FACULTY
OF INFORMATICS
Masaryk University

DisSim: the Disambiguation of Words for Computing the Similarity of Documents

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https://gitlab.fi.muni.cz/xnovot32/dissim-jupyter

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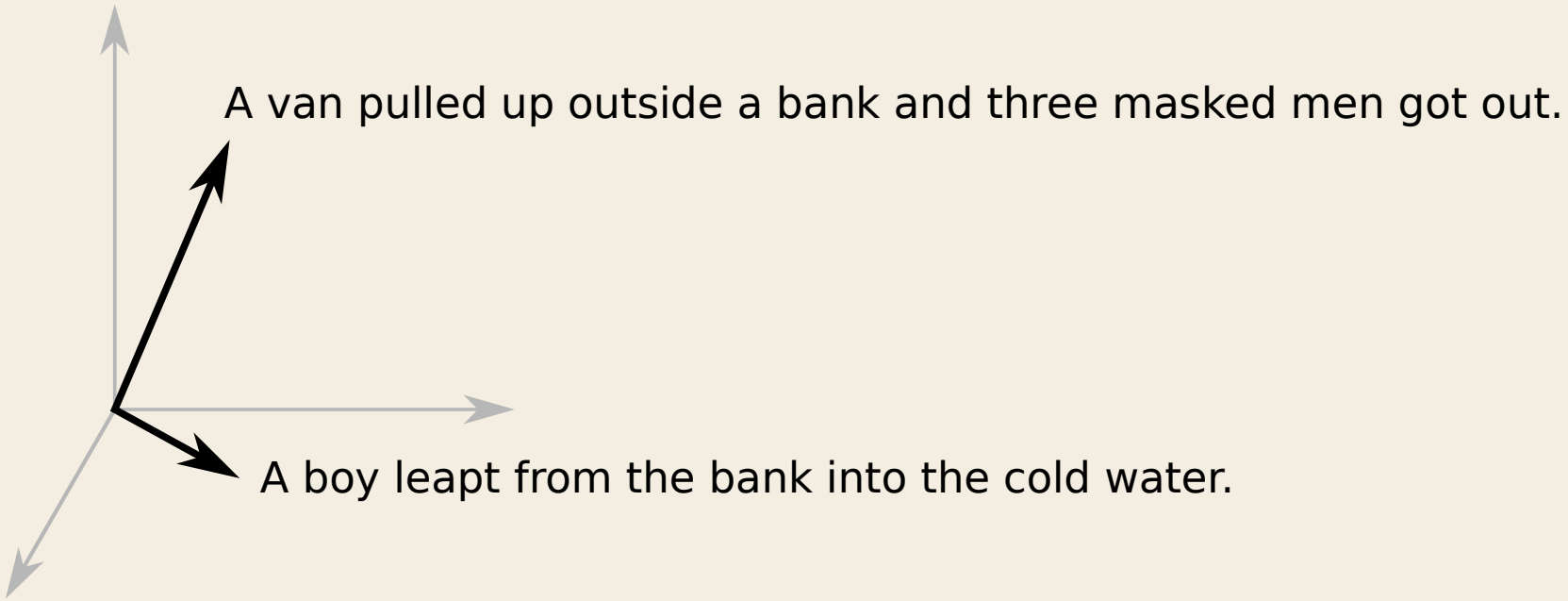
Section 1

Introduction

Introduction

Vector Space Document Model

A class of document representations that encode documents in a high-dimensional vector space:



The classic IR vector space model is due to Salton et al. (1975).

Introduction

Word Sense Disambiguation

In computational linguistics, word-sense disambiguation (WSD) refers to the problem of identifying the sense in which a word was used:

- A van pulled up outside a bank and three masked men got out.
- A boy leapt from the bank into the cold water.

One of the standard approaches is to perform clustering on the vector-space representation of words (Anaya-Sánchez et al., 2006; Rafael Berlanga LLavori, 2012).

Introduction

The DisSim Algorithm

The following steps are repeated until a termination condition is met:

- A vector-space document model is constructed from a corpus.
- Individual words are represented by the vectors of their parent documents. After clustering, each word is replaced with the name of its cluster:
  - A van pulled up outside a bank_1 and three masked men got out.
  - A boy leapt from the bank_2 into the cold water.
- A new vector-space document model is constructed from the updated documents.

It is expected that the diambiguated model will yield better results.

Section 2

Experimental Setup

Experimental Setup

Doc2vec, K-means, and Agglomerative Clustering

As the vector-space document model, the doc2vec algorithm by Le et al. (2014) in the skip-gram variant as implemented in the Gensim Python library was used. Semantically similar documents have been empirically shown to form clusters in this model.
For clustering, we used:

- several variants of *K*-means, where *K* was the number of senses of a word given by WordNet,
- agglomerative clustering using a linkage that minimizes the variance of the clusters being merged (Ward Jr, 1963),
- a novel graph-theoretic algorithm based on the authority-propagation algorithm of PageRank (Page et al., 1999).

Experimental Setup

Training Corpus, Gold Standard, and Evaluation

As the training corpus, we used various a mixture of various corpora: Aesop's Fables, BBC news and sport news, book reviews from amazon.com, Q&A from Yahoo! Answers, and articles from the English Wikipedia.

As the gold standard, we used test data from the SemEval competition. The test data consisted of 500 paragraph-sentence pairs with human-assigned semantic similarity score.

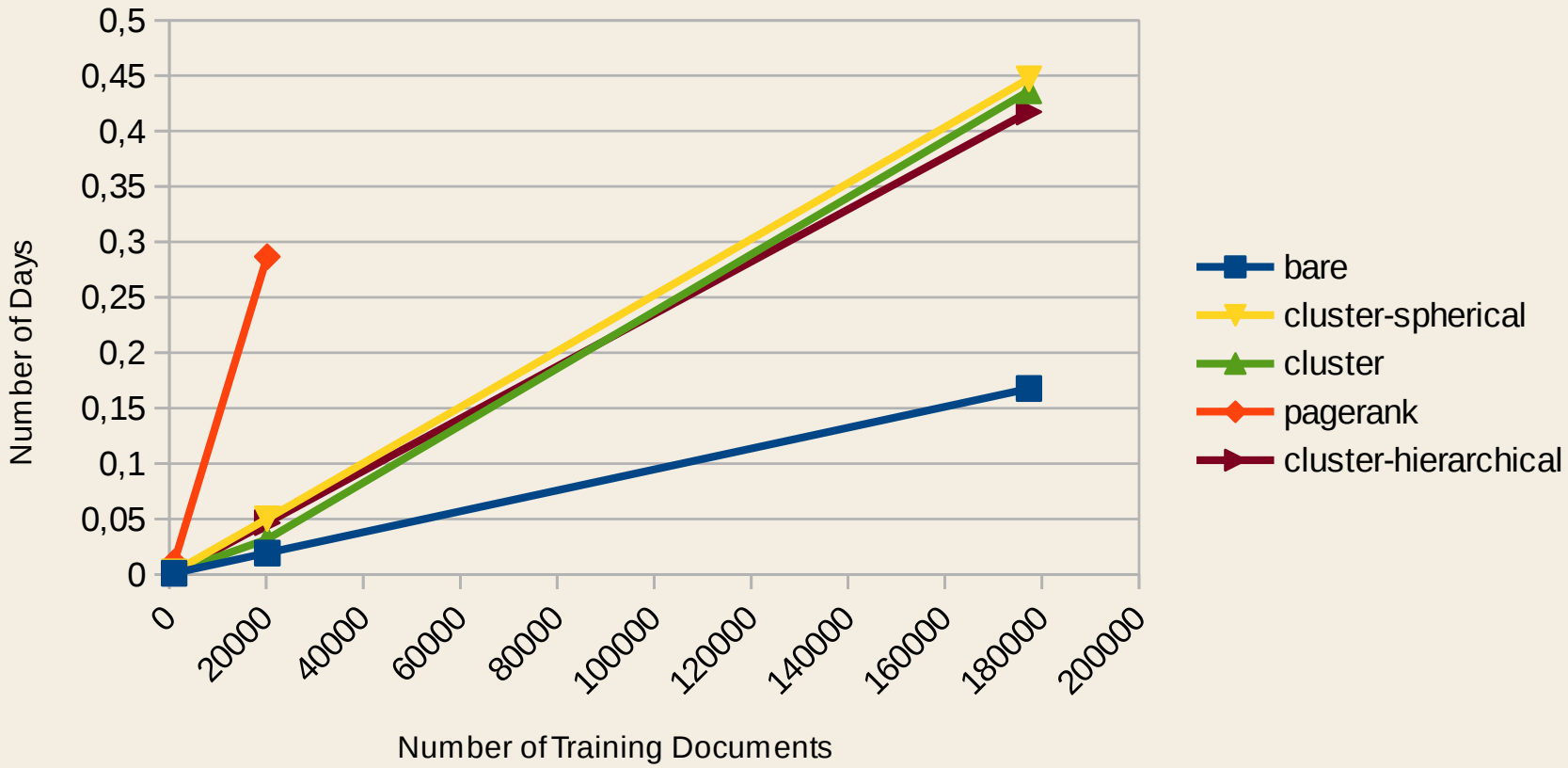
To evaluate a model, we predicted the semantic similarity of every test paragraph-sentence pair by computing cosine similarity between the vector-space representations of the paragraph and the sentence. Then we computed Pearson's correlation coefficient F between the human-assigned semantic similarity scores and the predictions.

Section 3

Results

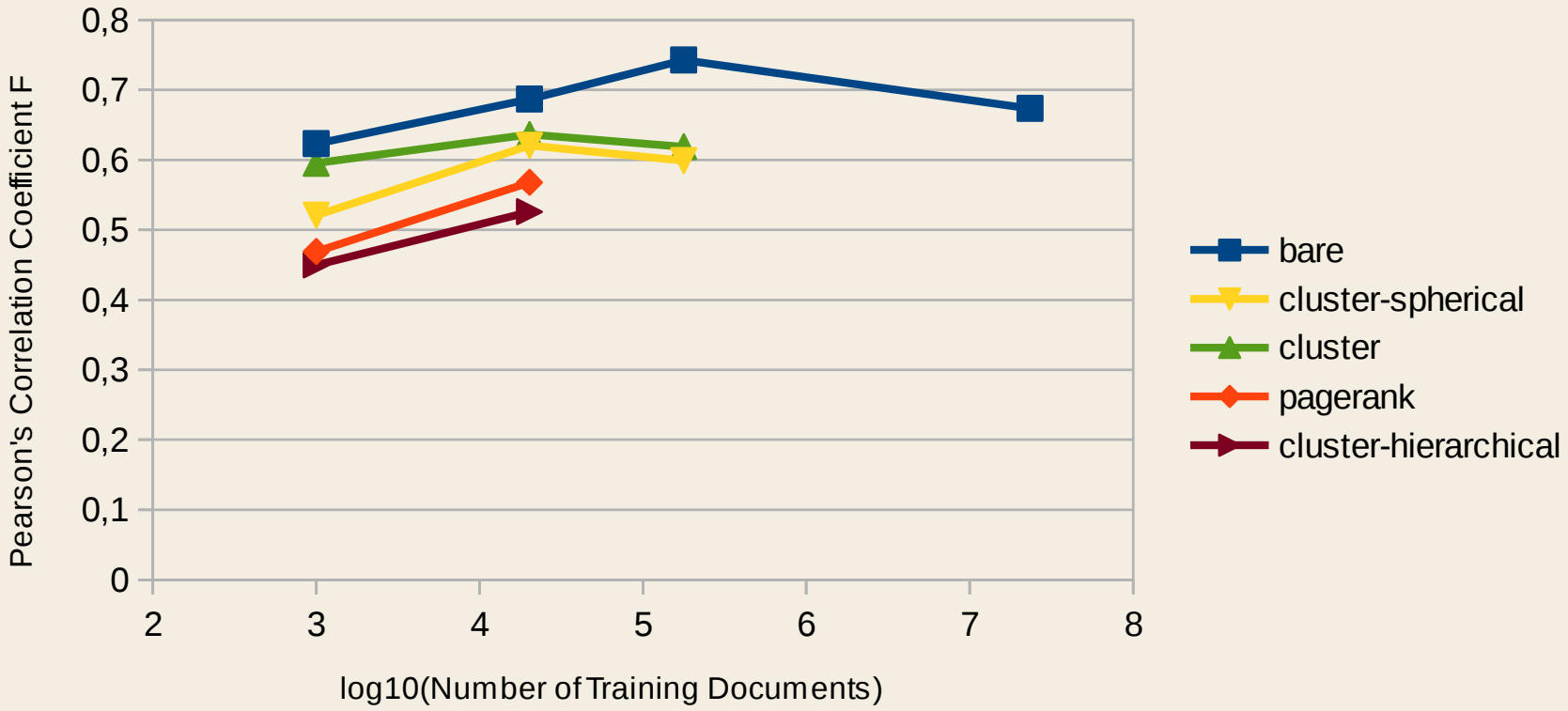
Results

Training Speed



Results

Correlation Between Predictions and Gold Scores



Section 4

Discussion

Discussion

- Compared to SemEval results, bare doc2vec model scores high.
  - A variant of this model won SemEval 2017.
- WordNet has been shown to overestimate the number of meaningful word senses, reducing the quality of clustering.
- A gold standard and an evaluation metric tailored specifically for WSD might yield better results.

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