

Monte Carlo Simulations;

Ensemble ,

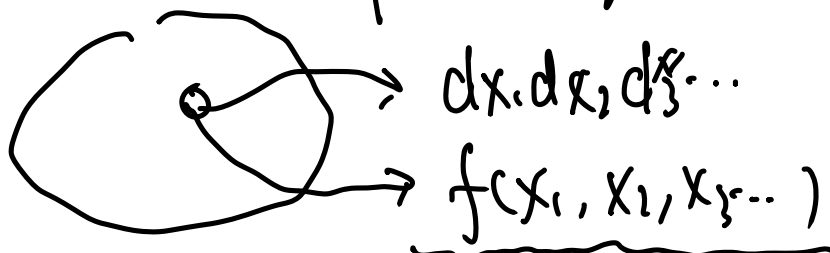
$$\langle M \rangle = \sum_i M_i \cdot P_i$$

$$= \frac{\int M(p, q) e^{-\beta H(p, q)} \cdot dp dq}{\int e^{-\beta H(p, q)} dp dq}$$

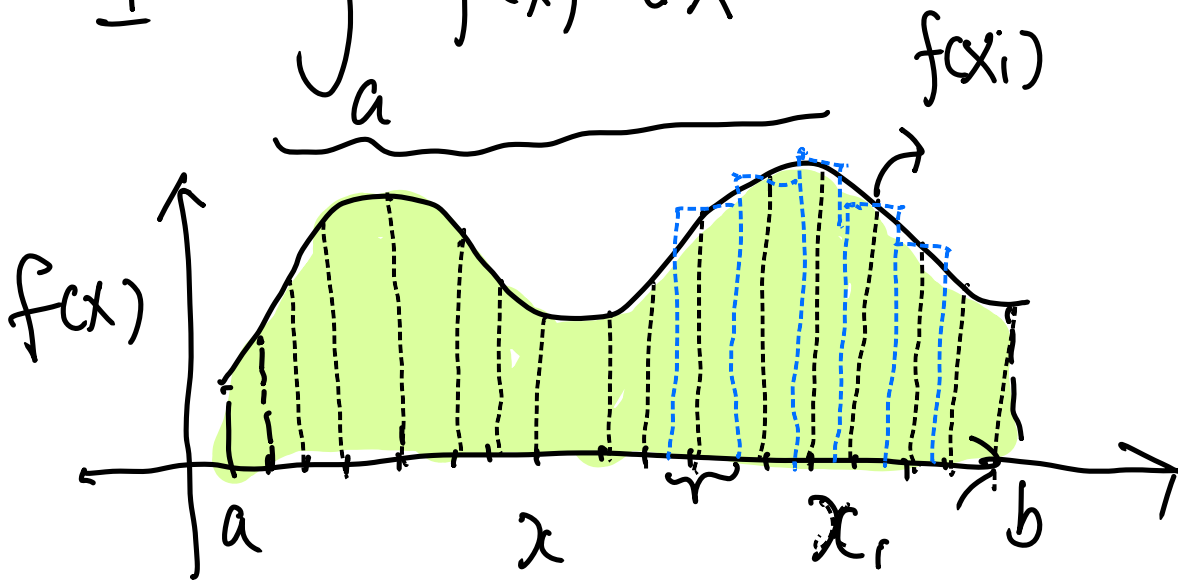
$$= \frac{I_A}{I_B}$$

b_1 b_i

$$I = \int_{a_1} \dots \int_{a_i} f(x_1, x_2, \dots) \underbrace{dx_1 dx_2 \dots}_{\text{phase space}}$$

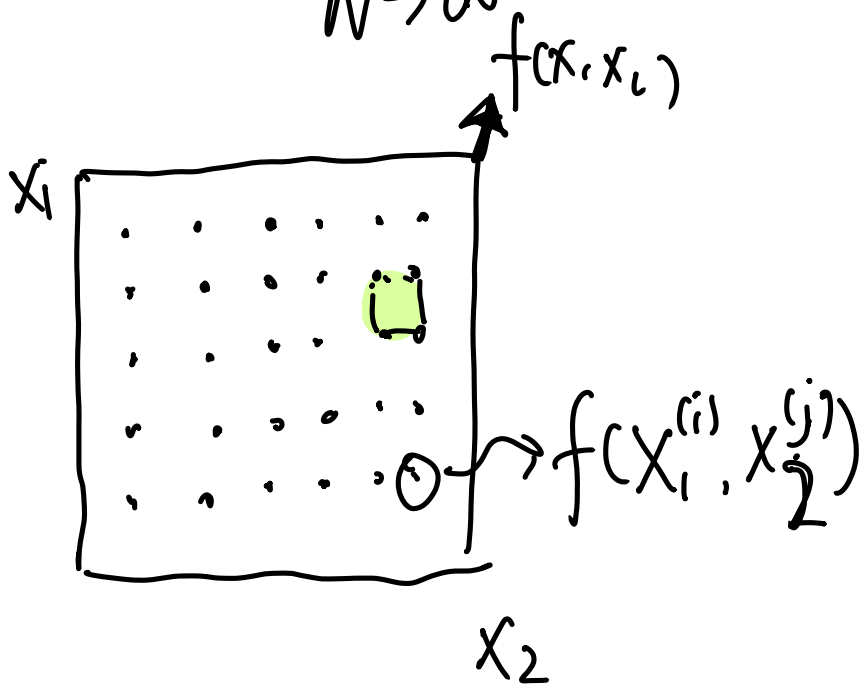


$$I = \int_a^b f(x) dx$$



$$\hat{I} = \sum_{i=1}^N f(x_i) \cdot \Delta \approx I$$

$$I = \lim_{N \rightarrow \infty} \hat{I}$$



$$\hat{I} = \sum_{i=1}^N \sum_{j=1}^M f(x_1^{(i)}, x_2^{(j)}) \Delta_{12}$$

$\rightsquigarrow I$

Simpson's

Quadrature.

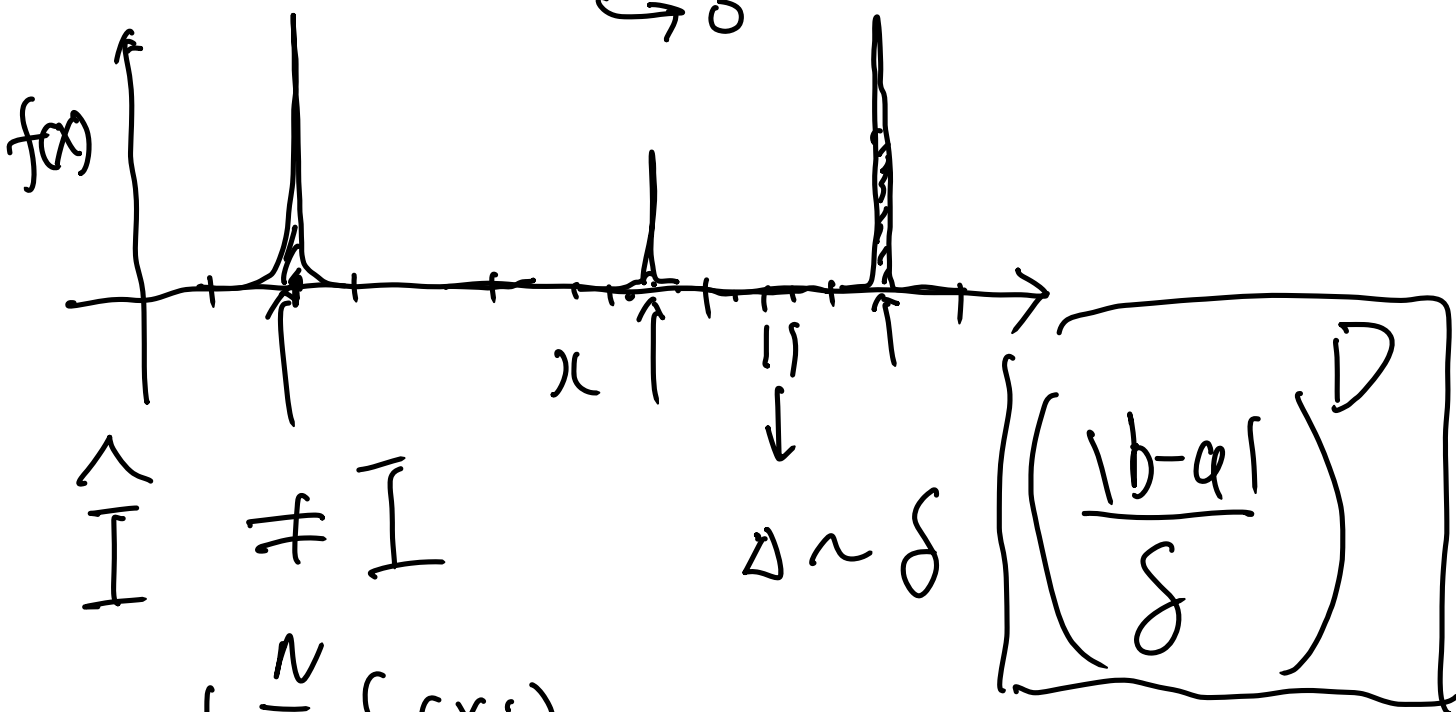
Curse of dimensionality

$$N = 10, \quad D = 10 \times 6 = 60$$

every dim \rightarrow divide 5 points.

$$= 5^{60}$$

$$f(x) \sim \underbrace{e^{-\beta E(x)}}_{\rightarrow 0}$$



$$= \frac{1}{N} \sum_{i=1}^N f(x_i)$$

$$f(x_i) \rightarrow 0$$

Monte Carlo Simulations:

Inferential Statistics:

Descriptive Stat:

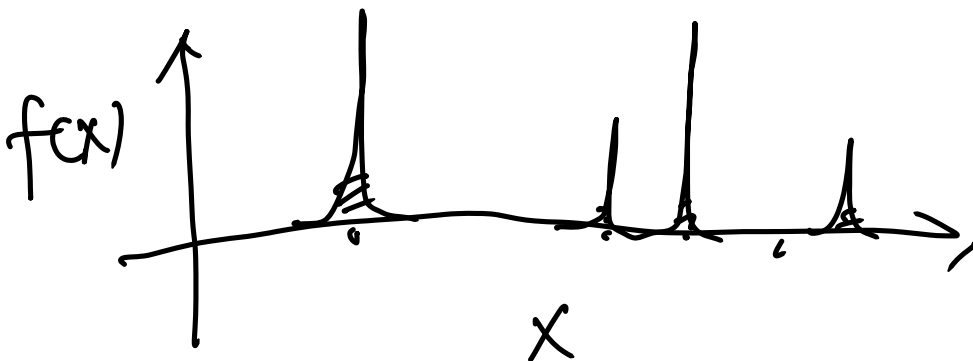
prediction from statistics of data:

① population: all possible states and distribution P_i

② sample: subset of population

③ Random sample can reflect mean properties of the entire population.

④ Law of large Number (Bernoulli's theorem)



$$I = \int_a^b f(x) dx = (b-a) \frac{\int_a^b f(x) dx}{b-a}$$

$$= (b-a) \frac{\int_a^b f(x) dx}{\int_a^b dx} = (b-a) \langle f(x) \rangle$$

$$\int_a^b dx \quad \hookrightarrow \text{random variable}$$

$X \in [a, b]$
uniform distribution

estimator

$$\hat{I} = (b-a) \frac{1}{L} \sum_{i=1}^L f(x_i) \approx I$$

sample

$$\lim_{L \rightarrow \infty} \hat{I} = I$$

$$I = \int_a^b f(x) dx$$

$$w(x) \geq 0$$

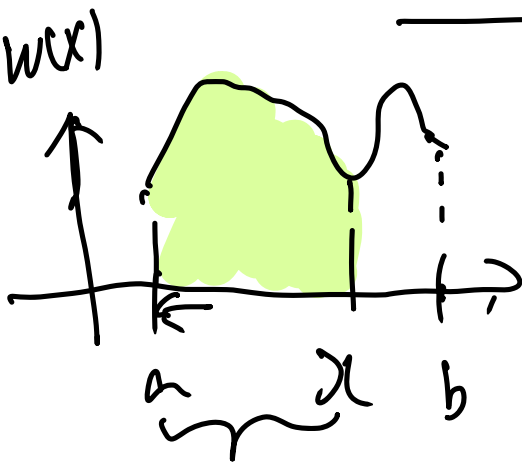
$$\int_a^b w(x) dx = 1$$

$$= \underbrace{\int_a^b \frac{f(x)}{w(x)} w(x) dx}_{\int_a^b w(x) dx} = \left\langle \frac{f(x)}{w(x)} \right\rangle_w$$

$$\int_a^b w(x) dx$$

define:

$$u(x) = \int_a^x w(x') dx'$$



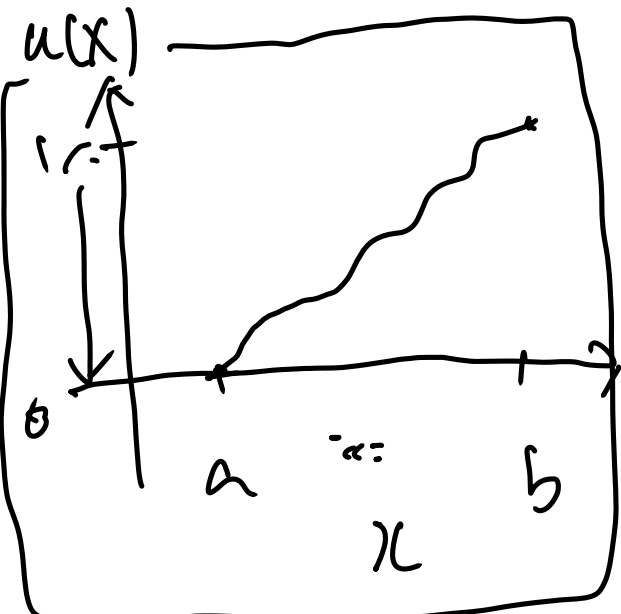
CDF:

cumulative distribution function

$$\frac{du(x)}{dx} = w(x)$$

$$du(x) = w(x) dx$$

$$I = \int_a^b \frac{f(x)}{w(x)} \underbrace{w(x) dx}_{du} \quad x \rightarrow u$$



$$x = \mathcal{U}^{-1}(x)$$

$$= \int_0^1 \frac{f(x(u))}{w(x(u))} du$$

$$\hat{I} = (1-0) \cdot \frac{1}{L} \sum_{i=1}^L \frac{f(x(u_i))}{w(x(u_i))}$$

$$u_i \in [0, 1]$$

$L \rightarrow \text{fixed}$

$\hat{I} \rightarrow I$

Monte Carlo: $L, \hat{I}^{(1)}$ ✓

Monte Carlo: $L, \hat{I}^{(2)}$ ✓

⋮

Monte Carlo: $L, \hat{I}^{(m)}$ ✓

$$\sigma^2 = \left\langle \left(\hat{I}^{(i)} - \underline{I} \right)^2 \right\rangle_m \quad m \rightarrow \infty$$

\underline{I}

$$\sigma^2, L, w$$

$$\sigma^2 = \left\langle \frac{1}{2} \sum_{i=1}^L \left(\frac{f(x(u_i^{(k)}))}{w(x(u_i^{(k)}))} - \underline{I} \right)^2 \right\rangle_m$$

$$\frac{1}{2} \sum_{j=1}^L \left(\frac{f(x(u_j^{(k)}))}{w(x(u_j^{(k)}))} - \underline{I} \right)^2 \right\rangle_m$$

$$= \left\langle \frac{1}{2} \sum_{i=1}^L \sum_{j=1}^L \left(\frac{f(x(u_i^{(k)}))}{w(x(u_i^{(k)}))} \cdot \frac{f(x(u_j^{(k)}))}{w(x(u_j^{(k)}))} \right) \right\rangle_m \quad \textcircled{1}$$

$$\underline{I} \left(\frac{f(x(u_i^{(k)}))}{w(x(u_i^{(k)}))} + \frac{f(x(u_j^{(k)}))}{w(x(u_j^{(k)}))} \right) + \underline{I}^2 \right\rangle_m$$

$\textcircled{1}$

$$\textcircled{I} \left\langle \frac{1}{L^2} \sum_{i \neq j} \frac{f_i^{(k)}}{w_i^{(k)}} \cdot \frac{f_j^{(k)}}{w_j^{(k)}} \right\rangle_m \quad f_i^{(k)} = f(x(u_i^{(k)}))$$

$$+ \left\langle \frac{1}{L^2} \sum_i \frac{f_i^{(k)2}}{w_i^{(k)2}} \right\rangle_m \quad k=1, \dots, m$$

$$= \frac{1}{L^2} \sum_{i \neq j} \left\langle \frac{f_i^{(k)}}{w_i^{(k)}} \cdot \frac{f_j^{(k)}}{w_j^{(k)}} \right\rangle_m \rightarrow \frac{1}{L^2} \sum_{i \neq j} I^2$$

$$+ \frac{1}{L^2} \sum_{i=1}^L \left\langle \frac{f_i^{(k)2}}{w_i^{(k)2}} \right\rangle_m$$

$$= \frac{1}{L^2} \sum_{i \neq j} I^2 + \frac{1}{L^2} \sum_{i=1}^L \left\langle \frac{f^2}{w^2} \right\rangle_m$$

$$= \frac{I^2}{L^2} \cdot L(L-1) + \frac{\left\langle \frac{f^2}{w^2} \right\rangle_m}{L^2} \times L$$

$$= \frac{L-1}{L} I^2 + \frac{1}{L} \left\langle \left(\frac{f}{w} \right)^2 \right\rangle_m$$

$$\textcircled{II} = -\frac{2I^2}{L^2} \cdot L^2 + I^2 = -I^2$$

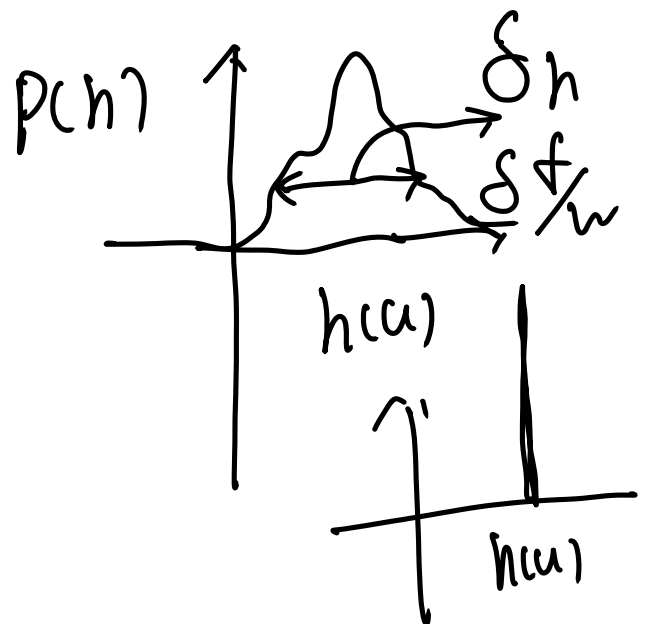
$$\sigma^2 = \frac{1}{L} \left\langle \left(\frac{f}{w} \right)^2 \right\rangle_m + \frac{L-1}{L} I^2 - I^2$$

$$= \frac{1}{L} \left(\left\langle \left(\frac{f}{w} \right)^2 \right\rangle_m - \left\langle \frac{f}{w} \right\rangle^2 \right)$$

$$= \frac{1}{L} \int \left(\frac{f}{w} \right)^2$$

$$\frac{h^{(u)}}{w(x(u))} = \frac{f(x(u))}{w(x(u))}$$

$$L \sigma \propto L^{1/2} \int \left(\frac{f}{w} \right)^2$$



$$\frac{f(x(u))}{w(x(u))} = h(u) = \text{const}$$

$$\hookrightarrow w(x) = \text{const} \cdot \underbrace{f(x)}_{-\beta H(x)}$$

$$= \text{const} \cdot \underline{e}$$

MC = L samples. $\vec{q}_i(N)$, $\vec{q}_i(N)$

n_i

$$\underline{n_i} \propto L \cdot \underbrace{p(\vec{q}_i(N))}_{e^{-\beta U(\vec{q}_i(N))}}$$

$$= L \cdot \underline{\underline{Z}}$$

$$\langle M \rangle = \frac{1}{L} \sum_{i=1}^M n_i \cdot M(\vec{q}_i(N))$$

two states

$$\begin{aligned}
 \frac{n_i}{n_j} &= \frac{\mathcal{L} \cdot p(\vec{q}_i)}{\mathcal{L} \cdot p(\vec{q}_j)} = \frac{e^{-\beta u(\vec{q}_i)}/Z}{e^{-\beta u(\vec{q}_j)}/Z} \\
 &= e^{-\beta(u(\vec{q}_i) - u(\vec{q}_j))}
 \end{aligned}$$

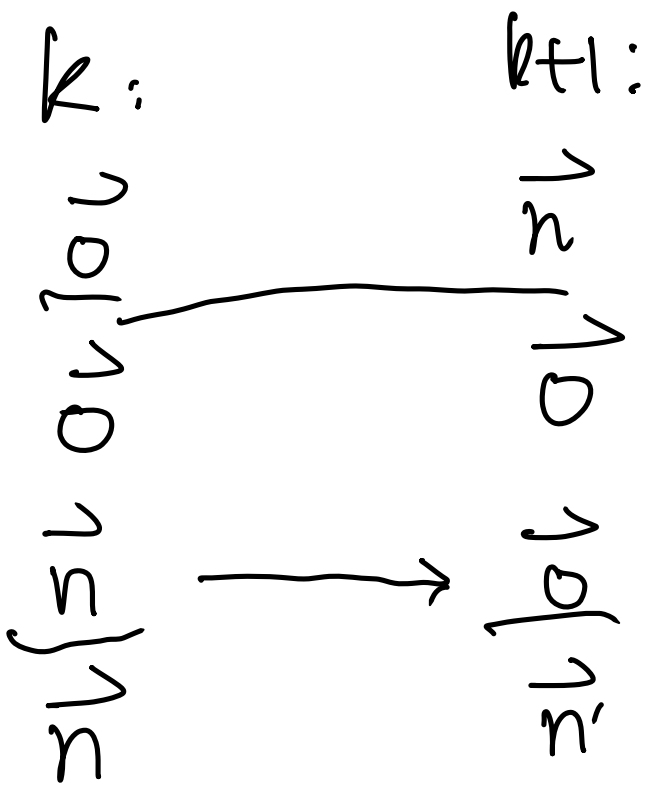
Transition Probability

$$\pi(\vec{q}_i \rightarrow \vec{q}_j)$$

Imagine M MC sampling
 for every MC sim
 k , sample. $\rightarrow \vec{q}_i, \vec{q}_j$
 $\vec{0}, \vec{n}$

$$\hat{p}(\vec{0}) = \frac{m(\vec{0})}{M} \approx p(\vec{0}) = \frac{e^{-\beta u(\vec{0})}}{Z}$$

how about $k+1$



$$\underline{m^{(k)}(\vec{0}) \longrightarrow m^{(k+1)}(\vec{0})}$$

$$\sum_{\{\vec{n}\}} m^{(k)}(\vec{0}) \cdot \underline{\pi(\vec{0} \rightarrow \vec{n})} \quad \swarrow$$

$$= \sum_{\{\vec{n}\}} m^{(k)}(\vec{n}) \underline{\pi(\vec{n} \rightarrow \vec{0})} \quad \checkmark$$



$$\frac{m^{(k)}(\vec{0})}{M} \pi(\vec{0} \rightarrow \vec{n})$$

$$= \frac{m^{(k)}(\vec{n})}{M} \pi(\vec{n} \rightarrow \vec{0})$$

detailed balance conditions.

$$p(\vec{0}) \pi(\vec{0} \rightarrow \vec{n}) = p(\vec{n}) \pi(\vec{n} \rightarrow \vec{0})$$

$$\frac{\pi(\vec{0} \rightarrow \vec{n})}{\pi(\vec{n} \rightarrow \vec{0})} = \frac{p(\vec{n})}{p(\vec{0})} = e^{-\beta(\mathcal{U}(\vec{n}) - \mathcal{U}(\vec{0}))}$$

$$\pi(\vec{0} \rightarrow \vec{n})$$

$$= \sum_{\vec{0} \rightarrow \vec{n}} \pi(\vec{0} \rightarrow \vec{n})$$

$$\frac{\pi(\vec{0} \rightarrow \vec{n})}{\pi(\vec{n} \rightarrow \vec{0})} = e^{-\beta(\mathcal{U}(\vec{n}) - \mathcal{U}(\vec{0}))}$$

$$\pi(\vec{0} \rightarrow \vec{n}) = \min(1, e^{-\beta(\mathcal{U}(\vec{n}) - \mathcal{U}(\vec{0}))})$$

$$\frac{\text{acc}(0 \rightarrow n)}{\text{acc}(n \rightarrow 0)} = \frac{\text{min}(\quad)}{\text{min}(\quad)}$$

MC algorithm:
randomly select

① Initialize $\vec{O}_0 \xrightarrow{\Delta} \vec{O}$

Repeat {

Given \vec{O} , generate \vec{n} at random.

generate random displacement $\vec{\Delta}$,

$$\vec{n} := \vec{O} + \vec{\Delta}$$

calculate $u(\vec{n})$, $f = e^{-\beta(u(\vec{n}) - u(\vec{O}))}$

if $f \geq r$ accept

or ~~if~~ generate a random number $r \in [0, 1]$

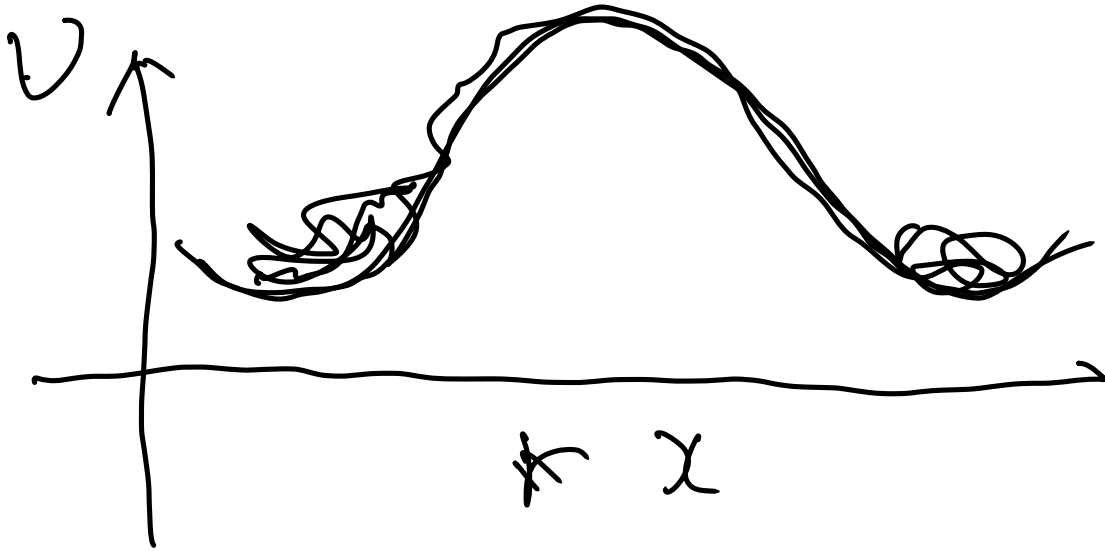
if $r < f$: accept

record the current state

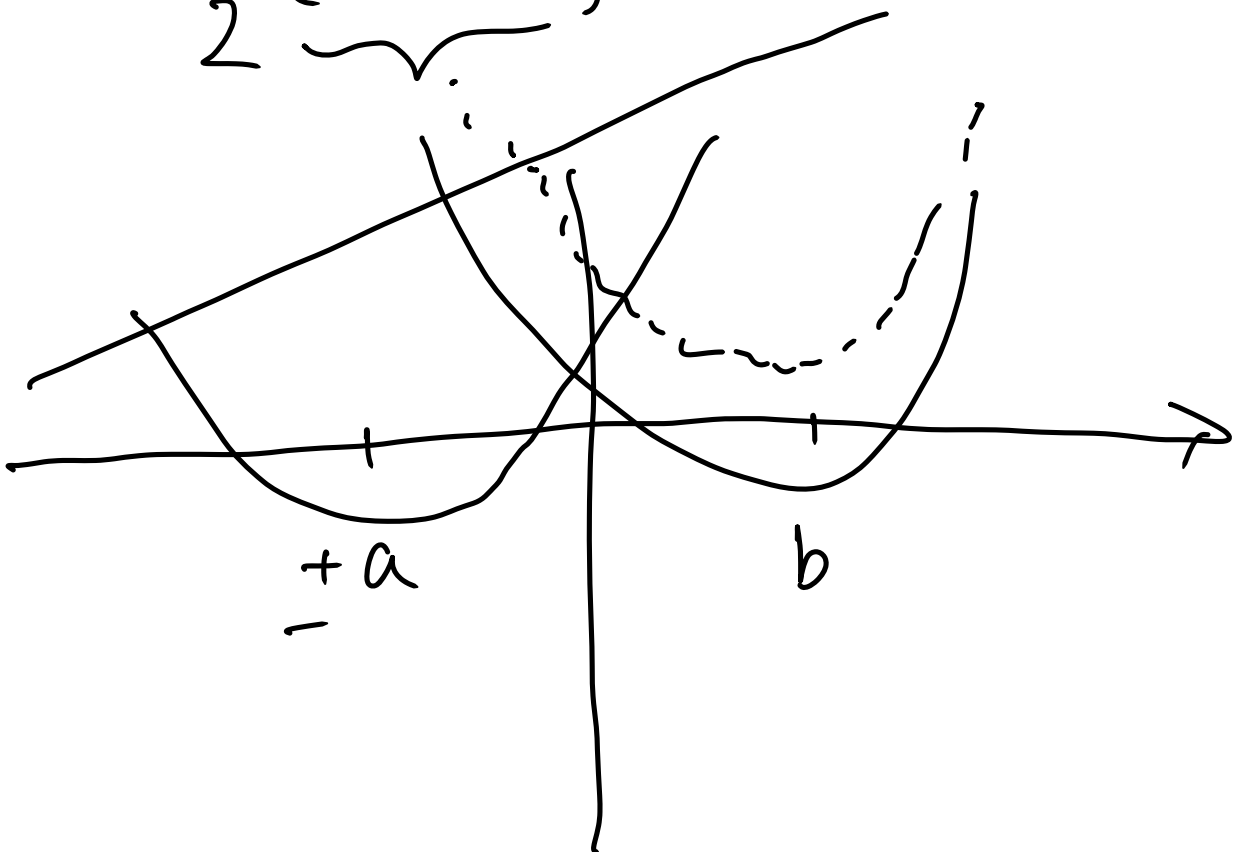
}

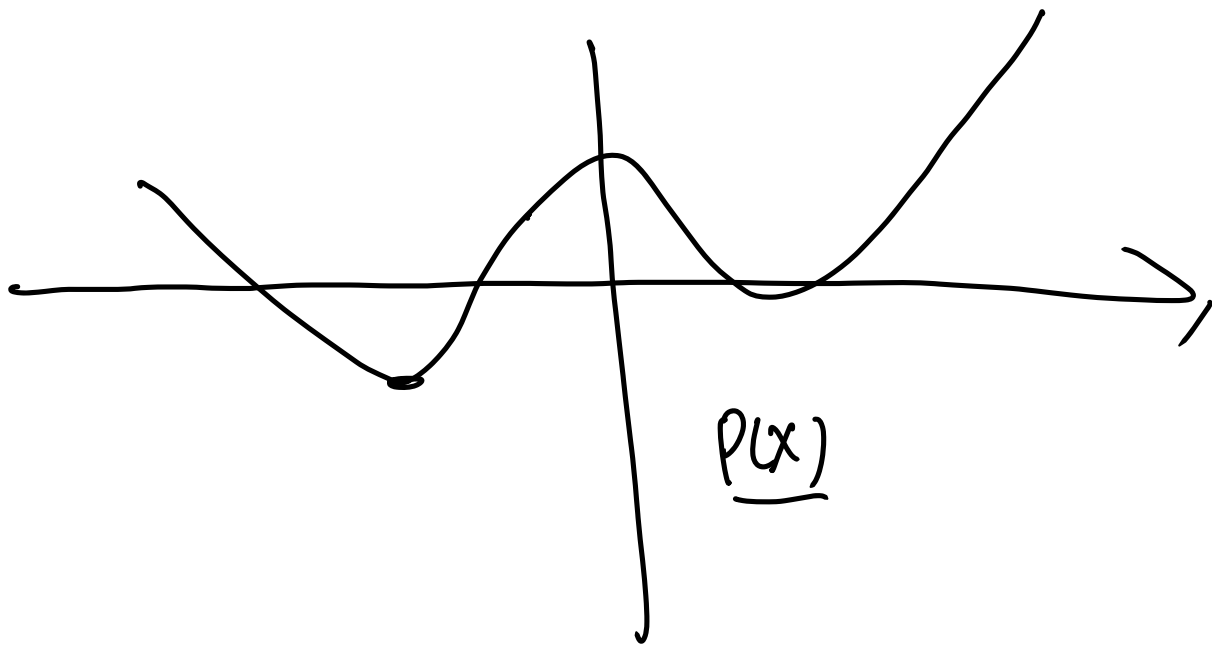
1D random walker in a 1D

potential energy surface.



$$V = \frac{1}{2} (\underbrace{x+a}_{\text{left well}})^2 - (x-b)^2 + c \cdot x$$





$$\vec{n} = \vec{0} + \vec{\Delta} \in [-a, b]$$

$$[-a, a)$$

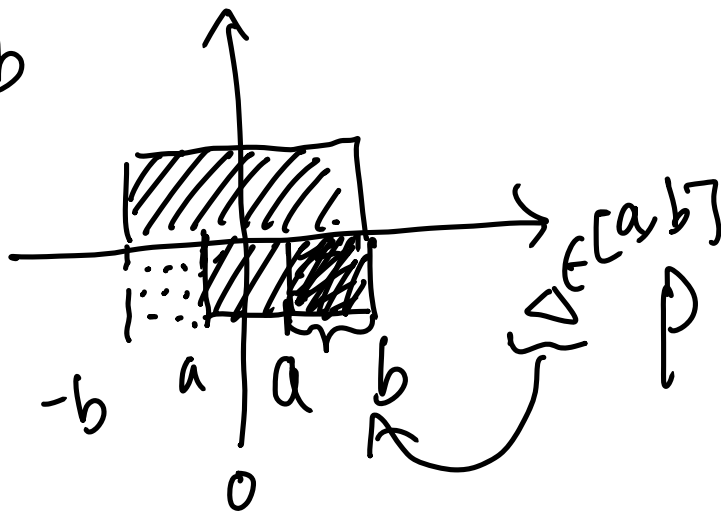
$$b = a$$

$$b \neq a$$

$$\alpha(\vec{0} \rightarrow \vec{n})$$

$$= \alpha(\vec{n} \rightarrow \vec{0})$$

$$a = 0.3b$$



$$p = \frac{b-a}{b+a}$$

$$a = 0.3b$$

$$\alpha(\vec{0} \rightarrow \vec{0} \mp \Delta \in [a, b])$$

$$\begin{aligned}
 & \mathcal{Q}(\vec{n} \rightarrow \vec{v}) \\
 & \quad \swarrow \\
 & \mathcal{Q}(\vec{0} + \Delta \in [a, b] \rightarrow \vec{v}) \\
 & \quad \swarrow \\
 & \mathcal{Q}(\vec{v} \rightarrow \underbrace{\vec{0} - \Delta \in [a, b]}_{+ \Delta' \in [-b, -a]}) \\
 & = 0
 \end{aligned}$$

[a]

$$\vec{0} \rightarrow \vec{0} + \vec{\Delta}$$

$$\mathcal{U}(\vec{0})$$

$$\begin{aligned}
 \mathcal{U}(\vec{0} + \vec{\Delta}) & \sim \mathcal{U}(\vec{0}) \\
 & = \mathcal{U}'(\vec{0}) \cdot \vec{\Delta}
 \end{aligned}$$

$$\vec{\Delta} \nearrow \quad \Delta \mathcal{U} \nearrow \quad \text{all} \searrow$$

$\vec{\Delta} \downarrow$

Slower exploration

$|\vec{\Delta}^2|$
