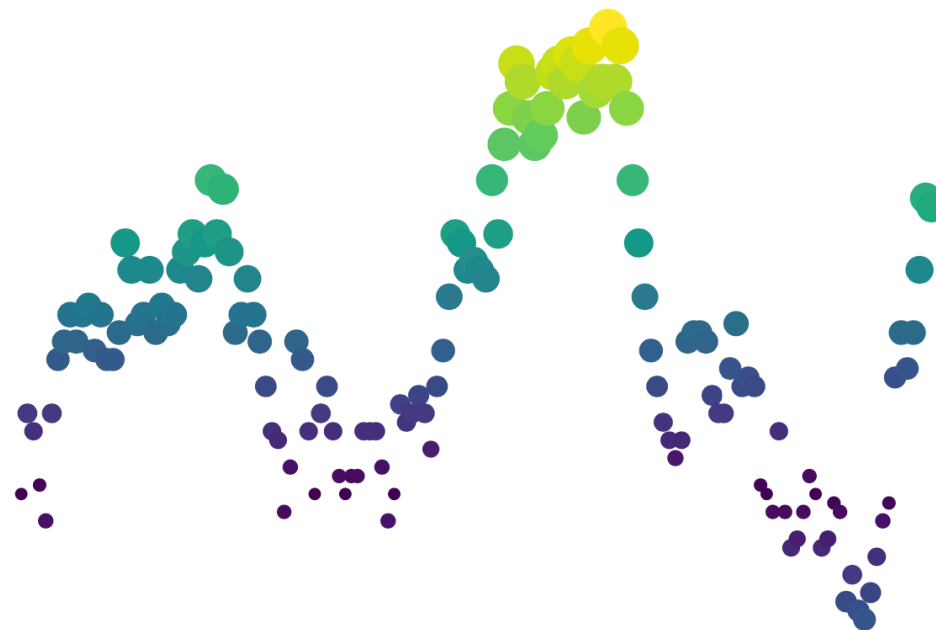
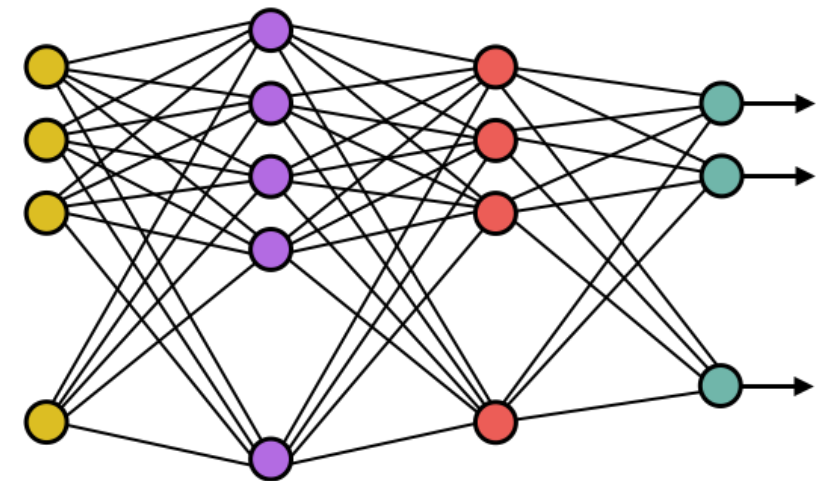
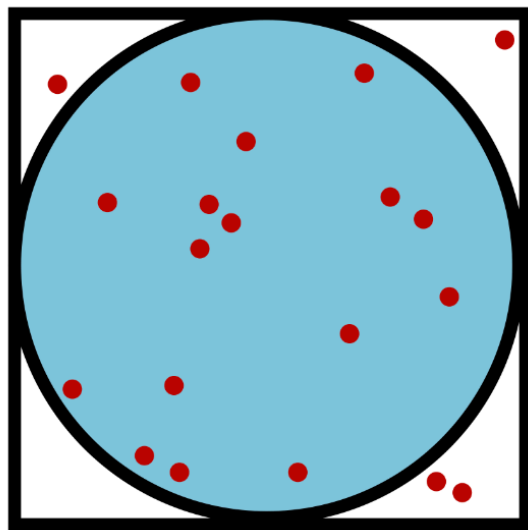


Numerical Methods

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PSI Start Online School



Outline

- ▶ Statistical physics and the Ising model
- ▶ Monte Carlo methods in statistical physics

LAST LECTURE

TODAY

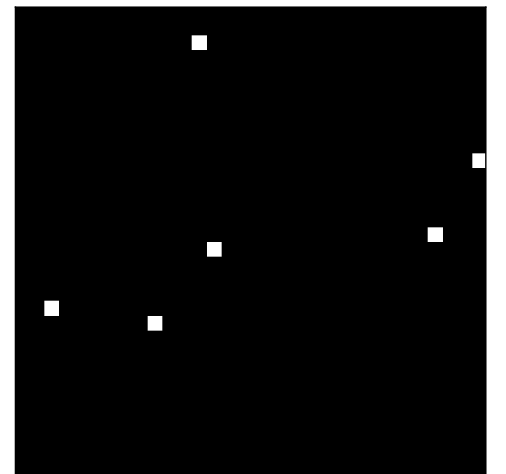
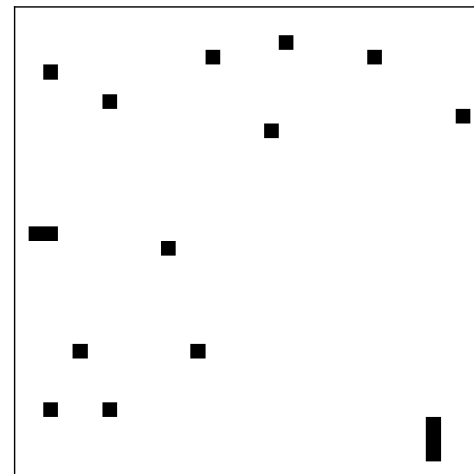
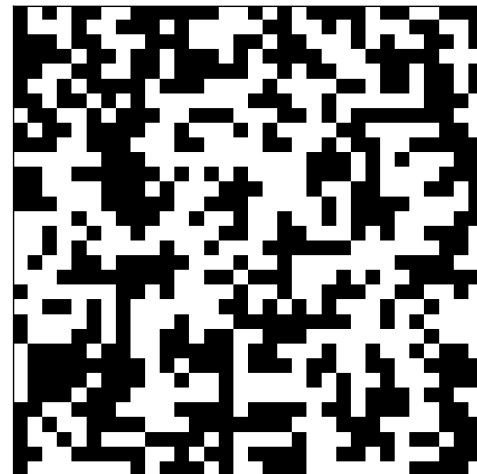


Last lecture: 2D Ising model

$$E = -J \sum_{\langle ij \rangle} s_i s_j$$

$$s_i = +1 \text{ or } -1$$

(■ or □)



Expectation values of observables

In the canonical ensemble, our system is in thermal equilibrium with a heat bath at fixed temperature T .

The expectation value of a quantity Q is:

$$\langle Q \rangle = \sum_{\mu} Q_{\mu} p_{\mu}$$

where:

▶ μ represents a microstate of the system

▶ $p_{\mu} = \frac{1}{Z} e^{-\beta E_{\mu}}$

▶ E_{μ} is the energy of state μ

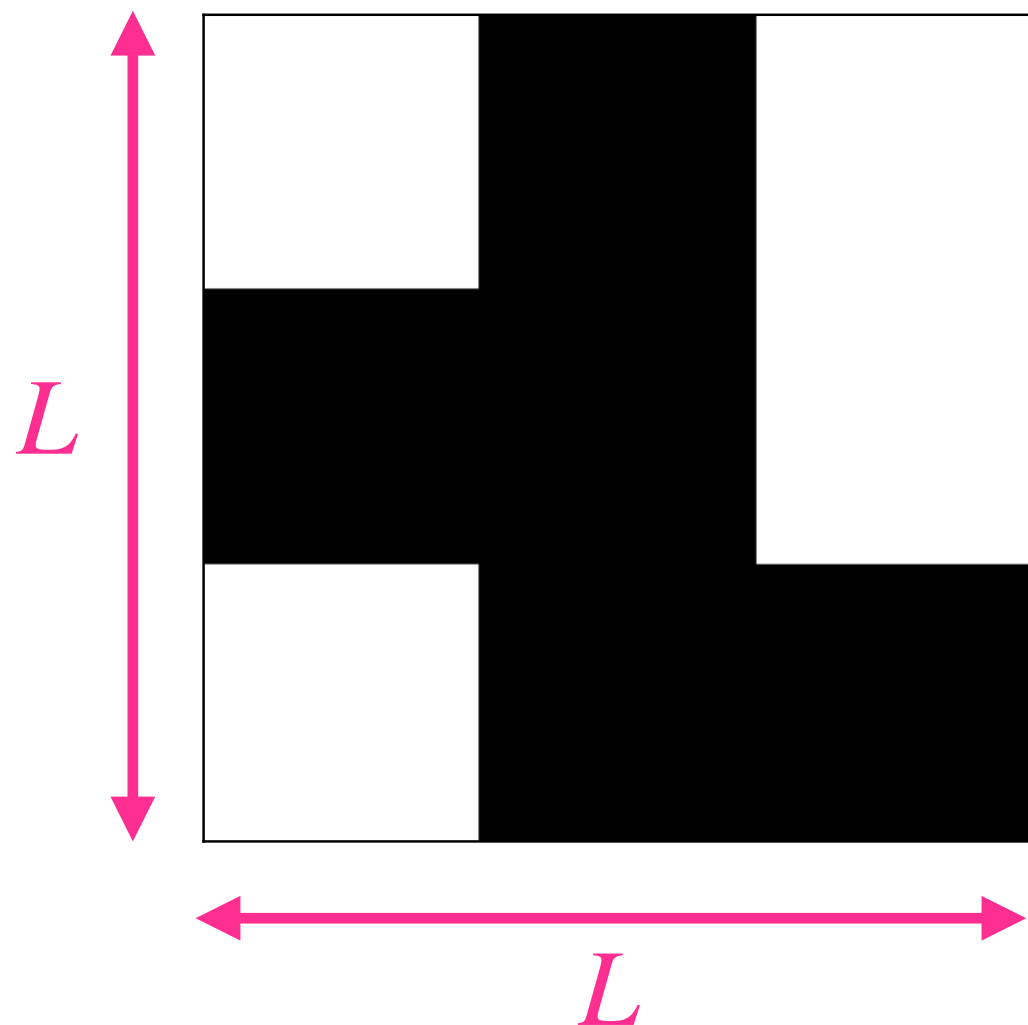
▶ $Z = \sum_{\mu} e^{-\beta E_{\mu}}$

▶ $\beta = \frac{1}{k_B T}$

Statistical physics

We would like to study the behaviour of expectation values in the limit where the number of particles N is large.

Consider the Ising model on a square lattice:



$$N = L^2$$

The total number of accessible microstates is:

$$2^N = 2^{(L^2)}$$

2D Ising model

For $N=25$, the fastest algorithms for computing the sums \sum_{μ} over all microstates require around a minute. The time to compute this sum directly scales as $2^N = 2^{(L^d)}$

N	time
25	~1 minute
30	~ 30 minutes
35	~ 20 hours
40	~20 days
50	~60 years
80	~ 7×10^{10} years

*longer than the age
of the universe!*



Monte Carlo methods in statistical physics

If we try to evaluate the sums \sum_{μ} directly, we are limited to $N=50$ to 60 , which corresponds to $L=7$ or 8 for the 2D Ising model. We need other methods to study bigger systems!

Monte Carlo methods address this exponential complexity by considering only M microstates $\mu_1, \mu_2, \dots, \mu_M$ selected at random.

Reference:

Newman & Barkema, “Monte Carlo methods in Statistical Physics”

Calculating the expectation value $\langle Q \rangle = \sum_{\mu} Q_{\mu} p_{\mu}$ using Monte Carlo sampling:

In particular, if each state μ_i ($1 \leq i \leq M$) is selected from the set of all states according to the desired prob. dist. p_{μ_i} , then:

$$\langle Q \rangle \simeq Q_M = \frac{1}{M} \sum_{i=1}^M Q_{\mu_i}$$

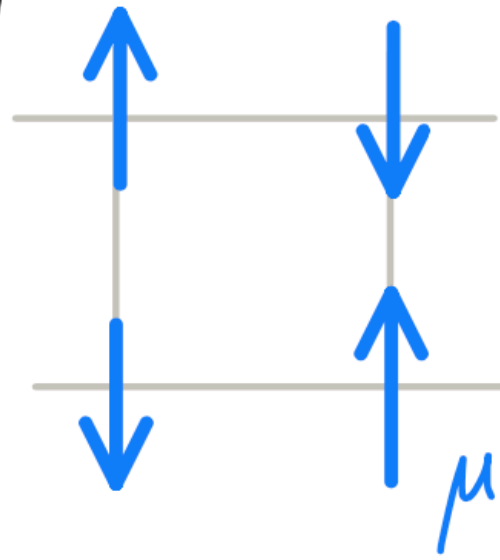
This estimate makes use of "importance sampling" (the more probable states are more likely to be selected.)

To implement this sampling, we can use Markov chain Monte Carlo (MCMC).

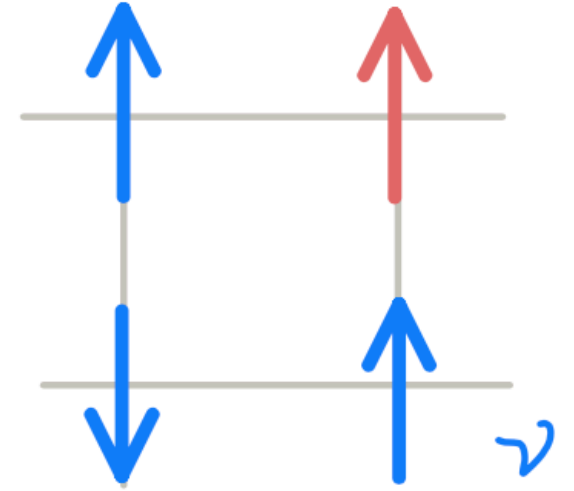
↳ use the current state μ to propose a move to a new related state ν , and then decide whether to accept or reject the move

eg) single spin flip moves:

Ising
model



propose
~~~~~→



Given  $\mu$ , propose  $\nu$  where:

- In principle, any proposal is allowed

↳ single-spin flip

↳ non-local "cluster" spin flips

⋮

- Once a proposal is generated, we choose to accept or reject it

The probability of moving from  $\mu$  to  $\nu$  is the "transition prob."  $T(\mu \rightarrow \nu)$ , where  $\sum_{\nu} T(\mu \rightarrow \nu) = 1$

We can choose any set of transition probs.  $\{T(\mu \rightarrow \nu)\}$  as long as we satisfy two conditions:

1 **Ergodicity**: there is a non-zero probability of transitioning (eventually) from  $\mu$  to and  $\nu$   
 $\mu \rightarrow \dots \rightarrow \nu$

2 **Detailed balance (DB)**

## 2 Detailed balance (DB):

The rate of transition into and out of any state  $\mu$  must be equal

$$\underbrace{\sum_v p_v T(v \rightarrow \mu)}_{\text{rate of transition into } \mu} = \underbrace{\sum_v p_\mu T(\mu \rightarrow v)}_{\text{rate of transition out of } \mu}$$

One way to satisfy this condition is:

$$p_v T(v \rightarrow \mu) = p_\mu T(\mu \rightarrow v)$$

DB

$$p_\nu T(\nu \rightarrow \mu) = p_\mu T(\mu \rightarrow \nu)$$

DB

When  $p_\mu = \frac{1}{Z} e^{-\beta E_\mu}$ , we have:

$$\frac{T(\mu \rightarrow \nu)}{T(\nu \rightarrow \mu)} = e^{-\beta(E_\nu - E_\mu)}$$

Recall that in MCMC, transitioning from  $\mu$  to  $\nu$  involves first proposing and then accepting the move. Let us introduce the notation:

$$T(\mu \rightarrow \nu) \equiv \underbrace{g(\mu \rightarrow \nu)}_{\text{selection prob.}} \underbrace{A(\mu \rightarrow \nu)}_{\text{acceptance prob.}}$$

For a given set of selection probabilities, we would like to make the acceptance probabilities  $A(\mu \rightarrow \nu)$  as close to 1 as possible so that we are more likely to sample different states.

From DB:

$$\frac{A(\mu \rightarrow \nu)}{A(\nu \rightarrow \mu)} = \frac{g(\nu \rightarrow \mu)}{g(\mu \rightarrow \nu)} e^{-\beta(E_\nu - E_\mu)}$$

Metropolis algorithm:  $A(\mu \rightarrow \nu) = \min \left( 1, \frac{g(\nu \rightarrow \mu)}{g(\mu \rightarrow \nu)} e^{-\beta(E_\nu - E_\mu)} \right)$

↳ ensures that  $A(\mu \rightarrow \nu)$  or  $A(\nu \rightarrow \mu)$  is equal to 1.

## Pseudocode for Monte Carlo sampling with single-spin-flip Metropolis moves:

(generates  $M$  samples  $\mu_1, \mu_2, \dots, \mu_M$  from the distribution  $p_\mu = \frac{1}{Z} e^{-\beta E_\mu}$  )

Choose sample  $\mu_1$  at random

for step = 2, ... , M:

    choose a lattice site  $i$  at random

    define state  $\nu$  to be the same as  $\mu_{\text{step}-1}$  but with the spin at site  $i$  flipped

    calculate  $\Delta E$  for the proposed move  $\mu_{\text{step}-1} \rightarrow \nu$

    generate  $r$  from a uniform random distribution  $U[0,1)$

    if  $r < e^{-\beta \Delta E}$  :

$\mu_{\text{step}} = \nu$  (accept the move)

    else:

$\mu_{\text{step}} = \mu_{\text{step}-1}$  (reject the move)

## Notes:

- In practice, we ignore the first several samples since they are not truly sampled from  $p_\mu$ .
- When calculating  $Q_M$ , we should use states  $\mu_i$  that are statistically independent. The Markov time required to get indep. samples depends on both the algorithm and the temperature.



# Monte Carlo for the 2D Ising model

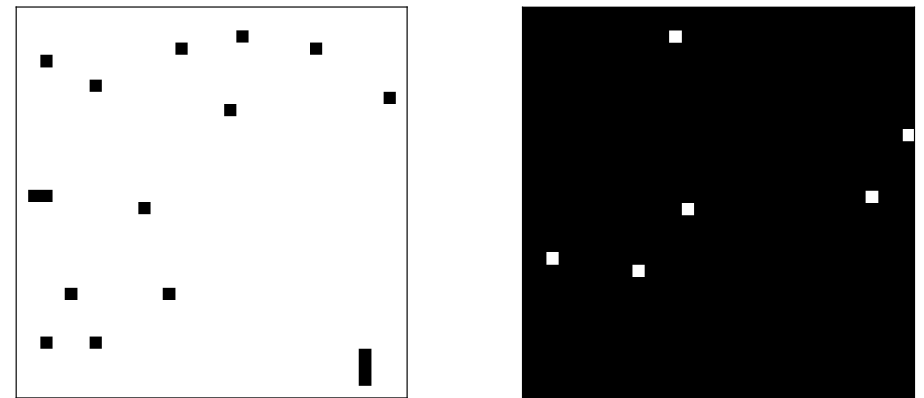
$$E = -J \sum_{\langle ij \rangle} s_i s_j$$

**At high temperatures:**



Paramagnetic phase

**At low temperatures:**



Ferromagnetic phase

# Monte Carlo to study high-temperature superconductivity

$$H = \frac{\rho_s}{2} \sum_{\langle ij \rangle} \left[ \sum_{\alpha=1}^2 (n_{i\alpha} - n_{j\alpha})^2 + \lambda \sum_{\alpha=3}^6 (n_{i\alpha} - n_{j\alpha})^2 \right] \\ + \frac{\rho_s a^2}{2} \sum_i \left[ g \sum_{\alpha=3}^6 n_{i\alpha}^2 + g' \left( \sum_{\alpha=3}^6 n_{i\alpha}^2 \right)^2 + w \left[ \left( n_{i3}^2 + n_{i4}^2 \right)^2 + \left( n_{i5}^2 + n_{i6}^2 \right)^2 \right] \right]$$

