



Semi-Discrete Social Recommendation (Student Abstract)

Fangyuan Luo¹, Jun Wu¹, HaishuaiWang²

¹Beijing Jiaotong University, Beijing ²Harvard University, Cambridge

Motivation

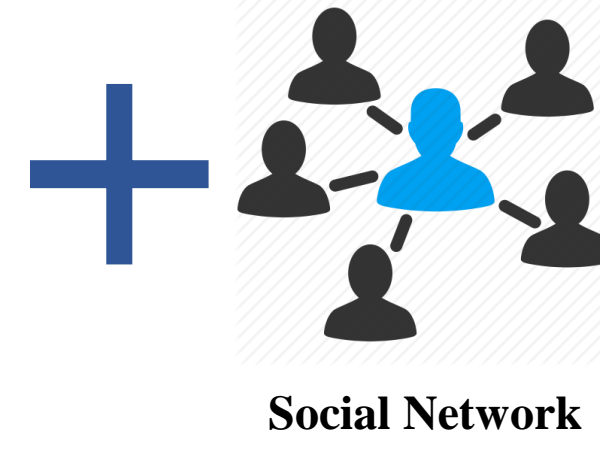
	Item1	Item2	Item3	...	Item n
User 1	5	?	4	...	?
User 2	?	1	?	...	3
User 3	?	?	4	...	5
...
User m	1	?	5	...	?

Highly sparsity
of U-I matrix

The explosive
growth of users
and items

Computation
and storage
cost?

	Item1	Item2	Item3	...	Item n
User 1	5	?	4	...	?
User 2	?	1	?	...	3
User 3	?	?	4	...	5
...
User m	1	?	5	...	?



Contributions

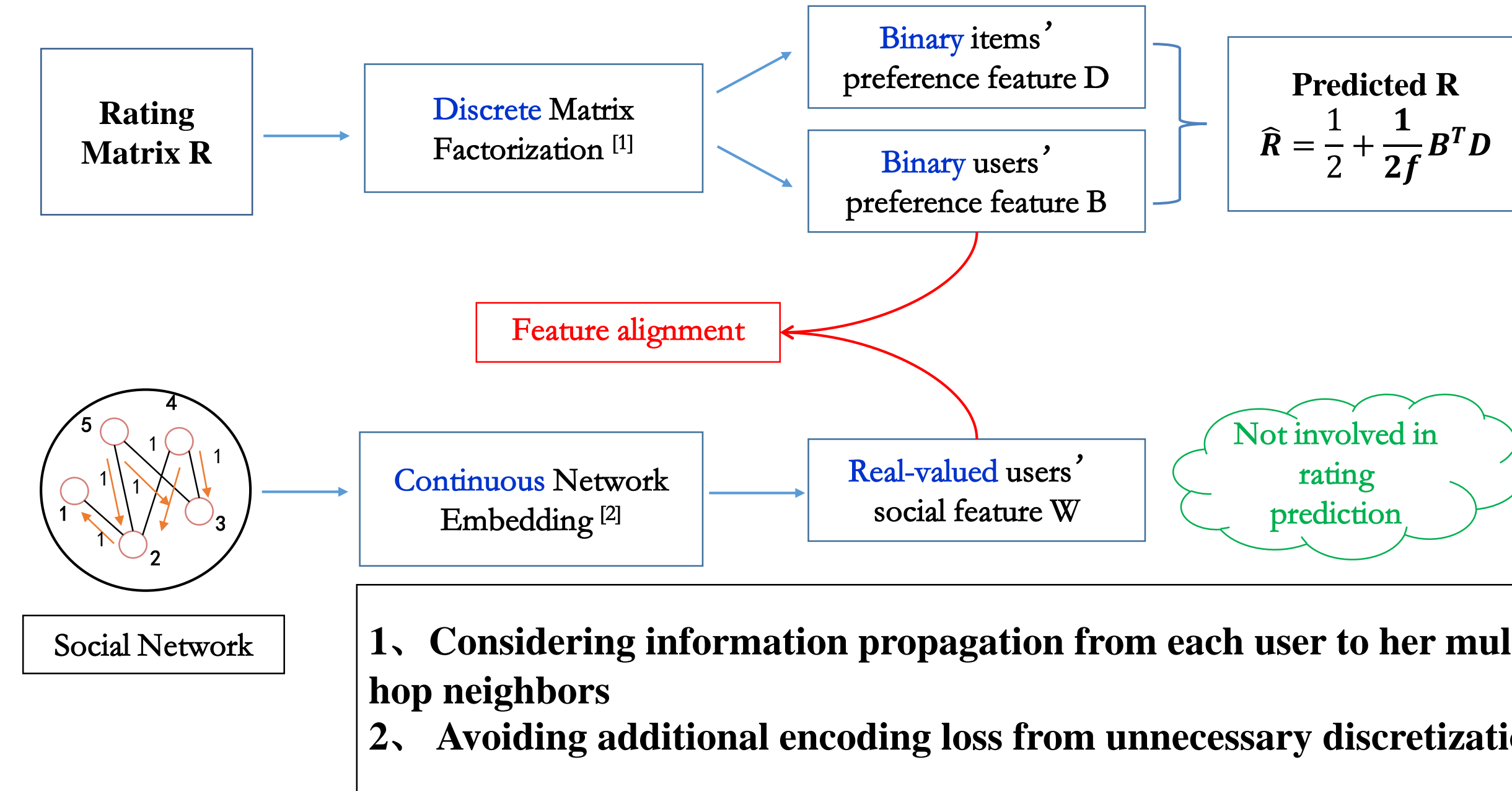
- 1、We combines MF model with NE model partially under the discrete constraints, which is essential in modeling the influence propagation process of users' interests over social network, as well as avoiding the extra encoding loss caused by the discretization on social embedding.
- 2、We develop an efficient alternating optimization algorithm to solve the proposed mixed-integer programming problem, which can yield informative and compact hash codes.

References

- [1] Zhang, H.; Shen, F.; Liu, W.; He, X.; Luan, H.; and Chua, T. S. 2016. Discrete Collaborative Filtering. In SIGIR, 325–334.
- [2] Perozzi, B.; Alrfou, R.; and Skiena, S. 2014. DeepWalk: online learning of social representations. In KDD, 701–710.
- [3] F. Shen, C. Shen, W. Liu, H. T. Shen, Supervised discrete hashing, in: CVPR, 2015, pp. 37-45.

Methods

Framework:



Formulation:

$$\arg \min_{\mathbf{B}, \mathbf{D}, \mathbf{W}, \mathbf{V}} \sum_{(u,i) \in \Omega} (r_{ui} - s_H(\mathbf{b}_u, \mathbf{d}_i))^2 + \alpha \sum_u \|\mathbf{b}_u - \mathbf{w}_u\|^2 - \beta \sum_u [\log \sigma(\mathbf{w}_u^T \mathbf{h}) + \log \sigma(-\mathbf{w}_u^T \bar{\mathbf{h}})] + \frac{\lambda}{2} (\|\mathbf{W}\|_F^2 + \|\mathbf{V}\|_F^2)$$

s.t. $\mathbf{B} \in \{\pm 1\}^{f \times m}, \mathbf{D} \in \{\pm 1\}^{f \times n}, \mathbf{B}\mathbf{1}_m = 0, \mathbf{D}\mathbf{1}_n = 0, \mathbf{B}\mathbf{B}^T = m\mathbf{I}_f, \mathbf{D}\mathbf{D}^T = n\mathbf{I}_f.$

Square Loss
Feature Alignment
Network Embedding Loss
Discrete, Balanced and Decorrelation Constraints

Optimization

NP-Hard \Rightarrow Soften B and D:

$$\mathbf{X} \in \mathcal{B} = \{\mathbf{X} \in \mathbb{R}^{f \times m} | \mathbf{X}\mathbf{1} = 0, \mathbf{X}\mathbf{X}^T = m\mathbf{I}\} \quad d(\mathbf{B}, \mathcal{B}) = \min_{\mathbf{X} \in \mathcal{B}} \|\mathbf{B} - \mathbf{X}\|_F$$

$$\mathbf{Y} \in \mathcal{D} = \{\mathbf{Y} \in \mathbb{R}^{f \times n} | \mathbf{Y}\mathbf{1} = 0, \mathbf{Y}\mathbf{Y}^T = n\mathbf{I}\} \quad d(\mathbf{D}, \mathcal{D}) = \min_{\mathbf{Y} \in \mathcal{D}} \|\mathbf{D} - \mathbf{Y}\|_F$$

$$\arg \min_{\mathbf{B}, \mathbf{D}, \mathbf{W}, \mathbf{V}} \sum_{(u,i) \in \Omega} (r_{ui} - s_H(\mathbf{b}_u, \mathbf{d}_i))^2 - \alpha \sum_u [\log \sigma(\mathbf{w}_u^T \mathbf{h}) + \log \sigma(-\mathbf{w}_u^T \bar{\mathbf{h}})] + \beta \sum_u \|\mathbf{b}_u - \mathbf{w}_u\|^2 + \frac{\lambda_w}{2} \|\mathbf{W}\|_F^2 + \frac{\lambda_v}{2} \|\mathbf{V}\|_F^2 + \lambda_B d^2(\mathbf{B}, \mathcal{B}) + \lambda_D d^2(\mathbf{D}, \mathcal{D})$$

s.t. $\mathbf{B} \in \{\pm 1\}^{f \times m}, \mathbf{D} \in \{\pm 1\}^{f \times n},$

B-subproblem:

$$\arg \min_{\mathbf{b}_u \in \{\pm 1\}^f} \sum_{i \in \Omega_u} \frac{1}{4f^2} (\mathbf{d}_i^T \mathbf{b}_u)^2 - \frac{1}{f} (r_{ui} - \frac{1}{2}) \mathbf{d}_i^T \mathbf{b}_u - 2\beta \mathbf{w}_u^T \mathbf{b}_u - 2\lambda_B \mathbf{x}_u^T \mathbf{b}_u$$

$$\arg \min_{\mathbf{b}_{uk} \in \{\pm 1\}} \hat{b}_{uk} b_{uk} \quad \hat{b}_{uk} = \sum_{i \in \Omega_u} \frac{1}{f} (r_{ui} - \frac{1}{2} - \frac{1}{2f} \mathbf{d}_i^T \mathbf{b}_u) d_{ik} + \frac{1}{2f^2} b_{uk} + 2\beta w_{uk} + 2\lambda_B x_{uk}$$

DCD [3]

D-subproblem:

$$\arg \min_{\mathbf{d}_i \in \{\pm 1\}^f} \sum_{u \in \Omega_i} \frac{1}{4f^2} (\mathbf{b}_u^T \mathbf{d}_i)^2 - \frac{1}{f} (r_{ui} - \frac{1}{2}) \mathbf{b}_u^T \mathbf{d}_i - 2\lambda_D \mathbf{y}_i^T \mathbf{d}_i$$

$$\arg \min_{\mathbf{d}_{ik} \in \{\pm 1\}} \hat{d}_{ik} d_{ik} \quad \hat{d}_{ik} = \sum_{u \in \Omega_i} \frac{1}{f} (r_{ui} - \frac{1}{2} - \frac{1}{2f} \mathbf{b}_u^T \mathbf{d}_i) b_{uk} + \frac{1}{2f^2} d_{ik} + 2\lambda_D y_{ik}$$

DCD

W & V-subproblems: SGD + BP

X & Y-subproblems: SVD + Gram-Schmidt orthogonalization

Experiment

Datasets:

Datasets	Users	Items	Ratings	Rating Density	Followers	Followees	Links	Linking Density
CiaoDVD	17,615	16,121	72,665	0.026%	1,438	4,299	40,133	0.649%
Epinions	40,163	139,738	664,824	0.012%	33,960	49,288	487,183	0.029%

- S2MF, DSR/DTMF > DCF: the effectiveness of social information to hash code learning
- S2MF > DSR/DTMF: the superiority of our solution to social information processing
- SMF > S2MF > MF > DSR/DTMF > DCF: the effectiveness of our proposed method

Results:

Methods	Metric	CiaoDVD				Epinions			
		8 Bits	16 Bits	32 Bits	64 Bits	8 Bits	16 Bits	32 Bits	64 Bits
SMF	NDCG@10	0.82807	0.83035	0.82818	0.83171	0.84666	0.84680	0.84639	0.84801
	Improve	-1.61%	-1.28%	-1.48%	-1.27%	-3.50%	-2.26%	-1.87%	-1.77%
MF	NDCG@10	0.75201	0.76588	0.76055	0.76881	0.79658	0.80503	0.80629	0.80686
	Improve	+8.34%	+7.03%	+7.28%	+6.81%	+2.57%	+2.81%	+3.01%	+3.24%
DSR/DTMF	NDCG@10	0.74898	0.75168	0.75942	0.76142	0.78722	0.78880	0.79586	0.79665
	Improve	+8.78%	+9.05%	+7.44%	+7.84%	+3.79%	+4.93%	+4.36%	+4.57%
DCF	NDCG@10	0.72930	0.73269	0.74305	0.74921	0.77929	0.78257	0.78837	0.79123
	Improve	+11.72%	+11.87%	+9.81%	+9.60%	+4.84%	+5.77%	+5.35%	+5.28%
S2MF	NDCG@10	0.81475	0.81969	0.81595	0.82114	0.81702	0.82769	0.83053	0.83302