# FACULTY OF ENGINEERING AND INFORMATION TECHNOLOGY

# Enhanced Group Recommender System and Visualization

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#### CERTIFICATE OF AUTHORSHIP/ORIGINALITY

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.

Signature of Candidate

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#### **ABSTRACT**

Requirement of group recommender systems (GRSs) is experiencing a dramatic growth due to intelligent services being applied more broadly and involved in more and more domains. However, effectivity and interpretability are still two challenges in GRSs. A typical scenario is: a group is formed randomly without active organizing in advance and sufficient negotiation between members before recommending, such as e-shopping and e-tourism. Therefore, deeply modeling the group profile is the first key part to generate recommendations. Moreover, accurately predicting should be a problem under biased and limited information provided by users. The interpretability challenge is that most of GRSs are black boxes for providing no necessary explanation of recommendations but only a list. It is quite important to convince members to make them understand why the specific recommendations are reasonable. Thus, explaining the reason generated recommendations and relationships between members needs to be investigated.

This research aims to handle these two challenges in both theoretical and practical aspects. A novel group recommendation approach is developed and aims to maximize satisfaction within random groups by modeling the group profiles through the analysis of contributed member ratings alone. First, the Contribution Score is defined to numerically measure each member's importance in terms of the sub-rating matrix which makes it practical even when the matrix is highly incomplete and sparse. Second, a local collaborative filtering method is developed to address the biased rating problem caused by severe preference conflicting in random groups. An adaptive average rating calculating model is proposed taking into consideration of the target item by reducing the set to those which are highly relevant to it. By integrating these two models, a Contribution Score-based Group Recommendation (CS-GR) approach is developed to efficiently depict groups. Also, a novel hierarchy graph-based visualization method, based on data visualization techniques, which are

powerful tools to offer intuitive abstractions of concepts, is suggested to offer explanations for users. First a higher level of abstraction of the overall recommender modules, such as group profile modeling and prediction calculating, is presented using a hierarchy graph. To do this, all the entities involved in a group recommender process are summarized and visualized as nodes in the graph and the edges in the graph represent information inherited. Second, the layout provides detailed information for individual members to track their influences in the system by adding pie charts at each single node to show individual influences for all involved members. This enables members to track and compare their influences with others in every single procedure.

This research provides the GRSs effectivity for the biased and sparse information which can be handled to model the group and generate the predictions. The scalability and efficiency are also guaranteed because only rating information is needed and matrix decomposition technique is employed. The visualization is used to provide both overall and detailed explanation for users.

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