

Monte Carlo Integration

Root equation

$$I = \int a(x) dx$$
$$= \int \underbrace{\frac{a(x)}{f(x)}}_{h(x)} f(x) dx = \mathbb{E}_{x \sim f(x)} \left[\frac{a(x)}{f(x)} \right]$$

→ designed
memorize

$$X_1, X_2, \dots, X_n \stackrel{\text{iid}}{\sim} f(x)$$

$$\hat{I} = \frac{1}{n} \sum_{i=1}^n \frac{a(X_i)}{f(X_i)}$$

Unnormalized Density

$$f(x) = \frac{1}{Z} \tilde{f}(x)$$

$$Z = \int \tilde{f}(x) dx$$

$$\int f(x) dx = 1$$

Physics: Gibbs Distribution (Boltzman)

$$f(x) = \frac{1}{Z} e^{-\frac{\epsilon(x)}{T} \rightarrow \text{temperature}}$$

\rightarrow energy function
 \downarrow
 (also called partition function)

Last time: $f(x) = \frac{1}{Z} e^{-\frac{x^2}{2}}$

Special case: Unif(A)

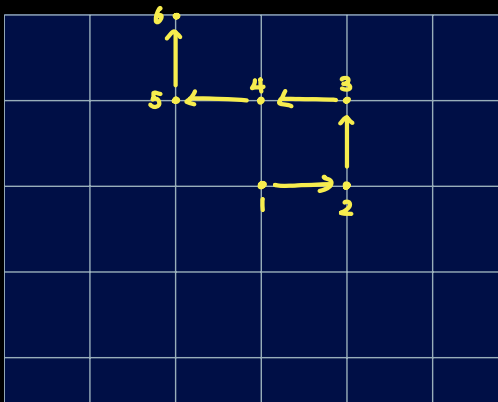
$$P(x) = \begin{cases} \frac{1}{|A|} & x \in A \\ 0 & x \notin A \end{cases}$$

$$= \frac{1(x \in A) \rightarrow \hat{f}(x)}{|A| \rightarrow Z}$$

unnormalized function

can approximate Z using root equation

Self avoiding walk



$A = \left\{ \begin{array}{l} \text{paths of length } N \text{ that} \\ \text{are self-avoiding} \end{array} \right\}$

$$P(x) = \frac{1(x \in A)}{|A|}$$

$$x = (x_1, x_2, x_3, \dots, x_N)$$

E.g. A = molecule configuration

$x = (x_1, x_2, \dots, x_n)$ input x are all coordinates

$E_p = (|x_n - x_1|^2)$ Euclidean distance

Suppose we want: $|A| = \sum_{x \in \Omega} 1(x \in A)$

$(A \subset \Omega)$

$$= \sum_{x \in \Omega} \frac{1(x \in A)}{q(x)} q(x)$$

each step is uniform
also includes shorter paths
where $x \notin A$

$$= \mathbb{E}_{x \sim q(x)} \left[\frac{1(x \in A)}{q(x)} \right]$$

How do we generate $q(x)$?

$q(x)$ = self-avoiding random walk.

Each x_i is sampled uniformly from available positions.

(stop if we get N points or there's no position available)

for $x \in A$, $x = (x_1, x_2, \dots, x_n)$

$$q(x) = \frac{1}{m_1} \cdot \frac{1}{m_2} \cdot \frac{1}{m_3} \dots \frac{1}{m_{n-1}}$$

m_t is the # of available positions at time t

e.g. $m_1 = 4$

$m_2 = 3$

$\dots \dots$ until $t = N - 1$ or $m_t = 0$

Monte Carlo

- Repeatedly do self-avoiding random walk n times (1000)
- Collect n_1 paths of length N . includes early stops

$$\{ \vec{x}^{(i)}, i=1, \dots, n_1 \}$$

$$|\hat{A}| = \frac{1}{n} \sum_{i=1}^{n_1} \frac{1}{\frac{1}{m_1^{(i)}} \frac{1}{m_2^{(i)}} \dots \frac{1}{m_{N-1}^{(i)}}}$$

$$= \frac{1}{n} \sum_{i=1}^{n_1} m_1^{(i)} m_2^{(i)} \dots m_{N-1}^{(i)}$$

(1) Discrete Case

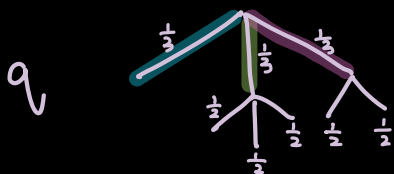
$$I = \sum_{x \in \Omega} a(x)$$

$$= \sum_{x \in \Omega} \frac{a(x)}{q(x)} q(x)$$

$$= E_{x \sim q(x)} \left[\frac{a(x)}{q(x)} \right]$$

How come different paths have different probabilities?
Because m is different for different paths

(2) Probability of path $q(x)$



of branches of length 2 = 5

$$P(\text{each branch of length 2}) = \frac{1}{5}$$

$\frac{1}{3}$ early stop	$\frac{1}{9}$	$\frac{1}{6}$
	$\frac{1}{9}$	$\frac{1}{6}$
	$\frac{1}{9}$	$\frac{1}{6}$

$q(x)$

each block is a branch

$$\begin{aligned}
& E_p(|X_N - X_1|^2) \\
&= \sum_{x \in A} |x_N - x_1| p(x) \\
&= \sum_{x \in A} |x_N - x_1| \frac{1}{|A|} \\
&= \frac{1}{|A|} \sum_{x \in A} |x_N - x_1| \\
&= \frac{1}{|A|} \sum_{x \in A} \frac{|x_N - x_1|}{q(x)} \cdot q(x) \\
&= \frac{1}{|A|} \cdot E_q \left[\frac{|x_N - x_1|}{q(x)} \right]
\end{aligned}$$

$\frac{1}{n}$ is cancelled

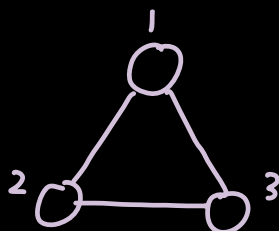
$$\approx \frac{1}{\sum_{i=1}^n m_i^{(i)} \dots m_{N-1}^{(i)}} \sum_{i=1}^n |x_N^{(i)} - x_1^{(i)}| m_1^{(i)} m_2^{(i)} \dots m_{N-1}^{(i)}$$

Part 3: MCMC

Markov Chain Monte Carlo

Markov chain / random walk

State space e.g.



Transition Probability

$$K_{ij} = P(X_{t+1} = j \mid X_t = i) \quad (\text{conditional prob.})$$

\downarrow State at $t+1$ \downarrow State at time t

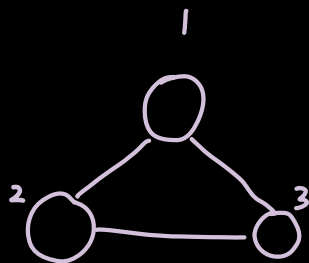
Markov Property

$$P(X_{t+1} = j \mid X_t = i, X_{t-1}, X_{t-2}, \dots, X_0)$$

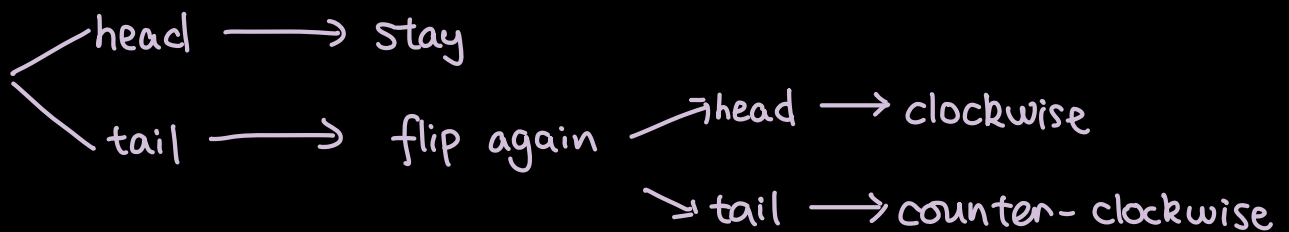
future Present Past

$$= P(X_{t+1} = j \mid X_t = i)$$
$$X_{t+1} = h(X_t, U_t)$$

Example:



At each state, randomly flip a fair coin.


$$K = \begin{array}{c|ccc} & \begin{array}{c} j \\ 1 \quad 2 \quad 3 \end{array} \\ \begin{array}{c} i \\ 1 \\ 2 \\ 3 \end{array} & \begin{array}{|c|c|c|} \hline \frac{1}{2} & \frac{1}{4} & \frac{1}{4} \\ \hline \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ \hline \frac{1}{4} & \frac{1}{4} & \frac{1}{2} \\ \hline \end{array} \end{array}$$

transition matrix

Example:

$$X_0 = 1 \rightarrow X_1 \rightarrow X_2 \rightarrow \dots$$

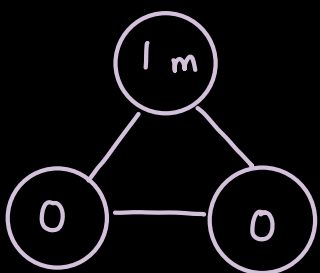
$$P_i^{(t)} = P(X_t = i)$$

e.g. $P_3^{(2)} = P(X_2 = 3)$

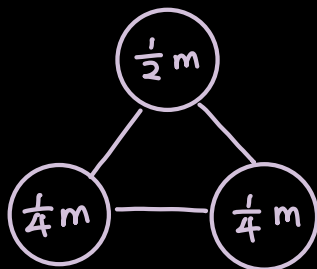
↑
Marginal Probability

Population migration

1 million people

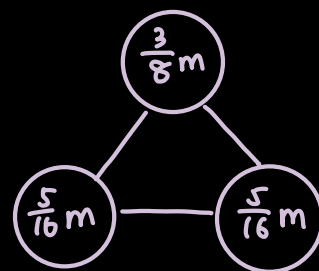


$t=0$



$t=1$

$$\frac{1}{2}m \times \frac{1}{2} + \frac{1}{4}m \times \frac{1}{4} + \frac{1}{4}m \times \frac{1}{4}$$

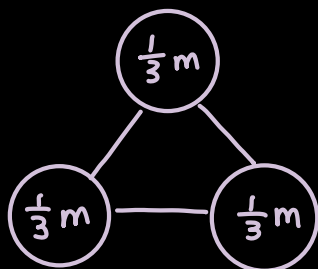


$t=2$

$$P_3^{(2)} = P(X_2 = 3) = \frac{5}{16}$$

eventually

.....



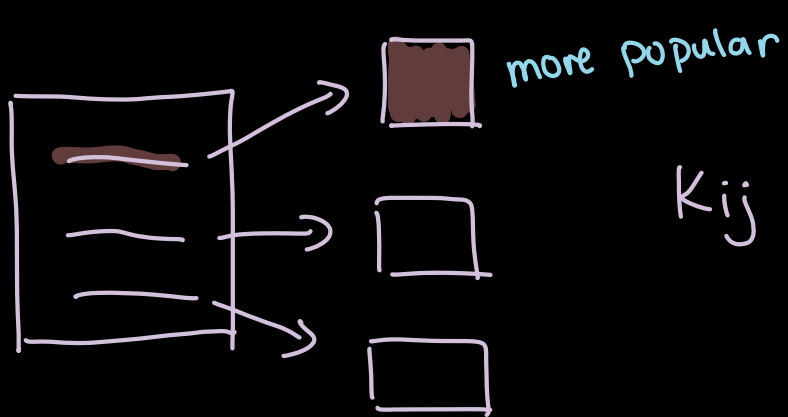
stationary distribution
(equilibrium) π

$$P^{(t)} = (P_1^{(t)} \ P_2^{(t)} \ P_3^{(t)}) \rightarrow \pi = \left(\begin{matrix} \pi_1 & \pi_2 & \pi_3 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{matrix} \right)$$

Example: Google Page Rank

Each page is a state

Random Server



$p^{(t)}$ \rightarrow π popularity

vs. Page Rank : given K , calculate π

MCMC : given π , design K

(card shuffling)