Unbiased Pairwise Learning From Implicit Feedback (at NeurIPS'19 CausalML Workshop)

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What is Implicit Feedback?

Implicit Feedback

- a **prevalent** type of feedback and **widely used** in real-world recommender systems.
- **natural user behaviours** such as clicks or views.

There are two difficulties concerning Implicit Feedback

- only positive-side feedback is observable and negative feedback is unobserved (positive-unlabeled problem).
- the probability of observing positive labels are not uniform among user–item pairs (missing-not-at-random problem).

Addressing both positive-unlabeled and missing-not-at-random problems is critical.

Overview of Related Work

The previous approaches to the challenges are

	Biased or Unbiased?	approach	technique
WMF [1]	Biased	Pointwise	Naive
ExpoMF [2]	Biased	Pointwise	EM Algorithm
Rel-MF [4]	Unbiased	Pointwise	Propensity Weighting
BPR [3]	Biased	Pairwise	Naive

The limitations of existing researches are

- the bias for the ideal loss functions
- depend on a simple pointwise approach
  (, which is not appropriate for the ranking task)

There is no Unbiased Pairwise Approach

Overview of the Proposed Method

I proposed the first unbiased pairwise learning algorithm called *Unbiased Bayesian Personalized Ranking (UBPR)*.

	Biased or Unbiased?	approach	technique
WMF [1]	Biased	Pointwise	Naive
ExpoMF [2]	Biased	Pointwise	EM Algorithm
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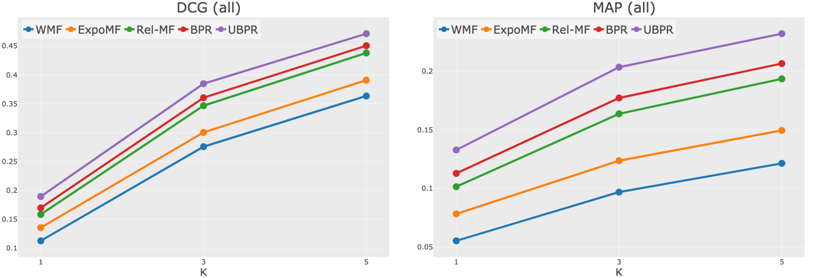
BPR [3]	Biased	Pairwise	Naive
UBPR (ours)	Unbiased	Pairwise	Propensity Weighting

The proposed method is **the first pairwise method to solve the positive-unlabeled and missing-not-at-random problems simultaneously**.

Experimental Results

Experimental Results with the Yahoo! R3 data demonstrates **the practical strength of our proposed method over the previous naive pairwise estimator and the pointwise approach**.



Thank You For Listening!

Please come to the poster for the detail.

(e.g., formulation, related work, proposed estimator, theory)

References

[1] Yifan Hu, Yehuda Koren, and Chris Volinsky. Collaborative filtering for implicit feedback datasets. In *2008 Eighth IEEE International Conference on Data Mining*, pages 263–272. Ieee, 2008.

[2] Dawen Liang, Laurent Charlin, James McInerney, and David M Blei. Modeling user exposure in recommendation. In *Proceedings of the 25th International Conference on World Wide Web*, pages 951–961. International World Wide Web Conferences Steering Committee, 2016.

[3] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. Bpr: Bayesian personalized ranking from implicit feedback. In *Proceedings of the twenty-fifth conference on uncertainty in artificial intelligence*, pages 452–461. AUAI Press, 2009.

[4] Yuta Saito, Suguru Yaginuma, Yuta Nishino, Hayato Sakata, and Kazuhide Nakata. Unbiased recommender learning from missing-not-at-random implicit feedback. In *Proceedings of the Thirteenth ACM International Conference on Web Search and Data Mining*. ACM, 2020.