Flexible Similarity Search of Semantic Vectors Using Fulltext Search Engines

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Illustrations by Jiří Franek.

Outline

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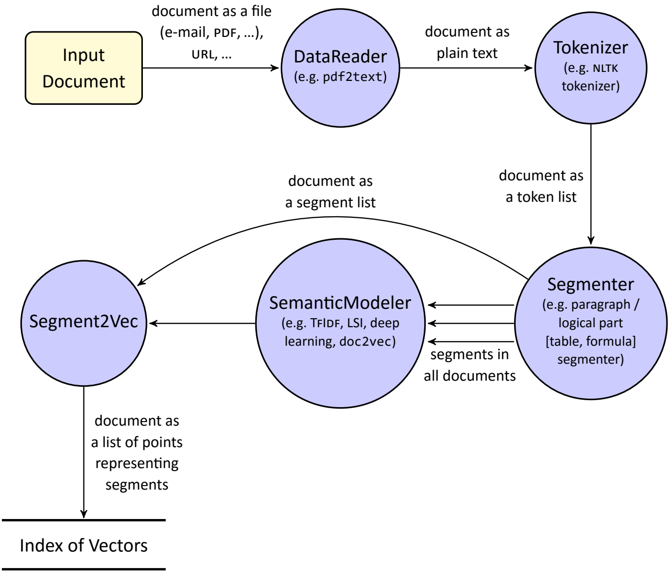
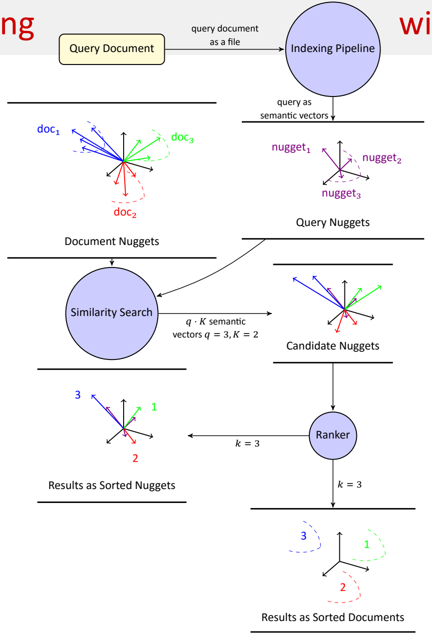
Semantic Indexing



Semantic Searching with Nuggets



Re-Ranking Techniques

1. **Fast:** find candidate nuggets via Elasticsearch.
2. **Slow but precise:** re-rank candidate nuggets with exact similarity metric.
    - Cosine similarity.
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  - Semantic vector of three dimensions:

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  - Feature tokens:
    - `0P2i0d12`
    - `1P2ineg0d13`
    - `2P2i0d07`

High-Pass Filtering – Speed Optimization

- High-pass filtering: $\vec{w} = [0.12, -0.13, 0.065]$

  trim Fixed threshold, for example 0.1:
  Keep only 0.12, -0.13 from $\vec{w}$, as $|0.065| < 0.1$.

  best Fixed number of the best values is used, for example only the best one:
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Speed optimization of the search for candidate nuggets *without significant impact on the quality*.

Outline

Datasets

en-wiki — The English Wikipedia dataset.

- **LSA** with 400 dimensions
- **doc2vec** with 400 dimensions.

wiki-2014+gigaword-5 — Pre-trained word vectors from Wikipedia and English Gigaword Fifth Edition.

- **GloVe** with 50, 100, 200, and 300 dimensions.

common-crawl — Pre-trained word vectors from the Common Crawl project.

- **GloVe** with 300 dimensions.

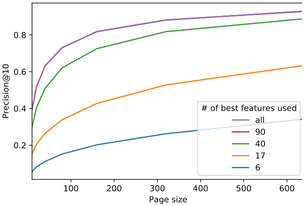
twitter — Pre-trained word vectors from the Twitter social network.

- **GloVe** with 25, 50, 100, and 200 dimensions.

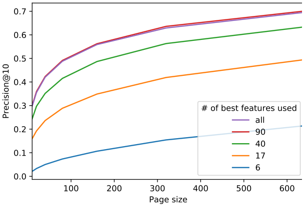
texmex — Image descriptors provided by the TEXMEX project.

- **SIFT** descriptors of images with 128 dimensions.

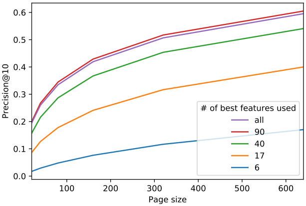
Comparison of Results



English Wikipedia
Cosine Similarity



TEXMEX SIFT Descriptors
Cosine Similarity



TEXMEX SIFT Descriptors
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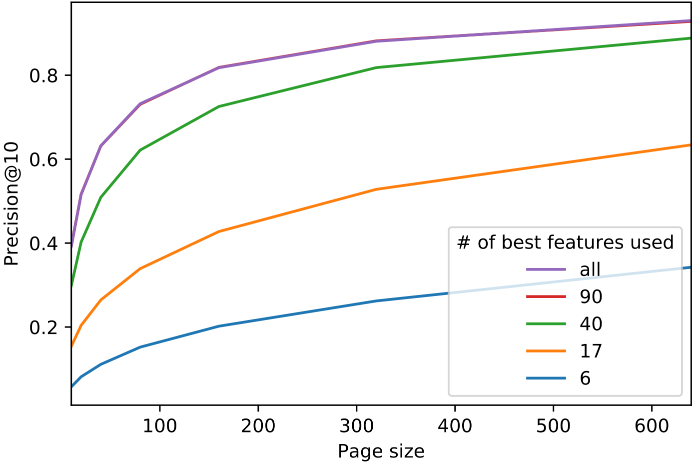

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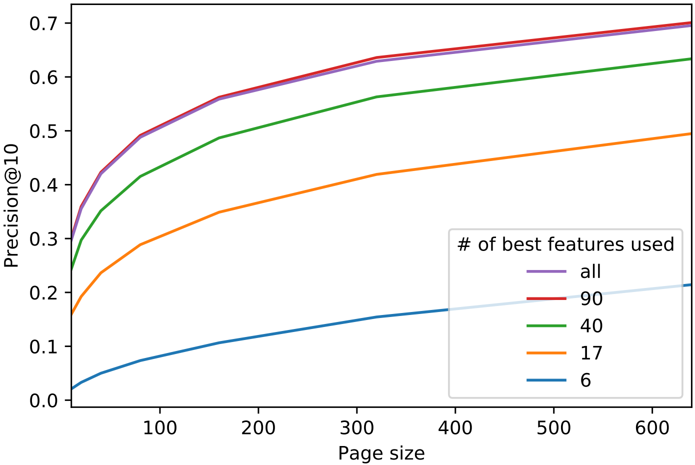

TEXMEX SIFT Descriptors Cosine Similarity

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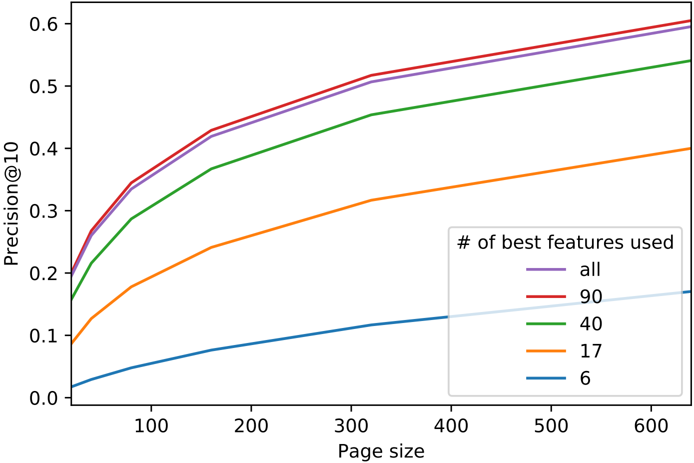
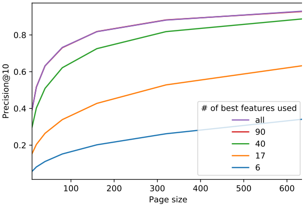


TEXMEX SIFT Descriptors Euclidean Similarity

Comparison of Results



English Wikipedia
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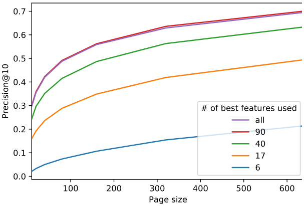

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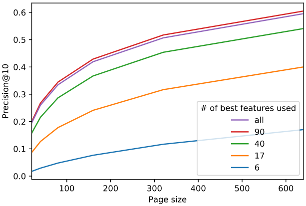
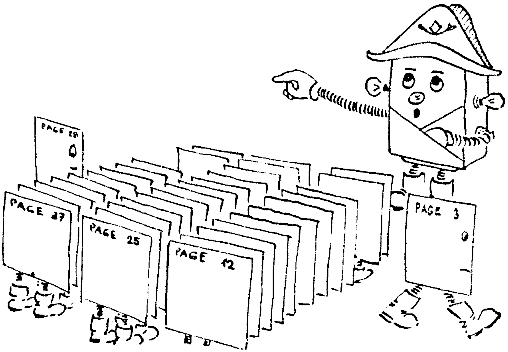


TEXMEX SIFT Descriptors
Euclidean Similarity

Summary

Flexible	Different input data formats / tokenizers / segmenters / semantic models / re-ranking methods / fulltext search engines / …
Similarity Search	Cosine / euclidean / … similarity.
of Semantic Vectors	LSI / deep learning / doc2vec / …
using Fulltext Search Engines	Sphinx, Lucene, Elasticsearch, Solr, …

Questions?



- Illustrations by Jiří Franek.
- RŮŽIČKA, Michal, Vít NOVOTNÝ, Petr SOJKA, Jan POMIKÁLEK and Radim ŘEHŮŘEK. Flexible Similarity Search of Semantic Vectors Using Fulltext Search Engines. In CEUR Workshop Proceedings, Vol. 1923. Vienna, Austria: Neuveden, 2017. p. 1–12, 12 pp. ISSN 1613-0073. `https://usc-isi-i2.github.io/ISWC17workshop/accepted-papers/HSSUES_2017_paper_2.pdf`
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