Time-Sensitive Trust Calculation Between Social Network Friends For Personalized Recommendation

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ABSTRACT

When creating social recommender systems, trust between various users in social networks emerges as an essential decisive feature. This paper aims at calculating trust among users by identifying all possible relations that may exist among those users and evaluate them. Although many models were proposed to analyze computational trust in different applications of social web, little importance is given to the time factor even by models that represent trust as a source of recommendation measurement. Emphasized in this paper is the temporal factor and its role in improving the accuracy of trust in social recommender systems. We propose to integrate the temporal factor in measuring trust between social network friends. A Trusted Friends’ Facebook application is developed to demonstrate the importance of time in the users’ interactions for determining social trusted friends. After that, this application will be used in a semantic social tourism recommender system as a smart e-tourism tool to motivate users to travel to Tunisia for medical purposes.

CCS Concepts

• Information systems—Personalization
• Information systems—Collaborative search
• Theory of computation—Semantics and reasoning
• Computing methodologies—Semantic networks
• Computing methodologies—Ontology engineering
• Software and its engineering—Search-based software engineering

Keywords

Smart Tourism; Semantic Web mining; Social Network; Preference representation; Recommender Systems; Ontology; Trust.

1. INTRODUCTION

The growth of medical tourism in Tunisia emanates from receiving an estimated 12 000 foreigners in 1998 to an estimated 42 000 in 2003 while 155 000 foreign patients went to Tunisia in 2013 [6]. We can say, therefore, that medical tourism is an important economic driver for developed countries as well as developing countries as its contribution to the growth of the economy, services and job creation is widely recognized. Additionally, in a competitive market, providers’ services should be able to offer an affordable cost for medical tourists. This means that cost saving is important to encourage foreign patients to choose Tunisia for their treatment and holidays.

Personalized recommender systems are now playing an important role in providing better tourism experience to many tourists[28]. Our primary objective in this study is to apply a personalized recommender system to Tunisian Medical Tourism. The reason behind this application is to provide tourists with better information searching experiences and to improve the individualization of tourism information. Personalized recommender systems include factors such as interpersonal interest, person’s interest and interpersonal influence [35]. They are found to be helpful in recommending items on social networks and they have as an objective relating recommended items to the person’s historical behavior and interpersonal relationship. The quality of the recommendation can be guaranteed based on the help of user interpersonal interests in a social network [42]. In order to improve the accuracy of recommendation, several social-trust based recommender systems have recently been suggested. Cold start and sparsity problems can be solved when taking into consideration interpersonal relationships in the friends’ circle of social networks [36], [3].

Time information can be useful in facilitating tracking the evolution of user interests and improving recommendation accuracy [8]. In fact, interactions are not perceived the same way over time because some interactions are more important than others when computing an opinion [23]. For example, user, had to comment on a hotel service for three times. While he described his/her satisfaction of the two early interactions, he expressed his/her dissatisfaction in the last interaction. If user, trusts user, to ask for his/her advice, logically, users still has more positive interactions than negative ones, which means that his opinion tends to be positive. However, if we take into consideration the temporal factor of interactions, the opinion would be that the service was generally good, but it degraded recently. Similarly, if we like to search the most trusted friends in a social network for a users, we need to compare all interactions between users, and each one of his/her friends taking into consideration the temporal factor of every interaction between them. That is because users can trust a friend in the past, but the value of trust can degrade with time. In this paper, we will focus on how to calculate trusted friends in a social network taking into consideration the time of every action between these friends.

The rest of the paper is organized as follows. Section 2 presents related works in tourism recommender systems, then we present the importance of social recommender system to improve the accuracy of recommended information. After that, we present an overview of trust in recommender system. Section 3 describes a time-sensitive method for calculating trusted friends on social networks,
while section 4 evaluates and accounts for the method of calculating trust on Facebook and compares it with preview works. Section 5 presents the smart tourism recommender system development for Tunisian medical tourism domain. Finally, section 6 concludes the paper and presents our future work.

2. RELATED WORK

2.1. Tourism Recommendation Types

[17] argued that current Tourism recommenders could suggest either a trip destination or a set of activities to perform once the user arrived at a certain place. These recommender systems face the problems of integrating heterogeneous sources of information (such as Web resources associated to flight and hotel companies) to find a trip that matches the user’s constraints and preferences. In fact, information extraction techniques and semantic technologies such as tailored ontologies are used to parse, interpret and integrate information stored in heterogeneous sources [7],[31]. Those systems store a set of preferences of the user and this allows them to rate and rank a collection of destinations. They also suggest places to visit in a certain geographical area taking into consideration the user profile by referring to a daily plan [25].

With reference to the recommendation strategy, recommender systems can be classified in three major types: content-based, collaborative and demographic approaches [5]. In collaborative filtering approaches, recommendations are made by relating users with similar preferences and suggesting items they like [11], [27]. Several ratings are, thus, required from the users before the system gives useful recommendations. This is known as the cold-start problem [4]. Content-based approaches [33] recommend items by taking into account the properties of the activities that users have enjoyed previously and only items closely related to those the user liked in the past are recommended. To make this kind of recommendation, one has to build a user profile that shows the degree of interest in each of the different criteria describing an activity. Demographic recommenders classify users according to stereo- typical classes and base the recommendations on general features related to those classes. In order to avoid the limitations of individual recommendation schemas, hybrid approaches were proposed [38], [37], [12]. These approaches combine some of the above-mentioned types.

Social networks have recently become of particular importance in the tourism industry. When planning their journeys, travelers, in addition to the personal experience and opinion of relatives and friends, refer to social networks during and after their trips, thus generating interest in viewers that can become travelers themselves [44]. In our recommender system, we consider an important role to the social network to make recommendation based on the user’s preferences as well as his/her friends’ preferences.

2.2. Social Recommender System

Although it was found to be key to the buying decisions of users, traditional collaborative filtering and its variations did not put emphasis on the semantic friend relations among users in a recommender system. The effect social networks have on product marketing has recently been subject of much research [43], [46]. In real everyday life, when we think of buying a particular and unfamiliar product, we most often tend to seek immediate advice from some of our friends who have come across this product or experienced it. We, similarly, tend to accept and use friends’ recommendations because we trust them. Therefore, integrating social networks in recommender systems can result in more accurate recommendations [36]. In other words, the information obtained about users and their friends makes it unnecessary to look for similar users and to measure their rating similarity. That is because of the fact that when two people are already friends, they may, accordingly, have things in common [24]. As a result, the data sparsity problem can be solved in this case. Additionally, the cold start issue can be overcome because users can still resort to recommendations retrieved from friends’ preferences even if they do not have history interests. In fact, if we think of the decisions we made in our daily life, such as finding restaurants, buying a house, and looking for a travel, we find that many of them are influenced by some factors. Intuitively, a customer’s buying decision or rating is decided by both his/her own preference for similar items and his/her knowledge about the characteristics of the target item [24].

All of these intuitions and observations are key to adopting this approach of social network-based recommender system [16] as it can take advantage of information in social networks. all these information extracted from social network are represented in a user interest ontology [14] that can help us in the recommendation process. In fact, in order to be able to recommend an object to the user, one must know his/her interests and the interests of some trusted friends. Our system uses social network and trust information to make a recommendation, which is found to be efficient in improving the accuracy of the recommendations [1],[2].

In our social recommender system, the user connects to his/her social network, and then the system extracts the preferences and relations to determine the user’s interest as well as his/her trusted friends’ preferences. Afterwards, the system generates specific recommendations by employing a recommendation algorithm [15] which contributes to the generation of results. By the same token, when the user connects to the social network (Facebook), the system collects all the data from the user’s profile and extracts his/her interests. The system, then, determines these trusted friends in the social networks. In the section 3, we will present our method for determining trusted friends in the social recommender system.

2.3. Trust-Aware Recommender Systems

Based on the assumption that users generally have a tendency to use items recommended by friends rather than strangers and that trust among friends positively correlates with user preference, we decided to refer to research conducted on the emerging field of trust-based recommender system. This field of study focuses on providing users’ personalized item recommendations with reference to the trust relationships among users (e.g., social friends). Trust-based recommender systems are referred to in this research paper because they are found to be useful in solving many of the issues associated with traditional systems, such as data sparsity [32] and cold start [19]. In recommender systems, trust is classified into explicit and implicit. Explicit trust emphasizes information explicitly stated by users. Although research on explicit trust-based recommender systems has been proposed [18], [19], [30] and its effectiveness has been tested, the system is found to have many caveats. In spite of the fact that specific trust values are possible in real systems, publicly available datasets such as FilmTrust [18] only contain trust links without real values due to the concern of privacy. The indifferent and binary trust will prevent achieving better performance.

Some of these caveats are related to the extra effort a user must make to provide trust information in addition to rating them [20], [47], [21]. Another limitation is represented in the lack of explicit trust information in some popular datasets like Jester. Additionally, the binary nature of trust in datasets does not give a precision value for the trusted person as most of the explicit public trust datasets
They can be comments or mentions "Like" on objects in the profile (from the user or from friends). We apply some trust metric to calculate the value of trust between users and each of his/her friends. Our goal is to demonstrate how an ego’s social activities and his/her friends can be used to calculate a “level of trust” between two friends. Finally, we choose friends who have the highest level of trust. The extraction of the trusted friends’ list of a user is performed to determine the preferences and interests of each friend. Indeed, these interests can be useful to know the interests of the ego user.

A social activity is a social interaction between two directly connected social network friends at a period d. An example of social activity can be joint tagging two friends on the same photo. We can define the P(users)x, y as a list of friends who are tagged on the same photo with the user, x at a period of time d. This period is precised starting from date d till now. For example P(users)x,y can be defined as:

\[ P(\text{users}))^d = \{\text{user}_a, \text{user}_b, \text{user}_c \} \] (1)

This means that userx is tagged with usera, userb and userc after the fixed date d. Formula 1 does not take in consideration the number of tags between our ego user and another tagged user. In fact, in our work, we do not take in consideration only the number of interaction the way [34] did because for any existing interaction between two users after the date d, a weight value is calculated. This value is a real number limited between 0 and 1. It is fixed according to the date of this interaction. That is to say, the more this interaction is recent, the more its value is near to 1 and vice versa. Formula 2 is used to calculate the weight value for any interaction between the user and his/her friend user:

\[ W_{\text{int}}(\text{User}_x, \text{User}_y) = \frac{100 - (\text{time} \times 10)}{100} \] (2)

Where time is a real variable that takes the duration of the interaction i from the time of its apparition. For example, the weight of an interaction between user and user, that is one year old (time=1.0) since it took place has a value of Wnu = 0.9 and the weight of an older interaction has a value inferior to this weight, etc. (in our work, we do not take in consideration interactions that are older than ten years old). Then, we calculate the sum of values of all interactions of the same kind between userx and user, from this prefixed date d with the following formula. N is a social activity between these users (i.e., Tag, Like, Comment, etc.).

\[ N(\text{User}_x, \text{User}_y)^d = \sum_{i=1}^{\text{interaction kind}} W_{\text{int}}(\text{User}_x, \text{User}_y) \] (3)

Where i is an interaction of kind N. N is a social activity between these users. For example, if N is a Tag, we calculate the sum of weight of all Tags between userx and usery that exist after date d. Formula 3 can be applied for any social activity. Different social networks have different types of social activities among users. To calculate a “level of trust” between two friends in a social network, we have to describe all social activities among these friends taking in consideration the temporal factor. Podobnik et al.’s social activity classification is going to be used in this study. Table 1 describes all the social activities:
Table 1. Lists of user,’ Facebook friends classified by different social activities on Facebook

<table>
<thead>
<tr>
<th>List label</th>
<th>Description of the list</th>
<th>Weight assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>P(user&lt;sub&gt;x&lt;/sub&gt;)</td>
<td>List of friends who are tagged on a same photo with the Facebook user&lt;sub&gt;x&lt;/sub&gt;</td>
<td>( W_P )</td>
</tr>
<tr>
<td>S(user&lt;sub&gt;x&lt;/sub&gt;)</td>
<td>List of friends who write on the Facebook user&lt;sub&gt;x&lt;/sub&gt;’s Wall</td>
<td>( W_S )</td>
</tr>
<tr>
<td>C(user&lt;sub&gt;x&lt;/sub&gt;)</td>
<td>List of friends who leave comments on the Facebook user&lt;sub&gt;x&lt;/sub&gt;’s Wall</td>
<td>( W_C )</td>
</tr>
<tr>
<td>L(user&lt;sub&gt;x&lt;/sub&gt;)</td>
<td>List of friends who like posts on the Facebook user&lt;sub&gt;x&lt;/sub&gt;’s Wall</td>
<td>( W_L )</td>
</tr>
<tr>
<td>I(user&lt;sub&gt;x&lt;/sub&gt;)</td>
<td>List of friends who write to the Facebook user&lt;sub&gt;x&lt;/sub&gt;’s inbox</td>
<td>( W_I )</td>
</tr>
<tr>
<td>M(user&lt;sub&gt;x&lt;/sub&gt;)</td>
<td>List of friends on whose Walls the Facebook user&lt;sub&gt;x&lt;/sub&gt; writes or comments</td>
<td>( W_M )</td>
</tr>
<tr>
<td>PL(user&lt;sub&gt;x&lt;/sub&gt;)</td>
<td>List of friends who like the Facebook user&lt;sub&gt;x&lt;/sub&gt;’s photos</td>
<td>( W_{PL} )</td>
</tr>
<tr>
<td>PC(user&lt;sub&gt;x&lt;/sub&gt;)</td>
<td>List of friends who leave comments on the Facebook user&lt;sub&gt;x&lt;/sub&gt;’s photos</td>
<td>( W_{PC} )</td>
</tr>
<tr>
<td>F(user&lt;sub&gt;x&lt;/sub&gt;)</td>
<td>List of all friends of the Facebook user&lt;sub&gt;x&lt;/sub&gt;</td>
<td>-</td>
</tr>
</tbody>
</table>

Social activities of the user<sub>x</sub> are described as the social_activity_set(User<sub>x</sub>) [34]. In other words, it is the set of lists where every list describes a different social activity. The lists summarized in Table 1 (except list F(user<sub>x</sub>)) form a complete set of social activities between the user<sub>x</sub> and all of their Facebook friends:

Social_activity_set(User<sub>x</sub>) = \{ P(user<sub>x</sub>) , S(user<sub>x</sub>) , C(user<sub>x</sub>) , L(user<sub>x</sub>) , I(user<sub>x</sub>) , M(user<sub>x</sub>) , PL(user<sub>x</sub>) , PC(user<sub>x</sub>) \} (4)

Every list from the set social_activity_set(User<sub>x</sub>) contains a list of users who have this specific activity with the user<sub>x</sub>. (Formula 1 is an example of the list of users who are tagged with the user<sub>y</sub]).

In order to calculate trust from interactions’ data contained in the social_activity_set(User<sub>x</sub>), we multiply the specific activity data from every list in the social_activity_set(User<sub>x</sub>) with certain weights peculiar to every interaction type. Formula 5 is used to calculate the level of trust between the social network ego user (user<sub>x</sub>) and one of his/her friends (user<sub>y</sub>):

\[
\text{Trust}(\text{User}_x, \text{User}_y)^d = \frac{\sum_{N \in \text{social_activity_set}(\text{User}_x)} W_N \times N(\text{User}_x, \text{User}_y)^d}{\sum_{N \in \text{social_activity_set}(\text{User}_x)} W_N}, \\
\forall \text{ User}_y \in F(\text{User}_x)
\]

(5)

Where user<sub>x</sub> is the ego user and user<sub>y</sub> is a friend with this ego user.

Trust(\text{User}_x, \text{User}_y)^d calculates the level of trust between the ego user and a direct friend with him/her according to all interactions between these users from a date \( d \). After the calculation of the level of trust between the ego user and all his/her friends, we conserve the 10 friends that have the higher level of trust as the “Trusted Friends” for this ego user.

4. EVALUATION OF THE PROPOSED METHOD FOR CALCULATING TRUST ON FACEBOOK

“Trusted Friends” is the Facebook application responsible for calculating trusted friends for a particular Facebook user. The implemented Facebook application collects activities (i.e., “liking” and commenting posts, inbox information “writing” on the Facebook Wall, etc.) of friends and calculates a trust level between the ego user and all of their friends. Figure 1 further illustrates the functioning of the process for determining the ego user’ trusted friends by our application.

The data collection process includes collecting personal and behavioral data of the ego user when connecting to his/her Facebook account, installing the “Trusted Friends” application, and allowing the application to access all these information (photos, user’s Wall, user’s inbox). Then, the system will extract some data to determine the user’s trusted friends. We mean by extracted data, the user’s list of friends, and those who write and make comments on the ego user’s wall. The list also comprises friends tagged with the ego user in their photos, friends who like posts on the ego user’s Wall, friends who comment on the ego user’s Wall, friends who write to the ego user’s inbox, friends on whose Walls the ego user writes or comments, friends who like ego user’s photos, and finally, friends who comment on ego user’s photos. When we extract any information for the user profile, we extract also its date when it happened. The data processing consists of a grouping of interactions (social activities) according to their type. Then for every friend, we will calculate the sum of their social activities taking in consideration the weight of every interaction to classify user’s friends according to the sum of their social activities. As it has been explained, every social activity has a weight that represents its importance for determining trust between users. [34] has proved that the following set (table 2) for weighting every social activity is the best among four proposed sets. In the rest of our work, we will use these weights presented in Table 2:

![Figure 1. Trusted Friends determination process](image-url)
To test our application, we have taken in consideration only the users who have installed the “Trusted Friends” application and allowed the application to access all the ego user’s photos, the ego user’s Wall, and the ego user’s inbox. The following figure presents life cycle of our “Trusted Friends” Facebook application.

We have chosen an objective evaluation to evaluate our suggested method. By objective evaluation, we mean a mathematical calculation of the precision measure used for the evaluation of recommender systems. Precision refers to the quality of recommendation. In other words, at what point those proposed friends confirm to the friends manually chosen by the user.

\[
\text{Precision} = \frac{\text{number of pertinent suggestion}}{\text{number of trusted friends suggested}}
\]

Every one of the users who tested our application, will be asked to choose his/her trusted friends manually at first. This step is necessary to calculate the precision of our application. Then we apply our algorithm and calculate its trusted friend automatically with our method. After that, we calculate the precision measure of our algorithm for this ego user. Next, we calculate the average of these precisions value given for all users that have accepted to install and test the “Trusted Friends” application (80 users have tested our application). The average of the precision (0.63) is superior to (0.51): the value found by [26]. We can conclude, then, that when we take in consideration the time duration of every interaction between the ego user and his/her friend and when we give a weight for the interaction taken in consideration its temporal factor, we can improve trusted friends determination process and give more precise results. Figure 3 shows the comparison result between the “Closest Friends” algorithm [34] and our “Trusted Friends” algorithm.

As a result, we can say that trust is sensitive to the interaction time between social network users. Many models were proposed to represent computational trust in different applications of social web. However, even models that represent trust as incremental measurement device do not give enough importance to the time axe. Consequently, exploiting temporal context is found to be an effective approach to improve recommendation performance. In the next section, we will explain the need of ontology to represent the user interest and to store the Tunisian Medical Tourism domain.

In our work, we have developed a user interest ontology [15] that represent all information about the user and his/her trusted friends preferences. When the trusted friends’ determination process was complete, our system extracted the user interests following several steps. After giving the user’s answers and obtaining the initial profile, we collected user data from his/her social profile and behaviors in the network. Then, we analyzed the user data to extract the interests of the user and their trusted friends. Finally, we presented all these data in the form of an ontology. The ontology’s main concepts are the user’s preferences and their trusted friends’ preferences. The user interest ontology is implemented using Protégé Ontology Editor and represented in the Ontology Web Language (OWL). When we represented a friend preference as a class in the user interest ontology, we indicated the name the trusted friend and the degree of trust (between the ego user and this friend) as two data types properties in this OWL class. In the next section, we will present our smart tourism recommender system.

### 5. SMART TOURISM RECOMMENDER SYSTEM

Medical Tourism is a domain rich of data that are stored in hundreds of data sources. Many of these sources are used in concerts during the development of tourism information systems. That is why, it is very important to create a referential model that represents the medical tourism in Tunisia (SPA centers and cures, clinics, hotels, thalassotherapy activities, surgical acts for medical tourism, etc.). In our research team, we have created a Tunisian Medical Tourism Ontology (TMT ontology) that represents all concepts and relations of medical tourism in Tunisia [16]. The e-tourism ontology provides a way to achieve integration and interoperability through the use of shared vocabulary and meanings for terms with respect to other terms [9].

To evaluate the performance of our system, we are developing a Java-based prototype named “Semantic social recommender system for Tunisian medical tourism”. It is an e-tourism recommender system for the promotion of medical tourism in Tunisia. It encapsulated two knowledge-based recommender system (the user interest ontology and the TMT ontology) to help user find the best
advice for his/her health and promote medical tourism in Tunisia. When the user accesses to the system, at first, he/she can connect with his/her Facebook account to pick up the user’s preferences and his/her trusted friends’ preferences for the creation of the user interest ontology. Then, the system will ask him/her to complete a forum and answer some questions to know his/her health situation. The main objective is to obtain as much information about his/her health interest as possible with the smallest number of questions. Afterwards, our semantic social recommender system will search the most adequate activity as well as the tourism provider service by applying a semantic social recommendation algorithm [16] taking in consideration all information represented in the user interest ontology. Figure 4 further illustrates the functioning of our system.

The system will create the user interest ontology based on these explicit information answered by the user and from the social network profile by adding the user preferences and trusted friends’ preferences. While user preference is collected from user’s profile, friends’ preferences are collected from the user social graph presented by Facebook. Before capturing the user preference, we must first analyze the entire user profile, the personalized friends’ list; the relations and the “likes” of the users and their friends. All these preferences will be represented in a user interest ontology [15]. Then, the social recommender system will generate recommendations with the help of the user interest ontology. By using social recommendation algorithm [16], our system will search for similar items to the user preferences in the TMT ontology. These preferences are important to decide which activities to recommend to the user. Recommendations are selected from the TMT ontology as the most similar to the user interests. Our semantic social tourism recommender system will calculate similarity between the user interest ontology and the TMT ontology. Then, the system will suggest the most similar items to the user. Our semantic social tourism recommender system will search the most adequate medical activities for the user taking in consideration all information about the user represented in the user interest ontology.

Our Smart tourism recommender system can suggest different types of recommendation (eg. Hotel, Clinic, Treatment Center) based on the information completed by the user. Otherwise, if the user does not like the recommendations suggested, he/she can select a hotel, for example, and click on “other similar activity” so that the system will suggest hotels that are similar to the selected one. The user can also select other hotels that are near by the selected one by clicking on “other activity around”. Generally, the user can select any recommended activity by clicking on “more details” and the system will give information about it. Once the user makes his decision about one of the suggested activities, he/she can reserve it for his/her medical travel to Tunisia.

6. CONCLUSION AND FUTURE WORK
In this work, we have presented the role of social networks as sources for the development of recommendation systems. In addition, we proposed a method for an implicit trust determination between social network friends and we have demonstrated that trust is sensitive to the temporal factor of interactions between users. All trusted friends’ preferences and user’s preferences are represented in the user interest ontology. We integrated the user interest ontology in a semantic social recommender system to deal with the lack of semantic information in personalized recommender system in tourism domain. In addition, a Tunisian medical tourism ontology has been developed to represent all medical tourism information. Our goal is to improve the Tunisian e-tourism domain by a smart tourism recommender system using trusted friends’ recommendations. The updating of our user interest ontology could be developed in future research work to encompass user interest and trusted friends’ preferences' changes. Currently, we are going to achieve this medical tourism prototype to be able to test users’ satisfaction of the system taking into consideration the temporal factor in calculating trust between users.

7. REFERENCES


