Efficient Vector Space Retrieval

Information Retrieval Project

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FSS 2020

Outline

1. Dataset
2. Preprocessing
3. Basic retrieval: TF-IDF & cosine similarity
4. Tiered index
5. Pre-clustering
6. Random projections
7. Evaluation of performance and results

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Dataset

We used development subset of NFCorpus.

- 3193 documents
- 325 queries (full text) with corresponding 325 query titles
- Relevance links between documents and queries

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Basic retrieval

Term frequency:

$$tf(t_i, d_j) = 1 + \log(ft_d)$$

Inverse document frequency:

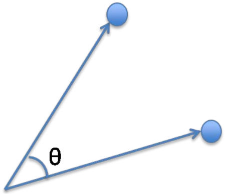
$$idf(t_i) = \log(\frac{N}{df_i})$$

TF-IDF:

$$idf(t_i) \cdot tf(t_i, d_j)$$

Cosine similarity:

$$sim(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$



Basic retrieval

Term frequency: { 0: { alkylphenol: 0.008, human: 0.026, milk: 0.026, .. }

Inverse document frequency: { alkylphenol: 6.122 }

TF-IDF: { 0: { alkylphenol: 0.052, human: 0.035, milk: 0.080, .. }

Cosine similarity:

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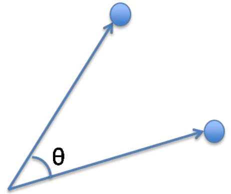

Basic retrieval

Shortcomings:

- for each query we have to compute all cosine scores
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Idea: Reduce the number of cosine computations

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Tiered index

Inverted index with tf scores:

{**dtt:** {135: **0.017**, 136: **0.007**, 1117: **0.006**, 1118: **0.014**, 1264: **0.008**, 1444: **0.006**, 2327: **0.018**, 3020: **0.004**} }

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How to effectively merge tieres from different postings?

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2. Expanding tieres: [135, 2327, 1118, 1264], [23, 24, 135, 210, 232 , 13, 28, 111, 1118, 2000]
3. Sorting tieres: [135, 1118, 2327, 1264], [13 23, 24, 28, 111, 135, 210, 232 , 1118, 2000] → [135, 1118, 2327] >= ***K***

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In this algorithm we perform intersection between tieres from term postings. What if no intersection is found between all query terms?

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why deep fried foods may cause cancer in the latest study on dietary patterns and breast cancer risk among women , healthier eating was associated with eliminating three-quarters of the odds of breast cancer , whereas less healthy eating was associated with up to nearly eight times the odds . included in the unhealthy eating pattern was the consumption of deep-fried foods , which have previously been linked to breast cancer , pancreatic cancer , lung cancer , oral and throat cancers , esophageal cancer , and cancer of the voicebox . no deep fried foods ? what ' s a southern belle to do ? instead of deep fried foods , how about the traditional southern diet , characterized by high intakes of cooked greens , beans , legumes , cabbage , sweet potatoes and cornbread , which may reduce the risk of invasive breast cancer significantly . what about the consumption of deep-fried foods and risk of prostate cancer ? researchers at the fred hutchinson cancer research center and the university of washington found that eating french fries , fried chicken , fried fish , and doughnuts was associated with about a third greater odds of prostate cancer . after stratifying for tumor aggressiveness , they found slightly stronger associations with more aggressive disease , suggesting that regular intake of deep-fried foods may contribute to the progression of prostate cancer as well . what in deep fried foods is so bad for us ? just heating oil that hot can generate potentially carcinogenic compounds , and then known carcinogens such as heterocyclic amines and polycyclic aro .....

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Conclusion: Tiered index in the form we implemented makes sense only for short queries - justification for using query titles in evaluation of model.

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Use to improve retrieval speed

Cluster pruning: consider only documents in a small number of clusters as candidates for which we compute similarity scores

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Offline preparation:

1. Pick $\sqrt{N}$ documents from a collection to be leaders of future clusters
2. Assign each document that is not a leader (call it follower) to the cluster with nearest leader

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Online process ‘on-the-fly’:

1. Compute the similarities of the query with all leaders
2. Choose the most similar documents from the cluster with closest leader

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measures the cosine of the angle between two documents

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K-means

is arguably the most common technique

non-parametric, distance-based clustering method

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Random Projections

Johnson-Lindenstrauss lemma:

A set of points in a high-dimensional space can be embedded into a space of much lower dimension in such a way that distances between the points are nearly preserved.

Johnson, W. B., Lindenstrauss, J., & Schechtman, G. (1986).

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Idea:

Reduce the number of cosine computations by dimensionality reduction.

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Random Projections

Given a matrix of document vectors - $X_{d \times N}$

(N – number of documents, d – the length of document vector)

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3. Apply a hash function to each element of the resulting matrix, creating a new hashed matrix $\boldsymbol{H^{RP}_{m \times N}}$, where

$$\boldsymbol{h^{RP}_{ij}} = \begin{cases} \boldsymbol{1} & \boldsymbol{if\ x^{RP}_{ij} \geq \theta} \\ \boldsymbol{0} & \boldsymbol{otherwise} \end{cases}$$

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- **Gaussian distribution with mean 0 and variance 1:** $\boldsymbol{X \sim \mathcal{N}(0,1)}$
  => **Threshold = 0**

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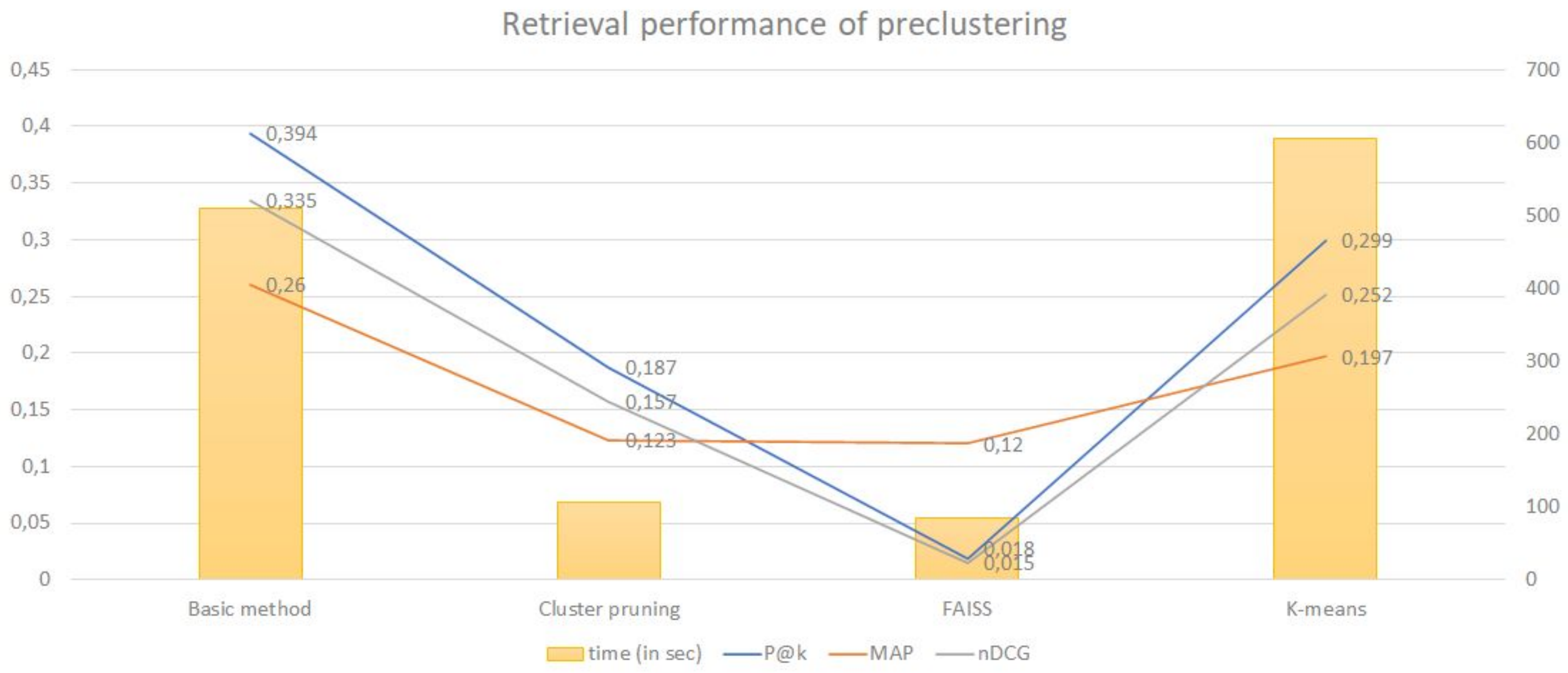

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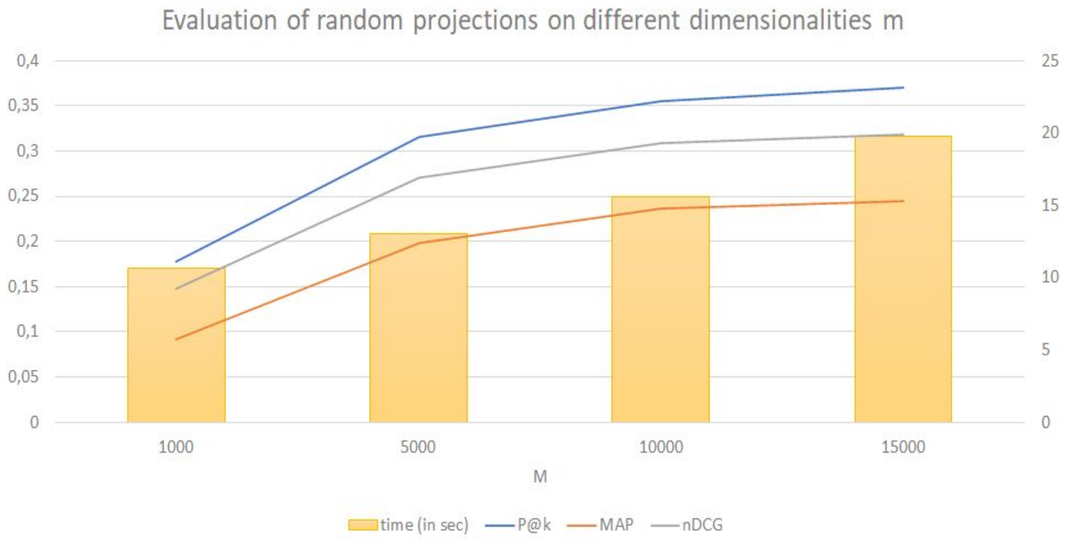

Basic retrieve

P@k	MAP	nDCG	Time (in sec)
0.394	0.260	0.336	495

Tiered index

Baseline: basic retrieval for query titles

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K = 4 number of tieres

Accuracy:

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Basic retrieval	0.328	0.238	0.286
Tiered index	0.165	0.11	0.141

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Still better, since vectorization of queries is performed outside of basic retrieval model, while tiered index performs is on the fly

Thank you for attention!