

Task-Oriented Dialogue System as Natural Language Generation

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Abstract

In this paper, we propose to formulate the task-oriented dialogue system as the purely natural language generation task, so as to fully leverage the large-scale pre-trained models like GPT-2 and simplify complicated delexicalization preprocessing. However, directly applying this method heavily suffers from the dialogue entity inconsistency caused by the removal of delexicalized tokens, as well as the catastrophic forgetting problem of the pre-trained model during fine-tuning, leading to unsatisfactory performance. To alleviate these problems, we design a novel GPT-Adapter-CopyNet network, which incorporates the lightweight adapter and CopyNet modules into GPT-2 to achieve better performance on transfer learning and dialogue entity generation. Experimental results conducted on the DSTC8 Track 1 benchmark and MultiWOZ dataset demonstrate that our proposed approach significantly outperforms baseline models with a remarkable performance on automatic and human evaluations.

Introduction

The increasing use of customer service and personal assistants has spurred interest in building task-oriented dialogue systems that help users to accomplish a wide range of tasks via natural language conversations, such as weather forecast, restaurant reservation, IT helpdesk and airplane booking. Facing the wide variety of tasks and domains, it is crucial for the dialogue system to maintain track of the dialogue flow, and achieve an effective conversation even when the user goal is complicated or the dialogue flow is suddenly changed.

The typical task-oriented dialogue system follows a pipeline structure that has four modules and executes sequentially, as shown in Figure 1(a). A natural language understanding (NLU) (Kim, Lee, and Stratos 2017; Lee et al. 2019) module identifies user intents and extracts associated information from user utterance input, based on which the dialogue state tracking (DST) module (Wu et al. 2019a; Zhang et al. 2019a; Le, Socher, and Hoi 2019; Goel, Paul, and Hakkani-Tür 2019; Kim et al. 2020) tracks the values of slots to update the belief state. Then the dialogue policy (POL) module (Peng et al. 2018; Zhao, Xie, and Eskénazi 2019; Zhang et al. 2019b) decides the next system action under

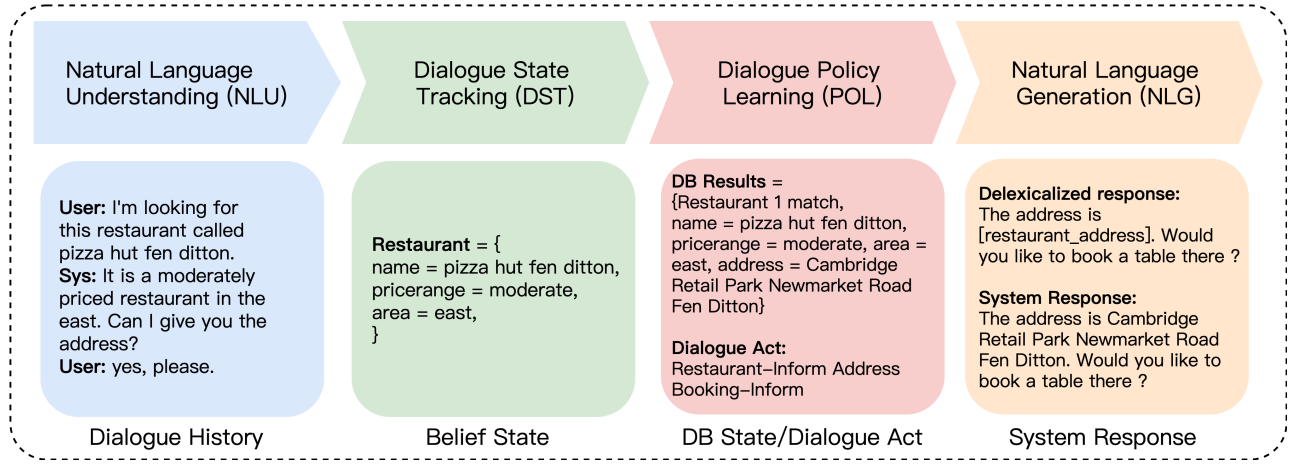
the belief state and database query results. Finally, the natural language generation (NLG) module (Chen et al. 2019) maps the system action to a natural language response. In practice, these different modules are usually optimized separately, which does not necessarily lead to overall optimized performance for task completion.

In order to overcome this drawback, one line of research attempts to integrate these pipeline modules into one single model, and builds up the end-to-end neural architecture for task-oriented dialogue systems, including Mem2Seq (Madotto, Wu, and Fung 2018), Sequicity (Lei et al. 2018a) and TransferTransfo (Budzianowski and Vulić 2019). Recently, as illustrated in Figure 1(b), researchers propose to incorporate GPT-2 (Radford et al. 2019), a large-scale pre-trained model, to construct a unified language model for task-oriented dialogue with a single sequence in format of dialogue history (Ham et al. 2020; Hosseini-Asl et al. 2020; Peng et al. 2020; Yang, Li, and Quan 2020).

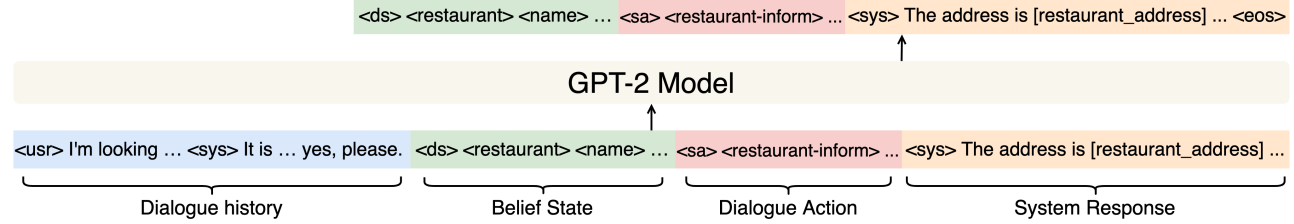
On the basis of this, we propose to further convert the entire pipeline structure into a purely prefix-given NLG task by removing complicated delexicalization preprocessing and special separators (e.g. “<usr>”), as shown in Figure 1(c). In this way, instead of making pre-training more similar to a downstream task, we reformulate the task itself to make it more similar to the pre-training objective of GPT-2, which takes full advantage of language generation ability of the pre-trained model. However, this method typically brings the dialogue entity inconsistency (e.g. names of hotels, postcodes of restaurants), which is not conducive to task completion. It is because that the current pre-trained models have no correspondent structure to ensure entity consistency, when we directly replace the delexicalized tokens with natural text. On the other hand, since only a handful of examples is available for building task-oriented dialogue systems, directly fine-tuning the whole pre-trained model on this purely NLG task easily suffers from the catastrophic forgetting problem (McCloskey and Cohen 1989), thereby degrading the pre-training performance.

In this paper, we design a novel GPT-Adapter-CopyNet network (GPT-ACN), which incorporates two simple and lightweight modules into GPT-2 during fine-tuning, to handle the aforementioned problems. Specifically, we first introduce adapter module, which is inserted between layers of the pre-trained GPT-2 model. When fine-tuning GPT-2 on the

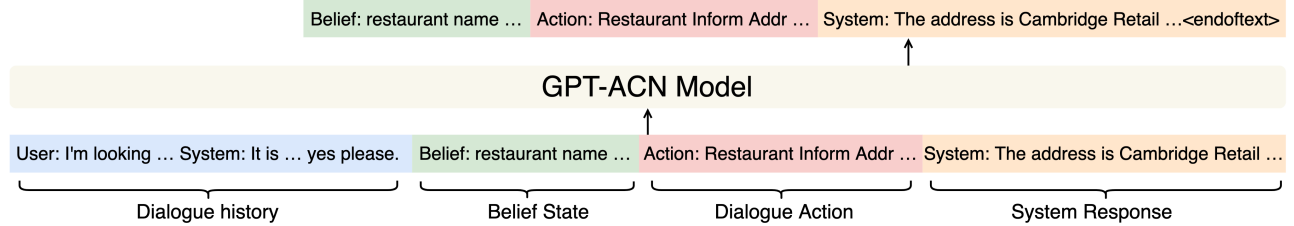
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(a) The pipeline structure of typical task-oriented dialogue system.



(b) The input representation of Neural Pipeline GPT-2.



(c) The input representation of our proposed GPT-Adapter-CopyNet network.

Figure 1: Illustration of a traditional modular task-oriented dialogue system, a pre-processed training exemplar for Neural Pipeline GPT-2 (Ham et al. 2020), and the corresponding input representation of our proposed approach.

downstream dataset, this model only updates parameters in adapter modules and keeps pre-trained parameters frozen to alleviate the catastrophic forgetting problem, thus achieving better performance of transfer learning. Besides, in order to ensure entity consistency in dialogue flow, we further build up a CopyNet module on the top of the GPT-2 model, which enables the model to directly copy entities from dialogue history instead of generating entities.

We evaluate the effectiveness of our proposed method on the DSTC8 Track 1 benchmark and MultiWOZ dataset. The experimental results prove that our proposed approach significantly outperforms previous state-of-the-art baseline models, achieving a remarkable performance on automatic and human evaluations.

Our main contributions can be summarized as follows:

- We propose to convert the task-oriented dialogue into a purely prefix-given NLG task to take full advantage of the pre-trained model.

- We incorporate the lightweight adapter and CopyNet modules into the GPT-2 model to achieve better performance on transfer learning and dialogue entity generation.
- We empirically validate the effectiveness of our proposed approach with automatic and human evaluations.

Method

In this section, we will introduce how we consider the end-to-end task-oriented dialogue as the purely NLG task and describe the GPT-Adapter-CopyNet network in detail.

Problem Formulation

The task-oriented dialogue system follows a pipeline structure consisting of NLU, DST, POL, and NLG modules. This whole process can be formulated as follows: at turn t of the dialogue, given the dialogue history with many utterances in several turns $H_{1:t} = \{U_0, S_0, \dots, S_{t-1}, U_t\}$, the dialogue

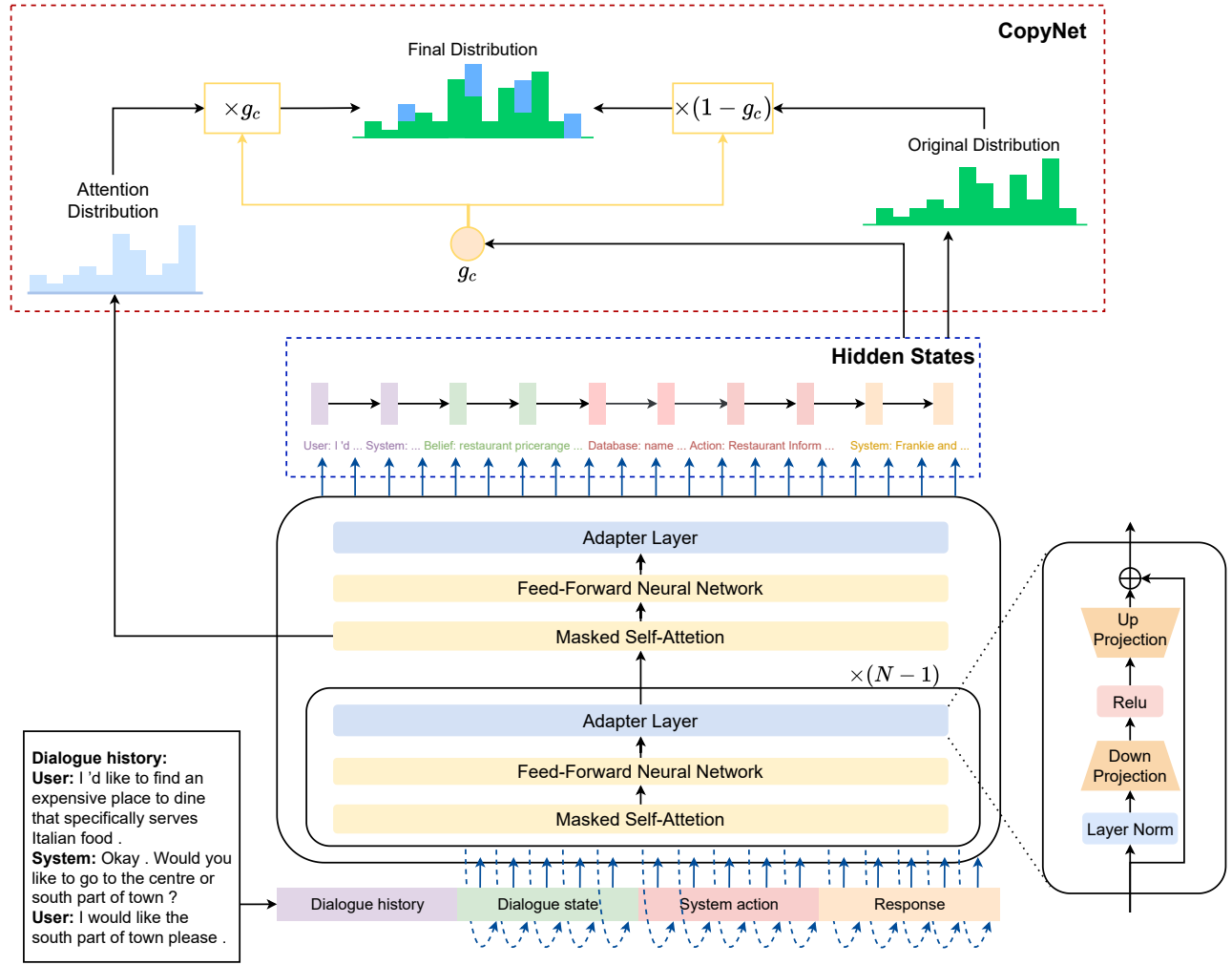


Figure 2: The overview of our proposed GPT-Adapter-CopyNet network (GPT-ACN).

system is supposed to obtain the belief state B_t , search the database results D_t , predict current system action A_t , and generate final system response S_t . Among them, the dialogue history $H_{1:t}$ includes previous user inputs $\{U_0, \dots, U_t\}$ and system responses $\{S_0, \dots, S_{t-1}\}$.

The conventional approach mainly splits this task into three sub-tasks, including dialogue state tracking $P(B_t|H_{1:t})$, dialogue policy prediction $P(D_t, A_t|H_{1:t}, B_t)$ and natural language generation $P(S_t|H_{1:t}, B_t, D_t, A_t)$. These sub-tasks are usually optimized separately, which does not guarantee to bring overall optimized performance for successful task completion. On the contrary, the end-to-end task-oriented dialogue system aims to directly optimize the entire probabilistic distribution $P(B_t, D_t, A_t, S_t|H_{1:t})$ with one single model. Specifically, previous methods (Ham et al. 2020; Hosseini-Asl et al. 2020; Peng et al. 2020) convert the dialogue state and system action to word tokens, and then concatenate the whole dialogue flow into a long sequence by delimiter tokens and additional special words. Then the dialogue process can be viewed as a single auto-regressive model and learned in a self-supervised manner. Figure 1(b) shows a pre-

processed training exemplar of Neural Pipeline GPT-2 (Ham et al. 2020).

However, the additional introduced special tokens still require complicated delexicalization preprocessing and bring inconsistency between the pre-training and fine-tuning stages, which hinders the model from fully employing the capacity of the pre-trained model. Therefore, in this paper, we further simplify the end-to-end task-oriented dialogue into a purely prefix-given NLG task by removing complicated delexicalization preprocessing and replacing special separators with natural text. In this way, we reformulate the dialogue task itself to make it more similar to the pre-training objective of GPT-2. Then, when fine-tuning GPT-2 on such downstream data, it is possible to better fully utilize the capacity of the pre-trained model, achieving significant gains. Since this process is independent of pipeline format, this approach could be naturally applied in all previous end-to-end task-oriented dialogue systems, such as Neural Pipeline GPT-2, SimpleTOD (Hosseini-Asl et al. 2020) and SOLOIST (Peng et al. 2020). For instance, as illustrated in Figure 1(b) and 1(c), Neural Pipeline GPT-2 introduces delimiter tokens “<usr>”,

“<sys>”, “<ds>” and “<sa>” to signal the beginning of sequence representations of user utterance, system response, dialogue state, and system action, while our proposed method directly replaces these tokens with corresponding natural text: “User:”, “System:”, “Belief:” and “Action:”. Also, all delexicalized tokens such as “[restaurant_address]” are replaced by its original entities.

GPT-Adapter-CopyNet Network

When converting task-oriented dialogue into a purely NLG task, it heavily suffers from the dialogue entity inconsistency caused by the removal of delexicalized tokens, as well as the catastrophic forgetting problem of the pre-trained model during fine-tuning. To address these problems, we design a novel GPT-Adapter-CopyNet network (GPT-ACN), as shown in Figure 2. This framework uses the GPT-2 model as the backbone, which consists of a stack of transformer decoder layers. The original transformer decoder layer has two components, masked self-attention layer and feed-forward neural network. Based on this, a simple and lightweight adapter layer is firstly injected between layers of GPT-2 transformer to alleviate the catastrophic forgetting problem. Then a CopyNet module is built on the top of GPT-2 transformer to improve entity consistency in dialogue.

Adapter. We adopt the original adapter structure proposed in Houlsby et al. (2019). Each residual adapter layer first performs layer normalization towards the output hidden states of previous transformer layer. Then it is followed by a down projection layer, a non-linear activation layer, and an up projection layer. The two projection layers produce a bottleneck for compression. The dimension of the bottleneck is an important hyper-parameter which can be tuned based on the input dimension. Last, the residual connection (He et al. 2016) is implemented between the input hidden states and output of up projection layer, to prevent the degradation problem in very deep model. Assume the output hidden states of the i -th layer is h_i , the output of adapter layer x_{i+1} can be computed as:

$$x_{i+1} = h_i + W_u \cdot (\text{ReLU}(W_d \cdot \text{LN}(h_i))) \quad (1)$$

where $W_u \in \mathbb{R}^{A \times H}$ and $W_d \in \mathbb{R}^{H \times A}$ are adapter parameters. A and H denote the size of adapter bottleneck and the hidden size respectively.

Copy Network. In the task-oriented dialogue, it is vital to keep some entities consistent over the dialogue flow, e.g. hotel names and restaurant postcodes. Actually, it is easily achieved by directly copying entities from dialogue history instead of generating entities. Based on this motivation, we introduce the CopyNet module (Gu et al. 2016) on the top of the GPT-2 model, which enables the model to generate words from both copying words via pointing, and original prediction distribution. Specifically, at j -th step of model prediction, we first obtain the embedding e_j of input tokens, the attention score a^L of last layer, the output hidden states h_j^L , and the original prediction probability $P_g(\omega)$ by the original model. Next, the copy probability $g_c \in [0, 1]$ is calculated as follows:

$$g_c = \sigma(W_c \cdot [e_j; h_j^L] + b_c) \quad (2)$$

where vectors $W_c \in \mathbb{R}^{2 \cdot H \times 1}$ and scalar b_c are learnable parameters, and σ is the sigmoid function. The final prediction distribution $P(\omega)$ is a soft linear combination of original prediction probability and attention score:

$$P(\omega) = (1 - g_c) \cdot P_g(\omega) + g_c \cdot \sum_{k: \omega_k = \omega} a_k^t. \quad (3)$$

Optimization. The training objective of the GPT-ACN model is the standard left-to-right language modeling objective (Bengio et al. 2000), which maximizes the likelihood of the next word-token from given the previous word tokens:

$$\mathcal{L}_{nll}(\omega_1, \dots, \omega_n) = \sum_i \log P(\omega_i | \omega_1, \dots, \omega_{i-1}).$$

Also, the GPT-ACN model does not require additional training objectives such as next-utterance classification used in Ham et al. (2020). For the model training, we first load pre-trained GPT-2 model checkpoint into our GPT-ACN model and then fine-tune this model with the task-oriented dialogue dataset. During fine-tuning, only the parameters in adapter and CopyNet modules will be updated in back-propagation, keeping parameters in the original GPT-2 model fixed.

Experiments

In this section, we evaluate the effectiveness of our proposed approach on several task-oriented dialogue benchmarks: The Eighth Dialogue System Technology Challenge (DSTC8) Track 1 End-to-End Multi-Domain Dialogue Challenge (Kim et al. 2019) and MultiWOZ 2.0 benchmark with three sub-tasks (Budzianowski et al. 2018).

Setup

Dataset and Evaluation Metrics. The DSTC8 is a world-wide public competition on dialogue systems, of which the first track is intended to foster progress in building complex bots span over multiple domains to accomplish a complex user goal. The automatic and human evaluations of DSTC8 Track 1 is carried out by ConvLab (Lee et al. 2019), an open-source multi-domain end-to-end dialogue system platform:

- Automatic evaluation with user simulator: Success Rate, Book Rate, Return, Turns, Precision, Recall, F1.
- Human evaluation with crowd-workers: Success Rate, Language Understanding Score, Response Appropriateness Score, Turns.

As for the *Success Rate*, the dialogue is considered as successful only if the requestable slots are correctly filled and book success if needed. The book success is achieved only if the reserved information fits into all informable slots, and it is considered as a sub-evaluation called *Book Rate*. Also, *Precision*, *Recall*, and *F1* measure the accuracy of requestable slot filling. *Return* is a reward score obtained from the user simulator when the task is finished. The *Return* of each dialogue is calculated as follows:

$$\text{Return} = -\text{Turns} + \begin{cases} 2 \cdot \max_turn & \text{If task success,} \\ -\max_turn & \text{otherwise.} \end{cases}$$

Model	Success Rate \uparrow	Book Rate \uparrow	Return \uparrow	Turns \downarrow	Precision \uparrow	Recall \uparrow	F1 \uparrow
ConvLab Baseline	62.00%	84.38%	30.41	7.67	0.72	0.83	0.75
NP-GPT (Ham et al. 2020)	78.60%	86.34%	48.92	7.40	0.87	0.89	0.87
NP-NLG	78.00%	81.33%	47.52	8.08	0.78	0.92	0.83
NP-GPT-ACN (Ours)	82.80%	90.97%	53.36	8.00	0.79	0.95	0.84
- w/o NLG	80.00%	89.25%	50.01	7.99	0.85	0.90	0.86
- w/o CopyNet	80.20%	85.45%	50.76	7.68	0.76	0.94	0.82

Table 1: Model performance on ConvLab automatic evaluation. NP-GPT and NP-NLG represent for Neural Pipeline GPT-2 and its natural text version, while NP-GPT-ACN stands for our proposed method.

where max_turn is the maximum limit of turns in one dialogue and set to 40 in our experiments. For the human evaluation, *Language Understanding Score* and *Response Appropriateness Score* are the metrics of how natural the response of the model is, with the 5 point scale.

MultiWOZ 2.0 is the large-scale human-to-human task-oriented dialogue corpus spanning over multiple domains and topics (attraction, hospital, police, hotel, restaurant, taxi, and train). It contains 8438/1000/1000 dialogues for training/validation/testing, respectively. Every human-to-human dialogue is fully-labeled with abundant belief state and system action annotations. We follow the automatic evaluation metrics to evaluate task completion and response quality: *Inform* measures whether a system has provided a correct entity, *Success* measures whether it has answered all the requested information, and *BLEU* (Papineni et al. 2002) is used to measure the fluency of the generated responses. A combined score (*Combined*) is also reported as an overall quality measure suggested in Mehri, Srinivasan, and Eskénazi (2019), which is computed with $(Inform + Success) \times 0.5 + BLEU$. Besides, *Joint Accuracy* is adopted to evaluate dialogue state tracking task.

Experimental Details. We develop our GPT-ACN model with HuggingFace’s Transformers (Wolf et al. 2019a) and our implementation is available at https://github.com/Victorwz/tod_as_nlg. We adopt GPT-2-small model ($n_{layer} = 12$, $n_{head} = 12$, $d_{embd} = 768$) with 117 million parameters as backbone.¹ The adapter bottleneck size is set as $A = 512$. The maximum number of turns in dialogue history is set to 15, which is same as previous work (Ham et al. 2020). The Adam (Kingma and Ba 2014) ($\beta_1 = 0.9$, $\beta_2 = 0.999$) optimizer with a learning rate of $3e-4$ is used in our experiments. We train all models with a batch size of 2 for 15 epochs, and the best model checkpoint is selected based on model performance on validation set. During inference, we adopt the simplest greedy decoding to generate the whole system response from the dialogue history. In addition, as our approach directly generates the natural text responses, we apply the delexicalization processing for the final model output in MultiWOZ 2.0, making it comparable to baselines.

Baselines. We compare our proposed model with several strong baseline methods. The selected baseline methods are

all end-to-end task-oriented dialogue systems based on GPT-2: (i) Neural Pipeline GPT-2 (NP-GPT) (Ham et al. 2020) integrates the pipeline modules into one single pre-trained auto-regressive language model. It realizes end-to-end training and inference. This model wins the DSTC8 Track 1 End-to-End Multi-Domain Dialogue Challenge with the No.1 performance on human evaluation; (ii) SimpleTOD (Hosseini-Asl et al. 2020), similar to NP-GPT, also simplifies pipeline modules to a long sequence, and use a self-defined format for dialogue pipeline. It is considered as our baseline for MultiWOZ 2.0.

We implement the purely natural text version of NP-GPT and SimpleTOD by removing delexicalization preprocessing and replacing special separators with natural text. These two baseline models are named NP-NLG and SimpleTOD-NLG respectively. Based on this, we apply the GPT-ACN model for these baselines and construct the corresponding version of our proposed approach, called NP-GPT-ACN and SimpleTOD-GPT-ACN. As our proposed method skips delexicalization stage, we insert up to three database query results between DST and POL modules in these four systems to leverage the database information. We mask the training loss of database results while fine-tuning.

DSTC8 Track 1 Performance

Automatic Evaluation. ConvLab automatic evaluation is conducted using user simulator. Following Ham et al. (2020), all systems are required to accomplish 500 dialogue tasks with pre-defined user goal and the same environment. The automatic evaluation results are listed in Table 1. We can find the performance degradation on precision and book rate between NP-GPT and its natural text version NP-NLG. It shows that simplifying end-to-end task-oriented dialogue as purely NLG makes it a harder task, in which the removal of delexicalization brings difficulty in entity generation consistency. Thus, directly fine-tuning GPT-2 cannot make accurate generation on requestable slots and values. Instead, the introduction of our GPT-ACN architecture solves this problem well, in which NP-GPT-ACN exceeds NP-GPT by 4.20% success rate, 4.63% book rate, and 4.44 return. Besides, removing NLG leads to significant performance degradation of NP-GPT-ACN, which indicates that converting end-to-end task-oriented dialogue into a purely NLG task will bring more improvement space for fully exploiting the pre-trained model.

¹<https://github.com/huggingface/transformers>

Model	Extra Data	Joint Accuracy	Inform	Success	BLEU	Combined
DST-Picklist (Zhang et al. 2020)		54.39	-	-	-	-
LaRL (Zhao, Xie, and Eskénazi 2019)		-	82.80	79.20	12.80	93.80
ARDM (Wu et al. 2019b)		-	87.40	72.80	20.60	100.70
DAMD (Zhang, Ou, and Yu 2020)	✓	-	89.20	77.90	18.60	102.15
SOLOIST (Peng et al. 2020)	✓	-	89.60	79.30	18.03	102.49
SimpleTOD (Hosseini-Asl et al. 2020)		50.22 [†]	88.90	67.10	16.90	94.90
SimpleTOD-NLG		56.23	84.80	70.30	14.88	92.43
SimpleTOD-GPT-ACN (Ours)		55.57	93.70	76.70	17.02	102.22

Table 2: Model performance on MultiWOZ 2.0 Dialogue State Tracking and Context-to-Text Generation. Joint accuracy of SimpleTOD with mark ([†]) is our reproduction due to the lack of result in Hosseini-Asl et al. (2020). Checking for “Extra Data” means that the model adds extra pre-trained data or performs data augmentation.

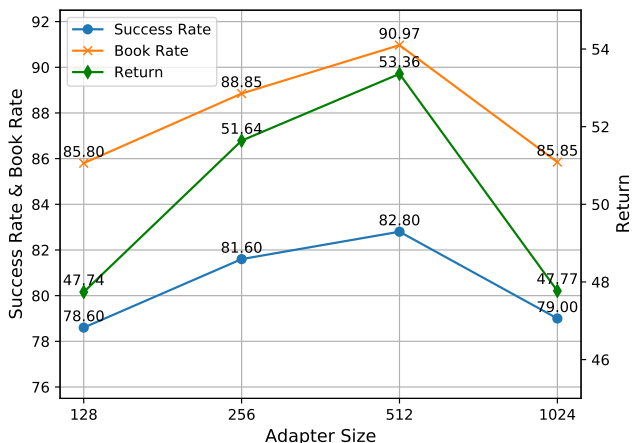


Figure 3: The effect of adapter bottleneck size on ConvLab automatic evaluation. The selected metrics are success rate, return and book rate.

Ablation Study. We further study the effectiveness of the adapter and CopyNet modules. As shown in the last row of Table 1, the NP-GPT-ACN suffers from an obvious loss on precision and book rate, when the CopyNet is removed from model architecture. It proves that incorporating CopyNet enables the model to directly copy entities, thus achieving better entity consistency in dialogue flow. Besides, the introduction of the adapter module yields better performance compared with NP-NLG, which verifies that keeping the original GPT-2 model fixed and only fine-tuning additional parameters can better alleviate the catastrophic forgetting problem. Since the adapter bottleneck size is the major hyperparameter in the NP-GPT-ACN model, we carry out another ablation study to evaluate its effectiveness with different sizes {128, 256, 512, 1024}, as illustrated in Figure 3. We can observe that the model with adapter bottleneck size of 512 performs best in our experiments.

Human Evaluation. For the human evaluation on ConvLab, the task-oriented dialogue systems are evaluated in

Model	Succe.↑	Under.↑	Appr.↑	Turns↓
NP-GPT	69.0%	4.02	4.46	16.52
NP-NLG	72.0%	4.10	4.64	17.02
NP-GPT-ACN	76.0%	4.32	4.72	15.44

Table 3: Results of ConvLab human evaluation. *Succe.*, *Under.* and *Appr.* are short for success rate, understanding score and appropriate score.

Amazon Mechanical Turk², in which crowd-workers communicate with systems and provide a rating based on the whole experience. In our experiment, every model is evaluated on 100 tasks sampled from the user goal list. Table 3 presents the results of ConvLab human evaluation. We can see that our proposed model NP-GPT-ACN significantly outperforms NP-GPT with a success rate of 76.0%, a language understanding score of 4.32, a response appropriateness score of 4.72, and average turns of 15.44. These results validate the effectiveness of our proposed method on fully exploiting the pre-trained model. Surprisingly, compared with NP-GPT, NP-NLG achieves better performance on success rate and response appropriateness score. It indicates that NP-NLG can produce more natural responses. Besides, crowd-workers tend to spend more turns to interact with NP-NLG, although NP-NLG leads to some entity inconsistency.

MultiWOZ Benchmark Performance

We conduct the end-to-end training for our proposed method with the MultiWOZ dataset and directly evaluate the performance on three sub-tasks:

Dialogue State Tracking. As illustrated in Table 2, we reproduce the SimpleTOD model with the joint accuracy of 50.22. There is a big performance degradation between SimpleTOD and SimpleTOD-NLG. It is because the SimpleTOD adopts delexicalization preprocessing, which leads to worse performance. It is also observed by Yang, Li, and Quan (2020). Besides, we compare our model with strong baseline

²<https://www.mturk.com/>

Model	Extra Data	Inform	Success	BLEU	Combined
Sequicity (Lei et al. 2018b)		66.41	45.32	15.54	71.41
HRED-TS (Peng et al. 2019)		70.00	58.00	17.50	81.50
DAMD (Zhang, Ou, and Yu 2020)	✓	76.40	60.40	16.60	85.00
SOLOIST (Peng et al. 2020)	✓	85.50	72.90	16.54	95.74
SimpleTOD (Hosseini-Asl et al. 2020)		84.40	70.10	15.01	92.26
SimpleTOD-NLG		79.60	63.80	14.23	85.93
SimpleTOD-GPT-ACN (Ours)		85.80	72.10	15.52	94.47

Table 4: Model performance on MultiWOZ 2.0 End-to-End Response Generation.

DST-Picklist (Zhang et al. 2019a), which holds the state-of-the-art performance on this task. SimpleTOD-NLG and SimpleTOD-GPT-ACN both outperform the strong baseline methods, in which SimpleTOD-NLG achieves state-of-the-art performance with a 56.23 joint accuracy.

Dialogue Context-to-Text Generation. This sub-task requires the system to generate actions and responses with ground truth belief states and database results. As shown in Table 2, our proposed method SimpleTOD-GPT-ACN significantly outperforms two baselines SimpleTOD and SimpleTOD-NLG in all metrics, which verifies the effectiveness of our method. In addition to SimpleTOD, we compare our proposed model with LaRL, ARDM, DAMD, and SOLOIST. We can observe that our proposed method outperforms most of the baselines with the combined score. Besides, SOLOIST is pre-trained on a large-scale task-oriented dialogue corpus containing 8 popular datasets and fine-tuned on the MultiWOZ dataset. Similarly, our proposed method could achieve better performance by adding the pre-training stage. We leave it as future work.

End-to-End Modeling. Table 4 presents the results on response generation in end-to-end modeling setting, where the dialogue systems are supposed to generate belief state, dialogue action and system response sequentially. SimpleTOD-GPT-ACN still gains significant improvements compared with SimpleTOD and SimpleTOD-NLG, same as Dialogue Context-to-Text Generation task. Also, our proposed model SimpleTOD-GPT-ACN achieves the best compared with most end-to-end systems, including Sequicity, HERD-TS, and DAMD. These three sub-tasks performances also demonstrate the simplicity of our proposed method that optimizes all pipeline modules jointly.

Related Work

Instead of training separate modules for a pipelined task-oriented dialogue system, end-to-end neural architecture for task-oriented dialogue system recently becomes the new paradigm (Madotto, Wu, and Fung 2018; Lei et al. 2018b; Budzianowski and Vulić 2019; Mehri, Srinivasan, and Eskénazi 2019; Le et al. 2020; Zhang, Ou, and Yu 2020; Ham et al. 2020; Hosseini-Asl et al. 2020; Peng et al. 2020; Yang, Li, and Quan 2020). Sequicity (Lei et al. 2018b) proposes a two-stage CopyNet that completes dialogue state tracking and response generation jointly with a sequence-to-sequence architecture. Taking advantage of one-to-many property in

task-oriented dialogue, DAMD (Zhang, Ou, and Yu 2020) works as an effective network architecture to generate diverse appropriate dialogue responses with specific data augmentation method. With the emergence of large-scale pre-trained language models, TransferTransfo (Wolf et al. 2019b) and its successor (Budzianowski and Vulić 2019) first incorporate GPT-2 (Radford et al. 2019), a large-scale pre-trained model, into chit-chat dialogue system and task-oriented dialogue system respectively.

Inspired by the success of TransferTransfo, Ham et al. (2020) proposes an end-to-end neural architecture that simplifies all pipeline modules to a long sequence and wins DSTC8 Tack 1 with the best human evaluation performance. SimpleTOD (Hosseini-Asl et al. 2020) also views the dialogue process as a single auto-regressive model and designs a self-defined format for dialogue pipeline. In addition, SOLOIST (Peng et al. 2020) extends this idea with the introduction of an additional pre-training stage on a large-scale task-oriented dialogue corpus, while Yang, Li, and Quan (2020) generalizes this idea to an end-to-end setting on a dialogue session-level. Different from them, we propose to formulate the task-oriented dialogue system as a purely NLG task by removing complicated delexicalization preprocessing and special separators, based on which we incorporate the adapter and CopyNet modules into the GPT-2 model for the first time to achieve better overall performance.

Conclusion

In this paper, we propose to simplify the end-to-end task-oriented dialogue system as a purely natural language generation task to alleviate the inconsistency of the pre-trained model between the pre-training and fine-tuning stages. Based on this, we further incorporate two simple and lightweight modules, adapter and CopyNet modules, into the GPT-2 model to achieve better performance on transfer learning and dialogue entity generation. Experiments conducted on the DSTC8 Track 1 benchmark and MultiWOZ dataset demonstrate that our proposed method can fully exploit the pre-trained model and achieve significant improvements over state-of-the-art baselines.

In the future, one interesting direction is to explore the performance of in-domain incremental pre-training with our model as suggested in Gururangan et al. (2020). Besides, we would like to unify task-oriented and chit-chat dialogues with our proposed model.

References

- Bengio, Y.; Ducharme, R.; Vincent, P.; and Janvin, C. 2000. A Neural Probabilistic Language Model. In *J. Mach. Learn. Res.*
- Budzianowski, P.; and Vulić, I. 2019. Hello, It’s GPT-2—How Can I Help You? Towards the Use of Pretrained Language Models for Task-Oriented Dialogue Systems. *arXiv preprint arXiv:1907.05774*.
- Budzianowski, P.; Wen, T.-H.; Tseng, B.-H.; Casanueva, I.; Ultes, S.; Ramadan, O.; and Gasic, M. 2018. MultiWOZ - A Large-Scale Multi-Domain Wizard-of-Oz Dataset for Task-Oriented Dialogue Modelling. In *EMNLP*.
- Chen, W.; Chen, J.; Qin, P.; Yan, X.; and Wang, W. Y. 2019. Semantically Conditioned Dialog Response Generation via Hierarchical Disentangled Self-Attention. In *ACL*.
- Goel, R.; Paul, S.; and Hakkani-Tür, D. 2019. HyST: A Hybrid Approach for Flexible and Accurate Dialogue State Tracking.
- Gu, J.; Lu, Z.; Li, H.; and Li, V. O. K. 2016. Incorporating Copying Mechanism in Sequence-to-Sequence Learning. *ArXiv*, abs/1603.06393.
- Gururangan, S.; Marasović, A.; Swayamdipta, S.; Lo, K.; Beltagy, I.; Downey, D.; and Smith, N. A. 2020. Don’t Stop Pretraining: Adapt Language Models to Domains and Tasks. *ArXiv*, abs/2004.10964.
- Ham, D.; Lee, J.-G.; Jang, Y.; and Kim, K.-E. 2020. End-to-End Neural Pipeline for Goal-Oriented Dialogue Systems using GPT-2. In *ACL*.
- He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep residual learning for image recognition. In *CVPR*, 770–778.
- Hosseini-Asl, E.; McCann, B.; Wu, C.-S.; Yavuz, S.; and Socher, R. 2020. A simple language model for task-oriented dialogue. *arXiv preprint arXiv:2005.00796*.
- Houlsby, N.; Giurghi, A.; Jastrzebski, S.; Morrone, B.; De Laroussilhe, Q.; Gesmundo, A.; Attariyan, M.; and Gelly, S. 2019. Parameter-efficient transfer learning for NLP. *arXiv preprint arXiv:1902.00751*.
- Kim, S.; Galley, M.; Gunasekara, C.; Lee, S.; Atkinson, A.; Peng, B.; Schulz, H.; Gao, J.; Li, J.; Adada, M.; et al. 2019. The eighth dialog system technology challenge. *arXiv preprint arXiv:1911.06394*.
- Kim, S.; Yang, S.; Kim, G.; and Lee, S.-W. 2020. Efficient Dialogue State Tracking by Selectively Overwriting Memory. In *ACL*, 567–582.
- Kim, Y.-B.; Lee, S.; and Stratos, K. 2017. Onenet: Joint domain, intent, slot prediction for spoken language understanding. In *2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, 547–553. IEEE.
- Kingma, D. P.; and Ba, J. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.
- Le, H.; Sahoo, D.; Liu, C.; Chen, N. F.; and Hoi, S. C. 2020. Uniconv: A unified conversational neural architecture for multi-domain task-oriented dialogues. *arXiv preprint arXiv:2004.14307*.
- Le, H.; Socher, R.; and Hoi, S. C. 2019. Non-Autoregressive Dialog State Tracking. In *ICLR*.
- Lee, S.; Zhu, Q.; Takanobu, R.; Li, X.; Zhang, Y.; Zhang, Z.; chao Li, J.; Peng, B.; Li, X.; Huang, M.; and Gao, J. 2019. ConvLab: Multi-Domain End-to-End Dialog System Platform. *ArXiv*, abs/1904.08637.
- Lei, W.; Jin, X.; Kan, M.-Y.; Ren, Z.; He, X.; and Yin, D. 2018a. Sequicity: Simplifying Task-oriented Dialogue Systems with Single Sequence-to-Sequence Architectures. In *ACL*.
- Lei, W.; Jin, X.; Kan, M.-Y.; Ren, Z.; He, X.; and Yin, D. 2018b. Sequicity: Simplifying task-oriented dialogue systems with single sequence-to-sequence architectures. In *ACL*, 1437–1447.
- Madotto, A.; Wu, C.-S.; and Fung, P. 2018. Mem2Seq: Effectively Incorporating Knowledge Bases into End-to-End Task-Oriented Dialog Systems. In *ACL*.
- McCloskey, M.; and Cohen, N. J. 1989. Catastrophic Interference in Connectionist Networks: The Sequential Learning Problem. *Psychology of Learning and Motivation*, 24: 109–165.
- Mehri, S.; Srinivasan, T.; and Eskénazi, M. 2019. Structured Fusion Networks for Dialog. In *SIGdial*.
- Papineni, K.; Roukos, S.; Ward, T.; and Zhu, W.-J. 2002. Bleu: a Method for Automatic Evaluation of Machine Translation. In *ACL*.
- Peng, B.; Li, C.; Li, J.; Shayandeh, S.; Liden, L.; and Gao, J. 2020. SOLOIST: Few-shot Task-Oriented Dialog with a Single Pre-trained Auto-regressive Model. *arXiv preprint arXiv:2005.05298*.
- Peng, B.; Li, X.; Gao, J.; Liu, J.; and Wong, K. 2018. Integrating planning for task-completion dialogue policy learning. *ArXiv*, abs/1801.06176.
- Peng, S.; Huang, X.; Lin, Z.; Ji, F.; Chen, H.; and Zhang, Y. 2019. Teacher-Student Framework Enhanced Multi-domain Dialogue Generation. *ArXiv*, abs/1908.07137.
- Radford, A.; Wu, J.; Child, R.; Luan, D.; Amodei, D.; and Sutskever, I. 2019. Language models are unsupervised multi-task learners. *OpenAI blog*, 1(8): 9.
- Wolf, T.; Debut, L.; Sanh, V.; Chaumond, J.; Delangue, C.; Moi, A.; Cistac, P.; Rault, T.; Louf, R.; Funtowicz, M.; and Brew, J. 2019a. HuggingFace’s Transformers: State-of-the-art Natural Language Processing. *ArXiv*, abs/1910.03771.
- Wolf, T.; Sanh, V.; Chaumond, J.; and Delangue, C. 2019b. TransferTransfo: A Transfer Learning Approach for Neural Network Based Conversational Agents. *ArXiv*, abs/1901.08149.
- Wu, C.-S.; Madotto, A.; Hosseini-Asl, E.; Xiong, C.; Socher, R.; and Fung, P. 2019a. Transferable multi-domain state generator for task-oriented dialogue systems. *arXiv preprint arXiv:1905.08743*.
- Wu, Q.; Zhang, Y.; Li, Y.; and Yu, Z. 2019b. Alternating roles dialog model with large-scale pre-trained language models. *arXiv preprint arXiv:1910.03756*.
- Yang, Y.; Li, Y.-H.; and Quan, X. 2020. UBAR: Towards Fully End-to-End Task-Oriented Dialog Systems with GPT-2. *ArXiv*, abs/2012.03539.

Zhang, J.; Hashimoto, K.; Wu, C.-S.; Wan, Y.; Yu, P. S.; Socher, R.; and Xiong, C. 2020. Find or Classify? Dual Strategy for Slot-Value Predictions on Multi-Domain Dialog State Tracking. *ArXiv*, abs/1910.03544.

Zhang, J.-G.; Hashimoto, K.; Wu, C.-S.; Wan, Y.; Yu, P. S.; Socher, R.; and Xiong, C. 2019a. Find or classify? dual strategy for slot-value predictions on multi-domain dialog state tracking. *arXiv preprint arXiv:1910.03544*.

Zhang, Y.; Ou, Z.; and Yu, Z. 2020. Task-oriented dialog systems that consider multiple appropriate responses under the same context. In *AAAI*, volume 34, 9604–9611.

Zhang, Z.; Li, X.; Gao, J.; and Chen, E. 2019b. Budgeted policy learning for task-oriented dialogue systems. *arXiv preprint arXiv:1906.00499*.

Zhao, T.; Xie, K.; and Eskénazi, M. 2019. Rethinking Action Spaces for Reinforcement Learning in End-to-end Dialog Agents with Latent Variable Models. *ArXiv*, abs/1902.08858.