Information Retrieval: Assignment 2 - Retrieval System

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1 Retrieval System

In this project, we have build a system which retrieves a ranked list of documents relevant to a query. We have used the provided collection of documents and we have evaluated the system performance on 40 queries and relevant statements.

The system retrieves the ranked document lists for multiple queries simultaneously. The process flow consists of several steps:

1. extract queries and relevance judgements from the files provided.
2. scan the collection of documents in a streaming manner, using *TipsterCorpusIterator* and build up maps with term and collection frequencies for the query words, inverse document frequencies and document lengths. This will be used by the different models to evaluate the relevance of a document.
3. for every query, calculate the score of every document in the collection and keep the top 100 documents in a map. The score is calculated either using the term-based model or the language model depending on the value of the boolean parameter "languageModel".
4. print the resulting ranking to a text file
5. evaluate the system's performance in terms of P, R, F_1 and MAP for the training set.

Both the queries and the documents are tokenized by splitting on various standard characters, stop words are removed and then each word is stemmed using the *PorterStemmer*. In the case of query words which contain hyphens, we have decided to keep both the hyphenated word and the individual terms to increase the chance of finding the term in the collection as queries are usually very short.

2 Models

We have experimented with various models and here we describe the best performing ones with the optimal parameters based on the test queries.

2.1 Term-based model

Initially we implemented the standard TF-IDF model as described in the lecture slides. As the performance was not satisfactory, we experimented with *augmented TF-IDF* and the *OKAPI BM25*[1] model. Both of those improved the performance over the standard function, with the **OKAPI BM25** ranking function 1 performing best. This was used in our system.

$$score(Q, D) = \sum_{q \in Q} IDF(q) * \frac{tf(q, D) * (k + 1)}{k(1 - b + b\frac{|D|}{avgDL}) + tf(q, D)}, \quad (1)$$

where k and b are parameters of the model controlling the scaling of the term frequencies and the normalization of the term frequencies by the document length.

The inverse documented frequency is defined as:

$$IDF(q) = \log \frac{N - df(q) + 0.5}{df(q) + 0.5}, \quad (2)$$

N - documents in collection, $df(q)$ - #docs in which q occurs

The IDF has the property that if a word occurs in more than half of the documents, the log term becomes negative, thus a document is penalized for containing the query word. This should not happen as we have removed stop words from the documents and queries, but just in case we limit the IDF to 0 from the bottom but capping the document frequency to half of the number of documents. This method has been used in other similar projects.

We experimented with different values for the model parameters and found the optimal values to be 0.35 and 1 for b and k respectively.

2.2 Language model

For the language model, we used the standard probabilistic scheme, where $P(q|d)$ is the probability of the query q given the document d and documents are ranked by their probability to generate q according to the maximum likelihood principle. Independence of query terms is assumed given the relevant document, so that the likelihood of the query is the product of the likelihoods of the individual query words 3.

$$P(q|d) = \prod_{w_i \in q} P(w_i|d) \quad (3)$$

We used the observed term frequencies in the collection to estimate the posterior probabilities of the query words given a document - $\hat{P}(w_i|d)$. However, as not all query words occur in all documents, for the likelihood $P(w_i|d)$ we experimented with different types of collection smoothing - Jelinek-Mercer, Dirichlet and two-stage smoothing which combines both [2]. We ended up using the two-stage smoothing as defined in equation 4 because it proved to be the most effective on the training data.

$$logP(w_i|d) = log\Big[(1 - \lambda)\frac{\hat{P}(w_i|d) + \mu * P(w_i)}{|d| + \mu} + \lambda P(w_i)\Big], \quad (4)$$

[1] S. Robertson, S. Walker, M. M. Beaulieu, M. Gatford, and A. Payne. Okapi at TREC-4. In NIST Special Publication 500-236: The Fourth Text REtrieval Conference (TREC-4), pages 73 96, Gaithersburg, MD, 1995.

[2] Zhai, Chengxiang, and John Lafferty. "A study of smoothing methods for language models applied to information retrieval." ACM Transactions on Information Systems (TOIS) 22.2 (2004): 179-214.

The prior $P(w_i) = \frac{cf(w_i)}{|C|}$ is the collection frequency of the word normalized by the size of the collection (in terms of words) and λ and μ are model parameters.

In terms of interpretation, λ roughly controls the noise in the query, thus the bigger it is, the less weight is given to the query terms. On the other hand, μ is the standard Dirichlet prior smoothing parameter and controls the collection smoothing to account for words not present in the document.

The optimal values were determined to be 0.1 for λ, which is expected given the short queries, and 1000 for μ.

3 Evaluation on training data

To evaluate our model, we have used the provided *qrels* statements. Any document not explicitly stated as relevant in the relevance judgements is assumed to be irrelevant, thus the scores represent worst-case behaviour in terms of accuracy. For each query we report the precision (P), recall (R), the harmonic mean F_1 and the AP, as well as the MAP for the whole system. All reported values are at rank 100 and the total number of relevant documents is assumed to be $min(TP + FN, 100)$ for the average precision calculations.

3.1 Performance values of OKAPI BM25 Model

Query: 51 Precision: 0.8 - Recall: 0.5797101449275363 - F1: 0.6722689075630253 - AP: 0.7146126238923501

Query: 52 Precision: 0.52 - Recall: 0.09719626168224299 - F1: 0.1637795275590551 - AP: 0.29455456562708354

Query: 53 Precision: 0.58 - Recall: 0.10157618213660245 - F1: 0.17287630402384502 - AP: 0.31497881614972956

Query: 54 Precision: 0.4 - Recall: 0.23391812865497075 - F1: 0.2952029520295203 - AP: 0.22937511090976187

Query: 55 Precision: 0.67 - Recall: 0.08271604938271605 - F1: 0.14725274725274726 - AP: 0.47059454279770024

Query: 56 Precision: 0.79 - Recall: 0.08997722095671981 - F1: 0.16155419222903886 - AP: 0.6394523522327801

Query: 57 Precision: 0.59 - Recall: 0.1279826464208243 - F1: 0.2103386809269162 - AP: 0.399094266998191

Query: 58 Precision: 0.67 - Recall: 0.42138364779874216 - F1: 0.5173745173745173 - AP: 0.47781502216670146

Query: 59 Precision: 0.25 - Recall: 0.04317789291882556 - F1: 0.07363770250368189 - AP: 0.09644209311471354

Query: 60 Precision: 0.05 - Recall: 0.08333333333333333 - F1: 0.0625 - AP: 0.030939639469882544

Query: 61 Precision: 0.56 - Recall: 0.27184466019417475 - F1: 0.36601307189542487 - AP: 0.45844065409895424

Query: 62 Precision: 0.34 - Recall: 0.11447811447811448 - F1: 0.17128463476070532 - AP: 0.16825827286767056

Query: 63 Precision: 0.22 - Recall: 0.10576923076923077 - F1: 0.14285714285714285 - AP: 0.07732793596436555

Query: 64 Precision: 0.12 - Recall: 0.032 - F1: 0.05052631578947369 - AP: 0.016788141481460586

Query: 65 Precision: 0.35 - Recall: 0.09067357512953368 - F1: 0.1440329218106996 - AP: 0.15436576238256985

Query: 66 Precision: 0.33 - Recall: 0.16751269035532995 - F1: 0.22222222222222224 - AP: 0.17906936753946223

Query: 67 Precision: 0.0 - Recall: 0.0 - F1: 0.0 - AP: 0.0

Query: 68 Precision: 0.1 - Recall: 0.05128205128205128 - F1: 0.06779661016949151 - AP: 0.027580874494638006

Query: 69 Precision: 0.23 - Recall: 0.4423076923076923 - F1: 0.3026315789473685 - AP: 0.19004873322895843

Query: 70 Precision: 0.26 - Recall: 0.4727272727272727 - F1: 0.33548387096774196 - AP: 0.1954595650918126

Query: 71 Precision: 0.72 - Recall: 0.18947368421052632 - F1: 0.3 - AP: 0.6203094200090942

Query: 72 Precision: 0.04 - Recall: 0.03361344537815126 - F1: 0.0365296803652968 - AP: 0.002711484943627801

Query: 73 Precision: 0.01 - Recall: 0.00546448087431694 - F1: 0.007067137809187279 - AP: 2.2222222222222223E-4

Query: 74 Precision: 0.05 - Recall: 0.01002004008016032 - F1: 0.01669449081803005 - AP: 0.0036018937409717

Query: 75 Precision: 0.16 - Recall: 0.043835616438356165 - F1: 0.06881720430107527 - AP: 0.02938972199378294

Query: 76 Precision: 0.04 - Recall: 0.013605442176870748 - F1: 0.02030456852791878 - AP: 0.012077691811734364

Query: 77 Precision: 0.37 - Recall: 0.26811594202898553 - F1: 0.3109243697478992 - AP: 0.1668433646727741

Query: 78 Precision: 0.6 - Recall: 0.37037037037037035 - F1: 0.4580152671755725 - AP: 0.3853030453188929

Query: 79 Precision: 0.02 - Recall: 0.008620689655172414 - F1: 0.012048192771084338 - AP: 0.0013

Query: 80 Precision: 0.19 - Recall: 0.05080213903743316 - F1: 0.08016877637130802 - AP: 0.04914780607961647

Query: 81 Precision: 0.19 - Recall: 0.3064516129032258 - F1: 0.23456790123456792 - AP: 0.13217721698168614

Query: 82 Precision: 0.88 - Recall: 0.14691151919866444 - F1: 0.25178826895565093 - AP: 0.7961039218085947

Query: 83 Precision: 0.15 - Recall: 0.023734177215189875 - F1: 0.04098360655737705 - AP: 0.03422501795708256

Query: 84 Precision: 0.12 - Recall: 0.030379746835443037 - F1: 0.048484848484848485 - AP: 0.015873622515920078

Query: 85 Precision: 0.74 - Recall: 0.08277404921700224 - F1: 0.1488933601609658 - AP: 0.6072964264442896

Query: 86 Precision: 0.21 - Recall: 0.09859154929577464 - F1: 0.134185303514377 - AP: 0.05768460362419949

Query: 87 Precision: 0.07 - Recall: 0.03723404255319149 - F1: 0.04861111111111111 - AP: 0.0072548615883809

Query: 88 Precision: 0.03 - Recall: 0.01818181818181818 - F1: 0.022641509433962263 - AP: 0.0014748316199929103

Query: 89 Precision: 0.11 - Recall: 0.06321839080459771 - F1: 0.08029197080291971 - AP: 0.08076415302963291

Query: 90 Precision: 0.5 - Recall: 0.18796992481203006 - F1: 0.27322404371584696 - AP: 0.2970042420617517

TOTAL VALUES

Precision: 0.32575 - **Recall:** 0.098704643587607 **F1:** 0.17184688781854043 -**Mean Average Precision:** 0.21089909722332584

3.2 Performance values of MLE Model with 2-stage smoothing

Query: 51 Precision: 0.85 - Recall: 0.6159420289855072 - F1: 0.7142857142857143 - AP: 0.7650476610626161

Query: 52 Precision: 0.58 - Recall: 0.10841121495327102 - F1: 0.1826771653543307 - AP: 0.3505273486955493

Query: 53 Precision: 0.59 - Recall: 0.10332749562171628 - F1: 0.1758569299552906 - AP: 0.3350223140384919

Query: 54 Precision: 0.42 - Recall: 0.24561403508771928 - F1: 0.3099630996309963 - AP: 0.22520739250822275

Query: 55 Precision: 0.69 - Recall: 0.08518518518518518 - F1: 0.15164835164835164 - AP: 0.5032396152090693

Query: 56 Precision: 0.83 - Recall: 0.09453302961275627 - F1: 0.16973415132924338 - AP: 0.7129519416902302

Query: 57 Precision: 0.57 - Recall: 0.12364425162689804 - F1: 0.20320855614973263 - AP: 0.3932100386158303

Query: 58 Precision: 0.64 - Recall: 0.4025157232704403 - F1: 0.4942084942084943 - AP: 0.44929373382548216

Query: 59 Precision: 0.35 - Recall: 0.06044905008635579 - F1: 0.10309278350515463 - AP: 0.1403662581510984

Query: 60 Precision: 0.08 - Recall: 0.13333333333333333 - F1: 0.1 - AP: 0.0444802285528092

Query: 61 Precision: 0.66 - Recall: 0.32038834951456313 - F1: 0.4313725490196079 - AP: 0.5640599907956146

Query: 62 Precision: 0.33 - Recall: 0.1111111111111111 - F1: 0.16624685138539042 - AP: 0.1746772441689847

Query: 63 Precision: 0.2 - Recall: 0.09615384615384616 - F1: 0.12987012987012989 - AP: 0.05329207475308931

Query: 64 Precision: 0.15 - Recall: 0.04 - F1: 0.06315789473684211 - AP: 0.03790941527086509

Query: 65 Precision: 0.18 - Recall: 0.046632124352331605 - F1: 0.07407407407407407 - AP: 0.027215455622701494

Query: 66 Precision: 0.28 - Recall: 0.14213197969543148 - F1: 0.18855218855218858 - AP: 0.15655983867610979

Query: 67 Precision: 0.01 - Recall: 0.0018726591760299626 - F1: 0.003154574132492114 - AP: 2.2727272727272727E-4

Query: 68 Precision: 0.11 - Recall: 0.05641025641025641 - F1: 0.07457627118644067 - AP: 0.02951663365031152

Query: 69 Precision: 0.18 - Recall: 0.34615384615384615 - F1: 0.23684210526315788 - AP: 0.13217016245583968

Query: 70 Precision: 0.16 - Recall: 0.2909090909090909 - F1: 0.20645161290322578 - AP: 0.13183331755580166

Query: 71 Precision: 0.76 - Recall: 0.2 - F1: 0.3166666666666667 - AP: 0.6578158023517631

Query: 72 Precision: 0.06 - Recall: 0.05042016806722689 - F1: 0.0547945205479452 - AP: 0.006385709827697658

Query: 73 Precision: 0.01 - Recall: 0.00546448087431694 - F1: 0.007067137809187279 - AP: 1.4705882352941175E-4

Query: 74 Precision: 0.03 - Recall: 0.006012024048096192 - F1: 0.01001669449081803 - AP: 0.0045

Query: 75 Precision: 0.14 - Recall: 0.038356164383561646 - F1: 0.06021505376344086 - AP: 0.0313141288849357

Query: 76 Precision: 0.17 - Recall: 0.05782312925170068 - F1: 0.08629441624365482 - AP: 0.08884608118040757

Query: 77 Precision: 0.38 - Recall: 0.2753623188405797 - F1: 0.319327731092437 - AP: 0.16588301012262985

Query: 78 Precision: 0.58 - Recall: 0.35802469135802467 - F1: 0.44274809160305345 - AP: 0.36677670503501986

Query: 79 Precision: 0.01 - Recall: 0.004310344827586207 - F1: 0.006024096385542169 - AP: 0.0011111111111111111

Query: 80 Precision: 0.19 - Recall: 0.05080213903743316 - F1: 0.08016877637130802 - AP: 0.05901166249784437

Query: 81 Precision: 0.17 - Recall: 0.27419354838709675 - F1: 0.20987654320987656 - AP: 0.0928925025237254

Query: 82 Precision: 0.87 - Recall: 0.14524207011686144 - F1: 0.24892703862660948 - AP: 0.7892735081352352

Query: 83 Precision: 0.18 - Recall: 0.028481012658227847 - F1: 0.049180327868852465 - AP: 0.05305551216404572

Query: 84 Precision: 0.07 - Recall: 0.017721518987341773 - F1: 0.028282828282828285 - AP: 0.007212480805854301

Query: 85 Precision: 0.66 - Recall: 0.0738255033557047 - F1: 0.13279678068410464 - AP: 0.5390522394589317

Query: 86 Precision: 0.2 - Recall: 0.09389671361502347 - F1: 0.12779552715654954 - AP: 0.05044473362638858

Query: 87 Precision: 0.08 - Recall: 0.0425531914893617 - F1: 0.05555555555555556 - AP: 0.006845435434577033

Query: 88 Precision: 0.07 - Recall: 0.04242424242424243 - F1: 0.05283018867924529 - AP: 0.00547052288191528

Query: 89 Precision: 0.11 - Recall: 0.06321839080459771 - F1: 0.08029197080291971 - AP: 0.07895958860083621

Query: 90 Precision: 0.52 - Recall: 0.19548872180451127 - F1: 0.28415300546448086 - AP: 0.31189912467965397

TOTAL VALUES

Precision: 0.328 - **Recall:** 0.09938641012044543 **F1:** 0.17079966121239837 - **Mean Average Precision:** 0.2135926214043023

4 The project

4.1 Run the code

The project consists of a main class, *Retrieval.scala*, that contains the main method, and of the *tinyir* library sources. We have added them to the project because we have modified some classes, which are therefore different from the original ones. The program can be launched with the command

```
scala Retrieval zippath
```

where *zippath* is the only command parameter and contains the path of the folder where the collection zips are located.

4.2 languageModel and trainingSet variables

The *Retrieval* object has 2 member variables that must be set to false or true in order to decide which model to use for the score of the queries and whether the queries that have to be processed are part of a training or of a test set. The explanation of the values to use is included in the code.

4.3 Log and result

During the execution the program prints to the console one line every 1000 processed documents. We introduced this counter to have a perception of the speed of the process and we found useful to leave it in the code. When the program finishes, in case of an execution on a training set, the performance values are displayed in the console. In both cases (training or test set), the rank of the first 100 documents for each query is saved in the file *result.txt*, created in the execution folder.