Cluster algorithms for the Ising model

Monte Carlo methods which overcome the problem of critical slowing down close to second order phase transitions

Ising model - Why?

▶ Phase transitions

Ising model - Why?

➤ Phase transitions

1. Phase transitions are important

Ising model - Why?

- Phase transitions
- One of the simplest statistical models that show a phase transition

Phase transitions
 One of the simplest statistical models that show

Ising model - Why?

└─Ising model - Why?

1. The Ising model is one of the simplest statistical models that shows a phase transition.

Ising model - Why?

- Phase transitions
- One of the simplest statistical models that show a phase transition
- Magnetic systems, opinion models, binary mixtures

Cluster algorithms for the Ising model

—Ising model - Why?

 Ising model can be used to simulate magnetic systems (ferromagnetic and antiferromagnetic), opinion models and binary mixtures.

Ising model - Why?

- Phase transitions
- One of the simplest statistical models that show a phase transition
- Magnetic systems, opinion models, binary mixtures



Figure : Ernst Ising (1900 - 1998)

 Phase transitions
 One of the simplest statistical models that show a phase transition
 Magnetic systems, opinion

Ising model - Why?



└─Ising model - Why?

Figure: Ernst Ising, lived from 1900 to 1998

- 1. Ising model invented by Wilhelm Lenz (1888 1957) (the same as the Lenz in the Laplace-Runge-Lenz vector) in 1920, his student Ernst Ising solved it in the one-dimensional case 1924.
- 2. Wolfgang Pauli (1900 1958), at whom the road outside is named after, was an assistant of Lenz.
- 3. Also Otto Stern (1888 1969) from the Stern-Gerlach experiment was an assistant of Lenz.

Cluster algorithms for the Ising model

1. Lattice with N sites.

$$\mathscr{H}(\sigma) = -J \sum_{\langle i,j \rangle} \sigma_i \sigma_j - H \sum_i \sigma_i$$

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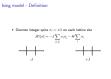
$$\mathscr{H}(\sigma) = -J \sum_{\langle i,j \rangle} \sigma_i \sigma_j - H \sum_i \sigma_i$$





Cluster algorithms for the Ising model

└─Ising model - Definition



- 1. Sum over nearest neighbours.
- 2. J: interaction, H: external field
- 3. J_{ij} in general case, J > 0: ferromagnetic, J < 0: antiferromagnetic

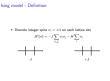
$$\mathscr{H}(\sigma) = -J \sum_{\langle i,j \rangle} \sigma_i \sigma_j - H \sum_i \sigma_i$$





Cluster algorithms for the Ising model

└─Ising model - Definition



1. For positive J: More favorable for the spins to be aligned!

Ising model - Canonical ensemble

Ising model - Canonical ensemble

$$p(\sigma, T) = \frac{e^{-\beta \mathscr{H}(\sigma)}}{\mathscr{Z}(T)}, \quad \beta = \frac{1}{k_B T}$$

└─Ising model - Canonical ensemble

1. Configuration probability given by boltzmann distribution, Z partition function, given as

$$\mathscr{Z}(T) = \sum_{\sigma} e^{-\beta \mathscr{H}(\sigma)}, \quad \beta = \frac{1}{k_B T}$$

2. So we are looking at a canonical system with constant temperature T.

Ising model - Canonical ensemble

$$p(\sigma, T) = \frac{e^{-\beta \mathcal{H}(\sigma)}}{\mathcal{Z}(T)}, \quad \beta = \frac{1}{k_B T}$$
$$\langle M \rangle_T = \sum_{\sigma} M(\sigma) p(\sigma, T)$$

└─Ising model - Canonical ensemble

 Measurement value of a function, e.g. magnetization, is given by the sum over all states of the measurement value at the configuration times the configuration probability.

Ising model - Monte Carlo I

Ising model - Monte Carlo I

• We can't compute all configurations (2^N)

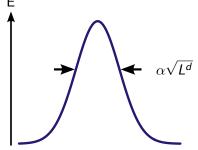
 \blacktriangleright We can't compute all configurations (2N)

└─Ising model - Monte Carlo I

- 1. Why not? \rightarrow 2^N = 2^{L^d} e.g. L = systemSize = 15 in 2 dimensions: $2^{15^2} = 2^{225} = 5 \cdot 10^{67}$
- 2. We can't compute the exact expectation value of an observable. But that's what we're interested in.

Ising model - Monte Carlo I

- ▶ We can't compute all configurations (2^N)
- ► We can't sample uniformely distributed over energy



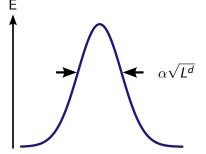
└─Ising model - Monte Carlo I



1. Because the distribution of the average energy gets sharper with increasing size $\left(\alpha \sqrt{L^d}\right)$.

Ising model - Monte Carlo I

- We can't compute all configurations (2^N)
- We can't sample uniformely distributed over energy



► Solution: Importance sampling using Metropolis algorithm.

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Single spin flip metropolis - Algorithm

-Single spin flip metropolis - Algorithm

If energy decreases, always accept. If energy increases, accept with probability $e^{-\beta \Delta E}$. Blazingly fast (Troells: 2 flips/ns?), easy to implement.

1. New state given by spinflip at this site.

Single spin flip metropolis - Algorithm

$$A(X \to Y) = \min\left(1, \frac{p(Y)}{p(X)}\right)$$

= $\min\left(1, e^{-\beta[E(Y) - E(X)]}\right)$

- 1. Choose one site (uniformly randomly)
- 2. Calculate energy difference
- 3. Accept new configuration with transition probability above

Single spin flip metropolis - Algorithm

```
Single spin flip metropolis - Algorithm A(X \to Y) = \min \left( 1 \frac{g(Y)}{f(X)} \right) \\ = \min \left( 1 e^{-f(X/Y) - f(X/Y)} \right)
1. Chase one site (uniformly andmhy): 2. Calculate seep difference
3. Accept new configuration with transition probability above
```

If energy decreases, always accept. If energy increases, accept with probability $e^{-\beta\Delta E}$.Blazingly fast (Troells: 2 flips/ns?), easy to implement.

1. New state given by spinflip at this site.

Cluster algorithms for the Ising model

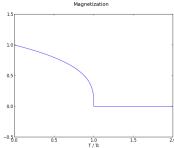
1. I implemented this single spin flip metropolis algorithm and would like to show you some results.

Magnetization
$$M(T) = \left\langle \frac{1}{N} \sum_{i=1}^{N} \sigma_i \right\rangle$$

1. Let's look at the spontaneous magnetization.

Single spin flip metropolis - Results

$$\begin{array}{c} \mathsf{Magnetization} \ \mathit{M}(\mathit{T}) = \left\langle \frac{1}{\mathit{N}} \sum\limits_{i=1}^{\mathit{N}} \sigma_i \right\rangle \\ \mathsf{Expected} \end{array}$$



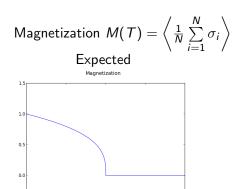
Cluster algorithms for the Ising model

Single spin flip metropolis - Results $\frac{\text{Magnetization } M(T) = \left\langle \frac{1}{N} \sum_{i=1}^{N} \sigma_i \right\rangle }{\text{Expected}}$

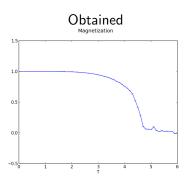
Single spin flip metropolis - Results

1. In theory, we expect a spontaneous magnetization below T_C . We expect a symmetry breaking (either positive or negative Magnetization in this case) and a discontinuity in the derivative of the magnetization at T_C . We want something linear to $(T - T_C)^{\nu}$.

Single spin flip metropolis - Results



1.0 T / Tc



-0.5L

Single spin flip metropolis - Results

Well, this is what we get. It looks perfect - right? We see a
spontaneous magnetization in the simulation. The discontinuity in
its derivative is not there, but this is okay, since we are looking at a
finite sized system. Well, life is not so easy. This result is in fact not
the truth. Let me show you what we expect for the spontaneous
magnetization.

Ising model - 2 spins

└─Ising model - 2 spins

Show that we should expect the magnetization to vanish.

2013-06-17

—Single spin flip metropolis - To flip or not to flip

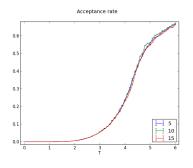
1. Now that we know that the magnetization should vanish, let's explore why it hasn't done so.

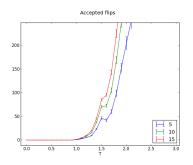
$$\mathscr{H}(\sigma) = -J \sum_{i,j} \sigma_i \sigma_j$$

2013-06-17

- 1. The hamiltonian of the system states clearly that the spins like to be aligned. They were all +1 at the beginning, and then thermalized (brought to thermodynamic equilibrium) in 3 sweeps (abbrevation for: 3 times number of sites spinflips).
- 2. The point is that the spins can also be aligned when they are all -1. But we didn't see that happen. Why?
- 3. I took 0.5 million measurement values, after every single spin flip. This means that the spin on every site could have flipped around 150 times. But it didn't. This is why:

$$\mathscr{H}(\sigma) = -J \sum_{i,j} \sigma_i \sigma_j$$





Single spin flip metropolis - To flip or not to flip

What we see here is the acceptance rate of a spin flip. It is one if
the suggested new configuration through the single spin flip was
accepted. Well, it's actually almost zero for low temperatures. So
we move ultra slow through phase space, which is no fun, because
we want to do an ergodic sampling.

2.

$$\frac{N}{a(T)} = \# \text{ trials}$$

3. We want to change flip the magnetization of the system completely at least 100 times to have good statistics. For uncorrelated measurements we then have an error of 10%.

Cluster algorithms for the Ising model

Definition and plots from measurements, magnetization and energy.

1. There is another approach to describe what's going on. Not accepting a spinflip or only flipping one spin at a time means that the new configuration is highly correlated to the old one.

$$\phi_{\mathcal{A}}(t) = rac{\langle \mathcal{A}(t_0)\mathcal{A}(t) \rangle - \langle \mathcal{A} \rangle^2}{\langle \mathcal{A}(t_0)^2 \rangle - \langle \mathcal{A} \rangle^2}$$

 $\phi_A(t) = \frac{\langle A(t_0)A(t)\rangle - \langle A\rangle^2}{\langle A(t_0)^2\rangle - \langle A\rangle^2}$

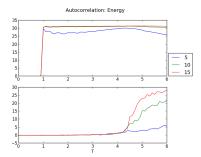
Autocorrelation time

 \sqsubseteq Autocorrelation time

Definition and plots from measurements, magnetization and energy.

1. We define the linear autocorrelation function of a measurement value as a ratio of the covariance of two observables at a given point in time and at time t_0 .

$$\phi_{A}(t) = \frac{\langle A(t_0)A(t)\rangle - \langle A\rangle^2}{\langle A(t_0)^2\rangle - \langle A\rangle^2}$$



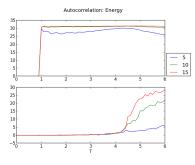
Cluster algorithms for the Ising model

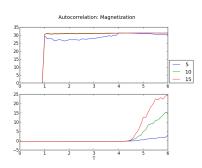
Autocorrelation time $\phi_A(t) = \frac{(A(b)A(t)) - (A^2}{(A(b)^2) - (A^2)}$

—Autocorrelation time

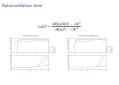
Definition and plots from measurements, magnetization and energy.

$$\phi_{\mathcal{A}}(t) = rac{\langle \mathcal{A}(t_0)\mathcal{A}(t) \rangle - \langle \mathcal{A} \rangle^2}{\langle \mathcal{A}(t_0)^2 \rangle - \langle \mathcal{A} \rangle^2}$$





Cluster algorithms for the Ising model



Definition and plots from measurements, magnetization and energy.

Binning analysis I

$$VarX := E[X^{2}] - E[X]^{2}$$

$$(\Delta X)^{2} = \frac{1}{N^{2}} \sum_{i,j=1}^{N} \left(E[X_{i}X_{j}] - E[X]^{2} \right)$$

$$= \frac{VarX}{N} + \frac{1}{N^{2}} \sum_{i \neq j} \left(E[X_{i}X_{j}] - E[X]^{2} \right)$$

$$= \frac{VarX}{N} + \frac{2}{N^{2}} \sum_{i=1}^{N} \sum_{t} \left(E[X_{i}X_{i+t}] - E[X]^{2} \right)$$

$$:= \frac{VarX}{N} (1 + 2\tau_{X})$$

—Binning analysis I

Binning analysis I $\begin{aligned} VaxX &= E\left[X^2\right] - E\left[X\right]^2 \\ \left(\Delta X\right)^2 - \frac{1}{R^2} \sum_{i,j=1}^{N} \left\{ \left[E\left[XX\right] - E\left[X\right]^2\right] \\ &- \frac{VaX}{R^2} + \frac{1}{R^2} \sum_{i,j=1}^{N} \left\{ \left[E\left[XX_i\right] - E\left[X\right]^2\right] \right. \\ &- \frac{VaX}{R^2} + \frac{1}{R^2} \sum_{i,j=1}^{N} \sum_{i,j=1}^{N} \left\{ \left[E\left[XX_i\right] - E\left[X\right]^2\right] \right. \end{aligned}$

For uncorrelated samples we know:

$$E[X_iX_j] = E[X_i]E[X_j]$$
 for $i \neq j$

The correlation time of a variable is defined as:

$$\tau_X := \frac{\sum_{t} \left(E\left[X_i X_{i+t} \right] - E\left[X \right]^2 \right)}{\mathsf{Var} X}$$

Binning analysis II

$$\begin{split} A_i^{(I)} &= \frac{1}{2} \left(A_{2i-1}^{(I-1)} + A_{2i}^{(I-1)} \right) \\ \Delta^{(I)} &= \sqrt{\mathsf{Var} A^{(I)} / M^{(I)}} \overset{I \to \infty}{\to} \Delta = \sqrt{(1 + 2\tau_A) \mathsf{Var} A / M} \\ \tau_A &= \lim_{I \to \infty} \left(\frac{2^I \mathsf{Var} A^{(I)}}{\mathsf{Var} A^{(0)}} - 1 \right) \end{split}$$

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-Binning analysis II

Binning analysis II
$$\begin{split} A_i^{(l)} &= \frac{1}{2} \left(d_{i-1}^{(l-1)} + A_{i}^{(l-1)} \right) \\ \Delta^{(l)} &= \sqrt{\log \ell^2 / M^{(l)}} \stackrel{l \rightarrow +}{\sim} \Delta - \sqrt{(1+2c_0) V \omega A_i / M} \\ &= c_0 - \lim_{r \rightarrow \infty} \left(\frac{2^r V \omega R^{(l)}}{V V H^{(l)}} \right) \end{split}$$

Draw graphics with the bins and the levels.

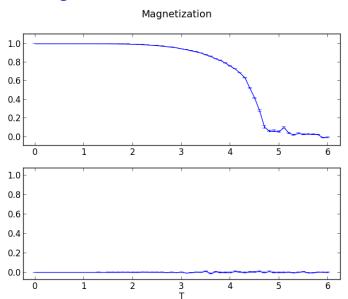
What really happens in the system

Cluster algorithms for the Ising model

└─What really happens in the system

Draw domains on board and show single spin flip only is useful at borders of domains.

Why cluster algorithms are better



Questions

Wolff or Swendsen-Wang?

Swendsen-Wang better for parallelization because it touches the whole lattice.

A sample slide

A displayed formula:

$$\int_{-\infty}^{\infty} e^{-x^2} \, dx = \sqrt{\pi}$$

An itemized list:

- ▶ itemized item 1
- ▶ itemized item 2
- ▶ itemized item 3

Theorem

In a right triangle, the square of hypotenuse equals the sum of squares of two other sides.