Textual Question Answering Systems- Frequently Asked Questions Retrieval

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***Abstract*—The objective of this project is to focus on the FAQ retrieval of the Question Answering System. We want to retrieve FAQ pairs from the database which are relevant to the user query, thus providing answers to the user. We do so by leveraging NLP models like BERT, SBERT and ranking functions like BM25. The best results is obtained when BERT is trained in a triplet fashion (question, paraphrase, non-matching question) and combined with BM25 model which compares query with FAQ question answer concatenation. The FAQIR dataset has been used to train and test the model.**

***Index Terms*—FAQ Retrieval, Question-Answering System, Information Retrieval**

I. Introduction

Building a Question Answering System is an important problem statement in the field of Natural Language Processing. It involves extracting the most relevant information from an abundance of information which may be classified into relevant, useful or irrelevant. Due to the information overload with respect to quantity and categories, searching for the relevant answer to the posed query is of utmost importance.
A question answering system can be built for two domains-

1) **Open Domain** There is no boundary on the category of content that is referred to for extracting the answer. *Example: Google search engine, Yahoo search engine*
2) **Closed Domain** There is a certain boundary on what queries this type of system can answer. This type of system restricts to a particular category of questions and in some cases even answers by referring to a document. *Example: QA services on various business websites, Solution providers for school textbooks*

Speed of deriving the answers to the user query plays a major role in such systems. This demands for a need to find methods that can extract relevant answers to the queries in the fastest manner possible. One method to do this is to look into the database of already asked and answered questions or FAQs and provide the top most relevant answers from that list.

Many questions have usually been answered in the FAQ section of a QA system. But the vast-ness of such a database might make it difficult for a user to search for the particular relevant query. Thus, answers to a user query posed to a closed domain QAS can be derived using the existing FAQ database. By checking if a similar question exists in the database, a faster and more efficient QAS can be built which does not need to access the original database for every query. We want to focus on the highlighted part of Figure 1

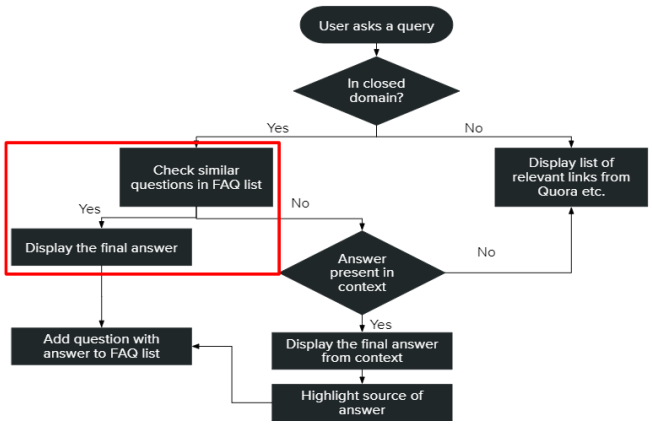

Fig. 1. Flowchart for a Question-Answering system. We are focusing on the red highlighted part.

We want to retrieve FAQ pairs from the database which are relevant to the user query, thus providing answers to the user. Initially, this problem statement was solved only by referring to the similarity between the FAQ question (referred to as Q henceforth) and user query (referred to as q henceforth). But in recent times, researchers are leaning towards a more robust modelling involving FAQ answers (referred to as A henceforth) as well in similarity comparison. This method tends to give better results as lexical gaps in either comparisons (q-Q or q-A) can be compensated by the other.

II. Related Work

A. RNN's

The use of RNNs for QA has been explained based on their commendable performance on the most-basic datasets. They have hidden layers which maintain relationships with the previous values, thus giving them the ability to model long span dependencies. However, more complex datasets require significant feature engineering and hyperparameter tuning to achieve decent results [8].

B. BERT

Bidirectional Encoder Representations from Transformers [1] is one of the recent NLP models which has accomplished

state-of-the-art results in a wide variety of NLP tasks, including Question Answering (SQuAD v1.1), Natural Language Inference (MNLI), and many others. BERT makes use of Transformer, an attention mechanism that learns contextual relations between words (or sub-words) in a text.

C. SBERT

Sentence-BERT [6], is a modification of the pretrained BERT network that uses siamese and triplet network structures to derive semantically meaningful sentence embeddings that can be compared using cosine-similarity. This reduces the effort for finding the most similar pair from 65 hours with BERT / RoBERTa to about 5 seconds with SBERT, while maintaining the accuracy from BERT.

D. DistilBERT

DistilBERT is a fast, cheap and light transformer based model based on the BERT architecture. This model is obtained using knowledge distillation during the pre-training phase to decrease the size of the BERT model by 40%. This model has 40 % less parameters than the original bert model but it preserves over 95 % of BERT's performance as mentioned in the paper [10].

E. XLNET

It depends on a summed up autoregressive pertaining strategy that empowers learning bidirectional settings by maximizing the normal probability over all permutations of the factorization order and consequently beats the restrictions of BERT [5].

F. SGNET

Syntax-Guided Machine Reading Comprehension [13] takes into focus the effective linguistic modeling of lengthy passages to get rid of the noises. The SG-Net model makes use of a context-aggregation mechanism for better representation of the linguistic dependence in the input sequence. This helps in speeding up of the model by significant amounts and creating a focus on the syntactical importance of specific words.

G. TSUBAKI for q-Q similarity and BERT for q-A relevance

[9] proposes a supervised technique for FAQ retrieval. It leverages the TSUBAKI model [11] for retrieving the q-Q similarity score. It is an unsupervised information retrieval system which is based on the OKAPI BM25 model [7]. For obtaining relevant q-A pairs, the BERT model is used. Refer Figure 2.

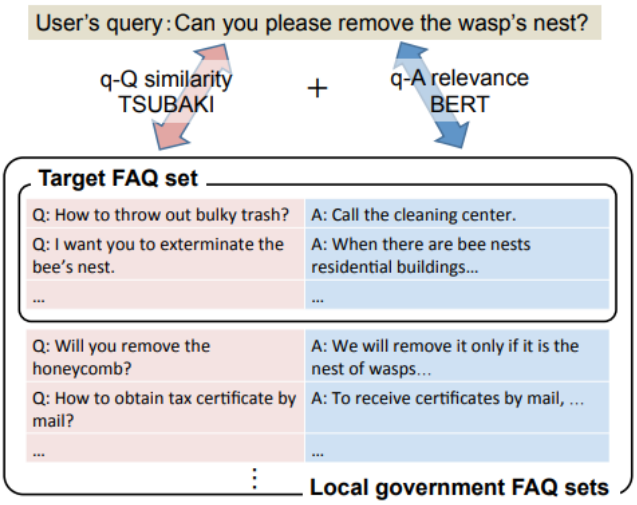

Fig. 2. Unsupervised model for FAQ retrieval using TSUBAKI and BERT [9]

H. BERT model for both q-Q and q-A similarity

This model [4] uses BERT for training q-Q and q-A models. The lack of q-Q training dataset is compensated by a novel technique which generates question paraphrases. For the re-ranking, it uses elastic search, passage re-ranking and finally ranks on the bases of q-A and q-Q similarity.

I. FAQ Retrieval Using Attentive Matching

[2] proposes an attention mechanism model for FAQ Retrieval. It compares various aggregation methods to effectively represent query, question and answer information. It is observed that attention mechanisms are consistently the most effective way to aggregate the inputs for ranking. The use of Attentive matching in FAQ retrieval eliminates the need for this feature engineering and effectively combines both query-question and query-answer representations.

III. Proposed Techniques and Algorithms

A. Preprocessing the data

The pre-processing steps for our models consists of:

1) **Lowercase**: The first step was to make the FAQ pairs and queries into lower case.
2) **Removing punctuations**: All punctuation marks were removed.
3) **Removing stopwords**: All stopwords were removed.
4) **Removing numbers**: All question numbers were also removed.

The SBERT and DistilBERT models used pre-processing steps 1, 2 and 4. The BM25 models used pre-processing steps 1, 2, 3 and 4. The BERT models used pre-processing steps 1 and 2.

*1) **Building the training dataset for q-A model**:* The original dataset consists of pairs of questions and answers from the FAQ database and queries with a list of questions from FAQ database that match the query. The final q-A model should be able to give a similarity score of whether the given answer matches the query or not. To build it we need to fine tune SBERT with a dataset that contains:

- (Q,A) the matching FAQ pair
- (Q,A') an FAQ question with a non-matching answer

This was done by randomly selecting A' for every question. The (Q,A') pairs were labeled as 0 whereas the (Q,A) pairs were labeled as 1 as in Figure 3

FaqQuestion	Answer	Label
how do you seal leaking dorme	fixing a leaky roof especially somethi	1
how do i connect a us water filt	lots of elbow grease wash down the	0
how do i install front door spea	carefully remove all the screws from t	1
how do i change rear brakes or	couldnt find exactly your vehicle but	0
how do i grease my slip yoke g	i own a repair shop and the clunk you	1
how do you replace a 3 way sw	go to your local hardware store hom	1
how do i fix a broiler in my gas	water pumps last less than 100k miles	0
how do you get to the actual sp	check with the owners manual also g	1
how to wire hbl insulgrip twist l	i m not sure what you are trying to wi	1

Fig. 3. A sample of the dataset used for training the q-A model

*2) **Building the training dataset for q-Q model**:* The model built with this dataset should be able to give a similarity score of whether an FAQ question matches the query. The training dataset was derived from the model proposed in [4]. Here is the link to the dataset used. The label 1 was assigned to the corresponding question-paraphrase pairs. The label 0 was assigned to the question pairs that did not match. The second half of the dataset was build by random selection of a question from the FAQ database.

B. Models

*1) **SBERT**:* SBERT for query-answer (qA) comparison was trained in two ways -

i Taking 1:1 ratios in A vs A' ratio for the dataset as described in Section III-A1.

ii Taking 1:5 ratios in A vs A' ratio for the dataset as described in Section III-A1.

Two variants of SBERT for query-question (qQ) comparison have been tried. SBERT encoding was directly used to obtain the similarity score for query and FAQ questions. Fine-tuned SBERT was built by training the SBERT model using the dataset described in Section III-A2.

For the query-answer (qA) comparison model, bert-base-uncased was used to fine tune the SBERT model. Dataset described in Section IV-A was used.

*2) **DistilBERT**:* For query-answer (qA) model, distilbert-base-uncased was used to fine tune the model. For query-question (q-Q) comparison model also, distilbert-bert-uncased was used to fine tune the model and obtain sentence embeddings. The datasets described in Section III-A1 and III-A2 were used for training.

*3) **BM25 qQ**:* The corpus is built using the pre-processing methods as mentioned in Section III-A on the FAQ questions. Then the BM25 model is applied using the rank-bm25 library. The top 100 results are retrieved and the performance metrics are calculated for them.

*4) **BM25 q(Q+A)**:* Each corresponding FAQ Question and Answer is concatenated and is represented as Q+A. The corpus is built using the pre-processing methods as mentioned in Section III-A on the FAQ Q+A. Then the BM25 model is applied using the rank-bm25 library. The top 100 results are retrieved and the performance metrics are calculated for them.

*5) **BM25 q(Q+A) + BERT qA**:* The BERT model is trained on triplets (question, corresponding answer, non-corresponding answer) to understand the intricacies of matching and non-matching answers. The learning rate is 2e-5 and number of epochs is 3.

Example of triplets used in training BERT qA model

Question - How do you change an alternator?
Answer - Depending on what model car you have it will require different steps most libraries have manuals for these operations chilton's is probably the best if you can't find one at the library I'm sure you can buy one for your car online good luck
AnswerDash - You need to flush out the water heater with a garden hose it is probably filled with little rocks the inlet is probably at the bottom of the tank

Top 100 FAQ pairs are picked using BM25 Q+A. The encoding of the answers of these 100 FAQ pairs is found and compared with the query encoding using cosine similarity. The FAQ pairs are re-ranked based on these cosine similarity scores.

The relevance of the retrieved FAQ pairs is cross-checked with the relevance score in the dataset and the performance metrics are calculated accordingly.

*6) **BM25 q(Q+A) + BERT qQ**:* The BERT model is trained on triplets (question, paraphrase, non-matching question) to understand the intricacies of matching and non-matching questions. The learning rate is 2e-5 and number of epochs is 3.

Example of triplets used in training BERT qQ model

Question - How to get rid of garbage disposal odor?
Paraphrase - How do I clean the disposal and how do I get rid of the smell of paraffinic garbage?
QuestionDash - How do you fix a heater for on a van?

Top 100 FAQ pairs are picked using BM25 Q+A. The encoding of the questions of these 100 FAQ pairs is found and compared with the query encoding using cosine similarity. The FAQ pairs are re-ranked based on these cosine similarity scores.

The relevance of the retrieved FAQ pairs is cross-checked

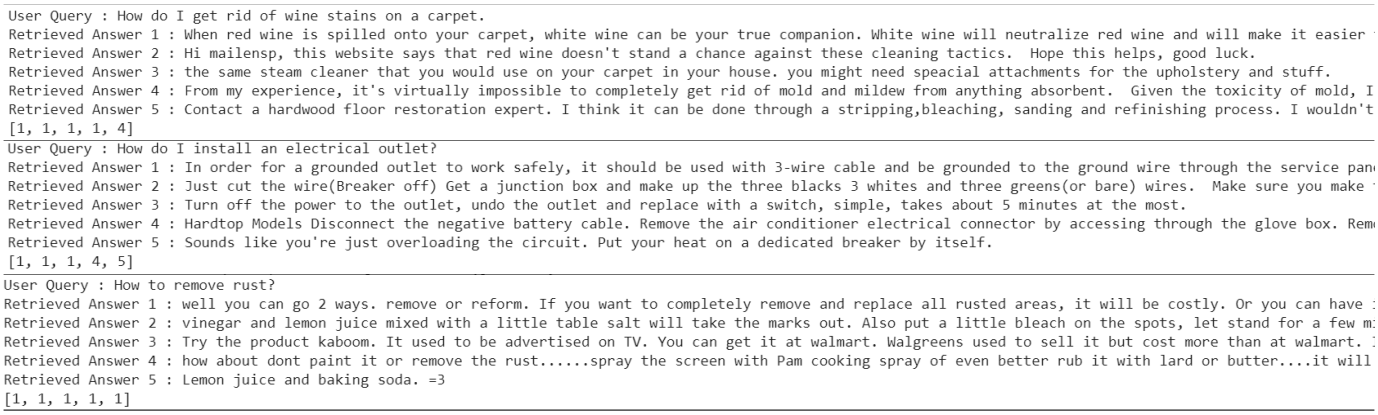

Fig. 4. Top 5 FAQs retrieved for some of the queries using BM25 q(Q+A)

with the relevance score in the dataset and the performance metrics are calculated accordingly.

IV. Datasets Used

A. FAQIR Dataset

We use FAQIR [3] dataset for evaluation.The FAQIR dataset was derived from the "maintenance & repair" domain of the Yahoo! Answers community website. It consists of 4313 FAQ pairs and 1233 queries with corresponding manually annotated relevance judgements. The judgements are described as: 1- relevant, 2- useful, 3- useless and 4- irrelevant. Each query has at least one FAQ-pair annotated as "relevant". However, it is possible for a FAQ-pair to be irrelevant for all queries.

B. Other Datasets

There are other datasets such as StackFAQ and COUGH Dataset [12] which provide FAQ Question and Answers along with the queries. StackFAQ holds some amount of ambiguity with respect to what is to be treated as FAQ pair and what is to be treated as query. If this ambiguity can be solved, this dataset can be utilised. The COUGH dataset is a multilingual dataset and can be explored too.

C. Reason for not using other datasets

There is a variety of other datasets available for the FAQ retrieval such as the Quora Question pairs. The reason for not utilising this dataset is that they don't contain data on the answer aspect of the FAQ; they only contain question pairs. The aim of the project is to also utilise the answers to retrieve relevant documents. Other datasets like SQuAD don't have descriptive answers which are necessary for qA model training.

V. Results

Various models and ranking techniques were explored. The following performance metrics have been used for the retrieval:

1) **Mean Precision at 5 (P@5)** is the measure of number of relevant documents in the top 5 retrieved documents. It helps to determine how many relevant document are ranked in top 5. The more documents in top 5, the better the information retrieval system is.
2) **Mean Average Precision (MAP)** is a measure of whether all of the relevant documents get ranked highly or not. It is needed because a relevant document being retrieved but present lower in the list would not be very useful for a user entering his/her query.
3) **Mean Reciprocal Rank (MRR)** is a measure of the rank at which the first relevant document occurs in the retrieved documents.

The metrics obtained for different models has been shown in Table I. An example of retrieval of FAQ questions is shown in Figure 4.

A. *Error Analysis*

We observe that the BM25 q(Q+A) + BERT qQ model gives the best results among all other models. This is because the BM25 model focuses on lexicons in the corpus and the BERT model focuses on the semantic meaning. Hence, they complement each other. BM25 q(Q+A) works better than BM25 qQ because concatenating the answer with the question provides more scope for matching lexicons. Words present in the query may be absent in the FAQ question but present in the FAQ answer.
The BM25 q(Q+A) + BERT qA model does not work well in comparison to BM25 q(Q+A) + BERT qQ model. This is because the semantics of a query and answer are usually very different. And hence, BERT qA does not perform that well. It is also observed that on adding the BERT qA model to the BM25 q(Q+A) model, the performance worsens.

B. *Web Interface*

The web interface was built using HTML, CSS, JavaScript and Flask. The model implemented in the frontend is the BM25 q(Q+A) + BERT qQ model described in Section III-B6. The frontend consists of a home page Figure 5 where the user enters the query and sees the results. The result has two

TABLE I
PERFORMANCE METRICS

Model	Ranking Method	P@5	MAP	MRR
1:1 qA training SBERT	(top qA, sort qQ)	0.14	0.32	0.33
1:5 qA training SBERT	(top qA, sort qQ)	0.19	0.35	0.37
1:5 qA + qQ training DistilBERT	(0.2*qA score+0.8*qQ score)	0.18	0.30	0.40
BM25 qQ training	(top 100 FAQ Q)	0.30	0.38	0.57
BM25 q(Q+A) training	(top 100 FAQ Q+A)	0.34	0.39	0.60
BM25 q(Q+A) + BERT qA training	(BM25 top 100 + rerank qQ)	0.27	0.32	0.52
BM25 q(Q+A) + BERT qQ training	(BM25 top 100 + rerank qQ)	0.42	0.51	0.69

aspects, an answer (Figure 6) and a "People also asked" section (Figure 7) which lists 5 pairs of FAQ which are similar to the query. Click here for the web interface demo.

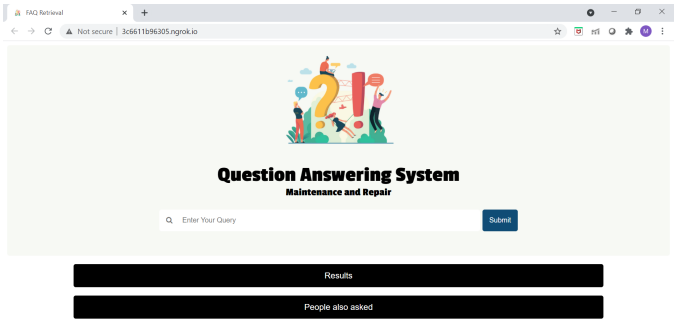

Fig. 5. The Home Page

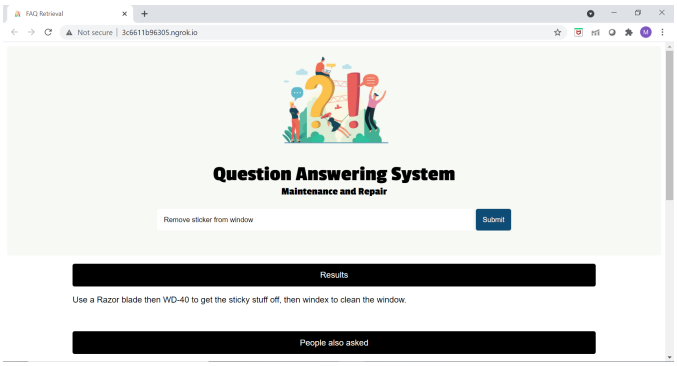

Fig. 6. The Result

VI. CONCLUSION

We have successfully trained all our models on FAQIR dataset to evaluate the task of FAQ retrieval. We have also used various ranking methods as shown in Table I.

We studied models based on BERT, TSUBAKI, BM25, Attentive Matching and taxonomy matching. We finally built a fusion model using the techniques from all models. Starting from vanilla SBERT model with a P@5, MAP and MRR of 0.14, 0.32 and 0.33 respectively, we present our final BERT qQ + BM25 q(Q+A) model with P@5, MAP and MRR of 0.42, 0.51, 0.69 respectively. Our final model is a fusion of

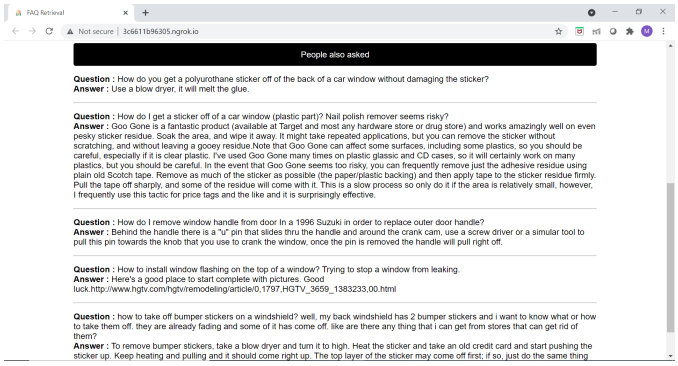

Fig. 7. "People also asked" section

triplet trained BERT and BM25 ranking function as described in Section III-B6.

We have also designed a web interface using HTML, CSS, JavaScript and Flask that uses our final FAQ model to fetch the most relevant answer and top 5 similar FAQ question and answer pairs.

VII. WORK UPDATE

A. Work completed

1) Learnt about the theoretical aspects of NLP and Q-A Retrieval Systems.
2) Carried out a literature review for FAQ models in Question Answering Systems in the field of information retrieval.
3) Learnt about the working and implementation of models like BERT, SBERT, BM25.
4) Experimented with various ranking techniques [weighted measures, re-ranking after initial retrieval] to rank top FAQ pairs.
5) Built a website using HTML, CSS, JavaScript and Flask and integrated our final model [BM25 q(Q+A) + BERT qQ training] with it.
6) Created an end-to-end website which gives top answer based on FAQ from the FAQIR dataset and 5 FAQ pairs that are similar to that category.

B. Future Work

1) Further improving the accuracy of our model by using alternative techniques.
2) Training and testing on other datasets like COUGH, StackFAQ.

3) Suggest better question framing (Like "Did you mean?" in Google).
4) Make a more generic FAQ system which caters to more than just one category.

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