Generative Adversarial Reward Learning for Generalized Behavior Tendency Inference

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Abstract—Recent advances in reinforcement learning have inspired increasing interest in learning user modeling adaptively through dynamic interactions, e.g., in reinforcement learning based recommender systems. In most reinforcement learning applications, reward functions provide the critical guideline for optimization. However, current reinforcement learning-based methods rely on manually-defined reward functions, which cannot adapt to dynamic, noisy environments. Moreover, they generally use task-specific reward functions that sacrifice generalization ability. We propose a generative inverse reinforcement learning for user behavioral preference modeling to address the above issues. Instead of using predefined reward functions, our model can automatically learn the rewards from user's actions based on discriminative actor-critic network and Wasserstein GAN. Our model provides a general approach to characterizing and explaining underlying behavioral tendencies. Our experiments show our method outperforms state-of-the-art methods in several scenarios, namely traffic signal control, online recommender systems, and scanpath prediction.

Index Terms—Inverse Reinforcement Learning, Behavioral Tendency Modeling, Adversarial Training, Generative Model

1 Introduction

Behavior modeling provides a footprint about user's behaviors and preferences. It is a cornerstone of diverse downstream applications that support personalized services and predictive decision-making, such as human-robot interactions, recommender systems, and intelligent transportation systems. Recommender systems generally use user's past activities to predict their future interest [1], [2], [3], and past studies integrate demographic information with user's long-term interest on personalized tasks [4], [5], [6], [7]. In human-robot interaction, a robot learns from user behaviors to predict user's activities and provide necessary support [8]. Multimodal probabilistic models [9] and teacher-student network [10] are often used to predict user's intention for traffic prediction or object segmentation.

Traditional methods learn static behavioral tendencies via modeling user's historical activities with items as a feature space [11] or a user-item matrix [12]. In contrast, reinforcement learning shows advantages in learning user's preference or behavioral tendency through dynamic interactions between agent and the environment. It has attracted lots of research interests in recommendation systems [6], intention prediction [13], traffic control [14], and human-robot interaction domains [15]. Reinforcement learning covers several categories of methods, such as value-based methods, policy-based methods, and hybrid methods. All these methods use the accumulated reward during a long term to indicate user's activities. The reward function is manually defined and requires extensive effort to contemplate potential factors [16], [17].

In general, user's activities are noisy, occasionally contaminated by imperfect user behaviors, and thus may not always reveal user's interest or intention. For example, in online shopping, a user may follow a clear logic to buy items and randomly add additional items because of promotions or discounts. This makes it difficult to define an accurate reward function because the noises also affect the fulfillment of task goals in reinforcement learning. Another challenge lies in the common practice of adding task-specific terms to the reward function to cope with different tasks. Current studies usually require manually adjusting the reward function to model user's profiles [2], [18], [19]. Manual adjustment tends to produce imperfect results because it is unrealistic to consider all reward function possibilities, not to mention designing reward functions for new tasks.

A better way to determine the reward function is to learn it automatically through dynamic agent-environment interactions. Inverse reinforcement learning recently emerged as an appealing solution, which learns reward function learning from demonstrations in a few scenarios [20]. It faces two challenges for user behavior modeling. First, it requires a repeated, computational expensive reinforcement learning process to apply a learned reward function [21]; second, given an expert policy, there could be countless reward functions for choice, making the selection of reward function difficult and the optimization computationally expensive. The only recommendation model [22] that adopts improved inverse reinforcement learning simply skips the repeated reinforcement learning process. Thus, it is hard to converge due to the lack of sampling efficiency and training stability. Furthermore, the model only works for recommender systems and lacks generalization ability.

Manually designed reward functions have less feasibility and generalizability to cope with such challenges. Although

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[22] employs inverse reinforcement learning to learn the reward from demonstration, this work still suffers the undefined problem due to the nature of the logarithm. To relieve this, we manipulate the function by adding an extra learnable term to avoid such a problem. In addition, existing studies have not considered the absorbing state problem such that agents will stop learning once the absorbing states are reached. The major reason is that the agent will receive zero rewards in absorbing states and may lead to a suboptimal policy. [13] first uses the inverse reinforcement learning to conduct the scanpath prediction. However, it suffers the same problem as [22], i.e., the reward could be zero in absorbing states and cannot be generalized into other tasks. [22] relies on GAN to integrate the actor-critic network and IRL, while GAN still suffers training instability. Moreover, the sample efficiency is another drawback for the on-policy actor-critic network. In this paper, we employ Wasserstein GAN [23] to improve model stability and importance sampling in the replay buffer to transfer it into off-policy learning with increased sample efficiency.

In this paper, we aim to construct user models directly from an array of various demonstrations efficiently and adaptively, based on a generalized inverse reinforcement learning method. Learning from demonstrations not only avoids the need for inferring a reward function but also reduces computational complexity. To this end, we propose a new model that employs a generative adversarial strategy to generate candidate reward functions and to approximate the true reward. We use the new model as a general way of characterizing and explaining tendencies in user behaviors. In summary, we make the following contributions:

- We propose a new inverse reinforcement-learning-based method to capture user's behavioral tendencies. To the best of our knowledge, this is the first work to formulate user's behavioral tendency using inverse reinforcement learning.
- We design a novel stabilized sample-efficient discriminative actor-critic network with Wasserstein GAN to implement the proposed framework. Our framework is off-policy and can reduce interactions between system and environment to improve efficiency. Besides, we integrate a learnable term into our reward function to increase the capability of our method.
- Our extensive experiments demonstrate the generalization ability and feasibility of our approach in three different scenarios. We use visualization to show the explainability of our method.

2 Problem Formulation and Preliminary

Behavioral tendency refers to user's preferences at a certain timestamp and is usually hard to be evaluated directly. The common way to evaluate behavioral tendencies is to examine how well the actions taken out of the learned behavioral tendencies match the real actions taken by the user. It is similar to reinforcement learning's decision-making process, where the agent figures out an optimal policy π such that each action of it could achieve a good reward.

In this work, we define behavioral tendencies modeling as an optimal policy-finding problem. Given a set of users $\mathcal{U} = \{u_0, u_1, \cdots, u_n\}$, a set of items $\mathcal{O} = \{o_0, o_1, \cdots, o_m\}$ and user's demographic information $\mathcal{D} = \{d_0, d_1, \cdots, d_n\}$. We first define the Markov Decision Process (MDP) as a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$, where $\mathcal{S}$ is the state space (i.e., the combination of the subset of $\mathcal{O}$, subset of $\mathcal{U}$ and its corresponding $\mathcal{D}$). $\mathcal{A}$ is the action space, which includes all possible agent's decisions, $\mathcal{R}$ is a set of rewards received for each action $a \in \mathcal{A}$, $\mathcal{P}$ is a set of state transition probability, and γ is the discount factor used to balance the future reward and the current reward. The policy can be defined as $\pi : \mathcal{S} \rightarrow \mathcal{A}$—given a state $s \in \mathcal{S}$, π will return an action $a \in \mathcal{A}$ so as to maximize the reward. However, it is unrealistic to find a universal reward function for user behavioral tendency, which is highly task-dependent. Hence, we employ Inverse reinforcement learning (IRL) to learn a policy π from the demonstration from expert policy π_E, which always results in user's true behavior. We formulate the IRL process using a uniform cost function $c(s, a)$ [20]:

$$\underset{\pi}{\text{minimize}} \max_{c \in \mathcal{C}} \mathbb{E}_{\pi}[c(s,a)] - \mathbb{E}_{\pi_E}[c(s,a)] \tag{1}$$

The cost function class $\mathcal{C}$ is restricted to convex sets defined by the linear combination of a few basis functions $\{f_1, f_2, \cdots, f_k\}$. Hence, given a state-action pair (s, a), the corresponding feature vector can be represented as $f(s,a) = [f_1(s,a), f_2(s,a), \cdots, f_k(s,a)]$. $\mathbb{E}_{\pi}[c(s,a)]$ is defined as (on γ-discounted infinite horizon):

$$\mathbb{E}_{\pi}[c(s,a)] = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t c(s_t, a_t)] \tag{2}$$

According to Eq.(1), the cost function class $\mathcal{C}$ is convex sets, which have two different formats: linear format [24] and convex format [25], respectively:

$$\mathcal{C}_l = \Big\{ \sum_i w_i f_i : \|w\|_2 \le 1 \Big\} \tag{3}$$

$$\mathcal{C}_c = \Big\{ \sum_i w_i f_i : \sum_i w_i = 1, \forall i \text{ s.t. } w_i \ge 0 \Big\} \tag{4}$$

The corresponding objective functions are as follows:

$$\|\mathbb{E}_{\pi}[f(s,a)] - \mathbb{E}_{\pi_E}[f(s,a)]\|_2 \tag{5}$$

$$\mathbb{E}_{\pi}[f_j(s,a)] - \mathbb{E}_{\pi_E}[f_j(s,a)] \tag{6}$$

Eq.(5) is known as feature expectation matching [24], which aims to minimize the l_2 distance between the state-action pairs that are generated by learned policy π and expert policy π_E. Eq.(6) aims to minimize the function f_j such that the worst-case should achieve a higher value [26]. Since Eq.(1 suffers the feature ambiguity problem, we introduce γ-discounted causal entropy [27] (shown below) to relieve the problem:

$$H(\pi) \triangleq \mathbb{E}_{\pi}[-\log \pi(a|s)] = \mathbb{E}_{s_t, a_t \sim \pi}\Big[-\sum_{t=0}^{\infty} \gamma^t \log \pi(a_t|s_t) \Big] \tag{7}$$

As such, Eq.(1) can be written by using the γ-discounted causal entropy as:

$$\underset{\pi}{\text{minimize}} -H(\pi) - \mathbb{E}_{\pi_E}[c(s,a)] + \max_{c \in \mathcal{C}} \mathbb{E}_{\pi}[c(s,a)] \tag{8}$$

Suppose Π is the policy set. We define the loss function $c(s, a)$ to ensure the expert policy receives the lowest

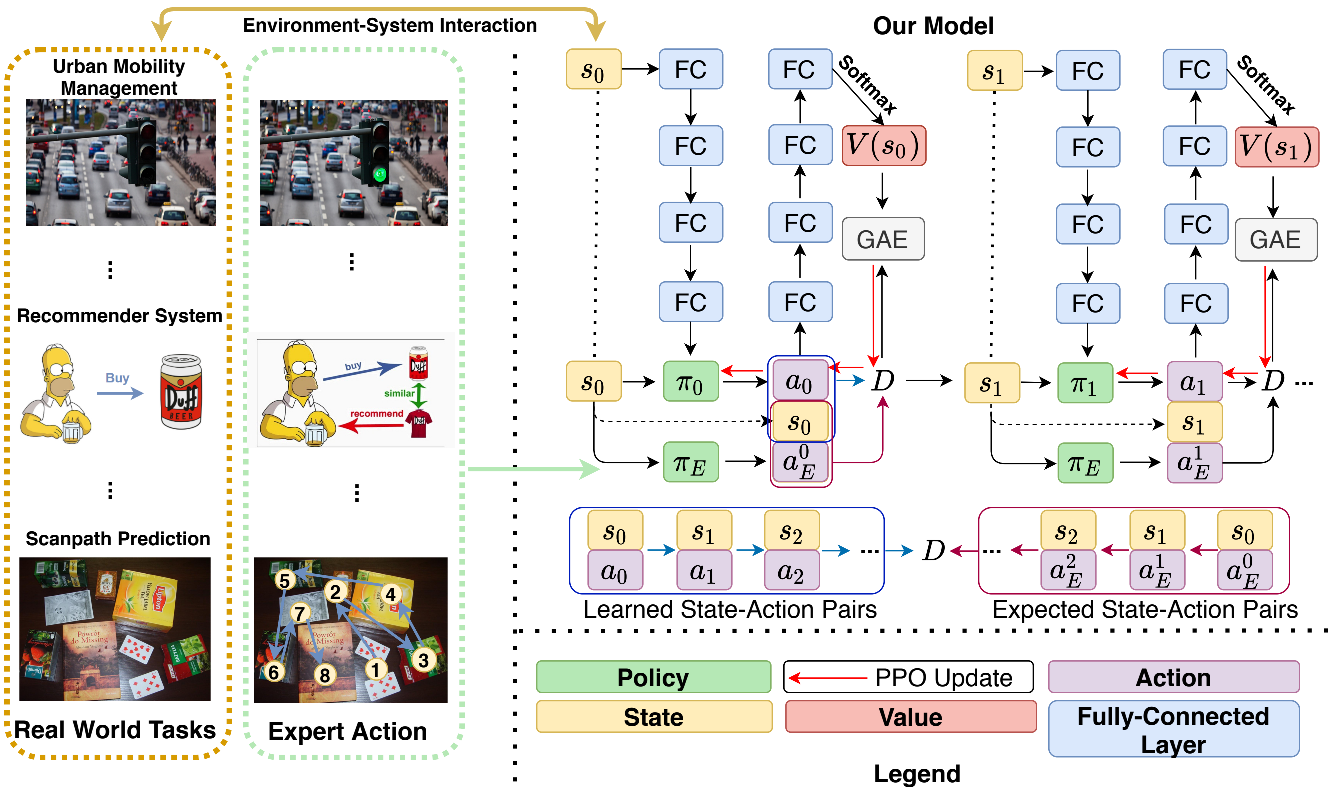


Fig. 1: Overall structure of the proposed framework. The left-hand side provides three example environments from top to bottom: urban mobility management, recommender system and scanpath prediction. The proposed model will interact with the environment to achieve the corresponding state representations for the current task. The expert actions will be achieved simultaneously and feed into our model to participate in the training procedure of the discriminator.

cost while all the other learned policies get higher costs. Referring to Eq.(8), the maximum causal entropy inverse reinforcement learning [28] works as follows:

$$\underset{c\in\mathcal{C}}{\text{maximize}}(\min_{\pi\in\Pi} -H(\pi) + \mathbb{E}_{\pi}[c(s,a)]) - \mathbb{E}_{\pi_E}[c(s,a)] \tag{9}$$

Then, the policy set Π can be obtained via policy generation. Policy generation is the problem of matching two occupancy measures and can be solved by training a Generative Adversarial Network (GAN) [29]. The occupancy measure ρ for policy π can be defined as:

$$\rho_{\pi}(s,a) = \pi(s|a)\sum_{t=0}^{\infty}\gamma^t P(s_t = s|\pi) \tag{10}$$

We adopts GAIL [21] and make an analogy from the occupancy matching to distribution matching to bridge inverse reinforcement learning and GAN. A GA regularizer is designed to restrict the entropy function:

$$\psi_{GA}(c(s,a)) = \begin{cases} \mathbb{E}_{\pi_E}[-c(s,a) - \log(1-\exp(c(s,a)))] & c<0 \\ \infty & c\geq 0 \end{cases} \tag{11}$$

The GA regularizer enables us to measure the difference between the π and π_E directly without the reward function:

$$\psi_{GA}(\rho_\pi - \rho_{\pi_E}) = \max_{D\in(0,1)^{\mathcal{S}\times\mathcal{A}}} \mathbb{E}_{\pi}[\log D(s,a)] + \mathbb{E}_{\pi_E}[\log(1-D(s,a))] \tag{12}$$

The loss function from the discriminator D is defined as $c(s,a)$ in Eq.(9); it uses negative log loss (commonly used for binary classification) to distinguish the policies π and π_E via state-action pairs. The optimal of Eq.(12) is equivalence to the Jensen-Shannon divergence [30]:

$$D_{JS}(\rho_\pi, \rho_{\pi_E}) = D_{KL}(\rho_\pi \| (\rho_\pi + \rho_{\pi_E})/2) + D_{KL}(\rho_{\pi_E} \| (\rho_\pi + \rho_{\pi_E})/2) \tag{13}$$

Finally, we rewrite inverse reinforcement learning by substituting the GA regularizer into Eq.(8):

$$\underset{\pi}{\text{minimize}} -\lambda H(\pi) + \underbrace{\psi_{GA}(\rho_\pi - \rho_{\pi_E})}_{D_{JS}(\rho_\pi, \rho_{\pi_E})} \tag{14}$$

where λ is a factor with $\lambda \geq 0$. Eq.(14) has the same goal as the GAN, i.e., finding the squared metric between distributions. Eq.(14) can be further extended into the following, which serves as the objective function for GAIL:

$$\underset{\pi}{\text{minimize}} -\lambda H(\pi) + \psi_{GA}(\rho_\pi - \rho_{\pi_E}) \equiv \min_{\pi}\max_{D} \mathcal{L}_{\mathcal{D}}$$
$$\mathcal{L}_{\mathcal{D}} = \mathbb{E}_{\pi}[\log D(s,a)] + \mathbb{E}_{\pi_E}[\log(1-D(s,a))] - \lambda H(\pi) \tag{15}$$

We summarized all the notations used in this paper in Table 1.

3 Methodology

The overall structure of our proposed method (shown in Fig. 1) consists of three components: policy and reward

TABLE 1: Main notations

Symbols	Meaning
$\mathcal{U}$	Set of users
$\mathcal{O}$	Set of items
$\mathcal{R}$	Set of rewards received
$\mathcal{D}$	Set of demographic information
$\lvert\cdot\rvert$	Number of unique elements in $\cdot$
γ	Discount Factor
$H(\pi)$	γ-discounted casual entropy
$\mathbb{E}$	Expectation
ρ	Occupancy Measure
S_t	State space at timestamp t
a_t	Action space at timestamp t
π	Policy
π_E	Expert Policy
D	Discriminator
D_{KL}	KullbackLeibler divergence
D_{JS}	Jensen-Shannon divergence
$\cdot\|\cdot$	Divergence

learning, stabilized sample efficient discriminative actor-critic network, and its optimization. Policy and reward learning aims to solve the reward bias and the absorbing state problem by introducing a learnable reward function and environment feedback. The stabilized actor-critic network aims to improve the training stability and sample efficiency for the ex sting methods. Optimization refers to the method to optimize the policy and the algorithms to train the overall approach.

3.1 Policy and Reward Learning

We consider behavioral tendencies inference as an agent policy learning problem and an agent policy as the abstraction of user's behavioral tendencies. Policy learning aims to make the learned policy π and expert policy π_E. We define the occupancy measure ρ in Eq.(10) and solve policy learning as an occupancy measure based distribution matching problem [24]. To this end, we define a reward function below to determine the performance in existing methods:

$$r(s, a) = \log(D(s, a)) - \log(1 - D(s, a)) \tag{16}$$

[31] design a dynamic robust disentangled reward function for the approximation by introducing the future state s'.

$$r'(s, a) = \log(D(s, a, s')) - \log(1 - D(s, a, s')) \tag{17}$$

The reward function defined in Eq.(16) is not robust for dynamic environments. Although Eq.(17) improves it by assigning positive and negative rewards for each time step to empower the agent to fit into different scenarios, both Eq.(16) and Eq.(17) have the absorbing state problem, i.e., the agent will receive no reward at the end of each episode, leading to sub-optimal policies [32]. Specifically, instead of exploring more policies, the reward function $r(s, a)$ will assign a negative reward bias for the discriminator to distinguish samples from the generated policies and expert policies at the beginning of the learning process. Since the agent aims to avoid the negative penalty, the zero reward may lead to early stops.

Moreover, the above two reward functions are more suitable for survival or exploration tasks rather than the goal of this study. For survival tasks, the reward used on GAIL is $\log D(s, a)$, which is always negative because $D(s, a)$ ($\in [0, 1]$) encourages the agent to end current episode to stop more negative rewards. For exploration tasks, the reward function $-\log(1-D(s, a))$ is always positive and may result in the agent looping in the environment to collect more rewards.

We add a bias term to the reward function $r(s, a)$, as defined by either Eq.(16) or Eq.(17) to overcome the reward bias. In addition, we introduce a new reward given by environment r_e for reward shaping. Finally, we have the following:

$$r_n(s, a) = \lambda_i \left(r(s, a) + \sum_{t=T+1}^{\infty} \gamma^{t-T} r(s_a, \cdot) \right) + r_e \tag{18}$$

where $r(s_a, \cdot)$ is a learnable reward function, which is trainable during the training process. We also add a dimension to indicate whether the current state is an absorbing state or not (denoted by 1 or 0, respectively). Besides, we simply sample the reward from the replay buffer, considering the bias term is unstable in practice.

3.2 Stabilized Sample Efficient Discriminative Actor-Critic Network

The stabilized sample efficient discriminative actor-critic network aims to enable the agent to learn the policy efficiently. We take a variant of the actor-critic network, *advantage actor-critic network* [33] as the backbone of our approach. In this network, the actor uses policy gradient and the critic's feedback to update the policy, and the critic uses Q-learning to evaluate the policy and provides feedback [34].

Given the state space at timestamp t, the environment determines a state s_t, which contains user's recent interest and demographic information embedded, via the actor-network [35], [36]. The actor-network feeds the state s_t to a network that has four fully-connected layers with ReLU as the activation function. The final layer of the network outputs a policy function π, which is parameterized by θ. Then, the critic network takes two inputs: the trajectory (s_t, a_t), and the current policy π_{θ_t} from the actor-network. We concatenate the state-action pair (s_t, a_t) and feed it into a network with four fully-connected layers (with ReLU as the activation function) and a softmax layer. The output of the critic-network is a value $V(s_t, a_t) \in \mathbb{R}$ to be used for optimization (to be introduced later).

The discriminator D is the key component of our approach. To build an end-to-end model that better approximates the expert policy π_E, we parameterize the policy with π_θ and clip the discriminator's output so that $D : \mathcal{S} \times \mathcal{A} \rightarrow (0, 1)$ with weight w. The loss function of D is denoted by $\mathcal{L}_D$. Besides, we use Adam [37] to optimize weight w (the optimization for θ will be introduced later). We consider the discriminator D as a local cost function provider to guide the policy update. During the minimization of the loss function $\mathcal{L}_D$, i.e., finding a point (π, D) for it, the policy will move toward expect-like regions (divided by D) in the latent space.

Like many other networks, Actor-critic network also suffers the sample inefficiency problem [38], i.e., the agent has to conduct sampling from the expert policy distribution, given the significant number of agent-environment interactions needed to learn the expert policy during the training process. In this regard, we use an off-policy reinforcement learning algorithm (instead of on-policy reinforcement learning algorithms) to reduce interactions with the environment. In particular, we introduce a replay buffer $\mathcal{R}$ to store previous state-action pairs; when training the discriminator, we sample the transition from the replay buffer $\mathcal{R}$ in off-policy learning (instead of sampling trajectories from a policy directly). We thereby define the loss function as follows:

$$\mathcal{L}_D = \mathbb{E}_{\mathcal{R}}[\log D(s,a)] + \mathbb{E}_{\pi_E}[\log(1 - D(s,a))] - \lambda H(\pi) \tag{19}$$

Eq.(19) matches the occupancy measures between the expert and the distribution induced by $\mathcal{R}$. Instead of comparing the latest trained policy π and expert policy π_E, it comprises a mixture of all policy distributions that appeared during training. Considering off-policy learning has different expectation from on-policy learning, we use importance sampling on the replay buffer to balance it.

$$\begin{aligned}\mathcal{L}_D = \mathbb{E}_{\mathcal{R}}\left[\frac{\rho_{\pi_\theta}(s,a)}{\rho_{\mathcal{R}}(s,a)} \log D(s,a)\right] \\ + \mathbb{E}_{\pi_E}[\log(1 - D(s,a))] - \lambda H(\pi)\end{aligned} \tag{20}$$

Considering GAN has the training instability problem [39], we employ the Wasserstein GAN [23] to improve the discriminator's performance. While a normal GAN minimizes JS-Divergence cannot measure the distance between two distributions, Wasserstein GANs uses the EM-distance and Kantorovich-Rubinstein duality to resolve the problem [40].

$$\begin{aligned}\mathbb{E}_{\pi}[\log D(s,a)] - \mathbb{E}_{\pi_E}[\log(D(s,a))] \\ + \mathbb{E}_{\pi_E}[(\|\nabla D(s,a)\| - 1)^2]\end{aligned} \tag{21}$$

We further use gradient penalty to improve the training for Wasserstein GANs [23], given the gradient penalty can improve training stability for JS-Divergence-based GANs [41]. We thereby obtain the final loss function as follows:

$$\begin{aligned}\mathcal{L}_D = \mathbb{E}_{\mathcal{R}}\left[\frac{\rho_{\pi_\theta}(s,a)}{\rho_{\mathcal{R}}(s,a)} \log D(s,a)\right] + \mathbb{E}_{\pi_E}[\log(1 - D(s,a))] \\ -\lambda H(\pi) + \mathbb{E}_{\pi_E}[(\|\nabla D(s,a)\| - 1)^2]\end{aligned} \tag{22}$$

3.3 Optimization

We conduct a joint training process on the policy network (i.e., the actor-critic network) and the discriminator. We parameterize the policy network with policy parameter θ and update it using trust region policy optimization (TRPO) [42] based on the discriminator. TRPO introduces a trust region by restricting the agent's step size to ensure a new policy is better than the old one. We formulate the TRPO problem as follows:

$$\begin{aligned}\max_{\theta} \frac{1}{T} \sum_{t=0}^{T} \left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} A_t\right] \\ \text{subject to } D_{KL}^{\theta_{old}}(\pi_{\theta_{old}}, \pi_\theta) \le \eta\end{aligned} \tag{23}$$

where A_n is the advantage function calculated by Generalized Advantage Estimation (GAE) [43]. GAE is described as follows:

$$\begin{aligned}A_t = \sum_{l=0}^{\infty} (\gamma \lambda_g)^l \delta_{t+l}^V \\ \text{where } \delta_{t+l}^V = -V(s_t) + \sum_{l=0}^{\infty} \gamma^l r_{t+l}\end{aligned} \tag{24}$$

where r_{t+l} is the test reward for l-step's at timestamp t, as defined on Eq.(18). Considering the high computation load of updating TRPO via optimizing Eq.(23), we update the policy using a simpler optimization method called Proximal Policy Optimization (PPO) [44], which has an objective function below:

$$\begin{aligned}\mathop{\mathbb{E}}_{\tau \sim \pi_{old}} \Big[\sum_{t=0}^{T} \min \Big(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} A_t, \\ \text{clip}\Big(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}, 1-\epsilon, 1+\epsilon \Big) A_t \Big) \Big]\end{aligned} \tag{25}$$

where ϵ is the clipping parameter representing the maximum percentage of change that can be made by each update.

The overall training procedure is illustrated in Algorithm 1, which involves the training of both the discriminator and the actor-critic network. For the discriminator, we use Adma as the optimizer to find the gradient for Eq.(22) for weight w at step i:

$$\begin{aligned}\mathbb{E}_{\pi}[\nabla_w \log(D_w(s,a))] + \mathbb{E}_{\pi_E}[\nabla_w \log(1 - D_w(s,a))] \\ + \mathbb{E}_{\pi_E}[(\|\nabla_w D(s,a)\| - 1)^2]\end{aligned} \tag{26}$$

4 Experiments

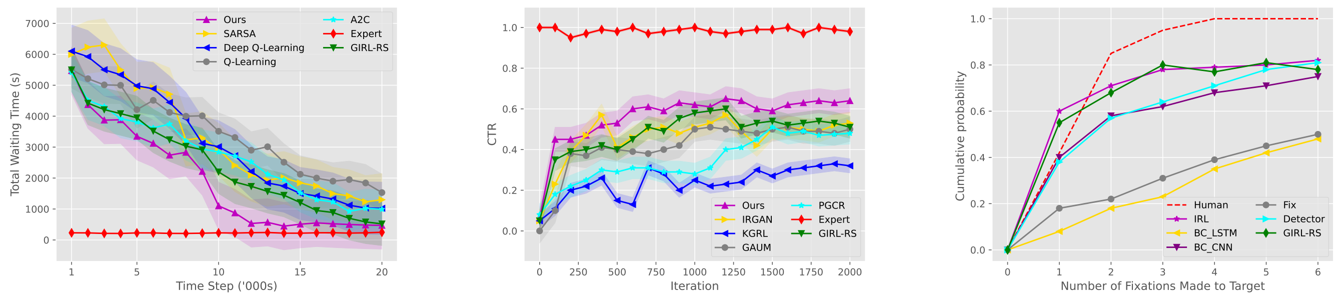
We evaluate the proposed framework and demonstrate its generalization capability by conducting experiments in three different environments: Traffic Control, Recommendation System, and Scanpath Prediction. Our model is implemented in Pytorch [45]. All experiments are conducted on a server with 6 NVIDIA TITAN X Pascal GPUs, 2 NVIDIA TITAN RTX with 768 GB memory.

4.1 Urban Mobility Management

In the traffic control scenario, the agent is required to control cars to conduct a certain task. The objective is to minimize the total waiting time in the trip.

4.1.1 Simulation of Urban Mobility

Traffic signal control is critical to effective mobility management in modern cities. To apply our model to this context, we use the Simulation of Urban MObility (SUMO) [46] library, a microscopic, space-continuous, and time-discrete traffic flow simulation tool, to test the method's performance. The agent controls traffic signals, and a car may take three actions facing traffic lights: go straight, turn left, or turn right, depending on user's preference. We design a simple two-way road network



(a) Total waiting time

(b) CTR in Recommendation

(c) Cumulative probability comparison for selected baseline methods

Fig. 2: Comparison results. From left to right, the subfigures represent the results in (a) Traffic Control, (b) Recommendation System, and (c) Scanpath Prediction. Our methods generally outperform baseline methods.

that contains eight traffic lights for testing. We employ an open-sourced library sumo-rl [1] to enable our agent can interact with the simulation environment (including receiving the reward) directly. The number of cars available in the environment is unlimited; the environment keeps generating cars until this simulation step ends or the road reaches its full capacity.

4.1.2 Expert Policy Acquisition

Since there is no official expert policy available for our customized road network, we use the same strategy as introduced by [47] to collect a set of imperfect expert policies from a pre-trained policy network. This policy network is built upon an actor-critic network, which is trained by using Deep Deterministic Policy Gradients (DDPG) [48]. Expert policies are stored via state-action pairs, which concatenate observed states and expert actions.

4.1.3 Baseline Methods

We evaluate our model against several traditional reinforcement learning methods in this scenario.

- Q-Learning: An off-policy reinforcement learning method that finds the best action given the current state.
- Deep Q-learning: A deep Q-learning method that employs the neural network to extract features.
- SARSA: Stateactionrewardstateaction (SARSA) is an improved Q-learning method commonly used for traffic signal control.
- Advantage Actor-Critic Network (A2C) [33]: An asynchronous method built on an actor-critic network for deep reinforcement learning.
- GIRL-RS [22]: An inverse reinforcement learning for recommendation. We modify the structure by removing the recommender to conduct the traffic control task.

Experiments are conducted in exactly the same environment to ensure a fair comparison. All the baseline methods are implemented by using PyTorch and are publicly available [2]. The reward provided by environment for each simulation step can defined as:

$$r = \sum_{n=0}^{N_{ts}} s * N_{cp} \tag{27}$$

where N_{ts} is the number of traffic signals available in the environment, s is the average car speed in this simulation step, and N_{cp} is number of cars passed this traffic signals at the end of this simulation step. The evaluate metric is the total waiting time defined below:

$$t = \sum_{i=0}^{1000} \sum_{c=0}^{N_c} t_c^i \tag{28}$$

where t_c^i is the time that the car c waits at traffic light i, and $1,000$ is the duration for one simulation step. If car c does not meet traffic light i, we set $t_c^i = 0$.

4.1.4 Hyper-parameters Setting and Results

DDPG parameters for the pre-trained model include $\gamma = 0.95, \tau = 0.001$, the size of the hidden layer 128, the size of the reply buffer $1,000$, and the number of episode $20,000$. Parameters for Ornstein-Uhlenbeck Noise include the scale 0.1, $\mu = 0, \theta = 0.15, \sigma = 0.2$. For our method, we set the number of time steps to $20,000$, the hidden size of the advantage actor-critic network to 256, the hidden size for discriminator to 128, the learning rate to 0.003, factor λ to 10^{-3}, mini batch size to 5, and the epoch of PPO to 4. For the generalized advantage estimation, we set the discount factor γ to 0.995, $\lambda_g = 0.97$, and $\epsilon = 0.2$. We also set $\lambda_i = 1$ for reward shaping and $\lambda = 1$ for $H(\pi)$. The results in Fig. 2 (a) show our method generally outperforms all baseline methods.

1. https://github.com/LucasAlegre/sumo-rl

2. https://github.com/hill-a/stable-baselines

Algorithm 1: Training algorithm for our model

```
input: Expert replay buffer $\mathcal{R}_E$, Initialize Policy
       Replay Buffer $\mathcal{R}$,Initialize policy parameter $\theta_0$,
       clipping parameter $\epsilon$
1  Function Absorbing($\tau$) is
2      if $s_T$ is a absorbing state then
3          $\{s_T, a_T, \cdot, s'_T\} \leftarrow \{s_T, a_T, \cdot, s_a\}$;
4          $\tau \leftarrow \tau \cup \{s_a, \cdot, \cdot, s_a\}$;
5      end
6      return $\tau$;
7  end
8  for $\tau = \{s_t, a_t, \cdot, s'_t\}_{t=1}^{T} \in \mathcal{R}_E$ do
9      $\tau \leftarrow$ Absorbing($\tau$);
10 end
11 $\mathcal{R} \leftarrow \emptyset$ ;
12 for $i = 1, 2, \cdots$ do
13     Sampling trajectories $\tau = \{s_t, a_t, \cdot, s'_t\}_{t=1}^{T} \sim \pi_{\theta_i}$;
14     $\mathcal{R} \leftarrow \mathcal{R} \cup$ Absorbing($\tau$) ;
15     for $j = 1, \cdots, |\tau|$ do
16         $\{s_t, a_t, \cdot, \cdot\}_{t=1}^{B} \sim \mathcal{R}$, $\{s'_t, a'_t, \cdot, \cdot\}_{t=1}^{B} \sim \mathcal{R}_E$ ;
17         Update the parameter $w_i$ by gradient on
             Eq.(26) ;
18     end
19     for $j = 1, \cdots, |\tau|$ do
20         $\{s_t, a_t, \cdot, \cdot\}_{t=1}^{B} \sim \mathcal{R}$;
21         for $b = 1, \cdots, B$ do
22             $r = \log(D_{w_i}(s_b, a_b)) - \log(1 - D_{w_i}(s_b, a_b))$
                 ;
23             Calculate the reshape reward $r'$ by Eq.(18) ;
24             $(s_b, a_b, \cdot, s'_b) \leftarrow (s_b, a_b, r', s'_b)$ ;
25         end
26         for $k = 0, 1, \cdots$ do
27             Get the trajectories $(s, a)$ on policy
                 $\pi_\theta = \pi(\theta_k)$ ;
28             Estimate advantage $A_t$ using Eq.(24);
29             Compute the Policy Update
                     $\theta_{k+1} = \arg\max_{\theta} \mathrm{Eq.}(25)$
               By taking $K$ step of minibatch SGD (via
               Adma)
30         end
31         $\theta_i \leftarrow \theta_K$;
32     end
33 end
```

4.2 Recommendation System

In the recommendation scenario, the agent aims to interact with a dynamic environment to mine user's interests and make recommendations to users.

4.2.1 VirtualTB

We use an open-source online recommendation platform, VirtualTB [49], to test the performance of the proposed methods in a recommendation system. VirtualTB is a dynamic environment built on OpenAI Gym[3] to test our method's feasibility on recommendation tasks. VirtualTB employs a customized agent to interact with it and achieves the corresponding rewards. It can also generate several customers with different preferences during the agent-environment interaction. In VirtualTB, each customer has 11 static attributes encoded into an 88-dimensional space with binary values as the demographic information. The customers have multiple dynamic interests, which are encoded into a 3-dimensional space and may change over the interaction process. Each item has several attributes (e.g., price and sales volume), which are encoded into a 27-dimensional space. We use CTR as the evaluation metric because the gym environment can only provide rewards as feedback. CTR is defined as follows:

$$CTR = \frac{r_{episode}}{10 * N_{step}} \tag{29}$$

where $r_{episode}$ is the reward that the agent receives at each episode. At each episode, the agent may take N_{step} steps and receive a maximum reward of 10 per step.

3. https://gym.openai.com/

Algorithm 2: PPO Update

```
input: Initialize policy parameter $\theta_0$, clipping
       parameter $\epsilon$
1  for $k = 0, 1, \cdots$ do
2      Get the trajectories $(s, a)$ on policy $\pi_\theta = \pi(\theta_k)$ ;
3      Estimate advantage $A_t$ using Eq.(24);
4      Compute the Policy Update
               $\theta_{k+1} = \arg\max_{\theta} \mathrm{Eq.}(25)$
       By taking $K$ step of minibatch SGD (via Adma)
5  end
6  $\theta_i \leftarrow \theta_K$;
```

4.2.2 Baseline Methods

We evaluate our model against five state-of-the-art methods covering methods based on deep Q-learning, policy gradient, and actor-critic networks.

- IRecGAN [50]: An online recommendation method that employs reinforcement learning and GAN.
- PGCR [51]: A policy-Gradient-based method for contextual recommendation.
- GAUM [52]: A deep Q-learning based method that employs GAN and cascade Q-learning for recommendation.
- KGRL [35]: An Actor-Critic-based method for interactive recommendation, a variant of online recommendation.
- GIRL-RS [22]: An inverse reinforcement learning based method for online recommendation.

Note that GAUM and PGCR are not designed for online recommendation, and KGRL requires a knowledge graph—which is unavailable to the gym environment—as the side information. Hence, we only keep the network structure of those networks when testing them on the VirtualTB platform.

4.2.3 Hyper-parameters Setting and Results

The hyper-parameters are set in a similar way as in the traffic signals control. We set the number of episodes to $200,000$ for both the pre-trained policy network and our method. To ease comparison, we configure each iteration to contain 100 episodes. The results in Fig. 2 (b) show our method outperform all state-of-the-art methods. KGRL's poor performance may be partially caused by its reliance on knowledge graph, which is unavailable in our experiments.

4.3 Scanpath Prediction

Scanpath prediction is a type of goal-directed human intention prediction problem [13]. Take the last task in Fig. 1 for example. Given a few objects, a user may first look at item 1, then follows the item numbers annotated in the figure, and finally reaches item 8. The task aims to predict user's intention (i.e., item 8), given the start item (i.e., item 1).

4.3.1 Experimental Setup

We follow the same experimental setup as [13] and conduct all experiments on a public COCO-18 Search dataset[4]. We replace the fully-connected layer in the actor-network with CNN to achieve the best performance of our method on images. The critic-network has a new structure with two CNN layers followed by two fully-connected layers. The discriminator contains all CNN layers with a softmax layer as output. We also resize the input image from the original size of 1680×1050 into 320×512 and construct the state by using the contextual beliefs calculated from a Panoptic-FPN with a backbone network (ResNet-50-FPN) pretrained on COCO2017. We use probability mismatch and scanpath ratio as the main evaluation metrics. Probability mismatch is defined as the sum of the absolute differences between the human and model cumulative probability of target fixation [13]; Scanpath ratio is calculated as the ratio of Euclidean distance between the initial fixation location and the center of the target to the summed Euclidean distances between fixations to the target.

4.3.2 Baseline Methods

We compare our method with several baseline methods, including simple CNN based methods, behavior-cloning based methods, and inverse reinforcement-learning-based method. Experiments are conducted under the same conditions to ensure fairness.

- Detector: A CNN-based architecture to predict the location of a target item.
- Fixation heuristics [13]: A method similar to *Detector* but using the fixation to predict the location of a target item.
- BC-CNN [53]: A behavior-cloning method that uses CNN as the basic layer structure.
- BC-LSTM [54]: A behavior-cloning method that uses LSTM as the basic layer structure.
- IRL [13]: A state-of-the-art inverse reinforcement-learning-based method for scanpath prediction.
- GIRL-RS [22]: A generative inverse reinforcement learning method of recommendation. We remove the recommender and replace it by the prediction components as [13] did.

4. https://saliency.tuebingen.ai/datasets/COCO-Search18/index_new.html

4.3.3 Performance Comparison

The hyper-parameters settings are the same as those used for the recommendation task. We also use the same evaluation metrics as used in [13] to evaluate the performance: cumulative probability, probability mismatch, and scanpath ratio. The results in Fig. 2(c) show the cumulative probability of the gaze landing on the target after the first six fixations. We report the probability mismatch and scanpath ratio in table 2.

TABLE 2: Results comparison for selected methods on probability mismatch and scanpath ratio

	Probability Mismatch ↓	Scanpath Ratio↑
Human	n.a.	0.862
Detector	1.166	0.687
BC-CNN	1.328	0.706
BC-LSTM	3.497	0.406
Fixation	3.046	0.545
IRL	0.987	0.862
GIRL-RS	0.990	0.870
Ours	**0.961**	**0.881**

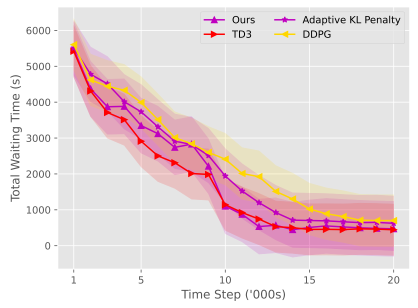
4.4 Evaluation on Explainability

Explainability plays a crucial role in understanding the decision-making process. By visualizing the learned reward map, we show in this experiment that our model can provide a certain level of interpretability. We evaluate the explanability for our model in the scanpath prediction scenario. Fig. 4 shows that the reward maps recovered by the our model depend heavily on the category of the search target. In the first image, the highest reward is assigned to the piazza when drinking beers. Similarly, the searching of road signal on the road, the stop signal get almost all of the reward while the car get only a few.

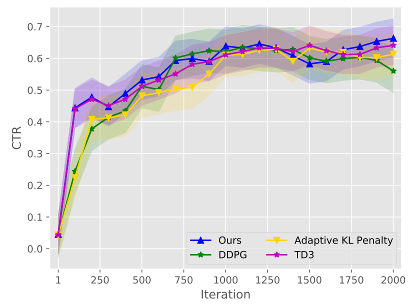
4.5 Ablation Study

We test using three different optimization strategies (DDPG, Adaptive KL Penalty Coefficient and Twin Delayed DDPG) to update the policy parameter θ. (TD3) [55]. The Adaptive KL Penalty Coefficient is defined as:

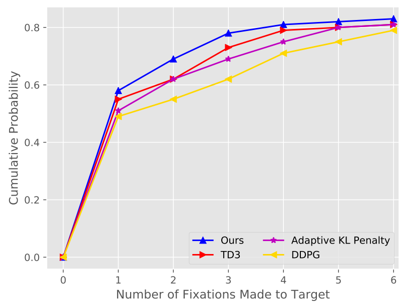
$$L(\theta) = \mathbb{E}_t\Big[\frac{\pi_{\theta'}(a_t|s_t)}{\pi_\theta(a_t|s_t)}A_t - \beta \mathrm{KL}[\pi_\theta(\cdot|s_t), \pi_{\theta'}(\cdot|s_t)]\Big] \quad (30)$$



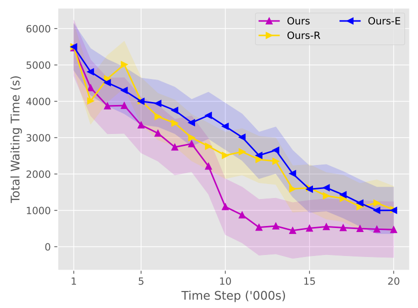
(a) Traffic



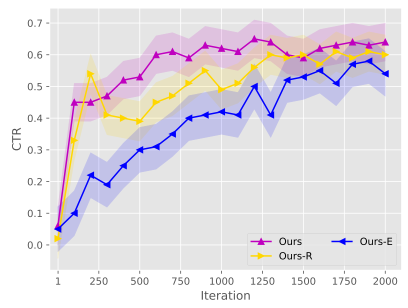
(b) Recommendation



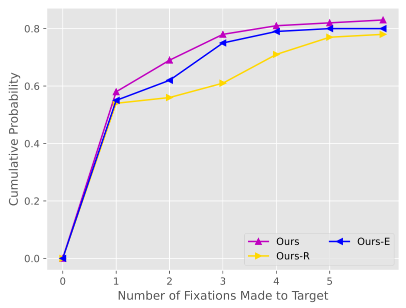
(c) Scanpath Prediction



(d) Traffic



(e) Recommendation



(f) Scanpath Prediction

Fig. 3: Results of ablation study for those three selected environments.

TABLE 3: CTR for Different Parameter Settings for GAE and PPO

		GAE: λ_g					
		0.94	0.95	0.96	0.97	0.98	0.99
PPO: ϵ	0.05	0.630 ± 0.063	0.632 ± 0.064	0.633 ± 0.062	0.630 ± 0.059	0.626 ± 0.060	0.629 ± 0.059
	0.10	0.632 ± 0.062	0.635 ± 0.060	0.636 ± 0.061	0.636 ± 0.058	0.634 ± 0.061	0.633 ± 0.060
	0.15	0.633 ± 0.060	0.635 ± 0.061	0.639 ± 0.061	0.640 ± 0.057	0.639 ± 0.059	0.638 ± 0.061
	0.20	0.634 ± 0.060	0.636 ± 0.060	0.641 ± 0.063	**0.643 ± 0.061**	0.643 ± 0.063	0.641 ± 0.058
	0.25	0.631 ± 0.061	0.635 ± 0.059	0.636 ± 0.060	0.637 ± 0.060	0.636 ± 0.061	0.634 ± 0.059
	0.30	0.630 ± 0.059	0.631 ± 0.061	0.632 ± 0.060	0.630 ± 0.059	0.630 ± 0.058	0.629 ± 0.050

where the β will be adjust dynamically by the following,

$$\begin{cases} \beta \leftarrow \beta/2 & d < d_{target} * 1.5 \\ \beta \leftarrow \beta * 2 & d >= d_{target} * 1.5 \end{cases} \tag{31}$$
$$\text{where } d = \mathbb{E}_t[\mathrm{KL}[\pi_{\theta_{old}}(\cdot|s_t), \pi_\theta(\cdot|s_t)]]$$

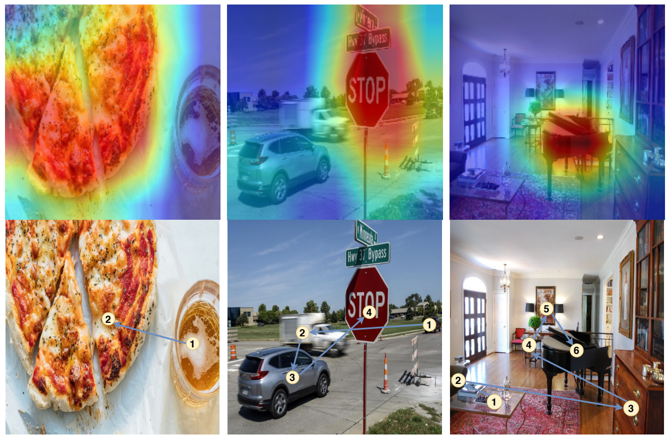
We empirically choose coefficient 1.5 and 2 and select total waiting time, CTR, and cumulative probability as the evaluation metrics to compare the three optimization strategies for traffic signal control, recommendation system, and scanpath prediction, respectively. The results (shown in Fig. 3) show our optimization method achieve a similar result as TD3 on all the three tasks but is better than TD3 on the recommendation task. Hence, we conduct a further step about the parameter selection about PPO and GAE, which can be found in Table 3.

Moreover, we investigate the effect of the proposed stabilized approach and sample efficiency. We report those results on Figure 4, where Our-S represents the proposed method without the stabilized training and Our-R represents the proposed method without the way we used to increase the sample efficiency.

5 Related Work

User behavior tendency modeling has been an active topic in research, and most previous efforts have been focusing on feature engineering rather than an end-to-end learning structure. Kim et al. [7] considers long-term interest as a reasonable representation of general interest and acknowledges its importance for personalization services. On this basis, Liu et al. [56] propose a framework that considers both long-term and short-term interest for user behavior modeling. Rather than establishing static models, Chung et al. [57] models long-term and short-term user profile scores to model user behaviors incrementally. Recently, Song et al. [58] propose to jointly model long-term and short-term user interest for recommendation based on deep learning methods. Pi et al. [59] further propose a MIMN model for sequential user behavior modeling. Despite good performance on their respective tasks, all the above methods are task-specific and lack generalization ability.

Reinforcement learning is widely used for user behavior modeling in recommendation systems. Zheng et al. [2] adopt deep Q-learning to build up user profiles during the interaction process in a music recommendation system. Zou et al. [60] improve the Q-learning structure to stabilize



(a) Piazza (b) Stop (c) Piano

Fig. 4: Reward maps learned by the our model for three different search targets which are piazza, stop signal and piano respectively in the context of Scanpath Prediction. The number means user's vision trajectory for searching target item which is the largest number refers to. For example, in (a) 2 represents piazza, in (b) 4 represents to stop sign and in (c), 6 represents to the piano. In addition, the hotmap represent the highest reward area which will be awarded to agent.

the reward function and make the recommendation robust. [35], [61], [62] apply reinforcement learning for extracting user's interest from a knowledge graph. Liu et al. [36] embed user's information into a latent space and conduct recommendation via deep reinforcement learning. Different from those mentioned works, Pan et al. [51] applies the policy gradient directly to optimize the recommendation policy. Chen et al. [52] integrates GAN into the reinforcement learning framework so as to enrich the latent space with user's side information to improve the recommendation accuracy. Shang et al. [63] consider the environment co-founder factors and propose a multi-agent based reinforcement learning method for recommendation. All the above studies require defining accurate reward functions, which are hard to obtain in the real world.

Inverse reinforcement learning emerges where reward functions cannot be defined [20]. Lee et al. [64] firstly use inverse reinforcement learning to learn user's behavior styles. However, general inverse reinforcement learning is computationally expensive. Ho et al. [21] propose a generative reinforcement learning approach to improve efficiency. Fu et al. [31] further extend the idea to a general form to obtain a more stable reward function. Kostrikov et al. [32] find a generative method may suffer instability in training, which can be relieved by using EM-distance instead of JS-divergence. Yang et al. [13] first introduce the inverse reinforcement learning into the scanpath prediction and demonstrate the superior performance. IRL demonstrates a huge potential and is widely used in robot learning as it can empower the agent to learn from demonstration in different environments and tasks without dramatic exploration about the environment or being familiar with the tasks. Chen et al. [22] expand this idea into recommender systems and show the feasibility of IRL in recommendation tasks.

6 Conclusion and Future Work

In this paper, we propose a novel method based on *advantage actor-critic network* with inverse reinforcement learning to overcome the adverse impact caused by inaccurate reward functions for user behavior modeling. In particular, we use the Wasserstein GAN instead of GAN to increase training stability and a replay buffer for off-policy learning to increase sample efficiency. A comparison with several state-of-the-art methods in three different scenarios (namely traffic signal control, recommendation system, and scanpath prediction) demonstrate our method's feasibility and superior performance to baseline methods. This work poses a promising direction towards applying inverse reinforcement learning to real life. It demonstrates the feasibility of generalized behavior modeling in several scenarios, such as recommender systems and traffic light control, which could be of importance in smart cities and related applications.

Although experience replay can boost sample efficiency by switching the sampling process from the environment to replay buffer, it may not be ideal as some tasks (e.g., recommendation) may have giant state and action spaces. Moreover, not every experience is useful even if it comes from demonstration because expert demonstrations are randomly sampled from replay buffer and may be orthogonal with the current state, which leads to adverse actions. Possible solutions include state-aware experience replay methods and prioritized experience replay based methods [65]. Another point for potential improvement is with Wasserstein GAN, as the Lipschitz constraint is hard to enforce and may lead to a model convergence issue.

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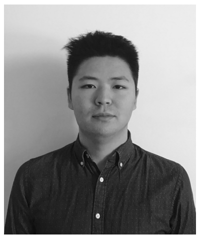

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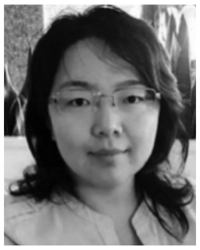

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