

# On the Dynamics of Information Accumulation in Recognition

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## Abstract

Inspired by a dynamic approach to recognition memory (Cox & Shiffrin, 2012), we present results from a recognition memory experiment in which the time at which diagnostic information arrives is unconsciously varied. Contrary to the predictions of most models, performance improves when diagnostic information is available later, rather than earlier. These results are accounted for by a dynamic model of recognition, where the time at which information starts to be accumulated for a recognition decision can vary independently of when features are available to be sampled from the test display. The same model is shown to be able to reproduce the priming results of Jacoby and Whitehouse (1989), originally attributed to a fluency heuristic. The ability to account for such seemingly disparate results with a single model illustrates the utility of a dynamic approach to recognition.

**Keywords:** Episodic memory; recognition memory; memory models.

## Introduction

Recognition continues to be a rich source of evidence regarding the processes and mechanisms that underly episodic memory performance. Throughout its long history in psychology and cognitive science, recognition memory experiments have collected measures of reaction time. Despite this, most theories in recognition memory have been concerned only with accuracy. Most of the few models of recognition that also make predictions about response time (Hockley & Murdock, 1987; Mewhort & Johns, 2005; Malmberg, 2008; Nosofsky & Stanton, 2006) assume nonetheless that the evidence is stationary over time (an exception is Brockdorff & Lamberts, 2000). Thus, it would appear that much work remains to be done to better understand the fine-grained temporal aspects of the recognition process.

As a step in that direction, Cox and Shiffrin (2012) introduced a model of recognition that was based on the gradual accumulation of features over time. As features are sampled, they are added to a memory probe which is then compared to all the traces in memory (or at least those above a certain threshold level of activation), resulting in a “familiarity” value. Familiarity will move up and down over time in a noisy fashion as features get sampled; positive changes in familiarity are evidence in favor of an “old” decision, while negative changes favor a “new” decision. However, because only a finite number of features can be sampled, familiarity will eventually reach a (noisy) asymptote. Thus, the evidence for the recognition process in this model is inherently nonstationary. Furthermore, its predictions will vary greatly with experimental manipulations that affect the timing with which different information becomes available.

There is evidence that, even outside of experimental manipulations to that effect, the nature of the evidence for recognition may vary over time. Information about the “oldness” of individual items is available quite early in processing, while associative information (e.g., whether a word pair was studied in intact or rearranged order) requires approximately an additional 200 ms to become available (Gronlund & Ratcliff, 1989). And Hintzman and Curran (1994, Experiment 3) found that, when tested with a foil that was a plural or singular form of a word that had been studied in the opposite plurality (e.g., “apple” was studied and “apples” was tested), subjects’ tendency to endorse the foil initially increased but then reversed at longer response lags. These results are consistent with a recognition process that accumulates information over time, but at different rates for different kinds of information (e.g., Brockdorff & Lamberts, 2000).

In an attempt to better understand the dynamics of the recognition process, we first present results from an experiment in which stimuli were constructed from a set of components which varied in diagnosticity as to whether the stimulus is old or new. In some conditions, components became visible at different times, allowing us to assess the effect of presenting diagnostic information later or earlier. These results are explained in the context of a dynamic model of recognition (Cox & Shiffrin, 2012). The mechanisms employed can also be used to explain the “fluency” results of Jacoby and Whitehouse (1989).

## Experiment 1: Dynamic Presentation

In this experiment, the diagnosticity of information arriving at different times was varied unconsciously.

## Participants

55 undergraduate students from Indiana University participated in the experiment for course credit.

## Stimuli

All stimuli for a given list were generated from two prototypes consisting of random consonant triads, displayed in a triangular manner to minimize the effect of a left-to-right reading preference, e.g.,  $x^L K$  and  $z^D J$ . An old item was made from a prototype by replacing one of its letters with another consonant. This resulted in 6 old items for each prototype (2 replacements each for the three letters) and a total of 12 old items for study. The prototypes were not studied. New items were generated in a similar manner by replacing a single prototype consonant with a new randomly selected consonant that did not appear at study. This structure allows the sin-

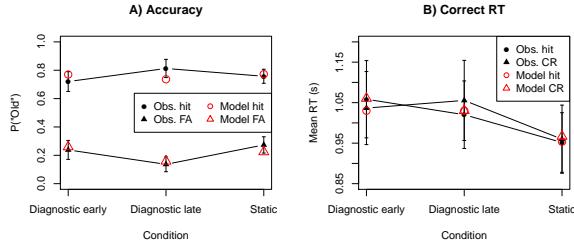


Figure 1: Observed and predicted mean accuracy (A) and mean correct RT (B) for Experiment 1. Error bars denote 95% confidence intervals.

gle unique consonant to be diagnostic as to whether an item is old and new.

## Procedure

The stimuli were presented centrally on a computer screen. During the study phase, participants were instructed to study the triads as they appeared on the screen and to remember them for a later test of memory. Individual triads were presented in random order for 1 s each with a 1 s blank screen between triads. During the test phase, the participants were instructed to respond whether the presented triad came from the previously studied list. Old and new responses were randomly mapped to the “A” or “L” key for each participant. In the static condition, all letters became visible at the same time. In the dynamic conditions, letters appeared sequentially at a rate of 30 ms (below the threshold for conscious detection) and stayed on until the end of the trial. For new triads, the unique consonant could appear as the first (diagnostic-early) or last (diagnostic-late) letter in the sequence. For old triads, the non-prototype consonant could appear second (diagnostic-early) or last (diagnostic-late). After a recognition judgment was made, the screen was cleared and the next test trial began after 1 s.

## Results

Observed hit rate (HR) and false alarm rate (FAR) are shown in Figure 1A. FAR for dynamic-late is significantly lower than for dynamic-early ( $t(54) = 2.73, p = 0.008$ ) or static presentation ( $t(54) = 3.42, p = 0.001$ ), which are not significantly different from one another. HR does not differ significantly between conditions. RT for both hits and correct rejections (CR; Figure 1B) is marginally slower in the dynamic conditions than static (for hits,  $t(51) = 2.04, p = 0.05$ ; for CR,  $t(53) = 2.06, p = 0.04$ ), but otherwise does not differ between conditions.

## A Dynamic Model for Recognition

We now provide a technical description of a model that can account for these effects of dynamic presentation. The model given here is a further development of the one described by Cox and Shiffrin (2012), although the present version is conceptually quite similar and is able to account for the same effects as the original version.

## Structure of Probe and Memory Traces

Events—for example, the study of a memory list item—result in the formation of a memory trace in long-term memory (LTM). Both a memory trace and a memory probe consists of a finite number of features, the number being determined by short-term memory capacity limitations.  $N_x$  features arise from the *context* in which the event occurs, for example, the time, location, and internal state of the participant. These features are stable across all study and test trials. There are also  $N_c$  *content* features which contain information about the event itself. For example, the memory trace formed from studying a word would include content features related to the word’s spelling, phonology, and semantics. For the moment, we do not specify the exact nature of each feature, nor do we assume that the memory system “knows” whether a given feature is a content or context feature. For simplicity, we assume that all features are binary, e.g., “0” or “1”, with an equal prior probability for each value.

In the full model, different kinds of events can be encoded with different kinds of features. For example, the trace formed from studying a word will contain orthographic, phonological, and semantic features while the trace formed from studying a picture of a face will contain features relating to the shape of the eyes, nose, mouth, etc., and their relative positions. The low degree of featural overlap between traces of different types means that probing with, for example, a word will not tend to activate traces of faces. In this paper, all items in a given experiment are of the same type, so this aspect of the model does not come into play.

## Feature Sampling

Prior to the presentation of a test item, the only features present in the probe are context features since those are persistent in the environment. Once a test item (or prime) is presented, content features may also enter the probe. We assume that content features are sampled as a Poisson process, with sampling events occurring at exponentially distributed intervals according to  $f(\tau) = \frac{1}{\rho_T} \exp(-\frac{\tau}{\rho_T})$  at test with rate  $\rho_T$  and rate  $\rho_S$  at study. On each sampling event, all the available content features have an equal probability of being selected for sampling. Whichever is selected, the correct value of the feature is stored in the probe with probability  $c$ , otherwise a random value is stored (in this case, either 0 or 1 with equal probability).<sup>1</sup> Note that, because all content features have an equal probability of being sampled on each sampling event, it is possible to sample a value for a feature that already has a value in the probe. In that case, the most recently sampled value replaces any previously stored value.

We assume that the same feature sampling process occurs at study. The probability that an available content feature will have a value stored, given limited study time  $T_s$  and sampling rate  $\rho_S$  features per second, is  $1 - (1 - 1/N_c)^{\rho_S T_s}$ , which in-

<sup>1</sup>The same noise process applies to context features; we simply assume that all context features are sampled at once at the beginning of the trial, rather than over time.

creases with both  $\rho_S$  and  $T_s$ . While not all  $N_c$  content features may end up being stored in a trace, we assume that all context features have a stored value.

### Comparison of Probe to Memory

At a given time  $t$ , the probe consists of a set of context features as well as whatever features of the test item have been sampled by that time. The probe is compared to each trace in LTM. These comparisons result in a set of likelihood ratios,  $\lambda_i(t)$  for each trace  $i$  in LTM, reflecting the likelihood that the probe and trace encode the *same* item versus the likelihood that they encode *different* items (c.f., Shiffrin & Steyvers, 1997; McClelland & Chappell, 1998).

**Likelihood** The features of the probe and a memory trace are aligned and compared individually. In the current restricted version of the model, the only features that affect the likelihood are those in which a value is stored in both the probe and trace, and the values either match or mismatch. For simplicity, we assume the same value of  $c$  at study and test, so there are four ways a feature value might match if the probe and trace encode the same item: the value was correctly copied at both study and test (with probability  $c^2$ ); a value was copied correctly at either study or test but not the other and matches by chance (with total probability  $c(1-c)$ ); or the value was copied incorrectly at both study and test but still matches by chance ( $2[\frac{1}{2}(1-c)]^2$ ). Summing these probabilities yields the probability of a feature value match given that the probe and trace encode the same item:  $\Pr(M|Same) = c^2 + c(1-c) + \frac{1}{2}(1-c)^2$ . Similarly, if the probe and trace encode the same item, the stored values could mismatch if the value in either the probe or the trace or both were sampled incorrectly and failed to match by chance:  $\Pr(N|Same) = c(1-c) + \frac{1}{2}(1-c)^2$ . If the probe and trace encode different events, then regardless of whether either value were sampled correctly, they could only match or mismatch by chance:  $\Pr(M|Diff.) = \Pr(N|Diff.) = \frac{1}{2}$ .

Since features are encoded independently of one another, the likelihood ratio across all features is the product of the likelihood ratios for the individual features. Letting  $N_M(t)$  and  $N_N(t)$  be the number of feature value matches and mismatches, respectively, the relative likelihood that a probe and trace encode the same versus different events is

$$\begin{aligned}\lambda_i(t) &= \left[ \frac{\Pr(M|Same)}{\Pr(M|Diff.)} \right]^{N_M(t)} \left[ \frac{\Pr(N|Same)}{\Pr(N|Diff.)} \right]^{N_N(t)} \\ &= (1+c^2)^{N_M(t)} (1-c^2)^{N_N(t)}.\end{aligned}$$

**Familiarity** Because the number of event traces in memory is likely to be quite large, we assume that there is a threshold for activation and only those traces whose likelihood ratios are greater than this threshold contribute to familiarity. For simplicity, we set this threshold equal to 1. The familiarity at time  $t$ ,  $\phi(t)$ , is the average likelihood ratio among the active traces:  $\phi(t) = \langle \lambda_i(t) : \lambda_i(t) > 1 \rangle$ .

### Making a Recognition Decision

The raw familiarity  $\phi(t)$  is not used directly to make a recognition decision, as its absolute value can fluctuate with a variety of factors that would preclude the setting of consistent decision criteria (Cox & Shiffrin, 2012). Rather, *changes* in  $\log \phi(t)$  are used to make a recognition decision<sup>2</sup>. Positive changes in  $\log \phi(t)$  are evidence that the test item is old while negative changes are evidence that the item is new. The evidence state at time  $t$ , denoted  $B(t)$ , is the accumulated change in  $\log \phi(t)$  since a given start time. If accumulation starts at  $t = 0$ , then  $B(t) = \sum_{\tau=1}^t \log \phi(\tau) - \log \phi(\tau-1) = \log \phi(t) - \log \phi(0)$ .

When  $B(t)$  reaches criterion  $\beta_O$ , an “old” response is made and if it reaches  $\beta_N$ , a “new” response is made. However, because at most  $N_c$  content features are available for sampling,  $\log \phi(t)$  will reach a noisy asymptote. As a result, criteria cannot be constant over time because, for some trajectories of  $B(t)$ , there is a non-zero probability that they will never reach either criterion. Thus, we allow the decision bounds to start at initial values  $\beta_O^0$  and  $\beta_N^0$  and gradually collapse according to a power function of time  $r(t) = \left(\frac{t}{t+1}\right)^{N_c}$ , scaled by the number of available features  $N_c$ . The resulting decision bounds are given by

$$\beta_O(t) = \beta_O^0 - r(t) \left( \frac{\beta_O^0 - \beta_N^0}{2} \right), \beta_N(t) = \beta_N^0 + r(t) \left( \frac{\beta_O^0 - \beta_N^0}{2} \right).$$

### Response Time Predictions

As is standard in RT modeling, we assume that the observed response time arises from a decision component and a residual component, i.e.,  $T_{obs} = T_D + T_R$ . The number of samples needed to reach criterion determines the decision component of the RT. If  $N_s$  samples are taken to reach criterion, then because sampling is a homogeneous Poisson process, the decision time is a sample from a Gamma distribution with rate  $\rho_T$  and shape  $N_s$  and expected value  $\bar{T}_D = \rho_T N_s$ .

The residual component of the RT is due to a number of factors, including the time needed to execute the motor actions needed to make a response.  $T_R$  may also vary with factors that affect the ability to successfully recognize a stimulus. We do not yet model this process in detail; instead, because we only predict mean RT in the studies reported here, we only assume that the residual process has some stationary mean value such that the mean predicted RT is  $\bar{T}_{obs} = \bar{T}_R + \bar{T}_D$ .

### Model fitting

To fit the model to each experiment reported here, we first selected by hand a set of reasonable values for the key memory parameters ( $N_c$ ,  $N_x$ ,  $c$ , and  $\rho_S$ ) and any experiment-specific parameters. The remaining parameters—principally the initial decision bounds  $\beta_O^0$  and  $\beta_N^0$ , sampling rate at test  $\rho_T$ , and mean residual time  $\bar{T}_R$ —were fit by minimizing the sum of squared error to each available group data point (hit and FA

<sup>2</sup>The effect of the logarithm is simply to put positive and negative changes on the same scale.

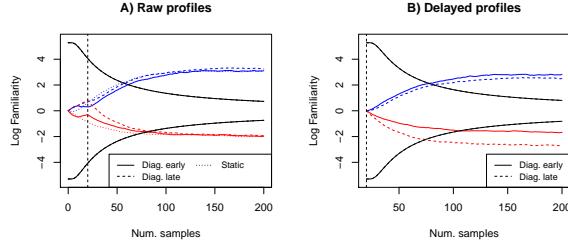


Figure 2: Mean values of  $\log \phi(t)$  for the conditions of Experiment 1. A) Raw profiles with accumulation starting at  $t = 0$ ; B) profiles for dynamic conditions with the start point of accumulation moved forward to  $t = 20$  (dashed vertical lines). Profiles for targets are in blue and foils in red; black lines show time-varying decision bounds.

rates and mean RTs for each response type in each condition) using the SIMPLEX algorithm from several different random start points. As a result, we cannot claim that the fits reported here are the best possible, but our aim is to demonstrate the qualitative behavior of the model, rather than a strict quantitative fit.

## Accounting For Experiment 1

We assume that the stimuli in Experiment 1 are represented by a set of  $N_c$  content features, where  $N_p$  features represent each of the three consonants and  $N_w$  features represent their configuration/conjunction ( $N_c = 3N_p + N_w$ ). Within the 2 categories defined by a prototype, items share  $2N_p$  features (i.e., 2 letters) but differ in their “diagnostic” (unique) letter and configural features. Foils also share  $2N_p$  features with one of the categories of studied items, but contain a third letter and configural features that differ from all studied items. In the static conditions, all  $N_c$  features are available to be sampled from the beginning of the trial ( $t = 0$ ). In the dynamic conditions, when the first letter appears ( $t = 0$ ), only the  $N_p$  features representing it are available for sampling into the probe. When the second letter appears ( $t = \delta$ ), its features become available for sampling as well. When the final letter appears ( $t = 2\delta$ ), all content features—including the  $N_w$  configural features—become available for sampling.

Because our interest is in explaining the qualitative patterns in Experiment 1, and because a wide variety of parameter values are capable of producing such patterns, we arbitrarily let  $N_p = 5$ ,  $N_w = 15$ , and  $\delta = 10$ . Study time was fixed at  $T_S = 1$  second. With these parameter values, along with others given in Table 1, the resulting mean value of  $\log \phi(t)$  for each condition is shown in Figure 2. All conditions reach the same asymptotes, but take very different routes to get there. In the early diagnostic condition, foil and target profiles separate widely early on, as would be expected, while in the late diagnostic condition, both foils and targets produce increasing mean familiarity before dividing.

A static model that only used the asymptotic value of familiarity would, incorrectly, make the same predictions for all three conditions. However, most dynamic models—including

Table 1: Parameter values used in the simulations.

Overall Param.	Value	Exp. 1		Exp. 2	
		Param.	Value	Param.	Value
$N_c$	30	$\rho_s$	40	$\rho_s$	57
$N_x$	30	$\beta_O^0$	5.279	$\beta_O^0$	6.160
$c$	0.86	$\beta_N^0$	-5.291	$\beta_N^0$	-5.975
		$\rho_T$	100	$\rho_T$	95
		$\bar{T}_R$	0.438	$\bar{T}_R$	0.360
		$N_p$	5	$\pi$	0.25
		$N_w$	15	$\eta$	0.76
		$\delta$	10	$K$	200
				$\bar{T}_C$	0.016

the one outlined above—would incorrectly predict an increase in FAs for the dynamic-late condition due to the increased probability of reaching  $\beta_O(t)$  early on. A critical feature of our model, however, is that it accumulates *changes* in familiarity, not absolute familiarity. If instead of accumulating  $\log \phi(t) - \log \phi(t-1)$  from  $t = 0$ , accumulation began when all features were available (at  $t = 2\delta$ ), the resulting evidence state would be  $B(t) = \log \phi(t) - \log \phi(2\delta)$ , as shown in Figure 2B. This delay leads to predictions that match the data: overall greater RT in the dynamic conditions, relatively little difference in HR, and a marked decrease in FAR for the dynamic-late condition (see Figure 1). The FAR prediction arises because the first  $2\delta$  samples for a foil in the dynamic-late condition all tend to match the studied items, so ignoring those early matching samples means that the later nonmatching samples are emphasized.

Why wait to begin accumulating changes? Although the dynamic presentation was fast enough that participants could not know which letters came on in what order, they could perceive that the display was noisy or “flickery”. Rationally, one would not want to risk accumulating noise and so it makes sense that participants would wait until the display was sufficiently clear to begin accumulating evidence for recognition (e.g., Smith, Ratcliff, & Wolfgang, 2004). This kind of waiting is also analogous to discounting in short-term recognition (Huber, Shiffrin, Lyle, & Ruys, 2001), in that evidence is down-weighted when it is attributed—perhaps erroneously—to noise.

## Experiment 2: Fluency

It turns out that essentially the same mechanism—missing the first few samples before beginning accumulation—can explain an apparently unrelated result in the recognition literature: the so-called “fluency effect”. It is based on the idea that the subjective feeling of familiarity, rather than the presence or absence of a memory trace, leads one to decide that an item is old, and that this feeling can arise from multiple sources (Jacoby & Dallas, 1981). One such source is a “fluency heuristic” in which people detect the relative ease of perceptual processing of a test item and use this as a sign of past experience. Jacoby and Whitehouse (1989) demonstrated that old and new words preceded by a subliminal matching prime increased the probability of judging a word as old. In terms of fluency, the subliminal flash provides a head start in processing thereby increasing fluency and giving the illusion of familiarity regardless of whether the word was old or new. We

present a replication of these results and show how a dynamic model of recognition can account for them without appealing to a fluency heuristic.

## Participants

81 undergraduate students from Indiana University participated in the experiment for course credit.

## Stimuli

Stimuli consisted of concrete nouns of moderate length and frequency drawn from the Toronto word pool. 90 words were selected for study, and another 90 served as foils at test. In addition, 60 words served as different primes at test.

## Procedure

The stimuli were presented in lowercase letters in the center of a computer monitor. In the study phase, participants were instructed to read words aloud as they appeared on the screen and to remember them for a later test of memory. The study phase was divided into two blocks, one with words presented for 1 s, another with words presented for 3 s (the order of the blocks was randomized).

During the test phase, participants were instructed to respond whether the presented test word came from the study list (“old”) or from the set of new words. Old and new responses were randomly mapped to the “A” or “L” key for each participant. Each recognition test word was preceded by a nondiagnostic subliminal prime: on 1/3 of trials, the prime was identical to the test word, on another 1/3 of trials, the prime was a different word that had not been previously seen, and on another 1/3, the prime was a neutral string of characters (XOXOXO). On each trial, a pre-mask (&&&&&&&) was presented for 500 ms followed by a prime (same, different, or neutral) for 50 ms and a post-mask for an additional 500 ms. The screen went blank for 300ms before the test word was presented. After the participant made a response, the screen was cleared for 1865 ms until the next test trial. Participants were not informed that the primes would be present.

## Results

Prior to analysis, trials with RT that were too fast (less than 200 ms) or too slow (longer than 3 s) were excluded (273 out of 14580 total trials). The observed mean probability of responding “old” in each condition is shown in Figure 3A. Replicating the original result of Jacoby and Whitehouse (1989), participants are significantly more likely to endorse an item that was preceded by an identity prime than a neutral prime ( $t(80) = 12.0, p < 0.001$ ). Surprisingly, they are also more likely to endorse an item that was preceded by a *different* prime than a neutral one ( $t(80) = 2.91, p = 0.005$ ), an effect also remarked on, but unexplained, in the original work of Jacoby and Whitehouse (1989). Observed mean correct RT are shown in Figure 3B. Identity primes speed hits ( $t(80) = -10.7, p < 0.001$ ), but slow CR ( $t(80) = 2.68, p = 0.009$ ) relative to neutral primes. Different primes also

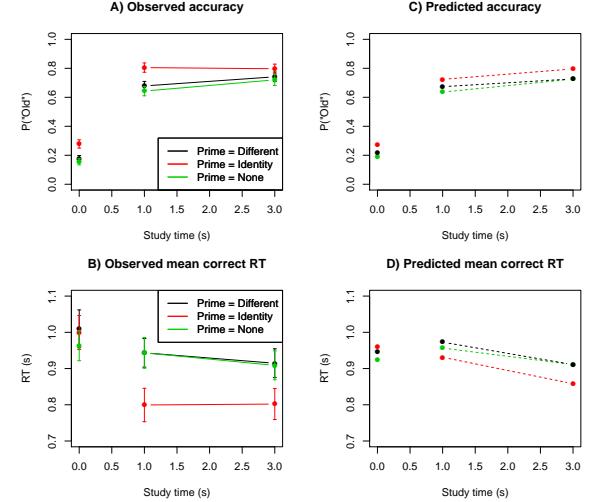


Figure 3: Observed and predicted mean accuracy and correct RT for Experiment 2. Predictions averaged over 2000 simulations. Error bars depict 95% confidence intervals.

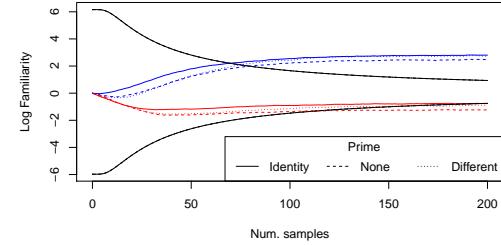


Figure 4: Mean familiarity over time for Experiment 1. Targets are in blue, foils in red, and black lines show time-varying decision bounds.

slow CR relative to neutral primes ( $t(80) = 3.21, p = 0.002$ ), but have no significant effect on RT for hits ( $t(80) = 0.93, p = 0.35$ ).

## The Dynamic Account of Fluency

The core of our account of the fluency effect lies in the assumption that the prime, if it is a word, contributes some features to the probe before features begin to be sampled from the test item and accumulation begins. In the case of an identical prime, this is exactly like changing the start time of accumulation in Experiment 1, since it eliminates the effects of the first few samples, as shown in Figure 4. Notice that, for both targets and foils, the first few samples in the neutral prime condition will, on average, produce negative changes in familiarity. If the prime word is identical to the subsequent test item, “pre-loading” the first few features eliminates some of these negative changes, making it harder to reach  $\beta_N(t)$  and increasing the probability of responding “old” for both targets and foils.

The initial negativity for targets is a consequence of how the set of activated traces changes over time as features accumulate in the probe, as outlined in Figure 5. Before any content features are sampled, the probe contains only context features and the active traces tend to be those from recent

	<b>Start</b>	<b>Early</b>	<b>Late</b>
<b>Features active</b>	Context only	Context and some content	Context and all content
<b>Traces active for target</b>	List traces (good match)	List traces (moderate match), target trace (moderate match)	Some list traces (poor match), target trace (good match), some history traces (poor match)
<b>Traces active for foil</b>	List traces (good match)	List traces (moderate match)	Some list traces (poor match), some history traces (poor match)

Figure 5: Outline of the evolution of familiarity as a function of feature and trace activation over time.

experience, i.e., the study list. If just a few content features are sampled, most or all list traces will remain active, even though most will not match on content features. As an example, say you had studied the list “table”, “moon”, “parent” and were shown “table” at test. If you had only sampled features of the first letter (“t”), they would only match 1 out of 3 study items. It is only after many content features have been sampled (e.g., another several letters) that list traces that do not match the target drop below the threshold for activation and the match to the target trace takes precedence, raising the average likelihood.

This kind of priming effect also operates for different primes. Because the first few sampled features will not match most of the list traces in any case, the features that leak from a different prime will also tend to eliminate some initial negative changes, leading to an increased probability to say old to both targets and foils. However, if the test word differs from a prime word, this also impairs word recognition by introducing competition between the prime word and the test word (McClelland & Rumelhart, 1981; Segui & Grainger, 1990). If we assume that, as in Experiment 1, participants wait until they have a clear percept before beginning accumulation, it is reasonable to suggest that participants wait until this competition is resolved (i.e., they have a clear percept of the word) before beginning accumulation. This takes some time, during which some of the prime features—which are no longer being actively sampled or maintained—have a chance of deactivating and losing their sampled values, thereby separating the different and same prime predictions.

In sum, we assume that each of the prime’s features has a probability  $\pi$  of being sampled into the probe by the time accumulation begins. There is a constant mean duration  $\bar{T}_C$  required to resolve the competition during word recognition in the different-prime condition, during which there is a probability  $\eta$  that any sampled prime feature will deactivate. The features of the study and test words are assigned randomly. We also assume that, because participants have prior experience with words, there are  $K$  traces of each word from life history that can be activated at test (their context features are assigned randomly; values used for these parameters are given in Table 1). As shown in Figure 3C-D, the model predicts the canonical “fluency” finding of increased  $p$  (“Old”) with an identical prime, as well as decreased RT for hits and increased RT for CR. It also exhibits the observed small positive priming effect for different primes.

## Discussion

We have shown how a dynamic model of recognition that allows the start time of accumulation to vary independently of feature sampling can account not just for the novel results of our dynamic presentation study, but for older findings previously attributed to a fluency heuristic. Further, this model is able to predict the observed positive priming from novel, different primes, a prediction made by no other extant recognition model. These seeming disparate predictions fall directly out of the core feature of the model, namely, that it is *changes* in familiarity from a given start time, not absolute familiarity, that drive recognition decisions.

The model and these results thus illustrate the importance of knowing when information for recognition becomes available. Here, we have assumed that unconscious priming and dynamic presentation result in features being sampled before changes get accumulated for recognition, but other manipulations (e.g., manipulations of salience or contrast) might also influence the start time of accumulation, which would be fruitful questions for further study. We suggested that, to account for results in the different-prime condition in Experiment 2, responses are slowed by an increased difficulty in recognizing the test word. Although this suggestion remains to be formalized in a model, it emphasizes the need to consider all the possible processes that contribute to recognition. Creating this kind of unified model requires a dynamic approach, which not only suggests new answers to issues like fluency, but new questions.

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