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## Random Graphs

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## Graph theory

- 1736 Euler solved the problem of Konisberg bridges


D
Does it exist a path that goes through each bridge only once and come back to the starting point?

## Random graphs

1947 Erdos paper introduce a probability space in graph theory.

- $n$ nodes
- $n(n-1) / 2$ total number of possible links
$\cdot 2^{n(n-1) / 2}$ total number of possible graphs
( $\Omega, \mathfrak{d}, \mathbf{P}$ ) -probability space
$\Omega$ family of graphs with $n$ nodes
$\mathscr{F}$ is the family of all subset of $\Omega$
$\mathbf{P}$ is the probability measure of each graphs
realization (G $\Omega$ ) $\subset$


## $\mathrm{G}(\mathrm{n}, \mathrm{p}) \& \mathrm{G}(\mathrm{n}, \mathrm{M})$


$G(n, p)$-Each couple of nodes are linked with probability $p$

$\mathrm{G}(\mathrm{n}, \mathrm{M})$ - Graphs with exactly M links
$n$ nodes
$M$ links

$$
P(G)=\binom{n(n-1) / 2}{M}^{-1}
$$

## Rule of thumb: Asymptotic equivalence between $\mathbf{G}(\mathrm{n}, \mathrm{p})$ and $\mathrm{G}(\mathrm{n}, \mathrm{M})$ when $n$ goes to infinity and $p(n) n(n-$ $1) / 2=M(n)$

In the following we will always refer to $\mathbf{G}(\mathrm{n}, \mathrm{p})$ as Erdos and Renyi graphs

Small subgraphs appears abruptly when we increase $p$
$\left(p \approx n^{-z}\right)$
or equivalently
the average number of links in the network

## Small subgraphs in ER networks

The average number of subgraphs $G$ of $v$ nodes and $e$ links is given by

$$
\boldsymbol{E}\left(X_{G}\right)=\binom{n}{v} \frac{\boldsymbol{v}!}{\operatorname{aut}(\boldsymbol{G})} \boldsymbol{p}^{e}(1-\boldsymbol{p})^{v(v-1) / 2-e} \approx \boldsymbol{n}^{v} \boldsymbol{p}^{e} \rightarrow\left\{\begin{array}{cc}
0 & \boldsymbol{p} \ll \boldsymbol{n}^{-v / e} \\
\infty & \boldsymbol{p} \gg \boldsymbol{n}^{-v / e}
\end{array}\right.
$$

Thus we have

$$
\boldsymbol{P}\left(X_{G}>0\right)=\boldsymbol{o}(1) \text { if } \boldsymbol{p} \ll \boldsymbol{n}^{-v / e}
$$

## Probability of having a subgraph G

The probability that the number of subgraphs of type G is greater than zero satisfy a slightly more subtle condition

$$
\boldsymbol{P}\left(\boldsymbol{X}_{G}>0\right) \rightarrow \begin{cases}0 & \boldsymbol{p} \ll \boldsymbol{n}^{-1 / \boldsymbol{m}(\boldsymbol{G})} \\ 1 & \boldsymbol{p} \gg \boldsymbol{n}^{-1 / \boldsymbol{m}(\boldsymbol{G})}\end{cases}
$$

Abrupt change

Where $\boldsymbol{m}(G)$ is the density of the denser subset of $\mathbf{G}$

$$
m(G)=\max \left\{\frac{\boldsymbol{e}_{H}}{\boldsymbol{v}_{\boldsymbol{H}}} \quad \text { for } \boldsymbol{H} \subset G\right\}
$$

## Inituition of the previous result

Suppose we want to look of subgraphs of type G: we know for sure that for $\mathrm{p} \ll \mathrm{n}^{-5 / 6}$ we don't have the network, what about $p \gg n^{-5 / 6}$ ?


Let's consider the subgraph H we know for sure that this graph is not present in the network for $\mathrm{p} \ll \mathrm{n}-4 / 5$ which is grater than $\mathrm{n}^{-5 / 6}$ !

## Subgraph thresholds



Subgraphs which appear at a given $z$ value.


## Finite

connectivity

## Finite connectivity random graphs $p(n)=c / n$

## Degree distribution of ER networks

- For each node we extract $n$ - 1 times a random number with probability $p$.
- The probability that the node has $k$ links is then



## But the properties of real graph are different!

## Scale-free degree distribution



## Clustering Coefficient-Average distance

Clustering: My friends will likely know each other!


Probability to be connected C $\gg$ p

$$
\mathrm{C}=\frac{\# \text { of links between } 1,2, \ldots \mathrm{k}_{\mathrm{i}} \text { neighbors }}{\mathrm{k}_{\mathrm{i}}\left(\mathrm{k}_{\mathrm{i}}-1\right) / 2}
$$

| Network | C | $\mathrm{C}_{\text {rand }}$ | L | N |
| :---: | :---: | :---: | :---: | :---: |
| WWW | 0.1078 | 0.00023 | 3.1 | 153127 |
| Internet | $0.18-0.3$ | 0.001 | $3.7-3.76$ | $3015-$ <br> 6209 |
| Actor | 0.79 | 0.00027 | 3.65 | 225226 |
| Coauthorship | 0.43 | 0.00018 | 5.9 | 52909 |
| Metabolic | 0.32 | 0.026 | 2.9 | 282 |
| Foodweb | 0.22 | 0.06 | 2.43 | 134 |
| C. elegance | 0.28 | 0.05 | 2.65 | 282 |

## Degree-degree correlations for example in Internet

- $k_{n n}(k)$ mean value of the connectivity of neighbors sites of a node with connectivity $k$
If
and $\alpha<0$ the network is called disassortative while if $\alpha>0$ the network is assortative
- C(k)Caverage clustering coefficient of nodes with connectivity $k$.
If the network is called modular.




## Community detection in the network of italian ministers



Givan, Newman algorithm

## Lets building up a random graph

 which has at least one of all these properties: the degree distribution
## Ensembles of random graphs with given degree distribution <br> - Molloy-Reed ensemble

To each node of the network $i$ it is assigned a degree $k_{i}$ from the desired degree distribution. Then edges are randomly matched.

- Hidden variable ensemble

To each node it is assigned a random variable $q_{f}$ from the desidered degree distribution. Each couple of nodes is linked with probability

$$
\boldsymbol{p}_{i, j}=\frac{\boldsymbol{q}_{i} \boldsymbol{q}_{j}}{\langle\boldsymbol{q}\rangle \boldsymbol{n}}
$$

## Ensembles of random graphs with given degree distribution

Molloy-Reed ensemble
Hidden variable


## In these ensembles one gets the high clustering for free!

In fact the clustering coefficient of a node is given by the average number of triangles divided by the total number of possible triangles passing through that node.

$$
\left.C\left(k_{i}\right)=\frac{1}{k_{i}\left(k_{i}-1\right)}<\frac{\left(k_{i}-1\right) k^{\prime}\left(k^{\prime}-1\right) k^{\prime \prime}\left(k^{\prime}-1\right) k_{i}}{\langle k\rangle^{3}}\right\rangle_{k^{\prime}, k+1}=\frac{\langle k(k-1)\rangle^{2}}{\langle k\rangle^{3}}
$$

## B But no correlations!!!

For $2<\gamma<3$ the numerator diverges 2nd we have a clustering coefficient much higher than the one of random graphs

$$
C(k) \approx \operatorname{cost} \approx N^{-(\gamma-1) / 2} \gg C_{E R} \approx N^{-1}
$$

## Giant component

 in random graphswith finite connectivity

## Generating functions

$$
P(k)
$$

Probability distribution

$$
F(z)=\sum_{k} P(k) z^{k}
$$

Generating function

The derivatives of the generating function provides the all the moments of the distribution

$$
\begin{aligned}
& \boldsymbol{F}^{\prime}(1)=<\boldsymbol{k}> \\
& \boldsymbol{F}^{\prime \prime}(1)=<\boldsymbol{k}(\boldsymbol{k}-1)>
\end{aligned}
$$

## Properties of generating functions

$\{f$ \}
$F(z)$
$\left\{h_{s}\right\}$
H(z)

## $s=s 1+s 2$

$$
\begin{aligned}
& h_{s}=\sum_{i, w} f_{i} f_{i} \delta_{j+t, s,} \\
& \sqrt{1} \\
& H(z)=F(z)^{2}
\end{aligned}
$$

Then it is clear that if

$$
s=s 1+s 2+. . s k
$$

$H(z)=F(z)^{k}$

## Generating functions for the degree distribution

Generating function for the degree distribution

$$
\left\{p_{k}\right\} \quad \Longleftrightarrow \quad G_{0}(z)=\sum_{k} p_{k} z^{k}
$$

$\begin{aligned} & \text { Generating function for } \\ & \text { the degree of the nodes that }\end{aligned}\left\{\boldsymbol{p}_{k-1}^{\prime}=\frac{\boldsymbol{k} \boldsymbol{p}_{\boldsymbol{k}}}{\langle\boldsymbol{k}\rangle}\right\} \Longrightarrow \boldsymbol{G}_{1}(z)=\frac{1}{\langle\boldsymbol{k}\rangle} \sum_{k} \boldsymbol{k} \boldsymbol{p}_{k} z^{k-1}$ the degree of the nodes that we arrive at by following a link

$$
\boldsymbol{G}_{0}(z)=G_{1}(z)=\boldsymbol{e}^{c(z-1)}
$$

## Generating functions for the cluster distribution

Generating function for the probability distribution that following a link we reach a cluster of finite size s

$$
H_{1}(z)=\boldsymbol{z} \boldsymbol{G}_{1}\left(\boldsymbol{H}_{1}(\boldsymbol{z})\right)
$$



Generating function for the probability distribution that choosing a node randomly we reach a cluster of finite size $s$

$$
H_{o}(z)=z G_{0}\left(H_{1}(z)\right)
$$

## Giant component

Probability that following a link we are not In the giant component $u$ satisfy:

$$
\left\{\begin{array}{l}
G^{\prime}(1)=\frac{\langle k(k-1)\rangle}{\langle k\rangle}>1 u<1 \quad \text { there is } a G C \\
G^{\prime}(1)=\frac{\langle k(k-1)\rangle}{\langle k\rangle} \leq 1 u=1 \quad \text { there is } n o G C
\end{array}\right.
$$

$$
H_{1}(1)=u=G_{1}(u)
$$


-In scale-free graphs with $\gamma<3$ there is always a GC $\cdot$ In ER graphs there is a phase transition the birth of the GC at $c=<k>=1$

## Birth of the giant component in ER graph

As we change c in a random ER graph we find a phase transition at $\mathrm{c}=1$ :
one cluster of size of order $n$ emerges.

This phase transition is exactly the same as percolation in infinite dimension and is naturally described by statistical mechanics methods.

## Description of the phase transition

$\boldsymbol{P} \approx(\boldsymbol{c}-1)^{\beta}$
$\langle\boldsymbol{s}\rangle \approx|\boldsymbol{c}-1|^{-r, y^{\prime}}$
$n_{s} \approx \boldsymbol{s}^{-\tau-1} e^{-s|c-1|^{\sigma}}$

Size of the giant component
Average size of the finite components

Distribution of the finite components

$$
\begin{aligned}
& \beta=\gamma=\gamma^{\prime}=1 \\
& \tau=\frac{3}{2} \\
& \sigma=2
\end{aligned}
$$

## Size of the giant component in ER graph

- $S=1-u$ is the probability that following a link we end in the giant component.
- $P$ is the probability that choosing randomly a node it belongs to the giant component
- In a ER graph $S$ satisfy

$$
\begin{gathered}
\boldsymbol{S}=1-\boldsymbol{e}^{-c S} \approx \boldsymbol{c S}-\frac{1}{2} c^{2} \boldsymbol{S}^{2} \Longleftarrow \begin{array}{l}
\boldsymbol{H}_{1}(z)=\boldsymbol{z} \boldsymbol{G}_{1}\left(\boldsymbol{H}_{1}(z)\right) \\
1-\boldsymbol{S}=\boldsymbol{G}_{1}(1-\boldsymbol{S})
\end{array} \\
\boldsymbol{S} \approx \frac{2(\boldsymbol{c}-1)}{\boldsymbol{c}^{2}}
\end{gathered}
$$

$$
\boldsymbol{P} \approx \boldsymbol{S} \approx(\boldsymbol{c}-1)^{\beta} \quad \beta=1
$$

$$
\begin{aligned}
\Leftarrow & \boldsymbol{H}_{o}(\boldsymbol{z})=\boldsymbol{z} \boldsymbol{G}_{0}\left(\boldsymbol{H}_{1}(\boldsymbol{z})\right) \\
& 1-\boldsymbol{P}=\boldsymbol{G}_{0}(1-\boldsymbol{S})
\end{aligned}
$$

## Average size of finite components

The average sizes of finite components are given by moment of $H^{\prime}(1)$.

- Lets calculate how the average size of these components diverges with (1-c) for $c<1$

$$
<s>=1+\frac{G_{0}^{\prime}(1)}{1-G_{1}^{\prime}(1)}=1+\frac{c}{1-c} \approx(1-c)^{-\gamma} \quad \gamma=1
$$

- For $c>1$ one has to be careful and calculate everything at $z=1$, and $H_{1}(1)=u$, one finds

$$
<s>\approx \frac{1}{1-G_{1}^{\prime}(u)}=\frac{1}{1-c(1-S)} \approx(c-1)^{-\gamma^{\prime}} \quad \gamma^{\prime}=1
$$

## Distribution of the size of finite clusters

$$
\begin{gathered}
n_{s} \approx s^{-\tau-1} \exp \left(-s|c-1|^{\sigma}\right) \\
\prod_{0} \\
P_{0}(s) \approx s^{-\tau} \exp \left(-s|c-1|^{\sigma}\right) \\
\quad \|^{2} \\
P_{1}(s) \approx s^{-\tau} \exp \left(-s|c-1|^{\sigma}\right)
\end{gathered}
$$

Distribution of clusters

Distribution of cluster of size s when choosing a random node

Distribution of cluster of size s when choosing a random link

## Distribution of clusters found following a link

If we suppose

$$
\begin{aligned}
& P_{1}(s)=s^{-\tau} \Phi\left(s|c-1|^{\sigma}\right) \\
& \quad H_{1}\left(e^{-\alpha}\right)=u-\alpha^{\tau-1} h\left(\alpha /|c-1|^{\sigma}\right)
\end{aligned}
$$

In fact we have

$$
\begin{aligned}
\boldsymbol{H}_{1}\left(\boldsymbol{e}^{-\alpha}\right) & =\boldsymbol{u}-\int \boldsymbol{d} \boldsymbol{s} \boldsymbol{s}^{-\tau} \Phi\left(\boldsymbol{s} \varepsilon^{\sigma}\right)\left(1-\boldsymbol{e}^{-\alpha s}\right) \\
& =\boldsymbol{u}-\alpha^{\tau-1} \boldsymbol{h}\left(\alpha / \varepsilon^{\sigma}\right)
\end{aligned}
$$

Where

$$
\varepsilon=|c-\mathbf{1}|
$$

## $\tau$ and $\sigma$ exponents

$$
\begin{gathered}
\boldsymbol{H}_{1}(\boldsymbol{z})=\boldsymbol{Z} \boldsymbol{G}_{1}\left(\boldsymbol{H}_{1}(\boldsymbol{z})\right) \\
\mathbf{1}-\alpha^{\tau-1} h(x)=(1-\alpha)\left(1-c \alpha^{\tau-1} h(x)+\frac{1}{2} c^{2} \alpha^{2 \tau-2} h^{2}(x)\right)+\mathrm{O}\left(\alpha^{3(\tau-1)}\right) \\
(1-c) \alpha^{\tau-1} h(x)-\alpha+\frac{\mathbf{1}}{\mathbf{2}} c^{2} \alpha^{2 \tau-2} h^{2}(x)+\ldots=0 \\
x^{-\sigma} \alpha^{\tau-1+\sigma} h(x)-\alpha+\frac{\mathbf{1}}{\mathbf{2}} c^{2} \alpha^{2 \tau-2} h^{2}(x)+\ldots=0 \\
\begin{cases}\tau=\frac{3}{2} \\
\sigma & = \\
2\end{cases}
\end{gathered}
$$

## Average distance in ER graph

The network is locally a tree the number of nodes $z_{m}$ at distance $m$ is given by

$$
z_{m} \approx c\left(\frac{z_{2}}{z_{1}}\right)^{m-1} \approx c^{m}
$$

The average distance is given by $d$ such that

$$
\sum_{m=0, d} z_{m} \approx c^{d}=n
$$

Thus $\boldsymbol{d}$ scales as the logarithm of the network size

$$
d \approx \log (n) / \log (c)
$$

## Summary

- Introduction to random graphs ensembles
- ER graphs
- Given degree distribution random graphs
- Abrupt appearance of small subgraphs in ER graphs
- Condition for existence of the giant component in any type of random graphs
- Description of the birth of the giant component in ER graphs


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[^0]:    These are preliminary lecture notes, intended only for distribution to participants

