Toward Self-Learning End-to-End Task-Oriented Dialog Systems

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Abstract

End-to-end task bots are typically learned over a static and usually limited-size corpus. However, when deployed in dynamic, changing, and open environments to interact with users, task bots tend to fail when confronted with data that deviate from the training corpus, i.e., out-of-distribution samples. In this paper, we study the problem of automatically adapting task bots to changing environments by learning from human-bot interactions with minimum or zero human annotations. We propose SL-AGENT¹, a novel self-learning framework for building end-to-end task bots. SL-AGENT consists of a dialog model and a pre-trained reward model to predict the quality of an agent response. It enables task bots to automatically adapt to changing environments by learning from the unlabelled human-bot dialog logs accumulated after deployment via reinforcement learning with the incorporated reward model. Experimental results on four well-studied dialog tasks show the effectiveness of SL-AGENT to automatically adapt to changing environments, using both automatic and human evaluations. We will release code and data for further research.

1 Introduction

The most common approach of building end-to-end task-oriented dialog systems is to train neural models to imitate human behaviors in fixed task-specific annotated corpora (Gao et al., 2018; Zhang et al., 2020). Existing state-of-the-art approaches usually adopt Pre-trained Language Models (PLMs) (Peng et al., 2020a; Ham et al., 2020; Hosseini-Asl et al., 2020) to build end-to-end dialog systems. However, these data-driven approaches assume an independent and identically distributed (IID) data setting², i.e., a static environment³, and usually exhibit a tendency of failure, when confronted with out-of-distribution (OOD) examples in real-world scenarios, i.e., changing environments.

In the context of task-oriented dialog systems, changing environments are quite common and arise from the following two aspects: (i) unseen user behaviors – real users may query with unseen language patterns and unknown user goals (i.e., unseen slot values and dialog flows) of the designated tasks outside the pre-built training corpora (Liu et al., 2018; Peng et al., 2020b). For example, real users may query entities in the database but not covered by the training examples. (ii) task definition extensions – dialog systems need to handle new functions or new tasks as user and business requirements evolve, i.e., add new slot types (Lipton et al., 2018; Gasic et al., 2014). For example, a restaurant bot designed for the table-booking service may also encounter queries about delivery service after deployment. These human-bot interactions accumulate...
mulated after deployment are cheap, dynamic and contain useful information (Hancock et al., 2019), *i.e.,* unseen user behaviors are related to the training examples and the probabilistic dialog model may generate appropriate responses. As shown in the upper part of Figure 1, when user queries casually about address, the system fails to provide address in the second response, but gives it in the third response, when user queries in a detailed way (similar to the training examples). Therefore, rather than merely imitating human behaviors in a fixed corpus, task bots are desired to spontaneously learn from the interactions with real users, progressively improve and adapt after being deployed in dynamic and constantly changing environments.

There are several attempts to leverage human-bot interactions to improve task bots in changing environments. For example, Liu et al. (2018); Shah et al. (2018); Dai et al. (2020) propose to query humans for adequate feedback scores or annotations. However, it relies on human annotations or user feedback, which can be costly and sometimes users are unwilling to give any feedback. In addition, these works center on dialog policy optimization or retrieval-based task bots. Automatically adapting task bots to changing environments is imperative for end-to-end dialog model yet under-explored. Furthermore, these works usually omit task definition extensions.

In this paper, we propose SL-AGENT, a novel self-learning framework for building end-to-end task bots in a more realistic changing environment setting with minimum or zero human annotations. It consists of a neural dialog model and a pre-trained reward model, where the dialog model generates responses and the reward model judges the quality of agent responses. Specifically, we devise a data augmentation strategy to construct positive and negative examples based on the given dialog training corpus to endow the reward model with the capability to judge the quality of responses for unlabeled human-bot dialog logs. The bot (including dialog model and reward model) is first trained with the same available training data, then deployed to converse with real users and collect human-bot dialog logs. After that, as shown in the lower part of Figure 1, the bot is refined with the unlabeled human-bot dialog logs via reinforcement learning, where the response quality is judged by the reward model. In this way, the bot can automatically adapt to unseen user behaviors, without extra human annotations. Regarding the problem of extensions in task definitions, machine teaching is utilized to correct representative failed dialogs with minimum human annotations to provide necessary instructions on how to handle new functions. After that, the bot quickly adapts to new functions through the self-learning procedure.

Our contributions are summarized as below:

- We propose a new research problem *i.e.,* how to enable task bots to automatically adapt themselves to changing environments by learning from interactions with minimum or zero human annotations.
- We propose a novel self-learning framework SL-AGENT that equips with a pre-trained reward model trained by the devised data-augmentation strategy to build generative end-to-end task bots in a realistic changing environment setting, with minimum or zero human annotations.
- We conduct comprehensive experiments on four datasets to demonstrate the effectiveness of SL-AGENT for enabling automatic adaptation to changing environments by learning from the unlabeled human-bot dialog logs using both automatic and human evaluations.

2 Related Work

### RL for Dialog Policy Learning

Reinforcement learning has been widely applied to dialog systems for policy optimization. Young et al. (2013); Peng et al. (2018, 2017); Liu and Lane (2017); Gasic et al. (2014); Tseng et al. (2021) formulate dialog policy learning as a sequential problem and use REINFORCE (Williams, 1992) and/or Q-learning (Watkins and Dayan, 1992) to optimize the dialog policy. SL-AGENT utilizes a similar REINFORCE algorithm but focuses on generative end-to-end optimization.

### Adapting to Changing Environments for Dialog Systems

Several attempts have been made to deal with changing environments after deployment. Rajendran et al. (2019); Dai et al. (2020) propose to learn from the human-bot interactions but requires lots of human corrections. Shah et al. (2018); Liu et al. (2018); Gašić et al. (2011); Gasic et al. (2014) propose to learn from human-bot interactions via reinforcement learning based on the queried human feedback scores after each dialog. To reduce the efforts of querying humans, Su et al. (2016)
introduces a session-level Bi-LSTM reward model trained with extra pre-collected classification corpus to predict the task success of each dialog. Nevertheless, session-level reward model may underestimate the quality of responses in single dialog turns. Different from the works mentioned above, SL-A\textsuperscript{GENT} leverages a turn-level pre-trained reward model built on the given dialog corpus using the devised data augmentation approach and focuses on generative end-to-end dialog systems. Another line of research is using data-augmentation methods to generate diverse user behaviors during the training stage (Gao et al., 2020; Li et al., 2020b). Additionally, Madotto et al. (2020); Liu et al. (2021) continually collect extra labeled data to train task bots but aim to overcome the catastrophic forgetting problem, which is a different research topic (i.e., continual learning) from our paper.

3 SL-A\textsuperscript{GENT}

3.1 Overview

As depicted in Figure 2, SL-A\textsuperscript{GENT} contains two components: (i) a dialog model for generating responses (Section 3.2); (ii) a pre-trained reward model for judging the quality of agent responses and outputting reward scores to guide the refinement of the dialog model (Section 3.3). Specifically, SL-A\textsuperscript{GENT} operates in the following steps: (i) First, the bot (both dialog model and pre-trained reward model) is fine-tuned with the same available annotated task-specific dialogs. (ii) Then, the bot is deployed online to converse with users and accumulate unlabeled human-bot dialog logs. (iii) Next, the dialog model is refined with these human-bot dialog logs via reinforcement learning, using the reward scores from the reward model (Section 3.4). (iv) For task definition extensions, machine teaching is utilized to correct representative failed dialogs to provide instructions on how to handle new functions (Section 3.5). After that, the bot further improves through the self-learning procedure.

3.2 Dialog Model

SL-A\textsuperscript{GENT} is a general framework that is compatible with any generative end-to-end dialog models (Peng et al., 2020a; Ham et al., 2020; Hosseini-Asl et al., 2020). In this paper, we employ SOLOIST (Peng et al., 2020a), a pre-trained end-to-end dialog model, resulting in an agent termed SL-SOLOIST\textsuperscript{4}.

We briefly review SOLOIST for completeness. SOLOIST formulates the end-to-end dialog generation as a sequence generation problem, by sequentially concatenating the inputs and outputs of 4 dialog modules (i.e., NLU, DST, POL, NLG) in a typical dialog system. Each dialog turn is represented as:

$$x = (s, b, c, r),$$

where $s$ is the entire dialog history, $b$ is the annotated belief state, $c$ refers to DB state fetched from database, and $r$ is the delexicalized agent response. SOLOIST employs a Transformer-based model with parameters $\theta_D$ to characterize the sequence generation probability $p_{\theta_D}(x)$. Initialized with GPT-2 (Radford et al., 2019), the model is pre-trained on large-scale annotated dialog corpora, and then fine-tuned with limited task-specific dialogs.

Synthetic Dialog Construction. To identify user behaviors with unseen slot values, we propose to synthesize dialog examples by exhausting database (DB) values and substitute corresponding slot values of in the training set. Specifically, for each dialog turn $x$, we replace slot values in the utterances and user goal with corresponding new values of the randomly sampled DB entry.

3.3 Reward Model

The human-bot dialog logs accumulated after deployment may contain previously unseen user behaviors with unseen language patterns and unknown user goals. To enable the dialog model to identify these new types of user inputs to which the previously trained system cannot respond appropriately, we propose a reward model that judges the

\textsuperscript{4}In this paper, SL-A\textsuperscript{GENT} refers to the proposed framework and SL-SOLOIST is an instance of it, which utilizes SOLOIST as its dialog model.
quality of an agent response through a reward score (a positive reward for an appropriate response, a negative reward for an inappropriate response).

We formulate the quality evaluation problem as a binary classification task. Dialog responses are jointly determined by the dialog history, generated belief state, and fetched DB state. Therefore, given the training data $D$ (annotated with belief states and DB states), we build a turn-level reward model $R$, which is parameterized by a Transformer $\theta$ (Edunov et al., 2018), to enhance the ability of the reward model to identify the original user utterance using back translation (Edunov et al., 2020a).

Based on the analysis on diverse language patterns, we consider two kinds of user utterances: (i) the original user utterance in the training set $D$, to identify the appropriate response to the user behavior; (ii) the paraphrased user utterances generated based on the original user utterance using back translation (Edunov et al., 2018), to enhance the ability of reward model for identifying user behaviors with diverse language patterns.

Positive Examples. For each dialog turn, we consider two kinds of user utterances: (i) the original user utterance in the training set $D$, to identify the appropriate response to the user behavior; (ii) the paraphrased user utterances generated based on the original user utterance using back translation (Edunov et al., 2018), to enhance the ability of reward model for identifying user behaviors with diverse language patterns.

Negative Examples. Based on the analysis on 200 human-bot dialog logs collected from the evaluation platform of DSTC8 Track 1 challenge (Li et al., 2020a), we summarize 5 types of dialog turns that have inappropriate responses (in Appendix J).

- **Repetition** The dialog model failed to understand the user’s repeated query and generated the same response twice. (Repeating the response from the previous turn.)
- **Inconsistency** The dialog model generated an incoherent belief state and response. (Randomly sampling a response from the dataset $D$ to replace the original response.)
- **Partial Information** The dialog model partially understood user request and answered incompletely. (For those user utterances with multiple slots request, randomly dropping a slot answer in the original response.)
- **Non-fluency** The dialog model generated a non-fluent response. (Randomly repeating some word tokens in the original response.)
- **Misunderstanding** The dialog model generated the incoherent belief state and response. (Randomly sampling a belief state and response from the dataset $D$ to replace the original belief state and response.)

To boost the model performance with limited annotated task-specific corpora, we propose to follow the pre-training and fine-tuning paradigm to build the reward model, i.e., pre-train the reward model using large-scale annotated heterogeneous dialog corpora, then fine-tune the pre-trained reward model with annotated task-specific data using the same training objective. The pre-training corpora is Schema dataset (Rastogi et al., 2019).

3.4 Refine with Reinforcement Learning

The interactions between the agent and users can be modeled as a sequential decision problem. As such, the dialog model can be refined via the REINFORCE algorithm (Williams, 1992). The policy is the trained dialog model $p_{\theta_D}(x)$, the initial state is the dialog history $s$, and the action space corresponds to the vocabulary set $\mathcal{V}$. The reward perceived by the dialog model is $R(s, b, c, r)$ from the reward model. The parameters $\theta_D$ are updated by maximizing the cumulative reward score. The refining procedure is described in detail as follows:

For each RL episode, we randomly sample a dialog turn with dialog history and delexicalized
response. We run the dialog model to generate belief state $\hat{b}$, based on the input dialog history sequence $s$. At each time step $t$, we sample a token $b_t$ according to the model distribution, where the logits’ distribution of the model is first filtered using Nucleus (top-p) filtering (Holtzman et al., 2019), then redistributed via softmax function. Then we retrieve DB state $\hat{c}$ from the database using $\hat{b}$, and sample the delexicalized response sequence $r$ following same sampling procedure, based on the token sequence $(s, \hat{b}, \hat{c})$. Note that the delexicalized response is given as part of the input. Then we feed the concatenation of dialog history $s$, generated belief state $\hat{b}$, retrieved DB state $\hat{c}$ and the response $r$, i.e. $(s, \hat{b}, \hat{c}, r)$ into the reward model $p_{\theta_\mathcal{R}}(x)$ to obtain the reward score $R(s, \hat{b}, \hat{c}, r)$. The positive reward is 1, negative reward is -1. The training objective for a single example is represented as:

$$
\mathcal{L}_{\theta_D} = - \sum_{t=1}^{T_b} \log p_{\theta_D}(b_t | \hat{b}_{<t}, s) \times R(s, \hat{b}, \hat{c}, r) \\
- \sum_{t=1}^{T_r} \log p_{\theta_D}(r_t | r_{<t}, \hat{b}, \hat{c}, s) \times R(s, \hat{b}, \hat{c}, r),
$$

(3)

where the length of generated belief state and input delexicalized response are $T_b, T_r$, respectively. Algorithm 1 (in Appendix A) summarizes the self-learning-based RL refining framework for refining the dialog model.

3.5 Minimum annotations via Machine Teaching

To handle the queries about new functions in additional dialog turns, we need to introduce new slot-value pairs, action templates, etc. (An example is in Appendix G.) Machine teaching is an efficient approach to training task bots (Simard et al., 2017; Williams and Liden, 2017). In this paper, we implement machine teaching via Conversational Learner (CL) (Shukla et al., 2020). The teaching process is conducted in three steps: (i) The trained task bot is deployed online to fulfill the given goals by interacting with real users, leaving a handful of human-bot dialog logs. (ii) Human experts select a few representative failed dialogs to construct training examples with new functions by adding new action templates, introducing new slot-value pairs, correcting inappropriate responses and annotations (i.e., belief states). (iii) The deployed task bot (i.e., both dialog model and reward model) is trained on these training examples to handle new functions.

| Domain   | Attraction | Train | Hotel | Restaurant |
|----------|------------|-------|-------|------------|
| #Train   | 50         | 50    | 50    | 50         |
| #Valid   | 50         | 50    | 50    | 50         |
| #Test    | 100        | 200   | 200   | 200        |

Table 1: Data statistics of four single-domain dialog datasets (Peng et al., 2020a; Budzianowski et al., 2018).

4 Experiments

4.1 Experimental Setup

We validate the efficiency and flexibility of proposed SL-AGENT on four different end-to-end dialog tasks using MultiWOZ single-domain dialog datasets (Budzianowski et al., 2018), reorganized by Peng et al. (2020a). Data statistics are shown in Table 1. Based on above datasets, we construct two settings to represent the changing environments – Setting I for unseen user behaviors and Setting II for task definition extensions.

Implementation Details. To implement the proposed reward model, we conduct experiments with several Transformer-based models and GPT-2 (Radford et al., 2019) (enhanced with auxiliary generation task) shows better performance than others. Therefore, we implement proposed reward model using GPT-2-117M and the multi-task training objective. Full details are in Appendix B.

Automatic Evaluation Metrics. We report the results using the same automatic evaluation metrics following Budzianowski et al. (2018): (i) Inform(%) evaluates whether the agent returns an appropriate entity. (ii) Success(%) judges whether the agent correctly answers all requested attributes. (iii) BLEU(%) measures the word overlap of the generated response against human response. (iv) Combined(%) assesses the overall quality, which is defined as: Combined = (Inform + Success) $\times$ 0.5 + BLEU.

Human Evaluation Metrics. Following the same evaluation protocol in the DSTC9 Track 1 challenge (Gunasekara et al., 2020), we conduct human evaluations to judge the agent quality. For each dialog session, Amazon Mechanic Turkers are presented with a goal and instructions, then they are required to converse with agent to achieve the goal via natural language. At the end of each dialog session, Turks are required to assess the overall dialog quality using the following five metrics: (i) Success without goal(%) judges whether the agent completes the task. (ii) Success with goal(%)
Table 3: Automatic evaluation results on four tasks in Real-Scenario Setting. The first row refers to previously reported SLOIST. The last three rows refer to refining with 30 real (unlabeled) human-bot dialog logs based on SLOIST. (SL-SOLOIST significantly outperforms all baselines in mean with p<0.01 based on Combined.)
language patterns and unknown user goals. Hence, it is applicable to simulate unseen user behaviors by modifying the remaining 45 dialogs as unlabeled imperfect human-bot dialog logs (through adding noise, *i.e.*, corrupting responses\(^7\)). These 45 unlabeled human-bot dialog logs are further used for refining SOLOIST\(_3\), resulting in SOLOIST-OA, SL-SOLOIST, SOLOIST-TH. This simulation setting allows us to perform a detailed analysis of the reward model in SL-AGENT without much cost and easily reproduce the experimental results.

**Simulation Evaluation Results.** The end-to-end evaluation results on four different tasks are presented in Table 2. SOLOIST\(_3\) significantly outperforms SOLOIST\(_3\) over all evaluation metrics on all tasks, which shows the effectiveness of the proposed synthetic dialog construction for identifying user behaviors with unseen slot values. SL-SOLOIST outperforms SOLOIST+PARG over all the metrics, which demonstrates the higher efficiency of directly learning from human-bot dialog logs. We observe that SL-SOLOIST outperforms SOLOIST-OA by a large margin, and achieves comparable performance with SOLOIST-TH (refining with turn-level human feedback score, *i.e.*, the upper bound). This shows the strong capability of the turn-level pre-trained reward model in SL-AGENT for predicting the quality of responses. We conjecture that our proposed reward model trained with the proposed data-augmentation strategy is more robust to unseen user behaviors and thus ports richer useful information to dialog models. The results verify the vast potential of the proposed SL-AGENT, allowing the bot to automatically adapt to unseen user behaviors without extra human annotations. Results of further policy improvement are shown in Appendix E.

**Real-Scenario Evaluation Setup.** Simulation setting allows effortless experimental studies to validate the effectiveness of the reward model in SL-AGENT. However, the results are likely biased. Therefore, in the real-scenario setting, we deploy SOLOIST\(_3\) online and recruit human users to converse with it. We collect 30 real (unlabeled) human-bot dialog logs to refine SOLOIST\(_3\), resulting in the agent SOLOIST-OA, SL-SOLOIST, SOLOIST-TH.

**Real-Scenario Evaluation Results.** The evaluation results on four tasks are shown in Table 3.

7Note that the associated labels of belief states are not used. Construction details are in Appendix D.

| Model                  | Restaurant-Ext |
|------------------------|----------------|
|                       | Inform | Success | BLEU  | Combined |
| SOLOIST\(_3\)         | 54.00  | 0.00    | 6.42  | 33.42    |
| SOLOIST\(_3\)+Teach   | 64.00  | 18.00   | 9.34  | 50.34    |
| SL-SOLOIST+Teach      | 68.00  | 24.00   | 11.76 | 57.76    |
| SOLOIST-TH+Teach      | 68.50  | 26.00   | 11.88 | 59.13    |

Table 4: Automatic evaluation results on task definition extensions. (Difference in mean is significant with \(p<0.01\) based on Combined.)

We observe that SL-SOLOIST refined using the reward model in SL-AGENT outperforms other methods over all evaluation metrics on all tasks. Furthermore, SL-SOLOIST achieves comparable performance with SOLOIST-TH, even achieves better performance on certain metrics. We conclude that the results of real-scenario evaluation and simulation evaluation are consistent, confirming that SL-SOLOIST enables effective self-learning after deployment by learning from interactions.

### 4.3 Results of Setting II – Task Definition Extensions

**Setup.** We follow the domain extension experiment setting in Lipton et al. (2018) to assess the ability of SL-SOLOIST to quickly handle task definition extensions. We extend existing Restaurant, denoted as Restaurant-Ext, with additional functions by introducing 4 new slots, *i.e.*, \([restaurant\_dish]\), \([value\_price]\), \([start\_time]\), \([end\_time]\) in added dialog turns (in Appendix G), and corresponding values for each DB entry (in Appendix H). The first slot is about the restaurant’s signature dish, and the last three are related to delivery service. We leverage Conversational Learner (CL) (Shukla et al., 2020), a practical machine teaching tool, to visualize and select dialogs for constructing training examples on the Restaurant-Ext domain by providing corrections and introducing new slots. Finally, 10 examples are obtained through machine teaching for training, 50 for validating and 50 for testing. We fine-tune the dialog model SOLOIST\(_3\) and the previously trained reward model\(^8\), using 10 corrected dialogs, resulting the agent denoted as SOLOIST\(_3\)+Teach. Then, SOLOIST\(_3\)+Teach is deployed to converse with real human to collect 20 real (unlabeled) human-bot dialog logs, which are then used to refine itself, resulting in SL-SOLOIST+Teach. To better show the effective-
ne of the reward model in SL-AGENT, we also report the result of SOLOIST-TH+TEACH, which is refined using the turn-level human feedback score.

**Results.** The evaluation results are presented in Table 4. We observe that SOLOIST₅ has zero success rate, which is predictable as it does not have any knowledge of the new functions. SOLOIST₅+TEACH outperforms the baseline by 17 points in terms of Combined score, which exhibits the effectiveness of machine teaching for handling new functions. SL-SOLOIST+TEACH lifts the Combined score by approximately 7 points, achieving comparable performance with SOLOIST-TH+TEACH. The results show that SL-SOLOIST+TEACH can adapt to new tasks and continually improve itself by automatically learning from the interactions, revealing, with minimum annotations from machine teaching, SL-AGENT enables flexible adaptations to new functions.

### 4.4 Interactive Human Evaluation

**Setup.** We conduct human evaluations to evaluate the performance of SOLOIST₅, SOLOIST-OA, SL-SOLOIST interacting with human users, following the evaluation protocol in DSTC9 track 1 challenge (Gunasekara et al., 2020), with 100 Turkers involved and 100 dialogs gathered for analysis, respectively.

**Results.** The human evaluation results on Restaurant domain are presented in Table 5. The results show that SL-SOLOIST outperforms SOLOIST₅, SOLOIST-OA over all the metrics, which are consistent with the automatic evaluation results. The significant improvement on two success rate metrics, especially success rate with grounding, verifies the effectiveness of the reward model in SL-AGENT for refining the dialog agent after deployment without additional human annotations, as it more adequately reflects the system’s capability of completing tasks in real scenarios. Two interactive examples are in Appendix F.

Table 5: Human evaluation results. SR w/o g: Success rate without grounding, SR w/ g: Success rate with grounding, Under.: Understanding score, Appr.: Appropriateness score.

| Model       | Restaurant SR w/o g | Restaurant SR w/ g | Under. | Appr. | Turns |
|-------------|---------------------|--------------------|--------|-------|-------|
| SOLOIST₅   | 31.82               | 29.54              | 3.86   | 4.13  | 10.00 |
| SOLOIST-OA | 33.42               | 30.86              | 3.89   | 4.12  | 9.97  |
| SL-SOLOIST | 43.10               | 36.21              | 3.97   | 4.13  | 9.89  |

Table 6: Ablation study results on using different PLMs for reward models. (Difference in mean is significant with p<0.01 based on Combined.)

| Reward model | Inform | Success | BLEU | Combined |
|--------------|--------|---------|------|----------|
| GPT-2        | 67.00  | 41.50   | 9.30 | 63.55    |
| BERT         | 68.00  | 42.50   | 9.55 | 64.80    |
| BERT-Large   | 66.00  | 44.00   | 11.09| 66.00    |
| RoBERTa      | 72.00  | 45.00   | 9.23 | 67.73    |
| RoBERTa-Large| 69.50  | 46.50   | 10.20| 68.20    |
| SL-SOLOIST   | 75.00  | 44.50   | 10.60| 70.35    |

### 4.5 Ablation Study

**Impact of different PLMs for reward models.**

We conduct ablation studies on Restaurant domain to analyze the influence of choosing different PLMs and multi-task training objective on the reward model. We choose several popular PLMs including BERT (Devlin et al., 2018) and RoBERTa (Liu et al., 2019). Note that all the models share the same pre-training and fine-tuning procedure, except that BERT and RoBERTa are trained with quality prediction task while SL-SOLOIST is optimized using multi-task learning. We show in Table 6 that RoBERTa performs better than BERT. GPT-2 (on which SL-SOLOIST is built) trained with single quality prediction task, yields significantly worse performance than other methods. We speculate that bidirectional Transformer encoder enables BERT and RoBERTa to capture richer context information. SL-SOLOIST achieves consistent performance improvements over all the metrics, showing the effectiveness of multi-task learning for the reward model.

**5 Conclusion**

In this paper, we propose a new research problem *i.e.*, how to enable task bots to automatically adapt themselves to changing environments by learning from interactions with minimum or zero human annotations. In addition, we propose SL-AGENT, a novel self-learning framework. We verify its effectiveness on automatically adapting to changing environments on four dialog tasks by learning from the unlabeled human-bot dialog logs via reinforcement learning with an incorporated pre-trained reward model. As for future work, there are more ways that a task bot could learn to improve itself, *e.g.*, during machine teaching, human experts could provide not only correct labels but also feedback in natural language. We leave the theme of effective machine teaching to future work.
6 Ethical Considerations

During the collection, annotation and evaluation procedure of the human-bot dialog logs, all involved Amazon Mechanical Turkers and human annotators have been informed of the research purpose in advance, and any of their privacy will not be disclosed or violated during the research period. All other used datasets are open-sourced datasets. In summary, we abide by all research ethics.

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A  RL Refining Algorithm

Algorithm 1  Self-learning-based RL refining framework.

Input:
1. Training examples $D$ in the form of dialog turns;
2. Trained agent with dialog model $p_{θ_D}(x)$ and reward model $p_{θ_R}(x)$.

Output:
1. Refined agent with updated dialog model $p_{θ_D^*}$.

1: while not converged do
2:       Randomly sample a dialog turn, i.e. token sequences of dialog history $s$;
3:       Run dialog model $p_{θ_D}$ on dialog history $x = (s)$ to generate belief state $\hat{b}$;
4:       Retrieve DB state $\hat{c}$ from a database using generated belief state $\hat{b}$;
5:       Sample corresponding response $r$ based on dialog history $s$, belief state $\hat{b}$ and DB state $\hat{c}$;
6:       Use the reward model to predict the quality of the belief state and response with reward score, $R(s, \hat{b}, \hat{c}, r)$;
7:       Calculate the loss according to Equation 3;
8:       Update the parameters of the dialog model, $θ_D ← θ_D + α∇_{θ_D} L_θ_D$.
9:   end while

B  Implementation Details

To construct training examples as shown in Figure 3, we tokenize the dialog turn sequence using byte pair encodings (Sennrich et al., 2015) and delexicalize responses by replacing slot values with corresponding special slot tokens (Lei et al., 2018). We conduct experiments with several Transformer-based models and GPT-2 (Radford et al., 2019) (enhanced with auxiliary generation tasks) shows...
better performance than others. Therefore, we implement proposed reward model based on Huggingface Pytorch Transformer (Wolf et al., 2020) using GPT-2-117M. We pre-train reward model for 10 epochs using Schema dataset (Rastogi et al., 2019), which contains 22,825 dialogs in 17 domains. The reward model is pre-trained on two 24G Nvidia P40 with a mini-batch of 8 and learning rate of 5e-5, using Adam optimizer (Kingma and Ba, 2014), where the training examples are truncated or padded to the max length of 500.

We fine-tune the pre-trained reward model and dialog model (i.e., pre-trained SOLOIST) for 20 epochs with limited number of labeled task-specific dialogs for new tasks. During refinement, top-p is selected as 0.5 for all models. We perform gradient clipping with the max norm as 1 for learning model parameters, with the batch size as 1 and learning rate as 5e-6. The dialog model is refined on a single 24G Nvidia P40 until converging on the validation set. During testing, Nucleus filtering is also used for decoding with top-p as 0.5.

### C Experimental Details

To demonstrate the effectiveness of SL-AGENT, we use SOLOIST as the dialog model to compare the performance of different methods, since existing state-of-the-art task-oriented dialog models share similar input-output pairs and training objectives as SOLOIST. (We report the results in mean of 5 runs with 5 different seeds.) (i) To obtain SOLOIST$_S$, we implement the synthetic dialog construction method by exhausting DB values. For each dialog turn of the 5 labeled dialogs, we randomly sample five DB values from the database to replace the original slot values. (ii) To obtain SOLOIST+PARG, we use the Transformer-based machine translation checkpoints (English-German, German-English) (Edunov et al., 2018) to generate 10 paraphrased user utterances for each dialog turn of the 5 labeled dialogs (based on the empirical analysis of translation quality). Then we use these annotated data (with paraphrased user utterances) to train SOLOIST$_S$ for obtaining SOLOIST+PAR. (iii) To obtain SOLOIST-OA, we use the method described in Section 8 to construct successful dialogs and failed dialogs. For successful dialogs, we use the original 5 labeled dialogs, and the dialogs containing paraphrased user utterances. To construct the failed dialogs, we randomly select 2-3 dialog turns in each dialog and corrupt responses according to the negative example construction method in Section 3.3. Then we use these annotated dialogs to train the session-level reward model of (Su et al., 2016). When testing the performance in the simulated setting, we refine the SOLOIST$_S$ with fully correct dialogs and dialogs containing corrupted responses. To achieve better performance, we largely query for session-level human feedback score in both simulated setting and real-scenario setting.

### D Simulated Human-Bot Corpora Construction

The unlabeled simulated human-bot corpora is constructed as follows: (i) we remove belief state annotations; (ii) we add negative examples by corrupting responses according to the negative example construction method in Section 3.3. We will release the simulated human-bot corpora for reproducible research. Note that directly replacing the belief states and responses with the generated ones is trivial. However, such approach cannot imitate realistic human-bot interactions. As the user utterances are strictly fixed, “users cannot react to the agent responses accordingly and appropriately”. Therefore, we also conduct experiments through conversing with real users in the real-scenario setting and demonstrate the results in Table 3. Furthermore, building a user simulator is inapplicable in our changing environment setting. (i) It is difficult to build reliable user simulators. Building agenda-based user simulators requires sophisticated human expertise for designing rules. (ii) Building model-based user simulators requires sufficient labeled data. Furthermore, model-based user simulators merely imitate expert behaviors in the training corpus, cannot provide user behaviors that are unseen from task bots.

| Model           | Inform | Success | BLEU | Combined |
|-----------------|--------|---------|------|----------|
| SOLOIST$_S$     | 62.50  | 41.50   | 7.33 | 59.33    |
| SL-SOLOIST      | 75.00  | 44.50   | 10.60| 70.35    |
| SL-SOLOIST+20   | 75.00  | 52.00   | 11.89| 75.39    |

Table 7: End-to-end evaluation results of Policy Improvement in the Restaurant domain. SL-SOLOIST+20 refer to continually refining with 20 real (unlabeled) human-bot dialogs based on SL-SOLOIST (reported in Table 2).
Figure 4: Two interactive examples. (a) An interactive example between user and SOLOIST. (b) An interactive example between user and SL-SOLOIST.

E Policy Improvement

Policy Improvement Setup. To demonstrate the effectiveness of SL-AGENT for continually learning from collected human-bot dialog logs, we deploy SL-SOLOIST online and recruit human users to converse with it to achieve the assigned user goal. We collect 20 real human-bot dialog logs to refine SL-SOLOIST, resulting in the agent SL-SOLOIST+20. (When refining the SL-SOLOIST, we do not use the knowledge about the user’s goal. The response quality is judged by the reward model in SL-SOLOIST.)

Policy Improvement Results. The evaluation results on Restaurant are shown in Table 7. We observe that SL-SOLOIST+20 refined with 20 real (unlabeled) human-bot dialog logs outperforms SL-SOLOIST by approximately 5 points in terms of Combined score. We conclude that SL-SOLOIST enables continual self-learning after deployment by automatically learning from interactions.

F Interactive Example

Figure 4 depicts two interactive examples where the same user interacts with SOLOIST and SL-SOLOIST to complete the same task. We observe that, in the first four dialog turns, the two agents have the same performance and both correctly recommend a satisfied restaurant. However, as shown in Figure 4 (a), when user queries about the phone number (“what’s the number?”) in the fifth turn, SOLOIST fails to understand user’s intent and generates incoherent response, still trying to provide recommendation. The user has to continually query about phone number in the following consecutive turns. As demonstrated in Figure 4 (b), SL-SOLOIST correctly provides the phone number, when user first queries about it. Comparing the two examples, we show that SL-AGENT enables adapting to unseen user behaviors in an automatic way.

G An Example of Task Definition Extensions

Figure 5 depicts an example of task definition extensions.

| t | Speaker | Utterance (x_t) |
|---|---------|----------------|
| 1 | User | Hi, I’m looking for a place with Tuscan food in any price range. |
| 2 | System | I’m sorry, there is not a Tuscan restaurant listed. Would you care to try something else? |
| 3 | User | How about any Korean restaurants? |
| 4 | System | Little Seoul is a Korean restaurant. |
| 5 | User | Phone number please. |
| 6 | System | The phone number is 01223308681. Is there anything else I can help you with? |
| 7 | User | Does the restaurant offer delivery service? How much does the delivery charge? |
| 8 | System | Yes, and the delivery fee is 4 pounds. Would you like more information about the service? |
| 9 | User | No. Thank you, goodbye. |
| 10 | System | Thank you. Goodbye. |

Figure 5: An example of task definition extensions. Task bots need learn to provide information about the extended delivery service in additional dialog turns (in Red) as user requirements evolve.

H An Example of Restaurant-Ext DB Entry

An example of Restaurant-Ext DB entry is shown in Figure 6.

I Item Examples of the Input Dialog Turn Sequence

J Negative Example Construction
Figure 6: An example of Restaurant-Ext DB entry. Newly added DB information about the extended function is in the red square.
Figure 7: Item examples of the input dialog turn sequence for SOLOIST, cited from (Peng et al., 2020a).

Figure 8: The summarized 5 types of dialog turns that have inappropriate or incoherent responses. (a) Dialog history (top). (b) 5 types of the inappropriate or incoherent responses (bottom).