# Memory access in language: how we store and retrieve linguistic information

# MEMLANG

To be able to talk and to understand each other, we have to continuously store and retrieve linguistic information. In linguistics, the dominant approach to studying the processes of storing and recall of linguistic information from short-term memory assumes that we can access all items in parallel and that the most highly activated items are the most likely to be retrieved. Activation, in turn, can be boosted by the requirements of the current cognitive context.

This model is related to theories of memory developed independently of linguistics. In linguistics, it has been supported by rich research on production and comprehension. The model, however, has been applied very narrowly. It focuses only on the recall of some syntactic items, for instance, the recall of arguments during the processing of a verb. Other functions of memory fall outside the approach.

The project's core idea is that the memory model can be applied to many other cases in which memory has a decisive role. We will do this by linking the model to theories of other language phenomena developed in linguistics, cognitive sciences and artificial intelligence. First, we will link it to computational models of lexical knowledge, which will enable us to fully and formally represent what the current cognitive context is and to build an indiscriminate and general approach to memory access. Second, we will link it to computational models of grammatical knowledge to understand how we store and recall grammatical rules. Finally, we will link it to discourse theories to have an analysis of storage and recall of textual information.

The project will lead to a new view on the memory model, one that is general and cross-domain. It will provide a more principled account of how memory affects language, will give us a new insight into why the theories of lexical knowledge, grammatical knowledge and discourse theories work, and it will make it possible to tie together accounts that are often treated as independent.

**Extended Synopsis of the scientific proposal**

Without memory and access to past information, we would have no language and we would have no communication. This is obvious to any second language learner who has to consciously remember words and idioms to speak a language. But memory recall is also crucial in correctly stringing words together to form and interpret sentences and discourses. Consider, as an example, the sentence in (1).

(1) Sue rarely knows the answer to this question.

In this example, the verb *knows* is dependent in its form and interpretation on the subject *Sue.* It is due to the subject *Sue* that the verb appears as *knows*, not as *know*. And it is the subject *Sue* that specifies what kind of knowing event (1) describes, namely, who the agent of knowing is. Neither interpretation nor production of the verb in (1) would be possible if we could not rely on memory and recall previous linguistic information, in this case, what the subject is when producing or comprehending the verb.

It has been a significant success for cognitive sciences and psycholinguistics that they have developed cognitively plausible and empirically adequate models of memory structures to characterise memory retrievals like the recall of the subject in (1). The theory of such memory structures has, in its core, one very simple idea: we do not search through elements one by one but have a parallel access to all elements at once and simply recall an element or elements with the highest activation. The activation, in turn, can be boosted by the cues we use for the recall. More concretely, for (1), such cues could be [+*subject*], [+*noun*] and [+*singular*], and they would ensure that even though every possible element is in principle retrievable, it is most likely that the subject *Sue* will be recalled. One particular instantiation of the theory is sometimes labeled as cue-based retrieval model (van Dyke et al., 2003, McElree, 2003, Lewis et al., 2005, 2006, among others), but I will use the term spreading-activation memory model, in order to highlight the main fact that the retrieval works due to the activation spreading from cues to elements in memory.

The predictions of the spreading activation model have been thoroughly tested on relations in language that require memory retrieval, like the subject-verb relation in (1). The empirical evidence supporting the model has come from various experimental methods, such as self-paced reading, eye tracking, production studies and speed-accuracy tradeoff (McElree, 2001, 2003, McElree et al., 2003, Badecker et al., 2007, Martin et al., 2008, Jäger et al., 2017, Slioussar, 2018, among others). The evidence has been predominantly driven by findings in subject-verb relations (van Dyke et al., 2003, 2006, van Dyke, 2007, Dillon et al., 2013, Nicenboim et al., 2018). However, there are other elements that require recall of another, previously mentioned language item for their interpretation and/or production. Following the standard terminology, I will call such elements dependents and the relation *dependency*. Subject-verb is one example of this, another is the antecedent-reflexive relation, as in (2), in which the form and the interpretation of the reflexive *themselves* is fully dependent on its antecedent, the subject *kids*.

(2) Kids saw themselves in the mirror.

While the issue of the resolution of reflexives is more controversial, there is some support for the spreading-activation memory in modeling this dependency (Jäger et al., 2020), and this also holds for other dependencies, such as wh-dependencies (Cunnings and Sturt, 2018, Brasoveanu and Dotlacil, 2020) and ellipsis-antecedent dependencies (Parker, 2022). The quantitative predictions of the theory also showed a good match against reading data (Nicenboim et al., 2018b). The theory has also been applied to the retrieval of parsing knowledge (Dotlacil and de Haan, 2021, Dotlacil, 2021).

There are several unresolved issues regarding the empirical validity of the spreading-activation model as it applies to the production and comprehension of dependents. Yet, it is undoubtedly fair to say that the model has been successful. In the last two decades, it has driven a significant portion of research in linguistics and psycholinguistics, it has connected the research on the role of memory in language to general theories of cognition and it has formed a significant springboard for the development of computational models of language production and comprehension, starting with Lewis et al. (2005). Last but not least, this research line played a significant role in improvements of data collection protocols and data analysis (Jäger et al., 2017, Vasishth et al., 2018, Vasishth, 2020, Schad et al., 2021).

Support for the spreading-activation model of memory is not limited to language. In fact, the model was developed outside the realm of language. It has, for example, been successfully applied to the recall of factual knowledge (propositional information), using the so-called fan-experiment design (Anderson, 1974, Anderson et al., 1999, Brasoveanu and Dotlacil, 2020). Since it has been developed and tested independently of language, there is a good argument to be made that this memory model represents a general cognitive mechanism and thus, implementing it for language is not an ad hoc solution to study memory, but a necessary step.

However, within the study of language, the research line is extremely limited in its scope. The theory of memory in linguistics only targets particular language elements: dependents. However, if the model is valid, it should offer a window into memory structures that are used in any of our language-bound abilities, not just the production or comprehension of dependents. But is the model valid beyond syntactic dependencies? Not only do we lack an answer to this question, we have not even started addressing it. This is odd, given the rich results from research just from the application of the model to the comprehension and production of dependents.

This brings us to the goal of this research proposal, summarized in the following box:

| **General objective of the project** |
| --- |
| To expand the spreading-activation models of memory beyond dependents and beyond simple cases like subject-verb dependency. To create a spreading-activation model of memory that meets up the challenge of language: the model is not idiosyncratically constructed for just some dependencies, but is general enough to meet *any* case of memory retrieval in language. |

In short, the MEMLANG project aims to prove the spreading-activation memory model as a general model of memory for language production and comprehension. To do so, it will meet three objectives:

i. to provide understanding which cues boost activation;

ii. to apply the model beyond syntactic dependents;

iii. to apply the model beyond syntax.

***Advancing memory models of language***

***Objective 1: We need to understand which cues boost activation***

Within the spreading-activation model, it has been assumed that only simple grammatical features like [+*singular*], [+*subject*] act as possible cues. When applied to lexical meaning, furthermore, it has often been the case that only very coarse cues like [+*animate*] are considered. Even though this is recognised as a simplifying assumption (see, e.g., Brasoveanu and Dotlacil, 2020), it has become so ingrained in spreading-activation models that it is hardly ever questioned whether this assumption is appropriate, even in computational models that are concerned with quantitative data fit (Lewis and Vasishth, 2005, Dillon et al., 2013, Rasmussen and Schuler, 2018). Such a simplification, however, can seriously harm the model (Smith et al., 2020). We need a more principled way of cue selection and a more principled way to understand how cues connect to elements in memory.

The current situation is somewhat reminiscent of what happened with the research into lexical meaning. There, the simple idea that lexical meanings could be represented with sets of features only scaled up and became an extremely successful and widely applied model with the advent of computational distributional semantics. In this approach, lexical meanings are real-valued vectors, representing a point in a rich meaning space, which is constructed either using co-occurrence statistics or context-predicting neural models (Mikolov et al., 2010, 2013, Baroni et al., 2014).

***Addressing objective 1***

The starting point for advancing the spreading-activation model of memory in language is the observation that the spreading-activation model is in fact compatible with lexical representations as vectors in meaning spaces in computational distributional semantics. There is a formal connection between vector spaces used to characterise the lexicon and spreading-activation. Word vector spaces are commonly created with (positive and smoothed) pointwise mutual information between a word and a context (e.g., Church and Hanks, 1990, Bullinaria and Levy, 2007 for co-occurrence matrices; Levy and Goldberg, 2014, for skip-gram neural models) and spreading-activation models calculate activations as weighted sums of pointwise mutual information between an element and a cue (see Brasoveanu and Dotlacil, 2020, Dotlacil, 2021). This allows us to interpret word vector spaces as a particular type of spreading-activation memory model, which is built under the assumption that elements correspond to lexical items and cues correspond to contexts.

This provides a virtually unexplored linking hypothesis between the research into memory structures and the rich study of vector space models. With this in mind, we now can address the following questions: (a) Are multidimensional vector space models good approximations for spreading activation? (b) Can they capture data that are used as evidence for the spreading-activation models, e.g., reading data in comprehension of dependents? These questions have barely been raised, with two exceptions: in Smith and Vasishth (2020) and Nouwens (2021), a BSc. thesis under my supervision. Both studies model cues as dimensions in multidimensional vector spaces and show that this way of modeling cues in a spreading-activation memory model shows a good fit of behavioural (reading) data for dependency resolutions, in particular, the resolution of wh-pronouns (Smith and Vasishth, 2020) and presuppositional anaphora (Nouwens, 2021). However, these are only promising first steps. In the MEMLANG project, we will significantly increase the empirical domain of the hypothesis. In an attempt to establish whether the link between spreading-activation models of memory and vector space models is valid, we will investigate the following issues:

- (PhD student 1) (PhD1) Spreading-activation models have been richly tested and validated on factual knowledge in so-called fan experiments (Anderson, 1974), in which people store and recall factual information about persons and locations. We will advance fan experiments by experimentally manipulating the distances of persons and locations measured in vector spaces to see whether retrieval time is affected, following predictions of spreading-activation memory models.

- PhD1 will study the role of vector spaces as memory models in other cases of dependencies beyond wh-pronouns and presupposition. PhD1 will run reading experiments. The methods to be used are eye-tracking while reading and self-paced reading experiments. In the experiments, we will manipulate the distances in vector spaces between the dependent (the verb *knows* in (1)), the target (the subject *Sue* in (1)) and the distractor (another noun than the subject; not present in (1)). The reading-time data will provide an argument whether memory structures in the resolution of subject-verb dependencies and anaphora should be modeled using vector space models.

- (post-doctoral researcher 1) PD1 will study the properties of dependencies in reading corpora. We will consider three reading corpora, i.e., large databases of texts that also store the information about reading patterns like reading times (GECO, Cop et al., 2016, ZuCO, Hollenstein et al., 2018, NSC, Futrell et al., 2018). PD1 will extract dependencies and model reading data as a fit to the spreading-activation model of memory that is constructed using vector spaces.

- PD1 will explore what vector spaces are the best candidates for dependencies by creating a quantitative fit between reading data and the memory model in which a vector space is used to estimate pointwise mutual information. The quantitative data fit will be achieved by embedding a memory model in a Bayesian model and exploring posterior predictive checks and other validation measures of the model (see Dotlacil, 2021 for a workflow).

***Objective 2: We need to go beyond dependents***

Comprehension and production of language relies on memory in recalling dependents, but there is another, even more basic role that memory plays in human parsing, i.e., the construction of interpretation. Language users have to rely on their memory of grammar rules when they try to produce or understand a written or a spoken message. For example, for (1) they have to remember grammar conventions like (i) subjects precede verbs in non-transformed clauses, (ii) adverbs can be sandwiched between subjects and verbs etc.

Currently, we have a detailed theory of memory structures for the processing of dependencies, but it is much less studied and almost unknown how the knowledge of grammar rules is structured, stored and recalled during production and comprehension. This is highly unsatisfactory. Ultimately, one should try to provide a single account of both language phenomena and try to construct a model in which one and the same memory structure can be deployed to study the retrieval of dependents *and* the recall of grammar knowledge.

This is the second objective of the project. We will generalise the application of memory structures beyond dependents to the knowledge of grammar and construct a parsing model using spreading-activation memory.

***Addressing objective 2***

The starting point is the observation that there is a class of parsers that are directly compatible with the memory structures assumed for dependents. The parsers that can be straightforwardly combined with the discussed memory structures are known as transition-based parsers. The connection between transition-based parsing and the spreading-activation models of memory is straightforward, but almost unexplored, excepting first steps in my own recent work, (Dotlacil, 2021, Dotlacil et al., 2021).

If successful, this connection will allow us to construct a model with a single type of memory structures that is used both for resolving dependencies and for parsing. Because of that, we will have a theory that is more parsimonious than approaches in which parsing is constructed as an independent module. Such a theory, moreover, could be tested on behavioural data that have been used to study the characteristics of each domain, parsing and dependencies, separately. We will proceed in three steps. All the steps involve a computational cognitive modeling that builds on Dotlacil (2021).

- (principal investigator) (PI) The preliminary work in Dotlacil (2021) and Dotlacil and de Haan (2021) should be improved upon. The cited works assume a bottom-up parser, but left-corner parsers are cognitively more realistic (Resnik, 1992, Hale, 2014), and furthermore, it has been shown that left-corner transition-based parsers do not necessarily suffer from the accuracy loss in transition-based parsing (Liu et al., 2017). The new parser will be implemented in the spreading-activation memory model, following the line of Dotlacil (2021).

- (PI) The transition-based parser implemented in Dotlacil (2021) only works with a feature classifier and a small list of cues and its parsing accuracy is low, arguably because of this property. We will improve the parser accuracy by exploring a wider range of cues and by assuming that a spreading-activation memory in the parser should also be modeled using vector space models.

- (PI) We explicitly investigate the fit of the parser to reading data from the psycholinguistic corpora. This is done by embedding the parser memory model in a Bayesian model and after fitting parameters, exploring the posterior fit (e.g., Brasoveanu and Dotlacil, 2020, Dotlacil, 2021). Furthermore, we will leverage the advantage of the current approach: the fact that we have a single theory that deals with the recall of grammatical knowledge (for the purposes of parsing) and the retrieval of dependencies. We will model data from experiments that inspected the processing profile affected by syntactic-structure building and the processing profile affected by the dependency resolution at the same time.

***Objective 3: We need to go beyond syntax***

Finally, the third objective of the project is to move beyond grammar knowledge on the sentence-level, i.e., syntactic knowledge, and to generalise the same memory model to the semantic knowledge and the knowledge of discourse rules as uncovered in discourse theories and semantic theories of texts (such as Discourse Representation Theory, Kamp 1981, Kamp and Reyle, 1993). Since various dependencies are not clause-bound, addressing Objective 3 is also vital if we ever want to have a general model of the resolution of dependencies.

***Addressing objective 3***

We start by noting that at least some discourse phenomena which are prime candidates to be treated as cases of memory retrieval follow the predictions of memory models and that the resolution of discourse information is sensitive to discourse structures, as expected in structured memory models (Kush et al., Schmitz et al., ms., Chen et al., 2018, Parker, 2022). Our goal is to collect further experimental evidence and develop a computational model following the lines of Objective 1 and 2. We will proceed as follows:

- (PhD student 2) (PhD2 will leverage the observation that memory models show a close affinity to vector space models. PhD2 will construct reading experiments (using the same methods as for Objective 1). In the experiments, we will consider both anaphoric presuppositions, such as in the example *John ran, too,* in which *too* signals the presence of a presupposition that is anaphoric to another running event, and discourse pronouns such as *she* in *She left* which is anaphoric to a linguistic antecedent carrying the female gender. The experiment will manipulate distances in vector space models between the anaphoric element (*ran too, she*) and the antecedent. Reading time data should be affected if we manipulate the distance in vector space models, which in turn would provide novel evidence for the hypothesis that spreading-activation models, approximated by vector spaces, can capture discourse dependencies.

- (PhD2) Anaphora and presuppositions are probably the most uncontroversial cases at the level of discourse in which memory retrieval is involved. But arguably, there are other cases. PhD2 will investigate discourse coherency and discourse anomalies as cases involving memory retrieval that could be approached from the theory of spreading-activation models. Consider, for instance, a case in which information given at one point about a character in a text is contradicted later. To spot the contradiction, it is necessary to be aware of the information presented in the past. However, it is not clear what memory structures are deployed for recalling of this information. We investigate the hypothesis that the spreading-activation model can be used here. This is done using reading experiments in which the distance between the cues in the current information and the past(contradicting or supporting) information is manipulated, i.e., we consider the same type of manipulation that was used to study dependencies. We want to see whether the spreading-activation model can be useful as a very general theory of language and understanding, of discourse information and texts.

- (post-doctoral researcher 2) (PD2) The experimental work in Objective 3 will be supplemented with corpus research and computational modeling. PD2 will use reading corpora (starting with GECO, ZuCO, NSC, see Objective 1) to collect discourse anaphoric dependencies and to study whether the spreading-activation model is supported by the corpus data. The last step is to use an existing discourse parser (Curran et al., 2007, Bos, 2008, van Noord et al., 2018), which can be used to predict reading data when complemented with spreading-activation memory models for the recall of the past information (e.g., anaphora).

**Goal:** Construct a spreading-activation memory model as a general model of memory access in language.

| **Objectives** | **1**: A general theory of cues | **2**: Grammar | **3**: Discourse |
|---|---|---|---|
| **How?** | We connect the spreading-activation model of memory and vector-space models of the lexicon. | We link the spreading-activation model of memory and a class of parsers well-known in computational linguistics (transition-based parsing). | We link the spreading-activation model with discourse interpreters and with theories on anaphora, presupposition and discourse (in)coherence. |
| **Data & Methods** | - Experimental research on reaction times using fan-design, eye-tracking and self-paced reading<br>- Computational cognitive modeling using reading corpora & reaction data from past exps. + exps. done in **1** | - Computational cognitive modeling using reading corpora<br>- Computational cognitive modeling using data from past experiments, including reaction data collected in **1** | - Experimental research on discourse processing using reading methods (eye-tracking, self-paced reading)<br>- Comp. cog. modeling using reading corpora & reaction data from past exps. + exps. done in **3** |

***Synthesis***

The proposed project ties several independent research lines into one theory that is formally explicit and implemented in a computational model. The synthesis addresses the last questions: what do individual memory-related phenomena have in common? Can these phenomena be modeled from the perspective of a single memory model? The PI will address this question by comparing models developed in individual subprojects.

***Feasibility and impact***

The project is built around one idea: to take the spreading-activation memory model, which has been successfully applied to some specific instances of recall in language, and to generalize it. This makes the project a high-risk endeavor since we are extending the model far and beyond the instances for which it was originally considered.

To increase the chance of success, we restrain the risks in three ways. First, the project has been structured into sub-domains. While the sub-domains share the overarching goal, they can be run in parallel and their own objectives are circumscribed and steps to achieve them are gradual and concrete (see also Table above). Second, there is a proof of concept showing that *it is possible* to extend the spreading-activation models into the specified domains. In case of the general theory of cues, Objective 1, the first preliminary steps have been done by Smith and Vasishth (2020) and Nouwens (2021). In case of the recall of grammatical knowledge, the first steps have been done by Dotlacil (2021) and Dotlacil and de Haan (2021). In case of discourse, the first steps have been done by Brasoveanu and Dotlacil (2020). Third, the extension of the spreading-activation model proceeds by combining the memory model with extremely well-established and carefully studied concepts in related fields, such as vector-space models, transition-based parsers and formal discourse semantics. This further limits the risks.

The PI's expertise also strengthens the feasibility of the project. The project needs the leader who is well-versed in linguistics as well as experimental work and computational modeling. The PI is involved in teaching and research in programs of linguistics and artificial intelligence at Utrecht University and has a track record in all the necessary fields (see *Section c: Early achievements track-record*).

What will be the gain of the project? Thanks to the MEMLANG project, the dominant and important theory of memory in psycholinguistics and language processing will become significantly more mature. Our understanding of the theory will be much more principled and the theory will be established outside of its current narrow domain, which is short-term memory and syntactic dependencies. This makes sense from the perspective of the theory. After all, spreading activation has never been intended just for short-term memory and just for some retrieval phenomena. In linguistics, this limitation has not been principally assumed or argued for, rather, it was just due to conventions that the main focus fell on the resolution of short-term syntactic dependencies but the spreading-activation model should describe properties of memory in general and even follow from general considerations of cognition, in particular, it can be seen as a particular application of the rational theory of cognition (Anderson, 1991, Anderson et al., 1998).

The MEMLANG project constructs a single model on how we retrieve information during production and comprehension. Because of that, it provides one algorithmic model of linguistic performance (Chomsky, 1965). Of course, not everything that affects linguistic performance would be captured in this model, but one aspect that is known to play a role, namely, memory limitations, will be captured across linguistic sub-domains and language phenomena. This makes it possible to construct an algorithmic model of human parsing that is general, which contrasts with the nowadays common situation in which models of human parsing usually work piecemeal and on a case-by-case basis (see, e.g., Futrell et al., 2020, for a discussion). The project finally allows us to link theories that were developed independently of each other and in separate disciplines, such as vector-based models and computational parsers. We know that these theories work. The MEMLANG project tells us *why* they work, namely, that they are just specific solutions to the problem of storing and retrieving given the properties of memory structures in the mind. Understanding this allows us to better understand how memory access in language shapes language and how it is possible that we can communicate with each other.

**References**

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?. *Behavioral and brain sciences*, *14*(3), 471-485.

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.

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.

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

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.

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. (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*.

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.

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.

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

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.

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.

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.

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.

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*.

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.

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

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

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

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

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.

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.