# Performance analysis of information propagation in DTN-like scale-free mobile social network

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## *Abstract*

Mobile social network can be seen as a specific application of the DTN (Delay Tolerant Network), in which the information propagation can be impacted by many social behaviors of the nodes. For a specific node, its social behaviors are various. For example, the node may not be interested in the information before receiving it and may also discard the information after getting it. On the other hand, people are more willing to forward the message to his friends. These interactive behaviors between nodes can be seen as social behaviors. It is easy to see that the impact of the social behaviors is related to the social ties, which can be manifested by the structure of the social network. State of the art works often simply assumes that the social networks can be divided into some communities. At present, some works find that the structure of some social networks is scale-free. To overcome this problem, this paper proposes a theoretical model to evaluate the impact of above social behaviors in the DTN-like scale-free network. Simulation shows the accuracy of the model. Numerical results show that both social behaviors and scale-free character have significant impact on information propagation. Moreover, the impact of social behaviors is related to the scale-free character of the networks.

***Keywords:*** mobile social network, delay tolerant network, information propagation, social behaviors

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## 1. Introduction

At present, many personal mobile devices (mobile phones with IOS, Android and Symbian operating systems, etc.) can communicate with each other in a peer-to-peer way. This ability is based on some short-range communication technologies, such as Bluetooth, WiFi, etc [1]. This communication method is much cheaper than the traditional cellular network. However, due to the limited communication range and the mobility of nodes, it is hard to keep the reliable end–to-end link between nodes. Therefore, the mobile social network formed by mobile users through short-range communication technologies belongs to the delay tolerant network (DTN) [2]. In particular, DTN denotes the network where the end-to-end paths between two given nodes may not exist at given time [3].

Due to the network partition, nodes in DTN adopt the stroe-carry-forward communication mode, in which the source makes other nodes as the relay nodes to help to forward the messages. Therefore, information propagation in DTN closely depens on the behaviors of nodes. For this reason, this paper tries to evaluate the impact of behaviors on information propagation in DTN-like scale-free mobile social network. In the real application, the behaviors are various. For example, some people are uninterested in obtaining the message at all at current time, but they may become interested in the message in the future [4]. In addition, the buffer space in smart devices is limited and the message may be no use any more. Therefore, people may discard the message after receiving it [6]. Consequently, the node become a free-rider. For example, one may delete the advertisement when he has seen it. On the other hand, nodes may be selfish and not be willing to help others [12]. In addition, the selfish level may depends on the social ties [2]. These behaviors may have certain impact on the performance of information propagation and need to be explored.

At present, there are some works in this field. For example, the paper [5] explores the impact of the free rider, black hole, supernova, hypernova, and wormhole. However, this work is based on the simulations, and does not give the theoretical models. The work in [6] proposes a theoretical framework to evaluate the performance of information propagation based on ODE (Ordinary Differential Equation) model. Numeric results show that above behaviors have certain impact on information propagation. However, both work [6] and work [7] assume that the network is simply divided into multiple communities(may be overlapped [8]), and cannot manifest the scale-free network efficiently.

The work in [9] proposes a theoretical model to evaluate the impact of social selfishness on epidemic routing (ER) in DTN based on a Markov process, and they then propose a model to evaluate the impact of both individual selfishness and social selfishness on the performance of information propagation [10]. The work in [11] explores the impact of the number of selfish nodes and the intensity of their selfishness on performance of information propagation in DTN. Besides, there are also many similar works [12][13][14][15]. However, none of these works consider the scale-free characters of the network. Wu *et al* [2] proposes a theoretical framework to evaluate the impact of selfishness in a scale-free netwok, but it does not consider the nodes' interest and free-riders, so it is too simple.

To our best knowledge, none of the works study all of the above behaviors in a scale-free network. To overcome this problem, this paper gets some new contributions, which are summarized as follows:

- This paper proposes a theoretical framework to evaluate the performance of information propagation in the scale-free social network. In particular, it considers all of the behaviors described above;

- This paper checks the accuracy of the model through simulations based on both synthetic and real motion trace, and shows that the average deviation is not bigger than 6.16%.
- Numerical results obtained based on our model show that all the above behaviors have significant impact on information propagation. Moreover, the impact of nodes' behaviors is related to the parameters of the scale-free structure.

The rest of this paper is organized as follows. Section 2 presents the network model and prepares for the theoretical framework constructed in Section 3. Simulation and numerical results are shown in Section 4, and we summarize our work in Section 5.

## 2. Network Model

In this paper, we consider a finite region where $N$ nodes move around all the time. These nodes form a mobile social network. At the beginning, only the source node owns the information. In addition, as shown in **Fig. 1**, the node state includes *uninterested*, *interested*, *satisfied* and *discarded*. The state *uniterested* denotes the node is not interested in the information, and the state *interested* means that is interested in the information. Similarly, the state *satisfied* denotes that the node gets the information, but the state *discarded* means that the nodes discard the information. The transition process between above states is defined in **Fig. 1**. Our work can be extended to the case with other transition processes. For example, after discarding the information, the node may be interested in the information again. In this case, nodes in state *discarded* may change to the state *interested*. For simplicity, this paper just considers the transition process defined in **Fig. 1**.

We use the state space $\{U, I, S, D\}$ to denote above four states, respectively. If an node in state *interested* encounters a node in state *satisfied*, the node in state *satisfied* sends the information to the node in state *interested* with certain probability. By this means, the information spreads in the network as time goes by.

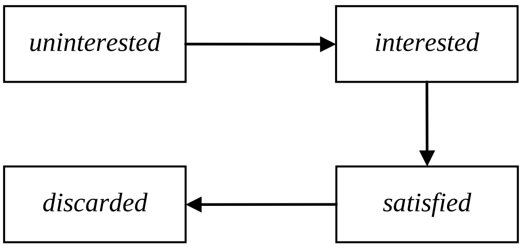



**Fig. 1.** State transition in DTN-like mobile social network

### 2.1 Movement Model

Conan *et al.* [16] find that the empirical distributions of inter-meeting times tend to be well fitted by an exponential curve. Karagiannis *et al.* [17] also finds that if you consider long traces, the tail of the distribution is exponential. This means that the exponential distribution of the inter-meeting time can fit the real-world movement model very well. In fact, many works use this simple assumption to model the mobile network [6][10][12].

Therefore, the assumption that inter-meeting time is exponentially distributed is rational in many applications. For this reason, we assume that the inter-meeting time of two consecutive contacts conforms to the exponential distribution. Based on this distribution, any two nodes in the network encounter with each other in time interval $[t, t+\Delta t]$ with probability,

$$p_e = 1 - e^{-\lambda \Delta t} \tag{1}$$

$\lambda$ denotes the parameter of exponential distribution.

### 2.2 Social Relations

The impact of the nodes' behaviors may depend on the social ties, so it is necessary to introduce the social relations between nodes. Existing study has revealed that the social relation between users has a scale-free character [18]. We therefore use the following power-law distribution to represent the social relation,

$$P(k) = \begin{cases} 0, k < m \\ C(m,\gamma)k^{-\gamma}, m \le k < N \end{cases} \tag{2}$$

$P(k)$ denotes the probability that a node has $k$ friends. $m$ is the smallest number of friends of a specific node. $\gamma$ represents the skewness of the degree distribution. $C(m,\gamma)$ is the normalization constant.

The information is transmitted in an epidemic routing way. If a node in state *satisfied* encounters a node in state *interested*, the information is transmitted based on their social relations. In particular, if they are friends, the node in state *satisfied* sends the information to the node in state *interested* with probability $p_1$. Otherwise, the probability is $p_2$. Due to the fact that nodes are more willing to help their friends in many applications, we often obtain $p_1 \ge p_2$.

### 2.3 Social Behaviors

As shown in **Fig. 1**, the node in state *uninterested* may become interested in the information. On the other hand, the node in state *satisfied* may discard the information. Similar to the works [6][19], we assume that a node in state *uninterested* changes its interest according to an exponential distribution with parameter $\rho$. On the other hand, the node in state *satisfied* discards message according to another exponential distribution with parameter $\mu$.

## 3. Theoretical Framework

The nodes' state space is denoted as $\{U, I, S, D\}$. For a node with $k$ friends, let $X(k,t)$ denotes the probability that a node is in the state $X$ at time $t$, and $\{X(k,t)\}$ represent the set of the nodes being in the state $X$ at time $t$. For example, $I(k,t)$ represents the proportion of the nodes in state *interested* with $k$ friends in all the nodes with $k$ friends at time $t$. $\{I(k,t)\}$ records the set of the nodes in state *interested* with $k$ friends at time $t$. Additionally, let $N(k)$ denotes the number of the nodes with $k$ friends. According to above definition, we can easily obtain,

$$N(k) = P(k)N \tag{3}$$

$$U(k,t) + I(k,t) + S(k,t) + D(k,t) = 1 \tag{4}$$

We then take the derivative of Eq. (4) with respect to time, and compute the expectation of each variable, then the following equation is resulted,

$$E(U(k,\dot{t}))+E(I(k,\dot{t}))+E(S(k,\dot{t}))+E(D(k,\dot{t}))=0 \quad (5)$$

Given a small time interval $\Delta t$, we can obtain,

$$N(k)U(k,t+\Delta t)=N(k)U(k,t)-\sum_{i\in\{U(k,t)\}}\varphi_i(k,t,t+\Delta t) \quad (6)$$

Where $\varphi_i(k,t,t+\Delta t)$ denotes the event whether the node $i$ in state *uninterested* with $k$ friends changes his interest and become interested in the information. If node $i$ changes his interest, we assign 1 to $\varphi_i(k,t,t+\Delta t)$, that is, $\varphi_i(k,t,t+\Delta t)=1$. Otherwise, $\varphi_i(k,t,t+\Delta t)=0$. As described in section 2.3, nodes in state *uninterested* alter their interest of information according to an exponential distribution with parameter $\rho$, therefore,

$$P(\varphi_i(k,t,t+\Delta t)=1)=1-e^{-\rho\Delta t} \quad (7)$$

Similar to the works [6][21], through combining Eq. (6) with Eq. (7), Eq. (8) follows,

$$\begin{aligned}&N(k)\lim_{\Delta t\to 0}\frac{E(U(k,t+\Delta t)\text{-}U(k,t))}{\Delta t}=-\lim_{\Delta t\to 0}\frac{E(N(k)U(k,t))E(1-e^{-\rho\Delta t})}{\Delta t}\\&\Rightarrow E(U(k,\dot{t}))\text{=-}\rho E(U(k,t))\end{aligned} \quad (8)$$

$k$ ranges from $m$ to $N-1$, thus, in fact, Eq. (8) represents $N-m$ equations. Using the similar method, we also can get Eq. (9),

$$E(D(k,\dot{t}))\text{=}\mu E(S(k,t)) \quad (9)$$

As shown in **Fig. 1**, at time $t$, a node in state *uninterested* may change its state to state *interested*. On the other hand, a node in state *interested* may receive the information from a node in state *satisfied* when encountering it. Hence, we can obtain,

$$N(k)I(k,t+\Delta t)=N(k)I(k,t)\text{-}N(k)I(k,t)T(k,t,t+\Delta t)\text{+}\sum_{i\in\{U(k,t)\}}\varphi_i(k,t,t+\Delta t) \quad (10)$$

Where $\varphi_i(k,t,t+\Delta t)$ is defined in Eq. (7), and $T(k,t,t+\Delta t)$ represents the probability that a node in state *interested* receive the message between $[t,t+\Delta t]$. Given time interval $\Delta t$, $p_e=1-e^{-\lambda\Delta t}$ (Eq. (1)) memorializes the probability that any two nodes of the network encounter with each other. So the probability that any node of the network encounters at least one of the rest of nodes is,

$$p_a=1-(1-p_e)^{N-1}=1-e^{-\lambda(N-1)\Delta t} \quad (11)$$

When the time interval is tiny enough, any given node can meet at most one node. In other words, we can regard Eq. (11) as the chance any specific node encounter another node. According to the work in [2], we can obtain the analytical expression of $T(k,t,t+\Delta t)$,

$$\begin{aligned}T(k,t,t+\Delta t)=&\ p_a p_1\frac{k}{N-1}\sum_{k'=m}^{N-1}\frac{k'P(k')}{N-1}S(k',t)\\&+p_a p_2\Big(\sum_{k'=m}^{N-1}P(k')S(k',t)-\frac{k}{N-1}\sum_{k'=m}^{N-1}\frac{k'P(k')}{N-1}S(k',t)\Big)\end{aligned} \quad (12)$$

Combing Eq. (10), Eq. (11) and Eq. (12), and let $\Delta t$ approaches zero, we can further have,

$$N(k)\lim_{\Delta t\to 0}\frac{E(I(k,t+\Delta t))-E(I(k,t))}{\Delta t}=\lim_{\Delta t\to 0}\frac{E(N(k)U(k,t))E(1-e^{-\rho\Delta t})}{\Delta t}$$
$$-N(k)\lim_{\Delta t\to 0}\frac{E(I(k,t))T(k,t,t+\Delta t)}{\Delta t}$$
$$\Rightarrow E(I(k,\dot{t}))=\rho E(U(k,t))-E(I(k,t))\lim_{\Delta t\to 0}\frac{T(k,t,t+\Delta t)}{\Delta t} \tag{13}$$
$$=\rho E(U(k,t))-E(I(k,t))\lambda p_2(N-1)\sum_{k'=m}^{N-1}P(k')E(S(k',t))$$
$$-E(I(k,t))\lambda(p_1-p_2)\frac{k}{N-1}\sum_{k'=m}^{N-1}k'P(k')E(S(k',t))$$

This expression also contains $N-m$ equations. Furthermore, let Eq. (5) deducts Eq. (8), Eq. (9) and Eq.(13), we have,

$$E(S(k,\dot{t}))=-\mu E(S(k,t))+E(I(k,t))\lambda p_2(N-1)\sum_{k'=m}^{N-1}P(k')E(S(k',t))$$
$$+E(I(k,t))\lambda(p_1-p_2)\frac{k}{N-1}\sum_{k'=m}^{N-1}k'P(k')E(S(k',t)) \tag{14}$$

Combining Eq. (8), Eq.(9), Eq. (13) and Eq. (14), we can obtain $4(N-m)$ equations and $4(N-m)$ unknowns. Therefore, when all the initial values are determined, we can get the values of these unknowns at any time easily by Matlab® ODE suite.

The main aim of information transmission in mobile social network is to maximize the number of the nodes that ever received the message. For example, the businessman hopes to maximize the number of peoples receiving the advertisement. If the total number of nodes is a constant, the target can also be described as maximizing the ratio of the nodes that ever got the message. For the nodes with $k$ friends, we can easily obtain the ratio by the time $t$,

$$R(k,t)=P(k)(S(k,t)+D(k,t)) \tag{15}$$

Where the value range of $k$ is all the integers between $[m,N)$. Furthermore, we compute the ratio of nodes that ever experienced the message,

$$R(t)=\sum_{k=m}^{N-1}R(k,t)$$
$$=\sum_{k=m}^{N-1}P(k)(S(k,t)+D(k,t)) \tag{16}$$

## 4. Performance Analysis

We check the accuracy of our model by conducting simulations using the ONE (Opportunistic Network Environment) simulator. We conduct the simulations in two different scenarios. Simulation in the first scenario is based on the classical RWP (Random Waypoint) movement model. In particular, all the nodes move within a 1,000m×1,000m terrain. Each node relocates directly at the given destination at a constant speed, pauses for a while, and then randomly gets a new, destination. The moving speed is selected in our experiments distributes between 0.5 m/s and 1.5 m/s uniformly and the time for pausing is uniformly distributed between 0 and 120s. The capacity of the transmission range is 5m. For the social relations, the skewness $\gamma$ is set to 3, which comes from the actual social networks [18]. We use 200 nodes, and each of them has at least 20 friends. That is, $N$ is equivalent to 200 and $m$ equals 20. In the second scenario, we use one real dataset gathered by the Haggle Project, referred to *Infocom05*. Number of the experimental devices (participants) is 41, and parameter $m$ is set to 5 and parameter $\gamma$ 3.

The remaining parameters can be valued continuously and it is impossible to carry out the simulations traversing all the possible values. For this reason, we simply set $\rho = 0.00004$, $\mu = 0.00002$. In addition, for both scenarios, we consider two different cases, Case 1, $p_1 = 1$, $p_2 = 0.8$; Case 2, $p_1 = 0.5$, $p_2 = 0.05$. At the beginning time, only one of the nodes has the information. Half of the other nodes stay in the state *uninterested* and others are in the state *interested*. For the first scenario, we run simulations for 100,000 seconds and 50 times, we get the results in **Fig. 2**. In the second scenario, we select the continuous 12 hours to carry out the simulations, which is the most active period. After running for 50 times, we obtain the results in **Fig. 3**.

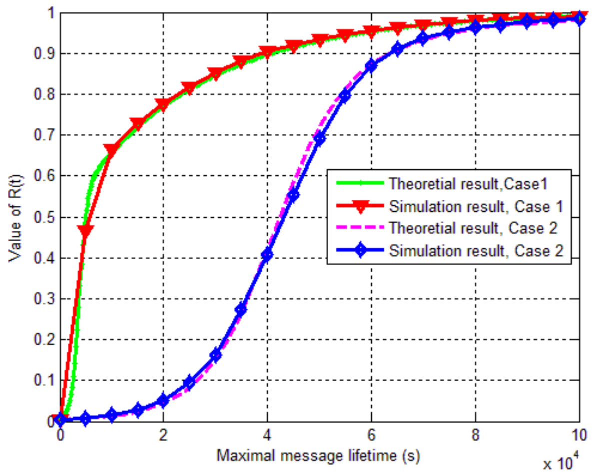



**Fig. 2**. Comparison between simulation and theoretical results with RWP model

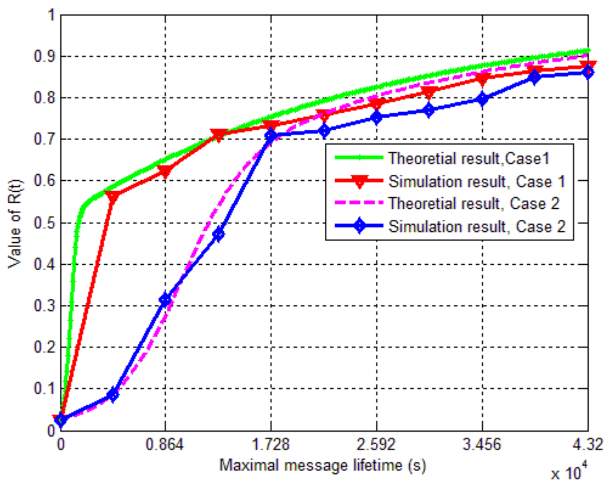


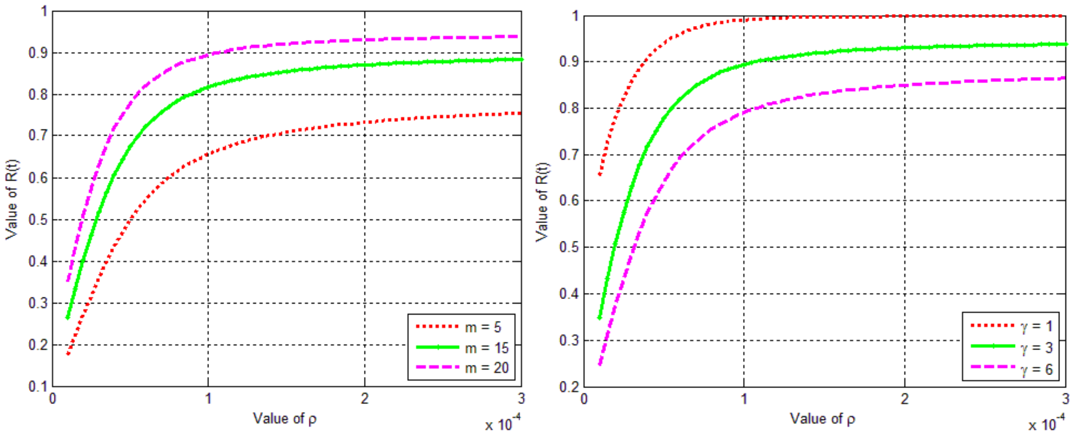

**Fig. 3**. Comparison between simulation and theoretical results with *infocom05* dataset

As shown in **Fig. 2** and **Fig. 3**, the average deviation between simulation and theoretical results is very small. In fact, the deviation is 0.13% for Case1 and 2.55% for Case 2 in the first scenario. The deviation of the second scenario is 3.35% and 6.16%, respectively, and it is also very small. This proves the accuracy of our theoretical framework. For this reason, we only employ the theoretical case for the performance analysis. On the other hand, in the first scenario, 80% of the nodes get the information by the time 23,509s (theoretical) for Case 1, while the percentage of the Case 2 is no more than 6.87% (theoretical) during the simulation time range. This result is imputable to social cooperative level ( $p_1$ ) and individual cooperative level ( $p_2$ ) [2]. We will explore them later in detail. In the rest of this section, we will carry out the analysis of the impact of node behaviors on information propagation.

As shown in **Fig. 2**, the behaviors of how a node treats the information before receiving it and how the node deals with the information after getting it may have impact on information propagation. Accordingly, we use the value of $\rho$ and $\mu$ to represent these two kinds of behaviors. In the following context, we will study the impact of parameter $\rho$ and $\mu$ on information transmission.

According to our assumption, any node in networks change its interest obeying an exponential distribution with the parameter $\rho$. Now we commence to canvass the impact of $\rho$. Let the value of $\rho$ increases from 0.00001 to 0.0003. We also take the structure of mobile social network into consideration. And it involves two cases: (a), $m = 5, 15, 20, \gamma = 3$, (b), $\gamma = 1, 3, 6, m = 20$. All the other settings stay the same as the Case 2 in **Fig. 2**. We observe $R(t)$ at time 50000s. Hence, we obtain the

**Fig. 4** followed.




(a) $m = 5, 15, 20, \gamma = 3$ (b) $\gamma = 1, 3, 6, m = 20$

**Fig. 4**. The impact of parameter $\rho$ on message transmission

The bigger $\rho$ is, the faster a node turns interested in the message. Consequently, the information spreads in the network much faster. This is proven by both subfigures in

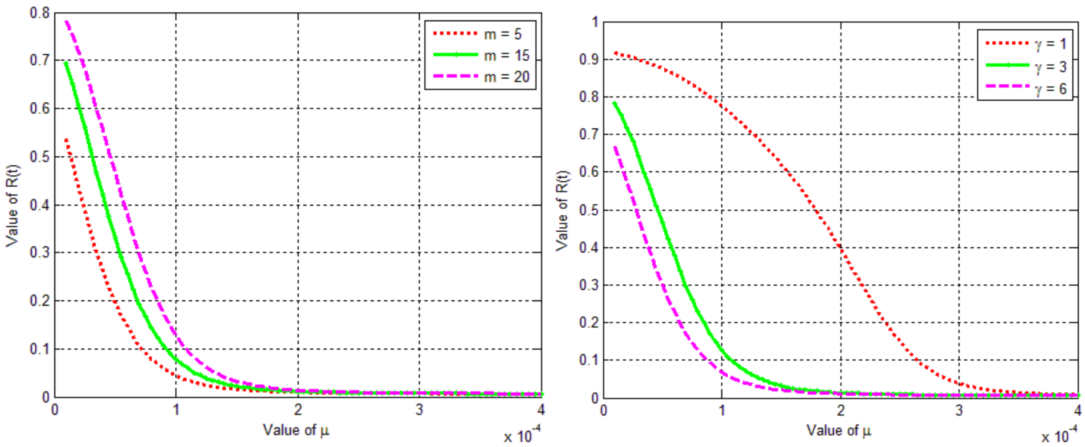
**Fig. 4**. For example, only 34.81% of the nodes get the message when $\rho$ equals 0.00001 for

$m = 20$ in

**Fig. 4** (a), while when $\rho$ changes to 0.0001, the proportion is 89.42%. That is, the interest switching speed has a significant impact on information transmission. We also conclude from

both subfigures in
Fig. 4 that increment is not obvious when is $\rho$ greater than 0.0001. This conclusion is applicable. For instance, the businessman can spend some specific time, but not too much, making the advertisement attractable. Additionally, the results also show that the information propagation is related to the structure of the network. The bigger $m$ is and the smaller $\gamma$ is, the more friends a node averagely has, the more nodes may receive the message.

The message occupies some storage space. And the node may discard the message because the message may become useless as time goes by. Now we pay some essential attention to this kind of behaviors. Let the parameter $\mu$ ranges from 0.00001 to 0.0004. All the other parameters remain unchanged. Similar to
Fig. 4, we plot
Fig. 5 (a) and
Fig. 5 (b) in
Fig. 5.




(a) $m = 5,15,20, \gamma = 3$ (b) $\gamma = 1,3,6, m = 20$

Fig. 5. The impact of parameter $\mu$ on message transmission

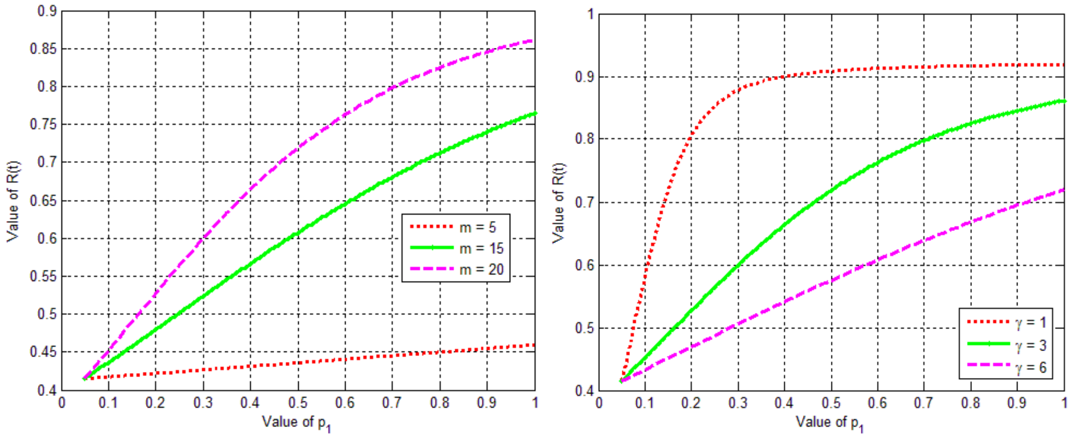
From the results shown in
Fig. 5 (a), we can see that the proportion $R(t)$ reduces dramatically before $\mu$ reaches 0.0002. When $\mu$ is greater than 0.0002, $R(t)$ equals to about 1/200=0.005. That is, only the source node own the message and none of the other nodes get the message. This is consistent with
Fig. 5 (b). However, when $m = 20$ and $\gamma = 1$, 39.66% of the nodes get the information under the condition that $\mu$ equals 0.0002. That is, the impact of parameter $\mu$ is related to the structure. To improve the performance of the information propagation, one can yield some hortative measures to encourage the nodes in network keeping the message for more time.

People may not be willing to send the message to others on account of the fact that the transmission process costs some power. On the other hand, people are more willing to help his friends but are less interested in helping the one not familiar with. However, all these statements are intuitive descriptions. We will later demonstrate them with numerical results and analysis.

We focus on two aspects, $p_1$ and $p_2$ respectively. Now we come to the analysis the impact of $p_1$ and $p_2$ on information dissemination. Considering $p_1 \geq p_2$, we set $p_2$=0.05 and the scope of $p_1$ [0.05,1]. All other parameters stay invariant. We can easily obtain

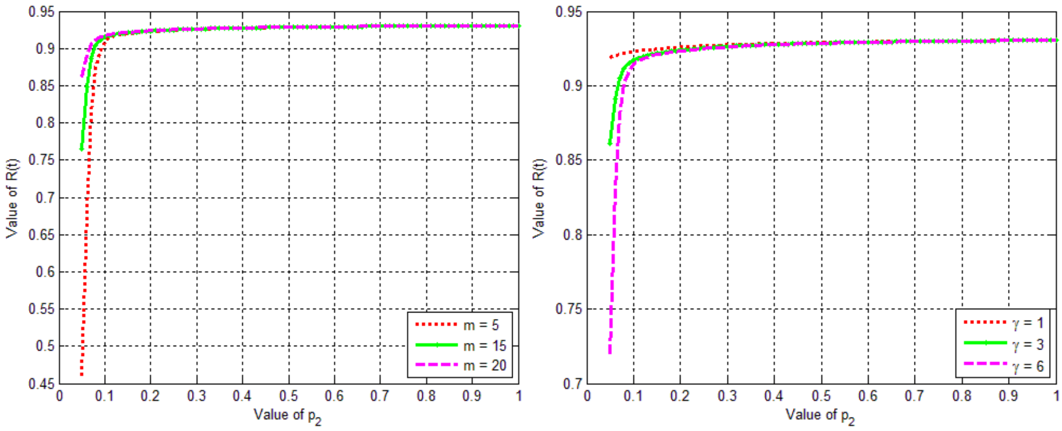
**Fig. 6**. Furthermore, we set $p_1$ as a constant and its value is 1. On the other hand, let $p_2$ ranges from 0.05 to 1. All other parameters stay changeless, and we plot the results in

**Fig. 7**.




(a) $m = 5, 15, 20, \gamma = 3$ (b) $\gamma = 1, 3, 6, m = 20$

**Fig. 6**. The impact of parameter $p_1$ on message transmission




(a) $m = 5, 15, 20, \gamma = 3$ (b) $\gamma = 1, 3, 6, m = 20$

**Fig. 7**. The impact of parameter $p_2$ on message transmission

As can be seen from both

**Fig. 6** and

**Fig. 7**, the social behaviors bring meaningful impact to information propagation. For example, as shown in

**Fig. 6** (a), only 41.51% of the nodes get the message by the time 50000s when $p_1$=0.05 while the proportion is 86.11% when $p_1$=1. Similar analysis can be conducted to

**Fig. 6** (b) and

Fig. 7. In addition, we also find some differences between two figures. As shown in Fig. 7, the performance increases sharply when $p_2$ changes its value from 0.05 to 0.1. It can be concluded that with a little promotion in $p_2$ when $p_2$ is small, the promotion in performance can be significant. This is because there exists more non-friend links than friend links in the social network. For example, considering the condition that $m$ =20 and $\gamma$ =3, we find the average number of friends a node has is 35.54 while the opposite number is 163.46. In our application scene, we only need spend little energy in encouraging nodes to send the message to their non-friends. However, if we want to improve the performance through $p_1$, more attention should be paid.

According to the above analysis, we can reason out that all social behaviors experience great impact on information propagation in DTN-like scale-free network. If most of the nodes change their interest in the message with a low speed or never become interested in it, the performance will exhibit bad results. In addition, if the message is discarded very fast, the message may disappear. Some measures should be conducted to prevent this ruinous situation occurring. On the other hand, low value of $p_1$ and $p_2$ lead to unsatisfactory effect. If all the nodes send the message to their friends unconditionally and don't tend to send a copy to his non-friends, unfriendly performance may occur. Additionally, the performance of information propagation is also related to the structure of the mobile social network. The bigger $m$ is and the smaller $\gamma$ is, the more friends a node averagely has, the more nodes may receive the message. This is because there are more opportunities for sending the message at the probability $p_1$ rather than $p_2$. Consequently, the message spreads in the network at a higher speed.

## 5. Summary

This paper presents a theoretical framework to evaluate the performance of information propagation in the DTN-like scale free mobile social network. Many kinds of social behaviors are explored. Furthermore, we take the realistic network structure into consideration. Simulation results show the accuracy of our theoretical model. We also study the impact of many parameters through extensive numerical results and find that the social behaviors have significant impact on information propagation. Moreover, the performance is related to the structure of the mobile social network. Finally, we propose some suggestions to prevent unfortunate results and improve the performance of the information propagation.

In this paper, we propose a theoretical model based on mean field limits, and it assumes that any node pair encounters with the same probability. However, this may not be satisfied in the real scenario, for example, friends meet each other more frequently than non-friends. On the other hand, we focus on the impact of many social behaviors on performance of the information propagation in DTN-like scale-free mobile social network, and some factors are not paid enough attention, for example, the energy consumption [20], the performance optimization [21], etc. We want to extend our work by taking these factors into consideration in the future.

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