

**CROSS-DOMAIN RECOMMENDATION SYSTEM FOR  
IMPROVING ACCURACY BY FOCUSING ON  
DIVERSITY**

Athauda Arachchilage Heshan Wikasitha Sandakelum Herath

209330K

Master of Science in Computer Science

Department of Computer Science and Engineering  
Faculty of Engineering

University of Moratuwa  
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## Declaration

I declare that this is my own work, and this dissertation does not incorporate without acknowledgment any material previously submitted for a degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief, it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

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Name of the supervisor: Dr Sapumal Ahangama

Signature of the supervisor: .....

Date: .....

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## Abstract

With the rapidly developing technology world, recommender systems also improving day by day since customer expectations also vary from new angles making new business trends. As a result of this kind of situation, enterprise-level recommender systems require more modifications with new improvements to achieve a high user satisfaction level. In that case it seems currently most commercial recommender systems are struggling with low recommender quality by decreasing user trust and expectations. On the other hand, it senses only the recommender accuracy is not sufficient to measure recommender quality. Under the major domain recommender system, the cross-domain recommender system is one of the not much-explored areas and it needs more research works focused on diversity like subjective metrics rather than accuracy. With the purpose of improving accuracy by focusing diversity on CDRS here, I have built a matrix factorization-based collaborative filtering cross-domain recommender system using explicit user feedback with movielens100k research data set. When it comes to cross-domain recommender systems, the most frequent approach is to measure and evaluate their relevancy using standard predicted accuracy metrics such as root mean squared error (RMSE), mean absolute error (MAE), and so on. Since the more need than accuracy to maintain high-quality recommendations, we need to pay attention to a few specific areas beyond accuracy like diversity and novelty. We have measured our CDRS model's performance via RMSE, MSE, MAE, FCP, hit ratio, and Precision@k and in all cases, CDRS has achieved good performance than the general CF model. Moreover, we measured the CDRS model's diversity and novelty and could see both are increasing when top-N increasing. These findings would be pretty much worthy when we are implementing enterprise-level cross-domain recommender systems in the future to achieve success in each modern business use case with enhancing user satisfaction.

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## LIST OF ABBREVIATIONS

Abbreviation	Description
CBRS	Content-Based Recommender System
CDRS	Cross Domain Recommender System
CF	Collaborative Filtering
CFRS	Collaborative Filtering Recommender System
DRS	Demographic Recommendation System
D <sub>S</sub>	Source Domain
D <sub>T</sub>	Target Domain
FM	Factorization Machines
HRS	Hybrid Recommender System
KBRS	Knowledge-Based Recommender System
MF	Matrix Factorization
RS	Recommender System