

统计物理与复杂系统暑期学校2015

郭文安

北京师范大学物理系

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参考文献:

- H.W.J. Blöte, Lecture notes: Nonlocal Monte carlo Methods
- A. Sandvik, Computational Studies of Quantum Spin Systems, AIP Conf. Proc. 1297, 135 (2010);

提纲

临界点的确定： Binder ratio

$$\text{Binder Ratio : } Q = \frac{\langle m^2 \rangle}{\langle |m| \rangle^2}, \text{ 或者, } Q = \frac{\langle m^4 \rangle}{\langle m^2 \rangle^2}$$

$$\chi = \frac{N}{T} (\langle m^2 \rangle - \langle m \rangle^2) \propto t^{-\gamma}$$

有限尺寸标度(finite-size scaling, 相变点以 L 代替 $\xi \propto t^{-\nu}$)

$$\chi(L, T_c) = \frac{N}{T} (\langle m^2 \rangle - \langle m \rangle^2) \propto L^{\gamma/\nu}$$

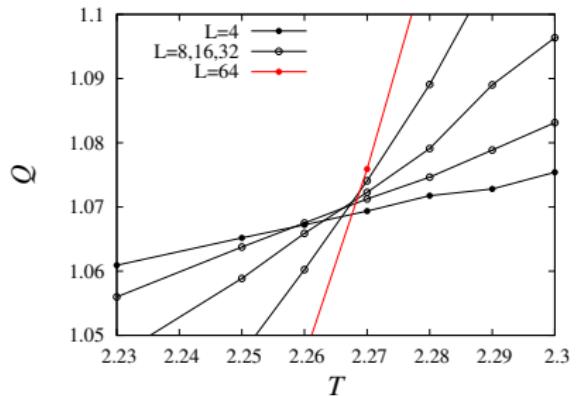
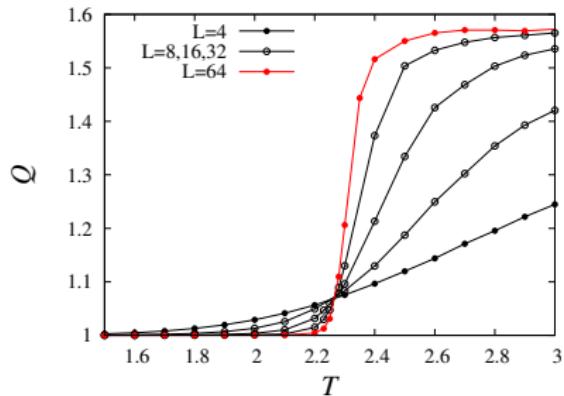
$$\langle m^2 \rangle \propto L^{\gamma/\nu-d} \quad \langle |m| \rangle \propto L^{\gamma/(2\nu)-d/2}$$

Q 在临界点与尺寸无关！

$Q \rightarrow 1$ 当 $T \rightarrow 0$; $Q \rightarrow constant$ 当 $T \rightarrow \infty$, 由于 m 的高斯分布

临界点的确定： Binder ratio

$$\text{Binder Ratio : } Q = \frac{\langle m^2 \rangle}{\langle |m| \rangle^2}$$



- 交点并不完全重合，由于**标度修正**：非关涉场，*RG*理论
- $L \rightarrow \infty$, 交点是真正的临界点
- 可以根据 $L, 2L$ 交点外推到 $L \rightarrow \infty$

自关联时间

设某个物理观测量在第 t MC步的值为 $Q(t)$

自关联函数测量它需要花多长‘时间’与之前数值独立?

$$A_Q(\Delta t) = \frac{\langle Q(t + \Delta t)Q(t) \rangle - \langle Q(t) \rangle^2}{\langle Q(t)^2 \rangle - \langle Q(t) \rangle^2}$$

一般满足

$$A_Q(\Delta t) \sim e^{-\Delta t/\tau}, \quad \tau \text{ 自关联时间}$$

Integrated autocorrelation time (决定独立样本数 $\approx n/(2\tau_{int})$)

$$\tau_{int} = \frac{1}{2} + \sum_{\Delta t=1}^{\infty} A_Q(\Delta t) \approx \tau$$

- 临界慢化(critical slowing down)

$\tau_{int} \propto \xi^z \rightarrow \infty$, 热力学极限下, 当 $T \rightarrow T_c$

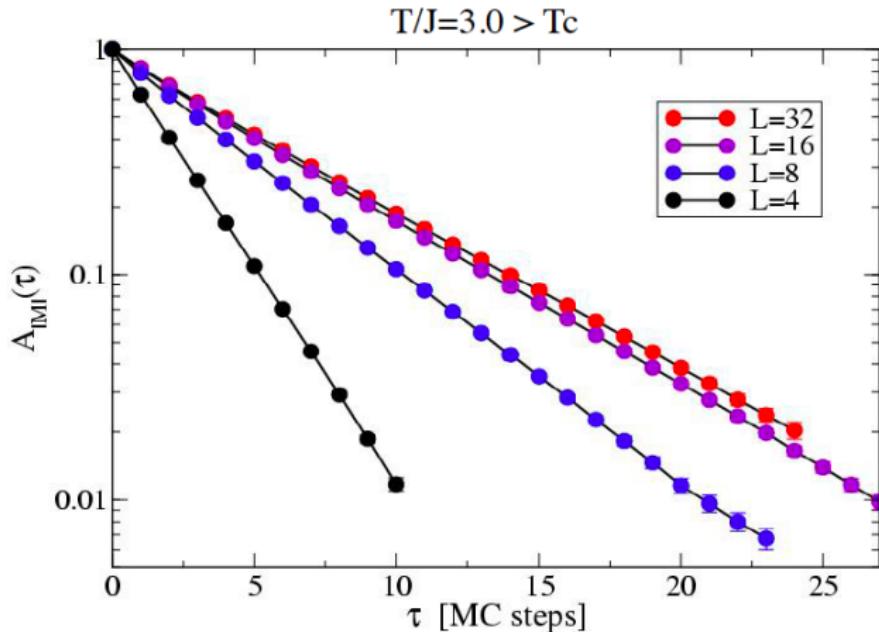
- 对于处于临界点 T_c 的有限尺寸系统, Q 为序参量

$$\tau_{int} \sim L^z,$$

z 动力学临界指数, 由实现平衡的动力学, 亦即算法, 决定!

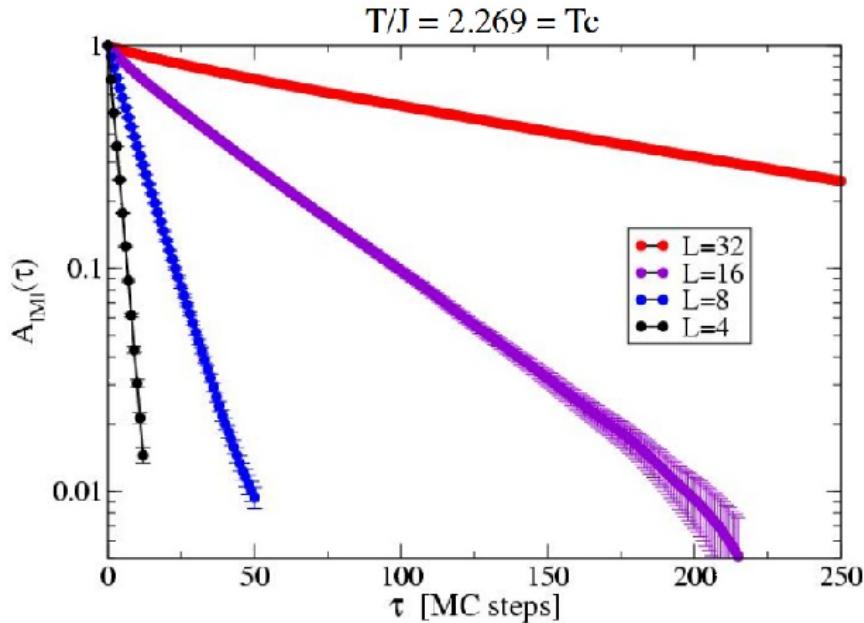
Metropolis算法的弱点, 考虑 $A_{|M|}(\Delta t)$

当温度高于 T_c



关联时间迅速收敛到与尺寸无关的值

Metropolis算法的弱点, 考虑 $A_{|M|}(\Delta t)$



$z \approx 2.2$: 对于局域算法(local algorithm), 由于每次尝试的 Γ' 与 Γ 相差很小(local 算法) 自关联时间很长

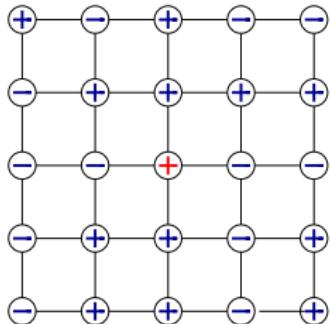
- 需要经过正比于 L^{d+z} 次操作后才可以得到一个独立的位形

Cluster algorithm: Wolff algorithm

在一步里翻转一个集团，而不是一个一个地翻 $N = L^d$ 次

步骤：

- 1 任意选取一个自旋 i

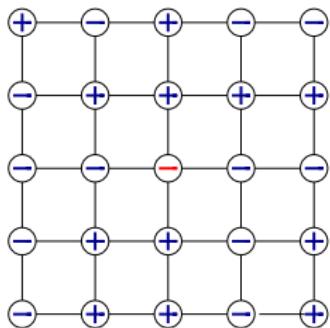


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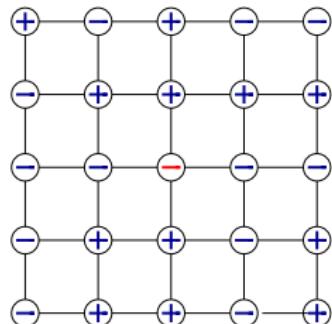
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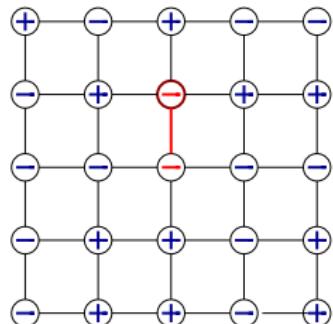


- 1 任意选取一个自旋*i*
- 2 翻转之: $s'_i = -s_i$
- 3 对*i*的所有最近邻*k*作如下操作:
 - 如果 $s_k = s_i$ 则以几率 $1 - e^{-2K}$,
 $K = J/k_B T$ 完成
 - i 翻转 $s_k \rightarrow s'_k = -s_k$.
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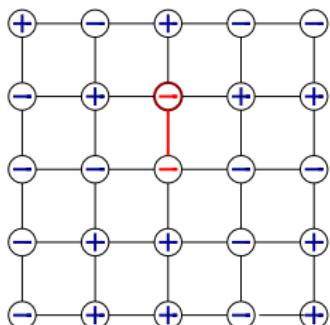
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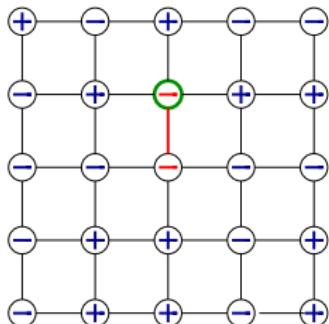
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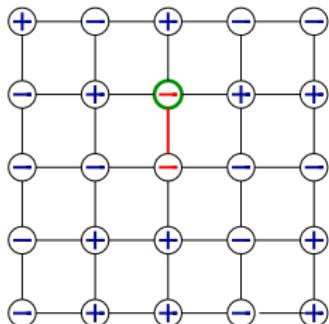


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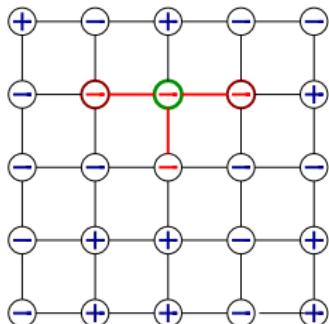


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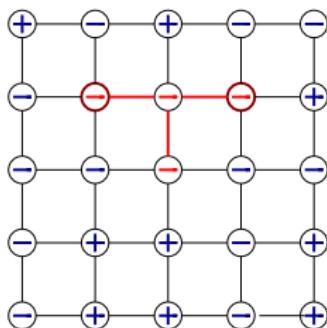


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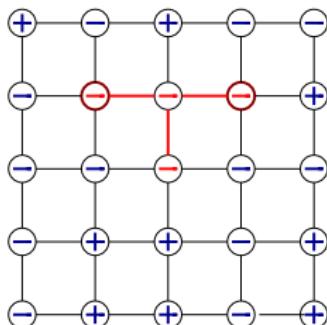


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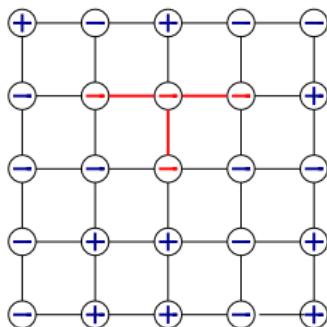


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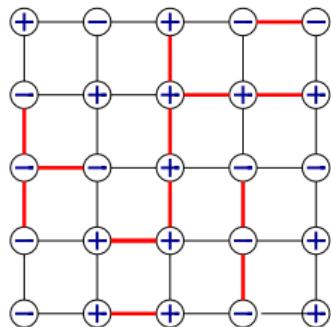
程序实现

```
s=rn()*n+1 !! rn()是随机数，随机选择一个自旋s (位置)
icsp=spin(s) !! icsp 是自旋s原来的状态
spin(s)=-icsp !! 翻转s
nstack=0 !! 堆栈里的成员数和当前成员标号
js=s !! 当前考虑的自旋 (位置)
104 continue
do 107 inb=1,4
  ks=nbor(inb,js) !! js 的4个邻居位置，事先算好保存在数组nbor中
  if ((spin(ks).eq.icsp).and.(rn().lt.bp)) then !! bp 是几率 $1 - e^{-2K}$ 
    nstack=nstack+1 !! ks 放入堆栈，成员数加一
    istn(nstack)=ks !! ks 是第nstack个成员，保存在数组istn中
    spin(ks)=-icsp !! 翻转ks
  endif
107 continue !! 完成对s 的4个邻居的操作
if (nstack.eq.0) goto 110 !! 堆栈里的成员处理完后，结束Wolff步骤
js=istn(nstack) !! 从堆栈中读取一个成员
nstack=nstack-1 !! 待操作的成员数减少一个
goto 104 !! 取处理当前成员
110 continue
```

为什么高效?

我们知道磁化率 $\chi = \frac{\langle (N_+ - N_-)^2 \rangle}{k_B TN}$, 即正比于磁矩的涨落

对同号自旋按几率 $1 - e^{-2K}$ 加棒连接, 一个自旋位形等价于一个
‘棒位形 + 集团符号’

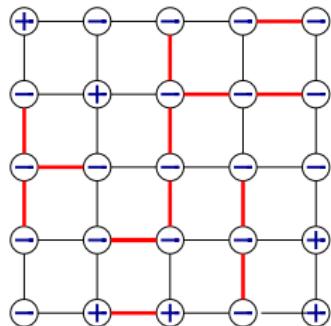


设棒位形有 M 个集团 $N_+ - N_- = \sum_{k=1}^M n_k \text{sig}_k$
可以证明:

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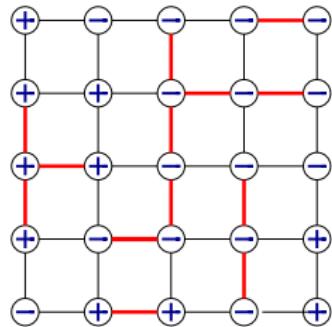


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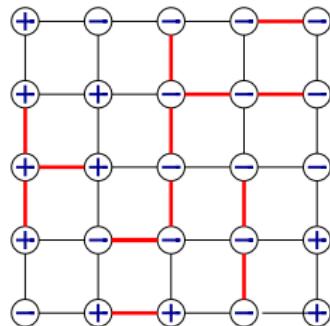


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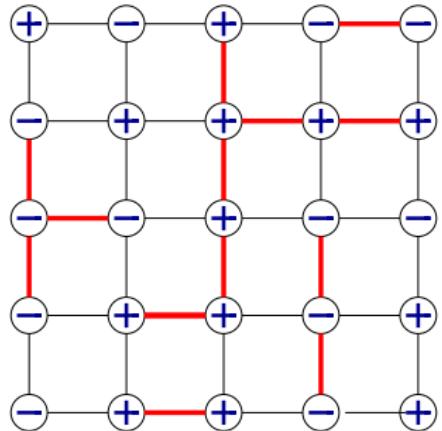


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可以证明:

$$\chi = \frac{1}{N} \langle \sum_k n_k^2 \rangle_B = \langle \sum_k \frac{n_k}{N} n_k \rangle_B$$

Wolff 算法随机选取一个自旋, 落在第 k 个集团的几率正是 n_k/N ,
所以平均 Wolff 集团的大小等于磁化率 χ !
或者说 Wolff 集团的大小是磁化率的 *estimator*!

为什么高效?



在临界点附近，我们知道 $\chi \propto t^{-\gamma} = \xi^{\gamma/\nu}$
对于有限尺寸系统，以 L 代替 ξ

$$\chi \propto L^{\gamma/\nu}$$

对于 2D Ising: $\gamma = 7/4, \nu = 1$ 集团大小随尺寸 L 发散！
一个 Wolff 集团翻转就可以在很大程度上改变位形！
动力学临界指数非常小！

细致平衡的证明

定义 $P(C, \Gamma)$ 为形成 C 内部连接棒位形的几率. 设边界棒(一端属于 C , 另一端不属于)的数目为 $n = n_a + n_p$, n_a 是两端自旋反号的棒数, n_p 是同号的棒数.

将同号自旋排除在 C 之外的几率: e^{-2Kn_p} , 反号自旋以几率 1 排除

将 C 翻转得到新位形, 整个过程的几率

$$T(\Gamma', \Gamma) = e^{-2Kn_p} P(C, \Gamma) \frac{1}{N}.$$

反之, 计算从 Γ' 到 Γ 的几率

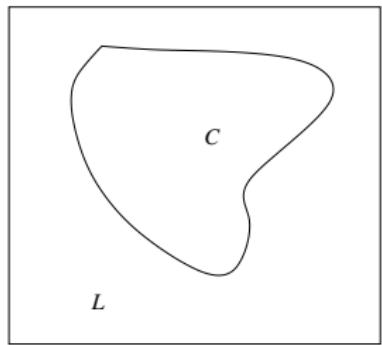
$$T(\Gamma, \Gamma') = e^{-2Kn_a} P(C, \Gamma') \frac{1}{N}.$$

注意到内部连接几率不变

$$P(C, \Gamma) = P(C, \Gamma').$$

因此

$$T(\Gamma', \Gamma) = e^{2K(n_a - n_p)} T(\Gamma, \Gamma').$$



C 表示 Wolff 集团, 是晶格 L 的子集

细致平衡的证明

由于集团的翻转只改变边界的相互作用能，

$$P_{\text{eq}}(\Gamma)/P_{\text{eq}}(\Gamma') = e^{-(E(\Gamma)-E(\Gamma'))/k_B T} = e^{2(n_p-n_a)K}$$

因此

$$P_{\text{eq}}(\Gamma)T(\Gamma', \Gamma) = P_{\text{eq}}(\Gamma')T(\Gamma, \Gamma')$$

魔术的秘诀在哪里？

配分函数

$$Z = \sum_S W(S), \quad S \text{是自旋位形}$$

连接棒之后

$$Z = \sum_{S,B} W(S)P(B|S) \equiv \sum_{S,B} W(S,B)$$

这里利用了从 S 生成棒位形 B 的几率 $P(B|S)$ 是归一的：

$$\sum_B P(B|S) = 1$$

位形空间多了一个维度 B ，而配分函数不变！

- 集团算法把 $\Gamma = \{S, B\} \rightarrow \Gamma' = \{S', B\}$
- 由于上页实际证明了 $W(S, B) = W(S', B)$, 所以这个 $S \rightarrow S'$ 的跃迁几率是 $T(\Gamma', \Gamma) = 1$.
- 哲学就是“高一维”的位形空间里两个等几率的位形，可以轻松互相跃迁，而其自旋位形相差很大！

好比开通了‘空中航线’

Cluster algorithm: Swendsen-Wang algorithm

与Wolff算法非常接近

- 1 从自旋位形开始
- 2 构造集团：与Wolff 算法一样，但是找到所有集团
- 3 以 $1/2$ 几率翻转集团
- 4 回到[1]

Swendsen-Wang

Swendsen-Wang

Swendsen-Wang

概述

The Metropolis algorithm can be used for any system

- ▶ Critical slowing down can be serious
- ▶ The dynamics can be slow also in non-critical systems, e.g., glassy system.

Cluster algorithms

- ▶ other versions, e.g., Geometry cluster
- ▶ not working for
 - ▶ Magnets with frustration: clusters span the whole system before reaching critical point
 - ▶ Magnets in external magnetic fields
 - ▶ Most systems of particles in continuous space, no way to construct clusters in general.

提纲

基本想法

Thermal expectation value of a quantum system

$$\langle A \rangle = \frac{1}{Z} \text{Tr}\{A e^{-\beta H}\}, \quad Z = \text{Tr}e^{-\beta H}$$

We don't know the eigenvalues and eigenstates of H .

We wish to write

$$\langle A \rangle = \sum_{\Gamma} A(\Gamma) \frac{W(\Gamma)}{Z}$$

where

$$Z = \sum_{\Gamma} W(\Gamma)$$

Then we can apply the basic idea of Monte Carlo: importance sampling

$$\langle A \rangle = \frac{1}{M} \sum_{l=1}^M A(\Gamma_l)$$

Path integral representation

Path integrals in quantum statistical mechanics

"Time slicing" of the partition function

$$Z = \text{Tr}\{\text{e}^{-\beta H}\} = \text{Tr}\left\{\prod_{l=1}^L \text{e}^{-\Delta_\tau H}\right\}, \quad \Delta_\tau = \beta/L$$

Choose a basis and insert complete sets of states

$$Z = \sum_{\alpha_0} \sum_{\alpha_1} \cdots \sum_{\alpha_{L-1}} \langle \alpha_0 | \text{e}^{-\Delta_\tau H} | \alpha_{L-1} \rangle \cdots \langle \alpha_2 | \text{e}^{-\Delta_\tau H} | \alpha_1 \rangle \langle \alpha_1 | \text{e}^{-\Delta_\tau H} | \alpha_0 \rangle$$

Approximation;

$$Z \approx \sum_{\{\alpha\}} \langle \alpha_0 | 1 - \Delta_\tau H | \alpha_{L-1} \rangle \cdots \langle \alpha_2 | 1 - \Delta_\tau H | \alpha_1 \rangle \langle \alpha_1 | 1 - \Delta_\tau H | \alpha_0 \rangle$$

Leads to error $\propto \Delta_\tau^2$. Limit $\Delta_\tau \rightarrow 0$ can be taken.

Example: hard-core bosons

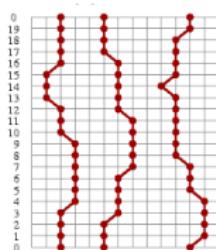
$$H = - \sum_{\langle i,j \rangle} K_{ij} = - \sum_{\langle i,j \rangle} (a_j^\dagger a_i + a_i^\dagger a_j) \quad n_i = a_i^\dagger a_i \in \{0,1\}$$

Equivalent to $S = 1/2$ XY model

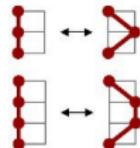
$$H = -2 \sum_{\langle i,j \rangle} (S_i^x S_j^x + S_i^y S_j^y) = - \sum_{\langle i,j \rangle} (S_i^+ S_j^- + S_i^- S_j^+), \quad S^z = \pm \frac{1}{2}$$

"World line" representation of

$$Z \approx \sum_{\{\alpha\}} \langle \alpha_0 | 1 - \Delta_\tau H | \alpha_{L-1} \rangle \cdots \langle \alpha_2 | 1 - \Delta_\tau H | \alpha_1 \rangle \langle \alpha_1 | 1 - \Delta_\tau H | \alpha_0 \rangle$$



World line moves for MC updating



$$Z = \sum_{\{\alpha\}} W(\{\alpha\}), \quad W(\{\alpha\}) = \Delta_\tau^{n_K}, \quad n_K = \text{number of "jumps"}$$

Expectation values

目标是计算 $\langle A \rangle$, 可写为

$$\langle A \rangle = \frac{1}{Z} \sum_{\{\alpha\}} \langle \alpha_0 | e^{-\Delta_\tau H} | \alpha_{L-1} \rangle \cdots \langle \alpha_2 | e^{-\Delta_\tau H} | \alpha_1 \rangle \langle \alpha_1 | e^{-\Delta_\tau H} A | \alpha_0 \rangle$$

我们把它写成适合MC importance sampling

$$\boxed{\langle A \rangle = \frac{\sum_{\{\alpha\}} A(\{\alpha\}) W(\{\alpha\})}{\sum_{\{\alpha\}} W(\{\alpha\})} = \langle A(\{\alpha\}) \rangle_W}$$

$W(\{\alpha\}) = \text{weight}$; $A(\{\alpha\}) = \text{estimator}$

- ▶ 对角算符(物理量): 粒子数, s_z ,

$$\boxed{A(\{\alpha\}) = \frac{1}{L} \sum_{l=0}^{L-1} A(\alpha_l)}$$

Expectation values

目标是计算 $\langle A \rangle$, 可写为

$$\langle A \rangle = \frac{1}{Z} \sum_{\{\alpha\}} \langle \alpha_0 | e^{-\Delta_\tau H} | \alpha_{L-1} \rangle \cdots \langle \alpha_2 | e^{-\Delta_\tau H} | \alpha_1 \rangle \langle \alpha_1 | e^{-\Delta_\tau H} A | \alpha_0 \rangle$$

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$W(\{\alpha\})$ = **weight**; $A(\{\alpha\})$ = **estimator**

- 非对角算符: Kinetic energy, Quantum Mechanics!

利用 $K e^{-\Delta_\tau K} \approx K$, 构造一个estimator $A(\{\alpha\})$!

$$\boxed{K_{ij}(\{\alpha\}) = \frac{\langle \alpha_1 | K_{ij} | \alpha_0 \rangle}{\langle \alpha_1 | 1 - \Delta_\tau K | \alpha_0 \rangle} \in \{0, \frac{1}{\Delta_\tau}\}}$$

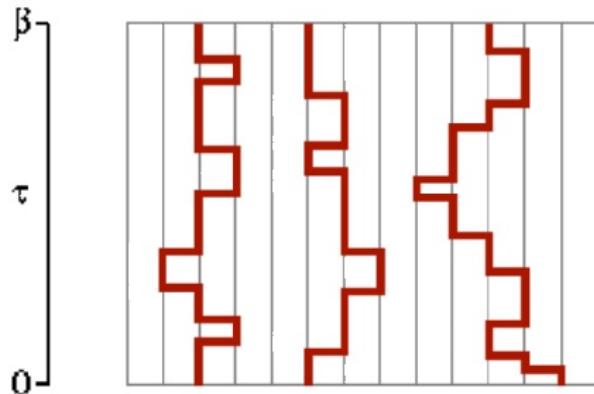
Average over all slices: count number of kinetic jumps

$$\langle K_{ij} \rangle = \frac{n_{ij}}{\beta}, \quad \langle K \rangle = -\frac{\langle n_K \rangle}{\beta} \quad \text{利用了} \Delta_\tau = \beta/L$$

$\langle K \rangle \propto N \rightarrow \langle n_K \rangle \propto \beta N$: There should be of the order βN

The continuous time limit

$\Delta\tau \rightarrow 0$: number of kinetic jumps remains finite, store events only



Worm updates, Prokofev et al (1996);
loop update, Evertz, Lana, Marcu (1993);

Stochastic Series Expansion

Quantum Monte Carlo method

Series expansion representation

Taylor expansion $e^{-\beta H} = \sum_n^\infty \frac{(-\beta)^n}{n!} H^n$

$$Z = \sum_{n=0}^{\infty} \frac{(-\beta)^n}{n!} \sum_{\{\alpha\}_n} \langle \alpha_0 | H | \alpha_{n-1} \rangle \cdots \langle \alpha_2 | H | \alpha_1 \rangle \langle \alpha_1 | H | \alpha_0 \rangle$$

Similar to the path integral!

For hard-core bosons, the allowed path weights is $W(\text{path}) = \beta^n / n!$

Series expansion representation

Taylor expansion $e^{-\beta H} = \sum_n^\infty \frac{(-\beta)^n}{n!} H^n$

$$Z = \sum_{n=0}^{\infty} \frac{(-\beta)^n}{n!} \sum_{\{\alpha\}_n} \langle \alpha_0 | H | \alpha_{n-1} \rangle \cdots \langle \alpha_2 | H | \alpha_1 \rangle \langle \alpha_1 | H | \alpha_0 \rangle$$

For any model,

$$E = \frac{1}{Z} \sum_{n=0}^{\infty} \frac{(-\beta)^n}{n!} \sum_{\{\alpha\}_{n+1}} \langle \alpha_0 | H | \alpha_n \rangle \cdots \langle \alpha_2 | H | \alpha_1 \rangle \langle \alpha_1 | H | \alpha_0 \rangle$$

$$= \frac{1}{Z} \sum_{n=0}^{\infty} \frac{(-\beta)^n}{n!} \frac{n}{\beta} \sum_{\{\alpha\}_n} \langle \alpha_0 | H | \alpha_{n-1} \rangle \cdots \langle \alpha_2 | H | \alpha_1 \rangle \langle \alpha_1 | H | \alpha_0 \rangle$$

$$Z = \sum_{\Gamma} W(\Gamma), \quad \Gamma \text{ 由 } \{\alpha\}_n \text{ 决定}, E = \frac{\sum_{\Gamma} \frac{n}{\beta} W(\Gamma)}{\sum_{\Gamma} W(\Gamma)} = \frac{\langle n \rangle}{\beta}$$

Series expansion representation

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$$Z = \sum_{n=0}^{\infty} \frac{(-\beta)^n}{n!} \sum_{\{\alpha\}_n} \langle \alpha_0 | H | \alpha_{n-1} \rangle \cdots \langle \alpha_2 | H | \alpha_1 \rangle \langle \alpha_1 | H | \alpha_0 \rangle$$

$$Z = \sum_{\Gamma} W(\Gamma), \quad \Gamma \text{ 由 } \{\alpha\}_n \text{ 决定}, E = \frac{\sum_{\Gamma} \frac{n}{\beta} W(\Gamma)}{\sum_{\Gamma} W(\Gamma)} = \frac{\langle n \rangle}{\beta}$$

similarly,

$$C = \langle n^2 \rangle - \langle n \rangle^2 - \langle n \rangle$$

Narrow n-distribution with $\langle n \rangle \approx N\beta, \sigma_n \approx \sqrt{N\beta}$

So, fix length of expansion: cut-off at L and fill in with unit operators
 $H_0 = 1$

$$Z = \sum_{\{\alpha\}_L} \sum_{\{H_i\}} \frac{(-\beta)^n (L-n)!}{L!} \langle \alpha_0 | H_{i(L)} | \alpha_{L-1} \rangle \cdots \langle \alpha_2 | H_{i(2)} | \alpha_1 \rangle \langle \alpha_1 | H_{i(1)} | \alpha_0 \rangle$$

n is the number of H_i with $i > 0$ in the sequence of L operators

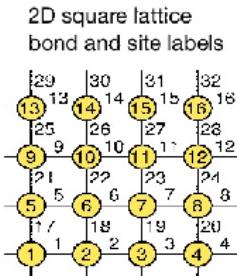
Stochastic Series expansion(SSE): $s = \frac{1}{2}$ Heisenberg model

Write H as a bond sum for arbitrary lattice

$$H = J \sum_{b=1}^{N_b} \mathbf{S}_{i(b)} \cdot \mathbf{S}_{j(b)}$$

Diagonal(1) and off-diagonal (2) bond operators

$$H_{1,b} = \frac{1}{4} - \mathbf{S}_{i(b)}^z \mathbf{S}_{j(b)}^z$$
$$H_{2,b} = \frac{1}{2} (\mathbf{S}_{i(b)}^+ \mathbf{S}_{j(b)}^- + \mathbf{S}_{i(b)}^- \mathbf{S}_{j(b)}^+)$$



$$H = -J \sum_{b=1}^{N_b} (H_{1,b} - H_{2,b}) + \frac{J N_b}{4}$$

Four Non-zero matrix elements= 1/2

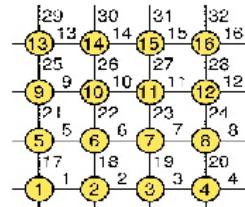
$$\langle \uparrow_i \downarrow_j | H_{1,b} | \uparrow_i \downarrow_j \rangle \quad \langle \downarrow_i \uparrow_j | H_{2,b} | \uparrow_i \downarrow_j \rangle \quad \langle \downarrow_i \uparrow_j | H_{1,b} | \downarrow_i \uparrow_j \rangle \quad \langle \uparrow_i \downarrow_j | H_{2,b} | \downarrow_i \uparrow_j \rangle$$

Stochastic Series expansion(SSE): $s = \frac{1}{2}$ Heisenberg model

Write H as a bond sum for arbitrary lattice

$$H = J \sum_{b=1}^{N_b} \mathbf{S}_{i(b)} \cdot \mathbf{S}_{j(b)}$$

2D square lattice
bond and site labels



Four Non-zero matrix elements= 1/2

$$\langle \uparrow_i \downarrow_j | H_{1,b} | \uparrow_i \downarrow_j \rangle \quad \langle \downarrow_i \uparrow_j | H_{2,b} | \uparrow_i \downarrow_j \rangle \quad \langle \downarrow_i \uparrow_j | H_{1,b} | \downarrow_i \uparrow_j \rangle \quad \langle \uparrow_i \downarrow_j | H_{2,b} | \downarrow_i \uparrow_j \rangle$$

Partition function

$$Z = \sum_{\alpha} \sum_{n=0}^{\infty} (-1)^{n_2} \frac{\beta^n}{n!} \sum_{S_n} \langle \alpha | \prod_{p=0}^{n-1} H_{a(p), b(p)} | \alpha \rangle = \sum_{\Gamma} W(\Gamma)$$

n_2 = number of off-diagonal op.

Configuration Γ : $|\alpha\rangle, S_n$: $a(p) = 1, 2; b(p) = b$

For fixed-length scheme

$$Z = \sum_{\alpha} \sum_{S_L} (-1)^{n_2} \frac{\beta^n (L-n)!}{L!} \langle \alpha | \prod_{p=0}^{L-1} H_{a(p), b(p)} | \alpha \rangle$$

State propagate $|\alpha(p)\rangle = \prod_{i=0}^{p-1} H_{a(i), b(i)} |\alpha\rangle$

$$\begin{array}{cccccccc} i & = & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\ \sigma(i) & = & -1 & +1 & -1 & -1 & +1 & -1 & +1 & +1 \end{array}$$

	p	$a(p)$	$b(p)$	$s(p)$
	11	1	2	4
	10	0	0	0
	9	2	4	9
	8	2	6	13
	7	1	3	6
	6	0	0	0
	5	0	0	0
	4	1	2	4
	3	2	6	13
	2	0	0	0
	1	2	4	9
	0	1	7	14

- n_2 is even for bipartite lattice!
- $s(p)$ = operator-index string
 - $s(p) = 2 * b(p) + a(p) - 1$
 - diagonal $s(p) = \text{even}$
 - off-diagonal $s(p) = \text{odd}$
- $\sigma(i)$ = spin state, $i = 1, \dots, N$
 - only one has to be stored

SSE: an effective discrete representation

Monte Carlo updating scheme

$$W(\alpha, S_L) = \left(\frac{\beta}{2}\right)^n \frac{(L-n)!}{L!}$$

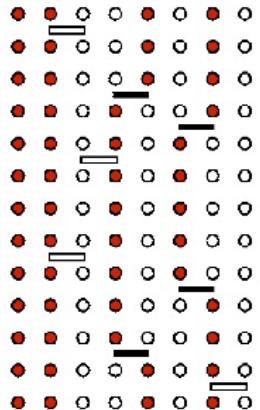
Change the configuration; $(\alpha, S_L) \rightarrow (\alpha', S'_L)$

$$P_{accept} = \min\left[\frac{W(\alpha', S'_L)}{W(\alpha, S_L)} \frac{P_{select}(\alpha', S'_L)}{P_{select}(\alpha, S_L)}, 1\right]$$

- Diagonal update: $[0, 0]_p \leftrightarrow [1, b]_p$



- Attempt at every p , need to know $|\alpha(p)\rangle$
(如果棒两端自旋同号, 不能加棒)
generated by flipping spins when off-diag op.



Monte Carlo updating scheme

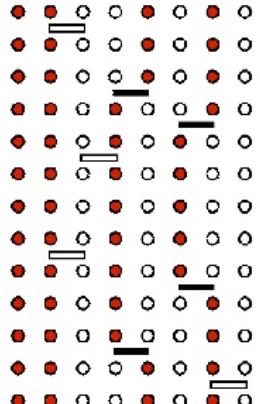
$$W(\alpha, S_L) = \left(\frac{\beta}{2}\right)^n \frac{(L-n)!}{L!}$$

Change the configuration; $(\alpha, S_L) \rightarrow (\alpha', S'_L)$

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- Diagonal update: $[0, 0]_p \leftrightarrow [1, b]_p$

$$\begin{array}{c|ccccc} & \cdots & \cdots & \cdots & \cdots & \cdots \\ \text{[0](p+1)} & \bullet & \circ & \circ & \bullet & \circ \\ \text{[0](p)} & \bullet & \circ & \circ & \circ & \bullet \end{array} \leftrightarrow \begin{array}{c|ccccc} & \cdots & \cdots & \cdots & \cdots & \cdots \\ \text{[1](p+1)} & \bullet & \circ & \circ & \bullet & \circ \\ \text{[1](p)} & \bullet & \circ & \circ & \circ & \bullet \end{array}$$



$n \rightarrow$ current power,

$$P_{select}(a = 0 \rightarrow a = 1) = 1/N_b, P_{select}(a = 1 \rightarrow a = 0) = 1$$

$$\frac{W(a=1)}{W(a=0)} = \frac{\beta/2}{L-n}, \quad \frac{W(a=0)}{W(a=1)} = \frac{L-n+1}{\beta/2},$$

acceptance prob.

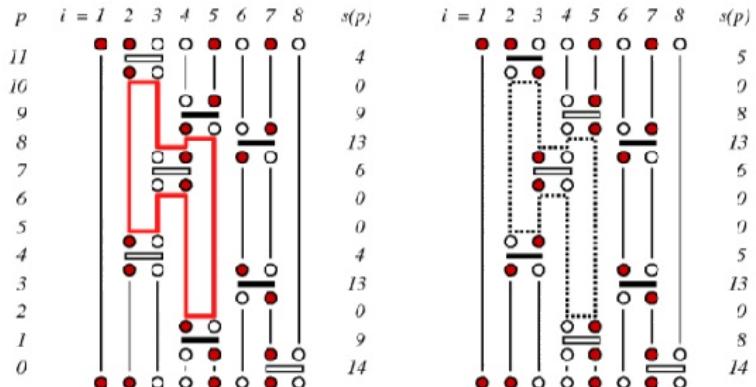
$$P_{accept}([0, 0] \rightarrow [1, b]) = \min\left[\frac{\beta N_b}{2(L-n)}, 1\right]$$

$$P_{accept}([1, b] \rightarrow [0, 0]) = \min\left[\frac{2(L-n+1)}{\beta N_b}, 1\right]$$

- ▶ $n \rightarrow n + 1$
 $(a = 0 \rightarrow a = 1)$
- ▶ $n \rightarrow n - 1$
 $(a = 1 \rightarrow a = 0)$

- 对角演化不会改变非对角算符, 非遍历!
- 我们需要另外的方式来实现非对角算符($\Gamma \iff \Gamma'$) 对角算符
- 考虑到这一过程中位形权重不变, 可以实现非常简单的集团算法: loop update

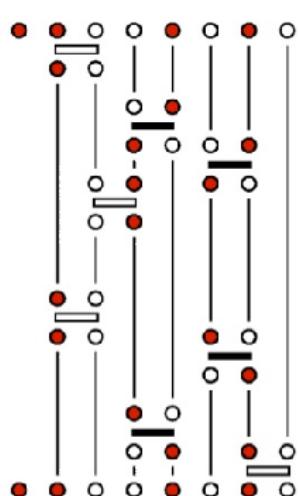
$$W(\Gamma = \{\alpha, S_L\}) = W(\Gamma' = \{\alpha', S'_L\}) = \left(\frac{\beta}{2}\right)^n \frac{(L-n)!}{L!}$$



Operator-loop update

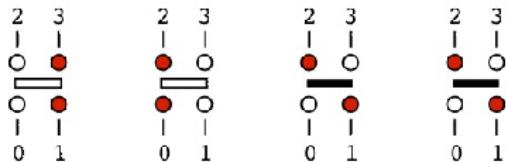
Linked vertex storage

Legs of a vertex represents the spin states before and after an operator has acted



p	$v X(v)$	$v X(v)$	$v X(v)$	$v X(v)$
11	44 18	45 30	46 16	47 17
10	40 -	41 -	42 -	43 -
9	36 31	37 7	38 4	39 5
8	32 14	31 15	34 12	35 0
7	28 19	29 6	30 45	31 36
6	24 -	25 -	26 -	27 -
5	20 -	21 -	22 -	23 -
4	16 46	17 47	18 44	19 28
3	12 34	13 2	14 32	15 33
2	8 -	9 -	10 -	11 -
1	4 38	5 39	6 29	7 37
0	0 35	1 3	2 13	3 1

$l=0$ $l=1$ $l=2$ $l=3$



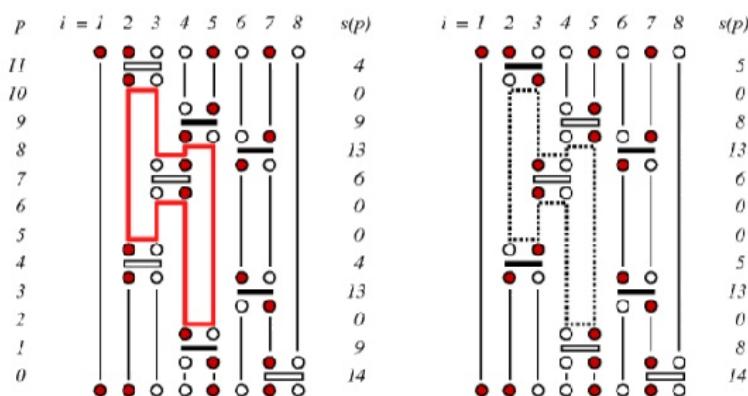
$X()$: vertex list

- operator at $p \rightarrow X(v)$
 $v = 4p + l, l = 0, 1, 2, 3$
- links to next and previous leg

Spin states between operations are represented by links
network of linked vertices will be used for loop updates of operator strings

Operator-loop update

Many spins and operators can be changed simultaneously



Use link $X(v)$
moving horizontally
corresponds to changing v
even \leftrightarrow odd
Label vertices

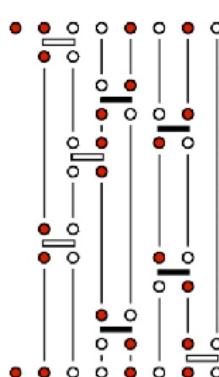
- ▶ a given loop is only constructed once
- ▶ $X(v) = -2$: flipped loop
- ▶ $X(v) = -1$: not flipped loop

constructing all loops, flip with probability 1/2; save the changed $s(p)$

modify the stored spin state

使用数组跟踪连接每个自旋的第一条腿和最后一条腿

- ▶ $V_{\text{first}}(i) = \text{location } v \text{ of first leg on site } i$
- ▶ $V_{\text{last}}(i) = \text{location } v \text{ of last (currently) leg}$
- ▶ initialize all elements to -1



p	$v X(v)$	$v X(v)$	$v X(v)$	$v X(v)$
11	44 18	45 30	46 16	47 17
10	40 -	41 -	42 -	43 -
9	36 31	37 7	38 4	39 5
8	32 14	31 15	34 12	35 0
7	28 19	29 6	30 45	31 36
6	24 -	25 -	26 -	27 -
5	20 -	21 -	22 -	23 -
4	16 46	17 47	18 44	19 28
3	12 34	13 2	14 32	15 33
2	8 -	9 -	10 -	11 -
1	4 38	5 39	6 29	7 37
0	0 35	1 3	2 13	3 1

$l=0$ $l=1$ $l=2$ $l=3$

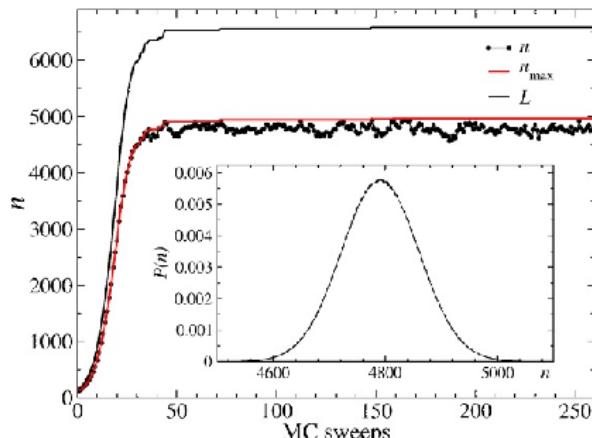
- ▶ spins with no operators, $V_{\text{first}} = -1$, flipped with probability $1/2$
- ▶ if $X(V_{\text{first}}(i)) = -2$, flip it
- ▶ if $X(V_{\text{first}}(i)) = -1$, no operation

Determination of the cut-off L

Adjust during equilibration

- ▶ start with arbitrary (small) n
- ▶ Keep track of number of operators n
 - ▶ increase L if n is close to current L : $L = \frac{4}{3}n$

- Example: 16×16 system, $\beta = 16$
 - evolution of L
 - n distribution after equilibration



程序下载

Anders Sandvik 提供了

A basic SSE program (Fortran 90) for the 2D Heisenberg model

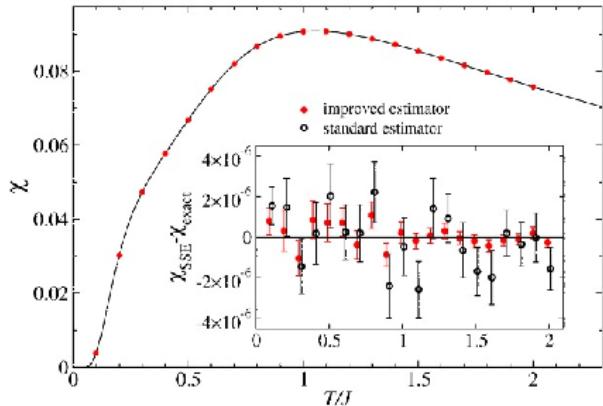
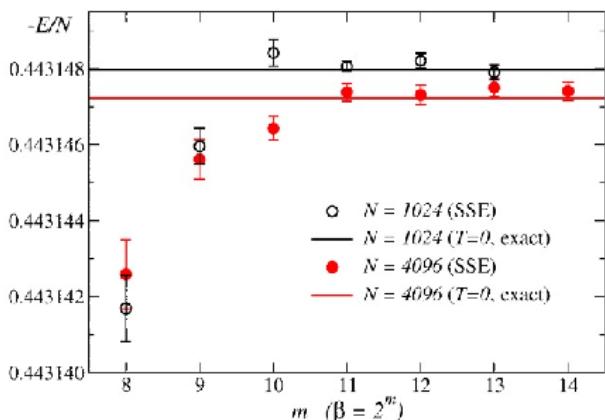
<http://physics.bu.edu/~sandvik/programs/index.html>

Compare with exact results

Susceptibility of the 4×4 lattice

- ▶ SSE results from 10^{10} sweeps

$$\chi = \frac{\beta}{N} \langle M_z^2 \rangle, M_z = \sum S_i^z$$



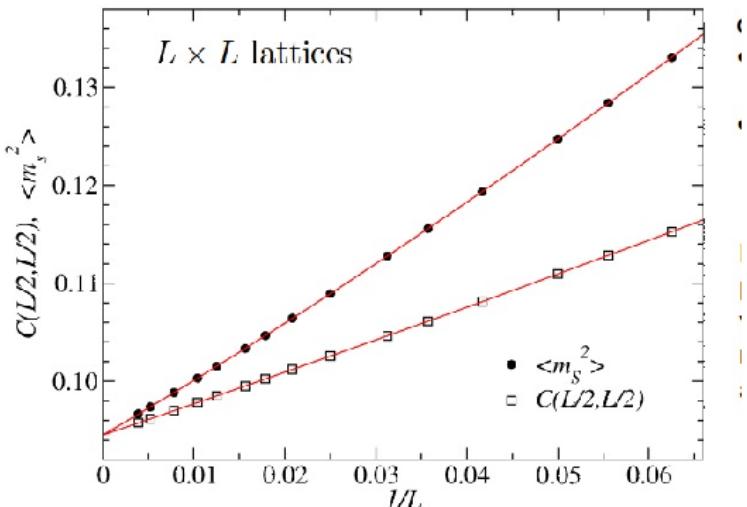
Beta Ansatz; Energy for long chains

- ▶ SSE results for 10^6 sweeps
- ▶ Beta Ansatz ground state E/N

2D Heisenberg model

Long-range order at $T = 0$; magnetization

- ▶ Spin-wave theory prediction: $\mathbf{m}_s = 0.3034$
- ▶ SSE gives $\mathbf{m}_s = 0.3074$



- ▶ 反铁磁磁化强度
$$\mathbf{m}_s = \frac{1}{N} \sum_i (-1)^{x_i + y_i} \mathbf{S}_i$$
长程序 $\langle m_s^2 \rangle > 0$, for $N \rightarrow \infty$
- ▶ $C(L/2, L/2)$ the spin correlation function at the longest distance in a finite system

Thank you!