



Social collaborative service recommendation approach based on user's trust and domain-specific expertise

Ahlem Kalai, Corinne Amel Zayani, Ikram Amous, Wafa Abdelghani,
Florence Sèdes

► To cite this version:

Ahlem Kalai, Corinne Amel Zayani, Ikram Amous, Wafa Abdelghani, Florence Sèdes. Social collaborative service recommendation approach based on user's trust and domain-specific expertise. Future Generation Computer Systems, 2018, 80, pp.355-367. 10.1016/j.future.2017.05.036 . hal-02562118

HAL Id: hal-02562118

<https://hal.science/hal-02562118>

Submitted on 4 May 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Open Archive TOULOUSE Archive Ouverte (OATAO)

OATAO is an open access repository that collects the work of Toulouse researchers and makes it freely available over the web where possible.

This is an author-deposited version published in : <http://oatao.univ-toulouse.fr/>
Eprints ID : 18270

To link to this article : DOI: 10.1016/j.future.2017.05.036
URL : <http://dx.doi.org/10.1016/j.future.2017.05.036>

To cite this version : Kalai, Ahlem and Zayani, Corinne Amel and Amous, Ikram and Abdelghani, Wafa and Sèdes, Florence *Social collaborative service recommendation approach based on user's trust and domain-specific expertise*. (2017) Future Generation Computer Systems. ISSN 0167-739X

Any correspondence concerning this service should be sent to the repository administrator: staff-oatao@listes-diff.inp-toulouse.fr

Social collaborative service recommendation approach based on user's trust and domain-specific expertise

Ahlem Kalai^{a,*}, Corinne Amel Zayani^a, Ikram Amous^a, Wafa Abdelghani^a, Florence Sèdes^b

^a Miracl Laboratory, Sfax University, Tunisia

^b IRIT Laboratory, Toulouse University, CNRS, INPT, UPS, UT1, UT2J, France

H I G H L I G H T S

- Proposing a novel Web service decentralized discovery approach.
- Our approach based on two disjoint service recommendation mechanisms.
- Recommending the Web services based on the social trust and the domain-specific expertise.
- Computing the social trust according to the time-aware users' interactions and the interest similarity.
- Computing the expertise of each recommender according to his past service invocation per domain.

A B S T R A C T

A few years ago, the Internet of (Web) Service vision came to offer services to all aspects of life and business. The increasing number of Web services make service recommendation a directive research to help users discover services. Furthermore, the rapid development of social network has accelerated the development of social recommendation approach to avoid the data sparsity and cold-start problems that are not treated very well in the collaborative filtering approach. On the one hand, the pervasive use of the social media provides a big social information about the users (e.g., personnel data, social activities, relationships). Hence, the use of trust relation becomes a necessity to filter and select only the useful information. Several trust-aware service recommender systems have been proposed in literature but they do not consider the time in trust level detection among users. On the other hand, in the reality, the majority of users prefer the advice not only of their trusted friends but also their expertise in some domain-specific. In fact, the taking into account of user's expertise in recommendation step can resolve the user's disorientation problem. For these reasons, we present, in this paper, a Web service decentralized discovery approach which is based on two complementary mechanisms. The trust detection is the first mechanism to detect the social trust level among users. This level is defined in terms of the users' interactions for a period of time and their interest similarity which are inferred from their social profiles. The service recommendation is the second mechanism which combines the social and collaborative approaches to recommend to the active user the appropriate services according to the expertise level of his most trustworthy friends. This level is extracted from the friends' past invocation histories according to the domain-specific which is known in advance in the target user's query. Performance evaluation shows that each proposed mechanism achieves good results. The proposed Level of social Trust (LoT) metric gives better precision more than 50% by comparing with the same metric without taking into account the time factor. The proposed service recommendation mechanism which based on the trust and the domain-specific expertise gives, firstly, a RMSE value lower than other trust-aware recommender systems like TidalTrust, MoleTrust and TrustWalker. Secondly, it provides a better response rate than the recommendation mechanism which based only on trust with a difference equal to 4%.

Keywords:

Service recommendation
Social profile
Past experience
Time
Trust
Expertise
Domain-specific

1. Introduction

1.1. Context & problem statement

In the last years, the massive use of Web services evolved the Web pages to Internet of Services (IoS) [1]. SOA (Service Oriented

* Corresponding author.

E-mail addresses: ahlem.kalai@gmail.com (A. Kalai), corinne.zayani@isecs.rnu.tn (C.A. Zayani), ikram.amous@isecs.rnu.tn (I. Amous), abdelghani_wafa@hotmail.fr (W. Abdelghani), sedes@irit.fr (F. Sèdes).

Architecture), Web 2.0 (Social Web) and Web 3.0 (Semantic Web) are among the technologies for IoS [2]. The aim of IoS is to offer services to all aspects of life and business [3]. In fact, all people, machines and goods have access to it by leveraging the network infrastructure. In the open service environment of IoS, Web services are increasing continuously. The service consumers (users) utilize different search tools such as public registries (e.g., UDDI,¹ Membrane,² WebServices Directory,³ etc.), public portal (e.g., ProgrammableWeb⁴) or search engine (e.g. Swoogle,⁵ Titan,⁶ etc.). However, all of these tools return a large number of services to the users. This causes a service overload problem [4,5]. Furthermore, these tools (i) do not take into account the user's profile, (ii) lack of dynamics [6], i.e., the user must query the registry regularly to look for the appropriate services, and (iii) based on centralized structure. Consequently, the service discovery and selection suffer from low precision results [7].

In fact, to enhance the service discovery, many research studies have been proposed in literature. The majority of these works are based only on semantic description of service with annotation (e.g., AWSDL, SA-WSDL) or ontology (e.g., OWL-S) to automatize the discovery level. While, others depend on non-functional properties, such as Quality of Service (QoS) [8] (e.g., response time, reliability) which is advertised by the service providers or collected on user's side. In another axis, several research works [9,10] paid more attention to the Collaborative Filtering (CF) based recommendation approach to help users out of service overload. But, this approach has some problems such as the data sparsity and the cold start problems [11]. With the advent of social Web, a Social Recommendation (SR) approach [12–14], which is based on users' social networks, emerged in order to reduce the CF problems. In this context, several social service recommendation approaches have been proposed to bring new opportunities to more personalize the service discovery. Some of these studies based on trust between service providers [15,16], service requesters [5,17] or between services [18,19]. In this paper, we focus on social service recommendation which based on mining trust from social networks of service requesters.

The success of users' social networks is largely due to their open and decentralized structure and also the great number of data were generated. In this context, the **first problem** is that some noisy information can infiltrate into a recommendation mechanism and damage the prediction accuracy [5]. Hence, the notion of trust becomes necessary to filter this big data [20]. Because the user's experience is vulnerable to his malicious manipulation [21], only the experience provided by trusted users should be taken into account. Based on this assumption, some research studies [22,23] have focused on users' interactions to compute the social trust by combining with other factors namely the interest similarity [24], the users' proximity [25,26]. However, all of them have neglected the impact of time in trust computing. Starting from our current life, the trust relationships change over time which implies that these links can grow stronger or weaker depending on the users' interactions and their affinities. In this direction, Moghaddam et al. [27] considered the temporal factor to rank trusted friends to be recommended.

The **second problem** is the insufficient use of the user's feedback in the rating prediction of service to be recommended. From our real life, the majority of users prefer the advice not only of their trusted friends but also their expertise. In literature, some service

recommendation approaches [4,28] have introduced the concept of expertise through different definitions and metrics. However, all of them do not consider the domain of user's query. In other words, we suppose a user A in his social network trusts another user B for his recommendation of medical domain. This does not automatically means that A trusts B's views on the travel domain.

1.2. Contribution

Compared to the existing research studies, our discovery approach aims the IoS and combines the Web 2.0 trends, especially the users' social networks, with SOA paradigm. In this paper, we present the enhancement of our previous service decentralized discovery approach [29]. The extended approach combines the social and collaborative filtering based on trust and domain-specific expertise. The advantage of this combination resides in the case where the social recommendation fails to return services to the user. Our objective is to reduce together the service overload and the user's disorientation problems.

The main contributions of the research reported in this article are as follows:

- We proposed to integrate the users and their invoked satisfactory services into the same structure of their social networks. Therefore, we have choose a SOAF (Service-Of-A-Friend)⁷ model [30] in order to benefit from social connections among users, services and users/services. This model is an extension of FOAF (Friend-Of-A-Friend)⁸ network structure which is augmented with service related information. The advantage of SOAF is to foster the creation of Web service ecosystems [30].
- We integrated two complementary mechanisms that can be used separately or conjointly: Social Trust Detection (STD) and Service Recommendation (SR). STD detects the social trust level among users. SR combines the social and collaborative approaches to recommend to the active user the appropriate services according to the domain-specific expertise level of his trustworthy friends.
- We introduced four concepts which are called respectively: (i) Level of the user's Interaction (LoI) to compute the degree of interaction between users based on their frequencies of social activities in the period of time. (ii) The Level of Similarity (LoS) is to compute the interest similarity between two users based on their social profiles. (iii) The Level of Trust (LoT) is to compute the confidence degree between users by aggregating the two last concepts. (iv) The Level of user's expertise (LoE) quantifies the usage experience of a friend in the domain-specific that indicated in advance by the active user in his query.
- We conducted a series of experiments based on three real datasets. The first service dataset is crawled from public portals (Xmethods, WebserviceX.Net, etc.), which include 15 Web services classified in 5 domains (currency, weather, travel, movie and localization). The second dataset is composed of 1326 real Facebook users from it a sample of 20 users have participated in the assessment of proposed mechanisms. The Epinions⁹ is the last used dataset to evaluate the accuracy of the proposed SR mechanism.

Organization of paper. This paper is organized as follows. In Section 2, we present the research background related to our previous work. In Section 3, we present a new motivating scenarios. In

¹ <http://uddi.xml.org/services>.

² <http://www.service-repository.com/>.

³ <http://www.webserviceX.net/New/Home/Directory>.

⁴ <http://www.programmableweb.com/>.

⁵ <http://swoogle.umbc.edu/>.

⁶ <http://ccnt.zju.edu.cn:8080/>.

⁷ <http://www.infosys.tuwien.ac.at/staff/treiber/soaf/index.rdf>.

⁸ <http://xmlns.com/foaf/spec/>.

⁹ <http://epinions.com>.

Section 4, we detail the global architecture of novel version of our proposed system. In Section 5, we detail the STD mechanism. In Section 6, we detail the SR mechanism and the proposed algorithm. In Section 7, we expose our experimental studies and the obtained results. In Section 8, we cite some related work. Finally, we conclude with our futures directions.

2. Research background

In [29], we proposed a decentralized discovery approach based on the user's egocentric social network. A discovery system, called SC-WSD (for Social Context based Web Service Discovery), is developed. In this system, we proposed firstly analyzing and filtering the user's social network based on Similarity Degree (SD) measure that we defined. Our purpose is to keep only the closest friends of an active user knowing that SD value must be greater than a static threshold α (equal to 0.5). Then, we extracted the past invocation histories of these closest friends and filtered this set based on the user's query (Q) without taking into account the domain. Finally, SC-WSD suggests to an active user a set of ranked services according to SD.

In the next subsections, we remind respectively the egocentric network structure and the user's social profile modeling.

2.1. Egocentric network structure

In our work, the structure of SOAF-based egocentric social network is viewed as a bipartite graph. (1) The nodes represent the users, i.e., requester or provider, and/or web services, i.e., individual or composite. Each user node represented by his social profile that describes his characteristics (e.g., interests, preferences, social activities, past experience). While, each service node described by a set of properties (e.g., name, description, endpoint) which are extracted from the WSDL service description. (2) The edges represent the links that define the social relationships between those nodes. These links may be: knowledge relation among users, usage relation between users and services, collaboration relation among services (see Fig. 2).

2.2. User's social profile modeling

The rapid development of social media services, such as Facebook and Twitter, helps users to easily communicate and express themselves. The massive use of these services generate a great social data. In our work, each user' social network is usually characterized by his profile that describes two types of information: (1) the *static* information refers to the personal data like: name, age, country, city, and (2) the *dynamic* information refers to evolved data like: interests, preferences, number of friendship relation, feedback, past experience with invoked services. To represent these data, we used the SOAF model [30] as presented in Fig. 1. This model is an extension of FOAF model which is augmented with Web service data in order to link services and users in the same structure network. The main goal is to leverage the creation of IoS vision [30].

3. Motivations

Fig. 2 depicted an example of a SOAF -based egocentric network of an active user (U). In this network, three types of nodes and interactions are represented.

Concerning the nodes, we find (i) a central circle node U represents the ego who is the current user, i.e., service requester that wants to look for a service. (ii) Others 5 circle nodes (f_1, f_2, f_3, f_4 and f_5) represent the directed friends who are connected to U . (iii) A rectangle nodes represent the list of satisfactory invoked services

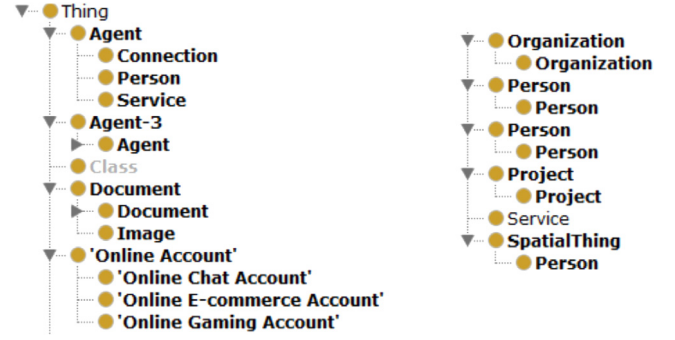


Fig. 1. SOAF ontology [30].

in the past by each user. Concerning the interactions, we find: (i) A *friendship* relation is undirected link from user to friend and friend to friend. (ii) A *usage* relation is a simple link between user or friend and his past invoked services. (iii) A *closeness* relation is a directed and weighted link from U to his friends. The weight of this link is computed based on SD defined in [29].

To improve the service discovery process that is developed in SC-WSD system, we present in the next subsections, two motivating scenarios. The purpose is deducing the necessity of using the concepts of *trust* and *domain-specific expertise* to make more accurate recommendation in social environment.

3.1. Need for a trust concept

In this network, SC-WSD suggests to U , based on his query (for example: $Q1 = \text{Weather}$), only his closest friends, i.e., f_1, f_2 and f_5 according to SD and α . However, we find in this network:

- f_5 shares a great number of friends with U . But, he is not necessarily share the same interests with him. Hence, it is important to take into account the interest similarity between them.
- f_1, f_2 and f_5 are closest friends but they have not invoked a web service that corresponds to $Q1$. Therefore, SC-WSD fails to suggest the appropriate services to U .
- There are some services, i.e., WS_{Weather} and $WS_{\text{WeatherForecast}}$ which invoked by f_3 and corresponded to $Q1$.

Synthesis. Based on this example, we noted that SD is insufficient to filter among closest friends since it is based only on the structure network similarity. Therefore, it is necessary to define another metric that takes into account the interest similarity between friends. Since we work within a social context, we find that the trust concept is a better relation than we must take it into account. In addition, the choice of static threshold ($\alpha = 0.5$) is not an effective way to select closest friends. Therefore, we propose to use a dynamic threshold for better friend filtering.

3.2. Need for a domain-specific expertise

In this second example, U looks for a hotel service based on his query (for example: $Q2 = \text{hotel}$). SC-WSD will suggested all services which are invoked by his closest friends, i.e., f_1, f_2 and f_5 . However, we note the following remarks:

- SC-WSD will return WS_{hotel} service that has been invoked by f_5 . But, the latter tends to use more services, i.e., $WS_{\text{MedicalDoctor}}$ and $WS_{\text{HospitalPrediction}}$, which related to medical domain; and one service, i.e., WS_{hotel} , which related to travel domain. Hence, f_5 is more expert in medical domain than in travel.

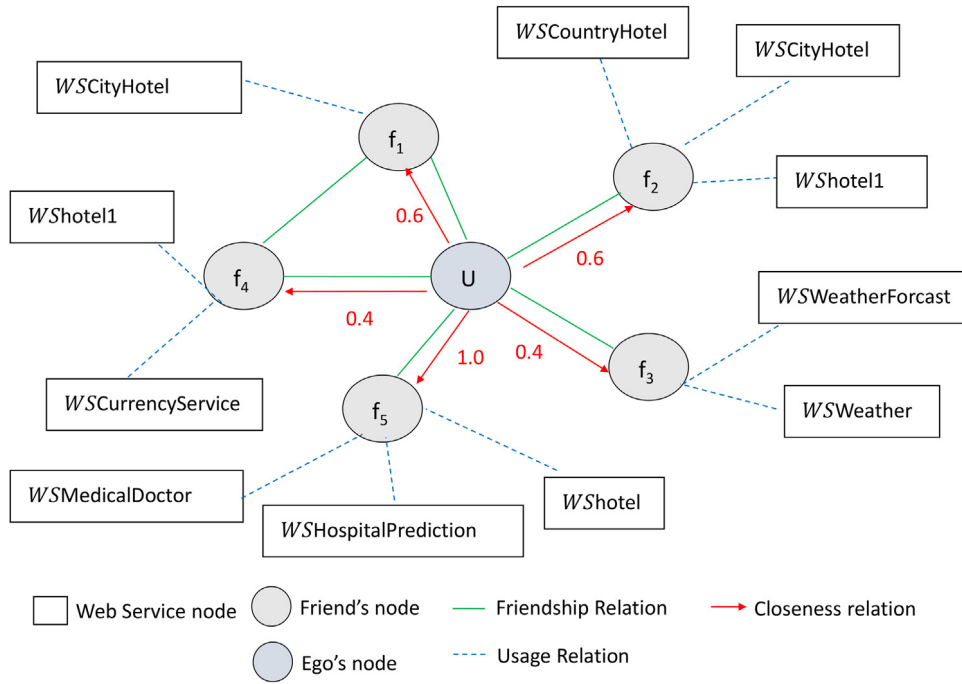


Fig. 2. An example of SOAF-based network of user U.

- SC-WSD will return also *WSCountryHotel*, *WSCityHotel*, *WShotel1* which are invoked by f_2 . Therefore, f_2 is more expert in travel domain more than f_5 .
- SC-WSD returns to U the previously selected services without any ranking. Therefore, it is more suitable to rank the recommended services in order to facilitate the service selection.

Synthesis. Based on this example, it is necessary to consider the user's expertise in order to provide a better recommendation quality. Therefore, we propose to calculate the friend's expertise level by domain of the active user's query. In addition, we propose to define a rating prediction metric for recommended services and rank its to reduce the disorientation problem.

In the next section, we will detail our novel architecture of SC-WSD system.

4. Decentralized service discovery approach

We extend the decentralized service discovery approach [29,31] to social collaborative recommendation by introducing the concepts of social trust, domain and expertise. Our purpose is to overcome the mentioned various limits (see Section 3) and the problem statement such as the service overload and disorientation problems.

As depicted in Fig. 3, the novel architecture of SC-WSD system has two main inputs: (1) the SOAF-based social profile that describes each user who involved in social network. This profile is used in the Social Trust Detection mechanism. (2) The domain specific-user's query Q is represented as a tuple $\langle D, K \rangle$ where: D stands for the query's category and express the domain of the service that the user is looking for. K represents the keywords which entered by the user. We choose to represent all domain by a vector representation where each domain represented by an identifier and name, i.e., [1, Weather], [2, Travel], etc. This query is necessary to carry out Service Recommendation mechanism.

The main output of SC-WSD to a target user is a ranked list of most web services. These latter are invoked by his trusted and expert friends according to indicated domain in the user's query.

After each interaction between user and recommended service, SC-WSD updates implicitly the user's social profile and the assigned score in the Rating matrix ($U \times S$) and the user's expertise level in the Expertise matrix ($U \times D$). It manages also the services, i.e., publish, add or remove in the global social network. These functions are the role of the Network Management and Updating (NMU) mechanism.

In addition, SC-WSD performs two main complementary mechanisms, such as:

1. **Social Trust Detection (STD).** We analyze the social profile of a target user to extract the interests and the interactions with his directed friends. These interactions are represented by a vector that contains the type of each interaction (e.g., message, comment or post), the date of interaction and the involved friends. After that, we compute the trust level among active user and his all friends.
2. **Service Recommendation (SR).** We propose adding to the social service recommendation (SSR), that is proposed in our previous work [31], a second CF service recommendation (CFSR) mechanism. This combination is performed when the SSR based on trust and expertise cannot return a result to an active user. Then, we take into account all directed friends who are connected to an active user and select only who are expert in the domain-specific that is mentioned in advance in the user's query. After that, it predicts the score of each recommended service based on the friend's expertise.

In the following sections, we will detail STD and SR.

5. Social trust detection

With the emergence of social networks and the growing number of its users, trust has become an important concept in social media. We propose to exploit the richness of social networks to detect trustworthy friends. In our daily life, trust between persons is dynamic and may be change over time [32]. We consider that this change may be influenced by two very important factors. The first factor concerns the frequency of social interactions between the

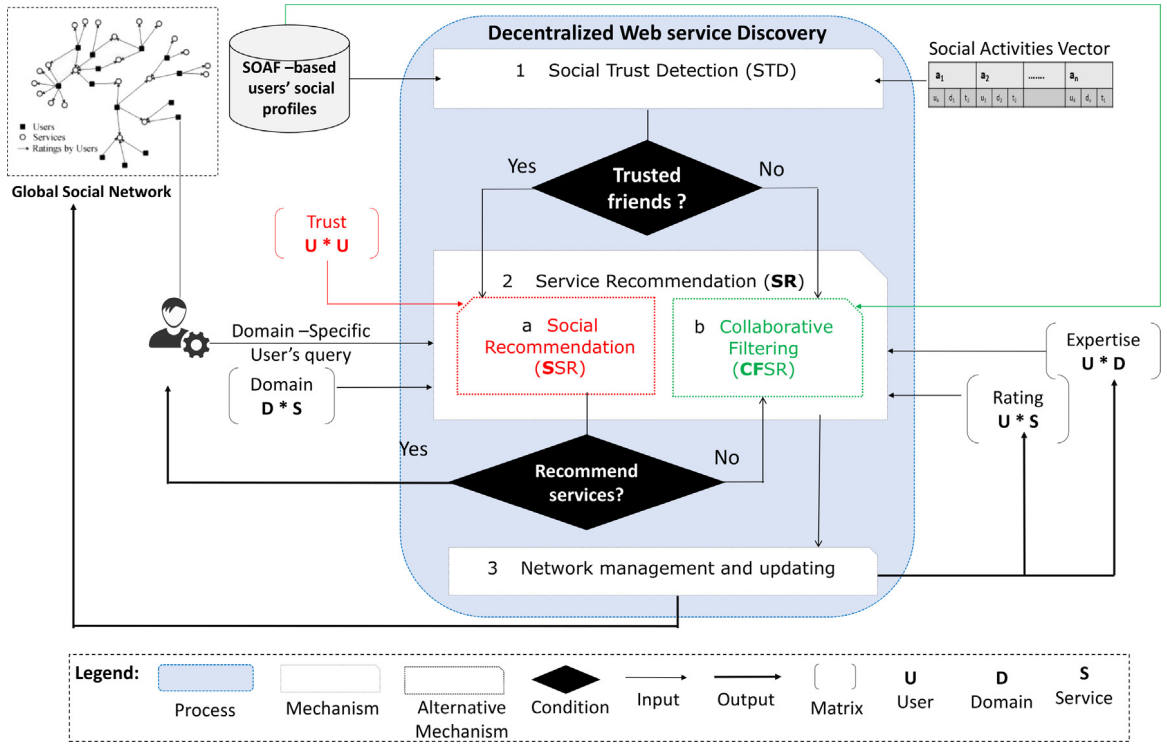


Fig. 3. Global architecture of our SC-WSD System.

users who depend necessarily on the period of time. The second factor concerns the similarity between users in terms of their interests.

As showing in Fig. 4, STD takes the user's profile as input; it involves three steps; and it returns as an output a Trust matrix ($U \times U$) that represent the trust egocentric network for a given user.

1. **Egocentric social network analysis.** We adopted an ego-centric analysis [33] of user's profile in order to detect and compute the trust level from the individual side. We propose two main factors that can influence in the social trust level. The first factor is the *Level of users' interactions (LoI)* (see Section 5.1). Indeed, the social media enables the users to communicate via various social activities, such as send messages, post comments, wall posts, share photo, etc. Consequently, the social interactions can affect the strength of the relationship. The second factor is *Level of Similarity (LoS)* (see Section 5.2). In fact, trusting someone does not perforce mean sharing the same interests and affinities with him. As consequence, the similarity between users proves necessary in terms of interests, interpersonal data, etc.
2. **Level of trust computing.** We proposed in this step to compute for each active user the trust value based on novel metric, called Level of trust metric (LoT), that we defined in [34]. This metric allows to discriminate between trusted and untrusted friends from egocentric network. LoT is based on LoI and LoS which are obtained in the previous step (see Section 5.3).
3. **Dynamic Trusted friends filtering.** We proposed in this last step to select only the most trusted friends for a target user by taking into account a dynamic trust threshold that we defined (see Section 5.4). With this threshold, the list of trusted friends differs from one user to another.

In the next subsections, we expose each metric of LoI, LoS, LoT and the dynamic trust threshold.

5.1. Level of Interaction (LoI) computing

Compared to the existing metrics [22,23], our LoT metric takes into account the time factor. At the first level, we compute the number of interactions (NI_f) between the *ego* and his friend f_i in the period of time Δ_t . At the second level, we calculate the total number of interactions (NI_{all}) of *ego*, with all his friends in the same period Δ_t . Eq. (1) show how to calculate LoI.

$$LoI(ego, f_i)_{\Delta_t} = \frac{NI_f(ego, f_i)_{\Delta_t}}{NI_{all}(ego)_{\Delta_t}} \quad (1)$$

where Δ_t is the period between the first and current date of interaction between *ego* and his friend f_i . with NI_f is the number of interactions between the *ego* and f_i and NI_{all} is the total number of interactions of the *ego* with all his friends in Δ_t .

5.2. Level of Similarity (LoS) computing

In service recommender system, the similarity between users is measured by comparing their rating attributed to the same service. However, the rating matrix is generally very sparse. For this reason, we compute the Level of Similarity *LoS* between friends based on the Jaccard similarity coefficient. For each pair of nodes (*ego*, f_i), the level of similarity *LoS* calculated, as shown in Eq. (2), in terms of the number of common interests in both users and the total number of their interests.

$$LoS(ego, f_i) = \frac{\|interests_{ego} \cap interests_{f_i}\|}{\|interests_{ego} \cup interests_{f_i}\|} \quad (2)$$

With $LoS(ego, f_i)$ is in $[0, 1]$.

5.3. Level of Trust (LoT) computing

In the objective of more personalize the Web service recommendation for each user, we consider the value of trust level *LoT* is local, non-transitive and asymmetric. This value is stored in a Trust

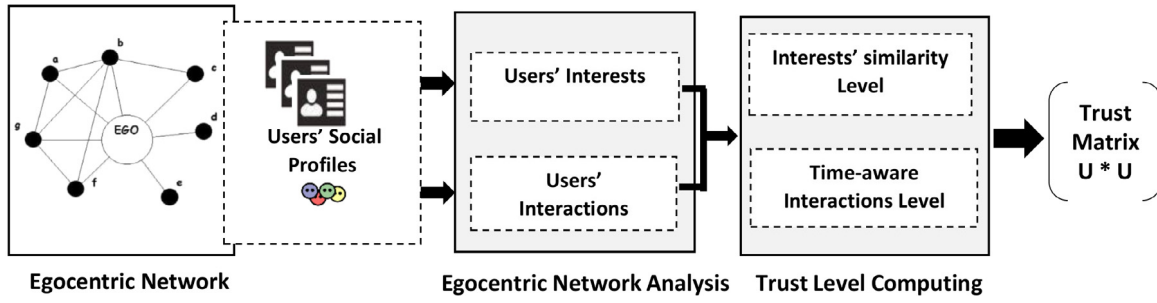


Fig. 4. Steps of STD mechanism.

Matrix($U \times U$). Eq. (3) denotes the LoT which calculated according to LoI and LoS .

$$LoT(ego, f_j) = \alpha \times LoI(ego, f_j)_{\Delta t} + \beta \times LoS(ego, f_j) \quad (3)$$

with α and β are the weighting parameters in $[0, 1]$ and $\beta = 1 - \alpha$.

5.4. Dynamic trust threshold computing

Compared to the existing works [29] that used a static threshold, we propose a dynamic trust threshold γ that will adapt for each user. Hence, the list of recommended trusted friends changes from one user to another which depends on the levels of confidence that is acquired by each user towards his/her directed friends. Eq. (4) shows how to compute the dynamic trust threshold γ .

$$\gamma = \frac{\sum_{Distinct(t_j) \in T} t_j}{j} \quad (4)$$

with T is the list of trust levels of f_j to all his/her friends, and $distinct(t_j)$ is the list of distinct values in T .

STD mechanism selects the most trusted friends in favor of SR mechanism if $LoT(ego, f_j) \geq \gamma$. In the next section, we will detail the SR.

6. Service recommendation

On the basis of the domain of the user's query, SC-WSD system must suggest to him a ranked list of best services which are invoked in the past by his/her friends who are both trustworthy and expert. However, we found that there are two cases where SC-WSD will fail to suggest services to the user:

- For an active user who has not trusted friends.
- No trusted friends is an expert in the domain-specific query.

For these reasons, we proposed to combine the social approach with the CF approach. The latter will extract all users of the entire egocentric social network of user's without any specific relationship and will select only who are expert in the domain-specific query.

In the next subsection, we detail the step of SR.

6.1. Step of SR

In Fig. 5, SR mechanism performs in six steps. These steps are the same when SR appeals, on the one hand the SSR mechanism; and/or on the other hand the CFSR mechanism.

- (1) **Extraction of recommenders.** The recommenders are the list of friends who are involved in social network and constitute the input of SR. In the case of SSR mechanism, these recommenders represent (i) the list of trusted friends who are already extracted from the STD mechanism (see Section 5). Or, in the case of CFSR mechanism, they represent (ii) the list of all directed friends of the entire social network.

- (2) **Level of Expertise (LoE) computing.** We proposed in this step to measure the expertise of each extracted recommender in the previous step by domain specified in the user's query. Indeed, we consider that the recommenders who have frequently used services in a given domain are able to provide a better quality recommendation. Eq. (5) computes the expertise of a recommender f_i in a domain $domain_j$.

$$LoE(f_i, domain_j) = \frac{Nb_{invok}(f_i, domain_j)}{\sum_{domain_k \in D} Nb_{invok}(f_i, domain_k)} \quad (5)$$

where $Nb_{invok}(f_i, domain_j)$ is the number of service invocation in the domain $domain_j$ of the current user's query, and $\sum_{domain_k \in D}$ is the sum of the service invocation number in the list of domains D presented in the system.

- (3) **Past experience extraction.** In this step, SR extracts for each recommender from his SOAF-based social profiles the information related to their web services (e.g., name, description, operation, endpoint) which were invoked in the past. This extraction is performed by using the SPARQL¹⁰ query. The result of this step is a list of services without redundancy.
- (4) **Web service filtering.** In this step, SR filters, from the web services extracted in the previous step, those which corresponded not only to the domain ($domain_j$) chosen in advance by the active user but also to the keywords (K) which composed his query (Q).
- (5) **Rating prediction.** In this step, SR predicts the rating of each service which was selected in the previous step according to Eq. (6). This prediction is based, on the one hand, on the expertise of recommenders who have invoked these services, and, on the other hand, on their past attributed ratings to them.

$$Rating_{pred}(ws_i, domain_k) = \frac{\sum_{f_j \in R} LoE(f_j, domain_k) \times Rating(f_j, ws_i)}{\sum_{f_j \in R} LoE(f_j, domain_k)} \quad (6)$$

where $LoE(f_j, domain_k)$ is the expertise level of the recommender which is calculated in Eq. (5), and $Rating(f_j, ws_i)$ is the service's score attributed by the recommender f_j to service ws_i in the past.

- (6) **Web service Ranking.** In this step, SR ranks the list of recommended services in descending order according to their predicted ratings which calculated in the previous step according to Eq. (6).

In the next subsection, we expose an extension of global algorithm of service discovery process proposed in [29].

¹⁰ <http://www.w3.org/TR/rdf-sparql-query/>.

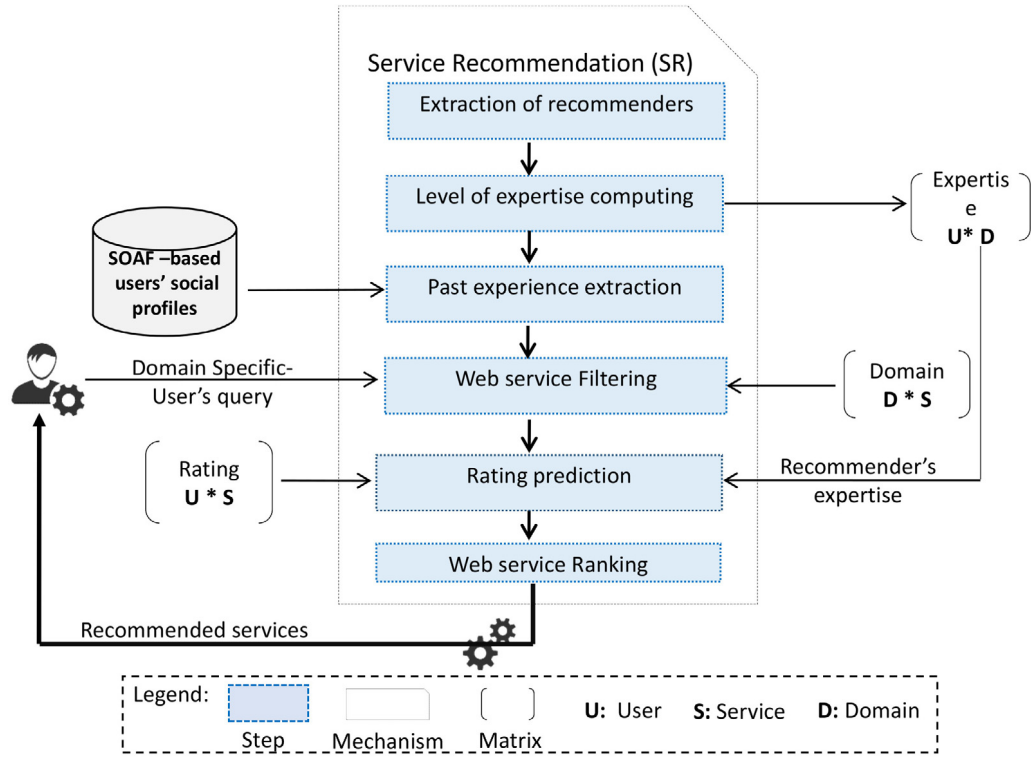


Fig. 5. Steps of social recommendation based on trust and expertise.

6.2. Global algorithm

In this section, we detail our proposed algorithm that we divided into two parts as shown in Algorithm 1- part 1 and Algorithm 2- part 2. The global algorithm takes as input the user's identifier *IdEgo*, his query *Query* and three following matrices: The trust matrix $mTrust[1..n][1..n]$ generated by STD mechanism, a rating matrix $mRate[1..n][1..m]$ that contains the scores which are given by users to their invoked services, and a domain matrix $mDom[1..m][1..p]$ that contains the domains of existing services in the dataset.

In part 1, the algorithm performs in Lines 2–4, a first friendship filtering of an active user (*IdEgo*) based not only on trust values from trust matrix but also on the dynamic trust threshold which calculated according to Eq. (4) by the function *getDynamicTresT* (Line 3). The latter allows to select only most trustworthy friends.

Once trustworthy friends are extracted (Lines 3–19, Algorithm2-part2), this algorithm calculates in Line 5, the expertise of each friend based on Eq. (5) (see Section 6.1). Then, for each friend, SOAF-based social profile is selected (Line 6) in order to extract their invoked or published web services by using respectively the functions *getUsedWS* (Line 7) and *getProvidedWS* (Line 8) by applying a SPARQL queries. In Lines (9–12), SC-WSD performs a second service filtering based on the domain of user's query (Line 10) by adding them to the list of trusted Web services *trustedWS* if these do not already exist (Lines 11–12). At the end of the loop (Lines 4–12), the list of *trustedWS* includes the satisfactory services without redundancy which are invoked by trustworthy friends and corresponded to the user's query.

In Lines 16–17, for each web service collected in the list of *trustedWS*, SC-WSD predicts its ratings by applying the function *getPredictedRate* (Line 17). This function takes as input the expertise values calculated in Line 5 and the rating matrix by applying Eq. (6) (see Section 6.1). In Line 19, the recommended list *bestWS* contains a ranked services (Line 18) according to their

Algorithm 1: Global Service Discovery – Part 1

Input: *IdEgo* : Integer, *Query* :
 $\$, mTrust[1..n][1..n]$: Double,
 $mRate[1..n][1..m]$: Integer,
 $mDom[1..m][1..p]$: Integer, *domQ*:String
Output: *bestWS* : List < Integer >
Var: *trustF* : List < Integer > ,
expertF : Map < Integer, Double > , *urlSoaf* : String ,
userWS = List < Integer > ,
trustedWS : Map < Integer, Double > ,
wsCat : String

```

1 begin
  // Recover trustworthy friends of ego
  // according to trust matrix
2 for (idF ∈ [0..n]) do
3   if ( $mTrust[idEgo][idF] \geq getDynamicTresT(idEgo)$ )
4     then
       trustF.add(idF);

```

predicted rating with the domain-specific expertise of friends by applying a *Tri* function. To overcome the problem of no response, we proposed that our algorithm uses an alternative recommendation mechanism by using the function *CFRecommendation* (in Algorithm 2-part 2) that will occurs in the one of the following cases:

- The set of trustworthy friends is empty (Lines 1–2).
- No service of trustworthy friends responds to the user's query (Lines 13–14).

In the next section, we present the experimentation.

Algorithm 2: Global Service Discovery – Part 2

```
1 if (trustF.isEmpty() = true) then
  // Call the collaborative filtering if there
  // is not a trustworthy friend
2   FCBasedRecommendation(idEgo, mRate, mDom, domQ);
3 else
  // For each friend
4   for f ∈ trustF do
    // Compute the expertise of friend
    // according to formula 5
5    expertF.put(f, getExpValue(f, domQ));
    // Recover the invocation histories
    // according to the SOAF profile
6    urlSoaf ← getUrlSoaf(f);
7    userWS.add(getUsedWS(urlSoaf));
8    userWS.add(getProvidedWS(urlSoaf));
9    for idWS ∈ userWS do
      // Filtering the list of Web services
      // based on the user query
10     if (mDom[idWS][domQ] = 1) then
11       if (trustedWS.contains(idWS) = false) then
12         trustedWS.add(idWS);
13 if (trustedWS.isEmpty() = true) then
14   FCBasedRecommendation(idEgo, mRate, mDom, domQ)
15 else
  // Predict the rating of service Eq. 6
16   for (idWS ∈ trustedWS) do
17     bestWS.put(idWS, getPredictedRate(idWS,
18       expertF, mRate))
  // Ranking of Web services
18   bestWS ← Tri(bestWS);
19   return bestWS;
```

7. Experimental studies

To validate our decentralized service discovery approach, we used three datasets in order to evaluate each mechanism such as : STD (Social Trust Detection, see Section 7.1) and SR (Service Recommendation, see Section 7.2).

7.1. Evaluation of social trust detection mechanism

In our work, we proposed a new Social Trust Level (LoT) measure which is based on the level of social interactions that depend on the time factor and the interest similarity between friends based on their SOAF-based social profiles. We proposed an implicit trust values that do not require the user's intervention. Through the evaluation step, we propose to validate the following points:

- the importance of considering the time factor in the trust measure,
- the use of dynamic trust threshold γ rather than static threshold λ .

7.1.1. Used dataset & evaluation metrics

For experimentation purpose, we need a real dataset that includes users' social profiles (RDF/FOAF) but we have not found it in Internet. For this reason, we have used another method to acquire some profiles. Therefore, we firstly crawled from Facebook online

social network the archive¹¹ of HTML files of social data of 20 users under their permission. This archive contains different types of information (e.g., name, country, interests, preferences, social interactions or activities, etc.). With this collected data, we formed a Facebook sub-network structure that contains 1326 connected friends. After that, we applied the technique of Web mining in HTML pages in order to extract only necessary information that we need, like: the social interactions, i.e., sent messages, the date of sending and the involved friends and their interests. Secondly, the evaluation process unrolls as follows. At the first time, we invited each user to connect into our SC-WSD system to select and save his real trusted friends. At the second time, we evaluated the obtained results of STD mechanism by using three popular metrics, such as the recall, the precision and the *F*-measure which are defined as follow.

The precision, as shown in Eq. (7), is the number of real trustworthy friends who are returned by the system compared to the total number of returned friends.

$$\text{Precision} = \frac{\text{Returned} \cap \text{RealTrusted}}{\text{Returned}}. \quad (7)$$

The recall, as shown in Eq. (8), corresponds to the number of trustworthy friends who are returned by the system compared to the total number of real trustworthy friends who are identified by each user.

$$\text{Recall} = \frac{\text{Returned} \cap \text{Trusted}}{\text{RealTrusted}}. \quad (8)$$

The *F*-measure is a combination of the two previous metrics as shown in Eq. (9).

$$\text{F-Measure} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}. \quad (9)$$

7.1.2. Obtained results

In this section, we perform two series of tests. The first series enables us to fix the value of the various parameters (α and β) and the threshold γ . The second series enables us to compare our STD mechanism with and without taking into account the time factor.

Adjustment of parameters α and β . The proposed metric LoT (see Section 5.3, Eq. (3)) is computed according two other metrics such as: Level of interaction (LoI) with the parameter α and Level of interest similarity (LoS) with the parameter β . Fig. 6(a) shows $\alpha = 0.8$ and $\beta = 0.2$ are the best *F*-measure value (=0.85). This demonstrates that the time factor associated with LoI among friends has an important influence on LoT computing. In others words, if α is closer to 1 and β is closer to 0 then LoT increase over time.

Effect of dynamic trust threshold γ . STD mechanism suggests to an active user a list of most trusted friends which are selected on the basis of threshold. We choose three static thresholds ($\lambda = 0.5, 0.6$ and 0.7) and we compare the obtained results, in terms of precision, recall an *F*-measure, with dynamic threshold γ . In Fig. 6(b), if λ increase (=0.6 or 0.7) then the number of trusted friends is reduced, else if λ decrease (=0.5) then some friends are selected and recommended to the user. Hence, we deduct that the dynamic filtering of friends with γ is much better than λ .

Impact of time in trusted friends detection. In order to evaluated the importance of time, we compared the obtained results by applying the LoT measure that we proposed with the same metric but without taking into account the time. As a result, in Fig. 7(a), we found that the precision of the obtained results by the Not Time-aware Trust metric is very low (precision average = 40.81%) than our Time-aware Trust metric (=51.88%). This

¹¹ <https://www.facebook.com/help/131112897028467/>.

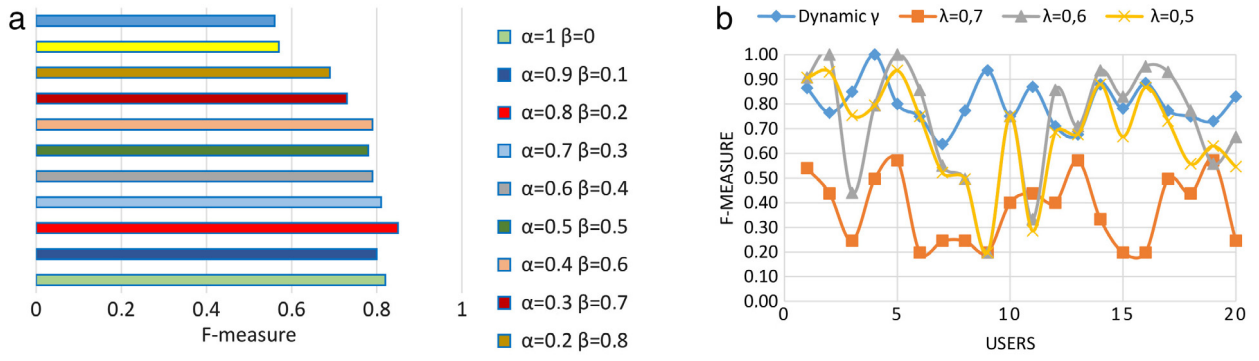


Fig. 6. (a) Obtained results of F-measure with variation of α and β parameters, and (b) Obtained results of F-measure with variation of static threshold ($\lambda = 0.5, 0.6$ and 0.7) compared to the dynamic threshold γ .

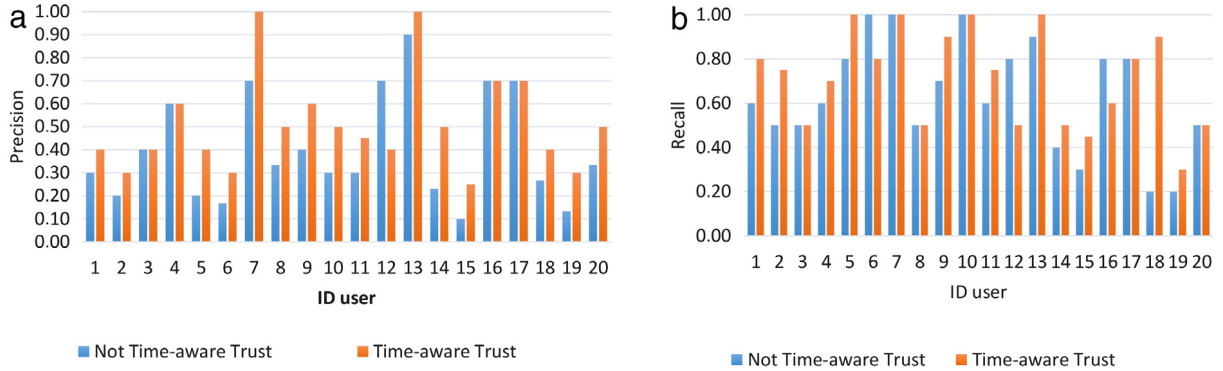


Fig. 7. (a) Obtained results of precision and (b) recall of Time- and Not Time-aware detection of trusted friends.

justifies our hypothesis that the not consideration of time factor may recommend to an active user his/her friends who were considered trusted in the past and they are no longer. Hence, the time factor of social interaction degree has a very strong impact in the trustworthiness friends detection. In addition, we found in Fig. 7(b) the recall average of the obtained results by our Time-aware trust metric is much better ($=73.44\%$) than the Not Time-aware Trust ($=68.725\%$). This justifies that our metric detects and recommends all trusted friends from the real trusted friends who are identified by each user.

In the next section, we will evaluate the accuracy of our SR mechanism.

7.2. Evaluation of service recommendation mechanism

In SR mechanism, we proposed to predict the rating of services according to the expertise of user's friends in domain-specific. In SC-WSD, we deduct that SSR in some cases cannot suggest to user any services. To overcome this limit, we proposed a CFSR as an alternative mechanism that takes into account only the expertise of all directed friends (see Section 6). Through this evaluation step, we try to validate the following points:

- the consideration of the user's expertise in the rating prediction,
- the proposed service recommendation (SR) mechanism in front of the response rate.

7.2.1. Used dataset & evaluation metrics

We used the Epinions dataset that includes (i) a trust matrix which contains the values of explicit confidence provided by users, (ii) a rating matrix which contains the ratings attributed to different items, and (iii) the category (or domain) matrix which contains

Table 1

Comparison between the values of RMSE.

RS	TidalTrust	MoleTrust	TrustWalker	SC-WSD
RMSE	1.216	1.430	1.192	1.011

the category for each item. In our context, we consider each item as a web service.

7.2.2. Obtained results

At the first level, we evaluated the impact of expertise in the service recommendation. At the second level, we evaluated the response rate in the cases of traditional social service recommendation (TSSR) which based only on trust; and our social collaborative service recommendation mechanism (SSR + CFSR).

Impact of Expertise in Rating Prediction. We compared the prediction measure used in our SC-WSD system with other recommender systems like TidalTrust [20], MoleTrust [25] and TrustWalker [26]. We used RMSE (Root Mean Squared Error) that is a popular accuracy metric to compute the difference between the predicted rate and the real rate as depicted in Eq. (10).

$$RMSE = \sqrt{\frac{\sum_{(u,s) \in R_{u,s}} (r_{u,s} - \hat{r}_{u,s})^2}{|\{(u,s) \in R_{u,s}\}|}} \quad (10)$$

with $R_{u,s}$ is a Boolean variable equal to 1 if the user u evaluate service s , $r_{u,s}$ is the real rate which is attributed by user u to a service s , and $\hat{r}_{u,s}$ is the predicted rate.

The obtained results in Table 1 showed that the gap between the real rate and the predicted rate in our system is lower (is equal to 1.011) than other systems such as TidalTrust ($=1.216$), MoleTrust ($=1.430$) and TrustWalker ($=1.192$). This is explained on the one hand that the trust relationship is an insufficient factor for the

Table 2
Response rate.

Mechanism	Successful queries	Failed queries	Response rate
TSSR	57	55	5%
SSR+FCSR	111	1	9.9%

recommendation. On the other hand, the importance of taking into account the domain-specific expertise factor can improve the recommendation quality.

Response rate. We propose to evaluate the response rate provided by the traditional social recommender system (TSRS) and our proposed service recommendation mechanism (SSR+FCSR). In our context, we define that the response rate, as shown in Eq. (11), is found by dividing the number of successful queries which returned services to the user by the total amount of queries in the dataset. This rate is usually presented as a percentage.

$$\text{ResponseRate} = \frac{\text{Successfulqueries}}{\text{Total}}. \quad (11)$$

For test, we have 20 users who interrogate the SC-WSD system with 112 queries in total, approximately 6 queries for each user. As result, as shown in Table 2, we found that only 57 users' queries are carried out successfully by the TSRS, with response rate equal to 5%. Contrariwise, we found that for 111 users' queries our proposed mechanism (SSR+FCSR) has succeeded to recommend services with response rate better than TSRS and it equals to 9.9%.

By relying on these rates, we prove that the recommendation quality provided by our mechanism (SSR+FCSR) is better than the traditional (TSSR). Therefore, the taking into account of trust, as a social factor, is not sufficient in recommendation. Therefore, some factors of quality must be taken into account like the expertise and the domain-specific. Besides, the obtained rate in this assessment complements the previous experimentations that indicate the significant impact of (i) time in trust detection and (ii) domain-specific expertise with trust in recommendation. In addition, we have used collaborative filtering as an alternative approach but we have not based on the usual criterion that is similarity among friends but we based on the user's expertise as a new filtering criterion between them. That is why 54 queries, which have not a responses in TSSR, are suggested results to their users in SSR+FCSR. In spite of these results, we must not forget that our recommendation approach has extended the response time.

8. Related work

The recommendation approach has evolved into interactive Web environment in order to help the users find the appropriate items (e.g., book, music, product). It attempts to predict the preferred items through the implicit or explicit data or information which has been acquired directly or indirectly from the users' interactions with the outside world. In [14], two categories of approaches are distinguished such as Collaborative Filtering (CF) and Social Recommendation (SR) that we present briefly in this section. Next, we present some service recommendation approaches.

8.1. Collaborative filtering recommendation

The CF approach predicts the user's preferences based on the assumption that if users have agreed with each other in the past, they are more likely to agree with each other in the future than to agree with randomly chosen users [11, 14]. Moreover, This approach paid a little attention to the cold-start and the data sparsity problems. (1) The cold start is mean that the system may fail to provide any recommendation (i) for new users who have not yet evaluate the

items since no historical information of these users are provided in the system, or (ii) for new items which have not yet been evaluated. (2) The data sparsity is frequently encountered in the calculation of the similarity between two vectors of ratings. In other words, CF approach uses a rating matrix (Users \times Items) which contains the scores which are given by users to each item. Usually, this matrix is very sparse suggesting that there are a lots of unknown rating.

Due to these problems, CF approaches suffer significant difficulties in identifying similar users or items via common similarity measures (e.g., Cosine measure, Pearson Correlation, etc.), in turn, deteriorating the recommendation performance.

8.2. Social recommendation

With the prevalence of Web 2.0, the SR approach has attracted the attention of several research fields and works [14]. In [13], the social recommender system defined as any recommender system that suggests any items (e.g., movie, person, tag, service, etc.) with online social relationships as an additional input. Unlike CF, that considers users as being independent of each other, meanwhile the SR considers the users are correlated and connected by various types of relationships [12] such as friendship, co-worker, business, etc. In addition, SR use not only the matrix of rating (Users \times Items) like in CF but also the adjacency matrix (Users \times Users) that represents the connection between users [14].

The main contributions of this approach are firstly solving the data sparsity and cold start problems, and secondly improving the quality and the accuracy of recommendation since the connected users provide different information from similar users for recommendation [26]. Indeed, CF must compute the similarity between all users of the system while the SR computes the similarity between users which are connected through a specific type of relationship. In fact, it is necessary for SR based an adequate mechanism for analyzing a specific social relationship among users. Therefore, SR involves the independent research field of Social Networks Analysis (SNA) [33] and takes full advantage of various works which are established in this area such as how to detect trust in social network [20, 25, 35, 22, 27, 36], etc.

In the next subsection, we present some trust-aware SR approaches.

8.3. Trust-aware recommendation approaches

Trust has been identified as an effective mean to utilize the social network information in order to improve the recommendation quality. The majority of Social Recommender Systems (SRS) based on, firstly, one or more metrics to compute the trust between users. Secondly, they based on another metric to predict the score may assign by a given user for each item. The interest of this metric is to classify the recommended items according to their predicted scores.

In social computing, the value of trust relationship was measured in several ways depending on properties which are considered differently in various SRS. These properties are listed as follows: global/local [37], direct/indirect [38], symmetric/asymmetric [32, 39], explicit/implicit, transitive/non-transitive [40], and static/dynamic [32].

In literature, some approaches proposed the use of local trust values [25, 20], others used global values [15, 16]. Both of these approaches have advantages. A local trust provides more personalized recommendations and considers the user's opinion based on his closest friends. However, a global trust expresses the user's reputation in the entire social network. In our work, we aim to offer a personalized recommendation by using a local trust.

In terms of trust values, several trust-aware SRS like TidalTrust [20], SocialMF [26], MoleTrust [25] are based on explicit

values of trust which are provided by their users. In our point of view, we note that asking a user to evaluate each member of his network may be a tedious task. Moreover, the experience actually shows that few users feel bothered to accomplish this task. However, in our work, we intend to compute the trust in implicit manner. However, other SRS used a binary values (0/1) to compute the trust level. We believe that this is a very restrictive measure that cannot be used to rank the users. In contrast, other researches [20,25] has suggested discrete values. We propose that the trust value is in interval $[0, 1]$ can discriminate between trusted and untrusted friends.

In terms of trust computing, some studies [24,41] combined the trust value with the similarity between users. This justifies that trusting someone does not necessarily mean sharing the same preferences or interests with him. Hence, it is obvious that using this similarity measure improves the quality of recommendation. Therefore, computing the similarity can reduce the data sparsity problem. In most of RS, the similarity between users is calculated on the basis of score matrix (Users \times Items) by applying a Cosine Similarity. In addition, most of users assign scores to few items. Hence, this matrix is very sparse and it becomes difficult to compare two users and calculate the similarity between them. However, in our work, we propose to compute the trust level by taking into account other impact factors like the users' social interactions [34].

In terms of trust propagation, Golbeck [20] considered that the trust is transitive and justified her views as follows: If a user X accepts a user Y to recommend him some items, so, why would not X accepts Y to recommend him/her a friend that he considers trustworthy. However, Moghaddam et al. [27] presume that the trust cannot be transitive, and a user cannot trust the strangers (those who do not have direct links with him). They calculated the trust only with respect to a direct association with the user. In the same sens, we propose to detect the trustworthy friends only who have direct connection with a given user.

In terms of trust state, Zhou et al. [32] affirmed that a user trusts in another only reflects his beliefs at a static point in time. Hence, the trust is not a static concept but it changes (increase or decrease) over time which often called trust dynamics. Then, trust may decay with users interactions or observations [42]. In the same vision, we propose to take into account the temporal factor of user's interactions in the trust computing.

8.4. Service recommendation approaches

The main goal of service recommendation approach is to help the users discover the services that meet their needs. CF is one of the most popular approaches to build service recommender system [9,10,43]. However, with the advent of social networks, the SR approach can potentially solve some challenging problems of CF approach, such as the data sparsity and the cold-start problems [14].

With the appearance of SR approach, there are rarely research studies [4,17–19,21,44,45] which have exploited the social links between users. Among them, some works take into account for example: the users' proximity [46], the trust relationship [5,15,17], the users' centrality [16] by using some metrics which related to SNA like centrality degree, proximity, prestige, etc. Moreover, Other studies used other metrics like Jaccard Coefficient, Cosine Similarity, Pearson Correlation Coefficient in order to compute the similarity between users. In our work, we focus particularly on trust relationship.

8.4.1. Trust: A social indicator

Actually, the social trust has become an important concept in service recommendation. It has been studied from different aspects: the data (or content), services (or applications), the providers (Web sites, organizations, governments or individuals) and the service consumers (organizations or individuals) [36].

By exploring the literature, Louati et al. [15] proposed a new discovery technique based on a social trust measure that ranks service providers belonging to the service requester's multirelation social network. The proposed measure is an aggregation of two measures: the sociability of provider (in terms of his position in social network, his social proximity and his similarity); and the expertise of an agent (in terms of reliability, usability and quality score).

In the same scope, Bansal et al. [16] proposed a RS of composed Web services which based on trustworthiness of service providers and on the QoS (Quality of Service) like the response time, the cost of service. The trust level is calculated implicitly according to the position of providers in his social network. The proposed RS provide for a service requester a classified services with their QoS which is calculated on the basis of trust level of provider.

In addition, Deng et al. [5] proposed a RS of services according to the trustworthy friends who involved in social network. The proposed trust metric combines two values such as: (i) the explicit trust provided by a user to his friend, and, (ii) the similarity between users by applying the cosine measure on rating vectors which are assigned by them. Finally, the proposed RS provide a rating prediction step for services that is realized randomly by browsing the social network to search a trustworthy user who evaluated a service in the past.

The majority of previous mentioned studies have used the user's feedback (rating) in the service score prediction step but we think that is insufficient. Hence, in our daily lives, we prefer the advice not only of our trustworthy friends but among them who are more expert in domain specific. Indeed, a user expert in the medical domain is not necessarily expert in the economic domain.

In the next section, we present a novel factor which may influences on the recommendation quality.

8.4.2. Domain-specific expertise: A quality indicator

In general, the concept of expertise has emerged in the document retrieval context. In this field, Xu et al. [47] proposed an approach that recommends for an active user a list of experts. This approach combines the SNA and the semantic concept analysis to improve the accuracy of personalized recommendation. In the context of service computing, we think that the expertise level of user can affects the recommendation quality. By browsing the literature, Yuan et al. [4] proposed to quantify the user's expertise in terms of how many times the user has used the required service. In the same sens, Louati et al. [15] compute the expertise of providers in terms of QoS (e.g usability, reliability, rating, etc.).

All mentioned recommendation works have proposed different definitions and metrics of expertise to make their service recommendation more accurate according to users' interests. However, these works do not take into account the domain-specific in expertise computing. In others words, there are several services which belong to different and sometimes to same domains (e.g., computer, food, travel, medical, etc.). For this reason, the consideration of domain of services is important in the steps of service filtering and user's expertise computing.

8.5. Synthesis

To outline, our decentralized service discovery approach is generic and it can be applied to any context of SRS for the recommendation of any type of items (API, tag, Internet of Thing

(IoT) service, etc.). In general, our approach is performed by a recommendation mechanism which is different to other related works in three levels, such as:

1. At the first level, we proposed two disjoint sub-mechanisms. The first mechanism (SSR) based on social recommendation approach according not only of most trustworthy friends who involved in social network but also their expertise. The second is an alternative mechanism based on collaborative filtering approach (CFSR) which based essentially on friends' expertise. This mechanism will perform in the worst case of SSR, i.e.; there are no trusted friends detected or no recommended service.
2. At the second level, our contribution is related to the temporal based-computing social trust that we have given an importance of time factor between users' interactions in order to calculate the trust level among them.
3. At the last level, another contribution is related to the expertise based-service recommendation from which the majority of research studies do not exploited the domain of user's query and the expertise of trustworthy friends in the recommendation purpose. We consider (i) the domain, as additional input in SR, can reduce the problem of user's disorientation and (ii) the expertise concept can enhance the precision of recommendation quality.

9. Conclusion & futures directions

Our research work is related mainly to Web service discovery regardless of its type (elementary or composed) based on two complementary mechanisms, i.e., social trust detection (STD) and service recommendation (SR). Our ultimate goal is to reduce the problems of service overload and the user's disorientation in the service selection step.

In this paper, we present firstly a background of various concepts which are used in our previous work. Next, we detailed our novel service discovery approach which based on two disjoint sub-mechanisms. The first sub-mechanism consists in applying a service recommendation mechanism based not only on trustworthy directed friends but also on their expertise in specific domain that is indicated in advance in the user's query. We proposed that the trust level is computed by aggregating two impact factors, such as interest similarity and time-aware interaction levels. In the worst case of recommendation (i.e., no recommendation of friends or services), we appeal a second alternative sub-mechanism which based on collaborative filtering approach. This latter takes into account the expertise of all directed friends for a given user in his egocentric social network. The output of these sub-mechanisms is a ranked list of recommended service according to their predicted rating based on the domain-specific expertise level. Finally, we conducted a series of experimentation and the obtained results show that each mechanism provides a better results than other related works. Nevertheless, we note that the response time of our proposed global service discovery algorithm has extended. In addition, we have already used the response rate but it is not the only metric to give an idea about the quality of recommended services.

In our future works, we envisage firstly, to add others evaluation metrics such as: (i) the response time to assess the proposed algorithm and find some solution to optimize it, (ii) the ranking quality metric like Discounted Cumulative Gain (DCG) to evaluate the usefulness of a service based on its position in the recommended list. Secondly, we will improve our SC-WSD system with another process like the social service composition in order to respond to the users' complex queries by taking into account the existing social links among services which are modeled in our SOAF-based global social network.

References

- [1] M. Pistore, P. Traverso, M. Paolucci, M. Wagner, From software services to a future internet of services, in: *Towards the Future Internet – A European Research Perspective*, 2009, pp. 183–192.
- [2] C. Schroth, T. Janner, Web 2.0 and SOA: Converging concepts enabling the internet of services, *IT Professional* 9 (3) (2007) 36–41.
- [3] R. Ruggaber, Internet of services SAP research vision, in: *16th IEEE International Workshops on Enabling Technologies: Infrastructure for Collaborative Enterprises WETICE*, 2007, p. 3.
- [4] Z. Yuan, Z. Shuai, W. Yan, C. Yanhong, Z. Wenyu, C. Xin, A social network-based expertise-enhanced collaborative filtering method for E-government service recommendation, *Adv. Inf. Sci. Serv. Sci.* 5 (10) (2013) 724–735.
- [5] S. Deng, L. Huang, G. Xu, Social network-based service recommendation with trust enhancement, *Expert Syst. Appl.* 41 (18) (2014) 8075–8084.
- [6] S. Dustdar, M. Treiber, A view based analysis on web service registries, *Distrib. Parallel Databases* 18 (2) (2005) 147–171.
- [7] Z. Maamar, L.K. Wives, Y. Badr, S. Elnaffar, K. Boukadi, N. Faci, LinkedWS: A novel Web services discovery model based on the Metaphor of social networks, *Simul. Model. Pract. Theory* 19 (1) (2011) 121–132.
- [8] E. Al-Masri, Q.H. Mahmoud, QoS-based discovery and ranking of web services, in: *IEEE 16th International Conference on Computer Communications and Networks, ICCCN*, Turtle Bay Resort, Honolulu, Hawaii, USA, 2007, pp. 529–534.
- [9] Q. Zhang, C.C. Ding, C. Chi, Collaborative filtering based service ranking using invocation histories, in: *IEEE International Conference on Web Services, ICWS*, Washington, DC, USA, 2011, pp. 195–202.
- [10] N.N. Chan, W. Gaaloul, S. Tata, A recommender system based on historical usage data for web service discovery, *Serv. Oriented Comput. Appl.* 6 (1) (2012) 51–63.
- [11] X. Su, T.M. Khoshgoftaar, A survey of collaborative filtering techniques, *Adv. Artif. Intell.* (2009) 1–19.
- [12] I. King, M.R. Lyu, H. Ma, Introduction to social recommendation, in: *Proceedings of the 19th International Conference on World Wide Web, WWW*, Raleigh, North Carolina, USA, 2010, pp. 1355–1356.
- [13] I. Guy, D. Carmel, Social recommender systems, in: *The 20th International Conference on World Wide Web, WWW*, Hyderabad, India, 2011, pp. 283–284.
- [14] J. Tang, X. Hu, H. Liu, Social recommendation: a review, *Social Netw. Analys. Mining* 3 (4) (2013) 1113–1133.
- [15] A. Louati, J.E. Haddad, S. Pinson, A distributed decision making and propagation approach for trust-based service discovery in social networks, in: *A Process-Oriented View – Joint INFORMS-GDN and EWG-DSS International Conference Group Decision and Negotiation GDN*, Toulouse, France, 2014, pp. 262–269.
- [16] S.K. Bansal, A. Bansal, Reputation-based web service selection for composition, in: *World Congress on Services SERVICES*, Washington, DC, USA, 2011, pp. 95–96.
- [17] M. Tang, Y. Xu, J. Liu, Z. Zheng, X.F. Liu, Trust-aware service recommendation via exploiting social networks, in: *IEEE International Conference on Services Computing*, Santa Clara, CA, USA, 2013, pp. 376–383.
- [18] S. Lin, Y. Yang, C. Lo, K. Chao, A social trust based recommendation mechanism for web service dynamic collaboration, in: *IEEE 6th International Conference on Service-Oriented Computing and Applications*, Koloa, HI, USA, 2013, pp. 318–322.
- [19] H. Fallatah, J. Bentahar, E.K. Asl, Social network-based framework for web services discovery, in: *International Conference on Future Internet of Things and Cloud, FiCloud*, Barcelona, Spain, 2014, pp. 159–166.
- [20] J. Golbeck, *Trust on the World Wide Web: A survey*, *Found. Trends Web Sci.* 1 (2) (2006) 131–197.
- [21] S. Mokarizadeh, N. Dokoochaki, M. Matskin, P. Küngas, Trust and privacy enabled service composition using social experience, in: W. Cellary, E. Estevez (Eds.), in: *IFIP Advances in Information and Communication Technology*, vol. 341, Springer Berlin Heidelberg, Buenos Aires, Argentina, 2010, pp. 226–236.
- [22] V. Podobnik, D. Striga, A. Jandras, I. Lovrek, How to calculate trust between social network users? in: *20th International Conference on Software, Telecommunications and Computer Networks, SoftCOM*, Split, Croatia, 2012, pp. 1–6.
- [23] S. Nepal, W. Sherchan, C. Paris, STTrust: A trust model for social networks, in: *IEEE 10th International Conference on Trust, Security and Privacy in Computing and Communications, TrustCom*, Changsha, China, 2011, pp. 841–846.
- [24] C. Ziegler, J. Golbeck, Investigating interactions of trust and interest similarity, *Decis. Support Syst.* 43 (2) (2006) 460–475.
- [25] P. Massa, P. Avesani, Trust-aware recommender systems, in: *ACM Conference on Recommender Systems RecSys*, Minneapolis, MN, USA, 2007, pp. 17–24.
- [26] M. Jamali, M. Ester, TrustWalker: a random walk model for combining trust-based and item-based recommendation, in: *The 15th ACM International Conference on Knowledge Discovery and Data Mining SIGKDD*, Paris, France, 2009, pp. 397–406.
- [27] M.G. Moghaddam, N. Mustapha, A. Mustapha, N.M. Sharef, A. Elahian, AgeTrust: A new temporal trust-based collaborative filtering approach, in: *International Conference on Information Science Applications, ICISA*, 2014, pp. 1–4.
- [28] F. Lalanne, A.R. Cavalli, S. Maag, Quality of experience as a selection criterion for web services, in: *Eighth International Conference on Signal Image Technology and Internet Based Systems, SITIS*, Sorrento, Naples, Italy, 2012, pp. 519–526.

- [29] A. Kalaï, C.A. Zayani, I. Amous, User's social profile -based web services discovery, in: 8th IEEE International Conference on Service-Oriented Computing and Applications, SOCA, Rome, Italy, 2015, pp. 2–9.
- [30] M. Treiber, H.L. Truong, S. Dustdar, SOAF - design and implementation of a service-enriched social network, in: 9th International Conference on Web Engineering ICWE, San Sebastián, Spain, 2009, pp. 379–393.
- [31] A. Kalaï, C.A. Zayani, I. Amous, F. Sèdes, Expertise and trust -aware- social recommendation for web services discovery, in: 14th IEEE International Conference on Service Oriented Computing, ICSOC, Alberta, Canada, 2016, pp. 517–533.
- [32] X. Zhou, Y. Xu, Y. Li, A. Jøsang, C. Cox, The state-of-the-art in personalized recommender systems for social networking, *Artif. Intell. Rev.* 37 (2) (2012) 119–132.
- [33] A. D'Andrea, F. Ferri, P. Grifoni, An overview of methods for virtual social networks analysis, in: *Computational Social Network Analysis: Trends, Tools and Research Advances*, Springer London, ISBN: 978-1-84882-229-0, 2010, pp. 3–25.
- [34] A. Kalaï, W. Abdelghani, C.A. Zayani, I. Amous, LoTrust: A social trust level model based on time-aware social interactions and interests similarity, in: 14th IEEE Fourteenth Annual Conference on Privacy, Security and Trust, Auckland, NewZeland, 2016, pp. 428–436.
- [35] P. Victor, C. Cornelis, M.D. Cock, P.P. da Silva, Gradual trust and distrust in recommender systems, *Fuzzy Sets and Systems* 160 (10) (2009) 1367–1382.
- [36] S. Nepal, C. Paris, A. Bouguettaya, Trusting the Social Web: issues and challenges, *World Wide Web* 18 (1) (2015) 1–7.
- [37] J. Rouchier, Cognition and multi-agent interaction: from cognitive modeling to social simulation, *J. Artif. Soc. Soc. Simul.* 10 (4) (2007).
- [38] J. Zeng, M. Gao, J. Wen, S. Hirokawa, A hybrid trust degree model in social network for recommender system, in: *Advanced Applied Informatics (IIAIAI)*, 2014 IIAI 3rd International Conference on, 2014, pp. 37–41.
- [39] W. Sherchan, S. Nepal, C. Paris, A survey of trust in social networks, *ACM Comput. Surv.* 45 (4) (2013) 47.
- [40] J. Golbeck, M. Rothstein, Linking social networks on the web with FOAF: A semantic web case study, in: *Proceedings of the Twenty-Third AAAI Conference on Artificial Intelligence*, 2008, pp. 1138–1143.
- [41] C.G. Akcora, B. Carminati, E. Ferrari, User similarities on social networks, *Soc. Netw. Anal. Min.* 3 (3) (2013) 475–495.
- [42] S. Nepal, C. Paris, S.K. Bista, W. Sherchan, A trust model-based analysis of social networks, *IJTMCC* 1 (1) (2013) 3–22.
- [43] M. Gong, Z. Xu, L. Xu, Y. Li, L. Chen, Recommending web service based on user relationships and preferences, in: *IEEE 20th International Conference on Web Services*, Santa Clara, CA, USA, 2013, pp. 380–386.
- [44] S. Deng, L. Huang, Y. Yinand, W. Tang, Trust-based service recommendation in social network, *Appl. Math. Inf. Sci.* 9 (3) (2015) 1567–1574.
- [45] S. Deng, L. Huang, J. Wu, Z. Wu, Trust-based personalized service recommendation: A network perspective, *J. Comput. Sci. Technol.* 29 (1) (2014) 69–80.
- [46] A. Maaradji, H. Hacid, R. Skraba, A. Lateef, J. Daigremont, N. Crespi, Social-based web services discovery and composition for step-by-step mashup completion, in: *IEEE International Conference on Web Services, ICWS*, Washington, DC, USA, 2011, pp. 700–701.
- [47] Y. Xu, X. Guo, J. Hao, J. Ma, R.Y.K. Lau, W. Xu, Combining social network and semantic concept analysis for personalized academic researcher recommendation, *Decis. Support Syst.* 54 (1) (2012) 564–573.



Ahlem Kalaï received her master's degree in computer science and multimedia from The Higher School of Computer Science & Multimedia of Sfax (Sfax University, Tunisia) in 2010. She is currently a Ph.D. Student from the Faculty of Economics and Management of Sfax since 2014. She is also a member of MIRACL laboratory of Sfax University, Tunisia. Her current research areas include adaptive systems, personalization & recommendation, Web service & social Computing.



Corinne Amel Zayani received her master's degree in computer science from the Faculty of Sciences of Sfax, the M.S. from Valenciennes and Hainaut-Cambresis University. She obtained her Ph.D. from the Paul Sabatier University (Toulouse III, France), France, in 2008. She is currently an associate professor of Computer Science in Faculty of Sciences of Sfax in Tunisia. She is also a member of MIRACL laboratory of Sfax University, Tunisia. Her current research areas include software engineering of adaptive distributed systems, user profile, social profile, semi-structured document.



Ikram Amous Ben Amor received her master's degree in data processing from Paul Sabatier University (Toulouse III, France), France, in 1999. She obtained her Ph.D. in informatics from the UPS University in December 2002. She is currently an associate professor at the Higher School of Electronic and Communication of Sfax in Tunisia. She is also a member of MIRACL laboratory of Sfax University, Tunisia. Her research interests include methodologies and approaches for adaptive Web applications, multimedia document personalization and finally multimedia document annotation and querying. She has participated in

several program committees of national and international conferences.



Wafa Abdelghani received her master's degree in computer science from the Faculty of Sciences of Sfax (Sfax University, Tunisia) in 2015. She is currently a Ph.D. Student from both the Faculty of Economics and Management of Sfax (Sfax University, Tunisia) and the Paul Sabatier University (Toulouse III, France). She is also a member of MIRACL laboratory (Sfax University, Tunisia) and IRIT Laboratory (Toulouse III- Paul Sabatier University, France). Her current research areas include Social Media, recommendation, Web service, Trust Management and Internet of Things.



Florence Sèdes is full Professor in Computer Science at the University Toulouse 3. She got her Ph.D. degree in 1987. From 2011 to 2013, she was appointed as the Deputy Director of the Toulouse Research Lab in Computer Science (Institut de Recherche en Informatique de Toulouse, IRIT), a joint unit with the National Scientific Research Center (CNRS). She led the national research network i3 (Information, Intelligence, Interaction). She is a member of the National University Council of the French Ministry. Her research areas concern data management and information systems. She leads international projects about Web

services, documents, multimedia metadata and data security. Applications in IoT, CCTV, forensic and social interactions illustrate her contribution on social media ecosystems.