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The Learning of Natural Configural Strategies

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The learning of natural configural strategies, strategies that match people intuitive theories about configural relationship between variables, is studied in a two-cue probability learning paradigm. The main focus is the learning of disjunctive strategy, a strategy in which response depends primarily on the high cue, and conjunctive strategy, a strategy in which response depends primarily on the low cue. We find that people learn disjunctive strategy better when the target of the prediction is human than when it is non-human, and that they learn conjunctive strategy better when the target is non-human. In addition, in a meaningful context, conjunctive strategy is learned better in the short run, but after a prolonged feedback, disjunctive strategy is learned better. In an abstract context, disjunctive strategy is learned better both in the short run and in the long run. The processes that lead to these differences in the learning of conjunctive and disjunctive strategies are discussed.

Learning from outcome feedback can be understood as the result of an hypothesis testing process. People generate hypotheses about the relationships between cues and outcome, examine these hypotheses against the feedback, maintain hypotheses that are compatible with the feedback, and discard hypotheses that are incompatible with it (Brehmer, 1974).

Within this framework, the origin of the tested hypotheses is not in the data but in the subject (Brehmer, 1980). People have at their disposal various hypotheses that they test against the data. These hypotheses vary in their "strength" in that some of them are tested (and used) prior to others. We label the prediction strategies associated with these hypotheses *natural strategies* (see Kahneman & Tversky, 1983, and Agnoli & Krantz, 1989). Thus, for example, Brehmer (1974) suggested that in learning the functional rule relating predictor to outcome, an hypothesis about positive linear relationship between the predictor and the outcome is tested first, followed by an hypothesis about negative linear relationship, and hypotheses about inverted U and U relationships (see also Sniezek, 1986). Similarly, Ganzach (1993a, 1994b) suggested that in learning a positive linear relationship between predictor and outcome, the first strategy to be used (and tested) is based on the representativeness heuristic. Predicted values are chosen so that their extremity would match the extremity of the predictor.

In this paper we use an hypothesis testing approach to study the learning of configural strategies, strategies in which the weight of cues depend on the level of the other cues (Meehl, 1954). In particular, we study the learning of *natural* configural strategies. We identify such strategies, we examine what makes them natural, and we investigate the process by which they are learned.

PREVIOUS RESEARCH ABOUT THE LEARNING OF CONFIGURAL STRATEGIES

A number of studies have investigated how people learn configural relationships between variables. The configural relationships that subjects were required to learn in these studies were chosen by the experimenter not because they were compatible with subjects' intuition about the configural relationship between variables, but because of some appealing mathematical characteristics. For example, Brehmer (1969) studied the learning of configural rules of the form $Y = a + bX_1/X_2$, $Y = a + bX_1X_2$; Mellers (1980) studied the learning of configural rules of the form $Y = (X_1 - 6)(X_2 - 6) + 20$ and $Y = .25(X_1 - 6)^2(X_2 - 6) + 20$; and Edgell (1978, 1980, 1983; Edgell & Morrissey, 1987) studied the learning of "pattern information" in a non-metric cue probability learning task.

Previous research of this kind indicated that people can learn to exhibit in their responses some of the configural components that exist in the stimuli. Edgell's (1978) work also suggests that this learning is associated with an hypothesis testing process rather than with inductive, stimulus-response based learning.

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NATURAL CONFIGURAL STRATEGIES: THE CONJUNCTIVE STRATEGY AND THE DISJUNCTIVE STRATEGY

In this paper we study the learning of two types of configural strategies: A disjunctive strategy, in which the response depends primarily on the high cue(s), and a conjunctive strategy, in which the response depends primarily on the low cue(s). One way to represent these strategies in a two cue probability learning paradigm in which Y is the response and X_1 and X_2 are equally scaled cues, is (respectively)[1]:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 \max(X_1,X_2), \qquad (1)$$

and

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 \min(X_1,X_2), \qquad (2)$$

We chose to study these strategies for two reasons. First, disjunctive and conjunctive relationships are structurally symmetrical.[2] This symmetry facilitates the interpretation of differences in their learning. Second, in our view, conjunctive and disjunctive strategies are natural configural strategies, because they are often used spontaneously in *judgment* (Einhorn, 1971, 1972, 1973; Einhorn, Komorita, & Rosen, 1972; Oglivie & Schmitt, 1979; Brannick & Brannick, 1989; Birnbaum & Stenger, 1979; Ganzach, 1993b, 1994a, 1994c; Weber, 1994). In particular, judgments that exhibit negativity bias can be viewed as the result of a conjunctive strategy, while judgments that exhibit positivity bias can be viewed as the result of a disjunctive strategy (for a recent review of negativity and positivity biases in judgment see Skowronski and Carlston, 1989).

Equations (1) and (2) depict disjunctive and conjunctive strategies as an adjustment to a linear strategy. That is, they suggest that when learning a disjunctive rule people learn to assign a higher weight to the higher cue, and when learning a conjunctive rule, they learn to assign a higher weight to the lower cue. However, another way by which conjunctive and disjunctive strategies can be described is as an adjustment to a linear strategy which takes into account the (absolute) gap between cue values. This is depicted by Eq. (3), which represents a disjunctive strategy, and Eq. (4), which represents a conjunctive strategy.

$$Y = \alpha' + \beta_1' X_1 + \beta_2' X_2 + \beta_3' \mathrm{ABS}(X_1,X_2) \qquad (3)$$

$$Y = \alpha' + \beta_1' X_1 + \beta_2' X_2 - \beta_3' \mathrm{ABS}(X_1,X_2) \qquad (4)$$

Thus, in learning configural strategies people may learn that they have to correct their linear strategy for the gap between the cues. In learning a conjunctive strategy, they may learn that the prediction derived from a linear combination rule has to be adjusted downward by a factor which is proportional to the gap, and in learning a disjunctive strategy, they may learn that the linear prediction has to be adjusted upward by a factor which is proportional to the gap.

The Appendix shows that the representation of disjunctive [conjunctive] strategy by Eq. (1) [2] is mathematically equivalent to its representation by Eq. (3) [4]. However, Eqs. (3) and (4) allow the partioning the explained variance of the response to non-overlapping linear and non-linear variances [$\mathrm{ABS}(X_1 - X_2)$ is orthogonal both to X_1 and to X_2]. Therefore the analyses below are based on Eqs. (3) and (4).

THE LEARNING OF DISJUNCTIVE AND CONJUNCTIVE RELATIONSHIPS: WHICH IS EASIER?

One question that may be asked about the learning of conjunctive and disjunctive relationships is which of the two is easier to learn. One line of reasoning suggests that the learning of the conjunctive relationship is easier, because this relationship is compatible with negativity bias (the spontaneous tendency to assign higher weight to negative information than to positive information), the most ubiquitous information integration bias (see for example, Parducci, 1968; Kanouse & Hanson, 1974; Fiske, 1980).

However, another line of reasoning suggests that it is easier to learn disjunctive relationship, because people learn about the positive aspects of the information (i.e., increasing the weight of the higher cue) faster than they learn about the negative aspects (i.e. increasing the weight of the lower cue).[3] For example, Meyer

[1] These representations of disjunctive and conjunctive strategies do not use the concept of *logical inclusive or* and *logical and* which are often used in describing conjunctive and disjunctive strategies in *choice*. However, these concepts apply primarily to choice, and it is less meaningful in the context of prediction and judgment. Our description is, however, more general. It is applicable for both decision modes, while still retaining the essence of what is meant by conjunction [disjunction] in choice, since it suggests that the attributes with low [high] values play a major role in the decision. In choice, this occurs due to the existence of threshold, and in judgment because of the dominance of the attributes whose values are low [high] (see Ganzach, in press). The generality of the current definition for conjunctive/disjunctive strategies become apparent by noting that the "standard" definition of these strategies can be represented by setting $\beta_1 = \beta_2 = 0$ in Eqs. (1) and (2).

[2] Note also that Eq. (1) can be written as: $Y = \alpha + \beta_1 X_1 + \beta_2 X_2 - \beta_3 \min(X_1,X_2)$, and Eq. (2) can be written as $Y = \alpha + \beta_1 X_1 + \beta_2 X_2 - \beta_3 \max(X_1,X_2)$.

[3] This argument is based on equations 1 and 2. However, as the equations in Footnote 2 indicate, it could be argued that in learning configural strategies people learn to decrease, rather than increase, weights. That is, in a disjunctive strategy they learn to decrease the

(1987) argued that in learning multi-attribute judgment strategies, people learn positive scale values faster than they learn negative scale values. From a different perspective, the learning of a disjunctive strategy can be viewed as learning positive relationship between the inter-cue gap and the criterion, whereas the learning of a conjunctive strategy can be viewed as learning negative relationship between the inter-cue gap and the criterion. Since the learning of positive relationships is easier than the learning of negative relationships (Brehmer, 1974), disjunctive strategy may be learned better.

THE ROLE OF CONTEXT

The learning of conjunctive and disjunctive relationships may be context dependent. One aspect of the context is whether variable labels do suggest a functional relationship between cues and criterion, or whether they do not (these two contexts are labeled meaningful and abstract contexts, respectively. See Sniezek, 1986). In particular, the role of judgment biases, such as the negativity bias, in facilitating the learning of configural relationships may be different among meaningful and abstract contexts, since these biases exist in the former, but not in the latter. The two experiments reported here explore the learning of configural strategies both in a meaningful context (Experiment 1) and in an abstract context (Experiment 2).

The learning of configural relationships in meaningful contexts can be further divided into the learning of configural relationships about human objects and the learning of configural relationships about non-human objects. Ganzach (1993b) examined the (spontaneous) use of configural strategies in judgment and found that often people tend to be more conjunctive in judging non-human objects than in judging human objects (and see also Einhorn, 1971). His explanation for these results is based on the *person positivity bias* (Sears, 1983): People are more lenient in judging fellow human beings than in judging nonhuman objects, and therefore put less emphasis on the negative aspects of the information when judging the human objects.

Ganzach's (1993b) findings suggest that learning conjunctive relationships about nonhuman objects will be easier than learning conjunctive relationships about human objects, and that the learning disjunctive relationships about human objects will be easier than learning disjunctive relationships about non-human objects.

weight of the weight of the lower cue and in a conjunctive strategy they learn to decrease the weight of the higher cue. However, this process is less likely, since people are more likely to learn positive than negative relationships (Brehmer, 1974).

EXPERIMENT 1

Two questions are examined in this experiment. First, whether there are differences in the learning of conjunctive and disjunctive relationships in a meaningful context, and second, whether these differences depend on whether the learning concern a human or non-human object.

Method

Subjects

One hundred thirty-eight first-year Business Administration students participated in the experiment to fulfill a class requirement. Subjects were assigned randomly to one of four groups (see Tables 1 and 2 for the number of subjects in each of the groups). The experiment was conducted in small groups of about 4 subjects.

Design

There were two parts in the experiment. In each part, subjects made predictions concerning either a human object (a student) or a non-human object (a motor) in a disjunctive or in a conjunctive environment. The two parts were divided by a shift: Both the object and the environment were different in the two parts. For example, if subjects in a given group had made predictions about a human object in a disjunctive environment in part I, they made predictions about a non-human object in a conjunctive environment in part II. As a result, in addition to this group—the student-disjunctive motor-conjunctive (SDMC) group—there were three other groups: The student-conjunctive motor-disjunctive (SCMD) group, the motor-disjunctive student-conjunctive (MDSC) group, and the motor-conjunctive student-disjunctive (MCSD) group.

Procedure

After entering the laboratory, subjects were seated in front of an IBM XT computer and told to read the initial instructions which explained that in the experiment there will be two separate prediction tasks. Subsequently, instructions about the prediction task of part I appeared. Subjects were informed that their task was either to predict potential for academic success (in the human-object conditions) or to predict how long a motor would last (in the non-human conditions); they were informed that the predictors would be presented as bar graphs, the longer the bar the higher the value of the predictor; and they were told that after each prediction they would receive feedback as to the true outcome. Three prizes were promised to the three students with the best performance. Performance was explained as predictions that are as close as possible to the true outcome.

In each trial, the computer first displayed the predictors. In the human object conditions, the predictors were labeled Mental Concentration and Abstraction Ability, and in the non-human conditions they were labeled Steal Quality and Production Quality. Two seconds after the predictors appeared on the screen, the computer prompted the subjects to type in their prediction. The prediction was typed in numerically. The computer then displayed the outcome for two seconds. Subsequently, the outcome was erased, and a new trial began. Subjects did not have a time limit and could examine their predictions and make corrections.

After completing the first part, subjects were informed that the second task was about to begin, and received instructions for this task. These instructions were similar to the instructions for the first task, except for the changes required by the new context. The trials in the second task were similar to those of the first task, except for the labels of the predictors.

Each of the two tasks included 5 practice trials and 90 experimental trials. There was no time limit for typing the predictions. To avoid including inadvertent mistakes, the predictions were examined, and if they were outside of the range of possible criterion values, subjects were prompted to type in their prediction again.

Stimuli

In each trial, the computer selected two cue values from a bivariate uniform distribution over the range of 1 to 79. These cue values were presented in the form of horizontal bar graphs on the computer screen. The bars varied in 78 steps of about 3 mm, and their length corresponded to the numerical cue values. The criterion values were presented numerically. They were generated by the following formulas:

$$Y = 437 + .6X_1 + .6X_2 + .55\mathrm{ABS}(X_1 - X_2)$$

$$Y = 437 + .6X_1 + .6X_2 - .55\mathrm{ABS}(X_1 - X_2),$$

where X_1 and X_2 are the numerical values for the two cues and Y is the criterion. The first formula was used to generate the criterion in the disjunctive conditions, and the second was used to generate the criterion in the conjunctive conditions.[4] This resulted in about 78% of the variance accounted for by the linear relationships and about 22% accounted for by the configural relationships.

[4] Using Eqs. (3) and (4), the generation of the stimuli of the disjunctive and conjunctive environments can be described, respectively, by: $Y = 485 + .05X_1 + .05X_2 + 1.10\max(X_1,X_2)$ and $Y = 485 + .05X_1 + .05X_2 + 1.10\min(X_1,X_2)$.

Post-experimental questionnaire: After completing the experiment, subjects were asked to answer the following open-ended question: "What was the difference between the strategy you used in Part I and the strategy you used in Part II."

Results

The analyses were done for each of the two parts separately. Each part can be viewed as a 2 (object: human vs non-human) × 2 (Environment: conjunctive vs disjunctive) between subjects design. Note that part II is independent of part I in that the four groups received different treatments on both factors in the two parts. It is not independent of part I in that the various groups began the second part with a different past experience, the experience they obtained in part I.

Two dependent variables were analyzed. One variable was the multiple linear correlation between cues and response (denoted below RLIN). This variable represents the extent to which subjects learned the linear aspects of the task. The other variable, denoted RNLN, was the correlation between the response and $\mathrm{ABS}(X_1-X_2)$ (in the disjunctive conditions), or the negative value of this correlation (in the conjunctive conditions). This variable represents the extent to which subjects learned the nonlinear, or configural, aspects of the environment. (In the conjunctive conditions, the correlation was multiplied by -1 so that higher values would represent better learning). Note that RNLN is the correlation between the variance unaccounted for by a linear multiple-regression in the task system and that unaccounted for by such regression in the subject's response system. This parameter is commonly used in the lens model as a measure for how well the nonlinear relationships are learned; (e.g. Hursch, Hammond, & Hursch, 1964).[5]

Each of the two independent variables was calculated for each subject and each 30 trial block, was transformed by Fisher's R to Z transformation, and was analyzed, separately for each of the two parts, by a 2 (object: motor vs student) × 2 (environment: conjunctive vs disjunctive) × 3 (block: first second and third) mixed ANOVA with repeated measures on the third factor.

Preliminary Analysis: The Learning of the Linear Relationships

The 2 × 2 × 3 mixed ANOVA on the multiple correlation between cues and responses (RLIN) did not reveal any significant main effects or any significant interactions for either of the two parts (the grand mean

[5] RNLN is also equal to the partial correlation between the response and the nonlinear terms of Eqs. (1) and (2).

of RLIN is 1.09 in part I and 1.04 in part II. The standard deviations are .34 and .38, respectively).

The Learning of the Configural Relationships: Part I

The mean RNLN by block and condition is given in Table 1. The results of the between subjects part of the ANOVA did not show a significant effect for environment ($p > .1$) or for object ($p > .2$), but did show a significant interaction, $F(1,134) = 4.2, p < .05$. As can be seen from the marginals (the last row in Table 1), when the object is human, the configural aspects of the environment were learned better in a disjunctive environment than in a conjunctive environment. On the other hand, when the object is non-human, configurality was learned better in a conjunctive environment than in a disjunctive environment. Thus, the hypothesis about object-dependent differences between the learning of conjunctive and disjunctive strategies is supported by the results.

However, there are also object-independent differences between the learning of conjunctive and disjunctive strategies. Initially there is a better learning of conjunctive strategy. In the first block, the mean RNLN in the conjunctive and disjunctive environments (collapsing over the object conditions) are .18 and .02, respectively; the simple main effect for environment in this block is highly significant, $F(1,137) = 13.6, p < .0005$ (in fact, in this block there is no evidence at all for the learning of a disjunctive strategy; the latter mean is not significantly different than zero). On the other hand, in the third block there is no evidence for higher level of learning in the conjunctive conditions. The mean RNLN in the conjunctive environments is even lower than the mean RNLN in the disjunctive environments, .25 and .31, respectively (although the simple main effect for environment in this block is not significant ($p > .2$).[6] This difference in immediate versus asymptotic learning results in a highly significant interaction between environment and block, $F(2,268) = 9.2, p < .0002$.

An even clearer demonstration of the difference between the learning processes in the two environments is obtained by calculating for each subject the correlation between block number (1, 2, or 3) and RNLN. In the disjunctive conditions these correlations were .59 (STD = .64) and .43 (.71) for the human and non-human conditions, respectively, while in the conjunctive conditions they were .10 (.56) and .04 (.53), respectively. Thus, while the learning of conjunctive environment almost ceases after the first block, the learning of disjunctive environment continues throughout the experiment.[7]

In our view, there are three factors that contribute to the pattern of results observed in the first part of the experiment: (1) a general negativity bias, which leads to a rapid adoption of conjunctive strategy; (2) a stronger negativity bias towards non-human objects that toward human objects, which leads to a better learning of conjunctive strategy in the former than in the latter conditions; and (3) more efficient processes for extracting the configural relationships from a disjunctive than from a conjunctive environment, which lead to a steady learning in the former environment, but not in the latter environment.

The Learning of the Configural Relationships: Part II

The mean RNLN by condition and block is given in Table 2. Note that negative values indicate that subjects used the *wrong* strategy, that is, they used disjunctive strategy in a conjunctive environment.

The results of the ANOVA showed that the interaction between object and environment is even stronger in part II than in part I, $F(1,134) = 10.6, p < .001$. As can be seen from the marginals (the last row in Table 2), a disjunctive strategy is learned better than a conjunctive strategy when the object is human, whereas a conjunctive strategy is learned better than a disjunctive strategy when the object is non-human.

In addition, the analyses of part II revealed also a

TABLE 1
Mean RNLN in Part I of Experiment 1

	Conjunctive environment		Disjunctive environment	
Block	Human object	Non-human object	Human object	Non-human object
n	34	35	35	34
1	.10 (.27)	.25 (.30)	.03 (.23)	.01 (.23)
2	.15 (.31)	.28 (.34)	.14 (.25)	.10 (.23)
3	.19 (.36)	.31 (.36)	.33 (.30)	.29 (.31)
Mean	.15 (.26)	.28 (.28)	.17 (.21)	.13 (.17)

Note. Numbers in parentheses are standard deviations.

[6] This main effect should be interpreted with caution, because there is also a significant interaction between environment and object. This interaction is associated with the higher tendency to rely on conjunctive strategy in judging non-human objects than in judging human objects.

[7] To examine the possibility that the increase in RNLN is indeed associated with an intra-individual learning process rather than with an increase in the number of subjects using configural rule, we examined the correlations between block and RNLN only for subjects whose RNLN in the last block was significantly positive (i.e., subjects who reliably learned the appropriate configural rule). The means [STD, n] of these correlations were, respectively, .83 [.45, 15], and .80 [.23, 13] in the disjunctive conditions and .33 [.30, 11], and .23 [.34, 12] in the conjunctive conditions. That is, they were even higher than the means for the entire subject population, lending support for the intra-individual learning hypothesis.

TABLE 2
Mean RNLN in Part II of Experiment 1

Block	Conjunctive environment		Disjunctive environment	
	Human object	Non-human object	Human object	Non-human object
n	34	35	35	34
1	−.12 (.24)	.09 (.30)	.04 (.24)	−.04 (.28)
2	.02 (.29)	.26 (.38)	.12 (.37)	.10 (.26)
3	.15 (.41)	.33 (.42)	.35 (.48)	.20 (.38)
Mean	−.02 (.23)	.23 (.30)	.17 (.30)	.09 (.21)

Note. Numbers in parentheses are standard deviations.

highly significant block effect, $F(2,268) = 30.3$, $p < .0001$, resulting from gradual learning.

The Learning of the Configural Relationships: Comparison between the Two Parts

Comparison between the two parts reveals that the asymptotic utilization of configural information in the two parts is about the same. The difference in RNLN between the *third* block of part I and the *third* block of part 2 is −.02, .09, .04, and −.02 for the student-disjunctive, motor-disjunctive, student-conjunctive, and motor-conjunctive conditions, respectively. None of these differences is significant.

On the other hand, there were significant differences between the two parts in initial learning. These differences occurred when the shift was from a disjunctive to a conjunctive environment, but not when the shift was from a conjunctive to a disjunctive environment. The differences in RNLN between the *first* block of part I and the *first* block of the part II are −.01, .05, .22, and .16, respectively. The latter two differences are significant, ($t(66) = 3.6$, $p < .0001$; $t(68) = 2.3$, $p < .005$), but the first two are not. Thus, it appears that a shift from disjunctive to conjunctive strategy is more difficult than a shift from conjunctive to disjunctive strategy. This is consistent with the notion that by the end of Part I, disjunctive strategy was learned better. The student-conjunctive condition of part II is a case in point. In the first block of this condition, the average RNLN was significantly negative, $t(33) = 2.8$, $p < .01$; that is, subjects used a disjunctive strategy in a conjunctive environment.

Finally, whereas in part I there was a strong interaction between environment and block, resulting from fast initial learning of conjunctive environments and gradual learning of disjunctive environments, in part II this interaction was not significant. The reason for this is that in part II initial learning of conjunctive strategy is impeded by a strong negative transfer from the previously learned disjunctive strategy (the strategy that subjects in the conjunctive conditions learned in part I).

The Learning of the Configural Relationships: Subjects' Reports about Their Strategies

Subjects' reports were coded by two judges into two categories: Reports that indicated reliance on configural strategies (correct reports) and reports that did not indicate reliance on these strategies (incorrect reports).[8] The initial agreement between the judges was 85%. The conflicting cases were agreed upon discussion.

This classification indicated that there were more correct reports in the two groups in which the environment was disjunctive when the object was human and conjunctive when it was non-human (that is, the SDMC and MCSD groups) than in the other two groups. The proportion of correct reports was 43 and 46% in the SDMC and MCSD groups, respectively and 21 and 24% in the SCMD and MDSC groups, respectively. These findings are consistent with the hypothesis that disjunctive strategy is learned better when the object is human, whereas a conjunctive strategy is learned better when the object is non-human.

In addition, the correct reports were examined to ascertain how subjects described the configural strategies they used. These reports were classified into three categories. (a) reports that mentioned value dependent weights (these reports correspond to Eqs. (1) and (2)), (b) reports that mentioned utilization of the gap between the predictors (these reports correspond to Eqs. (3) and (4)), and (c) reports that mentioned the utilization of rules based on the existence of sufficient and necessary conditions as the basis for disjunctive and conjunctive strategies, respectively. (These reports correspond to the way conjunctive and disjunctive *choice* strategies are usually depicted; see Footnote 1). Examples for subjects' reports associated with each of the three categories are presented in Table 3.

The classification was done by two judges. The initial agreement between the judges was 79%. Conflicting judgments were decided by discussion. The results indicated that 41% of the reports were associated with inter-cue gap explanations, 26% with value-dependent weight explanations, and 33% with explanations based on sufficient/necessary conditions.

In summary, these results suggest that: (1) subjects are able not only to use appropriate configural rules, but also to identify these rules (see, for example, Reber, 1989; Reber *et al.*, 1980 for a discussion of the relationship between explicit and implicit rule learning); (2) this ability is stronger when configurality in the envi-

[8] Answers that indicated reliance on the appropriate configural strategy in only one of the two parts were classified as correct.

TABLE 3

Examples of Subjects' Reports about Their Strategy

1. Value-dependent weight's explanation
—Only the length of the longer predictor was important [disjunctive environment].
—Take the longer predictor and increase it [disjunctive environment].
—The longer predictor had more influence [disjunctive environment]. The shorter predictor had more influence [conjunctive environment].

2. Inter-cue gap explanations
—If mental concentration is similar to abstraction ability then there is high chances for success [disjunctive environment].
—Both the length of the lines and the gap between them was important.
—In the first part there should be a gap of 1/3 between the two predictors to achieve a higher criterion [disjunctive environment]. In the second part, there should be a high correlation between the predictors [conjunctive environment].
—In the first part, the bigger the gap, the higher the prediction. In the second part, the bigger the gap the lower the prediction.
—The best results were obtained when the two predictors had about the same length [conjunctive environment].
—The more the two components are bigger *together,* the score is higher [conjunctive environment].

3. Explanations based on sufficient/necessary conditions
—The second experiment is based on facts. Either if the predictor is low or if the predictor is low the factory would fail [conjunctive].
—Only one attribute was important, the limiting condition to the machine [conjunctive environment].
—Each one of the two parameters was necessary, and parameters do not complete each other [conjunctive environment].
—There is a possibility for high success even if one of the two components is low [disjunctive environment]. There is a lot of importance to each of the components to get a high score [conjunctive environment].
—The two conditions are necessary for a high prediction [conjunctive enviroment]. Sometimes one was enough [disjunctive environment].
—It is enough that one of the conditions will be good for the student to succeed [disjunctive environment].

ronment matches people intuition about configurality; and (3) there are various mental representations of these rules.

Discussion

The hypothesis that learning conjunctive relationships about non-human objects will be easier than learning conjunctive relationships about human objects, and that learning disjunctive relationships about human objects will be easier than learning disjunctive relationships about non-human objects is unequivocally supported by the results. The effect appears to be stronger in part II than in part I. One reason for this is that the learning of configurality is harder in part II, since a negative transfer from part I makes facilitating factors (e.g. the match between environment and intuition about configural relationships) more important for learning.

The part I data on the question concerning which strategy is easier to learn are rather complex. Initially, conjunctive strategy is learned better than disjunctive strategy. However, later on it appears that disjunctive strategy is learned better than conjunctive strategy (this is particularly evident in that there is a negative transfer from a previously learned disjunctive environment, but not from a previously learned conjunctive environment). The initial learning is consistent with the notion that conjunctive environment is learned better because its compatibility with people's intuition about negativity bias. The latter learning is consistent with the notion that when the experiment progresses, the dominant factor in the learning process is the tendency to learn more about positive than about negative aspects of the information, and/or the tendency to learn more easily about positive than about negative relationships between criterion and inter-cue gap.

The above explanation suggests that two processes operate in our experiment: one that favors negative information, and one that favors positive information. In the literature, there are ample examples of the operation of these two processes in isolation. Examples of the operation of the former processes can be found in Kaplan (1976) and Matlin and Stang (1978). Examples of the operation of the later processes can be found in Kanouse and Hanson (1971), and Fiske (1980). However, to the best of our knowledge, only Meyer (1987) and Schul and Ganzach (1995) observed the operation of the two processes in the same experiment. For example, Meyer noticed that although positive information was learned faster than negative information, negative information had a higher impact on judgment. [Meyer refers to this phenomenon as a "paradox." "... it also presents something of a paradox: subjects followed a judgment rule that effectively placed greater weight on the attribute levels they know the least about" (p. 170)].

EXPERIMENT 2

In Experiment 1, subjects learned the relationships between cues and outcome in a meaningful context, a context in which variable labels do suggest functional relationships between cues and criterion. In this experiment, we study how subjects learn relationships between cues and outcome in an abstract context, a context in which variable labels do not suggest such functional relationships.

Previous research has shown that the learning of *linear* relationships is easier in a meaningful context than in an abstract context. This is particularly true when the context is congruent with the actual relationships in the stimuli (Adelman, 1981; Muchinsky & Dudycha, 1974), because such a context increases the tendency to test the correct hypotheses (Sniezek, 1986).

One implication of this hypothesis testing explanation for the effect of context on learning is that the faster learning of conjunctive strategy, observed in the early stages of part I of Experiment 1, may not exist in an abstract context, because negativity bias is a social-cognitive bias, which exist with regard to outcomes associated with meaningful objects, but not with regard to abstract outcomes (see for example Markus & Zajonc, 1985, and Skowronski & Carlston, 1989, for a discussion of the social-cognitive antecedents of negativity bias). Thus, one hypothesis examined in this experiment is that in the early phase of learning of abstract configural environments, conjunctive strategy will *not* be easier to learn than disjunctive strategy. Moreover, we expect that, as result of a higher tendency to learn about positive relationships and about positive cues, disjunctive environment will be learned better in *all* phases of the experiment. In other words, we expect a main effect for environment (rather than the interaction between environment and block that was observed in Experiment 1).

Another issue examined in Experiment 2 is the influence of numerical versus graphical representation of cue values on the learning of configural environments. In the first experiment, cue values were represented by bar graphs. Such a representation had been shown to facilitate the learning of *linear* relationships (Ganzach, 1993a).[9] Thus, the question of interest in regard to the representation manipulation is whether the enhanced learning of the linear relationship would facilitate the learning of the configural relationships.

[9] The effect of representation on the learning of linear relationships is due to more reliance on the representativeness heuristic when the predictors are represented graphically than when they are represented numerically. For a linear relationship between predictor and outcome, the representativeness heuristic reduces both acquisition and application difficulties (See Hammond and Summers, 1972, for a discussion of these concepts in CPL task), because it implies a linear relationship between predictor and prediction, and thus facilitate the learning of linear relationships (Ganzach, 1993a).

Method

Subjects

One hundred thirty first-year Business Administration students participated in the experiment to fulfill a class requirement. Subjects were assigned randomly to one of four groups. (See the first row of Tables 4, 5, and 6 for the number of subjects in each group). The experiment was conducted in small groups of about 4 subjects per group.

Design

Representation was a between subject manipulation. Half of the subjects made predictions based on cues which were represented numerically and the other half made predictions based on cues which were represented graphically. Environment was a within subject manipulation. In each of the two parts of the experiment the environment was either conjunctive or disjunctive. For example, if subjects in a given group made predictions from numerical cues in a disjunctive environment in part I, they made predictions from numerical cues in a conjunctive environment in part II. As a result, in addition to this group (the numerical disjunctive-conjunctive, or NDC group), there were three other groups: the numerical conjunctive-disjunctive (NCD) group, the graphical disjunctive-conjunctive (GDC) group, and the graphical conjunctive-disjunctive (GCD) group.

Procedure

The procedure was basically similar to that of Experiment 1, except that the task was presented as a standard cue probability learning task in which a content-free criterion has to be predicted from two content-free cues. That is, the cues were labeled "predictor 1" and "predictor 2" and the criterion was labeled "true outcome." The cues in the graphical conditions were presented in the same way as in Experiment 1 (i.e., as bar graphs) and the cues in the numerical conditions were presented as numbers. In both conditions the response was typed into the computer numerically. The shift was accompanied by a message stating that the second task was starting, and that in this task, the rule relating cues to outcome would be different from the rule in the first task.

Stimuli

The stimuli in the graphical conditions were generated in the same way as in Experiment 1. The stimuli in the numerical conditions were generated by presenting the numerical values of the cues rather than their bar-graph representations.

Results

The results were analyzed for each of the two parts separately. Each part can be viewed, as a 2 (representation: graphical vs numerical) × 2 (environment: conjunctive vs disjunctive) between subjects design. The analyses was similar to the analyses in Experiment 1. We analyzed both RLIN and RNLN in a 2 (representation: graphical vs numerical) × 2 (environment: conjunctive vs disjunctive) × 3 (block: first second and third) mixed ANOVA, with repeated measures on the third factor.

Preliminary Analysis: The Learning of the Linear Relationships

Unlike the first experiment, in this experiment the manipulations did affect the learning of the linear relationships.

Part I. The average RLINs and their standard deviations by block and condition are presented in Table 4. The analysis revealed three significant effects. First, it revealed a strong representation effect, $F(1,126) = 23.6$, $p < .0001$, resulting from higher RLIN in the graphical representation conditions than in the numerical representation conditions. These findings replicate those obtained by Ganzach (1993a). Second, the analysis revealed a strong block effect, $F(2,252) = 15.4$, $p < .0001$, resulting from increase in RLIN throughout the experiment. This effect—and the lack of block effect for RLIN in both parts of Experiment 1—is consistent with earlier findings about the learning of linear relationships in an abstract context (Adelman, 1981; Muchinsky and Dudycha, 1974; Sniezek, 1986). Third, the analysis revealed an interaction between block and environment, $F(2,252) = 4.1$, $p < .02$, resulting from larger increase in RLIN in the disjunctive conditions than in the conjunctive conditions. While in the first block there is no difference between the disjunctive and the conjunctive environment ($p > .9$), in the third block RLIN is higher in the disjunctive environment ($p < .05$).

Part II. The results of this part are similar to the results of part I in that both the representation effect and the block effect were significant, $F(1,126) = 25.6$, $p < .0001$, and $F(2,252)$, $p < .02$, respectively. However, the interaction between block and environment was not significant. The average RLINs in the graphical representation conditions (collapsing over the two environments) were .94, .1.02, and 1.05 in the first, second, and third blocks, respectively (standard deviations: .40, .43, and .43, respectively). The average RLINs in the numerical conditions were .54, .59, and .61, respectively (standard deviations: .59, .60, and .62, respectively).

The Learning of the Configural Relationships: Part I

The mean RNLN by block and condition is given in Table 5. As can be seen from the Table, in each of the conditions and each of the blocks, RNLN was higher when the environment was disjunctive than when it was conjunctive. The ANOVA revealed a highly significant main effect for environment, $F(1,126) = 19.5$, $p < .0001$. In particular, in sharp contrast to Experiment 1, disjunctive strategy was learned better than conjunctive strategy from the very first block (the main effect for environment in the first block was significant, $F(1,126) = 6.2$, $p < .01$).

The ANOVA also revealed a highly significant main effect for block, $F(2,252) = 14.6$, $p < .0001$, indicating that subjects gradually learned the configural aspects of the task during the course of the experiment. In addition, the interaction between block and environment was significant, $F(2,252) = 3.4$, $p < .05$. Inspection of the data in Table 5 reveals that this effect was due primarily to a lack of learning in the graphical-conjunctive condition.

TABLE 4
Mean RLIN in Part I of Experiment 2

	Conjunctive environment		Disjunctive environment	
Block	Graphical rep.	Numerical rep.	Graphical rep.	Numerical rep.
n	33	32	32	33
1	.94 (.49)	.59 (.44)	.94 (.49)	.59 (.51)
2	1.01 (.53)	.58 (.44)	1.12 (.45)	.79 (.56)
3	1.03 (.43)	.71 (.57)	1.27 (.45)	.82 (.50)
Mean	.99 (.42)	.62 (.43)	1.11 (.41)	.73 (.48)

Note. Numbers in parentheses are standard deviations.

TABLE 5
Mean RNLN in Part I of Experiment 2

	Conjunctive environment		Disjunctive environment	
Block	Graphical rep.	Numerical rep.	Graphical rep.	Numerical rep.
n	33	32	32	33
1	.02 (.24)	.00 (.29)	.17 (.27)	.09 (.29)
2	.02 (.28)	.10 (.45)	.38 (.40)	.31 (.39)
3	.03 (.30)	.22 (.38)	.37 (.40)	.36 (.46)
Mean	.03 (.20)	.11 (.30)	.31 (.28)	.25 (.32)

Note. Numbers in parentheses are standard deviations.

The Learning of the Configural Relationships: Part II

The mean RNLN by condition and block is given in Table 6. Note that negative values indicate that subjects used the wrong strategy, that is, they used a disjunctive strategy in an conjunctive environment.

The main findings of part I are replicated in the second part. First, in all three blocks, there was more reliance on the (appropriate) configural strategy in the disjunctive conditions than in the conjunctive conditions. The main effect for environment was highly significant, $F(1,126) = 22.0$, $p < .0001$. Second, the main effect for block, which is associated with the learning of the appropriate configural strategies, was highly significant, $F(2,252) = 15.6$, $p < .0001$. In addition, the interaction between block and environment was also significant, $F(2,252) = 3.4$, $p < .05$.

In part II of this experiment, as in part II of experiment 1, previous experience in a disjunctive environment had a negative effect on the learning of conjunctive environment. In this part of the current experiment, RNLN in the first block of the conjunctive conditions is negative; that is, there was a tendency to use a disjunctive strategy in a conjunctive environment. On the other hand, previous experience in a conjunctive environment does not result in a negative transfer. RNLN in the first block of the disjunctive conditions of part II is positive, and even more positive than RNLN in the first block of the corresponding disjunctive conditions in part I.

The Learning of the Configural Aspects of the Environment: Subjects' Reports about Their Strategies

Subjects' reports were coded in the same way as in Experiment 1. The results indicated that the proportion of subjects reporting reliance on configural strategies was about the same in the GCD, GDC, and NDC groups (36, 41, and 36%, respectively), but lower in the NCD group (16%).

The analyses of subjects' perception of the strategy they used showed that 55% of the correct reports were associated with value-dependent weight explanations and 43% with inter-cue gap explanations. In sharp contrast to Experiment 1, only one subject mentioned an explanation based on sufficient/necessary conditions. This finding suggests that the perception of configural strategies as strategies associated with necessary and sufficient conditions requires a concrete context (indeed, the examples for this type of explanation in Experiment 1 tended to include the name of the object; see Table 3).

TABLE 6
Mean RNLN in Part II of Experiment 2

	Conjunctive environment		Disjunctive environment	
Block	Graphical rep.	Numerical rep.	Graphical rep.	Numerical rep.
n	32	33	33	32
1	−.11 (.39)	−.06 (.18)	.21 (.34)	.15 (.37)
2	−.01 (.37)	−.06 (.31)	.34 (.44)	.30 (.54)
3	.16 (.45)	.14 (.42)	.48 (.44)	.17 (.38)
Mean	.01 (.37)	.00 (.22)	.34 (.33)	.21 (.36)

Note. Numbers in parentheses are standard deviations.

Discussion

The main hypothesis of the experiment, that in an abstract context it will be easier to learn disjunctive strategy than conjunctive strategy in *all* phases of the experiment, is supported by the results. The mean RNLN was higher in the disjunctive than in the conjunctive conditions in each of the blocks, both in part I and in part II. Thus it appears that when the effect of negativity bias, which is associated with a meaningful context, is removed, disjunctive strategy is learned better than conjunctive strategy even from the early phases of exposure to configural environment.

The second hypothesis, that the learning of the linear relationships would facilitate the learning of the configural relationships, is not supported by the results. While the linear relationships were clearly learned better when the predictors were represented graphically, the configural relationships did not appear to be learned better under graphical representation. If anything, the data support the notion that learning of configural relationships facilitate the learning of linear relationships, since in the disjunctive conditions of part I, in which there was clearly more learning of the configural relationships, there was also a better learning of the linear relationships.

GENERAL DISCUSSION

The concept of natural strategies appear (explicitly or implicitly) in two traditions in judgment and decision-making research: in the heuristic and biases tradition and in the cue probability learning tradition. In the former, the concept refers to the dominant strategies people use when making judgments or decisions. In the latter it refers to a prior hierarchy of hypotheses associated with the first hypotheses to be tested in a cue probability learning experiment.

One problem associated with the concept of natural strategies within both traditions is to find an a priori way to identify such strategies. For example, in cue probability learning, the definition of natural strategy should not be based on the learning process, since this may lead to circularity between the definition and the dependent variable, which is some measure of learning (see for example Sniezek and Naylor, 1978, for a learning-free identification of natural strategies).

In the current paper, this problem is dealt with by identifying natural strategies as the strategies people use in judgment, and using these a priori definitions to examine their learning in a cue probability learning paradigm. The results of the experiments indicate that factors that make the strategy natural also facilitate its learning. One example is the way negativity bias—a ubiquitous judgment bias—facilitates the rapid initial learning of conjunctive strategy. Another example is the object-dependent difference in the learning of disjunctive and conjunctive strategies, which is associated with people's beliefs about the relationships between predictors and criteria in the prediction of performance of human versus non-human objects.

There are, however, other factors that facilitate the learning of prediction strategies. One such factor is the difference in processing of negative and positive information. Our experiments contain two examples of such differential processing. First, disjunctive strategy is learned better than conjunctive strategy in an abstract context; and second, after prolonged outcome feedback, disjunctive strategy is also learned better in a meaningful context. The latter example is especially interesting, since it suggests that the natural strategy need not be the strategy that is learned better in the long run. In this example, conjunctive strategy is more natural than disjunctive strategy (i.e. this is the strategy subjects "bring" to the experiment) and therefore, initially, it is learned more easily. The better asymptotic learning of disjunctive strategy is due to other factors, and in particular, to valence-dependent processing.

One interesting question which emerge from the current research concerns the connection between the learning of the linear relationships and the learning of the configural relationships. On the one hand, there are ample evidence in judgment research that configural strategies are the most natural strategies. This would suggest that people would also use these strategies spontaneously in prediction tasks, such as multiple cue probability learning (MCPL). On the other hand, almost all the research in MCPL found that linear—and not configural—combination rules are the most natural combination rules (but see Brehmer, 1972). It is of course possible that researchers in MCPL found only what they looked for. However, it is also possible that the difference between the findings of judgment research and the findings of MCPL research stem from a fundamental dissimilarity between the processes underlying judgment, a task that does not involve feedback (or at least immediate feedback), and the processes underlying prediction, a task which involve immediate feedback. In a MCPL task—a prediction task—subjects are likely to rely heavily on the representativeness heuristic (Kahneman and Tversky, 1973), the most important prediction heuristic. In using this heuristic, people chose an output value (prediction) whose extremity on the outcome distribution matches the average extremity of the predictors (see Lichtenstein, Earle and Slovic, 1975; and Ganzach, 1993a, for a discussion of the role of representativeness in MCPL task). Such a strategy leads to a linear combination of cues. On the other hand, in judgment there is less reliance on representativeness, since it is not possible to assess the extremity of potential output values against an outcome distribution. In our view, this differences between prediction and judgment is an interesting issue for future research.

APPENDIX

To see that Eq. (1) is identical to Eq. (3), note that Eq. (1) can be expressed as

$$Y = \alpha + (\beta_1 + \beta_3)\,X_1 + \beta_2\,X_2 \quad \text{for } X_1 > X_2, \quad (1a)$$

$$Y = \alpha + \beta_1\,X_1 + (\beta_2 + \beta_3)\,X_2 \quad \text{for } X_2 > X_1, \quad (1b)$$

Similarly, Eq. (3) can be expressed as

$$Y = \alpha' + (\beta'_1 + \beta'_3)\,X_1 + (\beta'_2 - \beta'_3)\,X_2 \quad \text{for } X_1 > X_2 \quad (3a)$$

$$Y = \alpha' + (\beta'_1 - \beta'_3)\,X_1 + (\beta'_2 + \beta'_3)\,X_2 \quad \text{for } X_2 > X_1 \quad (3b)$$

Equation (1a) is identical to Eq. (3a) and Eq. (1b) is identical to Eq. (3b) if

$$\begin{aligned} \beta_1 &= \beta'_1 - \beta'_3 \\ \beta_2 &= \beta'_2 - \beta'_3 \\ \beta_3 &= 2\,\beta'_3 \end{aligned} \quad (4)$$

In the same way it can be shown that Eq. (2) is identical to Eq. (4).

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