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Title
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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 46(0)

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Publication Date
2024

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Comparing online and post-processing pronunciation correction during orthographic incidental learning: A computational study with the BRAID-Acq model

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Abstract

Reading acquisition primarily relies on orthographic learning. Behavioral studies show that familiarity with a novel word's pronunciation facilitates learning, particularly in semantically meaningful contexts. Two main components of orthographic learning are commonly described: perceptual processing of the visual stimulus, to infer corresponding phonological representations, and "pronunciation correction", to correct errors from perceptual processing. Currently, pronunciation correction has not been featured in reading acquisition computational models. This study uses BRAID-Acq, a reading acquisition model, to implement and compare two pronunciation correction mechanisms (an "online" and a "post-processing" variant). We simulated learning of words with and without prior phonological knowledge and explored the impact of context strength and size on learning. Results indicate that both mechanisms improve decoding. However, the post-processing mechanism induced implausible lexicalization for words without prior phonological knowledge, while the online mechanism did not. Overall, our simulation results suggest that pronunciation correction could be construed as an online process.

Keywords:

Reading acquisition; Computational modeling; Orthographic learning; Pronunciation correction; Semantic context.

Introduction

Learning to read is a gradual process that primarily relies on acquiring the orthography of novel words (Castles, Rastle, & Nation, 2018). This happens mostly incidentally, that is to say without direct teacher feedback, typically within meaningful context. The self-teaching theory is the dominant framework of incidental orthographic learning. It proposes that accurate decoding, i.e., accurately computing a pronunciation from a written form based on knowledge of the written-spoken relationship, is crucial for incidental learning (Share, 1995). However, decoding attempts by early readers may be partially accurate due to their early proficiency levels and the unpredictable pronunciation of words in some alphabetic languages such as English or French (Schmalz, Marinus, Coltheart, & Castles, 2015). Despite these challenges, behavioral studies indicate that incidental learning is achievable from the early stages of reading acquisition (Share & Shalev, 2004). Moreover, they also reveal that when the pronunciation of a target item is familiar, there is a facilitating effect of context on learning accuracy (Murray, Wegener, Wang, Parrila, & Castles, 2022). In the following, we refer to such items, that are known in oral, phonological form but not yet in written, orthographic form as "words with prior phonological knowledge". This contrasts with words that are novel in both modalities, which we refer to as "words without prior phonological knowledge".

Several mechanisms have been proposed to explain how the interaction between prior phonological knowledge and context makes incidental learning possible despite partially correct decoding. The self-teaching theory posits that context enables the identification of the correct phonological entry within the phonological lexicon, without specifying a precise mechanism. Venezky (1999) proposes that word identification involves successive attempts to correct pronunciation errors at the end of perceptual processing. This process would rely on context to evaluate the plausibility of the correction attempt (Elbro, de Jong, Houter, & Nielsen, 2012; Murray et al., 2022; Steacy et al., 2019; Tunmer & Chapman, 2012; Venezky, 1999). This widely supported pronunciation correction hypothesis is reinforced by studies demonstrating a correlation between, on the one hand, the ability to recognize phonologically familiar words from an approximate pronunciation, and on the other hand, decoding accuracy (Elbro et al., 2012).

However, this proposal does not explain how a reader could correct the pronunciation of words with prior phonological knowledge while avoiding lexicalization errors that might arise from attempting to correct the pronunciation of words without such prior phonological knowledge. This aspect is crucial since a reader encounters both types of novel words during incidental orthographic learning without knowing beforehand which category the novel word belongs to. Therefore, further specification on this aspect is needed. A second hypothesis, although not specifically investigated through behavioral studies, proposes that prior phonological knowledge of the target word could potentially offer support by providing lexical feedback throughout word processing. This influence

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would extend to the ongoing pronunciation computation during perceptual processing, that is, it would not be a separate correction step after processing (Nation & Cocksey, 2009). Further specification is required to understand the interplay between context and lexical feedback, and how this mechanism would correct words with prior phonological knowledge without negatively impacting the decoding of words without prior phonological knowledge.

As we lack quantitative results directly linked to pronunciation correction, our hypotheses will focus solely on the impact of context on reading accuracy and will remain qualitative. We expect that a stronger context will have more influence on results, as it would favor items within that context. This can be positive when it contains the correct item (we anticipate it would be often the case for words with prior phonological knowledge), but for words without prior phonological knowledge (which are not in the context), it would lead to incorrect word identification, resulting in a predominantly negative effect of context strength. Nevertheless, given the ability of most readers to learn novel words without prior phonological knowledge, we anticipate the existence of multiple context configurations where the positive impact on words with prior phonological knowledge is pronounced, while the negative effect on learning words without prior phonological knowledge remains minimal. We also expect context ambiguity to contribute to lexicalization errors for words with and without prior phonological knowledge. In particular, as context size (which relates to ambiguity) increases, the likelihood of confusing the target item with a word from the context should increase. However, when ambiguity is extremely high, the context should become less informative and have a smaller impact on results. In essence, we anticipate that most lexicalization errors would occur at intermediate levels of ambiguity.

Therefore, to precisely specify and compare these two mechanisms, we propose a computational study of pronunciation correction during incidental orthographic learning. To do so, we first present the computational models in this domain and discuss their ability to address this issue. This leads us to select the BRAID-Acq model of reading acquisition, that we present. We then describe the material and methods of our simulations, and our experimental results.

Computational models of incidental orthographic learning

Currently, and to the best of our knowledge, three computational models implement incidental orthographic learning: the Phonological Decoding Self-Teaching – Connectionist Dual Processing Model (Ziegler, Perry, & Zorzi, 2014), the Self-Teaching – Dual-Route Cascaded Model of Reading (Pritchard, Coltheart, Marinus, & Castles, 2018) and the Bayesian word Recognition with Attention, Interference and Dynamics – for Acquisition (BRAID-Acq) model (Steinhilber, 2023). The first two models are dual-route models, with distinct routes involved in reading novel words and reading known words. In both models, context primarily facilitates the identification of the target item at the end of processing, without influencing perceptual processing on itself. Furthermore, both only implement incidental learning for words with prior phonological knowledge, as learning requires the identification of an entry in the phonological lexicon. They also do not learn new phonological forms. Consequently, these models cannot compare incidental learning with and without prior phonological knowledge, providing an incomplete explanation of how the interaction of prior phonological knowledge and context facilitates learning. Finally, and more importantly for our central topic, these models do not implement any pronunciation correction mechanism.

The last computational model for incidental orthographic learning, the BRAID-Acq model, is a probabilistic single-route model. Due to its probabilistic nature, the model simulates the gradual accumulation of perceptual evidence during processing and can explain how multiple sources of information (decoding, context) combine. Indeed, identifying the most likely phonemes involves a combination of information provided by decoding and a pronunciation correction mechanism using context. Hence, this model seems well-suited for comparing both correction mechanisms through simulations. Moreover, it is capable of learning words with and without prior phonological knowledge, allowing for a comparison of incidental learning with and without prior phonological knowledge. Crucially, it is possible to investigate with the BRAID-Acq model whether the implementation of a correction mechanism designed for words with prior phonological knowledge adversely affects the accurate decoding of words without prior phonological knowledge. Therefore, in our study, we will use the BRAID-Acq model.

The BRAID-Acq model

The BRAID-Acq model (illustrated on Figure 1) is a hierarchical, probabilistic model, defined by a joint probability distribution over its variables. Given the current study's focus and space limitations, we do not provide a comprehensive description of its mathematical definition and only describe key components of the model. In particular, our goal is to clarify the fundamental differences between the two proposed mechanisms of pronunciation correction. Interested readers can refer to external sources for more details (Steinhilber, 2023).

In a nutshell, the BRAID-Acq model's architecture consists of seven submodels. The letter sensory submodel implements low-level visual processing (with features such as visual acuity, lateral interference between letters and visual similarity of letters). Three perceptual submodels on letter, phoneme and word representations allow for progressive accumulation of perceptual information during processing. An attentional submodel implements visual and phonological attention mechanisms. A lexical submodel implements the model's lexical knowledge. Finally, the semantic submodel implements the influence of the context on processing.

Simulating reading involves a "perceptual processing" stage implementing, during visual stimulus presentation, the

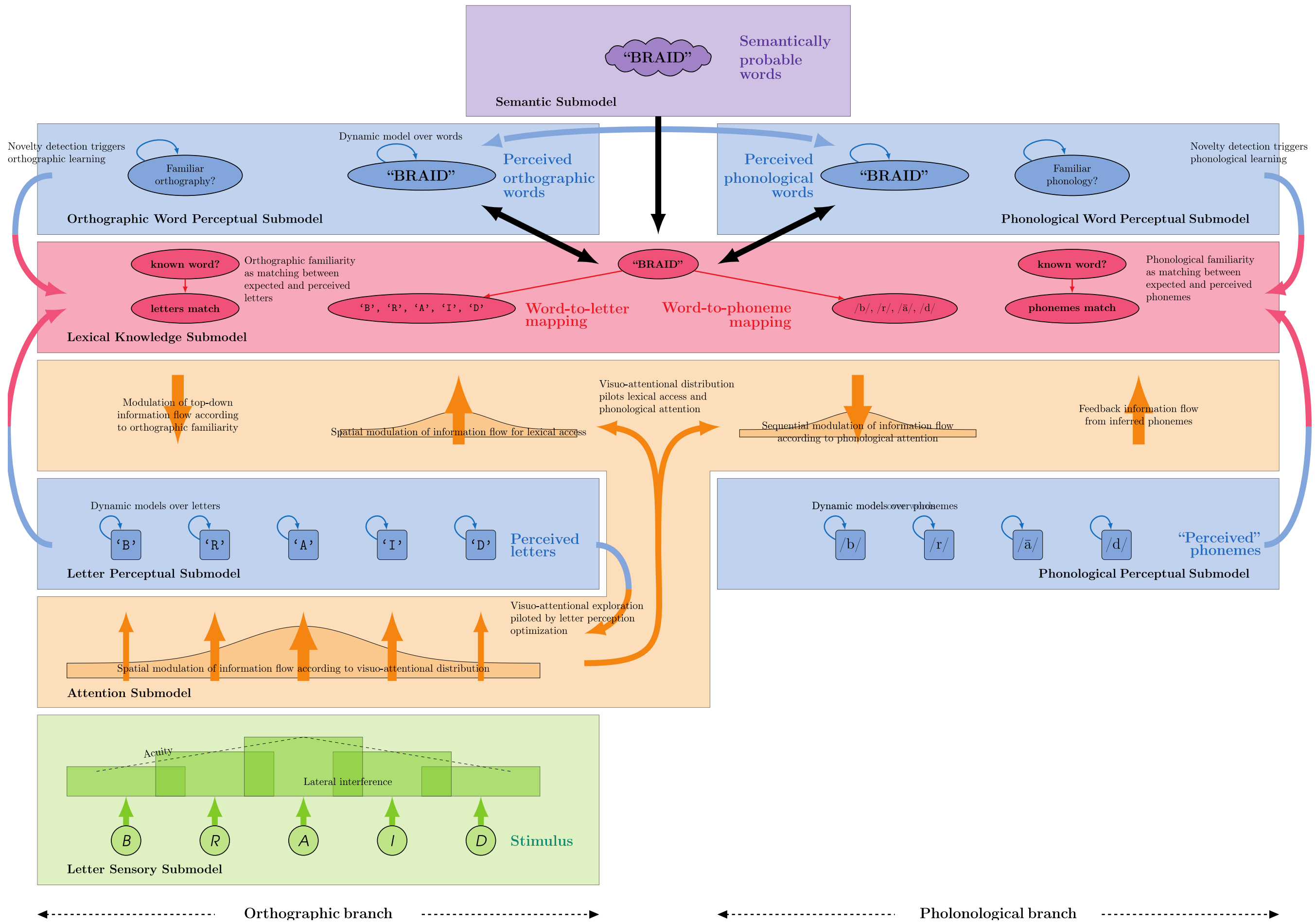

Figure 1: Conceptual representation of the BRAID-Acq model. Submodels are depicted by colored boxes. Green corresponds to the letter sensory submodel, blue to the perceptual submodels (letter, phoneme, word), orange to the attentional submodel, red to the lexical knowledge submodel, and finally, purple to the semantic submodel. Arrows represent information flow.

accumulation of perceptual evidence for letters, phonemes, words, as well as for lexical familiarity of the stimulus (to assess whether it is known or not; this serves both to speed up processing familiar words by modulating top-down lexical influence, and, at the end of processing, as novelty detection to take learning decisions). Perceptual processing simulation employs a visual exploration algorithm to determine the optimal position of successive visual-attentional fixations. Each visual-attentional fixation lasts a certain number of iterations (that are calibrated to correspond to 1 ms).

At each iteration, probability distributions for all perceptual submodels are updated. This involves several computation steps, dictated by Bayesian inference in the model. These steps can be interpreted as interleaving: letter perception considering sensory visual processing and visual attention; inference of phonemes from letters (decoding) through an analogy process in reference to the lexicon; word identification by comparing recognized letters and phonemes with lexical representations; lexical familiarity assessment using the same comparison; and, finally, top-down lexical support using lexical representations of the most likely words. The strength of top-down lexical support depends on stimulus familiarity: the greater it is, the stronger the support. Each fixation continues until the letters under the visual-attentional focus are adequately perceived (with respect to a fixation decision threshold on the entropy of letter probability distributions). Then, the model moves to the next optimal letter to process. The perceptual processing stage stops when all phonemes have been identified with sufficiently high probability (with respect to an exposure decision threshold on the entropy of phoneme probability distributions).

The semantic submodel in BRAID-Acq features a simplified semantic context through a probability semantic distribution, characterized by the context's size N_S (i.e., the number of words in the context) and strength p_S (the probability ratio between words in the context and others words). Simulating reading without context is performed mathematically seamlessly by keeping all mechanisms of the model untouched,

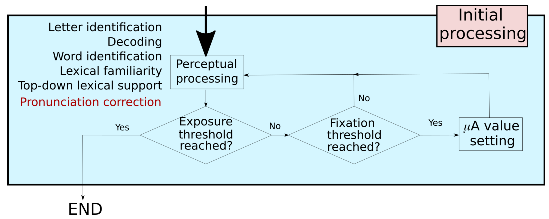

Figure 2: Decision diagram of the "online" variant of pronunciation correction. μA refers to the position of attention focus, which is selected by the visual exploration algorithm.

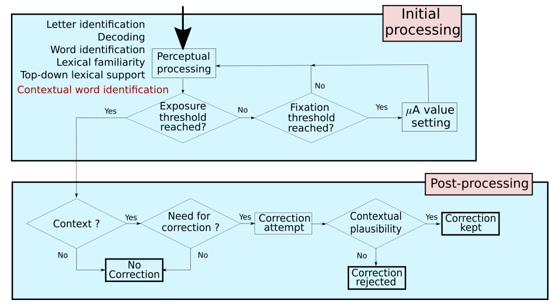

Figure 3: Decision diagram of the "post-processing" variant of pronunciation correction.

and using a uniform semantic distribution (i.e., $p_S = 1$). To simulate a situation of learning in context, if the stimulus is known in one of the two modalities (i.e., orthographically or phonologically), it is included in the semantic context; otherwise, it is excluded from the semantic context. In our simulations, this implies that the stimulus belongs to the context for words with prior phonological knowledge but not for phonologically novel words. The remaining words in the context are selected randomly from the lexicon, as in (Pritchard et al., 2018). The impact of the semantic distribution on processing varies depending on the mechanism employed for correcting pronunciation.

We defined and implemented two pronunciation correction mechanism. The first is the "online mechanism" (illustrated on Figure 2), which involves adding a computation step during perceptual processing (a Bayesian inference step): at each iteration, the model computes the product of the semantic distribution with the word phonological distribution. The phonological representations of the most probable words given this combination are then used for phoneme identification. Multiplying distributions can be interpreted as a probabilistic version of a logical "AND" operator: the probability of a word is high if the probability of that word is high in both distributions. Therefore, only words that are part of the semantic context AND whose phonological representations are sufficiently similar to the phonemes identified during decoding contribute to the pronunciation correction. Ultimately, when the stimulus belongs to the context, and decoding is partially incorrect, if the stimulus remains correctly identified at the lexical level, then the online mechanism gradually corrects decoding errors, thus yielding a correct pronunciation.

The second mechanism for pronunciation correction, referred to as the "post-processing mechanism" (illustrated on Figure 3), involves adding a computational step during perceptual processing, as well as a distinct pronunciation correction phase after perceptual processing. During perceptual processing, it prioritizes the identification of words belonging to the context, but does not impact phoneme identification. Then, at the end of perceptual processing, if phonological familiarity assessment yields a negative decision (i.e., the stimulus is considered phonologically novel), a correction attempt is made. Over 100 additional iterations, phonological representations of the most likely words, given the phonological word distribution (word identification), gradually adjust the computed phonemes. In cases where a word is clearly identified after perceptual processing (i.e., it has a high probability in the phonological word distribution), then after these 100 iterations, the identified phonemes usually match its phonological representation. In the final step, the obtained pronunciation's plausibility is assessed to determine if the correction should be retained: it is considered plausible (and is retained) if the pronunciation aligns with a word in the context. For words without prior phonological knowledge, the pronunciation should align with the phonological representation of the most phonologically similar word, often outside the context, thus yielding the correction to be discarded. Therefore, this mechanism enables reading words without prior phonological knowledge without making erroneous pronunciation corrections. This mechanism is more complex than the first one, but it was developed to closely align with the proposition of (Murray et al., 2022), for comparison purposes.

Material and methods

Material

In our simulations, we used the Lexique French lexicon (New, Pallier, Brysbaert, & Ferrand, 2004), with additional manual corrections applied[1]. It was used as the model's lexicon, and simulation stimuli were chosen among this lexicon. All presented simulations use an identical set of items as stimuli. More precisely, we randomly selected 500 words from the lexicon (100 words per length between 4 and 8 letters), that we either removed only from the orthographic lexicon, and thus considered as new words with prior phonological knowledge (PhonK words), or removed from both the orthographic and phonological lexicons, and thus considered as new words without prior phonological knowledge (PhonN words). This guarantees that stimuli have the same characteristics across conditions on all other aspects (word and letter frequencies, neighborhoods, etc.)

Procedure

The model was used to simulate incidental learning of orthographically novel words. Visuo-attentional exploration of

[1] This dataset is available at `https://osf.io/azkbr/`.

the stimulus was performed and continued until the stopping criterion on phoneme perception was met. There were four conditions, defined by varying the correction mechanism used (online vs post-processing) and type of stimulus, which are always orthographically novel, but can be phonologically known or novel (PhonK vs PhonN). Additionally, we investigated the influence of the two context parameters (its size N_S and strength p_S) on model performance. Recall that the context strength value $p_S = 1$, where the semantic distribution is uniform, simulates the context-free situation.

Measure

At the end of a simulation, the model extracts a single pronunciation from phoneme probability distributions. The model's pronunciation is then compared phoneme by phoneme with the expected pronunciation of the stimulus. It is categorized as correct if it matches the expected pronunciation for all positions. Thus, we measured Accuracy as the percentage of stimuli correctly decoded.

Results

Result data and scripts for data analysis are provided as Supplementary Material[2].

Accuracy according to context parameters (p_S and N_S), the type of mechanism and type of stimuli is illustrated in Figure 4. Results show that for PhonN words (top panels) accuracy decreases with an increase in the context strength parameter p_S for both mechanisms. Recall that PhonN items are assumed unknown both phonologically and orthographically, and thus not included in the context. Regarding the context size parameter N_S, accuracy consistently decreases with the post-processing mechanism, ranging from 81.2% when $N_S = 1$ to 20.2% when $N_S = 1,000$ at $p_S = 1,000$. In contrast, for the online mechanism, accuracy slightly decreases between $N_S = 1$ and $N_S = 50$ (from 80.0% to 72.4% at $p_S = 1,000$) and subsequently increases between $N_S = 50$ and $N_S = 1,000$ (from 72.4% to 80.8% at $p_S = 1,000$).

For PhonK words (bottom panels), which are known phonologically, and thus are included in the context, results show that, for the lowest context size values N_S, accuracy increases with the context strength parameter p_S for both mechanisms. However, for the post-processing mechanism, the difference in accuracy between $p_S = 1$ and $p_S = 2$ (a difference of 6.4% for $N_S = 1$) is greater than the difference in accuracy between $p_S = 2$ and $p_S = 1,000$ (a difference of 4.4% for $N_S = 1$). In contrast, the effect is more gradual concerning context strength for the online mechanism (a difference of 0.6% between $p_S = 1$ and $p_S = 2$ for $N_S = 1$, a difference of 11.4% between $p_S = 2$ and $p_S = 1,000$).

With the increase in N_S, the accuracy with the online mechanism declines. The decrease is more pronounced for higher values of p_S (a decline of 8.2% between $N_S = 1$ and $N_S = 50$ for $p_S = 1,000$, and only 0.4% for $p_S = 2$). Consequently, for higher values of N_S, the optimal scores are not achieved for the strongest contexts. In contrast, for the post-processing mechanism, there is no performance degradation with the increase in the parameter N_S (except between $N_S = 100$ and $N_S = 1,000$), and the best accuracy is consistently achieved for the strongest contexts.

Finally, for the largest value of N_S ($N_S = 1,000$), the strength of the context has no effect on the accuracy for the online mechanism (accuracy remains between 87.2% and 87.8%). In contrast, for the post-processing mechanism, the effect of context on accuracy is positive, but the difference in accuracy between $p_S = 1$ and $p_S = 2$ (5.8%) is greater than the difference in accuracy between $p_S = 2$ and $p_S = 1,000$ (1.6%). Therefore, the impact of context presence is more significant than the influence of context strength itself.

Discussion

In this study, we examined context effects in orthographic incidental learning using two pronunciation correction mechanisms: an "online mechanism" that corrects throughout processing, and a "post-processing mechanism" that corrects at the end of processing and only when necessary. We assessed decoding accuracy in various scenarios: with and without prior phonological knowledge, as well as with context varying in strength and size.

Simulations indicate a generally positive impact of context strength p_S on learning words with prior phonological knowledge (PhonK) using both mechanisms. However, a decrease of the positive effect with the increase of the context size N_S is only observed with the online mechanism. This appears more realistic, as this could result from expected lexicalization errors for the strongest and most ambiguous contexts. Moreover, with the largest contexts, a significant proportion of words belong to the context (around one third of the words used during decoding), meaning that no word truly stands out from the rest. Consequently, we suggest that the positive context effect should be minimal, especially for weak contexts. This only aligns with the observed behavior of the online mechanism. Therefore, the online mechanism appears more realistic when simulating learning words with prior phonological knowledge.

For words without prior phonological knowledge (PhonN), the distinction between the two mechanisms becomes more pronounced. As anticipated, the impact of context when learning words without prior phonological knowledge is consistently negative with both mechanisms. Notably, a stronger context consistently leads to a more negative effect. Additionally, as context size increases from the smallest to medium values, performance decreases. However, for larger context sizes, performance keeps decreasing for the post-processing mechanism, while it increases back up for the online mechanism. Indeed, when a context is too large, it becomes less informative (too many words are favored), especially when the context strength is low, resulting in a small impact on ac-

[2]They can be found at `https://gricad-gitlab.univ-grenoble-alpes.fr/steinhia/cogsci2024`. The code of the BRAID-Acq model is available at `https://gricad-gitlab.univ-grenoble-alpes.fr/diardj/braid-acq`.

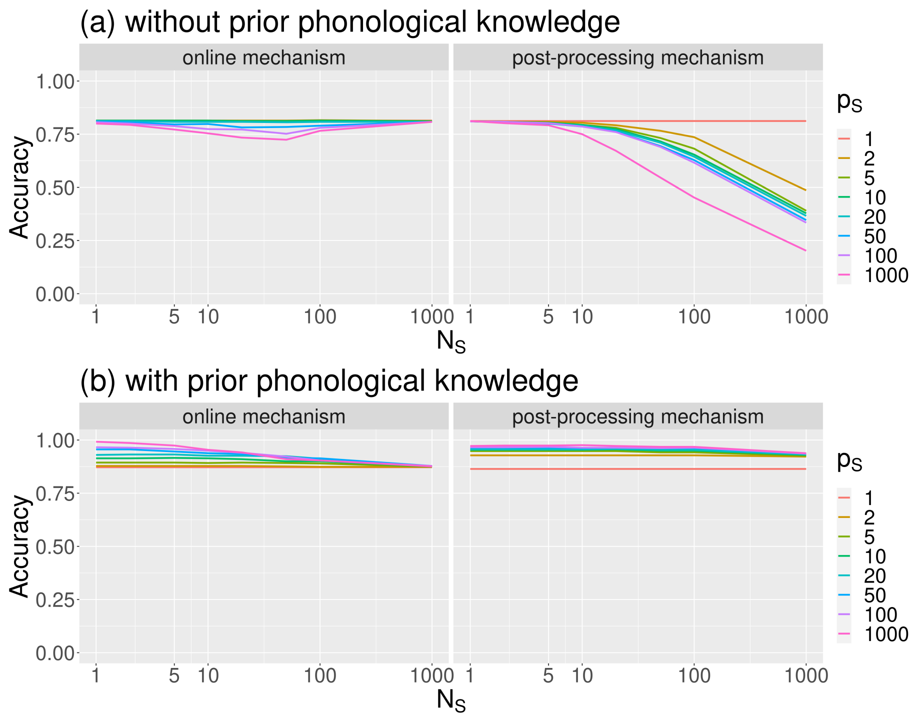

Figure 4: Decoding Accuracy (y-axis) as a function of context strength (p_S; colored curves) and size (N_S; x-axis), for words without prior phonological knowledge (PhonN; a, top panels) or words with prior phonological knowledge (PhonK; b, bottom panels), for the online mechanism (left panels) and post-processing mechanism (right panels).

curacy. Therefore, this suggests, once more, that the online mechanism is more plausible.

To interpret our simulation results, we recall the main difference between the two mechanisms. In the post-processing mechanism, there are two successive post-processing phases: the pronunciation correction in itself, where information is progressively conveyed without the use of semantic information; and then the binary decision on whether to retain or discard the resulting pronunciation, by assessing if the identified word belongs to the context or not. Our simulations suggest that a simultaneous integration of two sources of information (bottom-up and semantic information) during decoding is more realistic than incorporating them successively. This likely results from the mathematical property that combining two sources of information with uncertainty effectively reduces overall uncertainty.

Furthermore, we hypothesize that the binary nature of the decision is also responsible for the difference in results. Specifically, when dealing with larger context sizes, there is a high probability that the phonologically identified word (which cannot be the stimulus because the model has no prior phonological knowledge of it) belongs to the context. Consequently, it increases the probability of lexicalization errors, which can be avoided by a more refined mechanism.

One limitation of the current implementation of the model is that its context is composed of randomly chosen words, which is not realistic. However, it is unlikely that integrating a more realistic semantic context, with words semantically related to the stimulus, would significantly impact our results. Indeed, the crucial factor for pronunciation correction is the phonological distance between partial decoding and the pronunciation of context words. Semantically related words, when they are not from the same family as the stimulus, would display similar phonological diversity to randomly chosen words. Only for semantically related words that belong to the same family as the stimulus, phonological similarity would be higher, making it harder for the model to select the correct item. In that case, other factors, which are beyond the scope of the current model, like syntax or morphology could assist disambiguation.

To sum up, our results from simulations of incidental learning of words with and without prior phonological knowledge suggest that the online mechanism is more realistic. In this mechanism, the correction process occurs throughout the entire perceptual processing, by continuous integration of semantic information. This contrasts with the experimental psychology literature about orthographic learning, which so far frames pronunciation correction as a post-decision process, after the end of perceptual processing. Our computational modeling study therefore provides a novel theoretical account of pronunciation correction to explore, and our results on the different effects of context size and strength on decoding provide quantitative experimental predictions to distinguish these two theoretical accounts.

Acknowledgments

This work was supported by a French Ministry of Research (MESR) Ph.D. grant to AS. This work was also supported by the French government as part of the e-FRAN "FLUENCE" project (SV as PI) funded by the PIA2 "Investissement d'Avenir" program handled by the "Caisse des Dépôts et Consignations". This work also benefited from a grant from the French government (France 2030) operated by the Agence Nationale de la Recherche (ANR), with the reference ANR-22-FRAN-0008 (TRANS3 project; PI: Marie-Line Bosse).

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