Reducing Popularity-Opportunity Bias in Recommender System by Regularizing Prediction Score Difference

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H C C L A B S N U

Research Highlight

Simple Regularization Term to Reduce Popularity-Opportunity Bias

- Minimizing prediction score difference between positive(negative) items reduces bias
- Simple extension to Bayesian Pairwise Loss with no additional training needed

High Debias Performance while Maintaining Accuracy

- Proposed method shows almost no trade-off in accuracy and debias performance

Visual Illustration and Experiments

- The effect of the proposed method is illustrated using synthetic data
- Extensive experiments is performed with 4 RS models and 2 benchmark datasets

Popularity-Opportunity Bias in RS

- Popularity-Opportunity Bias : *conditioned on user preferences that a user likes both items*, the recommender system(RS) tends to recommend the more popular item
- Training RS on popularity skewed synthetic data results in popularity-opportunity bias

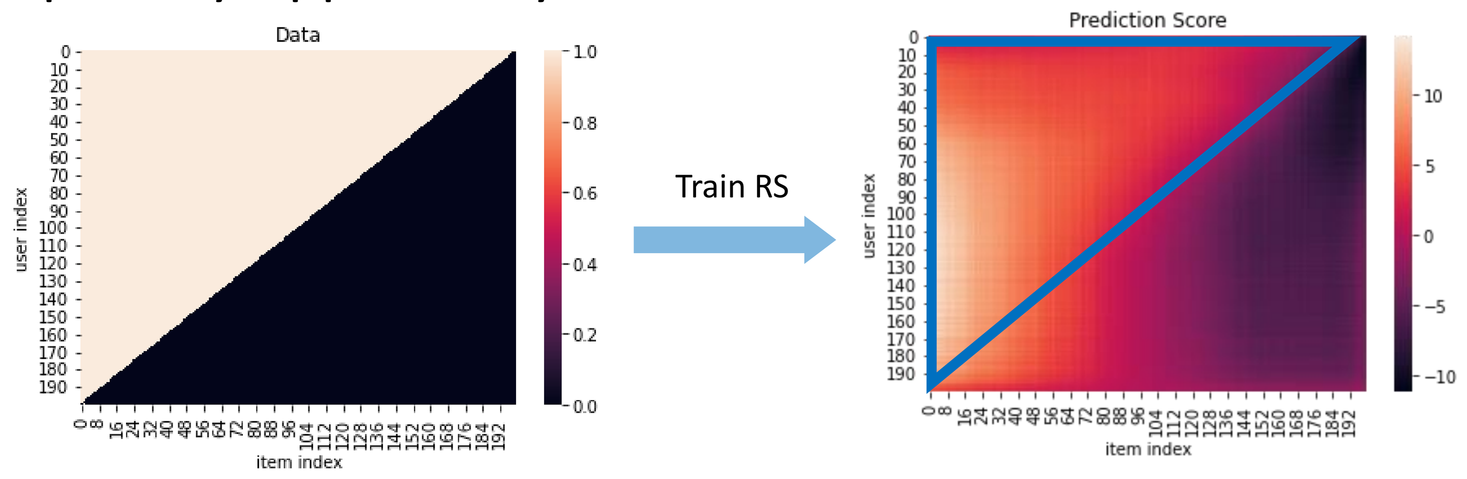

Figure 1: The left shows a user-item rating matrix R, where $R[u,i] = 1$ if user u consumed item i and 0 otherwise. The data shows skew in popularity where the item with smaller index is more consumed(popular). RS model(Matrix Factorization) is trained on the data. The right shows the resulting prediction score of the RS model. The prediction shows popularity-opportunity bias. That is, when conditioned on items that the user consumed, the more popular item has higher recommendation score.

Proposed Debias Method

- To alleviate bias, a regularization term is added to minimize the prediction score difference between positive items(items the user liked), and negative items(did not like), respectively.
- Baseline : BPR Loss
  - $Loss_{BPR} = -\Sigma_{u\in U}\Sigma_{pos\in Pos_u, neg\in Neg_u} \ln\sigma(\widehat{y_{u,pos}} - \widehat{y_{u,neg}})$
- Proposed Method : Regularization Term
  - $Loss_{Reg} = -\Sigma_u \Sigma \ln(1 - tanh(|\widehat{y_{u,p_1}} - \widehat{y_{u,p_2}}|)) + \ln(1 - tanh(|\widehat{y_{u,n_1}} - \widehat{y_{u,n_2}}|))$
  - $Loss_{Total} = Loss_{BPR} + Loss_{Reg}$
- The proposed regularization is a simple extension to the widely used BPR loss. It is model-agnostic and requires no additional training or parameters.

Visual Illustration of Proposed Method

- The debias performance of the proposed method is illustrated.
  - Baseline BPR(Left) : conditioned on the positive items, the more popular item has higher score, thus are recommended first.
  - Proposed Method(Right) : the score is similar across items of different popularity, thus items are recommended in order independent of popularity. At the same time, positive items are scored higher than negative items.

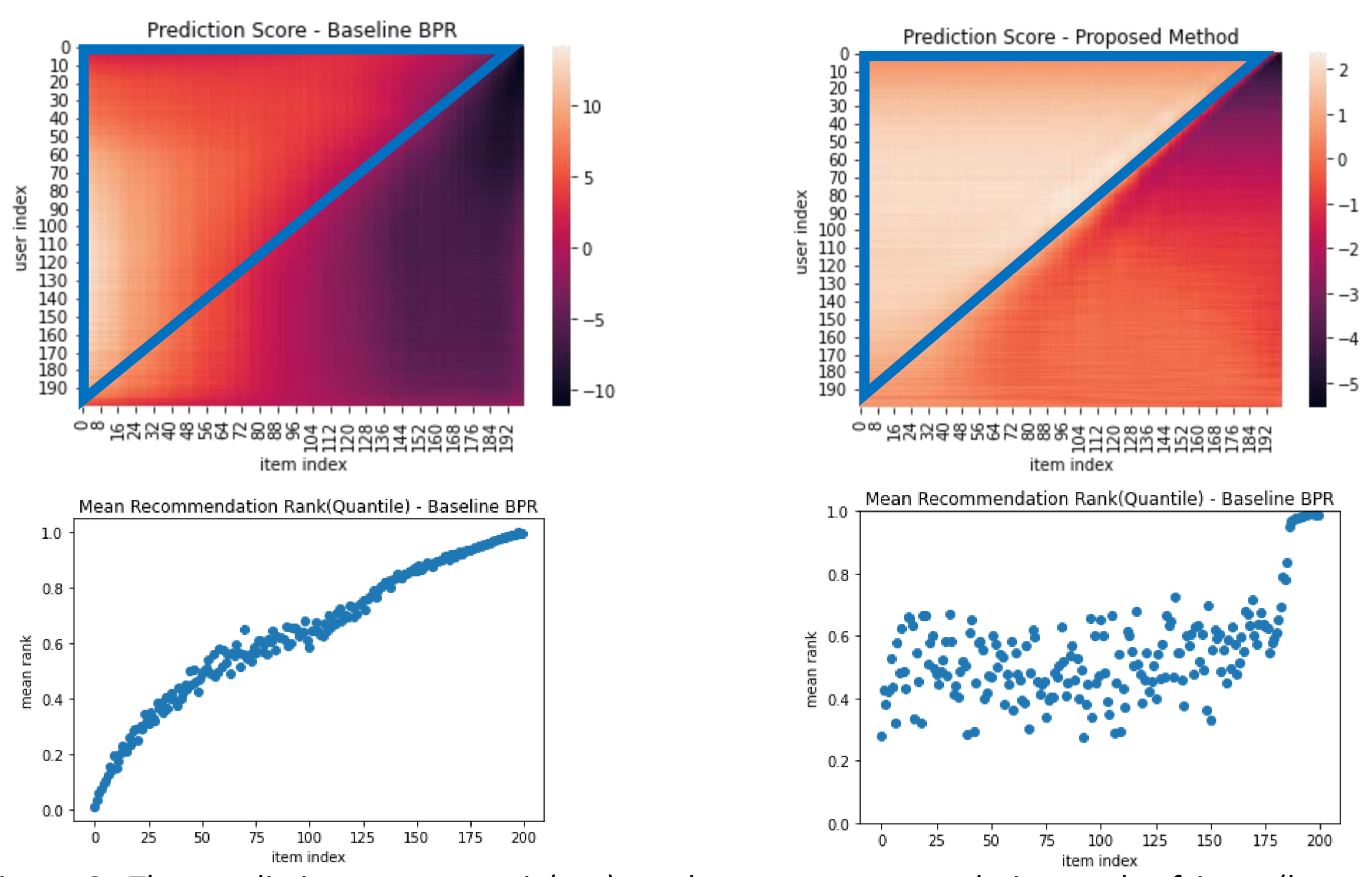

Figure 2: The prediction score matrix(top), and mean recommendation rank of items(bottom) is shown. The results of baseline BPR loss(left) and the proposed method(right) is compared. The training is done on the synthetic data with Matrix Factorization model.

Experiments and Evaluation

- Experiments on 2 benchmark datasets(ML-1M, Gowalla), using 4 RS algorithms(MF, NeuCF, NGCF, LightGCN)
- Evaluation Metric
  - Accuracy : Hit@10
  - Debias Performance : Popularity quantile of highest scored positive item

Dataset	Movielens-1M							
Model	MF		NeuCF		NGCF		LightGCN	
Method	Hit@10	Pop Q@1	Hit@10	Pop Q@1	Hit@10	Pop Q@1	Hit@10	Pop Q@1
BPR(Baseline)	0.697	0.25	0.689	0.16	0.709	0.16	0.705	0.13
Pearson	0.697	0.38	0.666	0.25	0.555	0.50	0.479	0.32
Post Process	0.609	0.69	0.681	0.36	0.411	0.82	0.540	0.72
Pointwise	0.706	0.11	0.686	0.16	0.583	0.07	0.678	0.05
Proposed	0.708	0.40	0.672	0.28	0.707	0.31	0.703	0.31

Dataset	Gowalla							
Model	MF		NeuCF		NGCF		LightGCN	
Method	Hit@10	Pop Q@1	Hit@10	Pop Q@1	Hit@10	Pop Q@1	Hit@10	Pop Q@1
BPR(Baseline)	0.908	0.16	0.827	0.21	0.896	0.12	0.876	0.10
Pearson	0.909	0.15	0.823	0.19	0.898	0.15	0.862	0.12
Post Process	0.857	0.74	0.761	0.15	0.752	0.79	0.661	0.80
Pointwise	0.705	0.15	0.646	0.16	0.804	0.06	0.719	0.05
Proposed	0.898	0.26	0.781	0.41	0.899	0.24	0.865	0.19

Table 1: Methods compared are BPR : vanilla BPR loss, Pearson : penalizes the square of pearson correlation of item popularity and prediction score, Post-process : compensates prediction score with proportion to the inverse of item popularity, Pointwise : the BCE loss is used as an additional loss term, Proposed : minimize prediction score difference with regularization term.

- The proposed method shows high debias performance as seen as Pop Q@1 become closer to 0.5.
- The proposed method maintains accuracy as seen as Hit@10 is similar to the baseline.

Compared with Conventional Popularity Bias

- Conventional debias method such as IPW, causal intervention identifies 'popularity bias in data' as the cause of 'popularity bias in model prediction'.
- Debias methods for bias in data is applied to bias in model prediction. This often requires additional assumptions.
- In contrast, the current approach separates bias in data and bias in model prediction.
- Sole focus is debiasing bias in model prediction from a ML perspective. Bias in data need not be considered.

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