

Spreading dynamics on small-world networks with wide connectivity fluctuations

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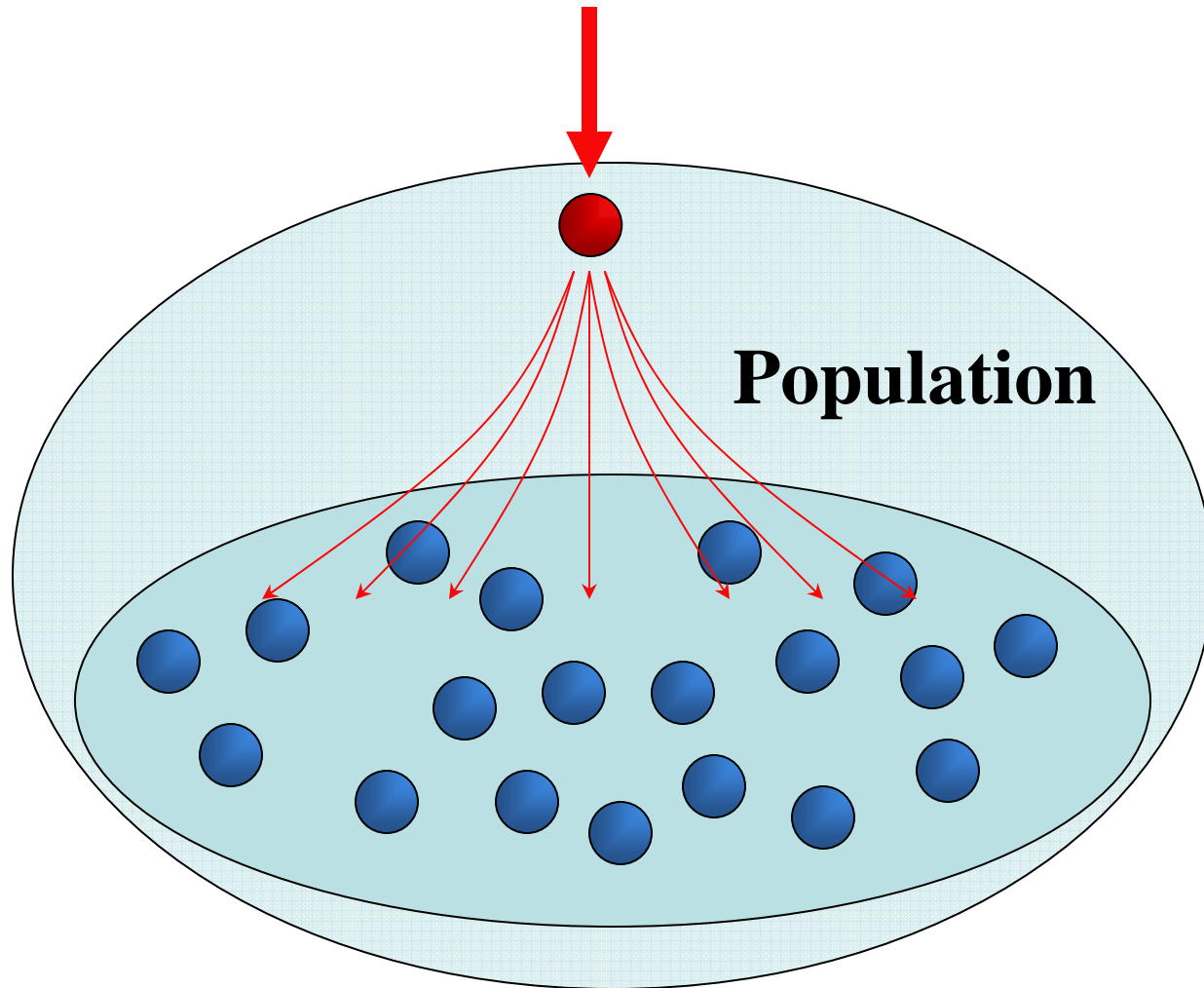
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University of Notre Dame

Epidemic outbreak

QuickTime™ and a
TIFF (Uncompressed) decompressor
are needed to see this picture.

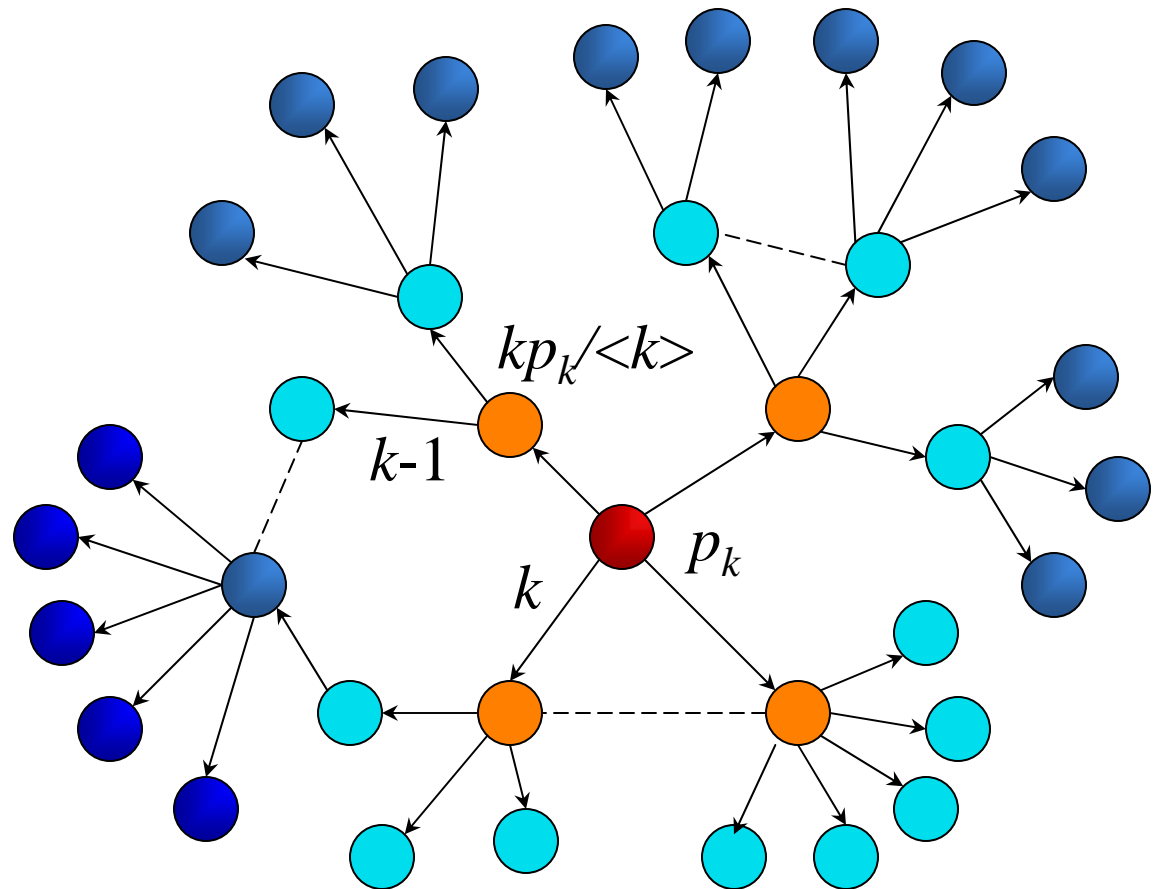
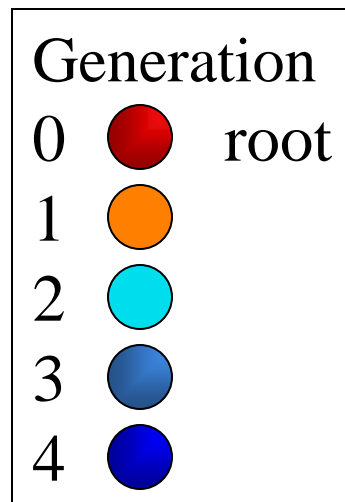
Model

External source

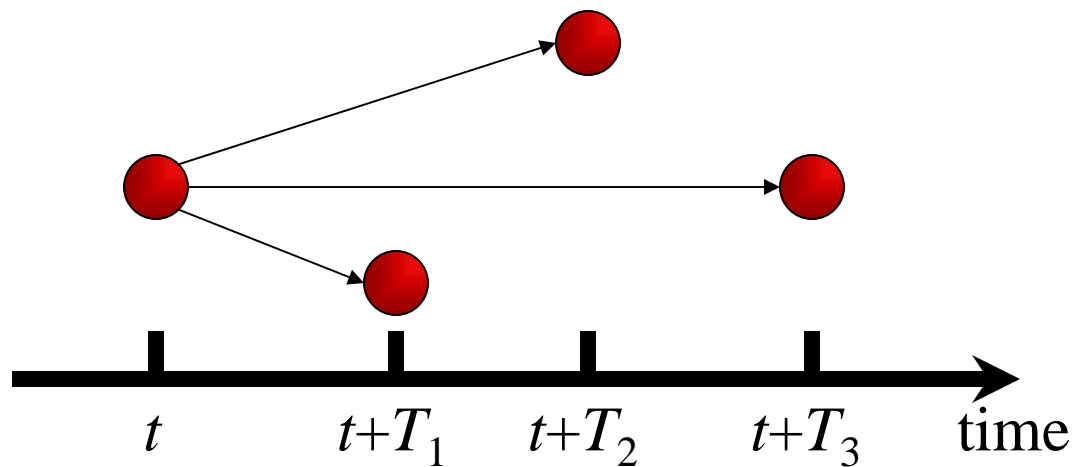
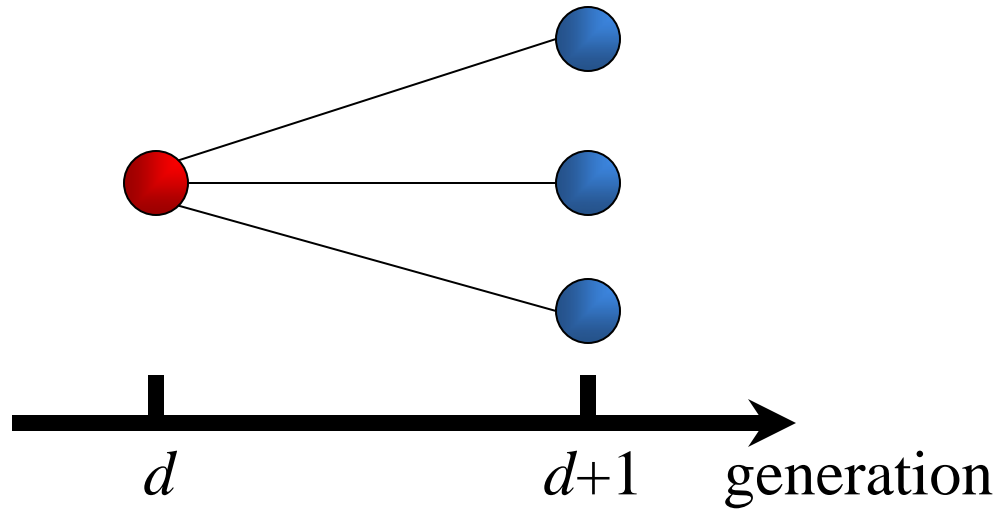


Population structure

Spanning tree



Timing



Generation time
 T

Distribution

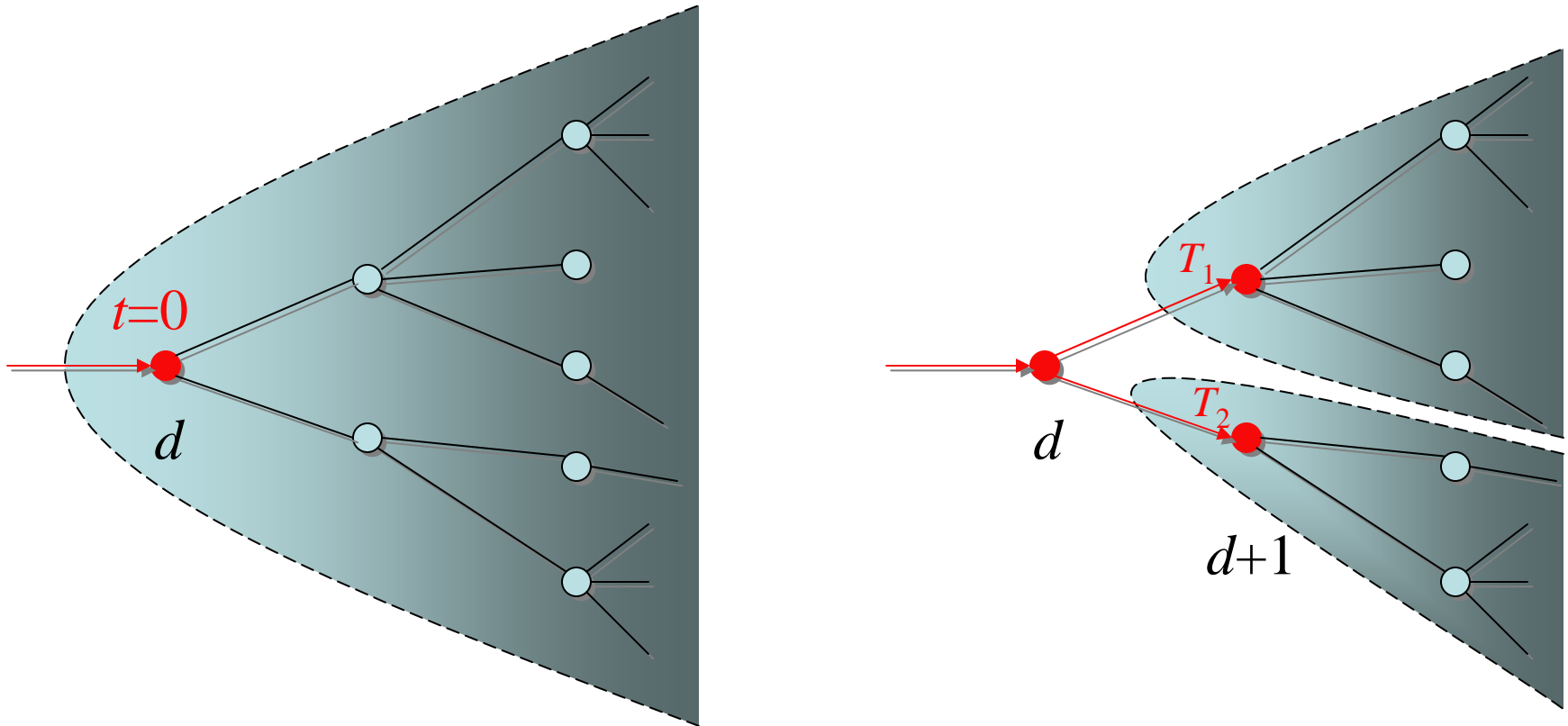
$$G(\tau) = \Pr(T \leq \tau)$$

Branching process model

1. The process start with a node ($d=0$) that generates k sons with probability distribution p_k .
2. Each son at generation $1 < d < D$ generates $k-1$ new sons with probability $kp_k / \langle k \rangle$.
3. Nodes at generation D does not generate any son.
4. The generation times are independent random variables with distribution function $G(\tau)$.

Note: Galton-Watson, Newman,
Bellman-Harris, Crum-Mode-Jagers

Iterative approach



$$N_d(t) = 1 + \tilde{R} \int_0^t dG(\tau) N_{d+1}(t - \tau)$$

Results

Constant transmission rate λ , $G(\tau)=1-e^{-\lambda\tau}$

$$I(t) = \frac{dN_0(t)}{dt} = \lambda R e^{-\lambda t} \sum_{d=1}^D \frac{(\lambda \tilde{R} t)^{d-1}}{(d-1)!} \approx \begin{cases} e^{(\tilde{R}-1)\lambda t} & t \ll t_0 \\ t^{D-1} e^{-\lambda t} & t \gg t_0 \end{cases}$$

$e^x = \sum_{d=1}^{\infty} \frac{x^{d-1}}{(d-1)!}$

$$\tilde{R} = \frac{\langle k(k-1) \rangle}{\langle k \rangle}$$

Excess degree/reproductive number

$$t_0 = \frac{D-1}{\tilde{R}} \frac{1}{\lambda}$$

Characteristic time scale

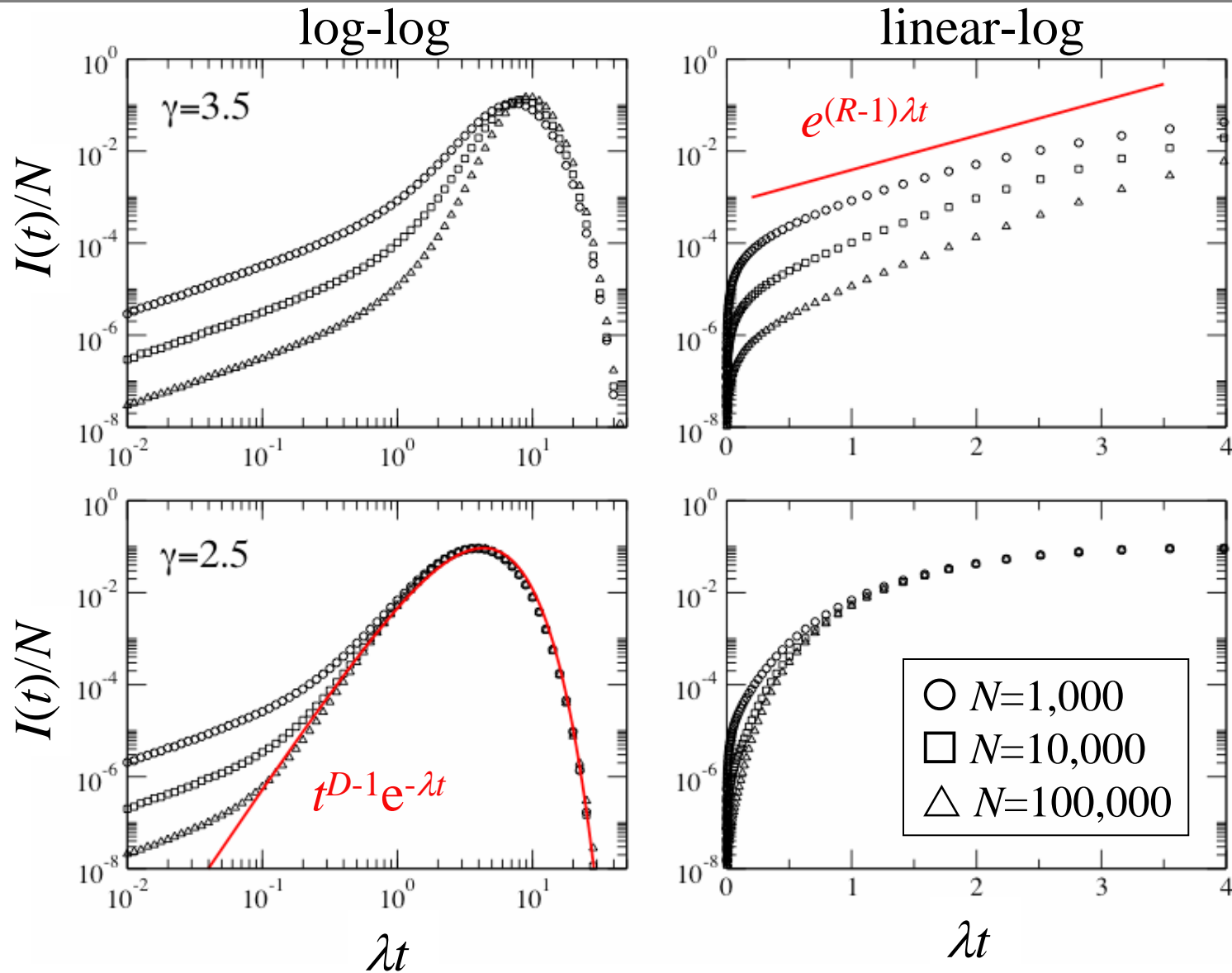
Numerical simulations

- Random graphs with a power law degree distribution: $p_k \sim k^{-\gamma}$

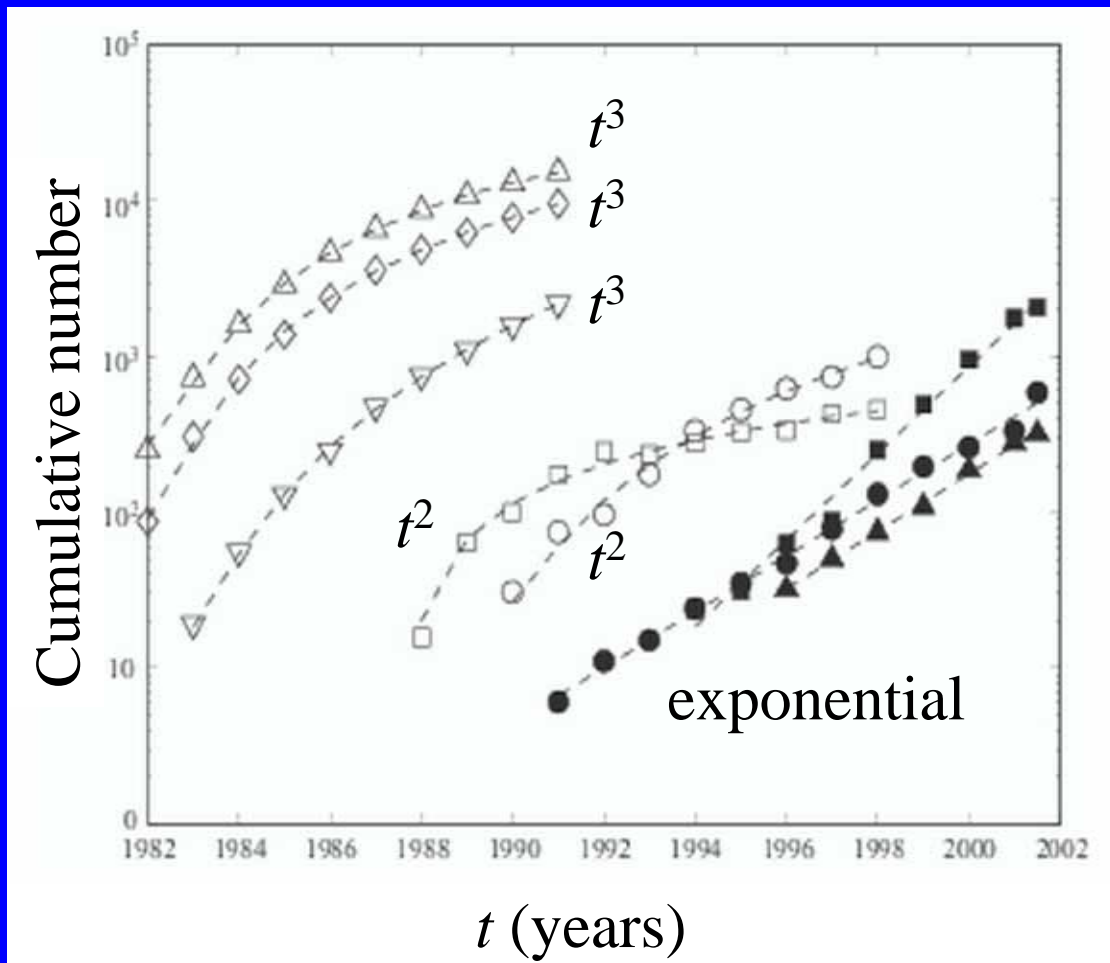
$$\tilde{R} = \frac{\langle k(k-1) \rangle}{\langle k \rangle} \sim \begin{cases} N^0 & \gamma > 3 \\ N^{(3-\gamma)/(\gamma-1)} & \gamma < 3 \end{cases}$$

$$\lambda t_0 \sim \begin{cases} \ln N & \gamma > 3 \\ \frac{\ln N}{N^{(3-\gamma)/(\gamma-1)}} & \gamma < 3 \end{cases}$$

Numerical simulations



AIDS epidemics

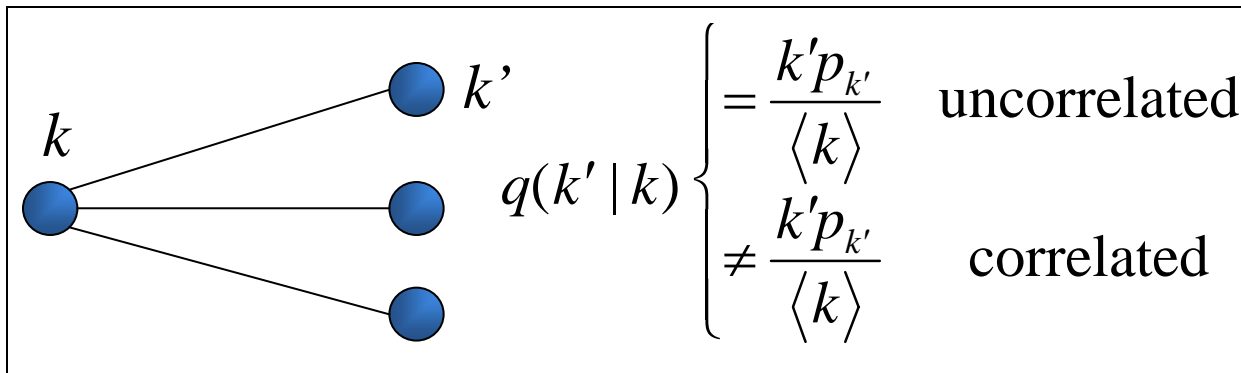


- \triangle New York - HOM
- ∇ New York - HET
- \diamond San Francisco - HOM
- \circ South Africa
- \square Kenya

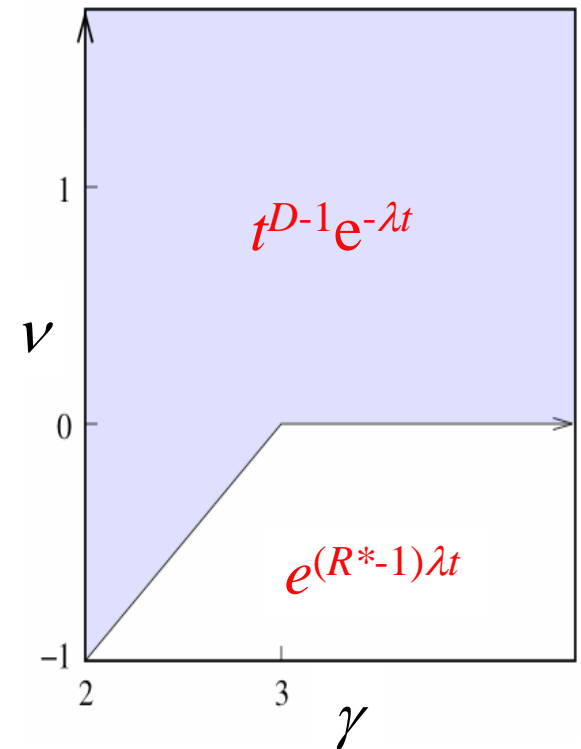
- \blacktriangle Georgia
- \blacksquare Latvia
- \bullet Lithuania

Generalizations

Connectivity correlations

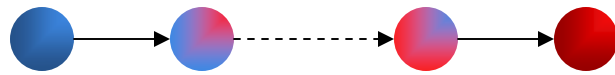


$$\tilde{R}_k = \sum_{k'} q(k' | k) k' \sim k^\nu \rightarrow \begin{cases} \nu < 0 & \text{disassortative} \\ \nu = 0 & \text{uncorrelated} \\ \nu > 0 & \text{assortative} \end{cases}$$



Generalizations

Intermediate states

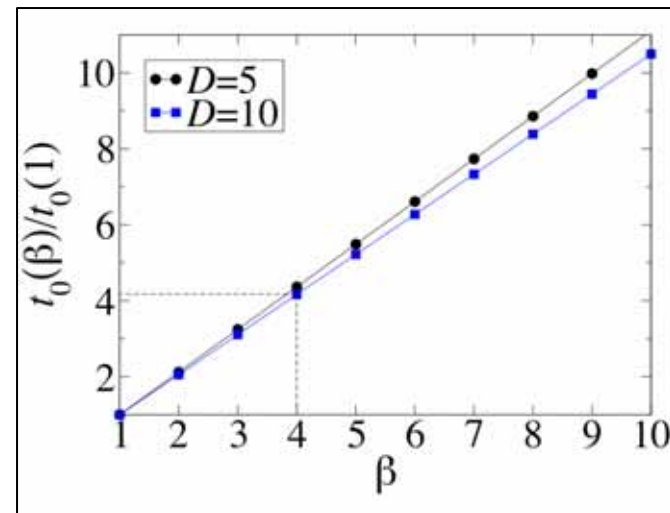
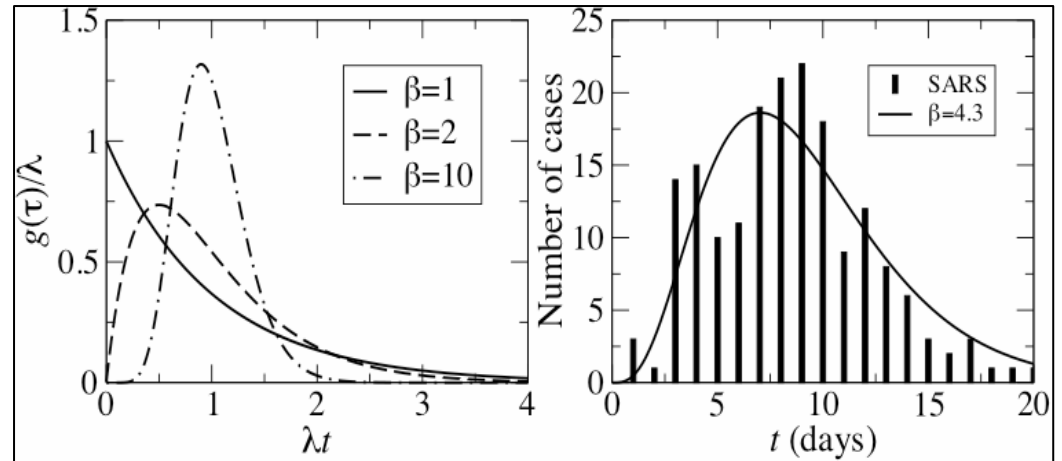


$$g(\tau) = \dot{G}(\tau) = \frac{\lambda(\lambda\tau)^{\beta-1} e^{-\lambda\tau}}{\Gamma(\beta)}$$

$$I(t) \sim \begin{cases} e^{(\tilde{R}-1)\lambda t} & t \ll t_0 \\ t^{\beta D-1} e^{-\lambda t} & t \gg t_0 \end{cases}$$

$$\tilde{R} = \beta \left(\frac{\langle k(k-1) \rangle}{\langle k \rangle} \right)^{1/\beta}$$

$$t_0(\beta) \approx \left[\frac{\beta(\beta D - 1) \cdots (\beta D - \beta)}{\tilde{R}} \right]^{1/\beta} \frac{1}{\lambda}$$

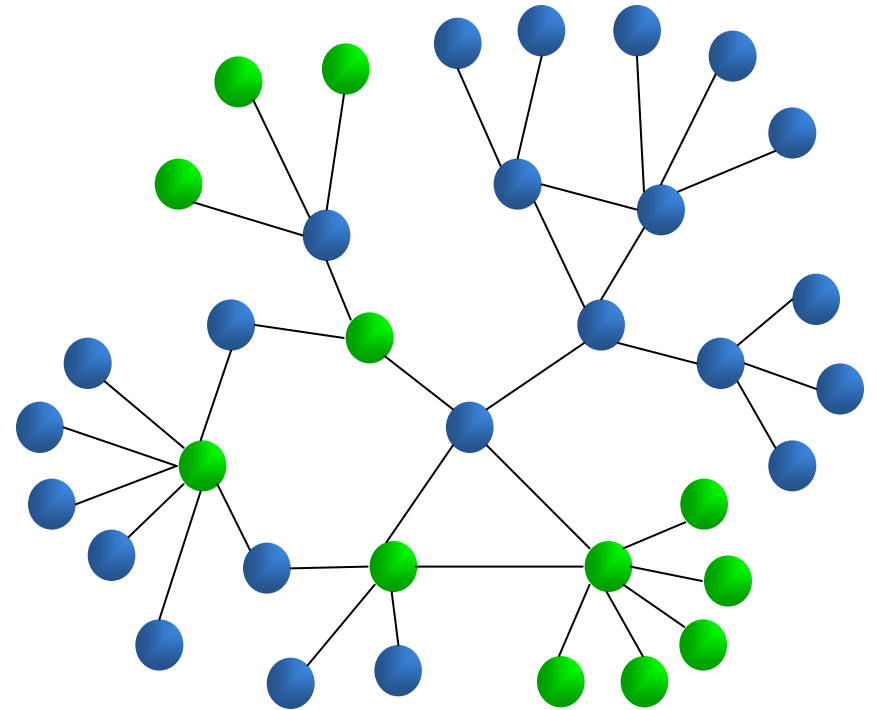


Generalizations

Multi-type

$i=1, \dots, M$ types

N_i number of type i agents
 $p_k^{(i)}$ type i degree distribution
 e_{ij} mixing matrix
 D average distance

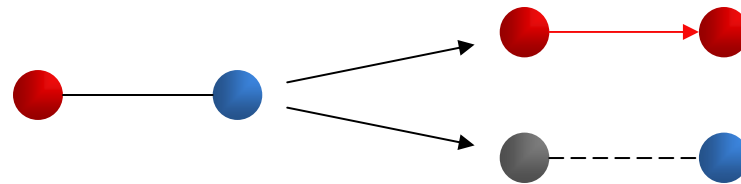


Reproductive number matrix

$$\tilde{R}_{ij} = \frac{\langle k_i(k_i - 1) \rangle}{\langle k_i \rangle} e_{ij}$$

Generalizations

Patient isolation (at rate μ)

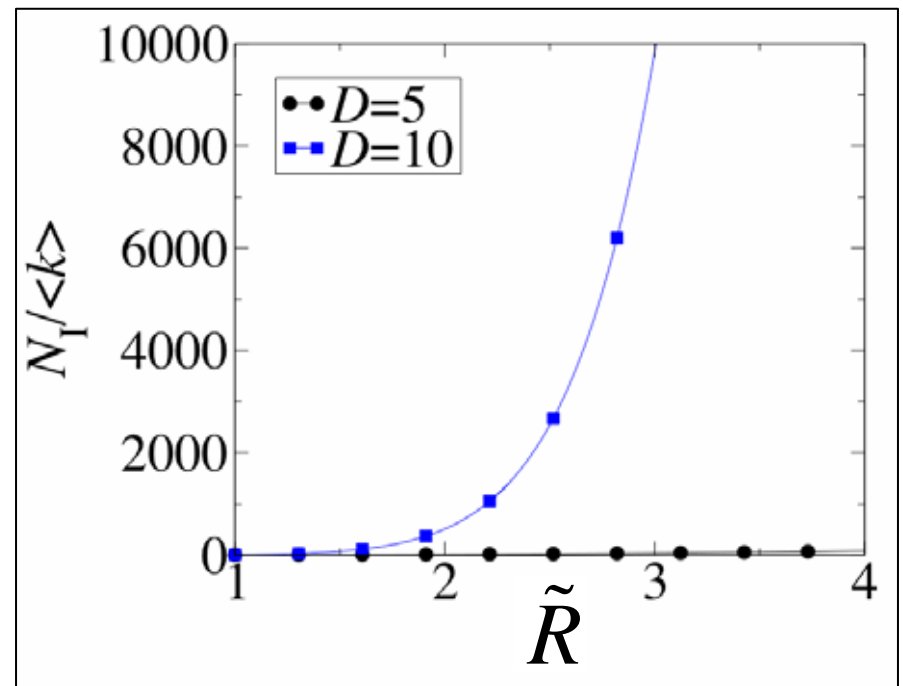


$$I(t) \approx \begin{cases} e^{(\tilde{R}-1)(\lambda+\mu)t} & t \ll t_0 \\ t^{D-1} e^{-(\lambda+\mu)t} & t \gg t_0 \end{cases}$$

$$t_0 = \frac{D-1}{\tilde{R}} \frac{1}{\lambda+\mu} \quad \tilde{R} = \frac{\lambda}{\lambda+\mu} \frac{\langle k(k-1) \rangle}{\langle k \rangle}$$

Final outbreak size

$$N_I = R \frac{\tilde{R}^D - 1}{\tilde{R} - 1}$$



Conclusions

- Truncated branching processes are a suitable framework to model spreading processes on real networks.
- There are two spreading regimes.
 - Exponential growth.
 - Polynomial growth followed by an exponential decay.
- The time scale separating them is determined by D/R .
- The small-world property and the connectivity fluctuations favor the polynomial regime.
- Intermediate states favor the exponential regime.
- The final outbreak size is determined by R and D .

Results

Outbreak size dynamics

$$N_I(t) = 1 + \sum_{d=1}^D z_d \Pr\left(\sum_{l=1}^d \tau_l \leq t\right)$$

mean number of nodes
at generation d

prob. of reaching a node at
generation d before time t

Incidence

$$I(t) = \frac{dN_I(t)}{dt}$$

$$z_d = \langle k \rangle K^{d-1}$$

$$K = \frac{\langle k(k-1) \rangle}{\langle k \rangle}$$

$$\Pr\left(\sum_{l=1}^d \tau_l \leq t\right) = G^{*d}(t)$$

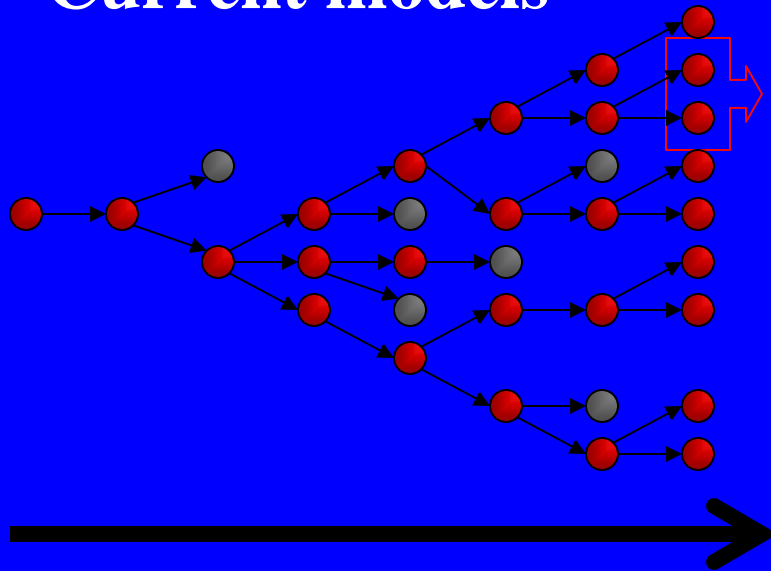
average
excess
degree

Example: constant transmission rate λ , $G(\tau) = 1 - e^{-\lambda\tau}$

$$I(t) = \lambda \langle k \rangle e^{-\lambda t} \sum_{d=1}^D \frac{(\lambda K t)^{d-1}}{(d-1)!}$$

Current models vs reality

Current models

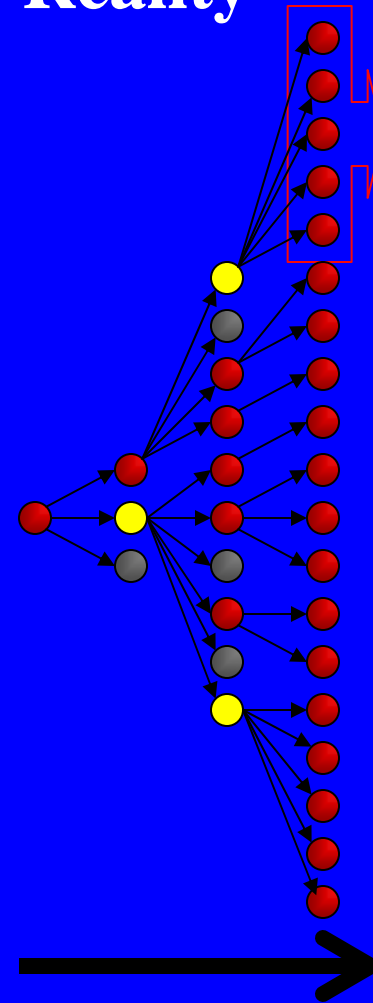


few
secondary
cases

several generations

- Infected
- Infected/super-spreader
- Infected/recovered

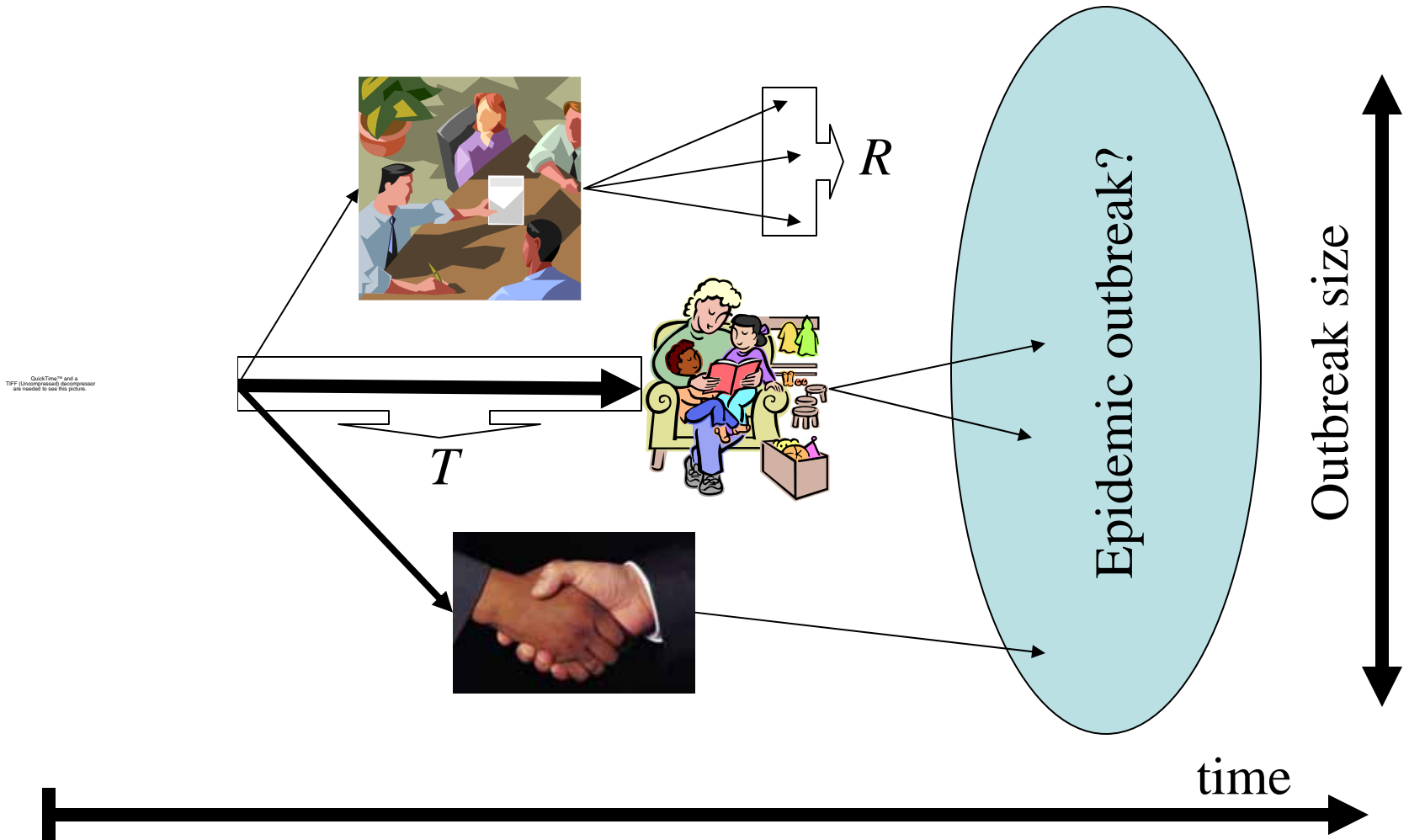
Reality



Super-
spreading

few generations

Epidemic outbreak



Annealed spanning tree (AST)

1. The process start with a node ($d=0$) that generates k decendants with probability distribution p_k .
2. Each decendant at generation $1 < d < D$ generates $k-1$ new decendants with probability $kp_k / \langle k \rangle$.
3. Nodes at generation D does not generate any decendant.

Approximations

1. Tree structure
2. Annealed average
3. Sharp truncation

Note: Galton-Watson, Newman