



A visual familiarity account of evidence for orthographic processing in pigeons (*Columbia livia*): a reply to Scarf, Corballis, Güntürkün, and Colombo (2017)

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Abstract

Scarf et al. (Proc Natl Acad Sci 113(40):11272–11276, 2016) demonstrated that pigeons, as with baboons (Grainger et al. in Science 336(6078):245–248, 2012; Ziegler in Psychol Sci. <https://doi.org/10.1177/0956797612474322>, 2013), can be trained to display several behavioural hallmarks of human orthographic processing. But, Vokey and Jamieson (Psychol Sci 25(4):991–996, 2014) demonstrated that a standard, autoassociative neural network model of memory applied to pixel maps of the words and nonwords reproduces all of those results. In a subsequent report, Scarf et al. (Anim Cognit 20(5):999–1002, 2017) demonstrated that pigeons can reproduce one more marker of human orthographic processing: the ability to discriminate visually presented four-letter words from their mirror-reversed counterparts (e.g. “LEFT” vs. “TFFL”). The current report shows that the model of Vokey and Jamieson (2014) reproduces the results of Scarf et al. (2017) and reinforces the original argument: the recent results thought to support a conclusion of orthographic processing in pigeons and baboons are consistent with but do not force that conclusion.

Keywords Orthographic processing · Autoassociative networks · PCA · Visual familiarity · Baboons · Pigeons

Introduction

Grainger et al. (2012) taught guinea baboons (*Papio papio*) to discriminate between four-letter words and nonwords in an analogue of the lexical decision task. Transfer tests demonstrated that baboons behaved *as if* they had learned orthographic structure. First, the baboons discriminated novel words from nonwords. Second, false-positive responses were correlated with orthographic structure: the baboons

had difficulty rejecting nonwords that were orthographically similar to the training words.

Ziegler (2013) extended the work of Grainger et al. (2012) by showing that the same baboons had difficulty rejecting nonwords that were constructed by transposing internal letters in a trained word (e.g. DONE → DNOE—also known as the transposed letter effect in the orthographic learning literature) versus nonwords constructed by substituting letters that did not appear in the trained word (e.g. DONE → DAGE). Consistent with the claim for orthographic processing (Grainger 2008), Ziegler (2013) reported that baboons exhibited a higher false-positive rate to nonwords composed by transposing letters. Hannagan et al. (2014) presented a deep neural network model of how the words perceived as images could be translated into an orthographic code.

Grainger et al. (2012) argued that their baboons engaged in orthographic processing and that “The [non-human] primate brain might therefore be better prepared than previously thought to process printed words, hence facilitating the initial steps towards mastering one of the most complex of human skills: reading” (p. 248). Ziegler (2013) reinforced that conclusion: “Reading

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and writing are recent cultural inventions in humans. Although baboons do not have human-like language, they are sensitive to a classic marker of orthographic processing. These findings suggest that the front end of reading (Grainger and Dufau 2012) is supported by neural mechanisms that are much older than the behaviour itself and are not linguistic in nature (Platt and Adams 2012)” (pp. 1610–1611).

In contrast to the claim of orthographic processing, Vokey and Jamieson (2014) argued that, although consistent with the claim of orthographic processing, the results might be explained as a corollary of familiarity-based visual classification (for related accounts, see also Linke et al. 2017; Platt and Adams 2012). To test the supposition, they applied a standard, autoassociative model of memory to the materials of Grainger et al. (2012) and Ziegler (2013) encoded as pixel maps (i.e. images). The analysis reproduced the results from both papers, opening the possibility that the critical empirical results can be explained as an example of simple, familiarity-based discrimination of pixel maps, without orthographic processing. Based on the result, Vokey and Jamieson (2014) concluded that although they could not rule out that the baboons performed orthographic processing, the results in hand do not force the conclusion that the baboons engaged in orthographic processing.

More recently, Scarf et al. (2016, 2017) replicated the results with pigeons (*Columba livia*) using the materials of Grainger et al. (2012) to show that pigeons, as with baboons, can behave as if they were engaged in orthographic processing. Scarf et al. (2016) demonstrated that pigeons can learn to discriminate words from nonwords and subsequently to discriminate novel words from nonwords. As with the baboons, pigeons had difficulty rejecting nonwords that were orthographically similar to learned words and displayed a transposed letter effect—all of the same effects that Grainger et al. (2012) and Ziegler (2013) demonstrated with baboons and had taken as evidence of orthographic processing, and that Vokey and Jamieson (2014) had successfully simulated.

In a follow-up experiment that is the focus of the current report, Scarf et al. (2017) also showed that the pigeons can discriminate words from their mirror-reflected counterparts—an ability that Scarf et al. (2017) interpreted as additional evidence that their pigeons engaged in orthographic processing, at least to the extent that their pigeons’ rejection of test items improved with the number of asymmetric mirrored letters they contained. Based on the results from both studies, Scarf et al. (2017) argued that pigeons, like baboons, can learn orthography and use that knowledge to perform lexical decision.

In the work that follows, we apply the autoassociative memory model of Vokey and Jamieson (2014) to the experiment and materials of Scarf et al. (2017) to evaluate the ability of a visual familiarity account to reproduce pigeons’

discrimination of words from mirror reflections of those words. Given that Vokey and Jamieson (2014) have already successfully simulated the work of Grainger et al. (2012) and Ziegler (2013), we forego an application of the approach directly to the experiments of Scarf et al. (2016) as they used precisely the same materials.

Simulating the effect of mirror-reversed words

As in Vokey and Jamieson (2014), we evaluated a visual familiarity account of Scarf et al.’s (2017) results using a principal components analysis (PCA), autoassociative neural network model of memory. The method is well known and has been used to model visual discrimination of human faces (e.g. Abdi et al. 1999; Turk and Pentland 1991; Vokey and Hockley 2012), chimpanzee faces (Vokey et al. 2004), fingerprints (Vokey et al. 2009), and artificial grammar letter strings (Vokey and Higham 2004).

As with Vokey and Jamieson (2014), we applied the same approach to the letter-string materials of Scarf et al. (2016) and, thus, also those of Grainger et al. (2012), Scarf et al. (2017), and Ziegler (2013). In this approach, letter strings in uppercase are represented as pictures that are constructed by drawing a four-letter character string into a 7×20 black-and-white pixel map, where each letter appeared as a 7×5 dot-matrix character.

These pixel maps were then converted into 140-element column vectors by assigning values 1 and 0 to elements corresponding to filled and unfilled pixels, respectively, concatenating rows into the transposed column vector of that letter string. The four pigeons in Scarf et al. (2017) were successfully trained with 30, 32, 60 and 62 words, respectively. We similarly modelled these pigeons by creating memories with the same numbers of words.¹ Because Scarf et al. (2017) do not report the actual words used, stipulating only that they were random samples of the words learned by the baboon named “Dan” from Grainger et al. (2012), we similarly used random samples of the words from that set.

For each simulated pigeon, we constructed an autoassociative memory of a random sample of the n_i learned words for a given simulated pigeon i by (a) forming a $140 \times n_i$ stimulus matrix, \mathbf{X} , that stored the representations of all n_i words the simulated pigeon i had learned, (b) performing the singular value decomposition (SVD) of \mathbf{X} to obtain the matrix, \mathbf{U}

¹ There is no good statistical reason to leave our simulations as under-powered as the pigeon experiments were: we could have, for example, used many more simulated pigeons, and with many more learned items. Instead, we aimed for verisimilitude: could we simulate similar effects with such limited training and memories?

(the matrix of eigenvectors of $\mathbf{X}\mathbf{X}^T$),² and (c) forming the autoassociative memory matrix, \mathbf{W} , where $\mathbf{W} = \mathbf{U}\mathbf{U}^T$. The model is equivalent to a linear autoassociative neural network trained with Widrow–Hoff learning,³ and in statistics is equivalent to the PCA of the original data matrix (e.g. Abdi et al. 1999).⁴ Widrow–Hoff learning is also consistent with previous work in comparative cognition as introduced by Blough (1975).

Finally (see Vokey and Jamieson 2014, for more details), the familiarity of each tested string, \mathbf{x}_i , for a given simulated pigeon, was computed relative to its \mathbf{W} as $\cos(\mathbf{x}_i, \hat{\mathbf{x}}_i)$, where $\hat{\mathbf{x}}_i = \mathbf{U}_{1:m}(\mathbf{U}_{1:m}^T \mathbf{x}_i)$ is the projection of \mathbf{x}_i into the space defined by the 1: m eigenvectors in \mathbf{U} and where the eigenvectors are ordered from first to last according to the magnitudes of their associated eigenvalues (Abdi et al. 1999). If the cosine familiarity for a given letter string exceeded the criterion defined by the midpoint between the mean cosine familiarity of words and nonwords for a given simulated pigeon, the item was identified as a word; else, it was identified as a nonword for that simulated pigeon. When computing the cosine familiarity of a training word, the “leave one out” technique (e.g. Abdi et al. 1995) was used: the training word was removed from \mathbf{X} prior to constructing the autoassociative memory, \mathbf{W} , leaving the remaining words to serve as the simulated pigeon’s memory for the testing of that word; for nonwords, \mathbf{X} was left intact. Thus, $\cos(\mathbf{x}_i, \hat{\mathbf{x}}_i)$ represents an item’s familiarity as a novel item in the experiment for both words and nonwords for each simulated pigeon.

As in Scarf et al. (2017), the mirror-reversed words were created by mirror-reversing the pixel maps of learned words for each simulated pigeon; mirror-reversing here means that both the order of the letters in the word and the orientation of each letter within the word were flopped left to right (e.g. “LEFT” becomes “TƆƎL”). We also added a few manipulations not found in Scarf et al. (2017). First, we tested transfer to all of the remaining 308 words from the Grainger et al. (2012) “Dan” word-set, not just the trained items, and also tested transfer to the complete set of the

308 words mirror-reversed. Similarly, we tested transfer to all 7832 nonwords from Grainger et al. (2012), not just the small, random samples used in Scarf et al. (2017). Last, we also tested mirror-reversed nonwords to determine whether the simulated pigeons would find that mirror-reversed nonwords were also less familiar than normally-oriented, words and nonwords.

Results

The principal results of the simulation are shown in Fig. 1, which depicts the mean proportion of the various word and nonword (normal and mirror-reversed) items labelled by the model as words as a function of the eigenvector range used to reproduce them. The maximum eigenvector range (1–29) reflects the limit set by the number of items in the smallest training-set.

As shown in the top two-thirds of the figure using solid lines, the model endorsed novel words from the study-set and unstudied words strongly and approximately equally, and rejected nonwords. That result confirms that, as with the pigeons, the model discriminates unstudied words from unstudied nonwords. As shown in the bottom third of the figure using dashed lines, the model rejected mirrored items strongly overall, but rejected mirror nonwords more strongly than mirror words. Finally, the discrimination of words from nonwords generally improved as the range of eigenvectors increased, reaching a rough asymptote at about the 1–10 eigenvector range, whereas the discrimination of mirror words from mirror nonwords generally deteriorated as the range of eigenvectors increased.

Confirming these observations, a within-subject analysis of variance on the proportions labelled as words as a function of 6 item-types \times the 29 eigenvector ranges crossing the 4 simulated pigeons confirmed these observations, and revealed a significant main effect of item-type [$F(5, 15) = 960.6, \text{MSE} = 0.014, p < .0001$], a significant main effect of eigenvector range [$F(28, 84) = 1.942, \text{MSE} = 0.0006, p = .0108$], and a significant interaction of item-type and eigenvector range [$F(140, 420) = 14.95, \text{MSE} = 0.0008, p < .0001$].

To make the results more directly comparable to those of Scarf et al. (2017), we analysed the data for just the 1–10 eigenvector range, the same as Vokey and Jamieson (2014) did for their simulations of Grainger et al. (2012) and Ziegler (2013). Figure 2 shows the mean word endorsement rate as a function of item-type based on the familiarity cosines derived from projections on the first 10 eigenvectors. As in Scarf et al. (2017), novel training words were endorsed as words significantly more often than nonwords, $t(3) = 8.487, p = 0.0034$, and novel training words were endorsed as words significantly more often than mirrored

² \mathbf{X}^T is the matrix transpose of \mathbf{X} .

³ Technically, the weight-matrix, \mathbf{W} , is given by $\mathbf{W} = \delta\mathbf{U}\mathbf{U}^T$, for which δ is the vector of corresponding eigenvalues. The effect of Widrow–Hoff error training is to spherize or “whiten” the weight-matrix, rendering each of the eigenvectors the same length; hence, dropping the eigenvalues from the expression produces the Widrow–Hoff error-correction (Abdi et al. 1999).

⁴ Which also means that every item stored in memory is necessarily perfectly reconstructed if every eigenvector is used in that reconstruction (which is why we have to resort to the “leave one out” approach for the test of training). That is, every individual training item is perfectly preserved in that memory, as a consequence of Widrow–Hoff learning, much as the original data matrix can be completely reconstructed from its PCA if every component is retained. That is why we characterize such models of memory as *instance-based*.

Fig. 1 Mean proportion of items labelled as words as a function of item-type and eigenvector range used to reconstruct the item to compute its cosine familiarity. Error bars are ± 1 within-cell standard deviation. Squares refer to words, circles to nonwords. Filled versus unfilled squares denote the actual words used for training versus the other training words from the “Dan” set of 308 words. Solid versus dashed lines denote actual versus mirror-reversed items

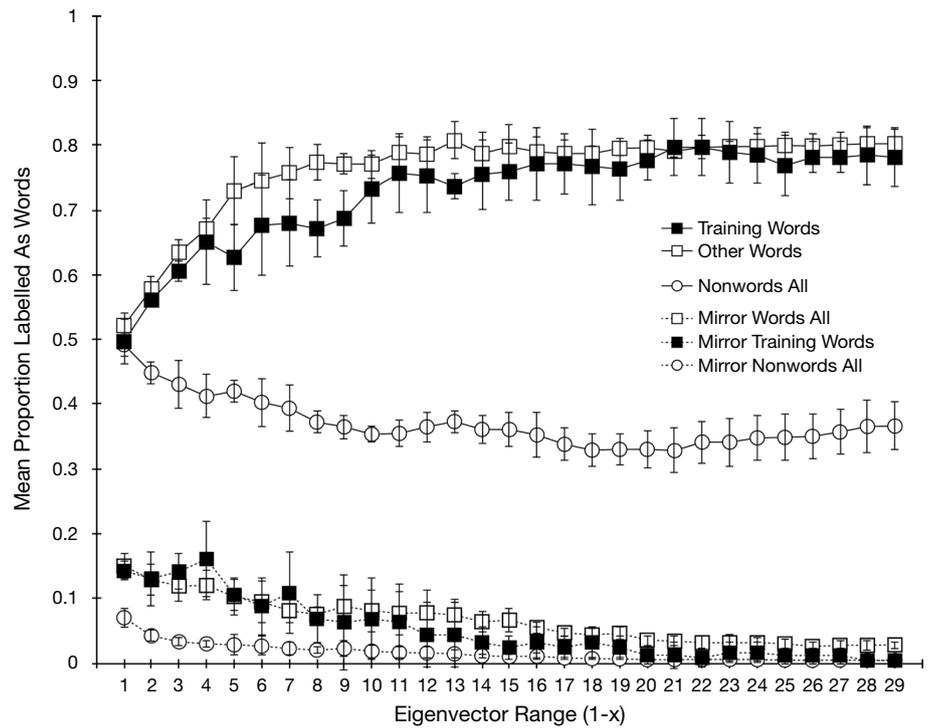
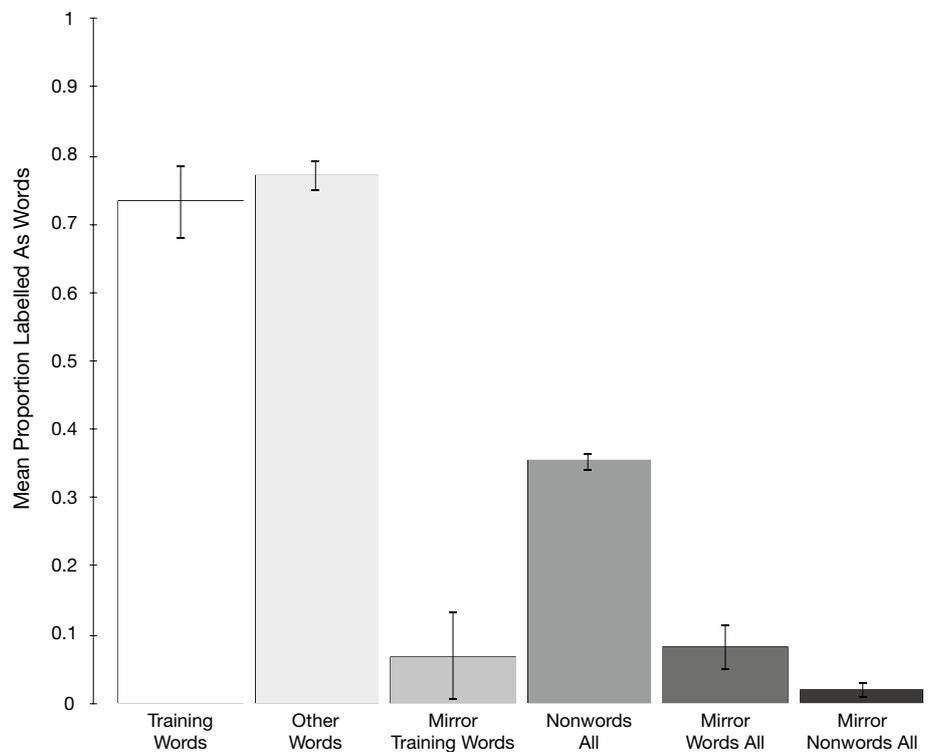


Fig. 2 Mean proportion of items labelled as words as a function of item-type condition derived from the familiarity cosines computed from projections on the first 10 eigenvectors. Error bars are ± 1 within-cell standard deviation



training words, $t(3) = 11.352, p = 0.0015$. But, unlike Scarf et al. (2017) who found no significant difference, mirrored training words were endorsed as words significantly less often than nonwords, $t(3) = 10.208, p = 0.002$.

But, as Scarf et al. (2017) asked: is it that they (their pigeons and our simulated pigeons) dislike mirrored words or merely mirrored letters? The Scarf et al. (2017) approach to answering this question is to look at the endorsement rates to the different

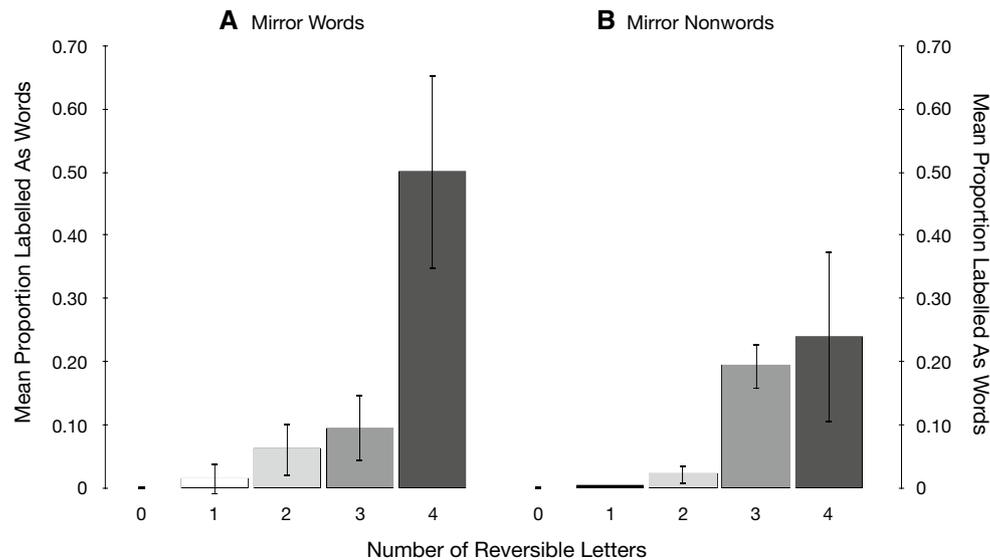


Fig. 3 Mean proportion of mirrored words (Panel A) and nonwords (Panel B) labelled as words as a function of the number of reversible letters each item contains, derived from the familiarity cosines com-

puted from projections on the first 10 eigenvectors. Error bars are ± 1 within-cell standard deviation

items as a function of the number of reversible letters each contains. For example, for the pixel maps we used, the word “ATOM” is completely reversible as the nonword “MOTA”—the individual characters within the word mirror reverse as the same pixel map, but a word such as “LEFT”, for example, has just one mirror-reversible letter, “T”, in creating the nonword “TLEF”, and a word such as “BEEF” (“BEEF”) has none.

Figure 3 shows the mean word endorsement rate of mirror-reversed words and nonwords projected into the 1–10 eigenspaces of training words of the simulated pigeons of all 308 of the mirrored “Dan” words in Grainger et al. (2012), and mirror nonwords of all 7382 of the nonwords in Grainger et al. (2012), as a function of the number of reversible letters. The word endorsement rate rose significantly as a function of the number of reversible letters for both mirror-reversed words (as in Scarf et al. 2017) and mirror-reversed nonwords [$F(4, 12) = 23.57, \text{MSE} = 0.008, p < .0001$].⁵ Mirror-reversed words were endorsed as words more frequently than were mirror-reversed nonwords

[$F(1, 3) = 23.36, \text{MSE} = 0.003, p = .0169$], although that effect may reflect nothing more than a distributional bias in letter strings with more reversible letters.⁶ Finally, there was a significant interaction of word-type (word vs. nonword) and the number of reversible letters [$F(4, 12) = 13.23, \text{MSE} = 0.002, p = 0.0002$] on word endorsement rate: the effect was larger for words than nonwords.

Discussion

A simple autoassociative model of memory reproduces the pattern of results that Scarf et al. (2017) and Scarf et al. (2016) cited as confirmation of orthographic processing (see Vokey and Jamieson 2014). Based on our analysis, those results are also consistent with the conclusion that pigeons could have discriminated words from nonwords without orthographic processing, using visual information that was correlated with the orthographic status of test items (cf. Hannagan et al. 2014). Evidence that is

⁵ Although our model captures the trend in performance as a function of number of reversible letters, the pigeons of Scarf et al. (2017) endorsed as words the tested, mirrored items at a higher rate than our model overall. Unfortunately, Scarf et al. (2017) made a much smaller set of comparisons than we did (e.g. the 80% achieved by their pigeons in the condition in which every letter could be reversed reflected performance on 4 of 5 items over the 4 pigeons for the mirrored words they actually used). Scarf et al. (2017) did not provide the particular words that each pigeon was trained and tested on; consequently, we could not derive a direct comparison to test whether the model not only predicts the relationship but also the particular details of that relationship.

⁶ For the pixel maps we used, there are only 31 nonreversible words, 72 words with just 1 reversible letter, 136 with 2, 61 with 3, and only 8 with 4. For nonwords, there are 759 nonreversible nonwords, 3593 nonwords with 1 reversible letter, 2734 with 2, 700 with 3, and 46 with 4. These distributional differences in the base-rates for mirror-reversed words and nonwords result in a significant bias, with words generally having more reversible letters than nonwords (linear trend chi-square test for ordinal data: $M^2(1) = 59.42, p < .0001$, Agresti 1996).

consistent with two competing theories lacks the necessary logical force to reject one in favour of the other. The current analysis challenges the claim that pigeons are capable of orthographic processing.

Unfortunately, the confounding of visual familiarity and orthographic structure is inherent to the problem under investigation. There is no easy way to manipulate orthography independent of visual form and no obvious way to learn orthography independent of visual processing. To derive clear evidence for either factor, it is necessary to disentangle visual and orthographic structure in test materials.

In the analysis presented here (see also Vokey and Jamieson 2014), we applied a familiarity-based approach in a post hoc manner to explain data from completed experiments—a strategy that allowed us to document and assess the confounding of visual familiarity and orthographic status. But, the strategy could be re-applied in a productive, a priori manner to design and to solve rather than evaluate and document the relationship between the two factors.

For example, the model could be applied to find a list of words and nonwords that the model itself cannot discriminate—where visual familiarity at least as assessed by the model is not correlated with orthographic status. With that list of items, researchers could test whether pigeons can still discriminate orthographic status independently of visual familiarity. That demonstration would bolster evidence that pigeons *are* capable of orthographic processing. In our estimation, the use of formal models to refine experimental materials and analysis offers a productive methodology to examine the exciting but controversial conclusion that nonhuman animals are capable of orthographic processing.

Vokey and Jamieson (2014) have previously applied the PCA network model to work with the baboons studied by Grainger et al. (2012) and Ziegler (2013) who showed the same differences but, in general, outperformed the pigeons studied by Scarf et al. (2016, 2017). So, what does the model present in terms of the baboons versus pigeons comparison?

Figure 2 presents a snapshot of the model's performance based on information in the first 10 eigenvectors. However, Fig. 1 gives a complete picture of the model's performance over all 1: x eigenvector ranges. The details of the simulations presented by Vokey and Jamieson (2014) for the baboons studied by Grainger et al. (2012) and Ziegler (2013), and the simulations reported here for the pigeons studied Scarf et al. (2016, 2017) differ in too many ways to support a meaningful direct comparison (as did the actual experiments). However, Fagot and Cook (2006) demonstrated that pigeons' memories are weaker than baboons' memories for the same tasks and materials, which suggests that the baboon/pigeon differences may be modelled by a difference in the eigenvector range

used when modelling the two species. For example, if one presumes the model is applicable to both species, pigeons might be modelled by performance where the range of eigenvectors (i.e. the precision of memory for the studied items) for pigeons is 1: n and the range of eigenvectors for baboons is 1: m , where $m > n$. Looking at Fig. 2 in the present paper or Figure 1 in Vokey and Jamieson (2014), the distinction would produce the correspondence in conclusions between the results with pigeons (Scarf et al. 2016) and baboons (Grainger et al. 2012; Ziegler 2013), but also track the fact that baboons outperformed the pigeons.

In summary, our analysis confirms that the behaviour of pigeons studied by Scarf et al. (2016, 2017) and of baboons studied by Grainger et al. (2012) and Ziegler (2013) can be understood as visual rather than orthographic discrimination of words and nonwords. From one perspective, the conclusion might be interpreted as a negative rebuttal of the interesting possibility that nonhuman species can engage in orthographic processing. But, from another perspective, the analysis points to a positive alternative. Scarf et al. (2016, 2017) demonstrated that pigeons can behave *as if* they engage in orthographic processing and are, therefore, possibly capable of the same cognitions as humans. But, the result can also be interpreted positively as motivation for researchers who study human lexical decision to rethink their conception of orthography and the methods they use to study it.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Human participants This article does not contain any studies with human participants or animals performed by any of the authors.

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