Tackling fairness, change and polysemy in word embeddings

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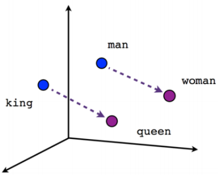
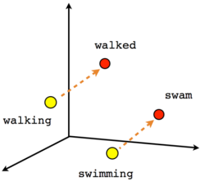
Word Embeddings

- The first step in computationally working with written language is to represent words as mathematical objects we can operate with.
- Representing words as numeric vectors a.k.a **embeddings** is a standard practice in **Natural Language Processing** (NLP).
- Word embeddings are a mapping of discrete symbols (i.e., words) to continuous vectors.
- Distance between vectors can be equated to distance between words.
- This makes easier to generalize the behavior from one word to another.
- Word embeddings have become a core component of natural language processing (NLP) downstream systems (e.g., sentiment analysis, machine translation, question answering).

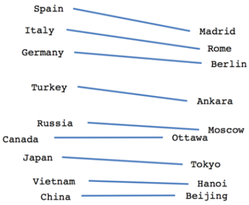
Word Embeddings



Male-Female



Verb tense



Country-Capital

Word embeddings can encode semantic and syntatic relationships between words.

Distributional Hypothesis

- The construction of word embeddings from document corpora is based on the **Distributional Hypothesis** [Harris, 1954]:

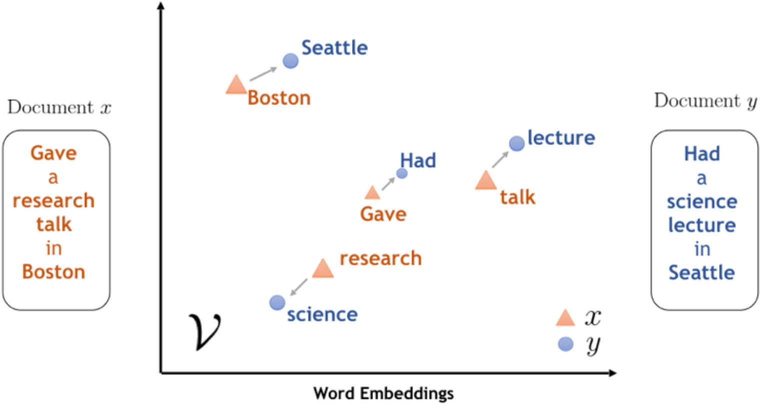
  *Words occurring in the same **contexts** tend to have similar meanings.*

- Or equivalently:

  *A word is characterized by the **company** it keeps.*

- The idea is to map words occuring in similar contexts to similar vectors.

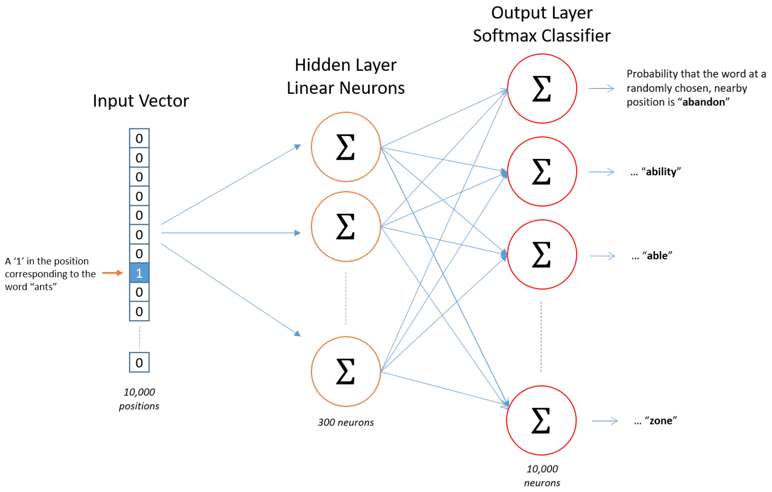
Word Embeddings



Word Embeddings Algorithms

- Word embeddings are build by training neural networks architectures on document corpora (e.g., books, papers, Wikipedia, tweets, the Web).
- These arquitectures formulate a predictive task (e.g., predict a missing word withing a contex window) in which word embeddings naturally arise from the network's parameters after training.
- Most popular models are:
  - Skip-gram negative sampling [Mikolov et al., 2013]
  - Continuous bag-of-words [Mikolov et al., 2013]
  - Glove [Pennington et al., 2014]
  - FastText [Bojanowski et al., 2016].

Skip-gram Model



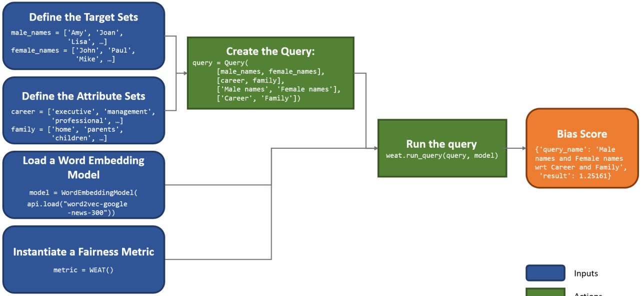
[0] Picture taken from: `http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/`

Limitations of Word Embeddings

- However they suffer from three major limitations:
  1. **Fairness**: they are prone to inherit stereotypical social biases from the corpus they were built on.
  2. **Change**: they are static. Thus they ignore words not observed during training and are unable to capture semantic drifts.
  3. **Polysemy**: they fail to capture the polysemous nature of many words (e.g., apple:company, apple:fruit), conflating their multiple senses into a single point.
- In this talk we will present our research addressing these three problems.

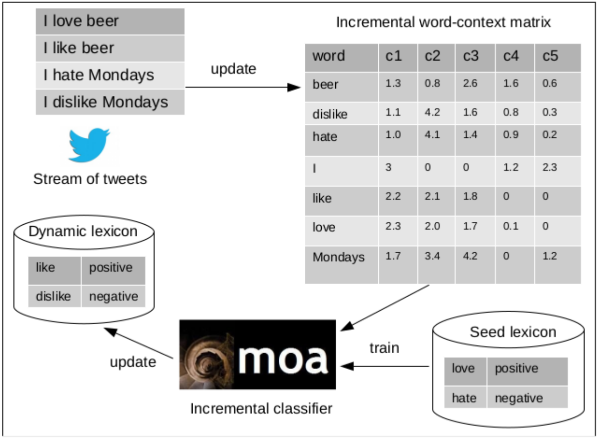
WEFE: The Word Embeddings Fairness Evaluation Framework

- The Word Embeddings Fairness Evaluation (WEFE) is a framework for measuring and mitigating bias in word embeddings (e.g. man is to programmer as woman is to housewife). [Badilla et al., 2020].



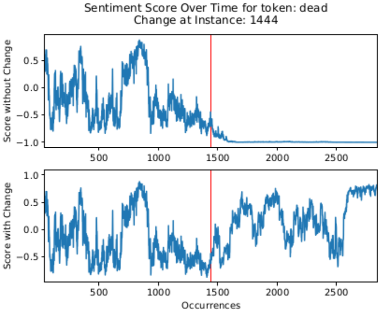
Incremental Word Vectors

- An algorithm capable of continuously learning word vectors and thus understanding how the meaning evolves over time (e.g., monitoring the word "estallido" in social networks during the Chilean social unrest). [Bravo-Marquez et al., 2021].



Incremental Word Vectors

- We simulate sentiment change by randomly picking some words and swapping their context with the context of words exhibiting the opposite sentiment.

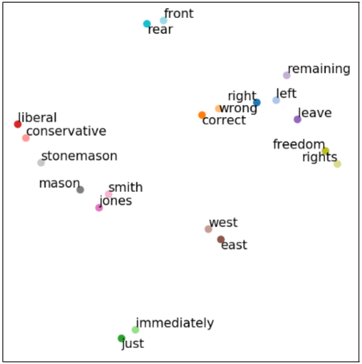


1. (a) dead

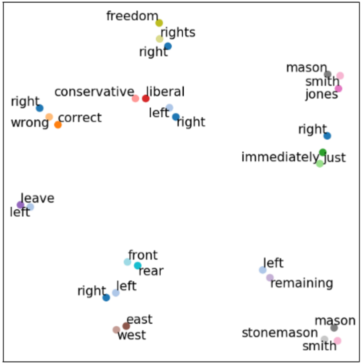
- Our approach allows for successfully tracking of the sentiment of words over time even when drastic change is induced.

PolyLM: a polysemous language model

- A language model capable of automatically learning multiple meanings of a word (e.g. apple:apple, apple:company) [Ansell et al., 2021].

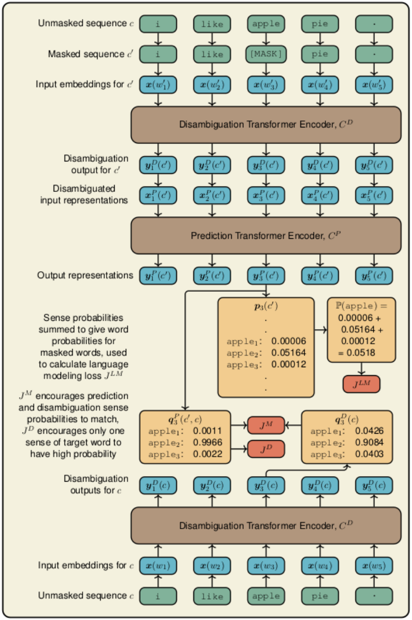


(a) Word embeddings



(b) Sense embeddings

PolyLM: a polysemous language model



Questions?

Thanks for your Attention!

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