A stimulus sampling theory of letter identity and order

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Running head: Letter identity and order

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Abstract

Early on during word recognition, letter positions are not accurately coded. Evidence for this comes from transposed-letter (TL) priming effects, in which letter strings generated by transposing two adjacent letters (e.g., *jugde*) produce large priming effects, more than primes with the letters replaced in the corresponding position (e.g., *junpe*). Dominant accounts of TL priming effect such as the Open Bigrams model (Grainger & van Heuven, 2003, Whitney & Cornelissen, 2008) and the SOLAR model (Davis & Bowers, 2006) explain this effect by proposing a higher level of representation than individual letter identities in which letter position is not coded accurately. An alternative to this is to assume that position coding is noisy (e.g., Gomez, Ratcliff & Perea, 2008). We propose an extension to the Bayesian Reader (Norris, 2006) that incorporates letter position noise during sampling from perceptual input. This model predicts "leakage" of letter identity to nearby positions, which is not expected from models incorporating alternative position coding schemes. We report five masked priming experiments testing predictions from this model. (170 words)

Keywords: Visual word recognition; Letter position coding; Transposed-letter (TL) effects; Position noise; Masked priming; Open Bigrams; SOLAR; Bayesian Reader.

A stimulus sampling theory of letter identity and order

Reading is critically dependent on our ability to encode the exact serial order of letters: SALT and SLAT contain the same letters, but are different words. However, despite the importance of understanding how letter order is coded in reading, our knowledge is still very rudimentary. One of the few definitive statements we can make about the coding of letter order is that it cannot be based entirely on accurate position-specific letter representations. We know this from a number of experiments (e.g., Perea & Lupker, 2004; Schoonbaert & Grainger, 2004) that have shown that word recognition is facilitated when words are primed by letter strings that contain the same letters, but in a different order. For example, letter strings generated by transposing two adjacent letters in a word (e.g., *JUGDE*) prime the base word (*JUDGE*) more than letter strings generated by replacing the same letters with other letters not in the word (e.g., *JUNPE*). These findings are inconsistent with the 'slot coding' schemes used in many models of word recognition. For example, in both the interactive activation model of McClelland and Rumelhart (1981; Rumelhart & McClelland, 1982), and the Bayesian Reader model of Norris (2006), both lexical representations and input representations are position-specific. An input letter in given position will only activate words with the same letter in the same position. In these models the slots corresponding to the third and fourth position letters in both *JUGDE* and *JUNPE* have the wrong letter identities to activate *JUDGE*. Strings with transposed letters (TLs) and substituted letters (SLs) should therefore be equally similar to the base word.

A number of solutions to the letter order coding problem have been proposed. These fall broadly into two classes: One that assumes a higher level of orthographic representation than letters which mediates between the letter level and the word level, and another that assumes that letter position coding is noisy. Of the first class, the two dominant models have been those based on open-bigrams (Dehaene, Cohen, Sigman & Vinkier, 2005; Grainger, Granier, Farioli, Van Assche, & Van Heuven, 2006; Grainger & Van Heuven, 2003; Grainger & Whitney, 2004; Schoonbaert & Grainger, 2004; Whitney, 2001; Whitney & Berndt, 1999; Whitney & Cornelissen, 2005, 2008), and the 'spatial-coding' SOLAR model (Davis, 1999, 2006; Davis & Bowers, 2006). All of the open-bigram models code words in terms of some subset of the bigrams contained in a word. So, for example, WORD, might be coded in terms of the bigrams WO, WR, WD, OR, OD and RD. The different flavors of open-bigram model differ in terms of which subset of bigrams is represented, and whether or not the bigrams are coded in terms of the distance between them. In the SOLAR model, order is represented as an activation gradient over all of the letters in the input, where the first letter has the highest activation and each subsequent letter has a progressively lower level of activation. All of these models can account for the fact that transposing letters in primes leads to less of a reduction in priming than does substituting letters in the same position. The letter strings WORD and WROD contain 5 out of 6 open-bigrams in common (assuming for the purpose of illustration that there is no representation of space at the end of the string), whereas WORD and WAFD share only one bigram. In SOLAR, letter transpositions have only a small effect in the similarity of the gradient representations, but letter substitution has a much larger effect.

The second solution to explaining letter position ambiguity is to assume that letter position coding is noisy. The idea that location of an object is not accurately perceived has been suggested in theories of visual object perception, most notably in the CODE (Contour Detector) theory of visual attention (Logan, 1996). The key assumption of the CODE model, that representation of location is not a point but is distributed across space (see also Ratcliff, 1981), has been adopted in the Overlap model of Gomez, Ratcliff, and Perea (2008). According to the Overlap model, the identities of the letters in any letter string are assumed to be normally distributed over position: For example, in the string *trail*, the letter *a* will be associated with Position 3 but also to a lesser degree, and depending on the size of the standard deviation parameters for each position, to Positions 2 and 4 and even to Positions 1 and 5.

Here we will argue that transposed-letter priming effects are not due to a level of representation that are higher level than letters such as open bigrams or spatial gradient used in SOLAR. Instead, we suggest that the representations used in visual word recognitions consist simply of a sequence of letters, and such effects emerge as a consequence of the way a noisy or ambiguous input representation is mapped onto these ordered sets of letters. The assumption that perception involves a noisy sampling process is a fundamental principle of the Bayesian Reader model of visual word recognition (Norris, 2006), and application of this principle to coding of letter position and order as well as letter identity is a natural extension of the model. The version of the Bayesian Reader presented here may be viewed as implementing the noisy-position coding assumption of the Overlap model (Gomez, et al., 2008), and the data we present here support the noisy position coding scheme over other letter position coding schemes such as open bigrams, SERIOL, and SOLAR. We should note however that the model we present here is only a partial implementation of our theory of orthographic processing (which we describe below), and is limited to recognition of letter strings of a single length where there are no letter insertions or deletions.

The outline of this paper is as follows. We first briefly describe the Bayesian Reader theory of visual word recognition as instantiated in the model described by Norris (2006). We then extend the original model to incorporate positional noise, and show that the positional noise assumption makes a novel prediction ("leakage" of letter identity to nearby positions) that is not made by models incorporating alternative letter position coding schemes. Next, we present simulations of masked priming in the lexical decision task and the same-different task to demonstrate that the noisy-position version of Bayesian Reader (but not the original model) produces the "leakage" effect, then report Experiments 1 and 2 that test the prediction. We then discuss the apparent discrepancy between these results and those reported by Schoonbaert and Grainger (2004), and report Experiment 3 which confirms that Schoonbaert and Grainger's methodology lacked sensitivity to detect the leakage effect.

The Bayesian Reader

The Bayesian Reader (Norris, 2006) is a stimulus sampling model, based on the assumption that readers approximate optimal Bayesian decision makers. It accumulates noisy evidence from the input and uses Bayes' theorem to make optimal decisions about the identity of the input, or whether the input is a word or not. In its existing instantiation, the model is effectively a slot model where words are represented as a concatenation of letter vectors. Each letter vector corresponds to a position-specific slot. This means that although there is uncertainty about the identity of letters (because of the sampling noise) the order of the letters is always known perfectly. However, this slot-coding scheme is merely a simplification to make the model more tractable. The assumption has always been that the noisy sampling procedure applies to all of the information that has to be extracted from the stimulus. A more general implementation of the theory would allow both item and order information to be accumulated gradually over time. Thus, early on, there will be uncertainty as to both the identity of the letters and their order. In fact, very early on, there may even be uncertainty about how many letters there are in the input. The idea that the system make allowance for the possibility that not all letter-objects may be detected early in processing is consistent with the results of a number of studies that have shown that it is possible to obtain priming from primes in which some of the letters of the target are missing, so long as the remaining letters appear in the same order as they do in the target (Davis, & Bowers, 2006; Grainger, Granier, Farioli, Van Assche, & van Heuven, 2006; Humphreys, Evett, & Quinlan, 1990; Peressotti & Grainger, 1999). For example, Peressotti and Grainger found priming between *blcn* and *BALCON,* but not between *bcln* and *BALCON*. If the input is so ambiguous that neither the order nor the number of letter objects is known for certain, then an optimal Bayesian decision process must also take account of the likelihood of omissions and insertions. Peressotti and Grainger also found that inserting hyphens in place of the deleted letters (e.g. *b-lc-n,* *BALCON*), so as to make the letters occupy the correct serial positions, did not increase priming. This is exactly what one would expect if the system is trying to recover order and not position.

In sum, according to the Bayesian Reader, the task of the perceptual system in visual word recognition is to discover the optimal mapping between the noisy representation of the input and lexical entries. One way to view this process is to think of visual processing as having to solve three problems. The first is to determine how many letters there are in the input. Very early in processing even this task may be difficult. Because of the perceptual noise, the system may initially postulate too many or too few letters. That is, some letters will be missing from the developing perceptual representation, and some spurious letters might be inserted. For example, at this point HAT might match THAT to some degree, because of uncertainty as to whether HAT is preceded just by white space or by a partially resolved letter. The second is to determine the order of the letters. Order will also be ambiguous, so it might be unclear whether D comes before or after G in JUGDE. So long as there is some possibility that D precedes G, JUGDE will match JUDGE to some degree. The third is to identify each of the letters. Until the system can be completely confident that the input contains the letter P, there will still be some degree of match between JUDPE and JUDGE. Of course, these three problems need to be solved in parallel; a potential letter might be detected, assigned some possible location and its identity partially resolved. The noisy sampling theory therefore leads us to expect transposed-letter priming, super- and subset-priming, and substitution priming. None of this requires us to postulate extra forms of orthographic representation such as open-bigrams.

Information about letter order must necessarily be derived from some spatial representation because the physical world does not directly represent order. If the input letters are A, L, S and T, then there are only two words consistent with the input, SLAT and SALT. In order to establish how well the input matches those two lexical entries, we wish to compute the probabilities of the two orderings P(order is SLAT|input) and P(order is SALT|input). Note that if the task is word recognition, the final probabilities P(SLAT|input) and P(SALT|input), will be influenced by word frequency, but here we are considering only the problem of recovering order.

Insert Figure 1 about here

The simplest way to conceive of the positional code for a letter is to assume that it is represented by a single value on a dimension corresponding to location of the letter on the horizontal axis. (Of course, the exact nature of the perceptual coding of distance will be a property of early stages of the visual system and is beyond the scope of the current theory.) Each letter will therefore have a location value associated with it, and this value will drive the noisy sampling process. So, if S has the positional value 1.0, then successive samples will be drawn from a distribution with a mean value of 1.0 and a variance determining the noise in the sampling process. Figure 1 shows the sampling distribution of the mean for the position values for four equally spaced letters. Early in processing the distributions will correspond to the broader curves, and there will be considerable ambiguity in position, and hence order. This means that there will be a significant probability that these location values were generated by the letters in the order corresponding to SALT as well as the order corresponding to SLAT. However, as more samples arrive, and the uncertainly in the input decreases, the probability that the string could have been generated by SALT will tend to decrease. Eventually, the input will only be consistent with SLAT.

There are a number of different algorithms that can be used to derive order from noisy input representations. For example, for each letter object one can determine the probability that it is the first letter by computing the probability that the positional value of that letter is smaller than the positional value of every one of the remaining letters. One can than calculate the probability that the letter appeared in the second position by computing the probability that its position value is larger than exactly one of the remaining values.

Note that in the process of deriving order from position, the input is mapped onto lexical representations in a way that is scale and translation invariant. Shifting the input by increasing the positional values by a constant from 1.0, 2.0, 3.0, 4.0 to 4.0, 5.0, 6.0, 7.0 would result in identical probabilities. Enlarging the image to give values of 2.0, 5.0, 6.0, 8.0, would have the effect of increasing the signal-to-noise ratio so as to make it easier to recover order.

The computations required to map position onto order are quite complex, and performing these calculations for all possible letter orders after each input sample is computationally very demanding (see Mueller & Shiffrin, 2005, for suggestions as to how similar computations could be performed that takes into account potential insertions and omissions). Here we therefore use a greatly simplified model to investigate the consequences of having noise in both letter identity and letter order. We do this simply by adding positional noise to the Bayesian Reader. In effect, this reduces to a noisy slot model, and is similar to the Overlap model of Gomez, Ratcliff and Perea (2008). Indeed, Gomez et al. note that "the Bayesian Reader model can easily use the Overlap module as a front-end of the model – instead of the position-specific coding scheme of the original implementation of the model (see Norris & Kinoshita, 2007)". The main difference between the current implementation and the Overlap model is that the Bayesian Reader simulates the entire process of accumulating information over time, and simulates performance in masked priming tasks, whereas the Overlap model just describes the uncertainty in the representation of the input at a single point in time. Furthermore, the model we present is only a partial implementation of our theory of orthographic processing. The implemented model does not have scale or translation invariance, and uses a fixed number of letter objects, so it will not be able to simulate superset and subset priming. Nevertheless, it makes some interesting predictions which do not follow from other models.

Implementing positional noise in the Bayesian Reader

One consequence of adding positional noise to the Bayesian Reader is that the positional noise can change the probabilities of letter identities at each position. Consider first the extreme case of trying to identify the word *CAT* when the identity of each letter object is known with certainty, but there is no order information. The identity of the letter in position 1 of the word is now equally likely to be *C, A*, or *T*. Although the system knows that there is a *C* in the input, the probability that position 1 contains a *C* will be only 0.33. More generally, any uncertainty over letter order will lead to a 'leakage' of letter identity between positions. For example, if the probability of the letter *A* appearing in positions 1, 2 and 3 is 0.25, 0.5, and 0.25 respectively, the probability that the letters in positions 1 and 3 are *A* will be larger than if there had been no positional noise, while the probabilities of C in position 1, and T in position 3, will be smaller.

It follows that adding positional noise to the Bayesian Reader leads to the prediction of "leakage", where substituting a letter with an adjacent letter results in a string that is "more similar" than substituting it with a letter that does not appear anywhere in the target. For example, *uueer* is more similar to *UNDER* than *ulger*. The *u* in position 2 will leak into position 1 and boost the probability of the letter in position 1 being identified as a *U*, and the *e* in position 3 will leak to the *E* in position 4. Primes with repeated substitutions (repeated substituted letters - repSL) should therefore be more effective than primes with two substituted letters (2SL).

This difference between repSL and 2SL primes is not predicted by any of the open-bigram models, or by SOLAR. Because in these models letter identity is independent of letter position, the letters in positions 2 and 3 in *uueer* and *ulger* will both mismatch the corresponding letters in *UNDER* equally. In contrast, the Overlap model, which assumes noisy position coding, generates greater overlap value between *uueer* and *UNDER* than between *ulger* and *UNDER*.

Insert Figure 2 about here

The mean match scores produced by the different letter position coding models are shown in Figure 2. The match scores for the slot-coding, SOLAR, the Constrained Open Bigram (Schoonbaert & Grainger, 2004), the most recent version of SERIOL (Whitney, 2008; Whitney & Cornelissen, 2008), and the Overlap Open Bigram (Grainger, et al., 2006) models for each of the primes and the target for the stimuli used in the experiments to be reported were calculated using Davis' Matchcalculator program. [Footnote] All models return a value of 1.0 for identical letter strings (id, e.g., *faith* and *faith*), and a value of 0 for letter strings that have no letters in common in any position (ALD, e.g., *noble* and *drift*). We also calculated the "overlap values" between each prime type and target from the Overlap model (Gomez, et al., 2008, Appendix C). To facilitate comparison with the other models, we scaled the overlap values by dividing the overlap values for each prime conditions by the overlap value for the identity prime, so that an identity prime produced an overlap value of 1.

It can be seen from Figure 2 that SOLAR, COB, SERIOL and the OOB model predict the ordering id > TL > 2SL >= repSL > ALD (the slot-coding model predicts no difference between TL and 2SL prime conditions, SOLAR predicts slightly greater priming for 2SL than repSL, and SERIOL and the OOB predict a very small advantage of repSL over 2SL), that is, a large difference between TL and repSL conditions, and little difference between the 2SL prime and repSL prime conditions. In contrast, the overlap model shows id > TL = repSL > 2SL > ALD.

In the present paper we will examine this prediction in masked priming experiments. The lexical decision task has been the standard task used in previous studies, and for this reason we use this task in Experiment 1, but we will also use the cross-case same-different matching task in Experiment 2. The masked priming procedure used in the same-different task (see Norris & Kinoshita, 2008) is the same as that used by Forster and Davis (1984), but with the extra feature that a reference string (in lowercase letters) is presented for 1000ms before the prime, at the same time as, and above the forward mask. The participant's task is to decide whether the target (in uppercase letters) is the same as the reference string, or different. In this task, as in lexical decision, masked priming in the same-different task is insensitive to cross-case letter similarity indicating that priming is based on abstract letter identities, and it shows robust transposed-letter effects (Kinoshita & Norris, 2009; Kinoshita, Castles, & Davis, 2009; Norris & Kinoshita, 2007). It should also be noted that there is an equal amount of priming for both words and nonwords on *Same* trials, but no priming for either on *Different* trials (see Norris & Kinoshita, 2008, for an explanation).

In the present context this task has two main advantages over lexical decision. The first is that priming effects in the same-different task are much larger than in lexical decision, so the task is much more sensitive to the small differences in priming between conditions that the present manipulations might be expected to produce. Second, masked priming in this task is not sensitive to lexical factors (see Norris & Kinoshita, 2008, regarding the effects of word frequency and lexical status, and Kinoshita, Castles, & Davis, 2009, regarding the effect of neighborhood density), so there is much less chance that any effects observed might be attributable to differences in the lexical properties of the stimuli. This is important as it is now clear that masked priming effects in the lexical decision task are not driven solely by orthographic similarity between the prime and the target (Guererra & Forster, 2008; Kinoshita & Norris, 2009). Note that match scores generated by the open bigram models and SOLAR are insensitive to lexical factors, hence the same-different task allows a more direct comparison between the Bayesian Reader and these models. Before reporting the experiments we will first present simulations using the Bayesian Reader to confirm that both the TL priming effect and the leakage results are predicted by implementing positional noise.

Bayesian Reader simulations

We will now present two sets of simulations for the same-different task comparing identity primes, TL primes, repSL primes, and 2SL primes, relative to all-letter-different (ALD) primes. The first set of simulations is similar to those presented by Norris and Kinoshita (2008), in that there is no position noise. The second set of simulations adds the position-noise coding scheme described here. Masked priming was simulated using the procedure described in Norris and Kinoshita. In principle, the probability of the target being *Same* would be continuously updated after each new sample, and there would be no discontinuity in processing between prime and target. However, for purely practical reasons we adopt the computationally equivalent procedure of first presenting the prime, then updating the probability that the response is *Same*, and then presenting the target. The prime is first presented for 30 samples, after which the probability that the target is *Same* is updated. The prime is then replaced by the target and the sampling process is reset. After each sample the model generates an estimate of the probability that the reference and target are the same. If that probability exceeds an upper threshold, the model responds *Same*, if the probability drops below a lower threshold, the model responds *Different*. The model's simulated RTs are given by the number of samples required to reach threshold. For both versions of the model the *Same* and *Different* response thresholds were set so as to produce approximately the correct level of accuracy. The pattern of priming does not depend on the exact threshold settings. However, as would be expected, the pattern does depend on the level of position noise.

Both simulations use the stimuli that will be used in Experiments 1 (lexical decision task) and 2 (same different task). The results of the simulations are shown in Figure 3. For all simulations there are 50 simulated trials of each item. This ensures that the simulated RTs for individual items are very stable.

Insert Figure 3 about here

Not surprisingly, the model with no position noise (see Figure 3a) behaves exactly as one would expect on the basis of a slot-coding scheme. There is no difference between the priming produced by the repSL, TL and 2SL conditions. All three conditions effectively mismatch at two letter positions, and this is all that determines priming. The simulations with position-noise (see Figure 3b) also behave exactly as expected. There is priming in both the TL and the repSL conditions, and these two conditions are very similar. In all of the simulations with position noise, there is more priming for both TL and repSL than 2SL. The effects are very consistent across items. Confidence limits for all of the critical differences are less than ± 4 samples. Furthermore, the pattern of priming across conditions remains qualitatively similar even when the amount of position noise relative to identity noise is increased substantially beyond that used to produce the simulations shown in Figure 3b.

Next, we use the model with position noise to compare the lexical decision task and the same-different task. Figure 4 shows the simulations with three different prime durations (30 samples, 50 samples, 100 samples) with a fixed value of the letter identity noise parameter (SD, set at 10) and position noise parameter (P, set at 5).

Insert Figure 4a, 4b, 4c about here

These simulations show that for the same-different task, the size of priming produced by repSL primes is consistently larger than that for the 2SL primes, and generally indistinguishable from the TL primes. The pattern for lexical decision is similar, but the size of priming effect is smaller overall than for the same-different task, and the difference between the repSL, TL and the 2SL prime is less consistent. The critical aspect of the simulations is that both repSL primes and TL primes produce more priming than 2SL primes. Experiments 1 and 2 test these predictions.

Experiment 1 (lexical decision task)

In Experiment 1, we use the lexical decision task. This is the task that to date has been used standardly in previous studies of letter position coding effects (e.g., Perea & Lupker, 2003; Guerrera & Forster, 2008; Schoonbaert & Grainger, 2004). As we have noted above, however, priming effects are smaller in lexical decision than in the same-different match task, and sensitive to lexical factors like frequency and neighbourhood density which is likely to obscure small orthographic effects. We use this task therefore not to test the critical leakage prediction, but to show that the standard effects that have been observed in previous studies – i.e., TL priming effect (relative to ALD primes), and the advantage of TL primes over 2SL primes – are replicated with the same stimuli used in the same-different task, to be reported next.

Method

Participants. Twenty-five psychology students from Macquarie University participated in Experiment 1 in return for course credit.

Design. The experiment constituted a 2 (Response type: *Word* vs. *Nonword*) x 5 (Prime type: identity, TL, 2SL, repSL, ALD, to be described below) factorial design, with both factors manipulated within subjects. The dependent variables were RT and error rate.

Materials. The critical stimulus materials used in this experiment were 100 5-letter words used as targets requiring a *Word* response. The words ranged in frequency between 9 to 707 occurrences per million according to Kucera and Francis (1967), with a mean of 92.6 per million.

For each target word (e.g., *UNDER, ABOVE*), five types of primes were generated. One was an identity prime, which was the same word as the target (e.g., *under, above*). The second was a transposed-letter (TL) prime, in which either the second and the third letter (e.g., *under*), or the third and the fourth letter (e.g., *abvoe*) were transposed. Half of the items had the second and the third letters transposed and the other half, the third and fourth letters transposed. The third was a two-letter-substituted (2SL) prime, which had two adjacent internal letters replaced with letters not contained in the target (e.g., *ulger, apive*). Vowels were replaced with vowels and consonants were replaced with consonants. The fourth was a repeated-substituted letter (repSL) prime, which replaced two adjacent internal letters with the letter contained in the target (e.g., *uueer, abbee*). This involved repeating the first and fourth letter (when the 2SL prime replaced the second and third letters) or repeating the second and last letter (when the 2SL prime replaced the third and fourth letters). As the letter transpositions were all word-internal (i.e., it involved letters in position 2 and 3 or position 3 and 4), this meant that the repeated letters were in position 1 and 4 (e.g., *uueer* for *UNDER*), or position 2 and 5 (e.g., *abbee* for *ABOVE*). The fifth type of prime was all-letter different (ALD) prime, which was a nonword different from the target that avoided overlap in letters in the same positions as target (e.g., *gypny* for *UNDER, lumid* for *ABOVE*). The critical target words and the primes are listed in Appendix A.

In addition to the 100 target words requiring a *Same* response, 100 nonword targets were generated from words selected using similar criteria as the critical stimuli. These targets were also 5-letters long, and ranged in frequency between 5 to 1815 occurrences per million (mean 92.1). Nonwords were generated by replacing one or two letters of these words (e.g., *AMOUT* from *ABOUT*). Each nonword target was paired with five primes generated in the same way as for the primes for word targets.

Both the 100 target words and the 100 nonword targets were divided into five sets containing 20 items each. Five list versions were constructed for the purpose of counterbalancing assignment of sets to the five prime types using a Latin Square design, so that within a list, each target word appeared only once, and across the five lists, appeared in each of the five prime conditions once.

Prior to the test trials, participants were given 20 practice trials that were representative of the items used and warm-up items preceded each half block. Warm-up and practice items were selected according to the same criteria as the test stimuli. These items were not included in the analysis.

Apparatus and Procedure. Participants were tested individually, seated approximately 40 cm in front of a CRT monitor, upon which stimuli were presented. Each participant completed 200 test trials presented in two blocks (each containing 100 trials each), with a different random order generated for each participant.

Participants were instructed at the outset of the experiment that on each trial they would be presented with a letter string, and their task was to decide whether it was a real word, as fast and accurately as possible. They were instructed to press a key on a response pad marked "+" for *Word* and a key marked "-" for *Nonword* response.

Stimulus presentation and data collection were achieved through the use of the DMDX display system developed by K.I. Forster and J.C. Forster at the University of Arizona (Forster & Forster, 2003). Stimulus display was synchronized to the screen refresh rate (13.3 ms).

Each trial started with the presentation of a forward mask for the prime consisting of 5 # signs. The reference remained on the screen for 500 ms. It then disappeared, and was replaced immediately by the prime presented for 53 ms in lowercase letters. In turn, the prime was replaced immediately by the target presented in uppercase letters for a maximum of 2,000 ms, or until the participant responded. Participants were given no feedback on either latencies or error rates during the experiment.

Results

For this and subsequent experiments, the preliminary treatment of trials was as follows. Any trial on which a participant made an error was excluded from the analysis of RT. To reduce the effects of extremely long and short latencies, the cutoff was set for each participant at 3 S.D. units from each participant's mean latency and those shorter or longer than the cutoff was replaced with the cutoff value. In Experiment 1, this affected 1.5% of trials.

In Experiment 1, the trials involving the critical stimuli (*Word* responses) were analyzed using a one-way analyses of variance (ANOVA) with Prime type (identity, TL, 2SL, repSL, ALD) as a factor. We report only the descriptive statistics of the nonword trials (see Table 1) because in lexical decision nonwords are insensitive to the prime type manipulation (the main effect of prime type was non-significant, $F_1 < 1.0$; $F_2 < 1.0$). The alpha level for effects reported as significant was .05. Prime type was a within-subject factor and within-item factor. The mean latency and error rates data for *Word* responses for Experiment 1 are shown in Table 1. (The Bayesian Reader simulation for the items are available from the electronic version of the article at the Science Direct website.) The model RTs correspond to those in Figure 4a. In the simulations of this experiment, the *Word* and *Nonword* thresholds were adjusted by hand to produce approximately the correct overall error rates.

Insert Table 1about here

For latency, the main effect of Prime type was significant, $F_1(4,96) = 18.55$, MSe = 468.29; $F_2(4, 396) = 13.64$, MSe = 2745.13; *minF*'(4, 369.15) = 7.86. Simple effects contrasts among the prime types showed the following: id < TL: $t_1(24) = 4.11$; $t_2(99) = 3.24$; TL < 2SL: $t_1(24) = 3.55$; $t_2(99) = 3.17$; repSL = 2SL = ALD, all $p > .22$. Thus, the lexical decision task showed the advantage of TL primes over SL primes. The repSL prime condition did not differ from the TL prime condition, but neither did it differ from the 2SL prime condition. Also, there was no difference between the 2SL and ALD prime conditions, and they did not differ from the repSL condition.

For error rate, the main effect of Prime type was significant, $F_1(4,96) = 4.81$, MSe = 36.88; $F_2(4,396) = 4.75$, MSe = 149.20; *minF*'(4, 311.44) = 2.39. Simple effects contrasts among the prime types showed the following: id < TL: $t_1(24) = 2.28$; $t_2(99) = 2.44$; 2SL > ALD: $t_1(24) = 2.18$; $t_2(99) = 2.22$; TL ≤ 2SL: $t_1(24) = 2.06$, $p = .05$; $t_2(99) = 1.95$, $p = .06$. None of the other effects reached significance.

Discussion

The results of the lexical decision experiment replicated the advantage of TL primes over the 2SL primes that has been reported often in the literature (e.g., Perea & Lupker, 2003), but the data concerning the expected "leakage effect" were inconclusive. Although repSL primes produced somewhat more priming than the 2SL primes, the difference was non-significant. Moreover, the 2SL prime condition did not differ from the ALD prime condition. The lack of difference between the 2SL and ALD prime condition in the lexical decision task has been reported before (e.g., Perea & Lupker, 2003; Lupker & Davis, 2009; Schoonbaert & Grainger, 2004). The fact that a letter string that is just two-letters different from a target word (e.g., *ulger-UNDER*) produces no more priming than a letter string that is completely different (e.g., *gypny-UNDER*) highlights the fact that masked priming in the lexical decision task is not a simple function of increasing orthographic similarity, a point noted by a several of authors recently (e.g., Guerrera & Forster, 2008; Kinoshita & Norris, 2009, Lupker & Davis, 2009). The result is at odds with the match scores of all models (see Figure 2), and also the Bayesian Reader simulation of lexical decision (see Figure 4a, 4b, and 4c). That the Bayesian Reader simulation did not reflect the absence of difference between 2SL and ALD primes in lexical decision suggests that some aspect of the lexical decision process (likely the role of mismatching letters) is not completely captured in the current implementation.

Experiment 2

We now test the prediction of the Bayesian Reader model with position noise in two experiments using the same-different match task. Experiments 2a and 2b were identical, except for the reference string used in the *Different* condition. In Experiment 2a, all the targets requiring *Different* response were all-letter-different from the reference string (e.g., *never-ABOUT*). In Experiment 2b, the difference ranged between one-letter (e.g., *focal-VOCAL*, *altar-ALTER*) to all five letters. The main purpose of Experiment 2b was to test the generality of the predicted pattern of priming under conditions varying in difficulty of decision: The critical prediction of the position noise assumption that distinguishes it from the others is that there should be no difference between the repSL and TL prime conditions, and that there will be a difference between repSL and 2SL. As the predicted pattern of priming is the same for the two experiments, the results will be discussed together after presenting both experiments.

Method

Participants. Twenty-five volunteers from the MRC Cognition and Brain Sciences Unit subject panel participated in Experiment 2a; twenty-five psychology students from Macquarie University participated in Experiment 2b for course credit.

Design. The experiment constituted a 2 (Response type: *Same* vs. *Different*) x 5 (Prime type: identity, TL, 2SL, repSL, ALD, to be described below) factorial design, with both factors manipulated within subjects. The dependent variables were RT and error rate.

Materials. The critical stimulus materials used in this experiment were 100 5-letter words used as targets requiring a *Same* response. They were identical to the word stimuli used in Experiment 1. The five types of primed generated for each target were also identical to Experiment 1.

In addition to the 100 target words requiring a *Same* response, 100 target word were selected to be used as targets requiring a *Different* response, using similar criteria. These targets were 5-letter words, and ranged in frequency between 5 to 1815 occurrences per million (mean 92.1). In Experiment 2a, each of the target was paired with a 5-letter reference word that was different from the target (e.g., reference: *never*, target: *ABOUT*). For Experiment 2b, 80 of the 100 reference words for the *Different* condition were changed, so that 20 of the reference and target words differed by one letter (e.g., *focal-VOCAL*, *altar-ALTER*), 20 differed by two letters (e.g., *aloud-ABOUT*, *toner-HONEY*), 20 differed by three letters (e.g., *snoop-UNION*, *scout-FLOUR*), 20 differed by four letters (e.g., *sneer-PRIOR*, *waste-CARGO*). The position of the differing letters was spread across the five positions. The remaining 20 reference-target pairs were unchanged from Experiment 1 so they differed by all five letters. For both Experiments 2a and 2b, the assignment of target words to the five prime conditions was identical to Experiment 1.

Prior to the test trials, participants were given 20 practice trials that were representative of the items used and warm-up items preceded each half block. Warm-up and practice items were selected according to the same criteria as the test stimuli. These items were not included in the analysis.

Apparatus and Procedure. Apparatus, the general task procedure, and task instructions were identical to Experiment 1, except for the fact that the task was the same-different match task, instead of lexical decision.

Participants were instructed at the outset of the experiment that on each trial they would be presented with two words, and their task was to decide whether they were the same or different, as fast and accurately as possible. They were instructed to press a key on a response pad marked “+” for *Same* and a key marked “-“ for *Different* response.

Each trial started with the presentation of a reference word, presented in lower case letters in Courier 10 point font, in the center of the screen, above a forward mask for the prime consisting of 5 # signs. The reference remained on the screen for one second. It then disappeared, and at the same time, the prime was presented for 53 ms in lowercase letters where the forward mask had been. The prime was replaced immediately by the target presented in uppercase letters for a maximum of 2000 ms, or until the participant responded. Participants were given no feedback on either latencies or error rates during the experiment.

Results

For both experiments, the preliminary treatment of trials was identical to Experiment 1, and the cut-off procedure affected 1.3% of trials in Experiment 2a, and 1.2% of trials in Experiment 2b. The analysis of the critical stimuli were identical to that of Experiment 1, using a one-way analyses of variance (ANOVA) with Prime type (identity, TL, 2SL, repSL, ALD) as a factor. As with the nonword data in Experiment 1, we report only the descriptive statistics for the *Different* responses, because as in previous experiments (e.g., Norris & Kinoshita, 2008; Kinoshita & Norris, 2009) using this task there were no priming effects for *Different* trials. The priming effects are shown in Figure 5, and the mean RTs and error rates are shown in Table 2. The model RTs correspond to those in Figure 3b, and the priming effects corresponds to those in Figure 4a. In the simulations of both Experiments 2a and 2b, the *Same* and *Different* thresholds were adjusted by hand to produce approximately the correct overall error rates. In other words, the simulated *Same* responses for the two experiments differ only in the response thresholds used.

Insert Figure 5 and Table 2 about here

Experiment 2a. For latency, the main effect of Prime type was significant, $F_1(4,96) = 69.46$, MSe = 571.35; $F_2(4, 396) = 53.54$, MSe = 3466.58; *minF*'(4, 359.84) = 30.24. Simple effects contrasts among the prime types showed the following: id ≤ TL =

repSL < 2SL < ALD, where repSL vs. 2SL, $F_1(1, 24) = 7.89$; $F_2(1, 99) = 10.79$; $minF'(1,63.68) = 4.56$. Thus, repSL primes behaved just like the TL primes and produced greater priming than the 2SL primes, a condition standardly used as the orthographic control for the TL primes. The greater priming by repSL primes than 2SL primes, and the equivalent priming by TL and repSL primes was predicted by the Bayesian Reader, but not from the match scores generated by the OB, SOLAR and SERIOL models.

For error rate, the main effect of Prime type was significant, $F_1(4,96) = 17.31$, $MSe = 33.22$; $F_2(4,396) = 26.80$, $MSe = 85.85$; $minF'(4, 236.18) = 10.52$. Simple effects contrasts among the prime types showed the following: id = TL = repSL ≤ 2SL < ALD, where repSL vs. 2SL: $F_1(1, 24) = 4.57$; $F_2(1,99) = 9.24$; $minF'(1, 50.69) = 3.06$.

Experiment 2b. For latency, the main effect of Prime type was significant, $F_1(4,96) = 52.26$, $MSe = 709.63$; $F_2(4,396) = 58.73$, $MSe = 3472.76$; $minF'(4,287.65) = 27.65$. Simple effect contrasts among the prime types showed the following: id ≤ TL = repSL < 2SL < ALD, where 2SL vs. repSL, $F_1(1, 24) = 14.52$; $F_2(1, 99) = 15.73$; $minF'(1, 73.55) = 7.55$. That is, as in Experiment 2a, repSL primes produced greater priming than 2SL primes, which was indistinguishable from TL priming.

For error rate, the main effect of Prime type was significant, $F_1(4,96) = 11.98$, $MSe = 64.28$; $F_2(4,396) = 24.04$, $MSe = 128.09$; $minF'(4, 203.28) = 8.00$. Paired sample *t*-tests among the prime types showed the following: id = TL = repSL = 2SL < ALD.

Comparison of Experiments 2a and 2b. To assess whether changing the nature of the *Different* reference-target pairs altered the pattern of priming we carried out a two-way ANOVA with *Prime type* and *Experiment* as factors. There were no significant interactions between Prime and Experiment for either RTs or errors (all *F*s < 1.06). Averaged across experiments, the latency data showed id ≤ TL = repSL < 2SL < ALD.

Discussion

The main finding of Experiments 2a and 2b using the same-different match task is that repSL primes that substituted the adjacent letters (e.g., *uueer* for *UNDER*) produced priming that was indistinguishable from TL primes (e.g., *udner-UNDER*) and significantly greater than 2SL primes that contained letters that are not in the targets (e.g., *ulger-UNDER*). The greater priming by repSL primes relative to 2SL primes was exactly as predicted by the noisy position coding assumption, but is at odds with SOLAR, Constrained OB, SERIOL, and the Overlap Open Bigram models (as well as the slot-coding model without positional noise), which predicted no difference.

Experiments 2a and 2b differed only in the nature of *Different* items. In Experiment 2a, the targets were all-letter-different from the reference, whereas in Experiment 2b, they differed between one-letter to all five letters. As expected, given that Experiment 2b used more similar *Different* reference-target pairs, responses were both slower and more error prone, but this did not alter the pattern of priming. Thus, the finding of greater priming observed with repSL primes than the 2SL primes, as well as the null difference between TL primes and repSL primes was reliable.

The noisy-position version of the Bayesian Reader predicted that repSL primes would produce greater priming than the 2SL primes due to leakage of letter identity to adjacent positions. Could another factor have produced the difference between repSL and 2SL prime conditions? For example, repSL primes (e.g., *uueer*) are orthographically less regular and less wordlike than 2SL primes (e.g., *ulger*). However, orthographic regularity is correlated with N. In contrast to lexical decision, the same-different task, is insensitive to N, and masked priming in this task is not modulated by N (Kinoshita, et al., 2009). This is expected from the assumption that unlike the lexical decision in which the perceptual input is matched against the orthographic representations of the whole lexicon, in the same-different task it is matched against only the reference string. This means that whereas in the lexical decision task orthographic regularity of the prime could modulate the size of priming (because the lexical space is not populated by orthographically illegal letter strings), there is little reason to expect it would affect priming in the same-different task. Consistent with this analysis, we have unpublished data indicating that masked priming effects in the same different-task do not differ in size for two-letter-substituted primes that are orthographically legal (e.g., *prake-PLACE*) vs. illegal (e.g., *pkare-PLACE*). We therefore consider unlikely that orthographic regularity, rather than leakage, was responsible for the difference between priming produced by the repSL prime and the 2SL prime in the same-different task.

Experiment 3

The fact that Experiment 2 showed a larger priming effect with the repSL primes relative to the 2SL primes might appear to be at odds with two findings reported by Schoonbaert and Grainger (2004) with the lexical decision task. One (their Experiment 2) is that nonword targets generated by omitting a repeated letter in the baseword (e.g., *BALNCE* generated from the baseword *balance*) were not rejected more slowly than nonword targets generated by omitting a unique letter (e.g., *BALACE*); second, in their

Experiment 1, when these nonword items were used as masked primes, they produced equal priming. As noted by Davis (2006), the positional noise assumption would regard *BALNCE* as orthographically more similar to the baseword *balance* than *BALACE,* because the letter A in *BALNCE* (letter A_2) should leak to other positions (here the fourth position A_4) and hence *BALNCE* “may be said to contain all seven letters of its addition neighbour” (p.195), whereas *BALACE* contains “only six of the letters of its addition neighbour”. Thus when *BALNCE* is presented as a nonword target, it is expected to be rejected more slowly than *BALACE*, which was not found to be the case (if anything, there was a trend towards the opposite). Also, when used as masked primes, *BALNCE* should produce more priming than *BALACE*. Again, this prediction was not confirmed, although there was a trend consistent with the prediction. We suggest that there is no real conflict between our results and those of Schoonbaert and Grainger; but rather, it is due to the methodology used by Schoonbaert and Grainger not being most suited to detecting a small difference produced by omitting a repeated letter vs. a unique letter.

Two reasons may be suggested as to why Schoonbaert and Grainger (2004, Experiment 2) did not observe a difference between the response to nonword targets generated by omitting a unique letter vs. a repeated letter. One is that they used an unprimed lexical decision task here and the task did not involve masked primes, but nonword targets presented clearly. According to the Bayesian Reader, perception is a noisy sampling process, but with clearly presented stimuli, when sufficient samples are accumulated from input there should be no uncertainty (either with letter identity or letter position). Similarly, in the Overlap model, when targets presented unmasked and for an unlimited viewing time, the standard deviation of position overlap is set to zero. Thus, just as people are able to distinguish a TL nonword from the baseword when the stimuli are presented clearly, effects due to position uncertainty that might be expected with masked primes will be much smaller with clearly presented targets. Second, the prediction of slower "nonword" response to *BALNCE* relative to *BALACE* assumes that the difference in latency reflects solely the interference caused by the nonword similar to the baseword wrongly accessing the lexical representation corresponding to the baseword. This assumption may not be correct. In correctly rejecting a nonword that closely resembles a specific word, it is often assumed that people carry out spelling check involving a detailed comparison between the orthographic representation of a word and the nonword target (e.g., Balota & Spieler, 1999; see O'Connor & Forster, 1981, for evidence that response to TL nonwords involves such a process). In order to correctly reject a nonword that is highly similar to the baseword, the misspelt segment (in the present case, the missing letter) must be identified. Locating a missing or additional repeated tokens is notoriously difficult – as attested by the well-known "Paris in the the spring" example (see Mozer, 1989), and the repetition blindness phenomenon (Kanwisher, 1987). Hence it may be easier to identify the missing unique letter (i.e., the missing *N* in *BALACE*) than the missing repeated letter (the missing *A* in *BALNCE*), with reference to the baseword (*balance*). Consistent with this, Schoonbaert and Grainger (2004, Experiment 1) found that nonword targets containing a repeated letter (e.g., *TOMBOUX*) were responded to more slowly than nonwords containing only unique letters (e.g., *CADRIEM*). In this case orthographic similarity and the ease of identifying the missing vs. repeated letter would trade off against each other, and depending on the relative contribution of each factor, nonword response latency could be faster, slower, or no different for the two types of nonwords.

Schoonbaert and Grainger's (2004, Experiment 1) failure to find greater priming of *BALANCE* by *balnce* than *balace* is more difficult to reconcile with the present results, because both studies used masked priming. However, consistent with the present results, there was a small trend towards greater priming by *BALNCE* primes than *BALACE* primes, and it is possible that Schoonbaert and Grainger's method lacked sensitivity to detect the difference. Specifically, unlike the present study (that compared repSL and 2SL primes), Schoonbaert and Grainger's repeated-letter manipulation: 1) involved one, rather than two letters; 2) involved non-adjacent letters (e.g., *BALANCE*) and hence the leakage of the critical letter (e.g., *a* in *balnce*) needed to span an intervening letter, and 3) they used the lexical decision task which, unlike the same-different task, is sensitive to lexical factors which could mask small orthographic effects.

To test our claim, we conducted Experiments 3 as a conceptual replication of Schoonbaert and Grainger's masked priming experiment (2004, Experiment 1), testing whether deleting a repeated letter in a word retains greater similarity to the word than deleting a unique letter. We made a couple of modifications to their procedure, in order to increase the opportunity for detecting a small difference. First, we used words that contained a repeated letter in adjacent positions (e.g., *ANNEX, FLOOR*). Second, we included an identity prime condition (e.g., *annex-ANNEX*) and used this as the baseline for assessing the cost of deleting a letter (e.g., *anex-ANNEX*). If deleting a unique letter results in greater cost than deleting a repeated letter, then there should be a greater difference between an identity prime and a deleted-letter prime for the unique-letter words (e.g., *ERUPT*) than the repeated-letter words (e.g., *ANNEX*). Third, we used the cross-case same-different task (Experiment 3a), as well as the lexical decision task (Experiment 3b), to test the possibility that the former might be able to detect priming effects not apparent in the lexical decision task because it is uninfluenced by lexical factors.

Experiments 3 involved critical stimuli of two types: 5-letter words containing repeated letters in internal adjacent positions (e.g., *ANNEX*), and 5-letter words containing five unique letters (e.g., *ERUPT*). These words were preceded by three types of primes: identity (e.g., *annex-ANNEX, erupt-ERUPT*), deleted-letter (e.g., *anex-ANNEX, eupt-ERUPT*), and substituted-letter (e.g., *alnex-ANNEX, emupt-ERUPT*). The main prediction was that if omitting a repeated letter leaves the string more similar to the baseword than omitting a unique letter, then the cost of deleting a letter from the identity prime would be less for the repeated-letter words than for unique-letter words.

Method

Participants. Sixty psychology students from Macquarie University participated in Experiments 3 in return for course credit. Thirty participated in Experiment 3a (same-different task); thirty in Experiment 3b (lexical decision task).

Design. Both Experiments 3a and 3b constituted a 2 (Word type: *Repeated-letter words* vs. *Unique-letter words*) x 3 (Prime type: identity, one-letter-deleted, one-letter-substituted) factorial design, with both factors manipulated within subjects. The dependent variables were RT and error rate.

Materials. The critical stimulus materials used in this experiment were 60 five-letter words containing repeated letters in positions 2 and 3 or positions 3 and 4 (e.g., *FLOOR, ANNEX*) and 60 five-letter words containing unique letters (e.g., *TRADE, ERUPT*). They were used as targets requiring a *Same* response in Experiment 3a, and as *Word* targets in Experiment 3b. They were selected from the English Lexicon Project Database (Balota, Cortese, Hutchison, Neely, Nelson, D., Simpson, & Treiman, 2002) on the basis that the word had mean lexical decision accuracy of .91 or above (mean .97), to ensure that they were familiar words. The words ranged in frequency between 2 to 158 occurrences per million according to Kucera and Francis (1967), with a mean of 34.9 per million. They ranged in Coltheart's N between 0 to 10, with a mean of 3.1. The repeated-letter words and unique-letter words were matched on these factors, with mean frequency 35.3 and 34.5; N 3.0 and 3.2, and mean lexical decision accuracy .97 and .98, respectively.

For each target word (e.g., *ANNEX, ERUPT*), three types of primes were generated. One was an identity prime, which was the same word as the target (e.g., *annex, erupt*). The second was a one-letter-deleted (1DL) prime, in which a letter from an internal position was omitted. For the repeated-letter words, this was a repeated letter (e.g., *anex*), and for the unique letter words, it was a letter in a matched position (e.g., *eupt*). The consonant-vowel status of the omitted letter was matched between the two types of words. The third was a one-letter-substituted (1SL) prime, where the omitted letter was replaced by another letter not contained in the word (e.g., *alnex, emupt*). Again, the consonant-vowel status of the substituted letter was matched between the two types of words, and vowels were replaced with vowels and consonants were replaced with consonants. The critical target words and the primes are listed in Appendix B.

In addition to the 120 target words requiring a *Same* response, 120 words were selected to be used as targets requiring a *Different* response in Experiment 3a. These words were also 5-letters long, and some contained repeated letters in internal positions, and others contained unique letters. Each of the target was paired with a 5-letter reference word that was different from the target. None of the reference words or target words requiring a *Different* response overlapped with the critical targets requiring a *Same* response. Nonword targets used in Experiment 3b were generated by replacing one or two letters of these words. Each of these targets was paired with three primes types (identity, 1DL, 1SL) generated in the same way as for the critical stimuli.

The 60 repeated-letter words and 60 unique-letter words were divided into three sets containing 20 words each. Three list versions were constructed for the purpose of counterbalancing assignment of sets to the three prime types using a Latin Square design, so that within a list, each target word appeared only once, and across the three lists, appeared in each of the three prime conditions once. We have not performed any simulations using these stimuli with the version of the Bayesian Reader used in the earlier simulations here as the model is restricted to stimuli of a fixed length and cannot simulate the 1DL priming condition.

Prior to the test trials, participants were given 10 practice trials that were representative of the items used and warm-up items preceded each half block. Warm-up and practice items were selected according to the same criteria as the test stimuli. These items were not included in the analysis.

Apparatus and Procedure. Apparatus, procedure, and task instructions were identical to the previous experiments.

Results

The preliminary treatment of data was identical to previous experiments. In Experiment 3a, the cut-off procedure affected 1.4% of trials, and in Experiment 3b, 1.5% of trials. Mean response latencies and error rates are presented in Table 3. Response latencies and error rates for the critical stimuli (requiring the *Same* responses in Experiment 3a and *Word* responses in Experiment 3b) were analyzed in terms of a 2 (Word type: repeated -letter words vs. unique-letter words) x 3 (Prime type: identity, 1DL, 1SL) factorial design. Both were within-subjects factors and the Word type was a between-item factor and Prime type was a within-item factor. The critical result here is that in both tasks deleting a unique letter from an identity prime (e.g. *eupt-ERUPT*) reduced priming, but deleting a repeated letter (e.g. *annex-ANNEX*) did not.

Insert Table 3 about here

Experiment 3a (same-different task). For latency, the interaction between Word type and the identity-1DL contrast did not reach significance, F_1 (1, 29) = 1.88, MSe = 1276.84, p = .18; F_2 (1, 118) < 1.0. The interaction between Word type and the contrast between 1DL and 1SL prime condition was significant by subjects only, F_1 (1, 29) = 4.16, MSe = 1276.84; F_2 (1, 118) = 1.66, MSe = 2802.12, p = .20. Pairwise comparisons showed that whereas for the repeated-letter words, the 6 ms difference between the identity prime condition and the 1DL prime condition was non-significant, $t_1(29)$ = .87, p = .39; $t_2(59)$ = .85, p = .40, for the unique-letter words, the 18 ms difference between the identity prime condition and the 1DL prime condition was significant, $t_1(29)$ = 2.81;

$t_2(59) = 1.98$. Conversely, for the repeated-letter words, the 1DL prime condition was significantly faster (by 15 ms) than the 1SL prime condition, $t_1(29) = 2.95$; $t_2(59) = 2.18$, whereas for the unique-letter words the 1 ms difference between the 1DL and 1SL prime condition was non-significant, $t_1(29) = .19$, $p = .85$; $t_2(59) = .16$, $p = .88$. We take these results as demonstrating that the cost of deleting a repeated letter is less than the cost of deleting a unique letter.

For error rate, the interaction between Word type and the identity-1DL contrast was non-significant, $F_1\ (1, 29) = 1.94$, MSe = 69.83; $F_2\ (1, 118) = 2.60$, MSe = 104.03, $p = .11$. The interaction between Word type and the contrast between 1DL and 1SL prime condition was significant, $F_1\ (1, 29) = 4.56$, MSe = 99.44; $F_2\ (1, 118) = 8.16$, MSe = 111.23, $minF'(1, 65.20) = 2.91$. Pairwise contrasts showed that none of the contrasts between identity and 1DL, and 1DL and 1SL reached significance, all $p > .08$, except the contrast between 1DL and 1SL conditions for unique-letter words, which was significant by items only, $t_2(59) = 2.36$, $p = .02$.

Experiment 3b (lexical decision task). For latency, the interaction between Word type and the identity-1DL contrast was non-significant, $F_1\ (1, 29) < 1.0$; $F_2\ (1, 118) = 1.96$, MSe = 3086.64. The interaction between Word type and the contrast between 1DL and 1SL prime condition was also non-significant, $F_1\ (1, 29) < 1.0$; $F_2\ (1, 118) < 1.0$. Pairwise comparisons showed that for the repeated-letter words, the 8 ms difference between the identity and 1DL prime condition was non-significant, $t_1(29) = .90$, $p = .38$; $t_2(59) = 1.12$, $p = .27$; in contrast, for unique-letter words, the 20 ms difference between identity and 1DL prime condition was significant, $t_1(29) = 2.58$; $t_2(59) = 3.32$.   For the repeated-letter words, the 12 ms difference between the 1DL and 1SL prime condition was non-significant, $t_1(29) = 1.64$, p = .11; $t_2(59) = 1.81$, p = .08, and for the unique-letter words, the 17 ms difference between the 1DL and 1SL prime condition was significant by subjects, $t_1(29) = 2.33$; and approached significance by items, $t_2(59) = 1.88$ p = .07.

For errors, the interaction between Word type and the identity-1DL contrast was non-significant, F_1 (1, 29) = 1.29, MSe = 73.92; F_2 (1, 118) = 1.42, MSe = 132.42. The interaction between Word type and the contrast between 1DL and 1SL prime condition was also non-significant, F_1 (1, 29) < 1.0; F_2 (1, 118) < 1.0. Pairwise comparisons showed that the only difference between prime conditions to reach significance was between the identity and 1DL condition for repeated-letter words, $t_1(29) = 2.53$, $t_2(59) = 2.90$.

In sum, the comparison between the identity prime and 1DL prime showed that deleting a letter from the identity prime reduced priming when the letter was a unique letter but there was no reduction in priming when it was a repeated letter, in both the same-different task and the lexical decision task. The comparison between 1DL prime and 1SL prime was less consistent across tasks. The lexical decision task showed that the costs of deleting a letter and substituting a letter were similar, and did not differ between the repeated letter and unique letter. The same-different task, on the other hand, showed that the cost of deleting a unique letter was the same as substituting a unique letter (e.g., *eupt-ERUPT = emupt-ERUPT*), whereas the cost of deleting a repeated letter (e.g., *anex-ANNEX*) was less than substituting a wrong letter (e.g., *almex-ANNEX*).

Note that it seems unlikely that the effect of deleting a repeated letter (vs. a unique letter) could be phonological in origin. Of the 60 repeated-letter words, only a quarter (16) were homophonous (e.g., anex-ANNEX). Homophone status made little impact on the size of the decrement in priming in the 1DL prime condition: In the same-different task, the difference between the identity prime and 1DL prime condition was 8 ms (nonhomophones) vs. 1 ms (homophones): $F_2(1,58) < 1.0$, MSe = 2734.89; and in the lexical decision task, 7 ms (nonhomophones) vs. 12 ms (homophones): $F_2(1,58) = 1.25$, MSe = 3448.63. .

Discussion

Experiment 3a using the same-different task and Experiment 3b using the lexical decision task both showed that omitting a unique letter from the identity prime (e.g., *eupt-ERUPT*) reduced priming but there was no cost of omitting a repeated letter (e.g., *anex-ANNEX*). These results are at odds with Schoonbaert and Grainger's (2004, Experiment 1) failure to find a difference in the amount of priming produced by these two types of primes (repeated-letter omitted vs. unique-letter omitted). However, Schoonbaert and Grainger did not include an identity prime condition, and compared the size of priming relative to the unrelated prime. It may be noted that the comparison between the 1DL and 1SL prime conditions in the present lexical decision task (but not in the same-different task) also showed no difference between repeated-letter words and unique-letter words, and had we based our interpretation only on this comparison, we too would have reached the conclusion that there is no difference between omitting a repeated-letter and a unique-letter. Comparing the 1DL and 1SL prime condition conflates the effect of deleting a letter and replacing a letter. In the lexical decision task (but not in the same-different task) the difference between the identity and the 1SL condition was numerically larger for the unique-letter words (36 ms) than the repeated-letter words (20 ms), suggesting that the cost of replacing a letter was not the same for the two type of words. Given this, a comparison between the 1DL and the 1SL condition may not be appropriate. The inclusion of the identity prime condition to assess the decrement in priming by deleting a letter, the use of the same-different task, and the use of words containing repeated letters in adjacent positions (e.g., *ANNEX, FLOOR*) allowed us to detect the difference in the cost of deleting a repeated letter vs. deleting a unique letter. We take these results to suggest that the null difference in priming reported by Schoonbaert and Grainger (2004, Experiment 1) was due to their using a less sensitive method for detecting the difference.

General Discussion

The main finding of the present study is the evidence of "leakage", in which substituting a letter with an adjacent letter instead of a letter not contained in the word results in greater priming. In Experiment 2a and 2b using the same-different task, this was observed in the comparison between the repSL primes (e.g., *uueer-UNDER*) which produced more priming than 2SL primes (e.g., *ulger-UNDER*), and as much as TL primes. (Experiment 1 using the same critical stimuli in a lexical decision task showed smaller priming effects overall, and the difference between repSL and 2SL primes and repSL and TL primes were less clear.) Experiment 3 showed that deleting a repeated letter in an identity prime (e.g., *anex-ANNEX*) did not reduce priming but deleting a unique letter (e.g., *eupt-ERUPT*) did. We predicted these results from the assumption that word recognition involves a process of mapping a noisy input onto orthographic representations which take the form of sequentially ordered letter strings. Crucially we assumed that, at least early on in processing, there is ambiguity in both the identity of the letters and their order, and it is this that produces the leakage of letter identity that gives repSL primes an advantage over 2SL primes, and deleting a repeated letter an advantage over deleting a unique letter.

These results are also consistent with the position noise assumption, as instantiated in the Overlap model (Gomez et al., 2008). However, their model only describes the uncertainty in letter position at a single point in time. Also, as noted by Gomez et al. (2008), the Overlap model does not have a mechanism to explain masked priming, therefore simulating the masked priming effects observed here is beyond the scope of the Overlap model, as currently formulated. These points make clear that the noisy position assumption needs to be implemented in a model of a task. Davis (2006; Davis & Bowers, 2006) has earlier argued against the noisy position assumption as an explanation of TL priming, on the basis that it would be difficult to implement it within an interactive activation framework. Specifically, Davis and Bowers (2006, p.549) noted that in the interactive activation model, "inhibitory signals are passed from active letter nodes to incompatible word nodes, and hence the introduction of noise to the slot-based code would require some significant changes to these models". But their concern relates to the implementation of positional noise assumption within a specific instantiation of the interactive activation framework, and it does not constitute a fundamental objection against the positional noise assumption per se, or even the implementation of positional noise within the interactive activation framework.

We also note that two of the models we have discussed already incorporate positional uncertainty. The Overlap Open Bigram model (Grainger, et al., 2006) uses a noisy representation of letter order (and as a consequence, transposed pairs of adjacent bigrams - e.g., the transposed bigrams 21, 32, 43 and 54 in the string 12345 - are coded explicitly), yet fails to predict the correct pattern of results. Similarly, the SOLAR model (e.g., Davis & Bowers, 2006) also assumes that order is not known accurately. In SOLAR the degree of position uncertainty is indicated by the σ parameter incorporated into the match calculations. SOLAR also fails to produce the correct pattern of data. (Increasing sigma from the current default value of 1.25 (Lupker & Davis, 2009, Appendix C) to 3, the default value in the original model (Davis & Bowers, 2006, Appendix A) did not allow the model to predict the pattern.) At least in the case of these two models, simply incorporating positional noise is not enough to account for the data we report here. These models explain TL priming effects in terms of ambiguity in letter position at a higher level of representation where there is already precise coding of letter identities. In the words of Gomez et al. (2008), the open bigrams models and the SOLAR model "include an intermediate stage that requires (and uses) accurate information about letter position" to extract order representation, and this "order representation is then used to produce a noisy representation of position" (p. 590). The leakage results found here are at odds with such an assumption.

Conclusions

The data on the representation of letter order has widely been assumed to reflect the way orthography is represented in the lexicon. However, this conclusion is not warranted by the data. All that can safely be concluded from these data is that the process of word recognition cannot involve a direct and unambiguous mapping between position-specific input letters and lexical representations. More specifically, it cannot be based on the kind of slot-coding schemes used in the McClelland and Rumelhart (1981) interactive-activation model or the Bayesian Reader (Norris, 2006), where letter 'slots' in the input are linked directly to letter 'slots' in lexical representations. However, none of the data supports the conclusion that lexical representations themselves are anything other than strictly sequential representations of letter-position or order. What TL priming effects tell us is that, at some point during recognition (for example, at the end of the prime in a masked priming experiment), the order information that can be extracted from the stimulus is ambiguous.

In the Bayesian Reader, as in the Overlap model (Gomez, et al., 2008), lexical representations are sequential, and letter-order effects come about purely because there is a period during processing where order has not been sufficiently well resolved to map precisely onto lexical representations. The ambiguous input provides evidence that is consistent with words that contain the correct set of letters, but where those letters may appear in the wrong order. In the simulations presented here, the ambiguity in the representation of order is implemented by adding noise to the representation of position. However, as noted earlier, a more complete model would focus on deriving a translation and scale-invariant representation of order from a set of noisy visual objects.

From Kinoshita and Norris (2009), we know that TL effects are not specifically lexical: they occur for nonwords as well as words. Given that there seems to be no independent justification for the assumption that nonwords might be represented as anything other that a serially ordered sequence of letters, this fact seems to be most parsimoniously explained by proposing that all order effects arise during the course of mapping input representations onto sequential orthographic representations stored in memory. The present data show that during this process, letter identity and letter order information accumulate simultaneously, such that ambiguity in order leads to ambiguity in identity.

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Appendix A

Critical stimuli used in Experiments 1 and 2

target	id	TL	2SL	repSL	ALD
UNDER	under	udner	ulger	uueer	gypny
TODAY	today	tdoay	timay	ttaay	astar
STORY	story	sotry	smiry	ssrry	amept
ASIDE	aside	aisde	amude	aadde	curmy
ANGLE	angle	agnle	arble	aalle	mapor
PANEL	panel	pnael	pisel	ppeel	exide
GIANT	giant	gaint	gount	ggnnt	cofal
LOGIC	logic	lgoic	lafic	lliic	haidy
USAGE	usage	uasge	umige	uugge	indur
HAVEN	haven	hvaen	hogen	hheen	idert
ABOVE	above	abvoe	apive	abbee	lumid
RIVER	river	rievr	rimor	riirr	pemal
SOLID	solid	soild	soved	soodd	narty
UNCLE	uncle	unlce	ungre	unnee	osive
PIANO	piano	pinao	piedo	piioo	slire
ARGUE	argue	aruge	arsie	arree	setin
LOVER	lover	loevr	lofur	loorr	snoky
ALIEN	alien	alein	aloun	allnn	eadel
ADOPT	adopt	adpot	adist	addtt	ulger
BATON	baton	baotn	bagin	baann	wilen
EARLY	early	eraly	eifly	eelly	cofal
MONEY	money	mnoey	midey	mmeey	astar
READY	ready	raedy	roudy	rrddy	amept
EMPTY	empty	epmty	ernty	eetty	indur
ANGER	anger	agner	asder	aaeer	exide
OWNER	owner	onwer	osler	ooeer	haidy
CABIN	cabin	cbain	cosin	cciin	idert
AWFUL	awful	afwul	andul	aauul	ulger
ACUTE	acute	aucte	amite	aatte	curmy
OVERT	overt	oevrt	osart	oorrt	mapor
POWER	power	poewr	podur	poorr	lumid
BASIC	basic	baisc	bomic	baacc	pemal
BEGIN	begin	beign	besan	beenn	narty
MINOR	minor	mionr	migar	miirr	osive
ADMIT	admit	adimt	adsut	addtt	slire
MERIT	merit	meirt	menat	meett	wilen
LABEL	label	laebl	lafil	laall	snoky
ORBIT	orbit	oribt	orgat	orrtt	eadel
ORGAN	organ	oragn	orbin	orrnn	gypny
CIGAR	cigar	ciagr	cimor	ciirr	setin
UNTIL	until	utnil	usgil	uuiil	cofal

MAJOR	major	mjaor	migor	mmoor	snoky
MORAL	moral	mroal	minal	mmaal	amept
RIFLE	rifle	rfile	ragle	rrlle	indur
ANGRY	angry	agnry	albry	aarry	exide
ALERT	alert	aelrt	amort	aarrt	haidy
NOBLE	noble	nbole	nisle	nnlle	idert
CHAOS	chaos	cahos	crios	ccoos	ulger
ALOUD	aloud	aolud	abeud	aauud	curmy
ELBOW	elbow	eblow	ensow	eeoow	mapor
ALONG	along	alnog	alirg	allgg	lumid
ALONE	alone	alnoe	alude	allee	pemal
COVER	cover	coevr	cofar	coorr	narty
AVOID	avoid	aviod	avead	avvdd	osive
MAGIC	magic	maigc	masuc	maacc	slire
MOVIE	movie	moive	modue	mooee	wilen
MERCY	mercy	mecry	melby	meeyy	astar
SOLAR	solar	soalr	somir	soorr	eadel
RIVAL	rival	riavl	ridel	riill	gypny
FORUM	forum	fourm	fobim	foomm	setin
WATER	water	wtaer	wiger	wweer	cofal
STUDY	study	sutdy	smidy	ssddy	mapor
LOWER	lower	lwoer	lader	lleer	amept
IDEAL	ideal	iedal	imoal	iiaal	snoky
ENJOY	enjoy	ejnoy	eldoy	eeooy	idert
SUGAR	sugar	sguar	sifar	ssaar	haidy
ACTOR	actor	atcor	asgor	aaoor	exide
OPIUM	opium	oipum	odaum	oouum	ulger
TOWER	tower	twoer	tiper	tteer	curmy
LUNAR	lunar	lnuar	lifar	llaar	setin
OFTEN	often	ofetn	ofsan	offnn	lumid
TABLE	table	talbe	tadre	taaee	pemal
EQUAL	equal	eqaul	eqiel	eqqll	narty
NOVEL	novel	noevl	nodul	nooll	osive
DIRTY	dirty	ditry	dimsy	diiyy	slire
EXACT	exact	excat	exint	exxtt	wilen
INPUT	input	inupt	indat	inntt	astar
CUBIC	cubic	cuibc	cusac	cuucc	eadel
LYRIC	lyric	lyirc	lymac	lyycc	gypny
UNITE	unite	untie	unome	unnee	indur
GIVEN	given	gvien	gasen	ggeen	cofal
PARTY	party	praty	pisty	pptty	mapor
IMAGE	image	iamge	iloge	iigge	amept
METAL	metal	mteal	mofal	mmaal	snoky
PILOT	pilot	pliot	padot	ppoot	idert
OCEAN	ocean	oecan	ofian	ooaan	haidy
MOTEL	motel	mtoel	madel	mmeel	astar

AMPLE	ample	apmle	ascle	aalle	exide
DEPOT	depot	dpeot	dagot	ddoot	curmy
TOKEN	token	tkoen	tifen	tteen	setin
HUMAN	human	huamn	hugen	huunn	ulger
MUSIC	music	muisc	mudoc	muucc	pemal
OLDER	older	oledr	olfar	ollrr	narty
EXIST	exist	exsit	exant	exxtt	osive
CRAZY	crazy	crzay	crimy	crryy	slire
ENTRY	entry	enrty	enshy	ennyy	wilen
ALIKE	alike	alkie	alame	allee	lumid
LIVER	liver	lievr	ligar	liirr	eadel
VENUS	venus	veuns	vedos	veess	gypny
DEMON	demon	deomn	desan	deenn	indur

Appendix B

List of critical stimuli used in Experiment 3

Repeated-letter words

TARGET	identity	1DL	1SL
FLOOR	floor	flor	flior
GREEN	green	gren	grein
UPPER	upper	uper	upler
SLEEP	sleep	slep	sloep
GREEK	greek	grek	groek
SHEET	sheet	shet	shuet
FUNNY	funny	funy	fulny
ERROR	error	eror	emror
TOOTH	tooth	toth	toath
MARRY	marry	mary	masry
TROOP	troop	trop	traop
CREEK	creek	crek	criek
SUNNY	sunny	suny	sunry
CREEP	creep	crep	croep
STOOL	stool	stol	stiol
SPOON	spoon	spon	spoin
GOOSE	goose	gose	goase
ALLOY	alloy	aloy	amloy
BROOM	broom	brom	bliom
SLEEK	sleek	slek	sleuk
ISSUE	issue	isue	islue
TEETH	teeth	teth	teoth
OFFER	offer	ofer	olfer
ALLOW	allow	alow	anlow
APPLY	apply	aply	arply
WORRY	worry	wory	worky
STEEL	steel	stel	stiel
QUEEN	queen	quen	quean
ESSAY	essay	esay	esmay
FLEET	fleet	flet	floet
SHEER	sheer	sher	shoer
BOOST	boost	bost	boist
BLOOM	bloom	blom	bloum
STEER	steer	ster	stier
CHEER	cheer	cher	chuer
KNEEL	kneel	knel	kniel
BOOZE	booze	boze	boize
CROOK	crook	crok	criok

SWOOP	swoop	swop	swaop
ANNEX	annex	anex	alnex
BLOOD	blood	blod	bleod
HAPPY	happy	hapy	hapry
CARRY	carry	cary	carpy
SWEET	sweet	swet	swuet
WHEEL	wheel	whel	whiel
SORRY	sorry	sory	somry
OCCUR	occur	ocur	oclur
HURRY	hurry	hury	hurpy
SHEEP	sheep	shep	shiep
CHEEK	cheek	chek	chiek
FLOOD	flood	flod	floud
ATTIC	attic	atic	athic
SWEEP	sweep	swep	swuep
GLOOM	gloom	glom	gloum
APPLE	apple	aple	arple
QUEER	queer	quer	quear
GROOM	groom	grom	groim
BROOK	brook	brok	briok
GREED	greed	gred	gried
ANNOY	annoy	anoy	alnoy

Unique-letter words

TRADE	trade	trde	trude
SPEAK	speak	spak	spiak
LEGAL	legal	leal	lemal
DRAWN	drawn	drwn	driwn
TRUCK	truck	trck	trock
PRIME	prime	prme	prame
CATCH	catch	cach	cagch
ADMIT	admit	amit	agmit
REALM	realm	relm	reolm
LIVER	liver	lier	limer
CRUDE	crude	crde	crade
BRACE	brace	brce	brice
BLADE	blade	blae	blafe
WRIST	wrist	wrst	wrast
BLOAT	bloat	blat	bliat
SPEAR	spear	sper	speir
CRUSH	crush	crsh	crosh
TRIBE	tribe	tibe	thibe
BLUSH	blush	blsh	blish
COMET	comet	comt	comut
EARTH	earth	eath	eanth

CHIEF	chief	chef	choef
SHARP	sharp	sarp	smarp
BLOCK	block	bock	bnock
CHEST	chest	cest	clest
BRUSH	brush	bruh	bruth
SMOKE	smoke	smke	smike
MAGIC	magic	magc	magec
RELAX	relax	reax	recax
WEARY	weary	wery	weory
STOVE	stove	stve	stive
ADOPT	adopt	adpt	adipt
LAYER	layer	layr	layor
FLOCK	flock	flck	fluck
SCRAP	scrap	scrp	scrop
REIGN	reign	regn	reagn
HAUNT	haunt	hant	haint
AVAIL	avail	avil	avoil
CRAVE	crave	crve	crive
ERUPT	erupt	eupt	emupt
STORY	story	stry	stary
MOUTH	mouth	mouh	mouch
ROUND	round	roud	rousd
BEACH	beach	bech	beich
RAISE	raise	rase	rause
ENJOY	enjoy	enoy	ensoy
URBAN	urban	uran	urgan
GUIDE	guide	guie	guime
BRICK	brick	brck	breck
SAINT	saint	sant	saunt
SOLAR	solar	solr	solur
MEDIA	media	meia	mefia
SPARK	spark	sprk	spurk
BACON	bacon	bacn	bacun
TRUNK	trunk	tunk	thunk
CANOE	canoe	cane	canie
AMBER	amber	ambr	ambor
WEAVE	weave	weve	weove
STINK	stink	stnk	stonk
SPIKE	spike	sike	smike

Table 1.

Mean Decision Latencies (RT, in ms), Standard Error (in parentheses) and Percent Error Rates (%E) in Experiment 1 (lexical decision task)

Response type and Prime type	*Example prime-target*	RT	%E
Word			
Identity	*under-UNDER*	493 (15)	4.8
TL	*udner-UNDER*	515 (16)	8.2
2SL	*ulger-UNDER*	536 (14)	11.8
repSL	*uueer-UNDER*	529 (14)	10.2
ALD	*gypny-UNDER*	538 (17)	7.6
Nonword			
Identity	*amout-AMOUT*	581 (21)	12.4
TL	*aomut-AMOUT*	584 (26)	10.4
2SL	*asiut-AMOUT*	587 (22)	8.4
repSL	*aauut-AMOUT*	591 (24)	10.2
ALD	*cavic-AMOUT*	594 (23)	12.4

Table 2.

Mean Decision Latencies (RT, in ms), Standard Error (in parentheses) and Percent Error Rates (%E) in Experiments 2a and 2b (same-different task)

		Experiment 2a		Experiment 2b	
Response type and Prime type	*Example prime-target*	RT	%E	RT	%E
Same response (Reference – *under*)					
Identity	*under-UNDER*	409 (16)	2.4	426 (18)	3.8
TL	*udner-UNDER*	422 (17)	2.4	440 (18)	4.4
2SL	*ulger-UNDER*	460 (16)	5.2	476 (18)	6.8
repSL	*uueer-UNDER*	437 (18)	2.0	446 (19)	5.2
ALD	*gypny-UNDER*	510 (15)	13.2	523 (17)	17.2
Different response (Reference – *never*)					
Identity	*about-ABOUT*	489 (19)	2.6	504 (19)	8.2
TL	*aobut-ABOUT*	480 (18)	2.8	505 (18)	8.2
2SL	*asiut-ABOUT*	484 (18)	2.0	507 (19)	6.4
repSL	*aauut-ABOUT*	481 (17)	1.6	514 (19)	6.6
ALD	*cavic-ABOUT*	489 (18)	2.4	505 (19)	5.4

Note. In Experiment 2a, the reference and target differed in all 5 letter positions. In

Experiment 2b, the difference in reference and target ranged between 1 to 5 letters (the example here is 5-letter different)

Table 3.

Mean Decision Latencies (RT, in ms), Standard Error (in parentheses) and Percent Error Rates (%E) in Experiments 3a (same-different task) and 3b (lexical decision task)

		Experiment 3a (Same-different)		Experiment 3b (Lexical decision)	
Target word type and Prime type	Example	RT	%E	RT	%E
Repeated-letter word	*ANNEX*				
Identity	*annex*	400 (13)	5.7	503 (12)	5.8
1DL	*anex*	406 (14)	7.8	511 (12)	10.8
1SL	*alnex*	420 (13)	5.8	523 (12)	11.0
Unique-letter word	*ERUPT*				
Identity	*erupt*	411 (16)	7.7	510 (12)	6.0
1DL	*eupt*	429 (13)	6.8	529 (13)	8.5
1SL	*emupt*	429 (14)	10.3	546 (13)	9.5

List of figures.

Figure 1. Idealized representation of the change in order information over time. The light curves indicate the likelihood functions at some point early in processing (say at the end of the prime) and the heavy curves represent the functions later in time when the location information has become more reliable. The likelihood functions represent the distribution of the expected input location for each letter. See text for an explanation of the relationship between location and order.

Figure 2. Match scores for the critical stimuli used in Experiments 1 and 2 for the Slot-code, SOLAR (Davis, 1999), Constrained Open Bigram (COB, Schoonbaert & Grainger, 2004), SERIOL (SERIOL, Whitney & Cornelissen, 2007), Overlap Open Bigram (OOB, Grainger, Granier, Farioli, Van Assche & van Heuven, 2006), and Overlap (Gomez et al, 2008) models

Figure 3. Bayesian Reader simulations of performance in the same-different task using the critical stimuli used in Experiment 2 with and without position noise. Simulations were performed using the version of the Bayesian Reader described in Norris (2009).

Figure 4. Priming effects produced by the Bayesian Reader model with position noise in the lexical decision task (LDT) and the same-different task (SD) using the critical stimuli used in Experiment 1 and 2.

Figure 5. Priming effects for the critical stimuli used in Experiments 1 and 2 (Error bars are standard error of the mean). Experiment 1 used the lexical decision task. Experiments 2a and 2b

used the same-different match task, and differed in the nature of reference string requiring *Different* response.

Figure 1

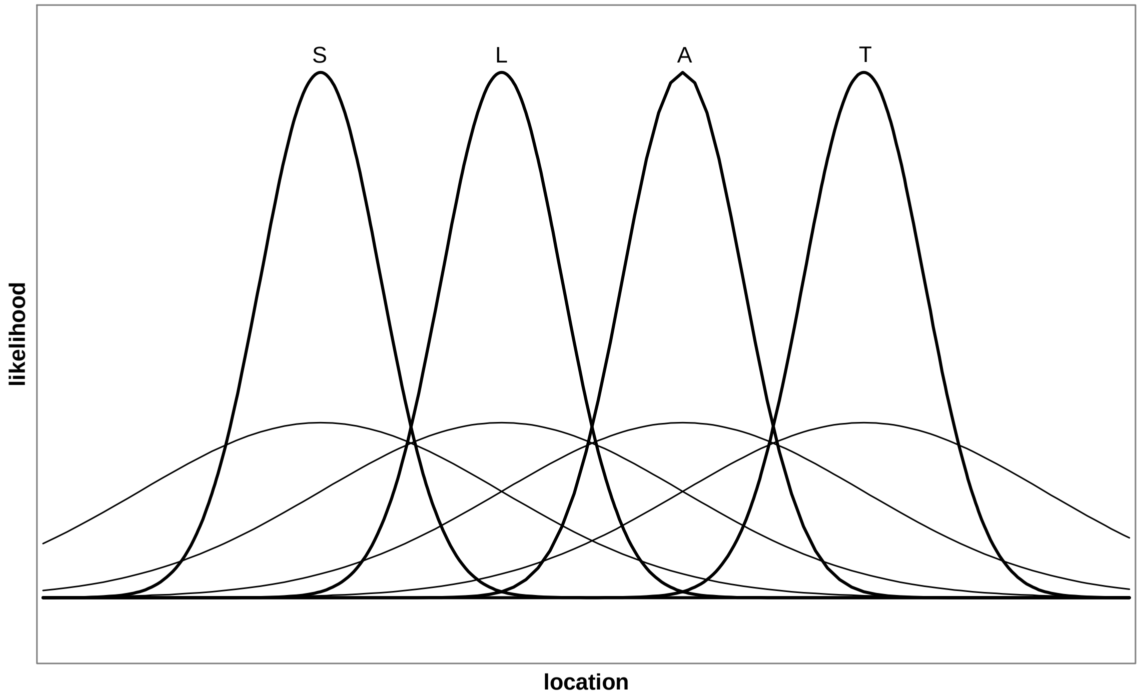


Figure 2

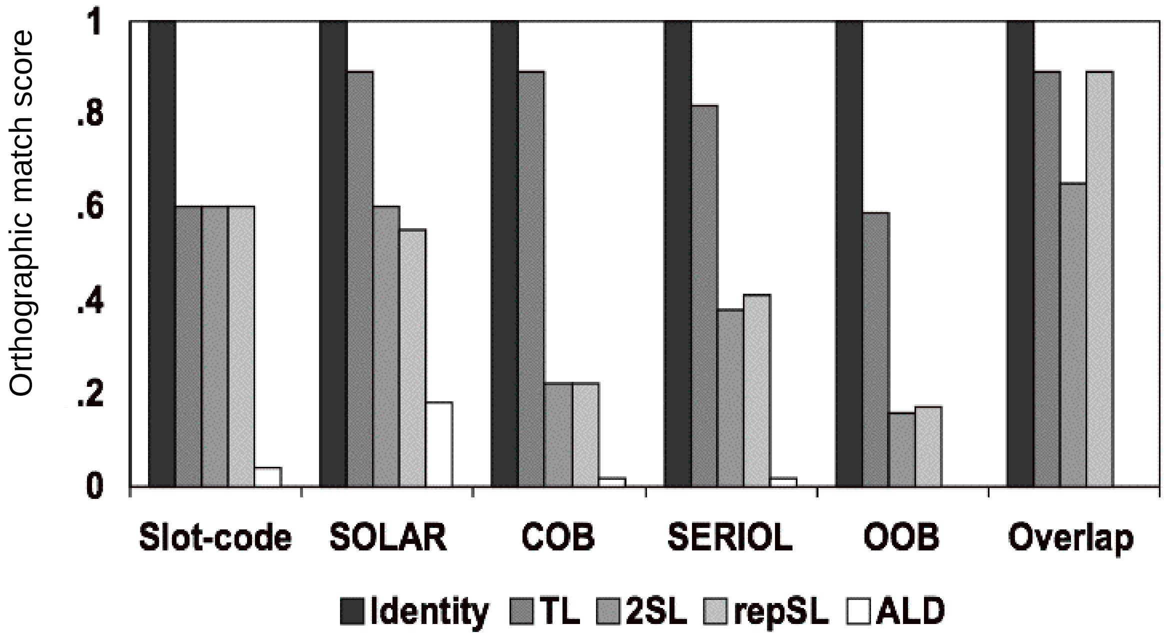

Orthographic match score
1
.8
.6
.4
.2
0
Slot-code
SOLAR
COB
SERIOL
OOB
Overlap
Identity
TL
2SL
repSL
ALD

Figure 3a

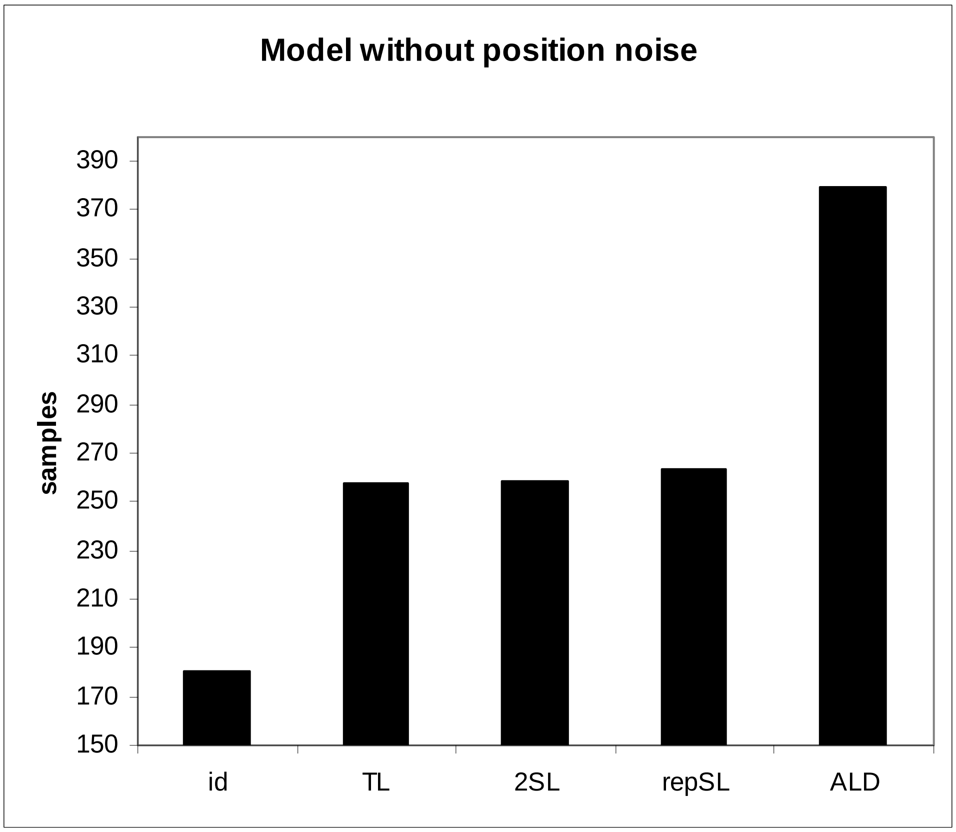

Model without position noise
samples
390
370
350
330
310
290
270
250
230
210
190
170
150
id
TL
2SL
repSL
ALD

Figure 3b

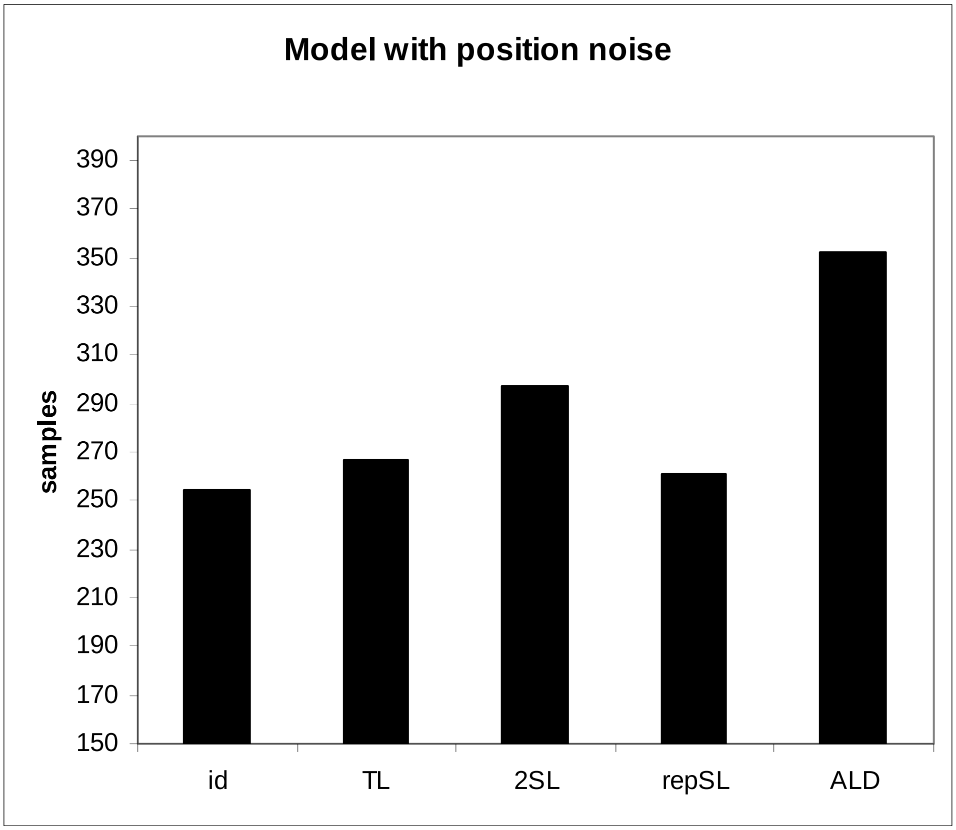

Model with position noise
samples
390
370
350
330
310
290
270
250
230
210
190
170
150
id
TL
2SL
repSL
ALD

Figure 4a

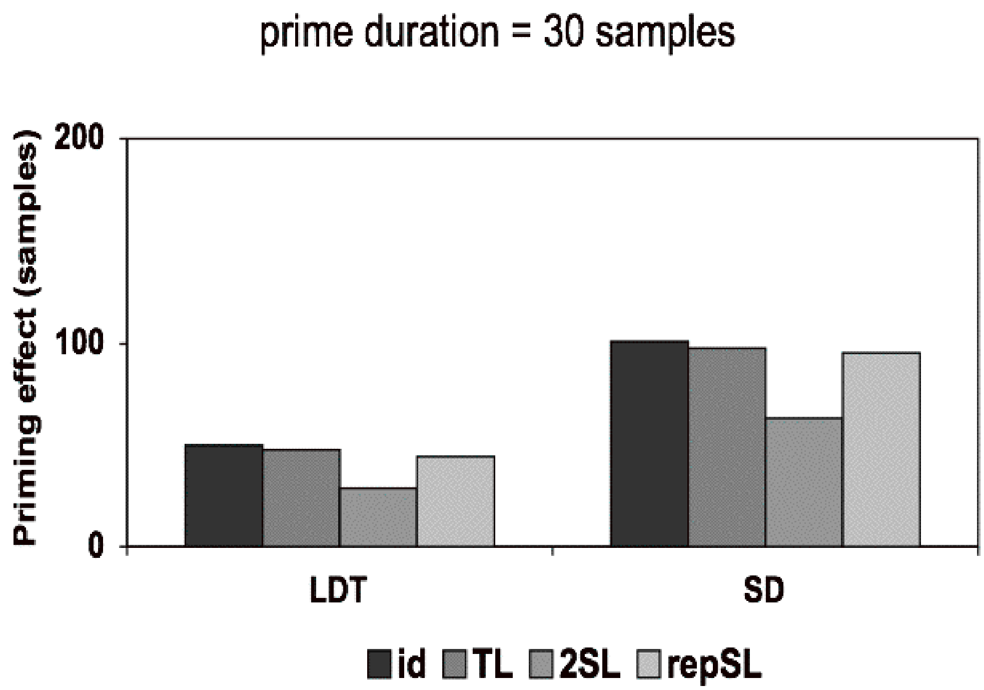

prime duration = 30 samples
Priming effect (samples)
200
100
0
LDT
SD
id
TL
2SL
repSL

Figure 4b

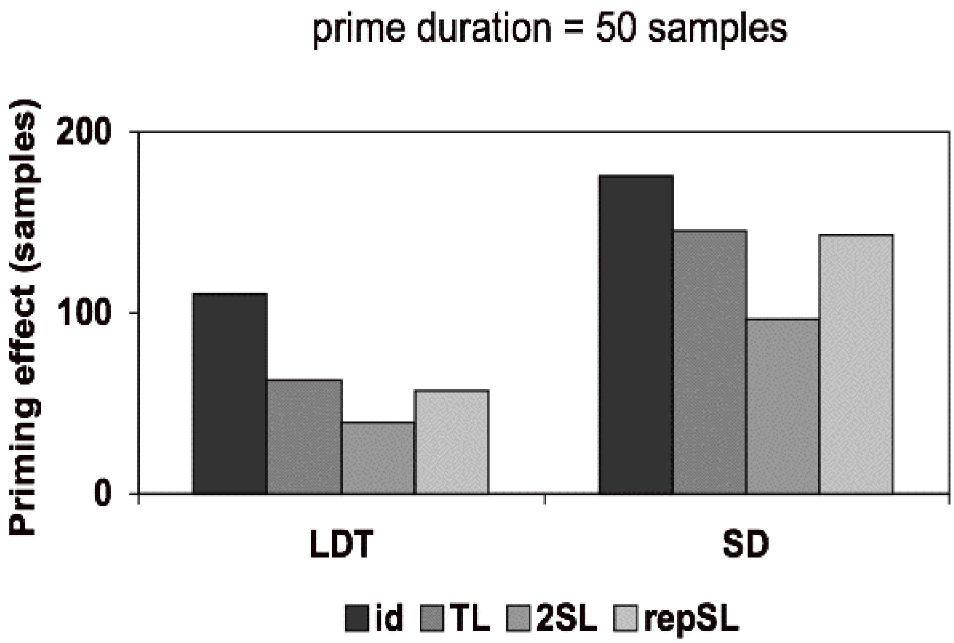

prime duration = 50 samples
Priming effect (samples)
200
100
0
LDT
SD
id
TL
2SL
repSL

Figure 4c

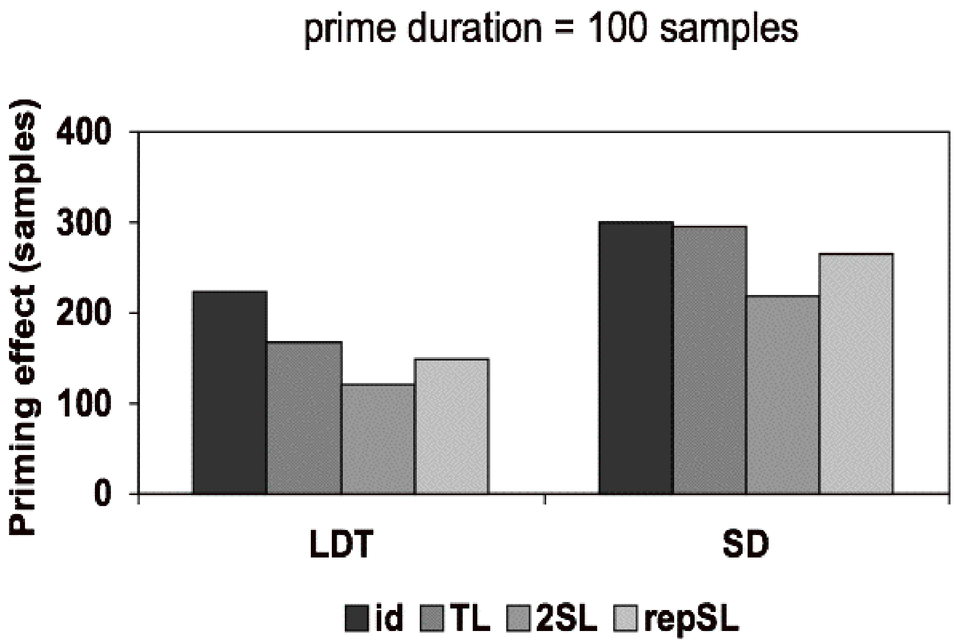
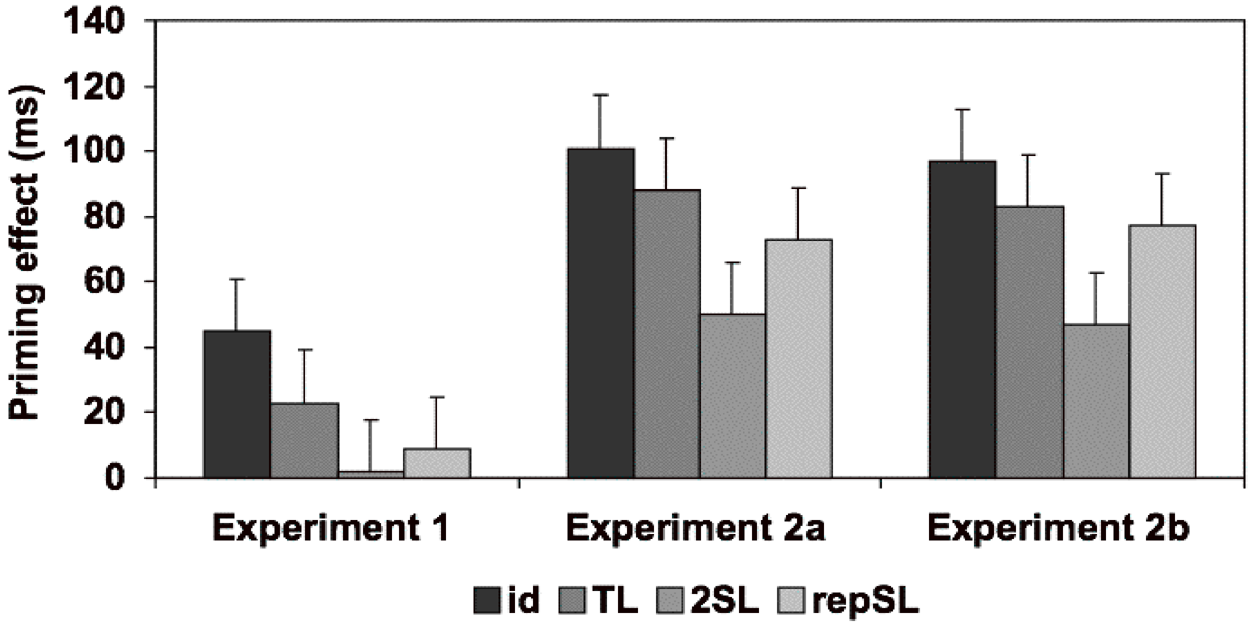

prime duration = 100 samples
Priming effect (samples)
400
300
200
100
0
LDT
SD
id
TL
2SL
repSL

Figure 5


140
120
100
80
60
40
20
0
Priming effect (ms)
Experiment 1
Experiment 2a
Experiment 2b
id
TL
2SL
repSL

Author notes

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Footnote

The Matchcalculator is available at Colin Davis' website http://www.pc.rhul.ac.uk/staff/c.davis/Utilities/. For the Overlap Open Bigram model, we followed the procedure described in the Appendix of Grainger et al. (2006).