Modeling Sense Structure in Word Usage Graphs with the Weighted Stochastic Block Model

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Introduction

- traditional approach to annotate word senses are binary assignments to sense descriptions
  - manual effort to create sense descriptions
  - ignores gradedness of word meaning
    (Kilgarriff, 1998)
- alternative: pairwise semantic proximity judgments of word use pairs
  - use pair judgments populate weighted graph
    (Erk et al., 2013)
  - senses are not annotated directly, but **inferred** on the graph
    → clustering procedure is needed
  - we use the weighted stochastic block model
    (McCarthy, Apidianaki, & Erk, 2016)
and taking a knife from her pocket, she opened a vein in her little arm,
And those who remained at home had been heavily taxed to pay for the arms, ammunition;
and though he saw her within reach of his arm, yet the light of her eyes seemed as far off
overlooking an arm of the sea which, at low tide, was a black and stinking mud-flat
twelve miles of coastline lies in the southwest on the Gulf of Aqaba, an arm of the Red Sea.
when the disembodied arm of the Statue of Liberty jets spectacularly out of the

Table 1: Sample of corpus.
(A) [...] and taking a knife from her pocket, she opened a vein in her little arm, and dipping a feather in the blood, wrote something on a piece of white cloth, which was spread before her.

(D) It stood behind a high brick wall, its back windows overlooking an arm of the sea which, at low tide, was a black and stinking mud-flat [...]
Scale

4: Identical
3: Closely Related
2: Distantly Related
1: Unrelated

Table 2: DURel relatedness scale.
Figure 1: Word Usage Graph of English *arm*. Nodes represent uses of the target word. Edge weights represent the median of proximity judgments between uses.
Figure 2: Word Usage Graph of German *zersetzen*.

\[\text{Schlechtweg, Tahmasebi, Hengchen, Dubossarsky, and McGillivray (2021):}\]
\[\text{https://www.ims.uni-stuttgart.de/data/wugs}\]
Figure 3: Word Usage Graph of German *Abgesang*. 
Figure 4: Word Usage Graph of German *Festspiel*.
Weighted Stochastic Block Model (WSBM)

- a generative probabilistic model for random graphs
  
  (Aicher, Jacobs, & Clauset, 2014; T. P. Peixoto, 2019)

- popular in biology, physics and social sciences
- models nodes as part of blocks (clusters)
- assumes that nodes in the same block are stochastically equivalent
- advantages:
  - allows model selection in absence of ground truth senses
  - captures gradedness by flexible distributions between blocks
  - allows simulation from fitted models
  - extensions allow block (sense) overlap
Inference of Block Structure

we maximize the Bayesian posterior probability

\[ P(b|A, x) = \frac{P(x|A, b)P(A|b)P(b)}{P(A, x)} \]

where \( b \) is the inferred block structure, \( A \) is the (unweighted) observed graph, and \( x \) are the observed edge weights \(^2\) (T. Peixoto, 2017)

approximation: multilevel agglomerative Markov chain Monte Carlo (T. P. Peixoto, 2014)

\(^2\)All experiments were done with graph-tool: https://graph-tool.skewed.de/. Additional code is provided at https://github.com/kicasta/Modeling_WUGS_WSBM.
InferredStructures

Figure 5: Inferred block structure for zersetzen.
Inferred Structures

Figure 6: Inferred block structure for *Abgesang*.
Inferred Structures

Figure 7: Word Usage Graph for *Festspiel*.
Figure 8: Correspondence to SemEval correlation clustering.
Model Checking – Link Prediction

- how well can a fitted model $P(b|A,x)$ predict weights on masked edges $E$?
- Inverse Mean Error

$$IME = 1 - \frac{1}{|E|} \sum_{e \in E} \frac{|e_o - e_p|}{4 - 1}$$

where $e_p$, $e_o$ correspond to predicted and observed edge weights
Figure 9: Evaluation result of link prediction.
Model Checking – Predicted/Sampled Graphs

Figure 10: Predicted graph for zersetzen.
Figure 11: Predicted graph for *Abgesang*. 
Figure 12: Predicted graph for *Festspiel*.
Figure 13: Fitted (line) and observed (bars) edge weight distributions for \textit{zersetzen}. 
Figure 14: Fitted (line) and observed (bars) edge weight distributions for Abgesang.
Model Checking – Fitted Edge Weight Distributions

Figure 15: Fitted (line) and observed (bars) edge weight distributions for \textit{Festspiel}.
Conclusion

- we inferred sense structure on WUGs exploiting patterns of semantic proximity
- model selection allows principled inference of sense structures
- the model can be rigorously compared to other probabilistic models (Duda & Hart, 1973; Hoff, Raftery, & Handcock, 2002)
- the inferred structures mostly reflect intuitive sense distinctions
- structural properties of observed graphs are often not very well preserved
  - → more flexible distributions for edge weights are needed
- inferred models can be used for simulation of realistic WUGs
- future: do senses overlap? Which model best describes the data?

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3https://www.ims.uni-stuttgart.de/data/wugs
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