REINFORCEMENT FOR ERRORS IN A SIGNAL-DETECTION PROCEDURE

MICHAEL DAVISON AND DIANNE McCarthy

UNIVERSITY OF AUCKLAND, NEW ZEALAND

Six pigeons were trained on a signal-detection procedure. They were required to peck the left key when a 5-second white light had been presented, and the right key when a 10-second light had been presented. These two correct responses were followed by food reinforcement with a probability of .7. Errors, left responses after the 10-second stimulus or right responses after the 5-second stimulus, were initially followed by a 3-second blackout of the chamber. In nine subsequent experimental conditions, errors were followed by food reinforcement with increasing probability while the probability of reinforcement for correct responses was kept constant. The percentage of correct responses decreased as error reinforcement probability increased. A matching model of detection performance, in which discrimination is a joint function of stimulus discriminability and stimulus-reinforcement association, provided a convincing fit to the data and to two sets of published data. The model also fitted published data on multiple and multiple-concurrent free-operant performance. This description of detection performance in terms of matching offers both accurate prediction of complex behavior and measures of discriminability with wide generality.

Key words: generalized matching law, signal-detection theory, discrimination, discriminability, response bias, pecking, pigeons

In the standard signal-detection yes-no task, the subject is trained to emit one response (P_1) in the presence of one stimulus (S_1) and another response (P₂) in the presence of another stimulus (S_2) . The two discriminative stimuli, S₁ and S₂, may be related on the same physical dimension, or may be related by one having an additive property to the other (e.g., noise, signal-plus-noise), or may be unrelated. The two choice responses, P_1 and P_2 , may be, for example, a left-key response and a rightkey response. The procedure is diagrammed in Figure 1. With two stimuli and two responses, four possible outcomes are defined. Correct responses $(P_w \text{ or } P_z)$ are generally reinforced (denoted R_w and R_z), while incorrect responses $(P_x \text{ or } P_u)$ usually have no consequence or

This experiment was conducted by Dianne McCarthy as part of the requirements for the PhD. We thank the University Grants Committee for a postgraduate scholarship to her and for equipment grants to Michael Davison. In addition, we are grateful to J. A. Nevin for valuable comments and criticisms of this research and for kindly supplying the data reanalyzed in Table 4. We also thank the cooperative of students who helped conduct this experiment, and John Milkins and John Tull who tended the subjects. Reprints may be ob-

tained from Michael Davison or Dianne McCarthy,

Department of Psychology, University of Auckland,

Private Bag, Auckland, New Zealand.

are punished in some way (e.g., timeout with animals; Hume & Irwin, 1974).

Data obtained from this procedure have typically shown that signal-detection measures of discriminability are independent of the arrangement of reinforcements for correct responses (Green & Swets, 1966; McCarthy & Davison, 1979). However, Nevin, Olson, Mandell, and Yarensky (1975) have shown that conventional measures of stimulus discriminability (e.g., A'; Grier, 1971) were not invariant with respect to payoffs when reinforcement was arranged for incorrect responses and the stimuli were held constant. (It is usual in this area of research to call responses in cells X and Y of the matrix in Figure 1 errors, even though they are occasionally reinforced). This finding led Nevin, Jenkins, Whittaker, and Yarensky (Note 1) to develop a behavioral model of detection performance which encompassed the reinforcement-forerrors situation.

Nevin et al. (Note 1) reasoned that, if the two stimuli S_1 and S_2 were indiscriminable, the effects of reinforcement obtained for one response in the presence of one stimulus would generalize completely to the same response emitted in the presence of the other stimulus. If, however, the stimuli were perfectly dis-

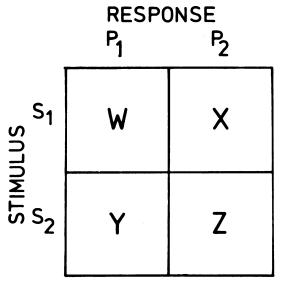


Fig. 1. The matrix of events in a typical, yes-no, signal-detection procedure. One of two responses (P_1, P_2) are emitted following presentation of one of two stimuli (S_1, S_2) . W, X, Y, and Z refer to the number of events occurring in each cell of the matrix.

criminable, no such generalization would occur. The degree of generalization is measured by a similarity parameter, η , which is zero for perfect discriminability, and unity when no discriminability is possible. Nevin et al. thus proposed two equations, based on the matching law (Herrnstein, 1970), to account for behavior in the presence of the two stimuli:

Given S_1 :

$$\frac{P_w}{P_x} = \frac{R_w + \eta R_y}{R_x + \eta R_z},\tag{1}$$

Given S_2 :

$$\frac{P_y}{P_z} = \frac{R_y + \eta R_w}{R_z + \eta R_z}, \qquad (2)$$

where P denotes responses, R denotes reinforcements, and the subscripts refer to the cells of the matrix in Figure 1.

In signal-detection theory (e.g., Green & Swets, 1966), and in matching models of signal detection (Davison & Tustin, 1978; McCarthy & Davison, 1979), discriminability is measured from the relative frequencies of correct responses in S_1 and in S_2 . Equations 1 and 2 suggest, therefore, that such conventional measures of discriminability will decrease when errors are reinforced. This effect was demonstrated by Nevin et al. (1975; Note 1). On the other hand, η , the proposed stimulus discrim-

inability parameter, should remain constant. However, an analysis of Nevin et al.'s (Note 1) data showed that η reliably decreased (i.e., discriminability increased) when errors were reinforced (Nevin, Note 2).

Davison and Tustin (1978) also proposed a behavioral model for detection performance but, in contrast to Nevin et al. (Note 1), Davison and Tustin used the generalized matching law (Baum, 1974), and described stimulus discriminability as a generalized matching law bias. For the no-error reinforcement situation, Davison and Tustin suggested that the obtained ratio of reinforcements for the two choice responses produced a general bias toward emitting one choice response compared with the other. They also suggested that performance in S₁ and in S₂ was additionally biased (to P_w in S_1 , and to P_z in S_2) by the discriminability of the stimuli. As biases are constant additive quantities in the logarithmic form of the generalized matching law, Davison and Tustin proposed two generalized matching law equations for behavior in the presence of each of the two stimuli (when only correct responses are reinforced, i.e., $R_x = R_y = 0$). Given S₁:

$$\log\left(\frac{P_{\kappa}}{P_{x}}\right) = a_{r_{1}}\log\left(\frac{R_{\kappa}}{R_{z}}\right) + \log d + \log c, \tag{3}$$

and, given S2:

$$\log\left(\frac{P_{\nu}}{P_{z}}\right) = a_{r} \log\left(\frac{R_{w}}{R_{z}}\right) - \log d + \log c, \quad (4)$$

where P and R denote number of responses emitted and number of reinforcements obtained, respectively, and the subscripts refer to the cells of the matrix in Figure 1.

The parameters a_{r_1} and a_{r_2} are the sensitivities of behavior to reinforcement changes. Log c is a performance bias in S_1 and S_2 which is inherent in the equipment or in the subject. It is assumed constant throughout the experiment, and is referred to as inherent bias (McCarthy & Davison, 1979). Log d is a performance bias caused by the discriminability of the two stimuli S₁ and S₂. Since both Equations 3 and 4 have P₁ responses as the numerator, $\log d$ is positive in Equation 3 (in which the bias is toward emitting P_1), and negative in Equation 4 (in which the bias is toward emitting P₂). Davison and Tustin (1978) noted that log d was a measure of stimulus discriminability identical to that used by some

detection theorists (e.g., Luce, 1963), and equivalent to that used by others (e.g., Green & Swets, 1966). The measure log d, then, is termed discriminability (Davison & Tustin, 1978; McCarthy & Davison, 1979). Evidence in support of this model was given by Davison and Tustin (1978) and by McCarthy and Davison (1979, 1980).

Davison and Tustin (1978) did not attempt to generalize their model to reinforcement for errors, but the extension is quite simple. Again, overall allocation of choice responses to the two alternatives is determined by the reinforcements obtained for the two responses. In the reinforcement-for-errors procedure, though, this reinforcement ratio will comprise all reinforcers and, as in the Davison and Tustin model, behavior will follow this reinforcement ratio according to a certain sensitivity, a_r (Baum, 1974).

While we assume that discriminability, log d (the maximal ability of a subject to tell two stimuli apart), remains constant when errors are reinforced, the data reported by Nevin et al. (1975) indicated that conventionally-measured discriminability shown by the subjects decreased when errors were reinforced. Thus, we make the additional assumption that the degree of discrimination which can be shown in the reinforcement-for-errors situation is a function of both the discriminability of the stimuli ($\log d$), and the degree of association between reinforcers and stimulus presentations. This latter measure is similar to a nonparametric measure of correlation. If only correct responses are reinforced, the value of the measure is +1.0, and if only errors are reinforced, the value is -1.0, but in both cases there is perfect association between stimuli and reinforcements. On the other hand, if the value of the measure is zero, reinforcers are equally likely to follow correct responses or errors, and there is no stimulus-reinforcer association. Discrimination, as distinct from discriminability, is thus given by:

Discrimination =
$$\left(\frac{R_c - R_e}{R_c + R_e}\right) \cdot \log d$$
, (5)

where R_c is the number of reinforcements obtained for correct responses $(R_w + R_z)$ in Figure 1), and R_e is the number of reinforcements obtained for errors $(R_x + R_y)$ in Figure 1). In other words, discrimination will be degraded by reinforcing errors.

Our full reinforcement-for-errors model is thus:

Given S₁:

$$\log\left(\frac{P_{w}}{P_{s}}\right) = a_{r_{1}}\log\left(\frac{R_{w} + R_{y}}{R_{s} + R_{s}}\right) + \left(\frac{R_{c} - R_{c}}{R_{c} + R_{c}}\right)\log d + \log c,$$
(6)

and, given S₂:

$$\log\left(\frac{P_y}{P_z}\right) = a_{r_2} \log\left(\frac{R_w + R_y}{R_z + R_z}\right) - \left(\frac{R_c - R_s}{R_c + R_s}\right) \log d + \log c. \tag{7}$$

When the association between reinforcement and stimulus presentation is 1.0 (i.e., only correct responses are reinforced), Equations 6 and 7 simplify to Equations 3 and 4 of the no-error reinforcement model (Davison & Tustin, 1978). When the association is -1.0, only errors are reinforced, and the equations again simplify to the Davison and Tustin model. When, however, the association is zero, no discrimination between S_1 and S_2 is shown, and both response ratios are a function only of the obtained reinforcement ratio. Discriminability (log d) cannot, therefore, be measured in the absence of the association of reinforcement and stimulus presentation.

Equations 6 and 7 can be used in the same way as Davison and Tustin's (1978) simpler equations (Equations 3 and 4) to provide the equivalents of a stimulus function, which relates behavior to the discriminative stimuli, and a bias function, which provides a description of how biasing variables affect behavior independent of discriminability (McCarthy & Davison, 1980). As the sensitivities to reinforcement are the same in the presence of S_1 and S_2 ($a_{r_1} = a_{r_2}$; McCarthy & Davison, 1979), a stimulus function is obtained by subtracting Equation 7 from Equation 6 to eliminate inherent bias and the choice reinforcement ratio terms:

$$\log\left(\frac{P_{w}}{P_{s}}\right) - \log\left(\frac{P_{y}}{P_{s}}\right) = 2\left(\frac{R_{c} - R_{e}}{R_{c} + R_{e}}\right) \log d.$$
 (8)

This equation indicates how discriminability as conventionally measured (the left of Equation 8; McCarthy & Davison, 1979, 1980) is degraded by reinforcing errors. When no errors are reinforced, or when only errors are reinforced, Equation 8 reduces to the simpler stimulus function of the Davison and Tustin model.

Likewise, a bias function is obtained by add-

ing Equation 7 to Equation 6 to provide a description of behavior independent of discrimination:

$$\log\left(\frac{P_{w}}{P_{x}}\right) + \log\left(\frac{P_{y}}{P_{z}}\right) = 2a_{r}\log\left(\frac{R_{w} + R_{y}}{R_{x} + R_{z}}\right) + 2\log c. \tag{9}$$

This equation defines how response bias, caused by the reinforcement of choice behavior and inherent bias, is to be measured (McCarthy & Davison, 1979).

The present experiment was designed to investigate the application of this reinforcement-for-errors model in a procedure close to the usual no-error reinforcement, yes-no signaldetection method. It is common, in detection procedures, to reinforce either each correct response (e.g., Hume, 1974a, 1974b; Hume & Irwin, 1974), or to reinforce correct responses intermittently on probabilistic or variableratio (VR) schedules (e.g., Elsmore, 1972; Hobson, 1975, 1978; Stubbs, 1976). Intermittent reinforcement scheduling has been carried out in two ways. Hobson (1975), for example, arranged reinforcements to follow correct responses in a probabilistic fashion with all correct responses contributing to a single VR-2 schedule. We have called this an uncontrolled reinforcement ratio procedure (McCarthy & Davison, 1980) as the number of reinforcements obtained can vary with the subject's behavior. Stubbs (1976), on the other hand, kept the obtained reinforcement ratio for correct responses fixed. Changes in preference, therefore, could not change the relative distribution of reinforcers between the two choices. We have called this a controlled reinforcement ratio procedure (McCarthy & Davison, 1980).

Likewise, intermittent reinforcement for errors may be introduced in the same two ways. Nevin et al. (Note 1), for example, used a procedure which completely controlled the obtained reinforcement ratio while Nevin et al. (1975), on the other hand, used an uncontrolled reinforcement ratio procedure. In the present experiment reinforcements for correct responses and errors were scheduled probabilistically on two separate VR schedules, one for all correct responses and one for all errors. Like the procedure used by Nevin et al. (1975), this allows the obtained reinforcement ratio to vary with preference as is typical in most signal-detection research.

METHOD

Subjects

Six experimentally naive homing pigeons, numbered 121 to 126, served. All birds were maintained at $80\% \pm 15$ g of their free-feeding body weights by providing supplementary feed in the home cage after each experimental session. Water and grit were available at all times in the home cage.

Apparatus

Conventional solid-state equipment was situated remotely from the standard sound-attenuated chamber. The chamber was fitted with an exhaust fan and contained three response keys 2 cm in diameter, 10 cm apart, and 27 cm from the grid floor. The keys, when illuminated, were operated by pecks exceeding about .1 N. A food magazine was situated beneath the center key and 12 cm from the grid floor. During reinforcement the keylights were extinguished and the food magazine raised for a nominal 3 sec. No other light was provided apart from the key and magazine lights.

Procedure

The birds were initially autoshaped to key peck and trained on different variable-interval schedules on all three keys for 20 sessions.

They were then trained to discriminate between two stimulus durations in ten experimental conditions. The sequence of conditions, and the number of sessions training given in each, are shown in Table 1. In all experimental conditions two white stimuli, differing in duration, were arranged with equal probability on the center key. One stimulus, designated S₁, was 5 sec in duration, and the other stimulus, designated S₂, was 10

Table 1
Sequence of experimental conditions and the number of sessions training given in each. The probability of food reinforcement for a correct response was .7 throughout.

Condition	P(food/incorrect)	Sessions		
1	0	47		
2	.1	23		
3	.2	30		
4	.3	32		
5	.4	27		
6	.5	34		
7	.6	23		
8	.7	19		
9	.8	15		
10	.9	19		

sec in duration. On completion of the center-key stimulus duration, the center-key light was extinguished and the two side keys were illuminated. On S_1 trials (when the shorter stimulus was presented on the center key), a peck on the red (left) side key was defined as correct. On S_2 trials (when the longer stimulus was presented on the center key), a peck on the green (right) side key was correct.

All correct responses produced 3-sec access to wheat with a probability of .7. When food reinforcement was not scheduled, correct responses produced a 3-sec magazine light. The probability of food reinforcement for errors (left after S_2 , right after S_1) was increased from 0 to .9, in steps of .1, in successive experimental conditions. When food reinforcement was not scheduled, errors produced 3-sec blackout during which all chamber lights were extinguished and responses were ineffective. A new trial (presentation of either S₁ or S₂ on the center key) began after either food reinforcement, magazine light, or blackout had been produced, and no responses to the center (stimulus) key were required.

The probability generator controlling food reinforcement for correct responses was interrogated only after each correct response had been emitted on either side key. Likewise, the probability generator controlling food reinforcement for errors was interrogated only after each incorrect response. Reinforcers not taken were saved so that reinforcement could be available for both correct responses and errors on some trials. This uncontrolled reinforcement procedure is different from that used by Nevin et al. (1975) in which the probability gates controlling correct and error reinforcements were tested on each trial, and reinforcements not taken were lost. Presumably, it was possible in the Nevin et al. study for reinforcements to be set up for both a correct response and an error on some trials.

Experimental sessions were conducted seven days a week and each continued until either 60 food reinforcements had been obtained or 45 minutes had elapsed. Sessions started and ended in blackout. The data collected were the number of responses emitted, and the number of reinforcements obtained, on the left and right keys on both S₁ and S₂ trials. Experimental conditions were changed when all birds had met a specified stability criterion five, not necessarily consecutive, times. The

criterion required that the median relative number of responses on S_1 trials over five sessions be within .05 of the median from the prior five sessions.

RESULTS

The number of responses emitted and the number of reinforcements obtained in the four cells of the signal-detection matrix (Figure 1), summed over the last five sessions of each experimental condition, are shown in Table 2. From this table it can be seen that often low, or even moderate, probabilities of error reinforcement produced only small frequencies of error reinforcement and little effect on behavior. This result can be seen more clearly in Figure 2 where the percentage of correct responses (left after S₁, right after S₂) is shown as a function of the arranged probability of an error being reinforced. With the exception of Bird 123, percent correct remained unaffected by increasing error-reinforcement probabilities until these probabilities reached moderate levels. The obtained frequencies for receiving reinforcement for a correct response relative to all obtained reinforcers is also shown in Figure 2. These measures also remained high in the initial conditions of the experiment, indicating that, because few error responses were emitted, few error reinforcements were obtained. As soon as the relative frequency of error reinforcements increased, however, the percentage of correct responses decreased.

The data obtained in all conditions (Table 2), except where they were infinite ratios, were analyzed for conformity to Equations 6 and 7 combined using multiple linear regression analyses. The dependent variables for the two equations were, respectively, the logarithm of the choice response ratio in S_1 , $\log(P_w/P_x)$, and the logarithm of the choice response ratio in S_2 , $\log(P_y/P_z)$. The independent variables were the logarithm of the ratio of the number of reinforcements obtained on the left and right keys, $\log[(R_w + R_y)/(R_x + R_z)]$, the degree of stimulus-reinforcer association, $[(R_c - R_e)/(R_c + R_e)]$. The latter variable was negated for S₂ performance. Two parameters, reinforcement sensitivity (a_r) and discriminability ($\log d$), were obtained together with a measure of inherent bias (log c). The results of this analysis are shown in Table 3.

The data are shown in Figure 3 as a func-

 $Table\ 2$ Number of responses emitted and number of reinforcements obtained on the left and right keys on S_1 and on S_2 trials. The data are summed over the last five sessions of each experimental condition.

		Responses			Reinforcements				
			Sı		S2		1	S2	
Condition	Bird	L	R	L	R	L	R	L	R
1	121	225	15	35	230	154	0	0	146
	122	220	16	18	213	152	0	0	148
	123	196	37	15	229	143	0	0	157
	124	162	114	27	257	119	0	0	181
	125	252	24	98	175	183	0	0	117
	126	201	16	23	219	142	0	0	158
2	121	250	8	28	194	163	0	2	135
	122	229	9	16	204	166	0	1	133
	123	210	56	35	209	149	5	3	143
	124	154	108	37	224	110	12	6	172
	125	272	6	81	127	202	1	8	89
	126	199	30	18	220	144	4	2	150
3	121	215	31	39	168	159	11	9	121
•	122	228	1	27	213	157	1	4	138
	123	221	57	71	164	148	11	20	121
	124	153	172	37	233	103	32	8	157
	125	173	29	42	240	123	6	5	166
	126	193	26	19	258	127	1	4	168
4	121	210	6	9	206	147	2	2	149
T	122	183	24	11	230	128	3	2	167
	123	298	6	316	10	200	1	85	8
	124	191	125	16	190	122	40	4	134
	125	184	19	60	189	135	6	21	138
	126	146	18	19	2 4 8	102	9	8	181
5	121	220	4	19	203	143	2	6	149
J	122	231	29	27	191	146	5	12	137
	123	257	0	300	1	179	0	120	137
	123	186	45	56	194	128	14	20	138
	125	148	62	20	198	110	31	12	147
	126	203	32	38	182	146	11	16	127
6									
6	121	212	4	22	213	134	2	10	154
	122	19	241	2	237	15	126	0	159
	123	223	2	279	4	157	1	127	3
	124	247	0	229	3	175	0	125	0
	125 126	3 77	212 184	0 0	265 222	2 53	10 4 91	0 0	194 156
_									
7	121	99	110	10	202	77	69	4	150
	122	76	155	1	227	49	88	1	162
	123	184	50	191	42	129	23	113	32
	124	223	2	220	24	147	1	134	18
	125	0 4 0	213 190	0 0	243 232	0 30	134 113	0 0	166 157
_	126								
8	121	110	137	5	198	79	89	4	128
	122	50	172	3	217	33	125	1	141
	123	0	236	0	205	0	162	0	138
	124	232	11	182	34	152	6	119	23
	125 126	0 13	195 221	0 1	234 180	0 7	137 164	0 1	163 128
0									
9	121 122	27 0	161 203	4 0	201 191	18 0	133 163	3 0	146 137
	122	1	203 222	0	191 174	0	180	0	120
									25
	124	208	12	147	32	144	11	120	
	125 126	0 0	184 191	0 1	214 226	0 0	152 145	0 1	148 154
10				5		30		5	124
10	121 122	43 4	155 195	5 3	195 181	30 3	141 173	2 2	124
			172	0	211	0	173	0	142
	123	0 176	1/2	188	6	131	158	163	142
	124 125	0	173	0	207	0	161	0	139
	143	U	1/3	U	407	U	101	U	139

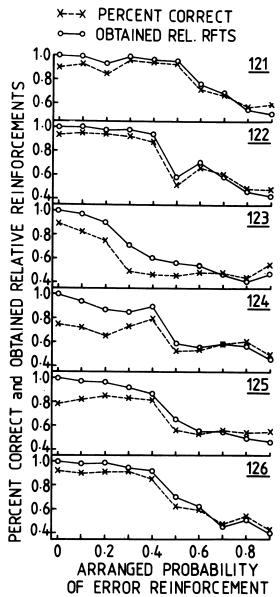


Fig. 2. The percentage of correct responses, and the obtained relative number of reinforcements for correct responses, as a function of the arranged probability of food reinforcement for errors. The data are those shown in Table 2.

tion of the predictions calculated from the obtained parameter values. The values of a_r and $\log d$, and their standard deviations, are shown on the right of Figure 3. The percentage of variance accounted for by the predictions and the standard error of the estimate are shown on the left. The estimated values of $\log c$, shown in Table 3, averaged .01 and varied between -.12 for Bird 124 and .13 for

Bird 121. Small standard deviations of parameter estimates were generally obtained, although some sensitivity-to-reinforcement (a_r) estimates were imprecise (e.g., Bird 125) because of insufficient variation in the left-to-right obtained reinforcement ratio (see Table 2). Over the six birds the predictions accounted for an average 94% of the data variance. All six birds' performances showed overmatching (a_r) greater than 1.0).

A bias function, Equation 9, relating behavior in the presence of S₁ and S₂ to the effects of changes in the left-to-right obtained reinforcement ratio, is shown in Figure 4. Here, the logarithm of the choice-response ratio on S₁ trials plus the logarithm of the choiceresponse ratio on S_2 trials, $\lceil \log(P_w/P_x) + \log \rceil$ (P_v/P_z)], is plotted as a function of the ratio of the number of reinforcements obtained on the left and right keys, $\log[(R_w + R_y)/(R_x +$ R_z)]. The equation of the best fitting straight line by the method of least squares, the variance accounted for, and the standard error of the estimate are shown for each bird. The mean value of a_r , which is one half the obtained slope, was 1.30, identical to that obtained from Equations 6 and 7 (Figure 3). The mean value of inherent bias ($\log c$), which is one half the obtained intercept, was .03, a similar value to that obtained from Equations 6 and 7 as shown in Table 3. The small left-toright reinforcement ratio variance for Bird 125, mentioned above as an explanation of the rather inaccurate sensitivity-to-reinforcement estimate, can be clearly seen in Figure 4.

The data were also analyzed for conformity to the stimulus function (Equation 8) using a least-squares linear regression with no intercept term. The obtained mean value for discriminability, again one half the obtained slopes, was .97, an identical value to that obtained using Equations 6 and 7 (Table 3).

DISCUSSION

The analyses of the present data shown in Figures 3 and 4, and Table 3, together with the measure of discriminability obtained from the stimulus function, show that our generalization of the Davison and Tustin (1978) detection model accounts for the obtained data very well. The model is able to extract a constant measure of discriminability from conditions in which error reinforcements may be

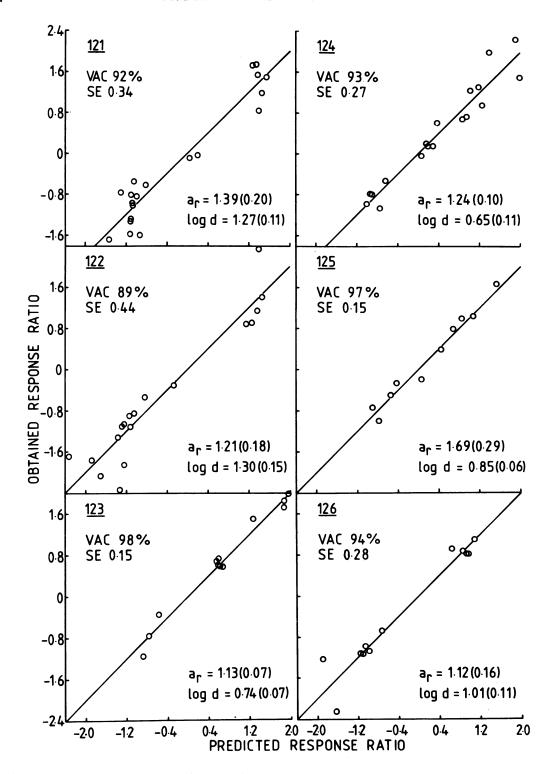


Fig. 3. The obtained response ratios in S_1 and in S_2 as a function of the response ratios predicted from Equations 6 and 7 on log-log coordinates. The obtained estimates of reinforcement sensitivity (a_r) and discriminability $(\log d)$, and their standard deviations, are shown on the right of each graph. The variance accounted for (VAC) by the predictions and the standard error of the estimate (SE) are shown on the left of each graph. The line drawn shows perfect prediction. The data are as shown in Table 2.

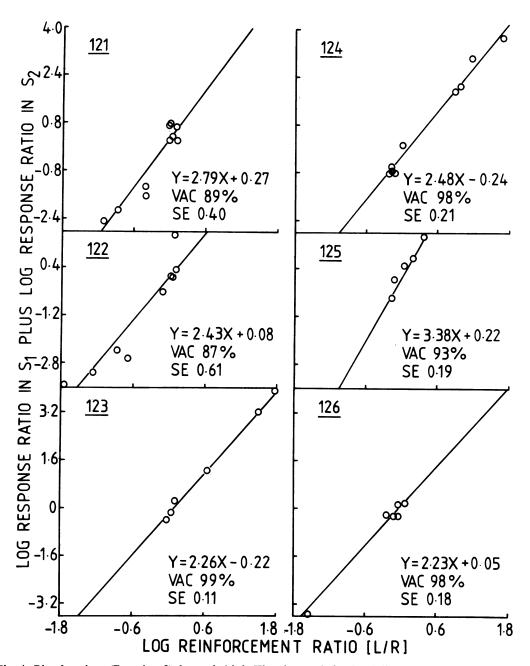


Fig. 4. Bias functions (Equation 9) for each bird. The slopes of the fitted lines are twice the sensitivity to reinforcement (a_r) estimates, and the intercepts are twice the inherent bias (log c) values. The variance accounted for by the fitted line and the standard error of the estimates are also shown.

either present or absent, and in which the obtained numbers of reinforcements in the cells of the detection matrix (Figure 1) vary widely as in the standard signal-detection procedure. Measures of sensitivity to reinforcement obtained from Equations 6 and 7, and from Equation 9, were consistent and indi-

cated quite reliable overmatching (Baum, 1974).

However, analyses of data already reported (Davison & Tustin, 1978; McCarthy & Davison, 1979) resulted in undermatching. It seems unlikely that the overmatching found in the present experiment is a function of reinforcing

Table 3 The parameters a_r and log d, the intercept log c, the standard deviation (SD), and the multiple correlation coefficient (MCC) obtained when Equations 6 and 7 combined were fitted to the data shown in Table 2. N tallies the number of data points used in each analysis.

Subject	a_r (SD)	log d (SD)	log c (SD)	МСС	N
121	1.39 (.20)	1.27 (.11)	.13 (.09)	.96	20
122	1.21 (.18)	1.30 (.15)	.04 (.14)	.94	18
123	1.13 (.07)	.74 (.07)	11 (.07)	.99	12
124	1.24 (.10)	.65 (.11)	12 (.08)	.96	18
125	1.69 (.29)	.85 (.06)	.11 (.06)	.98	10
126	1.12 (.16)	1.01 (.11)	.02 (.10)	.97	12

errors. Rather, the higher sensitivity-to-reinforcement values found in the present experiment are consistent with the results reported by McCarthy and Davison (1979). These data showed that, in a no-error reinforcement procedure, higher sensitivities to reinforcement were found in an uncontrolled reinforcement ratio procedure with probabilistic scheduling than in a controlled reinforcement ratio pro-

cedure with interval scheduling. If sensitivity to reinforcement is a function of controlled versus uncontrolled reinforcement scheduling procedures, the data reported by Nevin et al. (1975), using an uncontrolled reinforcement ratio procedure might show sensitivity-to-reinforcement values similar to those found in the present experiment, and these values should be greater than those obtained by Nevin et al.

Table 4
Sensitivity to reinforcement (a,), discriminability (log d), and inherent bias (log c) values obtained when Equations 6 and 7 combined were fitted to data obtained in the listed experiments using a multiple linear regression analysis. SD refers to the standard deviation of the parameter estimates. VAC refers to the percentage of data variance accounted for by the predictions from the obtained parameters. N tallies the number of data points used in each analysis.

	Subject	a_r	(SD)	<i>log</i> d	(SD)	log c	(SD)	VAC	N
\overline{A} .	Nevin, Olson, Mandell, & Yarensky (1975)								
	Rat D	.82	(.06)	.63	(.03)	.09	(.03)	93	48
	Rat E	.92	(.03)	.89	(.03)	.19	(.02)	97	47
	Rat F	.56	(.07)	.60	(.03)	.07	(.02)	91	48
\overline{B} .	Nevin, Jenkins,	Whittaker,	& Yarens	sky (Note 1): al	l data				
	Bird 58	.95	(.09)	.48	(.06)	.06	(.05)	89	24
	Bird 59	.89	(.08)	.57	(.05)	20	(.04)	94	24
	Bird 60	.86	(.09)	1.00	(.06)	.10	(.0 4)	97	24
C.	Nevin et al. (N	ote 1): no-er	ror-reinfor	cement condition	ıs				
	Bird 58	.83	(.21)	.48	(.10)	.02	(.10)	90	12
	Bird 59	.93	(.11)	.53	(.06)	20	(.06)	97	12
	Bird 60	.92	(.16)	.99	(80.)	.06	(.08)	98	12
\overline{D} .	Nevin et al. (N	ote 1): error	-reinforcen	nent conditions					
	Bird 58	1.08	(.12)	.66	(.13)	.08	(.06)	92	12
	Bird 59	.89	(.10)	.83	(.11)	23	(.05)	94	12
	Bird 60	.91	(.11)	.79	(.11)	.05	(.05)	93	12
\overline{E} .	Nevin, Mandell	l, & Whitta	ker (1978	")					
	Bird 90	.95	(.11)	.89	(.13)	05	(.09)	88	20
	Bird 91	.82	(80.)	.90	(.12)	.10	(80.)	87	24
	Bird 93	.76	(.11)	1.01	(.14)	.06	(.09)	82	26
\overline{F} .	Lobb & Davison (1977)								
	Bird 21	.69	(.11)	.66	(80.)	.19	(.08)	81	25
	Bird 22	.64	(.08)	.69	(.06)	.29	(.06)	85	29
	Bird 23	.98	(.10)	.94	(80.)	.23	(80.)	89	31
	Bird 24	.69	(.16)	.81	(.11)	.29	(.12)	72	28
	Bird 25	.53	(.09)	.62	(.06)	.18	(.06)	79	30
	Bird 26	.55	(.16)	.90	(.11)	.41	(.12)	71	29

(Note 1) using a controlled reinforcement ratio procedure.

As a check on the generality of the present model, and as an investigation of procedural effects on reinforcement sensitivity, we carried out a similar analysis on the data reported by Nevin et al. (1975) and Nevin et al. (Note 1). Nevin et al. (1975) trained rats on a brightness-detection task, and Nevin et al. (Note 1) trained pigeons to discriminate between a 2-sec and a 3-sec keylight duration. The data were analyzed by multiple linear regression to obtain the parameters of Equations 6 and 7, and all noninfinite response ratio data were used. The results are shown in Table 4A and B. The present model gave excellent parameter estimates, with consistently small standard deviations, and accounted for large proportions of the data variance.

The generality of the present model is thus extended to two procedural variations and to a second species, the rat (Nevin et al., 1975). However, reliable undermatching $(a_r < 1.0)$ was found for both the Nevin et al. (1975) and the Nevin et al. (Note 1) studies, indicating that uncontrolled reinforcement ratio procedures probably do not yield consistently higher sensitivity-to-reinforcement values. It seems doubtful that the other minor procedural variations between these two experiments and the present one could account for the reinforcement sensitivity differences.

It was in the Nevin et al. (Note 1) study that measures of stimulus discriminability (η) showed apparently better discriminability when errors were reinforced than when they were not. This implication seems quite counter-intuitive, and the data obtained from the six conditions of no-error reinforcement and the six conditions of error reinforcement in the Nevin et al. (Note 1) study were analyzed separately using Equations 6 and 7 combined. The results of this analysis (Table 4C and D) showed no evidence of consistent differences in estimated parameters between the two sets of conditions. In particular, measures of discriminability (log d) were not significantly different between the no-error reinforcement and the error-reinforcement conditions. But the fits to these smaller samples were, of course, less good than those to the larger sample (compare Table 4B with Table 4C and D). If discriminability is the maximal ability of a subject to detect one stimulus relative to another, then any measure of discriminability should indeed remain constant. In this sense, then, the present model is preferable to the Nevin et al. (Note 1) formulation. However, since only small amounts of data are as yet available, a critical empirical test of the merits of these two models is not possible at the present time.

Can the present model be used to obtain measures of discriminability from experimental data obtained when discrimination was not directly under investigation? For example, measurements of discriminability in multiple and concurrent schedule performances would be of major interest. Because the primary data for matching and signal-detection analyses are response ratios within each stimulus, it is unclear how to apply the model directly to conceptually simpler, but theoretically more complex, multiple schedules commonly used in stimulus control research. These procedures provide no assessment of the number of "errors" emitted. While an attempt to specify unmeasured responses and reinforcers (Herrnstein, 1970) might be profitable, the distribution of these between components is unclear. Although Herrnstein assumed equal distribution of these between components for convenience, he admitted that they are unlikely to be so distributed.

However, the generalized matching law can be expressed equally well in terms of time allocation, rather than response allocation (Baum & Rachlin, 1969), and two experiments have been reported which measured time allocation in multiple schedules (Bouzas & Baum, 1976; White, 1978). If we take time allocation measures as being equivalent to response allocation measures, and assume that time spent close to the manipulandum in a VI-schedule component, or away from it in an extinction-schedule component, as being equivalent to correct responses, it is then possible to analyze White's data. Since he reported only two experimental conditions, point estimates of discriminability and response bias were calculated using Equations 8 and 9 respectively, simplified for no-error reinforcements. The obtained discriminability measures were unaffected by changing either the VI schedules in White's Experiment 1 (mean $\log d$ values of .71 and .69), or changing the variable-time (VT) schedules in his Experiment 2 (mean log d values of .39 and .37). The differences in discriminability between White's two experiments may be due to the retractable lever in Experiment 1 acting as an added discriminative stimulus. Response bias measures, on the other hand, changed substantially when the VI schedules were varied (mean values of .02 to .38), and when the VT schedules were changed (mean values of -.01 to .46). Time allocation data, then, could be a useful way of obtaining measures of discriminability in multiple schedules.

Our model might also be applicable to performance in multiple concurrent schedules (Pliskoff, Shull, & Gollub, 1968) which have the same matrix of events as the signal-detection procedure with error reinforcements. The first test of the extension of the present model to multiple concurrent schedule data was to apply it to an experiment reported by Nevin, Mandell, & Whittaker (1978). These authors used pigeons as subjects and the discrimination was between red and white keylights. They also used a discrete-trials procedure which was almost identical to a signal-detection procedure with error reinforcement. The equivalent of VI, or extinction, schedules were arranged in the four components. The data were analyzed using a multiple linear regression analysis combining Equations 6 and 7, and all noninfinite response ratio data were used. The obtained parameters, their standard deviations, and the variance accounted for by the predictions of the obtained parameters are shown in Table 4E. Between 82% and 88% of the data variance was accounted for, generally less than that obtained in the signaldetection experiments reported above.

A second test of the applicability of our model to multiple concurrent schedule performance used data reported by Lobb and Davison (1977) using a free-operant procedure. Pigeons acted as subjects in this experiment and the discrimination was between blue and green keylights. Variable-interval or extinction schedules were arranged in all four components, and the data analyzed were all conditions in which reinforcements were arranged in all four components, and in which response ratios were not infinite. The data were again fitted to Equations 6 and 7 combined using a multiple linear regression analysis. The obtained parameters, together with their standard deviations and the variance accounted for by the predictions of the obtained parameters, are shown in Table 4F. Values of inherent bias were all strongly positive (mean = .27, range .18 to .41), indicating a bias toward the multiple schedule as reported by Lobb and Davison. Between 71% and 86% of the data variance was accounted for, again less than that obtained in the signal-detection experiments.

In conclusion, the present detection model appears to fit both discrete-trial, and freeoperant, conditioning experiments quite well. However, smaller percentages of data variance were accounted for by the model in the freeoperant experiments than in the signal-detection experiments, possibly because, in the former, control by the reinforcement schedules alone was of primary concern. As a result, the discriminative stimuli (i.e., keylight bulbs) were probably replaced with no particular consideration of intensity or hue variability. Perhaps the most interesting result from the analysis of these schedule control experiments is the obtained values of discriminability. In such experiments it is traditional to select the discriminative stimuli to maximize stimulus control and so study control by the reinforcement schedules in isolation. However, the obtained discriminability measures were only moderate, and by no means maximal.

REFERENCE NOTES

- Nevin, J. A., Jenkins, P., Whittaker, S., & Yarensky, P. Signal detection, differential reinforcement and matching. Paper presented at the Meeting of the Psychonomic Society, Washington, D.C., November 1977
- 2. Nevin, J. A. Personal communication, Spring 1979.

REFERENCES

Baum, W. M. On two types of deviation from the matching law: Bias and undermatching. Journal of the Experimental Analysis of Behavior, 1974, 22, 231-242.

Baum, W. M., & Rachlin, H. C. Choice as time allocation. Journal of the Experimental Analysis of Behavior, 1969, 12, 861-874.

Bouzas, A., & Baum, W. M. Behavioral contrast of time allocation. Journal of the Experimental Analysis of Behavior, 1976, 25, 179-184.

Davison, M. C., & Tustin, R. D. The relation between the generalized matching law and signal-detection theory. Journal of the Experimental Analysis of Behavior, 1978, 29, 331-336.

Elsmore, T. F. Duration discrimination: Effects of probability of stimulus presentation. Journal of the Experimental Analysis of Behavior, 1972, 18, 465-469.

- Green, D. M., & Swets, J. A. Signal detection theory and psychophysics. New York: Wiley, 1966.
- Grier, J. B. Nonparametric indexes for sensitivity and bias: Computing formulas. Psychological Bulletin, 1971, 75, 424-429.
- Herrnstein, R. J. On the law of effect. Journal of the Experimental Analysis of Behavior, 1970, 13, 243-266.
- Hobson, S. L. Discriminability of fixed-ratio schedules for pigeons: Effects of absolute ratio size. Journal of the Experimental Analysis of Behavior, 1975, 23, 25-35.
- Hobson, S. L. Discriminability of fixed-ratio schedules for pigeons: Effects of payoff values. Journal of the Experimental Analysis of Behavior, 1978, 30, 69-81.
- Hume, A. L. Auditory detection and optimal response biases. *Perception and Psychophysics*, 1974, 15, 425-433. (a)
- Hume, A. L. Optimal response biases and the slope of ROC curves as a function of signal intensity, signal probability, and relative payoff. *Perception and Psychophysics*, 1974, 16, 377-384. (b)
- Hume, A. L., & Irwin, R. J. Bias functions and operating characteristics of rats discriminating auditory stimuli. Journal of the Experimental Analysis of Behavior, 1974, 21, 285-295.
- Lobb, B., & Davison, M. C. Multiple and concurrent schedule performance: Independence from concurrent and successive schedule contexts. Journal of the Experimental Analysis of Behavior, 1977, 28, 27-39.
 Luce, R. D. Detection and recognition. In R. D. Luce,

- R. R. Bush, & E. Galanter, Handbook of mathematical psychology (Vol. 1). New York: Wiley, 1963.
- McCarthy, D., & Davison, M. Signal probability, reinforcement, and signal detection. Journal of the Experimental Analysis of Behavior, 1979, 32, 373-386.
- McCarthy, D., & Davison, M. On the discriminability of stimulus duration. Journal of the Experimental Analysis of Behavior, 1980, 33, 187-211.
- Nevin, J. A., Mandell, C., & Whittaker, S. Contrast and induction in multiple schedules of discrete-trial concurrent reinforcement. *Journal of the Experimental Analysis of Behavior*, 1978, 30, 53-61.
- Nevin, J. A., Olson, K., Mandell, C., & Yarensky, P. Differential reinforcement and signal detection. Journal of the Experimental Analysis of Behavior, 1975. 24, 355-367.
- Pliskoff, S. S., Shull, R. L., & Gollub, L. R. The relation between response rates and reinforcement rates in a multiple schedule. *Journal of the Experimental Analysis of Behavior*, 1968, 11, 271-284.
- Stubbs, D. A. Response bias and the discrimination of stimulus duration. Journal of the Experimental Analysis of Behavior, 1976, 25, 243-250.
- White, K. G. Behavioral contrast as differential time allocation. Journal of the Experimental Analysis of Behavior, 1978, 29, 151-160.

Received September 6, 1979 Final acceptance February 2, 1980