MTOP: A Comprehensive Multilingual Task-Oriented Semantic Parsing Benchmark

Haoran Li  
Facebook AI  
Applied Research

Abhinav Arora  
Facebook

Shuohui Chen  
Facebook AI  
Applied Research

Anchit Gupta  
Facebook

Sonal Gupta  
Facebook

Yashar Mehdad  
Facebook AI  
Applied Research

Abstract

Scaling semantic parsing models for task-oriented dialog systems to new languages is often expensive and time-consuming due to the lack of available datasets. Even though few datasets are available, they suffer from many shortcomings: a) they contain few languages and small amounts of labeled data for other languages b) they are based on the simple intent and slot detection paradigm for non-compositional queries. In this paper, we present a new multilingual dataset, called MTOP, comprising of 100k annotated utterances in 6 languages across 11 domains. We use this dataset and other publicly available datasets to conduct a comprehensive benchmarking study on using various state-of-the-art multilingual pre-trained models for task-oriented semantic parsing. We achieve an average improvement of +6.3% on Slot F1 for the two existing multilingual datasets, over best results reported in their experiments. Furthermore, we also demonstrate strong zero-shot performance using pre-trained models combined with automatic translation and alignment, and a proposed distant supervision method to reduce the noise in slot label projection.

1 Introduction

With the rising adoption of virtual assistant products, task-oriented dialog systems have been attracting more and more attention in both academic and industrial research communities. One of the first steps in these systems is to extract meaning from the natural language used in conversation to build a semantic representation of the user utterance. Typical systems achieve this by classifying the intent of the utterance and tagging the corresponding slots. With the goal of handling more complex queries, recent approaches propose hierarchical representations that are expressive enough to capture the task-specific semantics of complex nested queries.

Although, there have been sizable efforts around developing successful semantic parsing models for task-oriented dialog systems in English (Mesnil et al., 2013; Liu and Lane, 2016; Gupta et al., 2018; Rongali et al., 2020), we have only seen limited works for other languages. This is mainly due to the painstaking process of manually annotating and creating large datasets for this task in new languages. In addition to the shortage of such datasets, existing datasets (Upadhyay et al., 2018; Schuster et al., 2018) are not sufficiently diversified in terms of languages and domains, and do not capture complex nested queries. This makes it difficult to perform more systematic and rigorous experimentation and evaluation for this task across multiple languages.

Building on these considerations and recent advancements on cross-lingual pre-trained models (Devlin et al., 2019; Lample and Conneau, 2019; Conneau et al., 2020), this paper is making an effort to bridge the above mentioned gaps. The main contributions of this paper can be summarized as follows:

- **MTOP Dataset**: We release an almost-parallel multilingual task-oriented semantic parsing dataset covering 6 languages and 11 domains. To the best of our knowledge, this is the first multilingual dataset that contain compositional representations that allow complex nested queries.

- **We build strong benchmarks on the released MTOP dataset using state-of-the-art multilingual pre-trained model for both flat and compositional representations. We demonstrate the effectiveness of our approaches by achieving new state-of-the-art result on exist-
ing multilingual task-oriented semantic parsing datasets.

- We also achieve strong performance on zero-shot cross-lingual transfer using automatic translation and alignment, combined with a proposed distant supervision approach. We can achieve on average (across 6 langs) 87% of the performance of the best in-language models without any target language data.

## 2 Related Work

### Task-Oriented Semantic Parsing

Majority of the work on task-oriented dialog systems has been centered around intent detection and slot filling - for example, the representations used on the ATIS dataset (Mesnil et al., 2013) (Liu and Lane, 2016) (Zhu and Yu, 2017) and in the Dialog State Tracking Challenge (Williams et al., 2016). This essentially boils down to a text classification and a sequence labeling task, which works great for simple non-compositional queries. For more complex queries with recursive slots, state of the art systems use hierarchical representations, such as the TOP representation (Gupta et al., 2018), that is modeled using Recurrent Neural Network Grammars (Dyer et al., 2016) or as a Sequence to Sequence task (Rongali et al., 2020).

### Pre-trained Cross-lingual Representation

Over the past few years, pre-trained cross-lingual representations have demonstrated tremendous success in achieving state of the art in various NLP tasks. Majority of the earlier work was focused on cross-lingual embedding alignment (Mikolov et al. (2013); Ammar et al. (2016); Lample et al. (2018)). Schuster et al. (2019) further extend upon this by aligning contextual word embeddings from the ELMo model (Peters et al., 2018). Later with the success of transformer based masked language model pre-training, Devlin et al. (2019) and Lample and Conneau (2019) introduced mBERT and XLM, and Pires et al. (2019) show the effectiveness of these on sequence labeling tasks. Conneau et al. (2020) present XLM-R, a pre-trained multilingual masked language model trained on data in 100 languages, that provides strong gains over XLM and mBERT on classification and sequence labeling tasks.

The model discussed above are encoder-only. More recently, multilingual seq-to-seq pre-training has become popular. Liu et al. (2020a) introduce mBART, a seq-to-seq denoising auto-encoder pre-trained on monolingual corpora in many languages, which extends BART (Lewis et al., 2019) to multilingual setting. Lewis et al. (2020) is a seq-to-seq model pre-trained on a multilingual multi-document paraphrasing objective, which self-supervises the reconstruction of target text by retrieving a set of related texts and conditions on them to maximize the likelihood of generating the original. Tran et al. (2020) is another recent work that mines parallel data using encoder representations and jointly trains a seq-to-seq model on this parallel data.

### Cross-Lingual Task-Oriented Semantic Parsing

Due to the ubiquity of digital assistants, the task of cross-lingual and multilingual task-oriented dialog has garnered a lot of attention and few multilingual benchmark datasets have been released for the same. To the best of our knowledge, all of them only contain simple non-compositional utterances, suitable for the intent and slots detection tasks. Upadhyay et al. (2018) released a benchmark dataset in Turkish and Hindi, obtained by translating utterances from the ATIS corpus (Price, 1990). Schuster et al. (2018) released a bigger multilingual dataset for task-oriented dialog, containing around 57,000 utterances in English, Spanish and Thai. They also proposed various modeling techniques such as using XLU embeddings (see Ruder et al. (2017) for a review) for cross-lingual transfer and, ELMo (Peters et al., 2018) and translate train for target language training. He et al. (2020) further explore the idea of specific components to separately model language-dependent and language-invariant linguistic knowledge. BERT-style multilingual pre-trained models have also been applied to task-oriented semantic parsing. Castellucci et al. (2019) used multilingual BERT for joint intent classification and slot filling, but they didn’t evaluate on existing multilingual benchmarks. Instead, they introduced a new Italian dataset obtained via automatic machine translation of SNIPS (Coucke et al., 2018), which is of lower quality. For zero shot transfer, Liu et al. (2020b) study the idea of selecting some parallel word pairs to generate code-switching sentences for learning the inter-lingual semantics across languages and compared the performance using various cross-lingual pre-trained models including mBERT and XLM.
### 3 Data

Existing multilingual task-oriented dialog datasets, such as Upadhyay et al. (2018); Schuster et al. (2018), rely on expensive manual work for preparing guidelines and annotations for other languages; which is probably why they only contain very few languages and few labeled data for other languages. Furthermore, annotations will be more complicated and expensive if they were to include compositional nested queries. To this end we create an almost parallel multilingual task-oriented semantic parsing corpora which contains 100k examples in total for 6 languages (both high and low resource): English, Spanish, French, German, Hindi and Thai. Our dataset contains a mix of both simple as well as compositional nested queries across 11 domains, 117 intents and 78 slots. Table. 1 shows a summary of our MTOP data set.

We release the data at [https://fb.me/mtop_dataset](https://fb.me/mtop_dataset).

#### 3.1 Dataset Creation

Our approach for creating this dataset consists of two main steps: i) generating synthetic utterances and annotating in English, ii) translation, label transfer, post-processing, post editing and filtering for other languages. Annotation for English follows the process described in (Gupta et al., 2018). With an annotated English dataset, we build the multilingual data through the following steps:

**Translation:** We first extract slot text spans from English annotation and present the utterances along with slot text spans to human translators for translation to the target language. In our detailed guidelines, we ask the translators to make sure that the translation for each slot is exactly in the same way as it occurs in the translated utterance.

**Post-processing:** After we obtain translation of utterances and corresponding slot text spans, we use the tree structure of English and fill in the translated slot text spans to construct the annotation in the target languages. Our representation, that we describe in section 3.2.1, enabled us to construct the annotations in this way.

**Post-editing and Quality Control:** We further run two rounds of quality control over translated utterances and slots, and revise the data based on the feedback. In the first round, we ask translators to review and post-edit the errors in translations and slot alignments. In the second round, the constructed target language data is presented to separate vendors for a thorough quality review and low quality data is removed from the final dataset.

#### 3.2 Data Format

In this dataset, we release two kinds of representations, which we refer to as flat representations and compositional decoupled representations, that are illustrated in the examples shown in Figure 1. Most existing annotations for task-oriented dialog systems follow the intent classification and slot tagging paradigm, which is what we refer to as the flat representation. Since we also have compositional utterance that contain nested intents inside slots, flat representations for them are constructed by only using the top level slots. We include this flat representation so that the data and the discussed modeling techniques are comparable to other task-oriented dialog benchmarks. As
a part of the dataset, we also release the tokenization for each utterance that was obtained via our in-house multilingual tokenizer that we use in our experiments. In next section, we will discuss compositional decoupled representation in detail.

3.2.1 Compositional Decoupled Representation

Gupta et al. (2018) first demonstrated the inability of flat representations to parse complex compositional requests and proposed a hierarchical annotation scheme (TOP representation) for semantic parsing, that allows the representation of such nested queries. We further use a representation, called decoupled representation, that removes all the text from the TOP representation that does not appear in a leaf slot, as this text does not contribute to the semantics of the query. Figure 1 highlights the difference between this decoupled representation and the original TOP representation. The decoupled representation makes the semantic representation more flexible and allows long-distance dependencies within the representation. It also makes translation-based data creation approach feasible for different languages despite syntactic differences, as the representation is decoupled from the word order of the utterance. For example, in the German translation of the English example as shown in Figure 2, translations of message and Mike were separated by other words between them. However, it was still easy to construct a decoupled representation as the representation was not bound by a word-order constraint.

4 Model Architecture

4.1 Joint intent and slot tagging for flat representation

For flat representation where there is a single top-level intent, the traditional way is to model it as an intent classification and a slot tagging problem. Our baseline model is a bidirectional LSTM intent slot model as described in Liu and Lane (2016); Zhang and Wang (2016) with pre-trained XLU embeddings. We trained XLU embeddings ourselves using multiCCA following Ammar et al. (2016), since existing XLU embeddings like MUSE (Lample et al., 2018) do not provide embedding for Hindi and Thai. State-of-the-art models on existing multilingual datasets use Multilingual BERT (Liu et al., 2020b; Castellucci et al., 2019). Here we provide a stronger baseline using XLM-R(large) (Conneau et al., 2020) since it’s shown to outperform Multilingual BERT in cross-lingual performance. We used the same model architecture as in Chen et al. (2019) and replaced BERT encoder with XLM-R encoder.
4.2 Seq-to-seq for hierarchical representation

Although there are some existing work on cross-lingual transfer learning for parsing flat representation, we are not aware of any other work on cross-lingual study of parsing more complex queries. In this section, we outlined our modeling approaches for semantic representations including hierarchical representation.

Seq-to-seq with Pointer-generator Network

On modeling side Gupta et al. (2018) initially achieved the best performance by using a Shift-reduce parser based on Recurrent Neural Network Grammars (Dyer et al., 2016). Recently Rongali et al. (2020) used a unified architecture based on Sequence to Sequence models and Pointer Generator Network to handle all queries and achieved new state-of-the-art results. Our seq-to-seq model adopts similar architecture where source is the utterance and target is the compositional decoupled representation described in 3.2.1. Given a source utterance, let’s say the encoder hidden states are $[e_1, e_2, ..., e_n]$ and corresponding decoder hidden states are $[d_1, d_2, ..., d_m]$. At decoding time step $t$, the model can either generate an element from the ontology with generation distribution $p_{gt}$, or copy a token from the source sequence with copy distribution $p_{ct}$. Generation distribution is computed as:

$$p_{gt} = \text{softmax}(\text{Linear}_g[d_t])$$

Copy distribution is computed as:

$$p_{ct}, \omega_t = \text{MHA}(e_1, ..., e_n; \text{Linear}_c[d_t])$$

where $\omega_t$ is the attended vector used to compute weight of copying $p_{ct}$:

$$p_{ct} = \text{sigmoid}(\text{Linear}_a[d_t; \omega_t])$$

The final probability distribution is computed as a mixture of the generation and copy distributions:

$$p_t = p_{gt} \cdot p_{ct} + (1 - p_{gt}) \cdot p_{ct}.$$
Multilingual ATIS (Upadhyay et al., 2018) collected annotated utterances in Turkish and Hindi, it contains 4978 English utterances from the English ATIS Corpus for training and translated and annotated 600 examples in Turkish and Hindi respectively for supervision using human translators and Amazon Mechanical Turk to generate the phrase level slot annotation on the manual translations.

Multilingual TOP (Schuster et al., 2018) is a multilingual task-oriented parsing dataset of 57k annotated utterances in English (43k), Spanish (8.6k) and Thai (5k) across the domains weather, alarm, and reminder. Notice that both these data sets are intent and slot filling data and thus only include flat representation, while our data set contains hierarchical representations.

5.1 Experiment settings
For all these benchmarks, we have three different settings for evaluation:

- **IN-LANGUAGE MODELS**: in this setting we only use target language training data.
- **MULTILINGUAL MODELS**: we use training data in all available languages and train a single model for multiple languages in this setting.
- **ZERO-SHOT TARGET LANGUAGE MODELS**: in this setting we only use English training data.

Next in each subsection we talk about details of some approaches we use in these experiments.

5.1.1 Translate and Align
With zero or few target language annotated examples, translate-train is a common approach to augment target language training data. For semantic parsing tasks, besides translation we need alignment information to project slot annotations to target language. This process is similar to how we collect our dataset, but using machine translation and alignment methods. For translation, we tried Google Translate and our internal translation system and found it made no big difference in task performance. For alignment, we tried using attention weights from translation like in Schuster et al. (2018) and fastalign (Dyer et al., 2013) and found data generated through fastalign generally leads to better task performance. Thus results reported in Results section are using our internal translation system and fastalign.

5.1.2 Multilingual training
With the advancement of multilingual pre-trained models, single model trained on multiple languages has shown to outperform in-language models (Conneau et al., 2020; Hu et al., 2020). We also experimented with multilingual training on our benchmark, including training jointly on all in-language data and training on English plus translated and aligned data in all other languages for zero-shot setting. Different from concatenating data in all languages together as in XLM-R paper, we adopt a multitask training approach where for each batch we sample from one language based on a given sampling ratio meaning that you can upsample a certain language. We found this setting is better than mixed-language batches.

5.1.3 Distant supervision in zero-shot setting for flat representation
Alignment models are not perfect, especially for low resource languages. To combat the noise and biases introduced in slot label projection, we use another distant supervision in zero-shot setting for flat representation modeling: we replace the English slot text with MASK token at random (30% of the time) and give parallel data obtained from machine translation as input and predict overall intent and slot labels on the English source side. In this way, MASK token can also attend to its translation counterpart to predict its label.

6 Results and Discussions
6.1 Flat Representation Results
Table. 2 shows the result on our MTOP dataset for all languages, using the flat representation. When training a monolingual model using only the target language training data, XLM-R based models significantly outperform the BiLSTM models using XLU for all models. This is not surprising given that the XLM-R is pre-trained on large monolingual corpora of 100 languages. We also observe that both of these models exhibit an improved performance when trained in a multilingual setting. Interestingly, we observe that for Hindi and Thai (both non-European languages), the improvements obtained from multilingual training, are considerably higher for XLM-R as compared to XLU BiLSTM models. This observation highlights the remarkable cross-lingual transfer ability of the pre-trained XLM-R representations as fine-tuning on
In-language models (only use target language training data)

| Model       | en  | es  | fr  | de  | hi  | th  |
|-------------|-----|-----|-----|-----|-----|-----|
| XLU biLSTM  | 78.2| 70.8| 68.9| 65.1| 62.6| 68  |
| XLM-R       | 85.3| 81.6| 79.4| 76.9| 76.8| 73.8|

Multilingual models (use training data from multiple languages)

| Model       | en  | es  | fr  | de  | hi  | th  |
|-------------|-----|-----|-----|-----|-----|-----|
| XLU biLSTM  | 78.2| 73.8| 71.5| 65.8| 63.1| 68.7|
| XLM-R       | 86.3| 83.6| 81.8| 79.2| 78.9| 76.7|

Zero-shot target language models (only use English training data)

| Model                    | en  | es  | fr  | de  | hi  | th  |
|--------------------------|-----|-----|-----|-----|-----|-----|
| XLM-R on EN              | N/A | 69.1| 65.4| 64  | 55  | 43.8|
| XLM-R with mask in 5.1.3 | N/A | 68  | 69.5| 69.2| 63.3| 35.3|
| XLM-R on EN + translate all | N/A | 74.5| 72.6| 64.7| 58.3| 56.5|
| XLM-R with mask + translate all | N/A | 74.6| 72.2| 65.7| 62.5| 53.2|

Table 2: Results on flat representation for 6 languages. We use exact match accuracy as metric. Best result for zero-shot is in bold. Note that for zero-shot setting, we only use EN train and eval data without any target language data.

Syntactically different languages also improves target language performance.

For zero-shot cross-lingual transfer, we restrict ourselves to an XLM-R baseline that we try to improve using translate and align, and the distant supervision techniques as described in 5.1.1 and 5.1.3 respectively. We observe that distant supervision is able to considerably improve over the baselines for French, German and Hindi, while there is a small drop for Spanish. Performance for Thai significantly degrades compared to the baseline, which we believe is due to non-ideal Thai tokenization that leads to learning noisy implicit alignments through distant supervision. The translate and align approach consistently improves over the baseline for all languages. It also performs better than distant supervision for all languages except German and Hindi. One hypothesis here is that the complicating nature of German inhibits the learning of hard alignment from fastalign.

### 6.2 Compositional Decoupled Representation Results

Table 3 shows the result on our MTOP dataset using compositional decoupled representation. In all settings, using multilingual pre-trained models significantly outperform the baseline. Surprisingly mBART didn’t have very good performance compared to other models when fine-tuning on our task, even though fine-tuning BART on English achieved the best performance on English. We hypothesized that mBART was under-trained for these many languages and did not learn good cross-lingual alignments. Therefore, we further fine-tuned mBART on 50 languages to English translation task. By doing this, the obtained mBART on MT model significantly outperformed the original mBART. The performance of CRISS and MARGE are at par with each other, both of them are our best performing models in 5 languages except Thai. XLM-R performs the best on Thai, which makes sense because unlike XLM-R, neither CRISS nor MARGE are pre-trained on Thai.

For multilingual and zero shot settings, we just show the best performing models from the monolingual in-language setting. Similar to previous observations, multilingual training again improves over the monolingual results. With multilingual training, XLM-R or CRISS are the best performing models for every language. Since XLM-R uses a randomly initialized decoder, it makes intuitive sense that this decoder is better trained with multilingual training and thus sees higher gains from more training data. Interestingly, mBART performance also improved a lot, which is another evidence that mBART was under-trained. For zero-shot seq-to-seq generation, directly using the model fine-tuned on English does not perform well. Instead, utilizing translate and aligned data significantly improves the zero-shot performance.

### 6.3 Other Benchmark Results

Table 4 shows results on two previously released multilingual datasets: Multilingual ATIS and Mul-
In the zero-shot setting for Multilingual ATIS, our distant supervised masking strategy also shows considerable gains compared to direct transfer using English. Using translate and aligned data also helps in improve the results significantly. Com-

Table 4: Results on Multilingual ATIS and Multilingual TOP, metrics are exact match accuracy / intent accuracy / slot F1 respectively. For zero-shot, first line is from original dataset paper. MBERT MLT result is also from the referenced paper. Best result for zero-shot is in bold.
bined with masking, it achieved the best zero-shot performance on Hindi. For both languages this comes very close to the performance using target language training data. For multilingual TOP, direct transfer result is already very good for Spanish and, masking and translation generated data degrade its performance. One hypothesis for this is tokenization mismatch. We found that our tokenizer tokenizes time expressions etc quite differently compared to the original Multilingual TOP data, and thus we used the tokenized CoNLL-U format from their data. However, for translation data we had to use our tokenizer which led to a potential tokenization mismatch. Our hypothesis was validated via error analysis, where we found the model making a lot of mistakes on slot text boundaries. Best results from original paper use translation and align for both languages. For zero-shot Thai we obtained a lower performance compared to the original paper. We believe the lower performance is due to the same tokenization mismatch issue described above, that is further exaggerated in the case ofThai.

7 Conclusion

In this paper, we released a new multilingual task-oriented semantic parsing dataset called MTOP that covers 6 languages and includes both flat as well as compositional representations. We provided strong benchmarks for both representations using state-of-the-art multilingual pre-trained models in both: zero-shot and with target language settings. We hope this dataset along with proposed methods could benefit the community in easily and efficiently scaling task-oriented dialog systems to more languages.

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