Program Transfer and Ontology Awareness for Semantic Parsing in KBQA

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Abstract

Semantic parsing in KBQA aims to parse natural language questions into logical forms, whose execution against a knowledge base produces answers. Learning semantic parsers from question-answer pairs requires searching over a huge space of logical forms for ones consistent with answers. Current methods utilize various prior knowledge or entity-level KB constraints to reduce the search space. In this paper, we investigate for the first time prior knowledge from external logical form annotations and ontology-level constraints. We design a hierarchical architecture for program transfer, and propose an ontology-guided pruning algorithm to reduce the search space. The experiments on ComplexWebQuestions show that our method improves the state-of-the-art F1 score from 44.0% to 58.7%, with an absolute gain of 14.7%, which demonstrates the effectiveness of program transfer and ontology awareness.

1 Introduction

Semantic parsing in Knowledge Base Question Answering (KBQA) aims to parse natural language questions (utterances) into logical forms (e.g., λ-calculus (Zettlemoyer and Collins, 2005), query graph (Yih et al., 2015), program (Liang et al., 2017)), whose execution against a knowledge base (KB) produces the answers (denotations). It has emerged as a promising technique to provide interpretable access to KBs (Berant et al., 2013).

Early works focus on semantic parsing from annotations (Zettlemoyer and Collins, 2005; Dong and Lapata, 2016), which learn semantic parsers from the pairs of question and logical form. The primary limitation is that collecting logical forms requires expensive expert annotation. This has led to a body of work on semantic parsing from denotations (Yih et al., 2015; Liang et al., 2017), which learns semantic parsers only from question-answer pairs. This line of work poses two unique challenges as follows:

Prior Knowledge Utilization. Without explicit supervision, prior knowledge is required to guide the learning process, e.g., neural program induction methods inject hand-crafted rules (Ansari et al., 2019) or knowledge linking (Liang et al., 2017; Saha et al., 2019) when translating the question to a multi-step executable program. However, such prior knowledge is usually lacking or requires manual analysis. Recently, there emerge several valuable annotated resources, and how to utilize the prior knowledge from these external annotations remains an open question.

KB Constraints Exploitation. Diverse language expressions and large-scale KBs require the semantic parser to search in a huge search space. KB constraints are often employed to prune the search space, e.g., query graph generation (Yih et al., 2015; Lan and Jiang, 2020) grows a query graph that resembles subgraphs of the KB, naturally incorporating the KB constraints. However, current works only consider entity-level knowledge, ignoring to fully exploit the KB with the ontology-level knowledge, i.e., constraints over abstract concepts and
relations, which provides a high-level summary for the entity-level triples (Hao et al., 2019).

In this paper, we expect to exploit prior knowledge from external annotations and constraints from KB ontology for semantic parsing from denotations. Recently, a program annotation resource KQA Pro (Shi et al., 2020) is released. As illustrated in Figure 1, KQA Pro defines program as the composition of symbolic functions that are designed to perform basic operations on KBs. The composition of functions well captures the language compositionality (Baroni, 2019), and the functions are atomatic and general, making it possible to perform tranfer. Therefore, We take KQA Pro as the external annotations to conduct program transfer accross KBs. Nevertheless, the heterogeneity of KBs needs to be well addressed in the transfer. For the ontology constraints, which types of constraints should be considered and how to incorporate them into the program induction also need investigation.

As shown in Figure 1, program can be abstracted to a sketch (Solar-Lezama, 2009) by decoupling detailed arguments. Translation from questions to sketches is only relevant to language compositional structure, thus is general across KBs. Guided by the question and sketch, arguments can be retrieved from the KB, where pretrained language models can be employed to benefit the generalization (Gu et al., 2021). By selecting candidates for the argument parser under the ontology guide, ontology constraints can be incorporated to the parsing process. To this end, we propose a hierarchical program induction model, which contains 1) a high-level sketch parser aiming to decompose a language question into the program sketch; 2) a low-level argument parser which aims to get the detailed arguments for functions in the sketch.

We learn the parsers with a pretrain-finetune paradigm. Specifically, we pretrain the parsers with existing question-program pairs in KQA Pro. Further, we finetune the parsers with question-answer pairs in the target KB by searching for possible programs and employing the consistent ones to optimize the parsers. The parsing process is divided into two stages. At the first stage, we utilize the sketch parser to translate the question to a program sketch using a Seq2Seq model with attention mechanism. At the second stage, we utilize the argument parser to retrieve the arguments by matching the semantics of question-sketch pair and candidate arguments. Type constraints for entities, and domain, range constraints for relations are employed to prune the argument candidate space.

KQA Pro contains 11,790 question-program pairs and is based on a small subset of Wikidata (Vrandecic and Krötzsch, 2014). We take the Freebase (Bollacker et al., 2008)-based ComplexWebQuestions (Talmor and Berant, 2018) and WebQuestionSP (Yih et al., 2016) as the target domain datasets. Comparing with the state-of-the-art methods that learn from question-answer pairs, we improve the F1 score from 44.0% to 58.7% and 74.0% to 76.5%, with an absolute gain of 14.7% and 2.5% for ComplexWebQuestions and WebQuestionSP respectively. Experimental results demonstrate that exploiting prior knowledge from external annotations and constraints from KB ontology are practical and promising. Ablation studies demonstrate the effectiveness of our program transfer architecture and ontology-guided pruning algorithm.

2 Preliminaries

Knowledge Base. Knowledge base describes concepts, entities, and the relations between them. It can be formalized as $KB = \{C, E, R, T\}$. $C, E, R$ and $T$ denote the sets of concepts, entities, relations and triples respectively.

Relation set $R$ can be formalized as $R = \{r_e, r_c\} \cup R_l$, where $r_e$ is an instanceOf relation, $r_c$ is a subClassOf relation, and $R_l$ is the general relation set. $T$ can be divided into three disjoint subsets: 1) InstanceOf triple set $T_e = \{(e, r_e, c) | e \in E, c \in C\}$; 2) SubClassOf triple set $T_c = \{(c_i, r_c, c_j) | c_i, c_j \in C\}$; 3) Relational triple set $T_l = \{(e_i, r, e_j) | e_i, e_j \in E, r \in R_l\}$.

Program. Program is composed of symbolic functions with arguments and produces answer through execution on a KB. Each function defines a basic operation on KB and takes a specific type of argument. For example, the function Relate defines a basic operation to find entities that have a specific relation (i.e., argument type) with the given entity. Formally, a program $y$ is defined as a sequence of functions with arguments, denoted as $\langle o_1[\arg_1], \ldots, o_i[\arg_i], \ldots, o_{y_l}[\arg_{y_l}] \rangle$, $o_i \in O, \arg_i \in E \cup C \cup R$. Here, $O$ is a pre-defined function set with size 27 which covers basic and reasoning operations over KBs (Shi et al., 2020). According to the argument type, $O$ can be devided into four disjoint subsets: $O = O^E \cup O^C \cup O^R \cup O^B$. 
representing the functions whose argument type is entity, concept, relation and empty respectively. Table 1 gives some examples of program functions.

| Function | Argument Type | Argument | Description |
|----------|---------------|----------|-------------|
| Find     | entity        | “FC Barcelona” | Find the specific KB entity |
| Relate   | relation      | “arena stadium” | Find the entities that hold a specific relation with the given entity |
| FilterConcept | concept    | “sports facility” | Find the entities that belong to a specific concept |
| And      | -             | -        | Return the intersection of two entity sets |

Table 1: Examples of program functions.

**Program Transfer.** First, we define the semantic parsing task: given a $KB$, and a natural language question $x = \langle w_1, w_2, \ldots, w_{|x|} \rangle$, produces a program $y$ that generates the right answer $z$ when executed against $KB$.

Then, we define the program transfer task: we have access to the source domain data $S = \langle KB^S, D^S \rangle$, where $D^S$ contains pairs of question and program $\{ (x_i^S, y_i^S) \}_{i=1}^n$; and target domain data $T = \langle KB^T, D^T \rangle$, where $D^T$ contains pairs of question and answer $\{ (x_i^T, y_i^T) \}_{i=1}^n$. The task of program transfer aims to learn a semantic parser for the target domain. That is, learning a semantic parser to translate the question $x$ for $KB^T$ into program $y$ which can execute on $KB^T$.

3 Model Architecture

We propose to explicitly decompose semantic parsing into a high-level sketch parser and a low-level argument parser. Both of them can generalize across KBs. By grounding the sketch to concepts and relations in the ontology step by step, the search space is reduced progressively. The left part of Figure 2 depicts the flow of our parser and illustrates the ontology-guided pruning process. For model training, we employ the pretrain-finetune paradigm, by first training our parsers with question-program pairs in the source domain, and then finetuning in the target domain, where the prior knowledge from source domain plays an important role to guide the program search.

The rationale of such model design is that by decoupling arguments from programs, 1) At the sketch parsing stage, we can focus on the compositionality of language and program functions, without considering the detailed information. Because language compositional structure repeats across KBs, our sketch parser can generalize across KBs; 2) At the argument parsing stage, we match the semantics of question and argument sequences (e.g., sports team owner) by encoding them into a unified vector space and then calculating the semantic similarity. The pretrained contextual representations from Bert (Devlin et al., 2019), which has shown effectiveness in compositional and zero-shot generalization (Gu et al., 2021), benefit the generalization of our argument parser.

Specifically, first, we learn a high-level sketch parser $f^s$ to parse $x$ into the program sketch $y_s = \langle o_1, \ldots, o_t, \ldots, o_{|y_s|} \rangle$, which can be formulated as

$$ y_s = f^s(x). $$  \hfill (1)

Second, we learn an argument parser $f^a$ to retrieve the argument $arg_t$ from a candidate pool $P$ for each function $o_t$, which can be formulated as

$$ arg_t = f^a(x, o_t, P). $$ \hfill (2)

The candidate pool is the relevant KB items, including concepts, entities, and relations. In a real KB, candidate space is usually huge, which makes the learning from answers very hard. Therefore, we propose an ontology-guided pruning algorithm to dynamically update the candidate pool and progressively reduce the search space, which will be introduced in Section 3.3.

The parsers are pretrained with source domain data $S = \langle KB^S, D^S \rangle$ and then finetuned with target domain data $T = \langle KB^T, D^T \rangle$, which will be introduced in Section 3.4.

3.1 Sketch Parser

The sketch parser is based on encoder-decoder model (Sutskever et al., 2014) with attention mechanism (Dong and Lapata, 2016). We aim to estimate $p(y_s|x)$, the conditional probability of sketch $y_s$ given input $x$. We decompose $p(y_s|x)$ as:

$$ p(y_s|x) = \prod_{t=1}^{|y_s|} p(o_t|o_{<t}, x), $$ \hfill (3)

where $o_{<t} = o_1, \ldots, o_{t-1}$.

**Question Encoder** We utilize Bert (Devlin et al., 2019) as our encoder. Formally,

$$ \tilde{x}_t(x_1, \ldots, x_i, \ldots, x_{|x|}) = \text{BERT}(x), $$ \hfill (4)
Figure 2: We design a high-level sketch parser to generate the sketch, and a low-level argument parser to predict arguments for the sketch. The arguments are retrieved from candidate pools which are illustrated by the color blocks. The arguments for functions are mutually constrained by the ontology structure. For example, when the second function Relate finds the argument teams owned, the candidate pool for the third function Fil.Con. (short for FilterConcept) is reduced to the range of relation teams owned. For training, we use a pretrain-finetune paradigm to transfer the prior knowledge from source domain to target domain.

where \( \mathbf{x} \in \mathbb{R}^d \) is the question embedding, and \( \mathbf{x}_t \in \mathbb{R}^d \) is the hidden vector of word \( x_t \). \( \hat{d} \) is the hidden dimension.

**Sketch Decoder** We use Gated Recurrent Unit (GRU) (Cho et al., 2014), a well-known variant of RNNs, as our decoder of program sketch. The decoding is conducted step by step. After we have predicted \( o_{t-1} \), the hidden state of step \( t \) is computed as:

\[
\mathbf{h}_t = \text{GRU}(\mathbf{h}_{t-1}, o_{t-1}),
\]

where \( \mathbf{h}_{t-1} \) is the hidden state from last time step, \( o_{t-1} = [\mathbf{W}]_{o_{t-1}} \) denotes the the embedding corresponding to \( o_{t-1} \) in the embedding matrix \( \mathbf{W} \in \mathbb{R}^{O \times d} \). We use \( \mathbf{h}_t \) as the attention key to compute scores for each word in the question based on the hidden vector \( \mathbf{x}_t \), and compute the attention vector \( \mathbf{c}_t \) as:

\[
\alpha_t = \frac{\exp(\mathbf{x}_t^T \mathbf{h}_t)}{\sum_{j=1}^{\left|\mathbf{x}\right|} \exp(\mathbf{x}_j^T \mathbf{h}_t)},
\]

\[
\mathbf{c}_t = \sum_{i=1}^{\left|\mathbf{x}\right|} \alpha_i \mathbf{x}_i.
\]

The information of \( \mathbf{h}_t \) and \( \mathbf{c}_t \) are fused to predict the final probability of next sketch token:

\[
\mathbf{g}_t = \mathbf{h}_t + \mathbf{c}_t,
\]

\[
p(o_t | o_{<t}, x) = \text{Softmax}(\text{MLP}(\mathbf{g}_t))|_{o_t},
\]
Our ontology-guided pruning algorithm aims to reduce the space of candidate pool \( P \) in Section 3.2. The rationale is that the arguments for program functions are mutually constrained according to the KB ontology, and when the argument \( arg_i \) for \( o_i \) is determined, the possible candidates for \( \{o_i\}_{i=1}^{n+1} \) will be adjusted. For example, in Figure 2, when \( Relate \) takes “teams owned” as the argument, the candidate pool for the next FilterConcept is constrained to the range of relation “teams owned”, thus other concepts (e.g., “time zone”) will be excluded from the candidate pool; when FilterConcept takes “sports team” as the argument, the candidate pool for the next function \( Relate \) is constrained to the relations whose domain contains “sports team”.

Specifically, we utilize three ontology-oriented constraints \( C(e), R(r), D^{-}(c) \), which aim to find the type constraint for entity \( e \), the range constraint for relation \( r \), and the relations whose domain constraint contains \( c \). The details of these constraints are shown in Table 2. In addition, we maintain three global candidate pools \( P^E, P^R, P^C \) for entities, relations and concepts respectively, and take one of them as \( P \) according to the argument type of \( o_i \). When \( arg_i \) of \( o_i \) is determined, we will update \( P^E, P^R, \) and \( P^C \) using \( C(e), R(r), D^{-}(c) \).

Table 2: Details of the ontology-oriented constraints.

| Notation | Descriptions |
|----------|--------------|
| \( R(r) \) | the range constraint of relation \( r \). |
| \( D^{-}(c) \) | the relations whose domain constraint contains \( c \). |
| \( C(e) \) | \( C(e) = \{e | (e, r, c) \in T \} \), the type constraint of entity \( e \), \( r \), \( c \) denotes instanceOf. |

3.4 Training

We train our program parser using the popular pretrain-finetune paradigm. Specifically, we pretrain the parser on the source domain data \( D^S = \{(x^S_t, y^S_t)\}_{t=1}^{n^S} \) in a supervised way. After that, we conduct finetuning on the target domain data \( D^T = \{(x^T_t, z^T_t)\}_{t=1}^{n^T} \) in a weakly supervised way.

**Pretraining in Source Domain.** Since the source domain data provides complete annotations, we can directly maximize the log likelihood of the golden sketch and golden arguments:

\[
L_{\text{pretrain}} = - \sum_{(x^S, y^S) \in D^S} \left( \log p(y^S_s | x^S) \right)
+ \sum_{t=1}^{\left| y_s \right|} \log p(arg_{y^S_s} | x^S, o^S_t, P) \right).
\]

(Figure 2, page 10)

**Finetuning in Target Domain.** At this training phase, questions are labeled with answers while programs remain unknown. The basic idea is to search for potentially correct programs and optimize their corresponding probabilities. Specifically, we propose two training strategies:

- **Iterative maximum likelihood learning (IML).** At each training step, IML generates a set of possible programs with beam search based on current model parameters, and then executes them to find the one whose answers have the highest F1 score compared with the gold. Let \( \hat{y}^T \) denote the best program, we can directly maximize \( p(\hat{y}^T | x^T) \) like Equation 10.

- **Reinforcement learning (RL).** It formulates the program generation as a decision making procedure and computes the rewards for sampled programs based on their execution results. We take the F1 score between the executed answers and golden answers as the reward value, and use REINFORCE (Williams, 1992) algorithm to optimize the parsing model.

4 Experimental Settings

4.1 Datasets

**Source Domain.** KQA Pro (Shi et al., 2020) provides 117,970 question-program pairs based on a subset of Wikidata (Vrandecic and Krötzsch, 2014).

**Target Domain.** We use two KBQA benchmark datasets: WebQuestionSP (WebQSP) (Yih et al., 2016) and ComplexWebQuestions (CWQ) (Talmor and Berant, 2018), both based on Freebase (Bollacker et al., 2008). WebQSP contains 4,737 questions and is divided into 2,998 train, 100 dev and 1,639 test cases. CWQ is an extended version of WebQSP which incorporates more complex questions and thus is more challenging. It has four types of questions: composition (44.7%), conjunction (43.6%), comparative (6.2%), and superlative (5.4%). CWQ is divided into 27,639 train, 3,519 dev and 3,531 test cases.
We use the Freebase dump on 2015-08-09\(^1\), from which we extract type, domain, and range constraints to construct the ontology. The average domain, range, type constraint size is 1.43 per relation, 1.17 per relation, 8.89 per entity respectively.

Table 3 shows the statistics of the source and target domain KB. The target domain KB contains much more entities, relations, and concepts, and most of them are uncovered by the source domain.

| Domain | # Entities | # Relations | # Concepts |
|--------|------------|-------------|------------|
| Source | 16,960     | 363         | 794        |
| Target | 30,943,204 | 15,015      | 2,519      |

Table 3: The statistics for source and target domain KB.

### 4.2 Baselines

We choose the state-of-the-art methods which learn from question-answer pairs as our baselines.

Existing program induction methods use hand-crafted rules or knowledge linking. **NSM** (Liang et al., 2017) uses the prior entity, relation and type linking knowledge to solve simple questions. **NPI** (Ansari et al., 2019) designs rules such as disallow repeating or useless actions.

Query graph generation methods incorporate KB guidance by considering entity-level triples. **TEXTRAY** (Bhutani et al., 2019) prunes the search space by a decompose-execute-join approach. **QGG** (Lan and Jiang, 2020) incorporates constraints into query graphs in the early stage. **TeacherNet** (He et al., 2021) learns relation paths from the topic entity to answer entities utilizing bidirectional multi-hop reasoning.

Information retrieval based methods directly retrieve answers from the KB without generating interpretable logical forms. **GraftNet** (Sun et al., 2018) uses heuristics to create a question-specific subgraph and uses a variant of graph convolutional networks to retrieve the answer. **PullNet** (Sun et al., 2019) improves GraftNet by iteratively constructing the subgraph instead of using heuristics.

Besides, we compare our full model **Ours** with **Ours-f**, **Ours-p**, **Ours-pa**, **Ours-o**, which denotes our model without finetuning, without pretraining, without pretraining of argument parser, and without ontology constraints respectively.

### 4.3 Evaluation Metrics

Following prior works (Berant et al., 2013; Sun et al., 2018; He et al., 2021), we use F1 score and Hit@1 as the evaluation metrics. Since questions in the datasets have multiple answers, F1 score reflects the coverage of predicted answers better.

### 4.4 Implementations

We used the bert-base-cased model of HuggingFace\(^2\) as our Bert encoder with the hidden dimension \(d\) 768. The hidden dimension of the sketch decoder \(d\) was 1024. We used AdamW (Loschilov and Hutter, 2019) as our optimizer. We searched the learning rate for Bert parameters in \{1e-4, 3e-5, 1e-5\}, the learning rate for other parameters in \{1e-3, 1e-4, 1e-5\}, and the weight decay in \{1e-4, 1e-5, 1e-6\}. According to the performance on validation set, we finally used learning rate 3e-5 for Bert parameters, 1e-3 for other parameters, and weight decay 1e-5.

### 5 Experimental Results

| Models | WebQSP | CWQ |
|--------|--------|-----|
|        | F1     | Hit@1 | F1     | Hit@1 |
| GraftNet | 62.3   | 68.7 | - | 32.8* |
| PullNet  | -      | 68.1 | - | 47.2* |
| TeacherNet | 67.4   | 74.3 | 44.0 | 48.8 |
| TEXTRAY  | 60.3   | 72.2 | 33.9 | 40.8 |
| QGG      | 74.0   | -    | 40.4 | 44.1 |
| NSM      | -      | 69.0 | -    | -    |
| NPI      | -      | 72.6 | -    | -    |
| **Ours-f** | 53.8   | 53.0 | 45.9 | 45.2 |
| **Ours-p** | 3.2    | 3.1  | 2.3  | 2.1  |
| **Ours-pa** | 70.8   | 68.9 | 54.5 | 54.3 |
| **Ours-o** | 72.0   | 71.3 | 55.8 | 54.7 |
| **Ours**  | 76.5   | 74.6 | 58.7 | 58.1 |

Table 4: Performance comparison of different methods (F1 score and Hits@1 in percent). We highlight the best results in bold and second with underline. *: reported by PullNet on the validation set.

### 5.1 Overall Results

As shown in Table 4, our model achieves the best performance on both WebQSP and CWQ. Especially on CWQ, we have an absolute gain of 14.7% in F1 and 9.3% in Hit@1, beating previous methods by a great margin. Note that CWQ is much more challenging than WebQSP because it includes more compositional and conjunctional questions. Previous work mainly suffer from the huge search

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\(^1\)http://commondatastorage.googleapis.com/freebase-public/rdf/freebase-rdf-latest.gz

\(^2\)https://github.com/huggingface/transformers
space and sparse training signals. We conquer these challenges by transferring the prior knowledge and incorporating the ontology constraints, which reduce the search space substantially. On WebQSP, we achieve an absolute gain of 2.5% and 0.3% in F1 and Hit@1, respectively, demonstrating that our model can also handle simple questions well and can adapt to different complexities of questions.

Note that our F1 scores are higher than corresponding Hit@1. This is because we just randomly sampled one answer from the returned answer set as the top 1 without ranking them.

| Models | WebQSP | CWQ |
|--------|--------|-----|
| Top-1  | 76.5   | 58.7 |
| Top-2  | 81.1   | 61.2 |
| Top-5  | 85.4   | 63.3 |
| Top-10 | 86.9   | 65.0 |

Table 5: The highest F1 score in the top-k programs.

We utilize beam search to generate multiple possible programs and evaluate their performance. Table 5 shows the highest F1 score in the top-k generated programs, where top-1 is the same as Table 4. We can see that the best F1 in the top-10 programs is much higher than the F1 of the top-1 (e.g., with absolute gain 10.4% for WebQSP and 6.3% for CWQ). This indicates that a good re-ranking method can further improve the overall performance of our model. We leave this as our future work.

5.2 Ablation study

**Pretraining:** As shown in Table 4, when comparing Ours−pa with Ours, the F1 and Hit@1 on CWQ drop by 4.2% and 3.8% respectively, which indicates that the pretraining for the argument parser is necessary. Ours−p denotes the model without pretraining for neither sketch parser nor argument parser. We can see that its results are very poor, achieving just about 3% and 2% on WebQSP and CWQ, indicating that the pretraining is essential, especially for the sketch parser.

**Finetuning:** Without finetuning on the target data, i.e., in Ours−f, performance drops a lot compared with the complete model. For example, F1 and Hit@1 on CWQ drop by 12.8% and 12.9% respectively. It indicates that finetuning is necessary for model’s performance. As shown in Table 3, most of the relations and concepts in the target domain are uncovered by the source domain. Due to the semantic gap between source and target data, the prior knowledge must be properly transfered to the target domain to bring into full play.

**Ontology:** We implemented Ours−o by removing ontology constraints from KB and removing FilterConcept from the program. Comparing Ours−o with Ours, the F1 and Hit@1 on CWQ drops by 2.9% and 3.4% respectively, which demonstrates the importance of ontology constraint. We calculated the search space size for each compositional and conjunctive question in CWQ validation set, and report the average size in Table 6. The statistics shows that by incorporating the ontology constraint, Ours substantially reduces the search space.

| Model         | Composition | Conjunction |
|---------------|-------------|-------------|
| Ours−o        | 4,248,824.5 | 33,152.1    |
| Ours          | 11,200.7    | 1,066.5     |

Table 6: The average search space size for composition and conjunction questions in CWQ validation set for Ours and Ours−o.

**IML v.s. RL:** For both WebQSP and CWQ, training with IML achieves better performance. For RL, we simply employed the REINFORCE algorithm and did not implement any auxiliary reward strategy since this is not focus of our work. The sparse, delayed reward causes high variance, instability, and local minima issues, making the training hard (Saha et al., 2019). We leave exploring more complex training strategies as our future work.

| Models | WebQSP | CWQ |
|--------|--------|-----|
| F1     | Hit@1  | F1  | Hit@1 |
| IML    | 76.5   | 74.6 | 58.7  | 58.1  |
| RL     | 71.4   | 72.0 | 46.1  | 45.4  |

Table 7: Results of different training strategies.

5.3 Case Study

Figure 3 gives a case, where our model parses an question into multiple programs along with their probability scores and F1 scores of executed answers. Given the question “The person education institution is Robert G. Cole Junior-Senior High School played for what basketball teams?”, we show the programs with the largest, 2nd largest and 10th largest possibility score. Both of the top-2 programs get the correct answer set and are semantically equivalent with the question, while the 10th best program is wrong.
Error Analysis We randomly sampled 100 error cases whose F1 score is lower than 0.1 for manual inspection. The errors can be summarized into the following categories: 1) Wrong relation (53%): wrongly predicted relation makes the program wrong. e.g., for question “What language do people in the Central Western Time Zone speak?”, our model predicts the relation main country, meaning the main country that uses one language, while the ground truth is countries spoken in, meaning all the countries that use one language; 2) Wrong concept (38%): wrongly predicted concept makes the program wrong, e.g., for the question “What continent does the leader Ovadia Yosel live in?” our model predicted the concept location, whereas the ground truth is continent. 3) Model limitation (9%): Handling attribute constraint was not considered in our model, e.g., for the question “Who held his governmental position from before April 4, 1861 and influenced Whitman’s poetry?”, the start time constraint April 4, 1861 cannot be handled.

6 Related Work

Semantic Parsing from Denotations. Semantic parsing from denotations requires searching over an exponentially large space of logical forms and may be misled by spurious ones (Berant et al., 2013; Pasupat and Liang, 2015; Guu et al., 2017), which makes training extremely challenging. Attempts to address this problem either used prior knowledge to guide the learning process (e.g. hand-crafted rules (Ansari et al., 2019; Saha et al., 2019), gold entity, relation, type linking (Liang et al., 2017; Saha et al., 2019), etc.), or enforced KB constraints to ensure the semantical correctness of the logical form (Yih et al., 2015; Lan and Jiang, 2020; Bhutani et al., 2019) at the entity-level.

Our work has drawn inspiration from the works that abstract entities and relations from the logical forms (Zhang et al., 2017; Dong and Lapata, 2018; Herzig and Berant, 2018). However, their methods did not decompose semantic parsing into generic, reusable, atomic functions and investigate program transfer. In this paper, we investigate for the first time the problem of program transfer as far as we know.

Cross-domain Semantic Parsing. Cross-domain semantic parsing trains a semantic parser on some source domains and adapts it to the target domain. Some works (Herzig and Berant, 2017; Su and Yan, 2017; Fan et al., 2017) pooled together examples from multiple datasets in different domains and trained a single sequence-to-sequence model over all examples, sharing parameters across domains. These methods relied on annotated data in the target domain. To facilitate low-resource target domains, (Chen et al., 2020) adapted to target domains with a very limited amount of training data. Other works considered a zero-shot semantic parsing task (Givoli and Reichart, 2019), decoupling structures from lexicons for transfer. However, they only learned from the source domain without further learning from the target domain using the prior knowledge. In addition, existing works mainly focus on the domains in OVERNIGHT (Wang et al., 2015), which are much smaller than large scale KBs such as Wikidata and Freebase. To deal with the complex schema of large scale KBs, transfer in ours setting is more challenging.

7 Conclusion

In this paper we investigate program transfer and ontology awareness for semantic parsing in KBQA for the first time. We propose a hierarchical program induction model which composes a high-level sketch parser and a low-level argument parser. Both of them generalize across KBs. The ontology-guided pruning algorithm reduces the search space substantially by using three ontology-oriented constraints. The experimental results demonstrate that our program transfer and ontology constraints facilitate semantic parsing from denotations greatly.
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A Program

We list the functions of KQA Pro in Table 8. The arguments in our paper are the textual inputs. To reduce the burden of the argument parser, for the functions that take multiple textual inputs, we concatenate them to a single input.

B Ontology-guided Pruning

Algorithm 1 Ontology-guided Pruning

Input: natural language question $x$, program sketch $y$, knowledge base $KB = \{C, E, R, T\}$

Output: $\{arg_t\}^{y_s}_{t=1}$

$P^E \leftarrow E, P^R \leftarrow R, P^C \leftarrow C, P \leftarrow \emptyset$

for all $o_t$ in $y_s$ do

if $o_t \in O^E$ then

$p \leftarrow P^E$

$arg_t = f^a(x, o_t, P)$

$P^C \leftarrow C(arg_t)$

$P^R \leftarrow \bigcup_{c \in P^C} D^{-}(c)$

else if $o_t \in O^R$ then

$p \leftarrow P^R$

$arg_t = f^a(x, o_t, P)$

$P^C \leftarrow R(arg_t)$

else if $o_t \in O^C$ then

$p \leftarrow P^C$

$arg_t = f^a(x, o_t, P)$

$P^R \leftarrow D^{-}(arg_t)$

end if

end for

C Freebase Details

We extracted a subset of Freebase which contains all facts that are within 4-hops of entities mentioned in the questions of CWQ and WebQSP. We extracted the domain constraint for relations according to “/type/property/schema”, range constraint for relations according to “/type/property/expected_type”, type constraint for entities according to “/type/type/instance”. CVT nodes in the Freebase were dealt with concatenation of neiborhood relations.
| Function                  | Functional Inputs × Textual Inputs → Outputs | Description                                                                 | Example (only show textual inputs) |
|--------------------------|-------------------------------------------|------------------------------------------------------------------------------|-----------------------------------|
| Find                     | \((1) \times (1) \rightarrow (\text{Entities})\) | Return all entities in KB                                                    | Find(Kobe Bryant)                 |
| FilterConcept            | \((\text{Entities}) \times (\text{Name}) \rightarrow (\text{Entities})\) | Find those belonging to the given concept                                    | FilterConcept(athlete)           |
| FilterStr                | \((\text{Entities}) \times (\text{Key}, \text{Value}) \rightarrow (\text{Entities}, \text{Facts})\) | Filter entities with an attribute condition of string type, return entities and corresponding facts | FilterStr(gender, male)          |
| FilterNum                | \((\text{Entities}) \times (\text{Key}, \text{Value}, \text{Op}) \rightarrow (\text{Entities}, \text{Facts})\) | Similar to FilterStr, except that the attribute type is number              | FilterNum(height, 200 centimetres, \textgreater) |
| FilterYear               | \((\text{Entities}) \times (\text{Key}, \text{Value}, \text{Op}) \rightarrow (\text{Entities}, \text{Facts})\) | Similar to FilterStr, except that the attribute type is year                | FilterYear(birthday, 1980, \textgreater) |
| QFilterStr               | \((\text{Entities}, \text{Facts}) \times (Q\text{Key}, Q\text{Value}) \rightarrow (\text{Entities}, \text{Facts})\) | Filter entities and corresponding facts with a qualifier condition of string type | QFilterStr(language, English)     |
| QFilterNum               | \((\text{Entities}, \text{Facts}) \times (Q\text{Key}, Q\text{Value}, \text{Op}) \rightarrow (\text{Entities}, \text{Facts})\) | Similar to QFilterStr, except that the qualifier type is number             | QFilterNum(bonus, 20000 dollars, \textgreater) |
| QFilterYear              | \((\text{Entities}, \text{Facts}) \times (Q\text{Key}, Q\text{Value}, \text{Op}) \rightarrow (\text{Entities}, \text{Facts})\) | Similar to QFilterStr, except that the qualifier type is year              | QFilterYear(start time, 1980, \textgreater) |
| QFilterDate              | \((\text{Entities}, \text{Facts}) \times (Q\text{Key}, Q\text{Value}, \text{Op}) \rightarrow (\text{Entities}, \text{Facts})\) | Similar to QFilterStr, except that the qualifier type is date               | QFilterDate(start time, 1980-06-01, \textless) |
| Relate                   | \((\text{Entities}, \text{Facts}) \times (\text{Pred}, \text{Dir}) \rightarrow (\text{Entities}, \text{Facts})\) | Find entities that have a specific relation with the given entity           | Relate(capital, forward)          |
| And                      | \((\text{Entities}, \text{Facts}) \times (t) \rightarrow (\text{Entities})\) | Return the intersection of two entity sets                                   | -                                 |
| Or                       | \((\text{Entities}, \text{Facts}) \times (t) \rightarrow (\text{Entities})\) | Return the union of two entity sets                                         | -                                 |
| Count                    | \((\text{Entities}, \text{Facts}) \times (t) \rightarrow (\text{number})\) | Return the number of entities                                               | -                                 |
| QueryAttr                | \((\text{Entities}, \text{Facts}) \times (\text{Key}) \rightarrow (\text{Value})\) | Return the attribute value of the entity                                     | QueryAttr(height)                |
| QueryAttrUnderCondition  | \((\text{Entities}, \text{Facts}) \times (\text{Key}, \text{Value}, \text{Op}) \rightarrow (\text{Value})\) | Return the attribute value, whose corresponding fact should satisfy the qualifier condition | QueryAttrUnderCondition(population, point in time, 2016) |
| QueryRelation            | \((\text{Entities}, \text{Facts}) \times (t) \rightarrow (\text{Pred})\) | Return the predicate between two entities                                    | QueryRelation(Kobe Bryant, America) |
| SelectBetween            | \((\text{Entities}, \text{Facts}) \times (\text{Key}, \text{Op}) \rightarrow (\text{string})\) | From the two entities, find the one whose attribute value is greater or less and return its name | SelectBetween(height, Bryant, America) |
| SelectAmong              | \((\text{Entities}, \text{Facts}) \times (\text{Key}, \text{Op}) \rightarrow (\text{string})\) | From the entity set, find the one whose attribute value is the largest or smallest | SelectAmong(height, largest)       |
| VerifyStr                | \((\text{Value}) \times (\text{Value}) \rightarrow (\text{boolean})\) | Return whether the output of QueryAttr or QueryAttrUnderCondition and the given value are equal as string | VerifyStr(male)                    |
| VerifyNum                | \((\text{Value}) \times (\text{Value}) \rightarrow (\text{boolean})\) | Return whether the two numbers satisfy the condition                        | VerifyNum(20000 dollars, \textgreater) |
| VerifyYear               | \((\text{Value}) \times (\text{Value}) \rightarrow (\text{boolean})\) | Return whether the two years satisfy the condition                          | VerifyYear(1980, \textgreater)    |
| VerifyDate               | \((\text{Value}) \times (\text{Value}) \rightarrow (\text{boolean})\) | Return whether the two dates satisfy the condition                          | VerifyDate(1980-06-01, \textgreater) |
| QueryAttrQualifier       | \((\text{Entities}, \text{Facts}) \times (Q\text{Key}) \rightarrow (\text{Value})\) | Return the qualifier value of the fact                                       | QueryAttrQualifier(population, 23,390,000, point in time) |
| QueryRelationQualifier   | \((\text{Entities}, \text{Facts}) \times (\text{Pred}, Q\text{Key}) \rightarrow (\text{Value})\) | Return the qualifier value of the fact                                       | QueryRelationQualifier(spouse, start time) |

Table 8: Details of 27 functions in KQA Pro. Each function has 2 kinds of inputs: the functional inputs come from the output of previous functions, while the textual inputs come from the question.