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Get Smart on Information-Sharing in Social Networks

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***Abstract*—Social Networks now become popular and powerful platforms for people to share information. Everyone may share their interested information with their connections, or send messages to their friends. However, sharing information costs both computational and communicational resources, in addition to personal time/attention of both the sender and the receiver. Decision-making regarding which piece of information should be shared with whom, thus is important to individuals and the whole network. In this work, we study the effects of different information-sharing strategies using a social network simulator. This paper describes how social network is modeled, and the various factors relevant to the sharing decisions. We propose six information sharing strategies, and performed simulation experiments to examine their influences on individuals and the whole social network.**

keywords: Social Networks, Information Sharing, Strategies, Simulation.

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I. Introduction and Related Work

Social network here refers to a group of people connected through Internet via emails, websites, and social media such as Facebook, Twitter, blogs, and WeChat. Social Networks have become increasingly popular and fast-growing platforms for information sharing, job searching and product marketing [1], [2]. Information propagates fast in social network through direct personal social connections.

Given the six degree of separation, small world theory [3], and the fast communication speed of internet, the information propagated in social network may reach a very large population within a very short period of time [4]. However, this powerful and speedy circulation does not come free. The computational and communicational costs are obvious, the sharing of information increases the usage of computational resources and generates large amount of internet traffics. Other less-obvious costs include the personal time and attention of both the sender and the receivers. Additionally, the increasing amount of information reduces the receiver's attention to any particular piece of information, hence diminishes the influence of the shared information or even damages the social trust between the receiver and the sender. Therefore, it is important to share the right information with the right person.

However, this is not an easy task if an individual has to decide that with whom to share for each piece of received information. The goal of this study is to *develop automatic decision-making mechanisms to help each individual effectively and efficiently share information in a social network*. The automatic decision-making is based on the information relevance and the interest profile of each connected individual. Each piece of information can be either manually or more realistically, automatically classified for its relevance to different categories or subjects, with the help of context analysis and text mining tools [5], or structured meta-level data such as semantic web [6]. On the other hand, each individual may truthfully describe one's interested subjects in one's published interest profile, given the motivation to reduce undesired information. The focus of this work is to study different information-sharing strategies, assuming both information relevance and interest profile are available.

The uniqueness of this work lies in the aspect of *viewing each node as an intelligent individual and be able to make informed decision*. In traditional research on information propagation, some mathematic models such as Linear Threshold Model and Independent Cascade Models [7] are used to describe the diffusion process. With such models, each individual is simply a data object [8] behaved according to a fixed protocol and an pre-set attribute value, without freedom to make its own decision on which information to share with whom. In recent work on strategic networks with self-interested agents [9], each node is a strategic agent who benefits from producing and disseminating information. This is similar to the model used in our work: each individual may choose different information-sharing strategy according to its own goal and preference. Self-interested agents are used to model nodes in social network, and game theory is used to study information diffusion [10]. In addition, an adaptive information dissemination method is described in [11], which is used to select users aiming to target their influential neighbors. However, our study has different focus and model.

The contribution of this work lies in the following four aspects. First, we build a simulator that supports experiments on various information sharing strategies over different network structures, including creating network according to real social network structure data. Second, we developed a

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model of message relevance and user interest profile, various information sharing strategies may be developed using this model. Thirdly, we defined a matrix to evaluate information sharing strategies. Based on factors in this matrix, each individual node may further decide to change it connections and therefore change the network structure dynamically. Lastly, we proposed six information sharing strategies and conducted experiments to evaluate them using the matrix we developed. This verifies the functionality of this framework and the simulation methodology.

II. Social Network Structure and Modeling

In this work, we model social network as a graph, with *Node* representing individual person, and *Edge* (link) representing connection between two persons. Degree of a node measures the number of connections of this node. In a social network, nodes may have significantly different degree: some persons have a lot of connections while some may only have a few. A *cluster*, or *community* is a group of nodes with many connecting edges between them, and there are relatively fewer connecting edges between nodes that belong to different clusters [12], [13]. Inside each cluster, a leader node has the most number of connections within this cluster. A leader node may serve as an information hub that connects to other clusters.

Number of clusters and the size of each cluster have big influence on the propagation of information in the social network [13]. Hence we choose the following parameters to characterize the network structure in this work:

1) Number of small clusters, and the size (number of nodes) of a small cluster.
2) Number of medium clusters, and the size of a medium cluster.
3) Number of large clusters, and the size of a large cluster.
4) Number of edges: total number of edges in the network.

We build a simulator that takes the above six parameter values as input and create a network accordingly. The process of creating network based on the above parameters is described as the following.

1) According to the number and size of each type of cluster (small, medium or large), specified number of nodes are created in each cluster according to its type.
2) In each cluster, one node is randomly selected as the leader. All leader nodes are connected to each other.
3) Create edges within each cluster. Number of edges are equally distributed among all clusters. If the distributed edges exceeds the number of edges that makes the cluster fully connected, then the extra edges are added to the clusters that are not fully connected.

III. Information Relevance and Individual Interest Model

To describe how much an individual in social network is interested in a piece of information, we introduce the following model. Assume there are x categories (subjects) being modeled in this framework: $c_1, c_2, ..., c_x$, each message m is associated with a *Category List* CL_m:

$CL_m = \{(c_{m1}, r_{m1}), \cdots, (c_{mi}, r_{mi}), \cdots, (c_{mx}, r_{mx})\}$

c_{mi} is the ith category that message m is relevant to, and *Relevance Factor* $r_{mi} \in [0,1]$ describes how strong message m is relevant to category c_{mi}, where 1 stands for the strongest relevance and 0 means no relevance at all.

For example, a message m_a about how to choose running shoes has a category list CL_{m_a} as $\{$(Fitness, 0.5), (Shoes, 0.8)$\}$, and another message m_b on some health diet and exercise suggestions for losing weight has a category list CL_{m_b} as $\{$(Fitness, 0.4), (Diet, 0.8), (WeightControl, 1.0), (Health, 0.7)$\}$. Such category list can be automatically generated with natural language processing tools [5].

On the other hand, each individual n has a profile describing one's interest, represented as an *Interest Factor List*:

FL_n = $\{(c_{n1}, f_{n1}, f_{nr1}), \cdots, (c_{nj}, f_{nj}, f_{nrj}), \cdots, (c_{nx}, f_{nx}, f_{nrx})\}$

c_{nj} is the jth category that node n is interested in, interest factor f_{nj} represents how interested node n is in category c_{nj}. f_{nj} is assigned with an integer value in the range of [0, 5], where 5 stands for the highest interest and 0 means no interest at all. Relevance threshold f_{nrj} is the minimum value of the relevance factor in category c_{nj} for a message to be considered as relevant by node n. For example, an individual node n_p with interest profile FL_{n_p} $\{$(Fitness, 1, 0.6), (Diet, 3, 0.9), (Shoes, 2, 0.9), (Health, 5, 0.8)$\}$, is interested in four categories:with different interest levels. A message must has a relevance factor value no less than 0.6 for Fitness, or 0.8 for Diet, 0.9 for Shoes, or 0.8 for Health to be considered relevant by this individual, to each category respectively.

Each individual in social network may set up his/her interest profile to describe which categories one is interested and how much interest one has. One may also adjust the relevance threshold value dynamically based on the amount of information one receives and one's tolerance at that time.

Given a message m with category list CL_m, and an individual node n, *Interest Set* IS_{mn} is the set of categories that both message m is relevant to and also node n is interested in. More formally stated as:

$IS_{mn} = \{c | \exists i, c_{mi} \equiv c \wedge r_{mi} > 0 \wedge \exists j, c_{nj} \equiv c \wedge f_{nj} > 0\}$

Given a message m and an individual node n, the following parameters are defined based on this intersection set IS_{mn}:

1) size(IS_{mn}) = | IS_{mn} |, number of categories inside IS_{mn}.
2) $I(m,n) = \{f_{nj} | c_{nj} \in IS_{mn}\}$ the set of the interest factors, each for one category c_{nj} in IS_{mn}.
3) $R(m,n) = \{r_{mi} | c_{mi} \in IS_{mn}\}$ the set of the relevance factors, each for one category c_{mi} in IS_{mn}.
4) $I_a(m,n) = \frac{\sum_{c_{nj} \in I(m,n)} f_{nj}}{size(IS_{mn})}$, average interest factor value.
5) $R_a(m,n) = \frac{\sum_{c_{mi} \in I(m,n)} r_{mi}}{size(IS_{mn})}$, average relevance factor value.
6) $RT_a(m,n) = \frac{\sum_{c_{mi} \in I(m,n)} f_{nrj}}{size(IS_{mn})}$, average relevance threshold value.

Table I shows the above parameter values given example message m_a , m_b and individual node n_p.

TABLE I: Examples of Information Relevance and Individual Interest Model

Relevance of m_a	CL_{m_a}	$\{(Fitness, 0.5), (Shoes, 0.8)\}$
Relevance of m_b	CL_{m_b}	$\{(Fitness, 0.4), (Diet, 0.8), (WeightControl, 1.0), (Health, 0.7)\}$
Interest Profile of n_p	FL_{n_p}	$\{(Fitness, 1, 0.6), (Diet, 3, 0.9), (Shoes, 2, 0.9), (Health, 5, 0.8)\}$
Interest Set of CL_{m_a} and FL_{n_p}	IS_{m_a,n_p}	$\{Fitness, Shoes\}$
Interest Set of CL_{m_b} and FL_{n_p}	IS_{m_b,n_p}	$\{Fitness, Diet, Health\}$
Size of Interest Set	$\mid IS_{m_a,n_p} \mid$	2
Size of Interest Set	$\mid IS_{m_b,n_p} \mid$	3
Set of Interest Factors	$I(m_a, n_p)$	$\{1, 2\}$
Set of Interest Factors	$I(m_b, n_p)$	$\{1, 3, 5\}$
Set of Relevance Factors	$R(m_a, n_p)$	$\{0.5, 0.8\}$
Set of Relevance Factors	$R(m_b, n_p)$	$\{0.4, 0.8, 0.7\}$
Average Interest Factor Value	$I_a(m_a, n_p)$	$(1 + 2)/2 = 1.5$
Average Interest Factor Value	$I_a(m_b, n_p)$	$(1 + 3 + 5)/3 = 3$
Average Relevance Factor Value	$R_a(m_a, n_p)$	$(0.5 + 0.8)/2 = 0.65$
Average Relevance Factor Value	$R_a(m_b, n_p)$	$(0.4 + 0.8 + 0.7)/3 = 0.63$
Average Relevance Threshold Value	$RT_a(m_a, n_p)$	$(0.6 + 0.9)/2 = 0.75$
Average Relevance Threshold Value	$RT_a(m_b, n_p)$	$(0.6 + 0.9 + 0.8)/3 = 0.77$

TABLE II: Network Structure Information and Experimental Parameters

Network	# Small Clusters	Size Small	# Med. Clusters	Size Med.	# Large Clusters	Size Large	#Nodes	#Edges	# Seed Messages	# Time Steps
Simulation	7	10	5	20	3	30	260	2520	100	200
Real Data	Student Cooperation Social Network						185	360	100	200

IV. Information-Sharing Strategies

Based on the information relevance and individual interest model described in Section III, we propose six information-sharing strategies, described below. Table I provides information to understand how each strategy works on example message m_a , m_b and individual node n_p.

- **Strategy 1 Even Little Interested (ELI)**. Send message m to node n if there exists at least one common category in m's category list and also in n's interest profile, with a relevance of factor value no less than 0.1, formally represented as:
  $\mid IS_{mn} \mid \geq 1 \, \wedge \, min(R(m, n)) \geq 0.1$
  Using Strategy 1 (ELI), both message m_a and m_b should be sent to node n_p.
- **Strategy 2 Average Interest in message (AI)**. Send message m to node n if the average interest factor of all categories in IS_{mn} is no less than 3 and the average relevance factor value of all categories in IS_{mn} is no less than 0.3, formally represented as:
  $I_a(m, n) \geq 3 \, \wedge \, R_a(m, n) \geq 0.3$
  Using Strategy 2 (AI), m_b should be sent to node n_p but message m_a should not be sent to n_p.
- **Strategy 3 High Interested and Relevance (HIR)**. Send a message m to node n if n is very interested in any category in IS_{mn}, or the average interest factor $I_a(m, n)$ is no less than 3 and the average relevance factor value $R_a(m, n)$ is no less than the average relevance threshold value $RT_a(m, n)$, formally represented as:
  $max(I(m, n)) = 5$ or ($I_a(m, n) \geq 3 \, \wedge \, R_a(m, n) \geq RT_a(m, n)$)
  Using Strategy 3 (HI), m_b should be sent to node n_p but message m_a should not be sent to n_p.
- **Strategy 4 Unless Not Interested (UNI)**. Send message m to node n if there is at least one common category j in m's category list and also in n's interest profile, formally represented as:
  $\mid IS_{mn} \mid \geq 1$
  Using Strategy 4 (UNI), both message m_a and m_b should be sent to node n_p.
- **Strategy 5 Combined Interest and Relevance (CIR)**. Send message m to node n if the combined average of the average interest factor value (in percentage) and the average relevance factor value (in percentage) is no less than 50%, formally represented as:
  $\frac{\frac{I_a(m,n)}{5} + R_a(m,n)}{2} \geq 50\%$
  Using Strategy 5 (CIR), m_b should be sent to node n_p but message m_a should not be sent to n_p.
- **Strategy 6 Moderate Interest and Relevance (MIR)**. Send message m to node n if if there is at least one common category j in IS_{mn} that node n's interest factor for j is no less than 3 and message m's relevance factor for j is no less than 0.5, formally represented as:
  $\exists j \in IS_{mn}, f_{nj} \geq 3 \wedge r_{mj} \geq 0.5$
  Using Strategy 6 (MIR), m_b should be sent to node n_p but message m_a should not be sent to n_p.

V. Network Structure and Experiment Set up

Network structure may has significant influence on information propagation in the network. In this study, we conducted experiments with two networks shown in Table II. The first network is created using simulation parameters, it has 7 small clusters with10 nodes each, 5 medium clusters with 20 nodes each, and 3 large clusters with 30 nodes each. In total, this simulation network has 260 nodes and 2520 edges. The second network duplicates a real social network structure [14], a student cooperation social network that contains 185 participating students and 360 connecting edges. We choose a simulation network with cluster structure and a real social network structure to better understand how close the simulation network would resemble a real network concerning the issues to be studies here.

We created a pool of 10000 randomly-generated interest profiles, each with random interest factor values and random relevance threshold values. When a network is created, the specified number of nodes are generated, each node is associated with an interest profile drawn from this pool.

In each experiment with a given network, 100 seed messages are created, each with a randomly-generated category list. The experiment is running with synchronized simulation time steps. In the beginning of the simulation, each seed message is delivered to a randomly selected node. At each time step, each node makes decision for each message received in the previous time step. The decision includes whether to share this message to its connected nodes, and which nodes to share with, using its information-sharing strategy. This process continues until a pre-set number of time steps is reached, which is 200 steps in these experiments. Table II also reports these experiment parameter values.

VI. Evaluation Criteria

To evaluate how information-sharing strategy influence individuals and the social network, we define the following criteria.

- **Interest Ratio** measures how many messages are interesting to a node out of all its received contents. $Interest\_Ratio(n)$ for node n, is calculated as:
  $\frac{\#Interesting(High, Med., Low)\ Messages\ Received\ by\ n}{\#Received\ Messages\ of\ n}$
  Depending on interest degree, three measures are defined:
  - High Interest Ratio: the ratio of highly interesting messages, with maximum interest factor value $max(I(m,n))$ as 5.
  - Medium Interest Ratio: the ratio of medium interesting messages, with maximum interest factor value $max(I(m,n))$ as 3 or 4.
  - Low Interest Ratio: the ratio of low interesting messages, with maximum interest factor value $max(I(m,n))$ no more than 2.

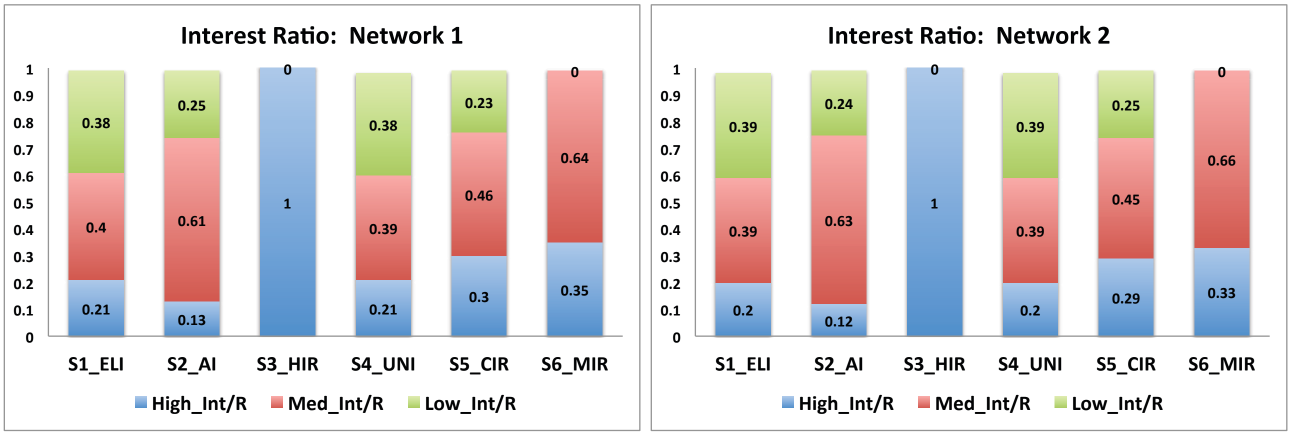
  The interest ratio for the whole social network is measured as the average interest ratio of all nodes.
- **Reachability Ratio** measures how many individuals actually receive the message that they are interested in out of all individuals who are interested in this message. $Reachability\_Ratio(m)$ for a seed message m is calculated as:
  $\frac{\#Nodes\ Interested(High, Med., Low)\ in\ m\ and\ Received\ m}{\#Nodes\ Interested(High, Med., Low)\ in\ m}$
  The reachability ratio measured is the average reachability ratio of all seed messages generated in this experiment.
- **Appreciation Ratio** measures how many messages forwarded by a node s are appreciated by the receiver node out of the total number of messages forwarded by this sender node s. A message m is *appreciated* by a receiver node n, if there exist a category j in IS_{mn} that the receiver's interest factor f_{nj} is no less than 3 and the message's relevance factor r_{mj} is no less than the receiver's relevance tolerance f_{nj}. $Appreciation\_Ratio(s)$ for a sender node s is calculated as:
  $\frac{\#Messages\ Forwarded\ by\ s\ and\ Appreciated\ by\ Receiver}{\#Messages\ Forwarded\ by\ s}$
  In one experiment, the appreciation ratio of each node is calculated, the average appreciation ratio of all nodes in this network is measured too. In addition, all nodes in this network are classified into three categories according to their appreciation ratio values: above 0.6, between 0.3 and 0.6, below 0.3. Results are reported later.
- **Message Node Ratio** measures the ratio of the total number of messages to the total number of nodes in the network, approximately the average number of messages received by each node during the entire experiment period. The Message Node Ratio relates to the cost associated with each message forwarded in the network.

VII. Simulation Results

Using the experimental set up described in Section V, we conducted 12 experiments with the six information-sharing strategies proposed in Section IV and two networks described in Section V. Each experiment is conducted with one of the three networks, and one of the six strategies, which is used by all nodes in the network. We collected all those measurements defined in Section VI.

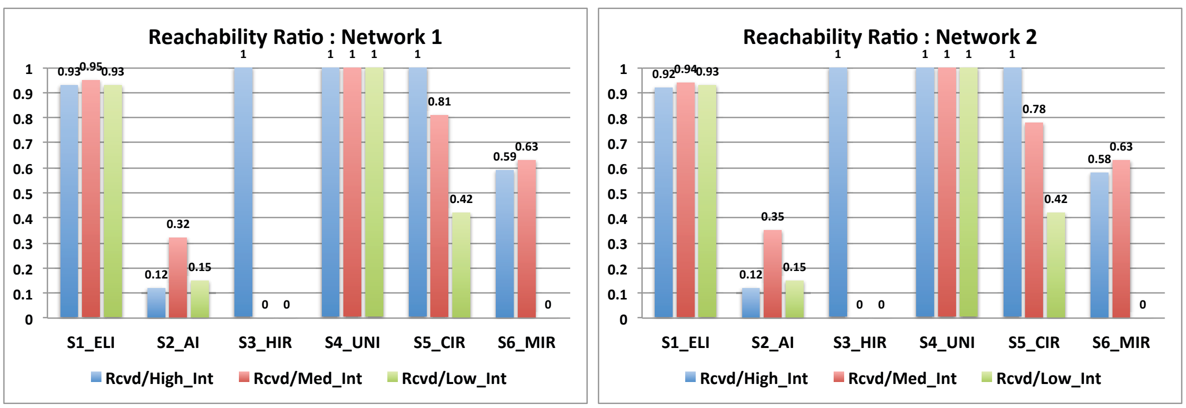
Figure 1 shows the comparisons of Interest Ratio for all six strategies and for both the simulation network and the real network. Three measurements, *High_Int/R, Med_Int/R, Low_Int/R*, each represents the number of High, Medium and Low interesting messages out of total number of received messages, respectively. These three ratios add up to 1 by definition. S3_HIR has *High_Int/R* as 1, and both S2_AI and S6_MIR has *Low_Int/R* as 0, both facts are consistent with how these strategies work. The three strategies S1_ELI, S2_AI and S5_CIR behave similarly, they all have *High_Int/R* around 0.5 (1/2), *Med_Int/R* around 1/3 and *Low_Int/R* close to 0.17 (1/6). When senders use S1_ELI, S2_AI or S5_CIR, receivers are highly interested in about half of the messages they received, moderately interested in one third of them and has low interest in the rest of them, which is about one six of the total received messages. These facts are consistent over the simulation network and the real network.

Figure 2 shows the comparisons of Reachability Ratio. Three measurements, *Rcvd/High_Int, Rcvd/Med_Int,* and *Rcvd/Low_Int* represent the ratio of the nodes who actually received the message among all nodes that are High, Medium or Low Interested in the message, respectively. S4_UNI has the highest reachability ratios in all three categories, closely followed by S1_ELI. S5_CIR reaches a larger percentage of highly interested nodes than medium interested nodes, and it reaches about a quarter of low interested nodes in the simulation network. S3_HIR reaches only highly interested nodes, while S2_AI and S6_MIR do not reach any low interested nodes. It is also noticed that all values are lower in the real network than their counter parts in the simulation



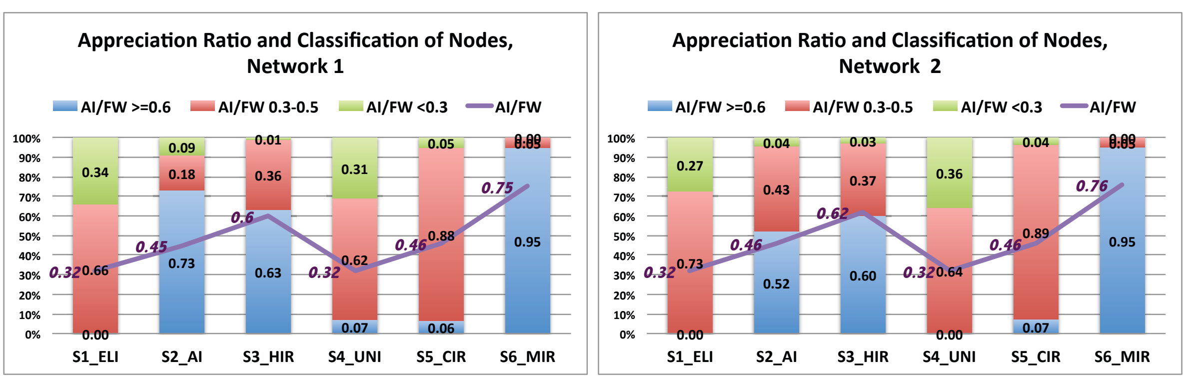
(a) Simulation Network (b) Real Network

Fig. 1: Interest Ratio: $\frac{\#Interesting(High,Med.,Low)Messages}{\#ReceivedMessages}$



(a) Simulation Network (b) Real Network

Fig. 2: Reachability Ratio: $\frac{\#NodesReceivedMessages}{\#NodesInterested(High,Med.,Low)inMessages}$



(a) Simulation Network (b) Real Network

Fig. 3: Appreciation Ratio and Classification of Nodes Accordingly

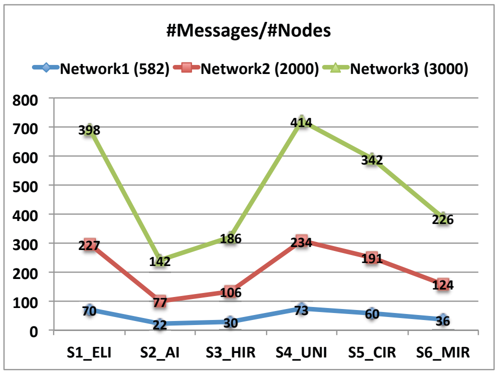


Fig. 4: Message Node Ratio: $\frac{\#TotalMessages}{\#Nodes}$

network, which may be caused by the fact that the real network is less connected than the simulation network. The average degree (number of connections per node) in the real network is 2, while in the simulation network, it is around 10. It is not hard to understand that the more connections there are, the more nodes can be reached in the network given the same amount of time.

Figure 3 shows the comparisons of Appreciation Ratio and the classification of nodes according to their appreciation ratio. S6_MIR has the highest appreciation ratio, followed by S2_AI and S5_CIR, and then S3_HIR. S1_ELI and S4_UNI have the lowest appreciation ratios. These facts are consistent in both networks. When a node uses S6_MIR strategy for sharing information, 95% to 100% of its neighbors would have a high appreciation ratio for it, which is above 0.6, meaning they appreciate more than 60% of messages shared by this node. When a node uses S2_AI, S5_CIR or S3_HIR, the percentage of highly appreciating neighbors drops to 90%, 80% or 74% in one case.

To further understand the communication cost of each strategy in large social networks, we conduct experiments with three much larger simulation networks. Figure 4 presents the average number of messages received by each node. Consider the communicational and computational cost of information-sharing, S2_AI has the lowest cost, followed by S3_HIR and then S6_MIR. The three high cost strategies are S4_UNI, S1_ELI and S5_CIR, in slightly decreasing order. Also noted that the message/node ratio increases significantly as the size of network increases, which can be explained by the fact that the possible number of connections is the square of the number of nodes in the network. Therefore, the choice of information-sharing strategy becomes even more important in large social networks.

Overall, S3_HIR has low cost, high interest ratio, reasonable reachability among highly interested node in well-connected networks, and good appreciation ratio $\approx 80\%$ highly appreciating neighbors. S6_MIR also has low cost but higher than S3_HIR, and the highest appreciation ratio. S2_AI has the lowest cost and very good appreciation ratio. Both S2_AI and S6_MIR have moderate interest ratio (no low interest message delivered), moderate reachability among highly interested and medium interested nodes without disturbing low interested nodes. The reachability of S6_MIR is slightly better than S2_AI.

VIII. Conclusion and Future Work

In this paper we presented a graph model of social network and a model of information relevance and node interest. Based on these models, we proposed six information-sharing strategies and defined a set of evaluation criteria including the interest degrees, reachability, appreciation degrees and communication cost. We conducted experiments to study the performance of each strategy in both a simulation network and a real social network. Some of the observations are intuitive given how the strategies work, which in fact verifies that the simulation framework works correctly, and the results can be used to predict the behavior of real social networks. In the future we will study more realistic scenario, where each node may choose different strategy and even dynamically change its strategy responding to its environment, i.e. the number of messages it receives. A node may also choose to response to received message differently depending on its source. We also plan to model the real communication cost and computational cost as a function of the number of messages in the network, in order to study the performance of each strategy in various settings. Intuitive conclusions rarely can be achieved in such complicated setting, this experimental study framework will be indeed appreciated.

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