First-order Knowledge Graph Question Answering for Unseen Domains

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Abstract

Knowledge Graph Question Answering (KGQA) for first-order questions, in its standard form, does not take into account that human-curated training data only cover a small subset of the relations that exist in a Knowledge Graph (KG), or even worse, that new domains covering unseen and rather different to existing domains relations are added to the KG. In this work, we study KGQA for first-order questions in a previously unstudied setting where new, unseen, domains are added during test time. In this setting, question-answer pairs of the new domain do not appear during training, thus making the task more challenging. We propose a data-centric domain adaptation framework that consists of a KGQA system that is applicable to new domains, and a sequence to sequence question generation method that automatically generates question-answer pairs for the new domain. Since the effectiveness of question generation for KGQA can be restricted by the limited lexical variety of the generated questions, we use distant supervision to extract a set of keywords that express each relation of the unseen domain and incorporate those in the question generation method. Experimental results demonstrate that our framework significantly improves over zero-shot baselines and is robust across domains.

1. Introduction

Large-scale structured Knowledge Graphs (KGs) such as Freebase [Bollacker et al., 2008] and Wikidata [Pellissier Tanon et al., 2016] store real-world facts in the form of subject–relation–object triples. KGs are being increasingly used in a variety of tasks that aim to improve user experience [Bota et al., 2016]. One of the most prominent tasks is Knowledge Graph Question Answering (KGQA), which aims to answer natural language questions by retrieving KG facts [Yih et al., 2015]. In practice, many questions can be interpreted by a single fact in the KG. This has motivated the first-order KGQA task [Bordes et al., 2015, Mohammed et al., 2018, Petrochuk and Zettlemoyer, 2018], which is the focus of this paper. In first-order KGQA, given a question, e.g. “what type of music do the smiths make?”, the system should interpret the question and arrive at a single KG fact that answers it: (The Smiths, music.artist.genre, Alternative Rock).
First-order KGQA systems are trained on manually annotated datasets that consist of question-fact pairs. In practice, the applicability of such systems in the real-world is limited by two factors: (i) modern KGs store millions of facts that cover thousands of different relations, but first-order KGQA training datasets can only cover a small subset of the existing relations in the KG [ElSahar et al., 2018], and (ii) KGs are dynamic, i.e. they are updated with new domains that cover new relations [Pellissier Tanon et al., 2016]. Solving (i) and (ii) by exhaustively gathering question-fact pair annotations would be prohibitively laborious, thereby we need to rely on automatic methods.

Motivated by the above, in this work, we study the first-order KGQA task in a setting where we are interested in answering questions about a new, unseen domain that covers relations, for which we have instances in the KG, but we have not seen any question-fact pair during training. We model this as a domain adaptation task [Mansour et al., 2009, Pan and Yang, 2010] and propose a data-centric domain adaptation framework to address it. Data-centric domain adaptation approaches focus on transforming or augmenting the training data, instead of designing specialized architectures and training objectives as model-centric domain adaptation approaches do [Chu and Wang, 2018]. Our framework consists of: (a) a KGQA system which can handle the unseen domain, and (b) a novel method that generates training data for the unseen test domain.

The KGQA system we introduce performs mention detection, entity candidate generation and relation prediction on the question, and finally selects the fact that answers the question from the KG. To improve relation prediction on questions that cover relations of the unseen domain, we automatically generate synthetic questions from KG facts of the unseen domain (i.e. knowledge graph question generation – QG). The resulting synthetic question-fact pairs are used to train the KGQA system for the unseen domain. We find that the effectiveness of QG for KGQA can be restricted not only by the quality of the generated questions, but also by the lexical variety of the questions. This is because users ask questions underlying the same relation using different lexicalizations (e.g. “who is the author of X”, “who wrote X”). To address this, we use distant supervision to extract a set of keywords for each relation of the unseen domain and incorporate those in the question generation method.

Our main contributions are the following: (i) we introduce a new setting for the KGQA task, over new, previously unseen domains, (ii) we propose a data-centric domain adaptation framework for first-order KGQA that is applicable to unseen domains, and (iii) we use distant supervision to extract a set of keywords that express each relation of the unseen domain and incorporate them in QG to generate questions with a larger variety of relation lexicalizations. We experimentally evaluate our proposed method on a large-scale first-order KGQA dataset that we adjust for this task and show that our proposed method consistently improves performance over zero-shot baselines and is robust across domains.\(^1\)

2. Problem Statement

Let \( E \) denote the set of entities and \( R \) the set of relations. A KG \( K \) is a set of facts \((e_s, r, e_o)\), where \( e_s, e_o \in E \) are the subject and object entities respectively, and \( r \in R \) is the relation between them. Each relation \( r \) has a unique textual label \( r_l \) and falls under a

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\(^1\) The code for reproducing all the experiments will be made publicly available upon acceptance.
single domain $D$ (each $D$ covers a subset of $R$). For instance, music.album.release.type and music.artist.genre fall under the Music domain. First-order questions mention a single entity and express a single relation. For instance, the question “what type of music do the smiths make?” mentions the entity “The Smiths” and expresses the relation music.artist.genre.

Given a first-order question $q$ that consists of a sequence of terms $t_1, t_2, \ldots, t_T$, the KGQA task is to retrieve a fact $(\hat{e}_s, \hat{r}, \hat{e}_o)$, where $(\hat{e}_s, \hat{r})$ accurately interprets $q$ (i.e., $\hat{e}_s$ is mentioned in $q$ and $\hat{r}$ is expressed in $q$) while $\hat{e}_o$ provides the answer to $q$. In our setting, we aim to build a first-order KGQA system that can perform well on a previously unseen domain. A domain is “unseen” when facts that cover relations of that domain do exist in $K$, but gold-standard question-fact pairs of that domain do not appear in the training data. This setting is an instance of domain adaptation, where a model is trained on data $S$, which is drawn according a source distribution, and tested on data $T$ coming from a different target distribution. Domain adaptation over KG domains is more challenging compared to domain adaptation over single KG relations [Yu et al., 2017, Wu et al., 2019], because it is less likely for relations with similar lexicalizations to appear in the training set.

3. First-order KGQA system

In this section, we detail our KGQA system for first-order questions. In Section 4, we will describe how we generate synthetic training data to make this system applicable to unseen domains. Following current state-of-the-art in first-order KGQA [Petrochuk and Zettlemoyer, 2018], we split the task into four sub-tasks, namely, entity mention detection (MD), entity candidate generation (CG), relation prediction (RP), and answer selection (AS). The skeleton of our KGQA system generally follows previous work, and we modify the MD and RP architectures.

Mention Detection (MD)  Given the question $q$, MD outputs a single entity mention $m$ in $q$, where $m$ is a sub-sequence of tokens in $q$. We model this problem as sequence tagging, where given a sequence of tokens, the task is to assign an output class for each token [Huang et al., 2015, Lample et al., 2016]. In our case, the output classes are entity (E) and context (C). For instance, the correct output for the question “where was walter chrysler born?” is “[C C E E C]”. We use a BiLSTM with residual connections (R-BiLSTM) [He et al., 2016], since it outperformed vanilla RNN, BiRNN, and a CRF on top of a BiRNN [Petrochuk and Zettlemoyer, 2018] in preliminary experiments.

Candidate Generation (CG)  Given the mention $m$ extracted from the previous step, CG maps $m$ to a set of candidate entities $C_S \subset E$. For instance, CG maps the mention “obama” to the entities { Barack Obama, Michelle Obama, \ldots}. The CG method we use was proposed in Türe and Jojic [2017]. Briefly, the method pre-builds an inverted index $I$ from n-grams of mentions to entities, and it looks-up the n-grams of $m$ in $I$ to obtain $C_S$.

Relation Prediction (RP)  Given the question $q$ and the set of entities $C_S$ extracted in the previous step, RP outputs a single relation $\hat{r} \in R$ that is expressed in $q$. Previous work models RP as a large-scale multi-label classification task where the set of output classes is fixed [Petrochuk and Zettlemoyer, 2018]. In our domain adaptation scenario, however, we want to be able to predict relations that we have not seen during training. Therefore, we model RP as a relation ranking task, as in [Yu et al., 2017], and use the textual label
to represent the relation $r$ (instead of using a categorical variable). This way we can in principle represent any relation $r \in R$ during inference time. Below we describe the architecture we use for RP and how we perform training and inference. Our architecture is a simpler version of [Yu et al., 2017], where they model a relation both as a sequence and a categorical variable, and they use more complex sequence encoders.

First we describe how we encode the question $q$ and the relation $r$. In order to generalize beyond specific entity names, we first replace the previously detected entity mention $m$ in $q$ with a placeholder token. We then map each term to its embedding and feed the word embeddings to an LSTM; embeddings are initialized with pretrained word2vec embeddings [Mikolov et al., 2013]. The final hidden state of the LSTM is used as the encoding of the question. In order to represent $r$, we use its label $r_t$ (e.g. music.artist.label). Similarly with the question encoding, we encode $r_t$ with an LSTM to obtain $\gamma^{(r)}$. However, since questions and relations significantly differ both grammatically and syntactically, the two LSTM encoders do not share any parameters. The ranking function $f$ is calculated as $f(q,r) = \cos(\gamma^{(q)}, \gamma^{(r)})$, where $\cos(\cdot)$ is the cosine similarity.

We train $f$ using standard pairwise learning to rank. The loss is defined as follows:

$$L(\theta) = \sum_r \sum_{r' \in R'} \max(0, \mu - f(q,r) + f(q,r')),$$

where $\theta$ are the parameters of the model, $\mu$ is a hyperparameter, and $R'$ is the set of sampled negative relations for a question $q$. We design a specialized negative sampling method to select $R'$. With probability $P_R^-$ we uniformly draw a sample from $R^- = \{r'|r' \in R \land r' \neq r\}$; the set of all available relations except the positive relation $r$. With probability $1 - P_R^-$ we draw a random sample from $\hat{R}^- = \{r'|r' \in D_R^+ \land r' \neq r\}$; the set of relations that are in the same domain as the positive relation $r$. This way, we expose the model to conditions it will encounter during inference.

At inference time, given a question $q$ and a set of relations we score all question-relation pairs $(q,r)$ with $f$ and select the relation $\hat{r}$ with the highest score. Unfortunately, computing a score with respect to all possible relations in $R$ leads to poor performance when there is no linguistic signal to disambiguate the choice. In order to address this issue, we constrain the set the potential output relations $R_c$ to be the union of the relations expressed in the facts where the entities in $C_S$ participate in [Petrochuk and Zettlemoyer, 2018]. Formally, we define the target relation classes to be $R_c = \{r \in R | (e_s, r, e_o) \in K \land e_s \in C_S\}$.\(^2\)

**Answer Selection (AS)** Given the set of entities $C_S$ obtained from CG, and the top ranked relation $\hat{r}$ obtained from RP, AS selects a single fact $(\hat{e}_s, \hat{r}, \hat{e}_o)$, where $\hat{e}_o$ answers the question $q$. The set of candidate answers may contain more than one facts $(e'_s, \hat{r}, e'_o)$, where $\forall e'_s \in C_S$. Since there is no explicit signal on which we can rely to disambiguate the choice of subject, all the potential answers are equally probable. We therefore use a heuristic based on popularity [Mohammed et al., 2018]: we choose $\hat{e}_s$ to be the entity that appears in the most facts in $K$ either as a subject or as an object. Having $\hat{e}_s$ and $\hat{r}$ we can retrieve the fact $(\hat{e}_s, \hat{r}, \hat{e}_o)$.

\(^2\) For instance, given the question “what position does Lionel Messi play?” we can safely ignore the relation basketball.basketball_position.players by taking into account that Lionel Messi does not appear in any basketball-related facts.
4. KGQA to unseen domains using question generation

Even though all the components of the aforementioned KGQA system were designed to work with unseen domains, preliminary experiments demonstrated that RP does not generalize well to questions originating from unseen domains. This is expected since RP is a large-scale problem (thousands of relations), and it is very challenging to model less frequent or even unknown relations that are expressed with new lexicalizations.

We therefore focus on improving RP for questions originating from unseen domains. Inspired from the recent success of data-centric domain adaptation in neural machine translation [Chu and Wang, 2018], we perform synthetic question generation from KG facts of the unseen domain to generate question-fact pairs for training the RP component (see Section 3).

In the remainder of this section we briefly describe the base question generation (QG) model we build upon and how we augment the model to more effectively use textual evidence and thus better generalize to relations of the unseen domain.

4.1 Base model for QG

Given a fact \((e_s, r, e_o)\) from the target domain, QG aims to generate a synthetic question \(\hat{q}\). During training, only question-fact pairs from the known domains are used. Our base model is the state-of-the-art encoder-decoder architecture for QG which we briefly describe below [ElSahar et al., 2018]. It takes as input the fact \((e_s, r, e_o)\) alongside with a set of textual contexts \(C = \{c_s, c_r, c_o\}\) for the fact. Those textual contexts are obtained as follows: \(c_s\) and \(c_o\) are the types of entities \(e_s\) and \(e_o\) respectively, whereas \(c_r\) is a lexicalization of the relation \(r\) obtained by simple pattern mining on Wikipedia sentences that contain instances of \(r\). For instance, given the fact \((\text{The Queen Is Dead}, \text{music.album.genre}, \text{Alternative Rock})\), the textual contexts are: \(c_s = \{\text{“album”}\}, c_r = \{\text{“album by”}\} \text{ and } c_o = \{\text{“genre”}\} \).

The encoder maps \(e_s, r\) and \(e_o\) to randomly initialized embeddings and concatenates those to obtain the encoding of the whole fact. Also, it encodes the text in \(c_s, c_r\) and \(c_o\) separately using RNN encoders. The decoder is a separate RNN that takes the representation of the fact and the RNN hidden states of the textual contexts to generate the output question \(\hat{q}\). It relies on two attention modules: one over the encoded fact and one over the encoded textual contexts. The decoder generates tokens not only from the output vocabulary but also from the input (using a copy mechanism) to deal with unseen input tokens.

4.2 Using Richer Textual Contexts for QG

The role of the textual contexts \(C\) in the aforementioned base model is critical, since it enables the model to provide new words/phrases that would have been unknown to the model otherwise [ElSahar et al., 2018]. Even though the base model generally generates high quality questions, in our task (KGQA), we aim to generate a larger range of lexicalizations for a single relation during training in order to generalize better at test time. This is because users with the same intend may phrase their questions using different lexicalizations (e.g.

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3. Note that Dong et al. [2017] also performed QG for improving the overall KGQA performance. However, their model is not applicable to our domain adaptation scenario since their model relies on modifying existing questions and all domains were predefined.
Table 1: Examples of relation textual contexts extracted by our keyword extraction approach.

<table>
<thead>
<tr>
<th>Relation</th>
<th>Textual Context</th>
</tr>
</thead>
<tbody>
<tr>
<td>music.artist.label</td>
<td>records, artists, album, released, label, signed, band</td>
</tr>
<tr>
<td>film.film.directed</td>
<td>film, director, directed, films, short, directing, producer</td>
</tr>
<tr>
<td>people.deceased_person.place_of_death</td>
<td>died, death, deaths, born, age, people, male, actors</td>
</tr>
</tbody>
</table>

“who is the author of X”, “who wrote X”). Thus, in this section we focus on how to provide the model with a diverse set of lexicalizations for a relation \( r \) instead of a single one as in the base model, in order to be able to generate a more diverse set of questions in terms of relation lexicalizations. More precisely, given a relation \( r \), we create a extract of \( k \) keywords that will constitute the relation’s textual context \( c_r \). To this end, we first extract a set of candidate sentences \( S_r \) that express a specific relation \( r \) between different pairs of entities. Second, we extract keywords from the set \( S_r \), rank them and select the top-\( k \) keywords that constitute the set \( c_r \). We detail each of these steps below.

**Extracting sentences** Given a set of facts \( F_r \) of relation \( r \) between different pairs of entities, we aim to create a set of sentences \( S_r \), where each sentence \( s \in S_r \) expresses a single fact \( (e_s, r, e_o) \) in \( F_r \). For this, for each fact \( (e_s, r, e_o) \) in \( F_r \), we need to (a) extract a set of candidate sentences \( S \) that might express \( (e_s, r, e_o) \) and (b) select the sentence that best expresses the relation. For (a), we collect the set of sentences \( S \) using distant supervision, similarly to [Mintz et al., 2009]: \( S \) consists of sentences that mention \( e_o \) in the Wikipedia article of \( e_s \) and sentences that mention \( e_s \) in the Wikipedia article of \( e_o \). For (b), we score each sentence \( s \in S \) w.r.t. the label \( r_l \) of the relation \( r \) using the cosine similarity \( \cos(e(s), e(r_l)) \), where \( \cos(\cdot) \) is the cosine similarity and \( e(x) \) is calculated as \( e(x) = (1/|x|) \sum_{t \in x} w_t \), where \( w_t \) is the embedding of word \( t \). Finally, we take the sentence \( s' \) with the highest score and add it to the set \( S_r \).

**Extracting keywords** After extracting the set of sentences \( S_r \), we aim to extract the set of keywords \( c_r \). For this, we treat \( S_r \) as a single document and score each word \( t \) that appears in \( S_r \) using tf-idf, \( \text{score}(t) = \text{tf}(t, S_r) \cdot \text{idf}(t, S_R) \), where \( S_R \) is the union of all \( S_{r', r' \in R} \). The top-\( k \) scoring words constitute the set of keywords \( c_r \). Table 1 depicts example keywords generated by the procedure described above.

The keyword extraction approach described above is conceptually simple yet we later show that it significantly improves upon the base model when applied to KGQA.

5. Experimental Setup

In this section, we discuss how we design the experiments to answer the following research questions: **RQ1** How does our method for generating synthetic training data for the unseen domain perform on RP compared to a set of baseline methods? **RQ2** How does our full method perform on first-order KGQA for unseen domains compared to state-of-the-art zero-shot data-centric methods? **RQ3** How does our data-centric domain adaptation method compare to a state-of-the-art model-centric method on RP?
Dataset In our experiments we use the SimpleQuestions dataset, which is an established benchmark for studying first-order factoid KGQA [Bordes et al., 2015]. The dataset consists of 108,442 questions written in natural language by human annotators, paired with the ground truth fact that answers the question. The ground truth facts originate from Freebase [Bollacker et al., 2008]. The dataset covers 89,066 unique entities, 1,837 unique relations and 82 unique domains. In our setup, we leave one domain out to simulate a new, previously unseen domain, and train on the rest. We choose six challenging domains as target domains: Film, Book, Location, Astronomy, Education and Fictional Universe; the first three are among the largest domains and the last three are medium-sized. The aforementioned domains are challenging because they have very low overlap in terms of relation lexicalization w.r.t. the rest of the domains used as source domains. The training data consists of the question-fact pairs that appear in the source domains, augmented with synthetically generated data of the target/unseen domain. In practice, we replace all questions from the target domain that initially appear in the full training set with their corresponding synthetically generated questions.

Baselines To answer RQ1, we keep the KGQA system unchanged and alternate the way of generating synthetic questions. We compare the RP performance on the unseen domain given the following ways of generating synthetic data of the unseen domain: (i) No synthetic data, (ii) Wiki-raw-sentences: uses the raw Wikipedia sentence that expresses the ground truth fact that answers the question (automatically extracted using the procedure in Section 4.2), and (iii) the state-of-the-art QG method proposed in ElSahar et al. [2018]. To answer RQ2, we replace our RP component with two state-of-the-art RP models: (i) Petrochuk and Zettlemoyer [2018], which uses a BiLSTM to classify relations, and (ii) Yu et al. [2017], a zero-shot RP model that uses a HR-BiLSTM and is specifically designed to deal with unseen or less frequently seen relations. To answer RQ3, we compare the performance of our data-centric model on RP against a state-of-the-art model-centric zero-shot approach [Wu et al., 2019]: it the HR-BiLSTM proposed by Yu et al. [2017] with an adversarial adapter combined and a reconstruction loss. The adapter uses embeddings trained on Freebase and Wikipedia by JointNRE [Han et al., 2018] and learns representations for both seen and unseen relations.

Evaluation metrics We run the experiments three times and report the median (only marginal and not significant differences were found among different runs) [Mohammed et al., 2018]. In contrast to the classic KGQA where the task is to retrieve a single entity, it is standard practice when using the SimpleQuestions dataset to treat the problem as question interpretation [Petrochuk and Zettlemoyer, 2018]. More specifically, the objective is to rewrite the natural language question in the form of subject-relation pair. We evaluate our overall approach in terms of top-1 accuracy, i.e. whether the retrieved subject-relation pair matches the ground truth. We measure accuracy both at a macro- (domains) and at a micro-level (samples). Statistical significance is determined using a paired two-sided t-test.

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4. One may hypothesize that since entities can appear in multiple domains (e.g. actors who are also singers), question generation becomes an unrealistically simple task. However, this is not the case because in our dataset, the entity overlap between seen and unseen domains is only 4.6%.
Table 2: Relation Prediction accuracy w.r.t. different ways of generating synthetic training data for the unseen domain. ▲ indicates a significant increase in performance compared to the top performing baseline ($p < 0.01$).

<table>
<thead>
<tr>
<th>Synthetic training data</th>
<th>Macro-avg. Accuracy (%)</th>
<th>Micro-avg. Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>30.21</td>
<td>29.06</td>
</tr>
<tr>
<td>Wiki-raw-sentences</td>
<td>37.89</td>
<td>36.51</td>
</tr>
<tr>
<td>QG [ElSahar et al., 2018]</td>
<td>67.52</td>
<td>69.78</td>
</tr>
<tr>
<td>QG (Ours)</td>
<td>69.86▲</td>
<td>70.95▲</td>
</tr>
</tbody>
</table>

6. Results and Discussion

In this section we present and discuss our experimental results. All the models used in this section have all their components fixed, except RP. Therefore, any improvement observed, is due to RP. The hyperparameters of our model and the baselines can be found in Appendix B.

Effect of synthetic data on RP To answer RQ1, we compare the RP performance of our method for generating synthetic training data with a set of baselines. For this experiment, the RP component of the KGQA system remains unchanged and we only alter the data it is trained with. Table 2 shows the results. We observe that our QG method is the best performing one. It significantly outperforms the baseline QG method, which confirms that our method for generating rich textual contexts for relations (Section 4.2) is beneficial for KGQA. As expected, Wiki-raw-sentences performs better than when not using training data from the target domain at all but performs much worse than the QG methods. This is expected since Wikipedia sentences are very different both syntactically and grammatically from the real questions that the KGQA system encounters during test time.

Overall KGQA performance for data-centric methods Next, to answer RQ2, we compare our full framework to variations that use state-of-the-art RP models. Table 3 shows the results. We observe that our full method (second to last row) improves over all the baselines and significantly outperforms the best performing baseline. As expected, we see that even though our full method holds strong generalization ability for unseen domains, there is a gap in the performance when using the automatically generated synthetic questions (second to last row) or the human generated questions (last row). This gap suggests that there is room for improvement for QG. Next, we test the systems under comparison in terms of generalization ability across domains. Figure 1 shows results. First, we observe that our method achieves an accuracy of at least 60% for all domains which shows that it is robust across domains. Also, it outperforms the baselines in all but one domain. In order to gain further insights, we sampled success and failure cases from the test set. We found that the errors in the failure cases generally originate from the fact that the model relies on lexicalizations that are frequent in the seen domains. We show such cases in Appendix Table 4. Furthermore, our analysis showed that one way of improving QG is to improve
Table 3: End-to-end accuracy on the KGQA task. ▲ indicates a significant increase in performance compared to the top performing baseline \((p < 0.01)\). Also, † is for ElSahar et al. [2018], ‡ for Petrochuk and Zettlemoyer [2018], and ⋆ for Yu et al. [2017].

<table>
<thead>
<tr>
<th>Synthetic training data</th>
<th>Relation Prediction (RP)</th>
<th>Macro-avg. Accuracy (%)</th>
<th>Micro-avg. Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>QG † BiLSTM ‡</td>
<td></td>
<td>55.49 55.11</td>
<td></td>
</tr>
<tr>
<td>QG ⋆ HR-BiLSTM</td>
<td></td>
<td>60.20 62.77</td>
<td></td>
</tr>
<tr>
<td>Ours</td>
<td></td>
<td>63.90 65.18</td>
<td></td>
</tr>
<tr>
<td>QG (Ours) Ours</td>
<td></td>
<td>66.49* 66.64▲</td>
<td></td>
</tr>
<tr>
<td>Gold Questions Ours</td>
<td></td>
<td>84.56 82.87</td>
<td></td>
</tr>
</tbody>
</table>

Figure 1: End-to-end accuracy on the KGQA task per domain.

keyword extraction by collecting a larger set of relevant sentences that express a single relation, possibly by looking into other sources of text (e.g. news articles).

Comparison to a model-centric method To answer RQ3, we compare our data-centric method for domain adaptation to a state-of-the-art model-centric method on RP [Wu et al., 2019]. In order to perform a fair comparison when testing for RP, we follow their setup (see Section 5.1. in [Wu et al., 2019]) and for this particular experiment we assume that MD and CG produce the correct output. Our method outperforms their method both on macro-accuracy (75.54% vs 75.02%), and micro-accuracy (77.08% vs 72.17%). Note that we use randomly initialized embeddings whereas in their work they use JointNRE relation embeddings trained on Wikipedia and Freebase, which provides an advantage to their method. Also note that their method (model-centric) is orthogonal to ours (data-centric) and therefore, an interesting future work direction would be to explore how to combine the two methods to further improve performance.
KGQA performance on seen domains  Finally, even though the focus of this paper is to perform KGQA on unseen domains and thus we do not aim to improve state-of-the-art on seen domains, we also test our KGQA system on the standard split of the SimpleQuestions dataset. Our model achieves an accuracy of 77.02%, which is ranked third among the state-of-the-art methods [Petrochuk and Zettlemoyer, 2018, Gupta et al., 2018], while having a simpler method than the top-performing ones.\footnote{Note that Zhao et al. [2019] reported an accuracy of 85.44%. However, they calculate accuracy w.r.t. the correctness of the object entity, which is not standard when testing on the SimpleQuestions dataset (see Section 5). If we calculate accuracy that way, [Petrochuk and Zettlemoyer, 2018] achieves an accuracy of 91.50% and our method achieves 87.31%.}

7. Related Work

Methods on first-order KGQA are split into two categories, specifically, those following an end-to-end and those following a pipeline approach (MD, CG, RP & AS). Following a pipeline approach, Türe and Jojic [2017] modeled MD with a BiLSTM and RP with a BiGRU. Mohammed et al. [2018], provided a detailed examination of various neural and non-neural baselines for MD, and RP. Petrochuk and Zettlemoyer [2018] used a CRF tagger on top of a BiLSTM for MD and a BiLSTM for RP. They increased performance on RP by using a constraint, which we also use in Section 3. Yu et al. [2017] only examined RP, from a zero/few-shot point of view, and followed a sequence matching and ranking approach in order to deal with unseen relations. We showed that we outperform their method on RP while using a simpler model. On the other end of the spectrum, Lukovnikov et al. [2017] trained their model in an end-to-end manner. Their model learns to rank subject-relation pairs via an encoding network that scores question-entity and question-relation pairs. Similarly, Gupta et al. [2018], directly rank entity-relation pairs against a question. We leave the exploration of end-to-end approaches for our task for future work.

Concerning domain adaptation for first-order KGQA, Wu et al. [2019] proposed a model-centric approach to tackle RP for unseen single relations. We experimentally showed that our proposed framework outperforms theirs for the setting of first-order KGQA for unseen domains.

8. Conclusion

In this paper, we proposed a data-centric domain adaptation framework for first-order KGQA that is applicable to unseen domains. Our framework performs QG to automatically generate synthetic training data for the unseen domains. We propose a keyword extraction method that when integrated in our QG model, it allows it to generate questions of various lexicalizations for the same underlying relation, thus better resembling the variety of real user questions. Our experimental results on the SimpleQuestions dataset show that our proposed framework significantly outperforms state-of-the-art zero-shot baselines, and is robust across different domains. We found that there is room for further improving QG particularly for KGQA, which is a promising direction for future work.
References


Appendix A. Synthetic Questions Examples

In the table below we present examples of success and failure cases of our QG method.

Table 4: Examples of success cases (top 2 rows) and failure cases (bottom 2 rows) of our QG method.

<table>
<thead>
<tr>
<th>Unseen Domain</th>
<th>Gold Questions</th>
<th>Synthetic Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Astronomy</td>
<td>what is something that carolyn shoemaker discovered</td>
<td>what is the astronomical objects discovered by carolyn shoemaker</td>
</tr>
<tr>
<td>Book</td>
<td>what’s the subject of the cognitive brain</td>
<td>what is the subjects of the written work the cognitive brain</td>
</tr>
<tr>
<td>Film</td>
<td>in what country did the film joy division take place</td>
<td>what country is joy division under</td>
</tr>
<tr>
<td>Book</td>
<td>who authored the book honor thyself</td>
<td>who was the director of the book honor thyself</td>
</tr>
</tbody>
</table>

Appendix B. Parameter configurations

We initialize word embeddings with pretrained 300-dimensional Google News embeddings [Mikolov et al., 2013]. We use the Adam optimizer [Kingma and Ba, 2014]. Our MD model consists of 2 hidden layers, 200 hidden units, 0.5 dropout rate, frozen embeddings, and learning rate of $10^{-3}$; 20 training epochs. For the RP model, we use 1 layer encoder for both questions and relations that consists of 400 hidden units, with a frozen embedding layer, and a learning rate of $10^{-3}$; trained for 10 epochs. Additionally, for training this model, we sample 10 negative questions per question using the procedure described in Section 3. We use a batch size of 200 for both models. For the QG model [ElSahar et al., 2018] and the model-centric RP [Wu et al., 2019] model we compare against, we use the hyperparameters as presented in their work. Note that for both our method and the baselines, the hyperparameters were tuned on the initial split of the SimpleQuestions dataset. We keep the parameters fixed for both our method and the baselines for all source-target domain setups. We set the number of keywords for each relation $k = 10$ (Section 4.2).