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A Model for Contextual Fluctuation

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Current theories of human memory frequently assume that the probability of recall depends on the similarity of the test context to the study context. A model for contextual fluctuation is developed that is based on Stimulus Sampling Theory. The model assumes that "context" can be represented by a set of so called contextual elements. Part of this set represents the current context. There is a continuous fluctuation between the active contextual elements (the current context) and the inactive contextual elements. During study, part of the current context is conditioned to (stored in) the memory trace. The model may be used to derive predictions for the overlap between the study and test contexts. The model is developed in the context of interference paradigms. It is shown that the model leads to a number of interesting predictions. The incorporation of this model in the SAM theory (Raaijmakers & Shiffrin (1981). *Psychological Review* **88**, 93–134) enables that theory to predict such phenomena as spontaneous recovery and proactive inhibition. © 1989 Academic Press, Inc.

Recent theories of memory have placed considerable emphasis on the role of contextual factors in retrieval from long-term memory (e.g., Anderson, 1983; Glenberg, 1979; Raaijmakers & Shiffrin, 1981). In particular, it has been assumed that the probability of recall depends on the similarity of the context at the time of retrieval to the context at the time of encoding. This factor is often assumed to be (at least partly) responsible for the gradual decrease in the probability of recall as a function of the retention interval. That is, it is assumed that the similarity of two contexts is determined by the distance in time: the context at time $t(i)$ will be more similar to the context at time $t(i+j)$ than to the one at time $t(i+k)$ where $k>j$. However, with the exception of Estes (1955) and Bower (1972), no attempts have been made to formally incorporate this notion in current mathematical models for learning and memory.

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In this article, we will develop a model for contextual fluctuation that will be incorporated in the SAM theory (Raaijmaker & Shiffrin, 1981). However, although our presentation will be in the context of that theory, we believe that our results have a wider applicability and might be incorporated in other models of memory. Special attention will be given to interference phenomena. A full account of this particular application is given in Mensink and Raaijmakers (1988). In the present paper we will focus mainly on the quantitative aspects of contextual fluctuation model.

The SAM theory is a cue-dependent probabilistic search theory that has been shown to be able to account for a large range of phenomena in the memory literature (see Raaijmakers & Shiffrin, 1980, 1981; Gillund & Shiffrin, 1984). The SAM theory assumes that context acts as a search cue similar to other cues such as item cues or category cues. In this theory, context has been used as the factor that allows the memory search to be focused on the target list of items. Moreover, Raaijmakers and Shiffrin (1981, p. 129–130) assume that contextual change is one of the major factors determining forgetting. For example, it can be easily shown that a decrease in the contextual retrieval strengths (as defined in this theory) leads to a decrease in the probability of recall. However, in order to be able to extend the SAM model to the explanation of time-dependent aspects of memory (e.g., simple forgetting), it is necessary to make at least one variable in the model time-dependent. In accordance with Raaijmakers and Shiffrin (1981) a likely candidate is the associative strength of the context cue to the stored memory images (or traces). In the next section we will develop a context fluctuation model. This model will then be incorporated in the SAM model and will be shown to be responsible for the prediction of a number of interference phenomena.

Description of the Model

The model that we will discuss is an element-based context model in the tradition of Stimulus Sampling Theory. We will present the model as it applies to the paired-associate learning paradigm although it could undoubtedly be generalized to other paradigms such as free recall.

Let us start with a verbal description of the model. Following Estes (1955) and Bower (1972), context (internal as well as external) will be represented as a set of contextual elements. At any given time only a part of this context is perceived by the subject and this subset is denoted as the current context. Elements that are part of the current context are said to be in the *active state*. All other elements are inactive. We assume that at any moment only a fixed number n of the elements are in the active state. The total number of elements is equal to $N+n$. Hence, the number of inactive elements equals N. With the passage of time, the current context changes due to a fluctuation process: inactive elements may become active and some active elements will become inactive.

Before applying these ideas to the paired-associate paradigm, we will first discuss how they are related to the concept of contextual information as used in the SAM theory. According to SAM, at the time of study both item and context information is stored in long-term memory. It is assumed that both the S–R pair and the contextual elements are encoded in the same image or episode (Mensink & Raaijmakers, 1988). Both the associative strength between the two members of a pair and the contextual associative strength are a function of the presentation time. In order to relate this to the present context model, it seems natural to assume that the number of active elements that will be encoded in the image, is a function of presentation time.

We will now apply these ideas to a paired-associate interference design (*A–B*, *A–C*). Imagine that a subject is given one study trial on a List-1 stimulus–response pair (*a–b*) and the one study trial on the corresponding *a–c* pair, followed by a retention test (*A–B* denotes a list of paired associates, whereas *a–b* symbolizes an individual pair). Thus, both "lists" contain only a single pair. This particular situation is illustrated in the following scheme:

$$a\text{–}b \xrightarrow{t_1} a\text{–}c \xrightarrow{t_2} \text{test}$$

where t_1 and t_2 represent the interlist interval and the retention interval, respectively.

Consider what happens when the *a–b* pair is presented for study. Any active contextual element may be encoded in the item's image. Such an element is denoted by x_1. Elements that are not encoded, are denoted as y-elements. During the interlist interval t_1 the fluctuation process causes a new sample of context elements to be active when the *a–c* pair is presented. This active set will contain x_1 and y elements. Some of the active y elements will be stored in the *a–c* image. These elements are called x_2 elements. An x_1 element that is stored in the corresponding List-2 *a–c* image now refers to two traces that belong to different lists and that involve the same stimulus terms. Such an element is denoted by x_0 (overlap element). At the end of the retention interval (t_2) the active set will contain x_1, x_2, x_0, and y elements. These elements constitute the context cue that is used to retrieve images from memory. Its associative strength to an image from List-i is assumed to be proportional to the sum of active x_i and x_0 elements, i.e., to the overlap of the set of elements stored in the image and the set of elements active at the time of testing.

In summary, there are always two sets of contextual elements, the active elements and the inactive elements. Active elements may be encoded during a study trial. The probability of recall on a test trial is a function of the overlap between the context elements active at test and the elements encoded in an image.

At this point we have to make some simplifying assumptions in order to keep the model mathematically tractable. It will be assumed that during a learning trial the contextual state remains fixed, i.e., active elements remain active and similarly for inactive elements. If one would assume that the context fluctuates within as well as between trials one would have to treat all items individually, which would make computation of model predictions quite complicated and practically unfeasible. The above assumption implies that we disregard an item's position in the list.

In addition, we will have to make some decisions concerning the relationship between the elements encoded on a given trial in the images corresponding to different items. It seems unlikely that the same subset of active elements is encoded in all images, especially since it is also assumed that the number of elements encoded depends on the presentation time. It will therefore be assumed that the encoding of active elements in a memory image is governed by a stochastic process and that the subsets of active elements that are encoded in the images of different items are independent samples from the set of elements that constitutes the current active context.

The Mathematical Model

The heart of our model is the equation that gives the number of elements of a given type v ($v = x_1, x_2, x_0$, or y) that are active following t seconds of fluctuation, given that the state at $t = 0$ is known. This equation is given by the solution of the differential equation

$$\frac{dA(t)}{dt} = \gamma A'(t) - \beta A(t)$$

$$A'(t) = K - A(t),$$

where $A(t)$ denotes the number of elements that are conditioned (i.e., encoded in the memory image) and active. $A'(t)$ gives the number of elements that are conditioned but inactive and K equals their sum: $A(t) + A'(t)$, i.e., the total number of conditioned elements. γ is the rate at which an inactive element becomes active and β gives the rate at which an active element becomes inactive. Note that during a fluctuation period, K is constant but $A(t)$ and $A'(t)$ are changing. Thus,

$$\frac{dA(t)}{dt} = \gamma K - (\beta + \gamma) A(t).$$

The solution of this differential equation is

$$A(t) = A(0) \exp\{-(\beta + \gamma) t\} + K \frac{\gamma}{\beta + \gamma} [1 - \exp\{-(\beta + \gamma) t\}]. \quad (1)$$

Thus, $A(t)$ gives the number of elements from class v that are active following t seconds of fluctuation. In this derivation we have implicitly assumed that the total number of contextual elements is reasonably large (otherwise the use of the differential equation technique would not have been appropriate). Hence, $A(t)$ might be considered as the expected number of active elements.

Next, we need a learning equation, i.e., a formula that gives the number of active elements that are stored in an image during a study trial as a function of the study time. We will assume that the increase in the number of stored elements is proportional to the number of active elements that are as yet not conditioned (not stored in the image under consideration). This leads to the differential equation

$$\frac{dA(\tau)}{d\tau} = \alpha[n - A(\tau)]$$

where τ gives the presentation time in seconds. The solution is

$$A(\tau) = A(0)\exp(-\alpha\tau) + n[1 - \exp(-\alpha\tau)].$$

Hence the probability that an active element that has not already been encoded in the image, is stored during a study trial of τ seconds is equal to

$$w = \frac{A(\tau) - A(0)}{n - A(0)} = 1 - \exp(-\alpha\tau). \tag{2}$$

Equations (1) and (2) will be used to derive formulae for the number of elements from class v that are active at the time of testing. Let us assume a multitrial list learning situation of the following kind where t_1 denotes the intertrial interval, t_2 the interlist interval and t_3 the retention interval:

$$A\text{–}B \xrightarrow{t_1} A\text{–}B \xrightarrow{t_1} A\text{–}B \xrightarrow{t_2} A\text{–}C \xrightarrow{t_1} A\text{–}C \xrightarrow{t_3} \text{TEST}$$

In this analysis we will use the following notation:

- $A_v(i, j, t)$ the number of contextual elements of type v that are active t seconds after the jth trial on List-2 and following i trials on List-1;
- $K_v(i, j)$ the total number of elements of type v (active plus inactive) after i trials on List-1 and j trials on List-2.

Let us start with List-1 trials ($i = 1, j = 0$). At the start of the first study trial, n y elements will be active. Immediately after the first trial, nw of these elements are conditioned and have become x_1 elements. During the intertrial interval fluctuation occurs and on the second trial another subset of the remaining y elements is transformed into x_1 elements. In general, we have the following difference equation for the number of x_1 elements:

$$K_1(i, 0) = K_1(i-1, 0) + w[n - A_1(i-1, 0, t_1)].$$

In words: the total number of x_1 elements on trial i is equal to the number on trial $i-1$ plus a proportion w of the unconditioned elements that are active at the end of the intertrial interval between trial i and trial $i-1$ (i.e., at the start of trial i). For the number of active x_1 elements we have

$$A_1(i, 0, 0) = A_1(i-1, 0, t_1) + w[n - A_1(i-1, 0, t_1)],$$

$$A_1(i, 0, t_1) = A_1(i, 0, 0)\exp\{-(\beta + \gamma)t_1\} + K_1(i, 0)h(t_1),$$

where $h(t)$ is defined as

$$h(t)=\frac{\gamma}{\beta+\gamma}[1-\exp\{-(\beta+\gamma)t\}].$$

Due to the conditioning process the number of y elements decreases. This leads to

$$\begin{aligned} A_y(i,0,0)&=n-A_1(i,0,0)\\ &=A_y(i-1,0,t_1)-w[A_y(i-1,0,t_1)],\\ K_y(i,0)&=K_y(i-1,0)-w[A_y(i-1,0,t_1)]\\ &=K_y(i-1,0)[1-wh(t_1)]-A_y(i-1,0,0)w\exp\{-(\beta+\gamma)t_1\}. \end{aligned}$$

With these equations and the initial conditions $A_1(0,0,0)=K_1(0,0)=0$, $A_y(0,0,0)=n$, and $K_y(0,0)=N+n$, these quantities can be calculated for all times during List-1 learning.

Suppose now that a second (interfering) list is presented t_2 seconds after the Ith trial on List-1. At the end of the interlist interval the number of elements of each type is given by

$$\begin{aligned} A_1(I,0,t_2)&=A_1(I,0,0)\exp\{-(\beta+\gamma)t_2\}+K_1(I,0)h(t_2),\\ A_2(I,0,t_2)&=A_0(I,0,t_2)=0,\\ A_y(I,0,t_2)&=n-A_1(I,0,t_2),\\ K_2(I,0)&=K_0(I,0)=0. \end{aligned}$$

During List-2 learning some of the y elements will become x_2 elements and some of the x_1 elements will become x_0 elements. The following set of difference equations describes the changes in the number of elements of each type:

$$\begin{aligned} A_1(I,j,0)&=(1-w)A_1(I,j-1,t_1),\\ K_1(I,j)&=K_1(I,j-1)-wA_1(I,j-1,t_1),\\ A_2(I,j,0)&=A_2(I,j-1,t_1)+wA_y(I,j-1,t_1),\\ K_2(I,j)&=K_2(I,j-1)+wA_y(I,j-1,t_1),\\ A_0(I,j,0)&=A_0(I,j-1,t_1)+wA_1(I,j-1,t_1)\\ K_0(I,j)&=K_0(I,j-1)+wA_1(I,j-1,t_1),\\ A_y(I,j,0)&=(1-w)A_y(I,j-1,t_1),\\ K_y(I,j)&=K_y(I,j-1)-wA_y(I,j-1,t_1). \end{aligned}$$

As in the case of List-1 learning, the composition of the active set of contextual elements changes during the intertrial interval (of length t_1 seconds):

$$A_v(I, j, t_1) = A_v(I, j, 0)\exp\{-(\beta+\gamma)t_1\} + K_v(I, j)h(t_1).$$

A similar equation describes the state of affairs at the end of the retention interval (t_3 seconds), i.e., the interval between the last List-2 trial and the final testing:

$$A_v(I, J, t_3) = A_v(I, J, 0)\exp\{-(\beta+\gamma)t_3\} + K_v(I, J)h(t_3).$$

We have not been able to derive a (closed) analytical solution for these difference equations. However, after insertion of the appropriate values for t_1, t_2, and t_3, these equations can be easily used to compute the state of activation at the end of the last List-2 trial. These results may then be used to calculate the number of active elements of each type at the time of test.

Implementation in SAM

In the original SAM model, the probability of recalling an item was a function of, among other things, the "contextual retrieval strength," the strength between the context cue and the memory image (or memory trace) corresponding to that item. The present notion of a fluctuating context may be incorporated in a natural way in the SAM model. We assume that the contextual retrieval strength is proportional to the overlap in the contextual elements that are active at the time of testing and the contextual elements stored in the memory image.

For any List-i image, the overlap is equal to the sum of the number of active x_i and x_0 elements. Hence, the contextual retrieval strength (s_i) between the context cue at test and a particular List-i image is equal to

$$s_i = \frac{[A_i(I, J, t_3) + A_0(I, J, t_3)]}{n}\, a.$$

In this formula we divide by n in order to eliminate a non-identifiable parameter: since all A_v are proportional to n, we cannot estimate n and a separately. Put in another way, the contextual retrieval strength is proportional to the proportion of the elements active at the time of testing that are encoded in the memory image. Since the value of n is arbitrary, we have scaled the A_v and K_v in units of n. That is, we have set n equal to 1 in all calculations.

The implementation of this contextual fluctuation model in SAM poses a number of other problems that we will briefly discuss. In SAM, associative strengths are incremented (increased) after a successful recall (a learning-during-retrieval assumption). For paired associates this means that the interitem strength (the strength of the stimulus item to the memory image) and the contextual strength will be incremented after recall of the response. Within the fluctuation model, the increment for the contextual strength should be proportional to the number of active elements that are not encoded in the image. This process can be understood as follows. The fact that the subject was able to recall a response means that the subject was able to recover the image (the representation of this pair in memory). This means that the content of such an image was activated at that moment. We assume that during this period the active contextual elements that were not already stored in this image, may now become associated to this memory image. That is, they are stored together with the other elements from the recovered image. When the subject is tested a second time on this item, the expected overlap between context cue and image will be larger than before which leads to a higher probability of recall. However, if one wants to work with this incrementing assumption, one will have to resort to complicated Monte Carlo simulation methods, treating all items individually. Since the data that we will consider do not seem to depend on such an incrementing assumption, we will work with the simplified model without the learning-during-retrieval assumption.

Finally, the present model assumes that when an item is presented on several trials, new contextual elements are always added to the same (single) memory image. This implies that an item is always "recognized," i.e., the image that was stored on the first presentation is always successfully recovered as it is presented on later study trials. The present model could be generalized by assuming that on a repeated presentation context elements are added to the memory image of a previous presentation, if that image is retrieved on the second presentation. If it is not recognized (i.e., not retrieved), then a new image would be formed. Such a more complicated study-phase retrieval model might be useful for the explanation of spacing effects, but does not seem to be necessary for the modeling of list learning paradigms.

Applications of the Model

In this section we will consider a number of predictions of the present contextual fluctuation model. We will focus on the effects of varous experimental variables on the contextual strengths. All calculations will be based on the following set of parameter values: $\gamma = 0.01$, $\beta = 0.035$, $a = 0.2$, $\tau = 4.0$, $\alpha = 0.62$, $t_1 = 10$, and $t_2 = 10$. In addition, we will show how this fluctuation model enables the SAM theory to account for a number of interference and forgetting phenomena. A full account of the application of SAM to interference and forgetting is presented elsewhere (Mensink & Raaijmakers, 1988). In this paper, we limit the presentation to those predictions of the new SAM model that are a more or less direct consequence of the incorporation of the contextual fluctuation model.

We will first examine the effects of the number of List-1 and List-2 trials. Figure 1 shows the total number of contextual elements of each type (K_v) immediately after each of five List-1 trials and three List-2 trials. Obviously, during List-1 study trials the number of x_1 elements increases steadily. Furthermore, during List-2 trials, a

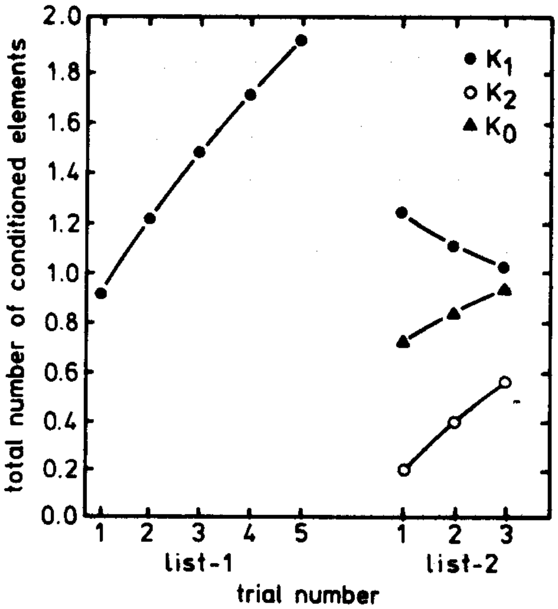

FIG. 1. Total number of class v ($v = x_1$, x_2, or x_0) elements immediately after each of five List-1 trials and three List-2 trials.

number of these x_1 elements transform into x_0 elements. At the same time the number of x_2 elements starts to increase.

Figure 2 gives the total number of elements of each type as a function of the length of the intertrial interval (t_1). These results show that the total number of stored elements (of whatever kind) increases with larger intertrial intervals. This can be easily understood: as the intertrial interval increases, the overlap between

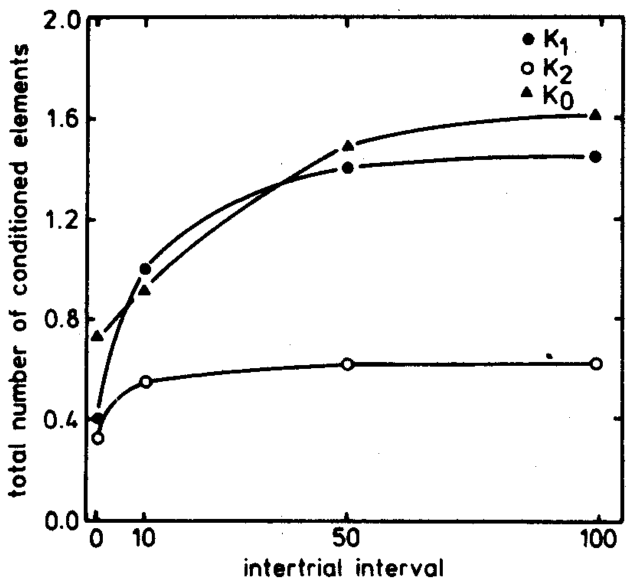

FIG. 2. Total number of class v elements as a function of intertrial interval lengths at the end of five List-1 trials and three List-2 trials.

the elements present on successive trials decreases and, hence, the number of elements that are already stored. In other words, there are more elements that can be stored and each element has a fixed probability of being stored on any given trial. This result implies that the model predicts that distributed learning should be better than massed learning. This so-called distributed learning effect is of course a well-known phenomenon (e.g., Robinson, 1921; Hovland, 1938).

The finding that the curves for K_1 and K_0 show a cross over is accidental and depends on the parameter values that are used. The number of overlap elements (K_0) depends both on the number of x_1 elements that remain in the active set during the intertrial interval and on the number of x_1 elements that fluctuate during that interval from the inactive to the active set. For small values of t_1, a relatively large number of elements remain in the active set, whereas for large values of t_1, a large number of the elements migrate to the active set.

In Fig. 3 it is shown that the distribution of the total numbers of elements over the various types of elements is strongly influenced by the interlist interval (t_2): an increase in the interlist interval leads to less overlap elements. This might explain why it is easier with larger interlist intervals to discriminate between items from the two lists. That is, most models for list discrimination or list membership decisions will assume that such decisions become easier when there is less overlap between the list contexts.

Figure 4 presents the changes in the set of *active* elements as a function of the retention interval. This figure shows a continuous growth in the number of active y elements as the retention interval increases. With this property of the model simple forgetting is easily explained since y elements are not connected to any of the to be recalled items. Another interesting result concerns the *increase* in the number

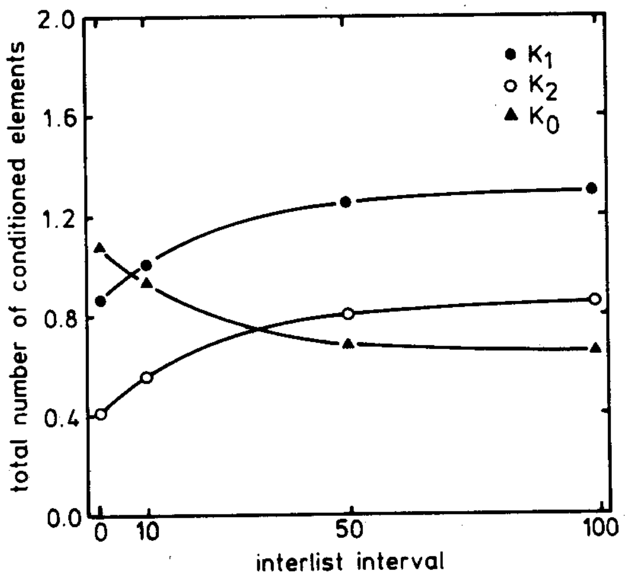

FIG. 3. The total number of overlap elements as a function of the interlist interval. Unique elements are also depicted.

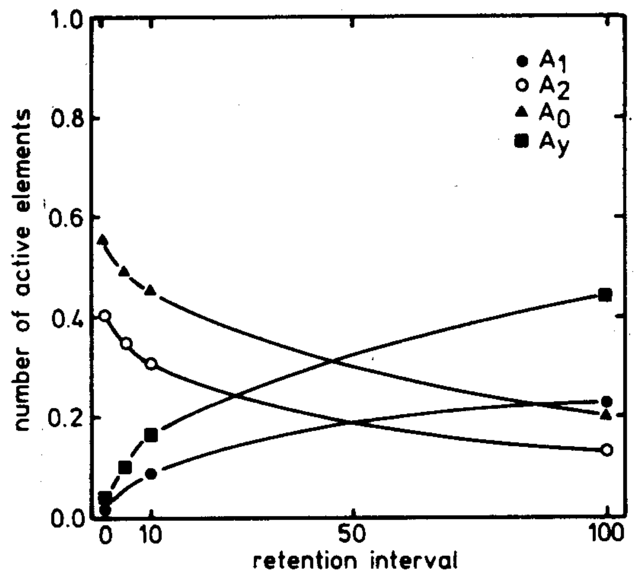

FIG. 4. The number of active class v elements as a function of the retention interval.

of active x_1 elements, especially when contrasted with the decrease in the number of active x_2 elements. This can be explained as follows: At the start of the retention interval, most *active* x_1 elements have been transformed into overlap elements. As the retention interval increases, more and more of the x_1 elements in the inactive set migrate into the active set.

This result has some very interesting consequences for the dependence of retroactive and proactive interference on the length of the retention interval. Let s_1 and s_2 be the contextual strengths for a List-1 and a List-2 item, respectively. Then, according to SAM, the probability of sampling a particular List-1 image is a function of the relative strength of the List-1 image. Thus, the probability of recalling response R_1 relative to R_2 depends on the ratio s_2/s_1. The behavior of this ratio as a function of the retention interval is shown in Fig. 5. The ratio s_2/s_1 *decreases* as the retention interval increases. This implies a *relative* and possibly an *absolute* increase in the probability of recalling List-1 responses, a phenomenon known as *spontaneous recovery*. Whether or not an absolute increase is observed depends in the SAM model not only on the relative value of s_1, but also on its absolute value. The latter is always a decreasing function of the retention interval. Hence, there are two opposing processes in the model that determine the probability of recall: the probability of sampling the List-1 image (a function of the relative strength) and the probability of recovering the item given that the image has been sampled (a function of the absolute strength). By the same mechanism, the probability of recalling a List-2 response decreases relative to a control condition (proactive interference) because this probability is also a function of s_2/s_1.

Thus far, we have examined the effects of some experimental variables on the predicted number of contextual elements of the different types. Although this is important, it does not follow that such predictions can be translated directly into

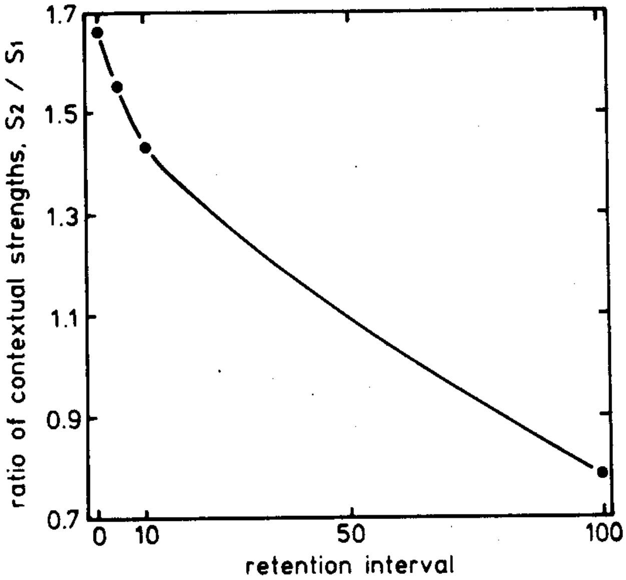

FIG. 5. Ratio of List-2 and List-1 context strength (s_2/s_1) as a function of the retention interval.

predictions for *recall*. The latter also depend on other characteristics of the larger model for recall of which the context fluctuation model is only a part. As we have already mentioned, we have developed a model based on the SAM theory that incorporates the present contextual fluctuation model.

Mensink and Raaijmakers (1988) present a full description of this new model and its application to a large number of interference and forgetting phenomena. In this paper, we present only a few examples in order to illustrate the increase in explanatory power obtained by the incorporation of the contextual fluctuation model.

The first phenomenon that we will discuss is proactive interference (PI). It has been shown in many experiments that the amount of PI depends on the length of the retention interval. As described above, this result follows quite naturally from the contextual fluctuation model. As the retention interval increases, the contextual strength for List-1 items increases relative to the contextual strength for List-2 items.

In order to investigate this further we simulated an experiment of Koppenaal (1963). In this simulation the two lists (AB–AC paradigm) consisted of 10 pairs each. List 1 was given 10 study trials and List 2 five study trials (of 2 seconds each). For the final recall test the MMFR method was used, that is the subject was asked to give both responses. The predicted results are shown in Fig. 6 for various retention interval lengths (arbitrary time units). Mensink and Raaijmakers (1988) present the equations that were used to generate these predictions.

The model predicts that recall decreases in both the control condition (C) and the PI condition (L2). However, recall decreases faster in the PI condition as shown by the standard difference measure for PI (C-L2). Hence, the model predicts an increase in PI as a function of the retention interval. This is due to the decrease in the ratio s_2/s_1.

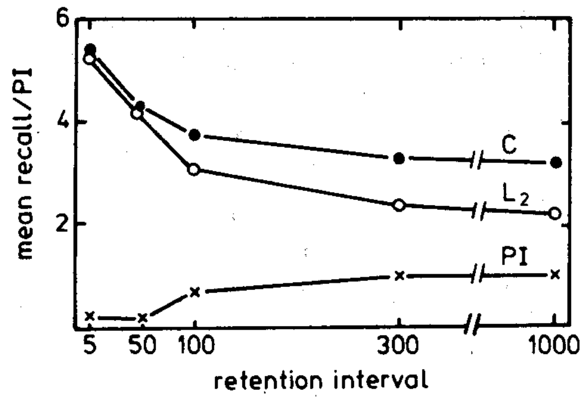

FIG. 6. Predicted patterns of recall for Koppenaal's (1963) study. Control group recall as well as MMFR List 2 recall are depicted . The difference is given by the PI curve.

Our second demonstration concerns spontaneous recovery. There has been much controversy concerning this phenomenon and its occurrence seems to depend on many procedural details of the experiment (see Brown, 1976). For example, with MMFR testing absolute spontaneous recovery is seldom observed. Briggs (1954) demonstrated spontaneous recovery using the MFR recall method. In such a test, subjects are asked to produce the first response that comes to mind. Briggs' subjects were interrupted at certain recall levels during learning. Immediately after such an interruption they were given a MFR recall test. Figure 7 shows the results predicted by our model. In this analysis, a MFR test was simulated whenever the "subject"

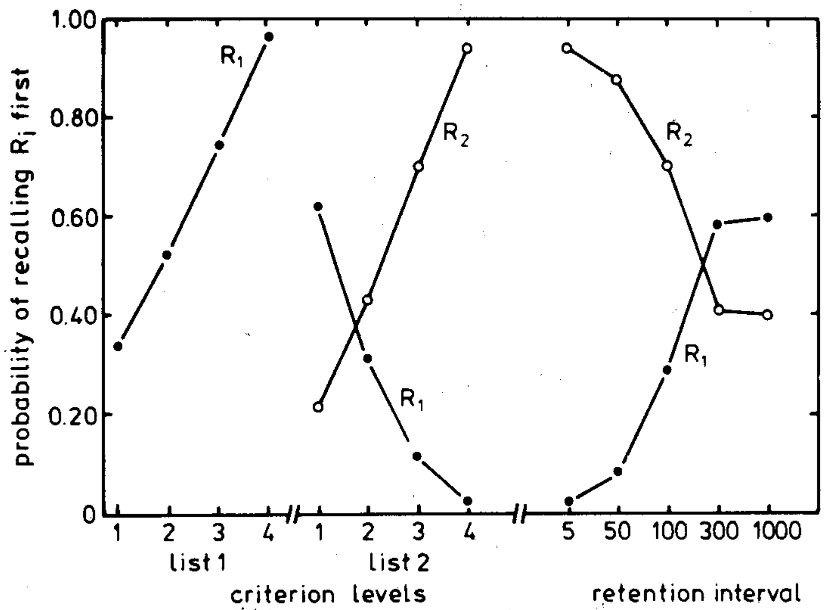

FIG. 7. Recall predictions for the Briggs' (1954) study. R_1 gives the List-1 MFR response curves. R_2 gives the second list MFR response curves. Criterion level i corresponds to the MFR test given during list learning when the 24 * i% correct criterion was reached.

reached a score of at least 24, 48, 72, or 96% correct. In addition, MFR tests were given after various retention intervals. MFR testing was simulated by calculating the probability that a particular response is recalled before the competing response is produced. For present purposes the most interesting aspect of the predictions is the *increase* in the List-1 responses produced as a function of the length of the retention interval. Again, this is due to the ratio s_2/s_1.

From these results it is evident that the present contextual fluctuation model greatly increases the scope of the SAM theory. We believe, however, that its relevance is not limited to the SAM theory. Many other models for recall incorporate the notion that the overlap between study and test contexts affects the probability of recall. Any such model might profit from the present contextual fluctuation model.

CONCLUSION

We have presented a model for contextual fluctuation and its implications for two-list or interference designs. We have shown that the combination of such a model with a more general memory theory (i.e., the SAM theory) leads to a powerful model that is able to predict a large number of well known phenomena. For a more complete account of this latter model we refer to Mensink and Raaijmakers (1988).

Although we have emphasized the relation to SAM, this does not mean that this is the only theory that might profit from the incorporation of such a fluctuation model. The idea that the probability of recall is a function of the overlap between test and encoding conditions (or retrieval and trace information, see Tulving (1983)) is much more general. The present contextual fluctuation model might be incorporated in any such model. For example, distributed memory models assume a vector representation for stimulus events. Part of these vectors might correspond to contextual information. The relation of the stimulus vectors at storage and test might be described by the present fluctuation model.

The notion of contextual fluctuation has obviously implications that go beyond the phenomena of interference and forgetting. For example, one of us (J.R.) is currently involved in a project on the application of SAM to spacing and repetition phenomena. In that project, the present contextual fluctuation model plays a prominent part.

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