Connecting User and Item Perspectives in Popularity Debiasing for Collaborative Recommendation

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Abstract

Recommender systems learn from historical data that is often non-uniformly distributed across items, so they may end up suggesting popular items more than niche items. This can hamper user interest and several qualities of the recommended lists (e.g., novelty, coverage, diversity), impacting on the future success of the platform. In this paper, we formalize two novel metrics that quantify how much a recommender system equally treats items along the popularity tail. The first one encourages equal probability of being recommended across items, while the second one encourages true positive rates for items to be equal. Then, we characterize the recommendations of representative algorithms with respect to the proposed metrics, and we show that the item probability of being recommended and the item true positive rate are directly proportional to the item popularity. To mitigate the influence of popularity, we propose an in-processing approach aimed at minimizing the correlation between user-item relevance and item popularity, leading to a more equal treatment of items along the popularity tail. Extensive experiments show that, with small losses in accuracy, our popularity-debiasing approach leads to important gains in beyond-accuracy recommendation quality.

Keywords: Recommender Systems, Collaborative Filtering, Popularity Bias.

1. Introduction

Recommender systems are bridging users and relevant products, services and peers on the Web. By leveraging past behavioural data, such automated systems aim to understand users’ preferences and predict their future interests \cite{1}. Notable examples are integrated in platforms from different contexts, including e-commerce (Amazon, eBay), multimedia (YouTube, Netflix), and education...
Figure 1: **Imbalanced feedback distributions.** Cumulative percentage of feedback for items in Movielens1M [5] (left) and COCO [6] (right). Each curve is divided in head, mid and tail based on 50% and 75% percentiles. Head items gather 50% of ratings. Section 4.1 provides a detailed description of the datasets.

(Coursera, Udemy). The future success of these platforms depends also on the effectiveness of the underlying recommender system.

The increasing adoption of recommender systems in online platforms has spurred investigations on issues of bias in their internal mechanisms. One aspect that has received attention so far is the recommender systems’ tendency of emphasizing a “rich-get-richer” effect in favor of few popular items [2]. Such a phenomenon leads to a loop where recommender systems trained on data non-uniformly distributed across items tend to suggest popular items more than niche items, even when the latter would be of interest. Hence, popular items gain more visibility and become more likely to be selected. The awareness of this type of bias might even lead providers to bribe users, so that they rate or increase the ratings given to their items, thus allowing these items to get more visibility [3, 4]. The train data will thus be imbalanced towards popular items more and more (Figure 1).

Recommender systems suggesting what is popular have been proved to be competitive baselines in terms of accuracy [7]. However, it has been recognized that other beyond-accuracy aspects, such as whether recommendations are novel and cover well the catalog, may positively impact on the overall recommendation quality [8]. In this view, popularity bias can lead to issues, such as filter bubbles, which may hamper user interest and beyond-accuracy aspects [9, 10, 11]. Since trading such qualities for item popularity might likely not be accepted, debiasing popularity can help to meet a better trade-off between accuracy and beyond-accuracy goals, improving the quality of recommendations on the whole [12].

Existing frameworks and procedures for popularity debiasing [13, 14, 15, 16] are often based on bias metrics that do not account for user preferences, thus being assessed only on the level of popularity of items in a recommended list. It should be noted that popularity cannot be an objective concept and it strongly depends on user preferences and on how data has been collected. It follows that popularity metrics and debiasing procedures need to account for user preferences.

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1 Please note that all the figures in this manuscript are best seen in color.
and the visibility that is given to the items thanks to recommendations, creating a bridge between these perspectives and beyond-accuracy objectives.

In this paper, we tackle this challenge with a new popularity-debiasing framework. Two novel metrics quantify how much a recommender equally treats items along the popularity tail. The first metric encourages similar probabilities of being recommended among items, that is important when platform owners may be interested in equally suggesting items (e.g., loan platforms). The second metric takes into account the ground-truth user preference, and encourages true positive rates of items to be equal. This becomes useful in contexts where the platform owners may desire to preserve the imbalance across items in data, while avoiding any further distortion on recommendations caused by algorithmic bias.

Then, we empirically prove that two widely-adopted classes of recommendation algorithms (i.e., point-wise and pair-wise) are biased towards item popularity with respect to the proposed metrics. To limit this side effect, we propose an approach based on (i) a data sampling that balances the input samples where the observed item is more (less) popular than the unobserved item, and (ii) a regularization term that minimizes the correlation between user-item relevance and item popularity. Experiments show that the proposed approach provides a more equal treatment of items along the popularity tail. With a minimum loss in accuracy, it also leads to important gains in novelty and catalog coverage, known to provide benefits to the overlying platform.

This paper is organized as follows: Section 2 presents related works on popularity in recommendation. Section 3 formalizes problem and metrics. Section 4 describes the exploratory analysis. Then, Sections 5 and 6 respectively describe and validate our countermeasure. Section 7 concludes the paper.

2. Related Work

This research relates with and builds on literature from the recommender system and machine learning communities.

2.1. Popularity Bias in Recommendation

Treating popularity bias has often required a multi-objective setting that investigates any accuracy loss resulting from taking popularity into consideration. Therefore, the final goal has been to strike a balance between accuracy (e.g., precision, recall) and pre-conceptualized bias metrics (e.g., average recommended item popularity, average percentage and coverage of tail items) \[16, 17\]. Bias metrics tend to measure distribution skews for a complete system rather than for individual items; often require knowing head/tail memberships for all items, which is indeed arbitrary and highly variable across datasets; and evaluate bias without considering the ground truth of the user interest. We seek to address this gap with two bias metrics tailored for individual items: the first one enforces ranking probabilities for items to be the same, and the second one encourages true positive rates of items to be the same.

Under this setting, pre-processing operations alter train data to reduce the impact of imbalance. For instance, \[18\] splits the item set into head and tail,
and separately clusters their ratings. Tail recommendations leverage ratings from the corresponding cluster, while the head ones use ratings from individual items. In [7], Jannach et al. sample input user-item pairs where the observed item is less popular than the unobserved one. The work in [19] suggests to pick up unobserved items following a probability distribution based on popularity. Differently, our data sampling balances cases where the observed item is more (less) popular than the unobserved item of the input sample, to better fit with our regularization.

In-processing countermeasures modify an existing algorithm to simultaneously consider relevance and popularity, doing a joint optimization or using one criteria as a constraint for the other. The authors in [20] consider the individual user popularity tendency to recommend tail items. In [13], the authors propose to enhance the statistical independence between a recommendation and its popularity. Similarly, the work in [16] pushes RankALS algorithm optimization towards recommended lists that balance accuracy and head/tail recommendations. In [14], common neighbours between two items with given popularity are retrieved, then a balanced common-neighbour similarity index is obtained, after pruning popular neighbours. Our work differs from prior literature in expressiveness and algorithmically. Furthermore, we experimented with learning-to-rank recommendation approaches, using point-wise and pair-wise as use cases.

Post-processing countermeasures seek to re-rank a recommended list according to certain constraints. The work in [17, 15] presents two approaches for controlling item exposure; the first one adapts the xQuAD algorithm for balancing the trade-off between accuracy and mid-tail item coverage; the second one multiplies the relevance score for a given item with a weight inversely proportional to the item popularity; items are re-ranked according to the weighted scores. In [7], user-specific weights help to balance accuracy and popularity. Post-processing countermeasures can provide elegant solutions, but often require knowing head/tail memberships for all items, may be really sensitive to predicted relevance distribution, and may influence the platform efficiency.

2.2. Bias Mitigation in Machine Learning

Existing literature has primarily focused on biases in classification, with definitions mostly targeting fairness [21]. In our study, we primarily reformulate the statistical parity and the equality of opportunity notions [22, 23] for the item popularity bias problem, as they were conceived to measure differences in accuracy across users in fairness-aware classification. Compared to previous works, our metrics measure bias on individual items rather than fairness on classes of protected users, and do not require any intrinsic notion of group membership for an item. Moreover, our metrics align with the probability of being recommended in a top-k list rather than being classified to a given label.

Many approaches have been proposed to address bias and fairness issues in machine learning. Notable examples of in-processing approaches mostly target fairness among user groups and include three main categories: constraint-based optimization [24, 25], adversarial learning [26, 27], and regularization over predictions [28, 29, 30]. Our approach builds on and reformulates the latter class of
strategies to fit with the popularity debiasing task. Differently from [28, 30], we relax the assumption of knowing group memberships of input samples, targeting individual items regardless of their head/tail membership. In our setting, we are concerned with relative differences in relevance and in popularity rather than in predicted labels and in group labels, which differently drives optimization during training and allows flexible data sampling strategies. Furthermore, as we tackle a popularity bias task rather than an unfairness mitigation task, our design choices lead to consider processes and model facets so far under-explored.

3. Preliminaries

In this section, we formalize the main concepts underlying our study, including the recommender system and the new popularity-bias metrics we introduce.

3.1. Recommender System Formalization

Given a set of $M$ users $U = \{u_1, u_2, ..., u_M\}$ and a set of $N$ items $I = \{i_1, i_2, ..., i_N\}$, we assume that users have expressed their interest for a subset of items in $I$. The collected feedback from observed user-item interactions can be abstracted to a set of $(u, i)$ pairs implicitly obtained from user activity or $(u, i, v)$ triplets explicitly constructed, with $v \in V$. Elements in $V$ may be either ratings or frequencies (e.g., play counts). We denote the user-item matrix $R \in \mathbb{R}^{M \times N}$ by $R(u, i) = 1$ for implicit feedback or $R(u, i) = v$ for explicit feedback or frequencies to indicate the (level of) preference of $u$ for $i$, $R(u, i) = 0$ otherwise.

Given this input, the recommender systems task is to predict unobserved user-item relevance scores, and deliver a set of ranked items. To this end, we assume that a function estimates relevance scores of unobserved entries in $R$ for a given user, and the recommender system uses them for ranking the items. Formally, it can be abstracted as learning $\tilde{R}(u, i) = f(u, i|\theta)$, where $\tilde{R}(u, i)$ denotes the predicted relevance, $\theta$ denotes model parameters, and $f$ denotes the function that maps model parameters to the predicted score.

We assume that each user/item is internally represented through a $D$-sized numerical vector. More precisely, the model includes a user-vector matrix $W$ and an item-vector matrix $X$. We also assume that the function $f$ is parametrized by $\theta$ and depends on the specific recommendation algorithm under consideration. The higher the $\tilde{R}(u, i)$ is, the higher the relevance of $i$ for $u$ is. To rank items, they are sorted by decreasing relevance, and the top-$k$ items are recommended.

3.2. Popularity Bias Metric Formalization

As we deal with item popularity biases, we define key concepts on what we consider as popularity bias and how we measure it throughout the paper.

**Item Statistical Parity (ISP).** Recommender system may be inherently influenced by the item popularity. More popular items remain more popular since they are more likely to appear at the top of the recommended list. This inadvertently leads to few mainstream items being recommended and to an impedance for items of the tail-end popularity spectrum to attract users. In this scenario,
we assume that the recommender systems powering online environments should equally cover items along the popularity tail. For instance, this notion may be useful when platform owners manage recommendations of individuals (e.g., people recommendations) or of particularly delicate elements (e.g., loans).

To measure this property, we reformulate the statistical parity principle introduced in fairness-aware machine learning [23], for the popularity debiasing task. This implies to control item statistical parity, i.e., equalizing the outcomes across the individual items. We operationalize this concept for items by computing the ratio between the number of users each item is recommended to and the number of users who can receive that item in the recommended list. We then encourage that such a ratio is similar among items. Considering that only top-k items are recommended, we assume that the outcome for an item is the probability of being ranked in the top-k list. We define such probability as:

\[
p(i|k, \theta) = \frac{\sum_{u \in U} \varphi(u, i|k, \theta)}{\sum_{u \in U} 1 - \min(R(u, i), 1)}
\] (1)

where \(\varphi(u, i|k, \theta) = 1\) if item \(i\) is being ranked in top-k for user \(u\) by model \(\theta\), 0 otherwise. In other words, the numerator counts the number of users are being recommended item \(i\) in top-k, while the denominator counts the number of users have never interacted with item \(i\), and thus may receive \(i\) as a recommendation.

Last, we compute the inverse of the Gini index as a measure of distribution equality among \(p(i|k, \theta)\) across items. The Gini index is a well-known scale-independent and bounded measure of inequality that ranges between 0 and 1. Higher values represent higher inequality. It is used as follows:

\[
ISP(k, \theta) = 1 - Gini\{p(i|k, \theta) | \forall i \in I\}
\] (2)

If there is a perfectly equal distribution of recommendations across items, then \(ISP = 1\) and the statistical parity is met. \(ISP\) decreases and gets closer to 0 when the distribution of the recommendations is more unequal. For example, this occurs if most of the items never appeared in the recommended lists. In the extreme, where the same \(n << N\) items appeared in all the recommendations, \(ISP\) is very close to 0. Thus, \(ISP\) will lie between 0 and 1, and the greater it is, the more equally the recommendations are distributed.

In some cases, platform owners would not equalize the recommendations along the entire popularity tail. High statistical parity could lead to situations in which even items of very low interest get recommended the same amount of times with respect to more-of-interest items. This motivated us to complement our measurement of popularity bias with another representative metric.

**Item Equal Opportunity (IEO).** Instead of equalizing the recommendations themselves, we can equalize some statistics of the algorithms effectiveness (e.g., true positive rate across items). In many applications, platform owners may care more about preserving and retaining a certain degree of item popularity, while checking that no further distortions are emphasized by algorithmic bias on recommendation distributions. For instance, guaranteeing a certain degree of
popularity into recommendations resulted in higher user acceptance in contexts like tourism [31]. In this view, an unbiased algorithm would recommend each item proportionally to its representation in the ground-truth user preference.

We operationalize the concept of equal opportunity across items by encouraging the true positive rates of different items to be the same. Its formulation builds upon the corresponding concept from the fairness-aware machine learning domain [22]. Specifically, we define the true positive rate as the probability of being ranked within top-$k$, given the ground-truth that the item is relevant for the user in the test set. This is denoted by $p(i|k, \theta, y = 1)$, where $y = 1$ defines that items are relevant for users in the ground truth. We formalize it as follows:

$$p(i|k, \theta, y = 1) = \frac{\sum_{u \in U} \varphi(u, i|k, \theta) \times R_{test}(u, i)}{\sum_{u \in U} R_{test}(u, i)}$$ (3)

where $R_{test}(u, i) = 1$ if item $i$ is relevant for user $u$ in the ground truth. The numerator counts the number of users who consider item $i$ as relevant in the test set and are being receiving item $i$ in top-$k$. The denominator counts the number of users who consider item $i$ as relevant in the test set. Last, we compute the inverse of the Gini index across these probabilities, as follows:

$$IEO(k, \theta) = 1 - Gini \left( \{ p(i|k, \theta, y = 1) \mid \forall i \in I \} \right)$$ (4)

If there is a perfect equality of being recommended when items are known to be of interest, then $IEO = 1$. Conversely, $IEO$ decreases and gets closer to 0 when the probability of being recommended is high for only few items of interest in the test set. This is the case occurring when most of the niche items never appeared in the recommended lists, even if they are of interest (i.e., algorithmic bias emphasized the popularity phenomenon). Thus, $IEO$ will range between 0 and 1, and the greater it is, the more (the less) the popularity bias is emphasized.

While it is the responsibility of scientists to bring forth the discussion about metrics for popularity bias, and possibly to design algorithms to control them by turning parameters, it should be noted that it is ultimately up to the stakeholders to select the metrics and the trade-offs most suitable for their context.

4. Exploratory Analysis on Point- and Pair-wise Recommendation

In this section, we show that representative algorithms from two of the most widely-adopted learning-to-rank families [32], namely point-wise and pair-wise, produce biased recommendations with respect to ISP and IEO.

\footnote{While in this work we focus on an offline evaluation setting and the test set represents our ground truth, in case of online evaluation (e.g., A/B testing) \( R_{test}(u, i) = 1 \) if the user accepted the recommendation.}
4.1. Datasets

Since there is no standard benchmark framework for popularity bias assessment in recommendation, we adopt two public datasets with diverse item distribution skews (Fig. 1). This analysis treats ratings as positive feedback to indicate that users are interested in the items they rated. Being oriented to learning-to-rank contexts, our analysis and the proposed debiasing approach can be applied to rating or frequency matrices as well.

- MovieLens1M (ML1M) \[5\] contains 998,131 ratings applied to 3,705 movies by 6,040 users of the online service MovieLens. The sparsity of the user-item matrix is 0.95. Each user rated at least 20 movies.

- COCO600k (COCO) \[6\] contains 617,588 ratings applied to 30,399 courses by 37,040 learners of an online platform. The sparsity of the user-item matrix is 0.99. Each learner rated at least 10 courses.

4.2. Recommendation Algorithms and Protocols

We consider four different methods, and investigate the recommendations they generate. Two of them are baseline recommenders (Random and MostPop) with opposite behavior with respect to item popularity: Random is insensitive to popularity and uniformly recommends items, while MostPop ignores tail items, and suggests the same few popular items to everyone\(^3\). The other two algorithms NeuMF \[34\] and BPR \[35\] belong to the point-wise and the pair-wise family, respectively. They were chosen due to their performance and wide adoption as a key block of several point- and pair-wise methods \[36, 37, 38\]. Our approach makes it easy to re-run our analyses on additional algorithms.

Point-wise approaches generally estimate model parameters \(\theta\) by minimizing the margin between the relevance \(f(u, i|\theta)\) predicted for an observed item \(i\) and the true relevance \(y = R(u, i)\), given interactions in \(R\):

\[
\begin{align*}
\argmin_{\theta} \sum_{u \in U, i \in I_u^+} f_{acc}((u, i), y|\theta) &= \sum_{u \in U, i \in I_u^+} f(u, i|\theta) - y^2 + ||\theta||^2
\end{align*}
\]

(5)

where \(I_u^+\) is the set of items of interest for \(u\). Conversely, pair-wise approaches estimate parameters \(\theta\) by maximizing the margin between the relevance \(f(u, i|\theta)\) predicted for an observed item \(i\) and the relevance \(f(u, j|\theta)\) predicted for an unobserved item \(j\), given interactions in \(R\):

\[
\begin{align*}
\argmin_{\theta} \sum_{u \in U, i \in I_u^+, j \in I_u^-} f_{acc}((u, i, j)|\theta) &= \sum_{u \in U, i \in I_u^+, j \in I_u^-} f(u, j|\theta) - f(u, i|\theta) + ||\theta||^2
\end{align*}
\]

(6)

\(^3\)Even though comparing an algorithm against Random and MostPop has been previously studied \[7, 33\], there is no evidence on how the new bias metrics model their outcomes.
where $I^+_u$ and $I^-_u$ are the sets of items of interest and not of interest for $u$.

We performed a temporal train-test split with the most recent 20% of ratings per user in the test set and the remaining 80% oldest ones in the training set. Embedding matrices are initialized with values uniformly distributed in the range $[0, 1]$. Each model is served with batches of 256 samples. For NeuMF, for each user $u$, we created $t = 4$ negative samples $((u, j), 0)$ for each positive sample $((u, i), 1)$. For BPR, we created $t = 4$ triplets $(u, i, j)$ per observed item $i$; the unobserved item $j$ is randomly selected. Such parameters were tuned in order to find a balance between training effectiveness and training efficiency.

4.3. Ranking Accuracy and Beyond-Accuracy Observations

First, we evaluated the ranking accuracy, considering Normalized Discounted Cumulative Gain (NDCG) as a support metric (i.e., the higher it is, the better the ranking). Figure 2 plots the performance achieved by BPR, NeuMF, MostPop, and Random on ML1M and COCO. To test statistic significance, we used paired two-tailed Students t-tests with a p-value of 0.05.

The performance achieved by MostPop (straight orange line) on the full test set seemed to be highly competitive, especially in ML1M. This might reveal that the user-item feedback underlying the test set is unbalanced towards popular items, and it can bias evaluation metrics in favor of popular items. We thus examined an alternative experimental configuration, which considers a subset of the original test set where all items have the same amount of test feedback instances [39]. NDCG scores decreased under the latter evaluation setup for BPR (dashed green line), NeuMF (dashed red line), and MostPop (dashed orange line) over cutoff. This observation confirms that all algorithms tended to be considerate as accurate because they mostly suggest popular items.

The fact that MostPop adheres to BPR and NeuMF may imply that a recommender system optimized for ranking accuracy would not by default result in recommending sets with low popularity bias estimates. We conjecture that optimizing for accuracy, without explicitly considering popularity bias, favors the latter. Motivated by the patterns uncovered on ranking accuracy, we analyzed the bias metrics introduced in Section 3, namely Item Statistical Parity (ISP) and Item Equal Opportunity (IEO). From Figure 3, we can observe that BPR, NeuMF, and MostPop failed to achieve good levels of item statistical parity (top two plots). NeuMF and BPR’s statistical parity is significantly lower than the Random’s statistical parity, which maximizes statistical parity by default. Moreover, the results on equal opportunity (bottom two plots) point to a view with algorithms leading to low IEO. Reaching low values of IEO may uncover situations where where (i) the true positive rates for popular items is high (i.e., the recommender’s error for them is low) and (ii) the true positive rate for all the rest of unpopular items is very low or even zero.

\[^4\text{In our study, we are more interested in better understanding beyond-accuracy characteristics of algorithms, so the further accuracy improvements that can probably be achieved through hyper-parameter tuning would not substantially affect the outcomes of our analyses.}\]
Figure 2: Ranking Accuracy. Normalized Discounted Cumulative Gain (NDCG) produced by different recommenders. Straight lines (-f post-fix) indicate results on the full test set, while dashed lines (-b post-fix) represent results under a subset of the test set where all items have the same amount of feedback. The higher the NDCG is, the higher the ranking accuracy.

Figure 3: Popularity Influence. Item Statistical Parity (ISP) that encourages equal probability of being recommended across items, and Item Equal Opportunity (IEO) that encourages true positive rates of items to be equal. The higher the value, the less the popularity influence.

Observation 1. Both point- and pair-wise optimization procedures reinforce disparate statistical parity and unequal opportunities across items. Such observed inequalities are stronger for pair-wise optimization, under highly sparsed datasets, at low cutoffs.

Low ISP and IEO values reveal a high degree of bias towards popularity,
Figure 4: **Beyond-Accuracy Metrics.** Novelty computed as the inverse of the average popularity of a ranked item, and Coverage calculated as the ratio of items appearing at least once into a top-k list. The higher the metric, the more the beyond-accuracy goal is met.

which may hamper the quality of a recommendation (i.e., an algorithm might fail to learn user-item preferences for niche items, even if they are known to be of interest). Due to variable social dynamics, information cascades, and highly subjective notions, it would not be feasible to come up with a plain definition of quality. Therefore, this study explored the quality of a recommended list as a trade-off between ranking accuracy and beyond-accuracy metrics \[12\]. These qualities are of particular importance in real-life systems, since users are most likely to consider only a small set of top-k recommendations. It is therefore crucial to make sure that this set is as interesting and engaging as much as possible.\[\textsuperscript{5}\] Figure 4 depicts novelty and item coverage over ML1M and COCO, obtained by applying the formulas defined in \[12\]. Both metrics range in \([0,1]\). Higher values mean that the novelty and the coverage are higher, respectively. The novelty of an item recommended by BPR and NeuMF is generally higher than the one measured for MostPop (top plots) on both datasets, but the presented values are still far from the maximum value of 1. While it can be easily noted that the two datasets obtain very different novelty values, this does not mean that one leads to a much better performance than the higher. These re-

\[\textsuperscript{5}\] While we bring forth the discussion about such metrics, it is ultimately up to the stakeholders to select the metrics and the trade-offs most suitable for their principles and context.
sults reflect the characteristics of the data, with COCO having a much larger number of users and items (i.e., having a lot of users means that an item can be easily novel for someone). Therefore, on COCO, even a difference of 1% in novelty would become relevant, given the huge number of users it has. Similar patterns and considerations came up on item coverage for BPR and NeuMF.

**Observation 2.** The higher the item statistical parity and equal opportunity are, the newer and wider the recommendations are, especially in sparsed data. This pattern comes at the cost of a loss in accuracy that is negligible if a balanced test set is considered.

4.4. Internal Mechanics Analysis

Motivated by our findings, we next explored internal mechanics of the considered recommendation algorithms to better understand how disparate statistical parity and unequal opportunity across items are internally emphasized.

Throughout training, each algorithm optimized an objective function which would make it possible to improve the algorithm’s ability of predicting a high relevance for items known to be of interest for users in the training set. The fact that MostPop’s NDCG is close to that of BPR and NeuMF, and that a low value of IEO was achieved by the considered models, suggested to further investigate such algorithm’s ability in relation to the popularity of the observed item. Therefore, we analyzed the performance of each recommender in terms of pair-wise accuracy while predicting relevance for head- and mid-tail observed items. We randomly sampled four sets of triplets \((u, i, j)\). Each triplet in the first set included an observed short-tail item as \(i\) and an unobserved short-tail item as \(j\). Triplets in the second set relied on observed short-tail items as \(i\) and unobserved mid-tail items as \(j\). The third set included observed mid-tail items as \(i\) and unobserved short-tail items as \(j\). The fourth set had observed mid-tail items as \(i\) and unobserved mid-tail items as \(j\). Short-tail and mid-tail popularity thresholds were set up according with popularity percentiles, as reported in Figure 1. For each set, we computed the recommender’s accuracy on predicting a higher relevance for the observed item than the unobserved one.

| Observed Item | Unobserved Item | ML-1M BPR | ML-1M NeuMF | COCO BPR | COCO NeuMF |
|---------------|----------------|-----------|-------------|----------|-----------|
| Short Tail    | Any            | 0.92      | 0.93        | 0.90     | 0.96      |
| Mid Tail      | Any            | 0.72      | 0.81        | 0.76     | 0.94      |
| Short Tail    | Short Tail     | 0.86      | 0.89        | 0.84     | 0.93      |
| Short Tail    | Mid Tail       | 0.98      | 0.97        | 0.97     | 0.99      |
| Mid Tail      | Short Tail     | 0.53      | 0.71        | 0.61     | 0.89      |
| Mid Tail      | Mid Tail       | 0.89      | 0.91        | 0.91     | 0.98      |

Table 1: **Pair-wise Accuracy Gap.** Pair-wise accuracies across user-item pairs spanning diverse parts of the popularity tail. The more the cases where the relevance for the observed item is higher than the relevance for the unobserved item, the higher the pair-wise accuracy.
From Table 1, we observed that the pair-wise accuracy achieved by BPR and NeuMF strongly depends on the popularity of the related items $i$ and $j$. Specifically, recommenders failed more frequently in giving higher relevance to observed mid-tail items, especially when they were compared against unobserved short-tail items. Conversely, recommenders performed significantly better when observed short-tail items were compared against unobserved mid-tail items.

**Observation 3.** Observed mid-tail items, even when of interest, are more likely to receive less relevance with respect to short-tail items. This effect is stronger when the feedback data is less sparse.

We conjecture that this result might depend on the fact that, in presence of popularity influence, the differences in relevance scores across items can play a key role in pair-wise accuracy. Thus, Figure 5 depicts the distribution of the user-item relevance scores obtained for observed short-tail items and observed mid-tail items in the train data. For each user, we randomly sampled pairs of items, each including a short-tail item and a mid-tail item that user interacted with in the train set. Then, we computed the short-tail item and the mid-tail item relevance for user $u$, and we repeat the process along the users’ population to build two probability distributions. It can be observed that the distributions are significantly different in all the setups, and that there is a tendency of mid-tail observed items of getting lower relevance. This should be considered as an
undesired behavior of the algorithm that is under-considering observed mid-tail items regardless of the real user’s interest.

Observation 4. User-item relevance distributions over observed short-tail items and mid-tail items are significantly different. Observed short-tail items are more likely to obtain more relevance than observed mid-tail items, and thus be over-represented in top-k lists.

Most of the observations seen so far are rooted in the fact that each recommendation algorithm emphasized a direct relation between item relevance and item popularity, emerged also throughout the training procedure (Figure 6). This effect makes the recommender system less accurate when mid-tail items are considered, even when they are known to be of interest. It is interesting to ask whether minimizing such a correlation might have a positive impact on popularity debiasing and beyond-accuracy metrics, retaining ranking accuracy.

5. The Proposed Debiasing Procedure

With an understanding of some point- and pair-wise internal mechanics, we investigate how we can devise a recommender system that limit their deficiencies while generating less popular recommendations. To this end, we propose a debiasing procedure that aims at minimizing both (i) the loss function targeted by the considered recommender (e.g., Eq. 5 or 6), and (ii) the correlation between the prediction residual and the popularity of the observed item in input. Even though we relied on BPR and NeuMF along our experiments, our approach can be seamlessly applied to other algorithms from the same family.

Correlation-based regularization approaches have been proved to be empirically effective in several domains [28, 30]. Differently from prior work, the popularity debiasing task requires to relax the assumption of knowing group memberships of input samples (i.e, we target individual items regardless of their head or mid membership). Our task inspects relative differences in relevance and in popularity rather than differences in predicted labels and in group labels. Further, we do not rely on any arbitrary split between head- and mid-tail items.
Lastly, as we tackle a popularity debiasing perspective, the design choices we made lead to examine training processes and model facets so far under-explored.

Our debiasing procedure relies on pre- and in-processing operations, which extend the common data preparation and model training procedures of a recommender (Figure 7). Specifically, with minimum differences between point- and pair-wise approaches, the proposed approach includes the following steps:

**Input Sample Mining (sam).** Under a point-wise recommendation task, \( t_{neg} \) negative pairs \(((u, j), 0)\) are created for each observed user-item interaction \(((u, i), v)\). The observed interaction \(((u, i), v)\) is replicated \( t_{neg} \) times to ensure that our correlation-based regularization can work. On the other hand, a pair-wise recommender task implies that, for each user \( u \), \( t_{neg} \) triplets \((u, i, j)\) per observed user-item interaction \((u, i)\) are generated. In both cases, the unobserved item \( j \) is selected among the items less popular than \( i \) for \( t_{neg}/2 \) input sample, and among the items more popular than \( i \) for the other half of the input sample. These operations enable our regularization, as the input samples equally represent elements subjected to correlation computing. We denote the set of input samples as \( D \).

**Regularized Optimization (reg).** Input samples in \( D \) are fed into a base recommendation algorithm \( a \) in batches \( D_{batch} \subset D \) of size \( m \) to set up an iterated stochastic gradient descent. Regardless of the family of the algorithm, the optimization approach follows a regularized paradigm derived from the standard point- or pair-wise optimization approach. The regularized loss function can be formalized as follows:

\[
\arg\min_\theta (1 - \lambda) f_{acc}(D_{batch}|\theta) + \lambda f_{reg}(D_{batch}|\theta)
\]

where \( \lambda \in [0, 1] \) is a parameter that expresses the trade-off between the accuracy loss and the regularization loss. With \( \lambda = 0 \), we yield the accuracy loss, not taking the regularization loss into account. Conversely, with \( \lambda = 1 \), the accuracy loss is discarded and only the regularization loss is minimized.

The accuracy loss term \( f_{acc(.)} \) depends on the class of the involved recommender system. For instance, it could be either Eq. [3] for point-wise recommenders or Eq. [4] for pair-wise recommenders. This aspect will make our debiasing procedure easily applicable to other algorithms, with no changes on
their original implementation. Lastly, $f_{\text{reg}}(\cdot)$ is introduced in this paper to define a regularization loss aimed at minimizing the correlation between (i) the residual prediction and (ii) the observed item popularity, as:

$$f_{\text{reg}}(D_{\text{batch}}|\theta) = |\text{Corr}(A_1, A_2)|$$

(8)

where $\text{Corr}$ indicates the function used to compute the correlation across two distributions $A_1$ (predicted residuals) and $A_2$ (observed item popularities):

$$A_1(b) = f_{\text{acc}}(D_{\text{batch}}(b)|\theta) \quad 0 \leq b < |D_{\text{batch}}|$$

(9)

and:

$$A_2(b) = \frac{1}{|U|} \sum_{u \in U} \min(R(u, D_{\text{batch}}(b), 1)) \quad 0 \leq b < |D_{\text{batch}}|$$

(10)

where $D_{\text{batch}}(b)$ identifies the observed item $i$ at position $b$ into the current batch $D_{\text{batch}}$, and $\sum_{u \in U} R(u, D_{\text{batch}}(b), 1)$ represents the ratio of users interested in item $i$ in the training dataset, i.e., the popularity of the observed item. The model is thus penalized if its ability to predict a higher relevance for an observed item is better when it is more popular than the unobserved item. The proposed regularization is defined in a way that it can be applied on a wide range of rating prediction and learning-to-rank approaches.

Following a common machine-learning training procedure, operations in $\text{sam}$ are performed after every epoch, while the regularized optimization in $\text{reg}$ is computed for every batch of the current epoch, until convergence.

6. Experimental Evaluation

In this section, we empirically evaluate the proposed approach over standard accuracy, beyond-accuracy, and popularity debiasing objectives. We conducted the evaluation under the same experimental setup described for the exploratory analysis, including the same datasets (Section 4.1), train-test protocols (Section 4.2), and metrics (Section 4.3). We aim to answer four key research questions:

- RQ1. What are the effects of our debiasing components, separately and jointly?
- RQ2. What is the impact of our treatment on internal mechanics?
- RQ3. To what degree of debiasing can an algorithm achieve the best recommendation quality?
- RQ4. How does our approach perform compared with other state-of-the-art debiasing solutions?
6.1. Effects of Debiasing Components (RQ1)

In this subsection, we run ablation experiments to assess (i) the influence of the new data sampling strategy and the new regularized loss on the model performance, and (ii) whether combining these two treatments can improve the trade-off between ranking accuracy and popularity bias metrics.

To answer these questions, we compare the base algorithm (base) against an instance of the same algorithm trained on data created through the proposed sampling strategy only (sam), the base algorithm optimized through the proposed regularized loss function only (reg), and the base algorithm combining both our treatments (sam+reg). The regularized optimization for the last two setup was configured with $\lambda = 0.2$, which gave us the best trade-off during experiments in Section 6.3. The results are presented and discussed below.

From Figure 8, we can observe that all the newly introduced configurations (green, orange, and red lines) have a loss in accuracy with respect to the base algorithm (blue line), if we considered the full test set (straight lines). However, the gap in accuracy among the base and the regularized models is positively reduced, when we consider the same number of test ratings for all the items (dashed lines). We argue that, as large gaps of recommendation accuracy in the full test set reflect only a spurious bias in the metric and the underlying test set

![Figure 8: Impact on Ranking Accuracy. Normalized Discounted Cumulative Gain (NDCG) produced by different recommenders. The base label indicates the original recommender, sam and reg refer to applying our treatment steps individually, an sam+reg combines both treatments. Straight lines indicate results on the full test set, while dashed lines represent results under a subset of the test set where all items have the same amount of feedback.](image-url)
Figure 9: **Popularity Bias Debiasing.** Item Statistical Parity (ISP) and Item Equal Opportunity (IEO) produced by treated recommenders. The base label indicates the original recommender, sam and reg apply our treatment steps individually, and sam+reg combines both treatments. Straight lines indicate results on the full test set, while dashed lines represent results under a subset of the test set where all items have the same amount of feedback.
The real impact of our treatments on accuracy should be considered on the balanced test set. In the latter case, there is a negligible gap in accuracy across models. NDCG seems to vary across datasets. On ML1M, with NeuMF, combining our data sampling and regularized loss slightly improves accuracy, while when the treatment are applied separately, there is no significant difference with respect to the base algorithm. On COCO, the loss in accuracy is smaller, with reg outperforming \texttt{sam+reg}, under NeuMF.

Figure 9 shows that our data sampling (\texttt{sam}: orange line) and our combination of data sampling and regularized loss (\texttt{sam+reg}: red line) positively impact ISP and IEO metrics, while our regularized loss alone (\texttt{reg}: green line) still keeps comparable bias with respect to the original algorithm (base: blue line). Furthermore, there is no statistical difference on ISP between \texttt{sam} (orange line) and \texttt{sam+reg} (red line). It follows that the regularized loss does not allow to increase ISP, directly. On other other hand, \texttt{sam+reg} can significantly increase IEO with respect to \texttt{sam}, better equalizing opportunities across items.

**Observation 5.** Combining our data sampling and regularization leads to higher ISP and IEO w.r.t. applying them separately. The loss in ranking accuracy is negligible with respect to the original algorithm, if a balanced test set across items is considered.

### 6.2. Impact on Internal Mechanics (RQ2)

In this subsection, we run ablation experiments on ML1M and COCO to assess whether our debiasing approach can effectively reduce (\textit{i}) the gap between short-tail and mid-tail relevance distributions, and (\textit{ii}) the gap in pair-wise accuracy among short-tail and mid-tail items.

To address the first point, we compute and plot the relevance score distributions for observed head-tail and mid-tail items in Figure 10. Orange lines are calculated on user-(head-tail-item) pairs, and the green lines are calculated on user-(mid-tail-item) pairs, with the same procedure followed during the exploratory analysis (Section 4.3). The proposed approach can effectively reduce the gap between the relevance score distributions, when compared with the results in Fig. 5. It follows that our intuition and the resulting debiasing approach have been demonstrated to be valid.

For the second point, we compute the pair-wise accuracy for observed short-tail and mid-tail items in Table 2. The (mid-tail, short-tail) setup experienced a statistically significant improvement in pair-wise accuracy. Conversely, as far as mid-tail items end up to be well-performing, pair-wise accuracy on the setups involving observed short-tail items slightly decreased. The improvement is generally higher for pair-wise (BPR) and less sparse datasets (ML1M). To assess the impact of our approach in cases where the algorithm does not show any biased performance across short- and mid-tail items, we included NeuMF trained on COCO into our evaluation (last column). In this situation, our approach led to a decrease in performance over all the observed/unobserved items setups. Therefore, it should be applied only when the gap is considerable.
Figure 10: **Internal Mechanics Debiasing**. Short-tail item and the mid-tail item relevance for users in ML1M and COCO after applying our sam-reg approach. The distributions are based on relevance scores over randomly-sampled pairs of items, including a short-tail item and a mid-tail item that user interacted with in the train set.

| Observed Item | Unobserved Item | BPR ML-1M | NeuMF ML-1M | BPR COCO | NeuMF COCO |
|---------------|----------------|----------|-------------|----------|-------------|
| Short Tail    | Any            | 0.88 (+0.04) | 0.91 (+0.04) | 0.92 (+0.02) | 0.84 (+0.14) |
| Mid Tail      | Any            | 0.78 (+0.04) | 0.85 (+0.01) | 0.89 (+0.06) | 0.82 (+0.14) |
| Short Tail    | Short Tail     | 0.77 (-0.11) | 0.87 (-0.05) | 0.89 (-0.06) | 0.85 (-0.11) |
| Short Tail    | Mid Tail       | 0.93 (-0.06) | 0.95 (-0.04) | 0.95 (-0.04) | 0.83 (-0.16) |
| Mid Tail      | Short Tail     | 0.68 (+0.10) | 0.80 (+0.06) | 0.82 (+0.13) | 0.82 (+0.10) |
| Mid Tail      | Mid Tail       | 0.89 (-0.02) | 0.90 (-0.04) | 0.94 (-0.04) | 0.81 (-0.18) |

Table 2: **Pair-wise Accuracy Debiasing**. Pair-wise accuracies across user-item pairs spanning different parts of the popularity spectrum, after applying our sam+reg approach. The more the cases where the relevance for the observed item is higher than the relevance for the unobserved item, the higher the pair-wise accuracy. Numbers between brackets indicate the difference in percentage-points with respect to the accuracy of the original algorithm.

**Observation 6.** Our correlation-based regularization, jointly with the enhanced data sampling, leads to a reduction of the gap in relevance score of items along the popularity tail. This is stronger for pair-wise approaches and sparsed datasets.

6.3. **Linking Regularization Weight and Recommendation Qualities (RQ3)**

We investigate how the recommender performs when we vary the regularization weight $\lambda$ in the new proposed loss function. With this experiment, we
seek to inspect to what degree the influence of popularity may be debiased to achieve the best quality of recommendation, according to ranking accuracy and beyond-accuracy objectives. For conciseness, we only report experimental results on ML1M, but results on COCO showed similar patterns.

We vary the regularizer weight $\lambda$ and plot the results on accuracy, popularity bias, and beyond-accuracy metrics in Figure 11. The x-axis coordinates indicate the value of $\lambda$, while the y-axis shows the value measured for the corresponding metric at that value of $\lambda$. It can be observed that the regularization procedure experienced quite stable performance at various $\lambda \geq 2$. Specifically, at the cost of a loss in NDCG on a full test set, our approach ensures comparable or even

![Figure 11: Degree of Debiasing. Normalized Discounted Cumulative Gain (NDCG), Item Statistical Parity (ISP), Item Equal Opportunity (IEO), Novelty, and Coverage obtained by BPR and NeuMF in ML1M at various varying $\lambda$.](image-url)
better NDCG values on the balanced test set, large gains in ISP and IEO, higher novelty and a more wider coverage of the catalog. Exception is made for catalog coverage under BPR. To balance ranking accuracy and other metrics, setting $\alpha = 0.2$ is a reasonable choice.

**Observation 7.** Debiasing popularity with our approach positively impacts on recommendation quality. Lower ISP and IEO, higher novelty, and a wider coverage are achieved at the cost of a small loss in NDCG, if the approach is evaluated on a balanced test set.

6.4. Comparison with Other Debiasing Approaches (RQ4)

We next compare the proposed sam+reg debiasing approach with representative state-of-the-art alternatives to assess (i) how the proposed model performs in comparison with other approaches, and (ii) how they manage the trade-off between popularity bias and recommendation quality. We highlight the fact that we do not aim to show that an in-processing procedure beats a post-processing procedure (or vice versa), also because they could be jointly combined. Our goal here is to assess how far an in-processing strategy is from a post-processing strategy to reach good trade-offs. We leave the joint employment of both pre- and post-processing as future work, to focus on the validation of our approach. We compare the trade-off achieved by the proposed regularized approach sam+reg against the one obtained by:

- **Pop-Weighted** [15]. It re-ranks the output of the original algorithm according to a weighted-based strategy. The relevance returned by the original algorithm for a given item is multiplied with a weight inversely proportional to the popularity of that item, before re-ranking.

- **Binary-xQuad** [17]. For each user, it iteratively builds the re-ranked list by balancing the contribution of the relevance score returned by original algorithm and of the diversity level related to short-tail and mid-tail item sets. It includes only the best mid-tail item it can. The split between short-tail and mid-tail was performed based on the percentiles, as shown in Figure 1.

- **Smooth-xQuad** [17]. It follows the same strategy of Binary-xQuad, but it takes into account the likelihood an item should be selected based on the ratio of items in the user profile belong to the short- and mid-tails.

To answer these questions, we report accuracy, popularity bias, and beyond-accuracy metrics for all the considered approaches in Table 3. The best performing approach per metric and algorithm is identified by a bold style. The same value of $\lambda$ is used for all the approaches to favor comparability.

From the top part of the table, it can be observed that the proposed sam+reg debiasing strategy experienced the larger loss in NDCG, when the full test set was considered. Conversely, it achieved comparable NDCG with Pop-Weighted on the balanced test set for both BPR and NeuMF. Conversely, highly sparsed datasets as COCO reduced the gap between sam+reg and the other strategies.
This may be also caused by the skewed popularity tail in COCO, where it is harder to find input samples where the observed item is less popular than the unobserved item.

Going in depth with popularity bias metrics, it can be observed that our sam+reg strategy largely improves ISP on both datasets. On ML1M, Pop-Weighted exhibited the highest bias on statistical parity. Binary- and Smooth-xQuad achieved comparable scores between each other, but lower than sam+reg. On COCO, ISP improved for NeuMF, but not for BPR. Smaller improvements of our proposal were achieved on ISP on both datasets. Similar patterns were observed for IEO, with sam+reg achieving higher values. Our proposal appeared highly competitive on both novelty and catalog coverage, especially on ML1M. This came at the cost of higher NDCG loss with the full test set. Conversely, it achieved comparable NDCG scores on the balanced test set.

| Metric               | Approach            | ML1M  | COCO  |
|----------------------|---------------------|-------|-------|
|                      |                     | BPR   | NeuMF | BPR  | NeuMF |
| NDCG F-T             | Pop-Weighted        | 0.128 | 0.098 | 0.031 | 0.019 |
|                      | Binary-xQuad        | 0.117 | 0.094 | 0.027 | 0.038 |
|                      | Smooth-xQuad        | 0.112 | 0.092 | 0.024 | 0.036 |
|                      | Sam+Reg (ours)      | 0.073 | 0.067 | 0.030 | 0.007 |
| NDCG B-T             | Pop-Weighted        | 0.012 | 0.014 | 0.007 | 0.007 |
|                      | Binary-xQuad        | 0.012 | 0.012 | 0.007 | 0.013 |
|                      | Smooth-xQuad        | 0.011 | 0.013 | 0.007 | 0.013 |
|                      | Sam+Reg (ours)      | 0.012 | 0.014 | 0.009 | 0.003 |
| ISP                  | Pop-Weighted        | 0.057 | 0.221 | 0.008 | 0.174 |
|                      | Binary-xQuad        | 0.073 | 0.213 | 0.010 | 0.069 |
|                      | Smooth-xQuad        | 0.093 | 0.215 | 0.016 | 0.041 |
|                      | Sam+Reg (ours)      | 0.132 | 0.347 | 0.017 | 0.256 |
| IEO                  | Pop-Weighted        | 0.081 | 0.203 | 0.014 | 0.041 |
|                      | Binary-xQuad        | 0.086 | 0.193 | 0.014 | 0.040 |
|                      | Smooth-xQuad        | 0.109 | 0.195 | 0.014 | 0.075 |
|                      | Sam+Reg (ours)      | 0.142 | 0.241 | 0.022 | 0.005 |
| Novelty              | Pop-Weighted        | 0.746 | 0.864 | 0.977 | 0.987 |
|                      | Binary-xQuad        | 0.776 | 0.869 | 0.981 | 0.982 |
|                      | Smooth-xQuad        | 0.806 | 0.870 | 0.014 | 0.983 |
|                      | Sam+Reg (ours)      | 0.933 | 0.924 | 0.981 | 0.995 |
| Catalog Coverage     | Pop-Weighted        | 0.316 | 0.644 | 0.105 | 0.550 |
|                      | Binary-xQuad        | 0.357 | 0.646 | 0.104 | 0.438 |
|                      | Smooth-xQuad        | 0.377 | 0.653 | 0.120 | 0.400 |
|                      | Sam+Reg (ours)      | 0.338 | 0.740 | 0.078 | 0.964 |

Table 3: Comparison between Debiasing Approaches. Ranking accuracy on the full test set (NDCG F-T) and on the balanced test set (NDCG B-T), item statistical parity (ISP), item equal opportunity (IEO), novelty, and catalog coverage of popularity-debiasing approaches.
6.5. Discussion

In this section, we aim at discussing the results and connecting the insights coming from the individual experiments. Having observed some differences in performance, we also turn to the implications and limitations of our results.

The increasing adoption of recommender systems is requiring platform owners to consider issues of bias in their internal mechanics, which may represent a key factor for the future success of the overlying platform. The outcomes of our exploratory analysis in Section 4.3 highlighted that two widely-adopted classes of algorithm, point-wise and pair-wise, emphasize algorithmic bias towards unpopular items; thus, the latter ones end up to be under-recommended even when of interest, reducing novelty and coverage in recommendations. The results presented on two fundamental optimization paradigms, which constitute a key block of several state-of-the-art recommenders, can have implications beyond the algorithms presented in this study.

Our results provide more evidence on the popularity perspective in recommendation, which primarily focused on popularity bias on traditional algorithms in the contexts of movies, music, books, social network, hotels, games, and research articles [33, 40, 7, 11, 42]. We extended existing knowledge by linking observations within internal mechanics to the level of popularity bias experienced by the recommender, uncovering a clear correlation between item relevance and item probability (Section 4.4). The methodology and the lessons learned throughout our exploration may provide one of the first attempts of linking internal mechanics to popularity bias and beyond-accuracy metrics.

Combining our input sample strategy with the correlation-based loss resulted in lower popularity bias at the cost of a decrease in ranking accuracy, which confirms the trade-off experienced by other debiasing procedures [17, 17, 7]. However, trading ranking accuracy for debiasing popularity has been proved to be good for improving recommendation quality (Section 6.3). This study additionally brings forth the discussion about popularity debiasing impacts on beyond-accuracy goals, which can better guide stakeholders to ultimately select the trade-offs based on their context, going beyond ranking accuracy and popularity analysis. Lastly, as the algorithms we analyzed in Section 6.4 showed very different trade-offs and patterns, our comparison among debiasing procedures make a first first in supporting stakeholders while choosing the most suitable debiasing strategy for their recommendation scenario.

Throughout this study, some limitations emerged at different levels of the pipeline. The most representative ones are related to the following aspects:

- **Limitations of data.** Our analysis was conducted with feedback extracted from the provided ratings. It does not account for the behaviour of users who interacted with items, without necessarily providing ratings for them. However, as we deal with learning-to-rank tasks, the debiasing approach can be applied to the cases where matrix does not include ratings (e.g., binary data or frequencies). Learning-to-rank tasks usually require to define what it is of interest for the user or what it is not of interest (e.g., applying thresholds.
to ratings or frequencies). Our approach does not make any assumption on the feedback type, which is a design choice of the algorithm under consideration.

- **Limitations of recommendation techniques.** While we have tested representatives of two key families of recommendation algorithms, there are many types of algorithms that we have not considered. However, our methodology makes it easy to re-run our analyses on additional algorithms. Our experiments highlighted that the proposed debiasing works well under pair-wise optimization, while it leads to lower gains on point-wise approaches. Finally, as we focused on learning-to-rank tasks in recommendation, we conclude that our debiasing procedure can be still applied on algorithms originally devised for rating prediction, when they are optimized for ranking accuracy.

- **Limitations of evaluation protocol.** Our data cannot distinguish whether the differences in measured performance are due to actual differences in the recommenders ability or differences in the evaluation protocols effectiveness at measuring popularity bias. Furthermore, there is no evidence on the real impact of the debiased recommendation on the user acceptance, which requires online evaluation studies, after offline algorithm testing.

- **Limitations of metrics.** There are many widely-used metrics that can be used to evaluate quality of recommendations. In our specific context, we focus our results on popularity, novelty, and coverage. We also measured NDCG as a proxy of recommendation utility. We remark that, while it is responsibility of scientists to operationalize trade-offs, the metrics and the target level of a trade-off are selected by the stakeholders.

As this study aims to promote, the scope of our debiasing procedure incorporates elements of beyond-accuracy importance, which can be shaped by adjusting the popularity of the recommendations. As recommender systems move further into platforms, it becomes more and more necessary that they investigate and consider strategies similar to ours.

### 7. Conclusions

In this paper, we first propose two new bias metrics designed specifically for measuring popularity bias in the recommendation task. Then, we empirically show that representative learning-to-rank algorithms based on point- and pair-wise optimization are vulnerable to imbalanced item data, and tend to generate biased recommendations with respect to the proposed bias metrics. To counteract this bias, we propose a debiasing approach that incorporates a new data sampling strategy and a new regularized loss. Finally, we conduct extensive experiments to measure the trade-off between popularity bias, ranking accuracy, and beyond-accuracy metrics. Based on results, we conclude that:

1. Predicted user-item relevance distributions for observed short- and mid-tail items are statistically different; the first one exhibits higher relevance values.
2. Pair-wise accuracy on observed mid-tail items is lower than for observed short-tail items; mid-tail items are under-ranked regardless of user interest.

3. The combination of our sampling strategy and our regularized loss leads to a lower gap in pair-wise accuracy between short- and mid-tail observed items; higher statistical parity, equal opportunity, and beyond-accuracy estimates can be achieved by the treated recommender system.

4. The treated models exhibit comparable accuracy against the original model, when the same number of test ratings is used for each item, which has been proved to be a proper testing setup when popularity bias is considered [39].

5. Compared to state-of-the-art alternatives, our treated model comparably reduces popularity bias while achieving competing beyond-accuracy scores and accuracy, generalizing well across populations and domains.

In our next steps, we are interested in investigating temporal- and relevance-aware bias metrics, which respectively take the item popularity or relevance at a given time into account, when treating popularity bias. It will be investigated the possibility of defining one-time post-processing mitigators, that optimize accuracy-only pre-trained embeddings for popularity bias reduction, at small learning rates. Moreover, we are interested in inspecting the inter-play between system-level and user-level tendency of preferring more (less) popular items and in linking the resulting observations to beyond-accuracy objectives.

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