BORT: Back and Denoising Reconstruction for End-to-End Task-Oriented Dialog

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Abstract

A typical end-to-end task-oriented dialog system transfers context into dialog state, and upon which generates a response, which usually faces the problem of error propagation from both previously generated inaccurate dialog states and responses, especially in low-resource scenarios. To alleviate these issues, we propose BORT, a **b**ack and den**o**ising **r**econs**t**ruction approach for end-to-end task-oriented dialog system. To improve the accuracy of dialog state that is essential for the task completion of dialog system, *back reconstruction* is used to reconstruct the original input context from the generated dialogue state since the inaccurate dialog state cannot recover its corresponding input context. To enhance the antinoise capability of the model, *denosing reconstruction* is used to reconstruct the corrupted dialog state and response. Extensive experiments conducted on MultiWOZ 2.0 and CamRest676 show the effectiveness of BORT which achieves state-of-the-art performance. Furthermore, BORT demonstrates its advanced capabilities in zero-shot domain scenarios and in low-resource scenarios.

1 Introduction

Recently, task-oriented dialog system, which aims to assist users to complete some booking tasks, has attracted great interest in the research community and the industry (Zhang et al., 2020c). Task-oriented dialog system has been usually established via a pipeline system, including several modules such as natural language understanding, dialog state tracking, dialog policy and natural language generation. The natural language understanding module converts user utterance into the structured semantic representation. The dialog state, which is generated by the dialog state tracking module, is used to query database to achieve the number of matched entities. The natural language generation module converts action state estimated by the dialog policy module to the natural language response. This modular system structure is highly interpretable and easy to implement, which is used in most practical task-oriented dialogue systems in the industry. However, it costs amounts of labeled dialog data such as dialog state and action state to train every module. Moreover, errors between modules would be accumulated, which affects the performance of the dialog system. Therefore, many researchers focus on end-to-end task-oriented dialog system to train an overall mapping from user natural language input to system natural language output (Lei et al., 2018; Zhang et al., 2020b). More recently, the pre-trained language model has been introduced to improve the performance of end-to-end task-oriented dialog system (Hosseini-Asl et al., 2020; Lin et al., 2020; Yang et al., 2021).

However, the end-to-end task-oriented dialog system usually faces the problem of error propagation from both previously generated inaccurate dialog states and responses, especially in low-resource scenarios. Firstly, the generated dialog state, which is crucial for the task completion of task-oriented dialog system, has been always inaccurate across the training of the end-to-end task-oriented dialog system. Secondly, the generated previous dialog state and response are encoded to generate current dialog state and response during inference while the oracle previous dialog state and response are encoded during training. There exists discrepancy between training and inference, affecting the quality of generated system responses. To alleviate these issues, we propose BORT, a back and denoising reconstruction approach for end-to-end task-oriented dialog system. To improve dialog state learning ability, back reconstruction is used to reconstruct the generated dialog state back to the original input context to ensure the information in the input side is completely transformed to the output side. To enhance the antinoise capability of the task-oriented dialog system, denosing reconstruction is used to reconstruct the corrupted dialog state and response to guarantee that the system needs to learn enough internal information of the dialog context to be able to recover the original version. This further bridges the gap between training and inference for task-oriented dialog system. In addition, the generated system response is usually delexicalized to reduce the effect of different slot values on evaluation. However, there exists inconsistency between the lexicalized user utterance and delexicalized system response, which adds extra burden for the system to generate delexicalized system response. To alleviate this issue, we first introduce delexicalized user utterance to improve the quality of system response. Experimental results on MultiWOZ 2.0 and CamRest676 show our proposed BORT substantially outperforms baseline systems, achieving state-of-the-art performance. This paper primarily makes the following contributions:

- We propose two effective reconstruction strategies, i.e., back and denoising reconstruction strategies to improve the performance of end-to-end task-oriented dialog systems.
- User utterance delexicalization strategy is first introduced to improve task completion.
- BORT achieves state-of-the-art performance on MultiWOZ 2.0 and CamRest676. It also achieves promising performance in zero-shot domain scenarios and alleviates poor performance in low-resource scenarios.

2 Task-Oriented Dialog Framework

As illustrated in Figure 1(a), we construct an encoder-decoder framework for an end-to-end task-oriented dialog system via dialog state tracking and response generation task. There are one shared encoder that encodes dialog context and two different decoders that decode dialog state and system response, respectively. The objective function $\mathcal{L}_{all}$ of the entire training process is optimized as:

$$\mathcal{L}_{all} = \mathcal{L}_B + \mathcal{L}_R, \tag{1}$$

where $\mathcal{L}_B$ is the objective function for dialog state tracking, and $\mathcal{L}_R$ is the objective function for response generation.

2.1 Dialog State Tracking

Motivated by Lin et al. (2020), we model the Levenshtein dialog state, which means the difference between the current dialog state and the previous dialog state, for dialog state tracking task to generate minimal dialog state and reduce the inference latency. The Levenshtein dialog state ΔB_t of dialog turn t, is generated based on the previous dialog state B_{t-1}, the previous system response R_{t-1}, and the current user utterance U_t via the encoder-decoder framework:

$$H_{eb} = encoder(B_{t-1}, R_{t-1}, U_t), \tag{2}$$

$$\Delta B_t = decoder_b(H_{eb}), \tag{3}$$

where H_{eb} denotes the hidden representation of the encoder for dialog state tracking. Therefore, the dialog state tracking objective function can be optimized by minimizing:

$$\mathcal{L}_B = \sum_{i=1}^{N}\sum_{t=1}^{n_i} -logP(\Delta B_t | B_{t-1}, R_{t-1}, U_t), \tag{4}$$

where N denotes the number of dialog sessions, n_i denotes the number of dialog turns in the dialog session i.

For inference, a predefined function $\Omega(\cdot)$ is used to generate the dialog state B_t as

$$B_t = \Omega(\Delta B_t, B_{t-1}). \tag{5}$$

The predefined function could delete the slot-value pair in B_{t-1} when the NULL symbol appears in the ΔB_t, and it updates the B_{t-1} when new slot-value pair or new value for one slot appears in the ΔB_t. Refer to Lin et al. (2020) for more details. The generated dialog state B_t is used to query the corresponding database. The database state embedding DB_t represents the number of matched entities and whether the booking is available or not. The embedding DB_t is used as the start token embedding of the response decoder for response generation.

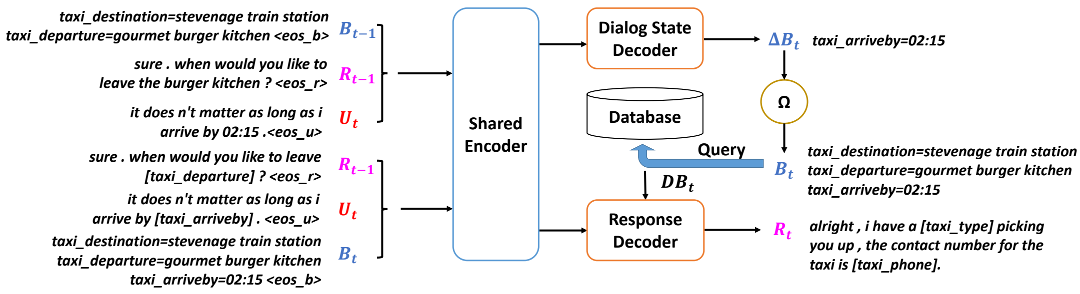
2.2 Response Generation

The response R_t of dialog turn t is generated based on the previous system response R_{t-1}, the current user utterance U_t, the current dialog state B_t, and the database state embedding DB_t, which is formulated as:

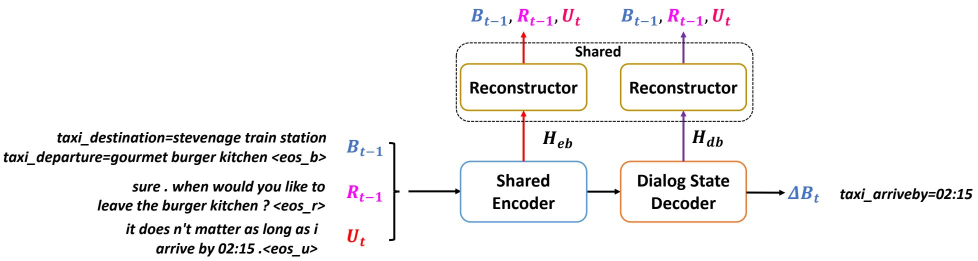
$$H_{er} = encoder(R_{t-1}, U_t, B_t), \tag{6}$$

$$R_t = decoder_r(H_{er}, DB_t), \tag{7}$$

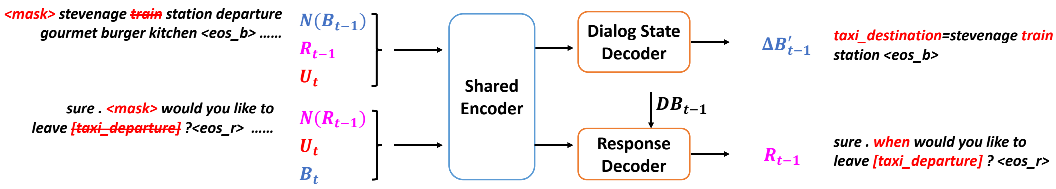
where H_{er} denotes the hidden representation of the encoder for response generation. Therefore,



(a) Base architecture of end-to-end task-oriented dialog system.



(b) Architecture of back reconstruction.



(c) Architecture of denoising reconstruction.

Figure 1: Illustration of task-oriented dialog system training process. We take turn t of a dialog session as an example.

the response generation objective function can be optimized by minimizing:

$$\mathcal{L}_R = \sum_{i=1}^{N} \sum_{t=1}^{n_i} -logP(R_t|R_{t-1}, U_t, B_t, DB_t). \quad (8)$$

3 Methodology

In this section, we propose two reconstruction strategies, i.e., back reconstruction and denoising reconstruction, respectively. In addition, we introduce user utterance delexicalization.

Generally, during task-oriented dialog training, objective functions $\mathcal{L}_{BR}$ and $\mathcal{L}_{DR}$ are added to enhance model learning ability. The general objective function of task-oriented dialog system can be reformulated as follows:

$$\mathcal{L}_{all} = \mathcal{L}_B + \mathcal{L}_R + \lambda_1 \mathcal{L}_{BR} + \lambda_2 \mathcal{L}_{DR}, \quad (9)$$

where $\mathcal{L}_{BR}$ and $\mathcal{L}_{DR}$ denote the objective functions for back reconstruction and denoising reconstruction. λ_1 and λ_2 are hyper-parameters that adjust the weight of the objective functions.

3.1 Back Reconstruction

Dialog state is essential for the task completion of task-oriented dialog system. To mitigate the generation of inaccurate dialog state, we propose back reconstruction strategy including encoder-reconstructor and encoder-decoder-reconstructor modules, as illustrated in Figure 1(b). For the encoder-reconstructor module, the dialog context $C(t) = (B_{t-1}, R_{t-1}, U_t)$ could be reconstructed to enhance encoder information representation by the encoder hidden representation H_{eb}. For the encoder-decoder-reconstructor module, the decoder hidden representation H_{db} could be used to reconstruct the dialog context $C(t)$ in order to encourage the dialog state decoder to achieve complete information of dialog context.

Therefore, the dialog state would be reconstructed back to the source input and the corresponding reconstruction score would be calculated to measure the adequacy of the dialog state. The objective function $\mathcal{L}_{BR}$ for the back reconstruction is optimized by minimizing:

$$\begin{aligned}\mathcal{L}_{BR} &= \mathcal{L}_{BR-e} + \mathcal{L}_{BR-d} \\ &= \sum_{i=1}^{N}\sum_{t=1}^{n_i} -logP(C(t)|H_{eb}) \\ &+ \sum_{i=1}^{N}\sum_{t=1}^{n_i} -logP((C(t)|H_{db}),\end{aligned} \tag{10}$$

where $\mathcal{L}_{BR-e}$ and $\mathcal{L}_{BR-d}$ denote the objective functions for encoder-reconstructor and encoder-decoder-reconstructor, respectively.

3.2 Denoising Reconstruction

To bridge the gap between training and inference for task-orient dialog system, we propose denoising reconstruction for dialog modeling, as illustrated in Figure 1(c). Motivated by denoising auto-encoder strategy that maps a corrupted input back to the original version (Vincent et al., 2010), we introduce noise in the form of random token deleting and masking in the source input to improve the dialog model learning ability. Specifically, we delete or mask every token in the previous dialog state and system response with a probability α. More concretely, we propose two denoising reconstruction modules, i.e., dialog state denoising and response denoising modules.

For dialog state denoising module, we reconstruct the new Levenshtein dialog state, which means the corrupted part of dialog state rather than the complete dialog state, compared with the original denoising auto-encoder. The Levenshtein dialog state $\Delta B'_{t-1}$ of dialog turn t, is generated based on the noisy dialog context $N_B(t) = (N(B_{t-1}), R_{t-1}, U_t)$. $N(B_{t-1})$ is the previous corrupted dialog state. For example, the Levenshtein dialog state '*taxi_destination=stevenage train station*' is reconstructed from the corrupted dialog state where '*taxi_destination*' is masked and '*train*' is deleted, as shown in Figure 1(c). For response denoising module, the previous system response R_{t-1} of dialog turn t is reconstructed based on the noisy dialog context $N_R(t) = (N(R_{t-1}), U_t, B_t, DB_{t-1})$. $N(R_{t-1})$ is the previous noisy system response. Therefore, the objective function $\mathcal{L}_{DR}$ for the denoising reconstruction is optimized by minimizing:

$$\begin{aligned}\mathcal{L}_{DR} &= \mathcal{L}_{DR-d} + \mathcal{L}_{DR-r} \\ &= \sum_{i=1}^{N}\sum_{t=1}^{n_i} -logP(\Delta B'_{t-1}|N_B(t)) \\ &+ \sum_{i=1}^{N}\sum_{t=1}^{n_i} -logP(R_{t-1}|N_R(t)),\end{aligned} \tag{11}$$

where $\mathcal{L}_{DR-b}$ denotes the objective function for dialog state denoising module; $\mathcal{L}_{DR-r}$ denotes the objective function for response denoising module.

3.3 User Utterance Delexicalization

Existing researches on task-oriented dialog system (Zhang et al., 2020b; Lin et al., 2020; Yang et al., 2021) usually perform system response delexicalization to reduce the influence of different slot values on evaluation. However, to track the dialog state, the user utterances are usually lexicalized. There exists inconsistency between the lexicalized user utterance and delexicalized system response, which adds extra burden for the system to generate delexicalized system response. To alleviate this issue, we first introduce delexicalized user utterances for response generation while lexicalized user utterances are still used for dialog state tracking. For example, '*02:15*' is converted into delexicalized form '*[taxi_arriveby]*' for response generation, as shown in Figure 1(a). Different forms of user utterances take better training of both tasks into account, ultimately improving task completion.

4 Experiments

4.1 Datasets and Evaluation Metrics

To establish our proposed end-to-end task-oriented dialog system, we consider two task-oriented dialog datasets, MultiWOZ 2.0 (Budzianowski et al., 2018) and CamRest676 (Wen et al., 2017).

MultiWOZ 2.0 is a large-scale human-to-human multi-domain task-oriented dialog dataset. The dataset consists of seven domains including attraction, hospital, police, hotel, restaurant, taxi and train. It contains 8438, 1000, and 1000 dialog sessions for training, validation, and testing dataset, respectively. Each dialog session covers 1 to 3 domains, and multiple different domains might be mentioned in a single dialog turn. Particularly, there are no hospital and police domain in the validation and testing dataset. To make our experiments comparable with previous work (Zhang et al., 2020b; Lin et al., 2020; Yang et al., 2021), we use the pre-processing script released by Zhang et al. (2020b) and follow the automatic evaluation metrics to evaluate the response quality for the task-oriented dialog system. **Inform** rate measures if a dialog system has provided a correct entity; **Success** rate measures if a dialog system has provided a correct entity and answered all the requested information; **BLEU** score (Papineni et al.,

2002) measures the fluency of the generated response; the **combined score**, which is computed by $(Inform + Success) \times 0.5 + BLEU$, measures the overall quality of the dialog system. The evaluation of dialog state tracking is provided in the Appendix A.4. We use the **joint goal accuracy** to measure the accuracy of generated dialog states.

CamRest676 is a small-scale restaurant-domain dataset. It contains 408, 136, 132 dialog sessions for training, validation, and testing dataset, respectively. To make our experiments comparable with previous work (Lei et al., 2018; Wu et al., 2021), we use the same delexicalization strategy and use **BLEU** score and **Success F1** to evaluate the response quality for the task-oriented dialog system. The success rate measures if the system answered all the requested information to evaluate recall while Success F1 balances recall and precision.

4.2 Settings

In the training process for the task-oriented dialog system, we select two backbone models (MinTL and DAMD) to establish our proposed BORT. For MinTL backbone, we use pre-trained T5-small (Raffel et al., 2020) to initialize the dialog system, based on HuggingFace Transformers library (Wolf et al., 2020). There are 6 layers for the encoder and the decoder. For DAMD backbone, we use one layer bi-directional GRU for the encoder and the decoder. For our proposed BORT, the hyper-parameter λ_1 is set to 0.05 and the hyper-parameter λ_2 is set to 0.03. For the denoising reconstruction strategy, the noise probability α is 0.15. Training early stops when no improvement on the combined score of the validation set for 5 epochs. One P40 GPU is used to train all task-oriented dialog systems. The more detailed training settings and hyper-parameter analysis is provided in the Appendix A.1 and A.2.

4.3 Baselines

Compared with other previous work, our proposed BORT is evaluated in two context-to-response settings: end-to-end modeling to generate dialog state and system response, and policy optimization to generate system response based on ground truth dialog state.

Sequicity (Lei et al., 2018) and DAMD (Zhang et al., 2020b) are RNN-based end-to-end task-oriented dialog systems with copy mechanism. Decoder based pre-trained model GPT-2 (Radford et al., 2019) is used in SimpleTOD (Hosseini-Asl et al., 2020), SOLOIST (Peng et al., 2020), and UBAR (Yang et al., 2021). Encoder-decoder based pre-trained model T5 (Raffel et al., 2020) and BART (Lewis et al., 2020) is used in MinTL (Lin et al., 2020). Reinforcement learning is used in LAVA (Lubis et al., 2020) and SUMBT+LaRL (Lee et al., 2020). Especially, SUMBT+LaRL merges a dialog state tracking model SUMBT (Lee et al., 2019) and a dialog policy model LaRL (Zhao et al., 2019) and fine-tune them via reinforcement learning, achieving the state-of-the-art performance. HDSA (Chen et al., 2019), ARDM (Wu et al., 2021), HDNO (Wang et al., 2021) are some additional policy optimization models.

4.4 Main Results

Table 1 presents the detailed inform rates, success rates, BLEU scores, and combined scores of end-to-end and policy optimization dialog models on the MultiWOZ 2.0. Our observations are as follows:

For the end-to-end setting, our proposed BORT significantly outperforms MinTL that used the same pre-trained T5-small model by 12.8 combined scores. BORT performs better than DAMD without pre-trained model, achieving the improvement of 15.0 combined scores. Moreover, BORT outperforms the previous state-of-the-art SUMBT+LaRL by 1.6 combined scores, achieving the best performance in terms of inform rate, success rate and combined score. This demonstrates the effectiveness of our proposed BORT.

For the policy optimization setting, the ground truth dialog state is used to query the database entities and generate system response. Our proposed BORT achieves performance comparable to the state-of-the-art LAVA in terms of inform rate. In addtion, compared with previous policy optimization methods, BORT achieves the state-of-the-art performance in terms of combined score even though BORT has not modeled action learning.

Compared with previous works, BORT achieved much more significant improvement in the end-to-end setting rather than policy optimization setting because our proposed reconstruction strategies pay more attention to improving the quality of dialogue state while the golden dialogue state is used in the policy optimization setting.

The detailed Success F1 and BLEU scores on the CamRest676 are presented in Table 2. Our proposed BORT outperforms the previous state-of-the-art SOLOIST by 4.8 Success F1, achieving

Model	Pre-trained	Dialog State	Inform	Success	BLEU	Combined
End-to-End models						
DAMD (Zhang et al., 2020b)	n/a	generated	76.3	60.4	16.6	85.0
SimpleTOD (Hosseini-Asl et al., 2020)	DistilGPT2	generated	84.4	70.1	15.0	92.3
MinTL-T5-small (Lin et al., 2020)	T5-small	generated	80.0	72.7	**19.1**	95.5
SOLOIST (Peng et al., 2020)	GPT-2	generated	85.5	72.9	16.5	95.7
MinTL-BART (Lin et al., 2020)	BART-large	generated	84.9	74.9	17.9	97.8
LAVA (Lubis et al., 2020)	n/a	generated	91.8	81.8	12.0	98.8
UBAR* (Yang et al., 2021)	DistilGPT2	generated	91.5	77.4	17.0	101.5
SUMBT+LaRL (Lee et al., 2020)	BERT-base	generated	92.2	85.4	17.9	106.7
BORT(DAMD)	n/a	generated	87.3	75.8	18.4	100.0
BORT(MinTL)	T5-small	generated	**93.8**	**85.8**	18.5	**108.3**
Policy Optimization models						
LaRL (Zhao et al., 2019)	n/a	oracle	82.8	79.2	12.8	93.8
SimpleTOD (Hosseini-Asl et al., 2020)	DistilGPT2	oracle	88.9	67.1	16.9	94.9
HDSA (Chen et al., 2019)	BERT-base	oracle	82.9	68.9	**23.6**	99.5
ARDM (Wu et al., 2021)	GPT-2	oracle	87.4	72.8	20.6	100.7
DAMD (Zhang et al., 2020b)	n/a	oracle	89.2	77.9	18.6	102.2
SOLOIST (Peng et al., 2020)	GPT-2	oracle	89.6	79.3	18.0	102.5
UBAR (Yang et al., 2021)	DistilGPT2	oracle	94.0	83.6	17.2	106.0
LAVA (Lubis et al., 2020)	n/a	oracle	**97.5**	**94.8**	12.1	108.3
HDNO (Wang et al., 2021)	n/a	oracle	96.4	84.7	18.9	109.5
BORT(DAMD)	n/a	oracle	89.6	80.5	19.1	104.2
BORT(MinTL)	T5-small	oracle	96.1	88.8	19.0	**111.5**

Table 1: Comparison of end-to-end and policy optimization models evaluated on MultiWOZ 2.0. Generated/oracle denotes either using generated or ground truth dialog state for the response generation. * denotes the re-evaluated result by the author-released model, since the result repoted in this original paper (Yang et al., 2021) was evaluated using the ground truth dialog state instead of generated dialog state to query the database entities.

the best performance in terms of Success F1. This demonstrates the generalization capability of our proposed BORT.

Model	Success F1	BLEU
Sequicity (Lei et al., 2018)	85.4	25.3
ARDM (Wu et al., 2021)	86.2	25.4
SOLOIST (Peng et al., 2020)	87.1	25.5
BORT(MinTL)	**91.9**	25.0

Table 2: Comparison of end-to-end task-oriented dialog systems on CamRest676.

Model	Inform	Success	BLEU	Combined
DAMD (Zhang et al., 2020b)	57.9	47.6	16.4	69.2
LABES (Zhang et al., 2020a)	68.5	58.1	18.9	82.2
AuGPT (Kulhánek et al., 2021)	76.6	60.5	16.8	85.4
MinTL-T5-small (Lin et al., 2020)	73.7	65.4	**19.4**	89.0
SOLOIST (Peng et al., 2020)	82.3	72.4	13.6	91.0
DoTS (Jeon and Lee, 2021)	80.4	68.7	16.8	91.4
UBAR (Yang et al., 2021)	83.4	70.3	17.6	94.5
BORT(MinTL)	**85.5**	**77.4**	17.9	**99.4**

Table 3: Comparison of end-to-end task-oriented dialog system evaluated on the standardized setting (Nekvinda and Dušek, 2021).

4.5 Further Evaluation Analysis

Nekvinda and Dušek (2021) identified inconsistencies between previous task-oriented dialog works in data preprocessing and evaluation metrics and introduced a standalone standardized evaluation script. BLEU score is computed with references, which have been obtained from the delexicalized MultiWOZ 2.2 span annotations.

In order to get a more complete picture of the effectiveness of reconstruction strategies, we also use this evaluation script to evaluate our proposed BORT, which is trained on MultiWOZ 2.0. As shown in Table 3, BORT also substantially outperforms the previous state-of-the-art UBAR by a large margin (4.9 combined scores), achieving the best performance in terms of inform rate, success rate and combined score. This further demonstrates the effectiveness of our proposed BORT.

4.6 Ablation Study

We empirically investigated the performance of the different component of BORT as shown in Table 4. Our introduced user utterance delexicalization strategy gains 1.9 combined scores, indicating the effectiveness of user utterance delexicalization strategy. Regarding the two proposed reconstruction strategies, back reconstruction performs slightly better than denosing reconstruction by 1 combined score. Moreover, the combination of both reconstruction strategies can complement each other to further improve the performance of the dialog system. The detail analysis on different modules of every reconstruction strategy are provided in the Appendix A.3.

Model	Inform	Success	BLEU	Combined
BORT(MinTL)	93.8	85.8	18.5	108.3
w/o DR	92.9	84.0	18.8	107.3
w/o BR	92.0	84.4	18.1	106.3
w/o BR & DR	90.4	81.4	17.8	103.7
w/o BR & DR& UD	89.0	78.8	17.9	101.8

Table 4: The performance of the different component of our proposed BORT. BR denotes back reconstruction strategy, DR denotes denoising reconstruction strategy, UD denotes user utterance delexicalization.

4.7 Case Study and Human Evaluation

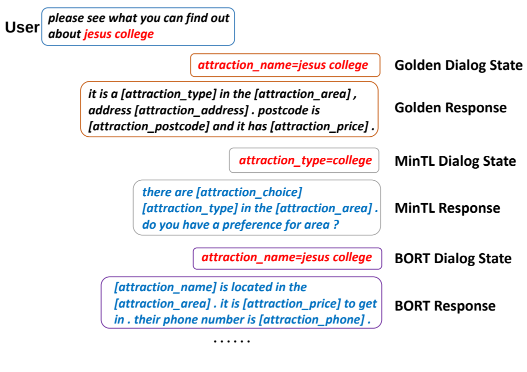


Figure 2: An example of the task-oriented dialog systems in dialog session PMUL4025.

Moreover, we analyze translation examples and conduct human evaluation to further analyze the effectiveness of BORT. Figure 2 shows an example generated by MinTL and BORT, respectively. More examples are provided in the Appendix A.5. MinTL generates the response to request for the preferred area about college since it generated inaccurate dialog state '*attraction_type=college*' rather than correct dialog state '*attraction_name=jesus college*'. In contrast, BORT generates accurate dialog state, achieving the appropriate response that provides the information of *jesus college*. These further demonstrate the effectiveness of our proposed reconstruction strategies.

For human evaluation, we manually evaluate the quality of generated responses on 50 dialog sessions, which are randomly extracted from MultiWOZ 2.0 testing set. We consider the fluency and appropriateness of the generated response, based on scores ranging from 1 to 5. The fluency metrics measures whether the generated response is fluent. The appropriateness metrics measures whether the generated response is appropriate and the system understand the user's goal. Three fluent English speakers are asked to evaluate these generated responses. The average scores evaluated by them is shown in Table 5. The results are consistent with the automatic evaluation, indicating that BORT could improve the quality of generated response.

Model	Fluency	Appropriateness
MinTL-T5-small	4.50	3.88
UBAR	4.50	3.81
BORT(MinTL)	**4.55**	**3.98**

Table 5: The human evaluation of the end-to-end task-oriented dialog systems on MultiWOZ 2.0.

4.8 Domain Adaptation Analysis

To investigate the domain adaptation ability of BORT to generalize to some unseen domains, we simulate zero-shot experiments by excluding one domain and training BORT on other domains. As shown in Table 6, the train and taxi domain achieve the highest combined scores because they have a high overlap in ontology with other domains. In addition, BORT and MinTL with an encoder-decoder based pre-trained model achieve significantly better domain adaptation performance, compared with DAMD without pre-trained model and UBAR with a decoder based pre-trained model, which demonstrates the encoder-decoder based pre-trained model have better domain transfer ability. Moreover, our proposed reconstruction strategy could further improve combine scores in the zero-shot domain scenario.

Model	Attraction	Hotel	Restaurant	Taxi	Train
DAMD	28.7	26.9	24.4	52.3	51.4
UBAR	28.3	29.5	23.5	59.5	53.9
MinTL	33.4	37.3	31.5	60.4	77.1
BORT(MinTL)	**33.6**	**38.7**	**32.0**	**62.7**	**85.6**

Table 6: Comparison of combined scores in the zero-shot domain scenario.

4.9 Low Resource Scenario Analysis

To better assess the robustness of our proposed BORT, we choose 5%, 10%, 20%, and 30% of training dialog sessions to investigate the performance

Model	5%				10%				20%				30%			
	Inform	Success	BLEU	Combined	Inform	Success	BLEU	Combined	Inform	Success	BLEU	Combined	Inform	Success	BLEU	Combined
DAMD	49.1	23.7	11.3	47.7	57.6	32.6	12.0	57.1	64.7	45.0	15.3	70.2	64.5	47.3	15.5	71.4
UBAR	35.7	21.2	11.0	39.5	62.4	43.6	12.7	65.7	76.2	58.3	14.1	81.4	81.2	65.4	14.7	88.0
MinTL	55.2	40.9	**13.9**	62.0	67.7	55.7	15.3	77.0	66.7	57.9	**17.3**	79.6	74.9	66.5	**17.3**	88.0
BORT	**69.8**	**45.9**	11.0	**68.9**	**74.5**	**60.6**	**15.5**	**83.1**	**82.1**	**65.5**	14.3	**88.1**	**83.8**	**69.9**	17.2	**94.1**

Table 7: Comparison of task-oriented dialog systems on the low resource scenarios.

of task-oriented dialog systems in the low resource scenario. As shown in Table 7, BORT substantially outperforms other systems in these low-resource scenarios. This is because error propagation problem in the low resource scenario is more serious while BORT could effectively alleviate error propagation problem. Moreover, our proposed BORT trained on the 30% dataset performs comparable to some baseline systems trained on all dataset as shown in Table 1. These further demonstrate that our proposed BORT is robust, alleviating poor performance in low-resource scenario.

5 Related Work

End-to-end task-oriented dialog system has attracted much attention in the dialog community. Two stage copynet framework was proposed to establish an end-to-end task-oriented dialogue system based on a single sequence-to-sequence model (Lei et al., 2018). Zhang et al. (2020b) proposed a multi-action data augmentation framework to improve the diversity of dialog responses. Recently, large scale language model pre-training has been shown to be effective for improving many natural language processing tasks(Peters et al., 2018; Radford et al., 2018; Devlin et al., 2019). Decoder based pre-trained language model such as GPT-2 (Radford et al., 2019) was used to improve the performance of end-to-end task-oriented dialog system (Budzianowski and Vulić, 2019; Hosseini-Asl et al., 2020; Peng et al., 2020; Yang et al., 2021).The Levenshtein dialog state instead of dialog state was generated to reduce the inference latency (Lin et al., 2020). In addition, they used encoder-decoder based pre-trained model such as T5 (Raffel et al., 2020) and BART (Lewis et al., 2020) to establish dialog system. In contrast with previous work, in which system response was generated, Wu et al. (2020) used encoder based pre-trained model such as BERT (Devlin et al., 2019) for task-oriented dialogue system, aiming to retrieve the most relative system response from a candidate pool instead of generating system response. The chit-chat data was added into task-oriented dialogue system to generate contextually relevant chit-chat responses (Sun et al., 2021). Liu et al. (2021) introduced the noisy channel model pre-training to generate better system response. Reinforcement learning could also be used to enable task-oriented dialogue systems to achieve more successful task completion (Lubis et al., 2020; Lee et al., 2020).

Tu et al. (2017) proposed encoder-decoder-reconstructor framework for neural machine translation to alleviate over-translation and under-translation problems. Reconstruction strategy was used to moderate dropped pronoun translation problems (Wang et al., 2018). In contrast, we considered the adequacy of semantic representations ranther than natural language sentences to build the reconstruction model. Vincent et al. (2010) proposed denoising autoencoder, in which random noise is added to enhance the robustness of the model, alleviating the overfitting problem of traditional auto-encoder. The denoising auto-encoder strategy was used as the language model to generate more fluent translation candidates for the unsupervised neural machine translation (Artetxe et al., 2018; Lample et al., 2018; Sun et al., 2019). In addtion, a denoising auto-encoder was used to pre-train sequence-to-sequence models on the large scale corpus (Lewis et al., 2020; Liu et al., 2020). In contrast, we proposed denoising reconstruction mechanism to alleviate error propagation problem along the multi-turn conversation flow.

6 Conclusion

In this paper, we have proposed back and denoising reconstruction strategies for the end-to-end task-oriented dialog system. Back reconstruction strategy has been proposed to mitigate the generation of inaccurate dialog state, achieving better task completion of task-oriented dialog system. Denoising reconstruction has been used to train a robust task-oriented dialog system, further alleviating error propagation problem. Moverover, user utterance delexicalization has been first introduced to improve task completion. Our extensive experiments and analysis demonstrate the effectiveness of our proposed strategies, achieving state-of-the-art performance on MultiWOZ 2.0 and CamRest676.

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A Appendix

A.1 Model Settings

For MinTL backbone, we use pre-trained T5-small (Raffel et al., 2020) to initialize the dialog system, based on HuggingFace Transformers library (Wolf et al., 2020). There are 6 layers for the encoder and the decoder. The dimension of hidden layers is set to 512 and the head of attention is 8. The batch size is set to 96. The AdamW optimizer (Loshchilov and Hutter, 2019) is used to optimize the model parameters. The learning rate is 0.0025, and the learning rate decay is 0.8. For DAMD backbone, we use one layer bi-directional GRU for the encoder and the decoder. The dimension of hidden layers is set to 100. The batch size is 128. The AdamW optimizer (Loshchilov and Hutter, 2019) is used to optimize the model parameters and the learning rate is 0.005.

For inference of dialog state tracking, generated previous dialog state, oracle previous system response, and current user utterance are used as the dialog context to generate the current Levenshtein dialog state. For inference of response generation, motivated by Yang et al. (2021), we use generated previous system response, instead of oracle previous system response to generate the current system response in order to maintain coherence throughout the whole dialog session, achieving better performance.

A.2 Hyper-parameter Analysis

In Figure 3, we empirically investigate how the hyper-paramters in Eq. 9 affects the dialog performance on the MultiWOZ 2.0 validation set. The selection of hyper-paramters λ_1 and λ_2 influence the role of the $\mathcal{L}_{BR}$ and $\mathcal{L}_{DR}$ across the entire end-to-end task-oriented dialog training process. Larger values of λ_1 or λ_2 cause the $\mathcal{L}_{BR}$ or $\mathcal{L}_{DR}$ to play a more important role than the original task-oriented dialog loss terms. The smaller the value of λ_1 or λ_2, the less important are the $\mathcal{L}_{BR}$ or $\mathcal{L}_{DR}$. As the Figure 3 shows, λ_1 ranging from 0.01 to 0.5 nearly all enhanced task-oriented dialog performance and when λ_2 is larger than 0.3, the performance would underperform the baseline system. When $\lambda_1 = 0.05$ and $\lambda_2 = 0.03$, our proposed BORT achieved the best performance on the validation set.

In addition, the influence of noise type and noise proportion on the performance of our proposed BORT on the MultiWOZ 2.0 validation set is empirically investigated, as shown in Figure 4. Both of the deletion and masking noise strategies could improve the dialog performance. In particular, the combination of them was further better than both of them. This demonstrates that both noise strategies can complement each other to further improve the dialog performance. As shown in Figure 4, when the noise proportion is 0.15, our proposed BORT achieved the best performance on the validation set.

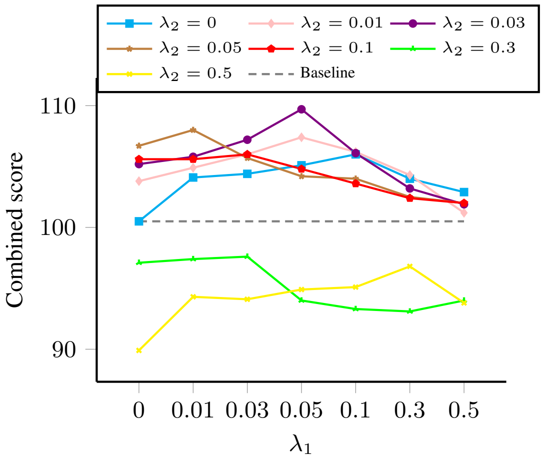

Figure 3: BORT(MinTL) performance (combined score) with different levels of hyper-parameters on the MultiWOZ 2.0 validation set.

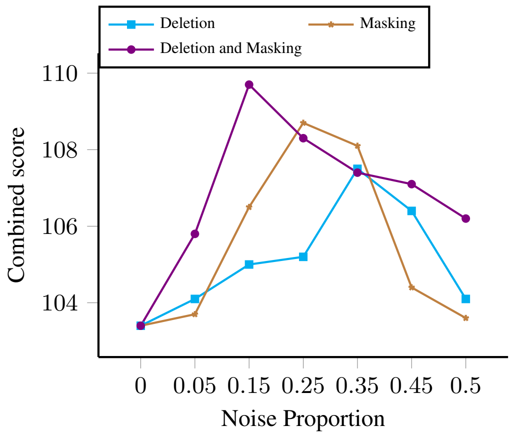

Figure 4: BORT(MinTL) performance (combined score) with different levels of noise type and noise proportion on the MultiWOZ 2.0 validation set.

A.3 Ablation Study

Moreover, we further investigate the performance of the different component of two proposed reconstruction strategies, respectively. As shown in Table 8, encoder-decoder-reconstructor module for back reconstruction strategy significantly outperforms encoder-reconstructor module by 2.2

combined scores because dialog state decoder could achieve more dialog context information for encoder-decoder-reconstructor. In addition, regarding to two denoising reconstruction modules, dialog state denoising and response denoising have achieved similar performance. These two modules could improve the antinoise capability of the task-oriented dialog system.

Model	Inform	Success	BLEU	Combined
Back reconstruction	92.9	84.0	18.8	107.3
w/o enc-rec	92.2	83.5	19.0	106.9
w/o enc-dec-rec	92.1	81.2	18.0	104.7
Denoising reconstruction	92.0	84.4	18.1	106.3
w/o dialog state denoising	91.7	83.0	17.9	105.3
w/o response denoising	92.8	81.2	18.6	105.6

Table 8: The performance of the different component of two proposed reconstruction strategies. enc-dec denotes encoder-reconstructor module, enc-dec-rec denotes encoder-decoder-reconstructor module.

A.4 Dialog State Tracking

Table 9 reports the dialog state tracking performance of the end-to-end task-oriented dialog systems on MultiWOZ 2.0. Our proposed BORT significantly outperforms MinTL (Lin et al., 2020) that used the same pre-trained T5-small model by 2.8 points, achieving 54.0 joint goal accuracy. Moreover, BORT achieves the highest joint goal accuracy among the end-to-end task-oriented dialog systems. This indicates that our proposed reconstruction strategies could improve dialog state learning ability.

Model	Joint Accuracy
MinTL-T5-small (Lin et al., 2020)	51.2
SUMBT+LaRL (Lee et al., 2020)	51.5
MinTL-BART (Lin et al., 2020)	52.1
UBAR (Yang et al., 2021)	52.6
SOLOIST (Peng et al., 2020)	53.2
BORT(MinTL)	**54.0**

Table 9: The dialog state tracking performance of end-to-end task-oriented dialog systems on MultiWOZ 2.0.

A.5 More examples

Figures 5 - 9 show several examples generated by MinTL and BORT, respectively. As shown in Figure 5, MinTL generates the inadequate dialog state, which may provide the hotel without internet. Our proposed BORT reconstructs the generated dialog state back to the original input context to ensure the information in the input side is completely transformed to the output side to achieve more adequate dialog state via back reconstruction strategy. Figure 6 shows that our proposed BORT generated the correct slot value '*european*' rather than the corrupted one '*europeon*' from the corrupted dialog context, indicating the robustness of denoising reconstruction strategy. As shown in Figures 7 - 9, MinTL generates the inaccurate dialog state, leading to the inaccurate response. The results are consistent with our opinion that the generated dialog state, which is crucial for the task completion of task-oriented dialog system, has been always inaccurate across the training of the end-to-end task-oriented dialog system. Moreover, Figure 9 shows that MinTL faces the problem of error propagation from both previously generated inaccurate dialog states and responses. Our proposed BORT can alleviate these issues via reconstruction strategies, further demonstrating the effectiveness of BORT.

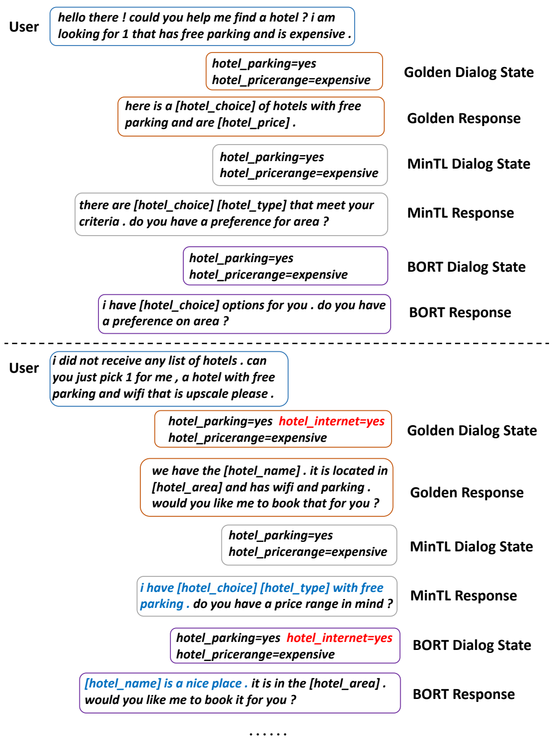

Figure 5: An example of the task-oriented dialog systems in dialog session MUL1139.

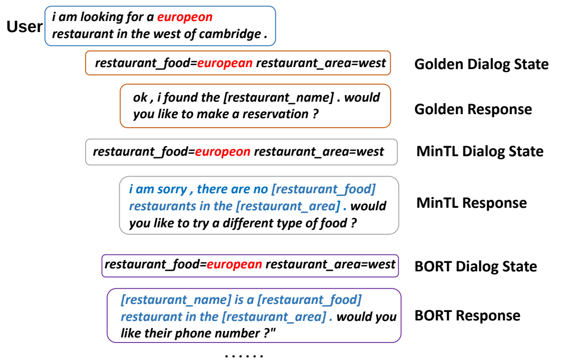

Figure 6: An example of the task-oriented dialog systems in dialog session PMUL0095.

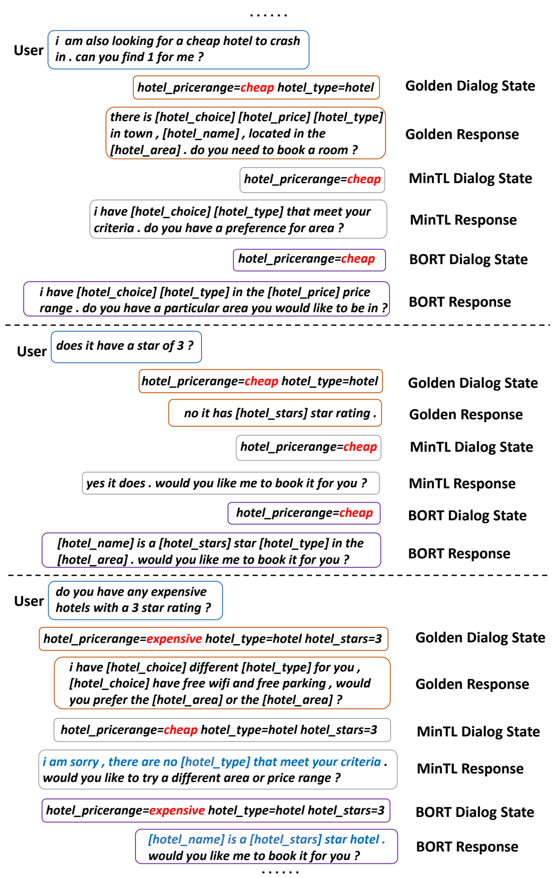

Figure 7: An example of the task-oriented dialog systems in dialog session PMUL3868.

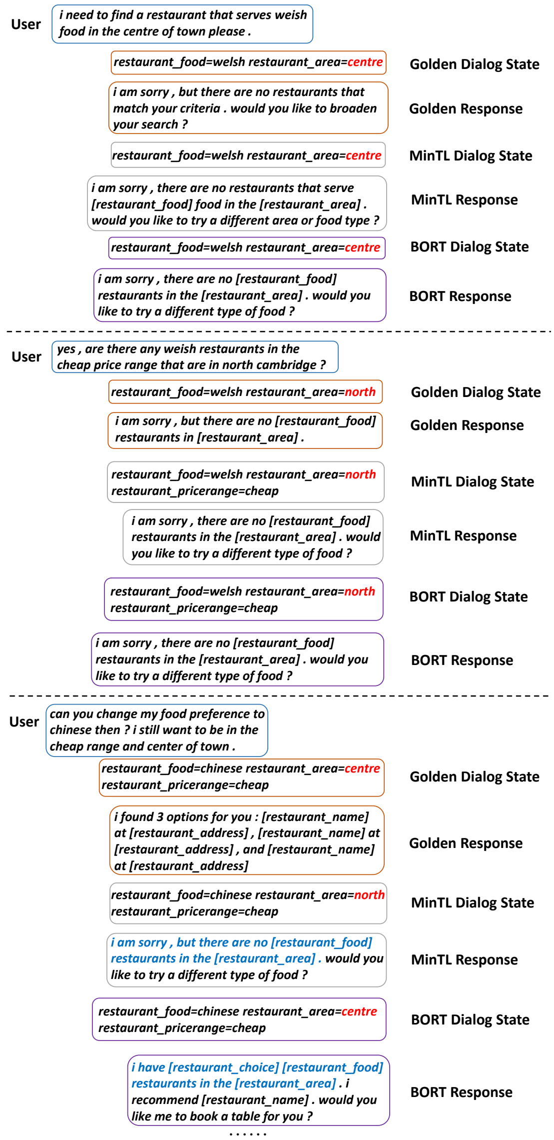

Figure 8: An example of the task-oriented dialog systems in dialog session MUL0286.

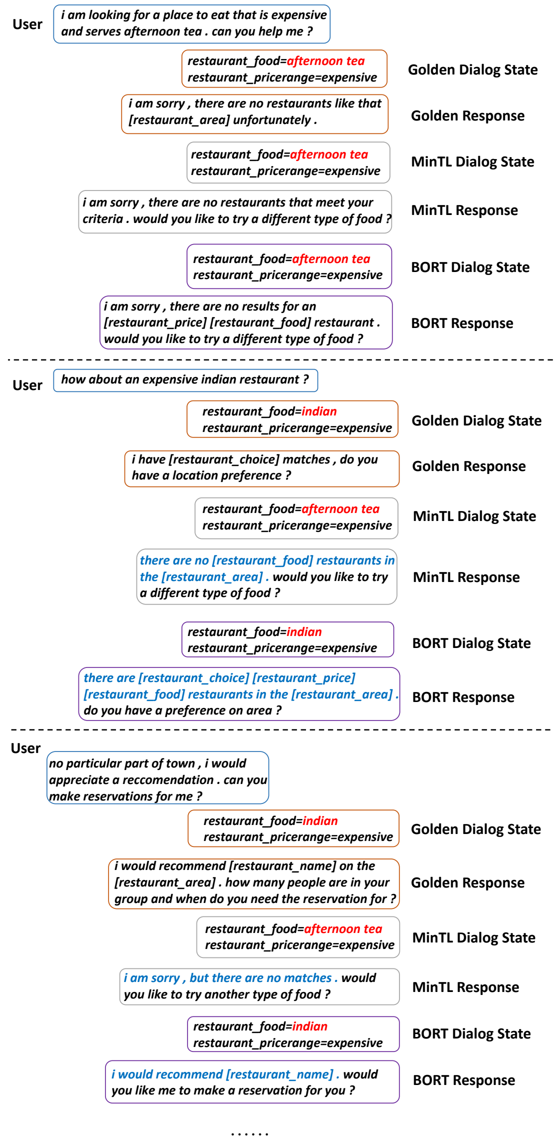

Figure 9: An example of the task-oriented dialog systems in dialog session PMUL3875.