Incorporating Bias-aware Margins into Contrastive Loss for Collaborative Filtering

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Abstract

Collaborative filtering (CF) models easily suffer from popularity bias, which makes recommendation deviate from users' actual preferences. However, most current debiasing strategies are prone to playing a trade-off game between head and tail performance, thus inevitably degrading the overall recommendation accuracy. To reduce the negative impact of popularity bias on CF models, we incorporate Bias-aware margins into Contrastive loss and propose a simple yet effective **BC Loss**, where the margin tailors quantitatively to the bias degree of each user-item interaction. We investigate the geometric interpretation of BC loss, then further visualize and theoretically prove that it simultaneously learns better head and tail representations by encouraging the compactness of similar users/items and enlarging the dispersion of dissimilar users/items. Over six benchmark datasets, we use BC loss to optimize two high-performing CF models. On various evaluation settings (*i.e.,* imbalanced/balanced, temporal split, fully-observed unbiased, tail/head test evaluations), BC loss outperforms the state-of-the-art debiasing and non-debiasing methods with remarkable improvements. Considering the theoretical guarantee and empirical success of BC loss, we advocate using it not just as a debiasing strategy, but also as a standard loss in recommender models. Codes are available at https://anonymous.4open.science/r/BC-Loss-8764/model.py.

1 Introduction

At the core of leading collaborative filtering (CF) models is the learning of high-quality representations of users and items from historical interactions. However, most CF models easily suffer from the popularity bias issue in the interaction data [1, 2, 3, 4]. Specifically, the training data distribution is typically long-tailed, *e.g.,* a few head items occupy most of the interactions, whereas the majority of tail items are unpopular and receive little attention. The CF models built upon the imbalanced data are prone to learn the popularity bias and even amplify it by over-recommending head items and under-recommending tail items. As a result, the popularity bias causes the biased representations with poor generalization ability, making recommendations deviate from users' actual preferences.

Motivated by concerns of popularity bias, studies on debiasing have been conducted to lift the tail performance. Unfortunately, most prevalent debiasing strategies focus on the trade-off between head and tail evaluations (see Table 3), including post-processing re-ranking [5, 6, 7, 8, 9], balanced training loss [10, 11, 12, 9], sample re-weighting [13, 14, 15, 16, 17, 18], and head bias removal by causal inference [19, 20, 21, 22]. Worse still, many of them hold some assumptions that are infeasible in practice, such as the balanced test distribution is known in advance to guide the hyperparameters' adjustment [23, 22], or a small unbiased data is present to train the unbiased model [24, 19]. Consequently, they pursue improvements on tail items but exacerbate the performance

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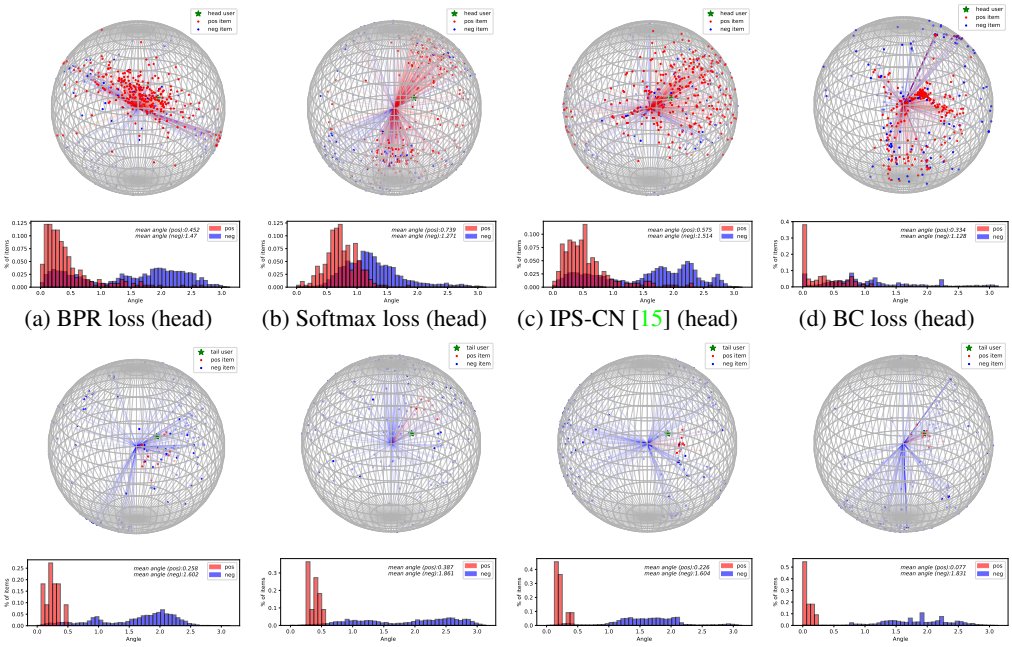


(a) BPR loss (head) (b) Softmax loss (head) (c) IPS-CN [15] (head) (d) BC loss (head)

(e) BPR loss (tail) (f) Softmax loss (tail) (g) IPS-CN [15] (tail) (h) BC loss (tail)

Figure 1: Visualizations of item representations learned by LightGCN [25] on Yelp2018 [25], where subfigures (a-d)/(e-h) depict the identical head/tail user as a green star, while the red and blue points denote positive and negative items, respectively. In each subfigure, the first row presents the 3D item representations projected on the unit sphere, while the second row shows the angle distribution of items *w.r.t.* the specific user and the statistics of mean angles. Compared to other losses, BC loss learns better head representations (*cf.* with the smallest mean positive angle, the vast majority of positive items fall into the group closest to the user) and tail representations (*cf.* a clear margin exists between positive and negative items for the tail user). BC loss learns a more reasonable representation distribution that is locally clustered and globally separated. See more details in Appendix A.1.

sacrifice of head items, leading to a severe overall performance drop. The trade-off between the head and tail evaluations results in suboptimal representations, which derails the generalization ability.

In this paper, we conjecture that an ideal debiasing strategy should learn high-quality head and tail representations with powerful discrimination and generalization abilities, rather than playing a trade-off game between the head and tail performance. Here we follow the prior studies [15, 23, 13, 14] to focus on one key ingredient in representation learning: the loss function. Figure 1 depicts the item representations, which is optimized via two non-debiasing losses (BPR [26] and Softmax [27]) and one debiasing loss (IPS-CN [15]). Wherein, representation discrimination is reflected in how well the positive items of a user are apart from the negatives. Our insights are: (1) For a user, the non-debiasing losses are inadequate to discriminate his/her positive and negative items well, since their representations are largely overlapped as Figures 4a and 4b show; (2) Although IPS-CN achieves better discrimination power in the tail group than BPR (*cf.* positive items get smaller angles to the ego user in Figure 4g, as compared to Figure 4e), it gets worse discrimination ability in the head (*cf.* positive items hold larger angles to the ego user in Figure 4c, as compared to Figure 4a).

Towards this end, we incorporate Bias-aware margins into Contrastive Loss and devise a simple yet effective **BC Loss** to guide the head and tail representation learning of CF models. Specifically, we first employ a bias degree extractor to quantify the influence of interaction-wise popularity — that is, how well an interaction is predicted, when only popularity information of the target user and item is used. Interactions involving inactive users and unpopular items often align with lower bias degrees, indicating that popularity fails to reflect user preference faithfully. In contrast, interactions with active users and popular items are spurred by the popularity information, thus easily inclining to high bias degrees. We then move on to train the CF model by converting the bias degrees into the angular margins between user and item representations. If the bias degree is low, we impose a larger margin to strongly squeeze the tightness of representations. In contrast, if the bias degree is large, we exert a small or vanishing margin to reduce the influences of biased representations. Through this

way, for each ego user's representation, BC quantitatively controls its bias-aware margins with item representations — adaptively intensifying the representation similarity among positive items, while diluting that among negative items. Benefiting from stringent and discriminative representations, BC loss significantly improves both head and tail performance.

Furthermore, BC loss has three desirable advantages. First, it has a clear geometric interpretation, as illustrated in Figure 2. Second, it brings forth a simple but effective mechanism of hard example mining (See Appendix A.2). Third, we theoretically reveal that BC loss tends to learn a low-entropy cluster for positive pairs (*e.g.,* compactness of matched users and items) and a high-entropy space for negative pairs (*e.g.,* dispersion of unmatched users and items) (See Theorem 1). Considering the theoretical guarantee and empirical effectiveness, we argue that BC loss is not only promising to alleviate popularity bias, but also suitable as a standard learning strategy in CF.

2 Preliminary of Collaborative Filtering (CF)

Task Formulation. Personalized recommendation is retrieving a subset of items from a large catalog to match user preference. Here we consider a typical scenario, collaborative filtering (CF) with implicit feedback [28], which can be framed as a top-N recommendation problem. Let $\mathcal{O}^+ = \{(u,i)|y_{ui}=1\}$ be the historical interactions between users $\mathcal{U}$ and items $\mathcal{I}$, where $y_{ui}=1$ indicates that user $u \in \mathcal{U}$ has adopted item $i \in \mathcal{I}$ before. Our goal is to optimize a CF model $\hat{y}: \mathbb{U} \times \mathbb{I} \to \mathbb{R}$ that latches on user preference towards items.

Modeling Scheme. Scrutinizing leading CF models [26, 25, 29, 30], we systematize the common paradigm as a combination of three modules: user encoder $\psi(\cdot)$, item encoder $\phi(\cdot)$, and similarity function $s(\cdot)$. Formally, we depict one CF model as $\hat{y}(u,i) = s(\psi(u), \phi(i))$, where $\psi: \mathbb{U} \to \mathbb{R}^d$ and $\phi: \mathbb{I} \to \mathbb{R}^d$ encode the identity (ID) information of user u and item i into d-dimensional representations, respectively; $s: \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ measures the similarity between user and item representations. In literature, there are various choices of encoders and similarity functions:

- Common encoders roughly fall into three groups: ID-based (*e.g.,* MF [26, 29], NMF [31], CMN [32]), history-based (*e.g.,* SVD++ [29], FISM [33], MultVAE [30]), and graph-based (*e.g.,* GCMC [34], PinSage [35], LightGCN [25]) fashions. Here we select two high-performing encoders, MF and LightGCN, as the backbone models being optimized.
- The widely-used similarity functions include dot product [26], cosine similarity [36], and neural networks [31]. As suggested in the recent study [36], cosine similarity is a simple yet effective and efficient similarity function in CF models, having achieved strong performance. For better interpretation, we take a geometric view and denote it by:

$$s(\psi(u), \phi(i)) = \frac{\psi(u)^\top \phi(i)}{\|\psi(u)\| \cdot \|\phi(i)\|} \doteq \cos(\hat{\theta}_{ui}), \tag{1}$$

  in which $\hat{\theta}_{ui}$ is the angle between the user representation $\psi(u)$ and item representation $\phi(i)$.

Learning Strategy. To optimize the model parameters, CF models mostly frame the top-N recommendation problem into a supervised learning task, and resort to one of three classical learning strategies: pointwise loss (*e.g.,* binary cross-entropy [37], mean square error [29]), pairwise loss (*e.g.,* BPR [26], WARP [38]), and softmax loss [28]. Among them, pointwise and pairwise losses are long-standing and widely-adopted objective functions in CF. However, extensive studies [9, 1, 39] have analytically and empirically confirmed that using pointwise or pairwise loss is prune to propagate more information towards the head user-item pairs, which amplifies popularity bias.

Softmax loss is much less explored in CF than its application in other domains like CV [40, 41]. Recent studies [36, 42, 43, 44, 45] find that it inherently conducts hard example mining over multiple negatives and aligns well with the ranking metric, thus attracting a surge of interest in recommendation. Hence, we cast the minimization of softmax loss [27] as the representative learning strategy:

$$\mathcal{L}_0 = -\sum_{(u,i)\in\mathcal{O}^+} \log \frac{\exp(\cos(\hat{\theta}_{ui})/\tau)}{\exp(\cos(\hat{\theta}_{ui})/\tau) + \sum_{j\in\mathcal{N}_u} \exp(\cos(\hat{\theta}_{uj})/\tau)}, \tag{2}$$

where $(u,i) \in \mathcal{O}^+$ is one observed interaction of user u, while $\mathcal{N}_u = \{j|y_{uj}=0\}$ is the set of sampled unobserved items that u did not interact with before; τ is the hyper-parameter known as

the temperature in softmax [46]. Nonetheless, modifying softmax loss to enhance the discriminative power of representations and alleviate the popularity bias remains largely unexplored. Therefore, our work aims to devise a more generic and broadly-applicable variant of softmax loss for CF tasks, which can improve the long-tail performance fundamentally.

3 Methodology of BC Loss

On the basis of softmax loss, we devise our BC loss and present its desirable characteristics.

3.1 Popularity Bias Extractor

Before mitigating popularity bias, we need to quantify the influence of popularity bias on a single user-item pair. One straightforward solution is to compare the performance difference between the biased and unbiased evaluations. However, this is not feasible as the unbiased data is usually unavailable in practice. Statistical metrics of popularity could be a reasonable proxy of the biased information, such as user popularity statistics $p_u \in \mathbb{P}$ (*i.e.,* the number of historical items that user u has interacted with before) and item popularity statistics $p_i \in \mathbb{P}$ (*i.e.,* the number of observed interactions that item i is involved in). If the impact of the interaction between u and i can be captured well based solely on such statistics, the model is susceptible to exploiting popularity bias for prediction. Hence, we argue that the popularity-only prediction will delineate the influence of bias.

Towards this end, we first train an additional module, termed popularity bias extractor, which only takes the popularity statistics as input to make prediction. Similar to the modeling of CF (*cf.* Section 2), the bias extractor is formulated as a function $\hat{y}_b : \mathbb{P} \times \mathbb{P} \rightarrow \mathbb{R}$:

$$\hat{y}_b(p_u, p_i) = s(\psi_b(p_u), \phi_b(p_i)) \doteq cos(\hat{\xi}_{ui}), \tag{3}$$

where the user popularity encoder $\psi_b : \mathbb{P} \rightarrow \mathbb{R}^d$ and the item popularity encoder $\phi_b : \mathbb{P} \rightarrow \mathbb{R}^d$ map the popularity statistics of user u and item i into d-dimensional popularity embeddings $\psi_b(p_u)$ and $\phi_b(p_i)$, respectively; $s : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$ is the cosine similarity function between popularity embeddings (*cf.* Equation (1)). $\hat{\xi}_{ui}$ is the angle between $\psi_b(p_u)$ and $\phi_b(p_i)$.

We then minimize the following softmax loss to optimize the popularity bias extractor:

$$\mathcal{L}_b = -\sum_{(u,i)\in\mathcal{O}^+} \log \frac{\exp\left(\cos(\hat{\xi}_{ui})/\tau\right)}{\exp\left(\cos(\hat{\xi}_{ui})/\tau\right) + \sum_{j\in\mathcal{N}_u} \exp\left(\cos(\hat{\xi}_{uj})/\tau\right)}. \tag{4}$$

This optimization enforces the extractor to reconstruct the historical interactions using only biased information (*i.e.,* popularity statistics) and makes the reconstruction reflect the interaction-wise bias degree. As shown in Appendix B.5, interactions with active users and popular items are inclining to learn well via Equation (4). Furthermore, we can distinguish hard interactions based on the bias degree, *i.e.,* the interactions that can be hardly predicted by popularity statistics ought to be more informative for representation learning in the target CF model. In a nutshell, the popularity bias extractor underscores the bias degree of each user-item interaction, which substantively reflects how hard it is to be predicted.

3.2 BC Loss

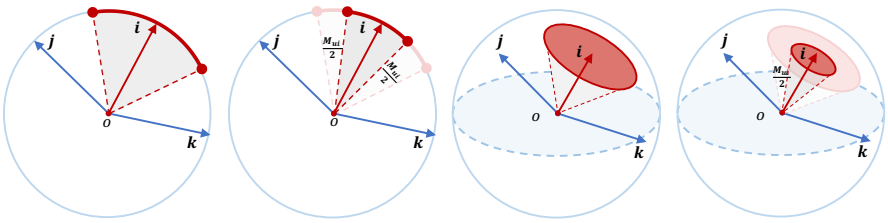
We move on to devise a new BC loss for the target CF model. Our BC loss stems from softmax loss but converts the interaction-bias degrees into the bias-aware angular margins among the representations to enhance the discriminative power of representations. Our BC loss is:

$$\mathcal{L}_{\text{BC}} = -\sum_{(u,i)\in\mathcal{O}^+} \log \frac{\exp\left(\cos(\hat{\theta}_{ui} + M_{ui})/\tau\right)}{\exp\left(\cos(\hat{\theta}_{ui} + M_{ui})/\tau\right) + \sum_{j\in\mathcal{N}_u} \exp\left(\cos(\hat{\theta}_{uj})/\tau\right)}, \tag{5}$$

where M_{ui} is the bias-aware angular margin for the interaction (u, i) defined as:

$$M_{ui} = \min\{\hat{\xi}_{ui}, \pi - \hat{\theta}_{ui}\} \tag{6}$$

where $\hat{\xi}_{ui}$ is derived from the popularity bias extractor (*cf.* Equation (3)), and $\pi - \hat{\theta}_{ui}$ is the upper bound to restrict $\cos(\cdot + M_{ui})$ to be a monotonically decreasing function. Intuitively, if a user-item



(a) Softmax Loss (2D) (b) BC Loss (2D) (c) Softmax Loss (3D) (d) BC Loss (3D)

Figure 2: Geometric Interpretation of softmax loss and BC loss in 2D and 3D hypersphere. The dark red region indicates the discriminative user constraint, while the light red region is for comparison.

pair (u, i) is the hard interaction that can hardly be reconstructed by its popularity statistics, it holds a high value of $\hat{\xi}_{ui}$ and leads to a high value of M_{ui}; henceforward, BC loss imposes the large angular margin M_{ui} between the negative item j and positive item i and optimizes the representations of user u and item i to lower $\hat{\xi}_{ui}$. See more details and analyses in Section 4.

It is noted that BC loss is extremely easy to implement in recommendation tasks, which only needs to revise several lines of code. Moreover, compared with softmax loss, BC loss only adds negligible computational complexity during training (*cf.* Table 5) but achieves more discriminative representations. Hence, we recommend to use BC loss not only as a debiasing strategy to alleviate the popularity bias, but also as a standard loss in recommender models to enhance the discriminative power. Note that the modeling of M_{ui} is worth exploring, such as the more complex version $M_{ui} = \min\{\lambda \cdot \hat{\xi}_{ui}, \pi - \hat{\theta}_{ui}\}$ where λ controls the strength of the bias-margin. Meanwhile, carefully designing a monotonically decreasing function helps to get rid of the upper bound restriction. We will leave the exploration of bias-margin in future work.

4 Analyses of BC Loss

We analyze desirable characteristics of BC loss. Specifically, we start by presenting its geometric interpretation, and then show its theoretical properties *w.r.t.* compactness and dispersion of representations. The hard mining mechanism of BC loss is discussed in Appendix A.2.

4.1 Geometric Interpretation

Here we probe into the ranking criteria of softmax loss and BC loss, from the geometric perspective. To simplify the geometric interpretation, we analyze one user u with one observed item i and only two unobserved items j and k. Then the posterior probabilities obtained by softmax loss are: $\frac{\exp(\cos(\hat{\theta}_{ui})/\tau)}{\exp(\cos(\hat{\theta}_{ui})/\tau)+\exp(\cos(\hat{\theta}_{uj})/\tau)+\exp(\cos(\hat{\theta}_{uk})/\tau)}$. During training, softmax loss encourages the ranking criteria $\hat{\theta}_{ui} < \hat{\theta}_{uj}$ and $\hat{\theta}_{ui} < \hat{\theta}_{uk}$ to model the basic assumption that the observed interaction (u, i) indicates more positive cues of user preference than the unobserved interactions (u, j) and (u, k).

Intuitively, to make the ranking criteria more stringent, we can impose an angular margin M_{ui} on it and establish a new criteria $\hat{\theta}_{ui} + M_{ui} < \hat{\theta}_{uj}$ and $\hat{\theta}_{ui} + M_{ui} < \hat{\theta}_{uk}$. Directly formulating this idea arrives at the posterior probabilities of BC loss: $\frac{\exp(\cos(\hat{\theta}_{ui}+M_{ui})/\tau)}{\exp(\cos(\hat{\theta}_{ui}+M_{ui})/\tau)+\exp(\cos(\hat{\theta}_{uj})/\tau)+\exp(\cos(\hat{\theta}_{uk})/\tau)}$. Obviously, BC loss is more rigorous about the ranking assumption compared with softmax loss. See Appendix A.2 for more detailed explanations.

We then depict the geometric interpretation and comparison of softmax loss and BC loss in Figure 2. Assume the learned representations of i, j, and k are given, and softmax and BC losses are optimized to the same value. In softmax loss, the constraint boundaries for correctly ranking user u's preference are $\hat{\theta}_{ui} = \hat{\theta}_{uj}$ and $\hat{\theta}_{ui} = \hat{\theta}_{uk}$; whereas, in BC loss, the constraint boundaries are $\hat{\theta}_{ui} + M_{ui} = \hat{\theta}_{uj}$ and $\hat{\theta}_{ui} + M_{ui} = \hat{\theta}_{uk}$. Geometrically, from softmax loss (*cf.* Figure 2c) to BC loss (*cf.* Figure 2d), it is a more stringent circle-like region on the unit sphere in the 3D case. Further enlarging the margin M_{ui} will lead to a smaller hypercycle-like region, which is an explicit discriminative constraint on a manifold. As a result, limited constraint regions squeeze the tightness of similar items and encourages the separation of dissimilar items. Moreover, with the increase of representation dimension, BC loss

has more restricted learning requirements, exponentially decreasing the area of constraint regions for correct ranking, and becomes progressively powerful to learn discriminative representations.

4.2 Theoretical Properties

BC loss improves head and tail representation learning by enforcing the compactness of matched users and items, while imposing the dispersion of unmatched users and items. See detailed proof in Appendix A.3.

Theorem 1. *Let* $\mathbf{v}_u \doteq \psi(u)$, $\mathbf{v}_i \doteq \phi(i)$, *and* $\mathbf{c}_u = \frac{1}{|\mathcal{P}_u|}\sum_{i\in\mathcal{P}_u}\mathbf{v}_i$, $\mathbf{c}_i = \frac{1}{|\mathcal{P}_i|}\sum_{u\in\mathcal{P}_i}\mathbf{v}_u$, *where* $\mathcal{P}_u = \{i|y_{ui}=1\}$ *and* $\mathcal{N}_u = \{i|y_{ui}=0\}$ *are the sets of user* u*'s positive and negative items, respectively;* $\mathcal{P}_i = \{u|y_{ui}=1\}$ *is the set of item* i*'s positive users. Assuming the representations of users and items are normalized, the minimization of BC loss is equivalent to minimizing a compactness part and a dispersion part simultaneously:*

$$\mathcal{L}_{BC} \geq \underbrace{\sum_{u\in\mathcal{U}}\|\mathbf{v}_u-\mathbf{c}_u\|^2+\sum_{i\in\mathcal{I}}\|\mathbf{v}_i-\mathbf{c}_i\|^2}_{\textit{Compactness part}}\underbrace{-\sum_{u\in\mathcal{U}}\sum_{j\in\mathcal{N}_u}\|\mathbf{v}_u-\mathbf{v}_j\|^2}_{\textit{Dispersion part}} \propto \underbrace{H(\mathbf{V}|Y)}_{\textit{Compactness}}\ \underbrace{-H(\mathbf{V})}_{\textit{Dispersion}}. \quad (7)$$

Discussion. $\mathbf{c}_u$ is the averaged representations of all items that u has interacted with, which describes u's interest; similarly, $\mathbf{c}_i$ profiles its user group. For the compactness part, BC loss forces the user's positive items to be user-centric and vice versa. From the entropy perspective, compactness part tends to learn a low-entropy cluster for positive interactions, *i.e.,* high compactness for similar users and items. For the dispersion part, for users and items from unobserved interactions, BC loss maximizes the pairwise euclidean distance between their representations and encourages them to be distant from each other; Hence, from the entropy viewpoint, dispersion part levers the spread of representations to learn a high-entropy representation space, *i.e.,* large separation degree for dissimilar users and items.

5 Experiments

We aim to answer the following research questions:

- **RQ1:** How does BC Loss perform compared with debiasing strategies in various evaluations?
- **RQ2:** Does BC loss cause the trade-off between head and tail performance?
- **RQ3:** What are the impacts of the components (*e.g.,* temperature, margin) on BC Loss?

Baselines & Datasets. SOTA debiasing strategies in various research lines are compared: sample re-weighting (IPS-CN [15]), bias removal by causal inference (MACR [22], CausE [19]), and regularization-based framework (sam+reg [12]). Extensive experiments are conducted on eight real-world benchmark datasets: Tencent [47], Amazon-Book [48], Alibaba-iFashion [49], Yelp2018 [25], Douban Movie [50], Yahoo!R3 [51], Coat [13] and KuaiRec [52]. For comprehensive comparisons, almost all standard test distributions in CF are covered in the experiments: balanced test set [22, 23, 24], randomly selected imbalanced test set [10, 53], temporal split test set [20, 21, 12], and unbiased test set [13, 52, 51]. See more experiments on KuaiRec, Yahoo!R3, and Coat for unbiased test evaluation in Appendix B.3 and more comparison results between BC loss and other standard losses (most widely used BPR [26], newest proposed CCL [54] and SSM [55]) in Appendix B.4.

5.1 Performance Comparison (RQ1)

5.1.1 Evaluations on Imbalanced and Balanced Test Sets.

Motivation. Many prevalent debiasing methods assume that test distribution is known in advance [22, 23, 10], *i.e.,* the validation set has similar distribution with the test set. Moreover, only an imbalanced or balanced test set is evaluated. However, in real-world applications, the test distributions are usually unavailable and can even reverse the prior in the training distribution. We conjecture that a good debiasing recommender is required to perform well on both imbalanced and balanced test distributions. In our settings, no information about the balanced test is provided in advance.

Data Splits. The models are identical across both imbalanced and balanced evaluations. The test distribution in the balanced evaluation is uniform, *i.e.,* randomly sample 15% of interactions with

Table 1: Overall debiasing performance comparison in balanced and imbalanced test sets.

	Tencent				Amazon-book				Alibaba-iFashion			
	Balanced		Imbalanced		Balanced		Imbalanced		Balanced		Imbalanced	
	Recall	NDCG	Recall	NDCG	Recall	NDCG	Recall	NDCG	Recall	NDCG	Recall	NDCG
MostPop	0.0002	0.0002	0.0384	0.0208	0.0001	0.0001	0.0102	0.0063	0.0003	0.0001	0.0212	0.0084
MF	0.0052	0.0040	0.0982	0.0643	0.0109	0.0103	0.0856	0.0638	0.0056	0.0028	0.0843	0.0411
+ IPS-CN	0.0075	0.0058	0.0686	0.0421	0.0132	0.0123	0.0765	0.0554	0.0050	0.0027	0.0551	0.0255
+ CausE	0.0056	0.0043	0.0687	0.0468	0.0115	0.0105	0.0720	0.0551	0.0005	0.0003	0.0185	0.0086
+ sam+reg	0.0070	0.0054	0.0406	0.0266	0.0141	0.0132	0.0599	0.0443	0.0067	0.0032	0.0305	0.0146
+ MACR	0.0067	0.0046	0.0326	0.0241	0.0181	0.0146	0.0292	0.0229	0.0086	0.0041	0.0650	0.0331
+ BC Loss	**0.0087***	**0.0068***	**0.1298***	**0.0904***	**0.0221***	**0.0202***	**0.1198***	**0.0948***	**0.0095***	**0.0048***	**0.0967***	**0.0487***
Imp. %	16.0%	17.2%	32.2%	40.1%	22.1%	38.4%	40.0%	49.6%	10.5%	17.1%	14.7%	18.5%
LightGCN	0.0055	0.0042	0.1065	0.0712	0.0123	0.0116	0.0941	0.0724	0.0036	0.0017	0.0660	0.0322
+ IPS-CN	0.0072	0.0054	0.0900	0.0599	0.0148	0.0136	0.0836	0.0639	0.0038	0.0017	0.0658	0.0317
+ CausE	0.0055	0.0040	0.0966	0.0665	0.0134	0.0121	0.0926	0.0717	0.0029	0.0013	0.0449	0.0221
+ sam+reg	0.0076	0.0056	0.0653	0.0436	0.0157	0.0149	0.0773	0.0600	0.0056	0.0027	0.0502	0.0252
+ MACR	0.0075	0.0050	0.0731	0.0532	0.0183	0.0153	0.0767	0.0600	0.0033	0.0015	0.0475	0.0238
+ BC Loss	**0.0095***	**0.0073***	**0.1194***	**0.0832***	**0.0257***	**0.0227***	**0.1123***	**0.0903***	**0.0077***	**0.0037***	**0.0992***	**0.0510***
Imp. %	25.0%	30.1%	12.1%	16.9%	40.4%	48.4%	19.3%	24.7%	37.5%	37.0%	50.3%	58.4%

equal probability *w.r.t.* items. Besides, the test splits for the imbalanced test are similarly long-tailed like the train and validation sets, *i.e.,* randomly split the remaining interactions into training, validation, and imbalanced test sets ($60\% : 10\% : 15\%$).

Results. Table 1 reports the comparison of performance in imbalanced and balanced test evaluations. The best performing methods are bold and starred, while the strongest baselines are underlined; Imp.% measures the relative improvements of BC loss over the strongest baselines. We observe that:

- **BC loss significantly outperforms the state-of-the-art baselines in both balanced and imbalanced evaluations across all datasets.** In particular, it achieves consistent improvements over the best debiasing baselines and original CF models by $12.1\% \sim 58.4\%$. This clearly demonstrates that BC loss not only effectively alleviates the amplification of popularity bias but also improves the discriminative power of representations. Moreover, Table 5 shows the computational costs of all methods. Compared to the backbone models, BC loss only adds negligible time complexity.
- **Debiasing baselines sacrifice the imbalanced performance and perform inconsistently across datasets.** Debiasing strategies generally achieve higher balanced performance at the expense of a large imbalanced performance drop. Specifically, the strongest baselines over all imbalanced test sets are the original CF models. Worse still, as the degree of data sparsity increases, some debiasing methods fail to quantify the popularity bias and limit their bias removal ability. For example, in the sparest Alibaba-iFashion dataset, the results of MF+IPS-CN, MF+CausE, LightGCN+MACR, and LightGCN+CausE on the balanced evaluation are lower than original CF models (MF or LightGCN). In contrast, benefiting from popularity bias-aware margin, BC loss can learn discriminative representations that accomplish more profound user and item understanding, leading to higher head and tail recommendation quality.

5.1.2 Evaluations on Temporal Split Test Set

Motivation.
In real applications, popularity bias dynamically changes over time. Here we consider temporal split test evaluation on Douban Movie where the historical interactions are sliced into the training, validation, and test sets (70%:10%:20%) according to the timestamps.

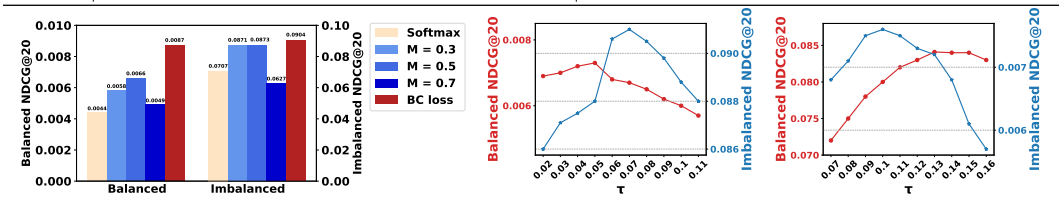
Table 2: The performance comparison on Douban dataset.

	MF			LightGCN		
	HR	Recall	NDCG	HR	Recall	NDCG
Backbone	0.2924	0.0294	0.0472	0.3543	0.0313	0.0602
+ IPS-CN	0.2514	0.0174	0.0324	0.3212	0.0261	0.0502
+ CausE	0.2725	0.0203	0.0376	0.3403	0.0275	0.0514
+ sam+reg	0.2826	0.0191	0.0390	0.2944	0.0252	0.0488
+ MACR	0.1084	0.0087	0.0163	0.3127	0.0271	0.0519
+ BC loss	**0.3742***	**0.0324***	**0.0601***	**0.3562***	**0.0346***	**0.0652***
Imp. %	28.0%	10.2%	27.3%	0.5%	10.4%	8.3%

Results. As Table 2 shows, BC loss is steadily superior to all baselines *w.r.t.* all metrics on Douban Movie. For instance, it achieves significant improvements over the MF and LightGCN backbones *w.r.t.* Recall@20 by 10.2% and 10.4%, respectively. This validates that BC loss endows the backbone models with better robustness against the popularity distribution shift and alleviates the negative influence of popularity bias. Surprisingly, none of the debiasing baselines could maintain a comparable performance to the backbones. We ascribe the failure to their preconceived idea of tail items, which possibly change over time.

Table 3: The performance evaluations of head, mid, and tail on Tencent dataset.

	Balanced NDCG@20				Imbalanced NDCG@20			
	Tail	Mid	Head	Overall	Tail	Mid	Head	Overall
MF	0.00004	0.00097	0.01250	0.00402	0.00021	0.00197	0.06837	0.06431
+ IPS-CN	0.00009$^{+125\%}$	0.00212$^{+119\%}$	0.01684$^{+35\%}$	0.00575$^{+43\%}$	0.00056$^{+167\%}$	0.00401$^{+104\%}$	0.04439$^{-35\%}$	0.04205$^{-35\%}$
+ CausE	0.00008$^{+100\%}$	0.00149$^{+54\%}$	0.01168$^{-7\%}$	0.00430$^{+7\%}$	0.00038$^{+81\%}$	0.00253$^{+28\%}$	0.04876$^{-29\%}$	0.04680$^{-27\%}$
+ sam-reg	0.00006$^{+50\%}$	0.00135$^{+39\%}$	0.01573$^{+26\%}$	0.00535$^{+33\%}$	0.00011$^{-48\%}$	0.00281$^{+43\%}$	0.02850$^{-58\%}$	0.02661$^{-59\%}$
+ MACR	**0.00188**$^{+4600\%}$	**0.00521**$^{+437\%}$	0.00555$^{-56\%}$	0.00456$^{+13\%}$	**0.00370**$^{+1662\%}$	0.00615$^{+212\%}$	0.02748$^{-60\%}$	0.02413$^{-62\%}$
+ BC loss	0.00024$^{+500\%}$	0.00355$^{+266\%}$	**0.01831**$^{+46\%}$	**0.00680**$^{+69\%}$	0.00142$^{+576\%}$	**0.00712**$^{+261\%}$	**0.09552**$^{+40\%}$	**0.09040**$^{+41\%}$
LightGCN	0.00025	0.00193	0.01136	0.00417	0.00094	0.00391	0.07561	0.07121
+ IPS-CN	0.00140$^{+460\%}$	0.00241$^{+25\%}$	0.01560$^{+37\%}$	0.00544$^{+30\%}$	0.00109$^{+16\%}$	0.00522$^{+34\%}$	0.06333$^{-16\%}$	0.05993$^{-16\%}$
+ CausE	0.00006$^{-76\%}$	0.00138$^{-29\%}$	0.01177$^{+4\%}$	0.00403$^{-3\%}$	0.00040$^{-57\%}$	0.00279$^{-29\%}$	0.06996$^{-7\%}$	0.06650$^{-7\%}$
+ sam-reg	0.00006$^{-76\%}$	0.00120$^{-38\%}$	0.01727$^{+52\%}$	0.00560$^{+34\%}$	0.00024$^{-74\%}$	0.00253$^{-35\%}$	0.04647$^{-39\%}$	0.04355$^{-39\%}$
+ MACR	**0.00287**$^{+1048\%}$	**0.00461**$^{+139\%}$	0.00454$^{-60\%}$	0.00501$^{+20\%}$	**0.00389**$^{+313\%}$	**0.00635**$^{+62\%}$	0.04058$^{-46\%}$	0.05323$^{-25\%}$
+ BC loss	0.00057$^{+128\%}$	0.00321$^{+66\%}$	**0.01943**$^{+71\%}$	**0.00730**$^{+75\%}$	0.00125$^{+33\%}$	0.00516$^{+32\%}$	**0.08823**$^{+17\%}$	**0.08320**$^{+17\%}$



(a) Varying margins. (b) MF+BC loss (c) LightGCN+BC loss

Figure 3: (a) Comparisons with a varying margin; (b-c) Temperature τ sensitivity analysis on Tencent.

5.2 Head, Mid, & Tail Performance (RQ2)

Motivation. To further evaluate whether BC loss lifts the tail performance by inevitably sacrificing the head performance, we divide the test set of Tencent into three subgroups, according to the interaction number of each item: head (popular items that are in the top third), mid (normal items in the middle), and tail (unpopular items in the bottom third). Most previous studies focus on average NDCG@20 for evaluation, especially balanced test evaluations [22, 23]. However, average metrics could be insufficient to reflect the performance of each subgroup. A trivial solution to achieve high performance is promoting the rankings of low-popularity items in the recommendations. In this case, only the average metrics are not reliable on the balanced test. Therefore, we report the performance of individual subgroups on both balanced and imbalanced test sets for a more comprehensive comparison.

Results. Table 3 shows the evaluations of the head, mid, and tail subgroups. The red and blue numbers in percentage separately refer to the improvement and decline of each method relative to the original CF model (MF or LightGCN). We find that:

- **BC loss is the only method that consistently yields remarkable improvements in every subgroup.** With a closer look at the head evaluation, BC loss shows its ability to learn more discriminative representations for popular items across imbalanced and balanced settings. In particular, it achieves significant improvements over MF and LightGCN *w.r.t.* head NDCG by 40% and 17% in the imbalanced test evaluation, respectively. We attribute improvements to the usage of bias-aware margin, which boosts the recommendation quality for the tail and head items.
- **As the performance comparison among subgraphs in the imbalanced scenario shows, the baselines enhance the tail performance but sacrifice the head performance.** Specifically, these baselines hardly maintain the head performance and show a clear trade-off trend between the head and tail performance. Taking MACR as an example, although the great improvement ($+1662\%$) over MF is achieved in the tail subgraph, it brings in the dramatic drop (-62%) in the head subgraph, which lowers the overall performance by a big drop (-60%). Here we ascribe the trade-off to blindly promoting the rankings of tail items for matched and unmatched, rather than improving the discriminative power of representations.

5.3 Study on BC Loss (RQ3)

Effect of Bias-aware Margin. Figure 3a displays the performance on balanced and imbalanced test sets on Tencent among softmax loss, BC loss with constant margin M [40], and BC loss with adaptive bias-aware margin. BC loss achieves the best performance, illustrating that bias-aware margin indeed is effective at reducing popularity bias and learning high-quality representations.

Effect of Temperature τ. BC loss has one hyperparameter to tune — temperature τ in Equation (5). In Figure 3b and 3c, both balanced and imbalanced evaluations exhibit the concave unimodal functions of τ, where the curves reach the peak almost synchronously in a small range of τ. For example, MF+BC loss gets the best performance when $\tau = 0.05$ and $\tau = 0.07$ in balanced and imbalanced settings, respectively; We observe similar trends on other datasets and skip them due to the space limit. This justifies that BC loss does not suffer from the trade-off between the balanced and imbalanced evaluations and improves the generalization without sacrificing the head performance.

6 Related Work

Prevalent popularity debiasing strategies in CF roughly fall into four research lines.

Post-processing re-ranking methods [5, 6, 7, 8, 9] are applied to the output of the recommender system without changing the representations of users and items. The purposes of modifying the ranking of models can be various: Calibration [5] ensures that the past interests proportions of users are expected to maintain at the same level; RankALS [6] aims to increase the diversification of recommendation; FPC [8] investigates the popularity bias in the dynamic recommendation by rescaling the predicted scores.

Regularization-based frameworks [10, 11, 12, 9] explore the use of regularization that provides a tunable mechanism for controlling the trade-off between recommendation accuracy and coverage. The difference among these methods is the design of penalty terms: ALS+Reg [11] defines intra-list distance as the penalty to achieve the fair recommendation; ESAM [10] introduces the attribute correlation alignment, center-clustering, and self-training regularization to learn good feature representations; sam-reg [12] regularizes the biased correlation between user-item relevance and item popularity; Reg [9] decouples the item popularity with the model preference predictions.

Sample re-weighting methods [13, 14, 15, 16, 17, 18], also known as Inverse Propensity Score (IPS) view the item popularity in the training set as the propensity score and exploit its inverse to re-weight loss of each instance. To address the high variance of re-weighted loss, many of them [15, 14] further employ normalization or smoothing penalty to attain a more stable output. However, the unreliability of methods is due to their measurement of the propensity score, leveraging the item frequency but failing to consider interaction-wise popularity bias.

Bias removal by causal inference methods [19, 24, 23, 20, 21, 22], getting inspiration from the recent success of counterfactual inference, specify the role of popularity bias in assumed causal graphs and mitigate the bias effect on the prediction. However, the causal structure is heuristically assumed based on the author's understanding, without any theoretical guarantee.

BC loss opens up a possibility of conventional debiasing methods in CF that mitigate the popularity bias by enhancing the discriminative power. Recent studies, boosting the discriminative feature spaces by modified softmax loss are mainly discussed in face recognition, where a constant margin is added [40] to better classify. We transfer it in CF and compare it with BC loss in Figure 3a.

7 Conclusion

Despite the great success in collaborative filtering, today's popularity debiasing methods are still far from being able to improve the recommendation quality. In this work, we proposed a simple yet effective BC loss, utilizing popularity bias-aware margin to eliminate the popularity bias. Grounded by theoretical proof, clear geometric interpretation and real-world visualization study, BC loss boosts the head and tail performance by learning a more discriminative representation space. Extensive experiments verify that the remarkable improvement in head and tail evaluations on various test sets indeed comes from the better representation rather than simply catering to the tail.

The limitations of BC loss are in three respects, which will be addressed in future work: 1) the modeling of bias-aware margin is worth exploring, which could significantly influence the performance of BC loss, 2) multiple important biases, such as exposure and selection bias, are not considered, and 3) more experiments comparing BC loss to standard CF losses (*e.g.,* cross-entropy, WARP) are needed to further demonstrate the power of BC loss in regular recommendation tasks (See comparison to BPR, CCL and SSM in Appendix B.4). We believe that this work provides a potential research direction to diagnose the debiasing of long-tail ranking and will inspire more works.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 7.
   (c) Did you discuss any potential negative societal impacts of your work? [No] This paper proposes a novel debiasing algorithm for recommendation system, which does not have any negative societal impacts.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes]
   (b) Did you include complete proofs of all theoretical results? [Yes] See Appendix A.3.
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We include code by URL in abstract.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Appendix B.1.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Appendix B.1.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
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   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

A In-depth Analysis of BC loss

A.1 Visualization of A Toy Experiment

Here we visualize a toy example on the Yelp2018 [25] dataset to showcase the effect of BC loss. Specifically, we train a two-layer LightGCN whose embedding size is three, and illustrate the 3-dimensional normalized representations on a 3D unit sphere in Figure 1 (See the magnified view in Figure 4). We train the identical LightGCN backbone with different loss functions: BPR loss, softmax loss, BC loss, and IPS-CN [15]. For the same head/tail user (*i.e.,* green stars), we plot 500 items in the unit sphere covering all positive items (*i.e.,* red dots) and randomly-selected negative items (*i.e.,* blue dots) from both the training and testing sets. Moreover, the angle distribution (the second row of each subfigure) of positive and negative items for a certain user quantitatively shows the discriminative power of each loss. We observe that:

- **BC loss learns more discriminative representations in both head and tail user cases. Moreover, BC loss learns a more reasonable representation distribution that is locally clustered and globally separated.** As Figures 4d and 4h show, for head and tail users, BC loss encourages around 40% and 55% of positive items to fall into the group closest to user representations, respectively. In other words, these item representations are almost clustered to a small region. BC loss also achieves the smallest distance *w.r.t.* mean positive angle. This verifies that BC loss tends to learn a high similar item/user compactness. Moreover, Figure 4h presents a clear margin between positive and negative items, reflecting a highly-discriminative power. Compared to softmax loss in Figures 4b and 4f, the compactness and dispersion properties of BC loss come from the incorporation of interaction-wise bias-aware margin.
- **The representations learned by standard CF losses - BPR loss and softmax loss - are not discriminative enough.** Under the supervision of BPR and softmax losses, item representations are separably allocated in a wide range of the unit sphere, where blue and red points occupy almost the same space area, as Figures 4a and 4b demonstrate. Furthermore, Figure 4e shows only a negligible overlap between positive and negative items' angle distributions. However, as the negative items are much more than the positive items for the tail user, a small overlap will make many irrelevant items rank higher than the relevant items, thus significantly hindering the recommendation accuracy. Hence, directly optimizing BPR or softmax loss might be suboptimal for the personalized recommendation tasks.
- **IPS-CN, a well-known popularity debiasing method in CF, is prone to lift the tail performance by sacrificing the representation learning for the head.** Compared with BPR loss in Figure 4e, IPS-CN learns better item representations for the tail user, which achieves smaller mean positive angle as illustrated in Figure 4g. However, for the head user in Figure 4c, the positive and negative item representations are mixed and cannot be easily distinguished. Worse still, the representations learned by IPS-CN has a larger mean positive angle for head user compared to BPR loss. This results in a dramatic performance drop for head evaluations.

A.2 Hard Example Mining Mechanism - one desirable property of BC loss:

We argue that the mechanism of adaptively mining hard interactions is inherent in BC loss, which improves the efficiency and effectiveness of training. Distinct from softmax loss that relies on the predictive scores to mine hard negative samples [56] and leaves the popularity bias untouched, our BC loss considers the interaction-wise biases and adaptively locates hard informative interactions.

Specifically, the popularity bias extractor $\hat{y}_b$ in Equation (3) can be viewed as a hard sample detector. Considering an interaction (u, i) with a high bias degree $cos(\hat{\xi}_{ui})$, we can only use its popularity information to predict user preference and attain a vanishing bias-aware angular margin M_{ui}. Hence, interaction (u, i) will plausibly serve as the biased and easy sample, if it involves the active users and popular items. Its close-to-zero margin makes (u, i)'s BC loss approach softmax loss, thus downgrading the ranking criteria to match the basic assumption of softmax loss.

In contrast, if the popularity statistics are deficient in recovering user preference via the popularity bias extractor, the interaction (u, i) garners the low bias degree $cos(\hat{\xi}_{ui})$ and exerts the significant margin M_{ui} on its BC loss. Hence, it could work as the hard sample, which typically covers the tail users and items, and yields a more stringent assumption that user u prefers the tail item over the other

popular items by a large margin. Such a significant margin makes the losses more challenging to learn.

In a nutshell, BC loss adaptively prioritizes the interaction samples based on their bias degree and leads the CF model to shift its attention to hard samples, thus improving both head and tail performance, compared with softmax loss (*cf.* Section 5.3).

A.3 Proof of Theorem 1

Theorem 1. *Let* $\mathbf{v}_u \doteq \psi(u)$, $\mathbf{v}_i \doteq \phi(i)$, *and* $\mathbf{c}_u = \frac{1}{|\mathcal{P}_u|}\sum_{i\in\mathcal{P}_u}\mathbf{v}_i$, $\mathbf{c}_i = \frac{1}{|\mathcal{P}_i|}\sum_{u\in\mathcal{P}_i}\mathbf{v}_u$, *where* $\mathcal{P}_u = \{i|y_{ui}=1\}$ *and* $\mathcal{N}_u = \{i|y_{ui}=0\}$ *are the sets of user* u*'s positive and negative items, respectively;* $\mathcal{P}_i = \{u|y_{ui}=1\}$ *is the set of item* i*'s positive users. Assuming the representations of users and items are normalized, the minimization of BC loss is equivalent to minimizing a compactness part and a dispersion part simultaneously:*

$$\mathcal{L}_{BC} \geq \underbrace{\sum_{u\in\mathcal{U}}\|\mathbf{v}_u-\mathbf{c}_u\|^2+\sum_{i\in\mathcal{I}}\|\mathbf{v}_i-\mathbf{c}_i\|^2}_{\textit{Compactness part}}\underbrace{-\sum_{u\in\mathcal{U}}\sum_{j\in\mathcal{N}_u}\|\mathbf{v}_u-\mathbf{v}_j\|^2}_{\textit{Dispersion part}} \propto \underbrace{H(\mathbf{V}|Y)}_{\textit{Compactness}}\ \underbrace{-H(\mathbf{V})}_{\textit{Dispersion}}. \tag{7}$$

Proof. Let the upper-case letter $\mathbf{V}\in\mathbb{V}$ be the random vector of representation and $\mathbb{V}\subseteq\mathbb{R}^d$ be the representation space. We use the normalization assumption of representations to connect cosine and Euclidean distances, *i.e.,* if $\|\mathbf{v}_u\|=1$ and $\|\mathbf{v}_i\|=1$, $\mathbf{v}_u^T\mathbf{v}_i = 1-\frac{1}{2}\|\mathbf{v}_u-\mathbf{v}_i\|^2, \forall u,i$.

Let $\mathcal{P}_u=\{i|y_{ui}=1\}$ be the set of user u's positive items , $\mathcal{P}_i=\{u|y_{ui}=1\}$ to be the set of item i's positive users, and $\mathcal{N}_u=\{i|y_{ui}=0\}$ be the set of user u's negative items. Clearly, there exists an upper bound m, *s.t.* $-1<\cos(\hat{\theta}_{ui}+M_{ui})\leq\mathbf{v}_u^T\mathbf{v}_i-m<1$. Therefore, we can analyze BC loss, which has the following relationships:

$$\begin{aligned}\mathcal{L}_{BC} &\geq -\sum_{(u,i)\in\mathcal{O}^+}\log\frac{\exp\left((\mathbf{v}_u^T\mathbf{v}_i-m)/\tau\right)}{\exp\left((\mathbf{v}_u^T\mathbf{v}_i-m)/\tau\right)+\sum_{j\in\mathcal{N}_u}\exp\left((\mathbf{v}_u^T\mathbf{v}_j)/\tau\right)}\\ &= -\sum_{(u,i)\in\mathcal{O}^+}\frac{\mathbf{v}_u^T\mathbf{v}_i-m}{\tau}+\sum_{(u,i)\in\mathcal{O}^+}\log(\exp\frac{\mathbf{v}_u^T\mathbf{v}_i-m}{\tau}+\sum_{j\in\mathcal{N}_u}\exp\frac{\mathbf{v}_u^T\mathbf{v}_j}{\tau}).\end{aligned} \tag{8}$$

We now probe into the first term in Equation (8):

$$\begin{aligned}-\sum_{(u,i)\in\mathcal{O}^+}\frac{\mathbf{v}_u^T\mathbf{v}_i-m}{\tau} &= \sum_{(u,i)\in\mathcal{O}^+}\frac{\|\mathbf{v}_u-\mathbf{v}_i\|^2}{2\tau}+\frac{m-1}{\tau}\\ &\overset{\mathsf{c}}{=}\sum_{(u,i)\in\mathcal{O}^+}\|\mathbf{v}_u-\mathbf{v}_i\|^2\\ &=\sum_{u\in\mathcal{U}}\sum_{i\in\mathcal{P}_u}(\|\mathbf{v}_u\|^2-\mathbf{v}_u^T\mathbf{v}_i)+\sum_{i\in\mathcal{I}}\sum_{u\in\mathcal{P}_i}(\|\mathbf{v}_i\|^2-\mathbf{v}_u^T\mathbf{v}_i)\\ &\overset{\mathsf{c}}{=}\sum_{u\in\mathcal{U}}\|\mathbf{v}_u-\mathbf{c}_u\|^2+\sum_{i\in\mathcal{I}}\|\mathbf{v}_i-\mathbf{c}_i\|^2,\end{aligned} \tag{9}$$

where the symbol $\overset{\mathsf{c}}{=}$ indicates equality up to a multiplicative and/or additive constant; $\mathbf{c}_u = \frac{1}{|\mathcal{P}_u|}\sum_{i\in\mathcal{P}_u}\mathbf{v}_i$ is the averaged representation of all items that u has interacted with, which describes u's interest; $\mathbf{c}_i = \frac{1}{|\mathcal{P}_i|}\sum_{u\in\mathcal{P}_i}\mathbf{v}_u$ is the averaged representation of all users who have adopted item i, which profiles its user group. We further analyze Equation (9) from the entropy view by conflating the first two terms:

$$-\sum_{(u,i)\in\mathcal{O}^+}\frac{\mathbf{v}_u^T\mathbf{v}_i-m}{\tau}\overset{\mathsf{c}}{=}\sum_{\mathbf{v}}\|\mathbf{v}-\mathbf{c}_v\|^2, \tag{10}$$

where $\mathbf{v}\in\{\mathbf{v}_u|u\in\mathcal{U}\}\cup\{\mathbf{v}_i|i\in\mathcal{I}\}$ summarizes the representations of users and items, with the mean of $\mathbf{c}_v$. Following [57], we further interpret this term as a conditional cross-entropy between

$\mathbf{V}$ and another random variable $\bar{\mathbf{V}}$ whose conditional distribution given Y is a standard Gaussian $\bar{\mathbf{V}}|Y \sim \mathcal{N}(\mathbf{c}_{\mathbf{V}}, I)$:

$$
\begin{aligned}
-\sum_{(u,i)\in\mathcal{O}^+} \frac{\mathbf{v}_u^T\mathbf{v}_i - m}{\tau} &\overset{\mathsf{c}}{=} H(\mathbf{V};\bar{\mathbf{V}}|Y) = H(\mathbf{V}|Y) + D_{KL}(\mathbf{V}||\bar{\mathbf{V}}|Y) \\
&\propto H(\mathbf{V}|Y),
\end{aligned} \tag{11}
$$

where $H(\cdot)$ denotes the cross-entropy, and $D_{KL}(\cdot)$ denotes the KL-divergence. As a consequence, the first term in Equation (8) is positive proportional to $H(\mathbf{V}|Y)$. This concludes the proof for the first compactness part of BC loss.

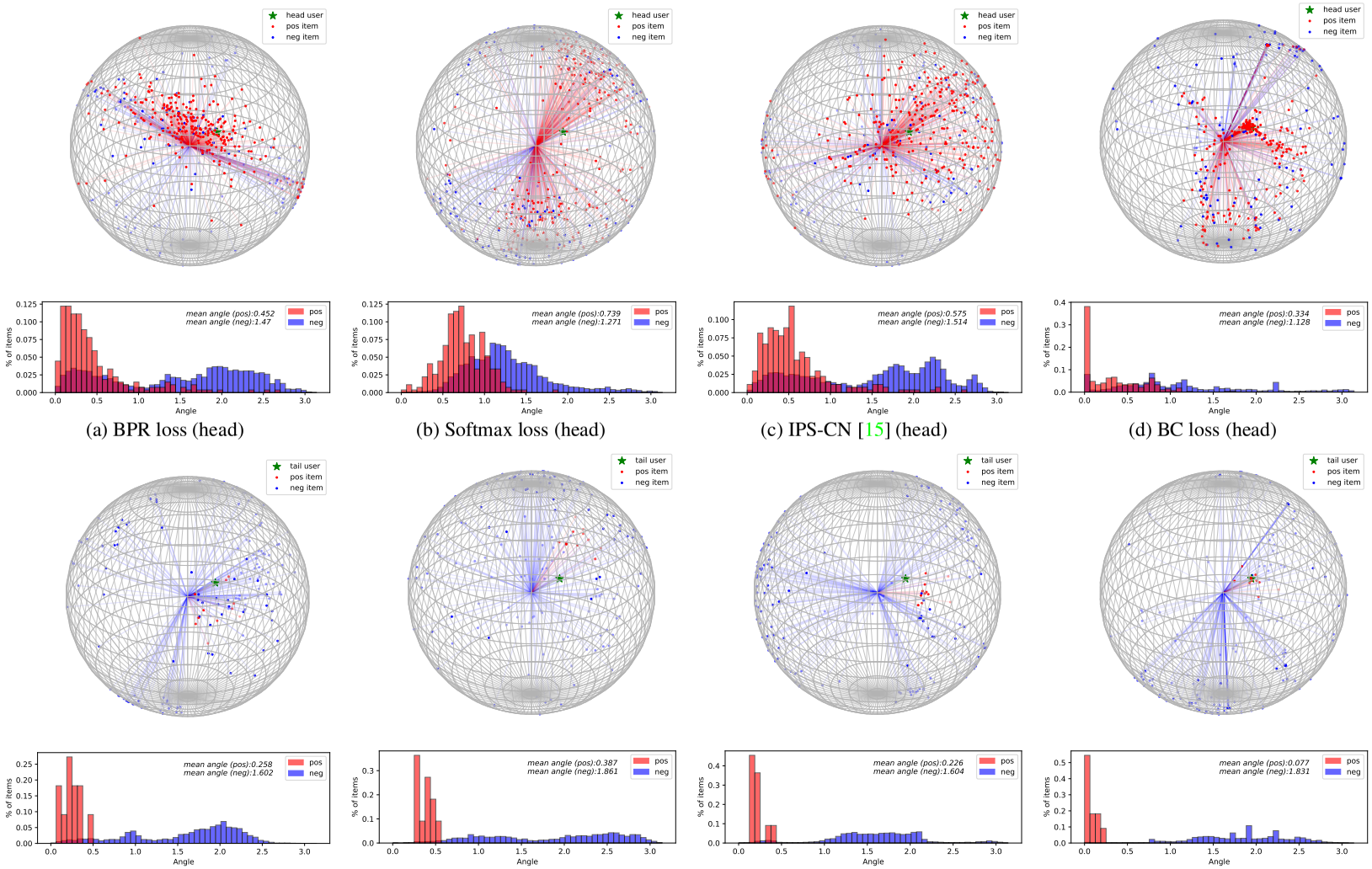
We then inspect the second term in Equation (8) to demonstrate its dispersion property:

$$
\begin{aligned}
&\sum_{(u,i)\in\mathcal{O}^+} \log(\exp\frac{\mathbf{v}_u^T\mathbf{v}_i - m}{\tau} + \sum_{j\in\mathcal{N}_u}\exp\frac{\mathbf{v}_u^T\mathbf{v}_j}{\tau}) \\
\geq &\sum_{(u,i)\in\mathcal{O}^+} \log\big(\sum_{j\in\mathcal{N}_u}\exp\frac{\mathbf{v}_u^T\mathbf{v}_j}{\tau}\big) \\
\geq &\sum_{u\in\mathcal{U}}\sum_{j\in\mathcal{N}_u}\frac{\mathbf{v}_u^T\mathbf{v}_j}{\tau} \\
\overset{\mathsf{c}}{=} &-\sum_{u\in\mathcal{U}}\sum_{j\in\mathcal{N}_u}\|\mathbf{v}_u - \mathbf{v}_j\|^2,
\end{aligned} \tag{12}
$$

where we drop the redundant terms aligned with the compactness objective in the second line, and adopt Jensen's inequality in the third line. As shown in prior studies [58], minimizing this term is equivalent to maximizing entropy $H(\mathbf{V})$:

$$
\sum_{(u,i)\in\mathcal{O}^+} \log(\exp\frac{\mathbf{v}_u^T\mathbf{v}_i - m}{\tau} + \sum_{j\in\mathcal{N}_u}\exp\frac{\mathbf{v}_u^T\mathbf{v}_j}{\tau}) \propto -\mathcal{H}(\mathbf{V}). \tag{13}
$$

As a result, the second term in Equation (8) works as the dispersion part in BC loss. □



(a) BPR loss (head) (b) Softmax loss (head) (c) IPS-CN [15] (head) (d) BC loss (head)

(e) BPR loss (tail) (f) Softmax loss (tail) (g) IPS-CN [15] (tail) (h) BC loss (tail)

Figure 4: Magnified View of Figure 1.

B Experiments

B.1 Experimental Settings

Datasets. We conduct experiments on five real-world benchmark datasets: Tencent [47], Amazon-Book [48], Alibaba-iFashion [49], Douban Movie [50], and KuaiRec [52]. All datasets are public and vary in terms of size, domain, and sparsity. Table 4 summarizes the dataset statistics, where the long-tail degree is monitored by KL-divergence between the item popularity distribution and the uniform distribution, *i.e.,* $D_{KL}(\hat{P}_{data}||\text{Uniform})$. A larger KL-divergence value indicates that the heavier portion of interactions concentrates on the head of distribution. In the stage of pre-processing data, we follow the standard 10-core setting [20, 59] to filter out the items and users with less than ten interactions.

Data Splits. For comprehensive comparisons, almost all standard test distributions in CF are covered in the experiments: balanced test set [22, 23, 24], randomly selected imbalanced test set [10, 53], temporal split test set [20, 21, 12], and unbiased test set [13, 52, 51]. Three datasets (*i.e.,* Tencent, Amazon-Book, Alibaba-iFashion) are partitioned into both balanced and randomly selected imbalanced evaluations. As an intervention test, the balanced evaluation (*i.e.,* uniform distribution) is frequently employed in recent debiasing CF approaches [22, 23, 24, 60]. Douban is split based on the temporal splitting strategy [61]. KuaiRec is an unbiased, fully-observed dataset in which the feedback of the test set's interaction is explicitly collected.

Evaluation Metrics. We adopt the all-ranking strategy [62], *i.e.,* for each user, all items are ranked by the recommender model, except the positive ones in the training set. To evaluate the quality of recommendation, three widely-used metrics are used: Hit Ratio (HR@K), Recall@K, Normalized Discounted Cumulative Gain (NDCG@K), where K is set as 20 by default.

Baselines. We validate our BC loss on two widely-used CF models, MF [26] and LightGCN [25], which are representatives of the conventional and state-of-the-art CF models. We compare BC loss with the popular debiasing strategies in various research lines: sample re-weighting (IPS-CN [15]), bias removal by causal inference (MACR [22], CausE [19]), and regularization-based framework (sam+reg [12]). We also compare BC loss to other standard losses used in collaborative filtering including most commonly used loss (BPR loss [26]) and newest proposed softmax losses (CCL [54] and SSM [55]).

Parameter Settings. We conduct experiments using a Nivida-V100 GPU (32 GB memory) on a server with a 40-core Intel CPU (Intel(R) Xeon(R) CPU E5-2698 v4). We implement our BC loss in PyTorch. Our codes, datasets, and hyperparameter settings are available at `https://anonymous.4open.science/r/BC-Loss-8764/model.py` to guarantee reproducibility. For a fair comparison, all methods are optimized by Adam [63] optimizer with the batch size as 2048, embedding size as 64, learning rate as 1e-3, and the coefficient of regularization as 1e-5 in all experiments. Following the default setting in [25], the number of embedding layers for LightGCN is set to 2. We adopt the early stop strategy that stops training if Recall@20 on the validation set does not increase for 10 successive epochs. A grid search is conducted to tune the critical hyperparameters of each strategy to choose the best models *w.r.t.* Recall@20 on the validation set. For softmax, SSM, and BC loss, we search τ in [0.06, 0.14] with a step size of 0.02. For CausE, 10% of training data with balanced distribution are used as intervened set, and cf_pen is tuned in $[0.01, 0.1]$ with a step size of 0.02. For MACR, we

Table 4: Dataset statistics.

	KuaiRec	Douban Movie	Tencent	Amazon-Book	Alibaba-iFashion	Yahoo!R3	Coat
#Users	7175	36,644	95,709	52,643	300,000	14382	290
#Items	10611	22,226	41,602	91,599	81,614	1000	295
#Interactions	1062969	5,397,926	2,937,228	2,984,108	1,607,813	129,748	2,776
Sparsity	0.01396	0.00663	0.00074	0.00062	0.00007	0.00902	0.03245
D_{KL}-Train	1.075	1.471	1.425	0.572	1.678	0.810	0.322
D_{KL}-Validation	1.006	1.642	1.423	0.572	1.705	0.779	0.279
D_{KL}-Balanced	-	-	0.003	0.000	0.323	-	-
D_{KL}-Imbalanced	-	-	1.424	0.571	1.703	-	-
D_{KL}-Temporal	-	1.428	-	-	-	-	-
D_{KL}-Unbiased	1.666	-	-	-	-	0.087	0.064

Table 5: Training cost on Tencent (seconds per epoch/in total).

	Backbone	+IPS-CN	+CausE	+sam+reg	+MACR	+BC loss
MF	15.5 / 17887	17.8 / 10662	16.6 / 1859	18.2 / 3458	160 / 17600	36.1 / 12815
LightGCN	78.6 / 4147	108 / 23652	47.2 / 3376	49.8 / 10458	135 / 20250	283 / 7075

Table 6: The performance comparison on KuaiRec dataset.

	Validation			Unbiased Test		
	HR	Recall	NDCG	HR	Recall	NDCG
LightGCN	0.299	0.069	0.051	0.104	0.0038	0.0064
+ IPS-CN	0.255	0.056	0.042	<u>0.109</u>	<u>0.0073</u>	<u>0.0083</u>
+ CausE	0.292	0.067	0.050	0.101	0.0056	0.0077
+ sam+reg	0.274	0.060	0.047	0.107	0.0069	0.0080
+ BC loss	0.343	0.076	0.062	**0.139***	**0.0077***	**0.0115***
Imp.%	-	-	-	27.5%	4.05%	38.6%

follow the original settings to set weights for user branch $\alpha = 1e-3$ and item branch $\beta = 1e-3$, respectively. We further tune hyperparameter $c = [0, 50]$ with a step size of 5. For CCL loss, we search w in $\{1, 2, 5, 10, 50, 100, 200\}$, m in the range $[0.2, 1]$ with a step size of 0.2. When it come to the number of negative samples, the softmax, SSM, CCL, and BC loss set 128 for MF backbone and in-batch negative sampling for LightGCN models.

B.2 Training Cost

In terms of time complexity, as shown in Table 5, we report the time cost per epoch and in total of each baselines on Tencent. Compared with backbone methods (*i.e.,* MF and LightGCN), BC loss adds very little computing complexity to the training process.

B.3 Evaluations on Unbiased Test Set

Motivation. Because of the missing-not-at-random condition in a real recommender system, offline evaluation on collaborative filtering and recommender system is commonly acknowledged as a challenge. To close the gap, Yahoo!R3 [51] and Coat [13] are widely used, which offer unbiased test sets that are collected using the missing-complete-at-random (MCAR) concept. Additionaly, newly proposed KuaiRec [52] also provides a fully-observed unbiased test set with 1,411 users over 3,327 videos. We conduct experiments on all these datasets for comprehensive comparison, and KuaiRec is also included as one of our unbiased evaluations for two key reasons: 1) It is significantly larger than existing MCAR datasets (*e.g.,* Yahoo! and Coat); 2) It overcomes the missing values problem, making it as effective as an online A/B test.

Results. Table 6 and 8 illustrate the unbiased evaluations on KuaiRec, Yahoo!R3, and Coat dataset using LightGCN and MF as backbone models, respectively. The best performing methods are bold and starred, while the strongest baselines are underlined; Imp.% measures the relative improvements of BC loss over the strongest baselines. BC loss is consistently superior to all baselines *w.r.t.* all metrics. It indicates that BC loss truly improves the generalization ability of recommender.

B.4 Performance Comparison with Standard Loss Functions in CF

Motivation. To verify the effectiveness of BC loss as a standard learning strategy in collaborative filtering, we further conduct the experiments over various datasets between BC loss, BPR loss, CCL loss [54], and SSM loss [55]. We choose these three losses as baselines for two main reasons: 1) BPR loss is the most commonly applied in recommender system; 2) SSM and CCL are most recent proposed losses, where SSM is also a softmax loss and CCL employs a global margin.

Results. Table 7 reports the performance on both balanced and imbalanced test sets on various datasets among different losses. We have two main observations: (1) Clearly, our BC loss consistently outperforms CCL and SSM; (2) CCL and SSM achieve comparable performance to BC loss in the imbalanced evaluation settings, while performing much worse than BC loss in the balanced evaluation

Table 7: The performance comparison on Tecent, Amazon-book and Alibaba-iFashion datasets.

	Tencent				Amazon-book				Alibaba-iFashion			
	Balanced		Imbalanced		Balanced		Imbalanced		Balanced		Imbalanced	
	Recall	NDCG	Recall	NDCG	Recall	NDCG	Recall	NDCG	Recall	NDCG	Recall	NDCG
BPR	0.0052	0.0040	0.0982	0.0643	0.0109	0.0103	0.0850	0.0638	0.0056	0.0028	0.0843	0.0411
SSM	0.0055	0.0045	0.1297	0.0872	0.0156	0.0157	0.1125	0.0873	0.0079	0.0040	0.0963	0.0436
CCL	0.0057	0.0047	0.1216	0.0818	0.0175	0.0167	0.1162	0.0927	0.0075	0.0038	0.0954	0.0428
BC Loss	**0.0087***	**0.0068***	**0.1298***	**0.0904***	**0.0221***	**0.0202***	**0.1198***	**0.0948***	**0.0095***	**0.0048***	**0.0967***	**0.0487***
Imp. %	52.6%	44.7%	0.1%	3.7%	26.3%	21.0%	3.1%	2.3%	20.3%	20.0%	0.4%	11.7%

Table 8: The performance comparison on Yahoo!R3 and Coat dataset.

	Yahoo!R3		Coat	
	Recall	NDCG	Recall	NDCG
IPS-CN	0.1081	0.0487	0.1700	0.1377
CausE	0.1252	0.0537	0.2329	0.1635
sam+reg	0.1198	0.0548	0.2303	0.1869
MACR	0.1243	0.0539	0.0798	0.0358
BPR	0.1063	0.0476	0.0741	0.0361
SSM	0.1470	0.0688	0.2022	0.1832
CCL	0.1428	0.0676	0.2150	0.1885
BC loss	**0.1487***	**0.0706***	**0.2385***	**0.1969***
Imp.%	1.2%	2.6%	2.4%	4.5%

settings. This indicates the superiority of BC loss in alleviating the popularity bias, and further justifies the effectiveness of the bias-aware margins.

Table 8 shows the unbiased evaluations on Yahoo!R3 and Coat dataset. With regard to all criteria, BC loss constantly outperforms all other losses. It verifies the effectiveness of instance-wise bias margin of BC loss.

B.5 Study on BC Loss (RQ3) - Effect of Popularity Bias Extractor

Motivation. To check the effectiveness of popularity bias extractor, we need to answer two main questions: 1) what kinds of interactions will be learned well by the bias extractor? What does the learned bias-angle distribution look like? 2) can BC loss benefit from the bias margin extracted according to the popularity bias extractor in various groups of interactions? We devise two distinct experiments to tackle these two problems.

Experiment Setting A. Users can be divided into three parts: head, mid, and tail, based on their popularity scores. Analogously, items can be partitioned into the head, mid, and tail parts. As such, we can categorize all user-item interactions into nine subgroups. We have visualized the learned angles for various types of interactions in the following table 5.

Results A. The table 5 shows the learned angles over all subgroups. We find that interactions between head users and head items tend to hold small angles. Moreover, as evidenced by the high standard deviation, the interactions stemming from the same subgroup types are prone to receive a wide range of angular values. This demonstrates the variability and validity of instance-wise angular margins.

Experiment Setting B. We partition interactions into disjoint subgroups on Tencent dataset, based on the bias degree estimated by our popularity bias extractor. These subgraphs are composed of (1) hard interactions with low bias degrees (40% of total interactions, Popularity rank > 1000), and (2) easy interactions with high bias degrees (15% of total interactions, Popularity rank < 100), respectively. Then, we use four losses (BPR, CCL, SSM, and BC losses) to train the same MF backbone.

Results B. Figure 4 depicts the performance of each loss in the hard-interaction subgroup, easy-interaction subgraph, and all-interaction group, during the training phase. With the increase of training epochs, the performance of BPR drops dramatically in the hard-interaction subgroup, while increasing in the all-interaction group. Possible reasons are BPR is easily influenced by the interaction-wise bias:

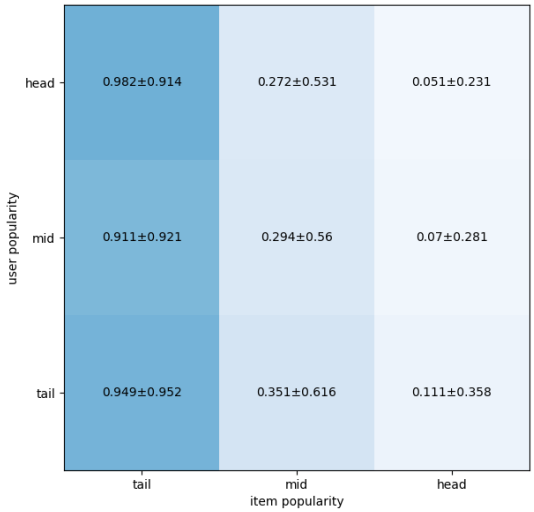
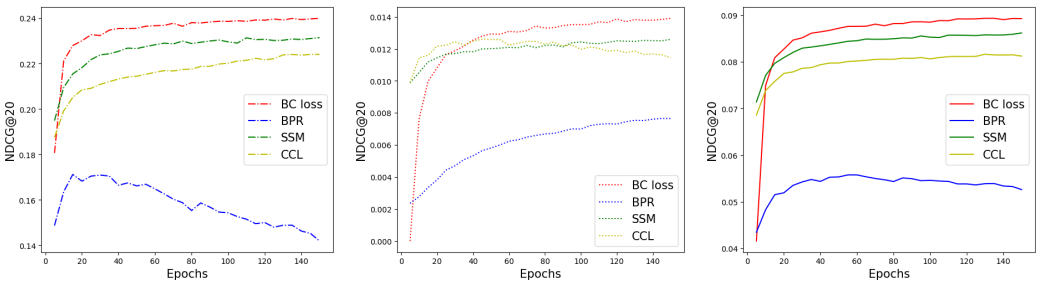


Figure 5: Visualization of popularity bias angle for different types of interactions on Tencent.

BPR focuses largely on the majority subgroups of easy interactions, while sacrificing the performance of the minority subgroups of hard interactions. In contrast, the performance of BC loss consistently increases over every subgroup during training. This indicates that BC loss is able to mitigate the negative influences of popularity bias, thus further justifying that the popularity bias extract captures the interaction-wise bias well.



(a) Hard interactions (b) Easy interactions (c) All interactions

Figure 6: (a) The performance of BPR loss on hard interactions consistently drops; (b)- (c). BC loss shows the promise to mitigate the popularity bias by utilizing the popularity bias extractor.