Enhancing Task-oriented Dialogue Systems with Generative Post-processing Networks

Atsumoto Ohashi **Ryuichiro Higashinaka**
Graduate School of Informatics, Nagoya University
ohashi.atsumoto.c0@s.mail.nagoya-u.ac.jp
higashinaka@i.nagoya-u.ac.jp

Abstract

Recently, post-processing networks (PPNs), which modify the outputs of arbitrary modules including non-differentiable ones in task-oriented dialogue systems, have been proposed. PPNs have successfully improved the dialogue performance by post-processing natural language understanding (NLU), dialogue state tracking (DST), and dialogue policy (Policy) modules with a classification-based approach. However, they cannot be applied to natural language generation (NLG) modules because the post-processing of utterances output by NLG modules requires a generative approach. In this study, we propose a new post-processing component for NLG, generative post-processing networks (GenPPNs). For optimizing GenPPNs via reinforcement learning, the reward function incorporates dialogue act contribution, a new measure to evaluate the contribution of GenPPN-generated utterances with regard to task completion in dialogue. Through simulation and human evaluation experiments based on the MultiWOZ dataset, we confirmed that GenPPNs improve the task completion performance of task-oriented dialogue systems[1].

1 Introduction

A typical task-oriented dialogue system has a pipelined structure consisting of four modules (Young et al., 2013; Zhang et al., 2020): natural language understanding (NLU), dialogue state tracking (DST), dialogue policy (Policy), and natural language generation (NLG). Many studies have used reinforcement learning (RL) to improve the task completion performance of an entire pipelined dialogue system by fine-tuning modules directly (Lee et al., 2021; Lin et al., 2021; Chen et al., 2023).

Recently, Ohashi and Higashinaka (2022b) proposed a novel method using Post-Processing Networks (PPNs) that can optimize pipelined dialogue systems that consist of arbitrary modules including non-differentiable ones (e.g., rule-based and Web API-based). Their method uses RL to optimize a neural-based component called a PPN, which modifies the output of each module. PPNs have been applied to three modules, namely NLU, DST, and Policy, and have been shown to improve the task completion performance of various pipelined systems. In PPNs, the post-processing of module outputs is treated as a binary classification task, i.e., adding or removing slots in the output of each module, and this classification task is modeled with a multi-layer perceptron (MLP). This means that the current PPNs could not be applied to NLGs, where the unit of output is not slots but a sequence of tokens, i.e., natural language.

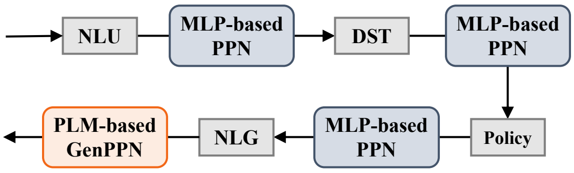


Figure 1: Diagrams of MLP-based PPN for NLU, DST, and Policy modules proposed by Ohashi and Higashinaka (2022b) and PLM-based GenPPN for NLG proposed in this study.

To overcome this limitation, we propose a Pre-trained Language Model (PLM)-based Generative Post-processing Network (GenPPN) that can post-process the output of NLGs in a manner similar to conventional PPNs (Figure 1). To optimize GenPPN via commonly used RL frameworks for PLMs (Ziegler et al., 2019; Stiennon et al., 2020), a reward for each utterance at each turn (an *utterance-level* reward) is required. In a task-oriented dialogue, however, a reward indicating success or failure is obtained only at the end of a multi-turn interaction (a *dialogue-level* reward). Therefore, we introduce a dialogue act (DA) contribution for distributing the dialogue-level reward to the utterance-

[1] Our code is publicly available at https://github.com/nu-dialogue/GenPPN

level reward. Here, a DA is the meaning representation of the information that NLG converts into an utterance, and DA contribution is a measure of how much the DA of each utterance contributes to the final task completion of the dialogue.

Experiments on the MultiWOZ dataset (Budzianowski et al., 2018) confirm that GenPPNs can improve the task performance of the entire dialogue system, regardless of the architecture of the NLG module. Furthermore, an ablation study reveals that the introduction of DA contribution is effective for learning GenPPNs to improve task completion. The contributions of this study are threefold:

- We propose the generative post-processing network (GenPPN) to modify the output utterances of the NLG module, which was impossible with conventional PPNs.
- We introduce DA contribution to optimize the GenPPN by evaluating the impact of each utterance on dialogue task completion.
- Simulation experiments on the MultiWOZ dataset confirm that the proposed GenPPN improves the task completion performance of the entire dialogue system, regardless of the architecture of the NLG module. We also validated that a GenPPN optimized using simulation is effective in human evaluation experiments.

2 Related Work

2.1 Optimization of Pipelined Task-oriented Dialogue Systems

Methods have been proposed to optimize the task completion performance of an entire pipelined system using RL. Zhao and Eskenazi (2016) and Li et al. (2017) optimized a Policy network implemented in MLP using the Deep Q-Network algorithm (Mnih et al., 2013) to achieve robustness against errors that occur in real dialogues. Mehri et al. (2019) proposed a method to add additional parameters to NLU, Policy, and NLG and optimize them using RL. By expressing a dialogue state output by a DST as a probability distribution, Lee et al. (2021) made the entire system differentiable and jointly optimized it via RL. A method of fine-tuning an NLU while optimizing a Policy in dialogue simulations was proposed (Lin et al., 2021). Tseng et al. (2021) proposed a domain-adaptive learning framework that simultaneously optimizes the Policy module of the dialogue system and the user simulator. An RL framework for online DST optimization was also proposed to improve dialogue management performance (Chen et al., 2023).

Instead of training each module, Ohashi and Higashinaka (2022b) proposed a generalized method that optimizes PPNs, classification-based models that modify the outputs of NLU, DST, and Policy, to enhance the task completion performance. In this paper, we propose a new generative-based PPN for post-processing NLG modules, which has not been supported by conventional PPNs.

2.2 Natural Language Generation Module for Task-oriented Dialogues

Conventional NLGs for task-oriented dialogues used template-based or rule-based methods (Walker et al., 2002; Stent et al., 2004). Later, data-driven methods using machine learning were proposed (Oh and Rudnicky, 2002; Angeli et al., 2010; Mairesse and Young, 2014) that do not require the cost of template and rule creation.

In recent years, many generative models based on deep learning have been proposed (Wen et al., 2016; Tran and Nguyen, 2017; Su et al., 2018). Wen et al. (2015) proposed an SC-LSTM that controls utterance generation using DA feature vectors and reading gates. SC-GPT (Peng et al., 2020) is the best NLG model of MultiWOZ. It achieves high performance by fine-tuning GPT-2 (Radford et al., 2019) on many task-oriented dialogue datasets such as MultiWOZ (Budzianowski et al., 2018) and the Schema-Guided Dialogue Dataset (Rastogi et al., 2020).

For task-oriented dialogue, it is crucial not only to generate natural utterances via maximum likelihood estimation (MLE) but also to accurately reflect the input DA's content. To achieve this, Balakrishnan et al. (2019) introduced a conditional decoding approach utilizing a tree-shaped semantic representation, enhancing the slot content in generated utterances. Furthermore, Li et al. (2020) offered a method to lower the slot error rate in utterances using an iterative RL framework for slot consistency. Ohashi and Higashinaka (2022a) presented a fine-tuning method for utterance generation that uses a user's NLU model so that the NLU can understand the DA accurately.

In all of the above studies, the optimization was performed at the utterance level using a fixed cor-

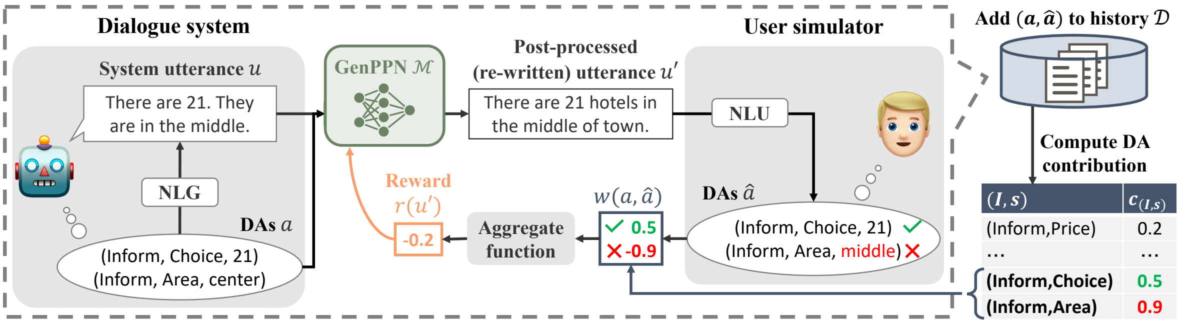


Figure 2: Schematic diagram of GenPPN and how it is optimized. GenPPN $\mathcal{M}$ rewrites utterance u generated by NLG of dialogue system into u'. This rewriting of $\mathcal{M}$ is optimized using reward $r(u')$ calculated on the basis of DA contribution $c_{(I,s)}$, so system's ability to complete task improves.

pus of utterances. In this study, we aim to optimize post-processing not only on the utterance level but also on the dialogue level to improve the task completion performance for multi-turn dialogues.

3 Method

3.1 Overview

Figure 2 shows a schematic diagram of GenPPN and how it is optimized. At the beginning of each interaction, the user is given a user goal consisting of a list of constraints to be informed to the system and information to be obtained from the system through the dialogue. During the dialogue, from the user's utterance at a certain turn t, the NLU and DST modules of the system first estimate the current belief state of the user. Then, on the basis of the belief state, the Policy module determines the next actions to be taken by the system as DAs a_t. The a takes a structure containing one or more triples of intent I, slot s, and value v:

$$a = \{(I_i, s_i, v_i) \mid i = 1, ..., |a|\} \tag{1}$$

The NLG module maps a_t to the system's utterance u_t. Here, GenPPN $\mathcal{M}$ post-processes, i.e., rewrites u_t. A prompt $x_t = \text{Prompt}(h_t, a_t, u_t)$ is created from the previous dialogue context h_t, a_t, and u_t, and $\mathcal{M}$ generates a new utterance u'_t: $u'_t \sim \mathcal{M}(x_t)$ (see Section 3.2 for details on GenPPN and the prompt format). The user then receives u'_t, estimates the system DAs $\hat{a}_t$, and the user's utterance is output for the next turn $t+1$ on the basis of the $\hat{a}_t$ and current status of the user goal. This exchange is repeated until the user goal is achieved or until the maximum number of turns is reached.

Let T be the number of turns at the end of a dialogue. In addition, the dialogue result $e \in \{0, 1\}$ of whether the user goal was achieved is determined, i.e., 0 means that the task failed, and 1 means that the task succeeded. The objective is to obtain the optimal parameters θ^* for the GenPPN $\mathcal{M}_\theta$ such that the expected value of e is maximized:

$$\theta^* = \arg\max_{\theta} \mathop{\mathbb{E}}_{U' \sim \mathcal{M}_\theta(X)} [e(U')] \tag{2}$$

where $U' = \{u'_1, u'_2, ..., u'_T\}$ are the system utterances sampled by $\mathcal{M}$ from prompts $X = \{x_1, x_2, ..., x_T\}$ at each turn.

Since the component to be trained is not the NLG itself but the GenPPN, our optimization is independent of the architecture and differentiability of NLG modules. In the following subsections, we describe the GenPPN, reward design for optimizing Eq. (2), and RL algorithm used.

3.2 Generative Post-processing with PLM

We assume that the model $\mathcal{M}$ of GenPPN is a language model based on the Transformer architecture (Vaswani et al., 2017). At turn t, the input prompt x_t is created from the previous dialogue context h_t, DA a_t, and system utterances u_t by using a hand-crafted prompt (specific prompts are shown in Section A.2 in the appendix).

Through RL, $\mathcal{M}$ learns to generate a rewritten system utterance u' such that the dialogue result e is maximized. However, even in the early stages of learning, if the system cannot produce at least reasonable system utterances, the dialogue always breaks down, and the training does not progress properly. For this reason, we adopt an instruction-tuned PLM (Wei et al., 2022; Chung et al., 2022; Taori et al., 2023), which has shown high performance on many NLP benchmarks including task-oriented dialogue modeling in few- and zero-shot settings (Pan et al., 2023; Hudeček and Dusek, 2023). Since the general PLM has a massive number of parameters, we use Low-Rank Adaptation (LoRA) (Hu et al., 2022), which has good parameter efficiency. That is, a small number of parameters θ is added to each self-attention module in the PLM, and only θ is optimized during training.

3.3 Reward with DA Contribution

Eq. (2) implies that only e or a dialogue-level reward at the end of a multi-turn dialogue should be used to evaluate the generated utterances U' for all T turns. However, since this reward is too sparse and it is not feasible to optimize $\mathcal{M}$, we approximate Eq. (2) by using the utterance-level reward r, which evaluates how much of an effect each utterance has on the final task completion:

$$\theta^* = \arg\max_{\theta} \mathop{\mathbb{E}}_{U' \sim \mathcal{M}_\theta(X)} \left[\sum_{u'_t \in U'}^{T} r(u'_t) \right] \qquad (3)$$

The role of NLG is to accurately convey DAs to the user, i.e., to generate utterances such that $a_t = \hat{a}_t$, but this kind of evaluation based on the consistency of a_t and $\hat{a}_t$ does not take into account e, so it cannot be used for r directly.

With this in mind, we design r by combining e with the consistency evaluation for a_t and $\hat{a}_t$. Specifically, we statistically measure the contribution of correctly conveying $(I, s, v) \in a_t$ to the user in terms of the impact on e on the basis of the dialogues we have sampled. Then, we give a contribution-weighted reward to the utterance u'_t that succeeds in conveying (I, s, v).

To realize this, first, at the end of each dialogue, triples $\{(a_t, \hat{a}_t, e) | t \in T\}$ consisting of a_t and $\hat{a}_t$ at each turn together with e are added to the DA history $\mathcal{D}$. Here, e is determined retrospectively on the basis of the outcome at the end of the dialogue; e of all turns in a successful dialogue is 1, $\{(a_t, \hat{a}_t, 1) | t \in T\}$, and e of all turns in a failed dialogue is 0, $\{(a_t, \hat{a}_t, 0) | t \in T\}$. Here, all $(a, \hat{a})$ pairs in $\mathcal{D}$ sampled so far are split into $\mathcal{S}$ and $\mathcal{F}$ depending on whether the task was successful:

$$\mathcal{S} = \{(a, \hat{a}) \mid (a, \hat{a}, e) \in D, e = 1\}$$
$$\mathcal{F} = \{(a, \hat{a}) \mid (a, \hat{a}, e) \in D, e = 0\}$$

Then, for each $(I, s, v) \in a_t$, the contribution $c_{(I,s)}$ of (I, s) is calculated as follows:

$$c_{(I,s)} = \frac{n^{\text{Rec},\mathcal{S}}_{(I,s)} + n^{\text{Unr},\mathcal{F}}_{(I,s)}}{n^{\text{Rec},\mathcal{S}}_{(I,s)} + n^{\text{Rec},\mathcal{F}}_{(I,s)} + n^{\text{Unr},\mathcal{S}}_{(I,s)} + n^{\text{Unr},\mathcal{F}}_{(I,s)}} \qquad (4)$$

where $n^{\text{Rec},\mathcal{S}}_{(I,s)}$ is the number of times that (I, s) has been correctly recognized by the user (subscript "Rec" for "recognized") in a successful dialogue $\mathcal{S}$:

$$n^{\text{Rec},\mathcal{S}}_{(I,s)} = \sum_{(a,\hat{a}) \in \mathcal{S}} \sum_{(I',s',v') \in a \cap \hat{a}} [(I, s) = (I', s')]$$

Similarly, $n^{\text{Unr},\mathcal{S}}_{(I,s)}$ indicates the number of times in $\mathcal{S}$ that (I, s) was not recognized by the user (subscript "Unr" for "unrecognized"), $\mathrm{n}^{\text{Rec},\mathcal{F}}_{(I,s)}$ indicates the number of times in $\mathcal{F}$ that (I, s) was recognized by the user, and $n^{\text{Unr},\mathcal{F}}_{(I,s)}$ indicates the number of times in $\mathcal{F}$ that (I, s) was not recognized by the user.

Since $c_{(I,s)}$ is the co-occurrence probability of (I, s) being recognized (or unrecognized) and the task being a success (or a failure), this quantifies how accurately conveying (I, s) leads to task success. Also, $c_{(I,s)}$ is a value that is updated as the number of dialogue samples increases during training. That is, $c_{(I,s)}$ can be computed adaptively to the current performance of the GenPPN at each learning step. Note that v is not taken into account for each count because the possible values of v are so large (e.g., instances of phone number, address, etc.) that counting them separately would yield unreliable statistics.

Finally, the reward $r(u'_t)$ for the utterance generated by GenPPN at turn t is calculated using this DA contribution $c_{(I,s)}$ as follows:

$$r(u'_t) = \text{Aggregate}(w(a_t, \hat{a}_t)) \qquad (5)$$

$$\begin{aligned} w(a_t, \hat{a}_t) = \{&\tau \cdot c_{(I,s)} \mid (I, s, v) \in a_t \cap \hat{a}_t\} \\ &\cup \{-\tau \cdot c_{(I,s)} \mid (I, s, v) \in a_t \cap \bar{\hat{a}}_t\} \end{aligned} \qquad (6)$$

Here, the DAs correctly recognized by the user $(a_t \cap \hat{a}_t)$ are given a default score τ, and conversely, the DAs not recognized by the user $(a \cap \bar{\hat{a}}_t)$ are given a negative score $-\tau$, and $w(a_t, \hat{a}_t)$ is the set of these scores weighted by each DA contribution $c_{(I,s)}$. The constant τ is a hyperparameter, and "Aggregate" is a function for aggregating $w(a_t, \hat{a}_t)$ into a scalar value for the reward. We design the following two types of Aggregate functions and empirically determine which one is better:

mean Output the mean of $w(a_t, \hat{a}_t)$

absmax Output the value with the highest absolute value among $w(a_t, \hat{a}_t)$. This is to emphasize the weighted score of (I, s, v) with the highest contribution.

At the beginning of learning, the number of DAs recorded in $\mathcal{D}$ is small, so it is expected that an appropriate $c_{(I,s)}$ cannot be calculated. Therefore, prior to learning, $(a, \hat{a})$ is sampled and recorded in $\mathcal{D}$ by conducting multiple dialogues between the dialogue system and the user simulator without using GenPPN.

3.4 Optimization via RL

Following Stiennon et al. (2020), the RL algorithm used in this method is Proximal Policy Optimization (PPO) (Schulman et al., 2017). As a value network, a linear layer that outputs a scalar value randomly initialized with the parameter ϕ is added, and the overall trainable parameters are set to $\psi = [\theta; \phi]$. Also, following (Ziegler et al., 2019), to prevent the probability distribution of $\mathcal{M}_\psi$ from deviating too far from that of the original $\mathcal{M}$ due to parameter updates and thus losing its naturalness, a Kullback-Leibler (KL) divergence penalty is added to $r(u'_t)$ as the final reward R_t for utterance u'_t at turn t:

$$R_t = r(u'_t) - \beta \log \frac{\mathcal{M}_\psi(u'_t|x_t)}{\mathcal{M}(u'_t|x_t)} \tag{7}$$

The clipped surrogate objective $\mathcal{L}(\psi)$ (Schulman et al., 2017) is used to optimize ψ with the advantage estimated from the reward and value network. Since we need the user's subjective understanding results $\hat{a}$, this study uses a user simulator to optimize the GenPPN. The learning algorithm is summarized in Algorithm 1 in the appendix.

4 Experiments

In our experiments, we first evaluated the effectiveness of GenPPNs using a user simulator. Then, using the optimized GenPPN, we conducted a dialogue evaluation experiment using human subjects.

4.1 Dataset and Platform

We evaluated the effectiveness of our GenPPN using a dialogue system and a user simulator implemented on the basis of the MultiWOZ dataset (Budzianowski et al., 2018). MultiWOZ is a task-oriented dialogue dataset between a clerk and a customer at a travel information center, collected in Wizard-of-OZ style. It contains a variety of tasks across a total of seven domains (attraction, hotel, hospital, restaurant, taxi, train, and police).

We used ConvLab-2 (Zhu et al., 2020), a platform for evaluating task-oriented dialogue systems that provide various modules for dialogue systems, a user simulator, and an evaluation tool. The following describes the dialogue system, user simulator, and user goals used in this experiment.

Dialogue System To make it easier to assess changes in the performance of utterance generation, the other modules (that is, NLU, DST, and Policy) should have stable performance. Therefore, we used the best-performing BERT (Devlin et al., 2019)-based NLU (Chen et al., 2019), rule-based DST, and rule-based Policy available in ConvLab-2. BERT-based NLU is a model that uses representations embedded by BERT to classify user intentions in user utterances and extract slots by sequence labeling. Rule-based DST and Policy are modules implemented using hand-crafted rules. Three models were selected as NLG modules (see Section 4.2 for the NLG models used), and GenPPN was applied to each of them to verify its generality.

User Simulator For the user simulator, we used a combination of BERT-based NLU, agenda-based Policy (Schatzmann et al., 2007), and template-based NLG. The agenda-based Policy models a user's behavior in MultiWOZ by using a stack-like agenda created using hand-crafted rules.

User Goal A user goal for each dialogue is randomly generated; the domains are randomly selected from one to three domains (out of all seven domains). The slots are also randomly selected on the basis of the slots' frequency in MultiWOZ.

4.2 NLG Baselines

We applied GenPPN to each of the three NLGs available in ConvLab-2 with different architectures in order to demonstrate that it works for a variety of NLGs. In addition, one NLG optimized with only utterance-level rewards, without considering task success, was also evaluated for comparison.

Template NLG An NLG model that uses the template utterances representing each DA. Because each utterance is carefully designed by hand, this model has significantly higher performance than other NLG baselines (Takanobu et al., 2020).

SC-LSTM (Wen et al., 2015) An LSTM-based model with a reading gate mechanism. This model takes binary feature vectors representing DAs as context and decodes utterances.

NLG	Task Success	Inform			Book Rate	Turn ↓	DA F1
		F1	Precision	Recall			
Template NLG	77.25	78.44	74.19	89.13	83.91	7.67	71.73
+ GenPPN$_{\text{mean}}$	77.93	79.75	**75.62**	89.41	84.33	7.63	76.98
+ GenPPN$_{\text{absmax}}$	**78.91***	**79.86**	75.58	**89.93**	**85.19**	**7.02**	**78.23**
SC-LSTM	54.00	67.45	68.07	72.48	67.69	11.65	60.56
+ GenPPN$_{\text{mean}}$	60.64**	75.40	75.42	81.01	**78.74**	9.42	**79.80**
+ GenPPN$_{\text{absmax}}$	**72.95****	**79.46**	**77.38**	**86.16**	78.46	**7.21**	79.08
SC-GPT	64.94	**78.06**	**73.60**	88.51	56.94	7.80	71.53
+ GenPPN$_{\text{mean}}$	**73.63****	76.54	71.81	87.79	**82.08**	8.03	73.07
+ GenPPN$_{\text{absmax}}$	73.34**	77.34	72.29	**89.03**	80.79	**7.50**	**73.72**
GPT-2 + RL	72.36	76.70	73.50	85.99	76.81	7.47	**81.17**
+ GenPPN$_{\text{mean}}$	74.02	77.10	73.87	86.82	79.19	7.54	80.98
+ GenPPN$_{\text{absmax}}$	**75.20****	**78.79**	**75.58**	**88.02**	**79.80**	**7.15**	80.08

Table 1: Performance of dialogue system with each NLG and with GenPPN applied to them. Subscripts in GenPPN indicate Aggregate function used in reward calculation. Highest score for each NLG is in bold. $*$ and $**$ indicate Task Success for GenPPN and were significantly better than original NLGs at $p < 0.05$ and < 0.01, respectively, in McNemar test with Bonferroni correction.

SC-GPT (Peng et al., 2020) A GPT-2 based model that generates utterances from DA text sequences. This has been trained on seven task-oriented dialogue corpora including MultiWOZ and the Schema-Guided Dialogue Dataset (Rastogi et al., 2020), and it is a SOTA on the MultiWOZ NLG benchmark.

GPT-2 + RL (Ohashi and Higashinaka, 2022a) A GPT-2-based NLG model optimized with an utterance-level reward. This model was trained to maximize the accuracy of a and $\hat{a}$ (as measured by F1) using the DA-system utterance pairs in the MultiWOZ corpus in an offline fashion.

Note that, since the purpose of our experiment is to verify whether GenPPN can enhance the performance of NLG irrespective of its architecture or base performance, the verification of methods that fine-tune NLG models themselves is outside the scope of this study.

4.3 Evaluation Metrics

In the evaluation of the dialogue system, we used common metrics for task-oriented dialogues: *Turn*, *Inform F1/Precision/Recall*, *Book Rate*, *Task Success*. Turn indicates the number of turns required for each dialogue; the smaller it is, the more efficiently the dialogue can be conducted. Inform F1/Precision/Recall indicate whether the system responded appropriately to the user's requests. Book Rate indicates whether the entity booked by the system correctly matched that of the user's goal. Task Success is evaluated by calculating whether Inform Recall and Match Rate both became one within the maximum number of turns. To evaluate the utterance-level performance of NLG, we additionally used *DA F1*, which measures the match rate of a and $\hat{a}$ at each turn by F1 (Ohashi and Higashinaka, 2022a; Guo et al., 2023).

4.4 Training GenPPN

Stanford Alpaca 7B (Taori et al., 2023) was used as the instruction-tuned PLM for the GenPPN. This model is a fine-tuned version of LLaMA-7B (Touvron et al., 2023) with a 52K instruction dataset. The input prompts include the dialogue history, the previous DA, the system utterances generated by NLG from that DA, and the instructions for rewriting that system utterance (specific prompts are shown in Section A.2 in the appendix). Throughout the experiment, we first sampled 1K dialogues to initialize the DA history and then trained 200 iterations. See Section A.3 for further training details.

For the evaluation, the GenPPN at the highest-reward iteration was used, and dialogue simulations were performed using 1,024 user goals prepared specifically for the test. We report the average scores in this paper.

4.5 Main Results

Table 1 shows the evaluation results[2]. For Template and SC-LSTM, GenPPN improved all evalua-

[2] We used the latest version of ConvLab-2 as of June 2023; we could not reproduce the scores reported on the leaderboard for some baseline systems. The main reason is probably due to the difference in the random seed and BERT NLU weights.

NLG	Success	Inf. F1	Book	DA F1
SC-LSTM + GenPPN	**72.95**	**79.46**	78.46	79.08
w/o adaptive $c_{(I,s)}$	62.11	74.80	78.15	70.12
w/o e	59.47	77.02	71.06	76.00
w/o $r(u')$	63.67	77.58	**80.83**	62.69
w/o context	68.46	76.25	74.17	**80.28**
w/o response	47.36	68.96	74.67	65.21

Table 2: Ablation results when applying GenPPN to SC-LSTM. "absmax" Aggregate function is used in calculation of rewards using DA contributions.

NLG	N	Success	Turns	Und.	App.	Sat.
SC-LSTM	54	33.33	17.72	**4.09**	**4.17**	**4.04**
+ GenPPN	50	**52.00***	**15.08****	4.04	4.14	3.98

Table 3: Human evaluation results. N is number of subjects who interacted with each system. "Und.," "App.," and "Sat." represent user's subjective evaluation of system's understanding, appropriateness of system utterance, and satisfaction with dialogue, respectively. Scores of SC-LSTM and our GenPPN were compared using the McNemar test; significant differences are indicated with $*$ ($p < 0.05$) and $**$ ($p < 0.01$).

tion metrics. The absmax aggregation function improved the final performance more than the mean. For SC-LSTM, Task Success was nearly 19 points better than the original SC-LSTM, especially when using absmax. These results indicate that a better strategy for evaluating each utterance is to prioritize learning to convey the DA with the highest contribution rather than to take the average. Considering that the improvement in Template NLG was only about 1.7%, the lower the performance of the original NLG, the more room there is for improvement by GenPPN.

For SC-GPT, Task Success, Book Rate, and Turn steadily improved. However, Inform Precision slightly decreased, unlike other cases where GenPPN was applied to other NLG modules. This suggests that GenPPN learned that improving Book Rate is more important for improving Task Success, even at the expense of Inform Precision.

GPT-2 + RL has a higher DA F1 than any of the GenPPNs. This is reasonable, given that GPT-2 + RL is optimized using DA F1 as a reward. GenPPN was able to further improve GPT-2 + RL's Task Success while the utterance-level metric DA F1 slightly decreased from the original score. This suggests that not only utterance-level rewards but dialogue-level rewards must be introduced to improve the task completion performance of the entire system.

Note that the performance of SC-LSTM + GenPPN and SC-GPT + GenPPN is lower than that of Template NLG baseline. However, the primary goal of our study is not to obtain an NLG model with SOTA performance but rather to enhance the performance of NLG irrespective of its architecture or its base performance. In our experiments, the dialogue performance of NLG models like SC-LSTM and SC-GPT, in addition to Template NLG, were improved using GenPPN, showing that our primary goal has been achieved.

4.6 Ablation Study

We analyzed the impact of each factor in the GenPPN optimization on the final performance. For the NLG model in this ablation study, we used SC-LSTM, which showed the greatest improvement in performance over the other NLGs in Table 1. Table 2 shows the results.

Adaptive DA Contribution "w/o adaptive $c_{(I,s)}$" is a reward design that does not update the DA history, and in all steps, uses the DA contribution calculated only from the 1,000 dialogues sampled prior to training. This resulted in a 10 points decrease in Task Success. Therefore, we found that it is important to constantly update the DA contributions as the GenPPN changes.

Dialogue-level Reward "w/o e" does not use DA contribution, and only an utterance-level reward based on the accuracy (F1) between a and $\hat{a}$ is used. That is, the reward design does not take into account the dialogue-level reward e related to task completion. As a result, Task Success decreased significantly, while DA F1 did not decrease much. Therefore, it was shown that the DA contribution is a useful factor in improving the task success rate.

Utterance-level Reward "w/o $r(u')$" does not use the utterance-level reward $r(u')$ but only the last dialogue evaluation result as a reward. That is, all utterances were given the dialogue result $e \in \{0, 1\}$ equally. Although Book Rate improved, Inform F1 did not, indicating that it is difficult to optimize GenPPN with only a sparse e reward, as described in Section 3.3.

Dialogue Context "w/o context" indicates that the input of GenPPN does not include the dialogue history. The slight decrease in Task Success, Inform F1, and Book Rate indicates that GenPPN should make use of the previous history to improve

Context	**User:** Hello, can you help me find a restaurant for my upcoming trip to Cambridge? Hmm, I 'll try Asian oriental food. I'm looking for an expensive restaurant. I also would like information on a place to eat in the centre. **System:** kymmoy serves asian oriental food. **User:** May I have the address? I would like their phone number.	
System DA	{(Inform, Attraction-Addr, pool way, whitehill road), (Inform, Attraction-Phone, 01223902088), (Inform, Restaurant-Addr, 52 Mill Road City Centre), (Inform, Restaurant-Phone, 01223311911)}	
System Response	**SC-LSTM:** Their address is	**+ GenPPN:** Their address is 52 Mill Road City Centre and phone number is 01223311911.
DA predicted by user	{}	{(Inform, Restaurant-Addr, 52 Mill Road City Centre), (Inform, Restaurant-Phone, 01223311911)}

Table 4: Response examples of systems using SC-LSTM and SC-LSTM + GenPPN in same context.

dialogue performance. Meanwhile, the improvement in DA F1 suggests that dialogue history is not necessary if we only want to optimize at the utterance level.

System Response "w/o response" does not rewrite the system utterance, but GenPPN generates it directly from the dialogue history and DA. It can be seen that the performance of all the methods significantly degraded. The reason for this is that the untrained GenPPN, i.e., Alpaca-7B, has never seen the mapping from DA to system utterance in MultiWOZ and thus has difficulty generating system utterances in a zero-shot setting. Therefore, it is considered more reasonable to learn to rewrite utterances rather than to generate them from scratch.

4.7 Human Evaluation

We tested whether GenPPN optimized by dialogue simulation is also effective for humans. In this experiment, we also used the system using SC-LSTM, which showed the best performance improvement over the other NLGs in Table 1. Over 50 crowd workers were recruited via Amazon Mechanical Turk, and each worker interacted once with one of the systems using SC-LSTM or SC-LSTM + GenPPN for up to 20 turns after being instructed about their user goal. Each worker had 20 turns to judge whether or not the task was successful; after 20 turns, the task was forced to fail. After the dialogue was completed, each worker was asked to rate the system's ability to understand the language (Und.), the accuracy of the system's responses (App.), and overall satisfaction with the dialogue (Sat.) on a 5-point Likert scale. See Section A.5 in the appendix for more details on the human evaluation settings.

Table 3 shows the results of the evaluations of each system. GenPPN significantly improved in terms of both Task Success and Turn, which are measures of task completion. However, the user's subjective ratings of understanding, appropriateness, and dialogue satisfaction showed no improvement, which is reasonable given that GenPPN is optimized for task completion only. This also means that GenPPN did not generate unnatural utterances to improve Task Success and Turn, which is considered a positive result. We would like to evaluate the effectiveness of GenPPN for other NLG baselines than SC-LSTM by humans in the future.

5 Case Study

Table 4 compares the behavior of two systems using SC-LSTM and using SC-LSTM + GenPPN in a dialogue. As a context, the user requested the address and phone number of the restaurant, but the Policy module of the dialogue system mistakenly decided to answer with the address and phone number of an attraction as well. Here, SC-LSTM was not able to generate sentences because there was no example in its training data, in which DAs in different domains occur at the same time. As a result, SC-LSTM failed to convey any information to the user. In contrast, GenPPN reflected the address and phone number of the restaurant in the post-processed utterance, and as a result, the information was correctly conveyed as requested by the user, and the task was successful.

It is worth noting that the utterance generated by post-processing does not contain any information about the attraction. This is probably because GenPPN judged from the dialogue context that the information about the attraction was not what the user requested, and that conveying this piece of information would interfere with the task completion. These results indicate that GenPPN can correct errors propagated from preceding modules beyond the realm of NLG so that the entire system's performance improves.

6 Summary and Future Work

Post-Processing Networks (PPNs), which modify the outputs of arbitrary modules including non-differentiable ones in task-oriented dialogue systems, have been applied to NLU, DST, and Policy modules. In this paper, we proposed Generative Post-processing Networks (GenPPNs) for NLG modules. We optimized GenPPN toward the task completion performance of the entire system by using DA contribution-based rewards. Experiments on the MultiWOZ dataset and dialogue simulations confirmed that our GenPPN could improve the task success rate of various dialogue systems, regardless of the NLG architecture. It was also confirmed that a GenPPN optimized with a dialogue simulation was effective in a human evaluation experiment.

In the future, we would like to integrate our GenPPN with the existing PPNs of NLU, DST, and Policy to realize the post-processing of all modules and further improve the systems performance. Since GenPPN is a generative model, we would like to extend it not only to text but also to the post-processing of speech recognition and speech synthesis modules in spoken dialogue systems.

Limitations

Our work has several limitations, which we aim to address in our future work.

First, this study implemented, trained, and evaluated the GenPPN using only the MultiWOZ dataset. Therefore, the applicability of the GenPPN to task-oriented dialogues other than MultiWOZ has not been verified. In particular, the DA-dependent reward design in this study needs to be improved for application to dialogues such as open-domain chats, where ontologies such as intent, slot, and value are not defined.

Second, this study used a user simulator for training the GenPPN. When applied to a new domain, the cost of implementing a user simulator is likely to be high. Therefore, a user simulator-free learning method is needed in this respect. In addition, a GenPPN optimized by a user simulator learns user-simulator-specific utterances, which may not be the best utterances for humans. To learn the optimal GenPPN for humans, it is essential to design a reward model that takes humans into account, using a human-in-the-loop approach.

Third, this study required running a PLM with a relatively large parameter size. During inference, in addition to the system's response generation, the GenPPN is required to rewrite utterances, which is expected to increase the operation cost and generation time. In addition, more computational resources are required during learning. Therefore, it is necessary to study ways to reduce learning and inference costs.

Ethics Statement

We used the publicly available MultiWOZ dataset in full compliance with its terms of use. Our use of the LLaMA language model was also entirely consistent with the prescribed usage guidelines. No private or confidential data was used at any stage of the research. For our human evaluation experiment, we underwent and passed an ethical review from our institution and strictly adhered to its rules and guidelines. The anonymity, privacy, and rights of the subjects were preserved throughout. We acknowledge that there are potential ethical concerns associated with the use of large pre-trained language models, such as the risk of generating harmful or discriminatory statements.

Acknowledgments

This work was supported by JSPS KAKENHI Grant Number 19H05692. We used the computational resources of the supercomputer "Flow" at the Information Technology Center, Nagoya University.

References

Gabor Angeli, Percy Liang, and Dan Klein. 2010. A simple domain-independent probabilistic approach to generation. In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*, pages 502–512.

Anusha Balakrishnan, Jinfeng Rao, Kartikeya Upasani, Michael White, and Rajen Subba. 2019. Constrained decoding for neural NLG from compositional representations in task-oriented dialogue. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 831–844.

Paweł Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Iñigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gašić. 2018. MultiWOZ - A Large-Scale Multi-Domain Wizard-of-Oz Dataset for Task-Oriented Dialogue Modelling. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 5016–5026.

Qian Chen, Zhu Zhuo, and Wen Wang. 2019. BERT for Joint Intent Classification and Slot Filling. *arXiv preprint arXiv:1902.10909*.

Zhi Chen, Lu Chen, Xiang Zhou, and Kai Yu. 2023. Deep reinforcement learning for on-line dialogue state tracking. In *Proceedings of Man-Machine Speech Communication*, pages 278–292.

Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2022. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4171–4186.

Ao Guo, Atsumoto Ohashi, Yuya Chiba, Yuiko Tsunomori, Ryu Hirai, and Ryuichiro Higashinaka. 2023. Personality-aware natural language generation for task-oriented dialogue using reinforcement learning. In *Proceedings of the 32nd IEEE International Conference on Robot and Human Interactive Communication*.

Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2022. LoRA: Low-rank adaptation of large language models. In *Proceedings of International Conference on Learning Representations*.

Vojtěch Hudeček and Ondrej Dusek. 2023. Are large language models all you need for task-oriented dialogue? In *Proceedings of the 24th Meeting of the Special Interest Group on Discourse and Dialogue*, pages 216–228, Prague, Czechia. Association for Computational Linguistics.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A Method for Stochastic Optimization. *arXiv preprint arXiv:1412.6980*.

Hwaran Lee, Seokhwan Jo, Hyungjun Kim, Sangkeun Jung, and Tae-Yoon Kim. 2021. SUMBT+LaRL: Effective Multi-Domain End-to-End Neural Task-Oriented Dialog System. *IEEE Access*, pages 116133–116146.

Xiujun Li, Yun-Nung Chen, Lihong Li, Jianfeng Gao, and Asli Celikyilmaz. 2017. End-to-End Task-Completion Neural Dialogue Systems. In *Proceedings of the Eighth International Joint Conference on Natural Language Processing*, pages 733–743.

Yangming Li, Kaisheng Yao, Libo Qin, Wanxiang Che, Xiaolong Li, and Ting Liu. 2020. Slot-consistent nlg for task-oriented dialogue systems with iterative rectification network. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 97–106.

Zichuan Lin, Jing Huang, Bowen Zhou, Xiaodong He, and Tengyu Ma. 2021. Joint System-Wise Optimization for Pipeline Goal-Oriented Dialog System. *arXiv preprint arXiv:2106.04835*.

François Mairesse and Steve Young. 2014. Stochastic Language Generation in Dialogue using Factored Language Models. *Computational Linguistics*, pages 763–799.

Shikib Mehri, Tejas Srinivasan, and Maxine Eskenazi. 2019. Structured Fusion Networks for Dialog. In *Proceedings of the 20th Annual SIGdial Meeting on Discourse and Dialogue*, pages 165–177.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. 2013. Playing Atari with Deep Reinforcement Learning. *arXiv preprint arXiv:1312.5602*.

Alice H Oh and Alexander I Rudnicky. 2002. Stochastic natural language generation for spoken dialog systems. *Computer Speech & Language*, pages 387–407.

Atsumoto Ohashi and Ryuichiro Higashinaka. 2022a. Adaptive natural language generation for task-oriented dialogue via reinforcement learning". In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 242–252.

Atsumoto Ohashi and Ryuichiro Higashinaka. 2022b. Post-processing networks: Method for optimizing pipeline task-oriented dialogue systems using reinforcement learning. In *Proceedings of the 23rd Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 1–13.

Wenbo Pan, Qiguang Chen, Xiao Xu, Wanxiang Che, and Libo Qin. 2023. A preliminary evaluation of chatgpt for zero-shot dialogue understanding. *arXiv preprint arXiv:2304.04256*.

Baolin Peng, Chenguang Zhu, Chunyuan Li, Xiujun Li, Jinchao Li, Michael Zeng, and Jianfeng Gao. 2020. Few-shot Natural Language Generation for Task-Oriented Dialog. In *Findings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 172–182.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Abhinav Rastogi, Xiaoxue Zang, Srinivas Sunkara, Raghav Gupta, and Pranav Khaitan. 2020. Towards Scalable Multi-Domain Conversational Agents: The Schema-Guided Dialogue Dataset. In *Proceedings of the 34th AAAI Conference on Artificial Intelligence*, pages 8689–8696.

Jost Schatzmann, Blaise Thomson, Karl Weilhammer, Hui Ye, and Steve Young. 2007. Agenda-Based User Simulation for Bootstrapping a POMDP Dialogue System. In *Proceedings of Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics*, pages 149–152.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. 2017. Proximal Policy Optimization Algorithms. *arXiv preprint arXiv:1707.06347*.

Amanda Stent, Rashmi Prasad, and Marilyn Walker. 2004. Trainable Sentence Planning for Complex Information Presentations in Spoken Dialog Systems. In *Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics*, pages 79–86.

Nisan Stiennon, Long Ouyang, Jeffrey Wu, Daniel Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul F Christiano. 2020. Learning to summarize with human feedback. In *Proceedings of Advances in Neural Information Processing Systems*, pages 3008–3021.

Shang-Yu Su, Kai-Ling Lo, Yi-Ting Yeh, and Yun-Nung Chen. 2018. Natural Language Generation by Hierarchical Decoding with Linguistic Patterns. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 61–66.

Ryuichi Takanobu, Qi Zhu, Jinchao Li, Baolin Peng, Jianfeng Gao, and Minlie Huang. 2020. Is Your Goal-Oriented Dialog Model Performing Really Well? Empirical Analysis of System-wise Evaluation. In *Proceedings of the 21st Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 297–310.

Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. 2023. Stanford Alpaca: An Instruction-following LLaMA model. `https://github.com/tatsu-lab/stanford_alpaca`.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023. LLaMA: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*.

Van-Khanh Tran and Le-Minh Nguyen. 2017. Natural Language Generation for Spoken Dialogue System using RNN Encoder-Decoder Networks. In *Proceedings of the 21st Conference on Computational Natural Language Learning*, pages 442–451.

Bo-Hsiang Tseng, Yinpei Dai, Florian Kreyssig, and Bill Byrne. 2021. Transferable Dialogue Systems and User Simulators. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing*, pages 152–166.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. In *Proceedings of Advances in Neural Information Processing Systems*, pages 5998–6008.

Marilyn A. Walker, Owen C. Rambow, and Monica Rogati. 2002. Training a sentence planner for spoken dialogue using boosting. *Computer Speech & Language*, 16(3):409–433.

Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V Le. 2022. Finetuned language models are zero-shot learners. In *Proceedings of International Conference on Learning Representations*.

Tsung-Hsien Wen, Milica Gašić, Nikola Mrkšić, Lina M. Rojas-Barahona, Pei-Hao Su, David Vandyke, and Steve Young. 2016. Multi-domain Neural Network Language Generation for Spoken Dialogue Systems. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 120–129.

Tsung-Hsien Wen, Milica Gašić, Nikola Mrkšić, Pei-Hao Su, David Vandyke, and Steve Young. 2015. Semantically Conditioned LSTM-based Natural Language Generation for Spoken Dialogue Systems. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1711–1721.

Steve Young, Milica Gašić, Blaise Thomson, and Jason D. Williams. 2013. Pomdp-based statistical spoken dialog systems: A review. *Proceedings of the IEEE*, pages 1160–1179.

Zheng Zhang, Ryuichi Takanobu, Qi Zhu, MinLie Huang, and XiaoYan Zhu. 2020. Recent advances and challenges in task-oriented dialog systems. *Science China Technological Sciences*, pages 1–17.

Tiancheng Zhao and Maxine Eskenazi. 2016. Towards End-to-End Learning for Dialog State Tracking and Management using Deep Reinforcement Learning. In *Proceedings of the 17th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 1–10.

Qi Zhu, Zheng Zhang, Yan Fang, Xiang Li, Ryuichi Takanobu, Jinchao Li, Baolin Peng, Jianfeng Gao, Xiaoyan Zhu, and Minlie Huang. 2020. ConvLab-2: An Open-Source Toolkit for Building, Evaluating, and Diagnosing Dialogue Systems. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 142–149.

Daniel M Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. 2019. Fine-tuning language models from human preferences. *arXiv preprint arXiv:1909.08593*.

A Appendix

A.1 GenPPN Optimization Algorithm

Algorithm 1 Optimization of GenPPN via PPO

```
Require: Dialogue system $\mathcal{A}$, User simulator $\mathcal{U}$
Require: GenPPN $\mathcal{M}$
Initialize DA history $\mathcal{D}$ by sampling several dialogues using $\mathcal{A}$ and $\mathcal{U}$
Prepare $\mathcal{M}_{\psi_{\text{old}}}$ with randomly initialized LoRA parameters $\theta$ and value network parameters $\phi$
for each training iteration do
    while #turns does not reach batch size do
        Sample a dialogue and $(a_t, \hat{a}_t)$ for each turn $t$ using $\mathcal{A}$, $\mathcal{M}_{\psi_{\text{old}}}$, and $\mathcal{U}$
        Obtain final evaluation result $e$
        Add $(a_t, \hat{a}_t, e)$ of each $t$ to $\mathcal{D}$
    end while
    Calculate reward $R_t$ using Eq. (7)
    Compute advantage estimates
    Optimize $\mathcal{L}(\psi)$ with a certain epoch and mini-batch size
    Update $\psi_{\text{old}} \leftarrow \psi$
end for
```

A.2 Prompt for GenPPN

At a given turn t, the input prompts to GenPPN include the DA a_t output by the system's Policy module and the original system utterance u_t generated by the NLG from a_t. As the dialogue context, we also included user utterances at $t-1$, DAs a_{t-1}, system utterances u'_{t-1} generated by GenPPN, and user utterances at t. The format of the instructional text in the prompts was adapted from the phrases in the Alpaca dataset (Taori et al., 2023). Examples of prompts are shown in Figure 3. In our experiments, due to the maximum input length of the model, the dialogue history was limited to the past one turn.

A.3 Details of GenPPN Training

As the model for GenPPN, we used Stanford Alpaca-7B trained weights for the prompts, which are publicly available on HuggingFace Hub[3]. The maximum number of input tokens for a prompt was set to 512, and the maximum number of generated tokens was set to 128. When generating utterances, sampling was performed with the beam size set to 1, temperature to 1.0, and top-p to 1.0. The τ used in the reward calculation (Eq. (6)) was set to 1.

Hyperparameter Name		Value
LoRA	Target projection matrix of self-attention module	query, key value, output
	Rank	16
	Scaling factor α	16
PPO	Total iterations	200
	Total batch size	512
	Epoch	4
	Total mini-batch size	32
	Learning rate	1e-5
	Optimizer	Adam
	Discount factor γ	1.0
	GAE factor λ	0.95
	Clipping ϵ	0.2
	Coef. of KL penalty β	0.01

Table 5: Hyperparameter settings

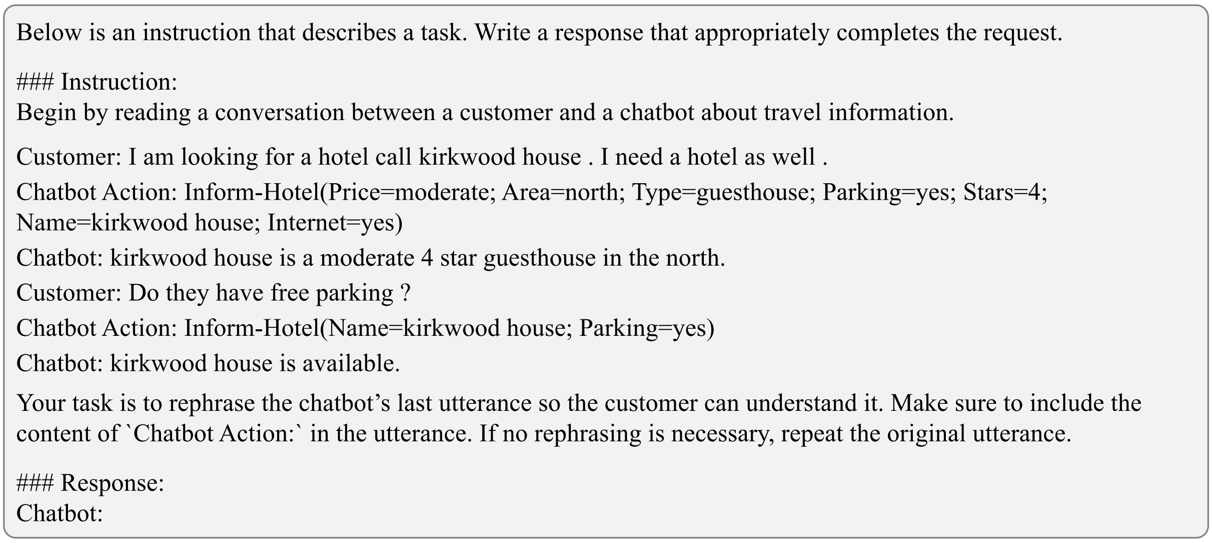
Table 5 shows the hyperparameters of LoRA and PPO during training. Throughout the experiment, we first sampled 1,000 dialogues to initialize the DA history and then trained 200 iterations, with a batch size of 512 turns per iteration (corresponding to about 50 dialogues) and a fixed learning rate of 1e-5 with Adam Optimizer (Kingma and Ba, 2014). We used 16 × V100 32-GB computational resources. Training of 200 iterations took about seven hours to complete.

Figure 4 shows the training curves when GenPPN is applied to Template NLG, SC-LSTM, SC-GPT, and GPT-2 + RL respectively. The figure shows that both the reward and Task Success are low at the start of training (i.e., before RL is applied) and improve as RL progresses, which means that fine-tuning LLMs with RL is important for our GenPPN. We have yet to investigate the effects of instruction tuning. We plan to validate this by comparing the performance of instruction-tuned models other than Alpaca (e.g., Flan-T5 (Chung et al., 2022)) and non-instruction-tuned models (e.g., LLaMA (Touvron et al., 2023)).

A.4 Additional Ablations

In addition to the study on SC-LSTM in Section 4.6, we conducted the same ablation study on two higher-performing NLGs: Template NLG and GPT-2 + RL. Table 6 shows the results. In Template NLG, the improvement with GenPPN was the greatest when no context was used. Nevertheless, for both Template NLG and GPT-2 w/ RL, there was a trend showing that adaptive DA contribution was important for performance improvement.

[3] https://huggingface.co/tatsu-lab/alpaca-7b-wdiff



Below is an instruction that describes a task. Write a response that appropriately completes the request.

Instruction:
Begin by reading a conversation between a customer and a chatbot about travel information.

Customer: I am looking for a hotel call kirkwood house . I need a hotel as well .

Chatbot Action: Inform-Hotel(Price=moderate; Area=north; Type=guesthouse; Parking=yes; Stars=4; Name=kirkwood house; Internet=yes)

Chatbot: kirkwood house is a moderate 4 star guesthouse in the north.

Customer: Do they have free parking ?

Chatbot Action: Inform-Hotel(Name=kirkwood house; Parking=yes)

Chatbot: kirkwood house is available.

Your task is to rephrase the chatbot's last utterance so the customer can understand it. Make sure to include the content of `Chatbot Action:` in the utterance. If no rephrasing is necessary, repeat the original utterance.

Response:
Chatbot:

Figure 3: Examples of prompts entered into GenPPN. "Customer:", "Chatbot Action:", and "Chatbot:" denote user utterance, system DA, and system utterance at each turn, respectively.

NLG	Success	Inf. F1	Book	DA F1
Template NLG + GenPPN	78.91	79.86	85.19	78.23
w/o adaptive $c_{(I,s)}$	76.27	78.07	83.00	75.05
w/o e	77.15	79.29	83.30	76.89
w/o $r(u')$	71.09	78.14	80.89	63.68
w/o context	**79.00**	**79.92**	**85.29**	**78.58**

(a) Template NLG

NLG	Success	Inf. F1	Book	DA F1
GPT-2 + RL + GenPPN	**75.20**	**78.79**	79.80	80.08
w/o adaptive $c_{(I,s)}$	67.68	76.75	79.31	81.04
w/o e	72.56	76.57	77.36	80.63
w/o $r(u')$	72.85	78.52	**81.82**	71.15
w/o context	73.24	77.18	77.14	**85.11**

(b) GPT-2 + RL

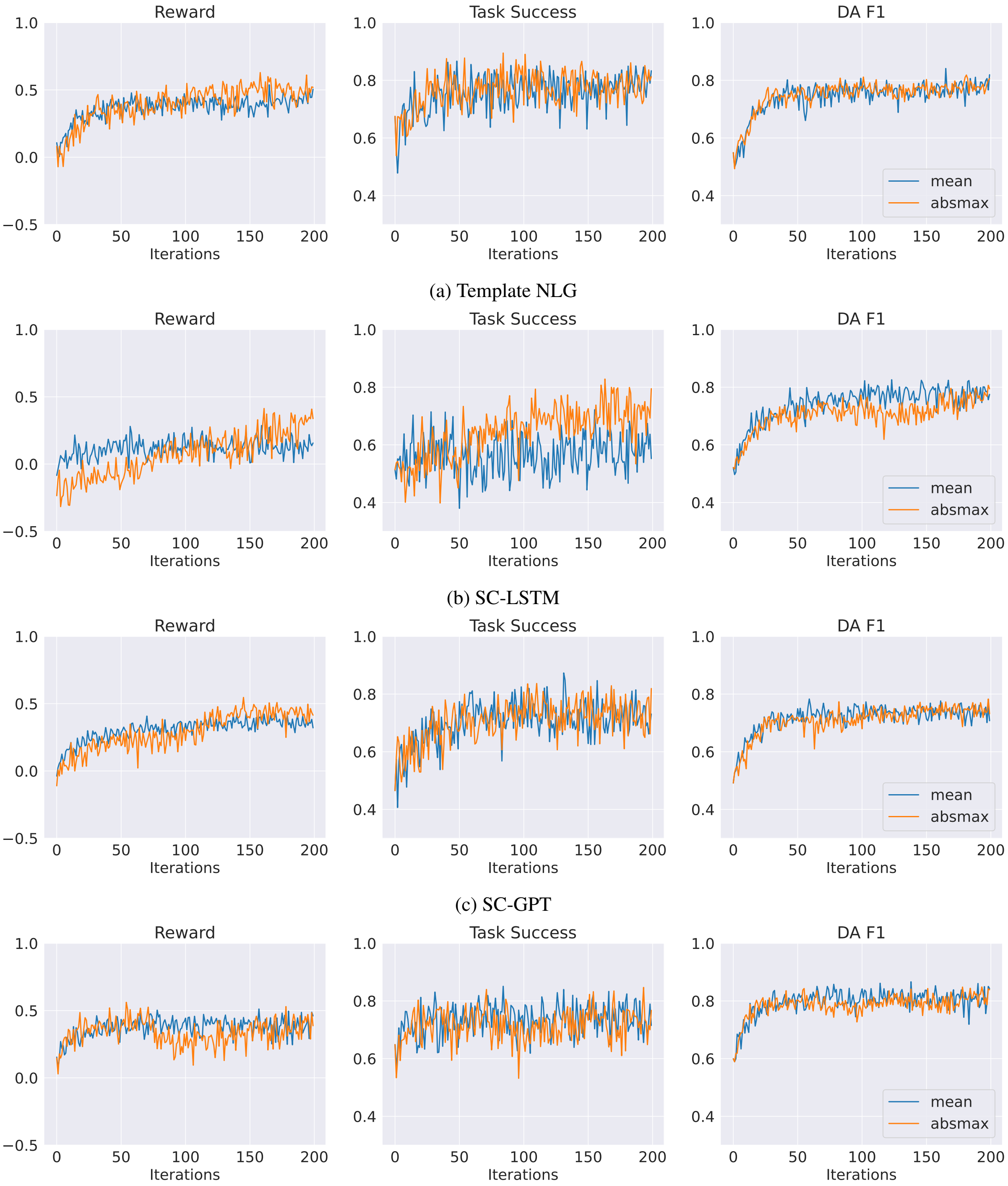
Table 6: Ablation results when applying GenPPN to Template NLG and GPT-2 + RL. "absmax" Aggregate function is used in calculation of rewards using DA contributions. **Bold** and underlined scores indicate top and second top, respectively.

A.5 Details of Human Evaluation

In collecting participants for the human evaluation via Amazon Mechanical Turk (AMT), we recruited workers who met the following four conditions: (1) had residence in an English-speaking county, (2) had at least 100 completed Human-Intelligence Tasks (HIT) on AMT, (3) had an acceptance rate of 95% or higher on the HIT on AMT, and (4) answered all five common sense questions correctly.

In the experimental procedure, each worker was first instructed about a certain user goal. The user goal was randomly generated by a program as in the dialogue simulation. Considering the high comprehension ability of humans, the number of domains included in the user goal was set to 3, which is a higher difficulty level than in the simulation. After reading the user goal, the workers interacted with either the system using SC-LSTM or the system using SC-LSTM + GenPPN. The maximum number of turns in the dialogue was 20, and each worker judged whether the task was completed within the maximum number of turns. After 20 turns, the task was forced to fail. After the dialogue, the workers answered the three-question questionnaire described in Section 4.7.

Considering that each HIT should take about 10 minutes to complete, the reward was set at $2, and the time limit was 30 minutes. The number of subjects was not equal because the system was randomly selected each time, resulting in 54 evaluators for SC-LSTM and 50 evaluators for SC-LSTM + GenPPN.



(a) Template NLG

(b) SC-LSTM

(c) SC-GPT

(d) GPT-2 + RL

Figure 4: Training curves when GenPPN is applied to each NLG. Either "mean" or "absmax" is used as aggregation function. "Reward" indicates value calculated by Eq. (5).