An Empirical Study of Cross-Lingual Transferability in Generative Dialogue State Tracker

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Abstract

There has been a rapid development in data-driven task-oriented dialogue systems with the benefit of large-scale datasets. However, the progress of dialogue systems in low-resource languages lags far behind due to the lack of high-quality data. To advance the cross-lingual technology in building dialog systems, DSTC9 introduces the task of cross-lingual dialog state tracking, where we test the DST module in a low-resource language given the rich-resource training dataset.

This paper studies the transferability of a cross-lingual generative dialogue state tracking system using a multilingual pre-trained seq2seq model. We experiment under different settings, including joint-training or pre-training on cross-lingual and cross-ontology datasets. We also find out the low cross-lingual transferability of our approaches and provides investigation and discussion.

Introduction

Dialogue state tracking is one of the essential building blocks in the task-oriented dialogues system. With the active research breakthrough in the data-driven task-oriented dialogue technology and the popularity of personal assistants in the market, the need for task-oriented dialogue systems capable of doing similar services in low-resource languages is expanding. However, building a new dataset for task-oriented dialogue systems for low-resource language is even more laborious and costly. It would be desirable to use existing data in a high-resource language to train models in low-resource languages. Therefore, if cross-lingual transfer learning can be applied effectively and efficiently on dialogue state tracking, the development of task-oriented dialogue systems on low-resource languages can be accelerated.

The Ninth Dialog System Technology Challenge (DSTC9) Track2 (Gunasekara et al. 2020) proposed a cross-lingual multi-domain dialogue state tracking task. The main goal is to build a cross-lingual dialogue state tracker with a rich resource language training set and a small development set in the low resource language. The organizers adopt MultiWOZ 2.1 (Eric et al. 2019) and CrossWOZ (Zhu et al. 2020) as the dataset and provide the automatic translation of these two datasets for development. In this paper’s settings, our task is to build a cross-lingual dialogue state tracker in the settings of CrossWOZ-en, the English translation of CrossWOZ. In the following, we will refer cross-lingual datasets to datasets in different languages, such as MultiWOZ-zh and CrossWOZ-en, and cross-ontology datasets to datasets with different ontologies, such as MultiWOZ-en and CrossWOZ-en.

The cross-lingual transfer learning claims to transfer knowledge across different languages. However, in our experiments, we experience tremendous impediments in joint training on cross-lingual or even cross-ontology datasets. To the best of our knowledge, all previous cross-lingual dialogue state trackers approach DST as a classification problem (Mrksic et al. 2017)(Liu et al. 2019), which does not guarantee the success of transferability on our generative dialogue state tracker.

The contributions of this paper are three-fold:

• This paper explores the cross-lingual generative dialogue state tracking system’s transferability.

• This paper compares joint training and pre-train then finetune method with cross-lingual and cross-ontology datasets.

• This paper analyzes and open discussion on colossal performance drop when training with cross-lingual or cross-ontology datasets.

Problem Formulation

In this paper, we study the cross-lingual multi-domain dialogue state tracking task. Here we define the multi-domain dialogue state tracking problem and introduce the cross-lingual DST datasets.

Multi-domain Dialogue State Tracking

The dialogue state in the multi-domain dialogue state tracking is a set of (domain, slot name, value) triplets, where the domain indicates the service that the user is requesting, slot name represents the goal from the user, and value is the explicit constraint of the goal. The organizers adopt MultiWOZ 2.1 (Eric et al. 2019) and CrossWOZ (Zhu et al. 2020) as the dataset and provide the
wants to find a tourist attraction with a ticket price equal to or lower than 20 dollars. An example is presented in Figure 1.

Our task is to predict the dialogue state at the $t^{th}$ turn, $B_t = \{ (D^i, S^i, V^i) | 1 \leq i \leq I \}$ where $I$ is the number of states to be tracked, given the historical dialogue context until now, defined as $C_t = \{ U_1, R_1, U_2, R_2, \ldots, R_{t-1}, U_t \}$ where $U_t$ and $R_i$ is the user utterance and system response, respectively, at the $t^{th}$ turn.

### Dataset

MultiWOZ is the task-oriented dataset often used as the benchmark dataset for task-oriented dialogue system tasks, including dialogue state tracking, dialogue policy optimization, and NLG. MultiWOZ 2.1 is a cleaner version of the previous counterpart with more than 30% updates in dialogue state annotations. CrossWOZ is a Chinese multi-domain task-oriented dataset with more than 6,000 dialogues, five domains, and 72 slots. Both of the above datasets collects human-to-human dialogues in Wizard-of-Oz settings. Table 1 lists the details of the dataset.

In DSTC9 Track 2, the organizers translate MultiWOZ and CrossWOZ into Chinese and English, respectively, and we refer the translated version of MultiWOZ and CrossWOZ as MultiWOZ-zh and CrossWOZ-en, respectively. The public and private test of CrossWOZ-en in DSTC9 has 250 dialogues, but only the public test set has annotations. Therefore, we use the public one as the test set in our experiments.

| Metric          | MultiWOZ       | CrossWOZ       |
|-----------------|----------------|----------------|
| Language        | English        | Chinese (Simplified) |
| # Dialogues     | 8,438          | 5,012          |
| Total # turns   | 113,556        | 84,692         |
| # Domains       | 7              | 5              |
| # Slots         | 24             | 72             |
| # Values        | 4,510          | 7,871          |

Table 1: Statistics of MultiWOZ and CrossWOZ. Note that the translated version of these two datasets have the same metrics.

### Related Work

**Dialogue State Tracker**

Traditionally, dialogue state tracking depends on fixed vocabulary approaches where retrieval-based models ranks slot candidates from a given slot ontology. (Ramadan, Budzianowski, and Gašić 2018) Lee, Lee, and Kim 2019) However, recent research efforts in DST have moved towards generation-based approaches where the models generate slot value given the dialogue history. (Wu et al. 2019) proposed a generative multi-domain DST model with a copy mechanism which ensures the capability to generate unseen slot values. (Kim et al. 2019) introduced a selectively overwriting mechanism, a memory-based approach to increase efficiency in training and inference. (Le, Socher, and Hovy 2020) adopted a non-autoregressive architecture to model potential dependencies among (domain, slot) pairs and reduce real-time DST latency significantly. (Hosseini-Asl et al. 2020) took advantage of the powerful generation ability of large-scale autoregressive language model and formulated the DST problem as a casual language modeling problem.

**Multilingual Transfer Learning in Task-oriented Dialogue**

(Schuster et al. 2019) introduced a multilingual multi-domain NLU dataset. (Mrkšć et al. 2017) annotated two additional languages to WOZ 2.0 (Mrkšć et al. 2017) and (Liu et al. 2019) proposed a mixed-language training for cross-lingual NLU and DST tasks. Noted that all previous multilingual DST methods modeled the dialogue state tracking task as a classification problem. (Mrkšć et al. 2017) (Liu et al. 2019)

### Methods

This paper considers the multi-domain dialogue state tracking as a sequence generation task by adopting a sequence-to-sequence framework.

### Architecture

Following (Liu et al. 2020), we use the sequence-to-sequence Transformer architecture (Vaswani et al. 2017) with 12 layers in each encoder and decoder. We denote seq2seq as our model in the following.

### DST as Sequence Generation

The input sequence is composed of the concatenation of dialogue context $x^t = \{ U_1; R_1; U_2; R_2; \ldots; R_{t-1}; U_t \}$ where $: ;$ denotes the concatenation of texts.

For the target dialogue state, we only consider the slots where the values are non-empty. The target sequence is consist of the concatenation of the $(domain, slot, value)$ triplets with a non-empty value, $y^t = \{ D^i; S^i; V^i | 1 \leq i \leq I \land S^i \neq \emptyset \}$.

$\hat{y}^t = seq2seq(x^t)$

We fix the order of the $(domain, slot name, value)$ triplets for consistency.

The training objective is to minimize the cross-entropy loss between the ground truth sequence $y^t$ and the predicted sequence $\hat{y}^t$.

### Post-processing

The predicted sequence $\hat{y}^t$ is then parsed by heuristic rules to construct $B_t = \{ D^i; S^i; \hat{V}^i | 1 \leq i \leq I \}$.

By utilizing the possible values of slots in the ontology, for predicted slot values $\hat{V}$ that do not appears in the ontology, we choose the one with the best match to our predicted value. $\hat{V}$

### Experiments

In the following section, we describe evaluation metrics, experiment setting and introduce experimental results.

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1This is implemented by `difflib.get_close_matches` in Python.
Hello, it is said that the reputation of Jinjiang Inn (Beijing Yizhuang Culture Park) is still good. Do you know the price?

Its price is 295 yuan.

Um, okay, please help me find an attraction with a duration of 1 hour. I hope the rating of the attraction is 4 points or above.

There are too many eligible, I suggest you go to Sanlitun Bar Street or China Great Wall Museum.

Evaluation Metrics
We use joint goal accuracy and slot F1 as our metrics to evaluate our dialogue state tracking system.

- Joint Goal Accuracy: The proportion of dialogue turns where predicted dialogue states match entirely to the ground truth dialogue states.
- Slot F1: The macro-averaged F1 score for all slots in each turn.

Experiments Settings
We want to examine how different settings affect the performance of the target low-resource dataset: CrossWOZ-en.

- Direct Fine-tuning
- Cross-Lingual Training (CLT)
- Cross-Ontology Training (COT)
- Cross-Lingual Cross-Ontology Training (CL/COT)
- Cross-Lingual Pre-Training (CLPT)
- Cross-Ontology Pre-Training (COPT)
- Cross-Lingual Cross-Ontology Pre-Training (CL/COPT)

Table 2 and 3 show the datasets for training and pre-training in different settings. For experiments with pre-training, all models are pre-trained on the pre-training dataset and then fine-tuned on CrossWOZ-en.

The baseline model provided by DSTC9 is SUMBT (Lee, Lee, and Kim 2019), the ontology-based model trained on CrossWOZ-en.

Multilingual Denoising Pre-training
All of our models initialize from mBART25 (Liu et al. 2020). mBART25 is trained with denoising auto-encoding task on mono-lingual data in 25 languages, including English and Simplified Chinese. Liu et al. 2020 shows pre-training of denoising autoencoding on multiple languages improves the performance on low resource machine translation. We hope using mBART25 as initial weights would improve the cross-lingual transferability.

Implementation Details
In all experiments, the models are optimized with AdamW (Loshchilov and Hutter 2017) with learning rate set to $1e^{-4}$ for 4 epochs. The best model is selected from the validation loss and is used for testing.

During training, the decoder part of our model is trained in the teacher forcing fashion (Williams and Zipser 1989). Greedy decoding (Vinyals and Le 2015) is applied when inference. Following mBART (Liu et al. 2020), we use sentencepiece tokenizer. For GPU memory constraints, source sequences longer than 512 tokens are truncated at the front and target sequences longer than 256 tokens are truncated at the back.

The models are implemented in Transformers (Wolf et al. 2019), PyTorch (Paszke et al. 2019) and PyTorch Lightning (Falcon 2019).

Results and Discussion
The results for all experiment settings are shown in Table 2 and 3.

Additional Training Data Cause Degeneration
Direct Fine-tuning significantly outperforms other settings, including the official baseline. We assume English and Chinese data with the same ontology to train the mBART would bridge the gap between the two languages and increase the
| Experiment          | Pre-training Data | Training Data | JGA | SF1 |
|---------------------|-------------------|---------------|-----|-----|
|                     |                  | MultiWOZ | CrossWOZ en |  |     |
| Baseline            |                  | ✓         | ✓            | 7.41 | 55.27* |
| Direct Fine-tuning  |                  | ✓         | ✓            | 16.82 | 66.35 |
|                     | CL/COT           | ✓         | ✓            | 4.10 | 26.50 |
|                     | COT              | ✓         | ✓            | 0.95 | 19.60 |
|                     | CLT              | ✓         | ✓            | 0.53 | 13.45 |

Table 2: Experimental results on CrossWOZ-en with different training data (%). *: This slot f1 is averaged over both the public and private test dialogues. JGA: Joint Goal Accuracy. SF1: Slot F1.

| Experiment | Pre-training Data | Training Data | JGA | SF1 |
|------------|-------------------|---------------|-----|-----|
| Direct Fine-tuning |                  | MultiWOZ | CrossWOZ en |  |     |
| CL/COPT    |                  | ✓         | ✓            | 5.94 | 38.36 |
| COPT       |                  | ✓         | ✓            | 2.52 | 27.01 |
| CLPT       |                  | ✓         | ✓            | 0.11 | 15.01 |

Table 3: Experimental results on CrossWOZ-en with pre-training (%).

performance. However, in Cross-Lingual Training, training on English and Chinese version of CrossWOZ leads to catastrophic performance on CrossWOZ-en.

In the Cross-Ontology Training where combine two data in the same language. However, with different ontologies, the performance marginally increases from Cross-Lingual Training, which shows more extensive mono-lingual data with the unmatched domain, slots, and ontology confuses the model during inference. In the Cross-Lingual Cross-Ontology Training, we collect all four datasets for training, and the performance is still far from Direct Fine-tuning.

In conclusion, additional data deteriorate the performance on CrossWOZ-en even whether the language or ontology matches or not.

Does "First Pre-training, then fine-tuning" Help?

We hypothesize that training with additional data causes performance degeneration, and therefore one possible improvement could be first pre-training the model on cross-lingual / cross-ontology data and then fine-tuning on the target dataset CrossWOZ-en. Table 3 shows the results.

By comparing COPT to COT and CL/COPT to CL/COP, the relative performance gain by over 37% with regards to slot F1. "Pre-training, fine-tuning" framework may partially alleviate the problem of catastrophic performance drop in joint training.

Domain Performance Difference across Experiment Settings?

This section further investigates the cause of the performance decrease by comparing the slot F1 of different models across five domains in Figure 2.

Generally speaking, in attraction, restaurant, and hotel domains, "pre-train then fine-tune" methods beat their "joint training" counterparts by an observable margin. By contrast, in metro and taxi domains, despite poor performance among all, "joint training" settings beat their "pre-train then fine-tune" counterparts.

The only two trackable slots in the metro and taxi domain, "from" and "to," usually take the address or name of buildings, are highly non-transferable across datasets. We conjecture that pretraining on cross-lingual or cross-ontology datasets does not help or even hurt those non-transferable slots.

Figure 2: Slot F1 across 5 domains in CrossWOZ-en in different settings.
Conclusion
In this paper, we build a cross-lingual multi-domain generative dialogue state tracker with multilingual seq2seq to test on CrossWOZ-en and investigate our tracker’s transferability under different training settings. We find that jointly trained the dialogue state tracker on cross-lingual or cross-ontology data degenerates the performance. Pre-training on cross-lingual or cross-ontology data, then fine-tuning framework may alleviate the problem, and we find empirically evidence on relative improvement in slot F1. A finding from the domain performance shift is that performance on some non-transferable slots, such as name, from, to, may be limited by the previous pretraining approach. A future research direction would investigate why such a significant performance declines in joint training and tries to bridge it.

References
Eric, M.; Goel, R.; Paul, S.; Kumar, A.; Sethi, A.; Ku, P.; Goyal, A. K.; Agarwal, S.; Gao, S.; and Hakkani-Tür, D. 2019. MultiWOZ 2.1: A Consolidated Multi-Domain Dialogue Dataset with State Corrections and State Tracking Baselines. Falcon, W. 2019. PyTorch Lightning. GitHub. Note: https://github.com/PyTorchLightning/pytorch-lightning-lightning-3.

Gunasekara, C.; Kim, S.; D’Haro, L. F.; Rastogi, A.; Chen, Y.-N.; Eric, M.; Hedayatnia, B.; Gopalakrishnan, K.; Liu, Y.; Huang, C.-W.; Hakkani-Tür, D.; Li, J.; Zhu, Q.; Luo, L.; Liden, L.; Huang, K.; Shuyande, S.; Liang, R.; Peng, B.; Zhang, Z.; Shukla, S.; Huang, M.; Gao, J.; Mehr, S.; Feng, Y.; Gordon, C.; Alavi, S. H.; Traum, D.; Eksnenazi, M.; Beirami, A.; Eunjoon; Cho; Crook, P. A.; De, A.; Geramifard, A.; Kottur, S.; Moon, S.; Poddar, S.; and Subba, R. 2020. Overview of the Ninth Dialog System Technology Challenge: DSTC9 URL https://arxiv.org/abs/2011.06486.

Hosseini-Asl, E.; McCann, B.; Wu, C.-S.; Yavuz, S.; and Socher, R. 2020. A Simple Language Model for Task-Oriented Dialogue URL http://arxiv.org/abs/2005.00796.

Kim, S.; Yang, S.; Kim, G.; and Lee, S.-W. 2019. Efficient Dialogue State Tracking by Selectively Overwriting Memory. arXiv URL http://arxiv.org/abs/1911.03906.

Le, H.; Socher, R.; and Hoi, S. C. H. 2020. Non-Autoregressive Dialogue State Tracking 1–21. URL http://arxiv.org/abs/2002.08024.

Lee, H.; Lee, J.; and Kim, T.-Y. 2019. SUMBT: Slot-Utterance Matching for Universal and Scalable Belief Tracking 5478–5483. doi:10.18653/v1/p19-1546.

Liu, Y.; Gu, J.; Goyal, N.; Li, X.; Edunov, S.; Ghazvininejad, M.; Lewis, M.; and Zettlemoyer, L. 2020. Multilingual Denoising Pre-training for Neural Machine Translation URL https://arxiv.org/abs/2001.08210.

Liu, Z.; Winata, G. I.; Lin, Z.; Xu, P.; and Fung, P. 2019. Attention-Informed Mixed-Language Training for Zero-shot Cross-lingual Task-oriented Dialogue Systems. arXiv URL http://arxiv.org/abs/1911.09275.

Loschilov, I.; and Hutter, F. 2017. Decoupled Weight Decay Regularization URL http://arxiv.org/abs/1711.05101.

Mrkšić, N.; Séaghdha, D.; Wen, T. H.; Thomson, B.; and Young, S. 2017. Neural belief tracker: Data-driven dialogue state tracking. ACL 2017 - 55th Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference (Long Papers) 1: 1777–1788. doi: 10.18653/v1/P17-1163.

Mrkšić, N.; Vulić, I.; Séaghdha, D. O.; Leviant, I.; Reichart, R.; Gašić, M.; Korhonen, A.; and Young, S. 2017. Semantic Specialisation of Distributional Word Vector Spaces using Monolingual and Cross-Lingual Constraints. arXiv URL http://arxiv.org/abs/1706.00374.

Paszke, A.; Gross, S.; Massa, F.; Lerer, A.; Bradbury, J.; Chanan, G.; Killeen, T.; Lin, Z.; Gimelshein, N.; Antiga, L.; Desmaison, A.; Kopf, A.; Yang, E.; DeVito, Z.; Raison, M.; Tejani, A.; Chilamkurthy, S.; Steiner, B.; Fang, L.; Bai, J.; and Chintala, S. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In Wallach, H.; Larochelle, H.; Beygelzimer, A.; d’Alché-Buc, F.; Fox, E.; and Garnett, R., eds., Advances in Neural Information Processing Systems 32, 8024–8035. Curran Associates, Inc. URL http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf.

Ramadan, O.; Budzianowski, P.; and Gašić, M. 2018. Large-Scale Multi-Domain Belief Tracking with Knowledge Sharing. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), 432–437. Melbourne, Australia: Association for Computational Linguistics. doi:10.18653/v1/P18-2069. URL https://www.aclweb.org/anthology/P18-2069.

Schuster, S.; Gupta, S.; Shah, R.; and Lewis, M. 2019. Cross-lingual Transfer Learning for Multilingual Task-oriented Dialog. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 3795–3805. Minneapolis, Minnesota: Association for Computational Linguistics. doi:10.18653/v1/N19-1380. URL https://www.aclweb.org/anthology/N19-1380.

Shan, Y.; Li, Z.; Zhang, J.; Meng, F.; Feng, Y.; Niu, C.; and Zhou, J. 2020. AContextual Hierarchical Attention Network with Adaptive Objective for Dialogue State Tracking 6322–6333. URL http://arxiv.org/abs/2006.01554.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention Is All You Need.

Vinyals, O.; and Le, Q. 2015. A neural conversational model. arXiv preprint arXiv:1506.05869.

Williams, R. J.; and Zipser, D. 1989. A learning algorithm for continually running fully recurrent neural networks. Neural computation 1(2): 270–280.
Q.; and Rush, A. M. 2019. HuggingFace’s Transformers: State-of-the-art Natural Language Processing. ArXiv abs/1910.03771.

Wu, C.-S.; Madotto, A.; Hosseini-Asl, E.; Xiong, C.; Socher, R.; and Fung, P. 2019. Transferable Multi-Domain State Generator for Task-Oriented Dialogue Systems 808–819. doi:10.18653/v1/p19-1078.

Zhu, Q.; Zhang, W.; Liu, T.; and Wang, W. Y. 2020. Counterfactual Off-Policy Training for Neural Response Generation URL http://arxiv.org/abs/2004.14507