Interventional Recommendation with Contrastive Counterfactual Learning for Better Understanding User Preferences

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ABSTRACT

Recently, there has been a surging interest in formulating recommendations in the context of causal inference. The studies regard the recommendation as an intervention in causal inference and frame the users’ preferences as interventional effects to improve recommender systems’ generalization. Many studies in the field of causal inference for recommender systems have been focusing on utilizing propensity scores from the causal community that reduce the bias while inducing additional variance. Alternatively, some studies suggest the existence of a set of unbiased data from randomized controlled trials while it requires to satisfy certain assumptions that may be challenging in practice. In this paper, we first design a causal graph representing recommender systems’ data generation and propagation process. Then, we reveal that the underlying exposure mechanism biases the maximum likelihood estimation (MLE) on observational feedback. In order to figure out users’ preferences in terms of causality behind data, we leverage the back-door adjustment and do-calculus, which induces an interventional recommendation model (IREC). Furthermore, considering the confounder may be inaccessible for measurement, we propose a contrastive counterfactual learning method (CCL) for simulating the intervention. In addition, we present two extra novel sampling strategies and show an intriguing finding that sampling from counterfactual sets contributes to superior performance. We perform extensive experiments on two real-world datasets to evaluate and analyze the performance of our model IREC-CCL on unbiased test sets. Experimental results demonstrate our model outperforms the state-of-the-art methods.

KEYWORDS

Recommender system; Causal inference; Contrastive Counterfactual learning; Interventional recommendation

1 INTRODUCTION

Recommender systems have been widely applied in various applications such as search engines, ad placement and e-commerce websites. The feedback data between users and items in recommender systems involve two sections: exposures and ratings. Chronologically, the system first provides users with a list of recommended items. Users click and rate items they like or dislike. Exposures indicate that users can not observe all items in each interaction, and the recommender system determines the exposure mechanism. Ratings express explicit preferences and reflect users’ interests in items. It’s essential to remember that we could only reveal users’ preferences on exposed items. Still, if the user does not see an item, we cannot conclude whether the user likes this item or not. Thereby, the underlying exposure mechanism may bias accurate inference for users’ preferences.

![Figure 1: An illustration of formulating recommendations in the context of causal inference.](image)

Recently, there has been growing interest in formulating recommendations in the context of causal inference [22, 29]. Specifically, the studies regard the recommendation that exposes an item to an user as an intervention in causal inference and frame estimating users’ preferences as solving the effect of interventions (a set of recommendations). In such manner, these approaches establish the spirit of recommender systems to answer a counterfactual question: “What would the response be if the user was recommended with other items?”

For example, Figure 1 shows the recommender system first selects two items from the exposure space for the user who is interested in photography and the user renders the ratings, which we obtain the observational data. The remaining items in the whole item set are not exposed to the user, which we call the counterfactual samples. Based on the observational interactions, the system predicts the user’s preferences on other items and then offers recommendations. It perhaps forecasts the user will be interested in the mouse due to the high relevance between the mouse and the computer. However, the user’s natural preference is photography. The user has a high rating on the computer simply because he only saw these two items. And perhaps the user needs the computer to post-process photos, or the computer and the camera both belong to electronic products. Consequently, the natural preference of users is submerged due to the underlying exposure mechanism.
Intuitively, we will ask what the user would respond if he saw the camera before, which is a perspective of causal inference.

Specifically, considerable literature has attempted to tackle the recommendation from the causal inference perspective and can be categorized into three groups: 1) Propensity score-based methods [22, 24] that borrow the concept of propensities from the causality, integrate inverse propensity scores into standard recommendation models and manipulate the observational distribution via inverse propensity re-weighting. [8, 10, 27] combine the imputed errors and propensities to obtain a doubly robust estimator. Introducing propensity scores reduces bias, nevertheless the propensity estimation induces extra variance, leading to performance instability. 2) Side information-based techniques assume that a small set of unbiased data or supplementary knowledge are obtainable. [2, 28] utilize unbiased data to re-weight biased ratings with domain adaptation and adaptive assignment. Note that the propensity estimation via naive Bayes also requires unbiased data. [11, 23] control social network confounders or leverage network information to mitigate biases and improve performance. Auxiliary knowledge is hard to obtain; therefore, this approach is limited in practice. 3) Information bottleneck-based methods [14, 30] learn unbiased representation from biased feedback from the perspective of information-theoretic learning. Nonetheless, this method is not valid for analyzing the data generation and resolving the interventional effects.

Despite the success of the existing models, we suggest that it is necessary to model the data generation and propagation process. The structured causal model (SCM) from causal inference has the potential to help us reveal the causality behind the data and infer the interventional effects. We leverage backdoor adjustment with do-calculus to understand the data generation and propagation process. Recently, some works [26, 31, 37] proposed to design a causal graph that represents causality generation processes behind data. These works model popularity bias, an intrinsic property of items, which are also limited in generalizing to handle various biases. Instead, we draw attention to counterfactual samples from the causal graph and then carry out interventional effects.

In this work, we first illustrate a causal graph that embodies the generation and propagation process for data in recommender systems. Based on the causal graph, we leverage the structured causal model (SCM) and do-calculus operator do(·) to reveal causality behind data regarding users’ natural preferences. We derive an interventional recommendation model (IREC) in contrast to the standard model fitting the observational feedback. Since the confounder variable may be inaccessible for measurement, we propose contrastive counterfactual learning (CCL) for simulating the intervention \( P(Y|do(U, I)) \) in which items are uniformly exposed to users in representation space. In addition to random counterfactual sampling, we propose two additional sampling strategies, i.e., propensity score-based or item popularity-based samplings, and render an exciting finding that sampling randomly from counterfactual sets yields superior performance. This encouraging finding draws our attention to the importance of rich counterfactual user-item pairs. Experiments on two real-world benchmarks demonstrate the effectiveness of our model IREC-CCL. Moreover, we conduct detailed evaluations and analyses, i.e., the performance evaluation, the comparison of various sampling strategies and the visualization study for distributions of users and items in the representation space.

The key contributions are summarized as follows.

- We formulate IREC, an interventional recommendation model, to analyze the counterfactual question “What if the user was recommended with other items?” by introducing the structural causal model and do-calculus.
- We propose an innovative contrastive counterfactual learning method (CCL) for simulating the intervention. Meanwhile, we present two extra novel sampling strategies integrated into contrastive learning. The sampling methods are informative and effective since they utilize estimated exposure possibility or counterfactual samples.
- We present an intriguing finding that sampling from counterfactual sets contributes to superior performance, which sheds light on the usefulness of a wealth of counterfactual samples existing in data.
- The extensive experimental results compared with ten baseline methods over two real-world benchmark datasets prove the effectiveness of our approach.

### 2 PROBLEM SETUP

We denote user and item sets as \( \mathcal{U} (|\mathcal{U}| = m) \) and \( \mathcal{I} (|\mathcal{I}| = n) \) respectively, with \( u \in \{1, \ldots, m\} \) and \( i \in \{1, \ldots, n\} \). Let \( O_{u,i} \in \{0, 1\} \) be the indicator for exposure status, \( \hat{y}_{u,i} \) be the true rating, and \( D \) be the observational feedback data for user-item pairs. Recall that we claim there are two data types in \( D \) chronologically: exposures and ratings. Some items are recommended to a user \((O_{u,i} = 1)\), but the user does not like them \((\hat{y}_{u,i} = 0)\), while a user may see some other items \((O_{u,i} = 1)\) and prefer them \((\hat{y}_{u,i} = 1)\). Note that the \( \hat{y}_{u,i} \) is missing and unknown if \( O_{u,i} = 0 \).

The causal view in recommendations suggests the underlying exposure mechanism, which is likely to be unfair (impacted by popular items), determines what each user sees and affects the inference for users’ preferences [12, 22]. Recall that in Figure 1, the recommendation model is likely to assume the user prefers the mouse and computer while he is interested in photography actually. In addition, the example in Figure 1 induces counterfactual thinking: “What if the user was recommended with the camera?” It’s equivalent to regarding the recommendation as an intervention in causal inference and the rating prediction equals solving interventional effects, which is \( y_{u,i} \) when we replace \( O_{u,i} = 0 \) with \( O_{u,i} = 1 \) [29]. Some studies leverage inverse propensity scores (IPS) to distort the observational data and weight the feedback as if samples came from an experimental distribution that items are randomly exposed to each user:

\[
\hat{R}_{IPS} = \frac{1}{|\{(u, i) \in D\}|} \sum_{(u, i) \in D: O_{u,i}=1} \frac{\delta(\hat{y}_{u,i}, y_{u,i})}{P_{u,i}}
\]  

where \( P_{u,i} \) is the propensity score representing the estimated exposure probability for the user-item pair and \( \delta \) is an arbitrary loss function.

We start from the causal view and apply causal inference to the problem. Imagine that every item is exposed with equal probability to users. In such a manner, we alleviate biases induced from the exposure model and could infer natural preferences for users.
Observational data $(x_u, x_i, y_{ui})^N$

(a) Recommendation model

Layer X

Neural Layers

Layer 1

CCL

Embedding Layer

$g_u, g_i$

$e_u, e_i$

$u, i$

Observational data $(x_u, x_i, y_{ui})^N$

(b) Contrastive Counterfactual Learning (CCL)

Maximize agreement $L_{ccl}$

$\mathcal{L}_{rec}$

$\hat{y}_{ui}$

Positive Sampling

Batch of samples

Random Counterfactual sampling

Propensity score-based sampling

Sorted by item popularity

Sorted by propensity score

Sorted by unobserved user-item pair

Anchor

Anchor

Feature Layer

Prediction Layer

Figure 2: Overall framework. (a) presents the structure of the recommendation model with the novel CCL module. $\mathcal{L}_{rec}$ denotes the empirical risk for preference prediction. (b) illustrates the contrastive counterfactual learning (CCL) module. It utilizes random counterfactual sampling or two other methods as data augmentation. Then it maximizes the agreement within two views via $L_{ccl}$. (c) shows three novel sampling methods, including random counterfactual sampling, propensity score-based and item popularity-based samplings.

3 THE PROPOSED METHOD

3.1 Interventional Recommendation Model

Recall that we argue the maximum likelihood estimation (MLE) that focuses on $P(Y|U, I)$ is likely to have spurious effects due to the underlying exposure mechanism, i.e., we mistakenly think that the user prefers the mouse more than the camera in Figure 1. This section explores how data generate into recommendation models. The structural causal model (SCM) can potentially be the model responsible for data generation [1, 18]. Preliminary works [26, 31] also attempt to illustrate the popularity bias behind data with SCM. Therefore, we introduce a causal graph to embody the typical variables in the recommendation model. In contrast to the association $P(Y|U, I)$, we formulate an interventional recommendation model that blocks the confounder path, which is identical to interventional effects in causality.

3.1.1 Causal Interpretation. The structure causal model (SCM) is a semantic framework for causality with information on variables of interest and their mechanical relations. The SCM is related to a directed acyclic graph. The vertices are associated with a set of variables $\{X_1, ..., X_n\}$ and the arrow between two vertices reflects the causal relationship, i.e., $X_1 \rightarrow X_2$ means $X_1$ is the cause of $X_2$.

We abstract a causal graph for the recommendation model in Figure 3. In particular,
Z refers to the confounder. This path makes sure the confounding is infeasible to perform actual interventions, i.e., randomized equivalent to adding an intervention to the latter variables. But blocked since it only contains chain and fork paths. Therefore, we d-separation in [19], the path from \( U, I \) to \( Y \).

- \( Z \) denotes the confounder that is unobserved or may be inaccessible for measurement. The confounder variable in this work represents the underlying exposure mechanism.
- \( U \) represents raw features for the user such as ID, gender and age.
- \( I \) refers to the item variable that includes raw features for the item, such as ID, colour and category.
- \( X \) is the concatenation of user and item representations.
- \( D \) denotes the mediator variable representing an indirect path from the confounder to the outcome.
- \( Y \) stands for the user preference variable.

We present a detailed interpretation of subgraphs in Figure 3. \( Z \rightarrow U, I \). The confounder may cause users only to see part of the whole collection of items. Thereby, spurious correlations between the user and specific items exist. For example, in Figure 1, the user is interested in photography but can only see the computer and fast food. Based on observational feedback, we infer that his preference is the computer, but actually his true interest is submerged in counterfactual samples.

\( \{U, I \rightarrow X \rightarrow Y\} \). The classic recommendation follows this path. The raw features for observed users and items are fed into encoder networks. The classifier takes the concatenation of users and items’ embeddings as input. And the classifier outputs the binary ratings.

\( \{Z \rightarrow D \rightarrow Y\} \). We also connect \( Z \) to the result label \( Y \) since \( Z \) refers to the confounder. This path makes sure the confounding impact from \( Z \) to \( Y \) via an undirected path except for \( U, I \).

The standard recommendation models estimate the conditional probability \( P(Y|U, I) \) or \( P(Y|X) \) based on observational feedback via the path \( \{U, I \rightarrow X \rightarrow Y\} \). We can distinguish another path from \( U, I \) to \( Y \), which is \( \{U, I \leftarrow Z \rightarrow D \rightarrow Y\} \). According to the d-separation in [19], the path \( \{U, I \leftarrow Z \rightarrow D \rightarrow Y\} \) is not blocked since it only contains chain and fork paths. Therefore, we need to block the path \( \{Z \rightarrow U, I\} \) and then obtain a more accurate inference for \( Y \).

### 3.1.2 Causal intervention

We need to find solutions to block the path \( \{Z \rightarrow U, I\} \), and blocking one path in the causal graph is equivalent to adding an intervention to the latter variables. But it is infeasible to perform actual interventions, i.e., randomized controlled trials. Causality provides do-calculus to calculate the intervention \( P(Y|do(U, I)) \) and a method for solving do-calculus is based on the backdoor criterion. That is:

\[
P(Y|do(U, I)) = \sum_{z \in Z} P(Y|U, I, z)p(z|U, I) 
= \sum_{z \in Z} P(Y|U, I, z)p(z) 
= \sum_{z \in Z} P(Y|X, z)p(z) 
\]

In this way, we require the prior distribution of the confounder \( p(z) \) and solve the sum operator based on the confounder. Some works stratify the confounder into pieces [5, 36] or encode the intervention as a new variable [33]. But \( Z \) refers to an unknown exposure mechanism in recommender systems, making it difficult to decompose and stratify. Since we cannot access the confounder \( Z \), we consider simulating the intervention [17, 35]. Intuitively, the intervention in a randomized controlled experiment represents that items are exposed to each user uniformly at random. Based on the uniform exposure mechanism, we can determine the user is unlikely to prefer the item if there is no click or interaction between the user and the item. We consider this and approximate \( do(X) \) in the representation space to realize that each item has an equal probability of being exposed to users.

Therefore, we propose a contrastive counterfactual learning method as a simulation for the intervention and obtain manipulated distribution in representation space. Moreover, we design two extra novel sampling methods and integrate them into contrastive learning, e.g., propensity score-based and item popularity-based samplings.

### 3.2 Contrastive Counterfactual Learning

Recall that we are required to block the path from the confounder to the user and item variables. Still, the solution for do-calculus in recommender systems is intractable. Therefore, this work employs contrastive self-supervised learning, a powerful representation learning technique, to simulate the intervention. We aim to create a manipulated distribution in which items are uniformly exposed to each user. We propose a random counterfactual sampling method and formulate a contrastive counterfactual learning method (CCL). Furthermore, we supplement two novel positive sampling methods, as shown in Figure 2(b) and (c).

#### 3.2.1 Contrastive Counterfactual Learning (CCL)

Contrastive SSL generates positive samples with the data augmentation operators and optimizes encoders by maximizing agreements between the anchor and the positive samples. Specifically, given a mini-batch samples with \( N \) examples, we use \( x_k \) to represent the concatenation of the user and item’s features \( x_\text{u} \oplus x_\text{i} \), which we obtain \( \{x_k, \hat{y}_k\}_{k=1}^N \).

We propose three informative samplers \( T \) and choose one of them \( t \in T \) to transform the mini-batch samples. In this section, we introduce random counterfactual sampling and present two supplementary sampling methods later. We obtain a total of \( 2N \) samples with \( \tilde{x}_{2k-1} = x_k \) and \( \tilde{x}_{2k} = t(x_k) \) as:

\[
\{x_1, \tilde{x}_1, x_2, \tilde{x}_2, ..., x_N, \tilde{x}_N\}
\]
where \( k \in \{1, 2, \ldots, N\} \). The anchor and the sample from random counterfactual sampling \((x_k, \tilde{x}_k)\) are considered as positive pairs, and we treat the remaining \(2(N-1)\) samples as negative samples.

\[
l_{ccl}(\tilde{h}_{2k-1}, \tilde{h}_{2k}) = -\log \frac{\exp(\text{sim}(\tilde{h}_{2k-1}, \tilde{h}_{2k})/\tau)}{\sum_{m=1}^{2N} \text{sim}(\tilde{h}_{2k-1}, \tilde{h}_m)/\tau)}
\]

where \( \text{sim}(\cdot, \cdot) \) is an indicator function and the indicator equals to 1 iff \( m \neq 2k - 1 \). Let \( \text{sim}(u, v) \) represent the dot product for measuring similarity between the vector \( u \) and \( v \). And \( \tau \) denotes the temperature parameter. The complete CCL loss is as follows:

\[
L_{ccl} = \frac{1}{2N} \sum_{k=1}^{N} [l_{ccl}(\tilde{h}_{2k-1}, \tilde{h}_{2k}) + l_{ccl}(\tilde{h}_{2k}, \tilde{h}_{2k-1})]
\]

**Random counterfactual sampling.** Data augmentation operations are crucial for learning good representations in contrastive SSL [4]. Unlike random operators, including crop or mask for sequential recommender systems [32, 40], our random sampling is to match an unexposed item for the user. For example, there is a toy user-item matrix with five users and items in Figure 2(c). The grey squares refer to uninteracted user-item pairs, and the others are interactions. We regard \((u_2, i_2)\) as the anchor and then \((u_2, i_0)\) may be a positive sample since \((u_2, i_0)\) is an uninteracted (counterfactual) pair for the user \( u_2 \). We intend to make items as evenly exposed to a user in the representation space and then excavate the real preferences of users. An interesting finding is that the simple augmentation method from random counterfactual samples contributes to superior performance.

### 3.2.2 Two Extra Positive Samplers

We propose two extra positive samplers as data augmentations in contrastive learning, as illustrated in Figure 2(c).

- **Propensity score-based sampling.** The propensity score-based sampling is motivated by [38] which sets the negative sampler as the propensity score function for unbiased candidate generation. As Eq.(1) shows, the propensity score \( p_{u,i} \) represents the estimated exposure probability for the user-item pair. In order to yield uniform exposure, we want to select the user-item pair with the most significant difference in exposure probability, value from the current sample and keep the user constant. For example, in Figure 2(c), we randomly choose one user-item pair like \((u_2, i_2)\) as the anchor from the matrix. Then we calculate the propensity score vector for the user \( u_2 \). We sort elements in the vector and choose the item among the interacted items with the largest difference in propagation score from the current user-item pair, which is \((u_2, i_0)\) in the example. There are two methods for estimating the propensity score [22] via a naive Bayes estimator with a small set of unbiased data or logistic regression with raw features of users and items.

- **Item popularity-based sampling.** In practice, the sparsity of the whole user-item matrix makes it challenging to estimate the popularity score precisely. Therefore, some works use the item popularity in replace propensity scores to ease estimation and avoid small propensities [15, 38]. To this end, we adopt item popularity as a sampling method in contrastive learning. Specifically, we count the number of interactions per item, equivalent to the sum of each column in the indicator matrix \( O \). Then we find the maximum number of interactions for every single item and divide the count by the maximum. At last, we use the root square of the result in the previous step as the item popularity. Once we estimate the item’s popularity, we sort the popularity and select the item with the most significant difference in popularity from the current item. Consequently, we pick out the positive sample via item popularity. For example, we choose \((u_2, i_1)\) as the positive sample for the anchor \((u_2, i_2)\) in Figure 2(c).

To sum up, these three samplings are reasonable and practical methods as they either utilize estimated exposure probability or take advantage of widespread counterfactual samples, which is consistent with the purpose of the simulated experimental distribution. We will evaluate and analyze the three methods in Section 4.4.1.

### 3.3 Training and Optimization

As Figure 2(a) shows, the total training process includes the contrastive learning module with \( L_{ccl} \) and the multi-layers prediction module with \( L_{rec} \). We leverage a multi-task training to optimize these two losses as follows:

\[
L = L_{rec} + \lambda L_{ccl}
\]

where \( \lambda \) is a hyper-parameter for controlling the weight of contrastive counterfactual learning. We summarize the training process in Algorithm 1. It’s also acceptable to pretrain \( L_{ccl} \) and then finetune \( L_{rec} \).

**Algorithm 1 : IREC-CCL training**

1. **Input:** Observed Feedback \( D \), hyper-parameters: \( \lambda \), temperature \( \tau \), batch size \( N \), embedding size for \( g_u \) and \( g_i \), number of hidden layers in \( f \).
2. **Output:** \( f, g_u, g_i \)
3. **repeat**
4. **for** sampled mini-batch \( \{(x_k, \tilde{x}_k)\}_{k=1}^N \) from \( D \) **do**
5. \( \text{if } \hat{x}_k \text{ is the concatenation of } x_k \text{ and } x_i \)
6. **for** all \( k \in \{1, 2, \ldots, N\} \) **do**
7. \( \text{draw random counterfactual sampling method } t \)
8. \( \tilde{x}_{2k-1} = x_k \)
9. \( \tilde{h}_{2k-1} = g_u(x_u) \oplus g_i(x_i) \)
10. \( \tilde{x}_{2k} = t(x_k) \)
11. \( \tilde{h}_{2k} = g_u(\tilde{x}_u) \oplus g_i(\tilde{x}_i) \)
12. **end for**
13. \( \text{Calculate contrastive counterfactual loss } L_{ccl} \text{ with Eq.(6)} \)
14. \( L_{ccl} = \sum_{k=1}^{N} l_{ccl}(\tilde{h}_{2k-1}) \text{ with Eq. (2)} \)
15. \( \text{Calculate total loss } L \text{ with Eq. (7)} \)
16. \( \text{Update networks } f, g_u, g_i \text{ to minimize } L \)
17. **end for**
18. **until** convergence

### 4 EXPERIMENTS

In this section, we evaluate our model on two real-world datasets, Coat and Yahoo! R3. These two datasets are specified as benchmarks in previous studies. In addition to performance evaluation, we provide an in-depth discussion of various positive sampling strategies and visualization studies and present the ablation study.
Table 1: Performance Evaluation on top-n ranking metrics. We report NDCG, Recall, MRR, Gini and Global utility for Coat and Yahoo! R3, where the bold represents the best, and the underline result is the second best.

| Dataset | Methods | NDCG@5 ↑ | NDCG@10 ↑ | Recall@1 ↑ | Recall@5 ↑ | MRR ↑ | Gini ↓ | Global Utility ↓ |
|---------|---------|----------|-----------|-----------|-----------|-------|-------|------------------|
| MF      | 0.618878 | 0.685805 | 0.143029  | 0.470560  | 0.724109  | 0.32857 | 0.51930 |
| +IPS    | 0.546103 | 0.642255 | 0.137241  | 0.445300  | 0.695958  | 0.37046 | 0.465517 |
| +SNIPS  | 0.619469 | 0.693272 | 0.130670  | 0.472532  | 0.702422  | 0.335425 | 0.509655 |
| +DR     | 0.610190 | 0.683095 | 0.142121  | 0.458575  | 0.723581  | 0.335808 | 0.506207 |
| +CVIB   | 0.635618 | 0.706618 | 0.154944  | 0.485840  | 0.753408  | 0.333855 | 0.515172 |
| Coat    |         |          |           |           |           |       |       |                  |
| NCF     | 0.615977 | 0.681484 | 0.158541  | 0.478001  | 0.727774  | 0.356257 | 0.502483 |
| +IPS    | 0.615375 | 0.692377 | 0.149823  | 0.469947  | 0.726316  | 0.347815 | 0.506897 |
| +SNIPS  | 0.619516 | 0.697859 | 0.156743  | 0.464328  | 0.739233  | 0.343668 | 0.509655 |
| +DR     | 0.636087 | 0.708855 | 0.152474  | 0.469774  | 0.726123  | 0.331799 | 0.519310 |
| +CVIB   | 0.627515 | 0.702538 | 0.155350  | 0.488107  | 0.742603  | 0.341349 | 0.5155862 |
| Ours    | 0.646099 | 0.715099 | 0.156814  | 0.490682  | 0.755027  | 0.312651 | 0.524828 |
| MF      | 0.634687 | 0.762871 | 0.381295  | 0.667766  | 0.436356  | 0.582162 | 0.252037 |
| +IPS    | 0.646120 | 0.765412 | 0.373860  | 0.700561  | 0.430910  | 0.557144 | 0.259889 |
| +SNIPS  | 0.638394 | 0.769369 | 0.381063  | 0.683709  | 0.432359  | 0.565564 | 0.251926 |
| +DR     | 0.656221 | 0.772937 | 0.385328  | 0.704601  | 0.444278  | 0.557533 | 0.263815 |
| +CVIB   | 0.696131 | 0.799171 | 0.412612  | 0.738788  | 0.489370  | 0.541144 | 0.278963 |
| Ours    | 0.654634 | 0.774168 | 0.383378  | 0.700092  | 0.443718  | 0.562444 | 0.260481 |
| Yahoo! R3 |        |          |           |           |           |       |       |                  |
| NCF     | 0.650373 | 0.775258 | 0.381428  | 0.710659  | 0.436361  | 0.548205 | 0.252037 |
| +IPS    | 0.652090 | 0.786611 | 0.390112  | 0.724687  | 0.452089  | 0.549243 | 0.261852 |
| +SNIPS  | 0.647838 | 0.780616 | 0.387093  | 0.718626  | 0.452037  | 0.559978 | 0.259259 |
| +DR     | 0.667489 | 0.780968 | 0.394774  | 0.716073  | 0.456541  | 0.547974 | 0.265923 |
| +CVIB   | 0.679553 | 0.827927 | 0.408328  | 0.740561  | 0.497704  | 0.557533 | 0.277519 |

4.1 Dataset Description

Coat\(^1\) \cite{22} first introduces the Coat dataset with customers’ data for shopping for a coat on an online website. The total user-item matrix includes 290 users and 300 items. In training data, each user rates 24 coats with self-selection and 16 randomly displayed coats for the test set. The rates are on a five-star scale, and we binarize the rates so that rates greater than or equal to three are regarded as positive feedback, and those smaller than three are negative.

Yahoo! R3\(^2\). This dataset is correlated with user-song ratings \cite{16}. The MNAR training set includes more than 300K ratings 15400 users selectively choose. The MCAR testing set contains ratings for 5400 users. The rates are on a five-star scale, and we binarize the rates so that rates greater than or equal to three are regarded as positive feedback, and those smaller than three are negative.

4.2 Baselines. We compare our IREC-CCL with the following baselines of state-of-the-art methods:

1. Base models: matrix factorization (MF) \cite{9} and neural collaborative filtering (NCF) \cite{7}.
2. Propensity score-based methods: Inverse-Propensity-Scoring (IPS) \cite{22}, Self-Normalized Inverse Propensity Scoring (SNIPS) \cite{24}, Doubly robust method combining imputed errors and propensities \cite{27}.
3. Information-based techniques require unbiased data or network information. But the two datasets are not correlated with the social network. We follow the procedure in \cite{22} that we adopt a small sample of MCAR data for propensities estimation in the Coat dataset. Therefore, we can regard IPS on Coat dataset as the side information-based method.
4. Information bottleneck-based methods: counterfactual variational information bottleneck (CVIB) \cite{30} utilizes information-theoretic representation learning for learning a balanced model between the factual and counterfactual domains. Note that each method can be regarded as a plugin and integrated into the two base models.

4.3 Performance Evaluation

In this section, we perform experiments with our model and ten baselines on two benchmark datasets. The evaluation results are reported in Table 1 and 2.

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\(^1\)https://www.cs.cornell.edu/schnafts/mnar/

\(^2\)https://webscope.sandbox.yahoo.com/catalog.php?datatype=r

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Table 2: Performance Evaluation on rating prediction. We report MAE and AUC for Coat and Yahoo! R3, where the bold represents the best result, and the underline is the second best.

| Methods | Coat        | Yahoo! R3   |
|---------|-------------|-------------|
|         | MAE ↓ | AUC ↑ | MAE ↓ | AUC ↑ |
| MF      | 0.058  | 0.702818   | 0.062  | 0.680819   |
| +IPS    | 0.104  | 0.632157   | 0.050  | 0.683447   |
| +SNIPS  | 0.053  | 0.708457   | 0.037  | 0.682086   |
| +DR     | 0.075  | 0.686495   | 0.046  | 0.687128   |
| +CVIB   | 0.336  | 0.751686   | 0.515  | 0.710261   |
| NCF     | 0.046  | 0.7487968  | 0.111  | 0.677314   |
| +IPS    | 0.053  | 0.7505703  | 0.035  | 0.683527   |
| +SNIPS  | 0.040  | 0.7533112  | 0.031  | 0.673665   |
| +DR     | 0.041  | 0.7682484  | 0.054  | 0.677911   |
| +CVIB   | 0.218  | 0.7645173  | 0.117  | 0.692956   |
| Ours    | **0.040** | **0.773700** | **0.072** | **0.702237** |

We first present results on seven top-n ranking metrics in Table 1, since ranking is a core task in recommender systems [20]. Ranking evaluation on unbiased datasets can estimate and prove the effectiveness of inferring natural users’ preferences. Table 1 presents an overview that our IREC-CCL obtains the best performance among all baselines under NDCG, Recall, MRR and Gini index on two benchmark datasets. In addition, our method achieves the best global utility on Coat and the second-best result on the Yahoo dataset. There is no doubt that our method obtains considerable ranking performance as Table 1 presents. Specifically, on the Coat dataset, our IREC-CCL model outperforms a popular baseline IPS and state-of-the-art CVIB by 2.3% and 1.3% in NDCG@10. The overall outperforming achievements of seven ranking metrics on two different datasets further confirm our method’s superiority in generating unbiased recommendations. What stands out in this table is the considerable performance of CVIB and ours, especially since they occupy the top-2 best results on the Yahoo dataset. Considering the Yahoo dataset is much larger than Coat, we guess representation learning-based methods contribute remarkable outcomes. Propensity scores may be competitive, but representation learning is a better solution for a larger dataset.

Then we present results on two rating prediction metrics (MAE and AUC). As shown in Table 2, our proposed method IREC-CCL consistently outperforms all baselines on the Coat dataset and achieves the second-best results on Yahoo! R3 dataset. The IPS and SNIPS estimate propensity scores via naive Bayes with a small set of unbiased data on Yahoo and via logistic regression on the Coat dataset. Although these methods utilize unbiased data, our approach, which is free of RCTs data, also outperforms or matches these baselines, i.e., 3% improvement of AUC on Yahoo! R3. Interestingly, a significant improvement of IREC-CCL and CVIB in terms of AUC metric on Yahoo! R3 dataset was also observed. Compared with other baseline methods, MF-CVIB and IREC-CCL achieve the top-2 best results and obtain 2%-3% improvements regarding AUC. The AUC is a more robust metric for prediction classification [6]. We guess that representation learning, i.e., informational theoretic learning or contrastive SSL, is a good solution for an unbiased recommendation, especially for a large dataset since Yahoo! R3 has a much larger data size than the Coat dataset. And this conclusion is consistent with results on ranking metrics.

Since rating prediction and top-n ranking belong to different types of metrics, practical recommender systems make a trade-off between these two metrics and normally focus on ranking metrics [30]. We report the results with two different training parameters in Table 1 and 2.

### 4.4 In-depth Discussion

#### 4.4.1 Comparison of positive samplings.

The purpose of this experiment is to verify the effectiveness of three sampling strategies proposed in Section 3.2 and compare their performance. We conduct comparative study on two benchmark datasets and explore the impacts of these sampling methods and find the optimal alternative. We first construct a sampling set \{w/cf, w/ps, w/pop, w/o ssl\} and the elements in this set separately indicate random counterfactual, propensity score-based, item popularity-based and no contrastive SSL strategies. Figure 4 presents the comparison results of NDCG@5 and Recall@5 on two datasets. We observe that the performance consistently degrades on both datasets in the order of \{w/cf, w/ps, w/pop, w/o ssl\}. It proves that all three sampling methods contribute to remarkable performance. We also note that the performance with propensity score-based sampling is comparable to item popularity-based method. Estimating precise propensity scores is difficult in practice, thus it seems reasonable that some works utilize item popularity in replace of propensity scores [38]. What stands out in the figure is that utilize of counterfactual samples outperforms the widely used propensity scores or item popularity. Furthermore, results in Table 1 and 2 also present CVIB and our methods both outperform other baselines and only these two methods utilize counterfactual samples. This finding sheds light on the usefulness of a wealth of counterfactual samples ignored by most studies.

![Figure 4: Performance comparison (NDCG@5 and Recall@5) w.r.t various sampling methods on Coat and Yahoo datasets. 'w/' and 'w/o' denotes whether applying the sampling or not.](image)

#### 4.4.2 Visualization

Recall that we design a contrastive SSL method to simulate a distribution in which the recommender system exposes items to each user uniformly. There are two critical questions:
We separately test the total loss $L$ with the contrastive counterfactual module (with whether we manipulate the exposure more uniformly and whether the uniform exposure is beneficial to the performance. To answer these two questions, we conduct the t-SNE visualization [25] by selecting a random user and all of the items, as Figure 5 shows. We choose the items in the training and testing set corresponding to this user. In the user-item shared representation space, items are much more uniformly distributed to the randomly selected user in the order of \{‘w/pop’, ‘w/ps’, ‘w/cf’\}. Combining with the result in Table 1 and 2, we conclude that uniform exposure of items contributes to better unbiased performance.

4.4.3 Ablation Study. We perform ablation experiment to examine the contribution of contrastive counterfactual module in our model. We separately test the total loss $L_{\text{rec}} + L_{\text{ccl}}$ and only $L_{\text{rec}}$. The results are shown in Table 3. We find that in all the metrics, whether it is rating prediction or top-n ranking metric, the results combining with the contrastive counterfactual module (with $L_{\text{ccl}}$) are better.

Table 3: Ablation Study. $L_{\text{ccl}} + L_{\text{rec}}$ is our proposed model and only $L_{\text{rec}}$ means the lack of CCL module in Figure 2.

| Dataset  | Metrics | $L_{\text{ccl}} + L_{\text{rec}}$ | $L_{\text{rec}}$ |
|----------|---------|---------------------------------|-----------------|
| Coat     | MAE ↓   | 0.040                           | 0.047           |
|          | AUC ↑   | 0.774                           | 0.761           |
|          | NDCG@5 ↑| 0.646                           | 0.609           |
|          | NDCG@10↑| 0.715                           | 0.690           |
|          | Recall@1 ↑| 0.157                        | 0.153           |
|          | Recall@5 ↑| 0.491                        | 0.448           |
|          | MRR ↑   | 0.755                           | 0.738           |
|          | Gini ↓   | 0.313                           | 0.334           |
|          | Global Utility ↑| 0.525               | 0.496           |
| Yahoo! R3| MAE ↓   | 0.072                           | 0.076           |
|          | AUC ↑   | 0.702                           | 0.701           |
|          | NDCG@5 ↑| 0.697                           | 0.596           |
|          | NDCG@10 ↑| 0.800                          | 0.736           |
|          | Recall@1 ↑| 0.413                        | 0.350           |
|          | Recall@5 ↑| 0.740                        | 0.647           |
|          | MRR ↑   | 0.487                           | 0.387           |
|          | Gini ↓   | 0.538                           | 0.585           |
|          | Global Utility ↑| 0.278               | 0.237           |

5 RELATED WORK

5.1 Causal Inference for Recommender systems

To date, many studies have linked causal inference with recommender systems, and they regard the recommendation as an intervention in causal inference. Some studies adopt the propensity score originating from causality and integrate it into recommendation models to obtain unbiased learning and evaluation approach [8, 10, 22, 24, 27, 39]. Other works assume the existence of a small set of unbiased data or extra knowledge. [2, 28] utilize unbiased data and [11, 23] leverage network information to mitigate biases and improve performance. However, most methods introduce extra variance or can not present the data generation process, and it’s difficult to obtain side information. In contrast, we consider analyzing the data generation and resolving the interventional effects via self-supervision learning and novel sampling methods.

5.2 Contrastive Learning For Recommendation

Some recent studies have applied contrastive SSL into recommender systems [13, 15, 34, 38]. The works [15, 34] focus on the sequential recommendation with contrastive SSL, but we concentrate on classic recommendations without any sequential information. Thereby, we cannot directly adopt augmentation operators from them [15]. Different from previous works [13, 38] that frame propensity score or item popularity as the negative distribution, we start from the perspective of a positive sampler. Moreover, our best sampling method is free of the propensity score or item popularity, which reduces computation cost. Our contrastive SSL pays attention to the usefulness of counterfactual samples. It provides a new perspective on solving causal inference for recommender systems.

6 CONCLUSION

This study sets out to follow the line of causal inference for recommender systems and frames the recommendation predictions as solving interventional effects. We induce an interventional recommendation model via SCMs and propose a novel contrastive counterfactual learning method for simulating the intervention and solving the intervention effects. We suggest two extra novel
sampling strategies and integrate them into contrastive learning. We present an interesting finding that the random counterfactual samples contribute to superior performance, which sheds new light on the usefulness of counterfactual samples existing in data. Extensive experiments on two benchmark datasets with real-world data demonstrate that our model outperforms the ten state-of-the-art baselines.

In the future, we intend to improve standard recommendation models with counterfactual samples. We also plan to develop metrics for estimating the causal effect of recommendations [21].
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