Kutty, Sangeetha, Chen, Lin, & Nayak, Richi (2012) A people-to-people recommendation system using Tensor Space Models. In Shin, DongWong (Ed.) *Proceedings of the ACM Symposium on Applied Computing*, ACM Press, Riva del Garda, Trento, pp. 187-192.

http://dx.doi.org/10.1145/2245276.2245312

A People-to-people recommendation system using Tensor Space Models

Sangeetha Kutty
s.kutty@qut.edu.au

Lin Chen
l33.chen@qut.edu.au

Richi Nayak
r.nayak@qut.edu.au

Faculty of Science and Technology
Queensland University of Technology
Brisbane, Australia

ABSTRACT

Existing recommendation systems often recommend products to users by capturing the item-to-item and user-to-user similarity measures. These types of recommendation systems become inefficient in people-to-people networks for people to people recommendation that require two way relationship. Also, existing recommendation methods use traditional two dimensional models to find inter relationships between alike users and items. It is not efficient enough to model the people-to-people network with two-dimensional models as the latent correlations between the people and their attributes are not utilized. In this paper, we propose a novel tensor decomposition-based recommendation method for recommending people-to-people based on users profiles and their interactions. The people-to-people network data is multi-dimensional data which when modeled using vector based methods tend to result in information loss as they capture either the interactions or the attributes of the users but not both the information. This paper utilizes tensor models that have the ability to correlate and find latent relationships between similar users based on both information, user interactions and user attributes, in order to generate recommendations. Empirical analysis is conducted on a real-life online dating dataset. As demonstrated in results, the use of tensor modeling and decomposition has enabled the identification of latent correlations between people based on their attributes and interactions in the network and quality recommendations have been derived using the 'alike' users concept.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

General Terms

Algorithms, Management, Design, Experimentation.

Keywords

People-to-people network; Recommendation; Tensor; Tensor Space Model; Two-way relationship; Decomposition;

1. INTRODUCTION

Recommender systems have become an ubiquitous tool to find our way of obtaining personalized information in the wealth of online data available to us. Broadly speaking, recommender systems are based on two strategies namely *collaborative filtering (CF)* and *content-based* [11]. In the former type of recommender systems, the user preferences are inferred from the past consumption patterns or explicit feedback given by the users, and recommendations are computed by analyzing other similar users. In the recommender systems using the content-based approach, the recommendations are based on the content about the items or users. This involves analyzing the content which is available in the form of profiles about users', their preferences, item descriptions, web logs.

The purpose of recommendation systems is to suggest a product (or an item) to a user according to their web visit histories or based on the product selections of other similar users [9]. In most cases, the recommendation is an item recommendation which is inanimate. On the contrary, the recommendation objects in people networks are people who can reject to be recommended. The goal of an e-commerce recommendation system is to find products most likely to interest a user, whereas, the goal of a people network recommendation system is to find the user who is most likely to interest other users and respond favorably to them. In comparison to item recommendation, people recommendation results by two way matching. Unfortunately, most of the current recommendations do not include this feature hence cannot be used for people recommendation [1].

Typical recommendation systems for recommending people-to-people examine either the content or the pairwise associations, in isolation. On one hand, the content-based analysis methods analyze the users' relationship based on their content similarity presented in the form of profiles that is commonality between these users according to what they share. On the other hand, social network analysis methods try to identify communities among people based on their online behavior such as any commonality according to their interactions [6]. Most of the previous researches have considered these two aspects independently. In these cases, a post-processing is required to combine the results from each of the analysis. Identifying the appropriate weighting factor for combining the two aspects itself is also a challenging problem. It is not only a computationally expensive task to conduct the analysis separately but also lacks in quality due to the inter-dependence of both information, user content and user interactions.

Traditional recommendation systems use the user-item pair-based model using Vector Space Model (VSM) that can be used successfully in several settings, however, it is unsuitable for people-to-people network. The VSM fails to capture the latent relations between the people based on both their profile and the interactions as either the interactions between the people in the network can be modeled in the VSM or their profile can only be modeled separately. People recommendations systems require modeling the additional variables such as users' profile and preference attributes along with their interactions in the network as these variables play significant role in the choice of the interaction. In order to model the multi-dimensional nature of users' behavior on a people network in an attempt to identify correlations between people, we propose to use the Tensor Space Model (TSM). Unlike the VSM, which uses a vector to model, Tensor Space Model (TSM) [5] is based on the multi-linear algebraic character level high-order tensors (generalization of matrices) [14]. Decomposition algorithms are applied on a TSM to analyze the relationships between various tensor dimensions and reveal hidden relations between them [5].

In this paper, we propose a novel Tensor-based People-to-people (TPP) recommendation method that utilizes a tensor to model the implicit information about the users such as interactions made on the networks as well as the explicit attributes of the users present in the user profile. The tensor is decomposed to identify latent relations between the users according to common attributes that they share and interactions they make. We utilize the most common decomposition algorithm, CANDECOMP PARAFAC (CP) which is well-known for its scalability, robustness [10] and ability to provide unique solution [5], to analyze the dataset. Finally, we demonstrate how the use of the proposed method helps to enrich the recommendation. The tensor model built is a generic model and can be extended further in the presence of more contextual information.

The contributions of this paper can be summarized as: (1) a novel higher-order representation for people-to-people network (2) a hybrid recommendation system based on tensor-based decomposition.

2. RELATED WORK

Recommender systems have been applied in diverse fields as they enable to sift through a wealth of information. The popular recommender systems such as Amazon, Netflix, Jester, Movielens and Ringo are used to recommend products such as books, music, movies, jokes [1, 11]. By providing these product recommendations to the customers, it increases the possibility of successful purchases of these products as the recommendations are personalized according to their previous purchasing behavior or based on the users having similar interests [1]. However, most of these recommender systems focus on user-product recommendations emphasizing on the one-way relationship between user and the products they are interested in buying. Due to the one-way nature of the relationship, these recommender systems cannot be directly applied for people recommendations due to the existence of two-way relationship between the two types of people in the network. Also, in contrast to product recommendations, the dataset for people recommendations is highly sparse as they do not interact with a large number of users as they view the products. Thus, applying the typical recommendation systems for people recommendations is challenging. There exist people-to-people matching systems using the Helen Fisher's algorithm (Chemistry.com), Buckwalter's algorithm (EHarmony.com) based on people's psychological and sociological attributes. This paper proposes a novel hybrid recommendation method for people-to-people recommendation by not only combining the collaborative-based information but also the content-based information.

The use of higher-order data model (tensor) for recommendation is an emerging research area. Recommender methods using HOSVD have been proposed for recommending personalized photos [15], music [13] and tags [12, 8]. Rendle et al. [7] utilize TSM based tag recommendation model which uses tensor factors by multiplying the three features matrices with core matrix each consisting of user, items and tags. Another collaborative filtering approach based on tensor factorization for making recommendations, where the users, items and related contextual information are modeled as a three dimensional tensor is proposed by [4]. However, most of these models utilizes only the one-way interaction and fails to model the two-way interaction that exists between users of people-to-people networks. Additionally, in people-to-people networks there are two types of people. For instance, in an online dating network there are females and males groups and in a job seeking network there are employer and employee groups. It is essential to model the interactions between the two groups separately in order to identify the latent relationships and to allow recommendation between the two groups such as employer to employee rather than one employer to another employer. Tensors have been used in social networks for analyzing the same type of users as in [10], although, to our best of knowledge, this paper is one of the first study to model the constrained social networks with tensor space model and utilize them for recommendation.

3. TENSOR-BASED PEOPLE-TO-PEOPLE (TPP) RECOMMENDATION

In this section, we provide the problem definition and preliminaries followed by the overview of the TPP approach and its details.

3.1 Problem Definition and preliminaries

Let there be a set of users $U = \{U^X, U^Y\}$ which is made up of two disjoint sets of users U^X and U^Y where $U^X \bigcap U^Y = \phi$. Let $U^X = \{u_1^x, u_2^x, \ldots, u_{n'}^x\}$ and $U^Y = \{u_1^y, u_2^y, \ldots, u_{n''}^y\}$ where $u_i^x \in U^X$ and $u_i^y \in U^Y$ are users having a profile with a set of attributes $A = \{A_1, A_2, \ldots, A_n\}$. Let I be the interaction between users u_i^x and u_j^y which has two possible values, $I = \{0, 1\}$. If $(u_i^x, u_j^y) = 1$ then it implies the two users have *positively interacted.* Two users, u_i^x and u_j^y, $(u_i^x, u_j^y) = 1$, are said to have positively interacted if u_i^x has sent a message to u_j^y requesting for an interaction and u_j^y has positively responded to the message. Two users, u_i^x and u_j^y, (u_i^x, u_j^y), are said to have negative or null interaction if the message initiated by u_i^x has negatively responded or not responded which shows that u_j^y is not interested in this interaction.

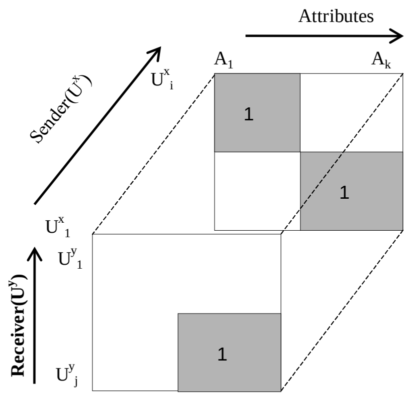

Figure 1: Visualisation of a third-order tensor for people-to-people network

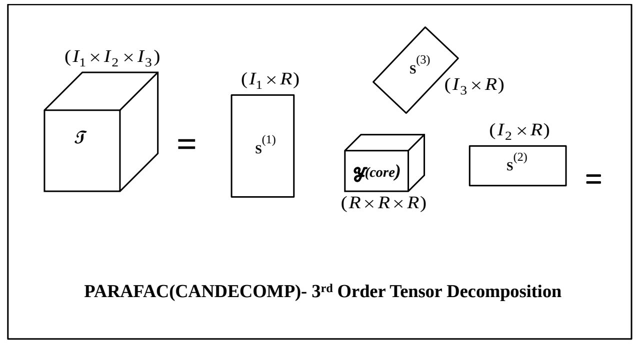

Figure 2: TSM decomposition using CP

The first step involves modeling the users attributes and their interactions in a tensor space model. The tensor notations and conventions used in this paper are akin to the notations used by previous works [3, 5, 14]. Let $\mathcal{T} \in \mathbb{R}^{I_1 \times I_2 \times I_3 \times \ldots I_N}$ be a tensor of N dimensions where I_i is a dimension (or mode or way). The order of a tensor is the number of dimensions.

In this work, we focus on the third-order tensor. Given one set of users U^X, its corresponding set of users U^Y and the A set of attributes of U^Y, a third-order tensor $\mathcal{T} \in \mathbb{R}^{U^X \times U^Y \times A}$ is represented. Entries of a tensor are shown using $t_{u_i^x u_j^y a_k}$ where $u_i^x \in U^X$, $u_j^y \in U^Y, a_k \in A$ respectively in each dimension. The tensor is populated with the presence of a positive or negative (or null) interaction between U^X and U^Y. Each element (or entry) of a tensor requires indexes same as rank of the tensor to represent or reference its precise position in a tensor. Fig. 1 visualizes a 3-order tensor built for the people-to-people network considered in this study.

***n-mode* (matrix) product**

The *n-mode (matrix) product* of a tensor $\mathcal{T} \in \mathbb{R}^{I_1 \times I_2 \times \ldots \times I_N}$ with a matrix $\mathbf{M} \in \mathbb{R}^{J \times I_n}$, denoted by $\mathcal{T} \times_n \mathbf{M}$ with a tensor of size $I_1 \times I_2 \times \ldots \times I_{n-1} \times J \times I_{n+1} \times \ldots I_N$. Essentially, this means that each n-mode fiber is multiplied by the matrix $\mathbf{M}$. Based on the elements it can be given by

$$(\mathcal{T} \times_n \mathbf{M})_{i_1 \ldots i_d j i_{n+1} \ldots i_N} = \sum_{i_n=1}^{I_n} t_{i_1 i_2 \ldots i_N} x j i_n \tag{1}$$

The *n-mode (matrix) product* of a tensor $\mathcal{T}$ with the matrix $\mathbf{M}$ is equivalent to multiplying $\mathbf{M}$ by the appropriate flattening of $\mathbf{M}$ which is expressed as:

$$\mathcal{Y} = \mathcal{T} \times_n \mathbf{M} \equiv \mathbf{Y}_{(n)} = \mathbf{M}\mathbf{Y}_{(n)} \tag{2}$$

Some interesting points to note are:

- if the modes of multiplication are different then the order of multiplication is irrelevant as shown in the equation below :

$$\mathcal{T} \times_m \mathbf{P} \times_n \mathbf{Q} = \mathcal{T} \times_n \mathbf{Q} \times_m \mathbf{P} \quad if \quad (m \neq n) \tag{3}$$

- if a tensor $\mathcal{T}$ is multiplied with two matrices with the same mode n, then the following equation holds true :

$$\mathcal{T} \times_n \mathbf{P} \times_n \mathbf{Q} = \mathcal{T} \times_n \mathbf{QP} \quad if \quad (m = n) \tag{4}$$

3.1.1 Tensor decomposition techniques

In order to analyze the tensors, decomposition techniques are applied in a manner similar to Singular Value Decomposition (SVD). SVD is a well-known factorization, which when applied on the matrix $\mathbf{M} \in \mathbb{R}^{I_1 \times I_2}$ is given by

$$\mathbf{M} = \mathbf{U}\Sigma\mathbf{V}^T \tag{5}$$

where $\mathbf{U} \in \mathbb{R}^{I_1 \times I_1}$ is a left-singular matrix, S is a diagonal matrix containing singular values and $\mathbf{V} \in \mathbb{R}^{I_2 \times I_2}$ is a right-singular matrix.
SVD decomposes a matrix into a sum of 1-mode matrices. In other words, the matrix $\mathbf{M} \in \mathbb{R}^{I_2 \times I_2}$ can also be expressed as a minimal sum of 1-mode matrices:

$$\mathbf{M} = \sigma_1(\mathbf{u}_1 \circ \mathbf{v}_1) + \sigma_2(\mathbf{u}_2 \circ \mathbf{v}_2) \ldots \sigma_r(\mathbf{u}_r \circ \mathbf{v}_r) \tag{6}$$

where $\mathbf{u}_i \in \mathbb{R}^{I_1}$ and $\mathbf{v}_i \in \mathbb{R}^{I_2}$ and $i = 1, 2, \ldots, r$. Also, $\mathbf{u}_i$ and $\mathbf{v}_i$ are the I_1^{th} and I_2^{th} columns of $\mathbf{U}$ and $\mathbf{V}$. The numbers σ_i on the diagonal of the diagonal matrix Σ are the singular values of $\mathbf{M}$ where r is the mode or rank of the matrix $\mathbf{M}$. Extending SVD to higher-mode tensors is complicated, since the mode concept for the tensors become indistinct [5].

In essence, the purpose of tensor decomposition is to rewrite the tensor as a sum of 1-mode tensors. For a tensor $\mathcal{T} \in \mathbb{R}^{I_1 \times I_2 \times I_3}$, it could be expressed as:

$$\mathbf{T} = (\mathbf{u}_1 \circ \mathbf{v}_1 \circ \mathbf{w}_1) + (\mathbf{u}_2 \circ \mathbf{v}_2 \circ \mathbf{w}_2) \ldots (\mathbf{u}_r \circ \mathbf{v}_r \circ \mathbf{w}_r) \tag{7}$$

where $\mathbf{u}_i \in \mathbb{R}^{I_1}$, $\mathbf{v}_i \in \mathbb{R}^{I_2}$, and $\mathbf{w}_i \in \mathbb{R}^{I_3}$ and $i = 1, 2, \ldots, r$.

The minimum representation for the tensor SVD is not always orthogonal, which implies that the vectors $\mathbf{u}_i$, $\mathbf{v}_i$, $\mathbf{w}_i$ do not necessarily form orthonormal sets. For this reason, tensor decomposition has no orthogonality constraint imposed on these vectors [5].

Tensor decompositions enable an overview of the relationships that can be further used in grouping them. There are several tensor decomposition techniques, amongst which the most popular CANDECOMP/PARAFAC (CP) [5] is used for decomposing the TSM as other decompositions algorithms fail to scale for this dataset.

CP decomposition of a tensor $\mathcal{T}$ is given by

$$\mathcal{T} \approx \sum_{r=1}^{m} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r \tag{8}$$

where m is a positive integer, $\circ$ represents vector outer product (which means that each element of the tensor is the product of its corresponding vector elements) and $\mathbf{a}_r \in \mathbb{R}^{I_1}$, $\mathbf{b}_r \in \mathbb{R}^{I_2}$, and $\mathbf{c}_r \in \mathbb{R}^{I_3}$.

3.2 Overview of TPP method

Having built the tensor, the next step is to apply the proposed method, Tensor-based People-to-People (TPP) recommendation, to decompose the tensor and then to reconstruct the tensor with reduced dimension generate the recommendations. Fig. 3 provides an overview of the TPP method.

1. Using the attributes and the relations of people-to-people network build a tensor $\mathcal{T} \in \mathbb{R}^{U^X \times U^Y \times A}$, where each tensor element is the presence of an interaction between U^X and U^Y in the presence of the attribute $A_k \in A$.
2. Apply a tensor decomposition algorithm, to the tensor $\mathcal{T}$ and get the resulting left singular matrices singular matrices S_{U^X}, S_{U^Y} and S_A.
3. Reduce the size of the left singular matrices by choosing $i \in \{1, |U^X|\}$, $j \in \{1, |U^Y|\}$,$k \in \{1, |A|\}$. The reduced matrices be represented as W_{U^X}, W_{U^Y} and W_A
4. Calculate the core tensor by: $\mathcal{Y} = \mathcal{T} \times_1 W_{U^X} \times_2 W_{U^Y} \times_3 W_A$
5. Reconstruct the original tensor, $\acute{\mathcal{T}} = \mathcal{Y} \times_1 W_{U^X} \times_2 W_{U^Y} \times_3 W_A$
6. Utilize the reconstructed tensor $\acute{\mathcal{T}}$ to generate the recommendations
7. Entries in $\acute{\mathcal{T}}$ which are not present in $\mathcal{T}$ having a value above the user-defined threshold are then ranked and presented as recommendations.

Figure 3: High level definition of TPP method

Our TPP method is to apply a tensor decomposition on the 3-order tensor constructed from a people network. In accordance with the decomposition techniques introduced in Section 3.1, the TPP is given in Figure 3.

3.3 Construction of TSM

From the people-to-people network data triplets (sender, receiver and attribute values of receiver), an initial third order tensor, $\mathcal{T} \in \mathbb{R}^{|U^X| \times |U^Y| \times |A|}$ is constructed, where $|U^X|$, $|U^Y|$, and $|A|$ are the numbers of senders(who sends a message to interact), receivers and attribute values of receivers, respectively. Each tensor element measures the association of a (sender, receiver) for an attribute in A. Table 1 shows a toy dataset showing the interactions between the users and their attribute. As discussed in preliminaries subsection 3.1, there are two types of interactions : positive and negative. The positive interaction implies that a sender has sent a message for interaction to a receiver and the receiver responded positively to the message. On the other hand, negative interaction implies that a receiver has negatively or not responded to the sender's message for interaction. The TSM is constructed using only the positive interaction as the negative or null interaction is not useful as we focus on generating positive recommendations for our study.

Sender	Receiver	Attributes	Interactions
u_1^x	u_2^y	A_1	1
u_1^x	u_2^y	A_2	1
u_3^x	u_4^y	A_1	1
u_3^x	u_4^y	A_2	1
u_3^x	u_8^y	A_1	1
u_5^x	u_6^y	A_3	1
u_5^x	u_6^y	A_4	1

Table 1: A Toy Dataset

Sender	Receiver	Attributes	Interactions
u_1^x	u_2^y	A_1	1.27
u_1^x	u_2^y	A_2	0.9906
u_3^x	u_4^y	A_1	3.53
u_3^x	u_4^y	A_2	2.9081
u_3^x	u_8^y	A_1	2.33
u_5^x	u_6^y	A_3	3.29
u_5^x	u_6^y	A_4	3.29
u_1^x	u_4^y	A_1	**0.92**
u_1^x	u_4^y	A_2	**0.72**
u_1^x	u_8^y	A_1	**0.58**

Table 2: Reconstructed Tensor: After application of TPP

3.4 Decomposition of TSM

Given the tensor $\mathcal{T}$, the next task is to find the hidden relationships between the orders or dimensions of the tensor model. The tensor decomposition algorithm enables an overview of the relationships that can be further used in recommendation. Let us now consider a toy problem using the dataset in Table 1 to explain the decomposition of TSM.

There are a total of 7 users, out of which odd numbered users represent the senders and the even numbered users represent the receivers. In this dataset, we have considered four attributes of the receivers. All the entries in this tensor will be 1 showing that there exists a positive interaction from the sender to the receiver.

After applying our proposed algorithm, TPP, we could see the reconstructed tensor in Table 2. There were about 48 entries in the reconstructed tensor however for ease of illustration we list only the top entries. By combining the left singular matrices corresponding to the three orders of the tensors and the core tensor results in unraveling the latent relations between the users of the same type based on the attributes of the receiver with whom they made positive interactions.

3.5 Generating recommendations from reconstructed tensor

In order to generate recommendations, the reconstructed tensor is used. The new tensor entries (shown in bold) in the reconstructed tensor in Figure 2 that are not present in the original tensor are considered as recommendations and provided to the user. In order to control the number of these recommendations, an user-defined threshold is set below which the tensor entries can not be considered for recommendation which is determined empirically.

It can be seen from the highlighted numbers in the last column of Table 2 that these three are the possible recommendations. It is interesting to note that there is a high correlation between u_1^x and u_4^y based on the attribute A_1 as well as for A_2 so u_4^y can be recommended for u_1^x. However, the success of this recommendation lies partly on the point whether u_4^y would accept the relationship after being recommended to u_1^x. A high chance of recommendation success in people-to-people recommendation require a two way matching between the users in the recommendation pair.

3.6 Two-way relationship in people network

As discussed earlier, we will now look at how to handle the two-way relationship in people network. The attributes in the mode-3 is of U^Y. A naive way of handling the two-way relationship is to include both the type of users in one tensor and then applying decomposition. As in the people network, there are usually two types of users namely employer-employee, male-female, doctor-patient. Each type of user (patient) seeks attributes in other type of user (doctor). For instance, a patient makes an interaction with the doctor based on his/her number of years of experience. On the other hand, a doctor makes an interaction with the patient based on his/her disease type. Hence, it is essential to separate the two types of interactions while building the tensor and consequently generating their interactions.

To handle the two-way relationship in people network, we generate two tensors, $\mathcal{T}^{\mathcal{M}} \in \mathbb{R}^{U_M^X \times U_F^Y \times A_{U_F^Y}}$ and $\mathcal{T}^{\mathcal{F}} \in \mathbb{R}^{U_F^X \times U_M^Y \times A_{U}^{Y_M}}$ where U_M^X are senders of messages who are males and U_M^Y are female senders. $A_{U_M^Y}$ and $A_{U_F^Y}$ correspond to the attributes of the male and female receivers respectively. After building the two tensors, each of the tensors are decomposed and the possible recommendations are generated individually by reconstructing the tensors as defined in Figure 3. Once the recommendations are generated, identify those pairs which has been recommended in both the reconstructed tensors and these pairs are finally recommended. This type of tensor building helps to reduce the computational complexity and also provide more meaningful results by generating recommendations from one group of users to other group of users rather than generating recommendations within the same group of users. This tensor building enables to avoid recommendations between the same type of users say male-male recommendation which is not useful constrained networks as in online dating or job seeking network.

4. EXPERIMENTS AND DISCUSSIONS

This section details the datasets used for the empirical analysis, evaluation criteria, experimental settings, results and discussions.

4.1 Dataset Description

The experiments were conducted with an objective to evaluate the proposed TPP method for people recommendation using a real world dataset. The real world dataset chosen for this purpose was from an online dating site which has about 2 million users in the network. For validating the effectiveness of the proposed approach, we utilized a training dataset with a week of interactions and a testing dataset using the subsequent week of interaction for testing the proposed recommendation system against other benchmarks. The statistics of the training and testing datasets are provided in Tables 3 and 4.

Attributes	Training Dataset	Testing Dataset
# Interactions	331,474	676,019
# Positive Interactions	63,201	129,193
# Negative and Null Interactions	268,273	546,826

Table 3: Details of the training and testing dataset

Attributes	Training Dataset
# Users	19,823
# Male Users	12,257
# Female Users	7,566
# Attributes	11
# Attribute values	63
# Tensor entries in Male TSM	170,285
# Tensor entries in Female TSM	81,949

Table 4: Details of the training dataset for tensor creation

4.2 Experimental design

Experiments were conducted on the High Performance Computing system, with a RedHat Linux operating system, 16GB of RAM and a 3.4GHz 64bit Intel Xeon processor core. The training datasets were used to build the tensor models and the testing datasets were used to evaluate the effectiveness of the generated recommendations. Experiments were conducted to evaluate the precision and recall of the recommendations. Following are the representation and the other existing algorithms used for comparing the outputs of the proposed TPP method.

We utilize the proposed TPP on other people-to-people networks such as CollabNet [2], extended version of collaborative filtering which is based on the idea that of modelling users who has initiated an interaction or having a positive response to the sender of the interaction, CF+ [1] and SocialCollab [1]. The Baseline is the proportion of successful interactions to all interactions in the dataset.

4.3 Evaluation Criteria

The method is evaluated to determine whether a user has contacted the other user recommended by the proposed system. Precision is measured to find out the ratio of recommended users who were contacted by the users that receive recommendation.

$$Precision = \frac{\#Positively\ interacted\ users}{\#Recommended\ \ Users} \tag{9}$$

Recall helps to identify how many users in the top-n recommendations were predicted correctly.

$$Recall = \frac{\#Positively\ interacted\ users}{\#Interacted\ \ users} \tag{10}$$

User coverage measure is used to understand how well the recommendation system covers the total users in the network.

$$User\ \ Coverage = \frac{\#Recommended\ \ Users}{\#Users\ \ in\ \ the\ \ network} \tag{11}$$

4.4 Empirical Analysis

Firstly, we compare the proposed method, TPP, against the benchmarks using their precision and recall . Table 5 shows that the proposed method performs much better than the benchmarks. Essentially, there is a significant increase

Method	Precision	Recall
TPP	**72.3%**	**5.8%**
SocialCollab	35%	2.45%
CollabNet	54%	2.5%
CF+	30%	1.19%
Baseline	31%	1.1%

Table 5: Precision & recall comparison for Top-100

in the precision of the proposed method. However, there is not much improvement with the recall but the improvement is significant compared to the baseline.

The precision and recall for top-N recommendations are provided in Figure 4 which demonstrates that there is no decrease in precision or recall with the increase in the number of Top-N recommendations.

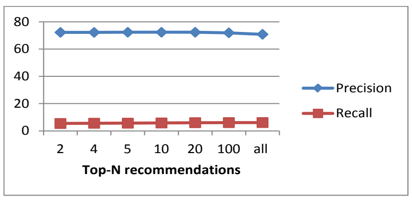

Figure 4: Top-N recommendations

An analysis of the user coverage shows that the proposed TPP could provide 65% coverage for the given dataset. The recommendations using the tensor decompositions of male user interactions provided 86% of coverage, however, the user coverage for female members recommendation is lower. The lower percentage of female recommendations is attributed to the very few interactions that the females have initiated with the males and this causes degradation in the coverage. In the given network, most of the communication are initiated by male members.

The proposed TPP method is very fast. The time required to decompose is only 0.5 seconds and 0.7 seconds for these large female and male tensor models respectively. We also conducted sensitivity analysis on the choice of the value used in reducing the size of the matrices as defined in step 3 of the TPP algorithm in Figure 3. As we utilized CP for decomposition, where $i = j = k$, it can be seen from Table 6 that these values do not play a significant role in altering the precision or recall.

Reduced dimension	Precision	Recall
2	72.3%	5.8%
5	71.6%	5.84%
10	70.5%	5.4%

Table 6: Sensitivity Analysis

5. CONCLUSION

In this paper, we have proposed a people to people recommendation system using tensor based decomposition. We utilized a real life dating network to understand the strengths of the proposed TPP method over the existing recommendation methods. Our empirical analysis clearly shows that the proposed method outperforms other existing benchmarks which have used the same dataset for their analysis. Also, the tensor model allows for building a hybrid recommendation method. Our future work will focus on utilizing TPP for solving cold start problems by utilizing clustering of new users to the system.

6. REFERENCES

[1] X. Cai, M. Bain, A. Krzywicki, W. Wobcke, Y. Kim, P. Compton, and A. Mahidadia. Collaborative filtering for people to people recommendation in social networks. In J. Li, editor, *AAI*, volume 6464 of *LNCS*, pages 476–485. Springer Berlin / Heidelberg, 2011.

[2] X. Cai, M. Bain, A. Krzywicki, W. Wobcke, Y. S. Kim, P. Compton, and A. Mahidadia. Learning collaborative filtering and its application to people to people recommendation in social networks. In *ICDM'10*, pages 743–748, 2010.

[3] A. Evrim, B, and Y. lent. Unsupervised multiway data analysis: A literature survey. *IEEE TKDE*, 21(1):6–20, 2009. 1477470.

[4] A. Karatzoglou, X. Amatriain, L. Baltrunas, and N. Oliver. Multiverse recommendation: n-dimensional tensor factorization for context-aware collaborative filtering. RecSys, pages 79–86, NY, USA, 2010. ACM.

[5] T. G. Kolda and B. W. Bader. Tensor decompositions and applications. *SIAM Review*, 51(3):455–500, 2009.

[6] R. Nayak. Utilizing past relations and user similarities in a social matching system. In *PAKDD (2)'11*, pages 99–110, 2011.

[7] S. Rendle, L. Balby Marinho, A. Nanopoulos, and S.-T. Lars. Learning optimal ranking with tensor factorization for tag recommendation. In *KDD*, pages 727–736, NY, USA, 2009. ACM.

[8] S. Rendle and S.-T. Lars. Pairwise interaction tensor factorization for personalized tag recommendation. In *WSDM*, pages 81–90, NY, USA, 2010. ACM.

[9] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl. Item-based collaborative filtering recommendation algorithms. In *WWW*, pages 285–295, NY, USA, 2001. ACM.

[10] S. Sizov, S. Staab, and T. Franz. Analysis of social networks by tensor decomposition. In B. Furht, editor, *Handbook of Social Network Technologies and Applications*, pages 45–58. Springer US, 2010.

[11] X. Su and T. M. Khoshgoftaar. A survey of collaborative filtering techniques. *Adv. in AI*, 2009:4:2–4:2, January 2009.

[12] P. Symeonidis, A. Nanopoulos, and Y. Manolopoulos. Tag recommendations based on tensor dimensionality reduction. RecSys, pages 43–50, NY, USA, 2008. ACM.

[13] P. Symeonidis, M. M. Ruxanda, A. Nanopoulos, and Y. Manolopoulos. Ternary semantic analysis of social tags for personalized music recommendation. In *ISMIR'08*, pages 219–224, 2008.

[14] C. E. Tsourakakis. MACH: Fast Randomized Tensor Decompositions. In *The SIAM Data Mining Conference (SDM 2010)*, pages 689–700, Columbus,Ohio, USA, 2010.

[15] N. Zheng, Q. Li, S. Liao, and L. Zhang. Which photo groups should i choose? a comparative study of recommendation algorithms in flickr. *Journal of Information Science*, 36(6):733–750, 2010.