# GRAPH RANKING-BASED RECOMMENDER SYSTEMS

A thesis submitted for the degree of

Doctor of Philosophy

By

Mingsong Mao

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University of Technology Sydney,

Faculty of Engineering and Information Technology

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#### CERTIFICATE OF ORIGINAL AUTHORSHIP

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

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

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"A teacher is one who could propagate the doctrine, impart professional knowledge, and resolve doubts."

Han Yu, 768AD

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#### **Abstract**

The rapid growth of web technologies and the volume of Internet users provide excellent opportunities for large-scale online applications but also have caused increasing information overloading problems whereby users find it hard to locate relevant information to exactly meet their needs efficiently by basic Internet searching functions. Recommender systems are emerging to aim to handle this issue and provide personalized suggestions of resources (items) to particular users, which have been implemented in many domains such as online shopping assistants, information retrieval tools and decision support tools. In the current era of information explosion, recommender systems are facing some new challenges. Firstly, there are increasing tree-structured taxonomy attributes as well as freeform folksonomy tags associated with items. Secondly, there are increasing explicit and implicit social relations or correlations available for web users. Thirdly, there is increasingly diverse contextual information that affects or reflects user preferences. Furthermore, the recommendation demands of users are becoming diverse and flexible. In other words, users may have changing multi-objective recommendation requests at different times.

This research aims to handle these four challenges and propose a set of recommendation approaches for different scenarios. Graph ranking theories are employed due to their ease of modelling different information entities and complex relations and their good extensibility. In different scenarios, different graphs are

generated and some unique graph ranking problems are raised. Concretely, we first propose a bipartite graph random walk model for a hybrid recommender system integrating complex item content information of both tree-structured taxonomy attributes and free-form folksonomy tags. Secondly, we propose a multigraph ranking model for a multi-relational social network-based recommendation system that is able to incorporate multiple types of social relations or correlations between users. Thirdly, we propose a multipartite hypergraph ranking model for a generic full information-based recommender system that is able to handle various parities of information entities and their high-order relations. In addition, we extend the multipartite hypergraph ranking model to be able to respond to users' multi-objective recommendation requests and propose a novel multi-objective recommendation framework.

We conduct comprehensive empirical experiments with a set of real-word public datasets in different domains such as movies (Movielens), music (Last.fm), e-Commerce products (Epinions) and local business (Yelp) to test the proposed graph ranking-based recommender systems. The results demonstrate that our models can generally achieve significant improvement compared to existing approaches in terms of recommendation success rate and accuracy. By these empirical experiments, we can conclude that the proposed graph ranking models are able to handle well the indicated four key challenges of recommender systems in the current era. This work is hence of both theoretical and practical significances in the field of both graph ranking and recommender systems.

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