SUMBT+LaRL: End-to-end Neural Task-oriented Dialog System with Reinforcement Learning

Hwaran Lee, Seokhwan Jo, HyungJun Kim, Sangkeun Jung, and Tae-Yoon Kim

***Abstract*—The recent advent of neural approaches for developing each dialog component in task-oriented dialog systems has remarkably improved, yet optimizing the overall system performance remains a challenge. In this paper, we propose an end-to-end trainable neural dialog system with reinforcement learning, named *SUMBT+LaRL*. The SUMBT+ estimates user-acts as well as dialog belief states, and the LaRL models latent system action spaces and generates responses given the estimated contexts. We experimentally demonstrate that the training framework in which the SUMBT+ and LaRL are separately pretrained and then the entire system is fine-tuned significantly increases dialog success rates. We propose new success criteria for reinforcement learning to the end-to-end dialog system as well as provide experimental analysis on a different result aspect depending on the success criteria and evaluation methods. Consequently, our model achieved the new state-of-the-art success rate of 85.4% on corpus-based evaluation, and a comparable success rate of 81.40% on simulator-based evaluation provided by the DSTC8 challenge.**

***Index Terms*—Goal-oriented dialog systems, End-to-end Multi-domain Task-completion Task, DSTC8, MultiWOZ2.0**

I. Introduction

TASK-ORIENTED dialog system aims for users to achieve goals such as finding attractions or booking restaurants. Developing such a system typically requires the following dialog components to construct a pipeline as illustrated in Fig.1: natural language understanding (NLU) to extract user's intents and slot-values [1], [2], dialog state tracking (DST) to update belief states [3], [4], querying database, dialog policy (POL) to decide the system's next action [5], and natural language generation (NLG) to generate system responses [6]. Although recent advances in neural approaches in the natural language domain have greatly improved the performance of individual dialog components, errors in each component are accumulated in the pipelined system, resulting in degradation of overall performance. Therefore, designing an effective architecture and optimizing the entire dialog system in an end-to-end fashion are still challenging.

Recently, several end-to-end (E2E) neural dialog systems have proposed [7]–[15]. Sequence-to-sequence approaches directly generate system responses given user utterance inputs, but they have limitations that querying the external database is unavailable [16], [17], and system actions are not interpretable [9], [10]. Moreover, a few previous researchers have investigated dialog policy optimization by reinforcement learning in end-to-end neural task-oriented dialog systems [8], [18], [19].

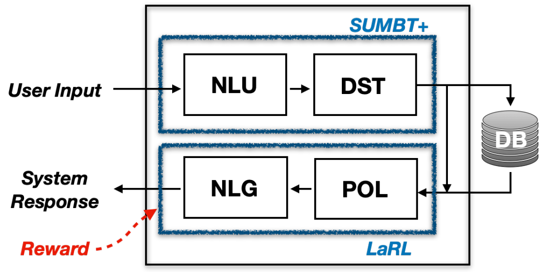

Fig. 1. The conventional pipeline task-oriented dialog systems and the proposed end-to-end trainable SUMBT+LaRL.

Meanwhile, recent approaches that transfer general linguistic knowledge from large pre-trained language model, GPT-2 [20], to goal-oriented dialog have shown remarkable improvements [12], [15], [21]. They employed the GPT-2 backbone as it is, and fine-tuned the model to auto-regressively generate dialog states, system actions, and responses in a sequence. Although leveraging the rich knowledge allows the models to generate more natural and appropriate responses, reinforcement learning on transformer-based architectures has been reported as unstable [22], and learning dialog policy on those models has not been explored yet.

In this paper, we present an end-to-end trainable neural dialog system with reinforcement learning for multi-domain task-completion tasks, *SUMBT+LaRL*, which consists of two components: (i) an extended version of SUMBT [3] for a word-level dialog state tracker and (ii) LaRL [23] for a word-level policy model. In addition to SUMBT that updates belief states employing the slot-utterance matching mechanism, SUMBT+ predicts domains and user-intents from the user utterance. Then given the predictions by SUMBT+, the LaRL models a categorical latent system action spaces and generates system responses. In our training framework, we emphasize the importance of *separately pre-train* SUMBT+ and LaRL and *fine-tune the entire model* in an end-to-end fashion. Then, the trained dialog policy is further optimized by *off-line reinforcement learning* using REINFORCE algorithm to succeed dialog tasks. During reinforcement training, the policy gradients at latent actions decouple the discourse-level decision making and language generation by the decoder, enabling stable and effective reinforcement learning. We further propose new success criteria in which the system has

Manuscript received September 22, 2020.

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to respond to more requestable slots and calculate the match performance using the belief state estimated by SUMBT+.

We demonstrated the efficacy of the proposed system on MultiWOZ2.0, implementing on ConvLab platform for user simulator-based evaluations. Our extensive experimental results on both corpus and simulator-based evaluation shows the effectiveness of the proposed pretraining and end-to-end fine-tuning framework as well as reinforcement learning on the latent action space. From the results and qualitative analysis of simulated dialog examples, we also present *the discrepancy problem of corpus and automatic evaluations*, *the limitations of off-line reinforcement learning for dialog systems*, and *the needs of advanced reward design and success criteria*. Our model achieved the new state-of-the-art success rate in the end-to-end corpus-based evaluation on the MultiWOZ2.0, as well as outperformed the challenge winner of the 8th dialog system technology challenge (DSTC8) challenge [1] in the simulator-based evaluation.

In summary, the main contributions of this paper are three-fold:

1) We propose an end-to-end trainable neural dialog system, SUMBT+LaRL, and experimentally verify the effectiveness of end-to-end fine-tuning.
2) We propose new success criteria for reinforcement learning as well as provide experimental analysis on a different result aspect depending on the success criteria and evaluation methods.
3) We present the new state-of-the-art success rate of 83.7% and 81.40% on the end-to-end corpus and simulator-based evaluation, respectively.

Sec.2 briefly reviews end-to-end multi-domain task-completion dialog systems and the DSTC8 Challenge. Sec.3 explains the detailed architecture of the proposed SUMBT+LaRL and training procedures. Related work is described in Sec.4 and experimental results are presented in Sec.5.

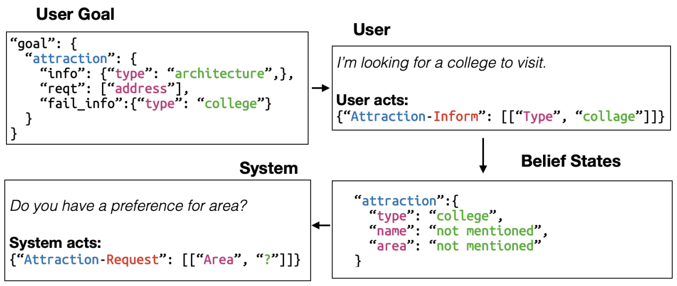
II. End-to-end Multi-domain Task-Completion Dialog Systems

In this section, we overview the end-to-end multi-domain task-completion task in the DSTC8 challenge Track 1.

A. *MultiWOZ Corpus*

The goal of the challenge is to develop an end-to-end goal-oriented dialog system on MultiWOZ 2.0 [24] corpus. The MultiWOZ dataset is a multi-domain task-oriented conversational corpus that helping a tourist such as booking a restaurant or finding an attraction. More specifically, it contains seven domains: *Attraction, Hospital, Hotel, Police, Restaurant, Taxi,* and *Train*. There is 10,438 annotated dialogs (8,438 train, 1,000 valid, and 1,000 test) which compose of 3,406 single-domain and 7,032 multi-domain dialogs. In multi-domain dialogs, 1 to 3 domains appear in each multi-domain dialog session.

Dialog states and system dialog acts are fully annotated at each turn as described in Fig.2. User dialog acts are additionally provided in the DSTC8 challenge [1].



```
"goal": {
  "attraction": {
    "info": {"type": "architecture",},
    "reqt": ["address"],
    "fail_info":{"type": "college"}
  }
}
```

I'm looking for a college to visit.

```
{"Attraction-Inform": [["Type", "collage"]]}
```

```
"attraction":{
  "type": "college",
  "name": "not mentioned",
  "area": "not mentioned"
}
```

Do you have a preference for area?

```
{"Attraction-Request": [["Area", "?"]]}
```

Fig. 2. An example of a user goal, a user utterance, belief states, and a system utterance in a MultiWOZ dialog.

More specifically, dialog states refer to information shared between system and user as the dialog progresses (*i.e.*, "attraction":{"type":*"college"*}). Dialog acts for system or user utterances indicate semantic frames about the turn including domains, intents, slots, and slot values (*i.e.*, "Attraction-Inform": [["Type", *"college"*]], "Attraction-Request": [["address", *"?"*]]). The set of intents and slots are different for users and systems, and there are separate lists for informable slots and requestable slots. The domains, intents, slots, and slot values are pre-defined in the ontology.

B. *User Goal*

User goals define the constraints of what users want that should be informed to systems and the information of what users have to request during the conversations. For example, the inform slot-value pairs (*i.e.*, {"type": *"architecture"*}) and the request slots (*i.e.*, ["entrance fee"]) are listed for each domain as user goals. Furthermore, wrong information is also stated as "fail info" to make the case that the system cannot find suitable items from the database.

C. *ConvLab and User Simulator*

DSTC8 offers an open-source platform, ConvLab[1] which allows participants to develop their systems and enables system-wise evaluation. ConvLab also provides several rule-based or neural-based dialog components of NLU, DST, POL, NLG, and end-to-end neural models. Moreover, it provides a user-simulator for automatic evaluations and a crowd-sourcing platform, Amazon Mechanical Turk, for human evaluations.

The user-simulator consists of an RNN-based NLU model called MILU (Multi-Intent Language Understanding, [25]), a rule-based DST, an agenda-based POL, and a retrieval-based NLG. At the start of a dialog session, a user goal is randomly generated or selected among the set of pre-defined user goals. For a given user goal, the agenda-based policy [26] stacks the agenda where each entry corresponds to a pending intention, which is the user aims to achieve. The stack-update process follows complex rules. The user simulator communicates with models through natural languages by the NLU and NLG components.

[1]https://github.com/ConvLab/ConvLab

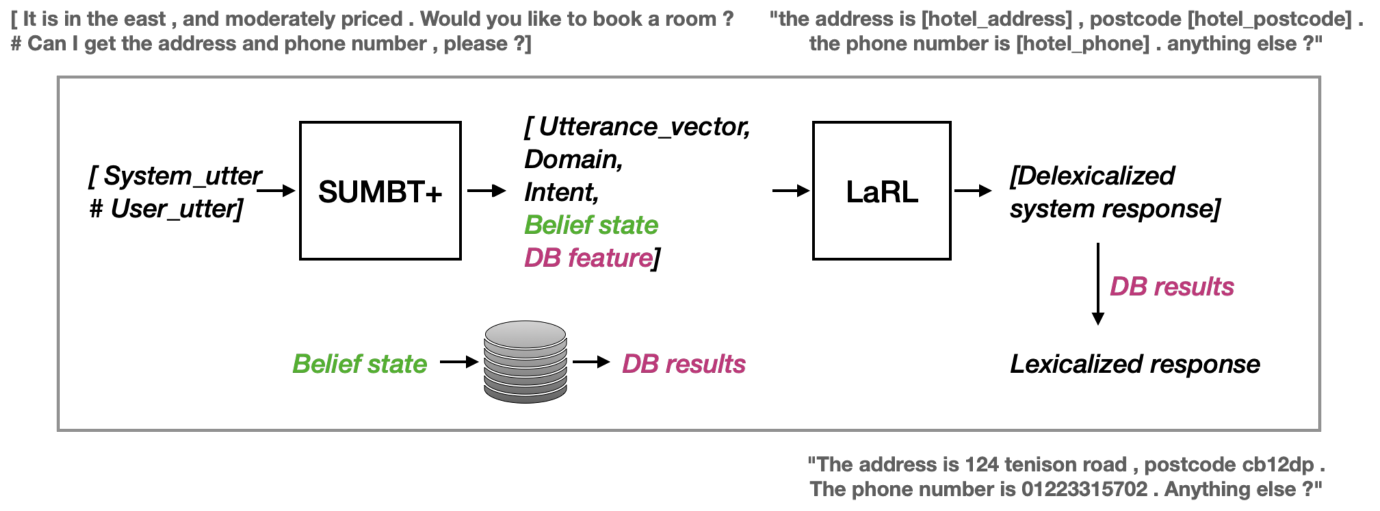

[It is in the east , and moderately priced . Would you like to book a room ?
# Can I get the address and phone number , please ?]
"the address is [hotel_address] , postcode [hotel_postcode] .
the phone number is [hotel_phone] . anything else ?"
[System_utter
# User_utter]
SUMBT+
[Utterance_vector,
Domain,
Intent,
Belief state
DB feature]
LaRL
[Delexicalized
system response]
DB results
Lexicalized response
Belief state
DB results
"The address is 124 tenison road , postcode cb12dp .
The phone number is 01223315702 . Anything else ?"

Fig. 3. The overall architecture of end-to-end trainable SUMBT+LaRL.

D. Evaluation Metric

For the automatic evaluation, dialog systems converse with the user-simulator. At the end of a dialog session, the dialog system is evaluated for how well it responded to the user's requests (*i.e.*, *Inform*) and whether the responses were consistent with the information spoken by the user (*i.e.*, *Match*). For the *Inform* category, the precision, recall, and F1 are calculated for the slots provided by the system. For the *Match* category, the system achieved *Booking Success* if the booked information matches the user's information described in the goal. Finally, when booking succeeds and inform recall is one, the dialog is *Success*.

Since the user-simulator is not perfect, the final ranking is determined by human evaluations. Crowd-workers randomly converse with submitted systems in natural languages and mark the *Success* of the user's goal as well as *natural language understanding* and *response appropriateness* on a scale of 1 to 5.

III. SUMBT+LaRL

In this section, we describe our end-to-end dialog system. First, we introduce the overall framework and explain the details of each model architecture followed by the training procedures.

A. Overall System Achitecture

As described in Fig.3, our end-to-end dialog system mainly consists of two neural sub-modules: the word-level dialog state tracker (SUMBT+) and the word-level policy model (LaRL).

There is a four-step procedure for the system to respond to the user. (i) The SUMBT+, which is an extended model of Slot-Utterance Matching Belief Tracker (SUMBT) [3], extracts domains and user intents of the current turn, and tracks belief states, simultaneously. (ii) Then, the system queries the domain-specific database (*i.e.*, restaurant, or movie) using the estimated current domain and dialog states. (iii) The Latent Action Reinforcement Learning (LaRL) module

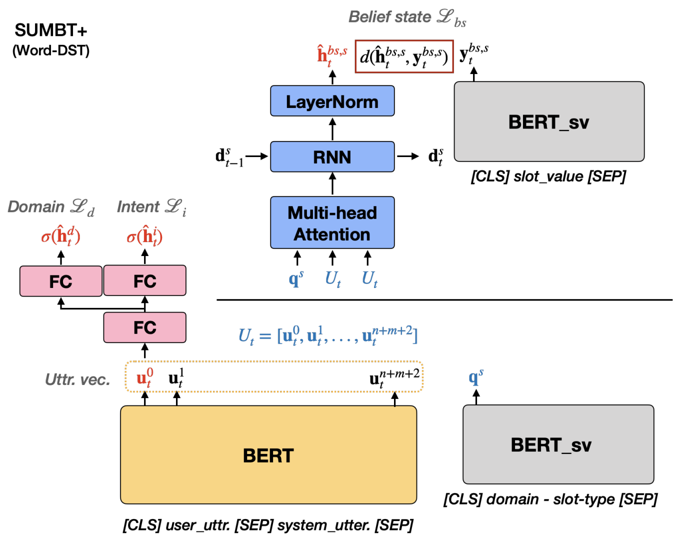

SUMBT+
(Word-DST)
Belief state $\mathcal{L}_{bs}$
$\hat{\mathbf{h}}_t^{bs,s}$
$d(\hat{\mathbf{h}}_t^{bs,s}, \mathbf{y}_t^{bs,s})$
$\mathbf{y}_t^{bs,s}$
LayerNorm
BERT_sv
$\mathbf{d}_{t-1}^s$
RNN
$\mathbf{d}_t^s$
[CLS] slot_value [SEP]
Domain $\mathcal{L}_d$
Intent $\mathcal{L}_i$
$\sigma(\hat{\mathbf{h}}_t^d)$
$\sigma(\hat{\mathbf{h}}_t^i)$
Multi-head Attention
FC
FC
$\mathbf{q}^s$ U_t U_t
FC
$U_t = [\mathbf{u}_t^0, \mathbf{u}_t^1, \ldots, \mathbf{u}_t^{n+m+2}]$
Uttr. vec.
$\mathbf{u}_t^0$ $\mathbf{u}_t^1$ $\mathbf{u}_t^{n+m+2}$
$\mathbf{q}^s$
BERT
BERT_sv
[CLS] domain - slot-type [SEP]
[CLS] user_uttr. [SEP] system_utter. [SEP]

Fig. 4. The architecture of extended Slot-Utterance Matching Belief Tracker (SUMBT+) that classifies domains and user actions at the dialog turn t and estimates belief states along the dialog.

[23] implicitly models the action spaces without any system-action supervision from the utterance semantic vector, and information of extracted domains, user intents, belief states, and database query results. Then it generates the delexicalized system response. (iv) Finally, the delexicalized tokens are lexicalized using the DB query results.

Sec.III-B and Sec.III-C describe the model architectures of SUMBT+ and LaRL, respectively. Sec.III-D and Sec.III-E describe the end-to-end training and the reinforcement learning of the proposed system, respectively.

B. SUMBT+: Natural Language Understanding and Dialog State Tracking

The proposed SUMBT+ estimates domain and user intent as well as belief state at the dialog turn t in multi-task learning fashion, as shown in Fig.4. Formally, for the pair of system and user utterances, $\mathbf{x}_t^{sys} = (w_{1,t}^{sys}, ..., w_{n,t}^{sys})$ and $\mathbf{x}_t^{usr} = (w_{1,t}^{usr}, ..., w_{m,t}^{usr})$, the model predicts domain labels $\mathbf{y}_t^d \in [0,1]^{n_d}$, user-intent labels $\mathbf{y}_t^i \in [0,1]^{n_i}$, and slot-values $\mathbf{y}_t^{bs,s}$ for each domain-slot-types s which is one-hot vector of dimension $|\mathcal{C}_s|$, where n_d and n_i are number of domains and user-intents, and $\mathcal{C}_s$ is a set of the candidate slot-values of slot-type s which is defined in the ontology. Note that the transition of dialog domain can occur at one dialog turn (*i.e.*, from restaurant reservation to seeking an attraction), and a user utterance can be a mixture of multiple intents (*i.e.*, 'Inform-Address' and 'Request-Name'). Therefore, they are multi-label binary classification tasks, whereas we assume only one slot-value exists for each domain-slot-type.

First, we employ the pre-trained BERT to encode each word w into a contextual semantic word vector $\mathbf{u}$, and the encoded utterances are represented in the following matrix representation:

$$U_t = \text{BERT}\left([\mathbf{x}_t^{sys}, \mathbf{x}_t^{usr}]\right). \tag{1}$$

We considered $\mathbf{u}_t^0$ vector as an utterance vector that represents the entire semantics of the sentence pair.

The utterance vector is then fed into the two fully connected (FC) layers to predict domain and intent labels. The network parameters are trained to minimize following the cross-entropy loss:

$$\begin{aligned}\mathcal{L}_d(\theta) &= -\sum_{t=1}^{T}\sum_{d=0}^{n_d} \mathbf{y}_t^d \log \mathbf{h}_t^d + (1-\mathbf{y}_t^d)\log(1-\mathbf{h}_t^d), \\ \mathcal{L}_i(\theta) &= -\sum_{t=1}^{T}\sum_{i=0}^{n_i} \mathbf{y}_t^i \log \mathbf{h}_t^i + (1-\mathbf{y}_t^i)\log(1-\mathbf{h}_t^i),\end{aligned} \tag{2}$$

where $\mathbf{h}_t^d = \sigma(\hat{\mathbf{h}}_t^d)$, $\mathbf{h}_t^i = \sigma(\hat{\mathbf{h}}_t^i)$. σ is a sigmoid function, and $\hat{\mathbf{h}}_t^d$ and $\hat{\mathbf{h}}_t^i$ are the domain and act FC layer output vectors, respectively.

For belief state tracking, the model literally encodes the words of domain-slot-types s and slot-values v_t at turn t likewise system and user utterances. Another pre-trained BERT, denoted as BERT$_{\text{sv}}$, is fixed during the training, and it encodes their word sequences $\mathbf{x}^s$ and $\mathbf{x}_t^v$ into contextual semantic vectors $\mathbf{q}^s$ and $\mathbf{y}_t^v$, respectively.

$$\begin{aligned}\mathbf{q}^s &= \text{BERT}_{\text{sv}}(\mathbf{x}^s), \\ \mathbf{y}_t^v &= \text{BERT}_{\text{sv}}(\mathbf{x}_t^v).\end{aligned} \tag{3}$$

We use the output vectors corresponding to the classification embedding token, [CLS], as the semantic vectors.

The model uses multi-head attention [27] to find the relevant information corresponding to the domain-slot-type from the utterances. Considering the encoded vector of the domain-slot-type $\mathbf{q}^s$ as a query, the model matches it to the contextual semantic vectors $\mathbf{u}$ at each word position, and then the attention scores are calculated. The multi-head attention maps a query matrix Q, a key matrix K, and a value matrix V with different linear h projections, and then the scaled dot-product attention is performed on those matrices. The attended context vector $\mathbf{h}_t^s$ between the slot s and the utterances at t is

$$\tilde{\mathbf{h}}_t^s = \text{MultiHead}(Q, K, V), \tag{4}$$

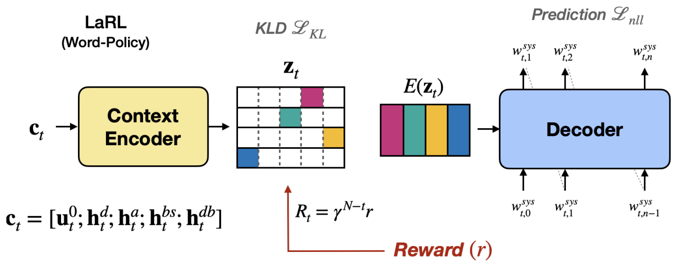

LaRL
(Word-Policy)
KLD $\mathscr{L}_{KL}$
Prediction $\mathscr{L}_{nll}$
$\mathbf{c}_t$
Context Encoder
$\mathbf{z}_t$
$E(\mathbf{z}_t)$
Decoder
$w_{t,1}^{sys}$ $w_{t,2}^{sys}$ $w_{t,n}^{sys}$
$w_{t,0}^{sys}$ $w_{t,1}^{sys}$ $w_{t,n-1}^{sys}$
$\mathbf{c}_t = [\mathbf{u}_t^0; \mathbf{h}_t^d; \mathbf{h}_t^a; \mathbf{h}_t^{bs}; \mathbf{h}_t^{db}]$
$R_t = \gamma^{N-t} r$
Reward (r)

Fig. 5. The Latent Action Reinforcement Learning (LaRL) model with Categorical latent variables.

where Q is Q^s, and K and V are U_t. A recurrent neural network (RNN) with a layer normalization layer inputs the attended vector and the previous RNN output vector $\mathbf{d}_{t-1}^s$ together, and outputs $\mathbf{d}_t^s$ and the predicted semantic vector $\hat{\mathbf{h}}_t^{bs,s}$. Note the RNN is shared across different domains and slot-types.

The model is trained to minimize the distance between outputs $\hat{\mathbf{h}}_t^{bs,s}$ and target slot-value's semantic vectors $\mathbf{y}_t^{bs,s}$ under a certain distance metric. The probability distribution of a slot-value v_t is calculated as

$$p\left(v_t|\mathbf{x}_{\leq t}^{sys}, \mathbf{x}_{\leq t}^{usr}, s\right) = \frac{\exp\left(-d(\hat{\mathbf{h}}_t^{bs,s}, \mathbf{y}_t^{bs,v})\right)}{\sum_{v' \in \mathcal{C}_s} \exp\left(-d(\hat{\mathbf{h}}_t^{bs,s}, \mathbf{y}_t^{bs,v'})\right)}, \tag{5}$$

where d is a distance metric such as Euclidean distance or negative cosine distance. This discriminative classifier is similar to the metric learning method proposed in [28], but the distance metric is measured in the fixed space that the pretrained BERT represents rather than in a trainable space.

The network is trained to minimize the log likelihood for all dialog turns t and slot-types $s \in \mathcal{D}$ as following:

$$\mathcal{L}_{bs}(\theta) = -\sum_{t=1}^{T}\sum_{s \in \mathcal{D}} \log p(v_t|\mathbf{x}_{\leq t}^{sys}, \mathbf{x}_{\leq t}^{usr}, s). \tag{6}$$

By training all domain-slot-types together, the model can learn general relations between slot-types and slot-values, leading to performance improvements.

Finally, the model is trained to minimize all above losses:

$$\mathcal{L}_{DST}(\theta) = \mathcal{L}_{bs}(\theta) + \lambda_d \mathcal{L}_d(\theta) + \lambda_i \mathcal{L}_a(\theta), \tag{7}$$

where λ_d and λ_i are hyper-parameters.

C. Latent Action Space and Response Generation

To model latent system action spaces and generate responses, we employed the LaRL model proposed in [23]. As described in Fig.5, the context encoder estimates $p(\mathbf{z}|\mathbf{c})$, the probability of latent variable $\mathbf{z}$ given context vectors $\mathbf{c}$. In our system, the context vector concatenates the utterance vector $\mathbf{u}^0$, the domain probability vector $\mathbf{h}^d$, the action probability vector $\mathbf{h}^i$, the belief state probability vector $\mathbf{h}^{bs}$, and the database query result vector $\mathbf{h}^{db}$. Note that the belief state probability in $\mathbf{h}^{bs}$ represents the estimated probability that the slot-value is *not 'none'* or *'not mentioned'*. Also, the database query results, such as the number of retrieved results and domain activation, are one-hot encoded into the vector.

The latent action variables can be modeled as continuous and discrete variables. Instead of continuous variables with Gaussian prior distribution, in this paper, we assume them as M independent K-way categorical random variables with Uniform prior distribution, resulting in K^M combinations for unique action spaces. The probability of Z_m is estimated by the context encoder F and a softmax function as follow:

$$\begin{aligned} p(Z_m|\mathbf{c}) &= \text{softmax}(\pi_m(F(\mathbf{c}))), \\ \mathbf{z}_m &\sim p(Z_m|\mathbf{c}). \end{aligned} \tag{8}$$

For each categorical random variable Z_m, there is a D-dimensional vector space $\mathbf{E}_m \in \mathbb{R}^{K\times D}$. Therefore, the sampled discrete latent variables $\mathbf{z}_m$ are then mapped into the vector space using their embeddings $\mathbf{E}_m(\mathbf{z}_m) \in \mathbb{R}^D$.

Finally a RNN decoder such as LSTM or GRU autoregressively generates a response given the latent embedding vectors:

$$p(\mathbf{x}^{sys}|\mathbf{z}) = p(\mathbf{x}^{sys}|[\mathbf{E}_1(\mathbf{z}_1); ...; \mathbf{E}_M(\mathbf{z}_M)]; \theta_d). \tag{9}$$

The summation of latent embedding vectors are fed into the initial state of decoder. In addition, the decoder selectively integrates latent information into decoding process by using attention mechanism:

$$\begin{aligned} \alpha_{mi} &= \text{softmax}(\mathbf{h}_i^T W_a \mathbf{E}_m(\mathbf{z}_m)), \\ \mathbf{c}_i &= \sum_{m=1}^{M} \alpha_{mi}\mathbf{E}_m(\mathbf{z}_m), \\ \tilde{\mathbf{h}}_i &= \tanh W_s([\mathbf{h}_i; \mathbf{c}_i]), \\ p(w_i|\mathbf{h}_i, \mathbf{c}_i) &= \text{softmax}(W_o\tilde{\mathbf{h}}_i), \end{aligned} \tag{10}$$

where $\mathbf{h}_i$ is the RNN output at i-th step, and W_a, W_s, W_o are learnable parameters. Thus the selective fusion enables different information fusion at each generation step.

The network is optimized to maximize the evidence lower bound (ELBO) via stochastic variational inference [29] in auto-encoding manner:

$$\mathcal{L}_{full}(\theta) = \mathbb{E}_{q(\mathbf{z}|\mathbf{x},\mathbf{c})}[p(\mathbf{x}|\mathbf{z})] - D_{KL}\left[q(\mathbf{z}|\mathbf{x},\mathbf{c})||p(\mathbf{z}|\mathbf{c})\right], \tag{11}$$

where $q(z|x, c; \phi)$ is the approximate posterior distribution parameterized by neural networks, and D_{KL} is KL-divergence. The ELBO is maximized by gradient ascent via a reparameterized trick. We use the Gumbel-Softmax [30] to backpropagate through categorical latent variables.

Nevertheless, ELBO training usually yields discrepancy problems between latent variables sampled from posterior and prior distributions, which results in poor generation results. In order to avoid this exposure-bias problem, the authors in [23] proposed a simplified ELBO by assuming the posterior and prior network are the same (*i.e.*, $q(\mathbf{z}|\mathbf{x}, \mathbf{c}; \phi) = p(\mathbf{z}|\mathbf{c}; \theta)$), and adding the additional regularization term $\beta D_{KL}\left[q(\mathbf{z}|\mathbf{c})||p(\mathbf{z})\right]$. The regularized term prevents overfitting and the posterior being apart from the prior. β is a hyper-parameter between 0 and 1, and the prior distribution $p(\mathbf{z})$ is Uniform distribution for categorical variables. Finally, the loss function of the policy model is the negative simplified ELBO:

$$\mathcal{L}_{POL}(\theta) = -\mathbb{E}_{p(\mathbf{z}|\mathbf{c})}[p(\mathbf{x}|\mathbf{z})] + \beta D_{KL}\left[p(\mathbf{z}|\mathbf{c})||p(\mathbf{z})\right]. \tag{12}$$

D. Pretraining and End-to-end Fine-tuning

Since the proposed neural dialog system is fully differentiable, the entire system can be optimized in end-to-end fashion by minimizing the total loss:

$$\mathcal{L} = \mathcal{L}_{DST} + \lambda\mathcal{L}_{POL}. \tag{13}$$

However, the total loss function is a combination of different types of losses that have different ranges of scales, so we expect that optimizing the whole system from scratch usually causes some criteria to be under-fitted. Therefore we separately *pretrain* SUMBT+ and LaRL models while freezing BERT encoder, and *fine-tune* the entire system with the loss Eq.13.

E. Reinforcement Learning

After end-to-end training, the dialog system is further optimized by off-line policy gradient reinforcement learning [31], [32] using the REINFORCE algorithm [5] to succeed task-dependent goals. For the system response at turn t, a turn-level reward r_t is given, and the expected discounted return through T-length dialog is calculated as $J(\theta) = \mathbb{E}[\sum_0^T \gamma^t r_t]$ with the discounting factor $\gamma \in [0, 1]$. In order to reduce the variance of the policy gradient, the reward uses a baseline function b is as follow:

$$R_t = \sum_{k=0}^{T-t} \gamma^k (r_{t+k} - b). \tag{14}$$

When it comes to word-level reinforcement learning where word generation at each step is considered as an action, the policy gradient is calculated as:

$$\nabla_\theta J(\theta) = \mathbb{E}_\theta\left[\sum_{t=0}^{T}\sum_{j=0}^{N_t} R_{tj}\nabla_\theta \log p_\theta(w_{tj}|w_{<tj}, \mathbf{c}_t)\right], \tag{15}$$

where N_t is sentence length. Therefore, it is prone to credit the assignment problem over long word sequences, and the number of action space is as large as the vocabulary size. It is well known that policy gradients through the decoder outputs cause training divergences.

To tackle the problem, applying REINFORCE to the latent action space is proposed in [23]:

$$\nabla_\theta J(\theta) = \mathbb{E}_\theta\left[\sum_{t=0}^{T} R_t\nabla_\theta \log p_\theta(\mathbf{z}|\mathbf{c}_t)\right]. \tag{16}$$

Note that the policy gradient at latent actions decouples the discourse-level decision making from language generation of the decoder. Furthermore, it shortens the horizon and has lower-dimensional latent action spaces.

The success criterion is whether the model informs all requested slots by the user. However, the existing success criterion in corpus-based evaluation [24] includes a part of requestable slots, leading the discrepancy to a real evaluation environment. We propose new success criteria and corresponding reward levels by adding more difficult slots as described in Table I.

Reward calculation and reinforcement learning procedures are as follow:

TABLE I
THE PROPOSED SUCCESS CRITERIA

Reward level	Success Criteria of Informed Slots
1 (baseline)	'phone', 'address', 'postcode', 'reference', 'trainid'
2	+ 'leaveAt', 'arriveBy', 'type'
3	+ 'price', 'duration', 'entrance'

1) For each RL episode, randomly sample a dialog from the training set.
2) At each pair of the previous system and the user turns, obtain SUMBT+ outputs, samples the latent system actions, and generate a system response.
3) According to the reward level, compute Success Rate based on the generated responses and the *estimated* belief states by SUMBT+.
4) Compute policy gradient using Eq.16 and update the parameters.

Note that we use the estimated belief state rather than the original belief state for the reward calculation.

IV. Related Work

In this section, we review related work in perspective of dialog state tracking, action policy and response generation, and end-to-end neural task-oriented dialog systems.

A. Dialog State Tracking

Recent neural dialog state tracking methods are categorized into two categories: classification among slot-value candidates [3], [25], [33], and generation slot-values [4], [34]. While the classification-based methods can obtain the probability distribution for the candidates, the generation-based methods are robust against out-of-vocabulary words by finding text spans. However, the latter methods have disadvantages that it requires slot-value normalization and it is hard to estimate the probability of generated slot-value over the candidates. Note also that SUMBT models the changes of belief states as dialog progress using neural network, not by rules, which enables error back-propagation through dialog histories.

B. Action Policy and Response Generation

To learn dialog policy and response generation given dialog contexts, the existing approaches can be divided into two categories depending on explicit or implicit action spaces. The explicit approaches are typically trained to classify the system actions with label supervision [6], [11], or generate dialog acts and response simultaneously [35]. However, the annotated system action labels are noisy and biased, thus resulting in performance bottlenecks of the entire system. Implicit approaches model the latent action spaces such as Gaussian or Categorical variables, and apply reinforcement learning [23] or hierarchical reinforcement learning in [36] to optimize the action policy for evaluation metrics as rewards. Nevertheless, those methods were trained and evaluated on oracle dialog contexts rather than end-to-end fashion.

C. End-to-End Neural Task-Oriented Dialog Systems

The first end-to-end trainable task-oriented dialog system framework was a pipeline consisting of five modules (Intent, Belief Tracker, Policy, Database, Generation) proposed in [7]. Recently, simplified pipeline architectures have been explored to reduce accumulated errors. Based on a sequence-to-sequence model, Sequicity [9] incorporates dialogue state tracking and it is jointly trained with response generation. MOSS [37] has a shared encoder and used modular supervisions likewise multi-task learning, and UniConv [14] generates dialog acts and response simultaneously. DAMD [13] aims to the one-to-many problem of dialog response, suggesting multi-action generation.

A recent line of research is employing the large-scale pre-trained language model, GPT-2 [20], and transfer the knowledge into task-oriented dialogs. They use the GPT-2 model as a pipeline without additional module network. The researchers in [38] fine-tuned GPT-2 on the MultiWOZ dataset, but they only dealt with oracle dialog context-to-text tasks. The challenge winner of the DSTC8 task [12] input dialog history to GPT-2 and generated belief states, system actions, and responses auto-regressively. Similarly, SimpleTOD [21] and SOLOIST [15], which are parallel but independent work, generate belief states, and then database query results are fed into the network, followed by response generations. Meanwhile, the difficulty of reinforcement learning on the transformer-based architecture has not been fully resolved yet [22], and thus dialog policy optimizations on those approaches require further research. Although the GPT-2 ease the human efforts for modeling each module, the auto-regressively generating all belief states, system acts and responses in a sequence would be a speed bottleneck when it comes to real-world applications.

V. Experimental Results

In this section, we experimentally demonstrate the efficacy of end-to-end fine-tuning of the pretrained SUMBT+LaRL model. Furthermore, we show that reinforcement learning improves the dialog success rate of the model in both end-to-end corpus-based and simulator-based evaluations, indicating the necessity and effectiveness of reinforcement learning. We present the experiment results with dialog examples depending on the proposed reward levels and the sort of belief states for reward calculations. Finally, we show a new state-of-the-art dialog success rate on end-to-end corpus-based evaluation as well as our DSTC8 challenge result, which is comparative to the challenge winner.

A. Experimental Settings

1) Preprocessing: Following the conventional delexicalization method in [24], we replaced the user and system utterances with placeholders. We additionally delexicalized several slot-values based on the user-act annotations provided by DSTC8. For the database features, we also followed the way described in [24] and concatenated them with query result dependent binary features, such as *'parking'* or *'internet'*.

TABLE II
BELIEF STATES, USER ACTION, AND DOMAIN CLASSIFICATION RESULTS OF PRETRAINED SUMBT+.

	Belief States		Domain			User Intents		
	Joint	Slot	Acc.	Precision	Recall	Acc.	Precision	Recall
SUMBT [3]	0.4881	0.9733	-	-	-	-	-	-
SUMBT+ (Fix BERT)	0.4901	**0.9759**	0.9696	0.8274	0.9165	0.9778	0.5843	0.7892
SUMBT+ (Finetune BERT)	**0.4920**	0.9750	**0.9896**	**0.9528**	**0.9622**	**0.9865**	**0.7695**	**0.8688**

TABLE III
CORPUS-BASED EVALUATION ON PRETRAINED LARL.

Posterior	PPL	Success	Inform	BLEU	F1
Lite [23]	4.05	0.5736	0.6798	**19.1**	N/A
Lite	**4.023**	**0.685**	**0.776**	18.89	0.510

2) Training Details: We developed our system employing the pre-trained $\text{BERT}_{\text{BASE}}$ model[2], and open-source repositories for SUMBT[3] and LaRL[4]. Overall, the SUMBT+ predicts 7 domains, 40 user intents, and slot-values for 38 slots in belief states. We described the hyperparameters used for our experimental results in Table XII, Appendix A. Note that in the case of reinforcement learning, we only trained the context encoder to fine-tune the parameters for probability function given the context vector, $p(\mathbf{z}|\mathbf{c})$.

3) Evaluation Metrics: For the SUMBT+, we measure the joint accuracy of belief state tracking and the classification accuracies of both domain and user intents. For the LaRL and the entire system, the evaluation metrics are categorized into corpus-based evaluations and simulator-based evaluations. For corpus-based evaluations, the performance of the MultiWOZ test split is measured in the perspective of success rate, inform rate, delexicalized-BLEU, and entity F1. The Success and Inform rate are whether the model provides requested information, and the model's recommendations are suited for the user's request. Entity F1 evaluates the entity coverage accuracy. For an overall measure, a combined score are calculated as $(Inform + Success) \times 0.5 + BLUE$. For simulator-based evaluations, the model converses with the simulator provided in ConvLab for 100 sessions, then the generated dialogs are evaluated for the dialog success ratio, book rate, inform, and the number of dialogue turns.

B. Pretraining SUMBT+ and LaRL

The pretraining SUMBT+ results are shown in Table II. Compared to SUMBT [3], SUMBT+ shows the similar belief state accuracy. Besides, although the classification accuracy of domains and user intents are high, the precision and recall are low because of the small number of positive samples. When the BERT encoder is fixed, the precision and recall are relatively less optimized than when the BERT parameters are fine-tuned. The BERT encoder will be fine-tuned in the following end-to-end fine-tuning step.

[2]https://github.com/huggingface/transformers
[3]https://github.com/SKTBrain/SUMBT
[4]https://github.com/snakeztc/NeuralDialog-LaRL

Table III presents the corpus evaluation results on the pretrained LaRL with the oracle labels. Compared with the results reported in [23], our model achieves a higher success rate by utilizing BERT encoder, user domain and intent labels as inputs, supplemental delexicalization, and database features.

C. End-to-end Fine-tuning

End-to-end training results of our proposed model are shown in Table IV including classification and corpus-based evaluation. In the table, we compared four end-to-end models: the combination of the pretrained models without fine-tuning (Comb. PTR), the end-to-end trained from scratch (E2E Scratch), the fine-tuned model except for the BERT encoder (E2E FT (Fix BERT)), and the end-to-end fine-tuned model (E2E FT).

First, when the two pre-trained SUMBT+ and LaRL are combined as a pipeline, the success rate degrades from 68.5% (pretrained LaRL) to 51.3% due to the accumulated errors in the pipeline. In the E2E FT model, the errors are reduced by back-propagation through the pipeline, resulting in the significant improvement of the success rate of 66.2%, as well as other classification metrics, perpelxity and BLEU scores. On the other hand, when training the entire model from scratch without pretraining procedures, it was difficult to optimize the system, resulting in a poor success rate of 31.5%. In addition, fine-tuning but fixing the BERT model significantly decreases the success rate (42.6%) and classification results, indicating that fine-tuning the BERT utterance encoder plays the key role in the E2E fine-tuning.

We also trained models without domain and user intent information to verify the impact of these information to the overall system performance. These models showed significantly lower success rate (26.9% for the combination model, 28.3% for end-to-end trained from scratch), indicating that understanding the user's intents, especially recognizing user requests, is critical to carry on successful dialogs.

D. Reinforcement Learning

The above end-to-end fine-tuned model (E2E FT) is further trained using REINFORCE algorithm with the three different reward levels, and the rewards are calculated using the oracle or estimated belief states as described in Sec.III-E and Table I.

1) End-to-end Corpus-based Evaluation: Table V shows the corpus-based evaluation results. Note that the table also presents the success rates on the proposed success criteria, which are denoted as Success 2 and Success 3. First, after RL

TABLE IV
CLASSIFICATION AND END-TO-END CORPUS-BASED EVALUATION RESULTS ON SUMBT+LARL.

	Belief States		Domain			User Intents			NLG	Corpus-based Evaluation			
	Joint	Slot	Acc.	P.	R.	Acc.	P.	R.	PPL	Success	Inform	BLEU	F1
Comb. PTR w/o UA	0.481	0.974	-	-	-	-	-	-	5.130	0.269	0.424	14.22	0.347
E2E Scratch w/o UA	0.481	0.974	-	-	-	-	-	-	5.139	0.283	0.442	14.22	0.347
Comb. PTR	0.491	0.976	0.970	0.827	0.917	0.978	0.584	0.789	4.211	0.513	0.708	16.25	0.432
E2E Scratch	0.484	0.975	0.990	0.954	0.965	0.987	0.767	0.876	4.810	0.359	0.548	15.48	0.380
E2E FT (Fix BERT)	0.488	0.977	0.959	0.749	0.903	0.971	0.411	0.735	4.112	0.426	0.716	16.77	0.430
E2E FT	**0.515**	**0.979**	**0.991**	**0.957**	**0.967**	**0.991**	**0.861**	**0.904**	**3.999**	**0.662**	**0.721**	**19.36**	**0.522**

TABLE V
END-TO-END CORPUS-BASED EVALUATION ON REINFORCE TRAINED SUMBT+LARL.

Belief States	Reward Level	PPL	Success	Match	BLEU	F1	Combined	Success 2	Success 3
Lite + RL [23]	-	5.22	0.792	0.828	12.8	N/A	93.8	N/A	N/A
Comb. PTR	-	4.21	0.513	0.708	16.25	0.432	61.21	0.41	0.30
E2E FT	-	**4.00**	0.662	0.721	**19.36**	**0.522**	88.51	0.54	0.44
	1	4.08	0.828	0.912	18.60	0.504	**105.60**	0.70	0.58
Oracle	2	4.06	0.811	0.890	18.80	0.508	103.85	0.67	0.55
	3	4.08	0.796	0.856	18.40	0.494	101.00	0.66	0.53
	1	4.10	**0.854**	**0.922**	17.90	0.501	106.70	**0.72**	**0.62**
Estimated	2	4.09	0.850	0.924	18.40	0.501	**107.10**	**0.72**	0.59
	3	4.09	0.804	0.880	18.40	0.490	102.60	0.67	0.53

TABLE VI
SIMULATOR-BASED EVALUATION ON REINFORCE TRAINED SUMTB+LARL.

Model	Reward Level	Turn	Inform			Book Rate (%)	Success (%)
			Precision	Recall	F1		
Comb. PTR	-	12.17	0.60	0.73	0.63	66.48	57.20
E2E FT	-	9.04	**0.69**	0.86	0.74	80.36	77.40
	1	9.18	0.64	0.85	0.71	84.30	74.20
Oracle	2	8.50	0.68	**0.90**	**0.75**	**86.53**	**81.40**
	3	7.88	0.67	0.87	0.73	83.64	79.20
	1	10.63	0.60	0.78	0.65	77.90	65.60
Estimated	2	8.27	0.63	0.86	0.70	81.08	76.60
	3	8.17	0.68	0.88	0.74	83.76	79.00

training, the success rate is improved from 66.2% to 85.4% (Estimated belief states with reward Level 1). Our models even outperform the reinforcement trained LaRL [23] that uses the oracle context inputs to generate responses. Also, note that the BLEU and perplexity of our proposed architecture shows relatively less degradation after reinforcement learning than [23]. In addition, when it comes to reward calculations, the use of the estimated belief states by SUMBT+ is more accurate and effective to increase the success and match rates than the use of the original belief states. Regarding the reward levels, the models trained with the more difficult success criteria perform the lower success rates. For the reason behind this result, we contend that the model was difficult to appropriately respond to *every* requested slots and receive reward signals, leading to inefficient reinforcement learning.

2) Simulator-based Evaluation: The trained models are automatically evaluated by the user-simulator and the results are presented in Table VI. The end-to-end fine-tuned model achieves the success rate of 77.40%, which is significantly improved than the combined pretrained models (57.20%). Also, the best reinforcement trained model uses the oracle belief states with reward level 2, resulting in 81.40%. The models show lower precision and recall of Inform than the E2E FT model, which implies they provides additional information at once to achieve rewards. In addition, reinforcement learning induces the model to finish and success in shorter turns.

Notably, according to the sort of belief states and the reward levels, the results of corpus and simulator evaluations have different tendencies. Training with the oracle belief states gains larger improvements than the estimated belief states when models are evaluated by the simulator. Also, while using the reward level 1 was effective in corpus evaluation, it degrades performance and gets even worse than E2E FT. We interpret the reason behind this phenomenon as due to the discrepancy

TABLE VII
DIALOG EXAMPLES OF REINFORCE TRAINED MODELS WITH DIFFERENT REWARD LEVELS.

Goal	{‘attraction’: {‘info’: {‘area’: ‘centre’, ‘type’: ‘park’}, ‘reqt’: {‘entrance fee’: ’?’}}, ‘train’: {‘info’: {‘destination’: ‘ely’, ‘day’: ‘friday’, ‘departure’: ‘birmingham new street’, ‘leaveAt’: ’21:45’}, ‘reqt’: {‘price’: ’?’}}}”
SUMBT+LaRL + RL w/ Oracle BS (Reward Level 1): Dialog Failed	
User	**Okay , are there any parks in the centre ? I am also looking for places to go in town . Maybe something in the centre .**
– Inferred user action	{‘Attraction-Inform (BS)’: [[‘Area’, ‘centre’], [‘Type’, ‘park’]], ‘Inform-Inform’: [[‘Area’, ”], [‘Type’, ”]]},
System	**there are 1 park in the centre. cambridge university botanic gardens is located in the centre and cambridge university botanic gardens is 4 pounds.**
– Inferred system action	{‘Attraction-Inform’: [[‘Name’, ‘cambridge university botanic gardens’], [‘Area’, ‘centre’], [‘Name’, ‘cambridge university botanic gardens’], [‘Fee’, ’4 pounds’], [‘Type’, ‘park’], [‘Choice’, ’1’], [‘Area’, ‘centre’]]},
User	**I am leaving for ely. I would like to leave after 21:45 . I will departing from birmingham new street . I ’ m looking to travel on friday.**
– Inferred user action	{‘Train-Inform (BS)’: [[‘Day’, ‘friday’], [‘Depart’, ‘birmingham new street’], [‘Dest’, ‘ely’], [‘Leave’, ’21:45’]], ‘Inform-Inform’: [[‘Day’, ’21:45’], [‘Depart’, ’21:45’], [‘Dest’, ’21:45’]]},
System	**tr8272 leaves at 23:00 and arrives at 23:51. would you like me to book that for you?**
– Inferred system action	{‘Train-Inform’: [[‘arrive’, ’23:51’], [‘Id’, ‘tr8272’], [‘Leave’, ’23:00’]], ‘Train-OfferBook’: [[‘none’, ‘none’]]},
User	**What is the price of a ticket , please ?**
– Inferred user action	{‘Request-Request’: [[‘Ticket’, ’?’]]}
System	**I have a train tr8272.**
– Inferred system action	{‘Train-Inform’: [[‘Id’, ‘tr8272’]]}
User	**What is the price for the train ?**
– Inferred user action	{‘Request-Request’: [[‘Ticket’, ’?’]]}
System	**I have a train tr8272.**
– Inferred system action	{‘Train-Inform’: [[‘Id’, ‘tr8272’]]}
User	**Thank you , goodbye.**
SUMBT+LaRL + RL w/ Oracle BS (Reward Level 2): Dialog Success	
User	**Okay , are there any parks in the centre ? I am also looking for places to go in town . Maybe something in the centre .**
– Inferred user action	{‘Attraction-Inform (BS)’: [[‘Area’, ‘centre’], [‘Type’, ‘park’]], ‘Inform-Inform’: [[‘Area’, ”], [‘Type’, ”]]},
System	**there is 1 park in the centre. it is called cambridge university botanic gardens. would you like more information?**
– Inferred system action	{‘Attraction-Inform’: [[‘Name’, ‘cambridge university botanic gardens’], [‘Choice’, ’1’], [‘Area’, ‘centre’], [‘Type’, ‘park’]], ‘general-reqmore’: [[‘none’, ‘none’]]},
User	**Is there an entrance fee ?**
– Inferred user action	{‘Attraction-Inform (BS)’: [[‘Name’, ‘cambridge university botanic gardens’]], ‘Request-Request’: [[‘Fee’, ’?’]]},
System	**cambridge university botanic gardens is free. their phone number is 01223336265.**
– Inferred system action	{‘Attraction-Inform’: [[‘Fee’, ‘free’], [‘Name’, ‘cambridge university botanic gardens’], [‘Phone’, ’01223336265’]]},
User	**Yes I would like to go to ely please . Yes , I need to leave sometimes after 21:45 . Thanks ! I also need a train departing from birmingham new street . I will leave on friday .**
– Inferred user action	{‘Train-Inform (BS)’: [[‘Day’, ‘friday’], [‘Depart’, ‘birmingham new street’], [‘Dest’, ‘ely’], [‘Leave’, ’21:45’]], ‘Inform-Inform’: [[‘Day’, ’21:45’], [‘Depart’, ’21:45’], [‘Dest’, ’21:45’]]},
System	**tr8272 leaves at 23:00 and arrives at 23:51. would you like me to book that for you?**
– Inferred system action	{‘Train-Inform’: [[‘Arrive’, ’23:51’], [‘Leave’, ’23:00’], [‘Id’, ‘tr8272’]], ‘Train-OfferBook’: [[‘none’, ‘none’]]},
User	**I need to know the price.**
– Inferred user action	{‘Request-Request’: [[‘Ticket’, ’?’]]}
System	**the price is 23.60 pounds.**
– Inferred system action	{‘Train-Inform’: [[‘Ticket’, ’23.60 pounds’]]},
User	**Ok , have a good day . Goodbye .**

of off-line RL (corpus-based training and evaluation) and on-line evaluation (simulator-based evaluation). In other words, the off-line RL for dialog system training has the limitation that the environment assesses whether the model generates sentences including requested slots after the dialog ends, but it does not consider at which turn the model responded. Moreover, during the corpus-based RL, the true pairs of system and user utterances are given to the model rather than the generated system utterance at the previous turn. Also, the model was over-fitted to the success criteria and it was trained to generate specific responses to attain the easy rewards that require few slots, thereby losing the ability to respond to other contexts. We further analyze the case with dialog examples in the next Sec.V-E.

E. Analysis on Simulated Dialogs

The dialog examples of REINFORCE trained SUMBT+LaRL and the user simulator are presented in Table VII. Given the same user goal, we compare the case when the model trained with reward level 1 fails the task and when the model successes with reward level 2. At each turn, the user and system utterances, the inferred user actions

TABLE VIII
END-TO-END CORPUS-BASED EVALUATION ON MULTIWOZ.

Models	Success	Match	BLEU	Combined
Sequicity [9]	45.3	66.4	15.54	71.41
HRED-TS [39]	58.0	70.0	17.50	81.50
Structured Fusion [11]	58.6	73.8	16.90	83.10
Neural pipeline GPT-2 (Challenge Winner) [12]	62.4	73.0	16.00	83.70
DAMD [13]	60.4	76.3	16.60	84.95
UniConv [14]	62.9	72.6	**19.80**	87.55
SimpleTOD [21]	70.1	84.4	15.01	92.26
SOLOIST [15]	72.9	85.5	16.54	95.74
SUMBT+LaRL (E2E Finetune)	66.2	72.1	19.36	88.51
SUMBT+LaRL + RL w/ Oracle BS	82.8	91.2	18.60	**105.6**
SUMBT+LaRL + RL w/ Estimated BS	**85.4**	**92.2**	17.90	**106.7**

TABLE IX
DST PERFORMANCE COMPARISON WITH PREVIOUS WORK

Models	Joint (%)	Slot (%)
SUMBT [3]	48.81	97.33
TRADE [4]	48.62	96.22
COMER [40]	48.79	-
DSTQA [25]	**51.44**	92.74
SOMDST [34]	**51.72**	-
SUMBT+ (FT BERT)	49.01	97.59
SUMBT+LaRL (E2E FT, Fix BERT)	48.79	97.69
SUMBT+LaRL (E2E FT)	**51.52**	**97.89**

TABLE X
DSTC8 RESULTS ON AUTOMATIC EVALUATION BY USER-SIMULATOR
†: OUR SUBMISSION APPLIED POST-PROCESSING

Team	E2E trainable	Turn	Inform P.	Inform R.	Inform F1	BR. (%)	Success (%)
T1		7.00	0.92	0.96	0.93	93.75	88.80
T2		6.69	0.83	0.94	0.87	96.39	88.60
T3		6.55	0.71	0.92	0.78	94.56	82.20
T10[†] *(ours)*	$\surd$	8.50	0.68	0.90	0.75	86.53	81.40
T4		7.21	0.78	0.89	0.81	86.45	80.60
T5	$\surd$	7.59	0.8	0.89	0.83	87.02	79.40
T6		7.90	0.61	0.73	0.64	75.71	58.00
T7		9.78	0.68	0.77	0.70	58.63	56.60
T10 *(ours)*	$\surd$	8.83	0.46	0.75	0.54	76.38	52.20

(belief states and user intents) by the model, and the inferred system actions by the user-simulator are described. When the user asks the price of the offered ticket, the success model gives the appropriated answer despite the wrong inferred user intents. However, the failed model provides the train id rather than the price, indicating the model is overfitted to the success criteria by reinforcement learning. Therefore, the example presents the discrepancy problem between corpus and automatic evaluations, and the limitations of off-line reinforcement learning for dialog systems. It also suggests the needs of advanced reward design and success criteria.

F. Comparison with Previous Work

In Table VIII, the end-to-end corpus-based evaluation performance of SUMBT+LaRL is compared with the previously proposed models. The SUMBT+LaRL with reinforcement learning obtained a new *state-of-the-art success rate* of 85.4%, a match of 92.2%, and a combined score of 106.7. Compared to the previous GPT-2 based models such as Neural pipeline GPT-2 (Challenge Winner) [12], SOLOIST [15], and SimpleTOD [21], the performance is largely improved, encouraging and emphasizing the importance of policy optimization through reinforcement learning.

Additionally, when it comes to dialog state tracking (DST) task, the performance of SUMBT+ (Fine-tune BERT) is similar to the one of SUMBT as 49.01% and 48.81%, respectively. This indicates that the additional supervision by domain and user intent information does not enhance the performance of DST itself. However, SUMBT+LaRL (E2E FT) shows the competitive dialog state tracking performance (51.52%) with the state-of-the-art methods. It means that the supervision from the next system response by back propagation through pipeline encourages SUMBT+ to predict the belief state more accurately.

G. DSTC8 Challenge Results

In the DSTC8 challenge, the submissions were evaluated by the user simulator provided in ConvLab and human evaluators through Amazon Machanic Turk. In the automatic evaluation, an agenda-based user simulator with MILU and a template-based NLG carried on 500 dialogs with each submitted system. For human evaluation, crowd-workers were given randomly selected goals and had conversations with systems. After a conversation, they scored the systems for their natural language understanding and response appropriateness on a scale of 1 to 5 as well as whether the system successes user's goal. We refer to the challenge results [41].

The automatic evaluation results are listed in Table X, and we marked each model whether it is end-to-end trainable. Except for our SUMBT+LaRL (T10) and Neural pipeline GPT-2 (T5, the challenge winner), the other submitted models mainly have a pipeline of 4 different modules (NLU-DST-Policy-NLG). First, the submission models (T1, T2, T4) are consisted of BERT-based NLU, and rule or template-based

TABLE XI
DSTC8 Results on Human Evaluation

Team	SR(%)	Under.	Appr.	Turns	Final Ranking
T5	68.32	4.15	4.29	19.51	1
T1	65.81	3.54	3.63	15.48	2
T2	65.09	3.54	3.84	13.88	3
T3	64.10	3.55	3.83	16.91	4
T4	62.91	3.74	3.82	14.97	5
T10 *(ours)*	54.90	3.78	3.82	14.11	6
T6	43.56	3.55	3.45	21.82	7
T7	25.77	2.07	2.26	16.80	9

DST, Policy, and NLG. T3 is similar to the first group but employed the DQN model for Policy, and HDSA with templates for NLG. T6 and T7 put their efforts to enhance policy learning. Except for T5 and our model (T10), all others include handcrafted-rules and templates, so end-to-end optimization is not possible.

Since our submission had a lack of several necessary post-processing methods for lexicalization and querying databases, we polished them by following the methods used in the T5. (See Appendix B for the details). As a result, our model achieves a success rate of 81.40% in automatic evaluation (denoted as †). Our competitive result indicates the room for replacing the sophisticated and complex hand-crafted rules with the proposed end-to-end trainable SUMBT+LaRL.

The human evaluation results and the final challenge ranking are listed in Table XI. T5 that employing GPT-2 was ranked the first by achieving the best success rate and the remarkably highest understanding and appropriateness scores. Although our submitted model showed a lower success rate due to the post-processing problem, it achieved the 2nd rank in the average score of appropriateness (3.82) and understanding (3.78).

VI. Conclusion

In this paper, we propose an end-to-end trainable task-oriented dialog system with reinforcement learning that consists of SUMBT+ and LaRL. The SUMBT+ estimates user-acts as well as dialog belief states, and the LaRL models latent system action spaces and generates responses given the estimated contexts. We experimentally demonstrated that the training framework in which the SUMBT+ and LaRL are pretrained, then the entire system is fine-tuned significantly increases dialog success rates. Besides, the end-to-end fine-tuning showed that the supervisions from the next system response also encourages to improve dialog state tracking, achieving the performance comparable to the state-of-the-art joint accuracy. We further trained the model with REINFORCE using the reward levels and success criteria we designed. Using the estimated belief states to assess the reward level 1 attained the best success rates in the end-to-end corpus evaluation, whereas the oracle belief states and reward level 2 achieved the highest in the automatic evaluations. The experiment results and the qualitative analysis of simulated dialog examples present the discrepancy problem of corpus and automatic evaluations, the limitations of off-line reinforcement learning for dialog policy, and the needs of advanced reward design and success criteria. Our model achieved the new state-of-the-art success rate of 85.4% in end-to-end corpus-based evaluation on MultiWOZ corpus, as well as outperformed the challenge winner of the DSTC8 Track 1 challenge by showing 81.4% in the simulator-based evaluation.

Appendix A
Training Details

The following Table XII lists the hyperparameters used for our experimental results.

TABLE XII
Training details for each training steps.

Pretraining SUMBT+	
RNN	GRU (300, 1 layer)
Dropout	0.5
Optimizer	BertAdam
Learning rate	0.0001
λ_d	1
λ_a	1
weight decay	0.0002
Pretraining LaRL	
Context Encoder	Linear (1 layer)
Decoder	Attn GRU(150)
Decoder vocab size	1000
Categorical z	M=10, K=20
Dropout	0.5
Optimizer	BertAdam
Learning rate	0.001
Weight decay	0.0002
β	0.01
Generation Beam Size	20
End-to-end finetuning	
Optimizer	BertAdam
Learning rate	0.0001
λ	1
Reinforcement Learning	
Optimizer	SGD(lr=0.01, grad_clip=0.5, momentum = 0, Nestrov = False)
γ	0.99

Appendix B
Post-processing Details

In our challenge submission, there were miscellaneous but largely influential bugs in our database query part. After fix the bugs, we applied the same post-processing methods of the challenge winner team (Neural pipeline GPT-2) [12] such as substitution several specific phrases that are not recognized by the user-simulator's NLU with other synonym words (*e.g.*, 'moderately priced' to 'moderate', 'center part of town' to 'center', 'gbp' to 'pounds'). The automatic evaluation results of our submission and its post-processing results are shown in Table XIII.

TABLE XIII
POST-PROCESSING DETAILS

Model	Turn	Inform			BR(%)	SR (%)
		P.	R.	F1		
Challenge Winner [12]	7.59	0.80	0.89	0.83	87.02	79.40
Our Submission	8.89	0.47	0.76	0.55	76.50	50.60
Fix DB Query	8.31	0.56	0.90	0.65	86.46	79.60
Post-processing	8.50	0.68	0.90	0.75	86.53	81.40

ACKNOWLEDGMENT

The authors would like to thank to SK Telecom Meta AI team for GPU cluster supports to conduct massive experiments.

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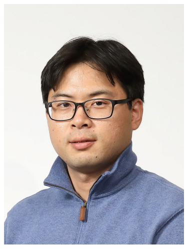

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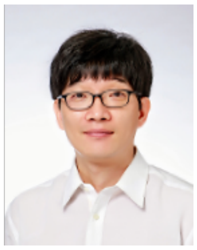

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