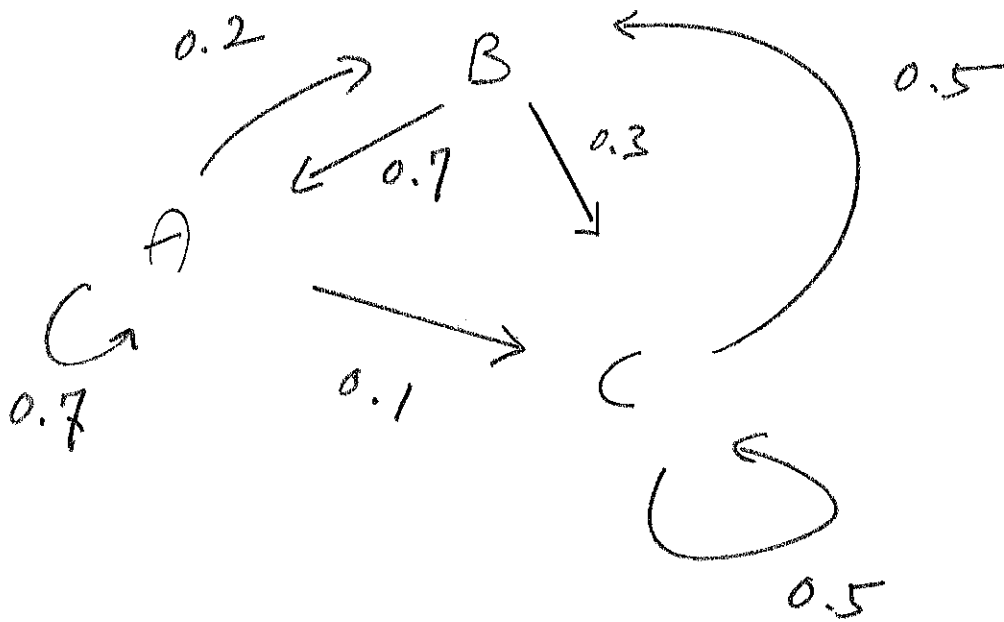


Markov Chain Monte Carlo

03.2026

①



$$P = \begin{bmatrix} 0.7 & 0.2 & 0.1 \\ 0.7 & 0 & 0.3 \\ 0 & 0.5 & 0.5 \end{bmatrix}$$

→ adds to 1

if we start from A

$$\vec{\pi}_1 = [1, 0, 0]$$

$$\vec{\pi}_2 \rightarrow \vec{\pi}_1^t P \quad \& \quad \text{keep going.}$$

$$\pi_1 \rightarrow \pi_2 \rightarrow \pi_3 \rightarrow \dots \rightarrow \underline{\pi_\infty}$$

→ Markov chain

↳ settles in Eq.

$$\vec{\pi}_{\infty} = \vec{\pi}_{\infty} P$$

→ (left) eigenvectors.

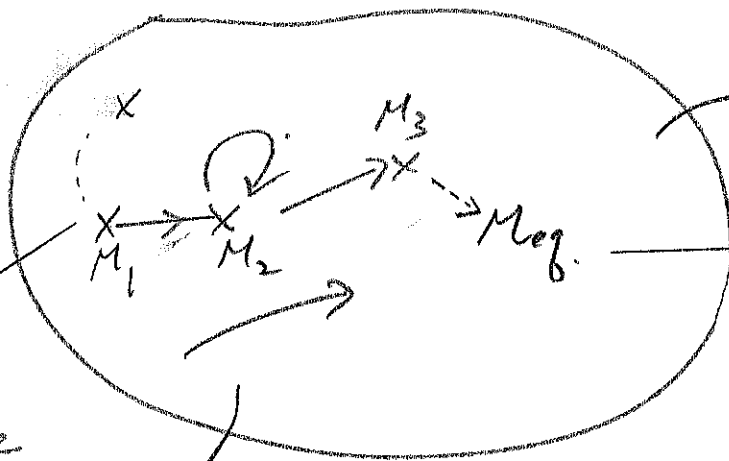
$\vec{\pi}_{\infty}$ can be obtained

by $\lambda_{\underline{P}^t} = 1$ for \underline{P}^t

the eigenvector $\leftrightarrow \vec{\pi}_{\infty}$.

generally

config. space.



can't solve for \underline{P}

equi. prob. density $N(M)$.

start anywhere

(ergodic)

Markov chain:

No memory
next step depends
only on current state

Metropolis

(Koonin
P. 212)

②

→ criteria to accept a new config :

$M_1 \xrightarrow{?} M_2$

$W = \text{prob. density}$

if $W(M_2) > W(M_1) \rightarrow$ do it

if $W(M_2) < W(M_1) \rightarrow$ accept with prob.

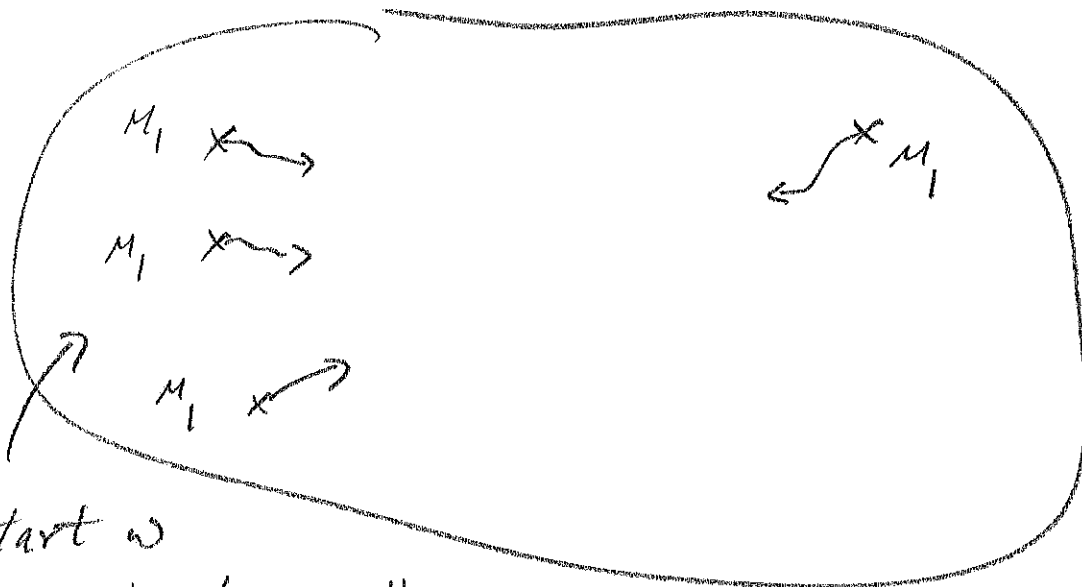
combining :

$$\gamma = \frac{W(M_2)}{W(M_1)}$$

→ accept w prob.

$$\min\left(1, \frac{W(M_2)}{W(M_1)}\right)$$

how this works ?



start w

many random walkers

at n -th steps,

$N_n(M)$ = no. of walkers in M -state

$$\Delta N_n(M) = N_n(M') \overset{\text{immigrants}}{P_{M' \rightarrow M}} - N_n(M) \overset{\text{leaving}}{P_{M \rightarrow M'}}$$

the change in # of states in M at next step.

$$= N_n(M) \frac{P_{M \rightarrow M'}}{P_{M' \rightarrow M}} \times$$

$$\left\{ \frac{N_n(M')}{N_n(M)} \frac{P_{M \rightarrow M'}}{P_{M' \rightarrow M}} \right\}$$

$$\Delta N_n(M) = 0$$

$$\text{if } \frac{N_n(M')}{N_n(M)} = \frac{N_{eq}(M')}{N_{eq}(M)} = \frac{P_{M \rightarrow M'}}{P_{M' \rightarrow M}}$$

if $N_n(M)$ is too large
or $N_n(M')$ too small

$$\Delta N_n(M) < 0 \quad N_n(M) \text{ will } \downarrow$$

$$\& N_n(M) \text{ too small } \rightarrow N_n(M) \text{ will } \uparrow$$

SO the system will reach $\Delta N_n(M) = 0$

Now we know

$$N_{\text{rel}}(M) \xrightarrow{\text{eventually}} N_{\text{eq}}(M)$$

but how do we know the prob. density?

$$N_{\text{eq}}(M) \leftrightarrow W(M) ?$$

Metropolis's idea

$$P_{M \rightarrow M'} = T_{M \rightarrow M'} A_{M \rightarrow M'}$$

transition
prob.

acceptance
prob.

if nothing blocking

$$M \rightarrow M'$$

e.g. $M' = M + \delta$



$$T_{M \rightarrow M'} = T_{M' \rightarrow M}$$

$$\frac{P_{M \rightarrow M'}}{P_{M' \rightarrow M}} = \frac{T_{M \rightarrow M'} A_{M \rightarrow M'}}{T_{M' \rightarrow M} A_{M' \rightarrow M}} \rightarrow \frac{A_{M \rightarrow M'}}{A_{M' \rightarrow M}}$$

$$r = \frac{A_{M \rightarrow M'}}{A_{M' \rightarrow M}}$$

recall

$$A_{M \rightarrow M'} = \begin{cases} 1 & \text{if } W_{M'} > W_M \\ \frac{W_{M'}}{W_M} & \text{if } W_{M'} < W_M \end{cases}$$

$$r = \frac{1}{\frac{W_M}{W_{M'}}} \quad \text{if } W_{M'} > W_M$$

$$r = \frac{W_{M'}}{W_M} \quad \text{if } W_{M'} < W_M$$

$$r = \frac{W_{M'}}{W_M} \quad \text{in any case.}$$

so the Metropolis rule will give

$$\frac{N_n(M')}{N_n(M)} \rightarrow r = \frac{W_{M'}}{W_M}$$

$$N_n(M) \propto W(M)$$

as required!

if $M \leftrightarrow M'$

e.g. w blocking

generally any T, A s.t.

$$\frac{T_{M \rightarrow M'} A_{M \rightarrow M'}}{T_{M' \rightarrow M} A_{M' \rightarrow M}} = \frac{W_{M'}}{W_M}$$

will work



Metropolis-Hastings

not

to the extreme:

$$T_{M \rightarrow M'} = W_{M'}$$

$A = 1 \rightarrow$ accept them all

$$\text{then } \frac{T_{M \rightarrow M'}}{T_{M' \rightarrow M}} = \frac{W_{M'}}{W_M}$$

\Rightarrow well, if we know $W(M)$
we would not need to do
the sampling...

Metropolis :

to decide whether to
accept a change $M \rightarrow M'$

$$P = \min(1, \gamma)$$

$$\gamma = \frac{W_{M'}}{W_M} \quad \text{or} \quad \gamma \propto W_{M'}$$

e.g. $W_M = e^{-\beta H[M]}$ in stat. mech.

$$\gamma = \frac{e^{-\beta H[M']}}{e^{-\beta H[M]}}$$

$$\rightarrow e^{-\beta(\Delta H)}$$

In Ising Model

M' = flip the spin at site i

$$\gamma = \frac{e^{-\beta} H[\sigma_1, \sigma_2, \dots, \sigma_i = s, \dots]}{\sum_{s''} e^{-\beta} H[\dots, \sigma_i = s'']}$$

$$\sum_{s''} e^{-\beta} H[\dots, \sigma_i = s'']$$

nearest neighbor ...

but σ_i only talks to σ_{i-1} & σ_{i+1}

$$\rightarrow \frac{e^{-\beta} [\beta] (\sigma_{i-1} + \sigma_{i+1}) s.]}{\sum_{s''} e^{-\beta} [\beta] (\sigma_{i-1} + \sigma_{i+1}) s''}$$

$$\sum_{s''} e^{-\beta} [\beta] (\sigma_{i-1} + \sigma_{i+1}) s''$$

much simpler

staple

$\sigma_{i-1} + \sigma_{i+1}$ can be

$$\left\{ \begin{matrix} -2 \\ 0 \\ 2 \end{matrix} \right\}$$

speed things up.

γ : given the trial s

\rightarrow s outcome to decide.