Chapter 1
Trust-Oriented Service Provider Selection in Complex Online Social Networks

Guanfeng Liu and Yan Wang

Abstract In recent years, Online Social Networks (OSNs) with numerous participants have been used as the means for rich activities. For example, employers could use OSNs to investigate potential employees, and participants could use OSNs to look for movie recommendations. In these activities, trust is one of the most important indication of participants decision making, greatly demanding the evaluation of the trustworthiness of a service provider along certain social trust paths from a service consumer. In this chapter, we first analyze the characteristics of the current generation of functional websites and the current generation of online social networks based on their functionality and sociality, and present the properties of the new generation of social network based web applications. Then we present a new selection model considering both *adjacent* and *end-to-end* constraints, based on a novel concept Quality of Trust and a novel complex social network structure. Moreover, in order to select the optimal one from massive social trust paths yielding the most trustworthy trust evaluation result, this chapter presents an effective and efficient heuristic algorithm for optimal social trust path selection with constraints, which is actually an NP-Complete problem. Experimental results illustrate that the proposed method outperforms existing models in both efficiency and the quality of delivered solutions. This work provides key techniques to potentially lots of service-oriented applications with social networks as the backbone.

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1.1 Introduction

Online Social Networks (OSNs) (e.g. Facebook[1] and MySpace[2]) have become increasingly popular recently and are being used as the means for a variety of rich activities. In service-oriented environment, OSNs can provide the infrastructure for the recommendation of service providers or services. According to a survey on 2600 hiring managers (i.e., service consumers) in 2008 by Career Builder[3] (a popular job hunting website), 22% of them used social networking sites to investigate potential employees (i.e., service providers). The ratio increased to 45% in June 2009, and 72% in January 2010. In addition, participants (i.e., service consumers) could look for the service of movie recommendation at FilmTrust[4], a movie recommendation OSN. In recent years, the new generation of social network based web application systems has drawn the attention from both academia and industry. The study in [20] has pointed out that it is a trend to build up social network based web applications (e.g., e-commerce or online recruitment systems). In Oct. 2011, eBay[5] announced their strategic plan to deepen the relationship with Facebook[1] for creating a new crop of e-commerce applications with social networking features, integrating both their e-commerce platform and social networking platform seamlessly[6]. In such a situation, trust is one of the most important indications for service consumers decision making, greatly demanding approaches and mechanisms for evaluating the trustworthiness between a service consumer and a service provider who don't konw each other.

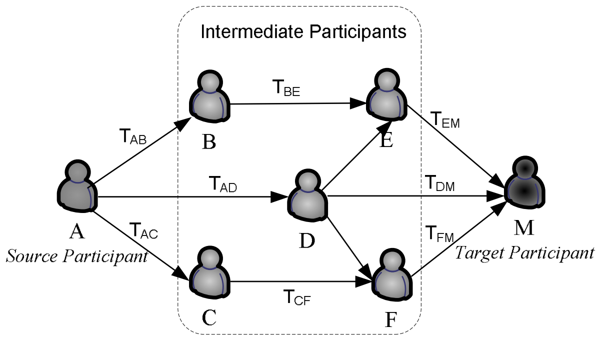

Fig. 1.1 social network structure

[1] http://www.facebook.com/
[2] http://www.myspace.com/
[3] http://www.careerbuilder.com/
[4] http://trust.mindswap.org/FilmTrust/
[5] http://www.ebay.com/
[6] refer to the Reuters news "eBay and Facebook unveil e-commerce partnership" at http://www.reuters.com/article/2011/10/12/ebay-facebook-idUSN1E79B22Y20111012

In OSNs, one participant can give a trust value to another based on their past interactions (e.g., T_{AB} in Fig. 1.1)). If there exist a trust path (e.g, $A \to B \to E \to M$ in Fig. 1.1) linking two nonadjacent participants (there is no direct link between them), the source participant (i.e., the service consumer) can evaluate the trustworthiness of the target participant (i.e., the service provider) based on the trust information between the intermediate participants along the path. The path with trust information linking the source participant and the target participant is called a *social trust path* [14, 16].

In the literature, several methods have been proposed for trust evaluation in OSNs [14, 16, 19, 35]. But these models have three main drawbacks: (1) As illustrated in social psychology [1, 31], the *social relationships* between participants (e.g., the one between an employer and an employee) and the *recommendation roles* of participants (e.g., a supervisor as a referee in his postgraduate's job application) have significant influence on trust and thus should be considered in the trust evaluation of participants. However, they are not considered by existing methods. (2) As there are usually many social trust paths between participants, existing methods evaluate the trustworthiness of a participant based on all social paths incurring huge computation time [14, 16]. Although a few methods [19, 35] have been proposed to address the path selection problem, they yet neglect the influence of social information on path selection. (3) In OSNs, a source participant may have different purposes in evaluating the trustworthiness of a target participant, such as *hiring employees* or *introducing products*. Therefore, a source participant should be able to set certain constraints on the *trust*, *social relationship* and *recommendation role* in trust path selection. However, existing methods do not support these selection criteria.

1.2 Related Work

The studies of social network properties can be traced back to 1960's when the small-world characteristic in social networks was validated by Milgram [30] (i.e., the average path length between two Americans was found to be about 6.6 hops). In recent years, sociologists and computer scientists investigated the characteristics of popular online social networks (OSNs) [32] (e.g., Facebook[1], MySpace[2] and Flickr[7]), and validated the small-world and power-law characteristics (i.e., the probability that a node has a degree k is proportional to k^{-r}, $r > 1$).

In the literature, the issue of trust becomes increasingly important in social networks. we review the existing approaches for evaluating the trustworthiness of participants in OSNs.

Trust Network Discovery. As indicated in the disciplines of Social Psychology [9, 28] and Computer Science [14, 21], a trust network from a source to a target can provide the basis for evaluating the trustworthiness of the target as it contains some important intermediate participants, the trust relations between them and the social

[7] http://flickr.com

context under which their interactions happened, all of which have an important influence on trust relationships and trust evaluation. Extracting such a contextual trust network is an essential step before performing any trust evaluation between two participants in social networks. In addition, the results of trust network discovery can affect the trustworthiness of the trust evaluation [14, 23, 24]. To address the NP-Complete trust network discovery problem [4]. In our previous work [25, 26], we have proposed a new social context-aware trust network discovery model which considers the influence of social context in trust network discovery. In addition, we have proposed two efficient and effective algorithms, i.e., an approximation algorithm, called SCAN, and a heuristic algorithm, called H-SCAN, to discover trust networks.

Trust Evaluation based on Ratings Only. In this type of trust evaluation models, only ratings given to a target participant are considered. For example, at eBay[5], after each transaction, a buyer can give feedback with a rating of "positive", "neutral" or "negative" to the seller according to the seller's service quality. The overall positive feedback rate of the seller is calculated to reveal his/her trustworthiness, which is valuable to buyer. However, this type of trust evaluation model neglects the implicit social relationships between buyers and sellers that actually have significant influence on trust evaluation.

Trust Evaluation based on All Social Trust Paths. In some other trust evaluation models, the trustworthiness of a target participant is evaluated based on all social trust paths between a source participant and the target participant. For example, in [14], the trust value of a target participant is computed by averaging all trust values along all social trust paths. In [35], Walter *et al.* propose a trust-based recommendation system. In their model, all social trust paths between a buyer and a seller selling the products preferred by the buyer are taken into account to evaluate the trustworthiness of the seller.

This type of trust evaluation methods neglects the social information with significant influence on trust evaluation. In addition, evaluating the trustworthiness of a target participant based on all social trust paths consumes huge computation time and thus they can not be applied in large-scale social networks.

Trust Evaluation based on Selected Social Trust Paths. In the literature, there are only a few works addressing the social path selection problem. In *SmallBlue* [19], an online social network constructed for IBM staff, between a source participant and a target participant, up to 16 social paths with no more than 6 hops are selected and the shortest one is taken as the optimal one that delivers the most trustworthy trust evaluation result. But this method neglects *trust information*, *recommendation roles* and *social relationships* between participants. In [16], the social trust path with the maximum of propagated trust value is selected as the most trustworthy one. Their model neglects recommendation roles and social relationships. In addition, none of these models considers different preferences of source participants.

Social Trust Influence on Service Selection. As indicated in social psychology [6, 12], in the reality of our society, a person prefers the recommendation from his/her trusted friends over those from others. In addition, in the discipline of computer science, based on statistics, Bedi *et al*., [5] has demonstrated that, given a choice between recommendations from trusted friends and those from recommender systems, trusted friends' recommendations are more preferred in terms of quality and usefulness. Furthermore, in several recent studies, some researchers [8, 10] have investigated how and to what extent a participant's service selection behavior (e.g., installing a specific application software) impacts on his/her friends' decision-making in service selection. These studies have indicated that the recommendations from trusted friends have significant influence on service or target selection, not only in the society in the real world, but also in online social networks.

Although a complete social network based trust-oriented service recommendation system does not yet exists, it has become an important research topic in recent years. Some researchers [15, 27] have proposed several models to provide more accurate recommendations of products and/or services by taking some social context information into consideration. In these studies, social trust path selection is a critical problem.

1.3 A New Categorization of Functional Websites and Online Social Networks

Golbeck *et. al* [13] propose the criteria of OSNs as follows. 1) OSNs could be accessible over the web with a web browser; 2) Users of OSNs must explicitly state their relationships with other people; 3) The web-based online social network system has explicit built-in support for users to make social connections, and 4) Each relationship is visible and browseable to users. Boyd *et. al* [7] propose the definition of social networking sites as Web-based services that allow individuals to 1) construct public or semi-public profiles within a bounded system; 2) articulate a list of other users with whom they share connections; and 3) view and traverse their list of connections and those made by others with the system. Obviously, Facebook[1] and MySpace[2] are in accordance with these definitions.

However, many other websites, lik eeBay[5], YouTube[8], Blogs and online forums, where people can share their experience and carry out business. But relationships between participants on this type of Websites are implicit. Thus, it is still a puzzling problem whether these Websites belong to the scope of OSNs. In the following context, we first analyze the characteristics of these websites based on their functionality and sociality and present the properties of the new generation of online social network based web applications [20].

[8] http://www.youtube.com

1.3.1 The Current Generation of Functional Websites

The current generation of functional websites are premature with rich functionality but implicit social relations, such as eBay[5] which supports e-commerce activities and the buying-selling relations by default but does not care other social relations among the set of buyers and seller. We summarize the characteristics of the current generation of functional websites as below.

1. They have weak sociality where the relationships between participants are implicit; and participants do not keep their friendship lists and thus they can not make new friends with friends of friends.
2. Then have rich functionality, such as email, Blogs, e-commerce, and video and photo sharing etc.

1.3.2 The Current Generation of OSNs

As the sociality of the above websites is too weak for people to make rich social interactions, the current generation of OSNs, such as MySpace[2] and Facebook[1] emerged in 2003 and 2005 respectively. They can explicitly express simple social relations, but the functionality is limited to a very small scope, like information sharing. We summarize the characteristics of the current generation of OSNs as below.

1. They have medium sociality where the social relationships between participants are explicit and binary (friendship or non-friendship) which can be specified by participants; and participants can make new friends with a friend's friends, which is stronger than that of the current generation of functional websites.
2. They provide a platform where participants can make new friends and conduct some simple activities (e.g., sharing photos and videos) which are not as rich as those in the current generation of functional websites.

1.3.3 The New Generation of Online Social Network based Web Applications

Technically, we can envisage that in the near future social networks can become the backbone to extend a number of traditional systems. For example, the traditional e-commerce system can have a social network of its buyers, and the friends' friends of buyers. Likewise, the traditional CRM (Customer Relation Management) systems can be extended to be supported by a social network of customers and other people with social relations to these customers. Thus, the new generation of social network systems can be expected to support both rich social relations and rich functionality. In these systems, it would be easier to introduce products (e.g., from a retailer) or good sellers (e.g., from a buyer) to buyers, and the friends or the friends' friends of buyers. We summarize the characteristics of the new generation of online social network based web applications as below.

1. They have strong sociality where the social relationships are explicit and complex rather than the binary (friendship or non-friendship) in the current generation of OSNs.
2. They provide a platform where participants can conduct rich activities, such as, e-commerce, CRM system, recommendation systems.

1.4 Complex Social Networks

As the current functional website and OSNs can hardly illustrate real-world complex social information of social networks in real world scenarios [22], we present a complex social network structure, as depicted in Fig. 1.2, modeling well the social networks in real life. It contains the attributes of three impact factors, i.e., *trust*, *social intimacy degree* and *role impact factor*, which influence trust evaluation and hence the decision making of participants.

1.4.1 A Complex Social Network Structure

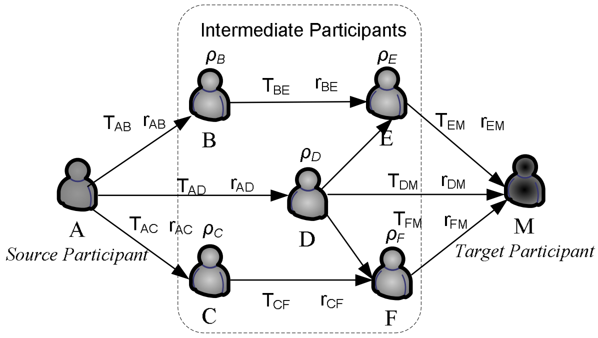

Fig. 1.2 Complex social network

1.4.2 Trust

In human societies, trust is a complex topic subject to a lot of factors, such as previous experience, and other people's recommendations [14]. Many different trust definitions have been proposed addressing different aspects. Alunkal *et al*. [2] define that "trust is the value attributed to a specific entity, including an agent, a service, or a person, based on the behaviors exhibited by the entity in the past". Golbeck *et al*. [14] define that "trust in a person is a commitment to an action based on a belief that the future action of that person will lead to a good outcome".

In the context of this chapter, trust between participants in social networks can be defined as follows.

Definition 1. *Trust* is the belief of one participant in another, based on their interactions, in the extent to which the future action to be performed by the latter will lead to an expected outcome.

Let $T_{AB} \in [0,1]$ denote the trust value that participant A assigns to participant B. If $T_{AB} = 0$, it indicates that A completely distrusts B while $T_{AB} = 1$ indicates A completely believes B's future action can lead to the expected outcome.

1.4.3 Social Intimacy Degree

As illustrated in social psychology [3], a participant can trust the participants with whom he/she has more intimate social relationships more than those with whom he/she has less intimate social relationships. Therefore, we introduce the social intimacy degree between participants into complex social networks structure, and give its definition as follows.

Definition 2. $r_{AB} \in [0,1]$ is the *Social Intimacy Degree* between any given participants A and B in online social networks. $r_{AB} = 0$ indicates that A and B have no social relationship while $r_{AB} = 1$ indicates they have the most intimate social relationship.

1.4.4 Role Impact Factor

Rich activities of participants in social networks can be categorized into different domains (e.g., hiring employees or product sale) based on their characteristics [36]. As illustrated in social psychology [1], in a certain domain of interest, recommendations from a domain expert are more credible than that from a beginner. Therefore, we introduce the role impact factor of a participant into the complex social network structure, and give its definition as follows.

Definition 3. $\rho_A \in [0,1]$ is the value of the *Role Impact Factor*, illustrating the impact of participant A's recommendation role on trust propagation. $\rho_A = 1$ indicates that A is a domain expert while $\rho_A = 0$ indicates that A has no knowledge in the domain.

Though it is difficult to construct social relationships and comprehensive role hierarchies in all domains for the whole society, and obtain their global values, it is feasible to build them up in a specific social community.

For example, in the work by Mccallum *et al.* [29], through mining the subjects and contents of emails in *Enron* Corporation[9], the social relationship between each email sender and receiver can be discovered and their roles can be known. Then the corresponding social intimacy degree and role impact factor values can be estimated based on probabilistic models. In addition, in academic social networks formed by large databases of Computer Science literature (e.g, DBLP[10] or ACM Digital Library[11]), the social relationships between two scholars (e.g., co-authors, a supervisor and his/her students) and the role of scholars (e.g., a professor in the field of data mining) can be mined from publications or their homepages. The social intimacy degree and role impact factor values can be calculated as an example by applying the PageRank model [34]. Furthermore, in addition to mine these values, the social position of a participant can be specified directly [37]. If the participant becomes a recommender, this social position information could illustrate his/her role impact factor in the recommendation of a specific domain.

Based on the above discussion, in addition to participants and the links between them, we propose a new structure for complex social networks that models trust, social intimacy degree and role impact factors, as depicted in Fig. 1.2.

1.5 Multiple QoT Constrained Social Trust Path Selection

To satisfy the different preferences of a source participant in social trust path selection, in this section, we introduce a novel concept Quality of Trust (QoT) and present a multiple QoT constrained social trust path selection model.

1.5.1 Quality of Trust (QoT)

Similar to the Quality of Service (QoS) in service-oriented computing, we present a new concept, *Quality of Trust* in social trust path selection.

Quality of Trust (QoT) is the ability to guarantee a certain level of trustworthiness in trust evaluation along a social trust path, taking trust (T), social intimacy degree (r), and role impact factor (ρ), as attributes.

[9] http://www.cs.cmu.edu/ enron/

[10] http://www.informatik.uni-trier.de/ ley/db/

[11] http://portal.acm.org/

1.5.2 QoT Constraint

To be adaptive to the rich activities in OSNs, a source participant should be able to set certain constraints of QoT attributes in selecting the optimal social trust path. They include two types: *Adjacent QoT Constraint (AQC)* and *End-to-End QoT Constraint (EEQC)*.

1.5.2.1 Adjacent QoT Constraint (AQC)

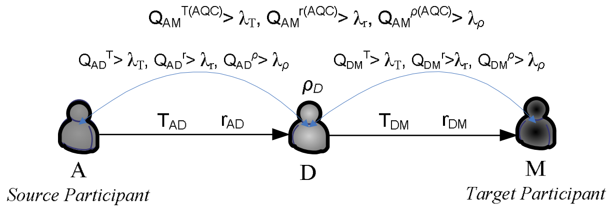

Fig. 1.3 Adjacent QoT constraints

An Adjacent QoT Constraint (AQC) is the constraint of a QoT attribute (i.e., T, r or ρ) between any two adjacent participants in a social trust path. In the complex social network depicted in Fig. 1.2, let $Q_{AM}^{\mu(AQC)}$ ($\mu \in \{T,\ r,\ \rho\}$) denote the AQC for the path between source participant A and target participant M. $Q_{AM}^{\mu(AQC)} > \lambda_\mu$ ($0 < \lambda_\mu < 1$) means that the value of QoT attribute μ between any two adjacent participants in a selected social trust path should be larger than λ_μ. For example, if the AQCs specified by A can be satisfied at $A \to D$, and $D \to M$, then social trust path $A \to D \to M$ satisfies the AQCs. In our model, a source participant can specify different AQCs. E.g., in *hiring employees*, A, a retailer manager specifies AQCs as $Q_{AM}^{T(AQC)} > 0.3$, $Q_{AM}^{r(AQC)} > 0.3$ and $Q_{AM}^{\rho(AQC)} > 0.8$. But when looking for new customers for *selling products*, A can specify $Q_{AM}^{r(AQC)} > 0.8$, if he/she believes the social relationships between participants are more important.

1.5.2.2 End-to-End QoT Constraint (EEQC)

In our model, a source participant can set multiple End-to-End QoT Constraints (EEQCs) for QoT attributes (i.e., T r and ρ) as the requirements of trust evaluation in a social trust path. In Fig. 1.2, let $Q_{AM}^{\mu(EEQC)}$ ($\mu \in \{T,\ r,\ \rho\}$) denote the EEQC between source participant A and target participant M. $Q_{AM}^{\mu(EEQC)} > \lambda_\mu$ ($0 < \lambda_\mu < 1$) means the aggregated value of QoT attribute μ in a social trust path between A and M should be larger than λ. In addition to AQC, a source participant can also specify

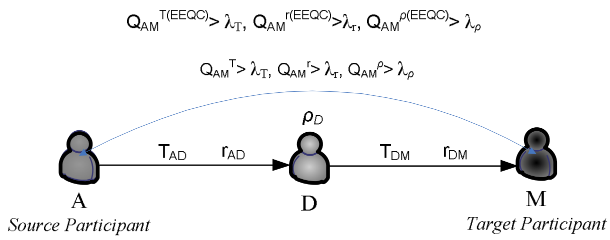

Fig. 1.4 End-to-End QoT constraints

different EEQCs. E.g., in *hiring employees*, A can set EEQCs as $Q_{AM}^{T(EEQC)} > 0.3$, $Q_{AM}^{r(EEQC)} > 0.3$ and $Q_{AM}^{\rho(EEQC)} > 0.8$. But when looking for new customers for *selling products*, A can specify $Q_{AM}^{r(EEQC)} > 0.8$, if he/she believes the social relationships between participants are more important.

1.5.3 Utility Function

Based on our proposed QoT attribute aggregation method [22], we define the utility (denoted as $\mathscr{F}$) in path $p(a_1,...,a_n)$ as Eq. (1.1), which is the measurement of the trustworthiness of $p(a_1,...,a_n)$ in trust evaluation.

$$\mathscr{F}_{p(a_1,...,a_n)} = \omega_T * T_{p(a_1,...,a_n)} + \omega_r * r_{p(a_1,...,a_n)} + \omega_\rho * \rho_{p(a_1,...,a_n)} \tag{1.1}$$

where $T_{p(a_1,...,a_n)}$, $r_{p(a_1,...,a_n)}$ and $\rho_{p(a_1,...,a_n)}$ are the aggregated value of trust, social intimacy degree and role impact factor of path $p(a_1,...,a_n)$ respectively, ω_T, ω_r and ω_ρ are the weights of T, r and ρ respectively; $0 < \omega_T, \omega_r, \omega_\rho < 1$ and $\omega_T + \omega_r + \omega_\rho = 1$.

1.6 A Heuristic Algorithm for the MQCSTP Selection Problem

In optimal social trust path selection, if we consider trust values only, Dijkstra's shortest path algorithm [11] works well. However, if multiple AQCs and EEQCs can be specified and should be considered, this problem becomes the classical Multi-Constrained Optimal Path (MCOP) selection problem, which is NP-Complete [17]. Therefore, we propose an effective and efficient heuristic algorithm H_MQCSTP. This algorithm first investigates whether there exists a *potential solution*, which satisfies the EEQCs and may or may not satisfy AQCs. If yes, it investigates whether there exists a *feasible solution*, which is satisfies both AQCs and EEQCs.

In order to investigate whether a path is a potential solution, we propose an objective function in Eq. (1.2). From Eq. (1.2), we can see that if and only if each aggregated QoT attribute of a social trust path p satisfies the corresponding EEQC,

$\delta(p) \leq 1$; otherwise $\delta(p) > 1$.

$$\delta(p) \triangleq max\{(\frac{1-T_p}{1-Q_p^{T(EEQC)}}),(\frac{1-r_p}{1-Q_p^{r(EEQC)}}),(\frac{1-\rho_p}{1-Q_p^{\rho(EEQC)}})\} \tag{1.2}$$

In addition, we adopt Dijkstra's shortest path algorithm [11] twice in both *backward* and *forward* search, together with our proposed novel heuristic search strategies to select the optimal social trust path.

Backward_Search: In the backward search, H_MQCSTP aims to identify the path p_s from the target v_t to the source v_s with the minimal δ based on Dijkstra's shortest path algorithm [11]. In this searching process, at each node v_k $(v_k \neq v_t)$, the path from v_t to v_k with the minimal δ (denoted as p_k) is identified. Meanwhile T_{p_k}, r_{p_k} and ρ_{p_k} are aggregated and recorded.

The *Backward_Search* procedure can always identify the path with the minimal δ. If $\delta_{min} > 1$, it indicates that there is no potential solution in the sub-network. If $\delta_{min} \leq 1$, it indicates that there exists at least one potential solution and the identified path is a potential one.

Forward_Search: If there exists one potential solution in the sub-network, a heuristic forward search is executed from v_s to v_t. This process adopts the information provided by the above *Backward_Search* to investigate whether there is a feasible solution p_t. In this procedure, H_MQCSTP first searches the path with the maximal utility from v_s. Assume node $v_m \in \{neighboring\ nodes\ of\ v_s\}$ is selected based on Dijkstra's shortest path algorithm [17] as the utility of the path from v_s to v_m (denoted as path $p^{(f)}_{v_s \to v_m}$) is the maximal. Let $p^{(b)}_{v_m \to v_t}$ denote the path from v_m to v_t identified in the *Backward_Search* procedure. Then a *foreseen path* from v_s to v_t via v_m (denoted as $fp_{v_s \to v_m \to v_t} = p^{(f)}_{v_s \to v_m} + p^{(b)}_{v_m \to v_t}$) is identified. According to whether $fp_{v_s \to v_m \to v_t}$ is feasible, H_MQCSTP adopts the following searching strategies.

Situation 1: If $fp_{v_s \to v_m \to v_t}$ is a feasible solution, then H_MQCSTP chooses the next node from v_m with the maximal utility following Dijkstra's shortest path algorithm.

Situation 2: If $fp_{v_s \to v_m \to v_t}$ is not a feasible solution, then H_MQCSTP does not search any path from v_m and link $v_s \to v_m$ is deleted from the sub-network. Subsequently, H_MQCSTP performs the *Forward_Search* procedure to search other path from v_s in the sub-network.

Since H_MQCSTP adopts twice Dijkstra's shortest path algorithm, they have the same time complexity of $O(N^2)$ when implementing the priority queue with a disordered array, which can be optimized to $O(NlogN+E)$ by adopting a Fibonacci heap to store the priority queue [11] (N is the number of nodes and E is the number of links in the sub-network). H_MCOP [17] which is the most promising algorithm for the NP-Complete MCOP selection problem, has the same time complexity as H_MQCSTP. But our proposed heuristic algorithm adopts a better objective function and better searching strategies and thus can significantly outperform H_MCOP in both efficiency and the quality of selected social trust paths

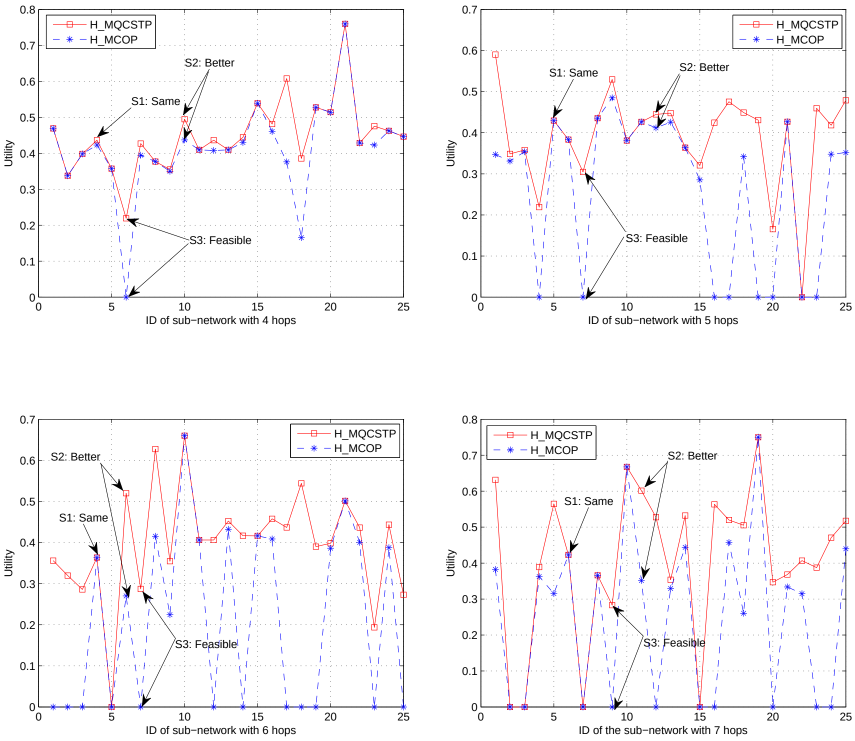

Fig. 1.5 Path utility of sub-networks

1.7 Experiments

1.7.1 Experiment Settings

In order to validate our proposed algorithm, we need a dataset which contains social network structures. The *Enron* email dataset[9] has been proved to possess the small-world and power-law characteristics of social networks, it has been widely used in the studies of social networks [21, 23, 24, 29, 33]. Thus, we select *Enron* email dataset[9], containing 87,474 nodes (participants) and 30,0511 links (formed by sending and receiving emails) for our experiments. From this dataset, social intimate degree and role impact factor can be mined from the subjects and contents of emails [29], fitting our proposed complex social network structure well.

H_MCOP is the most promising algorithm for MCOP selection [17]. Based on it, several approximation algorithms [18] [38] have been proposed for quality-driven service selection. But as pointed in [22], they can not be applied in large-scale complex social networks. Thus, to study the performance of our proposed heuristic al-

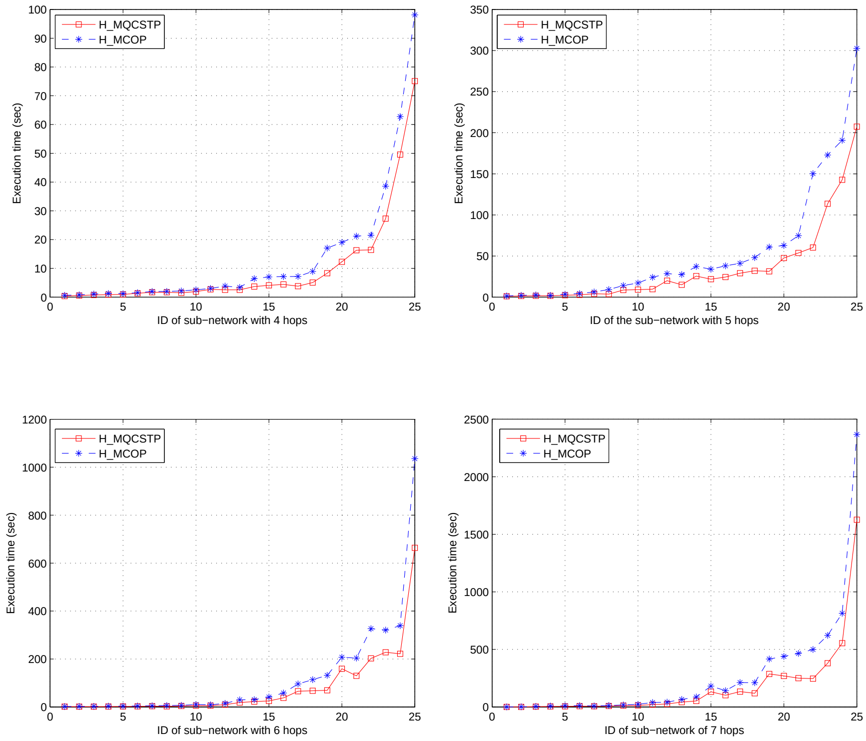

Fig. 1.6 Execution time of sub-networks

gorithm H_MQCSTP, we have a comparison with H_MCOP [17] in both execution time and the utilities of identified social trust paths. In our experiments, the T, r and ρ values are randomly generated. The EEQCs specified are set as $Q^{(EEQC)} = \{Q^{T(EEQC)} > 0.05,\ Q^{r(EEQC)} > 0.001,\ Q^{\rho(EEQC)} > 0.3\}$ and the adjacent QoT constraints are set as $Q^{(AQC)} = \{Q^{T(AQC)} > 0.1,\ Q^{r(AQC)} > 0.05,\ Q^{\rho(AQC)} > 0.1\}$. The weights of attributes in the utility function are set as $\omega_t = 0.25,\ \omega_r = 0.25$ and $\omega_\rho = 0.5$.

Each of H_MQCSTP and H_MCOP is implemented using Matlab R2008a running on an Lenovo ThinkPad SL500 laptop with an Intel Core 2 Duo T5870 2.00GHz CPU, 3GB RAM, Windows XP SP3 operating system and MySql 5.1.35 relational database. The results are plotted in Fig.1.5 to Fig. 1.6, where the execution time and the utilities of the extracted trust network for each of the algorithms are averaged based on 5 independent runs.

Table 1.1 The comparison in utility and execution time

Algorithm	Sum of utility				Sum of execution time (sec)			
	4 hops	5 hops	6 hops	7 hops	4 hops	5 hops	6 hops	7 hops
H_MQCSTP	11.2014	9.7113	9.9469	10.1747	245.8564	871.8128	1.9528e+003	4.3005e+003
H_MCOP	10.3047	6.5274	6.6006	6.1979	340.4162	1.3571e+003	3.0024e+003	6.6996e+003
difference	10.87% more	14.88% more	18.87% more	16.42% more	27.78% less	35.76% less	34.96% less	35.81% less

1.7.2 Performance in Social Trust Path Selection

In this experiment, we first randomly select 100 pairs of source and target participants from the *Enron* email dataset[9]. We then extract 100 corresponding sub-networks between them by using the exhaustive searching method, among which the maximal length of a social trust path varies from 4 to 7 hops following the *small-world* characteristic (i.e., the average path length between two nodes is about 6 hops in a social network [38]). The smallest case sub-network has 33 nodes and 56 links (4 hops), while the most complex sub-network has 1695 nodes and 11175 links (7 hops).

Fig. 2 plots the utilities of the social trust paths identified by H_MQCSTP and H_MCOP respectively, ordered by the number of hops. From Fig. 2, we can observe that in any case, our H_MQCSTP does not yield any utility worse than that of H_MCOP (see case $S1$ in Fig. 2) while in most sub-networks (61% of all sub-networks), the utilities of social trust paths identified by H_MQCSTP are better than those of H_MCOP (see case $S2$ in Fig. 2). In addition, H_MCOP sometimes returns an infeasible solution even when a feasible solution exists. In contrast, H_MQCSTP can identify a feasible solution if it exists, (see case $S3$ in Fig. 2). As illustrated in Table 1.1, the utility summarization of all social trust paths identified by our H_MQCSTP algorithms is greater than that of H_MCOP in all 4 groups. This is because when a social trust path with the maximal utility is a feasible solution in a sub-network, both H_MCOP and H_MQCSTP can identify it as the optimal solution; however, when the social trust path with the maximal utility is not a feasible solution, since the objective function is not well defined, H_MCOP can hardly find a solution that is as good as that from H_MQCSTP and may even return an infeasible one even when a feasible solution exists.

Fig. 3 plots the execution time of both H_MQCSTP and H_MCOP, each of which is average of 5 independent executions. From Table 1.1, we can see that our proposed heuristic algorithm is much faster than H_MCOP in all 4 groups. This is because that in the searching process of H_MQCSTP, the node leading to an infeasible solution is not regarded as a candidate to be selected for the next searching step, which can reduce much search space and thus significantly save execution time.

Through the above experiments, we can see that H_MQCSTP is much superior to H_MCOP in both efficiency and the quality of delivered solutions

1.8 Application Scenarios

Our proposed model and algorithm can provide key techniques to lots of potential applications with social networks as the backbone. Some examples are listed below.

1. A New Generation CRM System. Our proposed method can be applied into a new generation CRM (Customer Relation Management) system, which maintains a complex social network containing the social relationship between customers, and the recommendation roles of these customers. With this information, the new CRM system can help a retailer identify new trustworthy customers and introduce products to them, which can bring enormous commercial opportunities to retailers.
2. A New Generation Employment System. Our methods can also be applied in a new generation employment system which maintains a complex social network containing employees, their recommendation roles (e.g., a professor in computer science), and the social relationship between them (e.g., the relationship between a supervisor and his/her student). In such an application our methods can help a hiring manager evaluate the trustworthiness of all potential employees and find trustworthy persons to be employed, which in turn can bring great benefits for the employment of companies.
3. A New Generation Recommendation System. Our proposed method can be used in a new generation recommendation system, which maintains a social network of buyers, sellers and the complex social information, including social relationships and recommendation roles. In this system, our proposed method can be applied to help a buyer identify the most trustworthy seller from all those sellers selling the product preferred by the buyer.

1.9 Conclusions

In this chapter, we have analyzed the characteristics of the current generation of functional websites and the current generation of OSNs, and presented the properties of the new generation of online social network based web applications. Our proposed new complex social network takes *trust*, *social relationships* and *recommendation roles* into account, and can reflect the real-world situations better. In addition, our proposed heuristic algorithm H_MQCSTP can solve the optimal social trust path selection problem with multiple both adjacent and end-to-end QoT constraints. The results of experiments conducted on a real dataset of social networks demonstrate that H_MQCSTP significantly outperforms existing methods in both efficiency and the quality of delivered solutions. The proposed model and algorithm can provide key techniques to the new generation of social network based web applications.

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