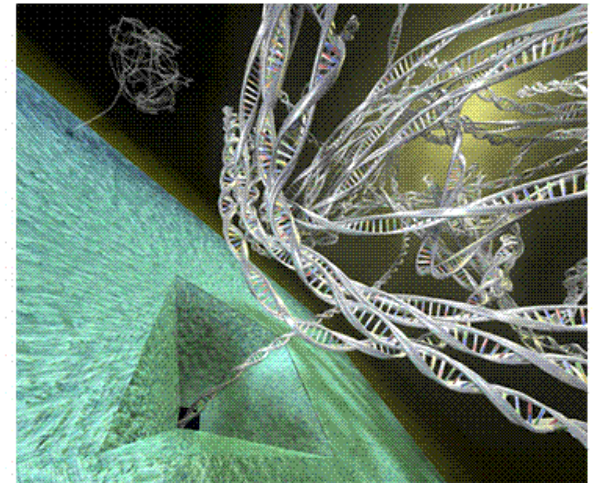


Basics of Monte Carlo simulations

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- basic MC, explained using Ising model
- Intermezzo I: anomalous dynamics
- advanced MC: cluster algorithms
- Intermezzo II: self-avoiding walks
- Current research: beyond detailed balance



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Ising model

- lattice with sites $i = 0 \dots N - 1$ (often square or cubic)
- spins σ_i on lattice sites $i = 0 \dots N - 1$
- Hamiltonian: $H = -J \sum_{\langle i,j \rangle} \sigma_i \sigma_j$

Here, $\langle \rangle$ is notation for nearest-neighbor sites

- Probability of a configuration $S \equiv \{ \sigma_i \}$:

$$P(S) = \frac{1}{Z} \exp(-\beta E(S))$$

in which $\beta \equiv (k_b T)^{-1}$ and $E(S)$ the energy (result of the hamiltonian)

Large β (low temperature): spins are mostly aligned

Small β (high temperature): spins are more or less random

Ising model

Goal of Monte Carlo simulations: generate a representative set of states

General approach: Markov process

- start from some initial state S_0
- in state S_i , propose some small change, resulting in S_{i+1}^T
- either *accept*, i.e., $S_{i+1} = S_{i+1}^T$, or *reject*, i.e., $S_{i+1} = S_i$, the proposed change.
- iterate the last two steps many times

What is a “small change”?

For Ising model, for instance random spin flip

What should the probability of acceptance be?

long answer...

Detailed Balance

Convergence to some steady state, in which S_i has a probability $p(S_i)$

Definitions:

$T(\mu \rightarrow \nu)$: proposition probability from μ to ν

$A(\mu \rightarrow \nu)$: acceptance probability from μ to ν

in the steady state:

$$\sum_{\mu} p(\mu) T(\mu \rightarrow \nu) A(\mu \rightarrow \nu) = \sum_{\mu} p(\nu) T(\nu \rightarrow \mu) A(\nu \rightarrow \mu)$$

$$\Leftrightarrow \forall \mu, \nu :: p(\mu) T(\mu \rightarrow \nu) A(\mu \rightarrow \nu) = p(\nu) T(\nu \rightarrow \mu) A(\nu \rightarrow \mu)$$

This is known as: **Detailed Balance**

Detailed Balance

In our simple example, in a system with N sites:

$T(\mu \rightarrow \nu) = 1/N$ if μ and ν differ in a single spin only. (Else it is zero.)

We want to sample the Boltzmann distribution with

$$\frac{p(\mu)}{p(\nu)} = \exp(-\beta(E_\mu - E_\nu))$$

Thus, detailed balance demands

$$\frac{A(\mu \rightarrow \nu)}{A(\nu \rightarrow \mu)} = \exp(-\beta(E_\nu - E_\mu))$$

Restriction: acceptance probabilities are limited to $[0, 1]$

Fastest simulations if either $A(\mu \rightarrow \nu)$ or $A(\nu \rightarrow \mu)$ is 1; thus

$$A(\mu \rightarrow \nu) = \text{Min} [1, \exp(-\beta(E_\mu - E_\nu))]$$

This is the **Metropolis algorithm**

Ergodicity

Detailed balance is not enough for correct sampling

[Simple counter-example: take $A(\mu \rightarrow \nu) = 0$ for all μ, ν]

Second demand is ergodicity:

With a finite number of steps, any configuration can be reached

In our case:

From any μ to any ν is done by sequentially flipping all different spins

Detailed Balance + Ergodicity \equiv Correct algorithm

i.e., eventually the Boltzmann distribution is sampled

Metropolis simulation of the Ising model

A simulation program thus looks like:

- initialize the spins (for instance all *up*)

Then do many iterations:

- select random site
- compute energy difference ΔE if flipped
- if $\Delta E < 0$ or if random number $< \exp(-\beta \Delta E)$: flip it
- occasionally, measure some observable(s), e.g. E or $M = \sum \sigma_i$

E and M keep fluctuating, but their averages converge slowly

Practical matter 1: Periodic boundary conditions

Interest in the thermodynamic limit (i.e., an infinite system)

Outside reach of simulation.

Natural choice: finite system with $L \times L$ sites (with open boundaries).

Better in practice are
periodic boundary conditions:

the neighbors of site (x, y) are
 $(x, (y \pm 1) \bmod L)$ and $((x \pm 1) \bmod L, y)$.

In two dimensions, this yields a torus

- No special sites
- finiteness only over distances $\geq L$.

(0,0)	(4,0)	(0,0)	(4,0)
(0,4)	(4,4)	(0,4)	(4,4)
(0,0)	(4,0)	(0,0)	(4,0)
(0,4)	(4,4)	(0,4)	(4,4)

Helical boundary conditions

A slight variation is helical boundary conditions

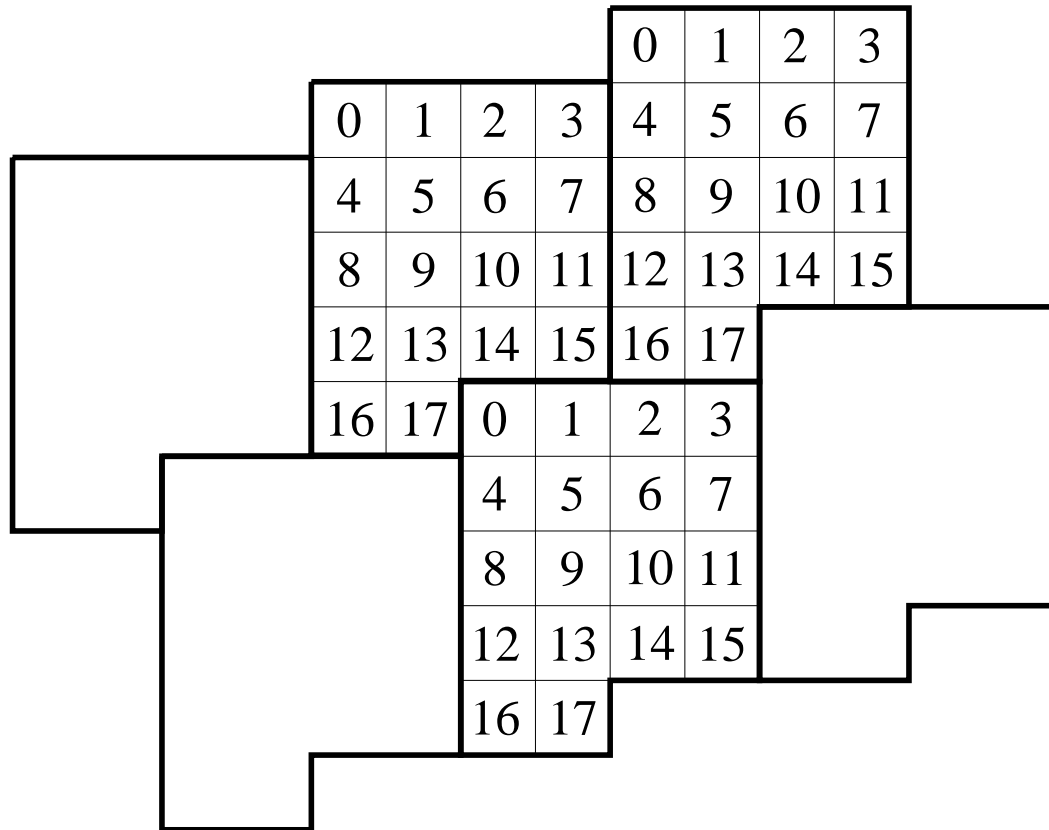
- enumerate the sites $i = 0 \dots N$
- neighbors of site i are $i \pm 1$ and $i \pm L$.

advantage: working with a single index is often faster

					0	1	2	3	4
0	1	2	3	4	5	6	7	8	9
5	6	7	8	9	10	11	12	13	14
10	11	12	13	14	15	16	17	18	19
15	16	17	18	19	20	21	22	23	24
20	21	22	23	24	0	1	2	3	4
0	1	2	3	4	5	6	7	8	9
5	6	7	8	9	10	11	12	13	14
10	11	12	13	14	15	16	17	18	19
15	16	17	18	19	20	21	22	23	24
20	21	22	23	24					

Helical boundary conditions

Number of sites does not need to be a multiple of L



Sometimes, it is computationally advantageous to take $N = 2^k$

energy differences

- Consider a single proposed flip of σ_k
- Acceptance probability depends on resulting change in energy ΔE

This is only determined by itself and its neighbor spins:

$$\Delta E = 2J\sigma_k(\sigma_{k+1} + \sigma_{k-1} + \sigma_{k+L} + \sigma_{k-L})$$

(on a square lattice, leaving out boundary conditions)

\Rightarrow no need to compute the energy before and after!

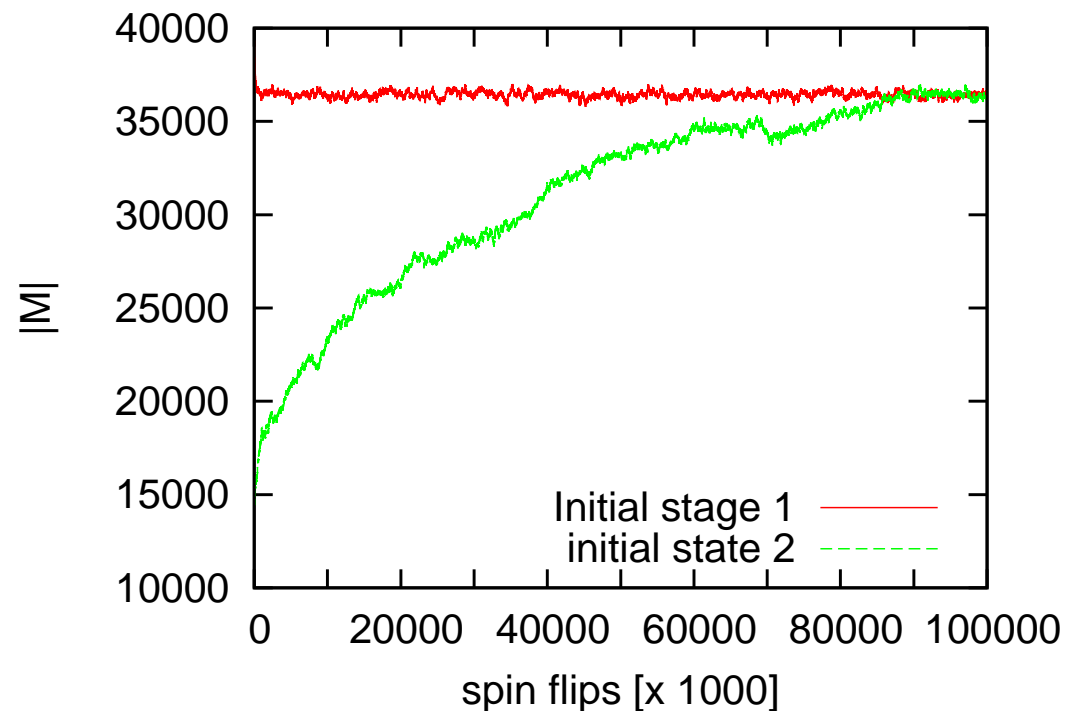
Thermalization

Another key question:

How many spin flips before steady state?

Answer: sometimes surprisingly long

- Consider some observable, for instance the energy E or magnetization $M \equiv \sum_i \sigma_i$
- Plot its value vs. time
- Once it fluctuates around a fixed value, apparently the system has thermalized



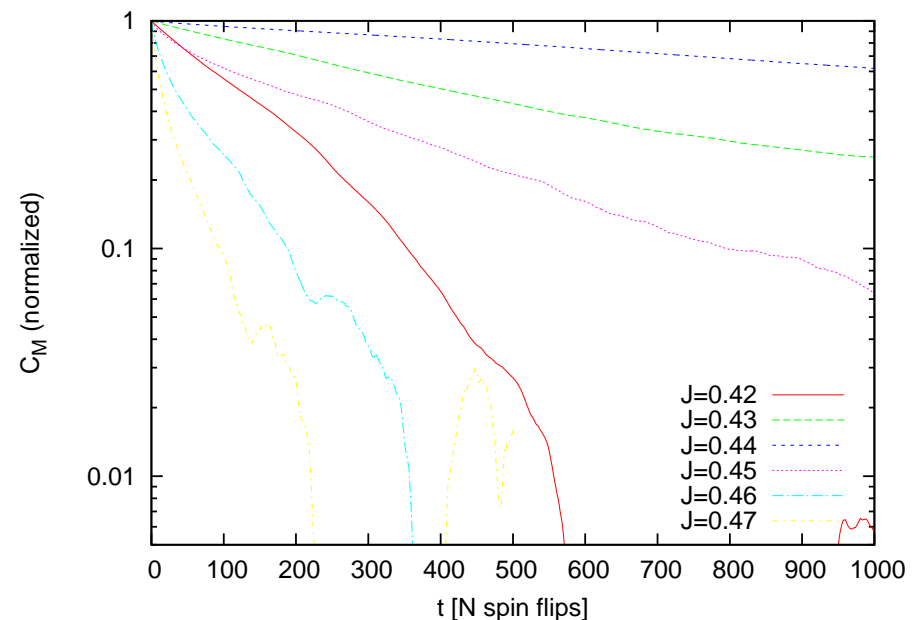
Thermalization

More insight can be obtained from the autocorrelation function:

$$C_M(\Delta t) = \langle (M(t) - \langle M \rangle) \cdot (M(t + \Delta t) - \langle M \rangle) \rangle$$

(measured in steady state; in practice second half of a long simulation).

- Often shows exponential decay:
 $C(\Delta t) \sim \exp(-t/\tau)$, defining the correlation time τ .
- Up to τ , surely the simulation is still correlated to the (arbitrarily) initial configuration.
- To be safe, thermalization should be at least 2 or 5 times τ .
- Knowledge of τ is also useful for statistical errors.



Thermalization

A crude estimate of τ near the critical temperature:
Magnetic susceptibility

$$\chi = \frac{\beta}{N} (\langle M^2 \rangle - \langle M \rangle^2) \sim L^{\gamma/\nu}$$

with (in two dimensions) $\gamma = 7/4$ and $\nu = 1$.

- a single spin changes M by ± 1
- if all spin flips are uncorrelated, M shows random-walk behavior with unit steps per accepted spin flip.
- ΔM^2 needs to cover a range of $N \cdot L^{\gamma/\nu} \sim L^{15/4}$
 \Rightarrow an $L \times L$ system has a correlation time of $\sim L^4$ spin flips

This means ~ 100 million spin flips in a system with 100×100 sites!

Cluster algorithms

Can severe critical slowing down ($\tau \sim L^2$ flips per site or worse) be avoided?

For a long time, the believe was not.

Conclusion: only progress by faster (special-purpose) computers

- DICE I and II (=Delft Ising Computing Engine)
- mTIS (megaspin model of the Tokyo University Ising spin)
- other ones in Bell labs, Santa Barbara, and in the Ukraine

Revolution in 1987!

Swendsen-Wang algorithm.

Two years later, an improvement was made by Ulli Wolff (1989).

A new generation of non-local algorithms, a.k.a. cluster algorithms.

Wolff algorithm

Wolff algorithm:

1. Randomly select a site k , which will act as the seed for a cluster.
2. For each newly added site, list all links to neighboring sites i , obeying:
 - i is not yet part of the cluster

- $\sigma_i = \sigma_k$

and each such link has a probability $P_{\text{add}} = 1 - \exp(-2\beta J)$ to be activated (i.e., site i is added to the cluster (after which also other links need to be considered)).

3. Flip all spins of sites in the cluster.

Correctness, Wolff algorithm

Correctness derived from Ergodicity + Detailed Balance

Detailed Balance:

$$\forall \mu, \nu :: \mathbf{p}(\mu) \mathbf{T}(\mu \rightarrow \nu) \mathbf{A}(\mu \rightarrow \nu) = \mathbf{p}(\nu) \mathbf{T}(\nu \rightarrow \mu) \mathbf{A}(\nu \rightarrow \mu)$$

All proposed cluster flips are accepted, $\Rightarrow \mathbf{A}(\mu \rightarrow \nu) = \mathbf{A}(\nu \rightarrow \mu) = 1$

Energy difference between μ and ν only due to neighboring spins $i \in C$ and $j \notin C$

$$\mathbf{E}_\mu - \mathbf{E}_\nu = -2\mathbf{J} \sum_{\langle i \in C, j \notin C \rangle} \sigma_i^{(\nu)} \sigma_j^{(\nu)}$$

some rewriting yields

$$\frac{\mathbf{p}_\mu}{\mathbf{p}_\nu} = \exp(-\beta(\mathbf{E}_\mu - \mathbf{E}_\nu)) = \prod_{\langle i \in C, j \notin C \rangle} \exp\left(2\beta\mathbf{J}\sigma_i^{(\nu)}\sigma_j^{(\nu)}\right)$$

Correctness, Wolff algorithm

Proposition probability $\mathbf{T}(\mu \rightarrow \nu)$:

- probability to select site k : $\frac{1}{N}$
- Each activated link adds a factor \mathbf{P}_{add}
- Each unactivated link between aligned spins adds a factor $1 - \mathbf{P}_{\text{add}} = \exp(-2\beta\mathbf{J})$
- (Each unactivated links between anti-aligned spins adds a factor 1)

$$\Rightarrow \mathbf{T}(\mu \rightarrow \nu) = \frac{1}{N} \cdot \prod_{\langle i \in C, j \in C \rangle} (\mathbf{P}_{\text{add}}) \cdot \prod_{\substack{\langle i \in C, j \notin C \rangle \\ \sigma_i = \sigma_j}} (1 - \mathbf{P}_{\text{add}})$$

$\mathbf{T}(\nu \rightarrow \mu)$ differs in the third factor since for $\langle \mathbf{i} \in \mathbf{C}, \mathbf{j} \notin \mathbf{C} \rangle$, $\sigma_{\mathbf{i}}^{(\mu)} \sigma_{\mathbf{j}}^{(\mu)} = -\sigma_{\mathbf{i}}^{(\nu)} \sigma_{\mathbf{j}}^{(\nu)}$

Consequence:

$$\frac{\mathbf{T}(\mu \rightarrow \nu)}{\mathbf{T}(\nu \rightarrow \mu)} = \prod_{\langle \mathbf{i} \in \mathbf{C}, \mathbf{j} \notin \mathbf{C} \rangle} \exp \left(-2\beta\mathbf{J} \sigma_{\mathbf{i}}^{(\nu)} \sigma_{\mathbf{j}}^{(\nu)} \right)$$

[Given $\sigma_{\mathbf{i}} = \sigma_{\mathbf{j}}$, we used $1 - \mathbf{P}_{\text{add}} = \exp(-2\beta\mathbf{J}\sigma_{\mathbf{i}}\sigma_{\mathbf{j}})$]

Correctness, Wolff algorithm

Putting pieces together:

$$\mathbf{A}(\mu \rightarrow \nu) = \mathbf{A}(\nu \rightarrow \mu) = 1$$

$$\frac{\mathbf{p}_\mu}{\mathbf{p}_\nu} = \exp(-\beta(\mathbf{E}_\mu - \mathbf{E}_\nu)) = \prod_{\langle \mathbf{i} \in \mathbf{C}, \mathbf{j} \notin \mathbf{C} \rangle} \exp\left(2\beta \mathbf{J} \sigma_{\mathbf{i}}^{(\nu)} \sigma_{\mathbf{j}}^{(\nu)}\right)$$

$$\frac{\mathbf{T}(\mu \rightarrow \nu)}{\mathbf{T}(\nu \rightarrow \mu)} = \prod_{\langle \mathbf{i} \in \mathbf{C}, \mathbf{j} \notin \mathbf{C} \rangle} \exp\left(-2\beta \mathbf{J} \sigma_{\mathbf{i}}^{(\nu)} \sigma_{\mathbf{j}}^{(\nu)}\right)$$

yields Detailed Balance:

$$\forall \mu, \nu :: \mathbf{p}(\mu) \mathbf{T}(\mu \rightarrow \nu) \mathbf{A}(\mu \rightarrow \nu) = \mathbf{p}(\nu) \mathbf{T}(\nu \rightarrow \mu) \mathbf{A}(\nu \rightarrow \mu)$$

Ergodicity: individual spin flips are possible, and can result in any configuration

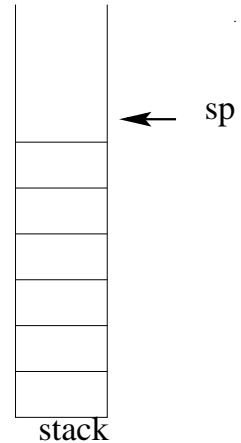
Combined, this provides a proof of correctness!

Implementation, Wolff algorithm

Useful data concept: 'stack'

Two basic operations:

- push (on stack)
- pop (from stack)



Implementation in C:

<code>stack[sp++] = a;</code>	\leftrightarrow	push a
<code>a = stack[--sp];</code>	\leftrightarrow	pop a
<code>if (sp == 0)</code>	\leftrightarrow	test if stack is empty
<code>sp = 0;</code>	\leftrightarrow	make stack empty

Implementation, Wolff algorithm

```
sp=0;
seed=random * N;
oldspin=spin[seed];
newspin= -oldspin;
stack[sp++]=seed;
spin[seed]=newspin;
while (sp) {
    k=stack[--sp];
    for (i=0;i<4;i++) {
        if (spin[nb[k][i]]==oldspin) {
            if (random < P_add) {
                stack[sp++]=nb[k][i];
                spin[nb[k][i]]=newspin;
            }
        }
    }
}
```

make stack empty

push cluster seed

while (stack not empty), pop
site and deal with neighbors

Alternatively, one can write a recursive program

Swendsen-Wang algorithm

Pre-dates Wolff algorithm by ~ 2 years

Difference with Wolff algorithm:

- cover entire lattice with clusters
- assign a random spin value to each cluster

The SW algorithm alternates between a spin representation and a cluster representation

In the cluster (a.k.a. Fortuin-Kasteleyn) representation, spin-spin correlations are easily determined

Computer power is spent on, on average, smaller clusters

This leads to slightly more critical slowing-down

Analysis, critical exponents

Scaling relations describe the system's behavior near its critical point

Definition of reduced temperature: $t \equiv \frac{T-T_c}{T_c}$

1. correlation length $\xi \sim |t|^{-\nu}$
2. magnetic susceptibility $\chi \sim |t|^{-\gamma}$
3. specific heat $c \sim |t|^{-\alpha}$
4. magnetization $m \sim (-t)^\beta$

These relations can be combined, for instance (1) + (2): $\chi \sim \xi^{\gamma/\nu}$

On a finite lattice with size L , ξ cannot exceed $L \Rightarrow \chi = \xi^{\gamma/\nu} \cdot \chi_0(L/\xi)$

$$\begin{aligned}\chi_0(\mathbf{x}) &\rightarrow \text{const} \text{ if } \mathbf{x} \gg 1 \\ \chi_0(\mathbf{x}) &\sim \mathbf{x}^{\gamma/\nu} \text{ if } \mathbf{x} \rightarrow 0\end{aligned}$$

Some rewriting then yields: $L^{-\gamma/\nu} \chi = \tilde{\chi}(L^{1/\nu} t)$

Analysis, critical exponents

from previous sheet: $L^{-\gamma/\nu}\chi = \tilde{\chi}(L^{1/\nu}t)$

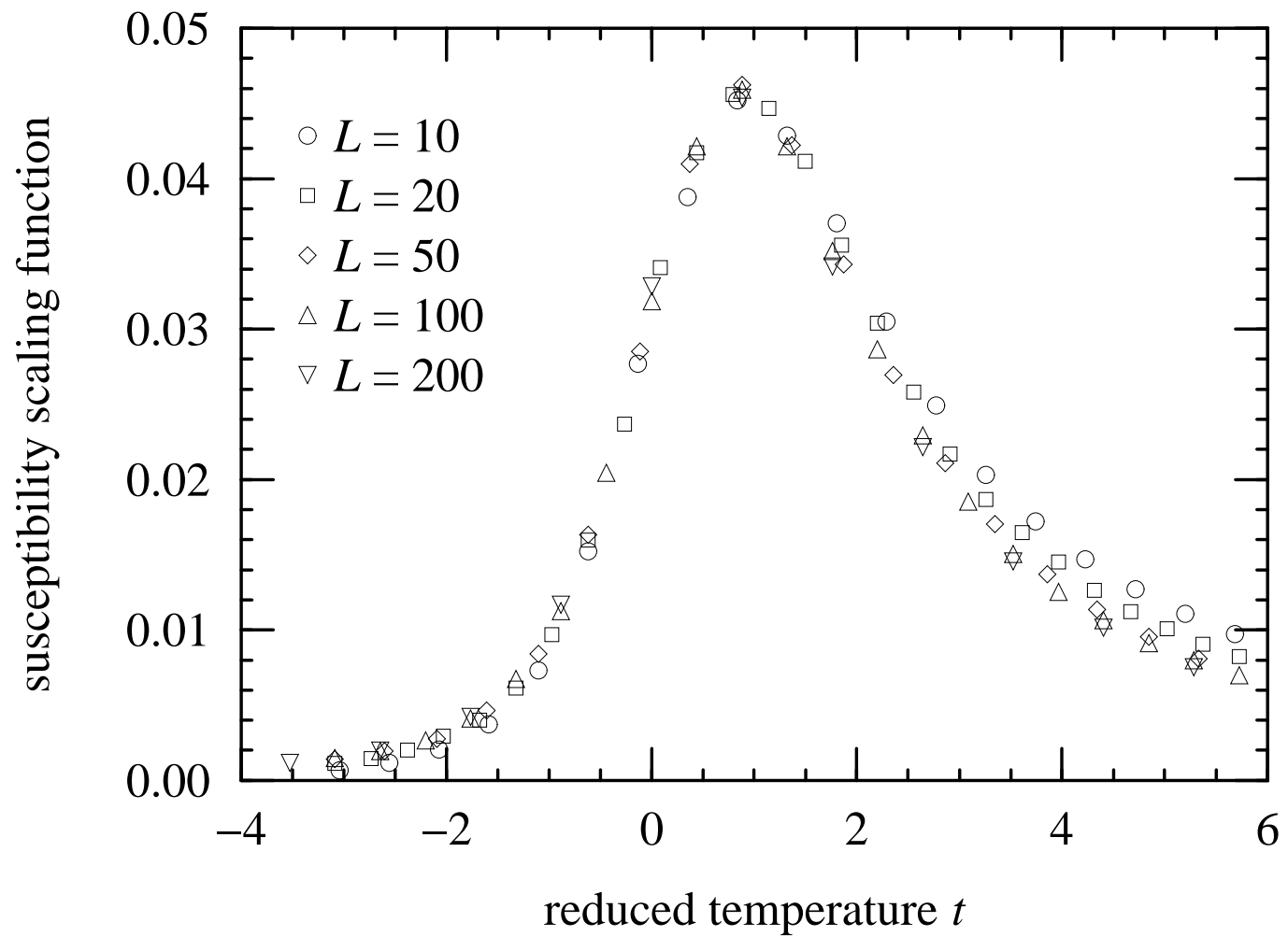
What does this mean?

- measure χ as a function of T in simulations with various sizes L
- if $L^{-\gamma/\nu}\chi$ is plotted as a function of $L^{1/\nu}t$, then these curves should collapse
- This only works with the proper choice of T_c , γ and ν
- \Rightarrow vary your estimates of T_c , γ and ν until a data collapse results
- Indirectly, this measures these!

A similar procedure can be used to determine other exponents

‘Data collapse’ is a much more general technique, with wide application!

Data collapse



Rejection-free implementation

Standard Metropolis approach:

- propose each spin flip with unit rate
- accept if with probability $P_{\text{acc}} = \text{Min}[1, \exp(-\beta\Delta E)]$

Same dynamics results if:

- propose each spin flip with its rate $\text{Min}[1, \exp(-\beta\Delta E)]$
- then always accept it

In practice:

- maintain lists Q_i with spins with equal number of aligned neighbors
- select a specific list k with probability $P_k ||Q_k|| / R$ with $R = \sum_i (P_i ||Q_i||)$
- flip a randomly selected spin from that list Q_k
- increment the time scale with $1/R$
- update the bookkeeping

Beyond ‘Detailed Balance’

Ballistic motion samples the Boltzmann distribution, violating ‘Detailed Balance’

Ballistic motion can explore phase space much faster than diffusion

Is there a general framework for MC simulations without ‘Detailed Balance’?

A first step:

- Increase the phase space with some discretized velocity $v = \pm 1$
- In a rejection-free algorithm, keep separate lists for up- and down-spins with total rate R_+ , resp. R_-
- If $v = 1$: if $(R_- < R_+)$ revert the velocity with probability R_-/R_+ else select a down-spin and flip it
- If $v = -1$: if $(R_+ < R_-)$ revert the velocity with probability R_+/R_- else select an up-spin and flip it

The idea is to satisfy ‘generalized detailed balance’:

$$R(\mu \xrightarrow{v=1} \nu) = R(\nu \xrightarrow{v=-1} \mu)$$

Beyond 'Detailed Balance'

- The resulting algorithm seems to be correct
- At short times, the magnetization fluctuations are significantly enhanced:
 $\langle (M_t - M_0)^2 \rangle \sim t^2$
- However, at longer times, the initial gain is lost; $\tau \sim L^z$ persists (same z)
- Similar scheme can be implemented in Wolff algorithm
- Result: smaller clusters are flipped, but again z seems unaffected

Current status:

- Correct MC algorithms can be designed which violate detailed balance
- There is yet no example with a significantly higher computational efficiency

Closing remarks

For all of you:

- Writing Monte Carlo simulation programs is not hard (you can do it!)
- Make sure that you thermalize before measuring
- Often sophisticated data analysis yields more than from brute force

For the future computational physicists:

- Monte Carlo is a very versatile, easy to use simulation technique
- It is intellectually challenging to think of new, efficient algorithms
- Help is appreciated in finding examples where DB-violation pays off

Thank you for your attention!