Extended Abstract: Explaining lexical processing times with cognitively plausible computational models.

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Abstract. Lexical processing times can yield valuable insights about structure in language and the cognitive processes that enable the use of language. The time a brain needs to process a chunk of information gives an estimation about how much cognitive effort is required to understand it. Previous studies show that lexical processing times of individual words are influenced by the context, i.e. the sentence they appear in. The reason can be that human brains predict lexical features like gender and lexical categories. This paper attempts to explain variation between lexical processing times of individual words by simulating a lexical predictive process. The simulation is done with two seperate cogntively plausible computational models that both try to predict lexical categories of words in sentences based on the lexical categories of previous words. The predictions of the models are compared with similar predictions by humans as well as human reading times (gaze durations) of the same sentences. The recurrent neural network (RNN) based model predictions explain more variance in the prediction errors of humans than the Rescorla-Wagner based model. However, the Rescorla-Wagner model explains more variance in the reading times. The results show that the RNN results match the conscious prediction process more closely, but the Rescorla-Wagner model may be a better model for explaining very quick predictions that humans make when reading or hearing natural language.

Keywords: Lexical Processing · Cognitive Modeling · Rescorla-Wagner · Recurrent Neural Networks · Reading.

1 Introduction

Human brains are able to process information at great speeds, but complex information requires more effort and therefore more processing time. Previous studies have shown that lexical processing times are influenced by the context words appear in (McDonald & Shillcock, 2001; Baayen, 2010). Baayen (2010) has shown that a character-level Rescorla-Wagner (Rescorla et al., 1972) based model can explain variance in lexical processing times. These lexical processing times can however also be influenced by lexical categories (Hinojosa et al., 2005) and grammatical gender (Van Berkum et al., 2005). Therefore, lexical processing times could be influenced by high-level morphosyntactic predictions (Baayen, 2010; Luke & Christianson, 2016). The influence of morphosyntactic predictions on lexical processing times of words in context has however not yet been studied extensively.

2 Method

To study the effect of morphosyntactic predictions on lexical processing times, the PROVO corpus (Luke & Christianson, 2018) is used. This corpus contains upcoming word predictions by 470 humans and reading times per word withing context for the same documents based on eye-tracking data.

To train the computational models, the Penn Treebank (Marcus et al., 1993) is used. A RNN model and a Rescorla-Wagner model are trained to predict upcoming part-of-speech (POS) tags in the sentences of the Penn Treebank based on the POS tags of the preceeding words.

3 Results

The trained models are evaluated on the POS tags of documents in the PROVO corpus. The human predictions in the PROVO corpus have the correct POS tag in 48% of their predictions whereas the RNN and Rescorla-Wagner models only achieve an accuracy of 37% and 32% respectively. Both model predictions show similar biases toward certain common lexical classes as human predictions. To explain variance in human prediction errors with model results, ordinary least sequares (OLS) models are fit on the results. The estimators include the actual POS tag, the word length and model outputs. The model outputs of both the RNN model and the Rescorla-Wagner model contribute significantly to the OLS model, but the RNN model estimators explain more variance than the Rescorla-Wagner model estimators.

Additionally, OLS models are fit to explain variance in the human reading times. The POS tags and word lengths already explain 69% of variation in reading times, but the RNN and Rescorla-Wagner estimators significantly improve the model fit. Interestingly, the Rescorla-Wagner model is a better estimator for reading times than the RNN model. Moreover, Rescorla-Wagner predictions are better estimators than the human prediction errors, but the combination of human prediction errors and Rescorla-Wagner predictions explain even more variance (Adj. $R^2 = 0.72$).

4 Conclusion

The results show that the RNN model makes predictions of lexical classes similarly as humans. Lexical processing times are however better explained by the Rescorla-Wagner model. The two models explain different, but complementary aspects of human lexical processing. Lexical processing times tell something about the effort that is required to read text. Therefore the estimations can be useful to evaluate readability of any text. To demonstrate this, a demo is available at https://lexical-processing.wietsedv.nl.

References

Baayen, R. H. (2010). Demythologizing the word frequency effect: A discriminative learning perspective. *The Mental Lexicon*, *5*(3), 436–461.

Hinojosa, J. A., Moreno, E. M., Casado, P., Muñoz, F., & Pozo, M. A. (2005). Syntactic expectancy: An event-related potentials study. *Neuroscience Letters*, *378*(1), 34–39.

Luke, S. G., & Christianson, K. (2016). Limits on lexical prediction during reading. *Cognitive Psychology*, *88*, 22–60.

Luke, S. G., & Christianson, K. (2018). The provo corpus: A large eye-tracking corpus with predictability norms. *Behavior research methods*, 1–8.

Marcus, M., Santorini, B., & Marcinkiewicz, M. A. (1993). Building a large annotated corpus of english: The penn treebank.

McDonald, S. A., & Shillcock, R. C. (2001). Rethinking the word frequency effect: The neglected role of distributional information in lexical processing. *Language and Speech*, *44*(3), 295–322.

Rescorla, R. A., Wagner, A. R., et al. (1972). A theory of pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. *Classical conditioning II: Current research and theory*, *2*, 64–99.

Van Berkum, J. J., Brown, C. M., Zwitserlood, P., Kooijman, V., & Hagoort, P. (2005). Anticipating upcoming words in discourse: evidence from erps and reading times. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*(3), 443.