German in Flux: Detecting Metaphoric Change via Word Entropy

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Introduction

- our aim:
  - **overall**: build a computational model detecting semantic change
  - **in this paper**: distinguish metaphoric change from semantic stability
- how we do it:
  - exploit the idea of **semantic generality** from hypernym detection
  - apply **entropy** to **distributional semantic model** (Santus, Lenci, Lu, & Schulte im Walde, 2014)
  - sample language German
  - introduce the first resource for evaluation of models of metaphoric change

Related Work

- previous work includes mainly:
  i) spatial displacement models
  ii) word sense induction models
- quantifies the degree of **overall change** rather than being able to qualify different **types**
- does not examine metaphoric change

Conclusions

- you *can* annotate semantic change in a corpus (so do it)
- entropy correlates strongly and significantly with degree of metaphoric change
- frequency correlates moderately, but non-significantly on small data set
- annotation and model are **generalizable** to different types of semantic change

`https://github.com/Garrafao/MetaphoricChange`

References

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Metaphoric Change

- frequent and important type of semantic change
- source and target concept are related by similarity or a reduced comparison (cf. Koch, 2016, p. 47)

  source: *... muß ich mich vmbweltzen / vnd kan keinen schlaff in meine augen bringen*
  '... I have to turn around and cannot bring sleep into my eyes.'

  target: *Kinadon wollte den Staat umwälzen ...*
  'Kinadon wanted to revolutionize the state ...'

  (i) creates **polysemy**
  (ii) often results in more abstract or **general** meanings
  → assumption: (i) and (ii) imply extension and dispersion in the range of linguistic contexts

Word Entropy

- derived from information-theoretic concept of entropy (Shannon, 1948)
- corresponds to **entropy of word vector**
- is assumed to reflect **semantic generality** in hypernym detection
- is given by

$$H(C) = -\sum_{i=1}^{n} P(c_i \mid w) \log_2 P(c_i \mid w)$$

  where $P(c_i \mid w)$ is the occurrence probability of context word c_i given target word w
- measures the **unpredictability** of w's co-occurrences

Evaluation

- **no standard test set** of semantic or metaphoric change
- we create a small but first test set via annotation (**28 items**)
- annotators judged **560 context pairs** for a metaphorical relation

  Workflow:
  i) preselect 14 changing words
  ii) add 14 stable distractors
  iii) identify a date of change
  iv) extract 20 contexts for each target from before and after date of change
  v) for each word combine contexts between time periods randomly
  vi) annotation of context pairs

Results

	1700-1800	**1800-1900**	**all**
entropy	**.64*** **	.10	**.39***
frequency	.29	-.07	.26

Table 1: Correlation (ρ) between predicted and gold ranks. Significance is determined with a t-test.

- analyzing the predicted ranks reveals interesting insights.
- e.g., entropy ranks *ausstechen* (see below) much better than frequency
- however, entropy ranks *Donnerwetter* (at the top of the gold rank) at the very bottom
- we suppose the reason is that in its later metaphoric sense 'blowup' *Donnerwetter* can be used as an interjection in very short sentences
- this narrows down *Donnerwetter*'s contextual distribution due to our model only considering words within a sentence as context
- ***ausstechen***

  1605: *Von einem Bawren / welcher einem Kalbskopff die Augen außstach.*
  'About a Farmer / who cut out the eyes of a calf's head.'

  1869: *Sie wollen ihre Aufgabe nicht nur lösen, sondern auch elegant, d. h. rasch lösen, um Nebenbuhler auszustechen.*
  'They not only wanted to solve their task, but also elegantly, i.e., solve it fast, in order to excel rivals.'

  – gold rank: 12/28, entropy: 13, frequency: 17
- ***Donnerwetter***

  1631: *Die Lufft ist heiß / vnd gibt viel Blitzen vnd Donnerwetter ...*
  'The air is hot / and there are many lightnings and thunderstorms ...'

  1893: *Potz Donnerwetter!*
  'Man alive!'

  – gold rank: 1/28, entropy: 27, frequency: 15
- shows that
  i) different factors play a role in determining the contextual distribution of a word (i.e., a model of semantic change should incorporate different types of information) and
  ii) frequency may still be helpful in detecting metaphoric change in certain settings