A Generalized and Fast-converging Non-negative Latent Factor Model for Predicting User Preferences in Recommender Systems

Ye Yuan
Chongqing Engineering Research Center of Big Data Application for Smart Cities
Chongqing Key Laboratory of Big Data and Intelligent Computing, Chongqing Institute of Green and Intelligent Technology, Chinese Academy of Sciences, Chongqing, China, yuanye@cigit.ac.cn

Xin Luo†
Chongqing Engineering Research Center of Big Data Application for Smart Cities
Chongqing Key Laboratory of Big Data and Intelligent Computing, Chongqing Institute of Green and Intelligent Technology, Chinese Academy of Sciences, Chongqing, China, luoxin21@cigit.ac.cn

Mingsheng Shang
Chongqing Engineering Research Center of Big Data Application for Smart Cities
Chongqing Key Laboratory of Big Data and Intelligent Computing, Chongqing Institute of Green and Intelligent Technology, Chinese Academy of Sciences, Chongqing, China, msshang@cigit.ac.cn

Di Wu
Chongqing Engineering Research Center of Big Data Application for Smart Cities
Chongqing Key Laboratory of Big Data and Intelligent Computing, Chongqing Institute of Green and Intelligent Technology, Chinese Academy of Sciences, Chongqing, China, wudi@cigit.ac.cn

ABSTRACT

Recommender systems (RSs) commonly describe its user-item preferences with a high-dimensional and sparse (HiDS) matrix filled with non-negative data. A non-negative latent factor (NLF) model relying on a single latent factor-dependent, non-negative and multiplicative update (SLF-NMU) algorithm is frequently adopted to process such an HiDS matrix. However, an NLF model mostly adopts Euclidean distance for its objective function, which is naturally a special case of *α-β*-divergence. Moreover, it frequently suffers slow convergence. For addressing these issues, this study proposes a generalized and fast-converging non-negative latent factor (GFNLF) model. Its main idea is two-fold: a) adopting *α-β*-divergence for its objective function, thereby enhancing its representation ability for HiDS data; b) deducing its momentum-incorporated non-negative multiplicative update (MNMU) algorithm, thereby achieving its fast convergence. Empirical studies on two HiDS matrices emerging from real RSs demonstrate that with carefully-tuned hyperparameters, a GFNLF model outperforms state-of-the-art models in both computational efficiency and prediction accuracy for missing data of an HiDS matrix.

† X. Luo (*Corresponding author*) is also with the Hengrui (Chongqing) Artificial Intelligence Research Center, Department of Big Data Analyses Techniques, Cloudwalk, Chongqing, China. Y. Yuan is also with the University of Chinese Academy of Sciences, Beijing, China.

WWW '20, April 20-24, 2020, Taipei, Taiwan

ACM ISBN 978-1-4503-7023-3/20/04
https://doi.org/10.1145/3366423.3380133

CCS CONCEPTS

• Computing methodologies • Machine learning • Machine learning approaches • Factorization methods

KEYWORDS

Non-negative latent factor, *α-β*-divergence, Momentum, High-dimensional and sparse, Recommender system, User preference

ACM Reference format:

Ye Yuan, Xin Luo, Mingsheng Shang and Di Wu. 2020. A Generalized and Fast-converging Non-negative Latent Factor Model for Predicting User Preferences in Recommender Systems. In *Proceedings of WWW '20: The Web Conference 2020 (WWW '20), April 20-24, 2020, Taipei, Taiwan*. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3366423.3380133

1 Introduction

The rapid expansion world-wide-web has caused the problem of information overload. How to develop an intelligent system to filter the useful information out of massive data has become a heated issue. In such context, RSs have been proven highly efficient in addressing information overload by connecting valuable information to people actively, rather than passively, according to their information usage history [1-6, 39, 40].

In RSs, a user-item rating matrix [7-9] is usually the fundamental data source, where each entry is modeled according to the corresponding user-item usage history. High values in a rating matrix commonly denote strong user-item preferences [10-12]. With exponentially growing quantities of users and items in RSs, only a few items can be observed by each user. This phenomenon leads to the rating matrix high-dimensional and

c) M2's computational efficiency is significantly higher than that of its peers. As recorded in Table 4, M2 obviously consumes less total time cost to achieve its lowest RMSE. For instance, on D1, M2 consumes 3197.3 seconds to achieve its lowest RMSE. This is 66.62% of 4799.3 seconds by M1, 64.44% of 4961.3 seconds by M3, 6.48% of 49343.1 seconds by M4, and 7.15% of 44712.8 seconds by M5. Note that although M2's time cost per iteration is slightly higher than that of M1 and M3 as shown in Figure 7, M2's iteration is obviously less due to adopting the generalized momentum method.

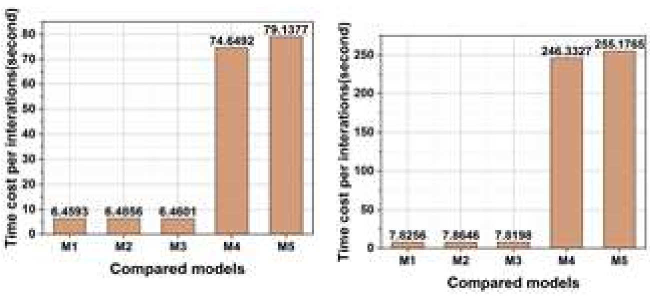

Figure 7: Time cost per iteration of compared models.

Table 4: Total time cost of compared models (second).

Dataset	M1	M2	M3	M4	M5
D1	4799.3	**3197.3**	4961.3	49343.1	44712.8
D2	6338.7	**1533.6**	6138.5	46064.2	44655.8

4.6 Summary

Based on the experimental results, we summarize that:

a) By carefully selecting appropriate α and β, GFNLF outperforms NLF with Euclidean distance on prediction accuracy;

b) The momentum-incorporated non-negative multiplicative update (MNMU) algorithm is able to significantly improve the convergence rate without accuracy loss;

c) When compared with state-of-the-art models, GFNLF can achieve obviously higher computational efficiency as well as competitive prediction accuracy for missing values in HiDS matrices.

5 Conclusion

High-dimensional and sparse matrices (HiDS) matrices with non-negativity constraints are commonly encountered in RSs. High values in an HiDS matrix usually denote strong user-item preferences. NLF can address such matrices efficiently. However, NLF mostly adopts Euclidean distance for its objective function, which is naturally a special case of α-β-divergence. Moreover, it frequently suffers slow convergence. To address this issue, this paper innovatively proposes a generalized and fast-converging non-negative latent factor (GFNLF) model. We first turn NLF into a generalized form by adopting α-β-divergence to enhance its representation ability for HiDS data. Subsequently, we design a momentum-based single latent factor-dependent, non-negative and multiplicative update (MNMU) to achieve its fast convergence. Empirical studies show that GFNLF outperforms state-of-the-art models in both computational efficiency and prediction accuracy for missing data of an HiDS matrix. Hence, it is useful for RSs to desire highly efficient, accurate and non-negative latent factor analysis.

However, the performance of GFNLF depends largely on carefully tuning hyperparameters (α, β and κ). In this work, we pre-tune their values, but the tuning process is an inefficient task. Consequently, making them self-adaptation is an essential issue. According to prior research [38], evolutionary computing-based frameworks may be useful for adaptive picking up the optimal hyperparameters. Of cause, great efforts are needed for redirecting such frameworks to GFNLF. We plan to address such issues in the future.

ACKNOWLEDGMENTS

This work is supported in part by the National Natural Science Foundation of China under grants 61772493, 61902370, 61602434 and 61702475, in part by the Natural Science Foundation of Chongqing (China) under grants cstc2019jcyj-msxmX0578 and cstc2019jcyjjqX0013, and in part by the Pioneer Hundred Talents Program of Chinese Academy of Sciences.

REFERENCES

[1] Paul Resnick and Hal R. Varian. 1997. Recommender systems. Communications of the ACM 40, 3 (1997), 56-59.

[2] Chao Wang, Qi Liu, Runze Wu, Enhong Chen, Chuanren Liu, Xunpeng Huang, and Zhenya Huang. 2018. Confidence-Aware Matrix Factorization for Recommender Systems. In Proceedings of the 32nd AAAI Conference on Artificial Intelligence (AAAI). 434-442.

[3] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In Proceedings Of the 26th International Conference on World Wide Web (WWW). 173-182.

[4] Gábor Takács, István Pilászy, Bottyán Németh, and Domonkos Tikk. 2009. Scalable Collaborative Filtering Approaches for Large Recommender Systems. Journal of Machine Learning Research 10, 623-656.

[5] Tianqiao Liu, Zhiwei Wang, Jiliang Tang, Songfan Yang, Gale Yan Huang, and Zitao Liu. 2019. Recommender Systems with Heterogeneous Side Information. In Proceedings Of the 28th International Conference on World Wide Web (WWW). 3027-3033.

[6] Cen Chen, Peilin Zhao, Longfei Li, Jun Zhou, Xiaolong Li, and Minghui Qiu. 2017. Locally connected deep learning framework for industrial-scale recommender systems. In Proceedings Of the 26th International Conference on World Wide Web (WWW). 769-770.

[7] Xin Luo, Mengchu Zhou, Shuai Li, Zhuhong You, Yunni Xia, and Qingsheng Zhu. 2016. A Nonnegative Latent Factor Model for Large-Scale Sparse Matrices in Recommender Systems via Alternating Direction Method. IEEE Transactions on Neural Networks and Learning Systems 27, 3 (2016), 579-592.

[8] Trong Dinh Thac Do and Longbing Cao. 2018. Coupled poisson factorization integrated with user/item metadata for modeling popular and sparse ratings in scalable recommendation. In Proceedings of the 32nd AAAI Conference on Artificial Intelligence (AAAI). 2918-2925.

[9] Jing Lin, Weike Pan, and Zhong Ming. 2018. MF-DMPC: Matrix Factorization with Dual Multiclass Preference Context for Rating Prediction. In Proceedings of the International Conference on Web Services (ICWS). 337-349.

[10] James Chambua, Zhendong Niu, and Yifan Zhu. 2019. User preferences prediction approach based on embedded deep summaries. Expert Systems with Applications 132, 87-98.

[11] Yixin Cao, Xiang Wang, Xiangnan He, Zikun Hu, and Tat-Seng Chua. 2019. Unifying Knowledge Graph Learning and Recommendation: Towards a Better Understanding of User Preferences. In Proceedings of the 28th International Conference on World Wide Web (WWW). 151-161.

[12] Qiang Liu, Shu Wu, Liang Wang. 2017. DeepStyle: Learning user preferences for visual recommendation. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR). 841-844.