# Cultural Shift or Linguistic Drift? Comparing Two Computational Measures of Semantic Change

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# Semantic Change

# What is Semantic Change?

| Word | Moving towards | Moving away | Shift start | Source |
|---|---|---|---|---|
| gay | homosexual, lesbian | happy, showy | ca 1950 | (Kulkarni et al., 2014) |
| fatal | illness, lethal | fate, inevitable | <1800 | (Jatowt and Duh, 2014) |
| awful | disgusting, mess | impressive, majestic | <1800 | (Simpson et al., 1989) |
| nice | pleasant, lovely | refined, dainty | ca 1890 | (Wijaya and Yeniterzi, 2011) |
| broadcast | transmit, radio | scatter, seed | ca 1920 | (Jeffers and Lehiste, 1979) |
| monitor | display, screen | — | ca 1930 | (Simpson et al., 1989) |
| record | tape, album | — | ca 1920 | (Kulkarni et al., 2014) |
| guy | fellow, man | — | ca 1850 | (Wijaya and Yeniterzi, 2011) |
| call | phone, message | — | ca 1890 | (Simpson et al., 1989) |

Figure 1: Examples of words that have changed meaning over time. The first six examples are words that shifted dramatically in meaning while the remaining four are words that acquired new meanings (while potentially also keeping their old ones). [Hamilton et al., 2016a]

Language is in constant flux: "Words acquire new meanings and lose old senses, new words are coined or borrowed from other languages and obsolete words slide into obscurity." [Tahmasebi et al., 2021]

# What is Semantic Change?

- language is variable - human language changes over time
- there are laws and regularities to linguistic change, e.g. law of phonological change
- semantic change: "innovations which change the lexical meaning rather than the grammatical function of a form"
- varied driving forces: linguistic, psychological, sociocultural
  $\rightarrow$ traditionally two important classes of semantic change: linguistic drift and cultural shifts

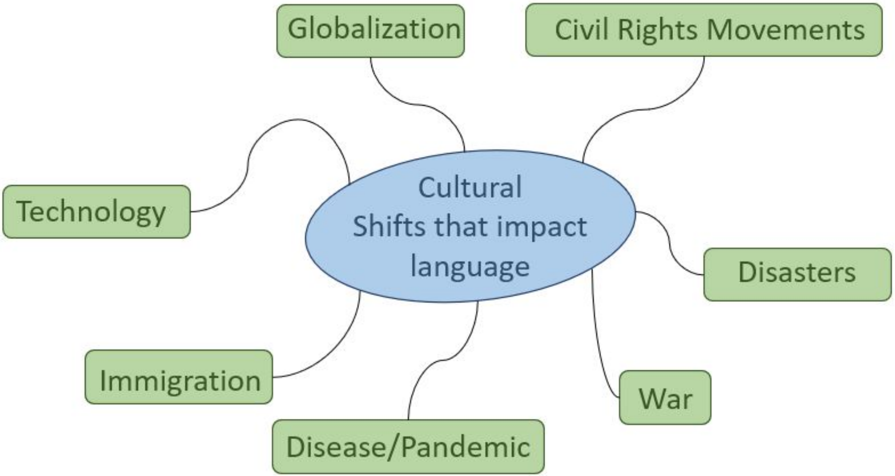
# Types of semantic change

**Linguistic drift**

- "slow and regular changes in core meaning of words" [Kutuzov et al., 2018]
  - generalization: "I promise." → "It promised to be exciting."
  - grammaticalization: "willan" (to want, to wish) → "I will ..."
  - subjectification: "actually did try" → "I actually agree"

→ long-term, somewhat slow semantic change

# Types of semantic change



# Types of Semantic Change

| Cultural Shift | Linguistic Shift |
|---|---|
| caused by a cultural phenomenon | caused by "regular processes" of language change |
| irregular | regular |
| → external, unpredictable | → intrinsic, predictable |
| fast | slow |
| affecting nouns more | affecting verbs more |

↓ noun mapping

↓ verb mapping

# Why do we want to detect Semantic Change?

- understanding historical texts

> I feel pretty, oh so pretty
> I feel pretty and witty and gay
> – *Maria (Juliet) in West Side Story, first Performance 1957*

- study of historical events
- study of gender and ethnic stereotypes

# Why do we want to detect Semantic Change?

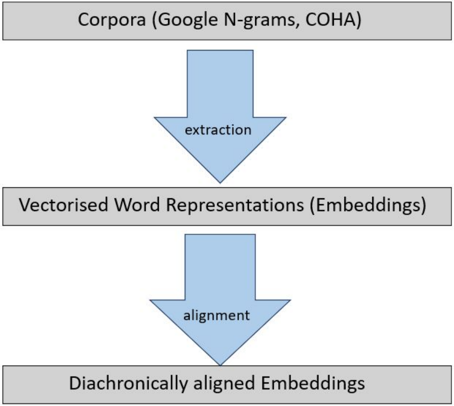
"Understanding how words change their meanings over time is key to models of language and cultural evolution." [Hamilton et al., 2016a]

Tasks/Fields connected to Lexical Semantic Change (LCS) detection

- computational studies of history
- measuring document across-time similarity
- IR from long-term diachronic corpora
- digital humanities
- computational social sciences (CSS)

# Detecting Semantic Change

# Diachronic Word Embeddings




Google N-grams
COHA

Skip-grams with negative sampling (SGNS) per time period
→ multiple embeddings of one word in different models (time periods)

use alignment methods to be able to compare models

# Data sets

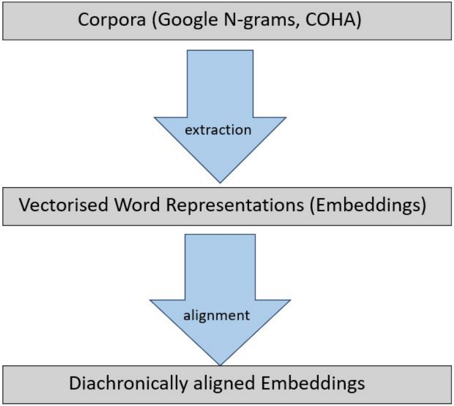
Google N-Grams

- published texts from 1500-2019 - the paper uses 1800-1990
- languages: English, French, German

Corpus of Historical American English

- biggest corpus of historical fiction
- contains words and lemmas
- 1850-2000

# Diachronic Word Embeddings

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# Skip-Gram with Negative Sampling

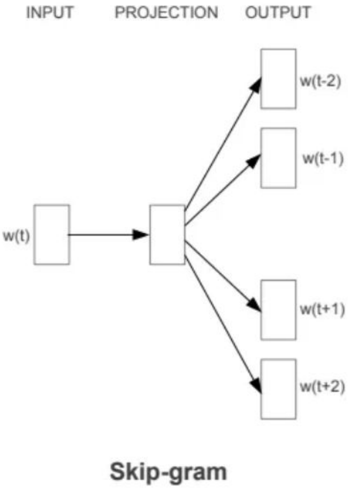
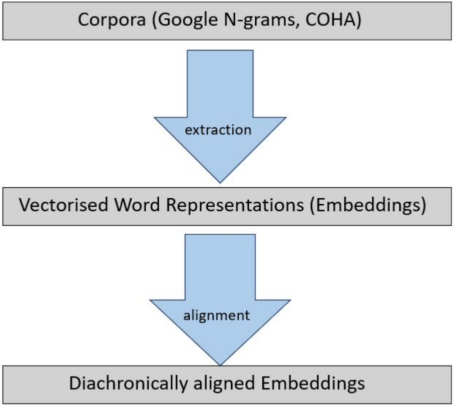



Figure 2: Illustration of the Skip-Gram model architecture. [Mikolov et al., 2013]

"The quick brown fox jumps over the lazy dog." Word vector size: 300

Vocabulary: 10,000
Weight matrix: 300 x 10,000
input: fox; correct output: brown
→ output of neuron is 1 "positive", all other neurons 0 "negative"
→ only update the weights of positive and a small number (5-20) of the negative neurons weights

# Diachronic Word Embeddings

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Skip-grams with negative sampling (SGNS) per time period
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# Aligning Embeddings

most embeddings are inherently stochastic:

- random initialization
  $\rightarrow$ separate learning runs will produce numerically different vectors (while preserving pairwise similarity)
  $\rightarrow$ stable word meaning will still have low cosine similarity between vectors from different corpora/time periods

$\rightarrow$ vectors need to be aligned to fit into the same vector space so cosine similarity across different models becomes meaningful

# Measures of Semantic Change

**Global Measure**

- analyzes global shifts in semantics
- cosine distance between a words two consecutive vectors
- uses orthogonal Procrustes transformations

$$d^G(w_i^{(t)}, w_i^{(t+1)}) = \text{cos-dist}(w_i^{(t)}, w_i^{(t+1)}) \quad (1)$$

# Orthogonal Procrustes

Given two matrices $\mathbf{A}$ and $\mathbf{B}$ find an orthogonal matrix $\mathbf{\Omega}$ that most closely maps $\mathbf{A}$ to $\mathbf{B}$.

$$minimize_{\mathbf{\Omega}} \|\mathbf{\Omega A} - \mathbf{B}\|_F$$

where $\| \quad \|_F$ is the Frobenius Norm. With $\mathbf{W}^{(t)}$ as the word embedding matrix learned at year $t$:

$$\mathbf{R}^{(t)} = argmin_{\mathbf{\Omega}^T\mathbf{\Omega}=\mathbf{I}} \|\mathbf{\Omega W}^{(t)} - \mathbf{W}^{(t+1)}\|_F \tag{2}$$

# Measures of Semantic Change

**Local Neighbourhood Measure**

- only a words nearest semantic neighbours are relevant
  - find k-nearest neighbours $N_k(w_i^{(t)})$ (cosine similarity) of word $w_i$ within each decade
  - compute "second order" similarity vector $s_i^{(t)}$
  - $s_i^{(t)}$ contains the cosine similarity and the k-nearest semantic neighbours vectors in the time period $t$ and $t+1$

$$s^{(t)}(j) = \text{cos-sim}(w_i^{(t)}, w_j^{(t)}) \tag{3}$$

$$\forall w_j \in N_k(w_i^{(t)}) \cup N_k(w_i^{(t+1)})$$

therefore:

$$d^L(w_i^{(t)}, w_i^{(t+1)}) = \text{cos-dist}(s_i^{(t)}, s_i^{(t+1)}) \tag{4}$$

# Measures of Semantic Change

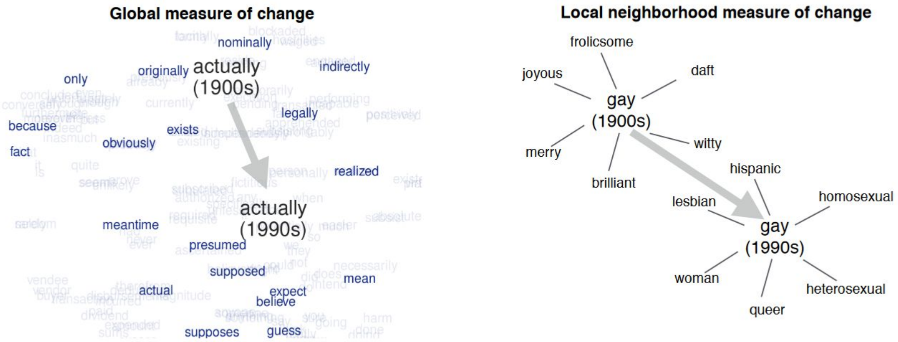


Figure 3: Illsutration of the two different measures of semantic change. [Hamilton et al., 2016b]

# Measures of Semantic Change

| Global Measure | Local Neighbourhood Measure |
|---|---|
| change in the word sense between decades | change in the closest semantic neighbours between decades |
| captures global syntagmatic (syntax/surface patterns) shifts | captures strong shifts in paradigmatic (conceptual) relations |
| sensitiv to subtle shift in usage and global shifts | drastic shifts in core meaning |
| common LSC measure | novel measure |

$\downarrow$

linguistic drift
should affect verbs

$\downarrow$

cultural shift
should affect nouns

# Results

# Methodology

Research Question: Do the different measures measure different notions of Semantic Change?

- mixed-model linear regression model
  - two per dataset
    dependent variables: $d^G$, $d^L$
    independent variables: word frequency, decade of change, noun or verb
  - examine change between consecutive decades
  - nouns/verbs within the top-10,000 by frequency
  - remove less frequent ($< 500$) words

# Results

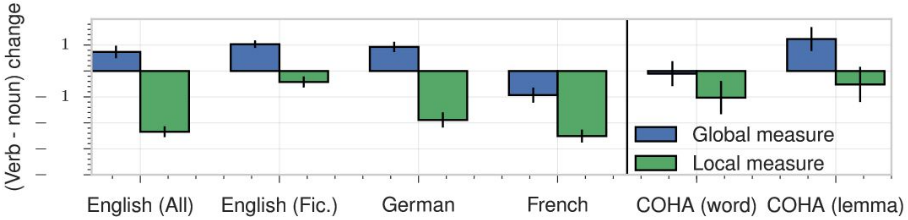


Figure 4: Figure showing coefficients of mixed-model logistic regression in the two data sets. 95% confidence intervals are shown. [Hamilton et al., 2016b]

→ the global measure is more sensitive to semantic changes in verbs - the local neighborhood measure is more sensitive to noun changes

# Results

| Word | 1850s context | 1990s context |
|---|---|---|
| actually | "...dinners which you have actually eaten." | "With that, I actually agree." |
| must | "O, George, we must have faith." | "Which you must have heard ten years ago..." |
| promise | "I promise to pay you...' | "...the day promised to be lovely." |
| gay | "Gay bridals and other merry-makings of men." | "...the result of gay rights demonstrations." |
| virus | "This young man is...infected with the virus." | "...a rapidly spreading computer virus." |
| cell | "The door of a gloomy cell..." | "They really need their cell phones." |

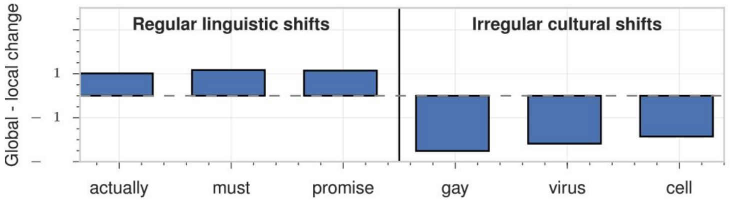


Figure 5: Figure showing the differences between the two measure using example words. The table shows three words per semantic change type and their historical contexts. [Hamilton et al., 2016b]

→ the global measure is more sensitive to regular shifts and vice-versa for the local measure

→ adverbs and adjectives behave similar to verbs

# Conclusion

# Conclusion

- novel semantic change measure sensitive to cultural shifts

→ different tasks need different semantic measures

- proves that nouns are more sensitive to cultural shifts and verbs more to linguistic drift
- adverbs and adjectives also change because of linguistic drift
- showed that alignment and second order embeddings can be used concurrently

# Thank you for your Attention

# Questions

What are practical applications of LSC detection?

What approaches do you think newer works take towards LSC?

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