Unbiased Recommender Learning from Missing-Not-At-Random Implicit Feedback

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Overview

- To obtain well-performing recommender using implicit feedback, **positive-unlabeled and missing-not-at-random problems** have to be addressed.
- We first define the ideal loss function that should be optimized and show **the previous solutions are biased toward the ideal loss function**.
- We developed **the first unbiased estimator for the ideal pointwise loss function** that can be estimated from only observable implicit feedback.

Problem Setting

$Y_{u,i}$ is implicit feedback (e.g., click or view). We assume the following feedback generation model:

$$Y_{u,i} = \underbrace{O_{u,i}}_{\text{exposure variable}} \cdot \underbrace{R_{u,i}}_{\text{relevance variable}}$$

$$P(Y_{u,i}=1) = \underbrace{P\left(O_{u,i}=1\right)}_{\theta_{u,i}} \cdot \underbrace{P\left(R_{u,i}=1\right)}_{\gamma_{u,i}}$$

Then, **the ideal pointwise loss function** is defined below.

Definition 1. *The ideal* ***pointwise*** *loss function is defined as*

$$\mathcal{L}_{ideal}^{point}\left(\widehat{\boldsymbol{R}}\right) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \gamma_{u,i} \log(\hat{R}_{u,i}) + (1-\gamma_{u,i}) \log(1-\hat{R}_{u,i})$$

This loss function is defined using the ground truth relevance information and is desirable. However, it cannot be calculated from implicit feedback. Thus, **estimating the ideal loss function from implicit feedback is critical to constructing a well-performing recommender offline**.

To achieve the goal, we have to address the following two difficulties.

- **Positive-Unlabeled Problem**: In the implicit feedback setting, one can only observe $Y_{u,i}$ and both $O_{u,i}$ and $R_{u,i}$ are unobserved. Thus, negative feedback is always unobserved because $Y_{u,i}=0 \Rightarrow O_{u,i}=0$ or $R_{u,i}=0$.
- **Missing-Not-At-Random Problem**: Exposure parameter $\theta_{u,i}$ is not uniform among instances. This introduces troublesome biases such as the item popularity bias.

Related Work

Weighted Matrix Factorization (WMF)

WMF relies on the following loss function.

$$\widehat{\mathcal{L}}_{WMF}\left(\widehat{\boldsymbol{R}}\right) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} cY_{u,i} \log(\hat{R}_{u,i}) + (1-Y_{u,i}) \log(1-\hat{R}_{u,i})$$

where $c \geq 1$ is a hyperparameter determining the weight of interacted data relative to non-interacted ones. This estimator is **biased** toward the ideal pointwise loss.

Exposure Matrix Factorization (ExpoMF)

ExpoMF addresses the positive-unlabeled problem of implicit feedback.

$$\widehat{\mathcal{L}}_{ExpoMF}\left(\widehat{\boldsymbol{R}}\right) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \theta'_{u,i} \left(Y_{u,i} \log(\hat{R}_{u,i}) + (1-Y_{u,i}) \log(1-\hat{R}_{u,i})\right)$$

where $\theta'_{u,i} = \mathbb{E}\left[O_{u,i} \,|\, Y_{u,i}\right]$ is the posterior probability represents the **confidence of how much relevance information an interaction indicator $Y_{u,i}$ includes**. This estimator is also **biased** toward the ideal pointwise loss.

Proposed Method

To alleviate the bias of implicit feedback, we propose **the first unbiased loss function** in the implicit feedback literature as follows.

$$\widehat{\mathcal{L}}_{Rel-MF}\left(\widehat{\boldsymbol{R}}\right) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \frac{Y_{u,i}}{\theta_{u,i}} \log(\hat{R}_{u,i}) + \left(1 - \frac{Y_{u,i}}{\theta_{u,i}}\right) \log(1-\hat{R}_{u,i}) \quad (1)$$

This estimator is **unbiased** toward the ideal pointwise loss.

Proposition 1. *The unbiased estimator is truly unbiased against the ideal loss function.*

$$\mathbb{E}\left[\widehat{\mathcal{L}}_{unbiased}\left(\widehat{\boldsymbol{R}}\right)\right] = \mathcal{L}_{ideal}\left(\widehat{\boldsymbol{R}}\right)$$

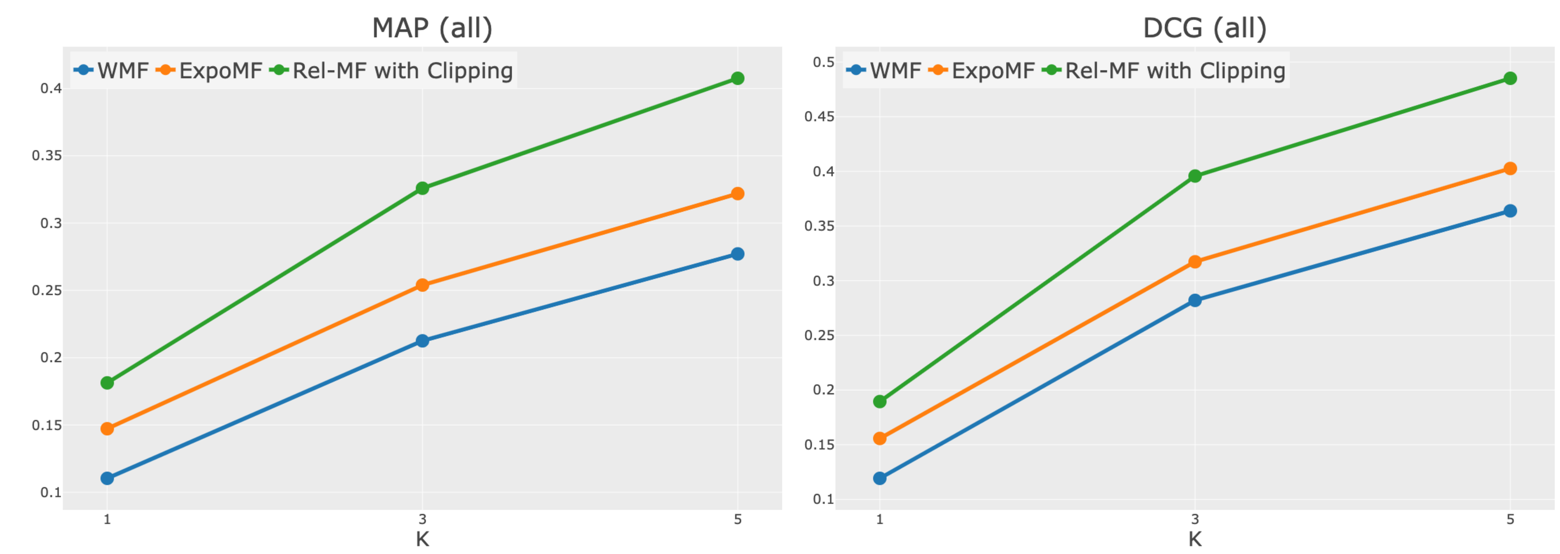
We also call the matrix factorization model optimizing the unbiased loss function as ***Relevance Matrix Factorization (Rel-MF)***

Experimental Results

Dataset: We used the **Yahoo! R3 dataset**. This is **an explicit feedback dataset** collected from a song recommendation service. Besides, **it contains users' ratings towards randomly selected sets of music as a test set**. Therefore, **this dataset is suitable for simulating the biased implicit feedback setting**. In the experiment, we treated items rated greater than or equal to 4 as relevant, and the other observed feedback was considered irrelevant.

Baselines: We compared **WMF, ExpoMF, and Rel-MF**. Hyperparameters were tuned using *Optuna* software for all methods.

Results: The following figures report MAP@K and DCG@K on the test set with $K \in \{1,3,5\}$. The result suggest that the proposed unbiased recommender learning framework performed the best in recommending relevant items in the randomly collected test set.



Conclusions

- It is critical to addressing the **positive-unlabeled & missing-not-at-random** nature of implicit feedback to obtain well-performing recommendation model
- Previous loss functions are **biased** toward the ideal loss function
- We proposed the **first unbiased loss function** & the corresponding matrix factorization model (**Rel-MF**).

Future Work

- Propensity score (exposure parameter) estimation
- Unbiased estimator for the pairwise method (e.g., unbiased version of Bayesian personalized ranking)
- Possible connection with other types of feedback