Self-Repairing Peer-to-Peer Networks

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In this paper we study the resilience of peer-to-peer networks to preferential attacks. We define a network model and experiment with three different simple repairing algorithms, out of which the so called ‘2nd neighbor’ rewiring algorithm is found to be effective and plausible for keeping a large connected component in the network, in spite of the continuous attacks. While our motivation comes from peer-to-peer file sharing networks, we believe that our results are more general and applicable in a wide range of networks. All this work was done as a student project in the Complex Systems Summer School 2004, organized by the Santa Fe Institute in Santa Fe, NM, USA.

I. INTRODUCTION

There has been an increasing interest in the field of complex networks recently. Describing complex systems as graphs has proven to be an effective approach and it is now widely adopted. Network analysis and modeling has contributed to understanding mechanisms and organization principles of various systems (Albert and Barabási, 2002; Dorogovtsev and Mendes, 2002; Newman, 2003).

In computer science much attention has turned to peer-to-peer computer networks, sometimes abbreviated as P2P networks. In a peer-to-peer computer network, every (node) computer has the same capabilities and responsibilities, there are no distinguished nodes. This is in contrast to client/server architectures, where the roles (and usually also the capabilities) of the client and server nodes differ.

Many peer-to-peer computer networks provide file-sharing services (but not all of them, see the work of Milojicic et al. 2002), the owners of the network nodes intend to share their files with the other node owners in the same network. It is observed that many nodes of these file sharing networks distribute illegal content, most often copyrighted audio and video files. The Recording Industry Association of America (RIAA) as a representative of the U.S. recording industry investigates the illegal distribution of sound recordings. The RIAA tries to identify the file sharing network nodes distributing large amount of illegal content in order to shut them down (i.e. removing them from the network).

The motivation of the present work is to find out whether the nodes can apply a simple local strategy to keep the peer-to-peer network in a working state, or by continuously removing the most active nodes from the network, the attacker can effectively prevent the network from fulfilling its function. By local strategy we mean an algorithm which uses only a constant amount of information, regardless of the size of the network. Although our motivation was specific, we believe that our model and results are more general and widely applicable to various other networks as well.

The outline of this report is as follows. In Section II we very briefly discuss the literature closely related to the project. In Section III we define our network model, and justify the model’s assumptions. In Section IV we present three different defensive strategies, and their performance analysis. Finally, in Section V we give our conclusions.

II. RELATED WORK

There has been some work done on measuring the resilience of different network structures, especially resilience of scale-free networks to random failure and targeted attack (Albert et al., 2000). Here failure means removing nodes randomly from the network, and targeted attack means removing the high degree nodes from the network. Albert and her co-workers showed that scale-free networks are not vulnerable to random failure but very vulnerable to targeted attacks. A similar approach was applied by Broder et al. (2000). Callaway et al. (2000) studied percolation, which is closely related to network resilience, on random graphs with arbitrary degree distributions. They used generating function methods to solve bond and site percolation problems, in which the occupation probability was a given function of the vertex degree.

III. MODEL DESCRIPTION

A. How to attack a network?

A network attack, i.e. node removal from the network, can cause various levels of damage to the structure (and function also) of the network. In the classic work on network tolerance Albert et al. (2000) studied how the diameter of the network changes after 1) removing nodes randomly and 2) removing preferentially higher degree nodes. The intuitive result was that scale-free networks...
are very resilient to random node removal (ie. a failure) and not at all resilient to preferential node removal (ie. a targeted attack).

In our model we assume that the attacker tries to inflict as much damage as possible and removes the higher degree nodes from the network. These nodes are not very difficult to find, even if the attacker doesn’t know the structure of the whole network (Cohen et al., 2003).

Let us assume that the degree distribution of the network is given by \( p_k(k = 0, \ldots, n-1) \) where \( n \) is the number of nodes in the network. Thus the probability that a randomly chosen node in the network has degree \( k \) is \( p_k \). Now, if we choose a random neighbor of the randomly chosen node (let us assume that it has one), the probability that this second node has degree \( k \) is proportional to \( kp_k \), since the more edges this second node has, the higher the probability is that it will be selected. (Here we assume that there are no correlations between node degrees in the network, the assortativity coefficient Newman (2002) is zero.) The same method is described by Cohen et al. (2003), in a different context.

In our model we assume that the attacker uses this method to find the nodes with high degree in the network.

B. The model assumptions

We consider only undirected networks. In real peer-to-peer networks, this is not always the case, most of them are directed. The reason for assuming mutual connections (undirectedness) is simplicity. The defensive strategies are more difficult to define on directed networks, and also keeping the number of edges constant (another assumption, comes later) is more difficult.

The network attacks are carried out in the way described in the previous section. A random neighbor of a randomly chosen node is removed with all its edges from the network. If the randomly chosen node has no neighbors at all, no node is removed. This method tends to remove the hubs (ie. high degree nodes) from the network.

We keep the number of nodes in the network constant. The reason for this is partly practical: we wanted to study the long term behavior of the model and didn’t want the network to shrink to a very small size. The other reason is that we assumed that there are new nodes joining to the network. The rate of the node removal and the rate of the new nodes joining are the same in the model, and this result.

Not only the number of nodes, but also the number of edges is kept constant in the model. This assumption is made because in real networks edges have costs associated with them. A fixed number of edges means fixed cost for maintaining the network. We wanted the network to repair itself without increasing this cost.

In order to keep the number of edges constant, after the attack the same number of edges are added to the network as the number of edges deleted with the attacked node. One edge is given to the newly added node, it will have degree one, and connects to a random node in the network. The remaining edges are given to the former neighbors of the attacked node (we will call these affected nodes in the following). While adding the new edges, we don’t check for self-loops (a node connects to itself) or multiple edges, in some cases they are even needed to keep the number of edges constant. We can look at self-loops as spare edges for the nodes, they can be used later to create a “real” connection. Multiple edges can be considered as stronger edges between two nodes.

The different defensive strategies for the network are defined as the methods the new edges are added to the affected nodes. A defensive strategy is an algorithm used by an affected node to decide which node it will connect to instead of the lost (attacked) node. The information a node has about the structure of the network is considered to be part of the algorithm. Sometimes we call these strategies rewiring strategies, because the affected nodes rewire from the attacked node to another one.

This is a discrete time model. The time steps of the simulation is defined by the attacks, there is one attack in each time step. Only the affected nodes are active in the network (the newly added node can also be considered active), the other nodes don’t initiate or remove connections. The affected nodes react to the attack by creating new edges.

There are various structural properties of networks considered to be important for their function. For efficient information flow, the characteristic path length or the diameter of the network should be small; if the edges have large costs, the redundancy of the network should be minimal, etc. In this study we’ve focused on a very basic structural property: the connectedness of the network. It is clear that in order to function, a peer-to-peer network should be connected. (For efficient function of course usually other properties are needed.) More precisely we’ve considered the size of the largest connected component of the network to compare the rewiring strategies, after a large number of attacks, when the network can be assumed to be in a steady state.

IV. RESULTS

A. The random rewiring strategy

Let us first consider a very simple (but promising) possible defensive strategy for the nodes. Here we do not mean a strategy which is easy to implement, but one which is easy to handle in simulations or even in analytical calculations.

The random rewiring strategy is indeed completely random. The affected nodes rewire to a randomly chosen node in the network (including also the newly added node).

It is known since Erdős and Rényi (1959) that a random graph has a giant connected component with proba-
FIG. 1 The degree distributions of a random graph (blue line, circles) and a random graph after attacks and random rewiring repair (red line, squares). The plot shows that the random rewiring strategy does not keep a random graph random. This is because the attacks remove preferentially the nodes with high degree.

FIG. 2 Phase transitions in random graphs (green line, squares) and attacked random graphs (read line, circles). Further calculations are needed to prove the existence of the transition in the attacked graph. The transition threshold for the attacked network seems to be higher.

bility 1 if the average node degree in the graph is greater than 1. We also know that when the average node degree is 1 there is a phase transition in the system: the probability of having a giant cluster jumps from probability 0 to probability 1.

These facts have strong implications for our model. So long as we can keep the network as a random graph, we will have a large connected component. In the model we keep both the number of nodes and the number of edges constant, thus the average node degree is also constant. So if we can be sure that the random rewiring strategy keeps the network in the random graph state, and we start with a random graph with an average degree high enough, the network will have a giant connected component even after the attacks. Note that starting with a random graph is a quite strong assumption which is usually not true in real peer-to-peer networks which show power-law degree distributions (Ripeanu et al., 2002).

So we’ve investigated whether the attacks and the random rewiring strategy keeps a random graph in the random state. Fig. 1 shows that the degree distribution of a random graph changes after the attacks and the random rewiring repair, the graph is not a random graph any more.

Even if the attacked network is not a random graph, it’s degree distribution is similar to a random graph so the random rewiring strategy is still promising. Fig. 2 indeed shows that it performs very well.

As the structure of the random graph changes by using the random rewiring strategy, it is an interesting question whether the giant component’s size in attacked graphs converges to a steady state and if yes, whether there is a phase transition in the size of the largest component in the attacked network controlled by the average degree of the nodes. Although we don’t give a proof for the existence of the phase transition, according to the experimental results shown on Fig. 2 there is also a phase transition in the attacked network, for which the phase transition threshold seems to be different than the standard degree 1 threshold in the random graphs. Further calculations are needed to calculate the exact position of the phase transition.

The random rewiring strategy is efficient, however it is not plausible in real networks. In order to choose a node from the whole network randomly, every single node has to know every other node in the network. This means that the nodes have complete information (almost complete, only the nodes have to be known, the edges don’t) of the whole network which is usually not true in real networks, especially not in peer-to-peer networks. We also investigate other strategies, which are implementable in practice.

B. The greedy rewiring strategy

The second rewiring strategy we’ve analyzed is a local algorithm. Every node is considered having only local information (it knows its neighbors), and behaving greedily, it tries to connect to a good node in its neighborhood. A node is considered good if it has many edges.

More precisely the greedy strategy is defined as follows: the affected node chooses a random neighbor and connects to the best neighbor of it. The best neighbor is the neighbor with the highest degree. If the affected node has no neighbors or second neighbors, the node creates a self loop in order to keep the number of edges constant. The affected nodes reconnect in random order.

This strategy is clearly local and easy to implement in practice. It is trivial however that it is not able to keep the network connected. This is because this strategy
cannot reconnect a network which has fallen into two separate components as the result of an attack. In the steady state the network consists almost exclusively of isolated nodes. For the actual performance, see Fig. 3.

C. The ‘2nd neighbor’ rewiring

The third strategy is motivated by the failure of the local greedy and the success of the global random strategy. This third strategy uses more information than the greedy rewiring, but it is still intended to be local.

The ‘2nd neighbor’ rewiring involves keeping a list of all its second neighbors by every node in the network. This list is used for an affected node to rewire to a former neighbor of the attacked node. After the rewiring, the lists of the nodes are updated.

The performance of the 2nd neighbor strategy is shown on Fig. 4. The plot shows that in the short run this strategy performs quite poorly, there is a steep decrease in the size of the giant component. In the long run however the performance is much better, the size of the largest components starts to increase and although it does not reach the original size in the starting random graph and there are also quite big fluctuations in it, its value is quite high.

According to Fig. 5 the performance of the 2nd neighbor strategy is adequate in the long run. However, it is unclear why this strategy is able to keep the network connected. We do not know what structural property changes in the graph in the decreasing regime, what structural changes initiate the increase, and what kind of network we get in the end. What we believe is the following. The 2nd neighbor strategy restructures the network to be resilient even against targeted attacks. In the first phase of the restructuring, the size of the largest component decreases, but as soon as some structural property is achieved, the largest component will be very resilient to the attacks and remains connected. This strong large component is also able to grow because the new nodes attach to it with significant probability. Still there are some weak parts in this component, which can be broken and separated by the attack, this causes the large fluctuations. In the final phase the network reaches a state of dynamic equilibrium, where new nodes are constantly attached to the large connected component, but also some small parts are broken from it.

Further work is needed to investigate how the structural properties of the network change as a result of the attacks and the rewiring.

It is an interesting question if there is also a phase transition in the networks resulted by the 2nd neighbor strategy by increasing the average degree of the nodes. We’ve addressed this question, and made experiments, for which the results are on Fig. 5. The results show that indeed there might be a phase transition in the system around average degree 2, but more work is needed to prove the existence of the phase transition. If this kind of transition really exists in the system, that means that networks having high enough average node degree and nodes applying the 2nd neighbor rewiring algorithm are very resilient to attacks.

Let us address the question of the amount of information required by the 2nd neighbor rewiring strategy. Clearly, for a single node this is proportional to the number of second neighbors it has. Ideally we want every node to have a constant number of second neighbors, independently of the size of the network; this is how a local...
strategy was defined.

After some exploratory numerical simulations our impression is that for networks without hubs the maximum number of second neighbors grows much slower than the network size, probably as the logarithm of it. For scale-free networks however, as they tend to contain big hubs, the required amount of information for a node is proportional to the size of the whole network.

V. CONCLUSIONS AND FUTURE WORK

In this report we have defined and analyzed a model for describing the effect of attacks on peer-to-peer networks and studying the efficiency of various defense mechanisms for the network. We’ve defined three such mechanisms, the random, greedy and second neighbor rewiring, and conclude that the last one offers fair performance on the long runs and seems to be implementable in practice.

For future work, the most important task lies in quantifying the amount of information needed by the nodes for the application of the 2nd neighbor rewiring strategy in various networks. There are promising results by Newman et al (2001) using generating functions to give the distribution in networks with arbitrary degree distributions. Also, more numerical experiments should be conducted to find out how the number of second neighbors scales with the network size for different networks.

It is also important to discover how the 2nd neighbor algorithm restructures the network, what structural properties change during the first (shrinking largest cluster) and second (growing largest cluster) phase of the simulation.

While to have a connected network is required for the function of the network, sometimes it is not enough and other structural properties are also needed. It is important to examine how the 2nd neighbor algorithm effects these, starting perhaps with the characteristic path length of the network.

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