An Alternative Explanation for the Rise and Fall of MySpace

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ABSTRACT

The rise and fall of online social networks has recently generated an enormous amount of interest among people, both inside and outside of academia. Gillette [Businessweek magazine, 2011] did a detailed analysis of MySpace, which started losing its popularity since 2008. Recently, Cannarella and Spechler [ArXiv, 2014] used a model of disease spread to explain this rise and fall of MySpace. In this paper, we give an alternative explanation for the same. Our explanation is based on the well-known Barabasi-Albert model of generating random scale-free networks using preferential attachment mechanism.

Keywords

MySpace, Preferential attachment, Barabasi-Albert model

1. INTRODUCTION

The last decade has seen the emergence of highly popular online social networks like MySpace, Orkut and Facebook. MySpace was founded in 2003 and it gained its peak popularity in 2008 [6]. However, most of the users have started abandoning it since 2008 [3, 6]. Cannarella and Spechler [3] have modified the SIR model of disease spread [1] to explain this phenomenon. The disease spread model has also been used to study the arrival and departure dynamics of the users in social networks [10].

In this paper, we give an alternative explanation of the rise and fall of MySpace. To begin with, we note that people join social networks due to the presence of their friends in these networks and leave them due to the inactivity of these friends [10]. It is also known that a large number of the social network friendships are not active or strong friendships between the users [5, 7, 8], where a *strong friendship* between a pair of social network friends is indicated by regular communication between them. In fact, the well-known Dunbar's number [4] says that an individual can comfortably maintain a stable relationship with around 150 other

people only. It means that the strong friendships are limited in a social network, even though there is no bound on the number of friends one can have in most social networks.

In order to identify the strong friendships between people in a social network, Onella et. al [9] did an empirical study to establish that greater neighbourhood overlap between a pair of friends corresponds to stronger friendships between them. The *neighbourhood overlap* between a pair of users A and B in a network is defined as the number of nodes who are neighbours of both A and B divided by the number of nodes who are neighbours of at least one of them.

Since strong or active friendships are important for a user to remain in a social network [10], we study the change in the number of users who have at least a certain minimum number of strong friendships in an evolving social network created by the Barabasi-Albert random graph model [2], where we define a pair of users to be strong friends if their neighbourhood overlap is larger than a certain constant.

We also study the change in the size of the largest connected component in the strong friendship subgraph of the evolving Barabasi-Albert random graph. This is motivated by the observation that the nodes in the core of a social network are more likely to survive than the nodes at the periphery [10]. We consider the largest connected component in the strong friendship subgraph of a social network to be its *core* that is important to retain most of its users.

2. MODEL

Our model is based on the well-known Barabasi-Albert model [2] of social networks. The Barabasi-Albert model is an algorithm to generate random scale-free networks based on preferential attachment and growth. The preferential attachment is the property that a node with a higher degree is more likely to get connected to new nodes as the network grows.

Starting with an initial collection of m_0 connected nodes, the Barabasi-Albert algorithm adds one node at a time to the network. Each new node is connected to $m \leq m_0$ existing nodes as follows. The probability that the new node is connected to node i is $\frac{d_i}{\sum_j d_j}$, where d_i is the degree of node i and $\sum_j d_j$ is the sum of the degrees of all the nodes in the current network. The degree distribution resulting out of Barabasi-Albert model follows power law.

Let G_0 be the initial graph with m_0 vertices, and G_t be the random graph after t nodes have been added by the Barabasi-Albert algorithm. For a constant $\epsilon > 0$, we define two users in G_t to be strong friends if their neighbourhood
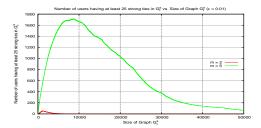
Figure 1: Number of users having at least 25 friends in the strong friendship graph vs. the size of the graph, for $\epsilon = 0.01$.
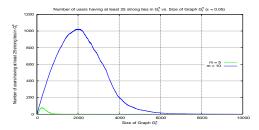

Figure 2: Number of users having at least 25 friends in the strong friendship graph vs. the size of the graph, for $\epsilon = 0.05$.

overlap is more than ϵ. For a given ϵ, the strong friendship subgraph G_t^s of G_t is defined as follows. The graph G_t^s contains the same set of nodes as G_t, and a pair of nodes A and B are connected by an edge in G_t^s if and only if they are connected by an edge in G_t and their neighbourhood overlap w.r.t. G_t is more than ϵ.

3. EXPERIMENTS AND RESULTS

We run our experiments with three different values of ϵ, the threshold for the strong friendship between a pair of users. In each of the cases, we start with a complete graph with $m_0 = m$ vertices, where m is the the number of nodes every new node is connected to. In Figures 1, 2 and 3, we plot the number of the users having at least 25 (25 and 10, respectively) strong friends in G_t^s against the size of the graph G_t^s for a given m and ϵ. In each of these plots, we observe that this number increases till a point before starting to decrease.

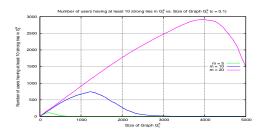In Figures 4, 5 and 6, we plot the size of the largest con-
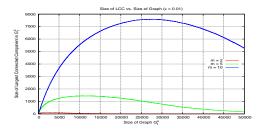

Figure 4: Size of the LCC in the strong friendship graph vs. the size of the graph, for $\epsilon = 0.01$.
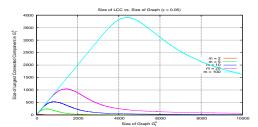

Figure 5: Size of the LCC in the strong friendship graph vs. the size of the graph, for $\epsilon = 0.05$.

nected component (LCC) in G_t^s against the size of the graph G_t^s for a given m and ϵ. In each of these plots, we observe that the size of the largest connected component increases till a point, before it reaches a peak and starts decreasing. Also, the decline is sharper for higher values of ϵ.

4. CONCLUSION

Our observations indicate that one possible explanation for the fall of MySpace is that many of the users started to abandon it after they had a few strong friendships left in the network. Moreover, the remaining users found it difficult to survive as the core of the strong friendship subgraph started reducing in size. Since this might be the effect of preferential attachment where a popular user is likely to befriend a large number of other users, it would be interesting to see whether the same observation doesn't hold for random evolving networks that have a restriction on the number of friends each person can have. It is also an interesting open problem to estimate the size of the network where the plots turn downward, as a function of m and ϵ, for either of the properties mentioned above.

Figure 3: Number of users having at least 10 friends in the strong friendship graph vs. the size of the graph, for $\epsilon = 0.1$.
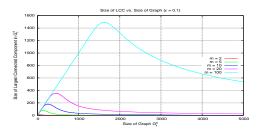

Figure 6: Size of the LCC in the strong friendship graph vs. the size of the graph, for $\epsilon = 0.1$.

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