



# Cross-domain Recommender System Through Tag-based Models

Peng Hao

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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.

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## Abstract

Nowadays, data pertaining to clients are generated at such a rapid rate it is completely beyond the processing ability of a human, which leads to a problem called *information explosion*. How to quickly and automatically provide personalized choices for someone from a large collection of resources has become a key factor in determining the success of many commercial activities. In this context, *recommender systems* have been developed as a type of software that aims to predict and suggest items which are relevant to a specific user by analyzing the user's previous interaction data with certain items. Recommender systems have a broad application in our daily life, such as product recommendation in Amazon, video and movie recommendation in Youtube, music recommendation in Spotify.

A fundamental brick in building most recommender systems is the *collaborative filtering*-based model, which has been widely adopted due to its outstanding performance and flexible deployment. However, this model together and its variations suffer from the so-called *data sparsity* problem, which results when user only rate a limited number of items. With the development of the *transfer learning* technique in recent years, cross-domain recommendation has emerged as an effective way to address data sparsity in recommender systems. The principle

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of cross-domain recommendation is to exploit knowledge from auxiliary source domains to assist recommendation making in a sparse target domain.

In the development of cross-domain recommender systems, the most important step is to build a bridge between the domains in order to transfer knowledge. This task becomes more challenging in disjoint domains where users and items in both domains are completely non-overlapping. In this respect, tags are studied and utilized to establish explicit correspondence between domains. However, how to effectively exploit tags to increase domain overlap and ultimate recommendation quality remains as an open challenge which needs to be addressed.

This thesis aims to develop novel tag-based cross-domain recommendation models in disjoint domains. First, it review the existing state-of-the-art techniques related to this research. It then provides three solutions by exploiting domain-specific tags, tag-inferred structural knowledge and tag semantics, respectively. To evaluate the proposed models, this thesis conducts a series of experiments on public datasets and compare them with state-of-the-art baseline approaches. The experimental results show the superior performance achieved by our models in different recommendation tasks under sparse settings. The findings of this research not only contribute to the state-of-the-art on cross-domain recommender systems, but also provide practical guidance for handling unstructured tag data in recommendation tasks.

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