GOAL-BASED FILTERING APPROACH FOR RECOMMENDER SYSTEM

MUHAMMAD WASEEM CHUGHTGAI

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"*To my beloved family, thanks for your love and support in every effort I did. To all my friends; thanks for your encouragement and for willing to lend your hands in the journey of dreams and hope.*"

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ABSTRACT

Recommender system is a sub part of information retrieval. It decreases the content searching time, increases the user's interest, and provides recommendations relevant to user's goals or interests. The major drawback of recommender system is user-based cold-start problem, which has two causes: new-user zero-rated profile recommendations and average-user low-rated profile recommendations. This research proposes goal-based filtering approach consisting of two hybrid parts; first is content-based filtering with collaborative features to overcome the first cause of user-based cold-start problem. The second is collaborative filtering with *k*-nearest neighbor scheme features to improve the second cause of user-based cold-start problem. The famous 'MovieLens' dataset is rich with its 927 entries of user's profile data, which makes it a choice for experiments on the proposed work. The cosine similarity and euclidean distance measurements have been used to compute the personalized profile similarities between users profile preferences according to their age, gender and occupation. These similarities are helpful to predict the recommendations to the zero-rated and low-rated users without using any extra information such as ratings, likes or dislikes. The evaluation of experiments has been performed using mean precision with result of 83.44% and mean recall with result of 85.22%. The results demonstrate that percentage of user's profile similarity measurements is probably effective for web-based system's recommendations.

ABSTRAK

Sistem pencadang adalah sebahagian daripada capaian maklumat semula. Ia mengurangkan penggunaan masa untuk mencari sebarang kandungan, meningkatkan minat pengguna, dan menyediakan cadangan yang berkenaan dengan tujuan atau kepentingan pengguna. Kelemahan utama sistem pencadang adalah masalah pengguna berasaskan *cold-start*, yang mempunyai dua punca: pengguna baru dengan cadangan-cadangan profil *zero-rated* dan pengguna ditahap sederhana dengan cadangan profil *low-rated*. Kajian ini mencadangkan pendekatan penapisan *goal-based* yang terdiri daripada dua bahagian hibrid; pertama adalah penapisan kandungan berasaskan dengan ciri-ciri kerjasama untuk mengatasi punca pertama masalah pengguna berasaskan *cold-start*. Kedua adalah penapisan dengan skim kerjasama ciri-ciri *k-nearest neighbor* untuk memperbaiki punca kedua masalah pengguna berasaskan *cold-start*. Set data terkenal iaitu 'MovieLens' yang kaya dengan 927 penyertaan daripada data profil pengguna yang membuatkannya menjadi satu pilihan bagi eksperimen ke atas kerja yang dicadangkan. Ukuran jarak keserupaan kosinus dan ukuran jarak euclid telah digunakan untuk mengira persamaan di antara pilihan profil mengikut umur, jantina dan pekerjaan mereka. Persamaan-persamaan ini berguna untuk meramalkan cadangan kepada pengguna-pengguna *zero-rated* dan *low-rated* tanpa menggunakan apa-apa maklumat tambahan seperti pengkadaran, suka atau tidak suka. Penilaian keputusan eksperimen telah dilakukan dengan menggunakan purata ketepatan dengan hasil 83.44% dan purata mengingat kembali sebanyak 85.22%. Keputusan-keputusan menunjukkan bahawa peratusan pengukuran persamaan profil pengguna mungkin berkesan untuk laman web berasaskan sistem cadangan ini.

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LIST OF SYMBOLS

SYMBOL	DESCRIPTION
D	Dataset
R	Total ratings by user to items
I	Items profile class
U	Users profile class
'$u \in U$'	One user 'u' belongs to the user's dataset class 'U'
'$i \in I$'	One Item 'i' belongs to the items dataset class 'I'
$R_{u\rightarrow i}$	Total rating of items by the user
T_R	Training set
T_S	Testing set
$dot(u, v)$	Dot product of user's class $u \in T_R$ and user's class $v \in T_S$
$norm$	Normalization
$Sim(T_{R1},T_{S1})$	Similarity between training set 1 and testing set 1
$Sim(T_{R2},T_{S2})$	Similarity between training set 2 and testing set 2
$[U_n \text{ x } V_n]$	Profile similarity factorization matrix with total user profiles U_n in training set and total user profiles V_n in training set
$R_{(u\rightarrow i)}$	Similar user rated items
Pr	Precision
Re	Recall
$T_{(U,V)}$	Total users in class classes U_n and V_n
$T_{(Sim(U,V)}$	Total similar users profiles between classes U_n and V_n
$T_{Relv(U,V)}$	Total number of relevant similarity users profiles

LIST OF ABBREVATION

AYNONYM		ABBRIVATION
AUP	-	Average-user profile
CBF	-	Content-based Filtering
CF	-	Collaborative Filtering
HF	-	Hybrid Filtering
IR	-	Information Retrieval
KNN	-	k-Nearest Neighbor
NUP	-	New-user profile
RS	-	Recommender System
SUP	-	Super-user profile

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CHAPTER 1

INTRODUCTION

1.1 Overview

Knowledge, technology and mutual environments enhancements in contrast to modern web-based systems become an important part of daily life for millions of users for achieving their required goals, e.g., what the user trying to achieve or what the user set out to achieve. Modern web-based systems provide many benefits to users, it may increase some difficulties too; the one and major difficulty is large content mismanagement by increasing the number of pages (Salmon, 2003). This page-to-page running environment discourages the user's interests and less helpful for retrieving the required item in a particular timeframe. However, the recommender system (a central part of information retrieval) could offer an appropriate way to overcome the large content mismanagement issue and retrieve the relevant items more quickly and easily (Shishehchi et al., 2010; Shishehchi et al., 2011).

Recommender system is a central part of information retrieval for retrieving the relevant information (Ghauth and Abdullah, 2010) that offers more flexibility for users to decrease the difficulty of large content management. It helps to decrease the item searching time, increase the user's interest, and provide the recommendations relevant to user's goals or interests (P.di Bitonto et al., 2010). A simple and clear definition of recommender system is:

> "A Recommendation works as a sub system, known as recommendation systems or some time called recommender systems RS, which aims to help a user or a group of users in a system to

> collect required items from a crowded content lists or information space (McNee et al., 2006). ”

The operations of recommender system based on three filtering approaches, which are content-based filtering CBF, collaborative filtering CF and hybrid filtering HF approaches (Lara, 2004). In content-based filtering CBF, the system recommend only those relevant items to users that are similar to the ones they preferred them self in the past (Adomavicius and Tuzhilin, 2005). While, the collaborative filtering CF, the system recommend those relevant items that other users with similar interest and preferences liked in the past (Ghazanfar and Prugel-Bennett, 2010). The hybrid filtering HF is a third way to tackle the filtering results (Burke, 2002). The hybrid approaches plays a controversial role to tackle the users required goals.

With respect to traditional research aspects, every filtering approach in hybrid filtering has its own limitations. The famous and well-known problem is user-based cold-start and identifies with two major causes, which are as follows:

i) New-user zero-rated profile recommendations, defined in (Section 1.2.1)
ii) Average-user low-rated profile recommendations, defined in (Section 1.2.1)

In this problem, the user unable to retrieve any or less items from the system, if user does not visit any or less items and rate or vote them or the user do not have any sufficient past profile preferences, as like or dislike.

To improve the expertise of recommender system and overcome the above causes, this research proposed the goal-based filtering approach that tolerates the user goals by measuring users personalized profile preferences “age, gender and occupation” similarities with other users personalized profile preferences “age, gender and occupation”. With respect to the above two causes of use-based cold-start problem, this research validate the users in three categories, that are new-user zero-rated profiles, average-user low-rated profiles and super-user high-rated profiles. The personalized profile similarities between these three category of users are helpful to predict their required items or goals and overcome the above two causes of use-based cold-start problem.

This research work constructed the goal-based filtering approach interwork with users personalized profile similarity measurements, instead of meta-keywords; predefine predictions or historical informational aspects. The filtering aspects of proposed work have been worked with the hybridization of content-based filtering with collaborative features to overcome the new-user zero-rated profile recommendations issue. Perhaps, the hybridization of collaborative filtering with k-nearest neighbor scheme features is helpful to improve the average-user low-rated profile recommendations.

1.2 Problem Background

The growing challenges in the problem domain affect the performance of recommender systems; however, one of the major challenge is user-based cold-start, which moderated against the user own historical (like or dislike, purchasing, reading, etc.) preferences (T. Qiu et al., 2011). The detail of user-based cold-start problem is defined as follows:

1.2.1 User-Based Cold-Start Problem

The cold-start is a well known in all types of recommender systems (F.Lecue, 2010). Generally, in this, the system led to none or poor recommendation and damaged the resultant filtered content of recommender system (Ghazanfar and Prugel-Bennett, 2010). This problem has encompasses by two issues, which are:

a) New-User Zero-Rated Profile Recommendation Issue

When the user is new in the system, the system is unable to extract sufficient information from the user profile that is required for the starter recommendations (Y. Blanco-Fernandez et al., 2008; Y.Blanco-Fernández et al., 2011). In other words, the recommender systems generally works with the users own historical or rated profile preferences. Therefore, the new-user in the system do not visit and rate any item, so the system does not acclaim the users required goals and unable to filter the starter or new recommendations.

b) **Average-User Low-Rated Profile Recommendation Issue**

The existing literature induced that the users, which are not new in the system are also facing the forecasting recommendation issues (Ge, 2011; Z. Mi and C. Xu, 2012). In other words, it has occurred when the user is not regular in the system, or user has not rated and visited much items. In both of cases, the system is not able to produce the recommendations, which loses the users interest.

1.3 Problem Statement

This study encompasses the main research question of this proposed study is as follows:

> "What methods are available to combine recommendation approaches or features and which of those methods are suitable for integrating the user-based personalized similarities to overcome the issue of new-users zero-rated profile recommendations and improve the average-users low-rated profile recommendations, with the help of super-users high-rated profiles?"

In order to answer this question, the following research points have to be answered:

(i) What methods are exists to combine the recommendation techniques and which of these methods are suited for the proposed work?

(ii) Which dataset have suitable user-based content for profiles similarity experimentation, how to validate and normalize it?

(iii) How to identify the new-user zero-rated profiles, average-user low-rated profiles and super-user high-rated profiles?

(iv) What similarity measurements are useful to measure the personalized profile similarities between new-user zero-rated profiles, average-user low-rated profiles and super-user high rated profiles?

(v) How the personalized profile similarity measures are useful to overcome the new-user zero-rated profile recommendation and improve the average-user low-rated profile recommendation?

1.4 Objectives

In order to fulfill the requirements of the research questions, following objectives were identified for this research study:

(i) To study the 'MovieLens' dataset and performs *f*-fold cross validation for the classification of users profiles as new-users with zero-rated profile, average-users with low-rated profile, and super-user with high-rated profiles from relevant dataset.

(ii) To propose goal-based filtering approach that hybridized content-based filtering with collaborative features to overcome the new-user zero-rated profile recommendations and collaborative filtering with k-nearest neighbor features to improve the average-user low-rated profile recommendations.

(iii) To operate the similarity, cosine and euclidean distance measurements have been used to tackle the user-based personalized profile similarities between zero-rated users, low-rated users, and high-rated users that help to predict the recommendations for new and average users.

1.5 Aim

The aim of this proposed research work is to focus the user-based cold-start problem through proposed goal-based filtering approach with the help of cosine and euclidean distance similarities between new-user zero-rated profiles and average-user low-rated profiles and super-user high-rated profiles personalized preferences "age, gender, and occupation" to overcome the new-user zero-rated profile recommendations and improve the average-user low-rated profile recommendations.

1.6 Scope

The scope of this research study has been confined as follows:

(i) This research focuses on the user-based cold-start problem and its two main causes, which are new-user zero-rated profile recommendations and average-user low-rated profile recommendations.

(ii) 'MovieLens' dataset has been used for experimental setup.

(iii) The *f*-fold cross validation has been studied for validating and normalizing the dataset that helps to classify the zero-rated profiles as new-user, low-rated profiles as average-user and high-rated profiles as super-users profiles.

(iv) The research used content-based filtering with collaborative features and collaborative filtering with k-nearest neighbor scheme features to fulfill the aspects of proposed goal-based filtering approach.

(v) The cosine and euclidean distance similarity measurements are being used to compute the similarities between new-user, average-user and super-user personalized profile preferences "age, gender and occupation."

(vi) These similarities are helpful to predict the recommendations for end user or group of users.

(vii) Precision and recall has been used to perform evaluation of uses personalized profile similarity experimental results.

1.7 Significance of Study

(i) Increase the user's interest and decrease the web-based item searching time.

(ii) Overcome the new-user zero-rated profiles recommendations issue and improve the average-user low-rated profile recommendations issue simultaneously.

(iii) Improve the recommendation prediction strategy with personalized profile similarities between two or group of users to accrue the users required goals.

1.8 Organization of Thesis

This research thesis consists of six chapters. Chapter 1 defined the **i**ntroduction, problem and their objectives, aim, scope and significance of study. The chapter presents the systematic review on the filtering approaches of recommender system. Moreover, it also prescribes the land-escape of problem domain. Chapter 3 defines the landscapes of research methodology of proposed work. The proposed goal-based filtering approach, its operational work and detailed description has been covered in Chapter 4. Chapter 5 shows the experimental results and discussion of research outcome. At last, the conclusion, research contribution, work limitation and future work of this research has been mentioned in Chapter 6.

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