Towards Long-term Fairness in Recommendation

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ABSTRACT

As Recommender Systems (RS) influence more and more people in their daily life, the issue of fairness in recommendation is becoming more and more important. Most of the prior approaches to fairness-aware recommendation have been situated in a static or one-shot setting, where the protected groups of items are fixed, and the model provides a one-time fairness solution based on fairnessconstrained optimization. This fails to consider the dynamic nature of the recommender systems, where attributes such as item popularity may change over time due to the recommendation policy and user engagement. For example, products that were once popular may become no longer popular, and vice versa. As a result, the system that aims to maintain long-term fairness on the item exposure in different popularity groups must accommodate this change in a timely fashion.

Novel to this work, we explore the problem of long-term fairness in recommendation and accomplish the problem through dynamic fairness learning. We focus on the fairness of exposure of items in different groups, while the division of the groups is based on item popularity, which dynamically changes over time in the recommendation process. We tackle this problem by proposing a fairness-constrained reinforcement learning algorithm for recommendation, which models the recommendation problem as a Constrained Markov Decision Process (CMDP), so that the model can dynamically adjust its recommendation policy to make sure the fairness requirement is always satisfied when the environment changes. Experiments on several real-world datasets verify our framework's superiority in terms of recommendation performance, short-term fairness, and long-term fairness.

CCS CONCEPTS

• Information systems → Recommender systems; • Computing methodologies -> Sequential decision making.

KEYWORDS

Recommender System; Long-term Fairness; Reinforcement Learning; Constrained Policy Optimization; Unbiased Recommendation

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INTRODUCTION

Personalized recommender system (RS) is a core function of many online services such as e-commerce, advertising, and online job markets. Recently, several works have highlighted that RS may be subject to algorithmic bias along different dimensions, leading to a negative impact on the underrepresented or disadvantaged groups [15, 17, 18, 39, 52]. For example, the "Matthew Effect" becomes increasingly evident in RS, where some items get more and more popular, while the long-tail items are difficult to achieve relatively fair exposure [27]. Existing research on improving fairness in recommendation systems or ranking has mostly focused on static settings, which only assess the immediate impact of fairness learning instead of the long-term consequences [26, 46]. For instance, suppose there are four items in the system, A, B, C, and D, with A, B belonging to the popular group G_0 and C, D belonging to the long-tail group G_1 . When using demographic parity as fairness constraint in recommendation and recommend two items each time, without considering the position bias, we will have AC, BC, AD, or BD to be recommended to consumers. Suppose D has a higher chance of click, then after several times, D will get a higher utility score than other items, but since D is still in G_1 , the algorithm will tend to recommend D more to maximize the total utility and to satisfy group fairness. This will bring a new "Matthew Effect" on G_1 in the long term. The above example shows that imposing seemingly fair decisions through static criteria can lead to unexpected unfairness in the long run. In essence, fairness cannot be defined in static or one-shot setting without considering the long-term impact, and long-term fairness cannot be achieved without understanding the underlying dynamics.

We define *static fairness* as the one that does not consider the changes in the recommendation environment, such as the changes in item utility, attributes, or group labels due to the user feedback/interactions throughout the recommendation process. Usually, static fairness provides a one-time fairness solution based on fairness-constrained optimization. Dynamic fairness, on the other hand, considers the dynamic factors in the environment and learns a strategy that accommodates such dynamics. Furthermore, longterm fairness views the recommendation as a long term process instead of a one-shot objective and aims to maintain fairness in the long run by achieving dynamic fairness over time.

Technically, we study the long-term fairness of item exposure in recommender systems, while items are separated into groups based on item popularity. The challenge is that during the recommendation process, items will receive different extents of exposure based on the recommendation strategy and user feedback, causing the underlying group labels to change over time. To achieve the aforementioned long-term fairness in recommendation, we pursue to answer the following three key questions:

- How to model long-term fairness of item exposure with changing group labels in recommendation scenarios?
- How to update the recommendation strategy according to realtime item exposure records and user interactions?
- $\bullet \ \ \text{How to optimize the strategy effectively over large-scale datasets?}$

In this work, we aim to address the above challenges simultaneously. Specially, we propose to model the sequential interactions between consumers and recommender systems as a Markov Decision Process (MDP), and then turn it into a Constrained Markov Decision Process (CMDP) by constraining the fairness of item exposure at each iteration dynamically. We leverage the Constrained Policy Optimization (CPO) with adapted neural network architecture to automatically learn the optimal policy under different fairness constraints. We illustrate the long-term impact of fairness in recommendation systems by providing empirical results on several real-world datasets, which verify the superiority of our framework on recommendation performance, short-term fairness, and long-term fairness. To the best of our knowledge, this is the first attempt to model the dynamic nature of fairness with respect to changing group labels, and to show its effectiveness in the long term.

2 RELATED WORK

2.1 Fairness in Ranking and Recommendation

There have been growing concerns on fairness recently, especially in the context of intelligent decision-making systems, such as recommender systems. Various types of bias have been found to exist in recommendations such as gender and race [1, 11], item popularity [52], user feedback [15] and opinion polarity [43]. Different notions of fairness and algorithms have since been proposed to counteract such issues. There are mainly two types of fairness definitions in recommendations: *individual* fairness and *group* fairness. The former requires treating individuals similarly regardless of their protected attributes, such as demographic information, while the latter requires treating different groups similarly. Our work focuses on the popularity group fairness, yet also addresses individual fairness through accommodation to dynamic group labels.

The relevant methods related to fairness in ranking and recommendation can be roughly divided into three subcategories: optimizing utility (often represented by relevance) subject to a bounded fairness constraint [8, 18, 39, 44], optimizing fairness with a lower bound utility [52], and jointly optimizing utility and fairness [7]. Based on the characteristics of the recommender system itself, there also have been a few works related to multi-sided fairness in multistakeholder systems [6, 16, 30]. These works have proposed effective algorithms for fairness-aware ranking and recommendation, yet they fall in the category of *static fairness* where the protected

attribute or group labels were fixed throughout the entire ranking or recommendation process. Therefore, it is not obvious how such algorithms can be adapted to dynamic group labels that change the fairness constraints over time. The closest literature to our work on *dynamic fairness* includes Saito et al. [35] and Morik et al. [32], which incorporated user feedback in the learning process, and could dynamically adjust to the changing utility with fairness constraints. However, they focused on the changing utility of items and did not consider the scenario where group labels could be dynamic due to the nature of recommendations being an interactive process. To the best of our knowledge, we make the first attempt on dynamic group fairness, focusing on the changing group labels of items.

2.2 RL for Recommendation

In order to capture the interactive nature of recommendation scenarios, reinforcement learning (RL) based solutions have become an important topic recently. A group of work [5, 24, 45] model the problem as contextual multi-armed bandits, which can easily incorporate collaborative filtering methods [9, 50]. In the meantime, some literature [28, 29, 37, 41, 42, 51] found that it is natural to model the recommendation process as a Markov Decision Process (MDP). In general, this direction can be further categorized as either *policy-based* [10, 12, 14, 47] or *value-based* [33, 48, 51] methods. Typically, policy-based methods aim to learn a policy that generates an action (e.g. recommended items) based on a state. Such policy is optimized through policy gradient and can be either deterministic [14, 25, 38, 47] or stochastic [10, 12]. On the other hand, value-based methods aims to model the quality (i.e. Q-value) of actions so that the best action corresponds to the one with best value.

There also exist several works considering using RL to solve fairness problems in machine learning [21, 40]. Jabbari et al. [21] considered to optimize the meritocratic fairness defined in [22] based on long-term rewards. Their work is designed for a specific fairness constraint and is not suitable for our problem setting. Wen et al. [40] studied a reinforcement learning problem under group fairness constraint, where the state consists of both the feature and the sensitive attributes. They developed model-free and model-based methods to learn a decision rule to achieve both demographic parity and near-optimal fairness. Different from our work that focuses on item-side fairness, they focused on the user-side fairness.

3 PRELIMINARY

3.0.1 **Markov Decision Processes.** In this paper, we study reinforcement learning in Markov Decision Processes (MDPs). An MDP is a tuple $M = (S, \mathcal{A}, \mathcal{P}, \mathcal{R}, \mu, \gamma)$, where S is a set of n states, \mathcal{A} is a set of m actions, $\mathcal{P}: S \times \mathcal{A} \times S \rightarrow [0,1]$ denotes the transition probability function, $\mathcal{R}: S \times \mathcal{A} \times S \rightarrow \mathbb{R}$ is the reward function, $\mu: S \rightarrow [0,1]$ is the starting state distribution, and $\gamma \in [0,1)$ is the discount factor. A stationary policy $\pi: S \rightarrow P(\mathcal{A})$ is a map from states to probability distributions over actions, with $\pi(a|s)$ denoting the probability of selecting action a in state s. We denote the set of all stationary policies by Π . In reinforcement learning, we aim to learn a policy π , which maximizes the infinite horizon discounted total return $J(\pi)$,

$$J(\pi) \doteq \mathop{\mathbb{E}}_{\tau \sim \pi} \left[\sum_{t=0}^{\infty} \gamma^{\mathsf{T}} R\left(s_{t}, a_{t}, s_{t+1}\right) \right], \tag{1}$$

where τ denotes a trajectory, i.e., $\tau = (s_0, a_0, s_1, a_1, \dots)$, and $\tau \sim \pi$ is a shorthand indicating that the distribution over trajectories depends on $\pi: s_0 \sim \mu, a_t \sim \pi\left(\cdot|s_t\right), s_{t+1} \sim P\left(\cdot|s_t, a_t\right)$. Let $R(\tau)$ denote the discounted return of a trajectory, we express the onpolicy value function as $V^{\pi}(s) \doteq \mathbb{E}_{\tau \sim \pi}\left[R(\tau)|s_0 = s\right]$, the on-policy action-value function as $Q^{\pi}(s, a) \doteq \mathbb{E}_{\tau \sim \pi}\left[R(\tau)|s_0 = s, a_0 = a\right]$, and the advantage function as $A^{\pi}(s, a) \doteq Q^{\pi}(s, a) - V^{\pi}(s)$.

3.0.2 **Constrained Markov Decision Processes.** A Constrained Markov Decision Process (CMDP) is an MDP augmented with constraints that restrict the set of allowable policies for that MDP. In particular, the MDP can be constrained with a set of auxiliary cost functions C_1, \ldots, C_m and the corresponding limits $\mathbf{d}_1, \ldots, \mathbf{d}_m$, which means that the discounted total cost over the cost function C_i should be bounded by \mathbf{d}_i . Each function $C_i: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$ maps transition tuples to costs, like the reward in traditional MDP. Let $J_{C_i}(\pi)$ denote the discounted total cost of policy π with respect to the cost function C_i :

$$J_{C_{i}}(\pi) = \mathop{\mathbb{E}}_{\tau \sim \pi} \left[\sum_{t=0}^{\infty} \gamma^{\top} C_{i} \left(s_{t}, a_{t}, s_{t+1} \right) \right]. \tag{2}$$

The set of feasible stationary policies for a CMDP is then $\Pi_C \doteq \left\{\pi \in \Pi : \forall i, J_{C_i}(\pi) \leq \mathbf{d}_i\right\}$, and the reinforcement learning problem in a CMDP is $\pi^* = \arg\max_{\pi \in \Pi_C} J(\pi)$, where $J(\pi)$ is the discounted total reward defined in Eq. (1). Finally, in analogy to V^π, Q^π , and A^π , we denote these by $V^\pi_{C_i}, Q^\pi_{C_i}$, and $A^\pi_{C_i}$, which replaces reward function R with cost function C_i , respectively.

3.0.3 **Constrained Policy Optimization**. Inspired by trust region methods [36], Achiam et al. [2] proposed Constrained Policy Optimization (CPO), which uses a trust region instead of penalties on policy divergence to enable larger step sizes. CPO has policy updates of the following form:

$$\pi_{k+1} = \arg \max_{\pi \in \Pi_{\theta}} \sum_{\substack{s \sim d^{\pi_k} \\ a \sim \pi}} \left[A^{\pi_k} \left(s, a \right) \right],$$
s.t. $J_{C_i} \left(\pi_k \right) + \frac{1}{1 - \gamma} \sum_{\substack{s \sim d^{\pi_k} \\ a \sim \pi}} \left[A^{\pi_k}_{C_i} \left(s, a \right) \right] \leq \mathbf{d}_i, \forall i$ (3)
$$\bar{D}_{KL} \left(\pi \| \pi_k \right) \leq \delta$$

where $\Pi_{\theta} \subseteq \Pi$ is a set of parameterized policies with parameters θ (e.g., neural networks with fixed architecture), d^{π_k} is the state distribution under policy π_k , \bar{D}_{KL} denotes the average KL-divergence, and $\delta > 0$ is the step size. The set $\{\pi_{\theta} \in \Pi_{\theta} : D_{KL} (\pi || \pi_k) \leq \delta\}$ is called the trust region. Particularly, for problems with only one linear constraint, there is an analytical solution, which is also given by Achiam et al. [2]. Denoting the gradient of the objective in Eq. (3) as g, the gradient of constraint as b, the Hessian of the KL-divergence as H, and defining $c = J_C(\pi_k) - d$, the approximation to Eq. (3) is

$$\theta_{k+1} = \arg \max_{\theta} g^{\top} (\theta - \theta_k)$$
s.t. $c + b^{\top} (\theta - \theta_k) \le 0$

$$\frac{1}{2} (\theta - \theta_k)^{\top} H (\theta - \theta_k) \le \delta$$
(4)

A more comprehensive review of CMDPs and CPO can be seen in [3] and [2] respectively.

4 PROBLEM FORMULATION

In this section, we first describe a CMDP that models the recommendation process with general constraints, and then, we describe several fairness constraints, which are suitable for recommendation scenarios. Finally, we combine these two parts together and introduce the fairness-constrained optimization problem.

4.1 CMDP for Recommendation

In each timestamp $(t_1, t_2, t_3, t_4, t_5, \ldots)$, when a user sends a request to the recommendation system, the recommendation agent G will take the feature representation of the current user and item candidates I as input, and generate a list of items $L \in I^K$ to recommend, where $K \geq 1$. User u who has received the list of recommended item/items L will give his/her feedback B by his/her clicks on this set of items. Thus, the state s can be represented by user features (e.g., user's recent click history), action a is represented by items in L, reward r is the immediate reward (e.g., whether user clicks on an item in L) by taking action a in the current state, and cost c is the immediate cost (e.g., whether the recommended item/items come from the sensitive group).

- State S: A state s_t is the representation of user's most recent positive interaction history H_t with the recommender, as well as his/her demographic information (if exists).
- Action \mathcal{A} : An action $a_t = \{a_t^1, \ldots, a_t^K\}$ is a recommendation list with K items to a user u at time t with current state s_t .
- **Reward** \mathcal{R} : Given the recommendation based on the action a_t and the user state s_t , the user will provide his/her feedback, i.e., click, skip, or purchase, etc. The recommender receives immediate reward $R(s_t, a_t)$ according to the user's feedback.
- Cost C: Given the recommendation based on the action a_t, the
 environment provides a cost value based on the problem-specific
 cost function, i.e., the number of items in the recommendation
 list that come from the sensitive group, and sends the immediate
 cost C(s_t, a_t) to the recommender.
- Discount rate γ_r and γ_c: γ_r ∈ [0, 1] is a factor measuring the present value of long-term rewards, while γ_c ∈ [0, 1] is another factor measuring the present value of long-term costs.

4.2 Fairness Constraints

To be consistent with the previous definition in CMDP for recommendation and solve the dynamic change of underlying labels, we define analogs of several frequently proposed fairness constraints.

4.2.1 **Demographic Parity Constraints**. Following [39], we can use exposure to define the fairness between different groups of items. Demographic parity requires that the average exposure of the items from each group is equal. In our setting, we enforce this constraint at each iteration t. Denoting the number of exposure in a group at iteration t as

Exposure_t
$$(G_j) = \sum_{a_t^l \in a_t} \mathbb{1}(a_t^l \in G_j), l = 1, ..., K$$
 (5)

Then we can express demographic parity constraint as follows,

$$\frac{\operatorname{Exposure}_{t}(G_{0})}{|G_{0}|} = \frac{\operatorname{Exposure}_{t}(G_{1})}{|G_{1}|},$$
(6)

where groups G_0 and G_1 are divided based on the item popularity in the recommendation scenario.

4.2.2 **Exact-**K **Fairness Constraints**. We define an Exact-K fairness in ranking that requires the proportion/chance of protected candidates in every recommendation list with length K remains statistically below or indistinguishable from a given maximum α . This kind of fairness constraint is more suitable and feasible in practice for recommender systems as the system can adjust the value of α . The concrete form of this fairness is shown as below,

$$\frac{\operatorname{Exposure}_{t}\left(G_{0}\right)}{\operatorname{Exposure}_{t}\left(G_{1}\right)} \leq \alpha \tag{7}$$

Note that when $\alpha = \frac{|G_0|}{|G_1|}$ and the equation holds strictly, the above expression would be exactly the same as demographic parity.

4.3 FCPO: Fairness Constrained Policy Optimization

An illustration of the proposed FCPO is shown in Fig. 1, containing one actor and two critics. Our goal is to learn the optimal policy for the platform, which is able to maximize the cumulative reward under a certain fairness constraint, as mentioned in previous section. Specially, in this work, the reward function and the cost function are defined as

$$R(s_t, a_t, s_{t+1}) = \sum_{l=1}^{K} \mathbb{1}(a_t^l \text{ gets positive feedback})$$
 (8)

$$C(s_t, a_t, s_{t+1}) = \sum_{l=1}^{K} \mathbb{1}(a_t^l \text{ is in sensitive group})$$
 (9)

where $a_t = \{a_t^1, \ldots, a_t^K\}$ represents a recommendation list including K item IDs, which are selected by the current policy at time point t. We can see that the expression of cost function is the same as Eq. (5), which represents the total number of items in a specific group exposed to users at time t. Let us consider the sensitive group as group G_0 , then we have

$$\begin{split} & \frac{\operatorname{Exposure}_{t}\left(G_{0}\right)}{\operatorname{Exposure}_{t}\left(G_{1}\right)} \leq & \alpha \\ & \operatorname{Exposure}_{t}\left(G_{0}\right) \leq & \alpha \operatorname{Exposure}_{t}\left(G_{1}\right) \\ & (1+\alpha)\operatorname{Exposure}_{t}\left(G_{0}\right) \leq & \alpha \operatorname{Exposure}_{t}\left(G_{0}\right) + \alpha \operatorname{Exposure}_{t}\left(G_{1}\right) \\ & (1+\alpha)\operatorname{Exposure}_{t}\left(G_{0}\right) \leq & \alpha K \\ & C(s_{t},a_{t},s_{t+1}) \leq \frac{\alpha}{1+\alpha}K = \alpha'K \end{split}$$

Let $C \le \alpha' K$ be satisfied at each iteration, we can get the discounted total cost,

$$J_{C}(\pi) = \mathop{\mathbb{E}}_{\tau \sim \pi} \left[\sum_{t=0}^{T} \gamma_{c}^{T} C(s_{t}, a_{t}, s_{t+1}) \right] \leq \sum_{t=0}^{T} \gamma_{c}^{t} \alpha' K$$
 (10)

where T is the length of a recommendation trajectory. Eq. (10) is the group fairness constraint for our optimization problem and we can denote the limit of the unfairness \mathbf{d} as

$$\mathbf{d} = \sum_{t=1}^{T} \gamma_c^t \ \alpha' K. \tag{11}$$

Once we finished defining the specific CMDP for recommendation and we have the specific reward function Eq. (8), cost function Eq. (9) and the limit of the constraint **d**, we can take them to Eq. (3) and build our fairness constrained policy optimization framework. It is worth noting that our model contains only one linear fairness

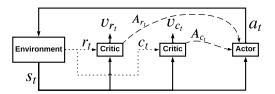


Figure 1: Illustration of the proposed method.

constraint, therefore, as mentioned in Preliminary, we can get an analytical solution by solving Eq. (4) if the problem is feasible. We then introduce the framework in the following section.

5 PROPOSED FRAMEWORK

Our solution to the aforementioned fairness constrained optimization problem follows an Actor-Critic learning scheme, but with an extra critic network designed for the fairness constraint. In this section, we illustrate how to construct and learn each of these components.

5.1 The Actor

The actor component π_{θ} parameterized by θ serves as the same functionality as a stochastic policy that samples an action $a_t \in \mathcal{I}^K$ given the current state $s_t \in \mathbb{R}^m$ of a user. As depicted in Fig. 2, s_t is first acquired by extracting and concatenating the user embedding $\mathbf{e}_u \in \mathbb{R}^d$ and user's history embedding \mathbf{h}_u :

$$s_t = [\mathbf{e}_u; \mathbf{h}_u], \ \mathbf{h}_u = \text{GRU}(H_t)$$
 (12)

where $H_t = \{H_t^1, H_t^2, \dots, H_t^N\}$ denotes the most recent N items from user u's interaction history, and the history embedding \mathbf{h}_u is acquired by encoding N item embeddings via Gated Recurrent Unites (GRU) [13]. Note that the user's recent history is organized as a queue, and it is updated only if the recommended item $a_t^l \in a_t$ receives a positive feedback.

$$H_{t+1} = \begin{cases} \{H_t^2, \dots, H_t^N, a_t^l\} & r_t^l > 0 \\ H_t & \text{Otherwise} \end{cases}$$
 (13)

This ensures that the state can always represent the user's most recent interests.

We assume that the probability of actions conditioned on states follows a continuous high-dimensional Gaussian distribution with mean $\mu \in \mathbb{R}^{Kd}$ and covariance matrix $\Sigma \in \mathbb{R}^{Kd \times Kd}$ (only elements at diagonal are non-zeros and there are actually Kd parameters). For better representation ability, we approximate the distribution via a neural network that maps the encoded state s_t to μ and Σ . Specifically, we adopt a Multi Layer Perceptron (MLP) with $\tanh(\cdot)$ as the non-linear activation function, i.e. $(\mu, \Sigma) = \text{MLP}(s_t)$. Then, we can sample a vector from the Gaussian distribution $\mathcal{N}(\mu, \Sigma)$ and convert it into a proposal matrix $W \sim \mathcal{N}(\mu, \Sigma) \in \mathbb{R}^{K \times d}$, whose k-th row, denoted by $W_k \in \mathbb{R}^d$, represents a proposed "ideal" item embedding. Then, the probability matrix $P \in \mathbb{R}^{K \times |\mathcal{I}|}$ of selecting the k-th candidate item is given by:

$$P_k = \operatorname{softmax}(W_k \mathcal{V}^\top), \ k = 1, \dots, K, \tag{14}$$

where $\mathcal{V} \in \mathbb{R}^{|I| \times d}$ is the embedding matrix of all candidate items. This is equivalent to using dot product to determine similarity between W_k and any item. As the result of taking the action at step

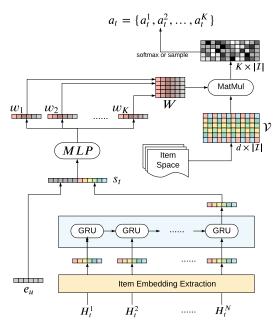


Figure 2: The architecture of the Actor. θ consists of parameters of both the Actor network in f_{θ} and the state representation model in Eq. (12).

t, the Actor recommends the *k*-th item as follows:

$$a_t^k = \underset{i \in \{1, \dots, |\mathcal{I}|\}}{\text{arg max}} P_{k,i}, \ \forall k = 1, \dots, K,$$
 (15)

where $P_{k,i}$ denotes the probability of taking the *i*-th item at rank k.

5.2 The Critics

5.2.1 *Critic for Value Function*. A Critic network $V_{\omega}(s_t)$ is constructed to approximate the true state value function $V_{\omega}^{\pi}(s_t)$ and be used to optimize the actor. The Critic network is updated according to temporal-difference learning that minimizes the MSE:

$$\mathcal{L}(\omega) = \sum_{t} \left(y_t - V_{\omega}(s_t) \right)^2 \tag{16}$$

where $y_t = r_t + \gamma_r V_{\omega}(s_{t+1})$.

5.2.2 *Critic for Cost Function*. In addition to the accuracy performance, we introduce a separate Critic network $V_{\phi}(s)$ for the purpose of constrained policy optimization as explained in section 3.0.3, which is updated similarly with Eq. (16),

$$\mathcal{L}(\phi) = \sum_{t} \left(y_t - V_{\phi}(s_t) \right)^2 \tag{17}$$

where $y_t = c_t + \gamma_c V_{\phi}(s_{t+1})$.

5.3 Training Procedure

We also present the detailed training procedure of our model in Algorithm 1. In each round, there are two phases — the trajectory generation phase (line 4-13) and model updating phase (line 14-23), where each trajectory contains T transition results between consumer and the recommendation agent.

Algorithm 1: Parameters Training for FCPO

```
1 Input: step size \delta, cost limit value d, and line search ratio \beta
 Output: parameters \theta, \omega and \phi of actor network, value function,
     cost function
   Randomly initialize \theta, \omega and \phi.
 4 Initialize replay buffer D;
 5 \text{ for } Round = 1 \dots M \text{ do}
        Initialize user state s_0 from log data;
         for t = 1 \dots T do
 7
              Observe current state s_t based on Eq. (12);
              Select an action a_t = \{a_t^1, \ldots, a_t^K\} \in I^K based on Eq.
               (14) and Eq. (15)
              Calculate reward r_t and cost c_t according to environment
10
               feedback based on Eq. (8) and Eq. (9);
              Update s_{t+1} based on Eq. (??);
11
              Store transition (s_t, a_t, r_t, c_t, s_{t+1}) in D in its
12
               corresponding trajectory.
13
        Sample minibatch of \mathcal{N} trajectories \mathcal{T} from D;
14
         Calculate advantage value A, advantage cost value A_c;
15
         Obtain gradient direction d_{\theta} by solving Eq. (4) with A and A_{c};
16
         repeat
17
              \theta' \leftarrow \theta + d_{\theta}
18
              d_{\theta} \leftarrow \beta d_{\theta}
19
         until \pi_{\theta'}(s) in trust region & loss improves & cost \leq d;
20
         (Policy update) \theta \leftarrow \theta';
21
         (Value update) Optimize \omega based on Eq.(16);
22
         (Cost update) Optimize \phi based on Eq.(17);
23
24 end
```

5.4 Testing Procedure

After finishing the training procedure, FCPO gets fine-tuned hyperparameters and well-trained parameters. Then we conduct the evaluation of our model on several public real-world datasets. Since our ultimate goal is to achieve long-term group fairness of item exposure with dynamically changing group labels, we propose both short-term evaluation and long-term evaluation.

5.4.1 **Short-term Evaluation**. This follows Algorithm 1, while the difference from training is that it only contains the trajectory generation phase without any updates to the model parameters. Once we receive the recommendation results in all trajectories, namely a_t , we can use the log data to calculate the recommendation performance, and compute the fairness performance based on the exposure records with fixed group labels. We will introduce how to get the initial group label in the experiment part.

5.4.2 **Long-term Evaluation**. This process follows Algorithm 1, instead of initializing random model parameters, we set well-trained model parameters into our model in advance. The model parameters will be updated throughout the testing process so as to model an online learning procedure in practice; meanwhile, the item labels will change dynamically based on the current impression results, which means that the fairness constraint will change through time. To observe long-term performance, we repeatedly recommend T times, so the total number of recommended items is TK.

6 EXPERIMENTS

6.1 Dataset Description

We use the user transaction data from *Movielens* [19] in our experiments to verify the recommendation performance of $FCPO^1$. We choose *Movielens* 100K and *Movielens* 1 M^2 datasets, which include one hundred thousand and one million user transactions, respectively (user id, item id, rating, timestamp, etc.).

For each dataset, we sort the transactions of each user according to the timestamp, and then split the records into training and testing sets chronologically by 4:1, and the last item of each user in the training set is put into the validation set. Some basic statistics of the experimental datasets are shown in Table 1. We split items into two groups G_0 and G_1 based on item popularity, i.e., the number of exposures for each item. Specifically, the top 20% items in terms of number of impressions belong to the popular group G_0 , and the remaining 80% belong to the long-tail group G_1 .

Moreover, for RL-based recommenders, the initial state for each user during training is the first five clicked items in the training set, and the initial state during testing is the last five clicked items in the training set. For simplicity, each time the RL agent recommends one item to the user, while we can adjust the length of the recommendation list easily in practice.

6.2 Experimental Setup

Baselines: We compare our model with the following baselines, including both traditional and RL based methods.

- MF: Collaborative Filtering based on matrix factorization [23] is a representative method for rating prediction. Basically, the user and item rating vectors are considered as the representation vector for each user and item.
- BPR-MF: Bayesian Personalized Ranking [34] is one of the most widely used ranking methods for top-K recommendation, which models recommendation as a pair-wise ranking problem.
- NCF: Neural Collaborative Filtering [20] is a simple neural networkbased recommendation algorithm. In particular, we choose Neural Matrix Factorization to conduct the experiments, fusing both Generalized Matrix Factorization (GMF) and Multiple Layer Perceptron (MLP) under the NCF framework.
- LIRD: It is the short for List-wise Recommendation based on Deep reinforcement learning [49]. The original paper simply utilizes the concatenation of item embeddings to represent the user state. For fair comparison, we replace the state representation with the same structure of FCPO, as is shown is Fig. 2.

In this work, we also include a classical fairness baseline called Fairness Of Exposure in Ranking (FOE) [39] in our experiment to compare the fairness performance with our model. **FOE** can be seen as a reranking framework based on group fairness constraints, and it is originally designed for searching problems, so we made a few modification to accommodate the recommendation task. We use ranking prediction model such as MF, BPR, and NCF as the base ranker, where the raw utility is given by the predicted probability of user *i* clicking item *j*. In our experiment, we have **MF-FOE**, **BPR-FOE** and **NCF-FOE** as our fairness baselines. Since

Table 1: Basic statistics of the experimental datasets.

Dataset	#users	#items	#act./user	#act./item	#act.	density		
Movielens100K	943	1682	106	59.45	100,000	6.305%		
Movielens1M	6040	3706	166	270	1,000,209	4.468%		

FOE assumes independence of items in the list, it cannot be applied to LIRD, which is a sequential model and the order in its recommendation makes a difference. Meanwhile, FOE for personalized recommendation needs to solve a linear program with size $|I| \times |I|$ for each consumer, which brings huge computational costs. In order to make the problem feasible, we let FOE rerank top-200 items from the base ranker (e.g. MF), and select the new top-K (K<200) as the final recommendation results.

We implement MF, BPR-MF, NCF, MF-FOE, BPR-FOE and NCF-FOE using *Pytorch* with Adam optimizer. For all the methods, we consider latent dimensions d from {16, 32, 64, 128, 256}, learning rate lr from {1e-1, 5e-2, 1e-2, ..., 5e-4, 1e-4}, and the L2 penalty is chosen from {0.01, 0.1, 1}. We tune the hyper-parameters using the validation set and terminate training when the performance on the validation set does not change within 5 epochs.

We implement **FCPO** with *Pytorch* as well. We perform PMF [31] to pretrain 100-dimensional user and item embeddings, and fix them through the whole experiment. We set $|H_t|=5$, and use 2 layer of GRU to get state representation s_t . For the policy network and each of the two critic networks, we use two hidden layer MLP with $\tanh(\cdot)$ as activation function. Critics are learned through LBFGS optimizer [4]. Finally, we fine-tune FCPO's hyperparameters on our validation set. In order to examine the trade-off between performance and fairness, we set different level of fairness constraint controlled by the values of α' in Eq. (10) and calculate the limit **d** using Eq. (11). We denote the resulting alternatives as **FCPO-1**, **FCPO-2**, and **FCPO-3**, whose corresponding fairness be constrained by setting $\alpha' = 1$, $\alpha' = 0.8$, and $\alpha' = 0.4$ correspondingly in our experiments.

Evaluation Metrics: We adopt several common top-K ranking metrics including Recall, F1 Score, and NDCG to evaluate each model's recommendation performance. In addition to these accuracy-based metrics, we also include two fairness measures – Gini Index and Popularity Rate, with respect to item exposures for individual items and groups, respectively. Gini Index measures the inequality among values of a frequency distribution (for example, numbers of impressions), which can be seen as an individual level measure. Given a list of impressions from all items, $\mathcal{M} = [g_1, g_2, ..., g_{|\mathcal{I}|}]$, the Gini Index can be calculated by Eq.(18),

Gini Index(G) =
$$\frac{1}{2|I|^2 \bar{g}} \sum_{i=1}^{|I|} \sum_{j=1}^{|I|} |g_i - g_j|,$$
(18)

where \bar{g} represents the mean of all item impressions. Popularity Rate, on the other hand, simply refers to the proportion of popular items in the recommendation list against the total number of items in the list, which can be seen as a popularity level measure of fairness. Both of the two fairness measures are the smaller, the fairer to the recommender system.

6.3 Experimental Results

The major experimental results are shown in Table 2, besides, we also plot the NDCG vs. Negative Gini Index and NDCG vs. Longtail Rate in Fig. 3 under the length of recommendation list K = 1

¹https://github.com/TobyGE/FCPO

²https://grouplens.org/datasets/Movielens/

Table 2: Summary of the performance on two datasets. We evaluate for ranking (Recall, F_1 and NDCG, in percentage (%) values, % symbol is omitted in the table for clarity) and fairness ($Gini\ Index$ and $Popularity\ Rate$, also in % values), whiles K is the length of recommendation list. When FCPO is the best, its improvements against the best baseline are significant at p < 0.01.

Methods	I	Recall (%) ↑			F1 (%) ↑		NDCG (%)↑		Gini Index (%)↓			Popularity Rate (%)↑			
	K=5	K=10	K=20	K=5	K=10	K=20	K=5	K=10	K=20	K=5	K=10	K=20	K=5	K=10	K=20
						N	Movielens	-100K							
MF	1.847	3.785	7.443	2.457	3.780	5.074	3.591	4.240	5.684	98.99	98.37	97.03	99.98	99.96	99.92
BPR-MF	1.304	3.539	8.093	1.824	3.592	5.409	3.025	3.946	5.787	98.74	98.17	97.01	99.87	99.87	99.78
NCF	1.995	3.831	6.983	2.846	4.267	5.383	5.319	5.660	6.510	99.70	99.39	98.80	100.0	100.0	100.0
LIRD	1.769	5.467	8.999	2.199	4.259	4.934	3.025	3.946	5.787	99.70	99.41	98.81	100.0	100.0	100.0
MF-FOE	1.164	2.247	4.179	1.739	2.730	3.794	3.520	3.796	4.367	86.29	84.05	82.98	92.90	91.89	90.98
BPR-FOE	0.974	2.053	4.404	1.496	2.568	3.933	3.127	3.514	4.332	86.50	84.38	83.78	92.17	91.36	90.70
NCF-FOE	1.193	1.987	4.251	1.759	2.398	3.698	4.033	3.897	4.633	96.92	94.53	90.44	100.0	100.0	100.0
FCPO-1	4.740	8.607	14.48	4.547	5.499	5.855	6.031	7.329	9.323	98.73	98.07	96.75	92.60	90.42	85.85
FCPO-2	3.085	5.811	10.41	3.270	4.164	4.953	4.296	5.203	7.104	97.95	96.88	94.78	70.07	68.28	65.5
FCPO-3	0.920	1.668	3.329	1.272	1.807	2.535	2.255	2.369	2.871	75.23	74.06	73.23	36.52	36.66	36.9
							Movielen	s-1M							
MF	1.152	2.352	4.650	1.701	2.814	4.103	3.240	3.686	4.574	99.44	99.18	98.74	99.92	99.90	99.80
BPR-MF	1.240	2.627	5.143	1.773	2.943	4.197	3.078	3.593	4.632	98.93	98.44	97.61	99.40	99.23	98.9
NCF	1.178	2.313	4.589	1.832	2.976	4.382	4.114	4.380	5.080	99.85	99.71	99.42	100.0	100.0	100.0
LIRD	<u>1.961</u>	3.656	5.643	<u>2.673</u>	<u>3.758</u>	4.065	3.078	3.593	4.632	99.87	99.73	99.46	100.0	100.0	95.00
MF-FOE	0.768	1.534	3.220	1.246	2.107	3.345	3.321	3.487	4.021	92.50	91.06	91.32	98.89	98.78	98.68
BPR-FOE	0.860	1.637	3.387	1.374	2.233	3.501	3.389	3.594	4.158	90.48	88.92	89.01	96.56	96.12	95.78
NCF-FOE	0.748	1.403	2.954	1.230	1.980	3.175	3.567	3.589	4.011	97.73	96.57	95.04	100.0	100.0	100.0
FCPO-1	2.033	4.498	8.027	2.668	4.261	5.201	4.398	5.274	6.432	99.81	99.67	99.34	99.28	96.93	91.70
FCPO-2	1.520	3.218	6.417	2.015	3.057	4.145	3.483	3.920	5.133	99.47	99.10	97.41	72.66	68.27	71.35
FCPO-3	0.998	1.925	3.716	1.449	2.185	2.948	2.795	2.987	3.515	88.97	88.34	87.70	63.43	62.73	61.4

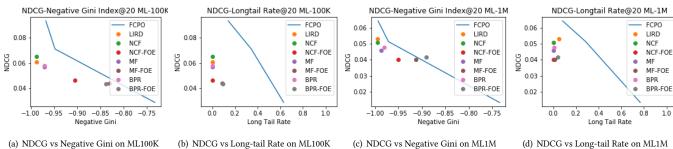


Figure 3: NDCG@20 vs. Negative Gini Index@20 and NDCG@20 vs. Long-tail Rate@20 in two datasets. x-axis is the negative gini index in 3(a) and 3(c), and is the long-tail rate in 3(b) and 3(d); y-axis represents the value of NDCG.

20. We analyze and discuss the results in terms of the following perspectives.

i) Recommendation Performance: For recommendation performance, we compare FCPO-1 with MF, BPR, NCF, and LIRD based on *Recall@k*, *F*1@*k* and *NDCG@k*. The results of the recommendation performance are shown in Table 2. The largest value on each dataset and for each evaluation measure is significant at 0.01 level. Among all the baseline models, NCF is the strongest on Movielens100K: when averaging across recommendation lengths, NCF gets 11.45% improvement than MF, 18.01% than BPR, and 6.17% than LIRD; and LIRD is the strongest on Movielens1M: when averaging across recommendation lengths, LIRD gets 17.69% improvement than MF, 14.50% than BPR, and 9.68% than NCF.

Our FCPO approach achieves the best top-K recommendation performance against all baselines on both datasets. On the one hand, when averaging across recommendation lengths on Movielens100K, FCPO gets 33.09% improvement than NCF; on the other hand, when averaging across recommendation lengths on Movielens1M, FCPO gets 18.65% improvement than LIRD. These observations imply that the proposed method does have the ability to capture dynamic useritem interactions, which captures better user preferences resulting in better recommendation results. Another interesting observation is that FCPO is better than LIRD even though they use the same state representation and similar training procedure. This may be attributed to the trust-region-based optimization method, which stabilizes the model learning process.

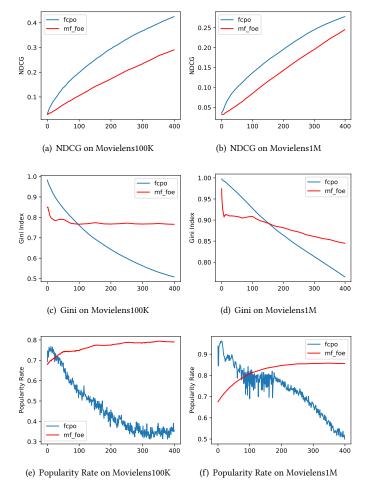


Figure 4: Long-term performance on Movielens100K (first column) and Movielens1M (second column). X-axis is recommendation step, y-axis is the evaluated metric (first row: NDCG, second row: Gini, third row: Popularity Rate) on accumulated item exposure from beginning to current step.

ii) Short-term Fairness Performance: For fairness performance, we compare three FCPOs with MF-FOE, BPR-FOE, and NCF-FOE based on Gini Index@k and Popularity Rate@k, which are also shown in Table 2. We can easily see that there exists a trade-off between the recommendation performance and the fairness performance both in FCPO and FOE, which is understandable, as most of the long-tail items have relatively fewer user interactions. In order to better illustrate the trade-off between FCPO and FOE, we fix the length of the recommendation list at 20 and plot NDCG against Negative Gini Index and Long-tail Rate in Fig. 3 for both datasets, where the long-tail rate is equal to one minus popularity rate. The blue line represents FCPO under three different levels of fairness constraint. We choose Negative Gini Index and Long-tail Rate instead of the original ones as they are the bigger, the better, which is easier for comparison. In most cases, for the same Gini Index, our method achieves much better NDCG; meanwhile, under

the same NDCG scores, our method achieves better fairness. In other words, our method FCPO can achieve much better trade-off than FOE in both individual fairness (measured by Gini Index) and group fairness (measured by Long-tail Rate). We can see that even with the light fairness constraint, FCPO-1 is better than traditional baselines and the FOE-based methods on group fairness.

iii) Efficiency Performance: We compare FOE-based methods with FCPO in terms of the single-core CPU running time to generate a recommendation list of size K = 100 for all users. The running time between the base ranker of FOE-based methods is relatively the same, but the additional reranking step of FOE may take substantial time. In our observation on Movielens100K dataset, the recommendation time is 90min, 6h30min, and 60h30min for reranking from 200, 400, and 800 items, respectively, while FCPO only takes around 3h and select items from the entire item set (1682 items). Our observation on Movielens1M dataset shows that FOE-based methods take 10h30min, 43h30min, and 397h to rerank from 200, 400, and 800 items, respectively, while FCPO takes around 11h33min selecting in the entire item set (3706 items). As mentioned before, these experiments are running on single-core CPU for fair comparison, therefore, we can easily speed them up by using parallel computing.

6.4 Long-term Fairness in Recommendation

We compared FCPO with a static short-term fairness solution (i.e., MF-FOE) for 400 steps of recommendation. For MF-FOE, we run 4 rounds of K=100 recommendations to let it capture the dynamics of the item group labels, while FCPO only needs to continuously run for 400 steps. In other words, MF-FOE keeps the same item group labels for K item recommendations and has to retrain its parameters after the labels updated at the end of each round. As mentioned in section 6.2, FOE-based method becomes significantly time-consuming when dealing with large candidate item sets. Thus, instead of doing whole item set fairness control, we first select the top 2K items as candidates, and then apply FOE to rerank the items and generate the final K recommendations.

As shown in Fig. 4(c), 4(d), 4(e), and 4(f), when model convergences, MF-FOE performs much worse than FCPO on both Gini Index and Popularity Rate on two datasets. Within each round of MF-FOE, fairness metrics quickly converges and they are further improved only when the item exposure information is updated. On the contrary, since FCPO makes adjustment of its policy according to the fairness feedback, it can successfully and continuously suppress the fairness metric to a much lower value during testing. As shown in Fig.4(e) and Fig.4(f), due to this dynamic change of recommendation policy, FCPO exhibits greater fluctuation and unstable behavior than MF-FOE. Though we kept skeptical whether the fairness performance gap between MF-FOE and FCPO will eventually vanish, we do observe that MF tends to much favor popular items than unpopular ones in Table 2. As a result, setting a very small K (e.g. K < 20) to speed up the recommendation could result in a candidate set filled with popular items and applying FOE becomes futile. Besides, the overall performance of MF-FOE - especially on accuracy metrics (corresponding to Fig. 4(a) and 4(b)) - is consistently outperformed by FCPO, which indicates that MF-FOE sacrifices the recommendation performance more than FCPO in order to control fairness.

7 CONCLUSION AND FUTURE WORK

In this work, we propose to model the long-term fairness in recommendation with respect to dynamically changing group labels. We accomplish the task by addressing the dynamic fairness problem through a fairness-constrained reinforcement learning framework. Experiments on standard benchmark datasets verify that our framework achieves better performance in terms of recommendation accuracy, short-term fairness, and long-term fairness. In the future, we will generalize the framework to optimize individual fairness constraints and other recommendation scenarios such as e-commerce recommendation and point-of-interest recommendation.

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