Title: Bilateral Self-unbiased Learning from Biased Implicit Feedback

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Venue: SIGIR

Main Problem:

Recommender systems utilize implicit and explicit feedback to determine the true relevance. Since observed feedback represents users' activity (being click logs), there will be a semantic gap between true relevance and observed feedback. Observed feedback usually suffers from popularity bias. Hence, the recommender system will overestimate the actual relevance of popular items. So, designing an unbiased recommender system that tackle the mentioned issues is going to be the main goal of this research.

Although explicit feedbacks contain richer information about the preferences, obtaining implicit feedbacks is less difficult. Implicit feedbacks are collected using users' behavior.

Using implicit feedbacks can be challenging. First, interaction with an item does not necessarily mean the user is interested in that. Second, user feedback is observed at uniformly not random.

Related Work:

There are studies that have proposed unbiased learning methods for recommender systems using implicit feedbacks with MNAR (missing not at random) assumption. They formulated a new loss function to address the bias issue of items using IPW (inverse propensity weighting). Also, there are some research that utilize causal graph that represents a cause effect relationship for recommendations and removes the effect of popularity.

Proposed Method:

If we denote *U* as a set of m users and *I* as a set of n items. We are given a user-item click matrix $Y \in \{0,1\}^{m\times n}$.

$$y_{ui} = \begin{cases} 1 & \text{if user } u \text{ interacted with item } i; \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

y_{ui} is modeled as a Bernoulli random variable, indicating the interaction of a user u on an item i.

To address the gap between relevance and exposure, they came up with the following equation:

o_{ui} is an element of the observation matrix $O \in \{0, 1\}^{m\times n}$ that represents whether the user u has observed the item i (oui = 1) or not (oui = 0), and rui is an element of the relevance matrix $R \in \{0, 1\}^{m\times n}$, representing true relevance regardless of observance.

$$P(y_{ui} = 1) = P(o_{ui} = 1) \cdot P(r_{ui} = 1) = \omega_{ui} \cdot \rho_{ui}, \quad (2)$$

The interaction matrix Y with biased user behavior is decomposed into element-wise multiplication of the observation and relevance components.

They use the point-wise loss function in this paper. Given a set of user-item pairs $D = U \times I$, the loss function for biased interaction data is:

$$\mathcal{L}_{\text{biased}}(\hat{\mathbf{R}}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \left(y_{ui}\delta^{+}_{ui} + (1 - y_{ui})\,\delta^{-}_{ui} \right), \tag{3}$$

where R^ is the prediction matrix for R, and δ_{ui+} and δ_{ui-} are the loss of user u on item i for positive and negative preference, respectively. So, the ideal loss function that relies purely on relevance is formulated as follows:

$$\mathcal{L}_{\text{ideal}}(\hat{\mathbf{R}}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \left(\rho_{ui}\delta^{+}_{ui} + (1 - \rho_{ui})\,\delta^{-}_{ui} \right), \tag{4}$$

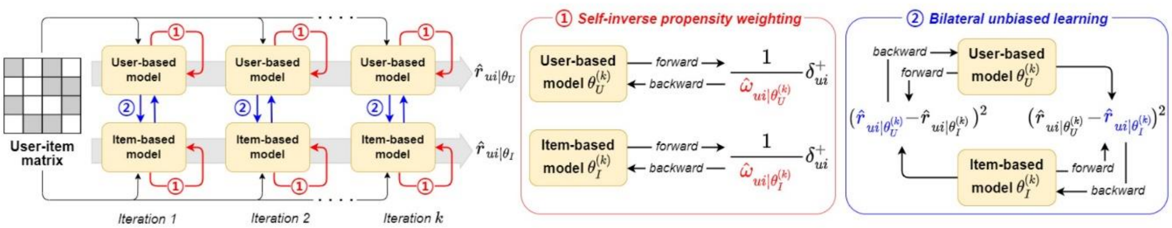
Now, a loss function using inverse propensity weighting (IPW):

$$\mathcal{L}_{\text{unbiased}}(\hat{\mathbf{R}}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \left(\frac{y_{ui}}{\omega_{ui}}\delta^{+}_{ui} + \left(1 - \frac{y_{ui}}{\omega_{ui}}\right)\delta^{-}_{ui} \right), \tag{5}$$

ω_{ui} is the inverse propensity score that indicates the probability of observing the item i by the user u. It is proved in [1] that expectation of the unbiased loss function in Eq. (5) is equivalent to the ideal loss function in Eq. (4):

$$\begin{aligned}\mathbb{E}\left[\mathcal{L}_{\text{unbiased}}(\hat{\mathbf{R}})\right] &= \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \left(\frac{\mathbb{E}\left[y_{ui}\right]}{\omega_{ui}}\delta^{+}_{ui} + \left(1 - \frac{\mathbb{E}\left[y_{ui}\right]}{\omega_{ui}}\right)\delta^{-}_{ui} \right) \\ &= \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \left(\rho_{ui}\delta^{+}_{ui} + (1 - \rho_{ui})\,\delta^{-}_{ui} \right).\end{aligned} \tag{6}$$

The model that is presented in this paper is called BISER (Bilateral Self-unbiased Recommender). It has two parts: self-inverse propensity weighting (SIPW) and bilateral unbiased learning (BU).



They adopt two recommender models with complementary characteristics, user- and item-based autoencoders that capture heterogeneous semantics and relational information from the users' and items' perspectives, respectively. This bypass the estimation overlap issue that occurs when the outputs of multiple models with the same structure and trained on the same training sets, converge similarly.

Input and Output:

The best summary for the stages that their method do is the pseudo code that was provided:

Algorithm 1: Bilateral self-unbiased recommender (BISER)

Input: Dataset $\mathcal{D} = \{\tilde{\mathcal{D}}, \mathcal{D} \backslash \tilde{\mathcal{D}}\}$, hyper-parameters λ_U, λ_I, the number of iterations K

Output: Predicted matrix $\hat{\mathbf{R}}$

1 Initialize $\theta_U^{(0)}$ and $\theta_I^{(0)}$ for user- and item-based AE.

2 **for** $k = 1$ *to* K **do**

3   Update $\theta_U^{(k)}$ for the user-based AE using Eq. (14).

4   Update $\theta_I^{(k)}$ for the item-based AE using Eq. (15).

5 **end**

6 Compute $\hat{\mathbf{R}}$ for user- and item-based AE using Eq. (16).

7 **return** $\hat{R}$

In the learning process, it first initializes the parameters θ_U and θ_I of both AE (line 1). Subsequently, θ_U and θ_I are updated using Eqs. (14) and (15) with the model predictions from the previous iteration, respectively (lines 2-5). At each iteration, it calculates the predictions of both models for all the clicked user-item pairs. After the two-model training is terminated, we obtain the predicted matrix R^ using the two model predictions (lines 6 and 7).

Eq 14: $\mathcal{L}_{UAE}(\hat{\mathbf{R}}; \theta_U^{(k)}) = \mathcal{L}_{SIPW}(\hat{\mathbf{R}}; \theta_U^{(k)}) + \lambda_U \mathcal{L}_{BU}(\hat{\mathbf{R}}; \theta_U^{(k)}, \theta_I^{(k)}),$

Eq 15: $\mathcal{L}_{IAE}(\hat{\mathbf{R}}; \theta_I^{(k)}) = \mathcal{L}_{SIPW}(\hat{\mathbf{R}}; \theta_I^{(k)}) + \lambda_I \mathcal{L}_{BU}(\hat{\mathbf{R}}; \theta_I^{(k)}, \theta_U^{(k)}),$

λ_U and λ_I are the hyperparameters to control the importance of L_{BU}

Pros:

- A novel approach that addresses exposure bias
- Not too much computational overhead
- Their approach is model-agnostic; two or more models may be used as long as they convey heterogeneous signals from the user-item interaction data.
- They outperform all of state-of-the art methods mentioned in the paper on benchmark datasets.

Cons:

Datasets:

1. Coat
2. Yahoo! R3
3. CiteULike
4. Movie Lense-100k
5. Movie Lense-10M
6. Movie Lense-1M

Code base:

https://github.com/Jaewoong-Lee/sigir_2022_BISER

References:

[1] Yuta Saito, Suguru Yaginuma, Yuta Nishino, Hayato Sakata, and Kazuhide Nakata. 2020. Unbiased Recommender Learning from Missing-Not-At-Random Implicit Feedback. In WSDM. 501–509