Small-World Reputation Management in E-Commerce Communities:
Results on Pivots, Clustering, and Scattering*

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Abstract

Successful commerce relies heavily upon the reputations that the different parties acquire through their dealings with each other. We consider a community whose members provide services as well as referrals for services to each other. The search for a service is initiated when a special need or opportunity (e.g., a solicitation from a business) arises. Personal agents assist users in evaluating the services and referrals provided by others, maintaining contact lists, and deciding whom to contact. The agents can communicate with anyone, but may communicate with only a small fraction of the members of the community. Agents and their users have full autonomy in deciding whether or how to respond to a request.

We view an e-commerce community as a social network, which supports reputations both for expertise (providing good service) and helpfulness (providing good referrals). We motivate metrics to estimate the effectiveness of a social network to support e-commerce. We use these metrics to compare heuristics through which the agents acquire opinions about and decide whether to help others. We study aggregate phenomena such as the emergence of subcommunities, pivot vertices (which link different subcommunities), and the sensitivity of the social network to the addition or removal of an agent.

Our main results are that the users’ reputations reflect their expertise and helpfulness and the social network improves in its support for service location. Importantly, we discovered that the quality of the network improves with the presence of a pivot, has an inverse relationship with clustering, and improves with respect to a concept we term cautious scattering.

Topics: Reputation and trust mechanisms and issues.

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1 Introduction

Successful commerce relies heavily upon the reputations that the different parties acquire through their dealings with each other. The reputations cover both the expertise (good service) and the helpfulness (good referrals) of the parties. Conventionally, two main kinds of techniques for service location are considered. Content-based filtering finds services or information based on a comparison of the contents of a specific request and a specific piece of information [Croft, 1993]. Collaborative or social filtering relies on recommendations being produced based on the opinions of others deemed similar to the given user [Shardanand and Maes, 1995]. Current reputation mechanisms are tied into some variant of an approach for collaborative filtering.

While we agree that some of the intuitions behind collaborative filtering must be incorporated in any architecture for reputation management and usage, we believe there need to be some important enhancements beyond current approaches. Our first concern applies to the importance of distribution and the second concern to the currently received wisdom about seeking clusters everywhere.

- Most current approaches to reputations are centralized in a server. They require users to explicitly make and reveal their ratings of others.
  
  It would be better if the ratings were learned by the users’ agents as they acted, and used to make recommendations but without placing them in a server. A distributed system would better preserve its user’s privacy. It will also provide higher availability. For example, if the server goes down, the centralized reputation mechanism goes down with it, but a decentralized one might continue to be useful. This is especially the case when mobile computing is considered, wherein it is possible with current technologies to have ad hoc, short-range broadcast-based networks. A user may be able to reach anyone else within a kilometer or so (i.e., “within earshot”), but not always be able or willing to reach a site farther away.

- Most current approaches to using information from other users require some form of clustering (of the users’ profiles or their preferences as learned by the system).

  Our concern is fundamental to the nature of collaborative filtering. Let’s consider the sociology literature dealing with small-world networks [Watts and Strogatz, 1998]. Small-world networks are neither fully regular nor fully random, but capture the structure of real-life human organizations. Watts & Strogatz observe that such graphs have clusters (like regular graphs) and short paths (like random graphs). Whereas sociologists and mathematicians merely study the properties of small-world networks, our goal is to develop a multiagent system that essentially converges to a small-world network, while requiring only local, autonomous decisions by its member agents. However, the sociologists have some well-thought out intuitions (empirically tested on human societies), to which we must pay attention. One of these intuitions is the notion of weak ties propounded by Granovetter [1973]. Granovetter’s observation was that a person all of whose social contacts were in the same cluster is worse off than someone who has social contacts in different clusters. This is because someone with widely distributed contacts is privy to a larger variety of information and has access to far more opportunities. This supports the common wisdom about heading out of one’s comfort zone to make a fortune.

  Consequently, it appears that the quality of a social network consisting of computational agents should also improve when the extent of their clustering decreases. This relationship is not trivial, because clustering can serve a useful purpose and some forms of it should remain desirable.
The above hypotheses are borne out by our experimental results in a setup where the agents maintain each other’s reputations in a fully distributed manner. Although the present experiments are not the last word on collaborative filtering, our results indicate that at least in some important situations, scattering is more desirable than clustering. We believe this is an important result and suggests an alternative paradigm to reputation management: small-world filtering.

Section 2 presents our architecture. Section 3 presents our experimental model and some basic results that we previously obtained. Section 4 introduces the notions of pivot agents and weak ties, and relates them to the quality of the network. Section 5 formalizes clustering and scattering in our framework, and relates them to the quality of the network. Section 6 concludes our paper with a discussion of the main results and directions for future research.

2 Architecture and Approach

We consider a community whose members provide services as well as referrals for services to each other. We view an e-commerce community as a social network, which supports reputations both for expertise (providing good service) and helpfulness (providing good referrals). Personal agents assist users in evaluating the services and referrals provided by others, maintaining contact lists, and deciding whom to contact. Agents and their users have full autonomy in deciding whether or how to respond to a request.

We distinguish between a user’s interests and his expertise. These two aspects are complementary in that a user will query others based on his interest, but answer others’ queries based on his expertise. Most approaches involving any variant of collaborative filtering do not distinguish between users’ interests and expertise. They tend to assume that the users will form clusters easily. However, when the users have different interest and expertise, then the people who need to know them are in general different from the people they need to know. This makes the clustering somewhat less clean.

We previously studied the application of social networks for referrals in information gathering [Yu et al., 1999]. While the present approach shares some intuitions with that work, there turn out to be a number of important differences in the modeling assumptions. Let’s first consider the basic model and architecture—the part that is the same in both cases.

Each user is associated with a personal agent. Users pose queries to their agents and peers. Intuitively, these queries are of the form Who can provide good service about ⟨topic⟩. For example, the user may wish to know who is a good plumber. The queries by the user are first seen by his agent who decides the potential contacts to whom to send the query. After consultation with the user, the agent sends the query to the agents for other likely people. The agent who receives a query can decide if it suits their user and let the user see that query. In addition or instead of just forwarding the query to the user, the agent may respond with referrals to other users. If the agent or user wish they can discard the query and never respond to it in any way.

A query includes the question vector as well as the requester’s ID and address and a limit on the number of referrals requested. A response may include an answer or a referral, or both, or neither (in which case no response is needed). An answer if given depends on the query and the expertise of the answering agent. An agent answers only if it is reasonably confident of its expertise matching the incoming query. A referral depends on the query and on the referring agent’s model of other agents; a referral is given only if the referring agent has some confidence in the relevance of the agent being referred.

In order to interact successfully with other agents, each agent has the following information:

- The user’s own areas of expertise to decide whether or not to accept incoming queries.
- Models of (some) colleagues to decide whether to send them a given query. These models are learned through interactions with others. The model for a colleague contains its address, expertise vector, a rating of the confidence, and a rating of the sociability. The agent must maintain this model for each neighbor, but may remember it also for some other agents (in a cache).

When the originating agent receives referrals, it integrates them into its models. Based on its models, it may decide to actually follow up a referral. When the agent receives an answer, it uses the answer as a basis for evaluating the expertise of the agent who gave the answer. This evaluation affects its model of the expertise of the answering agent, and its models of any agent who may have given a referral to this answering agent. As a result, if an agent sends in a good answer, the evaluation of its expertise goes up as does the sociability of any agents who referred to it (through any path).

2.1 E-Commerce versus Information Gathering

In information gathering, the agents learn from the answers they receive so their own expertise tends to improve from the queries they ask. By contrast, in e-commerce, receiving a service does not make you any better at delivering the service. For example, if you ask lots of questions about Chinese pottery, you might become an expert yourself, whereas just because you called the plumber a lot of times does not mean you will become a plumber yourself. For the same reason, the interests and expertise of each user tend to overlap in the case of information gathering whereas they tend to be disjoint in the case of e-commerce. In the case of information gathering, every agent represents a user who has wide interests and expertise. In the case of e-commerce, participants may have wide interests but will often have narrower expertise. For example, it will be unusual for a plumber to also be a dentist.

In many cases, in e-commerce, the participants will fall into three major categories based on their predominant role:

- Consumers, who have wide interests and little expertise (of the kind that is of commercial interest).
- Providers, who may have few interests and narrow but advanced expertise, e.g., dentists and plumbers.
- Brokers, who maintain large numbers of links to the others but have no significant interests or expertise of their own. There are usually only a few of such participants in a network.

The brokers provide referrals, but they do so out of commercial interest. The consumers provide referrals to each other and reciprocate in helping each other find good services or evaluate services that are known. The providers rarely give referrals to each other. For example, you won’t ask a dentist to refer you to a plumber.

2.2 Learning in the Network

In our approach learning takes place in a manner akin to relevance feedback.

The vector space model (VSM) is a classical information retrieval (IR) technique [Salton and McGill, 1983]. We adapt VSM to locate people rather than documents. In our formulation, VSM estimates the importance of each term in a query and the term’s power of discrimination among the users who may be sent that query based on the expertise that they have exhibited. Following the basic VSM idea, we represent the users’ interests and expertise (actual and modeled) as vectors in an n-dimensional information space. Then we systematically compare each query vector with the expertise vectors of other users to find the user whose expertise is the most similar to the query. Given an interest and an expertise vector, under VSM, the similarity between the two vectors is defined as the cosine of the angle between those vectors.
Definition 1 Given a query vector \( Q = \langle q_1, q_2, \ldots, q_n \rangle \) and an expertise vector \( E = \langle e_1, e_2, \ldots, e_n \rangle \), the similarity between \( Q \) and \( E \) is defined as:

\[
Q \odot E = \frac{\sum_{t=1}^{n} q_t e_t}{\sqrt{n \sum_{t=1}^{n} q_t^2}}
\]

The query vector is generated from the query the user makes. The expertise vector depends on each user that the user considers as a potential target of this query. Obviously, the true expertise of the other user may not be known to this user. Therefore, the querying user’s agent uses an estimate of the other user’s expertise that it has learned from previous interactions. The computed similarity predicts the the likelihood or confidence that a person will be able to answer the query of the user.

The computation of the above similarity measure identifies the potential known experts for the given query. The agent returns to the user a ranked list of these experts based on similarity. The user can choose a few of them to send the query. Each of them may respond with an answer to the query, or referrals to other users, or give no response at all. What the agent needs to learn about others is their potential usefulness for a given query, i.e., the likelihood of getting a good answer or a referral that (in as few steps as possible) yields a good answer.

\( Q \odot p_i \), the relevance of a query \( Q \) to a person \( p_i \), is defined as the weighted sum of the expertise and sociability components. The expertise component is essentially as above; the sociability component is a scalar, which effectively tells us how to rate the referrals given by this person.

Definition 2 \( Q \odot p_i = (1 - W_s) \cdot (Q \odot E_i) + (W_s \cdot S_i) \), where \( E_i \) and \( S_i \) are the expertise and sociability of \( p_i \), respectively, and \( W_s \) and \( (1 - W_s) \) are the weights of the sociability and expertise of \( p_i \).

Further, an absolute relevance threshold can be specified. The threshold can be adjusted to tune the number of purported experts found and to limit the number of referrals that this user will give other users.

Definition 3 Given a query vector \( Q \) and a threshold \( \theta \), a person with expertise \( E \) is relevant to \( Q \) if \( Q \odot E \geq \theta \).

A referral graph encodes how the computation spreads in our approach as a query originates from an agent and referrals or answers are sent back to this agent. Figure 1 shows an example referral graph. Here agent A asks a question of two of its neighbors, who send back two referrals apiece. Two of these referrals are dead-ends; one leads to a good answer and one to a bad answer. Using the referral graph, it is easy to visualize how the agents learn about each other in our approach.

Let \( Q \) be a query from user \( p_i \). We assume that, after a series of \( l \) referrals, this produces a response \( R \) from colleague \( p_j \). Let the entire referral chain in this case be \( \langle p_i, r_1, \ldots, r_{l-1}, p_j \rangle \). Now we can refine the estimate of the correspondent’s relevance toward certain queries, and use that to adapt the models that \( p_i \) has of everyone else involved in this process. In the following, let \( E_Q \) be the estimated expertise of \( p_j \) as is reflected in \( p_j \)’s response \( R \) to query \( Q \). There are three main possibilities. Here \( \alpha \) and \( \beta \) are learning rates; \( B \) is the branching factor, i.e., the maximum number of referrals that are allowed.

- A good answer. Then, the estimated expertise for \( p_j \) is updated as \( E_j = (1 - \alpha) E_j + \alpha E_Q \). For all intermediate vertices, the sociability is updated as \( S_k = S_k + \frac{(1 - S_k)}{B^{(l-k)}} \).
- A bad answer. Then, the estimated expertise for \( p_j \) is updated as \( E_j = (1 - \alpha) E_j + \alpha E_Q \) (same formula as above, but \( E_Q \) is lower in this case). For all intermediate vertices, the sociability is updated as \( S_k = S_k - \frac{S_k}{B^{(l-k)}} \).
- A non-answer. This is treated the same as a bad answer with the estimated expertise set to a low value. That is, for any referral chain which peters out into nothing, all members of the chain are penalized.

The learning is additive with respect to the referral chains. That is, we treat all referral chains one by one in some arbitrary order. If \( p_j \) is referred to be many users and produces a good answer, all of them gain in sociability. Conversely, if \( p_j \) produces a bad answer, all of them suffer in sociability.

3 Experimental Setup and Previous Results

Our approach is being implemented on a distributed system of Communicators (roughly, high-end PDAs with cellular phones) for use in a practical social network. However, in order both to refine our design and to understand the principles underlying social networks, we have conducted several experiments on a simulation of the above setup. All the heuristics used in the simulation are as in the actual system. However, the queries and responses are generated automatically, rather than by a human.

In our simulated setup, each agent has an interest vector, an expertise vector, and several peer models. In general, the peer models depends on how many agents know the given agent, how many agents he knows, which community he belong to, and so on. In our case, the peer models kept by an agent are the given agent’s representation of the other agents’ expertise and sociability.

An agent’s queries are generated based on his interest vector. The queries are generated as vectors by perturbing the interest vector of the given agent. The motivation for this is to capture the intuition that an agent will produce queries depending on his interests.

When an agent receives a query, he will try to answer it based on his expertise vector, or refer to other agents he knows. The originating agent collects all possible referrals, and continues the process by contacting some of the suggested referrals. At the same time, he changes his neighbor models for other agents.

Our experiments involve between 20 and 60 agents with interest and expertise vectors of dimension 5. The agents send queries, referrals, and responses to one another, all the while learning about each others’ interest and expertise vectors. The agents are limited in the number of neighbors they may have—in our case the limit is 4. The neighbors are the agents to whom a given agent may send a query or about whom the agent may issue a referral. The idea is that the agent should have few neighbors relative to the entire society.
of agents. This is similar to the intuition that people living in a town of 300,000 may only know, say, 200 people—i.e., a fairly small fraction of the entire set.

In general, the agents may keep track of more peers than just their neighbors. Periodically, they decide which peers to keep as peers, i.e., which are worth remembering. They also decide which of the peers to promote to neighbors based on the benefit they have drawn from these and other agents in terms of answers and referrals.

3.1 Metrics

Some aggregate properties of a social network must be defined so we can study networks and their evolution experimentally.

The effectiveness of a social network can be defined in terms of the likelihood of obtaining correct answers with the least number of messages. This leads us to define the following metric for the quality of a social network.

**Definition 4** The quality of a social network is given by the following, where \( \text{path}(i, j) \) gives the shortest path length from \( p_i \) to \( p_j \).

\[
\sum_{i,j} \frac{I_i \otimes E_j}{B \cdot \text{path}(i,j)}
\]

As a base-line for comparison, we also introduce the *direct query* metric, where the agents do not seek or grant referrals to anyone.

**Definition 5** The direct query metric of a social network is given by the following:

\[
\sum_{i,j} \frac{I_i \otimes E_j}{B}, \text{ where } j \text{ is a neighbor of } i
\]

3.2 Previous Results

We obtained some interesting results from the information gathering experiments that we ran [Yu et al., 1999]. In these experiments, the interest and expertise vectors were assigned randomly to the agents. What we found were the following interesting results.

**Result 1** The quality of the social network improves over time.

**Result 2** The social network stabilizes at an improved quality.

**Result 3** Giving and taking referrals has a significant payoff in finding the right experts for each member’s queries.

**Result 4** Giving consideration to others’ sociability improves the quality of the social network, but an overemphasis on sociability (to the cost of expertise) can hurt.

For the *sensitivity analysis* experiments, we began with a stable network and introduced an agent into it who was not in the best position in terms of neighbors.

**Result 5** A new person trying to embed into a social network will drift toward his own community.
4 Pivot Agents

Not all the members of a social network are equally important in terms of their contribution to improve the quality of the network, e.g., by giving referrals to others. Specifically, some members are more important in establishing contacts with the broader social realm. These persons can be thought of as belonging to a higher level in the information pyramid.

![Diagram of a social network with a pivot vertex]

Figure 2: A pivot in a social network

We call such vertices pivots, because they connect across different communities. The edges that connect a vertex to a pivot are termed weak ties in the sociology literature, as opposed to strong ties that connect a vertex to others in its own community. Sociologists have long known that weak ties are powerful beyond strong ties, precisely because they go beyond one’s own community [Granovetter, 1973]. People in the same community would generally tend to have the same knowledge as everyone else in that community [Gladwell, 1999, p. 61]. However, acquaintances that are outside of the community will bring in greater value added by having different knowledge and perspectives. Consequently, people who have a number of acquaintances are critical to a society. Pivots represent such people, which is why they are important to our work. Figure 2 illustrates the intuition about pivots that they relate to many subcommunities in the network, and thus help tie them together.

In our experiments, we modeled pivots as agents who have a significantly higher out-degree (i.e., number of neighbors) than other agents. Because of their higher out-degree, such agents are valuable to others and soon end up with a high in-degree as well. Our simulations confirmed the hypothesis that the existence of a pivot agent significantly improves the quality of the social network as perceived by all agents in the network. Figure 3 confirms Result 6.
Figure 3: Improvement in quality due to a pivot at different sociability weights

**Result 6** The existence of a pivot improves the quality at most weights of sociability

## 5 Cliquishness

The cliquishness of a graph is defined to capture how well the neighbors of a vertex are connected to each other. This captures the intuition that there are clusters or “cliques” in the graph. A clique is a maximal complete subgraph of three or more vertices [Wasserman and Faust, 1994, p. 254]. Watts & Strogatz propose a clustering coefficient to estimate the cliquishness of a graph [1998]. We first define clustering ($\chi$) as a directed graph version of their metric.

In the following, let $G$ be a graph with $|G|$ vertices; let $v$ be a vertex in $G$. Let $v$ have $k_v$ neighbors with $e_v$ edges among the neighbors (the neighbors may have up to $k_v(k_v - 1)$ edges among themselves).

**Definition 6** We define clustering as ($\chi_G$) as follows.

$$\chi(v) = \frac{e_v}{k_v(k_v - 1)}$$

$$\chi_G = \frac{\sum_{v \in G} \chi(v)}{|G|}$$

The above metric rates a vertex as contributing to the cliquishness merely if it has edges into a well-connected subgraph even if the members of that subgraph don’t have edges back to it. Conversely, the above metric also rates a vertex as contributing 0 to the cliquishness if it has edges to vertices who don’t know each other—such a vertex if of course a potential pivot. To accommodate both of these variations, we define another metric, which we term reflexive clustering ($\rho$). Now also let vertex $v$ have $k_v$ neighbors with $f_v$ edges among the neighbors and $v$ (there may be up to $k_v(k_v + 1)$ such edges).

**Definition 7** We define reflexive clustering as ($\rho_G$) as follows.

$$\rho(v) = \frac{f_v}{k_v(k_v + 1)}$$
Interestingly, although clustering and reflexive clustering appears to increase or decrease in unison (see below), the difference between the two is not constant. The difference reflects the existence of pivots in the social network, and leads to an interesting result. The difference between clustering and reflexive clustering captures a form of cautious scattering ($\sigma$) of the agents, which we define next. Figure 4 also shows the scattering coefficients for the different vertices (as $S$). Notice that the two graphs have fairly different scattering values because of the different role of vertex 3.

**Definition 8** We define scattering as ($\sigma_G$) as follows.

$$\sigma_G = \rho_G - \chi_G$$

![Diagram](image_url)

Figure 4: Clustering and reflexive clustering motivated

Figure 4 shows calculations of clustering and reflexive clustering on two different kinds of graphs to better motivate the reason for their definition. The clustering contribution of each vertex is shown as $C$ and its reflexive clustering contribution as $D$. Although the graphs are don’t look very different, they are structurally quite different in terms of the clusters they support.

We found that both clustering and reflexive clustering have a similar relationship with the quality of a social network. If either kind of clustering goes up, the quality of the network goes down. This is illustrated in Figures 5, 6, and 7.

The difference in these figures lies in the relationship between the interest and expertise vectors. For any given agent, they are set to be equal to each other in Figure 5; independent of each other in Figure 6; and opposite to each other in Figure 7, respectively. By opposite, we mean that if $I_t$ and $E_t$ are the $t$th terms in the interest and expertise vectors, respectively, then $I_t = 1 - E_t$. Notice that the improvement in quality and increase in scattering are more noticeable in the latter cases than when interest equals expertise (the traditional scenario in filtering).
Result 7 The quality of a network increases when its clustering and reflexive clustering decrease.

Interestingly, scattering has the opposite relationship with the quality of a social network than clustering. If scattering goes up, the quality of the network goes up as well. This is also illustrated in Figures 5, 6, and 7.

Result 8 The quality of a network increases when its cautious scattering increases.

6 Discussion

A social network targeted toward locating effective services has great potential advantages over conventional centralized techniques. Our approach to referrals through the social network enables a user to leverage the knowledge of several users and their personal agents to find services of the desired type and of high quality without causing excessive communication. This approach also preserves the autonomy and privacy of the users. If a user wishes not to give referrals it can simply ignore such requests. Of course, an agent who never contributes to others’ searches will soon fall out of favor with its peers, and they might also stop helping it when it needs help.

A number of relevant approaches have emerged recently. Kasbah is an electronic marketplace that includes a centralized reputation service called the “better business bureau” [Chavez et al., 1997]. Zacharia et al. describe two approaches for collaborative reputation management [1999]. In both methods, a central system keeps track of the users’ explicit ratings of each other, and uses these ratings to compute a person’s overall reputation or reputation with respect to a specific user.

Amalthaea is a multiagent system for information filtering, but geared to the support of one user at a time (i.e., the different users do not interact and are not aware of each other) [Moukas and Maes, 1999]. The agents collectively evolve to serve their one user. The basis for this evolution is the VSM similarity between the user’s interests and the documents being found.

Olsson describes a decentralized architecture for social filtering, which shares some intuitions with our approach [1998]. The agents learn confidence ratings of each other. Olsson’s is meant to be a prototype
Figure 6: Reduction in quality due to clustering and reflexive clustering: interest independent of expertise system for use, whereas we also wished to study the principles behind social filtering. A minor difference is that Olsson’s system is driven by dissemination of documents rather than queries.

Rasmusson & Janson proposed the notion of soft security based on social control through reputation [1996]. In soft security, the agents police themselves without ready recourse to a central authority. This class of approaches is especially attractive for loosely federated, open systems such as the Internet.

In future work, we plan to study more complex settings with a view to designing heuristics for multiagent learning by which a given system would tend to converge toward the right kind of a cautiously scattered small-world social network.

References


Figure 7: Reduction in quality due to clustering and reflexive clustering: interest opposite to expertise


