UBARv2: Towards Mitigating Exposure Bias in Task-Oriented Dialogs

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Abstract
This paper studies the exposure bias problem in task-oriented dialog systems, where the model’s generated content over multiple turns drives the dialog context away from the ground-truth distribution at training time, introducing error propagation and damaging the robustness of the TOD system. To bridge the gap between training and inference for multi-turn task-oriented dialogs, we propose session-level sampling which explicitly exposes the model to sampled generated content of dialog context during training. Additionally, we employ a dropout-based consistency regularization with the masking strategy R-Mask to further improve the robustness and performance of the model. The proposed UBARv2 achieves state-of-the-art performance on the standardized evaluation benchmark MultiWOZ and extensive experiments show the effectiveness of the proposed methods.

1 Introduction
Task-oriented dialog (TOD) systems assist users with various tasks via natural language conversations. The traditional task-oriented dialog systems follow a pipeline approach which consists of several consecutive modules. First, a dialog state tracker (DST) is to estimate the belief state from the user utterance. The belief state is then used to query a task-related database (DB) like the number of entities that match the user’s goal. Subsequently, a dialog policy learning module is applied to determine the next system act, followed by a natural language generation (NLG) module that converts the system action to a natural language response.

Recently, task-oriented dialog systems have achieved promising results by leveraging pre-trained language models (Radford et al., 2018) for end-to-end modeling in a unified way (Ham et al., 2020; Hosseini-Asl et al., 2020; Peng et al., 2020; Yang et al., 2021). These works cast task-oriented dialogs as a unified language generation task and fine-tune models with the language modeling objective. Particularly, UBAR (Yang et al., 2021) models task-oriented dialogs on a dialog session level, which is trained on the sequence of the entire dialog session composed of user utterance, belief state, database result, system act, and system response of every dialog turn. During inference, the dialog context uses the generated content rather than the ground-truth annotations. The successive works MTTOD (Lee, 2021), PPTOD (Su et al., 2021) and GALAXY (He et al., 2021) all follow such session-level modeling as the fundamental design when developing their methods. They achieve increasingly competitive performances via multi-task learning and large-scale in-domain pre-training.

Despite the effectiveness of session-level modeling, bringing in generated content at inference time inevitably introduces a gap between training and inference. Since the distribution of the ground-truth annotations at training time is different from the distribution of the model predictions at inference time. If a mistake has occurred in the dialog context, there can be error propagation which causes the model generation to continue to deviate from the optimal distribution. This problem is often referred to as exposure bias for auto-regressive models. In the case of TOD systems, the exposure bias problem can take place across multiple modules over multiple dialog turns. For example, a TOD system is asking about the food style of the requested restaurant, but the user replies with the price range. Though the model might be able to update the belief state correctly, it could be confused when generating the system action and response of the next turn, given that the training data is coherent and consistent while the model has not seen such off-the-mark answers during training. What’s more, being exposed to an unfamiliar situation where the dialog context contains low quality and erroneous generated content is detrimental to the model’s performance and robustness.
In an attempt to mitigate the exposure bias problem that exhibits in task-oriented dialog systems, we follow the session-level modeling of UBAR and propose a learning framework UBAr2 that explicitly exposes the model to heterogeneous data at training time. Specifically, we explore the sampling strategy for constructing the session-level training sequence and perform mixed training from both the distribution of the annotation and the distribution of the model prediction. In the initial stage of training, the ground truth sequence is learned to help the model converge quickly, and then the content generated by the model is sampled on turn level with a certain probability for mixed training. We further employ a dropout-based consistency regularization with a masking strategy named R-Mask, which carries out the forward pass twice for the parallel with a certain probability for mixed training. We describe the proposed session-level scheduled modeling as the building block of UBAr2 and UBArv2. Figure 1 is an overview of the sampling strategy and consistency regularization with a masking strategy named R-Mask, further employ a dropout-based consistency regularization with a masking strategy named R-Mask.

2 Methodology

In this section, we introduce the session-level modeling as the building block of UBArv2 and describe the proposed session-level scheduled sampling strategy and consistency regularization method R-Mask. Figure 1 is an overview of UBArv2.

2.1 Session-Level Modeling

Session-level modeling is first introduced by Yang et al. (2021) and adopted by numerous successive methods (Lee, 2021; Su et al., 2021; He et al., 2021). Two key factors of session-level modeling contribute to the effectiveness of a task-oriented dialog system: the incorporation of intermediate information such as belief state and system action into dialog context, and using all generated content in the dialog context.

As illustrated in Figure 1 (a), given a dialog session composed of multiple turns, the session-level modeling operates the process of a task-oriented dialog system as follows: In the first turn $\tau = 0$, the user puts in user utterance $U_0$, based on $U_0$, the model generates a belief state $B_0$. The belief state is applied to query a database to retrieve database search result $D_0$, which is the matched number of entities that satisfy the constraint inflicted by the belief state. Based on $\{U_0, B_0, D_0\}$, the model generates system action $A_0$ and system response $R_0$, accomplishing the interaction of the first turn. As the dialog proceeds to turn $\tau$, the model generates $B_\tau, A_\tau$ and $R_\tau$, based on context of user utterances and all previous generated outputs $\{U_0, B_0, D_0, A_0, R_0, \ldots, U_{\tau-1}, B_{\tau-1}, D_{\tau-1}, A_{\tau-1}, R_{\tau-1}, U_\tau\}$, eventually concluding the entire dialog session.

The model can be trained with language modeling objective (Bengio et al., 2003) for GPT-2-based architecture. The idea of session-level modeling also applies for Seq2Seq architectures (Su et al., 2021; Lee, 2021) or unified language model (He et al., 2021).

2.2 Session-Level Sampling

To bridge the gap between training and inference, we can draw inspiration from the domain of neural machine translation, where scheduled sampling is employed such that the input to the decoder at time step $t$ is chosen randomly between the ground-truth word and the model’s prediction (Bengio et al., 2015; Zhang et al., 2019).

Instead of simply considering the word-level exposure bias of autoregressive generation by sampling context words, this work focuses on addressing the discrepancy across multiple turns in a dialog session. Therefore, we propose to sample content in a turn-wise and modular-wise manner and construct session-level sequence mixed with ground-truth and generated modular
spans for training. Specifically, as shown in Figure 1 (b), in every turn we can decide with a certain probability whether to sample a generated modular span, such as belief state, database result, system action and system response. Take belief state for example, which is the determined sampling target of our method. As the dialog proceeds to turn $\tau$, UBARv2 takes dialog context $\{U_0, B_0, D_0, A_0, R_0, ..., U_{\tau-1}, B_{\tau-1}, D_{\tau-1}, A_{\tau-1}, R_{\tau-1}, U_{\tau}\}$ and generates $\hat{B}_\tau$. We choose with probability $\epsilon$ to sample the generated belief state span $\hat{B}_\tau$ and with probability $(1 - \epsilon)$ to sample the ground-truth span $B_\tau$. Performing sampling with chance every turn results in a full dialog session-level training sequence of $M$ turns: $\{U_0, \hat{B}_0, D_0, A_0, R_0, ..., U_M, \hat{B}_M, D_M, A_M, R_M\}$, where $\hat{B}_\tau$ is the generated content.

At the early stage (Stage 1) of learning, the model is trained with ground-truth sequences so that UBARv2 can effectively learn task-oriented dialogs. At the late stage (Stage 2), the model employs mixed training with sampling rate $\epsilon$ and exposes itself to the inference setting, learning to deal with inconsistent and incoherent dialogs. The objective is to minimize the negative log-likelihood of the session-level sampled sequence $\tilde{x} = \{\tilde{x}_0, \tilde{x}_1, ..., \tilde{x}_T\}$:

$$\mathcal{L}_N^{\text{NLL}} = - \sum_{t=1}^{T} \log P_{\theta}(\tilde{x}_i | \tilde{x}_{<t}) \quad (1)$$

It is important to note that the model is trained on the sampled sequence instead of always trained on the ground-truth tokens based on the last sampled word like previous methods (Bengio et al., 2015; Zhang et al., 2019). What’s more, We fix the sampling rate $\epsilon$ at Stage 2 instead of using scheduled rate or with decay for simplicity, while we focus more on the strategy such as which component of the dialog context to sample.

2.3 R-Mask

Inspired by R-Drop (Wu et al., 2021), which attempts to make models with dropout (Srivastava et al., 2014) be more consistent during training and inference, we explore dropout-based consistency training in helping mitigate the exposure bias problem in task-oriented dialogs. Other than explicitly making the model learn its sampled generated content, we hope such consistent regularization could expose the model to more non-ground-truth data, eventually reducing the gap.

There are two scenarios applying consistency regularization to the generation task of TOD systems: Stage 1 training and Stage 2 training. At the Stage 1, which is the early stage when training on the ground-truth sequences $X = \{x_0, x_1, ..., x_T\}$, the model goes through the forward pass twice and acquires two distinct distributions of the same sequence from the randomness in the model. The objective is to minimize the bidirectional KL diver-
gence between the two distributions:

\[
L_{KL} = \sum_{t=1}^{T} \frac{1}{2} [DKL(P_{\theta^1}(x_t | x_{<t}) || P_{\theta^2}(x_t | x_{<t})) + D_{KL}(P_{\theta^2}(x_t | x_{<t}) || P_{\theta^1}(x_t | x_{<t}))]
\]

(2)

In essence, by adding a KL divergence regularization term, R-Drop increases the robustness to dropout and forces the model output to be consistent under different dropouts.

Consistency training can introduce model-level regularization and data-level regularization which involves modification of the input data. Therefore, at Stage 2, the late stage training, we employ an addition masking strategy R-Mask to the sampled sequence to obtain different distributions. As shown in figure 1 (c), we randomly replace certain elements in the sampled sequence with the special token “[MASK]” and with more variants for the regularization term:

\[
L_{KL} = \sum_{t=1}^{T} \frac{1}{2} [DKL(P_{\theta^1} \hat{x}_t | \hat{x}_{<t}) || P_{\theta^2} \hat{x}_t | \hat{x}_{<t}) + D_{KL}(P_{\theta^2} \hat{x}_t | \hat{x}_{<t}) || P_{\theta^1} \hat{x}_t | \hat{x}_{<t})]
\]

(3)

It is important to maintain the KL divergence throughout training at both stages so that the model can be trained properly. If we apply this consistency training midway, the KL divergence loss would be too large and severely hinder the language modeling optimization. The training loss is a combination of language modeling loss and the KL divergence loss with hyper-parameter \(\alpha\) as regularization weight:

\[
L_{Stage1} = L_{NLL} + \alpha L_{KL}
\]

\[
L_{Stage2} = L_{NLL} + \alpha L_{KL}
\]

(4)

3 Experiments

3.1 Dataset and Evaluation Metrics

MultiWOZ (Budzianowski et al., 2018) is a human-human multi-turn task-oriented dialog dataset spanning multiple domains. The dataset is divided into a training set containing 8438 dialogs, a verification set and a test set, both of which contain 1000 dialogs. Multiple versions of MultiWOZ (Budzianowski et al., 2018; Eric et al., 2019; Zang et al., 2020) have been released as the benchmark developing. For a fair comparison, this work conducts experiments and reports results based on the standardized evaluation scripts of MultiWOZ Evaluation (Nekvinda and Dušek, 2021).

We follow the automatic evaluation metrics to evaluate task completion and response quality: **Inform** measures whether the system provides an appropriate entity, **Success** measures whether the system answers all the requested attributes, and BLEU (Papineni et al., 2002) is used to measure the fluency of the generated responses (Budzianowski et al., 2018). The BLEU score is calculated with references obtained from the MultiWOZ 2.2 span annotations (Nekvinda and Dušek, 2021). A combined score: (Inform + Success) \(\times 0.5 + \) BLEU is also reported as an overall quality measure suggested in Mehri et al. (2019).

3.2 Implementation Details

We initialize UBARv2 with DistilGPT2 (Sanh et al., 2019) and develop out method with HuggingFace’s Transformers (Wolf et al., 2019). Following Zhang et al. (2020), the dataset is preprocessed using domain-adaptive delexicalization. We reimplement UBAR (Yang et al., 2021) as UBArV1 and develop the two proposed method session-level sampling (SS) and R-Drop/R-Mask. Typically, UBArV1 and UBArV1+R-Drop and UBArV1+R-Mask are trained at Stage 1 for 60 to 75 epochs. UBArV1+SS is trained on top of UBArV1 at Stage 2 for 5 epochs. UBArV2, the final model is trained with R-Mask strategy at Stage 2 on top of UBArV1+R-Drop. UBArV2 uses the strategy of sampling the belief state every turn for session-level sampling and masking the ground-truth belief state for R-Mask. We select the model with the best performance on the validation set and evaluate it on the test set to get final results. The results in section 4 are mainly from the validation set. The batch size is 8, initial learning rate for AdamW is 1.5e-4, sampling rate \(\epsilon\) for SS is 0.01, regularization weight \(\alpha\) is 0.01 and the masking rate for R-Mask is 0.02. Code and models are included in the supplement and will be released.

3.3 Baselines

We compare UBArV2 with strong baselines on the benchmark as follows: DAMD (Zhang et al., 2020), MinTL (Lin et al., 2020), AuGPT (Kulhánek et al., 2021), SOLOIST (Peng et al., 2020), UBAR
Table 1: Main results on MultiWOZ Evaluation End-to-end modeling.

| Model                  | Inform | Success | BLEU | Comb |
|------------------------|--------|---------|------|------|
| DAMD (Zhang et al., 2020) | 57.9  | 47.6     | 16.4 | 84.8 |
| AuGPT (Kulhánek et al., 2021) | 76.6  | 60.5     | 16.8 | 85.4 |
| MinTL (Lin et al., 2020)   | 73.7  | 65.4     | 19.4 | 89.0 |
| SOLOIST (Peng et al., 2020) | 82.3  | 72.4     | 13.6 | 90.9 |
| UBAR (Yang et al., 2021)   | 83.7  | 70.3     | 17.6 | 94.4 |
| PPTOD (Su et al., 2021)    | 83.1  | 72.7     | 18.2 | 96.1 |
| BORT (Sun et al., 2022)   | 85.5  | 77.4     | 17.9 | 99.4 |
| MTTOD (Lee, 2021)         | 85.9  | 76.5     | 19.0 | 100.2 |
| GALAXY (He et al., 2021)  | 85.4  | 75.7     | 19.6 | 100.2 |
| UBARv1                  | 82.1  | 69.7     | 17.9 | 93.8 |
| UBARv1+SS               | 83.9  | 71.0     | 17.6 | 95.0 |
| UBARv1+R-Drop           | 86.8  | 76.8     | 18.5 | 100.3 |
| UBARv2                  | **87.5** | **77.6** | 19.0 | **101.6** |

As shown in Table 1, the proposed UBARv2 achieves the state-of-art performance in terms of inform rate, success rate, and combined score, surpassing the previous models MTTOD and GALAXY, raising the combined score by 1.4 points, which indicates that attempting to mitigate exposure bias in task-oriented dialogs can effectively improve the task completion ability of TOD systems. Note that UBARv2 does not require pre-training on supplementary data like SOLOIST, PPTOD, and GALAXY. The results in the second group show the variations of UBARv2, which serves as an ablation study. For starters, UBARv1+SS scores higher inform rate and success rate and lifting the combined score by 1.2 over UBARv1, which demonstrates the effectiveness of session-level sampling. Introducing R-Drop to the training process can bring a significant performance boost, UBARv1+R-Drop jumps the combined score from 93.8 to 100.3, which shows the effectiveness of the dropout-based consistency regularization. Combining R-Mask and SS at Stage 2, UBARv2 shows that the two proposed methods are complementary to each other and can further push the state-of-the-art performance.

To examine the domain transfer ability of UBARv2 generalizing to unseen domains, we perform zero-shot and few-shot experiments in Appendix 7.2.

4 Analysis and Discussion

In this section, we provide a detailed discussion of the sampling strategy and the context used in constructing a mixed training sequence. We investigate how the Sampling rate $\epsilon$ and regularization weight $\alpha$ affect the model performance. We also discuss the R-Mask strategy and provide case study to show how can UBARv2 improve task completion and mitigate exposure bias.

4.1 Sampling Strategy

Sampling task-oriented dialogs and constructing mixed training sequences require a more fine-grained sampling strategy considering different TOD components such as belief state and system action with a dependent relationship. Additionally, we need to consider the attribute of the dialog context on which the sampling is conditioned. First, we list five sampling strategies based on which
components to sample in the current turn when constructing a sampled sequence:

- **Sampling only the belief state**: The annotated belief state will be replaced by the generated one in the corresponding position.

- **Sampling only the system action**: The annotated system action and response will be replaced.

- **Sampling at most one**: First determine whether to sample the belief state, and if so, use the annotated action. Otherwise, sample the action and response.

- **System action follows the belief state**: Sample the belief state, action and response.

- **Random Sampling**: The sampling of the action is independent of the one of the belief state.

Then, we divide the dialog context into the context of the previous turns and the context of the current turn, and consider whether they are (1) mixed, with some elements sampled, or (2) ground-truth, with all elements from the dataset.

As shown in Figure 2, the dashed baseline is the validation score of UBARv1 + R-Drop and the histogram shows the score of UBARv1 + R-Drop after 5 epochs of mixed training with session-level sampling. For the sampling strategy, it can be seen that “Sampling only the belief state” and “System action follows the belief state” are more effective than the others. The effect of “Sampling only the belief state” is generally better than the one of “Sampling only the system action”, which indicates that sampling the belief state is more meaningful than the action. For the context attributes, using the mixed context is always better than using the ground-truth one, generating content that is more fluent and more relevant to the previous context, which aligns with the intuition of session-level modeling. Note that when the sampling strategy is fixed as “Sampling only the belief state”, the score is same for “Mixed cur” and “GT cur”. This is because only the ground-truth user utterance is available when generating the belief state. Therefore, the sampling strategy for UBARv2 is “Sampling only the belief state” and “Mixed context”.

### 4.2 Sampling Rate

Figure 3 shows the effect of different sampling rate $\epsilon$ of mixed training. With UBARv1 + R-Drop as the baseline, we explore $\epsilon$ ranging from 0% to 5%. When the sampling rate $\epsilon = 1\%$, the combined score reaches the highest, exceeding the baseline. $\epsilon$ of 2.5% or 5% can also lead to improvements. The sampling rate can hurt the system’s performance if not appropriate, and whether too small or too large rate can lead to a decrease in the score compared to the baseline. Note that $\epsilon = 1\%$ may seem small, but we believe that exposing the model to a small amount of data can make a difference, helping to mitigate the exposure bias. We provide more detailed results regarding the sampling rate in Appendix 7.3.

### 4.3 Regularization Weight

We discuss the effect of the weight $\alpha$ in the KL-divergence regularization term of either R-Drop or R-Mask during the training of UBARv2. Here, we use UBARv1+SS as the baseline and add the KL-divergence regularization term to compare the
The strategies for R-Mask tie closely with the sampled generated belief state or the ground-truth strategies: (1) For the mask target, it can be either the sampled generated belief state or the ground-truth belief state at different positions for the two sequences at Stage 2, which offers more diversity to the two sequences and thus improves the model’s generalization ability. We provide results regarding the masking rate in Appendix 7.5.

| Mask Target | Mask Position | Combined  |
|-------------|---------------|----------|
| -           | -             | 100.3    |
| Gen         | Same          | 100.1    |
| Gen         | Diff          | 100.5    |
| GT          | Same          | 100.0    |
| GT          | Diff          | **101.6**|

**Table 2:** The combined scores with different R-Mask Strategies. Gen and GT denotes generated and ground-truth belief state respectively. Same means the masking the same positions for the two sequences and Diff means masking different positions.

### 4.4 R-Mask Strategy

The strategies for R-Mask tie closely with the strategies for session-level sampling as we have already identified belief state as the sampling target. R-Mask also requires a thorough discussion on how to construct the two sequences for the KL-divergence term. Specifically, based on UBARv1 + R-Drop, we add a regularization term with R-Mask to UBARv2 at Stage 2 of mixed training. We investigate the impact of different R-Mask strategies: (1) For the mask target, it can be either the sampled generated belief state or the ground-truth belief state. (2) For the mask position, there are two options: the two sequences for the regularization term are masked at the same positions or the two sequences are masked at different positions with the same mask rate. We search for suitable masking rates for different strategies. As shown in Table 2, the best strategy is to mask the ground-truth belief state at different positions for the two sequences at Stage 2, which offers more diversity to the two sequences and thus improves the model’s generalization ability. We provide more detailed results regarding the regularization weight in Appendix 7.4.

![Figure 3: The combined score of different Sampling Rate $\epsilon$](image)

![Figure 4: Regularization Weight $\alpha$ from 0 to 0.05](image)

### 4.5 Case Study

In this section, we present further discussions and empirical analyses of the effectiveness of the proposed method for mitigating the exposure bias in dialogs through case study.

As UBARv2 achieves a decent improvement on the combined score over UBARv1, it understandably has more correct cases than UBARv1. By looking at the cases in which UBARv1 predicted incorrectly but UBARv2 predicted correctly, we find that, in the majority of cases, UBARv1 just incorrectly predicts information like the belief state, while UBARv2 can get it right in the first place. Therefore, we are more concerned about whether UBARv2 can make the dialog context stay more consistent and coherent, and whether it can really bridge the gap between distributions in training and inference.

As shown in Table 3, in the first turn, according to the ground truth, the user should be informed of the name and address of the hotel, but both models choose to ask for the hotel star rating to narrow down the choices. In the second turn, UBARv2 does a better job than UBARv1 at finding the missing hotel name in the context and providing it to
the user in time. This case shows that UBARv1 still suffers from not being able to supplement entity names. While UBARv2 can supplement entity name appropriately, which reflects the fact that UBARv2 also can adaptively supplement and make amends in response to the current user utterance in order to stay consistent and coherent throughout the entire session and do it better than UBARv1. However, it can be noted that the user also needs the address of the hotel, but UBARv2 does not supplement the address information. This indicates that UBARv2 can be further improved.

| User | i would like a moderate -ly priced hotel in the south, with free wifi. |
| GT Resp. | [value_name] is your choice. its located in [value_address] can i give you the address |
| UBARv1 | i have [value_choice] [value_type] that meet your criteria. do you have a star rating preference? |
| UBARv2 | i have [value_choice] [value_type] that fit your criteria. do you have a preference for star rating? |
| User | you just gave me the address. does it have free parking? |
| GT Resp. | yes, both free internet and free parking. can i help you with anything else today? |
| UBARv1 | yes, it does. |
| UBARv2 | [value_name] has free parking. |

Table 3: Case Study: codelexicalized responses generated by UBARv1 and UBARv2 of two consecutive dialog turns in dialog session PMUL0006 from MultiWOZ 2.0.

We also want to address that current automatic evaluation metrics and static human evaluation are not adequate to quantitatively measure whether the exposure bias problem has been mitigated or not. There is a call for a more sophisticated and less labor-extensive evaluation. We provide two more case study in Appendix 7.6.

5 Related Work

The architectures for end-to-end modeling of task-oriented systems can be coarsely divided into multi-decoder methods (Zhang et al., 2020; Zhang et al., 2020; Tseng et al., 2021; Wang et al., 2020; Jeon and Lee, 2022; Ramachandran et al., 2021) and pre-trained language models (Hosseini-Asl et al., 2020; Peng et al., 2020; Kulhánek et al., 2021; Lin et al., 2020; Yang et al., 2021; Su et al., 2021; Lee, 2021; Sun et al., 2022; He et al., 2021). In terms of how to model the dialog context, session-level modeling has become popular with recent works (Yang et al., 2021; Su et al., 2021; Lee, 2021; He et al., 2021). Pre-training on relevant dialog corpus and multi-task learning are also employed to improve task completion. SOLOIST (Peng et al., 2020) is further pre-trained on a large dialog corpus with a multi-task objective. GALAXY (He et al., 2021) is further pre-trained via semi-supervised learning which makes use of unlabeled dialog samples. PPTOD (Su et al., 2021) proposes a multi-task pre-training strategy for dialogs with prompts. MT-TOD (Lee, 2021) train a T5-based model with the auxiliary task.

The exposure bias problem is previously discussed and studied in the training process of neural machine translation (Bengio et al., 2015; Ranzato et al., 2015; Shen et al., 2015; Wiseman and Rush, 2016; Zhang et al., 2019). Contrastive learning is also used to reduce the exposure bias problem by learning in the representation space (Lee et al., 2020; Liu and Liu, 2021; Pan et al., 2021). Wu et al. (2018) and Wang and Sennrich (2020) shared some helpful insights on the relationship between exposure bias and error propagation. For TOD systems, exposure bias and error propagation exist in the multi-turn nature of dialogs. Some works have addressed the error propagation problem through data augmentation to increase the robustness of the systems (Zhang et al., 2020; Li et al., 2021; Sun et al., 2022). UBARv2 is the first work that designs methods for mitigating the exposure bias problem in task-oriented dialogs.

6 Conclusion

This work tries to mitigate the exposure bias problem in task-oriented dialog systems by proposing mixed training with session-level sampling and consistency regularization strategy R-Mask. UBARv2 achieves state-of-the-art performance on the end-to-end modeling task of MultiWOZ Evaluation, raising the combined score by over 1 point. By actively bridging the gap between training and inference, the model can stay more consistent and coherent with the generated context. We believe that the exposure bias problem exhibits in multi-turn dialogs is an interesting topic worth studying, and hope that UBARv2 can inspire future work to explore more methods to bridge the gap between training and inference for dialog systems.
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7 Appendix

7.1 Results on Policy Optimization

Table 4 shows the results of UBArv2 in the policy optimization setting. Notice that UBArv2 did not achieve much improvement over UBArv1. This is because session-level sampling and R-Mask all target belief state, using the ground-truth belief state may render their advantages obsolete.
Table 4: Policy Optimization results on MultiWOZ Evaluation using ground-truth dialog states to generate responses.

| Model                  | Inform | Success | BLEU | Comb |
|------------------------|--------|---------|------|------|
| UniConv (Le et al., 2020) | 66.7   | 58.7    | 18.1 | 80.8 |
| SFN (Mehri et al., 2019)    | 93.4   | 82.3    | 14.1 | 101.9|
| HDSA (Chen et al., 2019)     | 87.9   | 79.4    | 20.7 | 104.4|
| LAVA (Lubis et al., 2020)     | 95.9   | 93.5    | 10.8 | 105.5|
| HDNO (Wang et al., 2020)     | 93.3   | 83.4    | 17.8 | 106.1|
| MarCo (Wang et al., 2020)     | 94.5   | 87.2    | 17.3 | 108.1|
| GALAXY (He et al., 2021)      | 92.8   | 83.5    | 19.9 | 108.1|
| UBARV1                  | 85.8   | 78.3    | 19.4 | 101.5|
| UBARv2                  | 86.4   | 79.7    | 19.8 | 102.9|

7.2 Domain Transfer

To examine the transfer ability of UBARv2 generalizing to unseen domains, we run zero-shot and few-shot experiments on the end-to-end modeling setting by excluding one domain out of the five domains that are available in validation and test set, and training UBARv2 on other four domains. Table 5 shows the results.

7.3 Sampling Rate

As shown in Figure 6, with UBARv1 + R-Drop as the baseline, the model completes the tasks better when the sampling rate is appropriate. When $\epsilon$ is 0.01, it can maintain the fluency of responses.

7.4 Effect on the Regularization weight

As shown in Figure 7, among the results of all evaluation metrics corresponding to different regularization weight ranging from 0 to 0.05, the model achieves highest score when $\alpha = 0.01$. In order to find a better weight, we further explore it in a fine-grained setting from 0.005 to 0.05 in Figure 8, which shows that 0.01 is appropriate.

7.5 Masking Rate

Masking rate for “Diff GT” and “Same GT” ranging from 0 to 0.08 is plotted in Figure 5.

7.6 More Case Study

As shown in Table 6, where the user requests a recommendation for a modern European restaurant in downtown. In the third turn, the user should be given an explicit restaurant entity name according to the ground truth while UBARV1 and UBARv2 both choose to ask for the price of the restaurant to narrow down the choices. However, UBARV1 does not notice the context misses the necessary entity name and only simply provides the user with information such as an address, phone number, and price range in the fourth turn; on the contrary, UBARv2 can find logical inconsistency in context and provides key entity name in the fourth turn. From this case, we can see that UBAR using generated content as context does not completely avoid the problem of the missing entity name, and UBARV1 still has the error of not being able to supplement entity names. Instead, UBARv2 can supplement entity name appropriately, which reflects the fact that UBARv2 also can adaptively supplement and make amends in response to the current user utterance in order to stay consistent and coherent throughout the entire session and do it better than UBARV1. It is worth mentioning that at first we believe that the success of UBARV1 using all generated content comes from inconsistency between training and testing, i.e., the context that the model sees is not the ground truth but generated by the model itself.
Table 5: Results of domain transfer. The first row is the base model of UBARv2 trained on the four domains and evaluated in-domain. The second row is the results of the base model fine-tuned with 100 new domain examples on the four domains. The last three rows are evaluations on the new domains with zero-shot or few-shot BM or UBARv2 trained on full data, respectively.

| Evaluation on 4 Domains | Except Hotel | Except Train | Except Attraction | Except Restaurant | Except Taxi |
|-------------------------|-------------|-------------|------------------|------------------|------------|
| Base Model trained in-domain | **100.79** | 93.76 | 96.02 | 97.04 | 99.26 |
| Few-shot BM on new domain | **89.15** | 68.83 | 86.60 | 80.47 | 78.09 |
| UBARv2 on all domains | **106.81** | 99.38 | 100.08 | 100.58 | 101.75 |

| Evaluation on New Domain | Hotel | Train | Attraction | Restaurant | Taxi |
|--------------------------|------|------|------------|------------|------|
| Zero-shot BM              | 25.64 | 54.07 | 27.10 | 20.60 | **55.79** |
| Few-shot BM on new domain | 59.74 | 84.13 | 87.39 | 77.71 | **90.98** |
| UBARv2 on all domains     | 92.04 | **102.27** | 102.04 | 101.21 | 97.51 |

and are therefore concerned that removing exposure bias might cause UBARv2 to lose this helpful inconsistency, which means using mixed learning might cause the model to not learn to generate key entity words. Fortunately, this case eliminates our concerns and illustrates that the method used by UBARv2 to mitigate exposure bias in the dialog still retains and even improves the ability of the model to be consistent with the entire session.

It is difficult to determine whether the exposure bias is effectively mitigated and whether the difference between distributions in training and inference is bridged. Even work on machine translation and automatic summarization motivated by addressing exposure bias has also typically judged whether exposure bias is mitigated just based on the improvement in BLEU or ROUGE score. By this criterion, the improvement of UBARv2 is sufficient to prove that the motivation of the proposed method for mitigating the exposure bias in the dialog is reasonable, but we still want to find a case to show that UBARv2 can effectively mitigate exposure bias in the dialog.

As shown in Table 7, UBARv1 using the original context can generate the key entity name in the current turn, but it can not respond correctly with the generated context, which indicates that UBARv1 suffers from exposure bias in the dialog, i.e., UBARv1 has accumulated errors due to the generated context. However, again based on the generated context, UBARv2 still generates key entity names in the current turn, effectively mitigating the exposure bias.
Figure 6: Sampling Rate $\epsilon$

Figure 7: Regularization Weight $\alpha$ ranging from 0 to 0.05
actually, I don’t need a reservation. I am looking for a modern European restaurant in... the address is [value_address]. the phone number is [value_phone]. the price range is in [value_price] price range.

User: no problem. the address is [value_address]. the phone number is [value_phone]. it there anything else i can help you with?

User: actually, I don’t need a reservation. I am looking for a modern European restaurant in the center of town, though.

GT Resp. the [value_name] is good and is located at the [value_address]. can I reserve a table for you?

UBARv1: I have [value_choice] options for you. do you have a price range in mind?

UBARv2: there are [value_choice] restaurant-s that meet your criteria. do you have a price range in mind?

User: can I get the address, phone number, and price range please?

GT Resp. no problem. the address is [value_address]. the phone number is [value_phone]. it is in [value_price] price range.

UBARv1: the address is [value_address]. the phone number is [value_phone]. the price range is [value_price].

UBARv2: [value_name] is [value_price] and located at [value_address]. their phone number is [value_phone].

Table 6: Case Study: delexicalized responses generated by UBARv1 and UBARv2 of three consecutive dialog turns in dialog session MUL1273 from MultiWOZ 2.0.
not right now. i am also looking for an entertainment attraction on the east side of town. i 'll need their phone number and postcode.

okay we have 2. [value_name].

[value_name] is located on postcode [value_postcode] and the phone number is [value_phone].

sure! their phone number is [value_phone] and their postcode is [value_postcode].

[value_name] is located at postcode [value_postcode]. their phone number is [value_phone].

User: can you send me the phone number and postcode for the funky fun house?

GT Resp.: the phone number is [value_phone] with post code [value_postcode]

[value_name] is located at postcode [value_postcode]. their phone number is [value_phone].

is there anything else i can help you with?

| User | not right now. i am also looking for an entertainment attraction on the east side of town. i 'll need their phone number and postcode. |
|------|------------------------------------------------------------------------------------------------------------------------------------|
| GT Resp. | okay we have 2. [value_name]. |
| UBARv1 w/GT Context | [value_name] is located on postcode [value_postcode] and the phone number is [value_phone]. |
| UBARv1 | sure! their phone number is [value_phone] and their postcode is [value_postcode]. |
| UBARv2 | [value_name] is located at postcode [value_postcode]. their phone number is [value_phone]. |
| User | can you send me the phone number and postcode for the funky fun house? |
| GT Resp. | the phone number is [value_phone] with post code [value_postcode] |
| UBARv1 w/GT Context | the phone number is [value_phone] and the postcode is [value_postcode]. |
| UBARv1 | sure! the phone number is [value_phone] and the postcode is [value_postcode]. is there anything else i can help you with? |

Table 7: Case Study: delexicalized responses generated by UBARv1 and UBARv2 of two consecutive dialog turns in dialog session PMUL3834 from MultiWOZ 2.0. UBARv1 w/GT Context is the response using annotated intermediate information.