Toward Pareto Efficient Fairness-Utility Trade-off in Recommendation through Reinforcement Learning

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ABSTRACT

The issue of fairness in recommendation is becoming increasingly essential as Recommender Systems (RS) touch and influence more and more people in their daily lives. In fairness-aware recommendation, most of the existing algorithmic approaches mainly aim at solving a constrained optimization problem by imposing a constraint on the level of fairness while optimizing the main recommendation objective, e.g., click through rate (CTR). While this alleviates the impact of unfair recommendations, the expected return of an approach may significantly compromise the recommendation accuracy due to the inherent trade-off between fairness and utility. This motivates us to deal with these conflicting objectives and explore the optimal trade-off between them in recommendation. One conspicuous approach is to seek a Pareto efficient/optimal solution to guarantee optimal compromises between utility and fairness. Moreover, considering the needs of real-world e-commerce platforms, it would be more desirable if we can generalize the whole Pareto Frontier, so that the decision-makers can specify any preference of one objective over another based on their current business needs. Therefore, in this work, we propose a fairness-aware recommendation framework using multi-objective reinforcement learning (MORL), called MoFIR (pronounced "more fair"), which is able to learn a single parametric representation for optimal recommendation policies over the space of all possible preferences. Specially, we modify traditional Deep Deterministic Policy Gradient (DDPG) by introducing conditioned network (CN) into it, which conditions the networks directly on these preferences and outputs Q-value-vectors. Experiments on several real-world recommendation datasets verify the superiority of our framework on both fairness metrics and recommendation measures when compared with all other baselines. We also extract the approximate Pareto Frontier on real-world datasets generated by MoFIR and compare to state-of-the-art fairness methods.

CCS CONCEPTS

• Information systems \to Recommender systems; • Computing methodologies \to Sequential decision making.

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KEYWORDS

Recommender System; Multi-Objective Reinforcement Learning; Pareto Efficient Fairness; Unbiased Recommendation

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1 INTRODUCTION

Personalized recommender systems (RS), which are extensively employed in e-commerce platforms, have been acknowledged for their capacity to deliver high-quality services that bridge the gap between products and customers [7, 17, 44, 51]. Despite these huge advantages, several recent studies also raised concerns that RS may be vulnerable to algorithmic bias in several aspects, which may result in detrimental consequences for underrepresented or disadvantaged groups [19, 29, 43, 59]. For example, the "Matthew Effect" becomes increasingly evident in RS, which creates a huge disparity in the exposure of the producers/products in real-world recommendation systems [16, 18, 33]. Fortunately, these concerns about algorithmic fairness have resulted in a resurgence of interest to develop fairness-aware recommendation models to ensure such models do not become a source of unfair discrimination in recommendation [13, 15, 26, 28].

In the area of fairness-aware recommendation, the methods can be roughly divided into three categories: pre-processing, in-processing and post-processing algorithms [14, 29]. Pre-processing methods usually aim to remove bias in data, e.g., sampling from data to cover items of all groups or balancing data to increase coverage of minority groups. In-processing methods aim at encoding fairness as part of the objective function, while post-processing methods tend to modify the presentations of the results. Even though all of them could successfully alleviate the impact of unfair recommendations to some extent, the expected return of an approach may significantly compromise the recommendation accuracy due to the inherent trade-off between fairness and utility, which has been demonstrated by several recent work both empirically and theoretically [22, 23, 32, 55].

In light of the above, one fundamental research questions is asked, **RQ1**: Can we learn a recommendation model that allows for higher fairness without significantly compromising recommendation accuracy? And a more challenging one is, **RQ2**: Can we learn a single recommendation model that is able to produce optimal recommendation policies under different levels of fairness-utility trade-off

so that it would be more desirable for decision-makers of e-commerce platforms to specify any preference of one objective over another based on their current business needs?

To deal with **RQ1**, one conspicuous approach is to seek a Pareto optimal solution to guarantee optimal compromises between utility and fairness, where a Pareto efficient/optimal solution means no single objective can be further improved without hurting the others. To find solutions with different levels of trade-off between utility and fairness (**RQ2**), we need to generalize their Pareto frontier in the objective space, where Pareto frontier denotes a set, whose elements are all Pareto optimal. Unfortunately, state-of-the-art approaches of fairness-aware recommendation are limited in understanding the fairness-utility trade-off.

Therefore, in this work, we aim to address the above problems and propose a fairness-aware recommendation framework using multi-objective reinforcement learning (MORL) with linear preferences, called MoFIR, which aims to learn a single parametric representation for optimal recommendation policies over the space of all possible preferences. Technically, we first formulate the fairnessaware recommendation task as a Multi-Objective Markov Decision Process (MOMDP), with one recommendation objective, e.g., CTR, and one fairness objective, e.g., item exposure fairness (our method is able to generalize to more recommendation objectives as well as more fairness objectives). Second, we modify classic and commonly-used RL algorithm-DDPG [42] by introducing conditioned networks [3] into it, which is a representative method to deal with multi-objective reinforcement learning. Specially, we condition the policy network and the value network directly on the preferences by augmenting them to the feature space. Finally, we utilize the vectorized Q-value functions together with modified loss function to update the parameters. The contributions of this work can be summarized as follows:

- We study the problem of Pareto optimal/efficient fairness-utility trade-off in recommendation and extensively explore their Pareto frontier to better satisfy real-world needs;
- We formulate the problem into a MOMDP and solve it through a MORL framework, MoFIR, which is optimized over the entire space of preferences in a domain, and allows the trained model to produce the optimal policy for any specified preferences;
- Unlike prior methods for fairness-aware recommendation, the proposed framework does not employ any relaxation for objectives in the optimization problem, hence it could achieve stateof-the-art results;
- Experiments on several real-world recommendation datasets verify the superiority of our framework on both fairness measures and recommendation performance when compared with all other baselines.

2 RELATED WORK

2.1 Fairness in Recommendation

There have been growing concerns on fairness in recommendation as recommender systems touch and influence more and more people in their daily lives. Several recent works have found various types of bias in recommendations, such as gender and race [2, 8], item popularity [15, 16, 59], user feedback [13, 25, 27] and opinion polarity [54]. There are two primary paradigms adopted in recent

studies on algorithmic discrimination: individual fairness and group fairness. Individual fairness requires that each similar individual should be treated similarly, while group fairness requires that the protected groups should be treated similarly to the advantaged group or the populations as a whole. Our work focuses on the item popularity fairness from a group level, yet it can be used to solve multiple types of fairness simultaneously by properly defining and adding them as additional objectives.

The relevant methods related to fairness in ranking and recommendation can be roughly divided into three categories: preprocessing, in-processing and post-processing algorithms [14, 28, 29]. First of all, pre-processing methods usually aim to minimize the bias in data as bias may arise from the data source. This includes fairness-aware sampling methodologies in the data collection process to cover items of all groups, or balancing methodologies to increase coverage of minority groups, or repairing methodologies to ensure label correctness, remove disparate impact [14]. However, most of the time, we do not have access to the data collection process, but are given the dataset. Secondly, in-processing methods aim at encoding fairness as part of the objective function, typically as a regularizer [1, 4]. Finally, post-processing methods tend to modify the presentations of the results, e.g., re-ranking through linear programming [25, 43, 53] or multi-armed bandit [5]. However, there is no free lunch, imposing fairness constraints to the main learning task introduces a trade-off between these objectives, which have been asserted in several studies [22, 23, 32, 55], e.g., Dutta et al. [12] showed that because of noise on the underrepresented groups the trade-off between accuracy and equality of opportunity exists.

Unfortunately, there is very few work of fairness-aware recommendation that can be found to study the fairness-utility trade-off. The closest one to our work is [47], which mainly focused on the trade-off between two-sided fairness in e-commerce recommendation. [47] used a traditional multiple gradient descent algorithm to solve multi-objective optimization problem, meaning that they need to train one network per point on the Pareto frontier, while our MoFIR generates the full Pareto frontier of solutions in a single optimization run. Besides, the authors relaxed all their objectives to get their differentiable approximations, which, to some extent, hurt its performance, as is shown in the experiment part, Fig. 2.

2.2 Multi-Objective Recommendation

Recommendation with multiple objectives is a significant but challenging problem, with the core difficulty stemming from the potential conflicts between objectives. In most real-world recommendation systems, recommendation accuracy (e.g., CTR-oriented objectives) is the dominating factor, while some studies believed that other characteristics, such as usability, profitability, usefulness, or diversity should be considered at the same time [20, 21, 36]. When multiple objectives are concerned, it is expected to get a Pareto optimal/efficient recommendation [31, 39, 50].

The approaches on recommendation with multiple objectives to achieve Pareto efficiency can be categorized into two groups: evolutionary algorithm [60] and scalarization [31]. Ribeiro et al. [39, 40] jointly considered multiple trained recommendation algorithms with a Pareto-efficient manner, and conducted an evolutionary algorithm to find the appropriate parameters for weighted model

combination. Besides, Lin et al. [31] optimized GMV and CTR in e-commerce simultaneously based on multiple-gradient descent algorithm, which combines scalarization with Pareto-efficient SGD, and used a relaxed KKT condition. Our proposed method, MoFIR, belongs to scalarization, however, compared with earlier attempts in multi-objective recommendation [31, 47], our method learns to adapt a single network for all the trade-off combinations of the inputted preference vectors, therefore it is able to approximate all solutions of the Pareto frontier after a single optimization run.

2.3 RL for Recommendation

RL-based recommenders have recently become an important and attractive topic, as it is natural to model the recommendation process as a Markov Decision Process (MDP) and use RL agents to capture the dynamics in recommendation scenarios [34, 35, 41, 48, 49, 58]. Generally speaking, RL-based recommendation systems can be further classified into two categories: policy-based [6, 9, 11] or valuebased [37, 56, 58] methods. On one hand, policy-based methods aim to learn strategies that generate actions based on state (such as recommending items). These methods are optimized by policy gradient, which can be deterministic approaches [11, 30, 42] or stochastic approaches [6, 9]. On the other hand, value-based methods aims to model the quality (e.g. Q-value) of actions so that the best action corresponds to the one with the highest Q-value. Apart from using RL in general recommendation task, there also existed several works focusing on using RL in explainable recommendation through knowledge graphs [48, 49].

Currently, there are very few studies using MORL in recommendation. Xie et al. [50] studied multi-objective recommendation to capture users' objective-level preferences. However, unlike our proposed MoFIR, which learns a single parametric representation for optimal recommendation policies, they conducted a Pareto-oriented RL to generate the personalized objective weights in scalarization for each user, which is a totally different problem formulation.

3 PRELIMINARY

3.1 Markov Decision Processes

In reinforcement learning, agents aim at learning to act in an environment in order to maximize their cumulative reward. A popular model for such problems is Markov Decision Processes (MDP), which 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, $\mathcal{P}: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0,1]$ denotes the transition probability function, $\mathcal{R}: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$ is the reward function, $\mu: \mathcal{S} \to [0,1]$ is the starting state distribution, and $\gamma \in [0,1)$ is the discount factor. We denote the set of all stationary policies by Π , where a stationary policy $\pi \in \Pi: \mathcal{S} \to \mathcal{P}(\mathcal{A})$ 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 aim to learn a policy $\pi \in \Pi$, able to maximize a performance measure, $J(\pi)$, which is typically taken to be the infinite horizon discounted total return,

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

where τ denotes a trajectory, e.g., $\tau = (s_0, a_0, s_1, a_1, ...)$, and $\tau \sim \pi$ indicates that the distribution over trajectories depends on π : $s_0 \sim \mu$, $a_t \sim \pi(\cdot|s_t)$, $s_{t+1} \sim P(\cdot|s_t, a_t)$. We denote $R(\tau)$ as the

discounted rewards of a trajectory, the on-policy value function as $V^{\pi}(s) \doteq \mathrm{E}_{\tau \sim \pi}\left[R(\tau)|s_0=s\right]$, the on-policy action-value function as $Q^{\pi}(s,a) \doteq \mathrm{E}_{\tau \sim \pi}\left[R(\tau)|s_0=s,a_0=a\right]$, and the advantage function as $A^{\pi}(s,a) \doteq Q^{\pi}(s,a) - V^{\pi}(s)$.

3.2 Multi-Objective Markov Decision Processes

Multi-Objective Markov Decision Processes (MOMDP) are MDPs with a vector-valued reward function $\mathbf{r}_t = \mathbf{R}(s_t, a_t)$, where each component of \mathbf{r}_t corresponds to one certain objective. A scalarization function f maps the multi-objective value of a policy π to a scalar value. In this work, we consider the commonly-used class of MOMDPs with linear preference functions, e.g., $f_{\pmb{\omega}}(\mathbf{R}(s,a)) = \pmb{\omega} \cdot \mathbf{R}(s,a)$. It is worth noting that if $\pmb{\omega}$ is fixed to a single value, this MOMDP collapses into a standard MDP. An optimal solution for an MOMDP under linear f is a convex coverage set (CCS), e.g., a set of undominated policies containing at least one optimal policy for any linear scalarization.

3.3 Conditioned Network

Abels et al. [3] studied multi-objective reinforcement learning with linear preferences and proposed a novel algorithm for learning a single O-network that is optimized over the entire space of preferences in a domain. The main idea is called Conditioned Network (CN), in which a Q-Network is augmented to output weight-dependent multi-objective Q-value-vectors, as is shown in the right side of Fig. 1 (Conditioned Critic Network, where action and state representations together with weight vector are inputed to the network). Besides, to promote quick convergence on the new weight vector's policy and to maintain previously learned policies, the authors updated each experience tuple in a mini-batch with respect to the current weight vector and a random previously encountered weight vector. Specially, given a mini-batch of trajectories, they computed the loss for a given trajectory $(s_i, a_i, \mathbf{r}_i, s_{i+1})$ as the sum of the loss on the active weight vector ω_t and on ω_i randomly sampled from the set of encountered weights.

$$\frac{1}{2}\left[\left|\mathbf{y}_{\boldsymbol{\omega}_{t}}^{(j)}-\mathbf{Q}_{CN}\left(a_{j},s_{j};\boldsymbol{\omega}_{t}\right)\right|+\left|\mathbf{y}_{\boldsymbol{\omega}_{j}}^{(j)}-\mathbf{Q}_{CN}\left(a_{j},s_{j};\boldsymbol{\omega}_{j}\right)\right|\right]$$
(2)

$$\mathbf{y}_{\boldsymbol{\omega}}^{(j)} = \mathbf{r}_{j} + \gamma \mathbf{Q}_{CN}^{-} \left(\underset{a \in A}{\operatorname{argmax}} \mathbf{Q}_{CN} \left(a, s_{j+1}; \boldsymbol{\omega} \right) \cdot \boldsymbol{\omega}, s_{j+1}; \boldsymbol{\omega} \right)$$
(3)

where $\mathbf{Q}_{CN}\left(a,s;\omega\right)$ is the network's Q-value-vector for action a in state s and with weight vector ω . They claimed that training the same sample on two different weight vectors has the added advantage of forcing the network to identify that different weight vectors can have different Q-values for the same state. A more comprehensive review of MOMDPs and CN can be seen in [3].

In the original paper, the authors only proposed an algorithm based on Double DQN with discrete action space, which is not suitable for recommendation scenarios as the action space of recommendation is very large. Therefore, we modify the traditional DDPG [42] by introducing conditioned network into its policy network as well as critic network, and more importantly, we modify the original loss functions for both of them. We choose DDPG as it is a commonly adopted methods in RL, while our modification can be generalized to other reinforcement learning methods, such as trust

region ploicy optimization. More details about our modification will be introduced in Section 5.

4 PROBLEM FORMULATION

4.1 MOMDP for Recommendation

The recommendation agent will take the feature representation of the current user and item candidates I as input, and generate a list of items $L \in \mathcal{I}^K$ to recommend, where $K \geq 1$ after a user sends a request to it at timestamp $t \in (t_1, t_2, t_3, t_4, t_5, ...)$. User u who has received the list of recommended items L will give feedback B via clicking on this set of items, which can be used to measure the recommendation performance. Besides, based on the recommendation results, we will acquire the total number of exposure for each item group G, which can later be used to measure fairness. 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 \mathbf{r} is the immediate reward vector after taking action a, with each component of \mathbf{r} corresponds to one certain objective (e.g., whether user clicks on an item in L for utility objective or whether an item comes from predefined disadvantageous group for fairness objective). The problem formulation is formally presented

- State S: A state s_t is the representation of user's most recent positive interaction history H_t with the recommendation system, together with 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 .
- **Vector Reward Function** r: A vector-valued reward function $\mathbf{r}_t = \mathbf{R}(s_t, a_t)$, where each component of \mathbf{r}_t corresponds to one certain objective. In this work, the reward vector includes two elements: utility objective and fairness objective. The details of the definition of our task-specific objectives will be introduced in the following section.
- Scalarization function f: In this paper, we consider the class of MOMDPs with linear preferences functions f, which is a commonly-used scalarization function. Under this setting, each objective is given a weight ω_i , such that the scalarization function becomes $f_{\omega}(\mathbf{R}) = \omega \cdot \mathbf{R}$, where each $\omega_i \in [0, 1]$ and $\sum_i \omega_i = 1$.
- Discount rate γ: γ ∈ [0, 1] is a discount factor measuring the present value of long-term rewards.

We aim to learn a policy π , mapping from states to actions, to generate recommendations that achieve the Pareto efficient tradeoff between fairness and utility.

4.2 Multi-Objectives in Fair Recommendation

The reward vector is designed to measure the recommendation system's gain regarding utility and fairness. While our method is capable of dealing with multiple objectives simultaneously, for simplicity we deliberately select click through rate and item (group) exposure fairness as our two objectives recommendation utility and item exposure fairness respectively.

4.2.1 Utility Objective. On one hand, given the recommendation based on the action a_t and the user state s_t , the user will provide feedback, e.g. click or purchase, etc. The recommender receives immediate reward $R_u(s_t, a_t)$ according to the user's positive feedback.

We also normalize the reward value by dividing K, which is the length of the recommendation list.

$$R_{u}(s_{t}, a_{t}, s_{t+1}) = \frac{\sum_{l=1}^{K} \mathbb{1}(a_{t}^{l} \text{ gets positive feedback})}{K} \tag{4}$$

4.2.2 Fairness Objective. On the other hand, based on the recommendation list a_t , the total number of exposure of each item group will be counted and used to measure exposure fairness. Here, we calculate the ratio of items from sensitive group to the total number of recommended items, and use a hinge loss with margin β to punish the abuse of fairness. Usually, we set β to be the ratio of the number of items in sensitive group to the total number of items.

$$R_f(s_t, a_t, s_{t+1}) = \max\left(\frac{\sum_{l=1}^K \mathbb{1}(a_t^l \text{ is in sensitive group})}{K}, \beta\right)$$
 (5)

5 PROPOSED FRAMEWORK

5.1 The Conditioned Actor

The conditioned actor is almost the same as traditional actor except that we condition the predictions of the policy network to the preference vectors. Practically, we concatenate the state representation s_t with the vector $\boldsymbol{\omega}$ and train a neural network on this joint feature space, which is depicted in Fig. 1 (Conditioned Actor Network). The conditioned actor π parameterized by θ^{π} serves 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 and the preference vector $\boldsymbol{\omega}$.

First of all, we define s_t as the concatenation of the user embedding $\mathbf{e}_u \in \mathbb{R}^d$ and their recent history embedding \mathbf{h}_u :

$$s_t = [\mathbf{e}_u; \mathbf{h}_u], \tag{6}$$

where the recent history embedding $\mathbf{h}_u = \mathrm{GRU}(H_t)$ is acquired by encoding N item embeddings via Gated Recurrent Units (GRU) [10], and $H_t = \{H_t^1, H_t^2, \dots, H_t^N\}$ denotes the most recent N items from user u's interaction history. We define the user's recent history is organized as a queue with fixed length, and update it only if the recommended item $a_t^l \in a_t$ receives a positive feedback, which ensures that the state can always represent the user's most recent interests.

$$H_{t+1} = \begin{cases} \{H_t^2, \dots, H_t^N, a_t^I\} & a_t^I \text{ gets positive feedback} \\ H_t & \text{Otherwise} \end{cases}$$
 (7)

Secondly, we assume that the probability of actions conditioned on states and preferences follows a continuous high-dimensional Gaussian distribution. We also assume it has mean $\mu \in \mathbb{R}^{Kd}$ and covariance matrix $\Sigma \in \mathbb{R}^{Kd \times Kd}$ (only elements at diagonal are nonzeros and there are actually Kd parameters). In order to achieve better representation ability, we approximate the distribution via a deep neural network, which maps the encoded state s_t and preferences ω to μ and Σ . Specifically, we adopt a Multi Layer Perceptron (MLP) with $\tanh(\cdot)$ as the non-linear activation function,

$$(\mu, \Sigma) = \text{MLP}(s_t, \boldsymbol{\omega}).$$
 (8)

Once received μ and Σ , we sample a vector from the acquired 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 an "ideal" embedding of a virtual item.

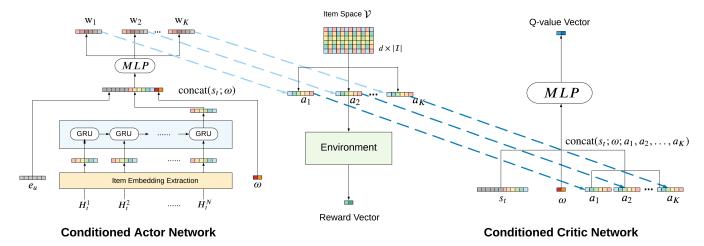


Figure 1: The architecture of the proposed MoFIR.

Finally, the probability matrix $P \in \mathbb{R}^{K \times |I|}$ of selecting the k-th candidate item is given by $P_k = \operatorname{softmax}(W_k \mathcal{V}^\top), \ k = 1, \dots, K$, 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 t, the actor recommends the k-th item as follows:

$$a_t^k = \underset{i \in \{1, ..., |I|\}}{\arg \max} P_{k,i}, \ \forall k = 1, ..., K,$$
 (9)

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

5.2 The Conditioned Critic

The conditioned critic μ also differs from the traditional critic in that we concatenate the state representation s_t with the vector ω as well as the embedding of action a_t , and require the output to be a Q-value-vector with the size equal to the number of objectives, which is depicted in Fig. 1 (Conditioned Critic Network). The conditioned critic μ is parameterized with θ^{μ} and is constructed to approximate the true state-action value vector function $\mathbf{Q}^{\pi}(s_t, a_t, \omega)$ and is used in the optimization of the actor. Following Eq. 2 introduced in conditioned network [3], the conditioned critic network is updated according to temporal-difference learning that minimizes the following loss function:

$$\mathcal{L}(\theta^{\mu}) = \mathbb{E}_{s,a,\omega} \left[\| \mathbf{y}_t - \mathbf{Q}_t \left(s, a, \omega; \theta^{\mu} \right) \|_2^2 \right]$$
 (10)

where $\mathbf{y}_t = \mathbf{r}_t + \gamma \mathbf{Q}_{\omega}(s_{t+1}, a_{t+1}, \boldsymbol{\omega}; \theta^{\mu}).$

5.3 Parameters Training Procedure of MoFIR

We present the detailed training procedure of our proposed model, MoFIR, in Algorithm 1 and the model architecture in Fig. 1. As mentioned before, we modify traditional single-objective DDPG into multi-objective DDPG by introducing the conditioned networks to both its actor network and critic network. In each episode, there are two phases — the trajectory generation phase (line 15-20) and model updating phase (line 22-32). In the trajectory generation phase, we sample one linear preference ω_0 and fix it to generate user-item interaction trajectories. Then in the model updating phase, we sample another \mathcal{N}_{ω} preferences together with ω_0 to update the conditioned actor network and the conditioned critic network. Here, we do not

follow the original setting in [3], which only uses one more random sampled preference vector, as Yang et al. [52] observed that increasing the number of sampled preference vectors can further improve the coverage ratio of RL agent and diminish the adaptation error in their experiments.

6 EXPERIMENTS

In this section, we first introduce the datasets, the comparison baselines, then discuss and analyse the experimental results.

6.1 Dataset Description

To evaluate the models under different data scales, data sparsity and application scenarios, we perform experiments on three realworld datasets. Some basic statistics of the experimental datasets are shown in Table 1.

- **Movielens:** We choose Movielens100K ¹, which includes about one hundred thousand user transactions, respectively (user id, item id, rating, timestamp, etc.).
- Ciao: Ciao was collected by Tang et al. [45] from a popular product review site, Epinions, in the month of May, 2011². For each user, they collected user profiles, user ratings and user trust relations. For each rating, they collected the product name and its category, the rating score, the time point when the rating is created, and the helpfulness of this rating.
- Etsy: We collect a few weeks of user-item interaction data on a famous e-commerce platform, Etsy. For each record, we collect user id, item id and timestamp. Since the original data is sparse, we filter out users and items with fewer than twenty interactions.

For each dataset, we first sort the records of each user based on the timestamp, and then split the records into training and testing sets chronologically by 4:1. The last item in the training set of each user is put into the validation set. Since we focus on item exposure fairness, we need to split items into two groups G_0 and G_1 based on item popularity. It would be desirable if we have the item impression/listing information and use it to group items, however, since Movielens and Ciao are public dataset and only have

¹https://grouplens.org/datasets/Movielens/

 $^{^2} https://www.cse.msu.edu/\ tangjili/datasetcode/truststudy.htm$

Algorithm 1: Multi-Objective DDPG Algorithm

```
1 Input:
2 A preference sampling distribution D_{\omega};
3 A multi-objective critic network \mu parameterized by \theta^{\mu};
 4 An actor network \pi parameterized by \theta^{\pi};
 5 Pre-trained user embeddings {\mathcal U} and item embeddings {\mathcal V}.
7 Parameters \theta^{\pi}, \theta^{\mu} of the actor network and critic network.
8 Initialization:
 9 Randomly initialize \theta^{\pi} and \theta^{\mu};
    Initialize target network \mu' and \pi' with weights
      \theta^{\pi\prime} \leftarrow \theta^{\pi}, \theta^{\mu\prime} \leftarrow \theta^{\mu};
11 Initialize replay buffer D.
12 for Episode = 1 ... M do
           Initialize user state s_0 from log data;
13
           Sample a linear preference \omega_0 \sim D_\omega;
14
          for t = 1 \dots T do
15
                 Observe current state, represent it as s_t based on Eq. (6);
16
                Select an action a_t \in I^K using actor network \pi based on
17
                 Calculate utility reward and fairness reward and get the
18
                   multi-objective reward vector \mathbf{r}_t according to
                   environment feedback based on Eq. (4) and Eq. (5);
                 Update s_{t+1} based on Eq. (6);
19
                Store transition (s_t, a_t, \mathbf{r}_t, s_{t+1}) in D.
20
          end
21
22
          if update then
                 Sample minibatch of \mathcal{N} trajectories \mathcal{T} from D;
23
24
                 Sample N_{\omega} preferences W = \{\omega_1, \omega_2, \dots, \omega_{N_{\omega}}\} \sim D_{\omega};
25
                 Append \omega_0 to W;
                 Select an action a' \in \mathcal{I}^K using actor target network \pi';
                 Set \mathbf{v} = \mathbf{r} + \gamma \mathbf{Q}' (s', a', \omega; \theta^{\mu \prime}), \omega \in W
27
                Update critic by minimizing \|\mathbf{y} - \mathbf{Q}(s, a, \boldsymbol{\omega}; \theta^{\mu})\|_{2}^{2}
28
                           \nabla_{\theta^{\mu}} \mathcal{L} \approx \frac{1}{NN_{\odot}} \left[ (\mathbf{y} - \mathbf{Q}(s, a, \omega; \theta^{\mu}))^T \nabla_{\theta^{\mu}} \mathbf{Q}(s, a, \omega; \theta^{\mu}) \right]
                 Update the actor using the sampled policy gradient:
29
                                \nabla_{\theta^{\pi}}\pi \approx \frac{1}{NN_{\omega}}\sum_{i}\omega^{T}\nabla_{a}\mathbf{Q}\left(s,a,\omega;\theta^{\mu}\right)\nabla_{\theta^{\pi}}\pi(s,\omega)
                Update the critic target networks:
                                                      \theta^{\mu\prime} \leftarrow \tau \theta^{\mu} + (1 - \tau) \theta^{\mu\prime}
31
                 Update the actor target networks:
                                                      \theta^{\pi'} \leftarrow \tau \theta^{\pi} + (1 - \tau) \theta^{\pi'}
```

Table 1: Basic statistics of the experimental datasets.

32

33 end

end

Dataset	#users	#items	#act./user	#act./item	#act.	density	
Movielens100K	943	1682	106	59.45	100,000	6.305%	
Ciao	2248	16861	16	2	36065	0.095%	
Etsy	1030	945	47	51	48080	4.940%	

interaction data, we use the number of interaction to group items in them. Specifically, for Movielens and Ciao, the top 20% items in terms of number of interactions belong to the popular group G_0 , and the remaining 80% belong to the long-tail group G_1 , while for Etsy data, we additionally collect the listing impressions per month for each item and group items based on this.

Moreover, for RL-based methods, we set the initial state for each user during training as the first five clicked items in the training set, and the initial state during testing as the last five clicked items in the training set. We also set the RL agent recommend ten items to a user each time.

Experimental Setup

6.2.1 Baselines: We compare our proposed method with the following baselines, including both traditional and reinforcement learning based recommendation models.

- MF: Collaborative Filtering based on matrix factorization [24] is a representative method for rating prediction. However, since not all datasets contain rating scores, we turn the rating prediction task into ranking prediction. Specifically, the user and item interaction vectors are considered as the representation vector for each user and item.
- BPR-MF: Bayesian Personalized Ranking [38] is one of the most widely used ranking methods for top-K recommendation, which models recommendation as a pair-wise ranking problem. In the implementation, we conduct balanced negative sampling on nonpurchased items for model learning.
- NGCF: Neural Graph Collaborative Filtering [46] is a neural network-based recommendation algorithm, which integrates the user-item interactions into the embedding learning process and exploits the graph structure by propagating embeddings on it to model the high-order connectivity.
- LIRD: The original paper for List-wise recommendation based on deep reinforcement learning (LIRD) [57] utilized the concatenation of item embeddings to represent the user state, and the actor will provide a list of K items as an action.

We also include two state-of-the-art fairness frameworks to show the fairness performance of our proposed method.

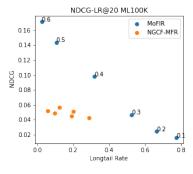
- FOE: Fairness of Exposure in Ranking (FOE) [43] is a type of postprocessing algorithm incorporating a standard linear program and the Birkhoff-von Neumann decomposition. It is originally designed for searching problems, so we follow the same modification method mentioned in [16, 47], and use ranking prediction model such as MF, BPR, and NGCF as the base ranker, where the raw utility is given by the predicted probability of user iclicking item j. In our experiment, we have MF-FOE, BPR-FOE and NGCF-FOE as our fairness baselines. Since 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.
- MFR: Multi-FR (MFR) [47] is a generic fairness-aware recommendation framework with multi-objective optimization, which jointly optimizes fairness and utility for two-sided recommendation. In our experiment, we only choose its item popularity fairness. We also modify it as the original fairness considers position bias as well, which is not the same setting as ours. Finally, we have MF-MFR, BPR-MFR and NGCF-MFR. For same reason as FOE, we do not include LIRD as well.

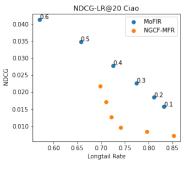
Table 2: Summary of the performance on three datasets. We evaluate for ranking (Recall, F1 and NDCG, in percentage (%) values, % symbol is omitted in the table for clarity) and fairness (KL Divergence and Popularity Rate, also in % values), while K is the length of recommendation list. Bold scores are used when MoFIR is the best, while underlined scores indicate the strongest baselines. When MoFIR is the best, its improvements against the best baseline are significant at p < 0.01.

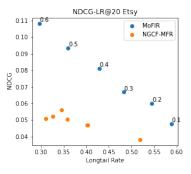
Methods	Recall (%)↑			F1 (%) ↑		NDCG (%) ↑		KL (%) ↓			Popularity Rate (%) \downarrow				
	K=5	K=10	K=20	K=5	K=10	K=20	K=5	K=10	K=20	K=5	K=10	K=20	K=5	K=10	K=20
							Movie	elens-100K							
MF	1.422	2.713	5.228	2.019	3.016	4.127	3.561	3.830	4.705	229.124	224.390	215.772	99.745	99.258	98.224
BPR-MF	1.304	3.539	8.093	1.824	3.592	5.409	3.025	3.946	5.787	230.531	230.531	229.464	99.873	99.873	99.777
NGCF	1.995	3.831	6.983	2.846	4.267	5.383	5.319	5.660	6.510	232.193	232.193	232.193	100.000	100.000	100.000
LIRD	2.798	6.586	13.711	3.198	4.850	5.855	4.583	6.217	8.840	209.845	193.918	176.644	97.434	95.058	92.121
MF-FOE	1.164	2.247	4.179	1.739	2.730	3.794	3.520	3.796	4.367	181.000	175.355	170.444	92.895	91.888	90.981
BPR-FOE	0.974	2.053	4.404	1.496	2.568	3.933	3.127	3.514	4.332	176.938	172.465	168.952	92.174	91.357	90.700
NGCF-FOE	1.193	1.987	4.251	1.759	2.398	3.698	4.033	3.897	4.633	232.193	232.193	232.193	100.000	100.000	100.000
MF-MFR	1.546	2.807	5.422	2.019	3.016	4.127	3.276	3.613	4.571	100.590	96.620	85.420	74.867	73.743	70.419
BPR-MFR	1.418	2.811	6.155	2.019	3.016	4.127	3.522	3.822	5.047	165.897	155.339	137.663	90.117	88.017	84.205
NGCF-MFR	1.456	2.900	6.570	2.846	4.267	5.383	3.041	3.472	4.928	212.497	202.306	185.518	97.794	96.352	93.674
MoFIR-1.0	6.580	12.753	22.843	5.658	7.178	7.858	8.026	10.848	14.683	232.193	232.193	232.193	100.000	100.000	100.000
MoFIR-0.5	4.679	9.520	19.918	4.438	5.808	7.421	6.633	9.300	14.370	173.672	170.303	162.386	91.580	90.954	89.433
MoFIR-0.1	0.323	0.781	1.550	0.521	1.008	1.483	1.251	1.404	1.598	0.795	0.608	0.306	24.305	23.754	22.646
								Ciao							
MF	0.518	1.938	3.100	0.395	0.687	0.599	0.408	0.924	1.264	81.154	65.458	47.848	69.088	63.835	57.098
BPR-MF	1.087	2.204	4.607	0.677	0.770	0.858	0.776	1.181	1.900	119.307	100.884	82.717	79.826	74.949	69.580
NGCF	1.721	2.816	4.380	1.056	0.958	0.783	1.670	2.027	2.450	142.025	96.789	59.561	85.181	73.792	61.693
LIRD	0.766	2.448	3.599	0.554	1.082	0.921	1.393	2.638	3.277	65.744	105.507	64.888	63.936	76.223	63.632
MF-FOE	0.685	1.208	1.914	0.458	0.474	0.396	0.475	0.669	0.864	19.720	11.167	7.622	43.068	37.033	33.915
BPR-FOE	1.442	2.111	3.693	0.812	0.663	0.731	0.934	1.154	1.657	55.999	46.858	40.626	60.347	56.686	53.987
NGCF-FOE	1.234	1.907	2.903	0.651	0.583	0.566	0.937	1.156	1.477	79.313	74.038	71.335	43.357	34.226	30.391
MF-MFR	0.307	0.619	1.281	0.395	0.687	0.599	0.237	0.345	0.535	0.185	0.096	0.068	18.003	18.553	18.784
BPR-MFR	1.146	1.962	2.667	0.395	0.687	0.599	1.011	1.314	1.534	4.303	2.540	1.454	30.304	27.829	25.868
NGCF-MFR	1.284	2.131	4.033	1.056	0.958	0.783	1.014	1.342	1.901	37.133	20.302	10.515	52.388	43.430	36.498
MoFIR-1.0	2.162	3.867	5.866	1.626	1.513	1.323	4.000	4.764	5.813	181.742	156.545	123.213	93.025	88.263	80.796
MoFIR-0.5	1.254	2.665	4.122	0.845	0.971	0.879	2.031	2.724	3.490	19.077	12.750	8.032	42.663	38.278	34.305
MoFIR-0.1	0.892	1.610	2.338	0.557	0.532	0.445	1.054	1.311	1.576	0.054	0.010	0.484	21.100	19.522	16.795
								Etsy							
MF	2.693	5.581	10.348	2.917	4.176	4.912	3.438	4.671	6.681	190.410	190.173	186.243	94.491	94.452	93.797
BPR-MF	3.113	5.850	11.704	3.309	4.320	5.385	3.700	4.880	7.341	179.815	176.447	169.740	92.687	92.085	90.849
NGCF	3.414	6.026	11.746	3.674	4.498	5.406	4.180	5.238	7.610	194.985	185.756	175.403	95.228	93.715	91.896
LIRD	<u>7.163</u>	12.176	24.056	4.158	4.493	4.967	6.587	9.289	13.833	212.890	197.336	166.047	97.847	95.597	90.145
MF-FOE	1.382	2.436	4.515	1.641	2.160	2.704	2.111	2.482	3.318	42.682	29.960	22.502	54.898	48.865	44.758
BPR-FOE	1.503	2.808	5.513	1.802	2.468	3.132	2.328	2.783	3.844	43.394	30.734	23.390	55.209	49.263	45.276
NGCF-FOE	1.958	3.135	5.478	2.227	2.593	2.923	2.705	3.106	4.024	47.548	30.829	21.678	56.974	49.311	44.268
MF-MFR	2.482	5.150	10.279	2.917	4.176	4.912	3.265	4.504	6.671	173.889	158.030	134.564	91.620	88.565	83.497
BPR-MFR	2.510	4.849	9.711	2.917	4.176	4.912	3.144	4.110	6.206	136.319	120.661	94.153	83.899	80.165	73.031
NGCF-MFR	2.325	4.146	7.946	3.558	4.820	5.616	2.994	3.636	5.210	104.348	91.557	74.402	75.907	72.270	66.901
MoFIR-1.0	6.690	13.87 1	24.72 8	4.833	5.932	6.238	9.183	13.629	19.822	139.319	134.627	129.318	84.578	83.511	82.270
MoFIR-0.5	5.333	10.342	19.383	3.460	3.979	4.218	4.626	6.614	9.798	70.154	67.961	64.956	65.470	64.714	63.657
MoFIR-0.1	1.340	2.966	5.864	1.151	1.641	1.895	1.778	2.839	4.425	0.569	0.545	0.396	23.628	23.550	23.016

We implement MF, BPR-MF, NGCF, MF-FOE, BPR-FOE, NGCF-FOE, MF-MFR BPR-MFR and NGCF-MFR using *Pytorch* with Adam optimizer. For all of them, 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. Further, since the FOE-based methods needs to solve a linear programming with size $|\mathcal{I}| \times |\mathcal{I}|$ for each consumer, which brings huge computational costs, we rerank the top-200 items from

the base model then select the new top-K (K<100) as the final recommendation. Similarly, we implement MoFIR with Pytorch. We first perform basic MF to pretrain 16-dimensional user and item embeddings, and fix them through training and test. We set $|H_t|=5$, and use two GRU layers to get the state representation s_t . For the actor network and the critic network, we use two hidden layer MLP with tanh(·) as activation function. Finally, we fine-tune MoFIR's hyper-parameters on our validation set. In order to examine the trade-off between performance and fairness, we use different level of preference vectors in test. Since MoFIR is able to approximate all possible solutions of the Pareto frontier, we simply input different







(a) NDCG vs Long-tail Rate on ML100K

(b) NDCG vs Long-tail Rate on Ciao

(c) NDCG vs Long-tail Rate on Etsy

Figure 2: Approximate Pareto frontier in three datasets generated by MoFIR and NGCF-MFR, where x-axis represents the Longtail Rate@20 (Longtail Rate equals to one minus Popularity Rate) and y-axis represents the value of NDCG@20.

preference vetors ω into the trained model to get variants of MoFIR and denote the resulting alternatives as **MoFIR-1.0**, **MoFIR-0.5**, and **MoFIR-0.1**, where the scalar is the weight on the recommendation utility objective.

6.2.2 **Evaluation Metrics:** We select several most commonly used top-K ranking metrics to evaluate each model's recommendation performance, including **Recall**, **F1 Score**, and **NDCG**. For fairness evaluation, we define **Popularity Rate**, which simply refers to the ratio of the number of popular items in the recommendation list to the total number of items in the list. We also employ **KL-divergence** (KL) to compute the expectation of the difference between protected group membership at top-K vs. in the over-all population, where d_{KL} $(D_1||D_2) = \sum_j D_1(j) \ln \frac{D_1(j)}{D_2(j)}$ with D_1 represents the true group distribution between G_0 and G_1 in top-K recommendation list, and $D_2 = \left[\frac{|G_0|}{|I|}, \frac{|G_1|}{|I|}\right]$ represents their ideal distribution of the overall population.

6.3 Experimental Results

The major experimental results are shown in Table 2, besides, we also plot the approximate Pareto frontier between NDCG and Longtail Rate (namely, 1-Popularity Rate) in Fig. 2. We analyze and discuss the results in terms of the following perspectives.

6.3.1 Recommendation Performance. For recommendation performance, we compare MoFIR-1.0 with MF, BPR, NGCF, and LIRD based on Recall@k, F1@k and NDCG@k and provide the these results of the recommendation performance in Table 2. Among all the baseline models, we can see that all sequential recommendation methods (LIRD, MoFIR-1.0) are much better than the traditional method, which demonstrates the superiority of sequential recommendation on top-K ranking tasks. Specifically, LIRD is the strongest baseline in all three datasets on all performance metrics: when averaging across recommendation lengths LIRD achieves 41.28% improvement than MF, 27.08% improvement than BPR-MF, and 8.97% improvement than NGCF.

Our MoFIR approach achieves the best top-K recommendation performance against all baselines on all datasets: when averaging across three recommendation lengths on all performance metrics, MoFIR gets 41.40% improvement than the best baseline on Movielens100K; MoFIR gets 46.45% improvement than LIRD on Ciao; and MoFIR gets 18.98% improvement than LIRD on Etsy. These above observations imply that the proposed method does have the ability to capture the dynamic nature in user-item interactions, which results in better recommendation results. Besides, unlike LIRD, which only concatenates user and item embeddings together, MoFIR uses several GRU layers to better capture the sequential information in user history, which benefits the model performance.

6.3.2 Fairness Performance. For fairness performance, we compare MoFIRs with FOE-based methods and MFR-based methods based on KL Divergence@k and Popularity Rate@k, which are also shown in Table 2. It is easy to find that there does exist a trade-off between the recommendation performance and the fairness performance, which is understandable, as most of the long-tail items have relatively fewer interactions with users. When comparing the baselines, we can easily find that MFR is able to achieve better trade-off than FOE as it is also a multi-objective optimization method.

From Table 2, MoFIR is able to adjust the degree of trade-off between utility and fairness through simply modifying the weight of recommendation utility objective. It is worth noting that MoFIR-0.1 can always closely achieve the ideal distribution as its KLs are close to zero. In Table 2, we can find that even MoFIR has the similar performance of fairness with other baselines, it can still achieve much better recommendation performance (for example, BPR-FOE and MoFIR-0.5 in Movielens100k or NGCF-FOE and MoFIR-0.5 in Ciao or MF-MFR and MoFIR-0.5 in Etsy), which indicates its capability of finding better trade-off.

6.3.3 Fairness-Utility Trade-off. We only compare MoFIR with MFR, since FOE is a post-processing method, which doesn't optimize the fairness-utility trade-off. In order to better illustrate the trade-off between utility and fairness, we fix the length of the recommendation list at 20 and plot NDCG@20 against Longtail Rate in Fig. 2 for all datasets, where Longtail Rate equals to one minus Popularity Rate. Each blue point is generated by simply changing the input weights to the fine-tuned MoFIR, while each orange point is generated by running the entire MFR optimization. The clear margin distance between the blue points' curve (Approximate

Pareto frontier) and the orange points' curve demonstrates the great effectiveness of MORL compared with traditional multi-objective optimization method in recommendation.

7 CONCLUSION

In this work, we achieve the approximate Pareto efficient trade-off between fairness and utility in recommendation systems and characterize their Pareto Frontier in the objective space in order to find solutions with different level of trade-off. We accomplish the task by proposing a fairness-aware recommendation framework using multi-objective reinforcement learning (MORL) with linear preferences, called MoFIR, which aims to learn a single parametric representation for optimal recommendation policies over the space of all possible preferences. Experiments across three different datasets demonstrate the effectiveness of our approach in both fairness measures and recommendation performance.

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