NIR Project

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1 Dateset and Indexing

Dataset

We obtained the following statistics

Statistic	Documents	Queries
Total	3,213,835	367,013
Min	0	1
Max	2,064,096	38
Median	3,577	6
Average	6,996.61	5.95

Table 1: Document and Query Statistics

The statistics provided shed illuminating light on the key characteristics of the MS MARCO dataset, which is composed of over 3.2 million documents and 367,013 queries. This large-scale dataset offers a substantial and diverse corpus for developing and testing information retrieval systems. However, certain aspects of the data distribution warrant further scrutiny and careful consideration during the modeling process.

Regarding the document corpus, we observe that the document length varies dramatically, ranging from 0 to over 2 million words. The presence of documents with a length of zero is particularly intriguing, possibly indicating the existence of empty or corrupted entries within the dataset. Such instances could inadvertently impact the performance and interpretability of the models and, as such, it is advisable to inspect these documents further and decide on a suitable strategy for their inclusion or removal.

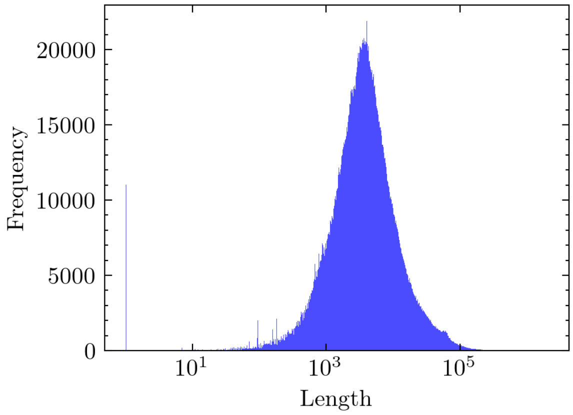
Moreover, the upper end of the document length distribution also reveals outliers, with the maximum length exceeding 2 million words. Documents of such extraordinary length may not represent typical instances and could potentially skew model performance or learning. Therefore, it would be prudent to investigate the nature of these long documents to ensure they don't contain repetitive or irrelevant information, and to assess their impact on the modeling process.

The median and average document lengths, at approximately 3577 and 7000 words respectively, suggest a diverse document length distribution. This variation is likely to expose models to a wide range of document structures and contents, thereby contributing to their robustness.

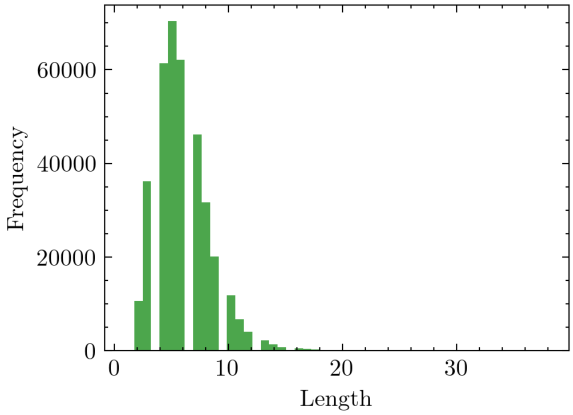
Turning our attention to the queries, the dataset presents a broad spectrum of search intents as reflected by the query lengths ranging from 1 to 38 words. The brevity of the shortest queries underscores the inherent challenge in information retrieval: discerning user intent from minimal input. On the other hand, the longest queries are surprisingly detailed, indicating more complex or specific user information needs.

The average and median lengths of queries hover around 6 words, aligning with expectations for search query distributions and underscoring the need for models capable of understanding and retrieving relevant information for a wide range of query complexities.

In conclusion, the MS MARCO dataset presents a rich and varied resource for developing and refining information retrieval systems. However, certain peculiarities in the data distribution, such as potentially empty documents and extremely long documents, necessitate careful preprocessing and scrutiny. Similarly, the diversity in query length calls for models that can adeptly handle a broad spectrum of user intents. With meticulous data handling and appropriate modeling strategies, this dataset offers fertile ground for advancements in the field of information retrieval.



(a) Histogram of document lengths (log x-axis)



(b) Histogram of query lengths

Figure 1: Histograms of document and query lengths

1.1 Indexing

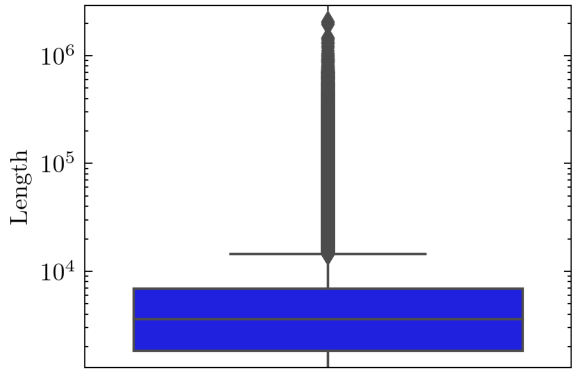
When discussing the results of our indexing strategies for the MSMARCO dataset, several points come to light. Four different types of indexes were created: a full index, one with stopwords removed, one employing stemming, and a combination of stopwords removed and stemming.

Table 2: Document and Query Statistics

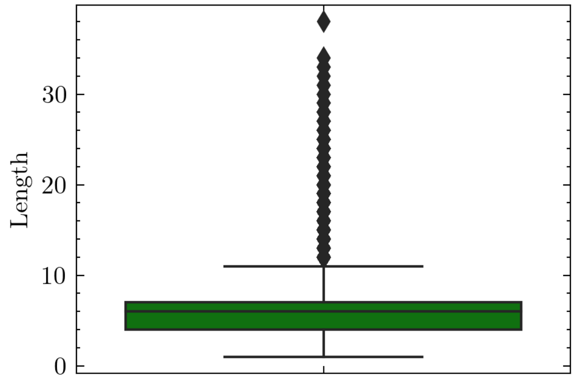
Statistic	Documents	Queries
Total	3,213,835	367,013
Min	0	1
Max	2,064,096	38
Median	3,577	6
Average	6,996.61	5.95

We obtained the statistics for each index as shown in table **??**.

The time taken to build each index varied. As expected, the full index, which did not undergo any form of preprocessing, was the quickest to construct. This is because both the removal of stopwords and the application of stemming introduce additional computational



(a) Box plot of document lengths (log y-axis)



(b) Box plot of query lengths

Figure 2: Boxplots of document and query lengths

complexity. Nevertheless, the added time taken for these processes can be justified when considering the potential benefits such as reduced index size and potentially improved retrieval performance.

All index variants processed the same number of documents, which was to be expected as the entire corpus was to be processed in each case.

The total number of terms displayed a significant reduction when stopwords were removed. This can be attributed to the omission of frequently occurring words, which generally do not contribute to the semantic relevance of a document. On the other hand, the total number of terms remained constant when only stemming was applied. This demonstrates that stemming does not inherently reduce the number of unique terms in an index, but standardizes them instead.

In terms of index size, the smallest was observed when both stopwords were removed and stemming was applied. This indicates the potential of these techniques to compress the size of an index. A smaller index size can lead to faster query processing times and less memory usage, which can be significant advantages for large-scale information retrieval systems.

However, the average search time was not the smallest for the stopwords removed stemming variant. This suggests that the additional computational costs of processing stemmed terms and handling stopwords during query processing may offset the advantages of a reduced index size in terms of search speed. In fact, the full index variant, despite having the largest index size, returned the fastest average search times.

In conclusion, the choice of an indexing strategy heavily depends on the specific requirements of the information retrieval system. If memory capacity is a concern, then an indexing strategy that employs stopword removal and stemming might be a better choice due to the significant reduction in index size. However, if the speed of search is a primary concern, an indexing strategy without these preprocessing steps might be more beneficial, given the computational overhead these steps introduce during query processing. This analysis does not consider retrieval effectiveness, which is another crucial factor in choosing an indexing strategy. Further research would be needed to explore the impact of these indexing strategies on retrieval effectiveness.

2 Ranking Models and Evaluation

The evaluation and ranking of the four indexing models were carried out using two different ranking models: Okapi BM25 and Language Model (LM). We used Pyserini, a python interface to the Anserini IR toolkit, for creating and evaluating these models. We chose this library for its cutting-edge capabilities in information retrieval tasks and its easy integration with Python.

For model tuning and evaluation, we employed a Group 5-Fold Cross Validation approach. This technique ensures that the same query does not appear in both the training and validation sets in each fold, thereby preventing data leakage between these sets. This method is a variant of the traditional k-fold cross-validation technique and is particularly useful when data includes groups or clusters. In our case, the group was formed by the unique queries.

The Group K-Fold Cross Validation technique partitions the data into 'k' equal-sized groups or 'folds'. We set aside each unique group as a test set while using the remaining groups as a training set. We then trained our model on the training set and evaluated it on the reserved test set. This process was repeated 'k' times so that each group was used as a test set exactly once. We then averaged the results from each of the 'k' experiments to provide a more comprehensive and robust measure of model performance.

The use of Group K-Fold Cross Validation, together with hyperparameter tuning through grid search, allowed us to systematically explore the performance of different model configurations. This approach provided valuable insights into how the choice of parameters and ranking models affects retrieval performance. It not only helped us identify the optimal configuration but also improved our understanding of how these models behave under different settings.

We statistics for each of the four indexing and models can be seen in the table 3.

Using 3,we conducted a comprehensive analysis and concluded that the combination of stemming and the BM25 model is the most effective for our given dataset and task. The Group K-Fold cross-validation technique provided a reliable and robust validation of this finding.

We tuned the parameters for both BM25 and LM using grid search, a hyperparameter tuning technique that methodically builds and evaluates a model for each combination of algorithm parameters specified in a grid. For BM25, the tuned hyperparameters were k1 and b. For LM, the tuned hyperparameter was mu.

We used Normalized Discounted Cumulative Gain (NDCG), Mean Reciprocal Rank (MRR), Precision, and Recall at 5, 10, and 20 cutoffs as evaluation measures. We used NDCG@10 for model tuning. Each of these metrics is widely used in information retrieval and provides a comprehensive analysis of the performance of the ranking models. However, each of these measures has its own limitations. For instance, NDCG and MRR are rank-sensitive measures, unlike Precision and Recall. On the other hand, Precision and Recall do not take into account the rank of the relevant documents. Therefore, the combination of these evaluation metrics gives a more complete understanding of the model's performance.

Upon examining the results, we found that stemming and removing stopwords significantly improve the performance of both ranking models. The BM25 model with stemming shows the best results across all evaluation metrics, closely followed by the LM model with stemming. This suggests that stemming, a process that reduces words to their root form, is an effective technique to improve the performance of the ranking models.

We also evaluated the response times of the ranking models. The BM25 model with stopwords removed shows the shortest mean response time, suggesting that removing stopwords can reduce the complexity of the task and speed up the retrieval process.

In terms of the relative impact of the index versus the ranking model on effectiveness, the results suggest that both play a significant role. However, the choice of the ranking model (BM25 or LM) appears to have less impact on the effectiveness than the type of preprocessing performed on the index (stopwords removal, stemming, or both). This observation is based

Index	Model	Best Config.	NDCG	MRR	P@5	P@10	P@20	Recall@5	Recall@10	Mean Resp. Time
full index	bm25	k1: 0.9, b: 0.6	0.019	0.006	0.004	0.002	0.032	0.043	0.043	0.001
full index	lm	mu: 1000	0.019	0.006	0.004	0.002	0.030	0.041	0.041	0.005
stopwords removed	bm25	k1: 0.9, b: 0.6	0.020	0.006	0.004	0.002	0.032	0.044	0.044	0.000
stopwords removed	lm	mu: 1000	0.020	0.006	0.004	0.002	0.031	0.045	0.045	0.003
stemming	bm25	k1: 0.9, b: 0.6	0.043	0.014	0.009	0.004	0.069	0.088	0.088	0.001
stemming	lm	mu: 1000	0.042	0.013	0.009	0.004	0.067	0.086	0.086	0.005
stopwords removed stemming	bm25	k1: 0.9, b: 0.6	0.037	0.012	0.008	0.004	0.060	0.080	0.080	0.001
stopwords removed stemming	lm	mu: 1000	0.040	0.013	0.008	0.004	0.065	0.085	0.085	0.003

Table 3: Retrieval Model Performance

on the smaller performance differences between the two ranking models compared to the differences observed between the different versions of the index.

In conclusion, this analysis provides a comprehensive evaluation of different retrieval approaches and underscores the importance of preprocessing and parameter tuning in information retrieval tasks. The combination of stemming and BM25 proved to be the most effective in our setting. However, the choice of techniques and models largely depends on the specific characteristics of the data and the task at hand.