

Uncertainty in Neural Network Word Embedding **Exploration of a Threshold for Similarity**

Navid Rekabsaz, Mihai Lupu, Allan Hanbury TU Wien, Vienna, Austria

surname@ifs.tuwien.ac.at

Problem

- In word embedding models, one can measure the *semantic similarity* of *any* two words, e.g. by Cosine function between the vector representations of the terms
- However an essential challenge in using this similarity measure is:

How to distinguish between similar and dissimilar terms?

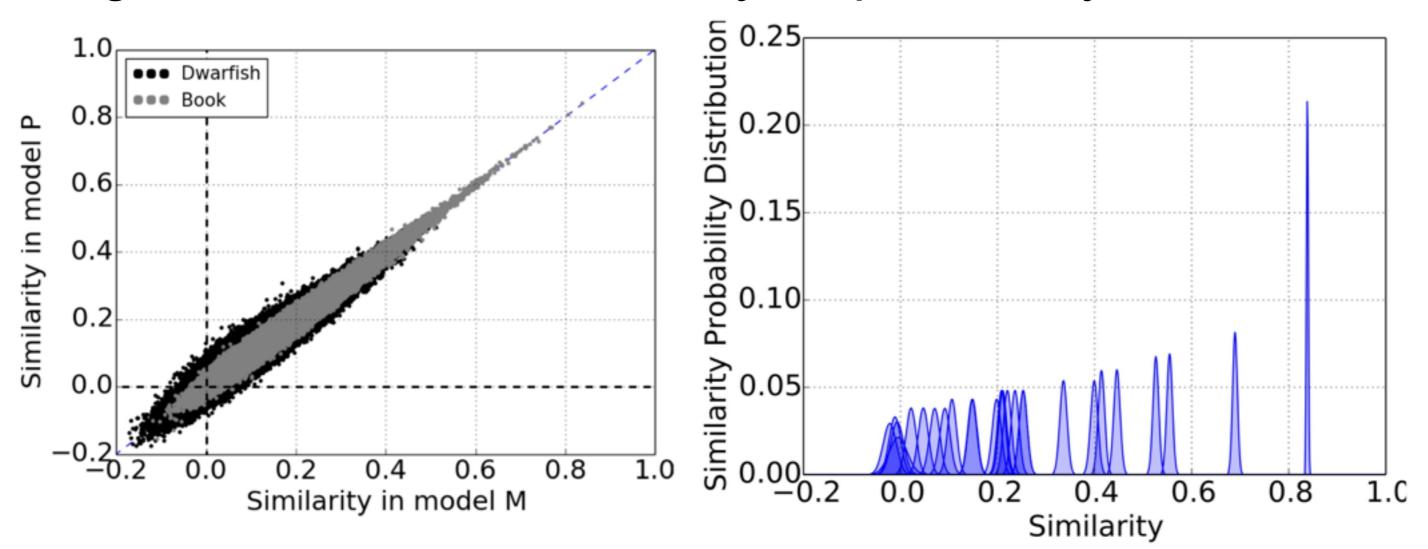
Proposed Solution

- We suggest a *general threshold* which effectively filters out dissimilar/less similar terms
- We explore this threshold through inherent uncertainty in the similarity of neural networkbased word embedding models

Term Similarity Threshold

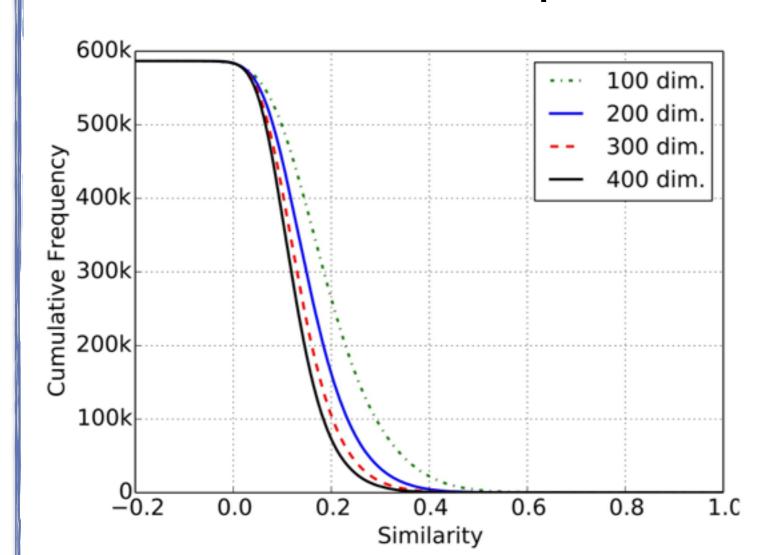
Uncertainty in Similarity:

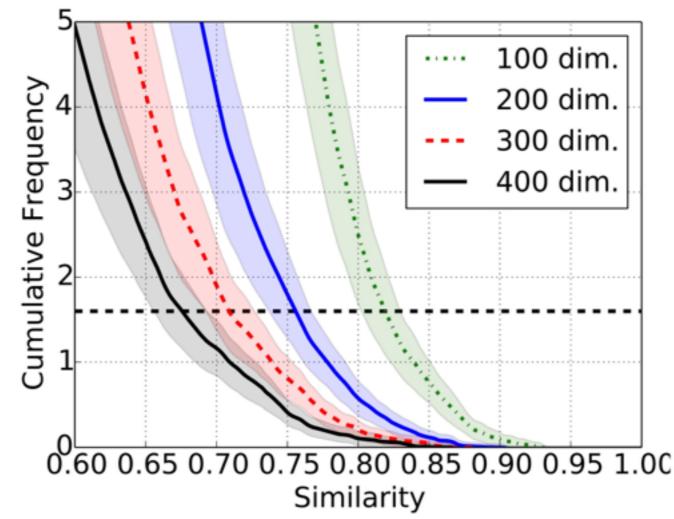
Left: Similarity of two words to all terms in two models. Right: Term-to-term similarity as probability distribution.



Continuous Distribution of Neighbours:

- Create the Cumulative Distribution Function (CDF) of similarities for 100 terms and average their values.
- Y-values: The expected number of neighbors.





Threshold:

- Average # of similar terms per _ term in WordNet is ~1.6
- Our thresholds is achieved by projecting 1.6 on CDF diagram.

Dimensionality	Threshold Boundaries		
	Lower	Main	Upper
100	0.802	0.818	0.829
200	0.737	0.756	0.767
300	0.692	0.708	0.726
400	0.655	0.675	0.693

Experiments on Document Retrieval

To use word embeddings in retrieval models, we use: Generalized Translation Models (GT) & Extended Translation Models (ET) for BM25 and Language Modeling (LM).

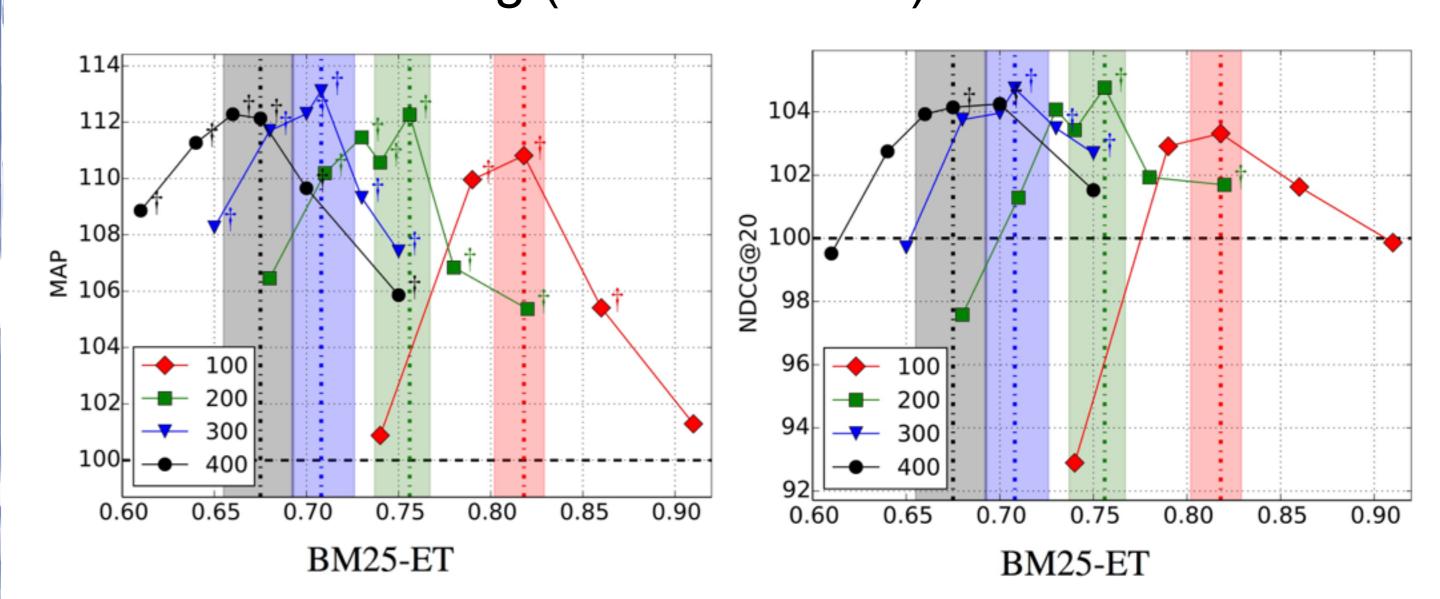
Rekabsaz et al. [2016], Zuccon et al. [2015]

Experiments:

Evaluation measures: MAP, NDCG

Name	Collection	# Documents	
TREC 6	Disc4&5	551873	
TREC 7 and 8	Disc4&5	523951	
	without CR		
HARD 2005	AQUAINT	1033461	

- We exhaustively evaluate the collections on various thresholds in [0.6-1.0] and dimensions of [100-400].
- Significance test against the original models without word embedding (BM25 and LM).



Results:

- The optimal results in all the dimensions are the same or in the range of the proposed thresholds.
- Results with the optimal thresholds are significantly better than the original models.

- Conclusion We propose a novel representation of the probability of the # of neighbors around a term
 - We propose optimal thresholds to select effective terms in different dimensions