Introduction to

Information Retrieval

BM25 and BM25F

Slides borrowed from Stanford with slight modifications

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BM25 The Next Generation of Lucene Relevance

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There's something new cooking in how Lucene scores text. Instead of the traditional "TF*IDF," Lucene just switched to something called BM25 in trunk. That means a new scoring formula for Solr (Solr 6) and Elasticsearch down the line.

Sounds cool, but what does it all mean? In this article I want to give you an overview of how the switch might be a boon to your Solr and Elasticsearch applications. What was the original TF*IDF? How did it work? What does the new BM25 do better? How do you tune it? Is BM25 right for everything?

Okapi BM25 [Robertson et al. 1994, TREC City U.]

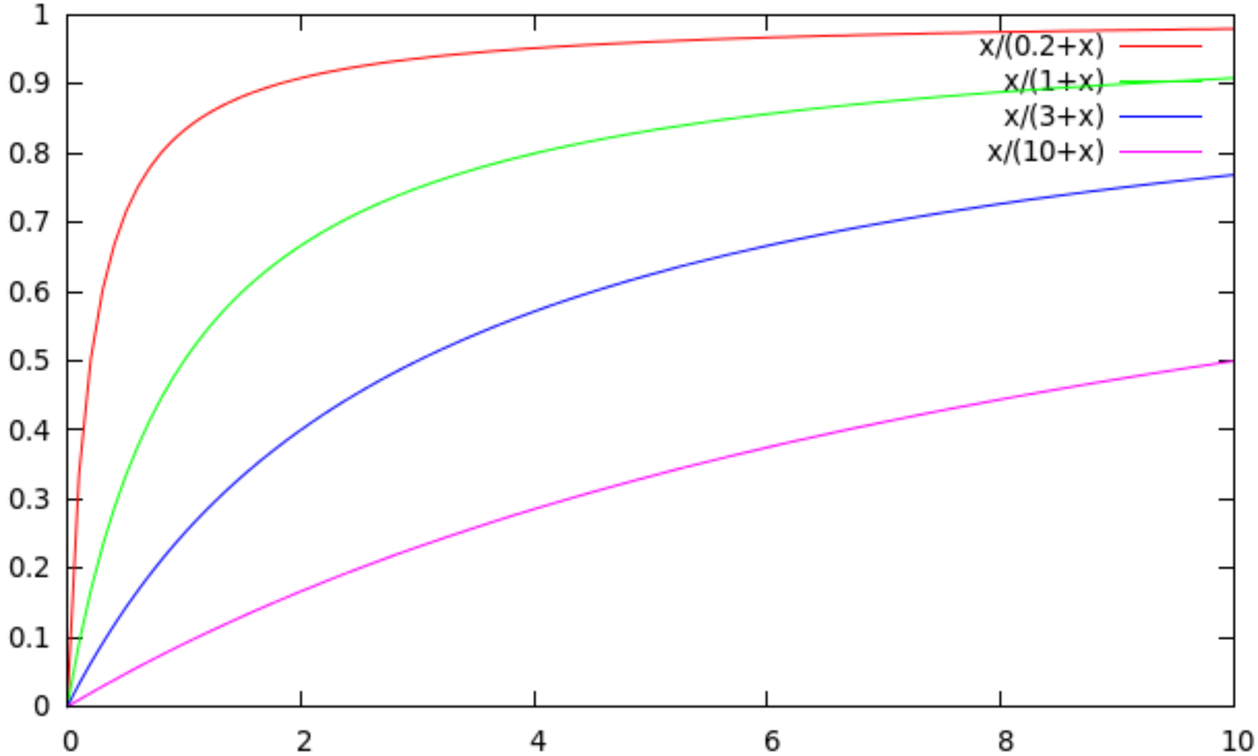
- BM25 “Best Match 25” (they had a bunch of tries!)
  - Developed in the context of the Okapi system
  - Started to be increasingly adopted by other teams during the TREC competitions
  - It works well
- Goal: be sensitive to term frequency and document length while not adding too many parameters
  - (Robertson and Zaragoza 2009; Spärck Jones et al. 2000)

The saturation function

$$\frac{tf}{k_1 + tf}$$

- If *tf = 0, its value = 0*
- *Its value increases* monotonically with *tf*.
- … but asymptotically approaches a maximum value as $tf \to \infty$ [not true for simple scaling of *tf*]

Saturation function



- For high values of k_1, increments in tf_i continue to contribute significantly to the score
- Contributions tail off quickly for low values of k_1

“Early” version of BM25

$$c_i^{BM25v2}(tf_i) = \log\frac{N}{df_i} \times \frac{(k_1+1)tf_i}{k_1+tf_i}$$

- (k_1+1) factor doesn’t change ranking, but makes term score 1 when $tf_i = 1$
- Similar to *tf-idf*, but term scores are bounded

Document length normalization

- Longer documents are likely to have larger tf_i values
- Why might documents be longer?
  - Verbosity: suggests observed tf_i too high
  - Larger scope: suggests observed tf_i may be right
- A real document collection probably has both effects
- … so should apply some kind of partial normalization

Document length normalization

- Document length:

$$dl = \sum_{i \in V} tf_i$$

- $avdl$: Average document length over collection
- Length normalization component

$$B = \left((1-b) + b \frac{dl}{avdl} \right), \qquad 0 \le b \le 1$$

  - $b = 1$ full document length normalization
  - $b = 0$ no document length normalization

Okapi BM25

- Normalize *tf* using document length

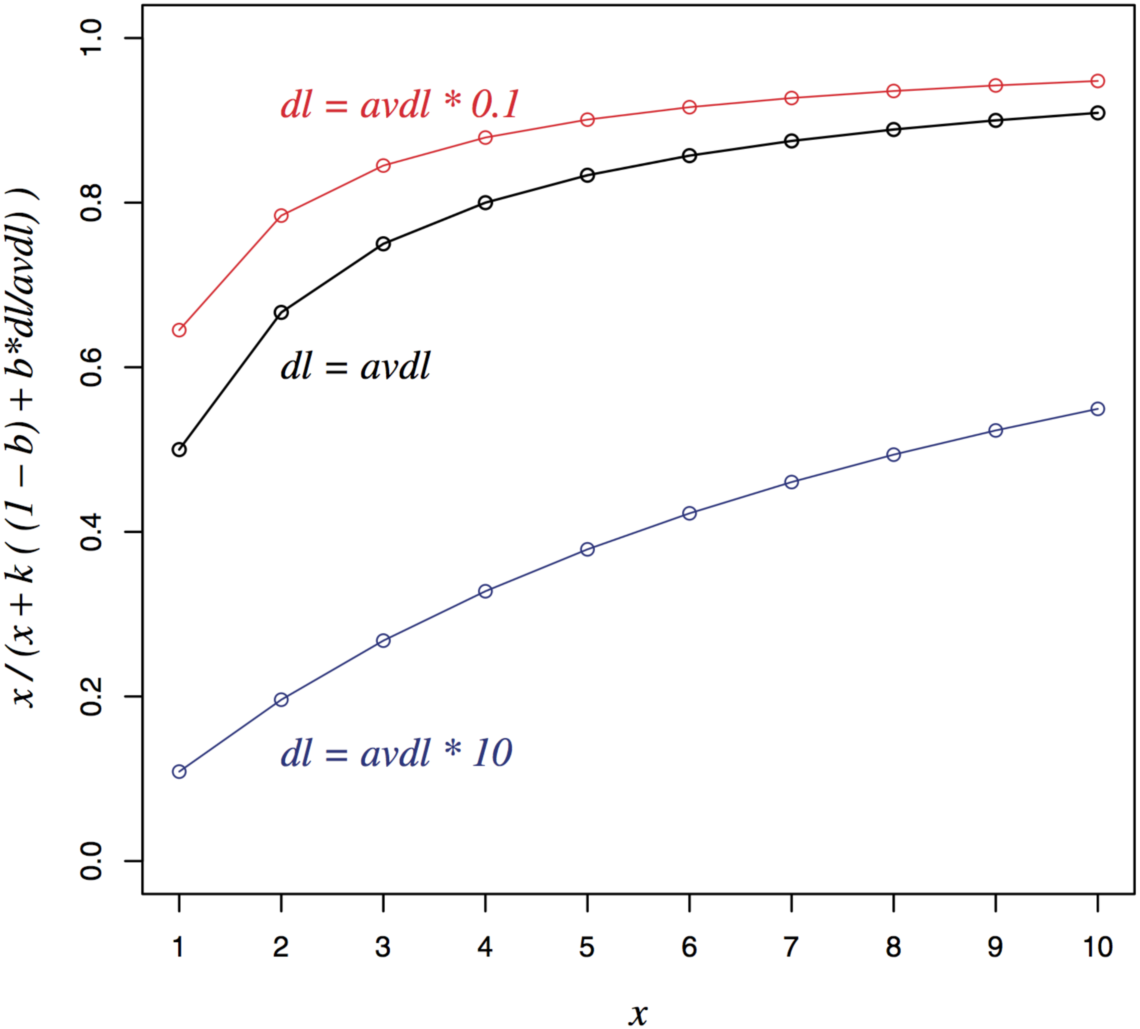
$$tf_i' = \frac{tf_i}{B}$$

$$c_i^{BM25}(tf_i) = \log \frac{N}{df_i} \times \frac{(k_1+1)tf_i'}{k_1 + tf_i'}$$
$$= \log \frac{N}{df_i} \times \frac{(k_1+1)tf_i}{k_1((1-b)+b\frac{dl}{avdl})+tf_i}$$

- BM25 ranking function

$$RSV^{BM25} = \sum_{i \in q} c_i^{BM25}(tf_i);$$

Document length normalization



Okapi BM25

$$RSV^{BM25} = \sum_{i \in q} \log \frac{N}{df_i} \cdot \frac{(k_1 + 1) tf_i}{k_1((1-b) + b\frac{dl}{avdl}) + tf_i}$$

- k_1 controls term frequency scaling
  - $k_1 = 0$ is binary model; k_1 large is raw term frequency
- b controls document length normalization
  - $b = 0$ is no length normalization; $b = 1$ is relative frequency (fully scale by document length)
- Typically, k_1 is set around 1.2–2 and b around 0.75
- *IIR* sec. 11.4.3 discusses incorporating query term weighting and (pseudo) relevance feedback

The BM25 formula

TF-IDF component for document TF component for query

$$rel(q,D)=\sum_{i=1}^{n}\boxed{IDF(q_i)\frac{tf_i(k_1+1)}{tf_i+k_1(1-b+b\frac{|D|}{avg|D|})}}\boxed{\frac{qtf_i(k_2+1)}{k_2+qtf_i}}$$

- b is usually set to [0.75]
- k_1 is usually set to [1.2, 2.0]
- k_2 is usually set to (0, 1000]

Vector space model with TF-IDF schema!

Why is BM25 better than VSM tf-idf?

- Suppose your query is [machine learning]
- Suppose you have 2 documents with term counts:
  - doc1: learning 1024; machine 1
  - doc2: learning 16; machine 8
- tf-idf: $(1+\log_2 \text{tf}) * \log_2 (N/df)$
  - doc1: 11 * 7 + 1 * 10 = **87**
  - doc2: 5 * 7 + 4 * 10 = **75**
- BM25: $k_1 = 2$, $(k_1+1)*\text{tf} / (k_1 + \text{tf}) * \log_2 (N/df)$
  - doc1: 7 * 3 + 10 * 1 = **31**
  - doc2: 7 * 2.67 + 10 * 2.4 = **42.7**

2. Ranking with features

- Textual features
  - Zones: Title, author, abstract, body, anchors, …
  - Proximity
  - …
- Non-textual features
  - File type
  - File age
  - Page rank
  - …

Ranking with zones

- Straightforward idea:
  - Apply your favorite ranking function (BM25) to each zone separately
  - Combine zone scores using a weighted linear combination
- But that seems to imply that the eliteness properties of different zones are different and independent of each other
  - …which seems unreasonable

Ranking with zones

- Alternate idea
  - Assume eliteness is a term/document property shared across zones
  - … but the relationship between eliteness and term frequencies are zone-dependent
    - e.g., denser use of elite topic words in title
- Consequence
  - First combine evidence across zones for each term
  - Then combine evidence across terms

BM25F with zones

- Calculate a weighted variant of total term frequency
- … and a weighted variant of document length

$$\tilde{tf}_i = \sum_{z=1}^{Z} v_z tf_{zi} \qquad \tilde{dl} = \sum_{z=1}^{Z} v_z len_z \qquad \tilde{avdl} =$$ Average $\tilde{dl}$ across all documents

where

v_z is zone weight

tf_{zi} is term frequency in zone z

len_z is length of zone z

Z is the number of zones

Simple BM25F with zones

$$RSV^{SimpleBM25F} = \sum_{i \in q} \log \frac{N}{df_i} \cdot \frac{(k_1 + 1)\tilde{tf}_i}{k_1((1-b) + b\frac{\tilde{dl}}{avd\tilde{l}}) + \tilde{tf}_i}$$

- Simple interpretation: zone z is "replicated" v_z times
- But we may want zone-specific parameters (b)

BM25F

- Empirically, zone-specific length normalization (i.e., zone-specific b) has been found to be useful

$$\tilde{tf}_i = \sum_{z=1}^{Z} v_z \frac{tf_{zi}}{B_z}$$

$$B_z = \left((1 - b_z) + b_z \frac{len_z}{avlen_z} \right), \qquad 0 \le b_z \le 1$$

$$RSV^{BM25F} = \sum_{i \in q} \log \frac{N}{df_i} \cdot \frac{(k_1 + 1)\tilde{tf}_i}{k_1 + \tilde{tf}_i}$$

See Robertson and Zaragoza (2009: 364)

Ranking with non-textual features

- Assumptions
  - Usual independence assumption
    - Independent of each other and of the textual features
  - Relevance information is ***query independent***
    - Usually true for features like page rank, age, type, …

Ranking with non-textual features

$$RSV = \sum_{i \in q} c_i(tf_i) + \sum_{j=1}^{F} \lambda_j V_j(f_j)$$

and λ_j is an artificially added free parameter to account for rescalings in the approximations

- Care must be taken in selecting V_j depending on *features*. E.g.

$$\log(\lambda'_j + f_j) \qquad \frac{f_j}{\lambda'_j + f_j} \qquad \frac{1}{\lambda'_j + \exp(-f_j \lambda''_j)}$$

- Explains why $RSV^{BM25} + \log(pagerank)$ works well

Resources

- S. E. Robertson and H. Zaragoza. 2009. The Probabilistic Relevance Framework: BM25 and Beyond. *Foundations and Trends in Information Retrieval* 3(4): 333-389.
- K. Spärck Jones, S. Walker, and S. E. Robertson. 2000. A probabilistic model of information retrieval: Development and comparative experiments. Part 1. *Information Processing and Management* 779–808.
- T. Joachims. Optimizing Search Engines using Clickthrough Data. 2002. *SIGKDD*.
- E. Agichtein, E. Brill, S. Dumais. 2006. Improving Web Search Ranking By Incorporating User Behavior Information. 2006. *SIGIR*.