



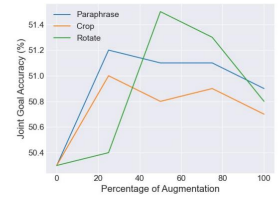
Introduction

- Dialogue State Tracking (DST) is an important step in task-oriented dialogue systems.
Slot filling based on the current user utterance and dialogue history.
We explore pre-training strategies and data augmentation methods to better leverage the power of large-scale, pre-trained language models (like BERT and T5) for DST.
Multi-Domain Wizard-of-Oz (MultiWoZ) Dataset [1]
Evaluation: Joint Goal Accuracy, Slot F1, Slot Accuracy.

Sys: Hi, what can I do for you?
User: Please find me a Chinese restaurant.
State: restaurant-food-chinese
Sys: Charlie Chan fits your criterion, can I book it for you?
User: Yes, I need a table on Monday at 12:15.
State: restaurant-food-chinese; restaurant-name-charlie chan; restaurant-book-day=monday; restaurant-book-time=12:15
Sys: Booking is successful. Is there anything else I can assist you with today?
User: I also need a taxi to get me to the restaurant on time.
State: restaurant-food-chinese; restaurant-name-charlie chan; restaurant-book-day=monday; restaurant-book-time=12:15; taxi-destination=charlie chan; taxi-arriveby=12:15

Data Augmentation for Dialogue Understanding

- LMs perform better when provided with huge amounts of training data [3].
Why Data Augmentation?
Additional training data without any human annotation effort.
Provides diversity for better generalizability of NLP models.
Noisy annotations in MutiWoZ dataset (multiple versions).
Rule-Based Augmentations: Entity Replacement, Crop and Rotate using dependency parse trees, Sequential augmentation to increase complexity.
Deep Learning Techniques: Paraphrasing using Pegasus, Reverse translation with English-Spanish NMT.
Data augmentation significantly improves performance on DST.
High levels of augmentation can at times hurt the performance too.



Original Utterance: Can you find an Indian restaurant for me that is also in the town centre?
Entity Replacement: Can you find an Mexican restaurant for me that is also in the town east?
Paraphrase: I want to go to an Indian restaurant in the centre of the town.
Translate: I am looking for an Indian restaurant that is also in the city center?
Sequential: Can you find an Indian restaurant for me that is also in the town centre?
Crop: I want to make a reservation for two people.
Rotate: find an Indian restaurant that is in the town centre
an Indian restaurant for me that is also in the town centre find you

Multi-phase Adaptive Pre-training

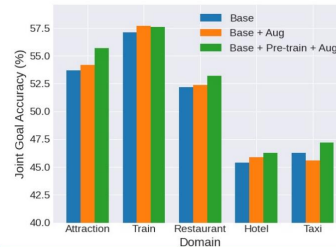
- Significant domain mismatch between large-scale text corpus (for language modelling) and dialogue datasets.
Domain adaptive pre-training on open-domain dialogues.
Task adaptive pre-training on target dataset.
Span-level objectives to reason across multiple turns and span-selection where entities are contiguous sequences of words.

Table showing performance metrics for Google Books, DAPT, and TAPT datasets across different models.

Table with columns: Model, Objective, Pre-training, MultiWOZ 2.0 (JGA, S F1, SA), MultiWOZ 2.1 (JGA, S F1, SA). Rows include BERT and T5 models with various pre-training objectives.

Domain Analysis

- Combining best pre-training method and data augmentation techniques.
Consistent gains in goal accuracy across all domains in MutiWoZ.



Conclusion & Future Work

- Incorporating language structure of dialogues through span-level pre-training and additional domain data through augmentation methods is helpful for DST.
Potential future direction would be to study the impact of these techniques on end-to-end dialogue systems including generation.

References

[1] Budzianowski et al., Multiwoz-a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling, EMNLP 2018
[2] Gururangan et al., Don't stop pretraining: Adapt language models to domains and tasks, ACL 2020
[3] Feng et al., A Survey of Data Augmentation Approaches for NLP, ACL 2021