

UNIVERSITY OF TECHNOLOGY, SYDNEY  
Faculty of Engineering and Information Technology

**Exploring Heterogeneous Social Information  
Networks for Recommendation**

by

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A THESIS SUBMITTED  
IN PARTIAL FULFILLMENT OF THE  
REQUIREMENTS FOR THE DEGREE

**Doctor of Philosophy**

Sydney, Australia

2017

## **Certificate of Authorship/Originality**

I certify that the work in this thesis has not been previously submitted for a degree nor has it been submitted as a part of the requirements for another degree except as fully acknowledged within the text.

I also certify that this thesis has been written by me. Any help that I have received in my research and in the preparation of the thesis itself has been fully acknowledged. In addition, I certify that all information sources and literature used are quoted in the thesis.

This research is supported by an Australian Government Research Training Program Scholarship.

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## ABSTRACT

### **Exploring Heterogeneous Social Information Networks for Recommendation**

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A basic premise behind our study of heterogeneous social information networks for recommendation is that a complex network structure leads to a large volume of implicit but valuable information which can significantly enhance recommendation performance. In our work, we combine the global popularity and personalized features of travel destinations and also integrate temporal sensitive patterns to form spatial-temporal wise trajectory recommendation. We then develop a model to identify representative areas of interest (AOIs) for travellers based on a large scale dataset consisting of geo-tagged images and check-ins. In addition, we introduce active time frame analysis to determine the most suitable time to visit an AOI during the day. The outcome of this work can suggest relevant personalized travel recommendations to assist people who are arriving in new cities.

Another important part of our research is to study how “local” and “global” social influences exert their impact on user preferences or purchasing decisions. We first simulate the social influence diffusion in the network to find the global and local influence nodes. We then embed these two different kinds of influence data, as regularization terms, into a traditional recommendation model to improve its accuracy. We find that “Community Stars” and “Web Celebrities”, represent “local” and “global” influence nodes respectively, a phenomenon which does exist and can help us to generate significantly better recommendation results.

A central topic of our thesis is also to utilize a large heterogeneous social information network to identify the collective market hyping behaviours. Combating

malicious user attacks is also a key task in the recommendation research field. In our study, we investigate the evolving spam strategies which can escape from most of the traditional detection methods. Based on the investigation of the advanced spam technique, we define three kinds of heterogeneous information networks to model the patterns in such spam activities and we then propose an unsupervised learning model which combines the three networks in an attempt to discover collective hyping activities. Overall, we utilize the heterogeneous social information network to enhance recommendation quality, not only by improving the user experience and recommendation accuracy, but also by ensuring that quality and genuine information is not overwhelmed by advanced hyping activities.

## Dedication

I dedicate my dissertation work to my parents, my wife and my baby daughter who also born on my thesis submission date. A special feeling of gratitude to my loving parents, Yaran Zhang and Miliang Qin whose words of encouragement and push for tenacity ring in my ears. My wife, Qing Deng has never left my side and always encourage me to move forward during this tough but exciting journey, especially considering we are new immigrants in Australia hence she should have lots of responsibility in many aspects during this tough time. We are proud of what we achieve when we think back many difficulties we have overcome in these years. I also dedicate this dissertation to my family, especially my grandmothers, who always encourage me to stick to my goal although they do not understand what I was doing.

In addition, I dedicate this thesis to many friends of mine who have supported me throughout the process. I will always appreciate all they have done, especially they always keep listening to me, about my concern and frustration, as well as my success in publication.

## Acknowledgements

I wish to thank my principal supervisor Professor Chengqi Zhang was more than generous with his expertise and precious time.

In addition, I would like to thank Dr. Guodong Long who supported me a lot in many aspects of my research. His support make my Phd studying being an enjoyable experience.

Finally, a special acknowledge and thanks to Dr. Peng Zhang whose office was always open whenever I ran into a trouble spot or had a question about my research or writing. His consistently allowed this thesis to be my own work, but steered me in the right the direction whenever he thought I needed it.

Qinzhe Zhang  
Sydney, Australia, 2017.

# List of Publications

## Journal Papers

- J-1. **Qinzhe. Zhang**, Jia. Wu, Guodong. Long, Peng. Zhang and Chengqi. Zhang, “Collective Hying Detection System for Identifying Online Spam Activities,” *IEEE Intelligent Systems*, 2017. (Accepted on 12th of January 2017)
- J-2. **Qinzhe. Zhang**, Jia. Wu, Guodong. Long, Peng. Zhang and Chengqi. Zhang, “Dual Influence Embedded Social Recommendation,” *Word Wide Web: Internet and Web Information Systems (WWW)*, 2017. (Accepted on 20th of July 2017)

## Conference Papers

- C-1. **Qinzhe. Zhang**, and Litao. Yu, Guodong. Long:, “SocialTrail: Recommending Social Trajectories from Location-Based Social Networks, *Australasian Database Conference (ADC 2015)*, pp. 314-317, May. 31, 2015.
- C-2. **Qinzhe. Zhang**, and Qin.Zhang, Guodong. Long, Peng. Zhang and Chengqi. Zhang:, “Exploring Heterogeneous Product Networks for Discovering Collective Marketing Hying Behavior, *The Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD 2016)*, pp. 40-51, Apr. 19-22, 2016.
- C-3. **Qinzhe. Zhang**, and Jia.Wu, Guodong. Long, Peng. Zhang and Chengqi. Zhang:, “Global and Local Influence-based Social Recommendation, *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management (CIKM 2016)*, pp. 1917-1920, Oct. 24-28, 2016.

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# Abbreviation

1-SMC - First-order Sliding Mode Control

2-SMC - Second-order Sliding Mode Control

2-D: Two-dimensional

3-D: Three-dimensional

DF - Describing Function

FRF - Frequency Response Function

FSSMC - Frequency Shaped Sliding Mode Control

HOSM: Higher-order sliding modes

LTI: Linear time-invariant

MIMO: Multi input multi output

MR - Magnetorheological

MDoF - Multiple Degree of Freedom

RMSE - Root Means Square error

SDoF - Single Degree of Freedom

SISO Single input single output

SMC - Sliding Mode Control

SVD: Singular value decomposition

TF - Transfer Function.

VSC: Variable structure control

## Nomenclature and Notation

Capital letters denote matrices.

Lower-case alphabets denote column vectors.

$(\cdot)^T$  denotes the transpose operation.

$I_n$  is the identity matrix of dimension  $n \times n$ .

$0_n$  is the zero matrix of dimension  $n \times n$ .

$\mathbb{R}$ ,  $\mathbb{R}^+$  denote the field of real numbers, and the set of positive reals, respectively.