

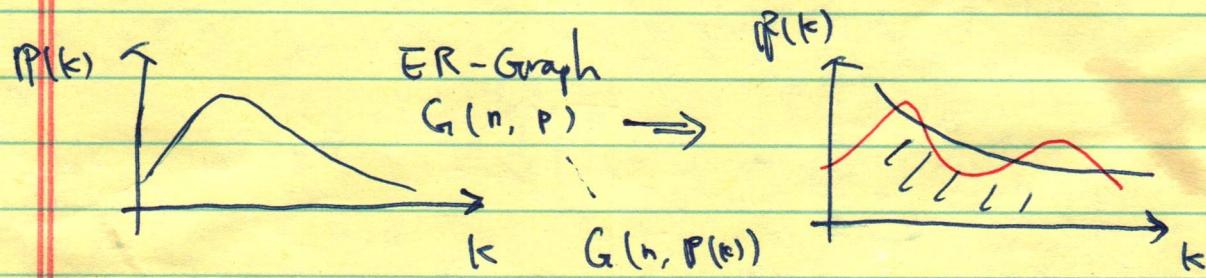
①

we still follow normal order, i.e., $\textcircled{1} \rightarrow \textcircled{2} \rightarrow \textcircled{3} \dots$
 $\underline{\underline{\text{not}}} \quad \textcircled{1} \rightarrow (\star_1) \rightarrow (\star_2) \rightarrow \textcircled{2} \rightarrow \textcircled{3}$

Lecture 4 - 1

Feb 6, 2024.

} Random Graphs — w/ heterogeneous degrees.



the configuration model $G(n, \{k_i\})$

} specified degrees
 (k_1, k_2, \dots, k_n)

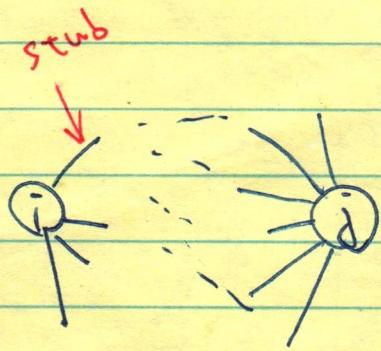
see
 $(*)$

$$\text{Hijj } A_{ij} = A_{ji} = \begin{cases} 1 & \text{w/ prob } \propto k_i k_j \\ 0 & \text{otherwise} \end{cases}$$

Ask: Can the empirical value of some ~~measure~~ measure $x = f(G)$ be explained by the observed deg structure ?
 (and randomness)

more
down

(2)

 k_i k_j

$$\forall i \neq j \quad A_{ij} = A_{ji} = \begin{cases} 1 & \text{w/ prob } \frac{k_i k_j}{2m} \\ 0 & \text{else} \end{cases}$$

Two ways to choose $\{k_i\}$

① from prob distri., k_i like $\text{Exp}(\lambda)$,

$\text{lognormal}(\mu, \sigma)$

$\text{Poisson}(\lambda)$

Power-law (α)

- math fun

$\langle k \rangle, \langle k^2 \rangle, \langle k^3 \rangle$

generating functions.

② From an empirical network.

computation.

- inference prob!

B_{ij}

Picture

((4 graph spaces
↓ draw

((8 graph spaces)

Configuration*
Molloy-Reed*
Chay-Law

graph simplification math

Generating a config. model graph:

(3)

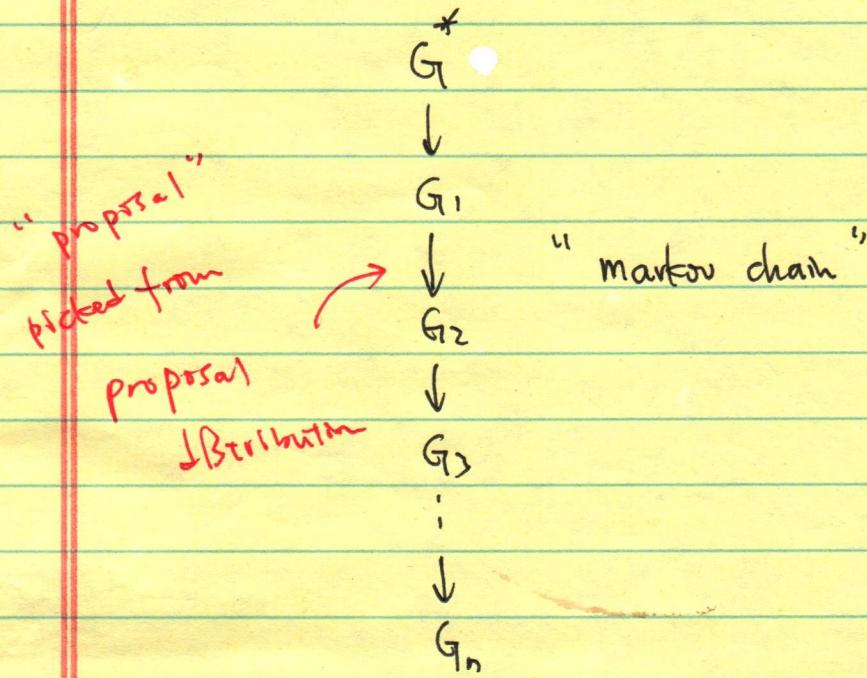
Two constraints

- ① which graph space
- ② Is it graphical

$$G(n, \{k\})$$

$$G^*$$

HM (Havel-Hakimi)



$$\sum_G f(G) P(G | \{k\})$$

$$\sum_G f(G) \cdot P(G)$$

so, with $f(G^*)$ we can now compute $\langle f(G) \rangle_{G \in \{G_i\}}$.

Use: the F. Sodick et al Meme.

Procedure:

1) obtain G_0

2) $G_t \rightarrow G_{t+1}$

use double-edge swap.

⇒ "the double edge swap"

⑨

Prop. of configuration model random networks $G(n, \{k\})$

simple ft. self-loop.

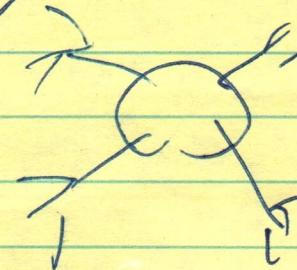
- four flavors of this model :
- connectivity is specified by $\{k\}$
- diameter : $\Theta(\log n)$ (could be $\Theta(\log \log n)$
depending on $\langle k^2 \rangle$)
- motif freq. = $\Theta(1/n)$, if $\#\#$ is sparse
 $\Delta \square$ locally-tree-like structure
 if $\langle k^2 \rangle \gg 1 \Rightarrow$ then bigger motif freq.
- size of Lcc usually $\Theta(n)$

Further: Does $\langle k^2 \rangle$ large



high degree nodes are central

CP
core-phenom



Yes!

LD - core
low-deg

(S)

(x₁)

Let's Try Something Different!

» Look at "example" first! «

Aaron's notes:

(catalogue)

Zachary Club:

D ~ 1000 samples

$P(l)$, $P(l_{max})$
geodesic
distance diameter.

But first, introduce the
notion of MCMC

see x₂

$$\textcircled{3} \quad \text{Harmonic centrality } h_i = \frac{1}{n-1} \sum_{j \neq i} \frac{1}{l_{ij}}$$

maybe not interesting ??

Dutch high school

$$\textcircled{4} \quad r^* = 0.74 \Rightarrow \langle r \rangle_{\{G\}}$$

$$\textcircled{5} \quad p(r^* = 0.74) < 10^{-4}. \quad \text{hypothesis test}$$

Chung-Lu,

Next Class: Motley-Reed,

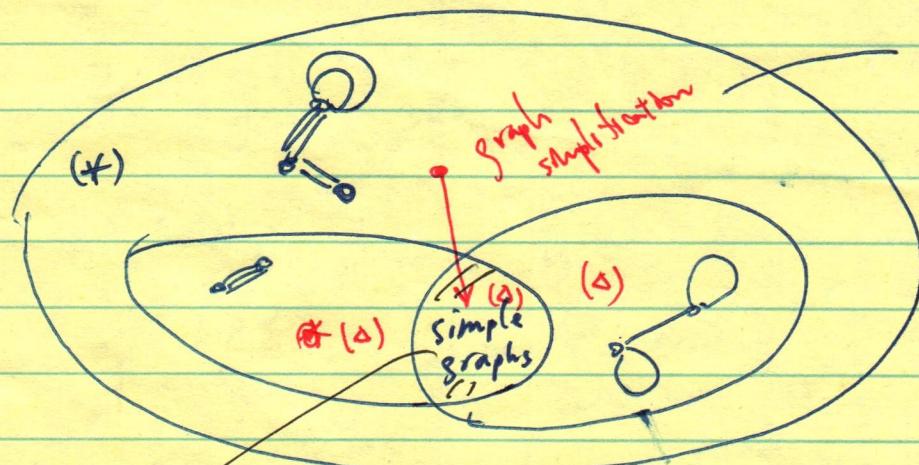
Math expressions of graph descriptors.

①

Lecture 4 - 2

Feb 8, 2024

Review



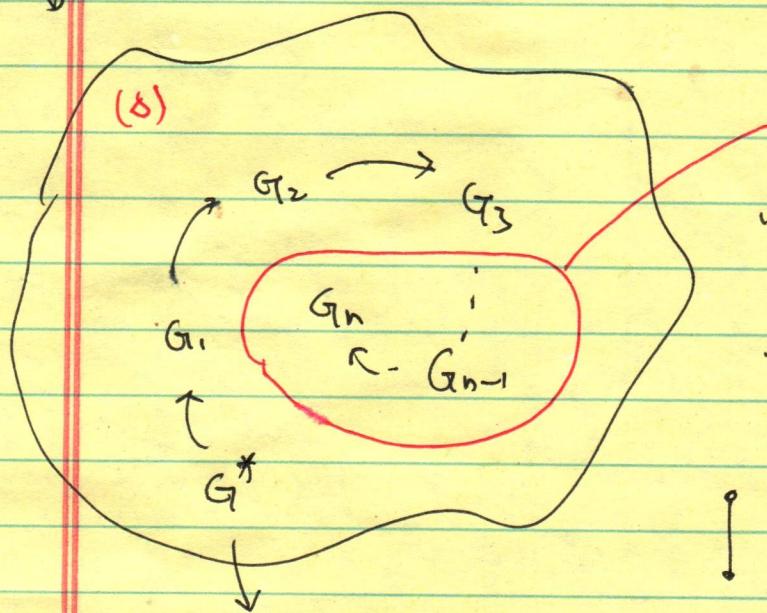
erase self-loops
or
collapse multiedges
↓
preferentially
impacts high-deg
nodes.

Question:

~~How to choose a~~
(Which) graph space to choose ?

» one that matches your data.

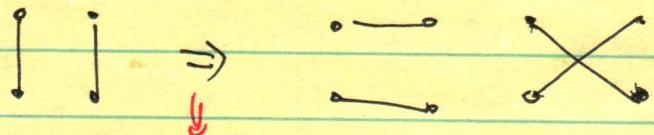
- ① check data for self-loops / multiedges
- ② think about underlying system.



2018
config model samples

"possible rejection"

"sampling gap"



from
1) Data

2) degree-seq. (HH algm)

Three steps :

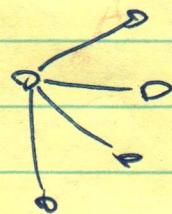
select → swap → accept.
(or reject)

(2)

- (*) Actually, depending on what we aim to randomize, we should consider 2 graph spaces.

Vertex labeled

ex: me + my friends

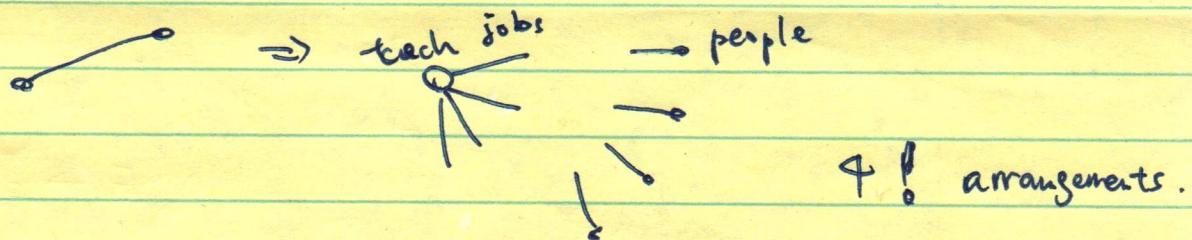


1 arrangement

Sub-labeled

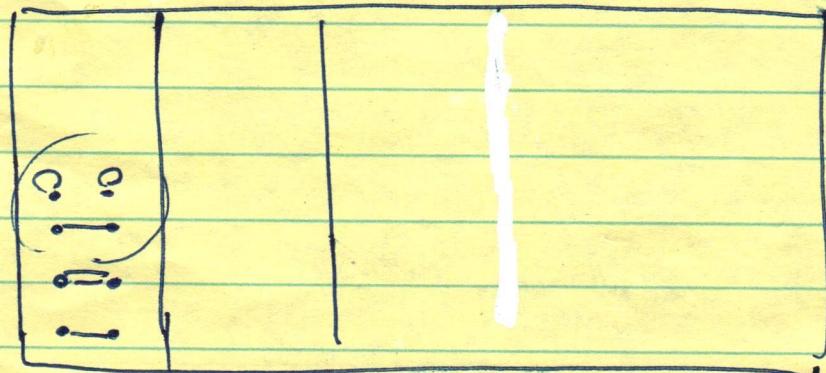
ex: people + jobs @ ~~tech.com~~

tech.com



* choose the graph space that matches your data !

* Next five min: see ~~activities~~ Actually, draw !



(3)

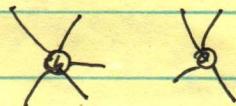
1995

(*) Molloy-Reed model (sub-matching algm.)

⇒ loopy graphs / directed or undirected.

"uniform random matching on subgs"

$$k_1 = 5 \quad k_2 = 4$$



Draw on-site

⇒ ...

node ID = 1 2

subgs = 1 1 1 1 2 2 2 2 ...

make ⚡ array S

 $S \leftarrow$ random-permutation (S)for $i = 1$ to $\text{length}(S) / 2$ $E \leftarrow E \cup \{S(i, i+2)\}$

(+) Counting

$$f_{\text{loop}}(G) = f_{\text{single}}(G) \frac{\prod_{i=1}^n w_{ii}!}{\prod_{i < j} w_{ij}!}$$

$$f_{\text{multi}}(G) = f_{\text{single}}(G) \frac{1}{\prod_{i < j} w_{ij}!}$$

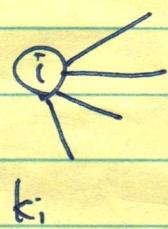
$$f_{\text{multi}}(G) = f_{\text{single}}(G) \frac{1}{\prod_{i < j} w_{ij}!}$$

④

2002

} Chung-Lu model (simple graphs or directed graphs)

⇒ like conf. model, but produces \bar{k} only in expectation.



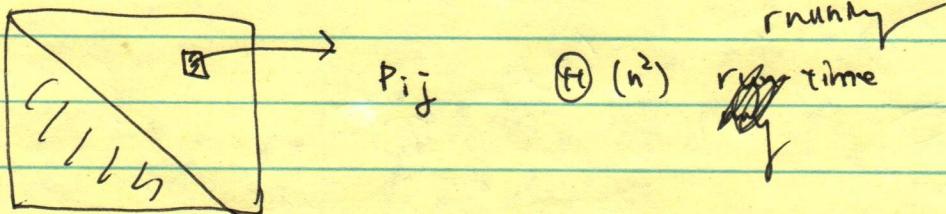
$$P_{ij} = \frac{k_j}{2m - k_i} \left(\frac{k_j}{2m - k_i} \right) \approx \frac{k_i k_j}{2m}$$

$$H_{i>j} A_{ij} = A_{ji} = \begin{cases} \frac{1}{2} & \text{w/ prob } P_{ij} \\ 0 & \text{else} \end{cases}$$

make $P_{ij} \leq 1$

we req. $\max_i k_i^2 < 2m$

Generating Chung-Lu:



Nuance :

iid assumption

simple graph

multigraph

actual outcome v.s. random outcome.
negligible.

(5)

§ Clustering coeff.

$$C = \sum_{k_i=0}^{\infty} \sum_{k_j=0}^{\infty} f_{k_i} f_{k_j} \frac{k_i k_j}{2m}$$

$$= \frac{1}{n} \frac{(\langle k^2 \rangle - \langle k \rangle)^2}{\langle k \rangle^3} = O\left(\frac{1}{n}\right)$$

(locally tree-like)

excess degree

$$f_k = \frac{(k+1) p_{k+1}}{\langle k \rangle}$$



P(neighbors deg k)

$$\left(\frac{\cancel{M} \cdot \cancel{P}_k}{\cancel{N} \cdot \cancel{P}_k} \right) \frac{1}{\langle k \rangle}$$

Other stuff,

see handout

(strong component,
labeled, etc.)

$$= \left(\frac{k}{2m} \right) \cdot n p_k$$

$$\langle k_{\text{neighbor}} \rangle = \sum_k k P(\text{nei of node deg } k)$$

frac of nodes

w/ deg k.

$$= \frac{\langle k^2 \rangle}{\langle k \rangle} \quad \text{friendship paradox!}$$

(6)

Conclusion

Choose your $P(G(\emptyset))$

edge density $\rightarrow G(n, p)$

(degrees $\rightarrow G(n, \{k\})$)

more practical!