Knowledge Base Completion using Web-Based Question Answering and Multimodal Fusion

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ABSTRACT

Over the past few years, large knowledge bases have been constructed to store massive amounts of knowledge. However, these knowledge bases are highly incomplete. To solve this problem, we propose a web-based question answering system which exploits unstructured textual snippets and structured information, to fill in missing information for knowledge bases.

To utilize unstructured information from the Web for knowledge base completion, we design a web-based question answering system using multimodal features and question templates to extract missing facts, which can achieve good performance with very few questions. We employ a few query-driven techniques for web-based question answering to reduce the runtime and provide fast responses to user queries.

To help improve extraction quality, the question answering system exploits structured information from knowledge bases, such as entity types and entity-to-entity relatedness.

1 INTRODUCTION

A knowledge base (KB) is usually a data store of structured information about entities, relations and facts. We implement web-based question answering (WebQA) to extract missing facts from textual snippets retrieved from the Web. We design novel multimodal features and an effective question template selection algorithm for WebQA, which can achieve better performance with fewer questions than previous work [16]. We implement the query-driven snippet filtering component in WebQA, which can greatly reduce the number of snippets for processing on-the-fly and improve the efficiency of the WebQA pipeline.

The WebQA system first transforms KBC queries to natural language questions and extracts candidate answers from textual snippets searched by these questions on the Web. It then maps candidate answers to entities in KBs, utilizes entity category information and relation schema to filter out incorrect candidate answers. We exploit unstructured textual snippets and structured information in knowledge bases such as entity-to-entity relatedness and entity descriptions inside KBs to extract multimodal features for answer ranking.

To improve WebQA efficiency, we need to reduce the number of questions and the number of snippets to process for each KBC query. We propose a greedy question template selection algorithm to select a small set of question templates with highest KBC performance for each relation. We conduct query-driven snippet filtering to greatly reduce the number of snippets to be processed. With fewer questions and snippets for each KBC query, WebQA can provide fast responses to user queries.

Our contributions are shown below:

- We design and implement a web-based question answering (WebQA) system to extract missing facts from the unstructured Web with effective multimodal features and question template selection, which can achieve better performance with fewer questions than previous work [16].

- To improve efficiency, we employ a few query-driven techniques for web-based question answering to reduce the runtime and provide fast responses to user queries.

- Extensive experiments have been conducted to demonstrate the effectiveness and efficiency of our system.

Overview Related work on question answering and multimodal fusion is introduced and discussed in Section 2. How we design and implement the web-based question answering system are explained in Section 3. We demonstrate the effectiveness and efficiency of our system through extensive experiments in Section 4. The conclusions and future work of our WebQA system are discussed in Section 5.

2 RELATED WORK

Knowledge bases are used for various applications, such as entity linking and entity disambiguation in NLP [5, 6]. In this section, we briefly discuss related work on question answering and multimodal fusion.

2.1 Question Answering

Open-domain question answering (QA) has been popular for a long time. QA returns exact answers to natural language questions posed by users. Since 1999, a specialized track related to QA has been introduced into the annual competition held at the Text Retrieval Conference [15]. Web-based QA systems are highly scalable and are among the top performing systems in TREC-10 [2]. Such systems issue simple reformulations of the queries as questions to a search engine, and rank the repeatedly occurring N-grams in the top snippets as answers based on named entity recognition (NER) and heuristic answer type checking.

In our system, we choose web-based question answering to extract missing facts from unstructured textual snippets for knowledge base completion because of its scalability, flexibility and effectiveness based on the massive information available on the Web. Our main focus is not developing better general QA systems, but rather addressing the issue of how to use and adapt such systems for knowledge base completion. In [16], West et al. proposed using question templates based on relevant information of entities to transform KBC queries to natural language questions and utilized in-house question answering systems to search for answers of these questions from the Web. Compared to [16], we design our own question templates and a novel template selection algorithm which can greatly reduce the number of questions and achieve high performance.
2.2 Multimodal Fusion
Multimodal fusion techniques have been widely used for tasks such as information retrieval, information extraction and classification tasks [4, 7–10]. Multimodal fusion can utilize information from multiple types of data sources and employ the correlative and complementary relationship between different modalities [10], to achieve higher performance than any single modality approaches in most cases. In the paper, we fuse unstructured and structured data to improve knowledge base completion quality in our WebQA system.

3 WEB-BASED QUESTION ANSWERING
In this section, we explain the web-based question answering system (WebQA) for knowledge base completion by fusing both unstructured data from the Web and structured data from knowledge bases. WebQA uses question templates to generate multiple natural language questions for each KBC query. Then textual snippets are crawled by searching these questions on the Web via search engines. Different from traditional question answering systems, we use entity linking to collect candidate answers from snippets. Various multimodal features are extracted for candidate answers by fusing information from both the unstructured snippets and structured knowledge in KBs. Then we rank the candidate answers by probability scores generated from classification on their features.

Compared to previous work [16], we design better question templates to achieve high KBC performance. We propose a greedy algorithm to effectively select a small set of best question templates for question generation. We design effective multimodal features through fusion of unstructured textual snippets and structured knowledge bases. We conduct query-driven snippet filtering to reduce the number of snippets for processing, which greatly improves the efficiency of WebQA. While previous work used batch-oriented question answering systems [13, 16], WebQA can provide fast responses to user queries. Experimental results in Section 4 demonstrate both the effectiveness and efficiency of WebQA.

3.1 WebQA Pipeline
There are four major components in the WebQA system pipeline, including question generation, data collection, answer extraction and answer ranking. The system pipeline of WebQA is illustrated in Figure 1. We briefly explain the design and implementation of these components. We use <Marvin_Minsky, wasBornIn, ?> as an example query and the correct answer to this query is New_York_City. More examples for different relations are shown in Table 1.

3.1.1 Question Generation. Structured queries are transformed into natural language questions using selected question templates, as shown in Table 1. Each relation has multiple corresponding question templates. For example, for relation wasBornIn, we use born, birth and birthplace as its templates. Then for the KBC query <Marvin_Minsky, wasBornIn, ?>, the corresponding questions are "Marvin Minsky born", "Marvin Minsky birth" and "Marvin Minsky birthplace". The benefit of using multiple question templates is it can increase the chance of finding true answers by crawling more snippets with different questions than using only one template.

As demonstrated by experiments, multiple questions can provide higher KBC performance than any single question.

In previous work [16], West et al. utilized relevant information about entities to augment the questions to design question templates. For example, for query <Frank_Zappa, mother, ?>, an example question generated by their templates is "Frank Zappa mother Baltimore", with Baltimore being the birthplace of Frank_Zappa. However, these complex templates tend to generate long questions, which may return many noisy snippets without true answers by search engines. For question "Frank Zappa mother Baltimore", search engines may find it hard to determine whether this question is asking about "Frank Zappa mother" or "Frank Zappa Baltimore", and then return snippets related to Frank_Zappa and Baltimore instead of the mother of Frank_Zappa.

On the contrary, search engines are better at finding relevant snippets to short questions. Based on this observation, we design question templates by selecting single words with their meanings close to the semantic meanings of relations. For example, for relation wasBornIn, born, birthplace and birth are selected as templates; for relation isMarriedTo, single words such as marriage, married and spouse are selected as templates. More examples about question templates are listed in Table 1.

Issuing all possible questions to search engines is problematic in terms of computational cost and KBC performance. To solve this problem, we propose a greedy template selection algorithm to select a small subset of question templates which achieves the highest KBC performance for each relation. The algorithm is explained in Section 3.2.1.

3.1.2 Data Collection. We search the generated questions on the Web via search engines and process the snippets returned by search engines to extract missing facts for KBC queries. A snippet is a small piece or fragment of text excerpted from the document which search engines find relevant to the queries. For query <Marvin_Minsky, wasBornIn, ?>, a top snippet we crawled from the Web is "Marvin Lee Minsky was born in New York City, to an eye surgeon father, Henry, and to a mother, Fannie ...", which contains the correct answer New_York_City. Examples of top snippets for more KBC queries are shown in Table 1.

We crawl up to 50 snippets for each question and hundreds of snippets for each KBC query. To reduce time waiting for responses from search engines for each relation, multithreading is employed to parallelize the snippet crawling step with multiple questions. However, entity linking on hundreds of snippets is still very time-consuming and far from being able to provide fast responses to user queries. Therefore, we implement a query-driven snippet filtering component to automatically select best snippets to extract candidate answers for knowledge base completion, which is explained in Section 3.2.2.

3.1.3 Answer Extraction. Noun phrases are extracted from the snippets and linked to entities in knowledge bases. These linked entities are treated as candidate answers for corresponding questions. Entity linking is the task to link entity mentions in text with their corresponding entities in a knowledge base [11]. Linking candidate answers in snippets to entities in knowledge bases has several remarkable advantages [13]. First, redundancy among candidate answers is automatically reduced. Second, the types of a candidate
answer can be effortlessly determined by its corresponding entity in knowledge bases. Third, we can develop semantic features for candidate answer ranking by utilizing the rich semantic information about entities in knowledge bases.

Since entity linking is beyond the scope of this paper, please refer to a survey paper [11] for more information. An open-source entity linking tool, TagMe [3, 14] is employed in our system to accomplish the entity linking task. We parallelize the entity linking process using multi-threading to reduce runtime waiting for responses from a TagMe server [14].

After entity linking, candidate answers with incorrect entity types for KBC queries are discarded. For example, the query <Marvin_Minsky, wasBornIn, ?> is looking for candidate answers with type city rather than person. In the snippet “Marvin Lee Minsky was born in New York City, to an eye surgeon father, Henry, and to a mother, Fannie …,” the entity Henry_Minsky, which is the father of Marvin_Minsky, is discarded because of wrong entity types. This type filtering step greatly reduces the number of candidate answers for ranking and thus helps improve answer ranking quality.

3.1.4 Answer Ranking. After obtaining a set of eligible candidate answers with correct entity types from snippets, we extract features for candidate answers from snippets and knowledge bases and apply classification on these features of candidate answers for ranking. For feature extraction, we design multimodal features to combine information from unstructured snippets and structured knowledge in knowledge bases. The probability scores from classification results are used to rank the candidate answers.

Feature Extraction. For feature extraction, we adopt the early fusion scheme, which combines information from multiple modalities at the feature level [1, 8, 10]. Both unstructured textual snippets from the Web and structured knowledge from KBs are fused together to produce various effective features in our system.

For each candidate answer, we extract 4 features as shown below.

- The feature snippet count represents the number of snippets in which a candidate answer appears.
- The feature average rank calculates the average rank of the snippets in which the candidate answer appears.
The feature average distance is average distance (number of words) between the candidate answer and the subject entity in the snippets.

The feature relatedness\(^1\) between the candidate answer and the subject entity measures the semantic relevance of these two entities in knowledge bases.

As shown above, these features combine information from both unstructured textual snippets and structured knowledge bases. The major advantage of applying multimodal fusion at the feature level is that multimodal features can provide more information than using only textual snippets or knowledge bases.

Classification and Ranking. Classification on feature vectors of candidate answers is challenging because of the highly imbalanced training datasets. The training datasets usually contain 30+ times more negative samples than positive samples, making the training datasets extremely biased. We employed resampling to solve the issue of imbalanced training datasets. The resampling approach samples the existing training datasets to create new balanced datasets with equal numbers of positive samples and negative samples. After using resampling, we usually get classifiers with 20% to 40% larger PRC (area under precision-recall curve) than regular classifiers.

Three classification methods have been tested in our system, logistic regression [16], decision tree [13] and support vector machines. Through extensive experiments, logistic regression usually performs better than the other two classifiers for most relations.

3.2 Query-Driven Optimization

We apply two query-driven techniques to reduce the number of questions and the number of snippets processed by WebQA for each KBC query, which can help WebQA achieve good KBC performance and efficiency. The models used in template selection and snippet filtering are trained offline.

3.2.1 Template Selection. Issuing all possible questions to search engines is problematic for two reasons. First, its computational cost is too high. Processing each question involves significant computational resources (CPU time and web searches) and requires a lot of time waiting for responses from search engines. Moreover, more questions return more snippets and entity linking on a large number of snippets is also very time-consuming. Second, the KBC performance may deteriorate with more questions. Not all questions are equally good. So by asking all possible questions, we are likely to get more false answers, which affects the performance of answer ranking.

According to previous work [16], greedy selection is the best selection strategy among a few selection strategies, including random selection and sampling-based selection. In [16], West et al. first evaluated the KBC performance of each question template and then greedily selected the top-performing question templates. However, their algorithm ignored the correlation between templates. We observe that some top-performing question templates produce mostly overlapping results. So we propose a more complex greedy algorithm to learn the best set of question templates as shown in Algorithm 1.

Let’s say there are three templates in descending order of individual performance, \(t_1, t_2\) and \(t_3\). Previous work [16] greedily selects top 1, top 2 and top 3 templates, producing three sets of templates \(\{t_1\}, \{t_1, t_2\}\) and \(\{t_1, t_2, t_3\}\) and chooses the set of templates with highest performance. However, \(t_1\) and \(t_2\) may produce mostly overlapping results. So \(t_1, t_2\) may not achieve as good KBC performance as \(\{t_1, t_1\}\). Our algorithm also starts with the set \(\{t_1\}\). Then we try to add a new template to the set \(\{t_1\}\) to get a larger set with 2 templates. We compare the performance of \(\{t_1, t_2\}\) and \(\{t_1, t_1\}\) (all possible size-2 sets with \(t_1\) in them) and choose the better set. The algorithm goes on to add more templates. Finally we choose the set of templates which achieves the best performance with smallest size. The details of the algorithm is shown in Algorithm 1.

\[\text{Algorithm 1: Greedy selection algorithm}\]

1: \(T = \{t_1, t_2, ..., t_n\}\): the set of \(n\) question templates
2: \(Q = \emptyset\): current set of selected question templates
3: \(QS = \emptyset\): the set of question template sets with different sizes
4: for \(i = 1; i <= n; i++\) do
5: Select \(t_j\) from \(T\) such that \(Q \cup \{t_j\}\) has the highest performance for all possible \(t\) in \(T\)
6: \(Q = Q \cup \{t_j\}\)
7: \(QS = QS \cup \{Q\}\)
8: \(T = T \setminus \{t_j\}\)
9: Select \(Q_m\) from \(QS\) with the highest performance and smallest size
10: return \(Q_m\)

The advantage of our greedy selection algorithm is by choosing templates which work best together, we can avoid computing the exponential combinations of question templates and solve the correlation problem between top-performing templates to quickly find the optimal set of question templates. As shown in experiments, our system can achieve quite good performance with two or three question templates compared to using all question templates.

3.2.2 Snippet Filtering. To reduce the number of snippets for processing, we propose a query-driven snippet filtering algorithm to select snippets most likely containing information relevant to knowledge base completion queries. An important observation is not all top snippets ranked by search engines contain useful information for KBC queries. For example, for question “Marvin Minsky born”, some of the top snippets returned by search engines focus on general information about Marvin Minsky rather than the birthplace of him. To solve this problem, we rerank the snippets by classification on features of them and select top snippets in the reranked list for candidate answer extraction and ranking.

The features we used for classification on snippets are:

- The original rank of a snippet returned by a search engine.
- A boolean indicator about whether the question template keyword appearing in the snippet or not, e.g. whether born appearing in the snippets returned by searching the question “Marvin Minsky born”.
- How many words of entity names appearing in the snippet. For instance, if “Marvin” and “Minsky” both appear inside a snippet for question “Marvin Minsky born”, the value of this feature is 2.

\(^1\)The entity relatedness implementation is provided by TagMe [14].
Clearly these features are designed to select snippets, which not only are originally high-ranking snippets returned by search engines, but also contain information about question template keywords and subject entities.

A logistic regression classifier is trained on training datasets and used to filter snippets on-the-fly in the data collection step of the WebQA pipeline. The confidence scores of these snippets generated by the classifier are used for snippet reranking. The original training dataset is also highly imbalanced with positive samples much fewer than negative samples. We resolve this issue by conducting resampling on these biased datasets to generate a new balanced training dataset.

4 EXPERIMENTAL RESULTS

In this section, we demonstrate the effectiveness and efficiency of our system through extensive experiments. We choose Yago as the knowledge base for its popularity in research community, its rich ontology and large amount of facts. We choose four relations (wasBornIn, isMarriedTo, hasChild, isCitizenOf), which are popular relations frequently studied in previous work.

For KBC performance, we evaluate the quality of candidate answer rankings using mean average precision (MAP). For a KBC query, the average precision is defined as \( AP = \frac{\sum_{k=1}^{n} p(k) \times r(k)}{n} \), where \( k \) is the rank in the sequence of candidate answers, \( n \) is the number of candidate answers, \( p(k) \) is the precision at cut-off \( k \) in the ranked list and \( r(k) \) is the change in recall from candidate answers \( k - 1 \) to \( k \). Averaging over all queries yields the mean average precision (MAP).

4.1 Datasets

Yago [12, 17] is a huge semantic knowledge base, derived from Wikipedia, WordNet and GeoNames. Currently, Yago has knowledge of more than 10 million entities (like persons, organizations, cities, etc.) and contains more than 120 million facts about these entities. The whole Yago knowledge base can be downloaded from Yago website 2.

We consider 4 relations from Yago (hasChild, isCitizenOf, isMarriedTo and wasBornIn) for evaluating our system. To collect training and testing data, we make the local closed-world assumption, which assumes if Yago has a non-empty set of objects \( O \) for a given subject-relation pair, then \( O \) contains all the ground-truth objects for this subject-relation pair. For each relation, we randomly sampled 500 queries (subjects and corresponding objects) from Yago as training datasets to train WebQA and 100 queries for testing.

4.2 KBC Performance

We first discuss the performance of the WebQA system and different approaches optimizing the performance of WebQA. Then we explain the runtime efficiency of our system and how we provide fast responses to queries on-the-fly.

Logistic regression was chosen as the classification method for answer ranking in WebQA. To balance training datasets, we applied resampling to the datasets. We first show experimental results of WebQA using templates selected by Algorithm 1 for 4 relations.

Then, we evaluate the performance of WebQA with query-driven snippet filtering.

4.2.1 Question Template Selection. We compare the performance of Algorithm 1 with the greedy algorithm described in previous work [16]. Since West et al. didn’t enclose the full set of question templates and the question answering system they used in [16], we implemented their algorithm with our templates and the WebQA pipeline. The results comparing these two algorithms for two relations (isCitizenOf and wasBornIn) are shown in Figure 2.

In Figure 2, we can see multiple questions have higher MAP than using only one question, although it is generated by the best template. Another important observation from the results is the KBC performance may deteriorate using more questions.

For both relations, our greedy algorithm can learn the best set of templates with fewer templates than the algorithm in WWW’14 [16]. For relation isCitizenOf, the two algorithm achieve the same highest performance with different numbers of templates. For relation hasChild, the best performance of our algorithm is higher than the algorithm in WWW’14. Other relations demonstrate similar results as isCitizenOf and hasChild.

To conclude, the experimental results in Figure 2 demonstrate our greedy algorithm can effectively select very few question templates to achieve high KBC performance. With only two or three questions selected by Algorithm 1, we can achieve the highest KBC performance. Hence we can improve the efficiency of the WebQA pipeline with fewer questions and fewer snippets crawled from them.

4.2.2 Overall System Performance. For each relation, we learned the smallest set of question templates which can achieve the highest KBC performance using Algorithm 1. Using these sets of question templates, we conducted experiments to evaluate the overall performance of WebQA for all 4 relations. These experiments used all snippets crawled from the Web.
Table 2: KBC performance of WebQA with template selection measured by MAP.

| Relation        | Perf. (WebQA) | Question # (WebQA) | Perf. (WWW’14) | Question # (WWW’14) |
|-----------------|---------------|--------------------|----------------|--------------------|
| wasBornIn       | 0.75          | 2                  | 0.67           | 8                  |
| hasChild        | 0.24          | 2                  | 0.18           | 8                  |
| isMarriedTo     | 0.52          | 3                  | 0.50           | 8                  |
| isCitizenOf     | 0.45          | 3                  | 0.93           | 32                 |

In previous work [16], West et al. designed their own question templates and employed an in-house question answering system. They didn’t provide their templates or their benchmark datasets.

In their experiments, they evaluated top search entities on Google.com, while we used randomly selected entities. We compare the KBC performance of WebQA on our benchmarks with their results for 4 relations, wasBornIn, hasChild, isMarriedTo and isCitizenOf. The results are shown in Table 2.

For three relations wasBornIn, hasChild and isMarriedTo, our system can achieve better performance than previous work [16] with much fewer questions, although we evaluated randomly selected entities. The performance gain is due to a few reasons. First, we design better templates and a better template selection algorithm than previous work, as discussed in Section 4. Second, we fuse information from both the unstructured text and structured knowledge bases to design features, while previous work only uses textual information to rank candidate answers. Only for relation isCitizenOf, our system fails to match previous work. The possible reason is, previous work [16] evaluated popular entities on the Web, while the entities we tested were more likely to be rare entities, which don’t have a lot of information for isCitizenOf. Even though with randomly selected entities, WebQA achieves better performance with much fewer questions than previous work [16] for wasBornIn, hasChild and isMarriedTo. So we can expect under the same circumstances, WebQA should achieve (much) better performance than WWW’14.

4.2.3 Performance with Snippet Filtering. To reduce the number of snippets for processing, we apply query-driven snippet filtering to select useful snippets which most likely contain relevant information to queries. While improving system efficiency, we want to demonstrate through experiments, selecting a subset of the snippets by query-driven snippet filtering does not cause severe loss of answer ranking quality. So we conducted a few experiments with different numbers of snippets and compare their KBC performance with experiments using all snippets and previous work [16]. The results are shown in Table 3.

The performance of WebQA using snippet filtering with 10, 20 or 30 snippets decreases very little compared to using all snippets, with less than 0.04 loss in MAP. And for relation hasChild, our system achieves the same MAP with 30 snippets as all snippets. Compared to previous work [16], WebQA still achieves better performance for relation wasBornIn, isMarriedTo and hasChild after using snippet filtering.

4.3 Efficiency

In our KBC system, we employ a few query-driven approaches to improve the efficiency of WebQA. Previous work [13, 16] built batch-oriented QA systems without query-driven optimization, which cannot provide fast responses to user queries. They didn’t provide runtime results of their systems for our system to compare with, and they didn’t focus on the runtime of a single query.

To evaluate the efficiency of our system, the experiments were run on a single machine with a 3.1GHz four-core CPU and 4GB memory. The system runtime varies with multiple environment factors such as network congestion and server speed. So we calculated average runtime through extensive experiments with multiple queries.

The bottleneck of WebQA is data collection and answer extraction, which involve web searches and server inquiries. First, we need to wait for responses from web servers after issuing queries to them. Second, when we issue multiple queries in parallel to web servers, there is a considerable delay at the server side to process all queries.

A sequential WebQA pipeline usually costs a few minutes to finish. So we employed multithreading to parallelize snippet crawling and entity linking to reduce the time waiting for responses from search engines and TagMe. A parallelized pipeline achieves about 10x speedups compared to a sequential pipeline. However, parallelization alone cannot provide fast responses to user queries, because too many queries are issued simultaneously, causing long network and server-side delays.

Figure 3: The average runtime of WebQA with different numbers of questions for relation isCitizenOf.
Table 3: KBC performance of WebQA with snippet filtering for different numbers of snippets. Performance is measured by MAP.

| Relation     | 10 snippets | 20 snippets | 30 snippets | All snippets | WWW'14 |
|--------------|-------------|-------------|-------------|--------------|--------|
| wasBornIn    | 0.70        | 0.71        | 0.70        | 0.75         | 0.67   |
| hasChild     | 0.21        | 0.21        | 0.24        | 0.24         | 0.18   |
| isMarriedTo  | 0.48        | 0.50        | 0.51        | 0.52         | 0.50   |
| isCitizenOf  | 0.39        | 0.40        | 0.41        | 0.45         | 0.93   |

4.3.1 Template Selection. Experimental results for evaluating the runtime of WebQA with different numbers of questions for relation isCitizenOf are shown in Figure 3. The results for other relations are similar to isCitizenOf. From Figure 3, the runtime of WebQA grows almost linearly as the number of questions increases. With more questions, WebQA has more snippets to process and entity linking on a lot of snippets is very time-consuming. Since our system needs much fewer questions compared to previous work [16], it is definitely more efficient under the same circumstances.

4.3.2 Snippet Filtering. Query-driven snippet filtering is conducted to further improve the runtime by reducing the number of snippets. Experimental results of our system using snippet filtering with different numbers of snippets for relation wasBornIn are shown in Table 4. Other relations have similar results. With 3 questions, we need to crawl up to $3 \times 50 = 150$ snippets per query. Using snippet filtering, we can reduce the number of snippets from 150 to 20/30 without too much quality loss as shown in Table 3. With the number of snippets increasing beyond 30, the server-side delay grows very fast. The runtime is about 3 seconds when the number of snippets decreases to 20/30, which is about 25% of the time when using all snippets. In conclusion, WebQA can provide fast responses to user queries, since it only spends a few seconds for each query.

Table 4: Average runtime of WebQA using snippet filtering for relation wasBornIn with 3 questions.

| Snippet number | 10   | 20   | 30   | 50   | 100  | 150  |
|----------------|------|------|------|------|------|------|
| Time (seconds) | 2.7  | 3.1  | 3.2  | 4.1  | 7.7  | 12.4 |

5 CONCLUSIONS

In this paper, we design and implement a web-based question answering (WebQA) system to extract missing facts from the unstructured Web with effective question templates and multimodal features, which can achieve better performance with fewer questions than previous work. To improve efficiency, we employ a set of query-driven techniques to reduce the runtime on-the-fly and provide fast responses to user queries. Extensive experiments have been conducted to demonstrate the effectiveness and efficiency of our system. For the future work, we plan to combine both question answering and rule inference via multimodal knowledge graphs to further improve knowledge base completion quality.

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