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A common-code for spelling and reading.

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Abstract

There is strong evidence that reading and spelling in alphabetical scripts depend on a shared representation (common-coding). However, computational models usually treat the two skills separately, producing a wide variety of proposals as to how the identity and position of letters is represented. This paper treats reading and spelling in terms of the common-coding hypothesis for perception-action coupling. Empirical evidence for common representations in spelling-reading is reviewed. A novel version of the Start-End Competitive Queuing (SE-CQ) spelling model is introduced, and tested against the distribution of positional errors in Letter Position Dysgraphia, data from intra-list intrusion errors in spelling to dictation, and dysgraphia due to non-peripheral neglect. It is argued that no other current model is equally capable of explaining this range of data. To pursue the common-coding hypothesis, the representation employed in SE-CQ is applied, without modification, to the coding of letter identity and position for reading and lexical access, and a lexical matching rule for the representation is proposed (Start End Position Code model, SE-PC). Simulations show the model's compatibility with benchmark findings from form priming, its ability to account for positional effects in letter identification priming and the positional distribution of perseverative intrusion errors. The model supports the view that spelling and reading use a common orthographic description, providing a well-defined account of the major features of this representation.

Keywords: common-coding; reading and spelling; letter position code; Start-End model; orthographic representation.

The mental processing of written words is one of the most active and fruitful topics of investigation in cognitive, developmental and educational psychology, and cognitive neuropsychology and neuroimaging. Many researchers in these fields have presented evidence that reading and spelling are linked at a fundamental level, sharing, for instance, a single orthographic lexicon and orthographic description of known words (supporting evidence is reviewed below). While this experimental work has been accompanied by a vigorous program of computational modelling, to a great extent the theoretical literatures on reading and spelling have remained separate. This paper describes a unified model of the mental representation of the identity and serial position of letters in written words that accounts for data from both spelling and reading.

The structure of the paper is as follows: Section 1 motivates the search for shared perception-action representations from the perspective of ideomotor theory, and summarises current evidence in support of the application of this perspective to reading and spelling. In Section 2, the Start End – Competitive Queuing (SE-CQ) model of spelling is described and tested against data from three different disorders of spelling. Section 3 describes the Start End – Position Coded (SE-PC) model of reading, which uses the SE-CQ letter representation without change. The model is evaluated with respect to data from both normal and reading-impaired subjects. Section 4 summarises the model and discusses a number of issues arising from it.

Section 1: A common-coding hypothesis for reading and spelling

The ideomotor perspective

The search for shared representations between spelling and reading is a specific case of the ideomotor approach to the perception-action relationships (Greenwald, 1970; Hommel , Müsseler, Aschersleben, & Prinz, 2004, Hecht, Vogt, & Prinz, 2001; Pattamadilok, Ponz, Planton & Bonnard, 2016; Shin, Proctor & Capaldi, 2010). On this view producing an action causes it to become associated with its sensory consequences. Later perception of similar “consequences” (intentional actions, or their results) facilitates their perception *in terms of the actions required to produce them* (Liberman & Mattingly, 1985; Rizzolatti & Arbib, 1998). For instance, Longcamp, Anton, Roth & Velay (2003) show that viewing letters selectively activates an area of left premotor cortex involved in writing them (Brodmann area 6). Anderson, Damasio and Damasio (1990) report that a surgical lesion to the same area was associated with severe impairment of both writing *and* reading.

This perspective has a long history, for instance, in the motor theory of speech perception, which claims that the “objects of speech perception are the intended phonetic gestures of the speaker” (Liberman & Mattingly, 1985; p. 2; Galantucci, Fowler & Turvey, 2006). However, other models directly link speech codes for perception and action, but without interpreting the latter in such concretely motoric terms (Hartley & Houghton, 1996; MacKay, 1987). Rather the representational “nodes” activated in perception are the same as those over which speech actions are defined (e.g., the syllable). In recent models in this tradition (e.g., Hommel et al., 2001), perception and action representations may converge at the highest level which is relevant to the task at hand. The model proposed here takes this form, being framed at the level of abstract letter representations, and their serial order.

In current information processing models of spelling and reading, the link between the two skills is invariably mediated by lexical and phonological routes (e.g., Barry, 1994; Link & Caramazza, 1994; Houghton & Zorzi, 2003; Kohnen et al., 2012; Miceli & Carpasso, 2006; Purcell, Turkeltaub et al., 2011; Sage & Ellis, 2004; Shallice & Cooper, 2011; Tainturier &

Rapp, 2003). Consider however the delayed copy transcoding of a briefly presented pseudoword such a CLEUGH. The lexical route would fail to recognise it; while the phonological route might pronounce it /*klu*/ (as does the model of Perry et al., 2007). A phonological spelling model (e.g., Houghton & Zorzi, 2003) will either lexicalise this phonological form (*clue*), or regularise it (e.g., *kloo*). Hence these mediated routes will fail to correctly reproduce such a stimulus. What would appear to be required is a direct orthographic route, whereby the orthographic representation generated in reading can be spelt out without mediation. The model proposed here achieves this goal (see Study 3.3). Further evidence in support of this position is now reviewed (Angelelli, Marinelli & Zoccolotti, 2011, for an earlier review of some of this material).

Experimental evidence for common coding

In adults, spelling and reading abilities are highly correlated (.8 or above across different languages, Ehri, 2000; Fayol, Zorman & Lete, 2009). This association in itself might be considered rather surprising, as (to my knowledge) there are no current models to suggest that the reading and spelling processes share major "peripheral" components (a state-of-affairs that is not challenged by the current work). Under such circumstances, dissociations between the abilities are to be expected (as in e.g., pure alexia, Damasio & Damasio, 1983; Epelbaum, Pinel, Gaillard et al, 2008). However, one possible explanation of the correlation is simply that each individual's ability reflects their degree of practice, and that practice on reading and spelling are likely to be highly correlated. For this reason, investigators have sought evidence of more specific (e.g., item level) associations between the two tasks.

A popular technique to investigate this relationship at the item level is to have subjects read words they do and do not misspell. For instance, Holmes and Carruthers (1998) examined college students' ability to detect correct spellings, when items were paired with the subjects' own spelling of the same word. Subjects distinguished the correct form of words they spelled correctly, but preferred their own incorrect version of words they misspelled. In a related study by Burt and Tate (2002), each subject made a lexical decision to correct versions of words that subject spelled correctly or incorrectly. Responses to the latter were both slower and less accurate, with highly reliable item-by-item concordance between spelling accuracy and word recognition. In both studies, the existence of significant item-level associations specific to each individual subject (independent of their overall literacy level) suggests that they read using the representation they use to spell.

Hanley et al. (1992), in a study of a surface dysgraphic adult, paired his consistent errors with their correct spellings, and his correct spellings with phonologically-acceptable misspellings. When asked to select the correct item from each pair, he preferred his own spelling in both conditions (Goulandris & Snowling, 1991, report very similar findings with a different subject). In a group study of dyslexic Italian children, Angelelli et al. (2011) had the children judge the correctness of words they either misspelled or spelled correctly. The dyslexics correctly judged words they could spell, and misjudged words they could not, a result replicated in younger non-dyslexic children. All of these authors argue for a shared lexical representation in reading and spelling as the most parsimonious explanation of these item- and subject-specific associations.

This position is supported by studies of acquired dyslexia and dysgraphia. Coltheart and Funnell (1987; acquired dyslexic HG) showed that HG's spelling performance on a set of test items was predicted item-wise by their reading accuracy on the same set. Similarly, Behrmann and Bub (1992; surface dyslexic subject MP) found significant item-level correlations between

MP's reading and spelling of irregular words (at all frequencies), with no test of asymmetry at the item level being significant. Tsapkini and Rapp (2010) describe the symptoms of a patient (DPT) who had undergone surgical resection of the mid-to-anterior left fusiform gyrus. DPT exhibited parallel deficits in the reading and spelling of words, with largely spared (phonological) processing of nonwords in both tasks (see below for fMRI studies involving this region).

Other studies report significant correlations in the type and positional distribution of errors in spelling and reading. For instance, Caramazza et al. (1996; dysgraphic subject LB, Caramazza et al., 1987) show that LB made very similar proportions of shift and transposition errors in the two tasks. Similarly, Tainturier and Rapp (2003; dysgraphic subject MC) report the same bowed serial position curve for MC's spelling errors and phonological errors in reading pseudowords. Caramazza and Hillis (1990; neglect dyslexic NG) report that NG made reading and spelling errors only on the "right" (i.e., end) half of words, with a qualitatively identical error pattern for the two tasks. This kind of association can be found between very specific aspects of orthographic structure. For instance, geminate letters can produce a distinctive spelling error in which the wrong letter (usually adjacent to the target) is doubled (e.g., SUPPER → SUUPER; Caramazza & Miceli, 1990; Fischer-Baum & Rapp, 2014; McCloskey et al., 1994; Kandel, Peereman & Ghimenton, 2013; Tainturier & Caramazza, 1996; the error is also found in skilled typing, Rumelhart & Norman, 1982). Models of the phenomenon associate a to-be-doubled letter with a distinct geminate marker (Glasspool & Houghton, 2005; Rumelhart & Norman, 1982). Recent studies suggest that this marker is also employed in reading words with geminate letters (Fischer-Baum, in press; Tomasino et al., 2015; see also Mozer, 1989). However, as Fischer-

Baum (in press) notes, doubled letters have no special status in current prominent models of reading.

These findings are supported by recent work by Fischer-Baum, McCloskey and colleagues on letter perseveration errors. In a study of the spelling of two dysgraphic subjects, Fischer-Baum, McCloskey & Rapp (2010) found that their perseverated letter responses tended to maintain the position they had in the "source" word. They propose a "both-ends model" to account for these positional relationships, which McCloskey, Fischer-Baum and Schubert (2013) show also provides the best account of the *reading* errors of an acquired dyslexic subject (Schubert & McCloskey, 2013, see also Fischer-Baum, Charny and McCloskey, 2011, for related findings using the illusory word paradigm; Mozer, 1983)

fMRI studies of reading have reported activation of an area of the left inferior temporal lobe (the "visual word form area", or VWFA,) to be implicated in word reading (Cohen & Dehaene, 2004; Lochy, van Belle & Rossion, 2015; Dehaene & Cohen, 2011, Tsapkini & Rapp, 2010, for review). Activation of the VWFA during spelling is reported in 12 literate adults by Beeson, Rapcsak, Plante et al. (2003), who compared writing words to writing the alphabet (Rapcsak & Beeson, 2004, also report impaired spelling of irregular words in patients with focal lesions to this area). In an fMRI study comparing spelling and reading in the same subjects, Rapp and Lipka (2011) report two major regions of overlap in activation; the left fusiform gyrus (Beeson et al., 2003), and also the inferior frontal gyrus (Rapp & Dufor, 2011, for converging evidence). Within these areas, no significant difference was found in the location of the activation peak between the two tasks. In a related study, Purcell, Napoliello and Eden (2011) had subjects type words that they also read. Spelling activated a left-hemisphere network including the inferior frontal gyrus and the inferior temporal (fusiform) gyrus. In the latter, spelling and reading both activated a region associated with the VWFA (Purcell, Turkeltaub, et al., 2011; Rapp, Purcell, Hillis et al., 2016, for related findings). All of these authors have argued for a shared orthographic lexicon.

To summarise, many researchers have proposed the common-coding of spelling and reading representations, on the basis of data from both normal and impaired subjects, using behavioural, neuropsychological, and neuroimaging methods. More concretely, the proposals are usually expressed in terms of a "shared orthographic lexicon" or "common orthographic description". Although strongly associated in practice, in principle the two ideas are not equivalent. For instance, even if there were a single "neural centre" for an orthographic word (shared lexicon), that single centre could still "look both ways", projecting into different orthographic spaces for reading and spelling. Conversely, connected but neurally distinct lexicons could project into the same space. The present work asserts that, at the very least, the orthographic space is shared, and hence reading and spelling representations are commensurate and functionally interchangeable. The architectural, or anatomical, question of whether there exists only one neural centre for written word representation is not addressed. Finally, it should also be emphasised that it is not claimed here that the spelling and reading processes do not have dissociable components; the spelling model described here (Section 2) does not consist of "running backwards" the machinery proposed for reading (Section 3).

Section 2. The Start End Competitive Queuing (SE-CQ) model of spelling

This section describes the SE-CQ model of spelling, and tests the distinctive features of its orthographic representation by simulating data from three acquired disorders of spelling.

Relation to previous work

Models of orthographic coding. Many models of orthographic representation have been proposed (for reviews, see Davis, 2006; Davis & Bowers, 2006; Fischer-Baum et al. 2010; Grainger, 2008). Broadly speaking, alphabetic models employ slot-, polygram- or position-codes. Slot-codes represent letter identity and position conjunctively, each distinct position being a “slot”. For instance, in McClelland and Rumelhart (1981), different position-specific units represent the R in the words *reap*, *trap*, *part* and *door*. There is consequently no context-independent representation of letter identity. Models differ with respect to how the slots are structurally defined (Coltheart, Curtis, Atkins & Haller, 1993; Gomez et al., 2008; Houghton & Zorzi, 2003; Jacobs & Grainger, 1992; Jacobs, Rey, Ziegler & Grainger, 1998; Plaut, McClelland, Seidenberg & Patterson, 1996; Zorzi, Houghton & Butterworth, 1998). Slot-coding is the dominant form of representation in models of the letter-to-sound mapping (Houghton & Zorzi, 2003; Perry, Ziegler & Zorzi, 2007; Plaut et al., 1996).

In a polygram code, only ordered combinations (in practice, pairs or triples) of letters are represented. For instance, the word *cat* might be represented by bigram units responding to $C, CA, AT, and T$ ($ is a boundary symbol; Brown & Loosemore, 1994; Dehaene, Cohen, Sigman & Vinckier , 2005; Grainger & van Heuven, 2003; Mozer, 1987; Whitney, 2001a; Wickelgren, 1969). A number of “open-bigram” schemes, in which bigram units can represent non-contiguous pairs of letters, have been proposed for lexical recognition, often in response to problems arising from slot-coding (Dehaene et al., 2005; Grainger & Van Heuven, 2003; Whitney, 2001a; see Grainger & Whitney, 2004; Goswami & Ziegler, 2006; Kinoshita & Norris, 2013; Lupker, Zhang, Perry & Davis, 2015, for discussion).

Position-coded models treat position as an independent dimension of representation, separate from object-identity, in itself a widely-supported view (Baylis & Driver, 1993; Chafee, Averbeck, & Crowe, 2007; Chen, 2009; Johnston & Paschler, 1990). Letter position-codes are always “object centred” (Chafee et al., 2007), being defined relative to some word-based anchor positions(s) (e.g., first letter, Davis, 2010a; Glasspool, Shallice & Cipolotti, 2006; first and last letters, Glasspool & Houghton, 2005; centre letters, Caramazza & Hillis, 1990). In contrast to both slot- and polygram-codes, letter identities are represented independently of context (Davis, 2010a; Glasspool & Houghton, 2005). Consequently, associations must be established between the position and identity representations. In addition, some way of dealing with a repeated letter, such the D in *dead*, is required (e.g., a type-token distinction); otherwise, attachment of the same letter representation to multiple positions may lead to positional averaging. Slot- and polygram-coding deal with these issues by, in effect, producing orthogonal long-term memory (LTM) representations of the same letter identity in all possible (or attested) contexts.

Glasspool and Houghton, 2005. The SE-CQ model proposed here is a Start-End position-coded model, using a token representation of letter responses/objects. Its precursor is the model of Glasspool and Houghton (2005; henceforth GH05). Here only the features of GH05 shared with the current work are summarised. GH05 represents the position of letters using a 2-dimensional code, of which privileged Start and End states form the axes (Houghton, 1990; Houghton, Glasspool & Shallice, 1994). The terminal (exterior) letters in a word are aligned with these states, while the positions of medial (interior) letters are distributed in the space between. There are thus only two “primitive” position codes, Start (denoted here ψ_S), and End (denoted, ψ_E). The terminal positions (and letters associated with them) are maximally salient. Intermediate positions (e.g., second letter) are not reified, but are expressed as an admixture of the primitive codes. The influence of each of the latter declines exponentially from its maximum, and summing (or superposing) the two at any point provides a position code ordered relative to both the start and the end. In the first half of word, the Start code has the stronger influence, while in the second half, the End code dominates (Figure 2.1). In addition, due to the limited representational space, in longer words the position codes becomes more crowded.

Figure 2.1 here

Letter responses are represented as discrete “item units” associated with both a position code and letter identity. At recall, activation of an item reflects the similarity between its position code and the time-varying state of a (word specific) Start-End context signal. This produces a primacy-gradient of activation over multiple letter identities, which compete for control of output (competitive queuing, CQ). Winning responses are selectively inhibited.

The model has been primarily tested against data from graphemic buffer dysgraphia. This acquired spelling disorder affects both word and nonword spelling in a similar way, with many phonologically implausible errors. It is widely believed to involve processes taking place in orthographic working memory (OWM, or the “graphemic buffer”; Caramazza, Miceli, Villa & Romani, 1987; Cotelli, Abutalebi, Zorzi & Cappa, 2003; Katz, 1991; Miceli & Capasso, 2006; Schiller, Greenhall, Shelton & Caramazza, 2001; Tainturier & Rapp, 2003)[1]. Rapp, Purcell, Hillis, Capasso and Miceli (2016), in an imaging study of 33 dysgraphic stroke patients, localise OWM processes mainly to the left parietal lobe (intraparietal sulcus; see also Purcell et al., 2011b).

[1] GH05 contains two additional components: the geminate mechanism, and the Consonant-Vowel (CV) template. The former represents geminates, as in *apple*, and predicts specific types of errors involving geminate letters (Pacton et al., 2014; Tainturier & Caramazza, 1996; Tomasino et al., 2015). The CV-template leads to a tendency for errors to preserve the CV structure of the target word (Buchwald & Rapp, 2003, 2006; Caramazza & Miceli, 1990; Jonsdottir et al., 1996). The current model is compatible with both these mechanisms, but they are omitted here in order to allow focus on the more basic questions.

The SE-CQ model works in essentially the same way as GH05, and remains compatible with the data simulated in that work. The main novelties are the following. First, the position code is represented as phase value in the Start-End space, rather than as a point. This permits the amplitude, or activation, of a code to vary without changing its “meaning” (Figure 2.2, and Appendix A). Processing units possessing such states are referred to as *p*-units. Second, the optimal distribution of position codes is determined by minimising a “crowding” or positional cost function (Appendix A). Finally, there is only one Start-End context signal, employed in recalling any known word, and distinct from the orthographic lexicon. The “item units” of GH05 are recast as response tokens.

Figure 2.2 here

Positional similarity: the resonance function

In GH05, the difference between letter position codes p_j, p_k is given by their Euclidean distance, $d_{jk} = |p_j - p_k|$; this value was then the argument to a positional tuning, or similarity, function, expressed as a negative exponential. This approach is preserved in spirit, but must be adapted to the use of a phase code, since the subtraction $p_j - p_k$ does not give the phase difference. Instead, the inner product of two states is used, which gives the product of their activations ($A_j A_k$) and the difference between their positions ($\theta_j - \theta_k$). This product is itself a valid *p*-unit state (Appendix A). When used with the negative exponential tuning curve, the phase difference is squared (removing negative values), yielding a Gaussian “resonance” function *R* of a *p*-unit state p_j,

$$R(p_j) = A_j e^{-c\theta_j^2} \qquad (1)$$

where A_j , θ_j are respectively the activation (amplitude) and phase of p_j, with tuning parameter c (Table A1; in most cases p_j is the inner product of two p-unit states). The resonance decreases as the phase increases, and so has its maximum A_j, when the phase is 0. All further references to the "resonance function" are to Equation 1.

In practice, this change has little discernible effect on the operation of SE-CQ serial recall process, compared with GH05, and the resonance function works well with the SE-CA code assignment mechanism (Appendix, A). It is maintained in the formulation of the reading model SE-PC (Section 3; Appendix C), appearing in the models of lexical access, letter priming, and perseveration; hence positional similarity is expressed identically in the spelling and reading models, and in all the proposed mechanisms[2].

Assignment of position codes

The Cartesian Start-End codes of GH05 are generated as a combination of a Start code, S_j which is maximal at the start of a word and declines exponentially to the right, and an End code, E_k which is maximal at the end and declines in the same manner to the left. It is due to this changing pattern that each letter position has a distinct code (S_j, E_k) with the amplitude of the S_j dominant over the first half of the word, and the E_k over the second. Because of the exponential nature of the change, the (Euclidean) distance between codes at medial positions is smaller than between more extremal positions, which in turn leads to greater response competition between medial letters during recall. These features are important to the account

[2] The resonance function is similar in form to the Gaussian positional uncertainty functions in the lexical access models of Davis (2010a) and Gomez et al. (2008). However, it used here, as in GH05, to express graded positional similarity, rather than uncertainty.

given by this model of a number of features of GBD data, including the serial position curves of various error types. It is important that the current version of the model retain these properties.

In the current model, the position codes are determined by the Start-End Code Assignment mechanism (SE-CA, Appendix 1), which seeks to minimise an objective cost or "crowing" function over phase codes. The requirement that terminal codes be more distinct is met if the GH05 Start-End gradient described above is implemented in the intrinsic amplitudes of response tokens. To this end, tokens associated with ψ_S , ψ_E have the maximum intrinsic amplitude (set to 1), which declines exponentially towards medial positions, as described above. This is controlled by a parameter σ, which expresses the "common ratio" (either falling or rising) between successive tokens (Equation C1 a,b; Figure 2.5 for examples). Unless otherwise stated σ has a value of 0.8, the same value as was used for the functionally equivalent parameter in GH05.

Model architecture and processing

The SE-CQ architecture is shown in Figure 2.2, and the associated spelling process is formally described in Appendix B. It contains the Lexical, Response Token, Letter-ID and Competitive Choice layers. Lexical representations activate letter response tokens, which associate an abstract letter identity (Letter-ID) with a position code. The Letter-ID units form a separate layer. The separation of letter type and token means that a word with a repeated letter, such as *prop*, contains the same number of tokens as an equally long word without repeats, such as *prod*. However, the two occurrences of the P lead to the activation of the same Letter-ID unit (Figure 2.3, for an example). The model contains no complex graphemes, such as CH, though it is not incompatible with them. Competitive queuing is used in the Letter-ID to Choice layer interactions. After selection of the most active Letter-ID, the winning unit is subject to specific inhibition. The time course of activation of the letter responses in two words, *sting* and *stint* are shown in Figure 2.3.

Figure 2.2 here

The Start-End signal, is comprised of two units whose activation and synchronised phase vary during the course of recall. The phases move from the Start state, ψ_S to the end state ψ_E in a series of steps, becoming synchronous with successive response tokens. At the same time, the amplitude of the Start unit falls, while that of the End units rises, as in previous work in this framework (Equations, B3a, b; Glasspool & Houghton, 2005; Henson, 1998; Houghton, 1990; Houghton et al., 1994, Figure 2.1). The Start-End signal SE_t is a sum of the Start and End unit signals (Appendix B, Equation B2). This combined signal interacts with the Response Tokens on the basis of their similarity, or “resonance” (Equations 1, B4a,). As the Start-End signal changes, so the activation of the Response Tokens changes. This in turn activates the Letter-ID units, contributing to a changing pattern of activation over the latter (Equation B4b, c).

Figure 2.3 here

Simulation studies.

The remainder of this section describes simulations of acquired disorders of spelling; letter position dysgraphia (LPD), perseverative intrusions, and central “neglect”. The first is simulated by the addition of noise to the letter selection process; the second requires a novel model of the interaction between a current and a previous response; the third simulates impairment to the End node during recall. The LPD simulations use the method employed by GH05 to simulate graphemic buffer dysgraphia, while the other studies depend on novel features of the model.

Model fits to the experimental data are given by the correlation (r), shared variance(r^2), and the root mean-squared difference (*rmsd*, the standard deviation of the model error). The last is a measure of the model's accuracy, used when the data and model outputs use the same scale. Where *p*-values are attached, they are for the correlation *r*, and are truncated at .001. The spelling studies in this section are numbered 2.1, 2.2 and so on, while the later reading studies are numbered 3.1, 3.2 etc. This is intended to make it easier to follow cross-references between studies in different sections.

Letter position dysgraphia

Gvion and Friedman (2010) describe the spelling of a Hebrew-speaking acquired dysgraphic, AE. The majority, 80%, of his writing errors were letter position errors. This pattern was robust across output modality (writing vs. typing), task (writing to dictation vs. written picture naming), and stimulus class (irregular words and nonwords). The word stimuli were chosen so that the great majority "could not be written correctly solely on the basis of grapheme-to-phoneme conversion" (p. 1103), therefore demanding the use of lexical information (see Friedman & Gvion, 2001; Kohnen et al., 2012 for a related reading problem, letter position dyslexia).

Study 2.1. Error rate and type as a function of word length

Aims and method. In graphemic buffer dysgraphia, the number of spelling errors typically increases with word length (Miceli & Carpasso, 2006). A linear increase can be predicted simply on the basis of the number of error opportunities. However, the SE-CQ model predicts an accelerated (i.e, faster than linear) rate for position errors. In longer words position codes are closer together, resulting in greater co-activation of letter responses, especially at medial positions. Since a 6-letter word has 4 times the number of medial letters as a 3-letter word, it should produce more than twice the number of errors. This prediction is tested against AE's error rate.

Calibration to global error rate. AE's performance on the writing to dictation test, 66% correct, was used to calibrate the standard deviation, η, of the noise used to impair the response buffer (Equation B4c). The model employed a vocabulary of 70 (English) words of lengths 3 to 8[3], none containing a geminated letter. The model's error rate on this vocabulary was close to that of AE at noise values $0.14 \leq \eta \leq 0.19$.This range was used in all simulations.

Length effects. The noise parameter σ was systematically varied (11 levels) in the stated range. At each level, the error rate at each word length was computed from 10 runs through the relevant vocabulary (700 trials per data point).

Measures of accuracy. A problem with assessing fits to monotonically increasing functions using the correlation is that a simple linear model is *a priori* likely to produce a high value, whether the underlying function is linear or not. For instance, the correlation between the (sigmoidal) rising portion of a sinusoid and its linearly increasing angle is about $r = .98$, leaving little room for improvement. For this reason, when the data and model output are

[3] Earlier testing of the model employed a much larger vocabulary (cf. Glasspool & Houghton, 2005), which resulted in very long run times for simulations with multiple parameter levels. The results with the more efficient sample were not found to differ in any essential way.

expressed on the same scale, the *rmsd* score (which measures *accuracy*) is preferred. A correlation can be high (indeed perfect), but completely inaccurate.

Figure 2.4 here

Results and discussion. As is shown in Figure 2.4, AE's error rate accelerates (shows a greater-than-linear increase), being for instance 11% on 3-letter words, but 41% on 6-letter words. The mean fit of the model was $r = 0.98$, s.d. = 0.003; $p < .001$. For the accuracy, the mean *rmsd* was 9.6%, with a range from 4% to 17%. The model fit was better at higher noise levels; the results for $\eta = 0.185$ ($r = 0.99$, *rmsd* = 4%; $p < .001$) are shown in Figure 2.6.

As noted earlier, a linear fit over the whole of such a curve is likely to be high. A more theoretically motivated approach is to estimate the cost of the addition of a single letter to a word at the shortest word lengths, and then extrapolate this unit increase across other lengths. Relatedly, one can compare the averaged error rate for short words with that for words twice as long. For AE, the increase in error rate on short words from 3- to 4-letter words was extrapolated to all word lengths (3-8). This produced a much less accurate fit than the model, *rmsd* = 31.4, including the 3- and 4-letter words.

This approach is supported by data from other subjects. For instance, subject LB (Caramazza et al., 1987) made 12.5% errors on words from 4 to 6 letters, but 60% errors on words of 7 to 9 letters, a 500% increase in errors over a 60% increase in mean length (from 5 to 8 letters). Likewise, subject AS (Jonsdottir et al., 1986) made an average of 17.5% errors on words of lengths 3-to-5 letters, but 64% on words of 6-to-8 letters, a 366% increase for less than a doubling in length. Subject MC (Tainturier & Rapp, 2003) showed a very similar pattern to AE, exhibiting an average error rate of about 17% on (spelling to dictation) 3- and 4-letter words, with only a 2-3% increase in errors between them. However, on 6- and 7-letter words the error rate was 55%, with a 14% increase between them.

In all these cases, what is clearly observed is that the effect of adding a single letter to a word interacts with word length, with a distinct acceleration in the error rate after about 4 or 5 letters. In the model, this is due to the crowding of the representational space as more items are encoded in the same "chunk". Given that this class of finding is usually considered to implicate orthographic working memory (Rapp et al., 2016), it is of some interest to note the relationship with the analogous effect in immediate serial recall. In Henson's (1998) Start-End CQ model of serial recall, error rate is a sigmoidal function of list length (as it is in GH05; cf. Henson, 1998, Figure 6; Glasspool & Houghton, 2005, Figure 7), with a distinct acceleration after lists of length 4. Henson notes that this is because "as the number of positions coded…increases, the resolution of each code decreases…[which is] an automatic consequence of [the] start and end markers" (p. 92-93). This is a striking convergence between models of phenomena that are traditionally treated in quite separate literatures, and is (to my knowledge) a feature unique to the current model of letter coding.

Transposition errors. With $\eta = 0.16$ the model averaged around 67% correct spelling, with between 70% and 85% of the errors being order errors. This is comparable to AE's scores of 66% of words spelled correctly, with order errors accounting for 77% of the errors. For these errors, the distance over which a misplaced letter moved was measured. The largest single category was adjacent transposition errors (93%), followed by a movement over 2 letter positions. A relatively small proportion (< 1%) of movements over three letter positions was observed, mainly in longer words (see Study 2.3 for related results in spelling, Study 3.3 for reading). As word length increased, the proportion of position errors accounted for by adjacent transpositions fell, e.g., from 98% in 5-letter words to 86% in 8-letter words. This is due to the position codes in longer words being closer together, increasing the probability that a non-adjacent letter identity might win the competition. Gvion & Friedmann do not analyse this effect in their data, and to my knowledge, the interaction has not been reported elsewhere.

Study 2.2. Serial position effects

Aims and method. Graphemic buffer dysgraphics usually show a U-shaped serial position curve for errors (Caramazza & Miceli, 1990; Tainturier & Rapp, 2003)[4]. For AE around 92% of his letter position errors occurred at medial positions, far greater than the relative proportion of medial vs. terminal letters. This effect relates to the relative salience of terminal positions in the model. In the SE-CQ model terminal letters are more salient, with more distinct position codes (Appendix A). It is proposed that this is the basis of these effects. However, even in the absence of these features, terminal letters may be less prone to positional errors as they only have one immediate neighbour ("edge-effects"). The aim of this study is to investigate the importance of Start-End salience in accounting for these effects.

To investigate this, three levels of relative Start-End salience were employed. In the model, the parameter σ expresses the "common-ratio" of the letter token activation levels as one moves away from the Start and End anchor points (Appendix C, Equation C1 a,b). Lower values of σ produce greater positional distinctiveness of terminal letters. In this study, three conditions were implemented: No-Salience, $\sigma = 1$; Weak-Salience $\sigma = 0.9$; and Strong-Salience, $\sigma = 0.8$ Note that the last value is the model's default (Table A1, used in Study 2.1),

[4] Some authors have reported a monotonically increasing error rate from first to last position (Costa et al., 2011; Katz, 1991; Miceli et al., 2004). This pattern is discussed in the General Discussion of this section.

and is the value employed for the analogous parameter in GH05. Figure 2.5 shows the distribution of token activations for 6-letter words in the weak and strong salience conditions (for no salience, all activations are equal).

Figure 2.5 here

The stimuli were words of length 5-to-7 letters, each tested 10 times. To focus on order errors, responses containing letter identity errors were removed (these were a minority, and showed a similar positional distribution to the order errors). For each response, the output position of any misplaced letter was marked as containing an order error. If the letter was not found at its target position, then that position was also marked as an error. The errors at all positions (at each word length) were summed, and medial and terminal positions compared in terms of the proportion of errors that they accounted for. The simulation was run 30 times with the noise parameter selected at random in the range $0.15 \leq \eta \leq 0.19$. If the percentage of errors found at medial versus terminal positions simply reflects the relative number of medial letters, then the expected percentages are, 5-letter words, 3/5 = 60%; 6-letter words, 4/6 = 66%; 7-letter words, 5/7 = 71% (mean = 66%)

Results and discussion. The mean and standard deviations of the proportions of medial vs. terminal position errors are shown in Table 2.1. The output of the model was analysed by a 3 x 3 ANOVA with factors SE-Salience (Zero, Low, High) and Word Length (5, 6, 7), with noise level as the random factor. The dependent variable was the proportion of letter-position errors at medial positions. All contrasts reported as significant are at $p < .0001$.

Table 2.1 here

The main effect of Salience was highly significant, $F(2,58) > 100$. The percentage of medial errors was lower in the No-Salience (66%) than in the Low-Salience condition (84%), and lower in the latter than in the High-Salience condition (91.4%; all contrasts, $p < .0001$). The effect of Word Length was also significant, $F(2,58) > 100$. Longer words showed a reduced concentration of medial errors compared to shorter words. This effect was consistent at all levels of salience, but nevertheless the Salience by Word Length interaction was significant, $F(4,116) = 11.95$, apparently due to length having a somewhat smaller effect at higher salience levels.

The principle result shows that simply being the first or last letter in a word is not sufficient to produce the degree of resistance to positional error found in letter-position dysgraphia. In the No Salience condition, the mean error rate at medial positions was largely accounted for by the relative percentage of medial letters (66% medial letters, 66% mean error rate). The High Salience condition on the other hand produced results quantitatively similar to those reported for AE, with a mean of 91.4% in the model compared with 92% in the data.

Longer words consistently showed a somewhat smaller concentration of medial errors. Further investigation of this effect found that it was largely accounted for by longer words showing an increased rate of errors affecting the final letter. This is an effect of the competitive queueing mechanism. Compared to initial letters, final letters spend more time in a state of “anticipatory” activation, competing with letters that should precede them. With noise added to the queue, this affords greater opportunity for order errors involving the final letter. A contributory factor is that in longer words, the position code of the last-but-one letter is closer to the end code. While the equivalent is also true for the initial letter, there is less opportunity for it to have an effect. Thus CQ can induce a start-end asymmetry in recall, even for a completely symmetric underlying representation. This asymmetry has been reported for spelling by

Tainturier & Rapp (2003; subject MC); it is also feature of immediate serial recall (Jahnke, 1962).

To conclude the first set of studies, the simulations of letter position dysgraphia provide support for the following features of the model's letter representation: the decrease in positional distinctiveness as word length increases, the crowding of medial positions and the relative distinctiveness of terminal positions, in support of previous simulations of similar phenomena in GBD subjects by Glasspool and Houghton (2005). The position codes and the relationship between codes in words of different lengths are tested in the next study.

Positional intrusion errors from previous responses

In immediate serial recall, perseverative intrusions from a previous list tend to preserve list position (Conrad, 1960; Fischer-Baum & McCloskey, 2015; Henson, 1999). Fischer-Baum et al. (2010) report an analogous effect in the spelling of two English-speaking subjects, CM and LSS, with acquired dysgraphia. Both subjects performed poorly on both word and nonword spelling, with word spelling unaffected by phonological regularity. On immediate transcoding (between letter case), the subjects were unimpaired, but showed substantial impairments in delayed copy transcoding. The authors conclude from these and other tests that both subjects are impaired on the activation and maintenance of abstract letter identity during the spelling process. Most of the errors produced by LSS and CM contained intruded letters found to occur at above chance rates in their immediately prior responses. The authors argue that the subjects' impaired ability to activate the correct abstract letter identities in a response leads to their being prone to perseverate letter identities employed in previous responses.

Fischer-Baum et al. analysed the relationship between the position of a perseverated letter in a *target* response and its original position in a *source* (previously produced response), assessing over 10 different letter coding schemes for their ability to account for the relationship[5]. Each scheme was also considered in discrete and graded versions. In the former, only exact position matches were counted in a model's favour; in the latter, positions adjacent to an exact match were included. The graded both-ends model (BEM, described below) "clearly outperformed the alternative schemes", with around 96% of all perseverated letters maintaining positions consistent with the model. For CM, the "hit rate" was 94%, compared to a chance rate of 60%, and for LSS, 97% with a chance rate of 55%.

Study 2.3. Modelling positional intrusions

Aims and method. In the BEM as proposed by Fischer-Baum et al., each letter position has both a start- and an end-anchored co-ordinate. For instance, the first letter of a 4-letter word has BEM co-ordinates (1,4), and the last (4,1)[6]. Fischer-Baum et al. classify the Start-End representation of Glasspool and Houghton (2005) as a graded BEM, though it is not equivalent to the model that produced the best account of their data. In addition, the authors note that "current CQ spelling simulations generate each spelling response without any influence of prior responses, and so cannot simulate perseverations." (p. 26). The present study attempts to reproduce the

[5] The schemes included; Left-edge schemes: (Coltheart, Curtis, Atkins & Haller, 1993; Coltheart, et al., 2001; Davis, 2010a; Ellis, Flude & Young, 1987; Glasspool et al., 2006); Centre scheme: (Caramazza & Hillis, 1990); Both-ends scheme: (Glasspool & Houghton, 2005); Letter-context scheme: bigram/trigram coding (Brown & Loosemore, 1994; Dehaene, et al., 2005; Grainger & Van Heuven, 2003; Whitney, 2001); and Syllabic schemes: (Caramazza & Miceli, 1990; Houghton & Zorzi, 2003; Plaut et al., 1996).

[6] The BEM is interpreted here as position-coded to make it easier to compare to the SE-CQ model. However, it is presented as being slot-coded, each letter occurring in two slots (e.g., McCloskey et al., 2013, Figure 1).

Fischer-Baum et al. results with the SE-CQ model, by permitting the "influence of prior responses" on the current response.

To generate a perseverative intrusion, it is proposed that a record of a previous response remains in episodic memory, with a decayed amplitude. When the next response is attempted, the response tokens in memory may "bind" the identities of the current tokens. Their success in doing so depends on their relative activation level. Hence weakly activated tokens are susceptible to perseverative intrusions. The model is formally described in Appendix B; the Supplementary Online materials (SEMxl) provides an application which permits the user to observe to the process in detail ("Worked Examples" worksheet).

Stimuli. The simulation used words from 4 to 7 letters long, presented in randomly selected "source-target" pairs (one trial), constrained not to share any letter identities (to aid the automated error analysis). The average word length was 5.5 letters. A single run of the model consisted of 32,000 trials. The mean and variance measures reported in each set of results are derived from 50 runs (1,600,000 trials).

Parameter fitting. The parameter $\delta(mem)$ was fixed at a value of 0.7. The model was fitted to the two subjects by setting the degree of letter identity impairment $\tau(\mathrm{id})$ to produce a similar overall accuracy, CM = 55%, LSS = 20%. For CM, a value of $\tau(\mathrm{id})$ = 0.48 produced an overall accuracy rate of 50-55%, while for LSS a value of $\tau(\mathrm{id})$ = 0.2 produced a rate of around 20%.

Error analysis. All perseverative errors were analysed as in Fischer-Baum et al. for the BEM, with each letter position assigned a Start and End coordinate. A perseverated letter was considered to maintain an exact position match if either of its source co-ordinates was unchanged (a D0 match). A graded position match was recorded if either co-ordinate was within one position of its source (a D1 match). Chance rates for all such position matches were estimated by Monte Carlo simulation of a uniform, random, distribution of perseverations into target words.

Table 2.2 here

Results and discussion. The results for combined D0 + D1 position matches (along with chance rates) are shown in Table 2.2. The global model fit (including chance rates) was very high, $r^2 = .99$, *rmsd* = 4.0%*;* p < .001. However, the fit was not so good when the proportion of D0 and D1 position matches were analysed separately. Fischer-Baum et al. report that for CM and LSS respectively the D0 + D1 proportions broke down as 78 + 16%, and 87 + 10%. In the simulation, using standard parameter values, the proportions were around 55 + 39%. While the effect was still reliably different from chance (= 29 + 33%, in the opposite direction), it is not as pronounced as that observed in the data.

Better fits were sought by narrowing the positional tuning (the parameter *c* in Equation 1), when comparing the previous response tokens in memory with the current ones (Equation B5a). While this will tend to narrow the distance over which perseverated items will "move", it is not obvious that this will improve the fit with the BEM analysis, as this code is rather different to the SE-CQ model's position code. It was found that a narrower tuning also decreased the model's error rate, and so for both subjects the value of the letter token decay $\tau(\mathrm{id})$ was changed to maintain an overall error rate close to that of the subjects.

For CM, a value of *c* = 14, $\tau(\mathrm{id}) = .4$ gave a good fit to CM, with proportions around D0 = 78%, D1 = 22%. (s.d. 6.5%); For LSS, a value of c = 50, $\tau(\mathrm{id}) = .01$ yielded position match proportions of D0 = 86%, D1 = 14% (s.d. 5.4%), while maintaining an error rate of around 75%. Under these conditions, the global fit of the model to the data distribution was *rmsd* = 3.6%.

This is the first time that perseverative intrusions have been simulated using the Start-End, or indeed any, model of spelling. The model provided a good fit to the aggregate BEM analysis results (combined D0 + D1 position matches), using its standard parameters. This setting also produced more D0 than D1 matches (contrary to the chance distribution), but did not reproduce the predominance of D0 matches reported in the data. It was found that narrowing the positional tuning in the perseveration model improved this, with D0 matches accounting for about 80%

The simulation results depend not only on the SE representation, but also on the mechanism proposed to lead to perseverations. Unfortunately, in this case there is no other model to compare it to. In broad outline, the proposed model follows Fischer-Baum et al.'s (2010) account of the process; for instance, their proposal that retrieval of letter identity is impaired is implemented directly. On the other hand, Fischer-Baum et al. do not describe the storage of previous processing episodes, or how position codes may interact. It would seem though that any account of such data must describe what constitutes the "memory trace" for a previous response (or stimulus, Study 3.3), and how it interacts with ongoing processing. The token-based letter representation employed here lends itself to an episodic (or "instance") account, whereas a model that codifies a letter string as a state of activation over long-term memory units (e.g., a slot-coded model) will most likely construe the influence of past processing in terms of residual activation of these units. I return to this question of representing more than one letter string simultaneously in the General Discussion ("On token coding").

Study 2.4: Selective loss of "End" cueing in neglect dyslexia

Aims and method. Caramazza and Hillis (1990) describe the spelling and reading of subject NG, whose deficit involves "processing the right side of internal representations" (p. 267). NG's overall accuracy on spelling was 24% correct, and the only factor found to affect her spelling was word length. However, the errors were overwhelmingly concentrated on the right half of a word, and increased from the centre of the word towards the end, being maximal at the last letter position. The rates and distribution of the errors were essentially identical in written, oral, and backward-oral spellings of words. In reading, NG showed a similar profile, making errors over the second half of a stimulus word, whether it was written horizontally, vertically or mirror-reversed. Furthermore, NG attempted to write words of the appropriate length, rather than stopping after the first half. This indicates that letter token activation was largely intact, but that activation of the associated letter identity was impaired.

To simulate NG's deficit, the Start-End weighting vector (Appendix B) was made asymmetric, and set to a value of $W_{SE} = (1, 0.05)$, Equation B2. This reduces the influence of the End node by 95%. As NG produced few errors in the first half of words (even in 7-letter words), somewhat lower values of Letter-ID noise were employed than in Studies 2.1-2, with the model tested on values in the range $0.09 \leq \eta \leq 0.13$ (8 levels). The test stimuli were words of length 4-to-7 letters, with 70 words at each length. This matches the word lengths reported by Caramazza and Hillis, with a similar number of stimuli in each category. Each word was spelled 10 times, and the error rate calculated at each position for each word length. These positional rates were normalised with respect to the total error rate at a given word length.

Results and discussion. In the region of $\eta = 0.1$, the model produced the correct spelling on around 20-25% of stimuli, close to NG's reported level of 24% correct. A length effect was evident, with longer words tending to show a higher error rate, for instance 30% correct on 4-letter words, 19% correct on 7-letter words ($\eta = 0.1$). The positional distribution of the letter errors was therefore analysed in this region.

Table 2.3 here

Results from the model, at the value of the noise parameter, $\eta = 0.105$, are shown in Table 2.3, along with a reformulation of the data from Caramazza and Hillis, 1990, Table 1 (the format of the latter is maintained). All error distributions are normalised with respect to the absolute error rate at each word length. The numbers in each row therefore sum to 100.

The global fit between the model and data was $r = 0.96, rmsd = 5.13; p < .001$. The model starts to produce errors around the middle letters of a word, with the proportion of errors increasing towards the end of the word. The fit to the data is best over words of lengths 4-to-6. For 7-letter words, it shows a relatively small increase in errors from the 4^{th} to 7^{th} letter positions (13% vs. 32%), compared to the subject data. Nevertheless, overall the model captures the pattern of increasing errors from the middle letters onwards.

These results are relevant to the distribution of position codes as a function of word length. The proportion of subject errors produced at the 3^{rd} letter position drops from 33% on 4-letter words, through 11%, 6% and 3% on progressively longer words (Table 2.3). The model shows precisely the same effect, with error proportions of 32%, 10%, 3% and 2% in the respective cases ($r^2 = .99,\ rmsd = 1.6; p < .002$). Thus performance at this letter position actually *improves* (in relative terms) as word length increases (the same pattern can be observed in the fourth letter position). In the model, this effect occurs because, as a word gets longer, the position code of the 3^{rd} letter changes. In a 4-letter word, it is in the 2^{nd} half of the word, where the influence of the impaired End-node predominates, whereas in a 7-letter word, it is in the first half, where the influence of the (unimpaired) Start-node predominates.

SE-CQ Spelling Model: General Discussion

Summary of results. This section assessed the SE-CQ model as a theory of letter representation in spelling. Studies 2.1-2 correctly reproduced the central elements of Letter Position Dysgraphia, (Gvion & Friedmann, 2010; Kohnen et al., 2012). The simulations provided a test of central aspects of the Start-End position code. Study 2.3 simulated data on the maintenance of letter position in perseverative intrusions. Success in this test is particularly telling, as Fischer-Baum et al., attempted to fit their data with versions of all current models of letter coding for both reading and spelling. Study 2.4 provided a test of the notion of Start-End positional cueing in recall, and the dependence of medial position codes on word length.

Comparison with other models. To my knowledge, there has been no attempt to simulate the kind of data modelled here (and in the previous work, GH05) using any form of slot or polygram coding. For position coded models, Glasspool et al. (2006) simulate a variety ("Type B") of graphemic buffer dysgraphia in which subjects also show substantial lexical effects (e.g., Cipolotti, Bird, Glasspool & Shallice, 2004; Sage & Ellis, 2004). The Glasspool et al. model is unique in its attempt to provide a unified account of this data. The following remarks pertain only to its letter position code.

The model employs the left-edge position code of the Burgess and Hitch (1999) model of verbal STM, in which the pattern of activation in a set of context-units begins in a distinguished start-state, and then shifts along by one unit for each successive position in a word. Compared to the SE-CQ model, there is no end-alignment, the space of position codes is not strictly limited, inter-letter positional distances are not affected by word length, and terminal items are not more positionally distinct than any others (*pace* edge effects). Consequently, the model would not be expected to show the central features of the data simulated here. For instance, when its CQ output mechanism is impaired, the model's positional error curve is essentially flat (Glasspool et al., Figure 4a, Figure 5), with a marked decrease only at the final position. It is unlikely that the model shows the concentration of errors at medial positions characteristic of subject AE (Gvion & Friedmann, 2010), and many other similar cases (Caramazza et al., 1997; Jonsdottir et al., 1997; Tainturier & Rapp, 2003). It should also make predictions at odds with the BEM analysis of Fischer-Baum et al. (2010).

In this regard, it was noted in GH05 that some subjects with GBD-like symptoms show a monotonically increasing error rate from first to last position, rather than a U-shaped curve, with a predominance of deletion errors (Cipolotti et al., 2004; Katz, 1991; Miceli et al., 2004; Schiller et al., 2001; Ward & Romani, 1998). Since such subjects often also show lexico-semantic effects (Cipolotti et al., 2004; Ward & Romani, 1998), Glasspool et al. (2006) propose that the input to orthographic working memory (OWM) from lexico-semantic representations is weakened, while OWM itself is largely intact. This leads in turn to "reduced activation of letter level units" (p. 500; Ward & Romani, 1998, for a very similar account). Glasspool et al. use this idea to successfully simulate this pattern, as part of their "Type B" model (e.g., their Figure 4b). Other authors (Costa et al., 2011; Katz, 1991; Schiller et al., 2001[7]) have proposed an abnormally high rate of decay of representations in OWM, so that later letters have decayed more by the time they should be produced. In either case, the pattern is held to be due to impairments not implemented here.

[7] Interestingly, Schiller et al. (2001; subject PB) argue, from probe tasks not requiring the spelling of the whole word, that PB had suffered no loss of knowledge of the end of words (p. 9). On the contrary, on these tasks PB showed a bowed serial position curve (p. 10), compatible with the relative Start-End salience proposed here.

To conclude this section, any model pursuing the common-coding hypothesis for spelling-reading should be able to address the data covered herein and in related previous work. The SE-CQ model and its predecessors constitute the currently most sustained and successful attempt to do so. With this in mind, the model's representation is now applied to data from reading.

Section 3. The Start End Position Coded (SE-PC) model of reading

In this section, the common coding hypothesis is advanced by applying the SE-CQ representation to letter coding in reading, and a novel model, the Start End Position Coded (SE-PC) model is described. The central features of the model are preserved, while deriving them from a plausible visuo-spatial representation of an input string. An additional requirement for the reading model is the provision of a lexical matching rule, allowing the spelling representation to be used as a lexical template for reading. This permits the model to address data from form priming studies. In addition, it provides a clear demonstration of the use of the SE-CQ spelling (action) representation in reading (perception), and vice versa, a key aim of the current work. SE-PC does not attempt to model lexical processes such as competitive activations, frequency and neighbourhood effects, or responses such as lexical decisions. The proposals are nonetheless intended to be compatible with the principles of the IA architecture as implemented in, for instance, Davis, 2010a; Perry et al., 2007.

The Start End Position Code model (SE-PC)

The model is shown in Figure 3.1. Each letter in the input is treated as distinct object (or *token*), to be associated with both an identity ("What") and a position ("Where") (Mozer, 1989). Here the key features of the model are summarised; a complete formal treatment is given in Appendix C (see also Supplementary Online Materials).

Letter identity. The initial representation is a spatially organised array of letter objects, assumed to be held in a visuo-spatial store. This store enables the identification of the start and end (edges) of the word (LaBerge, 1983; McCloskey et al., 2013) and individuation of its constituent letters as objects. Each of the 26 abstract letter identities has a local representation in long-term semantic memory. As the identity of a letter is established, its representation is retrieved. This representation is "tokenised" with respect to its location within a frame of reference defined by the start and end of the input string. If a letter type or identity is repeated in the input, that identity becomes bound to more than one token.

Figure 3.1 here

Letter location. The spatial indices indicate the distance of a letter token from the start and/or end (edge) of the word (edge-based coordinates, Findlay, Brogan & Wenban-Smith, 1993; Pollatsek & Rayner, 1982). First and last letters have zero distance from the associated end marker, and later (or earlier) letters have increasing distance. The unit of distance is that of one letter token, assumed to be adaptable to the spatial-frequency of the visual input (Jacobs et al., 1998; LaBerge, 1983; Davis, 2010a). Hence each letter location has a dual spatial code $s_{kj} = (k, j)$, where *j* is the Start-anchored coordinate, and the *k* the End-anchored. Figure 3.1 shows the spatial codes for the input STEAL. At a later stage, the position codes are remapped as a phase.

Letter tokenisation. A wide variety of visual phenomena have been explained in terms of visual tokens, including visual extinction (Baylis, Driver & Rafal, 1993); repetition blindness (Kanwisher, 1987); and feature binding and illusory conjunctions (Kahneman, Treisman & Gibbs, 1992). Letter stimuli are frequently used in these paradigms (e.g., Baylis, et al. 1993; Chen & Wyble, 2015; Harris & Morris, 2000; Kanwisher, 1991; Kanwisher, Driver & Machado, 1995; Mozer, 1989). However, I am not aware of any current model of reading expressed in terms of letter tokens.

The tokenisation process is proposed to be driven by location information (Chen & Wyble, 2015; Friedman-Hill, et al., 1995; Golomb, Kupitz & Thiemann, 2014; Haladjian &

Mathy, 2015). Each (letter) location in the input is associated with a structural marker that creates a token binding a letter's identity to its location relative to the start and end of the input string in which it occurs. There is therefore no point in the model at which letter identity information is completely "free floating" (Golomb et al. 2014; Johnston & Pashler, 1990). A location marker also assigns an amplitude to each token, which declines exponentially from both the start and the end of the input (ensuring compatibility with the Glasspool & Houghton, 2005, representation). The final step combines the phase codes derived from the spatial locations with the token representation (Equation C3).

Lexical template and matching. Each lexical unit ℓ is associated with a template, W_{ℓ}, its stored orthographic description, isomorphic to the lexical representation used in SE-CQ (Equation C4). The input representation P is assumed to be compared in parallel to all lexical templates W_{ℓ}.

Figure 3.2 here

The lexical match rule (Figure 3.2, Equation C4) embodies a very simple principle: every letter token in the input is compared with every token in the lexical template, each comparison generating a signal depending on how similar the tokens are, including their relative positions (Figure 3.2, 3.3). The token comparison requires the inner product rule, which gives the position code difference (Appendix A); comparing n input tokens with m template tokens requires $m \times n$ such comparisons. These two requirements are met by the matrix product of the input and template representations (Equation C4). The resonance function (Equation 1) is applied (elementwise) to the output of the letter matching process, producing an $m \times n$ array of signals (the "S-matrix", Equation C4). The latter represents the complete interaction between the input and template letters. The same process is employed to model letter priming (Study 3.2), with the interaction being between a prime and a probe letter string.

The match (or lexical net input) is an aggregate over this collection of letter-token signals. Figure 3.3 shows six examples of the interaction between input strings and a lexical template, S-matrix letter-match values (the columns being labelled by the input letter identities and the rows by the template. The relationships shown are single letter transposition, substitution, addition and deletion; a combined substitution and transposition and a reversal anagram[8]. These transformations are employed in Studies 3.1a,b.

Figure 3.3 here

Other things being equal, the best lexical candidate is that which generates the highest match score. No further attempt is made to model the lexical decision process, but these assumptions are intended to be in agreement with models in the IA tradition of lexical processing (Coltheart et al., 2001; Davis, 2010a; Jacobs & Grainger, 1992; Perry et al., 2007).

Study 3.1. Benchmark results from form priming

A wide variety of models exist for letter-coding in lexical recognition (Davis, 2010a; Dehaene et al., 2005; Gomez et al., 2008; Grainger & van Heuven, 2003; Norris, Kinoshita, & van Casteren, 2010; Whitney, 2001a; Norris, 2013 for review). These models have been strongly influenced by data from form priming studies (Davis & Bowers, 2006; Davis, 2006, 2010a; Forster, Davis, Schoknecht & Carter, 1987; Gomez et al., 2008; Schoonbaert & Grainger, 2004). A full review of this now extensive literature is beyond the scope of this article (see

[8] The Supplementary Online Materials contains a demonstration of the SE-PC lexical matching, a facility for batch processing a stimulus set, and a Worked Examples application, which shows all stages of processing in detail.

Davis, 2006, 2010a; Grainger, 2008; Norris, 2013). The basic finding is that nonwords which differ from real words only by the re-arrangement of letters (e.g., *judge* → JUGDE) often generate lexical priming effects close to those of the word itself (Andrews, 1996; Chambers, 1979; Evett & Humphreys, 1981; Norris, Kinoshita, & van Casteren, 2010; Perea & Lupker, 2003; Schoonbaert & Grainger, 2004). This finding has inspired investigation of numerous other transformations between letter strings (e.g., more distant transpositions, Perea & Lupker, 2004; multiple transpositions, Guerrera & Forster, 2008; deletions and additions, Grainger, Grainier, Farioli, et al., 2006; Van Assche & Grainger, 2006).

Aims and method. It is not feasible here to assess the model with respect to every such finding. In particular, since lexical decision is usually the probe task, full simulation requires the implementation of lexical level decision processes (Lupker & Davis, 2009; see Davis, 2010a, for a position-coded model that accounts for 90% of the variance from 61 form priming results). However, a number of relative similarity relationships between letter strings of the same length appear to be agreed upon by most authors, and may be considered to provide a set of basic "benchmarks" for letter coding. This aim of this study is to show that the model is compatible with these benchmarks.

Based on the review by Davis (2006), five criteria can be stated using same-length stimulus pairs related by the transformations, transposition (*T*) [9] and substitution (*S*), see Figure 3.3 for examples of how these pairs are matched up.

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[9]Key: *T* = transposition, *S* = substitution, D = deletion, *A* = addition. S_1 is a single letter substitution, and S_2 a double substitution; T_1 is an adjacent transposition, T_2 a transposition over two letter positions. S_1 T_1 is transposition combined with a substitution (of one of the transposed letters), e.g., peach-*parch* where the vowel letters are transposed, and the E *is* substituted by R. A_1, D_1 are single letter addition and deletion neighbours (Study 3.1b).

C1. T_1 pairs are more similar than S_1 pairs, e.g., *slat* is more similar to *salt* (T_1) than to *slot* (S_1). (Chambers, 1979; Perea & Lupker, 2003a, b; Rayner et al., 2006).

C2. S_1 pairs are more similar than T_2 pairs, e.g., *slate* is more similar to *slave* (S_1) than to *stale* (T_2). (Perea & Lupker, 2004)

C3. T_2 pairs are more similar than S_2 pairs, e.g., *slate* is more similar to *stale* (T_2) than to *spade* (S_2). (Perea & Lupker, 2004; Davis & Bowers, 2005)

C4. S_1 pairs are more similar than S_1 T_1 pairs, e.g., *peach* is more similar to *perch* (S_1) than it is to *parch* (S_1 T_1). (Davis & Bowers, 2006)

C5. S_1 T_1 pairs are more similar than S_2 pairs, e.g. *peach* is more similar to *parch* (S_1 T_1) than it is to *pouch* (S_2). (Davis & Bowers, 2004).

Criteria C1-3 give the ordering, $T_1 > S_1 > T_2 > S_2$, while criteria C4-5 give the compatible ordering, $S_1 > S_1\ T_1 > S_2$ (T_2 and S_1 T_1 pairs should produce similar results). The model was tested on pairs encoding all 5 relationships at medial positions, at word lengths from 5 to 7 letters. No stimuli contained repeated letters. Match scores were generated by the lexical matching rule (Equation C4). Reversal anagrams (RA) were included as a "baseline" as they provide a measure of the cumulative effect of positional discrepancy. Relevant data show they should produce substantially lower matches than any of the other conditions (Davis, 2006; Guerrera & Forster, 2008; Huntsman, 1998).

Figure 3.4 here

Results and discussion. Overall, **t**he model reproduces the two rankings described above (Figure 3.4). The conditions T_2 and S_1 T_1 both lie between S_1 and S_2, with a small advantage for S_1 T_1. RA pairs produced substantially lower matches. As expected, match values increase with word length, due to the increasing proportion of correct letters. It should be noted that the model's high match scores for T_1 pairs in reading mirrors the predominance of adjacent transposition errors in spelling found in Study 2.2 (Gvion & Friedmann, 2010). In the model, both effects can be attributed to the position code and the resonance function, supporting the common-coding hypothesis. This is the first time that compatibility with such results has been demonstrated for a Start-End model (more generally, any model that can also explain data from spelling).

Position of transformation. This study does not manipulate the position of a transformation, for instance an adjacent transposition involving medial versus terminal letters. The model's prediction for all such cases (letter transposition, substitution, addition and deletion) is straightforward; more medial transformations will be less disruptive of word identification, and/or produce more priming, than equivalent terminal letter transformations, e.g., *glove* is more similar to GOLVE that to LGOVE This phenomenon is well attested using a variety of measures (e.g., Chambers, 1979; Estes, Allmeyer & Reder, 1976; Friedman & Gvion, 2001; Holmes & Ng, 1993, Experiment 3; Mason, 1982; Perea & Lupker, 2003a; Schoonbaert & Grainger, 2004, Experiment 3; Rayner et al., 2006; White, Johnson, Liversedge & Rayner, 2008). Moving beyond form priming, Friedman and Gvion (2001) report that the reading problems of two subjects with acquired dyslexia (following left parieto-occipital lesions) were largely restricted to medial letter positions, these being 10 to 38 times more vulnerable to positional error than letters in first and last positions (p. 684; see Study 2.2 for simulation of the analogous result in spelling). Similarly, the dysgraphic subject MC (Tainturier & Rapp, 2003) produced phonological errors in *reading* pseudowords that showed a marked bowed serial position curve, with the pronunciation of terminal letters largely intact.

Reading models have attempted to account for such phenomena (at least in form priming) in a variety of ways. For instance, Gomez et al. (2008, Overlap model) propose that positional uncertainty is greater for medial than terminal letters. The SOLAR model (Davis, 2010a) supplements its start-anchored position-code with “end-letter marking”, implemented as “banks” of letter-identity units that respond to the first and last letters only (in a similar manner to positionally-defined slots). Polygram models sometimes include non-letter start- and end-symbols, and associate units containing these symbols with higher activation levels (Whitney, 2001b). These features are all different ways of assigning special status to the start and end of letter strings, and in this respect agree with each other, and with the SE-PC model. What makes the latter distinct is that the Start and End states define the axes of the positional space with respect to which *all* positions are defined (Figure 2.1).

End-letter marking. The most successful model of form priming of lexical decision is that of Davis (2010a), SOLAR, which (as noted earlier) accounts for 90% of the variance from 61 results. As in Glasspool & Houghton (2005) and the current model, SOLAR combines position coding with context-independent letter identities. However, the position codes of the two models are different; SOLAR employs a linear, start-anchored (left-edge) representation. In practice though, this is supplemented by the end-letter marking (henceforth, ELM) mechanism mentioned above. Davis (2010a, p.750) notes that without this mechanism, the model fails to account for data from nine priming studies manipulating position of transformation (contrasting medial vs. terminal positions). This raises the question of how “functionally similar” end-letter marking makes the SOLAR and SE-PC models, such that differences that would otherwise arise from their different position codes are masked. This issue is examined in the next study, in which SOLAR's representation is referred to as the Spatial Coding Model, abbreviated to SCM.

Study 3.1b

Aims and method. This question was addressed quantitatively by comparing the match scores generated by SE-PC with those generated by the SCM and the superposition matching algorithm (SMA) of SOLAR, both with and without end-letter marking, on a relevant set of stimulus pairs. The base words were 5-8 letters long, containing no repeated letters. These were subjected to five transformations, namely T_1, T_2, S_1, D_1 and A_1, (Figure 3.3, Footnote 9) applied at all possible positions, creating a total of 122 stimulus pairs (see the Supplementary Online Materials, for all stimuli and match scores). For the form priming literature (to which Davis, 2010a is primarily addressed), this sample covers the most widely studied transformations at all letter positions, at the typical range of stimulus lengths, and hence provides a relevant measure of the functional relatedness of the models.

The results from SE-PC were compared, by both correlation and rank order, with the match scores from the SMA, both with (S+ELM) and without (S–ELM) the end-letter marking mechanism activated. The SMA match scores were generated by the author's implementation of the SMA (see General Discussion, this section). This model was calibrated (and validated) with reference to Colin Davis's Match Calculator application, using the SMA tuning parameter (for positional uncertainty), $\sigma = 1.25$[10].

[10] The Match Calculator is available at http://www.pc.rhul.ac.uk/staff/c.davis/Utilities/MatchCalc/index.htm. The parameter value refers to its setting in this application. It effect is not quantitatively identical to its equivalent in Davis, 2010a, but it modulates the variance of the positional uncertainty in the same way. The Match Calculator

SE-PC was calibrated to the SMA via its two parameters, the Start-End gradient (SE-PC parameter σ, Equation C1) and positional sensitivity (parameter c, Equation 1). Manipulating the former permits a rough approximation to the degree of exterior letter salience implemented in the SMA (+ ELM), while the latter has an effect analogous to the tuning of positional uncertainty. In an attempt to calibrate "equally" to both versions of the SMA, the parameters were set to values that produced a match score in between those of S+ELM and S-ELM for 6-letter and 7-letter pairs with the first two letters transposed (word-initial T_1). It was found that this was achieved with values of $c = 2.3$, and $s = .7$ [11], not far from their default values.

Results. The results were very clear. The correlation of SE-PC with S–ELM was not significant, $r = .1,\ p = .32$; while that with S+ELM was $r = .72, p < .001$ (*rmsd* = .07). The difference between the correlations was significant, Fisher $z = 6.7, p < .001$. This result was reinforced by the models' rank ordering of the match values (Spearman's rho); the comparison between SE-PC and S+ELM was significant, $\rho = .64, p < .001$, while that between SE-PC and S-ELM was not, $\rho = .14, p = .124$.

For S+ELM and SE-PC, the lexical match scores covaried with position-of-transformation in a similar fashion, being generally higher at medial than terminal positions. In contrast, S–ELM either showed no positional variation (all same-length pairs), or showed a pattern opposite to both SE-PC and the experimental data (D_1, A_1 pairs), whereby a medial transformation leads to a *greater* reduction in the match score than the same transformation at a terminal position.

returns match scores for seven other models, and all were included in the analyses. For both SE-PC and S+ELM, the correlation and rank ordering results were maximal when compared to each other, usually by a large margin.

[11] In detail, the calibrated match values were: 6-letter T_1 pairs: S+ELM = .81, S-ELM = .91, SE-PC = .86; 7-letter T_1 pairs: S+ELM = .83, S-ELM = .92, SE-PC = .87.

To conclude, if SOLAR operates with only its bare position code then it is challenged by typical positional effects in reading (Davis, 2010a). With ELM added, on critical tests it resembles a Start-End model. This finding is important when considering the implications for theories of letter coding of SOLAR's unparalleled success in modelling form priming data. For instance, McCloskey et al. (2013) note the discrepancy between their preferred both-edges model and the SCM left-edge code, and the apparent contradiction of the latter with their findings (see Study 3.4). However, their discussion takes no account of the possible impact of end-letter marking (this is natural, as it is not clear what role it would play in generating perseverative intrusions). They nevertheless suggest that "theories adopting graded both-edges position representations could conceivably be as successful [as SOLAR]" (p. 422). This view is supported here, as SOLAR with ELM functions in relevant respects like a "both-edges" model.

The modelling of form priming of the lexical decision task is best done by models which can simulate the latter; in current models, this is a multiply-constrained, non-linear, process and provides a continuing source of debate regarding the interpretation of many such results (Kelly et al., 2013; Kinoshita & Norris, 2009; Lupker & Davis, 2009). The remaining studies in this section extend the empirical reach of the SE-PC model by investigating effects not considered to involve lexical processes, and not, to my knowledge, currently simulated by other letter-coding models for reading.

Study 3.2 Letter identification priming

Aims. This study compares the model against data from a priming study employing a non-lexical measure of orthographic similarity. Humphreys et al. (1990) report a series of studies in which the dependent measure was accuracy of letter identification in primed letter strings following a final mask. This technique is argued to allow more direct access to letter-coding processes than lexical level measures, which are susceptible to many orthogonal factors such as word frequency and neighbourhood size (Davis, 2010a; Davis & Lupker, 2009).

Humphreys et al. employed the four-field masking technique (Evett & Humphreys, 1981), in which each trial takes the form “mask – prime – target – mask”. Following the final mask, subjects were asked to identify as many letters from the trial as possible. Field durations were set for each subject at 40% correct letter identification. At that level, subjects reported perceiving only a single letter string per trial, identifying a letter unique to the prime in only .19% of trials. Primes sharing letters with the target generated positive priming compared to an all-letters-different baseline.

Method. The model of letter priming is formally described in Appendix 3, (Equations C5-7). After presentation of the prime, the probe activation may receive an initial boost by virtue of its interaction the prime representation. The interaction is defined by the matching rule used in Study 3.1a,b (Equations C4, C5). This generates a set of signals that support the activation levels of the probe letter tokens (C6-7)[12]. The activation levels of the (primed) probe tokens can be compared with those of a matched control to generate predictions regarding relative ease of letter identification. In principle, the model can do this at the level of the individual letter tokens in the probe. However, Humphreys et al. mostly report only the percentage of correct letter identifications for each experimental condition. This is modelled as the difference in the aggregate activation levels of the primed versus unprimed (control) stimuli[13] (Equation C7).

[12] This process can be examined in detail using the Worked Examples application provided in the Supplementary Online Materials.
[13] This assumption agrees with Humphreys et al.’s (1990, p. 534) own account of their data.

The data modelled are from Humphreys et al. (1990), experiments 1d, 4 and 6 (experiments 1 a-c, 2 a,b manipulated probe frequency, and are beyond the scope of this model; experiment 3 examined intrusion errors from the prime, which Humphreys et al. attribute to a different mechanism). Experiment 1d used same-length primes and probes, while experiments 4 and 6 used (mostly) different length.

In all cases the control was an all-letters-different prime, which produces zero priming in the model. Hence, for comparison, the subjects' baseline accuracy on the control condition was subtracted from that on the experimental conditions, to give an absolute measure of "priming effect". The same sets of primes and probes were submitted to the model, and the correlation between the model's "priming effect" (p.e., Equation C7) and the observed priming effect in letter identification was measured.

Results and discussion. The results are shown in Table 3.1. The prime type is shown in the first column using Humphreys et al.'s notation. For Experiment 1d, d = different letter, s = same letter (in the same position), e.g., a ddss prime: pram→TEAM. Experiments 4 and 6 used 5-letter probes, with mostly shorter (4- or 3-letter) primes. The numbers indicate at what position in the probe the prime letter is found, e.g., a 1245 prime: blck →BLACK; as before, d stands for different letter.

Table 3.1 here

For each priming condition, the absolute value of the empirical priming effect (experimental minus control) is paired with the aggregate amplitude of the model's priming effect measure, p.e. The two sets of scores are correlated separately for each experiment, with the *r* value shown next to the experiment number. As can be seen the individual fits are generally good, .9 or above. The global, cross-experiment fit is r = .84, p < .001.

Experiment 1d shows the effect of increasing number of shared letters, as well as positional effects; shared terminal letters tend to produce greater priming than shared medial letters. Experiments 4 uses different length primes and probes and shows relative position and Start-End alignment effects (e.g. 1dd5 vs. d24d). Experiment 6 reinforces the Start-End alignment, showing similar sized priming from 1ddd5, and 1d5 primes to 5-letter probes.

This study demonstrates that the model can provide an account of priming effects in letter identification, showing good agreement with relative position, terminal letter saliency, and Start-End alignment effects. Humphreys et al. argue from their data that the priming effects are not due to intrusions of prime letters into the probe. They propose rather that priming reflects a co-operative interaction (the prime reinforces the probe), whereas intrusions reflect a competitive interaction (prime letters overshadow, or displace probe letters). The following study simulates perseverative intrusions, and is in agreement with this idea.

Study 3.3a. Positional intrusion errors in reading

McCloskey et al. (2013) and Schubert and McCloskey (2013) analyse the performance of subject LHD, who showed impaired reading following damage to left posterior and medial brain areas. For both words and nonwords, her reading errors consisted largely of nonword responses that differed from the target “by the substitution of one or (occasionally) more letters” (McCloskey et al., p. 403). On a delayed copying task, LHD’s written errors showed an identical pattern, whereas on spelling without copying she performed normally. Schubert and McCloskey (2013) argue that LHD has a problem in activating abstract letter identities from their shape representations. As a result, when reading some letter identities are not properly retrieved, leaving them prone to substitution. One proposed source is “residual activation” from previous responses; for example, immediately after correctly reading the stimulus FLAG, LHD read SAILOR as SAILOG, suggesting that the G in SAILOG is a perseveration from FLAG.

McCloskey et al. (2013) investigated the source of perseverations by comparing the perseverated letter to the letters appearing in the previous five stimuli, *t*-1 to *t*-5. Items from *t*-1 to *t*-3 contained the perseverated letter at above chance levels, with *t*-1 alone accounting for almost 60% of cases. Perseverated letters tended to maintain their source position (cf. Fischer-Baum et al., 2010). To explain the relationship, the predictions from three classes of letter position scheme were contrasted; extrinsic anchor (e.g., left-edge), letter-context (e.g., open bigram), and orthographic syllable (e.g., onset maximization). These base models were also tested in graded versions, producing 20 different fits to the data. The best performing model was the graded both-edges model (BEM, Fischer-Baum et al., 2010), which accounted for the positions of up to 96% of the perseverations. The BEM always accounted for data not accounted for by other models, and no other model explained data that the BEM could not.

As in Fischer-Baum et al. (2010; Study 2.3), a perseverated letter was scored as an exact position match (D0) if it shared at least one of its BEM coordinates with its source position. Less exact position matches lay within a distance of one (D1) or two (D2) positions of the source. The D0 matches accounted for around 65% of perseverations, with the D1 matches contributing a further 27%, D0 + D1 = 92%. The D2 matches improved the fit only by a further 4%. Clearly, the vast majority (92%) of the perseverations have their sources in letters at or adjacent to one of the BEM coordinates.

Aims and method. The SE-PC model differs in many important respects from the BEM. For instance, the BEM is a slot-coded model (McCloskey et al., 2013, Figures 1 & 2), with each letter token represented in two independent slots. In the current model, each letter is represented by a single token, whose position code cannot be interpreted as a slot label. Similarly, the bounded Start-End space of the SE-PC model has no analogue in the BEM. The ability of the SE-PC model to account for the data as analysed by the BEM scheme must therefore be demonstrated.

The substitution of a target letter identity from a source token is simulated using the same perseveration mechanism as in Study 2.3 (Appendix B), but applied to representations generated by the SE-PC model. There are no additional novel parameters or assumptions. In Study 2.3, the source of the perseverations was assumed to lie in an output representation (an episodic record of a previous response). In the present case, the source is assumed to be from an episodic record of a previous stimulus.

Parameter settings. The two (scaling) parameters are: episodic memory decay, $\delta(\mathrm{mem}) = 0.7$; letter identity impairment, $\tau(\mathrm{id})$. Given the setting of the former, the latter was calibrated to give an overall error rate close to that of LHD on nonwords (55%), resulting in a value of $\tau(\mathrm{id}) \approx 0.39$.

Simulation. The delayed copying task is simulated from analysis of the visual word form through to its reproduction by spelling, showing that the model achieves the goal of the unification of perception-action codes. Word lengths were 4 to 7 letters, presented as source-target pairs, each pair being one trial. The members of each pair were randomly selected by length but did not share any letter identities (to aid the error analysis). The average word length was 5.5 letters, which is close to the average of 5.1 letters estimated for the McCloskey et al. study.

The source word was processed correctly, and then stored with token amplitudes scaled by $\delta(\mathrm{mem})$. Following this the target string was processed, but the amplitude of a single randomly selected letter token was scaled by $\tau(\mathrm{id})$. The source and target representations interact in such a way that all the letters in the source may bind each of the letters in the target (i.e., the weakened token was not singled out). Selection was by Monte Carlo simulation. The resulting spelling was compared with the canonical target, and any intrusion error matched to its source location according to the BEM analysis scheme.

Results and discussion.

Calibration to error rate. The 4 different word lengths employed generate 16 different source-target pairs. On a run of the model, each pair was tested 2000 times (32000 trials per run), with the location of the impaired letter token selected at random on each trial. At values of $\tau(\mathrm{id}) \approx 0.39$, $c = 5.5$, the model produced an average error rate close to that of LHD on the simulated task (55%). The reported means and variances of the model's output are based on 50 runs.

Perseveration baseline. To calculate the chance (random baseline) rate of BEM matches pseudo-perseverations were generated between randomly selected source and target letter positions (32,000 trials). The resulting chance position matches were D0 = 29%, D1 = 34%, D2 = 19%. The combined D0 + D1 chance rate was 63%, reasonably close to the estimated chance rate of 58% for the case study (McCloskey et al., p. 414).

True perseverations. The model's performance was evaluated on the basis of 50 runs of 32,000 trials, constructed as described under calibration. The results are shown in Figure 3.5. The global fit (including chance rates) was $r = .98$, *rmsd* = 6.1; *p* < .001. Of the perseverations generated by model, on average around 65% (s.d. 3.2%) of the source letters were found at a D0 position, compared to the model's chance rate of 29%. An additional 34% (s.d. 4.1%) of source letters were found at D1 positions, leading to a combined D0 + D1positional match score of 98%. This result is close to the empirical finding of 94%, and far higher than the simulation chance rate of 63% (58% for the subject data).

Figure 3.5 here

The model maintained D0 position at a rate very close to that of the data (65%), but with a somewhat greater average tendency to appear at D1 (27% data vs. 36% model). However, amongst the repeated runs of the model D1 perseveration rates of 26% and 29% were observed, closer to the empirical proportions.

Study 3.3b. Effect of Start-End Gradient

Aims and method. The BEM analysis scores a position match according to which coordinate gives the best fit. So for instance, if a target response SPORT is rendered as SPONT following BEAN, the perseverated N will be scored as a D0 match on the start coordinate (4 in both cases). However, in the Start-End model, this case occurs because the N of BEAN is the last letter, and similar in position to the last-but-one letter of SPORT. The Start-anchored position plays little if any role in the perseveration, and the N is not in the same position in BEAN and SPONT.

This rather subtle issue is recognised by McCloskey et al. (2013; also Fischer-Baum et al., 2010), who test the idea of Start-End gradients by applying the Start- and End-anchored BEM analyses separately to perseverations into the first and second halves of responses. They predicted that if the Start-anchored position is more important in the first half of a word, then a perseveration into that half will better maintain its Start- than End-based position, and vice versa for a perseveration into the second half of a word.

This prediction was confirmed. For the D0 + D1 positions (narrowly graded scheme), perseverations into the first half of a response gave a significantly higher match score for the Start- than the End-anchored BEM coordinate, approximately .82 (Start) vs. .56 (End), averaged across testing sessions. For perseverations into the 2nd half of a response, the opposite pattern was found: Start-anchored .72, End-anchored .82 (averaged). This pattern is also reported for spelling perseverations in Fischer-Baum et al. (2010).

To test whether the SE-PC shows this effect, the previous simulation was repeated, but perseverations were classified according to which half of a target word they affected (the middle letter position was excluded). Each perseveration was then scored for both its Start- and End-anchored position separately, reproducing McCloskey et al.'s analysis of the subject data. The chance rate of all measures was calculated by Monte Carlo simulation.

Results and discussion. Table 3.2 shows the proportions of position matches in the first and second half of words. For each half, the D0 and D1 matches are shown separately for the Start- and End-anchored coordinates, along with the chance rates. The final column shows D0 + D1. The basic phenomenon reported by McCloskey et al., is replicated: for a perseveration into the first half of a word, its Start coordinate better predicts the position of the source letter than does its End coordinate, while perseverations into the second half of a word show the opposite pattern. As would be expected, the model shows a rather exact mirror symmetry in this regard, whereas the subject data indicate that the effect may be stronger in the first than the second half of a word (though McCloskey et al. do not report the interaction).

Table 3.2 here

In combination with Study 3.3a, these results provide a very exacting test of this model. McCloskey et al. found that their BEM outperformed all other current proposals for letter position coding. Study 3.3a shows that the SE-PC model can match the BEM fit to the data, while not employing the identical representation. Study 3.3b provides perhaps an even more telling result. McCloskey et al. (also Fischer-Baum et al., 2010) were motivated to carry out the relevant analysis by the Start-End representation of Glasspool and Houghton (2005), in which neither reading nor perseverative errors are modelled. Study 3.3b confirms the insight that this model, applied to reading, does indeed predict this rather subtle pattern of results.

The SE-PC model: General Discussion

Summary of results. The major novelty of this section is the application of the SE-CQ spelling representation to data from reading. To achieve this, the following innovations have been necessary:

i) An account of the construction of the representation from a visuo-spatial representation, including an explicit description of the tokenisation process (Appendix C).

ii) A rule for lexical matching (more generally, similarity between representations, Equation C4).

iii) An account of priming in letter identification (Study 3.2).

iv) An account of perseverative intrusions in reading (Study 3.3).

Study 3.1 shows the model is compatible with basic benchmark results from the form priming and related literatures. Study 3.2 provides a novel account of letter priming, applying the lexical matching process of Study 3.1 to the interaction between letter strings (the first time this has been done, I believe). As well as providing support for the Start-End code in general, the data simulated includes primes and probes of different lengths. This provides a discriminative test between relative and absolute models of position coding, supporting the former.

Studies 3.3 a,b probably provide the most stringent test of the model's proposed position code, as the subject data were compared by McCloskey et al. (2013) to the predictions from most other models of orthographic coding. Application of the BEM analysis to the model's output closely reproduced the results for the subject data, including the relative maintenance of "word half" position (Study 3.3b). To my knowledge, this aggregate set of results has not been previously simulated by any other reading model. The remainder of the discussion considers these results in the context of other current models of letter coding for reading.

Comparison with other models. A greater range of models has been proposed for letter coding in reading than for spelling (e.g., Davis, 2010a; Dehaene et al., 2005; Gomez et al., 2008; Grainger & Van Heuven, 2003; Grainger & Whitney, 2004; Whitney, 2001a;) and it is not possible here to provide a detailed comparison with all individual cases (Frost, 2012; McCloskey at al., 2013; Norris, 2013). However, in terms of the broad model classes, the SE-PC model is quite distinct in all respects from polygram models (Dehaene et al., 2005; Grainger & Van Heuven, 2003; Whitney, 2001a). Since the work of Brown and Loosemore (1994) no such model has been pursued for spelling, and there is no realistic prospect that the idea will be revived. Polygram coding has also been rejected as the input representation for phonological reading (Goswami & Ziegler, 2006; Plaut et al., 1996). Hence, these representations are nowadays only employed to model letter processing for word recognition (Lupker et al., 2015), a situation clearly at odds with the common-coding hypothesis.

Slot-coded models are less restricted. Indeed, a previous example of common-coding is provided by the reading model of Perry et al. (2007), which employs the orthographic representation of the Houghton and Zorzi (2003) spelling model. However, this representation is unsuited to the data treated in this section (and also Section 2). First, it suffers from a general problem of slot-coding, that members of an adjacent transposition pair (T_1) are no more similar than a double substitution pair (S_2)[14] (Study 3.1). More specifically, its syllabic position code generates incorrect predictions with respect to data such as that of Humphreys et al. (1990), and McCloskey et al. (2013), simulated above. If one conflates slot-labels with position-codes, then the SE-PC model is more similar to models such as Jacobs et al. (1998) and Fischer-Baum et al. (2010). Neither model has so far been employed as the basis of simulations of the range of data considered in this section.

The only other explicitly position-coded model of reading is the SOLAR model, which has provided by a considerable margin the most extensive and detailed simulations of form priming data (Davis, 2010a; Lupker et al., 2015). As with SE-PC, this model combines position coding with context-independent letter identities (an approach first introduced for spelling by Houghton

[14] Gomez et al., (2008) propose a form of "fuzzy" slot-coding, which can explain some transposition effects. This representation has not however been employed in modelling the phonological route in ether reading or spelling.

et al., 1994; Shallice et al., 1995). A number of additional points of convergence between SOLAR and SE-PC should be noted:

(i) Davis (2010a, b) refers to SOLAR's position code as a "phase" code, and defends it as such on neurophysiological grounds. However, it is not explicitly implemented as a phase, being linear and (at least in principle) unbounded. For instance, the codes are the same as the linear start-anchored positions defined for the BEM by Fischer-Baum et al. (2010); McCloskey et al. (2013).

(ii) SOLAR employs a Gaussian "positional uncertainty" function (see also Gomez et al., 2008), which is related in some respects to the resonance function (Equation 1) of the current model. In SOLAR, its use is restricted to lexical matching in reading (the SMA), where it "blurs" the positions of input letters. On the other hand, the resonance function (which does not blur letter position) is employed in every model and simulation in the current paper, for both reading and spelling. It is a modified version of the positional tuning function of Glasspool & Houghton (2005), and plays the same role.

(iii) Lexical matching in both the SMA and the SE-PC model involves comparing all input letters with all letter representations in a lexical template, and computing a match based on some form of aggregate of the signals so generated. These rules, which are not reducible that standard dot product rule of the IA architecture, distinguish them from the great majority of slot- and polygram coded models (Whitney, 2008). Indeed, it has been suggested by a reviewer of this article that the matching mechanisms of the two models may be "almost or exactly mathematically

> equivalent". In work not included here[15], it is shown that this is not the case. More specifically, SOLAR's spatial coding model (SCM) and SMA can be formulated as computing the discrete cross-correlation (a signal processing technique) between a normalised lexical template and an input with positional uncertainty. The SE-PC does not implement this process, and the models can diverge quite drastically in the way they treat some relationships (e.g., "shifted-half" pairs, as in *drenchil* vs.*children;* see Figure 8, in Davis, 2010a). In other cases (including T_1 and some other same length pairs) the models will provide closely related results.

This last point means that if the SE-PC and SCM are evaluated with respect to data on form priming of lexical decision, that differences in both the position code and the lexical matching rule must be considered. For this reason, it is important to evaluate models of letter-coding with respect to sources of data not dependent upon lexical access; in particular, an important source of constraints can be found in neuropsychological data, such as the distribution of perseverative intrusions (McCloskey et al., 2013), "graphemic buffer" effects in reading (Caramazza et al., 1996; Tainturier & Rapp, 2003), and letter position effects in various forms of dyslexia (Friedman & Gvion, 2001; Kohnen et al., 2012).

Finally, returning to the main theme of this article, I would suggest that models of letter-coding for reading can also be evaluated with respect to data from spelling; if this view is rejected, then some account of how and why the brain should form two distinct and incommensurate representations of the same set of objects should be given.

[15] A copy of the analysis, which has also been implemented, is available from the author on request.

Section 4: Summary and Conclusions

The aim of the current work is to advance the common-coding hypothesis for orthographic representation in reading and spelling. The motivation for such an attempt was described in Section 1. The strongest current statement of such a position (in terms of both representation, and shared neural architectures) is probably to be found in the recent experimental work of Fischer-Baum, McCloskey, Rapp and colleagues (Fischer-Baum et al., 2010, 2011; McCloskey et al., 2013; Rapp et al., 2016), who have advanced the both-ends model (BEM) as an account of letter position representation in both spelling and reading. The model proposed here is based on a pre-existing computational model of spelling (Glasspool & Houghton, 2005; Houghton et al., 1994; Shallice et al., 1995), which employs a graded Start-End position code, and offers modelling support to the arguments of these authors.

The relationship of the model to other models of spelling and reading is discussed in Sections 2 and 3 respectively. With respect to previous and related work, the major innovations of the current paper are:

i) The unification of action-perception codes for written word representation.

ii) Modelling of data from both spelling and reading using the same model.

iii) The proposal of a token-based representation of letters, in which tokens bind letter identity and position.

From the narrower perspective of previous work with the Start-End model, the major innovations are:

iv) The extension of the model to reading and lexical access.

v) The re-formulation of the Start-End code as a phase code, along with assignment of codes by optimisation.

vi) In spelling, the separation of the Start-End context signal from the lexicon.

The most important innovation is that data from both spelling and reading are addressed and simulated in the same framework. The model was initially developed to account for data from acquired dysgraphia (Glasspool & Houghton, 2005; Houghton et al., 1994; Shallice et al., 1995). This still provides perhaps the strongest support for the model, since there is no other existing model capable of explaining the data simulated by SE-CQ (Section 2) and its predecessor, Glasspool and Houghton (2005; Glasspool et al., 2006; Goldberg & Rapp, 2008, for discussion). With respect to (lexical) reading, the array of alternative models cited in Section 3 is rather larger. However, none employs a letter coding scheme equivalent to that proposed here. While the lexical form-priming results simulated in Study 3.1 are compatible with some existing reading models, Studies 3.2, 3.3 introduce novel mechanisms to the study of orthographic processing in reading. I am not aware of any other attempt to explain spelling data using a model validated with respect to reading.

On token-coding.

A novel feature of the current model is its use of token-coding for "letter objects". While this agrees with some approaches to perception-action coupling (e.g., Hommel et al., 2002), it contrasts with both slot and polygram coding, in which the representation of a letter string is simply a state of activation of long-term memory (LTM) units ("LTM-only" models). Token coding requires both LTM representations and mechanisms to form the tokens, and is undoubtedly more complex.

But a major problem with the LTM-only models is that it is difficult to process (or have active) more than one letter pattern at a time, either in reading or spelling (something that is required here in Studies 2.3, 3.2, 3.3). This is because the superposition of two LTM states is just another LTM state, not two distinct states. For instance, in the Houghton and Zorzi (2003) model, the simultaneous representation of *bow low* would be indistinguishable from that of *blow* (this problem has been recognised for some time; e.g., McClelland, 1985; McClelland & Mozer, 1986, for a general discussion of this issue).

Evidence of multiple word processing (for reading) is provided by studies that briefly present more than one word simultaneously. For instance, some semantic priming designs simultaneously present two prime words, target and distractor (Marí-Beffa, Fuentes, Catena & Houghton, 2000; Marí-Beffa, Houghton, Estévez, & Fuentes, 2000). While subjects respond correctly to the target, they may also exhibit priming effects uniquely attributable to the distractor (Mari-Beffa, Fuentes et al., 2000). While comprehensible on a token-based model, on an LTM-only model superposition should impede processing of the target, and perhaps even more so of the distractor.

Similarly, in studies of letter-migration, two words are simultaneously presented then masked, after which one of the words (the target) is randomly marked for report (Davis & Bowers, 2004; Fischer-Baum et al., 2011; Mayall & Humphreys, 2002; Mozer, 1983). While letter-migrations to the target from the non-selected word do occur, subjects mostly report the target word correctly (Mozer, 1983), showing that superposition of the two stimulus words has not occurred. The model proposed here would explain this on the basis of two "word tokens" being formed, with letter migrations possibly occurring by a mechanism similar to that proposed for perseverations. The latter requires the existence "event tokens" in memory, distinct from the representation of the current target word.

In conclusion, the relative simplicity of LTM-only models is bought by limiting attention to studies using single-word presentation, and in which no memory effects are evident.

Extending such models to deal with more than one word at a time would require some form of grouping mechanism to prevent catastrophic superposition effects.

Orthographic structure.

The only sub-lexical structure employed in the proposed model is the individual letter. However, there is strong evidence that compound graphemes play a role in both spelling (Fischer-Baum & Rapp, 2014; Shen, Damian & Stadthagen-Gonzalez, 2013; Tainturier & Rapp, 2003), and reading (Havelka & Frankish, 2010; Lupker, Acha, Davis & Perea, 2012; Marinus & de Jong, 2011; Perry et al., 2007; Rastle & Coltheart, 1999; Rey, Jacobs, Schmidt-Weigand, & Ziegler, 1998; Rey, Ziegler & Jacobs, 2000). They have also proved essential to good performance in some models of phonological reading/spelling (Houghton & Zorzi, 2003; Perry et al., 2007; Plaut et al., 1996). The question arises as to whether the current proposals can accommodate the existence of such structures.

Virtually any model can accommodate compound graphemes by an extension of its alphabet, e.g., including a CH unit, independent of C and H. On this account, *church* contains the grapheme tokens CH-UR-CH (Houghton & Zorzi, 2003; Perry et al., 2007, based on British English pronunciation). The problem with this account is that each grapheme is unrelated to its constituent letters. Hence *church* is no more similar to the adjacent transposition (T_1) CHRUCH, than to the double substitution (S_2) CHAWCH, a prediction which is unlikely to be correct (Study 3.1; Lupker et al., 2012).

The current model represents letter grouping by the operation of superposition (Appendix C). In principle, this approach also permits the combination of individual letter tokens into a composite token[16], along with their position codes (provided the letter identities being combined are different). For instance, the grapheme CH would be represented as a single token composed of {C + H}, the letter order determined by the position codes. In this case, {C + H} resembles its constituents, as it is composed of them. Importantly, this proposal requires no change to the lexical matching/letter priming rules, Equations C4, C5, which will generate an aggregate signal from a composite token, while also recognising the similarity between say, C and {C + H}.

Of some importance, this proposal would require special treatment of geminates such as the EE in *breed* vs. *bred*, as superposition of the two E tokens would lead to perception of a single E at the average position of the two tokens. Interestingly, geminates require special treatment in the CQ spelling model, a prediction that has substantial empirical support from both handwriting and typing (Glasspool & Houghton, 2005; Houghton et al., 1994; Kandel, Peereman & Ghimenton, 2013; McClosky, et al. 1994; Miceli et al., 1995; Rumelhart & Norman, 1982; Tainturier & Caramazza, 1996; Tomasino et al., 2015). Hence, geminates may also require special handling in reading (Egeth & Santee, 1981; Fischer-Baum, in press; Harris & Morris, 2000; Mozer, 1989; Tomasino et al., 2015). For instance, Fischer-Baum (in press) reports, using the illusory word paradigm, that the abstract feature “doubled letter” may migrate from one word to another. This form of abstract marking of geminate letters is implemented in Glasspool & Houghton (2005), and gives rise to an analogous error in spelling. These findings provide an interesting example of how combining data from both reading and spelling may lead to greater insight the nature of orthographic coding.

[16] Formally, a single column or row in the matrix representation of a letter string.

Full circle

On this final point, it is noticeable that much of the experimental and theoretical literature on reading ignores data from spelling. Yet this literature has still failed to converge on a single *class* of orthographic representation for reading, let alone a single version of one class (Davis, 2010b; Frost, 2012, and commentaries; Goswami & Ziegler, 2006; Kinoshita & Norris, 2013; Lupker et al., 2015; Whitney, 2008). It has been argued that for the child learning to read and write, it is the precision of the representation required for correct spelling that most strongly constrains the mental orthography (Ehri, 1989; Ellis & Cataldo, 1992; Frith, 1980; Goulandris & Snowling, 1991; Hanley et al. 1992). It may therefore be that data from spelling provides the stronger constraint on theories of this representation (Fischer-Baum & Rapp, 2014). To take one example, despite their popularity in reading, there is currently no polygram model of spelling being pursued. The data covered both here and in Glasspool and Houghton (2005) appear to rule them out (Fischer-Baum et al., 2010).

Perhaps most importantly, modelling spelling requires a solution to the problem of serial order, and the common-coding hypothesis requires a common solution. The proposed model employs the competitive queuing theory. This basic mechanism is not specific to spelling (or even to humans, Averbeck et al., 2002; Seeds et al., 2014), but for flexible recall from long-term memory really *requires* a position code (Brown et al., 2000; Burgess & Hitch, 1999; Farrell, 2012; Fischer-Baum & McCloskey, 2015; Hartley et al., 2016; Henson, 1998, 1999; Hurlston et al., 2013). In summary, the task of explaining both spelling and reading data is more theoretically constraining than dealing with either in isolation, and should contribute to adjudication amongst the numerous different models of orthographic representation.

Envoi.

Written language processing has been one of the most fruitful areas of cognitive modelling for nearly four decades, giving rise for instance to the first implemented IA architecture, in the reading model of McClelland and Rumelhart (1981), and an early version of spelling by competitive queuing, in the typing model of Rumelhart and Norman (1982). These seminal works have continued to inform later and more sophisticated models, but the lines of theoretical research they have inspired, in reading and spelling, have largely remained separate, despite substantial evidence linking the two skills. This paper provides a first attempt in the modelling literature to heed the implications of this evidence.

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Tables

Table 2.1. *Mean and standard deviation (s.d.) of percentage (%) of letter position errors at medial letter positions. Data are from 30 runs of the model simulation at different levels of noise amongst letter identity units. N = number of letters in test words.*

	Start-End Salience		
	No Salience	Low Salience	High Salience
Word Length			
N = 5	71 (5.4)	89 (2.3)	94 (1.4)
N = 6	64 (1.8)	82 (1.8)	91 (1.1)
N = 7	64 (1.3)	80 (0.9)	89 (0.8)

Table 2.2. *Percentage of observed and chance D0 + D1 position matches in letter perseveration errors in dysgraphic subjects CM and LSS, and the model simulation (according to the BEM analysis of Fischer-Baum et al. 2010). The bottom row shows the absolute difference.*

	Subject CM		Subject LSS	
	observed	chance	observed	chance
Data	94	60	97	55
Model	95	53	94	53
Diff.	1	7	3	2

Table 2.3 *Comparison between single subject data and the model with End-node impaired: Distribution of spelling errors by letter position in words of different lengths.*

Word Length		Left					Word Centre X			Right			
Data													
4				0		5		33		62			
5			0		0		11		36		53		
6		0		0		6		18		30		46	
7	0		0		3		5		15		27		50
Model													
4				0		0		32		68			
5			0		0		10		36		54		
6		0		0		3		17		37		43	
7	0		1		2		13		22		30		32

Letter positions are arranged with respect to the center of the word (after Caramazza & Hillis, 1990, Table 1). The numbers show percentage of total errors at each word length accounted for by each letter position (each row sums to 100%; reformulated from Caramazza & Hillis, 1990, Table 1, “Spelling”). The error rate for the 3rd letter at each word length is underlined to assist comparison.

Table 3.1. *Results of Study 3.2, simulation of Humphreys et al. (1990).*

Prime	Observed (%)	Model, *p.e.*
	Experiment 1d. $r = .98$	
ssds	20.8	.42
sdds	14.5	.34
ssdd	11.1	.25
dsds	10.1	.25
sddd	6.5	.17
ddds	3.4	.17
dsdd	0	.09
	Experiment 4. $r = .96$	
1245	12.7	.45
1425	7.5	.36
1dd5	6.5	.3
d24d	3	.15
	Experiment 6. $r = .94$	
1ddd5	10.8	.28
d1d5d	0.5	.15
1d5	10.1	.33

Table 3.2 Study *3.3b. Proportions of position matches by perseverations into the first and second half of target words, broken down by BEM start and end coordinates. Chance (Monte Carlo) rates are shown in parentheses. S = Start, E = End.*

		Position match		
Word half	Coordinate	D0	D1	D0 + D1
1st	S	.58 (.19)	.39 (.31)	.97 (.50)
	E	.26 (.14)	.42 (.27)	.68 (.41)
2nd	S	.26 (.14)	.40 (.27)	.66 (.41)
	E	.59 (.19)	.58 (.31)	.97 (.50)

Table A1. *Standard values of main model parameters, with*

Parameter	Typical value	Function
		SE-CA (Appendix A)
c	.18	Tuning of resonance function R, between letter tokens. Eqs. 1, A1 b,c.
		SE-CQ (Appendix B)
s	.08	Start-End units; activation slope. Eqs. B3a,b.
σ	.8	Letter-token amplitude gradient. Eq. C1a,b.
W_{SE}	(1,1)	Start-End weights. Eq. B2.
c	.12	Tuning of R (between Start-End signal and response tokens). Eqs. 1, B4a, B5a.
g	1.4	Response token to Letter-ID weight. Eq. B4c.
δ	.8	Decay rate of Letter-ID unit activations. Eq. B4c.
ω^-	1.2	Feedback weight, competitive filter to Letter-ID units. Eq. B4c.
		SE-PC (Appendix C)
c	.18	Tuning of R between letter tokens. Eqs. 1, C4, C5.
σ	.8	Letter-token amplitude gradient. Eq. C1a,b.

Figures

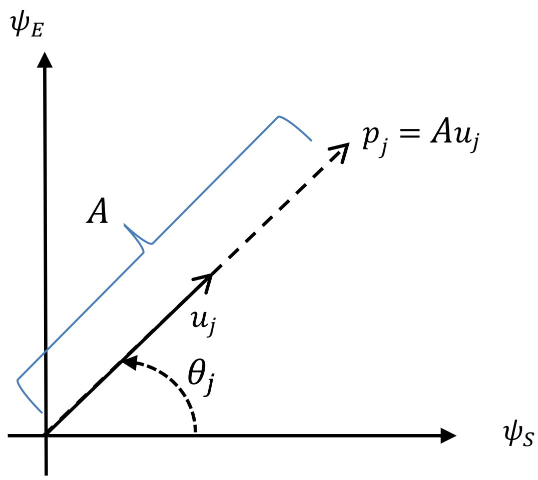


Figure 2.1. Start-End phase code. The start of a word is aligned to the Start state ψ_S and the end with the End state ψ_E. All other letter positions lie within this space. The position code is shown as a unit length vector u_j (solid arrow) with phase angle θ_j, and variable amplitude A.

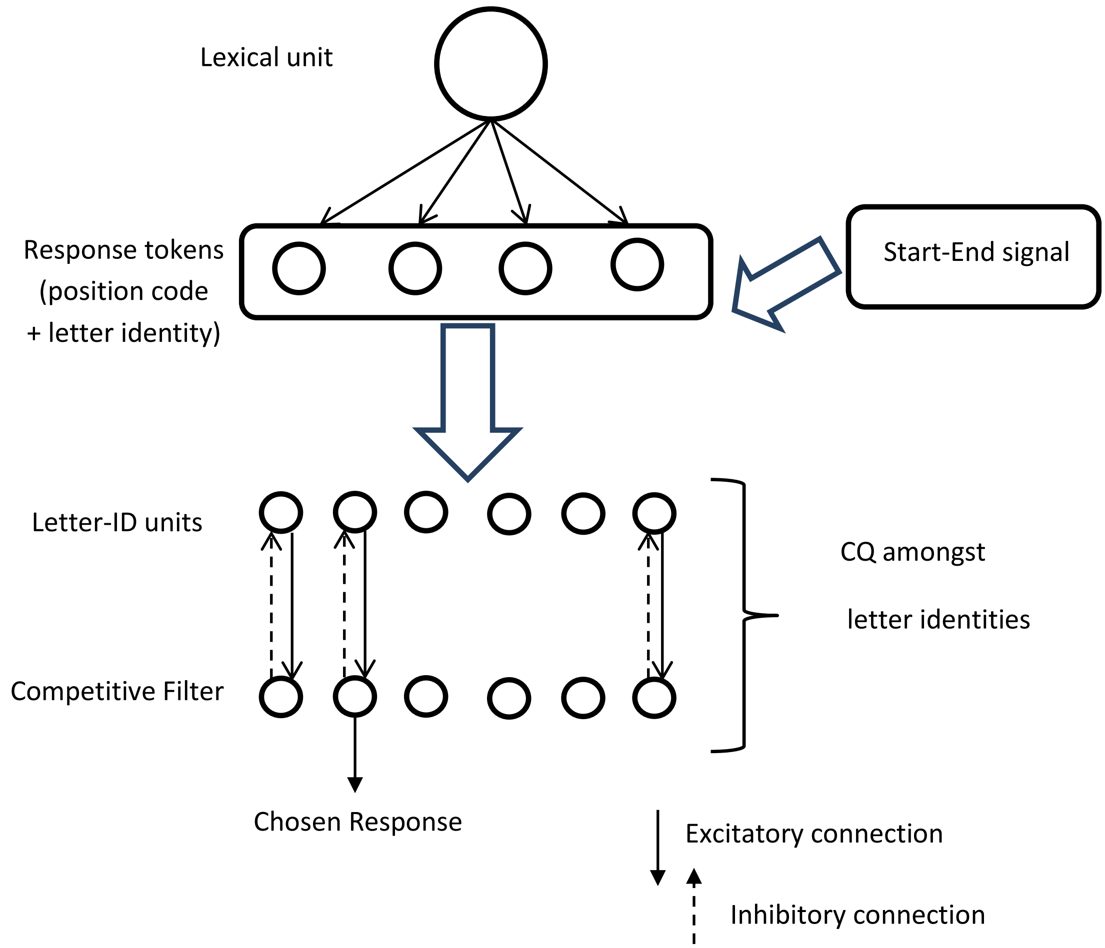


Figure 2.2. Architecture of the SE-CQ spelling model. Lexical units activate response tokens which are associated with both a position code (phase) and a letter identity (Letter-ID units). Positional cuing depends on the resonance between the Start-End signal and the position codes of active response tokens. Response selection and inhibition (Competitive Filter) is by competitive queuing (CQ) amongst Letter-IDs.

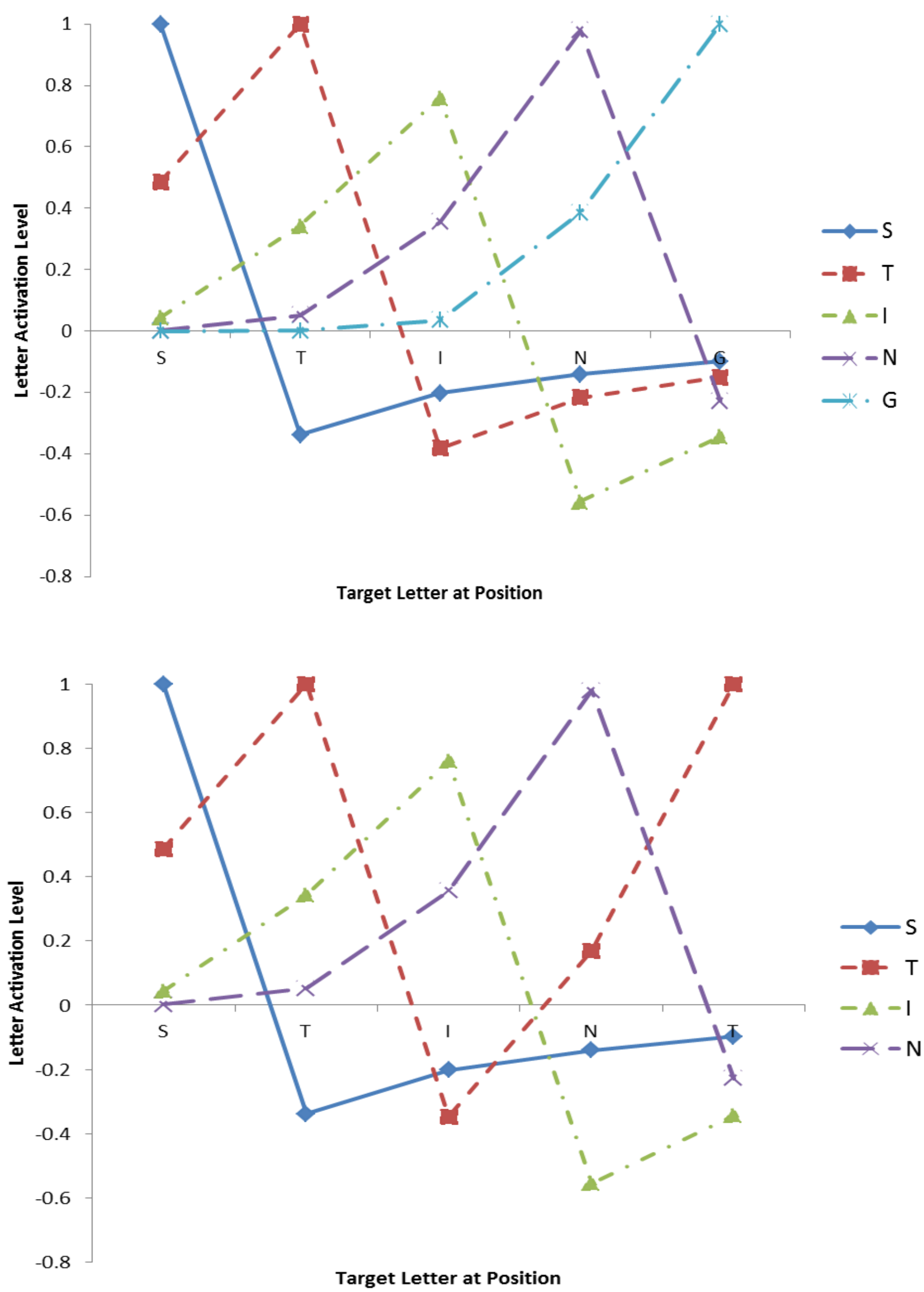


Figure 2.3 Pattern of Letter-ID unit activation over time in spelling of the words STING (upper) and STINT (lower). In the latter case, the repeated T leads to reactivation of the same response.

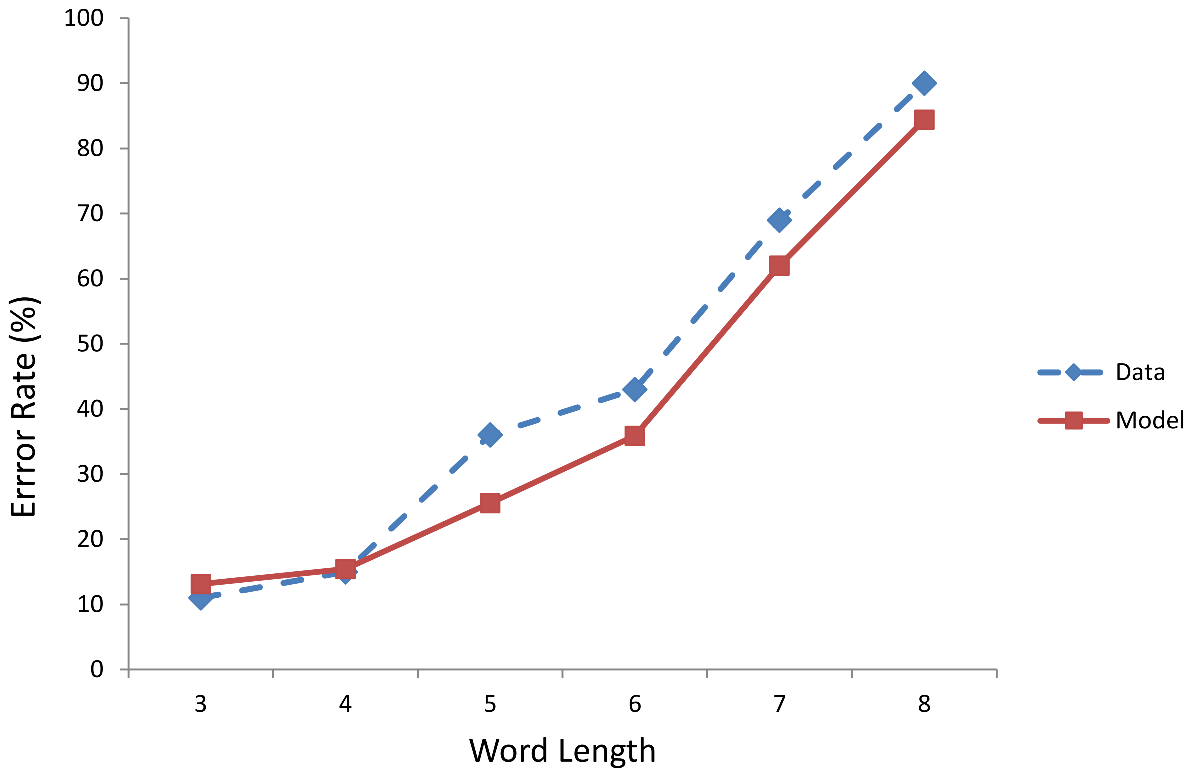


Figure 2.4. Results of Study 2.1. for noise level, $\sigma = 0.175$. The figure shows the error rate as a function of word length in the model and dysgraphic subject AE. The error rate at longer word lengths is accelerated compared to the shortest word lengths – it is easier to spell two 4-letter words than one 8-letter word.

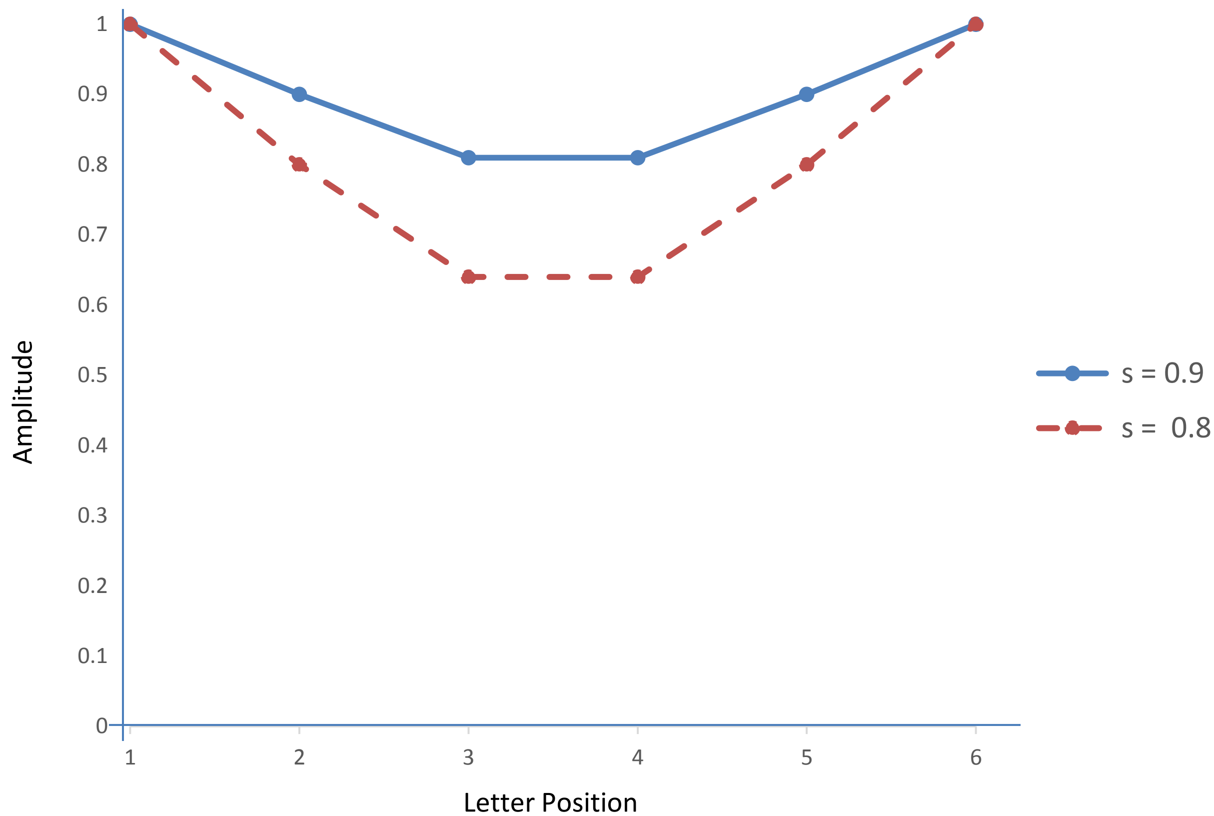


Figure 2.5. Different degrees of symmetric terminal (Start-End) letter bias, as implemented in study 2.2, illustrated for 6-letter words. Letter tokens towards the end of words are associated with higher amplitudes. In position code assignment, this leads to greater "crowding" of medial positions, and an increase in the proportions of medial letter errors.

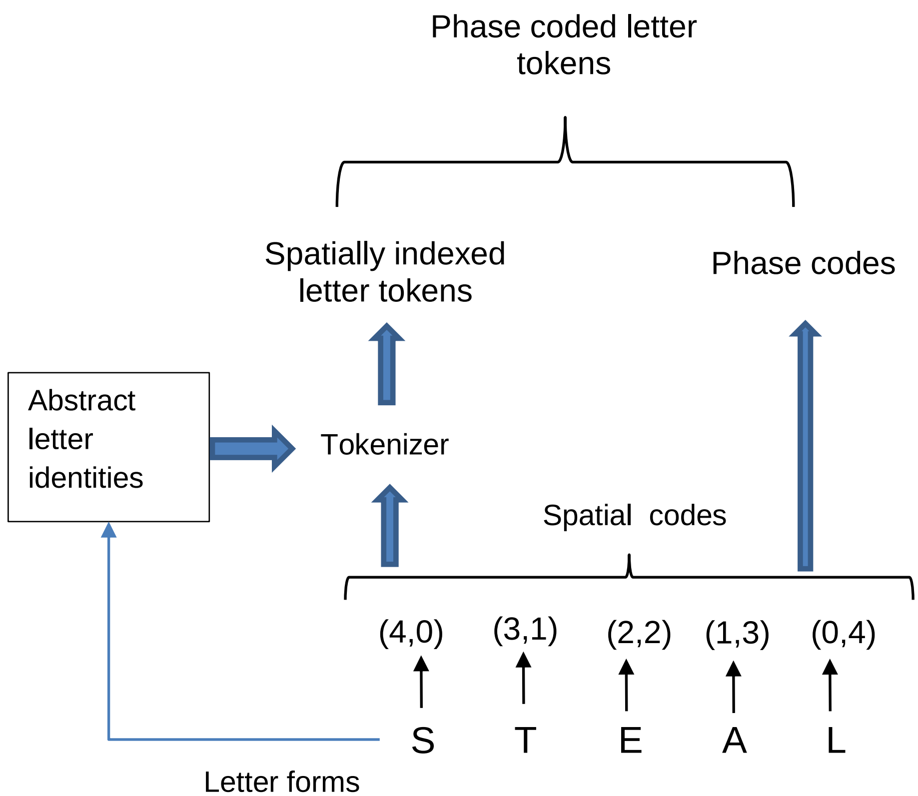


Figure 3.1. Input processing in the SE-PC reading model. The input STEAL is shown along with the word-centered spatial coordinates (k,j) assigned to its letters. On the left side of the figure, analysis of letter form retrieves abstract letter identity information, which is tokenized with respect to the spatial coordinates of the letter object. On the right, the spatial code is converted to phase co-ordinates, which are combined with the letter-tokens. The end result is a visual token representation which is isomorphic to the response token representation used in the SE-CQ spelling model.

Figure 3.2

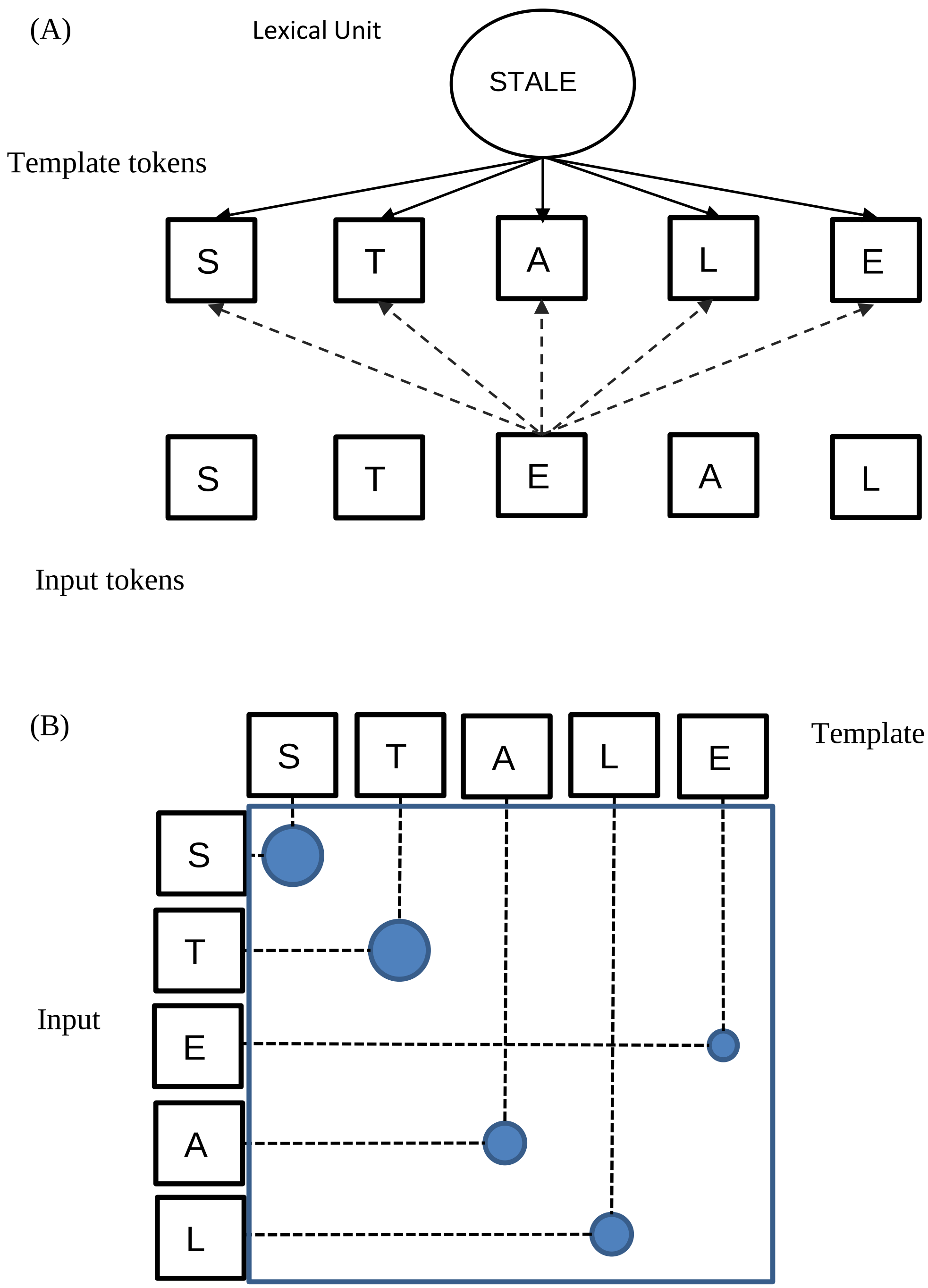

(A)
Lexical Unit
STALE
Template tokens
S
T
A
L
E
S
T
E
A
L
Input tokens
(B)
S
T
A
L
E
Template
S
T
Input
E
A
L

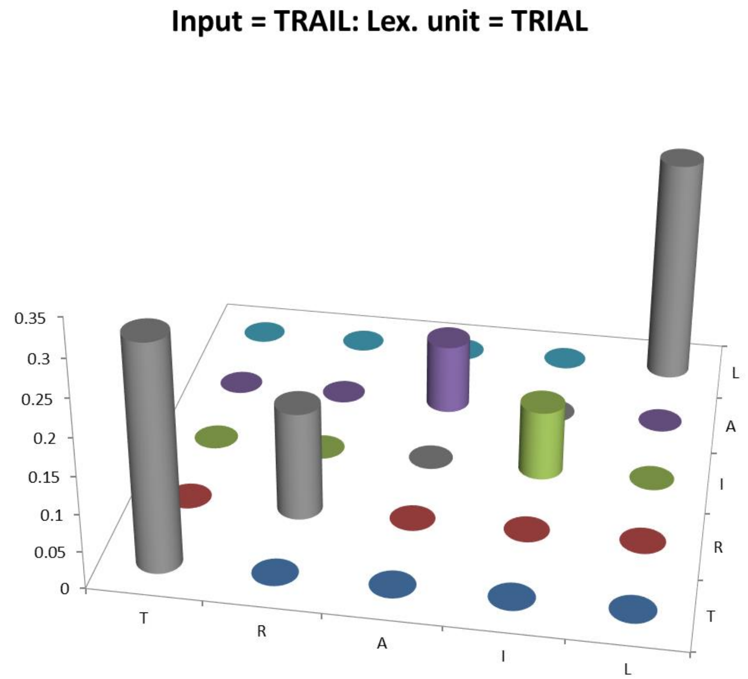
Figure 3.2. Lexical matching between a lexical unit *stale* and input STEAL.

(A) The letters in both the input and lexical template are represented as a group of positionally coded tokens, each shown as a square containing the associated letter identity (type). Every token in the input is compared to every token in the template. The dashed lines show just one set of comparisons, from the input letter E. This generates a non-zero signal at the final-E of the template, sensitive to the positional discrepancy between them.

(B) The comparison between any pair of token representations is given by their inner product. The whole-word comparison is then the matrix product of the input and template (Equation C4). Application of the resonance function R generates a matrix of input signals, each shown as a filled circle whose radius reflects the signal amplitude. Dashed lines connect the input and template units responsible for generating the signal.

Figure 3.3

(A)


Input = TRAIL: Lex. unit = TRIAL
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
T
R
A
I
L
L
A
I
R
T

(B)

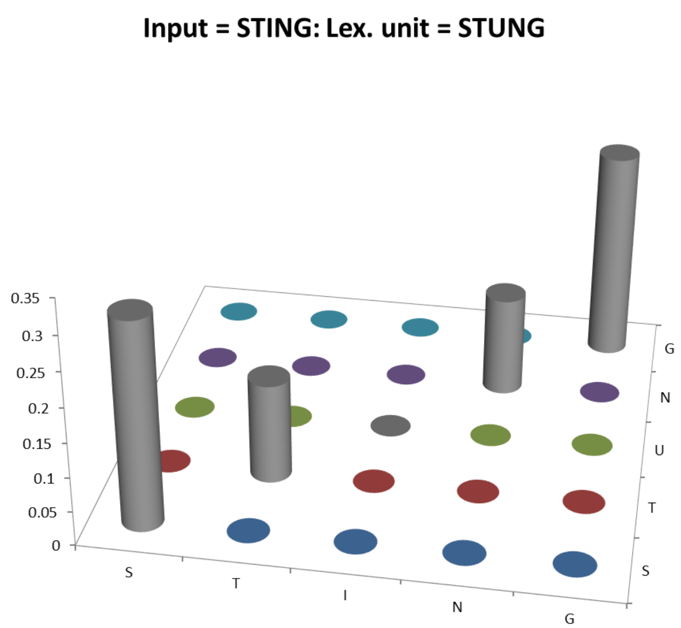
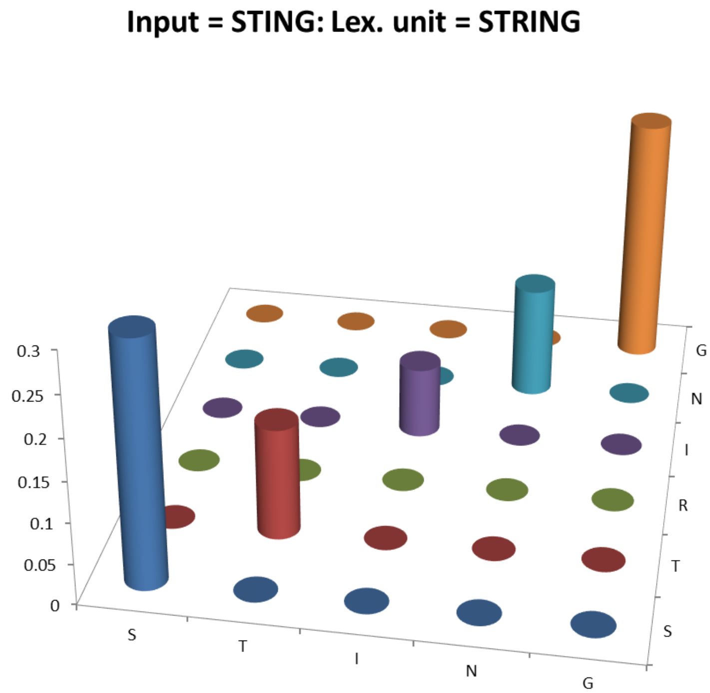

Input = STING: Lex. unit = STUNG
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
S
T
I
N
G
G
N
U
T
S

Figure 3.3

(C)


Input = STING: Lex. unit = STRING
0.3
0.25
0.2
0.15
0.1
0.05
0
S
T
I
N
G
S
T
R
I
N
G

(D)

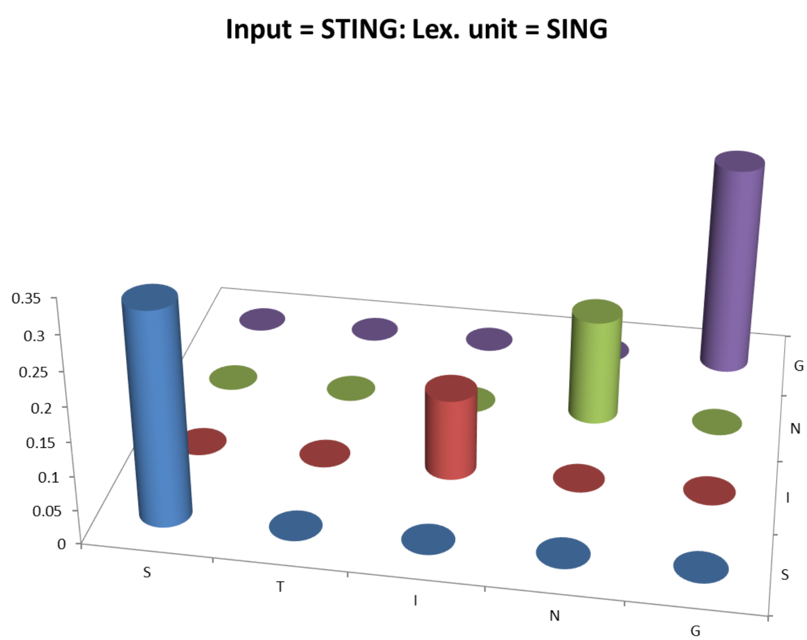
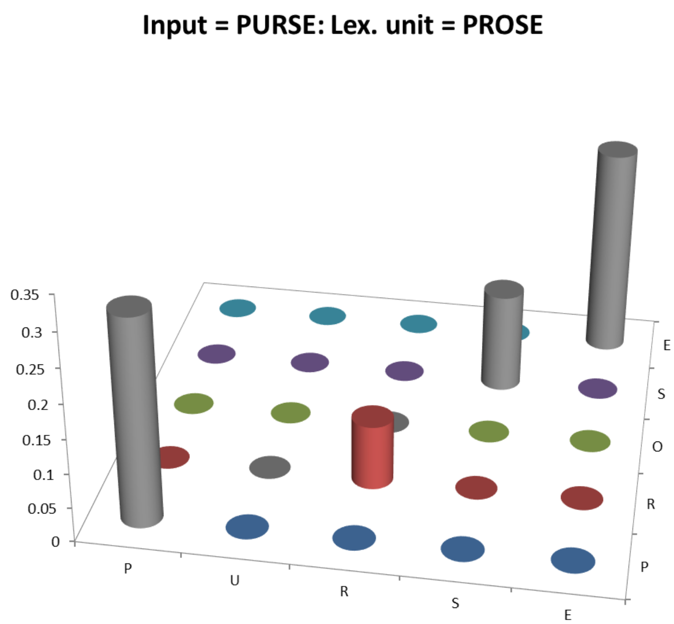

Input = STING: Lex. unit = SING
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
S
T
I
N
G
S
I
N
G

Figure 3.3

(E)


Input = PURSE: Lex. unit = PROSE
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
P
U
R
S
E
E
S
O
R
P

(F)

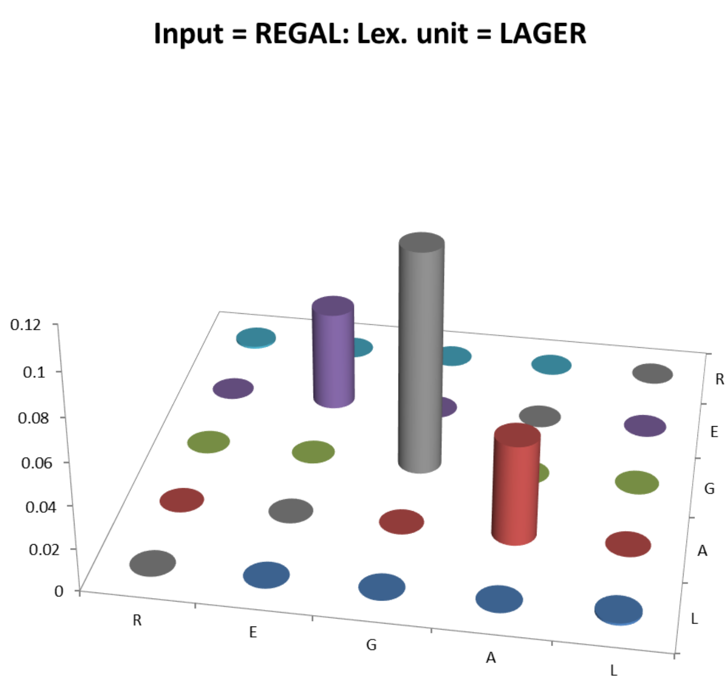

Input = REGAL: Lex. unit = LAGER
0.12
0.1
0.08
0.06
0.04
0.02
0
R
E
G
A
L
R
E
G
A
L

Figure 3.3. Examples of the signal matrix (S-matrix) generated by the interaction of an input string *P* with a lexical template (Lex. unit) *W* (Equation C4). In each case the columns (front-to-back) are labelled with the letters of the input, and the rows (left-to-right) with those of the template. The height of a column shows the strength of the signal, and its location the input and template letters that have combined to produce it. In the illustrated case, the lexical match score is the sum of the set of signals. (A) Adjacent transposition, T_1; (B) Single substitution, S_1; (C) Deletion, $D_{1;}$ (D) Addition, $A_{1;}$ (E) Combined transposition plus substitution, $S_1T_{1\ ;}$ (F) Reversal anagram, RA.

Figure 3.4

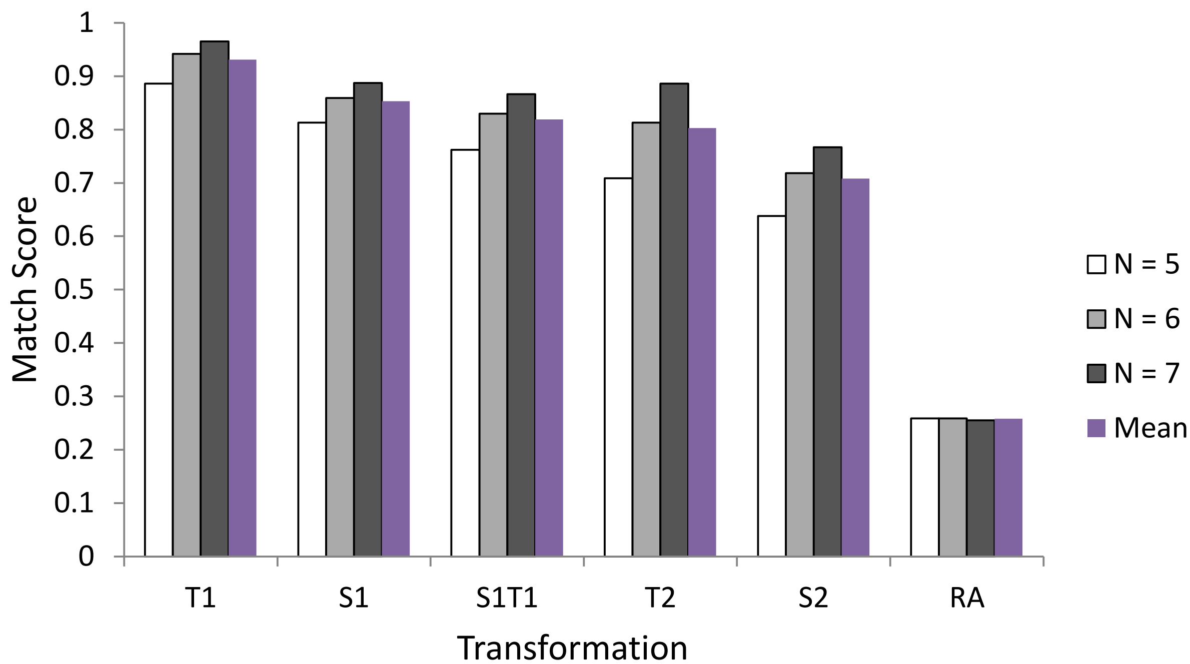


Figure 3.4: Results from study 3.1. Lexical match scores (y-axis) produced bySE-PC for 5 experimental conditions (x-axis), for 3 word lengths N (legend). The columns are grouped by the relationship (transformation) between the input pattern and lexical template (Key: see Footnote 9; Figure 3.3). The baseline condition, RA, is formed by reversal anagrams.

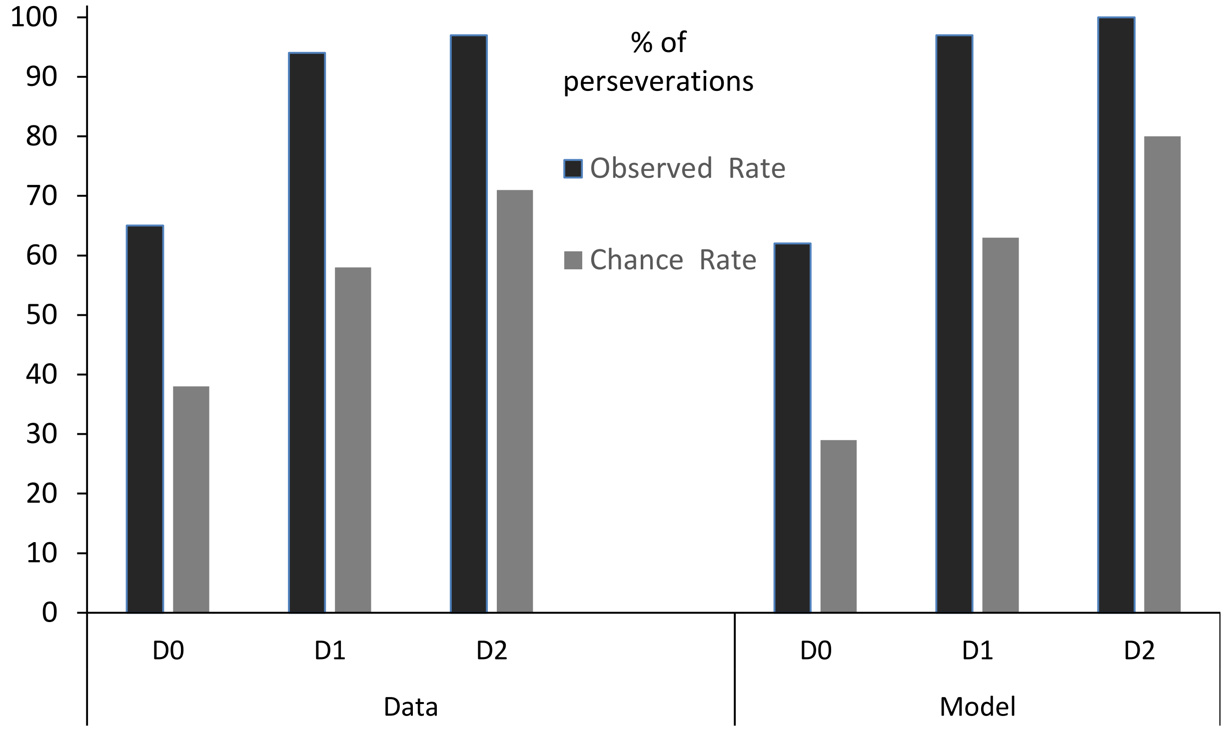


Figure 3.5. Results of study 3.3a, comparison of observed and model outcomes, along with chance rates. Y-axis shows proportion of all perseveration errors. Key: D0 = exact position match on at least one BEM coordinate. D1 = at least one BEM coordinate no further than one position from its source (D0 + D1). D2 = at least one BEM coordinate no further than two positions from its source (D0 + D1 +D2).

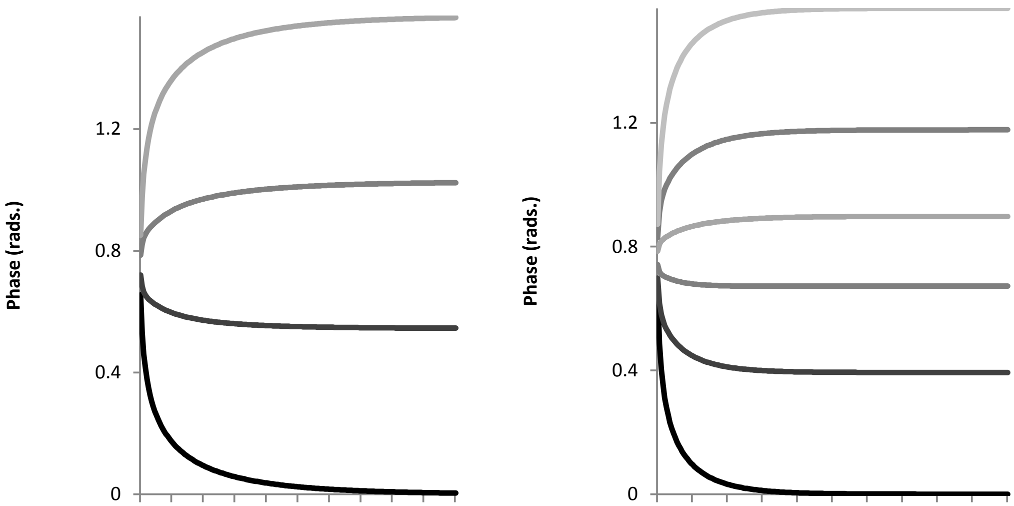


Figure A1. Position code alignment to the Start-End space via the SE-CA algorithm; left, a four-item sequence; right a six-item sequence. The position codes start out close together around the middle of the range of possible values (left of each figure). Through their interactions they spread out to fill the available space, the first and last items being aligned to the Start and End states. The resultant, stable, distribution of position codes preserves the order of the initial distribution, but is otherwise independent of it.

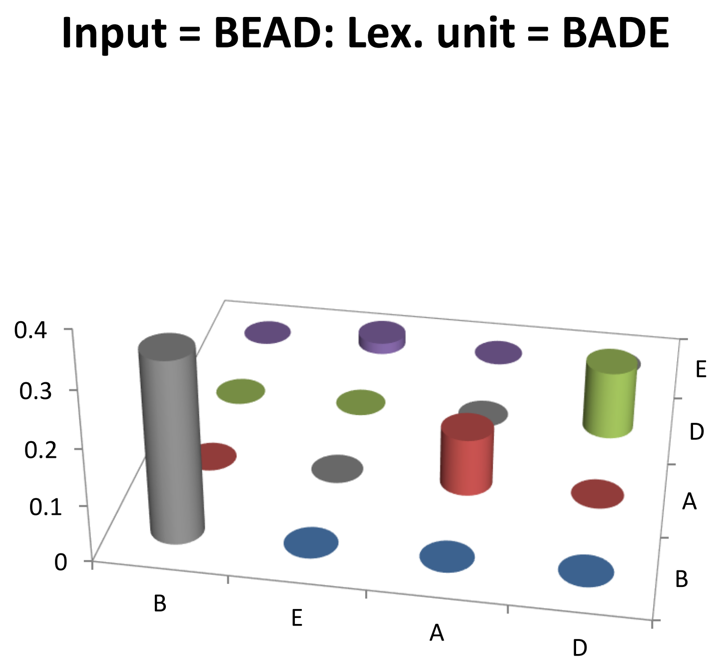


Figure C1.

The match signal (S-) matrix for the input BEAD to the lexical item *bade*, produced by Equation C4, as described in the text. Each row (left-to-right) contains all the signals generated at the template letter with which the row is labelled. The match score .57 is the sum of these signals.

Appendix A.

Representation and assignment of position codes.

Position codes are represented as the phases of *p*-unit states. The amplitude of a unit $p_j = A_j u_j$ is denoted $Am(p_j) = A_j$, and the phase $Ph(p_j) = u_j$, implemented as a complex number, $u_j \equiv e^{i\theta_j}$. This formalism permits the position code to be represented as a unit vector u_j in the direction θ_j (Figure 2.1; cf. Hartley et al., 2016; Mozer et al., 1992).

Note that the symbol i in $e^{i\theta_j}$ represents the unit element of the vertical axis, which in the present case is the End-axis (i is never used as an index symbol in the model description). Hence one can think of the exponent as expressing the degree of "rotation" of the unit position code in the direction of the End state. The Start-state is therefore $\psi_S = e^{i0}$, and the End-state, $\psi_E = e^{i\pi/2}$.

In Glasspool & Houghton (2005), the difference between position codes is given by their Euclidean distance. Identification of the position code with the phase requires a different approach. States p_j and p_k are compared via their inner product, $p_{jk} = p_j p_k^*$, where p^* denotes the complex conjugate. The latter negates the phase, $Ph(p_k^*) = e^{-i\theta_j}$, but leaves the amplitude unchanged. Hence, we have

$$p_j p_k^* = A_j A_k e^{i(\theta_j - \theta_k)}$$

The amplitude of p_{jk} is therefore the product of the amplitudes of p_j and p_k, $A_j A_k$, while its phase encodes their phase (position code) difference, $\theta_j - \theta_k$. For equal position codes, $\theta_j - \theta_k = 0$, the inner product is just the product of the amplitudes. This product is usually converted to a real-valued signal by the resonance function R (Equation 1). This acts as a (Gaussian) positional tuning curve, with the signal amplitude decreasing as the phase (positional distance) increases. For a position code difference of 0, R just returns the amplitude of it is input. Consequently, it is always the case that if two states have the same position code, their ("resonant") interaction is always just the product of their amplitudes. Though of less importance here, the amplitude of the sum of two equal position codes is likewise just the sum of their amplitudes (e.g., Equation C6).

The inner product generalises to vectors of *p*-unit states, in which case the pair-wise inner products of the vector elements (defined as above) are summed (vectors and matrices are denoted here by upper-case italics). Formally, for two *p*-unit vectors P, Q, the inner product $< P, Q >$ is therefore,

$$< P, Q >= \sum_{j=0}^{n-1} p_j q_j^*$$

This operation is used whenever two letter token representations (which are vectors) are compared.

When the asterisk (conjugate) notation is applied to a vector or matrix, W^*, it denotes the conjugate transpose of W, i.e., all the elements of the transposed object W^T are also conjugated. This permits the concise formulation of multiple letter token comparisons as a matrix product W^*P (e.g., Equations C4, C5), where W may be a lexical representation and P an input string. Each such comparison then takes the form of the inner product of one column (i.e., letter token) of P and one column of W (formally, a row of W^*, due to the transposition).

Table A1 here

Assignment of position codes by minimising crowding (SE-CA)

This mechanism assigns position codes by minimising a positional cost (or crowding) function (Table A1 for parameter values). The cost function for a set of letter tokens Q is the sum of the costs c_j of the individual tokens, being the degree to which they are "crowded" by each other. The cost c_j has a sign, opposite on opposite sides of the token, given by

$$c_j = E_j - L_j \qquad (A1a)$$

where,

$$E_j = 1/A_j \sum_{k<j} R(q_{jk}) \qquad (A1b)$$

$$L_j = 1/A_j \sum_{k>j} R(q_{jk}) \qquad (A1c)$$

E_j and L_j are aggregate signals from items respectively earlier and later than q_j. Each signal is the resonance function applied to the inner product of the letter token states. Division by the amplitude of q_j means that higher amplitude tokens have a greater effect. Each token q_j receives a crowding signal c_j, (Equation A1a), and shifts its position code θ_j so as to reduce it,

$$\tau \frac{d\theta_j}{dt} = B(\theta_j)c_j \qquad (A2)$$

The function, $B(\theta_j) = \theta_j(\psi_E - \theta_j)$, keeps the position codes in the allowed range [ψ_S, ψ_E]. The result is that when $E_j > L_j$ the code shifts to a later value, while when $E_j < L_j$, it shifts to an earlier value. Both shifts reduce the crowding cost c_j towards 0 (equilibrium). The process is illustrated in Figure A1 for 4- and 6-letter words. More examples can be found in the Supplementary Online Materials.

Figure A1 here

Appendix B.

The SE-CQ spelling model.

In the following, time- (or position-) dependent variables are denoted with a subscript *t*; *n* is the number of letters in a word; *d* is the number of letter identities; ψ_S, ψ_E denote the Start- and End-states respectively. Parameter values are in Table A1.

Each lexical item is associated with a *d* × *n* matrix representation W_ℓ of the letters it contains. On activation, W_ℓ is multiplied by the lexical activation a_ℓ, to generate a set of response tokens, Q**,**

$$Q = \mathrm{a}_\ell W_\ell \qquad \text{(B1)}$$

Unless otherwise stated, $\mathrm{a}_\ell = 1$. Each letter response token is represented by one column of Q , which specifies the identity and position code of the letter.

The Start-End signal p_{SE} is the weighted aggregate of two synchronised signals, p_s (Start) and p_e(End), with the same phase but differing amplitudes. With weighting vector W_{SE}, p_{SE} is given by,

$$p_{SE} = W_{SE} \cdot (p_s\, , p_e) \qquad \text{(B2)}$$

In most simulations, $W_{SE} = (1{,}1)$, and hence $p_{SE} = p_s + p_e$. During recall, the Start unit amplitude falls and the End unit rises (Glasspool & Houghton, 2005). To achieve this, the Start-End phase φ is normalised, being 0 at the start state and 1 at the end state. Then the amplitudes are given by,

$$Am(p_s) = Am(\psi_S)\; s^{\varphi} \qquad \text{(B3a)}$$

$$Am(p_e) = Am(\psi_E)s^{1-\varphi} \qquad \text{(B3b)}$$

where $s = .08$.

In the following, R is the resonance function; S_t is a matrix of excitatory signals from the response tokens to the response ID units; L_t contains the sum of these signals to each of the ID units; ID_t is the current state of the latter; F_t is the feedback to them from the response selection process (competitive filter). The model is given by,

$$S_t = R(p^*_{SE}\, Q) \qquad \text{(B4a)}$$

$$L_t = S_t U^n \qquad \text{(B4b)}$$

$$ID_{t+1} = \delta ID_t + gL_t + w^- F_t + \text{noise} \qquad \text{(B4c)}$$

B4a generates the top-down signals from the response tokens Q. The tokens are multiplied (inner product, Appendix A) by the Start-End signal, and the resonance function applied to the products (cf. Equation C4). In B4b the signals in each row of the matrix S_t are summed, to give one input per letter identity (U^n is a vector of *n* ones). In B4c the activation state of the Letter-ID unit vector is updated: the first term is the decay of the previous state; the second is the excitatory lexical input (weighted by a global gain parameter, g); the third is the inhibitory feedback from the competitive filter (global gain parameter w^-), and the last is 0-mean Gaussian noise, used to implement impairment to the graphemic buffer.

The state of the Letter-ID units ID_t is fed forward in a one-to-one fashion to the competitive filter layer F_t, which chooses the next response by winner-take-all competition. After a letter identity is selected for output, F_t is fed back to the Letter-ID layer with gain parameter w^{-}. As response latency is not exploited, the larger simulations were sped up by setting the filter unit receiving the strongest signal from the Letter-ID units to 1 and the rest to 0.

Studies 2.4 & 3.4, perseverative intrusions.

These studies simulate the interaction between a current and a previous processing episode.

Memory for the previous episode. The previous episode is stored verdically, but with all activation levels (amplitudes) decayed according to the parameter, $\delta(mem) = 0.7$.

Binding strength. The "binding strength" $B_{jk} \equiv B(s_j, t_k)$ between a source token s_j in memory and a target token t_k is given by the application of the resonance function R to a measure of the difference between them, d_{jk}

$$B(s_j, t_k) = R(d_{jk}) \qquad \text{(B5a)}$$

The amplitude and phase differences represented by d_{jk} are given respectively by,

$$Am(d_{jk}) = \max[0, Am(s_j) - Am(t_k)] \qquad \text{(B5b)}$$

$$Ph(d_{jk}) = Ph(s_j t_k^*) \qquad \text{(B5c)}$$

Hence d_{jk} encodes the amplitude advantage of the source over the target token (B5b), and the difference between their position codes (B5c). It is the former (Equation B5b) that marks this as a competitive process, and distinguishes it from the letter priming model (Appendix C).

Perseveration probability. Each binding strength B_{jk} at a target token t_k is converted to a probability that a perseverative substitution $t_k = s_j$ will take place according to

$$p(t_k = s_j) = \frac{B_{jk}}{\sum_j B_{jk} + Am(t_k) + w} \qquad \text{(B6)}$$

On the right, the numerator is the binding strength as defined by B5a-c. The first term in the denominator is the sum of binding strengths at target token t_k from all sources s_j; the second term is the amplitude of t_k; the third is a "bias" weight, which helps prevent collections of weak binding strengths from becoming large probabilities due to the normalisation. In all simulations, $w = 0.1$. Choice of substitution (if any) is made by Monte Carlo simulation over the probability distribution generated by B6.

The Supplementary Online Materials contains a Worked Example demonstration, in which the user can examine the above process in detail for arbitrary source-target pairs. The demonstration includes the Fischer-Baum et al. (2010) BEM analysis of the model's response.

Appendix C.

The SE-PC Reading model

This appendix describes the construction of the orthographic representation in reading, illustrated in Figure 3.1. Spatial indices start with 0, and N is the last index (i.e., $N = n - 1$). As before, d is the number of letter identities (dimensionality of the alphabet). Parameter values are in Table A1.

Forming position-coded letter-tokens

Each letter identity is represented as an (orthonormal) $d \times 1$ matrix, $\mathcal{A}_\alpha$, where α indexes the identity. When a letter is identified, its type $\mathcal{A}_\alpha$ is retrieved and converted to a spatial token tied to the Start and End edges of the input string. The spatial Start-index j runs rightward from 0 to N, while the End-index k runs leftward from 0 to N, giving each location a dual spatial code $s_{kj} = (k, j)$, obeying $j + k = N$ (the x and y-axes are "flipped", to eventually get the Start codes on the x-axis).

Each letter location s_{kj} in an *n*-letter input is associated with a pair of location markers, (G_j, G_k), implemented as $1 \times n$ matrices. The Start amplitude (j indices) falls exponentially from left to right, while the End (k indices) amplitude rises. The slope is controlled by a parameter σ, with $0 < \sigma \leq 1$, expressing the "common ratio" of the exponential change; it has default value σ = 0.8 (as in SE-CQ, Table A1). A location marker contains only one non-zero element, at its indexed location, given by,

$$G_j(j) = Am(\psi_S)\sigma^j \qquad \text{(C1a; Start)}$$

$$G_k(k) = Am(\psi_E)\sigma^k \qquad \text{(C1b; End)}$$

(by default, $Am(\psi_S) = Am(\psi_E) = 1$; c.f., Equations B3a, b for Start-End unit amplitudes during spelling). When a letter occurs at a location (j, k) the associated location markers convert its type $\mathcal{A}_\alpha$ to spatially-bound tokens of that type. Each binding is formed as the tensor product (or vector outer product) of the letter type and the associated location marker (a mechanism proposed for connectionist variable binding, Smolensky, 1990). For instance, for the Start representation of a letter $\mathcal{A}_\alpha$ with location G_j, the binding $\mathrm{B}_{\alpha j}$ is given by,

$$\mathrm{B}_{\alpha j} = \mathcal{A}_\alpha \otimes G_j$$

In this case, this operation takes two vectors (or single indexed objects), representing a letter identity and a location marker, and generates a matrix (or dual-indexed object), which associates the letter identity and the location. For instance, suppose we have an alphabet {A, B, C}, where $A = (1\ 0\ 0)\ , B = (0\ 1\ 0)$ etc. For the input CAB, the Start-representation of the C in the first letter position (start index, $j = 0$) would be formed as, $\mathcal{A}_C \otimes G_0 =$

$$(0\ 0\ 1) \otimes (\sigma^0\ 0\ 0) = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} [1\ 0\ 0] = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

The resultant matrix on the right associates (or "binds") the letter C with the first letter position, the desired outcome.

The Start- and End-representations of the whole string are formed by superposition of such letter tokens. For instance, for the Start-representation, T^S

$$T^S = \sum_j \mathrm{B}_{\alpha j} \qquad \text{(C2)}$$

The end-anchored representation is formed in the analogous manner, and the start and end representations are superposed to produce a unified representation W. This may be by element-wise addition, or by taking the maximum of two the superposed values at each location in the structure. Either method generates a U-shaped amplitude profile over the letter tokens.

To generate the phase codes, each spatial code s_{kj} is normalised, $|s_{kj}| = 1$ and represented in polar form, $s_{kj} = e^{i\theta}$. The code for the *j*th letter is stored at $C_{j,j}$ in a diagonal $n \times n$ matrix, C. The identity tokens T and position codes C are combined linearly into a single object P, as their product,

$$P = TC \qquad \text{(C3)}$$

(Matrix dimensions: $T = d \times n; C = n \times n;$ hence, $P = d \times n$)

The final reading representation P is in all important respects the same as the spelling representation Q, of the SE-CQ model. If passed to the latter, it can be spelled out.

The final manipulations of this representation prior to lexical matching are,

i) Application of the SE-CA algorithm (Appendix A) to the tokens.

ii) Normalisation of the token amplitudes, to give the lexical match score the character of a correlation.

Lexical matching

The lexical representation is that used for spelling by the SE-CQ model, with normalised amplitudes. Every input letter (token) is compared to every template token (main text), implemented as the application of the resonance function (Equation 1) to the matrix product of the input and (conjugate transposed) template. For an *n*-letter input P to an *m*-letter template W_ℓ, this produces an $m \times n$ matrix of signals, S_ℓ, given by

$$S_\ell = R(W_\ell^* P) \qquad \text{(C4)}$$

(Matrix dimensions: $W_\ell^* = m \times d$; $P = d \times n$; hence, $S_\ell = m \times n$).

The matrix product computes the inner product of every input token with every template token (Appendix A), the signal in the *j*th row and *k*th column, $S_\ell(j,k)$**,** being formed from the comparison between template token *j* and input token *k*. This is followed by the application of the resonance function. As a result, row *j* of S_ℓ contains all the signals generated at the *j*th template token (Figure 3.3, for examples; and the Supplementary Online Materials).

The lexical net input (or match score) is an aggregate of the signals produced by this process, and generally lies in the range [0,1] (facilitating comparison with other models of lexical access, Study 3.1b). Two aggregation rules have been implemented: (i) summation of all the signals, (ii) summation of the maximum signal at each template token (formally, each row of S_ℓ). The rules differ only in their treatment of repeated letters (e.g., *r* in *rarer*). The model generates "cross signals" between tokens of the same type, which rule (ii) ignores. The issue of the effect of letter identity repetition is of interest, both in spelling and reading, but is not treated in this article (Fischer-Baum, in press; Mozer, 1989).

An example. To simplify the illustration, suppose we have a 4-letter alphabet {A, B, D, E}, $A = (1\ 0\ 0\ 0), B = (0\ 1\ 0\ 0)$, etc. The set of signals generated at the lexical item W_ℓ = *bade* by the input $P =$ BEAD, is formed from the "cross" product, $W_\ell^* \times P$, shown below (for W_ℓ^* the letter tokens form the rows, while for P they form the columns):

$$W_\ell^* \qquad \times \qquad P \qquad = \qquad M$$

$$\begin{array}{c} B \\ A \\ D \\ E \end{array} \begin{bmatrix} 0 & w_1^* & 0 & 0 \\ w_2^* & 0 & 0 & 0 \\ 0 & 0 & w_3^* & 0 \\ 0 & 0 & 0 & w_4^* \end{bmatrix} \times \begin{array}{c} \begin{array}{cccc} B & E & A & D \end{array} \\ \begin{bmatrix} 0 & 0 & p_3 & 0 \\ p_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & p_4 \\ 0 & p_2 & 0 & 0 \end{bmatrix} \end{array} = \begin{bmatrix} w_1^* p_1 & 0 & 0 & 0 \\ 0 & 0 & w_2^* p_3 & 0 \\ 0 & 0 & 0 & w_3^* p_4 \\ 0 & w_4^* p_2 & 0 & 0 \end{bmatrix}$$

Each element m_{jk} of the matrix M on the right is formed as the inner product of the jth row (letter token) of W_ℓ^* and the kth column (letter token) of P (Appendix A). Hence all input letters are compared to all template letters. The initial letters B of the input and template match in both identity and position, hence the phase (position code) difference, $Ph(w_1^* p_1)$, will be 0. The other matches will have a non-zero phase difference. To generate the match signal matrix S_ℓ, the resonance function is applied element-wise to $M = W_\ell^* P$ (Equation C4; Figure C1).

Figure C1 here

For the letter B, the result of the letter match is just the product of the amplitudes of the input and template letters, and this is not changed by the resonance function (Appendix 1). For the other three letter matches however, there is a positional mismatch, producing a weaker signal the greater the mismatch. The aggregate match score (= .568 in this case) is the sum of these letter match signals. The signal matrix S_ℓ is shown in Figure C1. The examples shown in Figure 3.3 are generated in precisely the same manner, but with the full alphabet.

The Supplementary Online Materials contains a Worked Examples demonstration, in which the user can observe the above process in detail for arbitrary letter strings. The application also provides a facility for batch processing of multiple stimulus pairs.

Study 3.2. Letter identification priming.

Study 3.2 requires a model of priming of letter identification. The proposed model avoids the introduction of novel parameters. The *n*-letter prime P_1 and *m*-letter probe P_2 appear in succession and are processed as described above, without scaling. The two representations interact via the matching rule, Equation C4, with the probe taking the place of the lexical template. This generates an $m \times n$ signal matrix S

$$S = R(P_2^* P_1) \qquad \text{(C5)}$$

(Matrix dimensions; $P_2^* = m \times d;\ P_1 = d \times n;$ hence $S = m \times n$). Row *j* of S contains the signals from the prime to the *j*th letter token in the probe. To aggregate the signals to each probe letter, the signals in each row of S are summed, and represented as a diagonal $m \times m$ matrix, $S' = diag(SU^n)$. Denoting the initial (unprimed) state of the probe as $P_2(0)$, the state after priming, $P_2(1)$, is given by the linear model,

$$P_2(1) = P_2(0) + P_2(0)S' \qquad \text{(C6)}$$

(Matrix dimensions; $P_2 = d \times m;\ S' = m \times m;$ hence $P_2(0)S' = d \times m$). The additive priming term on the far right is the product of the prime-to-probe signals with the unprimed state of the probe. If an unrelated prime is used as a control, then this term is null.

Hence the *aggregate* priming effect, $p.e.$, on a probe stimulus, is the summed amplitudes of the signals in the priming term. Denoting the elements of the latter p_{jk} , then

$$p.e. = \sum_{j,k} Am(p_{jk}) \qquad \text{(C7)}$$

An example: Assume the same 4-letter alphabet as in the lexical matching example, and let the prime P_1 be BEAD and the probe P_2 BADE (a 1423 prime). The initial interaction between the prime and probe, Equation C5, is exactly that of the lexical match model (described above), with the initial probe representation $P_2(0)$ taking the place of the lexical template. The signals in each row of the match signal matrix S (Figure C1, now interpreted as the priming signals to each probe letter,) are summed, to form a diagonal 4×4 matrix S'; that is, the diagonal element s_{jj} of S' represents the aggregate priming signal to the *j*th probe letter. The unprimed state of the probe BADE, $P_2(0)$, is then multiplied by these signals (Equation C6), generating a priming effect matrix $P_2(0)S' = PE$, as shown here.

$$P_2(0) \quad \times \quad S' \quad = \quad PE$$

$$\begin{array}{cccc} \mathrm{B} & \mathrm{A} & \mathrm{D} & \mathrm{E} \\ \end{array}$$
$$\begin{bmatrix} 0 & p_2 & 0 & 0 \\ p_1 & 0 & 0 & 0 \\ 0 & 0 & p_3 & 0 \\ 0 & 0 & 0 & p_4 \end{bmatrix} \times \begin{bmatrix} s_1 & \cdots & & \\ \vdots & s_2 & & \\ & & s_3 & \vdots \\ & & \cdots & s_4 \end{bmatrix} = \begin{bmatrix} 0 & s_2 p_2 & 0 & 0 \\ s_1 p_1 & 0 & 0 & 0 \\ 0 & 0 & s_3 p_3 & 0 \\ 0 & 0 & 0 & s_4 p_4 \end{bmatrix}$$

Clearly, the probe representation P_2 and the priming effect PE have the same structure, and so can be summed (this will be the case no matter how many rows are in P_2). Since corresponding elements in the two matrices have the same phase (position code), the summation

(Equation C6) simply adds the amplitudes of the elements in PE to those in the probe, $P_2(1) = P_2(0) + PE$. Hence the aggregate priming effect is given by the summed amplitudes of PE (Equation C7).

The Supplementary Online Materials contains a Worked Examples demonstration, in which the user can observe the above process in detail for arbitrary letter strings, along with a facility for batch processing of multiple prime-probe pairs.