

Probabilistic Inductive Classes of Graphs

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 - Inductive class of graphs
 - Probabilistic ICG
- 3 Expected order and size of PICG
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 - Spread of rumors
 - Dynamics of acquaintanceships
 - Dynamic of social balance processes

A way to formally describe evolution of networks

- graph — a "skeleton" of the network
- model a process of graph evolution
- modelling with stochastic processes:
 - preferential attachment mechanism (Barabási, 1999)
 - copying mechanism (Kumar et al, 2000)
- **inductive definition of graphs** with probability transitions (transformations by rules) are viewed as implicit time steps

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ICG is defined as $\mathcal{I} = (\mathcal{B}; \mathcal{R})$ (Curry, 1963):

- 1 class \mathcal{B} of initial graphs, the **basis** of ICG,
- 2 class \mathcal{R} of **generating rules**, which consists of a distinguished **left element** (part of a graph) to which the rule is applied (the left element is transformed into the **right element** of the rule).

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The inductive class consists exactly of the graphs that can be **obtained from the basis** in finite number of steps **using the generating rules**.

Inductive class of graphs

Nice properties of generating rules:

- **locality** (the part of the graph, where to apply the rule is connected)
- **expansion** (the rule increases a selected property of graphs; i.e. number of vertices)

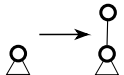
Example

$$\mathcal{I} = (\mathcal{B}; \mathcal{R}), \mathcal{B} = \{B\}, \mathcal{R} = \{R1, R2\}$$

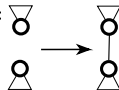
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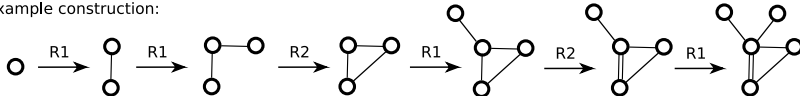
R1:



R2:



Example construction:



Probabilistic ICG

Probabilistic inductive class of graphs

PICG is defined as $\mathcal{P} = (\mathcal{B}; \mathcal{R}; f_B; f_R; \mathcal{F}_L)$:

- 1 class \mathcal{B} of initial graphs, the **basis**,
- 2 class \mathcal{R} of **generating rules**
- 3 probability distribution f_B specifying how the initial graph is chosen from class \mathcal{B} ,
- 4 probability distributions f_R specifying how the rules from class \mathcal{R} are applied,
- 5 a set of $|\mathcal{R}|$ probability distributions — \mathcal{F}_L specifying how the left elements for every rule in class \mathcal{R} are chosen.

Probabilistic ICG

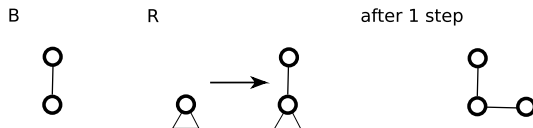
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- 4 probability distributions f_R specifying how the rules from class \mathcal{R} are applied,
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We limit on **simple** PICG definitions in which the left part of the selected rule can always be found.

Preferential attachment model as PICG



$$\mathcal{P} = (\mathcal{B}; \mathcal{R}; f_B; f_R; \mathcal{F}_L);, \mathcal{B} = \{B\}, \mathcal{R} = \{R\}$$

- $f_B = 1$

- $f_R = 1$

- $f_u = \frac{\deg(u)}{\sum_v \deg(v)}, \quad \forall u \in V, f_u \in \mathcal{F}_L$

Expected number of vertices — order

Expected change in the number of vertices has to be positive (otherwise graph dies out).

Probability for number of vertices (recursive expression):

$$p_t(N = n) = \sum_{R_i \in \mathcal{R}} r_i p_{t-1}(N = n - \Delta n_i)$$

- N — random variable for number of vertices
- t — time step
- $r_i \equiv f_R(R_i)$ — probability of selecting rule R_i
- Δn_i the number of vertices, that rule R_i adds to the graph

Initial values for graphs from the basis:

$$p_0(N = n) = \sum_{B_i; |B_i|=k} f_B(B_i)$$

Expected change in number of vertices

Expected order in time t :

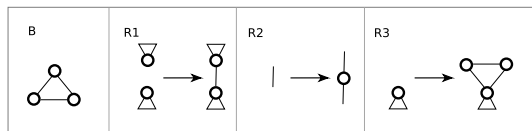
$$E_t[N] = \sum_{i=0}^{\infty} i p_t(i)$$

It can be shown, that in the limit of large t :

$$\lim_{t \rightarrow \infty} \frac{E_t[N]}{t} = \sum_{R_i \in \mathcal{R}} r_i \Delta n_i$$

Similarly, this holds for number of edges.

Application — 2-edge-connected graphs



$$\mathcal{P}_{2E} = (B; \{R1, R2, R3\}; 1; f_R, \mathcal{F}_L)$$

- $f_R = \begin{pmatrix} R1 & R2 & R3 \\ q & r & s \end{pmatrix}$

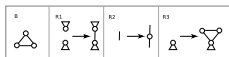
- $\mathcal{F}_L = \{f_{R1}, f_{R2}, f_{R3}\}$

- $f_{R1}(u, v) = \frac{1}{n(n-1)}$

- $f_{R2}(e) = \frac{1}{m}$

- $f_{R3}(u) = \frac{1}{n}$

... 2-edge-connected graphs



From the recursive relation:

$$p_t(n) = qp_{t-1}(n) + rp_{t-1}(n-1) + sp_{t-1}(n-2)$$

we get

$$p_t(n) = \sum_{j=\lfloor \frac{n}{2} \rfloor}^{n-2} \binom{j-1}{n-j-2} \binom{t}{t-j+1} q^{t-j+1} r^{2j-n+1} s^{n-j-2}$$

Therefore **expected change in vertices**:

$$\frac{E_t[N]}{t} \approx r + 2s$$

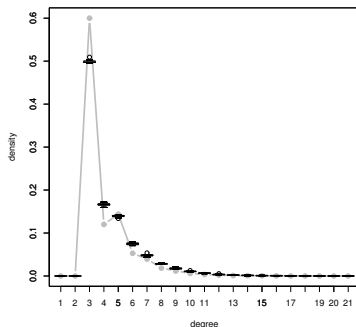
Similarly — **expected change in edges**:

$$\lim_{t \rightarrow \infty} \frac{E[M]}{t} = (q + r) + 3s$$

... 2-edge-connected graphs

Degree distribution (p_k — probability for a vertex to have a degree k):

$$(n+r+2s)p'_k = np_k + r(\delta_{k2}) + q(p_{k-1} - p_k) + s(p_{k-2} + 2\delta_{k2} - p_k)$$



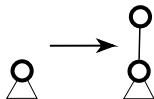
Spread of rumors

- basis — person with "information"
- $R1$ — a person with a rumor disseminates information to a person without
- $R2$ — two people with knowledge of a rumor discuss it

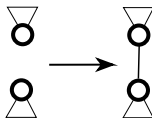
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R1:

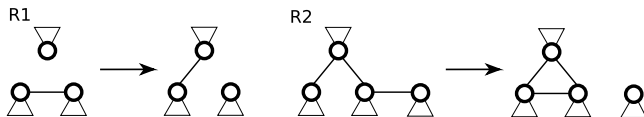


R2:



Dynamics of acquaintanceships

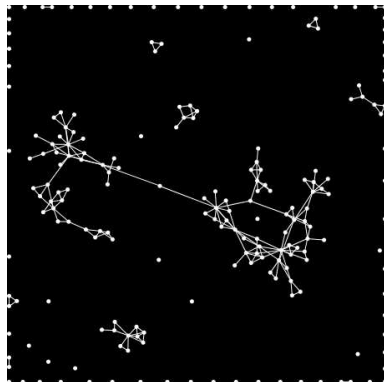
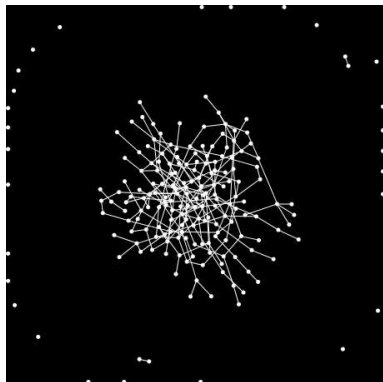
- basis — any graph with n vertices and m edges (i.e. ER random graph)
- $R1$ — breaking up of an acquaintanceship for a more "advantageous" one
- $R2$ — creation of "stronger" relationships by forming connected triads (friendship)



Dynamics of acquaintanceships

Left: basis; ER model, 200 vertices and 200 edges

Desno: graph over 1000 steps ($p_1 = 0.11$ in $p_2 = 0.89$)



Dynamic of social balance processes

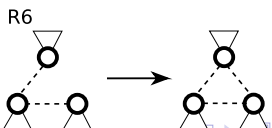
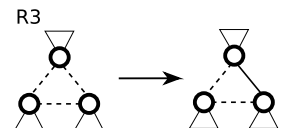
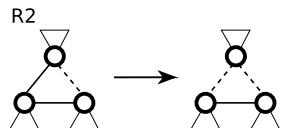
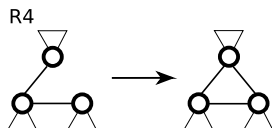
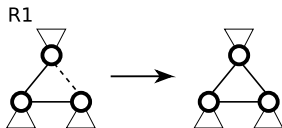
Structural balance theory (Cartwright, Harary 1956): signed edges between two vertices

Balanced triads: signs of edges among all three vertices multiply into a positive sign

People tend to gravitate towards balanced triads with other people.

Dynamic of social balance processes

- basis — simple graph with n vertices and m signed edges
- $R1, R2, R3$ — balancing rules
- $R4, R5, R6$ — process of induction (Heider 1946)



Conclusion

- PICG is a framework which enables a formal description of many network models.
- adding and deleting of properties of edges and vertices can be included
- more results about some formal models (i.e. degree distribution) can be obtained at [arXiv:math/0612778v1](https://arxiv.org/abs/math/0612778v1) [math.DS]

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