

Enhanced Recommender Systems with Diffusion Dynamics and Machine Learning

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Thesis submitted in fulfilment of the requirements for
the degree of

Doctor of Philosophy

under the supervision of
Associate Professor Guangquan Zhang
and Distinguished Professor Jie Lu

University of Technology Sydney
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June 2022

CERTIFICATE OF ORIGINAL AUTHORSHIP

I, *Ximeng Wang*, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Computer Science at the Faculty of Engineering and Information Technology at the University of Technology Sydney. This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree at any other academic institution except as fully acknowledged within the text. This thesis is the result of a Collaborative Doctoral Research Degree program with Beijing Jiaotong University. This research is supported by the Australian Government Research Training Program.

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Signature removed prior to publication.

DATE: *26, June, 2022*

ACKNOWLEDGMENTS

It is a memorial and exciting journey at the University of Technology Sydney for pursuing my Ph.D. degree in the past years. I am sincerely grateful to the people who inspired and helped me in many ways.

I would like to express my thankfulness to my principal supervisor, Associate Professor Guangquan Zhang. Without his encouragement and guidance, I would not have been able to complete this Ph.D. program. His wisdom and critical comments leave a deep impression on me, which point out the directions of my research. Meanwhile, I am greatly indebted to my co-advisor, Distinguished Professor Jie Lu. Her confidence and enthusiasm inspired me to do the right thing even when the road got tough. She facilitated the collaborative doctoral research degree program between UTS and BJTU, and offered me an opportunity to join UTS. It is fair to say that I would not have been able to study at UTS without her contribution and help. In addition, I express sincere gratitude to my advisors at BJTU, Professor Yun Liu and Professor Fei Xiong. Their urge and instruction motivated and encouraged me to face difficulties and challenges positively.

I would like to thank every member of the DeSI Lab in the Australian Artificial Intelligence Institute. It was a wonderful experience to learn from these dedicated researchers. I especially thank Dr. Yi Zhang, Dr. Feng Liu, Dr. Hua Zuo, Dr. Junyun Xuan and Dr. Zheng Yan who provided insightful comments related to my research problems during my Ph.D. candidature, and thank Dr. Anjin Liu, Dr. Hang Yu, Dr. Ruiping Yin, Dr. Qian Liu, Dr. Bin Wang, Dr. Chenlian Hu, Dr. Yiliao Song, Dr. Shan Xue, Dr. Fan Dong, Dr. Fujin Zhu, Dr. Adi Lin, Dr. Qian Zhang, Dr. Guanjin Wang and Dr. Zhen Fang who have shared their opinions and comments with me. Furthermore, I want to thank for the kind help from Prof. Shirui Pan, Dr. Zhedong Zheng, Dr. Qingji Guan, Dr. Zhun Zhong and other friends, may our friendship last forever.

At last, I would like to express my heartfelt appreciation to my wife, parents, and families for their love and support.

ABSTRACT

Recommender systems are an effective tool for solving problems with information overload. As such, they have not only received much attention from academia, they have also been widely used in industry. However, although recommender systems have seen many significant research outcomes, they also face some challenges and problems.

This thesis focuses on enhancing recommender systems through the use of diffusion dynamics and machine learning, and solves four problems faced by existing recommendation methods: 1) Can diffusion-based recommendation methods get a better balance between accuracy and diversity; 2) How can trust diffusion processes be modeled in social networks and how can social information be introduced into diffusion-based recommendation methods; 3) Can opinion dynamics be integrated with machine learning to make better recommendations; and 4) How can the issue of preference conflicts in group recommender systems be alleviated such that the recommendations generated meet the requirements of most of the users in a group.

To address Problem 1), this thesis presents a mixed similarity diffusion process that integrates two kinds of similarity measures from both explicit and implicit feedback data. It also considers the degree of balance for

different kinds of nodes in a bipartite network. This new diffusion process enhances both the accuracy and diversity of the recommendations.

To address Problem 2), a trust diffusion process is simulated via a trust network that introduces explicit trust into the diffusion process, while the similarity between users indicates implicit trust. Moreover, a special resource allocation process, designed for a tripartite network, combines both kinds of trust to model user preferences in a more exact manner.

To address Problem 3), a social recommendation model is used to integrate opinion dynamics and user influence into a matrix factorization framework. The model characterizes the impact of neighbors on user opinions through evolutionary game theory and uses a payoff matrix to improve the training process of the matrix factorization. In addition, user influence that originates from the trust network is added to the proposed recommendation model.

To address Problem 4), a virtual coordinator combined with group recommendation solves preference conflicts through a negotiation process. The virtual coordinator brings a global perspective to optimizing the evaluation processes of individual user preferences in a group in order to create a balanced set of group recommendations. Additionally, personal influence is inferred from the trust relations to define the impact of the virtual coordinator on each group member.

To conclude, this thesis proposes a set of recommendation methods for both personalized and group recommendation that go some way to solving current challenges in recommender systems.

LIST OF PUBLICATIONS

1. **Wang, X.**, Liu, Y., Lu, J., Xiong, F. & Zhang, G., 2019, ‘TruGRC: Trust-aware group recommendation with virtual coordinators’, *Future Generation Computer Systems*, vol. 94, pp. 224-236.
2. **Wang, X.**, Liu, Y., Zhang, G., Xiong, F. & Lu, J., 2017, ‘Diffusion-based recommendation with trust relations on tripartite graphs’, *Journal of Statistical Mechanics: Theory and Experiment*, vol. 2017, no. 8, p. 083405.
3. **Wang, X.**, Liu, Y., Zhang, G., Zhang, Y., Chen, H. & Lu, J., 2017, ‘Mixed similarity diffusion for recommendation on bipartite networks’, *IEEE Access*, vol. 5, pp. 21029-21038.
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