

Networks Out of Control: Real-World Networks 4

Announcement:
 Project Selection

+ Project

Details:

- Pair project
- 4 page (2-column) report due Wednesday 23rd May.
- 15 min presentation + 5 min questions on Monday 28th May to be scheduled between 2pm-7pm.

Contact Farnood with the following by Friday 20 April:

- Who your team is (pairs)
 - In case you do not find a team, respond to the other two points and we will match you with someone
- List of 3 preferred papers, in order, on which you would like to do your project (ties get broken by when the email was sent).
- Availability to present in the 2pm-4pm time slot on Monday.

Real-World Example 1: The Internet Graph

Internet Graph (Virtual Layer)

- Nodes are webpages. (Directed) edges are hyperlinks from one webpage to another.
- Analyze properties of this network as a first step in order to understand efficiency of routing algorithms, vulnerability to attacks on vertices or edges, predicting user behavior, etc.

+ Internet Graph Structure



Internet Graph Structure

- The graph is *directed*, so $uv \in E \Rightarrow vu \in E$
- We say nodes u and v are strongly connected if there is a path from u to v and also a path from v to u.
- A strongly connected component $S \subseteq V$ is a maximal set such that all pairs of vertices in S are strongly connected.

+ Internet Graph Structure



The Bowtie Structure of the Internet

+ Degree Distribution

- Let *D* be the degree of a randomly selected node.
- The degree distribution is: $\mathbb{P}[D = d]$

• G(n,p):
$$\mathbb{P}[D=d] = \begin{pmatrix} n-1 \\ d \end{pmatrix} p^d (1-p)^{n-1-k}$$

• G(n,k):
$$\mathbb{P}[D=d] = \begin{cases} 1 & \text{if } d=k \\ 0 & \text{otherwise} \end{cases}$$

Using the same matching method used for G(n,k), can construct networks with arbitrary degree distributions!

Power Law Degree Distributions

- Degree distributions in the internet graph resemble a power law.
- Let *D* be the degree of a randomly selected node.
 - Power law: $\mathbb{P}[D > d] \sim d^{-\gamma}$
 - Most distributions we have been working with have "light tails":
 - Exponential, Geometric, Gaussian, Poisson, ... $\mathbb{P}[D > d] \sim e^{-\alpha d}$
- Networks with power-law degree distributions are called Scale-Free Networks.
 - In effect, such networks have a large number of "hubs", i.e., vertices of very large degree.

+ Pareto Distribution

The Pareto Distribution:

$$\mathbb{P}[D > d] = \begin{cases} \frac{d}{\beta}^{-\gamma} & \text{if } d \ge \beta \\ 1 & \text{otherwise.} \end{cases}$$

lacksquare The moments of a Pareto distribution only exist up to γ

$$\mathbb{E}[D^{k}] = \begin{cases} \left(\frac{\gamma \cdot \beta}{\gamma - k}^{k}\right) & \text{if } k \leq \gamma \\ \infty & \text{otherwise} \end{cases}$$

+ Examples of Observed Power Laws

- Sizes of cities
- Phone call length
- Wealth & income distribution
- Word frequencies in prose
- Internet graph degree distribution

- If you were new to Switzerland, would you take an apartment in Prevange or Lausanne?
 - More likely Lausanne, because more people are already there
- The "rich-get-richer" phenomena:
 - It is easier to make \$1 when you have \$1,000,000 than when you have \$10.
- Dynamic model.

+ Preferential Attachment

- Directed graph (in the homework will see an undirected version).
- In-degree, denoted by $d_{in}(v)$, measures "popularity" of a node

Preferential Attachment

- Nodes arrive one-by-one and connect one edge to an existing node.
- Probability of connecting to a node is proportional to it's indegree.

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Preferential Attachment

- Nodes arrive one-by-one and connect one edge to an existing node.
- Probability of connecting to a node is
 - With probability α uniformly at random.
 - With probability $1-\alpha$ proportional to it's indegree.

- Let $X_j(t)$ be the number of nodes with in-degree j at time t.
 - Total number of nodes and edges at time t is exactly t

• How does $X_i(t)$ change with time?

 $\mathbb{P}[X_{i}(t+1) = X_{i}(t)+1] =$

 $\mathbb{P}[X_{j}(t+1) = X_{j}(t) - 1] =$

 In general, such stochastic processes are difficult to analyze. Instead of doing it directly, we will use a *continuous mean-field approximation*.

• Assume the mean (i.e., expected) number of nodes at each step $\mathbb{E}[X_j(t+1) - X_j(t)] = \alpha \frac{X_{j-1}(t) - X_j(t)}{t} + (1-\alpha) \frac{(j-1)X_{j-1}(t) - j X_j(t)}{t}.$

- Let X_j(t) be the number of nodes with in-degree j at time t.
 Total number of nodes and edges at time t is exactly t
- How does $X_i(t)$ change with time?

$$\mathbb{P}[X_{j}(t+1) = X_{j}(t) + 1] = \alpha \frac{X_{j-1}(t)}{t} + (1 - \alpha)$$
$$\mathbb{P}[X_{j}(t+1) = X_{j}(t) - 1] = \alpha \frac{X_{j}(t)}{t} + (1 - \alpha) \frac{j \cdot X_{j}(t)}{t}.$$

- In general, such stochastic processes are difficult to analyze. Instead of doing it directly, we will use a *continuous mean-field approximation*.
 - **Take the continuous limit**

$$\frac{dX_{j}(t)}{dt} = \alpha \frac{X_{j-1}(t) - X_{j}(t)}{t} + (1 - \alpha) \frac{(j-1)X_{j-1}(t) - jX_{j}(t)}{t}$$

$$\frac{dX_{j}(t)}{dt} = \alpha \frac{X_{j-1}(t) - X_{j}(t)}{t} + (1 - \alpha) \frac{(j-1)X_{j-1}(t) - jX_{j}(t)}{t}$$

- We can now evaluate this dynamical system, which we can analyze using our standard tools.
- Note that the degree distribution in this case is given by

$$\mathbb{P}[D=d] = \frac{X_d}{t}$$

To sketch the remainder of the proof, assume that the degree distribution converges (this requires proof!), i.e.,

$$\frac{X_d}{t} \to c_d \text{ as } t \to \infty$$

We now just have to solve for c_d

$$\frac{dX_{j}(t)}{dt} = \alpha \frac{X_{j-1}(t) - X_{j}(t)}{t} + (1 - \alpha) \frac{(j-1)X_{j-1}(t) - j X_{j}(t)}{t}$$

• Rearranging the above equation using $c_d = \frac{X_d}{t}$ we get that

$$\frac{c_{j}}{c_{j-1}} = \frac{\alpha + (1-\alpha)(j-1)}{1+\alpha + (1-\alpha)j} = 1 - \frac{2-\alpha}{1+\alpha + (1-\alpha)j}$$

• Using standard approximations for large enough *j*, we get $\frac{c_j}{c_{j-1}} \approx 1 - \frac{2 - \alpha}{1 - \alpha} \cdot j^{-1} \approx \left(1 - \frac{1}{j}\right)^{\frac{2 - \alpha}{1 - \alpha}} \approx \left(\frac{j}{j - 1}\right)^{-\frac{2 - \alpha}{1 - \alpha}}$

• So $c_j \approx j^{-\frac{2-\alpha}{1-\alpha}}$

Power Law vs Lognormal

Power Law:

- Asymptotically like a Pareto Distribution
- Generative Mechanism: "rich-get-richer"

Log-normal Law:

- All moments exist (not heavy-tailed), but "looks like" a power law.
- Generative mechanism: product of many independent random variables (log satisfies the central-limit theorem).
- Long-running controversy.
- More generally preferential attachment is not the only way to get a heavy-tailed distribution.

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Complex Networks

- So far, all the networks we have studied are composed solely of nodes and edges.
 - What if there is additional structure to the network?

- ◆ Affiliation Networks: more than one type of *node*.
 - People and affiliations (e.g., clubs/employers)

- Signed Networks: more than one type of *edge*.
 - Positive and negative edges (e.g., friends and enemies)

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Affiliations

+ Note Types

- Nodes are either "individuals" or "clubs" (also called *foci*).
- ◆ Affiliation Networks: The graph is *bipartite*
 - Edges are only between individuals and clubs.
 - Individuals are (implicitly) linked if they are affiliated with the same club, and clubs are (implicitly) linked if they have the common individuals affiliated with them.
- Social-Affiliation Networks: A social network superimposed with an affiliation network.
 - Edges from individual to club, or from individual to individual (not from club to club)

+ Closure

- Recall from earlier lectures:
 - Clustering coefficient (e.g., fraction of possible triangles) tends to be high in social networks.
 - Triadic closure: "friends of friends" are likely to meet and form an edge.
- Social-Affiliation Networks: Two more kinds of closure can form.
 - Focal closure: Edges between individuals who have a focus in common are likely to form.
 - Membership closure: Edges between an individual and a focus that a friend participates in are likely to form.

(a) Triadic closure

(c) Membership closure

- How much more likely is a link to form between two people in a social network if they have a friend in common?
- How much more likely is a link to form between two people in a social network if have multiple friends in common?

- Empirical Study:
 - Take two snapshots of the network at different points in time.
 - For each k, identify all pairs of nodes that have exactly k friends in common at the first snapshot but are not connected by an edge.
 - Let T(k) be the fraction of pairs that have formed an edge in the second snapshot.

• Empirical Study:

- Take two snapshots of the network at different points in time.
- For each k, identify all pairs of nodes that have exactly k friends in common at the first snapshot but are not connected by an edge.
- Let T(k) be the fraction of pairs that have formed an edge in the second snapshot.

- Mathematical baseline:
 - Suppose that each common friend ads an (independent) probability p of forming a link on a given day.
 - If two people have k friends in common, then the probability that they do not form a link on a given day is (1-p)^k
 - Thus, our baseline probability that it does form is:

$$T_{b}(k) = 1 - (1-p)^{k}$$

 Compare data against T_b(k) and T_b(k-1).

- How much more likely is a link to form between two people in a social-affiliation network if they have a focus in common?
- How much more likely is a link to form between two people in a social-affiliation network if have multiple foci in common?

- How much more likely is a link to form between a person and a focus if they have a friend that has that focus?
- How much more likely is a link to form between a person and a focus if have multiple friends that have that focus?

• Which effect is taking place if Bob and Daniel form an edge?

- Consider an "inferred" social network created from a (bipartite) affiliation network where there is an edge between two nodes in the inferred social network if they are neighbors of the same focus in the affiliation network.
 - Can the same inferred social network arise from different affiliation networks?

+ Signed Networks

+ Signed Networks

Edges have sentiment:

- ◆ In the simplest form, all edges are labeled either + or -
- A triangle in the network is either *balanced* or *unbalanced*.
 - A triangle is balanced if it has either 1 or 3 positive edges.

(b) A is friends with B and C, but they don't get along with each other: not balanced.

(c) A and B are friends with C as a mutual enemy: balanced.

(a) A, B, and C are mutual friends: balanced.

(d) A, B, and C are mutual enemies: not balanced.

 A complete network is balanced if each of its complete triangles are balanced.

• What about non-complete graphs?

• A non-complete graph is balanced if *all missing edges can be added* in a way such that the resulting network is balanced.

• Given an arbitrary (unsigned) network, can one always label the edges such as the resulting signed network is balanced?

- Yes! (e.g., all positive edges).
- Given a signed network, can we give a global characterization of balanced vs unbalanced networks?

- Theorem: A complete graph is balanced if and only if it can be decomposed into sets X and Y as below.
 - Assume we have a complete graph with this structure.
 - Check that any triangle has either 3 positive edges or exactly 1 positive edge.
 - In fact true even without completeness assumption!

- Theorem: A complete graph is balanced if and only if it can be decomposed into sets X and Y as below.
 - Assume we have a balanced complete graph.
 - If no negative edge, put all nodes in set X!
 - Otherwise, pick a vertex A and let X be the set A with all of its friends, and let Y be the set of all of its enemies.
 - Two nodes in X must be friends
 - Two nodes in Y must be friends
 - A node in X and a node in Y must be enemies.
 - True without the completeness assumption?

 Theorem: Any graph is balanced if and only if it can be decomposed into sets X and Y as above.

- Lemma: If a network has a negative cycle of odd length, then it cannot be decomposed into X and Y.
 - Corollary: If it cannot be decomposed into X an Y then it is not balanced (adding edges won't help!).
- Suffices to show: A graph is balanced if and only if it contains no cycle with an odd number of negative edges.
 - We will conduct a process that always either
 - Results in an X/Y decomposition (which implied balancedness from the complete graph theorem), or
 - Results in an odd-length negative cycle (which implies nonbalancedness from the above Corollary.

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