中国人民大學
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Towards More Realistic User Long Term Engagement Modeling in Recommender Systems

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Background

Information Overload

SIGIR 2021

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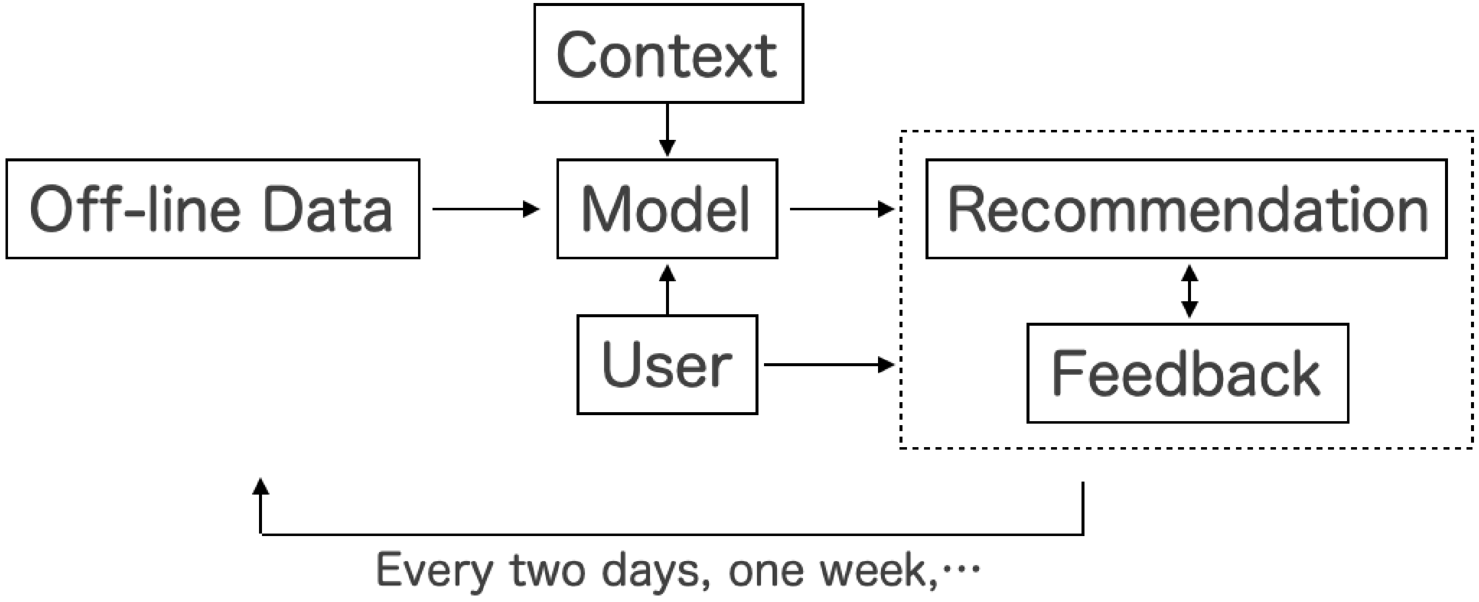
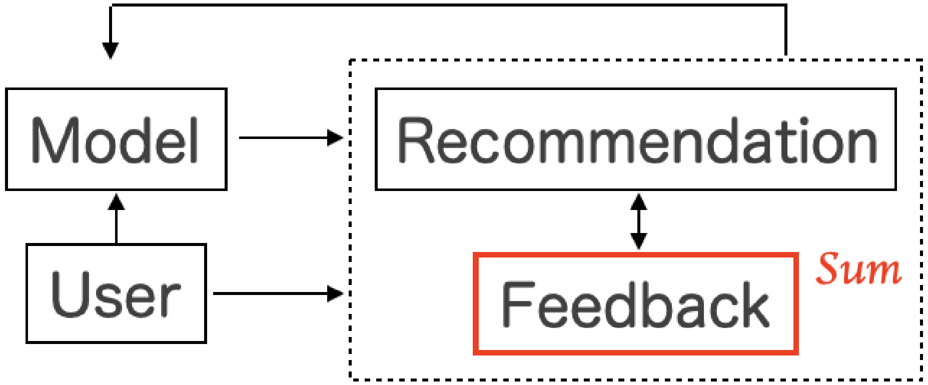
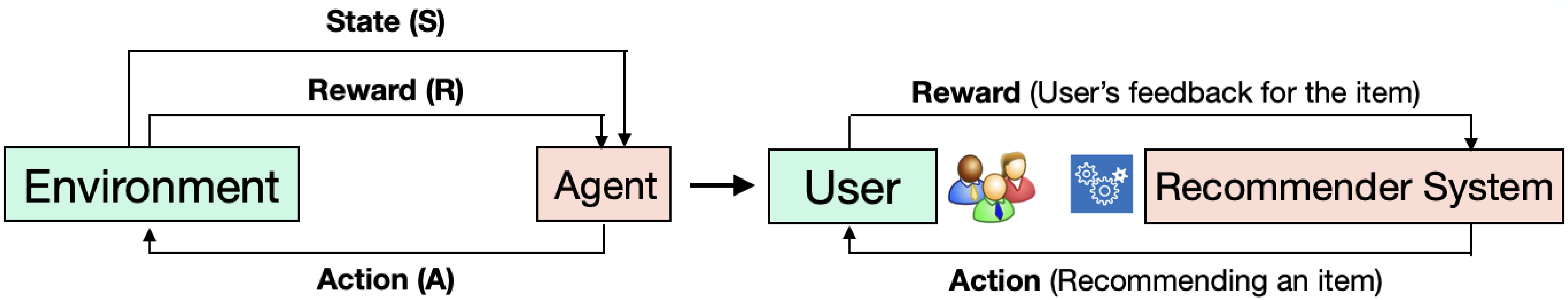


1. Interactive Nature

2. Long-term Utilities





Recommender -> Agent

User -> Environment

Recommend an item -> Action

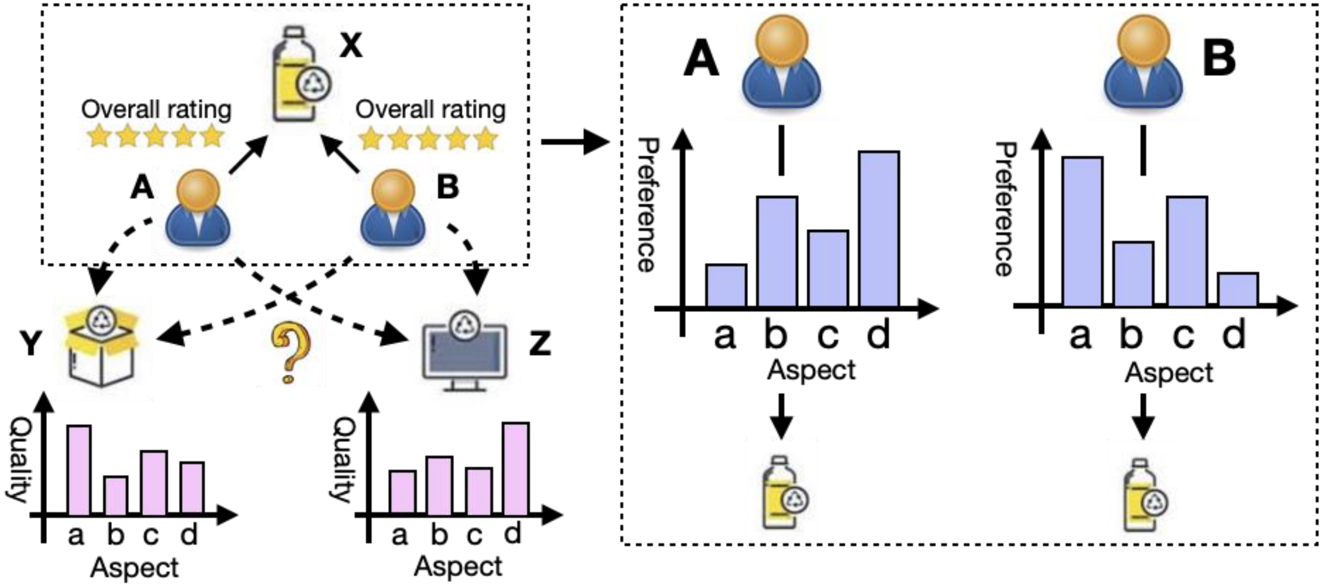
User's historical behaviour -> State

User's rating on the item -> Reward

How to consider the characters of the user preference? E.g., Diversity, Dynamic, …

Modelling User Diverse Preference

Diverse user preference



Different aspect preferences are not always aligned!

Definition 1. Pareto dominance. Suppose we have two parameters θ_A and θ_B, we say θ_A can dominant θ_B (denoted by $\theta_A \succ \theta_B$), if and only if $\mathcal{L}_i(\theta_A) \leq \mathcal{L}_i(\theta_B)$, $\forall i \in \{1, 2, \ldots M\}$ and $\mathcal{L}_i(\theta_A) < \mathcal{L}_i(\theta_B)$, $\exists i \in \{1, 2, \ldots M\}$.

Definition 2. Pareto efficiency. For a parameter θ^*, if there is no other $\hat{\theta}$, such that $\hat{\theta} \succ \theta^*$, then we say θ^* is a Pareto efficient solution.

Critic learning:

$$\arg\min_{\phi_m} \sum_{i=1}^{N} (y_{i,m} - Q_m(s_i, a_i|\phi_m))^2, \; m = 1, 2, \ldots M$$

Actor learning:

$$l(\theta) = -\sum_{m=1}^{M} w_m \sum_{i=1}^{N} Q_m(s_i, \mu(s_i|\theta))$$

$$L(\theta) = \sum_{i=1}^{N} y_i \log \sigma(\boldsymbol{q}_o^T \mu(s_i|\theta)) + (1 - y_i) \log(1 - \sigma(\boldsymbol{q}_o^T \mu(s_i|\theta))) \longrightarrow L(\theta) = \tilde{Q}((o, y_i), \mu(s_i|\theta))$$

$$\min_{\boldsymbol{w}} || \sum_{m=1}^{M} w_m \nabla_\theta \sum_{i=1}^{N} Q_m(s_i, \mu(s_i|\theta))||_2^2$$
$$s.t. \; \boldsymbol{e}_k^T \boldsymbol{w} \geq b_k, \; \forall \, k \in [1, K]$$
$$\boldsymbol{1}^T \boldsymbol{w} = 1, \; w_m \geq 0, \; \forall \, m \in [1, M]$$

Theorem 1. *If $\boldsymbol{w}$ is determined by solving the quadratic programming (QP) problem of (5), then either one of the following holds:*
i) The solution to the optimization problem is 0, then the local Pareto efficient solution is achieved.
ii) $\boldsymbol{d} = \sum_{m=1}^{M} w_m \nabla_\theta \sum_{i=1}^{N} Q_m(s_i, \mu(s_i|\theta))$ is a gradient direction which does not decrease any Q function.

Algorithm 1: Pareto Deterministic Policy Gradient

Initialize Actor parameter $\boldsymbol{\theta}$ and Target Actor parameter $\boldsymbol{\theta}' \leftarrow \boldsymbol{\theta}$.
Initialize Critic parameter $\boldsymbol{\phi}_m$ and Target Critic parameter $\boldsymbol{\phi}'_m \leftarrow \boldsymbol{\phi}_m, \forall m \in [1, M]$.
Initialize Pareto weights $\boldsymbol{w} = \{\frac{1}{M+1}, \frac{1}{M+1}, \dots, \frac{1}{M+1}\}$ and replay buffer B.
for *episode number in [1, K]* **do**
  i) Trajectory Generation
  Get start state s_1
  for *step t in [1, T]* **do**
    Select an action according to $a_t = \mu(s_t|\boldsymbol{\theta}) + N_t$, N_t is an exploration noise.
    Execute a_t to obtain the new state s_{t+1} and the reward vector $\boldsymbol{r}_t = \{r_{t,1}, r_{t,2}, \dots, r_{t,M}\}$.
    Push $\{s_t, a_t, \boldsymbol{r}_t, s_{t+1}\}$ into the replay buffer B
  end
  ii) Update Critic
  Sample Z instances $\{s_i, a_i, \boldsymbol{r}_i, s_{i+1}\}$ from B
  for *critic m in [1, M]* **do**
    for *i in [1, Z]* **do**
      Compute $y_i = r_{i,m} + \gamma Q_m(s_{i+1}, \mu(s_{i+1}|\boldsymbol{\theta}')|\boldsymbol{\phi}'_m)$.
    end
    $\boldsymbol{\phi}_m \leftarrow \boldsymbol{\phi}_m - \alpha_\phi \nabla_{\boldsymbol{\phi}_m}\{\frac{1}{Z}\sum_{i=1}^{Z}(y_i - Q_m(s_i, a_i|\boldsymbol{\phi}_m))^2\}$.
  end
  iii) Update Pareto Weight
  for *i in [1, Z]* **do**
    for *m in [1, M]* **do**
      $\boldsymbol{p}_{i,m} = \nabla_a Q_m(s,a)|_{s=s_i, a=\mu_\theta(s_i)} \nabla_{\boldsymbol{\theta}}\mu(s|\boldsymbol{\theta})|_{s=s_i}$.
    end
    $\tilde{\boldsymbol{p}}_i = \nabla_a \tilde{Q}(s,a))|_{s=(o,y_i), a=\mu_\theta(s_i)} \nabla_{\boldsymbol{\theta}}\mu(s|\boldsymbol{\theta})|_{s=s_i}$.
  end
  Update $\boldsymbol{w} = \{w_1, w_2, \dots, w_M, \tilde{w}\}$ by Solving (5).
  iv) Update Actor
  $\boldsymbol{d} = \frac{1}{Z}\sum_{i=1}^{Z}\sum_{m=1}^{M} w_m \boldsymbol{p}_{i,m} + \tilde{w}\tilde{\boldsymbol{p}}_i$.
  $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha_\theta \boldsymbol{d}$.
  $\boldsymbol{\theta}' \leftarrow \tau\boldsymbol{\theta} + (1-\tau)\boldsymbol{\theta}'$.
  $\boldsymbol{\phi}'_m \leftarrow \tau\boldsymbol{\phi}_m + (1-\tau)\boldsymbol{\phi}'_m \quad \forall m \in [1, M]$.
end

$$G = \left|\mathbb{E}_{\boldsymbol{B}_i}\left[\sum_{m=1}^{M+1} w_m(\boldsymbol{B}_i)\left(\frac{1}{Z}\sum_{s_b \in \boldsymbol{B}_i} f_m(s_b;\boldsymbol{\theta}) - \mathbb{E}_s[f_m(s;\boldsymbol{\theta})]\right)\right]\right|$$

Theorem 2. *Suppose i) $\nabla_a Q_m(s,a)$ and $\nabla_{\boldsymbol{\theta}}\mu(s|\boldsymbol{\theta})$ are bounded by X_m and Y, that is, $||\nabla_a Q_m(s,a)||_2 \le X_m$ and $||\nabla_{\boldsymbol{\theta}}\mu(s|\boldsymbol{\theta})||_2 \le Y$. ii) The batched gradient of the action-value function for each objective is unbiased, that is: $\mathbb{E}_{\boldsymbol{B}_i}[\frac{1}{Z}\sum_{s_b \in \boldsymbol{B}_i} f_m(s_b;\boldsymbol{\theta})] = \mathbb{E}_s[f_m(s;\boldsymbol{\theta})]$. iii) $f_m(s_b;\boldsymbol{\theta})$ follows a normal distribution $\mathcal{N}(\mathbb{E}_s[f_m(s;\boldsymbol{\theta})], \sigma^2 I)$, where $I \in \mathbb{R}^{d\times d}$ is an identity matrix and σ is a scalar. Then we have:*

$$G \le \sum_{m=1}^{M+1}\mathbb{E}_{\boldsymbol{B}_i}\left[w_m(\boldsymbol{B}_i)\left(\left|\frac{1}{Z}\sum_{s_b \in \boldsymbol{B}_i} f_m(s_b;\boldsymbol{\theta}) - \mathbb{E}_s[f_m(s;\boldsymbol{\theta})]\right|\right)\right] \quad (14)$$

$$\le \frac{X_{m*} Y \sqrt{d}}{\sqrt{Z}} \quad (15)$$

where $m^* = \arg\max_m |\frac{1}{Z}\sum_{s_b \in \boldsymbol{B}_i} f_m(s_b;\boldsymbol{\theta}) - \mathbb{E}_s[f_m(s;\boldsymbol{\theta})]|$.

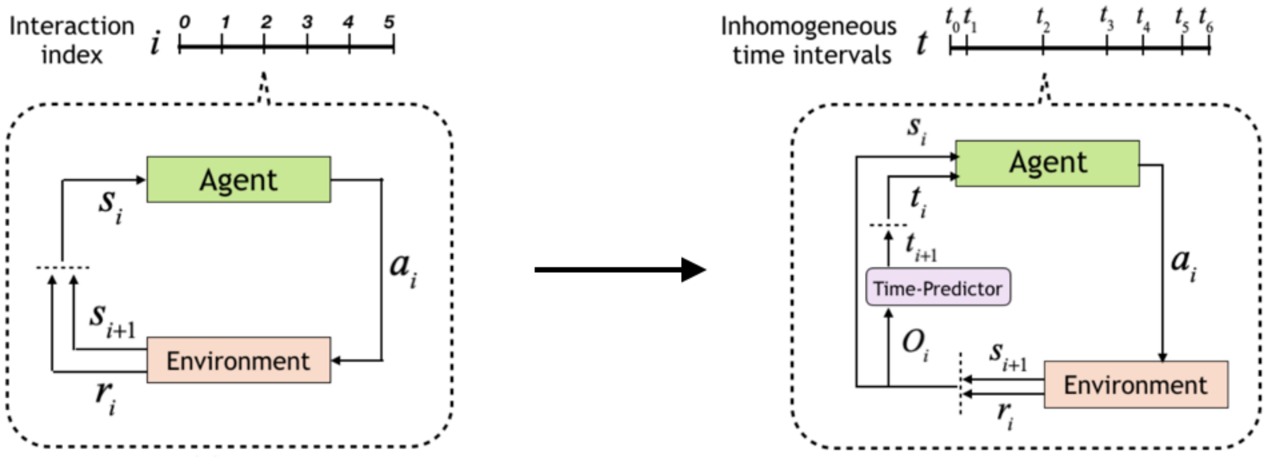
Weight-reuse mechanism. In this method, we introduce a container $\boldsymbol{W} \in \mathbb{R}^{L\times(M+1)}$ for storing previously derived Pareto weights. For each training batch $\boldsymbol{B}_i$, $\boldsymbol{w} \in \mathbb{R}^{M+1}$ is not always computed by solving problem (5). We firstly check the weights in the container:

(1) If there is a candidate $\boldsymbol{w}^* \in \boldsymbol{W}$, such that its corresponding $\boldsymbol{d}^* = \sum_{m=1}^{M+1} w_m^* \nabla_{\boldsymbol{\theta}} \left(\frac{1}{Z} \sum_{s_b \in \boldsymbol{B}_i} Q_m(s_b, \mu(s_b|\boldsymbol{\theta})) \right)$ can increase all the Q functions, that is, $(\boldsymbol{d}^*)^T \nabla_{\boldsymbol{\theta}} \left(\frac{1}{Z} \sum_{s_b \in \boldsymbol{B}_i} Q_m(s_b, \mu(s_b|\boldsymbol{\theta})) \right) > 0, \forall m \in [1, M+1]$, then we set $\boldsymbol{w} = \boldsymbol{w}^{*3}$. Since the weights in $\boldsymbol{W}$ is not derived from $\boldsymbol{B}_i$, the bias G becomes 0 at this moment.

(2) If there is no such weight in $\boldsymbol{W}$, we solve problem (5) to derive $\boldsymbol{w}$, which is then pushed into the container for future "reuse". In this scenario, G is not 0, which is bounded by equation (15).

Modelling User Dynamic Preference

Dynamic user preference



Inhomogeneous DQN

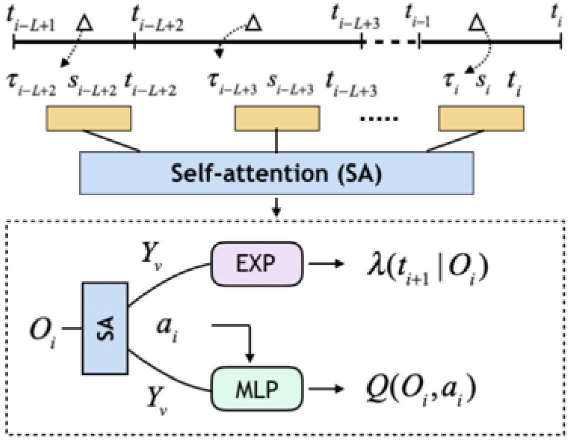
Trajectory $\tau = \{s_0, a_0, t_0, s_1, a_1, t_1, ..., s_T, a_T, t_T\}$

Objective $J = \mathbb{E}_{\tau \sim p_{\theta,\psi}(\tau)}[\sum_{i=0}^{T} \gamma^i \kappa(t_0 - t_i) r(s_i, a_i, t_i))]$

Bellman Operator

$$(TQ)(s_i, a_i, t_i)$$
$$= r(s_i, a_i, t_i) + \sum_{s_{i+1} \in \mathcal{S}} \mathcal{P}(s_{i+1}|s_i, a_i)\{\mathbb{E}_{t_{i+1} \sim \mathcal{T}(\cdot|O_i)}[\gamma \kappa(t_i - t_{i+1})$$
$$\max_{a_{i+1} \in \mathcal{A}} Q(s_{i+1}, a_{i+1}, t_{i+1})]\}$$

Theorem 1 (T is a contractive operator.). *Let Q_1 and Q_2 be two value functions. Then, the Lipschitz condition $||TQ_1 - TQ_2||_\infty \leq \alpha||Q_1 - Q_2||_\infty$ holds, where $\alpha \in [0, 1)$ is a constant.*



$$Q(O_i, a_i|\boldsymbol{\phi}_Q, \boldsymbol{\phi}_Y) = f_Q^n(f_Q^{n-1}(\ldots(f_Q^1(Y_v \boldsymbol{w}_3, \boldsymbol{p}_i))\ldots))$$

$$\lambda^*(t_{i+1}|\boldsymbol{\phi}_\lambda, \boldsymbol{\phi}_Y) = \lambda(t_{i+1}|O_i; \boldsymbol{\phi}_\lambda, \boldsymbol{\phi}_Y)$$
$$= \exp\big(\underbrace{\boldsymbol{w}_1^T Y_v \boldsymbol{w}_2}_{A} + \underbrace{w_t(t_{i+1} - t_i)}_{B} + \underbrace{b}_{C}\big)$$

$$\boldsymbol{x}_j = [\boldsymbol{e}_j; \boldsymbol{\tau}_j] + \boldsymbol{v}_j$$

$$\boldsymbol{Q} = \boldsymbol{X}^T \boldsymbol{W}_Q, \boldsymbol{K} = \boldsymbol{X}^T \boldsymbol{W}_K, \boldsymbol{V} = \boldsymbol{X}^T \boldsymbol{W}_V,$$
$$\boldsymbol{X}_1 = \mathrm{SOFTMAX}(\frac{\boldsymbol{Q}\boldsymbol{K}^T}{\sqrt{d_K}})\boldsymbol{V},$$
$$Y_1 = \boldsymbol{W}_2^F \mathrm{ReLU}(\boldsymbol{W}_1^F \boldsymbol{X}_1^T + \boldsymbol{b}_1^F) + \boldsymbol{b}_2^F,$$

$$L(\phi_Q, \phi_Y, \phi_\lambda) = E_{(O_i, a_i, r_i, s_{i+1}, t_{i+1})}[(y_i - Q(O_i, a_i))^2]$$

$$= \int_{O_i} \underbrace{p(O_i)}_{A} \underbrace{E_{(a_i, r_i, s_{i+1}, t_{i+1} | O_i)}[(y_i - Q(O_i, a_i))^2]}_{B} \mathrm{d}O_i$$

A

$$L_P(\phi_\lambda, \phi_Y) = \sum_{O_i} \sum_{j=1}^{i} \log p(t_j | O_{j-1}) = \sum_{O_i} \sum_{j=1}^{i} \log f^*(t_j | O_{j-1})$$

$$= \sum_{O_i} \sum_{j=1}^{i} \{\log \lambda^*(t_j | \phi_\lambda, \phi_Y) - \int_{t_{j-1}}^{t_j} \lambda^*(\tau | \phi_\lambda, \phi_Y) \mathrm{d}\tau\}$$

B

$$L_Q(\phi_Q, \phi_Y) = \sum_{D} (y_i - Q(O_i, a_i | \phi_Q, \phi_Y))^2$$

Theorem 2 (Finite-time bound for IDQN). *Suppose we have K training iterations in the optimization process, and for the kth iteration, the Q-network is updated from Q_{k-1} to Q_k as follows:*

$$Q_k = \arg\min_{f \in \mathcal{F}} \sum_{i=1}^{N} [y_i - f(O_i, a_i)]^2 \\ y_i = r_i + \gamma\kappa(t_i - t_{i+1}) \max_{a_{i+1}} Q_{k-1}(O_{i+1}, a_{i+1}) \tag{14}$$

where we have N training samples, and (O_i, a_i) in each instance is drawn from a distribution σ.

Suppose (i) $k(m; \mu, \sigma)$ is the concentration coefficient as defined in [37], where μ is the distribution on (O_i, a_i) after m MDP steps, and $k(m; \mu, \sigma)$ measures the similarity between μ and σ. (ii) l^k is the minimum time interval spanning k steps in all trajectories, that is, $l^k = \min_{i,\tau}(t^{\tau}_{i+k} - t^{\tau}_{i})$, where t^{τ}_{i} is the agent-environment interaction time for the ith step in trajectory τ (iii) $e_{k+1} = TQ_k - Q_{k+1}$ and $s = \max_i ||e_i||_{\sigma}$. We assume (i) the immediate reward is bounded by R_{max}, (ii) $\sum_{m\geq 1}[\gamma^{m-1} m k(m; \mu, \sigma)]^2 \leq \phi_{\mu,\sigma}$, and (iii) $\sum_{k=0}^{\infty} \kappa(-l^k)^2 \leq \phi_{\kappa}$.

Let π_K be the one-step greedy policy of Q_K, and Q^{π_K} be the action-value function corresponding to π_K. $Q^*(O, a) = sup_{\pi} Q^{\pi}(O, a)$ is the optimal Q-function. Then, the upper bound of the error between Q^* and Q^{π_K} is:

$$|Q^* - Q^{\pi_K}|_{1,\mu} \leq 2\gamma s(\phi_{\mu,\sigma}\phi_{\kappa})^{\frac{1}{2}} + \frac{4\gamma^{K+1} R_{max}}{(1-\gamma)^2} \tag{15}$$

Outlook

What if the logged user preference is biased?

Counterfactual trajectory generation

Debiased user preference learning

...

How to build high reliable simulator?

Not limited to RL-based Recsys

Potential to promote the Recsys research

...

Thanks & QA