

LECTURE 4:
BASICS OF
MONTE CARLO
SIMULATIONS

GOAL:

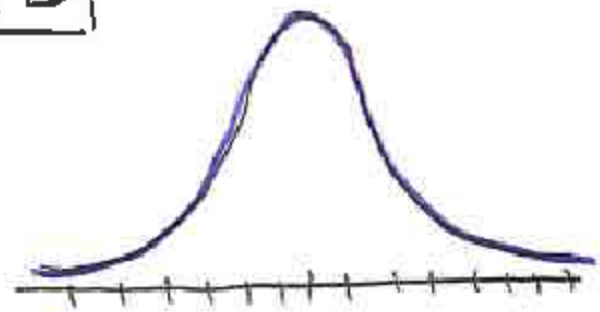
calculate expectation values

$$\langle O \rangle = \int \prod_x d\phi(x) O[\phi] e^{-S} / Z$$

$$Z = \int \prod_x d\phi(x) e^{-S}$$

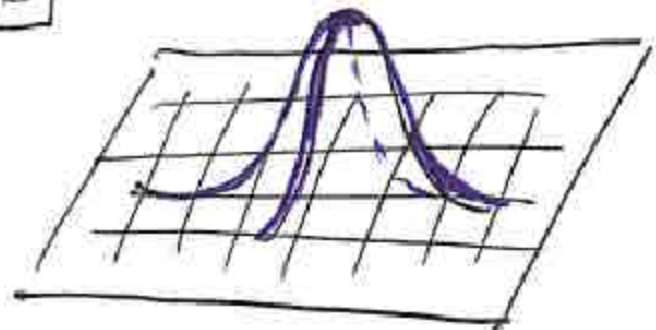
$N_s^3 N_t$ points
 N_F field components } $N_s^3 N_t N_F$ dimensional integral

1D



N fn. evaluations

2D



N^2 fn. evaluations

N^{64^4}

fn. evaluations



MONTE CARLO METHODS

1

random field configurations

if uniform distributed $\rightarrow$ just as bad as quadrature

IMPORTANCE SAMPLING

take random configs $\Phi_1, \dots, \Phi_N$
with probability

$$W[\Phi] \propto e^{-S[\Phi]}$$

obtain expectation values as

$$\langle O \rangle = \lim_{N \rightarrow \infty} \underbrace{\frac{1}{N} \sum_i O[\Phi_i]}_{\overline{O_N}}$$

def. of an expectation value

$$\text{Var}(\overline{O_N}) = \frac{1}{N^2} N \text{Var}(O) = \frac{\text{Var}(O)}{N} \quad (\text{indep. samples})$$

$$\text{stat. error of average} \sim \frac{1}{\sqrt{N}}$$

TYPES OF SAMPLING

2

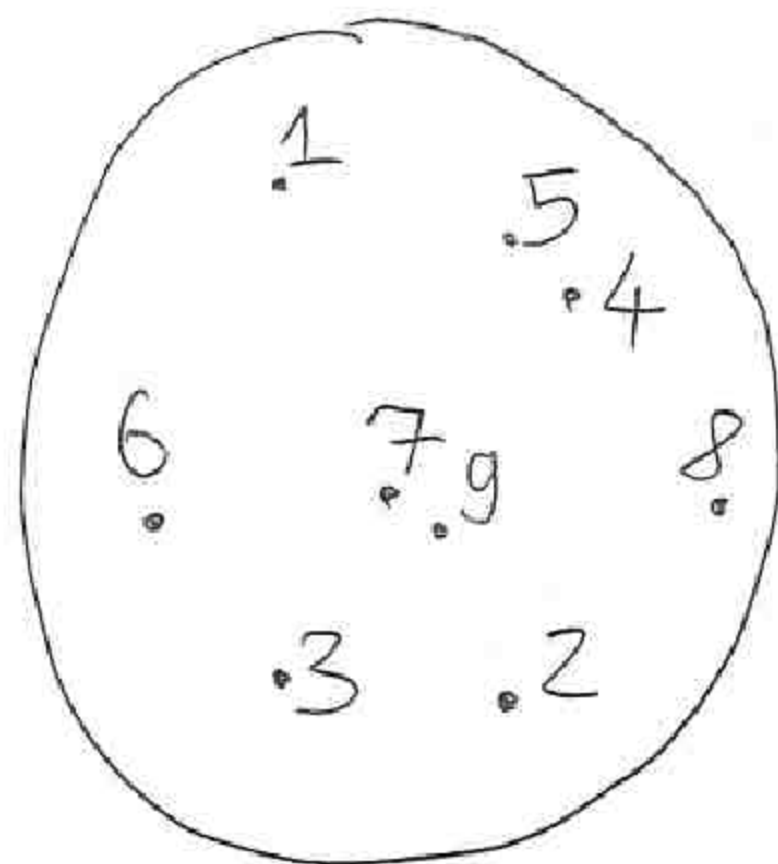
DIRECT

- * independent samples
- * can be done in 1D for an arbitrary distribution
- * in many dims only for simple distributions

e.g. o Gaussians $e^{-\frac{1}{2} \phi_i M_{ij} \phi_j}$

o uniform point on sphere S^n

...



- * more complicated MC algorithms also feature direct sampling as an intermediate step

MARKOV CHAIN

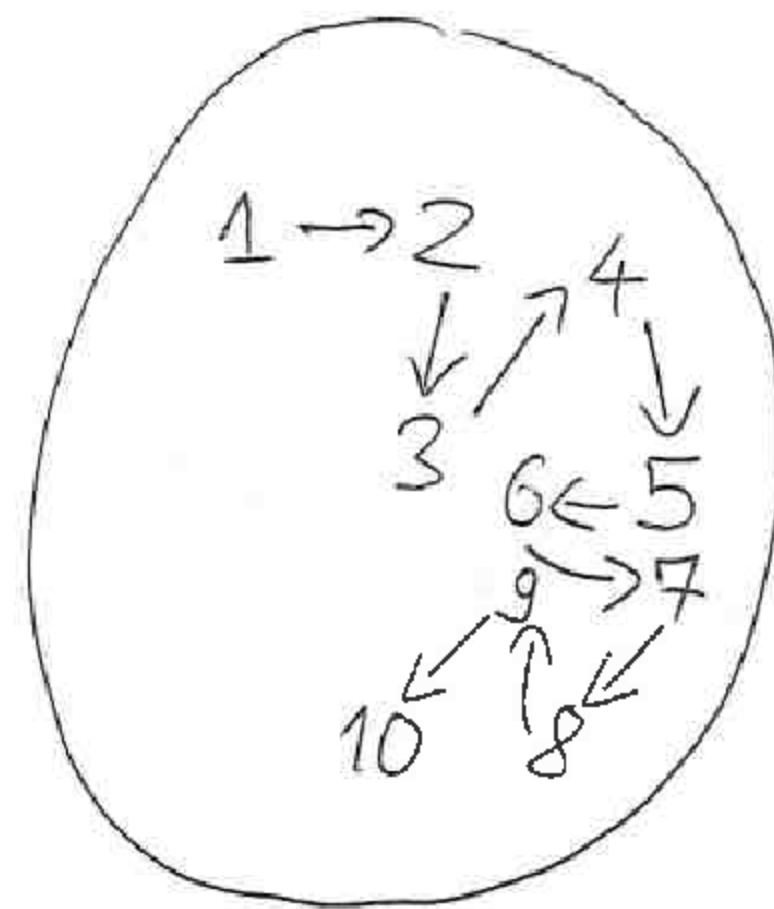
MCMC = Markov Chain Monte Carlo

$$\Phi_1 \rightarrow \Phi_2 \rightarrow \Phi_3 \rightarrow \dots$$

defined by transition probabilities $P(\Phi_{i+1} \leftarrow \Phi_i)$

- * with a proper choice of the transition probabilities, can sample from arbitrarily complicated multidim. prob. distributions

BUT: if we don't take enough steps, the chain will remember where it started



the samples are not independent
autocorrelation fn.

$$C_A(\tau) = \langle A_n A_{n+\tau} \rangle - \langle A_n \rangle \langle A_{n+\tau} \rangle \neq 0$$

BASICS OF MCMC ALGORITHMS

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TRANSITION PROBABILITIES $P[\Phi_{i+1} \leftarrow \Phi_i]$

IF THE CURRENT PROB. DISTR. IS $W[\Phi]$

AFTER ONE STEP $W'[\Phi'] = \int D\Phi P[\Phi' \leftarrow \Phi] W[\Phi]$

OR IN MATRIX NOTATION $W' = PW$

CONDITIONS FOR CORRECTNESS

① $0 \leq P(\Phi' \leftarrow \Phi) \leq 1 \quad \forall \Phi, \Phi'$ it is a probability

① normalization $\int D\Phi' P(\Phi' \leftarrow \Phi) = 1$

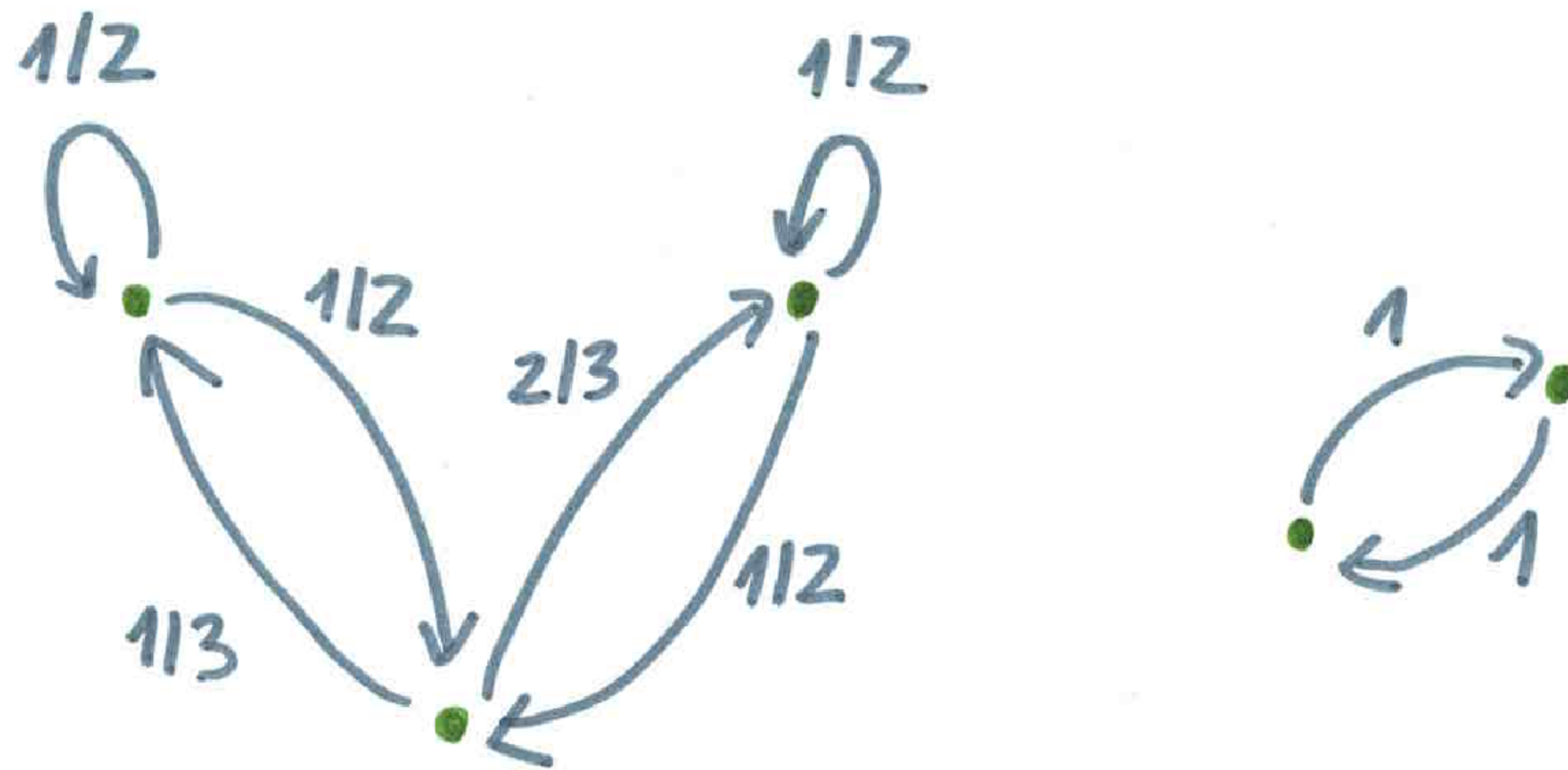
$$\Rightarrow \int D\Phi' W'[\Phi'] = \int D\Phi W[\Phi]$$

② ergodicity two types

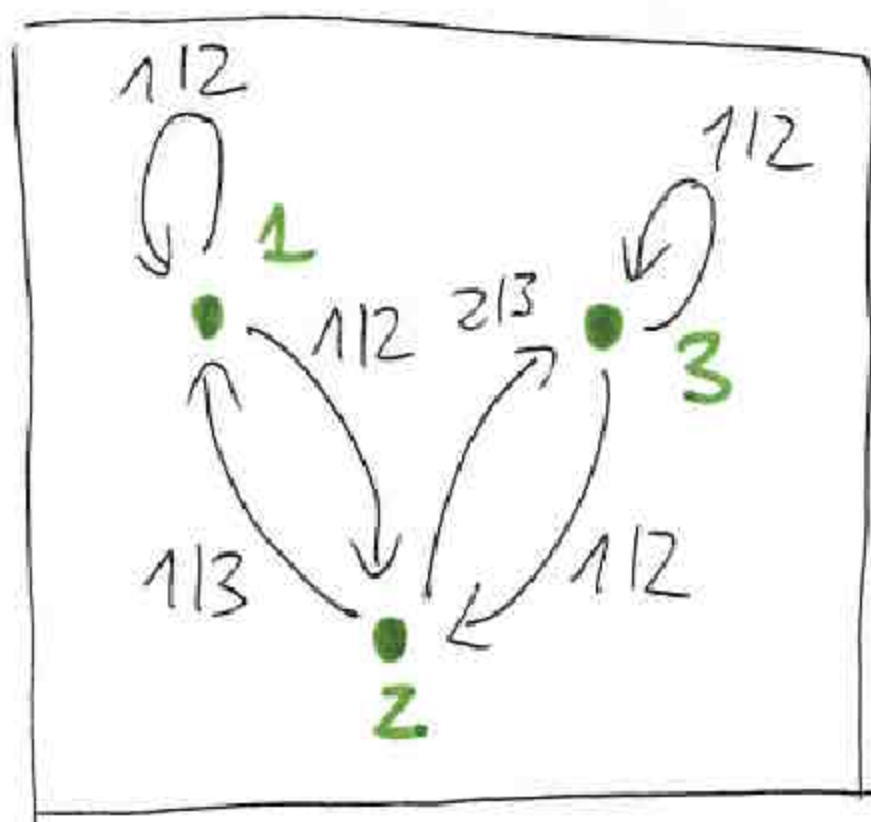
STRONG $P(\Phi' \leftarrow \Phi) > 0 \quad \forall \Phi' \neq \Phi$ WEAK $P^k(\Phi' \leftarrow \Phi) > 0$ for some k

EXAMPLE OF A NON-ERGODIC MC

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THE CONFIGURATIONS DECOMPOSE INTO GROUPS
STARTING FROM ONE YOU WILL NEVER
GET TO THE OTHER



$$P(1 \leftarrow 1) = 1/2$$

$$P(2 \leftarrow 1) = 1/2$$

$$P(3 \leftarrow 1) = 0$$

$$P(1 \leftarrow 2) = 1/3$$

$$P(2 \leftarrow 2) = 0$$

$$P(3 \leftarrow 2) = 2/3$$

$$P(1 \leftarrow 3) = 0$$

$$P(2 \leftarrow 3) = 1/2$$

$$P(3 \leftarrow 3) = 1/2$$

$$P = \begin{pmatrix} 1/2 & 1/3 & 0 \\ 1/2 & 0 & 1/2 \\ 0 & 2/3 & 1/2 \end{pmatrix}$$

suppose I start from
state 1 $\Rightarrow W_0 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$

1 step $P W_0 = \begin{pmatrix} 1/2 \\ 1/2 \\ 0 \end{pmatrix}$

2 steps $P^2 W_0 = \begin{pmatrix} 5/12 \\ 1/4 \\ 1/3 \end{pmatrix}$

5 steps $\begin{pmatrix} 0.2396 \\ 0.3438 \\ 0.4167 \end{pmatrix}$

$\exists$ equilibrium distribution
Claim: unique for all ergodic tr. mat.

different starting point

$$W_0 = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$$

1 step $\begin{pmatrix} 1/3 \\ 0 \\ 2/3 \end{pmatrix}$

many steps $\rightarrow$ same

i.e. as $n \rightarrow \infty$ the
columns of P^k will
become the same

Q: How to choose P so
that I have the eq.
distr. that I want?

③ GLOBAL BALANCE / CORRECT EQUILIBRIUM DISTR.

$$W_{eq}[\Phi] = \int D\Phi' P[\Phi \leftarrow \Phi'] W_{eq}[\Phi']$$

$$\underbrace{\int D\Phi' P[\Phi' \leftarrow \Phi] W_{eq}[\Phi]}_1 = \int D\Phi' P[\Phi \leftarrow \Phi'] W_{eq}[\Phi']$$

a sufficient, but not
necessary condition is

DETAILED BALANCE

$$P[\Phi' \leftarrow \Phi] W_{eq}[\Phi] = P[\Phi \leftarrow \Phi'] W_{eq}[\Phi']$$

THE METROPOLIS ALGORITHM

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- ① choose a config. Φ' with some proposal probability $T_0[\Phi' \leftarrow \Phi]$
- ② accept proposal w. prob. $T_A(\Phi' \leftarrow \Phi) = \min \left\{ 1, \frac{T_0[\Phi \leftarrow \Phi']}{T_0[\Phi' \leftarrow \Phi]} \frac{W[\Phi']}{W[\Phi]} \right\}$
- ③ goto 1

the full transition prob. is $P[\Phi' \leftarrow \Phi] = T_0(\phi' \leftarrow \phi) T_A(\phi' \leftarrow \phi)$

detailed balance $P(\Phi' \leftarrow \Phi) e^{-S[\Phi]} \stackrel{?}{=} P(\phi \leftarrow \phi') e^{-S[\phi']}$

$$\begin{aligned} P(\phi' \leftarrow \phi) e^{-S[\phi]} &= T_0(\phi' \leftarrow \phi) \min \left\{ 1, \frac{T_0(\phi \leftarrow \phi')}{T_0(\phi' \leftarrow \phi)} \frac{e^{-S[\phi']}}{e^{-S[\phi]}} \right\} e^{-S[\phi]} \\ &= \min \left(T_0(\phi' \leftarrow \phi) e^{-S[\phi]}, T_0(\phi \leftarrow \phi') e^{-S[\phi']} \right) \\ &= \min \left\{ 1, \frac{T_0(\phi' \leftarrow \phi)}{T_0(\phi \leftarrow \phi')} \frac{e^{-S[\phi]}}{e^{-S[\phi']}} \right\} e^{-S[\phi']} T_0[\phi \leftarrow \phi'] = P(\phi \leftarrow \phi') e^{-S[\phi']} \end{aligned}$$

COMMENTS:

- ① DON'T NEED TO NORMALIZE W_{eq}
DON'T NEED TO CALCULATE Z : IMPORTANT
- ② THE ACCEPT/REJECT STEP GUARANTEES DETAILED BALANCE
THE PROPOSAL STEP MUST GUARANTEE ERGODICITY

SPEC. CASE

$$T_0(\phi' \leftarrow \phi) = T_0(\phi \leftarrow \phi')$$

$$\Rightarrow T_A(\phi' \leftarrow \phi) = \min[1, e^{-\Delta S}] \quad \Delta S = S[\phi'] - S[\phi]$$

LOCAL UPDATES

IF proposal of T_0 local change & action is local

$\Rightarrow$ calculation of ΔS is only $O(1)$
(say the contrib. of the $2d$ neighbors of the updated field)

EXPONENTIAL AUTOCORRELATION TIME

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HOW FAST DOES THE MARKOV CHAIN APPROACH EQUIL.?

For an ergodic Markov matrix

There is 1 eigenvalue $\lambda_1 = 1$

all others are $\lambda < 1$

$$P^k = 1 P_1 + \lambda_2^k P_2 + \lambda_3^k P_3 + \dots$$

↑
projection to the
 $\lambda = 1$ subspace

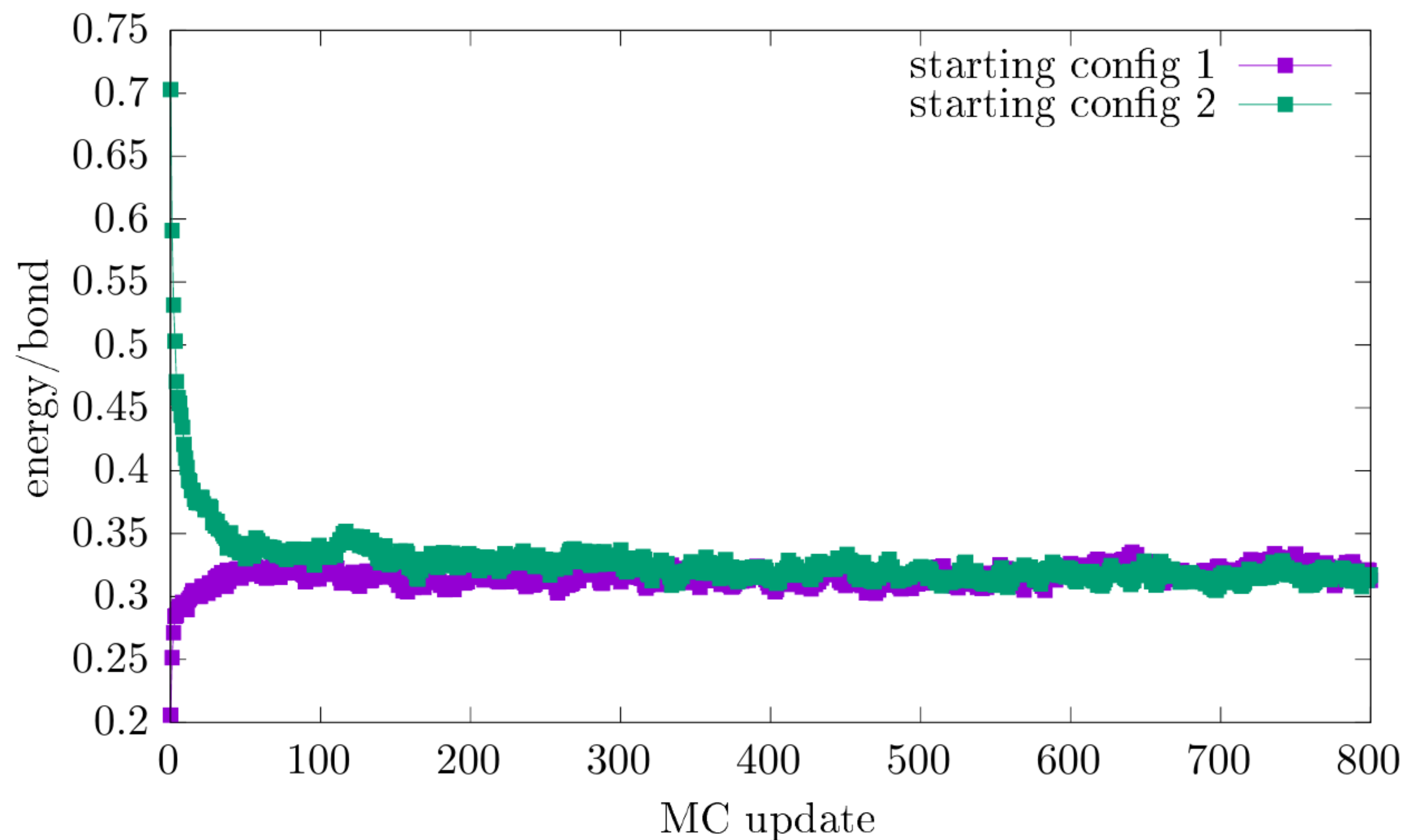
$$P^k W_0 = W_{eq} + \underbrace{\lambda_2^k}_{e^{-k/\tau_{exp}}} P_2 W_0 + \dots$$

exponential autocorrelation time $\frac{1}{\tau_{exp}} = -\ln \lambda_2$

slowest timescale in the MC "dynamics"

THERMALIZATION

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CRITICAL SLOWING DOWN

near a 2nd order PhTr

$$\tau_{exp} \sim \xi^z$$

z = dynamical critical exponent, depends on the dynamics (i.e. the update algorithm)

STATISTICAL ERRORS & INTEGRATED AUTOCORR. TIME 11

$$\text{Var}(\bar{O}) = \left\langle \frac{1}{N^2} \sum_{i,j=1}^N (O_i - \langle O \rangle) (O_j - \langle O \rangle) \right\rangle = \frac{1}{N^2} \sum_{i,j=1}^N \underbrace{\langle (O_i - \langle O \rangle) (O_j - \langle O \rangle) \rangle}_{C_O(|i-j|)}$$

$$= \frac{1}{N^2} \sum_{t=-N+1}^{N-1} \sum_{i=1}^{N-|t|} C_O(|t|) = \frac{1}{N^2} \sum_{t=-N+1}^{N-1} (N-|t|) C_O(|t|) = \sum_{t=-N}^N \frac{N-|t|}{N^2} C_O(|t|)$$

$$= \frac{C_O(0)}{N} \sum_{t=-N}^N T_O(|t|) \left(1 - \frac{|t|}{N} \right) \underset{\substack{\uparrow \\ \text{large } N}}{\approx} \frac{\text{Var}(O)}{N} 2 \underbrace{\left(\frac{1}{2} + \sum_{t=1}^N T_O(|t|) \right)}_{\equiv \tau_{\text{int},O}} = \frac{\text{Var}(O)}{N} 2 \tau_{\text{int},O}$$

$$T_O(t) = \frac{C_O(t)}{C_O(0)}$$

$\Rightarrow$ # of effectively independent data $N_{\text{indep}} = \frac{N}{2 \tau_{\text{int},O}}$

suppose the autocorr. fn. is a single exponential

$$T(t) \sim e^{-t/T_{\text{exp}}}$$

$$T_{\text{int}} = \frac{1}{2} \left(1 + 2 \sum_{t=1}^{\infty} e^{-t/T_{\text{exp}}} \right) = \frac{1}{2} \left[1 + \frac{2e^{-1/T_{\text{exp}}}}{1 - e^{-1/T_{\text{exp}}}} \right] \underset{T_{\text{exp}} \gg 1}{\approx} \frac{1}{2} \left[1 + \frac{2 - \frac{2}{T_{\text{exp}}}}{\frac{1}{T_{\text{exp}}}} \right] = \frac{1}{2} (2T_{\text{exp}} - 1) \approx T_{\text{exp}}$$

if (more realistically) we have more exponentials

$$T(t) = \sum_{n=1}^K c_n e^{-t/\tau_n}$$

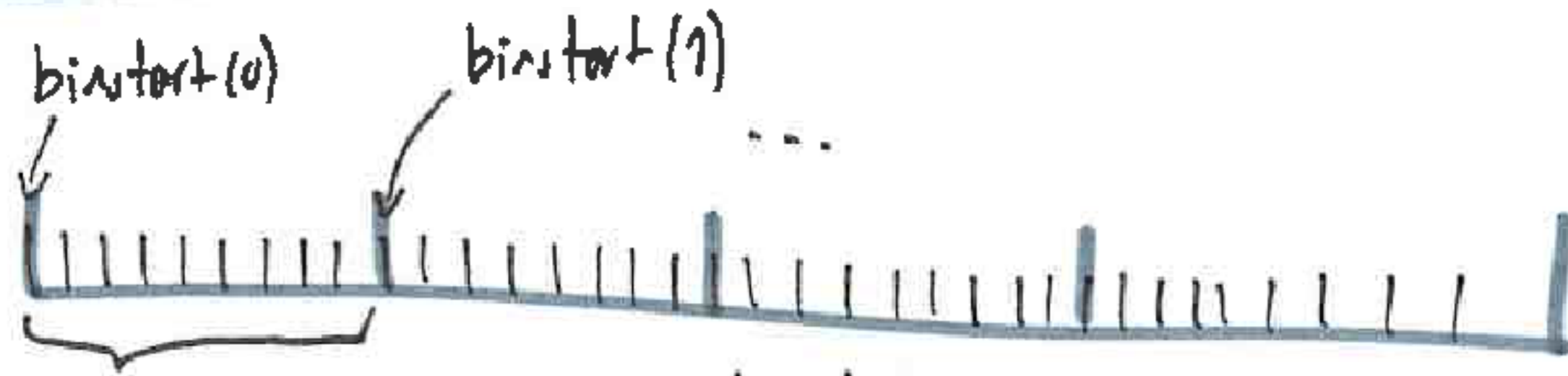
$$\text{assume } \tau_1 = T_{\text{exp}} > \tau_2 > \dots > \tau_K \gg 1$$

$$\sum_c c_n = 1 \quad \text{since } T(0) = 1$$

$$T_{\text{int}} \approx \sum_n c_n \tau_n < \tau_1 = T_{\text{exp}}$$

BINNING / DATA BUNCHING

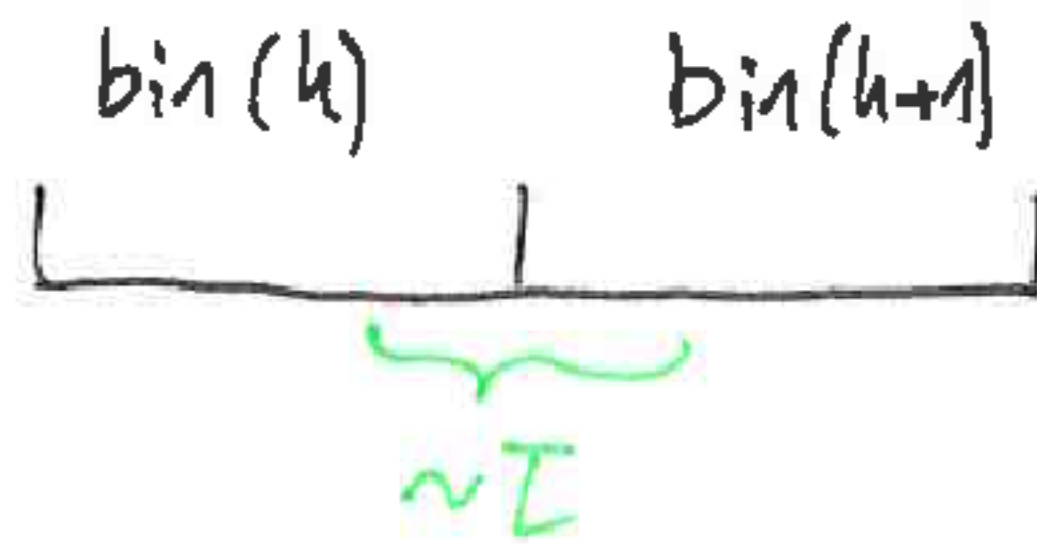
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$$O_{\text{bin average}}^{(k)} = \frac{1}{N_{\text{bin size}}} \sum_{i=\text{binstart}(k)}^{\text{binstart}+\text{bin size}-1} O_i$$

if $N_{\text{bin size}} \gg \tau_{\text{int}}$

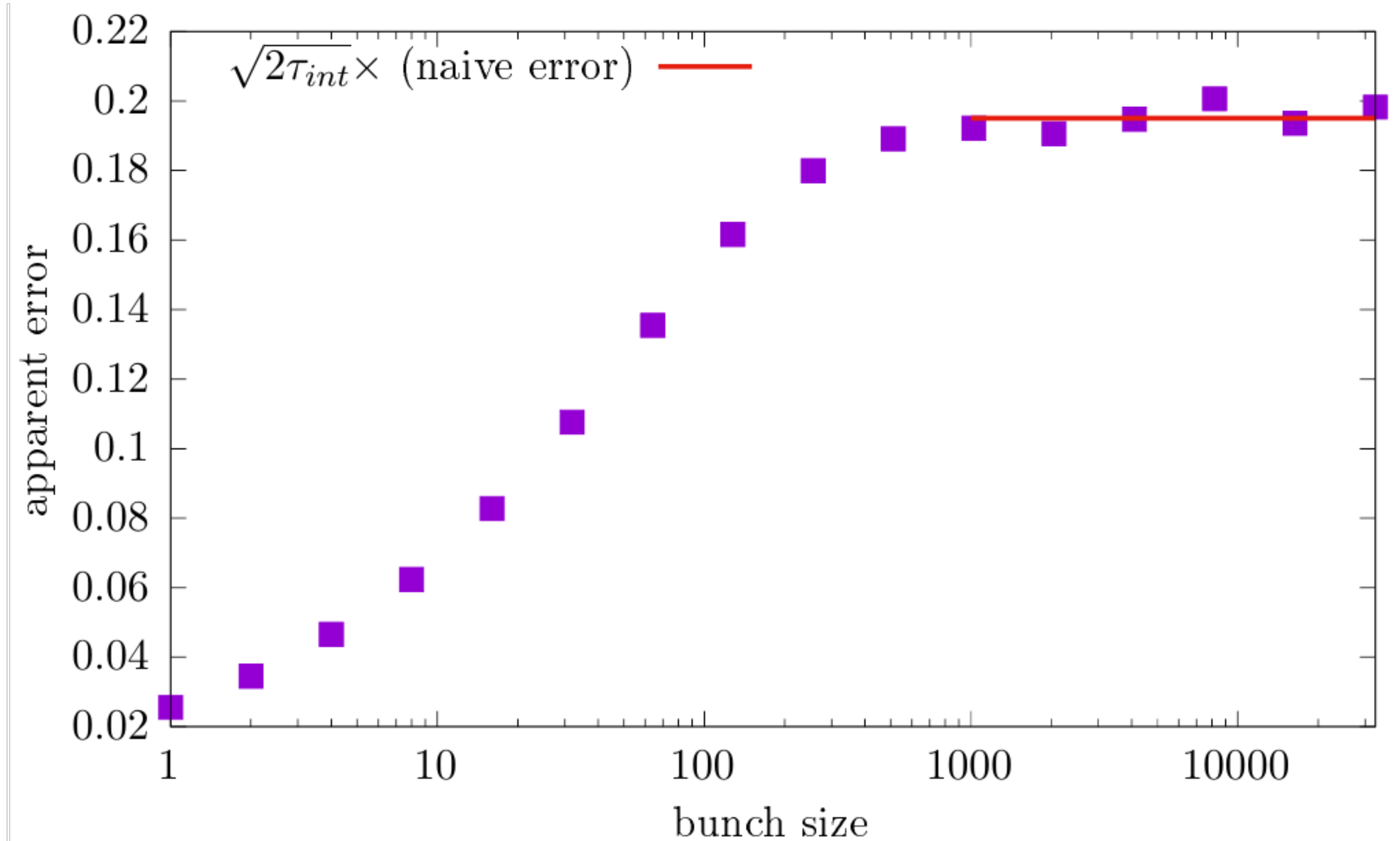
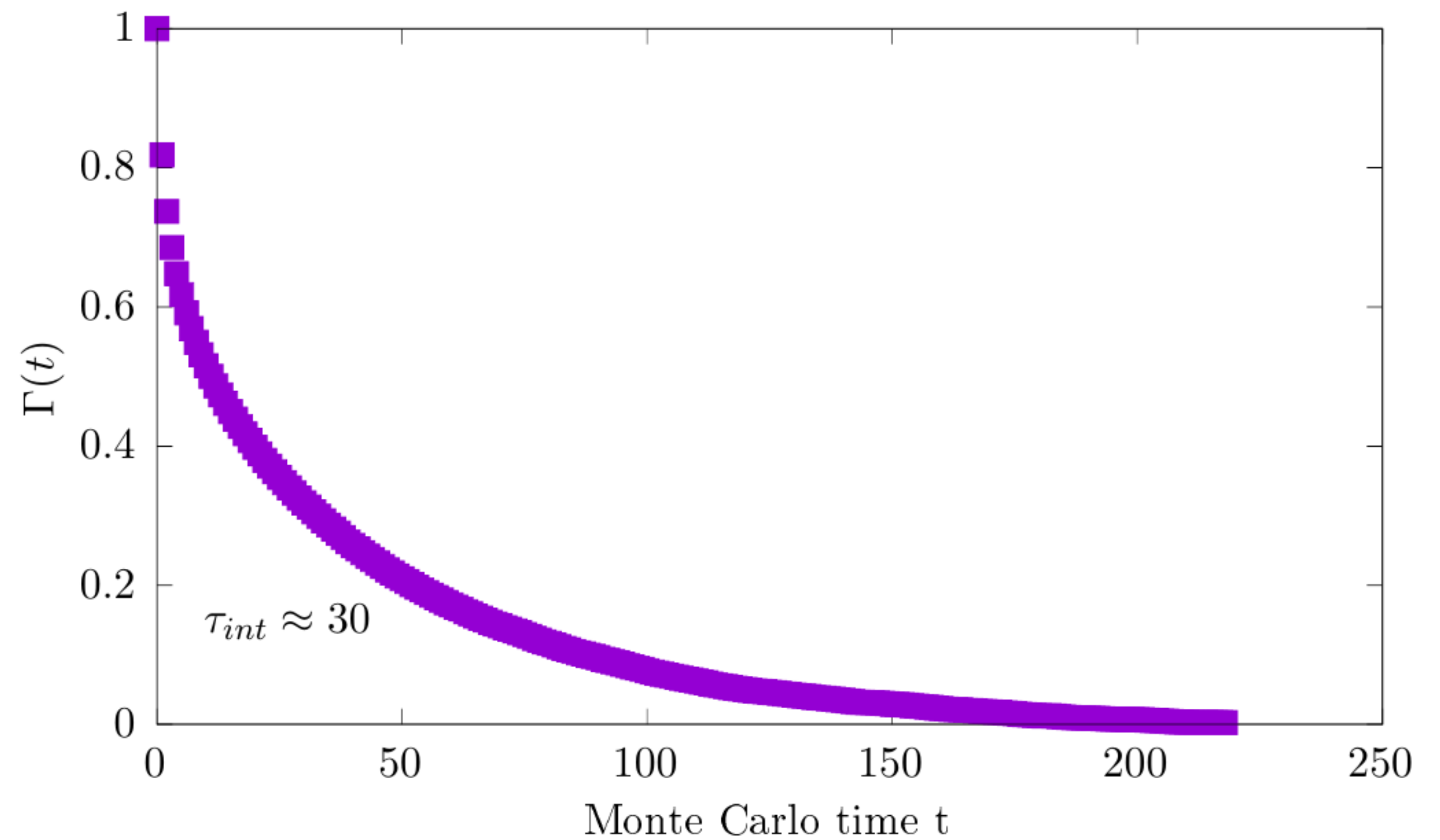
$\Rightarrow O_{\text{bin average}}^{(k)}$ are to a good approx. uncorrelated



simplest analysis method:

* make bins, pretend they are uncorrelated

* check what happens when you change the bin size



STRUCTURE OF A BASIC MC PROGRAM

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INITIALIZATION

- init. random num generator
- init. tables (e.g. neighbor indices)
- init. field configurations

LOOP OVER THERMALIZATION UPDATES

```
for (n=1 ... ntherm)  
  update confg  
end for
```

LOOP OVER MC UPDATES W. MEASUREMENTS

```
for (n=1 ... nmeasure)  
  for (k=1 ... ndiscarded)  
    update confg  
  end for
```

```
  measure observables (magnetization, correlation fns, ...) , write to output file  
end for  
write final confg & status of random generator for future restart
```

A SHORTCUT

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$$M_{\text{spontaneous}} = \lim_{H \rightarrow 0^+} \lim_{N_{\text{spins}} \rightarrow \infty} \frac{1}{N_{\text{spins}}} \langle M \rangle$$

$$N_{\text{spins}} = N$$

quite inconvenient, mostly not done (except for cases like spin glasses, where the ordering is hard to understand)

what can be done at $H=0$?

There are a few options

$$M_{\text{rms}} = \sqrt{\langle M^2 \rangle} \frac{1}{N}$$

$$M_{\parallel} = \langle |M| \rangle \frac{1}{N}$$

$$M_{\text{corr}} = \sqrt{\langle \sigma(1) \sigma(2) \rangle} \frac{1}{N}$$

in the thermodynamic limit all of these will agree

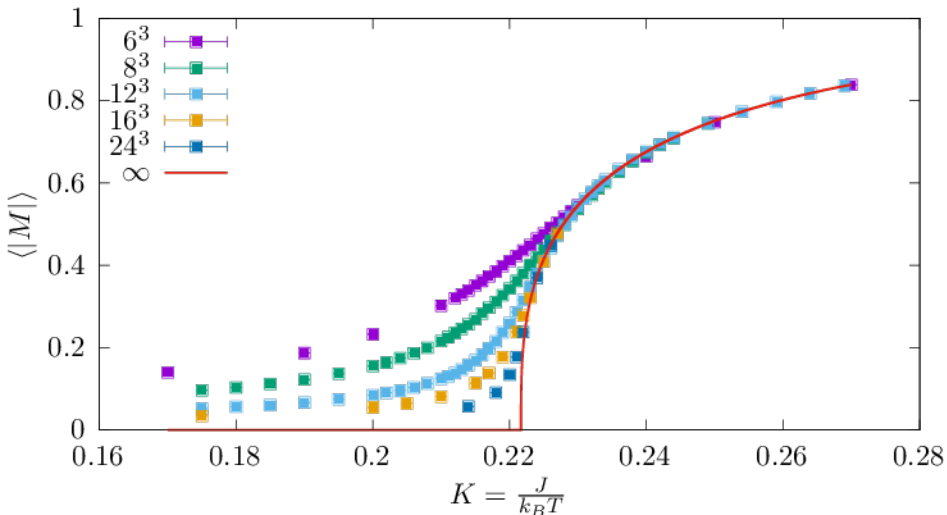
susceptibility: can use:

$$\chi_M = \frac{1}{N} (\langle M^2 \rangle - \langle M \rangle^2)$$

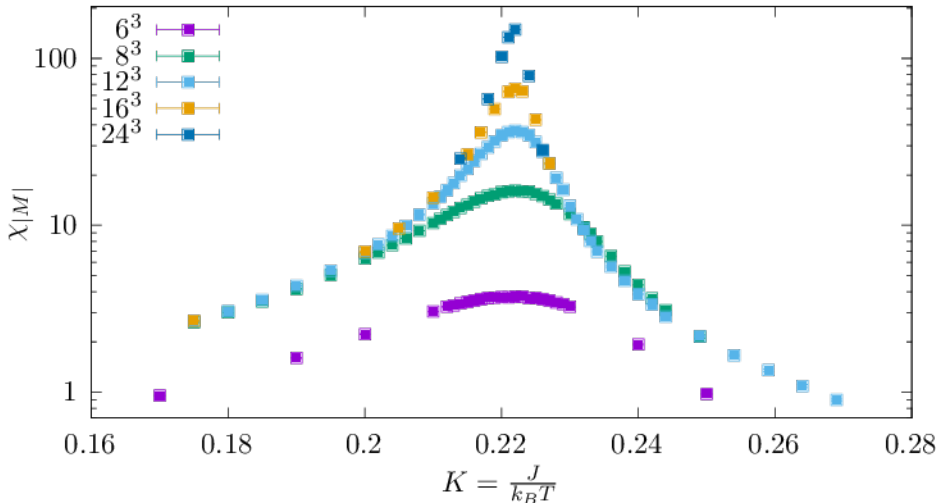
of course for the energy, can simply use

$$\chi_E = \frac{1}{N} (\langle E^2 \rangle - \langle E \rangle^2)$$

Magnetization of the 3D Ising model



Susceptibility of the 3D Ising model



FINITE-SIZE SCALING NEAR A 2ND ORDER PhTr

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suppose $\langle O \rangle_{\infty} \sim |t|^{-p}$ where $t = \frac{T-T_c}{T_c}$ reduced temperature

scaling ansatz:

$$\langle O \rangle_L \sim L^w \hat{f}_0(L/\xi)$$

$\hat{f}_0$ some function

i.e. finite volume effects are dictated by how many corr. lengths fit in a volume

$$\xi \sim |t|^{-\nu} \Leftrightarrow \text{def. of critical exponent } \nu \Rightarrow \frac{L}{\xi} \sim L t^{\nu} \sim (L^{1/\nu} t)^{\nu}$$

let $\hat{f}_0(L/\xi) = f_0(L^{1/\nu} t)$

in order for $\langle O_L \rangle \sim L^w f_0(L^{1/\nu} t) \sim t^{-p}$

we need $f_0(x) \sim x^{-c}$ (as $x \rightarrow \infty$) with $c = p$ so that we have t^{-p}

$$\Rightarrow \langle O_L \rangle \sim L^{\frac{p}{\nu}} f_0(L^{1/\nu} t)$$

and $w = \frac{p}{\nu}$ so that we have L^0

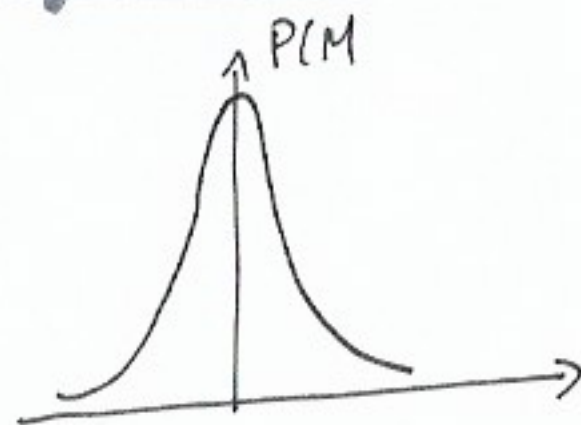
at the critical temperature ($t=0$) $\langle O_L \rangle \sim L^{p/\nu} \underbrace{f_0(0)}_{\text{number}}$

RULE OF THUMB if at $L=\infty$ $\langle O \rangle \sim |t|^{-p} \sim \xi^{p/\nu}$
 then at $L=\text{finite}$ and $t=0$ $\langle O \rangle_L \sim L^{p/\nu}$

PROBABILITY DISTR. OF THE ORDER PARAM. (M)

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symmetric phase



close to a Gaussian

variance $\sim$ susceptibility

near T_c

scaling ansatz

$$P(M, L) \approx L^a \hat{P}(L^b M, \frac{L}{\xi})$$

normalization

$$\int dM P(M, L) = 1$$

$$L^{a-b} \int dz \hat{P}(z, \frac{L}{\xi}) = 1$$

$$a=b$$

match def. of crit. exponents

$$T \rightarrow T_c^+$$

$$L d\chi = \int dM M^2 P(M, L)$$

$$= L^{-2a} \int dz z^2 \hat{P}(z, \frac{L}{\xi})$$

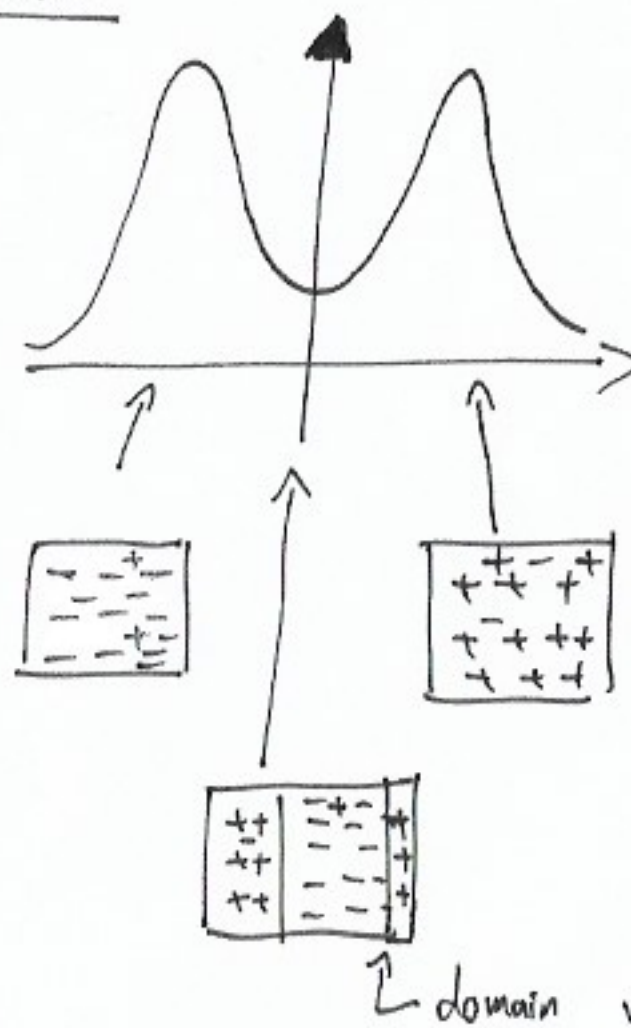
$$\sim L^{-2a} \sim L^{\frac{\sigma}{\nu} + d}$$

$$a = -\frac{1}{2} \left(\frac{\sigma}{\nu} + d \right)$$

$$\langle M^{2n} \rangle \sim L^{-2na}$$

broken phase

bimodal



$\uparrow$ domain wall

at large volumes turns to a double delta fn.

$$P(M) \approx \frac{1}{2} [\delta(M - M_0) + \delta(M + M_0)]$$

BINDER CUMULANT

$$\frac{\langle M^4 \rangle}{\langle M^2 \rangle^2} = B$$

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symmetric phase

$P(M)$ almost Gaussian

$\rightarrow 3$
 $L \rightarrow \infty$

at T_c

we expect

$\propto \text{const.}$

as a fn of volume
near T_c we expect

$$B \approx \frac{\int dz \hat{P}(z, L/\xi) z^4}{\left[\int dz \hat{P}(z, L/\xi) z^2 \right]^2}$$

$$= F(L/\xi) = F\left[L^{\frac{1}{\nu}}(K - K_c)\right]$$

broken phase

$$P(M) \approx \frac{1}{2} [\delta(M - M_0) + \delta(M + M_0)]$$

$\rightarrow 1$
 $L \rightarrow \infty$

