

Stochastic Simulations

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CENTRO DE **SISTEMAS
COMPLEJOS**

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Jardines de la Reina

EPIDEMICS ON NETWORKS

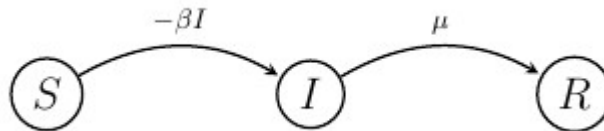
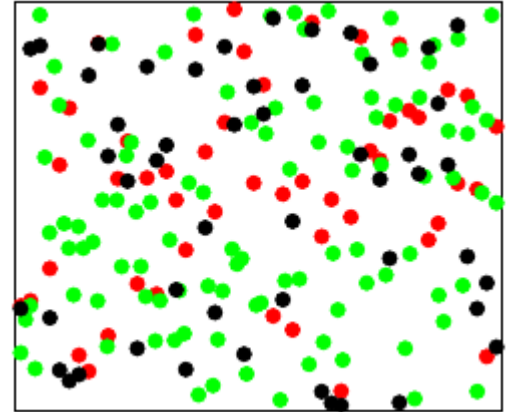
1. Mathematical epidemiology, origins, early results. The compartmental model family.
 2. The mean field description of SIR models. Short and long time limits in SIR.
3. **Monte Carlo simulations of epidemics. Gillespie algorithm.**
4. **Monte Carlo simulations Practical Python Class.**
5. Complex networks. Main results. Types and properties. Famous networks. Benchmarks.
 6. **Playing with networks in Python. Networkx. Plotting. Nice plotting.**
7. Master equation of epidemics on networks. The mean field solution and pair based solution.
 8. **Simulating epidemics on networks. Python libraries.**
9. Inference and belief propagation.
 10. The zero patient problem. The contamination source detection problem.
11. The infectious backbone as a cascade process.
 12. The effect of contact tracing.

PREVIOUSLY ON EPIDEMICS ...

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Epidemics are (matheamtically):

- Stochastic processes
- Discrete states (S, I, R)
- Continuous time
- Good approximation: Markovian

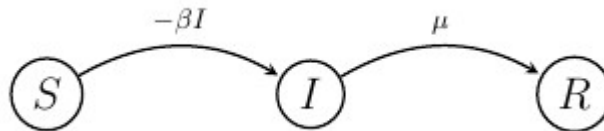
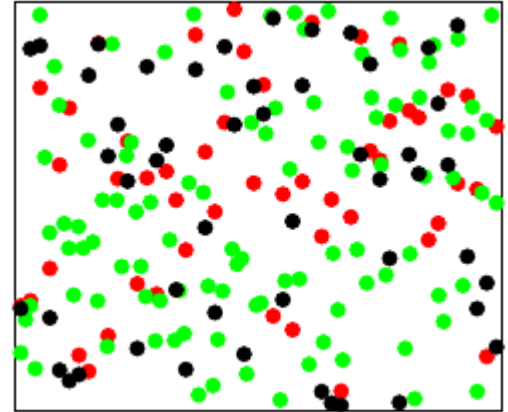


PREVIOUSLY ON EPIDEMICS ...

$$\begin{aligned}\frac{dS}{dt} &= -\beta SI \\ \frac{dI}{dt} &= \beta SI - \mu I \\ \frac{dR}{dt} &= \mu I\end{aligned}$$

Epidemics are (matheamtically):

- Stochastic processes
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PREVIOUSLY ON EPIDEMICS ...

$$\frac{dS}{dt} = -\beta SI$$

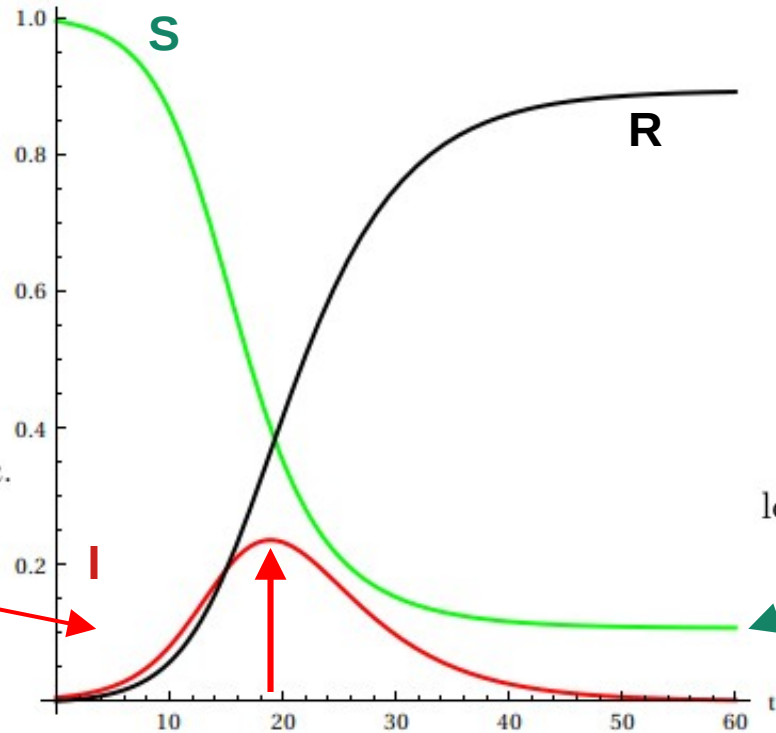
$$\frac{dI}{dt} = \beta SI - \mu I$$

$$\frac{dR}{dt} = \mu I$$

$$\frac{dI}{dt} = \lambda I(t), \quad \text{where } \lambda = \beta - \mu.$$

$$I(t) = I(0) \exp(\lambda t).$$

$$R_0 = \beta\tau = \beta/\mu$$



$$\log(S_0/S_\infty) = \frac{\beta}{\mu}(1 - S_\infty)$$

STOCHASTIC SIMULATIONS

I. Introduction: Exponential distribution

Rates and exponentials

II. Gillespie Stochastic Simulation Algorithm (SSA)

Derivation

Pseudo code

III. Practical Python Class

10 min Python introduction

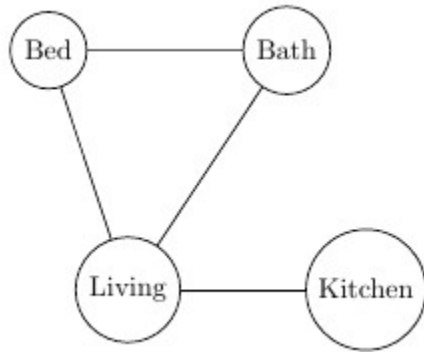
Gillespie algorithm

Drunken man problem

SIR model

SIS model

DRUNKEN MAN PROBLEM

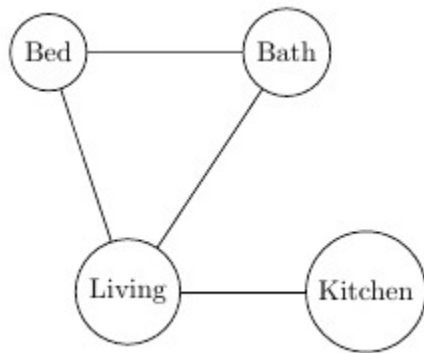


Discrete time $\vec{p}(k+1) = M \cdot \vec{p}(k)$

$$M = \begin{bmatrix} 1-\delta & \delta/2 & \delta/3 & 0 \\ \delta/2 & 1-\delta & \delta/3 & 0 \\ \delta/2 & \delta/2 & 1-\delta & \delta \\ 0 & 0 & \delta/3 & 1-\delta \end{bmatrix}$$

Bed	$\xrightleftharpoons[\delta/2]{\delta/2}$	Bath
Bed	$\xrightleftharpoons[\delta/3]{\delta/2}$	Living
Bath	$\xrightleftharpoons[\delta/3]{\delta/2}$	Living
Living	$\xrightleftharpoons[\delta]{\delta/3}$	Kitchen

DRUNKEN MAN PROBLEM



Discrete time $\vec{p}(k+1) = M \cdot \vec{p}(k)$

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$$\vec{p}(k) = M^k \vec{p}(0)$$

Stationary state

$$\vec{p}_\infty = M \cdot \vec{p}_\infty$$

Continuous time limit

$$\vec{p}(k+1) - \vec{p}(k) = (M(\delta/T) - \mathbb{I}) \cdot \vec{p}(k)$$

Exponential
solutions

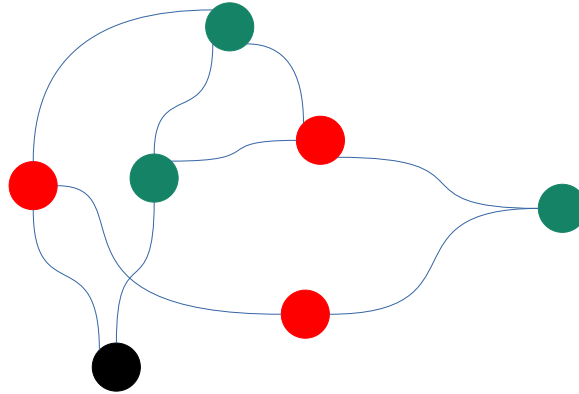
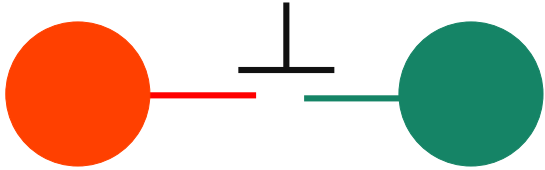
$$\longrightarrow \frac{d\vec{p}}{dt} = (M(\delta) - \mathbb{I}) \cdot \vec{p}$$

Eigenvalue problem:

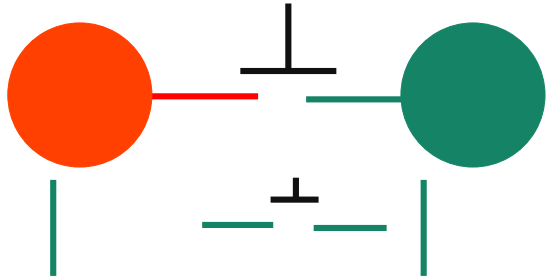
$$\frac{d\vec{p}}{dt} = 0 \Rightarrow (M(\delta) - \mathbb{I}) \cdot \vec{p} = 0$$

$$\vec{p}_\infty = (2, 2, 3, 1)/8$$

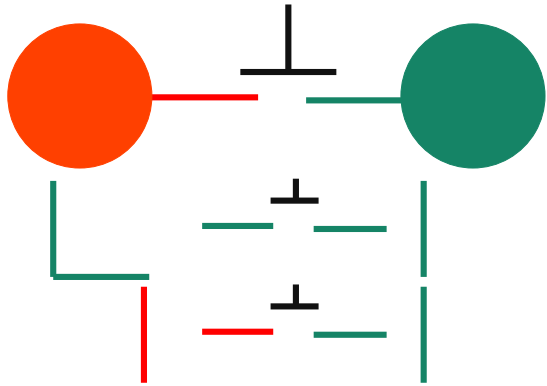
RATES AND EXPONENTIALS



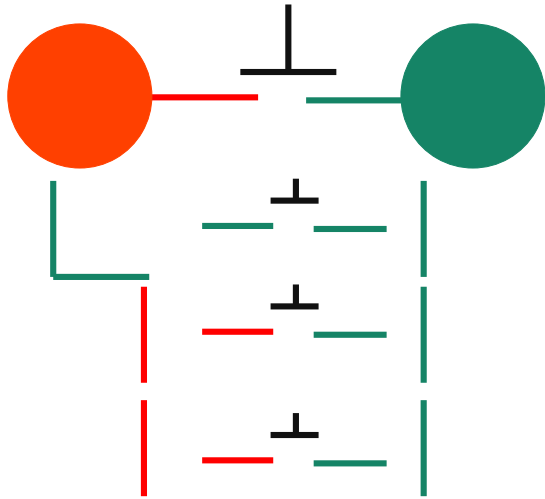
RATES AND EXPONENTIALS



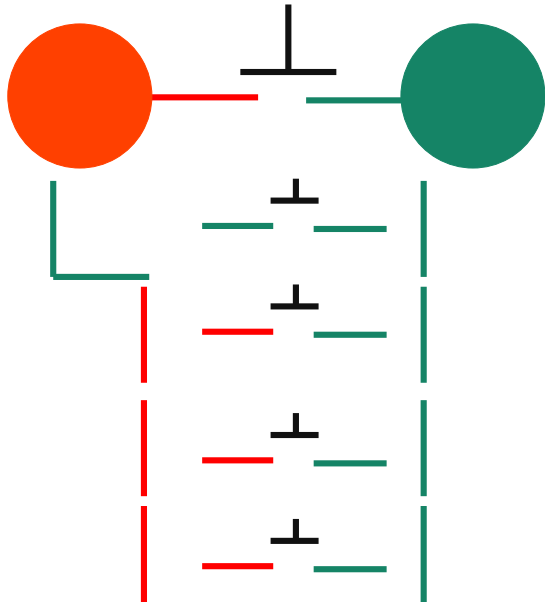
RATES AND EXPONENTIALS



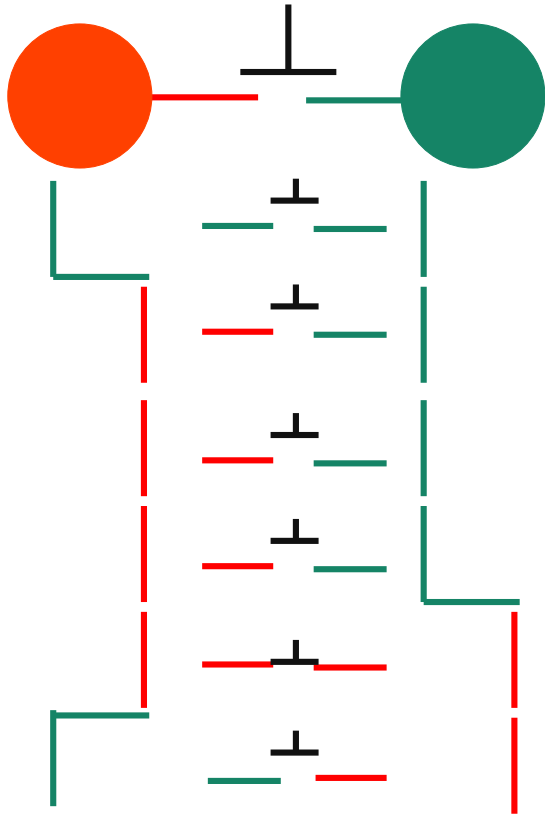
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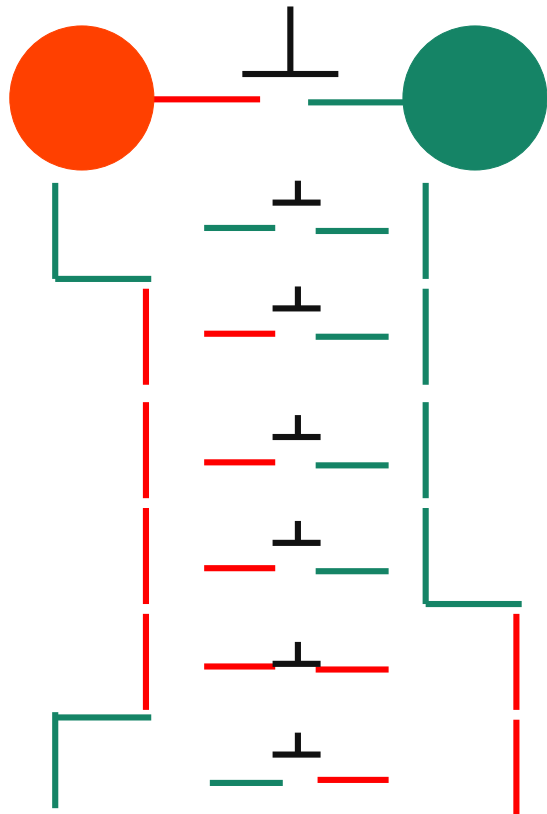
RATES AND EXPONENTIALS



RATES AND EXPONENTIALS



RATES AND EXPONENTIALS



Waiting times: geometric distribution

$$P(K = k) = (1 - q)^{k-1}q$$

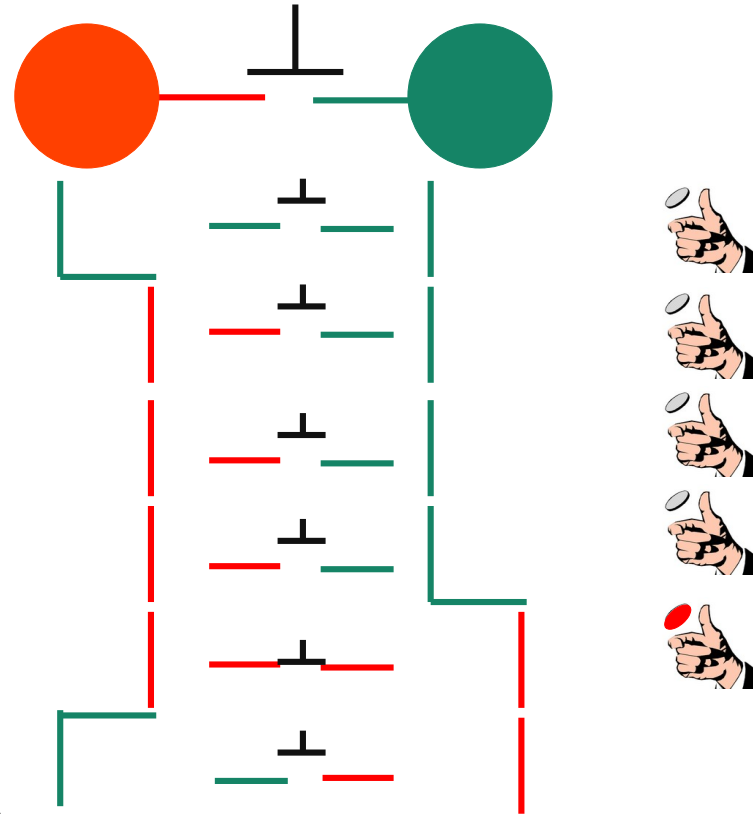
Continuous time limit $q = q'/N$

$$\begin{aligned} P(X = k/N) &= P(K = k) = (1 - q)^{k-1}q \\ &= \left(1 - \frac{q'}{N}\right)^{Nx-1} \frac{q'}{N} \end{aligned}$$

$$f(x) = \lim_{N \rightarrow \infty} \frac{P(X = k/N)}{1/N} = q' e^{-xq'}$$

RATES AND EXPONENTIALS

When something **happens at a rate**:
It will happen in **exponential time**

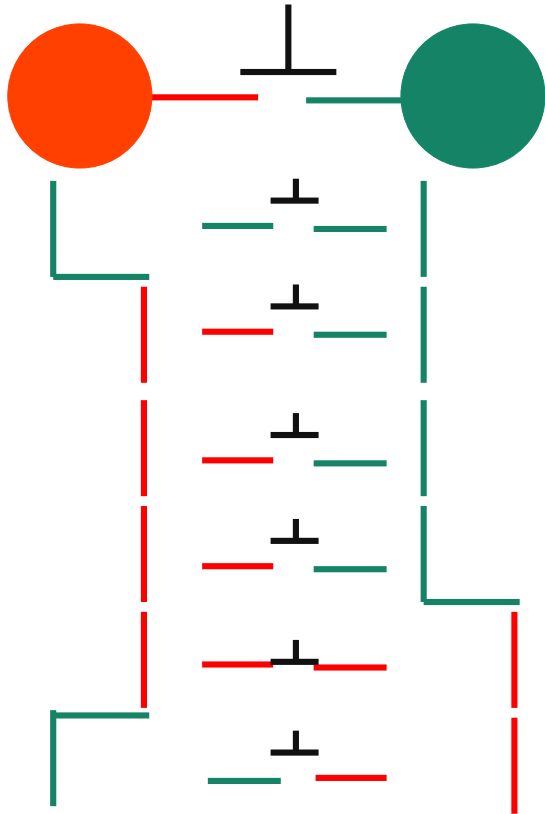


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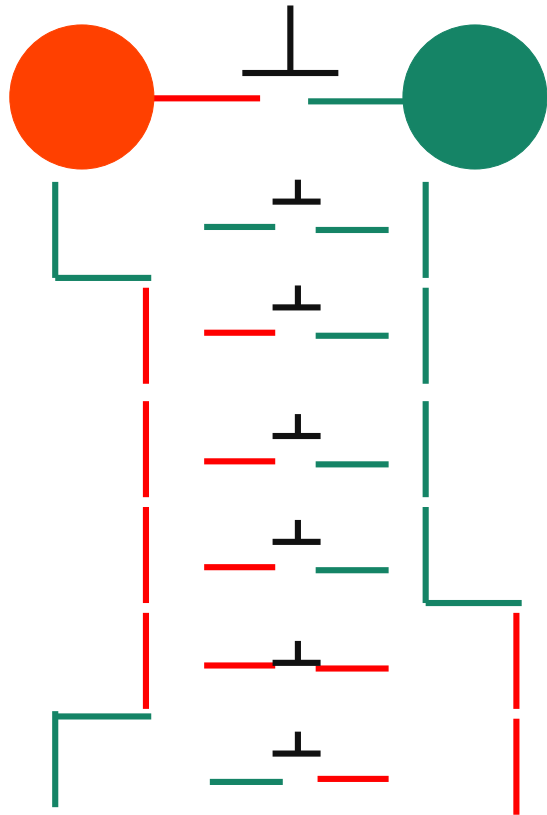
RATES AND EXPONENTIALS

Properties of exponential distributions $f(x) = \lambda e^{-\lambda x}$

Mean $\langle X \rangle = \frac{1}{\lambda}$.



RATES AND EXPONENTIALS

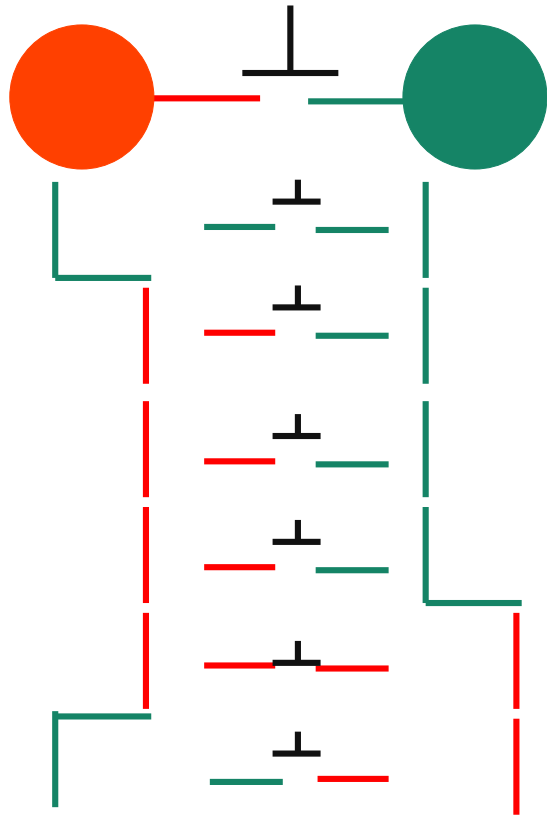


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RATES AND EXPONENTIALS



Properties of exponential distributions $f(x) = \lambda e^{-\lambda x}$

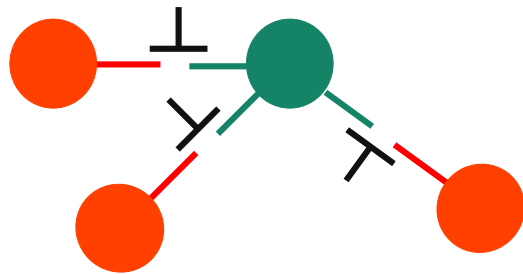
Mean $\langle X \rangle = \frac{1}{\lambda}$

Cumulative distribution $F(x) = \int_{-\infty}^x f(x) = 1 - e^{-\lambda x}$

Memorylessness

$$P(X > s+t | X > s) = \frac{P(X > s+t)}{P(X > s)} = \frac{e^{-\lambda(s+t)}}{e^{-\lambda s}} = e^{-\lambda t} \\ = 1 - F(t) = P(X > t)$$

RATES AND EXPONENTIALS



Law of the minimum

$$\begin{cases} X_i \sim \text{Exp}(\lambda_i), \\ Y_i = \min_i X_i, \\ Z_i = \operatorname{argmin}_i X_i \end{cases} \Rightarrow \begin{cases} Y \sim \text{Exp}(\sum_i \lambda_i) \\ \mathbb{P}(Z = i) = \frac{\lambda_i}{\sum_j \lambda_j} \end{cases}$$

Properties of exponential distributions $f(x) = \lambda e^{-\lambda x}$

Mean $\langle X \rangle = \frac{1}{\lambda}$.

Cumulative distribution $F(x) = \int_{-\infty}^x f(x) = 1 - e^{-\lambda x}$

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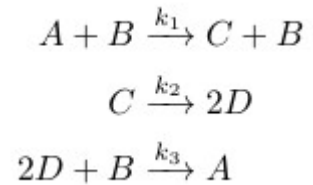
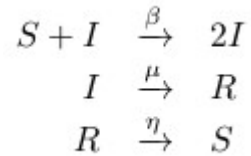
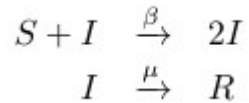
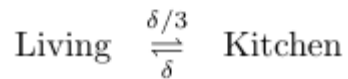
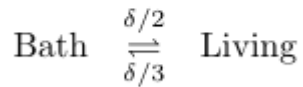
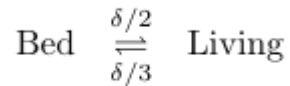
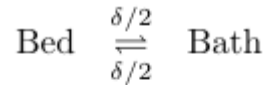
CHEMICAL REACTIONS

Drunken man

SIR

SIRS

Any chemical reaction



How do the rates depend on the state?

$$\begin{aligned} a_1 &= k_1[A][B] \\ a_2 &= k_2[C] \\ a_3 &= k_3[D]^2[B] \end{aligned}$$

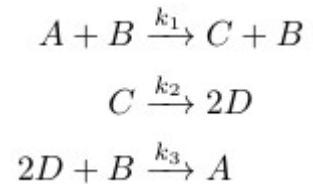
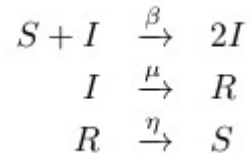
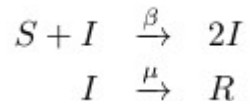
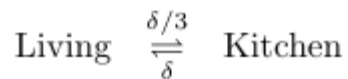
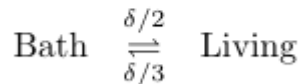
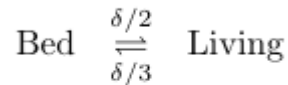
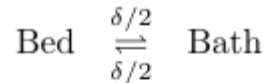
CHEMICAL REACTIONS

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How do the rates depend on the state?

How to simulate such processes?

- Stochastic
- Discrete in states
- Continuous in time

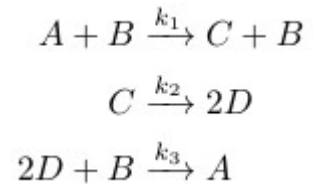
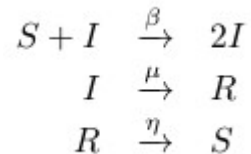
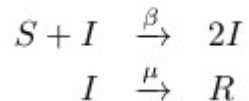
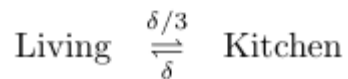
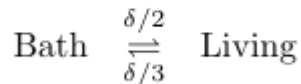
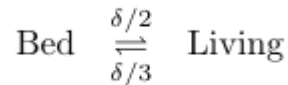
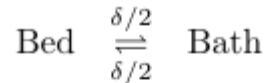
CHEMICAL REACTIONS

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Any chemical reaction

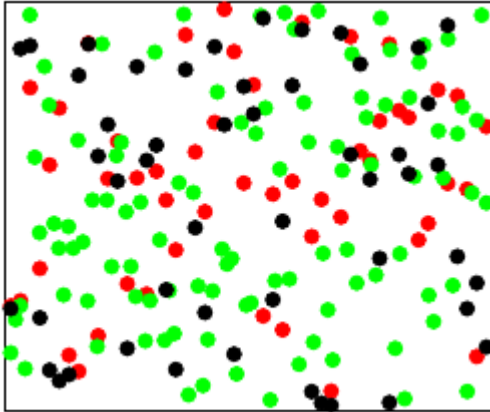


How do the rates depend on the state?

How to simulate such processes?

- Stochastic
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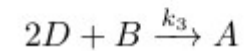
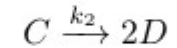
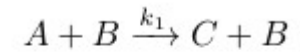
CHEMICAL REACTIONS



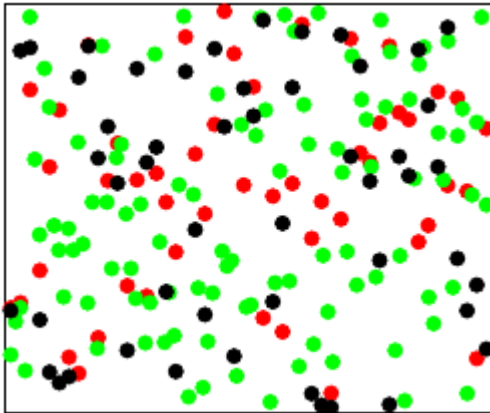
State of the system

$$X = (n_A, n_B, n_C, n_D)$$

Any chemical reaction



CHEMICAL REACTIONS



State of the system

$$X = (n_A, n_B, n_C, n_D)$$

Remains unchanged until
one of this take place

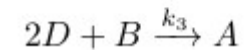
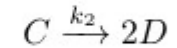
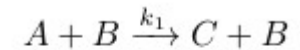
One occurrence is defined by

$$\mathcal{P} = \{(t_1, r_1), (t_2, r_2)..\}$$

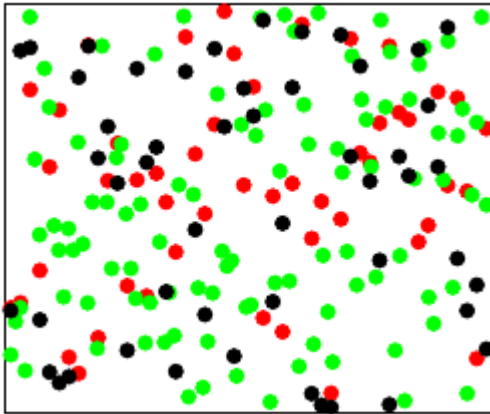
Two random values:

- Time for jumping
- Reaction to use

Any chemical reaction



CHEMICAL REACTIONS



State of the system

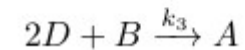
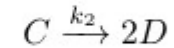
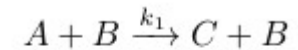
$$X = (n_A, n_B, n_C, n_D)$$

Remains unchanged until
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One occurrence is defined by

$$\mathcal{P} = \{(t_1, r_1), (t_2, r_2)..\}$$

Any chemical reaction



Stoichiometric matrix

Two random values:

- Time for jumping
- Reaction to use

$$X(t) = X(t_{k-1}) + \Delta X_{r_k}$$

$$\Delta X_1 = \begin{pmatrix} -1 \\ 0 \\ 1 \\ 0 \end{pmatrix} \quad \Delta X_2 = \begin{pmatrix} 0 \\ 0 \\ -1 \\ 2 \end{pmatrix} \quad \Delta X_3 = \begin{pmatrix} 1 \\ -1 \\ 0 \\ -2 \end{pmatrix}$$

GILLESPIE SSA

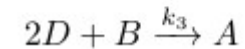
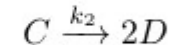
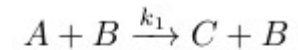
Total rate

$$a_0 = \sum_i a_i$$

State of the system

$$X = (n_A, n_B, n_C, n_D)$$

Any chemical reaction



One occurrence is defined by

$$\mathcal{P} = \{(t_1, r_1), (t_2, r_2) \dots\}$$

$$a_1 = k_1[A][B]$$

$$a_2 = k_2[C]$$

$$a_3 = k_3[D]^2[B]$$

Two random values:

- Time for jumping
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$$\Delta X_1 = \begin{pmatrix} -1 \\ 0 \\ 1 \\ 0 \end{pmatrix}$$

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GILLESPIE SSA

Total rate

$$a_0 = \sum_i a_i$$

Minimum i.i.d exponentials,

Jumping time:

$$\tau = \frac{1}{a_0} \ln \frac{1}{r_1}$$

State of the system

$$X = (n_A, n_B, n_C, n_D)$$

One occurrence is defined by

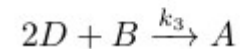
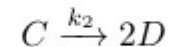
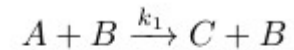
$$\mathcal{P} = \{(t_1, r_1), (t_2, r_2) \dots\}$$

Two random values:

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Any chemical reaction



$$a_1 = k_1[A][B]$$

$$a_2 = k_2[C]$$

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GILLESPIE SSA

Total rate

$$a_0 = \sum_i a_i$$

Minimum i.i.d exponentials,

Jumping time:

$$\tau = \frac{1}{a_0} \ln \frac{1}{r_1}$$

Next reaction:

$$P_i = \frac{a_i}{\sum_j a_j}$$

$$X(t) = X(t_{k-1}) + \Delta X_{r_k}$$

State of the system

$$X = (n_A, n_B, n_C, n_D)$$

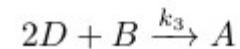
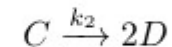
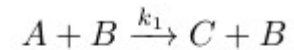
One occurrence is defined by

$$\mathcal{P} = \{(t_1, r_1), (t_2, r_2) \dots\}$$

Two random values:

- Time for jumping
- Reaction to use

Any chemical reaction



$$a_1 = k_1[A][B]$$

$$a_2 = k_2[C]$$

$$a_3 = k_3[D]^2[B]$$

$$\Delta X_1 = \begin{pmatrix} -1 \\ 0 \\ 1 \\ 0 \end{pmatrix}$$

$$\Delta X_2 = \begin{pmatrix} 0 \\ 0 \\ -1 \\ 2 \end{pmatrix}$$

$$\Delta X_3 = \begin{pmatrix} 1 \\ -1 \\ 0 \\ -2 \end{pmatrix}$$

GILLESPIE SSA

Total rate

$$a_0 = \sum_i a_i$$

Minimum i.i.d exponentials,

Jumping time:

$$\tau = \frac{1}{a_0} \ln \frac{1}{r_1}$$

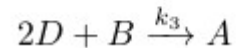
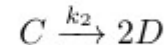
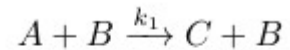
Next reaction:

$$P_i = \frac{a_i}{\sum_j a_j}$$

Algorithm 1

Gillespie SSA

```
1:  $t = 0$ 
2:  $X(0) = X_0$ 
3: while  $t < t_{end}$  do
4:   Update( $a_i$ )
5:    $a_0 = \sum_i a_i$ 
6:   for  $i = 1 \dots K$  do
7:      $P_i = \frac{a_i}{a_0}$ 
8:    $r_1 \sim U(0, 1)$ 
9:    $r_2 \sim U(0, 1)$ 
10:   $\tau = \frac{1}{a_0} \ln \frac{1}{r_1}$ 
11:   $k = i | P_{i-1} < r_2 < P_i$ 
12:   $X(t + \tau) = X(t) + \Delta X_k$ 
13:  Set  $t = t + \tau$ 
```



$$a_1 = k_1[A][B]$$

$$a_2 = k_2[C]$$

$$a_3 = k_3[D]^2[B]$$

PRACTICAL PYTHON CLASS

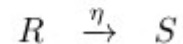
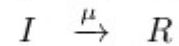
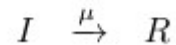
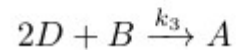
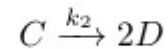
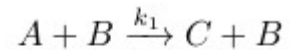
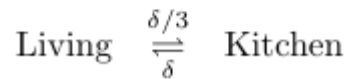
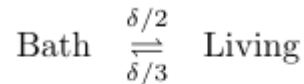
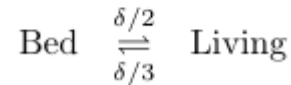
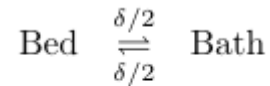
Algorithm 1

Gillespie SSA

```

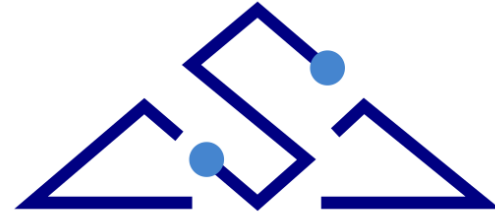
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```





你好



CENTRO DE **SISTEMAS
COMPLEJOS**

Facultad de Física
Universidad de La Habana