

Markov Chain

$$X_1, X_2, X_3, \dots \quad X_j \in \{S_1, S_2, \dots\}$$

$$P_{ij} = P(X_n = S_j \mid X_{n-1} = S_i)$$

transition matrix

Defn.

A Markov chain is called an ergodic chain if it is possible to go from every state to every state (not necessarily in one move)

Defn.

A Markov chain is called a regular chain if some power of the transition matrix has only positive elements.

Clearly, regular \Rightarrow ergodic but not the other way round.

The fundamental theorem about ergodic Markov chains is the existence of a stationary measure

$$W P = W$$

$$W = (w_1, w_2, \dots, w_n)$$

$$w_i > 0$$

$$P^n \rightarrow W = \begin{pmatrix} \leftarrow w \rightarrow \\ \vdots \\ \leftarrow w \rightarrow \end{pmatrix}$$

the interpretation of w_i

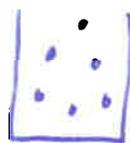
Mean recurrence

time for state s_i is $\frac{1}{w_i}$

Examples

1. Ehrenfest chain (1904)

Imagine p molecules distributed in two containers A and B



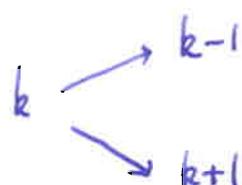
A



B

The state of the system is the number of molecules in container A.

Thus the states are $\{0, 1, 2, \dots, p\}$

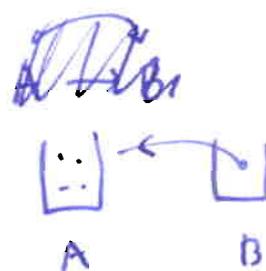


At each stage a molecule is chosen and moved to the opposite container. The probability that a molecule in A is chosen if there are k molecules in container A is $\frac{k}{p}$; and hence, the prob. that a molecule in B is chosen is $\frac{p-k}{p}$.

Thus

$$p_{k, k+1} = \frac{p-k}{p} = 1 - \frac{k}{p}$$

$$p_{k, k-1} = \frac{k}{p}$$



Thus

$$P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & \dots & p \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ \vdots \\ p-1 \\ p \end{matrix} & \left[\begin{array}{cccccc} 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 1/p & 0 & 1-1/p & 0 & \dots & 0 \\ 0 & 0 & 2/p & 0 & 1-2/p & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \dots & 1/p \\ 0 & 0 & 0 & 0 & 0 & \dots & 1 & 0 \end{array} \right] \end{matrix}$$

Find stationary measure

$$WP = W$$

$$W = (w_0, w_1, \dots, w_p)$$

$$(WP)_k = \sum_{j=0}^p w_j P_{jk} = w_{k+1} P_{k+1,k} + w_{k-1} P_{k-1,k}$$

$$P_{k,k+1} = 1 - \frac{k}{p} \quad k \rightarrow k-1 \quad P_{k-1,k} = 1 - \frac{k-1}{p}$$

$$P_{k+1,k} = \frac{k+1}{p} \quad k \rightarrow k+1 \quad P_{k+1,k} = \frac{k+1}{p}$$

$$w_{k+1} \cdot \frac{k+1}{p} + \left(1 - \frac{k-1}{p}\right) w_{k-1} = w_k$$

$$w_{-1} = 0$$

$$w_{p+1} = 0$$

then
holds for
 $k=0, 1, \dots, p$.

$$\text{Let } f(x) = \sum_{k=0}^p w_k x^k$$

$$\frac{1}{p} \sum_{k=0}^p (k+1) w_{k+1} x^k + \sum_{k=0}^p w_{k+1} x^k$$

$$+ -\frac{1}{p} \sum_{k=0}^p (k-1) w_{k-1} x^k = \cancel{\frac{1}{p}} \sum_{k=0}^p w_k x^k$$

$$\begin{aligned} \sum_{k=0}^p (k+1) w_{k+1} x^k &= w_1 + 2w_2 x + \dots + p w_p x^{p-1} \\ &= f'(x) \end{aligned}$$

$$\begin{aligned} \sum_{k=0}^p w_{k+1} x^k &= w_0 x + w_1 x^2 + \dots + w_{p-1} x^p \\ &= x (w_0 + w_1 x + \dots + w_{p-1} x^{p-1}) \\ &= x (f(x) - w_p x^p) \end{aligned}$$

$$\begin{aligned} \sum_{k=0}^p (k-1) w_{k-1} x^k &= w_1 x^2 + \overset{2}{w_2} x^3 + \dots + \cancel{w_{p-1}} (p-1) w_{p-1} x^p \\ &= x^2 (w_1 + 2w_2 x + \dots + (p-1) w_{p-1} x^{p-2}) \\ &= \cancel{x (f'(x))} = x^2 (f'(x) - p w_p x^{p-1}) \end{aligned}$$

Thus

$$\frac{1}{p} f'(x) + x(f(x) - w_p x^p) - \frac{1}{p} x^2 (f'(x) - p w_p x^{p-1}) = f(x)$$

$$\frac{1}{p} f'(x) + x f(x) - \cancel{w_p x^{p+1}} - \frac{1}{p} x^2 f'(x) + \cancel{w_p x^{p+1}} = f(x)$$

$$\frac{1}{p} (1-x^2) f'(x) = (1-x) f(x)$$

$$\frac{1}{p} (1+x) f'(x) = f(x)$$

$$\frac{f'(x)}{f(x)} = p \frac{1}{1+x}$$

$$\int \frac{f'}{f} dx = \int \frac{p}{1+x} dx$$

$$\log f = p \log(1+x) + c$$

$$f(x) = c (1+x)^p = c \sum_{k=0}^p \binom{p}{k} x^k$$

$$\text{f(0)} \quad f(1) = \sum_{k=0}^p w_k = 1$$

$$f(1) = c 2^p = 1$$

$$c = 2^{-p}$$

$$f(x) = \sum_{k=0}^p \frac{1}{2^p} \binom{p}{k} x^k$$

Thus
$$W_k = \frac{1}{2^p} \binom{p}{k}$$

p = total # of molecules

k = # of molecules in container A

Physical Interpretation

Whatever the initial number of molecules in the first container, after a long time the probability of finding k molecules in it is nearly the same as if the p molecules had been distributed at random, each molecule having probability $\frac{1}{2}$ to be in the first container.

Let $D = \frac{k}{p}$ = density of gas in container A

Now
$$k = \frac{1}{2} p + \sigma \sqrt{p} X$$

↑
random variable

↑
random variable with $N(0,1)$

Thus

$$D = \frac{k}{\rho} = \frac{1}{2} + \frac{\sigma}{\sqrt{\rho}} X$$

\uparrow \uparrow
 Thermodynamics

- Thus fluctuations about the mean are of order $\frac{1}{\sqrt{\rho}}$

- for $\rho \approx 10^{23}$, fluctuations are very small.

Let $\rho = 2N$.

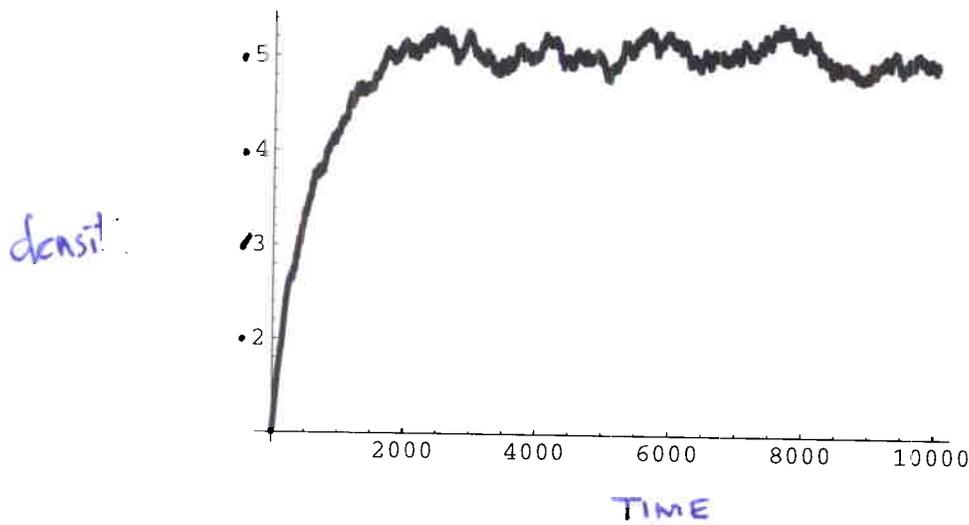
$$W_k = \frac{1}{2^{2N}} \binom{2N}{k}$$

Look at $W_N = \frac{1}{2^{2N}} \binom{2N}{N} \sim \frac{1}{\sqrt{\pi N}}$

Thus $r_N \sim \sqrt{\pi N}$ large recurrence times.

$$W_{N+k} \sim \frac{1}{\sqrt{\pi N}} e^{-\frac{1}{2} \frac{k}{\sqrt{N}} \sigma}$$

$$r_{N+k} \sim \sqrt{\pi N} e^{\frac{1}{2} \frac{k}{\sqrt{N}} \sigma}$$



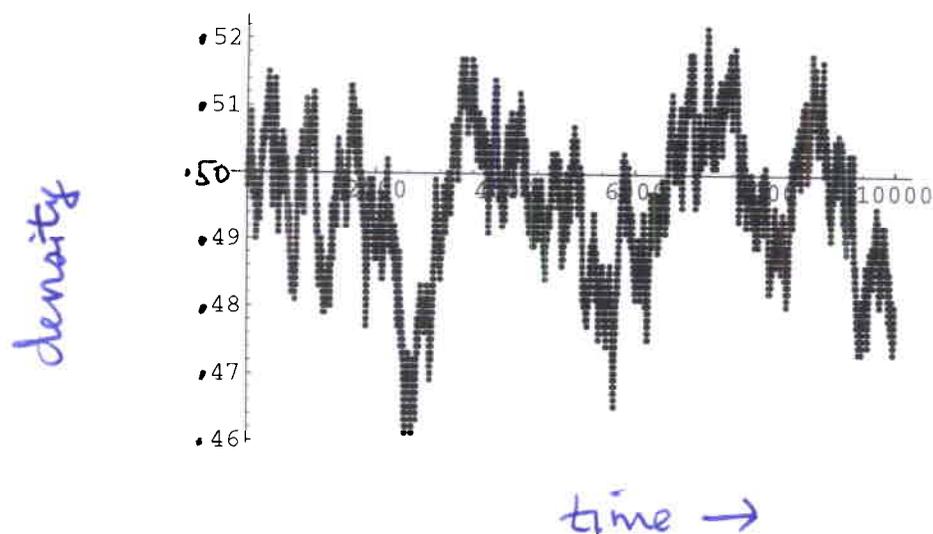
$n = 1000$ molecules total

$k = 100$ molecules in container A initially.

Above plot gives future k 's as a function of time. I have divided k by n and plotted density.

We know that density $\rightarrow \frac{1}{2}$ for very large n . Here we can see approach to $\frac{1}{2}$ with the fluctuations around $\frac{1}{2}$.

Ran for 10,000 time steps



$N = 1000$ molecules

$k = 500$ molecules initially
in container A.

Above plot shows the density fluctuations around the value $\frac{1}{2}$. Note change of the density scale. We expect, roughly, fluctuations to be of order $\frac{1}{\sqrt{N}}$. Note

$$\frac{1}{\sqrt{1000}} \approx 0.03$$

which is pretty good.

Simulation ran for 10,000 time steps.

Ergodic Theorem

$$w \underline{P} = w$$

Let $N_i(t)$ be the number of visits to the state i during times $0, 1, 2, \dots, t-1$.

Then for any initial distribution

$$\frac{1}{t} N_i(t) \rightarrow w_i \quad \text{as } t \rightarrow \infty.$$

(this is a.s. convergence)

Two-State Markov Chain - Use of eigenvalues/eigenvectors

$$P = \begin{pmatrix} 1-\alpha & \alpha \\ \beta & 1-\beta \end{pmatrix} \quad 0 < \alpha, \beta < 1.$$

In this case we can compute P^n explicitly.

Eigenvalues are

$$1, 1-\alpha-\beta$$

with corresponding eigenvectors

$$\begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad \begin{pmatrix} -\alpha/\beta \\ 1 \end{pmatrix}$$

Thus

$$P = \begin{pmatrix} 1 & -\alpha/\beta \\ 1 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1-\alpha-\beta \end{pmatrix} \begin{pmatrix} 1 & -\alpha/\beta \\ 1 & 1 \end{pmatrix}^{-1}$$

Thus

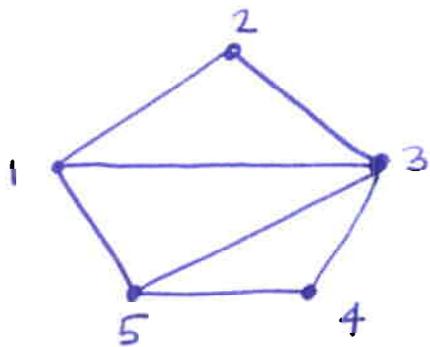
$$P^n = \begin{pmatrix} 1 & -\alpha/\beta \\ 1 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & (1-\alpha-\beta)^n \end{pmatrix} \begin{pmatrix} 1 & -\alpha/\beta \\ 1 & 1 \end{pmatrix}^{-1}$$

$$c = (1-\alpha-\beta)^n$$

$$P^n = \begin{pmatrix} \frac{\beta + \alpha c}{\alpha + \beta} & \frac{\alpha - \alpha c}{\alpha + \beta} \\ \frac{\beta(z-1)}{\alpha + \beta} & \frac{\alpha + \beta z}{\alpha + \beta} \end{pmatrix}$$

Simple Random walk on a graph

Graph = (E, V)
↓ — vertices
↑ edges



We say vertices i and j are neighbors if there is an edge joining i and j

$\text{deg}(i) = \#$ of neighbors of vertex i

State space = set of vertices

At each step the walker chooses one of its neighbors at random (uniform)

~~In ab~~

For above graph

$$P = \begin{matrix} & \begin{matrix} 1 & 2 & 3 & 4 & 5 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} & \begin{bmatrix} 0 & 1/3 & 1/3 & 0 & 1/3 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 1/4 & 1/4 & 0 & 1/4 & 1/4 \\ 0 & 0 & 1/2 & 0 & 1/2 \\ 1/3 & 0 & 1/3 & 1/3 & 0 \end{bmatrix} \end{matrix}$$

More formally

$$P_{ij} = \begin{cases} \frac{1}{\deg(i)} & \text{if } i \text{ and } j \text{ are neighbors} \\ 0 & \text{otherwise} \end{cases}$$

Look at invariant measure

$$wP = w$$

Proposition

~~Let~~ Consider an ergodic Markov chain with state space S . Assume that there exists positive numbers $w_i, i \in S$ such

that $\sum w_i = 1$ and

$$w_i P_{ij} = w_j P_{ji} \quad \text{for every } i, j \in S$$

Then $w = (w_1, w_2, \dots)$ is the equilibrium distr.

Proof

Must show $wP = w$

$$\sum_{i \in S} w_i P_{ij} = \sum_{i \in S} w_j P_{ji} = w_j \sum_i P_{ji} = w_j$$

since
row sums = 1.

Observe that if we can find positive numbers v_i such that

$$v_i p_{ij} = v_j p_{ji}$$

then we take

$$w_i = \frac{v_i}{\sum v_i}$$

this only assumes $\sum v_i < \infty$.

Return to simple random walk on Graph G

Claim $w_i = \frac{\deg(i)}{Z}$ $Z = \sum_{k \in S} \deg(k)$

Let $v_i = \deg(i)$

if i and j are not neighbors

$$v_i p_{ij} = 0 = v_j p_{ji} \quad \checkmark$$

if i and j are neighbors

$$\begin{aligned} v_i p_{ij} &= \deg(i) \cdot \frac{1}{\deg(i)} \\ &= 1 = \deg(j) \cdot \frac{1}{\deg(j)} = v_j p_{ji} \end{aligned}$$

Thus

$$w = \left(\frac{3}{14}, \frac{2}{14}, \frac{4}{14}, \frac{2}{14}, \frac{3}{14} \right) \quad \text{in above example}$$

Defn.

A markov chain is called symmetric

$$\text{if } p_{ij} = p_{ji}$$

$$\text{Thus if } w_i = \frac{1}{|S|} \quad \text{for all } i$$