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Frédéric Dandurand*, Jonathan Grainger and Stéphane Dufau

Laboratoire de Psychologie Cognitive, CNRS & Aix-Marseille University, 3, place Victor Hugo, 13331 Marseille, France

Neural networks were trained with backpropagation to map location-specific letter identities (letters coded as a function of their position in a horizontal array) onto location-invariant lexical representations. Networks were trained on a corpus of 1179 real words, and on artificial lexica in which the importance of letter order was systematically manipulated. Networks were tested with two benchmark phenomena – transposed-letter priming and relative-position priming – thought to reflect flexible orthographic processing in skilled readers. Networks were shown to exhibit the desired priming effects, and the sizes of the effects were shown to depend on the relative importance of letter order information for performing location-invariant mapping. Presenting words at different locations was found to be critical for building flexible orthographic representations in these networks, since this flexibility was absent when stimulus location did not vary.

Keywords: reading; orthographic processing; supervised learning; artificial neural networks

1. Introduction

Several recent computational models of visual object recognition posit a hierarchical system of processing in which simple and local features are gradually integrated into more abstract and complex features using receptive fields of increasing size (Riesenhuber and Poggio 1999). These hierarchical architectures account for the progressive invariance to size, shape, and location, that is achieved as one moves through the visual pathways from V1, V2 up to occipital and temporal cortex. The mechanisms that we develop to process printed words while learning to read, borrow heavily from the basic machinery of visual object recognition (Dehaene, Cohen, Sigman, and Vinckier 2005; Grainger 2008). Therefore visual word recognition shares many of the characteristics of object recognition. Location invariance is one such characteristic, since skilled readers are able to identity words that are displaced relative to a central fixation point without having to re-fixate the centre of the word. Given that even very small shifts of location imply a complete change in retinal activity, this implies that some form of non-retinotopic code is involved in visual word recognition. The key question concerns the precise nature of this location-invariant, word-centred code, and how it is activated by retinotopic features.

*Corresponding author. Email: frederic.dandurand@univ-provence.fr

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Some psychological models have postulated that the shift from a location-specific, retinotopic orthographic code to a location-invariant orthographic code is achieved by coding for combinations of letters in the correct order for both contiguous and non-contiguous letter sequences (Grainger and Whitney 2004; Dehaene et al. 2005). For example, in the models of Grainger and van Heuven (2003) and Whitney (2001), the so-called open bigrams code two-letter combinations in a position-independent yet ordered, but not necessarily contiguous fashion. For example, WITH is composed of the following open bigrams: WI, WT, WH, IT, IH, and TH. In certain versions of these models activation of open bigrams can be modulated by distance (i.e., contiguous bigrams like WI are more active than non-contiguous bigrams such as IH). An important characteristic of open bigrams is that, while they allow for non-contiguous letter combinations, they preserve letter order. For example, IW is not an open bigram for the word WITH.

The theoretical backbone of the present study is Grainger and van Heuven's (2003) model of orthographic processing (Grainger, Granier, Farioli, Van Assche, van Heuven 2006) illustrated in Figure 1. In this model, a bank of location-specific letter detectors perform parallel independent letter identification. A given configuration of visual features at a specific location along the horizontal meridian signals the presence of a given letter at that location (see Dufau, Grainger and Holcomb 2008; Tydgat and Grainger 2009, for evidence in favour of such retinotopic letter detectors). These location-specific letter detectors then activate location-independent open-bigram units. Open-bigrams then send activation to all compatible word representations in an interactive-activation network.

In the present study, we apply backpropagation neural networks to investigate to what extent the constraints of learning location-invariant lexical representations leads naturally to the development of the kind of flexible relative-position code described in the Grainger and van Heuven model. Following the Grainger and van Heuven model, we implemented location-specific letter detectors as input, and simulated presentation of the same word at different locations by activating different sets of letter detectors. The task consisted in recognising these words presented at different locations as identical, location-independent lexical units (orthographic word forms). The network was trained on a corpus of real words, and on artificial lexica in which the importance of letter order was manipulated systematically.

One prior study has investigated the learning of location-independent orthographic representations using backpropagation. Shillcock and Monaghan (2001) used a task that they

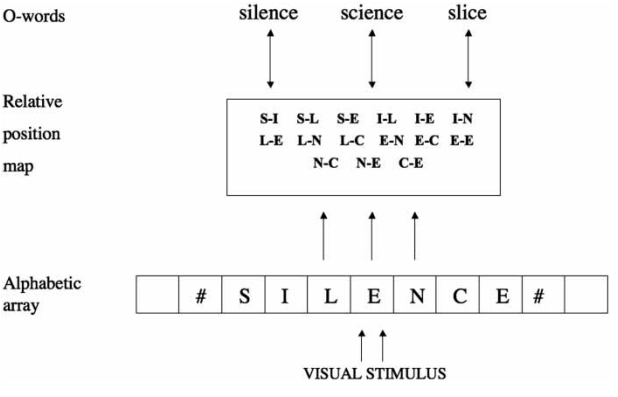

Figure 1. Grainger and van Heuven's model of orthographic processing. Visual features extracted from a printed word feed activation into a bank of location-specific alphabetic character detectors (the alphabetic array). Each slot in the array codes for the presence of a given letter identity at a given location along the horizontal meridian. The next level of processing combines information from different processing slots in the alphabetic array to provide a relative position code for letter identities. These relative-position coded letter identities control activation at the level of whole-word orthographic representations (O-words) via bi-directional connections with all units at the relative position level.

called shift invariant identity mapping that consists in mapping location-specific letters into a location-independent representation of the same letters. For example, a neural network would learn to associate patterns WITH##, #WITH#, and ##WITH (in which # represent blanks) to the common output WITH coded as a given letter identity at each of the four possible positions (slot-coding). In their model, Shillcock and Monaghan simulated visual hemifields by splitting processing of the input slot at its centre, sending these split inputs to two independent processing streams. Model splitting accounted for the superiority effect of the exterior (i.e., first and last) letters of words in reading – network error was lower for the exterior letters in the split model, but not lower in a non-split model. The present study provides an adaptation of Shillcock and Monaghan's modelling strategy, applied here to the learning of location-invariant orthographic representations.

We present three sets of simulations: (1) artificial lexica with seven locations, (2) real word lexicon with seven locations, and (3) real word lexicon in a single location. These simulations were designed to explore the nature of the internal representations that are developed when learning to map a location-specific orthographic representation onto a location-invariant lexical representation (whole-word orthographic representation); that is, learning certain ordered combinations of letters as representing words. The networks were tested with two key behavioural effects thought to reflect flexible orthographic coding in human participants: the transposed-letter priming effect, and the relative-position priming effect. Both effects have been observed, using a masked priming paradigm that eliminates the role of various types of strategic responding associated with standard priming. The transposed-letter effect is a superior priming effect from primes formed by transposing two of the target's letters (e.g., gadren-garden) compared with a prime formed by substituting two of the target's letters (e.g., galsen-garden). The relative-position priming effect is a processing advantage for targets preceded by primes formed of a subset of the target's letters (e.g., grdn-garden) compared with a prime formed of the same subset of letters in the wrong order (e.g., gdrn-garden). Both of these priming effects argue against rigid slot-based coding schemes for letter encoding and are in favour of proposals for more flexible orthographic coding (Whitney 2001; Grainger and van Heuven 2003; Gomez, Ratcliff, and Perea 2008; Grainger 2008).

Other research has also investigated flexible coding of letter order, attempting to account for phenomena such as letter transposition, letter migration, repeated letters, and relative-position priming. For example, Gomez et al. (2008) account for such flexibility in their model using uncertainty about letter positions. In contrast to rigid, slot-based coding used in interactive-activation like models, letter position is represented as a probability distribution in their model, so that a letter present at a given position also provides evidence, albeit to a lesser extent, for the presence of that letter at neighbouring positions. However, letter position in the overlap model and similar approaches is defined as letter position in the word, independently of where the word is located. These models therefore fail to address the difficult issue of how information coded as being present at a particular location on the retina is mapped onto a word-centred representation. In the present study, we train networks to map a set of location-specific letter identities (where location refers to location along the horizontal meridian) onto location-invariant lexical representations via a layer of hidden representations. We then examine whether these networks can simulate the kind of flexible orthographic processing seen in human experiments.

2. Methods

All simulations used standard feed-forward neural networks that were trained with a standard gradient descent technique with momentum (McClelland and Rumelhart 1988). We used a learning

rate of 0.1, and a momentum value of 0.9. The criterion for successful training was reaching a target level for the sum of squared errors (SSE) between targets and network outputs. For the number of hidden units, we used the square root of the number of training patterns, rounded up to the closest integer. Connection weights were initialised randomly within a range of −1.0 and 1.0.

2.1. *Input coding*

We used sparse, local coding (Quiroga, Kreiman, Koch, and Fried, 2008): each letter slot was encoded using 26 binary values, indicating the presence or absence of a given letter, in alphabetical order. For instance, presence of letter *A* was encoded as [1 0 0 . . . 0], *B* as [0 1 0 . . . 0], and *Z* as [0 0 . . . 1]. Blanks were coded using zeros in all positions [0 0 0 . . . 0]. Words were presented in seven positions along a 10-slot input vector. As an illustration, Table 1 presents the encoded input pattern for word WITH in central position (###WITH###). The input pattern presented to the network would simply have been concatenation of rows 1–10 into a 260 binary-valued vector.

2.2. *Output coding*

Each word is coded onto an output unit. Presence of the corresponding word is coded using a value of 1, absence is coded as 0. For example, if target words are ABCD, EFGH, IJKL, MNOP, and QRST, an input of #ABCD##### would correspond to the output 1 0 0 0 0, whereas ####IJKL## would be associated with the output vector 0 0 1 0 0. An output value of 1 coded for the presence of the word in the input vector, and 0 coded for its absence. As an illustration, Table 2 presents a sample of training patterns from the target words only condition.

Table 1. Example of encoded input pattern for word WITH presented in central position (###WITH###).

Presence of letter coding (1 bit per letter)																									
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: The first column indicates slot position. In this example, slots 1–3 and 6–10 contain blanks. This input vector is 260 bits long (10 slots × 26 letters per slot × 1 bit per letter).

Table 2. Example of input and output for different words presented at different locations (#s represent blanks).

Input vector										Output vector				
A	B	C	D	#	#	#	#	#	#	1	0	0	0	0
#	A	B	C	D	#	#	#	#	#	1	0	0	0	0
#	#	#	#	A	B	C	D	#	#	1	0	0	0	0
E	F	G	H	#	#	#	#	#	#	0	1	0	0	0
#	#	#	#	#	#	E	F	G	H	0	1	0	0	0
#	#	#	M	N	O	P	#	#	#	0	0	0	1	0

2.3. *Composition of the training sets*

In building training sets, we presented target words in different contexts to investigate if letter sequence or order influenced the representation built by backpropagation networks. We presented two types of training sets: (1) artificial lexica of four-letter strings in order to manipulate the relative importance for letter order for determining lexical identity, and (2) a realistic corpus of 1179 real four-letter words.

2.3.1. *Artificial lexica*

We used four types of artificial lexica. All these lexica comprised the following five target words: ABCD, EFGH, IJKL, MNOP, and QRST. They also optionally included filler patterns designed to manipulate the importance of letter order, as illustrated in Figure 2.

The first training set contained the five target words only, which were the same across replications: (1) ABCD, (2) EFGH, (3) IJKL, (4) MNOP, and (5) QRST, for a total of 35 training patterns (5 words $\times$ 7 positions). Networks learning this training set had six hidden units (i.e., the square root of 35, rounded up). Replications differed in the networks' initial conditions (random weights) only.

The second training set, dubbed 'target words and letter recombinations' or 'recombinations' for short, included five filler words made of the same letters as the target words, but randomly recombined. This was done by pooling letters A to T and making filler words by randomly drawing letters, without replacement. Although target words were the same across replications, due to random selection, filler words were different in each replication. An example of a recombinations training set is as follows: (1) ABCD, (2) EFGH, (3) IJKL, (4) MNOP, (5) QRST, (6) TMEK, (7) QGAP, (8) CHNI, (9) BJFS, and (10) RDOL, for a total of 70 training patterns (10 words $\times$ 7 positions). Networks trained under this condition had nine hidden units. Replications differed in the composition of the filler words, and in network initial conditions (random weights).

The third training set, dubbed 'target words and anagrams' or simply 'anagrams' for short, included one anagram for each of the five target words. To maximise distance, we built the anagram by reversing the letter order (i.e., ABCD $\rightarrow$ DCBA). The anagrams training set was the same across replications, and contained the following words: (1) ABCD, (2) EFGH, (3) IJKL, (4) MNOP, (5) QRST, (6) DCBA, (7) HGFE, (8) LKJI, (9) PONM, and (10) TSRQ, for a total of 70

Importance of letter order

min → max

Training sets	Target words	Target words & recombinations	Target words & anagrams	Target words & anagrams & recombinations
Examples containing letter A	ABCD	ABCD & QJAP	ABCD & DCBA	ABCD & DCBA & QJAP

Figure 2. Importance of letter order in the artificial lexica.

training patterns (10 words × 7 positions). Networks trained under this condition had nine hidden units (i.e., the square root of 70, rounded up). Replications differed in network initial conditions (random weights) only.

The fourth training set, dubbed 'target words, anagrams and letter recombinations', or 'combo' for short, included the five target words, five anagrams (as described above) and five recombinations (as described above). Combo sets contained 105 training patterns (15 words × 7 positions), and replications differed in the composition of the filler words, and in the network initial conditions (random weights). Networks trained under this condition had 11 hidden units.

With the target words only training set, a single letter determines lexical identity (for instance, letter A is evidence for one and only one word, ABCD, therefore letter combinations are not a requisite for successful learning). This is not the case with the recombinations training set that also requires coding of letter combinations for successful learning, as the same letter appears in different words, but precise order information is not a requisite for successful encoding. Finally, the anagrams training set where letter order becomes critical for determining lexical identity, Therefore, the different training sets impose different levels of relevance of order information in learning to map location-specific letter identities onto location-invariant word representations. Order is least relevant in the target words only training set, more relevant in the recombinations condition and most relevant to the anagrams and combo conditions.

2.3.2. *Real word lexicon*

We also trained networks using a realistic corpus of 1179 real four-letter words, previously used by McClelland and Rumelhart (1988).

2.4. *Discrimination of words and non-words*

As a general evaluation of a network's success in correctly learning to map letter representations onto lexical identity, we measured how well the network could discriminate words from non-words. For a word to be considered correct, the activation of the correct corresponding lexical output unit had to be higher than a threshold value, empirically found to be appropriate at a level of 0.99. For a non-word to be considered correctly rejected, activations of all output lexical units had to be below this threshold.

2.5. *Network evaluation*

We investigated the nature of the internal representations built by the backpropagtion algorithm while learning to map location-specific letter representations onto location-invariant lexical representations. More precisely, we wanted to know whether the model would develop some form of flexible orthographic code similar to the type of code revealed in recent research on orthographic processing in skilled readers (Grainger 2008). We investigated these representations using test sets based on priming. In humans, priming effects are often explained by spreading activation among related or shared cognitive representations. These activation spreads may facilitate or hinder subsequent access to these related representations. This is generally measured as faster reaction times for better primes. In our models, operational definitions of priming are based on the principle that the more a given input primes a given target item, the more that target output will be activated. More specifically, we measured the amount, or quality, of priming using two methods (note that primes were never seen during training). First, the prime-target output discrepancy, dubbed 'discrepancy' for short, measures the mean square difference between network output for the prime and the vector for the corresponding target word (a single one for the target word in a vector of

zeros). In other words, the better the input prime, the closer we expect network output to be to the target word. Second, the target supremum measure quantifies the ability of the prime to activate the output unit associated with the target word more than any other output unit. For a given prime given as input, the item-level target supremum value was set to 1 when the prime activated the output unit associated with the target lexical item more than any other unit; it was set to 0 otherwise. The target supremum measure of a set of primes was computed as the mean of item-level values for the primes in the set. This simulates a winner-takes-all, lateral-inhibition-driven process in which network output units would compete to produce a single system response.

We manipulated two factors: the composition of the training set (four levels of artificial lexica: (1) target words only; (2) target words and recombinations; (3) targets words and letter anagrams; (4) target words, letter recombinations and anagrams; and (5) a real word lexicon), and the priming regime used for testing (two levels: relative-position priming, and transposed-letter priming). We combined train and test regimes in a combinatorial fashion, for a total of 10 simulations.

We tested model performance under two priming manipulations: relative-position priming and transposed-letter priming.

2.5.1. *Relative-position priming*

We studied a network's ability to simulate relative-position priming using primes formed of a subset of the target's letters, namely three-letter sequences from four-letter target words. We manipulated two parameters of the prime letters: (1) order (two levels: forward and backward) and (2) contiguity (two levels: contiguous and non-contiguous). The exhaustive set of test patterns is given in Table 3.

During training, input words were presented at seven locations but, as shown in Table 4, networks were tested on central locations only (i.e., slots no. 5, 6, and 7). With this design, each letter of some training word was seen exactly once at each testing location. Therefore, letters were seen equally frequently in any position they may appear in a test prime (i.e., regardless of contiguity and order). Thus, differences in network performance could not be attributed to certain letter-slot combinations trained more than others, and would therefore reflect relationships between letters.

2.5.2. *Transposed-letter priming*

A network's ability to simulate transposed-letter priming was examined using primes formed by transposing the two central letters of targets (e.g., ABCD–ACBD) and comparing the effects of these primes with primes formed by replacing the two central letters with letters from a different

Table 3. Exhaustive set of test patterns for the relative-position priming task.

	Order of letters in primes		
Contiguity	Forward	Backward	Target word
Contiguous	ABC, BCD	CBA, DCB	ABCD
	EFG, FGH	GFE, HGF	EFGH
	IJK, JKL	KJI, LKJ	IJKL
	MNO, NOP	ONM, PON	MNOP
	QRS, RST	SRQ, TSR	QRST
Non-contiguous	ABD, ACD	DBA, DCA	ABCD
	EFH, EGH	HFE, HGE	EFGH
	IJL, IKL	LJI, LKI	IJKL
	MNP, MOP	PNM, POM	MNOP
	QRT, QST	TRQ, TSQ	QRST

Table 4. Illustration of training and test data for the relative-position priming task.

	1	2	3	4	5	6	7	8	9	10
	Relative-position test prime (three characters)									
	#	#	#	#	X	X	X	#	#	#
	Training patterns									
1	A	B	C	D	#	#	#	#	#	#
2	#	A	B	C	D	#	#	#	#	#
3	#	#	A	B	C	D	#	#	#	#
4	#	#	#	A	B	C	D	#	#	#
5	#	#	#	#	A	B	C	D	#	#
6	#	#	#	#	#	A	B	C	D	#
7	#	#	#	#	#	#	A	B	C	D

Note: Xs indicate where the three letters of the test strings were presented (always in the centre). Each word in the training set was presented in the seven locations of the table. We see that central locations (slots 5–7) were trained on all the letters of the training data.

word (e.g., AGFD). These priming effects were compared with simple repetition priming where the prime is the same stimulus as the target (e.g., ABCD) and another prime condition with different central letters (e.g., AFGD). Therefore two factors were manipulated. First, the origin of central, or inner, letters: (1) from the target word, or (2) from a different word from the target word. Second, the order of central letters: (1) forward, or (2) backward. The exhaustive set of test

Table 5. Primes in the transposed-letter priming experiment.

	Order of central letters		
Origin of central letters	Forward	Backward	Target word
Same word	ABCD	ACBD	ABCD
	EFGH	EGFH	EFGH
	IJKL	IKJL	IJKL
	MNOP	MONP	MNOP
	QRST	QSRT	QRST
Different word	AFGD	AGFD	ABCD
	EJKH	EKJH	EFGH
	INOL	IONL	IJKL
	MRSP	MSRP	MNOP
	QBCT	QCBT	QRST

Table 6. Illustration of training and test data for the transposed-letter priming task.

	1	2	3	4	5	6	7	8	9	10
	Transposed-letter priming test patterns (four characters)									
	#	#	#	X	X	X	X	#	#	#
	Training patterns									
1	A	B	C	D	#	#	#	#	#	#
2	#	A	B	C	D	#	#	#	#	#
3	#	#	A	B	C	D	#	#	#	#
4	#	#	#	A	B	C	D	#	#	#
5	#	#	#	#	A	B	C	D	#	#
6	#	#	#	#	#	A	B	C	D	#
7	#	#	#	#	#	#	A	B	C	D

Note: Xs indicate where the four letters of the test strings were presented (always in the centre). Each word in the training set was presented in the seven locations of the table. We see that central locations (slots 4–7) were trained on all the letters of the training data.

patterns is presented in Table 5. It should be noted that in the condition with the same letters in the correct direction the prime is the same word as the target, a condition referred to as repetition priming in behavioural literature.

Similarly to the experiment with relative-position priming, we presented primes in central locations, as shown in Table 6, such that letters in test patterns were seen exactly once per location during training.

3. Results

3.1. *Artificial lexica*

For the artificial lexica, a sample of 20 networks was generated for each condition. The target SSE for successful completion was 1. We measured the network's ability to discriminate words from non-words in the combo condition. Networks' accuracy for words was 98.0% while correctly rejecting 98.0% of non-words.

3.1.1. *Relative-position priming*

A summary of target supremum results for the relative-position task are presented in Figure 3. As we can see, the target supremum measure for the backward primes decreases as the importance of letter order increases (left to right), while the target supremum measure for the forward primes remains high. The networks therefore reveal a relative-position priming effect, the size of which is determined by the importance of letter order in the training set. Contiguity had an overall smaller

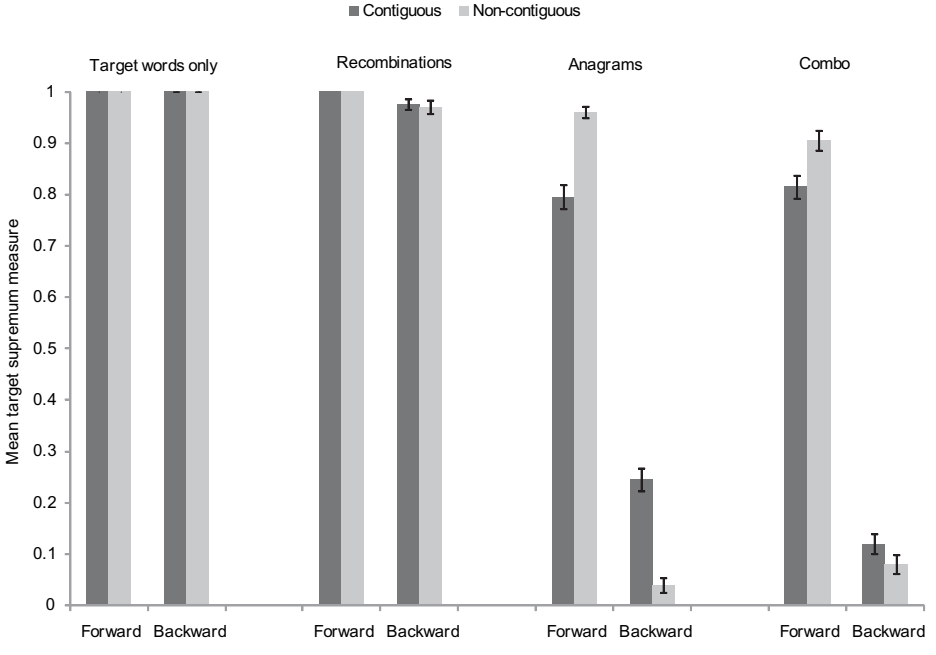

Figure 3. Summary of target supremum results for the relative-position priming task. Example primes for the target ABCD are: ABC for the forward and contiguous condition, ABD for the forward and non-contiguous, CBA for the backward and contiguous and DBA for the backward and non-contiguous.

Table 7. Network error (mean squared error, or MSE) for the relative-position priming task by training condition.

Training condition	Contiguity	Order	
		Forward	Backward
Target words only	Contiguous	0.3 (0.1)	2.8 (2.5)
	Non-contiguous	1.7 (1.6)	2.7 (2.9)
Recombinations	Contiguous	1.2 (0.9)	11 (9)
	Non-contiguous	6 (4)	12 (9)
Anagrams	Contiguous	28 (8)	125 (9)
	Non-contiguous	14 (5)	140 (10)
Anagrams and recombinations (combo)	Contiguous	22 (6)	89 (6)
	Non-contiguous	16 (5)	89 (9)

Note: Values presented in parentheses represent standard deviations. Values presented in table should be multiplied by 10^{-3}.

influence on network performance, with an advantage for non-contiguous primes emerging in certain conditions. Prime-target output discrepancy results are presented in Table 7.

With the relative-position priming task and the training set containing target words only, target words were always the most active lexical items in all four conditions (i.e., target supremum values of 1). A two-way ANOVA on discrepancy with contiguity and order as repeated factors revealed a main effect of order, $F(1, 19) = 8.5$, $p < 0.01$, a significant interaction, $F(1, 19) = 5.2$, $p < 0.05$, but no effect of contiguity, $F(1, 19) = 3.4$, $p > 0.05$. Discrepancy was lower in forward ($M = 1.0 \times 10^{-3}$) than backward ($M = 2.7 \times 10^{-3}$) primes, and the difference between forward and backward primes was larger in the contiguous (2.4×10^{-3}) condition than the non-contiguous condition (0.1×10^{-3}).

With the relative-position priming task and the training set containing recombinations, a two-way ANOVA on the target supremum measure with contiguity and order as factors revealed a main effect of order, $F(1, 19) = 12.8$, $p < 0.01$, but no effect of contiguity, $F(1, 19) < 1$, and no interaction, $F(1, 19) < 1$. In contrast, a two-way ANOVA on discrepancy revealed a main effect of order, $F(1, 19) = 31$, $p < 0.001$, an effect of contiguity, $F(1, 19) = 5.9$, $p < 0.05$, and no interaction, $F(1, 19) = 4.8$, $p < 0.05$. The target supremum measure was larger for the forward primes ($M = 1.0$) than backward primes ($M = 0.97$) and discrepancy was lower for forward primes ($M = 0.003$) than backward primes ($M = 0.012$). In addition, discrepancy was lower in contiguous ($M = 6.1 \times 10^{-3}$) than non-contiguous primes ($M = 9 \times 10^{-3}$), and the difference between contiguous and non-contiguous primes was larger in the forward condition (4.8×10^{-3}) than the backward (1.0×10^{-3}) condition.

With the relative-position priming task and the training set containing anagrams, a two-way ANOVA on the target supremum measure with contiguity and order as factors revealed a main effect of order, $F(1, 19) = 1777$, $p < 0.001$, and a significant interaction, $F(1, 19) = 96$, $p < 0.001$, but no effect of contiguity, $F(1, 19) = 1.1$, $p > 0.05$. Similarly, a two-way ANOVA on discrepancy revealed a main effect of order, $F(1, 19) = 2935$, $p < 0.001$, no effect of contiguity, $F(1, 19) = 2.2$, $p > 0.05$, and a significant interaction, $F(1, 19) = 94$, $p < 0.001$. The target supremum measure was larger for forward primes ($M = 0.88$) than backward primes ($M = 0.14$), and discrepancy was lower for forward primes ($M = 0.02$) than backward ($M = 0.13$) primes. The interaction stems from the fact that these differences were larger for non-contiguous primes than for contiguous primes.

With the relative-position priming task and the training set containing anagrams and recombinations (combo), a two-way ANOVA on the target supremum measure with contiguity and order as factors revealed a main effect of order, $F(1, 19) = 1650$, $p < 0.001$, and a significant interaction, $F(1, 19) = 9.4$, $p < 0.01$, but no effect of contiguity, $F(1, 19) = 2.1$, $p > 0.05$. Similarly, a

two-way ANOVA on discrepancy revealed a main effect of order, $F(1, 19) = 2045$, $p < 0.001$, no effect of contiguity, $F(1, 19) = 3.8$, $p > 0.05$, and a significant interaction, $F(1, 19) = 8.4$, $p < 0.01$. This pattern of results is identical to the anagrams condition: larger target supremum measure for forward primes ($M = 0.86$) than backward primes ($M = 0.10$), and lower discrepancy for forward primes ($M = 0.02$) than backward ($M = 0.09$) primes. The interaction stems from the fact that these differences were larger for non-contiguous primes than for contiguous primes.

Finally, we tested for a three-way interaction between order, contiguity and training regime – an independent factor of four levels: target words only, recombinations, anagrams and combo. We found the interaction to be significant for both the target supremum measure, $F(3, 76) = 34.22$, $p < 0.001$, and for discrepancy, $F(3, 76) = 57.3$, $p < 0.001$.

In sum, we found a robust effect of letter order (namely, a higher target supremum measure on forward than on backward primes), a relative-position priming effect, whereby an ordered subset of the target's letters provides a better match to the target than the same subset of letters in reversed order. As expected and supported by significant three-way interactions, this effect was strongest in the anagrams and combo conditions where letter order matters the most, but it was also present in the recombinations condition. It was nearly inexistent for the condition in which letter order does not matter, that is the target words only condition. We also found an order by contiguity interaction, which was significant only in the anagrams and combo conditions, and reflected an advantage for the non-contiguous primes in the forward condition.

3.1.2. *Transposed-letter priming*

A summary of target supremum results for the transposed-letter priming task are presented in Figure 4. As can be seen in this figure, the networks successfully simulated the transposed-letter priming effect, and the size of this effect was practically as large as the effect of repetition priming. Prime-target output discrepancy results are presented in Table 8.

With the transposed-letter priming task and the training set composed of the target words only, a two-way ANOVA on the target supremum measure with origin and order as factors revealed a main effect of origin, $F(1, 19) = 107$, $p < 0.001$, but no main effect of order, $F(1, 19) < 1$, and no interaction, $F(1, 19) < 1$. Similarly, a two-way ANOVA on discrepancy revealed a main effect of origin, $F(1, 19) = 187$, $p < 0.001$, but no main effect of order, $F(1, 19) = 3.8$, $p > 0.05$, and no interaction, $F(1, 19) = 4.0$, $p > 0.05$, although the latter two effects were trending. The target supremum measure was higher for primes with central letters from same word as the target ($M = 1.0$) than from a different word ($M = 0.49$) and discrepancy was smaller ($M = 1.7 \times 10^{-4}$ for same, and $M = 0.13$ for different).

With the transposed-letter priming task and the training set comprising recombinations, the two-way ANOVAs revealed a similar pattern of results as for the target words only condition: a main effect of origin on the target supremum measure, $F(1, 19) = 268$, $p < 0.001$, and on discrepancy, $F(1, 19) = 386$, $p < 0.001$, but no effect of order, nor interactions, Fs < 2.6, ps > 0.1.

With the transposed-letter priming task and the training set comprising anagrams, a two-way ANOVA on the target supremum measure revealed a similar pattern of results, that is, a main effect of origin, $F(1, 19) = 73$, $p < 0.001$, but no effect of order and no interaction, $Fs < 1.1$. However, a two-way ANOVA on discrepancy revealed an additional significant effect of order, $F(1, 19) = 5.4$, $p < 0.05$, in addition to the main effect of origin, $F(1, 19) = 267$, $p < 0.001$. The interaction between order and origin was not significant, but trending, $F(1, 19) = 3.7$, $p > 0.05$.

The pattern of results is the same with the training set comprising anagrams and recombinations (combo) as with the training set comprising only anagrams: a main effect of origin on the target supremum measure, $F(1, 19) = 180$, $p < 0.001$, but no effect of order nor interactions

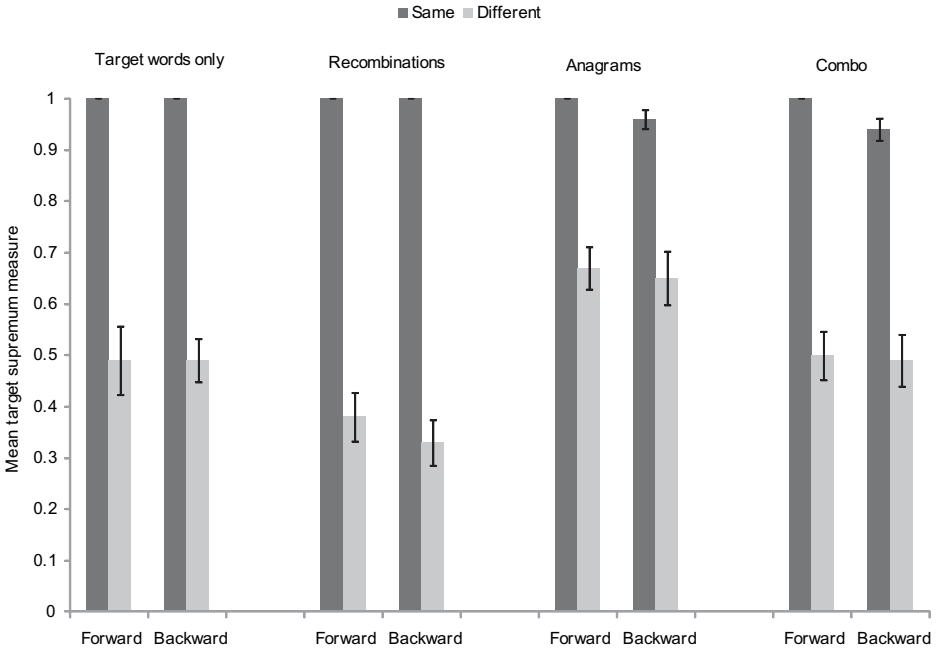

Figure 4. Summary of target supremum results for the transposed-letter priming task. Example primes for the target ABCD are: ABCD for the forward and same condition, AFGD for the forward and different condition, ACBD for the backward and same condition, and AGFD for the backward and different condition. The forward-same vs. forward-different comparison measures repetition priming, and the backward-same vs. backward-different comparison measures transposed-letter priming.

Table 8. Network error (mean squared error, or MSE) for the transposed-letter priming task by training condition.

		Order of central letters	
Training condition	Origin of central letters	Forward	Backward
Target words only	Same	0.04 (0.01)	0.3 (0.3)
	Different	140 (60)	130 (40)
Recombinations	Same	0.007 (0.003)	0.12 (0.2)
	Different	80 (20)	90 (20)
Anagrams	Same	0.014 (0.010)	11 (10)
	Different	60 (20)	60 (20)
Anagrams and recombinations (combo)	Same	0.0028 (0.0016)	9 (7)
	Different	51 (12)	54 (10)

Note: Values presented in parentheses represent standard deviations. Values presented in table should be multiplied by 10^{-3}.

Fs < 1.9. For discrepancy, we found main effects of order, $F(1, 19) = 26$, $p < 0.001$, and of origin, $F(1, 19) = 564$, $p < 0.001$, but no interaction between order and origin, $F(1, 19) = 3.1$, $p > 0.05$.

In short, the pattern across artificial lexica was consistent: higher target supremum measure and lower prime-target output discrepancy when central letters were from the same word (i.e., the target) than from a different word, an intuitively appealing conclusion (see Figure 4). We also found a weaker effect of direction, which turned out to be significant only for discrepancy and when order was most relevant to the task (i.e., in conditions in which anagrams were included as

fillers). This effect of direction reflects the stronger effects of repetition priming compared with effects of transposed-letter priming.

3.2. *Real word lexicon*

A single network was trained with the real word training set of 1179 words of four letters in length. The target SSE for successful completion was 30. The training set contained $7 \times 1179 = 8253$ patterns, and the backpropagation network had 91 hidden units. In order to test word–non-word discrimination in this network a set of non-words were derived from each real word by changing one letter (e.g., darm, stob), for a total of 1179 non-words. The replacement location and identity of the substitution letter were randomly chosen. Our model exhibited perfect recognition accuracy for words (100.0%). The rate of correctly rejecting non-words was 94.1%. Most incorrectly accepted non-words (92.3%) were anagrams of real words (e.g., UDLY for DULY and ICOL for COIL).

3.2.1. *Relative-position priming*

Target supremum results for relative-position priming are presented in Figure 5 and prime-target output discrepancy results in Table 9. The results show a relative-position priming effect with an advantage of forward primes over backward primes.

3.2.2. *Transposed-letter priming*

Target supremum results for transposed-letter priming are presented in Figure 6 and prime-target output discrepancy results in Table 10. The results show a transposed-letter priming effect. The

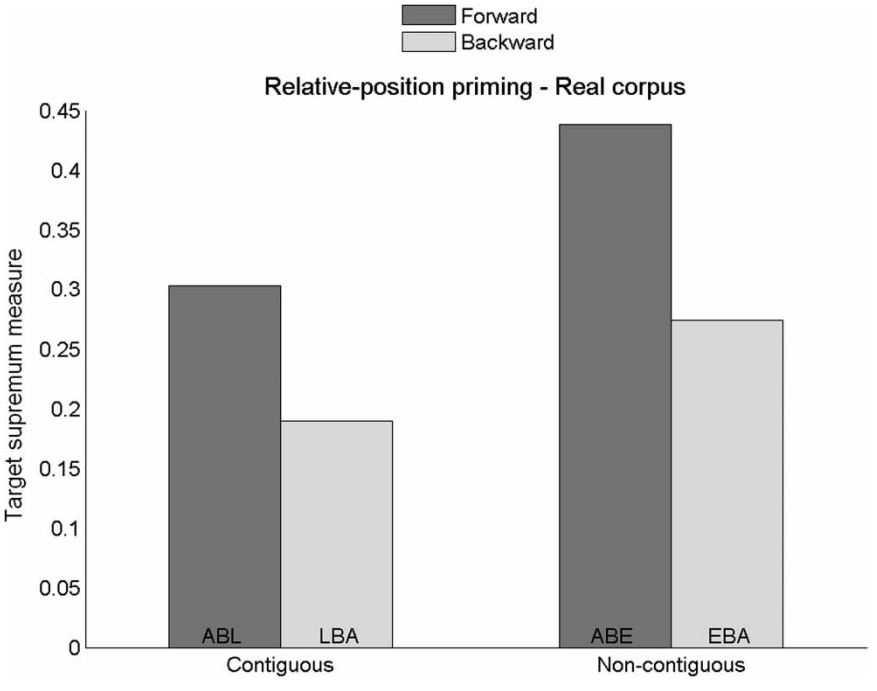

Figure 5. Target supremum results for the relative-position priming task, and the training set containing real words. No error bar is provided for these single data points. Examples are given for real word ABLE.

Table 9. Network error (mean squared error, or MSE) for the relative-position priming task, and the training set containing real words.

	Order	
Contiguity	Forward	Backward
Contiguous	0.77	0.81
Non-contiguous	0.68	0.78

Note: Values presented in table should be multiplied by 10^{-3}.

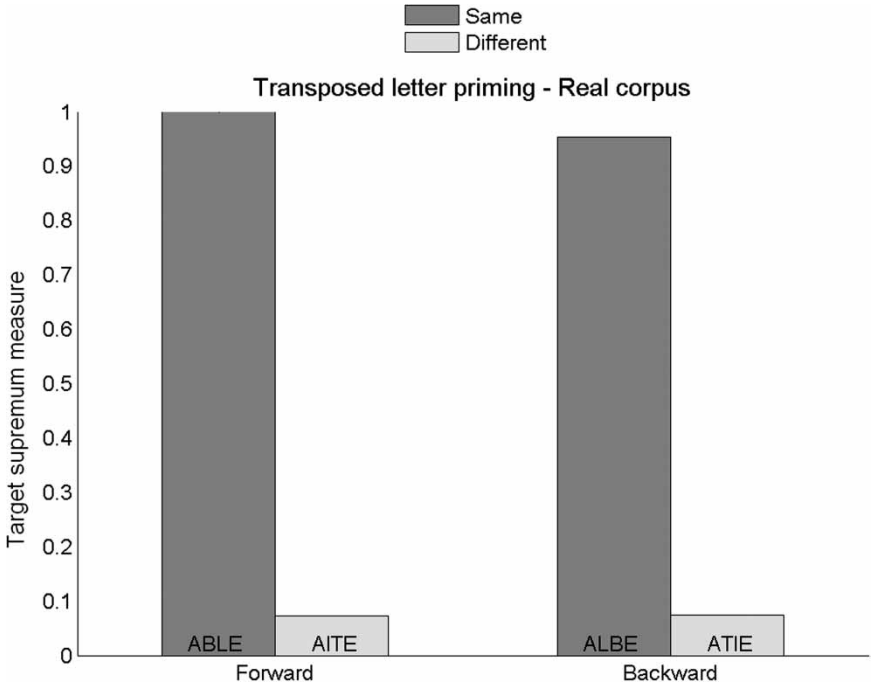

Figure 6. Target supremum results for the transposed-letter priming task, and the training set containing real words. No error bar is provided for these single data points. Examples are given for the target word ABLE.

Table 10. Network error (mean squared error, or MSE) for the transposed-letter priming task and the training set composed of real words.

Origin of central	Order of central letters	
Letters	Forward	Backward
Same	0.0	0.1
Different	1.1	1.1

Note: Values presented in table should be multiplied by 10^{-3}.

target supremum measure is higher when central letters are from the target word than when they are from a different word even when the order of letters is reversed (backward condition). For the target supremum measure, this transposed-letter priming effect is practically as strong as the repetition priming effect.

3.2.3. *Priming effects in a network trained with words at a single location*

The network trained with a real word training set exhibited relative-position and transposed-letter priming effects. We interpret this ability to simulate such priming effects as reflecting an intervention of the type of flexible orthographic code that is developed when learning to map location-specific orthographic representations onto location-invariant representations. More precisely, the key hypothesis here is that it is the constraints involved in mapping totally independent sets of letter identities (i.e., the same letters appearing at different locations) onto the same lexical identity that forces the network to develop intermediate orthographic representations that acquire the kind of flexibility that is seen in experiments testing skilled readers. Therefore, such flexibility, as reflected in the simulated priming effects, should not be visible when the network is only trained at one location. Our final simulation study puts this prediction to test by training the network on only the central location.

In Figure 7, we present target supremum results for the relative-position priming task and the training set containing real words when words are only presented at the central location during training. As we can see, the priming effect is still present, as illustrated by a higher target supremum measure with forward than backward primes. However, the target supremum measure for non-contiguous primes is now very small ($<5\%$) suggesting that networks have not developed orthographic representations that are as flexible as when words are presented at different positions (compare Figures 5 and 7).

In Figure 8, we present target supremum results for the transposed-letter priming task and the training set containing real words when words are only presented at the central location during training. As we can see, the transposed-letter priming effect effectively disappears when training only the central location (compare Figures 6 and 8). This confirms our hypothesis that networks

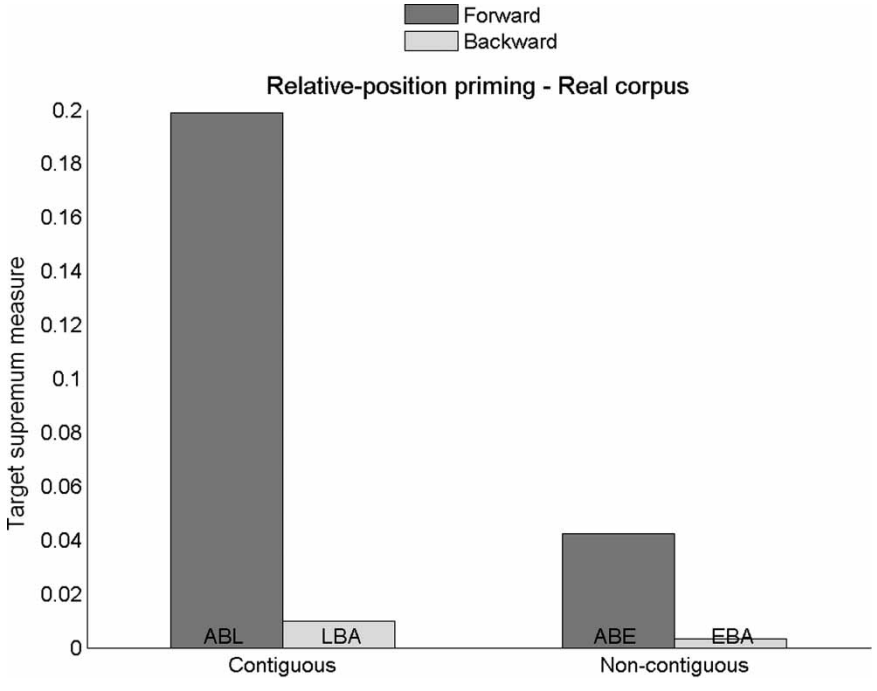

Figure 7. Target supremum results for the relative-position priming task using the training set comprising real words but trained on central positions only. Examples are given for real word ABLE.

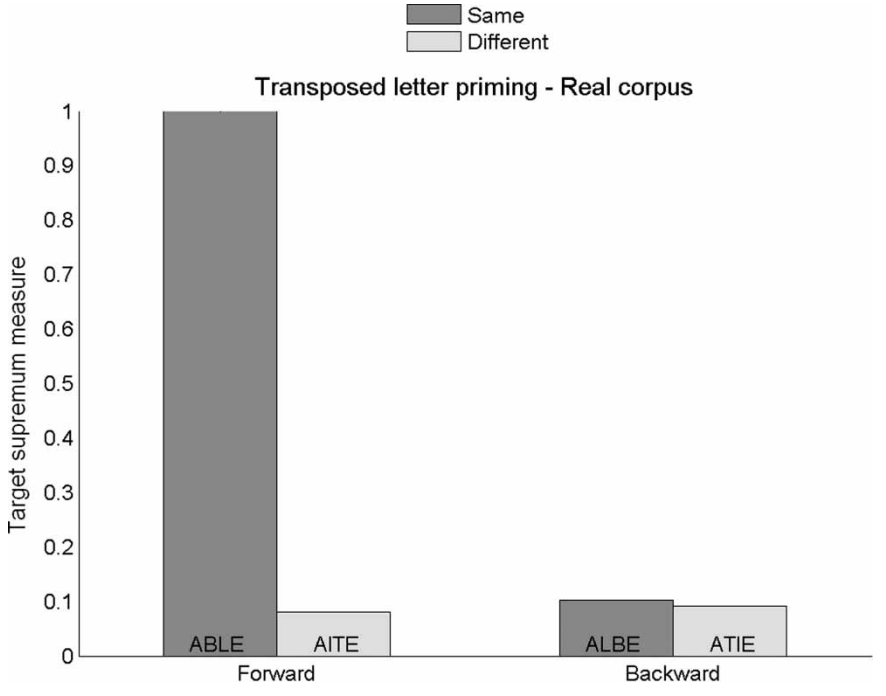

Figure 8. Target supremum results for the transposed-letter priming task using the training set comprising real words but trained on central positions only. Examples are given for real word ABLE.

develop flexible orthographic representations only when the task involves processing input words presented in different positions.

4. General discussion

Neural networks were trained using backpropagation networks to map location-specific letter identities onto location-invariant lexical identities. The location-specificity of letter representations implied that when the same 'word' input was presented at different locations, the network had to learn to map completely independent input representations onto the same output. In other words, the networks were trained to recognise that a given word is the same word independently of its location (location-invariance). According to one account of orthographic processing in skilled readers (Grainger and van Heuven 2003), location-invariance is already achieved at a prelexical level of orthographic representation, where letter identities are coded independently of their position on the retina but relative to their position in the word. Furthermore, at this level of representation, letter position information is thought to be coded in a flexible manner, contrary to the rigid position-specific coding used in slot-based approaches. It is this flexibility that enables the Grainger and van Heuven model to capture empirical phenomena such as transposed-letter priming and relative-position priming.

The present study examined whether neural networks trained to map location-specific letter identities onto location-invariant lexical representations would acquire intermediate representations that would allow the network to exhibit the properties associated with flexible orthographic processing. The networks were trained with a variety of training regimes, including a real word lexicon, and artificial lexica in which the importance of letter order was systematically manipulated. These artificial training regimes forced the network to pay varying levels of attention to

order information by varying the relevance of this information for the task. All networks were successful in learning the task, and the real word lexicon as well as the most complete artificial lexicon (the combo training set) exhibited accurate word–non-word discrimination following training. The networks were further evaluated on the two benchmark phenomena: transposed-letter priming and relative-position priming. The target supremum measure (percentage of trials in which the target is the most activated output representation) and the prime-target output discrepancy revealed transposed-letter priming and relative-position priming. In the simulations run on the networks trained with artificial lexica, transposed-letter priming effects were found even when letter order was not important to solve the task (the target words only condition). In contrast, relative-position priming effects increased as the importance of letter order increased. The effects were small in the target words only condition, larger in the recombinations condition and largest in the conditions containing anagrams.

The simulations run on the network trained with a corpus of real words showed very large effects of transposed-letter priming that were practically as large as the effects of repetition priming. Relative-position priming effects were also evident, but the size of the priming effect was much smaller than that found with transposed-letter primes. This is in line with the results typically found with human participants (Grainger 2008). Furthermore, relative-position priming effects were, if anything, greater for non-contiguous primes, a result that is in line with certain models of orthographic processing (Whitney 2001; Grainger and van Heuven 2003). However, it could be the case that the advantage for non-contiguous primes is the result of these primes having both of the target's outer letters appearing as outer letters in the prime (i.e., preceded or followed by a space). This was not the case for contiguous primes for which the last letter in the prime stimulus was not the last letter in the target word. Finally, both transposed-letter and relative-position priming effects disappeared with the network trained on words presented at a single location, thus demonstrating the importance of shifts in location at the input for generating flexible, intermediate orthographic representations.

Summing up, two critical elements were found to be necessary for networks to develop flexible orthographic coding: (1) learning to map location-specific representations onto a location-invariant representation (i.e., having the same word presented at multiple locations in the input), and (2) training the network on a corpus in which letter position provides important information for constraining lexical identity. The real corpus had this characteristic, as many words differed only by a single letter, and the corpus included several anagrams. The results of the present simulations therefore suggest that, given the characteristics of natural language, flexible orthographic processing might emerge as a natural consequence of having to learn to map location-specific letter identities onto location-invariant lexical representations during reading acquisition.

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