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Feedback Representation and Prediction Strategies

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The influence of feedback representation on prediction is examined in a single cue probability learning paradigm. Two types of feedback representation are examined: *deviation representation*, in which the feedback is the magnitude, or even just the sign, of the prediction error, and *standard representation*, in which the feedback is the outcome itself. It is found that when the predictor is represented visually (rather than numerically), and when the outcome scale is unknown, deviation representation results in higher prediction extremity than standard representation. In addition, deviation representation results in higher prediction consistency than standard representation. These findings are explained as resulting from more reliance on the representativeness heuristic in the deviation representation conditions.

Prediction behavior may be conceptualized within a theoretical framework in which people have at their disposal various prediction strategies, which differ in their "strength," or probability of being selected. This framework was used primarily to investigate the learning of the functional rule relating predictor to outcome in Cue Probability Learning (Brehmer, 1974, 1979, 1980; Sniezek, 1986; Sawyer, 1991). For example, Brehmer (1974) suggested that people have a hierarchy of hypotheses about this functional rule in the order of positive linear, negative linear, and inverted U and U, where rules that are higher in the hierarchy have higher probability of being utilized.

Recently, this framework was also used to investigate prediction strategies within the heuristics and biases tradition (Kahneman, Slovic, & Tversky, 1982). Agnoli and Krantz (1989) suggested that people often have available few heuristics which vary in strength and that these heuristics compete for the determination of prediction output. While the strength of these heuristics may vary as a function of training and expe-

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rience, some heuristics are "naturally" stronger and determine prediction when there is little learning involved.[1]

Among these natural heuristics, the representativeness heuristic (Kahneman & Tversky, 1972, 1973) is especially important. According to this heuristic, people base their predictions on some perception of the dispersions of the predictor and outcome. Based on this perception, a *matching strategy* is used to arrive at a prediction. The predicted value is chosen so that its extremity (deviation from central tendency) matches the extremity of the predictor.

Prediction by representativeness leads to excessively extreme predictions (Kahneman & Tversky, 1973). One reason is that while normative predictions are regressive (the position of the predicted value on the distribution of the outcome is less extreme than the position of the predictor on its distribution), intuitive predictions are—at least when little learning is involved—nonregressive. Another reason, which is of special importance to this paper, is biased perception of the width of the outcome distribution. Since predictions by representativeness rely on some perception of the outcome distribution as an input, factors that make the perceived distribution wider than the actual distribution may lead to excessive extremity (see Nisbett & Kunda, 1985, for an example of factors that may influence the perception of distribution width).

The manner by which information is presented may influence heuristic selection, and therefore the output of prediction. To illustrate, consider recent studies in which the influence of *predictor* representation on prediction was examined (Ganzach, 1993). The results of one study indicate that predictions are more extreme and more consistent when the predictor is represented visually (as a bar on a computer screen), rather than numerically. Most likely there is more reliance on representativeness in the former representation than in the latter, since in the former representation there is a natural "frame of reference"—the computer screen—against which the extremity of the predictor can be assessed. This frame of reference facilitates the use of representativeness, since it eases estimation of predictor extremity. Indeed, when predictor frame of reference is induced quite differently, by representing it on a familiar (e.g., percentile) rather than an unfamiliar scale, similar results are obtained.

In this paper I investigate how feedback representation influences prediction. Consider the two following representations of feedback. In one, the feedback is the outcome itself. I will call this representation *standard*

[1] While in Brehmer's (1974) theorizing there is no direct parallel to the concept of natural heuristic, hypotheses that are high in the hierarchy are conceptually similar to natural heuristics.

representation, since this is the way feedback is usually represented in Cue Probability Learning experiments. In the other, it is represented as the deviation of the prediction from the outcome (e.g., the magnitude, or even just the sign, of the prediction error). I will call this representation *deviation representation.*

Since a main difference between standard representation and deviation representation is that the outcome distribution can be learned more easily in the former representation than in the latter, two opposing hypotheses about the influence of feedback representation on prediction strategies can be advanced. The first hypothesis is that reliance on representativeness is stronger in standard representation than in deviation representation. The second hypothesis, which is my working hypothesis, suggests the opposite: reliance on representativeness is stronger in deviation representation.

The logic behind the first hypothesis is that since reliance on representativeness requires a knowledge of the outcome's distribution, factors that hinder the learning of this distribution—such as deviation representation—will also hinder reliance on representativeness. Furthermore, deviation representation may easily lead to the abandonment of representativeness and the adoption of less biased (i.e., more moderate) prediction strategies. The reason is that by focusing attention on the deviation of the prediction from the outcome, the systematic bias in responses based on representativeness may be highlighted, since the deviation's sign tends to be positive (negative) when predictions are based on a predictor whose value is below (above) the predictor average. This may suggest a direction for correction of the bias.

On the other hand, the second hypothesis suggests that since deviation representation does not supply (subjectively) clear feedback, subjects do not develop moderate prediction strategies, but rather tend to keep their natural strategy, i.e., representativeness (see Sawyer, 1991, and Ganzach, 1993, for discussion of how strategies are changed). A critical question that arises from this line of reasoning is which outcome distribution subjects use, if their predictions are based on representativeness, since such predictions require the outcome distribution as an input. I believe that there are two important factors that influence the outcome distribution used by subjects in deviation representation. First, this distribution is likely to be inferred from contextual details of the experimental procedure, which are required to direct subjects to the appropriate outcome range (e.g, the numbers of digits in the example introducing the experiment, the number of digits required as an output, etc.). Second, this distribution is likely to be wider than the distribution used by subjects in standard representation (as well as the actual distribution), because the process of narrowing down the range of outcome values becomes more difficult. Thus, in deviation representation, excess extremism may result not only from nonregressiveness, but also from biased perception of the outcome distribution.

In summary the two hypotheses differ in the effect they assign for the added opacity involved in making predictions when feedback is represented in a deviation form. The first hypothesis suggests that this added opacity impedes the learning of the outcome distribution and therefore weakens reliance on representativeness. The second suggests that this opacity interferes with the use of all possible heuristics and therefore strengthens reliance on representativeness—the simplest, most natural, heuristic to use.

Dependent measures. Two dependent measures were used as indicators for reliance on representativeness: extremity and consistency. Extremity is widely used as an indictor for prediction by representativeness (e.g., Kahneman & Tversky, 1973; Fischoff, Slovic, & Lichtenstein, 1979; Yates & Jagacinski, 1979). It is operationalized in this paper as the ratio between the prediction slope—the regression slope relating subjects' predictions to predictor values—and the normative slope—the regression slope relating outcome values to predictor values (see Brehmer & Lindberg, 1970, for the use of this ratio as a measure for extremity).[2] Note that extremity may also be influenced by experience. If predictions are excessively extreme (or excessively moderate) in early trials, decrease (or increase) in extremity may occur throughout the experiment as a result of learning.

In addition to extremity, reliance on representativeness may also influence prediction consistency—the correlation between predictor and prediction (Ganzach, in press). The reason is that when a linear relationship between predictor and outcome exists, the representativeness heuristic reduces both acquisition and application difficulties (see Hammond & Summers, 1972a,b for a discussion of these concepts in cue probability learning task), because it implies a linear relationship between predictor and prediction (i.e., "pure" matching results in predictor–prediction correlation of 1). Thus, it is expected that the higher the reliance on representativeness, the higher the consistency. Note also that in addition to representativeness, experience may also influence consistency. Specifically, learning would cause consistency to increase over trials, while reliance on representativeness would cause consistency to be high in early trails and remain relatively steady throughout the experiment.

[2] Note that extremity as defined here is also equal to $(r_{CR} * \sigma_R)/(r_{CE} * \sigma_E)$, where C is the predictor, R is the prediction, and E is the outcome. Thus, as defined here, extremity does not depend on the predictor scale.

EXPERIMENT 1

The experiment was a Single Cue Probability Learning experiment. It included two crossed factors: a feedback representation factor and a predictor representation factor. There were three levels of feedback representation: a standard representation level and two deviation representation levels. In the first of the two deviation representation levels, the feedback was the prediction error [i.e., (R-E), where R is the prediction and E the outcome]. I will call this level *magnitude deviation*. In the second, the feedback was simply the sign of the error. I will call this level *sign deviation*. Magnitude deviation representation and standard representation are similar in respect to the objective information available for subjects, but differ in the ease by which the outcome distribution can be learned. It is more difficult to learn it in magnitude deviation. In the third level of feedback representation—sign deviation—the learning of the outcome distribution becomes even more difficult. This level also differs from the other two levels in that less information is available.

The predictor representation factor had two levels. In *visual representation* the predictor was presented in the form of a bar graph. In *numerical representation* it was presented as a number. This factor was included to contrast the effect of feedback representation in conditions in which predictor representation induces strong reliance on representativeness (the visual conditions) and conditions in which it induces weak reliance on representativeness (the numerical conditions).

Method

Subjects. One hundred twenty-three first year business administration students participated in the experiment to fulfill a class requirement. Subjects were assigned randomly to one of six conditions.

Procedure. Subjects participated in the experiment in groups numbering between four and eight. After entering the laboratory, they were seated in front of an IBM XT computer and told to read the initial instructions, which explained the task. The instructions gave a description of the experiment, explained that its purpose is to study how people learn relationships between two variables, and emphasized that the relationship between the predictor and the outcome is positive but probabilistic. Subjects were given a practice trial in which the response was typed for them on the computer screen, were instructed that their responses should be three digit numbers, and received six additional practice trials in which they themselves entered the responses. After finishing the practice trials, the experimenter verified that each of the subjects understood how to operate the computer. Subsequently, subjects completed the 120 experimental trials at their own pace.

In each trial, the computer first displayed the predictor. In the numerical conditions, the predictor was a number located in the center of the screen. In the visual conditions, the predictor was a horizontal bar, whose length was proportional to the value of the number in the numerical conditions. After 2 s the computer prompted the subjects to type their predictions. Subjects typed their predictions numerically in all conditions. After each prediction was typed, the predictor and the prediction were erased and the computer displayed the feedback. In the standard representation conditions, this feedback was the true outcome, in a numerical form. In the magnitude deviation condition, it was the absolute value of the prediction error accompanied with a short sentence indicating to the subjects whether their predictions were above or below the true outcome. In the sign deviation conditions, the feedback simply informed the subject whether their prediction was above or below the true outcome. The feedback was displayed to the subject for 2 s. Subsequently, the feedback was erased, and a new trial began.

Subjects did not have a time limit in typing their predictions. To avoid responses that are completely out of range, the predictions were examined, and if they were numbers of four or more digits or two or less digits, subjects were prompted to type their predictions again.

Stimuli. Four 30-trial blocks were sampled from a parent bivariate normal distribution with a correlation of .709. The mean (standard deviation) of the outcome variable was 585 (50) and that of the predictor variable 150 (18.4). Blocks were chosen so that this statistical structure will be preserved within each block, with the condition that no outcome values smaller than -2.5 standard deviations and higher than $+2.5$ standard deviations will occur.[3]

In the visual conditions, the predictor was a horizontal bar whose value was proportional to the numerical value of the predictor in the corresponding trial in the numerical conditions. An increase of 1 cm in the bar corresponded to an increase of about 3.5 units in the predictor in the numerical conditions.

Results

Extremity. The ratio between the prediction slope and the normative slope was calculated for each subject and each 30-trial block. These ratios were subjected to a 2 (predictor representation) $\times$ 3 (feedback representation) $\times$ 4 (block) analysis of variance with repeated measures on the third factor (four subjects whose regression slopes were negative were

[3] Upper and lower limits were needed to fit all stimuli in the visual condition into the computer screen.

TABLE 1
SUMMARY TABLE FOR ANOVA ON PREDICTION SLOPE IN EXPERIMENT 1

Source	*df*	*F*	*p*
Between groups	118		
Feedback representation	2	8.9	.0003
Predictor representation	1	47.0	.0001
Feedback × Predictor	2	12.6	.0001
Error	113		
Within subjects	357		
Block	3	29.5	.0001
Block × Feedback	6	8.5	.0001
Block × Predictor	3	21.6	.0001
Block × Feedback × Predictor	6	5.0	.0002
Error	339		

omitted from the analyses).[4] The results of this analysis are summarized in Table 1, the means are plotted in Fig. 1, and the standard deviations are given in the legend to Fig. 1.

Several facts are evident from the results. First, feedback representation has a strong impact on extremity when the predictor is represented visually, but has negligible effect when it is represented numerically. A 3 (feedback representation) × 4 (block) ANOVA, which was performed separately for the numerical and visual conditions, revealed a significant effect for feedback representation within the visual conditions ($F(2,55) = 13.8$, $p < .0001$) but not within the numerical representation conditions ($F(2,58) = .4$, $p > .7$).

Second, in spite of this interaction between feedback representation and predictor representation, the main effect for predictor representation is meaningful, since extremity is higher in all three visual representation conditions.

Third, the within subject part of the analysis reveals a learning effect (see the main effect for block in Table 1): Predictions become more moderate during the course of the experiment. This learning effect replicates some earlier findings (Ganzach & Krantz, 1990; Fig. 3; Ganzach, in press; Fig. 1), but not others (Brehmer & Lindberg, 1970; Fig. 3; Brehmer, 1973, Fig. 2). However, this learning effect should be understood in light of the triple interaction of predictor representation, feedback representation, and block. This triple interaction results from the fact that learning occurs mainly in conditions in which extremity is high in the early phases of the

[4] One was in the visual predictor standard feedback; one of the visual predictor deviation feedback; one in the numerical predictor standard feedback; and one in the numerical predictor sign feedback.

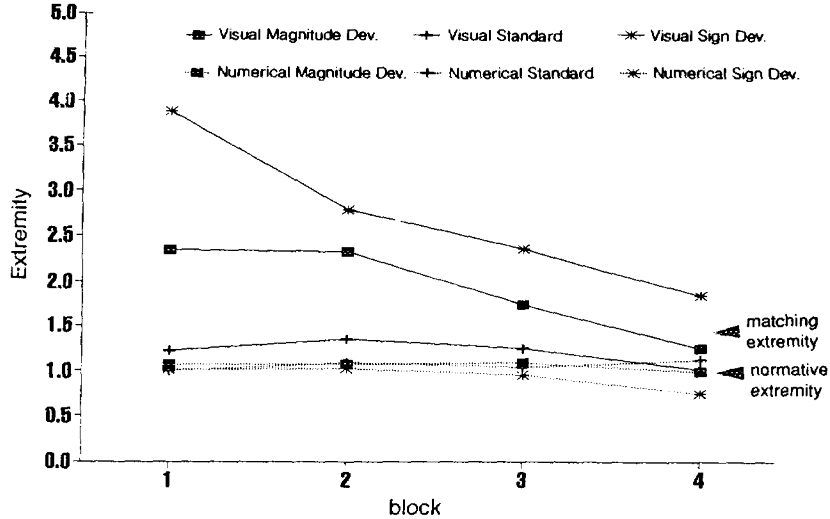

FIG. 1. Mean extremity as a function of predictor representation, outcome representation and block for Experiment 1. Standard deviations, in ascending block numbers are 1.47, 1.34, 1.21, and 1.63 for the visual sign deviation condition; 1.24, 1.06, 1.06, and .93 for the visual magnitude deviation condition; .72, .49, .50, and .39 for the visual standard condition; .99, .63, .59, and .49 for the numerical sign deviation condition; .72, .77, .41 and .72 for the numerical magnitude deviation condition; and .66, .49, .45, and .35 for the numerical standard condition.

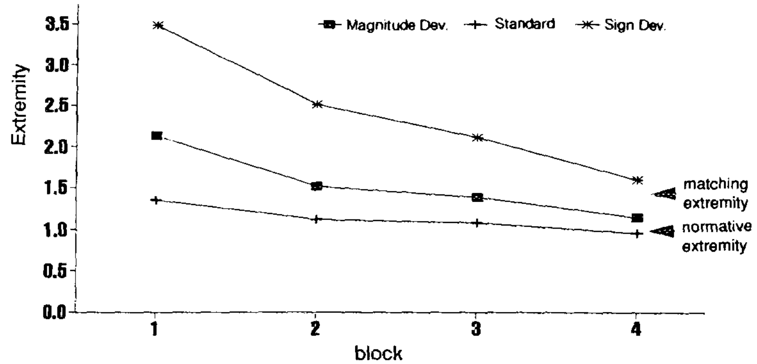

FIG. 2. Mean extremity as a function of outcome representation and block, for Experiment 2. Standard deviations, in ascending block number, are 1.54, 1.38, 1.08, and .85 for the sign deviation condition; 1.21, .94, .25, and .27 for the magnitude-deviation condition; and .96, .37, .26, and .39 for the standard condition.

experiment and particularly in the two visual-predictor/deviation-feedback conditions. The 3×4 ANOVA within the visual conditions revealed both a significant block effect ($p < .0001$), indicating a decrease in extremity throughout the experiment in all three conditions, and a significant interaction between block and feedback representation ($p < .0001$), resulting from a larger decrease in extremity the steeper the initial extremity. The same ANOVA within the numerical conditions revealed neither a block effect ($p > .5$) nor an interaction between block and feedback representation ($p > 5$).

Subjects extremity in the various conditions could also be compared to the "matching extremity," the extremity that would be obtained if subjects used a "pure" matching strategy (the value of the matching extremity is 1.41)[5] and to the "normative extremity," the extremity that would be obtained if subjects followed the normative strategy (the value of this extremity is 1.00). In the numerical conditions subjects extremity does not differ significantly from the normative extremity ($t(21) = .6, p > .6$; $t(20) = .4, p > .7$; and $t(20) = .6, p > .6$ for the sign deviation, magnitude deviation, and standard representation condition, respectively), whereas it does differ significantly from the matching extremity ($t(21) = 4.1, p < .0006$; $t(20) = 2.7, p < .01$; $t(20) = 3.8, p < .001$, respectively). (Since in these conditions there is no trend, the averages over four blocks were used in these tests.)

The picture is quite different in the visual conditions. In the standard representation condition, subjects extremity tends to lie between the normative extremity and the matching extremity. On the other hand, subjects extremity in the deviation representation conditions if far above the matching extremity in the first part of the experiment ($t(19) = 3.3, p < .004$; $t(19) = 3.4, p < .004$, for the first two blocks of the magnitude deviation, respectively; and $t(17) = 6.9, p < .0001$; $t(17) = 4.2, p < .0006$, for the sign deviation, respectively). These effects are quite dramatic. For example, in the first block, subjects extremity in the sign deviation condition is almost three times the matching extremity. In the second part of the experiment, after some learning has occurred, subjects extremity approaches not only the matching extremity, but also the normative extremity. In the last block, subjects extremity is quite similar to the normative extremity in the magnitude deviation condition ($t(19) = 1.2, p > .3$), but still differs from it in the sign deviation condition ($t(17) = 2.1, p < .05$).

Consistency. For each subject and each 30-trial block, the correlation between predictor and prediction was calculated. These correlations were then subjected to Fisher's Z transformation. The means and standard

[5] Prediction by matching implies $r_{CR} = 1$ and $\sigma_R = \sigma_E$. Since in the stimuli $R_{CE} = .707$, using the equation in footnote 2 we obtain a matching extremity of 1.41.

deviations of the transformed correlations by condition and block are given in Table 2. The transformed correlations were subjected to a 3 × 2 × 4 analysis of variance with repeated measures on the third factor (block). The results of this analysis revealed only a significant main effect for block [$F(3,339) = 10.7, p < .0001$], which occurred primarily because of lower consistency in the first block, i.e., from a learning effect (see Dudycha & Naylor, 1966, or Naylor & Clark, 1968, for early documentation of a learning effect in regard to consistency).

A further 3 (feedback) × 4 (block) mixed ANOVA was conducted on the numerical and visual conditions separately. For the numerical conditions, this analysis revealed a significant main effect for block ($p < .0007$) but no significant effect associated with the feedback representation factor. For the visual conditions, this analysis revealed, in addition to the block main effect ($p < .0004$), a marginally significant interaction between block and feedback representation ($p < .06$). This interaction results from large differences in consistency in the first block ($p < .03$), but small differences in the latter blocks. These findings (see Table 2 for the pattern of the means) give only a weak support to the notion that there is more reliance representativeness, and therefore higher consistency, in the deviation conditions (these differences decrease in the latter blocks, most likely as a result of learning). However, in Experiment 2, in which predictions are less "noisy," a stronger effect of feedback representation on consistency is observed.

Discussion

The conditions in which the predictor is represented visually are the

TABLE 2
MEAN CONSISTENCY BY CONDITION AND BLOCK IN EXPERIMENT 1

	Visual			Numerical		
Block	Standard	Magnitude deviation	Sign deviation	Standard	Magnitude deviation	Sign deviation
1	.72	.90	1.05	.80	.78	.69
	(.47)	(.33)	(.27)	(.41)	(.41)	(.45)
2	1.08	1.17	1.07	1.00	.98	.82
	(.51)	(.39)	(.54)	(.31)	(.52)	(.42)
3	1.11	1.12	1.01	.98	.93	1.02
	(.53)	(.38)	(.50)	(.41)	(.45)	(.67)
4	.95	.93	1.02	1.09	.91	.93
	(.61)	(.53)	(.65)	(.39)	(.53)	(.68)
Mean	.97	1.03	1.04	.97	.90	.86
	(.48)	(.30)	(.43)	(.27)	(.36)	(.50)

Note. Entries are the mean Fisher's Z transformation of the correlation between predictor and prediction. Numbers in parentheses are standard deviations.

critical conditions for the test of the hypotheses about the influence of feedback representation, since these are the conditions in which representativeness is most likely to operate. Indeed, in these conditions there is a strong effect of feedback representation on extremity. The pattern of the cell means suggests that deviation representation increases, rather than decreases, extremity, and that the more powerful the deviation manipulation (i.e., sign vs magnitude deviation), the greater the extremity. These results are in line with the hypothesis suggesting that deviation representation in general, and sign deviation representation in particular (the representation which supply the most ambiguous feedback), enhances reliance on representativeness.

The overall difference in extremity between the numerical and visual conditions is consistent with reliance on representativeness when the predictor is represented visually but not when it is represented numerically (Ganzach, 1993). However, more relevant to the subject of this paper is that while feedback representation has a strong effect in the visual conditions, it has no effect in the numerical conditions. This suggests that the influence of predictor representation and feedback representation on prediction strategies is not additive. This lack of additivity may be explained by the fact that in the numerical conditions, the strategies that are used do not depend on feedback representation. For example, in these conditions subjects may predict using an arithmetic rule relating prediction to predictor. Predictions using such a rule are less likely to be dependent on feedback representation than predictions by representativeness (e.g., they do not necessarily require the outcome distribution as an input). Indeed, the fact that subjects extremity in the numerical conditions do not deviate significantly from the normative extremity, and are significantly lower than the matching extremity, suggests that representativeness is not very important here.

That the extremity of prediction in the visual-predictor/deviation-feedback conditions exceeds not only the normative predictions, but also far exceeds predictions by matching, suggests that in addition to nonregressiveness, which is generally involved in the process leading to excess extremity, biased perception of the outcome distribution is involved as well. As the data indicate, this biased perception can be quite significant. For example, if one assumes that subjects use a pure matching strategy in the visual-predictor/sign-deviation-feedback condition, the relationship between the perceived outcome distribution and the actual outcome distribution is the same as the relationship between subjects extremity and the matching extremity, which implies that in the first block of this condition, the perceived distribution is almost three times as large as the actual distribution.

It should be noted that in past research, extremity-based inferences about reliance on representatives were made under the implicit assumption that the outcome distribution is perceived accurately (i.e., extremity was explained as resulting from nonregressiveness rather than biased perception of outcome distribution). The notion that reliance on representativeness is also associated with extremity resulting from biased perception of the outcome distribution is new to this article. Must the representativeness explanation be invoked to explain the results of this study, or could the results be simply attributed to differences in biased perception of the outcome distribution? In my view, a biased perception explanation is insufficient by itself, since an additional assumption about reliance on a heuristic that utilizes the perceived outcome distribution as an input (i.e., representativeness) is required. Furthermore, the difference between the numerical and the visual conditions in regard to extremity gives strong support to the representativeness explanation, since this difference is readily explained by the notion that there is more reliance on representativeness when the predictor is represented visually than when it is represented numerically.

The effect of feedback representation on consistency in the first block of the visual conditions (higher consistency in the deviation representation conditions and in particular in the sign deviation) provides some support for the representativeness explanation of the differences in extremity in the visual conditions. It could be questioned, however, why the consistency effect appears only in the first block, while the extremity effects occur in all four blocks. One reason is probably that the influence of representativeness on extremity is stronger than its influence on consistency (see Ganzach, in press, for other examples of this differential influence). However, in the next two experiments, when conditions are more favorable to obtain an effect for consistency, such an effect is indeed observed.

EXPERIMENT 2

One reason for the weak effect of feedback representation on consistency in Experiment 1 may be a lack of motivation. Increased motivation may lead to more pronounced differences between conditions because it decreases noise in prediction (see Hogarth, Gibbs, McKenzie, and Marquis, 1991). Furthermore, increased motivation may strengthen between conditions differences in heuristic use since in a situation in which various heuristics compete for the determination of prediction output, it is likely that the higher the motivation the higher the reliance on the dominant heuristic. (see Zajonc, 1965, for discussion of the relationship between motivation and the elicitation of dominant response). In this study, therefore, I replicate the three critical conditions—the conditions in which the predictor is represented visually—in a situation in which there is an increased motivation to produce less noisy predictions.

Method

Subjects. Fifty-eight first year business administration students participated in the experiment to fulfill a class requirement. Subjects were assigned randomly to one of six conditions.

Procedure. The experimental procedure was exactly identical to that of Experiment 1, except that subjects were told that the three who make the most accurate predictions would receive monetary rewards of 100, 50, and 20 New Israeli Shekels (about \$50, \$25, and \$10).

Stimuli. The same stimuli as those of the visual conditions of Experiment 1 were used.

Results and Discussion

Extremity. Extremity was calculated in the same way as in the previous experiment. The means by condition and block are plotted in Fig. 2 and standard deviations are given in the legend to Fig. 1 (one subject from the magnitude deviation condition whose regression slope was negative was omitted). A 3 (feedback representation) × 4 (block) mixed ANOVA revealed a main effect for feedback representation [$F(2,54) = 14.9$, $p < .0001$], a main effect for block [$F(3,162) = 31.5$, $p < .0001$], and a significant block × feedback interaction [$F(6,162) = 5.1$, $p < .0005$]. These effects parallel the effects found for extremity in Experiment 1.

Consistency. Consistency was calculated in the same way as in the previous experiment. The means and standard deviations by condition and block are given in Table 3. A 3 × 4 mixed ANOVA with repeated measures on the second factor (block) revealed a significant main effect for feedback representation [$F(2,54) = 6.2$, $p < .004$], but no other significant effects. The effect of feedback representation on consistency was significant in each of the four blocks ($p < .006$, $p < .04$, $p < .03$, and $p < .04$, respectively. The F values, with 2 and 54 degrees of freedom, are 5.6, 3.4, 3.9, and 3.6, respectively). In line with our hypothesis, consistency is highest in the sign deviation condition and lowest in the standard representation condition.[6] Note, however, that even though an effect of feedback representation on consistency is observed in this experiment, it is again weaker than the effect of feedback representation on extremity.

[6] Although there was no random assignment of subjects in regard to experiments 1 and 2, it is interesting to compare consistency in these two experiments. This comparison reveals that subjects were more consistent in Experiment 2 than in Experiment 1, $F(1,68) = 4.3$, $p < .04$. This lends some support to the notion that incentives reduce noise in prediction (see footnote 3).

TABLE 3
MEAN CONSISTENCY BY CONDITION AND BLOCK IN EXPERIMENT 2

Block	Standard	Magnitude deviation	Sign deviation
1	.83	1.05	1.23
	(.35)	(.32)	(.46)
2	.98	1.23	1.32
	(.40)	(.44)	(.43)
3	.93	1.15	1.29
	(.37)	(.51)	(.34)
4	.93	1.09	1.29
	(.42)	(.40)	(.34)
Mean	.92	1.13	1.28
	(.33)	(.33)	(.32)

Note. Entries are the mean Fisher's Z transformation of the correlation between predictor and prediction. Numbers in parentheses are standard deviations.

While this finding is in line with previous research indicating that extremity may be more sensitive measure of reliance on representativeness than consistency (Ganzach, 1993), under certain conditions consistency may be more sensitive. Experiment 3 demonstrates a condition in which the effect of feedback representation on consistency is stronger than its effect on extremity.

EXPERIMENT 3

This experiment includes the three "critical" conditions of Experiment 1—the conditions in which the predictor is represented visually. The major change in this experiment is that the scale of the outcome is known to the subjects in all three conditions, and predictions are allowed only within the range of this scale. Under this condition, the effect of feedback representation on extremity is likely to be reduced and even disappear, because the response scale is limited. However, the effect of feedback representation on consistency must not necessarily disappear. Such difference between consistency and extremity when biased perception of the outcome range is prevented is particularly important, since it supports the notion that biased perception is not sufficient for explaining the effects of feedback representation and that reliance on representativeness is involved in producing these effects.

Method

Subjects. Sixty-four first year business administration students participated in the experiment to fulfill a class requirement. Subjects were assigned randomly to one of six conditions.

TABLE 4
MEAN CONSISTENCY BY CONDITION AND BLOCK IN EXPERIMENT 3

Block	Standard	Magnitude deviation	Sign deviation
1	.94	1.15	1.25
	(.45)	(.41)	(.46)
2	.96	1.26	1.36
	(.49)	(.45)	(.49)
3	.92	1.11	1.40
	(.38)	(.49)	(.52)
4	.84	1.11	1.39
	(.42)	(.51)	(.60)
Mean	.92	1.16	1.35
	(.36)	(.41)	(.47)

Note. Entries are the mean Fisher's Z transformation of the correlation between predictor and prediction. Numbers in parentheses are standard deviations.

Procedure. The experimental procedure was identical to that of Experiment 1 except that subjects were instructed that the scale of the outcome ranges from 470 to 700 (a minimum symmetric range that includes all outcome values). The range also appeared on the top of the computer screen in each of the trials. Predictions were limited to this range. If subjects typed a prediction below or above this range they were informed that a mistake was made and prompted to type their predictions again.

Stimuli. The same stimuli as those of the visual conditions of Experiments 1 and 2 were used.

Results and Discussion

Extremity. Extremity was calculated in the same way as in the previous two experiments. A 3 (feedback representation) × 4 (block) mixed ANOVA revealed neither a main effect for feedback representation [$F(2,59) = 1.0, p > .4$], nor an interaction between block and feedback [$F(6,177) = .5, p > .5$], but a significant main effect for block [$F(3,177) = 8.3, p < .0001$],[7] resulting from decrease in extremity during the course of the experiment.

Consistency. Consistency was calculated in the same way as in the previous two experiments. The means and standard deviations by condition and block are given in Table 4. A 3 × 4 mixed ANOVA with repeated measures on the second factor (block) revealed a significant main effect for feedback representation [$F(2,59) = 5.6, p < .006$], but no other significant effects. The significance levels of the effect of feedback repre-

[7] Two subjects whose regression slopes were negative, one in the standard representation condition and one in the sign deviation condition, were omitted from the analyses.

sentation on consistency in each of the four blocks were $p < .09$, $p < .03$, $p < .007$, and $p < .005$, respectively (F values with 2 and 59 degrees of freedom are 2.5, 3.8, 5.4, and 5.8, respectively). The pattern of the means is in line with the hypothesis that there is more reliance on representativeness in the deviation representation conditions, and in particular in the sign deviation condition. Interestingly enough, the effect of feedback representation on consistency appear to be stronger in this experiment than in the other two experiments. The reason for this is that the limits put on the response supply subjects with a "frame of reference" for the outcome scale. This frame of reference facilitates the assessment of outcome extremity and therefore enhances reliance on representativeness.

GENERAL DISCUSSION

The results of the first study indicate that (under conditions favoring reliance on representativeness, such as visual representation of the predictor) predictions are more extreme when feedback is provided in a deviation form than when it is provided in a standard form. The results of the second study indicate that when incentives are involved, deviation representation leads not only to more extreme, but also to more consistent, predictions. These effects were traced to a higher reliance on representativeness in the deviation representation conditions than in the standard representation condition. The results of the third study show that the effect of feedback representation on extremity, but not its effect on consistency, disappears when the predictions are limited to the actual outcome scale. This difference gives further support for the representativeness explanation over a mere biased perception explanation.

The difference between standard representation and deviation representation is of interest because it allows investigation of the processes underlying prediction in CPL in general and the operation of the representativeness heuristic in particular. Reliance on representativeness can explain some apparently unrelated phenomena associated with the influence of feedback representation on prediction. First, it explains the finding that "less can be more" in regard to feedback information provided to the subjects; less information is available to the subjects in the sign deviation condition than either in the magnitude deviation condition or in the standard feedback condition. Nevertheless, performance in regard to consistency is superior in the former condition than in the latter two conditions, since higher reliance on representativeness in this condition leads to higher consistency (see also Hammond, Summers, & Deane, 1973, for another "less is more" effect associated with feedback representation manipulation). Second, it explains the finding that feedback representation influences extremity when the predictor is represented visually but not when it is represented numerically: The effect of feedback representation stems from reliance on representativeness, which operates primarily in the visual conditions. Third, it explains the finding that deviation representation results in more optimal responses in regard to consistency but in less optimal responses in regard to extremity: representativeness increases consistency but also leads to overly excessive predictions. And fourth, it explains the finding that, in Experiment 1, feedback representation affects extremity but not consistency, while in Experiment 3, it affects consistency, but not extremity. Reliance on representativeness often affects extremity more than consistency when the outcome scale is not known (Ganzach, 1993). On the other hand, knowledge of the outcome scale minimizes differences in extremity, while at the same time increasing differences in consistency due to the operation of a frame of reference effect. Note also that the differences between consistency and extremity observed in the three experiments suggest that variations in consistency cannot be explained by variations in extremity (i.e., variation in prediction range) nor can variations in extremity be explained by variations in consistency (i.e., variations in prediction noise).

I suggested the possibility that deviation representation will lead to less, rather than more, extremity in prediction, since subjects may be more attuned to aspects of feedback that highlight systematic biases entailed in predicting by representativeness. Why did subjects not use these aspects of the feedback to arrive at moderate predictions in the (visual) deviation conditions? In my view, the reason is that the process of learning from experience in a probabilistic environment is primarily deductive, rather than inductive (Brehmer, 1974, 1980). People use feedback primarily to (1) examine the adequacy of pre-existing heuristics, thereby replacing natural, but less accurate, heuristics with more accurate ones and (2) determine the parameters (e.g., the width of the outcome distribution) of these heuristics (e.g., representativeness). However, when the feedback is ambiguous, as is the case with deviation representation, it tends to be ignored and, therefore, (1) there is less of a tendency to abandon natural heuristics in spite of their inaccuracy and (2) the necessary parameters are determined by contextual details that may be quite irrelevant and inaccurate.

It is important to note that ambiguity may play various roles in the process by which people use feedback to develop and improve prediction strategies. The current results indicate that ambiguity is detrimental for performance, since subjects adhere to inappropriate "strong" or "natural" strategies (i.e., representativeness). Sniezek's (1986) results also indicate that ambiguity decreases performance (e.g., congruent predictors' labels improved performance versus neutral labels), since it decreases the probability that the appropriate rule will be chosen by the subject (by increasing the strength of inappropriate rules). On the other hand, Sawyer

(1991) found that ambiguity increases performance (subjects better learned nonlinear prediction strategies when the predictor's label was ambiguous rather than unambiguous), most likely since it reduced the tendency to use natural strategies inappropriate for the task (i.e., linear strategies). Thus, it appears that the relationship between ambiguity and performance is rather complex. It may depend on the type of ambiguity (e.g., ambiguiy in the label or in the feedback) and on the type of rule people are required to learn. The study of this relationship is an important issue, since it may facilitate our understanding of learning from experience in a probabilistic environment.

I suggest that the process of learning from experience in the deviation conditions is impeded by the ambiguity of the feedback. But it should also be emphasized that even in these conditions learning occurs; subjects do learn to moderate their predictions through the course of the experiment. However, so far it is not clear what processes lead to this moderation. One explanation, offered by Sawyer (1991), is the operation of an anchoring and adjustment process, by which people anchor to the initial "natural" strategy (e.g., use the entire outcome range and match the extremity of the predictor to the extremity of the outcome) and adjust based on the data (decrease the outcome range; predict values that are less extreme than the matching values). An important goal for future research is to find direct evidence for the operation of this process.

REFERENCES

Agnoli, F., & Krantz, D. H. (1989). Suppressing natural heuristics by formal instructions: The case of the conjunction fallacy. *Cognitive Psychology*, **21**, 515–550.

Brehmer, B. (1973). Single-cue probability learning as a function of the sign and magnitude of the correlation between cue and criterion. *Organizational Behavior and Human Performance*, **9**, 377–395.

Brehmer, B. (1974). Hypothesis about the relations between scaled variables in the learning of probabilistic inference tasks. *Organizational Behavior and Human Performance*, **11**, 1–27.

Brehmer, B. (1979). Note on hypothesis testing in probabilistic inference tasks. *Scandinavian Journal of Psychology*, **20**, 155–158.

Brehmer, B. (1980). In one word: Not from experience. *Acta Psychologica*, **45**, 223–241.

Brehmer, B., & Lindberg, L. (1970). The relation between cue dependency and cue validity in single-cue probability learning with scaled cue and criterion variables. *Organizational Behavior and Human Performance*, **5**, 542–554.

Dudycha, L. W., & Naylor, J. C. (1966). Characteristics of the human inference process in complex choice behavior situations. *Organizational Behavior and Human Performance*, **1**, 110–128.

Fischoff, B., Slovic, P., & Lichtenstein, S. (1979). Subjective sensitivity analysis. *Organizational Behavior and Human Performance*, **23**, 339–359.

Ganzach, Y. (1993). Predictor representation and prediction strategies. *Organizational Behavior and Human Performance*.

Ganzach, Y., & Krantz, D. H. (1990). The psychology of moderate prediction. I. Experience with multiple determination. *Organizational Behavior and Human Performance*, 47, 177–204.

Ganzach, Y., & Krantz, D. H. (1991). The psychology of moderate prediction. II. Leniency and uncertainty. *Organization Behavior and Human Performance*, **48**, 169–192.

Ganzach, Y., & Czaczkes, B. (1992). The natural selection of prediction heuristics: Intuitive regressiveness vs representativeness. Unpublished manuscript, The Hebrew University, Jerusalem.

Hammond, K. R., Summers, D., & Deane, H. D. (1973). Negative effects of outcome-feedback in multiple cue probability learning. *Organizational Behavior and Human Performance*, **9**, 30–34.

Hammond, K. R., & Summers, D. A. (1972a). Cognitive control. *Psychological Review*, **79**, 58–67.

Hammond, K. R., & Summers, D. A. (1972a). Acquisition and application of knowledge in complex inference tasks. *Journal of Experimental Psychology*, **92**, 20–26.

Hogarth, R. M., Gibbs, B. J., McKenzie, C. R. M., & Marquis, M. A. (1991). Learning from feedback: Exactingness and incentives. *Journal of Experimental Psychology: Learning, Memory and Cognition*, 17, 734–752.

Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, **80**, 237–251.

Kahneman, D., & Tversky, A. (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology*, **3**, 430–454.

Kahneman, D., Tversky, A., & Slovic, P. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge: Cambridge University Press.

Lichtenstein, S., Earle, T. C., & Slovic, P. (1975). Cue utilization in a numerical prediction task. *Journal of Experimental Psychology: Human Perception and Performance*, **104**, 77–85.

Naylor, J. C., & Clark, R. D. (1968). Intuitive inference in interval tasks as a function of validity magnitude and sign. *Organizational Behavior and Human Performance*, **3**, 378–399.

Nisbett, R. E., & Kunda (1985). Perception of social distribution. *Journal of Personality and Social Psychology*, **48**, 297–311.

Sawyer, J. E. (1991). Hypothesis sampling, construction, or adjustment: How are inferences about nonlinear monotonic contingencies developed? *Organizational Behavior and Human Decision Processes*, **49**, 124–150.

Sniezek, J. E. (1986). The role of variable labels in cue probability learning tasks. *Organizational Behavior and Human Decision Processes*, **38**, 141–161.

Tversky, A., & Kahneman, D. (1983). Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment. *Psychological Review*, **90**, 293–315.

Yates, J. F., and Jagacinski, C. M. (1979). Nonregressiveness of subjective forecasts. In *Proceedings of the 11th annual meeting of the American Institute of Decision Sciences, New Orleans*.

Zajonc, R. B. (1965). Social facilitation. *Science*, **149**, 269–274.

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