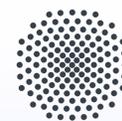


# German in Flux: Detecting Metaphoric Change via Word Entropy

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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:
  - spatial displacement models
  - 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 umbweltzen / 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

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

- where  $P(c_i | w)$  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:
  - preselect 14 changing words
  - add 14 stable distractors
  - identify a date of change
  - extract 20 contexts for each target from before and after date of change
  - for each word combine contexts between time periods randomly
  - annotation of context pairs

## Results

	1700-1800	1800-1900	all
<b>entropy</b>	<b>.64***</b>	.10	<b>.39*</b>
<b>frequency</b>	.29	-.07	.26

**Table 1:** Correlation ( $\rho$ ) 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 auszustecken.*  
‘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
  - 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
  - frequency may still be helpful in detecting metaphoric change in certain settings