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A novel tourism recommender system in the context of social commerce

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ABSTRACT

Web 2.0 and its services, such as social networks, have significantly influenced various businesses, including e-commerce. As a result, we face a new generation of e-commerce called Social Commerce. On the other hand, in the tourism industry, a variety of services and products are provided. The dramatic rise in the number of options in travel packages, hotels, tourist attractions, etc. put users in a difficult situation to find what they need. For a reason, tourism recommender systems have been considered by researchers and businesses as a solution. Since tourist attractions are often the reason for travelling, this research proposes a social-hybrid recommender system in the context of social commerce that recommends tourist attractions. The purpose of the research is presenting a personalized list of tourist attractions for each tourist based on the similarity of users' desires and interests, trust, reputation, relationships, and social communities. Compared with the traditional methods, collaborative filtering, content-based, and hybrid, the advantage of the proposed method is the use of various factors and the inclusion of trust factors in recommendation resources, (such as outlier detection in user ratings), and employing social relationships among individuals. The experimental results show the superiority of the proposed method over other common methods. The proposed method can also be used to recommend other products and services in the tourism industry and other social commerce.

1. Introduction

Having had approximately 11% of global Gross Domestic Product (GDP), employed 200 million people and served 700 million tourists through the world, the tourism industry is considered as one of the largest manufacturing sectors in the world, and it is expected to double in 2020 (Kabassi, 2010). Planning a trip not only is selecting a destination but also it includes deciding on associated resources such as accommodation, restaurant, museums, transports or events. The astonishing progress of Information and Communication Technology (ICT), the Internet and its services provides access to more detailed information for users; in addition to dramatically increasing options for them. As the list of options is grown for tourists, it gets more complex and time-consuming to find an appropriate option tailored to his/her needs (Nemade, Deshmane, Thakare, Patil & Thombre, 2017). Customers usually surf the web, search about different options, book, and pay their order directly. In other words, they tend to analysis information by themselves (Nemade et al., 2017). According to researches (Wolfe, Hsu & Kang, 2004), the scarcity of personalized services, security, lack of experience and time-consuming search are the most reasons for not buying online tourism products.

Recommender systems solve the problem of information overhead and increase the number/value of the sales in e-commerce (Schafer et al., 1999). These systems help users to find attractive, required and suitable options for a wide range of options. The main purpose of the systems is predicting the user's desire based on available information in the form of recommendation list. The accuracy of the recommendations is depended on the information (Thasal, Yelkar, Tare & Gaikwad, 2018). In this way, there are three conventional approaches including collaborating filtering, content-based filtering and hybrid (Esmaeili, Nasiri & Minaei-Bidgoli, 2011; Kumar & Varsha, 2018). The approaches have some challenges and weaknesses such as cold start or outlier rating detection (Gope & Jain, 2017; Revathy & Anitha, 2019; Vairachilai, 2018).

Moreover, the rapid development of Social Media and Web 2.0 provides a great potential for changing electronic commerce from

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a product-driven environment to a social and customer-driven one (Busalim & Hussin, 2016; Gretzel & Yoo, 2008; Esmaeili & Hashemi, 2019 ; Han, Xu & Chen, 2018; Shanmugam & Jusoh, 2014). In this environment, customer's access to social experience and knowledge lead to a better understanding of online shopping purposes and more deliberate, accurate decisions (Dennison, Bourdage-Braun & Chetuparambil, 2009). Since in the eyes of most people, shopping is a social experience, they tend to know the opinion of their friends. Hence, people make decisions and purchase under the influence of their social relationships (Hajli, 2015, 2017; Hashemi, Esmaeili, Mardani, & Mutallebi, 2016; Lu, Fan & Zhou, 2016; Shin, 2013; Wang, Yeh & Imron, 2016). Thus, E-Commerce has faced a new evolution called Social Commerce that applies Web 2.0 capabilities and features to engage customers and encourage them to have communication (Kim & Srivastava, 2007; Liang, Ho, Li & Turban, 2011) and provides more economic values for businesses (Parise & Guinan, 2008). Gretzel and Yoo (2008) express that 75% of passengers consider online reviews as an essential resource for their trip planning.

There are two main categories for social commerce websites: the first category is based on the e-commerce websites that uses web 2.0 concept and tools (e.g. www.amazon.com). The second category is made based on the web 2.0 platform and then added e-commerce features (e.g. www.facebook.com/ Starbucks) (Busalim & Hussin, 2016; Esmaeili & Hashemi, 2019; Han et al., 2018; Huang & Benyoucef, 2013; Shanmugam & Jusoh, 2014). In the first category, social features such as content sharing and user communications are less considered. In contrast, the second category has less potential for buying and selling in such a way that it lacks user purchase history, pricing, and so on. Therefore, recommender systems in social commerce websites have considered only one group of features (social factors or user purchase history).

Given the provided platform in Social Commerce, a new and less considered approach is introduced in the field of recommender systems, especially in tourism recommender systems (Camacho & Alves-Souza, 2018). The new method uses social relations between people as a rich information resource. In most recommender systems, information source includes user purchases transactions, user ratings to items, demographic information of user, and item profiles (García-Crespo et al., 2009; Huang & Bian, 2009; Pi, Ji & Yang, 2018; Schiaffino & Amandi, 2009; Yang & Marques, 2005). Whereas based on Homophily Principle (McPherson, Smith-Lovin & Cook, 2001) in Social Networks, similarity causes communication and relationship. It means individuals have common characteristics with whom communicate with (Ferreyra, Hecking, Hoppe & Heisel, 2018; Tang, Gao, Hu & Liu, 2013). Also, the density of the user's connections in the social network is not similar. The difference leads to Community in networks. A community is a network segment (subgraph) that includes higher internal density and a lower crossing density with other segments. These communities can provide a lot of information about individuals without reviewing their personal information (Zardi, Romdhane & Guessoum, 2014). Most commercial tourism recommender systems are used demographics information while people are affected by the opinion of their friends, families, experts, and people with common interests due to their similarity. Thus, given the importance of social relationships, it is reasonable to use the relations as a source of information and develop a recommender system based on relations and social communities.

The purpose of this study is to provide a new method for recommender systems in the context of social commerce that is customized for the tourism industry. The proposed method will benefit social relationships as well as transaction information and user ratings of items. Therefore, the research hypothesis is providing a more efficient recommender system using social relations and in particular similarity, communities, trust, and reputation increasing the accuracy and confidence of forecasting. In fact, social relationships affect the decision of users and their purchases (Hajli, 2015; Hajli et al., 2017; Hashemi, Esmaeili, Mardani, & Mutallebi, 2016; Lu et al., 2016; Shin, 2013; Wang et al., 2016).

In order to cover the weaknesses of each category, this paper proposes a new tourism recommender system with a hybrid-social approach. The system recommends tourist attractions that are the main reason for travelling (Lew, 1987; Richards, 2002). The proposed model recommends reliable and tailor-made tourism attractions to each user using the collective intelligence of its social network. In addition to social commerce websites, the suggested model can also be used in other social commerce websites and platforms.

Hence, in this paper, a new method for recommending tourist attraction in the context of social commerce is proposed. Our innovation is the use of interactive factors and human relationships such as trust (Chang & Chu, 2013; Kim, Ferrin & Rao, 2008), reputation (Mui, Mohtashemi & Halberstadt, 2002; Xiong & Liu, 2003), social relations (He & Chu, 2010) and social community (Kamahara, Asakawa, Shimojo & Miyahara, 2005) that have not been used in pervious recommender systems simultaneously and specifically in tourism systems yet. Some works use the factors independently but not simultaneously. Therefore, in our study, we define and formulate the factors in terms of the problem space and then measure and combine them to obtain an efficient recommender system.

The paper is organized as follows. Section 2 reviews related work in this subject and Section 3 proposes the new hybrid-social recommender model. The dataset, strategy, and requirements that are used for the recommender system are explained in Section 4. Section 5 and 6 provides results, and discussion respectively and in the final Section 7, conclusion and future work is presented

2. Related work

2.1. Tourism recommender systems

Recommender systems help users to find an appropriate and attractive required option among others. They have been used to solve information overhead problem (Schafer et al., 1999) and increased sales in e-commerce websites. The main purpose of the systems is estimating users' desire and predicting items list based on the proper information (Esmaeili et al., 2011).

There are different approaches to develop recommender systems. The most common ones are content-based filtering, collaborative filtering and hybrid filtering (Esmaeili, Minaei-Bidgoli, Alinejad-Rokny & Nasiri, 2012). The main idea of the first approach is selecting and recommending those items that are similar to what user bought in the past. Content-based filtering measures similarity between items by analyzing content information. This approach will be failed if enough and appropriate information is not available (Ahn, 2008). Collaborating filtering is one of the most effective algorithms for recommender systems that detect similar users and analyzes their interests to make a recommendation. Cold start and new item set are its most popular problems. A lot of works have combined collaborative filtering and content-based filtering in parallel or sequentially to improve recommendations (Esmaeili et al., 2011).

There is two information collecting methods for personalized recommendations tailored to user interest: explicit and implicit (Hanani, Shapira & Shoval, 2001). The implicit method collects information about user behavior to identify user interests. If the user's behavior changes, the information related to her/his interests will also change (Adomavicius & Tuzhilin, 2005). In contrast, the explicit method analyzes user' interaction to determine user interest (Alton-Scheidl, Schumutzer, Sint & Tscherteu, 1997).

Tourism recommender systems were almost based on collaborating filtering approach (García-Crespo et al., 2009; Shelar, Kamat, Varpe & Birajdar, 2018; Yang & Marques, 2005) and hybrid approaches (Huang & Bian, 2009; Schiaffino & Amandi, 2009). Also, most of them used both explicit and implicit methods to identify user interest (García-Crespo et al., 2009; Huang & Bian, 2009). Schiaffino and Amandi (2009) used demographic information to determine similar users. They recommended tourist attractions using a semantic network and combining collaborative filtering and content-based filtering. Their criteria were attraction type, price, location, and time of travel. García-Crespo et al. (2009) proposed a method that was based on a collaborative filtering approach and used users' interests and their ratings to attractions explicitly and the information of users' social network implicitly. They used location, time and weather as criteria. Yang and Marques (2005) offer a tourism recommendation based on collaborative filtering approach and implicit criteria.

In addition to content-based filtering, collaborative filtering, and hybrid filtering, there are some different works that use other methods such as the method based on artificial immune systems (Cabanas-Abascal, García-Machicado, Prieto-González & de Amescua Seco, 2013; Colomo-Palacios, García-Peñalvo, Stantchev & Misra, 2017), interest score (Klotz, Lisena, Troncy, Wilms & Bonnet, 2017)) and opinion mining (Colomo-Palacios et al., 2017). Also one of the implementation challenges in recommender systems is huge data. Thus, some papers focus on the best implementation methods and propose some solutions such as Map-reduce functionality of Hadoop (Thasal et al., 2018).

In this paper, we propose a hybrid-social recommender model based on the graph theory, social analysis and by combining collaborative filtering and content-based filtering approaches. This model uses both explicit and implicit information and applies trust, reputation and community factors that are resulted from users' relations and his/her similarity with others to recommend tourist attractions. It provides a list of recommended items using different criteria and considering the effect of social relationships on user's/customer's decision in a purchase. Such a consideration has not been taken into account in previous studies that have focused on developing a tourism recommender system, while according to the surveys (Hajli, 2015; Hajli et al., 2017; Hashemi, Esmaeili, Mardani, & Mutallebi, 2016; Lu et al., 2016; Shin, 2013; Wang et al., 2016), the social relationships of individuals affect their willingness to buy and their decision to purchase items. Now, the information on social relations in the context of social commerce is considered a potential for improving recommender systems. Thus, with the assumption of a social tourism system (including social networks and user transactions), all information needed for use in the model will be available.

2.2. Trust and reputation in social commerce

An online community is one of the social commerce features and allows users to express their opinion easily. Also, people can determine which users are trusted or which product/service they are interested in. On many online transactions, buyers do not have enough information about new sellers or new products which is bought from a known seller. It makes buying at risk. If there is a factor that is ensured seller credit, the risk of buying will be reduced significantly (Esmaeili, Mutallebi, Mardani & Golpayegani, 2015; Hashemi, Esmaeili, Mardani, & Mutallebi, 2016). Trust and reputation are among the factors that reduce the risk of purchase (Jøsang, Ismail & Boyd, 2007; Mui et al., 2002). Total risk of a transaction is a function of some trust variables such as transaction cost, transaction history and compensation (Manchala, 2000).

- *Trust*: trust is a subjective quantity that determines someone's expectations of others' actions and affects his/her interaction with others (Hashemi, Esmaeili, Mardani, & Mutallebi, 2016).
- *Reputation*: reputation is a general and social quantity that is made based on the behavior of someone with others in his/her previous interaction (Hashemi, Esmaeili, Mardani, & Mutallebi, 2016).

Therefore, the main difference between trust systems and reputation systems is explained as follows: trust system produces a rating that reflects the personal attitude of an individual to the level of reliability to another person; whereas reputation system calculates the reliability to someone based on the whole community view. Moreover, the inputs of the trust system are merely general and subjective factors while the inputs of the reputation system are the information about transactions (such as ratings and reviews) (Jøsang et al., 2007). Nowadays, there are several methods for calculating trust and reputation, some of which are used in commercial systems, but some are still in the range of suggested ideas (Jøsang et al., 2007; Mui et al., 2002). In this research, we consider trust provided and made using reputation.

2.3. Social community

Several data sets can be defined based on network structure. Considering graph theory, a node shows an entity (e.g. individual) and an edge displays a relation between nodes (e.g. friendship or being classmate). A common feature among all networks is community structure that points to a group of nodes with a high density of edges. The group has low communication with other groups. Community detection by focusing on such a network structure is recently more considered. There are several methods and approaches for detecting community such as centrality-based methods, modularity maximization methods, local methods and spectral separation techniques. There is a complete overview of these methods in Meghanathan, (2018), Nguyen, Dinh, Shen and Thai, (2014), Plantié & Crampes, 2013.

People have different features that are placed them in a wide range of descriptive-qualitative classes. Some features could be seen more clearly in some class. For example, women are emotional or educated people are independent. Such features cause to ignore the great variety of descriptive classes. Individuals get similar to some people that they communicate with. Thus, some features will become local and centralized. The communication between similar individuals is formed at a higher rate than different ones, called Homophily principle.

According to Homophily principle and community structures, it can be resulted that: a social community that has strong internal relations between their nodes, and has weak external relations with other communities, includes the nodes with acceptable similarities with each other. This principle is considered in our paper for detecting communities to present a recommender model.

3. Social-hybrid recommender model

In the tourism industry, tourist attractions affect travelling decisions. Traveler s, like other service/product customers, incline to question and get recommendations from their close friends, people with similar taste and professional traveler s for selecting a destination. Close friends may have not enough experience or even a similar taste. Professional traveler s have visited desired destinations at least one time and can share their experience with others through a review. But, it can be hard to trust an unknown professional traveler's recommendations. Due to the variety of tourist attractions, a traveler has to use different recommendation source and compose them to select a destination. Thus, an

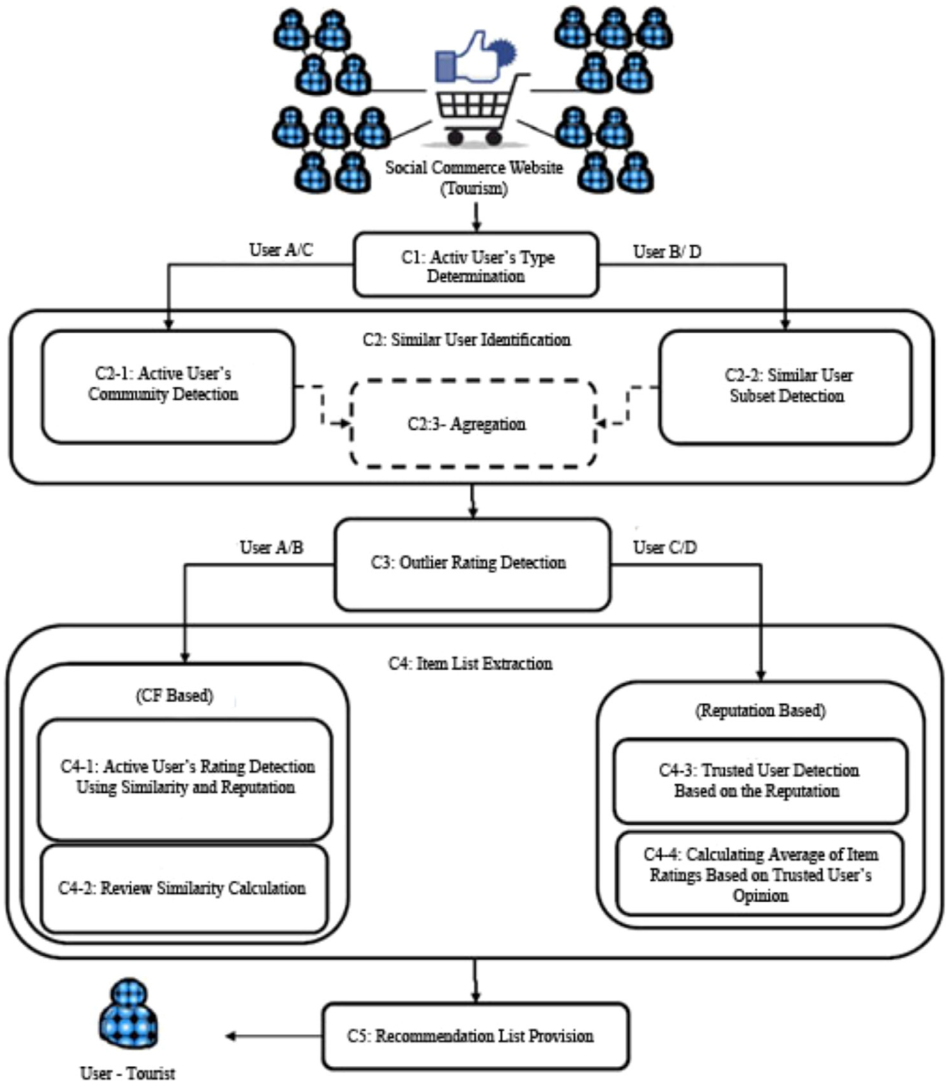


Fig. 1. The proposed social-hybrid recommender system (dotted line arcs and rectangles shows they are not mandatory).

Table 1
Active user types.

Communication/ Review	User with communication	User without communication
User with review	Type A	Type C
User without review	Type C	Type D

effective tourism recommender system combines different sources to recommend a suitable destination. In this paper, a social-hybrid recommendation model is proposed for recommending tourist attractions that it uses the information about individual's communications and other traveler s' opinions to provide a personalized recommendation list for each active user based on trust, reputation and similarity. An active user is a user whom the recommender system recommends a list of destination to.

The architecture of our proposed recommender system is presented in Fig. 1. Five components are developed for analyzing data in tourism social commerce platform. Each component is explained as follow:

- Active user's type determination component assigns an active user to a group (presented in Table 1) based on the implicit and explicit information about the user and tourist attractions (Appendix A).
- Similar user identification component extracts a subset of users based on the similarity of their community or demographic features with the active user.
- Outlier rating detection component detects the ratings which are presented by low-knowledgeable users or fake users for an attraction.
- Item list extraction component calculates a rate of each attraction for the active user based on its group.
- Recommendation list provision component creates a list of destinations tailored to the active user based on their ratings.

For each user (traveler), the system provides a list of recommended attractions based on reliable and similar users. The proposed components have not been considered in pervious tourism recommender systems. The systems evaluated items, determined a score for them and then provided a recommended item list without considering similar users to the active user. In our proposed framework, we have defined the components with the aim of increasing trust and reducing purchase risk for tourists. However, each component and method proposed here can also be employed in other recommender systems, because each component contains an innovation that can be redefined and reused in the context of social commerce. The main process of the recommender system is described as follow.

3.1. User's type determination

Active user's (u_a) type determination component determines user type based on the existence or absence of communication between the active user and other users in social commerce and also based on the ratings which are given by the active user to an attraction.

3.2. Similar user identification

Individuals with similar taste and behavior are interested in similar items, even though they have never seen each other (Abdul-Rahman & Hailes, 2000; Camacho & Alves-Souza, 2018; De Meo, Nocera, Terracina & Ursino, 2011). Based on the users' activities in a special social context, it is possible to identify similar users. The interest of an active tourist for a tourist attraction can be predicted based on a group of tourists who have similar desires. Depending on the type of user, similar users are identified using two methods: (1) based on the Homophily principle and similar community and (2) based on the similarity of demographic information of users.

If the user is in type *A* or *C*, a subset of user communication graph that active user belongs to will be extracted using a community detection method (Fig. 1: C2-1). According to Homophily principle, individuals in a similar community have acceptable common interests. In Formula (1), *U* is the set of users of social commerce system and $c_{u_i}$is the community that user i is belonged to. UC_i shows the set of users who are in a similar community with user *i*; in such a way that it includes each user *j* that is in the community of user *i*.

$$UC_i = \left\{UC_i \subseteq U, u_j \in UC_i | c_{u_j} = c_{u_i}\right\} \tag{1}$$

If the active user does not have any relation with other users (type B and D), a subset of similar users is selected based on the user's demographic features (Fig. 1: C2-2). Formula (2), F_{u_i} shows the set of demographic features of user *i* that includes *n* different features. UD_i is the set of users that have a common demographic feature with user *i*.

$$\begin{aligned} &F_{u_i} = \{f_1, \ldots, f_n\} \\ &UD_i = \left\{UD_i \subseteq U, u_j \in UD_i | \exists F_1 = F_{u_i} \cap F_{u_j}, |F_1| = m, m \le n\right\} \end{aligned} \tag{2}$$

Generally, a user is assigned to one of four groups, *A, B, C*, or *D* and Formula (1) or 2 determines its similar users. In some situations, the size of a similar user group is not sufficient for decision or recommendation. In this situation, an alternative method is used. Formula (3) shows different ways of determining final similar user group for user *i* (US_i). According to Formula (3), if the number of users in UC_i reaches the desired threshold, *w*, the set is selected as the final group. If the number of users in UCi is less than the desired threshold, some users from UD_i who have registered a review are selected accidentally and are added to the similar user group of active user. For users in type *B* or *D* that it is not possible to make UC_i, the set UD_i is created. If the size of UD_i is less than the defined threshold, *w*, the number of common demographic features is decreased until the desired population result. Formula (3) shows this selection way.

$$US_i = \begin{cases} UC_i & n_{UC} \ge w \\ UD_i & n_{UD} \ge w \\ UC_i \cup \{Ud_i \subseteq UD_i\} & n_{UC} < w \\ UD_i, m\_new < m\_old & n_{UD} < w \end{cases} \tag{3}$$

3.3. Outlier rating detection

In social rating systems, ratings may be not valuable and valid. For example, because the user is fake, the user does not have enough knowledge, or user registers unreal review or rating. Such a user should be detected and limited. Thus, at first, user-attraction matrix, *UPoA* is formed for each type of attraction, *CP*. Each attraction (*P*) belongs to a special group (*CP*). Each element of matrix *UPoA* is equal to a rating which is registered by user *i* for attraction *j*. Based on the statistical outlier detection (Normal Distribution) (Esmaeili et al., 2012), an outlier score is determined for each attraction in the matrix. Finally, matrix *UO* is made that its every element is the outlier score of user *i* in attraction type k. Formula (4) shows it.

$$\begin{aligned} CP &= \{cp_1, \ldots, cp_k\}\; P = \left\{p_1, \ldots, p_j\right\} \\ UPoA_k &= \left[UP_{u_i p_j}\right], i \le n_u, j \le n_p, k \le n_{cp}, cat_{p_j} = k \\ UO &= \left[UP_{u_i cp_k}\right], i \le n_u, k \le n_{cp} \end{aligned} \tag{4}$$

The number of outlier score for each user affects its reputation. User reputation in each attraction type, $\mathrm{Re}_{u_i cp_k}$, is calculated separately and is equal to the ratio of the number of reviews which is registered by user *i* for the tourist attraction in group k to the total number of reviews of that group. If a user has an outlier rating, its reputation is reduced using a fall-factor. Matrix *R_Re* is the reputation matrix of a user in each attraction type (Formula (5)).

$$\begin{aligned} &R\_\mathrm{Re} = \left[\mathrm{Re}_{u_i} cp_k * fall\_factor_{u_i cp_k}\right] \\ &\mathrm{Re}_{u_i cp_k} = \frac{num\_of\_reviews\_for\_u_i\_to\_cp_k}{total\_num\_of\_rewiews\_for\_cp_k} \\ &fall\_factor_{u_i cp_k} = \sigma UO_{u_i cp_k}, 0 \le \sigma \le 1 \end{aligned} \tag{5}$$

3.4. Item list extraction

Type *A* and *B*: users in these groups are those who have already registered reviews in the system. The item list is extracted for these users using collaborative filtering. Since the user rating is not a numeral score, but it is a vector of parameters (response to some question), the collaborating filtering is a little more complicated. At first, considering user reputation, the rating of active user u_a is estimated for each attraction in a group which the user have not registered any rating for (*P_Ra(a, j)*). Then, the similarity of ratings for a pair of attraction *i* and *j*, $sim(r_{p_i}, r_{p_j})$, is considered as a weight for predicted scores in the previous step. Eventually, the final rating of the user for a destination *i* is predicted (Formula (6)).

$$\begin{aligned} &R\_Ra = \left[Ra_{u_i p_j} * R\_\mathrm{Re}_{ik}\right], cat_{p_j} = k \\ &\overline{R\_Ra_i} = \frac{1}{P_i}\sum_{j \in P_i} R\_Ra_{ij}, \forall i \in U \\ &similarity(a, i) = \\ &\frac{\sum_{j \in P_i \cap P_a}\left(R\_Ra_{aj} - \overline{R\_Ra_a}\right)\left(R\_Ra_{ij} - \overline{R\_Ra_i}\right)}{\sqrt{\sum\limits_{j \in P_i \cap P_a}\left(R\_Ra_{aj} - \overline{R\_Ra_a}\right)^2}\sqrt{\sum\limits_{j \in P_i \cap P_a}\left(R\_Ra_{ij} - \overline{R\_Ra_i}\right)^2}} \\ &P\_Ra(a, j) = \overline{R\_Ra_i} + \frac{\sum\limits_{i \in U} simlarity(a, i)\left(R\_Ra_{ij} - \overline{R\_Ra_i}\right)}{\sum\limits_{i \in U}|simlarity(a, i)|} \end{aligned}$$

$$sim(r_{p_i}, r_{p_j}) = \cos(\vec{r_{p_i}}, \vec{r_{p_j}})$$
$$P\_P(a,j) = \frac{\sum_{all\_similar\_reviews,N} sim(r_{p_j}, N) * P\_Ra(a,N)}{\sum_{all\_similar\_reviews,N} (|sim(r_{p_j}, N)|)} \quad (6)$$

Type *C* and *D*: There is not any rating history for users in these groups. Thus, Item list is extracted based on other users rating. In this way, the attractions with the highest average score among trusted users, TU, are considered as a user item list. Trusted users are users who have a reputation score, R_Re_{ik}, more than α, a specified threshold (Formula (7)).

$$TU = \{u_i \in U | R\_Re_{ik} \geq \alpha\}$$
$$\overline{R\_Ra_{p_j}} = \frac{\sum_{i \in TU} R\_Ra_{ij}}{|TU|} \quad (7)$$

3.5. Recommendation list provision

Final scores for each attraction in group *A* and *B* is calculated in step C4-1 and C4-2 (Fig. 1). After sorting scores, *n* items from the top of the list are selected as the recommended list. *n* can change in different situations. For users in group *C* and *D, n* items from the top of the list that is extracted in step C4-3 and C4-4 (Fig. 1) are considered as the recommended list.

4. Experiment

In this section, an experimental study of proposed social-hybrid recommender model is explained. Also, the result of the execution of the proposed model is compared with conventional and traditional approaches to evaluate their efficiency.

4.1. Dataset

Our experiments were done on a real dataset of an international travel agency in Asia as follow (we cannot expose its name due to privacy):

- DR01-User profile: it includes the demographic information of 57,847 users such as gender, language, and country. Only 1487 users have registered reviews.
- DR02-Friendship communication: it includes 211,963 explicit relations. Therefore, most users do not have communication.
- DR03-Destination: it includes 2781 attraction in 27 groups.
- DR04-User review: it includes 3027 reviews for the attractions. Although the travel agency encouraged users to contribute to registering reviews, but also some attractions lack any review.

4.2. Recommendation strategy

In this research, our proposed model (SociHeybrid Rec) is compared with two main approaches to evaluate its efficiency. Given to our proposed model and the available data set, other approaches are not appropriate for comparing. Two selected approaches are:

- Content-based (Rec M1): in this strategy, we use the method presented in Lops, De Gemmis and Semeraro, (2011) that makes a profile from user interest based on the feature of items that already have been rated by that user. Then, new similar items are recommended based on user interest.
- Collaborative filtering (Rec M1): in this strategy, we use the method presented in Resnick, Iacovou, Suchak, Bergstrom and Riedl, (1994) that identifies similar users based on similar rating to items. Then, their rating on new items is used for recommending attractions.

5. Evaluation

To evaluate and compare the efficiency of different strategies, we selected 3027 records of user rating accidentally and divided it based on the Pareto principle (Pareto principle, 2020) to an 80% part for learning and a 20% part for testing. The experiments were executed for 20 times. In the following, the average of evaluation results for the test set is presented. Also, evaluation like other research (Bahabadi, Golpayegani & Esmaeili, 2014; Camacho & Alves-Souza, 2018; Silveira, Zhang, Lin, Liu, & Ma, 2019) is presented in two sections: (1) evaluation of predicted ratings and (2) evaluation of recommendations. Based on the evaluation criteria in each section, if the results of the proposed method are better, its efficiency is verified. Indeed, the defined components and their measures – also the combination of trust, reputation, similarity, and social communities - will improve the recommended list for users.

5.1. Evaluation of predicted ratings

The comparison of real ratings of an attraction that is registered by a user with a predicted rating by different strategies is used to evaluate the recommendation methods. This comparison can be done in two ways: First, comparing the behavior patterns of rating charts for different strategies, and second, comparing failed ratings with actual ratings (MSE measure (Mean squared error)). MSE calculates the mean squared error.

Given the variety of experiments, only some graphs are presented in this paper. Fig. 2 shows the predicted ratings in comparison with the actual ratings in different strategies. Two charts show data for 50 attractions that are selected accidentally. In Fig. 2, the horizontal axis shows the users and the vertical axis depicts user ratings in a range of 0 to 5 [0,5]. Regardless of the difference in ratings in the recommendation methods with actual ratings, the behavior of SociHybrid Rec is more similar to actual behavior. Maximum and minimum points in actual rating and the rating of SociHybrid Rec are close to each other.

The value of the MSE measure for three strategies is shown in Table 2. The less value of MSE shows more accuracy in score prediction. Based on the result, the proposed method estimates attraction ratings with more similarity and fewer differences than actual ratings compared to other methods.

5.2. Evaluation of recommendations

The three methods are evaluated based on three common measure: precision, recall, and F-measure (Esmaeili et al., 2011, 2012; Kumar & Varsha, 2018). A precision measure is a ratio of the number of effective recommendations to the total number of recommendations provided to an active user. Recall measure is a ratio of the number of effective recommendations to the number of user desirable items. The F-Measure is the weighted average of the precision and recall that is calculated by the ratio of multiplication of two numbers to the sum of them. The value of all three measures is in [0, 1] and 1 is the best value. Fig. 3 shows the value of these three measures for the three recommendation strategies.

After predicting active user ratings for items that have not yet rated, the ratings are sorted in descending order, and n tourist attractions in the top of the list are recommended to the active user. According to Fig. 3, the three measure show more efficiency for the proposed method compared to other methods (Rec M2 and Rec M1) in the case where $n = 5$. The collaborative filtering (Rec M2) also had better results than the content-based method (Rec M1).

Although the proposed method is more complex in terms of computing, but also the evaluation results show the positive impact of identifying similar individuals based on the Homophily

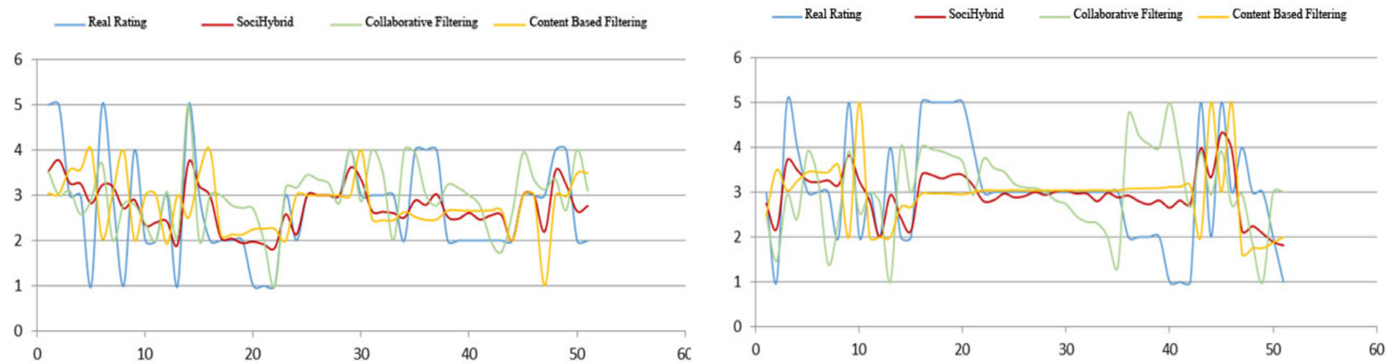
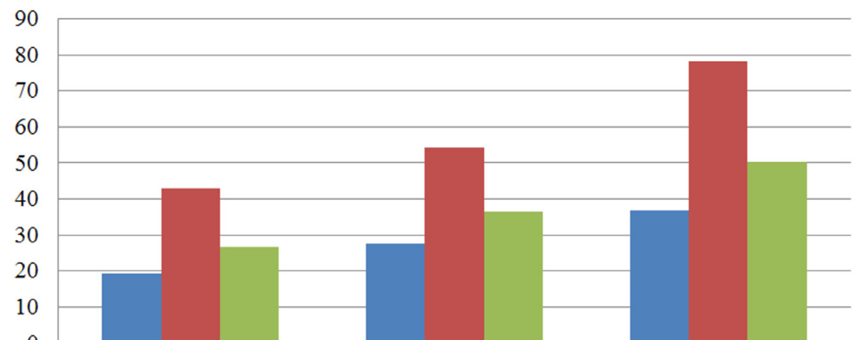


Fig. 2. The comparison of behavior patterns of attraction rating for 50 attractions (selected accidentally).



	Rec M1	Rec M2	SociHybrid Rec
Precision@5	19.3	27.5	36.9
Recall@5	42.8	54.4	78.21
F-Measure@5	26.6	36.53	50.14

Fig. 3. The comparison of the value of evaluation measures for the three methods.

Table 2
The value of MSE for each recommendation method.

Content-based Filtering (Rec M1)	Collaborative Filtering (Rec M2)	SociHybrid
2.22	1.6	0.78

principle, outlier rating detection, and the use of trust and reputation in the recommender system. When purchasing is risky due to various reasons, the recommendation based on the proposed method is more reliable and has more effect on the user's purchase decision.

The value of the recall measure is greater than the value of precision one because the number of reviewed tourist attractions is less than the number of recommended attractions. According to the dataset, users recorded review for an average of two tourist attractions, while the list of tourist attractions includes five attractions (@5). Hence, in all strategies, the value of the recall measure is greater than the precision measure. Also, the value of the precision measure is less than 40%. Although this amount seems to be low at first glance, but also this is also justifiable. Since the average number of tourist attractions that are rated by users is equal to two, in the best case if these two attractions are in the set of recommended items, the value of precision will be 40%. Therefore, the value of 35.1% for precision in the proposed method is desirable compared to the maximum possible value (40%). Therefore, all values of evaluation measures show the superiority of the proposed method compared to collaborative filtering and content-based filtering methods.

The results of evaluation measures for the recommended list (n items) are presented in Table 3 and Fig. 4. Due to selecting n items from the top of the recommended list and the presence of desired items there, the values of the recall measure show less change than the values of the precision and the value of precision measure reduces dramatically by decreasing the size of the recommended list.

Table 3
The result of evaluation measures for the tree methods in different size of the recommended list.

#N	Method	Precision	Recall	F-Measure
@2	SociHybrid Rec	91.64	69.35	78.95
	Rec M1	39.7	35.8	37.65
	Rec M2	43.2	39.6	41.32
@3	SociHybrid Rec	63.51	72.8	67.84
	Rec M1	29.2	36.3	32.37
	Rec M2	37.87	45.5	41.34
@4	SociHybrid Rec	47.65	76.56	58.74
	Rec M1	22.34	40.4	28.77
	Rec M2	31.6	49.34	38.53
@5	SociHybrid Rec	36.9	78.21	50.14
	Rec M1	19.3	42.8	26.6
	Rec M2	27.5	54.4	36.53
@6	SociHybrid Rec	31.81	82.43	45.91
	Rec M1	14.5	43.21	21.73
	Rec M2	22.7	55.3	32.19

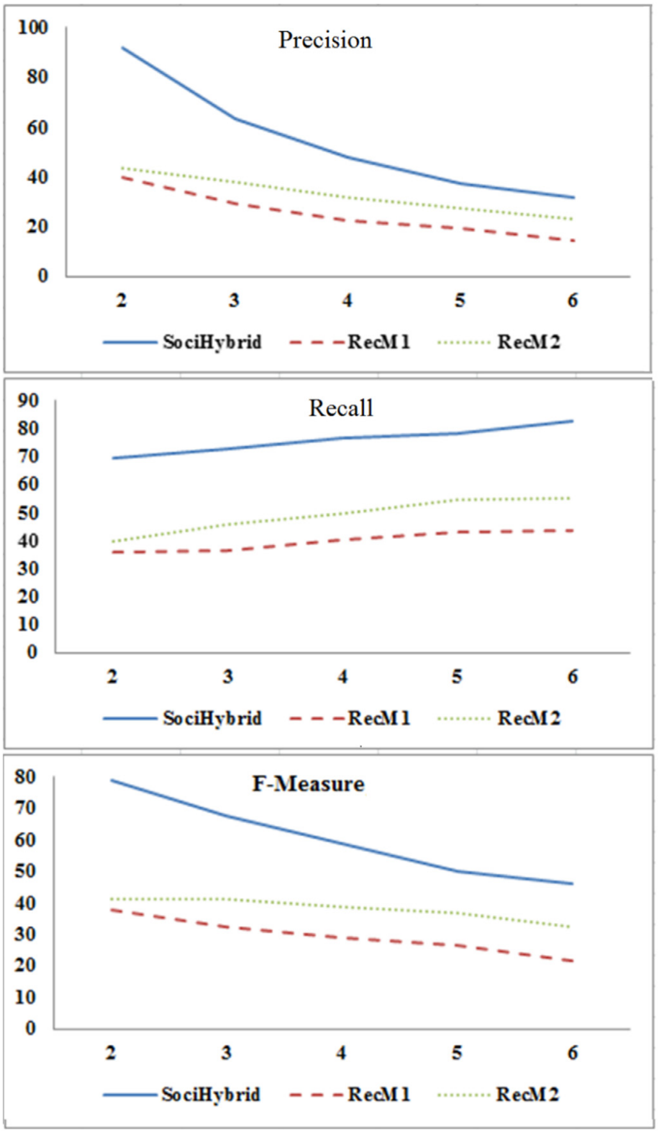


Fig. 4. The comparison of evaluation measures for the tree methods in different size of recommended list.

The reason is that the average number of desire items is equal to two. Therefore, by increasing the size of the recommended list, the value of precision measure decreases, and it cannot exceed a certain amount.

6. Discussion

In online shopping, people are impressed by the suggestions and tips of similar people, professional buyers, experts or their close friends. However, many social network platforms such as Twitter, as well as e-commerce systems such as Amazon and Yahoo, are still operating independently. Recently, some social networks like Facebook have made changes to provide some suggestion to their users.

Today, social networks can be more than just communicating with each other. Influenced by the capabilities and information potential of these networks, e-commerce systems have stepped into a new realm that is called Social Commerce. Social commerce has increasingly been considered in terms of practical and scientific aspects and has stimulated businesses, policies, and investments. Hence, the development of recommender systems, such as Amazon and eBay that are based on the individual purchase history and gathering of member's views (Schafer, Konstan & Riedl, 2001), will no longer be effective and sufficient. They do not take into account the connections between members and the power of social network.

On the other hand, the tourism industry is one of the most important and profitable industries. According to studies, tourist attractions are the motivation of individuals to travel. Hence, given the importance of the tourism industry and in order to consider the social effects of individuals and to balance the various factors, in this paper a social-hybrid recommender system is suggested for tourism industry that applies the similarity of people in the communities derived from social structure, along with the correlation of people's opinions and the trust based on the reputation for providing recommendations. The experimental result of our study verifies the result of the surveys done by other researchers (Hajli et al., 2017; Hashemi, Esmaeili, Mardani, & Mutallebi, 2016; Shin, 2013; Wang et al., 2016). In fact, the social relations of individuals are influential on their trust and their intention of purchase. The results of experiments on a dataset in the tourism industry show the effectiveness of our recommendation method over other main approaches.

We modeled the problem using Graph Theory, and we also used network analysis methods. We aimed to make a combination of collaborative filtering and content-based methods to provide reliable and valid recommendations. The recommended list contained a number of tourist attractions. Obviously, the number of tourist attractions in recommended list increase, the amount of recall increases and the amount of precision decrease. In addition, the predicted score error of our proposed method was less than other methods.

6.1. Innovation

There are some innovations in the proposed model:

- From the aspect of system innovation, as recommending items is expanding, the design of social recommender systems becomes a more important issue. On the other hand, the growing development of social commerce and Internet of Thing makes its solving more necessary. In this research, we also introduced a tourism recommender system based on the capabilities and features of social commerce systems) Curty & Zhang, 2013; Huang & Benyoucef, 2013)
- From a methodological point of view, we consider not only the similarity of individuals in terms of demographic characteristics, but also the similarity resulted of Homophily and community that is obtained from the social structure is considered. In addition, we have engaged the trust based on the reputation of users in recommendations. Therefore, the source of information for recommendations is similar people with the user and reliable reviews. On the other hand, in most e-commerce systems, the user's opinion is an item including text, general rating and some other ratings for different aspects of products. Since text processing is time-consuming, the user reviews are generally not used in recommender systems, and the recommendation is only based on the ratings. However, in the proposed recommender system, in addition to a general score, each review contains a vector of nominal values that are considered in the prediction of the active user rating for items.
- In terms of efficiency, the value of precision, recall, and F-Measure in the proposed method are better than other methods. Therefore, our method retrieves reliable information related to the user's taste and interest. Also, the selection of a subset of users that are similar to the target user has reduced computational load.

6.2. Implications

The proposed recommendation method can be effectively used by business owners in the context of social commerce to encourage users to purchase. Due to the increasing development of social commerce, the proposed mechanism can be used in other business areas such as e-shopping and other industries. In cases where the risk of purchase is high for the user due to the high price of goods/services, the proposed method can provide more reliable recommendations than other methods.

Our proposed method has five components and 4 data sources in the context of social commerce systems. Thus, it is sufficient to specify an equivalent for 4 data sources in each application domain. For example, in a digital-good store, product specifications can be considered DR03. It is also evident that for the DR02, we need a social network of users to extract their relations. It is called a social commerce system. In the absence of such a network, we can create it implicitly (for example based on IP or geographical location of users). It can affect the final result, but it may not be effective enough. Also, we can use the contact list of user with his/her permission, if our e-commerce system is based on the mobile platform. Totally, the methods and measures in each component either are reusable or can be replaced by other methods or measures. Therefore, our proposed recommender system can be generalized in different applications and domains.

6.3. Limitations

There are several limitations to this research, which include:

- Although social commerce services have grown and e-commerce sites are somewhat equipped with these facilities, but it is used more as an apparent credential, and the owners of social commerce platforms do not share their information because of privacy. Our dataset was also obtained from a not-so-famous tourism website, with a very limited number of registered comments, and users. Therefore, if businesses can encourage users to contribute to the presentation of their views, this restriction will be eliminated, and richer data can be used for the recommender system.
- There was no way to get feedback from users in this research. If we were able to receive user feedback, the recommendation systems would also be evaluated for users of type C and D. Considering the characteristics of the model, in this situation, the results of evaluation would be different compared with other approaches, and the size of recommendation list would not influence on the result.
- The proposed model was implemented on a small volume dataset. Since in reality and in the context of social commerce, the number of users and items is higher and more transactions occur, there should be experiments on large volume datasets. Also, the proposed method should be optimized for high volume applications (for example by using parallel processing).

7. Conclusion and future work

Due to the transformation of e-commerce into social commerce, business systems not only include information about items, users, and transactions, but also contain the social relationships of users and their opinions. Therefore, an appropriate information platform is provided to identify and measure similar users, user interests, and trust among individuals based on social theory. In the business world, especially in travel and tourism industry, when the risk of decision is high, or there is a wide range of options for customers, they should be helped to find a safest and most suitable option. Recommender systems can provide this assistance to users.

However, the use of user social relations and their opinion in tourism recommender systems have been less considered. In this research, with the assumption of the social relationship's impact on decision making in travelling, we proposed a social-hybrid recommender system based on trust, reputation, similarity, and social communities. In the system, graph theory and social theory (such as Homophily) and network analysis methods (such as community detection) were employed. The proposed system contains five main components that can be tailored to the type of application, and personalize based on the needs. The results of the experiments verified the performance of the methods employed in each component and their defined measures, and show the superiority of the proposed method to the previous methods.

7.1. Future work

Some orientations for future studies are as follow:

- Strengthen the structure of the social network by extracting social relationship from other social networks in order to identify similar users
- generalization of the proposed method for providing a context-aware recommender system
- Improvement of the proposed method for solving sparse data problem: collaborative filtering methods are sensitive to data sparsity that causes to inappropriate results. Our method also suffers from this problem due to using collaborative filtering approach.
- Investigating the impact of other methods of community detection, trust and reputation calculation and similarity identification on the results of the proposed method in order to achieve the best methods.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.eswa.2020.113301.

Appendix A

On the tourism social commerce website, in addition to travel and shopping information, the user communication information is also available. Since tourist attraction is the most important motivation for travelling, the system recommends tourist attractions for stimulating users to purchase tours. There are different explicit and implicit information about users and tourist attractions in the existing system. Some of the information which is used in our proposed model is presented in Table 4. Implicit information requires calculation and processing based on other information. Also, each user can submit a comment or review for each tourist attraction in the system. It includes a general score, user profiles (Table 4), and some questions about a tourist attraction with specific responses. Information elements of a comment are given in Table 5.

Table 4
The information of users and attractions in the social tourism systems (■ used in the proposed recommender system and □ not used).

User information (Status: Title: Data Type: Type)	Attraction information (Status: Title: Data Type: Type)
■: Gender: Nominal: Explicit	■: Rate: Relative: Implicit
■: Language: Nominal: Explicit	■: Attraction Type: Nominal: Explicit
■: Country: Nominal: Explicit	■: Location: Nominal: Explicit
□: Age: Interval: Implicit	□: Payment Type: Nominal: Explicit
□: Education: Sequential: Explicit	□: Facilities: Nominal: Explicit
□: Job: Nominal: Explicit	□: Introduction: Text: Explicit
□: Marital Status: Nominal: Explicit	□: Special circumstance: Text: Explicit
□: Reputation: Relative: Implicit	

Table 5
Items of in a review.

User Information	Table 4
Rate	Data Type: Sequential Type: Explicit
Question (Title: Data Type: Type)	Purpose: Nominal: Explicit Attendant: Nominal: Explicit Tour Type: Nominal: Explicit Time (Season): Nominal: Explicit Traveling Method: Nominal: Explicit

Credit authorship contribution statement

Leila Esmaeili: Conceptualization, Methodology, Validation, Investigation, Data curation, Writing - original draft, Writing - review & editing, Supervision, Project administration. **Shahla Mardani:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Visualization. **Seyyed Alireza Hashemi Golpayegani:** Investigation, Resources, Supervision. **Zeinab Zanganeh Madar:** Software, Validation, Data curation, Visualization.

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