

A Preprocessing

The MultiWoZ 2.0 dataset has a JSON metadata that maintains a dictionary of slot-value pairs provided by the user to the agent in every utterance. We use this metadata to construct a local and a global knowledge of slot-value shared by the user and split to relabel the dataset for single domain and multidomain dialogues. The preprocessing step removed the noise in the labeling of dialogues. We used this approach to keep a test set of multidomain dialogues to evaluate the model performance on compositional tasks. On the clean split of single domain dialogues we generate synthetic multidomain dialogues using two different approaches:

A.1 Random Synthetic (RS)

In this approach, we pick a single task dialogue ${}^i D^{SNG}$ and randomly select a set of K single task dialogues, $({}^i D_{noise}^{SNG})_{k=1}^K$, to inject noise in D^{SNG} . With an hyperparameter, *percentCopy*, we select the number of utterances to be copied from every dialogue in the set noiseDialogues and add it as a prefix to D^{SNG} . This results in K negative samples of synthetic multidomain dialogues, $({}^i D_{RS}^{MUL})_{k=1}^K$, for every single domain dialogues in the dataset.

A.2 Targetted Synthetic (TS)

We bucket the single domain dialogues based on the conversation domain (*taxi, hotel, attraction* etc.). Similarly, we bucket the multi-task dialogues in the training set to measure the topic distributions in multi-task dialogues. Using the computed distribution of composite tasks in *true* multidomain dialogues and the domain label of every ${}^i D^{SNG}$, we constrain the selection of random dialogues to conform to the training distribution of *true* composite tasks in the training set. The hyperparameters and the remainder of the procedure is similar to RS except when combining the single domain dialogues from two different domains (${}^i Dom, {}^j Dom$), we inject the topic change exchanges randomly sampled from $TC({}^j Dom1, {}^i Dom2)$.

For training the proposed Domain Invariant Transformer model, we create the labels for the auxiliary tasks using the preprocessing steps used to split the dataset into single and multi-domain dialogues

A.3 Experiments varying α

α	BLEU (MUL)	BLEU(BOTH)
0.0	14.07	13.94
0.00001	13.74	13.31
0.0001	14.13	14.11
0.001	15.06	14.81
0.01	14.61	14.40
0.1	14.70	14.41

Table 4: Varying the α to understand the effect of the discriminator on decoder performance

We experimented with different values of α to understand the influence of the discriminator loss. The results in Table 4 show that Domain Invariant Transformer performed better when α is 0.001. The experiment also shows consistent performance improvement in all the experiments with different α highlighting the usefulness of training an auxiliary network to train domain invariant encoder representations.

B Token distribution

We analyze the token distribution in the dataset to understand the negative result further. We observed that despite the task distributions are matched the underlying token distribution in different set up is not (Table 5). We looked at the overlap of the distribution of 4-grams in conversations on the different splits we used for training. We observed that Multi-task dialogues (MUL) training set has as much 4-gram overlap with MUL Valid and SNG (Single task dialogues) Valid sets as the combined (SNG + MUL) training data.

The analysis raises doubts in the performance of transformer model with increased MUL train dialogues that the performance improvement cannot be only because of the model’s ability to decompose multiple tasks but may be because the MUL train has higher 4-gram overlap with SNG Valid and MUL Valid. This shows that despite the dialogues carrying rich information in task oriented dialogues, the model at best only mimics the surface level token distribution. Hence, it is not clear if the Transformer model can generalize to multi-task dialogues with an understanding of the underlying task structure.

USER:I'm looking for the Lensfield Hotel. Can you help me find it ?
ASSISTANT:Yes of course, it is located in 53-57 lensfield road. Would you like me to book you a reservation ?
USER: No thank you. Could you give me the postcode and tell me if they have free parking ?
ASSISTANT: Yes, they have free parking. The postcode is cb21en. Is there anything else you'd like to know about this hotel ?
USER:No, that's all I needed. Thanks! Bye!
ASSISTANT: You are welcome. Goddbye!

USER:I'd like to find a train that leaves after 17:00 on Saturday.
ASSISTANT: Absolutely, I need departure and destination information and a time you need to arrive by.
USER: I will be departing from Broxbourne and I'd like to go to Cambridge.
ASSISTANT: I have 7 available. The first leaves at 17:32, and arrives at 18:32. Would you like me to book that for you ?
USER:I am not looking to book at the moment, can I just get the train ID? Thanks.
ASSISTANT: Of course! TR0811 leaves at 17:32, arrives at 18:32, with a duration of 60 minutes. The price is 14.32 pounds. May I assist you with anything else ?
USER: That is all I need for today. Thank you. Good bye.
ASSISTANT: Okay glad I could help you. Enjoy your trip.

USER:I'm looking for the Lensfield Hotel. Can you help me find it ?
ASSISTANT:Yes of course, it is located in 53-57 lensfield road. Would you like me to book you a reservation ?
USER: No thank you. Could you give me the postcode and tell me if they have free parking ?
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USER: That is all I need for today. Thank you. Good bye.
ASSISTANT: Okay glad I could help you. Enjoy your trip.

Figure 2: An example of combining two single-task dialogues in **color1** and **color2** together to form a single multi-task dialogue.

(a) Table 1		(b) Table 2	
MUL Train	492688	MUL Train	492688
SNG Valid	16907	MUL Valid	104261
Intersection	9238	Intersection	48076
% Unseen	45.36	% Unseen	53.89%

(c) Table 3		(d) Table 4	
SNG Train	124038	SNG Train	124038
MUL Valid	104261	SNG Valid	16907
Intersection	22254	Intersection	6562
% Unseen	78.66%	% Unseen	61.19%

(e) Table 5	
SNG+MUL Train	568674
SNG Valid	104261
Intersection	49999
% Unseen	52.04%

(f) Table 6	
SNG+MUL Train	568674
SNG Valid	16907
Intersection	9746
% Unseen	42.36%

Table 5: Analysis of 4-gram overlap across different combinations of train and validation splits that were used in the experiments. The analysis show that the %Unseen in validation set is higher when training with SNG (Single domain dialogues) but considerably lower when trained with MUL. The composition task requires models to understand the underlying task structure but the data distribution and performance of transformer strongly correlate to show that the transformer model at best mimics the surface level token distribution than understanding the nature of task.