Mars: Semantic-aware Contrastive Learning for End-to-End Task-Oriented Dialog

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Abstract

Traditional end-to-end task-oriented dialog systems first convert dialog context into dialog state and action state, before generating the system response. In this paper, we first empirically investigate the relationship between dialog/action state and generated system response. The empirical exploration shows that the system response performance is significantly affected by the quality of dialog state and action state. Based on these findings, we argue that enhancing the relationship modeling between dialog context and dialog/action state is beneficial to improving the quality of the dialog state and action state, which further improves the generated response quality. Therefore, we propose **Mars**, an end-to-end task-oriented dialog system with se**m**antic-**a**ware cont**r**a**s**tive learning strategies to model the relationship between dialog context and dialog/action state. Empirical results show our proposed Mars achieves state-of-the-art performance on the MultiWOZ 2.0, CamRest676, and CrossWOZ.

1 Introduction

Task-oriented dialog system (Zhang et al., 2020c) aims to assist users in completing some specific tasks such as table reservations, hotel reservations, ticket booking, and online shopping. Traditional task-oriented dialog system has been built through dialog state tracking (Lee et al., 2019; Wu et al., 2019), dialog policy (Schulman et al., 2017; Takanobu et al., 2019) and natural language generation (Wen et al., 2015) tasks. Dialog state tracking transfers dialog context to dialog state, which is the structured semantic representation capturing the whole dialog context information. The dialog state is used for the dialog system to query the database to obtain matched entities. Dialog policy selects an action state, a semantic representation guiding the dialog system to generate a system response based on the current dialog context and database information. System response is generated through a natural language generation task.

Model	**Inform**	**Success**	**BLEU**
End-to-end model	83.2	70.3	19.4
w/ oracle state	90.8	87.4	30.6
Reference Corpus	93.7	90.9	100.0

Table 1: Comparison of task-oriented dialog models evaluated on MultiWOZ 2.0. w/ oracle state denotes the system using ground truth dialog state and action state for the response generation. Reference results are reported on the official leaderboard of MultiWOZ (https://github.com/budzianowski/multiwoz).

With the widespread application of large-scale pre-training models (Devlin et al., 2019; Radford et al., 2019; Raffel et al., 2020), researchers gradually focus on the end-to-end task-oriented dialog system (Lin et al., 2020; Hosseini-Asl et al., 2020; Yang et al., 2021), which converts the whole dialog context into system response through multi-task training. Generally, an end-to-end task-oriented dialog modeling task is formulated as a cascaded generation problem (Su et al., 2021). Before generating a system response, the end-to-end task-oriented dialog system must first transfer dialog context into dialog and action states, respectively. It is worth mentioning that, as illustrated in Figure 1, dialog and action states are *semantic representations* of *dialog context* which is **hierarchical**, i.e., recursively hybrid of previous dialog context and semantic representations for multi-turn dialog.

To investigate the impact of dialog state and action state on the performance of end-to-end task-oriented dialog, we empirically conduct preliminary experiments on MultiWOZ 2.0 (Budzianowski et al., 2018). The detailed experimental settings are given in Section 5. As shown in Table 1, the system using ground truth dialog state and action state substantially outperforms the traditional end-to-end task-oriented dialog systems, achieving performance comparable to reference in terms of task

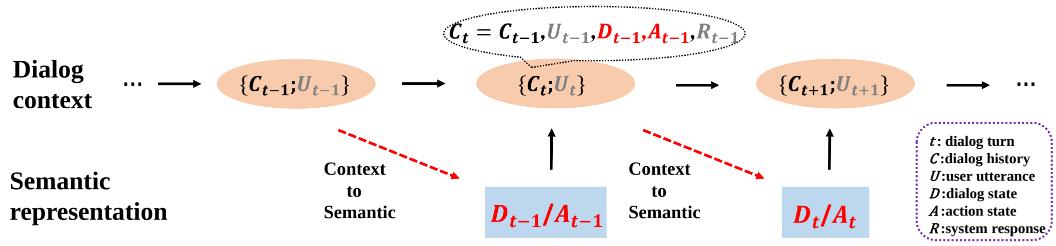


Figure 1: Illustration of the dialog context composition. Context to semantic represents dialog state tracking and dialog policy tasks. The previous dialog context $\{C_{t-1}, U_{t-1}\}$ is included in the dialog context $\{C_t, U_t\}$ of turn t.

completion. This demonstrates that the quality of dialog state and action state greatly influence on the end-to-end task-oriented dialog performance.

Based on these observations, we argue that enhancing the relationship modeling between *dialog context* and its *semantic representations*, i.e., dialog and action states, is beneficial to improving the quality of dialog/action state generation, which further improves the generated response quality. We propose **Mars**, an end-to-end task-oriented dialog system with two se**m**antic-**a**ware cont**r**a**s**tive learning strategies, i.e., point-wise context-state and group-wise context-state contrastive learning. Specifically, (1) the point-wise context-state contrastive learning strategy focuses more on narrowing the gap in the representation space between dialog context and corresponding semantic representations for the same dialog turn. This strategy aims to obtain a continuous representation of the dialogue context that is semantically more consistent with its semantic representation. (2) Group-wise context-state contrastive learning strategy enlarges the overall continuous representation margin between dialog context and semantic representation, regardless of specific dialog context and semantic representation pairing relationship. The meaning behind this is to fully model the hierarchical structure of dialog context, which makes it easy to distinguish dialog context and the corresponding semantic representations for all dialog turns.

Extensive experiments and analysis on the response generation and dialog state tracking tasks show the effectiveness of Mars. Mars achieves state-of-the-art performance on the MultiWOZ 2.0, CamRest676, and CrossWOZ. Moreover, Mars achieves remarkable performance in the low-resource scenario. Finally, we perform detailed error analysis and visualization to better apply our proposed Mars to real-world scenarios. This paper primarily makes the following contributions:

- We find that enhancing the relationship modeling between dialog context and corresponding semantic representations could effectively improve the quality of the dialog state and action state, which further improves the generated response quality.
- We propose two semantic-aware contrastive learning strategies to enhance dialog context representation of task-oriented dialog.
- Empirical results show Mars achieves state-of-the-art performance on the MultiWOZ 2.0, CamRest676, and CrossWOZ.

2 Related Work

End-to-end task-oriented dialog systems (Lei et al., 2018; Zhang et al., 2020a,b) are established via copy-augmented seq2seq learning (Gu et al., 2016). Zhang et al. (2020b) proposes a multi-action data augmentation method to improve the diversity of generated system responses. Large-scale pretrained language models, including BERT (Devlin et al., 2019), GPT-2 (Radford et al., 2019), T5 (Raffel et al., 2020), and UniLM (Dong et al., 2019), have been demonstrated effective for improving the performance of task-oriented dialog systems (Hosseini-Asl et al., 2020; Peng et al., 2021; Lin et al., 2020; Yang et al., 2021; Jeon and Lee, 2021; He et al., 2022) on MultiWOZ 2.0 (Budzianowski et al., 2018), a large-scale English multi-domain task-oriented dialog dataset. Recently, auxiliary tasks and auxiliary dialog corpora have been introduced to further improve dialog modeling ability. MTTOD (Lee, 2021) introduces a span prediction task to enhance the natural language understanding performance. BORT (Sun et al., 2022) proposes reconstruction strategies to alleviate the error propagation problem. PPTOD (Su et al., 2021) proposes a dialog multi-task pre-training strategy to model task completion from auxiliary heterogeneous dialog corpora.

GALAXY (He et al., 2022) introduces a dialog act prediction task to explicitly learn dialog policy from auxiliary dialog corpora.

Recently, contrastive Learning (He et al., 2020; Chen et al., 2020; Grill et al., 2020; Chen and He, 2021) has attracted much attention in the computer vision community and has been applied to natural language processing to enhance sentence representation learning (Fang and Xie, 2020; Wu et al., 2020; Yan et al., 2021; Gao et al., 2021; Giorgi et al., 2021). In contrast, we propose contrastive learning strategies to strengthen semantic-aware dialog context representation for task-oriented dialog modeling. In addition, we don't introduce data augmentation methods, which are used in most contrastive learning works.

3 Task-Oriented Dialog Framework

Generally, an end-to-end task-oriented dialog modeling task is formulated as a cascaded generation problem (Su et al., 2021). Before generating a system response, the end-to-end task-oriented dialog system would transfer dialog context into dialog state and action state, respectively. Dialog state is a semantic representation of dialog context, including dialog domain, slot name, and slot value. Action state is a semantic representation of system response, including dialog domain, dialog act, and slot name. For example, the dialog state is '*[attraction] type theatre*', and the action state is '*[attraction] [inform] name area*'.

We construct an end-to-end task-oriented dialog system via the seq2seq framework, including one shared encoder and two different decoders, as illustrated in Figure 2. One shared encoder encodes dialog context, one decoder $decoder_d(\cdot)$ decodes dialog state, and another decoder $decoder_a(\cdot)$ decodes action state and system response.

For end-to-end dialog modeling, a dialog state is first generated. Consider a dialog in turn t, dialog history C_t, which contains dialog information for all previous turns, is formulated as $\{C_{t-1}, U_{t-1}, D_{t-1}, DB_{t-1}, A_{t-1}, R_{t-1}\}$, where U represents the user utterance, D represents the dialog state, DB represents the database state, A represents the action state, and R represents the system response. The dialog history C_t and the current user utterance U_t are firstly encoded into hidden representation H_{cd} through the shared encoder, and the dialog state D_t is generated through

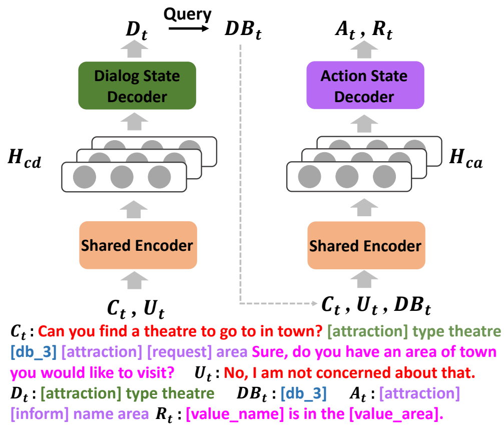


Figure 2: Illustration of a general task-oriented dialog system. For clarity, we take dialog turn $t = 1$ as an example. C_t is formulated as $\{U_0, D_0, DB_0, A_0, R_0\}$. [db_3] denotes the amount of matched entities.

the dialog state decoder:

$$\begin{aligned} H_{cd} &= encoder(C_t, U_t), \\ D_t &= decoder_d(H_{cd}). \end{aligned} \tag{1}$$

The dialog state tracking process is optimized by minimizing the following objective function:

$$\mathcal{L}_D = -logP(D_t|C_t, U_t). \tag{2}$$

We use the generated dialog state D_t to query the specific database to achieve the database state DB_t, which means the amount of matched entities.

As described by MTTOD (Lee, 2021), the second decoder would be used to generate action state and system response simultaneously. The combination of the dialog history C_t, the current user utterance U_t, and the database state DB_t are encoded into hidden representation H_{ca} through the shared encoder. The action state A_t and system response R_t are generated in turn through the action state decoder:

$$\begin{aligned} H_{ca} &= encoder(C_t, U_t, DB_t), \\ A_t, R_t &= decoder_a(H_{ca}). \end{aligned} \tag{3}$$

Therefore, the action state and response generation process is optimized by minimizing the following objective function:

$$\mathcal{L}_R = -logP(A_t, R_t|C_t, U_t, DB_t). \tag{4}$$

In summary, the entire end-to-end task-oriented dialog system can be optimized by minimizing:

$$\mathcal{L}_{all} = \mathcal{L}_D + \mathcal{L}_R. \tag{5}$$

4 Methodology

To achieve better task completion of the task-oriented dialog system described in Section 3, we

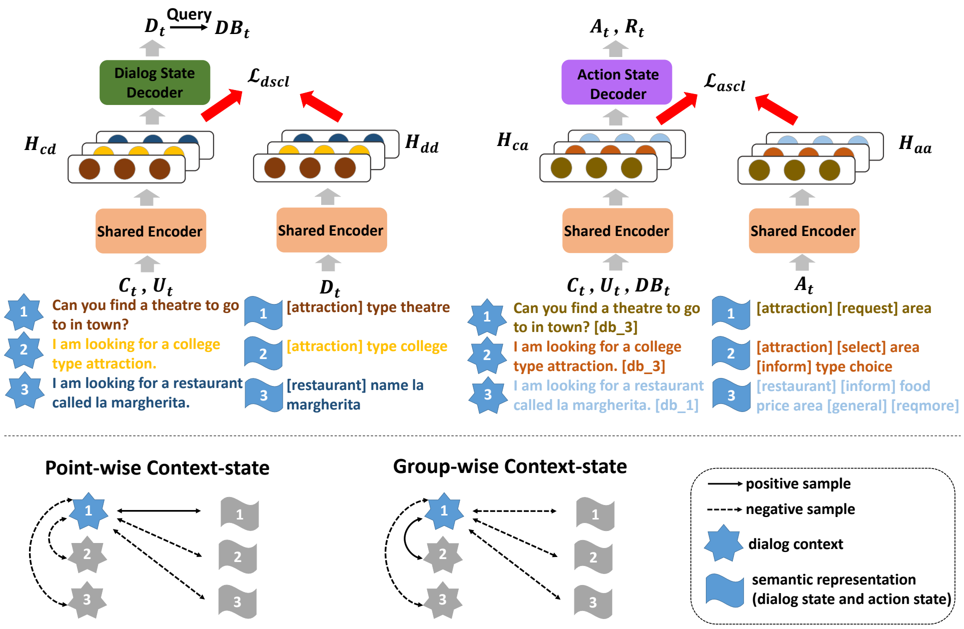


Figure 3: Illustration of the task-oriented dialog system with semantic-aware contrastive learning strategies. We take dialog turn $t = 0$ and batch size $N = 3$ as an example.

propose two contrastive learning methods: point-wise context-state and group-wise context-state contrastive learning. Figure 3 illustrates the architecture of a task-oriented dialog system with our proposed methods. Generally, for any contrastive learning method, contrastive learning objective functions $\mathcal{L}_{dscl}$ and $\mathcal{L}_{ascl}$ are added for dialog state tracking and response generation tasks, respectively, to enhancing the relationship modeling between dialog context and its semantic representations during end-to-end dialog training. The general objective function can be reformulated as follows:

$$\begin{aligned}\mathcal{L}_{all} &= \mathcal{L}_{D'} + \mathcal{L}_{R'},\\ \mathcal{L}_{D'} &= \mathcal{L}_{D} + \lambda_1 \mathcal{L}_{dscl},\\ \mathcal{L}_{R'} &= \mathcal{L}_{R} + \lambda_2 \mathcal{L}_{ascl},\end{aligned} \tag{6}$$

where λ_1 and λ_2 are hyper-parameters that adjust the weight of the objective functions.

4.1 Point-wise Context-state Contrastive Learning

To enhance the relationship modeling between dialog context and corresponding semantic representations, we propose a point-wise context-state contrastive learning strategy (Mars-P) to close the continuous representation gap between dialog context $\{C_t, U_t\}$ and corresponding semantic representations, including dialog state D_t and action state A_t, for the same dialog turn.

We consider the dialog context $\{C_t, U_t\}$ and the dialog state D_t from the same dialog to be as consistent as possible in the representation space, while the dialog context is as far away from other dialog states as possible. As illustrated in Figure 3, the source continuous representation of the dialog context '*can you find a theater to go to in town?*' should be similar to that of the dialog state '*[attraction] type theatre*' rather than other dialog states '*[attraction] type college*' and '*[restaurant] name la margherita*'.

Specifically, the dialog state D_t would be encoded into a hidden representation H_{dd} through the shared encoder:

$$H_{dd} = encoder(D_t). \tag{7}$$

For every dialog context input, we treat the corresponding dialog state from the same dialog as a positive sample and other dialog states and dialog contexts in the same batch as negative samples. Therefore, this dialog model is optimized by minimizing the objective function:

$$\begin{aligned}\mathcal{L}_{dscl} &\triangleq \mathcal{L}_{dscl\_P}\\ &= -log \frac{e^{cos(H^i_{cd}, H^i_{dd})/T}}{\sum\limits_{\substack{k=1\\k\neq i}}^{N} e^{cos(H^i_{cd}, H^k_{cd})/T} + \sum\limits_{k=1}^{N} e^{cos(H^i_{cd}, H^k_{dd})/T}},\end{aligned} \tag{8}$$

where $cos(\cdot)$ denotes the cosine similarity function. T is a temperature hyperparameter. N is the batch size. H^i_{cd} denotes dialog context hidden representation of the ith element in the batch. H^k_{dd} denotes a dialog state hidden representation of the kth element in the batch.

During response generation, we would close the continuous representation gap of dialog context $\{C_t, U_t, DB_t\}$ and action state A_t. As illustrated in Figure 3, the source continuous representation of the user utterance '*i am looking for a restaurant called la margherita.*' and database information '*[db$_1$]*' should be similar to that of the action state '*[restaurant] [inform] food price area [general] [reqmore]*' rather than other action states '*[attraction] [request] area*' and '*[attraction] [select] area [inform] type choice*'.

Specifically, the action state A_t would be encoded into a hidden representation H_{aa} through the shared encoder:

$$H_{aa} = encoder(A_t). \tag{9}$$

For every dialog context input, we treat the corresponding action state from the same dialog as a positive sample and other action states and dialog contexts in the same batch as negative samples. Therefore, this dialog model is optimized by minimizing the objective function:

$$\begin{aligned}\mathcal{L}_{ascl} &\triangleq \mathcal{L}_{ascl\_P} \\ &= -log\frac{e^{cos(H^i_{ca},H^i_{aa})/T}}{\sum\limits_{\substack{k=1\\k\neq i}}^{N} e^{cos(H^i_{ca},H^k_{ca})/T} + \sum\limits_{k=1}^{N} e^{cos(H^i_{ca},H^k_{aa})/T}},\end{aligned} \tag{10}$$

where H^i_{ca} denotes dialog context hidden representation of the ith element in the batch. H^k_{aa} denotes action state hidden representation of the kth element in the batch.

4.2 Group-wise Context-state Contrastive Learning

Traditional dialog models directly encode dialog context, including previous dialog context and semantic representations, and do not distinguish between dialog context and semantic representations. Therefore, we propose a group-wise context-state contrastive learning strategy (Mars-G). Takes turn t as an example. Mars-G enlarges the overall continuous representation margin between dialog context and semantic representation, regardless of the pairing relationship between specific dialog context, e.g., $\{C_i, U_i\}$, and semantic representation, e.g.D_i/A_i (turn $i = 0, ..., t$). The meaning behind is to fully modeling the hierarchical structure of dialog context, which makes it easy to distinguish dialog context and the corresponding semantic representations for all dialog turns.

Specifically, for every dialog context input, we treat all semantic representations in the same batch as negative samples and any one dialog context in the same batch as a positive sample. Besides, considering that every dialog input contains a unique context, narrowing the in-batch context distance makes it hard to distinguish different contexts, which may be counterproductive to deriving the context representation. To resolve such an issue, we also select the rest in-batch dialog context inputs except the positive one as negative samples for every dialog context input. Therefore, the contrastive learning objective function can be reformulated as follows:

$$\begin{aligned}\mathcal{L}_{dscl} &\triangleq \mathcal{L}_{dscl\_G} \\ &= -log\frac{e^{cos(H^i_{cd},H^j_{cd})/T}}{\sum\limits_{\substack{k=1\\k\neq i}}^{N} e^{cos(H^i_{cd},H^k_{cd})/T} + \sum\limits_{k=1}^{N} e^{cos(H^i_{cd},H^k_{dd})/T}},\end{aligned} \tag{11}$$

$$\begin{aligned}\mathcal{L}_{ascl} &\triangleq \mathcal{L}_{ascl\_G} \\ &= -log\frac{e^{cos(H^i_{ca},H^j_{ca})/T}}{\sum\limits_{\substack{k=1\\k\neq i}}^{N} e^{cos(H^i_{ca},H^k_{ca})/T} + \sum\limits_{k=1}^{N} e^{cos(H^i_{ca},H^k_{aa})/T}},\end{aligned} \tag{12}$$

where H^j_{cd} and H^j_{ca} denote dialog context hidden representation of the jth element ($j \neq i$) in a batch.

5 Experiments

5.1 Datasets and Evaluation Metrics

We conduct experiments on three task-oriented dialog datasets: MultiWOZ 2.0 (Budzianowski et al., 2018), CamRest676 (Wen et al., 2017), and CrossWOZ (Zhu et al., 2020). MultiWOZ 2.0 (Budzianowski et al., 2018) and CamRest676 (Wen et al., 2017) are English task-oriented dialog datasets. CrossWOZ (Zhu et al., 2020) is a Chinese multi-domain task-oriented dialog dataset. A detailed description of the datasets is provided in Appendix A.

We test our proposed Mars on two benchmark task-oriented dialog tasks: end-to-end dialog modeling response generation and dialog state tracking. We evaluate the performance of response generation on MultiWOZ 2.0 and CamRest676. Inconsistencies exist between previous task-oriented dialog works in data preprocessing and evaluation metrics on MultiWOZ 2.0 (Nekvinda and Dušek, 2021). To fairly compare our experiments with previous work,

Model	Pre-trained	Extra corpora	Dialog State Tracking Joint Accuracy	Act F1	Response Generation Inform	Success	BLEU	Combined
DAMD (Zhang et al., 2020b)	-	no	-	-	57.9	47.6	16.4	69.2
LABES (Zhang et al., 2020a)	-	no	-	-	68.5	58.1	18.9	82.2
AuGPT (Kulhánek et al., 2021)	GPT-2	yes	-	-	76.6	60.5	16.8	85.4
MinTL (Lin et al., 2020)	T5-small	no	51.2	-	73.7	65.4	19.4	89.0
SOLOIST (Peng et al., 2021)	GPT-2	yes	53.2	-	82.3	72.4	13.6	91.0
DoTS (Jeon and Lee, 2021)	BERT-base	no	-	-	80.4	68.7	16.8	91.4
UBAR (Yang et al., 2021)	DistilGPT2	no	52.6	-	83.4	70.3	17.6	94.5
PPTOD (Su et al., 2021)	T5-base	yes	53.4	-	83.1	72.7	18.2	96.1
BORT (Sun et al., 2022)	T5-small	no	54.0	-	85.5	77.4	17.9	99.4
MTTOD (Lee, 2021)	T5-base	no	53.6	-	85.9	76.5	19.0	100.2
GALAXY (He et al., 2022)	UniLM-base	yes	-	-	85.4	75.7	19.6	100.2
Baseline	T5-small	no	53.8	53.0	83.2	70.3	19.4	96.2
Mars-P	T5-small	no	54.4	**53.9**	86.6	75.5	19.6	100.7
Mars-G	T5-small	no	**55.1**	53.7	**88.9**	**78.0**	**19.9**	**103.4**

Table 2: Comparison of end-to-end models evaluated on MultiWOZ 2.0. The results of previous work are reported on the official leaderboard of MultiWOZ.

we use the pre-processing strategy (Zhang et al., 2020b) and the standalone standardized evaluation script released by Nekvinda and Dušek (2021). We follow the automatic evaluation metrics to evaluate the response quality for task-oriented dialog system on MultiWOZ 2.0. **Inform rate** measures whether a dialog system has provided an accurate entity; **Success rate** measures whether a dialog system has provided an accurate entity and answered all requested information; **BLEU score** (Papineni et al., 2002), which is computed with references, which have been obtained from the delexicalized MultiWOZ 2.2 span annotations, measures the fluency of the generated response; **Combined score**, which is calculated by $(Inform+Success)\times 0.5+BLEU$, measures the overall quality of the dialog system. Moreover, we use the **Act F1** to measure the accuracy of generated action states. To make our experiments comparable with previous work (Zhang et al., 2020a; He et al., 2022) on CamRest676, we use the same pre-processing strategy and use **Inform rate**, **Success F1**, **BLEU score**, and **Combined score**, which is computed by $(Inform + SuccessF1) \times 0.5 + BLEU$, to evaluate the response quality for the task-oriented dialog system. The success rate whether if the system answered all requested information to assess recall, while Success F1 balances recall and precision.

We evaluate the performance of dialog state tracking on MultiWOZ 2.0 and CrossWOZ. We use the **joint goal accuracy** to measure the accuracy of generated dialog states.

5.2 Settings

We use a pre-trained T5 language model (Raffel et al., 2020) to initialize the dialog system based on the HuggingFace Transformers library (Wolf et al., 2020) and follow the settings of Lee (2021). We select T5-small (Raffel et al., 2020) for MultiWOZ 2.0 and CamRest676 and T5-base-Chinese (Raffel et al., 2020; Zhao et al., 2019) for CrossWOZ. The batch size is 8. The AdamW optimizer (Loshchilov and Hutter, 2019) optimizes the model parameters with linear learning rate decay. The initial learning rate is 0.0005, and the ratio of warm up is 0.2. The hyper-parameters λ_1 and λ_2 are set to 1 and 0.1, respectively. T is set to 0.1 for Mars-P, and T is set to 0.5 for Mars-G. The hyper-parameter analysis is provided in Appendix D. We train all dialog systems on one NVIDIA A100 GPU for 10 epochs and select the checkpoint model with the best performance on the validation dataset. One model is trained for approximately five hours. In addition, the model is trained for 20 epochs for the low resource scenarios. The description of baseline systems is provided in Appendix B. Another baseline is the general architecture of a task-oriented dialog system, as illustrated in Figure 2.

5.3 Main Results

The detailed inform rates, success rates, BLEU scores, combined scores, act F1 scores, and joint goal accuracies for end-to-end task-oriented dialog models on the MultiWOZ 2.0 benchmark are presented in Table 2. Our re-implemented baseline system performs comparable with PPTOD (Su et al., 2021), and our proposed Mars-P and Mars-G outperform our re-implemented baseline system by 4.5 and 7.2 combined scores. Moreover, Mars-G, which doesn't use auxiliary corpora, substantially outperforms the previous state-of-the-art GALAXY (He et al., 2022) and MTTOD (Lee, 2021) by 3.2 combined scores, achieving the state-of-the-art performance in terms of inform rate, success rate, BLEU score, and combined score. In addition, Mar-G achieves the highest joint goal accuracy among the end-to-end task-oriented dialog systems, outperforming BORT (Sun et al., 2022) by 1.1 points. Compared with the baseline system, Mars-P and Mars-G achieve a better act F1 score. This demonstrates our proposed contrastive learning could effectively improve the quality of the dialog state and action state, which further improves the generated response quality. Regarding the two proposed methods, Mars-G performs better than Mars-P. The reason may be that obtaining specific dialog context representation through distinguishing the dialog context and semantic representation is more beneficial to achieving task completion. Further dialog context representation analysis is provided in Appendix C.

Model	Match	Success F1	BLEU	Combined
Sequicity (Lei et al., 2018)	92.7	85.4	25.3	114.4
LABES (Zhang et al., 2020a)	96.4	82.3	25.6	115.0
SOLOIST (Peng et al., 2021)	94.7	87.1	25.5	116.4
GALAXY (He et al., 2022)	**98.5**	87.7	24.2	117.3
Mars-P	97.0	87.2	25.9	118.0
Mars-G	96.2	**89.6**	**26.1**	**119.0**

Table 3: Comparison of end-to-end task-oriented dialog systems on CamRest676.

Table 3 presents the performance of task-oriented dialog systems on the CamRest676. Mars-G outperforms the previous state-of-the-art GALAXY (He et al., 2022) by 1.7 combined scores, achieving the state-of-the-art performance in terms of success F1, BLEU score, and combined score.

Model	Joint Accuracy
TRADE (Wu et al., 2019)	36.1
BART-CSP (Moradshahi et al., 2021)	53.6
GEEX (Li et al., 2021)	54.7
Mars-P	59.3
Mars-G	**59.8**

Table 4: Comparison of dialog state tracking performance on CrossWOZ.

Table 4 reports the dialog state tracking performance on CrossWOZ. Mars-P and Mars-G substantially outperform the previous state-of-the-art GEEX (Li et al., 2021) by 4.6 and 5.1 points, achieving 59.3 and 59.8 joint goal accuracy. This further indicates that our proposed semantic-aware contrastive learning strategies could improve dialog state learning ability, and Mars has good generalization ability. In addition, we provide an example to visualize our proposed Mars-G's dialog state tracking process in Appendix E.

5.4 Ablation Study

Table 5 shows the performance of the different components of Mars-P and Mars-G. Both state modules of Mars-P and Mars-G could improve the performance of the dialog system. Regarding two modules of contrastive learning strategies Mars-P and Mars-G, the action state module performs better than the dialog state module by 1.7 and 1.6 combined scores, respectively, because the quality of the action state has a more direct impact on the response generation quality and action state module could improve action state learning ability. Moreover, the combination of both modules can complement each other to further improve end-to-end dialog modeling performance. The further ablation analysis is provided in Appendix F.

Model	Inform	Success	BLEU	Combined
Mars-G	88.9	78.0	19.9	103.4
w/o DSC	88.3	76.6	19.5	102.0
w/o ASC	86.3	75.1	19.7	100.4
Mars-P	86.6	75.5	19.6	100.7
w/o DSC	85.4	75.0	19.7	99.9
w/o ASC	83.7	73.0	19.8	98.2
Baseline	83.2	70.3	19.4	96.2

Table 5: The performance of the different components of our proposed methods on MultiWOZ 2.0. DSC represents the dialog state module of contrastive learning, and ASC represents the action state module.

5.5 Different Dialog Turn Analysis

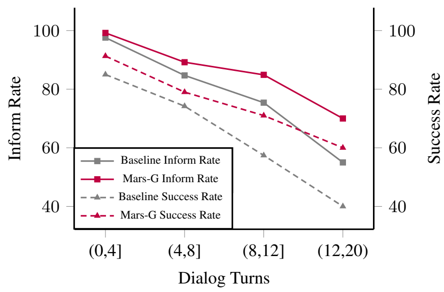


Figure 4: Performance of dialog systems on the test set with respect to dialog turns.

To better assess the effectiveness of proposed semantic-aware contrastive learning strategies, we investigate the performance (inform rate and success rate) of Mars-G and the baseline system on the test set with respect to dialog turns. Specifically, we divide each test set into four groups according to the dialog turn. As shown in Figure 4, Mars-G is superior to the baseline system in every dialog turn group. This indicates our proposed semantic-aware contrastive learning strategies are

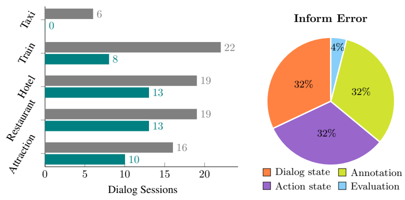
Model	5%				10%				20%				50%			
	Inform	**Success**	**BLEU**	**Combined**	**Inform**	**Success**	**BLEU**	**Combined**	**Inform**	**Success**	**BLEU**	**Combined**	**Inform**	**Success**	**BLEU**	**Combined**
DAMD	36.8	17.3	11.2	38.3	40.9	23.0	12.2	44.2	48.3	30.3	14.2	53.5	58.8	44.3	15.7	67.3
MinTL	52.5	38.1	13.9	59.2	55.5	44.9	15.6	65.8	64.3	54.9	16.2	75.8	70.3	62.2	18.0	84.3
UBAR	37.4	22.1	11.3	41.1	50.3	34.2	13.5	55.8	65.5	48.7	14.5	71.6	77.6	63.3	16.3	86.8
MTTOD	54.3	37.4	11.3	57.2	66.9	55.2	13.8	74.9	75.0	**63.3**	14.3	83.5	78.5	67.5	15.2	88.2
PPTOD	**65.5**	**48.3**	**14.3**	**71.2**	68.3	53.7	**15.7**	76.7	72.7	59.2	16.3	82.3	74.8	62.4	17.0	85.6
Mars-G	57.6	43.4	13.9	64.4	**69.4**	**55.3**	15.6	**78.0**	**76.7**	62.9	**17.2**	**87.0**	**82.2**	**71.2**	**18.6**	**95.3**

Table 6: Comparison of task-oriented dialog systems in the low resource scenarios on MultiWOZ 2.0. 5% (400 dialogs), 10% (800 dialogs), 20% (1600 dialogs), 50% (4000 dialogs) of training data is used to train each model.

beneficial to task-oriented dialog systems. Especially, as dialog turn increases, the performance of the baseline system decreases rapidly, and the performance gap between the baseline system and our proposed Mars-G is increased. Because the baseline system is hard to model long-range semantic dependencies to generate inaccurate system responses. In contrast, Mars-G enhances the relationship modeling between dialog context and corresponding semantic representations to better capture long-range semantic dependencies in the long dialog turns.

5.6 Low Resource Scenario Analysis

To investigate the performance of task-oriented dialog systems in the low resource scenario, we choose 5%, 10%, 20%, and 50% of training dialog sessions to do stimulated experiments on the MultiWOZ 2.0. Considering the inconsistency of data distribution with different random seeds in the stimulated low resource scenario, we re-implement all baseline systems with the same random seed to ensure the consistency of data distribution. In addition, we train all dialog systems five times with different random seeds and report the average scores in Table 6. The detailed results of five runs are provided in Appendix G. As shown in Table 6, PPTOD achieves the best performance in the extreme low-resource scenario (5% training data) because auxiliary corpora used in PPTOD have many similar dialog sessions with MultiWOZ 2.0 and this benefits PPTOD in the stimulated low-resource scenario. In contrast, Mars-G doesn't use auxiliary corpora to improve performance in the low-resource scenario. Apart from this, Mars-G substantially outperforms all baseline systems in other low-resource scenarios. Moreover, Mars-G trained on the 50% training data performs better than some baseline systems such as MinTL and UBAR trained on all training data, as shown in Table 2. These further demonstrate that Mars-G is robust, achieving comparable performance in the low-resource scenario.



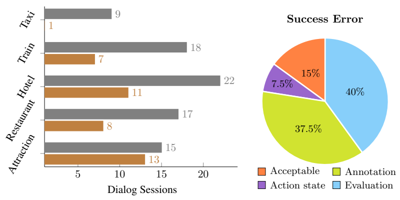
(a) (b)

Figure 5: The domain distribution (a) and primary reason distribution (b) of inaccurate dialog sessions according to the inform rate metric. The gray bars denote the total number of dialog sessions that contain the corresponding domain; the teal bars denote the number of dialog sessions with errors in the corresponding domain.

5.7 Error Analysis

To better apply our proposed Mars-G to real-world scenarios, we perform error analysis based on inform rate (informable slot) and success rate (requestable slot) metrics. In detail, we randomly extract 40 inaccurate dialog sessions, evaluated by the standalone standardized evaluation script (Nekvinda and Dušek, 2021), from the MultiWOZ 2.0 testing set, respectively. Considering the inclusion relationship of the two metrics described in Section 5.1, we select dialog sessions with the wrong success rate and accurate inform rate for success rate error analysis.

The detailed domain distribution and primary reason distribution of inaccurate dialog sessions are presented as shown in Figures 5 and 6. The error rate of the dialogs in the taxi and train domains is very low in both inform rate and success rate because informable and requestable slots in these two domains are few and simple. For example, the informable slot in the taxi domain only has '*phone*'. The error rate of the dialogs in the attraction domain is very high in the success rate. As illustrated in Figure 5(b), 64 percent of dialog informable slot errors are caused by the inaccurate dialog states and action states, and the noisy dialog annotations generate 32 percent. 4 percent of that are caused by automatic evaluation scripts and are judged ac-



(a) (b)

Figure 6: The domain distribution (a) and primary reason distribution (b) of inaccurate dialog sessions according to success rate metric. The gray bars denote the total number of dialog sessions that contain the corresponding domain; the brown bars denote the number of dialog sessions with errors in the corresponding domain.

curately by human evaluation. As illustrated in Figure 6(b), 77.5 percent of dialog requestable slot errors are caused by the noisy dialog annotations and automatic evaluation scripts. 15 percent of generated system responses are acceptable. When users request some information about something and do not ask for a specific requestable slot, Mars-G generates system responses that lack some requestable slots such as '*postcode*' and '*address*'. In addition, Mars-G requests users some other useful information instead of providing booked reference directly. We think system responses generated by Mars-G in both cases are reasonable. Inaccurate action states cause 7.5 percent of dialog requestable slot errors. More examples for detailed error analysis are provided in Appendix H. In the future, we will focus on solving errors caused by the inaccurate dialog states and action states to better apply Mars-G to real-world scenarios.

6 Conclusion

This study focuses on enhancing the relationship modeling between dialog context and corresponding semantic representations for end-to-end task-oriented dialog systems. Specifically, we propose two semantic-aware contrastive learning strategies to explicitly model the relationship between dialog context and semantic representation, achieving better task completion of a task-oriented dialog system. Extensive experiments and analysis on two benchmark task-oriented dialog tasks demonstrate the effectiveness of our proposed Mars, achieving state-of-the-art performance on the MultiWOZ 2.0, CamRest676, and CrossWOZ.

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A Datasets

MultiWOZ 2.0 (Budzianowski et al., 2018) is a large-scale English multi-domain task-oriented dialog dataset containing 8438, 1000, and 1000 dialog sessions for training, validation, and testing datasets. It consists of seven domains: attraction, hotel, restaurant, taxi, train, hospital, and police. CamRest676 (Wen et al., 2017) is a small-scale English restaurant-domain dataset, which is split 3/ 1/ 1 for training, validation, and testing datasets. CrossWOZ (Zhu et al., 2020) is a large-scale Chinese multi-domain task-oriented dialog dataset containing 5012, 500, and 500 dialog sessions for training, validation, and testing datasets. It comprises five domains: attraction, restaurant, hotel, taxi, and metro.

B Baselines

Sequicity (Lei et al., 2018), DAMD (Zhang et al., 2020b), and LABES (Zhang et al., 2020a) are copy-augmented GRU-based end-to-end task-oriented dialog systems. Bidirectional auto-encoding language model BERT (Devlin et al., 2019) is used for the context encoder in DoTS (Jeon and Lee, 2021). Unidirectional auto-regressive language model GPT-2 (Radford et al., 2019) is used in AuGPT (Kulhánek et al., 2021), SOLOIST (Peng et al., 2021), and UBAR (Yang et al., 2021). Seq2seq language model T5 (Raffel et al., 2020) is used in MinTL (Lin et al., 2020), PPTOD (Su et al., 2021), and MTTOD (Lee, 2021). The unified language model UniLM (Dong et al., 2019) is used in GALAXY (He et al., 2022). In addition, auxiliary task-oriented dialog corpora are used to pre-train in AuGPT (Kulhánek et al., 2021), SOLOIST (Peng et al., 2021), PPTOD (Su et al., 2021), and GALAXY (He et al., 2022). TRADE (Wu et al., 2019), BART-CSP (Moradshahi et al., 2021), and GEEX (Li et al., 2021) are some additional dialog state tracking models.

C Dialog Context Representation Analysis

To further verify the effectiveness of Mars-P, we use the average cosine similarity to measure the similarity of encoder continuous representation between dialog context and corresponding dialog/action state on the MultiWOZ 2.0 test set, as illustrated in Figure 7. As shown in Table 7, Mars-P achieves higher similarity, thus obtaining a continuous representation of the dialogue context that is semantically more consistent with its semantic representation.

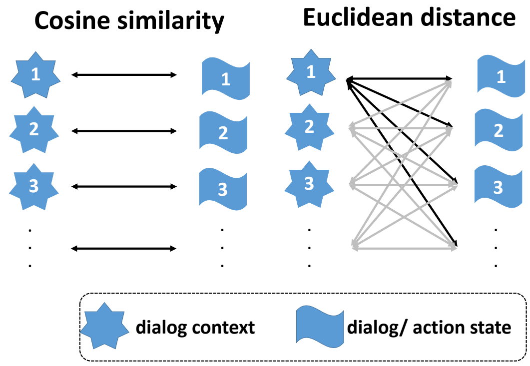

Figure 7: The calculation of cosine similarity and Euclidean distance.

Model	Context-Dialog State	Context-Action State
Baseline	0.63	0.47
Mars-P	0.93	0.83

Table 7: The similarity between dialog context and corresponding state representation on MultiWOZ 2.0.

Moreover, we use the average Euclidean distance to measure the distance of encoder continuous representation space between all dialog contexts and all dialog/action states for Mars-G and the baseline system, as illustrated in Figure 7. Specifically, for every dialog context representation, we compute the distance expectation between it and all dialog/action state representations, representing the distance between two representation spaces. As shown in Table 8, the distance of the encoder representation space in Mars-G is significantly farther than that of the baseline system. This indicates that Mars-G could expand the boundary between the two representation spaces, thus making it easier for the model to distinguish dialog context and dialog/action states for all subsequent turns.

Model	Context-Dialog State	Context-Action State
Baseline	1.22	1.12
Mars-G	5.77	5.60

Table 8: The distance between dialog context and state representation space on MultiWOZ 2.0.

D Hyper-parameter Analysis

We empirically investigate how the hyper-parameters λ and T for both modules of Mars-G affect the performance of task-oriented dialog on the MultiWOZ 2.0, respectively. The selection of λ influences the role of the contrastive learning objective function across the entire task-oriented dialog training process. As Figure 8 shows, λ ranging from 0.01 to 5 nearly all improve task-oriented dialog performance. This indicates our proposed Mars-G is robust and effective. When $\lambda = 0.1$, w/ ASC achieves the best performance. When $\lambda = 1$, w/ DSC achieves the best performance. The selection of T affects the differentiation of hard negative samples. The smaller the value of T is, the more attention is paid to distinguishing complex negative samples. As shown in Figure 9, combined scores increase for almost all T values ranging from 0.01 to 10, and the best performance is achieved when $T = 0.5$ for both modules of Mars-G.

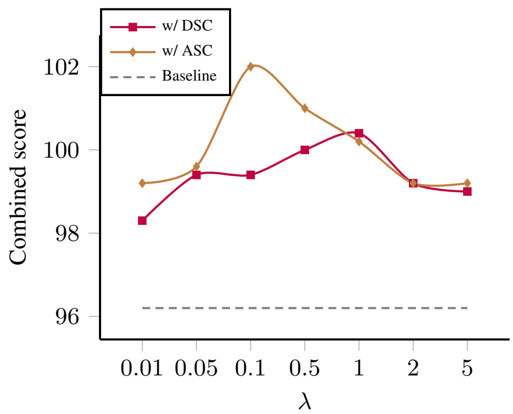

Figure 8: The Mars-G performance with different levels of hyper-parameter λ on the MultiWOZ 2.0. w/ DSC denotes dialog state module, w/ ASC denotes action state module. T is set to 0.5.

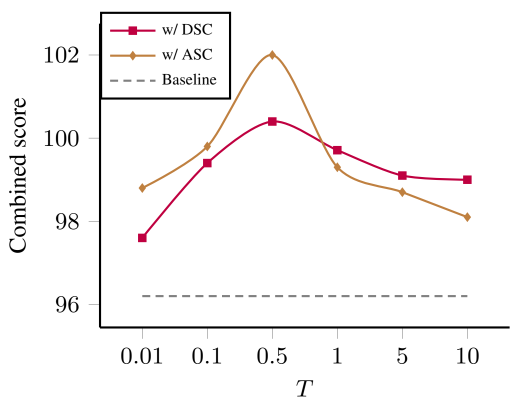

Figure 9: The Mars-G performance with different levels of hyper-parameter T on the MultiWOZ 2.0. λ_1 is set to 1 for w/ DSC, and λ_2 is set to 0.1 for w/ ASC.

E Visualization

We provide an example to visualize the dialog state tracking process of our proposed Mars-G and baseline system. The cross-attention weights between dialog context and generated dialog states from the last layer of the transformer decoder stack are shown in Figures 10 and 11. Compared with the baseline system, Mars-G could achieve more accurate attention weights. The slot '*arrive 09:00*' assigns high attention weights for the user utterance '*09:00*' and previous dialog state '*arrive 09:00*'. Similarly, the slots '*destination mumford theatre*' and '*departure wagamama*' accurately give high attention weights for the corresponding user utterance. The visualization further demonstrates that Mars-G could achieve semantically more consistent dialog context representation to generate accurate dialog states.

F Further Ablation Analysis

Model	**Inform**	**Success**	**BLEU**	**Combined**
Baseline	83.2	70.3	19.4	96.2
Mars-variant	85.7	74.8	19.6	99.9
Mars-P	86.6	75.5	19.6	100.7

Table 9: The performance of the different methods on MultiWOZ 2.0. Mars-variant denotes semantic-aware similarity strategy.

To get a more complete picture of the effectiveness of Mars-P, we introduce a semantic-aware similarity strategy (Mars-variant). We use the cosine similarity function to narrow the distance between the continuous representation of dialog contexts and states for the same dialog session to model the relationship between dialog context and corresponding semantic representations. We don't distinguish the continuous representation of dialog context and states for different dialog sessions. As shown in Table 9, Mars-variant outperforms the baseline system by 3.7 combined scores, indicating the effectiveness of the relationship modeling between dialog context and corresponding semantic representations. In addition, Mars-variant underperforms Mars-P by 0.8 combined scores. This demonstrates that distinguishing the continuous representation of dialog context and states for different dialog sessions is beneficial for dialog modeling.

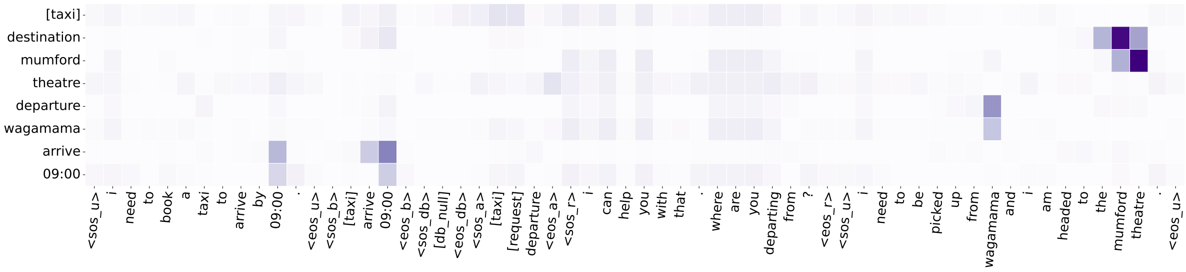

Figure 10: Visualization of the cross-attention weights between dialog context and generated dialog states for our proposed Mars-G. The horizontal axis is the dialog context, and the vertical axis is the generated dialog state.

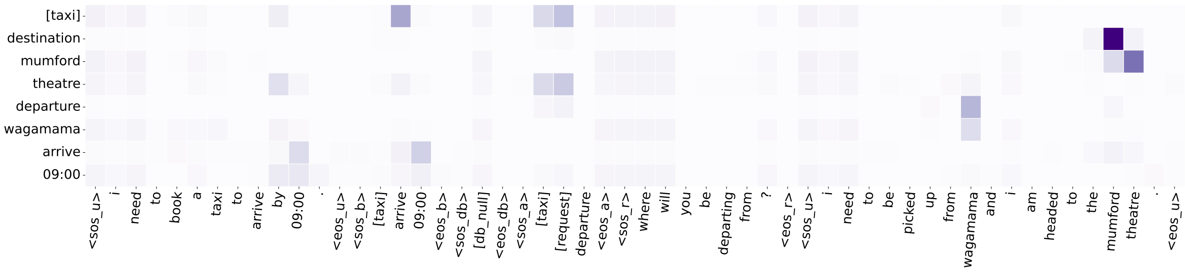

Figure 11: Visualization of the cross-attention weights between dialog context and generated dialog states for the baseline system.

G Low Resource Scenario Results

We train all dialog systems five times with different random seeds in the low resource scenario. The detailed results of 5 runs are provided in Table 10.

H Examples for Error Analysis

Tables 11 - 19 show several examples generated by Mars-G for detailed error analysis. As shown in Table 11, Mars-G generates the inaccurate dialog state '*food jamaican*' rather than '*food italian*', leading to the informable slot error. Table 12 shows that Mars-G generates the inadequate action state, not including the slot name '*name*', leading to the informable slot error. Table 13 shows that the informable slot error is caused by automatic evaluation. Mars-G provides the accurate response in turn 7. However, the automatic evaluation script estimates the wrong active domain '*[taxi]*' rather than '*[attraction]*' from the dialog state. The informable slot error in Table 14 is caused by noisy dialog annotations. The informable slot 'pricerange moderate' does not appear in the conversation.

As shown in Table 15, Mars-G generates the inaccurate action state '*[request] people*' provided in the dialog state '*people 1*', leading to the requestable slot error. Table 16 shows that the requestable slot error is caused by automatic evaluation. Mars-G provides the accurate response in turn 2, while the automatic evaluation script only determines if it offers a reference in turn 3. We think system responses generated by Mars-G in Tables 17 and 18 are acceptable. When users request some information about something and do not ask for a specific requestable slot, Mars-G generates system responses, lack of the requestable slot '*postcode*', as shown in Table 17. In addition, Mars-G requests users whether to make a reservation instead of providing booked references directly, as shown in Table 18. Noisy dialog annotations cause the requestable slot error in Table 19. The requestable slot 'postcode' does not appear in the conversation.

Model	5%				10%				20%				50%			
	Inform	**Success**	**BLEU**	**Combined**	**Inform**	**Success**	**BLEU**	**Combined**	**Inform**	**Success**	**BLEU**	**Combined**	**Inform**	**Success**	**BLEU**	**Combined**
DAMD																
run 1	35.4	17.2	10.9	37.2	41.3	23.7	12.4	44.9	51.8	31.9	14.1	56.0	60.1	44.2	15.6	67.8
run 2	40.8	20.9	12.0	42.9	41.5	25.3	11.2	44.6	50.4	32.4	13.8	55.2	54.7	39.5	14.8	61.9
run 3	38.5	14.5	10.6	37.1	40.0	23.9	12.3	44.3	42.5	26.8	15.4	50.1	59.1	45.7	15.1	67.5
run 4	35.4	16.5	10.2	36.2	42.3	20.2	12.0	43.3	46.1	29.2	14.0	51.7	57.2	43.0	16.1	66.2
run 5	34.0	17.6	12.4	38.2	39.5	21.9	13.0	43.7	50.8	31.3	13.6	54.7	63.1	49.3	17.1	73.3
Average	36.8	17.3	11.2	38.3	40.9	23.0	12.2	44.2	48.3	30.3	14.2	53.5	58.8	44.3	15.7	67.3
MinTL																
run 1	54.4	41.1	14.2	62.0	55.8	44.0	15.3	65.2	62.5	54.2	17.3	75.7	71.7	62.7	16.9	84.1
run 2	54.8	36.8	13.6	59.4	51.6	42.0	15.7	62.5	65.8	56.3	15.5	76.6	67.4	59.7	18.7	82.3
run 3	53.3	39.3	14.2	60.5	55.1	44.7	16.1	66.0	68.0	59.0	16.6	80.1	70.6	62.6	17.5	84.1
run 4	52.4	37.1	13.8	58.6	58.4	47.3	15.2	68.1	58.3	48.4	14.4	67.8	68.9	61.3	18.2	83.3
run 5	47.5	36.3	13.8	55.7	56.8	46.4	15.9	67.5	66.9	56.8	17.0	78.9	73.1	64.5	18.6	87.4
Average	52.5	38.1	13.9	59.2	55.5	44.9	15.6	65.8	64.3	54.9	16.2	75.8	70.3	62.2	18.0	84.3
UBAR																
run 1	37.4	23.0	11.6	41.8	52.3	34.8	13.0	56.6	61.7	45.7	15.9	69.6	77.2	61.5	15.5	84.9
run 2	33.3	20.6	11.2	38.2	48.5	35.9	14.5	56.7	63.4	47.8	15.5	71.1	78.0	63.8	16.9	87.8
run 3	40.0	23.1	11.7	43.3	50.3	33.2	13.6	55.4	67.8	50.0	13.1	72.0	77.4	64.6	16.2	87.2
run 4	38.2	22.4	10.7	41.0	52.5	34.6	12.5	56.1	68.3	51.7	14.4	74.4	78.5	64.1	16.8	88.1
run 5	38.0	21.3	11.3	41.0	47.8	32.3	13.7	53.8	66.2	48.3	13.8	71.1	76.8	62.4	16.2	85.8
Average	37.4	22.1	11.3	41.1	50.3	34.2	13.5	55.8	65.5	48.7	14.5	71.6	77.6	63.3	16.3	86.8
MTTOD																
run 1	51.4	37.5	12.0	56.5	70.9	58.0	13.8	78.3	71.1	59.0	14.2	79.3	74.7	64.4	15.2	84.8
run 2	53.8	41.7	11.3	59.1	64.1	53.7	13.8	72.7	69.5	60.7	14.0	79.1	79.3	67.7	15.0	88.5
run 3	55.7	31.1	11.5	54.9	61.0	50.8	13.7	69.6	78.4	65.1	14.7	86.5	82.3	71.1	15.5	92.2
run 4	52.4	33.3	10.6	53.5	73.0	59.3	14.0	80.2	80.2	67.4	14.5	88.3	76.6	65.6	15.3	86.4
run 5	58.0	43.2	11.3	61.9	65.4	54.2	13.7	73.5	75.9	64.3	14.1	84.2	79.8	68.7	15.1	89.4
Average	54.3	37.4	11.3	57.2	66.9	55.2	13.8	74.9	75.0	63.3	14.3	83.5	78.5	67.5	15.2	88.2
PPTOD																
run 1	70.7	46.8	13.7	72.5	65.2	50.6	14.2	72.1	72.3	55.0	14.9	78.6	74.8	60.4	15.8	83.4
run 2	64.6	45.8	13.8	69.0	69.3	52.9	15.3	76.4	70.5	57.7	17.7	81.8	74.1	64.2	16.4	85.6
run 3	64.4	51.1	15.1	72.9	65.7	53.6	15.8	75.5	74.8	64.6	16.9	86.6	74.3	61.8	17.2	85.3
run 4	63.9	47.0	14.7	70.2	70.1	55.4	17.8	80.6	71.8	57.3	16.0	80.6	76.4	63.7	18.0	88.1
run 5	63.7	50.7	14.4	71.6	71.2	55.8	15.6	79.1	74.1	61.6	15.8	83.7	74.4	61.9	17.5	85.7
Average	65.5	48.3	14.3	71.2	68.3	53.7	15.7	76.7	72.7	59.2	16.3	82.3	74.8	62.4	17.0	85.6
Mars-G																
run 1	55.8	41.1	14.0	62.5	68.7	55.0	16.7	78.6	72.4	60.2	18.1	84.4	82.6	70.2	18.8	95.2
run 2	57.0	43.2	12.9	63.0	68.4	55.9	15.2	77.4	76.0	61.4	17.1	85.8	78.4	66.9	18.7	91.4
run 3	61.4	46.7	14.5	68.6	68.9	53.8	14.0	75.4	76.6	63.8	17.0	87.2	82.8	73.6	17.9	96.1
run 4	56.1	42.4	14.1	63.4	73.1	60.3	16.6	83.3	80.6	63.9	17.1	89.4	82.5	71.3	19.0	95.9
run 5	57.8	43.5	13.8	64.5	67.7	51.5	15.7	75.3	77.7	65.0	16.8	88.2	84.6	74.2	18.7	98.1
Average	57.6	43.4	13.9	64.4	69.4	55.3	15.6	78.0	76.7	62.9	17.2	87.0	82.2	71.2	18.6	95.3

Table 10: Comparison of task-oriented dialog systems on the MultiWOZ 2.0 in the low resource scenarios.

Goal:	[restaurant]: {informable: food italian area east} {requestable: reference}
User (Turn 0):	i am looking for a jamaican restaurant in the east.
Golden R:	there are no [value_food] restaurants in the [value_area]. would you like to try another food type or area?
Golden DS:	[restaurant] food jamaican area east
Golden AS:	[restaurant] [nooffer] food area [request] area food
Mars-G R:	i am sorry, there are no [value_food] restaurants in the [value_area]. would you like to try another area or another type of food?
Mars-G DS:	[restaurant] food jamaican area east
Mars-G AS:	[restaurant] [nooffer] food area [request] area food
User (Turn 1):	i am looking for a place that serves jamaican food in the east. if not, italian will do.
Golden R:	there is [value_choice] [value_food] place in the [value_area], [value_name].
Golden DS:	[restaurant] food italian area east
Golden AS:	[restaurant] [inform] choice name food area
Mars-G R:	i am sorry, there are no [value_food] restaurants in the [value_area]. would you like to try another type of food?
Mars-G DS:	[restaurant] food jamaican area east
Mars-G AS:	[restaurant] [nooffer] food area [request] food
User (Turn 2):	ok, i would like to make a reservation there.
Golden R:	i can do that for you, i just need details such as day, time, and the size of your party.
Golden DS:	[restaurant] food italian area east
Golden AS:	[restaurant] [offerbook] [request] time day people
Mars-G R:	what day and time would you like to dine? and how many people will be in your party?
Mars-G DS:	[restaurant] food jamaican area east
Mars-G AS:	[restaurant] [request] day time people
User (Turn 3):	i need a table for 7 at 14:45 on friday.
Golden R:	i booked you a table for [value_people] on [value_day] at [value_time] at [value_name], reference: [value_reference]. can i assist you further today?
Golden DS:	[restaurant] food italian area east time 14:45 day friday people 7
Golden AS:	[restaurant] [offerbooked] time reference name day people [general] [reqmore]
Mars-G R:	booking was successful. the table will be reserved for 15 minutes. reference number is: [value_reference].
Mars-G DS:	[restaurant] food jamaican area east time 14:45 day friday people 7
Mars-G AS:	[restaurant] [offerbooked] reference

Table 11: An example in dialog session pmul0367. The informable slot error is caused by the inaccurate dialog state. R denotes response, DS denotes dialog state, and AS denotes action state.

Goal:	[attraction]: {informable: area centre}
User (Turn 3):	i am also looking for places to go in town. perhaps an attraction in the city centre.
Golden R:	i have the [value_name] located at [value_address] and it's [value_price] entrance.
Golden DS:	[attraction] area centre
Golden AS:	[attraction] [recommend] address price name
Mars-G R:	there are [value_choice] attractions in the city centre. do you have a preference for type?
Mars-G DS:	[attraction] area centre
Mars-G AS:	[attraction] [inform] choice [request] type
User (Turn 4):	that sounds perfect. thanks!
Golden R:	can i help you with anything else?
Golden DS:	[attraction] area centre
Golden AS:	[general] [reqmore]
Mars-G R:	is there anything else i can help you with?
Mars-G DS:	[attraction] area centre
Mars-G AS:	[general] [reqmore]

Table 12: An example in dialog session pmul2563. The informable slot error is caused by the inaccurate action state. .

Goal:	[attraction]: {informable: area south} {requestable: postcode}
User (Turn 4):	i would also like to go to some attractions in the same area as the restaurant.
Golden R:	there are [value_choice] attractions in the area. there's a [value_type], [value_type], [value_type], [value_type], [value_type]... do any of these appeal to you in particular?
Golden DS:	[attraction] area south [restaurant] food indian pricerange expensive area south
Golden AS:	[attraction] [select] type [inform] choice
Mars-G R:	there are [value_choice] attractions in the area. do you have a preference for type?
Mars-G DS:	[attraction] area south [restaurant] food indian pricerange expensive area south
Mars-G AS:	[attraction] [inform] choice [request] type
User (Turn 5):	restaurant is what i am looking for, entrance fee and postcode please. get me a taxi from the attraction by 10.15, get me its contact number and car type.
Golden R:	just to clarify you are looking for another restaurant and not an attraction?
Golden DS:	[attraction] area south [restaurant] food indian pricerange expensive area south
Golden AS:	[attraction] [select] [restaurant] [select]
Mars-G R:	[value_name] is located in postcode [value_postcode]. the phone number is [value_phone]. the entrance fee is [value_price]. can i help you with anything else?
Mars-G DS:	[taxi] leave 10.15 destination tandoori palace departure the nirala [attraction] area south [restaurant] food indian pricerange expensive area south
Mars-G AS:	[attraction] [inform] price phone name postcode [general] [reqmore]
User (Turn 6):	oh, yeah, i do want information on attractions! in the same area. after that, i will need a taxi.
Golden R:	if you like parks the [value_name] has [value_price] admission and is in the [value_postcode] postcode. or i can tell you about the other attractions?
Golden DS:	[attraction] area south [restaurant] food indian pricerange expensive area south
Golden AS:	[attraction] [recommend] name postcode price [general] [reqmore]
Mars-G R:	there are [value_choice] attractions in the [value_area]. [value_choice] are [value_type], [value_choice] are [value_type], and [value_choice] is [value_type]. do you have a preference?
Mars-G DS:	[taxi] leave 10.15 destination tandoori palace departure the nirala [attraction] area south [restaurant] food indian pricerange expensive area south
Mars-G AS:	[attraction] [inform] area type choice [request] type
User (Turn 7):	that sounds wonderful, is it also in the south part of town? if so, i would like a taxi from there to my hotel.
Golden R:	yes, [value_name] is in the [value_area]. in order to help you book a taxi between the park and your hotel, i need to know what hotel you're at.
Golden DS:	[taxi] departure wandlebury country park [attraction] area south [restaurant] food indian pricerange expensive area south
Golden AS:	[attraction] [inform] area name [taxi] [request] destination
Mars-G R:	yes, [value_name] is in the [value_area].
Mars-G DS:	[taxi] leave 10.15 destination tandoori palace departure the nirala [attraction] area south [restaurant] food indian pricerange expensive area south
Mars-G AS:	[attraction] [inform] area name

Table 13: An example in dialog session mul2491. The informable slot error is caused by automatic evaluation.

Goal:	[restaurant]: {informable: pricerange moderate area west }{requestable: reference}
User (Turn 0):	hi! i am planning a trip in cambridge and i am looking for a restaurant in the west part of town.
Golden R:	there are [value_choice] restaurants in the [value_area]. is there any kind of food you're looking for?
Golden DS:	[restaurant] area west
Golden AS:	[restaurant] [inform] choice area [request] food
Mars-G R:	there are [value_choice] restaurants in the [value_area] part of town. do you have a price range or type of food in mind?
Mars-G DS:	[restaurant] area west
Mars-G AS:	[restaurant] [inform] choice area [request] food price
User (Turn 1):	how about you suggest one a book a table for 4 on tuesday at 15:45 and i need the reference number too please
Golden R:	i was able to book [value_name], reference number is [value_reference]
Golden DS:	[restaurant] area west time 15:45 day tuesday people 4
Golden AS:	[restaurant] [offerbooked] name reference
Mars-G R:	i have booked you at [value_name]. your reference number is [value_reference]. is there anything else i can help you with?
Mars-G DS:	[restaurant] area west time 15:45 day tuesday people 4
Mars-G AS:	[restaurant] [offerbooked] reference name [general] [reqmore]

Table 14: An example in dialog session pmul3992. The informable slot error is caused by noisy dialog annotations.

Goal:	[train]: {informable: leave 17:00 destination birmingham new street day monday departure cambridge} {requestable: reference}
User (Turn 0):	what train do i take to get to birmingham new street? i need to leave after 17:00.
Golden R:	there are trains departing hourly at 1 minute past the hour [value_leave]. all are [value_price], and take [value_time].
Golden DS:	[train] destination birmingham new street leave 17:00
Golden AS:	[train] [inform] price leave time
Mars-G R:	where will you be departing from and what day would you like to travel ?
Mars-G DS:	[train] destination birmingham new street leave 17:00
Mars-G AS:	[train] [request] departure day
User (Turn 1):	i am looking to travel on monday. the first train at 17:01 would be fine. can i get that train info?
Golden R:	sure the trainid is [value_id]. it leaves at [value_leave] and arrives at [value_arrive]. would you like to make a reservation?
Golden DS:	[train] destination birmingham new street day monday departure cambridge leave 17:00
Golden AS:	[train] [inform] arrive leave id [offerbook]
Mars-G R:	[value_id] leaves at [value_leave] and arrives at [value_arrive]. would you like me to book that for you?
Mars-G DS:	[train] destination birmingham new street day monday departure cambridge leave 17:00
Mars-G AS:	[train] [inform] arrive leave id [offerbook]
User (Turn 2):	yes please make a reservation and give me the reference number.
Golden R:	your reservation is book. the reference number is [value_reference]. can i assist you with anything else today?
Golden DS:	[train] destination birmingham new street day monday departure cambridge people 1 leave 17:00
Golden AS:	[train] [offerbooked] reference [general] [reqmore]
Mars-G R:	how many tickets do you need?
Mars-G DS:	[train] destination birmingham new street day monday departure cambridge people 1 leave 17:00
Mars-G AS:	[train] [request] people

Table 15: An example in dialog session mul1624. The inaccurate action state causes the requestable slot error.

Goal:	[restaurant]: {informable: food international pricerange moderate area centre} {requestable: reference}
User (Turn 0):	what restaurants in the centre serve international cuisine?
Golden R:	the [value_name] and the [value_name] serve [value_food] food and are in the [value_area] of town.
Golden DS:	[restaurant] food international area centre
Golden AS:	[restaurant] [inform] food area name
Mars-G R:	there are [value_choice] restaurants that meet your criteria. do you have a price range in mind?
Mars-G DS:	[restaurant] food international area centre
Mars-G AS:	[restaurant] [inform] choice [request] price
User (Turn 1):	how about a place in the moderate price range?
Golden R:	[value_choice] of the named restaurants are in the [value_pricerange] price range.
Golden DS:	[restaurant] food international pricerange moderate area centre
Golden AS:	[restaurant] [inform] choice price
Mars-G R:	there are [value_choice] restaurants that meet your criteria. [value_name] and [value_name]. would you like me to book one of these for you?
Mars-G DS:	[restaurant] food international pricerange moderate area centre
Mars-G AS:	[restaurant] [inform] choice name [offerbook]
User (Turn 2):	ok, can you book a table for 6 at 12:00 on tuesday at the varsity restaurant? i will need a reference number too, please.
Golden R:	certainly. i will have that reference number for you in just one second.
Golden DS:	[restaurant] food international pricerange moderate area centre
Golden AS:	[restaurant] [offerbook]
Mars-G R:	booking was successful. the table will be reserved for 15 minutes. reference number is: [value_reference]. is there anything else i can help you with?
Mars-G DS:	[restaurant] food international pricerange moderate area centre time 12:00 day tuesday people 6
Mars-G AS:	[restaurant] [offerbooked] reference [general] [reqmore]
User (Turn 3):	thanks. looking forward to it.
Golden R:	yes i can. i have booked you a table for [value_time] on [value_day] for [value_people] people. your reference number is [value_reference]. anything else i can help you with?
Golden DS:	[restaurant] food international pricerange moderate area centre time 12:00 day tuesday people 6
Golden AS:	[restaurant] [offerbooked] time reference people day
Mars-G R:	you're welcome. have a great day!
Mars-G DS:	[restaurant] food international pricerange moderate area centre time 12:00 day tuesday people 6
Mars-G AS:	[general] [welcome] [bye]

Table 16: An example in dialog session sng0636. The requestable slot error is caused by automatic evaluation.

Goal:	[attraction]: {informable: area north} {requestable: postcode phone }
User (Turn 0):	i am looking for something to do in town. are there any interesting attraction in the north part of town?
Golden R:	yes , there are [value_choice] places: i see a [value_type], a [value_type], and two [value_type]. would one of these work for you?
Golden DS:	[attraction] area north
Golden AS:	[attraction] [inform] type choice [general] [reqmore]
Mars-G R:	there are [value_choice] [value_type] and [value_type] in the [value_area]. do you have a preference?
Mars-G DS:	[attraction] area north
Mars-G AS:	[attraction] [inform] area type choice [request] type
User (Turn 1):	ooh, a pool would be fun. can you give me their contact info?
Golden R:	great! [value_address] is located at [value_address], kings hedges postcode is [value_postcode] and their phone is [value_phone]. is there anything else i can help you with?
Golden DS:	[attraction] area north
Golden AS:	[attraction] [inform] name postcode phone address [general] [reqmore]
Mars-G R:	[value_name] is located at [value_address]. their phone number is [value_phone].
Mars-G DS:	[attraction] area north type swimming pool
Mars-G AS:	[attraction] [inform] name phone address

Table 17: An example in dialog session mul1811. The requestable slot error is acceptable.

Goal:	[train]: {informable: destination stansted airport day friday arrive 15:30 departure cambridge} {requestable: reference}
User (Turn 3):	i will also need a train leaving cambridge.
Golden R:	sure, what is your arrival information?
Golden DS:	[train] departure cambridge
Golden AS:	[train] [request] destination
Mars-G R:	what day will you be traveling, and where will you be traveling to?
Mars-G DS:	[train] departure cambridge
Mars-G AS:	[train] [request] destination day
User (Turn 4):	i need to go to stansted airport on friday.
Golden R:	we have [value_choice] different departure times. any time table your looking at?
Golden DS:	[train] destination stansted airport departure cambridge
Golden AS:	[train] [inform] choice [request] leave
Mars-G R:	there are [value_choice] trains that meet your criteria. do you have a preferred departure or arrival time?
Mars-G DS:	[train] destination stansted airport day friday departure cambridge
Mars-G AS:	[train] [inform] choice [request] leave arrive
User (Turn 5):	i need to be in stansted airport by 15:30 please.
Golden R:	the soonest it will get you there is [value_arrive] your reference number is [value_reference], anything else?
Golden DS:	[train] destination stansted airport arrive 15:30 departure cambridge people 1
Golden AS:	[train] [offerbooked] arrive reference [general] [reqmore]
Mars-G R:	[value_id] will arrive at [value_arrive]. would you like me to book that for you?
Mars-G DS:	[train] destination stansted airport day friday arrive 15:30 departure cambridge
Mars-G AS:	[train] [inform] arrive id [offerbook]

Table 18: An example in dialog session pmul3247. The requestable slot error is acceptable.

Goal:	[attraction]: {informable: type architecture area centre} {requestable: address phone postcode}
User (Turn 0):	i want to find a place to go in the centre to enjoy some entertainment. can you help?
Golden R:	there are [value_choice] attraction types in the [value_area], did you have one in mind?
Golden DS:	[attraction] area centre
Golden AS:	[attraction] [inform] area choice [request] name
Mars-G R:	i am sorry, there are no [value_type] attractions in the [value_area]. would you like to try another area?
Mars-G DS:	[attraction] area centre type entertainment
Mars-G AS:	[attraction] [nooffer] area type [request] area
User (Turn 1):	yes, i am looking for something with the type of architecture. thanks!
Golden R:	i would recommend [value_name] as a great place to see interesting [value_type].
Golden DS:	[attraction] area centre type architecture
Golden AS:	[attraction] [recommend] name type
Mars-G R:	there are [value_choice] [value_type] attractions in the [value_area]. i recommend [value_name].
Mars-G DS:	[attraction] area centre type architecture
Mars-G AS:	[attraction] [recommend] name [inform] type choice area
User (Turn 2):	okay, could you give me the address and phone number?
Golden R:	sure. the address is [value_address]. the phone number is [value_phone]. is there anything else i can help you with today?
Golden DS:	[attraction] area centre type architecture
Golden AS:	[attraction] [inform] address phone [general] [reqmore]
Mars-G R:	the address is [value_address] and the phone number is [value_phone].
Mars-G DS:	[attraction] area centre type architecture
Mars-G AS:	[attraction] [inform] address phone

Table 19: An example in dialog session pmul1320. Noisy dialog annotations cause the requestable slot error.