# **Network Models**

Thanks to Jure Leskovec, Stanford and Panayiotis Tsaparas, Univ. of Ioannina for slides



- Erdös-Renyi Random Graph Model
- The Small-World Model
- The Configuration Model

Erdös-Renyi Random Graph Model

# **Simplest Model of Graphs**

- Erdös-Renyi Random Graphs [Erdös-Renyi, '60]
   Two variants:
  - G<sub>n,p</sub>: undirected graph on n nodes and each edge (u,v) appears i.i.d. with probability p
  - $G_{n,m}$ : undirected graph with *n* nodes, and *m* uniformly at random picked edges

# What kinds of networks does such model produce?

# **Random Graph Model**

#### n and p do not uniquely determine the graph!

The graph is a result of a random process

 We can have many different realizations given the same *n* and *p*



# Random Graph Model: Edges

- How likely is a graph on E edges?
- P(E): the probability that a given  $G_{np}$  generates a graph on exactly E edges:

$$P(E) = \begin{pmatrix} E_{\max} \\ E \end{pmatrix} p^{E} (1-p)^{E_{\max}-E}$$

where  $E_{max} = n(n-1)/2$  is the maximum possible number of edges in an undirected graph of *n* nodes

Normal p.d.f



# Degree distribution:P(k)Path length:hClustering coefficient:C

What are values of these properties for *G<sub>np</sub>*?

## Node Degrees in a Random Graph

#### What is expected degree of a node?

- Let  $X_v$  be a rnd. var. measuring the degree of node v
- We want to know:  $E[X_v] = \sum_{i=0}^{n-1} j P(X_v = j)$ 
  - For the calculation we will need: Linearity of expectation
    - For any random variables  $Y_1, Y_2, ..., Y_k$
    - If  $Y = Y_1 + Y_2 + ... Y_k$ , then  $E[Y] = \sum_i E[Y_i]$

#### An easier way:

- Decompose  $X_v$  to  $X_v = X_{v,1} + X_{v,2} + ... + X_{v,n-1}$ 
  - where X<sub>v,u</sub> is a {0,1}-random variable which tells if edge (v,u) exists or not

$$E[X_{v}] = \mathop{a}\limits^{n-1}_{u=1} E[X_{vu}] = (n-1)p$$

#### How to think about this?

- Prob. of node *u* linking to node *v* is *p*
- *u* can link (flips a coin) to all other (*n*-1) nodes
- Thus, the expected degree of node u is: p(n-1)

# **Degree Distribution**

Fact: Degree distribution of G<sub>np</sub> is <u>Binomial</u>.
Let P(k) denote a fraction of nodes with degree k:





Mean, variance of a binomial distribution

$$\overline{k} = p(n-1)$$

$$S^2 = p(1 - p)(n - 1)$$



By the law of large numbers, as the network size increases, the distribution becomes increasingly narrow—we are increasingly confident that the degree of a node is in the vicinity of k.

1/17/2017

Jure Leskovec, Stanford CS224W: Social and Information Network Analysis, http://cs224w.stanford.edu

# Clustering Coefficient of G<sub>np</sub>

• Remember: 
$$C_i = \frac{2e_i}{k_i(k_i - 1)}$$

Where e<sub>i</sub> is the number of edges between i's neighbors

• Edges in  $G_{np}$  appear i.i.d. with prob. p

So: 
$$e_i = p \frac{k_i(k_i - 1)}{2}$$
  
Each pair is connected  
with prob.  $p$   
Number of distinct pairs of  
neighbors of node  $i$  of degree  $k_i$   
Then:  $C_i = \frac{p \cdot k_i(k_i - 1)}{k_i(k_i - 1)} = p = \frac{\overline{k}}{n-1} \approx \frac{\overline{k}}{n}$ 

Clustering coefficient of a random graph is small. For a fixed avg. degree (that is p=1/n), C decreases with the graph size n.

# Network Properties of G<sub>np</sub>

#### **Degree distribution:**

# **Clustering coefficient:**

$$P(k) = \binom{n-1}{k} p^{k} (1-p)^{n-1-k}$$
$$C = p = \overline{k}/n$$

Path length:

# Def: Random k-Regular Graphs

- We need to define two concepts
- 1) Define: Random k-Regular graph
  - Assume each node has k spokes (half-edges)
  - Randomly pair them up!
- 2) Define: Expansion
  - Graph G(V, E) has expansion α:
     if ∀ S ⊆ V: #edges leaving S
    - $\geq \alpha \cdot \min(S/, V \setminus S/)$
  - Or equivalently:

$$\alpha = \min_{S \subseteq V} \frac{\# edges \ leaving \ S}{\min(|S|, |V \setminus S|)}$$



# Def: Random k-Regular Graphs

- To prove the diameter of a G<sub>np</sub> we define few concepts
   Define: Random k-Regular graph
  - Assume each node has k spokes (half-edges)
    - k=1:

Graph is a set of cycles

Graph is a set of pairs



Arbitrarily complicated graphs

• k=2:

# **Expansion: Intuition**



# $\alpha = \min_{S \subseteq V} \frac{\# edges \ leaving \ S}{\min(|S|, |V \setminus S|)}$

#### (A big) graph with "good" expansion

# **Expansion: Measures Robustness**

 $\alpha = \min_{S \subseteq V} \frac{\#edges \ leaving \ S}{\min(| \ S |, |V \setminus S |)}$ 

- Expansion is measure of robustness:
  - To disconnect l nodes, we need to cut  $\geq \alpha \cdot l$  edges
- Low expansion:



High expansion:



- Social networks:
  - "Communities"



# **Expansion: k-Regular Graphs**

- k-regular graph (every node has degree k):
  - Expansion is at most k (when S is a single node)
- Is there a graph on *n* nodes  $(n \rightarrow \infty)$ , of fixed max deg. *k*, so that expansion  $\alpha$  remains const?

#### **Examples:**

- **n×n grid:**  $k=4: \alpha = 2n/(n^2/4) \rightarrow 0$ (S=n/2 × n/2 square in the center)
- Complete binary tree:  $\alpha \rightarrow 0$  for /S/=(n/2)-1



Make this into 6x6 grid!

*#edges leaving S* 

 $\min(|S|, |V \setminus S|)$ 

 $\alpha = \min$ 



Fact: For a random 3-regular graph on n nodes, there is some const α (α >0, independent. of n) such that w.h.p. the expansion of the graph is ≥ α (In fact, α=d/2 as d→∞)

# Diameter of 3-Regular Rnd. Graph

- Fact: In a graph on *n* nodes with expansion *α*, for all pairs of nodes *s* and *t* there is a path of O((log n) / α) edges connecting them.
   Proof:
  - Proof strategy:
    - We want to show that from any node s there is a path of length O((log n)/α) to any other node t
  - Let S<sub>j</sub> be a set of all nodes found within j steps of BFS from s.

#### How does S<sub>i</sub> increase as a function of j?



# Diameter of 3-Regular Rnd. Graph

#### Proof (continued):

Let S<sub>j</sub> be a set of all nodes found within j steps of BFS from s.

Expansion

We want to relate S<sub>i</sub> and S<sub>i+1</sub>

 $\left|S_{j+1}\right| \geq \left|S_{j}\right| + \frac{\alpha \left|S_{j}\right|}{I_{r}} =$ 





 $\left|S_{j+1}\right| \ge \left|S_{j}\right| \left(1 + \frac{\alpha}{k}\right) = S_{0} \left(1 + \frac{\alpha}{k}\right)^{j+1}$ 

At most k edges

"collide" at a node

where  $S_0 = I$ 

# Diameter of 3-Regular Rnd. Graph

#### Proof (continued):

- In how many steps of BFS do we reach >n/2 nodes?
- Need j so that:  $S_j = \left(1 + \frac{\alpha}{k}\right)^j \ge \frac{n}{2}$

• Let's set: 
$$j = \frac{k \log_2 n}{\alpha}$$

Then:

$$\left(1+\frac{\alpha}{k}\right)^{\frac{k\log_2 n}{\alpha}} \ge 2^{\log_2 n} = n > \frac{n}{2}$$

In 2k/α·log n steps /S<sub>j</sub>/ grows to Θ(n).
 So, the diameter of G is O(log(n)/ α)



Claim: 
$$\left(1 + \frac{\alpha}{k}\right)^{\frac{k \log_2 n}{\alpha}} \ge 2^{\log_2 n}$$

 $e = \lim_{x \to \infty} \left( 1 + \frac{1}{r} \right)^{x}$ 

Remember n > 0,  $\alpha \le k$  then: if  $\alpha = k : (1+1)^{\frac{1}{1}\log_2 n} = 2^{\log_2 n}$ if  $\alpha \to 0$  then  $\frac{k}{\alpha} = x \to \infty$ : and  $\left(1 + \frac{1}{x}\right)^{x\log_2 n} = e^{\log_2 n} > 2^{\log_2 n}$ 

# Network Properties of G<sub>np</sub>

#### **Degree distribution:**

# **Clustering coefficient:**

# $P(k) = \binom{n-1}{k} p^{k} (1-p)^{n-1-k}$

$$C=p=k/n$$

## Path length:

 $O(\log n)$ 



Paul Erdös

# $G_{np}$ is so cool! Let's also look at its evolution

# "Evolution" of a Random Graph

#### • Graph structure of $G_{np}$ as p changes:



Emergence of a Giant Component: avg. degree k=2E/n or p=k/(n-1)

- $k=1-\varepsilon$ : all components are of size  $\Omega(\log n)$
- $k=1+\varepsilon$ : 1 component of size  $\Omega(n)$ , others have size  $\Omega(\log n)$

# **G**<sub>np</sub> Simulation Experiment





Fraction of nodes in the largest component

• 
$$G_{np}$$
, *n*=100,000, *k*=*p*(*n*-1) = 0.5 ... 3

# Back to MSN vs. G<sub>np</sub>



# Real Networks vs. G<sub>np</sub>

#### Are real networks like random graphs?

- Average path length: ③
- Giant connected component: <sup>(C)</sup>
- Clustering Coefficient: S

#### Problems with the random network model:

- Degreed distribution differs from that of real networks
- Giant component in most real networks does NOT emerge through a phase transition
- No "local" structure clustering coefficient is too low

#### Most important: Are real networks random?

The answer is simply: NO!

# Real Networks vs. G<sub>np</sub>

#### If G<sub>np</sub> is wrong, why did we spend time on it?

- It is the reference model for the rest of the class
- It will help us calculate many quantities, that can then be compared to the real data
- It will help us understand to what degree is a particular property the result of some random process

#### So, while G<sub>np</sub> is WRONG, it will turn out to be extremly USEFUL!

# The Small-World Model

Can we have high clustering while also having short paths?



# **Six Degrees of Kevin Bacon**

# Origins of a small-world idea:The Bacon number:

- Create a network of Hollywood actors
- Connect two actors if they co-appeared in the movie
- Bacon number: number of steps to Kevin Bacon
- As of Dec 2007, the highest (finite) Bacon number reported is 8
- Only approx. 12% of all actors cannot be linked to Bacon



Elvis Presley has a Bacon number of 2.





Find out your Erdos number: http://www.ams.org/mathscinet/collaborationDistance.html

# **The Small-World Experiment**

- What is the typical shortest path length between any two people?
  - Experiment on the global friendship network
    - Can't measure, need to probe explicitly
- Small-world experiment [Milgram '67]
  - Picked 300 people in Omaha, Nebraska and Wichita, Kansas
  - Ask them to get a letter to a stock-broker in Boston by passing it through friends
- How many steps did it take?





# **The Small-World Experiment**

#### 64 chains completed:

(i.e., 64 letters reached the target)

It took 6.2 steps on the average, thus
 "6 degrees of separation"

#### Further observations:

- People who owned stock had shorter paths to the stockbroker than random people: 5.4 vs. 6.7
- People from the Boston area have even closer paths: 4.4



# **Milgram: Further Observations**

- Boston vs. occupation networks:Criticism:
  - Funneling:
    - 31 of 64 chains passed through 1 of 3 people as their final step → Not all links/nodes are equal
  - Starting points and the target were non-random
  - There are not many samples (only 64)
  - People refused to participate (25% for Milgram)
    - Not all searches finished (only 64 out of 300)
  - Some sort of social search: People in the experiment follow some strategy instead of forwarding the letter to everyone. They are not finding the shortest path!
  - People might have used extra information resources





# **Two Questions**

(Today) What is the structure of a social network?

<u>(offline)</u> What kind of mechanisms do people use to route and find the target?



# 6-Degrees: Should We Be Surprised?

- Assume each human is connected to 100 other people Then:
  - Step 1: reach 100 people
  - Step 2: reach 100\*100 = 10,000 people
  - Step 3: reach 100\*100\*100 = 1,000,000 people
  - Step 4: reach 100\*100\*100\*100 = 100M people
  - In 5 steps we can reach 10 billion people
- What's wrong here?
  - 92% of new FB friendships are to a friend-of-a-friend [Backstom-Leskovec '11]





Jure Leskovec, Stanford CS224W: Social and Information Network Analysis, http://cs224w.stanford.edu

# **Clustering Implies Edge Locality**

 MSN network has 7 orders of magnitude larger clustering than the corresponding G<sub>np</sub>!
 Other examples:

Actor Collaborations (IMDB): N = 225,226 nodes, avg. degree  $\overline{k} = 61$ Electrical power grid: N = 4,941 nodes,  $\overline{k} = 2.67$ Network of neurons: N = 282 nodes,  $\overline{k} = 14$ 

Network	$\mathbf{h}_{actual}$	$h_{random}$	$C_{actual}$	<b>C</b> <sub>random</sub>
Film actors	3.65	2.99	0.79	0.00027
Power Grid	18.70	12.40	0.080	0.005
C. elegans	2.65	2.25	0.28	0.05

- h ... Average shortest path length
- C ... Average clustering coefficient
- "actual" ... real network
- "random" ... random graph with same avg. degree

# The "Controversy"

#### Consequence of expansion:

#### Short paths: O(log n)

- This is "best" we can do if we have a constant degree
- But clustering is low!
- But networks have "local" structure:
  - Triadic closure:

Friend of a friend is my friend

 High clustering but diameter is also high

#### How can we have both?



Low diameter Low clustering coefficient



High clustering coefficient High diameter

# Small-World: How?

- Could a network with high clustering be at the same time a small world?
  - How can we at the same time have high clustering and small diameter?





- Clustering implies edge "locality"
- Randomness enables "shortcuts"

[Watts-Strogatz, '98]

# Solution: The Small-World Model

#### **Small-world Model [Watts-Strogatz '98]** Two components to the model:

- (1) Start with a low-dimensional regular lattice
  - (In our case we using a ring as a lattice)
  - Has high clustering coefficient
- Now introduce randomness ("shortcuts")

#### (2) Rewire:

- Add/remove edges to create shortcuts to join remote parts of the lattice
- For each edge with prob. p move the other end to a random node



#### [Watts-Strogatz, '98]

# **The Small-World Model**



## Rewiring allows us to "interpolate" between a regular lattice and a random graph

# **The Small-World Model**



Jure Leskovec, Stanford CS224W: Social and Information Network Analysis, http://cs224w.stanford.edu

# **Diameter of the Watts-Strogatz**

#### Alternative formulation of the model:

- Start with a square grid
- Each node has 1 random long-range edge
  - Each node has 1 spoke. Then randomly connect them.



$$C_i = \frac{2 \times e_i}{k_i (k_i - 1)} = \frac{2 \times 12}{9 \times 8} \ ^3 \ 0.33$$

There are already 12 triangles in the grid and the long-range edge can only close more.

What's the diameter? It is O(log(n))Why?

# **Diameter of the Watts-Strogatz**

#### Proof:

- Consider a graph where we contract 2x2 subgraphs into supernodes
- Now we have 4 edges sticking out of each supernode
  - 4-regular random graph!
- From Thm. we have short paths between super nodes
- We can turn this into a path in a real graph by adding at most 2 steps per long range edge (by having to traverse internal nodes)
- $\Rightarrow \text{Diameter of the model is} \\ O(2 \log n)$



4-regular random graph

# Small-World: Summary

- Could a network with high clustering be at the same time a small world?
  - Yes! You don't need more than a few random links
- The Watts Strogatz Model:
  - Provides insight on the interplay between clustering and the small-world
  - Captures the structure of many realistic networks
  - Accounts for the high clustering of real networks
  - Does not lead to the correct degree distribution
  - Does not enable navigation (offline lecture)

## How to Navigate a Network?

#### • (offline) What mechanisms do people use to navigate networks and find the target?



# The Configuration Model

# Intermezzo: Configuration Model

Goal: Generate a random graph with a given degree sequence k<sub>1</sub>, k<sub>2</sub>, ... k<sub>N</sub>
 Configuration model:



#### Useful as a "null" model of networks

We can compare the real network G and a "random" G' which has the same degree sequence as G