Deconfounded Recommendation for Alleviating Bias Amplification

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\section*{ABSTRACT}
Recommender systems usually amplify the biases in the data. The model learned from historical interactions with imbalanced item distribution will amplify the imbalance by over-recommending items from the major groups. Addressing this issue is essential for a healthy ecosystem of recommendation in the long run. Existing works apply bias control to the ranking targets (e.g., calibration, fairness, and diversity), but ignore the true reason for bias amplification and trade off the recommendation accuracy.

In this work, we scrutinize the cause-effect factors for bias amplification, identifying the main reason lies in the confounder effect of imbalanced item distribution on user representation and prediction score. The existence of such confounder pushes us to go beyond merely modeling the conditional probability and embrace the causal modeling for recommendation. Towards this end, we propose a \textit{Deconfounded Recommender System} (DecRS), which models the causal effect of user representation on the prediction score. The key to eliminating the impact of the confounder lies in backdoor adjustment, which is however difficult to due to the infinite sample space of the confounder. For this challenge, we contribute an approximation operator for backdoor adjustment which can be easily plugged into most recommender models. Lastly, we devise an inference strategy to dynamically regulate backdoor adjustment according to user status. We instantiate DecRS on two representative models FM \cite{29} and NFM \cite{16}, and conduct extensive experiments over two benchmarks to validate the superiority of our proposed DecRS.

\section*{CCS CONCEPTS}
\textbullet \ Information systems \rightarrow \ Recommender systems; Collaborative filtering.

\section*{KEYWORDS}
Deconfounded Recommendation, User Interest Imbalance, Bias Amplification

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\section*{1 INTRODUCTION}
Recommender System (RS) has been widely used to achieve personalized recommendation in most online services, such as social networks and advertising \cite{39}. Its default choice is to learn user interest from historical interactions (e.g., clicks and purchases), which typically exhibit data bias, i.e., the distribution over item groups (e.g., the genre of movies) is imbalanced. Consequently, recommender models face the bias amplification issue \cite{32}: over-recommending the majority group and amplifying the imbalance. Figure 1(a) illustrates this issue with an example in movie recommendation, where 70\% of the movies watched by a user are action movies, but action movies take 90\% of the recommendation slots. Undoubtedly, over-emphasizing the items from the majority groups will limit a user’s view and decrease the effectiveness of recommendations. Worse still, due to feedback loop \cite{7}, such bias amplification will intensify with time, causing more issues like filter bubbles \cite{22} and echo chambers \cite{14}.

Existing works alleviate bias amplification by introducing bias control into the ranking objective of recommender models, which are mainly from three perspectives: 1) fairness \cite{21,31}, which pursues equal exposure opportunities for items of different groups; 2) diversity \cite{6}, which intentionally increases the covered groups in a recommendation list, and 3) calibration \cite{32}, which encourages the distribution of recommended item groups to follow that of interacted items of the user. However, these methods alleviate bias amplification at the cost of sacrificing recommendation accuracy \cite{31,32}. More importantly, the fundamental question is not answered: what is the root reason for bias amplification?

After inspecting the cause-effect factors in recommender modeling, we attribute bias amplification to a confounder \cite{25}. The historical distribution of a user over item groups (e.g., [0.7, 0.3] in Figure 1(a)) is a confounder between the user’s representation and the prediction score. In the conventional RS, the user/item features (e.g., ID and attributes) are first embedded into the representation vectors, which are then fed into an interaction module (e.g., factorization machines (FM) \cite{29}) to calculate the prediction score for the user-item pair \cite{17}. In other words, recommender models estimate the conditional probability of clicks given user/item representations. From a causal view, user and item representations can be regarded as the causes of the prediction score, and the interaction module should encode the causal relations between them \cite{25}. But inspecting the causal relations, we find that the
hidden confounder, i.e., the user historical distribution over item groups, affects both the user representation and the prediction score. Due to the modeling of conditional probability, recommender models are affected by the confounder and thus suffer from a spurious correlation between the user and the prediction score. That is, given two item groups, the one that the user interacted more in the history will receive higher prediction scores, even though their items have the same ratings (e.g., ratings = 4), the ones in the majority group will receive higher prediction scores. Therefore, the items in the majority group, even including those undesirable or low-quality ones (see example in Figure 1(c)), could deprive the recommendation opportunities of the items in the minority group.

The key to addressing bias amplification lies in eliminating the spurious correlation in the recommender modeling. To achieve this goal, we need to push the conventional RS to go beyond modeling the conditional probability and embrace the causal modeling of user representation on the prediction score. We propose a novel Deconfounded Recommender System (DecRS), which explicitly models the causal relations during training, and leverages backdoor adjustment [25] to eliminate the impact of the confounder. However, the sample space of the confounder is huge, making the traditional adjustment [25] to eliminate the impact of the confounder. However, the sample space of the confounder is huge, making the traditional implementation of backdoor adjustment infeasible. To this end, we derive an approximation of backdoor adjustment, which is followed by the introduction of the proposed DecRS.

2 METHODOLOGY
In this section, we first analyze the conventional RS from a causal view and explain the reason for bias amplification, which is followed by the introduction of the proposed DecRS.

2.1 A Causal View on Bias Amplification
To study bias amplification, we build up a causal graph to explicitly analyze the causal relations in the conventional RS.

2.1.1 Causal Graph. We scrutinize the causal relations in recommender models and abstract a causal graph, as shown in Figure 2(a), which consists of five variables: \( U, I, D, M, \) and \( Y \). Note that we use the capital letter (e.g., \( U \)), lowercase letter (e.g., \( u \)), and letter in the calligraphic font (e.g., \( U \)) to represent a variable, its particular value, and its sample space, respectively. In particular, • \( U \) denotes user representation. For one user, \( u = \{u_1, \ldots, u_K\} \) represents the embeddings of \( K \) user features (e.g., ID, gender, and age) [29], where \( u_k \in \mathbb{R}^H \) is one feature embedding.
• \( I \) is item representation and each \( i \) denotes the embeddings of several item features (e.g., ID and genre) which are similar to \( u \).
• \( D \) represents the user historical distribution over item groups. Groups can be decided by item attributes or similarity [32]. Given \( N \) item groups \( \{g_1, \ldots, g_N\}, \) \( d_u = \{p_u(g_1), \ldots, p_u(g_N)\} \in \mathbb{R}^N \) is a particular value of \( D \) when the user is \( u \), where \( p_u(g_i) \) is the click frequency of user \( u \) over group \( g_i \) in the history. For instance, for the user \( u \) in Figure 1(a), \( d_u = [0.7, 0.3] \) if \( N = 2 \).
• \( M \) is the group-level user representation. A particular value \( m \in \mathbb{R}^H \) is a vector which describes how much the user likes different item groups. \( m \) can be obtained from the values of \( U \) and \( D \). That is, \( M \) is deterministic if \( U \) and \( D \) are given so that we can represent \( m \) by a function \( M(d, u) \) with \( d \) and \( u \) as inputs. To keep generality, we incorporate \( M \) into the causal graph because many recommender models (e.g., FM) have modeled the user preference over item groups explicitly or implicitly by using the group-related features (e.g., movie genre).
• \( Y \) with \( y \in [0, 1] \) is the prediction score for the user-item pair.

The edges in the graph describe the causal relations between variables, e.g., \( U \rightarrow Y \) means that \( U \) has a direct causal effect [25] on \( Y \), i.e., changes on \( U \) will affect the value of \( Y \). In particular,
2.1.2 Conventional RS. Due to the confounder, existing recommender models that estimate the conditional probability $P(Y|U, I)$ face the spurious correlation, which leads to bias amplification. From Eq. (1d), we can find that $d_u$ does not only affect the user representation $u$ but also affects $Y$ via $M(d_u, u)$, causing the spurious correlation: given the item $i$ in a group $g_n$, the more items in group $g_n$ the user $u$ has clicked in the history, the higher the prediction score $Y$ becomes. In other words, the high prediction scores are caused by the users’ historical interest in the group instead of the items themselves. From the perspective of model prediction, $d_u$ affects $u$, which makes $u$ favor the majority group. In Eq. (1d), a higher click frequency $p_u(g_n)$ in $d_u$ will make $M(d_u, u)$ represent a strong interest in group $g_n$, increasing the prediction scores of items in group $g_n$ via $P(Y|u, i, M(d_u, u))$. As such, the items in the majority group, even including the low-quality ones, are easy to have high prediction scores due to the effect of the confounder $D$. They occupy the recommendation opportunities of items in the minority group, and thus bias amplification happens.

The spurious correlation is harmful for most users because the items in the majority group are likely to dominate the recommendation list and narrow down the user interest. Besides, the undesirable and low-quality items in the majority group will dissatisfy users, leading to poor recommendation accuracy. Worse still, by analyzing Eq. (1d), we have a new observation: the prediction score $Y$ heavily relies on the user historical distribution over item groups, i.e., $d_u$. Once users’ future interest in item groups changes (i.e., user interest drift), the recommendations will be dissatisfying. For instance, as shown in Figure 3(a), the user interest in item groups is not stable, and thus the correlation caused by the confounder $D$ will not be reliable if the distribution $d_u$ is inconsistent between training and testing data.

2.2 Deconfounded Recommender System

To resolve the impact of the confounder, DecRS estimates the causal effect of user representation on the prediction score. Experimentally, the target can be achieved by collecting intervened data where the user representation is forcibly adjusted to eliminate the impact of confounder. However, such an experiment is too costly to achieve in large-scale and faces the risk of hurting user experience in practice. DecRS thus resorts to the causal technique: backdoor adjustment [25, 26, 41], which enables the estimation of causal effect from the observational data.

2.2.1 Backdoor Adjustment. According to the theory of backdoor adjustment [25], the target of DecRS is formulated as: $P(Y|do(U = u), I = i)$ where $do(U = u)$ can be intuitively seen as cutting off the edge $D \rightarrow U$ in the causal graph and blocking the effect of $D$ on $U$ (cf. Figure 2(b)). We then derive the specific expression of backdoor adjustment. Formally,

$$
P(Y|do(U = u), I = i) = \sum_{d \in D} P(d)P(Y|do(U = u), i, M(d, do(U = u)))$$ (2a)

$$= \sum_{d \in D} P(d)P(Y|do(U = u), i, M(d, do(U = u)))$$ (2b)

where the derivation of Eq. (2a) is the same as Eq. (1c), which follows the law of total probability and Bayes rule. Besides, Eq. (2b) and Eq. (2c) are obtained by two do calculus rules: insertion/deletion of actions and action/observation exchange in Theorem 3.4.1 of [25].
As compared to Eq. 1(d), DecRS estimates the prediction score with consideration of every possible value of \( D \) subject to the prior \( P(D) \), rather than the probability of \( d \) conditioned on \( u \). Therefore, the items in the majority group will not receive high prediction scores purely because of a high click probability in \( d_u \). And thus backdoor adjustment alleviates bias amplification by removing the effect of \( D \) on \( U \).

Intuitively, as shown in Figure 3(b), \( D \) has extensive possible values in a specific dataset, i.e., users have various historical distributions over item groups. In DecRS, the prediction score \( Y \) considers various possible values of \( D \). As such, 1) inevitably, DecRS removes the dependency on \( d_u \) in Eq. 1(d) and mitigates the spurious correlation, and 2) theoretically, when user interest drift happens in the testing data, DecRS can produce a more robust and accurate prediction because the model has “seen” many different values of \( D \) during training and doesn’t heavily depend on the unreliable distribution \( d_u \) in Eq. 1(d).

2.2.2 Backdoor Adjustment Approximation. Theoretically, the sample space of \( D \) is infinite, which makes the calculation of Eq. (2c) intractable. Therefore, it is essential to derive an efficient approximation of Eq. (2c).

- **Sampling of \( D \).** To estimate the distribution of \( D \), we sample users’ historical distributions over item groups in the training data, which comprise a discrete set \( \tilde{D} \). Formally, given a user \( u \), \( d_u = [p_u(g_1), ..., p_u(g_N)] \in \tilde{D} \) and each click frequency \( p_u(g_n) \) over group \( g_n \) is calculated by

\[
p_u(g_n) = \frac{\sum_{i \in I} p(g_n | i) p(i | u)}{|H_u|},
\]

where \( I \) is the set of all items, \( H_u \) denotes the clicked item set by user \( u \), and \( q^d_{g_n} \) represents the probability of item \( i \) belonging to group \( g_n \). For instance, \( q^d = [1, 0, 0] \) with \( q^d_{g_1} = 1 \) denotes that item \( i \) only belongs to the first group. In this work, we sample \( D \) according to the user-item interactions in the training data, and thus the probability \( P(d_u) \) of user \( u \) is obtained by \( \sum_{d \in \tilde{D}} |H_u| \), where \( \tilde{H} \) represents the user set. As such, we can estimate Eq. (2c) by

\[
P(Y | do(U = u), I = i) = \sum_{d \in \tilde{D}} P(d) P(Y | u, i, M(d, u)) = \sum_{d \in \tilde{D}} P(d) f(u, i, M(d, u)),
\]

where each \( d \) is a distribution from one user, and we use a function \( f(x) \) (e.g., FM [29]) to calculate the conditional probability \( P(Y | u, i, M(d, u)) \), similar to conventional recommender models.

- **Approximation of \( \mathbb{E}_d[f(x)] \).** The expected value of function \( f(x) \) of \( d \) in Eq. 4 is hard to compute because we need to calculate the results of \( f(x) \) for each \( d \) and the possible values in \( \tilde{D} \) are extensive. A popular solution [1, 35] in statistics and machine learning theory is to make the approximation \( \mathbb{E}_d[f(x)] \approx f(u, i, M(\mathbb{E}_d[d], u)) \). Formally, the approximation takes the outer sum \( \sum_d P(d) f(x) \) into the calculation within \( f(x) \):

\[
P(Y | do(U = u), I = i) \approx f(u, i, M(\sum_{d \in \tilde{D}} P(d) f(x))).
\]

The error of the approximation \( e \) is measured by the Jensen gap [1]:

\[
e = \mathbb{E}_d[f(x)] - f(u, i, M(\mathbb{E}_d[d], u)).
\]

**Theorem 2.1.** If \( f \) is a linear function with a random variable \( X \) as the input, then \( \mathbb{E}[f(X)] = f(\mathbb{E}[X]) \) holds under any probability distribution \( P(X) \). Refer to [1, 13] for the proof.

**Theorem 2.2.** If a random variable \( X \) with the probability distribution \( P(X) \) has the expectation \( \mu \), and the non-linear function \( f : G \rightarrow \mathbb{R} \) where \( G \) is a closed subset of \( \mathbb{R} \), following:

1. \( f \) is bounded on any compact subset of \( G \);
2. \( |f(x) - f(\mu)| = O(|x - \mu|^\beta) \) for \( \mu > 0 \);
3. \( |f(x)| = O(|x|^\beta) \) as \( x \rightarrow +\infty \) for \( \beta > 0 \),

then the inequality holds: \( |\mathbb{E}[f(X)] - f(\mu)| \leq T(\rho^\beta + \rho^{\gamma}) \), where

\[
\rho^\beta = \sqrt[\gamma]{\mathbb{E}[|X - \mu|^\beta]}, \quad T = \sup_{x \in G} (\mu f(x) - f(x)/|x - \mu|^\beta),
\]

and \( \rho^\gamma \) does not depend on \( P(X) \). The proof can be found in [13].

From Theorem 2.1, we know that the error \( e \) in Eq. 6 is zero if \( f(x) \) is in Eq. 5 is a linear function. However, most existing recommender models use non-linear functions to increase the representation capacity. In these cases, there is an upper bound of \( e \) which can be estimated by Theorem 2.2. It can be proven that the common non-linear functions in recommender models (e.g., sigmoid in [29]) satisfy the conditions in Theorem 2.2, and the upper bound is small, especially when the distribution of \( D \) concentrates around its expectation [13].

2.3 Backdoor Adjustment Operator

To facilitate the usage of DecRS, we design the operator to instantiate backdoor adjustment, which can be easily plugged into recommender models to alleviate bias amplification. From Eq. 5, we can find that in addition to \( u \) and \( i \), \( f(x) \) takes \( M(d, u) \) as the model input where \( d = \sum_{d \in \tilde{D}} P(d) f(x) \). That is, if we can implement \( M(d, u) \), existing recommender models can take it as one additional input to achieve backdoor adjustment.

Recall that \( M \) denotes the group-level user representation which describes the user preference over item groups. Given \( d = [p(g_1), ..., p(g_N)] \), item group representation \( q = [q_1, ..., q_N] \), and user representation \( u = [u_1, ..., u_K] \) with feature values \( x_u = \)
As mentioned before, DecRS alleviates bias amplification and will change it easily in future. And thus backdoor over item groups in the history, we assume that he/she has diverse item ranking. If the user is easy to change the interest distribution over item groups in the history, we divide the historical interaction sequence of user $u$ into two parts according to the timestamps. For each part, we calculate the historical distribution over item groups by Eq. 3, obtaining $\bar{d}^1_u = [p^1_u(q_1), \ldots, p^1_u(q_N)]$ and $\bar{d}^2_u = [p^2_u(q_1), \ldots, p^2_u(q_N)]$. Then, the distance between these two distributions is measured by the symmetric KL divergence:

$$
\eta_u = KL(\bar{d}^1_u|\bar{d}^2_u) + KL(\bar{d}^2_u|\bar{d}^1_u)
$$

where $\eta_u$ denotes the distribution distance of user $u$. A higher $\eta_u$ represents that the user is easier to change the interest distribution over item groups. Here, we only divide the historical interaction sequence into two parts to reduce the computation cost. More fine-grained division can be explored in future work if necessary.

Based on the signal of $\eta_u$, we utilize an inference strategy to adaptively fuse the prediction scores from the conventional RS and DecRS. Specifically, we first train the recommender model by $P(Y|U = u, I = i)$ and $P(Y|do(U = u), I = i)$, respectively, and their prediction scores are then automatically fused to regulate the impact of backdoor adjustment. Formally,

$$
Y_{u,i} = (1 - \hat{\eta}_u) \cdot \hat{Y}^{RS}_{u,i} + \hat{\eta}_u \cdot \hat{Y}^{DE}_{u,i},
$$

where $Y_{u,i}$ is the inference score for user $u$ and item $i$, $\hat{Y}^{RS}_{u,i}$ and $\hat{Y}^{DE}_{u,i}$ are the prediction scores from the conventional RS and DecRS, respectively. In particular, $\hat{\eta}_u$ is calculated by

$$
\hat{\eta}_u = \alpha \frac{\eta_u - \eta_{min}}{\eta_{max} - \eta_{min}}
$$

where the normalized $\hat{\eta}_u \in [0, 1]$, $\eta_{min}$ and $\eta_{max}$ are the minimum and maximum symmetric KL divergence values across all users, respectively. Besides, $\alpha \in [0, \infty)$ is a hyper-parameter to further control the weights of $Y^{RS}_{u,i}$ and $Y^{DE}_{u,i}$ by human intervention. Specifically, $\eta_u$ becomes larger if $\alpha \rightarrow 0$ due to $\hat{\eta}_u \in [0, 1]$ which makes $Y^{DE}_{u,i}$ favor $Y^{RS}_{u,i}$, and $\eta_u$ decreases if $\alpha \rightarrow \infty$.

From Eq. 11, we can find that the inference for the users with high $\hat{\eta}_u$ will rely more on $\hat{Y}^{DE}_{u,i}$. That is, $\eta_u$ automatically adjusts the balance between $\hat{Y}^{RS}_{u,i}$ and $\hat{Y}^{DE}_{u,i}$. Besides, we can regulate the impact of backdoor adjustment by tuning the hyper-parameter $\alpha$ in Eq. 12 for different datasets or recommender models. Theoretically, $\alpha$ is usually close to 0 because mitigating the spurious correlation improves the recommendation accuracy for most users. To summarize, the proposed DecRS has three main differences from the conventional RS:

- DecRS models the causal effect $P(Y|do(U = u), I = i)$ instead of the conditional probability $P(Y|U = u, I = i)$.
- DecRS equips the recommender models with a backdoor adjustment operator (e.g., Equation 7).
- DecRS makes recommendations with a user-specific inference strategy instead of the simple model prediction (e.g., a forward propagation).
3 RELATED WORK

In this work, we explore how to alleviate bias amplification of recommender models by causal inference, which is highly related to fairness, diversity, and causal recommendation.

**Negative Effect of Bias Amplification.** Due to the existence of feedback loop [7], bias amplification will become increasingly serious. Consequently, it will result in many negative issues: 1) narrowing down the user interest gradually, which is similar to the effect of filter bubbles [22]. Worse still, the issue might evolve into echo chambers [14], in which users’ imbalanced interest is further reinforced by the repeated exposure to similar items; 2) low-quality items that users dislike might be recommended purely because they are in the majority group, which deprive the recommendation opportunities of other high-quality items, causing low recommendation accuracy and unfairness.

**Fairness in Recommendation.** With the increasing attention on the fairness of machine learning algorithms [19], many works explore the definitions of fairness in recommendation and information retrieval [20, 24, 27]. Generally speaking, they have two categories: individual fairness and group fairness. Individual fairness denotes that similar individuals (e.g., users or items) should receive similar treatments (e.g., exposure or clicks), such as amortized equity of attention [3]. Besides, group fairness indicates that all groups are supposed to be treated fairly where individuals are divided into groups according to the protected attributes (e.g., item category and user gender) [46]. The particular definitions span from discounted cumulative fairness [44], fairness of exposure [31], to multi-sided fairness [5].

Another representative direction in fairness to reduce bias amplification is calibrated recommendation [32]. It re-ranks the items to make the distribution of the recommended items follow the proportion in the browsing history. For example, if a user has watched 70% action movies and 30% romance movies, the recommendation list is expected to have the same proportion of movies. Although the fairness-related works, including calibrated recommendation, may alleviate bias amplification well, they are making the trade-off between ranking accuracy and fairness [21, 31, 32]. The reason possibly lies in that they neglect the true cause of bias amplification.

**Diversity in Recommendation.** Diversity is regarded as one essential direction to get users out of filter bubbles in the information filtering systems [32]. As to recommendation, diversity pursues the dissimilarity of the recommended items [8, 33], where similarity can be measured by many factors, such as item category and embeddings [6]. However, most works might recommend many dissatisfying items when making diverse recommendations. For example, the recommender model may trade off the accuracy to reduce the intra-list similarity by re-ranking [47].

**Causal Recommendation.** Causal inference has been widely used in many machine learning applications, spanning from computer vision [23, 34], natural language processing [11, 12, 43], to information retrieval [4]. In recommendation, most works on causal inference [25] focus on debiasing various biases in user feedback, including position bias [18], clickbait issue [37], and popularity bias [45]. The most representative idea in the existing works is Inverse Propensity Scoring (IPS) [2, 28, 41], which first estimates the propensity score based on some assumptions, and then uses the inverse propensity score to re-weight the samples. For instance, Saito et al. estimated the exposure propensity for each user-item pair, and re-weighted the samples via IPS to solve the miss-not-at-random problem [30]. However, IPS methods heavily rely on the accurate propensity estimation, and usually suffer from the high propensity variance. Thus it is often followed by the propensity clipping technique [2, 30]. Another line of causal recommendation studies the effect of taking recommendations as treatments on user/system behaviors [48], which is totally different from our work because we focus on the causal relations within the models.

4 EXPERIMENTS

We conduct extensive experiments to demonstrate the effectiveness of our DecRS by investigating the following research questions:

- **RQ1:** How does the proposed DecRS perform across different users in terms of recommendation accuracy?
- **RQ2:** How does DecRS perform to alleviate bias amplification, compared to the state-of-the-art methods?
- **RQ3:** How do the different components affect the performance of DecRS, such as the inference strategy and the implementation of function $M(\cdot)$?

4.1 Experimental Settings

**Datasets.** We use two benchmark datasets, ML-1M and Amazon-Book, in different real-world scenarios. 1) ML-1M is a movie recommendation dataset, which involves rich user/item features, such as user gender, and movie genre. We partition the items into groups according to the movie genre. 2) Amazon-Book is one of the Amazon product datasets, where the book items can be divided into groups based on the book category (e.g., sports). To ensure data quality, we adopt the 20-core settings, i.e., discarding the users and items with less than 20 interactions. We summarize the statistics in Table 2.

| Dataset | #Users | #Items | #Interactions | #Features | #Group |
|---------|--------|--------|---------------|-----------|--------|
| ML-1M   | 13,408 | 29,115 | 1,712,409     | 19,408    | 18     |
| Amazon-Book | 9,883 | 8,040 | 375,276 | 16,845 | 6,040 |

In this table, we use two benchmark datasets, ML-1M and Amazon-Book, in different real-world scenarios. 1) ML-1M is a movie recommendation dataset, which involves rich user/item features, such as user gender, and movie genre. We partition the items into groups according to the movie genre. 2) Amazon-Book is one of the Amazon product datasets, where the book items can be divided into groups based on the book category (e.g., sports). To ensure data quality, we adopt the 20-core settings, i.e., discarding the users and items with less than 20 interactions. We summarize the statistics of datasets in Table 2.

For each dataset, we sort the user-item interactions by the timestamps, and split them into the training, validation, and testing subsets with the ratio of 80%, 10%, and 10%. For each interaction with the rating $\geq 4$, we treat it as a positive instance. During training, we adopt the negative sampling strategy to randomly sample one item that the user did not interact with before as a negative instance.

**Baselines.** As our proposed DecRS is model-agnostic, we instantiate it on two representative recommender models, FM [29] and NFM [16], to alleviate bias amplification and boost the predictive performance. We compare DecRS with the state-of-the-art methods that might alleviate bias amplification of FM and NFM backbone models. In particular,

- **Unawareness** [15, 19] removes the features of item groups (e.g., movie genre in ML-1M) from the input of item representation $I$.  

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1https://grouplens.org/datasets/movielens/1m/.
2https://jmcauley.ucsd.edu/data/amazon/.
Table 3: Overall performance comparison between DecRS and the baselines on ML-1M and Amazon-Book. %improv. denotes the relative performance improvement achieved by DecRS over FM or NFM. The best results are highlighted in bold.

| Method        | ML-1M | Amazon-Book |       |       |       |       |       |       |       |       |       |
|---------------|-------|-------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|               | R@10  | R@20        | N@10  | N@20  | R@10  | R@20        | N@10  | N@20  | R@10  | R@20        | N@10  | N@20  |
| FM            |       |             |       |       |       |             |       |       |       |             |       |       |
| Unawareness   | 0.0676| 0.1162 | 0.0566 | 0.0715| 0.0213| 0.0370 | 0.0154 | 0.0187| 0.0659| 0.1135 | 0.0551 | 0.0697 |
|               |       |             |       |       |       |             |       |       |       |             |       |       |
| FairCo        | 0.0679| 0.1179 | 0.0575 | 0.0730| 0.0216| 0.0377 | 0.0138 | 0.0191| 0.0648| 0.1143 | 0.0556 | 0.0708 |
|               |       |             |       |       |       |             |       |       |       |             |       |       |
| Calibration   | 0.0676| 0.1165 | 0.0570 | 0.0720| 0.0212| 0.0370 | 0.0135 | 0.0188| 0.0651| 0.1152 | 0.0554 | 0.0708 |
| Diversity     | 0.0647| 0.1149 | 0.0539 | 0.0695| 0.0202| 0.0359 | 0.0129 | 0.0181| 0.0636| 0.1131 | 0.0526 | 0.0682 |
| IPS           | 0.0670| 0.1159 | 0.0555 | 0.0706| 0.0207| 0.0369 | 0.0131 | 0.0185| 0.0641| 0.1133 | 0.0540 | 0.0693 |
| DecRS         | 0.0663| 0.1188 | 0.0556 | 0.0718| 0.0213| 0.0369 | 0.0135 | 0.0187| 0.0648| 0.1135 | 0.0544 | 0.0692 |
| %improv.      | 4.14% | 5.94%      | 2.12% | 3.08%| 8.45% | 9.46%      | 10.45%| 9.63%| 5.31% | 7.31%      | 5.26% | 6.46% |
|               |       |             |       |       |       |             |       |       |       |             |       |       |
| FM/DecRS      |       |             |       |       |       |             |       |       |       |             |       |       |
|               |       |             |       |       |       |             |       |       |       |             |       |       |
| NFM           |       |             |       |       |       |             |       |       |       |             |       |       |
|               |       |             |       |       |       |             |       |       |       |             |       |       |
| NFM/DecRS     |       |             |       |       |       |             |       |       |       |             |       |       |

Table 4: Performance comparison across different user groups on ML-1M and Amazon-Book. Each line denotes the performance over the user group with $\eta_u >$ the threshold. We omit the results of threshold $> 4$ due to the similar trend.

| Method | ML-1M | Amazon-Book |       |       |
|--------|-------|-------------|-------|-------|
|        | R@20  | R@20        | N@20  | N@20  |
| FM     |       |             |       |       |
|        |       |             |       |       |
| NFM    |       |             |       |       |
|        |       |             |       |       |

- **FairCo** [21] introduces one error term to control the exposure fairness across item groups. In this work, we calculate the error term based on the ranking list sorted by relevance, and its coefficient $\lambda$ in the ranking target is tuned in $\{0.01, 0.02, ... , 0.5\}$.
- **Calibration** [32] is one state-of-the-art method to alleviate bias amplification. Specifically, it proposes a calibration metric $C_{KL}$ to measure the imbalance between the history and recommendation list, and minimizes $C_{KL}$ by re-ranking. Here the hyper-parameter $\lambda$ in the ranking target is searched in $\{0.01, 0.02, ... , 0.5\}$.
- **Diversity** [47] aims to decrease the intra-list similarity, where the diversification factor is tuned in $\{0.01, 0.02, ... , 0.2\}$.
- **IPS** [30] is a classical method in causal recommendation. Here we use $P(d_u)$ as the propensity of user $u$ to down-weight the items in the majority group during debiasing training, and we employ the propensity clipping technique [30] to reduce propensity variance, where the clipping threshold is searched in $\{2, 3, ... , 10\}$.

**Evaluation Metrics.** We evaluate the performance of all methods from two perspectives: recommendation accuracy and effectiveness of alleviating bias amplification. In terms of accuracy, two widely-used metrics [40], Recall@K (R@K) and NDCG@K (N@K), are adopted under all ranking protocol [36, 39], which test the top-K recommendations over all items that users never interact with in the training data. As to alleviating bias amplification, we use the representative calibration metric $C_{KL}$ [32], which quantifies the distribution drift over item groups between the history and the new recommendation list (computed by the top-20 items). Higher $C_{KL}$ scores suggest a more serious issue of bias amplification.

**Parameter Settings.** We implement our DecRS in the PyTorch implementation of FM and NFM. Closely following the original papers [16, 29], we use the following settings: in FM and NFM, the embedding size of user/item features is 64, log loss [17] is applied and the optimizer is set as Adagrad [9]; in NFM, a 64-dimension fully-connected layer is used. We adopt a grid search to tune their hyperparameters: the learning rate is searched in $\{0.001, 0.01, 0.05\}$; the batch size is tuned in $\{512, 1024, 2048\}$; the normalization coefficient is searched in $\{0, 0.1, 0.2\}$, and the dropout ratio is confirmed in $\{0.2, 0.3, ... , 0.5\}$. Besides, $\alpha$ in the proposed inference strategy is tuned in $\{0.1, 0.2, ... , 10\}$, and the model performs the best in $\{0.2, 0.3, 0.4\}$, where $\alpha$ is close to 0, proving the advantages of our DecRS over the conventional RS as discussed in Section 2.4. We use Eq. 8 to implement $M(d, u)$ and the backbone models take $M(d, u)$ as one additional feature. The exploration of the late-fusion manner is left to future work because it is not our main contribution. Furthermore, we use the early stopping strategy [38, 42] — stop training if R@10 on the validation set does not increase for 10 successive epochs. For all approaches, we tune the hyper-parameters to choose the best models w.r.t. R@10 on the validation set, and report the results on the testing set. We released code and data at https://github.com/WenjieWJ/DecRS.
4.2 Performance Comparison (RQ1 & RQ2)

4.2.1 Overall Performance w.r.t. Accuracy. We present the empirical results of all baselines and DecRS in Table 3. Moreover, to further analyze the characteristics of DecRS, we split users into groups based on the symmetric KL divergence (cf. Eq. 10) and report the performance comparison over the user groups in Table 4. From the two tables, we have the following findings:

- Unawareness and FairCo only achieve comparable performance or marginal improvements over the vanilla FM and NFM on the two datasets. Possible reasons are the trade-offs among different user groups. To be more specific, for some users, discarding group features or preserving group fairness is able to reduce bias amplification and recommend more satisfying items. However, for most users with imbalanced interest in item groups, these approaches possibly recommend many disappointing items by pursuing group fairness.
- Calibration and Diversity perform worse than the vanilla backbone models, suggesting that simple re-ranking does hurt the recommendation accuracy. This is consistent with the findings in [32, 47]. Moreover, we ascribe the inferior performance of IPS to the inaccurate estimation and high variance of propensity scores. That is, the propensity cannot precisely estimate the effect of $D$ on $U$, even if the propensity clipping technique [30] is applied.
- DecRS effectively improves the recommendation performance of FM and NFM on the two datasets. As shown in Table 3, the relative improvements of DecRS over FM w.r.t. R@20 are 5.94% and 9.46% on ML-1M and Amazon-Book, respectively. This verifies the effectiveness of backdoor adjustment, which enables DecRS to remove the effect of confounder for many users. As a result, many less-interested or low-quality items from the majority group will not be recommended, thus increasing the accuracy.
- As Table 4 shows, with the increase of $\eta_u$, the performance gap between DecRS and the backbone models becomes larger. For example, in the user group with $\eta_u > 4$, the relative improvements w.r.t. N@20 over FM and NFM are 23.87% and 28.97%, respectively. We attribute such improvements to the robust recommendation produced by DecRS. Specifically, DecRS equipped with backdoor adjustment is superior in reducing the spurious correlation and predicting users’ diverse interest, especially for the users with the interest drift (i.e., high $\eta_u$).

4.2.2 Performance on Alleviating Bias Amplification. In Figure 4, we present the performance comparison w.r.t. $C_{KL}$ between the vanilla FM/NFM, calibrated recommendation, and DecRS on ML-1M. Due to space limitation, we omit other baselines that perform worse than calibrated recommendation and the results on Amazon-Book which have similar trends. We have the following observations from Figure 4. 1) As compared to the vanilla models, calibrated recommendation achieves lower $C_{KL}$ scores, suggesting that the bias amplification is reduced. However, it comes at the cost of lower recommendation accuracy, as shown in Table 3. 2) Our DecRS consistently achieves lower $C_{KL}$ scores than calibrated recommendation across all user groups. More importantly, DecRS does not hurt the recommendation accuracy. This evidently shows that DecRS solves the bias amplification problem well by embracing causal modeling for recommendation, and justifies the effectiveness of backdoor adjustment on reducing spurious correlations.

![Figure 4: The performance comparison between the base-lines and DecRS on alleviating bias amplification.](image)

![Figure 5: Ablation study of DecRS on ML-1M.](image)

### Table 5: Effect of the design of $M(\cdot)$.

| Method   | R@10  | R@20  | N@10  | N@20  |
|----------|-------|-------|-------|-------|
| FM       | 0.076 | 0.116 | 0.056 | 0.071 |
| DecRS-EP | 0.068 | 0.120 | 0.057 | 0.073 |
| DecRS-FM | 0.070 | 0.123 | 0.058 | 0.073 |

4.3 In-depth Analysis (RQ3)

4.3.1 Effect of the Inference Strategy. We first answer the question: Is it of importance to conduct the inference strategy for DecRS? Towards this end, one variant “DecRS (w/o)” is constructed by disabling the inference strategy and only using the prediction $y^{DE}$ in Eq. 11 for inference. We illustrate its results in Figure 5 with the following key findings. 1) The performance of “DecRS (w/o)” drops as compared with that of DecRS, indicating the effectiveness of the inference strategy. 2) “DecRS (w/o)” still outperforms FM and NFM consistently, especially over the users with high $\eta_u$. This suggests the superiority of DecRS over the conventional RS. It achieves more accurate predictions of user interest by mitigating the effect of the confounder via backdoor adjustment approximation.

4.3.2 Effect of the Implementation of $M(\cdot)$. As mentioned in Section 2.3, we can implement the function $M(\cdot)$ by either Eq. 7 or Eq. 8. We investigate the influence of different implementations and construct two variants, DecRS-EP and DecRS-FM, which employ the element-wise product in Eq. 7 and the FM module in Eq. 8, respectively. We summarize their performance comparison over FM on ML-1M in Table 5. While being inferior to DecRS-FM, DecRS-EP still performs better than FM. This proves the superiority of DecRS-FM over DecRS-EP, and also shows that DecRS with different implementations still surpasses the vanilla backbone models, which further suggests the stability and effectiveness of DecRS.
5 CONCLUSION AND FUTURE WORK

In this work, we explained that bias amplification in recommender models is caused by the confounder from a causal view. To alleviate bias amplification, we proposed a novel DecRS with an approximation operator for backdoor adjustment. DecRS explicitly models the causal relations in recommender models, and leverages backdoor adjustment to remove the spurious correlation caused by the confounder. Besides, we developed an inference strategy to regulate the impact of backdoor adjustment. Extensive experiments validate the effectiveness of DecRS on alleviating bias amplification and improving recommendation accuracy.

This work takes the first step to incorporate backdoor adjustment into existing recommender models. In future, there are many research directions that deserve our attention. 1) The discovery of more fine-grained causal relations in recommendation models. This work starts to mitigate the spurious correlations caused by the confounder while recommendation is an extremely complex scenario, involving many observed/hidden variables that are waiting for causal discovery. 2) The proposed DecRS has the potential to reduce various biases in information retrieval and recommendation, such as position bias and popularity bias. The causes of the biases are also related to the imbalanced training data. 3) Bias amplification is one essential cause of the filter bubble [22] and echo chambers [14]. The effect of DecRS on mitigating these issues can be studied in future work.

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