Unbiased Implicit Recommendation and Propensity Estimation via Combinational Joint Learning

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Introduction

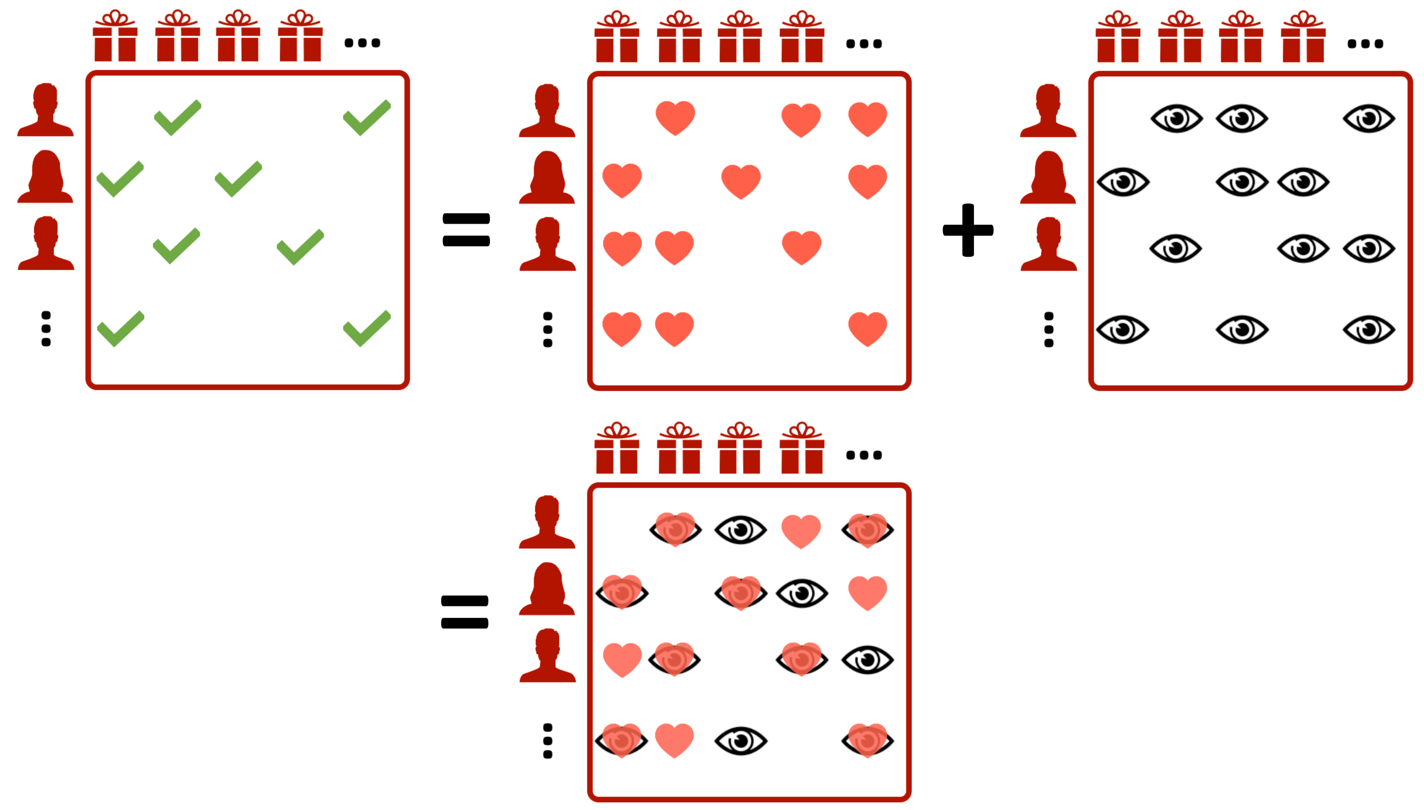
RecSys learned by biased implicit feedback (missing not at random) will provide biased recommendation results. Previous works address this issue by inverse propensity scoring, but rely on a heuristic propensity estimation, which leads to compromised performance.

Contributions:

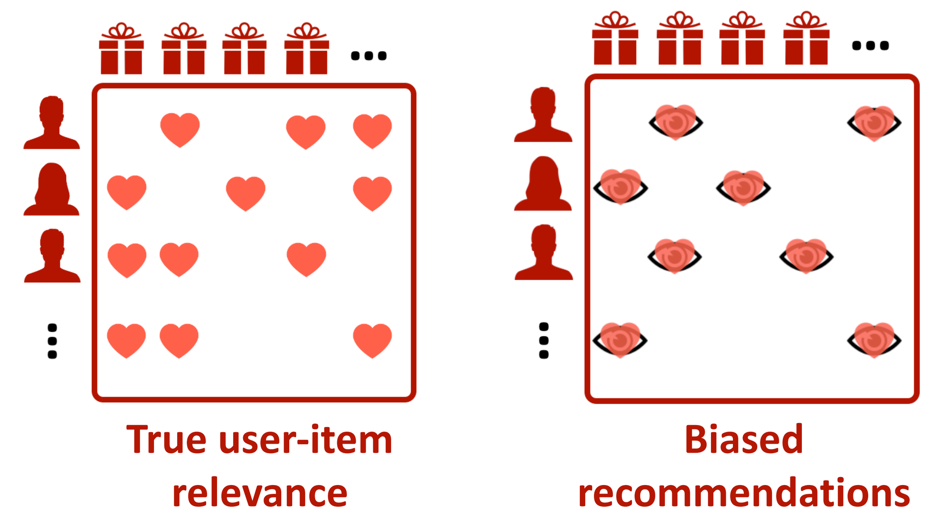
- Propose a new **combinational joint learning model** to learn **user-item relevance** and **propensity** simultaneously to provide unbiased recommendation results.
- Extensive experiments on two public datasets demonstrate the effectiveness of the proposed model in terms of estimation accuracy for both user-item relevance and propensity.

Biased Recommendation with Implicit Feedback

- Widespread **implicit feedback** (such as clicks, views, etc.) is determined by two sources of information: 1) **User-item relevance**; 2) **User-item exposure**.



- Hence, a RecSys model learned by this implicit feedback data cannot predict accurate user-item relevance. Instead, it predicts how likely an item is **both exposed and liked** by a user, which is a **biased recommendation result**.



Unbiased Loss via IPS (from Saito et al.)

- The ideal loss:

$$\mathcal{L}_{ideal} = \sum_{(u,i)\in\mathcal{D}} R_{u,i}(log(\widehat{R}_{u,i})) + (1-R_{u,i})(log(1-\widehat{R}_{u,i}))$$

where $R_{u,i}$ is a Bernoulli variable for user-item relevance, which is **unobservable** in practice. Conventionally, $R_{u,i}$ is replaced by $Y_{u,i}$, which is the Bernoulli variable for observed user-item feedback.

- The unbiased loss via **Inverse Propensity Scoring** (IPS):

$$\mathcal{L}_{IPS} = \sum_{(u,i)\in\mathcal{D}} \frac{Y_{u,i}}{\theta_{u,i}}(log(\widehat{R}_{u,i})) + (1-\frac{Y_{u,i}}{\theta_{u,i}})(log(1-\widehat{R}_{u,i}))$$

where $\theta_{u,i}$ is the probability of item *i* being exposed to user *u*, i.e., the propensity. Easy to prove:

$$\mathbb{E}[\mathcal{L}_{IPS}] = \mathbb{E}[\mathcal{L}_{ideal}]$$

Propensity Estimation

- **Power-law function** of item popularity in existing works:

$$\theta_{*,i} = (\sum_{u\in\mathcal{U}} Y_{u,i}/max_{i\in\mathcal{I}}(\sum_{u\in\mathcal{U}} Y_{u,i}))^{\eta}$$

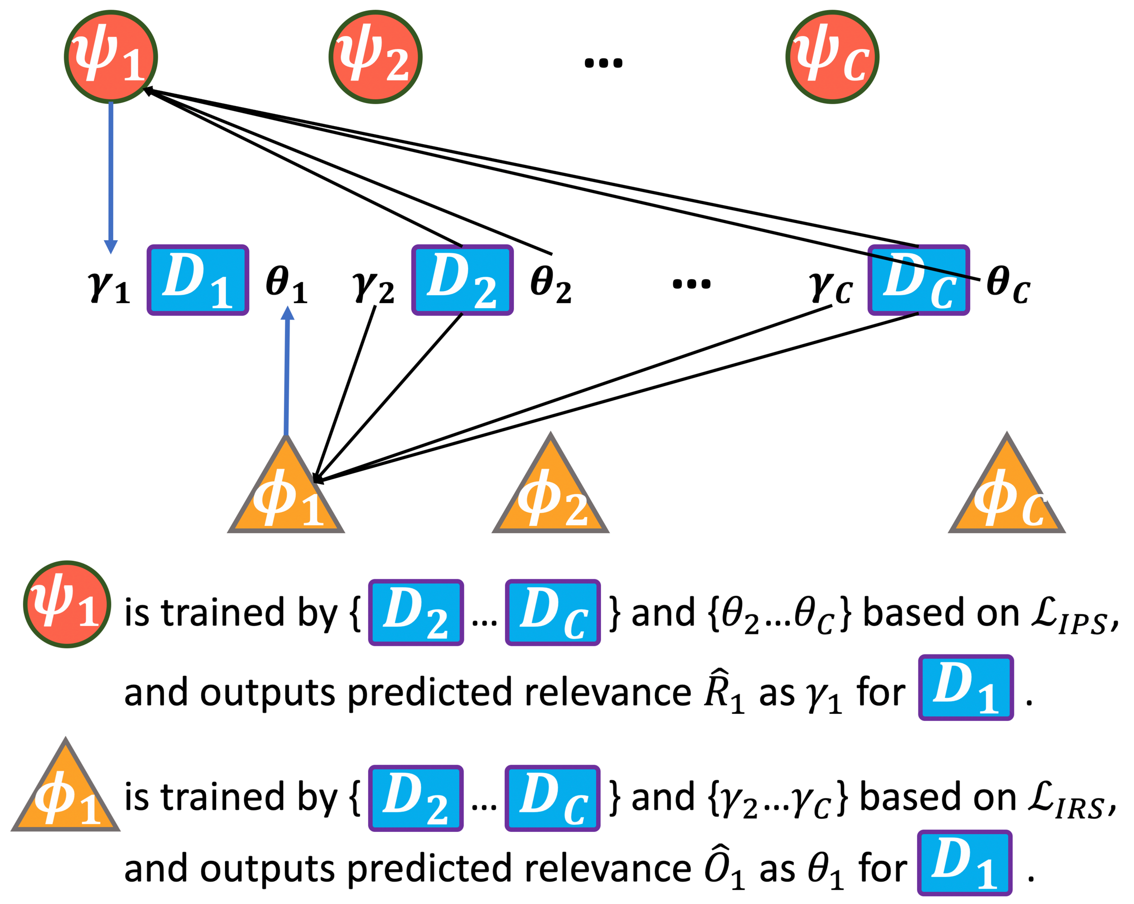
which is not an unbiased estimation of the exposure probability: item popularity only considers the observed positive user-item interactions, but item exposure is determined by both observed positive interactions and unobserved negative feedback.

- Unbiased propensity estimation by **Inverse Relevance Scoring**:

$$\mathcal{L}_{IRS} = \sum_{(u,i)\in\mathcal{D}} \frac{Y_{u,i}}{\gamma_{u,i}}(log(\widehat{O}_{u,i})) + (1-\frac{Y_{u,i}}{\gamma_{u,i}})(log(1-\widehat{O}_{u,i}))$$

where $\gamma_{u,i}$ is the probability of item *i* being relevant to user *u;* and $\widehat{O}_{u,i}$ is the predicted propensity, modeled as $\widehat{O}_{u,i} = (w\cdot a + (1-w)\cdot K_i)^e$, with $w = f_w(\mathrm{Q}_i)$, $a = f_a(\mathrm{Q}_i)$, $e = f_e(\mathrm{Q}_i)$, and $K_i = \sum_{u\in\mathcal{U}} Y_{u,i}/max_{i\in\mathcal{I}}(\sum_{u\in\mathcal{U}} Y_{u,i})$.

Combinational Joint Learning



- $\Psi_c = \{\mathbf{P_c}, \mathbf{Q_c}\}$ is the relevance sub-model, and $\Phi_c = \{f_w^c, f_a^c, f_e^c\}$ is the propensity sub-model for data chunk $\mathcal{D}_c$.
- $\overline{\Psi}_c = \{\overline{\mathbf{P}}_c, \overline{\mathbf{Q}}_c\}$ and $\overline{\Phi}_c = \{\overline{f_w^c}, \overline{f_a^c}, \overline{f_e^c}\}$ are the corresponding residual sub-models for $\mathcal{D}_c$.

Algorithm 1: Training algorithm.

```
repeat
    for D_c in {D_1, ..., D_C} do
        for (u, i) in D_c do
            Calculate γ_{u,i} and θ_{u,i} by Ψ_c and Φ_c;
            Update {Ψ_1, ..., Ψ_C} \ Ψ_c by L_IPS, and update {Φ_1, ..., Φ_C} \ Φ_c by L_IRS;
            with {Ψ_1, ..., Ψ_C} and {Φ_1, ..., Φ_C} fixed:
                Update {Ψ̄_1, ..., Ψ̄_C} by L_IPS with R̂_{u,i} calculated by {Ψ_1 + Ψ̄_1, ... Ψ_C + Ψ̄_C};
                Update {Φ̄_1, ..., Φ̄_C} by L_IRS with Ô_{u,i} calculated by {Φ_1 + Φ̄_1, ..., Φ_C + Φ̄_C};
until converge;
```

Compare Recommendation Performance

- The proposed method outperforms conventional biased methods and SOTA unbiased methods.

Table 1. Recommendation performance comparison, where best baselines are marked by underlines.

			Point-wise models							Pair-wise models			
			MF -RMSE	MF -CE	RelMF -RMSE	RelMF -CE	NJMF	CJMF	Δ	BPR	UBPR	CJBPR	Δ
Yahoo	DCG	@1	0.5314	0.5275	<u>0.5364</u>	0.5339	0.5403	**0.5610**	4.58%	0.5409	<u>0.5433</u>	**0.5648**	3.96%
		@2	0.7297	0.7385	0.7353	<u>0.7398</u>	0.7434	**0.7746**	4.71%	0.7451	<u>0.7493</u>	**0.7750**	3.42%
		@3	0.8520	0.8582	0.8595	<u>0.8616</u>	0.8678	**0.8960**	4.00%	0.8672	<u>0.8777</u>	**0.8972**	2.22%
	MAP	@1	0.5314	0.5275	<u>0.5364</u>	0.5339	0.5403	**0.5610**	4.58%	0.5419	<u>0.5433</u>	**0.5648**	3.96%
		@2	0.6189	0.6178	0.6203	<u>0.6220</u>	0.6256	**0.6475**	4.09%	0.6263	<u>0.6295</u>	**0.6496**	3.19%
		@3	0.6420	0.6419	0.6433	<u>0.6465</u>	0.6486	**0.6694**	3.54%	0.6491	<u>0.6532</u>	**0.6721**	2.88%
Coat	DCG	@1	0.5305	0.5485	0.5485	<u>0.5612</u>	0.5696	**0.5907**	5.26%	0.5316	<u>0.5738</u>	**0.5907**	2.94%
		@2	0.7608	0.7695	<u>0.7881</u>	0.7848	0.7949	**0.8223**	4.34%	0.7739	<u>0.7868</u>	**0.8223**	4.51%
		@3	0.9190	0.9298	0.9337	<u>0.9367</u>	0.9431	**0.9679**	3.33%	0.9300	<u>0.9387</u>	**0.9595**	2.21%
	MAP	@1	0.5305	0.5485	0.5485	<u>0.5612</u>	0.5696	**0.5907**	5.26%	0.5316	<u>0.5738</u>	**0.5907**	2.94%
		@2	0.6118	0.6203	0.6371	<u>0.6435</u>	0.6477	**0.6709**	4.26%	0.6181	<u>0.6392</u>	**0.6709**	4.95%
		@3	0.6255	0.6399	<u>0.6498</u>	0.6494	0.6572	**0.6741**	3.73%	0.6378	<u>0.6596</u>	**0.6818**	3.36%

Effectiveness of Estimated Propensity

- Baselines can perform better with the learned propensity from the proposed combinational joint learning method than with the power-law function propensity estimation.

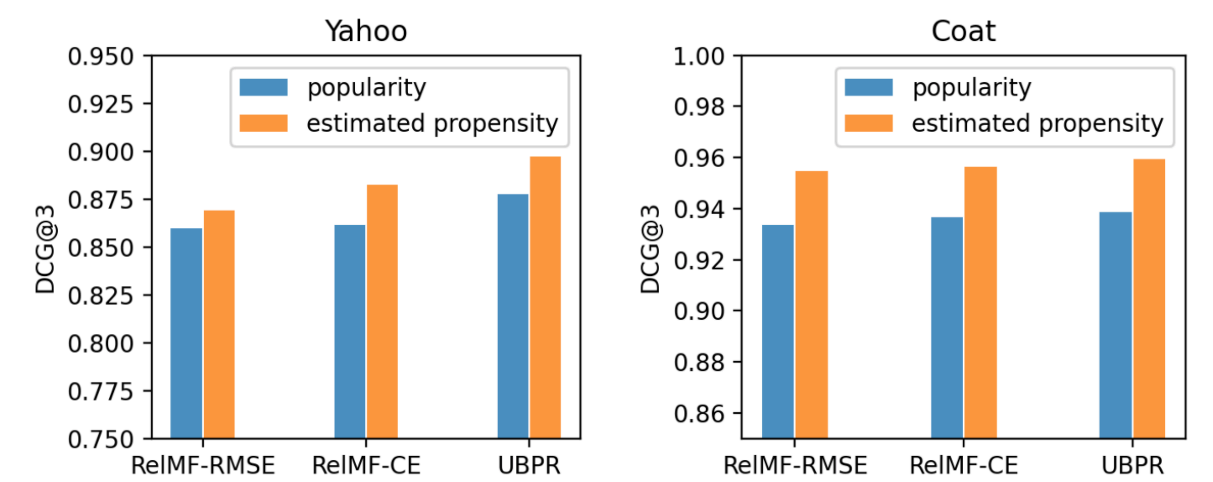


Fig. 1. Comparing unbiased models with item popularity as propensity and with estimated propensity from proposed models.

Effectiveness of Estimated Propensity

- Performance of CJMF improves rapidly then converges as C increases, reaching a peak level when $C \geq 5$
- Without the residual component, the proposed model is less effective than the complete version of the proposed model.

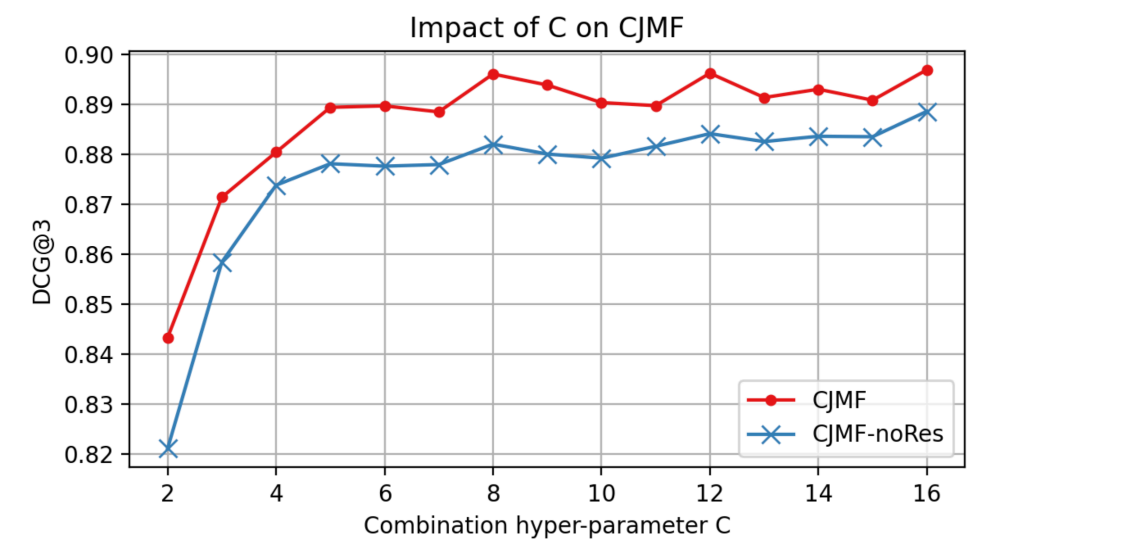


Fig. 2. *DCG@3* of CJMF and CJMF without residual components on the Yahoo dataset, with varying *C*.