

# Markov Chains

## Lecture 9



**PHYS 246 class 9**

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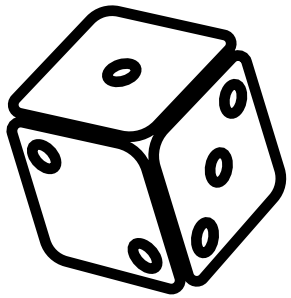
<https://jnoronhahostler.github.io/IntroductionToComputationalPhysics/intro.html>

# Announcements

- TBD

# Memory-less process

Throw (weighted) dice: odd or even number?



$$P_{\text{odd}} = 0.6$$

Odd

$$P_{\text{even}} = 0.4$$

Odd

Even

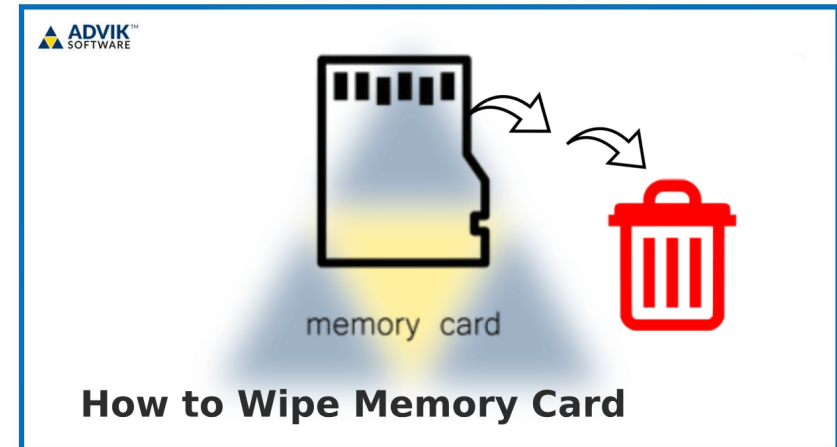
Odd

Even

Odd

Even

Sample from 0 – 1



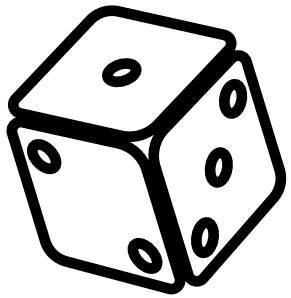
$$P_{\text{odd}} = 0.6$$

$$P_{\text{even}} = 0.4$$

What are examples of processes that depend on time, where each step does not have memory of the previous step?

# Start sampling

Throw (weighted) dice: odd or even number?



$$P_{\text{odd}} = 0.6$$

Odd

$$P_{\text{even}} = 0.4$$

Odd

Even

Odd

Even

Odd

Even

Start at state  $x_t$  (odd)

For  $x_{t+1}$ , sample from  $r = \text{sample}[0 - 1]$

If  $r \leq 0.6$ , odd. Else even

Ex.  $r = 0.27$ . Odd

$x_{t+2}$ ,  $r = \text{sample}[0 - 1]$  (repeat process)

...

$t = t_{\text{end}}$

# Performed a Markov Chain

**Now what?**

- What is the probability of rolling 3 even numbers in a row?
- What is the probability of rolling odd, even, odd, even, odd?
- What is your averaged (over many, many samples) probability of getting an odd number?
- Random walks are examples of Markov chains: continuous (position) vs discrete variables (binary choices)

# Equilibration time

## Approaching a steady state

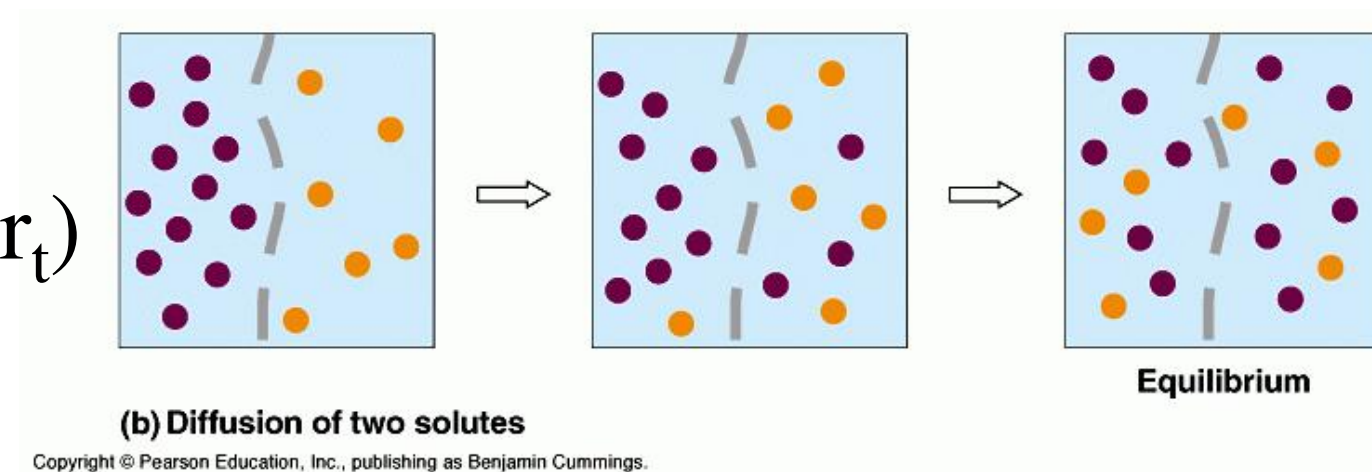
Averages:

$$\langle O(x) \rangle = \int O(x) \rho(x) dx$$

$$\langle \text{odd}(t_{\text{step}}) \rangle = \frac{1}{t_{\text{step}}} \sum_t^{t_{\text{step}}} \Theta(P_{\text{odd}} - r_t)$$

For  $t_{\text{step}} \rightarrow \infty$ ,  $\langle \text{odd}(\infty) \rangle = 0.6$

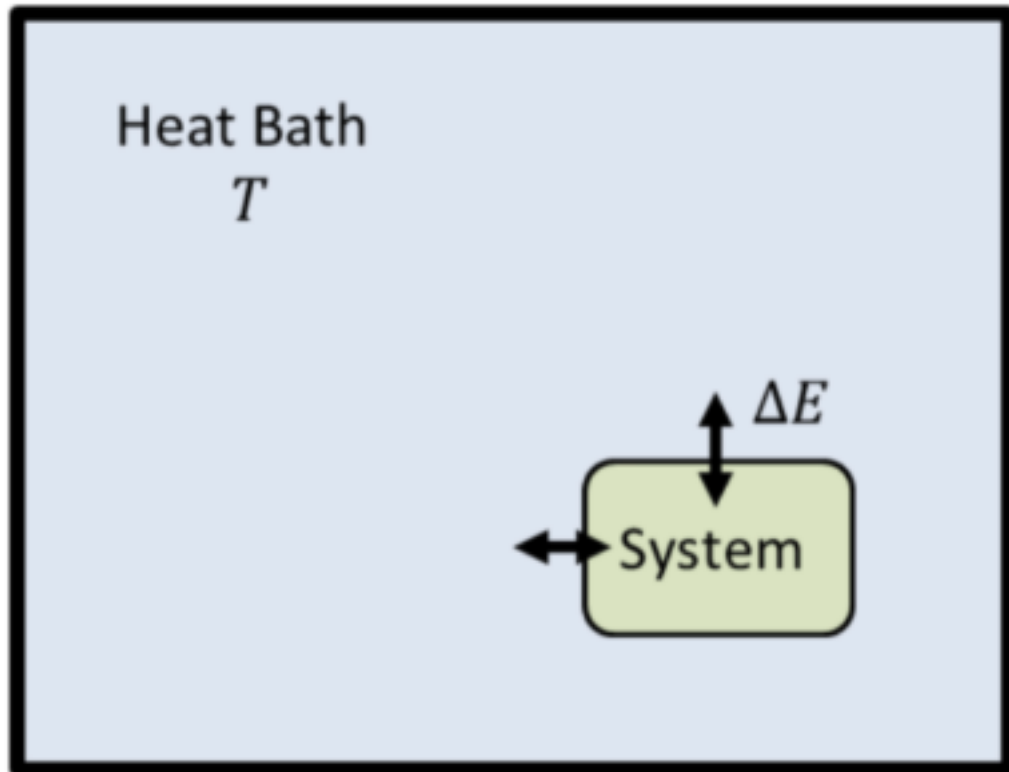
If  $P_{\text{odd}} = 0.6$  and  $P_{\text{even}} = 0.4$



Equilibration time  $t_{eq}$ , time when  $t_{\text{step}}$  reaches a steady state of  $\langle \text{odd}(t_{\text{step}}) \rangle \sim 0.6$

# Statistical Mechanics

## Thermal Equilibrium



Boltzmann:

$$P(x) = \frac{e^{-\frac{E(x)}{kT}}}{\int e^{-\frac{E(x)}{kT}} dx} \equiv \frac{e^{-\frac{E(x)}{kT}}}{Z}$$

Where  $x$  is the states of the system

# Monte Carlo integration

## Expectation values

Boltzmann:

$$P(x) = \frac{e^{-\frac{E(x)}{kT}}}{\int e^{-\frac{E(x)}{kT}} dx} \equiv \frac{e^{-\frac{E(x)}{kT}}}{Z}$$

Averages:

x might be very  
high dimensional!

$$\langle O(x) \rangle = \int O(x) P(x) dx$$

Expectation

value

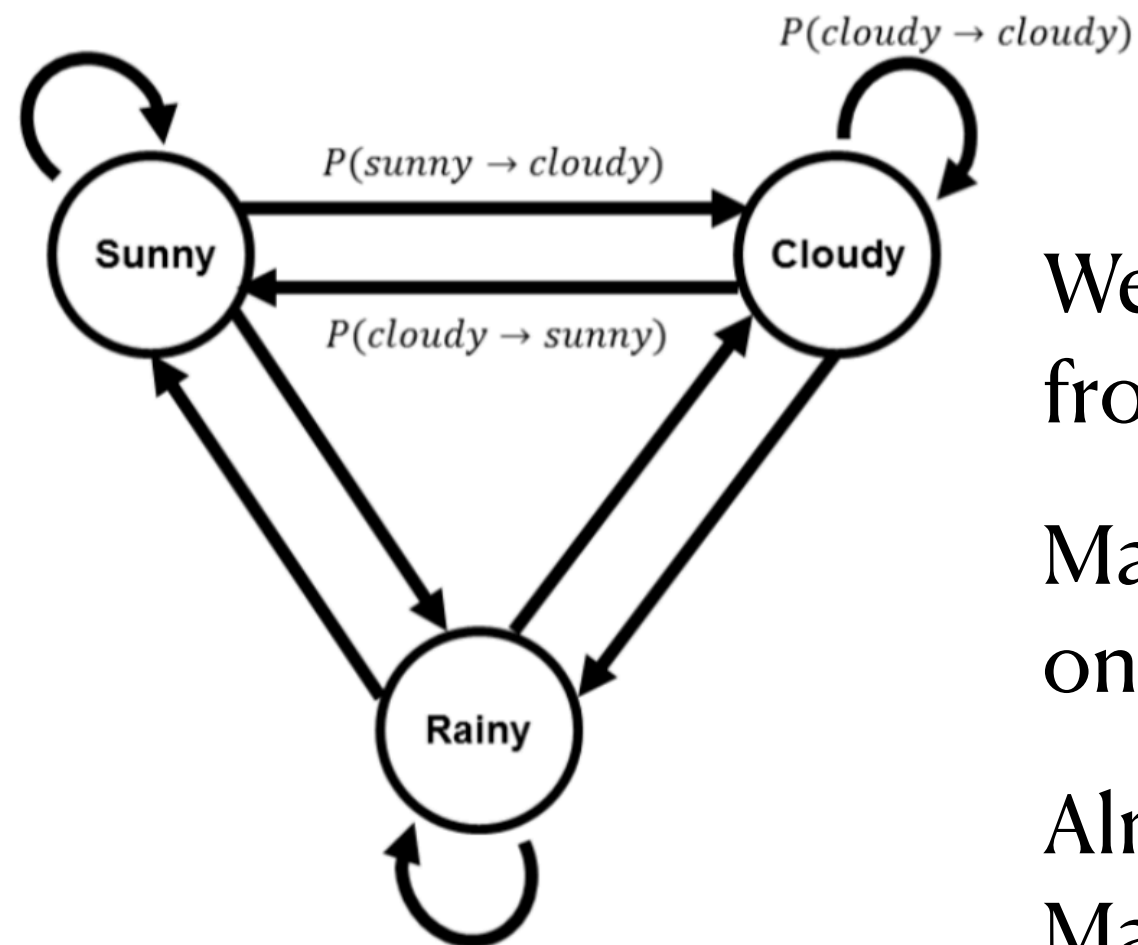
$$\langle O(x) \rangle = \int O(x) P(x) dx = \langle O(x) \rangle_{x \sim P}$$

Sample average where x is  
drawn from  $P(x)$



# Markov Chains

## Solving the weather



We will use Markov chains to generate  $x$  from the Boltzmann distribution.

Markov chains are random processes that only depend on the current state.

Almost everything can be written as a Markov chain..

# Metropolis algorithm: simple case

If you are in state A:

With probability 0.5, move to state B

With probability 0.5, stay in state A

If you are in state B:

With probability 1, move to state A

Question: what is the probability distribution we will sample?

# Metropolis: general case

Looping over  $i$

1. Start at point  $x_i$
2. Choose point  $t$  at random (note some caveats)
3.  $x_{i+1}$  is set to  $t$  with probability  $\min\left(1, \frac{P(t)}{P(x_i)}\right)$ , otherwise  $x_{i+1} = x_i$

# Notes and tricks

We work with unitless numbers  $h = \frac{\mu B}{kT}$  and  $\frac{\epsilon}{kT}$ , which are the only things that change the physics. High temperature is small  $h$  and low temperature is large  $h$ .

Make sure that if you reject a move, you average the old position again.