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Semantic Based Friend Recommendation System: Review

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ABSTRACT

In recent years, recommendation systems which help to suggest several items such as movie, friends, books to users have become more and more famous. These systems gather and analyze data from user's behavior, activities or preferences. After that it predicts what users will like depending on similarity among users. Now-a-days, friend recommendations have become most popular with the development in social networking systems. The existing system recommends a friend based on mutual friends. This does not reveal users' choices about their friend selection in real life. Recommending friends based on the user life styles prove to be more realistic. In this paper various friend recommendation techniques are surveyed and comparison among them is done. Also several models are studied and analyzed to form the base of this paper.

Key words: Friend recommendation, mobile sensing, sensors, social networks, life style

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INTRODUCTION

In mankind's history, individuals have dependably been attempting to make predictions and forecasts for a scope of issues. There are various types of predictions. Some depend on historical data, for instance, weather forecasting and some depend on the understandings of the hidden systems, for instance, the election results. A few scientists additionally attempted to characterize in between of prediction and forecast. Both of these prediction and forecast refer to recommendation. Despite the fact that the recommendation or prediction practices have existed for quite a while, with the improvement of modern technologies and knowledge amassed after some time, it turns into a well known research area since mid-1990. Recommendation systems focus on these two areas: link recommendation and object recommendation. Different social networking sites like focus on link recommendation where friend recommendations are presented to users. Different Companies give emphasis on object recommendation where products are recommended to users based on earlier behavioral patterns. Basically recommendation system is classified into two main categories:

Content Based Systems

It evaluates system based on things recommended for example, if a Netflix user has watched many cowboy movies, and then recommends a movie classified in the database as having the 'cowboy' genre.

Collaborative Filtering Systems

It finds out similarity measures among the users or items and recommend accordingly. It is based on similarity search and clustering phenomenon. In early times, individuals normally made friends with individuals who work or live near themselves, for example, partners or neighbors. This relationship can be characterized as G-friends, where G-friends stand for geographical location based friends as they are affected by the geological separations between one another. With the large advances in social networks, administrations, for example, Google+, Twitter, Facebook have given us various radical ways for making new friends. As per one of the famous social networks 'Facebook' data, single user has a normal of 130 friends, possibly bigger than some other time ever. One of the challenging task with recent social networking is the manner by which to prescribe suitable friend to a user. A large portion of them rely on upon effectively existing user connections to choose friend. For instance, Facebook depend on a social connection investigation among the individuals who as of now share similar friends and prescribes proportioned users as probable friends. Deplorably, this methodology may not be the most proper based on friend findings. This method suffers the drawback of interest mismatch and it is useless to expand the circle of the members, because someone who has many common friends with you probably already known to you. According to these studies the rules to group people together include:

1) Habits or life style
2) Attitudes
3) Tastes
4) Moral standards
5) Economic level; and
6) People they already know.

Apparently, rule #3 and rule #6 are the mainstream factors considered by existing recommendation systems.

LITERATURE REVIEW

Bian [2] proposed an online friend recommendation based on personality matching and collaborative filtering. An automated collaborative filtering system that recommends friends to users on Facebook by analyzing and matching user's online profile with the profiles of TV characters is utilized. The goal is to leverage the social information and mutual understanding among people in existing social network connections and produce friend recommendations based on rich contextual data from people's physical world interactions using relationships in TV programs as a parallel comparison matrix. It projects these relationships into reality to help people find friends whose personality and characteristics have been voted to suit them well by their social network. This system also encourages more TV content viewing by using the social network context and connections to provoke people's curiosity of TV characters whom they have been matched with in their social network. The system recommends friends to Facebook users based upon the TV characters they have been matched with. Fig. 3 depicts the relationship schema in a more visual way.For example let the Facebook users be X and Y. The TV characters be M and N .To recommend Y as friend of X the following steps are followed.

'Facebook user X has matching personality to TV character M according to friends ranking',

'Facebook user Y also has matching personality to TV character N according to friends ranking',

and if TV character M and TV character N are friends in the same TV show, then the system recommends user X to become friend with user Y, if user X and user Y are not already friends on Facebook.The main advantage of the system is it uses social networking site information and mutual understanding among users. Personality matching provides more contextual information about the recommended friends. The disadvantage is that this application is limited only to TV shows [2].

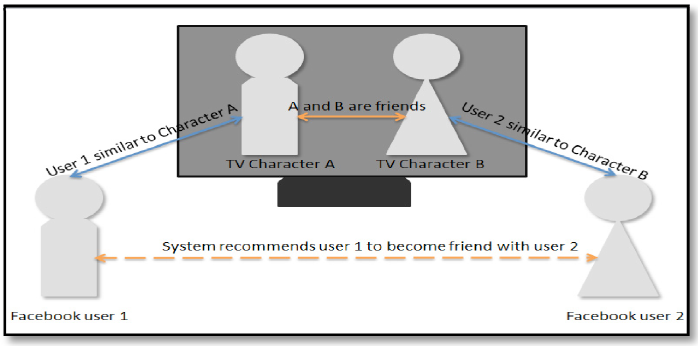

Fig. 1 A System Overview [2]

Naruchitparames [3] proposed a friend recommendation system based on and genetic algorithm and network topology. It is based on link recommendation approach. There are various attributes like location, age, religion, language, general interests, education which are extracted from the user profile. There are two step filtering process using friends of friends (FOF) and Pareto optimal genetic algorithm. It applies filter which will throws irrelevant individuals using complex network theory before applying genetic algorithm. The attributes that follows the friendship criteria is extracted from the user profile. A social graph is created where nodes are users. Then filter based on friends of friends is used to decrease number of potential friends. Hence those friends are chosen from the graph that have more outlinks and fitness value is found for each of the friends and is iterated for few generations. The sorting in descending order of fitness value is done. Top ten results are provided which will be shown as recommended friends. The advantage is that the network based approach consistently performs better than the social based approach. Another merit of this approach is that it also ensures the likelihood of a person pursing a friendship of someone they know than someone they do not know.

Kwon [4] proposed friend recommendation which is used in context aware applications. These context-aware systems provide the user with adaptive recommendations from available huge information. The recommendation method using context A challenging research issue in social computing is the recommendation method using context. The author proposes a friend recommendation method using both physical and social context. The key idea of the proposed method is consisted of the following three stages; in first step it computes the friendship score based on similar behavior using physical context. For computing score the traditional regular information retrieval method, BM25 weighting scheme is used. Secondly, a social context is used in which the method computes friendship score with friend relation in the friendship graph. At last, all of the calculated friendship scores are combined and then recommend friends from ranking of the scoring values. The physical contexts define the spiritual friendship and social friendship is computed by social contexts. The length of edges between nodes of graph that is distance between friends in the friendship graph is used for computing social friendship score.The main merit of this method is finding friends to satisfy user's present context. However physical and social context is not clearly defined and how the information is extracted. The personalized recommendation system with friends-of-friends method to recommend new friends to users is provided by different social network sites. The drawback is that it is more probable a person will know a friend of their friends rather than a random person. However, this approach does not consider social interactions of the user.

Hao [5] proposed a system which recommends friends who have the similar interests. Instead of utilizing the data from social networks, such as interests, the idea of real-time location information and dwell time is being used in the proposed approach. These two methods are compared and results are provided which will give quality friend recommendation. The method uses both context and content based recommendation techniques. Firstly the dwell time at certain location positioned using GPS is gathered and is used for constructing Voronoi diagram .Also data of users interest is collected from social networking sites. Voronoi diagram is constructed using the existing landmark and user's dwell time at certain landmark. After that analysis of data is done using Voronoi diagram and interest similarity Affinity matrix and graph is constructed. The server finds for similar users in a location based on location similarity and interest similarity. Depending on the similarity an acceptable degree is determined. If the value is greater than the threshold, recommend that user as friend. The merit of this method is that it uses the concept of real time location and dwell time. However it has drawback that it failed to track activity of user in a location.

Silva [6] proposed a friend recommendation system for social network based on the topology of the network graphs. The existing topology of network that connects a user to his friends is evaluated and a new local social network called Oro-Aro is formed. For further evaluation it is used in the experiments. An algorithm is used that analyses the sub-graph formed by a user and all the others connected users separately by three scale of division However, only users separated by two scale of division are candidates to be advised as a friend. The algorithm uses various patterns examined by their connections to search those users who have similar activities as of the root user. Based on the characterization the recommendation mechanism was developed. It also analyses the network formed by the user's friends and friends-of friends (FOF).

Nagamalai [7] proposed a trust based friend recommendation system. It extracts fundamental and behavioral attributes from the user profile. Users having similar interests are being computed. For improving effectiveness of recommendation real valued genetic algorithm is used which evaluate user preferences based on individual features in an efficient manner. Hence an enhanced neighborhood set based on the trust propagation is generated. The collaborative filtering algorithm is used for recommendation. The weights are applied to each of the attributes of users and similarities between them are found. On the basis of user preference the weights are applied. To create different weights genetic algorithms are used. The optimization of better recommendation is done. It is checked by the Fitness value whether the goal is obtained or not. It will look out also the sparsity issue using trust. There will be challenging task of designing a collaborative filtering system which will assure accurate recommendation with sparse user profile. If the user profile is new, and the system failed to capture the user's preference because of lack of ratings, system will come to know about the preference of the user by how repeatedly he uses the system. Hence trust values are used to improve neighborhood set in order to provide accurate recommendation with sparse data. The system has many advantages. One is that weights are calculated by real value which improves performance.

Also it deals with sparsity issue in collaborative based friend recommendation .The trust value is calculated which shows to what extent a user A trusts another user B, if they are unknown to each other. It is calculated by difference of rating assigned by A and B to their mutual friends.

Table -1 Basic and Behavioural Attributes

A1 Language	A7 Here for
A2 Religion	A8 Carrier interest
A3 Age	A9 Movies A11 Activities Interest
A4 Gender	A10 Music
A5 Hometown	A12 Nature
A6 Relationship Status	A13Books

Due to development and popularization of GPS-enabled mobile devices it leads the social network researchers to develop cyberphysical social network. In cyber physical social network, data is gathered with help of sensors. Xiao Yu [8] proposed a friend recommendation system which identifies geographically related friends. Data of location and routes will be available, so more accurate and geographically related results will be generated. This will help web-based social service users to search more friends in the real world. Such type of friend recommendation systems proves very helpful if people wanted to organize real life events like football game, party. The method consists of three-step statistical framework which combines geo information with social analysis. There are different types of GPS information available which are captured by defining and generating four types of GPS patterns from GPS history data. The GPS patterns are gathered depending on mutual routines, meetings, hangout and common location. These attributes were included for similarity evaluation among users. Then, a pattern based diverse information network is developed which connects the users with the GPS patterns. A evolution probability matrix is defined to describe all evolution probabilities on the edge set of this diverse network. A random walk process on this information network is applied and link relevance between different nodes could be determined. By submitting a query for friend recommendation, potential geo-friends would be recommended. The drawback of this approach is that it only considers the users current geographical locations. The similarities among users interests were not included which lacks the user's preference on friend selection in real world.

Chin et al [9] proposed a friend recommendation based on physical context. The physical context is based on meetings and encounters here. The method uses the perception that users who meet in conference can be recommended as friends. It will help the conference attendees to better conduct their schedule and enlarge their social network. It develops a friend recommendation system which uses proximity and homophily. Proximity defines physical context based on meetings and encounters. Homophily defines common contents, co-authored papers, giving comments on same blog, mutual friends etc. The communication between the users was captured by an application Find & Connect. It uses both location and encounters data, together with the conference basic services in order to capture the user interactions. The weights are assigned for each attribute using proximity and homophily. Then the relevance vector is estimated for each user and also recommendation score is being computed for each user. Then top N users with the highest score will be recommended. The advantage is that this recommendation mechanism based on physical context is better than FOF approach. And also it provides a motivation why one should a person as his friend ie they know each other before and have encountered before. The main drawback is that it supports only indoor activity.

Table-2 Comparison of Different Friend Recommendation Approaches

Title	Friend Recommendation Technique	Basis of Similarity found	Remarks	Merits	Demerits
Friendbook: A Semantic-based Friend Recommendation System for Social Networks [1]	Probabilistic	Lifestyles and activities	Proposed model which recommends friends based on lifestyle and has fixed threshold for friend matching graph	It extracts lifestyle from user centric data collected from sensors on smartphone	It uses fixed threshold factor in friend matching graph
Friend Recommendation through personality matching and collaborative filtering [2]	Collaborative	Rating given by friends	Application limited to TV shows.	It uses collaborative filtering for friend recommendation system based on personality matching.	It uses personal profiles from social networks for retrieving information of TV characters.
Friend Recommendation using physical and social context [4]	Context	Attributes from user profile	Used in context aware application. Method to extract context based information was not proposed.	It finds friends to satisfy user's present context.	Physical and social context is not clearly defined and how the information is extracted. Also this approach does not consider social interactions of the user
Trust Enhanced friend recommendation [7]	Collaborativ	Attributes from user profile	Solves the sparsity problem	Weights are calculated by real value which improves performance. Alsoit deals with sparsity issue in collaborative based friend recommendation	Limited to user's profile information.
Friend recommendation for Location based mobile social network [5]	Context and Content	Location similarity	Do not capture user's interest similarity	It uses the concept of real time location and dwell time	It failed to track activity of user in a location
Friend recommendation using proximity and homophily [9]	Context	Proximity and homophily	Provides the reason why a user is recommended as friend	This recommendation mechanism based on physical context is better than FOF approach	It supports only indoor activity.

Gou [10] proposed a novel system SFviz used to support users to explore and find friends interactively under the context of interest. This approach describes both semantic structure of activity data and topological structures in social networks. In this system a hierarchical structure of social tags is generated. It will support users to navigate through a network of interest. To support users in finding potential friends multi-scale and cross-scale aggregations of similarity among users are presented in the hierarchy. The advantage of this system is that it finds friends interactively under the context of similar interest. Also it has limitation that it has restrictive category assignment of users and it is restricted only to tag information. After discussion of literature review of various existing techniques the analysis is done by doing comparison between some of above discussed techniques..The comparison parameters are basis of similarity found in different techniques, remarks and their strengths and weaknesses. It is shown in table -2.

VARIOUS MODELS

Latent Dirichlet Allocation (LDA) Model

Latent Dirichlet allocation (LDA) is an example of a topic model and was first presented as a graphical model for topic discovery by Blei et al in 2003 [12].It is a generative model that allows sets of observations to be explained by unobserved groups that explain why some parts of the data are similar. For example, if observations are words collected into documents, it posits that each document is a mixture of a small number of topics and that each word's creation is attributable to one of the document's topics. It is a generative probabilistic model of a corpus. The basic idea is that documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words.

LDA assumes the following generative process for each document **w** in a corpus *D*:

1. Choose N$\sim$ Poisson (ξ).
2. Choose $\theta \sim$ Dir (α).
3. For each of the *N* words w_n:
   (a) Choose a topic $z_n \sim$ Multinomial (θ).
   (b) Choose a word w_n from $p(w_n \mid z_n, \beta)$, a multinomial probability conditioned on the topic z_n.

Several simplifying assumptions are made in this basic model, some of which are removed in subsequent sections.

First, the dimensionality *k* of the Dirichlet distribution (and thus the dimensionality of the topic variable *z*) is assumed known and fixed. Second, the word probabilities are parameterized by a k × V matrix β where $\beta_{ij} = p(w^j = 1 \mid z^i = 1)$, which for now we treat as a fixed quantity that is to be estimated. Finally, the Poisson assumption is not critical to anything that follows and more realistic document length distributions can be used as needed. Furthermore, note that *N* is independent of all the other data generating variables (θ and **z**). It is thus an ancillary variable and we will generally ignore its randomness in the subsequent development [11].

A *k*-dimensional Dirichlet random variable θ can take values in the $(k-1)$-simplex (a *k*-vector θ lies in the $(k-1)$-simplex if $\theta_i \geq 0$, $\sum_{i=1}^{k} \theta_i = 1$), and has the following probability density on this simplex:

$$p(\theta \mid \alpha) = \frac{\Gamma\left(\sum_{i=1}^{k} \alpha_i\right)}{\prod_{i=1}^{k} \Gamma(\alpha_i)} \theta_1^{\alpha_1 - 1} \dots \theta_1^{\alpha_k - 1}, \tag{1}$$

where the parameter α is a *k*-vector with components $\alpha i > 0$, and where $\Gamma(x)$ is the Gamma function[11].

The Dirichlet is a convenient distribution on the simplex—it is in the exponential family, has finite dimensional sufficient statistics, and is conjugate to the multinomial distribution. These properties will facilitate the development of inference and parameter estimation algorithms for LDA. Given the parameters α and β, the joint distribution of a topic mixture θ, a set of *N* topics **z**, and a set of *N* words **w** is given by:

$$p(\theta, \mathbf{z}, \mathbf{w} \mid \alpha, \beta) = p(\theta \mid \alpha) \prod_{n=1}^{N} p(z_n \mid \theta)\, p\left(w_n \mid z_{n,} \beta\right), \tag{2}$$

where $p(zn \mid \theta)$ is simply θi for the unique *i* such that $z_n^i = 1$.Integrating over θ and summing over *z*, we obtain the marginal distribution of a document:

$$p(\mathbf{w} \mid \alpha, \beta) = \int p\,(\theta \mid \alpha)\left(\prod_{n=1}^{N} \sum p\,(z_n \mid \theta)\, p(w_n \mid z_n, \beta)\right) d\theta \tag{3}$$

Finally, taking the product of the marginal probabilities of single documents, we obtain the probability of a corpus:

$$p(D \mid \alpha, \beta) = \prod_{d=1}^{M} \int p\,(\theta_d \mid \alpha)\left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn} \mid \theta_d)\, p(w_{dn} \mid z_{dn}, \beta)\right) d\theta_d. \tag{4}$$

There is analogy between users' daily lives and documents According to studies existing friend recommendation is done based on various similar attributes among users like their pre-existing relationship known as mutual friends, tastes, various likings ,interests, attitudes, economic levels, posts, habits, moral standards, etc. As capturing users' life styles is difficult and challenging task, so it is not widely used for recommendation. These user's life styles are closely correlated to daily routines and activities. If we are able to collect information from users' daily routines and activities, it will help in recommending friends to users based on their similar life styles. In our day-to-day lives there are many activities form meaningful sequence which depicts our lives. The activities refer to different actions and lifestyle refers to high level abstraction of daily lives. Hence, life styles and activities are reflections of our daily lives at two different levels where daily lives can be treated as a mixture of life styles and life styles as a mixture of activities. To model daily lives analogy between users' daily lives and documents is studied. The recent developments and research on probabilistic model in text mining model daily lives of users' as life documents, life styles as topics and activities as words[1].

Extraction of Lifestyle using Probabilistic Topic Model

The probabilistic topic model can find out the probabilities of topics in the given documents. Similarly probabilities of hidden life style can be discovered from life documents. In this model probabilities are depend on frequency of vocabulary as different frequency of words denotes their information entropy variances. The bag of activity model is described to replace the original sequences of activities recognized based on the raw data with their probability distributions.

Hence, each user will have a bag-of-activity representation of his/her life document, which consists of a mixture of activity words.

Mathematically the probabilistic model is described as follows:

Let x={$x_1,x_2,\ldots.x_X$} denote as set of the activities, where x_i will be i^{th} activity and X will be total number of activity. Also let y={$y_1,y_2,\ldots.y_Y$} denote a set of life styles where y_i will be i^{th} activity and Y will total number of life styles. Let d={$d_1,d_2,\ldots.d_n$} denote a set of documents where d_i will the i^{th} life document and n will total number of users. Let $p(x_i \mid d_k)$ denote probability of activity x_i in a certain life document d_k, $p(x_i \mid y_j)$ denote probability of how much activity x_i contribute to life style y_j and $p(y_j \mid d_k)$ denote the probability of life style y_j embeded in life document d_k. According to probabilistic topic model it can be evaluated as

$$p(x_i \mid d_k) = \sum_{j=1}^{Y} p(x_i \mid y_j)p(y_j \mid d_k) \quad (5)$$

By using bag-of-activity model $p(x_i \mid d_k)$ can be easily calculated. Hence the life document d_k can be represented as follows:

$$p(x_i \mid d_k) = \frac{f_k(x_i)}{\sum_{i=1}^{X} f_k(x_i)} \quad (6)$$

where $f_k(x_i)$ denotes frequency of x_i in d_k.

The life style of a user can be represented as life style vector ,denoted by $L_k = [\, p(y_1 \mid d_k), p(y_2 \mid d_k),\ldots, p(y_Y \mid d_k)]$.Though $p(x_i \mid d_k)$ has been calculated in Eq.(5),it needs to be calculated $p(x_i \mid y_j)$ and $p(y_j \mid d_k)$ from hidden features of life styles.

The values of $p(x_i \mid d_k)$ is calculated using activity recognition. After that the Latent Dirichlet Allocation decomposition is used to solve Eq.(5) in order to obtain life style vector.

From the given life documents the matrix decomposition problem can represent as:

$$p(\mathbf{x} \mid \mathbf{d}) = p(\mathbf{x} \mid \mathbf{y})p(\mathbf{y} \mid \mathbf{d}), \quad (7)$$

where

- The activity document matrix is $p(\mathbf{x} \mid \mathbf{d}) = [p(\mathbf{x} \mid d_1), p(\mathbf{x} \mid d_2),\ldots, p(\mathbf{x} \mid d_n)]$ as shown in Fig.2 which comprises the probability of each activity over each life document. Also $p(\mathbf{x} \mid d_k) = [p(x_1 \mid d_k), p(x_2 \mid d_k),\ldots, p(x_X \mid d_k)]^T$ is the k^{th} column in the activity document matrix which represents the probabilities of activities over life document d_k of user k.

-The activity topic matrix is $p(\mathbf{x} \mid \mathbf{y}) = [p(\mathbf{x} \mid y_1), p(\mathbf{x} \mid y_2),\ldots, p(\mathbf{x} \mid y_Y)]$ as shown in Fig.2 which represents the probability of each activity over each life style(topic), and $p(\mathbf{x} \mid y_k) = [p(x_1 \mid y_k), p(x_2 \mid y_k),\ldots, p(x_X \mid y_k)]^T$ is the k^{th} column in the activity topic matrix which represents the probabilities of activities over life style y_k.

-Finally the topic-document matrix is $p(\mathbf{y} \mid \mathbf{d}) = [p(\mathbf{y} \mid d_1), p(\mathbf{y} \mid d_2),\ldots, p(\mathbf{y} \mid d_n)]$ as shown in Fig.2 contains the probability of each topic over each life document, and $p(\mathbf{y} \mid d_k) = [p(y_1 \mid d_k), p(y_2 \mid d_k),\ldots, p(y_Y \mid d_k)]^T$ is the k^{th} column in the topic-document matrix which represents the probabilities of life styles over life document d_k of user k [1].

This matrix decomposition described above is nothing but Latent Dirichlet Allocation model. Thus the Expectation-Maximization (EM) method can be used to solve the LDA decomposition, where the E-step is used to estimate the free variational Drichilet parameter γ and multinomial parameter Φ in the standard LDA model and the M-step is used to maximize the log likelihood of the activities under these parameters [1].

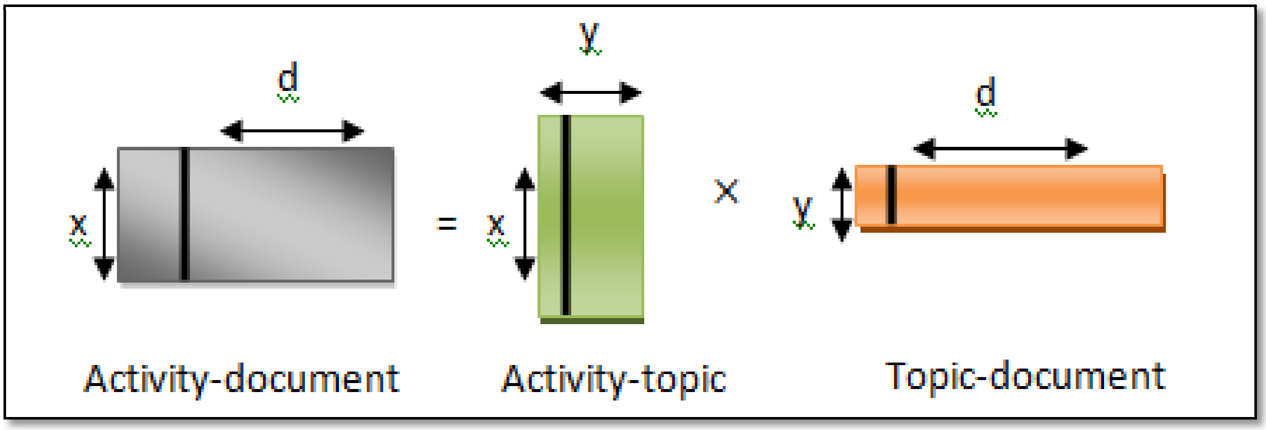

Fig. 2

PROBLEMS AND DIRECTIONS

Several friend recommendation methodologies are described above. The observations based on the study conducted are as follows.

Similarity Calculation Based on Attributes from User Profile

In most recommendation system, similarity among users is estimated based on the attributes gathered from the user profile. This explicit mechanism becomes more expensive.

Use of Social Graph for Friend Recommendation

It means that the existing system recommends a friend based on mutual friends. This does not reveal users' choices about their friend selection in real life. Recommending friends based on the user life styles prove to be more realistic.

Privacy Issue

It is important for users to keep their sensitive information safe. It should not do information leakage.

Reliability

All The recommendations methodologies discussed above have not dealt with reliability. There is doubt whether the friends recommended by the system are reliable or spam.

Performance

There will be an effect on performance of the system with increasing load in the social network. So the main goal of researchers who work in this field will be to secure the privacy of user. Several new techniques should be introduced in order to improve the performance and reliability of the system. For that more sensors like accelerometer; gyroscope should be used to capture different life styles of the users.

CONCLUSION

Friend recommendation system contributes to best suggestions of friends for a user. It is done by extracting information from the profile of users or sensors. From this study the conclusion can be made that the primary issue in existing methodologies is friend recommendation is done on the basis of contextual information and mutual friends. Also users are not satisfied in exposing their privacy to the system. Hence, user life styles can be captured by employing several sensors. This will provide better input for estimating similarity among the users in order to recommend semantic friends.

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