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Letters in Time and Retinotopic Space

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Main text incl. abstract: 6,335 words. Appendix: 803 words.

Model web page at: `http://www.warwick.ac.uk/~pssgar/ltrs/`

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Abstract

Various phenomena in tachistoscopic word identification and priming (WRODS and LTRS are confused with and prime WORDS and LETTERS) suggest that position-specific channels are not used in the processing of letters in words. Previous approaches to this issue have sought alternative matching rules because they have assumed that these phenomena reveal which stimuli are good but imperfect matches to a particular word, such imperfect matches being taken by the word recognition system as partial evidence for that word. The new Letters in Time and Retinotopic Space model (LTRS) makes the alternative assumption that these phenomena reveal the rates at which different features of the stimulus are extracted, because the stimulus is ambiguous when some features are missing from the percept. LTRS is successfully applied to tachistoscopic identification and form priming data with manipulations of duration and target-foil and prime-target relationships.

Reading relies on identifying words. A word's stored representation must be accessed by the matching visual perceptual representation. The response to mismatching visual stimuli — in masked form priming and tachistoscopic identification experiments — has been extensively studied to inform theories of this representation and matching. Contemporary theories all assume that the matching is graded: Stored representations of mismatching words are accessed in spite of information that indicates the mismatch, but such access is less efficient the more severe the mismatch. The calculation of such graded matches is explicit in the spatial coding model (SCM; Davis, 2010), the overlap model (Gomez, Ratcliff, & Perea, 2008), SERIOL (Whitney, 2001), and other open bigram models (e.g., Schoonbaert & Grainger, 2004). Moreover, the (expected and/or normalized) log.-likelihood plays the same role as a similarity metric in the Bayesian Reader (Norris, Kinoshita, & van Casteren, 2010). To calculate such graded matches in a way that accords with the data requires extensive machinery. It is my contention that the problem is complex because the assumption of graded matches is unnecessary, and that the data can be more simply explained by an alternative type of theory.

The alternative theory posits — in common with a class of models of categorization (e.g., Cohen & Nosofksy, 2003; Lamberts, 1998) — that visual information is incomplete early in processing, and incomplete visual information can match more than one stored representation or response alternative. The posited incomplete information is composed of discrete pieces of information; it is not simply a weakened copy of the ideal information, as in activation-based models, nor is it information contaminated with noise or error, as in the Bayesian Reader. Indeed, the predictions can be made without considering the possibility that visual information may be misperceived: Information has either been perceived or not, and the system can remain wholly agnostic as to information that is yet to be perceived. As a consequence, all phenomena can reflect the timing of information availability, and not its strength, so no use of graded matching is needed[1].

The claims of this paper are that an appropriate characterization of letter identification processes is stochastic and piecemeal, and that phenomena attributed by other accounts to imperfect or graded matching in masked form priming and tachistoscopic identification are a consequence of these letter identification processes, rather than the details of lexical matching processes.

The Letters in Time and Retinotopic Space model (LTRS) implements these claims by specifying detailed assumptions about this piecemeal letter processing, but specifying only the bare minimum of assumptions about lexical processing: that the lexical system can distinguish a match to a particular known word from a non-match for that word (which is necessary for stimulus identification to be possible at all), and that the lexical system is susceptible to a head start from additional stimulus exposure (which is necessary for priming to be possible at all). As such, the model cannot, of course, address phenomena that are clearly lexical, such as frequency effects or neighborhood effects, nor even lexical decision itself, only the (relative amount of) priming that occurs in that task.

Thus, all of LTRS's explanations are that relevant information has yet to be perceived during a brief presentation; the timing of such information is a concrete concept, measurable in identification tasks. Models that rely on some form of similarity (match score) calculation must further specify several intervening hypothetical mechanisms: how such simliarity is calculated, its influence on lexical access, and how the underlying representation gives rise to confusions when all information is present. LTRS is simpler because it does not require these explanatory mechanisms. In the light of other accounts, LTRS may appear to do little explanation, but this is because these other accounts interpose explanations where none are required.

This paper presents (i) a description of LTRS; (ii) discussion of some core aspects of the model; (iii) LTRS fits to new word tachistoscopic identification data with manipulation of target duration for transposed-letter (TL) and 1-, 2-, and 4-letter-different (1LD; 2LD;

4LD) foils; (iv) LTRS fits to nonword tachistoscopic identification data for a wide range of target-foil relationships; (v) LTRS fits for form priming data with a manipulation of prime duration; and (vi) LTRS fits for priming with a range of prime-target relationships.

The Letters in Time and Retinotopic Space Model (LTRS)

LTRS[2] specifies letter processing in terms of the timing of initiation of processing; the rates of processing that determining the timing of identity and approximate and precise positional information; and specifies the inferences licenced by this positional information in the context of the usefulness of retinotopic location and distance information.

Start of processing. On a given trial, processing of all letters begins at the same random point in time after onset. As an approximation, this time is normally distributed with mean α and standard deviation σ. That assumption that this time is equal for all letters is supported by tachistoscopic identification data specifically seeking — but not finding — time points at which identification of left-hand letters in words is above chance and right-hand letters is at chance (Adelman, Marquis, & Sabatos-DeVito, 2010).

Processing strengths. Whilst processing begins at the same time for each letter, positional effects (such as left-to-right trends in accuracy at intermediate durations, e.g., Stevens & Grainger, 2003) are accommodated in the model by processing strengths: A letter in any position i has a processing strength β_i that would be determined by the attentional gradient and the visibility of the letter (due to factors like lateral masking and distance from fixation). As a simplification, these strengths are the same on every trial.

Identity processing. The identity of the letter in position i becomes available at an exponentially distributed time after the start of processing, with processing rate proportional to β_i; that is, once an amount of time t has elapsed since the start of processing, the probability that the letter i has been identified is $1 - \exp(-k\beta_i t)$. Without loss of generality, $k = 1$. This assumption is the same as that for feature extraction in some models of categorization (e.g., Lamberts, 1998).

Approximate positional information. Once a letter is identified, some information about its retinotopic location is available. This information is assumed to accurately specify a single point or small region within the letter (because a single letter spans several retinotopic letter detectors). As such, if (and only if) two letters have been identified, it is possible to (immediately) determine their order correctly, but other information is not reliably diagnostic as to stimulus identity (see below). That is, the identity/location of W in SWAN is enough to tell the word is not SCAN, but because the W in SWAN could appear anywhere on the retina, further positional information, such as the (approximate) position of the A it is, is needed to tell SWAN from SAWN.

Precise positional information. After identification of each letter, a more precise positioning process occurs for that letter (even if other letters remain to be identified); this process has similar temporal properties to the identification process, but with a different constant of proportionality. That is, for a letter in position i, once a duration t has elapsed since identification of that letter, the probability that the precise positional information has become available is $1 - \exp(-\lambda\beta_i t)$. The precise positional information is such that if this information is available for two letters, then it is known whether the two letters are adjacent, because this information reveals the retinotopic location of the left and right edges of the letters[3].

Retinotopic distance information is unreliable. Although the retinotopic information that is posited to be available might allow estimation of the retinotopic distance between two letters, it is assumed that this information is usually discarded as unreliable (at least for short words). Absolute retinotopic distance information is unreliable because of size constancy: The same stimuli may become larger or smaller due to font size, viewing distance or viewing position. Relative retinotopic distance information is treated as unreliable because it usually is; proportional fonts and handwriting are often read: For instance — as illustrated in Figure 1 — in the word MAIL in proportional fonts, the A is positioned largely to the right of centre, because the standard widths of these letters are in ratio 10:6:3:3, whereas in the word LAMB, it is close to left edge of the word, because the widths are in ratio 3:6:10:6, despite it being the second letter of four in both cases.

Specialization for forced-choice tachistoscopic identification

Forced-choice tachistoscopic identification involves a brief, masked presentation of a word or nonword stimulus, following by a forced-choice alternatives for its identity, as illustrated in Figure 2. To apply LTRS to forced-choice tachistoscopic identification, specification must be given of the details of the consequences of masking and the absence of the stimulus, and how responses are selected given the available information.

Loss of information. After stimulus offset, all information about each letter has a small probability ϕ of being lost due to interference from the mask, or the identification of the response alternatives; no loss can occur whilst the stimulus is present on the display. When information is lost, all information about the relevant letter is lost; that is, identity information about a letter cannot be spared when its precise positional information is lost. Only stored letter information is used to determine a response; any other form of information is ignored because it has been rendered unusable or unreliable during the identification the response alternatives.

Response selection. Information distinguishes between the available options if (and only if) it could have been obtained from one alternative, but not the other. If the available information does not distinguish between the available options, guessing occurs. In experiments where the correct response is available (as modeled here) this can only occur because of missing information, because the possibility of misperception is not used in LTRS's predictions. When the available information does distinguish between the options, there is a small probability ϵ that participants make a premature guess response (or motor error)[4]. Otherwise, responding is correct. Guessing produces the right-hand response with probability ρ, modeling response bias; when trial-by-trial data is not used, this parameter is not required, and chance accuracy is assumed.

Specialization for masked form priming

Masked form priming involves a brief (and usually forward-masked) presentation of a (typically lower-case) prime stimulus (typically a nonword) before presentation of a (typically upper-case) target word (sometimes with intervening mask or blank) on which another task, usually speeded lexical decision, is performed. To apply LTRS to form priming, specification must be given of (i) how priming occurs, and (ii) the cause of differences in magnitude of priming between different prime-target relationships.

2.1.1 *Priming as savings*. The effectiveness of the prime (compared to an unrelated prime that evokes no lexical processing of the target) is equal to the period of time for which it evokes initial lexical processing of the target (Forster, Mohan, & Hector, 2003, call this priming as savings), which is precisely the time for which some consistent and no inconsistent information is available. That is, priming of a lexical entry begins if and when the first consistent letter is perceived; identity primes are more effective than other primes not because they evoke a stronger instantaneous response (higher graded match), but because they do not contain inconsistent information that would terminate priming. That the lexical processing occurs if and only if the lexical entry is a viable match to the current percept is the only assumption that is needed to generate ceteris paribus priming predictions.

That is, priming is defined as a headstart in processing that occurs during the period where the target is a candidate for lexical identification of the prime. The precise nature of the lexical processing involved could moderate the effects, but this paper explores the extent to which phenomena in word identification can be explained by essentially perceptual aspects of letter processing; including a detailed lexical processing mechanism would detract from this goal. A bare bones mechanism could be used to produce lexical decision times in combination with LTRS without modifying the priming predictions, such as a set of non-competing non-noisy accumulators with drift related to log.-frequency. Whilst such a mechanism would produce a reasonable correlation with the word lexical decision data[5], it would have no bearing on the priming predictions. Most lexical mechanisms that could reasonably be posited in a priming model would be similarly susceptible to the posited headstart, and therefore still show approximately the same behavior if the perceptual assumptions were the same.

Termination of priming. In LTRS, the cessation of priming occurs stochastically (unlike the Forster et al., 2003, entry-opening account which posits an approximate stage of fixed duration), when (i) the target is no longer a match to the information from the
2.1.2 prime, which occurs at a random time, distributed according to the assumptions
2.4 described above; or (ii) the offset of the prime is noted — on average, some time ω after
onset — because letter processing of the target begins or an intervening mask or blank is noted[6].

What is the representation in LTRS?

I would hope that the assumptions described so far seem neither implausible nor counterintuitive. These assumptions do, however, lead to what may be the most counterintuitive aspect of LTRS, particularly in the light of the emphasis in other approaches on representation and similarity: LTRS's assumptions suffice to make (good) predictions about data such as the effects of prime type on priming without specifying very many details of the representation. The representation needs (i) to be able to specify which letters have been perceived without specifying anything about letters that have yet to be perceived, (ii) to be able to specify that two letters are adjacent in a particular order, (iii) to be able to specify that two letters are non-adjacent without specifying the number or identity of the intervening letters, (iv) to be able to specify the order of two letters without specifying anything about adjacency.

There are several representations that meet these criteria. I do not specify which representation is part of the model because it has no consequences for the predictions at a behavioral level: Short of single-cell recording, differences between these representations (if the rest of LTRS is true) cannot be detected, because of the all-or-nothing nature of the computations. Such representations include:

Globbing. This representation consists of an ordered letter string with unknown information indicated by a special character, as in wildcard matching for computer filenames, such as `*` for any number of unknown letters, and + for at least one unknown letter. The representation is initially unspecified, i.e. `*`. Thereafter, the pattern would become more specific as more information is identified. For instance, `*c*`, `*a*`, `*t*`, `c*`, `*t`, `*c*a*`, `*c*t*`, `*a*t*`, `c+t`, `c*a*`, `c*t*`, `*c*t`, `*a*t*`, `ca+`, `+at`, `*c*a*t*`, `c*a*t*`, `*c*a*t`, `ca*t*`, `c*a*t`, `*c*at`, and `cat` are the possible states in this representation that could be produced by the stimulus CAT with the LTRS assumptions (though the representation could express other states consistent with CAT). Matching could occur via a serial scan, but parallel constant-time solutions exist for these kind of problems (Chung, 1996).

Bigrams with multiple states. In this representation, there would be nodes (or other representational units) for different open bigrams (i.e., ordered pairs of letters) that could carry additional information than just the presence of an open bigram by virtue of having multiple states that do not correspond to strengths. One state would indicate that no relevant letter has been detected, the second would indicate partial satisfaction (i.e., that one letter of the pair is present), the third the presence of the open bigram with no further information, the fourth that the open bigram is present and is also a closed bigram (i.e., adjacent), and the last that the open bigram is present but is not a closed bigram (i.e., non-adjacent). The activation values of these states would be arbitrary as they would not be treated as strengths, but rather treated in an all-or-none fashion.

Letters, open bigrams, adjacent bigrams, non-adjacent bigrams. In this representation, multiple types of representational units (e.g., nodes, or a list) are taken to code the identity of the stimulus. These are abstract, position-free units for individual letters, open bigrams (i.e., ordered pairs of letters of any distance), adjacent bigrams (i.e., ordered pairs of letters that are adjacent) and non-adjacent bigrams (i.e., ordered pairs of letters that are non-adjacent). This representation — as a textual list of each type of unit that is implied by the information in the percept — is used in the implemented code for calculating most of the predictions made here, but other representations would yield the same results. This representation could be used in a network; this would yield a proliferation of units and connections to the (unspecified) word level, but it does not proliferate connection strengths that can make the model flexible: Information is combined by the logical-AND rule; such high-threshold logic is not sensitive to strengths. In terms of input to word units, any amount of feed-forward inhibition stops facilitation of the word unit regardless of the amount of active facilitatory connections, and in the absence of inhibition, any non-zero amount of active facilitatory feed-forward connections produces the maximum effective net input to the word unit.

It bears emphasis that whilst these representations and mechanisms are complex, such complexity is not what gives LTRS the scope to capture the data, nor does it lend the model extra flexibility: Unlike in models based on match scores, the details of such complex machinery do not form the explanation of the effects in LTRS. Instead, the core explanatory mechanism in LTRS is that primes prime more if they diverge in processing from the target on average later in processing and foils are harder to reject if they are less likely to have diverged in processing from the target at the time of the post-mask. I now illustrate how effectively such an explanation can account for the data.

Tachistoscopic identification: stimulus duration

LTRS was first applied to new[7] experimental data involving tachistoscopic word identification at different display durations to demonstrate that it accounts for the time course of letter identity and position. The detailed method is presented in the Appendix. Four participants performed two-alternative forced-choice word identification for masked presentations of four-letter words that varied in duration from 0–42 ms, as illustrated in Figure 2, with the target-foil relationship being on one of 13 major categories.

The full LTRS model for four-letter strings with 10 parameters was fitted to each participant separately by maximum likelihood (exact predictions are achieved by numerical integration); the parameter values are presented in Table 1. The data and fitted model predictions for each participant are summarized by major target-foil relationship categories in Figure 3. To assess the quality of the fit, LTRS was compared to a saturated model — a literal restatement of the data — in which any model with a guessing component (including LTRS) is nested. For each of the 19 minor target-foil relationship categories that LTRS distinguishes, and for each duration, the saturated model had a parameter for the probability a guess would occur, plus one parameter parameter for the probability that the guess would be a right-hand response; if guessing does not occur, the response is correct. This permitted a formal lack-of-fit test for restricting 143 parameters (153 in saturated, 10 in LTRS) for each participant. The misfit was not significant for any participant: $\chi^2(143) = 156.91, 130.36, 126.54, 138.92$, $p = .202, .768, .835, .581$. That is, there was no evidence the model did not fit the data; it captures the functional form of the duration effect, the left-to-right pattern in 1LD slopes (without differing take-offs). and the 4LD>2LD>1LD and 2LD>TL patterns.

Findings involving stimuli where letters are transposed with an adjacent letter, such as the above 2LD vs. TL comparison, and the corresponding priming comparison (e.g., Perea & Lupker, 2003), have formed much of the impetus for modeling of letter position coding. In LTRS, double-substitution foils/primes diverge from the target sooner than transposed-letter foils/primes primarily because information about one letter suffices to tell that a double-substitution prime is not the target, whilst information about two is needed to tell that a transposed-letter prime is not the target. In particular, for the example of 1dd4 and 1324: The identity/location of either the second or the third letter suffices for 1dd4 (the first or second d). In contrast for 1324, one of the following sets of information (inconsistent with 1234) is needed: (i) the identity/location of both the second and third letter (3 before 2); or (ii) precise location information for both (a) the first and second letter (1 adjacent-to 3); (b) the third and fourth letter (2 adjacent-to 4); (c) the first and third letter (1 not-adjacent-to 2); or (d) the second and fourth letter (3 not-adjacent-to 4). One can have the identity/location of either the second or the third letter without being in one of these cases, but not vice versa. Therefore, there are times at which 1dd4 can be distinguished from 1234 and 1324 can not be distinguished from 1234, but there are no times when the reverse is true.

Tachistoscopic identification: target-foil relationships

LTRS was then applied to a wider range of target-foil relationships from five experiments by Gomez et al. (2008) at a single presentation duration in studies they used to support the overlap model, most of which used 5-letter nonword stimuli. In their Experiment 1, 1LD, 2LD (both adjacent and non-adjacent) and TL (both adjacent and non-adjacent) were used (Experiment 1b was a replication of 1a with the foils differing in the first letter excluded). Experiment 2 was similar to 1a but contained word-nonword and word-word trials (but no nonword-nonword trials). In addition to 1LD and adjacent TL foils, Experiment 3 used foils in which one letter was more than one position removed from its location in the target and the other letters shifted (e.g., 31245) and these with an additional letter replacement (e.g., d1245). In addition to typical 1LD, and adjacent and non-adjacent TL foil conditions, Experiment 4 used targets and foils in which some letters were repeated. Finally, in Experiment 5, 1LD, adjacent TL, letter insertion (6-letter foil) and letter deletion (6-letter target) foil conditions were used.

2.3.1 This analysis was restricted to conditions where the lexical status of both options was the same (i.e., Experiment 2 was excluded) and the stimuli were five letters long (i.e., part of Experiment 5 was excluded) because (i) the goal of LTRS is to examine factors that can be explained perceptually without detailed lexical processes[8], and (ii) comparisons between 5- and 6-letter options could be based on size relative to the mask, adding an additional process.

Gomez et al. (2008) fitted parameters of the overlap model separately to each experiment; for these fitted values, the SSE for overlap is 0.192 ($BIC = -538.75$ with 31
2.3.3 parameters), against a total sum-of-squares of .905[9]. The ten-parameter LTRS model — with parameters optimized simultaneously for all experiments — has a comparable SSE of 0.213 for its many fewer parameters ($BIC = -627.91$, substantially superior). The fit for LTRS is illustrated in Figure 4. Attempting to reduce the number of parameters in the overlap model to seven by using the simultaneously optimized parameters for all
2.3.3 experiments — to be more comparable to LTRS — increased its SSE to 0.477 ($BIC = -552.84$, improved, but still inferior to LTRS), suggesting the loss of parameters compromised its ability to account for the data.

Although SCM does not have mechanisms to identify nonwords, its graded match scores, which are controlled by 2 parameters,[10] can be used in 2-parameter regression equation (i.e., there is a total of 4 parameters — the other models do not require a regression equation because they produce probabilities directly) to approximate predictions that would result from such a mechanism. The most favorable parameters (intercept = 1.258; slope = -0.659; $\sigma = 1.964$; initial letter weight = 3.224) gave an SSE of 0.407 ($BIC = -584.03$, intermediate between overlap and LTRS).

Masked form priming: prime duration

Next, LTRS was applied to form priming data with variation in prime duration, given by Forster et al. (2003) in support of the account of priming by savings.

A highly simplified version of LTRS is suitable for these data because they include only identity and 1LD priming, and they are averaged over stimulus lengths and all positions of difference. Only three parameters were estimated: α, ω, and B, using $\beta_{i|l} = B/l$ for any given length l; σ was set to zero, and λ has no role in 1LD or identity priming predictions, because letter order is irrelevant. (The remaining parameters are for identification only.) The entry-opening account of priming — in which identity priming is linear (with slope 1) in the prime duration and 1LD priming is linear (with slope 1) in the prime duration up to the completion of the first (approximate) phase, after which it is constant — can also be characterized by a three-parameter model; the parameters are the intercept for identity priming, the intercept for 1LD priming, and the maximum value of 1LD priming. Against a total sum of squares of 3812 ms^2, the minimum SSE for this model is 284 ms^2 (with intercept for identity 9.29 ms, intercept for 1LD -2.47 ms, and maximum for 1LD 36.25 ms). LTRS can achieve a comparable fit (when evaluated by Monte Carlo simulation; see Figure 5) giving an SSE of 286 ms^2 (with $\alpha = 11$ ms, $\omega = 32$ ms, $B = .095$ MHz).[11] Predictions were also obtained for the SCM (see Figure 5) without changing the original parameter set; optimizing the parameters to maximize the fit for the full priming SCM would be impracticable (both in terms of time, and the type of software that is available to run the model) and no systematically optimized parameters were offered by Davis[12], though some changes that improve fit have clearly occurred throughout the development of the model. The SSE for SCM was 2867 ms^2, primarily because the model underestimated the effects by about 11 ms; without further data, it is unclear whether the slight curvature in the 1LD predictions that LTRS and entry-opening models capture is systematic or noise. The constant underestimate by SCM does not correspond to a trivial parameter change because rescaling cycles would change the prime durations, and a change in residual time would affect both control and primed conditions.

Masked form priming: prime-target relationships

The most extensive data regarding apparent letter string similarity effects come from manipulation of prime-target relationships in form priming, so finally, LTRS was applied to these data. Davis (2010) recently reviewed such data in assessing SCM; from his Table 4, I extracted those (47 out of 61) results that were obtained under standard priming conditions with manipulations of prime-target relationship in terms of letter identity and/or position. That is, nonword-word priming was included, and word-word priming, sandwich priming (where a brief preview of the target precedes the prime; Lupker & Davis, 2009), and frequency and neighborhood manipulations were excluded, because LTRS does not model the word-specific influences involved in these phenomena.
2.5 The range of prime types covers 1–5LD conditions (index 10–14 in Davis's table and Figure 6, and 7–9 and 51 for additional 2LD conditions), adjacent TL (21–22) and non-adjacent TL (28 with 27 & 29 as baselines; and 54) conditions, letter addition (superset) conditions (38–45), letter deletion conditions (46–50, 52, 56–61), a combined deletion plus TL condition (53), neighbor-once-removed conditions (23 & 24 vs. 25 & 26, described and discussed below), and various severe disruptions of letter ordering (30–35, 55).

Again, to avoid excessive proliferation of β parameters for the various lengths of stimuli, it was necessary to add an ad hoc equation constraining the β values with only a few parameters. Given the greater number of conditions to be fit, some of which were defined by position, two were used — B and η_i — the former being the sum of the rates, the latter reflecting increased processing strength (efficiency) for the initial position (cf. Table 2), such that $\beta_{1|l} = (1+\eta_i)B/(l+\eta_i)$, and $\beta_{i|l} = B/(l+\eta_i)$ for $i \neq 1$.

The observed and LTRS-predicted priming (evaluated by quadrature), with the
2.5 parameters given in Table 3, are illustrated in Figure 6. The effects occurring for substitution primes and letter-reordered primes come about for much the same reasons as the effects for the identification task: Greater disruption of order in the prime or more inconsistent letters in the prime give more opportunities to perceive that the prime is not the target. Prime duration also accounts for some variability between experiments. A couple of other important comparisons are, however, somewhat more subtle.

One of the most important comparisons comes from Davis and Bowers's (2006; points 23 & 24 vs. 25 & 26) examination of a type of prime they labeled neighbor-once-removed (N1R); these are generated by a transposition of adjacent letters and a replacement of one of those letters. Contrary to certain simple open-bigram schemes, N1R primes produced less priming than 1LD primes. According to LTRS, N1R primes (13d45) diverge from the target sooner than 1LD primes (1d345 or, better, 12d45) because the precise positional information about both of the two letters that should not be adjacent (1 and 3) will sometimes be extracted before the mismatching letter (d), whilst for both types of prime extracting the mismatching letter alone is sufficient. Consider the prime BLETS, which is a N1R of BOLTS and 1LD from BLOTS. Any pattern consistent with `*e*` (including, for instance, `*e*s*`) is sufficient to terminate priming of either BOLTS or BLOTS, but if `bl*` (or `bl*t*` etc.) is reached, priming of BOLTS ceases, whilst priming of BLOTS continues.

Superset primes are another form of prime — ones in which an extra letter is inserted relative to the target — that can distinguish between models. In particular, LTRS predicts that when the extra letter repeats one already in the target, priming should be greater than if the extra letter is unique, because both the inserted letter and the letter it repeats must be detected to stop priming if there is an adjacent repeat, but only the new letter needs to be detected to stop priming if it is unique. Whilst SERIOL and other open-bigram schemes sensitive to the distance between pairs of letters also make this prediction, SCM makes the contrasting prediction that these conditions should be equivalent. One experiment that has examined this (Van Assche & Grainger, 2006, Experiment 1, points 43 and 45) did not find a 2 ms difference to be significant, but this experiment lacked power to some extent: Other differences examined in the experiment whose observed magnitudes were around 10 ms did not reach significance and this is roughly the size of effect LTRS predicts. In a near-replication with two inserted letters they (Experiment 2, not in the database) found that a 7 ms difference did not reach significance: Similar power issues apply, and LTRS predicts a 12 ms effect.

Against a total sum-of-squares of 12390 ms^2, LTRS's SSE with 6 parameters was 3645 ms^2 ($BIC = 227.60$). By comparison, the predictions from Davis's (2010) SCM using the default parameter settings and 55 ms prime duration (as used by Davis) obtained an SSE of 1395 ms^2 (for the 18 parameters the SCM has, $BIC = 228.66$). When the same parameter settings were used with the actual prime durations of the various experiments were used, the SSE was 2735 ms^2 ($BIC = 260.30$); the difference suggests that mechanisms in SCM designed to capture prime type differences between experiments might in fact be capturing differences caused by prime duration[13]. Again, parameters could not practicably be optimized for this model. This, the probable minimal impact of some parameters on the predictions, and the exclusion of data bearing on the lexical component mean that these BIC values have not allowed SCM to take advantage of its parametric flexibility and so may overpenalize SCM for its flexibility/complexity. It is therefore difficult to assess the extent to which SCM's advantage in SSE is due to its capturing systematic aspects of the data, or having mechanisms that have been adapted to idiosyncratic properties of, and noise in, some experiments; replications may go some way to addressing this issue. I would nevertheless argue that — in terms of the necessity of the properties of perception, number of parameters, or in terms of description length — LTRS is less complex than SCM, and this should be weighed in any model assessment.

It is perhaps more telling to examine the predictions of a model for experiments of the type that it is designed to explain, but which were not examined in its development, as their idiosyncrasies will not have been built into the model. Table 4 presents predictions for 28 observations from seven experiments not examined by Davis (2010); of these, five are from articles whose other experiments were in Davis's Table 4, and two are from a more recent article (Norris et al., 2010). The overall fit for this set somewhat favors LTRS; this could well, of course, simply reflect the selection I have made. One might also take as important that the Norris et al. found a (significant by-subjects, marginal by-items) 17ms difference between 1-deletion primes (acde-ABCDE) and 1LD control primes (axcde-ABCDE) where no difference is anticipated by SCM, but some (11 ms) is predicted by LTRS, because the deletion primes take two specific letters to be perceived (plus their adjacency) for priming to cease, but the 1LD control primes take only one specific letter. Nevertheless, such agglomerations are likely to be misleading because of biases in publication and selection; idiosyncratic properties of laboratories or experiments that models cannot capture; and the relatively poor estimation of the magnitude of priming effects[14]. Only experiments that are designed to produce databases with a large number of conditions in a single laboratory can truly test the detailed quantitative assumptions in the kinds of models considered here.

Discussion

The Letters in Time and Retinotopic Space model accounted for effects of manipulations of duration and relationships between letter strings in both tachistoscopic identification and form priming. It did so by recourse to the idea that different information about letter strings becomes available at different times. The account asserts neither the notion that lexical processing partially tolerates imperfect matches in the presence of negative evidence, nor the notion that the cause of ambiguity in a percept is contamination by noise. Other models have yet to be applied to this range of types of data, and there may be difficulties in doing so. For instance, the matching process in SCM is based on word nodes, which causes difficulty in accounting for nonword identification data, even if a decision rule to fit the effect of duration in the word identification data were found; the overlap model has no account of the influence of exposure duration; and the functional form of the exposure duration effect is not the half-normal cumulative distribution that would be expected under simple signal detection accounts[15]. In contrast, in LTRS, a precise account of these duration effects is the starting point of an understanding of all the other effects, and a predictable link between identification and priming is expected; indeed, some effects, such as differences between standard and sandwich priming may be attributed to differing visual properties of the prime.

3.4 Moreover, in LTRS, there is no single number that describes the relationship between a target and a prime or foil: There is no constant graded match score, and a foil (or prime) that is more probably distinguishable than another from the target at an early time point, may be less probably distinguishable at a later time point. For instance, in the fits plotted for Participant 4 in Figure 4, the d234 condition is predicted to be more accurate than the 1243 condition at shorter (e.g., 18 ms) durations but not at longer (e.g., 42 ms) durations. This occurs at the level of the information available in the percept and not due to any top-down process (as there is none). The pattern results from the distribution of time taken for one piece of information having a different shape to the distribution of time taken for two pieces of information. A similar pattern can occur with different prime conditions, and can be exacerbated by the influence of the delay in registering the onset of the target (i.e., ω). The predicted effects are, however, subtle, and would need careful manipulation of visual parameters to exacerbate them to an extent they would be detectable in a feasible experiment.

The predictions of LTRS are derived with specification of only the most basic properties of lexical processing relating to targets; effects of word primes, and of word neighbors of primes, would require further specification of lexical processing (and lexical decision). The extent to which LTRS is successful — without reference to detailed lexical processing — as an account of core phenomena relating to the identification, confusion and priming of letter strings over time is suggestive that priming and tachistoscopic identification phenomena need not be understood in terms of tolerance for partial matches, but may — in whole or in part — be explained by reference to the stochastic timing of information extraction from the stimulus.

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Appendix

Experimental Method

Participants

Four postgraduates of the Department of Psychology at the University of Warwick acted as observers in this experiment; three were paid £100 (ca. US$170), and the fourth was the author. All reported normal or corrected-to-normal vision, and had English as their first language.

Stimuli

One hundred and eight four-letter English words were used to construct 432 target-foil pairings for this experiment. Each word acted as a foil for four targets, and these were also the foils when this word acted as target. Each pairing (symmetrically) represented one of four transformation types, their subtypes (conditions) denoted by four-letter codes representing their relation to the string *1234*: (a) replacement of four letters (e.g., CODE vs. WASP, denoted *dddd*, of which there were 216 pairs (counting both versions of a pairing as distinct); (b) replacement of two letters, either adjacent to one another (e.g., WHIP vs. WRAP), or at the two ends (e.g., SEAL vs. TEAM), denoted *dd34, 1dd4, 12dd* or *d23d*, 20 of each subtype; (c) replacement of one letter (e.g., ABLE vs. AXLE), denoted *d234, 1d34, 12d4* or *123d*, 24 of each subtype; and (d) reversal of two letters either in adjacent positions (e.g., SAWN vs. SWAN) or at the two ends (e.g., MEAT vs. TEAM), denoted *2134, 1324, 1243* or *4231*, 10 of each subtype. The severe selection criteria were not perfectly met, so a few of the pairings realised other relationships than those described above, due to the inclusion of the words EVER, VEER and PASS among the stimuli, and the use of ACID-DUET as a pairing. All modeling takes into account the true relationship between the targets and foils. However, in the graphs, these pairings are averaged with the intended condition.

Apparatus

Stimuli were presented on a Sony CPD-G200 computer monitor driven at 166.67 Hz by an NVidia GeForce 2 MX based graphics card. The resolution of this display was 640x480 on a 17" monitor (see Stewart, 2006a, for a description of this system). Tests with a photodiode confirmed that this system had a resolution of 6 ms. Internal monitoring of display times indicated that for approximately 1 in every 2000 trials the stimulus was displayed one frame (6 ms) too long; these were analyzed with the actual display time (DT), not the intended display time, provided this was within the experimental range. Responses were collected using a custom parallel-port button box (Stewart, 2006b), with two lateral buttons, designed to be operated with both hands, and an extra central button.

Design

Accuracy was measured on two-alternative forced-choice identification of the targets for each target-foil pairing in each of the thirteen pairing subtypes, for each of eight display times spaced evenly from 0 to 42 ms. Six replications of each target-foil-DT combination were tested, half associated with each response button, giving a total of 20,736 trials per observer. Over all trials, critical information was equally likely to appear in each of the four letter positions; and given two alternatives, each was equally likely to be correct. Every 3,456 trials observers had seen each target-foil-DT combination an equal number of times. Every 6,912 trials, observers had seen each target-foil-DT-button combination an equal number of times.

Procedure

Observers completed 12 sessions of approximately one hour, each containing 16 blocks of 108 trials. Before each trial a mask of ten hash (#) symbols in a 32 point Courier font was displayed centrally horizontally approximately 12% from the bottom of the screen for an inter-trial interval varying randomly between 900 and 1100 ms, notwithstanding delays due to the parallel port failing to reset. This was then replaced by the target word in a 24 point Courier font in lower case in the same position for a DT from 0 to 42 msec (no target stimulus was shown in the 0 msec condition). The screen was then blank for 6 msec. Then the mask was displayed again with two response options, both target and foil, in lateral positions in a line below that of the mask. Observers pressed the matching lateral button of the button box to indicate their response. After this, the alternatives were removed from the display, and the mask remained for the inter-trial interval. At the end of each block, accuracy for that block was displayed, and breaks were taken as needed between blocks.

Footnotes

[1]Some earlier models of tachistoscopic identification (Rumelhart, 1970; Rumelhart & Siple, 1974) also use incomplete visual information as an explanatory mechanism in combination with a (partially) Bayesian decision. However, they give an account of neither transposed-letter (TL) effects — such as confusions between SWAN and SAWN (a TL pair) being more frequent than those between SWAN and SCAN (a one-letter-different, or 1LD, pair) and SWAN and STUN (a 2LD pair) — which are the critical starting point for current models, nor masked form priming, which is the most commonly used experimental paradigm in the area.

[2]Details of all the modeling and the implemented LTRS model (executable and source code) are available at `http://www.warwick.ac.uk/~pssgar/ltrs/`.

[3]It might be more realistic to assume that left and right edge information are extracted independently, not simultaneously.

[4]This parameter may also mimic a skew distribution of the onset of processing

[5]Indeed, using $\log(20 + freq)$ for the drift would obtain a correlation of .61 for the data considered for item-level variance by Davis (2010), to be compared with SCM's .51. Starting the no accumulator with an appropriate drift only when all possible words had been eliminated would trivially produce a qualitative match to the nonword N effect, the lexicality effect and the nonword legality effect. It is possible, though not likely, that SCM can only make good priming predictions when its frequency predictions are slightly off.

[6]That is, priming is linked to prime duration, not stimulus onset asynchrony.

[7]The term "new" is used loosely: The data were collected in 2003 and previously submitted for publication by Adelman and Brown (2006).

[8]In the case of these apparent context enhancement effects, a version of Johnston's (1978) account of the effects could be based on assuming ϕ is higher when the percept is
2.3.1 consistent with a word, because this familiarity guards against forgetting. If all options

being fitted are of the same lexical status, no additional parameter is required.

[9] The six parameters for Experiment 5 could have been refitted (because only 8 out of its 18 conditions were used to calculate the SSE, whereas other experiments were included or excluded in their entirety) but its points contribute only .011 to the SSE, and an SSE of 0.181 leads to the same conclusions.

[10]In the most recent version — if only a single length (in this case, five) is considered — the adjustment to match scores considered by Gomez et al. (2008) is equivalent to adjusting the initial letter weight parameter, if regression parameters are also included. Using $\sigma = 1.25$ and initial letter weight of 3.1 gives an SSE of 0.478.

[11]Better fits could be achieved with lower values of α that would be too inconsistent with the identification data. Using a different rate for the initial letter might fix this problem, but I did not explore this as the benefit would be minimal relative to the cost of the extra parameter.

[12]In the context of models of word naming, Adelman and Brown (2008) have criticized the approach of producing models without optimized parameters (and with no easy way to optimize them) because it creates a false barrier to falsification: The possibility of data inconsistent with the model being attributed to a need for parameter changes poses an unreasonable challenge for other researchers.

3.1 [13] Davis (2010) suggests that the 55 ms prime duration assumption corrects somehow for differences in display conditions. Even if there is some error in the effective prime duration, not using the intended durations seems to me to be compounding error upon error. Moreover, it seems to assume a systematic bias such that short prime durations are used with good viewing conditions and long prime durations are used with poor viewing conditions; it is not clear why this should be the case.

[14]This problem is often exacerbated by the re-use of a single control condition as the subtraction for priming effects, because any misestimation in this one condition modifies

all the priming effects in the experiment, and it is rarely (if ever) given more trials than the other conditions in line with its importance.

[15]Such signal detection accounts are in some cases equivalent to the Bayesian Reader's sensitivity to presentation duration in identification, and where they are not, they are still often good approximations to it.

Parameter		Participant 1	2	3	4	units
Onset mean	α	17.721	21.767	17.343	11.935	ms
Onset s.d.	σ	3.077	6.491	6.126	3.421	ms
Rate 1	$\beta_{1\|4}$	0.243	0.475	0.106	0.553	MHz
Rate 2	$\beta_{2\|4}$	0.333	0.472	0.096	0.270	MHz
Rate 3	$\beta_{3\|4}$	0.118	0.171	0.080	0.187	MHz
Rate 4	$\beta_{4\|4}$	0.117	0.071	0.081	0.146	MHz
Premature guess	ϵ	.017	.043	.026	.012	(probability)
Right-hand bias	ρ	.549	.405	.540	.646	(probability)
Information loss	ϕ	.092	.187	.069	.038	(probability)
Position:identity ratio	λ	0.021	0.194	3.145	0.068	($\text{time}^{-1}/\text{time}^{-1}$)

Table 1
LTRS parameter values for experimental data by participant.

LTRS			Overlap	
α	17.663	ms	s_1	0.473
σ	14.062	ms	s_2	1.225
$\beta_{1\|5}$	0.278	MHz	s_3	1.168
$\beta_{2\|5}$	0.023	MHz	s_4	1.302
$\beta_{3\|5}$	0.023	MHz	s_5	1.201
$\beta_{4\|5}$	0.018	MHz	a	4.350
$\beta_{5\|5}$	0.020	MHz	a_{rep}	3.804
ϵ	0.145	(prob.)		
ϕ	0.061	(prob.)		
λ	0.150	(ratio)		

Table 2
Parameter values fitted to data from Gomez et al. (2008).

	LTRS	
α	21.298	ms
σ	12.262	ms
ω	31.086	ms
B	0.198	MHz
η	0.362	(ratio: $\text{time}^{-1}/\text{time}^{-1}$)
λ	3.530	(ratio: $\text{time}^{-1}/\text{time}^{-1}$)

Table 3
Parameter values fitted to data summarized by Davis (2010).

Target	Related Prime	Control Prime	Observed Priming (ms)	Predicted priming (ms): LTRS	Predicted priming (ms): SCM (55 ms)	Predicted priming (ms): SCM (actual)
Schoonbaert & Grainger (2004), Experiment 4; 53 ms						
ABCDE	bacde	vwxyz	5	16	19	18
ABCDE	abdce	vwxyz	24	23	33	32
ABCDE	abced	vwxyz	8	19	18	17
ABCDEFG	bacdefg	tuvwxyz	33	22	28	27
ABCDEFG	abdcefg	tuvwxyz	36	32	31	30
ABCDEFG	abcdegf	tuvwxyz	36	26	28	27
Norris, Kinoshita, & van Casteren (2010), Experiment 1; 53 ms						
ABCDE	abcde	vwxyz	45	57	51	49
ABCDE	acbde	vwxyz	23	22	34	33
ABCDE	awxde	vwxyz	2	10	2	2
ABCDE	aadde	vwxyz	9	18	4	4
Norris, Kinoshita, & van Casteren (2010), Experiment 3b; 53 ms						
ACCDE	accde	axcde	20	34	28	27
ACCDE	acde	axcde	12	18	6	6
ABCDE	abcde	axcde	36	34	25	24
ABCDE	acde	axcde	17	11	0	1
Grainger et al. (2006), Experiment 5; 33 ms						
ABCDEFG	abcd	wxyz	16	20	13	5
ABCDEFG	defg	wxyz	5	16	8	5
ABCDEFG	aceg	wxyz	17	21	6	3
Van Assche & Grainger (2006), Experiment 2; 50 ms						
ABCDEFG	abcdefg	rstuvwxyz	45	54	51	45
ABCDEFG	abcccdefg	rstuvwxyz	43	31	34	30
ABCDEFG	abeecdefg	rstuvwxyz	40	24	34	30
ABCDEFG	abtucdefg	rstuvwxyz	36	19	34	30
Van Assche & Grainger (2006), Experiment 3; 50 ms						
ABCDEFG	abcdefg	tuvwxyz	52	54	51	45
ABCDEFG	abvwefg	tuvwxyz	26	16	12	11
ABCDEFG	abvdeyg	tuvwxyz	22	16	12	11
ABCDEFG	abdeg/acdfg	tuvwxyz	39	32	17	16
Van Assche & Grainger (2006), Experiment 4; 50 ms						
ABCDEFG	abcdefg	qrstuvwxyz	63	54	51	45
ABCDEFG	abstucdefg	qrstuvwxyz	22	14	25	21
ABCDEFG	abscudwefg	qrstuvwxyz	22	14	21	18
			Sum-squared error (ms^2):	2377	2414	2980

Table 4
Observed and predicted priming for some standard masked primed lexical decision experiments that were not considered by Davis (2010), with structural descriptions of the nonword primes and word targets. SCM (55 ms) = spatial coding model with fixed prime duration of 55 ms; SCM (actual) = spatial coding model with actual prime duration used in experiment (listed).

Figure Captions

Figure 1. Relative position of the letter A in MAIL and LAMB in a proportional font.

Figure 2. Sequence of events on an experimental trial.

Figure 3. Data (points) and LTRS fit (lines) for brief word identification at various durations with 1-letter-different (1LD), 2-letter-different (2LD), 4-letter-different (4LD) and transposed-letter (TL) foils, for four participants.

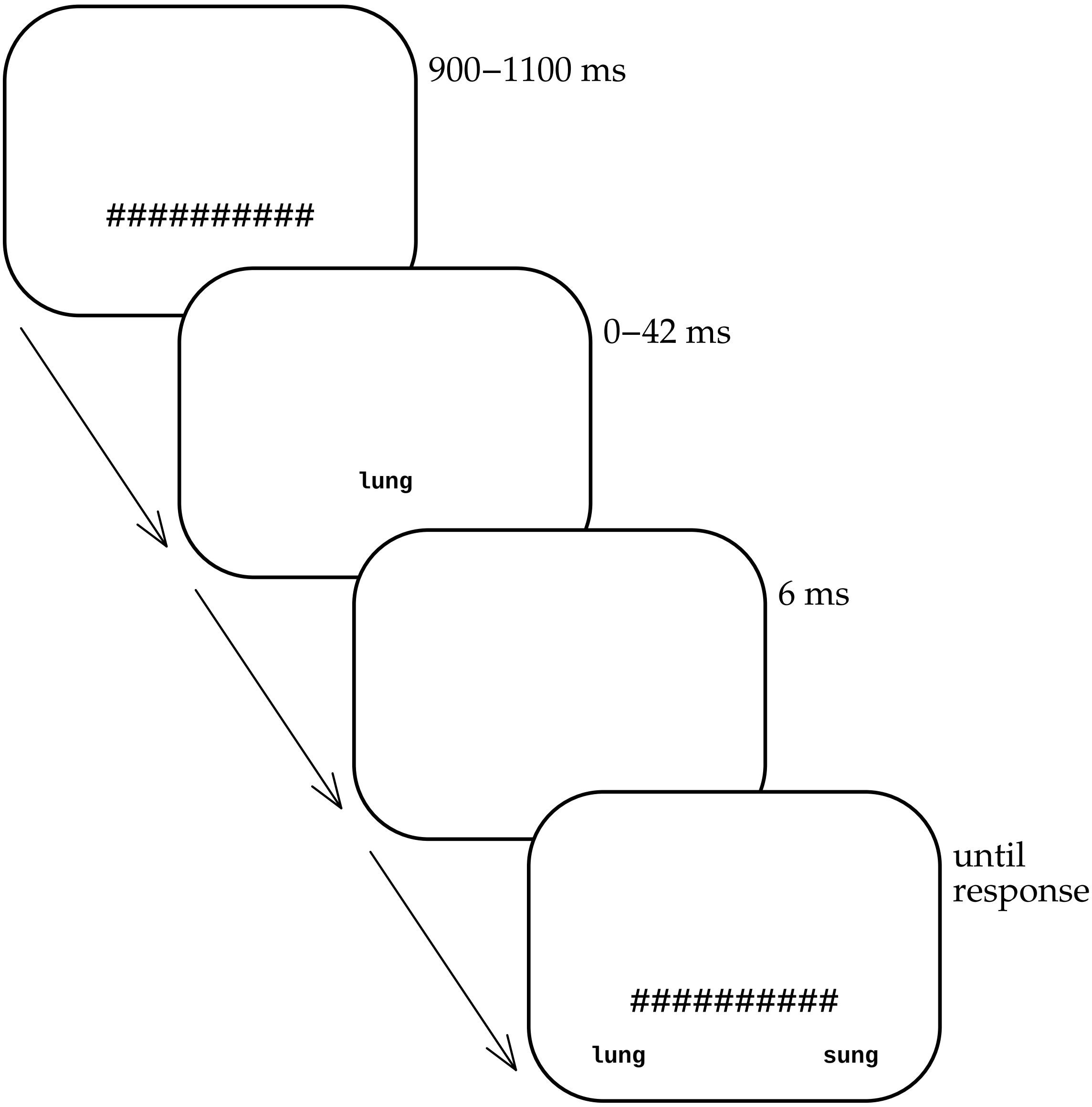
2.3.2 *Figure 4.* Observed accuracy and LTRS fit for Gomez et al.'s (2008) Experiments 1a, 1b, 3, 4 and 5; each point is a target-foil relationship condition (both 5 letters) at 60 ms duration. Foil generated from target by: r* or r** = 1- or 2-letters different in numbered positions; t** = transposition of numbered positions; m** = remove from first numbered position and re-insert at second numbered position (e.g., m13 = abcde → bcade); c** = remove from first numbered position and insert new letter at second numbered position (e.g., c13 = abcde → bcxde); e** = duplicate letter from first numbered position in place of letter at second numbered position (e.g., e23 = abcde → abbde); d** = numbered positions in target are same letter, second numbered position is replaced with new letter (e.g., d23 = abbde → abcde); b**** = duplicated letters in first two numbered positions move to last two numbered positions (e.g., b3423 = abdde → addbe).

Figure 5. Observed (points), LTRS (solid lines), and SCM (dashed lines) priming for Forster et al.'s (2003) priming experiments with manipulation of prime duration.

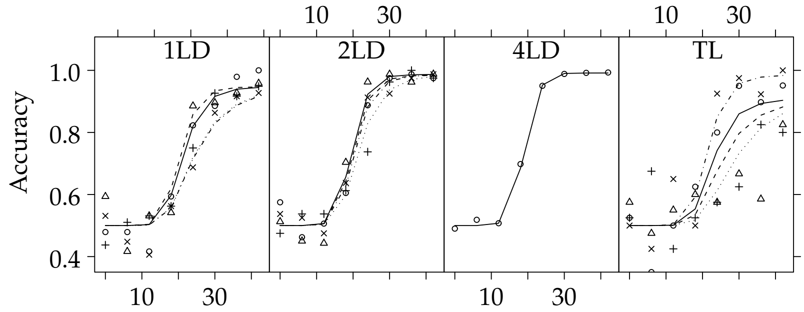
Figure 6. Observed priming and LTRS fit for nonword-word conditions considered by Davis (2010).

lamb

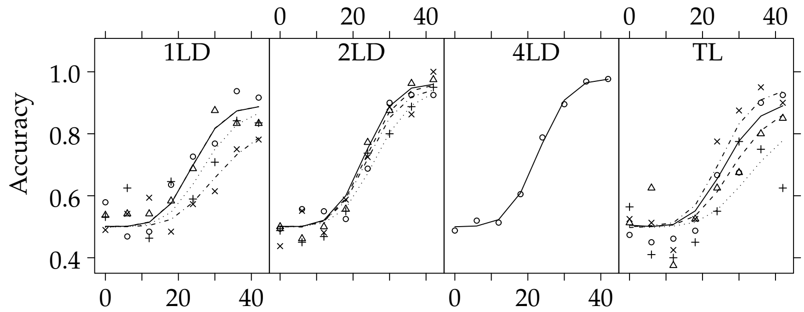
mail


900–1100 ms
##########
0–42 ms
lung
6 ms
until
response
##########
lung
sung

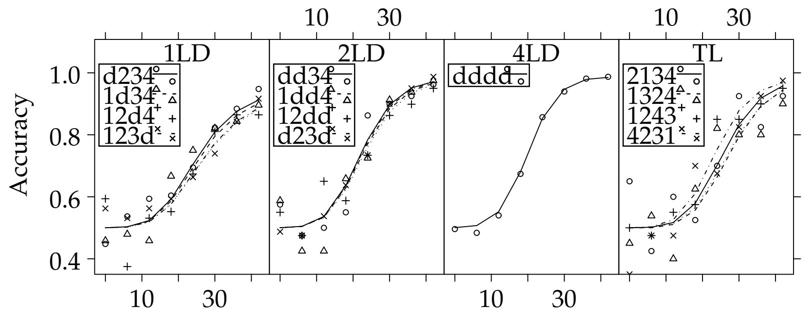
1.


1LD
2LD
4LD
TL
Accuracy
1.0
0.8
0.6
0.4
10
30

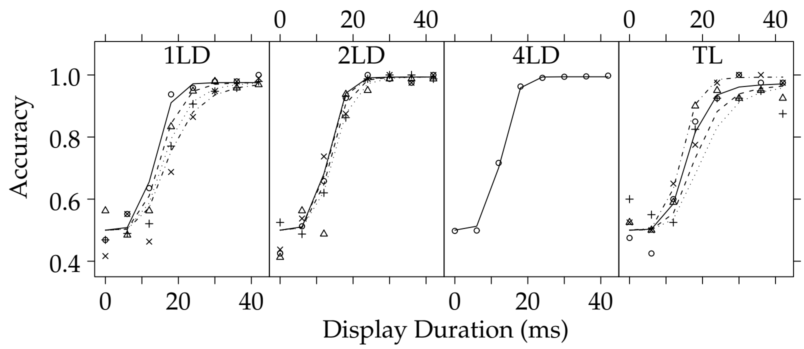
2.

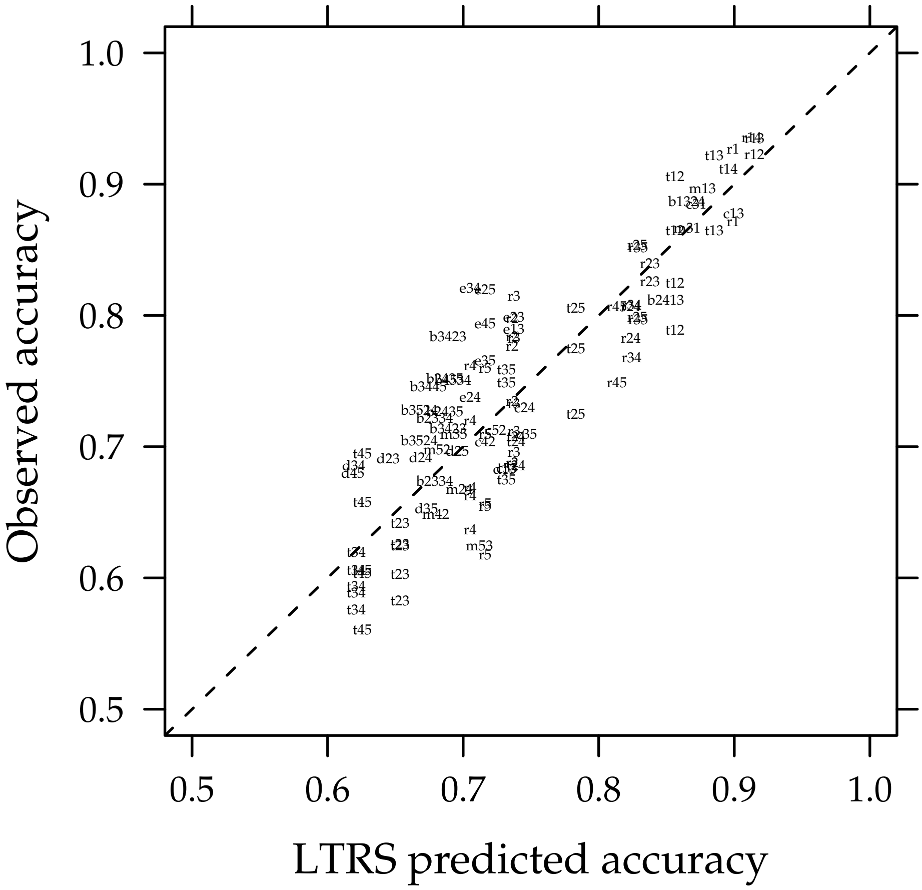

1LD
2LD
4LD
TL
Accuracy
1.0
0.8
0.6
0.4
0
20
40

3.

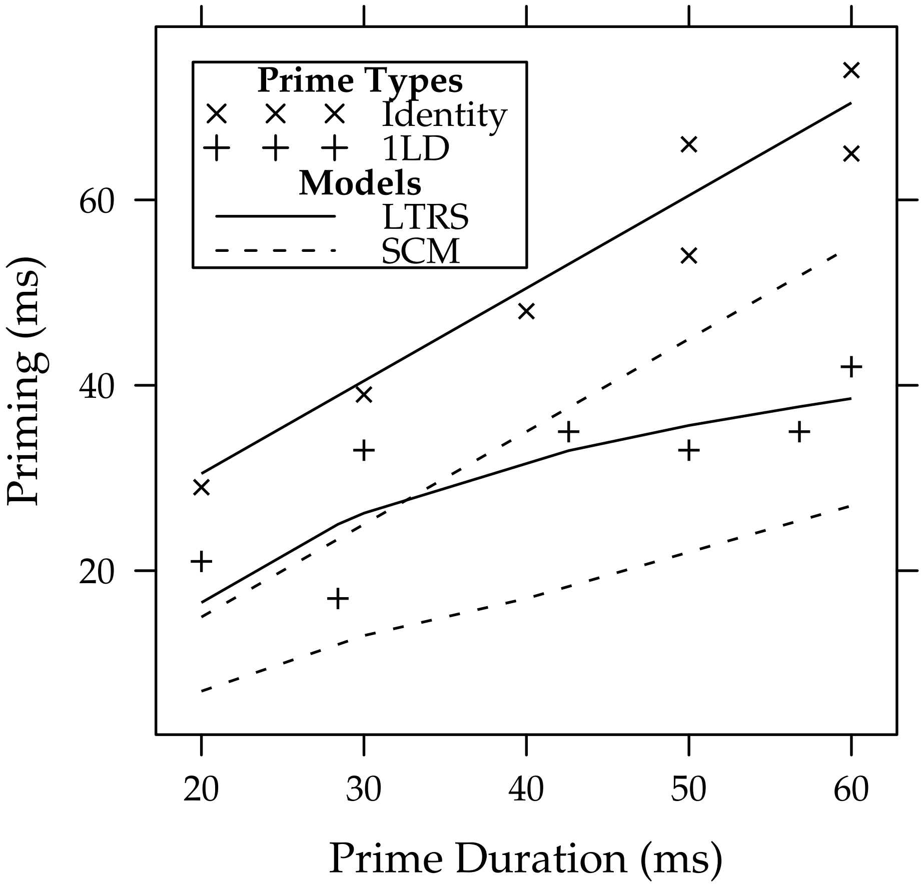

1LD
2LD
4LD
TL
d234
1d34
12d4
123d
dd34
1dd4
12dd
d23d
dddd
2134
1324
1243
4231
Accuracy
1.0
0.8
0.6
0.4
10
30

4.

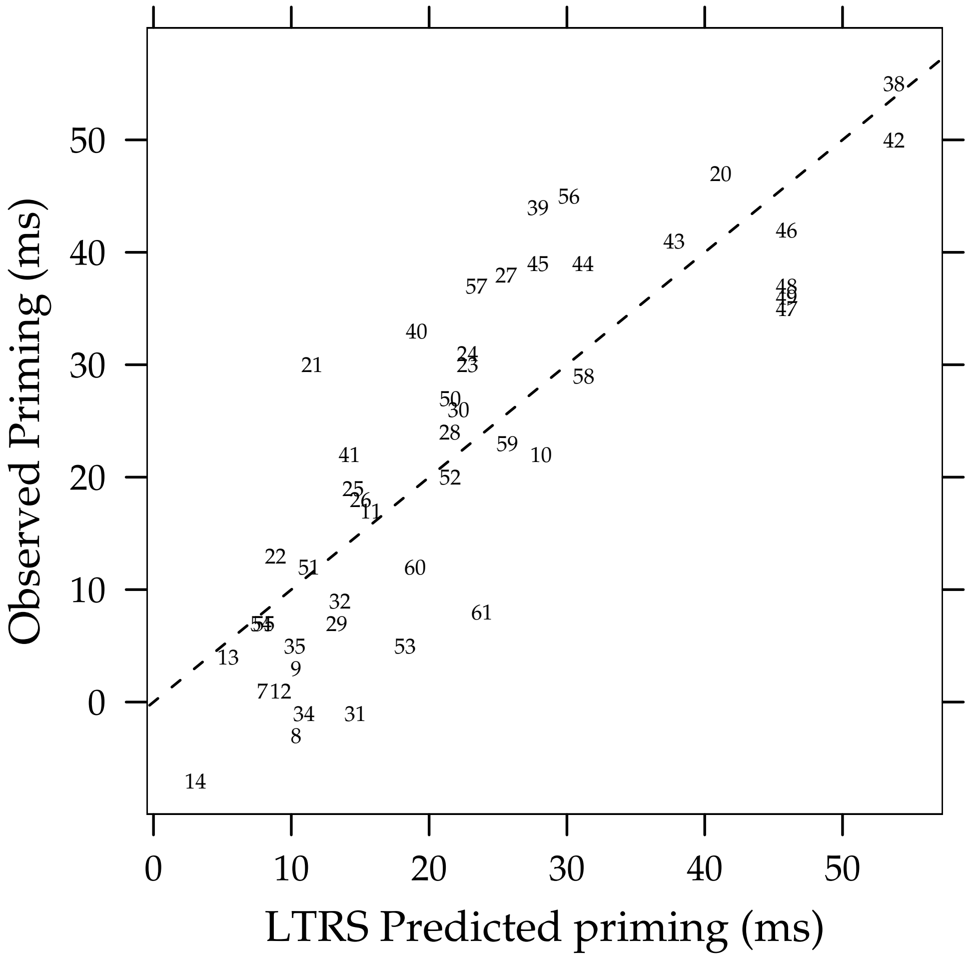

1LD
2LD
4LD
TL
Accuracy
1.0
0.8
0.6
0.4
0
20
40
Display Duration (ms)



Observed accuracy
LTRS predicted accuracy
0.5
0.6
0.7
0.8
0.9
1.0



Prime Types
Identity
1LD
Models
LTRS
SCM
Priming (ms)
20
40
60
20
30
40
50
60
Prime Duration (ms)


Observed Priming (ms)
LTRS Predicted priming (ms)
0
10
20
30
40
50