Modeling the Evolution of Word Senses with Force-Directed Layouts of Co-occurrence Networks

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Abstract

Languages evolve over time and the meaning of words can shift. Furthermore, individual words can have multiple senses. However, existing language models typically only reflect one word sense per word and don't deal with semantic changes over time. While there are language models that can either model semantic change of words or multiple word senses, none of them cover both aspects simultaneously. We propose a novel force-directed graph layout algorithm to draw a network of frequently co-occurring words. In this way, we are able to use the drawn graph to visualize the evolution of word senses. In addition, we hope that jointly modeling semantic change and multiple senses of words results in improvements for the individual tasks.

1 Introduction

Language is dynamic and constantly evolving which leads to changes in the context in which individual words are used and thereby shifting the meaning of words over time. In addition to this semantic change, novel words are introduced or existing words get additional meanings. On the other hand, certain old word meanings can also disappear from active usage in a language. This results in *multiple word senses* per word which in turn can change or shift their *meaning over time*. Current language models typically do not reflect the dynamic and multi-sense aspect of words. There are approaches which tackle one of the aspects, for example, multiple senses (Reisinger and Mooney, 2010) or semantic change (Hamilton et al., 2016).

Static word embeddings, such as word2vec (Mikolov et al., 2013), can only reflect the prevalent meaning a the word as it appears in the training data. Contextualized word embeddings, such as BERT (Devlin et al., 2019), circumvent this issue by including the surrounding words for each usage of the word. However, by using this approach, the representation of a word has to be computed for each time it appears. Furthermore, these models cannot inherently tell which or even how many different senses a word has or how it changed over time.

The boundary between a new word sense and a shift in meaning is blurred. To illustrate this, consider the term "rock". It has various meanings, e.g., in the context of geology: stone and in the context of music: genre. But those individual meanings are not static. Rock music in the 1960's is a lot different compared to rock in the 1990's, for example. Nevertheless, in this case we would argue that the meaning has evolved — the context of usage has changed, and not that there was a new sense added. The problem naturally decomposes into two parts: identifying a sense for a given word in context and tracking the shift in meaning over time.

In this work, we propose a novel data-driven approach that can reflect multiple senses of words as well as how word senses change by jointly modeling different senses over time. We deliberately refrain from defining the senses of a word to be able to also model subtle nuances of different contexts and word usage. To do so, we define a special force-directed graph layout algorithm to align networks of frequently co-occurring words. By modeling words as nodes and connecting co-occurring words via edges, we create a web of language (Dorogovtsev and Mendes, 2001). The algorithm explicitly models multiple word senses by dividing the input data into time slices and duplicating nodes to accommodate changing co-occurrence frequencies. The resulting network layout allows for easy interaction and can be easily explained and understood. This is in contrast to complex embedding models, which function as a black box and are hard to intuitively understand.

2 Related Work

Modeling language as a graph has a long tradition (Dorogovtsev and Mendes, 2001; Mihalcea and Radev, 2011; Cong and Liu, 2014; Nastase et al., 2015). We propose to employ word co-occurrence graphs to jointly solve the problems of multiple senses and diachrony.

When representing or analysing words, embeddings are the state-of-the-art in NLP nowadays. Contextualized word embeddings, such BERT, account for different word senses by computing individual vectors for a word based on its context. Classical, static word embeddings, susch as word2vec, use a single vector to represent a word. This is problematic because they fail to capture polysemy. Reisinger and Mooney (2010) presented a multi-prototype vector-space model (VSM). The meaning of a word is represented as a set of sense specific vectors. Based on that, Huang et al. (2012) developed a neural network architecture that learns multiple word embeddings per word. However, both of these approaches use a fixed number of clusters, even though different words might have a different number of senses. In 1986, Lesk (1986) developed an algorithm to automatically disambiguate word senses, by comparing the glosses of words in a given phrase. The glosses are extracted from traditional dictionaries. Similarly, Banerjee and Pedersen (2002) adaped the idea and applied it to WordNet. Brody and Lapata (2009) use a model based on latent Dirichlet allocation (LDA) to solve the word sense induction (WSI) problem. While this approach uses a fixed number of senses across all words, Lau et al. (2012) combine LDA with a varying number of senses per word. Their experiments show that LDA with a variable number of senses outperforms their benchmark baseline. However this approach requires the knowledge of the number of senses per word in advance. More importantly, they also show that hierarchical Dirichlet process (HDP), which is an extension of LDA, can effectively be applied to the WSI problem. The advantage of HDP over LDA is that the number of topics (or senses in this case) is learned from the data automatically.

Besides the work on detecting word senses, also the work on diachronic modeling has seen an increase in interest due to the popularity of deep learning in general and word embeddings in particular. Kim et al. (2014) separated the text corpus into multiple time slices and trained a model on each time slice to get different word embedding models over time. Diachronic word embeddings were investigated by aligning embeddings trained on consecutive time slices (Hamilton et al., 2016). Bamler and Mandt (2017) developed the concept of *dynamic* word embeddings. Each document has a timestamp. This allows the word embeddings to change over time. Unlike previous approaches, a single model is used to derive the shifts of word embeddings over time. This has multiple advantages, such as the complete training data is used for a single model. While these papers focus on shifts of words over time, they do not discover if a word has multiple senses. Spitz and Gertz (2018) use a network to model the co-occurrence of terms in documents. Terms that are co-occurring together are connected by an edge. Topics are discovered by finding edges of frequently co-occurring terms. For each document, the publication time is stored which allows filtering the results by a given time span. Gad et al. (2015) use a layout with multiple vertical line segments to visualize the trends of topics over time. Each vertical line segment corresponds to a time slice. For each time slice, the topic distribution is calculated. Common terms of the underlying topics are grouped together and plotted on the vertical line segments. This visualization shows how different topics split up or converge over time. Very recently, SemEval-2020 (Schlechtweg et al., 2020) featured a task for unsupervised lexical semantic change detection, which has led to a plethora of diachronic approaches.

Mitra et al. (2014) use co-occurrence networks to find changes in word senses over time. They distinguish between four different types of the evolution of language senses: the birth of new sense; splits of a sense; joins of senses; death of senses. Candidate nodes for splits are computed with a distributed thesaurus. For each candidate node, a clustering algorithm is run on the neighborhood graph. Each cluster represents a sense of the term associated with the candidate node. As shown by Ehmüller et al. (2020) however, matching clusters across more than two or three time slices causes problems such as sense shifting when matching partially overlapping clusters. Hu et al. (2019) use deep contextualized embeddings to track the senses of words over time. For each word, the distribution of the senses is calculated on a temporal slice of the corpus. Over time, these distributions show which senses gain or loose importance. While this

approach tracks the senses over time, it does not discover them. Instead, the senses are extracted from the Oxford dictionary.

3 Force-Direct Graph Layout Algorithm

In this section we describe our force-directed graph layout algorithm for a network of co-occurring words. In this network, each node corresponds to a word in the vocabulary. We first split the corpus in to disjunct sets of documents based on their publication date to create partial corpora across time. For each set, we compute a network of frequently co-occurring words, where the weighted edges represent the frequency of how often words appear in the same context. In our preliminary experiments, we saw promising results by limiting the vocabulary to nouns and using sentences as context windows. We call the sub-networks for individual time periods *period graphs* and edges in the respective compontents*intra-edges*. We connect the network compontents by adding *inter-edges* between identical words that appear in each time slice. All edges are undirected.

Force-Directed Layout. A traditional force-directed layout usually embeds a graph onto a 2D plane. Attractive and repulsive forces act on the nodes and therefore determine their position. We retain this general concept, but apply different forces for each type of edge. Therefore, nodes of each period graph are restricted to only move along a vertical one dimensional line as done in arc diagrams. For each time period corresponding to a sub-corpus and its period graph, there is a vertical line arranged from left to right in their temporal order. As in traditional force layout algorithms, we iteratively adjust the position of nodes for each period graph. The higher the value of the intra-edge, the higher the attractive force of the spring that pulls the two nodes together. Repulsive forces between nodes prevent that all nodes are clustered together. Additionally, we introduce another force to reduce the angle of inter-edges. The goal of the layout algorithm is to reduce the overall stress of the graph.

Let V_t be the set of nodes of the period graph for time slice t and P_v the position along the vertical axis for node v. The updated position of each node in each period graph in an iteration is defined as

$$P_v := P_v + \psi\Big(\alpha F_{intra} + (1-\alpha)F_{inter} - F_r\Big)$$

where ψ is the learning rate and F_{intra}, F_{inter} and F_r are the forces between nodes in the current layout. We add α to balance the attractive forces within and between different period graphs. The forces between a pair of nodes u, v within each period graph are defined as

$$F_{intra} := \sum_{w \in N_t(v)} k \times w(\{u,v\}) \times (P_v - P_u)^2.$$

where $w(\{u,v\})$ is the edge weight and $N_t(v)$ is the set of nodes directly connected to v in the current period graph and $I_{t+1}(v)$ is the set of neighbor nodes of v from the next period graph. Corresponding nodes in different period graphs are vertically aligned by

$$F_{inter} := \sum_{v' \in I_{t-1}(v) \cup I_{t+1}(v)} \frac{k}{(P_{v'} - P_v)^2}.$$

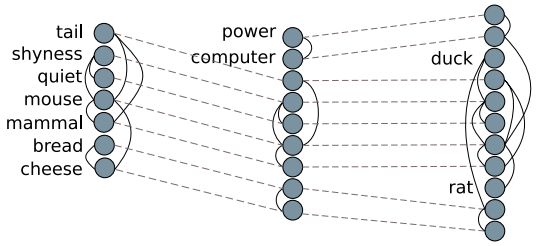
We use k as a parameter to control the overall strength of the forces in our system. In physics, this k is a proportionality constant called *Coulomb's constant* (Gerthsen, 2006). The value of k is proportional to the electric permittivity of the charged particles in a vacuum. As in other force-directed graph layout algorithms, we use a repulsive force to prevent overlapping nodes:

$$F_r := \sum_{u \in V_t} \frac{k}{(P_u - P_v)^2}$$

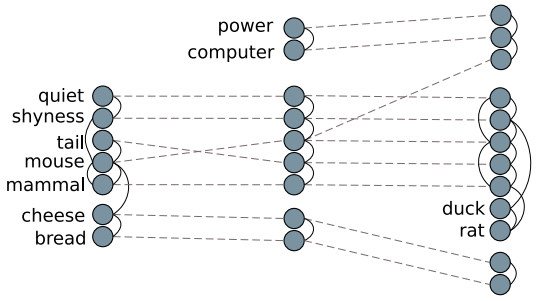
Typically, repulsive forces are computed pairwise between all nodes. However, due to the clear separation of the different time slices, we can limit the calculation of repulsive forces to nodes within the same period graph.

Representing Multiple Meanings. Thus far, we described a layout for a graph based on a fixed vocabulary with only one meaning for each word. To reflect multiple senses of a word, we allow the addition of duplicate nodes in a period graph. During the iterative updates of the graph layout, words with multiple senses will cause significantly more stress in the force-directed layout than others. This is due to the fact, that they are associated with different domains, which are likely located far from one another.

We use this to our advantage to discover ambiguous words. First, we run the layout algorithm as described above until it converges to initialize the layout. Afterwards, we identify nodes that cause



(a) Single-sense pre-layout



(b) Final Layout

Figure 1: Example layout over three time slices.

significant stress to the overall layout and duplicate them when the forces of the connecting edges exceed a threshold. Let node v be such an ambiguous word, then we split it into two nodes v' and v''. The intra-edges that were previously incident to v are replaced by

$$\forall \hat{v} \in N_t(v) : \begin{cases} (\hat{v}, v'), & \text{if } P_u > P_w \\ (\hat{v}, v''), & otherwise. \end{cases}$$

Afterwards, we add inter-edges to connect v' and v'' to their respective nodes in the previous and following period graphs. This splitting operation can be repeated for the same word again to reflect more than two meanings.

Figure 1 shows an example of the layout before and after adjustment for multiple meanings of words and balancing the forces. Over time, the vocabulary expands and a new meaning of the word "mouse" appears in the context of computers. Note, that in the early days of computing, mice were not used as input devices yet, thus the new sense surfaces only in the last time slice.

4 Evaluation

Word sense detection is hard to evaluate given the lack of annotated ground truth data (Usama et al., 2019). General thesauri could be used but only for the period graph for the latest time slice. To our knowledge, there are no established datasets to evaluate both, the multi-sense aspect of a model, as well as the dynamic evolution of senses. Thus, it is necessary to evaluate our approach with respect to both aspects individually and compare results to respective state-of-the-art approaches.

Evaluation of Word Similarities. Even though our proposed algorithm focuses on word sense detection, the underlying co-occurrence network can as well be used for other analysis tasks, e.g., word similarity. The vicinity of nodes in a period graph should roughly compare to the neighborhood of vectors in word embeddings trained or fine-tuned on the same set of documents of one time slice.

Evaluation of the Number of Senses. The Merriam-Webster dictionary stores metadata for its entries, e.g., a section "First Known Use of . . . ", which lists the year where a sense of that word was first used. Unfortunately, this information does not exist for all entries. However, we can use the existing ones to estimate how well our model performs in finding senses for a specific time period. In addition, manually created thesauri, such as WordNet (Miller, 1995), can also be used.

Contextualized Word Representations State-of-the-art embedding models, such as BERT, compute the representation of a word based on the context it appears in. A competitive baseline could be based on contextual word embeddings. Using a pre-trained model, we apply it to each appearance of a word in a corpus. Each meaning of a word should form a cluster of contextual embedding vectors. By doing this for every time slice, we can compare the number of clusters and their similarity neighborhoods to the layout of our graph.

Qualitative Evaluation of Selected Word Sense Changes. In a collaboration with digital humanities experts, we developed a use case for a qualitative evaluation by analyzing the different contexts of mentions of natural phenomena in German fiction novels. This allows to qualitatively compare selected parts of our layout to expected changes discussed in relevant literature on digital eco-criticism.

5 Conclusion

In this paper, we proposed a novel approach for a multi-sense time-sensitive word similarity model. As it is based on a force-directed graph layout of aligned co-occurrence networks, it allows direct and intuitive interpretation as opposed to most black box embedding models. In future work, we are developing the model further and compare it

to state-of-the-art language models as discussed in the evaluation section.

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