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A Scale-Free Network Evolution Model Based on the Growth Characteristics of Social Networks

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Abstract. In this paper, based on the classic BA scale-free network model, we proposed a new evolution model that gives a more realistic description of the people's behavior on social networks. In the process of growth, there are local preferential attachment mechanisms and random attachment or removal between the old and new edges. We proved that the extended model follows the power-law distribution and the power exponent is between 2 and 3, which provides a theoretical support for analyzing the similar social network. Compared with the classic BA model, the extended model has a smaller average path length and a larger clustering coefficient, which is more consistent with the real social network.

Keywords: BA scale-free network, social network, local preferential attachment, random attachment

1. Introduction

As an important tool to study the complexity problem, complex networks have aroused research upsurge in recent years. A amount of complex networks exist in the real world, such as aeronautical networks, biological networks, social networks and so on. It is found that more and more real networks follow the power-law distribution, called scale-free network [1]. The BA scale- free model [2] focuses on characterizing the power-law distribution of actual networks. In order to be more in line with the logic of real network evolution, it is of great theoretical significance and application value to extend the basic BA scale-free network model. Albert and Barabasi [3] proposed an extended model (EBA model) of network evolution that has more practical significance in the study of local processes. Bianconi and Barabasi [4] assigned a fitness parameter to each node and defined the fitness model. The fitness model have such characteristics of 'first- mover-wins, fit-gets-richer and winner-takes-all'.

There are some other extension models. Watts and Strogatz [5] explored a small-world model, which has short-path, high clustering features and satisfies the characteristics of the small world networks [6-7] that mimic the evolution of a social network process. Barabasi and Albert [8-9] studied the World Wide Web (WWW) and proposed a BA scale-free model based on growth and prioritization. Li, Jin and Chen [10] studied complexity and synchronization of the World Trade Web (WTW), and investigated some scale-free features of the WTW. In [11] , based on the new concept of local-world connectivity, Li and Chen proposed a local-world evolving network model. In the last few years, Wang, Xu and Pang studied the internal structure of online social networks and combined the inside growth, outside growth, and edge replacement base on those of complex networks, then proposed an evolution model in [12].

The model we proposed here is grounded on a modification of the model presented by Barabasi (BA model) [2]. The mathematical definition of BA model:

- Growth: start with a network of n_0 nodes. A new node is added at each timestep with m $(\le n_0)$ edges that connect the new node to m existing nodes.
- Preferential attachment: the probability Π_i of the new node connect the existing node i depends on the degree k_i of node i as

$$\Pi_i = \frac{k_i}{\sum_{j=1}^{n} k_j}, \tag{1}$$

where n is total number of nodes.

2. Model description

Base on BA scale-free network, our algorithm is defined as follows:

Initialization. Start with a network of n_0 nodes. Initial $n_1, n_2, m_1, m_2, m_3, m_4$.

Step 1. Growth: n_1 nodes are added to the network and each new node connected to m_1 existing nodes by preferential attachment probability Π_i (as defined in (1)).

Step 2. Preferential attachment: n_2 new nodes are added simultaneously. And each new node connected to a random existing node, denoted by j. Add $m_2 - 1$ edges between the new node and the neighbor nodes of node j. The edges are selected with probability:

$$\Pi_i^{'} = \frac{k_i}{\sum_{s \in N(j)} k_s}, i \in N(j), \tag{2}$$

where $N(j)$ is the set of neighbor nodes of node j.

Step 3. Aggregation: break m_3 edges randomly, then add m_4 $(m_4 > m_3)$ edges that selected with equal possible probability.

Output. Repeat step 1 to 3 t times. The network has $N(t) = n_0 + (n_1 + n_2)t$ nodes and $M(t) = (n_1 m_1 + n_2 m_2 + m_4 - m_3)t$ edges.

In the above algorithm, as a widespread social network, Step 2 shows that a node recommended by a friend to the network is not only a friend of the recommender, but also a friend of his friend. This is in line with our natural situation. Another point is the preferential attachment in this step is only for the range of friends around the recommender, it is the local world of the node. The purpose of Step 3 is to make the network aggregate and satisfy the characteristics of the small world networks.

3. Main result

In this section, we prove that the extended network model follows the power-law distribution which is the property of scale-free networks. And we obtain some statistical properties of the extended model. We present some numerical results to performance of the extended model that is better than BA model. Degree distribution

Let $k_i(t)$ denote the degree of node i at time step t. Node i is added to the network at timestep t_i, we suppose that

$$k_i(t_i) = c_0, \tag{3}$$

where c_0 is a constant. The rate at which the node i acquires new edges is given by our algorithm:

$$\frac{dk_i(t)}{dt} = n_1 m_1 \Pi_i + n_2 \frac{1}{N(t)} + n_2(m_2 - 1)(1 - \frac{1}{N(t)}) \frac{1}{< k_{nn} >} + (m_4 - m_3) \frac{1}{N(t)}, \tag{4}$$

where $< k_{nn} >$ denotes the residual average degree of node i (that is the average degree of the neighbors of node i) [13]. According to [14], we suppose that $< k_{nn} > = k_i(t) + b$ and b is a small constant.

The network has $M(t) = (n_1 m_1 + n_2 m_2 + m_4 - m_3)t$ edges after t time steps. Then we have