PREDICTING RELEVANT EMPTY SPOTS IN SOCIAL INTERACTION

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Received: August 15, 2007
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Abstract An empty spot refers to an empty hard-to-fill space which can be found in the records of the social interaction, and is the clue to the persons in the underlying social network who do not appear in the records. This contribution addresses a problem to predict relevant empty spots in social interaction. Homogeneous and inhomogeneous networks are studied as a model underlying the social interaction. A heuristic predictor function approach is presented as a new method to address the problem. Simulation experiment is demonstrated over a homogeneous network. A test data in the form of baskets is generated from the simulated communication. Precision to predict the empty spots is calculated to demonstrate the performance of the presented approach.

Key words Communication, Empty spot, Predictor function, Social interaction, Social network

1 Problem - empty spots

The activity of an organization is often under the influence of invisible but relevant persons. The activity is a decision-making and action. The organization may be a family, school, company, community, society etc. For example, a financially supporting conspirator, who provides commanders with money, communication means, or weapons, is hidden behind terrorism attacks. Commanders would appear one after another if such a conspirator were not detected and arrested. It is, therefore, critical to infer the presence of such invisible but relevant persons from the observed records on the social interactions of an organization. Based on the inference, we will invent a hypothetical scenario to turn a threat to opportunity. The hypothetical scenario is a sequence of events, which is to be achieved potentially by our present decision-making rather than a sequence of events predicting the future.

We define the above problem more specifically with the 3 ideas: a social interaction, social network, and empty spots.

- Social interaction is dynamic influence dissemination among persons through conversation, meeting, collective action etc. Communication is of particular interest since it often takes place on the electronic media, which is one of the major targets of surveillance.
The organization itself is modeled as a social network which underlies below the social interaction. Nodes are persons. Links are relationship such as friendship, business partnership, chain of command etc. The topology of the network varies largely in many aspects. A scale-free network and a small-world network are quite different. A model for contemporary inter-working terrorists, a model for a self-organizing on-line community, and a model for a purposefully organized business team have quite different structures.

The empty spot in the social interaction is the main topic of this contribution. It refers to an empty hard-to-fill space, which can be found in the records of the social interaction, and is the clue to the persons in the underlying social network who do not appear in the records.

In this contribution, the problem we address is to discover relevant empty spots in a complex social interaction. We study a heuristic predictor function approach to discover relevant empty spots in communication records as a social interaction. The approach is presented in detail in 4 after studying the related works in 2 and the network models (homogeneous and inhomogeneous network) in 3. Simulation experiment is demonstrated in 5. A test data is generated in the form of baskets as the simulated communication records over a homogeneous network. Precision to discover the empty spots is calculated to evaluate the performance of the approach for 3 trial cases. Concluding remarks are presented in 6.

2 Related Work

The problem is related to a node discovery problem. Expertise in computer and social sciences is significant. Complex networks such as scale-free networks (Barabási-Albert model) and small-world networks (Watts-Strogatz model) presented us insight on the structure and evolution of a large-scale network: scientists’ collaboration, actors in movies etc. Power law governing the scale-free network appears from the preferential attachment of the nodes in a growing network. A few very big hub nodes emerge, accounting for the winner-takes-all phenomena. The small-world network is highly clustered like a regular lattice, but has small diameter like a random graph. The name originates in the small-world phenomena known as six degree of separation.

Search efficiency in a network is of particular interest for practical applications. The hub nodes in scale-free networks are useful in designing local search strategies. The hub nodes improve the efficiency to access relevant nodes. Error and attack tolerance were studied. Scale-free networks display a surprisingly high degree of tolerance against random errors. Other networks do not have such a property. The error tolerance is, however, at the expense of attack survivability. The network is broken into many isolated fragments when the hub nodes are targeted. Centrality and brokerage measures are convenient values summarizing the network topology. Degree, betweenness, closeness, and eigenvector centrality are popular among them. They have been studied in many cases of the social network analysis.

Empirical study on social networks uncovered many aspects of the criminal and terrorist organizations in the past and at present. Intelligence sharing, knowledge management, and simulation techniques are described as well as the social network analysis. Hidden Markov model and Bayesian network are applied to predicting terrorist attacks. Activities are modeled and patterns of anomalous behavior are identified. It helps intelligence analysts connect the fragmented facts more quickly. Keila applied factor analysis (singular value decomposition and semi-discrete decomposition) to study email exchange in an American energy company: Enron Corporation, which ended in bankruptcy due to the institutionalized accounting fraud.
in 2001[7]. The word use in the emails is correlated to the function within the organization. The word use among those involved in the alleged criminal activity is distinctive.

Criminal organizations tend to be strings of inter-linked small groups that lack a central leader but coordinate their activities along logistic trails and through bonds of friends, and that hypothesis can be built by paying attention to remarkable white spots and hard-to-fill positions in a network[8]. [9] investigated the 9/11 terrorist network in 2001. It reveals the relevance of conspirators who reduce the distance between hijackers, enhance communication efficiently, and act as a conduit for money and knowledge. The 9/11 terrorist network was also investigated[15] from the viewpoint of efficiency and security trade-off by analyzing the change in degree, betweenness and closeness centrality measures. It is suggested that more security-oriented structure arises from longer time-to-task of the terrorists’ objectives. Conspirators improve communication efficiency, preserving hijackers’ small visibility and exposure.

3 Network Model

Social network modeling[4] is a basic tool to describe an organization like a family, school, company, community, society etc. A node represents a person. A link represents relationship between 2 persons, which, we simply assume, is equal to the presence of communication between the persons. Information dissemination with the communication is a social interaction. An origin of complexity of the social interaction is the complexity and variability of the underlying network topologies. Different networks describe different organizations. We can classify the networks into 2 classes: inhomogeneous networks and homogeneous networks.

The definition is as follows. A homogeneous network refers to one that consists of the nodes which have similar local topological characteristics. The network is homogeneous when the variance of the nodal degree (σ(d)/μ(d)) is small. The standard deviation and mean of the nodal degree d are denoted by σ(d) and μ(d). Many random networks including an Erdos-Renyi model and a Watts-Strogatz model are homogeneous. On the other hand, an inhomogeneous network refers to one that consists of the nodes which have variable local topological characteristics (σ(d)/μ(d) is large). A strong center-and-periphery structure or a leader-follower relationship is the indicator of an inhomogeneous network.

3.1 Inhomogeneous network

A typical inhomogeneous network is a scale-free network derived from a Barabási-Albert model[3]. The scale-free network is used to describe World Wide Web, scientist’s collaboration, actors in a movie etc. An example is illustrated in Figure 1. The network consists of |n| = 490 nodes. The inset shows the occurrence probability distribution P(d) of nodal degree[5] d. The horizontal axis is normalized: degree divided by the average degree (d/μ(d)). It is governed by a power law:

\[ P(d) \propto d^{-2.1}. \]

The average degree is μ(d) = 3.6. The deviation in the nodal degree is very large. It indicates a center-and-periphery structure. About 10 big hub nodes are easily identified. The hub nodes influence the way the network operates. A self-organizing community and a purposefully organized business team are often inhomogeneous. Relevant empty spots usually correspond to the unobserved hub nodes. It is relatively easy to obtain a clue on the missing hub nodes because of their large activeness in communication. Such a problem was studied in [12].
Figure 1: Example of an inhomogeneous network consisting of $|n| = 490$ nodes. It is a scale-free network governed by a power low (Barabási-Albert model). Center-and-periphery structure is evident. The inset shows the occurrence probability distribution $P(d)$ of the nodal degree $d$ as a function of the normalized degree $d/\mu(d)$. 
Figure 2: Example of a homogeneous social network consisting of $|n| = 995$ nodes. The inset shows the occurrence probability distribution $P(d)$ of the nodal degree $d$ as a function of the normalized degree $d/\mu(d)$. The nodes indicated by [a] (red circle), [b] (blue), and [c] (green) are used in the simulation study in 5.

### 3.2 Homogeneous network

A typical homogeneous network is illustrated in Figure 2. The network consists of $|n| = 995$ nodes. It is governed by an exponential law:

$$P(d) \propto e^{-3.1d}. \quad (2)$$

The degree ranges from 3 to 8. The average degree is $\mu(d) = 3.9$. The deviation in the degree is very small. It is the characteristics of the homogeneous network. A small-world network (Watts-Strogatz model) is homogeneous compared with the Barabási-Albert model. The Watts-Strogatz model does not possess big hub nodes but short-cut links. It looks difficult to distinguish one node from another from the local topological properties such as the nodal degree.

Such characteristics are suitable for terrorist and criminal organizations\cite{8,9}. Absence of hub nodes is disadvantageous in communication and search efficiency\cite{1}, but advantageous in security against exposure and detection\cite{2,15}. It looks a big technical challenge to obtain a clue on a missing node by identifying relevant empty spots within the communication records observed as a social interaction. A homogeneous network is of particular interest. This network is used in the simulation study in 4.
4 Approach

We present our approach to discover the empty spots. We employ a heuristic predictor function which evaluates the likeliness of the individual data being an empty spot. Heuristic predictor function is suitable to handle a very large amount of data observed in a very large network.

The input to the approach is the records $D$, observed for nodes. The records are the collection of the data in the form of baskets in eq.(3). The content of the basket $b_j$ are a set of nodes $n_i$ which are observed simultaneously, or grouped under a specific subject. The number of the baskets is denoted by $|b|$. The number of the nodes in a basket $b_i$ is denoted by $|n_i|$. The number of the variability of the nodes is denoted by $|n|$.

$$D = \{ b_j \} \ (0 \leq j \leq |b| - 1), \ b_j = \{ n_i \} \ (0 \leq i \leq |b| - 1). \quad (3)$$

The output from the approach is a clue on empty spots generated by the predictor function. More specifically, our aim is to identify the basket $b_i$ which is related to the empty spots the most likely. The core of our approach is, therefore, to design a predictor function $W(b_i|D)$ to evaluate the likeliness of the individual baskets $b_i$. The basket $b_i$ evaluated as the most likely should have included the empty spots: an invisible node $n_x$, and links $r_{xj}$ between the node $n_x$ and a visible gateway node $n_j \in c_j$, where $c_j$ denotes a cluster found within the observation. The invisibility arises from the limited capability of the observation method for the social interaction, or from the limited prior understanding of the targets appearing in the social interaction.

The nodes are clustered into vertex groups based on the distance. Distance (or closeness) between nodes are defined according to the occurrence and co-occurrence frequency of the nodes. Occurrence frequency of a node $F(n_i)$ is defined by eq.(4) using a Boolean function $B(s)$ in eq.(5).

$$F(n_i) \equiv \sum_{j=0}^{|b|-1} B(n_i \in b_j). \quad (4)$$

$$B(s) = \begin{cases} 
1 & \text{if } s \text{ is TRUE} \\
0 & \text{otherwise}
\end{cases} \quad (5)$$

The frequency is the number of the baskets where $n_i$ appears. The frequency is increased by 1 when $n_i$ appears once or more in a single basket. We use Jaccard’s coefficient defined by eq.(6) as a measure of the co-occurrence. Jaccard’s coefficient is used widely in link discovery, web mining, or text processing\[15\]. Co-occurrence or dependence coefficient may also be used instead of Jaccard’s coefficient.

$$J(n_i, n_j) = \frac{F(n_i \cap n_j)}{F(n_i \cup n_j)}. \quad (6)$$

Eq.(6) is converted into eq.(7) using eq.(4).

$$J(n_i, n_j) = \frac{\sum_{k=0}^{|b|-1} B((n_i \in b_k) \land (n_j \in b_k))}{\sum_{k=0}^{|b|-1} B((n_i \in b_k) \lor (n_j \in b_k))}. \quad (7)$$

We employ k-medoid clustering algorithm\[6\] because the amount of necessary calculation is small. It is simple and efficient. It is an EM (expectation-maximization) algorithm similar to
k-means algorithm for numerical data. A medoid node $n_{\text{med}(j)}$ is a node locating most centrally within a cluster $c_j$. They are initially selected at random. Other $|n| - |c|$ nodes are classified into the clusters based on the closeness to the medoids. The number of clusters is denoted by $|c|$. Then, a new medoid is selected within the individual cluster so that the sum of closeness from nodes within the cluster to the modoid is maximal. The sum of closeness is evaluated by eq. (8).

$$M(c_j) \equiv \sum_{(n_i \in c_j) \land (n_i \neq n_{\text{med}(j)})} J(n_{\text{med}(j)}, n_i).$$

Eq. (9) is repeatedly executed until the medoid $n_{\text{med}(j)}$ converges. The resulting clusters are denoted by $c_j$. We can also employ unsupervised learning techniques such as self-organizing map [6] instead of the k-medoids clustering algorithm.

Select $n_{\text{med}(j)}$ to maximize $M(c_j)$. (9)

The predictor function $W(b_i|D)$ in eq. (10) is used to evaluate the likeliness of the individual baskets $b_i$ as a candidate which should have included empty spots. The empty spots are the hidden participants to the basket, which is the origin of attraction in the empty spots among clusters. The baskets ranked more highly are retrieved by the baskets.

$$W(b_i|D) \equiv \frac{1}{|c|} \sum_{j=0}^{|c|-1} \max_{n_k \in c_j} B(n_k \in b_i) \sum_{l} B(n_l \in b_i).$$

Eq. (10) is converted into a simpler formula (eq. (11)) using eq. (4).

$$W(b_i|D) \equiv \frac{1}{|c|} \sum_{j=0}^{|c|-1} \min_{n_k \in c_j \land (n_k \in b_i)} F(n_k).$$

The predictor function approach ranks and sorts the baskets by the largeness of the value of $W(b_i|D)$, and retrieves the highly ranked baskets when the number of the retrieved baskets is given.

5 Evaluation

We study how precisely the heuristic predictor function approach described above retrieves information on the relevant empty spots from the test data generated as communication (typical social interaction) records. The homogeneous social network shown in Figure 2 is employed as a model for the communication among 995 persons. We use precision as a measure of the performance. In information retrieval, precision has been used as evaluation criteria, which is the fraction of the amount of relevant data to the amount of the all data returned by search (the heuristic predictor function in this case).

5.1 Test data generation

The test data is generated in the 2 steps below. Note that the observed communication records $b_i$ are different from the simulated communication $\beta_i$. The difference, however, does not affect the communication itself. This difference is the target to infer by our approach.
• Communication is simulated and its records is configured into basket data. Basket data representing neighbor nodes $\beta_i$ was generated from the homogeneous network shown in Figure 2. The nodes under a direct influence from a node are grouped into a basket $\beta_i$. For example, we can imagine a situation where a person starts talking and a conversation takes place among neighboring persons. The area of such influence is specified approximately with the distance from a node. The distance can be measured in the number of hop count. One hop is as long as one link on the network. An example basket is $\beta_0 = \{n_{954}, n_{1930}, n_{3261}, n_{5093}, n_{5223}, n_{7743}, n_{7808}, \ldots\}$, representing communication initiated by the node $n_{954}$.

• Test data representing observation records (with a missing node) are generated by deleting nodes of interest from the basket $\beta_i$. The deleted nodes and the links connecting them to other nodes are the empty spot hidden in the social interaction. The example basket results in $\beta_0 = \{n_{954}, n_{1930}, n_{3261}, n_{5093}, n_{7743}, n_{7808}, \ldots\}$ when the node $n_{5223}$ is configured to be the empty spot. The baskets $b_i$ are like records of email senders and receivers which lacks in participants expressing their opinions in the oral communication, or like records of participants of on-line chat meetings which lacks in participants using a satellite telephone. The baskets are the input to the predictor function $W(b_i|D)$ in eq.(10). The node $n_{5223}$ may appear in multiple baskets $\beta_i$. The predictor function ranks and tries to retrieve all of $b_i$ which are different from the corresponding $\beta_i$, as candidates of the empty spots.

In the simulation, we made up 995 baskets ($\beta_0$ to $\beta_{994}$) consisting of nodes within 5 hops from the initiator node in the 1st step. The number of nodes within 5 hops is about 20% of the whole nodes on average. This is a relatively long-distance communication. The nodes deleted in the 2nd step are the 15 nodes within 2 hops from the node $n_{5223}$. The baskets where the 15 nodes had been deleted are the target of retrieval of the predictor function. These nodes are remarkable in that they are equally close to every other node in the network. The nodes in either the larger cluster on the left or the smaller cluster on the right in figure 2 do not occupy such an unbiased position. They are not like a board of directors governing a whole company in a hierarchical construct, but like terrorism sponsors hidden behind the attacks.

5.2 Precision evaluation

We evaluate precision of the output of the approach in 4 in the 3 trial cases. In each case, about 10 nodes around the node labeled [a], [b], or [c] in figure 2 are configured as the empty spot. The node [a] has the largest nodal degree. The node [b] has the smallest standard deviation of the distance (hop counts to travel) to the other nodes. The node [c] has the smallest mean of the distance to the other nodes. The nodes [b] and [c] occupy a unique position in terms of a global network topology. Note that the nodal degree is similar in a homogeneous network (actually, 3 to 8 in figure 2), and that the node [a] is not particularly unique though its degree is the largest.

Precision is defined by eq.(12). The number of the retrieved baskets by the heuristic predictor function is denoted by $m_{\text{ret}}$. It can be 1 to $|b|$. Individual baskets in the retrieval are denoted by $b_{\text{ret}}^i$.

$$p = \frac{\sum_{i=0}^{m_{\text{ret}}-1} B(b_{\text{ret}}^i \neq \beta_i)}{m_{\text{ret}}}.$$  

Eq.(12) is the ratio of the number of correct baskets to the number of the retrieved baskets.
Figure 3: Precision to discover the empty spot: the baskets where nodes had been deleted ($b_i \neq \beta_i$) as a function of the number of the retrieved baskets ($m_{ret}$). The node [a] has the largest nodal degree. The node [b] has the smallest standard deviation of the distance to the other nodes. The node [c] has the smallest mean of the distance to the other nodes.

The correct baskets are those where the node had been deleted in the 2nd step in 5.1. It means that if $b_i^{ret} \neq \beta_i$, the retrieval is correct. Precision should be 1, and decreases gradually as $m_{ret}$ increases if the approach works properly. That is, precision is a monotonically decreasing function.

Figure 3 shows the calculated precision for the 3 cases (top for [a], middle for [b], and bottom for [c]). The horizontal axis is the number of the retrieved baskets ($m_{ret}$). The order of the retrieved baskets is according to the largeness of the value which the predictor function outputs. Precision is very good when we try to identify the baskets where the nodes around the node [b], or the nodes around the node [c] are missing. The predictor function is suitable to discover the empty spot: the nodes and related links, which occupy a unique position in terms of a global network topology. On the other hand, precision degrades more steeply as $m_{ret}$ increases in case of the node [a]. The results indicate that the approach can provide important information on the nodes which are missing, but relevant globally in a homogeneous network even if their local characteristics look quite similar. The nodes included in the retrieved baskets are the clues to plan the detailed pinpoint investigation.
6 Concluding Remark

This contribution presented a heuristic predictor function approach which is suitable to predict relevant empty spots in social interaction. The empty spot refers to an empty hard-to-fill space which can be found in the records of the social interaction. It is the clue to the persons in the underlying social network who do not appear in the records. Simulation experiment was demonstrated. This contribution, in particular, focused on the social interaction in homogeneous networks, where we believe that the problem to predict the empty spots is more difficult than that in inhomogeneous networks[12]. A test data in the form of baskets was generated from the simulated communication. Precision was high: demonstrating that the baskets related to invisible persons could be correctly identified by the value of the predictor function.

The idea of relevant empty spots in social interaction can be generalized to relevant unknown items working in a complex interacting system. We are seeking the possibility where something very new or just emerging is recognized, as well as the possibility where something hidden spatially is discovered. [13] studied application to creative thinking. An experiment was demonstrated to invent a new technical idea from existing technical expertise forest (patents on knowledge acquisition, for example) for corporate research and development. Group members discussed about the identity of a new technical means as an empty spot locating near many the technical expertise forests. A few interesting and practical ideas were invented. [11] studied application to designing catalyst personality fostering mutual understanding among groups. The personality of a new person was inferred, who can activate and foster communication among groups indicating opposing preference. We are combining these experiences in many application fields into a new method: human-interactive annealing[10]. It is designed to induce discovery from the difference between the individual human’s prior understanding of the problem and the computer’s analysis and visualization of the observed data on the problem.

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