Computational approaches to semantic change detection
Day 2
Learned representations for semantic change detection
part 1: static embeddings

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Introduction

Diachronic semantic change

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- Our main task:
  - Diachronic semantic shift detection
  - Lexical semantic change detection (LSCD) [Schlechtweg et al., 2019]

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- Distributional hypothesis [Firth, 1957]:
- Word meaning $\approx$ word contexts

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- Temporal cultural and linguistic changes influence the contexts

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How to automate this?

- Distributional hypothesis [Firth, 1957]:
- Word meaning $\approx$ word contexts
- Changes in contexts $\approx$ changes in meaning
- Temporal cultural and linguistic changes influence the contexts
- Let's use distributional word embeddings to trace these changes!

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Word embeddings per se

Word embeddings

- Distributional semantic representations efficiently capture word meaning
  - static word embeddings or type-based word embeddings: *word2vec* [Mikolov et al., 2013], *fastText* [Bojanowski et al., 2017]
  - every word type is assigned a dense vector, so that semantically similar words have similar vectors (embeddings)
- These representations are trained on large text corpora, usually on the task of language modeling.
- For example, `word2vec CBOW`, context window = 5, vector size 300
- Extremely important for modern NLP.

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Can be used to capture semantic change in an unsupervised manner.

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Word embeddings in LSCD

- Linguistics: hand-picking examples
  [Traugott and Dasher, 2001, Dobrushina and Daniel, 2016]

Word embeddings in LSCD

- Linguistics: hand-picking examples
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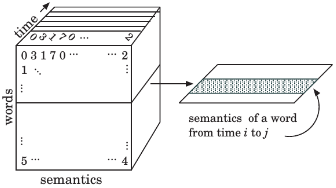
- NLP: large-scale diachronic shift mining using distributional semantic models.

Word embeddings in LSCD

- Linguistics: hand-picking examples
  [Traugott and Dasher, 2001, Dobrushina and Daniel, 2016]
- NLP: large-scale diachronic shift mining using distributional semantic models.
- Word embedding changes largely correspond to diachronic semantic change.
- *'Semantic change equals to cosine distance between the word vectors in time period* 1 *and time period* 2*'*



Tensor representation of a semantic space

[Jurgens and Stevens, 2009]

Word embeddings in LSCD

- NLP practitioners faced several challenges when applying this approach
- Technical:
  - how to make diachronic embedding spaces comparable?
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Word embeddings in LSCD

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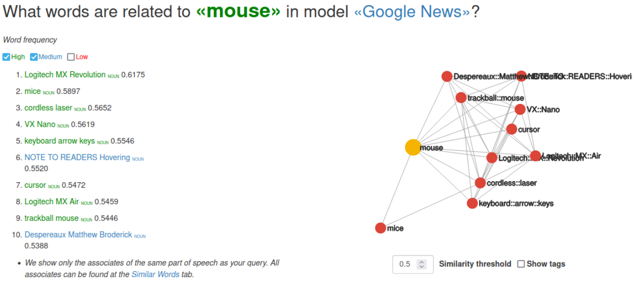
- Technical:
  - how to make diachronic embedding spaces comparable?
  - how to control for word frequencies?
- Conceptual:
  - different senses and grammatical meanings are expressed in identical word usages
  - ...and are mixed into a word embedding together.



- Still, significant results are achieved.

Word embeddings in LSCD

SemEval-2020 featured the first shared task on LSCD [Schlechtweg et al., 2020]

Task 1: Unsupervised Lexical Semantic Change Detection

- Two subtasks:
  1. classification task
  2. ranking task
- 4 languages: German, English, Swedish, Latin

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Systems employing type-based word embeddings clearly outperformed the rest
(token-based word embeddings and topic models).

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Comparing words across static embedding models

Methods of using type-based word embeddings in LSCD are surveyed in [Kutuzov et al., 2018] and [Tang, 2018].

- Problem: embeddings of one and the same word trained in different runs are not comparable
  - especially if trained on different corpora

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- Various algorithms of making word embeddings actually diachronic:

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  - Training models incrementally [Kim et al., 2014]
  - Training separate models for each time period (time bin):
    - Aligning embedding spaces [Hamilton et al., 2016b]
    - Comparing distances between a given word and all others (second-rank similarity) [Yin et al., 2018]
    - Compare only sets of *n* nearest neighbors

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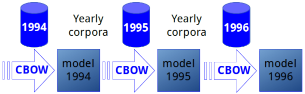
    - Compare only sets of *n* nearest neighbors
  - Training models jointly across time bins (did not attract much attention) [Bamler and Mandt, 2017, Yao et al., 2018, Rosenfeld and Erk, 2018]
  - ...

Comparing words across static embedding models

Different ways of training ‘diachronic’ word embeddings

For n time bins:

- ‘Incremental’ models
  - Model trained on time bin tb_0,
  - Model trained on time bin tb_1, initialized with tb_0 weights,
  - ...
  - Model trained on time bin tb_n, initialized with tb_{n-1} weights.
- ‘Separate’ models:
  - Model trained on time bin tb_0,
  - Model trained on time bin tb_1,
  - ...
  - Model trained on time bin tb_n



Comparing words across static embedding models

Methods for actually comparing word embeddings fall into two conceptual classes:

Local methods for semantic shift detection

Comparing words' nearest neighbors:

- Jaccard similarity [Jaccard, 1901]
- Kendall's τ [Kendall, 1948]

Global methods for semantic shift detection

Comparing words' vectors (or semantic spaces in general):

- Procrustes alignment [Hamilton et al., 2016b]
- Global Anchors [Yin et al., 2018]

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...and many more!

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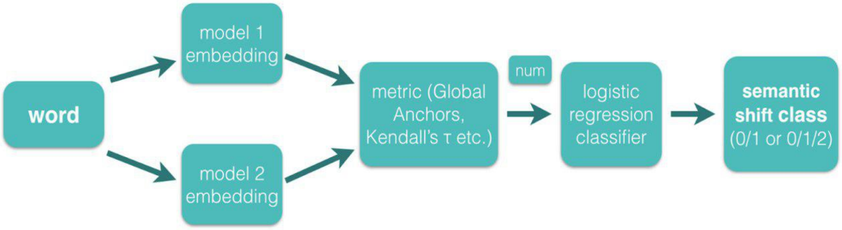

General workflow for an LSCD method using type-based word embeddings.

Local methods

Jaccard similarity

$$J(X, Y) = \frac{|X \cap Y|}{|X \cup Y|} \tag{1}$$

[Jaccard, 1901]

Nearest neighbors for '*quarantine*':

- X = '*prison, illness, plague, ship*'
- Y = '*self-isolation, covid, regime, epidemics*'

$J(X, Y) = 0$

Can you guess the years for X and Y?

Local methods

Kendall's τ

Takes into account the ranking of neighbors [Kendall, 1948]

$$\tau = \frac{2}{n(n-1)} \sum_{i<j} sgn(x_i - x_j)\, sgn(y_i - y_j) \tag{2}$$

Nearest neighbors for '*corona*' ($x = 2019$, $y = 2021$):

$$\begin{aligned} x_1 = crown &\Rightarrow y_1 = virus \\ \ldots\ldots &\Rightarrow \ldots\ldots \\ x_{10} = virus &\Rightarrow y_{10} = crown \end{aligned} \tag{3}$$

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Local Neighborhood Distance: similarity between target word similarities to n nearest neighbors [Hamilton et al., 2016a].

Global methods

Orthogonal Procrustes Analysis

- First, we ‘align’ two models [Hamilton et al., 2016b].
- Given embedding matrices A and B, find an orthogonal matrix R that maps A to B via singular value decomposition, SVD.
- Then, simple cosine similarity between $word^A$ and $word^B$ is calculated.

$$R = \underset{R}{\operatorname{argmin}} ||R \cdot A - B||^2 \tag{4}$$

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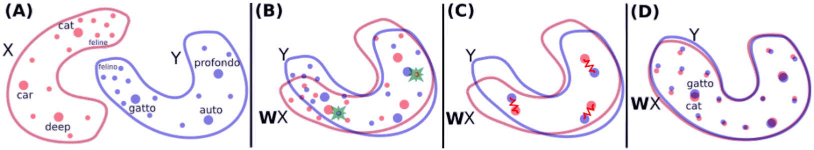

Aligning English and Italian word embeddings for machine translation

Global methods

Global Anchors

[Yin et al., 2018] define semantic shift of word w from year x to year y like this:

$$\begin{aligned} similarities_x &= (x_1, ..., x_n) \\ similarities_y &= (y_1, ..., y_n) \end{aligned} \tag{5}$$

- x_i and y_i are cosine similarities between the word w and the i$^{\text{th}}$ word in the intersection of x and y vocabularies (of size n).

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- x_i and y_i are cosine similarities between the word *w* and the i^th word in the intersection of *x* and *y* vocabularies (of size *n*).
- We compare global positions of *w* in the semantic space.
- Semantic similarity between different time periods = $cos(similarities_x, similarities_y)$
- With Global Anchors, no explicit alignment needed.

Comparing words across static embedding models

Temporal referencing

- Time labels as tags [Dubossarsky et al., 2019]
- When training a `word2vec` model, each target word is replaced with a time-specific token:
  - in the 1920s corpus: *computer* $\rightarrow$ *computer*$_{1920}$

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- If it is a context word, it remains unchanged.
- One vector space is learned for all time periods.
- Change is measured as cosine distance between $\textit{computer}_{1920}$ and $\textit{computer}_{1980}$ vectors.
- Again, no post-hoc alignment necessary!

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Contradicting reports: [Schlechtweg et al., 2019] say it fails on German data.

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Empirical results on static word embeddings

- Global methods work better for semantic change detection
- Procrustes alignment is clearly the best [Schlechtweg et al., 2019, Schlechtweg et al., 2020]
  - clearly wins on granular time spans
  - criticised for instability with respect to different embedding spaces [Gonen et al., 2020].
- Local methods are still applicable (but sometimes worse than random)
- Combining methods is a good idea
- Incrementally trained models are worse than separate models aligned to the common space
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- Combining methods is a good idea
- Incrementally trained models are worse than separate models aligned to the common space
  - incremental training is largely abandoned now.
- Some issues are addressed by using contextualized embeddings (pre-trained large language models). More on this tomorrow!

Practical session

Thanks! Any questions?

And then we will get our hands dirty with word embeddings for LSCD.

https://github.com/lmphcs/semshift_esslli2023

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