Postdoctoral researcher – objectives and the work package plan

1. Objective

In the short description of the spreading-activation memory model, we assumed only simple grammatical features like [+/-*Plural*] or very coarse features encapsulating lexical meaning like [+/-*Animate*] as possible cues. Even though these assumptions are recognized as simplifying, they became so ingrained in the memory models of language that it is commonly not questioned whether they are appropriate, even in computational models that are concerned with quantitative data fit (Lewis and Vasishth, 2005, Rasmussen and Schuler, 2018, Vasishth and Engelmann, 2021). Such simplifications, however, are problematic. One worry is that since cues are hand-selected in models, the research suffers from unconstrained degrees of freedom (Smith and Vasishth, 2020). Another worry is that the simplified model of memory can work for those experiments in which it is carefully controlled which features are present or absent, but the model could not scale up to richer data, e.g., corpus data, in which it is open-ended which features play a role (Dotlacil, 2018, Dotlacil, 2021). This could be one reason behind failures of spreading-activation models of memory in the past when fitting reading data from a corpus (Boston et al., 2021). In sum, abandoning the simplification should make the memory model more realistic and, as a consequence, more useful and more widely applicable.

The current situation is somewhat reminiscent of research into lexical meaning. There, a simple idea that the representation of lexical meanings could be represented with sets of features took off and scaled up with the advent of computational distributional semantics, in which the process of selecting features was made data driven and corpus-based and lexical meanings became real-valued vectors, representing a point in a rich meaning space that represents contexts. We want to proceed along a similar path, taking the advantage of advances in NLP and creating a memory model that is informed by findings in language modeling.

2. Work package for postdoc: computational cognitive modeling of cues in spreading-activation models

The starting point of advancing spreading-activation models of language is the observation that the spreading-activation model is directly compatible with lexical representations as vectors in vector semantics. This provides an almost unexplored linking hypothesis between the research into memory structures and the rich study of distributional models of meaning in NLP. We will take up this hypothesis and study how it can help us model the recall and memory access in language.

There are several lines of research to be explored in this project.

2.1 Linking static/contextualized vector-space models with spreading-activation memory models

Many co-occurrence (counting) models, as well as neural models like skip-gram with negative sampling represent a target word and its contextual word as a (positive, smoothed, shifted) pointwise mutual information (pmi). It is less known that the same is also true for spreading-activation memory models, where we often talk of cues, rather than contextual words, but the formal link is the same (see, e.g., Brasoveanu and Dotlacil, 2020, Chapter 6, for some formal details). This fact provides a linking a hypothesis between vector models like word2vec (Mikolov et al., 2013) and memory models used, e.g., in ACT-R (Anderson and Lebiere, 1998). It also provides an interpretation of vector space of lexical representations as a particular spreading-activation memory model, which is built under the assumption that items are lexical elements and cues correspond to contexts. Usually, the models used in psycholinguistics only work with a few cues and each cue only carries 0 and 1 values, but this is only an extreme, trivial example of a space within spreading activation can take place. With the linking hypothesis, we can go beyond this trivial model.

The just-mentioned linking hypothesis leaves several things unclear and unexplored, which should be tackled in this project. In particular:

- Is the formal connection between spreading-activation memory models and static vector-space models of the lexicon empirically justified? Do we see that vector-space models like word2vec (Mikolov et al., 2013) can model data from memory studies, like retrieval times in recall (Anderson and Lebiere, 1998)?
- What is the status of contextualized vector models like BERT? How can we connect those to memory models?

- How can we connect static vector models with the memory models that underly spreading-activation memory models? More concretely, it is known that spreading-activation memory models are linked to Hopfield networks (Hopfield, 1982, Hertz et al., 1991) – but how should we re-interpret the link between memory and the lexicon in Hopfield networks?

2.2 Dependencies in corpora

Can richer memory structures model reading times on dependents? This part of the project complements research of PhD students, who address the same question in experiments. By dependents, we mean elements that depend in their meaning/form on another linguistic item – like English (present-tense) verbs, which depend on subjects for their form and interpretation, or anaphora, which depend on antecedents. More details on dependents are also provided in the short description.

The goal of this sub-project is to investigate the application of memory structures to dependencies in psycholinguistic corpora. It is important to go beyond experiments and collect extra evidence from psycholinguistic corpora since corpora provide a more varied and much larger source of data than we could achieve using experimental studies. Furthermore, it happened in the past that findings in individual experiments were not confirmed in corpus research (Demberg and Keller, 2007), and this should serve as a cautionary tale.

We are planning to use (at least) three psycholinguistic reading corpora: the GECO corpus (Cop et al., 2016), Natural Stories Corpus (Futrell et al., 2018), ZuCO corpus (Hollenstein et al., 2018). These are corpora of natural or semi-natural texts in which along with the texts we also have reading data, collected using eye tracking or self-paced reading. We collect dependencies from the corpora, along with targets that resolve dependencies and with distractors (elements that are similar to targets but do not resolve dependencies).

Reading corpora have been used for the validation of memory models (Demberg and Keller, 2007, Shain et al, 2016) but corpus data were used less extensively to inform spreading-activation memory models than individual experiments. Thus extracting the dependencies along with the corresponding behavioural measures from reading corpora will already be useful for the research into memory and dependency resolution. In addition, the aim of this sub-project is to study how such data compare to the hypothesis that vector spaces approximate spreading-activation models. The focus in this part of work will be on dependencies in syntax (subject-verb dependencies, anaphora dependencies) but could be extended beyond syntax if possible.

2.3 Investigations of dependencies and parsing

A parsing (syntactic-structure building) can be seen as another application of a spreading-activation memory model. Using transition-based parsers, one can interpret transitions (steps from one partial representation of a parsed sentence to another partial representation) as a case of memory retrieval that is subject to spreading activations. For details, see Dotlacil and de Haan (2021), and Dotlacil (2021).

Given this, one can see parsing and the recalling of dependencies as instances of the underlyingly same phenomenon: memory recall. The close connection between parsing and memory retrieval will be leveraged in this sub-project. We will model data from psycholinguistic corpora and from experiments that targeted cognitive difficulties due to expectations in syntactic-structure building and, at the same time, difficulties due to non-trivial dependency resolution. An example of relevant experiments to be modeled are: (i) experiments on relative clauses, in which parser expectations interact with the wh-pronoun resolution (see Staub, 2010, for discussion); (ii) data in which parser's expectations interact with memory load due to dependency resolution (Futrell et al., 2020); (iii) experiments investigating the trade-off between memory load independently manipulated (e.g., since people had to remember particular information) and parsing (e.g., Fedorenko et al., 2006). The goal is to model behavioral/neural data, namely, reaction times (in key presses and eye fixations) and EEG in one memory model which achieves both – parsing and dependency resolution. This investigation should provide evidence for (or against) the uniformity of memory across different language-related goals – be these a (short-term) recall of targets for the resolution of dependencies, or a (long-term) recall of grammatical knowledge for the construction of parsing structures and for guiding expectations about the upcoming linguistic material.

References

Altmann, G., & Steedman, M. (1988). Interaction with context during human sentence processing. *Cognition*, *30*(3), 191-238.

Anderson, J. R. (1974). Retrieval of propositional information from long-term memory. *Cognitive psychology*, *6*(4), 451-474.

Anderson, J. R. (1991). Is human cognition adaptive?. *behavioural and brain sciences*, *14*(3), 471-485.

Anderson, J. R. (2007). *How can the human mind occur in the physical universe?*. Oxford University Press.

Anderson, J. R., & Lebiere, C. J. (1998). *The atomic components of thought*. Lawrence Erlbaum Associates.

Anderson, J. R., & Reder, L. M. (1999). The fan effect: New results and new theories. *Journal of Experimental Psychology: General*, *128*(2), 186.

Anderson, J. R., & Lebiere, C. J. (1998). *The atomic components of thought*. Psychology Press.

Badecker, W., & Kuminiak, F. (2007). Morphology, agreement and working memory retrieval in sentence production: Evidence from gender and case in Slovak. *Journal of memory and language*, *56*(1), 65-85.

Baroni, M., Dinu, G., & Kruszewski, G. (2014). Don't count, predict! a systematic comparison of context-counting vs. context-predicting semantic vectors. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Long Papers),* 238-247.

Bengio, Y., Ducharme, R., & Vincent, P. (2003). A neural probabilistic language model. *Advances in Neural Information Processing Systems*, 13.

Bos, J. (2008). Wide-coverage semantic analysis with boxer. In *Semantics in text processing. step 2008 conference proceedings* (pp. 277-286).

Bos, J., Basile, V., Evang, K., Venhuizen, N. J., & Bjerva, J. (2017). The groningen meaning bank. In *Handbook of linguistic annotation* (pp. 463-496). Springer, Dordrecht.

Boston, M. F., Hale, J. T., Vasishth, S., & Kliegl, R. (2011). Parallel processing and sentence comprehension difficulty. *Language and Cognitive Processes*, *26*(3), 301-349.

Brasoveanu, A., & Dotlačil, J. (2020). *Computational cognitive modeling and linguistic theory* (p. 294). Springer Nature.

Bullinaria, J. A., & Levy, J. P. (2007). Extracting semantic representations from word co-occurrence statistics: A computational study. *Behavior research methods*, *39*(3), 510-526.

Chen, S.Y. and Husband, E.M. (2018). Comprehending anaphoric presuppositions requires memory retrieval *too*. *Proceedings of the Linguistic Society of America*, 3, 44, 1-11.

Chomsky, N. (1965). *Aspects of the Theory of Syntax* (Vol. 11). MIT press.

Church, K., & Hanks, P. (1990). Word association norms, mutual information, and lexicography. *Computational linguistics*, *16*(1), 22-29.

Cop, U., Dirix, N., Drieghe, D., & Duyck, W. (2016). Presenting GECO: An eyetracking corpus of monolingual and bilingual sentence reading. *Behavior Research Methods*, 49, 602–615.

Cunnings, I., & Sturt, P. (2018). Retrieval interference and semantic interpretation. *Journal of Memory and Language*, *102*, 16-27.

Curran, J. R., Clark, S., & Bos, J. (2007). Linguistically motivated large-scale NLP with C&C and Boxer. In *Proceedings of the 45th annual meeting of the Association for Computational Linguistics Companion,* 33-36.

Demberg, V., & Keller, F. (2008). Data from eye-tracking corpora as evidence for theories of syntactic processing complexity. *Cognition*, *109*(2), 193-210.

Dillon, B., Mishler, A., Sloggett, S., & Phillips, C. (2013). Contrasting intrusion profiles for agreement and anaphora: Experimental and modeling evidence. *Journal of Memory and Language*, *69*(2), 85-103.

Dotlačil, J. (2018). Building an ACT-R reader for eye-tracking corpus data. *Topics in cognitive science*, *10*(1), 144-160.

Dotlačil, J. (2021). Parsing as a Cue-Based Retrieval Model. *Cognitive Science*, *45*(8), e13020.

Dotlačil, J., & de Haan, P. (2021). Parsing model and a rational theory of memory. *Frontiers in Psychology*, *12*.

Drenhaus, H., Demberg, V., Köhne, J., & Delogu, F. (2014). Incremental and predictive discourse processing based on causal and concessive discourse markers: ERP studies on German and English. In *Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 36, No. 36).

Van Dyke, J. A. (2007). Interference effects from grammatically unavailable constituents during sentence processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*(2), 407.

Van Dyke, J. A., & Lewis, R. L. (2003). Distinguishing effects of structure and decay on attachment and repair: A cue-based parsing account of recovery from misanalyzed ambiguities. *Journal of Memory and Language*, *49*(3), 285-316.

Van Dyke, J. A., & McElree, B. (2006). Retrieval interference in sentence comprehension. *Journal of memory and language*, *55*(2), 157-166.

Eberhard, K., Cutting, J. C., & Bock, K. (2005). Making syntax of sense: Number agreement in sentence production. *Psychological Review*, 112, 531–558.

Engelmann, F., L. A. Jäger, and S. Vasishth. (2019). The effect of prominence and cue association on retrieval processes: A computational account. *Cognitive Science*, 43.

Fedorenko, E., Gibson, E., & Rohde, D. (2006). The nature of working memory capacity in sentence comprehension: Evidence against domain-specific working memory resources. *Journal of memory and language*, *54*(4), 541-553.

Frank, S. L., Koppen, M., Noordman, L. G., & Vonk, W. (2003). Modeling knowledge-based inferences in story comprehension. *Cognitive Science,* 27(6), 875–910.

Frank, S. L., Otten, L. J., Galli, G., & Vigliocco, G. (2015). The ERP response to the amount of information conveyed by words in sentences. *Brain and language*, *140*, 1-11.

Frank, S. L., & Willems, R. M. (2017). Word predictability and semantic similarity show distinct patterns of brain activity during language comprehension. *Language, Cognition and Neuroscience*, *32*(9), 1192-1203.

Futrell, R., E. Gibson, H. J. Tily, I. Blank, A. Vishnevetsky, S. T. Piantadosi, & E. Fedorenko. (2018). The natural stories corpus. *Proceedings of LREC 2018, Eleventh International Conference on Language Resources and Evaluation*, 76–82. Miyazaki, Japan.

Futrell, Richard, Edward Gibson, and Roger P. Levy. (2020). Lossy-context surprisal: An information-theoretic model of memory effects in sentence processing. *Cognitive Science*, 44.

Gibson, E. A. F. (1991). *A computational theory of human linguistic processing: Memory limitations and processing breakdown*. Carnegie Mellon University.

Gibson, E. (2000). The dependency locality theory: A distance-based theory of linguistic complexity. *Image, language, brain*, *2000*, 95-126.

Goodkind, A., & Bicknell, K. (2018, January). Predictive power of word surprisal for reading times is a linear function of language model quality. In *Proceedings of the 8th workshop on cognitive modeling and computational linguistics (CMCL 2018)* (pp. 10-18).

Grodner, D., & Gibson, E. (2005). Consequences of the serial nature of linguistic input for sentenial complexity. *Cognitive science*, *29*(2), 261-290.

Hale, J. (2001). A probabilistic Earley parser as a psycholinguistic model. In *Second meeting of the north american chapter of the association for computational linguistics*.

Hale, J. (2003). The information conveyed by words in sentences. *Journal of Psycholinguistic Research*, *32*(2), 101-123.

Hale, J. T. (2011). What a rational parser would do. *Cognitive Science*, *35*(3), 399-443.

Hale, John T. 2014. *Automaton theories of human sentence comprehension*. Stanford: CSLI Publications.

Hao, Y., Mendelsohn, S., Sterneck, R., Martinez, R., & Frank, R. (2020). Probabilistic predictions of people perusing: Evaluating metrics of language model performance for psycholinguistic modeling. *arXiv preprint arXiv:2009.03954*.

Hertz, A., Krogh, A., & Palmer, R. (1991). *Introduction To The Theory Of Neural Computation*. Santa Fe Institute Studies in the Sciences of Complexity.

Hollenstein, N., Rotsztejn, J., Troendle, M., Pedroni, A., Zhang, C., & Langer, N. (2018). ZuCo, a simultaneous EEG and eye-tracking resource for natural sentence reading. *Scientific data, 5*(1), 1-13.

Hollenstein, N., Pirovano, F., Zhang, C., Jäger, L., & Beinborn, L. (2021). Multilingual language models predict human reading behavior. *NAACL*.

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the national academy of sciences*, 79(8), 2554-2558.

Jäger, L. A., Engelmann, F., & Vasishth, S. (2017). Similarity-based interference in sentence comprehension: Literature review and Bayesian meta-analysis. *Journal of Memory and Language, 94*, 316-339.

Jäger, L. A., Mertzen, D., Van Dyke, J. A., & Vasishth, S. (2020). Interference patterns in subject-verb agreement and reflexives revisited: A large-sample study. *Journal of Memory and Language, 111*, 104063.

Kamp, H. (1984). A theory of truth and semantic representation. *Truth, interpretation and information*, *277*, 322.

Kamp, H., & Reyle, U. (1993). *From discourse to logic: Introduction to modeltheoretic semantics of natural language, formal logic and discourse representation theory*. Springer.

Kehler, A., Kertz, L., Rohde, H., & Elman, J. L. (2008). Coherence and coreference revisited. *Journal of semantics, 25*(1), 1-44.

Kush, D., Lidz, J., & Phillips, C. (2015). Relation-sensitive retrieval: Evidence from bound variable pronouns. *Journal of memory and language, 82*, 18-40.

Lago, S., Shalom, D. E., Sigman, M., Lau, E. F., & Phillips, C. (2015). Agreement attraction in Spanish comprehension. *Journal of Memory and Language, 82*, 133-149.

Levy, R. (2008). Expectation-based syntactic comprehension. *Cognition*, *106*(3), 1126-1177.

Levy, R. (2011). Integrating surprisal and uncertain-input models in online sentence comprehension: formal techniques and empirical results. In *Proceedings of the 49th annual meeting of the Association for Computational Linguistics: Human Language Technologies*.

Levy, O., & Goldberg, Y. (2014). Neural word embedding as implicit matrix factorization. *Advances in neural information processing systems, 27*.

Lewis, R. L., & Vasishth, S. (2005). An activation-based model of sentence processing as skilled memory retrieval. *Cognitive science, 29,* 375-419.

Lewis, R. L., Vasishth, S., & Van Dyke, J. A. (2006). Computational principles of working memory in sentence comprehension. *Trends in cognitive sciences*, *10*, 447-454.

Liu, Jiangming, and Yue Zhang. 2017. In-order transition-based constituent parsing. *Transactions of the Association for Computational Linguistics*, 5, 413-424.

Van Maanen, L., & Van Rijn, H. (2019). The observed locus of semantic interference may not coincide with the functional locus of semantic interference: A commentary on Shitova et al. *Cortex*, 111 . doi: 10.1016/j.cortex.2018.10.025

Van Maanen, L., Van Rijn, H., & Borst, J. P. J. (2009). Stroop and picture-word interference are two sides of the same coin. *Psychonomic Bulletin & Review*, 16 (6), 987–999. doi: 10.3758/ PBR.16.6.987

Van Maanen, L., Van Rijn, H., & Taatgen, N. A. (2012). RACE/A: An architectural account of the interactions between learning, task control, and retrieval dynamics. *Cognitive Science*, 36 (1), 62–101. doi: 10.1111/j.1551-6709.2011.01213.x

Martin, A. E., & McElree, B. (2008). A content-addressable pointer mechanism underlies comprehension of verb-phrase ellipsis. *Journal of Memory and Language*, 58(3), 879-906.

McElree, B. (2001). Working memory and focal attention. *Journal of experimental psychology. Learning, memory, and cognition*, 27(3), 817.

McElree, B. et al. (2003) Memory structures that subserve sentence comprehension. *Journal of Memory and Language, 48*, 67–91.

McElree, B., Foraker, S., & Dyer, L. (2003). Memory structures that subserve sentence comprehension. *Journal of Memory and Language*, 48(1), 67-91.

Meyer, L., Obleser, J., Kiebel, S., & Friederici, A. (2012). Spatiotemporal Dynamics of Argument Retrieval and Reordering: An fMRI and EEG Study on Sentence Processing. *Frontiers in Psychology*, 3.

Mikolov, T., Karafiát, M., Burget, L., Cernocký, J., & Khudanpur, S. (2010). Recurrent neural network based language model. *Interspeech*, 2, 1045-1048.

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

Mikolov, T., Grave, E., Bojanowski, P., Puhrsch, C., & Joulin, A. (2017). Advances in pre-training distributed word representations. *arXiv preprint arXiv:1712.09405*.

Miller, G. A., & Charles, W. G. (1991). Contextual correlates of semantic similarity. *Language and cognitive processes*, *6*(1), 1-28.

Mirman, D., & Magnuson, J. S. (2008). Attractor dynamics and semantic neighborhood density: Processing is slowed by near neighbors and speeded by distant neighbors. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 34 (1), 65–79. Retrieved 2023-09-27, from http://doi.apa.org/getdoi.cfm?doi=10.1037/0278-7393.34.1.65 doi: 10.1037/0278-7393.34.1.65

Pecher, D., Zeelenberg, R., & Wagenmakers, E.-J. (2005). Enemies and Friends in the Neigh-

borhood: Orthographic Si

Mitchell, J., Lapata, M., Demberg, V., & Keller, F. (2010). Syntactic and semantic factors in processing difficulty: An integrated measure. In *Proceedings of the 48th annual meeting of the association for computational linguistics* (pp. 196-206).

Nicenboim, B., Vasishth, S., Engelmann, F., & Suckow, K. (2018). Exploratory and confirmatory analyses in sentence processing: A case study of number interference in German. *Cognitive science*, *42*, 1075-1100.

Nicenboim, B., & Vasishth, S. (2018b). Models of retrieval in sentence comprehension: A computational evaluation using Bayesian hierarchical modeling. *Journal of Memory and Language*, *99*, 1-34.

Van Noord, R., Abzianidze, L., Toral, A., & Bos, J. (2018). Exploring neural methods for parsing discourse representation structures. *Transactions of the Association for Computational Linguistics*, *6*, 619-633.

Nouwens, J. (2021). Correlation between memory recall and word similarity in sentence processing. Bsc thesis, Utrecht university.

Parker, D. (2022). Ellipsis interference revisited: New evidence for feature markedness effects in retrieval. *Journal of Memory and Language*, 124.

Pearlmutter, N. J., Garnsey, S. & Bock K. (1999). Agreement processes in sentence comprehension. *Journal of memory and language*, 41, 427–456.

Rasmussen, N. E., & Schuler, W. (2018). Left-corner parsing with distributed associative memory produces surprisal and locality effects. *Cognitive science*, *42*, 1009-1042.

Resnik, P. (1992). Left-corner parsing and psychological plausibility. In *Proceedings of the Fourteenth International Conference on Computational Linguistics*. Nantes, France.

Saebo, K. J. (2004). Conversational contrast and conventional parallel: Topic implicatures and additive presuppositions. *Journal of Semantics*, *21*(2), 199-217.

van der Sandt, R. A. (1992). Presupposition projection as anaphora resolution. *Journal of semantics*, *9*(4), 333-377.

Schad, D. J., Nicenboim, B., Bürkner, P. C., Betancourt, M., & Vasishth, S. (2021). Workflow techniques for the robust use of Bayes Factors. *Psychological Methods.*

van Schijndel, M., & Linzen, T. (2018). A neural model of adaptation in reading. *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP 2018)*, pages 4704–4710.

Schmitz, T., J. Dotlacil, M. Hoeks, R. Nouwen, J. Winkowski, ms., Semantic accesibility and interference in pronoun resolution. Submitted.

Shain, C., Van Schijndel, M., Futrell, R., Gibson, E., & Schuler, W. (2016). Memory access during incremental sentence processing causes reading time latency. In *Proceedings of the workshop on computational linguistics for linguistic complexity (CL4LC)* (pp. 49-58).

Smith, G., & Vasishth, S. (2020). A principled approach to feature selection in models of sentence processing. *Cognitive science, 44*(12)

Slioussar, N. (2018). Forms and features: The role of syncretism in number agreement attraction. *Journal of Memory and Language*, *101*, 51-63.

Staub, A. (2010). Eye movements and processing difficulty in object relative clauses. *Cognition*, *116*(1), 71-86.

Steedman, M. (2000). *The syntactic process*. Cambridge, MA: MIT press.

Stewart, A. J., Kidd, E., & Haigh, M. (2009). Early sensitivity to discourse-level anomalies: Evidence from self-paced reading. *Discourse Processes*, *46*(1), 46-69.

Trueswell, J. C., Tanenhaus, M. K., & Garnsey, S. M. (1994). Semantic influences on parsing: Use of thematic role information in syntactic ambiguity resolution. *Journal of memory and language*, *33*(3), 285-318.

Tucker, M. A., Idrissi, A., & Almeida, D. (2015). Representing number in the real-time processing of agreement: Self-paced reading evidence from Arabic. *Frontiers in psychology*, *6*, 347.

Vasishth, S. (2020). Using Approximate Bayesian Computation for estimating parameters in the cue-based retrieval model of sentence processing. *MethodsX*, *7*

Vasishth, S., Mertzen, D., Jäger, L. A., & Gelman, A. (2018). The statistical significance filter leads to overoptimistic expectations of replicability. *Journal of Memory and Language*, *103*, 151-175.

Vasishth, S,, B. Nicenboim, F. Engelmann, & F. Burchert (2019). Computational models of retrieval processes in sentence processing. *Trends in Cognitive Sciences*, 23, 968–982.

Vasishth, S., & Engelmann, F. (2021). *Sentence Comprehension as a Cognitive Process: A Computational Approach*. Cambridge: Cambridge University Press.

Venhuizen, N. J., Crocker, M. W., & Brouwer, H. (2019). Expectation-based comprehension: Modeling the interaction of world knowledge and linguistic experience. *Discourse Processes*, *56*(3), 229-255.

Vigliocco, G., Butterworth, B., & Semenza, C. (1995). Constructing subject–verb agreement in speech: The role of semantic and morphological factors. *Journal of Memory and Language*, 34, 186–215.

Villata, S., Tabor, W., & Franck, J. (2018). Encoding and retrieval interference in sentence comprehension: Evidence from agreement. *Frontiers in psychology*, *9*, 2.

Wagers, M., E. F Lau, & C. Phillips (2009). Agreement attraction in comprehension: Representations and processes. *Journal of Memory and Language*, 61, 206–237.