
Propensity Estimation Matrix Factorization Through Mixed-Quantized Dataset

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Abstract

1 The abstract paragraph should be indented $\frac{1}{2}$ inch (3 picas) on both the left- and
2 right-hand margins. Use 10 point type, with a vertical spacing (leading) of 11 points.
3 The word **Abstract** must be centered, bold, and in point size 12. Two line spaces
4 precede the abstract. The abstract must be limited to one paragraph.

5 1 Introduction

6 Selection bias is one of the most prevalent source of biases in a dataset for recommender systems.
7 Selection bias happens when there is a pattern in the items that a user rates, either implicitly or
8 explicitly. For example, in a recommender system for movies, users might only watch and rate
9 the movies that are attractive to them in the first place. Selection bias is particularly relevant to
10 recommender systems because when the system actively recommends items that the users like, it is
11 creating bias by preventing users from accessing uncovered items. Selection bias introduces a Missing
12 Not At Random (MNAR) condition to the observed dataset by conditioning it on the predictions of
13 the recommender system. Tackling the selection bias in a recommender dataset has been a constant
14 challenge in designing recommender algorithms

15 Quantization is a practical way to categorize an input from a continuous distribution to a discrete set
16 of bins. We assume the ground truth of a user's rating is a continuous distribution over items because
17 of the inherent impossibility of numerically expressing the feeling of enjoyment and excitement.
18 We treat a recommender dataset as a noised quantization of the ground truth. In other words, users
19 convert their feelings into one of the discrete choices when they rate an item. Recommender datasets
20 are quantized into different degrees. For example, a typical movie rating dataset uses a 5-quantization.
21 A tinder like/dislike dataset uses a 2-quantization.

22 We hypothesize that quantization and the effect of selection bias on the recommender system is
23 positively correlated: the more quantized the dataset is (the fewer bins there are), the more severe
24 the selection bias becomes in terms of the recommender system's performance. Therefore, a good-
25 performing recommender system should prioritize training data that is less quantized.

26 In reality, however, less quantized data might only represent a small subset of all the data one is
27 capable of collecting. This is because less quantized data is typically explicit while more quantized
28 data is typically implicit. That is to say, less quantized data would require a user explicitly rating an
29 item, while more quantized data would be more easily gathered by observing the users' behaviors.
30 For example, by observing the movie a user spontaneously chooses to see or if a user watches a
31 movie's trailer to the end, we can easily create a 1-quantized or 2-quantized dataset, correspondingly,
32 without the user paying any effort. In this paper, we propose a novel framework that utilizes these
33 data. Our framework specifically exploits the fact that more quantized data is more susceptible to
34 selection bias and treats it as an advantage that helps less quantized dataset better overcome the
35 damage caused by selection bias.

36 The main contribution of this work is two-fold:

- 37 1. We design experiments under a simulated environment and shows that a more quantized
38 dataset is more susceptible to selection bias (and thus the MNAR condition.)
- 39 2. We propose a cross-dataset learning framework that empowers existing recommender
40 algorithms to make use of the more quantized, implicit data. **EXPLAIN MORE HERE**

41 Our hypothesis and theoretical results are verified through a series of empirical evaluation in a
42 simulated environment where users' behaviors are carefully modeled. We show that our learning
43 framework is significantly better than baseline recommender systems that neglects selection bias. We
44 also show that our methods are substantially better than its single-dataset counterpart. **EXPLAIN**
45 **MORE HERE**

46 2 Related Work

47 2.1 Recommender Systems Against Selection Bias

48 2.2 Quantization

49 3 Cross-Dataset Learning Framework

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

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

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

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

53

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

54

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

55

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

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

58 4 Experiment

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

62 4.1 Experiment Setup

63 4.2 Controlling Bias

64 4.3 Results

65 5 Conclusion

66 6 Draft Area

67 (Consider using 2-dimensional Gaussian?)

68 Assume the (flattened) ground truth ratings is a standard Gaussian with differential entropy

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

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

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

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

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

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

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

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

$$\mathbb{H} = p \log p + (1 - p) \log(1 - p)$$

77

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

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