

A discussion of 'Statistical Mechanics of Complex Networks' Part I

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Introduction

Key Concepts

Small Word Networks

Clustering Coefficient

Scale-Free Networks

Case Studies

Random Graph Theory

Erdős-Rényi model

Conclusions

Introduction

- ▶ cover only parts I, II, and IIIa (pages 1-9)
- ▶ more questions than answers...

Small World Networks

What is a small-world network?

- ▶ “relatively short” path between any two nodes
- ▶ ”six degrees of separation”
- ▶ *distance* \equiv the shortest path between two nodes
- ▶ *diameter* of graph \equiv longest distance between any two nodes
- ▶ no hard definition, but diameter similar to random graph ($\sim \ln N$)

Clustering Coefficient

How well do your friends know each other?

- ▶ a metric between 0.0 and 1.0
- ▶ ratio of edges (E_i) over maximum possible (complete subgraph)

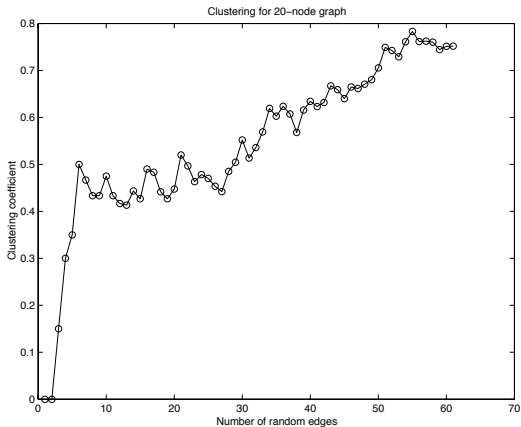
- ▶ for each node : $C_i \equiv E_i / \binom{k_i}{2} = \frac{2E_i}{k_i(k_i-1)}$

- ▶ for graph, take average over nodes $C = \frac{1}{N} \sum_{i=1}^N C_i$

Can be interpreted as

- ▶ the probability that two neighbor nodes are connected ($p = C_i$)

Clustering Coefficient Simulations



Clustering Coefficient Observations

Metric is convenient to define, but

- ▶ $C = 1$ does NOT imply that graph is completely connected
- ▶ $C = 0$ does NOT imply that all nodes are isolated
- ▶ C is NOT monotonic as more edges are added (!)

Shortcomings

- ▶ doesn't understand the notion of “components”
- ▶ uses only one “generation” of information
- ▶ “all-or-nothing” metric may be too crude (?)

Is this what we really want to measure . . . ?

Weird Clustering Examples

- ▶ a collection of isolated 3-cycles has $C = 1$
- ▶ a n -dimensional grid has $C = 0$, although $k = 2n$
- ▶ example of graph where adding more edges **lowers** C
 - ▶ take two disconnected subgraphs and bridge them

Clustering Examples

Consider a graph with N vertices arranged in

- ▶ 1-d ring: $k=2$, $d(G) = N/2$, $C = 0$ ¹
- ▶ 2-d grid: $k=4$, $d(G) = \sqrt{2N}$, $C = 0$
- ▶ 3-d cube: $k=6$, $d(G) = \sqrt{3} N^{1/3}$, $C = 0$
- ▶ ...
- ▶ n-d hypercube: $k=2n$, $d(G) = \sqrt{n} N^{1/n}$, $C = 0$

Is the last considered a small-world network?

¹This is why Watts-Strogatz used a 1-d ring with 4 nearest neighbors to bump up C to $3/4$.

Scale-Free Networks

Degree distributions

- ▶ not all nodes have same degree
- ▶ distribution function $P(k)$ denotes probability that random node has k edges
- ▶ for random graphs, this is a Poisson distribution with a peak at $\langle k \rangle$ with value $P(\langle k \rangle)$
- ▶ for some real networks, the tail of $P(k)$ follows a power-law distribution:
 - ▶ $P(k) \sim 1/k^\gamma$ for $1 < \gamma < 3$
- ▶ other real networks exhibit exponential tails
- ▶ graphs with $P(k)$ different than Poisson distribution are termed "scale-free"

Issues with Scale-Free Networks

- ▶ no hard definition
- ▶ why the big fuss? Because physics has properties with power-law tails... (statistical mechanics)
- ▶ where does the cut-off for k take effect...?
- ▶ the "tail" has tiny portion of nodes... is it really that relevant?

Complex Network Cheat Sheet

	Random Graphs	“Real” Graphs
small-world	YES $d(G) \sim \ln(N)$	YES $d(G) \sim d(G_{random})$
clustering coeff	LOW $(C = p) \ll 0.01$	HIGH ~ 1.0
scale-free	NO Poisson dist.	YES $P(k) \sim 1/k^\gamma$ for $1 < \gamma < 3$

Complex Network Cheat Sheet

	Random Graphs	"Real" Graphs	n -d lattices
<i>structure</i>	NO	YES (?)	YES
small-world	YES $d(G) \sim \ln(N)$	YES $d(G) \sim d(G_{random})$	NO (?) $d(G) \sim N^{1/n}$
clustering coeff	LOW $(C = p) \ll 0.01$	HIGH ~ 1.0	0.0 $2n$ neighbors
scale-free	NO Poisson dist.	YES $P(k) \sim 1/k^\gamma$ for $1 < \gamma < 3$	YES $P(2n) = 1, 0$ otherwise

Cases Studied

- ▶ WWW
- ▶ Internet
- ▶ movie actors
- ▶ science collaboration
- ▶ STDs
- ▶ cellular networks
- ▶ ecological networks
- ▶ phone call network
- ▶ citation networks
- ▶ linguistic networks
- ▶ power grid and neural nets
- ▶ protein folding

WWW Studies

- ▶ at various levels (internet domain, site level, hyperlinks)
- ▶ at the hyperlink level:
 - ▶ largest network studied (2002)
 - ▶ **directed** graph, very **unsymmetric** ($k_{out} \ll k_{in}$)
 - ▶ both $P_{out}(k)$ and $P_{in}(k)$ have power-law tails
 - ▶ with $\gamma_{out} \sim 2.5 \pm 0.25$ and $\gamma_{in} = 2.1$
- ▶ Adamic (1999) computed clustering coefficients by making each edge bidirectional (!)
- ▶ Faloutsos (1999): an edge is drawn between two domains if there is at least one route that connects them (!)

Movie Actor Collaboration Network

Hooray for IMDb.com!

- ▶ Size: half a million actors (!) in 2000
- ▶ two actors have an edge if they worked together on a film
- ▶ model does not take into account weighted edges (such as # of films worked on together)
- ▶ average distance is close to that of random graph

Observations of Table I

- ▶ key values:
 - ▶ size (N)
 - ▶ average degree ($\langle k \rangle$)
 - ▶ average distance (ℓ)
- ▶ $C \gg C_{rand}$
- ▶ $\ell \approx \ell_{rand}$

Things to look at:

- ▶ scatter plot of C vs. how "dense" the graph is ($\langle k \rangle / N$)
- ▶ scatter plot of density vs. ℓ / ℓ_{rand}

Observations of Table II

- ▶ $\gamma_{in} = 2.1$ is quite popular...
- ▶ $1 < \gamma < 3$ for both γ_{in} and γ_{out}
- ▶ \mathbf{k} (cut-off) seems pretty high, compared to $\langle k \rangle$
- ▶ ℓ_{power} is not as good an estimator as ℓ_{rand} ...

Random Graph Models

Erdős-Rényi (1959)

- ▶ N nodes, n edges, chosen randomly from $\binom{N}{2}$ possibilities

Binomial Model

- ▶ N nodes, every edge has p probability
- ▶ actual # of edges is a random variable
 - ▶ Poisson distribution with expected value $p\binom{N}{2}$
- ▶ with $p = n / \binom{N}{2}$ this is **similar** to Erdős-Rényi, but is it the same?

Graph Enumeration

An undirected graph with N vertices,

- ▶ has $M \equiv \binom{N}{2} = N(N-1)/2$ possible edges
- ▶ # of graphs with exactly n edges, is $\binom{N(N-1)/2}{n} = \mathbf{HUGE!}$

Graph Enumeration

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Given

- ▶ $\binom{M}{n} \equiv \frac{M!}{n!(M-n)!}$
- ▶ *Stirling's approximation*: $\ln n! \approx n(\ln n - 1)$, for large N

Graph Enumeration Examples

Name	Vertices	$\langle k \rangle$	# graphs
	10	1	3×10^9
	100	1	$\sim 10^{211}$
	1,000	1	$\sim 10^{3,132}$
	10,000	1	$\sim 10^{41,332}$
math authors	70,975	3.9	$\sim 10^{1,200,000}$
movie actors	225,226	61	$\sim 10^{50,000,000}$

If every atom in the universe ($\sim 10^{80}$) was a Petaflop computer, computing since the beginning of time (13 billion years ago) you would just need 10^{100} such universes to enumerate the (100, $\langle 1 \rangle$) case...

Do we really know the landscape?

HELP!

- ▶ we are looking at only tiny microcosm of graph space for simulations
- ▶ how robust are our conclusions?
- ▶ importance sampling (?)
- ▶ concern with 1-d parameterization ala Watts-Strogatz...
- ▶ what if we made random changes to a "real" network? How long before it starts losing its "realness"?
- ▶ would any of these metrics help...?

Conclusions and Discussion

- ▶ is “small-world” really relevant...? (social networks rarely interact beyond three links...)
- ▶ not clear if current metrics really capture the right thing...
 - ▶ given $(N, C, \langle k \rangle, \gamma, \ell)$ what can one say about a network?
- ▶ introduce new(?) metrics that better recognize components and structure
 - ▶ cluster coefficient should be extended for weighted, bidirectional graphs
- ▶ power-tail distribution model needs high cut-off values for k
 - ▶ what percentage of the available nodes **is** this?

Conclusions ...?

Why is this so hard...?

- ▶ because we are trying to **theoritize arbitrary structure** ...