Exploring Exposure Bias in Recommender Systems from Causality Perspective

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***Abstract*—Exposure bias widely exists in recommender systems, particularly in the case of with implicit feedbacks. It seriously influences user's satisfaction of recommendations. There are a number of methods for mitigating the exposure bias from different perspectives. In this paper, we survey the publications that focus on addressing the exposure bias issue in RS with the help of causal inference ideas. We propose a simple taxonomy consisting of bias discovery, evaluation estimator, recommendation modeling, ranking algorithm for the debiasing methods in our study. Based on the taxonomy, we discuss how those methods are beneficial to recommender systems to mitigate the exposure bias using causal graph and propensity score. Finally, we conduct the challenges and point out the future research directions.**

Keywords-exposure bias; causal inference; implicit feedback; survey; causality; recommender system.

I. INTRODUCTION

Recommender System (RS) is a critical technique in the field of Information Retrieval and widely used in many domains. In many cases, biases appear in RS caused by different types of reasons. Researchers have studied this problem in various point of views. Causal inference is a useful tool to figure out the relationship between cause and effect. It is treated as an effect way to mitigate biases in RS. In this paper, we focus on two points: exposure bias and causal solution. We proposes a survey of the causality-inspired debiasing methods for the exposure bias problem in RS. We collect the reviewed papers that focus on causal methods for the exposure bias in RS from the important conferences and journals in recent years, such as *SIGIR*, *WWW*, *KDD*, *WSDM*, *RecSys*, and *CIKM*. This paper can be beneficial for three groups: RS researchers who specifically work on the exposure bias issue; causal inference researchers who focus on the causal inference-inspired approaches applied for RS; and machine learning researchers who are interested in debiasing methods with the causality perspective. In this paper, we make the following contributions: we summarize the characteristics of the exposure bias in RS; we propose a taxonomy for the causal debiasing methods; we discuss the future research directions in terms of causality for the exposure problem.

The rest of the paper is organized as follows. Section 2 depicts the technical background. Section 3 presents our investigation of the causal inference-inspired unbiased methods in RS. Finally, conclusion and future work are given in Section 4.

II. TECHNICAL BACKGROUND

A. Recommender System

RS [1][2] works on addressing the information overloading problem of users. It is widely applied to provide personalized services in many fields [3][4][5]. RS models user interest by analyzing the user's behaviors and item features. The work [6] proposed a cross-domain citation RS for publications regarding the specified patent. Gao et al. [7] focused on the cross-domain RS for Cyber-Physical Systems. Kumar et al. [8] showed a latent sematic-based recommendation method using topic model in distinct domains. Collaborative Filtering (CF) [9] is an effective way to find out potential interesting items by mining the co-occurrence of users' behaviors. The model-based CF learns complex behavior patterns with machine learning [10], such as Bayesian Belief Network CF [11] and clustering CF [12].

B. Explicit and Implicit Feedback

In RS, user behavior basically presents the user action with item, as well as interactions among users. The user interaction is treated as feedback when a system shows recommendations to a user and she gives responses. Feedback can be categorized into two groups: explicit feedback and implicit feedback. Explicit feedback usually means the user's rating behavior for items, which explicitly indicates the user interest. Implicit feedback [13] is the interaction that is indirectly related to the user interest, such as click, view, and purchase. With implicit feedback, it cannot directly observe the user's opinion.

C. Bias and Exposure Bias in Recommendation

Biases widely exist in quite a lot machine learning methods [14][15][16]. There exist certain kinds of biases in different stages of RS, which seriously influences the recommendation, particularly the model-based recommendation. Thus, debiasing methods are largely developed in the recent research work. Chen et al. [17] summarize a feedback loop framework describing the relations among user interaction, data and model in RS. In the loop, it introduces types of biases, such as popularity bias [18], exposure bias [19], selection bias [20], conformity bias [21], position bias [22], and inductive bias [23]. This abstraction illustrates the generation mechanism of bias in RS.

Exposure bias in RS is mostly caused by implicit feedback. With implicit feedback, it is hard to distinguish the situations of either the user does not like an item or the user is not exposed to the item. The unclicked-action cannot be clearly understood because it may represent either negative feedback or unlabeled positive feedback. The exposure bias will lead negative influences in training phase and evaluation phase in RS.

D. Missing Data

The work [24] considers that biases are caused by missing data, i.e., Missing-Not-At-Random (MNAR) problem. Missing data is defined as the user feedback without observed labels. Take click data for example, a clicked item can be assigned with a positive label by the observed data because click-action means positive opinion. However, an unclicked item cannot be definitely assigned by observation because the unclick-action represents either negative opinions or not. The unclicked items are defined as the missing data in this case. There are two intuitive strategies for the missing data problem. All Missing as Negative (AMAN) strategy treats all missing data as negative samples; and All Missing as Unknown (AMAU) strategy simply ignore the missing data.

Most of the existing methods for missing data try to imbalance between AMAN and AMAU. Pan et al. [25] apply AMAN with random sampling strategy to select unclicked impressions as negative examples. The work proposes three kinds of weighting scheme for missing data regarding AMAN-oriented, user-oriented, and item-oriented. In terms of exposure bias, the missing data in implicit feedback, e.g., unclicked items, can be separately handled: the exposed unclicked items can be assigned with the negative labels; and the unexposed items will have a likelihood to be either positive or negative.

E. Causal Inference

Causal inference works on finding the causal relations between cause and effect [26][27]. In this field, the widely used methods are propensity score in Rubin Causal Model (RCM) [28], e.g., Inversed Propensity Scoring (IPS/IPW), and causal graph in Structured Causal Model (SCM) [29], e.g., backdoor criterion. The research work aiming at exposure bias in RS focuses on analyzing the unobserved feedback, i.e., the missing data. The causal inference-inspired counterfactual reasoning is treated as a critical method that can predict the unobserved data with observed data.

III. Debias with Causal Inference

In this paper, we build a simple taxonomy for the research articles regarding exposure bias in RS. The taxonomy is inspired by the work [17] and extended with more new characteristics. In the taxonomy, we categorize the unbiased methods according to four phases which the methods belonging to: Bias Discovery, Evaluation Estimator, Recommendation Modeling, and Ranking Algorithm. Articles in Bias Discovery phase focus on proving the existence of exposure bias in RS theoretically and experimentally. Papers in Evaluation Estimator phase work on building novel estimators for the unbiased evaluation. Publications in Recommendation Modeling phase study new models of the unbiased recommendation. Papers in Ranking Algorithm phase concentrate on the unbiased ranking algorithm of RS. We summarize the reviewed articles in Table 1 with three basic attributes: phase, causality relevance, and article reference.

Table 1 Reviewed methods for exposure bias in RS

Phase	Causality Relevance	Article
Bias Discovery	-	[30], [31], [32], [33], [34]
Evaluation Estimator	propensity score	[35], [39]
Recommendation Modeling	propensity score	[38],[42], [43], [51], [53]
	causal graph	[37], [41], [44], [45], [47], [48], [49], [52]
Ranking Algorithm	Propensity score	[57], [59], [60]

A. Bias Discovery Phase

Schnabel et al. [30] perform experiments to evaluate the effects of the well-known unbiased methods in RS. This paper summarizes the quality estimators for the propensity score-based unbiased recommendation algorithms. The work uses the Empirical Risk Minimization (ERM) framework for learning recommendation models with these estimators. The authors applies propensity score-base matrix factorization for ERM in order to generate the error bound. The work [31] empirically investigates the generation of exposure/popularity bias of the algorithms and effects of the bias for different stakeholders in the fields of music and movie. The work considers the exposure bias from the users' perspective as well as the item perspective. Experiments show the relations between these perspectives in the MovieLens and Last.fm datasets. A finding is that the lower the bias from the users' perspective the lower proportional bias for the item perspective will be. The research also discover that accuracy and bias are not definitely correlated. Wasilewski and Hurley [32] perform an empirical evaluation considering the exposure of items to different types of users rather than only the exposure times. The authors group the users into different segments according to their types by using a clustering algorithm. The work compares the biased distribution and the ideal distribution using Jensen-Shannon divergence. The experiments show that the experimental movies indeed have target users but the recommendation algorithms may not reach these users because of biases. Ferraro et al. [33] perform experiments for music recommendation in order to evaluate the effect of bias. They compare the distributions of different recommendations regarding style-based exposure with the users' listening behaviors. The results show that the bias strongly effects the matrix factorization-based collaborative filtering methods in the field of music recommendation. Banerjee et al. [34] perform an experimental study with the distance-based evaluation for location-based information retrieval. This work uses the datasets of Google place, Yelp, and Booking. An important finding is that the unintended exposure bias exists because of popularity bias and position bias in location-based retrievals. The experiments show that the exposure bias indeed exists in commonly used recommendation algorithms.

B. Evaluation Metric Phase

Yang et al. [35] study the evaluation bias that widely exists in the MNAR data-based evaluations. Thus, debias of evaluator can effectively improve RS. The paper investigates the existence of position/exposure bias by comparing the ideal estimator and Average-Over-All (AOA) estimator. The ideal recommendation estimator (see Eq. (1)) calculates the evaluation reward $R(\hat{Z})$ for the predicted item's rank $\hat{Z}$, where $\hat{Z}_{u,i}$ is the predicted rank of item i for user u, and the function c denotes any top-N metric, e.g., Recall, DCG, and AUC, S_u is the preferred item set of u. The AOA estimator defines $R(\hat{Z})$ as the average over all observed feedback. The AOA estimator is formulated as Eq. (2), where $O_{u,i}$ represents whether (u,i) is observed and follows the Bernoulli distribution.

$$R(\hat{Z}) = \frac{1}{|\mathcal{U}|}\sum_{u\in\mathcal{U}}\frac{1}{|S_u|}\sum_{i\in S_u} c(\hat{Z}_{u,i}) \tag{1}$$

$$\hat{R}_{AOA}(\hat{Z}) = \frac{1}{|\mathcal{U}|}\sum_{u\in\mathcal{U}}\frac{1}{\sum_{i\in S_u} O_{u,i}}\sum_{i\in S_u} c(\hat{Z}_{u,i})\cdot O_{u,i} \tag{2}$$

This article applies the propensity score-based idea to build an unbiased Self-Normalized Inverse-Propensity-Scoring (SNIPS) evaluator in order to estimate the reward by using the observed part S_u^* of the preferred item set S_u. It is formulated as Eq. (3).

$$\hat{R}_{SNIPS}(\hat{Z}|P) = \frac{1}{|\mathcal{U}|}\sum_{u\in\mathcal{U}}\frac{1}{\sum_{i\in S_u^*}\frac{1}{P_{u,i}}}\sum_{i\in S_u^*}\frac{c(\hat{Z}_{u,i})}{P_{u,i}} \tag{3}$$

For estimating propensity scores, this paper built a way to generate user-item interactions with two steps: Select step and Interact step. Both of the probability of select and the probability of Interaction can be modeled by the statistic model, respectively regarding occurrence times and interaction times. In this way, the reward can be estimated with observed data. The experiment works on evaluators rather than performance of recommendation models. The experiment also shows important findings that (1) the biased evaluators usually over-estimate the performance of recommendation algorithm; (2) the unbiased evaluator can more significantly discover the performance difference between algorithms; (3) the unbiased estimator is more robust than the biased estimators. The work follows two assumptions: user-independent propensity assumption and selection-independent interaction assumption. For the first one, the next goal is to add more auxiliary information for User-dependent propensity; for the second one, the next move is to mine the influence of ranking for better modeling the interaction.

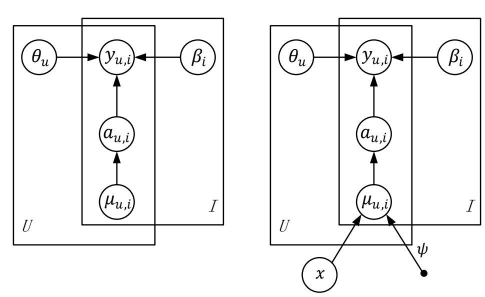
C. Recommendation Modeling Phase

Hu et al. [36] propose a model named *Weighted Matrix Factorization (WMF)* that assigns less weights unclicked items. It means that the unclicked items correspond to less confidence in prediction than clicked items. Usually, the item without interactions with the specific user will be simply treated as negative feedback. However, for a counter example, a movie that a user watched cannot indicate the preference of the user because she probably feels bad after watching the movie. For implicit CF, the paper proposes a confidence level for weighting the observed user-item interactions in matrix factorization-based models. The confidence increases with the growing feedback so that models can represent the user preference more accurately. Although this paper does not consider the situation of exposure bias, it is an important fundamental work inspiring the later methods for exposure bias. This work provides confidence for the case of "click represents like". However, the proposed model works under the assumption of "unclick represents dislike". It brings exposure bias into WMF model. The loss function is defined as Eq. (4) with an assumption preference can be represented as inner product $P_{u,i} - x_u^T y_i$, where x_u represents preference of user u and y_i is feature of item i. The confidence $c_{u,i}$ in observing $P_{u,i}$ is defined as Eq. (5) with parameter α and observation variable $r_{u,i}$.

$$\min_{x,y}\sum_{u,i} c_{u,i}\left(P_{u,i} - x_u^T y_i\right)^2 + \lambda\left(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2\right) \tag{4}$$

$$c_{u,i} = 1 + \alpha r_{u,i} \tag{5}$$

Liang et al. [37] propose a method called *ExpoMF* to reduce the exposure bias in the implicit feedback that includes action part and non-action part, e.g., click and unclick. The WMF model focuses on extracting more reliable information from the click part for evaluating the preference, while ExpoMF aims to better understand the unclick part. Towards the unclicked items, the user may either really does not like the items or only has not seen them. The exposure data is considered as the missing data. ExpoMF selectively adjusts the feature weights of click matrix rather than completely reweighting by WMF. The paper builds the exposure model using the assignment mechanism RCM. This paper defines an exposure model as a generative process containing various factors of user distribution, item attribute, exposure, and consumption (click-action).



(a) Exposure MF

(b) Exposure MF with exposure covariates

Figure 1 Causal graph of ExpoMF [37]

For better understanding the exposure model, the paper builds a causal graph to describe the generative process (see Figure 1). In fact, the causal graph is not a standard causal graph but a probabilistic graphical model. Nevertheless, the graph can be considered as a simple causal graph because it is helpful to understand the proposed matrix factorization model in the point of causal view. According to different settings of $\mu_{u,i}$, this paper discusses two cases. In the way of per-item $\mu_{u,i}$ (see Figure 1 (a)), the work straightforward describes item popularity as the only exposure covariates without taking external information into account and defines $\mu_{u,i}$ as a Beta distribution. Oppositely, the paper extends the basic exposure model with a hierarchical modeling of exposure that means the parameter $\mu_{u,i}$ is also described as a generative process with two parameters (see Figure 1 (b)). In this case, the external information, such as content features of text and location, can be treated as covariates. With these covariates, $\mu_{u,i}$ can be defined as a sigmoid function. The parameters of ExpoMF will be estimated by EM algorithm. After obtaining the parameter θ_u and β_i, the click probability $y_{u,i}$ can be predicted by dot production of θ_u and β_i. The loss function is formalized as Eq. (6). Experiments shows that the two strategies of $\mu_{u,i}$ are suitable for prediction in respective situations. The per-item $\mu_{u,i}$ is more suitable for $\theta_u^T\beta_i$, while the covariates-related prediction model works well with exposure covariates. However, ExpoMF model will lead popularity bias because it up-weights items with high exposure probability.

$$\begin{aligned}\log p\left(a_{u,i}, y_{u,i} \mid \mu_{u,i}, \theta_u, \beta_i, \lambda_y^{-1}\right) &= \log Bernoulli\left(a_{u,i} \mid \mu_{u,i}\right) \\ &+ a_{u,i} \log \mathcal{N}\left(y_{u,i} \mid \theta_u^T \beta_i, \lambda_y^{-1}\right) \\ &+ \left(1 - a_{u,i}\right) \log \mathbb{I}\left[y_{u,i} = 0\right]\end{aligned} \tag{6}$$

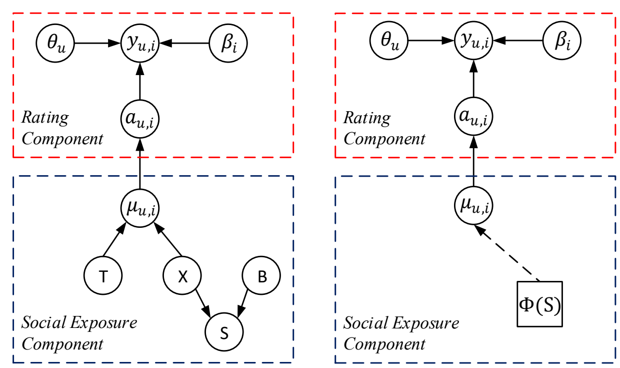
Saito et al. [38] argue that ExpoMF model also does not completely mitigate exposure bias because the items frequently expose in the training data will lead the larger local loss weight. The paper defines an ideal loss function for optimizing the recommendation regarding the highest relevance. With the help of the ideal loss function, this paper theoretically proves the widely used methods, ExpoMF and WMF, still suffer from bias issues even if they take big efforts to mitigate biases. This paper proposes an unbiased estimator for addressing both the positive-unlabeled problem by using propensity score-based ideas. The proposed method follows an assumption: item will be clicked when it has been exposed to a user and she is relevant to it. This paper uses “relevance” instead of “interest” for a more general purpose. An important shortcoming of propensity score-based estimator is that it usually has a high variance. This paper addresses this issue by using a clipped propensity score instead the original one in the loss function. It needs a balance between the variance and the clipped loss because the clipped loss will also lead another bias. The loss function is formalized as Eq. (7), where $\delta_{u,i}^{(R)}$, $R \in \{0,1\}$ indicates the local loss for pair (u,i). The propensity score is used as weight $\omega_{u,i}$ of pair (u,i) and defined as Eq. (8).

$$\hat{\mathcal{L}}_{unbiased}\left(\hat{R}\right) = \frac{1}{|S|} \sum_{(u,i)\in S} \left[\frac{Y_{u,i}}{\omega_{u,i}} \delta_{u,i}^{(1)} + \left(1 - \frac{Y_{u,i}}{\omega_{u,i}}\right) \delta_{u,i}^{(0)}\right] \tag{7}$$

$$\omega_{u,i} = P\left(O_{u,i} = 1\right) = P\left(Y_{u,i} = 1 \mid R_{u,i} = 1\right) \tag{8}$$

Gupta et al. [39] apply causal concepts for link prediction in graph-based RS. The paper proposes estimators that mitigate the exposure bias by using exposure probability. The work builds a loss function for learning the exposure probabilities from data. In this paper, the exposure issue appears between different nodes. The work defines the link probability of a node to another node as the propensity score. The authors show a fact by an example, which the link probability will be underestimated for the nodes with a lower propensity in RS trained on the observed data.

Wang et al. [40] propose a causal inference-inspired method for social network, namely *SERec*, consisting of two basic phases (see Figure 2). First, it estimates the exposure weights for each user; then, it evaluates the model. This paper builds a causal inference-based prediction model for user's ratings. The model is divided into two parts: rating matrix factorization and social exposure modeling. The first part calculates the prediction with exposure factors by matrix factorization; the second part aims at modeling the social exposure mechanism for calculating the exposure factor. The work proposes two ways to construct the social exposure models: social regularization (see Figure 2 (a)) and social boosting (see Figure 2 (b)), which make sense from the respective social perspectives. One is a matrix factorization-based model as regularization for estimating exposure factor; another is a boosting model that a user’s feeling is effected by her social friends’ opinions with a Beta distribution.



(a) SERec with social regularization

(b) SERec with social boosting

Figure 2 Causal graph of SERec [38]

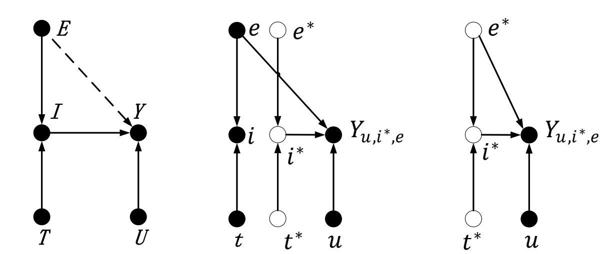
Wang et al. [41] introduce a *Deconfounded Recommender System (DecRS)* to mitigate bias amplification in the feedback loop. They define a causal graph to represent the causal effect of user’s representation on the prediction. By using the backdoor criterion, it can eliminate the confounders in the causal graph.

The paper [42] proposes a causality-related deconfounded RS to deal with the unobserved confounders in matrix factorization models. For addressing the multiple causal inference problem, the work uses the dependencies among the exposure as potential context information for confounders. The proposed method consists of an exposure model formulated by the Poisson factorization, and an outcome model defined by a probabilistic matrix factorization. Poisson factorization learns latent variables from the exposure matrix for each user. Experiment shows that the proposed recommendation model is more robust than traditional methods. The predicated outcome $y_{u,i}$ is formalized in Eq. (9), where a denotes the observed exposure matrix $\epsilon_{u,i}$

following Gaussian distribution, denotes confounders, and γ_u denotes how much the confounder $\hat{a}_{u,i}$ contributes to the ratings.

$$y_{u,i}(a) = \theta_u^T \beta_i \cdot a + \gamma_u \cdot \hat{a}_{u,i} + \epsilon_{u,i} \tag{9}$$

Khenissi and Nasraoui [43] build a popularity and exposure aware regularization with propensity for matrix factorization-based recommendations. The work uses the Jensen-Shannon divergence instead of the commonly used Kullback-Leibler divergence for modeling the regularization. Sato et al. [44] investigate the recommendation influence factors on exposure. The work proposes an exposure modeling method *RecExpoMF* in consideration of two influence factors. One is the direct influence that represents user-related item recommendation; another is the indirect influence that represents the relations between the focused item and other recommended items. Wang et al. [45] focus on the clickbait problem that the title does not correctly describe the item for deceptively obtaining attraction. This paper treats it as a particular exposure bias issue not to items but to title features because the user is not exposed to the actual features. This paper proposes a causal graph-based method that represents the causal effect of the clickbait issue (see Figure 3). Figure 3 (a) shows the causal graph. The sub-graph with solid lines is the conventional model with which prediction score *Y* is caused by item feature *I* and user feature *U*, while *I* is caused by exposure feature *E* and content feature *T*. The paper add an additional dash line to the causal graph in order to represent that a user probably clicks an item only because she is interested in the exposure features. Figure 3 (b) separates the exposed features, i.e., the factual part and the unexposed features, i.e., the counterfactual part in the graph. Figure 3 (c) rebuilds the causal graph with the unexposed features in order to formulate the mechanism of the counterfactual reasoning. With the help of this causal model, the paper can estimates the click likelihood of the unobserved features by counterfactual reasoning for addressing the clickbait problem.



(a) Causal Graph (b) Counterfactual (c) Reference situation

Figure 3 Causal graph for clickbait issue [45]

The exposure bias issue in social recommendations widely exist. Chen et al. [46] propose *SoEXBMF* that is a social exposure-based recommendation model. It integrates social information related to users' exposure into ExpoMF model for mitigating the exposure biases. The paper considers both social knowledge and social consumption as the influence on the exposure (see Figure 4). The work builds a social-based exposure model for the social knowledge influence and considers the positive feedback for the social consumption influence. It uses the Bernoulli distribution for ExpoMF instead of the commonly used Gaussian distribution for representing the binary implicit feedback.

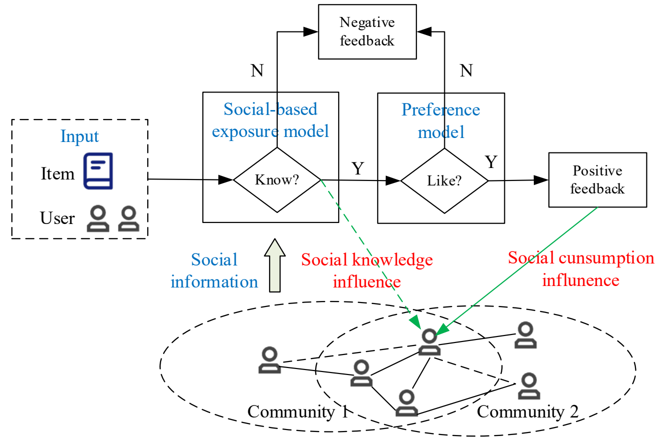


Figure 4 Basic idea of SoEXBMF [46]

Sun and Shi [47] integrate the social relations into the ExpoMF model for build a social exposure-based recommender *SoEx++*. The authors consider not only the explicit social relations but also the implicit relations for addressing the sparse issue in social recommendations. Chen et al. [48] propose a method namely *SamWalker* for social RS. It assigns various weights to different data as the confidence levels according to the social relations. SamWalker applies a social context aware function rather than the individual variational parameter. It applies a combinational weighting strategy for the users' social relations instead of using the posterior expectation of user's exposure. The confidence weights can be integrated into convolutional neural networks as the weight parameters of convolutional layers for optimizing deep learning models.

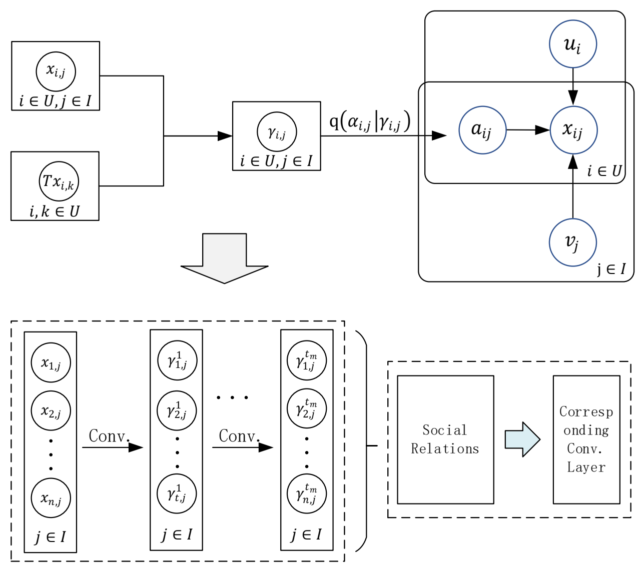


Figure 5 Framework of SamWalker [48]

Li, Wang, and Xu [49] propose an unbiased prediction model called *DENC* for users' ratings by building a causal graph model. The paper concludes that the training space is not equal to the reference space because the reference space has more exposed items. Thus, there are exposure bias between the training and reference phase. The proposed method disentangles the rating into three factors (see Figure 6): inherent factors, confounder, and exposure. It builds a model for each factor, respectively.

Social network confounder model uses a node2vec model to encode users. Deconfounder model calculates the adaptive weights for rating scores by using propensity. Exposure model applies an Integral Probability Metric model using Wasserstein-distance in order to estimate the inherent factor.

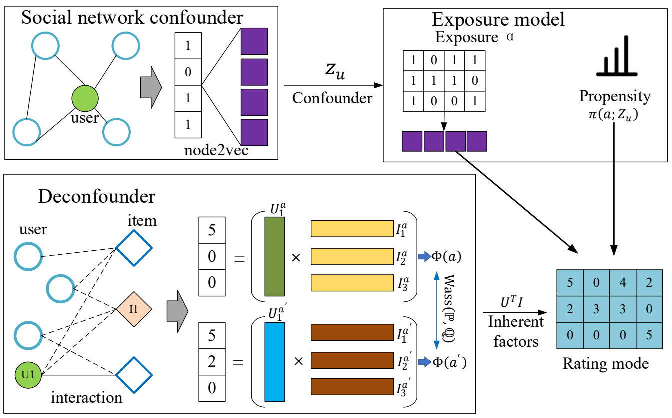


Figure 6 DENC framework [49]

Deep learning methods are good at finding patterns from big data. Causal inference can be combined with deep neural networks for addressing the exposure bias issue. Chen et al. [50] introduce a Variational Auto-Encoder-based fast adaptively weighted matrix factorization (*FAWMF*) for adaptive weighting and better model learning (see Figure 7). The proposed model learns both data confidence weights and latent factors of matrix factorization by building a Variational Auto-Encoder.

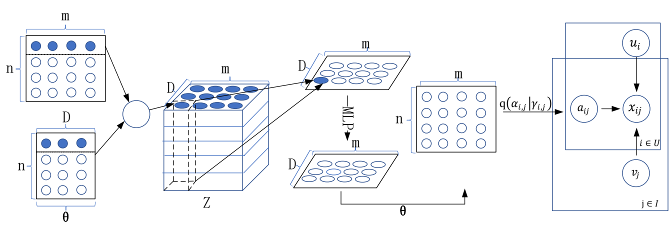


Figure 7 FAWMF model [50]

Zhou et al. [51] construct a contrastive learning-based approach in order to improve fairness, effectiveness, and efficiency of deep learning-based recommendation methods with large-scale candidates. This paper optimizes the deep candidate generation model that learns a user behavior encoder and an item encoder. The paper defines the contrastive loss function as a sampling-based approximation method with inverse propensity weight. Pan et al. [52] build a dynamic exposure model that is able to dynamically correct exposure biases for rating prediction in RS. In this paper, the probability distribution of the rating order is defined as the exposure probability. The paper encodes each user's temporal rating history as an embedding using GRU (Gated Recurrent Unit) model. The proposed dynamic exposure model estimates the sequential exposure probability using a probabilistic graphical model. This work trains an inverse propensity scoring-inspired rating predictor with the dynamic exposure probabilities. Zhang et al. [53] propose an integrated method to mitigate exposure biases in implicit recommendations. The proposed method builds a Causal Neural Fuzzy Inference (CNFI) model that combines causal inference, neural network, and fuzzy set theory. This paper applies fuzzy set theory to model the missing data as impact factors of user exposure probability to items in implicit recommendations. CNFI model learns the weights of fuzzy rules by the neural-fuzzy inference network. CNFI works with matrix factorization-based method to predict the user's opinions.

The reinforcement learning-based recommendations also have exposure biases. Mansoury et al. [54] study the exposure bias in Linear Cascade Bandits algorithm of reinforcement learning. The work provides an unbiased representation for items and suppliers in recommendations. Due to mitigate the exposure bias, this paper proposes a discounting factor in order to sequentially controlling the exposure of items.

D. Ranking Algorithm Phase

Researchers focus on the fairness of ranking algorithms in RS in recent years [55][56][57], particular of the Learning-To-Rank (LTR) algorithms. Usually, with ranking algorithms, the item highly ranked is more likely to be consumed. It may bring more serious Matthew Effect of recommendations. The exposure allocation on ranking can cause exposure biases which is more likely as the popularity bias issue. Morik et al. [58] introduce a control-based algorithm, namely *FairCo*, for the fairness of dynamic Learning-To-Rank (dLTR) algorithms. The proposed algorithm contains propensity score-based unbiased estimators. The work can improve fairness and mitigate the Mathew Effect. Yadav et al. [59] propose *FULTR* framework that can address unfairness in LTR models while learning ranking policies from implicit feedback data. The proposed framework applies IPS for the unbiased estimator of utility. Damak et al. [60] focus on the explanation of the pairwise ranking models by applying causal inference ideas for implicit RS. The paper proposes a matrix factorization-based Explainable Bayesian Personalized Ranking (*EBPR*) model that predicts recommended items and the corresponding item-based explanations. This work builds an IPS-based unbiased estimator on explainability weighting for EBPR loss.

E. Experiment Methods

The experiment for the exposure bias research contains important factors: dataset, baseline, and metric.

The experimental datasets for evaluating the debiasing methods consists of open datasets and self-made datasets. The widely used open datasets in RS, such as Yahoo! R3 [61], Last.FM [62], and Epinions [63], MovieLens [64] are usually used in the reviewed research. A number of research works made datasets by themselves in order to satisfy their particular experiment requirements. The datasets provide implicit feedback data for model training and test.

Another important factor of experiment is baseline. WMF [36], BPR [65], and ExpoMF [19] are classic debiasing models that are often used as baselines in experiments. BPR is a classic personalized ranking method for implicit feedback and widely used as a baseline for the ranking metric NDCG. WMF is usually applied for debias. ExpoMF is treated as a good baseline for modeling the exposure bias.

The metrics commonly used in RS are also applied in the exposure bias research. For unbiased methods, MAE and MSE are standard metrics used to evaluate errors of the methods; Precision and Recall are usually used for estimating TopN recommendations; NDCG is very popularly applied to qualify the methods for ranking tasks.

IV. Conclusion

In this paper, we have reviewed research publications that work on exposure bias issue in RS. We propose a taxonomy that assigns the debiasing methods into four categories according to different phases in RS. In this survey, we focus on the methods inspired by causal inference. The causal methods can solve the problems that the correlation-based methods are not available for. We have studied and discussed the existing methods and their evolutions. We conclude that the combination of causal inference and deep learning will be an effect way for addressing the exposure bias issue in RS.

In the future, we will focus on the experimental comparisons of the unbiased methods. Moreover, a universal framework for mitigating the exposure biases in RS is also meaningful.

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