**UNIVERSITI PUTRA MALAYSIA**

***TEMPORAL INTEGRATION BASED FACTORIZATION TO IMPROVE PREDICTION ACCURACY OF COLLABORATIVE FILTERING***

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**FSKTM 2016 40**

# TEMPORAL INTEGRATION BASED FACTORIZATION TO IMPROVE PREDICTION ACCURACY OF COLLABORATIVE FILTERING

By

**ISMAIL AHMED AL-QASEM AL-HADI**

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy**

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# DEDICATION

Dedicated to the human beings

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

**TEMPORAL INTEGRATION BASED FACTORIZATION TO IMPROVE PREDICTION ACCURACY OF COLLABORATIVE FILTERING**

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**Chairman: Nurfadhlina Mohd Sharef, PhD**
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A recommender system provides users with personalized suggestions for items based on the user's behaviour history. These systems often use the collaborative filtering (CF) for analysing the users' preferences for items in the rating matrix. The rating matrix typically contains a high percentage of unknown rating scores which is called the data sparsity problem. The data sparsity problem has been solved by several approaches such as Bayesian probabilistic, machine learning, genetic algorithm, particle swarm optimization and matrix factorization. The matrix factorization approach through temporal approaches has the accurate performance in addressing the data sparsity problem but still with low accuracy. The existing temporal-based factorization approaches used the long-term preferences and the short-term preferences. The difference between long-term preferences is that it utilizes the whole recorded preferences while the short-term preferences utilizes the recorded preferences within a session (e.g. week, month, season, etc.). However, there are four issues when a factorization approach is adopted which are latent feedback learning, score overfitting, user's interest drifting and item's popularity decay over time.

This study proposes three approaches which are (i) the Ensemble Divide and Conquer (EDC) which achieved accurate latent feedback learning, (ii) two personalized matrix factorization (MF) based temporal approaches, namely the LongTemporalMF and ShortTemporalMF to solve overfitting during the optimization process, user's interest drifting and item's popularity decays over time and (iii) TemporalMF++ approach which solved all the issues. The TemporalMF++ approach relies on the k-means algorithm and the bacterial foraging optimization algorithm.

The Root Mean Squared Error metric is used to evaluate the prediction accuracy. The factorization approaches such as the Singular Value Decomposition, Baseline, Matrix Factorization and Neighbours based Baseline are used to be compared against the proposed approaches. In addition, the Temporal Dynamics, Short-Term based Latent, Short-Term based Baseline, Long-Term, and Temporal Interaction approaches are used to benchmark the proposed approaches.

The MovieLens, Epinions, and Netflix Prize are real-world datasets which are used in the experimental settings. The experimental results show the TemporalMF++ approach is higher prediction accuracy compared to the approaches of EDC, LongTemporalMF, and ShortTemporalMF. In addition, the TemporalMF++ approach has a prediction accuracy higher than the benchmark approaches of factorization and temporal. In summary, the TemporalMF++ approach has a superior effectiveness in improving the accuracy prediction of the CF by learning the temporal behaviour.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**PENGINTEGRASIAN TEMPORAL BAGI MEMPERBAIKI KETEPATAN RAMALAN KEJARANGAN DATA DI DALAM PENAPISAN BERKOLABORASI**

Oleh

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Sesebuah sistem cadangan memberikan pengguna cadangan item secara personalisasi berdasarkan sejarah kelakuan pengguna. Sistem-sistem ini selalunya menggunakan penapisan berkolaborasi (CF) untuk menganalisa kecenderungan pengguna-pengguna bagi item-item di dalam matriks perkadaran. Matriks perkadaran biasanya mengandungi skor pekadaran dengan peratusan yang tinggi dan ini dikenali sebagai permasalahan kejarangan data. Masalah kejarangan data telah diselesaikan oleh beberapa pendekatan seperti kebarangkalian bayesian, pembelajaran mesin, algoritma genetik, pengoptimuman partikel paya dan pemfaktoran matriks. Pendekatan pemfaktoran matriks menerusi teknik-teknik temporal mempunyai pencapaian yang tepat di dalam menangani permasalahan kejarangan data tetapi masih dengan ketepatan yang rendah. Pendekatan-pendekatan pemfaktoran berdasarkan temporal yang ada menggunakan kecenderungan jangkamasa panjang dan kecenderungan jangka masa pendek. Perbezaan di antara kecenderungan jangka masa panjang dan jangka masa pendek ialah kecenderungan jangka masa panjang menggunakan keseluruhan rekod kecenderungan manakala kecenderungan jangkamasa pendek menggunakan kecenderungan yang direkod di dalam satu sesi (cth, minggu, bulan, musim, dll). Walaubagaimanapun, terdapat empat isu di mana pendekatan pemfaktoran digunapakai iaitu pembelajaran suapbalik pendam, skor terlebih muat, kehanyutan minat pengguna-pengguna dan pereputan populariti item dalam suatu tempoh.

Kajian ini mencadangkan tiga pendekatan iaitu (i) Ensembel Pecah dan Takluk (EDC) yang mencapai pembelajaran suapbalik pendam yang tepat, (ii) dua pemfaktoran matriks berpersonalisasi berdasarkan pendekatan temporal, yang dinamakan TemporalPanjangMF dan TemporalPendekMF bagi menyelesaikan terlebihmuat semasa proses optimisasi, hanyutan minat pengguna-pengguna dan pereputan populariti item dalam tempoh masa, dan (iii) pendekatan TemporalMF++ yang menyelesaikan semua isu. Pendekatan TemporalMF++ bergantung kepada algoritma k-means dan algoritma optimisasi bakteria pengumpul makanan.

Metrik Ralat Punca Min Kuasa Dua digunakan untuk menilai ketepatan ramalan. Pendekatan-pendekatan pemfaktoran seperti algoritma Nilai Penguraian Tunggal, Garis Asas, Pemfaktoran Matriks dan Garis Asas Berdasarkan-Jiran digunakan untuk perbandingan dengan pendekatan yang dicadangkan. Sebagai tambahan, pendekatan-pendekatan dinamik temporal, pemendaman berdasarkan jangkamasa-pendek, garis asas berdasarkan jangkamasa-panjang, jangkamasa-panjang dan interaksi temporal digunakan sebagai penanda aras kepada pendekatan yang dicadangkan.

MovieLens, Epinions dan Hadiah Netflix adalah dataset dunia sebenar yang digunakan di dalam eksperimen. Hasil eksperimen menunjukkan yang pendekatan TemporalMF++ mempunyai ketepatan ramalan yang lebih tinggi dibandingkan dengan pendekatan EDC, TemporalPanjangMF dan TemporalPendekMF. Tambahan lagi, pendekatan TemporalMF++ mempinya ketepatan ramalan yang lebih tinggi daripada pendekatan pemfaktoran dan temporal. Ringkasnya, pendekatan TemporalMF++ lebih efektif di dalam memperbaiki pencapaian ramalan CF dengan mempelajari kelakuan temporal.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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# LIST OF ABBREVIATIONS

| | |
|---|---|
| BFOA | Bacteria foraging optimization algorithm |
| CF | Collaborative filtering |
| DCI | Divide and conquer based on similarity of items |
| DCU | Divide and conquer based on the similarity of users |
| DCUI | Combination between DCU and DCI |
| EDC | Ensemble Divide and Conquer approach |
| KNN | k-nearest neighbour |
| MAE | Mean Absolute Error |
| MF | matrix factorization |
| PMCF | Probabilistic Memory-based Collaborative Filtering |
| RMSE | Rroot mean squared error |
| RS | Recommendation System |
| SVD | Singular Value Decomposition |

# CHAPTER 1

# INTRODUCTION

## 1.1 Motivation

Recommendation system (RS) is becoming popular due to its great utility of users interests to recommend personalized items (Hong et al., 2012). Collaborative filtering (CF) is one of the most popular techniques of the personalized recommendations, where CF generates personalized predictions based on the similarities among members in the rating matrix. However, the rating matrix contains a high percentage of unknown rating scores which lowers the quality of the prediction. The similarity evaluation among the common users will be impossible or not reliable when the percentage of unknown rating scores (data sparsity) are high which lower the quality of the prediction (Sharma and Gera, 2013; Verbert et al., 2011; Bobadilla et al., 2011; Bobadilla et al., 2013).

Several factorization approaches have addressed the data sparsity problem (Koenigstein et al., 2011; Zhou et al., 2011; Mirbakhsh and Ling, 2013). The factorization approaches use the latent feedback of preferences, the baseline variants and the latent factors which are the combination between the baseline variables and the latent feedback in several formulas. The Singular Value Decomposition (SVD) is one of the algorithms which provide the latent feedback of preferences. During streaming the rating scores of the users into the memory, some rating scores have misplaced from its appropriate cell in the rating matrix which lower the quality of the latent feedback and this limitation has been solved by the divide and conquer matrix factorization approach (Mackey et al., 2011). However, the divide and conquer matrix factorization approach relies on randomize matrix factorization and it has not used the similarity of users or the similarity of items in learning the accurate latent feedback. The Ensemble Divide and Conquer approach (EDC) is proposed for learning the accurate latent feedback of preferences based on the similarities among the members in the rating matrix.

The temporal recommendation system is designed to recommend the items to the users at a suitable time where the time is a significant factor to learn the interest of users and the popularity of items over time (Koenigstein et al., 2011; Hong et al., 2012). Thus, the temporal preference with matrix factorization is one of the successful collaborative-based approaches compared to the factorization based approaches in addressing data sparsity. The Temporal Dynamics approach by Koren (2010a) has improved the prediction accuracy of the CF, where this approach divides the time of preferences into static numbers of bins while the time preferences are changed over time. This approach learns a global weight based on the stochastic gradient descent algorithm for minimizing the overfitting. However, the global weight has a weakness in term of personalized preferences, which motivates to find other weights based on personalized preferences and find the suitable learning algorithm for learning these weights.

Ye and Eskenazi (2014) improved the prediction performance of the CF technique using the temporal interaction between two kinds of temporal preferences which are the long-term preferences and the short-term preferences. The short-term preferences are represented by the shrunk neighbour method. In addition, the short-term technique based on the shrunk neighbour (Koren, 2008; Ye and Eskenazi, 2014) gives the short-term feedback of users and incorporated it into the baseline variants which suffer from overfitting (Koren, 2010a). The overfitting in the predicted rating scores means a few of the predicted values are bigger than the range scale of the rating scores, e.g. the range scale of MovieLens dataset [0-5] when the predicted rating scores are such as {5.3; 6.2; 5.5}. Although the overall performance of the prediction accuracy of the Temporal Integration approach by Ye and Eskenazi (2014) is better than the Short-Term based Latent approach by Yang et al. (2012), the performance of the prediction accuracy is still poor and it needs more improvements. Besides, the concept drift is the most significant challenge for recommendation systems based temporal where the customer interest is drifting over time (Koren, 2010a; Ma et al., 2007; Saha et al., 2010). The prediction performance in the sparse rating matrix is still low by the latent feedback of the preferences due to concept drift in the users' preferences and also in the popularity of items over time. Therefore, the TemporalMF++ approach, which is the integration of the LongTemporalMF and ShortTemporalMF approaches is proposed to solve the current limitations of temporal approaches.

## 1.2 Problem Statement

CF is one of the most popular techniques of the recommendation system due to the least computational demand required (Abdelwahab et al., 2012). CF suffers from a high percentage of unknown rating scores in the rating matrix which is called the data sparsity problem. Besides, during data streaming into memory, some rating scores are misplaced from its appropriate cell in the rating matrix which lowers the quality of the latent feedback by the SVD. Mackey et al. (2011) proposed the divide and conquer matrix factorization approach to address this problem based on the approximation among the randomize MF. However, neither the user similarity nor the item similarity have not exploited, which might yield the accurate prediction accuracy.

Recently, the temporal preferences with matrix factorization is one of the successful collaborative-based approaches compared to the factorization based methods (SVD, baseline, matrix factorization (MF) and Neighbours based Baseline) in addressing data sparsity. Koren (2010a) has addressed the data sparsity through the Temporal Dynamics approach which suffer from the difficulties in splitting the timeline to static numbers of bins while the user's preferences are changed over time. This approach minimizes the overfitting of the predicted rating scores in the latent space by a global weight. However, global weight has weaknesses in terms of personalized preferences. Meanwhile, Yang et al. (2012) has addressed the data sparsity problem by temporal approach using the Short Term-based Latent approach which focus on learning the short-term preferences through the latent feedback of the neighbours' preferences. This approach has a weakness in terms of the long-terms, drift behaviours of the users, and item's popularity decay over time. In addition, Ye and Eskenazi (2014) have addressed the data sparsity problem through the Temporal Interaction approach using long-term and short term-based baseline techniques which focus on the drift issue. However, this approach has weaknesses in terms of personality, and also in terms of learning the drift and the items' popularity decay over time where the prediction accuracy of the CF is still low.

Presently, the latent feedback learning, the scores overfitting, the drift of the user's preferences and the time decay of the item's popularity are the current limitations of the temporal recommendation system which typically utilize the long-term and/or the short-term user preferences. This is because users' behaviours are changing throughout the course of time. Furthermore, the popularity of items also decays over time (indicated by decreasing rating scores). Therefore, the temporal terms are the significant factors in learning the users' behaviours and the interest for each item over the stretch of time. MF combines the latent feedback by SVD, baseline variants and the temporal factors of long-term and short-term techniques. However, MF needs to be improved for the short-term technique and it is also still weak in handling the drifting of user preferences. Besides, the weaknesses of the Temporal Dynamics , Short Term-based Latent and Temporal Interaction approaches are that they neither give the solution for the drift of the user's preferences nor the decay time of the item's popularity during the long-term. For the short-term, the best approach is the neighbourhood with the base features by Ye and Eskenazi (2014), while the long-term approach (Ye & Eskenazi, 2014) is used to learn the drift in the user's preferences because the drift in the popularity of items is caused by an evolution of the user's taste. The hybrid of short-and long-term (Ye & Eskenazi, 2014) is used to learn the drift in the user's interest over time.

## 1.3 Research Objectives

The main objective is to propose a temporal integration approach based on matrix factorization namely TemporalMF++ to improve prediction accuracy of the data sparsity in the collaborative filtering. The detail objectives are as follow:

1. To propose Ensemble Divide and Conquer approach for solving latent feedback learning which provides the accurate prediction scores.

2. To propose the personalized temporal-based approach using bacterial foraging optimization algorithm to solve scores overfitting, user's interest drifting and item's popularity decay over time which provides the accurate prediction scores.

3. To integrate the approaches of long-term and short-term to solve the latent feedback learning, scores overfitting, user's interest drifting, item's popularity decay over time which provides the accurate prediction scores.

## 1. 4 The Scope of Research

This research focuses on improving the prediction performance of CF based on extracting the knowledge from the explicit rating scores and its temporal vectors. Three datasets are explored for testing all the experimental approaches, which are MovieLens, Netflix Prize and Epinions. Due to the exploitation of the data sparsity concept in the

Recommendation System, it is important to mention some critical assumptions about using this model, as follows:

- The data sparsity is the main problem addressed in this study, which is explored according to the factorization and temporal based factorization approaches.
- The process of classification after clustering the global rating matrix has been used for solving the problem of cold-start (new items/new users). Therefore, the measures of classification as precision, recall and F1 are not used in evaluating the experimental approaches.
- For the personalized differences in the users' behaviours, the root mean squared error (RMSE) is computed for the whole test set of the target users, where each target user has a different accuracy prediction from another target user.
- One of the swarming algorithm which is the bacterial foraging optimization algorithm is used for extracting the optimum weights of short-term preferences, which improve the performance of data according to the CF technique.

## 1.5 The Contribution of The Thesis

The primary contribution of this research work is improving the prediction accuracy in the CF technique based on data sparsity issue by devising the temporal integration based factorization approaches which learn the accurate latent effects of the temporal behaviours of the user's preferences. The novel features of the proposed approaches are as follows:

1. Data sparsity issue: The approach of ensemble divide and conquer has reduced the data sparsity error and also the combination of time convergence, personalized duration and personalized temporal weighting methods are incorporated in matrix factorization to reduce data sparsity error.
2. Personalized recommendation issue: The combination of time convergence and personalized duration approaches is proposed to improve the preference drifting factor and personalized recommendation.
3. Overfitting; drift; decay: The bacterial foraging optimization algorithm based personalized temporal weight approach is proposed to normalize the overfitting in the predicted rating scores based on the regularizing weights. The swarming function in BFOA has tracked the duration drift and the duration decay.

The novel features of the proposed approaches are as follows:

- The proposed personalized duration of each user has improved the personalized preferences of the long-term.
- Incorporating the baseline variants, latent feedback and temporal preferences into one approach has improved the quality of prediction accuracy.
- The clustering based on the time converges among users has provided the controlling weights for normalizing the overfitting.
- TemporalMF++ approach has solved the sparsity problem and the weaknesses of neighbours, overfitting, drift and time decay based on integrating the feedback of factorization approaches and the learning temporal vectors dynamically.

## 1.6 Thesis Outlines

The rest of this thesis is organized as follows: Chapter 2 provides background knowledge of recommendation system and temporal recommendation system based on CF technique. This chapter will give an overview about the prediction approaches and the techniques which are used for the RS and explore the limitations of the current factorization approaches and the temporal approaches. In addition, this chapter covers the concepts of bacterial foraging optimization algorithm which will be used for extracting the temporal features. Chapter 3 presents the review of the issues of RS and temporal RS according to the limitations and the proposed solutions. The data preparation will be described in this chapter and the metric evaluations. Chapter 4 is dedicated to experimental results for the proposed approaches. It presents the results of EDC, LongTemporalMF, ShortTemporalMF and TemporalMF++. All results are implemented on the datasets of MovieLens, Epinions and Netflix Prize, according to two scales which are [0-1] and [0-5]. Furthermore, all proposed approaches will be compared to the previous approaches in the same major. Chapter 5 presents the experimental results and analysis. Chapter 6 presents the conclusion of all the experimental works and recommending for the future work.

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