

Lecture 7b:

Stochastic Processes



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**Bayesian Data Analysis and
Machine Learning for Physical
Sciences**



Course Map

Module 1	Maximum Entropy and Information, Bayes Theorem
Module 2	Naive Bayes, Bayesian Parameter Estimation, MAP
Module 3	MLE, Lin Regression
Module 4	Model selection I: Comparing Distributions
Module 5	Model Selection II: Bayesian Signal Detection
Module 6	Variational Bayes, Expectation Maximization
Module 7	Hidden Markov Models, Stochastic Processes
Module 8	Monte Carlo Methods
Module 9	Machine Learning Overview, Supervised Methods
Module 10	Unsupervised Methods
Module 11	ANN: Perceptron, Backpropagation
Module 12	ANN: Basic Architecture, Regression vs Classification, Backpropagation again
Module 13	Convolution and Image Classification and Segmentation
Module 14	Graphs and GNNs
Module 15	RNNs and LSTMs
Module 16	Transformer and LLMs



Outline

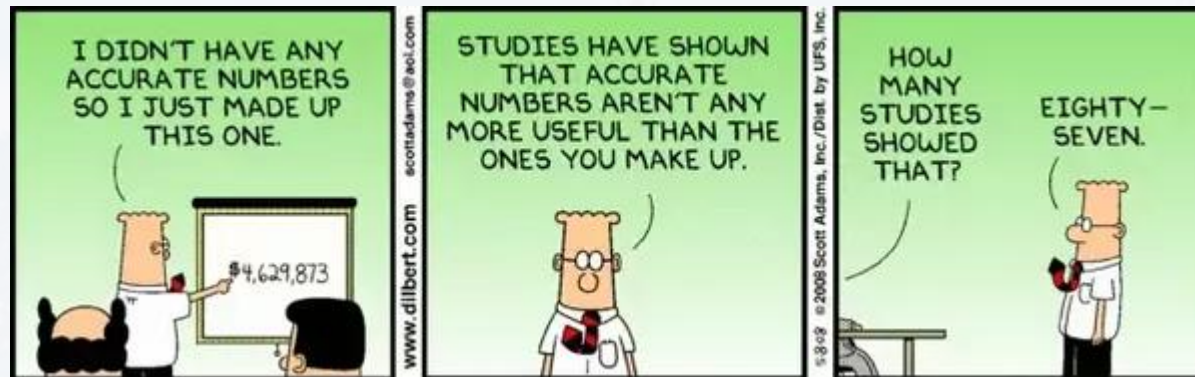
The Poissonian Stepper

Examples of Stochastic Processes

- Radioactive Decay
- Chem. Reactions
- Predator Prey
- Gene Expression

Diffusion Processes

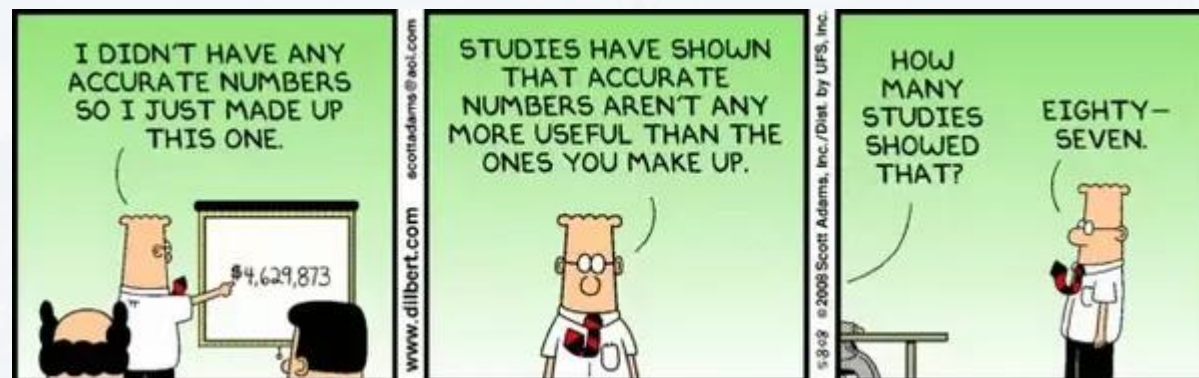
Fokker-Planck Equation





Outline

The Poissonian Stepper



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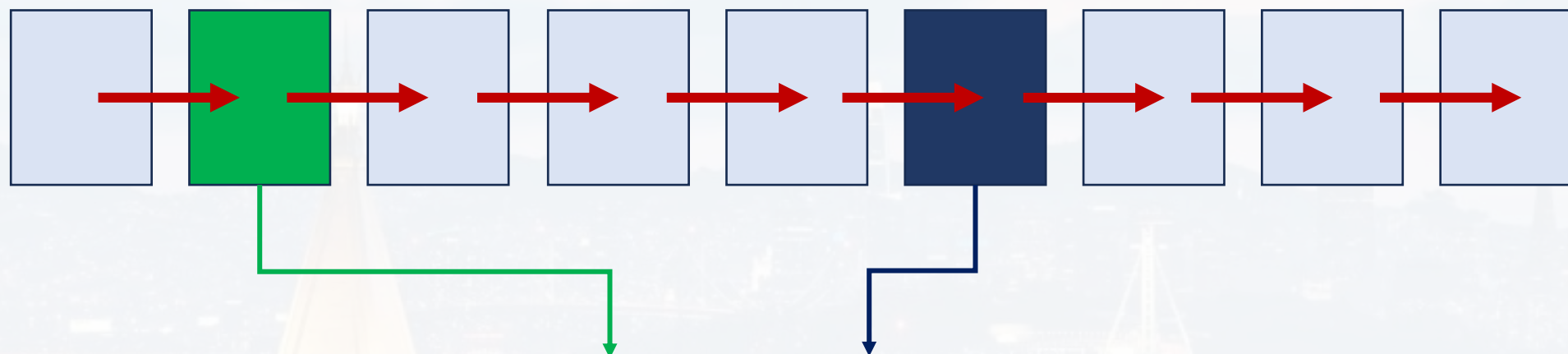
Diffusion Processes

Fokker-Planck Equation



HMM: sequence of states

set of different states/classes

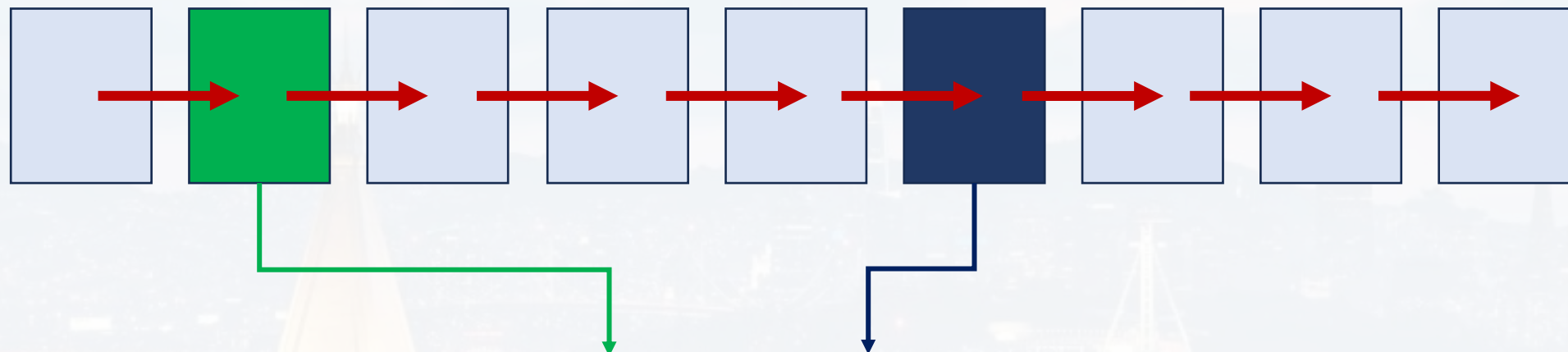


a set of T observations O $O = (O_1, O_2, O_3, \dots O_t, \dots O_T)$ drawing randomly from the states



HMM: sequence of states

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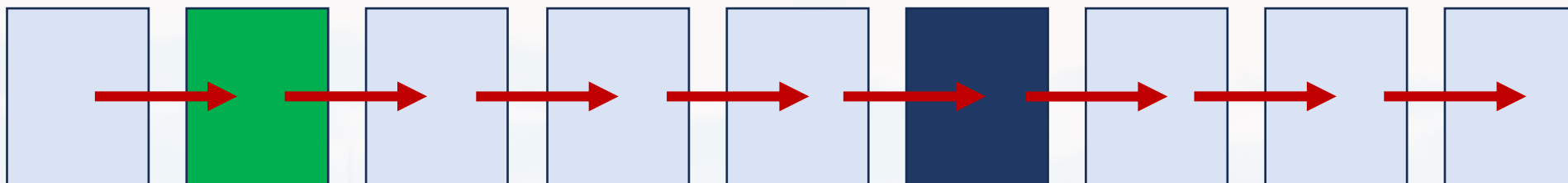


a set of T observations O $O = (O_1, O_2, O_3, \dots O_t, \dots O_T)$ drawing randomly from the states

- goal:**
- focus on the states
 - better understand the processes wrt time t
 - model the processes as a function of time t
 - later: **Monte Carlo** sampling, but we need to understand the processes first!



sequence of states, but now: state graph **is not ergodic at all!**

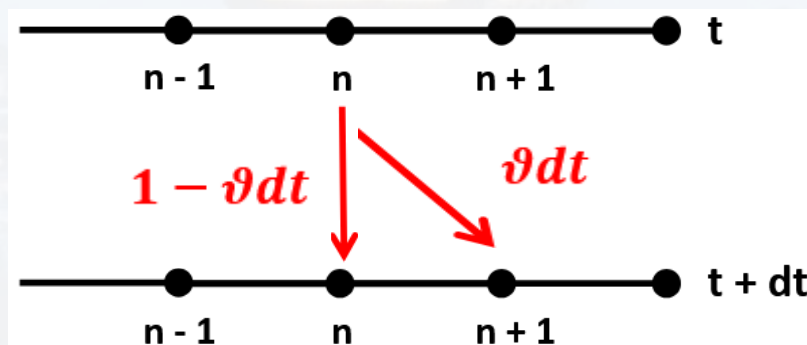
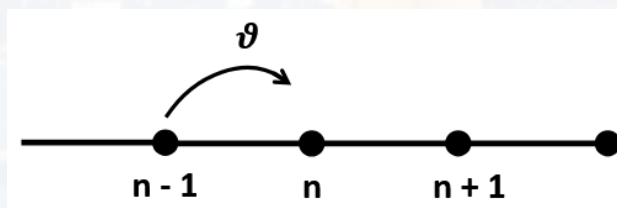


n : different states

ϑ : hopping rate

- for now: $\vartheta = \text{const}$

- $[\vartheta] = \text{probability/time}$

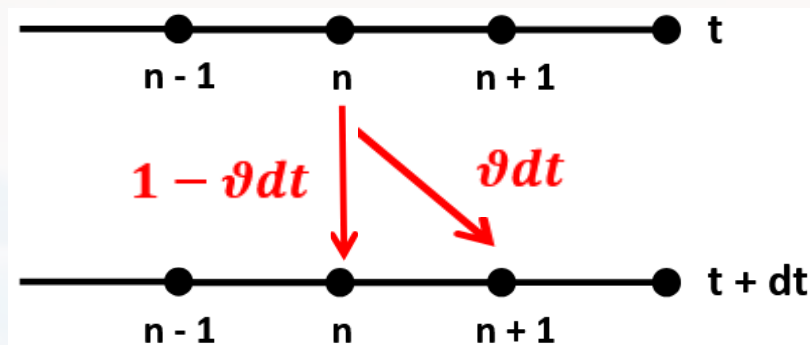


assumption:

- we can resolve the process such, that the system performs either **one step** or **no step** within a **timestep dt**

$P(n, t + dt)$:

probability that we observe the system in state n at time $t + dt$



n : different states
 v : hopping rate (*probability/time*)
 dt : time increment

$P(n, t + dt)$:

probability that we observe the system in state n at time $t + dt$

$$P(n, t + dt) = P(n - 1, t) v dt + P(n, t) (1 - v dt)$$

system was in state $n - 1$,
 but jumped to state n
 within dt

system was in state n
 and did not jump
 within dt

for now, states only change from
 $n \rightarrow n + 1$

$$= P(n - 1, t) v dt + P(n, t) - P(n, t) v dt$$

$$P(n, t + dt) \approx P(n, t) + \frac{dP(n, t)}{dt} dt$$

dt is small

$$\frac{dP(n, t)}{dt} = v P(n - 1, t) - v P(n, t)$$

Master Equation



$$\frac{dP(n, t)}{dt} = \nu P(n - 1, t) - \nu P(n, t)$$

Master Equation

n:	different states
ν:	hopping rate (<i>probability/time</i>)
dt:	time increment

$$\begin{aligned} \frac{d}{dt} P(n, t) = & P(\text{jump up} | \text{at } n - 1) P(\text{at } n - 1) \\ & - P(\text{jump down} | \text{at } n) P(\text{at } n) \end{aligned}$$



$$\frac{dP(n, t)}{dt} = \nu P(n - 1, t) - \nu P(n, t)$$

Master Equation

n : different states
 ν : hopping rate (*probability/time*)
 dt : time increment

goal: find $P(n, t)$

$P(n, t + dt)$:

probability that we observe the system in state n at time $t + dt$

real-valued **moment-generating function**

$$G(z, t) = \sum_{n=0}^{\infty} P(n, t) z^n$$

k^{th} moment:

$$\left. \frac{\partial^k G(z, t)}{\partial z^k} \right|_{z=1}$$

for now, states only change from $n \rightarrow n + 1$

$$\frac{d}{dt} G(z, t) = \sum_{n=0}^{\infty} \frac{dP(n, t)}{dt} z^n = \sum_{n=0}^{\infty} [\nu P(n - 1, t) - \nu P(n, t)] z^n$$

$$= \sum_{n=0}^{\infty} \nu P(n - 1, t) z^n - \sum_{n=0}^{\infty} \nu P(n, t) z^n$$

both sums have independent indices

$$= \sum_{m=0}^{\infty} \nu P(m, t) z^{m+1} - \sum_{n=0}^{\infty} \nu P(n, t) z^n$$



$$\frac{dP(n, t)}{dt} = \nu P(n - 1, t) - \nu P(n, t)$$

Master Equation

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both sums have independent indices

$$= \sum_{n=0}^{\infty} \nu P(n, t) z^{n+1} - \sum_{n=0}^{\infty} \nu P(n, t) z^n$$

$$= \sum_{n=0}^{\infty} \nu P(n, t) [z^{n+1} - z^n] = \sum_{n=0}^{\infty} \nu P(n, t) z^n [z - 1] = \nu [z - 1] G(z, t)$$



$$\frac{dP(n, t)}{dt} = \nu P(n - 1, t) - \nu P(n, t)$$

Master Equation

n : different states
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for now, states only change from
 $n \rightarrow n + 1$

$$\frac{d}{dt} G(z, t) = \nu [z - 1] G(z, t)$$

the system always starts at $n = 1$ at $t = 0$

$$P(n \neq 0, t = 0) = 0$$

$$P(n = 0, t = 0) = 1 \quad \rightarrow \quad G(z, t = 0) = 1$$

$$G(z, t) = e^{\nu(z-1)t}$$

$$e^{-\nu t} e^{\nu z t} = \sum_{n=0}^{\infty} P(n, t) z^n$$

Taylor Series of $e^{\nu z t}$ wrt to z



$$\frac{dP(n, t)}{dt} = \nu P(n - 1, t) - \nu P(n, t)$$

Master Equation

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$$G(z, t) = e^{\nu(z-1)t}$$

$$e^{-\nu t} e^{\nu z t} = \sum_{n=0}^{\infty} P(n, t) z^n$$

Taylor Series of $e^{\nu z t}$ wrt to z

$$e^{-\nu t} \sum_{n=0}^{\infty} \frac{(\nu t)^n}{n!} z^n = \sum_{n=0}^{\infty} P(n, t) z^n$$

$$P(n, t) = \frac{(\nu t)^n}{n!} e^{-\nu t}$$

Poissonian distribution



$$\frac{dP(n, t)}{dt} = \nu P(n - 1, t) - \nu P(n, t)$$

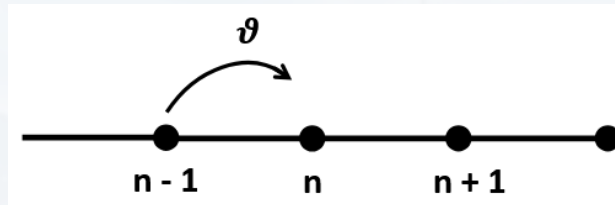
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$P(n, t + dt)$: probability that we observe the system in state n at time $t + dt$

for now, states only change from $n \rightarrow n + 1$



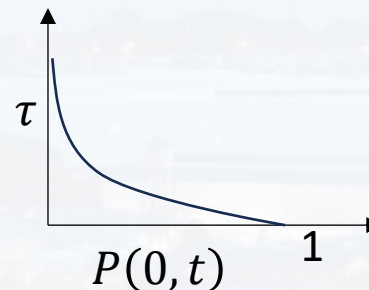
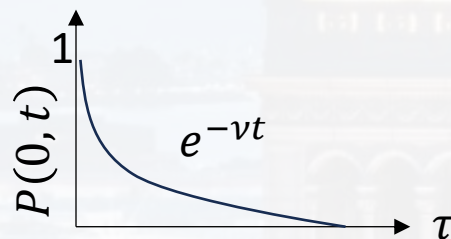
calculating the **waiting time** (time τ between two events)

$$P(0, t) = \frac{(\nu t)^0}{0!} e^{-\nu t}$$

$$\tau = -\frac{1}{\nu} \ln[P(0, t)]$$

$$P(0, t) = e^{-\nu t}$$

is the probability that the stepper **has not** moved \rightarrow cdf



$$\bar{P} = 1 - e^{-\nu t}$$

is the probability that the stepper **has moved**

see later, Gillespie algorithm



$$\frac{dP(n, t)}{dt} = \vartheta P(n - 1, t) - \vartheta P(n, t)$$

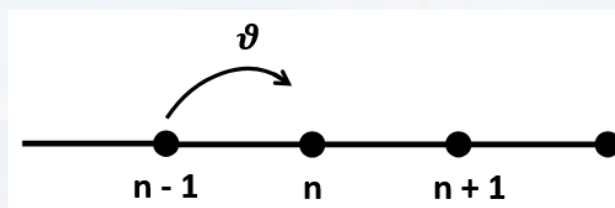
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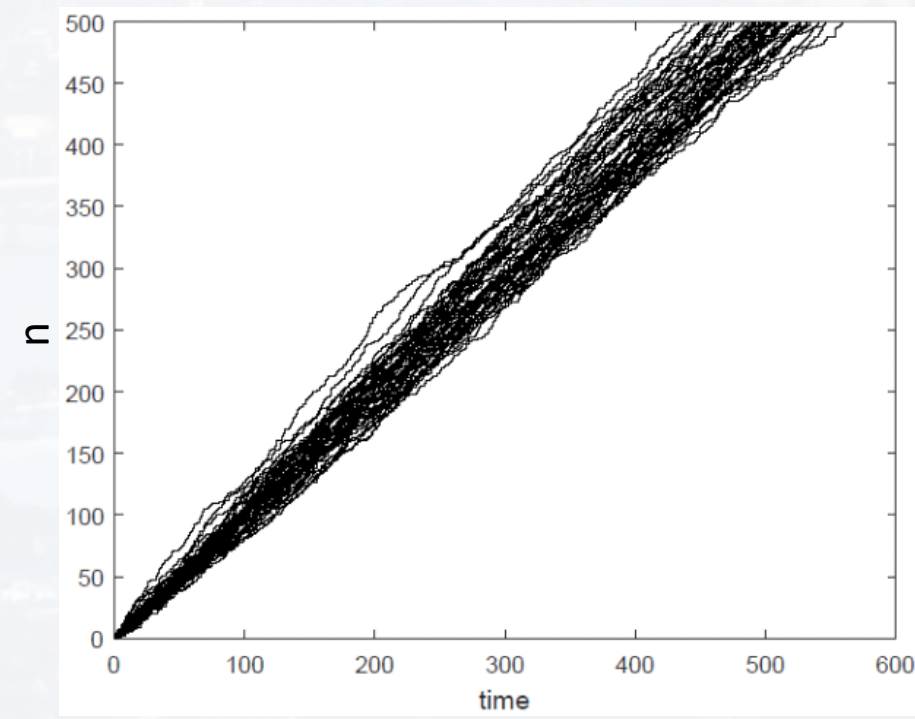
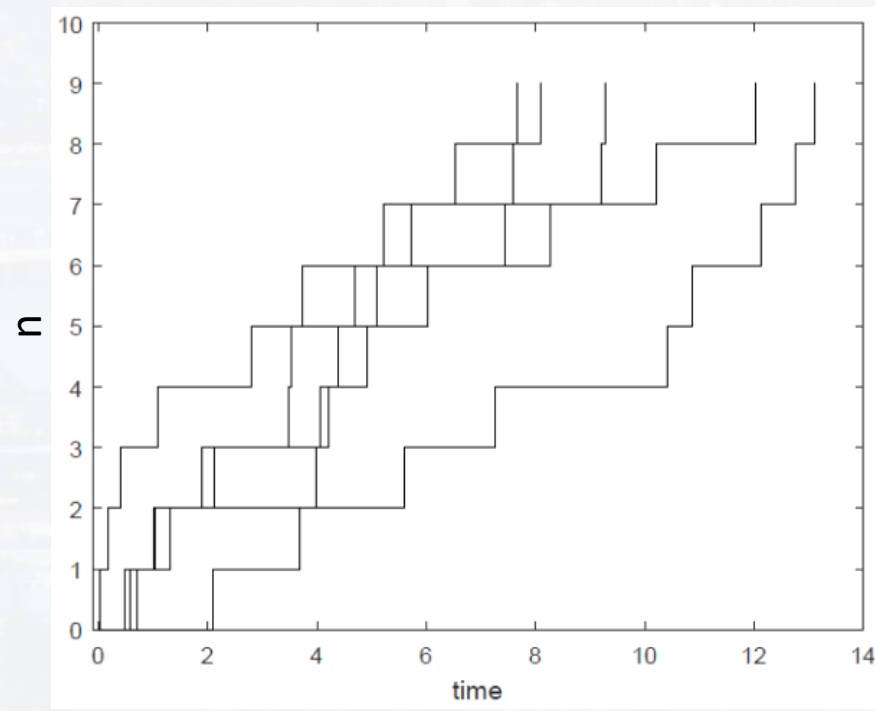
$$P(n, t) = \frac{(\vartheta t)^n}{n!} e^{-\vartheta t}$$

$P(n, t + dt)$: probability that we observe the system in state n at time $t + dt$

for now, states only change from $n \rightarrow n + 1$



$$\tau = -\frac{1}{\vartheta} \ln[P(0, t)]$$





Outline

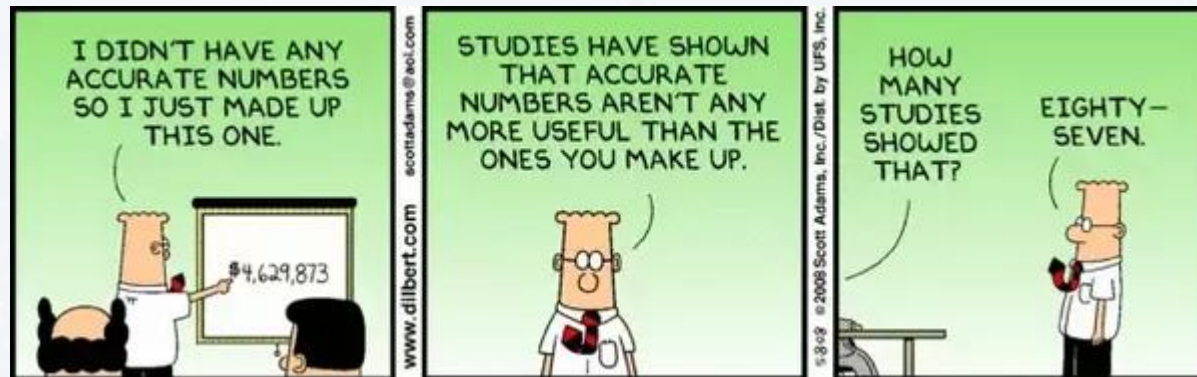
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- Radioactive Decay
- Chem. Reactions
- Predator Prey
- Gene Expression

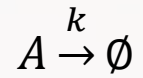
Diffusion Processes

Fokker-Planck Equation





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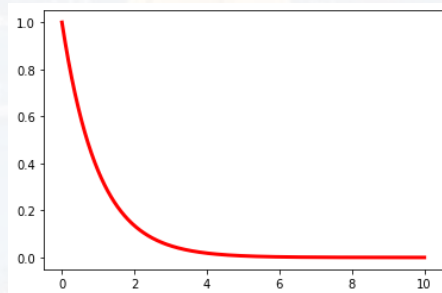
deterministic scenario:

$A(t)$ can be a concentration or a number!

$$\frac{\Delta A(t)}{A(t)} \frac{1}{\Delta t} = -k$$

constant **relative change** per **time step**

$$\frac{dA(t)}{A(t)} = -k dt$$



$$A(t) = A(t = 0) e^{-kt}$$

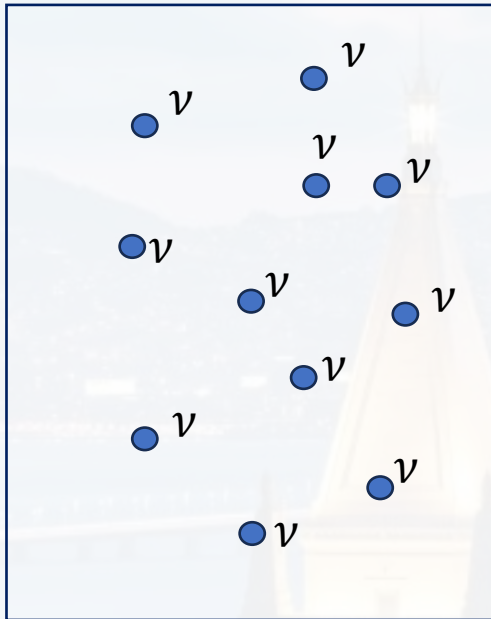


- Radioactive Decay
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$A \xrightarrow{k} \emptyset$ stochastic scenario: number n of particles A

n : different states
 ϑ : hopping rate
 dt : time increment
 $\tau = -\ln[P(0, t)] / \vartheta$: waiting time

t



for $t = 0$ **many** atoms
 $\rightarrow \tau$ is small

Δt

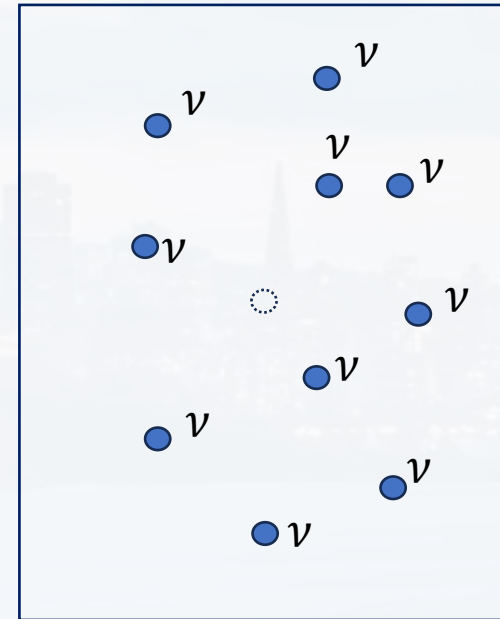
each atom has the probability ν to decay per time

logical **or** \rightarrow **adding** the probabilities

$$\nu \rightarrow \nu n(t)$$

$$\Delta t = -\frac{1}{\nu n(t)} \ln[P(0|t)]$$

$t + \Delta t$



$$\frac{dP(n, t)}{dt} = \nu [n + 1]P(n + 1, t) - \nu n P(n, t)$$

Master Equation

path leading from $n + 1$,
to state n within dt

path leading away
from state n



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$A \xrightarrow{k} \emptyset$ stochastic scenario:

$$\frac{dP(n, t)}{dt} = \nu [n + 1]P(n + 1, t) - \nu n P(n, t)$$

Master Equation

n : different states
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initial conditions:

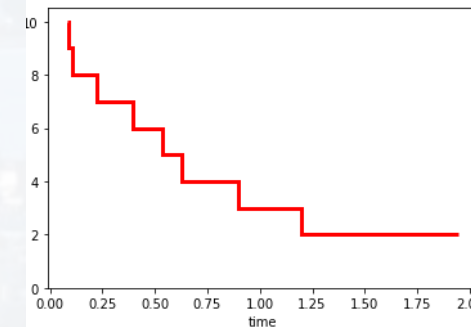
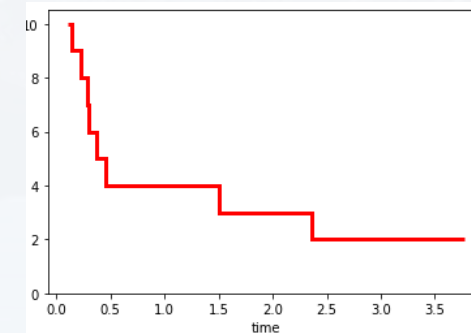
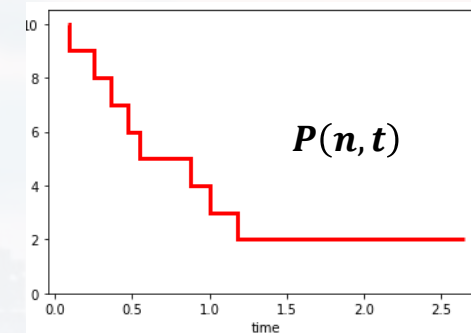
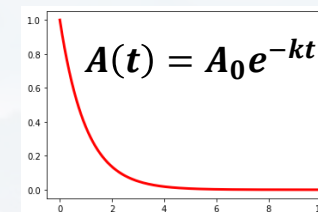
$$\frac{dP(n, t)}{dt} = -\nu n_o P(n, t)$$

$$P(n_o, t) = e^{-\nu n_o t} \quad P(n_o, t) = 1$$

solving for $P(n, t)$ using the initial conditions,
the master equation and $G(z, t) = \sum_{n=0}^{\infty} P(n, t) z^n$ leads to:

$$P(n, t) = e^{-\nu n_o t} \binom{n_o}{n} [1 - e^{-\nu t}]^{n_o - n}$$

mean of $n(t)$ over n : $A(t) = \sum_{n=0}^{n_o} n P(n, t) = \sum_{n=0}^{n_o} n e^{-\nu n_o t} \binom{n_o}{n} [1 - e^{-\nu t}]^{n_o - n} = n_o e^{-\nu t}$





- Radioactive Decay
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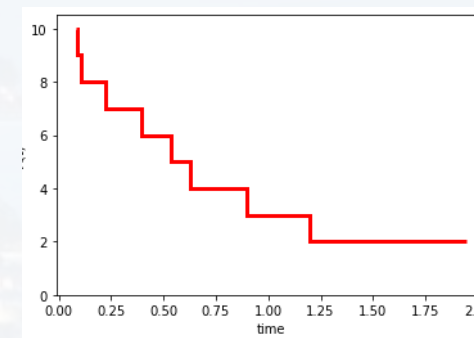
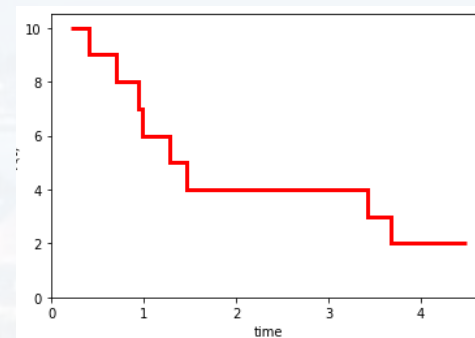
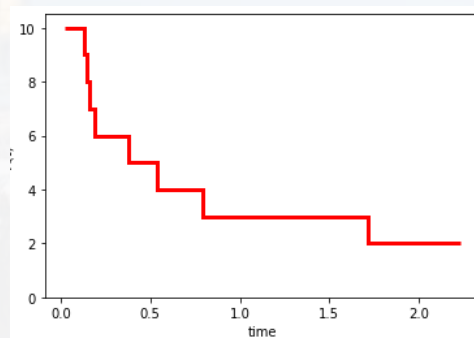
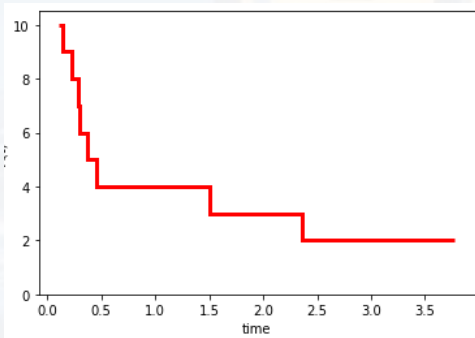
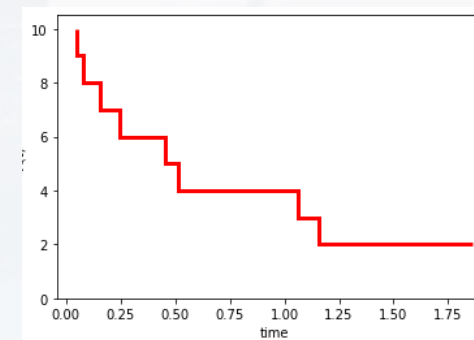
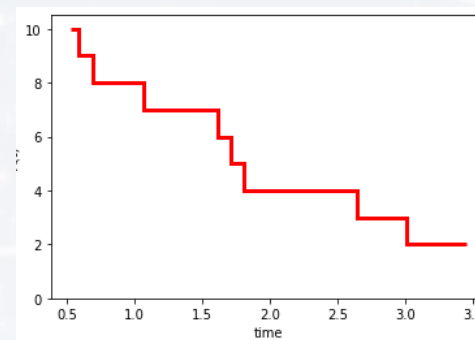
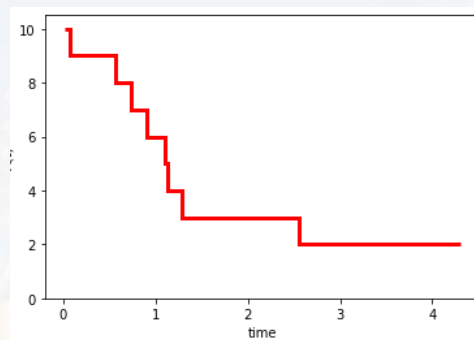
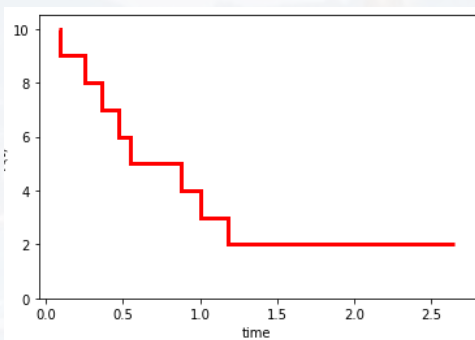
$A \xrightarrow{k} \emptyset$ stochastic scenario:

$$\frac{dP(n, t)}{dt} = \nu [n + 1]P(n + 1, t) - \nu n P(n, t)$$

Master Equation

$$P(n, t) = e^{-\nu n_0 t} \binom{n_0}{n} [1 - e^{-\nu t}]^{n_0 - n} \quad \Delta t = -\frac{1}{\nu n(t)} \ln[P(0|t)]$$

n : different states
 ϑ : hopping rate
 dt : time increment
 $\tau = -\ln[P(0, t)] / \nu$: waiting time





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$A \xrightarrow{k} \emptyset$ stochastic scenario:

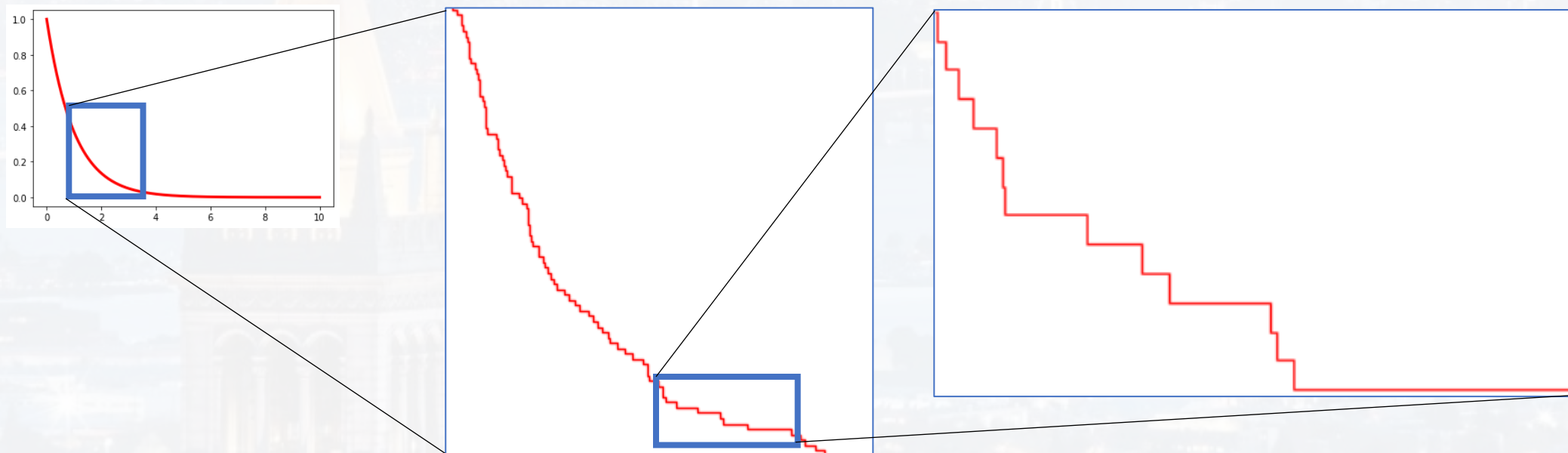
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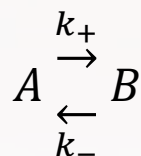
n :	different states
ϑ :	hopping rate
dt :	time increment
$\tau = -\ln[P(0, t)] / \nu$:	waiting time

one run, but large n





- Radioactive Decay
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n : number of particles of A
 m : number of particles of B

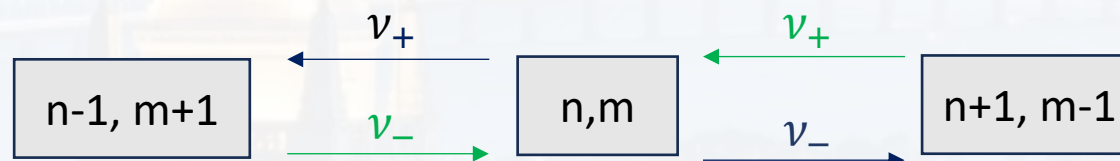
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 ϑ : hopping rate
 dt : time increment
 $\tau = -\ln[P(0, t)] / \nu$: waiting time

$$\nu(A) \rightarrow \nu_+ n(t) \quad \nu(B) \rightarrow \nu_- m(t) \quad \nu_{tot} = \nu(A) + \nu(B) = \nu_+ n(t) + \nu_- m(t)$$

$$\Delta t = -\frac{1}{\nu_+ n(t) + \nu_- m(t)} \ln[P(0|t)]$$

time that elapses until **a** reaction to occur

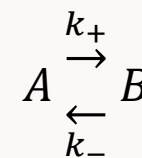
next: deciding **which** reaction should occur (next lecture)



$$\frac{dP(n, m, t)}{dt} = \nu_+ (n+1)P(n+1, m-1, t) + \nu_- (m+1)P(n-1, m+1, t) - \nu_+ n P(n, m, t) - \nu_- m P(n, m, t)$$



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n :

ϑ :

dt :

$\tau = -\ln[P(0, t)] / \nu$:

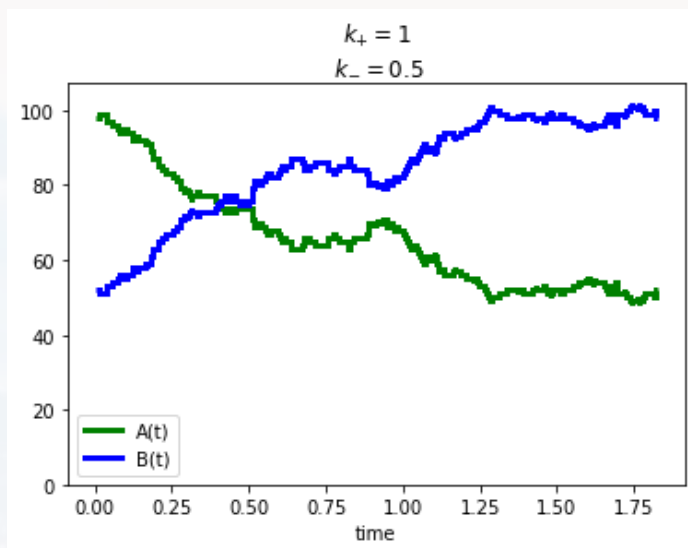
different states

hopping rate

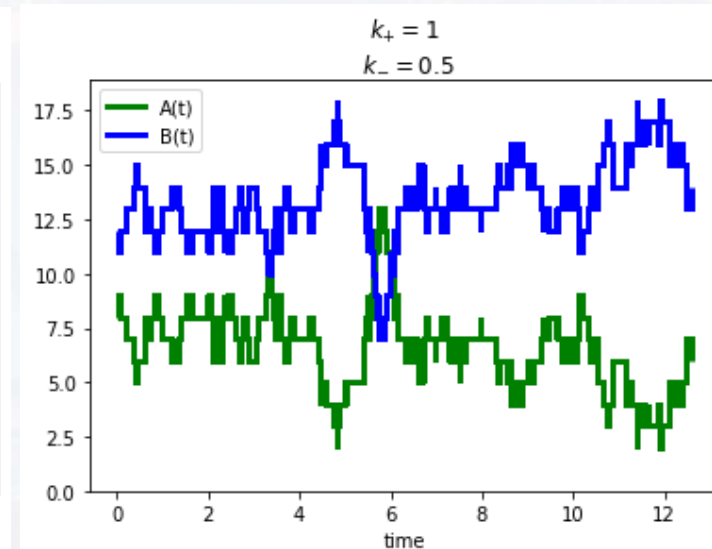
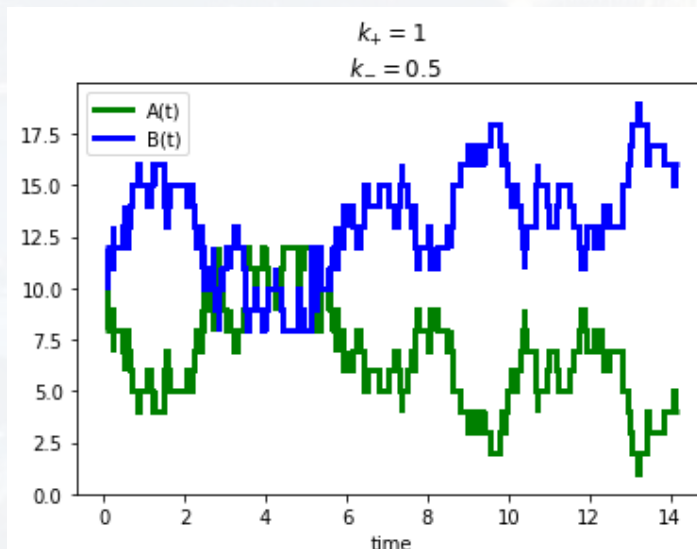
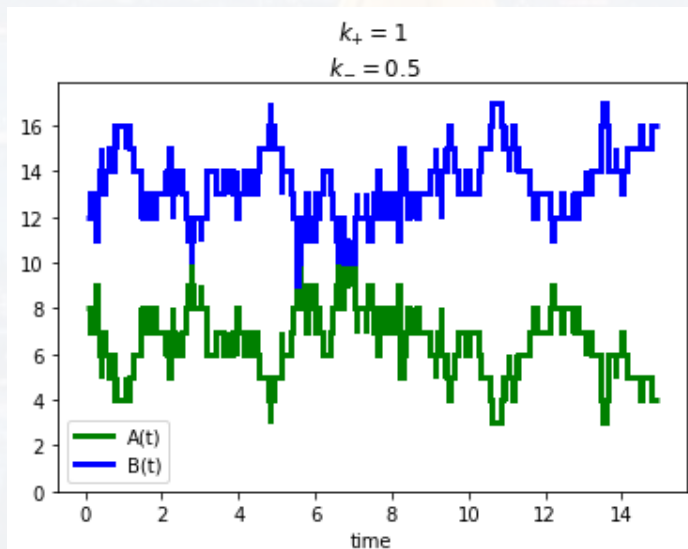
time increment

waiting time

equilibrium at $\frac{A}{B} = \frac{k_-}{k_+}$

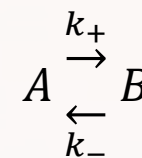


$N = 10$





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n :

ϑ :

dt :

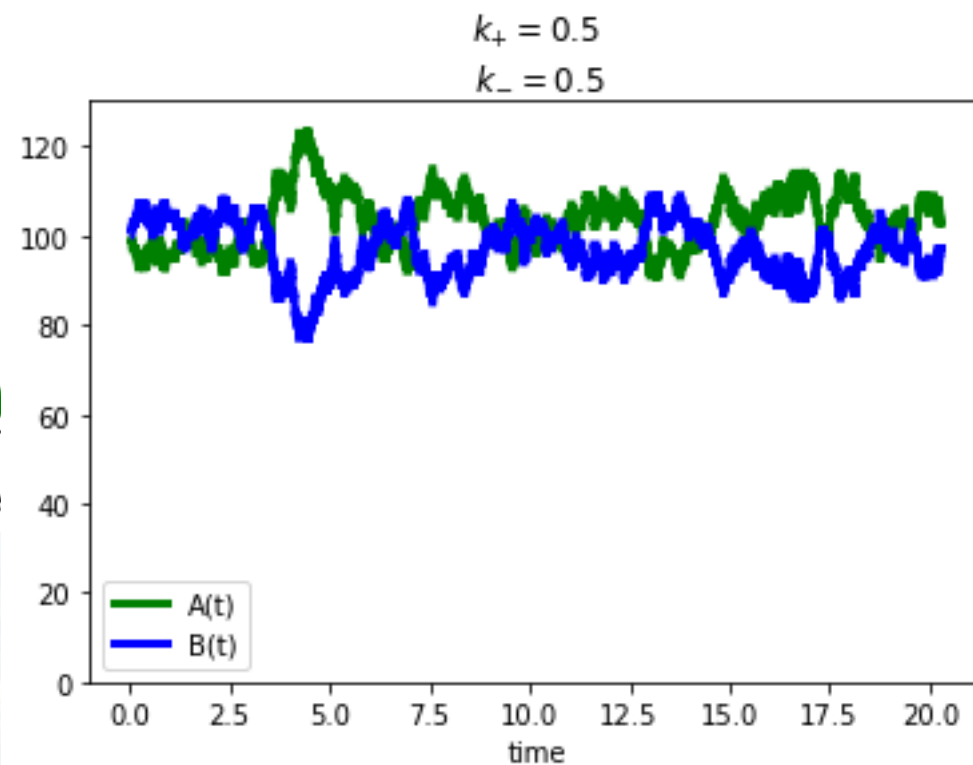
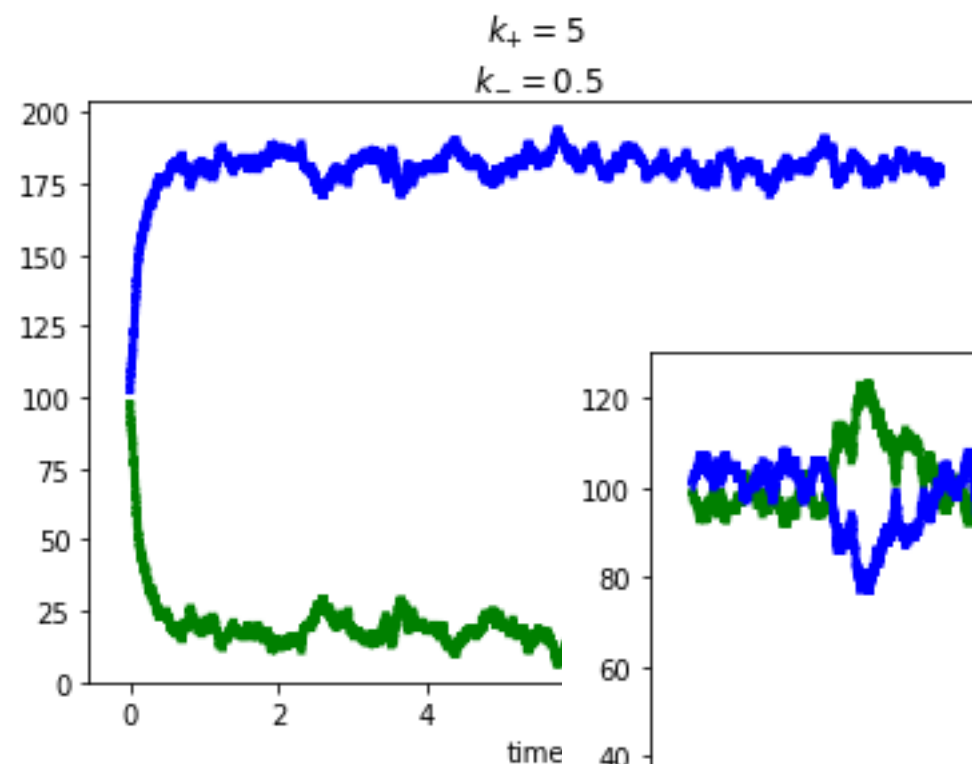
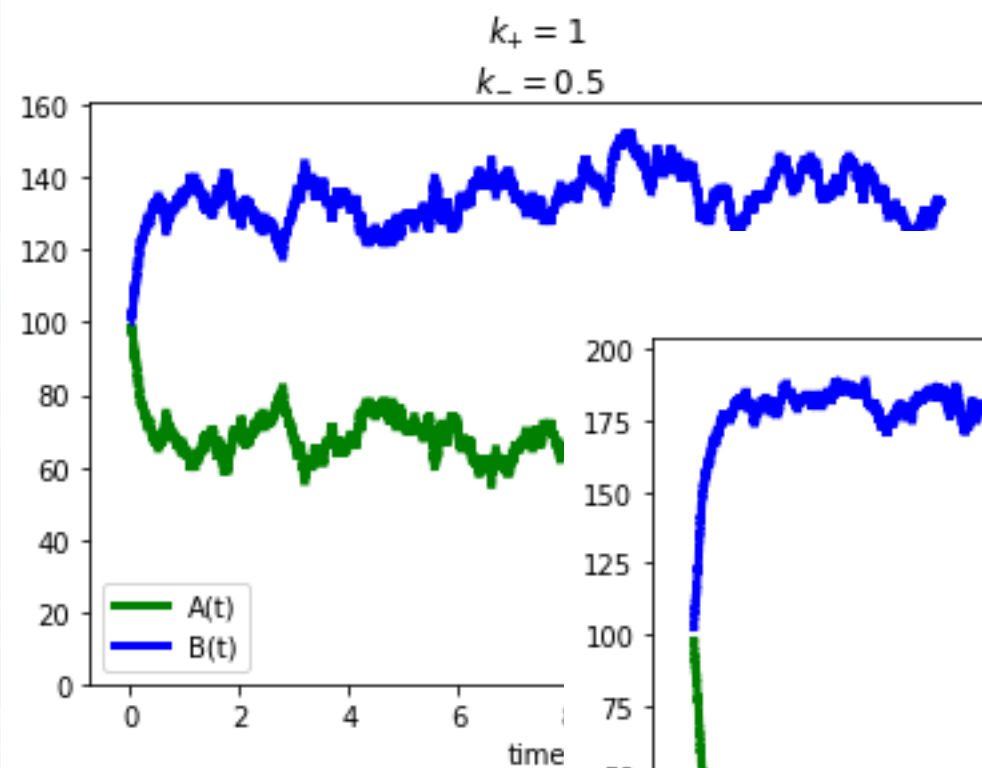
$\tau = -\ln[P(0, t)] / \nu$:

different states

hopping rate

time increment

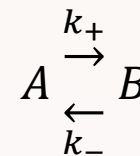
waiting time





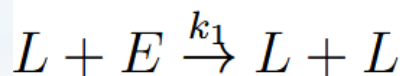
- Radioactive Decay
- Chem. Reactions
- Predator Prey
- Gene Expression

L: sheep (lambs)
W: wolves
E: “empty”

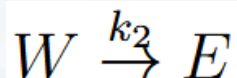


n : different states
 ϑ : hopping rate
 dt : time increment
 $\tau = -\ln[P(0, t)] / \nu$: waiting time

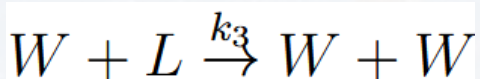
original model:



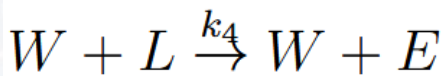
lambs reproduce



wolves starve

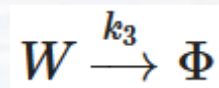
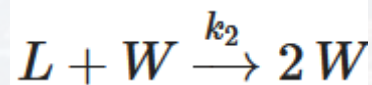
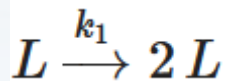


sometimes a wolf kills a lamb and then reproduces



sometimes a wolf just kills a lamb

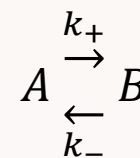
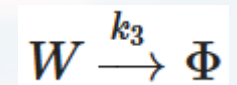
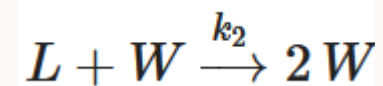
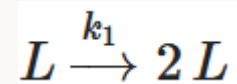
same:



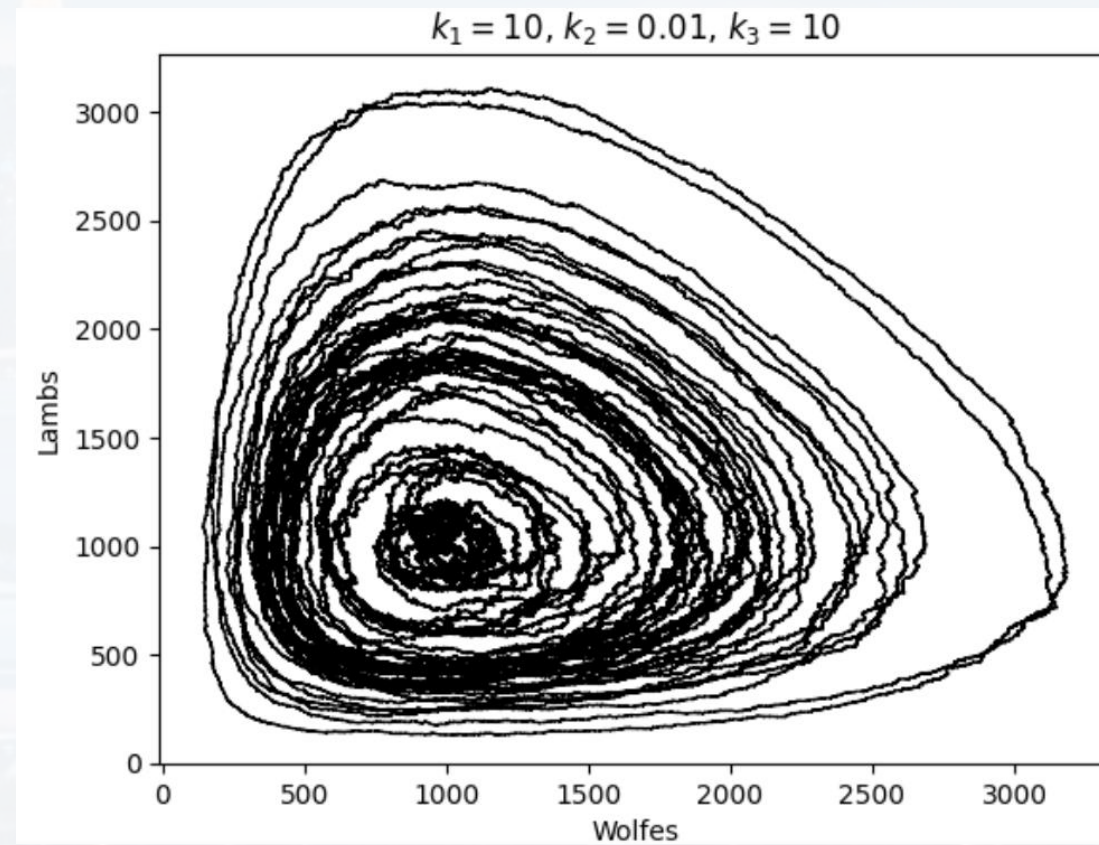
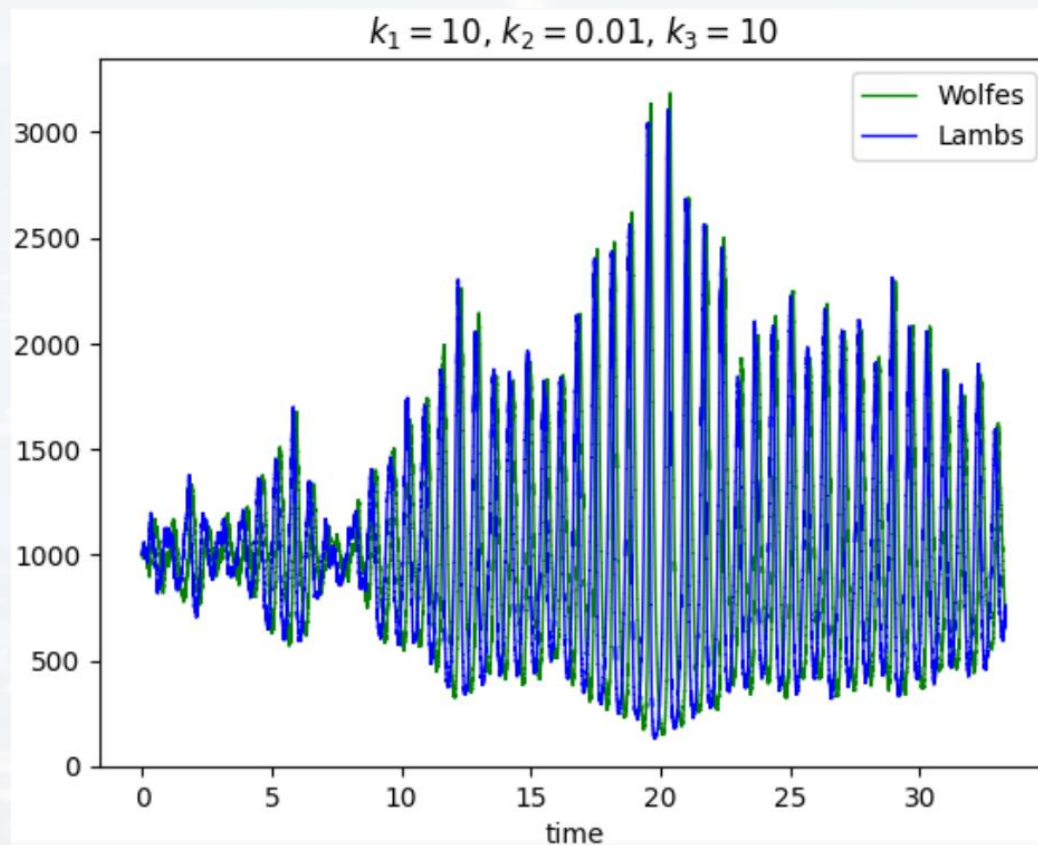


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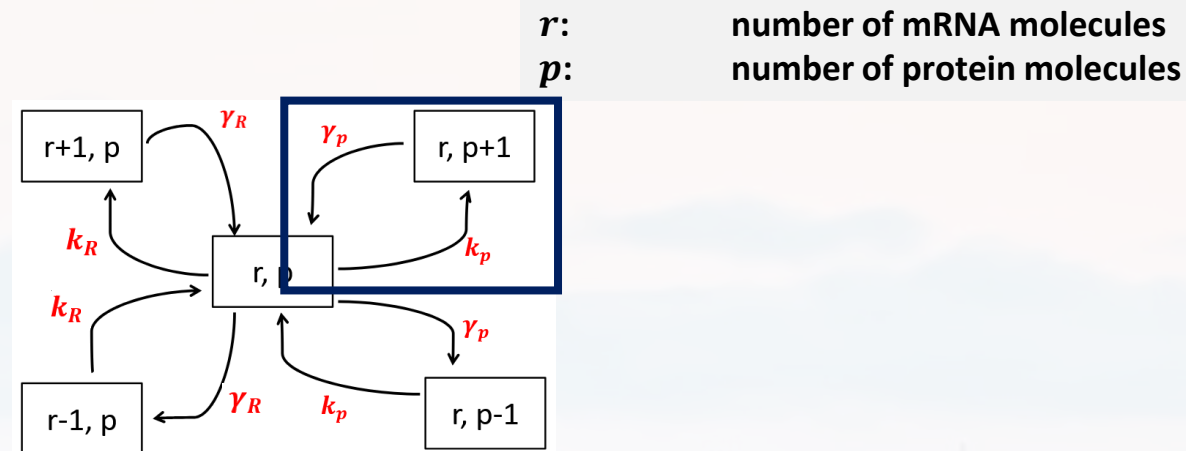
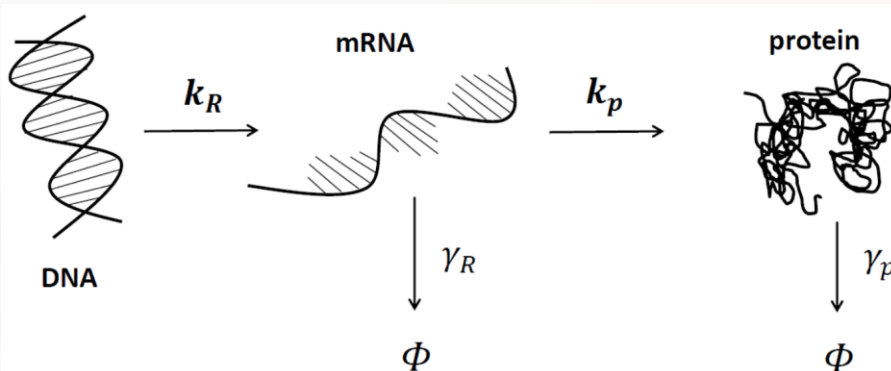
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- Radioactive Decay
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simplest model aka “central dogma”



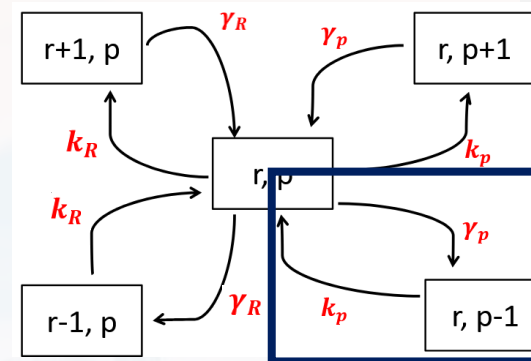
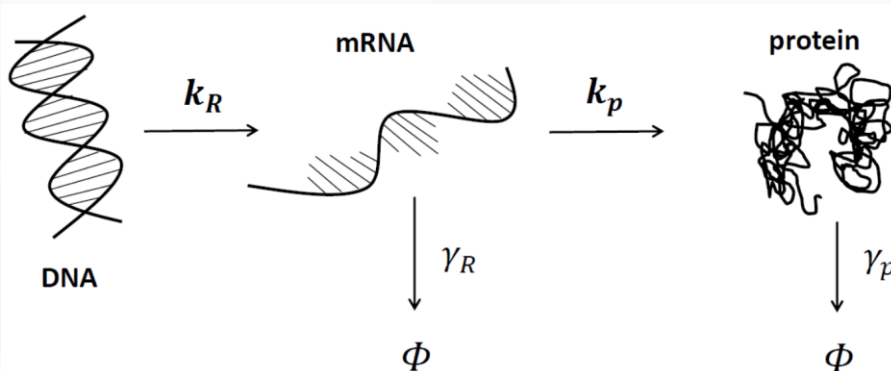
$w(r, p, t)$: probability to observe the system with r mRNA molecules and p protein molecules

$$\frac{dw(r, p, t)}{dt} = \gamma_p (p + 1)w(r, p + 1, t) - k_p r w(r, p, t)$$



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simplest model aka “central dogma”



r : number of mRNA molecules
 p : number of protein molecules

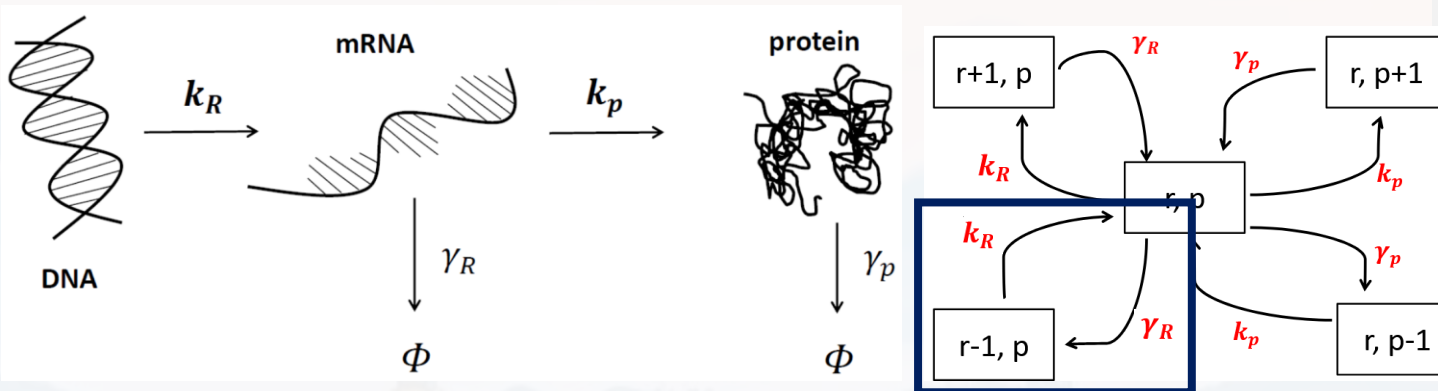
$w(r, p, t)$: probability to observe the system with r mRNA molecules and p protein molecules

$$\begin{aligned} \frac{dw(r, p, t)}{dt} = & \gamma_p (p + 1)w(r, p + 1, t) - k_p r w(r, p, t) \\ & + k_p r w(r, p - 1, t) - \gamma_p p w(r, p, t) \end{aligned}$$



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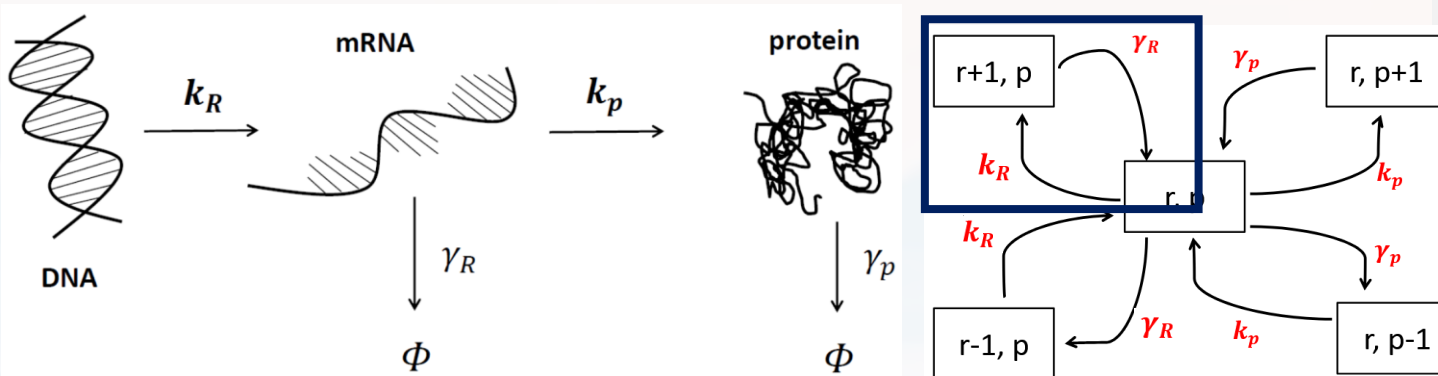
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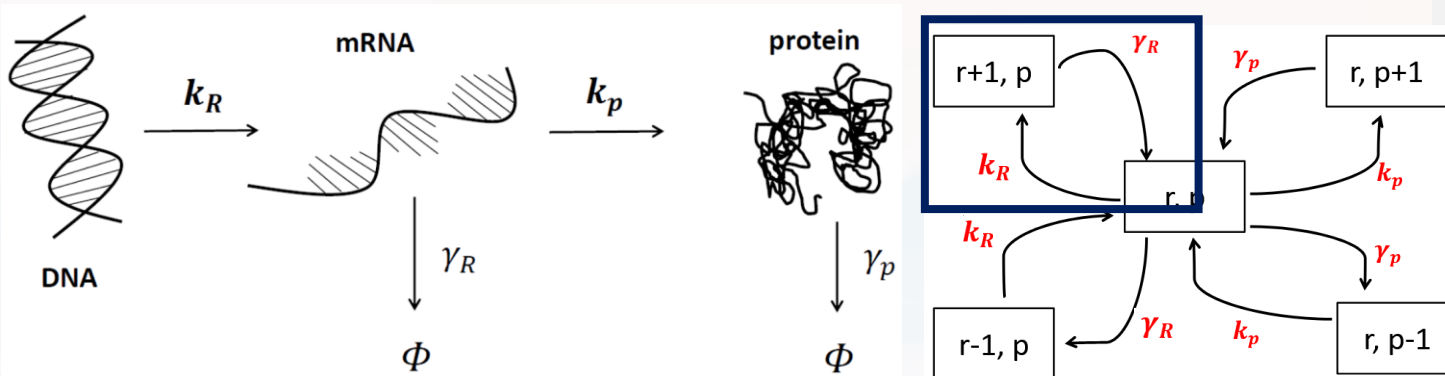
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$w(r, p, t)$: probability to observe the system with r mRNA molecules and p protein molecules

$$\begin{aligned} \frac{dw(r, p, t)}{dt} = & k_R w(r - 1, p, t) + \gamma_R (r + 1) w(r + 1, p, t) + k_p r w(r, p - 1, t) \\ & + \gamma_p (p + 1) w(r, p + 1, t) - [k_R + \gamma_R r + k_p r + \gamma_p p] w(r, p, t) \end{aligned}$$

$$G(y, z, t) = \sum_{r, p=0}^{\infty} w(r, p, t) y^r z^p$$

$$G(y = 1, z = 1, t) = \sum_{r, p=0}^{\infty} w(r, p, t) = 1$$



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simplest model aka “central dogma”

r : number of mRNA molecules
 p : number of protein molecules

$$\begin{aligned} \frac{dw(r, p, t)}{dt} = & k_R w(r - 1, p, t) + \gamma_R (r + 1) w(r + 1, p, t) + k_P r w(r, p - 1, t) \\ & + \gamma_P (p + 1) w(r, p + 1, t) - [k_R + \gamma_R r + k_P r + \gamma_P p] w(r, p, t) \end{aligned}$$

$$G(y, z, t) = \sum_{r, p=0}^{\infty} w(r, p, t) y^r z^p \qquad G(y = 1, z = 1, t) = \sum_{r, p=0}^{\infty} w(r, p, t) = 1$$

expressing the generating function in terms of the master equation

$$\frac{\partial G(y, z, t)}{\partial t} = G(y, z, t) [k_R y - k_R] + \frac{\partial G(y, z, t)}{\partial y} [\gamma_R + k_P y z - \gamma_R y - k_P y] + \frac{\partial G(y, z, t)}{\partial z} [\gamma_P - \gamma_P z]$$



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$$\frac{\partial G(y, z, t)}{\partial t} = G(y, z, t) [k_R y - k_R] + \frac{\partial G(y, z, t)}{\partial y} [\gamma_R + k_P yz - \gamma_R y - k_P y] + \frac{\partial G(y, z, t)}{\partial z} [\gamma_P - \gamma_P z]$$

in equilibrium $\frac{\partial G(y, z, t)}{\partial t} = 0$ and calculating the moments:

$$\begin{aligned} \left. \frac{\partial}{\partial y} G(y, z, t) \right|_{y=z=1} &= \langle r \rangle & \left. \frac{\partial^2}{\partial z^2} G(y, z, t) \right|_{y=z=1} &= \sum_{r, p=0}^{\infty} \frac{\partial}{\partial z} [p w(r, p, t) y^r z^{p-1}] \Big|_{y=z=1} \\ & & &= \sum_{r, p=0}^{\infty} (p^2 - p) w(r, p, t) \\ & & &= \langle p^2 \rangle - \langle p \rangle \end{aligned}$$

$$\begin{aligned} \left. \frac{\partial^2}{\partial y^2} G(y, z, t) \right|_{y=z=1} &= \langle r^2 \rangle - \langle r \rangle & \left. \frac{\partial^2}{\partial y \partial z} G(y, z, t) \right|_{y=z=1} &= \langle rp \rangle \end{aligned}$$



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simplest model aka “central dogma”

in equilibrium $\frac{\partial G(y,z,t)}{\partial t} = 0$ and calculating the moments, we find

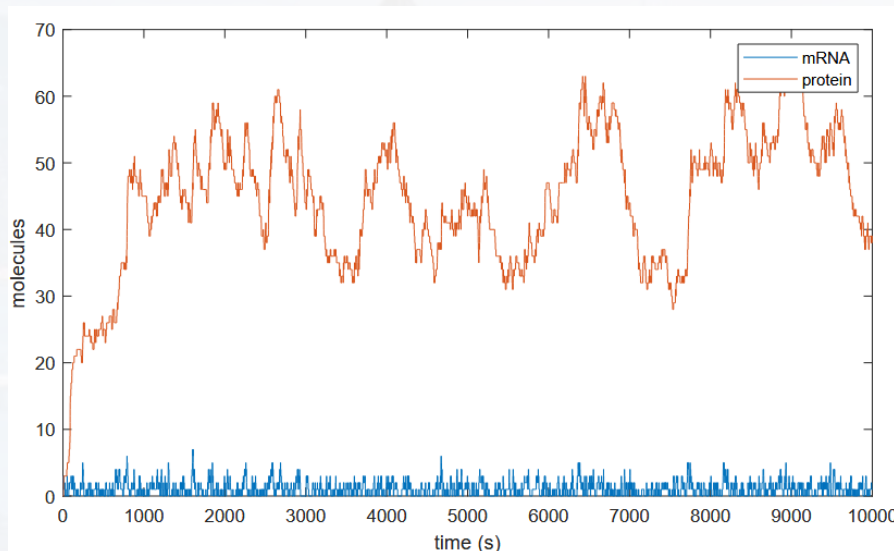
$$\langle r \rangle = \frac{k_R}{\gamma_R}$$

$$\langle p \rangle = \frac{k_P k_R}{\gamma_P \gamma_R}$$

$$\sigma_r^2 = \langle r \rangle$$

$$\langle pr \rangle = \frac{k_R \langle p \rangle + k_P \langle r \rangle (\langle r \rangle + 1)}{\gamma_R + \gamma_P}$$

$$\sigma_p^2 = \frac{k_P}{\gamma_P} \langle pr \rangle + \langle p \rangle + \langle p \rangle^2$$



one mRNA molecule produces ≈ 50 protein molecules

We need a model for the expression noise in order to compare differential expression of different samples!

noise for r is poissonian, but not for p

$$\frac{\sigma_3^2}{\langle n_3 \rangle^2} = \underbrace{\frac{1}{\langle n_3 \rangle}}_{\text{Poisson}} + \underbrace{\frac{1}{\langle n_2 \rangle} \frac{\tau_2}{\tau_3 + \tau_2}}_{\substack{\text{Poisson} \\ \text{One-step} \\ \text{time-averaging}}} + \underbrace{\frac{1 - P_{\text{on}}}{\langle n_1 \rangle} \frac{\tau_2}{\tau_2 + \tau_3} \frac{\tau_1}{\tau_1 + \tau_3} \frac{\tau_1 + \tau_3 + \tau_1 \tau_3 / \tau_2}{\tau_1 + \tau_2}}_{\substack{\text{Binomial} \\ \text{Two-step} \\ \text{time-averaging}}}$$

actual model (Physics of Life Reviews 2 (2005) 157–175)



Outline

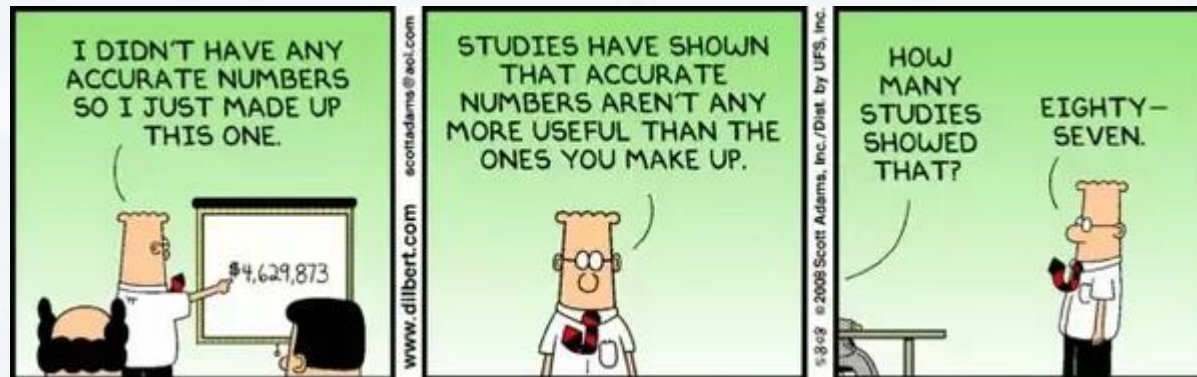
The Poissonian Stepper

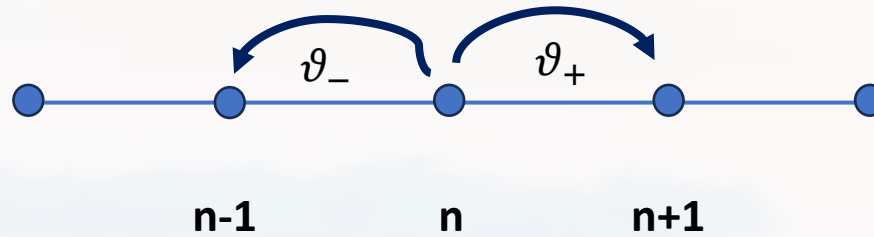
Examples of Stochastic Processes

- Radioactive Decay
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Diffusion Processes

Fokker-Planck Equation





n :	state
ϑ_+ :	hopping rate $n \rightarrow n+1$
ϑ_- :	hopping rate $n \rightarrow n-1$
c :	concentration
D :	diffusion constant

$$\frac{d}{dt}P(n, t) = \vartheta_+ P(n-1, t) + \vartheta_- P(n+1, t) - \vartheta_- P(n, t) - \vartheta_+ P(n, t)$$

in case $\vartheta_- = \vartheta_+ = \vartheta$

$$\begin{aligned} \frac{d}{dt}P(n, t) &= \vartheta P(n-1, t) + \vartheta P(n+1, t) - 2\vartheta P(n, t) \\ &= \vartheta [P(n-1, t) + P(n+1, t) - 2P(n, t)] \end{aligned}$$

$$\left. \frac{d^2 f}{dx^2} \right|_{x=x_0} = \lim_{\Delta x \rightarrow 0} \frac{f(x_0 + \Delta x) - 2f(x_0) + f(x_0 - \Delta x)}{\Delta x^2}$$

$$\frac{\partial}{\partial t}P(n, t) = \vartheta \frac{\partial^2}{\partial n^2}P(n, t)$$

$$\frac{\partial}{\partial t}P(n, t) = \vartheta \Delta P(n, t)$$

$$\frac{\partial c(x, y, z, t)}{\partial t} = D \Delta c(x, y, z, t) \quad \text{Fick's 2nd law}$$



$$\frac{\partial c(x, y, z, t)}{\partial t} = D \Delta c(x, y, z, t) \quad \text{Fick's 2nd law}$$

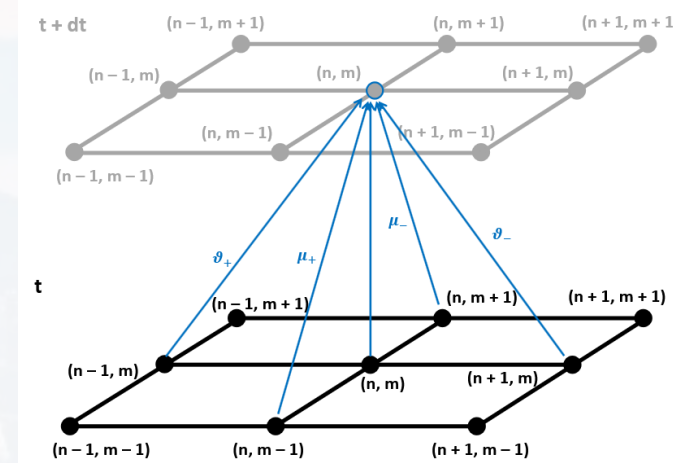
The Laplace operator indeed describes diffusion!

numerically:

$c(x_0, y_0, t_0 + \Delta t) =$ We can calculate c in the **future**

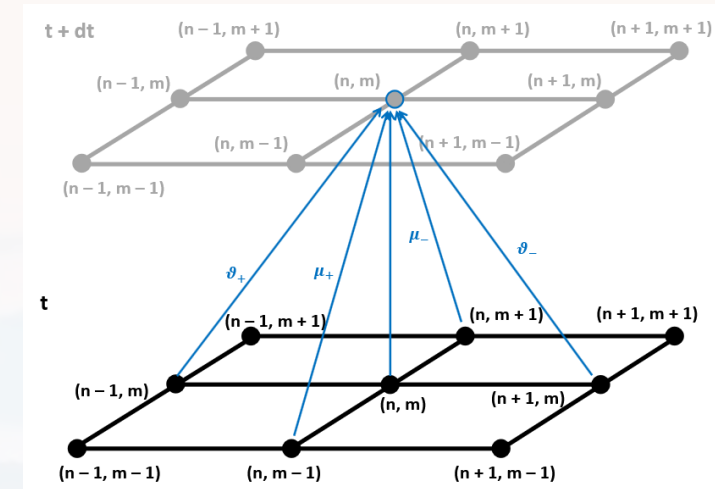
$$2\Delta t D \left[\frac{c(x_0 + \Delta x, y_0, t_0) - 2c(x_0, y_0, t_0) + c(x_0 - \Delta x, y_0, t_0)}{\Delta x^2} + \frac{c(x_0, y_0 + \Delta y, t_0) - 2c(x_0, y_0, t_0) + c(x_0, y_0 + \Delta y, t_0)}{\Delta y^2} \right] + c(x_0, y_0, t_0 - \Delta t)$$

n :	state
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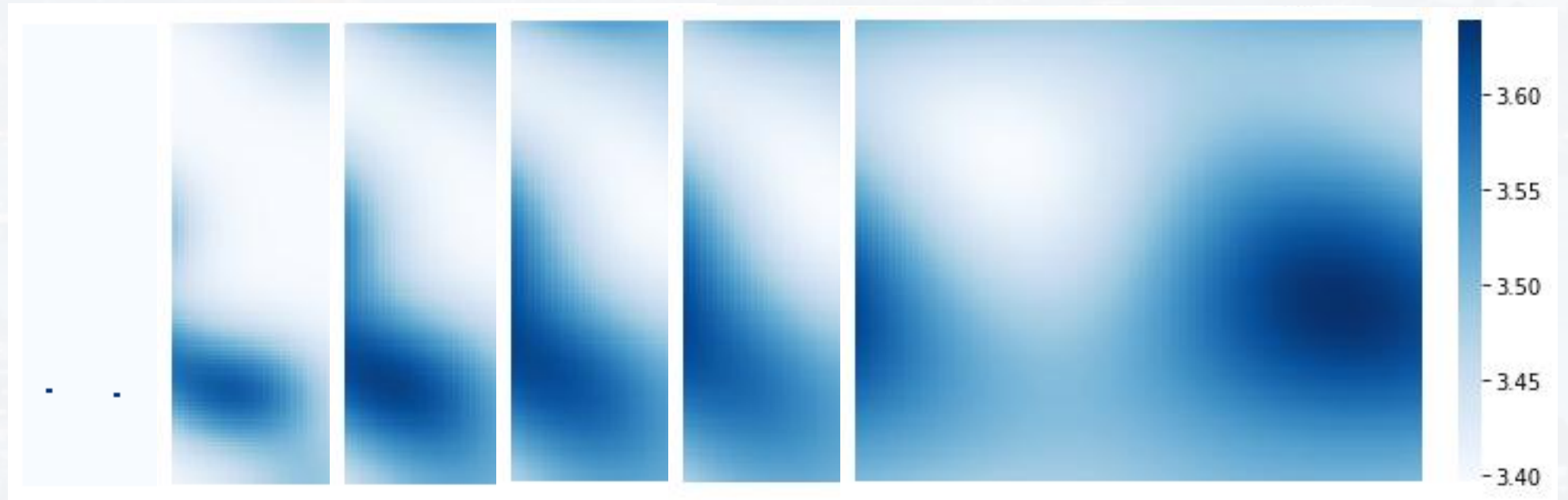


by using all adjacent **current** values

and the immediate **past** value

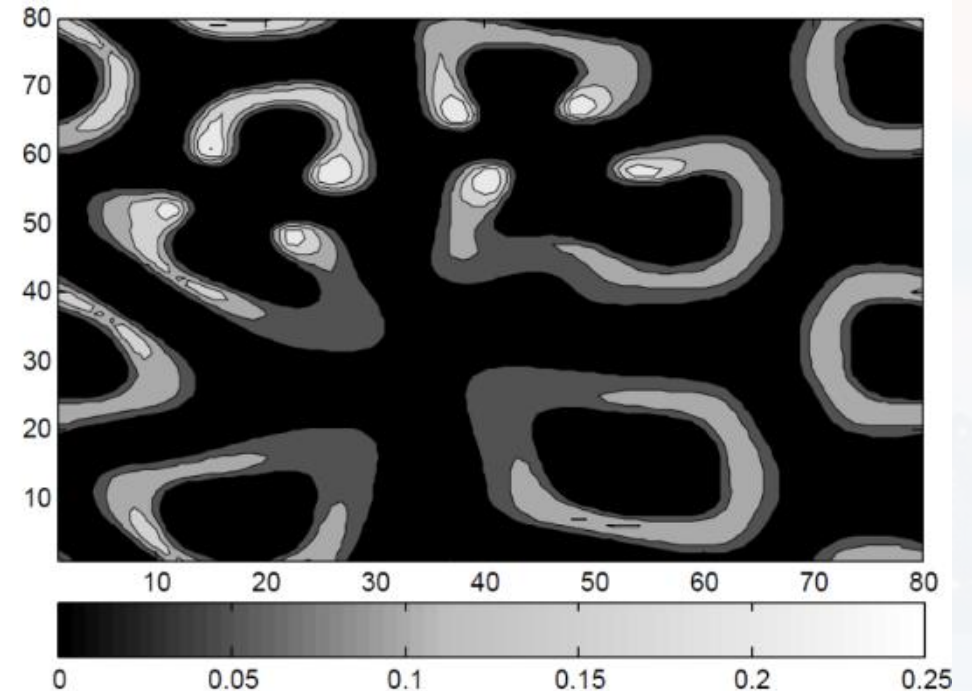
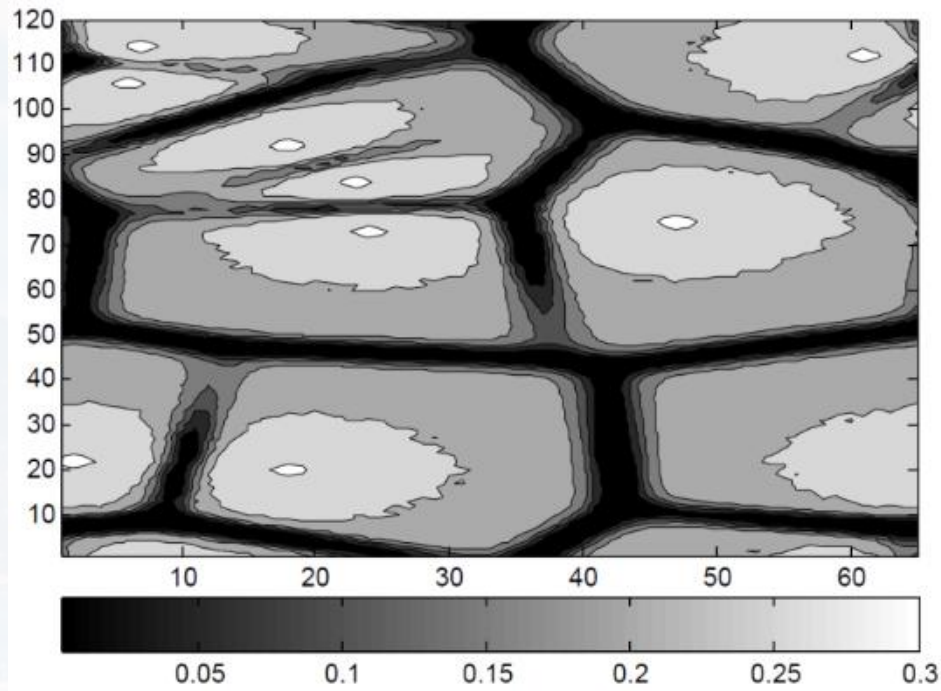


initial condition





modelling fur and skin pattern:





Outline

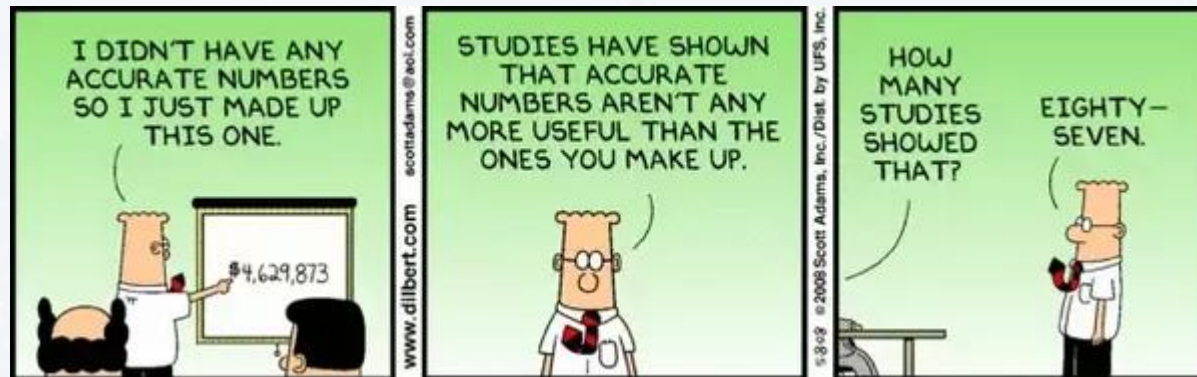
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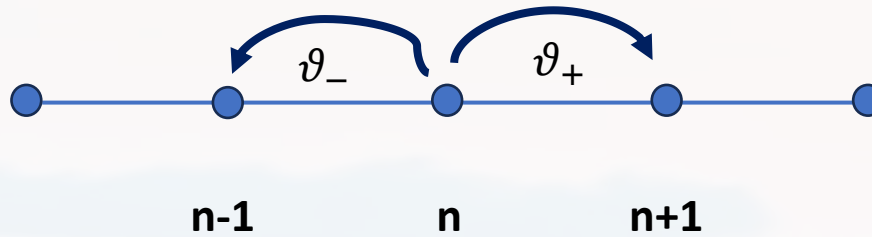
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$$\frac{d}{dt} P(n, t) = -\frac{\vartheta_+ - \vartheta_-}{2} [P(n+1, t) - P(n-1, t)] + \frac{\vartheta_+ + \vartheta_-}{2} [P(n+1, t) + P(n-1, t) - 2P(n, t)]$$

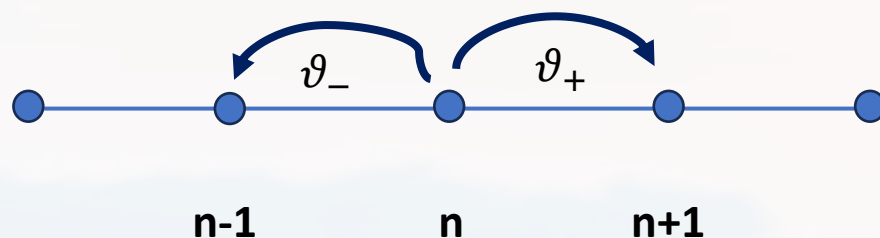
$$\frac{\partial}{\partial t} P(n, t) = -\frac{\vartheta_+ - \vartheta_-}{2} \frac{\partial}{\partial n} P(n, t) + \frac{\vartheta_+ + \vartheta_-}{2} \frac{\partial^2}{\partial n^2} P(n, t)$$

drift term with $v = \frac{\vartheta_+ - \vartheta_-}{2}$

diffusion term as before

$$\frac{\partial c(x, y, z, t)}{\partial t} = -\vec{v} \cdot \text{grad } c(x, y, z, t) + D \Delta c(x, y, z, t)$$

Smoluchowski equation



n :	state
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D :	diffusion constant

$$\frac{\partial}{\partial t} P(n, t) = -\frac{\vartheta_+ - \vartheta_-}{2} \frac{\partial}{\partial n} P(n, t) + \frac{\vartheta_+ + \vartheta_-}{2} \frac{\partial^2}{\partial n^2} P(n, t)$$

$$\frac{\partial c(x, y, z, t)}{\partial t} = -\vec{v} \cdot \text{grad } c(x, y, z, t) + D \Delta c(x, y, z, t)$$

Smoluchowski equation

both, ϑ_+ and ϑ_- can be functions of n , hence of x

$$\frac{\partial P(\vec{x}, t)}{\partial t} = -\sum_{i=1}^N \frac{\partial}{\partial x_i} [v_i(\vec{x}, t) P(\vec{x}, t)] + \sum_{i=1}^N \sum_{j=1}^N \frac{\partial^2}{\partial x_i \partial x_j} [D_{ij}(\vec{x}, t) P(\vec{x}, t)]$$

Fokker-Planck equation

$$i\hbar \frac{\partial \Psi(\vec{x}, t)}{\partial t} = \left[\frac{-\hbar^2}{2m} \Delta + V(\vec{x}, t) \right] \Psi(\vec{x}, t)$$

Schrödinger equation



Thank you very much for your attention!

