

The effects of feedback in psychophysical tasks

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Previous results of the reinforcement effects of feedback in psychophysical tasks have been interpreted as changes in the S's response bias in the uncertain sensory state. The present study varied the percentage of feedback in a two-alternative loud-soft recognition task. The values of the probability of correct feedback were 1, .8, .6, .4, .2, and 0. The results indicated that Ss learned to respond to agree with the experimental feedback rather than with the actual cue presented on a trial. The probability of a response on Trial $n + 1$ was highly dependent upon the response and feedback of Trial n only when the two trials were the same. It was concluded that feedback must influence the response probability vector associated with a given detection state.

In a two-alternative psychophysical task, Ss identify which of two stimuli was presented on a given trial. Two responses, A_1 and A_2 , identifying Stimuli T_1 and T_2 , respectively, are available to the S. Two feedback events, E_1 and E_2 , indicate to the Ss whether T_1 or T_2 was presented.

The effects of information feedback in this paradigm have been investigated (Atkinson & Kinchla, 1965; Friedman, Carterette, Nakatoni, & Ahumada, 1968). The results have indicated that the probability of an A_1 response, $P(A_1)$, is positively related to $P(E_1)$. The analysis of this bias in the learning models of Atkinson and Kinchla (1965) and those discussed by Friedman et al (1968) has assumed that feedback can change the response probability vector associated with the uncertain sensory state, S_0 . Furthermore, letting States S_1 and S_2 be the detection of T_1 and T_2 , respectively, it was sufficient to assume that $P(A_1 | S_1) = 1$ and $P(A_1 | S_2) = 0$. That is, given Detection States S_1 or S_2 , the S's response is determined with Probability 1.

As suggested by Atkinson and Kinchla (1965), it may be that feedback also influences the response vectors associated with the Detection States S_1 and S_2 . For example, the results of a discriminative probability learning study (Massaro & Moore, 1968) indicated that the response probabilities to *identified* cues were highly dependent on the response and feedback of the previous trial. The S's task in that study was to indicate whether a loud or soft tone was presented and then predict which of two events, E_1 or E_2 would appear on that trial. Under reinforcement schedules of $\pi_1 = P(E_1 | T_1) = .8$ and $\pi_2 = P(E_1 | T_2) = .2$, Ss learned to respond appropriately to the identified cues. When the Ss were reinforced for responding appropriately (i.e., predicting the most frequent event given the cue), they would be more likely to predict the most frequent event given the identified cue on the following trial. More specifically, when Trials $n + 1$ and n were identified as the same, $P(A_1 | A_1 E_1) > P(A_1 | A_1 E_2) > P(A_1 | A_2 E_1) > P(A_1 | A_2 E_2)$. When Trials $n + 1$ and n were identified as different, the rank-ordering of the conditional response probabilities was exactly the opposite of that given when the trials were identified as the same. Hence, it seems likely that Ss could learn also to behave appropriately to *identified* cues in a psychophysical detection task. In the framework of the learning models, feedback should also affect the response probability vectors associated with the detection states, S_1 and S_2 .

Carterette, Friedman, and Wyman (1966) studied the effects of information feedback in a two-alternative, temporal forced-choice

auditory-signal-detection task. The authors concluded that feedback reinforces the S to change his criterion following incorrect responses and, hence, depress the sensitivity measure of d' of signal-detectability theory.

It is possible that feedback does not lead to changes in the S's criterion, which is usually some monotonic function of the likelihood of a "signal trial" required for the response appropriate for the "signal trial." As mentioned earlier, feedback may, in fact, determine the *appropriate* response after the S has concluded whether or not the present trial is a "signal trial." Therefore, in the Carterette et al study, if feedback was simply determining the probability of an appropriate response given the detection state, the reinforcement effects could lead to increases or decreases of d' while not affecting marginal response probabilities.

To explain the overall decrease of d' with random feedback, Carterette et al concluded that random feedback distorts the S's memory for the signal. This need not be the case. Random feedback could reinforce nonoptimal strategies of responding given a detection state. These strategies, adopted to agree with the experimental feedback rather than the actual cue presented on a particular trial, would lower values of d' considerably.

The present study is an attempt to elucidate the role of feedback in psychophysical tasks by investigating marginal and sequential response probabilities under different levels of probability of correct feedback in a loud-soft recognition task. In the present study, T_1 and T_2 refer to the loud and soft tones, respectively. Two responses, A_1 and A_2 , identifying Tones T_1 and T_2 are available to the Ss. Two feedback events, F_1 and E_2 indicate to the Ss whether T_1 or T_2 was presented. On both T_1 and T_2 trials, Ss are given correct feedback with Probability π and incorrect feedback with Probability $1 - \pi$. The values of π were 1, .8, .6, .4, .2, and 0.

It was predicted that Ss would learn to behave appropriately to the information feedback rather than to the subjective loudness of the tones presented. Therefore, feedback should affect the response probability given a detection state. For example, if Ss will learn to respond in order to agree with the experimental feedback rather than with the actual cue presented on the trial, they must first identify the tone before they know the appropriate response given that trial type.

METHOD

Subjects

The Ss were 66 University of Massachusetts undergraduates and they were assigned randomly to the experimental treatments.

Apparatus

Up to four Ss were run at a time, each seated at a tabletop enclosure containing a Masonite panel consisting of a white center warning light and two red feedback lights each positioned above a spring-loaded lever switch and labeled "loud" or "soft." Tones were generated by Hewlett-Packard Model 200 audio oscillator and were presented over matched headphones with a continuous white masking noise. Experimental events were controlled by Lehigh Valley 1620 Probability Randomizers, Hunter Interval Timers, and relays. Stimuli, feedback and responses were recorded on an Esterline-Angus event recorder.

Procedure

The onset of a tone started a trial. The tone lasted .5 sec. The warning light followed and lasted 1.5 sec during which Ss were required to make a loud or soft identification response by pressing the respective switch. The feedback light was illuminated for .5 sec immediately following the end of the warning light. Hence, each trial lasted 2.5 sec. The intertrial interval was 2.5 sec. Each S received 600 trials in which all stimuli and feedback were presented by an appropriate setting on the probability randomizers. The trial types (loud and soft) were programmed to occur equally often. The intensity pairings of the 800-Hz tones were 73 and 75 dB SPL for the soft and loud tones, respectively. Ss were given the following instructions:

"You will be receiving two tones differing slightly in loudness over the headphones. On each trial, your task will be to indicate which of the tones was presented. When the white light at the center of the panel comes on, you will press one of the two switches. You will press the left (right) switch for the louder tone and the right (left) switch for the softer tone. Notice the switches are labeled loud and soft. You are expected to guess if you are not sure of your decision. You will have 1½ sec to make your choice.

"After 1½ sec, one of the two red lights will come on indicating whether the loud or soft tone was presented on that trial. Are there any questions?"

Design

Six feedback schedules were employed in the present study. The probabilities of correct feedback, π , were 1, .8, .6, .4, .2, and 0. Thus, there were 11 Ss in each cell of a factorial design for a total of 66 Ss. The analysis of variance of $P(A_1)$, the probability of a loud response, included the between variable of feedback condition and the two within variables, cue (loud or soft tone) and trial block (three blocks of 200 trials).

RESULTS

Marginal Statistics

Table 1 presents values of $P(A_1)$ as a function of π , cue, and trial blocks. Table 1 shows that $P(A_1 | T_1) - P(A_1 | T_2)$ decreased as the probability of correct feedback (π) decreased, $F(5,60) = 22.46$, $p < .001$. Both the Cue by Trial Block, $F(2,120) = 7.55$, $p < .001$, and the π by Cue by Trial Block, $F(10,120) = 4.00$, $p < .005$, interactions indicate that Ss increased or decreased correct identifications over training in order to agree with the feedback in the situation. That is, with only correct feedback, Ss improved over training in identification responding. On the other hand, with sufficient incorrect feedback, Ss learned to respond so that their identifications

Table 1

Marginal Probabilities of Identification Responding as a Function of Cue, Trial Block and Percentage of Correct Feedback (π)

π		Trial Block		
		1	2	3
1.0	$P(A_1 T_1)$.82	.84	.85
	$P(A_1 T_2)$.34	.20	.16
.8	$P(A_1 T_1)$.75	.75	.73
	$P(A_1 T_2)$.32	.27	.33
.6	$P(A_1 T_1)$.77	.71	.66
	$P(A_1 T_2)$.28	.28	.39
.4	$P(A_1 T_1)$.70	.62	.58
	$P(A_1 T_2)$.41	.40	.43
.2	$P(A_1 T_1)$.49	.39	.39
	$P(A_1 T_2)$.56	.62	.60
0	$P(A_1 T_1)$.41	.34	.28
	$P(A_1 T_2)$.66	.76	.80

Table 2
Observed Values of $P(A_1, n+1 | T_{i, n+1} T_{j, n} A_{k, n} E_{\ell, n})$ for $\pi = .6$ Pooled over Trial Blocks

$T_{i, n+1}$	$T_{j, n}$	$A_{k, n}$	$E_{\ell, n}$		
1	1	1	1	.782	(763)
1	1	1	2	.685	(422)
1	1	2	1	.602	(284)
1	1	2	2	.462	(158)
1	2	1	1	.768	(202)
1	2	1	2	.747	(277)
1	2	2	1	.740	(466)
1	2	2	2	.766	(597)
2	1	1	1	.300	(644)
2	1	1	2	.236	(467)
2	1	2	1	.264	(231)
2	1	2	2	.232	(198)
2	2	1	1	.571	(238)
2	2	1	2	.438	(208)
2	2	2	1	.398	(460)
2	2	2	2	.259	(622)

Note: Entries in parentheses are the number of cases contributing to the denominators of each conditional probability.

would agree with the experimental feedback rather than the actual cue presented on that trial.

Sequential Statistics

The marginal response probabilities have indicated that Ss learn to respond loud or soft with respect to the feedback in the situation rather than according to the actual loudness of the cue. The reinforcement effects should indicate whether Ss are reinforced on a trial-to-trial basis or if, after a number of trials, they choose a strategy and behave according to the strategy independent of the events on the previous trial. For example, if Ss were receiving 80% incorrect feedback they could respond according to the following strategy: Respond "loud" to the soft tone, respond "soft" to the loud tone, and respond randomly if the cue is not identified.

Table 2 presents the first-order conditional probabilities for the group with 60% correct feedback pooled over trial blocks. The trends shown in the table also hold for the other groups. As can be seen in the table, the probability of a response on a given trial appears to be highly dependent upon the response and feedback of the previous trial only when the cues presented on the two trials are the same. A statistical test of this hypothesis was performed by computing a χ^2 value between the conditional probabilities in Table 2 and their appropriate marginal response probabilities, $P(A_1 | T_i T_j)$, $i, j = 1, 2$. Summing the χ^2 values when $T_{i, n+1} = T_{j, n}$ gives a χ^2 value on 6 df. The χ^2 value of 166.86, $p < .001$, indicates that $P(A_1)$ was highly dependent on the response and feedback of the previous trial when the trial types were the same. More specifically, when the tones presented on Trial n and Trial $n+1$ were the same, $P(A_1 | A_1 E_1) > P(A_1 | A_1 E_2) > P(A_1 | A_2 E_1) > P(A_1 | A_2 E_2)$. These results agree with the sequential statistics found in two-choice discriminative probability learning (Massaro, 1969).

On the other hand, when the tones presented on the two trials are different, there is no particular rank-ordering among these conditional response probabilities and they do not appear to differ significantly from one another. The χ^2 value (computed as above) for the conditional probabilities when $T_{i, n+1} \neq T_{j, n}$ was 8.39, $p > .2$. Therefore, it is reasonable to conclude that Ss in the present study were not influenced by the response and feedback on Trial n in determining their response on Trial $n+1$ when the two trials were identified as different.

DISCUSSION

The results have indicated that Ss learn to respond

appropriately as defined by the feedback in the experimental setting rather than according to the subjective loudness of the tones. Therefore, with sufficient incorrect feedback, Ss learned to call a loud tone "soft" and a soft tone "loud." The assumption of extant learning models of detection performance that feedback only changes response probability in the uncertain state does not seem to be sufficient to predict these results. Also, it is difficult to see how the fluctuating criterion proposed by Carterette et al (1966) can account for the results. However, the view that feedback influences response probability, given a detection state, handles the results very nicely.

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NOTE

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