Cross-Dataset Recommender System for Overcoming Selection Bias

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Abstract

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1 Introduction

Selection bias is one of the most prevalent sources of biases for recommender systems [2]. Selection bias happens when there is a pattern in the users' ratings that is unique to the training set. For example, in a recommender system for movies, users might mainly rate movies that are recommended to them, which is a small section of movies already tailored to the users' tastes [5]. However, the environment the recommender system is deployed on contains all movies regardless of personal tastes. This discrepancy produces a misalignment between training and deployed settings, which is known as a distribution shift. Tackling the selection bias in a recommender dataset has been a constant challenge in designing recommender algorithms[6].

When recommender systems are deployed in real-world platforms, it is arguably likely that the clients are able to collect rating-associated data from different source distributions. These data (or feedbacks) are either implicit or explicit [1], while implicit data often comes in a highly-quantized, binary form and explicit data is usually less quantized. For example, a user's explicit rating of a movie is usually quantized to a number between 1 and 5, while the implicit feedback, such as if a user spontaneous searches for a movie, is often binary (more quantized.) We extend our hypothesis and argue that implicit data contains less or no selection bias compared to explicit data. This is because implicit data are often from users' spontaneous actions while explicit data are prejudiced toward the output of the recommender system in the previous feedback loop and also users' innate biases.

In this paper, we attempt to take advantage of datasets from differently quantized sources. More specifically, we proposed a way to feed both a 5-quantized dataset and a binary dataset to any gradient-based recommender algorithm. To ensure both datasets do not significantly lose their values in the presence of selection bias, we first examine the susceptibility to selection bias of differently quantized datasets from a single distribution. We design experiments under a simulated environment and shows that susceptibility to selection bias is not correlated with the way a dataset is quantized.

Then, since a less-quantized dataset inherently contains more information than a more-quantized dataset [9] and thus is more suitable for training, we decided to use it as the training data of

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matrix factorization and use the more-quantized dataset for propensity scoring and deriving the inverse-probability-scoring (IPS) estimator [8] [3], a causal inference approach applicable to matrix completion-based recommender algorithms. In this way, our cross-dataset learning framework empowers existing recommender algorithms to make use of the more quantized, less biased data. We carried out experiment and found our method outperforming baselines by a significant margin.

2 Related Work

Prior works on overcoming selection bias-induced distribution shift via a propensity-based approach begins with the seminal paper [6], which introduces the IPS method into recommender systems. Follow-up works aim at providing a learning-based or behavioral model of user feedbacks for propensity estimation [4] [10], which remains the central concern of this approach. In this work we add to previous attempts the idea of using a more quantized, implicit dataset for more accurate propensity estimation.

The IPS method in our context is, essentially, a method of weighting training examples to correct the bias in the training data. Equivalent approaches such as importance weighting are widely used for domain adaptation in fields other than recommender systems [7] [11]. Discussions on the IPS-based domain adaptation for countering selection bias, which is most relevant to recommender systems, remain limited.

3 Susceptibility to Selection Bias

3.1 Simulated Environment for Controlling Bias

3.2 Results

4 Cross-Dataset Propensity Estimation

$$\arg\min_{V,W,A} \frac{1}{N} \left(\frac{(Y_{u,i} - (V_u^T W_i + A))^2}{P_{u,i}} \right) + c\|A\|^2$$

where $A = \{b_u, b_i, \mu\}$ represents the standard bias parameters (offset), $\hat{Y} = V_u^T W_i + A$ is the predicted rating, and $c\|A\|^2$ is the regularizer.

Stochastic gradient descent (SGD) step for one sample rating (i, j):

$$b_u \leftarrow b_u - \alpha(b_u - \frac{1}{P_{i,j}}(r_{i,j} - \hat{r}_{i,j}))$$

$$b_i \leftarrow b_i - \alpha(b_i - \frac{1}{P_{i,j}}(r_{i,j} - \hat{r}_{i,j}))$$

$$V_i \leftarrow V_i - \alpha(V_i - \frac{1}{P_{i,j}}W_j(r_{i,j} - \hat{r}_{i,j}))$$

$$W_j \leftarrow W_j - \alpha(W_j - \frac{1}{P_{i,j}}V_i(r_{i,j} - \hat{r}_{i,j}))$$

where α is the learning rate, which can be tuned independently for each parameter. In our experiments, we fix α across parameters.

5 Experiment

We designed experiments under simulated environments that verify the results introduced above. We first verify that more quantized dataset is more susceptible to selection bias and MNAR. We then runs our learning framework and compares it with multiple baselines.

5.1 Dataset and Baselines

5.2 Results

6 Conclusion

Acknowledgements

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7 Draft Area

(Consider using 2-dimensional Gaussian?)
Assume the (flattened) ground truth ratings is a standard Gaussian with differential entropy

$$\begin{aligned}\mathbb{H}(R \sim N(0,1)) &= \frac{1}{2}\log 2\pi e &(1)\\ &= 2.05 &(2)\end{aligned}$$

We can show that quantization (discretization) loses information. Consider a simple binary quantization that splits the ratings around the mean. Denote the quantized r.v. as Q_1.

$$\mathbb{H}(Q_1) = -2 \cdot \frac{1}{2}\log\frac{1}{2} = 1$$

Consider another quantized r.v. Q_2 that divides the distribution four-fold based on the four quantiles.

$$\mathbb{H}(Q_2) = -4 \cdot \frac{1}{4} \log \frac{1}{4} = 2$$

We can see that different quantization schemes loses different amount of information.

$$\mathbb{H}(R) > \mathbb{H}(Q_2) > \mathbb{H}(Q_1)$$

Next, we can prove that selection bias causes information loss. Assuming the selection bias causes ratings to have unequal probability to be sampled, and higher ratings are more likely to be sampled. The distribution of the observed ratings would then be right-skewed. We prove that, in the binary case, this reduces the information loss. Let p be the probability that the sampled rating is positive.

$$\mathbb{H} = p \log p + (1-p)\log(1-p)$$
$$\frac{d\mathbb{H}}{dp} = 1 + \log p + \frac{1-p}{p-1} - \log(1-p) = 0$$

which is optimized when $p = 0.5$. This result extends to all n-quantizations (can be proved using Lagrange multipliers.) See `http://pillowlab.princeton.edu/teaching/statneuro2018/slides/notes08_infotheory.pdf`.