Technical Appendix

Paper ID: 2262

1 Dataset Details

In this section, we provide more information about the MultiWOZ 2.0 dataset. The training set of MultiWOZ contains 8438 dialogs, a total turns of 115424 and tokens of 1520970. The average number of turns per dialog is 13.68 and the average number of token per turn is 13.18. The original number of slots and values are 25 and 4510 respectively. The ontology after our domain adaptive pre-processing is slightly different than the original one, we show the new ontology in Table 1.

| act type | inform* / request* / nooffer ¹²³⁴ / recommend ¹²³ / select ¹²³⁴ / offerbook ¹²⁴ / offerbooked ¹²⁴ / nobook ¹² / bye* / greet* / |
|-------------|---|
| | reqmore* / welcome* |
| slot | car ⁵ / address ¹²³⁶⁷ / postcode ¹²³⁶⁷ / phone ¹²³⁵⁶⁷ / internet ² / parking ² / type ²³ / |
| | pricerange ¹² / food ¹ / stars ² / area ¹²³ / |
| | reference ¹²³⁴ / time ¹⁴ / |
| | leave 45 / price 45 / arrive 45 / id 4 / |
| | $stay^2$ / day^{124} / $leave^{45}$ / $people^{123}$ / $name^{123}$ / |
| | destination ⁴⁵ / departure ⁴⁵ / department ⁶ |

Table 1: Full ontology for all domains. The upper script indicates which domains it belongs to. *:universal, 1: restaurant, 2: hotel, 3:attraction, 4:train, 5:taxi, 6:hospital, 7:policy.

2 More implementation Details

UBAR is trained on a single 12 GB Nvidia GeForce 2080Ti. We use gradient accumulation to achieve bigger batch size. Specifically, on end to end modeling, the hyperparameters of the best version of UBAR on MultiWOZ 2.0 is an AdamW optimizer with initial learning rate of 0.0001 and a schedule that first linearly increasing during 2000 warmup steps then decrease linearly. The batch size is 32 with a gradient accumulation steps of 16. UBAR is trained for 60 epochs with no early stopping, we evaluate the performance of UBAR in policy optimization setting since it takes more time to generate belief states. The best version is trained for 43 epochs. We observe that UBAR is able to generate response very well within the first 10 epochs. However, it requires much more effort to learn to generate accurate belief states and dialog act.

As for dialog state tracking (DST), we trained DST-UBAR with training data consisting of user utterances, belief states, database results, dialog acts and **non-delexicalized** responses. The learning rate is 6e-5 and batch size is 24 with gradient accumulation steps of 12. In the stage of evaluating, generated belief states from previous turns are included in the input. In the experiment, we observed that including belief states slots with *not mentioned* value in the training sequences will get a better performance. In evaluation, the belief states are generated by DST-UBAR based on dialog context of user utterances, generated belief states and ground truth dialog acts and non-delexicalized responses. It is important to use ground truth non-delexicalized responses for they contains specific slot values to be extracted. DST-UBAR is trained for 60 epochs, we choose the best performing model on Validation set. The best model is trained for 41 epochs and the joint accuracy is 53.19 on Validation set, 53.04 in Test set on MultiWOZ 2.0.

3 Overall Results on Validation and Test sets

After selecting the best model based on the performance on the Validation set, we only run evaluation once in every setting on the Test set. We observes that the results on Validation set generally correlates with the results on Test set. In the section we provide the performance of UBAR on Validation set in Table 2 and Table 3.

| Belief | Act | Inf. | Succ. | BLEU | Comb. | Inf. | Succ. | BLEU | Comb. |
|-----------|---------------------|-------|-------|-------|--------|-------|-------|-------|--------|
| oracle | oracle generated | 97.20 | 94.29 | 27.58 | 123.32 | 96.90 | 92.20 | 28.61 | 123.16 |
| oracle | generated | 95.40 | 85.89 | 16.97 | 107.62 | 94.00 | 83.60 | 17.22 | 106.02 |
| generated | generated | 95.50 | 83.28 | 16.63 | 106.02 | 95.40 | 80.80 | 17.00 | 105.05 |

Table 2: Results on Dev and Test set of UBAR in different settings on MultiWOZ 2.0.

| Belief | Belief Act | | Succ. | BLEU | Comb. | Inf. | Succ. | BLEU | Comb. |
|-----------|----------------------------------|-------|-------|-------|--------|-------|-------|-------|--------|
| oracle | oracle | 95.80 | 92.49 | 27.92 | 122.06 | 95.4 | 91.4 | 28.75 | 122.15 |
| oracle | generated | 92.99 | 82.38 | 16.19 | 103.88 | 92.7 | 81.0 | 16.72 | 103.57 |
| generated | oracle generated generated | 95.30 | 82.48 | 16.03 | 105.92 | 95.70 | 81.80 | 16.52 | 105.27 |

Table 3: Results on Dev and Test set of UBAR in different settings on MultiWOZ 2.1.

4 More Comprehensive Study of the Context of UBAR

In the section, we provide a much more comprehensive study of how the dialog context affect the performance of UBAR in multiple settings.

Specifically, Table 4 reports the results of UBAR evaluated in the end-to-end modeling setting. We discuss how the number of turns in the context, whether to use generated or the ground truth belief states, database results and Dialog act/response in the context vary the results. Note that we constrain dialog act and response are coupled since they are highly correlated.

Table 5 reports the results of UBAR evaluated in policy optimization setting where the belief states and DB results are ground truth and UBAR generates dialog act and response. We discuss how the number of turns in the context, whether to use generated or the ground truth dialog act and response in the context vary the results. Note that here we separate dialog act and response to see which matters more in the context.

Table 6 reports the results on UBAR evaluated in response generation setting where belief states, DB results and dialog acts are all ground truth.

In the end-to-end setting, we can make several observation from the results.

- Using all previous turns is better than using just the last turn.
- The best performing setting is to use ground truth belief states and DB results in the context.
- In a more realistic setting where the content in the context are all generated, UBAR performs generally well.
- The generated dialog act and response result in high inform rate and success rate, but not higher BLEU score. Using generated dialog act and response contributes to task completion.

In policy optimization setting, we observe that:

- Using all previous turns is better than using just the last turn.
- Generated dialog act and response contributes to task completion.
- Generated dialog act contributes more to task completion than generated response, if only one of them is generated.

In response generation setting, we observe that:

- Using all previous turns is better than using just the last turn.
- Using just the generated response in the context can still improve the performance.

| #Turns | Belief State | DB result | Dialog Act | Response | Inf. | Succ. | BLEU | Comb. |
|--------|--------------|-----------|------------|----------|-------|-------|-------|--------|
| All | GT | GT | GT | GT | 88.80 | 79.00 | 17.79 | 101.69 |
| All | GT | Gen | GT | GT | 88.40 | 76.60 | 17.57 | 100.07 |
| All | GT | GT | Gen | Gen | 95.80 | 83.10 | 17.40 | 106.85 |
| All | GT | Gen | Gen | Gen | 95.40 | 82.30 | 17.24 | 106.09 |
| All | Gen | GT | GT | GT | 88.90 | 79.10 | 17.78 | 101.78 |
| All | Gen | Gen | GT | GT | 87.60 | 75.60 | 17.50 | 99.10 |
| All | Gen | GT | Gen | Gen | 95.40 | 80.90 | 16.96 | 105.11 |
| All | Gen | Gen | Gen | Gen | 95.40 | 80.70 | 17.00 | 105.05 |
| Prev | GT | GT | GT | GT | 89.30 | 78.50 | 16.88 | 100.78 |
| Prev | GT | Gen | GT | GT | 87.20 | 75.30 | 16.79 | 98.04 |
| Prev | GT | GT | Gen | Gen | 92.70 | 80.40 | 16.66 | 103.21 |
| Prev | GT | Gen | Gen | Gen | 92.70 | 79.00 | 16.64 | 102.49 |
| Prev | Gen | GT | GT | GT | 88.00 | 76.50 | 16.76 | 99.01 |
| Prev | Gen | Gen | GT | GT | 86.90 | 73.30 | 16.77 | 96.87 |
| Prev | Gen | GT | Gen | Gen | 92.70 | 79.10 | 16.40 | 102.30 |
| Prev | Gen | Gen | Gen | Gen | 92.70 | 77.70 | 16.36 | 101.56 |

Table 4: A more comprehensive evaluation of UBAR with different kind of dialog context in end-to-end setting. #Turns denotes the number of previous turns in context, All means all previous turn, Prev means just the last turn. GT or Gen denotes the context are ground truth or generated. The more realistic setting is shaded.

| #Turns | Dialog Act | Response | Inf. | Succ. | BLEU | Comb. |
|--------|------------|----------|-------|-------|-------|--------|
| All | GT | GT | 90.40 | 80.80 | 17.87 | 103.47 |
| All | GT | Gen | 91.70 | 81.40 | 17.47 | 104.02 |
| All | Gen | GT | 92.20 | 82.10 | 18.16 | 105.31 |
| All | Gen | Gen | 94.00 | 83.60 | 17.22 | 106.02 |
| Prev | GT | GT | 89.60 | 80.40 | 17.23 | 102.23 |
| Prev | GT | Gen | 90.20 | 80.60 | 16.90 | 102.30 |
| Prev | Gen | GT | 89.90 | 80.60 | 17.33 | 102.58 |
| Prev | Gen | Gen | 93.00 | 82.90 | 16.65 | 104.60 |

Table 5: A comprehensive evaluation of UBAR with different kind of dialog context in policy optimization setting. In this setting, the belief state and database result are all ground truth, so we only discuss whether to use generated dialog act and response. The more realistic setting is shaded

| #Turns | Response | Inf. | Succ. | BLEU | Comb. |
|--------|----------|-------|-------|-------|--------|
| All | GT | 96.60 | 91.40 | 28.63 | 122.63 |
| All | Gen | 96.90 | 92.20 | 28.61 | 123.16 |
| Prev | GT | 96.80 | 92.10 | 27.76 | 122.21 |
| Prev | Gen | 96.90 | 92.40 | 27.89 | 122.54 |

Table 6: A comprehensive evaluation of UBAR with different kind of dialog context in response generation setting. In this setting, the belief state, database result and dialog act are all ground truth, so we only discuss whether to use generated response. The more realistic setting is shaded

4.1 Context Length

It has been demonstrated that UBAR can achieve satisfying performances conditioned on context of only the previous turn. We further discuss how context length affects the combined scores in multiple settings.

As the max length of GPT-2 is 1024, we set the input context length from 100 to 900 and plot their corresponding combined scores. As shown in Figure 1, the performances of UBAR are very consistent across different context lengths in all settings. This indicates another advantage of UBAR, which provides computational efficiency with shorter input length.

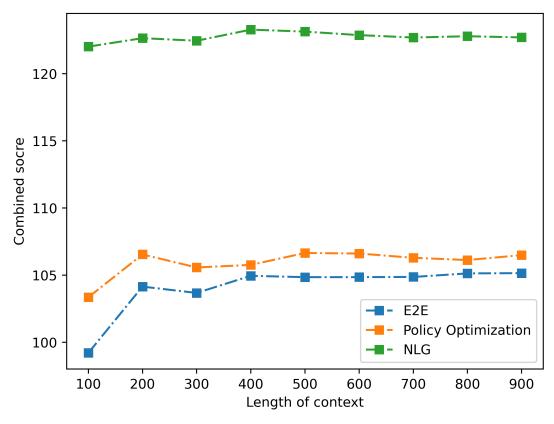


Figure 1: Caption

On the other hand, the turn-level GPT-2-based methods must rely on all the dialog history to infer the belief states, which makes them computationally less efficient.

5 More Case and Error Study

In this section, we provide a case study of UBAR modeling a task-oriented dialog session in end-to-end setting. Additionally, we perform error analyses of dialog state tracking.

5.1 Example of a whole dialog session

Given the limited space in paper, we can only show part of a dialog session to demonstrate the superiority of UBAR. Here we provide an example of a whole dialog session with complete dialog context and full generated content of UBAR. Concretely, UBAR takes previous user utterances, generated belief states, database results, generated dialog acts and responses, and generates belief state, dialog act and response of the current turn.

As shown in Table 7, UBAR successfully helps user by providing information about a restaurant, booking a reservation, requesting for more information, providing information about a train etc.. It is encouraged to take a closer look at this exemplar dialog session to appreciate how good UBAR is at task completion and generating fluent responses.

5.2 Error Analysis of Dialog State Tracking

Although achieving state-of-the-art performance on DST, DST-UBAR still makes several types of errors.

We demonstrate a representative error in Table 8, where DST-UBAR fails to extract belief states from the system response and all generated belief states from turn 2 miss out *parking yes internet yes type guest house*. This is because DST-UBAR mainly relies on the generated belief state of the previous turn and the current user utterance to generated new belief state, once *parking yes internet yes type guest house* are missed out in turn 2, it is difficult for DST-UBAR to recover such information in later turns.

However, if the user specifies a state slot's value, DST-UBAR is able to revise the value. As shown in Table 9, in turn 4, DST-UBAR assumes the user only needs to book one ticket, so it predicts *people 1*, which is not within the ground truth belief state. But in the next turn, the user requests for 7 tickets, DST-UBAR is able to revise its previous mistake and adaptively change the value. A similar example is shown in Table 10, where DST-UBAR is able to revise the belief state given new user utterance.

| 1 | Context | <sos_u> hi, i am trying to find out more about a restaurant called cocum. what can you tell me?<eos_u> <sos_b></sos_b></eos_u></sos_u> |
|--------|---------|--|
| Turn 1 | Taget | |
| | UBAR | <pre><sos_r> it is an [value_food] restaurnat in the [value_area] . it is [value_price] . <eos_r> <sos_b> [restaurant] name cocum <eos_b> <sos_db> [db.1] <eos_db> <sos_a> [restaurant] [inform] food area name [offerbook]</sos_a></eos_db></sos_db></eos_b></sos_b></eos_r></sos_r></pre> |
| | UBAK | <pre> <sos_b> [restaurant] name cocum <eos_b> <sos_db> [db_1] <eos_db> <sos_a> [restaurant] [inform] food area name [offerbook] <eos_a> <sos_r> [value_name] is a [value_food] restaurant in the [value_area] . would you like me to make a reservation for you? <eos_r> </eos_r></sos_r></eos_a></sos_a></eos_db></sos_db></eos_b></sos_b></pre> |
| Turn 2 | Context | <pre><sos_u> hi, i am trying to find out more about a restaurant called cocum. what can you tell me? <eos_u> <sos_b> [restaurant] name cocum</sos_b></eos_u></sos_u></pre> |
| | Taget | <pre><sos_b> [restaurant] name cocum <eos_b> <sos_db> [db_1] <eos_db> <sos_a> [restaurant] [request] day time<eos_a> <sos_r> i would be happy to make your reservation. what day and time would you like to make it for? <eos_r></eos_r></sos_r></eos_a></sos_a></eos_db></sos_db></eos_b></sos_b></pre> |
| | UBAR | <pre>would be happy to make your reservation. what day and time would you like to make it for: \(\cos_a \) \</pre> |
| Turn 3 | Context | thanks! i would like to book a table for 3. <eos_u> <sos_b> [restaurant] name cocum <eos_b> <sos_db> [db_1] <eos_db> <sos_a> [restaurant] [request] day time <eos_a> <sos_r> what day and time would you like the reservation for? <eos_r> <sos_u> i would like to book a table for 3 on saturday at 13:30. are there any trains that go to broxbourne on sunday? <eos_u> <sos_b></sos_b></eos_u></sos_u></eos_r></sos_r></eos_a></sos_a></eos_db></sos_db></eos_b></sos_b></eos_u> |
| | Taget | <pre><sos_b> [restaurant] name cocum time 13:30 day saturday people 3 <eos_b> <sos_db> [db_1] <eos_db> <sos_a> [restaurant] [offer-booked] reference <eos_a> <sos_r> reference number is [value_reference] . <eos_r></eos_r></sos_r></eos_a></sos_a></eos_db></sos_db></eos_b></sos_b></pre> |
| | UBAR | |
| Turn 4 | Context | <sos_u> i would like to book a table for 3 on saturday at 13:30. are there any trains that go to broxbourne on sunday? <eos_u> <sos_b> [restaurant] name cocum time 13:30 day saturday people 3 <cos_b> <sos_db> [db.1] <cos_db> <sos_a> [restaurant] [offerbooked] reference <cos_a> <sos_r> reference number is [value_reference] . <cos_r> <sos_u> i am also looking for a train departing from cambridge on sunday and arriving at broxbourne by 09:15. <cos_u> <sos_b></sos_b></cos_u></sos_u></cos_r></sos_r></cos_a></sos_a></cos_db></sos_db></cos_b></sos_b></eos_u></sos_u> |
| | Taget | <sos_b> [train] destination broxbourne day sunday arrive 09:15 departure cambridge [restaurant] name cocum time 13:30 day saturday people 3 <eos_b> <sos_db> [db_3] <eos_db> <sos_a> [train] [inform] arrive id leave [offerbook] <eos_a> <sos_r>[value_id] leaves at [value_leave] and arrives at [value_arrive]. can i book that for you? <eos_r></eos_r></sos_r></eos_a></sos_a></eos_db></sos_db></eos_b></sos_b> |
| | UBAR | <sos_b> [train] destination broxbourne day sunday arrive 09:15 departure cambridge [restaurant] name cocum time 13:30 day saturday people 3 <eos_b> <sos_d> [db_3] <eos_db> <sos_a> [train] [inform] choice [request] leave<eos_a> <sos_r> there are [value_choice] trains that meet your criteria. is there a particular time you would like to leave? <eos_r></eos_r></sos_r></eos_a></sos_a></eos_db></sos_d></eos_b></sos_b> |
| Turn 5 | Context | <sos_u> i am also looking for a train departing from cambridge on sunday and arriving at broxbourne by 09:15. <eos_u> <sos_b> [train] destination broxbourne day sunday arrive 09:15 departure cambridge [restaurant] name cocum time 13:30 day saturday people 3 <eos_b> <sos_db> [db_3] <eos_db> <sos_a> [train] [inform] arrive id leave [offerbook] <eos_a> <sos_r> [value_id] leaves at [value_leave] and arrives at [value_arrive] . would you like me to book that for you? <eos_r> <sos_u> that is quite early. are there any trains closer to 09:00? <eos_u> <sos_b></sos_b></eos_u></sos_u></eos_r></sos_r></eos_a></sos_a></eos_db></sos_db></eos_b></sos_b></eos_u></sos_u> |
| | Taget | <sos_t> (sos_t) (sos_b) [train] destination broxbourne day sunday arrive 09:15 departure cambridge [restaurant] name cocum time 13:30 day saturday people 3 <eos_b> <sos_db> [db_3] <eos_db> <sos_a> [train] [inform] arrive id destination departure leave [offerbook] <eos_a> <sos_t>yes. [value_id] leaves [value_departure] at [value_leave] and arrives in [value_destination] at [value_arrive]. would this be better for you? <eos_t></eos_t></sos_t></eos_a></sos_a></eos_db></sos_db></eos_b></sos_t> |
| | UBAR | <pre><sos_b> [train] destination broxbourne day sunday arrive 09:15 departure cambridge [restaurant] name cocum time 13:30 day saturday peo- ple 3 <eos_b> <sos_db> [db_3] <eos_db> <sos_a> [train] [inform] arrive id <eos_a> <sos_r> yes, [value_id] arrives at [value_arrive] .<eos_r></eos_r></sos_r></eos_a></sos_a></eos_db></sos_db></eos_b></sos_b></pre> |
| Turn 6 | Context | <sos_u> that is quite early. are there any trains closer to 09:00? <eos_u> <sos_b> [train] destination broxbourne day sunday arrive 09:15 departure cambridge [restaurant] name cocum time 13:30 day saturday people 3 <eos_b> <sos_db> [db_3] <eos_db> <sos_a> [train] [inform] arrive id <eos_a> <sos_r> yes, [value_id] arrives at [value_arrive] . <eos_r> <sos_u> yes, that would be great. what is the total travel time? <eos_u> <sos_b></sos_b></eos_u></sos_u></eos_r></sos_r></eos_a></sos_a></eos_db></sos_db></eos_b></sos_b></eos_u></sos_u> |
| | Taget | <pre><sos_b> [train] destination broxbourne day sunday arrive 09:15 departure cambridge [restaurant] name cocum time 13:30 day saturday peo- ple 3 <eos_b> <sos_db> [db_3] <eos_db> <sos_a> [train] [inform] time [offerbook] <eos_a> <sos_r> total travel time is [value_time] . can i book that for you?<eos_r></eos_r></sos_r></eos_a></sos_a></eos_db></sos_db></eos_b></sos_b></pre> |
| | UBAR | |

Table 7: Example of a whole dialog session. Dialog ID: MUL1649

| Turn 1 | Context GT BS Gen BS | User: hello. i really need to find a cheap place to stay in the east. is there anything like that? [hotel] area east pricerange cheap [hotel] area east pricerange cheap |
|--------|----------------------------|--|
| Turn 2 | GT BS Gen BS | System: i have found 3, all of them are guest house and all of them have free internet and parking. would you like me to give your their information? User: sure, that sounds great. [hotel] area east pricerange cheap parking yes internet yes type guest house [hotel] area east pricerange cheap |
| Turn 3 | GT BS Gen BS | System: okay i will give you the information i have on them. User: can you book it for 8 people for 4 nights starting on thursday? [hotel] area east pricerange cheap parking yes internet yes type guest house stay 4 day thursday people 8 [hotel] area east pricerange cheap people 8 day thursday stay 4 |
| Turn 4 | GT BS Gen BS | System: ok i have you booked at the allenbell for 4 nights for 8 people. your reference number 7sn0baat. do you need anything else? User: i would like an indian restaurant in the same price range as the hotel please. [hotel] area east pricerange cheap parking yes internet yes type guest house stay 4 day thursday people 8 [restaurant] food indian pricerange cheap [hotel] area east pricerange cheap people 8 day thursday stay 4 [restaurant] food indian pricerange cheap |
| Turn 5 | GT BS Gen BS | System: there are 4 cheap indian place -s, 3 in city centre, and 1 on the north end. User: whichever 1 is fine, surprise me! tickests. [hotel] area east pricerange cheap parking yes internet yes type guest house stay 4 day thursday people 8 [restaurant] food indian pricerange cheap [hotel] area east pricerange cheap people 8 day thursday stay 4 [restaurant] food indian pricerange cheap |

Table 8: Example of error propagation from MultiWOZ2.1, dialog id:PMUL1182. To save space, we only show the user utterances and system responses in the context. Since second turn, belief states *parking yes internet yes type guest house* are missed in the generated belief states.

| Turn 1 | Context GT BS Gen BS | User: i need a train to peterborough that will be there no later than 17:15. [train] destination peterborough arrive 17:15 [train] destination peterborough arrive 17:15 |
|--------|----------------------------|--|
| Turn 2 | GT BS Gen BS | System: i have several choices, do you have a time for your departure? User: i am looking for a train arriving in peterborough. [train] destination peterborough arrive 17:15 [train] destination peterborough arrive 17:15 |
| Turn 3 | Context GT BS Gen BS | System: and where will you be leaving from? User: i'll be leaving cambridge on sunday. [train] destination peterorough arrive 17:15 day sunday departrue cambridge destination peterorough arrive 17:15 day sunday departrue cambridge |
| Turn 4 | GT BS Gen BS | System: i have train tr1086 that leaves at 16:06 and will have in peterborough at 16:56 would this work for you? User: yes, that will be fine can you get me a ticket? [train] destination peterorough arrive 17:15 day sunday departrue cambridge [train] destination peterorough arrive 17:15 day sunday departrue cambridge |
| Turn 5 | Context GT BS Gen BS | System: how many tickets will you need? User: i need 7 tickests. [train] destination peterorough arrive 17:15 day sunday departrue cambridge people 7 [train] destination peterorough arrive 17:15 day sunday departrue cambridge people 7 |

Table 9: Example of error correction from MultiWOZ2.1, dialog id:PMUL1801. To save space, we only show the user utterances and system responses in the context. As shown on the table, when condition on context *yes, that will be fine can you get me a ticket?*, DST-UBAR generated wrong belief state *people 1*. While in the next turn, DST-UBAR revised the number of people when given to a new context.

| Turn 1 | Context GT BS | User: i am looking for a nice restaurant with price range high and book a table for 4. |
|---------|------------------|--|
| | Gen BS | [restaurant] pricerange expensive |
| Turn 2 | Context | System: i am sorry, there seems to be an error. can you please restate your request? User: i actually need a train |
| Tuili 2 | GT BS | |
| | Gen BS | [restaurant] pricerange expensive |
| Turn 3 | Context | System: what are your departure and destination location -s? User: departing from cambridge and going to leicester on tuesday. |
| | GT BS | [train] destination leicester day tuesday departure cambridge |
| | Gen BS | [train] destination leicester day tuesday departure cambridge |

Table 10: Example of error correction from MultiWOZ2.1, dialog id:PMUL3886.To save space, we only show the user utterances and system responses in the context. As shown on the table, when condition on context *i am looking for a nice restaurant with price range high and book a table for 4*, DST-UBAR generated wrong belief states [restaurant] pricerange expensive. While in the third turn, DST-UBAR revised the belief states when given to new context.

6 More Visualizations

In this section, we visualize how belief state, dialog act, response attend to the context. Specifically:

- We use attention from last layer of Transformer block and average the attention weight of each attention head in that block.
- GPT-2 uses BPE tokenization, in such setting, a word like *pricerange* will be tokenized into sub words $\dot{G}pr$, *icer* and *ange*, we merge the sub words and average the corresponding attention weights to improve readability.
- For belief state, we show the attention between current belief state and previous belief state, dialog action, data base query result, response and current user utterance in heat map, where X-axis is context, Y-axis is current belief state.
- For dialog act, we show the attention weight between current dialog act and current user utterance, belief state, data base query result in heat map, where X-axis is context, Y-axis is current dialog act.
- For dialog response, since reponse and current dialog act have a high corelation, we just show the attention weight between current dialog response and current dialog act in heat map, where X-axis is current dialog act, Y-axis is current dialog response.

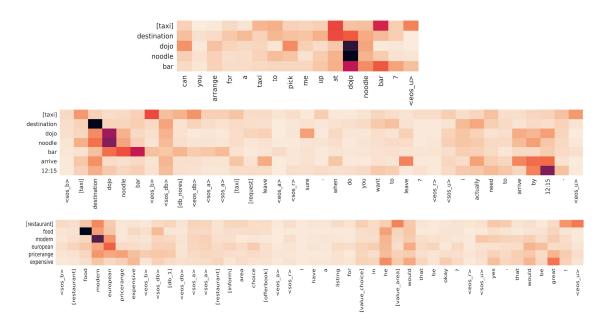


Figure 2: Heat map of belief state. X-axis is context, which consists of previous belief state, data base query result, dialog act, response and current user utterance.

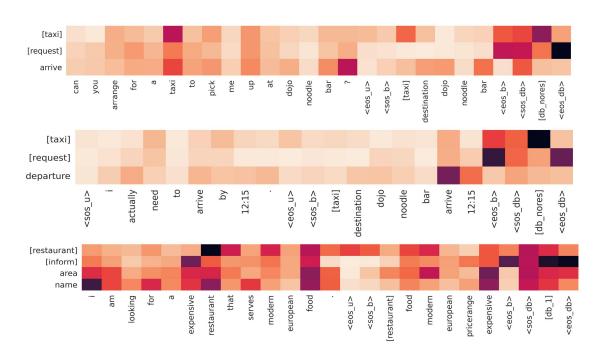


Figure 3: Heat map of dialog act. X-axis is context, which consists of current belief state, data base query result.

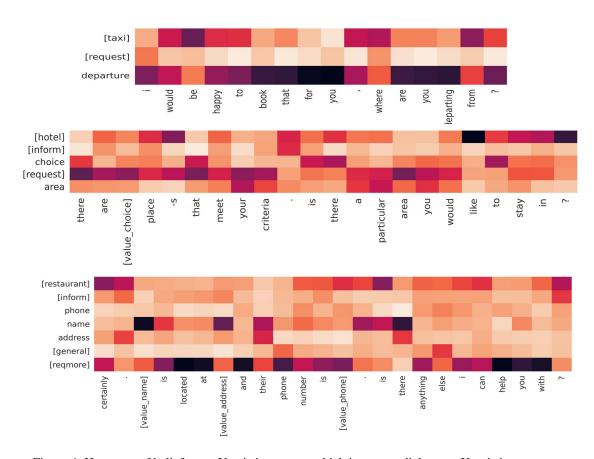


Figure 4: Heat map of belief state. Y-axis is context, which is current dialog act, X-axis is response.