Performance Evaluation

Lecture 1: Complex Networks

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INRIA – EPI Maestro
6 December 2013
Outline

- Properties of Complex Networks
  - Small diameter
  - High Clustering
  - Hubs and heavy tails
- Physical causes
- Consequences
Small Diameter (after Milgram's experiment)

Six degrees - the science of a connected age, 2003

Six degrees of separation is the idea that everyone is on average approximately six steps away, by way of introduction, from any other person in the world, so that a chain of "a friend of a friend" statements can be made, on average, to connect any two people in six steps or fewer.

J. Vaucher, Small World Networks, April 2005
Small Diameter, more formally

- A linear network has diameter N-1 and average distance $\Theta(N)$
  - How to calculate it?
- A square grid has diameter and average distance $\Theta(\sqrt{N})$
- Small Diameter: diameter $O((\log(N))^a)$, $a>0$
- Lessons from model: long distance random connections are enough
Erdös-Rényi graph

- A ER graph $G(N,q)$ is a stochastic process
  - $N$ nodes and edges are selected with prob. $q$
- Purpose: abstract from the details of a given graph and reach conclusions depending on its average features
Erdös-Rényi graph

- A ER graph $G(N,q)$ is a stochastic process
  - $N$ nodes and edges are selected with prob. $q$
  - Degree distribution: $P(d) = \binom{N-1}{d} q^d (1-q)^{N-1-d}$
    - Average degree: $\langle d \rangle = q(N-1)$
    - For $N \to \infty$ and $Nq$ constant: $P(d) = e^{-\langle d \rangle} \langle d \rangle^d / d!$
      - $\langle d^2 \rangle = \langle d \rangle (1 + \langle d \rangle)$
  - Average distance: $\langle l \rangle \approx \log N / \log \langle d \rangle$
    - Small diameter
Clustering

- "The friends of my friends are my friends"

- Local clustering coefficient of node i
  - $(\# \text{ of closed triplets with } i \text{ at the center}) / (\# \text{ of triplets with node } i \text{ at the center}) = (\text{links among } i\text{'s neighbors of node } i) / (\text{potential links among } i\text{'s neighbors})$

- Global clustering coefficient
  - $(\text{total \# of closed triplets}) / (\text{total \# of triplets})$
    - $\# \text{ of closed triplets} = 3 \# \text{ of triangles}$
  - $\text{Or } 1/N \sum_i C_i$

$C_i = 2/(4*3/2) = 1/3$
Clustering

- In ER
  - $C \approx q \approx \langle d \rangle / N$
Clustering

- In real networks

### Table: Clustering Coefficients

<table>
<thead>
<tr>
<th>Network</th>
<th>Size</th>
<th>$\langle k \rangle$</th>
<th>$\ell$</th>
<th>$\ell_{\text{rand}}$</th>
<th>$C$</th>
<th>$C_{\text{rand}}$</th>
<th>Reference</th>
<th>Nr.</th>
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<td>WWW, site level, undir.</td>
<td>153,127</td>
<td>35.21</td>
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<td>Internet, domain level</td>
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<td>3.52–4.11</td>
<td>3.7–3.76</td>
<td>6.36–6.18</td>
<td>0.18–0.3</td>
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<td>Watts and Strogatz, 1998</td>
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<td>Movie actors</td>
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<td>1.8×10^{-4}</td>
<td>Pastor-Satorras et al., 2001</td>
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<td>MEDLINE co-authorship</td>
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<td>E. coli, substrate graph</td>
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<td>Words, synonyms</td>
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<td>Power grid</td>
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<td>C. Elegans</td>
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<td>0.28</td>
<td>0.05</td>
<td>Watts and Strogatz, 1998</td>
<td>15</td>
</tr>
</tbody>
</table>

- Good matching for avg distance
- Bad matching for clustering coefficient
How to model real networks?

Regular Graphs have a high clustering coefficient but also a high diameter.
Random Graphs have a low diameter but a low clustering coefficient.

--> Combine both to model real networks: the Watts and Strogatz model

Regular Graph (k=4)
Long paths
L = n/(2k)
Highly clustered
C = 3/4

Random Graph (k=4)
Short path length
L = log_k N
Almost no clustering
C = k/n

Regular ring lattice

Watts and Strogatz model

Random rewiring of regular graph

With probability $p$ rewire each link in a regular graph to a randomly selected node

Resulting graph has properties both of regular and random graphs

--> High clustering and short path length

Small World

- Usually to denote
  - small diameter + high clustering
Intermezzo: navigation

- In Small world nets there are short paths $O((\log(N))^a)$
- But can we find them?
  - Milgram's experiment suggests nodes can find them using only local information
  - Standard routing algorithms require $O(N)$ information
Kleinberg’s result

- **Model:** Each node has
  - Short-range connections
  - 1 long-range connection, up to distance \( r \) with probability prop. to \( r^{-\alpha} \)
  - For \( \alpha=0 \) it is similar to Watts-Strogatz model: there are short-paths
Kleinberg’s result

- If $\alpha=2$ the greedy algorithm (forward the packet to the neighbor with position closest to the destination) achieves avg path length $O((\log(N))^2)$
Kleinberg's result

- If $\alpha > 2$ no local information algorithm can take advantage of small world properties
- Avg path length $\Omega(N^{\beta/2})$
  - where $\beta = (2 - \alpha)/3$ for $0 \leq \alpha \leq 2$
  - $\beta = (\alpha - 2)/(\alpha - 1)$, for $\alpha > 2$
Kleinberg's result

- **Conclusions**
  - The larger $\alpha$ the less distant long-range contacts move the message, but the more nodes can take advantage of their "geographic structure"
  - $\alpha=2$ achieved the best trade-off
Hubs

- 80/20 rule
  - few nodes with degree much higher than the average
  - a lot of nodes with degree smaller than the average
  - (imagine Bill Clinton enters this room, how representative is the avg income)

- ER with $N=1000$, $\langle d \rangle = 5$, $P(d) \approx e^{-\langle d \rangle} \langle d \rangle^d / d!$
  - #nodes with $d=10$: $N \times P(10) \approx 18$
  - #nodes with $d=20$: $N \times P(20) \approx 2.6 \times 10^{-4}$
Hubs

Power law:

$P(d) \sim d^{-\alpha}$
Power law degree distributions

coauthorship
... and more

Deaths in terrorist attacks

Pr(X≥x)

Severity (deaths), x

Pr(X>x)

10⁻⁵

10⁻⁴

10⁻³

10⁻²

10⁻¹

10⁰

10¹

10²

10³

10⁴

Meme popularity

Breadth of user attention

Daily

Weekly

Monthly

eme on Twitter
Power Law

Where does it come from?

- Albert-Barabasi’s growth model
- Highly Optimized Model
- And other models
  - See Michael Mitzenmacher, A Brief History of Generative Models for Power Law and Lognormal Distributions
Albert-Barabasi’s model

- Two elements
  - Growth
    - $m_0$ initial nodes, every time unit we add a new node with $m$ links to existing nodes
  - Preferential attachment
    - The new node links to a node with degree $k_i$ with probability

$$
\Pi(k_i) = \frac{k_i}{\sum_{j=1}^{N} k_j}
$$
Albert-Barabasi’s model

Node i arrives at time $t_i$, its degree keeps increasing

With a continuum approximation:

$$\frac{\partial k_i}{\partial t} = \frac{m k_i}{\sum_{j=1}^{N} k_j} = \frac{m k_i}{2tm} = \frac{k_i}{2t} \rightarrow k_i(t) = m\left(\frac{t}{t_i}\right)^\beta, \beta = \frac{1}{2}$$

Then degree distribution at time $t$ is:

$$P(k_i(t) < k) = P(t_i > t \frac{m^{1/\beta}}{k^{1/\beta}})$$
Albert-Barabasi’s model

At time $t$ there are $m_0 + t$ nodes, if we consider that the $t$ nodes are added uniformly at random in $[0, t]$, then

$$P(t_i > x) = \frac{t - x}{t + m_0}$$

$$P(k_i(t) < k) = \frac{t}{t + m_0} \left(1 - \frac{m^{1/\beta}}{k^{1/\beta}}\right)$$
Albert-Barabasi’s model

- The PDF is

$$P(k_i(t) = k) = \frac{\partial P(k_i(t) \leq k)}{\partial k} = \frac{t}{t + m_0} \frac{1}{\beta} \frac{m^{1/\beta}}{k^{1/\beta+1}}$$

- For $t \to \infty$

$$P(k_i(t) = k) \xrightarrow{t \to \infty} \frac{1}{\beta} \frac{m^{1/\beta}}{k^{1/\beta+1}} \propto k^{-\gamma}, \quad \gamma = 3$$
Albert-Barabasi’s model

- **If** \( \Pi(k_i) \propto a + k_i \), \( P(k) \propto k^{-\gamma} \), \( \gamma = 3 + \frac{a}{m} \)

- **Other variants:**
  - With fitness \( \Pi(k) = \frac{\eta_i k_i}{\sum_{j=1,N} \eta_j k_j} \)
  - With rewiring (a prob. \( p \) to rewire an existing connection)
  - Uniform attaching with "aging": A vertex is deactivated with a prob. proportional to \( (k_i+a)^{-1} \)