MULTIPLE SOCIAL NETWORK INTEGRATION FRAMEWORK FOR RECOMMENDATION ACROSS SYSTEM DOMAIN

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Computer Science)

School of Computing
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JUNE 2019

DEDICATION

This thesis is dedicated to my beloved grandmother Rashida Begum for her love, concern and support to make sure I achieve higher targets.

This thesis is dedicated to my father Muhammad Tariq Khan, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother Mehnaz Sarwar, who taught me that even the largest task can be accomplished if it is done one step at a time.

No words can express my gratitude for my wife Amna Ahmad, my siblings Mohsin Khan and Sidra Khan. They have always been in the forefront of love, concern, dua, advice and guidance to make sure I achieve the best of both worlds.

It is also dedicated to all of my UTM friends who eased my journey, especially, Muhammad Umar Khan, Usman Ahmad, Mudassar Ahmad, Juliet, Debby, Mia, Muhammad Younas, Khurram Ejaz, Syed Hamid Hussain Madni and many more.

Finally, I am most thankful to my Sponsor, Government College University Faisalabad.

ACKNOWLEDGEMENT

First of all, All praise and glory to the Almighty ALLAH (Subhanahu Wa Ta'ala) who gave me the courage and patience to carry out this work. Peace and blessings of ALLAH be upon His last Prophet MUHAMMAD (Sallulaho-Alaihe-Wassalam).

I also cannot thank enough my Sponsor, Government College University Faisalabad, for giving me this opportunity that has changed my life. In the course of this research, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts throughout my research. In particular, I would like to express my gratitude to my supervisor, **Assoc. Prof. Dr. Roliana Binti Ibrahim** for her guidance, advice, patience, encouragement and support to complete this work. I also acknowledge the support received from lecturers, faculty members and staff of school of computing, faculty of engineering, Universiti Teknologi Malaysia for the series of programmes which aided this work.

I am extremely grateful to my family for their generous support throughout my PhD, and indeed the whole of my life. Their wisdom, kindness and excellent advice have made me who I am today and I hope that I have made them proud. I want to thank my parents, my wife, my siblings and my friends for their unconditional support.

Many thanks to my friends and colleagues especially Dr. Umar Khan, Dr. Muhammad Younas, Dr. Syed Hamid Hussain Madni, Dr. Ali Shahid, Dr. Khurram Ejaz, Dr. Usman Ahmad, Dr. Mudassar Ahmad, Dr. Ramzan Talib, Dr. Kashif Qureshi and Arif for all their inputs during the numerous discussions and moral support through their fervent prayers. I am lucky and glad to have them in my life. Finally, I would like to thank all the persons who are not mentioned here, but have been a great help during my period of study.

ABSTRACT

A recommender system is a special software that recommends items to a user based on the user's history. A recommender system comprises users, items and a rating matrix. Rating matrix stores the interactions between users and items. The system faces a variety of problems among which three are the main concerns of this research. These problems are cold start, sparsity, and diversity. Majority of the research use a conventional framework for solving these problems. In a conventional recommender system, user profiles are generated from a single feedback source, whereas, Cross Domain Recommender Systems (CDRS) research relies on more than one source. Recently researchers have started using "Social Network Integration Framework", that integrates social network as an additional feedback source. Although the existing framework alleviates recommendation problems better than the conventional framework, it still faces limitations. Existing framework is designed only for a single source domain and requires the same user participation in both the source and the target domain. Existing techniques are also designed to integrate knowledge from one social network only. To integrate multiple sources, this research developed a "Multiple Social Network Integration Framework", that consists of two models and three techniques. Firstly, the Knowledge Generation Model generates interaction matrices from "n" number of source domains. Secondly, the Knowledge Linkage Model links the source domains to the target domain. The outputs of the models are inputs of the techniques. Then multiple techniques were developed to address cold start, sparsity and diversity problem using multiple source networks. Three techniques addressed the cold start problem. These techniques are Multiple Social Network integration with Equal Weights Participation (MSN-EWP), Multiple Social Network integration with Local Adjusted Weights Participation (MSN-LAWP) and Multiple Social Network integration with Target Adjusted Weights Participation (MSN-TAWP). Experimental results showed that MSN-TAWP performed best by producing 47% precision improvement over popularity ranking as the baseline technique. For the sparsity problem, Multiple Social Network integration for K Nearest Neighbor identification (MSN-KNN) technique performed at least 30% better in accuracy while decreasing the error rate by 20%. Diversity problem was addressed by two combinations of the cold start and sparsity techniques. These combinations, EWP + MSN-KNN, TAWP + MSN-KNN and TAWP + MSN-KNN outperformed the rest of the diversity combinations by 56% gain in diversity with a precision loss of 1%. In conclusion, the techniques designed for multiple sources outperformed existing techniques for addressing cold start, sparsity and diversity problem. Finally, an extension of multiple social network integration framework for content-based and hybrid recommendation techniques should be considered future work.

ABSTRAK

Sistem pencadang merupakan perisian khusus yang mencadangkan item kepada pengguna berdasarkan dapatan sejarah pengguna. Sistem pencadang merangkumi pengguna, item dan matriks penilaian. Matriks penilaian menyimpan interaksi antara pengguna dan item. Sistem ini menghadapi pelbagai masalah di mana tiga adalah perhatian utama dalam kajian ini. Masalah tersebut adalah mula sejuk, jarang dan kepelbagaian. Kebanyakan kajian menggunakan rangka kerja konvensional untuk mengatasi masalah tersebut. Dalam sistem pencadang konvensional, profil pengguna dihasilkan dari sumber maklum balas tunggal sedangkan kajian Sistem Pencadang Domain Silang (CDRS) bergantung kepada lebih dari satu sumber. Kebelakangan ini, penyelidik telah mula menggunakan Rangka Kerja Intergrasi Rangkaian Sosial yang menggabungkan rangkaian sosial sebagai sumber maklum balas tambahan. Walaupun rangka kerja sedia ada mengurangkan masalah cadangan lebih baik dari rangka kerja konvensional, ia masih mempunyai batasan. Rangka kerja yang sedia ada direka hanya untuk sumber domain tunggal dan memerlukan penyertaan pengguna yang sama dalam kedua-dua sumber dan domain sasaran. Teknik sedia ada juga direka untuk menggabungkan pengetahuan dari satu rangkaian sosial sahaja. Untuk menggabungkan pelbagai sumber, kajian ini membangunkan Rangka Kerja Integrasi Rangkaian Sosial Pelbagai, yang terdiri daripada dua model dan tiga teknik. Pertama, Model Penjana Pengetahuan menghasilkan matriks interaksi untuk bilangan "n" domain sumber. Kedua, Model Pautan Pengetahuan menghubungkan domain sumber ke domain sasaran dengan pemetaan pengguna sasaran ke pengguna sumber. Kemudian beberapa teknik telah dibangunkan untuk menangani masalah mula sejuk, jarang dan kepelbagaian menggunakan sumber rangkaian pelbagai. Teknik-teknik ini adalah *Multiple Social Network integration with Equal Weights Participation* (MSN-EWP), *Multiple Social Network integration with Local Adjusted Weights Participat*ion (MSN-LAWP) dan *Multiple Social Network integration with Target Adjusted Weights Participation* (MSN-TAWP). Hasil kajian menunjukkan bahawa MSN-TAWP adalah yang terbaik yang dicadangkan mengatasi teknik sedia ada sekurang-kurangnya 20% bagi cadangan mula sejuk, sebanyak 30.1% bagi cadangan jarang dan sebanyak 56% bagi pelbagaian untuk kehilangan piawaian ketepatan sebanyak 1%. Keputusan eksperimen menunjukkan bahawa MSN-TAWP tampil terbaik dengan menghasilkan peningkatan ketepatan 47% ke atas kedudukan populariti sebagai teknik asas. Untuk masalah jarang, teknik *Multiple Social Network with K Nearest Neighbor* (MSN-KNN) dilakukan sekurang-kurangnya 30% dengan ketepatan yang lebih baik sambil menurunkan kadar ralat sebanyak 20%. Masalah kepelbagaian ditangani oleh dua kombinasi mula sejuk dan teknik jarang. Gabungan ini, EWP + MSN-KNN, TAWP + MSN-KNN dan TAWP + MSN-KNN mengatasi keseluruhan kombinasi kepelbagaian dengan keuntungan 56% dalam kepelbagaian dengan kehilangan piawaian ketepatan sebanyak 1%. Kesimpulannya, teknik yang direka untuk pelbagai sumber mengatasi teknik yang sedia ada untuk menangani mula sejuk, jarang dan kepelbagaian. Akhirnya, pelanjutan kerangka integrasi rangkaian sosial untuk teknik cadangan berasaskan kandungan dan hibrid dianggap sebagai kerja masa depan.

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LIST OF ABBREVIATIONS

API	-	Application Programing Interface
AWS	-	Amazon Web Services
CDRS	-	Cross Domain Recommender Systems
CG1	-	Classification Group 1
CG2	-	Classification Group 2
CG3	-	Classification Group 3
CSV	-	Comma Separated Values
Df	-	Degree of freedom
Ds	-	Source Domain
Dt	-	Target Domain
FDG	-	Facebook Fandango Page Dataset
GOR	-	Group Oriented Recommendation
IDE	-	Integrated Development Environment
IId	-	Item Identifier
IMDB	-	Facebook IMDB Page Dataset
Is	-	Items of the source domain
It	-	Items of the target domain
JRE	-	Java Runtime Environment
KNN	-	K Nearest Neighbors
MAE	-	Mean Absolute Error
MAP	-	Mean Average Precision
MC	-	MovieClips
MSN	-	Multiple Social Network
MSN-EWP	-	Multiple Social Network integration with Equal Weights Participation
MSNIF	-	Multiple Social Network Integration Framework
MSN-KNN	-	Multiple Social Network integration for K Nearest Neighbor
MSN-LAWP	-	Multiple Social Network integration with Local Adjusted

		Weights Participation
MSP-TAWP	-	Multiple Social Network integration with Target Adjusted Weights Participation
Rec Sys	-	Recommender Systems
ROT	-	RottenTomatoes
RS	-	Recommender Systems
SLR	-	Systematic Literature Review
TH	-	Threshold
UId	-	User Identifier
UOR	-	User Oriented Recommendation
URL	-	Uniform Resource Locator
Us	-	Users of the source domain
Ut	-	Users of the target domain

LIST OF SYMBOLS

$\bar{r}_a$	-	Mean rating for user a
$\bar{r}_u$	-	Mean rating for user u
I_{SMx}	-	Items liked by a social network user
$I_{training}$	-	Items liked by the test users from the target domain
$P_{a,i}$	-	Prediction generated for an item i for a user a
$Post_{[SnPage]}$	-	Post published on the social network
$PostsList_{[SnPage]}$	-	List of all posts published on the social network
S_{i_x}	-	Sum of the number of user who liked an item
S_{r_x}	-	Sum of the ratings given to an item
S_i	-	Interaction based reputation score list
S_p	-	Items list ranked by the test users
S_r	-	Rating based reputation score list
T_P	-	Rank list based on Sp
T_{actual}	-	Items list ranked by the test users
T_{final}	-	Generated ranked list of items
T_{final}	-	Average of Si and Sr reputation lists
$r_{a,j}$	-	Rating provided for an item j by user a
$r_{u,j}$	-	Rating provided for an item j by user u
t_i	-	Rank of the item
$w_{a,u}$	-	Similarity weight between two users
x^2	-	Chi-square
$\|I\|$	-	Number of items in the list of items
$\|M\|$	-	Number of items in the list of users
IMz	-	Interaction matrix generated using like interactions
Mz	-	Final interaction matrix generated using *IMz* and *RMz*
RMz	-	Rating matrix generated using comment interactions
Uz	-	Set of unique users extracted from *Lz* and *Cz*

Cz	-	List of all users who have commented on any of the matched post
Lz	-	List of all users who have liked any of the matched post
PLz	-	List containing posts that are match with the target movies
SMx	-	Source matrix (mapped)
$SnPage$	-	Social Network
$mList$	-	Number of movies in the target domain

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview

This chapter starts by explaining conventional Recommender Systems (RS) and how Cross Domain Recommender Systems (CDRS) approach assist in the conventional recommendation for improving cold start, sparsity and diversity problem. Next, the existing social network integration framework for cross-domain recommendation is explained in detail for addressing identified problems, followed by issues faced by the existing framework. The research hypothesis is formulated in the problem statement section, which leads to research questions and objectives. After delineating the aim of the research, the scope of the research is outlined, which brings the chapter to an end by presenting thesis organizations.

1.2 Recommender System

A recommender system is a special software that recommends items to a user based on the user's history. A recommender system comprises users, items and a rating matrix. Rating matrix stores the interactions between users and items. A recommender system can be explained using a generic framework known as "Duine Framework", represented in Figure 1.1(a) (Beel et al., 2016; De Pessemier et al., 2015; Dooms et al., 2015; Guo et al., 2015; Jäschke et al., 2009; Monteserin, 2016; Villavicencio et al., 2016a,b,c). According to the framework, a recommender system is able to accept user feedback and process it using three components illustrated in Figure 1.1(a).

The first component is a feedback processor, the main task of which is to accept user feedback and convert it into information that can be used for generating user profiles. User feedback can be explicit or implicit as shown in Figure 1.1(b), where Figure 1.1(b) represents a rating matrix, which is an essential part of a recommender system. The second component of the framework is user profile, an abstract concept that represents everything that is known about a user. In its most basic form, a user profile is maintained using a rating matrix where each row of the matrix represents items rated or interacted by a user, as shown in Figure 1.1(b). Together, user, item and rating matrix create an eco-system known as the domain. Finally, third component of a recommender system is a prediction technique that takes two inputs, a rateable item (test item) and the set of user profiles. Prediction technique calculates user's interest towards the rateable item based on provided history.

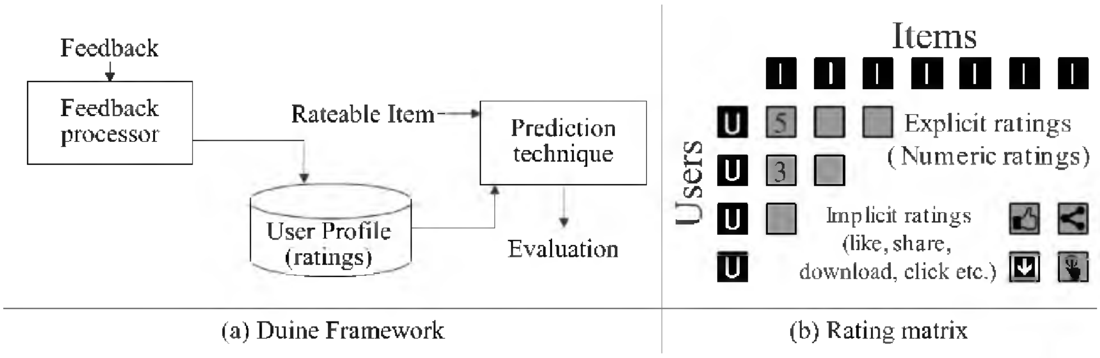

Figure 1.1 (a) Duine Framework (b) Rating Matrix

1.3 Cross Domain Recommender Systems (CDRS)

The majority of recommender systems provide recommendations for a single domain, for example, YouTube recommends videos to its users. Such recommender systems have been deployed by numerous websites and their functionality is not perceived as a limitation, rather realized as their focus on the specific market (Iván Cantador, 2015).

Although single domain recommender systems are market specific, sometimes they are found to possess less data related to users and items as compared to their competitors. One way is to assist such recommender systems by transferring knowledge from similar domain hence laying the foundation of cross domain recommender systems. Therefore, identified generic framework in Figure 1.1 is updated to accommodate CDRS concept illustrated in Figure 1.2.

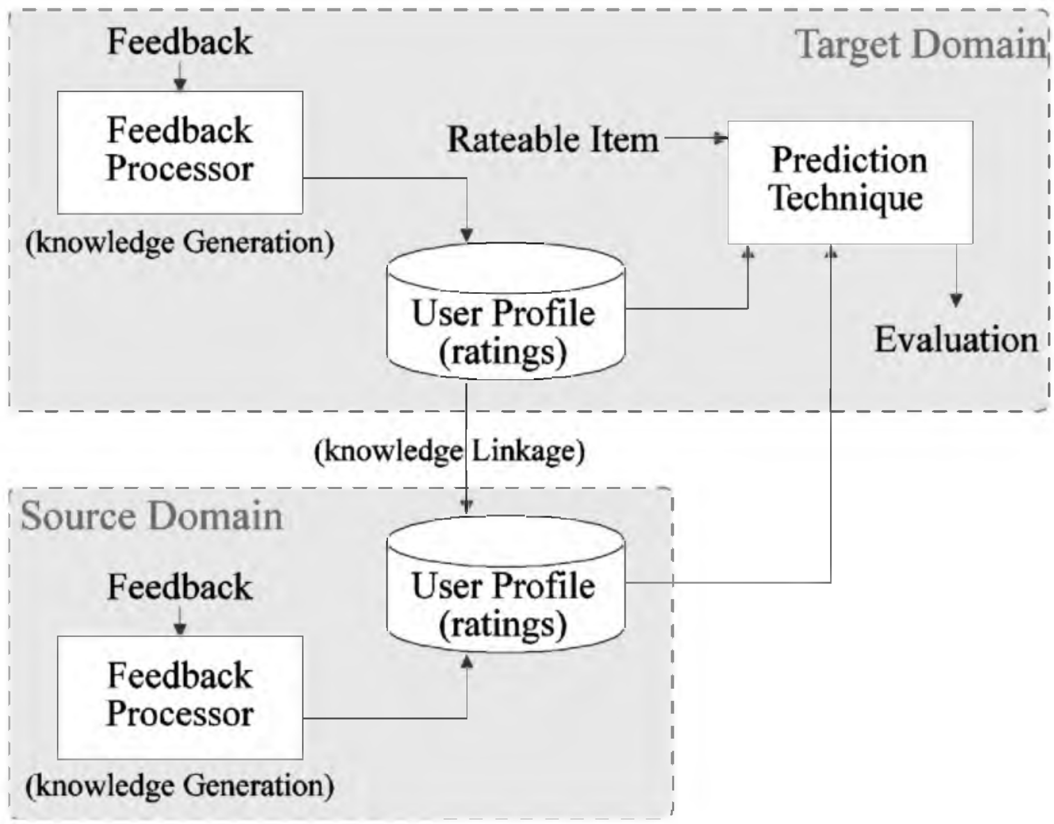

Figure 1.2 Generic Cross Domain Recommendation Framework

CDRS is defined as a combination of methods, techniques and approaches related to transferring knowledge from a source domain to target domain for recommendation improvement (Iván Cantador, 2015). Usually, source domain is considered to have more ratings as compared to the target domain. Both source and target domain have their own users, items and rating matrix. Cross domain recommender systems transfer knowledge based on three attributes, which are domain, user-item overlap and recommendation tasks described as follows. Although domain is defined under multiple contexts, this thesis relies on system domain definition as follows:

System Domain: A rating matrix (Figure 1.1(b)) is considered as a domain, which is generated by a specific recommender system, for example, MovieLens rating matrix is generated by GroupLens recommender systems, NETFLIX generates its independent rating matrix (Iván Cantador, 2015; Li, 2011). Both rating matrices belong to distinct system, hence, are different system domain. A common assumption about distinct system domain is that their users do not overlap.

Recommendation Scenarios: Some relation needs to exist between users and items of participating domains in order to assist transfer learning between domains. Usually, this relation is formed when users and items are found common in both domains. This relation overlap is highlighted by (Cremonesi et al., 2011a). They identified four scenarios, which are no user - no item overlap, user - no item overlap, no user - item overlap and user - item overlap. However, in this research, items are common between the participating domains.

Recommendation Task: Recommendation task is associated with identification of the test user for which recommendation is generated. In the context of this thesis, test user exists in the target domain, hence, cross domain recommendation task attempts to improve recommendation for target domain users using knowledge of both source and target domain (Cremonesi et al., 2011a; Iván Cantador, 2015).

1.4 Recommender Systems Problems

The Recommender System (RS) consists of two basic entities: users and items, where users provide their opinions (ratings) about items. Users are denoted by $U = \{u_1, u_2, ..., u_M\}$, where the number of users using the system is $|U| = M$. Items are denoted by $I = \{i_1, i_2, ..., i_N\}$, and the number of items are represented using $|I| = N$. A user is represented by a unique User Identifier (UId), whereas the item is represented by an Item Identifier (IId). Recommender systems store the history of the user's interactions in rating matrix, hence, based on the available data, recommendation techniques attempt to answer following questions:

i. How to accurately **rank items** for a **new user,** when **no ratings** are previously provided by the respective user?
   This question is associated with cold start problem. **Cold Start problem** is the unavailability of data for new users, and is linked with the limitation of recommender system to rank items for new users (Cantador and Castells, 2012a; Iván Cantador, 2015; Purushotham and Kuo, 2016). The existing method of solving this problem is to recommend items based on group behavior of the other users, known as **"Group-oriented recommendation"** (Cantador and Castells, 2012a; Iván Cantador, 2015; Purushotham and Kuo, 2016), and if no other user is present then items are **ranked randomly** (Park and Chu, 2009a). Group-oriented recommendation works by ranking items based on ratings made available by the other users. In the scope of a conventional framework, these users (and training data) come from single domain only, whereas in the scope of cross domain recommendation framework, these users come from both source and target domain.
ii. How to accurately **rate items** for an **existing user**, when some items have already been rated by the respective user?
   This question is associated with the sparsity problem. **Sparsity problem** refers to a situation in which feedback data is sparse (very few ratings) and insufficient to identify similarities between users having few rating (Iván Cantador, 2015). The existing method of solving this problem is by identifying similar users having relatively more ratings and the process of identifying similar users is known as collaborative filtering and fall under **"user-oriented recommendation"** techniques (Cantador and Castells, 2012a; Iván Cantador, 2015; Lian et al., 2018). User-oriented recommendation techniques rely on the identification of similar users for enriching recommendation accuracy. Similar users come from the single

domain only in the case of a conventional framework, whereas in the case of cross domain recommendation framework, similar users are identified based on data of both source and target domains.

iii. How to **diversely recommend** items for an **existing user,** when **some ratings** have been previously provided by the respective user?

Diversity problem is associated with recommending less popular items having good ratings. In order to do so, current methodology is to inversely rank items based on a group-oriented recommendation (in order to identify less popular item), generate their ratings based on user-oriented techniques (in order to identify personalized ratings of the item) and recommend Top N items to users having highest relative ratings (Adomavicius and Kwon, 2012), which helps in recommendation diversification. Conventional and cross-domain user and group-oriented techniques are utilized for recommendation diversification, where cross-domain recommendation diversity outperforms conventional recommendation diversity.

1.5 Cross Domain Recommendation Using Social Network Integration

This section first explains the concepts related to social network integration, followed by a description of the existing social network integration framework. Finally, the limitations of the social network integration framework are presented.

1.5.1 Related Concepts

Social Network is defined as Community consisting of users with a shared relationship or interest (Borgatti and Halgin, 2011; Chua et al., 2011; Stanley and Robins, 2005). Social network such as Facebook construct communities based on relationships such as friends and families. On the other hand, LinkedIn utilizes the professional connections to build the community. Twitter also allows its users to be a part of a community by following other or having followers. One thing common between all these platforms is that they allow their users to create a neutral community, a community based on interest. Such communities are represented as “Facebook Pages”, ”LinkedIn Pages” and “Twitter Handle” (Chua et al., 2011).

Social Interactions are interactions available on the social networks. Interaction means the act of affecting others, hence in the context of the social network, social interactions are identified as a set of node’s actions that affect another node (Song et al., 2011). In context of this thesis and collected primary studies, social interaction is referred to as a binary interaction “like” or a textual interaction “comment” between nodes (Fernandez, 2013; Li et al., 2013a).

Social Network Integration for recommendation is associated with utilization of content available on the social network (social interactions such as “likes” and “comments”) for the recommendation improvement in target domain (Cantador and Castells, 2012a; Rosli et al., 2014; Shapira et al., 2013a). Social network integration for recommendation is associated with utilization of content available on the social network (social interactions such as “likes” and “comments”) for the recommendation improvement in target domain (Cantador and Castells, 2012a; Rosli et al., 2014; Shapira et al., 2013a).

1.5.2 Social Network Integration Framework

Social network integration framework was found as an emerging area of research based on the conducted systematic literature review. Multiple studies utilize the social network content for improving recommendation in the target domain. Bedi et al., (2015); Quijano-Sanchez et al., (2011, 2014) use social network based popularity ranking approach for generating cold start recommendation for the target domain. Bedi et al., (2015); Díaz-Agudo et al., (2018); Rosli et al., (2014); Shapira et al., (2013a); Vinayak et al., (2016), on the other hand, utilize social network collaborative filtering approaches for improving recommendation accuracy for the sparse target domain. Adomavicius and Kwon (2012); Shapira et al., (2013a) illustrated the benefits of recommendation diversity based on popularity ranking and collaborative filtering approaches, and compared conventional, existing approaches.

Figure 1.3 represents the framework of mentioned studies. The framework consists of a knowledge generation model, knowledge linkage model, and recommendation techniques. Knowledge generation model collects data from users and generates rating matrices (user profiles). Because there are two feedback sources, two matrices are generated. Target feedback is numeric ratings, whereas source feedback is social network interactions. Hence, the target rating matrix contains numeric ratings, whereas source interaction matrix contain user interactions. User interaction is binary in nature. Knowledge linkage model links the two generated matrices which are then passed to recommendation techniques. Recommendation techniques rely on both domain for addressing recommendation problems. A recommendation technique is proposed for each problem, that is, cold start, sparsity, and diversity.

All of the shortlisted studies implemented the designed framework using a Facebook application. Facebook application is designed using the Facebook Application Programming Interface (API) and is hosted on a secure web server (Bedi et al., 2015; Díaz-Agudo et al., 2018; Rosli et al., 2014; Shapira et al., 2013a; Vinayak et al., 2016). The hosted application consists of four parts; the first part is a recommender system that takes input rating from Facebook users against presented items; the second part searches Facebook user's profile for the item that was liked or commented by a user; the third part is responsible for recommending items to the user, whereas the fourth part compares recommendation performance. Existing techniques generated recommendation using both domains, whereas conventional techniques only require a rating matrix for recommendation generation. Generated recommendation are evaluated for cold start, sparsity and diversity problems. Summary of comparison conducted by existing techniques is summarized in Table 1.1.

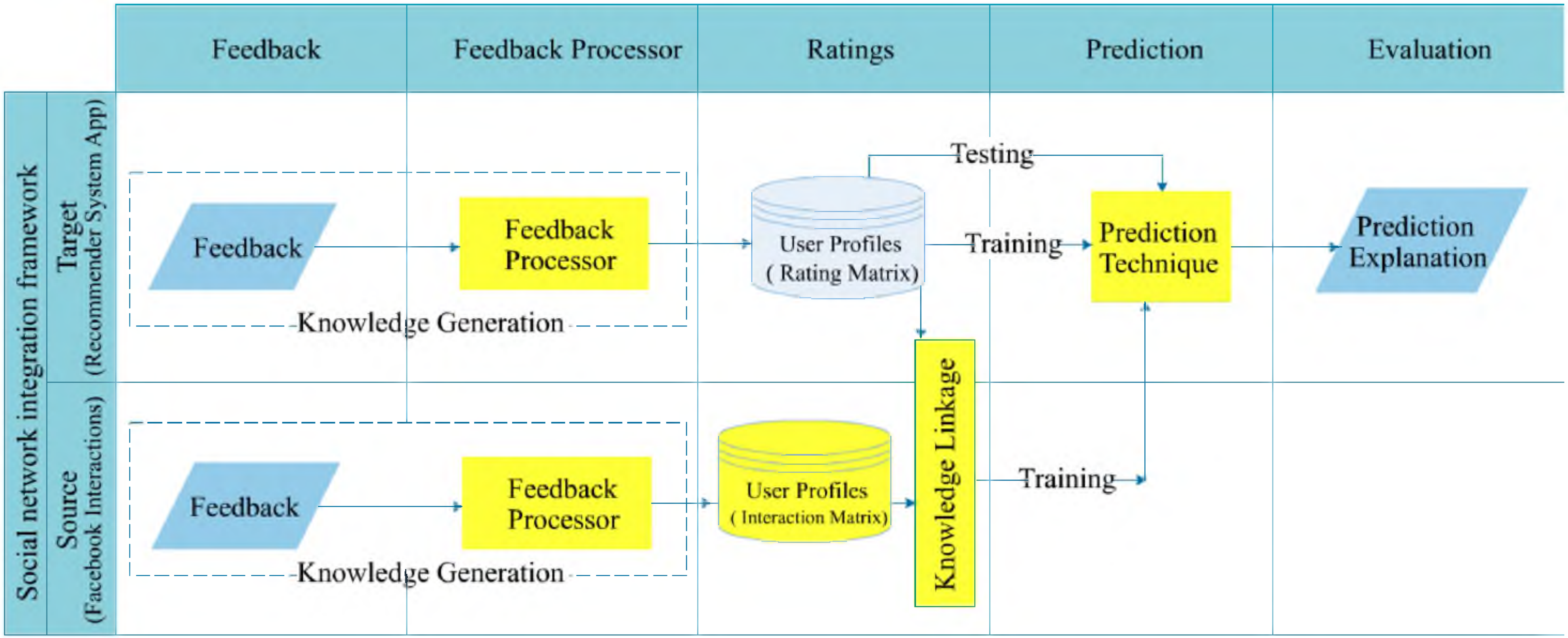

Figure 1.3 Social Network Integration Framework

Table 1.1 Summary of Comparison between Conventional and Existing Framework

Framework	Problems	User Type	Techniques	Depends On
Conventional (baseline) (Figure 1.1)	Cold Start	New	Group oriented recommendation techniques	Single domain (target dataset) / Random function
	Sparsity	Existing (with few ratings)	User oriented recommendation techniques	Single domain (target dataset)
	Diversity	Existing (with few ratings)	Both	Single domain (target dataset)
Social network integration (Existing) (Figure 1.3)	Cold Start	New	Group oriented recommendation techniques	Both domain (Single target / single source)
	Sparsity	Existing (with few ratings)	User oriented recommendation techniques	Both domain (Single target / single source)
	Diversity	Existing (with few ratings)	Both	Both domain (Single target / single source)

Table 1.1 presents a summary of the problems addressed by conventional and existing social network recommendation framework. The comparison is based on the involvement of users from the participating domain(s) of the respective frameworks. The conventional framework relies on a single domain (rating matrix) for training the prediction techniques, whereas social network integration framework relies on the source (social network) and the target domain (rating matrix) for improving recommendation in the target domain. Finally, based on the techniques, proposed cold start and sparsity recommendation are used for diversity computation.

1.5.3 Issues Related to Social Networking Integration Framework

The main limitation of existing work is the use of single social network for improving recommendation in target domain (Rosli et al., 2014; Shapira et al., 2013a). This limitation is rooted in the method they used for data retrieval and the proposed techniques. All of the existing studies designed a recommender system application for collecting data related to items (target domain) and host it on a server. The same application is used for collecting user's data available from their personal wall. In order to link the two domains, they used Facebook authentication for recommender system application, enabling the Facebook user to rate items in the target domain and request personal data access from the same user to collect their personal wall data (as source preferences). Although Facebook application links the two domain, it also limits them to a single source (user preference from a single social network), with the compulsion of the same user participation from both domains.

The second limitation pointed out by existing approach (Shapira et al., 2013a) is the size of data generated for evaluation purposes. Shapira et al. (2013a) conducted an experiment and collected data from 95 participants, who rated 170 movies. Shapira et al. (2013a) connected participation of fewer users with the "personal data access from social network", as it acted as resistance, such that users hesitated to share their personal data. This hesitation is based on a fear that Facebook application can collect a variety of personal data which can be out of research scope, hence, Facebook applications can be exploited to extract users personal information and use for ill purpose as done by researchers of Cambridge Analytica (Isaak and Hanna, 2018).

The third limitation is related to the type of data that is not used for recommendation improvement, such as users comment on different posts. Comments can be analyzed to extract the sentiment related to an item. In response, this research attempts to analyze the effect of integrating multiple social networks for the cross-domain recommendation.

The first direction of improvement is to propose a framework that integrates content from multiple social networks for the cross-domain recommendation. This requires upgrading existing cross-domain recommendation model, that is, knowledge extraction and knowledge linkage. Knowledge extraction has to be generalized so that it can extract knowledge from multiple social networks without user's permission, that is, accessing public data related to a user. As multiple social networks do not guarantee the same user participation in all domain, knowledge linkage model needs to be extended. Similarity technique has to be applied between participating users in order to link the users of the participating domains.

Once knowledge is generated and linked between the multiple sources and target domain, second direction for improvement is to extend existing techniques to be compatible with multiple domains. Currently, cold start, sparsity and diversity techniques rely on one source and one target domain, and hypothesizes that data from multiple social networks can enable techniques to make a better recommendation than existing single social network based techniques. Hence, based on identified problems and improvement directions, next section proposes the research hypothesis and formulates research questions.

1.6 Problem Statement

Recommender systems face a variety of problems such as cold start and diversity, which are addressed by a number of conventional recommendation techniques. Conventional recommendation techniques rely on a single domain for the recommendation, which is considered as research gap by the existing studies. In response, existing studies attempt to fill this gap by integrating knowledge from a single social network. Social network integration framework enables recommendation techniques to utilize an additional source for improving recommendation in the target domain. However, they are limited to the use of one source only. This is identified as the research gap in existing studies, hence problem statement for this research is formulated as follows:

"How can multiple social networks be integrated for recommendation across the system domain and is the integration of multiple social networks more effective than single social network integration?"

The problem statement is used to create two research hypothesis which are discussed in Section 3.6 of Chapter 3. The first hypothesis is related to the validation of data created for each participating social network, whereas the second hypothesis is related to the validation of techniques compared for solving cold start, sparsity, and diversity problem.

1.7 Research Questions

This study aims to overcome the aforementioned issues by exploiting social interactions available on different social networks (Facebook pages) in order to generate recommendation outside Facebook. Research questions are written as follows:

i. How can the multiple social networks be integrated for recommendation across system domain?
ii. How can existing cold start recommendation technique be enhanced to make it compatible with multiple social network integration?
iii. How can existing sparse recommendation technique be enhanced to make it compatible with multiple social network integration?
iv. How can recommendation based on proposed cold start and sparse recommendation techniques be diversified?

1.8 Aim of Research

The aim of this research is to propose a multiple social network integration framework comprised of two models and three techniques. Models are responsible for data generation and linkage, whereas techniques are responsible for improving identified recommendation problems.

1.9 Objective of Research

Based on the identified research question, objectives of the research are explained as follows:

i. To propose a multiple social network integration framework for improving cold start and sparse recommendation accuracy and recommendation diversity across system domain.
ii. To enhance the existing popularity ranking technique and make it compatible with multiple social network integration for improving cold start recommendation.
iii. To enhance the existing collaborative filtering technique and make it compatible with multiple social network integration for improving sparse recommendation.
iv. To design and develop threshold based diversity technique depending on enhanced popularity ranking and collaborative filtering technique for improving recommendation diversity.

1.10 Scope of Research

The study is limited to the following aspects:

i. Facebook public social interactions are hosted at variety of Facebook pages (social network), however, not all pages can be used for item recommendation. For this research, we focus only on those pages that are verified and discuss multiple items (movies) in their page posts. As a result, four Facebook pages were identified, which are further discussed in Chapter 4.
ii. Social interactions available on Facebook's public pages contain implicit interactions such as like, comment and share. However, Facebook does not

allow access to retrieve “share” data, hence, social interaction used for integration are likes and comments only.

iii. Movielens, the industry standard dataset, is used as the target domain hence items (movies) are common between multiple sources (Facebook pages) and the target domain.

iv. Time complexity for the proposed and existing techniques is not in the scope of this thesis.

v. Compared studies utilized popularity and random ranking as group oriented recommendation techniques for addressing the cold start recommendation problem, whereas for the sparsity problem, social collaborative filtering technique is used as a user-oriented recommendation technique. Hence, identified techniques are enhanced for multiple social network integration framework and are compared with identified techniques.

1.11 Significance of Research

The research is important from theoretical and practical perspectives. The significance of research is as follows:

i. Systematic literature review related to cross-domain recommender systems research is conducted, which helped in the classification of existing CDRS research with respect to highlighted definition, identification of existing algorithms, related evaluation methods, existing problems, and future directions.

ii. This research also presents multiple social network integration framework for the cross-domain recommendation.

iii. This research enhances the existing cold start and sparsity techniques by making them compatible with multiple social networks. Proposed cold start and sparsity techniques also improve recommendation diversity.

iv. This research provides a social network knowledge extraction tool built on open source technologies.

1.12 Thesis Organization

Chapter 1, "Introduction", introduces cross domain recommender systems research and highlight limitations of existing social network integration framework. Problem background results in the identification of problem statement which leads to research questions. Research questions further helped in the creation of research objectives. Near the end of the chapter, aim and significance of the research are delineated and finally, the summary is presented.

Chapter 2, "Literature review", helps in the identification of problem background and statement. This chapter starts with explanation of the cross-domain recommender systems and its building blocks. Systematic literature review helped in identification of main issues associated with CDRS research. SLR findings also helped in scope identification of the main research i.e. social network integration for the cross-domain recommendation. Problems addressed by the selected framework were discussed and techniques used to solve respective problems were analyzed. Finally, existing literature identifying improvement directions was discussed.

Chapter 3, "Research methodology", outlines research methodology used to plan and solve the proposed problem. After describing the common terminologies, the research framework is presented in connection with the operational framework. Operational framework outline research phases. This study has four research phases, which are constructed based on the proposed objectives in Chapter 1. Chapter 3 presents the methodology used to achieve the objective which resulted in the creation of separate chapters for each objective. At the end of chapter 3, the connection between the research question, objectives and following chapters is presented.

Chapter 4, "Multiple social network integration framework", visually presents the proposed framework. This chapter explains in detail the knowledge generation and linkage model and how enhanced techniques will take generated input for generating the recommendation. This chapter also introduces the tool used for generating data from the social network. While explaining each model, a sample of the generated data is also discussed, which at the end of the chapter is compared with the target domain in order to identify the similarity between the participating domain.

Chapter 5, “Multiple social networks based popularity ranking algorithm for cold start recommendation”, proposed three variations of popularity ranking algorithm based on multiple social networks. Proposed popularity ranking algorithms were compared with existing and baseline popularity ranking algorithms. Results are discussed at the end of the chapter.

Chapter 6, “Multiple social network popularity based neighbor selection algorithm for sparse recommendation”, first explains baseline and existing social network based collaborative filtering technique, followed by proposed multiple social networks based collaborative filtering technique. In the end, technical analysis is presented based on the generated results.

Chapter 7, “Multiple social networks based diverse recommendation”, generates recommendation diversity using baseline, existing and proposed cold start and sparse recommendation techniques proposed in Chapter 5 and Chapter 6. Finally, generated results show performance comparison.

Chapter 8, “Conclusion and future work”, discusses in detail how each objective was achieved and what contributions were made during the process. Next, the conclusion was presented and finally, future work is highlighted.

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