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Integrating Generic and Contextual Knowledge

Analysing Lexical Semantic Change with Contextualised Word Representations

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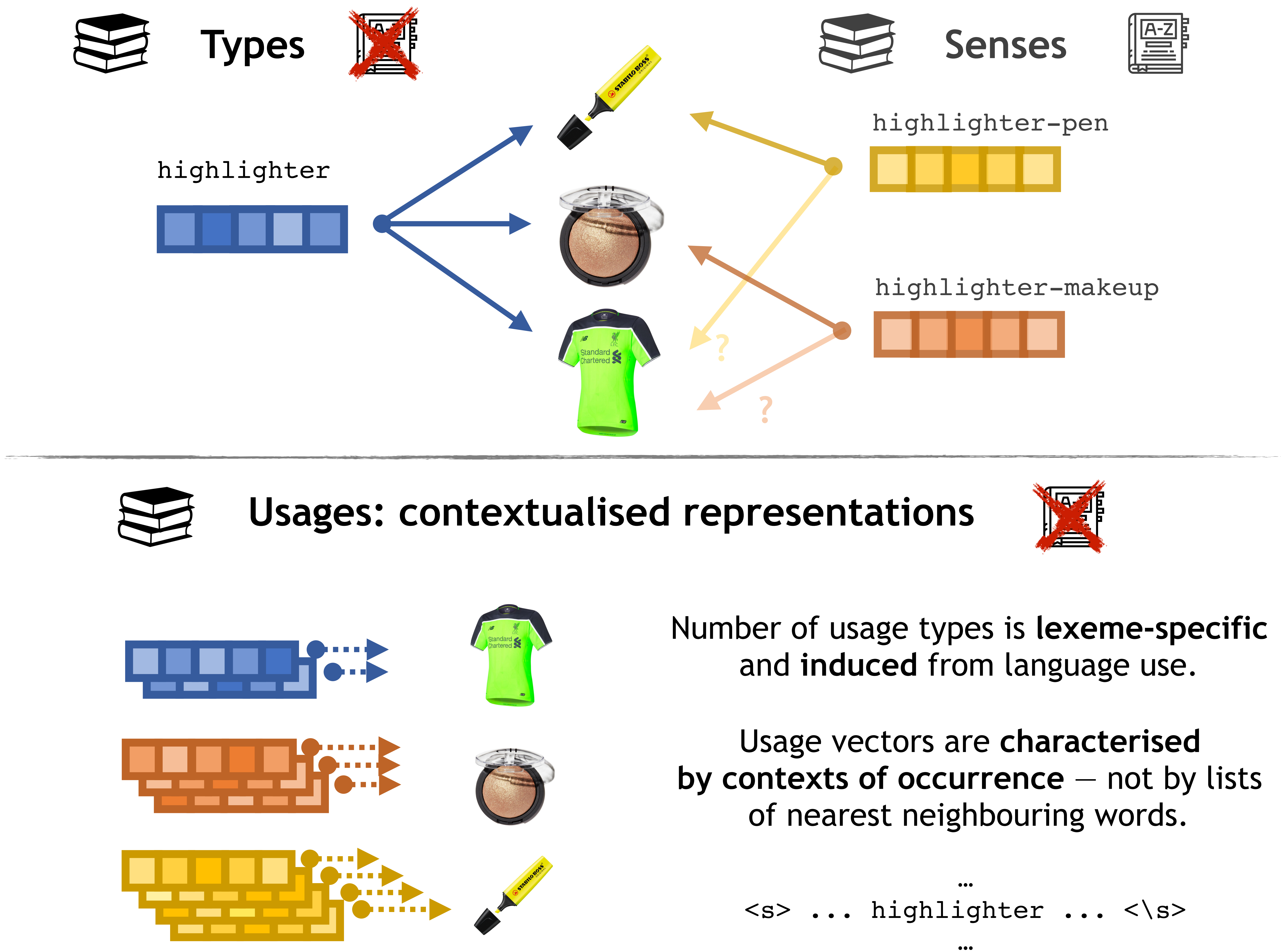


Types
A-Z
Senses
A-Z
highlighter
STABILO BOSS
highlighter-pen
highlighter-makeup
Standard Chartered
?
?
Usages: contextualised representations
A-Z
Standard Chartered
STABILO BOSS
Number of usage types is **lexeme-specific** and **induced** from language use.
Usage vectors are **characterised by contexts of occurrence** — not by lists of nearest neighbouring words.
…
<s> ... highlighter ... <\s>
…

Method

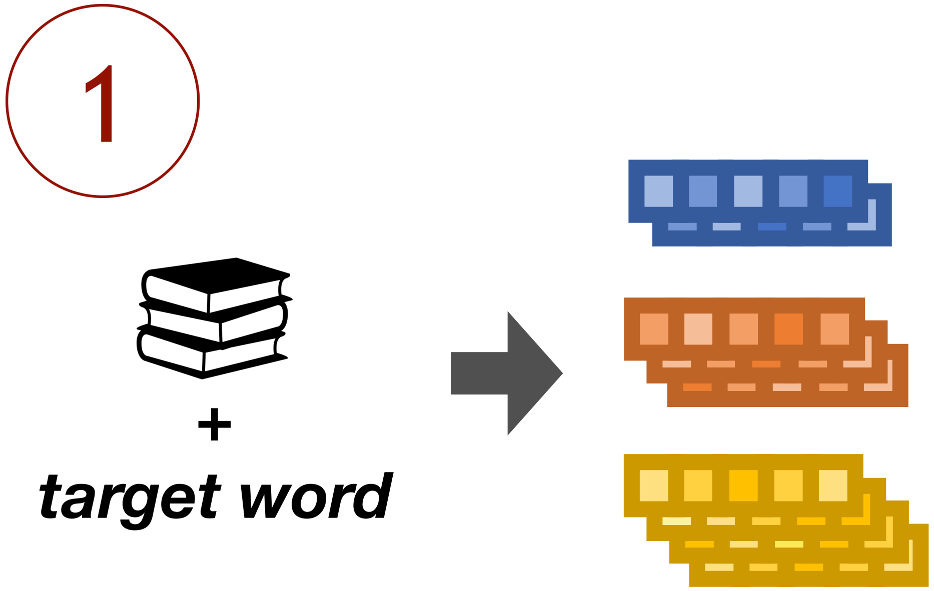
For each word of interest *w*

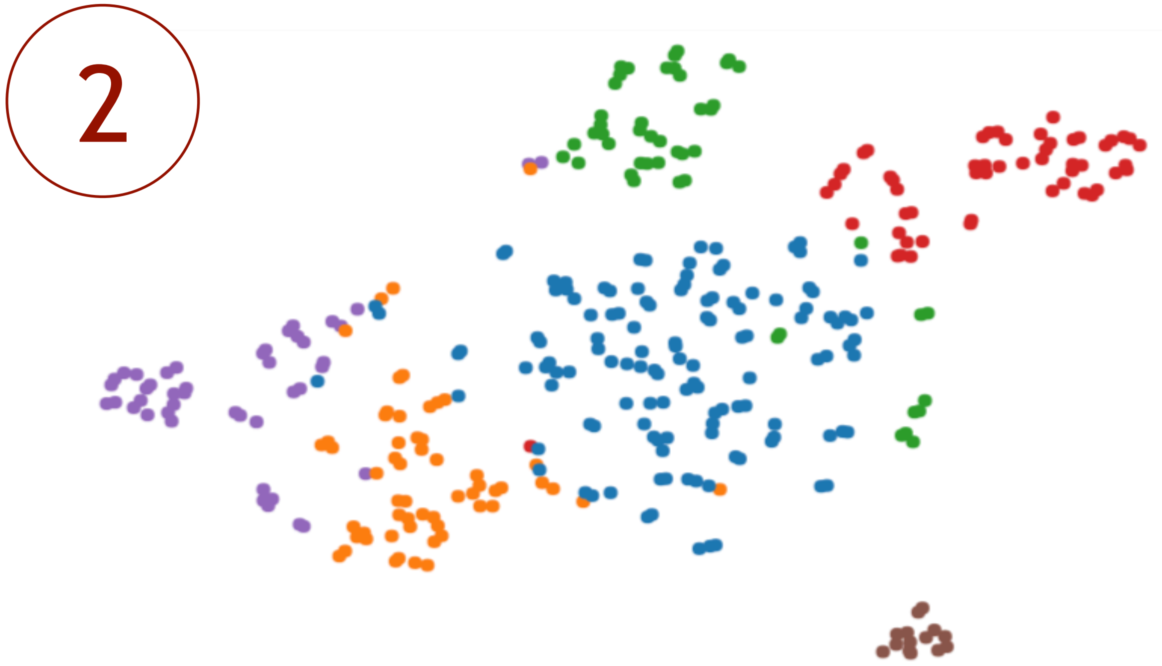
(1) **extract** contextualised representations for all occurrences of *w* in the corpus, using a language model (e.g., BERT or ELMo)

(2) **cluster** all representations of *w* into usage types by automatically selecting the optimal number of clusters (e.g. K-Means + silhouette score or Affinity Propagation)

(3) **organise** usage clusters into diachronic usage distributions (frequency-based or probability-based)

(4) **quantify** degree of change by comparing representations and usage distributions





PCA visualisation of all contextualised representations for the word *users* as it occurs in COHA (Davies, 2012)

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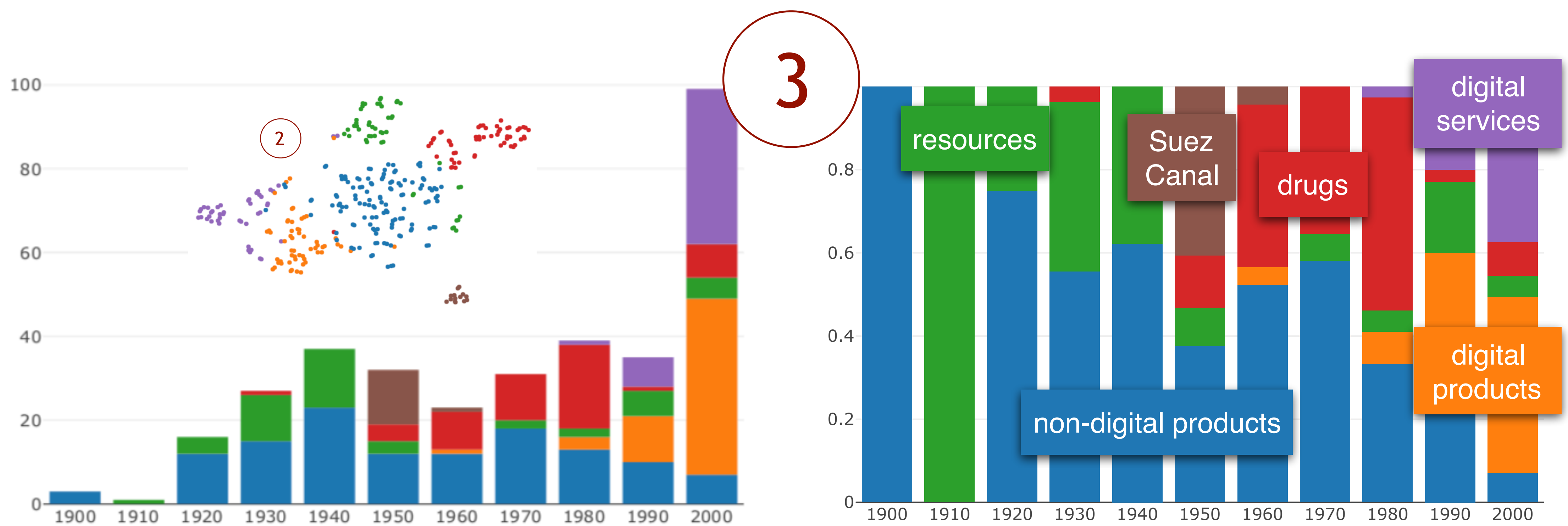

Contextualised representations (left) and usage type distributions (right) for the word *users* as it occurs in COHA (Davies, 2012)

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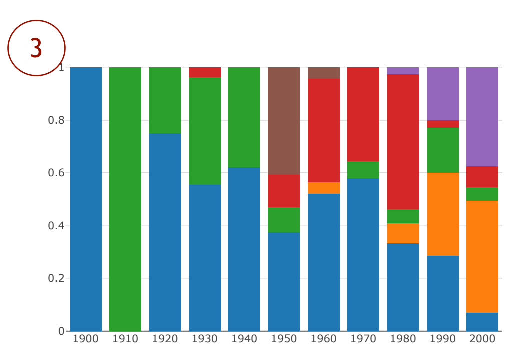
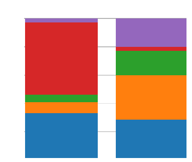
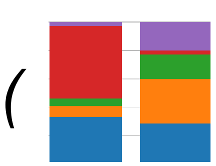


Jensen-Shannon Divergence ( *)*

Entropy Difference ( *)*

Average Pairwise Distance ( *)*

between two time periods

or

average over pairs of time periods

Are the resulting usage clusters interpretable?

literal vs metaphorical

*‘the **ceiling** of a church’*

*‘prefer the open sky to a **ceiling**’*

*‘**ceiling** prices’*

*‘breaking through the **ceiling**’*

polysemy and homonymy

*‘full of questions, intensely **curious**’*

*‘half fearful, half **curious**’*

*‘the most **curious** reading’*

*‘a **curious** sense of gratitude’*

entity names

*‘**wireless** device’*

*‘**wireless** network’*

*‘verizon **wireless** theater’*

affixation

*‘**wireless**ly’*

syntactic functionality

*‘**refuse** to hire’*

*‘**refuse** or neglect to perform’*

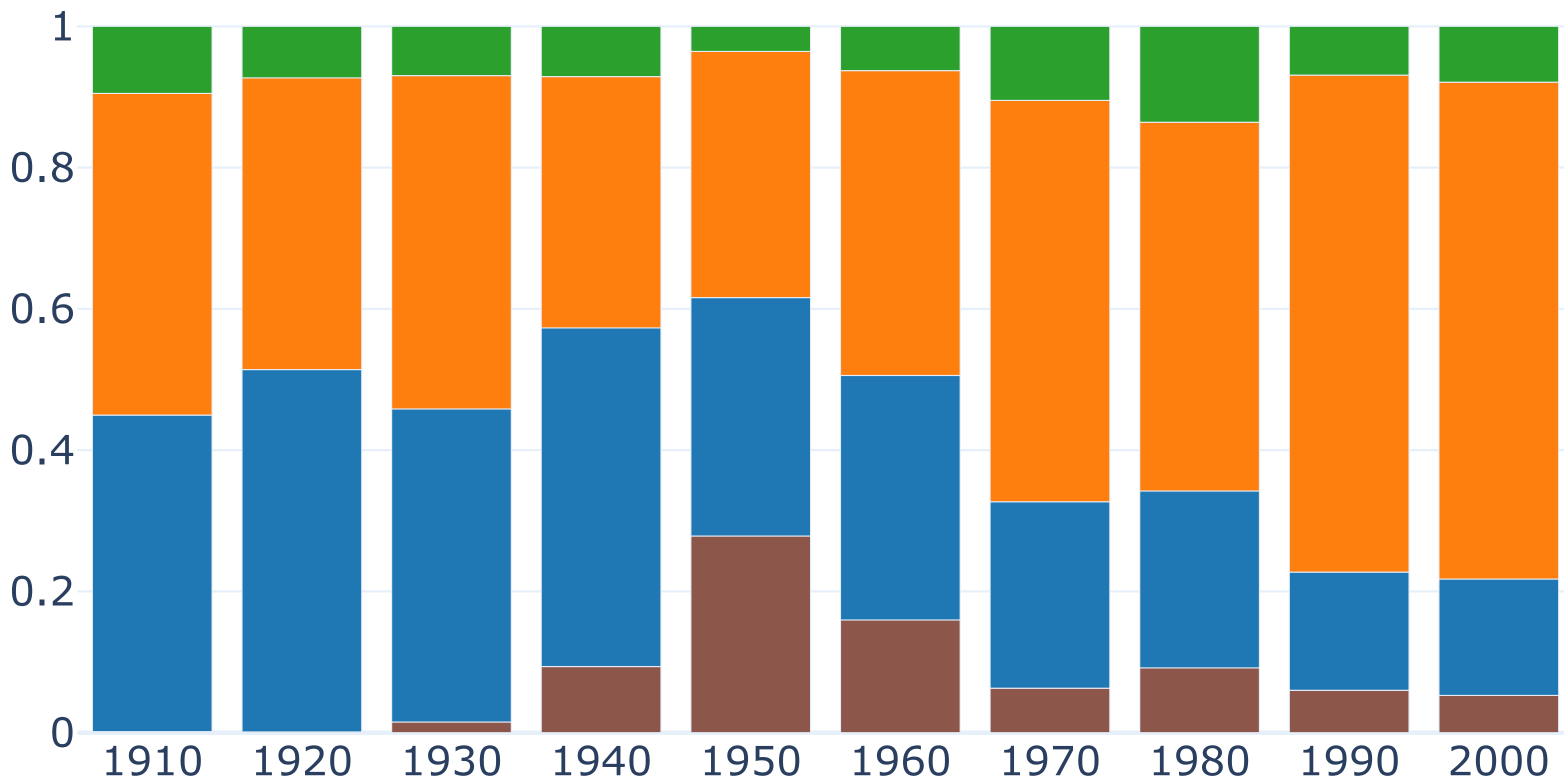
*‘the **refuse** of the schools’*

*‘**refuse** a draft’*

*‘**refuse**, and you die’*

What types of lexical change are detected?

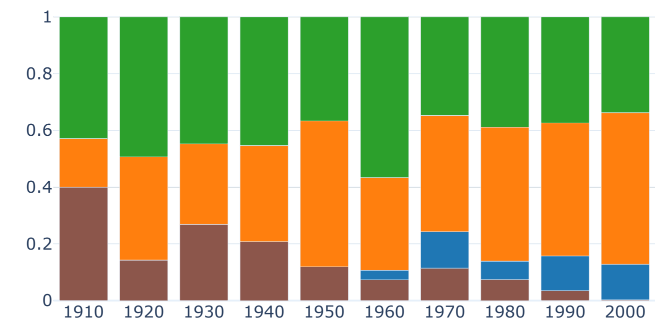
broadening (incl. metaphorisation): "*curtain*"



- I hung colored lights around my *curtain*less windows
- inflatable *curtain*-type head-protection bags
- raising the *curtain* on its [...] tax-reform program
- bureaucracies [...] on both sides of the *curtain*

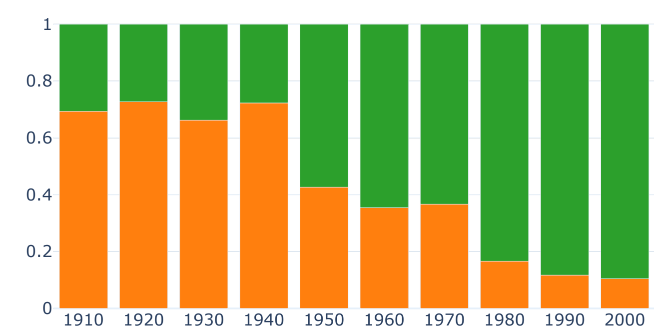
COHA (Davies, 2012) COCA (Davies, 2010)

narrowing: "*tenure*"



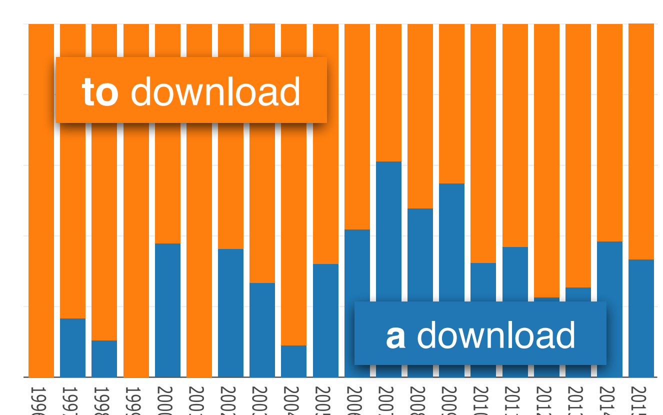
- employment and *tenure* // minority faculty in *tenure*
- *tenure* of office
- *tenure*-track faculty position
- reasons for short term leases and insecurity of *tenure*

shift: "*coach*"



- you can always go *coach* // stage *coach*
- cinderella - here comes your *coach*

new syntactic role: "*download*"



Correlation with human judgements

Diachronic Usage Pair Similarity

A crowdsourced dataset of similarity judgements for more than 3K English word usage pairs (16 lemmas) from different time periods.

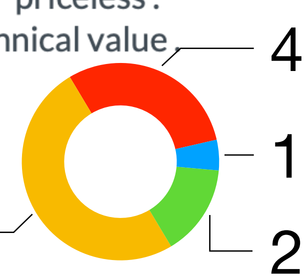
NEW DATASET: DUPS

federal

Please read carefully the following two sentences where the word [[federal]] occurs:

- robert m . hitchcock , who prosecuted the amerasia case in 1945 , testified today that he had been gravely handicapped because the government ' s best evidence had been produced by illegal seizures by [[federal]] agents . the prosecution , he asserted , was in fact fortunate under the circumstances to have done as well as it did .
- there should be such a fire every saturday afternoon at the same time with the same actual damage . this time it was the records and documents of the [[federal]] trade commision , said to be " priceless . " also the reels of official motion pictures of historical or technical value

How similar are the two occurrences of [[federal]]?



Significant rank correlation between averaged human similarity judgements and BERT similarity scores for 10 out of 16 words.

Data: GEMS (Gulordava & Baroni, 2011) 100 words w/ shift scores.

Shift score: average human judgement on a word's meaning change between 1960 and 2000 (on a 4-points scale).

Metric: Spearman rank correlation between annotated change score and our three measures of change.

Frequency difference	0.068
Entropy difference (*max*)	0.278
Jensen-Shannon divergence (*max*)	0.276
Average pairwise distance (*Euclidean*, *max*)	0.285
Gulordava and Baroni (2011)	0.386
Fremann and Lapata (2016)	0.377

but wait for it...

Algorithm	*English*	*German*	*Latin*	*Swedish*
Word2vec CBOW cosine similarity baseline				
Incremental	0.210	0.145	0.217	-0.012
Procrustes	0.285	0.439*	0.387*	0.458*
Fine-tuned contextualised embeddings (top layer)				
ELMo Cosine similarity	0.254	**0.740***	0.360*	0.252
ELMo Average pairwise distance	**0.605***	0.560*	-0.113	**0.569***
BERT Cosine similarity	0.225	0.590*	**0.561***	0.185
BERT Average pairwise distance	0.546*	0.427*	0.372*	0.254

(Kutuzov and Giulianelli, 2020)

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