PhD 1 – objectives and 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 (see, e.g., Brasoveanu and Dotlacil, 2020), they became so ingrained in spreading-activation models 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 could only take off and scale 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. The vectors are often constructed either using co-occurrence statistics or context-predicting neural models (Miller and Charles, 1991, Bullinaria and Levy, 2007, Mikolov et al., 2010, 2013, Baroni et al., 2014).

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 constructed multidimensional spaces. Co-occurrence models are commonly created using (positive and smoothed) pmi between a word and a context (e.g., Church and Hanks, 1990, Bullinaria and Levy, 2007 and literature therein) and skip-gram neural models reach optimum in a shifted version of pmi (Levy and Goldberg, 2014). The memory model also works with pmi, namely, spreading activation is calculated as the weighted sum of pmi between an item and a cue (Brasoveanu and Dotlacil, 2021). Thus, we can interpret multidimensional 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. Obviously, we want to go beyond this simplified model.

The starting point provides a virtually unexplored linking hypothesis between the research into memory structures and the rich study of distributional semantic models. We will take up this hypothesis and study how it can help us model and experimentally investigate the resolution of dependencies.

2. Work package for PhD1: experimental investigations of cue properties

This work package (WP1) investigates the question of whether memory cues can be systematically studied using distributional semantic models (Objective 1).

Linking multidimensional spaces from computational distributional semantics to retrieval makes it theoretically possible to deploy the space in the studies of memory structures. We want to address the following questions: (a) Are the multidimensional word vector spaces good models for spreading activation? (b) Can they capture data that are used as the evidence for the spreading-activation models, e.g., reading data in comprehension of dependents? These questions have not often been raised. I am aware of two studies that consider them. First, Smith and Vasishth (2020) provide one piece of evidence that the multidimensional spaces can model spreading activation. They consider reading data from Cunnings and Sturt (2018) summarized on the examples (1) and (2), in which an object relative clause appears either in a plausible condition (1, since plates can be shattered) or an implausible condition (2, since letters cannot be shattered). The plausibility is crossed with the presence/absence of a distractor that either could not be shattered (1a, 2a, *tie*) or could be shattered (1b, 2b, *cup*). Focusing on the implausible condition, (2), since the distractor *cup* matches more closely the cues/contexts supporting the objects of the verb shattered than the distractor *tie*, *cup* should receive more spreading activation during the resolution of the object relative-clause dependency. The higher activation leads to better recall and faster retrieval times (due to the theory of spreading activation), and we would expect a speed-up oinreading times in the implausible condition in (2b) compared to (2a). This is indeed what Cunnings and Sturt (2018) observed. As Smith and Vasishth (2020) show, they can capture the finding using their own constructed co-occurrence vector space model. As expected, the size of the speed-up effect is correlated with the closeness of the position of distractors to the relevant cues/contexts in their word vector space model.

(1a) Sue remembered the plate that the butler with the tie accidentally shattered...

(1b) Sue remembered the plate that the butler with the cup accidentally shattered...

(2a) Sue remembered the letter that the butler with the tie accidentally shattered...

(2b) Sue remembered the letter that the butler with the cup accidentally shattered...

The second piece of evidence that word vector spaces are on the right track comes from Nouwens (2021), a BSc. thesis under my supervision. Nouwens (2021) modeled reading data from Winkowski et al. (submitted), see (3). In this study, a presupposition, triggered by the particle *too*, needs to be resolved by recalling the antecedent that matches the meaning of the predicate to which *too* is attached. For example, in (3a) the presupposition is resolved by recalling the antecedent *(the cook) is a dancer*. Using the FastText word representation model (Mikolov et al., 2017), Nouwens (2021) found a moderate correlation (r=0.4) between the distance of the predicates to the antecedent in the meaning space and the difference of reading times on *too* vs. the corresponding baseline, i.e, *often* in (3b).

(3a) The cook is a dancer and the waiter dances too.

(3b) The cook is a swimmer and the waiter dances often.

The two studies provide promising preliminary evidence that computational distributional semantics can model memory structures and that such models can supply richer and more realistic estimates for spreading activation than the simplified models used so far. Deploying such richer models will potentially lead to advancements in psycholinguistics and studies of memory in language. However, we first need to collect significantly more empirical and experimental evidence before we can be confident that these mutlidimensional word vector spaces are appropriate as models of spreading activation.

A popular methodology to investigate memory structures in psycholinguistics is to study reading time patterns on dependents and reaction times on recall of factual knowledge in fan experiments (see below). PhD1 will use both methods to probe the empirical adequacy of meaning spaces as models of memory. These methods will also be supplied by EEG experiments, which will enable PhD1 to study cognitive stages underlying processes such as memory retrieval.

Below, we discuss several directions that the project will take. This is a plan and the actual research might diverge from it. Exact details will be worked out in collaboration with PhD1.

WP1a: fan experiments

Fan experiments (Anderson, 1974, Anderson and Lebiere, 1998, Anderson and Reder, 1999) are experiments in which the recall of factual, episodic knowledge is tested and which by the design target one of the core predictions of the spreading-activation memory models. In this setup, participants have to memorize various facts about person-location pairs, e.g.,:

(4a) A hippie is in a park.

(4b) A hippie is on a street.

(4c) A doctor is in a bank.

Researchers then study how much time it takes participants to recall correct facts (i.e., facts learned during the memorization phase). It has been observed that with the increase of number of facts for a particular person/location, retrieval takes longer. This follows from the spreading-activation memory model. The basic idea behind the explanation is that when cues are shared among more facts, the slowdown is predicted compared to facts that share cues with fewer facts (see Anderson and Lebiere, 1998, for details). For the case at hand, this would mean that (4c) should be easier and faster to recall than each of (4a,b), which share the cue *hippie*.

In the past, fan experiments considered exact matches of persons/locations to calculate and study fan effects and the experimental results confirmed the predictions of the spreading-activation model. In WP1a, we will re-use the basic insight of those studies, but rather than relying on exact matches, we will run a series of experiments that use either persons/locations that are very close in distributional meaning spaces or that are far apart. Consider, for example, the following triplet (the {} indicate that one location would be used per triplet, and it is randomly decided which one would be used, as long as it has not been used in other pairs):

(5a) A hippie is in {a museum/a bank/a street}.

(5b) A bohemian is in {a museum/a bank/a street}.

(5c) A doctor is on a {a museum/a bank/a street}.

Let me first say a word about locations.

In (5a) and (5b) person cues are close to each other (word similarity in word2vec 0.62), compared to (5c) (word similarity below 0.1). Locations, on the other hand, are comparable in the word2vec meaning space (word similarity between 0.1 and 0.2). Since these locations are comparable from the perspective of word2vec, we would use them for counter-balancing, i.e., to remove the effect of the stereotypicality between persons and locations that might affect a memory task. Turning back to persons, even though none of the words are identical, we predict, if distributional semantic models are good estimates for spreading-activation memory models, that the person in (5b) should serve as a stronger distractor for (5a) (and vice versa) than either of those affects (5c). Consequently, the recall and retrieval times of the first two facts should be negatively affected compared to the recall of (5c). From this perspective, the original fan effect studies were just a particular version of the proposed experimental research, one in which the distance was either 0 (exact match) or greater than that (no match).

If the effect is found, the question is, is it driven by the fact that people have to memorize mentioned semantically related word pairs (such as *hippie* and *bohemian* in (5))? Or could the finding be replicated outside of this tightly controlled experimental setup? A follow-up experiment would investigate that. We hypothesize that in general recall times should be predicted by the density of the meaning neighbourhood (Mirman & Magnuson, 2008; Pecher, Zeelenberg, & Wagenmakers, 2005). That is, words that share similarities with many other words should be retrieved slower than words that are more unique. Using lexical decision and categorization tasks, similar effects have been reported already (Mirman & Magnuson, 2008), and the second experiment would investigate whether the same holds in fan-type experiments in which people have to recall facts.

Various studies showed that semantic relatedness slows down lexical retrieval (semantic interference effect; both in sentence-processing studies – e.g., van Dyke, 2007 – as well as single-word contexts – e.g., Anders et al., 2015, Van Maanen et al., 2010). An important finding is that associative recognition tasks, which induce fan effects, can be broken down into sequential cognitive stages. Simulation-based modeling revealed five such stages (van Maanen et al., 2012, 2019). A question is whether any of these stages can be meaningfully identified with semantic distances. We will construct an EEG experiment to study whether the stage identified as the retrieval stage in previous research positively correlates with semantic distance. A confirmatory answer will strongly validate the link between memory structures and meaning spaces and it will also provide novel validation for the method of stage detections in EEG data.

WP1b: subject-verb dependencies in reading data

We observed that two studies tested the empirical adequacy of distributional semantic models for modeling the retrieval of dependents: one on the retrieval of wh-pronouns in object-relative clauses, one on the retrieval to satisfy the anaphoric presupposition of *too*. We will design reading studies (using self-paced reading and eye-tracking-while-reading methods) to establish much more firmly that meaning spaces are appropriate models for memory structures used in the retrieval of dependencies. In the design of the experiments, we will in particular measure the effect of distance of distractors on retrieval times. This effect will be studied on two empirical phenomena: subject-verb dependencies and anaphora.

First, we will investigate how meaning spaces can be used as appropriate models for spreading activation observed in subject-verb dependencies. This is a promising field of investigation, since distractors matching in cues like animacy are known to affect retrieval times (e.g., van Dyke, 2007). It is likely that animacy is just a proxy for closeness in lexical meaning. This hypothesis will be further investigated by constructing reading experiments in which distractors in subject-verb dependencies are close/far away from targets in a multidimensional meaning space. The expectation is that manipulating the distance will affect retrieval times and in particular, the distance in the multidimensional space of the distractor is a predictor for behavioural (in particular, reading-time) data.

The follow-up experiment would supplement the reading study with an EEG data, in which participants listen to a sentence, rather than reading it (cf. Meyer et al., 2012). This will allow us to still study the time course of processing, including decomposition in cognitive processing stages that may be affected by the subject-verb semantic distance.

WP1c: anaphora in reading data

The second dependency to be investigated is sentence-internal anaphora. The procedure is the same as for WP1b, but instead of the subject-verb dependency, WP1c focuses on the antecendent-anaphora dependency and manipulates the distance of distractors in multidimensional spaces to the antecedent. Anaphora has been chosen as a second investigated phenomenon for several reasons. First, the reading time during the resolution of the presupposition of *too*, which distributional semantics could model (Nouwens, 2021), is arguably a case of anaphora according to discourse analyses of presuppositions (van der Sandt, 1992). Extending this research to other cases of anaphora, including classical cases (reflexives, pronouns) have a good chance of success.

The second reason to investigate anaphora is that this particular dependency has been challenging for spreading-activation models of memory since several studies failed to find the expected facilitatory/inhibitory interference that distractors should exhibit (Dillon, 2013, Jäger et al., 2017), while other studies did observe the predicted effect (Jäger et al., 2020). That some experiments failed to observe the effect predicted by the spreading-activation model might have been caused by the low power of those studies (see Vasishth et al., 2018) but it could also be partly caused by the fact that the experimental studies were designed with a simplistic model of memory in mind. If it is correct that the effect of distractors on retrieval times of anaphora resolution is more subtle than in other dependents, improving memory models would likely be another way to increase the chance of finding the effect predicted by the spreading-activation memory framework.

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