



**ENHANCED RECOMMENDER
SYSTEMS THROUGH
CROSS-DOMAIN KNOWLEDGE
TRANSFER**

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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 the requirements for a degree except as fully acknowledged within the text.

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Abstract

Recommender systems are widely used and have developed rapidly with the explosion of Web 2.0 technologies. The aim of recommender systems is to provide users with items (products or services) that match the users' preferences. Recommender systems provide users with personalized online product and service recommendations and are a ubiquitous part of today's online entertainment smorgasbord.

However, many real-world recommender systems suffer from data sparsity and user-preference drift issues which degrade the recommendation performance and lead to a poor user experience. For the user-preference drift issue, time-window and instance decaying approaches are widely applied, but one research gap is that existing methods proposed for adaptation and weighting decay are biased, since the direction of user preference drift was not appropriately addressed in their study. For the data sparsity issue, cross-domain recommender systems are used to handle data sparsity issues. These systems transfer knowledge from one domain that has adequate preference information to another domain that does not. One significant research gap in the existing methods is that they cannot ensure the knowledge extracted from the source domain is consistent with the target domain, which may impact the accuracy of the recommendations. This research addresses the aforementioned research gaps.

In this research, to solve these problems and enhance recommender systems, a user profile is enhanced with more information in various domains, including data in different time windows and different categories. For recommender systems with time labels, fuzzy set and fuzzy relation theories are adopted to model uncertain user behavior. A distance measure together with a related statistical guarantee is proposed to detect whether a user preference has drifted or not. A fuzzy user-preference drift detection-based recommendation method is proposed to model user preference and predict user ratings in temporal dynamics. For a cross-domain recommender system, to ensure knowledge consistency between the two domains, two sets of methods are developed for two different scenarios. For cross-domain recommender systems with non-overlapping entities, an adaptive knowledge transfer method for cross-domain recommender systems with consistent information transfer is proposed and applied to a telecom product recommender system and a business partner recommender system (Smart BizSeeker). Knowledge consistency is based on user and item latent groups, and domain adaptation techniques are used to map and adjust these groups in both domains to maintain consistency during the transfer learning process. For cross-domain recommender systems with partially overlapping entities, a kernel-induced knowledge transfer method is proposed. Domain adaptation is used to adjust the feature spaces of overlapping entities and diffusion kernel completion is used to obtain the non-overlapping entity correlations between two domains. It shows even with a small number of overlapping entities, knowledge transferred from the source domain to the target domain is very applicable and beneficial.

To conclude, this research addresses user-preference inconsistency which occurs in recommender systems in both different time windows and different categories.

Different contexts (e.g. time) can be treated as different domains. Thus, this research aims to improve prediction accuracy and enhance recommender systems through cross-domain knowledge transfer. Extensive experiment results show that our proposed methods can generally achieve significant improvement in accuracy compared with the existing approaches.

Table of Contents

| | |
|---|------------|
| CERTIFICATE OF AUTHORSHIP/ORIGINALITY | ii |
| Acknowledgements | iii |
| Abstract | v |
| List of Figures | ix |
| List of Tables | x |
| 1 Introduction | 1 |
| 1.1 Motivation | 1 |
| 1.2 Research Questions and Objectives | 6 |
| 1.3 Research Significance | 8 |
| 1.3.1 Theoretical Significance | 8 |
| 1.3.2 Practical Significance | 9 |
| 1.4 Thesis Structure | 10 |
| 1.5 Publications Related to This Thesis | 13 |
| 2 Literature Review | 14 |
| 2.1 Recommender Systems | 15 |

| | | |
|----------|---|-----------|
| 2.1.1 | Content-based Recommender Systems | 16 |
| 2.1.1.1 | Item representation | 16 |
| 2.1.1.2 | User profiling | 17 |
| 2.1.1.3 | Filtering and recommendation | 17 |
| 2.1.2 | Collaborative Filtering-based Recommender Systems . . . | 18 |
| 2.1.2.1 | Memory-based Collaborative Filtering | 19 |
| 2.1.2.2 | Model-based Collaborative Filtering | 23 |
| 2.1.3 | Knowledge-based Recommender Systems | 28 |
| 2.2 | Transfer Learning | 31 |
| 2.2.1 | Instance-based Transfer Learning | 32 |
| 2.2.2 | Feature Representation-based Transfer Learning | 34 |
| 2.2.3 | Parameter-based and Relational Knowledge-based Transfer Learning | 36 |
| 2.3 | Cross-domain Recommender Systems | 37 |
| 2.3.1 | CDRSs with Side Information | 39 |
| 2.3.2 | CDRSs with Non-overlapping Entities | 40 |
| 2.3.3 | CDRSs with Partially or Fully Overlapping Entities | 41 |
| 3 | A Recommender System by User-preference Drift Detection | 44 |
| 3.1 | Introduction | 44 |
| 3.2 | Preliminary of Fuzzy Logic | 46 |
| 3.3 | Fuzzy User-preference Consistency Model | 47 |
| 3.3.1 | Fuzzy User Preferences | 47 |
| 3.3.2 | Fuzzy User-preference Consistency Modeling | 50 |
| 3.4 | User-preference Drift Detection | 55 |
| 3.4.1 | Interval-UP Density Decrement | 55 |

| | | |
|----------|---|-----------|
| 3.4.2 | Statistical Guarantee | 57 |
| 3.4.3 | Interval-UP Density Decrement-based Drift Detection Method | 58 |
| 3.5 | Fuzzy User-preference Drift Detection based Recommender System | 60 |
| 3.5.1 | System Overview | 60 |
| 3.5.2 | Experiment | 61 |
| 3.5.2.1 | Experiment Setup | 62 |
| 3.5.2.2 | Evaluating User-preference Drift Detection Method | 63 |
| 3.5.2.3 | Result and Parameter Analysis | 64 |
| 3.6 | Summary | 66 |
| 4 | A Cross-domain Recommender System with Consistent Information Transfer | 67 |
| 4.1 | Introduction | 67 |
| 4.2 | Problem Formulation and Motivation | 70 |
| 4.2.1 | Recommendation Task based on Tri-factorization in One Domain | 70 |
| 4.2.2 | Cross-domain Transfer Learning Recommender System . | 71 |
| 4.2.3 | Motivation for Developing CIT | 72 |
| 4.3 | A CDRS with Consistent Information Transfer | 75 |
| 4.3.1 | CIT Method Overview | 75 |
| 4.3.2 | CIT Method | 76 |
| 4.3.2.1 | Step 1: Clustering of users and items in both domains | 77 |
| 4.3.2.2 | Step 2: Domain adaptation of the user and item groups | 78 |

| | | |
|----------|---|------------|
| 4.3.2.3 | Step 3: Consistent knowledge extraction | 82 |
| 4.3.2.4 | Step 4: Group representation regulation | 85 |
| 4.3.2.5 | Step 5: Recommendation in target domain | 87 |
| 4.3.3 | Architecture of CIT | 88 |
| 4.4 | Experiments and Analysis | 89 |
| 4.4.1 | Dataset and Evaluation Metrics | 89 |
| 4.4.2 | Experimental Settings and Baselines | 91 |
| 4.4.3 | Results | 93 |
| 4.4.4 | Parameter Analysis | 100 |
| 4.5 | Discussion | 101 |
| 4.5.1 | Guidelines for Recommender System Developers | 102 |
| 4.5.2 | Practical Applications | 103 |
| 4.6 | Summary | 104 |
| 5 | A Cross-domain Recommender System with Kernel-induced Knowledge Transfer | 106 |
| 5.1 | Introduction | 106 |
| 5.2 | Preliminaries and Problem Formulation | 109 |
| 5.2.1 | Recommendation Task based on Matrix Factorization in One Domain | 109 |
| 5.2.2 | Problem Definition | 110 |
| 5.3 | A CDRS with Kernel-induced Knowledge Transfer | 112 |
| 5.3.1 | KerKT Method Overview | 112 |
| 5.3.2 | KerKT Method | 113 |
| 5.3.2.1 | Step 1: Extracting and aligning user features in both domains | 113 |

| | | |
|----------|--|------------|
| 5.3.2.2 | Step 2: Item feature regulation in both domains | 117 |
| 5.3.2.3 | Step 3: Entity similarity measures in one domain | 119 |
| 5.3.2.4 | Step 4: Kernel induced completion of inter-domain user similarity | 120 |
| 5.3.2.5 | Step 5: Collective matrix factorization with user similarity constraints | 123 |
| 5.4 | Experiments and Analysis | 125 |
| 5.4.1 | Datasets and Evaluation Metrics | 126 |
| 5.4.2 | Experimental Settings and Baselines | 127 |
| 5.4.3 | Results | 129 |
| 5.4.4 | Parameter Analysis | 136 |
| 5.5 | Summary | 138 |
| 6 | Conclusion and Future Research | 139 |
| 6.1 | Conclusions | 139 |
| 6.2 | Future Study | 142 |
| | Bibliography | 145 |
| | Abbreviations | 176 |
| | Appendix A Geodesic Flow Kernel (GFK) Operators | 177 |
| | Appendix B Proof of Maps Ensuring Consistency | 179 |

List of Figures

| | | |
|-----|---|-----|
| 1.1 | Thesis structure | 11 |
| 3.1 | An example of point-UP graph | 56 |
| 3.2 | Architecture of fuzzy user-preference drift detection-based recom- mender system | 61 |
| 3.3 | Parameter analysis of user-preference drift detection-based method. | 65 |
| 4.1 | An example for CDRS | 74 |
| 4.2 | The CIT method procedure | 76 |
| 4.3 | An example of user group information adjustment in two domains | 83 |
| 4.4 | Conception framework of cross-domain recommender system using CIT. | 89 |
| 4.5 | Comparison results for CIT and five other baselines. | 100 |
| 4.6 | Parameter analysis of CIT. | 102 |
| 5.1 | Different scenarios of overlapping entities. | 108 |
| 5.2 | Procedure of the KerKT method. | 114 |
| 5.3 | Graphical view of user relationships in source and target domains | 122 |
| 5.4 | Parameter analysis of λ_u, λ_v on KerKT on Movielens dataset. . . | 137 |
| 5.5 | Parameter analysis of λ on KerKT on Movielens dataset. | 137 |

List of Tables

| | | |
|-----|--|-----|
| 2.1 | Comparison of different recommendation techniques | 30 |
| 2.2 | Summary of literature reviews of cross-domain recommender systems. | 43 |
| 3.1 | Movie Representation for User u | 49 |
| 3.2 | Special value for fuzzy point-UP consistency relation. | 54 |
| 3.3 | Synthetic item similarities for user-preference drift detection. | 63 |
| 3.4 | Synthetic user ratings for user-preference drift detection. | 64 |
| 3.5 | Comparison of UDD and a traditional method on Movielens Dataset | 64 |
| 4.1 | Statistical information on the original datasets for experiments on CIT | 90 |
| 4.2 | Description of data subsets in three categories for experiments on CIT | 92 |
| 4.3 | Prediction performance of CIT on a movie target domain | 94 |
| 4.4 | Prediction performance of CIT on a book target domain | 95 |
| 4.5 | Prediction performance of CIT on a music target domain | 96 |
| 4.6 | Comparison results of average MAE between CIT and five baselines | 99 |
| 4.7 | Comparison results of average RMSE between CIT and five baselines | 100 |
| 5.1 | Statistics of original datasets for experiments on KerKT | 126 |
| 5.2 | Description of data subsets for four tasks on KerKT. | 128 |

| | | |
|-----|--|-----|
| 5.3 | Overall comparison results between KerKT and six baselines on the Movielens data. | 132 |
| 5.4 | Overall comparison results between KerKT and six baselines on the Netflix data. | 133 |
| 5.5 | Overall comparison results between KerKT and six baselines on the AmazonBook data. | 134 |
| 5.6 | Overall comparison results between KerKT and six baselines on the Douban data. | 135 |
| 5.7 | Comparison result of average MAE and RMSE on four tasks between KerKT and six baselines. | 136 |