Judging from an intuitive frequency count, one must infer that encoding (coding or recoding) is a truly central concept in modern theories of memory. My suspicion is that variability of reference accounts in part for the high frequency of the term in theoretical discourse. The concept of encoding is used in many different senses, and it would take a practicing semanticist forty days hard labor to disentangle all its senses and their commonality of reference.

Those contributing to this volume agree that coding is a critical component in any psychological account of behavior. This is because we do not believe in the empty organism nor conceive of the person as a reliable through-put channel. In fact, the empty-organism view is today a barren strawman, held by very few psychologists. Rather, most psychologists today agree that responses of the organism to stimulation are mediated by that organism’s cognitive state, which provides a context for and an interpretation of the stimulus as it makes contact with the record of his past experiences. We believe that a most significant aspect of the record of an event is how it comes to be represented in the person’s memory.

The representation of an event in memory is significant for later performance. Let us enumerate a few of these reasons.

1. The representation of a set of events determines the proximity metric or psychological distances among those events. The psychological distance between the representations of event A and event B determines performances such as recognition of identity from memory, identification, differentiation, and stimulus generalization between the two events. In practice, of course, the theorist usually

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works in the reverse direction; given an observed pattern of generalization among stimuli, the theorist infers a set of distances between their representations expressed as points in a Euclidean space (Shepard, 1962), and these relations typically imply further generalization effects.

2. The representation of an event in memory also determines the types of other events that will interfere with memory of it. Recall of a given event can be drastically reduced by interpolation of extraneous material that is encoded in a similar manner. A good illustration of this is the research on release from proactive interference by Wickens (this volume); memory declines over a series of tests with items from the same class of materials, but it can be reinstated to a high level by switching to items that are encoded in significantly different ways.

3. The representation of an event in memory also determines the effectiveness of certain kinds of cues for retrieving that event. Tulving and Oster (1968) and Tulving and Thomson (1971) have conjectured that a given cue will serve as a retrieval cue for a to-be-remembered item only if the item is encoded in relation to that cue. A good illustration of this is an experiment on cued recall of ambiguous words by Bobrow and Light (cited in Bower, 1970). Their subjects studied a list of adjective-noun pairs, with the adjective stipulating one particular meaning of the ambiguous noun. A cued recall test followed in which the cue given was appropriate or inappropriate to the studied meaning of the noun. Recall was best when the cues corresponded to the studied noun meaning. The category name bird, for example, was a good retrieval cue for the word cardinal if it had been studied in the context chirping cardinal but not if it had been studied in the context church cardinal.

There are doubtless other effects of the memory representation of an event, for example, the usefulness of various representations for verbal problem solving. However, the three mentioned—the proximity structure of events, their interference properties, and retrieval-cue effectiveness—illustrate the significance for memory theorists of the concepts of internal representations and encoding as the process of activating a given internal representation from the nominal input stimulus.

As stated earlier, encoding is used in several different ways by memory theorists. I will indicate briefly what I view as the several main senses of the concept. In brief, they involve coding viewed as selection, as rewriting, as componential description, and as elaboration. These several uses of the coding concept will be briefly illustrated.

**Coding as stimulus selection.** In this usage, the concept of coding refers to explicit selection by the subject of a component of a complex but fractionable stimulus pattern, which selected element is used as the critical element of the entire complex. Examples would be responding to the color but not the shape of concept identification patterns, or selecting the first letter of a trigram to cue the response in paired-associate learning. In the case of concept identification (e.g., Trabasso & Bower, 1968) and discrimination learning (e.g., Sutherland & Mackintosh, 1971), the selection of an attribute or dimension of stimulus variation is done by an observing response or attentional response of some kind. This selection is presumed to be learned and governed by simple reinforcement principles, as "win-stay, lose-shift," and the theories in this area are supported by an extensive array of evidence. Similar cue selection is observed in paired-associate learning. In recognition of such
facts, Underwood (1963) and others have distinguished the nominal (full) stimulus from the functional (selected fractional) stimulus. The main principles assumed to govern stimulus selection are those of Gibsonian differentiation (Gibson, 1940) along with differential reinforcement. A component is likely to be selected if it enables effective differentiation between the nominal stimulus in question and the others on the list. Richardson (this volume) addresses his paper directly to these issues of stimulus selection.

Coding as rewriting. Rewriting was the sense of coding used initially in Miller's (1956) "Magical Number 7" paper. The explicit example cited was Sydney Smith's experiment on recoding of series of binary digits into octal digits. This required Smith to learn and apply a dictionary in which triplets of binary digits were rewritten (in immediate memory) as octal digits. Thus, 000 was rewritten as 0, 001 as 1, 010 as 2, 011 as 3, and so forth. In this manner, Smith could recode a string of 21 binary digits into 7 octal digits and, by this ruse, increase his immediate memory span for strings of binary digits. Slak (1970) has reported elaborations of these basic results, using a "decimal digit-plus-location to phoneme" dictionary to code three-digit numbers into distinct, pronounceable syllables. These two illustrations are transparent examples of rewriting of the input into another mode, which is then remembered and later decoded to mediate recall of the original string. A less obvious but nonetheless equally compelling illustration of coding is verbal encoding (descriptions) of visual stimulus patterns. A clear example is the verbal encodings of binary sequences studied by Glanzer and Clark (1963). A briefly presented binary sequence was well remembered if it tended to arouse a short verbal description, for example, "alternating 1s and 0s." A more remote illustration of coding as rewriting is Johnson's (this volume) use of the term "code" to denote an abstract name for a sequence of a few letters in the chunked letter strings that Johnson's subjects learned. Johnson does not coordinate his hypothetical codes with the occurrence of actual names to the subject (e.g., "second chunk of first half") although nothing in his theory prescribes such identifications.

Coding as componential description. In this third sense, an item presented to the memory system becomes represented in terms of a list of components, attributes, properties, or features, where the ith entry on the list specifies the value of attribute i for that item. For words, the list of features might include the phonemes in the word, a set of semantic markers characterizing the meaning of the word, semantic categories to which it belongs, its ratings on the Value-Potency-Activity poles of the Semantic Differential Scale, and so forth. Papers by Bower (1967a), and especially Underwood (1969) and Wickens (this volume) should be consulted for illustrative details. The general belief is that presentation of an item leads to a relatively complete analysis or activation of its various features. (Shulman, 1970, has conjectured that acoustic properties become available sooner than semantic components of a briefly presented word that is being committed to memory.) These models represent similarity of two events in terms of geometrical distance between the vectors (points) corresponding to those events. For instance, Wickens assesses the similarity of coding of items in class A versus those in class B by his release-from-PI technique. If the shift from A to B causes no release from PI, then items in the two classes are said to be encoded similarly.
On this view, the location of a given item in the feature space may vary from one presentation to another if its interpretive context changes. Thus the semantic markers representing occurrence of the word jam will vary depending on whether the person interprets it as traffic jam or strawberry jam (see Light & Carter-Sobell, 1970).

Coding as elaboration. In this sense of coding, the input is assumed to give rise to associated operators that qualitatively transform the to-be-remembered item. The best illustration of this type of coding is the occurrence of natural language mediators for learning nonsense syllables (see Prytulak, 1971). In such cases, a CVC stimulus is altered in some way to make it into a word—a suffix or prefix is added, a letter is inserted in the middle, a letter is replaced by another, letters are permuted, or a sequence of two or more such elementary operations may be used (as in PYM → PaYMen). Prytulak classified such operations, ranked them in priority or preference of their use, and showed that syllables transformable to a word by a high-priority operation also tend to have a high association value. Regarding learning of a CVC, the basic idea is that the person first searches for a transformation that converts the CVC to a word, and then he remembers the word plus the transformation. At the time of recall, the inverse transformation (e.g., “delete the suffix”) is applied to the word to yield the original CVC. Prytulak showed that this hypothesis gave a decent account of the memorability of different CVCs as well as the types of decoding errors subjects made while recalling. So, in this illustration, the word plus transformation serve as a code for the original CVC.

A second illustration of coding as elaboration is that by Bower (in press), Paivio (1969), and others investigating mental imagery as a way of remembering words. Under appropriate instructional conditions, the person can apparently substitute a mental image for a word having the same referent. One might say that the image codes the word. Under circumstances of serial, paired-associate, or free recall learning, this conversion apparently enhances the person’s learning rate (Paivio, 1969). Why this happens is still to be explained, despite much effort expended on the issue. One can obtain a similar facilitation of paired-associate and serial learning of unrelated words if the individual words are bound together by meaningful phrases or sentences. In this latter case, we might say that the subject’s action phrase “flower sprouting out of a gun” codes the unrelated word pair flower-gun, and that he recalls the pair by redintegrating the phrase from the cue of flower.

Having briefly reviewed the several uses of the concept of coding in discussions of memory, I turn now to the main task of my paper. What I hope to do is to provide an abstract theoretical framework within which ideas about encoding and encoding variability of stimulus events achieve a natural representation. Because I am primarily interested in memory, the implications of this theory for recognition memory will be the primary focus of my discussion. Moreover, I will attempt to show also how the theory applies to other mnemonic phenomena such as list differentiation, temporal lag judgments, retrograde amnesia, and to the relations between recall and recognition in paired-associate learning. That is a tall order and I will be satisfied if a fraction of the hypotheses prove viable.
THE THEORY

Review of Martin's Formulation

The theoretical framework to be developed is an amalgamation of the approach of Lawrence (1963) and Martin (1968) with the stimulus sampling theory of Estes (1959). I will show this correspondence, then proceed to theoretical derivations of phenomena within the context of stimulus sampling theory. We begin by some review of Lawrence's and Martin's main concepts.

As in all such theories, the basic idea is that stimulus control of responding is mediated through an encoding process. Both Lawrence and Martin thought of encoding as representable as a response process operating on the nominal stimulus, which process has as output one or another functional stimulus. The output of an encoding operation applied to a stimulus will be a particular "stimulus-as-coded," which term we will abbreviate as s-a-c. Martin's system is schematized in Figure 1, showing a nominal stimulus leading to one of three encoding operations. Regarding the encoding operation, Martin says "r₁-r₂ is a central event composed of a perceptual response, r₁, plus the consequent functional encoding, s₁, of the nominal stimulus S" (p. 422). From comments throughout Martin's paper, it is clear that he usually thinks of these perceptual encoding responses as selective focusing on one or another fragment of a verbal stimulus, like the first or third letter of a consonant trigram. This is similar to the observing response theory of selection in discrimination learning (e.g., Zeaman & House, 1963).

![Diagram](image)

**FIG. 1.** Illustration of encoding of a nominal stimulus by one of several perceptual-encoding responses, r₁, leading to the stimulus-as-coded, s₁.

Central to Martin's theory is the idea that selection of an encoding response is a probabilistic matter, that we can define a probability-of-selection distribution over the several encoding responses. In fact, his chief auxiliary hypothesis was that this distribution is more variable for low-meaningful than for high-meaningful trigrams. However, it is supposed that this distribution may change with learning so that one (or one of two) encodings is occurring on every trial. In this view, one and only one encoding response can occur at a given moment in time; in fact, during the presentation time of an experimental trial, it is usually assumed that only one encoding occurs.
As in other encoding or attention theories of learning (e.g., Trabasso & Bower, 1968), it is assumed that the s-a-c on a trial controls the response (if any) performed on that trial. Also the s-a-c is the unit that enters into any new associations to overt responses due to the reinforcing events that terminate the trial. These reinforcing events are usually assumed also to affect the selective encoding probabilities in an adaptive manner, enabling differentiation of the present nominal stimulus from other stimuli in the list.

Two further remarks will complete our review of the main concepts. First, the discriminability of two nominal stimuli depends on the identity of their encoding. So long as two stimuli are encoded in the same way, differential responses cannot be attached to them. Similarity of coding causes a cluster of item interactions labelled by names such as “false-alarm recognitions,” “stimulus generalization errors,” and “inter-item associative interference.”

The second remark is related to the foregoing and it concerns recognition of identity from memory. A nominal stimulus will be recognized as a repeat of one seen earlier (will be confused with itself) only if it is encoded in the same way on its two presentations. We may conceive of this as follows: At the first presentation of a nominal stimulus, the s-a-c is marked or tagged as having occurred; then upon the second presentation of the nominal complex, the s-a-c at that time is checked for a tag. If it is tagged, the subject decides that this stimulus occurred earlier in the experiment; if it is not tagged, the subject is likely to guess that he has not seen this stimulus before in the experimental context. This is not a very sophisticated model for the decision process in recognition-memory judgments, but Martin was not concerned with elaborating the model in this respect in his paper. He was more concerned with testing assumptions regarding stimulus-meaningfulness, negative transfer and unlearning in A-B, A-Br paradigms, which elaborations seem to have encountered a few empirical difficulties (see Williams & Underwood, 1970).

Before leaving this review of encoding theory in verbal learning, one should note the fundamental similarity of such theories to the class of two-process theories of discrimination learning and concept identification. The basic concepts and ideas are much the same; encoding responses (Lawrence, 1963; Martin, 1968), mediating responses (Kendler & Kendler, 1962), observing responses (Zearman & House, 1963), attentional selection (Trabasso & Bower, 1968), and switched-in stimulus analyzers (Sutherland & Mackintosh, 1971) are all theoretical devices for converting a nominal into a functional stimulus that controls performance in an adaptive way. The ideas differ somewhat because of details of the reference experiments. For example, the stimuli in concept identification experiments are typically highly dimensionalized patterns (e.g., geometric figures varying in size, color, and shape), and to each dimension is coordinated a “dimensional encoding process” of some kind. Also the nature of the usual S-R reinforcement contingencies in concept identification enables the subject to “solve” by applying the same encoding operation to each stimulus pattern of the entire set, for example, asking in effect “What size is the nominal stimulus?” The verbal learning applications differ insofar as the usual dimensions of fractionation are the letter positions, and it is rarely the case that one and the same encoding operation (such as “look at the first letter”) will suffice to discriminate all the list stimuli that require different responses.
Coordinating Encoding Concepts to Stimulus-Sampling Theory

Stimulus-sampling theory provides a mathematical framework for representing stimulus variability, S–R associations, and the effects of variability on learning and performance. It also provides a natural account of forgetting in terms of spontaneous alterations in the stimulus-encoding process. The main ideas and their coordinating encoding concepts may be enumerated as follows:

1. Each nominal stimulus in the experiment (e.g., presentation to the subject of the trigram XQH) may give rise to a number of possible stimulus elements or components. We let N denote the total number of these potential stimulus elements that could ever be aroused in a given subject by presentations of the item XQH. Herein, each stimulus element will be conceived of as the output of a particular encoding response or encoding operation. That is, the terms, “stimulus element” and “s-a-c” will be taken to have the same referents.

2. For each distinct experimental item, there will be a corresponding set of stimulus elements. The sets corresponding to two nominal stimuli may share common elements (overlap), and these will be the basis for stimulus generalization. For instance, the encoding operation “select first letter” would produce a common element in the stimulus populations corresponding to the trigrams XQH and XZK, and such encoding would produce generalization between the two trigrams.

3. Each stimulus element may be associated in all-or-none fashion to one or more responses or other cognitive elements (ideas or thoughts). Admitting association of ideas retreats from a strict S–R framework, but I think it is needed to handle several facts including, for example, associations from an item to an implicit list marker. Furthermore, admitting that a stimulus element may be simultaneously associated to two or more responses or ideas departs from established convention in stimulus-sampling theory, but I feel it too is a necessary breach. There is simply too much evidence showing that learning a second association to a stimulus need not cause unlearning of an earlier association but rather only edited differentiation or temporary suppression of the earlier response.

4. Performance to a nominal stimulus is dependent upon the associative connections of the elements in the active sample. The response in most cases will be, in effect, a decision made with respect to criteria required by a particular memory test. For instance, for each nominal stimulus, the subject may be asked to decide whether it was presented before in a training series, or whether it appeared in List 1 rather than List 2, or how long ago was an earlier presentation of the item. Theoretical interpretations of particular judgments will be discussed as the theory is applied to the respective contexts.

The assumptions above are the modified framework of stimulus-sampling theory as I shall use it here. Since I believe that people are better at remembering pictures, I offer Figure 2 as a pictorially encoded summary of the main stimulus-sampling ideas. This shows a nominal stimulus going through the encoding process, which is represented as a set of N operators or encoding responses. The probabilities, θ_i, are to be interpreted as the likelihood that operator i will be used, thus leading to activation of s-a-c or stimulus element s_i. These elements comprise the population of potential stimulus elements that could be aroused by presentation of a particular
item such as the trigram XQH. On the far right are shown illustrative associative connections between the s-a-cs and responses or ideas.

As noted above, a number of sampling schemes are possible, but relatively few are mathematically tractable. The particular sampling scheme that will be used in this paper is called the fixed-sample-size scheme. It is assumed that exactly \( n \) encoding operators are active on each trial, resulting in \( s \) active stimulus elements whenever a nominal stimulus complex is presented. The \( s \) operators that will be active on a given trial are partly described by a theory that is elaborated below as the "contextual drift" hypothesis.

The value of \( s \) is a theoretical parameter, but it could be coordinated to the molecular, moment-by-moment processes of stimulus scanning and extraction of descriptions. On that account, \( s \) would vary with exposure duration from extremes of tachistoscopic presentations up to slow, 4-second presentations of items. Also if we were to conceive of the encoding operators as selective naming ("there's an X in the first position") or as implicit associations ("looks like Headquarters backwards"), then these operators would be applied serially rather than in parallel, and the products of s-a-cs of the \( s \) operators would be stored serially in short-term memory. From that short-term "scratchsheet" a response would be made first by a dictionary look-up and retrieval of information associated with the s-a-cs, and then by a deliberative decision based on that retrieved information. From these sorts of considerations, I would expect the parameter \( s \) to be in the range 5 to 10 with the usual presentation rates prevalent in verbal learning studies.

**Contextual Determination of Encoding**

Figure 2 also reveals my assumption that a complex set of contextual factors affect the probability distribution over the encoding operations. I think of "con-
text" in terms of background external and interoceptive stimulation prevailing during presentation of the phasic experimental stimuli. Included here would be internal factors like posture, temperature, room and apparatus cues, and stray noises, as well as internal physiological stimuli such as a dry throat, pounding heartbeat, stomach gurgles, nausea, and boredom. But more significant than any of these is what the subject is thinking about, what his mental set is, at the time the experimental stimulus intrudes. I think of this psychological context as being produced by the free flow of the "stream of consciousness," the internal monologue as the subject describes to himself what is going on around him and comments upon or free associates to his descriptions. These descriptions provide his moment-by-moment conception of the structure of the experimental task, his instructions, the nature of the materials he has been encountering, strategies of encoding and learning he thinks have been helpful, and what he thinks the experiment is really about. The free associations contain thoughts about the experimenter's stupidity, the subject's stupidity, what he ate for lunch, what he will do with his earnings, and similar wool-gatherings.

I will suppose that all of these factors, acting through multiple means, influence the state of the encoding machinery such that some encoding operators become temporarily more probable at the expense of others. In other words, changes in context will effect changes in the encoding process. These changes are of two types, systematic (intentional) and random (unintentional).

Systematic context changes. The simplest way to produce systematic changes in context is for the experimenter to present nonlearning material (as context) alongside the to-be-remembered items. The subject is effectively asked to think of the item in relation to the context material. In recognition memory, if the context word is changed between study and test, recognition of the memory item is worse than if the context remains constant (Light & Carter-Sobell, 1970; Tulving & Thomson, 1971). The loss in recognition is particularly great with polysemous words when different meanings are aroused at study (e.g., strawberry jam) versus test (e.g., traffic jam). In this instance, the context word is clearly altering the semantic associations to the grapheme. A similar result could doubtless be shown with recognition memory for ambiguous sentences and ambiguous pictures.

A similar biasing of encoding by manipulation of a phasic context occurs with emphasers that point to selected features of a nominal stimulus (Trabasso, 1963). An example is coloring one letter red in a trigram stimulus or printing an item in red letters in a word-plus-trigram compound stimulus. The emphasized component is now likely to be selected for encoding.

Background context can also be systematically altered as when we test subjects before versus after lunch, in the morning versus at night, in one laboratory room versus another, standing versus sitting, with items printed on white versus blue cards, and so forth (see Bilodeau & Schlosberg, 1951; Strand, 1970). Generally speaking, performance is poorer if learning occurs in one context but is tested in a different context. It is possible to think about this decrement as resulting from altered encoding of the experimental stimuli because the changes in context bring in different encoding operators.

Random contextual drift. From the foregoing remarks about background stimuli and the psychological components of context, it is reasonable to suppose
further that there is a slow drift or gradual change in the prevailing context as other items and events occur during a lapse of time. The change in context presumably grows progressively over elapsed time. As the context changes, so does the setting of the encoding operators, thus making active a somewhat different set of $s$ of the $N$ possible operators. This change in context is rarely total; states of the mind recur many times over—a fact developed in intriguing ways in Crovitz's book "Galton walk" (1970). Nonetheless, the average overlap between the contexts at times $t$ and $t + k$ will decrease to some asymptotic proportion as $k$ increases.

**Mathematical Development of Fluctuation Theory**

The notions of gradual and spontaneous changes in contextual stimulation are essentially those of stimulus fluctuation theory as developed by Estes (1955). He also developed the necessary mathematical concepts and representations of this problem. From our position, we are interested in contextual fluctuation insofar as it affects which $s$ of the $N$ encoding operators will be active at the time a particular nominal stimulus is presented.

To begin derivations, suppose that a particular nominal stimulus like XQH has just been presented in a learning experiment and encoded by $s$ of its $N$ possible operators. Call this moment "time 0" and call the $s$ active operators the "active set" and the remaining $N - s$ operators the "inactive set." We assume that if XQH were to be presented immediately once again, the same $s$ operators would still be active and so the item would be encoded in exactly the same way as before. But suppose instead that other items and other thoughts intervene between the initial presentation of XQH and a later test presentation of it. The change of context may change which encoding operators are active upon the second presentation.

The change in the active set can be formulated as a Poisson process. In each small time-unit of length $\Delta t$, there is either no change or exactly one random change; in this latter case, an operator in the active set becomes inactive and is replaced by a formerly inactive operator. The process constitutes a Markov chain. The two states of a given operator are that it is active at time $t$, which event we will write as $A_t$, or inactive at time $t$, written as $\bar{A}_t$. Letting $c$ denote the probability of an interchange in each time unit, the matrix of transition probabilities is:

$$
\begin{bmatrix}
A_{t+1} & \bar{A}_{t+1} \\
A_t & \bar{A}_t
\end{bmatrix}
\begin{bmatrix}
1 - \frac{c}{s} & \frac{c}{s} \\
\frac{c}{N - s} & 1 - \frac{c}{N - s}
\end{bmatrix}
$$

The entries $c/s$ and $c/(N - s)$ follow from the assumptions that when an interchange occurs (with probability $c$), an operator is picked at random from the $s$ active operators to be replaced by an operator picked at random from the $N - s$ inactive operators.

Let $a_t$ denote the probability that an operator is in the active state $A_t$. A difference equation for $a_t$ is
\[ a_{t+1} = (1 - \frac{s}{s})a_t + (1 - a_t) \frac{c}{N-s} \]  

(1)

Equation 1 is a linear difference equation having as solution

\[ a_t = \frac{s}{N} - \frac{c}{N} a_0 \left[ 1 - \frac{c}{s} - \frac{c}{N-s} \right]^t. \]  

(2)

If we let \( J = s/N \) and \( h = 1 - c/s - c/(N-s) \), then Equation 2 can be rewritten as

\[ a_t = J \left( J - a_0 \right) h^t. \]  

(3)

Here \( J \) is the proportion of active operators, \( h \) is a fraction dependent upon the rate of contextual change, and \( a_0 \) is 1 or 0 according to whether the operator in question began in the active or inactive state, respectively, at some arbitrary time 0. Equation 3 describes an exponential growth (or decay) curve starting at \( a_0 \) (0 or 1) and asymptoting at \( J \), the unconditional proportion of active operators. It is to be understood that Equation 3 applies separately and independently to each item in the experiment. The initial presentation, or the end of some learning period with each item, defines “time 0” for calculating encoding changes over time before the second or retention-test presentation of that specific item.

**Associations to List-Markers**

In the following we shall be concerned with applying this fluctuation theory to experiments on recognition memory and on list differentiation. In recognition memory, the model needs some way to tag or mark those encodings elicited by an initial presentation of a nominal stimulus. The presence of these tags on encodings of later test items is used to decide whether the test item was presented earlier. For a learning theorist, the easiest way to think of these “list tags” or “list markers” is in terms of direct associations between the s-a-cs and a cognitive element (idea, response) called “LIST.” It shall be assumed that in a simple recognition-memory experiment, the s active s-a-cs, occasioned by presentation during study of a nominal stimulus item, are each associated fully to LIST upon that occasion. In later applications to list-differentiation experiments, we will postulate conditioning of s-a-cs to appropriate List-1 or List-2 markers which will enable efficient list discriminations.

**SIMPLE RECOGNITION MEMORY**

**General Concepts**

An elementary experiment to model is one in which a nominal stimulus is presented once in a block of study items and then is tested later for recognition. The subject is asked to indicate for each test stimulus whether it is one that was in the study list. Usually, 50 percent of the test items are “new” or “distractors,” mixed in randomly among the old items.
In any recognition model one is required to handle false positives or false alarms, the subject incorrectly saying "old" to new test items not seen before. In common with most others, we will suppose that these result from stimulus generalization or overlap of the s-a-cs of the new test stimulus with those elicited by other stimuli during study and successfully tagged at that earlier time. We shall assume that for a homogeneous population of study and test items, there is some small probability \( p \) that each s-a-c resulting from a new nominal test stimulus may nonetheless have been aroused by earlier stimuli and tagged during study. The parameter \( p \) is an index of the amount of overlap of each new stimulus with all other prior stimuli in the experiment; it will be related to the false alarm rate, and will increase with the number of homogeneous training stimuli.

The "Noise" Distribution

When a new test item is presented, a set of \( s \) s-a-cs (elements) will be activated, and more or less of these will have been tagged (due to overlap) with an association to the list marker. Let \( Z_n \) denote the number of tagged elements activated when a new item is presented. If each element has independent probability \( p \) of having been tagged earlier, then \( Z_n \) will have the binomial distribution given by

\[
Pr\left\{ Z_n = x \right\} = \binom{s}{x} p^x(1-p)^{s-x}.
\]  

The mean of \( Z_n \) is \( sp \) and the variance is \( sp(1-p) \). A significant feature about a binomial distribution is that for moderate values of \( s \), it rapidly approximates the normal distribution with the same mean and variance. That normal approximation to \( Z_n \) will be used later.

The "Signal" Distribution

Consider the test presentation of an old item. On its first presentation at time 0, its \( s \) active elements became tagged, but over time and interfering items (assumed to be confounded here) these have changed according to the fluctuation process described by Equation 3. Consider that the lag or time between study and test presentation is \( t \) units. The proportion of the active sample at time \( t \) which will be tagged is \( p(t) \), expressed as

\[
p(t) = \frac{1}{s} \left[ \alpha t \left\{ 1 - \left( 1 - J \right) h^t \right\} + \left( N - s \right) p J (1 - h^t) \right].
\]  

The first part of this expression is the proportion of elements active at time 0 \((\alpha_0 = 1\) in Equation 3\) which are still active at time \( t \); the second part of the equation is the proportion of elements that were inactive at time 0, which may have been tagged unintentionally with probability \( p \) due to their overlap with other study items, and that have become active by time \( t \) \((\alpha_0 = 0\) in Equation 3\). Equation 5 can be simplified, since \( J(N-s)/s = 1 - J \), to yield

\[
p(t) = p^* + (1 - p^*) h^t,
\]  

where

\[
p^* = \frac{1}{s} \left( N - s \right) p J.
\]
where \( p^* = J + (1 - J)p \) is the overall proportion of tagged elements in the population of encodings of a given experimental item. Equation 6 describes a decay curve going from 1 at \( t = 0 \) to an asymptote of \( p^* \).

Upon test presentation of a target item at lag \( t \), the probability is \( p(t) \) that any given s-a-c in the active set is marked. Let \( Z_0(t) \) be the number of marked s-a-cs in the active sample provided by an old stimulus at lag \( t \). Then \( Z_0(t) \) has the binomial distribution given by

\[
Pr \left\{ Z_0(t) = x \right\} = \binom{s}{x} [p(t)]^x [1 - p(t)]^{s-x}.
\]

(7)

An important statistic is the mean or expected value which is

\[
\mu_0(t) = s p(t) = s [p^* + (1 - p^*) h^t].
\]

This describes an exponentially decaying mean for the binomial distribution given in Equation 7.

The Decision Rules

Yes-no decisions. The most elementary judgment in recognition memory tests is a binary indication of whether the subject thinks the test item was on the study list. In the theory, the test stimulus gives rise to \( s \) encoded elements. It will be presumed that the decision is based on the number of tagged elements in the active sample. Figure 3 depicts the theoretical situation, showing the probability distribution of tagged elements for new items and for old items presented at a lag of \( t \) before the test.

The test item gives rise to a certain number of tagged active elements and the subject must decide whether that observation came from the \( Z_n \) or the \( Z_0(t) \) distributions. It is assumed that the subject resolves this decision by selection of a criterion, \( C \), the number of tagged elements required for a positive response. For instance, \( C \) might be chosen so as to maintain a constant false alarm rate on tests involving a mixture of new and old items of varying strength. An example criterion is shown in Figure 3.

The location of \( C \) with respect to the means \( \mu_0(t) \) and \( \mu_n \) determines the hit rate and false-alarm rate, respectively. Graphically, the false-alarm rate is the area above \( C \) in the \( Z_n \) distribution. The hit rate for old items presented at lag \( t \) is the area above \( C \) in the \( Z_0(t) \) distribution. This hit rate will be higher the greater the distance between the two means. The distance between the two means, scaled with respect to the standard deviation of the \( Z_n \) distribution, is the basic parameter, \( d'(t) \):

\[
d'(t) = \frac{s [p(t) - p]}{\sqrt{sp(1-p)}}.
\]

For moderate values of \( p \), the square-root of \( p(1-p) \) will be near .50. Using this simplifying approximation, the equation for \( d'(t) \) will be
\[ d'(t) \approx \sqrt{2s} (1 - p) [J + (1 - J)ht]. \] (8)

Some comment on Equation 8 is warranted, since it is a basic theorem of the theory regarding recognition performance. The higher \( d'(t) \) is, the more discriminating will be the memorial performance. First, the lower is \( p \), the amount of stimulus generalization between old and new items, the greater is \( d' \). Second, the greater is \( J \), the proportion of population elements active upon any one trial, the better the discrimination, due to tagging of more elements during study of old items. Third, the lag \( t \) between study and test contributes an exponentially decaying component to \( d'(t) \). This exponential decay of \( d'(t) \) in recognition memory has been confirmed a number of times (e.g., Wickelgren, 1967; Wickelgren & Norman, 1966). A final comment regarding Equation 8 is that \( d'(t) \) is expected to increase with \( s \), the number of active elements. This is a consequence of the statistical law of large numbers, but it can also be appreciated intuitively that a decision will be more discriminating the more evidence (active s-a-cs) examined before the decision is taken.

**Rating scales and MOC curves.** The simple Yes-No decision can be replaced by a more refined rating scale of 5 to 10 categories. In effect, the subject judges the likelihood that the test item came from the old rather than the new distribution. Such multiple-category decisions can be implemented by multiple criteria or cutpoints placed along the Z-axis of Figure 3.

![Diagram](image)

**FIG. 3.** Probability distributions of tagged elements for new and old test items. The parameter values are \( s = 10, p_R = .3, p_B(t) = .5 \), and \( C = 4.5 \).
A standard analytic procedure is to calculate the cumulative probability that a new or an old item receives a rating of \( C_i \) or higher. A plot of the cumulative probabilities \( Pr \{ Z_n(t) > C_i \} \) against \( Pr \{ Z_o(t) > C_i \} \) as \( i \) is varied yields the memory operating characteristic (MOC) curve. Figure 4 plots hypothetical MOC curves generated for different values of \( d'(t) \).

If \( Z_n \) and \( Z_o(t) \) are normal or almost normal distributions, then MOC curves will plot as straight lines on normal probability paper. Results confirming normality assumptions for recognition ratings have been reported by Bernbach (1964), Wickelgren and Norman (1966), and many others. Although the present view implies binomial distributions of the \( Z \) scores, for moderate values of \( s \) and \( p \) these are “almost normal” in shape. Also, the pooled population of old items is typically comprised of items of varying strengths tested at varying lags, so one is often pooling many different \( Z_o(t) \) variables to obtain a composite \( Z_o \) distribution. Of course, the effect of this pooling of variable binomial distributions is to make the average appear even more “normal like” than any individual distribution.

Multiple-choice tests. The theory applies directly to multiple-choice tests of various kinds. The simplest is two-alternative forced choice in which one old item (at lag \( t \)) is presented with one new item, and the subject chooses that one he thinks is more likely to be the old item. If we assume that each item is processed independently, then the subject will be comparing one observation sampled from the \( Z_n \) distribution to one from the \( Z_o(t) \) distribution, choosing as “old” that item...
leading to the greater number of tagged elements. Therefore, the probability of a
correct response in a situation, with no response biases, is

\[ p(c) = \sum_{x=1}^{\infty} Pr\left\{Z_o(t) = x\right\} Pr\left\{Z_n < x\right\} + .5 \sum_{x=0}^{\infty} Pr\left\{Z_o(t) = x\right\} Pr\left\{Z_n = x\right\}. \]

The first term in \( p(c) \) is the probability that \( Z_o \) exceeds \( Z_n \); the second term is the probability of a correct guess in case \( Z_o \) and \( Z_n \) are tied.

These calculations proceed on the assumption that multiple-choice test items are
processed and encoded independently, for which there is some good evidence
(Kintsch, 1968). This assumption may be slightly in error for meaningful words
(see Tulving & Thomson, 1971). The distractor item, serving as a new context, may
partially change the encoding of the old stimulus item, thus producing a more
radical shift in the encoding-operator probabilities than would be caused by con-
textual drift acting alone. But the net effect mathematically would be to lower \( p(t) \)
in Equation 6 by a constant fraction, as in \( \beta p(t) \). Since \( p^* \) in Equation 6 is a
parameter to be estimated anyhow, multiplication by \( \beta \) will be of no consequence.
The effect of this new context could be estimated by comparing recognition ratings
on each item when a word was studied alone or along with another, and then is
later tested alone or together with the same or a new context word. The effect in
multiple-choice tests might be to produce lower \( d' \) estimates than one observes in
comparable Yes-No procedures with simple stimuli.

Experimental Variables and Recognition Memory

*Lag between repeated presentations.* Any learning theory must predict an
increase in recognition memory if the subject receives a second study trial on a
given item. This second trial on an item will increase the hit rate on a later test
because it provides an opportunity for another set of \( s \) elements of the population
to be sampled and to become associated to the list marker. How much advantage
is added by this second opportunity depends on the change in encoding over the
interval between presentations, since the more new codes that are aroused, the
more total codes that are tagged.

As a paradigmatic case, consider a continuous Shepard and Teghtsoonian (1961)
recognition memory experiment in which a particular target item occurs three
times. Let \( \tau \) denote the lag between the first and second presentations, and let \( t \)
denote the lag between the second and third presentations. The following function,
derivable from the fluctuation theory, gives the expected proportion of tagged
elements active at the third presentation of the item:

\[ p(\tau; t) = J \ast (1 - J)h^t + (1 - J)(1 - h^t)[p + (1 - p)J(1 - h^\tau)]. \]

If we fix \( t \) and concentrate only upon the lag between the first two presentations, it
may be seen that the equation simplifies to an exponential function in \( \tau \), namely,
\[ p(\tau, n) = J + (1 - J)h^\tau + (1 - J)(1 - h^\tau) \left[ 1 - (1 - p)[1 - J(1 - h^\tau)]^{n - 1} \right] \]

\[ = 1 - (1 - p)(1 - \alpha - h^\tau)(1 - \alpha)^n - 1, \]

where \( \alpha = J(1 - h^\tau). \)

It is clear that \( p(\tau, n) \) asymptotes at one as \( n \) increases, since \( (1 - \alpha) \) is a fraction converging to zero as it is raised to higher powers. The rate of learning—the increase in \( p(\tau, n) \) as \( n \) increases—depends positively on the interpresentation interval, \( \tau. \) If \( \tau \) is large, \( \alpha \) is large, which implies rapid learning.

**Latency of recognition responses.** In statistical decision theory, specifically sequential-sampling theory, it is customary to suppose that the speed (reciprocals latency) of the decision is faster the more extreme is the evidence in favor of one versus the other response. Murdock (personal communication, 1971) has collected evidence that agrees very well with this supposition. Mathematically, the assumption means that response latency decreases as the distance between the number of tagged elements, \( Z, \) and the criterion, \( C, \) increases. In equation form, response speed will be

\[ s(Z) = \omega | Z - C |, \]

where \( s(Z) \) is the speed associated with a given \( Z \) score and \( \omega \) is a conversion constant. This sort of relation would be produced, for example, by a decision mechanism that scans the \( s \) encoded stimulus elements sequentially, in random order, accumulating a count of the number of marked versus unmarked elements, and responding as soon as either counter exceeds its criterion of \( C \) or \( s - C. \)
Considering only positive responses to old items (hits) and weighing each value of \( Z \) according to its probability, then the average recognition speed will be

\[
\tilde{r} = \omega \mu(t) - \omega C \\
= s^* + (s_0 - s^*) \mu t
\]

where \( s_0 = \omega(s - C) \) and \( s^* = \omega(s_p^* - C) \). This describes response speed as an exponentially decreasing function of the lag between a first presentation and a test trial.

Hintzman (1969a) has collected recognition latencies that accord with these implications. He used distinct words as test items in a continuous recognition design. With the short (up to 16) lags he used, practically perfect recognition performance was observed, that is, \( P \{ Z > C \} \approx 1 \). Nonetheless, recognition latency varied appreciably with lag, being slower at the longer lags.

Hintzman also varied \( \tau \) and \( t \) in a three-presentation design as discussed above. Just as increasing lag between the first two presentations increases recognition accuracy on the third test (Kintsch, 1966; Olson, 1968), so did it also quicken recognition latencies in Hintzman's experiment. The results are consistent with a strength-like theory that can accommodate variation in recognition latency while recognition accuracy remains constant near 100 percent.

**TEMPORAL LAG JUDGMENTS**

**General Ideas**

The general problem to be addressed now is how it is that memory keeps track of *when* an event happened. Stated differently, the issue is how we judge from memory how long ago (or conversely, how recently) it was that a particular event occurred. For example: When was the Cuban missile crisis? When did Goldwater run for U.S. President? When did you first meet your wife or girl friend?

Many events of that kind, both personal and impersonal, are stored along with a calendar date that is retrieved directly. However, for the larger set of our memories we have to reconstruct or infer an approximate calendar date by retrieval of some of the causal context in which the event was located; by judicious searching and self-questioning we eventually stumble across a memory that is temporally dated. In such cases, one essentially calculates the time of an event from associated information.

But suppose that the task and the environment are artificially constrained and impoverished so that no specific, distinctive marking events occur, and the items to be remembered occur independently in no logical or causal sequence. Examples would be the order of arrival of pupils before a class begins, of concert goers at a symphony hall, or in-bound aircraft at Kennedy airport. In laboratory experiments simulating these impoverished conditions (see Hinrichs, 1970) the subject may be exposed to a long series of items such as names, pictures, words, letters, numbers, or nonsense syllables. Each item might appear exactly twice, the two presentations separated by a controlled number of intervening items. The second presentation
a given item is accompanied by a question mark, which is the instructed cue for a test response. To this cue, the subject is required to make a judgment regarding how far back in the sequence had been the first presentation of the test item. The subject's usual response mode is to indicate how many presentations of other items have intervened between the first and second presentations of the test item. This is analogous to an absolute judgment made along a category scale. A different kind of testing situation involves a comparative judgment. Two test items are shown, both of which may have been presented earlier, and the subject decides which of the two items occurred more recently. These have been called "relative recency" judgments (Yntema & Trask, 1963).

**Trace-Strength Theory**

**Absolute judgments of recency.** If the strength of a memory trace declines regularly as a function of the number of items interpolated since its presentation, then the strength of the trace at the time of test provides an index of its age. Whether strength is a reliable index of age of the trace depends on how much "noise" from one or another source is in the system. "Noise" in this instance corresponds to variability of strengths for memories of a particular age, and it could be a result of differences across items in degree of learning or rate of decay as well as inherent variability in the trace retrieval process. In any event, an appreciation of variability in the strengths leads one to use of statistical decision criteria for judging a trace at a particular strength to have a particular age.

One is led, in fact, to a model for multiple category judgments such as Thurstone’s theory of “successive intervals” scaling (see Torgerson, 1958). Corresponding to each age (or lag) of memory trace is a theoretical distribution of strengths having an average value that decreases with the age of the items. To calculate a response, a number of category boundaries or cutpoints are ordered along the strength scale, such that a particular observation (of trace strength) is assigned to age \( i \) if its strength falls between the boundaries for categories \( i \) and \( i+1 \). This describes the model for lag judgments published by Hinrichs (1970). He successfully fit several sets of data assuming that trace strength decayed exponentially with lag, and estimating a variance parameter for the normal (Gaussian) strength distribution corresponding to each lag. A particularly impressive confirmation of his model involved separation of the memory component from the decision component of the model. That experiment varied the number of judgmental categories used by the subject, 6, 9, or 12, but used the same distribution of actual lags in memory (equiprobability of lags 1 to 9). In each case, the means of the theoretical distributions of strengths at given lags could be fit by the same memory-strength decay function; the number of judgment categories affected only the decision process, that is, the number and location of category boundaries along the strength scale, and not the underlying memory strengths on which the judgments were based.

The present model may be applied similarly to lag-judgment tasks since it effectively specifies for each item something like a strength that decays as a function of lag. Equation 6 specifies how \( p(i) \), the proportion of marked elements in the active set, declines as a function of lag since presentation of a given item. Thus, the
judgment of the lag since presentation of an item could be made according to the number of marked elements in the set active at the time of the test presentation. This number will be binomially distributed around a mean of $sp(t)$. For moderate values of $s$ and $p$ the binomial approximates the normal distribution used by Hinrichs (1970) in fitting his data. It would thus appear that the encoding variability model, along with the contextual drift hypothesis, might account in principle for Hinrichs' data on temporal lag judgments from memory.

A consequence of implicating memory strength of items in judgments of their recency is that other variables that affect strength may thereby be expected to affect temporal recency judgments. One such variable is frequency of experience. If several repetitions of an item result in a high strength of association between it and its context, then its apparent recency should be enhanced on a later test requiring a recency judgment. The evidence on this implication is conflicting. Peterson (1967) reported no effect of item frequency on recency judgments, whereas Fozard and Yntema (1966) and Morton (1968) reported a strikingly positive influence of frequency on apparent recency. That is, in these latter experiments, more frequent items were judged to be more recent, as predicted by the trace-strength theory. The exact procedural variations producing these conflicting results have not yet been tracked down.

Comparative judgments of recency. Just as it is possible to have absolute ratings and comparative tests of recognition memory, so is it possible to have ratings and comparative tests of recency judged from memory. Ratings are analogous to absolute judgments, whereas comparative recency judgments involve multiple-choice tests. After being exposed to a continuous stream of items, the subject is tested by having to choose which of two test items has occurred more recently (see Yntema & Trask, 1963). In the general case, each item of the test pair has been presented just once; to establish notation, we suppose that the more recent item was presented at lag $n$ back whereas the more distant item was presented at lag $n + k$ back in the continuous series.

The proposed model applies directly to such comparative judgments. Each test item gives rise to $s$ encodings, some of which are marked by an association to LIST. We assume that the subject chooses as more recent that test item having the greater number of marked elements in its set of active encodings. In case of ties, the subject chooses randomly.

Mathematically, the decision is based on the sign of

$$ Y(n, k) = Z_0(n) - Z_0(n + k). $$

The $Z_0$s are binomial random variables with means of $sp(n)$ and $sp(n + k)$, respectively, as given by Equation 6. Using the continuous normal approximation to the binomial, it follows that $Y(n, k)$ will be a normally distributed random variable with mean and variance equal to

$$ \mu(Y) = s \left( p(n) - p(n + k) \right) $$

$$ = s(1 - \hat{p}^n) h^n (1 - h^k), $$

$$ \sigma^2(Y) = s p(n) [1 - p(n)] + s p(n + k) [1 - p(n + k)]. $$
The probability of a correct response, saying that the item at lag $n$ is more recent than the item at lag $n + k$, is given by the likelihood that $Y$ exceeds zero. This is the area above $-\mu(Y)/\sigma(Y)$, which cutoff is approximately $-Qn(1 - h^k)$, where $Q$ is a constant.

![Graph showing the probability of a correct response as a function of lag distance between recentness](image)

**FIG. 5.** Probability that an item presented at lag $n$ is judged to have occurred more recently than an item presented at lag $n + k$. Parameters of the curves are $s = 8$, $h = 0.9$, and $p^* = .1$.

Figure 5 shows this function plotted against $n$, the shorter lag, with different curves for the parameter $k$, the distance between the shorter and longer lags. Such curves resemble those reported by Yntema and Trask (1963); the more recent item is better identified the more recent it is (the smaller $n$ is) and the greater is the difference in age, $k$, between the more and less recent items. The curves in Figure 6 are intuitively reasonable, and reveal something like a Weber-Fechner function for discrimination between times in memory.

**LIST DIFFERENTIATION**

**General Ideas**

One of the more recent developments in research on verbal learning and retention is the increasing emphasis on "response set" differentiation and suppression rather than the older concepts of stimulus-specific unlearning, spontaneous recovery, and associative interference (see Martin, 1971; Postman & Stark, 1969). However, along with this increasing use to the concept of list differentiation, there has not been much empirical or theoretical elaboration of the concept itself. The notion of list differentiation has been used without specifying whether it is based on time tags, relative strengths of traces, familiarity, retrieval of other list items, or whatever.
A recent paper by Anderson and me (1972) touches on this topic of list differentiation in the course of theorizing more generally about recognition memory. A critical viewpoint of our theory is that we conceived of list identification as analogous to a paired-associate learning task, in which items as stimuli are becoming associated to list tags or list markers as responses. A list marker or tag denotes a particular subset of list-context elements (thoughts, cognitive events, cues) active at the time a particular item occurs. We elaborated upon what we meant by list-context cues, the set of stimulus events that combine to identify for the subject that time block of item presentations he calls List \( i \), \( i = 1, 2, 3, \ldots \). For instance, one simple list context cue is a subjective count or label, as “first list,” “second list,” and so on, sustained by the subject throughout presentation of a given list. Thus at the time the item cat appears in List 1, the subject may be in a particular state of arousal, may be thinking of his stupidity, that this is the first set of items, and worrying about how well he will be able to remember them. The combination of these several cognitive elements that happened at a particular time (when cat was presented) during List 1 serves to identify a list marker.

A further point to be added is that list contexts, conceived as sets of stimulus elements, are not completely disjoint or separate from one another. On the contrary, there will be overlap among the sets of adjacent list-context elements, so that a collection of List \( i \) elements (a marker for List \( i \)) may later refer ambiguously to Lists \( i - 1 \) or \( i + 1 \) as well as to List \( i \), depending on the degree of degradation of information over a retention interval.

**Acquisition and Retention of List Identification**

We will consider the case in which a given item occurs several times in List 1. List 1 is then followed by a certain number of presentations of items in List 2, and then a list-differentiation test follows. In the test, the subject is shown a mixed series of List 1 and List 2 test items, and has to guess whether each item occurred in List 1 or List 2.

Suppose that the target item occurs \( n \) times in List 1, with a constant lag of \( \tau \) between presentations, and a net lag of length \( t \) intervenes between the last presentation of the item in List 1 and its ultimate test after List 2. Let \( p(t, n, \tau) \) denote the proportion of stimulus elements (s-a-cs) aroused by such an item during the test that are associated to a List 1 marker. The function implied by the theory, similar to that given previously in Equation 9 for \( n \) presentations, is

\[
p(t, n, \tau) = J + (1 - J)h\tau + (1 - J)(1 - h\tau)\left[1 - \left(1 - J(1 - h\tau)\right)^{n-1}\right]
\]

\[
= r(\tau) + (1 - r(\tau)) \cdot p(n, \tau).
\]

In Equation 10, \( r(\tau) \) is defined in the obvious manner as the retention function over an interval of length \( t \) since the last presentation of the item.

In order to simplify the following mathematical analyses, I shall revise the response rule of the model to the assumption that the subject chooses or responds “List \( i \)” with a probability equal to the proportion of active s-a-cs aroused by a test
item that are associated to List \(i\) markers. In case an element is sampled that is not associated to either of the available list markers, it is assumed to lead to a guess among the available list-identifying responses. In a two-list discrimination test, for instance, this is equivalent to the assumption that half the potential stimulus elements (s-a-cs) start out associated to List 1 and half to List 2.

With these response axioms, then, the probability of a correct list identification in a two-list experiment for an item presented \(n\) times in List 1 and tested at interval \(t\), is

\[
c(t, n, r) = p(t, n, r) + .5 \left[1 - p(t, n, r)\right]
= .5 + .5 r(t) + .5 \left[1 - r(t)\right] p(n, r).
\] (11)

The terms \(r(t)\) and \(p(n, r)\) were defined in Equation 10. A few curves for \(c(t, n, r)\) are shown in Figure 6 for differing values of the number of presentations, \(n\), plotted against the retention interval \(t\). List identification increases with the number of times an item occurred in a list and decreases with the retention interval before testing.

A side comment is appropriate here. Equation 11 shows that list identification should improve with the number of repetitions of a word in the list. This seems
obvious within the paired-associate framework. However, it appears superficially discrepant from data on list-differentiation reported by Winograd (1968). However, his results may be due to optimal guessing strategies inadvertently introduced by his method of manipulating item frequency. Winograd presented List 1, a set of 25 unrelated nouns, as a unit either 1, 3, or 6 times, followed by List 2 (25 different nouns) presented as a unit for either 1, 3, or 6 times. Different subjects experienced different combinations of trials on List 1 and List 2 before the final test, when all words were shown in mixed order and judged as having been on List 1 or List 2. We will refer to the various condition by a pair of numbers, \((i, j)\), which will denote \(i\) trials on List 1 and \(j\) trials on List 2.

Most of Winograd’s results were consistent with our paired-associate theory; for example, list identification was more accurate in the \((6, 6)\) case than in the \((3, 3)\) case, which was in turn more accurate than in the \((1, 1)\) case. The sole disturbing point is that accuracy in the cases of the unbalanced frequencies, \((1, 3)\) and \((3, 1)\), was a bit higher than in the \((3, 3)\) case. To offer an excuse, this advantage could have arisen from differential guessing in these unbalanced cases as compared to the \((3, 3)\) case. To simplify the argument, imagine that a test word is either associated to a List 1 tag, to a List 2 tag, or to neither. In the last case, the subject must guess a list for the test item. In the \((1, 3)\) and \((3, 1)\) cases, an optimal strategy is to guess that the unknown or uncertain test item belongs to the less frequent list. This is because the item is more likely to have been associated to a list tag if it had been in the more frequent list. Therefore, absence of a list tag on a test word is fairly good evidence that the item was in the less frequent list. This optimal guessing strategy may thus inflate the list-identification scores for the \((1, 3)\) and \((3, 1)\) cases compared to the \((3, 3)\) case for which no optimal guessing strategy exists. This account, by the way, is not very much different from Winograd’s, who conceived of identification accuracy as a combined result of the relative strengths and absolute strength of associations between the background contextual cues and the two lists of items.

An alternative experiment that eliminates this guessing bias is to manipulate item frequency within each list independently. In a recent experiment of ours, subjects studied and were later tested on list identification with three lists in each of which some words (unrelated nouns) appeared once, some twice, and some three times. By this method, frequency of pairing a word with a list tag is not confounded with which list is involved. As our theory expects, in that experiment accuracy of list identification increased directly with the frequency with which a word occurred in a list.

**Generalization Among List Contexts**

Several theoretical devices exist for representing and dealing with the phenomena of generalization among lists. I will illustrate one of the more obvious approaches to this issue. This approach assumes that the sets of list-context elements overlap, and that they overlap more the closer in time are the two lists. In particular, it is assumed that the successive sets of list-context elements, for Lists 1, 2, 3, \ldots, N, form a continuum of overlapping sets (see Atkinson & Estes, 1963, p. 203). The proportion overlap, or shared elements, between Lists \(i\) and \(i+k\) is
assumed to be $\omega^k$, where $\omega$ is a fraction identified as the basic generalization parameter. Figure 7 shows a Venn diagram illustrating the overlapping subsets and their probability measures for three lists given in succession. As is obvious, Lists 1 and 3 have an advantage over List 2 in terms of the number of unique identifying elements. This is simply because these are the ends of the continuum of three sets.

Recall now that a List $i$ marker was defined as a random subset of the context elements prevailing during presentation of List $i$. To the extent that list contexts share common elements, the random subsets denoted as markers will consist of some elements unique to List $i$ and some elements later found to be shared with adjacent lists. In effect, the test word may retrieve a marker established during presentation of List $i$, and yet the subject may err in interpreting that marker as referring to List $i-1$ or $i+1$ rather than to List $i$. Let $\pi_{ij}$ denote the probability that a marker established during presentation of List $i$ refers later to List $j$, possibly because of overlap of context elements. For the generalization coefficients illustrated in Figure 7, the corresponding values of $\pi_{ij}$ are as follows:

\[
\begin{align*}
\pi_{11} &= \pi_{33} = 1 - \omega + (\omega - \omega^2)^\frac{1}{2} + \omega^2 \frac{1}{3} \\
\pi_{12} &= \pi_{32} = (\omega - \omega^2)^\frac{1}{2} + \omega^2 \frac{1}{3} \\
\pi_{13} &= \pi_{31} = \omega^2 \frac{1}{3} \\
\pi_{22} &= (1 - \omega)^2 + 2\omega(1 - \omega) \frac{1}{2} + \omega^2 \frac{1}{3} \\
\pi_{21} &= \pi_{23} = (\omega - \omega^2)^\frac{1}{2} + \omega^2 \frac{1}{3} \cdot 
\end{align*}
\]

(12)

---

**FIG. 7.** Venn diagram illustrating overlapping sets of contextual elements for three successive lists, assigning measure $\omega^k$ to the proportionate overlap of sets $k$ units apart on the stimulus scale.
The values of $\pi_{ij}$ in Equation 12 are calculated on the assumption that areas in Figure 7 representing overlap of two or three sets lead to the appropriate list response with probabilities 1/2 or 1/3, respectively.

Consider now applying these ideas to a three-list discrimination situation. Suppose that each list is presented a fixed number of times. Assume too that the time of testing after input, $t$ in Equation 10, is very large, so that $p(t, n, r)$ is asymptotic in $t$. We interpret $p(n, r)$ as the probability that an active s-a-c of an item is conditioned to a corresponding list marker. In case the s-a-c is not conditioned to any list marker, it is assumed to produce random guesses among the three lists. Let $d_{ij,n}$ denote the probability that an item presented $n$ times in List $i$ is later judged to have occurred in List $j$. The equation for $d_{ij,n}$ is

$$d_{ij,n} = p(n, r)\pi_{ij} + \frac{1}{3}[1 - p(n, r)].$$  \hspace{1cm} (13)

Illustrative values of $d_{ij,n}$ are depicted in Figure 8, which gives the expected probability that an item of List 1, 2, or 3 (the parameter of the curves) will be judged to have been in the list indicated on the abscissa. These are list generalization gradients, showing confusion decreasing with distance between the actual and the judged list context. The gradient for responses to List 2 items is predicted to be shallower than for the other lists, reflecting more generalization between it and its adjacent lists. The gradients for Lists 1 and 3 are equal in these graphs because they are calculated on the assumption of a long retention interval after the block of three study lists. Had this test been given immediately following the third study list, then $t$ would have been significantly shorter for List 3 than for List 1 items. Consequently, $p(t, n, r)$ would have been larger and the percentage correct for List 3 would have been larger than in List 1.

The worry about these predictions is whether equiprobable guessing is the proper way to describe the person's strategy with nonassociated s-a-cs. If memories decay over time, then an optimal guessing strategy is to guess List 1 for a nonassociated (forgotten?) s-a-c. Such guessing strategies would perturb somewhat the qualitative predictions depicted in Figure 8.

**Recognition versus List Discrimination**

A basic premise of the theory (see Anderson & Bower, 1972) is that recognition memory and list identification involve similar processes. In recognition, the person decides whether he has seen a test item before in a specified context; in differentiation, he decides in which of several contexts he has seen the test item. The context specified in the yes-no recognition experiment is usually "in this experiment," as when we ask the subject "Did you see the word dog earlier in this word series I've shown you in this experiment?" The context specified in the list differentiation experiment is more restricted, involving, for instance, "first" versus "second" temporal blocks within this experiment.

The model supposes that both judgments are mediated (when successful) through retrieval of markers, that is, through retrieval of bundles of cognitive elements referring to temporal contexts. However, our earlier assumptions about overlap and generalization of list-context elements imply that a marker does not
unambiguously identify a list. Thus, a test word may retrieve an associated marker—leading the subject to judge with assurance that the item has occurred earlier—but yet he may mistakenly assign the item to the wrong list because the marker refers ambiguously to several lists.

Winograd (1968) reported just this sort of difference between recognition and differentiation. Yes-no recognition memory for, say, the (3, 3) condition was around 97 percent at the same time that list discrimination was around 80 percent correct. This corresponds, then, to what our model would expect.

Multiple-List Memberships

The list-differentiation experiments examined heretofore are ones in which each item appears in just one of the several lists presented. But there is no legislation proscribing experiments in which a given item appears in several different lists. Given our assumption that each s-a-c may become associated to several different responses, there is no particular reason to expect any unlearning of a List 1 tag during learning of a List 2 tag for the same item. This is not to rule out the possibility of negative transfer and also list generalization when a given item appears in two or more lists.

Hintzman and Block (1971) have reported relevant data on multilist memberships of the same item. Their subjects judged the frequency of occurrence in each list of words that occurred either 0, 2, or 5 times in List 1 and in List 2. The average frequency estimate given from subjects' memory increased directly with an
item's frequency in the list being judged. But there was also negative transfer insofar as the differentiation of frequencies of 0, 2, 5 was poorer for items in List 2 than for the same items in List 1. The authors also observed clear list-generalization effects: Holding constant the true frequency of the item in the list being judged, its mean judged frequency increased directly with its frequency in the alternate list. This is precisely the result expected if there were some confusion about the list identification of the markers associated to a word.

Another example of apparent negative transfer in list tagging occurs in an experiment by Anderson and Bower (1972). Their subjects were exposed to a sequence of 15 overlapping lists of 16 items, each list drawn from a master set of 32 words. Each list overlapped with each other list in respect to 8 words, but a different set of 8 for each pair of lists. As one might expect, in this confusing situation it is very difficult for the subject to keep track of exactly which lists a given item has been in. Anderson and I tested after each list-input trial for free recall of the master set of 32 words, and this improved continuously over lists as more items were presented and recalled frequently. The subject was also asked to indicate, for his recalled words, which ones were presented on the most recent list of 16 words he had just studied and which ones were not presented in that most recent list (but were members of the master set presented in earlier lists). This is a list-differentiation judgment, reflecting the ability to discriminate items that were in the most recent list. This ability to discriminate items in the most recent list declined across lists as items occurred haphazardly in progressively more lists. This result was exactly as expected if there were negative transfer in associating a new list tag to an item that already had several prior list tags associated to it. A fine detail confirming this hypothesis was that an individual item presented in the most recent list was more likely to be later remembered (correctly) as having been in the most recent list the less frequently it had occurred in lists prior to the one being judged. Thus, the more prior list-tags associated to a given word presented in the most recent list, the less likely it was to become associated to the tag denoting the most recent list.

This notion of negative transfer in tagging of items in multiple lists may help explain other puzzling phenomena such as negative transfer in part-to-whole or whole-to-part transfer studies of free recall (see Tulving, 1966). A subject pretrained with part of a free-recall list will subsequently learn the whole list more slowly than a control subject pretrained on an irrelevant list before receiving the whole list. The difficulty is largely localized in very poor improvement in recall of old (part-list) items (see Bower & Lesgold, 1969). This outcome would be predicted if there were negative transfer in associating a List 2 marker to an item previously associated to List 1, and if whole-list recall were monitored and edited for a List 2 tag associated to the items. Thus, part-list items previously associated to a List 1 tag would acquire List 2 tags more slowly and would thus be edited out from recall.

This outcome hinges critically upon the experimental subject not being aware that all part-list items are contained in the whole list. If he were to be informed of this fact, then there would be no list discrimination problem, and the monitor would recall any candidate item retrieved having either a List 1 or List 2 tag associated to it. Thus, informed subjects should give only positive part-to-whole
transfer. This is indeed the case, as has been found by Tulving (personal communication, 1971).

Nontemporal List Cues

My next comment is not on a theoretical point but on a methodology that prevails in research and thinking about list differentiation. The point concerns our common means for specifying what is a list of items. Almost always in current discussions, a list is defined by a time reference, as “all those items presented between a beginning-of-list signal and an end-of-list signal.” Other common temporal designations are “first list” or “second list,” or the “most recent list,” which refer to an implicit temporal order.

Our theory about list tagging of items leads us to a broader view of what constitutes a list. A list tag can be any discriminable cue or marker enabling differentiation of items associated to that cue as opposed to other cues. On this basis, a list would simply be a collection of items that share an association to a distinguishing cue or marker. That distinguishing cue need not be a temporal one. It could be a spatial location (e.g., items shown on the left), a characteristic of the visual or auditory presentation of the items (e.g., words printed in red letters, or words spoken in a female voice), a common verbal context of their presentation (e.g., items paired with the cue auto versus those paired with the cue kitchen), or a simple numerical but nontemporal context cue. In this latter case, for instance, one might first show a few items designated as List 2 items, then some List 1 items, then some more List-2 items, then more List 1 items, alternating this way through the two sets.

In these several examples, the subject would be associating the items to a designated list cue according to a paired-associate procedure. That list cue becomes the instructional cue for commencing retrieval of the various list items in a free-recall test. That list cue is also the implicit response term when the subject is later asked whether a stimulus item occurred in a particular list. Asking whether dog was presented in that collection of words shown in Location 1 is analogous to asking whether the subject recognizes the pairing dog-Location 1, by either forward or backward association.

The import of these remarks is methodological. We may view list differentiation as a special kind of paired-associate learning, and investigate variables other than “time” as list cues. This may give us more flexibility in manipulating experimental variables such as list-cue discriminability, temporal blocking versus randomized presentations of items belonging to several lists, and compound list-cue redundancy.

Tulving has pointed out to the author that such nontemporal list cues nonetheless must still have implicit reference to a temporal span. When an experimenter presents some words in red letters, some in black letters, and later asks for the black word list, he is implicitly adding the differentiating instruction “Those black-letter words seen here since the experiment began,” and he excludes such words read in the instructions or prior to the present exposures. Similar arguments, of more or less cogency, can be advanced for other nontemporal list cues. The observation is correct but immaterial to the multiple-list differentiation issues being addressed. For instance, items presented in two locations (two lists) are
differentiated from one another only by that property; time of their presentation differentiates them at least from all other items, but serves not at all to differentiate one set from another. In this respect, although time and time-tagging is necessarily implicated in all memories for episodic happenings (e.g., the episode that the word *chair* appeared in Location 1), that time tag need not be the feature distinguishing two experimentally defined sets (lists) of items in memory.

**PAIRED-ASSOCIATE LEARNING AND STIMULUS RECOGNITION**

**General Ideas**

Stimulus fluctuation theory was applied earlier by Estes (1959; also Bower, 1967b) to paired-associate recall. I will not review those applications but will address myself briefly to the relationship between stimulus recognition, stimulus-response pair-recognition, response recall when cued with the stimulus, and the confidence rating of the recalled response. All these indices should be closely related in some way (see Adams & Bray, 1970). Stimulus-sampling theory as elaborated herein implies a particular set of relationships.

In applications to paired-associate learning with familiar unitary response terms, the basic idea is that each reinforced (or study) trial associates the correct response to that set of s encodings of the stimulus member active upon presentation of the pair. As time passes after study, there is fluctuation in the contextual determinants of the encoding process, so that a later presentation of the same nominal stimulus may activate a new sample of encodings. The probability that an earlier "conditioned" encoding is reactivated at the time of test is given by the derived retention function, *r(t)* (see Equation 10). The probability of recall of the correct response is the proportion of elements active in the test-trial sample that is associated to the correct response.

For present purposes, it will be assumed that each s-a-c active during study acquires two simultaneous associations, one to a list marker and one to the paired-associate response term. These distinct associations provide the hypothetical subject with the information necessary to do later stimulus recognition as well as paired-associate response recall. The stimulus will be recognized later if a sufficient number of its active elements are marked, as prescribed in the earlier subsection *The Decision Rules*. Similarly, the stimulus-response pairing shown on a test trial will be recognized as a correct "old" pairing if a sufficient number of the active encodings of the test stimulus are associated to the test response. The stimulus as a cue will lead to recall of the response, we assume, according to the proportion of its active elements associated to that response. The confidence that the person has in his recalled response, we assume, would depend upon the number of active elements associated to both the recalled response and the list marker.

**Conditional Relationships**

It is not yet obvious how to diagram or conceptualize the pattern of associations among the three terms of the paired-associate, namely, the stimulus, the list
context, and the response. The simplest diagram in some ways just assumes that each stimulus-as-coded (S-a-c element) acquires two quite independent connections, one to a list-context marker and another to a response term. Assuming independent forgetting of the two associations then would predict instances of paired-associate recall without list identification as well as list identification without paired-associate recall. Moreover, paired-associate recall would be predicted to be above chance even when stimulus recognition failed. The first and third of these implications are contradicted by the available data (e.g., Bernbach, 1967; Martin, 1967).

An alternative associative diagram supposes that a stimulus plus a list context become jointly associated as a compound unit to the paired-associate response. That is, the diagram would be (S \rightarrow \text{LIST context}) \rightarrow \text{R}. The stimulus would acquire an association to the list context, of course; but only the joint compound, of stimulus plus context, would be conditioned to the paired-associate response term. At the time the S-R pair is studied, the encoded elements of the stimulus would be presumed to become associated to a set of contemporaneous contextual events (a marker), and the stimulus-plus-context as a unit would also become associated to the response term on that study trial.

Several theoretical implications follow from such ideas. First, this approach provides a basis for the learning of different responses to the same nominal stimulus in different contexts. This is clearly needed to handle the subject's ability to learn to say "dog" to cat in List 1 but to say "bird" to cat in List 2. The list-context cue augments the nominal stimulus and provides the means for such conditional discriminations.

Second, the cue-plus-context viewpoint readily leads to the prediction that paired-associate recall is dependent upon stimulus recognition. Putting matters in the converse way, if the subject fails to recognize the stimulus term (i.e., if insufficient list-context cues are retrieved from the stimulus alone), then recall of the paired-associate response will only be at the chance level.

Third, the cue-plus-context viewpoint would appear to provide a richer framework within which to represent interaction effects among two or more lists learned in succession with the same nominal stimuli. In the A-B, A-C paired-associate paradigm, we may suppose that stimulus A comes to function in two successive compounds, in the A+L₁ compound, and then in the A+L₂ compound. The diagram in Figure 9 illustrates the state of the system after successful learning of the two lists. Depending on instructional cues, the cue A by itself may retrieve either the List-1 context cues which combine with A to be associated as a unit to response B; or A may retrieve the List-2 context cues, and the two as a unit are associated to response C. Or, given enough time, cue A may retrieve or re-integrate both of these compounds in succession, leading to recall of both B and C.

Several remarks are warranted regarding the relations diagrammed in Figure 9. First, in a test following A-B, A-C learning where cue A is presented and the subject tries to recall both B and C (the MMFR test), any response recalled should be assigned to the correct list (as well as to the correct stimulus). This prediction accords with fact; list identification of recalled responses in MMFR tests is usually
perfect, as is the assignment of responses to stimuli (if original learning was assured). Second, in retroactive- or proactive-inhibition studies with instructions to retrieve only the first- or second-list response to the cue A alone, the model predicts that the subject will frequently be able to retrieve the wrong response but recognize and reject it as coming from the wrong list. Thus, retrieval of list-context cues provides a means for list editing.

Third, as the comment above indicates, a major component of forgetting in Figure 9 is the branch from cue A alone to reintegration of the "A plus list-context" compound that is associated to the paired-associate response. Loss of access to this link could be caused by fluctuation in the stimulus-encoding process over the retention interval, so that re-presentation of cue A leads predominantly to s-a-cs not associated to a list marker. Another possible reason for loss of access to the "A plus List-1 context" bundle might be unlearning during interpolated A-C learning. The notion is that the ability of A alone to reinteegrate the bundle can be lost because of A-C learning in the second list. The present status of such unlearning is much in dispute.

There are several implications of these last remarks. First, a retrieval attempt with cue A alone may fail initially, but then succeed later if sufficient context cues are reinstated by one or another means (e.g., reconstructive free associations). The relevant context cues needed are not the name "List 1" or "first list," but rather the things that the subject was thinking about at the time he first learned the A-B pair in List 1. Second, an A-B pair recognition test may succeed where A-B recall
has failed following A-C learning. Failure of B recall would be due to inability of A to re-integrate the set of List-1 context cues prevailing at the time A-B was studied. On the other hand, multiple-choice recognition tests or associative matching tests provide reinstatement of some context cues (namely, other items in the list), which is a help to remembering; such recognition tests also require less supporting evidence for a correct response than does recall. Moreover, even though the forward association from A to B may have been unlearned due to A-C interpolation, the pair may still be recognized because the backward association from B to A is still intact. On this latter basis, one would expect interpolation of an A-Br list, composed of the same responses but re-paired with the stimuli, to cause unlearning of both forward and backward associations, and thus to produce a large loss in recognition of the original A-B pair. This pattern seems to accord with the facts of the matter (see Postman & Stark, 1969).

These particular ideas about multiple-list learning can be brought into correspondence with recent theories about response set suppression, differentiation, and recovery. For example, if we equate list-context cues with particular response-selection criteria as well as a train of thoughts, then it is easy to imagine how the List-2 context cues persist for awhile and intrude themselves even when the subject is trying to revive or re-integrate the old context cues of List-1. As time passes after List-2 learning, however, the List-2 context dissipates and the List-1 context becomes easier to re-integrate so that List-1 responses become more available for cued recall. These ideas apply to the loss in A-B recall following C-D learning as well as following A-C learning. These notions are essentially those proposed by Postman and Stark (1969). However, much more conceptual development is needed to decide the explanatory power of these tentative ideas.

**CONSOLIDATION AND RETROGRADE AMNESIA**

The encoding fluctuation theory would appear to provide a means for interpreting the retrograde effect produced by traumatic brain injuries such as concussions, electroconvulsive shock (ECS), drug-induced convulsions, and coma. The basic facts of trauma-induced amnesia are clear enough: A convulsion, concussion, or similar trauma seems to temporarily obliterate memories for events that happened just before the trauma, with the probability of memory loss increasing with proximity of the event to the trauma. This disruptive effect of convulsion or concussion has been offered as primary evidence in favor of a consolidation hypothesis, which assumes that the amount of long-term memory about an event accumulates over time until some disruptive event stops fixation of memory for that earlier event. This interpretation is not without its competitors (see Lewis & Maher, 1965; Lewis, 1969), and the correct theoretical interpretation is still in doubt. For example, the consolidation hypothesis does not account for the human clinical observation that many memories do return over time, with forgotten events farthest from the trauma being recovered earlier.

An interpretation of retrograde amnesia effects in terms of stimulus fluctuation theory was first suggested by Kohlenberg and Trabasso (1968). Their idea was that stimulus elements active at the time of the trauma or ECS acquire, as a
consequence, a low sampling probability for some time after the ECS. This hypothesis can be restated in terms of an encoding-response theory such as proposed here. The basic approach is to conceive of an encoding operation as a response that can be selectively activated or inhibited. A second assumption is that ECS or a similar brain trauma causes inhibition to be attached to those encoding responses active at the time of the ECS or trauma. This is conceived along the lines of the ECS acting like a punishment that suppresses coincident observing responses; but that analogy cannot be taken literally since a painful footshock, which is also a punishment, does not at all have the same amnestic effect as an ECS.

Notice the assumption is that certain perceptual encoding responses are inhibited or suppressed by the ECS; the assumption is not that inhibition of all behavior has been conditioned to cues coincident with ECS. This latter position is like that of Lewis and Maher (1965), and it has been justly criticized as failing to explain data showing amnesia through preservation of an active but punished response, for example, where a rat shows amnesia for having received a painful shock by continuing to press a lever actively for a water reward. Postulating that certain perceptual responses are inhibited is like claiming that certain stimulus elements in the standard experimental situation have almost zero sampling probabilities.

A third optional assumption is that the suppression or inhibition may dissipate over a long time of several days or weeks, slowly returning all encoding responses to their pre-ECS level of availability. It just is not clear now how much of this recovery from amnesia needs to be allowed for, since the evidence is conflicting.

A few comments are required to relate these assumptions to the ECS studies of retrograde amnesia. Recall that the hypothesis of contextual drift implies a steady turnover of active encoding operators as time passes. Therefore, the probability that an encoding response active at time t before ECS is still active at the time of ECS (and hence becomes inhibited) is the exponential function, $J + (1 - J)e^{ht}$.

A concrete illustration may aid comprehension here. Suppose that over several days a thirsty rat has been trained to drink in a distinctive experimental box. In the diagram in Figure 10, we identify the open dots with stimulus elements of the box associated with drinking in this situation. On a particular day, the rat is placed in the drinking box and after a few minutes receives a painful electric shock to its feet. This, we assume, causes the stimulus elements (s-a-cs) active at that time to become conditioned immediately to an emotional response (anxiety) which would compete with drinking. Elements conditioned to the emotional response are indicated by black filled dots in Figure 10. Then, for half the subjects, ECS is given immediately after the painful footshock experience; for the other subjects, a much longer delay intervenes between the footshock and the ECS.

We assume that encoding responses active at the time of ECS are driven into an inhibitory state. This implies that the s-a-cs (elements) corresponding to those inhibited encodings will have zero sampling probabilities for some time thereafter. For illustrative emphasis, these inhibited s-a-cs are encapsulated by a small circle in the diagram of Figure 10. Figure 10 shows the expected composition of this capsule as a function of the interval between footshock and ECS; the capsule contents in the beginning are in fact the set of encoding responses that were active at the time of ECS.
FIG. 10. Diagram of conditioning status of active versus inactive s-a-cs immediately after footshock, then immediately after ECS at zero delay (upper branch) or ECS at a long delay (lower branch), each followed by a test trial much later. Open dots denote stimulus elements associated with drinking; filled dots denote elements associated to the anxiety reaction elicited by footshock. The boundary encircling four elements after ECS represents the inhibition and near-zero sampling probability of those encoding responses present at the time of ECS.

As Figure 10 shows, with a longer delay between footshock and ECS there is more opportunity for change in the active encoding responses. Thus, encoding responses active at the time of footshock, (with s-a-cs leading to an anxiety reaction) are replaced by new ones, and the former ones thus escape being inhibited by the ECS. The differences in the immediate versus delayed ECS become apparent later (shown as the “Later Test” in Figure 10) in terms of the likelihood of the conditioned emotional response in the test situation. Indexing rate of drinking by the proportion of active s-a-cs conditioned to drinking (as opposed to fear), subjects that received ECS immediately show complete amnesia for the footshock experience, whereas those receiving delayed ECS will display emotional responses, inhibit drinking, and generally show obvious memory for the footshock experience.

The difference in retrieval of the footshock experience between these two conditions depends systematically in theory on the delay between footshock and ECS. The fluctuation theory supposes that this will be an exponential function, with more memory of the footshock experience the greater the delay. Furthermore, certain drugs that act as central nervous system stimulants or depressants may shorten or lengthen the consolidation time constant by altering the time rate of stimulus intake and encoding-response fluctuation. Thus, if picrotoxin or strychnine enhances the speed of stimulus sampling and speed of shifting among
different encoding operations, then one would expect subjects given such drugs to remember more later for a given delay before ECS (McGaugh, 1966).

It is of interest that this hypothesis supposes that all subjects learn and store the requisite experience; what differs among them is the degree of blocking of retrieval of the learned information. Lewis (1969) has also considered retrieval difficulties as a viable explanation for ECS effects. We can say that the amnesic rat who drinks without fear would be frightened if he could perceive the situation in the way he had at the time of the painful footshock. But the ECS has made those perceptual modes of operation improbable for the moment.

The issue of whether there is any ultimate recovery, how much and its time course, is a quite independent matter from the assumptions above. The strict consolidation hypothesis expects no recovery of disrupted memories. On the other hand, some of the clinical literature as well as an increasing portion of the experimental literature shows some recovery of the lost memories over time. For instance, with our example of the drinking rat, a rat given immediate ECS after footshock will show no anxiety on a one-day retention test but will show increasing anxiety and suppression of drinking on tests given after several days or weeks (Kohlenberg & Trabasso, 1968).

I have not thought about the encoding-suppression hypothesis long enough to see now how to differentiate it experimentally from the consolidation hypothesis. Possibly some of Lewis’ (1969) experiments on “footshock reminders” will prove interpretable within the encoding-retrieval framework while remaining outside the fold of consolidation theory. Perhaps techniques of perceptual alterations (e.g., wearing of prisms, sensory isolation, sensory adaptation) can be brought to bear creatively on the perceptual hypothesis regarding “amnesic” effects of ECS.

CONCLUDING REMARK

I have claimed here that the stimulus sampling theory of Estes, with a few emendations, provides a determinate framework within which to investigate the effects of encoding variability on memory. One purchases the power of stimulus sampling theory at the price of giving up certain cherished complexities and accepting idealized sample schemes, such as equal-sampling probability of all elements. But perhaps the range of phenomena explained by the model is worth the small purchasing price for those believers in encoding-variability theory.

I have made explicit the correspondences and connections between the stimulus sampling approach and Martin’s theory of encoding variability. I would argue that the correspondences range as well into some of the other senses of encoding discussed at the outset, namely, coding as selection (or fractionation), as componential description, and as elaboration of the nominal stimulus. In each of these senses, we may investigate variability (across trials) in the full encoding of a given stimulus, and consider each code pattern as a distinct element or s-a-c to which the sampling theory might apply. I will not pursue the argument here, but will leave you with the claim that stimulus-sampling theory will provide a plausible abstract representation of the effects of encoding variability, contextual determination, and time-dependent drift in encoding, no matter what the exact nature of the
encoding envisaged by the differing approaches. I am not saying that those approaches can now be pre-empted by stimulus-sampling theory; quite the contrary, the bases, varieties, and usages of different encoding systems in memory must continue to be systematically explored. Such investigations identify the stimulus elements, the mechanisms of their selection, and the sampling processes that stimulus-sampling theory refers to in only an abstract and elliptical manner. Thus, I view the hypotheses proposed in this paper as useful when one addresses himself to encoding variability (of whatever sort) of an episode that is to be remembered for later recognition of identity or recognition of its context of earlier occurrence.

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THEORY OF ENCODING VARIABILITY


