

Impact of Clustering on Epidemics in Random Networks

Joint work with Marc Lelarge

INRIA-ENS

2 April 2012

Outline

- 1 Introduction : Social Networks and Epidemics
- 2 Random Graph Model
- 3 First Epidemic Model : Diffusion
- 4 Second Epidemic Model : Contagion

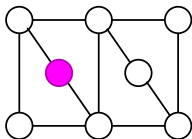
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- I. Diffusion (classical SI model)
- II. Contagion (from Game Theory)

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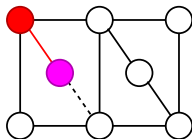


SEED of the epidemic

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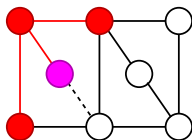
— transmission

- - - no transmission

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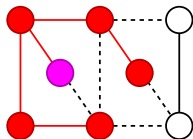


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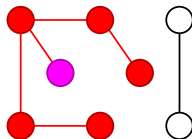
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DIFFUSION MODEL



Infected nodes
at the end
of the epidemic

BOND PERCOLATION



Connected component
of the seed in the
bond percolated graph

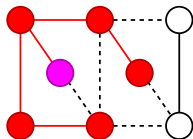


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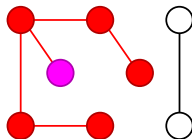
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Each infected neighbor can transmit the epidemic *independently*.

II. Game-theoretic CONTAGION model on a given graph $G = (V, E)$, with parameter $q \in (0, 1/2)$:

Two possible choices :  (\leftrightarrow susceptible) or  (\leftrightarrow infected)

Initially : all use , except one who uses 

Possible switch  \rightarrow , but no switch  \nrightarrow 

Situation	Payoff (for both users)
	q
	$1 - q > q$
	0

Total payoff
= sum of payoffs from
all your neighbors

Switch from  to  $\Leftrightarrow \frac{|\text{Neighbors using Skype}|}{|\text{Neighbors}|} > q.$

Infinite deterministic graph $G = (V, E)$

Parameter q varies :

q small \Rightarrow CASCADE
 q higher \Rightarrow NO cascade

More precisely :

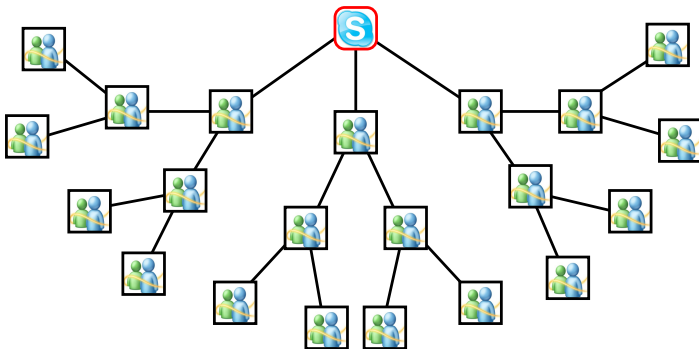
$q_1 \geq q_2$, cascade for $q_1 \Rightarrow$ cascade for q_2

Contagion threshold $q_c^{(G)} := \sup \{ q \mid \text{CASCADE in } G \text{ for parameter } q \}$



Switch from  to  $\Leftrightarrow \frac{|\text{Neighbors using Skype}|}{|\text{Neighbors}|} > q$

Example : $G = d$ -regular tree



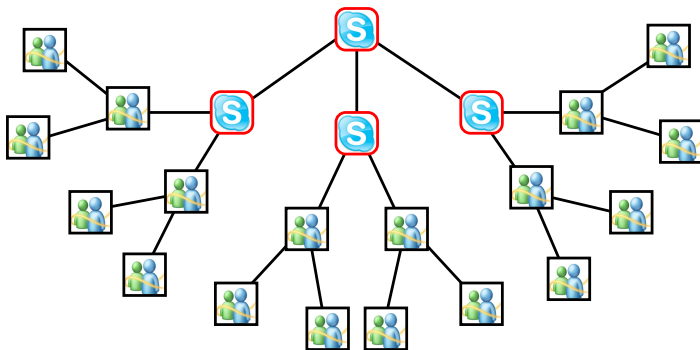
$q \geq 1/d \Rightarrow$ NO cascade

$q < 1/d \Rightarrow$ CASCADE

$$\Rightarrow q_c^{(G)} = 1/d$$

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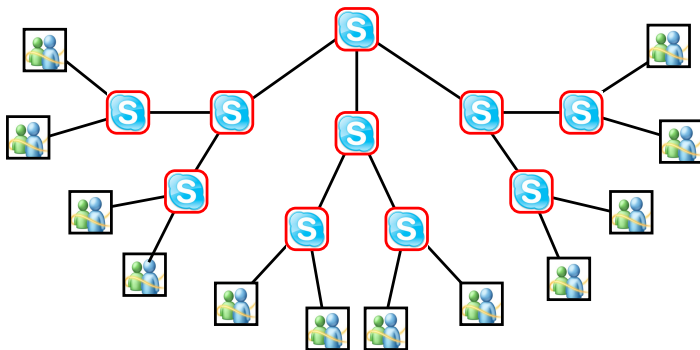
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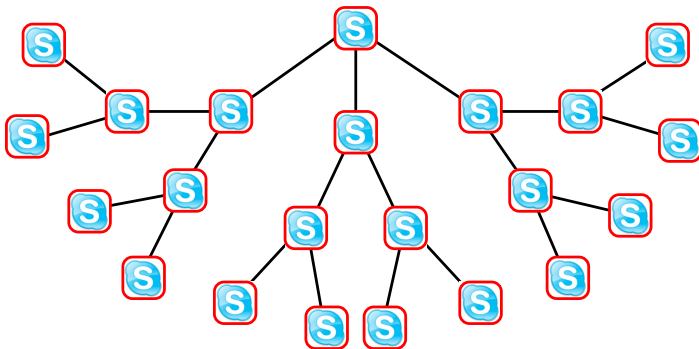
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Define a model of *finite random graphs* (whose size tends to infinity)

- having (asymptotically) the observed properties :
 - ▶ *scale-free networks* \Leftrightarrow power law degree distribution
i.e. there exists $\tau > 0$ such that, for all $k \geq 0$, $p_k \propto k^{-\tau}$
(small number of nodes having a large number of edges)
 - ▶ *networks with clustering*
("The friends of my friends are my friends", Newman, '03)
- tractable

Epidemic models on finite random graphs :

Final nb of infected nodes negligible or not / population size ?

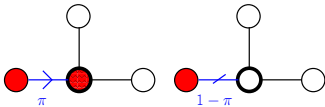
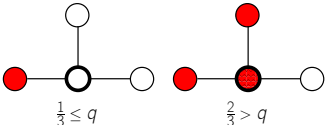
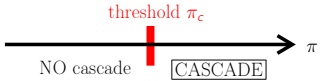
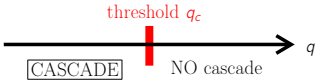
G_n = random graph of size n

S_n = final size of the epidemic in G_n

$$\begin{aligned} \text{CASCADE} & \text{ if } S_n \underset{n \rightarrow \infty}{=} \Theta_p(n), \\ \text{NO cascade} & \text{ if } S_n \underset{n \rightarrow \infty}{=} o_p(n). \end{aligned}$$

Epidemic models on finite random graphs :

Final nb of infected nodes negligible or not / population size ?

	DIFFUSION MODEL	CONTAGION MODEL
Ref.	Bond percolation	Morris, Watts
Para-meter	π = probability that an edge transmits the epidemic 	A vertex is infected \Leftrightarrow fraction of infected neighbors $> q$ 
Thm		

Effect of clustering on these thresholds and on the cascade size

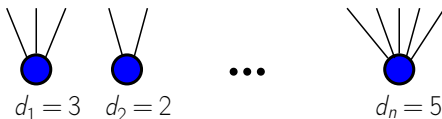
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- (ii) Add clustering

(i) Original graph (with given vertex degrees) :

- $n \in \mathbb{N}$, $\mathbf{d} = (d_i)_1^n$ sequence of non-negative integers
(s.t. \exists a graph with n vertices and degree sequence \mathbf{d}).
- $G(n, \mathbf{d})$ = uniform random graph (among the graphs with n vertices and degree sequence \mathbf{d}).



Ref. : (Lelarge,'11) for the study of contagion and diffusion models on graphs with given vertex degrees

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Condition : Assume there exists a probability distribution $\mathbf{p} = (p_r)_{r=0}^\infty$ such that :

- (i) $\#\{i : d_i = r\}/n \rightarrow p_r$ as $n \rightarrow \infty$, for every $r \geq 0$
- (ii) $\lambda := \sum_r r p_r \in (0; \infty)$
- (iii) $\sum_i d_i^3 = O(n)$

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(ii) Clustering Coefficient of $G = (V, E)$:

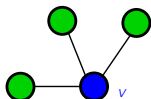
$C^{(G)} :=$ probability that two vertices share an edge together, knowing that they have a common neighbor

$$C^{(G)} = \frac{3 \times \text{nb of triangles}}{\text{nb of connected triples}} = \frac{\sum_v P_v}{\sum_v N_v}$$

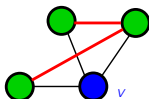
$P_v :=$ nb of pairs of neighbors of v sharing an edge together,

$N_v :=$ nb of pairs of neighbors of v : $N_v = d_v(d_v - 1)/2$.

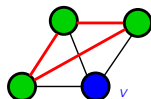
Example : $N_v = 3$



$$P_v = 0$$

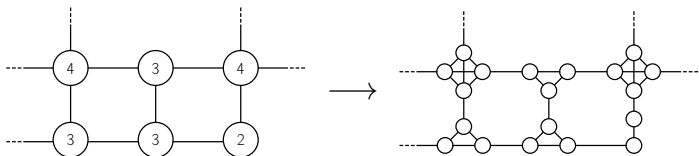
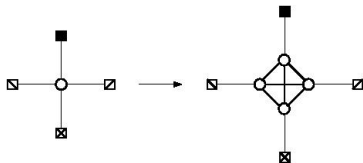


$$P_v = 2$$

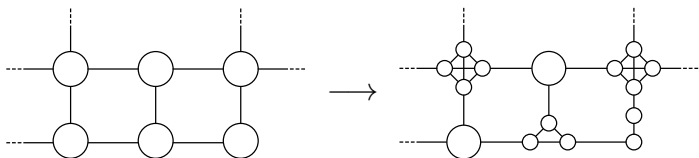


$$P_v = 3$$

- **Idea** : Replace a vertex of degree r in $G(n, d)$ by a clique of size r :



- **Idea** : Replace a vertex of degree r in $G(n, \mathbf{d})$ by a clique of size r .
- **Adding cliques randomly** : Let $\gamma \in [0, 1]$.
Each vertex is replaced by a clique with probability γ (independently for all vertices).



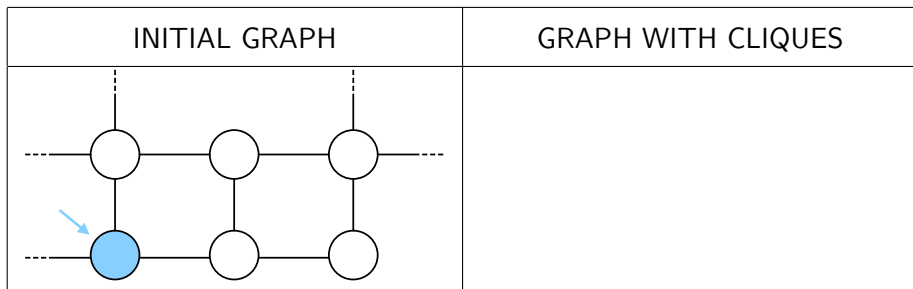
- $\tilde{G}(n, \mathbf{d}, \gamma)$ = resulting random graph (with additional cliques)
Similar model : (Trapman,'07), (Gleeson,'09)
- **Particular cases** :
 - ▶ $\gamma = 0 \Rightarrow \tilde{G}(n, \mathbf{d}, \gamma) = G(n, \mathbf{d})$,
 - ▶ $\gamma = 1 \Rightarrow$ all vertices in $G(n, \mathbf{d})$ have been replaced by cliques.
- **New asymptotic degree distribution** $\tilde{\mathbf{p}} = (\tilde{p}_k)_{k \geq 0}$
- **Asymptotic clustering coefficient** $C > 0$

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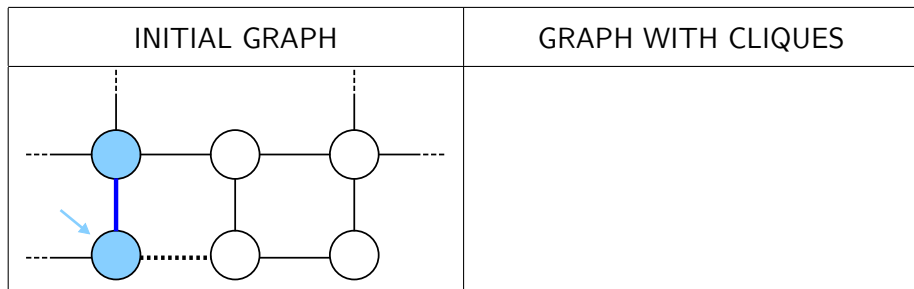
Diffusion model with a given probability π of transmission, on the (random) graph $\tilde{G}(n, \mathbf{d}, \gamma)$:

- At the beginning, activate a given vertex (= the seed of the epidemic)
- **Transmit** the epidemic through any edge with probability π



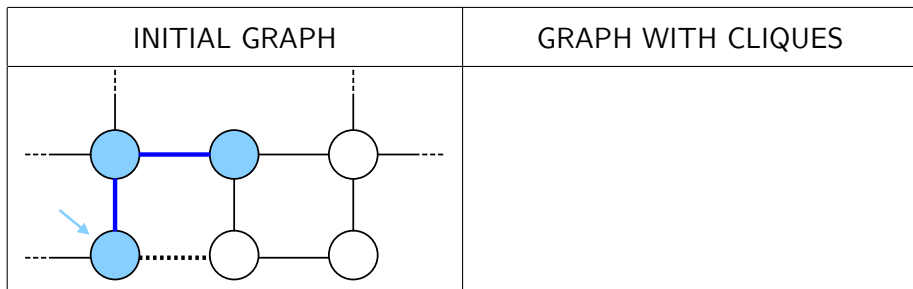
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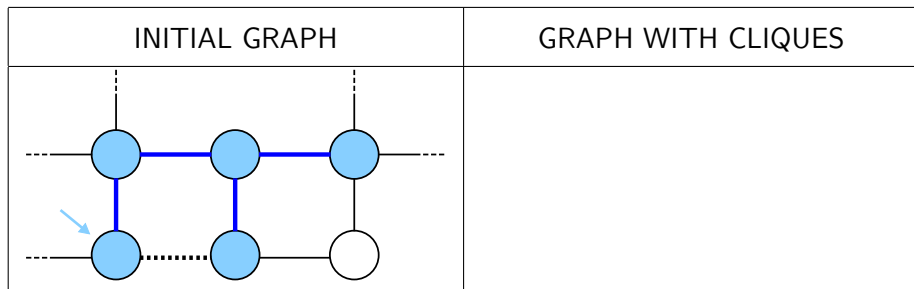
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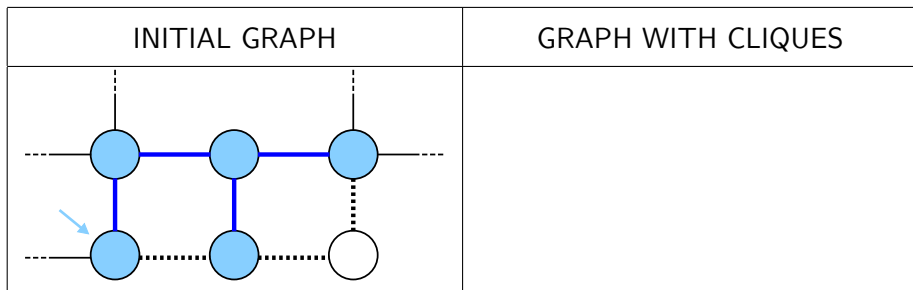
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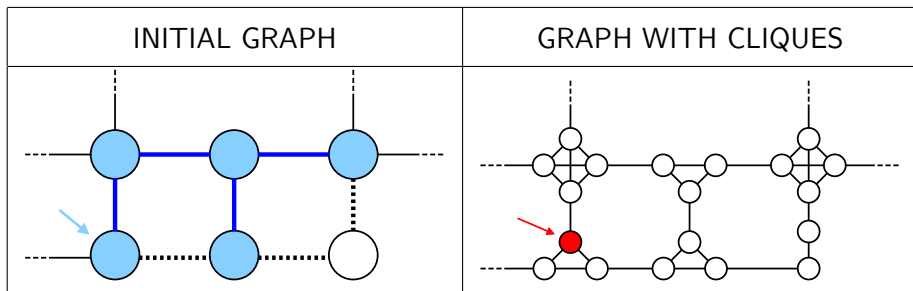
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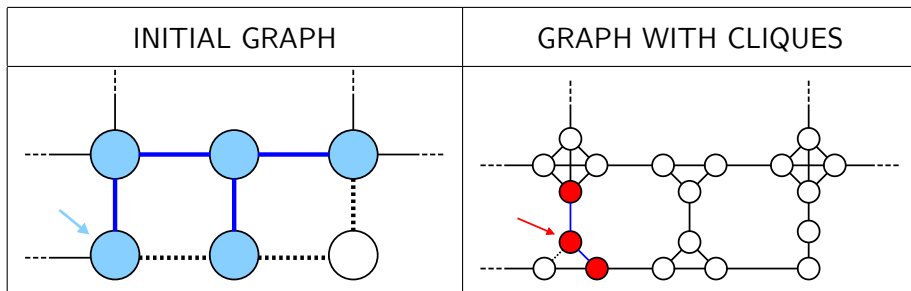
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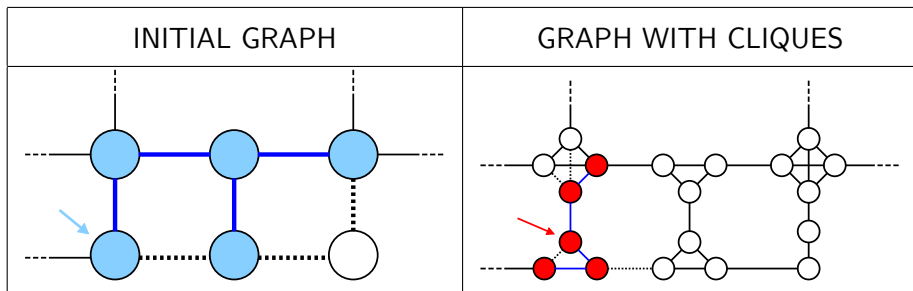
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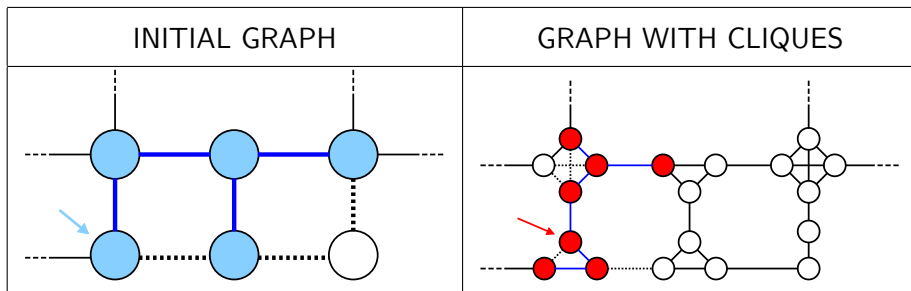
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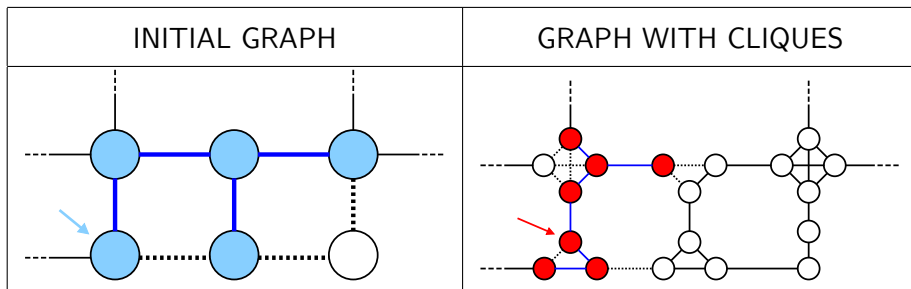
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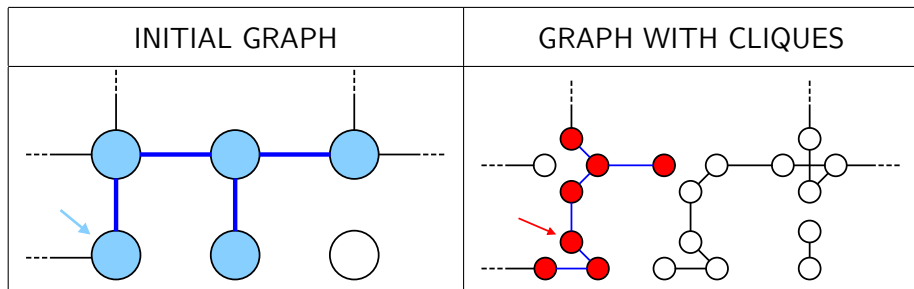
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Connected component of the seed
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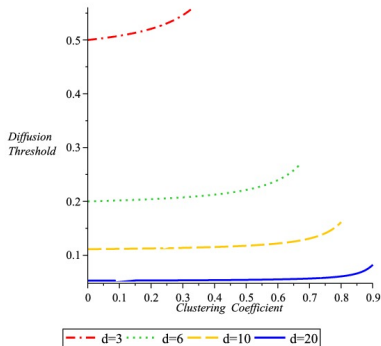
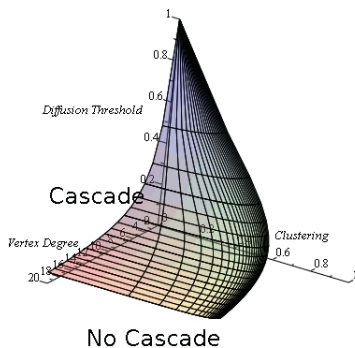
Theorem (DIFFUSION THRESHOLD)

Let π_c be the solution of the equation : $\pi' = \frac{\mathbb{E}[D_{\pi'}]}{\mathbb{E}[D_{\pi'}(D_{\pi'}-1)]}$,

where $D_{\pi'}$ is a random variable with a given distribution that depends on p , γ and π' .

- $\pi > \pi_c$: There exists *whp* a giant component in the percolated graph, *i.e.* a single node can trigger a **global cascade**.
- $\pi < \pi_c$: The size of the epidemic generated by a vertex u (chosen uniformly at random) is **negligeable** : $o_p(n)$.

Diffusion Threshold π_c vs Clustering (in random d -regular graphs)



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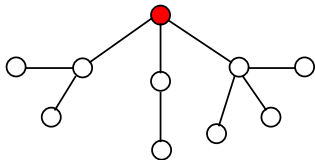
- At the beginning, one infected vertex (= the seed of the epidemic)
- At each step, each vertex becomes infected if :

$$\text{proportion of its infected neighbors} > q$$

Heuristically...

The random graph $G(n, d)$ converges locally to a random tree such that :

$$\mathbb{P}(r-1 \text{ children}) = rp_r/\lambda$$



$$q = \frac{1}{4}$$

Infected nodes = those with degree $< 1/q$

Infinite tree (of infected nodes)

$$\Leftrightarrow \sum_{r < 1/q} (r-1) \frac{rp_r}{\lambda} > 1$$

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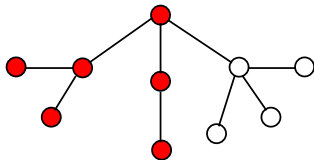
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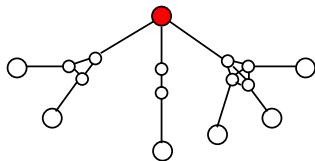
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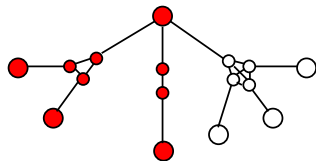
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$$q_c := q_c(\mathbf{p}) = \sup \left\{ q' : \sum_{r < 1/q'} (r-1) \frac{rp_r}{\lambda} > 1 \right\}$$

Fixed q , $\mathcal{P}^{(n)}$ = set of **pivotal players** in $\tilde{G}(n, \mathbf{d}, \gamma)$:

- G_0 = induced subgraph with vertices of degree $< 1/q$
- Pivotal players = vertices in the largest connected component of G_0

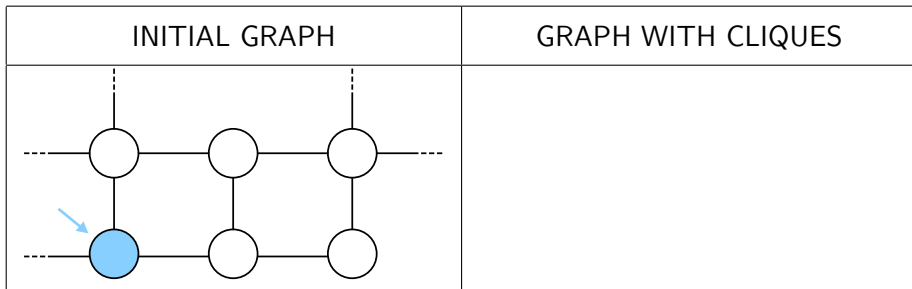
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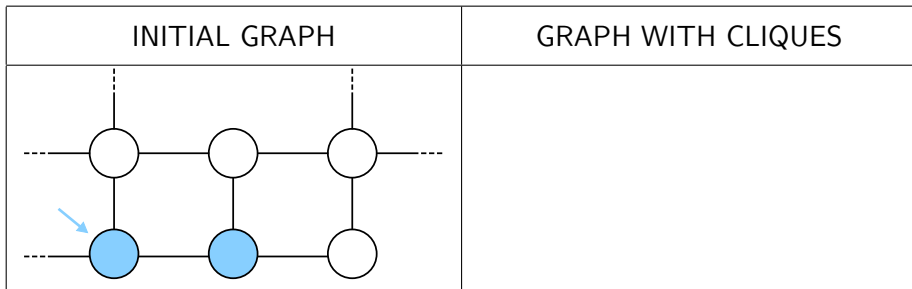
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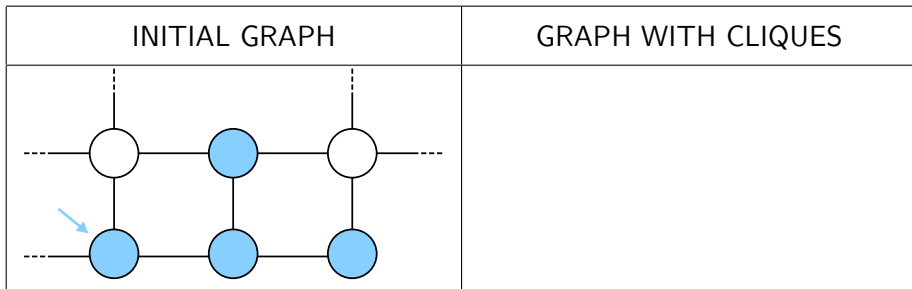
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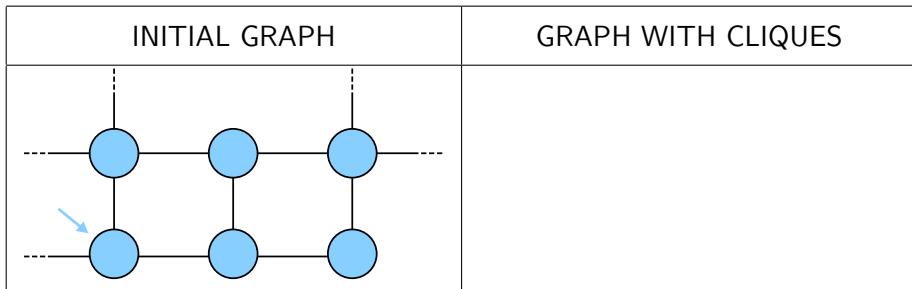
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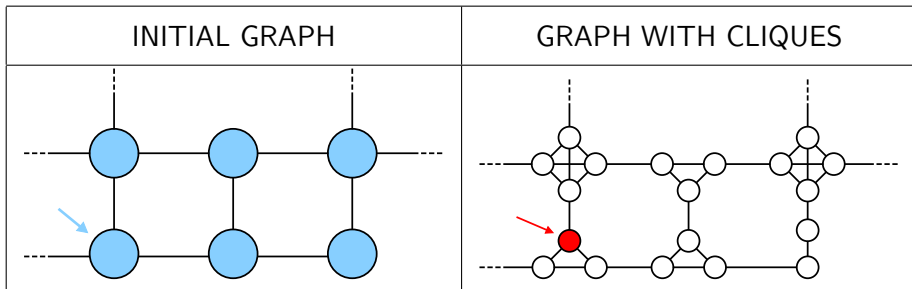
$$\text{proportion of its infected neighbors} > q = \frac{1}{4}$$



Contagion model with parameter q :

- At the beginning, one infected vertex (= the seed of the epidemic)
- At each step, each vertex becomes infected if :

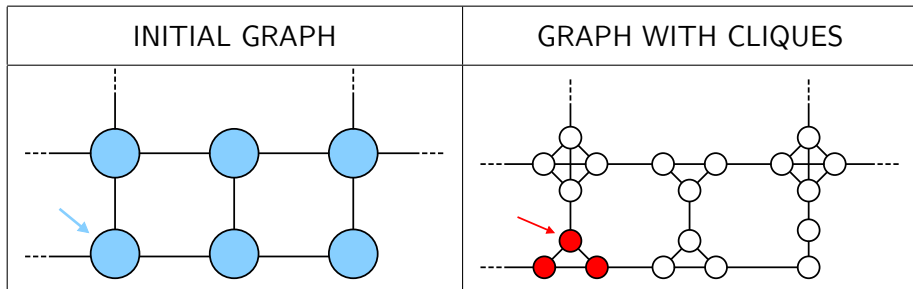
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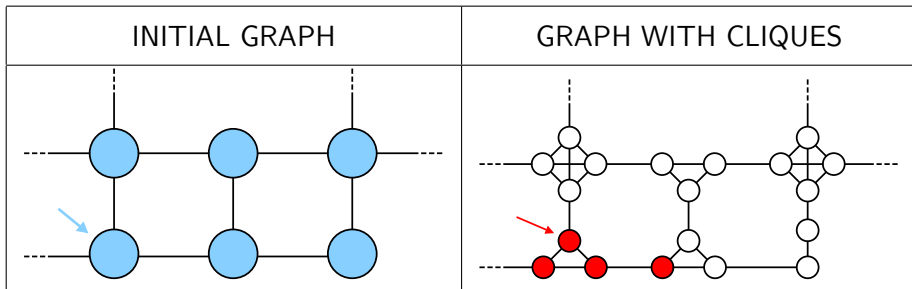
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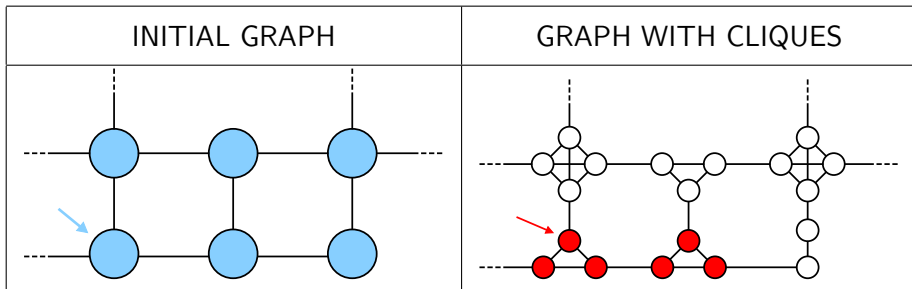
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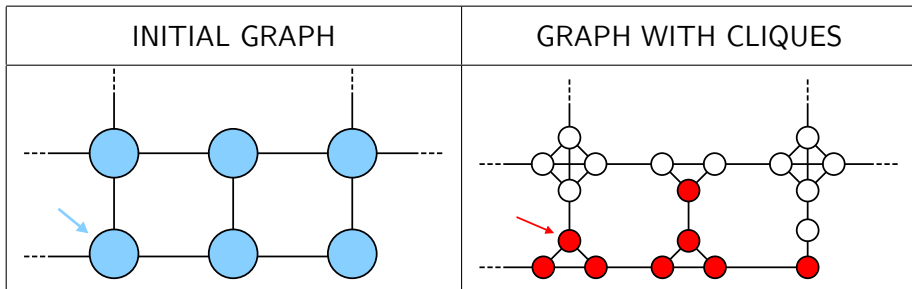
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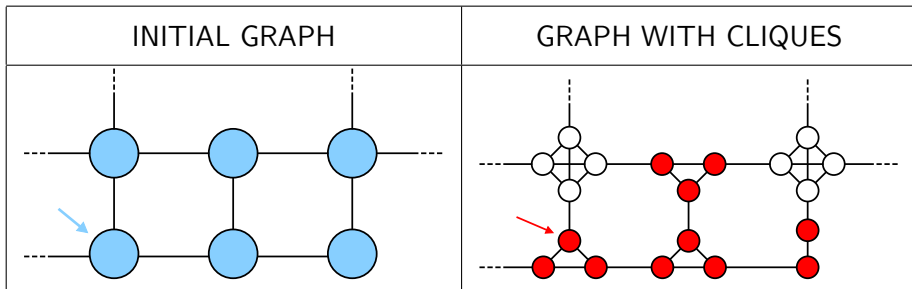
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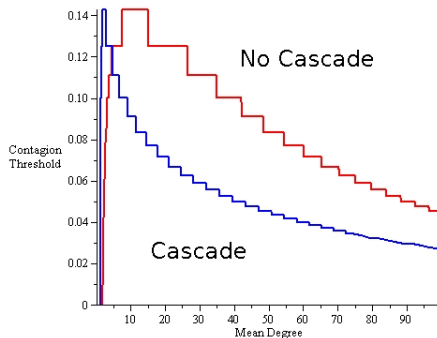


\Rightarrow Clustering decreases the cascade size.

Contagion Threshold (q_c) vs Mean Degree

Graphs with the SAME asymptotic degree distribution :

$$\tilde{p}_k \propto k^{-\tau} e^{-k/50}$$



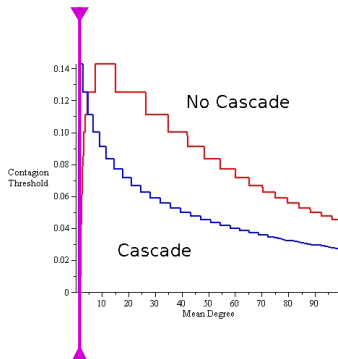
- Graph with clustering (cliques)
- Graph with no clustering

Effect of Clustering on the Contagion Threshold

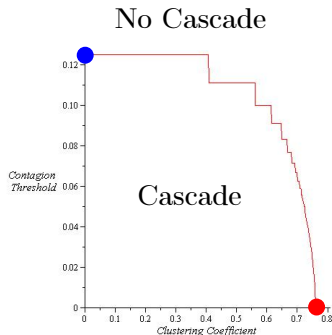
Asymptotic degree distribution :

$$\tilde{p}_k \propto k^{-\tau} e^{-k/50}$$

Mean degree $\tilde{\lambda} \approx 1.65$



- Graph with maximal clustering coefficient
- Graph with no clustering

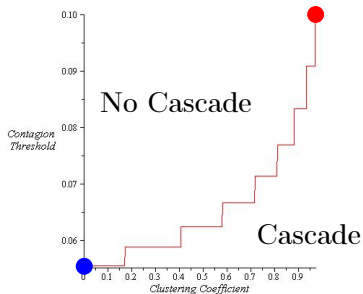
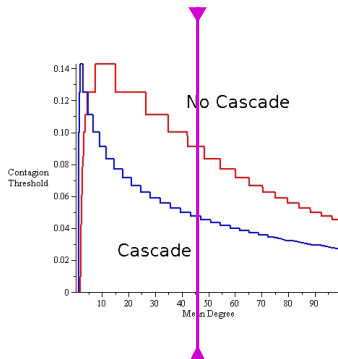


Effect of Clustering on the Contagion Threshold

Asymptotic degree distribution :

$$\tilde{p}_k \propto k^{-\tau} e^{-k/50}$$

Mean degree $\tilde{\lambda} \approx 46$



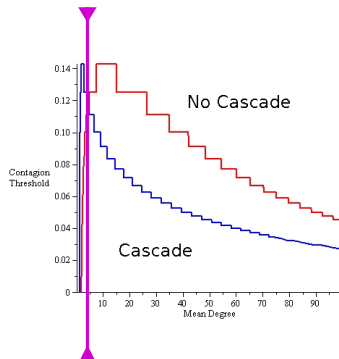
- Graph with maximal clustering coefficient
- Graph with no clustering

Effect of Clustering on the Contagion Threshold

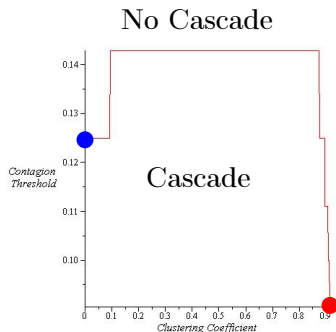
Asymptotic degree distribution :

$$\tilde{p}_k \propto k^{-\tau} e^{-k/50}$$

Mean degree $\tilde{\lambda} \approx 3.22$



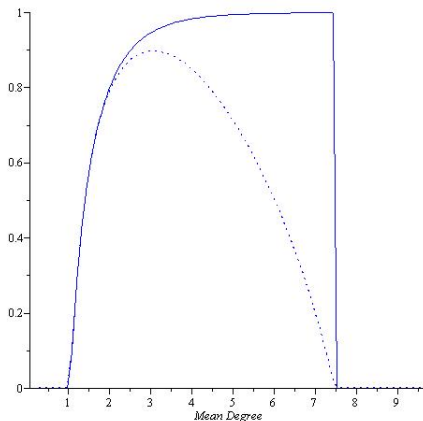
- Graph with maximal clustering coefficient
- Graph with no clustering



Effect of Clustering on the Cascade Size

Fraction of infected neighbors needed
to become infected :
 $q = 0.15$ (fixed)

- $\tilde{p}_r = \frac{0.2r+0.8}{0.2\lambda+0.8} \frac{e^{-\lambda}\lambda^r}{r!}$
- $C = 0$

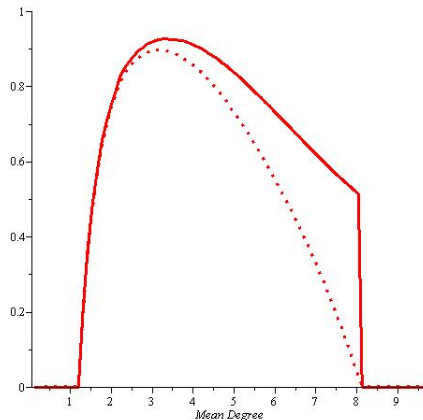


- • • Pivotal players in the graph with no clustering
- Cascade size in the graph with no clustering

Effect of Clustering on the Cascade Size

Fraction of infected neighbors needed to become infected :
 $q = 0.15$ (fixed)

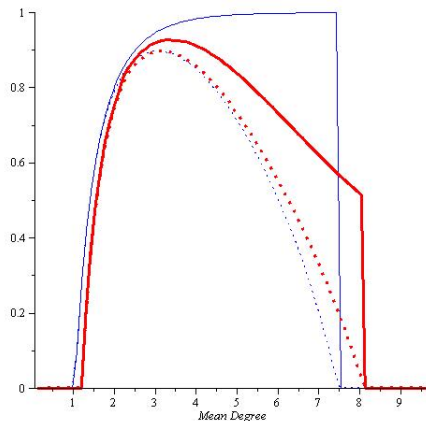
- $\tilde{p}_r = \frac{0.2r+0.8}{0.2\lambda+0.8} \frac{e^{-\lambda}\lambda^r}{r!}$
- $C = \frac{0.2\lambda}{0.2\lambda+1.2} > 0$



- Pivotal players in the graph with positive clustering
- Cascade size in the graph with positive clustering

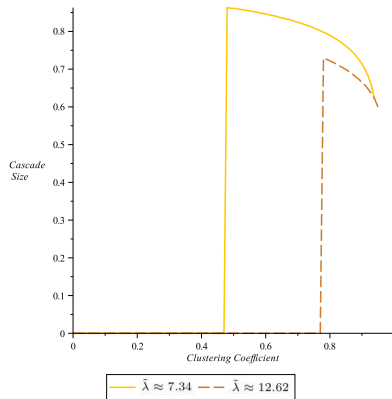
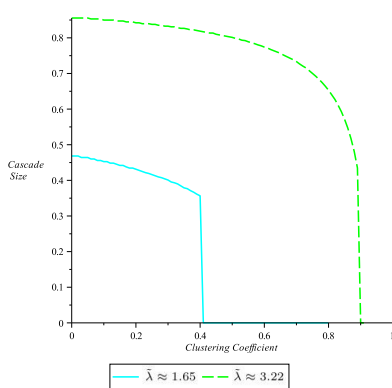
Effect of Clustering on the Cascade Size

Fraction of infected neighbors needed
to become infected :
 $q = 0.15$ (fixed)



- ... Pivotal players in the graph with no clustering
- Cascade size in the graph with no clustering
- ... Pivotal players in the graph with positive clustering
- Cascade size in the graph with positive clustering

Effect of Clustering on the Cascade Size



Asymptotic degree distribution : $\tilde{p}_k \propto k^{-\tau} e^{-k/50}$

Conclusion

- Model of random graphs with a given degree distribution, and a tunable clustering coefficient
- Effect of clustering on the diffusion model :
 - ▶ Clustering increases the diffusion threshold
 - ▶ Clustering decreases the cascade size
- Effect of clustering on the contagion model :
 - ▶ Clustering decreases the contagion threshold for low values of the mean degree, while the opposite happens in the high values regime
 - ▶ Clustering decreases the cascade size (when a cascade is possible)

Conclusion

- Model of random graphs with a given degree distribution, and a tunable clustering coefficient
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 - ▶ Clustering increases the diffusion threshold
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- Effect of clustering on the contagion model :
 - ▶ Clustering decreases the contagion threshold for low values of the mean degree, while the opposite happens in the high values regime
 - ▶ Clustering decreases the cascade size (when a cascade is possible)

Thanks for your attention !

References



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