Negative-Aware Collaborative Filtering

Sheng-Chieh Lin*,Yu-Neng Chuang†, Sheng-Fang Yang†, Ming-Feng Tsai†, Chuan-Ju Wang*
***Academia Sinica, †National Chengchi University**
{jacklin_64, cjwang}@citi.sinica.edu.tw, {107753011, 106753011, mftsai}@nccu.edu.tw

Motivation

With the rapid development of online services over the last decade, **collaborative filtering (CF)** is a common powerful approach that generates user recommendations. Existing traditional CF treating the majority of **unseen interactions as negative ones.** Yet this may introduce noise into the modeling process as unseen interactions are not necessarily to be negative instances.

Disadvantages of Traditional CF:

- ✘ Treating the majority of unseen interactions as negative ones.
- ✘ Introducing noise into the modeling process.
- ❓ If a user has not purchased a certain item, the user is not interested in it.

Approach:

- Quantifying the degree of uncertainty for unseen associations by leveraging user preference similarity.
- Modeling the likelihood of each unseen association being a potentially positive user preference.

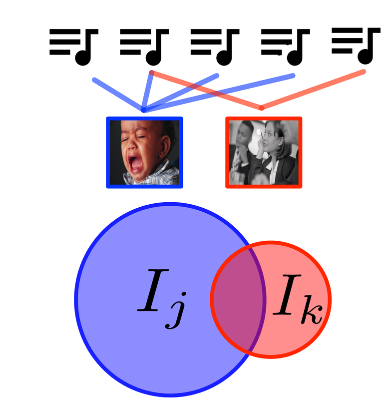
Methodology

Negative-aware matrix construction:

- **Negative-aware** Matrix:

$$④\quad n_{ui} = \begin{cases} 0 & \text{if } \sum_{k=1}^{|U|} \hat{s}_{uk} a_{ki} = 0, \\ \dfrac{\left(\sum_{k=1}^{|U|} \hat{s}_{uk} a_{ki}\right)}{\left(\sum_{k=1}^{|U|} 1_{\{\hat{s}_{uk}>0\}} a_{ki}\right)} & \text{otherwise.} \end{cases}$$

where $a_{ki} \in$ ② and $\hat{s_{uk}} \in$ ③ .



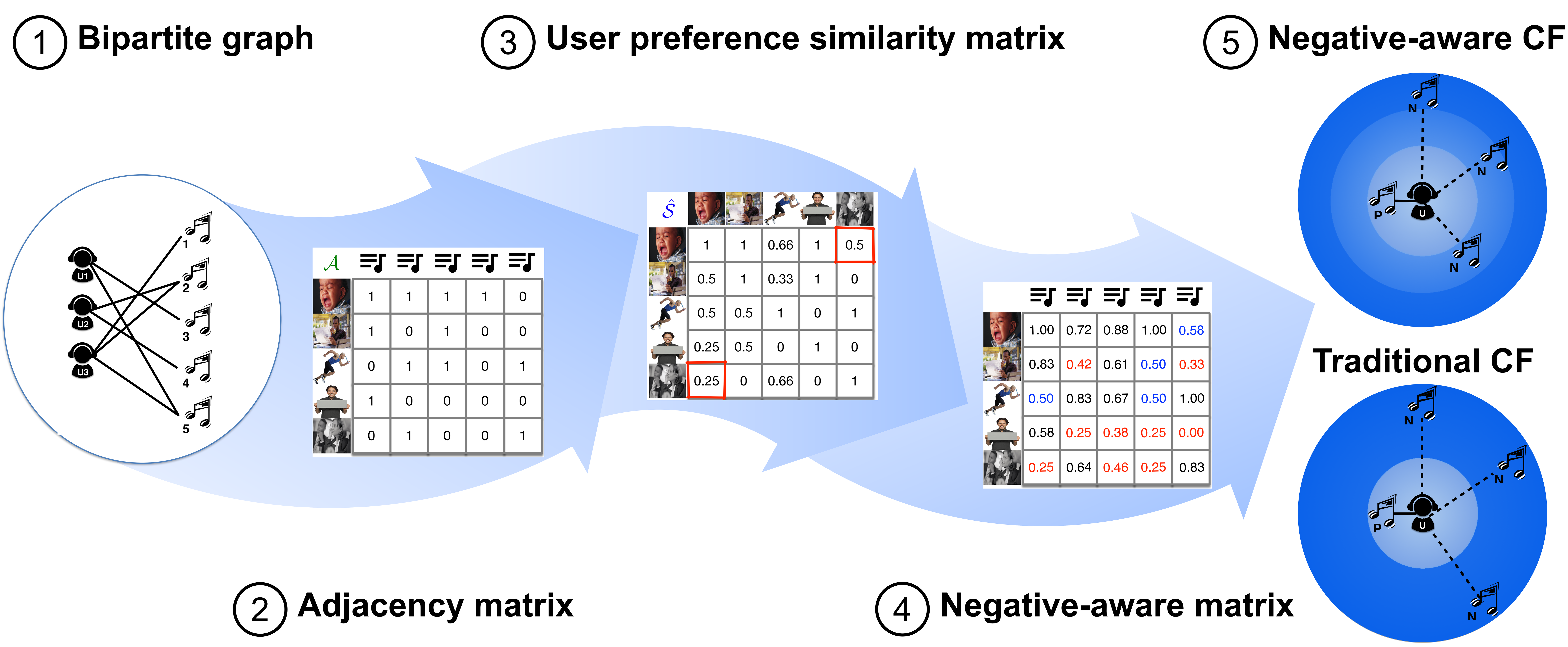
- **Asymmetric** user preference similarity matrix:

$$③\quad \hat{s}_{jk} = \frac{|I_j \cap I_k|}{|I_k|}$$

Negative-aware pointwise and pairwise approaches:

$$⑤\quad \mathcal{L}^N_{\mathrm{MF}} = \sum_{u,i} a_{ui}\,(1-\theta_u^\top\theta_i)^2 + (1-a_{ui})\,(n_{ui}-\theta_u^\top\theta_i)^2 + \lambda\,\|\Theta\|_2^2$$

$$⑤\quad \mathcal{L}^N_{\mathrm{BPR}} = -\sum_{u,(i,i')} \log\left(\frac{1}{n_{ui'}}\right) \log\sigma(\theta_u^\top\theta_i - \theta_u^\top\theta_{i'}) + \lambda\,\|\Theta\|_2^2$$



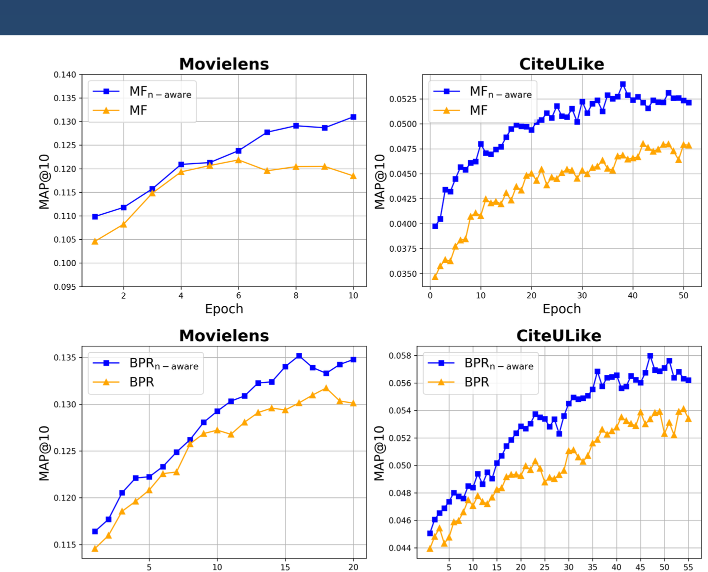
Experiments

Dataset:

- **MovieLens-100k:** Users to Movies Data
- **Citeulike:** Citation Data

Baseline of CF approach:

- **Pointwise:** Matrix Factorization (MF)
- **Pairwise:** Bayesian Personalized Ranking (BPR)



Top-N recommendation:

Dataset	Movielens				CiteULike			
	P@5	MAP@5	P@10	MAP@10	P@5	MAP@5	P@10	MAP@10
MF	0.237	0.169	0.199	0.123	0.060	0.058	0.045	0.048
MF$_{n\text{-aware}}$	*0.241	*0.173	*0.202	*0.125	0.062	*0.061	*0.048	*0.052
BPR	0.257	0.189	0.211	0.136	0.064	0.064	0.049	0.054
BPR$_{n\text{-aware}}$	*0.262	***0.195	**0.214	**0.140	*0.066	0.066	*0.050	0.055

- Observation 1: Negative-aware works in both two approaches.
- Observation 2: Negative-aware models are generally capable of maintaining better performance than the traditional models at each training epoch.

Conclusion

Remarks:

- Negative-aware collaborative filtering …
  - ✔ explicitly addresses the uncertainty of unseen user-item associations by leveraging asymmetric user preference.
  - ✔ can be seen as a **generic device** applicable to other recommendation algorithms with the use of negative sampling.
- Empirical results show that our approach improves the performance of both pointwise and pairwise recommendation models.

Takeaway:

- Negative-aware approach initiates a study of further tailoring negative sampling by quantifying the degree of uncertainty for unseen associations.

Paper link

The Thirteenth ACM Conference on Recommender Systems, Late-Breaking Result track (RecSys 2019 LBRS)   CFDA & CLIP Labs