Computational approaches to semantic change detection

Day 5

Part I: Applications

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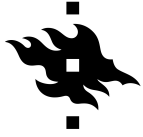
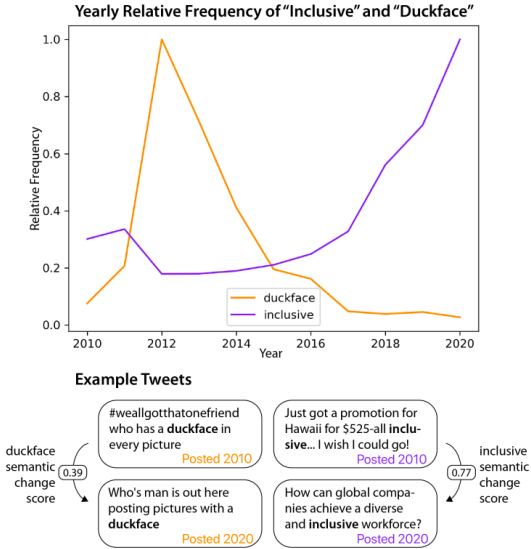


Language Studies



[Keidar et al., 2022]:

- Study of differences between slang and standard language
- Slang words tends to preserve their meaning over time but may have large variety in frequency

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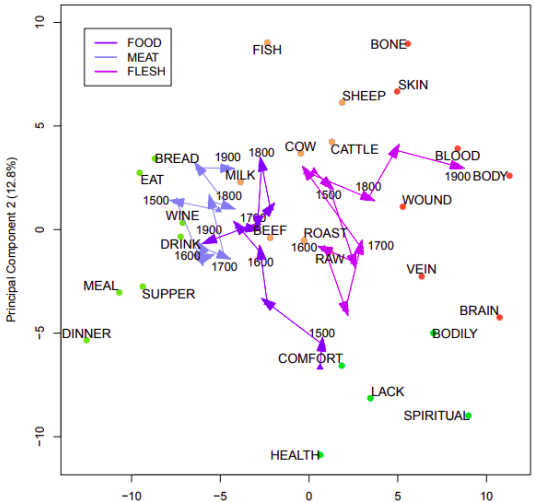
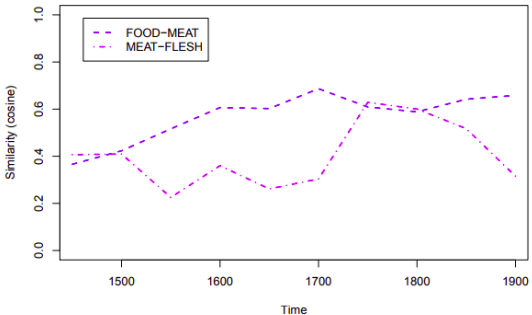
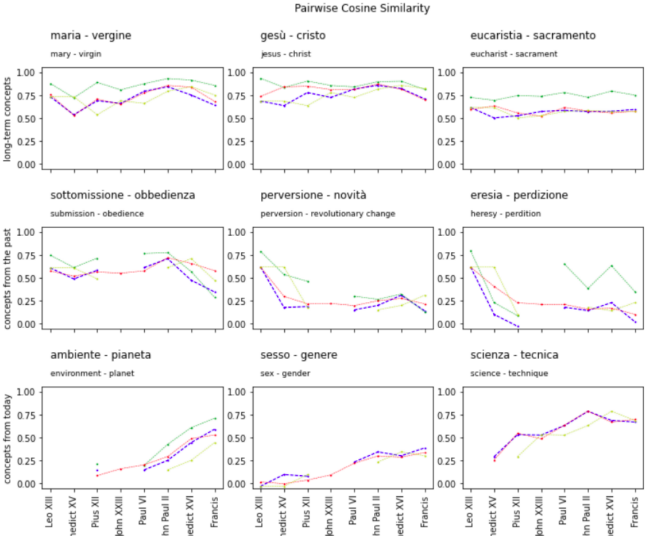


[Zimmermann, 2019]:
a chain of semantic change
FOOD -> MEAT -> FLESH



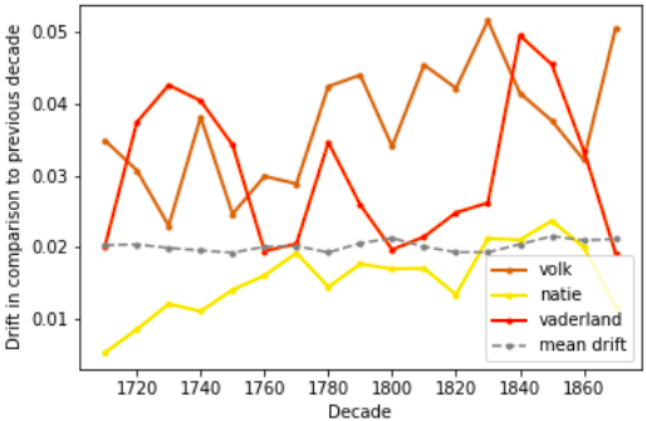
Historical Studies

[Castano et al., 2022]: Vatican publications study



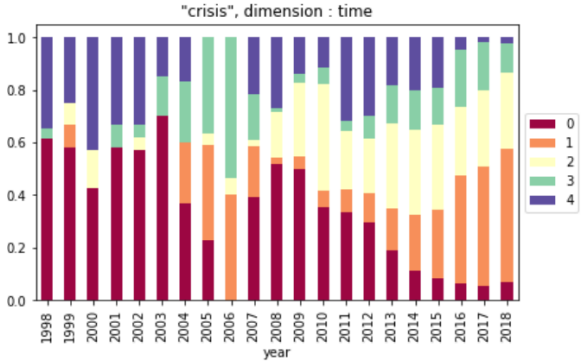
Historical Studies

[Timmermans et al., 2022]: nation building as presented in the 18th century Dutch fiction



Media Montiroting

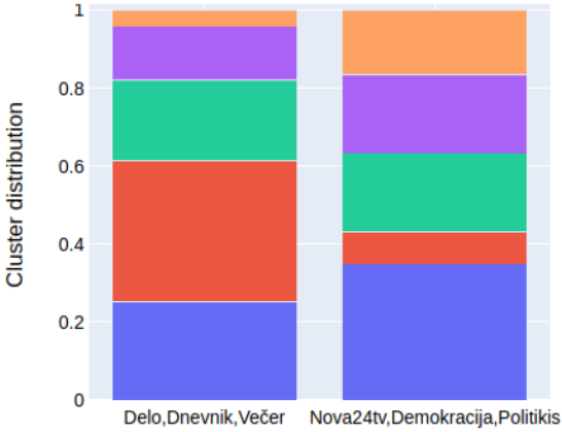
[Montariol et al., 2020]: tracking word usage change in financial domain



N^o	Keyword examples - Word = *crisis*
0	liquidity, funding, contingency, cash, collateral, outflows
1	marketing, business, management, design, advertising, media
2	european, debt, credit, sovereign, countries, eurozone, banks
3	financial, accident, capital, regulatory, loss, liquidity, funding
4	credit, financial, global, markets, debt, european, recession

Media Montiroting

[Martinc et al., 2021]: same techniques can be used to track difference across other dimensions, e.g. conservative vs. liberal media



#	Keywords
	partnership, homosexual relationship, polygamous relationship, intimate relationship, problem
	family relationship, end work relationship, woman, field, less
	power in the relationship, relationship between people, percentage, man and woman, story
	family relationship, marriage, children, Ljubljana, coalition for children
	woman, love relationship, work relationship, film, meet

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- Computational approaches to semantic shift detection have a large potential for applications in
  - Linguistics
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  - Linguistics
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  - Media monitoring
- Interpretable methods are strogly preferred in downstream applications
- Currently, most of this research are rather at the proof-of-concept stage

Laws of Semantic Change

- In addition to classifying *individual words* as either changing or non-changing it would be interesting to find *general regularities* of word meaning change
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- We discuss the **latest** papers on this topic, since it learns from previous studies and correct their drawbacks
  - If you interested, read the paper and then look at the previous work it is referring to

[Kawasaki et al., 2022]

Research Question

- Whether a tendency to change meaning correlates with
  - frequency,
  - length,
  - polysemousness?

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Cognate Study

- Spanish, French, and Italian cognates, 794 in total

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  - Cognates *by definition* originated from the same (Latin) word
  - If cognates have different meanings at least one of them experienced a semantic change
    e.g. Latin LONGU -> French *long* (long) vs. Spansh *luengo* (erudite wording)
  - If cognates still share the same meaning, they likely remain unchanged

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Main idea

- Regression analysis to predict semantic distance between cognates in a pair of languages from their frequency, length, polysemy, etc.

[Kawasaki et al., 2022]

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Main idea

- Regression analysis to predict semantic distance between cognates in a pair of languages from their frequency, length, polysemy, etc.
  - Semantic distance is measured as a **cosine similarity** between vectors that represent cognates in an **aligned** embedding space

[Kawasaki et al., 2022]

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Results

35% of variety in data can be explained by

- the polysemy of Latin etymon (*POLY*$_{lat}$),
- the length of Latin etymon (*LEN*$_{lat}$),
- an averaged frequency in Romance languages (*FREQ*$_{rom}$),
- and an averaged edit distance between Latin etymon and Romance cognates (*EDIT*).

	Coef.	SE	t	$p > \|t\|$
Intercept	0.00	0.03	0.00	1.00
FREQ_{lat}	-0.08	0.04	-1.82	0.07
POLY_{lat}	**0.10**	**0.04**	**2.28**	**0.02**
LEN_{lat}	**-0.21**	**0.03**	**-6.29**	**0.00**
FREQ_{rom}	**-0.54**	**0.03**	**-18.40**	**0.00**
NORM_{rom}	–	–	–	–
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- Most probably because length, polysemy and frequency are interdependent

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Edit distance indicates the difference between words that were in the language from the very beginning

CAPUT (head) -> *chef* (fr), *jefe* (es)

from those that were borrowed from the Medieval Latin

ANIMAL (animal) -> *animal* (fr), *animal* (es)

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Is it possible to predict meaning change from the state of word in the origin language only?

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Results

Is it possible to predict meaning change from the state of word in the origin language only?

- A negative correlation with the frequency and length of a Latin etymon is statistically significant
- However, only 6% of variance is explained, which means other factors play a more important role

	Coef.	SE	t	$p > \|t\|$
Intercept	0.00	0.03	0.00	1.00
FREQ_{lat}	**-0.10**	**0.04**	**-2.74**	**0.01**
POLY_{lat}	–	–	–	–
LEN_{lat}	**-0.27**	**0.04**	**-7.10**	**0.00**

[Kawasaki et al., 2022]

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- the **longer** word exist in a language, the more it is prone to change
- effect is **stronger for verbs than for nouns** and adjectives:
  - **nouns** are more susceptible to extra-linguistic factors such as socio-cultural circumstances, technological advances, language contacts

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  ? Why did not they use Latin embeddings?
- Many factors remain unexplained: a lot of work for all of you!

References I

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