A CONTRAST/SURPRISE MODEL FOR UPDATING BELIEFS

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Although the updating of beliefs is a central concern in many fields, empirical research has produced complex and conflicting results. We first present a psychological model of updating that assumes equal attention is given to all information. The model is based on an anchoring-and-adjustment

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered) process that incorporates a contrast or surprise effect; in particular, the larger the current opinion, the more it is discounted by negative evidence and the less it is increased by positive evidence. The model predicts strong recency effects for conflicting evidence and, no order effects for consistent evidence. These predictions are contrasted with those of alternative models and tested in a series of six experiments involving the evaluation of written scenarios containing varying amounts and types of information. Thereafter, we generalize the model to include the effects of differential attention and show the conditions under which attention decrement can lead to primacy rather than recency. Specifically, under attention decrement, people with strong prior beliefs are more prone to primacy than those with weak priors. We then discuss our theoretical framework and results with respect to procedural variables that can affect judgment, the "optimal inattention problem," comparisons with alternative models of updating (e.g., Bayesian models), and limitations and extensions of the present approach.

A CONTRAST/SURPRISE MODEL FOR UPDATING BELIEFS

A central problem in the psychology of judgment concerns the process by which new information is integrated with current beliefs. Indeed, the updating of beliefs is an essential component in such diverse areas as probabilistic inference (Peterson & Beach, 1967; Edwards, 1968; Gettys & Willke, 1969; Slovic & Lichtenstein, 1971; Hogarth, 1975; Schum, 1980; Fischhoff & Beyth-Marom, 1983; Einhorn & Hogarth, in press), decision theory (Raiffa & Schlaifer, 1961; Winkler, 1972), impression formation (Fishbein & Ajzen, 1975; Anderson, 1981), communication and persuasion (Hovland, Janis & Kelley, 1953), attitude change (Triandis, 1971; Cooper & Croyle, 1984), causal inference (Jones, 1979; Einhorn & Hogarth, 1985), and psychophysics (Green & Swets, 1966). An important aspect of the updating process has been stated by Anderson (1981),

> In everyday life, information integration is a sequential process. Information is received a piece at a time and integrated into a continuously evolving impression. Each such impression, be it of a theoretical issue, another person, or a social organization, grows and changes over the course of time. At any point in time, therefore, the current impression looks both forward and back. (1981, p. 14).

Given the sequential nature of the judgment process, several questions immediately suggest themselves; e.g., Does the order in which information is presented affect the final judgment?; Does one's initial position affect later positions?; Is there a best way to structure arguments so as to have maximal impact?; Does the nature of the content (e.g., length and complexity) affect the judgment?; and so on. Many studies have already been done on these issues from a variety of perspectives. Furthermore, the often conflicting results indicate a highly complex phenomenon. Our purpose, however, is not to review this work. Rather, we wish to ask what contributes to observed regularities and irregularities in the sequential updating of beliefs. For the former, our goal is to provide a descriptive theory of the updating process that is general enough to be applied to many substantive areas. As to the latter, we argue that empirical irregularities in this domain arise largely from the fluctuating effects of attention. That is, whereas variations in attention can and do influence sequential judgments, the effects are often highly unpredictable. Thus, to develop a theory of the updating process, it is first necessary to model the underlying regularities prior to considering how these are perturbed by attentional shifts.

This paper is organized as follows. We first present a sequential anchoring-and-adjustment model for discounting the strength of beliefs on the basis of negative evidence. A parallel model to handle the case of positive evidence is then developed. Both models are incorporated into a general updating model that deals with mixed or conflicting evidence. Various predictions implied by both the consistent and mixed evidence models are then tested in six experiments. Moreover, we show that the pattern of results contradicts the predictions of other models proposed in the literature. Our model is then generalized to incorporate the possible effects of attention; in particular, the notion that attention decreases with later pieces of evidence. Finally, we discuss the implications of our theory and results for understanding the nature of the updating process.

The Discounting Model

We assume that the basic way beliefs change is via a sequential anchoring-and-adjustment process (Tversky & Kahneman, 1974; Lopes, 1981; Wallsten & Barton, 1982; Einhorn & Hogarth, in press; 1985). That is, one's current position provides an anchor and adjustments to the anchor are made on the basis of new information. Once the adjustment is accomplished, the new position becomes the anchor for the next adjustment and the process continues sequentially. From a cognitive viewpoint, the advantage of an anchoring-and-adjustment strategy is that it allows one to keep a "running total" of the effects of prior information while reducing memory load. It is therefore a particularly useful heuristic for processing information over time (cf. Hogarth, 1981).

To formalize the anchoring-and-adjustment process within the context of a discounting model, let,

s_0 = initial strength of some hypothesis, belief, or attitude; $(0 \le s_0 \le 1)$.

a_k = strength of the kth piece of negative evidence; $(0 \le a_k \le 1)$.

$s(a_k)$ = subjective strength of the kth piece of negative evidence; $(0 \le s(a_k) \le 1)$.

S_k = strength of belief after evaluating k pieces of negative evidence; $(0 \le S_k \le 1)$.

To illustrate the process, consider the effect of the first piece of negative evidence, a_1, on one's initial position. We assume that,

$$S_1 = s_0 - w_0\, s(a_1) \qquad (1)$$

where, w_0 = adjustment weight.

Equation (1) contains several hypothesized processes. First, negative evidence must be attended to and evaluated regarding its strength $[s(a_1)]$. Thus, the <u>effective</u> strength of evidence is a function of both attention and the subjective strength of the evidence. In the models to be presented here, we initially assume that equal attention is paid to all pieces of evidence that are evaluated sequentially. The effects of attention are, therefore, not shown explicitly in equation (1). However, the effects of differential attention are explored later in the paper. Second, the model assumes that once evidence is evaluated, it is used to discount current beliefs according to equation (1). Of most importance in this regard is the interpretation of the adjustment weight, w_0. In the present model, this weight reflects how the size of the anchor affects the adjustment process. Indeed, we highlight the notion that the adjustment weight is a function of the anchor by providing both with the same subscript. The rationale for this is as follows: imagine that your initial position is weak and a strong piece of negative evidence is received. Since your current position is already low, the new information cannot reduce s_0 a great deal (in absolute terms). Now consider the effect of the same negative evidence if your original position was strongly held. We argue that the reduction of strength will be larger in the latter case. Note that this assumption implies a "contrast" or "surprise" effect since it says that large anchors are "hurt" more than smaller ones (given the same negative evidence). To borrow a boxing metaphor, the contrast effect implies that the bigger the anchor, the more it will fall.

Given the above, equation (1) can be generalized as

$$S_k = S_{k-1} - w_{k-1}s(a_k) \qquad (2)$$

To make equation (2) operational, we need to specify the relations between S_{k-1} and w_{k-1} on the one hand, and $s(a_k)$ and a_k on the other. For the former, assume that the adjustment weight in the discounting process is equal to the anchor; i.e.,

$$w_{k-1} = S_{k-1} \qquad (3)$$

Note that by setting the adjustment weight equal to the anchor, the model incorporates a contrast effect since larger anchors imply larger adjustment weights. For the case of $s(a_k)$ and a_k, assume that the subjective strength of the evidence is affected by one's attitude toward negative evidence in the following way;

$$s(a_k) = a_k^{\alpha} \tag{4}$$

where $\alpha(\geq 0)$ represents one's attitude toward negative/disconfirming evidence. The rationale for this is that the subjective strength of evidence is affected by both its "objective" strength <u>and</u> one's general attitude toward disconfirming information. In addition, the use of a power function to represent the relation between objective and subjective strength has appeal since many psychophysical functions are of this type (Stevens, 1955), and, a power function bounds $s(a_k)$ between 0 and 1. Moreover, the interpretation of the α parameter is straightforward; an attitude of "disconfirmation avoiding" is implied by $\alpha > 1$ since negative evidence is itself discounted; a "disconfirmation neutral" attitude is assumed when $\alpha = 1$; when $0 \leq \alpha < 1$, this indicates an attitude that is "disconfirmation prone."

The full discount model can now be obtained by substituting (3) and (4) into (2);

$$S_k = S_{k-1} - S_{k-1}\, a_k^{\alpha} \tag{5a}$$

$$= S_{k-1}[1 - a_k^{\alpha}] \tag{5b}$$

The discount model implies that the strength of belief after k pieces of negative evidence is a function of two factors: (1) the size of the $k-1$ anchors (and thus the size of the adjustment weights); and (2) the subjective strength of negative evidence, which is due both to the "objective" strength of negative evidence and one's attitude toward disconfirming information, α.

We now consider various implications of the model. First, note from (5b) that discounting involves a proportional reduction in the anchor at each of the k steps of the process. Moreover, as long as evidence is not worthless, S_k will asymptote at 0 as k approaches ∞. Second, when the subjective strength of evidence is 0, S_k remains unchanged; when the subjective strength of evidence is 1, S_k is 0. This latter result means that when evidence unequivocally disconfirms the hypothesis or belief, the strength of the new belief is zero. Third, the model implies no order effects when negative evidence is evaluated sequentially. To see this, consider equation (5b) when $k = 2$ (substituting $s(a_k)$ for a_k^{α});

$$S_2 = S_1[1 - s(a_2)] = s_0[1 - s(a_1)][1 - s(a_2)] \qquad (6)$$

Note that S_2 is the product of the original anchor and the complements of the two subjective strengths of evidence. Since multiplication is commutative, S_2 is not affected by the order of a_1 and a_2. Hence, the discount model implies no order effects. Moreover, this result is easily generalized to the case where $k > 2$.

The Accretion Model

The accretion model closely parallels the discount model in that a sequential anchoring-and-adjustment process is also assumed. The form of the model is given by,

$$S_k = S_{k-1} + r_{k-1}\, s(b_k) \qquad (7)$$

where, r_{k-1} = adjustment weight for positive evidence;

b_k = strength of the kth piece of positive evidence; $(0 \leq b_k \leq 1)$.

$s(b_k)$ = subjective strength of the kth piece of positive evidence; $[0 \leq s(b_k) \leq 1]$.

Equation (7) follows the same general form as the discount model except that the final position results from an anchoring and <u>upward</u> adjustment process. The basic assumption in the accretion model is that weak beliefs are increased more by positive evidence than are strong beliefs. Thus, the same positive evidence "helps" a weaker position more than a stronger one. Note that this assumption implies a contrast or surprise effect for positive evidence analogous to the contrast effect in the discount model. That is, the smaller the anchor, the larger the adjustment weight. As was the case in the discount model, we posit a simple form to capture the relation between r_{k-1} and S_{k-1}. Specifically, let

$$r_{k-1} = (1 - S_{k-1}) \tag{8}$$

Note that by making the adjustment weight inversely proportional to the anchor, the model incorporates a contrast effect. The relation between $s(b_k)$ and b_k also parallels the discount model; i.e.,

$$s(b_k) = b_k^{\beta} \tag{9}$$

where, β (≥ 0) represents one's attitude toward positive/confirming evidence. When $\beta > 1$, positive evidence is reduced in strength and we call this attitude, "confirmation avoiding." Indeed, as β increases, the strength of positive evidence approaches zero. When $\beta = 1$, we label the attitude "confirmation neutral." When $0 \leq \beta < 1$, confirming evidence gains in strength and we call this attitude, "confirmation prone."

The full accretion model is obtained by substituting (8) and (9) into (7); thus,

$$S_k = S_{k-1} + (1 - S_{k-1})\, b_k^{\beta} \tag{10a}$$

$$= S_{k-1}(1 - b_k^{\beta}) + b_k^{\beta} \tag{10b}$$

The implications of the accretion model closely follow those of the discount model. Specifically: (1) S_k asymptotes at 1 as k approaches ∞; (2) When the subjective strength of evidence is 1, S_k becomes 1; when evidence is worthless, $S_k = S_{k-1}$; (3) There are no order effects when positive evidence is evaluated sequentially. To see this for the case of $k = 2$, it can be shown using equation (10a) that,

$$S_2 = s_0 + (1 - s_0)[s(b_1) + s(b_2) - s(b_1)s(b_2)] \qquad (11)$$

Note that the order of b_1 and b_2 is irrelevant to S_2 since addition and multiplication are commutative. Hence, the accretion model implies no order effects. As with the discount model, this result can be generalized to the case where $k > 2$.

The Mixed Evidence Model

To develop an updating model for positive and negative evidence, parsimony suggests using the discount model for negative evidence and the accretion model for positive evidence. Therefore, our mixed evidence model uses whichever adjustment process is appropriate for the evidence at hand. That is, when the evidence is seen as negative, the discount model is used; when the evidence is seen as positive, the accretion model is used. Moreover, we assume that the evidence is coded as either positive or negative before being integrated into the present belief (we consider the "coding" issue in the discussion section). Thus, the mixed evidence model is given by,

$$\begin{aligned} S_k &= S_{k-1} - S_{k-1}\, a_k^{\alpha}, && \text{(for negative evidence)} \\ S_k &= S_{k-1} + (1-S_{k-1})\, b_k^{\beta}, && \text{(for positive evidence)} \end{aligned} \qquad (12)$$

An important aspect of the mixed evidence model concerns the substantive meaning of the joint distribution of the two parameters, α and β. To examine this, consider Table 1, which shows the four combinations that result from crossing high and low levels of α and β. In the upper left-hand cell, both parameters are large. This means that both positive and negative

Insert Table 1 about here

information will have little effect on changing one's initial position. (Recall that large values of the parameters mean that evidence has little impact.) A person with this combination of parameter values is relatively insensitive to new information. In other words, current beliefs are strongly held and unlikely to change much in either direction. (Bayesians might consider this as representing a "tight" prior distribution.) In the lower right-hand cell, both parameters are low, implying great sensitivity to evidence such that shifts from the initial position are large. In Bayesian terms, this represents a loosely held prior distribution. The two off-diagonal cells represent differential treatment of positive and negative evidence. In the upper-right cell, negative information has little effect on changing one's beliefs, but positive evidence is weighted heavily. This might characterize a strong advocate of a particular position. In the lower-left cell, negative information is weighted heavily but positive information is not. This cell could characterize those who adhere to Popperian notions that disconfirming evidence is the best way to test hypotheses.

Whereas the above scheme is approximate, it highlights the importance that attitudes toward new information, as reflected in the α and β parameters, have on belief change. Furthermore, although we have not made α and β depend on k, it is possible to do so. Thus, the weight or importance of one type of information or the other could change over time as experience accumulates. Exactly how various "progressions" from one cell to another might occur undoubtedly involves individual differences in interpreting outcomes and learning from experience. Since this is an important and complex topic in its own right, we simply mention it without further comment.

The structure of the mixed evidence model is quite different from other models of belief change. Of particular importance is the fact that the adjustment weight for the kth piece of evidence depends on the size and sign of previously evaluated evidence. To see this more clearly, consider Figure 1, which shows the adjustment weights as a function of the anchor. Note that

Insert Figure 1 about here

when the anchor is less than .5, the weight for positive evidence, r_{k-1}, is larger than for negative evidence, w_{k-1}; when the anchor is greater than .5, the reverse is true. This means that the contrast effect is greater for positive evidence when the anchor is small; and, for negative evidence when the anchor is large. Thus, the adjustment weight attached to a particular piece of information depends on how prior information has affected the current anchor. Indeed, even one's initial belief is important since it affects the size of anchors at later stages in the process. In addition, note that the difference in adjustment weights for positive and negative evidence also changes with the size of the anchor. This means that the relative weighting of positive and negative evidence is also a function of the size of the anchor. Therefore, the differential importance of both types of evidence shifts as beliefs change over time.

An important implication of the above is that the mixed evidence model predicts strong recency effects in belief change. To see why, consider the strength of belief after receiving positive and negative information, S(+, -), versus negative and positive information, S(-, +). Figure 2 shows the effects of these two orders at starting level s_0.

Insert Figure 2 about here

Compare the effects of the (+, -) and the (-, +) orders. Note that the slope of the line connecting $S_{k=0}$ and $S_{k=1}$ in the (-,+) order is less steep than when negative evidence occurs in the (+, -) order. The reason is that the same negative evidence has a larger discounting weight after positive evidence because of the contrast effect. Similarly, the slope of $S_{k=1}$ to $S_{k=2}$ in the (-, +) order is steeper than the slope for positive evidence from the initial position. These differences in slopes lead to crossing lines that resemble "fish-tails." Note that the "fish-tail" pattern implies recency effects since the final position after the (+, -) order is lower than for the (-, +) order. The conditions affecting order effects can also be derived analytically. To do so, let,

$$D = S(-,+) - S(+,-) \tag{13}$$

where,

$S(-,+)$ = final position after negative then positive evidence.

$S(+,-)$ = final position after positive then negative evidence.

When $D = 0$, no order effects exist. When $D > 0$, recency effects are indicated since the evidence processed last has greater influence than the evidence processed first. When $D < 0$, this indicates primacy effects; i.e., the evidence that appears first has greater influence than later evidence. We show in Appendix A that,

$$D = s(a)\ s(b) \tag{14}$$

This means that the model predicts recency effects in the sequential evaluation of mixed evidence. Furthermore, recency will be largest when both positive and negative evidence are strong. Finally, (14) implies that initial position, s_0, has no impact on the size of recency effects.

To summarize, the contrast model predicts strong recency effects with mixed evidence; however, it implies no order effects for consistent evidence (both discounting and accretion models). We now turn to the experimental testing of these hypotheses.

Experimental Evidence

Rationale. Several strategies could be used to test the contrast/surprise model. In this work, we have chosen to test the qualitative predictions concerning order effects. We have done this for two reasons, one of which is technical, the other conceptual. At the technical level, one could obtain judgments of initial positions on various issues, present positive and negative evidence (independently measured), and then fit parameters of the model to final judgments. The major difficulty with this approach concerns the independent measurement of positive and negative evidence, $s(a_k)$ and $s(b_k)$, and the fitting of parameters in a nonlinear recursive formula. Since we wished to test the model on scenarios that were rich in content, we took the view that these difficulties would introduce an unacceptable level of equivocality into the experimental results. More importantly, at the conceptual level, the focus on order effects permits us to test the predictions of the contrast/surprise model against those of alternative formulations. This is particularly important since the predictions from the contrast/surprise model represent a unique pattern in this respect (see below).

In considering alternative models, we first note that within the class of anchoring-and-adjustment models, different assumptions can be made about the adjustment weight process. In particular, we consider the following: (1) The constant weight model. Here the adjustment weight is a constant that depends neither on the anchor nor the evaluation of evidence. It may, however, differ for the accretion and discounting models; (2) The weight proportional to scale value model. In this case, the size of the adjustment weight for a specific piece of evidence is proportional to the strength of the evidence (i.e., its scale value). For example, extreme evidence gets more weight than more moderate evidence; (3) The assimilation model. Like the constrast/surprise model, the adjustment weight is hypothesized to be a function of the anchor. However, the larger the anchor, the less it is discounted by negative evidence and the more it is increased by positive evidence. These three models are specified in greater detail in Appendix B. What is important for our purposes is that the various models imply order effects, or the lack thereof, for both consistent and mixed evidence. These predictions are summarized in Table 2.

Insert Table 2 about here

Note that the constant weight and proportional weight to scale value models predict no order effects for any of the types of evidence. The assimilation model, like the constrast/surprise model, predicts no order effects for consistent evidence, but primacy as opposed to recency for mixed evidence.

Three other models make up Table 2. In row 4, we show the "crystallization" hypothesis (Anderson, 1981, p. 191). This states that as one processes information across time, there is an increasing tendency for early judgments to become "crystallized" and thus to become increasingly resistant to change. This naturally leads to primacy effects irrespective of the type of evidence. The "grain size" effect model (row 5), on the other hand, implies recency. In this model (see Lopes, 1982), people are assumed to sequentially average the information received over time. However, to achieve an accurate arithmetic average, the weight given each piece of evidence should reflect its serial position; specifically, $1/(k+1)$. As k increases, this implies that the person weights the incoming evidence by increasingly small fractions. However, such discriminations become more difficult to execute cognitively, with the result that later evidence is overweighted. The last alternative is the

Bayesian model, which implies no order effects. Finally, we note that in contrast with most of the literature on order effects in sequential judgment, our treatment of this topic distinguishes between different types of evidence, i.e., consistent vs. mixed. As can be seen in Table 2, this is particularly important since it discriminates the predictions of the contrast/surprise model from those of its competitors.

A further issue in testing the contrast/surprise model concerns the method of eliciting judgments after new information is presented. There are two main possibilities, a step-by-step procedure (denoted S-b-S), in which judgments are elicited after each piece of new evidence (cf. Stewart, 1965); and, an end-of-sequence procedure (E-o-S), in which a single judgment is elicited after the presentation of all the evidence. Since various authors have suggested that E-o-S procedures usually lead to primacy rather than recency (see, e.g., Anderson, 1981 for a review), we decided to examine both methods.

Finally, many different tasks could have been chosen for studying the updating of beliefs. In Experiments 1-5, we examine how new information changes beliefs in a causal hypothesis. Since much scientific and lay inference concerns causal hypotheses and beliefs, this task is both important and sufficiently general to incorporate the essential aspects of the updating process. To anticipate the sequel, Experiments 1 and 2 were designed to test the prediction that no order effects occur with the sequential processing of consistent evidence (i.e., all positive or all negative). Experiments 3 through 5, however, tested the prediction of recency effects for mixed evidence. In Experiment 6, we re-analyze a study concerned with probabilistic inference and estimation (Shanteau, 1970).

EXPERIMENT 1

The purpose of Experiment 1 was to test for order effects in the updating of beliefs based on consistent positive evidence.

Subjects. Twenty four subjects were recruited through ads placed in various parts of the University of Chicago. Subjects were offered $5/hour for participating in an experiment on decision making. The median age of the subjects was 22.5 years and their mean educational level was 4.2 years beyond high school level.

Stimuli. The stimuli involved a set of 4 scenarios, each of which involved an initial description (the stem) and 2 additional pieces of information presented in separate paragraphs. Excluding response scales and instructions, the stems of the scenarios varied in length between 68 and 109 words (mean of 88) with the additional pieces of information averaging 52 words each. The content of the four scenarios involved: (1) A defective stereo speaker thought to have a bad connection; (2) A baseball player whose hitting has dramatically improved after a new coaching program; (3) An increase in sales of a supermarket product following an advertising campaign; and (4) The contracting of lung cancer by a worker in a chemical factory. In each case, the stem provided information regarding the hypothesis that the particular cause was responsible for the effect of interest. After reading the stem, subjects were asked to rate how likely the suspected factor was the cause of the outcome on a rating scale from 0 to 100 (e.g., in the stereo scenario, subjects were asked, "How likely do you think that the malfunction in the speaker is caused by a loose connection between the speaker and the amplifier?"). After responding to this question, subjects turned the page of their experimental booklets and were presented with two pieces of additional information regarding the causal hypothesis. These two pieces consisted of strong positive and weak positive information about the hypothesis. The new information was presented in either a strong-weak or weak-strong order. In the step-by-step condition, the two pieces of new information were presented on separate pages with a 0-100 point rating scale at the bottom of each page. Subjects were asked to respond after each piece to the question, "Now, how likely do you think X caused Y?" In the end-of-sequence procedure, the two pieces of information were presented continuously as paragraphs. At the end of the last paragraph, subjects were asked to rate the likelihood that X caused Y.

Design and procedure. The experimental design involved three factors: order of evidence strength; i.e., strong-weak vs. weak-strong; response elicitation procedure, step-by-step vs. end-of-sequence; and the four different scenarios. The first two factors were factorially crossed (resulting in 4 combinations) and set-up as within-subjects factors. The four scenarios were presented in a 4 × 4 Latin square arrangement. Thus, subjects evaluated each of the four scenarios in one of the four combinations resulting from crossing the order and elicitation factors. The 24 subjects were randomly assigned to one of the four groups making up the Latin-square (6 subjects per group). The dependent variable was the difference between the judgment after both pieces of evidence (S_2) and the initial judgment (s_0); $Y = S_2 - s_0$.

Subjects were given the experimental materials in booklet form and told to work carefully and at their own pace. To provide variety in the experimental task, after each scenario they worked on another task before starting the next scenario. On average, subjects completed all tasks in one hour. It is important to stress that, while rich in content, the information in the scenarios was not lengthy and subjects were under no time pressure. Also, they worked on the tasks in a laboratory under the supervision of an experimenter with at most three other subjects present at the same time. Thus, whereas we cannot state with certainty that subjects' attention did not fluctuate unduly while considering the experimental stimuli, conditions were created to minimize such effects. At the completion of the experiment, subjects were asked to reconsider all the arguments and rate them on a scale from -100 (completely disconfirms the hypothesis) to +100 (completely confirms the hypothesis). These data were used to provide a manipulation check on whether the information was of the hypothesized size and sign.

Results

We first discuss the manipulation check for the strengths of the strong and weak positive evidence. Across all four scenarios, the mean rating of the strong positive evidence was 63 while the weak positive evidence was rated as 33 ($t = 9.0$, $p < .001$). Furthermore, in each scenario, the strong evidence was rated significantly higher than the weak evidence ($p < .001$). Therefore, we were successful in manipulating the differential strength of the new information.

Our major results concern the dependent variable, $Y = S_2 - S_0$. This measure was subjected to a 2 × 2 × 4 analysis-of-variance using the appropriate repeated-measures-Latin-square design. Only one effect was significant; a main effect for scenarios ($F = 12.9$, $p < .001$). This effect was due to the fact that one scenario (the stereo speaker), increased much more than the others (31 vs. 9, 10, and 12). From our perspective, the major finding is the predicted lack of an order effect. Indeed, the mean increases for the strong-weak and weak-strong orders were 15.2 and 15.8, respectively.

EXPERIMENT 2

The purpose of the second experiment was to test for order effects in the updating of beliefs based on negative evidence.

Subjects. Twenty-four subjects were recruited through ads placed in various parts of the University of Chicago. The subjects were from the same population as those used in Experiment 1.

Stimuli, design, and procedures. Experiment 2 used the same stimuli, design, and procedures as Experiment 1. The only difference was that subjects were presented with two pieces of negative evidence that varied in strength. Thus, subjects saw either a strong-weak or weak-strong order of negative information, made judgments in either a step-by-step or end-of-sequence response mode, and did this for all four scenarios. The dependent variable in the discount experiment was the difference between the initial opinion and the final judgment, i.e., $Y = s_0 - S_2$.

Results

The manipulation check showed that over the four scenarios, strong negative evidence was rated as being more negative than weak negative evidence (-30 vs. -12, $t = -5.14$, $p < .001$). This result also held in all four scenarios, although at different levels of statistical significance (two scenarios at $p < .001$; one at $p < .10$; and one at $p < .16$). Therefore, we were generally able to manipulate the perceived strength of negative information so as to provide an adequate test of the model.

The 2 × 2 × 4 analysis-of-variance on $Y = s_0 - S_2$ showed no effect for order, in accord with our prediction. However, there was a main effect for response mode ($F = 3.9$, $p < .05$), and a response mode × scenario interaction ($F = 3.5$, $p < .02$). The main effect occurred because the initial judgments decreased by 32 under the step-by-step procedure versus 25 under the end-of-sequence method. The interaction was due to the fact that one scenario (the stereo speaker) had a larger decrease in the end-of-sequence method than the three other scenarios (which showed larger decreases in the step-by-step procedure).

EXPERIMENT 3

The lack of order effects observed in Experiments 1 and 2 could also be predicted by alternatives to the contrast/surprise model (see Table 2). Thus, the purpose of Experiment 3 was to test the prediction that the updating of beliefs based on mixed evidence results in recency effects (see equation (14)).

Subjects. There were 24 subjects from the same population as those in Experiments 1 and 2.

Stimuli, design, and procedures. All materials and procedures were the same as in Experiments 1 and 2 except that subjects received either a positive-negative vs. negative-positive order of information. The positive and negative pieces of evidence for each scenario were the same as those used in the accretion and discount experiments (in all cases the strong positive and strong negative items of information were used). Hence, subjects saw either a positive-negative or negative-positive order of information, made judgments in either a step-by-step or end-of-sequence response mode, and responded to all four scenarios. The dependent variable was the difference between initial opinion and final judgment, i.e., $Y = s_0 - S_2$.

Results

The manipulation check showed that over all four scenarios, the positive evidence was rated 65 ($t = 24.0$, $p < .001$) and the negative evidence was rated -38 ($t = -11.2$, $p < .001$). In addition, this pattern held in each of the four scenarios ($p < .001$). Thus, subjects perceived the positive and negative evidence as we intended.

The 2 × 2 × 4 analysis-of-variance showed the hypothesized recency effect ($F = 9.8$, $p < .003$). Specifically, the positive-negative order resulted in a decrease in the final judgment of 9.2; the negative-positive order resulted in an increase of 2.7. Therefore, the recency effect was quite strong and followed the "fish-tail" pattern predicted by the model. In addition to the main effect for order, both the scenario main effect and the scenario × response mode interaction were significant. Since these effects are similar to those found in Experiments 1 and 2, we do not consider them further.

EXPERIMENTS 4 AND 5

Experiment 4 was designed to provide a more stringent test for our prediction concerning mixed evidence by using cases involving four as opposed to two pieces of evidence. Moreover, parts of the various scenarios were rewritten and lengthened, with the effect that the amount of information to be processed increased by 32% (as measured by number of words). Experiment 5, which also involves mixed evidence with four pieces of information, investigates whether belief change is affected by giving subjects an initial position rather than having them generate their own.

Subjects. There were 60 subjects in Experiment 4 and 32 subjects in Experiment 5.

Stimuli, design, and procedures. Experiment 4 follows Experiment 3 in all respects except that there are four rather than two pieces of evidence and, as noted above, parts of the scenarios were lengthened. The two orders are therefore (+,+,-,-) vs. (-,-,+,+). Moreover, within the two positive and negative pieces, the orders were held constant. The dependent variable was the difference in initial and final positions, i.e., $Y = s_0 - S_4$. In Experiment 5, instead of having subjects rate their initial beliefs after reading the stem of the scenario, they were told to imagine that their initial beliefs were a particular value. The values given were based on the averages for the stems of the scenarios that we had obtained in the earlier experiments. All other aspects of Experiment 5 were identical to Experiment 4.

Results

The manipulation checks showed that all positive arguments were seen as positive and all negative arguments as negative. All means were significantly different from zero and in the right direction ($p < .02$).

Since the results for Experiments 4 and 5 are virtually identical, we consider them together. In both experiments, the strongest results show order effects due to recency. These results are shown in Table 3 and the combined results are illustrated in Figure 3.

Insert Table 3 and Figure 3 about here

Note that the positive-negative order generally results in a larger difference between S_0 and S_4 than the negative-positive order. The one exception is the "Disease" story in Experiment 4. Furthermore, since the initial starting positions are exactly the same in Experiment 5 (and not very different in Experiment 4), recency means that the final position after the positive-negative order is lower than after the negative-positive order. Figure 3 shows the combined order effects for the two experiments by scenario.

In addition to order effects, the analyses-of-variance show main effects for scenarios (similar to the previous results), and the scenarios × response mode interaction also found in the previous experiments. Since we did not control for the factors comprising scenario content (indeed, it is not even clear what these factors are), the differential sensitivity of belief change to particular scenarios under various procedures raises many interesting questions that are beyond the scope of the present model.

EXPERIMENT 6

Rationale. Experiment 6 is a re-analysis of work published by Shanteau (1970). The importance of this work for our model is twofold: (1) Shanteau's tasks involved probabilistic inference and estimation on the basis of information drawn from urns containing proportions of colored beads. Since this task has often been used to test Information Integration Theory and/or Bayesian approaches to updating (see, e.g., Pitz, Downing & Reinhold, 1967; Edwards, 1968; Anderson, 1981), it provides a well-researched, but different task, from those used in the first five experiments; (2) Since Shanteau was concerned with the sequential processing of probabilistic information, he investigated the role of order effects in such judgments. Hence, his study speaks directly to the predictions of our model.

Method. "The Ss were shown sequences of beads drawn with replacement from boxes containing red and white beads. After each sample bead was drawn, Ss either estimated the proportion of white beads in the box (Estimation condition) or judged the probability that the box contained more white than red beads (Inference condition). After S was familiar with the task, red and white lights were used to represent the beads" (Shanteau, 1970, p. 182).

We paraphrase the remaining details of the procedures for the experiments. Forty-two subjects were asked to judge 16 sequences which contained from 5 to 9 lights. Only the first four judgments in each sequence were considered. The sequences were constructed according to a 2^4 factorial design so that all possible combinations of red and white lights were possible. The group of 16 sequences was presented to each subject three times in random order. In the simultaneous condition, cards with red and white circles represented the drawing of beads. The stimulus sets were the five combinations of 4 beads; R-R-R-R, R-R-R-W, R-R-W-W, R-W-W-W, and W-W-W-W. Each of these five combinations was presented three times in random order.

In the estimation task, subjects estimated the proportion of white beads in the box; in the inference task, they were told to estimate the probability that the box contained more white than red beads.

Results. Since the results for the estimation and inference tasks were basically the same, this distinction need not concern us here. Consider the results for the sequential presentation involving the different orders of white and red beads. (Note that white beads provide positive evidence for the hypothesis while red beads provide negative evidence.) Figure 4, which is adapted from Shanteau's original article, shows the results. Note the

Insert Figure 4 about here

prevalance of "fish-tails," indicating recency effects throughout these data. Indeed, Shanteau found strong recency effects for both group and individual data.

ATTENTION AND SERIAL POSITION

Up to this point, we have ignored the possible effects of attention on sequential updating. In addition, we have shown that the contrast/surprise model provides a parsimonious explanation for the order (and lack of order) effects observed in our experiments. Moreover, the pattern of results was not predicted by any of the alternative models considered in Table 2. On the other hand, whereas the contrast/surprise model does not predict primacy effects, these have been observed empirically. As we now demonstrate, the model can be generalized to incorporate the effects of attention and thus account for primacy effects. To do so, re-write the mixed evidence model given in equation (12) as

$$S_k = S_{k-1} - S_{k-1}\, a_k^{\alpha}\, \theta_k\,, \quad \text{(for negative evidence)}$$
$$S_k = S_{k-1} - (1-S_{k-1})\, b_k^{\beta}\, \theta_k, \quad \text{(for positive evidence)} \qquad (15)$$

where θ_k = proportion of full attention given to the kth piece of evidence ($0 \leq \theta_k \leq 1$). When θ_k is a constant (> 0) for all k, the order effect predictions of the contrast/surprise model summarized in Table 2 still hold. However, fluctuations in θ_k can induce many kinds of effects depending on how attention is allocated to evidence in different serial positions.

From the perspective of the more general version of the contrast/surprise model given in equation (15), it is illuminating to consider why primacy occurs and the conditions that affect it. To begin, imagine reading a long and complex manuscript. At the outset, attention is high, fatigue is low, and information is scrutinized carefully. However, as one continues, attention may begin to wane and information that occurs later in the manuscript receives less careful consideration. Such a process, in which attention decreases with the serial position of information, means that evidence that occurs early in a sequence has more influence than when it appears later. The primacy effect observed is thus seen to result from a process of "attention decrement" (Anderson, 1981). The inclusion of attentional factors in the sequential updating of beliefs has important consequences for understanding order effects. In particular, if the amount of attention given to a particular piece of evidence affects its "weight" or importance in the final judgment, then serial position effects can result from many factors; e.g., the length and complexity of evidence, time pressure, motivation and incentive to "pay" attention, and, procedural variables such as the number and spacing of "rests," calling for judgments at different intervals, and so on. Since a large number of variables can affect attention, it is likely that order effects will be extremely sensitive to seemingly minor changes in tasks. In fact, this sensitivity has been empirically observed (cf., Slovic & Lichtenstein, 1971, for a review of the conflicting findings on order effects in probabilistic judgment).

We now discuss how attentional effects, and attention decrement in particular, affect the various updating models considered earlier. To aid our discussion, re-consider Table 2, in which the six alternative models are listed. What are the predictions of these models when attention decreases with serial position? For the constant weight model, attention decrement should always lead to primacy since the model implies no order effects for either consistent or mixed evidence. The same is true for the weight proportional to scale value model. For the assimilation model, primacy should hold for both consistent and mixed evidence. On the other hand, the contrast model implies that primacy should hold for consistent evidence, but the situation for mixed evidence is more complicated since two opposing forces are at work We discuss this further below. In the crystallization hypothesis, primacy is already implied so that attention decrement simply accentuates primacy effects. In the grain size hypothesis, attention decrement will work against recency effects but the net effect should be the same for consistent and mixed evidence. Finally, in the Bayesian model, no order effects are allowed.

The conclusion to be reached from the above is that many models predict primacy when there is attention decrement. Indeed, for consistent evidence, the demonstration of primacy does not discriminate between the constant weight, proportional weight, assimilation, contrast, and crystallization models. For mixed evidence, only the contrast and grain size models predict that recency can occur with attention decrement, although the conditions need to be spelled out in detail (see below). In any event, our earlier analysis and experiments, in which attention is held constant, provide the crucial test of alternative updating processes since the pattern of no order effects for consistent evidence and recency for mixed evidence unequivocally rules out models other than the contrast/surprise approach.

Whereas attention decrement implies a force toward primacy, the contrast assumption implies a force toward recency in the evaluation of mixed evidence within the contrast/surprise model. Thus, since order effects observed in this case result from the net effect of conflicting forces, under what conditions will primacy, recency, or no order effects be observed? To examine these conditions, reconsider equation (13), which is reproduced here for convenience,

$$D = S(-,+) - S(+,-)$$

Assume (without loss of generality) that $\theta_1 = 1$ and $\theta_2 < 1$. We show in Appendix B that D can then be expressed as,

$$D = \theta_2\, s(a)\, s(b) - (1-\theta_2)\, [(1-s_0)s(b) + s_0 s(a)] \qquad (16)$$

Equation (16) implies that primacy (i.e., $D < 0$) will result when,

$$[\theta_2/(1-\theta_2)] < [s_0 s(a) + (1-s_0)\, s(b)]/[s(a)\, s(b)] \qquad (17)$$

Equation (17) implies that: (1) As attention decrement increases (i.e., θ_2 decreases), primacy becomes more likely; (2) For a given level of attention decrement, consider the right-hand side of (17) and denote it as R. To determine the relations between R and its various components, we take the partial derivatives of R with respect to s(a), s(b) and s_0. These are,

$$\partial R/\partial s(a) = -(1-s_0)/[s(a)]^2 < 0 \qquad (18a)$$

$$\partial R/\partial s(b) = -s_0/[s(b)]^2 < 0 \qquad (18b)$$

$$\partial R/\partial s_0 = [s(a) - s(b)]/s(a)\, s(b) \qquad (18c)$$

Note that R decreases as the strength of both negative and positive evidence increase; and, when $s(a) > s(b)$, R increases with s_0. Since primacy will be most likely when R is large (see equation (17)), this occurs when negative and positive evidence is weak. Furthermore, recall that both types of evidence will be weak when α and β are large; i.e., positive and negative evidence receive little weight. From Table 1, such attitudes indicate someone with strong prior opinions. If we call such a person an "expert," then our results imply that, "inattentive experts are prone to primacy." On the other hand, those with weak prior opinions ("novices"), show the opposite effect. That is, "attentive novices are apt to recency."

DISCUSSION

We now discuss our theory with regard to the following issues: (1) The importance of developing a procedural theory of judgment; (2) Off-setting "biases" in the evolution of behavior; (3) Similarity of the contrast model to other updating approaches; (4) Limitations and future directions for research.

Toward A Procedural Theory of Judgment

In recent years, the greatest challenge to those interested in decision making has been the extreme sensitivity of judgment and choice to seemingly minor changes in tasks (Einhorn & Hogarth, 1981; Lopes, 1982; Payne, 1982). The importance and pervasiveness of various "context" effects (including "framing," Tversky & Kahneman, 1981; "response modes," Slovic, Fischhoff & Lichtenstein, 1982; and so on) may create a view of decision making as a fragmented and chaotic field; after all, if judgments and choices are sensitive to small changes in tasks, what hope is there of obtaining generalizable knowledge (cf. Cronbach, 1975)? We believe that one answer lies in developing what Lopes (1982) has called a "procedural theory of judgment." That is, by focusing on the effects of task variables on information processing strategies, complex behavior can be seen to arise from the interaction of simple psychological processes with an infinitely varied environment. Indeed, this general approach underlies our attempt to understand the updating of beliefs. That is, we have posited a sequential anchoring-and-adjustment model that requires little memory and minimal computational ability. However, such a strategy, when combined with factors such as order of information presentation, the strength of positive and negative evidence, and the like, leads to complex and highly contingent behavior (cf. Payne, 1982).

While our experimental data are consistent with the contrast model (and rule out various alternatives), the full complexity of environmental effects on judgment can be appreciated when attention decrement is included in the model. Since attention decrement leads to primacy while contrast/surprise implies recency, the model highlights the conflict between these opposing forces. Our analysis shows that the net effect of this conflict is a complex function of the absolute and relative strengths of positive and negative evidence, attitudes toward confirming and disconfirming information, and initial position. Hence, we very much doubt if the issue of "primacy vs. recency" will ever be resolved by a purely experimental approach. Indeed, since attention is so difficult to control (in both the natural environment and the laboratory), the best we can do is to specify the conditions under which one type of order effect is more likely to occur than another. However, it is only by positing a theoretical model that these conditions can be specified.

The difficulty of controlling attention implies that arbitrary but subtle changes in tasks can cause large response differences. Moreover, procedural manipulation can occur without awareness that responses have been affected (e.g., Plott & Levine, 1978). A good example is the recent work of Hoch (1984), who asked people to generate reasons for buying and not buying a product in either a pro-con or con-pro order. He found a strong primacy effect for judgments regarding the probability of purchasing the product. However, in another condition, subjects first generated either pro or con reasons and were then interrupted by asking them to perform another task. After the interruption, the subjects generated the other reasons. The results showed strong recency effects on the probability of purchase judgment. Thus, the interruption had a marked effect on reversing the type of order effect (presumably by directing more attention to the later reasons).

An extension of our model also demonstrates the importance of simple procedural changes in affecting judgment. Consider that people do not sequentially update as has been assumed; instead, they suspend judgment until all the evidence is at hand. The total evidence is then evaluated "as a whole," and integrated with their prior belief. For example, a judge may tell a jury to suspend judgment until all the evidence has been heard. Our model can be extended to handle such a process. To do so, we first consider how two pieces of negative evidence might be evaluated when they are taken together (the details and extension to positive evidence are shown in Appendix C). Let $s(a_1,a_2)$ denote the evaluation of two pieces of negative evidence taken-as-a-whole. We assume that the two pieces are integrated according to the accretion model and <u>then</u> evaluated as to their subjective strength; i.e.,

$$s(a_1,a_2) = [a_1 + (1-a_1)a_2]^\alpha = [a_1 + a_2 - a_1a_2]^\alpha \qquad (19)$$

Now compare the difference between judgments that result from sequentially discounting a_1 and a_2 versus discounting on the basis of $s(a_1,a_2)$ (call this latter judgment S*); i.e., from equations (6) and (19),

$$S_2 - S^* = s_0[1 - s(a_1)][1 - s(a_2)] - [s_0 - s_0 s(a_1, a_2)] \quad (20)$$

It is shown in Appendix C that under full (or equal) attention, the difference between S_2 and S^* is positive if $\alpha > 1$. Moreover, under attention decrement, $S_2 > S^*$, if $\alpha > m$, where $0 \le m < 1$ (the exact size of m depends on the amount of attention decrement). The implication is that the "simultaneous" evaluation of negative evidence results in greater discounting than the sequential processing of the same evidence. We call this a "dilution effect" to denote the fact that sequential processing weakens the total impact of the evidence. Similarly, the dilution effect also occurs for positive evidence. Hence, the simultaneous presentation of consistent information results in more extreme responding than the sequential processing of the same information. The study by Shanteau (1970) discussed earlier in Experiment 6 speaks directly to this prediction. That is, in addition to having subjects revise their opinions after each new datum, another group was given the data in a simultaneous form and asked to express their revised opinion. The results are shown in Figure 5. Note that simultaneous presentation leads to more extreme responses for both consistent positive and negative evidence.

Insert Figure 5 about here

That is, the simultaneous presentation of positive evidence leads to a greater increase in belief than the sequential. Similarly, negative evidence has a greater discounting effect when it is processed simultaneously rather than sequentially. Therefore, Shanteau's results strongly support the prediction of a "dilution" effect.

Off-Setting Biases

While much of the work in judgment and decision making has been concerned with the errors that result from the use of heuristics, more recent work has stressed the adaptive nature of simplified strategies in sequential tasks (Hogarth, 1981; Klayman & Ha, 1985; Kleinmuntz, in press). If one considers our sequential anchoring-and-adjustment model as a cognitive strategy that makes limited demands on memory, attention (via sensitivity to surprise), and computational skill, then the issue arises as to what the organism "gives up" to attain such ease of processing. One such cost is our extreme sensitivity to arbitrary and irrelevant factors. However, whereas most discussions of heuristics posit a trade-off between positive and negative aspects of simplified rules, our model suggests another possibility. To illustrate, imagine that one was designing an organism with limited memory and limited attention (cf. Toda, 1962). Since these limitations could result in systematic errors or biases in judgment, it would be important to have off-setting biases (cf. Campbell, 1959; Hogarth, 1981). Indeed, off-setting biases allow the organism to incur low information processing costs <u>and</u> low amounts of error. For example, if limitations in attention restrict our ability to monitor information across time and thereby induce the "cost" of primacy, a processing model that reflects surprise, and thus a tendency toward recency, is an effective way of combatting this cost. That is, since the two errors are in the opposite direction, they can cancel each other out. We denote this the "optimal inattention problem"; i.e., the proclivity toward recency can counterbalance tendencies toward primacy that result from attentional limitations so that their net effect is zero. While we do not know how many biases have this off-setting character, more attention to this possibility seems warranted.

Similarity to Alternative Models

Given the importance of updating beliefs, many models have been proposed. However, two types have received the most attention; Bayesian models for the updating of probabilistic judgments and, models developed within Information Integration Theory. We consider each in turn.

The Bayesian model explicitly proposes a sequential updating process in which new evidence is integrated with one's current beliefs (called the "prior" probability). To see the similarities of the Bayesian approach to our model, consider the log-odds form of Bayes' theorem; i.e.,

$$\log \Omega_k = \log \Omega_{k-1} + \log LR_k \tag{21}$$

where, Ω_k = the posterior odds in favor of hypothesis A vs. hypothesis B after the kth piece of evidence.

Ω_{k-1} = prior odds; i.e., belief before seeing the kth piece of data.

LR_k = likelihood ratio for the kth piece of evidence.

Equation (21) posits a sequential process in which the posterior odds after the kth piece of data become the prior odds for the k+1st piece. Note that (21) implies that new beliefs are an additive function of prior beliefs (similar to an "anchor") plus the strength of new evidence. However, in the Bayesian model there is no "adjustment weight" for the log likelihood ratio. On the other hand, to make the Bayesian model more descriptive, Edwards (1968) proposed that the log likelihood ratio be weighted by a parameter called the "accuracy ratio" (c). Equation (21) then becomes,

$$\log \Omega_k = \log \Omega_{k-1} + c \log LR_k \tag{22}$$

which is similar in spirit to our formulation.

Since there is much research demonstrating the inadequacy of Bayes' theorem as a descriptive model of human judgment (see, e.g., Slovic & Lichtenstein, 1971; Tversky & Kahneman, 1974), we do not consider it a serious alternative for describing the updating of beliefs. Indeed, the Bayesian model does not allow for order effects (which is part of its prescriptive appeal), nor can it account for "dilution effects." Furthermore, there are other aspects of the Bayesian model that do not accord with the way people update their beliefs. For example, Fischhoff and Beyth-Marom (1983) point out that people often fail to evaluate evidence with respect to its diagnostic impact on alternative hypotheses (also see Schum & Martin, 1980). Rather, they tend to evaluate evidence with respect to a single hypothesis which is cognitively simpler. Note that this aspect of updating beliefs is captured in our model since evidence always concerns the strength of a single hypothesis.

The second important class of updating models has been developed by Anderson and colleagues within the framework of Information Integration Theory. The present work owes an important debt to this stream of research since it has emphasized the development of a descriptive theory of updating based on psychological processes. Indeed, Anderson first formulated and tested the attention decrement hypothesis to account for primacy effects. However, our work differs from that done within Information Integration Theory in at least three respects. First, whereas Anderson has developed a methodology for studying the judgmental rules that best describe molar judgments after those judgments have been elicited, we have hypothesized a model based on explicit assumptions about the process and then tested the predictions from that model. Second, we have assumed a model in which the weights and scale values (i.e., strengths of evidence) are highly dependent and changing from trial to trial. Indeed, even the <u>relative</u> importance accorded to positive vs. negative evidence changes as a function of the current anchor. Since most information integration models assume some form of independence between scale values and weights, our model is quite different in this regard. Finally, we have focused on qualitative predictions and by-passed the difficult questions of independently measuring scale values, fitting parameters, and the like. On the other hand, Information Integration Theory is set up to deal with these issues.

Limitations and Extensions

We now discuss several limitations of our model and suggest directions for further theoretical and empirical work. First, it has been assumed throughout that new evidence is coded as either for or against the hypothesis of interest. Once this "coding" has been accomplished, the appropriate discount or accretion model is used in the updating process. To make our approach more precise, we need to specify the factors that affect the coding process. However, note that this issue is part of the more general problem concerning the encoding of information prior to the use of decision rules and strategies (e.g., the coding of payoffs as gains vs. losses in prospect theory, Kahneman & Tversky, 1979; aspiration level effects in risky choice, Payne, Laughhunn & Crum 1980; and so on). In the context of updating beliefs, the coding issue is intimately related to the way new evidence relates to previous evidence. For example, imagine that symptom X is highly diagnostic of disease Y. However, if you knew that a person with X had already experienced the disease, the symptom might be irrelevant because of an acquired immunity. Therefore, knowledge of previous medical history conditions the interpretation of new evidence. In Bayesian statistics, issues like these have to do with what is called "conditional independence." In our model, we have implicitly assumed that the outcomes of the coding process already include whatever conditioning the subject has done based on prior evidence. However, this issue needs to be studied in its own right, and particularly in cases where information is rich in content and engages world knowledge. Indeed, Schum and Martin (1982) report that when subjects did not receive information (in a judicial context) in a decomposed form so that the structure was clear, positive evidence was sometimes evaluated as negative (and vice versa). However, when subjects were given decomposed information that highlighted the structure of the data, fewer errors of this type were made. Finally, a related problem concerns the updating of beliefs on the basis of new but redundant evidence. While we have not dealt with this issue, we note that Schum and Martin (1982) found that, "The most systematic result in our study concerns the holistic tendency to 'double count' corroboratively redundant testimony" (p. 144). While such "double-counting" is consistent with our sequential anchoring-and-adjustment model, much work will be necessary to understand how, and why, redundant information is integrated with existing beliefs.

Finally, our approach suggests that judgment should be sensitive to the experimental manipulation of attention via task variables. For example, the imposition of deadlines, varying the length and complexity of evidence, and so on, should increase the chances of observing primacy effects. Furthermore, it may also be possible to experimentally vary attitudes toward confirming and disconfirming evidence by appropriate instructions and/or incentives. Since the α and β parameters have a major effect on the type and magnitude of order effects, there may be complex interactions between attention decrement and shifting attitudes toward evidence that can also be studied within our framework.

CONCLUSION

The updating of beliefs plays an important role in many areas of psychology. We have proposed and tested a sequential anchoring-and-adjustment model to capture the updating process. The model incorporates two opposing psychological forces; a contrast/surprise effect that leads to recency effects and, an attention decrement process that leads to primacy effects. The model illustrates how a simple psychological process based on the sequential and nonindependent processing of information can interact with task variables to produce a wide range of judgmental effects. Indeed, we view our approach as providing a bridge between the idea that people are limited information processors and the complexity and sensitivity of behavior to environmental changes. Thus, our approach can be seen as an attempt to bring "chaos" (on the response side), out of order (on the input side).

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APPENDIX A

Order Effects in the Mixed Evidence Model

Following equation (13) in the text, define

$$D = S(-,+) - S(-,+) \qquad (A.1)$$

This can be written

$$\begin{aligned} D &= [s_0 - w_0 s(a) + r_1 s(b)] - [s_0 + r_0 s(b) - w_1 s(a)] \\ &= s(b)[r_1 - r_0] + s(a)[w_1 - w_0] \qquad (A.2) \end{aligned}$$

By definition of the contrast model, we have $r_0 = (1 - s_0)$ and $r_1 = \{1 - [s_0 - w_0 s(a)]\}$ such that $(r_1 - r_0) = w_0 s(a)$ or $s_0 s(a)$. Similarly, $w_0 = s_0$ and $w_1 = [s_0 + r_0 s(b)]$ such that $(w_1 - w_0) = r_0 s(b)$ or $(1-s_0)s(b)$. Substituting these values into equation (A.2) we obtain

$$\begin{aligned} D &= s(b) s_0 s(a) + s(a)(1-s_0)s(b) \\ &= s(a)s(b) \qquad (A.3) \end{aligned}$$

which is equation (14) in the text.

To show the effect of attention decrement, assume that $\theta_1 = 1$ and $\theta_2 < 1$ such that equation (A.2) can be rewritten as

$$D = s(b)[\theta_2 r_1 - r_0] + s(a)[\theta_2 w_1 - w_0] \qquad (A.4)$$

Expanding and rearranging the terms within parentheses, we obtain

$$\begin{aligned} \theta_2 r_1 - r_0 &= \theta_2\{1-[s_0 - w_0 s(a)]\} - (1-s_0) \qquad (A.5) \\ &= \theta_2 s_0 s(a) + (1-s_0)(\theta_2 - 1) \end{aligned}$$

and
$$\Theta_2 w_1 - w_0 = \Theta_2\{s_0 + r_0 s(b)\} - s_0 \qquad (A.6)$$
$$= \Theta_2(1-s_0)s(b) + s_0(\Theta_2 - 1)$$

such that
$$D = s(a)s(b)\Theta_2 s_0 + s(b)(1-s_0)(\Theta_2-1) \qquad (A.7)$$
$$+ s(a)s(b)\Theta_2(1-s_0) + s(a)s_0(\Theta_2-1)$$

or
$$D = \Theta_2 s(a)s(b) - (1-\Theta_2)[1-s_0)s(b) + s_0 s(a)] \qquad (A.7)$$

which is equation (16) in the text.

APPENDIX B

Order Effect Predictions for Alternative Models

For three of the models summarized in Table 2, order effect predictions do not require explanation and are therefore not discussed here. (These are the crystallization hypothesis, "grain effect" and Bayesian models.) For the remaining models, we consider predictions concerning the discount, accretion and mixed evidence models separately. This is shown here for cases involving only two pieces of evidence. However, the generalization beyond 2 pieces is straightforward.

Discount predictions. Let $s(a_w)$ and $s(a_s)$ be the subjective strengths of weak and strong negative evidence, respectively. Moreover, denote $S(S,W)$ and $S(W,S)$ as the final judgments after evaluating the evidence in the two orders. Therefore, order effects occur if,

$$d = S(S,W) - S(W,S) \neq 0 \qquad \text{(B.1)}$$

Thus the condition for no order effects can be expressed as $d = 0$ or

$$s_0 - w_0 s(a_s) - w_1 s(a_w) = s_0 - w_0' s(a_w) - w_1' s(a_s) \qquad \text{(B.2)}$$

This can be simplified to

$$s(a_w)[w_0' - w_1] = s(a_s)[w_0 - w_1'] \qquad \text{(B.3)}$$

From (B.3), it is clear that no order effects are predicted if the adjustment weight is constant (model 1) since this implies $w_0' = w_1 = w_0 = w_1'$ and both sides of (B.3) equal zero. Similarly, if adjustment weights are proportional to scale values (model 2), there are no order effects since this model implies $w_0' = w_1$ and $w_0 = w_1'$.

No order effects are also predicted when adjustment weights depend on the anchor. First, in both cases, the model assumptions imply $w_0' = w_0$. However, in the assimilation model (3a) $w_0' < w_1$, $w_0 < w_1'$, and $w_1 > w_1'$. This means that $(w_0' - w_1)$ and $(w_0 - w_1')$ are both negative and $(w_0' - w_1) < (w_0 - w_1')$. This therefore implies that in equation (B.3) the difference between $s(a_w)$ and $s(a_s)$ will be counterbalanced by the difference between $(w_0' - w_1)$ and $(w_0 - w_1')$. Moreover, this compensatory effect is exact when anchors reflect the scale values of previously processed stimuli. Second, the assumptions of the contrast/surprise model (3b) imply that $(w_o' - w_1) > (w_0 - w_1')$ since $w_0' = w_0$ and $w_1 < w_1'$. This also implies differential weight to counterbalance the fact that $s(a_s) > s(a_w)$. (See also proof of no order effects in the text.)

<u>Accretion predictions</u>. Let $s(b_w)$ and $s(b_s)$ be the subjective strengths of weak and strong positive evidence, respectively. Moreover, denote $S(S,W)$ and $S(W,S)$ as the final judgments after evaluating the two orders. Therefore, order effects occur if

$$\delta = S(S,W) - S(W,S) \neq 0 \qquad \text{(B.4)}$$

The condition for no order effects or $\delta = 0$ is

$$s_0 + r_0 s(b_s) + r_1 s(b_w) = \text{[illegible]} + r_0' s(b_w) + r_1' s(b_s) \qquad \text{(B.5)}$$

This can be simplified to

$$s(b_w)[r_1 - r_0'] = \text{[illegible]}(b_s)[r_1' - r_0] \qquad \text{(B.6)}$$

Following analogous arguments to those given above concerning the discount model, it follows that neither the constant weight (1), weight proportional to scale value (2), nor either form of the weight as function of anchor models

(3a and 3b) will show order effects.

Mixed predictions. Order effects occur if

$$D = S(-,+) - S(+,-) \neq 0 \qquad (B.7)$$

or order effects do not occur if

$$s_0 - w_0 s(a) + r_1 s(b) = s_0 + r_0 s(b) - w_1 s(a) \qquad (B.8)$$

This can be simplified to

$$s(b)[r_1 - r_0] = s(a)[w_0 - w_1] \qquad (B.9)$$

From (B.9), it is clear that neither the constant weight (1) nor weight proportional to scale value (2) models predict order effects.

For the assimilation model (3a) note that $r_0 > r_1$ and $w_0 > w_1$. This implies primacy. On the other hand, in the contrast/surprise model, $r_0 < r_1$ and $w_0 < w_1$ thereby implying recency.

APPENDIX C

We wish to show the conditions under which "dilution effects" result for negative and positive evidence. The basic assumption is that evidence "taken-as-a-whole" is first combined via the accretion model and then evaluated as to its strength. For example, consider two pieces of negative evidence, a_1 and a_2. The overall strength of this evidence taken together is,

$$s(a_1,a_2) = [a_1 + (1 - a_1)a_2]^{\alpha} \tag{C.1}$$

Note that the order of combining the evidence is irrelevant since we have already shown that there are no order effects for consistent evidence (see equation (11)). Furthermore, we assume that when evidence is taken together, there is no attention decrement. Let S^* be the judgment that results from discounting $s(a_1,a_2)$; i.e.,

$$S^* = s_0 - s_0\ s(a_1,\ a_2) = s_0[1 - s(a_1,a_2)] \tag{C.2}$$

Now consider the sequential discounting of a_1 and then a_2. From equation (6), this is given as,

$$S_2 = s_0\ [1 - s(a_1) - s(a_2) + s(a_1)\ s(a_2)] \tag{C.3}$$

We can now define the difference between S_2 and S^* as reflecting the degree to which evidence taken together differs from the sequential processing of the same information. In particular, when $S_2 > S^*$, this implies that sequential processing results in less discounting, which we have labeled a "dilution effect." Subtracting (C.2) from (C.3) yields,

$$S_2 - S^* = s_0\ \{s(a_1,a_2) - [s(a_1) + s(a_2) - s(a_1)\ s(a_2)]\} \tag{C.4}$$

Substituting for $s(a_1,a_2)$ and using equation (4) for $s(a_k)$, $S_2 > S^*$ when,

$$[a_1 + a_2 - a_1a_2]^\alpha > (a_1)^\alpha + (a_2)^\alpha - (a_1)^\alpha(a_2)^\alpha \qquad (C.5)$$

Note that when $\alpha = 1$, the two terms are equal. However, when $\alpha > 1$, the inequality in (C.5) holds and a "dilution effect" occurs. This result assumes that sequential processing is done under full or equal attention. If there is attention decrement, then dilution effects will occur over a wider range of α. That is, under attention decrement (see equation (15)), $S_2 > S^*$ when,

$$[a_1 + a_2 - a_1a_2]^\alpha > (a_1)^\alpha\theta_1 + (a_2)^\alpha\theta_2 - (a_1)^\alpha(a_2)^\alpha\theta_1\theta_2 \qquad (C.6)$$

Since the right-hand side of (C.6) is less than in (C.5), dilution will occur when $\alpha > m$, where $0 \leq m < 1$.

Now consider the case for positive evidence, b_1 and b_2. The strength of the evidence taken together is given by,

$$s(b_1,b_2) = [b_1 + b_2 - b_1b_2]^\beta \qquad (C.7)$$

Let S' denote the revised judgment after updating on the basis of $s(b_1,b_2)$; i.e.,

$$S' = s_0 + (1-s_0)\ s(b_1,b_2) \qquad (C.8)$$

Now compare S' with the sequential updating of b_1 and b_2.

$$S' - S_2 = (1-s_0)[s(b_1,b_2) - s(b_1) - s(b_2) + s(b_1)s(b_2)] \qquad (C.9)$$

Therefore, $S' > S_2$ when,

$$[b_1 + b_2 - b_1b_2]^\beta > b_1{}^\beta + b_2{}^\beta - b_1{}^\beta b_2{}^\beta \qquad (C.10)$$

Therefore, dilution will occur when $\beta > 1$ for full attention and, $\beta > m$ $(0 \leq m < 1)$ under attention decrement (analogous to the discount model).

FOOTNOTE

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TABLE 1

Attitudes Toward Confirming and Disconfirming Evidence

		β (confirm) HI	β (confirm) LOW
α (disconfirm)	HI	STRONG PRIORS	ADVOCATE
α (disconfirm)	LOW	POPPERIAN	WEAK PRIORS

TABLE 2

Order Effect Predictions of Different Models

Model[a]	Type of Evidence: Consistent — Discount	Consistent — Accretion	Mixed
1. Constant weight	No effect	No effect	No effect
2. Weight proportional to scale value	No effect	No effect	No effect
3. Weight as function of anchor:			
(a) Assimilation	No effect	No effect	Primacy
(b) Contrast/surprise	No effect	No effect	Recency
4. Crystallization hypothesis	Primacy	Primacy	Primacy
5. "Grain size" effect	Recency[b]	Recency[b]	Recency[b]
6. Bayesian	No effect	No effect	No effect

[a]For descriptions of the various models, see text.

[b]Recency is particularly likely to be observed for long as opposed to short series of judgments.

TABLE 3

Recency Effects for Experiments 4 and 5

SCENARIOS	Experiment 4 S_0	S_4	Diff.	Experiment 5 S_0	S_4	Diff.
Stereo						
+ + - -	57	44	13	50	39	11
- - + +	56	61	-05	50	52	-02
Baseball						
+ + - -	76	66	10	70	50	20
- - + +	70	68	02	70	60	10
Advertising						
+ + - -	55	30	25	60	38	22
- - + +	60	54	06	60	47	13
Disease						
+ + - -	73	58	15	75	56	19
- - + +	74	56	18	75	62	13

FIGURE CAPTIONS

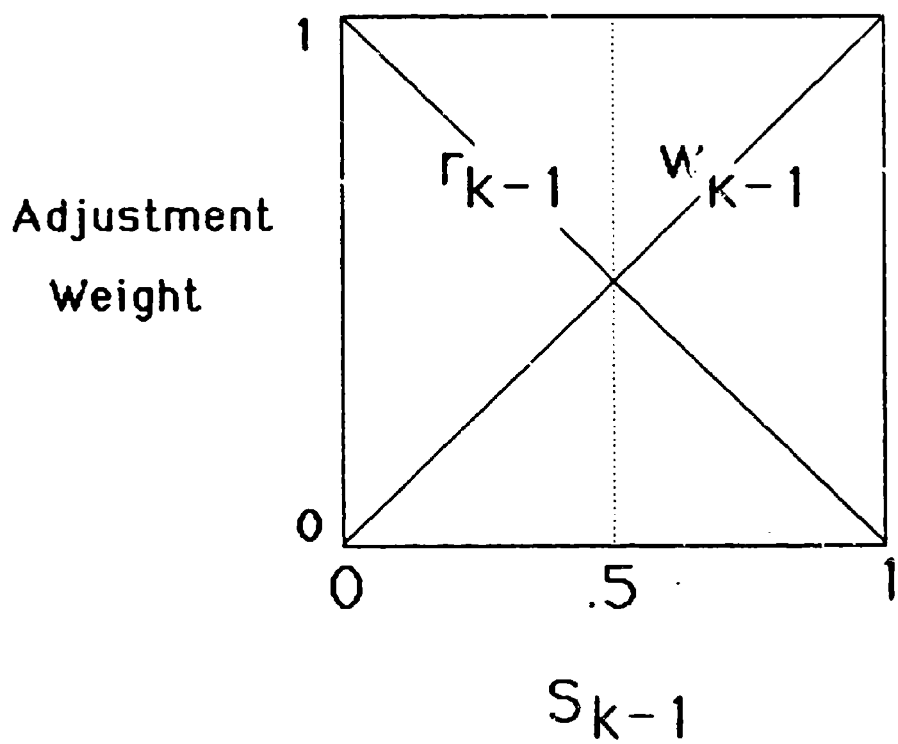
Figure 1. Adjustment weight functions for mixed evidence.

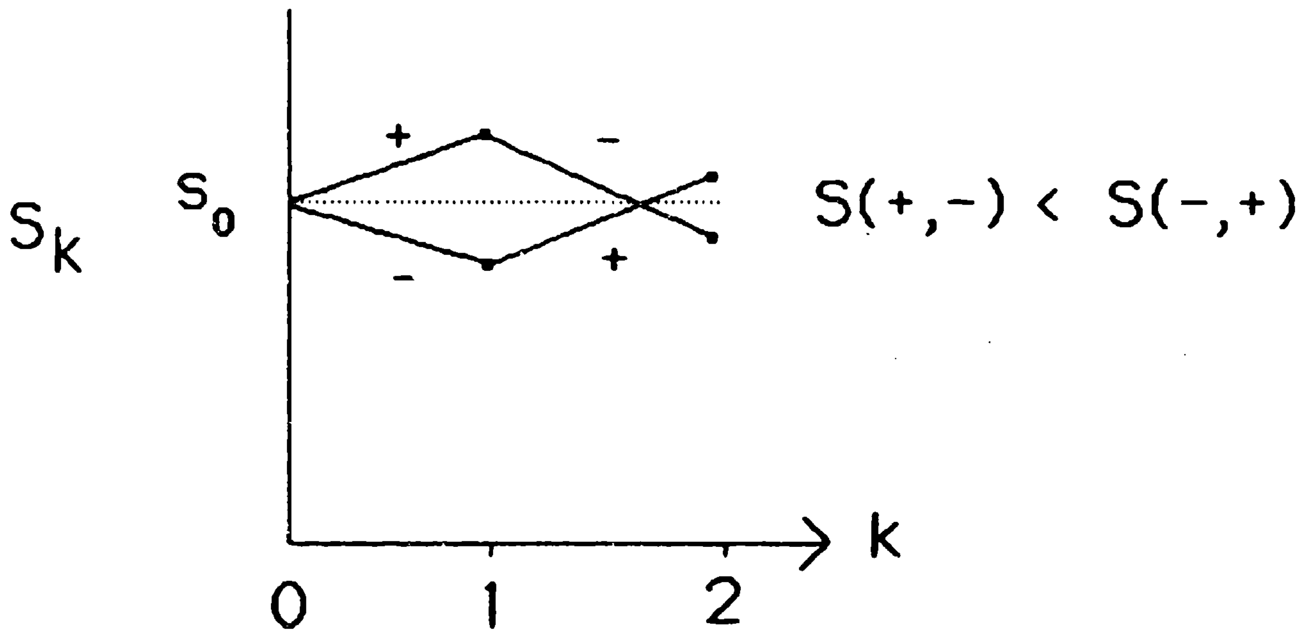
Figure 2. Recency effects for mixed evidence.

Figure 3. Recency effects for the four scenarios.

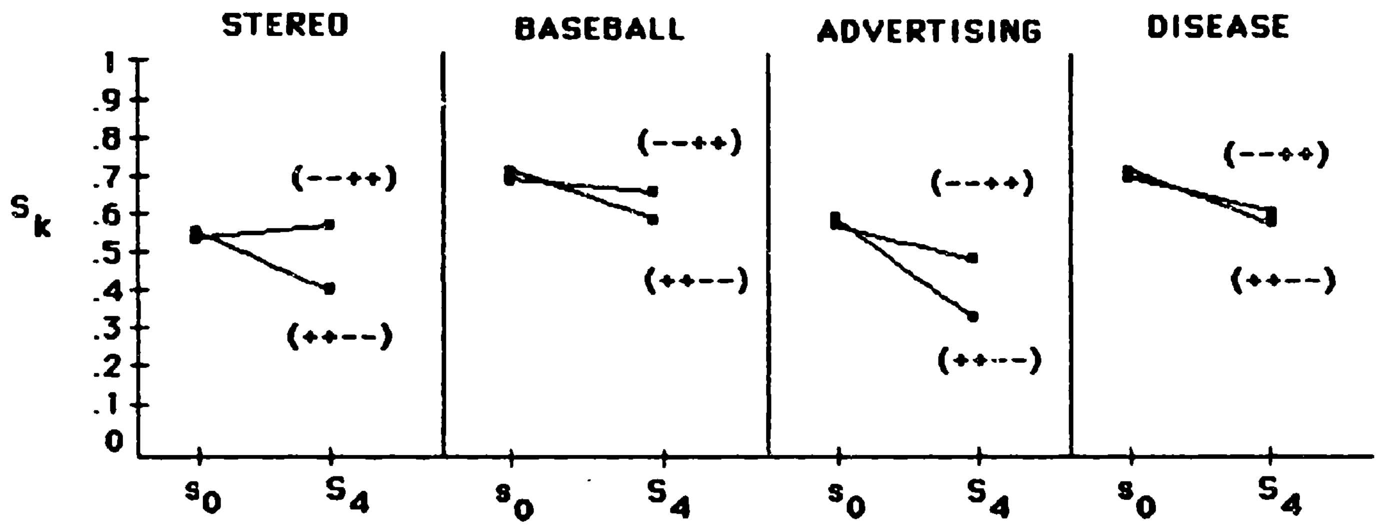
Figure 4. Recency effects in probabilistic inference and estimation.

Figure 5. Dilution effects for consistent and mixed evidence.

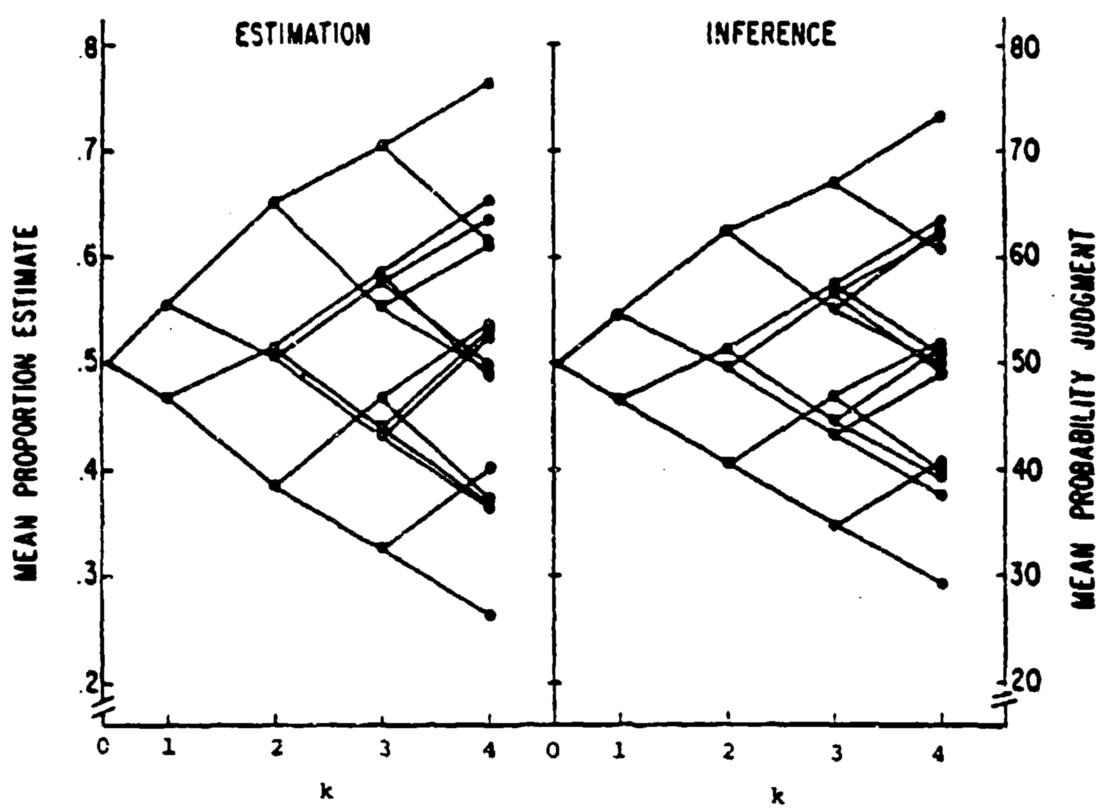

1
0
Adjustment
Weight
r_{k-1}
w'_{k-1}
0
.5
1
S_{k-1}



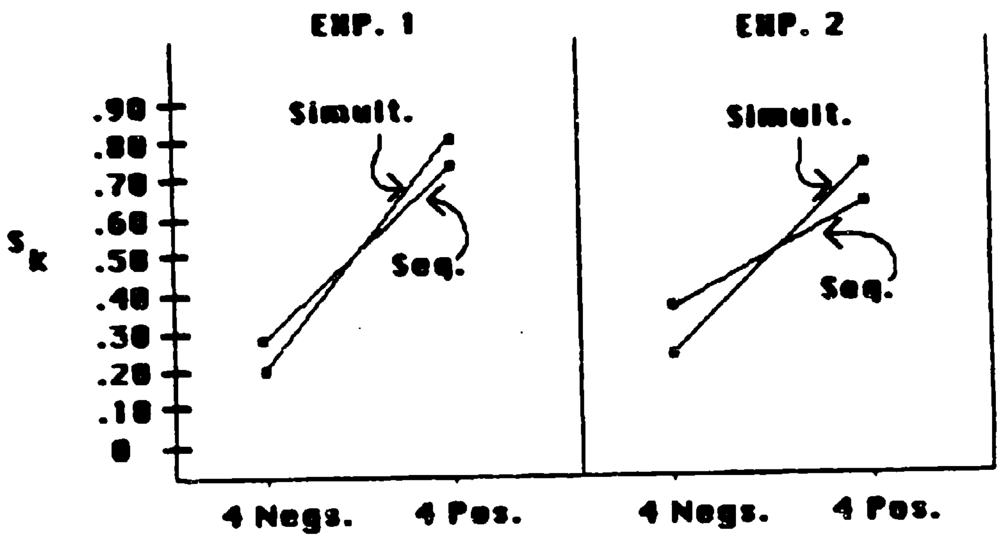
S_k
S_0
+
−
−
+
$S(+,-) < S(-,+)$
k
0
1
2



STEREO
BASEBALL
ADVERTISING
DISEASE
S_k
1
.9
.8
.7
.6
.5
.4
.3
.2
.1
0
(--++)
(++--)
(--++)
(++--)
(--++)
(++--)
(--++)
(++--)
s_0
S_4
s_0
S_4
s_0
S_4
s_0
S_4



ESTIMATION
INFERENCE
MEAN PROPORTION ESTIMATE
MEAN PROBABILITY JUDGMENT
.8
.7
.6
.5
.4
.3
.2
80
70
60
50
40
30
20
0
1
2
3
4
k
k


EXP. 1
EXP. 2
.90
.80
.70
.60
.50
.40
.30
.20
.10
0
S_k
Simult.
Seq.
Simult.
Seq.
4 Negs.
4 Pos.
4 Negs.
4 Pos.

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