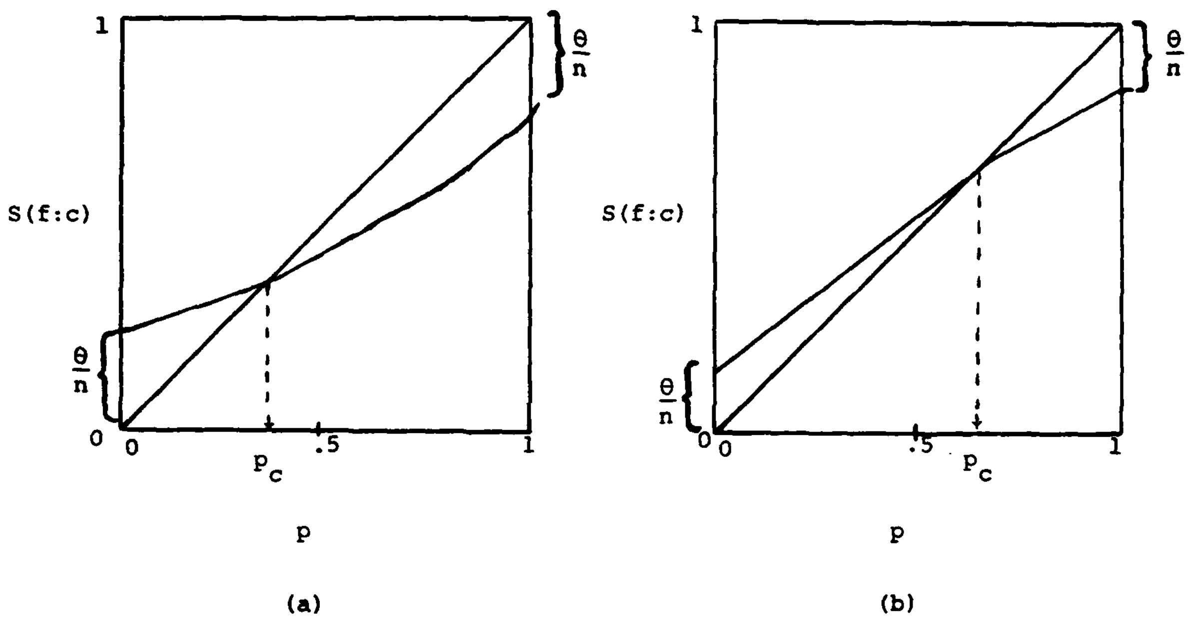

Figure 3. Two examples of S(f:c) as a function of p. In (a), $\beta < 1$ implies $p_c < .5$; in (b), $\beta > 1$ implies $p_c > .5$.

Experimental evidence

We have tested our model and its implications in a series of four experiments.

(1) Using a scenario involving a hit-and-run accident and witnesses' conflicting responses as to the color of the offending car, we have tested and fitted equation (9) on both group and individual data. We have (a) demonstrated how subjects trade-off p and n in assessing the impact of evidence, and (b) as implied by our model, subjects' judgments of the probabilities of complementary events do not necessarily sum to one. More specifically, the parameters of our model (i.e., θ and β) define the conditions under which such judgments will be additive (i.e., sum to one), sub-additive, or super-additive. Moreover, our data bear out these predictions for both groups and individual subjects.

(2) In a replication experiment we demonstrated the validity of the model over four additional scenarios involving different content.

(3) In a factorial experiment, we manipulated both the credibility and dissimilarity of the sources of evidence in order to induce differences in the θ and β parameters. Source credibility was seen to have a significant effect on both parameters (i.e., on the means of the parameters of individual subjects), but no effect was observed for source dissimilarity. Moreover, these results were obtained in both between- and within-subject designs. In addition, we investigated and found consistent individual differences in subjects' judgmental strategies. That is, subjects' individual θ and β parameters were significantly correlated across tasks involving different scenarios. In addition, the extent to which subjects made adjustments for "what might have been," as measured by their θ parameters, was significantly related to the mean absolute deviations between their actual judgments and

model predictions. We interpret this finding as evidence that the ability to execute a judgmental strategy consistently is inversely related to the amount of mental simulation used in generating responses.

(4) We investigated whether individuals' choices between gambles could be predicted from knowledge of their θ and β parameters estimated from a separate inference task. Not only did we find that such choices between gambles could be predicted quite well, but strength of preference between gambles was related to the θ and β parameters in a theoretically consistent manner.

To summarize, our experimental data support our descriptive model of how people handle the ambiguity inherent in a diagnostic inference task via a cognitive anchoring-and-adjustment strategy. We believe that the success of our modeling efforts underscores the importance of incorporating the effects of ambiguity in the perception of uncertainty as well as on risky choice. Important real-world risks are rarely defined explicitly (i.e., unambiguously) and thus it is essential to understand how people treat ambiguous evidence. Second, in trying to analyze our subjects' inference task from a normative perspective, we were struck by the number of assumptions one would need to make to apply an appropriate model, let alone the need for computation such a model would impose. And yet, our subjects were able to provide consistent responses to the experimental stimuli by essentially striking a compromise between "what was" (i.e., the data) and "what might have been" (i.e., the result of the imagined outcomes) via a quite simple cognitive strategy. In addition, whereas the subjects' judgments deviated consistently from some normative prescriptions, it would be difficult to say that they were not acting sensibly.

Some Commonalities

The development of our theory of diagnostic inference has followed two complementary paths. We now discuss some commonalities between these two lines of research.

(1) Anchoring-and-adjustment strategies. Both our models are based on the notion that people use cognitive anchoring-and-adjustment strategies to handle complex inference tasks. In the causal model, it is assumed that people anchor on the gross strength of the hypothesis and then adjust, sequentially, for the strength of specific alternatives. Moreover, we posit that the adjustment weight at each stage is a function of the associated anchor. In the ambiguity model, there is also an adjustment for alternatives that "might have been." Note that in both models the assumed details of the anchoring-and-adjustment processes have been made quite explicit. More generally, we believe that anchoring-and-adjustment strategies are prevalent in many sequential judgment tasks. Thus, the payoff from investigating such strategies carefully in these tasks could also be substantial in other areas of judgment and choice.

(2) Construction in diagnosis. Diagnosis is largely a constructive activity. This is particularly evident in the causal model when one examines the role of the causal background. People respond very quickly to cues in the causal background that allow them to shift the perspective within which a problem is viewed (recall the hammer and watch face example). In the ambiguity model, expectations and imagination clearly play important roles in simulating "what might have been." Neither of our models could be said to provide an account of construction in the diagnostic process. However, since both models incorporate some aspects of construction, they do provide a foundation upon which this crucial cognitive activity can be investigated.

(3) Surprise in inference. Our models can also be thought of as throwing some light on the importance of surprise in diagnostic inference. Surprise is a reaction to discrepancies between expectations and reality. Thus, in the causal model we note that surprise, in the form of deviations-in-a-field, is an important stimulus to diagnostic activity. Also, since the cues-to-causality can induce expectations, when these are violated the resulting surprise will trigger diagnostic activity and attempts to reinterpret experience. In the context of the ambiguity model, we note that data can create surprise (relative to expectations) either because they are "too good" or "not good enough." Indeed, when data are perceived to reach a given level of unreliability, our model predicts that if data are "too good," the surface meaning will suggest the opposite conclusion. To illustrate, consider your reaction if you were assessing whether a particular car had been speeding (i.e., travelling at more than 55 m.p.h.) and 10 eyewitnesses each independently stated that the car had been travelling at 73 m.p.h. Both the complete agreement of the witnesses and the level of precision of their responses are such that you would probably dismiss the data. From equation (9), and assuming that θ (the source unreliability parameter is at its maximum of n), we obtain

$$S(f:c) = 1 - p^{\beta} \qquad (10)$$

which, since $p = (f/n) = 1$ (all witnesses agreed) becomes 0. In other words, when high source unreliability is attributed to witnesses, our model specifically predicts a constructive rejection of the evidence. On the other hand, our model cannot handle situations where data are "not good enough" since the resolution of this type of surprise requires a creative re-organization of the hypotheses being considered. This extension is one of several challenges for future work.

(4) Normative issues. In research on judgment and decision making it is almost mandatory to compare subjects' responses with normative benchmarks. However, this is problematic in the present research. First, there is no normative theory for judgments of causality. Second, it is unclear what the normative model should be in reference to our model of judgment under ambiguity. To be sure, the latter model deviates from Bayesian prescriptions in two respects: (1) as n increases judgments asymptote at p instead of 0 or 1. However, this result can also be obtained in some cascaded inference models that are based on Bayes' theorem; (2) under certain circumstances, judgments of the probabilities of complementary events do not sum to one in our model. Whereas this possibility might be considered a "mistake," we note that there is currently considerable interest in the normative status of non-additive probabilities, the role of the "weight of evidence" in determining probabilistic belief, and so on. Our descriptive model, however, specifies the precise conditions under which additivity/non-additivity will occur, and in doing so captures how people respond to the "weight of evidence" in their judgments.

Given the lack of a normative theory of causality, what contribution can our model of causal judgment make to assessing the quality of diagnostic inference? Whereas we have no definitive answer to this question, we note that our model does highlight two relevant trade-offs. First, our conceptualization of the cues-to-causality posits that these are imperfect, probabilistic indicators of causal relations. Thus, whereas the cues will indicate appropriate causal relations in the environment, they can also indicate invalid relations thereby inducing mistaken beliefs. For a limited organism dealing with a vastly more complex environment, it is certainly appropriate to deal consistently with a limited number of cues-to-causality, and particularly since these can combine in myriad ways. On the other hand, the use of these cues will inevitably imply a trade-off between acquiring some valid causal knowledge, on the one hand, and some superstitions, on the other.

Second, the causal field and the cues-to-causality both play an important role in limiting the number of interpretations people make in inferential tasks, and thus in creating "order-out-of-chaos." Furthermore, the adoption of a particular background and the use of the cues proceed quickly and are often marked by a lack of awareness that a delimiting process has taken place. The benefits to be gained from such automatized processes are large. However, they come at the cost of reducing the probability that people can achieve more creative representations of inferential tasks. In short, the organism may often face a trade-off between stable representations of problems, on the one hand, and the possibility of generating more creative representations of the same stimuli, on the other.

Finally, whereas this report has described the work accomplished to date in the construction of our theory of diagnostic inference, it should be realized that a comprehensive theory is far from complete. However, we do believe that we now have solid foundations on which to examine both the psychology of causal reasoning and the interpretation of fallible, conflicting evidence. It is on these foundations that we are extending our theoretical and empirical investigations.

Technical Reports and Publications

Technical Reports

1. Einhorn, H. J., and Hogarth, R. M. Prediction, diagnosis and causal thinking in forecasting. University of Chicago, Graduate School of Business, Center for Decision Research, September 1981.

2. Einhorn, H. J., and Hogarth, R. M. A theory of diagnostic inference: I. Imagination and the psychophysics of evidence. University of Chicago, Graduate School of Business, Center for Decision Research, June 1982.

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