

AN ASYNCHRONOUS UPDATING REINFORCEMENT LEARNING FRAMEWORK FOR TASK-ORIENTED DIALOG SYSTEM

Sai Zhang, Yuwei Hu, Xiaojie Wang* and Caixia Yuan

Beijing University of Posts and Telecommunications, Beijing, China
{zs, hyw724, xjwang, yuancx}@bupt.edu.cn

ABSTRACT

Reinforcement learning has been applied to train the dialog systems in many works. Previous approaches divide the dialog system into multiple modules including DST (dialog state tracking) and DP (dialog policy), and train these modules simultaneously. However, different modules influence each other during training. The errors from DST might misguide the dialog policy, and the system action brings extra difficulties for the DST module. To alleviate this problem, we propose **Asynchronous Updating Reinforcement Learning** framework (AURL) that updates the DST module and the DP module asynchronously under a cooperative setting. Furthermore, curriculum learning is implemented to address the problem of unbalanced data distribution during reinforcement learning sampling, and multiple user models are introduced to increase the dialog diversity. Results on the public SSD-PHONE dataset show that our method achieves a compelling result with a 31.37% improvement on the dialog success rate. The code is publicly available via <https://github.com/shunjia/AURL>.

Index Terms— Task-oriented dialog system, multi-agent reinforcement learning, curriculum learning, user simulator

1. INTRODUCTION

Task-oriented dialog systems are widely employed for customer service, e.g., automatic ticket booking. A dialog system is usually composed of four modules: natural language understanding (NLU), dialog state tracking (DST), dialog policy (DP) and natural language generation (NLG) [1]. DST, which maintains the dialog state from the beginning of the dialog to the current turn, is usually trained using supervised learning (SL). DP, which decides the system action to guide the direction of the dialog, can be trained via SL [2] with labeled data or reinforcement learning (RL) [3, 4] with a user simulator serving as a part of interacting environment.

In previous works, when training DP using RL, rule-based DST is usually applied [4, 5] to ignore errors from DST. However, the DST module is unstable in real scenarios. DP should guide the dialog successfully under the influence of DST errors. [6, 7] train the modules with SL along with RL loss from

Level	Dialog
Easy	Last System State [159]
	Last System Utterance 然后呢 ? (And then?) <i>[req more]</i>
	User Utterance 4307 <i>[inform norm]</i>
	Generated Belief State [159, 4307]
	Oracle Belief State [159, 4307]
Hard	Last System State [159, 4307]
	Last System Utterance 那应该是多少(What should that be?) <i>[req correct]</i>
	User Utterance 我记错了, 是807, 307错了 <i>[update sub]</i> (I misremembered, it is 807, 307 is wrong.)
	Generated Belief State [159, 807]
	Oracle Belief State [159, 4807]

Fig. 1: Example of *easy* and *hard* dialogs, different user actions bring different challenges for the system DST module. The user action *[inform norm]* is easy for system while *[update sub]* is hard. The errors from the DST module may misguide the decision from the system DP module. The user action is related to the system action decided by the system DP module.

DP. But the modules will influence each other when training simultaneously. If DST tracks wrong slot values, the system may collect a wrong slot under the right policy, leading to the policy incorrectly learning. Meanwhile, suppose the dialog policy module often chooses actions that user can respond easily, the DST module can not be trained sufficiently and may lose the ability to understand the hard user actions. As an example, Figure 1, shows that different user actions pose different challenges for the DST module, which brings bias when training. Furthermore, the DP is usually trained by interacting with a predefined user simulator [5], though stochastic yet monotonous. As observed in [6], different users bring diverse dialogue states, thus the dialog policy can be trained sufficiently.

To overcome these problems, we first propose a new updating reinforcement learning framework for dialog systems, where DST and DP modules are both trainable cooperatively, but each is updated asynchronously with different updating frequency. We then construct a **Multi-User Reinforcement Learning** (MURL) with the AURL framework, where multiple user models are used to interact with one dialog system to get more diverse dialog strategies. In addition, we use curriculum

*Corresponding author.

learning [8] to boost the DST learning by gradually increasing the complexity of the data samples used during the training process.

To better verify our approach, we conduct experiments on the SSD-PHONE dataset [9], a large action space dialog dataset with diversity phenomena. A hierarchical neural network dialog system and a user model are built. The results demonstrate that the system trained using the proposed framework achieves a new start-of-the-art in online test. In summary, the contributions of this paper are as follows.

- We propose a novel asynchronous updating reinforcement learning framework for dialog systems which trains DP and DST modules asynchronously in a cooperative setting, and applies curriculum learning to solve the bias during training.
- We propose a novel reinforcement learning framework for training one dialog agent with multiple user models, which increases the dialog diversity and sufficiently promotes dialog policy learning.
- We conduct experiments on the real-world SSD-PHONE dataset. Results show the superiority of our approach to several strong baselines. Significantly, it increases by 31.37% on dialog success rate than the current SOTA.

2. METHOD

2.1. Asynchronous Updating Reinforcement Learning Framework

2.1.1. Framework

Figure 2 shows the general architecture and information flow of our framework, composed of one system agent and N user agents. System and Users communicate with each other via script language. After completing one dialog, the inputs, outputs, labels or rewards for each module are kept in replay buffer BF_{user_DP} , BF_{user_NLU} , BF_{sys_DP} and BF_{sys_DST} respectively. We update each module asynchronously using experience replay[10].

System DST produces ϕ that updates the dialog belief state of the current turn. Inspired by TRADE [11], we use two encoders to encode the dialog history $[U_{t-1}^s; U_t^u]$ and last system belief state BS_{t-1}^s respectively, where U_{t-1}^s is the system response at $t-1$ turn, U_t^u is the user utterance at current turn t . A state generator [12] is applied to generate the current turn's belief state BS_t^s . User action \hat{a}_t^u is obtained from a multi-layer perceptron with input the hidden states of two encoders. System DST is formulated as:

$$(BS_t^s, \hat{a}_t^u) = \phi(BS_{t-1}^s, [U_{t-1}^s; U_t^u]). \quad (1)$$

System DP produces π that decides the current turn's system action a_t^s and system slot s_t^s according to the dialog state. The

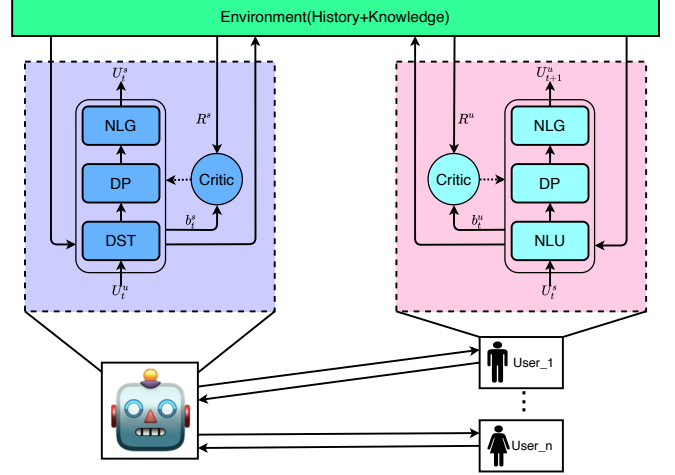


Fig. 2: AURL framework on multi-agent learning. System and users interact with each other via written language. The system DST module and DP module are updated asynchronously.

dialog state at dialog turn t is the concatenation of (1) the system action at last turn a_{t-1}^s , (2) the belief state at current turn BS_t^s , (3) the hidden state from dialog history encoder H_t^{ctx} , (4) the query results q_t from DB. System DP is formulated as:

$$(a_t^s, s_t^s) = \pi(a_{t-1}^s; BS_t^s; H_t^{ctx}; q_t). \quad (2)$$

User NLU yields η that understands the system action \hat{a}_t^s and system slot \hat{s}_t^s according to system utterance U_t^s and user's goal value G . User NLU is formulated as:

$$(\hat{a}_t^s, \hat{s}_t^s) = \eta(G; U_t^s). \quad (3)$$

User DP yields μ that decides user action a_{t+1}^u and user slot s_{t+1}^u to interact with system agent. And then, a state vector BS_{t+1}^u records each slot or each part of slot if provided or need to be updated. Each slot uses a Likert scale of 0-2, which respectively represent *not provided*, *provided* and *need updated*. To model errors brought by Automatic Speech Recognition(ASR), we randomly replace the slot with a similar one. The input to the user policy module is the concatenation of (1) the user action at last turn a_t^u , (2) the system action \hat{a}_t^s , (3) the system slot \hat{s}_t^s and (4) the user state vector at last turn BS_t^u . User policy is formulated as:

$$(a_{t+1}^u, s_{t+1}^u) = \mu(a_t^u; \hat{a}_t^s; \hat{s}_t^s; BS_t^u). \quad (4)$$

To mitigate the errors entangling of DST and DP, we train them asynchronously with different updating frequency. We train both modules by experience replay which samples training examples when the experience pools are full. The DP is updated more frequently by examples from a smaller experience pools, while the DST is updated slowly by examples from a bigger one. In so doing, DP can optimize its policy quickly in a relative stable environments, while DST can learn with the latest DP module.

2.1.2. Curriculum Learning

During reinforcement learning, training examples are randomly sampled from experience pools. To imitate how humans learn, we introduce curriculum learning to schedule the training process. After pretrained on the offline dialog dataset, the DST model is evaluated on test dataset and obtains the joint accuracy of user action understanding. The joint accuracy is then used as difficulty measurer [13] to split the data in BF_{sys_DST} into *easy*, *middle* and *hard* levels.

Firstly, we train the DST module using *easy*, *middle* and *hard* levels of data in order. Secondly, using *middle* and *hard* levels since the *easy* data takes account of 75% of the whole data and the model has learned well on them. Thirdly, just using *hard* data. At last, all levels of data are exploited in order to review.

2.1.3. MURL

Multiple user models, which are pretrained on the dialog corpus, are used to train one dialog system. The system interacts with each user in order after completing one dialog session. The users, trained independently of each other, will have different personalities during the RL training due to the random number. For the same system utterance, different users may use different actions to respond, which brings more dialog diversities to promote the system dialog policy learning.

2.2. Reward

Reward is essential for reinforcement learning to guide policy learning. The roles of the system and the user are different. System should complete the dialog successfully in shorter turns for task-oriented dialog task. c System and Users communicate cooperatively in our setting to accomplish the dialog. The reward settings for each role are shown below.

For system reward R^s , it consists of (1) dialog success reward and dialog failed penalty at the end of the dialog; (2) a minor dialog length penalty at each turn; (3) action and slot mismatch penalty in order to avoid the system confirming empty slot value, and so on; (4) few inappropriate system actions penalty based on user action.

Different from the system, user policy should be diverse and suitable to prompt the system policy learning. User reward R^u is similar to system reward. We remove the length of dialog turns penalty for user because we cannot restrict users from ending the dialog quickly.

2.3. Optimization

Algorithm 1 shows the entire AURL algorithm under one user setting. For the system DST module and user NLU module, we can get the label outputs when interacting with each other. So we use cross-entropy loss to update both modules.

Algorithm 1: AURL Framework with one user.

Input: Dialog corpus D ; system model and user model; system DST buffer size n

Output: Trained system model.

```

1 Initialize weights  $\phi, \pi, \eta, \mu, V^s, V^u$  randomly;
2 Pretrain  $\phi, \pi, \eta, \mu$  on dialog corpus  $D$  using SL.
3 foreach train epoch do
4   foreach step do
5     Initialize user goal value  $G$ , user state and
       system state.
6     System gives the utterance  $U_0^s$  at the first turn.
7     repeat
8       User understands system utterance  $U^s$ ,
       samples action and slot using  $\eta, \mu$ , gives
       response  $U^u$ .
9       System updates its dialog state  $BS^s$ 
       according to the user response using  $\phi$ ,
       and then samples action and slot using  $\pi$ ,
       gives response  $U^s$ .
10      Get terminal signal  $T$  according to  $BS^s$ ,
        $G$  and the dialog length.
11      Observe rewards  $R^s$  and  $R^u$ .
12      Four replay buffers record inputs, outputs,
       labels or rewards for each module.
13    until the dialog ends according to  $T$ ;
14  end
15  Update two critic networks, two dialog policy
       modules and user NLU module. Clear three
       buffers.
16  if  $|BF_{sys\_DST}|$  equals  $n$  then
17    Update system DST module using curriculum
       learning. Clear  $buffer_{system\_DST}$ 
18  end
19 end

```

Advantage actor-critic (A2C) algorithm is used to optimize both policy modules. For each role, a critic network V is applied to evaluate the state value. The critic networks aim to minimize the following loss functions:

$$L_V^s = (R^s + \gamma V^s(b_{t+1}^s) - V^s(b_t^s))^2, \quad (5)$$

$$L_V^u = (R^u + \gamma V^u(b_{t+1}^u) - V^u(b_t^u))^2, \quad (6)$$

where $b_t^s = [a_{t-1}^s; BS_t^s; H_t^{history}; q_t]$, $b_t^u = [a_t^u; a_t^s; s_t^s; BS_t^u]$.

The actor network (policy) aims to maximize the returns. Advantage function $A(a, s; b_t) = R + \gamma V(b_{t+1}) - V(b_t)$ evaluates if the chosen action and slot are better. The loss functions for policy modules are below:

$$L_\pi^s = A(a^s; s^s, b^s)(\log_\pi(a^s|b^s) + \log_\pi(s^s|b^s)), \quad (7)$$

$$L_\mu^u = A(a^u; s^u, b^u)(\log_\mu(a^u|b^u) + \log_\mu(s^u|b^u)). \quad (8)$$

Besides, different sizes of replay buffers are applied to update the system DST and other modules asynchronously.

3. EXPERIMENTS

3.1. Experimental Setup

Dataset. SSD-PHONE [9] is a real-world task-oriented dialog corpus that contains 30 actions, 11, 000 dialog sessions, 3, 135 different dialog paths and plenty of diversity phenomena. The corpus also provides a wealth of annotation information. To verify the ability of reinforcement learning in more challenging scenario, we further expand the number of dialog actions to 41 according to the diversity phenomena, including 16 system actions and 25 user actions.

Evaluation Metrics. We evaluate model performances by online interacting with the FSA-based user simulator provided by [9]. After interacting three times with 1, 000 dialogs each, we calculate the following metrics. **Dialog succ** is the main metric. A dialog is successful if and only if the slot values collected by the system is equal to the user goal value within limited turns. **Avg turn** shows the average turn number of successful dialogs. **Avg reward** is the average of the system reward for each dialog. **DST acc** means whether the slot values are correctly collected at each turn. **Avg time** measures the average response time interacting with users.

Implementation Details. The size of reply buffer is 6, 6, 6, 3k for BF_{user_DP} , BF_{user_NLU} , BF_{sys_DP} and BF_{sys_DST} respectively. During RL training, 100k epochs and 6 dialogs in each epoch are trained. In terms of reward design, the rewards for system and user are both set to 2.0 if dialog succeeds, otherwise, both set to -1.0 . Penalties of other types for system are set to -0.05 and for user are all set to -0.02 . γ is set to 0.99.

3.2. Baselines

In addition to the baselines in [9], we compare AURL with different methods. **DAMD**[2] trains dialog policy using SL, considering that a dialog state may correspond to many system actions. **SL** is the system model pretrained on the SSD-PHONE dataset first. The following baselines all use the pretrained system model and user model. We conduct experiments using REINFORCE [14], A2C, asynchronous advantage actor-critic [15] and proximal policy optimization [16] algorithm, finally adopt A2C as our learning algorithm since A2C has a more stable learning curve. **RL-fixed_DST** is the traditional RL setting, in which just the system policy module and the user policy module are updated. **RL-train_DST** denotes that all modules are trained simultaneously.

3.3. Results and Analysis

The online evaluation results of each model are summarised in Table 1. Among the supervised learning settings, the proposed model performs the best, with an 11.40% improvement over GPT2 [17] based models (SimpleTOD [18]). Furthermore, our model is lighter than other baselines, and with a shorter

Model	Dialog succ	Avg turn	Avg reward	DST acc	AVG time
TRADE*	30.45	9.77	-	-	111
DAMD	46.40	6.52	-	-	489
UBAR	57.70	11.39	-	-	376
SimpleTOD	63.20	8.18	-	-	-
SL	75.73	7.35	1.19	71.12	28
RL-fixed_DST	77.23	6.93	1.28	66.78	-
RL-train_DST*	71.00	5.94	1.11	75.58	-
AURL	84.13	7.36	1.47	70.92	-
AURL-1v2	94.57	8.32	1.82	81.11	-

Table 1: Results of different models on interaction with the FSA-based user simulator. AURL-1v2 denotes using two user models to train the system model. Only one user model is applied under the other RL settings. * is the ablation study.

response time per turn, which gives responses more quickly when interacting with users when deployed on a real dialing platform.

Under the RL setting, the comparison between RL-fix_DST and RL-train_DST indicates the bias in the simultaneous training method. When using one user model to train the dialog system, AURL reaches a higher dialog success than SL with an 8.40% improvement. With the aid of the asynchronous updating and curriculum learning, the DP module even makes right decision with the DST errors.

When using two user models to train one dialog system, the dialog success rate is improved from 84.13% to 94.57%. Besides, the accuracy of the DST module reaches 81.11%. More user models bring more different dialog paths like various humans in reality, even though they are initialized with the same pretrained parameters. The dialog system is trained more adequately than using only one user model.

4. CONCLUSIONS

In this paper, we proposed an asynchronous updating reinforcement learning framework for DST and DP modules of task-oriented dialog system. We conducted multi-agent reinforcement learning in asynchronous updating framework to train both models. With the benefit of curriculum learning and multiple user models training, our approach achieves a new SOTA, with a 31.37% improvement over original GPT2-based models on the online test. In the future, more work will be done under the MURL setting, especially for introducing more user models to train the system agent.

5. ACKNOWLEDGMENTS

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