Query Generation with External Knowledge for Dense Retrieval

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Abstract

Dense retrieval aims at searching for the most relevant documents to the given query by encoding texts in the embedding space, requiring a large amount of query-document pairs to train. Since manually constructing such training data is challenging, recent work has proposed to generate synthetic queries from documents and use them to train a dense retriever. However, compared to the human labeled queries, synthetic queries do not generally ask for hidden information, therefore leading to a degraded retrieval performance. In this work, we propose Query Generation with External Knowledge (QGEK), a novel method for generating queries with external knowledge related to the corresponding document. Specifically, we convert a query into a triplet-based template to accommodate external knowledge and transmit it to a pre-trained language model (PLM). We validate QGEK in both in-domain and out-domain dense retrieval settings. The dense retriever with the queries requiring external knowledge is found to make good performance improvement. Also, such queries are similar to the human labeled queries, confirmed by both human evaluation and unique & non-unique words distribution.

1 Introduction

Information retrieval (IR) is the task of collecting relevant documents from a large corpus when given a query. IR not only plays an important role in the search system by itself, but is also crucially applied to various NLP tasks such as Open-Domain QA (Kwiatkowski et al., 2019) and Citation-Prediction (Cohan et al., 2020) with its ability to find grounding documents. As the simplest retrieval method, traditional term-based sparse models such as TF-IDF and BM25 (Robertson and Zaragoza, 2009) are widely used. However, these sparse retrieval models are unable to capture the semantic similarities without explicit lexical overlaps between the query and its relevant documents. As a solution, dense retrieval models are recently proposed where query and document representations are embedded into the latent space (Gillick et al., 2018; Karpukhin et al., 2020), though they require a large amount of paired query-document training samples for notable performance, which is very challenging and expensive. In response, a zero-shot setting is often adopted, but dense retrievers are known to show poor performance on a new target domain (Ma et al., 2021; Wang et al., 2021; Xin et al., 2021).

One possible solution is to generate synthetic queries by fine-tuning a pre-trained language model (PLM) on a large IR benchmark dataset, and to use such queries for training dense retrievers (Ma et al., 2021; Thakur et al., 2021; Wang et al., 2021). However, this method does not yet provide synthetic queries whose quality is comparable to that of human labeled ones, thus hindering retrieval performance.

In particular, we argue that, for the effective training of dense retrievers, query samples should be allowed to contain external knowledge that is not explicitly shown in documents. As Figure 1
show, the human labeled query contains the external knowledge that Canada and North America are related, which is easily grasped by humans but not by the machine. Also, unique words in the query, often considered as external knowledge, are more frequently included in the human labeled queries than in the synthetic queries. The dense retrievers would better capture semantic relations if they are trained with such queries that show more characteristics of human labeled ones.

In this paper, we focus on generating queries with external knowledge by employing a simple method of explicitly transmitting document-related information to a PLM. Even though PLMs can handle hidden information to some extent by learning from a large amount of data, we argue that transmitting additional pieces of external knowledge to a PLM contributes positively to generating queries requiring external knowledge. Specifically, we first interpret the given query into a triplet-based template to consider the given document and related external knowledge together. A PLM is then fine-tuned to generate queries from triplet-based templates, together with a processed KB-QA dataset. The dense retriever is trained with the synthetic queries from the template extracted from the given document and corresponding external knowledge. A PLM is thereby referred to as Query Generation with External Knowledge (QGEK), is schematically illustrated in Figure 2.

We validate QGEK in both in-domain and out-domain (zero-shot) dense retrieval settings with diverse evaluation metrics. The experimental results show that queries that require external knowledge to answer are helpful for improving retrieval performance. Furthermore, we provide detailed qualitative analyses of synthetic queries and discuss which aspects of queries should be considered when training dense retrieval models.

Our contributions in this work are threefold:

- We propose a generation method of queries that require hidden information, not present in the document, from external sources.
- We experimentally show that generated queries are similar to the gold queries that are labeled by human annotators.
- We evaluate the quality of generated queries with respect to dense retrieval performance and distribution of unique words so as to find optimal queries in training a dense retriever.

2 Related Work

2.1 Dense Retriever

The sparse retriever, a traditional IR system, retrieves the target documents based on the lexical values such as frequency of terms and documents. BM25 (Robertson and Zaragoza, 2009) has been arguably the most frequently used method for such IR. However, as the retriever mainly handles the
match of the lexical entries, ‘semantically similar’ but not the same lexical entries are not considered in the search for documents, affecting the user experience (Berger et al., 2000).

The dense retriever (Karpukhin et al., 2020) has received much attention as a solution to handle the problem, triggered by the Transformer (Vaswani et al., 2017) network and PLM. A dense retriever fetches the documents located closest to the query vector in the dense vector space with the results recorded in advance for retrieval performance. The model maps queries and documents to the dense vector space using a bi-encoder structure initialized from a PLM such as BERT (Devlin et al., 2019a).

The dense retriever requires a large-scale dataset for model training, and curating such datasets is a much arduous endeavor. Thakur et al. (2021) proposed a zero-shot setting where dense retrievers are trained on a single large IR corpus, rather than on every dataset. Nonetheless, retrieval in such setting is still quite challenging.

2.2 Query Generation

Query generation is a simple method that addresses the shortage of training data for a dense retriever (Ma et al., 2021; Thakur et al., 2021; Wang et al., 2021). The most commonly used method has been to fine-tune the T5-base model (Raffel et al., 2020) to the MS MARCO dataset (Nguyen et al., 2016) and create a synthetic query in the target domain. Exploiting the size and domain of MS MARCO, we can obtain an effective retrieval performance by fine-tuning the T5 model. Info-HCVAE (Lee et al., 2020) achieved good performance by designing the relationship between document, query, and answer as a probability distribution and learning the latent vectors based on an auto-encoder. Answers and documents are used as inputs when creating queries. In these two methods, however, the processing of hidden information in the document still depends only on PLMs.

The existing methods focus only on the given document when generating queries, without much consideration of hidden information. In contrast, QGEK includes not only the document but also the hidden information that can be inferred from the given document with external knowledge.

2.3 Exploiting External Knowledge

External knowledge has been widely used along with PLMs for several NLP tasks. (Wang et al., 2020) augmented PLMs using ConceptNet (Speer et al., 2017) for a commonsense question answering (QA) task and showed that KB, such as Concept-Net, contributes to the explicit grounding of the output, resulting in better reasoning abilities.

Furthermore, Zhou et al. (2018) proposed to generate knowledge-based dialogues for an Open-Domain Dialogue system. Dinan et al. (2019) confirmed that the additional external knowledge positively affects dialogue generation. In addition, Shuster et al. (2021) showed that the related external knowledge can be exploited to address critical issues, such as factual incorrectness and hallucination, in dialogue systems.

While external knowledge from KB has proved helpful in Commonsense QA and Open-Domain Dialogue domains, it is relatively underexplored for generating synthetic queries for dense retrieval. In this work, we adopt KB into a PLM for query generation and show the effectiveness of training dense retrievers with the synthetic queries on IR benchmark datasets.

3 Methods

QGEK is designed to generate a new synthetic query that requires an implicit inference process for the answer by exploiting both the given document and external knowledge hidden in the document. First, we interpret the query as the triplet $<S,R,O>$ that can easily utilize both of them, where the triplet is converted into a single-text template to simplify the transmission to a PLM. Then, we construct triplet-based template & query pairs as training datasets for fine-tuning a PLM. For generating a query from target documents, the triplet-based template is extracted from a general document.

3.1 Preliminaries

The dense retriever maps query $q$ and document $d$ into an $n$-dimensional vector space with query encoder $E_Q(\cdot, \theta_q)$ and document encoder $E_D(\cdot, \theta_d)$ where $\theta$ is the encoder’s parameter. The similarity score $f(q,d)$ between query $q$ and document $d$ is computed as a dot product:

$$f(q,p) = E_Q(q, \theta_q)^T \cdot E_D(d, \theta_d)$$

Training the dense retriever targets the vector space of which the relevant query and document pairs have a high similarity score compared to irrelevant pairs. Given query $q$, let $(D^+_q, D^-_q)$ be the pairs of the sets of relevant documents and irrelevant documents. The objective function of dense
retriever is as follows:

$$\min_{\theta} \sum_{q} \sum_{d^+ \in D^+_{d}} \sum_{d^- \in D^-_{d}} L(f(q, d^+), f(q, d^-))$$

The loss $L$ is the negative log likelihood of the positive passage.

### 3.2 Query Interpretation as Triplet Form

Queries can be simply mapped to the $<S, R, O>$ triplet. The query $<S, R, O>$ asks for the answer $O$, which has relationship $R$ with subject $S$. For example, the query "big little lies season 2 how many episodes" and the answer "7 episodes" can be mapped to $<"big little lies season 2", "number of episodes", "7 episodes">.

Information of each item in a triplet can be largely divided into sentences or words units. We use two types of information to express each item of a triplet in more detail. Let $W_x = \{w_{x1}, \ldots, w_{xn}\}$ and $l_x$ be the set of word unit information and the single sentence unit information of the item $x$, respectively. Then, query $Q$ can be interpreted as the triplet items with their own information:

$$Q = \{(W_S, l_S), (W_R, l_R), (W_O, l_O)\}$$

For generating a query that requires an implicit inference, a form of query that can utilize both the document and external knowledge is required. The proposed triplet simply handles both document and external knowledge by arranging information into the appropriate positions in the triplet. When transmitting such triplets to a PLM, we use the simple form of a single text template. The triplet-based template consists of triplet items delimited by special tokens as shown in Figure 3.

### 3.3 Dataset Construction for Query Generator

We construct a dataset consisting of triplet-query pairs for fine-tuning PLM. The KB based query can be converted into the proposed triplet. A canonical logical form of a KB based query is a representation that expresses the same meaning as the relationship between entities in KB. A simple interpretation of the proposed triplet can be seen as a canonical form consisting of two entities and a relationship between them.

For example, suppose that the entity, ‘Michael Dotson’, is first selected as subject $S$ and has word unit information, ‘Actor’, and sentence unit information, ‘Michael Dotson is an actor’. Suppose also that there is an entity, ‘Frenso’, linked by ‘place-of-birth’ relationship with ‘Michael Dotson’. The other entity and relationship may have their own information from KB. The triplet-based template is created by combining all of them.

### 3.4 Applying Template for General Document

The fine-tuned PLM with the dataset constructed in Section 3.3 needs the triplet-based template to generate a query from a general document. We extract triplet items from the given document, and...
collect external knowledge to fill the template from the open web.

For example, suppose that there is a document about zebra mussels (cf. Figure 3). The subject $S$, relation $R$ and object $O$ are selected as ‘zebra mussels’, ‘location’ and ‘Canada’, respectively. The document alone is not enough to fill the information of object $O$, ‘Canada’. The external knowledge, ‘Canada is a country in North America’, is extracted from the open web. Both given document and external knowledge are arranged into the appropriate positions in the template.

4 Experimental setups

We evaluate the performances of the dense retriever when trained with the synthetic queries compared to the human labeled queries. The dense retriever used in our experiments is the DPR (Karpukhin et al., 2020). The train dataset of the dense retriever is the pairs of the documents of Natural Question (NQ) (Kwiatkowski et al., 2019), also exploited as the source of the query generator, and the synthetic queries of the proposed method.

4.1 Datasets

We evaluate the effectiveness of the generated queries when using external knowledge on IR benchmark datasets. We conduct experiments in two settings: in-domain and out-domain (zero-shot). We measure the in-domain performance on the NQ and the out-domain performance on 13 representative IR datasets (Thakur et al., 2021).

**In-Domain Dataset**  NQ (Kwiatkowski et al., 2019) is a benchmark dataset for the open-domain question answering task, fetched by Google search engine and from Wikipedia. We use the preprocessed version of the NQ following DPR (Karpukhin et al., 2020), which includes 58,880 training pairs and 7,405 test queries. The documents in NQ is used as input of query generator.

**Out-Domain Dataset** To validate the quality of generated queries for training the dense retriever, it is necessary to show the retrieval performance of diverse tasks. Each dataset used in out-domain experiments has diverse tasks and domains and requires retrieval models for finding grounding documents. They are shown in Table 1.

| Task                          | Domain          | Dataset                                      |
|-------------------------------|-----------------|----------------------------------------------|
| Argument Retrieval            | Misc.           | ArguAna (Wachsmuth et al., 2018)             |
| Entity-Retrieval              | Misc.           | TomoBio-2020 (Bostan-zadeh et al., 2020)    |
| Question Answering            | Wikipedia       | HotpotQA (Yang et al., 2018)                 |
| Question Answering            | Finance         | FiQA-2018 (Ma et al., 2018)                  |
| Duplicate-Question Retrieval  | Quesa           | Quesa (Thakur et al., 2021)                  |
| Fact Checking                 | Wikipedia       | FEVER (Thorne et al., 2019)                  |
| Question Answering            | Scientific      | Climate-Fever (Leippold and Diggelmann, 2020) |
| Citation-Prediction           | Scientific      | SciFact (Wahabzadeh et al., 2020)            |
| Duplicate-Question Retrieval  | MS MARCO (Nguyen et al., 2016)            |
| Bio-Medical IR                | Bio-Medical     | SCIDOCS (Cohan et al., 2020)                 |
| Bio-Medical IR                | Bio-Medical     | TRAC-COVID (Vithanage et al., 2021)          |
| Passage-Retrieval             | Quora           | NFCorpus (Bitwiza et al., 2016)              |

Table 1: Datasets for Out-Domain Experiments

4.2 Metrics

We explain the metrics for evaluating the performance of a dense retriever. In the basic setting, the retriever searches for top k relevant documents on a given query. We employ 4 metrics for top k documents: ACC@k, MRR@k, MAP@k, and nDCG@k. The in-domain experiment is evaluated with these 4 metrics, and the out-domain performance is evaluated with only nDCG@10.

**ACC@k** is the percentage of whether the correct documents are included in the top-k hits. It ignores the rank of retrieved documents.

**MRR@k** (Mean Reciprocal Rank) computes the average of the ranks of the first correct document from top-k documents. The rest of the correct documents are not included in computing MRR.

**MAP@k** (Mean Average Precision) first computes the average precision score of the correct documents’ ranks in top-k hits for a given query. The mean of the average precision scores is the value of the MAP@K.

**nDCG@k** (Normalised Cumulative Discount Gain) is similar to MAP@k, but reflects the fact that the more relevant document is the more highly ranked in top-k documents.

4.3 Implementation Details

**Query Generator** We used BART (Lewis et al., 2020), one of the widely used PLMs, to generate the synthetic query from the proposed template. BART based on the transformer seq2seq architecture is trained by reconstructing text from noised input. The de-noising ability of BART is suitable for generating queries from text with noise from the external source.

SimpleQuestions (Bordes et al., 2015) (SQ), a question answering dataset based on KB, is se-
Table 2: In-domain and Out-domain performance of DPR. The scores for out-domain denote nDCG@10. The scores over the gold query are marked in bold, and the better scores between queries from QGEK are underlined.

In-Domain

| Train Query | ACC@10 | ACC@100 | MRR@10 | MRR@100 | MAP@10 | MAP@100 | NDCG@10 | NDCG@100 |
|-------------|--------|---------|--------|---------|--------|----------|---------|----------|
| Gold        | .6374  | .8974   | .3372  | .3493   | .3146  | .3296    | .3892   | .4543    |
| QGEK        | .4901  | .7488   | .2375  | .2484   | .2220  | .2354    | .2841   | .3449    |
| (-) Ext. Knowledge | .4860  | .7285   | .2348  | .2457   | .2162  | .2295    | .2745   | .3357    |

Out-Domain

| Train Query | Arguana | DBpedia | fbqa | HotpotQA | NFC | Quora | SciFact | Touch-2020 | C-Fever | Fever | MN MARCO | SciDocs | TREC-COVID | Avg. |
|-------------|---------|---------|------|-----------|-----|-------|---------|------------|---------|-------|----------|---------|------------|------|
| Gold        | 2203    | 2585    | 1763 | 3205      | 2226 | 5778  | 4476    | 2334       | 1609    | 5160  | 1858     | 1022    | 5152       | 3109 |
| QGEK        | 0.048   | 0.023   | 1.142 | 0.4326    | 0.472 | 2.492 | 2.3436  | 2.2923     | 0.774   | 0.733 | 0.737    | 0.645   | 0.4411     | 0.441 |
| (-) Ext. Knowledge | 0.0568 | 0.0255  | 1.138 | 0.4015    | 0.475 | 2.396 | 3.005   | 3.1906     | 0.831   | 0.752 | 0.769    | 0.8096  | 0.4427     | 0.269 |

5 Result & Discussion

5.1 Overall Result

Our main results are shown in Table 2. We evaluate the retrieval performance of the dense retriever trained with the synthetic queries from QGEK against the gold query in the NQ train split. In the in-domain experiments, the dense retriever with the gold query of NQ showed superior performance over the retriever with QGEK. QGEK shows better performance in all metrics than the ablation case not including external knowledge in the proposed triplet. The average of NDCG@10 in out-domain experiments shows a small difference (-0.0108) between the gold queries and QGEK. In detail, the retriever trained with QGEK shows better performance on 4 datasets: DBpedia, HotpotQA, Fever, and Climate-Fever. The rest of the 9 datasets show that the retriever with the gold queries is more appropriate.

Using external knowledge gives rise to generating more appropriate queries for most datasets than not using one, though human labeled queries are more appropriate for training the dense retriever in the in-domain experiments. On the other hand, we see that QGEK gives comparable performance to the one with human labeled queries in the out-domain experiments and even outperforms on some datasets.

5.2 Analysis of Synthetic Queries

Experiments are conducted to compare against query generator baselines. We selected GenQ (Thakur et al., 2021) and Info-HCVAE (Lee et al., 2020) models as the baselines. The models receive the documents in NQ train split as input. The size of the train batch is 8 and the learning rate is initialized with $2 \cdot 10^{-5}$.
and documents of the dataset are the same as those of the NQ train split except for synthetic queries.

**Baseline Comparison** A comparison with other query creation methods is made, as shown in Figure 4. The average of the NDCG@10 performance in in-domain and out-domain experiments is calculated by training the dense retriever through the generated queries. The models trained with synthetic queries are sorted as GenQ, QGEK, and Info-HCVAE in descending order. QGEK shows somewhat lower performance than the one with gold queries, but GenQ shows the best performance, indicating that many queries suitable for the IR tasks are generated by training on the MS MARCO dataset.

The MS MARCO dataset is most widely used for dense retriever training, and training a dense retriever with MS MARCO is known to give a higher performance than training it on other datasets such as NQ. Also, it has a huge amount of data, more than 500,000 pairs. This has the advantage of generating queries suitable for IR tasks based on abundant and task-appropriate data. However, the proposed method is trained on a relatively small amount of 47,180 data from SimpleQuestions, a KB-QA dataset. There is a possibility that the generated queries are largely incompatible with the IR task. However, the proposed method focuses on utilizing external knowledge, and it can be applied orthogonally to the MS MARCO dataset, which we leave for future work.

**Unique & Non-Unique Words in Query** We analyze whether the words in a query are from the corresponding documents. The implicitly inferring query has a higher probability of including unique words not present in the document. So, the distribution of unique & non-unique words can indirectly tell the existence of such queries. The stop words, such as the interrogative word and articles, in a query are excluded from the analysis.

The distribution of unique words in a query is shown in Figure 5. The 27% of gold labels of NQ contain 3 unique words, and 80% of the cases contain 4 or fewer unique words. QGEK shows a similar pattern of non-unique words compared with the gold, and over 40% of queries contain more than 5 unique words. The distribution of GenQ shows a similar pattern to that of the gold queries in both unique and non-unique words. Unlike other models, the Info most frequently includes 2 non-unique words.

Note that QGEK generates queries with more unique words than other queries, together with a similar distribution of non-unique words to that of gold queries. This implies that QGEK can generate queries requesting hidden information not present in the document. Given the performance of the dense retriever (Figure 4) and the distribution of unique & non-unique words (Figure 5), generating queries both close to the human labeled ones and appropriate to the IR tasks is an important factor for an optimal training of the dense retriever. Our future work includes generating queries not only close to human labeled ones but also optimized for IR tasks, such as exploiting the MS MARCO dataset.

**Manual Evaluation** We use human evaluation to check whether the synthetic queries are similar to human labeled ones. The randomly sampled 30
We presented a novel query generation method, QGEK, that generates synthetic queries in a form more similar to human labeled queries by using external knowledge. In order to use unprocessed external knowledge, we convert a query into a triplet-based template, which can include information of subjects and answers. Remarkably, when dense

Table 3: Examples of documents and the corresponding queries. The non-unique words are underlined, and the unique words are marked in bold.

| Query | Relevance | Grammaticality | Difficulty |
|-------|-----------|----------------|------------|
| Gold  | 3.95 ±1.38| 3.80 ±1.12      | 2.10 ±1.43|
| QGEK  | 3.66 ±1.50| 4.07 ±1.04      | 2.39 ±1.50|
| Info-HCVE | 3.66 ±1.45| 4.01 ±1.13      | 2.31 ±1.52|
| GenQ  | 4.12 ±1.20| 4.02 ±1.26      | 1.90 ±1.21|

Table 4: The result of human evaluation. Statistically significant difference compared to gold via t-test (p < 0.05) is marked in bold.

As shown in Table 4, QGEK shows statistically higher degrees of grammaticality and difficulty than the gold labels. These results indicate that queries from QGEK need more hidden information not present in the documents compared to other queries.

Case Study Examples of the documents and corresponding queries are shown in Table 3.

Document 1 is about the water treatment problem caused by mussels. In answering the gold label, external knowledge that Canada is in North America is needed for the inference from the document. However, other generated queries do not require much external information. In the case of Document 2, the introduction of the game "Call of Duty", the gold label does not require hidden information in the document. However, in the case of GenQ, the additional information that PlayStation 3, Xbox 360, and Wii are gaming consoles is required for a suitable answer. This gives evidence that there are cases in which queries requiring inference from external knowledge are generated through the proposed method. In the case of Document 3, introduction of Call the Midwife, the query from QGEK needs external information about the gender of actors to answer.

Although QGEK generates the queries that need external knowledge to answer, they have a similar pattern that begins with an interrogative word. In the case of GenQ and Info-HCVE, different patterns exist through the queries of Document 3. It can be inferred that the triplet-based template makes the logical structure simple, and that the syntactic diversity of the generated query tends to decrease. For future work, we plan to propose a template that can include more logical structures, developed from the current triplet-based template.

6 Conclusion

We presented a novel query generation method, QGEK, that generates synthetic queries in a form more similar to human labeled queries by using external knowledge. In order to use unprocessed external knowledge, we convert a query into a triplet-based template, which can include information of subjects and answers. Remarkably, when dense
retrieval models are trained with the queries generated from QGEK, the performance has improved much compared to using the queries without external knowledge. Also, we have shown that including external knowledge give rises to the distribution of the unique words similar to that of the human labeled queries. We believe that QGEK can also be applied to the other generation methods by orthogonally adding some external knowledge processing modules. For future work, we plan to generate queries both close to human labeled ones and optimized for IR tasks and to allow the template to accept more general logical forms for diverse high-quality queries. The code and data will be made available for public access.

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