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

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<u>Web Search and Data Mining (WSDM20)</u>

February 4th, 2020 (Tue)





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

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

Binary Relevance Indicator of u and i

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Prediction for relevance level of u and i

Ideal Loss function of Interest (Pointwise)

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Arbitrary loss function

Example) Cross-entropy loss

(e.g., cross-entropy, squared 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

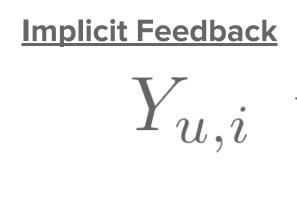
However, it is often *Expensive* or *Time Consuming* to use relevance information as the label

- <u>Explicit Rating Feedback</u> (Time Consuming)
- **Expert Annotation** (Expensive, Time Consuming)
- <u>Crowdsourcing</u> (Time Consuming, Noisy)

Alternative Solution: Implicit Feedback

Implicit Feedback is Cheap and Easy to collect

and used as an alternative for the Relevance Label



- 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

$$\begin{array}{ll} \textit{ideal loss} & \frac{1}{|\mathcal{D}|} \sum_{(u,i) \in \mathcal{D}} \left[\underline{R_{u,i}} \delta_{u,i}^{(1)} + (1 - \underline{R_{u,i}}) \, \delta_{u,i}^{(0)} \right] \\ & \downarrow \\ \textit{imputed loss} & \frac{1}{|\mathcal{D}|} \sum_{(u,i) \in \mathcal{D}} \left[\underline{Y_{u,i}} \delta_{u,i}^{(1)} + (1 - \underline{Y_{u,i}}) \, \delta_{u,i}^{(0)} \right] \\ \end{array}$$

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

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Question: Is this direct imputation valid?

Implicit Feedback ≠ Relevance

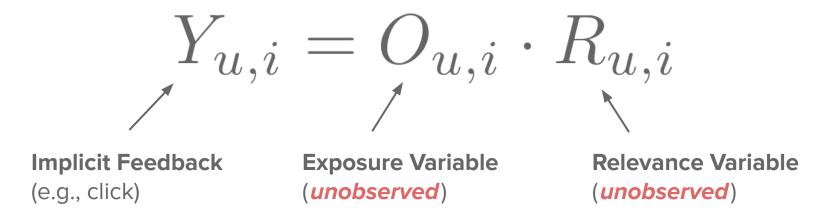
example) Top-2 recommendation by most-popular policy

Item Ranking	Recomme nded?	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 <u>not</u> equal to
Relevance Label

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

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



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

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

Exposure model also assumes the following decomposition

$$P(Y_{u,i} = 1) = P(O_{u,i} = 1) \cdot P(R_{u,i} = 1)$$
click prob
exposure prob
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	Recomme nded?	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

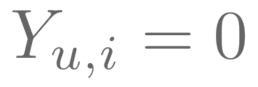
Item Ranking	Recomme nded?	Relvance (R)	Exposure (O)	Click (Y)
1	Yes!			Y=1
2	Yes!			Y=0
		Unobserved		
99	No	Ollobs	erveu -	Y=0
100	No			Y=0
	·			

The problem is how to optimize R using only Y

Exposure Model characterizes the difficulties

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

Only **positive-side feedback is observed**, and the **negative feedback is always unobserved**



*

 $R_{u,i} = 0$

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)

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

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 funcular 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*

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

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

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

The proposed loss function 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

	<u>Approach</u>	<u>Unbiased?</u>
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

	<u>Approach</u>	<u>Unbiased?</u>
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.,

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

$$\mathbb{E}\left[\widehat{\mathcal{L}}_{ExpoMF}(\widehat{R})\right]$$

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

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