Probabilistic Permutation Graph Search:
Black-Box Optimization for Fairness in Ranking

Group 36

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Introduction

- The paper discusses fairness measures in search and recommendation systems, focusing on optimizing fairness in ranking.
- In modern ranking systems, fairness is crucial.
- Different fairness measures (e.g., Disparate Treatment Ratio, Expected Exposure Loss).
- Challenge: Optimizing fairness while balancing ranking performance.
- Objective: Flexible, black-box optimization method (PPG) for multiple fairness definitions.

Fairness in ranking has several important applications, especially in areas where algorithmic decisions impact individuals or groups. Here are some key applications:

- Hiring Platforms: In recruitment or hiring systems, fair ranking ensures that candidates from different demographic groups (e.g., gender, race) are treated equitably, preventing biased exposure towards certain groups.
- Loan and Credit Approval Systems: Financial institutions use algorithms to rank loan applicants based on creditworthiness. Ensuring fairness in ranking helps avoid biased treatment of individuals from minority groups, ensuring that decisions are based solely on financial factors and not influenced by irrelevant demographic factors.
- Online Marketplaces and Product Recommendations: Platforms like Amazon use ranking algorithms to recommend products. Fairness in ranking helps ensure that small businesses or minority-owned businesses are not overshadowed by more popular or larger competitors, giving them equitable exposure based on product quality and relevance.

- Disparate Treatment Ratio(DTR) : Equality to exposure, each group should get exposed proportional to their utility.
  - It can be used for deterministic rankers , which produce one ranking per query.

- Expected exposure loss (EEL) : It is based on the premise that groups (or individuals) with the same relevance level should have equal expected exposures.
  - It should be used for stochastic rankers.
  - It is also assumed in EEL that the relevance levels have discrete values

Optimizing fairness measures :

Since we deal with different aspects of fairness, and more importantly, it has been shown that there is an inherent trade-off between some fairness conditions , which makes it impossible to have a unified fairness measure.

Our aim to accomplish is to provide a general framework that can be used for optimizing any fairness measure.

utility value of the items can be obtained from:

1) External Sources such as Unbiased clicks
2) Learning to rank (LTR) model

The framework should work with black-box access to the function that evaluates ranking fairness.

Optimization of fairness in ranking is a special case of permutation optimization, and reinforcement learning (RL).

- Using the well-known REINFORCE algorithm and sampling from a Plackett-Luce (PL) distribution, it is possible to optimize any fairness objective function on permutations.

Plackett-Luce (PL) Model

- **What is PL?**

  - Uses pointwise logits as parameters for permutations.

  - REINFORCE algorithm optimizes fairness objectives.

- **Limitations:**

  - High variance with few repeating sessions.

  - Minimal improvement with noisy utility estimates.

- However, there are two directions in which PL-based optimization has room for improvement.
  1. When the number of repeating sessions for a query is very small, the high variance of PL leads to sub-optimal results.
  2. When an accurate estimate of the utilities is available, the solutions obtained from PL are only slightly improved over the case of noisy utility values.

Black-box permutation optimization

To bridge the performance gap left by PL in the above two cases, we propose a novel permutation distribution for black-box permutation optimization with the REINFORCE algorithm.

- The function is treated as a "black box," where its output is queried based on different input permutations
- It is useful for non-differentiable problems like fairness in ranking, where traditional gradient-based methods cannot be applied.
- Methods like Plackett-Luce and Probabilistic Permutation Graph distributions, along with REINFORCE, are used to explore and optimize permutation spaces.
- This approach is often used for complex, non-differentiable problems like fairness in ranking, where traditional gradient-based optimization techniques cannot be applied.

Probabilistic Permutation Graph (PPG)

- PPG Definition:
  - - Represents ranking permutations using pairwise inversion probabilities.
  - - More flexible than PL (uses logits).
- Advantages:
  - - Works for deterministic and stochastic ranking scenarios.
  - - Sets reference permutation to the best-sampled permutation.
- Mathematical Formula:
  - $P(E_\pi \mid w) = \prod w_e * \prod (1 - w_e)$

PPG vs. PL in Fairness Optimization

- PL’s Limitation:
  - - Struggles with small session numbers due to high variance.
- PPG’s Advantage:
  - - Improves deterministic rankings by isolating noisy utility estimates.

PPG Search Algorithm

- **PPG Search Steps:**
  1. Initialize with a reference permutation and graph with inversion probabilities.
  2. Sample permutations using Bernoulli sampling.
  3. Update parameters (inversion probabilities, reference).

- **Gradient Formula:**
  - $\nabla_\theta F(\theta) \approx 1/\lambda \sum f(b_i) * \nabla_\theta \log P(b_i \mid \theta)$

Gradient estimators for permutations. The group of all permutations of size n is called the *symmetric group* and is denoted by S_n. Permutation optimization can be stated as follows:

$$\min f(b), \quad b \in S_n,$$

where $f : S_n \to \mathbb{R}$ can be any general function on permutations. For this combinatorial optimization problem, the gradient solution is not as clear as continuous differentiable optimization. Instead, a policy-based RL approach can be used to optimize the expectation of $f(b)$ over a differentiable probability distribution $P(b \mid \theta)$, represented by a vector of continuous parameters θ [4]:

$$F(\theta) = \mathbb{E}_{P(b|\theta)} \left[f(b) \right]. \tag{1}$$

$F(\theta)$ is optimized when $P(b \mid \theta)$ is totally concentrated on b^*, the optimum solution of $f(b)$. For Eq. (1), the REINFORCE estimator [45] can be used:

$$\nabla_\theta F(\theta) = \mathbb{E}_{P(b|\theta)} \left[f(b) \cdot \nabla_\theta \log P\left(b \mid \theta\right) \right]. \tag{2}$$

Finally, since S_n is exponentially large, the expectation in Eq. (2) can be estimated through Monte-Carlo (MC) sampling:

$$\nabla_\theta F(\theta) \approx \frac{1}{\lambda} \sum_{i=1}^{\lambda} f(b_i) \cdot \nabla_\theta \log P\,(b_i \mid \theta), \tag{3}$$

where $b_1, \ldots, b_\lambda \in S_n$ are samples drawn from $P(b \mid \theta)$.

It remains to discuss the probability distribution on S_n. For a thorough exploration of probability distributions for permutations we refer the reader to [12]. The PL model [24, 32] is by far the most widely used permutation distribution in the REINFORCE algorithm, both in general permutation optimization [13] and the fairness literature [30, 38]. PL is represented by a parameter vector $\theta \in \mathbb{R}^n$, and the probability of a permutation $b = [b_1, \ldots, b_n] \in S_n$ under PL is calculated as:

$$P(b \mid \theta) = \prod_{i=1}^{n-1} \frac{\theta_{b_i}}{\sum_{j=i}^{n} \theta_{b_j}}. \tag{4}$$

- Given a list of items D and a reference permutation $\pi 0$ on D, a PPG corresponding to π is a weighted complete graph $G = (D, E, w)$, whose edges are weighted by a probability value obtained from $w : E \longrightarrow [0, 1]$. For each edge $e \in E$, its weight $w(e)$ indicates the Bernoulli sampling probability that e is included in a permutation graph over $\pi 0$ sampled from G.
- PPG represents a permutation distribution. To sample a permutation from a given PPG, a Bernoulli sampling process is run on the edges of G with their corresponding weights.
- Suppose that, after edge sampling, $E\pi \subset E$ is the set of edges that are selected (i.e., positively sampled) by the sampler and $E \setminus E\pi$ is the set of remaining, left out edges (i.e., negatively sampled). The probability of this outcome is calculated as

$$P(E_\pi \mid w) = \prod_{e \in E_\pi} w_e \cdot \prod_{e \in E \setminus E_\pi} (1 - w_e)$$

Efficient Sampling in PPG

- Sampling Method:
  I. - Divide and conquer approach for efficient permutation graph sampling.
  II. - Adjust probabilities to ensure valid sampling without unnecessary inversions.

Pairwise Constraints

- What are Pairwise Constraints?

  - Rules ensuring items maintain relative order (e.g., item d1 ranked higher than d2).

- Types:

  1. Intra-group: Items within a group maintain order.
  2. Inter-group: One group of items ranked higher than another.

- Use Cases: Time-aware and context-aware ranking.

Model and Dataset used

- The paper uses a Learning to Rank (LTR) model for ranking tasks. Specifically, it implements a neural network-based LTR with two hidden layers (each of width 256), ReLU activations, dropout of 0.1, and a learning rate of 0.01. The pointwise loss function used is the mean-squared error (MSE), and the LTR scores are min-max normalized for calibration
- For fairness optimization, the paper introduces a novel model called Probabilistic Permutation Graph (PPG) as a substitute for the more widely used Plackett-Luce (PL) model, which is a common choice in ranking optimization. The REINFORCE algorithm is applied for combinatorial optimization using this PPG distribution

Model and Dataset used

- 1) MSLR-WEB30K (Microsoft Learning to Rank): This dataset contains 5-level relevance labels and is widely used in counterfactual learning-to-rank research as well as fairness studies. In the experiments, a subset of the test set is selected based.
- 2) TREC Fair Ranking Track (2019 and 2020 editions): These datasets are used for academic search fairness evaluations, with documents divided into groups based on the h-index of their authors. The datasets have been previously used in fair ranking research on relevance and group characteristics.
- These datasets are used to evaluate the performance of the proposed PPG method compared to the baseline PL model across various fairness and ranking metrics, such as Disparate Treatment Ratio (DTR) and Expected Exposure Loss (EEL).

Experimental Results

- Datasets: TREC 2019, TREC 2020, MSLR.
- Fairness Metrics:

  - Disparate Treatment Ratio (DTR), Expected Exposure Loss (EEL).

- Results:

  - PPG outperforms PL in fairness, especially with fewer sessions.

  - Significant improvement when accurate utility estimates are available.

Conclusion

- PPG Benefits:
  1. More flexible and effective than PL for fairness optimization.
  2. Performs better with small session numbers.
  3. Allows fine-tuning fairness and ranking performance with constraints.

- Applications: Search engines, recommender systems, fairness in ranking scenarios.

References

ACM Reference Format: Ali Vardasbi, Fatemeh Sarvi, and Maarten de Rijke. 2022. Probabilistic Permutation Graph Search: Black-Box Optimization for Fairness in Ranking. In Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR ’22), July 11–15, 2022, Madrid, Spain. ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3477495.3532045

Thank You!