

1. see above
 2. application of smoothing
 - a. results:
 - a 0.048
 - the 0.2453333333333335
 - from 0.03466666666666665
 - retrieval 0.005333333333333333
 - sun 0.08
 - rises 0.0773333333333332
 - in 0.17600000000000002
 - BM25 0.002666666666666666
 - east 0.07200000000000001
 - sets 0.0773333333333332
 - west 0.07200000000000001
 - and 0.1093333333333334
 - b. $u = .01$
 - a 0.00016348773841961853
 - the 0.27263396911898274
 - from 0.00011807447774750229
 - retrieval 1.8165304268846504e-05
 - sun 0.09087193460490463
 - rises 0.0908628519527702
 - in 0.1817983651226158
 - BM25 9.082652134423252e-06
 - east 0.09084468664850136
 - sets 0.0908628519527702
 - west 0.09084468664850136
 - and 0.0909718437783833
- $u = 100$
- a 0.16216216216216217
 - the 0.18018018018018017
 - from 0.11711711711711711
 - retrieval 0.018018018018018018
 - sun 0.05405405405405406
 - rises 0.04504504504504504
 - in 0.16216216216216217
 - BM25 0.009009009009009009
 - east 0.02702702702702703
 - sets 0.04504504504504504

west 0.02702702702702703
and 0.15315315315315314

As u increases weight increases. This makes sense because looking at the formula for Dirichlet prior smoothing u is multiplied by $p(w|C)$, however it is not multiplied by anything in the denominator. Thus no matter what u is, as it increases the numerator will increase at a faster rate than the denominator, and thus we would expect $p(w|d)$ to increase.

c. $\lambda = .1$
a 0.0018
the 0.27169999999999994
from 0.0013000000000000002
retrieval 0.0002
sun 0.0905
rises 0.0904
in 0.18159999999999998
BM25 0.0001
east 0.0902
sets 0.0904
west 0.0902
and 0.0916
 $\lambda = .5$
a 0.09
the 0.22136363636363637
from 0.065
retrieval 0.01
sun 0.07045454545454546
rises 0.06545454545454546
in 0.1709090909090909
BM25 0.005
east 0.05545454545454546
sets 0.06545454545454546
west 0.05545454545454546
and 0.12545454545454546

 $\lambda = .9$
a 0.162
the 0.18027272727272728
from 0.117
retrieval 0.018000000000000002
sun 0.05409090909090909

rises 0.04509090909090909
in 0.1621818181818182
BM25 0.009000000000000001
east 0.02709090909090909
sets 0.04509090909090909
west 0.02709090909090909
and 0.1530909090909091

The Dirichlet prior has less smoothing than the Jelinek mercer, which makes sense because for Dirichlet prior the amount of smoothing is weighted by document length, and in this case the length of our document is quite short.

$$19, \quad p(w|d) = \frac{c(w,d) + N \cdot p(w|c)}{|d| + N}$$

$$= \frac{|d|}{|d| + N} \frac{c(w,d)}{|d|} + \frac{N}{|d| + N} \cdot p(w|c)$$

$$= \lim_{d \rightarrow \infty} \frac{c(w,d)}{|d| + N} + \frac{N}{|d| + N} \cdot p(w|c)$$

$$= \lim_{d \rightarrow \infty} \frac{c(w,d)}{|d|} + 0$$

$$\approx \frac{c(w,d)}{|d|}$$

$$\lim_{N \rightarrow \infty} \frac{|d|}{|d| + N} \frac{c(w,d)}{|d|} + \frac{N}{|d| + N} \cdot p(w|c)$$

$$= 0 + \lim_{N \rightarrow \infty} \frac{N}{N + |d|} \cdot p(w|c)$$

$$= p(w|c)$$

□

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$$= \lim_{d \rightarrow \infty} \frac{c(w,d)}{|d| + N} + 0$$

$$\approx \frac{c(w,d)}{|d|}$$

$$\lim_{N \rightarrow \infty} \frac{|d|}{|d| + N} \frac{c(w,d)}{|d|} + \frac{N}{|d| + N} \cdot p(w|c)$$

$$= 0 + \lim_{N \rightarrow \infty} \frac{N}{N + |d|} \cdot p(w|c)$$

$$= p(w|c)$$

□

3 q.

$$O(R=1 | Q, D) = \frac{p(R=1 | Q, D)}{p(R=0 | Q, D)} = \frac{p(Q, D | R=1) p(R=1)}{p(Q, D | R=0) p(R=0)}$$

↑
Constant

$$\propto \frac{p(Q, D | R=1)}{p(Q, D | R=0)}$$

$$p(Q, D | R) = p(D | Q, R) p(Q | R)$$

$$\propto \frac{p(D | Q, R=1) p(Q | R=1)}{p(D | Q, R=0) p(Q | R=0)}$$

↑
Constant

Let $D = d_1, \dots, d_k$ be 0 or 1 for their presence and absence in the document.

$$\prod_{i=1, d=1}^k \frac{p(A_i=1 | Q, R=1)}{p(A_i=1 | Q, R=0)} \prod_{i=1, d=0}^k \frac{p(A_i=0 | Q, R=1)}{p(A_i=0 | Q, R=0)}$$

↑
abs of k does not depend on relevance

$$\prod_{i=1, d_i=1}^K \frac{p(A_i=1|Q, R=1)}{p(A_i=1|Q, R=0)}$$

$$\text{Score}(Q, D) = \prod_{j=1, d_j=1}^{|V|} \left(\frac{p(w_j|Q, R=1)}{p(w_j|Q, R=0)} \right)^{c(w_j, D)}$$

$$\text{Score}(Q, D) = \sum_{j=1, d_j=1}^{|V|} c(w_j, D) \log \left(\frac{p(w_j|Q, R=1)}{p(w_j|Q, R=0)} \right)$$

~~the~~ we will need to estimate probability of relevance and non relevance

$$3b. \quad p(w|Q, R=0) = \frac{\sum_{i=1}^N c(w, d_i)}{\sum_{i=1}^N |D_i|}$$

$$3c. \quad \frac{c(w, Q)}{|Q|}$$

3d.

$$p(w | q, R=1) = \frac{(1-\lambda) \frac{c(w|q)}{|q|} + \lambda p(w|c)}{1}$$

3E.

$$\sum_{w \in V} \left(\log \left[\frac{(1-\lambda) \frac{c(w|q)}{|q|} + \lambda p(w|c)}{\sum_{d \in D} \frac{c(w, d_i)}{|D|}} \right] \right)$$

Yes it captures TF, IDF and document length normalization. IDF is in the denominator, as well as document length normalization.