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MEMORY AND DECISION ASPECTS OF RECOGNITION LEARNING[1]

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Recognition learning may be described as a discrete state process involving transitions between an initial state, a temporary memory state, and a learning state. It is assumed that Ss judge the familiarity of learning items on an essentially continuous scale, but that decision criteria are established which divide this scale into separate regions corresponding to the states of the model. With the assumption of an underlying continuous familiarity scale the learning model can account for confidence judgments during recognition learning. Memory-operating characteristics derived from the model were found to be in general agreement with experimental data. The learning, forgetting, and decision assumptions of the model were discussed with respect to relevant empirical evidence.

There are two important aspects of recognition learning which appear superficially to be inconsistent with each other. On the one hand, learning may usefully be regarded as a process of transitions between discrete memory states, rather than an incremental acquisition process. On the other hand, introspection shows that we are quite sensitive to differences in the goodness of memory traces when we attempt to recognize something. In fact, familiarity judgments have become very important for the distinction between decision processes and memory itself in the recognition experiment. It remains to reconcile the apparently continuous familiarity judgments with the discrete learning states postulated above.

The recognition experiments discussed here follow a design introduced by Shepard and Teghtsoonian (1961). The subject (*S*) is shown a learning item and asked to memorize it. Later, he must decide whether a test item, which may or may not be identical with the learning item, is "old" or "new." A particular item may be presented repeatedly, and we shall refer to successive presentations of the same items as learning trials. Because *S*s only rarely make recognition errors with meaningful material, meaningless letter or number combinations constitute the items used in recognition learning studies. Usually the interval between trials is filled with presentations and tests of other items. Note that when an item is presented *S* both decides whether to call the item old or new and stores it for further reference.

The pertinent results obtained with this experimental procedure are twofold. First, Shepard and Teghtsoonian (1961) explored the relationship between correct recognitions and the length of the presentation-test interval. They obtained a rapid decay of memory over the first few intervening items, similar to the short-term memory function observed with other testing procedures. Second, if *S*'s response on each trial is coded as correct or incorrect, the resulting symbol sequence may be described by a three-state Markov

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model (Kintsch, 1966). The model is a memory model of the type suggested by Atkinson and Crothers (1964) and distinguishes a learning state, a temporary memory state, and an initial state. Learning is thought to be a discrete process, corresponding to the entry into the learning state. Before learning is completed items are stored in short-term memory at each presentation, but they drop out of memory with a probability depending upon the length and content of the presentation-test interval.

The learning model refers to the sequence of correct and incorrect recognition responses. However, problems arise as soon as we broaden the range of relevant data. Suppose we not only record whether or not a recognition response was correct, but also the subjective impression of familiarity which accompanies that response, or, a little more formally, *S*'s confidence ratings. It is easy to show that *S*s can judge their confidence in their response better than implied by a three-state learning model. This ability of *S*s to rate their familiarity with a recognition item quite accurately provided the basis for the construction of memory-operating characteristics (Egan, 1958; Murdock, 1965; Norman & Wickelgren, 1965; Parks, 1966). The memory-operating characteristic (MOC) is a plot of the proportion of acceptances of old items (the hit rate) versus the proportion of acceptances of new items (corresponding to the false-alarm rate in detection experiments). Different points on the curve are obtained by varying *S*'s acceptance criterion in accordance with his confidence judgments. Suppose *S* rates his confidence in his recognition response on a four-point scale, from 1 (pure guess) to 4 (absolutely certain). Each rating category may be regarded as establishing a cut-off point on a familiarity scale, such that only items with a familiarity value greater than this cut-off will be given a higher rating. Thus, we may estimate a hit rate associated with the cut-off point Yes-2 by calculating the proportion of all old items with a rating of Yes-2 or less. Similarly we can calculate the proportion of all new items which were rated Yes-2 or less to obtain an estimate of the probability of a false acceptance for this cut-off point. Figure 2 shows such a plot. The data come from three different experimental conditions which will be described later. Here it is sufficient to point out that memory strength is apparently unequal for the three conditions. The distance of each MOC from the chance line serves as an unbiased estimate of memory strength.

MOCs make possible an explicit distinction between the memory and decision aspects of recognition. As long as these remain confounded, successful analysis of the recognition process cannot be achieved. The new techniques have already been put to use in the reanalysis of some important psychological problems, such as the serial position effect in short-term recognition memory (Wickelgren & Norman, 1966) and the role of testing conditions in recognition performance (Kintsch, 1967).

A model which reconciles continuous familiarity judgments with discrete learning states may be obtained by redefining the states of the Markov model as regions on a familiarity scale. Figure 1 shows a diagram of the three-state Markov model and its reinterpretation with an underlying familiarity continuum. The assumptions of the model may be stated as follows:

1. *Distributions of familiarity values of items:* The familiarity of each item in a recognition experiment is represented by a values s on a continuous scale. Let the familiarity values of

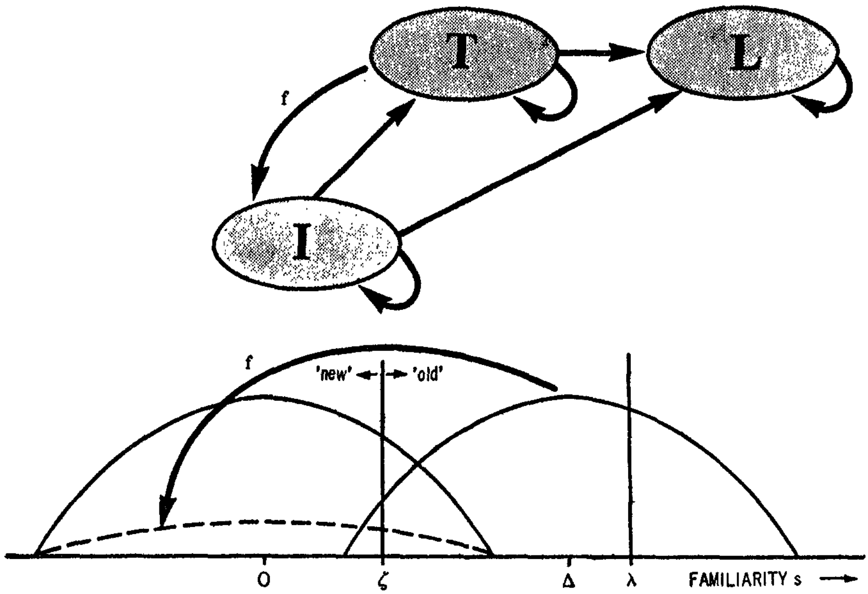

FIG. 1. Two representations of a three-state Markov model for recognition memory.

items which are presented for the first time be distributed according to the frequency distribution $\psi(s)$. Let $\phi(s)$ be a distribution of familiarity values which is identical with $\psi(s)$ except that it is pushed up the familiarity scale by an amount Δ, that is, $\psi(s-\Delta)=\phi(s)$. In general, experimental conditions assure that Δ is sufficiently small relative to the standard deviation of $\phi(s)$ so that the two distributions overlap.

2. *Response assumptions:* When an item is presented for a test trial *S* has available only the familiarity value s of that item and he must make his decision to call the item old or new on the basis of its familiarity value. The *S*s are assumed to establish a decision criterion ζ such that whenever an item with familiarity $s > \zeta$ is encountered, the item will be called old; whenever $s < \zeta$, the item will be called new. Thus, a false recognition is made whenever a new item has an s-value greater than ζ. Let g be the proportion of new items for which a false recognition occurs.

3. *Forgetting assumptions:* Following Norman and Wickelgren (1965), we assume that items presented for study receive a familiarity value which, on the average, is higher than the familiarity value of the new item. However, this increase in familiarity is not always permanent. Between presentation and test of an item forgetting may occur. Forgotten items are equivalent to items never presented before, that is, they are reassigned a familiarity value according to $\psi(s)$. The probability of forgetting is assumed to depend upon the duration and content of this retention interval, as well as other relevant experimental conditions. In addition, the forgetting probability depends upon the familiarity value of an item: if s is sufficiently high, no more forgetting occurs within the limits of the experimental session. Thus, a cut-off point λ may be defined

such that whenever $s > \lambda$ items are no longer subject to forgetting. On the other hand, whenever an item is studied and receives a familiarity value $s < \lambda$, forgetting is possible. Let f be the average forgetting probability for items below the cut-off λ.

4. *Learning assumptions:* Learning in this model is a discrete event and consists in the assignment of a new familiarity value s' to an item when it is presented for study. The following rules are assumed to govern this assignment:

a. If an item is presented which has a familiarity value $s < \zeta$, a new value s' is assigned according to the probability distribution $\phi(s)$. Two parameters of the model are defined as follows: a is the probability that the newly assigned s-value will be greater than ζ, and ac is the probability that this value will be greater than λ.

b. If an item is presented with a familiarity value $\zeta < s < \lambda$, a new value s' is assigned according to the probability distribution $\phi(s)$ truncated at ζ and normalized. Thus, if an item has a familiarity value high enough for a false recognition, learning will not decrease this value below the criterion value. Note that $\Pr(s' > \lambda \mid \zeta < s < \lambda) = c$.

c. If an item is presented for study with a familiarity value $s > \lambda$, it will not be processed further.

An item is said to be in the learning state L if its familiarity value $s > \lambda$; if $\zeta < s < \lambda$, the item is in the temporary memory state T; if $s < \zeta$, the item is in the initial state I. The transition probabilities between these three states can easily be derived from the assumptions stated above. New items are in the initial state with probability $(1 - g)$ and in State T with probability g. The probability of a transition from I to T is ac, according to 4a. The probability of a transition from I to T consists of several terms: first, with probability $a\,(1 - c)$ items may receive a familiarity value $\zeta < s < \lambda$, and are not forgotten with probability $(1 - f)$; another group of items also receives familiarity values between ζ and λ, $(a[1 - c])$, but are then forgotten (f), and reassigned an s-value high enough for a false recognition (g); finally, some items acquire a familiarity $s < \zeta$ upon presentation $(1 - a)$, but are then forgotten and a false recognition occurs (fg). The transition probabilities from State T are obtained similarly; the probability of a transition from T to L is c according to 4b above; the probability of remaining in T equals the probability that an item does not enter L, $(1 - c)$, and the probability that it is either not forgotten or, if forgotten, a false recognition occurs $(1 - f + fg)$. State L is an absorbing state. Thus, we have

$$\begin{array}{l} \\ L(s>\lambda) \\ T(\zeta<s<\lambda) \\ I(s<\zeta) \end{array} \begin{array}{c} \begin{array}{ccc} \quad L \quad & \qquad T \qquad & \qquad I \qquad \end{array} \\ \begin{bmatrix} 1 & 0 & 0 \\ c & (1-c)(1-f+fg) & (1-c)(f-fg) \\ ac & a(1-c)(1-f+fg)+(1-a)fg & a(1-c)(f-fg)+(1-a)(1-fg) \end{bmatrix} \end{array}. \quad [1]$$

The starting vector for this model is $\pi = (0,\ g,\ 1 - g)$. The model is a three-parameter model as far as the learning data are concerned because g, the false recognition rate, may be estimated from new items. The following relationships between the graph in Figure 1 and the parameters of the model hold:

$$g = \int_{\zeta}^{\infty} \psi(s)ds, \quad a = \int_{\zeta}^{\infty} \phi(s)ds, \quad c = \frac{\int_{\lambda}^{\infty} \phi(s)ds}{\int_{\zeta}^{\infty} \phi(s)ds}. \qquad [2]$$

Solutions for ζ, λ, and Δ in terms of the model parameters may be obtained from these expressions. For numerical calculations it is, of course, necessary to assume that $\psi(s)$ and $\phi(s)$ are normal with equal variance. Predicted MOCs based entirely upon the learning sequence may be obtained from this model. The MOC is a plot of the probability of correct acceptances of an item against the probability of a false recognition. The two expressions are easily obtained from Equation 1:

$$\begin{aligned} &P(\text{acceptance/no prior presentation of an item}) = g. \\ &P(\text{acceptance/one prior presentation of an item}) \\ &\quad = g\{c + (1-c)(1-f+fg)\} + (1-g)\{ac + a(1-c)(1-f+fg) \\ &\qquad + (1-a)fg\}. \qquad [3] \end{aligned}$$

Substituting the values obtained in Equation 2 and varying the decision criterion from small (lax criterion) to large (strict criterion), a predicted MOC can be traced out which is independent of the confidence judgments upon which the observed MOC is based.

An experiment was conducted to test the feasibility of predicting the MOC in this manner from a Markov model. The *S*s were presented with a sequence of 250 items, some of which were repetitions, and responded to each number with either "old" or "new." The items were four-place numbers, with the restriction that 0 was not used in first place and that no digits appeared more than twice in each number. Sixty undergraduates served as *S*s, 10 for each of six different lists. The first 10 numbers in each list were warm-up trials and are not included in the data analysis. Thirty items were presented five times each. The number of other items intervening between successive presentations of the 30 experimental items was one for a third of the items (Delay 1), three for a second third (Delay 3), and 10 for the last third (Delay 10). Twenty items were presented twice with a delay varying from 0 to 19. Fifty filler items were presented only once. The *S*s were tested separately. Items were printed on 3 × 5 inch index cards. The experimenter presented the items at a rate of one every 4 seconds for the first four lists, and one every 1½ seconds for the last two lists. The *S*s rated their confidence in the correctness of their responses on a five-point scale.

The experimental results were in agreement with the results commonly obtained in experiments of this kind with respect to false recognition rates, effects of delay, and effects of repetitions (Kintsch, 1966; Shepard & Teghtsoonian, 1961). MOCs were computed separately for each delay condition from *S*s' responses to the first and second presentations of each item and are shown in Figure 2. In order to compare the obtained MOCs with theoretical curves, numerical estimates for the parameters of the model were obtained. The parameter g of the model was estimated from the proportion of "old" responses to items presented for the first time. The re-

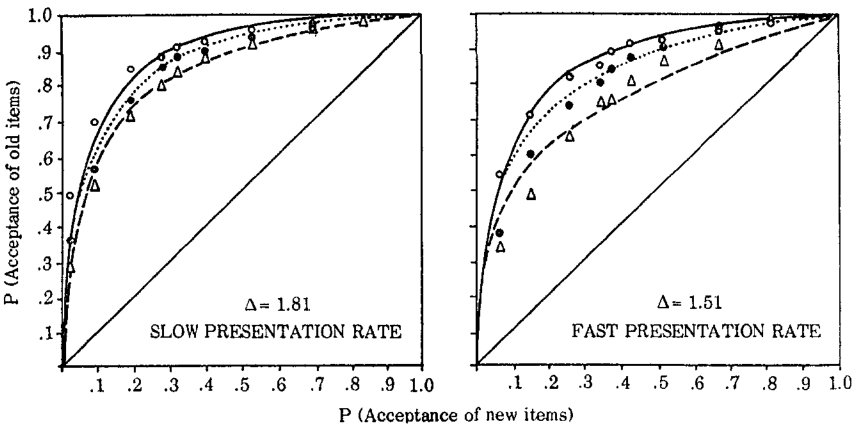

FIG. 2. Memory-operating characteristics for fast and slow presentation rates. (The data for the Delay 1, Delay 3, and Delay 10 conditions are represented by open circles, closed circles, and triangles, respectively. The smooth curves are the predictions derived from the theory.)

sponses to items presented for the second, third, and fourth time were used to estimate the remaining parameters of the model. A computer searched for values of a, c, and f which minimized the chi square between the observed and expected response triplets for Trials 2–4. Separate estimates were obtained for each delay condition under both the fast and slow presentation rate with the restriction that the same a value was used for all delay conditions of a given presentation rate. This restriction was necessary because the values of a and g together determine the distance Δ between the means of $\phi(s)$ and $\psi(s)$, which should be independent of the presentation-test interval. The resulting minimum chi-square values were 23.49 for the fast presentation rate and 12.10 for the slow presentation rate. Since three sets of eight response triplets were used for each estimation, and three values of c and f, respectively, as well as one a value were estimated, each chi square has $21 - 7 = 14$ degrees of freedom. Thus, theoretical values do not deviate significantly from the data at the 5% level. When the a estimates were not restricted, somewhat lower minimum chi-square values were obtained. The statistical significance of the reduction in minimum chi square occasioned by allowing a to vary freely may be ascertained by taking the difference between the two minimum chi squares and interpreting it as a chi square with two degrees of freedom (Young, 1966). A significant value was obtained for the fast presentation rate ($\chi^2 = 9.99$) but not for the slow presentation rate ($\chi^2 = 3.29$).

The parameter estimates described above were substituted in Equation 3, and the MOCs predicted from the model were calculated by varying ζ. A comparison between data and theory is presented in Figure 2. The model manages to reflect the principal features of the data, although the quantitative fit is not perfect. Note that the three predicted MOC curves in each case are based upon the same Δ values, differences among them being due to different short-term forgetting and learning parameters which alone depend upon the presentation-test interval.

The present data demonstrate that there is no inherent contradiction between Markov learning models and the approach to recognition learning which stresses the role of decision processes in memory. However, these results do not constitute incontrovertible support for the proposed theory because we are unable at this time to exclude several possible alternative explanations. As is the case in psychophysics, there seems to be no easy way of deciding between discrete-state models, continuous models, or the hybrid suggested here. One might, for example, reject the idea of a continuous familiarity dimension and devise a low-threshold recognition system following the example of Luce (1963) in psychophysics. Wickelgren and Norman (1966), on the other hand, have developed a decision theory for recognition memory employing response strength as a basic concept. Bernbach (1967) has combined continuous and discrete aspects in a way similar to the present model. Since memory-operating characteristics obtained from confidence ratings are useless for a decision between continuous and discrete models (Larkin, 1965), a choice between these alternatives must be made on the basis of the old-new responses alone. Although the present report does not permit an unambiguous choice, the available evidence does provide some support for several features of the proposed model and thereby restricts alternative theories. The following observations concerning the present model should be noted:

1. The forgetting assumptions of the model derive support from the fact that estimates of the forgetting probability f are correlated with the length of the retention interval in both the present study and earlier work (Kintsch, 1966). The observation that the theoretical forgetting probability covaries appropriately with experimental manipulations strengthens the interpretation given to the model. In addition, it might be pointed out that the idea of looking at the learning process from the standpoint of intertrial forgetting has been very successful in other areas of verbal learning and has received quite direct empirical support in a study of paired-associate learning (Bjork, 1966).

2. The experiment reported above provides data relevant to the assumption that new items with a familiarity value s greater than the response criterion ζ are learned faster than items with a lower familiarity value. An index of how "new" items seem when they are first presented was computed by assigning an arbitrary scale value of -5 to a response "old, 5," a -4 to a response "old, 4," and so on up to a $+5$ for a response "new, 5." The average value on this scale was computed separately for items which were always called old on later learning trials and items for which one or more errors occurred later. Averages of 1.13 and 2.42, respectively, were obtained for the slow presentation rate. The corresponding values for the fast presentation rate are .67 and 1.90. Obviously, items which will always be called old look older even on the very first presentation. This observation is in agreement with the assumption that items relatively high on the familiarity scale have a greater probability of entering the learning state than items with a low familiarity value.

3. The principal support for the assumption of the existence of a cut-off point which defines the learning state of the model has been presented by Kintsch (1966). It has been observed that the probability of entering the learning state depends upon the intertrial interval. As the intertrial interval increases, more forgetting occurs, and the familiarity value of an item must be increasingly higher for it to enter

the learning state, since the latter is defined with respect to the absence of forgetting. The learning state literally decreases in size as the task becomes more difficult. A transfer design provided support for this argument: If the task is very easy, some items will be in the learning state without having acquired a high familiarity value; if the task is suddenly made more difficult, the the criterion for the learning state will be increased and the familiarity value of these items is no longer sufficient for inclusion in the learning state. The long-term superiority of distributed over massed practice was attributed to this effect.

4. The argument presented above, that the learning state is not something fixed by the experimental material, but, in addition, depends upon task difficulty, provides some of the motivation for the assumption of a familiarity continuum underlying the states of the model. At least, this assumption helps to understand how variations in the learning state may arise.

The present model may be regarded as a more general version of the Kintsch (1966) model. The latter is a special case of Equation 1 with $a = 1$. It is interesting to note that goodness of fit is very little impaired by the $a = 1$ restriction, as measured by the minimum chi-square criterion. However, the more general model is necessary if we want to predict MOCs successfully because when $a = 1$, Δ must be large, that is, we are restricted to the case of two essentially nonoverlapping distributions $\psi(s)$ and $\phi(s)$. Thus the parameter a may be disregarded when one is merely concerned with the goodness of fit of the learning data, since its introduction leads to only negligible improvement. However, if other aspects of the data are to be included, the extra degree of freedom afforded by this parameter becomes important.

Kintsch and Carlson (in press) have used the MOC to confirm the prediction of the simple one-trial learning model that precriterion performance in recognition learning is stationary. They used a two-alternative paired-associate task, an experimental design which is well known to provide stationary precriterion data. With the present steady-state procedure, performance before the last error is not stationary but improves consistently, whether measured by the MOC or by response probabilities. Also, Equation 1 does not imply stationarity when $a \neq 1$. Stationarity, then, is not a general requirement of Markov models but is restricted to some particularly simple conditions.

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