Bootstrapping a Crosslingual Semantic Parser

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Abstract

Datasets for semantic parsing scarcely consider languages other than English and professional translation can be prohibitively expensive. In this work, we propose to adapt a semantic parser trained on a single language, such as English, to new languages and multiple domains with minimal annotation. We evaluate if machine translation is an adequate substitute for training data, and extend this to investigate bootstrapping using joint training with English, paraphrasing, and resources such as multilingual BERT. Experimental results on a new version of ATIS and Overnight in German and Chinese indicate that MT can approximate training data in a new language for accurate parsing when augmented with paraphrasing through multiple MT engines.

1 Introduction

Semantic parsing is the task of mapping natural language utterances to machine-interpretable expressions such as SQL or a logical meaning representation. It has emerged as a key technology for developing natural language interfaces, especially in the context of question answering (Kwiatkowski et al., 2013; Berant et al., 2013; Liang, 2016; Kollar et al., 2018), where a semantically complex question is translated to an executable query to retrieve an answer, or denotation.

A popular approach to semantic parsing has been the application of recurrent neural networks to frame the task as sequence transduction between natural and formal languages (Jia and Liang, 2016; Dong and Lapata, 2016). Under this sequence-to-sequence framework (Sutskever et al., 2014), recent modeling innovations have included learning intermediate representations (Dong and Lapata, 2018; Guo et al., 2019), constrained decoding (Yin and Neubig, 2017; Krishnamurthy et al., 2017; Lin et al., 2019) and graph-based representations (Bogin et al., 2019; Shaw et al., 2019).

Given the surge of interest in neural semantic parsing and the training requirements of neural methods, it comes as no surprise that many datasets have been released in the past decade (Wang et al., 2015; Zhong et al., 2017; Iyer et al., 2017; Yu et al., 2018, 2019). However, these have widely used English as synonymous for natural language. English is neither linguistically typical (Dryer and Haspelmath, 2013) nor the most widely spoken language worldwide (Eberhard et al., 2019), but is presently the lingua franca of both utterances and knowledge bases in semantic parsing. Natural language interfaces intended for international deployment must be adaptable to multiple locales beyond an English prototype. However, it is unrealistic to expect that datasets will be created from scratch for every new language and domain.

The bulk of previous work has focused on multilingual semantic parsing, i.e., the task of employing multiple natural languages in parallel, which implies the availability of multilingual training data. Examples of multilingual datasets include GeoQuery (Zelle and Mooney, 1996), ATIS (Dahl et al., 1994) and NLMaps (Haas and Riezler, 2016), which are each limited to a single domain. Professional translation can nevertheless be prohibitively expensive for larger datasets and often require many man-hours from subject experts and native speakers. Recently, Min et al. (2019) reproduced the public partitions of the SPIDER dataset (Yu et al., 2018) into Chinese, but this required three expert annotators for verification and agreement. We posit that there may exist a better strategy for expanding semantic parsing to a new language.

In this work, we consider crosslingual semantic parsing, adapting a semantic parser trained on English, to another language. Specifically, we propose to expand executable semantic parsing to new languages and multiple domains by bootstrapping from in-task English datasets, task-agnostic multilingual resources, and publicly available machine translation (MT) services, in lieu of expert transla-
tion of training data. We investigate a core hypothesis that MT can provide a noisy, but reasonable, approximation of training data in a new source language. We further explore the benefit of augmenting noisy MT data using pre-trained models, such as BERT (Devlin et al., 2019), and multilingual training with English. Additionally, we examine approaches to ensembling multiple machine translations as approximate paraphrases.

To evaluate our hypothesis, we first present an updated version of the ATIS dataset (Dahl et al., 1994) in Chinese (ZH) and German (DE), paired with SQL queries, for a direct comparison between “real” utterances, from native speakers, and MT as training data. We then present a new version of the multi-domain Overnight dataset (Wang et al., 2015) where only the development and test partitions are utterances from native speakers of Chinese and German. This establishes a challenging task to generalize to real questions without gold-standard training data in two new languages.

Aside from creating new resources which we hope will encourage further work in crosslingual semantic parsing, our contributions include: (a) a cost-effective methodology for bootstrapping semantic parsers to new languages using minimal new annotation; (b) a proposal to overcome the paucity of gold-standard training data using pre-trained models, joint training with English, and paraphrases through MT engines and (c) a combined encoder-decoder attention mechanism to ensemble over multiple Transformer encoder submodels.

## 2 Related Work

Across logical formalisms, there have been several proposals for multilingual semantic parsing which employ multiple natural languages in parallel (Jones et al., 2012; Andreas et al., 2013; Lu, 2014; Susanto and Lu, 2017b; Jie and Lu, 2018).

For example, Jie and Lu (2014) ensemble monolingual hybrid tree parsers to generate a single parse tree from up to five source languages for GeoQuery (Zelle and Mooney, 1996). Similarly, Richardson et al. (2018) propose a polyglot automaton decoder for source-code generation from API documentation in 45 languages. Susanto and Lu (2017a) explore a multilingual neural architecture for four languages for GeoQuery and three languages for ATIS by extending Dong and Lapata (2016) with multilingual encoders. Both single- and multi-language sources are compared, with larger ensembles generally improving parsing. Other work focuses on multilingual representations for semantic parsing based on universal dependencies (Reddy et al., 2017) or embeddings of logical forms (Zou and Lu, 2018).

We capitalize on existing semantic parsing datasets to bootstrap from English to another language, and we therefore, do not assume that multiple languages are available as parallel input. Our work is closest to Duong et al. (2017), who explore how MT can bridge between languages for multilingual parsing. Extending this prior result, we investigate how to best leverage MT, from one or multiple sources, to parse queries from native speakers without observing real utterances during training. Beyond economizing on existing resources, our work further adds to recent efforts which enable crosslingual language understanding for various tasks such as entailment (Conneau et al., 2018) or semantic textual similarity (Cer et al., 2017). There has also been considerable interest in parsing into interlingual graphical meaning representations (Dammont and Cohen, 2018; Zhang et al., 2018) and \( \lambda \)-calculus expressions (Kwiatkowski et al., 2010; Lu and Ng, 2011; Lu, 2014). Since we focus on grounded logical forms in this work, we do not consider such systems further.

## 3 Problem Formulation

Throughout this work, we consider the real-world scenario in which an average software engineer wishes to develop a semantic parser to facilitate QA from an existing commercial database to customers in a new locale. Without the resources of high-valued technology companies, costs for annotation and machine learning resources need to be minimized to maintain some commercial viability. To economize this task, the developer intends to use minimal new annotation or professional translation, and instead bootstrap a system with public resources. At a minimum, a test and development set of utterances from native speakers are required for evaluation. However, the extent of annotation and the utility of domain adaptation for training are unknown. Therefore, our main question is how successfully can a semantic parser learn with alternative data resources to generalize to novel queries in a new language?

### 3.1 Neural Semantic Parsing

We focus on analyzing the utility of data for crosslingual transfer learning, and therefore we use the same parser throughout our results. We
Figure 1: (A) Machine Translation (MT) from English into some language L, for training data. J is the MT approximation of this language to be parsed. (B) Human translation of the development and test sets from English into language L. (C) Translation from language L into English using MT. Any system parsing language L must perform above this “back-translation” baseline to justify development.

approach this task using a SEQ2SEQ network comprised of a self-attentional (Transformer) encoder-decoder network (Vaswani et al., 2017). Considering input $X = \{x_i\}_{i=0}^N$ where $x_i \in \mathbb{R}^{d_x}$, the encoder computes multiple parallel dot-product attention scores between for the full input sequence. Each head is combined to produce a contextual approximation of this language to be parsed. (B) Knowledge base (KB) executes the logical form to predict a denotation, $d$. Approaches to crosslingual modeling involve: (A) using machine translation (MT) to approximate training data in language L; (B) training SP on both MT data and source English data; (C) using multiple MT systems to improve the approximation of L.

3.2 Crosslingual Modeling

Consider a parser, $SP(x)$, which transforms utterances in language $L$, to some executable logical form, $y$. We express a dataset in some language $L$ as $D^L = \{(x_i^L, y_n, d_n)_{n=1}^N, KB\}$, for $N$ examples where $x_i^L$ is an input utterance, $y$ is a logical form and $d$ is a denotation from knowledge base, $d = KB(y)$. The MT approximation of language L is described as $J$; using MT from English, $x'^J = MT(x^EN)$. Therefore, our hypothesis under consideration is that $J \approx L$ such that prediction $\hat{y} = SP(x'^L)$ for test example $x'^L$ approaches the gold logical form, $y_{gold}$, conditioned upon the quality of MT. Therefore, an optimal system will generate some prediction, $\hat{y}$, to return an equal denotation to that of $y_{gold}$ upon execution, $KB(\hat{y}) = d_{gold}$. Dataset $D^J$ diverges from $D^L$ only in training data, as we evaluate on only queries from native speakers e.g. $D^J_{dev} = D^L_{dev}$ and $D^J_{test} = D^L_{test}$ but $D^J_{train} \neq D^L_{train}$.

We evaluate our hypothesis on two languages to compare transfer learning from English into varied locales. We investigate German, a similar Germanic language, and Mandarin Chinese, a dissimilar Sino-Tibetan language, due to the purported quality of existing MT systems (Wu et al., 2016) and availability of native speakers to verify or rewrite crowdsourced annotation. Similar to Conneau et al. (2018), we implement a “back-translate into English” baseline wherein the test set in ZH/DE is translated back into English using MT and logical forms are predicted through a semantic parser for English. Figure 1 indicates how each dataset is generated. Performing above this
baseline is critical for our scenario to justify the development of any crosslingual semantic parser. Note that we do not claim to be investigating semantic parsing for low-resource languages since, by virtue, we require adequate MT into languages of interest to generate training data. We use Google Translate (Wu et al., 2016) as our primary MT system and complement this with systems from other global providers. The selection and use of MT is further discussed in Appendix A.

### 3.3 Feature Augmentation

Beyond using MT for in-language training data, we now describe our approach to further improve parsing using external resources and transfer learning. These approaches are described in Figure 2.

**Pre-trained Representations.** Motivated by the success of contextual word representations for semantic parsing of English by Shaw et al. (2019), we extend this technique to Chinese and German using implementations of BERT from Wolf et al. (2019). Rather than learning embeddings for the source language *tabula rasa*, we experiment with using pretrained 768-dimensional inputs from *bert-base*, *bert-base-chinese/german*¹ and *bert-base-multilingual* (104 languages) as a frozen input to the encoder. To account for rare entities which may be absent from pre-trained vocabularies, we concatenate BERT representations to a randomly initialised learnable embedding. Target language embeddings are learned from scratch as none of the above models are trained on meaning representations (i.e., λ—DCS or SQL queries). We also attempted the above using multilingual word representations (Conneau et al., 2017; Song et al., 2018), however this augmentation yielded no performance improvement. These results are omitted for brevity.

**Multilingual “Shared” Encoder.** Following Duong et al. (2017) and Susanto and Lu (2017a), we experiment with an encoder trained with batches from multiple languages as input. This is most similar to the All model from Duong et al. (2017), however, we consider English data as “support” for learning ZH/DE only, rather than multitask objective measuring performance on two languages. Our model learns unified parameters from both noisy data in the language of interest and gold-standard English data. Errors in the MT data are purportedly mitigated through the model observing an equivalent English utterance for the same logical form. The joint training dataset is described as $D_{\text{train}}^{EN+J} = D_{\text{train}}^{EN} \cup D_{\text{train}}^{J}$ for $J = \{ZH, DE\}$. Consistent with Section 3.2, we measure validation and test performance using only utterances from native speakers, $D_{\text{dev}}^{JL}$ and ignore the performance on English. For comparison on ATIS, we also experiment with a multilingual encoder training using human translations i.e., $D_{\text{train}}^{EN+L}$, $L = \{ZH, DE\}$.

### Machine Translation as Paraphrasing

Paraphrasing is a common augmentation for semantic parsers to improve generalization to unseen utterances (Berant and Liang, 2014; Dong et al., 2017; Iyer et al., 2017; Su and Yan, 2017). While there has been some study of multilingual paraphrase systems (Ganitkevitch and Callison-Burch, 2014), we instead use MT as a paraphrase resource, similar to Mallinson et al. (2017). Each MT system will have different outputs from different language models and therefore we hypothesize that an ensemble of multiple systems, $(J_1, \ldots, J_N)$, will provide greater linguistic diversity to better approximate $L$. Whereas prior work uses back-translation or paraphrasing a beam search, a developer in our scenario lacks the resources to train their own NMT system for such techniques. As a shortcut, we input the same English sentence into three public APIs for machine translation to retrieve a set of candidate paraphrases in the language of interest.

We experiment with two approaches to utilising these pseudo-paraphrases. The first, MT-Paraphrase, uniformly samples one paraphrase as input to the model during training. The second approach, MT-Ensemble, is an ensemble architecture similar to Garmash and Monz (2016); Firat et al. (2016) combining attention over each paraphrase in a single decoder. For $N$ paraphrases, we train $N$ parallel encoder models, $\{e_n\}_{n=1}^N$, and ensemble across each paraphrase by combining $N$ sets of encoder-decoder attention heads. For each encoder output, $E_n = e_n(X_n)$, we compute multi-head attention, $z_i$ in Eq 2, with the decoder state, $D$, as the query and $E_n$ as the key and value (Eq. 5). Attention heads are combined through some combination function (Eq. 6) and output $m_{ne}$ replaces $z_i$ in Eq. 3. We compare ensemble strategies using two combination functions: the mean of heads (Eq. 7a) and a gating network (Garmash and Monz 2016; Eq. 7b) with gating function $g$ (Eq. 8) where $W_g \in R^{N \times |V|}, W_h \in R^{V \times |N| \times |V|}$.

¹deeplab.ai/german-bert
\[ m_n = \text{MultiHeadAttention}(D, E_n, E_n) \]  
\[ m_{ie} = \text{comb}(m_1, \ldots, m_N) \]  
\[ \text{comb} = \begin{cases} \frac{1}{N} \sum_{m=1}^{N} m_n & \text{(a)} \\ \sum_{n=1}^{N} g_n m_n & \text{(b)} \end{cases} \]  
\[ g = \text{softmax}(W_g \tanh(W_h[m_n, \ldots, m_N])) \]  

Each expert submodel uses a shared embedding space to exploit similarity between paraphrases. During training, each encoder learns a language model specific to an individual MT source, yielding diversity among experts in the final system. During prediction, the test utterance is input to all \( N \) models in parallel. Previous LSTM-based ensemble approaches propose training full parallel networks and ensemble at the final decoding step, however we found this to be too expensive given the non-recurrent Transformer model. Our hybrid mechanism permits the decoder to attend to every paraphrased input and maintains a tractable model size with a single decoder.

### 4 Data

We consider two datasets in this work. Firstly, we evaluate our hypothesis that MT is an adequate proxy for “real” utterances using the ATIS dataset (Dahl et al., 1994). This single-domain dataset contains 5,418 utterances paired with SQL queries pertaining to a US flights database. This was previously translated into Chinese by Susanto and Lu (2017a) for semantic parsing into \( \lambda \)-calculus and we present these Chinese utterances aligned to the SQL queries from Iyer et al. (2017). We use the split of 4473/497/448 examples for train/validation/test from Kwiatkowski et al. (2011). The SQL from Iyer et al. (2017) contained 135 misaligned or absent requests, which we patch using data from Dahl et al. (1994). Additionally, we examine the eight-domain Overnight dataset (Wang et al., 2015), which contains 13,682 English questions paired with \( \lambda \)–DCS logical forms executable in SEMPRE (Berant et al., 2013). We partition a fixed development set from 20\% of the training data and use 8754 examples for training, 2188 for validation and 2740 for testing.

As part of this work, we present a translation of the full ATIS dataset into German for comparison to substituting MT for translated training data.

### Table 1: Examples from ATIS (Dahl et al., 1994) and Overnight (Wang et al., 2015)

| ATIS | Overnight |
|------|-----------|
| What are the flights from Phoenix, Arizona to St. Paul, Minnesota on Tuesday? | What article is about a venue of Annals of Statistics or Computational Linguistics? |
| Overnight Number of cuisines? | Which flights are from Phoenix, Arizona to Minneapolis, Sao Paulo |
| Which flights are from Phoenix, Arizona to St. Paul, Minnesota? | Which article is about the location of the statistical year or the location of the computing language? |
| Which flights are from Phoenix, Arizona to Minneapolis, Sao Paulo? | Several flavors |

However, as Overnight is 2.5\times larger than ATIS, we consider a complete parallel translation as uneconomical in our engineer’s scenario. As a compromise, we obtain human translations for only the test and validation set of Overnight and employ methods outlined in Section 3.3 to maximize parsing accuracy. We argue that this is a better reflection of the explicit crosslingual transfer learning required to port a parser to new languages. Datasets are translated using Amazon Mechanical Turk in a three-stage process following best practices from literature (Callison-Burch, 2009;
Zaidan and Callison-Burch, 2011; Behnke et al., 2018; Sosoni et al., 2018). The first task collects three candidate utterances from workers per English source question. The second stage asks workers to choose the best translation of three candidates, with the option to rewrite the translation if none were satisfactory. As an additional quality filter, we recruited bilingual native speakers to verify or rewrite every human translation with an additional MT candidate. Example translations, and translation errors, are shown in Table 1, and further details concerning our crowdsourcing methodology can be found in Appendix A.

5 Experimental Setup

For ATIS, we implement models trained on both real and machine translated utterances in German and Chinese. The former is our upper bound, representing the ideal case, and the latter is the minimal scenario for our developer. Comparison between these cases demonstrates both the capability of a system in the new locale and delineates the adequacy of MT for the task. Following this, we explore the multi-domain case of the Overnight dataset wherein there is no gold-standard training data in either language.

**Preprocessing** Data are preprocessed by removing punctuation and lowercasing with NLTK (Bird and Loper, 2004), except for cased pre-trained vocabularies and Chinese. Logical forms are split on whitespace and natural language is tokenized using the sentencepiece tokenizer\(^2\) to model language-agnostic subwords. We found this critical for Chinese, which lacks whitespace delimitation in sentences, and for German, to model word compounding. For ATIS, we experimented with the entity anonymisation scheme from Iyer et al. (2017), however, this was found to be detrimental when combined with pre-trained input representations and was subsequently not used.

**Evaluation and Model Selection** Neural models are optimised through a grid search between a embedding/hidden layer size of \(2\{7,\ldots,10\}\), the number of layers between \(2,\ldots,8\) and the number of heads between \(4,\ldots,8\). All weights are initialized with Xavier initialization (Glorot and Bengio, 2010) except pre-trained representations which remain frozen. Model weights, \(\theta\), are optimised using sequence cross-entropy loss against gold-standard logical forms as supervision.

\(^2\)github.com/google/sentencepiece

|                | DE  | ZH  |
|----------------|-----|-----|
| Backtranslation to EN | 53.9 | 57.8 |
| +BERT-base      | 56.4 | 58.9 |
| SEQSSEQ        | 66.9 | 66.2 |
| +BERT (de/zh)  | 67.8 | 67.4 |
| Shared Encoder | 69.3 | 68.3 |
| +BERT-ML       | 69.5 | 68.9 |

(a) training on gold-standard data

|                | DE (MT) | ZH (MT) |
|----------------|---------|---------|
| Backtranslation to EN | 53.9 | 57.8 |
| +BERT-base      | 56.4 | 58.9 |
| SEQSSEQ        | 55.2 | 61.0 |
| +BERT-(de/zh)  | 57.3 | 64.8 |
| Shared Encoder | 58.7 | 64.1 |
| +BERT-ML       | 59.9 | 66.4 |
| MT-Paraphrase  | 64.5 | 62.2 |
| +BERT-ML       | 65.0 | 67.8 |
| MT-Ensemble    | 68.1 | 66.6 |
| +Shared Encoder | 68.1 | 66.6 |
| +BERT-ML       | 65.5 | 64.3 |
| +Shared Encoder | 67.8 | 65.7 |

(b) training on machine translated (MT) data

Table 2: Test set denotation Accuracy for ATIS in German (DE) and Chinese (ZH).

Each experiment trains a network for 200 epochs using the Adam Optimizer (Kingma and Ba, 2014) with a learning rate of 0.001. We follow the Noam learning rate scheduling approach with a warmup of 10 epochs. Minimum validation loss is used as an early stopping metric for model selection, with a patience of 30 epochs. We use teacher forcing for prediction during training and beam search, with a beam size of 5, during inference.

Predicted logical forms are input to the knowledge base for ATIS, an SQL database, and Overnight, SEMPRE (Berant et al., 2013), to retrieve denotations. All results are reported as exact-match (hard) denotation accuracy, the proportion of predicted logical forms which execute to retrieve the same denotation as the reference query. Models are built using PyTorch (Paszke et al., 2017), AllenNLP (Gardner et al., 2018) and HuggingFace BERT models (Wolf et al., 2019).

6 Results and Analysis

We compare the neural model defined in Section 3.1 (SEQ2SEQ) to models using each augmentation outlined in Section 3.3, and a combination thereof, and the back-translation baseline. Table 2(a) details experiments for ATIS using human translated training data, contrasting to Table 2(b) which substitutes MT for training data in ZH and DE. Similar results for Overnight are then presented in Table 3.
To the best of our knowledge, we present the first results for executable semantic parsing of ATIS and Overnight in any language other than English. While prior multilingual work using $\lambda$-calculus logic is not comparable, we compare to similar results for English in Appendix B.

**ATIS** Table 2(a) details the ideal case of translating the full dataset. While this would be the most expensive route for our developer, all models demonstrate performance above back-translation with a best improvement of +13.1% and +10.0% for DE and ZH respectively. This suggests a parallel implementation is preferable over MT into English. Similar to Shaw et al. (2019) and Duong et al. (2017), we find that pre-trained BERT representations and a shared encoder are respectively beneficial augmentations, with the best system using both for ZH and DE. However, the latter augmentation seems less beneficial for ZH than DE, potentially due to decreased lexical overlap between EN and ZH, with only 20.1% vocabulary similarity compared to a 51.9% between EN and DE. This could explain the decreased utility of the shared embedding space. For comparison, the accuracy of our English model is 75.4%, we observe a penalty of -6.1% for DE and -6.5% for ZH. Difficulty in parsing German, previously noted by Jie and Lu (2014), may be an artefact of comparatively complex morphology for indicating semantic intent. We found similar issues to Min et al. (2019) in parsing Chinese, namely word segmentation and dropped pronouns, which compound with poor translations to likely explain weaker parsing compared to English.

Contrasting to back-translation, the SEQ2SEQ model without BERT, using MT as training data (Table 2(b)), improves upon the baseline by +3.2% for ZH and +1.3% for DE. We find that the translation approach for Chinese supersedes back-translation for all models, justifying the development of an in-language parser. However for German, the SEQ2SEQ approach requires any further augmentation to improve over the best 56.4% back-translation accuracy. Overall, the best systems use paraphrasing and multilingual BERT, with additional encoder sharing for German. The MT-Ensemble model proved marginally weaker than MT-Paraphrase overall, but appeared competitively performant in some cases e.g. the base paraphrase model for Chinese and the base models with BERT-multilingual for German. Comparing between human translations, we find similar best case penalties of -1.2% for DE and -1.1% for ZH for using MT training data. Given this small generalisation error from using machine generated training data, we consider our approach to expanding parsing to a new language justified in feasibility.

**Overnight** We now extend our experiments to the multi-domain Overnight dataset, wherein we have only utterances from native speakers for evaluation, in Table 3. Whereas back-translation appeared nearly viable for ATIS, here we observe the collapse of parsing capability for the baseline. The SEQ2SEQ model with BERT improves upon this approach by a considerable +28.1% for DE and +32.3% for ZH. Under inspection, we find this is a consequence of error with MT into English, with examples shown in Table 1 for “St. Paul” and “cuisines”, which compound across eight domains. Our results indicate an in-language parser can better interpret utterances across many domains than back-translation. Our reference English parser attains an average 79.8% accuracy, inferring...
a penalty from crosslingual transfer of -14.9% and -14.7% penalty for DE and ZH respectively with the SEQ2SEQ model only. With the best model for each language, this penalty is minimised to -5.9% for DE and -9.5% for ZH, which further highlights the earlier result that parsing German is easier using MT from English. Similar to ATIS, we find that single augmentations yield marginal improvement, or are slightly detrimental in some cases, and combining approaches is broadly the most beneficial strategy. The best approach for both DE and ZH is using paraphrasing with a single encoder and additionally training with English and BERT-multilingual input features. This approach improved by +9.0% and 5.2% over the SEQ2SEQ model respectively. Comparing these improvements supports the notion that the MT systems from English are superior for German, but Chinese requires further modeling for optimal parsing. We found the MT-Ensemble approach extremely poor by comparison for this dataset, requiring additional augmentation to yield accuracy comparable to our other approaches. This could be attributed to how encoders are combined, and we leave investigating this to future work.

**Improvements from Feature Augmentation**

Considering instances wherein augmented models improve upon the SEQ2SEQ approach, we find three emergent patterns of error minimization from our feature augmentations. Firstly, using BERT improves modeling spatial and temporal language used to specify flight times in ATIS and in the Calendar and Blocks domain of Overnight. This appears largely due to orthographic inconsistencies between translation, e.g., different MT and translators using either “Cavs” or “coach”, which are ambiguous to resolve as “Cleveland Cavaliers” and “Economy Class”, respectively. By pairing the same logical form with the source English utterance, the system improves resolving the translation of these entities in DE/ZH.

Secondly, the shared encoder approach specifically mitigates translation errors, both human and MT, arising from insufficient real-world knowledge or context. This affects phrases such as “the Cavs” or “coach”, which are ambiguous to resolve as “Cleveland Cavaliers” and “Economy Class”, respectively. By pairing the same logical form with the source English utterance, the system improves resolving the translation of these entities in DE/ZH.

Finally, paraphrases particularly benefit parsing expressions in DE/ZH equivalent to peculiar, or KB-specific, English phrases. For example, the Restaurant domain heavily discusses “dollar-sign ratings” for price and “star sign” rating for quality. There is high variation in how native speakers translate such phrases and subsequently, the linguistic diversity provided through paraphrasing benefits parsing of these widely variable utterances. Additionally, this diversity assists in interpreting queries using domain-specific entities. The SEQ2SEQ model commonly confuses entities between the smaller Overnight domains (*Recipes, Calendar, Publications, Housing*), however this is not the case for the best model with paraphrasing in both languages.

**7 Conclusion**

We present an investigation into bootstrapping a crosslingual semantic parser for Chinese and German using only public resources. Our contribution includes new versions of ATIS and Overnight in Chinese and German. We also find that pre-trained models and joint training with English data are the most beneficial augmentations to train parsers with MT data. Additional usage of paraphrases through different MT engines can further improve performance if a paraphrase can translate an entity adequately. Our comparison of paraphrasing approaches indicates that a single encoder trained with diverse inputs is superior to an ensemble approach. However when considering the small dataset size, our second model could be improved in future work.

**References**

Jacob Andreas, Andreas Vlachos, and Stephen Clark. 2013. Semantic parsing as machine translation. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 47–52, Sofia, Bulgaria.

Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E. Hinton. 2016. Layer normalization.

Maximiliana Behnke, Antonio Valerio Miceli Barone, Rico Sennrich, Villeimmi Sosoni, Thanasis Naskos, Eirini Takoulioudou, Maria Stasimioti, Menno Van Zaanen, Sheila Castilho, Federico Gaspari, Panayota Georgakopoulou, Vilia Kordoni, Markus Egg, and Katia Lida Kermanidis. 2018. Improving Machine Translation of Educational Content via Crowdsourcing. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation*, pages 3343–3347, Miyazaki, Japan.

Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In *Proceedings of the 2013 Conference on Language Resources and Evaluation*, pages 3343–3347, Miyazaki, Japan.

Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In *Proceedings of the 2013
Conference on Empirical Methods in Natural Language Processing, pages 1533–1544, Seattle, Washington, USA.

Jonathan Berant and Percy Liang. 2014. Semantic Parsing via Paraphrasing. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1415–1425, Stroudsburg, PA, USA.

Steven Bird and Edward Loper. 2004. NLTK: The natural language toolkit. In Proceedings of the ACL Interactive Poster and Demonstration Sessions, pages 214–217, Barcelona, Spain.

Ben Bogin, Matt Gardner, and Jonathan Berant. 2019. Representing Schema Structure with Graph Neural Networks for Text-to-SQL parsing. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 4560–4565, Florence, Italy. Association for Computational Linguistics.

Chris Callison-Burch. 2009. Fast, cheap, and creative: evaluating translation quality using Amazon’s Mechanical Turk. In Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing, pages 286–295, Singapore.

Daniel Cer, Mona Diab, Eneko Agirre, Iñigo Lopez-Gazpio, and Lucia Specia. 2017. SemEval-2017 task 1: Semantic textual similarity multilingual and crosslingual focused evaluation. In Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017), pages 1–14, Vancouver, Canada.

Alexis Conneau, Guillaume Lample, Marc’Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégoü. 2017. Word translation without parallel data. arXiv preprint arXiv:1710.04087.

Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. XNLI: Evaluating cross-lingual sentence representations. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2475–2485, Brussels, Belgium. Association for Computational Linguistics.

Deborah A. Dahl, Madeleine Bates, Michael Brown, William Fisher, Kate Hunnicke-Smith, David Pallett, Christine Pao, Alexander Rudnicky, and Elizabeth Shirberg. 1994. Expanding the scope of the ATIS task: The ATIS-3 corpus. In Proceedings of the Workshop on Human Language Technology, HLT ’94, pages 43–48, Stroudsburg, PA, USA.

Marco Damonte and Shay B. Cohen. 2018. Cross-Lingual Abstract Meaning Representation Parsing. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1146–1155, Stroudsburg, PA, USA.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. (BERT): Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North {A}merican Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota.

Li Dong and Mirella Lapata. 2016. Language to Logical Form with Neural Attention. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 33–43, Stroudsburg, PA, USA.

Li Dong and Mirella Lapata. 2018. Coarse-to-Fine Decoding for Neural Semantic Parsing. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 731–742, Melbourne, Australia.

Li Dong, Jonathan Mallinson, Siva Reddy, and Mirella Lapata. 2017. Learning to paraphrase for question answering. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 875–886, Copenhagen, Denmark.

Matthew S. Dryer and Martin Haspelmath, editors. 2013. {WALS Online}. Max Planck Institute for Evolutionary Anthropology, Leipzig.

Long Duong, Hadi Afshar, Dominique Estival, Glen Pink, Philip Cohen, and Mark Johnson. 2017. Multilingual Semantic Parsing And Code-Switching. In Proceedings of the 21st Conference on Computational Natural Language Learning, pages 379–389, Vancouver, Canada.

David Eberhard, Gary Simons, and Charles. 2019. Languages of the World. Ethnologue: Languages of the World. Twenty-Second Edition, 22.

Catherine Finegan-Dollak, Jonathan K. Kummerfeld, Li Zhang, Karthik Ramanathan, Sesh Sadasivam, Rui Zhang, and Dragomir Radev. 2018. Improving Text-to-SQL Evaluation Methodology. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 351–360, Melbourne, Australia.

Orhan Firat, Baskaran Sankaran, Yaser Al-Onaizan, Fatos T. Yarman Vural, and Kyunghyun Cho. 2016. Zero-Resource Translation with Multi-Lingual Neural Machine Translation. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 268–277, Stroudsburg, PA, USA.

Juri Ganitkevitch and Chris Callison-Burch. 2014. The multilingual paraphrase database. In Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC’14), pages 4276–4283, Reykjavik, Iceland.
Matt Gardner, Joel Grus, Mark Neumann, Oyvind Tafjord, Pradeep Dasigi, Nelson F. Liu, Matthew E. Peters, Michael Schmitz, and Luke S. Zettlemoyer. 2018. AllenNlp: A deep semantic natural language processing platform. \textit{ArXiv}, abs/1803.07640.

Ekaterina Garmash and Christof Monz. 2016. \textit{Ensemble Learning for Multi-Source Neural Machine Translation}. In \textit{Proceedings of the 26th International Conference on Computational Linguistics: Technical Papers}, pages 1409–1418, Osaka, Japan.

Xavier Glorot and Yoshua Bengio. 2010. Understanding the difficulty of training deep feedforward neural networks. In \textit{Proceedings of the International Conference on Artificial Intelligence and Statistics (AISTATS’10). Society for Artificial Intelligence and Statistics}.

Jiaqi Guo, Zecheng Zhan, Yan Gao, Yan Xiao, Jian-Guang Lou, Ting Liu, and Dongmei Zhang. 2019. Towards complex text-to-SQL in cross-domain database with intermediate representation. In \textit{Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics}, pages 4524–4535, Florence, Italy. Association for Computational Linguistics.

Carolin Haas and Stefan Riezler. 2016. \textit{A Corpus and Semantic Parser for Multilingual Natural Language Querying of OpenStreetMap}. In \textit{Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies}, pages 740–750, Stroudsburg, PA, USA.

Kotaro Hara, Abigail Adams, Kristy Milland, Saiph Savage, Benjamin V Hanrahan, Jeffrey P Bigham, and Chris Callison-Burch. 2019. \textit{Worker Demographics and Earnings on Amazon Mechanical Turk: An Exploratory Analysis}. \textit{CHI’19 Late Breaking Work}.

Jonathan Herzig and Jonathan Berant. 2017. \textit{Neural Semantic Parsing over Multiple Knowledge-bases}. In \textit{Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)}, volume 2, pages 623–628, Stroudsburg, PA, USA.

Huseyin A. Inan, Gaurav Singh Tomar, and Huapu Pan. 2019. Improving semantic parsing with neural generator-reranker architecture. \textit{ArXiv}, abs/1909.12764.

Srinivasa Iyer, Alvin Cheung, and Luke Zettlemoyer. 2019. \textit{Learning Programmatic Idioms for Scalable Semantic Parsing}. In \textit{Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing}, pages 5425–5434, Hong Kong, China.

Srinivasa Iyer, Ioannis Konstas, Alvin Cheung, Jayant Krishnamurthy, and Luke Zettlemoyer. 2017. \textit{Learning a neural semantic parser from user feedback}. In \textit{Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)}, pages 963–973, Vancouver, Canada.

Robin Jia and Percy Liang. 2016. \textit{Data Recombination for Neural Semantic Parsing}. In \textit{Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)}, pages 12–22, Stroudsburg, PA, USA.

Zhanming Jie and Wei Lu. 2014. \textit{Multilingual Semantic Parsing : Parsing Multiple Languages into Semantic Representations}. In \textit{Proceedings of the 25th International Conference on Computational Linguistics: Technical Papers}, pages 1291–1301, Dublin, Ireland.

Zhanming Jie and Wei Lu. 2018. \textit{Dependency-based Hybrid Trees for Semantic Parsing}. In \textit{Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing}, pages 2431–2441, Brussels, Belgium.

Bevan Keeley Jones, Mark Johnson, and Sharon Goldwater. 2012. \textit{Semantic Parsing with Bayesian Tree Transducers}. In \textit{Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers - Volume 1}, pages 488–496, Stroudsburg, PA, USA.

Diederik P. Kingma and Jimmy Ba. 2014. \textit{Adam: A method for stochastic optimization}. \textit{CoRR}, abs/1412.6980.

Thomas Kollar, Danielle Berry, Lauren Stuart, Karolina Owczarzak, Tagyoung Chung, Lambert Mathias, Michael Kayser, Bradford Snow, and Spyros Matsoukas. 2018. \textit{The Alexa meaning representation language}. In \textit{Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 3 (Industry Papers)}, pages 177–184, New Orleans - Louisiana.

Jayant Krishnamurthy, Pradeep Dasigi, and Matt Gardner. 2017. Neural semantic parsing with type constraints for semi-structured tables. In \textit{Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing}, pages 1516–1526, Copenhagen, Denmark.

Tom Kwiatkowski, Eunsol Choi, Yoav Artzi, and Luke Zettlemoyer. 2013. \textit{Scaling semantic parsers with on-the-fly ontology matching}. In \textit{Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing}, pages 1545–1556, Seattle, Washington, USA.

Tom Kwiatkowski, Luke Zettlemoyer, Sharon Goldwater, and Mark Steedman. 2010. \textit{Inducing probabilistic CCG grammars from logical form with higher-order unification}. In \textit{Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing}, pages 1223–1233, Stroudsburg, PA, USA.
Tom Kwiatkowski, Luke Zettlemoyer, Sharon Goldwater, and Mark Steedman. 2011. **Lexical Generalization in CCG Grammar Induction for Semantic Parsing.** In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 1512–1523, Edinburgh, Scotland, UK.

Percy Liang. 2016. **Learning executable semantic parsers for natural language understanding.** *Comm. ACM*, 59(9):68–76.

Percy Liang, Michael I Jordan, and Dan Klein. 2013. **Learning Dependency-based Compositional Semantics.** *Comput. Linguist.*, 39(2):389–446.

Kevin Lin, Ben Bogin, Mark Neumann, Jonathan Berant, and Matt Gardner. 2019. **Grammar-based neural text-to-sql generation.** *CoRR*, abs/1905.13326.

Wei Lu. 2014. **Semantic parsing with relaxed hybrid trees.** In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1308–1318, Doha, Qatar.

Wei Lu and Hwee Tou Ng. 2011. **A probabilistic forest-to-string model for language generation from typed lambda calculus expressions.** In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 1611–1622, Edinburgh, Scotland, UK.

Jonathan Mallinson, Rico Sennrich, and Mirella Lapata. 2017. **Paraphrasing revisited with neural machine translation.** In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, pages 881–893, Valencia, Spain.

Qingkai Min, Yuefeng Shi, and Yue Zhang. 2019. **A Pilot Study for Chinese SQL Semantic Parsing.** In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing*, pages 3643–3649, Stroudsburg, PA, USA.

Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. 2017. **Automatic differentiation in PyTorch.** In *NIPS Autodiff Workshop*.

Ellie Pavlick, Matt Post, Ann Irvine, Dmitry Kachaev, and Chris Callison-Burch. 2014. **The Language Demographics of Amazon Mechanical Turk.** *Transactions of the Association for Computational Linguistics*, 2.

Matt Post, Chris Callison-Burch, and Miles Osborne. 2012. **Constructing Parallel Corpora for Six Indian Languages via Crowdsourcing.** In *Proceedings of the Seventh Workshop on Statistical Machine Translation*, pages 401–409.

Siva Reddy, Oscar Täckström, Slav Petrov, Mark Steedman, and Mirella Lapata. 2017. **Universal semantic parsing.** In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 89–101, Copenhagen, Denmark.

Kyle Richardson, Jonathan Berant, and Jonas Kuhn. 2018. **Polyglot Semantic Parsing in APIs.** In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, New Orleans, Louisiana.

Peter Shaw, Philip Massey, Angelica Chen, Francesco Piccinno, and Yasemin Altun. 2019. **Generating logical forms from graph representations of text and entities.** In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 95–106, Florence, Italy. Association for Computational Linguistics.

Yan Song, Shuming Shi, Jing Li, and Haisong Zhang. 2018. **Directional skip-gram: Explicitly distinguishing left and right context for word embeddings.** In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 175–180, New Orleans, Louisiana.

Vilemmini Sosoni, Katia Lida Kermanidis, Maria Stasinopoulou, Thanasis Naskos, Eirini Takoulidou, Memno Van Zaanen, Sheila Castillo, Panayota Georgakopoulou, Valia Kordoni, and Markus EGG. 2018. **Translation Crowdsourcing: Creating a Multilingual Corpus of Online Educational Content.** In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation*, Miyazaki, Japan.

Yu Su and Xifeng Yan. 2017. **Cross-domain semantic parsing via paraphrasing.** In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 1235–1246, Copenhagen, Denmark.

Raymond Hendy Susanto and Wei Lu. 2017a. **Neural Architectures for Multilingual Semantic Parsing.** In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 38–44, Stroudsburg, PA, USA.

Raymond Hendy Susanto and Wei Lu. 2017b. **Semantic parsing with neural hybrid trees.** In *AAAI Conference on Artificial Intelligence*, San Francisco, California, USA.

Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. **Sequence to sequence learning with neural networks.** *CoRR*, abs/1409.3215.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. **Attention is all
you need. In Advances in Neural Information Processing Systems 30, pages 5998–6008. Curran Associates, Inc.

Bailin Wang, Richard Shin, Xiaodong Liu, Oleksandr Polozov, and Matthew Richardson. 2019. Rat-sql: Relation-aware schema encoding and linking for text-to-sql parsers.

Chenglong Wang, Po-Sen Huang, Alex Polozov, Marc Brockschmidt, and Rishabh Singh. 2018. Execution-guided neural program decoding. CoRR, abs/1807.03100.

Yushi Wang, Jonathan Berant, and Percy Liang. 2015. Building a Semantic Parser Overnight. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), volume 1, pages 1332–1342, Stroudsburg, PA, USA.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, R’emi Louf, Morgan Funtowicz, and Jamie Brew. 2019. Huggingface’s transformers: State-of-the-art natural language processing. ArXiv, abs/1910.03771.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaohong Liu, Łukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. CoRR, abs/1609.08144.

Pengcheng Yin and Graham Neubig. 2017. A syntactic neural model for general-purpose code generation. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 440–450, Vancouver, Canada.

Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasunaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, Zilin Zhang, and Dragomir Radev. 2018. Spider: A Large-Scale Human-Labeled Dataset for Complex and Cross-Domain Semantic Parsing and Text-to-SQL Task. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium.

Tao Yu, Rui Zhang, Michihiro Yasunaga, Yi Chern Tan, Xi Victoria Lin, Suyi Li, Heyang Er, Irene Li, Bo Pang, Tao Chen, Emily Ji, Shreya Dixit, David Proctor, Sungrok Shim, Jonathan Kraft, Vincent Zhang, Caiming Xiong, Richard Socher, and Dragomir Radev. 2019. SPaC: Cross-domain semantic parsing in context. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4511–4523, Florence, Italy. Association for Computational Linguistics.

Omar F. Zaidan and Chris Callison-Burch. 2011. Crowdsourcing Translation: Professional Quality from Non-Professionals. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 1220–1229.

John M. Zelle and Raymond J. Mooney. 1996. Learning to parse database queries using inductive logic programming. In Proceedings of the Thirteenth National Conference on Artificial Intelligence - Volume 2, AAAI’96, pages 1050–1055.

Sheng Zhang, Xutai Ma, Rachel Rudinger, Kevin Duh, and Benjamin Van Durme. 2018. Cross-lingual Decompositional Semantic Parsing. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1664–1675, Brussels, Belgium.

Victor Zhong, Caiming Xiong, and Richard Socher. 2017. Seq2SQL: Generating structured queries from natural language using reinforcement learning. CoRR, abs/1709.00103.

Yanyan Zou and Wei Lu. 2018. Learning Cross-lingual Distributed Logical Representations for Semantic Parsing. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 673–679, Melbourne, Australia.
A Data Collection

Translation through Crowdsourcing  For the task of crosslingual semantic parsing, we consider the ATIS dataset (Dahl et al., 1994) and the Overnight dataset (Wang et al., 2015). The former is a single-domain dataset of utterances paired with SQL queries pertaining to a database of travel information in the USA. Overnight covers eight domains using logical forms in the $\lambda$–DCS formalism (Liang et al., 2013) which can be executed in the SEMPRE framework (Berant et al., 2013).

ATIS has been previously translated into Chinese and Indonesian for the study of semantic parsing into $\lambda$–calculus logical forms (Susanto and Lu, 2017a), however Overnight exists only in English. To the best of our knowledge, there is presently no multi-domain dataset for executable semantic parsing in more than two languages. As previously mentioned in Section 4 , we consider Chinese and German in this paper to contrast between a language similar and dissimilar to English and also due to the reported availability of crowd-sourced workers for translation (Pavlick et al., 2014) and bilingual native speakers of each language for verification.

To facilitate evaluation of the task in all languages of interest, we require a full parallel translation of ATIS in German, for comparison to the existing Chinese implementation, and a partial translation of Overnight in both German and Chinese. As previously discussed, we translate only the development and test set of Overnight for evaluation and bootstrap the training data. Therefore, we translate all 5,473 utterances in ATIS and 4,311 utterances in Overnight. Note we only consider Simplified Mandarin Chinese (zh-CN) in this work. The original Overnight dataset did not correct spelling errors from collected English paraphrases, however, we consider it unreasonable to ask participants in our task to translate misspelled words, as ambiguity in correction could lead to inaccurate translations. We subsequently identified and corrected spelling errors using word processing software as a pre-processing stage.

For this task, we use Amazon Mechanical Turk (MTurk) to solicit three translations per English source sentence from crowdsourced workers (Turkers), with the hypothesis that this will collect at least one adequate translation (Callison-Burch, 2009). Our task design largely followed practices for translation without expert labels on MTurk (Zaidan and Callison-Burch, 2011; Post et al., 2012; Behnke et al., 2018; Sosoni et al., 2018). The task solicits translations by asking a Turker to translate 10 sentences and answer 3 demographic questions. Submissions were restricted to Turkers from Germany, Austria and Switzerland or China, Singapore, and the USA for German and Chinese respectively. We built an AMT interface such that Turkers were unable to input empty submissions and were also barred from copying or pasting anywhere within the webpage. Attempts to copy or paste in the submission window also trigger a warning that using online translation tools will result in rejection. Inauthentic translations were rejected if they held an $>80\%$ average BLEU to reference translations from Google Translate (Wu et al., 2016), as were nonsensical or irrelevant submissions. For the Chinese data collection, we also rejected submissions using Traditional Chinese Characters or Pinyin romanization.

Turkers submitted 10 translations per task for $0.70 and $0.25 to rank 10 candidate translations, at an average rate to receive an equivalent full-time wage of $8.23/hour. This is markedly above the average wage for US workers of $3.01/hour discovered by Hara et al. (2019). To ensure data quality and filter disfluencies or personal biases from Turkers, we then recruited bilingual postgraduate students, native speakers of the task language, to judge if the best chosen translation from Turk was satisfactory or required rewriting. If an annotator was dissatisfied with the translation ranked best from Turk then they provided their own. Verifiers preferred the MT candidate over the Turk submissions for 29.5\% of German rankings and 22.6\% of Chinese rankings, however this preference is almost entirely owing to translations of simple sentences with 5 or fewer English words. We paid $12 an hour for this verification but to minimize cost, we did not collect multiple judgements per translation. We found that verification was completed at a rate of 60 judgements per hour, leading to an approximate cost of $2200 per language for Overnight and $2500 for ATIS into German. While this may be considered expensive, this is the minimum cost to permit comparable evaluation in every language. We now describe how we minimised costs for bootstrapping training data from publicly available resources.

Machine Translation  In this work, we evaluate the feasibility of using machine translation (MT) as a proxy to generate in-language training data for semantic parsing of two languages. All MT systems
| DE  | MT1  | MT2  | MT3  | ZH  | MT1  | MT2  | MT3  |
|-----|------|------|------|-----|------|------|------|
| G   | 0.732| 0.576| 0.611| G   | 0.517| 0.538| 0.525|
| MT1 | —    | 0.650| 0.667| MT1 | —    | 0.660| 0.645|
| MT2 | —    | —    | 0.677| MT2 | —    | —    | 0.738|

(a) ATIS

Table 4: Corpus BLEU between gold-standard translations (G) and machine translations from sources 1–3 for (a) ATIS and (b) Overnight. For German (DE): MT1 is Google Translate, MT2 is Microsoft Translator Text and MT3 is Yandex. For Chinese (ZH): MT1 is Google Translate, MT2 is Baidu Translate and MT3 is Youdao Translate.

| ATIS | Overnight |
|------|-----------|
| Wang et al. (2015) | — |
| Su and Yan (2017)  | — |
| Herzig and Berant (2017) | — |
| Iyer et al. (2017) | 82.5 |
| Wang et al. (2018) | 77.9 |
| Iyer et al. (2019) | 83.2 |
| Inan et al. (2019) | — |
| SEQ2SEQ  | 74.9 |
| +BERT-base | 75.4 |

Table 5: Test denotation accuracy on ATIS and Overnight for reference model for English. Best accuracy is bolded. Note that Inan et al. (2019) evaluate on ATIS, but use the non-executable $\lambda$—calculus logical form and are therefore not comparable to our results. Domains are Basketball, Blocks, Calendar, Housing, Publications, Recipes, Restaurants, and Social Network.

are treated as black-box models without inspection of underlying translation mechanics or recourse to correct translations. For most experiments in this work, we retrieve translations from English to the target language using the Google Translate API (Wu et al., 2016). We use this system owing to the purported translation quality (Duong et al., 2017) and because the API is publicly available, contrasting to the closed MT used in Conneau et al. (2018).

Additionally, we explore two approaches to modeling an ensemble of translations from multiple MT sources. We expect, but cannot guarantee, that each MT system will translate each utterance differently to produce a training corpus with greater diversity in the target language. For this approach, we consider two additional MT systems each for Chinese and German. For Mandarin, we use Baidu Translate and Youdao Translate. For German, we use Microsoft Translator Text and Yandex Translate. To verify that the ensemble of multiple MT systems provides some additional corpora diversity, we measure the corpus level BLEU between training utterances from each source. These scores for ATIS and Overnight are detailed in Table 4, with an additional comparison to gold translation for ATIS.

Overall, we find that each MT system provides a different set of translations, with no two translation sets notably more similar than any other pair. We also find that for ATIS in German, Wu et al. (2016) provides the most similar training dataset to the gold training data. However, we find that Microsoft Translator Text appears to marginally improve translation into Chinese by +0.021 BLEU. This arises as an effect of a systematic preference for a polite form of Chinese question, beginning with 请 [please], preferred by the professional translator. We collect all machine translated training data for < $50 across both datasets and languages. This is a considerable saving compared to efforts such as Min et al. (2019), for which no cost is given, but under our framework would cost approximately $4900 to replicate.
B English Results

We compare our reference model for English to prior work in Table 5. Our best system for this language uses the SEQ2SEQ model outlined in Section 3.1 with input features from the pre-trained BERT-base model. We acknowledge our system performs below the state of the art for ATIS by -7.8% and Overnight by -3.9%, but this is most likely because we omit any English-specific feature augmentation other than BERT. In comparison to prior work, we do not use entity anonymization, paraphrasing, execution-guided decoding or a mechanism to incorporate feedback for incorrect predictions from humans or neural critics. The closest comparable model to ours is reported by Wang et al. (2018), implementing a similar SEQ2SEQ model demonstrating 77.0% test set accuracy. However, this result uses entity anonymization for ATIS. While this technique generally yields performance improvements (Iyer et al., 2017; Dong and Lapata, 2016; Finegan-Dollak et al., 2018), a crosslingual implementation requires crafting multiple language-specific translation tables for entity recognition. We attempted to implement such an approach but found it to be unreliable and largely incompatible with the vocabularies of pre-trained models.