

A Steady State Model for Graph Power Laws

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Abstract

Power law distribution seems to be an important characteristic of web graphs. Several existing web graph models generate power law graphs by adding new vertices and non-uniform edge connectivities to existing graphs. Researchers have conjectured that preferential connectivity and incremental growth are both required for the power law distribution. In this paper, we propose a different web graph model with power law distribution that does not require incremental growth. We also provide a comparison of our model with several others in their ability to predict web graph clustering behavior.

1 Introduction

The growth of the World Wide Web (WWW) has been explosive and phenomenal. Google [1] has more than 2 billion pages searched as of February 2002. The Internet Archive [2] has 10 billion pages archived as of March 2001. The existing growth-based models [6, 8, 21] are adequate to explain the web's current graph structure. It would be interesting to know if a different model will be needed as the web's growth rate slows down [3] while its link structure continues to evolve.

1.1 Why Power Laws?

Barabási et al. [9, 10] and Medina et al. [24] stated that preferential connectivity and incremental growth are both required for the power law distribution observed in the web. The importance of the preferential connectivity has been shown by several researchers [8, 16].

Faloutsos et al. [15] observed that the internet topology exhibits power law distribution in the form of $y = x^\alpha$. When studying web characteristics, the documents can be viewed as vertices in a graph and the hyper-links as edges between them. Various researchers [7, 8, 19, 22] have independently showed the power law distribution in the degree sequence of the web graphs. Huberman and Adamic [5, 16] showed a power law distribution in the web site sizes. See [20] for a summary of works on web graph structure.

Medina et al. [24] showed that topologies generated by two widely used generators, the Waxman model [32], and the GT-ITM tool [13], do not have power law distribution in their degree sequences. Palmer and Steffan [27] proposed a power law degree generator that recursively partitions the adjacency matrix into an 80-20 distribution. However, it is unclear if their generator actually emulates other web properties.

The power law distribution seems to be an ubiquitous property. The power law distribution occurs in epidemiology [30], population studies [28], genome distribution [17, 29], various social phenomena [11, 26], and massive graphs [4, 6]. For the power law graphs in biological systems, the connectivity changes appear to be much more important than growth in size due to the long time-scale of biological evolution.

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1.2 Properties for Graph Model Comparison

Another important web graph property that has been looked at is diameter. However, there are conflicting results in the published papers. Albert et al. [7] stated that web graphs have the *small world phenomenon* [25,31], in which the diameter Δ is roughly $0.35 + 2.06 \lg n$, where n is the size of the web graph. For $n = 8 \times 10^8$, $\Delta \approx 19$. Lu [23] proved the diameters of random power law graphs are logarithmic function of n under the model proposed by Aiello et al. [6]. However, Broder et al. [12] showed that, over 75% of the time, there is no directed path between two random vertices. If there is a path, the average distance is roughly 16 when viewing web graph as directed graph or 6.83 in the undirected case.

Currently, there are few theoretical graph models [6, 8, 21, 27] for generating power law graphs. There are very few comparative studies that would allow us to determine which of these theoretical models are more accurate models of the web. We only know that the model proposed by Kumar et al. [21] generates more bipartite cliques than other models. They believe clustering to be an important part of web graph structures that was insufficiently represented in previous models [6, 8].

1.3 New Contributions

In this paper, we show power law graphs do not require incremental growth, by developing a graph model which (empirically) results in power laws by evolving a graph according to a Markov process while maintaining constant size and density.

We also describe an easily computable graph property that can be used to capture cluster information in a graph without enumerating all possible subgraphs. We use this property to compare our model with others and with actual web data.

2 Steady State Model

Our *SteadyState* (SS) model is very simple in comparison with other web graph models [6, 8, 21, 27]. It consists of repeatedly removing and adding edges in a sparse random graph G .

Let m be $\Theta(n)$. We generate an initial sparse random graph G with m edges and n vertices, by randomly adding edges between vertices until we have m edges. As discussed below, the initial random distribution of edges is unimportant for our model.

We then iterate the following steps r times on G , where r is a parameter to our model.

1. Pick a vertex v at random. If there is no edge incident upon v , we repeat this step until v has nonzero degree.
2. Pick an edge $(u, v) \in G$ at random.
3. Pick a vertex x at random.
4. Pick a vertex y with probability proportional to degree.
5. If (x, y) is not an edge in G and x is not equal to y , then remove edge (u, v) and add edge (x, y) .

One can view our model as an aperiodic Markov chain with some limiting distribution. If we repeat the above steps long enough, the random graphs generated by this model will be close to this limiting distribution, no matter what the initial random sparse graph is. Note that unlike other models [6, 21], the graphs generated by our model do not contain self-loops nor multiple edges between two vertices.

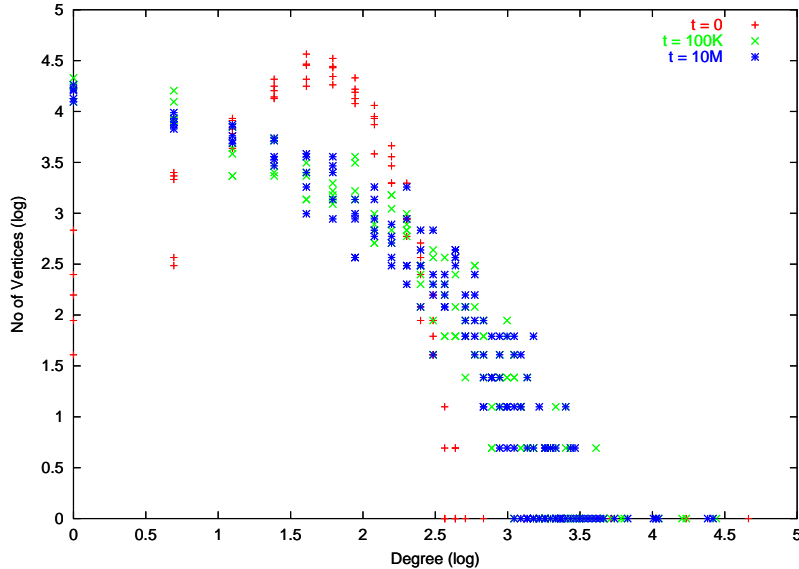


Figure 1: Initial $G(500, 1500)$, & G After 100K and 10M Steps

Barabási et al. [9] also proposed a non-growth model, which failed to produce a power law distribution. Both models have preferential connectivity features. However, there are several differences between our model and theirs. First, our edge set is fixed and the initial graph is generated via classical random graph models [14,18]. Second, our model has “rewiring” feature similar to one in the small world model [9,25,31].

2.1 Simulation Results

We simulated our model on graphs of different sizes, ($500 \leq n \leq 5000$), and densities $\frac{m}{n}$, ($1 \leq \frac{m}{n} \leq 3$). We repeated each simulation 5 times, and performed $r = 10000000$ edge deletion/insertion operations on each graph. The vertices’ degree distributions appear to converge to power law distributions as the number of edge deletion/insertion operations increases. Some of our simulation results are shown in Figures 1 - 4. Figures 1 and 3 show degree distributions at various stage of simulations. Figures 2 and 4 show degree distributions for graphs with different densities $\frac{m}{n}$.

3 Cluster Information

Given a subgraph S of G , $d_S(v)$ is the degree for vertex v in S . Here we examine the maximum degree d_{max} in all subgraphs, which is defined as

$$d_{max} = \max_S \min_{v \in S} d_S(v).$$

We use d_{max}^M to denote the value obtained under graph model M .

To compute d_{max} for a graph G , we perform the following steps until G becomes empty:

1. Select a minimum degree vertex v from G .
2. Set d_{max} to $d(v)$ if $d(v) > d_{max}$.

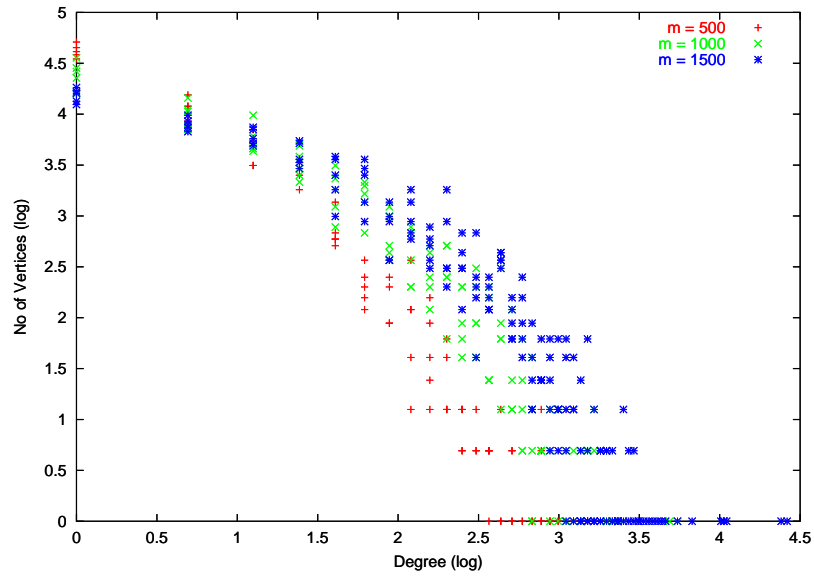


Figure 2: $G(500, 500)$, $G(500, 1000)$, and $G(500, 1500)$ After $10M$ Steps

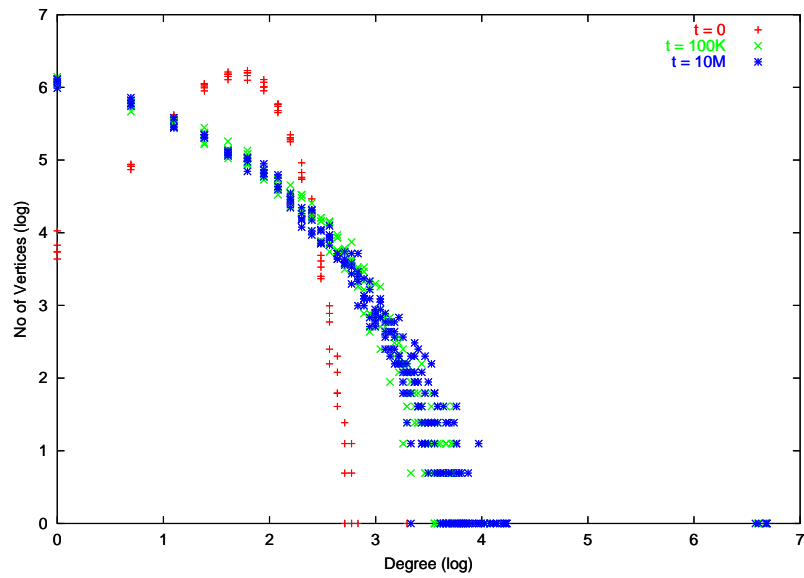


Figure 3: Initial $G(3000, 9000)$, & G After $100K$ and $10M$ Steps

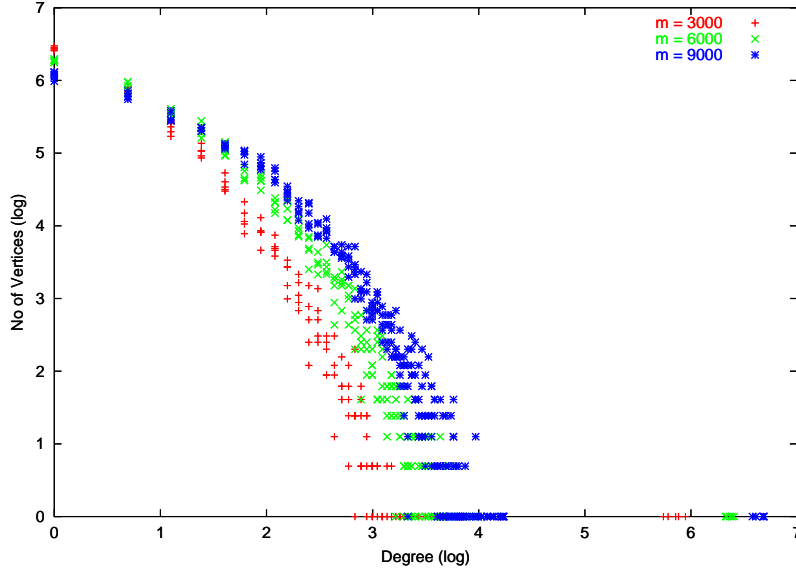


Figure 4: $G(3000, 3000)$, $G(3000, 6000)$, and $G(3000, 9000)$ After $10M$ Steps

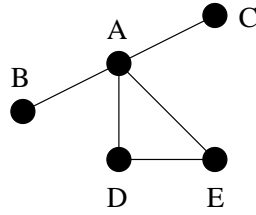


Figure 5: Minimal Degree Vertex Elimination

3. Remove vertex v and its edges from G .

The above steps correctly compute d_{max} because we cannot remove any vertices of S until the degree of the current subgraph reaches d_{max} . The minimal degree elimination sequence for graph in Figure 5 will be B, C, A, D , and E . The degrees when those vertices got eliminated are 1, 1, 2, 1, and 1. d_{max} is 2 since $\max\{1, 1, 2, 1, 1\} = 2$.

Observation 1 For any model M that constructs a graph by adding a vertex at a time, and for which each newly added vertex has the same degree $d = \frac{m}{n}$, $d_{max}^M = d$.

Thus the Barabási and Albert model (BA) [8] or the linear growth copying model in [21] have the same value for d_{max} for graphs of all sizes once $d = \frac{m}{n}$ is fixed.

Observation 2 The web graph generated by the linear model has minimum vertex degree of $d = \frac{m}{n}$.

Hence, the linear model may not encapsulate all the crucial properties in a web graph if there are significant numbers of vertices with degree less than $\frac{m}{n}$.

3.1 Web Crawl and Simulation Data

We performed a web crawl on various Computer Science department web sites. We then used the *ACL* model [6] to generate new graphs from degree sequences in the actual web graphs. We

also ran the *SS* model using n and m values from the actual web graphs with 10000000 edge insertion/deletion steps. For each graph, we run both models 5 times. The following table shows the means μ and the standard deviations σ for d_{max} values using the *ACL* model and the *SS* model.

Site	n	m	d_{max}	μ_{ACL}	σ_{ACL}	μ_{SS}	σ_{SS}
arizona	5315	16892	15	10	0	8	0
berkeley	2826	22957	45	21.6	0.547	16	0
caltech	622	4830	7	5.8	0.447	12.8	0.447
cmu	2052	23821	57	37.2	0.447	20	0.707
cornell	7145	14919	17	19.4	0.547	6	0
harvard	915	9327	21	12.6	0.894	16.4	0.547
mit	4861	15360	31	24.4	0.547	7	0
nd	1913	16328	33	29.2	0.447	15.4	0.547
stanford	2553	25693	27	14.6	0.547	18.4	0.547
ucla	2718	19755	22	16.6	0.547	14.2	0.447
ucsb	5236	10338	22	13.8	0.447	5	0
ucsd	553	3885	15	7.2	0.447	11.8	0.447
uiowa	1410	12258	8	8.8	0.447	15.2	0.447
uiuc	5623	28872	29	21	0	11.8	0.836
unc	1465	5446	17	9.8	0.447	8	0
washington	7001	24901	17	12	0	9	0

Table 1: d_{max} from Actual Web Crawl and Model Simulation

In general, the *ACL* model and the *SS* model are generating less clustered graphs than what we see on actual web graphs. This implies that we need a more detailed model of web graph clustering behavior.

4 Conclusion and Open Problems

Previously, researchers have conjectured that preferential connectivity and incremental growth are necessary factors in creating power law graphs. In this paper, we provide a model of graph evolution that produces power law without growth. Our *SteadyState* model is very simple in comparison with other graph models [21]. It also does not require prior degree sequences as in the *ACL* model [6].

The difficulty in comparing various models [6, 8, 21] is that each model has different parameters and inputs. Here we provide a simple graph property d_{max} that captures the clustering behavior of graphs without complicated subgraph enumeration algorithm. It can be useful in gauging the accuracy of various models.

From our web crawl data, we know that the linear models such as Barabási’s [8] are not the best ones to use when considering d_{max} . Both *ACL* and *SS* models are not generating dense-enough subgraphs when comparing against the actual web graphs. Thus, we need a better web graph model that mimics actual web graph clustering behavior.

Here are some of our open problems:

1. Can one prove theoretically that the *SS* method actually has a power law distribution?
2. How long does it take for our model to reach a steady state?

3. What are other simple web graph properties that we can use to determine the accuracy of various models?
4. Are there any technique such as graph products that we can use to generate realistic massive web graphs in relatively short times?

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