Unbiased Implicit Feedback via Bi-level Optimization

Can Chen¹, Chen Ma², Xi Chen³, Sirui Song¹, Hao Liu⁴ and Xue Liu⁴

¹ McGill University ² City University of Hong Kong ³ Huawei Noah’s Ark Lab ⁴ The Hong Kong University of Science and Technology (Guangzhou)

{can.chen, sirui.song}@mail.mcgill.ca, chenma@cityu.edu.hk, xi.chen11@mcgill.ca, liuh@ust.hk, xueliu@cs.mcgill.ca

Abstract

Implicit feedback is widely leveraged in recommender systems since it is easy to collect and provides weak supervision signals. Recent works reveal a huge gap between the implicit feedback and user-item relevance due to the fact that implicit feedback is also closely related to the item exposure. To bridge this gap, existing approaches explicitly model the exposure and propose unbiased estimators to improve the relevance. Unfortunately, these unbiased estimators suffer from the high gradient variance, especially for long-tail items, leading to inaccurate gradient updates and degraded model performance. To tackle this challenge, we propose a low-variance unbiased estimator from a probabilistic perspective, which effectively bounds the variance of the gradient. Unlike previous works which either estimate the exposure via heuristic-based strategies or use a large biased training set, we propose to estimate the exposure via an unbiased small-scale validation set. Specifically, we first parameterize the user-item exposure by incorporating both user and item information, and then construct an unbiased validation set from the biased training set. By leveraging the unbiased validation set, we adopt bi-level optimization to automatically update exposure-related parameters along with recommendation model parameters during the learning. Experiments on two real-world datasets and two semi-synthetic datasets verify the effectiveness of our method.

1 INTRODUCTION

Recent years have witnessed the fast development of the recommender system. It has been successfully deployed in many web services like E-commerce and social media. Learning from historical interactions, a recommender system can predict the relevance or preference between users and items. Based on which, the system recommends items that the user may prefer. To enable these, there are two types of feedback: explicit feedback and implicit feedback. Explicit feedback can be the ratings on items that explicitly represent the preferences of the users. However, the collection of explicit feedback requires the user active participation, which makes explicit feedback unavailable in most real-world scenarios. Compared with explicit feedback, implicit feedback such as clicks is widely used because of its ubiquity and wide availability. Though easier to collect, implicit feedback is one-sided and positive only [Yang et al., 2018], which means the recommender can only observe the users’ interactions with relevant items. A missing link between a user and an item can either be that the user dislikes the item or that the item is not exposed to the user [Liang et al., 2016b].

Many important works have tried to improve recommendation performances in implicit feedback by explicitly modeling the user-item exposure. For example, [Yang et al., 2018] find implicit feedback subject to popularity bias, and propose an unbiased evaluator based on the Inverse-Propensity-Scoring (IPS) technique [Joachims and Swaminathan, 2016], which significantly reduces the evaluation bias. Exposure matrix factorization (ExpoMF) [Liang et al., 2016b] introduce exposure variables to build a probabilistic model, and consider external information when estimating exposure. Yet, [Saito et al., 2020] find that ExpoMF is biased towards popular items and yields unsatisfied results for rare items. Based on IPS, [Saito et al., 2020] propose an unbiased estimator to maximize the user-item relevance. In [Saito et al., 2020], both the user-item relevance and the user-item exposure are modeled as Bernoulli random variables, and the click probability is the product of exposure probability and relevance probability. [Saito et al., 2020] better achieve the objective of the unbiased recommendations than alternatives [Liang et al., 2016b; Hu et al., 2008]. Using the same unbiased estimator in [Saito et al., 2020], [Zhu et al., 2020] propose a combinational joint learning framework to more accurately estimate exposure.

However, we find [Saito et al., 2020][Zhu et al., 2020] suffers from the high gradient variance problem. Inaccurate gradient updates occur in the learning process, which degrades the model performance. Moreover, these existing approaches [Hu et al., 2008][Yang et al., 2018][Saito et al., 2020][Zhu et al., 2020] adopt some simple heuristic-based strategies or only leverage the biased training set to estimate exposure, which inevitably leads to a biased recommendation model.

To tackle the high gradient variance problem, we develop a low-variance estimator from a probabilistic perspective. To better estimate exposure, we model exposure by incorporating both user and item information and construct a small
amount of unbiased validation set to guide exposure estimation. Specifically, with the unbiased set, we introduce bi-level optimization [Colson et al., 2007] with exposure parameters as the outer variable and relevance parameters as the inner variable, to update exposure parameters automatically. Overall, we propose **UBO (Unbiased Implicit Feedback via Bi-level Optimization)** to update exposure parameters simultaneously with relevance parameters. We further analyze the inner mechanism of bi-level optimization in UBO and compare bi-level optimization with other optimization methods. We verify the effectiveness of UBO on both real-world and semi-synthetic datasets.

To summarize, our work has three contributions:

1. We propose a low-variance unbiased estimator which effectively bound gradient variance.
2. We connect exposure estimation to both user and item information and introduce bi-level optimization to update exposure parameters by leveraging an unbiased set.
3. Furthermore, we give a natural interpretation of why bi-level optimization works by gradient analysis, and compare it with other optimization methods to better understand its necessity.

## 2 METHOD

In this section, we begin by introducing some preliminaries including notations and the previous unbiased estimator. Then we show the high gradient variance problem and derive our low-variance unbiased estimator from a probabilistic perspective. Further, we parameterize the user-item exposure by considering both user and item information and propose to use a small unbiased validation set to guide exposure estimation via bi-level optimization.

### 2.1 Preliminaries

**Notations.** Assume we have an implicit feedback dataset $D$ with $N$ users indexed by $u$ and $M$ items indexed by $i$. Let $R_{ui}$ denote the observed feedback between $u$ and $i$. $R_{ui} = 1$ indicates positive feedback, while $R_{ui} = 0$ indicates either positive unlabeled feedback or negative feedback.

To precisely formulate implicit feedback, [Saito et al., 2020] introduces two kinds of Bernoulli random variables $R_{ui}$ and $O_{ui}$. $R_{ui}$ represents the user-item relevance between $u$ and $i$ with $\gamma_{ui}$ as the Bernoulli parameter. $R_{ui} = 1$ means $u$ and $i$ are relevant, and $R_{ui} = 0$ means $u$ and $i$ are not relevant. Similarly, $O_{ui}$ represents the user-item exposure between $u$ and $i$ with $m_{ui}$ as the Bernoulli parameter. $O_{ui} = 1$ means $i$ is exposed to $u$, and vice versa. We denote $\tilde{m}_{ui}$ as the estimated exposure between $u$ and $i$ in the following paper. Note that both $R_{ui}$ and $O_{ui}$ can not be observed in implicit feedback.

\[ \tilde{R}_{ui} = R_{ui}O_{ui} \]  

(1)

The Bernoulli parameter of $\tilde{R}_{ui}$ can be written as:

\[ P(\tilde{R}_{ui} = 1) = m_{ui}\gamma_{ui} \]  

(2)

From Eq (1), we can see that a positive feedback $R_{ui} = 1$ means that $i$ is exposed to $u$ and $u$ likes $i$.

The task of the implicit recommendation system is to provide an ordered set of items for users based on the predicted user-item relevance. We use $p_{ui} = p(\tilde{R}_{ui} = 1|\omega)$ to represent the predicted user-item relevance where the relevance parameters $\omega$ include the user embedding $\omega_u$ and the item embedding $\omega_i$. Since matrix factorization is the most widely used technique [Koren et al., 2009] in the recommender system, in this paper we compute the predicted user-item relevance as:

\[ p_{ui} = \sigma(\omega_u^T\omega_i) \]  

(3)

where $\sigma(\cdot)$ represents the sigmoid function. Note that UBO can also be easily applied on other neural network based models [He et al., 2017][Wang et al., 2019a].

**Unbiased Estimator.** [Saito et al., 2020] find the top-k recommendation metrics such as the mean average precision [Yang et al., 2018] can not directly signify relevance, and thus are not proper to measure recommendation results. To optimize the performance metric of relevance, [Saito et al., 2020] propose an unbiased estimator from the IPS technique, and the log loss form can be written as:

\[ L_1(\omega) = -\sum_{(u,i)\in D} \tilde{R}_{ui} \log p_{ui} + (1 - \tilde{R}_{ui}) \log(1 - p_{ui}) \]  

(4)

Once we have the expectation of $L_1(\omega)$, we will find the optimal solution for $p_{ui}$ is $\gamma_{ui}$ given an accurate exposure estimation $\tilde{m}_{ui} = m_{ui}$. This proves this estimator unbiased. In this paper, we mainly consider the log loss form since it is the most widely used form. Other loss forms such as the mean squared loss can be analyzed similarly.

### 2.2 Proposed Unbiased Estimator

**High gradient variance.** The gradient of $L_1(\omega)$ to $p_{ui}$ is:

\[ \frac{\partial L_1(\omega)}{\partial p_{ui}} = -\frac{\tilde{R}_{ui}}{\tilde{m}_{ui}} \frac{1}{p_{ui} + \frac{1}{1 - p_{ui}}} - \frac{1}{1 - p_{ui}} \]  

(5)

The variance of $\frac{\partial L_1(\omega)}{\partial p_{ui}}$ can be calculated by:

\[ V\left(\frac{\partial L_1(\omega)}{\partial p_{ui}}\right) = \frac{\gamma_{ui}(1 - \tilde{m}_{ui}\gamma_{ui})}{\tilde{m}_{ui}p_{ui}(1 - p_{ui})^2} \]  

(6)

For rare items, $\tilde{m}_{ui}$ can be very small so that $V\left(\frac{\partial L_1(\omega)}{\partial p_{ui}}\right)$ becomes unbounded. This problem leads to inaccurate gradient updates and decreases the model performance.

**Low-variance unbiased estimator.** Instead of deriving from the IPS technique, which leads to the high gradient variance problem, we propose a low-variance unbiased estimator from a probabilistic view. To be specific, we first write the cross-entropy loss as:

\[ L(\omega) = -\sum_{(u,i)\in D} \tilde{R}_{ui} \log p(\tilde{R}_{ui} = 1|\omega) \]  

+ $(1 - \tilde{R}_{ui}) \log p(\tilde{R}_{ui} = 0|\omega)$  

(7)

Recall that we are caring about the user-item relevance prediction $p_{ui}$. From the probabilistic perspective, we have:

\[ p(\tilde{R}_{ui} = 1|\omega) = \tilde{m}_{ui}p_{ui} \]  

(8)

\[ p(\tilde{R}_{ui} = 0|\omega) = 1 - \tilde{m}_{ui}p_{ui} \]  

(9)
Our estimator is defined as:
\[
L_2(\omega) = -\sum_{(u,i) \in D} \hat{R}_{ui} \log(\hat{m}_{ui} p_{ui}) + (1 - \hat{R}_{ui}) \log(1 - \hat{m}_{ui} p_{ui})
\] \hfill (10)

After computing the expectation of \(L_2(\omega)\), we can easily find the optimal solution for \(p_{ui}\) as also \(\gamma_{ui}\) given an accurate exposure estimation \(\hat{m}_{ui} = m_{ui}\). This proves our estimator unbiased (See Appendix A for details). Besides, our unbiased estimator yields better gradient properties for rare items. The variance of \(\frac{\partial L_2(\omega)}{\partial p_{ui}}\) is calculated as:
\[
V(\frac{\partial L_2(\omega)}{\partial p_{ui}}) = \frac{\hat{m}_{ui} \gamma_{ui} (1 - \hat{m}_{ui} \gamma_{ui})}{p_{ui} (1 - \hat{m}_{ui} p_{ui})^2}
\] \hfill (11)

\(V(\frac{\partial L_2(\omega)}{\partial p_{ui}})\) stays bounded as \(\hat{m}_{ui}\) becomes small, and thus this estimator yields stable gradient updates. We don’t consider the possible high gradient variance problem on \(p_{ui} = 0\) or \(p_{ui} = 1\) since this occurs in both estimators. Our estimator only solves high gradient variance problems related to \(m_{ui}\).

2.3 Exposure Estimation

Exposure Modeling

It is not realistic to assign every \(O_{ui}\) entry a learnable parameter to represent the user-item exposure due to the space limit, so we need a distributed representation for all \(O_{ui}\) entries. In this paper, we parameterize the user-item exposure \(m_{ui}\) with one MLP (multi-layer perceptron) and \(N\) user-wise embeddings and connect exposure estimation with both user and item information. On one hand, \(m_{ui}\) is large if the item is popular, which means we should consider the item popularity when estimating \(m_{ui}\). Note that the popularity [He et al., 2016] of the item \(i\) can be approximated as:
\[
\theta_i = \left(\frac{\sum_u \hat{R}_{ui}}{\max_u \sum_u \hat{R}_{ui}}\right)^{0.5}
\] \hfill (12)

On the other hand, \(m_{ui}\) becomes large if the item is exposed to the user often or the user is active, which means we should also consider the impact of the user. We introduce a new user-wise embedding \(e_u\) and use \(\sigma(e_u^T \omega_i)\) to represent the user’s impact. Note that the introduced user embedding \(e_u\) can be learned directly through external user information [Liang et al., 2016b], whereas, in this paper, we assume we do not have the external information, which is more general. To sum up:
\[
m_{ui}(u, i, \omega) = r(\omega_i)\sigma(e_u^T \omega_i) + (1 - r(\omega_i))\theta_i
\] \hfill (13)

Here \(r(\cdot)\) learns the trade-off between the impact of the user and the popularity of the item, and we use one layer MLP followed by a sigmoid function to parameterize \(r(\cdot)\). We use \(\alpha\) to denote exposure parameters, which include the introduced user embeddings and the MLP parameters in \(r\). For convenience, we still use \(\hat{m}_{ui}\) instead of \(m_{ui}(u, i, \omega)\) to represent the estimated exposure in the following paper.

Bi-level Optimization

Previous work [Hu et al., 2008; Yang et al., 2018; Saito et al., 2020; Zhu et al., 2020] adopt some simple heuristics or only use the biased training set to estimate exposure, which inevitably results in a biased model. We propose to leverage a small unbiased validation set to guide exposure estimation via bi-level optimization. Specifically, we select the most popular positive item and negative item for each active user to form the unbiased validation set. The reason why the validation set can be treated as unbiased is that these items are very likely to be exposed to these users and we approximate \(m_{ui}\) as 1 in the validation set.

**Formulation.** We use the proposed estimator Eq (10) to calculate the training loss \(L_{\text{train}}\) and the validation loss \(L_{\text{val}}\). Given an unbiased training set, we obtain the optimal user and item embeddings \(\omega^*\) by minimizing \(L_{\text{train}}(\omega)\). Whereas, in a biased training set, different user-item pairs have different exposure. Thus for a biased training set, we need to first estimate the user-item exposure \(\hat{m}_{ui}\) parametrized by \(\alpha\). Given \(\hat{m}_{ui}\), the optimal \(\omega\) is computed as:
\[
\omega^*(\alpha) = \arg \min_{\omega} L_{\text{train}}(\omega, \alpha)
\] \hfill (14)

The exposure parameters \(\alpha\) can be seen as a special type of hyper-parameter and we update \(\alpha\) automatically by minimizing the validation loss \(L_{\text{val}}(\omega^*(\alpha))\) on the unbiased validation set. Note that \(L_{\text{val}}(\omega^*(\alpha))\) does not explicitly contain any \(\alpha\) term since the user-item exposure \(m_{ui}\) is approximated as 1 in the unbiased validation set.

Our formulation implies a bi-level optimization problem with exposure parameters \(\alpha\) as the outer variable and the model parameters \(\omega\) as the inner variable:
\[
\min_{\alpha} \quad L_{\text{val}}(\omega^*(\alpha)) \quad \text{(UBO)}
\]
\[
\text{s.t.} \quad \omega^*(\alpha) = \arg \min_{\omega} L_{\text{train}}(\omega, \alpha) \quad \text{(2UBO)}
\]

For efficiency, we use a gradient step with the learning rate \(\eta\) to approximate \(\omega^*(\alpha)\) in the inner loop:
\[
\omega^*(\alpha) \approx \omega - \eta \frac{\partial L_{\text{train}}(\omega, \alpha)}{\partial \omega}
\] \hfill (15)

Similarly, in the outer loop, we update \(\alpha\) by minimizing \(L_{\text{val}}(\omega^*(\alpha))\) via a gradient descent step with the outer loop learning rate \(\eta'\).

**Interpretation by gradient analysis.** By analyzing gradients, we give a natural interpretation of bi-level optimization in UBO. In the validation set, assume \(u\) likes \(i_1\) and dislikes \(i_2\) (\(i_1 \neq i_2\)); \(u_1\) likes \(i\) and \(u_2\) dislikes \(i\) (\(u_1 \neq u_2\) can not be \(u\)). We first compute the gradient for \(\hat{R}_{ui} = 1\) (See Appendix B for details):
\[
\frac{\partial L_{\text{val}}'}{\partial \hat{m}_{ui}} = 0
\] \hfill (16)

This means \(\hat{m}_{ui}\) will not be updated explicitly for the positive feedback. Denote \(\omega^*_u \omega_i\) as \(\hat{R}_{ui}\) and then we compute the gradient for \(\hat{R}_{ui} = 0\) (See Appendix C for details):
\[
\frac{\partial L_{\text{val}}'}{\partial m_{ui}} = \frac{\eta \sigma(\hat{R}_{ui}) \sigma(-\hat{R}_{ui})}{(1 - \hat{m}_{ui} \sigma(\hat{R}_{ui}))^2} [\omega_{i2}^T \omega_i \sigma(-\hat{R}_{ui2}) - \omega_{i2}^T \omega_i \sigma(-\hat{R}_{ui1})] \quad \text{where } \hat{R}_{ui2} = 0 \quad \text{and } \hat{R}_{ui1} = 1
\] \hfill (17)
Datasets

3.1 Experimental Setup

Coat and Yahoo are the only two public datasets that contain users’ ratings for randomly selected items, and we use the two datasets to measure the true recommendation performance of UBO and the comparison methods. See [Saito et al., 2020] for dataset details. Both datasets use the following preprocessing procedure. Suggested by [Yang et al., 2018], we treat ratings ≥ 4 as positive feedback and others as negative feedback. We first select the most popular negative item and the most popular positive item for the most active 20% users to form the validation set, which can be approximated as unbiased since the items are very likely to be exposed to the users. Besides, we select 10% data from the training set to form a hyper-validation set to tune hyperparameters.

Comparison methods

We mainly compare UBO with the following methods:

- RelMF [Saito et al., 2020] adopts an unbiased estimator and uses the item popularity to approximate exposure.
- ExpoMF [Liang et al., 2016b] introduces exposure variables to build a probabilistic model and estimates exposure via the Expectation-Maximization algorithm.
- CJMF [Zhu et al., 2020] leverages different parts of the training dataset to jointly train multiple models for exposure estimation.
- BPR [Rendle et al., 2012] is the most widely used algorithm for the top-N recommenders in implicit feedback.
- UMF uses the same exposure estimation as that in RelMF but adopts our unbiased low-variance estimator.

Evaluation protocols

Suggested by [Saito et al., 2020], we report the DCG@K (Discounted Cumulative Gain) and MAP@K (Mean Average Precision) to evaluate the ranking performance of all methods. We set K=1,2,3 in our experiments since the number of exposed items in the test set is small: Yahoo has 10 items and Coat has 16 items.

Training details

We use Pytorch to implement UBO and optimize it with Adam. We set the learning rate as 10^{-3}, the hidden dim as 50, the batch size as 1024, the training epoch as 100 for all methods on all datasets unless otherwise specified. For other hyperparameters such as weight decay, we tune them via the performance on the hyper-validation set using the SNIPS [Yang et al., 2018] estimator. We run every experiment five times and report the average. Besides, we report one standard deviation in the Appendix D.

3.2 RQ1: UBO outperforms other methods.

In this subsection, we aim to answer RQ1: Does UBO outperform other methods? Table 1 and Table 2 show the performances for all six methods including UBO on Yahoo and Coat respectively.

Firstly, we observe UBO achieves the best performance among all methods on the two datasets. This verifies the effectiveness of UBO. Secondly, UMF outperforms RelMF in DCG@3 by about 7.4% in Yahoo. This can be explained by the high gradient variance of RelMF. High gradient variance causes inaccurate gradient updates and thus reduces the recommendation performance. Note that we cannot visualize the gradient variance since the gradient variance comes from the assumption of the randomness of the dataset. A single dataset can be seen as a single data point and thus cannot compute its variance. The advantage of UMF over RelMF in Coat is smaller. The reason may be that the size of Coat is small and can not reveal the difference between UMF and RelMF.

Thirdly, UBO outperforms UMF in DCG@3 by about 4% in both datasets because UBO connects exposure estimation not only with the item information but also with the user information. See Appendix E for time complexity discussion.
3.3 RQ2: Necessity of bi-level optimization

In this subsection, we aim to answer RQ2: Is bi-level optimization necessary in our method? To better understand the necessity of bi-level optimization in UBO, we investigate two baseline strategies, where the exposure parameters and the relevance parameters are jointly optimized and alternately optimized, respectively. We denote the two baseline strategies as JointOpt and AlterOpt respectively. As we can see in Figure 1, JointOpt and AlterOpt yield similar results, and UBO outperforms both of them in DCG3 by around 3% in both datasets. The reason is that JointOpt and AlterOpt do not leverage the information of the unbiased validation set when updating the exposure parameters.

Inspired by [Ma et al., 2020], we also consider another baseline strategy of bi-level optimization. Instead of using the unbiased validation set, we treat every train batch as the validation set and perform bi-level optimization:

\[
\min_{\alpha} \quad L_{train}(\omega^*(\alpha), \alpha) \tag{1BiOpt2}
\]

s.t. \[\omega^*(\alpha) = \arg \min_{\omega} L_{train}(\omega, \alpha) \tag{2BiOpt2}\]

Note that exposure in the validation set can not be approximated as 1 anymore, so we use the estimated \( \hat{m}_{ui} \) to represent the user-item exposure. We denote this new bi-level optimization strategy as BiOpt2. BiOpt2 receives no guidance from the unbiased validation set and thus is worse than UBO. BiOpt2 improves DCG3 over JointOpt and AlterOpt, by around 3% in Yahoo and 1% in Coat. The reason may be that BiOpt2 considers the relation between \( \omega \) and \( \alpha \), which narrows down optimization space to a more reasonable one and thus improves training similar to [Ghosh and Lan, 2021].

4 SEMI-SYNTHETIC EXPERIMENTS

We further investigate the correctness of the estimated exposure of UBO on semi-synthetic datasets. Specifically, we aim to answer RQ3: Does UBO learn exposure correctly?

4.1 Datasets

To answer RQ3, we need to know ground-truth exposure parameters in the dataset. Similar to [Schnabel et al., 2016][Saito et al., 2020], we create two semi-synthetic datasets based on MovieLens (ML) 100K and Amazon CDs respectively. See Appendix F for details.

4.2 Training and Evaluation

Denote \( m_{ui} \) as the estimated exposure between \( u \) and \( i \). To measure the correlation between the estimated exposure \( \hat{m}_{ui} \) and the true exposure \( m_{ui} \), we introduce Pearson Correlation Coefficient(PCC) [Wright, 1921]. The PCC value ranges from -1 to 1. A value approximating to 1 means a strong positive linear relationship between the two variables, and a value approximating to -1 means a strong negative linear relationship. A zero value means no linear correlation between the two variables. For every user \( u \), we compute the PCC value between \( \hat{m}_{ui} \) and \( m_{ui} \) against all \( M \) items. We report the average PCC for all users.

4.3 RQ3: Does UBO learn exposure correctly?

In experiments, we find the performance of JointOpt is very similar to that of AlterOpt so we only report the results of JointOpt. We analyze the PCC value for ExpoMF, CJMF, JointOpt, and UBO since only the four methods estimate exposure during training. For Amazon, we find the exposure estimated by ExpoMF barely changed in the whole training process and the exposure updating frequency of ExpoMF is much lower. To better visualize the trend for all four methods, we only plot the PCC line for the first 100 iterations and use a straight line with the mean PCC value to represent the PCC line of ExpoMF.

Performance. In Figure 2 we observe that UBO is still the best performing method in Amazon CDs and outperforms other methods except for CJMF on ML 100k. One possible explanation is that CJMF leverage \( C = 8 \) models and one residual component simultaneously, which improves train-
The results of ExpoMF in Figure 2. The reason may be that ExpoMF forms the unbiased set from the training set, which is consistent with the unsatisfying results of ExpoMF in Figure 2. The reason may be that ExpoMF is a biased estimator [Saito et al., 2020].

Furthermore, we compare JointOpt with UBO. In Amazon CDs, the UBO line is higher than JointOpt all the time, in accordance with that UBO outperforms JointOpt in Figure 2. For ML 100k, although the PPC line of JointOpt is higher than UBO at the early training iterations, the JointOpt line experiences a gradual decrease. In real-world datasets, we do not have access to the PPC value which relies on the ground-truth exposure so we can not stop the training process early to get a good result of JointOpt. After some training iterations, the JointOpt line becomes very low in accordance with the results in Figure 2. The explanation may be that JointOpt updates exposure parameters and relevance parameters on the training set simultaneously, and thus experiences instability during training. In contrast, guided by a small unbiased validation set, UBO can enjoy a stable training process and thus estimate exposure more accurately than JointOpt.

Last but not least, we make a comparison between CJMF and UBO. In Amazon CDs, the low PPC line of CJMF in Figure 3 corresponds to the unsatisfying results in Figure 2. Yet, on ML 100k, CJMF outperforms UBO in terms of performance in Figure 2 while the PPC line of CJMF is lower than that of UBO in Figure 3. The reason may be CJMF leverages an extra residual component to improve training, which is not included in the exposure estimation process in Figure 3.

5 RELATED WORK

Many important work [Steck, 2010] [Steck, 2013] [Hernández-Lobato et al., 2014] [Wang et al., 2018] [Wang et al., 2019b] [Joachims and Swaminathan, 2016] [Wang et al., 2020] [Liang et al., 2016a] [Bonner and Vasile, 2018] [Schnabel et al., 2016] have studied the bias in the explicit rating data. For example, as the user can choose which items to rate freely, the observed ratings cannot serve as a representative sample of all ratings. Thus the biased rating data leads to challenges for both recommendation evaluation and training. To correct this bias, many methods [Wang et al., 2018] [Wang et al., 2019b] [Joachims and Swaminathan, 2016] [Wang et al., 2020] [Liang et al., 2016a] use causal inference to learn from biased data and achieve better recommendation performances.

Figure 3: (RQ3) Trend of the PCC value between the ground-truth exposure and the learned exposure for ExpoMF, CJMF, JointOpt, and UBO.

Compared with explicit feedback, implicit feedback is much easier to collect and thus plays a more important role, which renders debiasing in implicit feedback an important topic. [Yang et al., 2018] develop an unbiased offline evaluator which significantly reduces the bias toward popular items. To debias in model training, [Hu et al., 2008] [Devoogdt et al., 2015] adopt a heuristic-based strategy, where unobserved interactions are assigned with a lower weight. Furthermore, [Pan et al., 2008; Pan and Scholz, 2009] associate the weight with the user’s activity and [He et al., 2016] [Yu et al., 2017] specify the weight with the item popularity. [Gupta et al., 2021] propose to leverage known exposure probabilities to mitigate exposure bias for link prediction. From a casual perspective, [Liang et al., 2016b] directly incorporate exposure into collaborative filtering and build a probabilistic model. Based on the IPS technique, [Saito et al., 2020] propose an unbiased estimator with the item popularity as exposure estimation. For better exposure estimation, [Zhu et al., 2020] propose a combinatorial joint learning framework to solve the estimation-training overlap problem. The estimated exposure can still be biased since it only leverages biased training data. Besides, we find the unbiased estimator in [Saito et al., 2020; Zhu et al., 2020] suffers from the high gradient variance problem. In this paper, we propose an unbiased estimator with low variance from a probabilistic view. [Chen et al., 2021] leverages another set of data to debias data by solving the bi-level optimization problem. The main differences between [Chen et al., 2021] and UBO are a) UBO has a low-variance unbiased estimator while [Chen et al., 2021] does not and b) [Chen et al., 2021] requires an unbiased set in advance, while UBO forms the unbiased set from the training set, which means we can not directly compare the two methods.

6 CONCLUSION

To bridge the gap between the implicit feedback and the user-item relevance, existing approaches explicitly model the user-
item exposure while the proposed unbiased estimators suffer from high gradient variance. In this paper, we propose a low-variance unbiased estimator from a probabilistic view and this estimator effectively bounds the gradient variance. Besides, we connect exposure estimation with both user and item information and then collect an unbiased set to guide exposure estimation. By leveraging the unbiased set, we update exposure parameters and relevance parameters simultaneously via bi-level optimization. Experiments on real-world datasets and semi-synthetic datasets verify the effectiveness of UBO.

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