Abstract

Semantic parsing allows humans to leverage vast knowledge resources through natural interaction. However, parsers are mostly designed for and evaluated on English resources, such as CFQ (Keysers et al., 2020), the current standard benchmark based on English data generated from grammar rules and oriented towards Freebase, an outdated knowledge base. We propose a method for creating a multilingual, parallel dataset of question-query pairs, grounded in Wikidata, and introduce such a dataset called Compositional Wikidata Questions (CWQ). We utilize this data to train and evaluate semantic parsers for Hebrew, Kannada, Chinese and English, to better understand the current strengths and weaknesses of multilingual semantic parsing. Experiments on zero-shot cross-lingual transfer demonstrate that models fail to generate valid queries even with pretrained multilingual encoders. Our methodology, dataset and results will facilitate future research on semantic parsing in more realistic and diverse settings than has been possible with existing resources.

1 Introduction

In recent years, semantic parsers grounded in knowledge bases (KBs) have shown promise in enabling knowledge base question answering (KBQA) for complex questions. Many semantic parsers are grounded in KBs such as Freebase (Bollacker et al., 2008), DBpedia (Lehmann et al., 2015) and Wikidata (Pel-lissier Tanon et al., 2016), and models learn to answer questions about unseen entities and properties (Herzig and Berant, 2017; Cheng and Lapata, 2018; Shen et al., 2019; Sas et al., 2020). A particular focus has been placed on compositional generalization—namely, the ability of parsers to generalize to unseen combinations of known components (Keysers et al., 2020; Oren et al., 2020; Kim and Linzen, 2020). However, a majority of work in this area is still dominated by English, despite a pressing need to expand systems to other languages (Joshi et al., 2020).

The current barrier to extending these approaches beyond English is a lack of parallel dataset from multilingual databases as well as supervision for semantic parsing. Presently, one of the most widely used datasets for benchmarking KB semantic parsers is CFQ (see §2), which is built from English patterns, and is integrated with Freebase, an English-only KB that is no longer publicly accessible. Consider the following English question from CFQ (with entities surrounded by brackets):

“Was [United Artists] founded by [Mr. Fix-it]’s star, founded by [D. W. Griffith], founded by [Mary Pickford], and founded by [The Star Boarder]’s star?”

Parsers trained on CFQ translate this question into a SPARQL query, which can subsequently be executed against a KB to answer the original question (in this case, the answer is “Yes”). However, semantic parsing of this same utterance in any another language to a Freebase-compatible query would require linking the entities to their corresponding Freebase entries (overcoming any difference in spelling, possibly in a non-Latin script), which raises the level of entry for working in other languages, and hinders evaluation of multilingual semantic parsers.

Wikidata is a multilingual KB, with entity and property labels in a multitude of languages. In this work, we leverage Wikidata
and the CFQ dataset to create a new multilingual dataset of compositional questions grounded in Wikidata. Beyond the original English, an Indo-European language using the Latin script, we create parallel datasets of questions in Hebrew, Kannada and Chinese, which use different scripts and belong to different language families: Afroasiatic, Dravidian and Sino-Tibetan, respectively.

We present Multilingual Compositional Wikidata Questions, a multilingual KBQA dataset grounded in and executable over Wikidata. Our dataset includes questions in four languages, and their associated SPARQL queries. Our contributions are: (i) Methodology for automatically migrating Freebase datasets to Wikidata, a currently accessible and routinely updated KB, and extending to diverse languages and domains, (ii) A dataset containing questions in four languages for benchmarking semantic parsers against Wikidata, (iii) Experimental investigation and analysis of the performance of different semantic parser architectures in four languages, and (iv) Experimental investigation and analysis of cross-lingual zero-shot semantic parsing using pretrained multilingual encoders.

Our code for generating the dataset and for the experiments, as well as the dataset itself, is publicly available on https://github.com/coastalcph/seq2sparql.

2 Compositional Freebase Questions

CFQ (Compositional Freebase Questions: Keysers et al., 2020) is a dataset for measuring compositional generalization in semantic parsing. It targets the task of parsing questions in English into SPARQL queries executable on the Freebase KB (Bollacker et al., 2008). CFQ uses the Distribution-Based Compositionality Assessment (DBCA) method to generate multiple train-test splits with maximally divergent examples in terms of compounds, while maintaining a low divergence in terms of primitive elements (atoms). In these maximum compound divergence (MCD) splits, the test set is constrained to examples containing novel compounds, i.e., new ways of composing the atoms seen during training. For measuring compositional generalizations, named entities in the questions are anonymized so that models cannot simply learn the relationship between entities and properties. CFQ contains 239,357 English question-answer pairs, which encompass 49,320 question patterns and 34,921 SPARQL query patterns. Table 1 shows selected fields of an example in CFQ.

In their experiments, Keysers et al. (2020) trained semantic parsers using several architectures on various train-test splits. They demonstrated strong negative correlation between models’ accuracy (correctness of the full generated SPARQL query) and compound divergence across a variety of system architectures, including LSTM+attention (Hochreiter and Schmidhuber, 1997), Transformer (Vaswani et al., 2017), Universal Transformer (Dehghani et al., 2019) and Evolved Transformer (So et al., 2019). All models generalized poorly in the high-divergence settings, highlighting the need for further development of semantic parsers to improve compositional generalization.

By the time CFQ was released, Freebase had already been shut down and partially migrated to Wikidata (Pellissier Tanon et al., 2016). On that account, to our knowledge, there is no existing semantic parsing dataset grounded in a currently usable KB that targets compositional generalization. Moreover, only few studies have evaluated semantic parsers’ performance in a multilingual setting, due to the scarcity of multilingual KBQA datasets (Usbeck et al., 2018; Korablinov and Braslavski, 2020).

3 Compositional Wikidata Questions

CFQ provides questions and corresponding SPARQL queries against Freebase. Since Freebase was shut down in 2015, the queries in CFQ cannot be executed to retrieve the actual answers to the questions in the dataset. It is therefore beneficial to migrate the dataset to a serviceable KB. Wikidata is an ideal option, as it is widely accepted as the replacement for Freebase, is actively maintained and represents knowledge in a multitude of languages and domains, and also supports SPARQL. The migration process, however, is not trivial, as there is no bijective mapping between Freebase and Wikidata properties and entities.
Table 1: Selected fields in a CFQ entry. `questionWithBrackets` is the full English question with entities surrounded by brackets. `questionPatternModEntities` is the same question, with the entities replaced by placeholders (M0, M1 etc.). In `questionWithMids`, the entity codes (Freebase machine IDs; MIDs) are given instead of their labels. `sparql` is the fully executable SPARQL query for the question, and in `sparqlPatternModEntities` the entity codes are replaced by placeholders. While full KBQA requires transforming the full question to the full query, in CFQ the evaluation is on transforming `questionPatternModEntities` to `sparqlPatternModEntities`, to focus on the compositionality aspect rather than named entity recognition, and to avoid memorization of entities.

### 3.1 Property Mapping

CFQ uses 73 unique properties in its SPARQL queries, all belonging to the cinematography domain. As a first step in the migration process, we check which Freebase properties used in CFQ have corresponding Wikidata properties. As can be seen in Table 1, the `WHERE` clause in a SPARQL query consists of a list of triples, where the second element in each triple is the property, e.g., `ns:people.person.gender`. These Freebase properties cannot be applied directly to Wikidata, which uses different property codes known as P-codes, e.g., P21. We therefore need to map the Freebase properties into Wikidata properties.

Using a publicly available repository providing a partial mapping between the KBs, we identify that 25 out of the 73 Freebase properties in CFQ can be mapped to Wikidata properties. As can be seen in Table 1, the `WHERE` clause in a SPARQL query consists of a list of triples, where the second element in each triple is the property, e.g., `ns:people.person.gender`. These Freebase properties cannot be applied directly to Wikidata, which uses different property codes known as P-codes, e.g., P21. We therefore need to map the Freebase properties into Wikidata properties.

Using a publicly available repository providing a partial mapping between the KBs, we identify that 25 out of the 73 Freebase properties in CFQ can be mapped to Wikidata properties. For example, Freebase properties `ns:film.film.film_art_direction_by` and `ns:film.cinematographer.film` do not have mappings to Wikidata. After filtering out questions with any unmappable properties, we remain with 19,194 entries in CFQ that contain only fully-mappable properties. These are only 8% of all entries, but can still be used as a parsing evaluation benchmark. In these entries, we use our mapping to replace Freebase properties with their mapped Wikidata properties. We additionally make necessary SPARQL syntax modification for Wikidata.

### 3.2 Entity Substitution

A large number of entities in Freebase are absent in Wikidata. For example, neither of the entities in Table 1, “‘Murder’ Legendre” and “Lillian Lugosi” exists in Wikidata. Furthermore, unlike the case of properties, to our knowledge, there is no comprehensive or even partial mapping of Freebase entity IDs (i.e., Freebase machine IDs, MIDs, such as `s:m.05zppz`) to Wikidata entity IDs (i.e., Q-codes, such as `wd:Q6581097`). We therefore replicate the grounding process carried out by Keysers et al. (2020), substituting entity placeholders with compatible entities codes in questions and their corresponding queries by executing the queries—in our case, however, against Wikidata instead of Freebase:

1. By replacing entity placeholders with `SPARQL variables`, we obtain queries that return sets of compatible candidate
entity assignments instead of simply an answer for a given assignment of entities.

2. We add constraints that the returned entities should be distinct, to avoid forming questions with nonsensical redundancies.

3. Since entities representing nationalities and genders are regarded as part of the question patterns in CFQ (and are not replaced with placeholders), before we run the queries, we look up all such entities and replace them with corresponding Wikidata Q-codes (and not variables).

4. We execute the queries to get the satisfying assignments of entity combinations, with which we replace the placeholders in sparqlPatternModEntities fields.

5. Finally, we insert the Q-codes into the English questions in the questionWithMids field and the corresponding entity labels into the questionWithBrackets to obtain the English questions for our dataset.

Along this process, 43.4% of the queries did not have any satisfying assignments and were discarded. We are left with 10,848 questions and their associated SPARQL queries. The question-query pairs form our English dataset, which maintain the SPARQL patterns in CFQ, but the queries are all executable on Wikidata.

Due to the Wikidata query service API time limit, some queries time out even though a satisfying assignment of entities exists. We thus run each query 10 times to determine whether a set of entities can satisfy a CFQ question pattern. The querying process took 41 hours.

We obtain 10,848 question-query pairs, of which 5,479 are yes/no questions and 5,369 are wh-questions. The expected responses of yes/no questions in our dataset were positive due to our data generation methodology, whilst CFQ has both positive and negative responses to yes/no questions. To make CWQ comparable, we sample alternative queries to 2,000 out of 5,479 queries by replacing entities with ones from other queries whose preceding predicates are the same. Our negative sampling results in 1,945 questions with “no” answers.

3.3 Migration Example

Taking the question-query pair in Table 1 as an example, we replace the Freebase properties and reserved entities, here the gender male from ns:m.05zzp to wd:Q6581097, in the SPARQL pattern:

```
SELECT count(*) WHERE { ?x0 ns:film.actor. film/ns:film.performance.character M0 . ?x0 ns:people.person.gender ns:m.05zzp . ?x0 ns:people.person.spouse_s/ns:fictional_universe. marriage_of_fictional_characters.spouses M2 . FILTER ( ?x0 != M2 )}
```

This results in:

```
SELECT count(*) WHERE { ?x0 wdt:P453 M0 . ?x0 wdt:P21 wd:Q6581097 . ?x0 wdt:P26 M2 . FILTER ( ?x0 != M2 )}
```

Thereafter, we replace the placeholders with variables and add constraints for getting only one assignment (which is enough for our purposes) with distinct entities. The resulting query is:

```
SELECT ?v0 ?v1 WHERE { ?x0 wdt:P453 ?v0 . ?x0 wdt:P21 wd:Q6581097 . ?x0 wdt:P26 ?v1 . FILTER ( ?x0 != ?v1 ) . LIMIT 1
```

After executing the query against the Wikidata query service,4 we get wd:Q50807639 (Lohengrin) and wd:Q1560129 (Margarete Joswig) as satisfying answers for v0 and v1 respectively. Note that these are different from the entities in the original question (‘Murder’ Legendre and Lillian Lugosi)—in general, there is no guarantee that the same entities from CFQ will be preserved in our dataset. Then we put back these answers into the query, and make necessary SPARQL syntax modification for Wikidata. The final query for this entry is:

```
ASK WHERE { ?x0 wdt:P453 wd:Q50807639 . ?x0 wdt :P21 wd:Q6581097 . ?x0 wdt:P26 wd: Q1560129 . FILTER ( ?x0 != wd:Q1560129 )}
```

As for the English question, we map the Freebase entities in the questionWithMids field with the labels of the obtained Wikidata entities. Therefore, the English question resulting from this process is:

Did [Lohengrin]’s male actor marry [Margarete Joswig]?

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4https://query.wikidata.org/
3.4 Question Complexity

CWQ has 2,444 question patterns (mod entities, verbs, etc.), i.e., 22.5% questions cover 100% of unique question patterns, whereas the percentage for original CFQ is 20.6% of questions. There are 1,835 unique SPARQL query patterns in our dataset, resulting in 16.9% instances covering 100% of unique SPARQL query patterns. The corresponding number for CFQ is 14.6%. Our dataset thus poses a greater challenge for compositional semantic parsing, and exhibits less redundancy in terms of duplicate patterns.

The complexity of questions is measured by the number of rule applications used to generate a question, which encompass grammar, knowledge, inference and resolution rules (Keysers et al., 2020). We compare the complexity distribution of the two datasets in Figure 1. Both CFQ and our dataset follow a similar overall trend in complexity distribution. While the complexity in CFQ is mostly uniform after complexity level 18, the number of questions per complexity level in our dataset fluctuates, since migration failures due to unmappable properties or unsatisfiable queries are not uniformly distributed across complexity levels.

3.5 Data Splits

Keysers et al. (2020) design the MCD splits generated with the DBCA method in CFQ to have significantly high compound divergence while maintain relatively low atom divergence compared to other split methods, thus are more compositionally challenging. As CWQ employs fully mappable atoms from CFQ and leaves the compounds intact, we derive train-test splits of our dataset by inducing the train-test splits from CFQ on the corresponding subset of instances in our dataset. Most importantly, we are interested in the MCD splits. Whilst the compound divergence of CWQ and CFQ are analogous, we compare the question complexity distribution of the two datasets in one of the three compositional splits, MCD1, as shown in Figure 2. While the training, development and test sets of the split in CFQ and CWQ follow a similar trend in general, the training set’s complexity in both datasets is lower than that of the development and test sets. The fluctuation in complexity of questions in the CWQ splits reflects the dataset’s full distribution.

Stemming from its entities and properties, CFQ questions are limited to the domain of movies. The entities in CWQ, however, can in principle come from any domain, owing to our flexible entity replacing method. But since properties are still a subset of those used in CFQ, they are mostly in the movies domain as well. We also observe a few questions from literature, politics, and history in CWQ.

4 Multilingual CWQ

To extend our English dataset to other languages, we translate questions to create new question-query pairs. SPARQL queries remain unchanged, as both property and entity IDs
are language-independent in Wikidata, which contains labels in different languages for each property and entity.

To create a typologically diverse dataset, starting from our English dataset (an Indo-European language using the Latin script), we translate questions to three other languages from different families (Afroasiatic, Dravidian and Sino-Tibetan), which use different scripts: Hebrew, Kannada and Chinese.

4.1 Generating Translations

Both question patterns and bracketed questions are translated separately with Google Cloud Translation from English. We attempted to translate bracketed questions and consequently replace the bracketed entities with placeholders as question patterns. In post hoc analysis, we found that separate translation of question patterns is of higher translation quality. Therefore, we choose to translate question patterns and bracketed questions individually. Table 2 shows an example for a question in our dataset (which is generated from the same question as the CFQ instance from Table 1), as well as the resulting translations.

As an additional technical necessity, we add a question mark to the end of each question before translation (as the original dataset does not include question marks), and remove trailing question marks from the translated question before including it in our dataset. We find this step to be essential for translation quality.

4.2 Translation Quality

To ensure the quality of the translated patterns, the authors perform a manual evaluation of translation quality and fluency for one randomly selected example from each of the 40 complexity levels represented in our dataset. For each selected example and for each target language, we compare the original English question with bracketed entities to the corresponding translation, also with brackets around translated entities. We rate the patterns on a scale of 1–5 for fluency, and on a scale of 1–5 for meaning preservation, with 1 being poor, and 5 being optimal.

Despite occasional translation issues, mostly attributed to lexical choice or morphological agreement, we find that the translations are of high quality. Across all translated languages, we find that over 80% of examples have high levels of fluency and meaning preservation, with 1 being poor, and 5 being optimal.

As a control experiment to evaluate how natural original CFQ questions are, a native English speaker evaluated the fluency for the English patterns from the same sample. 62% of patterns were rated 3 or above. While all English questions are grammatical, many suffer from poor fluency, tracing back to their

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Table 2: An example from the CWQ dataset with the English question generated from a template, its translations in He, Kn, and Zh, along with the corresponding SPARQL query, recursion depth, and the expected response.

| Lang. | CWQ field       | Content                                                                 |
|-------|-----------------|-------------------------------------------------------------------------|
| En    | questionWithBrackets | Did [Lohengrin] 's male actor marry [Margarete Joswig]                   |
| He    | questionPatternModEntities | Did M0 's male actor marry M2                                            |
| Kn    | questionWithBrackets | [לשירבגהןקחשהםאה][ןירגנהול] [םעןתחתה][גיווסויטרגרמ]                       |
| Zh    | questionWithBrackets | [Lohengrin]的男演员嫁给了[Margarete Joswig]                              |

| sparql | ASK WHERE | wd:Q50807639 . ?x0 wd:P21 wd:Q6581097 . ?x0 wd:P26 wd:Q1560129 . FILTER ( ?x0 != wd:Q1560129 ) |
|---------|------------|-------------------------------------------------------------------------|
| sparqlPatternModEntities | ASK WHERE | wd:Q50807639 . ?x0 wd:P21 wd:Q6581097 . ?x0 wd:P26 . FILTER ( ?x0 != M2 ) |
| recursionDepth | 20         |                                                                           |
| expectedResponse | True       |                                                                           |

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5https://cloud.google.com/translate

6At least one author is a native speaker for each language present in our dataset
automatic generation using a grammar (Keysers et al., 2020). Some translations are rated higher in terms of fluency. This might be attributed to two reasons (i) annotators were more lenient, focusing on issues that might result from translation and not on issues with questions that were unnaturally phrased in the first place, (ii) machine translation helps to smooth the unnatural structure of the original English questions, especially for languages of lower complexity. To conclude, despite unnatural questions inherited from CFQ, we find that multilingual CWQ contains high-quality translations, and is therefore suitable for evaluating multilingual semantic parsers.

5 Experiments

To evaluate semantic parsers on multilingual CWQ, we train and evaluate models on the three MCD splits. Wikidata entities are masked during training, except those that are part of the question patterns (genders and nationalities), i.e., the input for each instance is questionPatternModEntities and the output is sparqlPatternModEntities.

The standard evaluation metric for text-to-SPARQL is exact match of SPARQL queries. However, such a metric limits query generalization to only one interpretation and ignores query equivalence. We additionally propose an answer-based metric, which matches the SPARQL query result with the gold answer and avoids the pitfalls of the first method.

5.1 Standard Evaluation

We replicate the experiments by Keysers et al. (2020) on our dataset for each language. Specifically, we evaluate two representative neural
sequence-to-sequence (seq2seq) architectures: (i) LSTM (Hochreiter and Schmidhuber, 1997) with attention mechanism (Bahdanau et al., 2015) and (ii) Evolved Transformer (So et al., 2019). The experiments are implemented using the Tensor2Tensor (Vaswani et al., 2018) library. We use the hyperparameters tuned on the CFQ random split by Keysers et al. (2020). Separate models are trained and evaluated per language, with randomly initialized (not pre-trained) encoders.

The results are shown in Table 3. It suggests while it is easy for the models to parse for all four languages in a random split, i.e., all scores are above 72%, the accuracies are mostly below 20% in the three compositionally challenging MCD splits. On CWQ, the two systems are 12.5% and 17.6% accurate on average, for English. When compared with the Mean-MCD results on the CFQ leaderboard\footnote{https://github.com/google-research/google-research/tree/master/cfq}, the same models are 14.9% and 20.8% accurate, respectively. One obvious reason for this decrease in performance is the smaller training data: due to migration challenges, the CWQ dataset is much smaller than CFQ. Additionally, we did not tune hyperparameters on CWQ—we reused the hyperparameters from CFQ. Furthermore, CWQ has less redundancy than CFQ in terms of duplicate question and SPARQL patterns, rendering models’ potential strategy of simply memorizing patterns, less effective. Interestingly, Evolved Transformer does not significantly improve when compared with LSTM+attention for non-English question-query pairs.

Comparing the performance across languages, the two systems are, on average, 2% and 7% better in English than on the other three languages. A potential cause for this decrease is that most semantic query languages were initially designed to represent and retrieve data stored in English databases, and thus have a bias towards English. Consequently, SPARQL also has its syntactic structure closer to English than Hebrew, Kannada and Chinese, making their parsers harder to learn.

To investigate when the systems succeed and fail, we plot the complexity distribution of true predictions per language by the two systems in Figure 3. While both systems struggle to compositionally generalize to high complexities, Evolved Transformer generalizes better than LSTM+attention except in Chinese. English and Chinese are the only two languages for which models generate any correct queries for complexities over 30.

Interestingly, translated questions seem to make the parsers generalize better at lower complexity, as shown in the figure. Each of the three non-English models successfully parse more than 30 questions within the complexity range 9-14, but this number is capped at 15 for English. As is discussed in Section 4.2, machine-translated questions tend to have higher fluency than English questions; we conjecture such a smoothing method helps the parser to understand and learn from low complexity questions.

5.2 Answer-based Evaluation

In addition to standard evaluation, we propose an answer-based metric to evaluate parser performance. The entities that were masked during training are put back in the predicted queries. We execute the predicted queries, match their answers with the gold answers and calculate the percentage of answer matches. Such method is more lenient, but also more pragmatic than standard evaluation from an end-user perspective; the query format and triples’ order are not decisive so long as the expected answers are returned.

We show the answer-based evaluation results of the systems in Table 4. We find that even for wh- questions, answer-based evaluation accuracies are higher than standard evaluation across all languages. This suggests the new metric is de facto more forgiving but realistic for semantic parsing evaluation. Similar to standard evaluation, Evolved Transformer generally outperforms LSTM+Attention in both yes/no questions and wh- questions.

Our second observation is that Chinese is easier to parse than Hebrew and Kannada. Despite the overall satisfying translation quality, we found Google Cloud Translation is better at English-Chinese translation than Hebrew and Kannada due to the differences of resource abundance. Therefore, the parsing performance for Chinese is superior among the three non-English languages.
### 5.3 Analysis

We perform an empirical analysis by sampling 400 random SPARQL queries generated by the models across languages and report our findings here. Though there is a large gap between English and other languages in terms of accuracy, we see similar error patterns emerge in all languages: (i) Comparatively, parsers perform well on short questions on all four languages. This is expected as the compositionality of these questions is inherently low. (ii) On languages other than English, the models perform well when the translations are faithful. In occasions when they are less faithful or fluent but still generate correct queries, we hypothesize that translation acts as data regularizers, especially at lower complexities, as demonstrated in Fig. 3. (iii) The most common error across languages is the shuffling of entity masks. In the example shown below, we see that the model generates $M1 \ wdt:P58 \ M2$ instead of $M0 \ wdt:P58 \ M2$, which indicates incorrect predicate-argument structure interpretation. (iv) Another interesting pattern that most model errors follow is that they only generate the last required condition and ignore the others. In the below example, we see that the model only generates the final condition $M0 \ wdt:P58 \ M3$ and ignores the others ($M0 \ wdt:P57 \ M3$, $M0 \ wdt:P58 \ M1$, and $M0 \ wdt:P57 \ M2$).

#### 6 Zero-shot Cross-lingual Transfer

To verify if we can effectively transfer between languages, we train a multilingual Transformer model only on the English part of the CWQ dataset and test it on the other languages, in a zero-shot setting. We initialize the encoder of the model with the mBERT (Devlin et al., 2018) checkpoint, as it has been pre-trained on all four languages of interest. The decoder is similar to the encoder, but is randomly initialized. The model is trained for 100 epochs with a patience of 25, a batch size of 128, and a learning rate of $5 \times 10^{-5}$ with a linear decay.

In addition to the standard evaluation of exact-match accuracy, we report the BLEU scores (Papineni et al., 2002) of the predictions,
as a large portion of the generated queries are partially (but not fully) correct, especially in the zero-shot setting.\textsuperscript{10}

The results are shown in Table 5. Both accuracy and BLEU scores drastically reduce when the model is evaluated on Hebrew, Kannada and Chinese. The model achieves 11.4\% accuracy in standard evaluation on MCD\textsubscript{m}English, but less than 2\% for zero-shot transferring to three non-English languages. Even not for compositionality evaluation, as can be seen in Random split, the accuracies for zero-shot is still upsetting. The relatively high BLEU scores are artefacts of the limited vocabulary of the decoder. To conclude, multilingual zero-shot transfer from English to Hebrew, Kannada and Chinese fails to generate valid queries in CWQ. A potential cause for such unsuccessful transfer is that all four languages in CWQ belong to different language families and have low linguistic similarities. It remains to be investigated whether such cross-lingual transfer will be more effective on related languages, such as from English to German (Lin et al., 2019).

We also observe that, when tested on English, the results for the multilingual seq2seq model is lower than that of LSTM+Attention and Evolved Transformer. We postulate this might be a result of this much bigger model overfitting on the training data.

7 Related Work

Furrer et al. (2020) showed that pretrained language models rival other neural architectures tailored for compositionality with experiments on CFQ and SCAN (Lake and Baroni, 2018). Herzig et al. (2021) combined intermediate representations and pretrained models to improve compositional generalization on CFQ and text-to-SQL datasets. Sherborne and Lapata (2021) explored zero-shot cross-lingual semantic parsing by aligning latent representations with MultiATIS++, a cross-lingual NLU corpus (Xu et al., 2020). To the best of our knowledge, our work is the first on studying cross-lingual transfer learning in KBQA.

Comparing to machine reading comprehension (Rajpurkar et al., 2016; Joshi et al., 2017; Shao et al., 2018; Dua et al., 2019; d’Hoffmann et al., 2020), KBQA is less diverse in terms of datasets. Datasets such as WebQuestions (Berant et al., 2013), SimpleQuestions (Bordes et al., 2015), ComplexWebQuestions (Talmor and Berant, 2018), FreebaseQA (Jiang et al., 2019), CFQ (Keyser et al., 2020) and *CFQ (Tsarkov et al., 2021) were proposed on Freebase, a now discontinued KB. SimpleQuestions2wikidata (Dießenbach et al., 2017) and ComplexSequentialQuestions (Saha et al., 2018) are based on Wikidata, but like most others, they are monolingual English datasets. RuBQ is related to CWQ (Korablinov and Braslavski, 2020; Rybin et al., 2021), which is a Russian dataset for KBQA over Wikidata. While the dataset is bilingual, it uses crowdsourced questions and is not designed for compositionality analysis. Recently, Thorne et al. (2021) propose WIKINLDB, a Wikidata-based English KBQA dataset, focusing on the scalability rather than the compositionality.

Wikidata has been leveraged across many NLP tasks such as coreference resolution (Aralkatte et al., 2019), frame-semantic parsing (Sas et al., 2020), entity linking (Kannan Ravi et al., 2021) and named entity recognition (Nie et al., 2021). As for KBQA, the full potential of Wikidata has yet to be explored, which we begin to address here.

8 Conclusion

The field of KBQA has been saturated with work on English, due to both the inherent challenges of translating datasets and the reliance on English-only DBs. In this work, we presented a method for migrating the existing CFQ dataset to Wikidata, and created a challenging multilingual dataset, Multilingual Compositional Wikidata Questions, targeting compositional generalization in multilingual semantic parsing. In our experiments, we observe that seq2seq semantic parsers struggle to generalize compositionally on CWQ and that zero-shot cross-lingual transfer fails to generate valid queries with pretrained multilingual encoders. The experiments demonstrate that multilingual KBQA remains a challenge. Our work will facilitate building robust multilingual semantic parsers by providing a benchmark.
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