

The BM25 Model

COMP3009J: Information Retrieval

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Okapi BM25

- The BM25 Model (“BM” stands for “Best Match”) came about from a series of experiments that were carried out to extend the classic probabilistic model.
- First implemented in the Okapi system that was created in London City University in the 1980s and 1990s.
- Many variants have been proposed: we will look only at BM25 itself.
- Today, BM25 is considered to be a state-of-the-art retrieval method that operates using the same principles as TF-IDF but generally performs better than the classic version we have already studied.
- Pages 104-107 of Modern Information Retrieval (2nd Edition)

BM25: Reasoning

- Based on the belief that good term weighting comes from three principles:
 - **Inverse document frequency**: (terms that are rare across a collection should carry more weight).
 - **Term frequency**: (terms that are common within a document should carry more weight).
 - **Document length normalisation**: (so that longer documents do not get an unfair advantage if they contain query terms often simply because of their length).
- The formula evolved over time in response to many experiments being conducted.

BM25 Formula

$$sim_{BM25}(d_j, q) \sim \sum_{k_i \in d_j \wedge k_i \in q} \frac{f_{i,j} \times (1 + k)}{f_{i,j} + k \left((1 - b) + \frac{b \times len(d_j)}{avg_doclen} \right)} \times \log \left(\frac{N - n_i + 0.5}{n_i + 0.5} \right)$$

- Again, we calculate a similarity score for each document d_j .

BM25 Formula

$$sim_{BM25}(d_j, q) \sim \sum_{k_i \in d_j \wedge k_i \in q} \frac{f_{i,j} \times (1 + k)}{f_{i,j} + k \left((1 - b) + \frac{b \times len(d_j)}{avg_doclen} \right)} \times \log \left(\frac{N - n_i + 0.5}{n_i + 0.5} \right)$$

More words in common with the query =>
Good!

- The similarity score increases whenever a term k_i is in document d_j and also in the query.

BM25 Formula

$$sim_{BM25}(d_j, q) \sim \sum_{k_i \in d_j \wedge k_i \in q} \frac{f_{i,j} \times (1 + k)}{f_{i,j} + k \left((1 - b) + \frac{b \times len(d_j)}{avg_doclen} \right)} \times \log \left(\frac{N - n_i + 0.5}{n_i + 0.5} \right)$$

Common words are less important (similar to IDF)

- N is the total number of documents in the collection.
- n_i is the total number of documents in the collection that contain term k_i .

BM25 Formula

$$\text{sim}_{\text{BM25}}(d_j, q) \sim \sum_{k_i \in d_j \wedge k_i \in q} \frac{f_{i,j} \times (1 + k)}{f_{i,j} + k \left((1 - b) + \frac{b \times \text{len}(d_j)}{\text{avg_doclen}} \right)} \times \log \left(\frac{N - n_i + 0.5}{n_i + 0.5} \right)$$

Repetition of query words in the document =>
Good

- $f_{i,j}$ is the frequency of k_i in d_j (i.e. the number of times the term appears in the document)
- k and b are constants that can be set to suit the document collection and the desired behaviour. For general collections. $k=1$ and $b=0.75$ have been found to work well.

BM25 Formula

$$\text{sim}_{\text{BM25}}(d_j, q) \sim \sum_{k_i \in d_j \wedge k_i \in q} \frac{f_{i,j} \times (1 + k)}{f_{i,j} + k \left((1 - b) + \frac{b \times \text{len}(d_j)}{\text{avg_doclen}} \right)} \times \log \left(\frac{N - n_i + 0.5}{n_i + 0.5} \right)$$

Repetitions are important, but are less important than different query words.

- $\text{len}(d_j)$ is the length of d_j (i.e. the number of terms in it)
- avg_doclen is the average length of a document in the collection.

BM25 Formula

$$\text{sim}_{BM25}(d_j, q) \sim \sum_{k_i \in d_j \wedge k_i \in q} \frac{f_{i,j} \times (1 + k)}{f_{i,j} + k \left((1 - b) + \frac{b \times \text{len}(d_j)}{\text{avg_doclen}} \right)} \times \log \left(\frac{N - n_i + 0.5}{n_i + 0.5} \right)$$

Repetition is more important if the document is long (relative to the average document length).

- $\text{len}(d_j)$ is the length of d_j (i.e. the number of terms in it)
- avg_doclen is the average length of a document in the collection.

BM25 Example (calculation for one document)

- **Query:** "President Lincoln"
- $N = 500,000$ documents
- "president" occurs in 40,000 documents ($n_i = 40,000$)
- "lincoln" occurs in 300 documents ($n_i = 300$)
- "president" occurs 15 times in this document ($f_{i,j} = 15$)
- "lincoln" occurs 25 times in this document ($f_{i,j} = 25$)
- The document is 90% of the length of the average ($\frac{\text{len}(d_j)}{\text{avg_doclen}} = 0.9$)
- $k = 1, b = 0.75$

BM25 Calculation

$$\begin{aligned} \text{sim}_{BM25}(d_j, q) \sim & \frac{15 \times 2}{15 + (0.25 + 0.75 \times 0.9)} \times \log \left(\frac{500,000 - 40,000 + 0.5}{40,000 + 0.5} \right) + \left. \vphantom{\frac{15 \times 2}{15 + (0.25 + 0.75 \times 0.9)}} \right\} k_i = \text{president} \\ & \frac{25 \times 2}{25 + (0.25 + 0.75 \times 0.9)} \times \log \left(\frac{500,000 - 300 + 0.5}{300 + 0.5} \right) \left. \vphantom{\frac{25 \times 2}{25 + (0.25 + 0.75 \times 0.9)}} \right\} k_i = \text{lincoln} \end{aligned}$$

$$= 27.27$$

BM25 Variations

- There are a number of variations on BM25, of which two are particularly notable:
 - BM25F: Allows different fields to be given different importance in the document (e.g. document title, headlines, main text, etc.).
 - BM25+: addresses an issue with BM25 whereby very short documents would be given scores that are too high.

BM25: Usefulness

- Unlike probabilistic model, BM25 does not require relevance information.
- Most IR researchers agree that it outperforms the vector model on general collections.