Social behaviours applied to P2P Systems: An efficient algorithm for resources organisation

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Abstract—P2P systems are a great solution to the problem of distributing resources. The main issue of P2P networks is that searching and retrieving resources shared by peers is usually expensive and does not take into account similarities among peers. In this paper we present preliminary simulations of PROSA, a novel algorithm for P2P network structuring, inspired by social behaviours. Peers in PROSA self-organise in social groups of similar peers, called “semantic-groups”, depending on the resources they are sharing. Such a network smoothly evolves to a small-world graph, where queries for resources are efficiently and effectively routed.

I. INTRODUCTION

In the last years social communities have been deeply studied not only by psychologists or sociologists, but also by computer scientists. The main point is that social communities seem to naturally possess really interesting characteristics that can be exploited in computer science. Studying collaboration communities, researchers have found an interesting structure that seems to arise whenever a network of relationships among entities is involved: the so-called “small-world” graphs. A small-world graph is a graph which presents a high clustering coefficient (i.e., similar peers usually link each other) and a relative small average path length (i.e., the average number of intermediates between two peers is small).

The small-world property seems to be a characteristic of many human communities, such as mathematicians, actors, scientists. A small-world arises almost naturally whenever social contacts among people are involved: many researchers are trying to understand the reasons of this behaviour. In this work we’re not interested in answering this question. Our target is just to develop a P2P system using rules and concepts inspired by human behaviours and relationships dynamics.

In a social network there are several kinds of links among people, from simple acquaintance to friendship. Note that usually social links are not symmetric: all British people know who is the prime minister of UK, but the prime minister himself doesn’t directly know all of them. We say that a person has an “acquaintance-link” to somebody else if he simply knows him. In real life it is really simple to gain acquaintance-links to anybody: a person met on the stairs and a taxi driver can be exploited in computer science. Studying collaboration seems to naturally possess really interesting characteristics that can be exploited in computer science. Studying collaboration communities, researchers have found an interesting structure that seems to arise whenever a network of relationships among entities is involved: the so-called “small-world” graphs. A small-world graph is a graph which presents a high clustering coefficient (i.e., similar peers usually link each other) and a relative small average path length (i.e., the average number of intermediates between two peers is small).

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“similar” peers, to facilitate resource search and retrieval based on semantic queries. In particular in SETS [1] the network is split in semantic areas by a super–peer which also maintains a table of groups centroids; a centroid represents the “topic” of a given area. The main drawback of SETS is the introduction of a network manager, which represents a single point of fault. In GES [7] peers maintains two sets of links to other peers: semantic–links and random–links. Queries for resources are first forwarded to a so–called “semantic–target”, which is the first peer that can answer the query, and then flooded to this peer neighbours (the semantic group).

**PROSA** is an early attempt to implement a bio–inspired link management algorithm into a pure P2P overlay network. We think it is really interesting to study real networks, such as social communities, in order to find new and effective algorithms for sharing, searching and distributing resources in P2P environments.

### III. PROSA

**PROSA** is a P2P network based on acquaintance– and semantic–links, where peers join the network in a way similar to a “birth”, then achieve more links to other peers according to the social model, i.e. by linking (semantically) with peers which have similar interests, culture, hobbies, works and so on, and maintaining a certain number of “random” acquaintances. In P2P networks the culture or knowledge of a peer is represented by the resources (documents) it shares with other peers. On the other hand, different types of “links” among peers simulate acquaintances and semantic–links. To implement such a model it is necessary to have:

- A system to model knowledge, culture, interests etc...
- A self–organising network management algorithm

#### A. Modelling Knowledge

In **PROSA**, knowledge (each resource) is modelled through Vector Space Model (VSM) [5] . In this approach each document is represented by a state–vector of (stemmed) terms called Document Vector (DV); each term in the vector is assigned a weight based on the relevance of the term itself inside the document. This weight is calculated using a modified version of TF–IDF [4] schema, as follows:

\[ w_{t,P} = 1 + \log(f_t) \]

where \( f_t \) is the term frequency into the document. It has been proved [5] that this way of calculating relevance is a good approximation of TF–IDF ranking schema. The VSM representation of a document is necessary to calculate the relevance of a document with respect to a certain query. We model a query by means of a so–called Query Vector (QV), that is the VSM representation of the query itself. Since both documents and queries are represented by state–vectors, we define the relevance of a document (D) with respect to a given query (Q) as follows:

\[ r(D, Q) = \sum_{t \in D \cap Q} w_{t,D} \cdot w_{t,Q} \]  

(1)

Using VSM we obtain also a compact description of a peer knowledge. This description is called “Peer-Vector” (PV), and is computed as follows:

- For each document hosted by the peer, the frequencies of terms it contains are computed (\( F_{t,D} \)).
- Terms frequencies for different documents are summed together, obtaining overall frequency for each term:
  \[ F_t = \sum F_{t,D} \]
- Then a weight is computed for each term, using:
  \[ w_{t,P} = 1 + \log(F_t) \]
- Finally all weights are put into a state–vector and the vector is normalised.

The obtained PV is a sort of “snapshot” of the peer knowledge, since it contains information about the relevant terms of the documents it shares.

The relevance of a peer (P) with respect to a given query (Q) is defined as follows:

\[ r(P, Q) = \sum_{t \in P \cap Q} w_{t,P} \cdot w_{t,Q} \]

This relevance is used by the **PROSA** query routing algorithm. It is worth noting that a high relevance between a QV and a PV means that probably the given peer has documents that can match the query.

#### B. Network Management algorithm

As stated above, relationships among people are usually based on similarities in interests, culture, hobbies, knowledge and so on. And usually these kind of links evolve from simple “acquaintance–links” to what we called “semantic–links”.

To implement this behaviour three types of links have been introduced:

- Acquaintance–Link (AL)
- Temporary Semantic–Link (TSL)
- Full Semantic–Link (FSL)

TSLs represent relationships based on a partial knowledge of a peer. They are usually stronger than ALs and weaker than FSLs.

Since usually relationships are not symmetric, it is necessary to specify what are the source peer (SP) and destination peer (DP) of a link. Figure 1 shows the representations for the three different types of links.

![Fig. 1. Link types](image)

Each peer into **PROSA** maintains a list of known peers, that we call Peer List (PL). This list contains all the links gained

\[ SP \quad DP \]

Acquaintance Link

\[ SP \quad DP \]

Temporary Semantic Link

\[ SP \quad DP \]

Full Semantic Link
By a peer during his “life”. It is similar to a personal phone book: when we meet a person we link to him with an AL. If we share interests, knowledge or anything else with him, the AL pointing to him smoothly becomes a semantic–link. It first evolves to a Temporary Semantic Link, and then to a Fully Semantic Link.

1) Joining: The case of a node that wants to join an existing PROSA network is similar to the birth of a child. At the beginning of his life a child “knows” just a couple of people (his parents). A new peer which wants to join, just searches other peers (for example using broadcasting, or by selecting them from a list of peer that are supposed to be up, as in Freenet[3] or Gnutella) and adds some of them in his PL as Hals. These are ALs because a new peer doesn’t know anything about its “relatives” until he doesn’t make query to them for resources. This behaviour is quite easy to understand: when a baby comes to life he doesn’t know anything about his parents. He doesn’t know his father’s job, neither that is mother is a biologist. The joining phase is represented in figure 2 where “N” is the new peer; N chose some other peers (P) at random as initial ALs.

2) Updating: In PROSA FSLs dynamics are strictly related to queries. When a user of PROSA requires a resource, he performs a query and specifies a certain number of results he wants to obtain. The relevance of the query with respect to the resources hosted by the user’s peer is first evaluated, using equation 1. If none of the hosted resources has a sufficient relevance with respect to the query, the query has to be forwarded to other peers. The mechanism is quite simple:

- A query message containing the QV, a (possible) unique QueryID, the source address and the required number of results is built.
- If the peer has neither FSLs nor TSL, i.e. it has just AL, the query message is forwarded to one link at random.
- Otherwise, the peer computes the relevance between the query and each entry of his Peers–List.
- It selects the link with a higher relevance, if it exists, and forwards the query message to it.

When a peer receives a query forwarded by another peer, it first updates its PL. If the requesting peer is an unknown peer, a new TSL to that peer is added in the PL, and the QV becomes the corresponding Temporary Peer Vector (TPV). If the requesting peer is a TSL for the peer that receives the query, the corresponding TPV in the list is updated, adding the received QV and normalising the result. If the requesting peer is a FSL, its PV is in the PL yet, and no updates are necessary.

After PL update, the relevance of the query and the peer resources is computed. There are three possible cases:

- None of the hosted documents has a sufficient relevance. In this case the query is forwarded to another peer, using the same mechanism used by the forwarder peer. The query message is not modified.
- The peer has a certain number of relevant documents, but they are not enough to full-fill the request. In this case a response message is sent to the user. If a response is received, the peer contacts the peer owning that resource and asks it for download. If download is accepted, the resource is sent to the requesting peer, together with the Peer Vector of the serving peer. This case is illustrated in figure 4 where peer “N” received a response from peer “Pr” and decided to download the corresponding resource. Note that Pr established a TSL with N, because it received a QV from it, and N established a FSL with Pr, because it successfully received a resource from it.

This situation is showed in figure 5 where peer “N” forwards a query to one of his ALs randomly chosen, since it has neither TSLS nor FSLs. In our example the chosen peer is “P1”. As soon as P1 receives the QV, it automatically establish a TSL with N (see figure 5) and then it forwards the query if needed.

When the requesting peer receives a response message it presents the results to the user. If the user decides to download a certain resource from another peer, the requesting peer contacts the peer owning that resource and asks it for download. If download is accepted, the resource is sent to the requesting peer, together with the Peer Vector of the serving peer. This case is illustrated in figure 4 where peer “N” received a response from peer “Pr” and decided to download the corresponding resource. Note that Pr established a TSL with N, because it received a QV from it, and N established a FSL with Pr, because it successfully received a resource from it.

IV. PROSA SIMULATIONS AND RESULTS

The main target of this work is to show that a relationships–inspired network naturally evolves to a small–world. Simulation results confirm that PROSA is a small–world network: it presents a high clustering coefficient and a small average path length.

Since links between peers in PROSA are not symmetric, it is possible to represent a PROSA network as a directed graph G(V,E). The Clustering Coefficient for a node (CCn) in a directed graph can be defined as follows:
where \( n \)'s neighbours are all the peers to which \( n \) as linked to, \( E_{n,\text{real}} \) is the number of edges between \( n \)'s neighbours and \( E_{n,\text{tot}} \) is the maximum number of possible edges between \( n \)'s neighbours. Note that if \( k \) is in the neighbourhood of \( n \), the vice-versa is not guaranteed, due to the fact that links are directed. The clustering coefficient of a graph (CC) is defined as the mean graph coefficient for all the vertices (nodes) in the graph:

\[
CC = \frac{1}{|V|} \sum_{n \in V} CC_n
\]

(3)

In figure the CC and average path length (APL) of PROSA is compared to those of the “equivalent” random graph (rnd). Given a graph G(V,E), its equivalent random graph has the same number of nodes and edges and a random out-degree distribution.

The CC and the APL of a random graph with \( |V| \) vertices and \( |E| \) edges has been computed using equations [4] and [5].

\[
CC_{\text{rnd}} = \frac{|E|}{|V| \cdot (|V| - 1)}
\]

(4)

\[
apl_{\text{rnd}} = \frac{\log |V|}{\log (|E|/|V|)}
\]

(5)

These measures regard the case of PROSA networks where each peer starts with 20 documents on average. The CC and APL are computed after 10,000 queries. Each query contains 4 terms, on average. A query is considered “successfully” when at least one matching document is found. The maximum number of required document is 5.

Looking at the results, it is clear that PROSA networks always present a higher clustering coefficient than the corresponding random graphs. This means that each peer is linked with a strongly connected neighbourhood, which represents (a part of) the “semantic group” joined by the peer. This behaviour is due to the fact that links are mainly “semantic links” (both FSLs and TSLs) with nodes that provided (or requested) resources belonging to a given field. Note also that the APL for a PROSA network decreases when the number of nodes increases, while it seems to linearly depend on the network size for the correspondent random graph. Note that the APL for PROSA is measures as the average deepness of a query, so it represents a very accurate estimation of the real APL.

Fig. 4. Query forwarding: new FSL arises

Fig. 5. Clustering coefficients and APL for different network size

Fig. 6. Percentage of successful queries

To evaluate the efficiency of PROSA we compared it with a pure flooding network and a random walk network. In a flooding network queries are routed using a classical flooding algorithm; in a random walk network query are forwarded through randomly chosen links. Figure 6 shows the rate of successful queries for PROSA, a pure flooding network and a random–walk network. The highest percentage is (obviously!) obtained with a pure flooding, because in that case the most part of the network is visited, and if matching resources do exist, they will eventually found. PROSA results to be more efficient than a random walk for different network sizes. This is due mainly to the fact that peers in PROSA do not forward queries at random, but using the algorithm described in Section III-B.2. If a peer does not have relevant documents for a given query, it forwards the query to one of the peers it links to, choosing the one that has the best “relevance” with the query. This way the query is routed to those peers that can (probably) answer it. Note that the efficiency of PROSA with respect to the percentage of successful queries is related to the number of query performed by peers, since semantic–links are a side–effect of searching and retrieving resources. We obtain a decreasing percentage of successful queries when network size grows, because the total number of queries is the same for all simulation reported.

In figure [7] we show the average number of different links visited for a successful query, both for PROSA and for a pure random–walk search. Using PROSA we obtain a smaller average amount of walks for successful query than that obtained with a pure random search. We can explain this fact as a consequence of both the query routing algorithm

1Results for pure flooding are not reported, since they are from 100 to 150 times larger that those of PROSA and random walk
used by PROSA and the linking updating policy. In PROSA new links among similar peers arise almost naturally: a new FSL is established for every document gained by a peer as a query result. Since a peer interested into a particular field usually makes query for resources in that field, the higher the number of queries performed, the higher the number of new FSL to a specific semantic group. After a (small) amount of queries, a peer results to be strongly connected to other peers in the same group. New queries will be directly forwarded to the best–matching group, in a small number of steps.

V. FUTURE WORKS

In this paper a novel P2P self–organising algorithm for resource searching and retrieving has been presented. The algorithm emulates the way social relationships among people naturally arise and evolve, and finally produces a really small–world network topology, as confirmed by simulation results. PROSA is a valid alternative to actual P2P structures based on simple flooding or random walk. In fact similar peers in PROSA form strong interconnected “semantic–groups”, allowing fast and efficient query routing. Future work will focus on extending PROSA in order to include other mechanisms typically found in social communities, such as:

- Random meetings among peers (that allows peer to connect, via ALs, also to non–similar peers)
- Advertising of new resources
- Semantic–Links scoring, to simulate various possible degrees of acquaintance among people

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2 In terms of number of walks needed to satisfy a query