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Personalized Recommendation through Disentangled Representation Learning of Consumers' Multiple Digital Footprints

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Abstract

The pervasiveness of multiple types of digital footprints recorded on e-commerce platforms have added fuel to the design of personalized recommender systems. Despite the abundance, consumers' digital footprints can be confounded with many causes, both internally and externally. To disentangle the causes driving consumers' behaviors, a causal recommendation method, i.e., DIPC, based on cause disentanglement at various consumption stages is proposed in the paper. Referring to related theories, interest and item popularity are recognized as causes driving consumer behaviors in the need recognition stage, while behaviors in the pre-purchase and purchase stages are assumed to be motivated by interest and conformity. To rigorously evaluate the performance of DIPC, extensive experiments are conducted on a real-world dataset with carefully designed intervention in terms of modeling multiple digital footprints and causality learning. The results show that DIPC outperforms all baselines significantly and possesses good interpretability, demonstrating the superiority of the proposed causal recommendation method.

Keywords: Recommender system, multiple digital footprints, causal graph, disentangled representation learning

Introduction

Personalized recommendation plays a vital role on modern e-commerce platforms. The click-through rate and subsequent purchases are found to drop drastically once the personalized recommendation is turned off (Sun et al. 2021). On e-commerce platforms nowadays various digital footprints of consumers are recorded and provide abundant fuel for designing personalized recommender systems (RSs). Conventional RSs are usually trained on consumers' observational digital footprints such as ratings and clickstream data, among which the former is regarded as explicit feedback while the latter implicit feedback. Because consumers are increasingly reluctant to provide ratings due to costs like time and effort (Godes and Silva 2012, Hu et al. 2017), modern RSs usually have to deal with consumers' implicit feedback reflected through clickstream data, e.g., clicking on an item, adding it to the cart, etc. Compared with explicit feedback, implicit feedback from consumers is less effortful and consequently more noisy and biased. For instance, consumers can easily be distracted from a top-ranked or recommended item and click on it, thus rendering the implicit feedback that does not actually represent their interest. In other words, an observed click and even purchase can result from either the focal consumer's genuine interest or just trivial side causes. If a recommendation policy is generated by confounding all the causes together, it cannot fully reflect consumers' interests and may harm consumers' trust in the RSs. Moreover, confounding causes together gives rise to poor interpretability of recommendations. Hence, to deliver personalized recommendations based on implicit feedback, it is desirable for RSs to disentangle the causes that drive consumers' purchase decisions.

A typical online shopping process can be categorized into four stages, i.e., need recognition, pre-purchase, purchase, and post-purchase. The first three stages involve multiple types of implicit feedback, e.g., clicking on an item, adding an item to the cart, and purchasing an item, while the post-purchase stage usually contains explicit feedback like ratings. Due to the aforementioned reasons, we focus on the first three stages that include abundant implicit feedback, where each of consumer behaviors is entangled with multiple driving factors. For instance, clicking on an item can be driven by consumers' interest and recommendation-induced item popularity simultaneously, while purchasing an item can be impacted by consumer interest and other consumers' purchase decisions. To disentangle different factors behind consumers' observed behaviors, it is important to take into account the characteristics of different stages. Extant works try to disentangle users' behaviors from the perspective of interest and conformity (Zheng et al. 2021), while failing to differentiate the determinants of various stages. In this paper, we seek to study the consumption stages thoroughly and propose a recommendation strategy based on disentangled representation learning using causal graph modeling.

Disentangling different factors behind consumers' implicit feedback at various shopping stages is challenging. First, because there are no predefined labels for consumers' different behaviors, pattern recognition needs to be performed on noisy data. Second, the influencing factors of different stages are different but intervened, for which the disentanglement mechanism needs to be carefully designed. Third, the stages of consumers' shopping journeys can be flexible. In other words, consumers can either undergo a complete shopping journey including need recognition, pre-purchase evaluation, and then purchase, or directly jump to purchase impulsively. Hence, the transition paths of different stages are in multiple forms, rendering the disentanglement of different factors more challenging.

To cope with the above-mentioned challenges, we refer to the consumer behavior literature for theoretical support for consumers' various types of implicit feedback at different stages, based on which we seek to propose a causal graph-based method to disentangle different factors. According to the literature on consumer behavior, different behavioral biases like non-standard preferences, beliefs, as well as decision-making, exist in various implicit feedback at different stages (Dowling et al. 2020). In other words, consumers' implicit feedback at various stages can either be driven by their intrinsic interest or some external factors. Concretely speaking, consumers' need recognition can either be due to intrinsic interest or external stimuli like item popularity induced by advertisements or recommendations (Lee et al. 2018). Thus, when disentangling the factors behind consumers' implicit feedback at the need recognition stage, consumers' intrinsic interest and extrinsic item popularity should be considered. In the pre-purchase phase, consumers tend to search insufficiently and overact to salient information like bestsellers (Brynjolfsson and Smith 2000, Ghose et al. 2013). Hence, for consumers' implicit feedback in the pre-purchase stage, intrinsic interest and conformity to extrinsic salient signals are considered two driving factors. In terms of the purchase stage, the most prominent implicit feedback information is consumers' purchase behavior, which is considered the most important type of input when designing RSs. The standard purchase stage involves weighing various attributes of the products and making a purchase decision. However, the purchase decision and timing can be biased compared with the standard ones in terms of preferences and the decision-making process (Iyer et al. 2020, Dowling et al. 2020). For instance, consumers can make purchase decisions impulsively by jumping to the purchase decision directly without going through the pre-purchase evaluation stage (Beatty and Ferrell 1998). Similarly, the motivating factors can also be categorized intrinsically and externally, where the intrinsic driver is consumers' thirst for the product, i.e., interest, while the external one is conformity to others' purchase decisions.

With the above analysis, the causes behind consumers' various types of implicit feedback can be categorized as intrinsic and external ones. While the intrinsic one refers to consumers' genuine interest persistently existing in different stages, the external stimuli differ at different stages, e.g., item popularity at the need recognition stage and conformity to others' purchase decisions at the pre-purchase and purchase stages. According to the extant literature in behavior science, the impacts of external stimuli can make consumers' observed behavior deviate from the standard one, referred to as behavior bias (Dowling et al. 2020). To disentangle different factors that drive such behavior bias, we establish a causal graph to model consumers' multi-stage implicit feedback and seek to learn the disentangled causes with the observational data. Specifically, three types of consumers' implicit feedback are considered, i.e., *view*, *add-to-cart,* and *purchase*, representing the need recognition, pre-purchase, and purchase stages, backed by different causes, respectively. Given the potential impulsive purchase behavior of consumers, the three types of implicit feedback form a triangle structure as shown in Figure 1, which brings extra challenges to the inference of the causal graph. That is, the triangle structure implies a ternary decision where choices are not completely opposite, hampering the decision mechanism modeling and incurring a *negative sample attribution* problem of cause disentanglement. In this paper, a probabilistic inference framework is proposed to determine the decision path of consumers and the joint probability of the entire causal graph can thus be derived accordingly. An expectation-maximization (EM) algorithm is used to learn the parameters of the proposed model and therefore, given a recommendation policy, whether a consumer will purchase a certain product can be predicted. To evaluate the performance of the proposed method, an intervened dataset is constructed as the testbed for comparing against various baseline recommendation methods. Through extensive experiments, our proposed method is found to outperform all types of baseline methods, showing the superiority of our proposed casual graph-based approach. Furthermore, the causal graph-based approach also disentangles the factors behind consumers' various types of implicit feedback and facilitates interpretable recommendations to both consumers and retailers. For retailers, the proposed method can help tell the more prominent factors driving consumers' purchase decisions, which can be further used to nudge consumers in a personalized manner. For consumers, the summary of the driving factors of one's purchase could help mitigate behavioral biases.

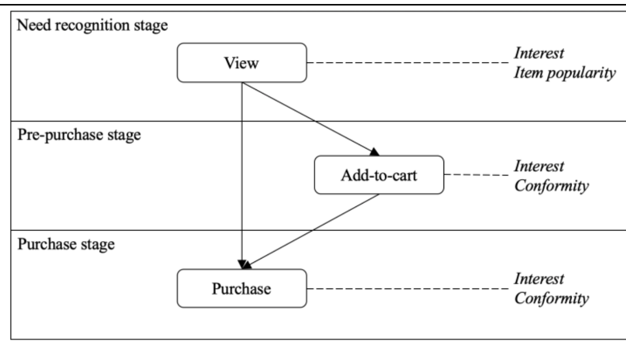


Figure 1. Consumers' Digital Footprints and Causes of Each Behavior

Related Work

This section reviews three streams of literature related to our work, i.e., consumers' behavioral biases, debiasing-oriented recommendation, and recommendation using multiple types of implicit feedback, in order to lay a solid foundation for our work both theoretically and methodologically.

Behavioral Biases in Consumers' Online Shopping Journey

The noises and biases in consumers' implicit feedback result from consumers' behavioral biases, which have been documented in a series of related works. A recent review (Dowling et al. 2020) attributes consumers' behavioral biases to three types, i.e., non-standard preferences, beliefs, and decision-making. The three types of behavioral biases exist in various stages of consumers' purchase processes, leading the observed consumer behavior data to be biased. During the need recognition phase, consumers recognize a need due to either internal thirst or external signals like advertising, formulating non-standard preferences and beliefs (Lee et al. 2018). In the pre-purchase phase, consumers search for and evaluate alternatives by making forecasts about future events and behaviors, where belief-based biases are prominent due to forecast uncertainty (Dowling et al. 2020). In terms of product search, consumers may overestimate their private information relative to that acquired by search efforts, resulting in overoptimism and inadequate search (Brynjolfsson and Smith 2000). During the purchase stage, consumers make decisions regarding whether to make a purchase, where non-standard decision-making can result from others' persuasion as well as conformity to the preferences of relevant groups (Akerlof 1991). Furthermore, consumers' decision-making process can also be non-standard. For instance, in scenarios like impulsive purchases, consumers may directly jump to the purchase phase (Iyer et al. 2020). Hence, to leverage consumers' digital footprints for personalized recommendation and marketing, it is crucial to recognize the sources of behavioral biases and develop a debiasing-oriented method accordingly.

Debiasing Recommendation Methods

Given the above-illustrated consumers' behavioral biases, recommendation methods that fail to consider the causes of biases will lead to recommendations that cannot fully reflect consumer interest. Related works in recommendation system design regard the problem as a debiasing problem and propose three perspectives to solve the problem, including the inverse propensity score (IPS) approach, the exposure-based model, and causal embedding.

IPS Approach

The IPS approach seeks to optimize an unbiased objective function (i.e., IPS estimator), which is constructed by weighting the error of each prediction with the inverse propensity of observation on user-item interaction (Liang et al. 2016a, Saito et al. 2020). The propensity can be estimated in many ways such as relative item popularity (Saito et al. 2020), logistic regression (Schnabel et al. 2016), and low nuclear norm constraint (Ma and Chen 2019). It is proved that the empirical prediction error is closely related to the estimated propensity (Schnabel et al. 2016). Hence, the inaccuracy of propensity can result in poor debiasing performance. Even with an accurate propensity, the IPS estimator may be ineffective out of its uncontrolled variance. To alleviate this issue, other estimators, such as the self-normalized IPS estimator (Schnabel et al. 2016) and the doubly robust estimator (Wang et al. 2019), have been developed. Yet these estimators are not guaranteed to be unbiased.

Exposure-based Model

The exposure-based model is a probabilistic framework that assumes a latent exposure state before a consumer's interaction with a product. For example, Liang et al. (2016b) consider exposure as a precondition for purchase and construct a hierarchical predictive model, based on which a dynamic version of the model is developed (Wang et al. 2018). By incorporating the bias formation mechanism in exposure modeling, this approach can debias by maximizing the joint likelihood. However, inferring the latent exposure probability that is formulated with a large scale of parameters easily leads to an over-fitting problem, which hampers the debiasing performance.

Causal Embedding Approach

The causal embedding approach aims to capture each cause that motivates user-item interaction with respective embeddings. Consumer interest, as a critical cause of behaviors, is extracted to achieve debiasing while preserving interpretability. In order to make embeddings capture causes, the model needs to be trained on cause-specific data that imply causality information. For instance, in addition to training on a large dataset of observed implicit feedback, Bonner and Vasile (2018) propose to employ a small dataset consisting of consumer behavior logs under a random treatment policy for domain adaption, which provides the causality information of consumers' interest. However, such behavior logs are scarce in reality due to the considerable costs of data collection. Therefore, the effect of domain adaption is severely impeded. To effectively utilize causality information, recent work of causal embedding combines causal graph modeling with disentangled representation learning, which is also the backbone method adopted in this study.

A causal graph is a directed acyclic graph where a node represents a variable and an edge denotes a causal relation between two variables (Pearl 2009). Since a causal graph depicts the mechanism of data generation, it can be used to guide the design of causal recommendation methods. For example, confounders in recommendation will be identified to conduct an intervention and therefore some paths in a causal graph can be blocked to eliminate undesired effects by causal inference (Wang et al. 2021, Wei et al. 2021). Disentangled representation learning is developed for a similar purpose. As data are generated according to different factors which may change independently in terms of input distribution, learning disentangled representations of these factors is crucial for robust prediction (Bengio et al. 2013, Suter et al. 2019). Some studies have employed disentangled representation learning in RSs to capture consumers' fine-grained preferences (Ma et al. 2019, Wang et al. 2020), yet other causes such as conformity are ignored. With a causal graph modeling consumers' behaviors and the causes, disentangled representation learning techniques can utilize causality information to disentangle consumers' interest from other causes, therefore achieving debiasing. A recent effort disentangles consumers' interest and conformity by taking advantage of the common effect in causal inference to construct cause-specific data, based on which interest-related and conformity-related embeddings are inferred to represent respective causes independently (Zheng et al. 2021). Nevertheless, the proposed causal embedding is still oversimplified. Consumers' multiple digital footprints are not explored and the causes behind consumers' behaviors in their shopping journey have not been systematically examined. Hence, our work seeks to move the extant research forward by incorporating multiple types of implicit feedback and comprehensively disentangling the causes behind it.

Recommendation with Multiple Implicit Feedback

With the pervasiveness of consumers' multiple types of digital footprints, a research stream focusing on recommendation method design with multiple implicit feedback has emerged in recent years (Chen et al. 2020b). Compared with RSs based on the records of a single type of behaviors, recommendations with multiple implicit feedback can leverage more information to improve performance. Generally, in multiple-implicit-feedback-based RSs, a target behavior like purchase is concerned that needs to be predicted, while other behaviors such as view provide auxiliary information to aid in learning consumers' preferences. For example, collective matrix factorization is extended to utilize multiple implicit feedback for recommendation, where information from different behaviors is integrated by embedding sharing (Zhao et al. 2015). Recent work has developed models with deep structure to further improve the capacity of learning correlations among multiple behaviors (Chen et al. 2020a, Gao et al. 2019). Despite achieving satisfactory prediction performance, these methods do not model consumers' flexible decision process properly. Therefore, the decision mechanisms are unclear.

Model

To develop a causal recommendation method that disentangles consumers' genuine interest from the effects of item popularity and conformity, we investigate the generation mechanisms of consumers' digital footprints to build the causal graph. Our method belongs to the stream of research on causal graph with disentangled representation learning. The mechanism of cause disentanglement is training embeddings with cause-specific data that imply the extent to which user-item interactions source from each cause. That is, with cause-specific data, each type of embeddings will only capture the corresponding factor while being immune to others. Such embeddings are termed as causal embeddings.

For a better illustration of the proposed method, important notations are outlined in Table 1, where $u \in \{1, 2, \dots, U\}$ indexes a user and $i \in \{1, 2, \dots, I\}$ indexes an item.

Notations	Descriptions
r_{ui}	u's interest in i.
b_{ui}	Effect of item popularity in u's interaction with i.
c_{ui}	Effect of conformity in u's interaction with i.
v_{ui}	Indicator of whether u views i, $v_{ui} \in \{0,1\}$.
a_{ui}	Indicator of whether u adds i to cart, $a_{ui} \in \{0,1\}$.
z_{ui}	Indicator of whether u purchases i, $z_{ui} \in \{0,1\}$.
s_{ui}	u's decision path after she views i, $s_{ui} \in \{0,1\}$. $s_{ui} = 0$ stands for u deciding whether to add i to cart. $s_{ui} = 1$ stands for u deciding whether to purchase i directly after she views i.

θ_{ui}	Parameter that controls the distribution of s_{ui}.
p_u^r	Embedding of u that is related to interest, $p_u^r \in \mathbb{R}^K$.
p_u^b	Embedding of u that is related to item popularity effect, $p_u^b \in \mathbb{R}^K$.
p_u^c	Embedding of u that is related to conformity effect, $p_u^c \in \mathbb{R}^K$.
q_i^r	Embedding of i that is related to interest, $q_i^r \in \mathbb{R}^K$.
q_i^b	Embedding of i that is related to item popularity effect, $q_i^b \in \mathbb{R}^K$.
q_i^c	Embedding of i that is related to conformity effect, $q_i^c \in \mathbb{R}^K$.
ψ_u	Latent factor of u that controls decision path choice, $\psi_u \in \mathbb{R}^K$.
γ_i	Latent factor of i that controls decision path choice, $\gamma_i \in \mathbb{R}^K$.
α_t, β_t ($t \in \{1,2,3,4\}$)	Weights of causes in consumer's decision-making.

Table 1. Basic Notations

Model Description

The causal graph of our model for *Disentangling consumer Interest, item Popularity effect, and Conformity effect* (DIPC) is illustrated in Figure 2. We describe the proposed method in detail as follows.

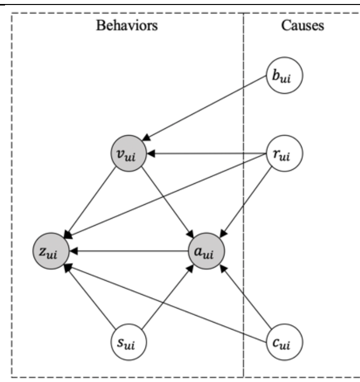


Figure 2. Causal Graph of Consumers' Digital Footprints

Causes

We start by formulating the causes (i.e., interest, item popularity effect, and conformity effect) to develop our model. Following the latent factor manner (Koren et al. 2009), user u's interest in item i can be factorized as

$$r_{ui} = {p_u^r}^T q_i^r, \quad (1)$$

where p_u^r and q_i^r are the interest-related embeddings of u and i, respectively.

Extant works usually assume that item popularity effects and conformity effects only depend on the item and treat them as statically item-specific terms (Saito et al. 2020, Wei et al. 2021). However, these effects may also vary across different users due to consumers' heterogeneity in taking in such causes (Zheng et al. 2021). For instance, some consumers are more likely to follow others in decision-making, giving rise to a more significant conformity effect than other consumers. Therefore, we model the effects of item popularity and conformity in a similar way to that of interest, that is,

$$b_{ui} = {p_u^b}^T q_i^b, \quad (2)$$

$$c_{ui} = {p_u^c}^T q_i^c, \tag{3}$$

where p_u^b and q_i^b are the popularity-effect-related embeddings of u and i, and p_u^c and q_i^c are the conformity-related embeddings of u and i.

Consumer Behaviors

View. Consumers start their shopping with viewing items. On the one hand, selective exposure theory (Jonas et al. 2001) implies that consumers may be selectively exposed to items they are interested in. On the other hand, RSs recommend popular products more frequently than their values would warrant, exposing consumers to them with a higher probability (Ciampaglia et al. 2018, Fleder and Hosanagar 2009, Nikolov et al. 2019). Therefore, the intention of user u viewing item i can be formulated as a weighted sum of interest r_{ui} and item popularity effect b_{ui},

$$\bar{v}_{ui} = \alpha_1 r_{ui} + \beta_1 b_{ui}, \tag{4}$$

where $\alpha_1 > 0$ and $\beta_1 > 0$ are the weights of causes to be learned (similarly hereinafter).

Being consistent with the Logit model, we assume the view probability

$$P(v_{ui} = 1 | r_{ui}, b_{ui}) = \Lambda(\bar{v}_{ui}) = \Lambda(\alpha_1 r_{ui} + \beta_1 b_{ui}) \equiv \Lambda_{ui}^v, \tag{5}$$

where $\Lambda(x) = \frac{\exp(x)}{1+\exp(x)}$, which is the cumulative distribution function (CDF) of a Logistic distribution; and the notation "≡" represents "denoted as" or "equivalent to".

Choice of decision paths. After user u views item i, she may purchase it directly, add it to the cart for further consideration, or do nothing, forming the triangle structure in Figure 1. Instead of modeling the decision process behind the triangle structure, extant works focus on the correlations in view, add-to-cart, and purchase behaviors to construct a deep learning frame. For instance, a transition matrix can be employed for transforming the parameters controlling behavior into those controlling subsequent behaviors (Chen et al. 2020a). These models are intuitive yet ignore the critical causality information in decisions, hindering accurate predictions of purchase under different recommendation policies. Moreover, the behavior branch in the triangle structure implies a ternary decision where choices are not completely opposite. In other words, after u views i, the choice of doing nothing is opposite to purchasing i directly and adding i to cart, while the latter two choices are not opposite to each other. We cannot even conclude the extent of preference behind the choice of purchasing i directly and that of adding i to cart, for this decision depends on other factors like consumers' shopping habits. Therefore, the triangle structure severely hampers decision mechanism modeling and causality learning.

To capture the causality behind the triangle structure, we introduce s_{ui}, the indicator of decision path after u views i, to model the decision process, that is,

$$s_{ui} = \begin{cases} 0, & \textit{the path that } u \textit{ decides whether to add } i \textit{ to cart is chosen,} \\ 1, & \textit{the path that } u \textit{ decides whether to purchase } i \textit{ directly is chosen.} \end{cases} \tag{6}$$

where $s_{ui} = 1$ implies u chooses an impulsive decision path that bypasses the add-to-cart stage, while $s_{ui} = 0$ suggests a more cautious decision path. This choice depends on u's shopping habits as well as the characteristics of i. For example, $s_{ui} = 1$ may hold with a high probability if u is an impulsive decision maker or i is in a less differentiated market. Therefore, we assume the Bernoulli distribution of s_{ui} to be

$$P(s_{ui} = 1 | \theta_{ui}) = \theta_{ui} \equiv \Lambda(\psi_u^T \gamma_i). \tag{7}$$

That is, $s_{ui} \sim Bernoulli(\theta_{ui})$ with θ_{ui} factorized as $\Lambda(\psi_u^T \gamma_i)$, where ψ_u and γ_i are the latent factors of u and i that are related to the decision path choice.

With the latent variable s_{ui} indicating the decision path, we transform the ternary decision to a mixture of two binary decisions that the decision mechanisms can be effectively modeled as follows.

Add-to-cart. After user u views item i and chooses a decision path, she steps into the pre-purchase or purchase stage. According to utility theory that consumers make decisions seeking to maximize utility (Fishburn 1970), u will add products she likes to cart for consideration of purchase. Meanwhile, social influence theory indicates that consumers tend to follow others in decision-making while neglecting their own judgments, showing the effect of conformity (Baeza-Yates 2018, Karaman 2021, Muchnik et al. 2013).

To consider both the consumer's interest r_{ui} and conformity effect c_{ui}, we assume the probability of u adding i to cart as follows:

$$P(a_{ui} = 1 | v_{ui} = 1, s_{ui} = 0, r_{ui}, c_{ui}) = \Lambda(\alpha_2 r_{ui} + \beta_2 c_{ui}) \equiv \Lambda_{ui}^{a}. \tag{8}$$

If u has not viewed i, or u has chosen the decision path of deciding whether to purchase i directly after view (i.e., u bypasses the pre-purchase stage), the probability of u adding i to cart will be zero, that is,

$$P(a_{ui} = 1 | v_{ui} = 0, s_{ui}, r_{ui}, c_{ui}) = 0, \tag{9}$$

$$P(a_{ui} = 1 | v_{ui} = 1, s_{ui} = 1, r_{ui}, c_{ui}) = 0. \tag{10}$$

Purchase. The purchase decision mechanism can be explained with utility theory (Fishburn 1970) and social influence theory (Muchnik et al. 2013) as well. That is, consumers purchase products they like to maximize utility while influenced by others in making such a decision. There are two ways that can lead to purchasing, i.e., purchase directly after view and purchase after add-to-cart. Hence, we model the purchase probability in different cases as follows.

If user u has viewed item i and chosen the decision path to decide whether to purchase i directly (i.e., $v_{ui} = 1, s_{ui} = 1$),

$$P(z_{ui} = 1 | v_{ui} = 1, s_{ui} = 1, a_{ui}, r_{ui}, c_{ui}) = \Lambda(\alpha_3 r_{ui} + \beta_3 c_{ui}) \equiv \Lambda_{ui}^{vz}. \tag{11}$$

If u has viewed i and chosen the decision path to decide whether to add i to the cart, the purchase probability depends on the add-to-cart decision. That is, if u has indeed added i to the cart (i.e., $v_{ui} = 1, s_{ui} = 0, a_{ui} = 1$), the probability is

$$P(z_{ui} = 1 | v_{ui} = 1, s_{ui} = 0, a_{ui} = 1, r_{ui}, c_{ui}) = \Lambda(\alpha_4 r_{ui} + \beta_4 c_{ui}) \equiv \Lambda_{ui}^{az}, \tag{12}$$

if u has decided not to add i to cart (i.e., $v_{ui} = 1, s_{ui} = 0, a_{ui} = 0$), she cannot purchase i, the probability is

$$P(z_{ui} = 1 | v_{ui} = 1, s_{ui} = 0, a_{ui} = 0, r_{ui}, c_{ui}) = 0. \tag{13}$$

Finally, since view is the premise for purchase, the following probability holds

$$P(z_{ui} = 1 | v_{ui} = 0, s_{ui}, a_{ui}, r_{ui}, c_{ui}) = 0. \tag{14}$$

Note that the weights for causes (i.e., α_t, β_t ($t \in \{1,2,3,4\}$)) are differentiated to capture different mechanisms of the decisions.

Likelihood. As illustrated in Figure 2, for each user-item pair (u, i), v_{ui}, a_{ui}, and z_{ui} are observable while s_{ui} is not. The marginal likelihood of behaviors within (u, i) can be formulated as

$$\begin{aligned} &P(v_{ui}, a_{ui}, z_{ui} | r_{ui}, b_{ui}, c_{ui}, \theta_{ui}) \\ &= \sum_{s \in \{0,1\}} P(z_{ui} | v_{ui}, s_{ui}, a_{ui}, r_{ui}, c_{ui}) P(a_{ui} | v_{ui}, s_{ui}, r_{ui}, c_{ui}) P(v_{ui} | r_{ui}, b_{ui}) P(s_{ui} = s | \theta_{ui}). \end{aligned} \tag{15}$$

By taking advantage of the behavior sequence, we only need to consider four cases to derive the likelihood, that is, the probability of u not viewing i (Equation (16)), the probability of u viewing i without adding i to cart or purchasing i (Equation (17)), the probability of u purchasing i directly after view (Equation (18)), and the probability of u adding i to cart (either purchasing i or not) (Equation (19)).

$$P(v_{ui} = 0 | r_{ui}, b_{ui}) = 1 - \Lambda_{ui}^{v}, \tag{16}$$

$$P(v_{ui} = 1, a_{ui} = 0, z_{ui} = 0 | r_{ui}, b_{ui}, c_{ui}, \theta_{ui}) = \Lambda_{ui}^{v}\big(\theta_{ui}(1 - \Lambda_{ui}^{vz}) + (1 - \theta_{ui})(1 - \Lambda_{ui}^{a})\big), \tag{17}$$

$$P(v_{ui} = 1, a_{ui} = 0, z_{ui} = 1 | r_{ui}, b_{ui}, c_{ui}, \theta_{ui}) = \Lambda_{ui}^{v} \theta_{ui} \Lambda_{ui}^{vz}, \tag{18}$$

$$P(v_{ui} = 1, a_{ui} = 1, z_{ui} | r_{ui}, b_{ui}, c_{ui}, \theta_{ui}) = \Lambda_{ui}^{v}(1 - \theta_{ui}) \Lambda_{ui}^{a} (\Lambda_{ui}^{az})^{z_{ui}} (1 - \Lambda_{ui}^{az})^{1 - z_{ui}}. \tag{19}$$

We utilize the negative log-likelihood as the loss function of behavior modeling, that is,

$$\mathcal{L}_{behavior} = -\sum_{u=1}^{U}\sum_{i=1}^{I}\begin{pmatrix}\mathbb{I}(v_{ui}=0)\log P(v_{ui}=0|r_{ui},b_{ui}) \\ +\mathbb{I}(v_{ui}=1,a_{ui}=0,z_{ui}=0)\log P(v_{ui}=1,a_{ui}=0,z_{ui}=0|r_{ui},b_{ui},c_{ui},\theta_{ui}) \\ +\mathbb{I}(v_{ui}=1,a_{ui}=0,z_{ui}=1)\log P(v_{ui}=1,a_{ui}=0,z_{ui}=1|r_{ui},b_{ui},c_{ui},\theta_{ui}) \\ +\mathbb{I}(v_{ui}=1,a_{ui}=1)\log P(v_{ui}=1,a_{ui}=1,z_{ui}|r_{ui},b_{ui},c_{ui},\theta_{ui})\end{pmatrix}, \quad (20)$$

where $\mathbb{I}(\cdot)$ is the indicator function.

With $\mathcal{L}_{behavior}$ as the objective function, parameters can be learned for predicting behaviors. However, causes are just conceptual at this step and do not capture practical patterns. To learn the causality, we next introduce the disentangled representation learning task to assign practical meanings to r_{ui}, b_{ui}, and c_{ui}.

Causal Embedding Learning

In order to make r_{ui}, b_{ui}, and c_{ui} capture causes, the model needs to be trained on cause-specific data. In other words, the information of the extent to which a behavior is driven by a cause is indispensable for causality learning. Yet the behaviors only reflect effects where causes are entangled. Hence, other clues related to the cause need to be exploited. We assume there exist proxy variables of item popularity effect and conformity effect, which can be constructed from training data; and then, cause-specific data can be built for disentangling causes based on the property of the common effect. Since a consumer's interest is mixed with item popularity effect (in view) or conformity effect (in add-to-cart and purchase), we disentangle r_{ui} from b_{ui} and c_{ui}.

Disentangling interest and item popularity effect. Let $\pi = (\pi_1, \pi_2, \dots, \pi_I)^T$ be the proxy variable for the item popularity effect. That is, if $\pi_i > \pi_j$, we expect $b_{ui} > b_{uj}$ for $u \in \{1, 2, \dots, U\}$. In the causal graph (Figure 2), view depends on the consumer's interest and item popularity, forming a common effect structure (i.e., collider) (Pearl 2009). This structure implies that r_{ui} and b_{ui} are dependent if v_{ui} is observed, which provides necessary information for causality inference. For example, if user u views unpopular item i, it can be concluded that the behavior is probably driven by u's interest in i. We discuss two cases to utilize causality information for disentangling interest and item popularity effects.

Case 1: $v_{ui} = 1, v_{uj} = 0, \pi_i < \pi_j$. Since u views i with less item popularity effect rather than j, according to the common effect structure, it is probable that u's interest in i is higher than that in j. Therefore, the inequalities of causes can be derived as follows.

$$b_{ui} < b_{uj} \text{ and } r_{ui} > r_{uj}. \quad (21)$$

Case 2: $v_{ui} = 1, v_{uj} = 0, \pi_i > \pi_j$. As u views an item with more item popularity effect, we cannot infer the relationship between u's interests in i and j. Hence, only the inequality of item popularity effect can be derived, that is,

$$b_{ui} > b_{uj}. \quad (22)$$

Note that the proxy variable may be inconsistent with item popularity effects in practical use due to the error of variable construction, along with behavior being probabilistic. Hence, to achieve a robust inference, the above established inequalities are not regarded as constraints but incorporated into the objective function. The loss function of disentangling interest and item popularity effect is formulated as

$$\mathcal{L}_{rb} = -\sum_{u=1}^{U}\sum_{(i,j)}\mathbb{I}\big(v_{ui}=1, v_{uj}=0\big)\begin{pmatrix}\mathbb{I}(\pi_i < \pi_j)\left(\log\Lambda(r_{ui}-r_{uj}) + \log\Lambda(b_{uj}-b_{ui})\right) \\ +\mathbb{I}(\pi_i > \pi_j)\log\Lambda(b_{ui}-b_{uj})\end{pmatrix}. \quad (23)$$

Disentangling interest and conformity effect. Let $\delta = (\delta_1, \delta_2, \dots, \delta_I)^T$ be the proxy variable for conformity effect. That is, if $\delta_i > \delta_j$, we expect $c_{ui} > c_{uj}$ for $u \in \{1, 2, \dots, U\}$. Nevertheless, disentangling r_{ui} and c_{ui} is more challenging than disentangling r_{ui} and b_{ui} because of the triangle structure in Figure 1. When we focus on a single behavior, the inequalities of causes cannot be derived. For example, if we study the circumstance that $a_{ui} = 1, a_{uj} = 0$, the causality cannot be identified directly. It may be possible that u has not viewed j (i.e., $v_{uj} = 0$), where there is no information of conformity; or it could be that u purchases i directly after view (i.e., $z_{uj} = 1$). Consequently, we cannot infer the inequalities of causes due to different decision mechanisms. Essentially, the property of the common effect is *decision-path-dependent*. Causality information can be identified with respect to $(a_{ui}=1, a_{uj}=0)$ if and only if both $v_{ui}=v_{uj}=1$ and $s_{ui}=s_{uj}=0$ hold, i.e., both i and j are considered by u through the add-to-cart decision path.

Decision path dependence further brings a negative sample attribution problem to model training that some negative sample cases are ambiguous because they depend on latent variables. Specifically, as shown in Figure 3, a (u,j) pair (i.e., u views j without add-to-cart or purchase) can be the negative case of a (u,i) pair (i.e., u purchases i directly after view) or a (u,i') pair (i.e., u adds i' to cart), depending on the unobserved decision path choice variable s_{uj}. To handle this problem, we employ the posterior probability of s_{uj}

$$Q(s_{uj}) \equiv P(s_{uj} | v_{uj}=1, a_{uj}=0, z_{uj}=0) \tag{24}$$

to weigh the negative sample case (u,j) with respect to different decision paths. Therefore, the loss function of disentangling interest and conformity effect can be formulated as

$$\begin{aligned}\mathcal{L}_{rc} = -\sum_{u=1}^{U}\sum_{(i,j)} &\begin{pmatrix}\mathbb{I}(a_{ui}=1, a_{uj}=0, v_{ui}=v_{uj}=1, z_{uj}=0)Q(s_{uj}=0)\\ +\mathbb{I}(z_{ui}=1, z_{uj}=0, v_{ui}=v_{uj}=1, a_{ui}=a_{uj}=0)Q(s_{uj}=1)\\ +\mathbb{I}(z_{ui}=1, z_{uj}=0, v_{ui}=v_{uj}=1, a_{ui}=a_{uj}=1)\end{pmatrix}\\ &\times\begin{pmatrix}\mathbb{I}(\delta_i<\delta_j)\left(\log\Lambda(r_{ui}-r_{uj})+\log\Lambda(c_{uj}-c_{ui})\right)\\ +\mathbb{I}(\delta_i>\delta_j)\log\Lambda(c_{ui}-c_{uj})\end{pmatrix}.\end{aligned} \tag{25}$$

We integrate the three loss functions with a multi-task learning framework. The objective function to be minimized is

$$\mathcal{L} = \mathcal{L}_{behavior} + \lambda_1\mathcal{L}_{rb} + \lambda_2\mathcal{L}_{rc}, \tag{26}$$

where $\lambda_1 > 0$ and $\lambda_2 > 0$ are hyperparameters controlling the weights of the causality learning tasks.

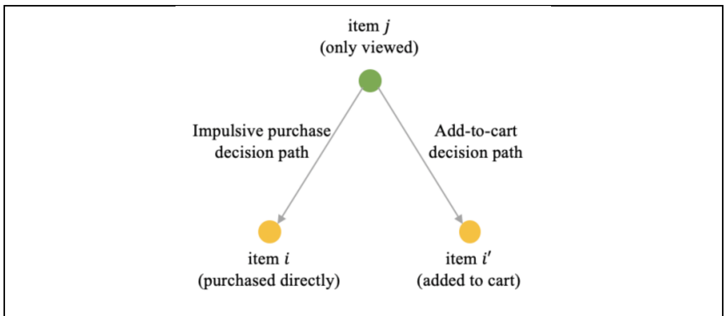


Figure 3. Negative Sample Attribution Problem

Model Inference

Since the latent variable that indicates decision path choice, s_{ui}, leads to a log-sum structure in $\mathcal{L}_{behavior}$ (Equation (20)), we employ an EM algorithm for parameter learning. Specifically, in the E-step, we infer the posterior probability of s_{ui}. In the M-step, we first derive the upper bound of the log-sum structure in $\mathcal{L}_{behavior}$ by Jensen's inequality. Then, the upper bound of the loss function $\mathcal{L}$ (Equation (26)) can be minimized.

Consumers' purchase behavior can be predicted given the estimated parameters. For item i that has not been purchased by user u, if u has not viewed i yet (i.e., $v_{ui}=0$), the purchase probability will be

$$\hat{P}_{z_{ui}=1} = \hat{\Lambda}^{v}_{ui}\left(\hat{\theta}_{ui}\hat{\Lambda}^{vz}_{ui} + (1-\hat{\theta}_{ui})\hat{\Lambda}^{a}_{ui}\hat{\Lambda}^{az}_{ui}\right), \qquad if\ v_{ui}=0, \tag{27}$$

where $\hat{}$ represents the estimated result.

If u has viewed i but has not added i to cart (i.e., $v_{ui}=1, a_{ui}=0$), the purchase probability will be

$$\hat{P}_{z_{ui}=1} = \hat{\theta}_{ui}\hat{\Lambda}^{vz}_{ui} + (1-\hat{\theta}_{ui})\hat{\Lambda}^{a}_{ui}\hat{\Lambda}^{az}_{ui}, \qquad if\ v_{ui}=1, a_{ui}=0. \tag{28}$$

Finally, if u has added i to cart (i.e., $a_{ui} = 1$),

$$\hat{P}_{z_{ui}=1} = \hat{\Lambda}_{ui}^{az}, \qquad if\ a_{ui} = 1. \tag{29}$$

Causal Recommendation

Conventional RSs research commonly assumes the environment to be stationary to generate recommendation policy. That is, conventional RSs do not consider entangled causes of consumer behaviors but treat them as a whole; consequently, predictions are made based on the entangled causes. However, the stationary assumption is too strong to hold in the constantly changing marketplace, because the distribution of the item popularity as well as conformity can differ from one scenario to another. For example, if the recommendation is interest-oriented, only consumers' interest should drive behaviors in test scenario; therefore, predictions made with entangled causes will work poorly in practice.

Unlike conventional works, our work can generate desirable recommendation policies to accommodate different scenarios. To achieve the target, *counterfactual inference* should be made according to interest, popularity, and conformity effects in a particular scenario to form casual recommendations. That is, given the observed digital footprints of consumers (i.e., actual data), we need to infer what the purchase probability would be (i.e., counterfactual outcomes) if causes (i.e., antecedent) were changed (Pearl et al. 2016). With the EM algorithm, the parameters of the model have been estimated given the actual data. Based on the learnt model, the counterfactual purchase probability can be computed in a way similar to intervention in causes. Since the causes are root nodes in casual graph, the operation can be conducted through directly modifying causes, which is a trivial case of backdoor criterion (Pearl et al. 2016). Specifically, suppose the effects of item popularity and conformity are b'_{ui} and c'_{ui} in RS's serving scenario, the counterfactual purchase probability will be obtained by setting

$$\hat{b}_{ui} = b'_{ui}\ and\ \hat{c}_{ui} = c'_{ui}. \tag{30}$$

Particularly, when the recommendation policy is interest-oriented, the effects of item popularity and conformity need to be eliminated, that is,

$$\hat{b}_{ui} = b'_{ui} = 0\ and\ \hat{c}_{ui} = c'_{ui} = 0, \qquad for\ all\ (u, i). \tag{31}$$

Thus, the purchase likelihood driven by interest can be derived by putting Equation (31) into Equation (27)-(29), which can be used for ranking the top-n list for the focal consumer. Note that such a task is comparable to the debiasing-oriented tasks (Zheng et al. 2021), which will be included as baselines in the evaluation.

Evaluation

Extensive experiments are conducted on a real-world dataset to evaluate the performance of the proposed method (DIPC). We seek to answer the following three experimental questions. *EQ1*: How does DIPC perform compared with the state-of-the-art methods in terms of purchase behavior prediction? *EQ2*: Can DIPC outperform the state-of-the-art methods in terms of learning consumers' interests? *EQ3*: What are the roles of modeling view and add-to-cart in the casual recommendation?

Dataset

We use a real-world dataset *Beibei* (available at https://github.com/chenchongthu/EHCF) for evaluation, which records multiple digital footprints including view, add-to-cart, and purchase during the time period from 2017/11/25 to 2017/12/03. The data are preprocessed to retain users with more than 20 records of purchase. The descriptive statistics are shown in Table 2.

#users	#items	#views	# add-to-carts	# purchases	# purchases after add-to-cart
3,152	7,024	398,186	138,697	88,418	86,684

Table 2. Descriptive Statistics of Beibei dataset

To evaluate the purchase behavior prediction performance as is described in EQ1, the purchase data are split at 4:1 randomly for training and testing. For the training data, we include the view and add-to-cart records of the users for training. That is, purchase data for testing follow the same distribution as that in training data. Hyperparameters λ_1, λ_2, and common ones including training epochs and learning rate are tuned on the training set by cross-validation.

For EQ2 and EQ3 concerning causality learning, an ideal test set is a collection of consumers' genuine interests obtained with a survey or other experimental tools. However, such data are scarce due to the considerable costs of data collection. Therefore, we employ intervened purchase data for validation and testing, which is widely adopted in the out-of-sample tests of causal recommendation methods (Bonner and Vasile 2018, Liang et al. 2016a, Wei et al. 2021, Zheng et al. 2021). The intervened data seek to reweigh the observational data to mimic the outcome that is not driven by side factors, thus providing a debiased testbed to evaluate the performance of causal recommendation. Following previous works (Liang et al. 2016a, Bonner and Vasile 2018, Zheng et al. 2021), we construct the intervened data that works for multiple types of digital footprints as follows. First, we sample μ% of view records with equal probability in terms of items. The sampled view records can be regarded as behaviors generated under a random policy (Bonner and Vasile 2018). Since consumers are not exposed to popular products with a higher probability in the sampled data, the side effect brought by item popularity is reduced. Subsequently, add-to-cart and purchase records are filtered correspondingly, that is, the subsequent behavior records of non-sampled views will be eliminated. Then, μ% of the remaining add-to-cart records are sampled in a similar way to get an add-to-cart set under the random policy, along with the purchase records that happened after the add-to-cart being filtered once again. As consumers do not follow public decisions in the new samples like that in the original add-to-cart records, the side effect of conformity on add-to-cart is decreased. Finally, μ% of the remaining purchase records are sampled with the same strategy to form the intervened purchase data. We tune the parameter μ to obtain a 7:1:2 split for the training set (observational), validation set (intervened), and test set (intervened) of purchase records, where the validation set and test set are balanced with little item popularity effect and conformity effect, following a distribution different from the purchase data for training. View and add-to-cart records are used for training as well. Hyperparameters are tuned according to the performance on the validation set and then used for testing.

Generally, the number of views on a product reflects its popularity. A large number of views usually lead to a significant item popularity effect. Thus, the number of views can be a natural proxy variable for the item popularity effect (i.e., π). Considering that the total sales of a product show other consumers' purchase decisions, indicating the effect of social influence, we adopt the number of purchases as the proxy variable for the conformity effect (i.e., δ).

Baselines and Metrics

To comprehensively evaluate the performance of DIPC in terms of both modeling multiple digital footprints and learning consumers' interests (or equivalently, debiasing), we compare DIPC with four groups of baselines, which are summarized in Table 3, the details of which are omitted due to space limit.

	Purchase-based	Multiple-digital-footprints-based
Without debiasing mechanism	PMF (Mnih and Salakhutdinov 2007)	NMTR (Gao et al. 2019) (Information used: view, add-to-cart, purchase.) EHCF (Chen et al. 2020a) (Information used: view, add-to-cart, purchase.)
With debiasing mechanism	ExpoMF (Liang et al. 2016b) (Bias considered: item popularity.) CausE (Bonner and Vasile 2018) (Bias considered: conformity.) DICE (Zheng et al. 2021) (Bias considered: conformity.)	IPS-Pop (Saito et al. 2020) (Information used: view, purchase. Bias considered: item popularity.) IPS-Logit (Schnabel et al. 2016) (Information used: view, purchase. Bias considered: item popularity.) IPS-1BITMC (Ma and Chen 2019) (Information used: view, purchase.

		Bias considered: item popularity.)

Table 3. Baseline Methods for Performance Comparison

A top-n list can be built for each user by ranking items according to the predictions. For EQ1 concerning purchase behavior, all methods make predictions following a conventional manner that assumes stationary causes or biases, and DIPC predicts purchase likelihood according to Equation (27)-(29). In terms of EQ2 where the performance of interest learning is concerned, methods with a debiasing mechanism can generate predictions by eliminating bias, and DIPC predicts the likelihood through setting item popularity effect and conformity effect as Equation (31). Commonly used ranking-based metrics including precision (P), mean average precision (MAP), DCG, and NDCG are adopted for performance measurement.

Results

EQ1: The results of purchase behavior prediction on *Beibei* are shown in Table 4, where DIPC outperforms all baseline methods, showcasing the effectiveness of in-sample fitness that the behavioral patterns embedded in multiple digital footprints are well captured. Since purchase-based baselines and IPS methods cannot utilize the full information of data, their predictions of purchase behaviors are hampered. NMTR performs poorly because its assumed cascading relationship does not hold practically, resulting in model misspecification. The performance of EHCF is inferior to DIPC as well, which can be attributed to that EHCF pays much attention to the correlations of multiple behaviors while neglecting some sequence information.

Methods	P@5	MAP@5	NDCG@5	P@10	MAP@10	NDCG@10
PMF	0.1295	0.2438	0.1486	0.1040	0.2422	0.1591
ExpoMF	0.0998	0.1844	0.1117	0.0849	0.1871	0.1232
CausE	0.0631	0.1383	0.0739	0.0583	0.1469	0.0870
DICE	0.1065	0.1986	0.1195	0.0918	0.2013	0.1334
NMTR	0.1688	0.3163	0.1942	0.1381	0.3120	0.2153
EHCF	0.3444	0.5956	0.4174	0.2410	0.5659	0.4298
IPS-Pop	0.1440	0.2290	0.1487	0.1503	0.2491	0.2067
IPS-Logit	0.0708	0.1426	0.0767	0.0694	0.1594	0.1008
IPS-1BITMC	0.2919	0.4835	0.3383	0.2323	0.4606	0.3769
DIPC	**0.4674**	**0.6647**	**0.5414**	**0.3821**	**0.6203**	**0.6280**

Table 4. Results of Purchase Behavior Prediction

EQ2: To evaluate the performance of learning consumer's interest, intervened validation set and test set with little item popularity effect and conformity effect are employed. The comparison results on *Beibei* are shown in Table 5, where the performance of DIPC surpasses the others to a large extent. The superior performance can be attributed to the proper disentanglement of different causes. Firstly, baselines without a debiasing mechanism can only accomplish the task through tuning hyperparameters according to the validation set, which barely results in satisfactory performance. Secondly, baselines with a debiasing mechanism in Table 3 cannot model view, add-to-cart, and purchase simultaneously. Less information also makes the methods hard to capture interests. Failing to utilize abundant add-to-cart records, IPS methods performs rather poorly, while CausE gets the worst performance due to the extreme sparsity of its training data. Thirdly, the causality learning mechanism of DIPC, which disentangles causes with causal graph, is superior. Since the excellent performance of DIPC may be owed to both more information used and the causality learning mechanism, we carry out a finer-grained inspection in EQ3.

Methods	P@5	MAP@5	NDCG@5	P@10	MAP@10	NDCG@10
PMF	0.0085	0.0208	0.0119	0.0070	0.0234	0.0141

ExpoMF	0.0122	0.0273	0.0153	0.0113	0.0323	0.0196
CausE	0.0039	0.0088	0.0044	0.0038	0.0111	0.0059
DICE	0.0139	0.0327	0.0176	0.0122	0.0376	0.0215
NMTR	0.0190	0.0418	0.0221	0.0182	0.0484	0.0271
EHCF	0.0314	0.0706	0.0374	0.0280	0.0791	0.0445
IPS-Pop	0.0736	0.1610	0.0890	0.0685	0.1753	0.1108
IPS-Logit	0.0636	0.1311	0.0719	0.0637	0.1485	0.0953
IPS-1BITMC	0.0615	0.1248	0.0689	0.0624	0.1431	0.0924
DIPC	**0.2908**	**0.4525**	**0.3332**	**0.2774**	**0.4331**	**0.4301**

Table 5. Results of Consumers' Interest Learning

EQ3: The effect of modeling auxiliary digital footprints (i.e., view and add-to-cart) on interest learning is analyzed with an information ablation study. We modify DIPC to take into account only view and purchase (DIPC-VZ) or to model add-to-cart and purchase (DIPC-AZ). Results in Table 6 indicate that a lack of either view or add-to-cart information harms the performance. The degree of performance deterioration depends on the amount of information ablated. Therefore, as shown by the results on *Beibei*, removing a large amount of add-to-cart records leads to a sharp decrease in performance.

Furthermore, it should be noted that DIPC-VZ utilizes the same information as IPS methods but achieves a better performance of learning interest, which manifests the superiority of the causality learning mechanism (i.e., disentangled representation learning with causal graph) adopted by our method.

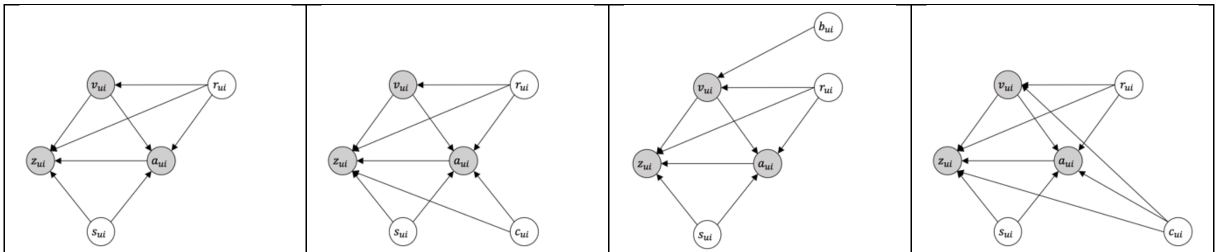
	P@5	MAP@5	NDCG@5	P@10	MAP@10	NDCG@10
DIPC-VZ	0.0815	0.1636	0.0938	0.0792	0.1802	0.1220
DIPC-AZ	0.2680	0.4290	0.3069	0.2619	0.4127	0.4027
DIPC	0.2908	0.4525	0.3332	0.2774	0.4331	0.4301

Table 6. Results of Information Ablation Study

Remark. With the proposed model, we can estimate the causes that drive consumer behaviors and the weights of causes in consumers' decisions. Since these parameters indicate prominent factors driving consumer behaviors, retailers can develop effective marketing strategies to nudge consumers. For example, if item popularity effect is shown to play an important role in a consumer's shopping journey, the retailer can intervene through personalized advertisements to enhance purchase probability, the effect of which can be estimated with the counterfactual evaluation. Our model can also benefit consumers by providing summaries of their behavioral biases with severity in decision making, which can help consumers become conscious of side causes and pay more attention to genuine interest. Moreover, EC platforms can generate casual recommendations to accommodate different needs with our method.

Discussion

This section further examines the necessity of considering item popularity and conformity. To figure it out, several alternative causal graphs are constructed with DIPC being adapted accordingly, which are illustrated in Figure 4. DIPC-*r* assumes all behaviors (i.e., view, add-to-cart, and purchase) are completely driven by consumers' interests. DIPC-*rc* removes item popularity effect from DIPC, i.e., view is motivated by interest only. DIPC-*rb* instead omits the conformity effect, which modifies add-to-cart and purchase modeling to make these behaviors totally depend on interest. DIPC-*rbias* assumes that item popularity effect and conformity effect are the same while the weight on causes of different decisions can be different.



(a) DIPC-r (b) DIPC-rc (c) DIPC-rb (d) DIPC-$rbias$

Figure 4. Alternative Causal Graphs

To evaluate the causality learning performance of these model versions with different assumptions, we conduct experiments on *Beibei*. The results in Table 7 show that omitting either item popularity effect or conformity effect worsens the performance of learning consumer interests, demonstrating the necessity of considering both effects. Moreover, omitting the conformity effect incurs a larger decrease in performance than omitting the item popularity effect, indicating the relative importance of focusing on conformity. Such a phenomenon can be attributed to that conformity works in the pre-purchase and purchase stages and influences purchase in a more direct way. In contrast, item popularity affects view in the need recognition stage, which is far from making a purchase. Though consumers cannot buy products they have not viewed, their interests can motivate the exposure to alleviate the influence of item popularity. In addition, without differentiating item popularity effect and conformity effect, the performance of DIPC-$rbias$ becomes poorer than that of DIPC due to model misspecification. Therefore, the causality behind consumer behaviors recognized in this study is further confirmed.

Methods	P@5	MAP@5	NDCG@5	P@10	MAP@10	NDCG@10
DIPC-r	0.1683	0.2423	0.1730	0.2169	0.2833	0.2927
DIPC-rc	0.2474	0.3878	0.2763	0.2514	0.3821	0.3758
DIPC-rb	0.1908	0.2829	0.2013	0.2259	0.3109	0.3146
DIPC-$rbias$	0.2549	0.3984	0.2851	0.2558	0.3881	0.3827
DIPC	**0.2908**	**0.4525**	**0.3332**	**0.2774**	**0.4331**	**0.4301**

Table 7. Results of Different Model Versions on Consumer's Interest Learning

Conclusion

In this study, we design a causal recommendation method, i.e., DIPC, based on cause disentanglement at various consumption stages. Referring to related theories, interest and item popularity are recognized as causes driving consumer behaviors in the need recognition stage, while behaviors in the pre-purchase and purchase stages are assumed to be motivated by interest and conformity. A causal graph is constructed with which disentangled representation learning is employed. To rigorously evaluate the performance of the DIPC, extensive experiments are conducted on a real-world dataset with carefully designed intervention in terms of modeling multiple digital footprints and causality learning. The results show DIPC outperforms all baselines significantly and possesses good interpretability, demonstrating the superiority of the proposed causal recommendation method. The causality assumption of DIPC is further checked to be rational by fitting consumers' behavior data to alternative causal graphs. Our work contributes to the research of RS as follows. Theoretically, we analyze consumers' behavioral mechanisms in the shopping journey, revealing the causality behind consumers' multiple implicit feedback. Methodologically, our work is one of the first studies to disentangle the causes behind consumers' implicit feedback at various stages and provide interpretable recommendations. We have handled the challenging triangle-structured digital footprints of consumers, providing a foundational component for modeling consumers' flexible shopping journey. Therefore, the proposed method broadens the way for modeling more types of consumer implicit feedback. On the other hand, the causality learning performance of our model is robustly excellent even if the information of consumers' implicit feedback is highly restricted. Moreover, a consolidated framework is designed to comprehensively evaluate the proposed method in terms of both modeling multiple digital footprints and causality learning. We also offer several implications for business practice. With the introduction of a causal graph, our method provides insights from the perspectives of both consumers and retailers. For consumers, the summary of the driving factors of one's purchase could help mitigate behavioral biases. For retailers, the proposed method can tell the more prominent factors in driving consumers' purchase decisions, which can be used to nudge consumers in a personalized manner. Moreover, the shortcoming of conventional RSs making predictions based on entangled causes is overcome, such that EC platforms can generate casual recommendations to accommodate different scenarios with the proposed method. Our work is not without limitations, which call for future research. First, we only consider three primary types of implicit feedback in our model, while neglecting secondary ones. Based on our method, more types of implicit feedback can be incorporated with more available information as proxy variables. Second, we only have the dataset before COVID-19, it would be interesting to further look into the change in consumer behavior before and after the pandemic.

Acknowledgements

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References

Akerlof GA (1991) Procrastination and obedience. *The American Economic Review* 81(2):1-19.

Baeza-Yates R (2018) Bias on the web. *Communications of the ACM* 61(6):54-61.

Beatty SE, Ferrell ME (1998) Impulse buying: Modeling its precursors. *Journal of retailing* 74(2):169-191.

Bengio Y, Courville A, Vincent P (2013) Representation learning: A review and new perspectives. *IEEE transactions on pattern analysis and machine intelligence* 35(8):1798-1828.

Bonner S, Vasile F (2018) Causal embeddings for recommendation. *Proceedings of the 12th ACM conference on recommender systems*, 104-112.

Brynjolfsson E, Smith MD (2000) Frictionless commerce? a comparison of Internet and conventional retailers. *Management science* 46(4):563-585.

Chen C, Zhang M, Zhang Y, Ma W, Liu Y, Ma S (2020a) Efficient heterogeneous collaborative filtering without negative sampling for recommendation. *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, 19-26.

Chen X, Li L, Pan W, Ming Z (2020b) A survey on heterogeneous one-class collaborative filtering. *ACM Transactions on Information Systems (TOIS)* 38(4):1-54.

Ciampaglia GL, Nematzadeh A, Menczer F, Flammini A (2018) How algorithmic popularity bias hinders or promotes quality. *Scientific reports* 8(1):1-7.

Dowling K, Guhl D, Klapper D, Spann M, Stich L, Yegoryan N (2020) Behavioral biases in marketing. *Journal of the Academy of Marketing Science* 48(3):449-477.

Fishburn PC (1970) Utility theory for decision making. Technical report, Research analysis corp McLean VA.

Fleder D, Hosanagar K (2009) Blockbuster culture's next rise or fall: The impact of recommender systems on sales diversity. *Management science* 55(5):697-712.

Gao C, He X, Gan D, Chen X, Feng F, Li Y, Chua TS, Yao L, Song Y, Jin D (2019) Learning to recommend with multiple cascading behaviors. *IEEE transactions on knowledge and data engineering* 33(6):2588-2601.

Ghose A, Goldfarb A, Han SP (2013) How is the mobile internet different? search costs and local activities. *Information Systems Research* 24(3):613-631.

Godes D, Silva JC (2012) Sequential and temporal dynamics of online opinion. *Marketing Science* 31(3):448-473.

Hu N, Pavlou PA, Zhang JJ (2017) On self-selection biases in online product reviews. *MIS Q.* 41(2):449-471.

Iyer GR, Blut M, Xiao SH, Grewal D (2020) Impulse buying: a meta-analytic review. *Journal of the Academy of Marketing Science* 48(3):384-404.

Jonas E, Schulz-Hardt S, Frey D, Thelen N (2001) Confirmation bias in sequential information search after preliminary decisions: an expansion of dissonance theoretical research on selective exposure to information. *Journal of personality and social psychology* 80(4):557.

Karaman H (2021) Online review solicitations reduce extremity bias in online review distributions and increase their representativeness. *Management Science* 67(7):4420-4445.

Koren Y, Bell R, Volinsky C (2009) Matrix factorization techniques for recommender systems. *Computer* 42(8):30-37.

Lee L, Inman JJ, Argo JJ, Böttger T, Dholakia U, Gilbride T, Van Ittersum K, Kahn B, Kalra A, Lehmann DR, et al. (2018) From browsing to buying and beyond: The needs-adaptive shopper journey model. Journal of the Association for Consumer Research 3(3):277-293.

Liang D, Charlin L, Blei DM (2016a) Causal inference for recommendation. *Causation: Foundation to Application, Workshop at UAI. AUAI.*

Liang D, Charlin L, McInerney J, Blei DM (2016b) Modeling user exposure in recommendation. *Proceedings of the 25th international conference on World Wide Web*, 951-961.

Ma J, Zhou C, Cui P, Yang H, Zhu W (2019) Learning disentangled representations for recommendation. *Advances in neural information processing systems* 32.

Ma W, Chen GH (2019) Missing not at random in matrix completion: The effectiveness of estimating missingness probabilities under a low nuclear norm assumption. *Advances in Neural Information Processing Systems* 32.

Mnih A, Salakhutdinov RR (2007) Probabilistic matrix factorization. *Advances in neural information processing systems* 20.

Muchnik L, Aral S, Taylor SJ (2013) Social influence bias: A randomized experiment. *Science* 341(6146):647-651.

Nikolov D, Lalmas M, Flammini A, Menczer F (2019) Quantifying biases in online information exposure. *Journal of the Association for Information Science and Technology* 70(3):218-229.

Pearl J (2009) *Causality* (Cambridge university press).

Pearl J, Glymour M, Jewell NP (2016) *Causal Inference in Statistics: A Primer* (John Wiley & Sons).

Saito Y, Yaginuma S, Nishino Y, Sakata H, Nakata K (2020) Unbiased recommender learning from missing-not-at-random implicit feedback. *Proceedings of the 13th International Conference on Web Search and Data Mining*, 501-509.

Schnabel T, Swaminathan A, Singh A, Chandak N, Joachims T (2016) Recommendations as treatments: Debiasing learning and evaluation. *international conference on machine learning*, 1670-1679 (PMLR).

Sun T, Yuan Z, Li C, Zhang K, Xu J, et al. (2021) The value of personal data in internet commerce: A high-stake field experiment on data regulation policy. Technical report.

Suter R, Miladinovic D, Sch□olkopf B, Bauer S (2019) Robustly disentangled causal mechanisms: Validating deep representations for interventional robustness. *International Conference on Machine Learning*, 6056-6065 (PMLR).

Wang M, Gong M, Zheng X, Zhang K (2018) Modeling dynamic missingness of implicit feedback for recommendation. *Advances in neural information processing systems* 31.

Wang W, Feng F, He X, Wang X, Chua TS (2021) Deconfounded recommendation for alleviating bias amplification. *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 1717-1725.

Wang X, Jin H, Zhang A, He X, Xu T, Chua TS (2020) Disentangled graph collaborative filtering. *Proceedings of the 43rd international ACM SIGIR conference on research and development in information retrieval*, 1001-1010.

Wang X, Zhang R, Sun Y, Qi J (2019) Doubly robust joint learning for recommendation on data missing not at random. *International Conference on Machine Learning*, 6638-6647 (PMLR).

Wei T, Feng F, Chen J, Wu Z, Yi J, He X (2021) Model-agnostic counterfactual reasoning for eliminating popularity bias in recommender system. *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 1791-1800.

Zhao Z, Cheng Z, Hong L, Chi EH (2015) Improving user topic interest profiles by behavior factorization. *Proceedings of the 24th International Conference on World Wide Web*, 1406-1416.

Zheng Y, Gao C, Li X, He X, Li Y, Jin D (2021) Disentangling user interest and conformity for recommendation with causal embedding. *Proceedings of the Web Conference 2021*, 2980-2991.