Variational Reward Estimator Bottleneck: Learning Robust Reward Estimator for Multi-Domain Task-Oriented Dialog

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Abstract

Despite its notable success in adversarial learning approaches to multi-domain task-oriented dialog system, training the dialog policy via adversarial inverse reinforcement learning often fails to balance the performance of the policy generator and reward estimator. During optimization, the reward estimator often overwhelms the policy generator and produces excessively uninformative gradients. We propose the Variational Reward estimator Bottleneck (VRB), which is an effective regularization method that aims to constrain unproductive information flows between inputs and the reward estimator. The VRB focuses on capturing discriminative features, by exploiting information bottleneck on mutual information. Empirical results on a multi-domain task-oriented dialog dataset demonstrate that the VRB significantly outperforms previous methods.

1 Introduction

While deep reinforcement learning (RL) have emerged as a promising solution for complex and high-dimensional decision-making problems, the determination of an effective reward function remains a challenge, especially in multi-domain task-oriented dialog systems. Many recent works have struggled on sparse-reward environments and employed a handcrafted reward function as a breakthrough [Zhao and Eskenazi, 2016] [Dhingra et al., 2017] [Shi and Yu, 2018] [Shah et al., 2018]. However, such approaches are often unable to guide the dialog policy through user goals. For instance, as illustrated in Figure 1, the user can’t reach the goal because the system (S1) that exploits the handcrafted rewards completes the dialog session too early. Moreover, the user goal usually varies as the dialog proceeds.

Inverse Reinforcement Learning (IRL) (Russell, 1998; Ng and Russell, 2000) and MaxEnt-IRL (Ziebart et al., 2008) tackles the problem of recovering reward function and using this reward function to generate optimal behavior. Although Generative adversarial imitation learning (GAIL) (Ho and Ermon, 2016), which exploits the GANs framework (Goodfellow et al., 2014), has proven that the discriminator can be defined as a reward function, GAIL fails to generalize and recover the reward function. Adversarial inverse reinforcement learning (AIRL) (Fu et al., 2018) enables GAIL to take advantage of disentangled rewards. Guided dialog policy learning (GDPL) (Takanobu et al., 2019) uses AIRL framework to construct the reward estimator for multi-domain task-oriented dialogs. However, these methods often encounter difficulties in balancing the performance of the policy generator and reward estimator, and produce excessively uninformative gradients.

In this paper, we propose the Variational Reward Estimator Bottleneck (VRB), an effective regularization algorithm. The VRB uses information bottleneck (Tishby et al., 1999; Alemi et al., 2016; Peng et al., 2019) to constrain unproductive information flows between dialog state-action pairs and internal representations of the reward estimator, thereby ensuring highly informative gradients and robustness. The experiments demonstrate that the VRB achieves the state-of-the-art performances on a multi-domain task-oriented dataset.
2 Background

2.1 Dialog State Tracker And User Simulator

The dialog state tracker (DST) (Wu et al., 2019), which takes dialog action \(a\) and dialog history as input, updates the dialog state \(x\) and belief state \(b\) for each slot \(^1\). For example, in Figure 2 DST observes the user goal where the user wishes to go. At dialog turn \(t\), the dialog action is represented as a slot and value pair (e.g. Attraction: (area, centre), (type, concert hall)). Given the dialog action, DST encodes the dialog state as \(x_t = [a^u_t; a_{t-1}; b_t; q_t]\). The user simulator \(\mu(a^u, t^u|x^u)\) (Schatzmann et al., 2007; Gur et al., 2018) extracts the dialog action \(a^u\) corresponding to the dialog state \(x^u\). \(t^u\) stands for whether user goal is achieved during conversation. Note that the DST and the user simulator can’t achieve the user goal without well-defined reward estimation.

2.2 Reward Estimator

The reward estimator (Takanobu et al., 2019), which is a core component in multi-domain task-oriented dialog systems, evaluates dialog state-action pairs at dialog turn \(t\) and estimates the reward that is used for guiding the dialog policy through the user goal. Based on MaxEnt-IRL (Ziebart et al., 2008), each dialog goal without well-defined reward estimation. Note that the DST and the user simulator can’t achieve the user goal without well-defined reward estimation.

2.3 Policy Generator

The policy generator (Schulman et al., 2015; Schulman et al., 2017) encourages the dialog policy \(\pi^\theta\) to determine the next action that maximizes the reward function \(\hat{r}_{\zeta,\psi}(x_t, a_t, x_{t+1}) = f_{\zeta,\psi}(x_t, a_t, x_{t+1}) - \log \pi^\theta(a_t|x_t)\) (the full derivation is available in Appendix A.3):

\[
L^{CLIP}_\pi(\theta) = \mathbb{E}_{x,a \sim \pi}[\min(\xi_t(\theta)\hat{A}_t, \text{clip}(\xi_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}_t)]
\]

\[
L^V_F(\theta) = -\left( V_0 - \sum_{k=t}^{T} \gamma^k \hat{r}_k \right)^2
\]

where \(\hat{A}_t = \delta_t + \gamma \lambda \hat{A}_{t+1}, \delta_t = \hat{r}_{\zeta,\psi} + \gamma V(x_{t+1}) - V(x_t), \) and \(\delta\) is the TD residual (Schulman et al., 2016). \(\xi_t(\theta) = \frac{\pi^\theta(a_t|x_t)}{\pi^\theta(a_t|x_t)}\) and \(V_0\) is the state-value function. Epsilon and \(\lambda\) are hyper-parameters.

3 Variational Reward Estimator Bottleneck

The Variational information bottleneck (Tishby et al., 1999; Alemi et al., 2016; Peng et al., 2019) is an information-theoretic approach that restricts unproductive information flow between inputs and the discriminator. Inspired by this concept, we propose a regularized objective that constrains the mutual information between encoded state-action pairs and original inputs, thereby ensuring highly informative internal representations and robust adversarial model. Our proposed method learns an encoder that is maximally informative regarding human dialogs. To this end, we employ a stochastic encoder and an upper bound constraint on the mutual information between the dialog states \(X\) and latent variables \(Z\):

\[
L_{f,E}(\zeta, \psi) = \mathbb{E}_{x,a \sim D}[\mathbb{E}_{z \sim \mathbb{E}(z|x_t, x_{t+1})}[f_{\zeta,\psi}(z_g, z'_b, z_h)]] - \mathbb{E}_{x,a \sim \pi}[\mathbb{E}_{z \sim \mathbb{E}(z|x_t, x_{t+1})}[f_{\zeta,\psi}(z_g, z'_b, z_h)]]
\]

s.t. \(I(Z, X) \leq I_c\)

\[
(3)
\]

\(^1\) For background and notations on MDP, see Appendix A.1.
where \( f_\psi(z_g, z'_h, z_h) = D_g(z_g) + \gamma D_h(z'_h) + D_h(z_h) \) and \( D \) is modeled with nonlinear function. Note that \( f_\psi(z_g, z'_h, z_h) \) is divided into the three terms \( D_g(z_g) \), \( \gamma D_h(z'_h) \), and \( D_h(z_h) \), based on GANs (Goodfellow et al., 2014), GAN-GCL (Finn et al., 2016), and AIRL (Fu et al., 2018). \( D_g \) represents the encoded disentangled reward approximator with the parameter \( \zeta \) and \( D_h \) is the encoded shaping term with the parameter \( \psi \). Stochastic encoder \( E(z|x_t, x_{t+1}) \) can be defined as \( E(z|x_t, x_{t+1}) = E_g(z_g|x_t) \cdot E_h(z_h|x_t) \cdot E_h(z'_h|x_{t+1}) \) which maps states to a latent distribution \( z : E(z|x_t) = N(\mu_E(x_t), \Sigma_E(x_t)) \). 

\[
\begin{align*}
  I(Z, X) &= \text{KL}[p(z, x) | p(z)p(x)] \\
  &= \int dz \, dx \, p(z, x) \log \frac{p(z, x)}{p(z)p(x)} = \int dz \, dx \, p(x) E(z|x) \log \frac{E(z|x)}{p(z)} \\
  &\leq I_c = \int dz \, dx \, \pi_\theta(x) E(z|x) \log \frac{E(z|x)}{r(z)} = \mathbb{E}_{x, a \sim \pi}[\text{KL}[E(z|x) || r(z)]]
\end{align*}
\]

In Equation 4, the VRB minimizes the mutual information with dialog states to focus on discriminative features. The VRB also minimizes the KL-divergence with the human dialogs, while maximizing the KL-divergence with the generated dialogs, thereby distinguishing effectively between samples from human dialogs and dialog policy. Our proposed model is summarized in Appendix B.

4 Experiments

4.1 Dataset

We evaluate our proposed method on Multi-domain wizard-of-oz (Budzianowski et al., 2018) (MultiWOZ), which contains approximately 10,000 of large-scale, multi-domain, and multi-turn conversational dialog corpora. MultiWOZ consists of seven distinct task-oriented domains, 24 slots, and 4,510 slot values. The dialog sessions are randomly divided into training, validation, and test set. The validation and test sets contain 1,000 sessions each.
4.2 Training Details

To demonstrate the robustness of our model, we conduct experiments over 30 times for each user simulator and average the results. We use the agenda-based user simulator (Schatzmann et al., 2007) and VHUS-based user simulator (Gür et al., 2018). The policy network $\pi_\theta$ and value network $V$ are MLPs with two hidden layers. $g_\zeta$ and $h_\psi$ are MPLs with one hidden layer each. We use the ReLu activation function and Adam optimizer for the MLPs. The hyper-parameters are presented in Appendix C.

4.3 Results

We compare the proposed method with the following existing methods: GP-MBCM (Gai et al., 2015), ACER (Wang et al., 2017), PPO (Schulman et al., 2017), ALDM (Liu and Lane, 2018), and GDPL (Takanobu et al., 2019). Moreover, we evaluate our proposed model using four metrics: (i) Turns: we record the average number of dialog turns between the dialog agent and user simulator. (ii) Match rate: we conduct match rate experiments to analyze whether the booked entities are matched with the corresponding constraints in the multi-domain environment. For instance, in Figure 2, entertainment should be matched with concert hall in the centre. The match rate ranges from 0 to 1, and scores 0 if an agent fails to book the entity. (iii) Inform F1: we test the ability of the model to inform all of the requested slot values. For example, in Figure 1, the price range, food type, and area should be informed if the user wishes to visit a high-end Cuban restaurant in Cambridge. (iv) Success rate: in the success rate experiment, a dialog session scores 0 or 1. We obtain 1 if all required information is presented and every entity is booked successfully.

Table 1 presents the empirical results on both simulators and MultiWOZ. In the agenda-based setting, we observe that our proposed method achieves a new state-of-the-art performance. Note that an outstanding model should obtain high scores in every metric, not just a single one, because to regard a dialog as having ended successfully, every request should be informed precisely, thereby guiding a dialog through the user goal. Although GDPL achieves the highest score in Inform F1, our proposed model acts more human-like with respect to Turns, and provides more accurate slot values and matched-entities than the other methods. In VHUS setting, on the other hand, although PPO behaves more human-like in Turns, PPO exhibits greater difficulty in providing accurate information, while our model doesn’t because our method constrains unproductive information flows. Both results in Table 1 demonstrate that our proposed model outperforms existing models, providing more definitive information than the other methods.

5 Conclusions

In this paper, we develop a novel and effective regularization method known as the Variational reward estimator bottleneck (VRB) for multi-domain task-oriented dialog systems. VRB contains a stochastic encoder which enables the reward estimator to be maximally informative, as well as provides information bottleneck regularization, which constrains unproductive information flows between the inputs and reward estimator. The empirical results demonstrate that VRB achieves a new state-of-the-art performance on two different user simulators and a multi-turn and multi-domain task-oriented dialog dataset.
References

Alexander A. Alemi, Ian Fischer, Joshua V. Dillon, and Kevin Murphy. 2016. Deep variational information bottleneck. arXiv:1612.00410

Pawel Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Inigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gasić. 2018. MultiWOZ - a large-scale multi-domain wizard-of-Oz dataset for task-oriented dialogue modelling. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 5016–5026, Brussels, Belgium, October-November. Association for Computational Linguistics.

Bhuwan Dhingra, Lihong Li, Xiujun Li, Jianfeng Gao, Yun-Nung Chen, Faisal Ahmed, and Li Deng. 2017. Towards end-to-end reinforcement learning of dialogue agents for information access. Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers).

Chelsea Finn, Sergey Levine, and Pieter Abbeel. 2016. Guided cost learning: Deep inverse optimal control via policy optimization. In Proceedings of the 33rd International Conference on International Conference on Machine Learning - Volume 48, ICML16, page 4958. JMLR.org.

Justin Fu, Katie Luo, and Sergey Levine. 2018. Learning robust rewards with adverserial inverse reinforcement learning. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings. OpenReview.net.

M. Gai, N. Mrki, P. Su, D. Vandyke, T. Wen, and S. Young. 2015. Policy committee for adaptation in multi-domain spoken dialogue systems. In 2015 IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU), pages 806–812.

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial nets. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, editors, Advances in Neural Information Processing Systems 27, pages 2672–2680. Curran Associates, Inc.

Izzeddin G¨ur, Dilek Hakkani-T¨ur, Gokhan T¨ur, and Pararth Shah. 2018. User modeling for task oriented dialogues. In 2018 IEEE Spoken Language Technology Workshop (SLT), pages 900–906. IEEE.

Jonathan Ho and Stefano Ermon. 2016. Generative adversarial imitation learning. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, Advances in Neural Information Processing Systems 29, pages 4565–4573. Curran Associates, Inc.

Bing Liu and Ian Lane. 2018. Adversarial learning of task-oriented neural dialog models. In Proceedings of the 19th Annual SIGdial Meeting on Discourse and Dialogue, pages 350–359, Melbourne, Australia, July. Association for Computational Linguistics.

Andrew Ng and Stuart Russell. 2000. Algorithms for inverse reinforcement learning. ICML ’00 Proceedings of the Seventeenth International Conference on Machine Learning, 05.

Xue Bin Peng, Angjoo Kanazawa, Sam Toyer, Pieter Abbeel, and Sergey Levine. 2019. Variational discriminator bottleneck: Improving imitation learning, inverse RL, and GANs by constraining information flow. In International Conference on Learning Representations.

Stuart Russell. 1998. Learning agents for uncertain environments. In Proceedings of the eleventh annual conference on Computational learning theory, pages 101–103.

Jost Schatzmann, Blaise Thomson, Karl Weilhammer, Hui Ye, and Steve Young. 2007. Agenda-based user simulation for bootstrapping a POMDP dialogue system. In Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics: Companion Volume, Short Papers, pages 149–152, Rochester, New York, April. Association for Computational Linguistics.

John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. 2015. Trust region policy optimization. In Francis Bach and David Blei, editors, Proceedings of the 32nd International Conference on Machine Learning, volume 37 of Proceedings of Machine Learning Research, pages 1889–1897, Lille, France, 07–09 Jul. PMLR.

John Schulman, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. 2016. High-dimensional continuous control using generalized advantage estimation. International Conference on Learning Representations.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. 2017. Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347.
Pararth Shah, Dilek Hakkani-Tür, Bing Liu, and Gokhan Tür. 2018. Bootstrapping a neural conversational agent with dialogue self-play, crowdsourcing and on-line reinforcement learning. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 3 (Industry Papers), pages 41–51, New Orleans - Louisiana, June. Association for Computational Linguistics.

Weiyan Shi and Zhou Yu. 2018. Sentiment adaptive end-to-end dialog systems. Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers).

Ryuichi Takanobu, Hanlin Zhu, and Minlie Huang. 2019. Guided dialog policy learning: Reward estimation for multi-domain task-oriented dialog. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 100–110, Hong Kong, China, November. Association for Computational Linguistics.

Naftali Tishby, Fernando C. Pereira, and William Bialek. 1999. The information bottleneck method. In Proc. of the 37-th Annual Allerton Conference on Communication, Control and Computing, pages 368–377.

Ziyu Wang, Victor Bapst, Nicolas Heess, Volodymyr Mnih, Rémi Munos, Koray Kavukcuoglu, and Nando de Freitas. 2017. Sample efficient actor-critic with experience replay. In 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings. OpenReview.net.

Chien-Sheng Wu, Andrea Madotto, Ehsan Hosseini-Asl, Caiming Xiong, Richard Socher, and Pascale Fung. 2019. Transferable multi-domain state generator for task-oriented dialogue systems. Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics.

Tiancheng Zhao and Maxine Eskenazi. 2016. Towards end-to-end learning for dialog state tracking and management using deep reinforcement learning. In Proceedings of the 17th Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 1–10, Los Angeles, September. Association for Computational Linguistics.

Brian D Ziebart, Andrew L Maas, J Andrew Bagnell, and Anind K Dey. 2008. Maximum entropy inverse reinforcement learning. In AAAI, volume 8, pages 1433–1438. Chicago, IL, USA.
Appendix

A  Mathematical Details

A.1 Background and Notations on MDP

To represent Inverse reinforcement learning (IRL) as a Markov decision process (MDP), we consider a tuple $M = (X, A, T, R, \rho_0, \gamma)$, where $X$ is state space and $A$ is the action space. The transition probability $T(x_{t+1}|x_t, a_t)$ defines the distribution of the next state $x_{t+1}$ given state $x_t$ and $a_t$ at time-step $t$. $R(x_t, a_t)$ is the reward function of the state-action pair, $\rho_0$ is the distribution of the initial state $x_0$, and $\gamma$ is the discount factor. The stochastic policy $\pi(a_t|x_t)$ maps a state to a distribution over actions.

Supposing we are given an optimal policy $\pi^*$, the goal of IRL is to estimate the reward function $R$ from the trajectory $\tau = \{x_0, a_0, x_1, a_1, \ldots, x_T, a_T\} \sim \pi^*$. However, constructing an effective reward function is challenging, especially in multi-domain task-oriented dialog system.

A.2 Gradient-Based Optimization

To imitate human behaviors, the reward estimator should learn the distributions of human dialog sessions using the KL-divergence loss:

$$L_\pi(\theta) \approx -KL \left( \frac{\exp(\mathcal{R}_\zeta)}{Z} \right) = \sum \pi_\theta(\tau) \log \left( \frac{\exp(\mathcal{R}_\zeta)}{\pi_\theta(\tau)} \right)$$

$$= E_{\tau \sim \pi}[\log \left( \frac{\exp(\mathcal{R}_\zeta)}{Z} \right) - \log \pi_\theta(\tau)]$$

$$= E_{\tau \sim \pi}[f_\zeta - \log \pi_\theta(\tau)]$$

$$= E_{x,a \sim D}[f_\zeta(x_t, a_t, x_{t+1})] + H(\pi_\theta)$$

where $H(\pi_\theta)$ is the entropy of dialog policy $\pi_\theta$. The reward estimator maximizes the entropy, which represents maximizing the likelihood of observed dialog sessions. Therefore, the reward estimator is trained to discern between human dialog sessions $\mathcal{D}$ and dialog sessions that are generated by the dialog policy:

$$L_f(\zeta, \psi) = -KL \left( \frac{\exp(\mathcal{R}_\zeta)}{Z} \right) - KL \left( \frac{\exp(\mathcal{R}_\zeta)}{Z} \right)$$

$$= E_{x,a \sim D}[f_\zeta(x_t, a_t, x_{t+1})] + H(\mathcal{D}) - E_{x,a \sim \pi}[f_\zeta(x_t, a_t, x_{t+1})] - H(\pi_\theta)$$

Note that $H(\mathcal{D})$ and $H(\pi_\theta)$ are not dependent on the parameters $\zeta$ and $\psi$. Thus, the reward estimator can be trained using gradient-based optimization as follows:

$$L_f(\zeta, \psi) = E_{x,a \sim D}[f_\zeta(x_t, a_t, x_{t+1})] - E_{x,a \sim \pi}[f_\zeta(x_t, a_t, x_{t+1})]$$
A.3 Discriminative Reward Function

The reward function \( \hat{r}_{\zeta,\psi} \) can be simplified in the following manner:

\[
\hat{r}_{\zeta,\psi}(x_t, a_t, x_{t+1}) = \log \left[ \frac{1}{1 - D_{\zeta,\psi}(x_t, a_t, x_{t+1})} \right] - \log \left[ 1 - D_{\zeta,\psi}(x_t, a_t, x_{t+1}) \right]
\]

\[
= \log \left[ \frac{1}{1 - D_{\zeta,\psi}(x_t, a_t, x_{t+1})} \right] - \log \left[ \frac{\exp[f_{\zeta,\psi}(x_t, a_t, x_{t+1})]}{\pi_\theta(a_t|x_t)} \right]
\]

\[
= f_{\zeta,\psi}(x_t, a_t, x_{t+1}) - \log \pi_\theta(a_t|x_t)
\]

B Algorithm

**Algorithm 1** Variational Reward Estimator Bottleneck

Initialize dialog policy generator \( \pi_\theta \) and reward estimator \( f_{\zeta,\psi} \)

for \( i \leftarrow 0 \) to \( N \) do

- Obtain random samples from human dialog corpus \( D \)
- Gather dialog sessions using user simulator \( \mu(a^u, t^u|x^u) \) and policy generator \( \pi_\theta(a|x) \)
- Encode dialog sessions using stochastic encoder \( E(z|\cdot) = \mathcal{N}(\mu_E(\cdot), \Sigma_E(\cdot)) \)
- Compute information bottleneck \( E(x,a \sim \pi)[KL[E(z|x)||r(z)]] \)
- Update reward estimator \( f_{\zeta,\psi} \) by optimizing \( L_{f,E}(\zeta, \psi) \) (Equation 4)
- Estimate reward function \( \hat{r}_{\zeta,\psi} \) for each state-action pair
- Update state-value function \( V(X) \) and dialog policy \( \pi_\theta \) given the reward \( \hat{r}_{\zeta,\psi} \) (Equation 2)

end

C Hyperparameters

| Hyperparameter               | Value |
|------------------------------|-------|
| Lagrange multiplier \( \varphi \) | 0.001 |
| Upper bound \( I_c \)        | 0.5   |
| Learning rate of dialog policy | 0.0001 |
| Learning rate of reward estimator | 0.0001 |
| Learning rate of user simulator | 0.001 |
| Clipping component \( \epsilon \) for dialog policy | 0.02 |
| GAE component \( \lambda \) for dialog policy | 0.95 |

Table 2: VRB hyperparameters.