

Intro to computer simulations

Goal : compute averages N, V, T

$$\langle A \rangle = \int d\vec{x} P(\vec{x}) A(\vec{x})$$

mostly

$$\beta = (k_B T)^{-1}$$

$$P(\vec{x}) = e^{-\beta H(\vec{x})}$$

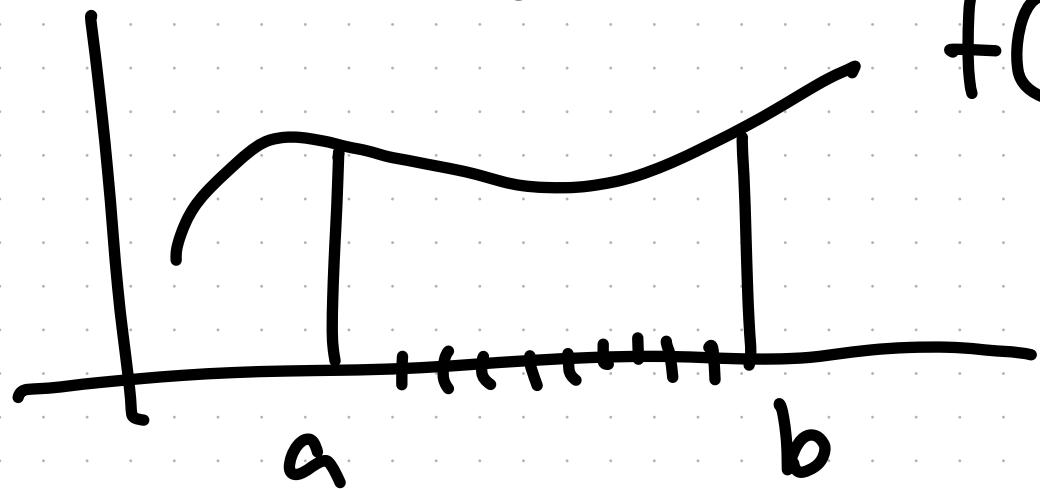
If we knew $P(\vec{x})$, in 1d

$$\langle A \rangle = \sum_{i=1}^N A(x_i) P(x_i) \Delta x_i$$

$$\Delta x_i = x_{i+1} - x_i$$



Solving by "quadrature"



$f(x)$

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

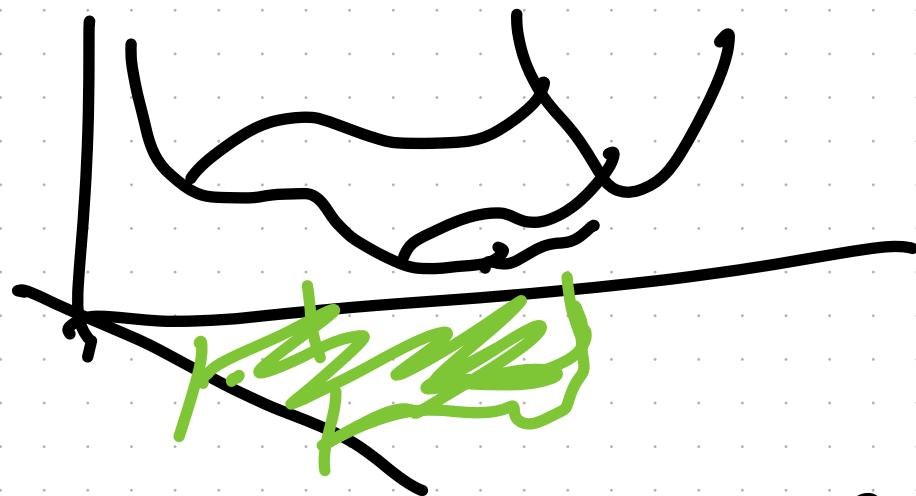
N points

$$\Delta x = \frac{b-a}{N}$$

$$x_i = a + i \left(\frac{b-a}{N} \right)$$

$i \in 0 \text{ to } N$

In not 1d but "d" dimensions
length L in each dimension $(b-a)$



$$\int dx \int dy P(x, y) A(x, y)$$

$$\approx \Delta x \Delta y \sum_{i,j} P(x_i, y_j) A(x_i, y_j)$$

$$x_i, y_j = \left\{ x_{min} + i \frac{x_{max} - x_{min}}{N_x} \right\}$$

$$y_{min}, y_{max} \left\{ \frac{y_{max} - y_{min}}{N_y} \right\}$$

$$N_{bins} = \frac{L}{\Delta x}$$

$$N_{bins}^d = \left(\frac{L}{\Delta x} \right)^d = e^{d(\ln(\frac{L}{\Delta x}))}$$

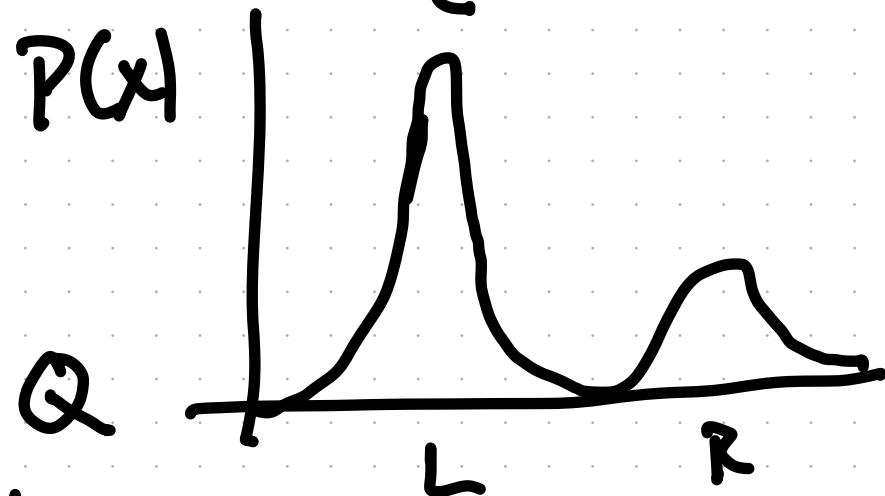
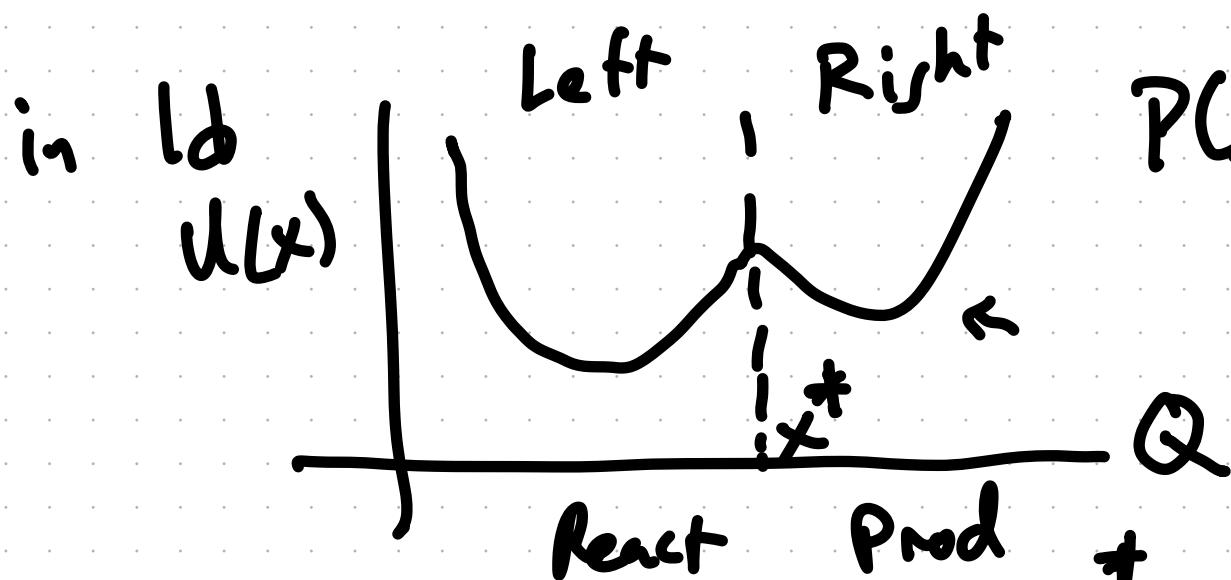
In a stat mech problem

$$\langle A \rangle = \int d\vec{x} P(\vec{x}) A(\vec{x}) \quad \vec{x} \text{ is } n \text{ dim}$$

$d \approx 6000 - 6N_A$

$$\vec{x} = \{\vec{r}_1, \vec{r}_2, \dots, \vec{r}_N, \vec{p}_1, \vec{p}_2, \dots, \vec{p}_N\}$$

$6N$ degrees of freedom



"A"

$$A(x) = \begin{cases} 1 & x < x^* \\ 0 & x > x^* \end{cases}$$

"Indicates function"

Simulations:

can't do integration by quadrature

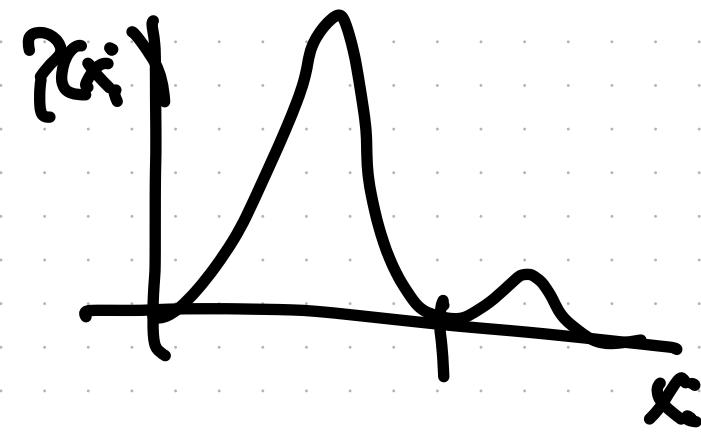
instead: integration by sampling

$\langle A \rangle$

a bunch of samples of
 \vec{x}_i , if \vec{x}_i appears

with prob $P(\vec{x}_i)$ then

$$\langle A \rangle \approx \frac{1}{N} \sum_{i=1}^N A(\vec{x}_i)$$



Generate "Markov Chain"

Markov chain:

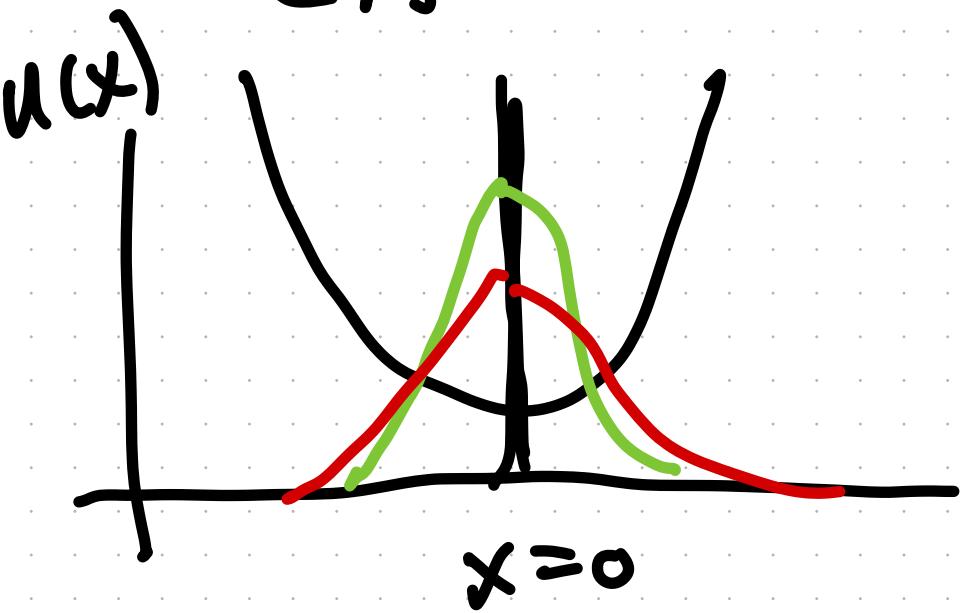
rule takes $x_i \rightarrow x_{i+1}$

only depends on x_i ← Markovian

To sample from $P(x)$, also ensure
"detailed balance"

$$P(x_i) P(x_i \rightarrow x_{i+1}) = P(x_{i+1}) P(x_{i+1} \rightarrow x_i)$$

If enforce detailed balance then
distribution of \vec{x} converges to $P(\vec{x})$



Initial $P_0(x) = \delta(x)$

simulate

at long time $P(x) = \frac{e^{-\beta u(x)}}{Z}$

Detailed Balance

$$\text{Want: } P(x_i)P(x_i \rightarrow x_{i+1}) = P(x_{i+1})P(x_{i+1} \geq x_i)$$

$$P(x_i \rightarrow x_{i+1}) = P_{gen}(x_i \rightarrow x_{i+1}) P_{acc}(x_i \rightarrow x_{i+1})$$

$$P(x_i) P_{gen}(x_i \rightarrow x_{i+1}) P_{acc}(x_i \rightarrow x_{i+1})$$

$$= P(x_{i+1}) P_{gen}(x_{i+1} \rightarrow x_i) P_{acc}(x_{i+1} \rightarrow x_i)$$

$$P_{acc}(x_i \rightarrow x_{i+1}) = \frac{P(x_{i+1}) P_{gen}(x_i \rightarrow x_{i+1}) P_{acc}(x_i \rightarrow x_{i+1})}{P(x_i) P_{gen}(x_i \rightarrow x_{i+1})} \cdot r(x_i \rightarrow x_{i+1})$$

Metropolis:

$$P_{acc}(\vec{x}_i \rightarrow \vec{x}_{i+1}) = \min(1, \Gamma(\vec{x}_i \rightarrow \vec{x}_{i+1}))$$

$$P_{acc}(x_i \rightarrow x_{i+1}) = \frac{P(x_{i+1}) P_{gen}(x_i \rightarrow x_{i+1}) P_{acc}(x_{i+1} \rightarrow x_i)}{P(x_i) P_{gen}(x_i \rightarrow x_{i+1})} \Gamma(x_i \rightarrow x_{i+1})$$

$$\frac{P_{fwd}}{P_{backward}} = \begin{cases} \Gamma & \\ 1/\Gamma & \end{cases} = \Gamma e^{-\beta \Delta H}$$

$$P(x) = e^{-\beta \mathcal{H}(x)} / Z \rightarrow \frac{P(x_{i+1})}{P(x_i)} = e^{\frac{-\beta \mathcal{H}(x_{i+1})}{-\beta \mathcal{H}(x_i)}}$$

for molecular system

$$x_{i+1} = x_i + s \cdot r$$

another example
swap 2
positions

Algorithm!

O! initial configuration = x_0

1) propose x_{i+1} from $x_i \sim p_{\text{gen}}(x_i - x_{i+1})$

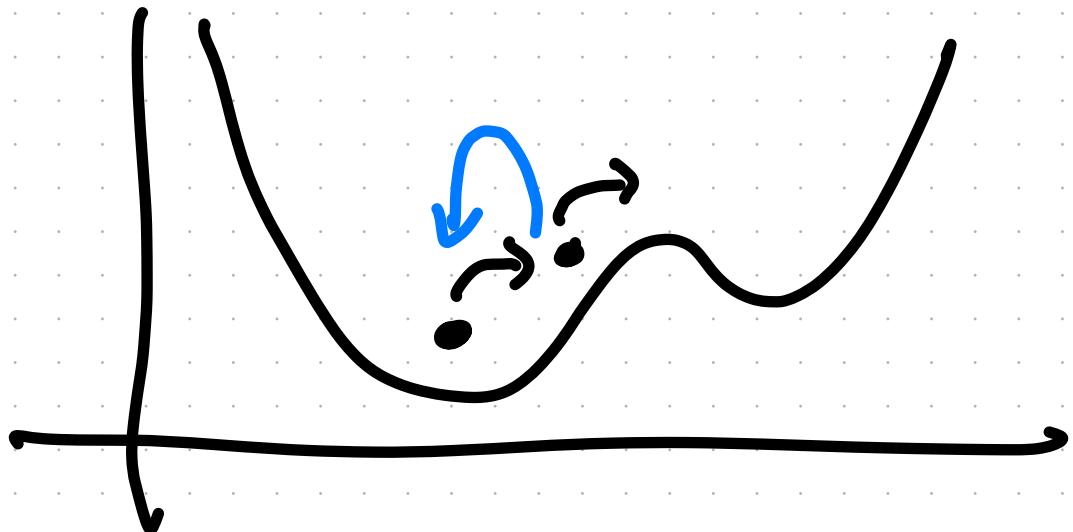
2) random number $\tilde{r} \in (0, 1)$

2) Random walk:
If $r < r(x_i \rightarrow x_{i+1})$: keep x_{i+1}
else: $x_{i+1} = x_i$

1 → 2 → 2 → 2 → 2 → 2 → 3 → 2 → 2 → 1

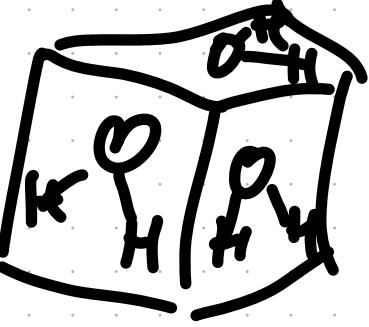
for Boltzmann:

$$\Gamma(x_i \rightarrow x_{i+1}) = \min \left\{ 1, e^{-\beta(H(x_{i+1}) - H(x_i))} \right\}$$



Summarize!

Monte Carlo is a powerful & general
downsides:
method

- ① 1 thing happens at a time

reject a lot of moves
- ② gives static properties
most of the time

