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

Yuta Saito, Suguru Yaginuma, Yuta Nishino,

Hayato Sakata, and Kazuhide Nakata

Web Search and Data Mining (WSDM20)

February 4th, 2020 (Tue)

Tokyo Tech

SMN

Introduction & Problem Setting

Objective of Recommendation

Recommend **Relevant (R) Items** to Each User!!!

example) Top-3 Recommendation

Ranking	Recommender A	Recommender B
1	R=1	R=0
2	R=1	R=1
3	R=1	R=0
———	———	———
9	R=0	R=1
10	R=0	R=1

Recommender A
is better than
Recommender B

simply because

Recommender A
recommends
more relevant items

Ideal Loss function of Interest (Pointwise)

To optimize the relevance, the following loss function should be optimized ***(ideal)***.

Definition) Ideal Pointwise Loss Function

$$\mathcal{L}_{ideal}^{point}(\widehat{R}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \left[R_{u,i}\delta^{(1)}\left(\widehat{R}_{u,i}\right) + (1 - R_{u,i})\,\delta^{(0)}\left(\widehat{R}_{u,i}\right) \right]$$

Binary Relevance Indicator of u and i

Ideal Loss function of Interest (Pointwise)

To maximize relevance, the following loss ***should be*** optimized

Definition) Ideal Pointwise Loss Function

$$\mathcal{L}_{ideal}^{point}(\widehat{R}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \left[R_{u,i}\delta^{(1)}\left(\underline{\widehat{R}_{u,i}}\right) + (1 - R_{u,i})\,\delta^{(0)}\left(\underline{\widehat{R}_{u,i}}\right) \right]$$

Prediction for relevance level of u and i

Ideal Loss function of Interest (Pointwise)

To maximize relevance, the following loss ***should be*** optimized

Definition) Ideal Pointwise Loss Function

$$\mathcal{L}_{ideal}^{point}(\widehat{R}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \left[R_{u,i} \underline{\delta^{(1)}} \left(\widehat{R}_{u,i}\right) + (1 - R_{u,i}) \underline{\delta^{(0)}} \left(\widehat{R}_{u,i}\right) \right]$$

Arbitrary loss function

(e.g., cross-entropy, squared loss)

Example) Cross-entropy loss

$$\delta^{(1)}(\hat{R}_{u,i}) = -\log(\hat{R}_{u,i}), \delta^{(0)}(\hat{R}_{u,i}) = -\log(1 - \hat{R}_{u,i})$$

Challenge: Relevance Label is hard to collect

It is ***desirable to optimize ideal loss function***

for our objective of relevance maximization

Challenge: Relevance Label is hard to collect

It is **desirable to optimize ideal loss function** for our objective of relevance maximization

However, it is often ***Expensive*** or ***Time Consuming*** to use relevance information as the label

- **Explicit Rating Feedback** (Time Consuming)
- **Expert Annotation** (Expensive, Time Consuming)
- **Crowdsourcing** (Time Consuming, Noisy)

Alternative Solution: Implicit Feedback

Implicit Feedback is ***Cheap*** and ***Easy to collect***
and used as an alternative for the Relevance Label

Implicit Feedback

$$Y_{u,i}$$

- **Natural user behaviour (clicks, views, log-in)**
- **Easily collected in real-world recommender systems**
- **Used by many Tech companies**

Why not use Implicit Feedback as Relevance Label ???

One possible way to use implicit feedback is ***direct imputation***

ideal loss

$$\frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}}\left[\underline{R_{u,i}}\,\delta^{(1)}_{u,i} + \left(1-\underline{R_{u,i}}\right)\delta^{(0)}_{u,i}\right]$$

imputed loss

$$\frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}}\left[\underline{Y_{u,i}}\,\delta^{(1)}_{u,i} + \left(1-\underline{Y_{u,i}}\right)\delta^{(0)}_{u,i}\right]$$

Neural Collaborative Filtering (He et al.) optimizes the imputed loss function by DNN

Why not use Implicit Feedback as Relevance Label ???

One possible way to use implicit feedback is ***direct imputation***

<u>***ideal loss***</u>

$$\frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}}\left[\underline{R_{u,i}}\,\delta^{(1)}_{u,i} + \left(1-\underline{R_{u,i}}\right)\delta^{(0)}_{u,i}\right]$$

<u>***imputed loss***</u>

$$\frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}}\left[\underline{Y_{u,i}}\,\delta^{(1)}_{u,i} + \left(1-\underline{Y_{u,i}}\right)\delta^{(0)}_{u,i}\right]$$

Question: Is this direct imputation valid?

Implicit Feedback ≠ Relevance

example) Top-2 recommendation by most-popular policy

Item Ranking	Recommended?	Relvance (R)	???	Click (Y)
1	Yes!	R=1		Y=1
2	Yes!	R=0		Y=0
———	———	———	———	———
99	No...	R=1		Y=0
100	No...	R=0		Y=0

It seemes **Implicit Feedback** is **not** equal to **Relevance Label**

Exposure Model *(Liang et al., WWW'16)*

Exposure model assumes the following connection between implicit feedback and relevance label

$$Y_{u,i} = O_{u,i} \cdot R_{u,i}$$

Implicit Feedback
(e.g., click)

Exposure Variable
(***unobserved***)

Relevance Variable
(***unobserved***)

Item is ***clicked*** = Item is ***exposed*** **&** Item is ***relevant***

Exposure Model *(Liang et al., WWW'16)*

Exposure model also assumes the following decomposition

$$\underbrace{P(Y_{u,i}=1)}_{\text{click prob}} = \underbrace{P(O_{u,i}=1)}_{\text{exposure prob}} \cdot \underbrace{P(R_{u,i}=1)}_{\text{relevance level}}$$

$$= \theta_{u,i} \cdot \gamma_{u,i}$$

This assumption is equivalent to the ***Unconfoundedness*** in causal inference

Implicit Feedback ≠ Relevance

example) Top-2 recommendation by most-popular policy

Item Ranking	Recommended?	Relvance (R)	Exposure (O)	Click (Y)
1	Yes!	R=1	O=1	Y=1
2	Yes!	R=0	O=1	Y=0
———	———	———	———	———
99	No...	R=1	O=0	Y=0
100	No...	R=0	O=0	Y=0

Exposure Model
can clearly explain
the situation

Implicit Feedback ≠ Relevance

example) Top-2 recommendation by most-popular policy

Item Ranking	Recommended?	Relvance (R)	Exposure (O)	Click (Y)
1	Yes!			Y=1
2	Yes!			Y=0
———	———			———
99	No...			Y=0
100	No...			Y=0

Unobserved

The problem is ***how to optimize R using only Y***

Exposure Model characterizes the difficulties

Challenge 1: Positive-Unlabeled (PU)

$$Y_{u,i} = O_{u,i} \cdot R_{u,i}$$

Only ***positive-side feedback is observed***,

and the ***negative feedback is always unobserved***

$$\underline{Y_{u,i} = 0} \quad \not\Rightarrow \quad \underline{R_{u,i} = 0}$$

The lack of implicit feedback | **doesn't imply** | **Irrelevance between u and i**

Challenge 2: Missing-Not-At-Random (MNAR)

The positive-labels of some items are much more frequently observed (*popularity bias*)

$$P\left(Y_{u,i}=1\right)=\underline{P\left(O_{u,i}=1\right)}\cdot P\left(R_{u,i}=1\right)$$

Exposure probability is ***not uniform among user-item pairs***

In summary,

- We want to maximize ***relevance*** in recsys
  using only available ***implicit feedback***

- How to define theoretically justified loss function
  with implicit feedback is the critical problem

- We aimed to ***statistically estimate*** the ideal loss func
  using only implicit feedback in our work

Solutions & Experiments

Our Approach: Relevance Matrix Factorization (Rel-MF)

We propose the ***first unbiased estimator*** combining the ***inverse propensity weighting*** & ***positive-unlabeled learning***

$$\widehat{\mathcal{L}}^{point}_{unbiased}(\widehat{R}) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \left[\underline{\frac{Y_{u,i}}{\theta_{u,i}}} \delta^{(1)}_{u,i} + \left(1 - \underline{\frac{Y_{u,i}}{\theta_{u,i}}}\right) \delta^{(0)}_{u,i} \right]$$

The basic idea is to weight each implicit feedback by ***the inverse of the exposure parameter (the propensity score)***

Our Approach: Relevance Matrix Factorization (Rel-MF)

This estimator is proved to be ***theoretically unbiased for the ideal loss function***

$$\underbrace{\mathbb{E}\left[\widehat{\mathcal{L}}^{point}_{unbiased}(\widehat{R})\right]}_{\text{The proposed loss function}} = \underbrace{\mathcal{L}^{point}_{ideal}(\widehat{R})}_{\text{The ideal loss function}}$$

Summary of Solutions to the Challenges

Our main contribution is to develop the first unbiased loss func for the ideal loss func using only implicit feedback

	Approach	**Unbiased?**
WMF (Hu et al., ICDM'08)	Positive sample weighting	**No...**
ExpoMF (Liang et al., WWW'16)	EM Algorithm	**No...**
Rel-MF (saito et al., WSDM'20)	Inverse Propensity Weighting	**Yes!**

Real-World Experiment (with Yahoo! R3 dataset)

We conduct performance comparisons using **Yahoo data**

Yahoo! R3 dataset

- contains ***ground-truth relevance label*** (5 star-rating)
- contains train-test data with ***different item distributions***

This dataset is convenient for the evaluation of
Implicit feedback recommenders with MNAR formulation

Real-World Experiment (with Yahoo! R3 dataset)

The unbiased Rel-MF generally outperforms the others

For all items

	DCG@5	Recall@5	MAP@5
WMF (Hu et al., ICDM'08)	0.363	0.502	0.277
ExpoMF (Liang et al., WWW'16)	0.402	0.530	0.321
Rel-MF (saito et al., WSDM'20)	**0.485**	**0.582**	**0.407**

Real-World Experiment (with Yahoo! R3 dataset)

Ours also outperforms for the rare items

For rare items

	DCG@5	Recall@5	MAP@5
WMF (Hu et al., ICDM'08)	0.329	0.526	0.242
ExpoMF (Liang et al., WWW'16)	0.382	0.557	0.307
Rel-MF (saito et al., WSDM'20)	**0.428**	**0.593**	**0.345**

Conclusions

- Implicit feedback is often used but is biased (***positive-unlabeled & missing-not-at-random***)
- Previous solutions are ***biased*** toward the ideal loss func
- We proposed ***the first unbiased loss function for unbiasedly learning recsys from biased implicit feedback***

Thank you for Listening & Please Come to the Poster !!!

Appendix

How to estimate the propensity score?

We used the simple relative item popularity as the propensity score

$$\widehat{\theta}_{*,i} = \left(\frac{\sum_{u \in \mathcal{U}} Y_{u,i}}{\max_{i \in T} \sum_{u \in \mathcal{U}} Y_{u,i}} \right)^{\eta}$$

A more sophisticated way of estimating propensities is a future work

Previous Solutions to the Challenges

Weighted Matrix Factorization (WMF) and ***Exposure Matrix Factorization (ExpoMF)*** are the most basic methods

	Approach	Unbiased?
WMF (Hu et al., ICDM’08)	Positive sample weighting	**No...**
ExpoMF (Liang et al., WWW’16)	EM Algorithm	**No...**

Previous Solutions are biased for the ideal loss func

In the paper, the loss function of the previous methods are proved to be ***biased***, i.e.,

$$\begin{aligned} &\mathbb{E}\left[\widehat{\mathcal{L}}_{WMF}(\widehat{R})\right] \\ &\mathbb{E}\left[\widehat{\mathcal{L}}_{ExpoMF}(\widehat{R})\right] \end{aligned} \neq \mathcal{L}_{ideal}^{point}(\widehat{R})$$

Future Work

- Propensity score estimation
- Unbiased estimator for the **pairwise** method

  (e.g., unbiased version of bayesian personalized ranking)
- Theoretical Analysis on the Learnability
- Possible connection with other types of feedback

References

(Liang et al., WWW'16): Dawen Liang, Laurent Charlin, James McInerney, and David M Blei. 2016. Modeling user exposure in recommendation. In Proceedings of the 25th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 951–961.

(Saito et al., WSDM'20): Yuta Saito, Suguru Yaginuma, Yuta Nishino, Hayato Sakata, and Kazuhide Nakata. 2020. Unbiased Recommender Learning from Missing-Not-At-Random Implicit Feedback. In The Thirteenth ACM International Conference on Web Search and Data Mining (WSDM'20), February 3–7, 2020, Houston, TX, USA. ACM, New York, NY, USA.

(Hu et al., ICDM'08): Yifan Hu, Yehuda Koren, and Chris Volinsky. 2008. Collaborative filtering for implicit feedback datasets. In 2008 Eighth IEEE International Conference on Data Mining. Ieee, 263–272.

(Schnabel et al., ICML'16) : Tobias Schnabel, Adith Swaminathan, Ashudeep Singh, Navin Chandak, and Thorsten Joachims. 2016. Recommendations as Treatments: Debiasing Learning and Evaluation. In International Conference on Machine Learning. 1670–1679

(Rendle et al., UAI'09) : Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2009. BPR: Bayesian personalized ranking from implicit feedback. In Proceedings of the twenty-fifth conference on uncertainty in artificial intelligence. AUAI Press, 452–461.

References

(Yang et al., RecSys'18): Longqi Yang, Yin Cui, Yuan Xuan, Chenyang Wang, Serge Belongie, and Deborah Estrin. 2018. Unbiased offline recommender evaluation for missing-not-atrandom implicit feedback. In Proceedings of RecSys '18. ACM, 279–287.

(Wang et al., WSDM'18): Xuanhui Wang, Nadav Golbandi, Michael Bendersky, Donald Metzler, and Marc Najork. 2018. Position Bias Estimation for Unbiased Learning to Rank in Personal Search. In Proc. of the 11th ACM International Conference on Web Search and Data Mining (WSDM). 610–618.

(Ai et al., SIGIR'18): Qingyao Ai, Keping Bi, Cheng Luo, Jiafeng Guo, and W Bruce Croft. 2018. Unbiased Learning to Rank with Unbiased Propensity Estimation. In Proc. of the 41st International ACM SIGIR Conference on Research & Development in Information Retrieval (SIGIR). 385–394.

(Marlin et al., RecSys'09): Benjamin M Marlin and Richard S Zemel. 2009. Collaborative prediction and ranking with non-random missing data.

(Wang et al., ICML'19): Xiaojie Wang, Rui Zhang, Yu Sun, and Jianzhong Qi. 2019. Doubly robust joint learning for recommendation on data missing not at random. In International Conference on Machine Learning, pages 6638–6647.

(Liang et al., UAI'16 Causal WS): Dawen Liang, Laurent Charlin, and David M Blei. 2016. In Causation: Foundation to Application, Workshop at UAI.