

The Lanczos Method

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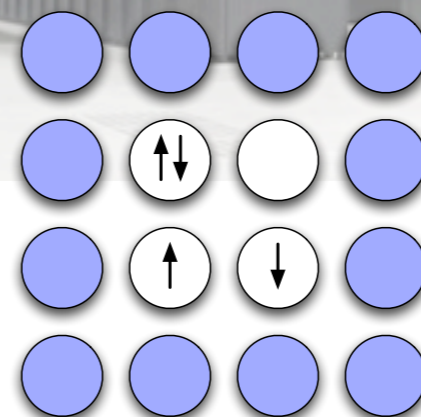
German Research School for Simulation Sciences, Jülich

$$\frac{\delta E[\psi]}{\delta \langle \psi |} = \frac{H|\psi\rangle - E[\psi]|\psi\rangle}{\langle \psi | \psi \rangle} = |\psi_a\rangle$$

$$\mathcal{K}^L(|v_0\rangle) = \text{span}(|v_0\rangle, H|v_0\rangle, H^2|v_0\rangle, \dots, H^N|v_0\rangle)$$

$$H = -t \sum_{\langle i,j \rangle, \sigma} c_{j,\sigma}^\dagger c_{i,\sigma} + U \sum_i n_{i,\uparrow} n_{i,\downarrow}$$

$$G_k(\omega) = \frac{b_0^2}{\omega - a_0 - \frac{b_1^2}{\omega - a_1 - \frac{b_2^2}{\omega - a_2 - \frac{b_3^2}{\omega - a_3 - \dots}}}}$$



References

- C. Lanczos:
An Iterative Method for the Solution of the Eigenvalue Problem of Linear Differential and Integral Operators
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- C.C. Paige:
The Computation of Eigenvalues and Eigenvectors of Very Large Sparse Matrices
PhD thesis, London University, 1971
- G.H. Golub and C.F. van Loan:
Matrix Computations
Johns Hopkins University Press, 1996
- L.N. Trefethen and D. Bau III:
Numerical Linear Algebra, Lect. 32-40: Iterative Methods
SIAM, Philadelphia, 1997
- G.W. Stewart:
Afternotes goes to Graduate School: Lect. 19-24: Krylov Sequence Methods
SIAM, Philadelphia, 1998

finite difference methods

example: 1-dim harmonic oscillator

$$\underbrace{\left(-\frac{\hbar^2}{2m_e} \frac{d^2}{dx^2} + \frac{m_e \omega_0}{2} x^2 \right)}_{=:H} \phi(x) = E \phi(x)$$

represent wavefunction on equidistant mesh:

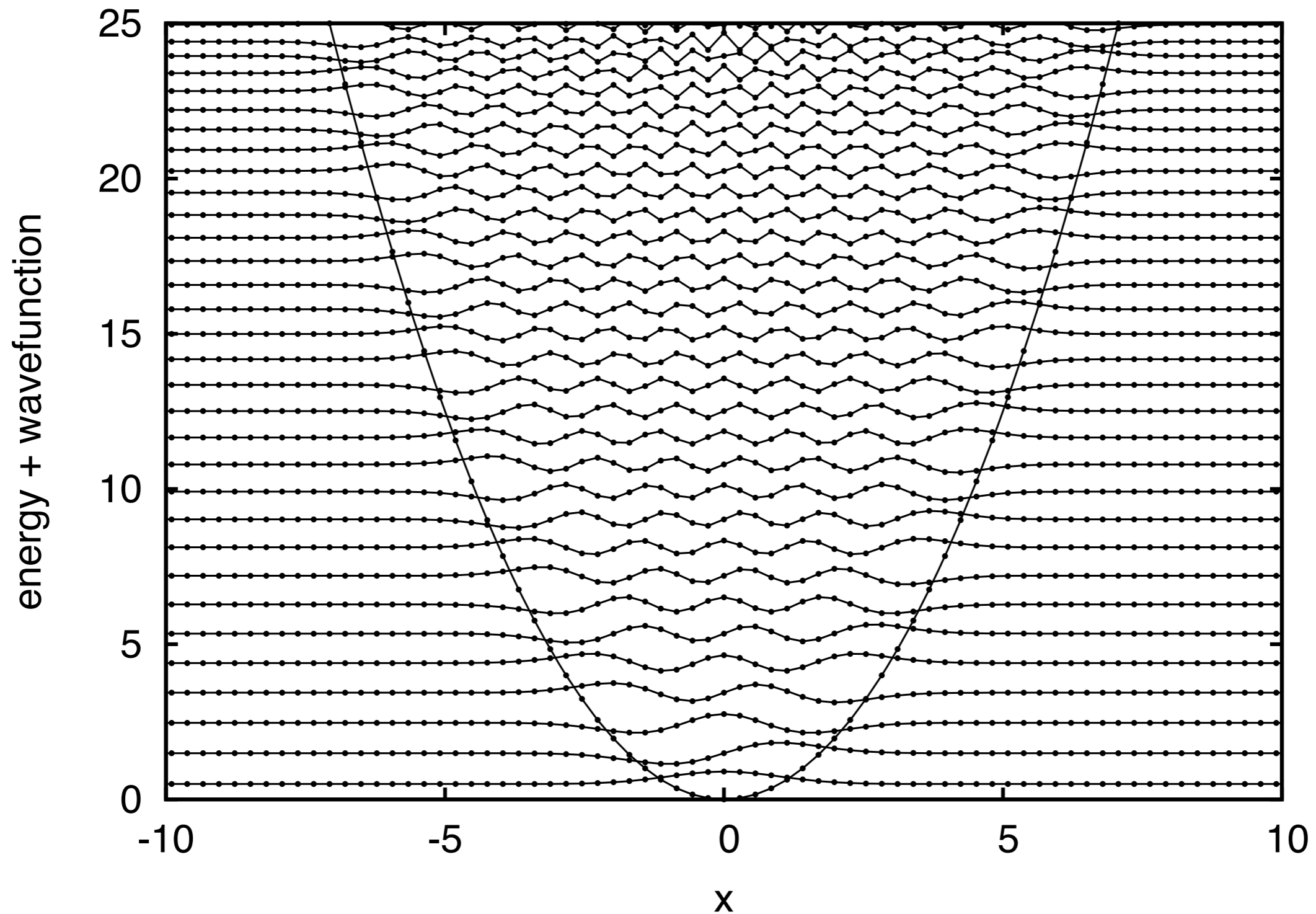
$$\frac{d^2 \phi(x_i)}{dx^2} \approx \frac{\phi(x_{i-1}) - 2\phi(x_i) + \phi(x_{i+1}))}{h^2}$$

sparse symmetric matrix

$$H_{\text{mesh}} = \begin{pmatrix} 1/h^2 + V(x_0) & -1/2h^2 & 0 & 0 & \dots & 0 & 0 \\ -1/2h^2 & 1/h^2 + V(x_1) & -1/2h^2 & 0 & \dots & 0 & 0 \\ 0 & -1/2h^2 & 1/h^2 + V(x_2) & -1/2h^2 & \dots & 0 & 0 \\ \vdots & & & & & & \vdots \\ 0 & 0 & 0 & 0 & \dots & -1/2h^2 & 1/h^2 + V(x_N) \end{pmatrix}$$

finite difference methods

discretization: only lower eigenstates are correct



Why Lanczos?

- numerically exact solution
- efficient for sparse Hamiltonians
- ground state ($T=0$) or finite (but low) temperature
- spectral function on real axis

- only finite (actually quite small) systems
 - efficient parallelization to use shared memory
 - optimal bath parametrization

minimal eigenvalue: steepest descent

energy functional

$$E[\psi] = \frac{\langle \psi | H | \psi \rangle}{\langle \psi | \psi \rangle}$$

direction (in Hilbert space) of steepest ascent

$$\frac{\delta E[\psi]}{\delta \langle \psi |} = \frac{H|\psi\rangle - E[\psi]|\psi\rangle}{\langle \psi | \psi \rangle} = |\psi_a\rangle \in \text{span}(|\psi\rangle, H|\psi\rangle)$$

minimize energy in $\text{span}(|\psi\rangle, H|\psi\rangle)$

minimal eigenvalue: steepest descent

minimize energy in $\text{span}(|\psi\rangle, H|\psi\rangle)$

construct orthonormal basis

$$|v_0\rangle = |\psi\rangle / \sqrt{\langle\psi|\psi\rangle}$$

$$b_1 |v_1\rangle = |\tilde{v}_1\rangle = H|v_0\rangle - |v_0\rangle\langle v_0|H|v_0\rangle$$

define: $a_n := \langle v_n|H|v_n\rangle$ $b_1 := \sqrt{\langle\tilde{v}_1|\tilde{v}_1\rangle}$

$$H|v_0\rangle = b_1 |v_1\rangle + a_0 |v_0\rangle$$

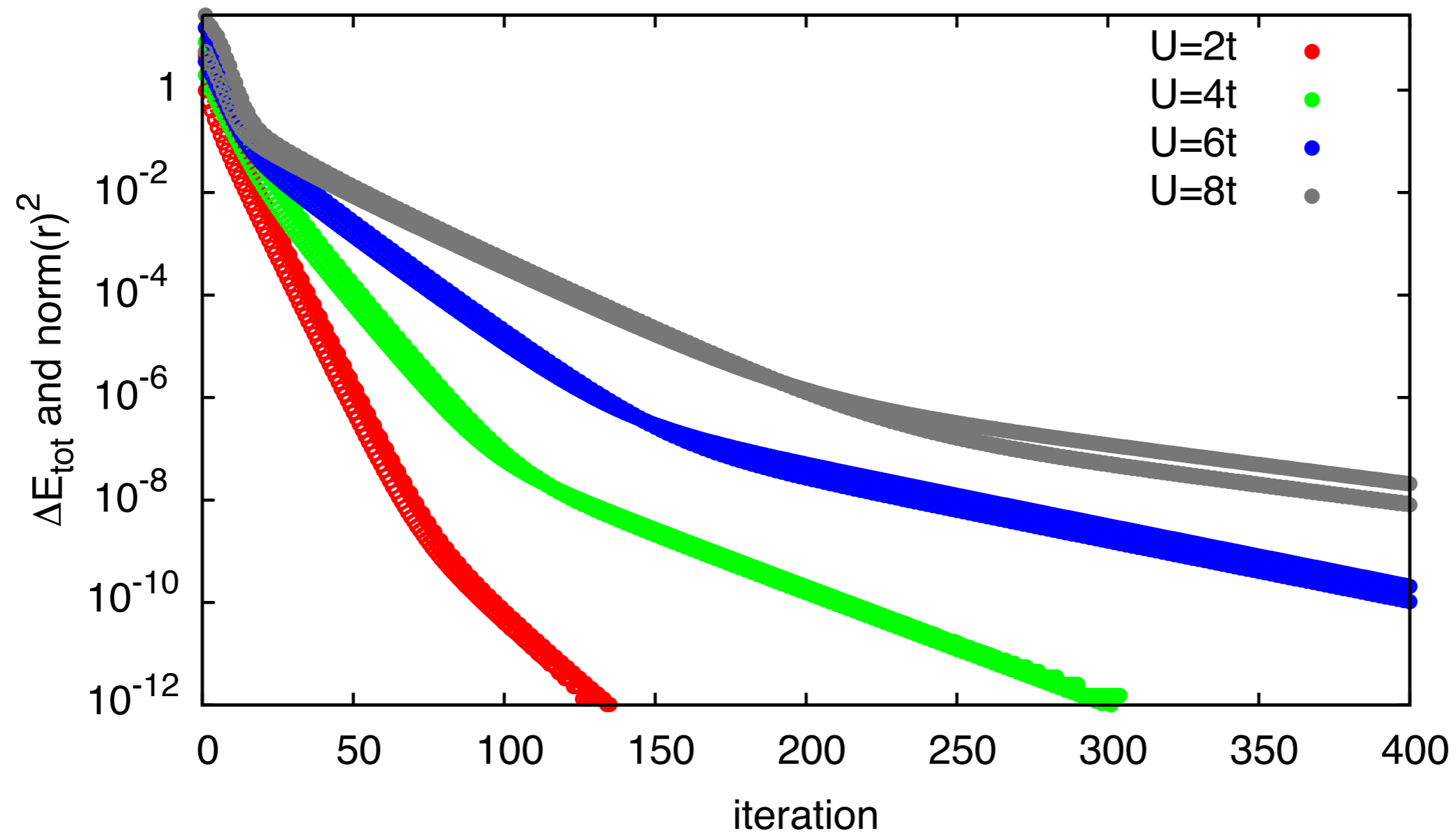
$$H_{\text{span}(|\psi\rangle, H|\psi\rangle)} = \begin{pmatrix} a_0 & b_1 \\ b_1 & a_1 \end{pmatrix}$$

diagonalize to find lowest eigenvector

iterate!

convergence

10-site Hubbard-chain, half-filling; dim=63,504



Lanczos idea

minimize on span $(|\psi_0\rangle, H|\psi_0\rangle)$ to obtain $|\psi_1\rangle$

minimize on span $(|\psi_1\rangle, H|\psi_1\rangle) \in \text{span}(|\psi_0\rangle, H|\psi_0\rangle, H^2|\psi_0\rangle)$

minimize on span $(|\psi_2\rangle, H|\psi_2\rangle) \in \text{span}(|\psi_0\rangle, H|\psi_0\rangle, H^2|\psi_0\rangle, H^3|\psi_0\rangle)$

etc.

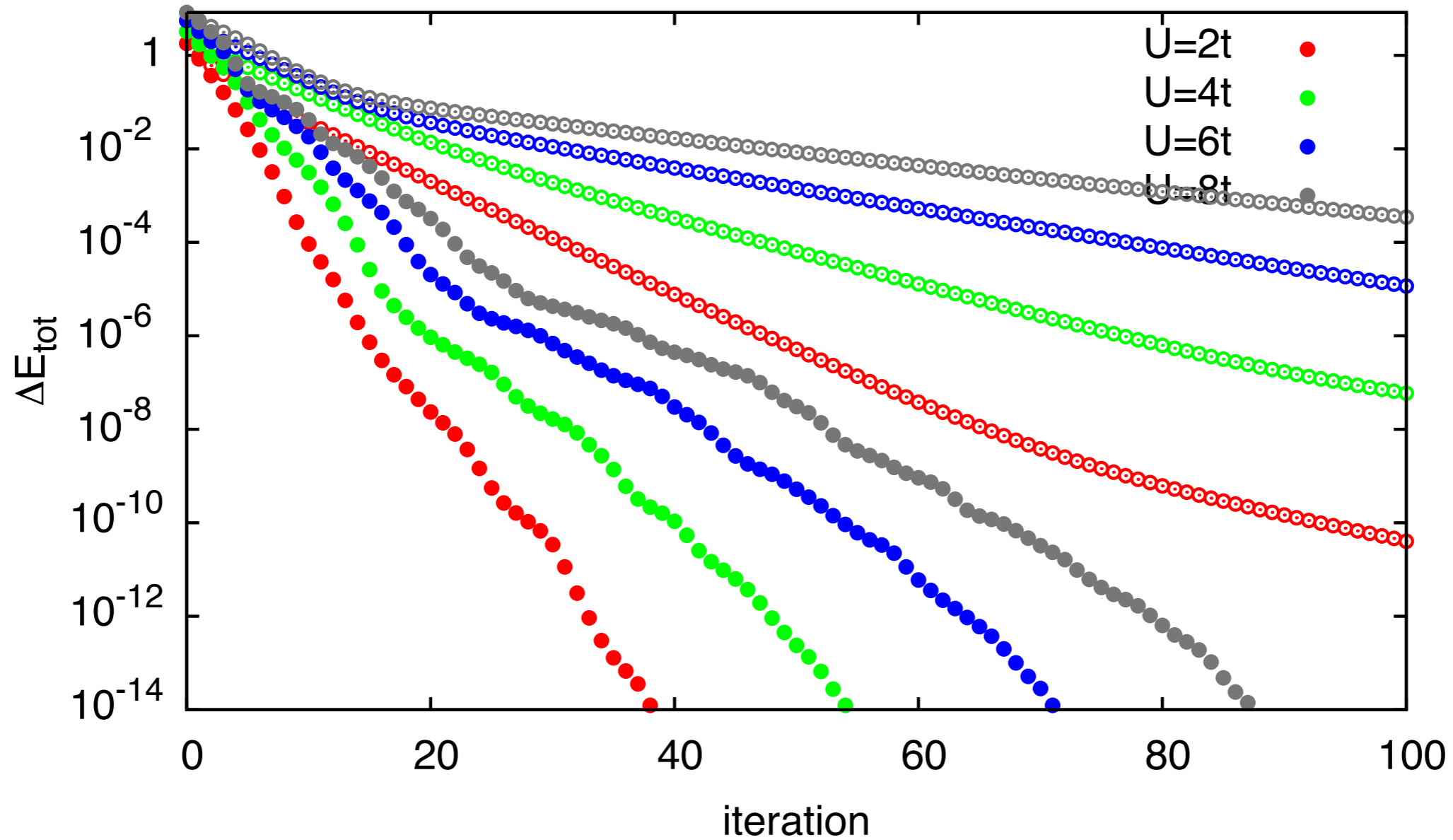
instead of L -fold iterative minimization on two-dimensional subspaces
minimize energy on $L+1$ dimensional **Krylov space**

$$\mathcal{K}^L(\psi_0) = \text{span}(|\psi_0\rangle, H|\psi_0\rangle, H^2|\psi_0\rangle, \dots, H^L|\psi_0\rangle)$$

more variational degrees of freedom \Rightarrow even faster convergence

convergence to ground state

10-site Hubbard-chain, half-filling; dim=63,504



Lanczos iteration

construct orthonormal basis in Krylov space

$$b_{n+1}|v_{n+1}\rangle = |\tilde{v}_{n+1}\rangle = H|v_n\rangle - \sum_{i=0}^n |v_i\rangle \langle v_i|H|v_n\rangle$$

define: $a_n := \langle v_n|H|v_n\rangle$ $b_n := \sqrt{\langle \tilde{v}_n|\tilde{v}_n\rangle}$

$$\langle v_m| : \quad b_{n+1} \delta_{m,n+1} = \langle v_m|H|v_n\rangle - \sum_{i=0}^n \langle v_m|H|v_n\rangle \delta_{m,i}$$

$$\langle v_m|H|v_n\rangle = \begin{cases} \langle v_m|H|v_n\rangle & \text{for } m < n \\ a_n & \text{for } m = n \\ b_{n+1} & \text{for } m = n + 1 \\ 0 & \text{for } m > n + 1 \end{cases} \quad H = \begin{pmatrix} a_0 & ? & ? & \cdots & ? \\ b_1 & a_1 & ? & & ? \\ 0 & b_2 & a_2 & & ? \\ & & & \ddots & \\ 0 & 0 & 0 & & a_L \end{pmatrix}$$

H has upper Hessenberg form
 symmetric/hermitian \Rightarrow tridiagonal

Lanczos iteration

orthonormal basis in Krylov space

$$|v_0\rangle$$

$$b_1 |v_1\rangle = H|v_0\rangle - a_0|v_0\rangle$$

$$b_2 |v_2\rangle = H|v_1\rangle - a_1|v_1\rangle - b_1|v_0\rangle$$

$$b_3 |v_3\rangle = H|v_2\rangle - a_2|v_2\rangle - b_2|v_1\rangle$$

...

$$H|v_n\rangle = b_n|v_{n-1}\rangle + a_n|v_n\rangle + b_{n+1}|v_{n+1}\rangle$$

$$H_{\mathcal{K}^L(|v_0\rangle)} = \begin{pmatrix} a_0 & b_1 & 0 & 0 & & 0 & 0 \\ b_1 & a_1 & b_2 & 0 & \dots & 0 & 0 \\ 0 & b_2 & a_2 & b_3 & & 0 & 0 \\ 0 & 0 & b_3 & a_3 & & 0 & 0 \\ & \vdots & & & \ddots & \vdots & \\ 0 & 0 & 0 & 0 & & a_{L-1} & b_L \\ 0 & 0 & 0 & 0 & \dots & b_L & a_L \end{pmatrix}$$

Lanczos algorithm

```
v=init
b0=norm2(v)
scal(1/b0,v)
w=0
w=w+H*v
a[0]=dot(v,w)
axpy(-a[0],v,w)
b[1]=norm2(w)
for n=1,2,...
  if abs(b[n])<eps then exit
  scal(1/b[n],w)
  scal(-b[n],v)
  swap(v,w)
  w=w+H*v
  a[n]=dot(v,w)
  axpy(-a[n],v,w)
  b[n+1]=norm2(w)
  diag(a[0]..a[n], b[1]..b[n])
  if converged then exit
end
```

not part of tridiagonal matrix

$$v = |v_0\rangle$$

$$w = H|v_0\rangle$$

$$w = |\tilde{v}_1\rangle = H|v_0\rangle - a_0|v_0\rangle$$

invariant subspace

$$w = |v_n\rangle$$

$$v = -b_n|v_{n-1}\rangle$$

$$w = H|v_n\rangle - b_n|v_{n-1}\rangle$$

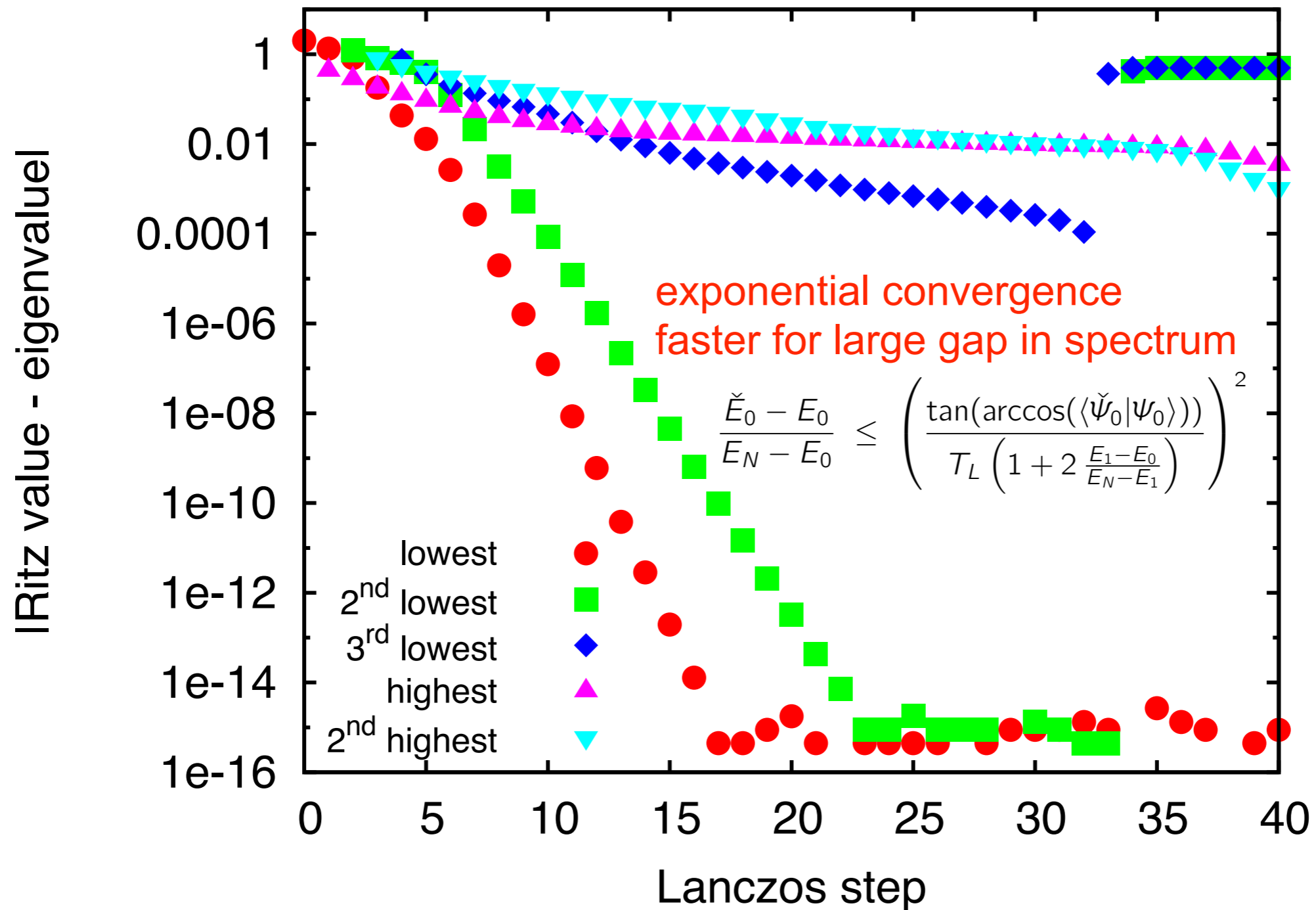
$$a[n] = \langle v_n | H | v_n \rangle - b_n \langle v_n | v_{n-1} \rangle$$

$$w = |\tilde{v}_{n+1}\rangle$$

getting a_{n+1} needs another $H|v\rangle$

convergence to extremal eigenvalues

toy problem: matrix with eigenvalues -3, -3, -2.5, -2, -1.99, -1.98, ... -0.01, 0



convergence of Ritz values

E_n : eigenvalues of H in ascending order, $n=0, \dots$

$E_n^{(L)}$: eigenvalues of Lanczos matrix $H^{(L)}$ (Ritz values)

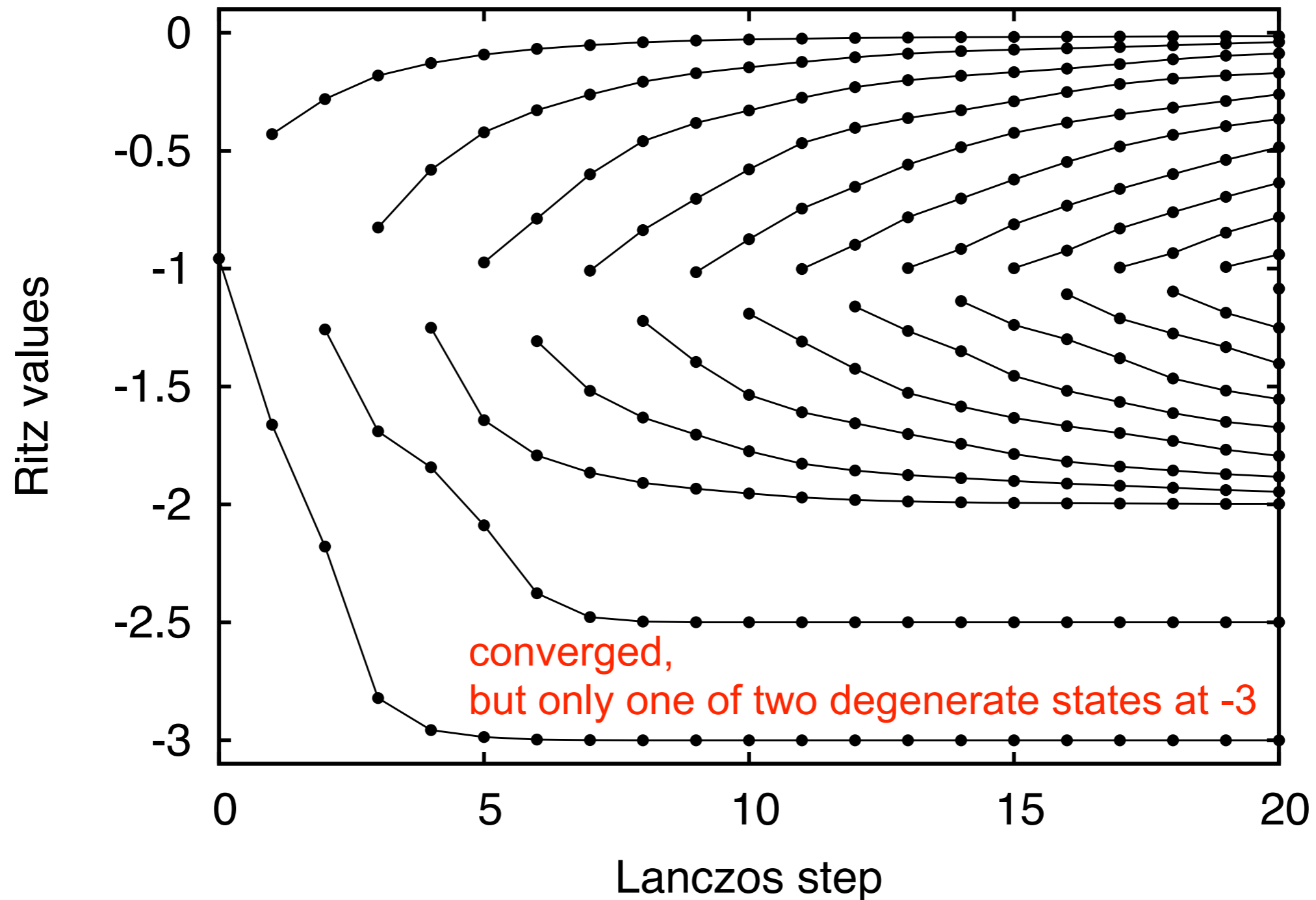
Ritz value n approaches eigenvalue n with increasing L from above:

$$E_n \leq E_n^{(L+1)} \leq E_n^{(L)}$$

general basis-set methods: MacDonald's theorem
Phys. Rev. **43**, 830 (1933)

spectrum of tridiagonal matrix

toy problem: matrix with eigenvalues $-3, -3, -2.5, -2, -1.99, -1.98, \dots, -0.01, 0$



Krylov space cannot contain degenerate states

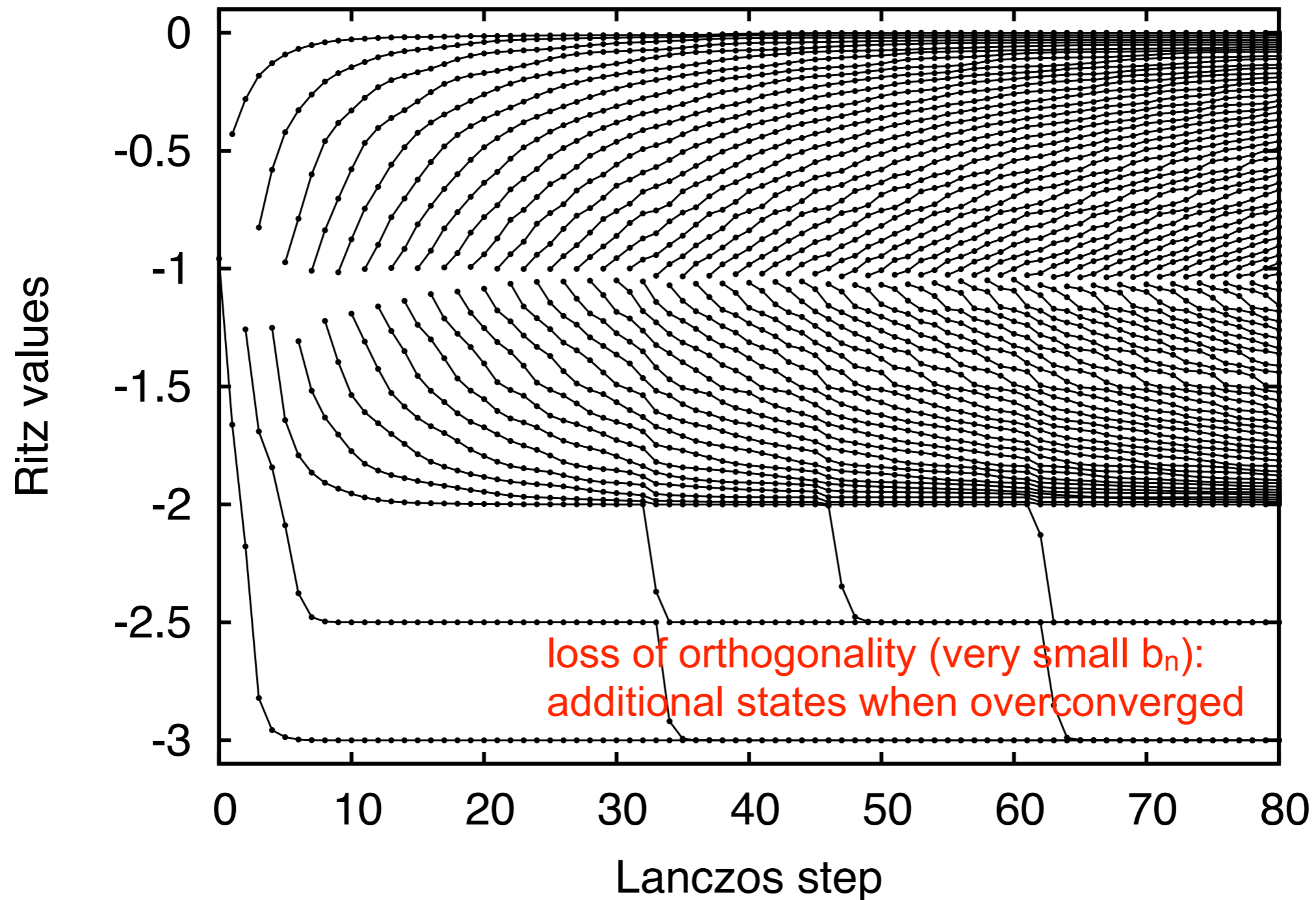
assume $|\varphi_1\rangle$ and $|\varphi_2\rangle$ are degenerate eigenstates with eigenvalue ε ,
then their expansion in the orthonormal basis of the Krylov space is

$$\langle v_0 | H^n | \varphi_i \rangle = \varepsilon^n \langle v_0 | \varphi_i \rangle$$

$\Rightarrow |\varphi_1\rangle$ and $|\varphi_2\rangle$ are identical up to normalization

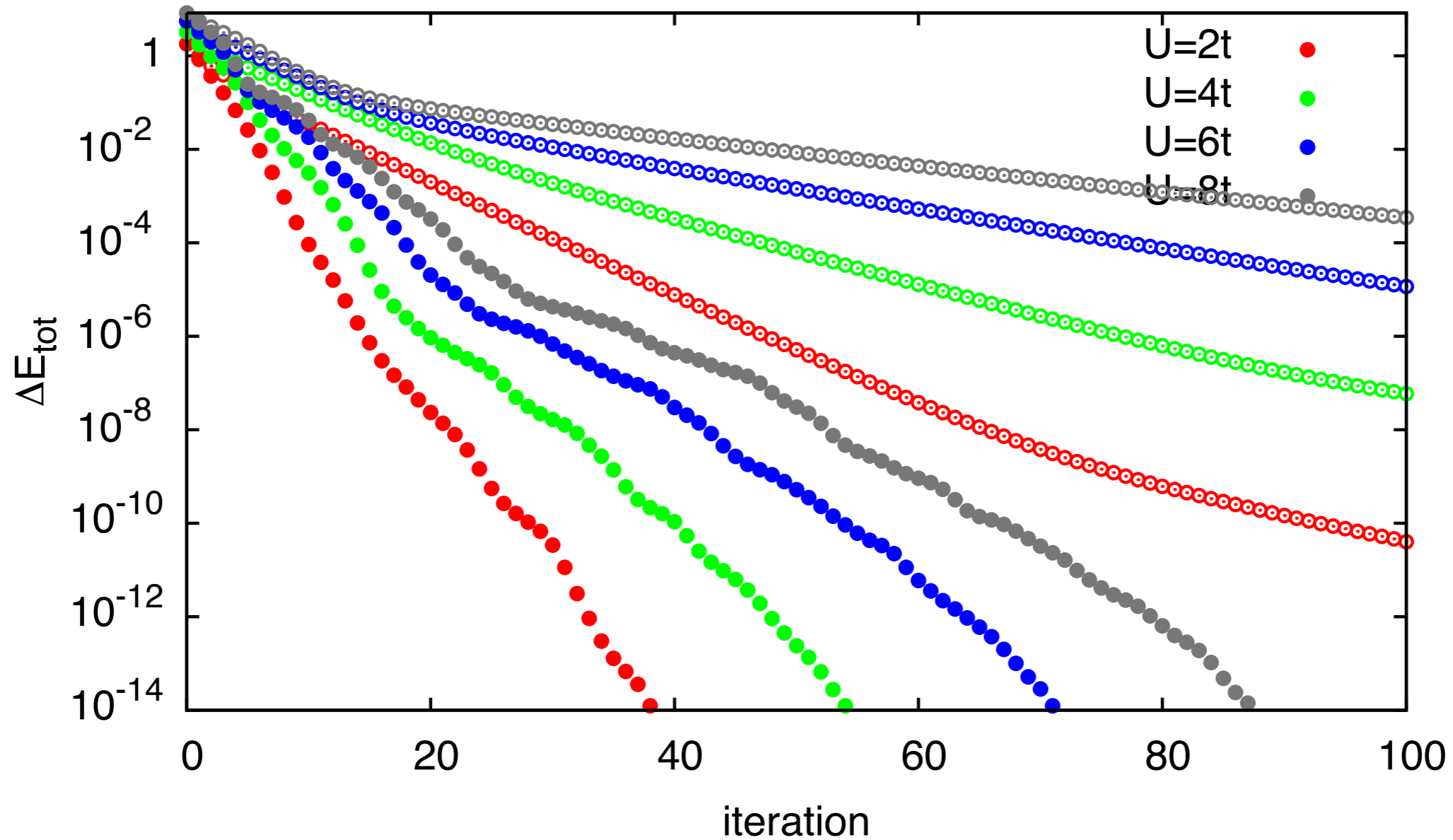
loss of orthogonality

toy problem: matrix with eigenvalues $-3, -3, -2.5, -2, -1.99, -1.98, \dots -0.01, 0$



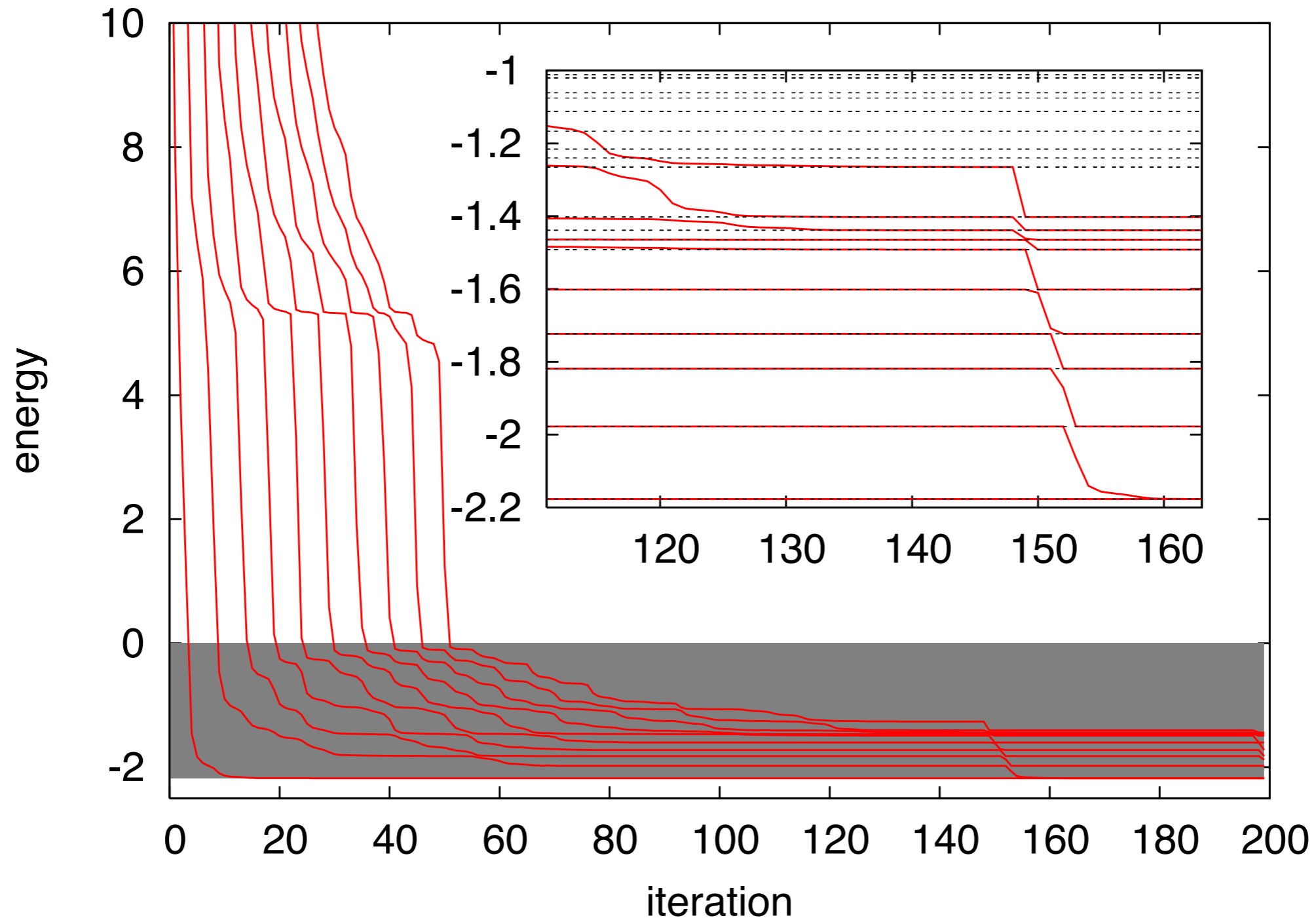
convergence to ground state

10-site Hubbard-chain, half-filling; dim=63,504



$$\frac{\check{E}_0 - E_0}{E_N - E_0} \leq \left(\frac{\tan(\arccos(\langle \check{\Psi}_0 | \Psi_0 \rangle))}{T_L \left(1 + 2 \frac{E_1 - E_0}{E_N - E_1} \right)} \right)^2$$

over-convergence: ghost states



$$b_{n+1}|v_{n+1}\rangle = H|v_n\rangle - a_n|v_n\rangle - b_n|v_{n-1}\rangle$$

construction of eigenvectors

let $\check{\psi}_n = (\check{\psi}_{n,i})$ be the n^{th} eigenstate of the tridiagonal Lanczos matrix

$$H_{\mathcal{K}^L(|v_0\rangle)} = \begin{pmatrix} a_0 & b_1 & 0 & 0 & & 0 & 0 \\ b_1 & a_1 & b_2 & 0 & \dots & 0 & 0 \\ 0 & b_2 & a_2 & b_3 & & 0 & 0 \\ 0 & 0 & b_3 & a_3 & & 0 & 0 \\ & \vdots & & & \ddots & \vdots & \\ 0 & 0 & 0 & 0 & & a_{L-1} & b_L \\ 0 & 0 & 0 & 0 & \dots & b_L & a_L \end{pmatrix}$$

the approximate eigenvector is then given in the Lanczos basis

$$|\check{\Psi}_n\rangle = \sum_{i=0}^L \check{\psi}_{n,i} |v_i\rangle$$

need all Lanczos basis vectors \Rightarrow need very large memory

instead: rerun Lanczos iteration from same $|v_0\rangle$

and accumulate eigenvector on the fly

spectral function

$$G_c(z) = \left\langle \psi_c \left| \frac{1}{z - H} \right| \psi_c \right\rangle = \sum_{n=0}^N \frac{\langle \psi_c | \psi_n \rangle \langle \psi_n | \psi_c \rangle}{z - E_n}$$

need to calculate entire spectrum?

resolvent / spectral function

$$G_c(z) = \left\langle \psi_c \left| \frac{1}{z - H} \right| \psi_c \right\rangle = \sum_{n=0}^N \frac{\langle \psi_c | \psi_n \rangle \langle \psi_n | \psi_c \rangle}{z - E_n}$$

$$\check{G}_c(z) = \left\langle \psi_c \left| \frac{1}{z - \check{H}_c} \right| \psi_c \right\rangle = \sum_{n=0}^L \frac{\langle \psi_c | \check{\psi}_n \rangle \langle \check{\psi}_n | \psi_c \rangle}{z - \check{E}_n}$$

$$z - \check{H}_c = \left(\begin{array}{c|ccccccc} z - a_0 & -b_1 & 0 & 0 & \dots & 0 & 0 \\ \hline -b_1 & z - a_1 & -b_2 & 0 & \dots & 0 & 0 \\ 0 & -b_2 & z - a_2 & -b_3 & \dots & 0 & 0 \\ 0 & 0 & -b_3 & z - a_3 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & z - a_{L-1} & -b_L \\ 0 & 0 & 0 & 0 & \dots & -b_L & z - a_L \end{array} \right)$$

resolvent / spectral function

$$z - \check{H}_c = \begin{pmatrix} z - a_0 & B^{(1)T} \\ B^{(1)} & z - \check{H}_c^{(1)} \end{pmatrix}$$

inversion by partitioning

$$\begin{aligned} [(z - \check{H}_c)^{-1}]_{00} &= \left(z - a_0 - B^{(1)T} (z - \check{H}_c^{(1)})^{-1} B^{(1)} \right)^{-1} \\ &= \left(z - a_0 - b_1^2 \left[(z - \check{H}_c^{(1)})^{-1} \right]_{00} \right)^{-1} \end{aligned}$$

recursively

$$\check{G}_c(z) = [(z - \check{H}_c)^{-1}]_{00} = \frac{1}{z - a_0 - \frac{b_1^2}{z - a_1 - \frac{b_2^2}{z - a_2 - \dots}}}$$

downfolding

partition Hilbert space

$$H = \begin{pmatrix} H_{00} & T_{01} \\ T_{10} & H_{11} \end{pmatrix}$$



resolvent

$$G(\varepsilon) = (\varepsilon - H)^{-1} = \begin{pmatrix} \varepsilon - H_{00} & -T_{01} \\ -T_{10} & \varepsilon - H_{11} \end{pmatrix}^{-1}$$



inverse of 2x2 block-matrix

$$G_{00}(\varepsilon) = \left(\varepsilon - \left[H_{00} + T_{01}(\varepsilon - H_{11})^{-1}T_{10} \right] \right)^{-1}$$



downfolded Hamiltonian

$$H_{\text{eff}} \approx H_{00} + T_{01}(\varepsilon_0 - H_{11})^{-1}T_{10}$$

good approximation: narrow energy range and/or small coupling

inversion by partitioning

2×2 matrix

$$M = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \quad M^{-1} = \frac{1}{ad - bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$$

invert block-2×2 matrix

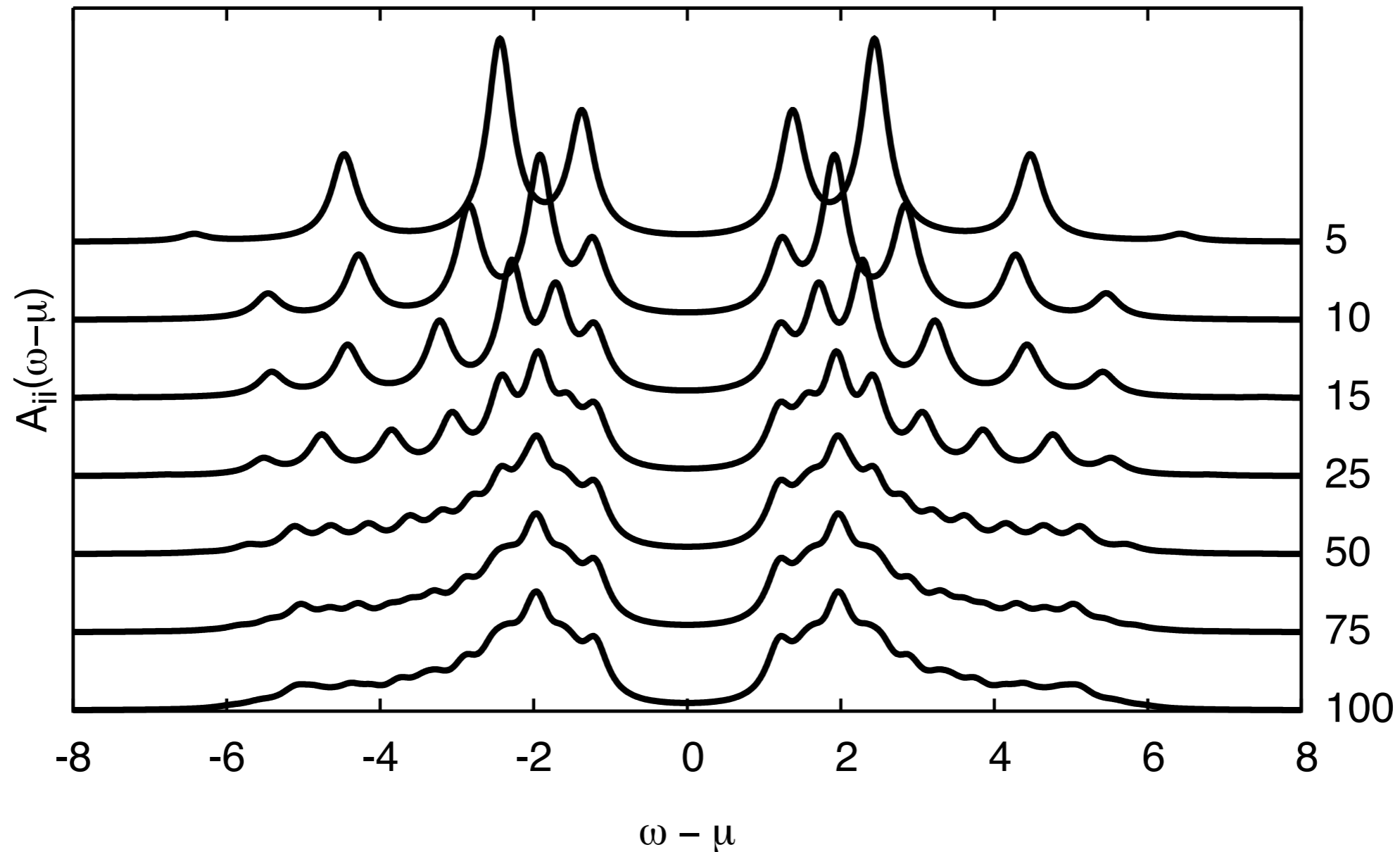
solve

$$M = \begin{pmatrix} A & B \\ C & D \end{pmatrix} \quad M^{-1} = \begin{pmatrix} \tilde{A} & \tilde{B} \\ \tilde{C} & \tilde{D} \end{pmatrix} \quad \begin{pmatrix} A & B \\ C & D \end{pmatrix} \begin{pmatrix} \tilde{A} & \tilde{B} \\ \tilde{C} & \tilde{D} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

$$A\tilde{A} + B\tilde{C} = 1 \quad = (A - BD^{-1}C)\tilde{A}$$

$$C\tilde{A} + D\tilde{C} = 0 \quad \rightsquigarrow \tilde{C} = -D^{-1}C\tilde{A}$$

convergence: moments



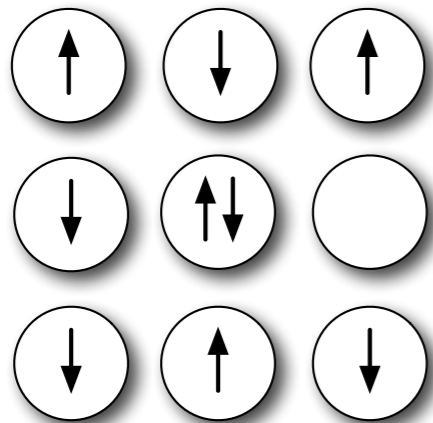
$$\int_{-\infty}^{\infty} d\omega \omega^m \check{A}(\omega) = \sum_{n=0}^L |\check{\psi}_{n,0}|^2 \check{E}_n^m = \sum_{n=0}^L \langle \psi_c | \check{\psi}_n \rangle \langle \check{\psi}_n | \psi_c \rangle \check{E}_n^m = \langle \psi_c | \check{H}^m | \psi_c \rangle$$

application to Hubbard model and
shared-memory parallelization

dimension of many-body Hilbert space

$$H = -t \sum_{\langle i,j \rangle, \sigma} c_{j,\sigma}^\dagger c_{i,\sigma} + U \sum_i n_{i,\uparrow} n_{i,\downarrow}$$

solve finite clusters



$$\dim(H) = \binom{M}{N_\uparrow} \times \binom{M}{N_\downarrow}$$

M	N_\uparrow	N_\downarrow	dimension of Hilbert space	memory
2	1	1	4	
4	2	2	36	
6	3	3	400	
8	4	4	4 900	
10	5	5	63 504	
12	6	6	853 776	6 MB
14	7	7	11 778 624	89 MB
16	8	8	165 636 900	1 263 MB
18	9	9	2 363 904 400	18 GB
20	10	10	34 134 779 536	254 GB
22	11	11	497 634 306 624	3708 GB
24	12	12	7 312 459 672 336	53 TB

choice of basis

real space: sparse Hamiltonian

$$H = -t \sum_{\langle i,j \rangle, \sigma} c_{j,\sigma}^\dagger c_{i,\sigma} + U \sum_i n_{i,\uparrow} n_{i,\downarrow}$$

hopping only connects states of same spin
interaction diagonal (even for long-range interaction!)

k-space

$$H = \sum_{k\sigma} \varepsilon_k c_{k\sigma}^\dagger c_{k\sigma} + \frac{U}{M} \sum_{k,k',q} c_{k\uparrow}^\dagger c_{k-q,\uparrow} c_{k'\downarrow}^\dagger c_{k'+q,\downarrow}$$

choice of basis

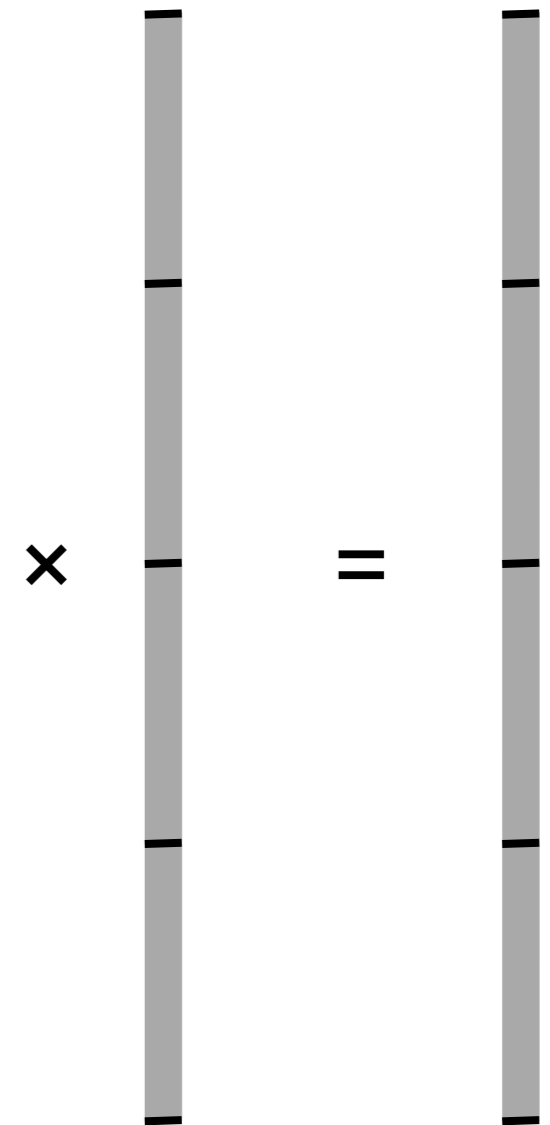
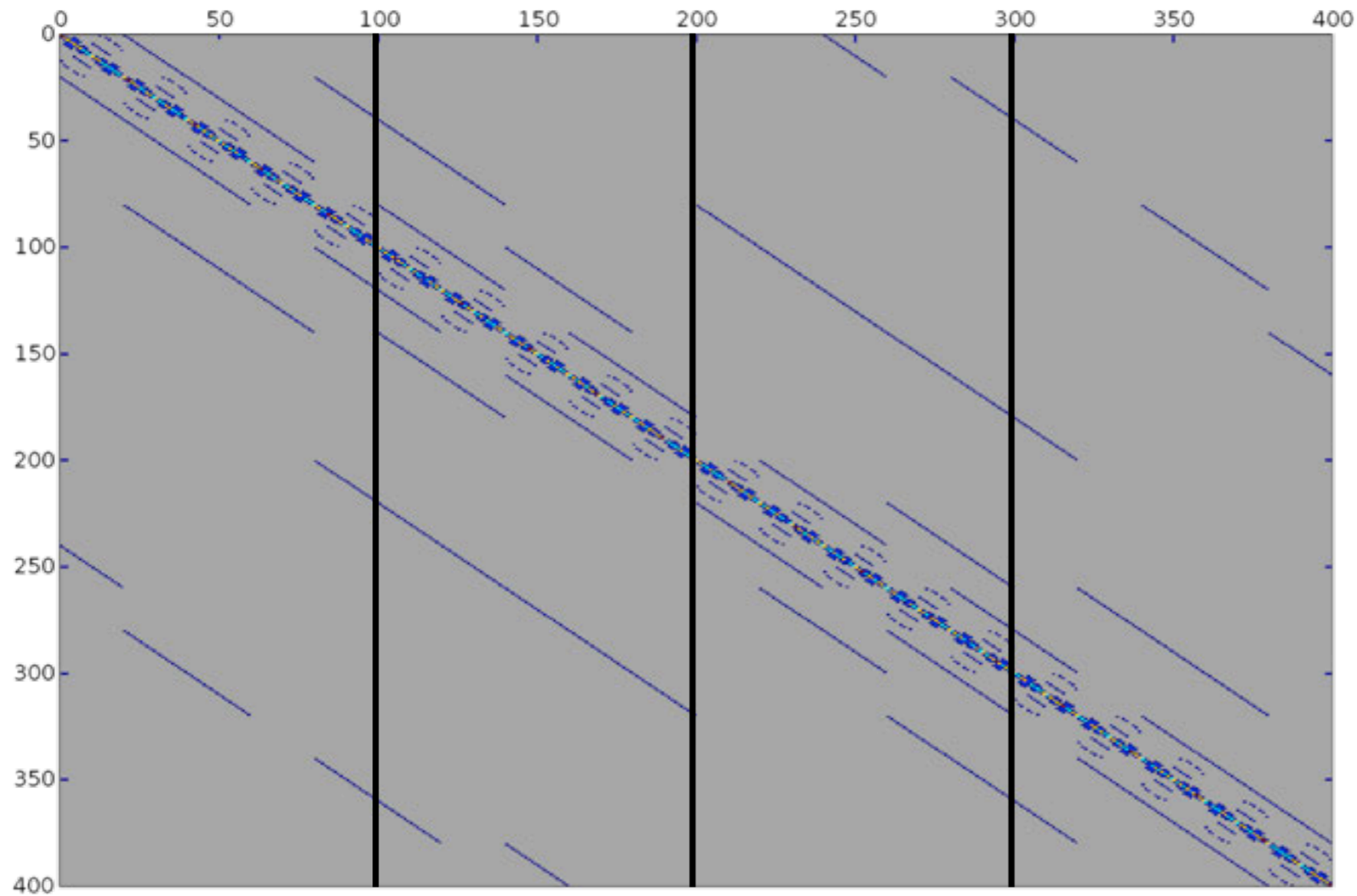
work with operators that create electrons in Wannier orbitals

$$|\{n_{i\sigma}\}\rangle = \prod_{i=0}^{L-1} \left(c_{i\downarrow}^\dagger\right)^{n_{i\downarrow}} \left(c_{i\uparrow}^\dagger\right)^{n_{i\uparrow}} |0\rangle$$

m_\uparrow	bits	state	i_\uparrow	m_\downarrow	bits	state	i_\downarrow					
0	000			0	000			0	—	↑	↑↓	(0,0)
1	001			1	001	$c_{0\downarrow}^\dagger 0\rangle$	0	1	↑	—	↑↓	(0,1)
2	010			2	010	$c_{1\downarrow}^\dagger 0\rangle$	1	2	↑	↑	↓	(0,2)
3	011	$c_{0\uparrow}^\dagger c_{1\uparrow}^\dagger 0\rangle$	0	3	011			3	—	↑↓	↑	(1,0)
4	100			4	100	$c_{2\downarrow}^\dagger 0\rangle$	2	4	↑	↓	↑	(1,1)
5	101	$c_{0\uparrow}^\dagger c_{2\uparrow}^\dagger 0\rangle$	1	5	101			5	↑	↑↓	—	(1,2)
6	110	$c_{1\uparrow}^\dagger c_{2\uparrow}^\dagger 0\rangle$	2	6	110			6	↓	↑	↑	(2,0)
7	111			7	111			7	↑↓	—	↑	(2,1)
								8	↑↓	↑	—	(2,2)

sparse matrix-vector product

$$H |\Psi_i\rangle = |\Psi_{i+1}\rangle$$



sparse matrix-vector product: OpenMP

$$w = w + H v$$

$$H = \sum_{\langle ij \rangle, \sigma} t_{i,j} c_{j,\sigma}^\dagger c_{i,\sigma} + U \sum_i n_{i,\uparrow} n_{i,\downarrow}$$

```

subroutine wpHtruev(U, v,w)
c --- full configurations indexed by k=(kdn-1)+(kup-1)*Ndnconf+1
...
!$omp parallel do private(kdn,k,i,lup,ldn,l,D)
do kup=1,Nupconf
do kdn=1,Ndnconf
k=(kdn-1)+(kup-1)*Ndnconf+1
w(k)=w(k)+U*Double(kup,kdn)*v(k)
enddo
do i=1,upn(kup)
lup=upi(i,kup)
do kdn=1,Ndnconf
k=(kdn-1)+(kup-1)*Ndnconf+1
l=(kdn-1)+(lup-1)*Ndnconf+1
w(k)=w(k)+upt(i,kup)*v(l)
enddo
enddo
do kdn=1,Ndnconf
k=(kdn-1)+(kup-1)*Ndnconf+1
do i=1,dnn(kdn)
ldn=dni(i,kdn)
l=(ldn-1)+(kup-1)*Ndnconf+1
w(k)=w(k)+dnt(i,kdn)*v(l)
enddo
enddo
enddo
end

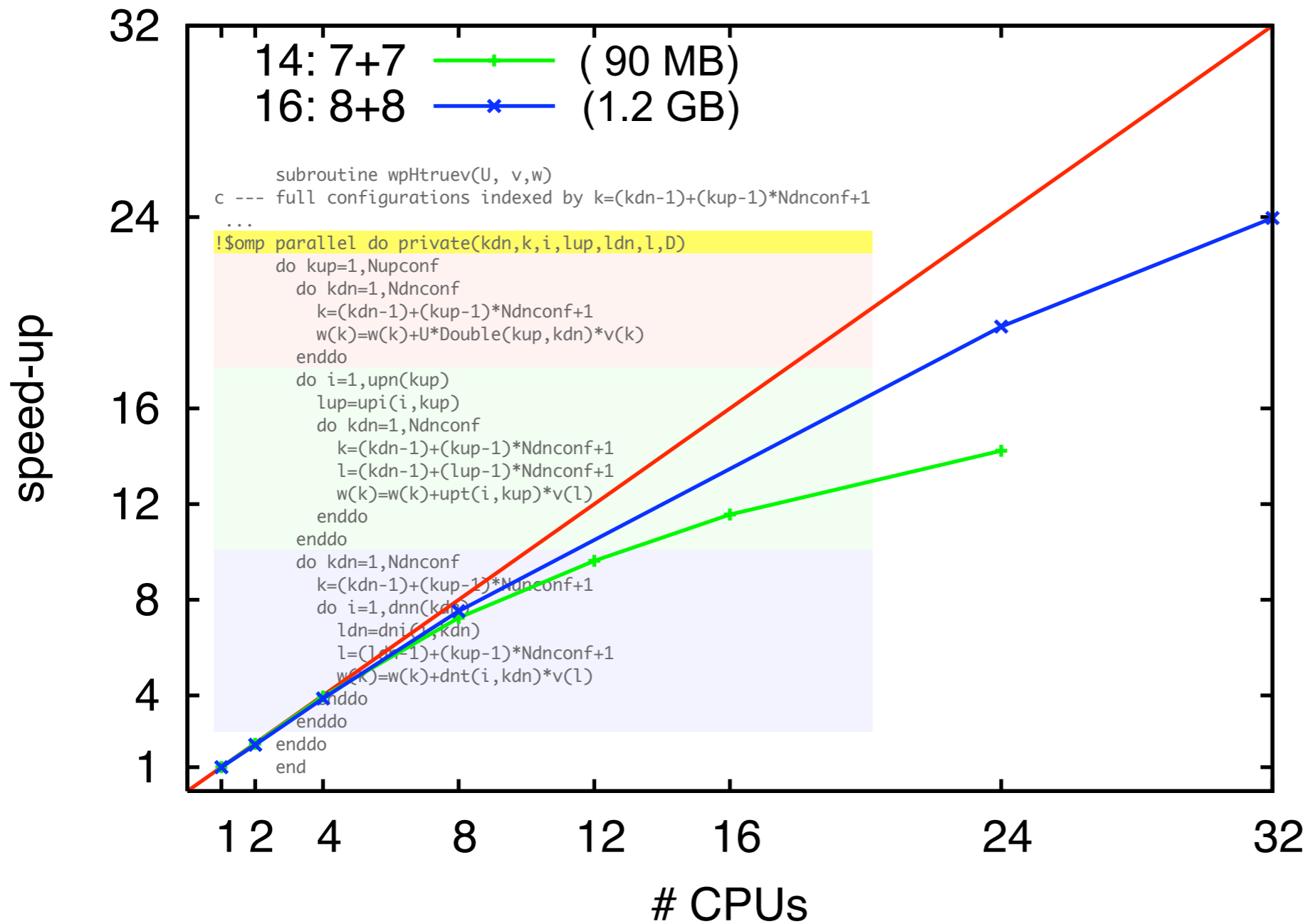
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$$U \sum_i n_{i,\uparrow} n_{i,\downarrow}$$

$$\sum_{\langle ij \rangle, \sigma = \uparrow} t_{i,j} c_{j,\sigma}^\dagger c_{i,\sigma}$$

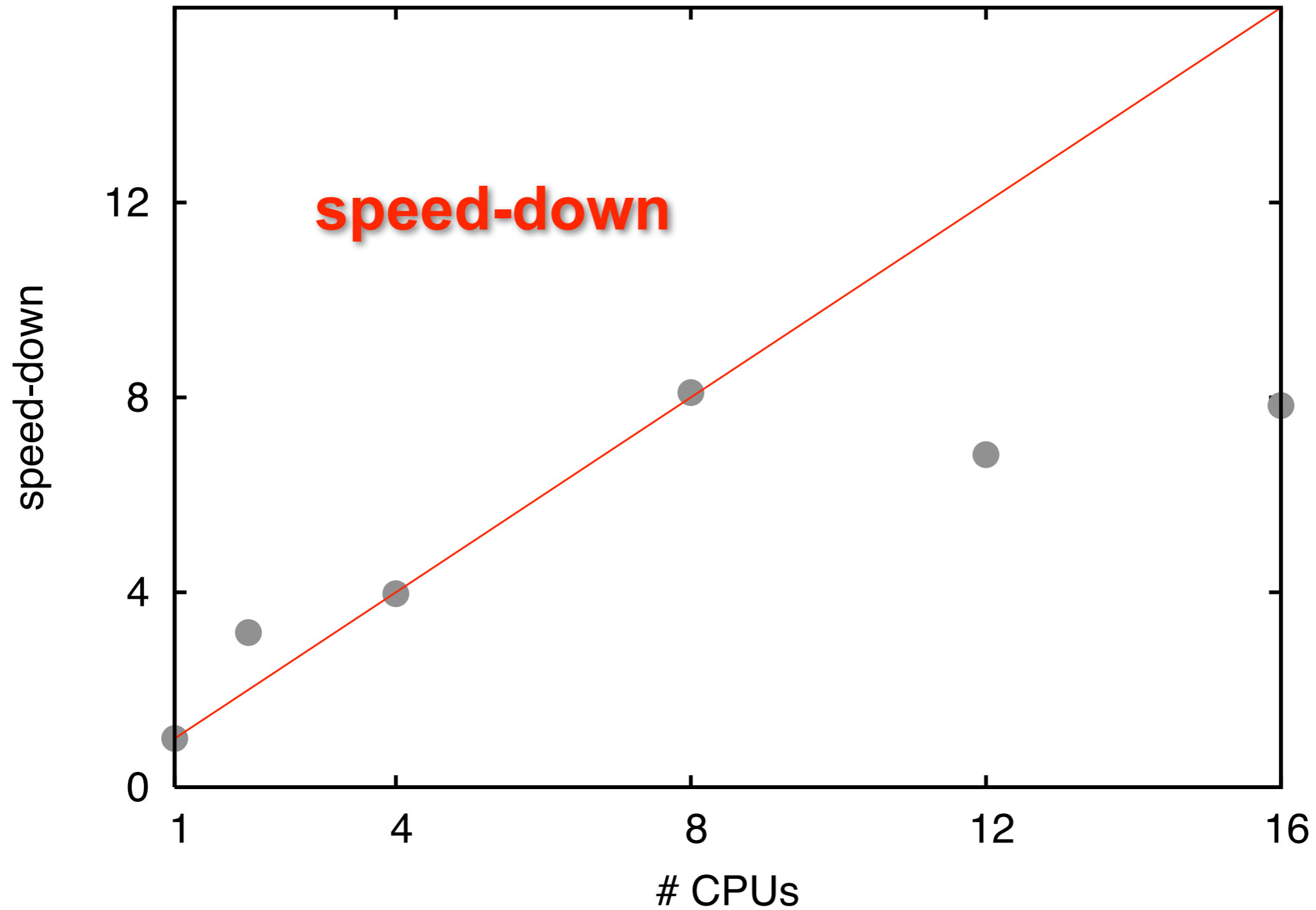
$$\sum_{\langle ij \rangle, \sigma = \downarrow} t_{i,j} c_{j,\sigma}^\dagger c_{i,\sigma}$$

OpenMP on Jump



distributed memory

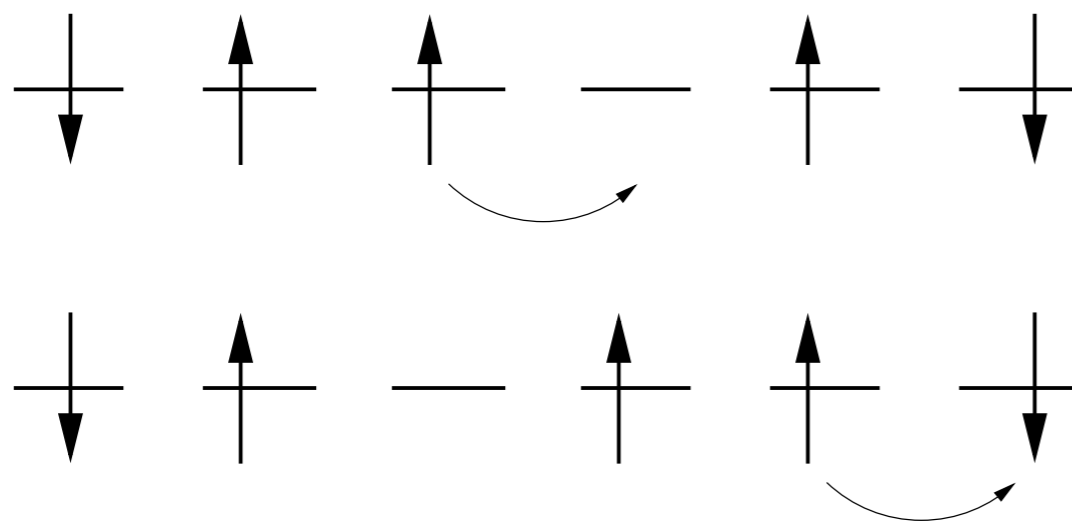
MPI-2: one-sided communication



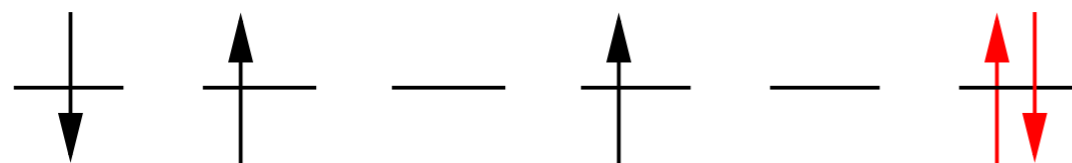
Hubbard model

$$H = \sum_{\langle ij \rangle, \sigma} t_{i,j} c_{j,\sigma}^\dagger c_{i,\sigma} + U \sum_i n_{i,\uparrow} n_{i,\downarrow}$$

hopping: spin unchanged

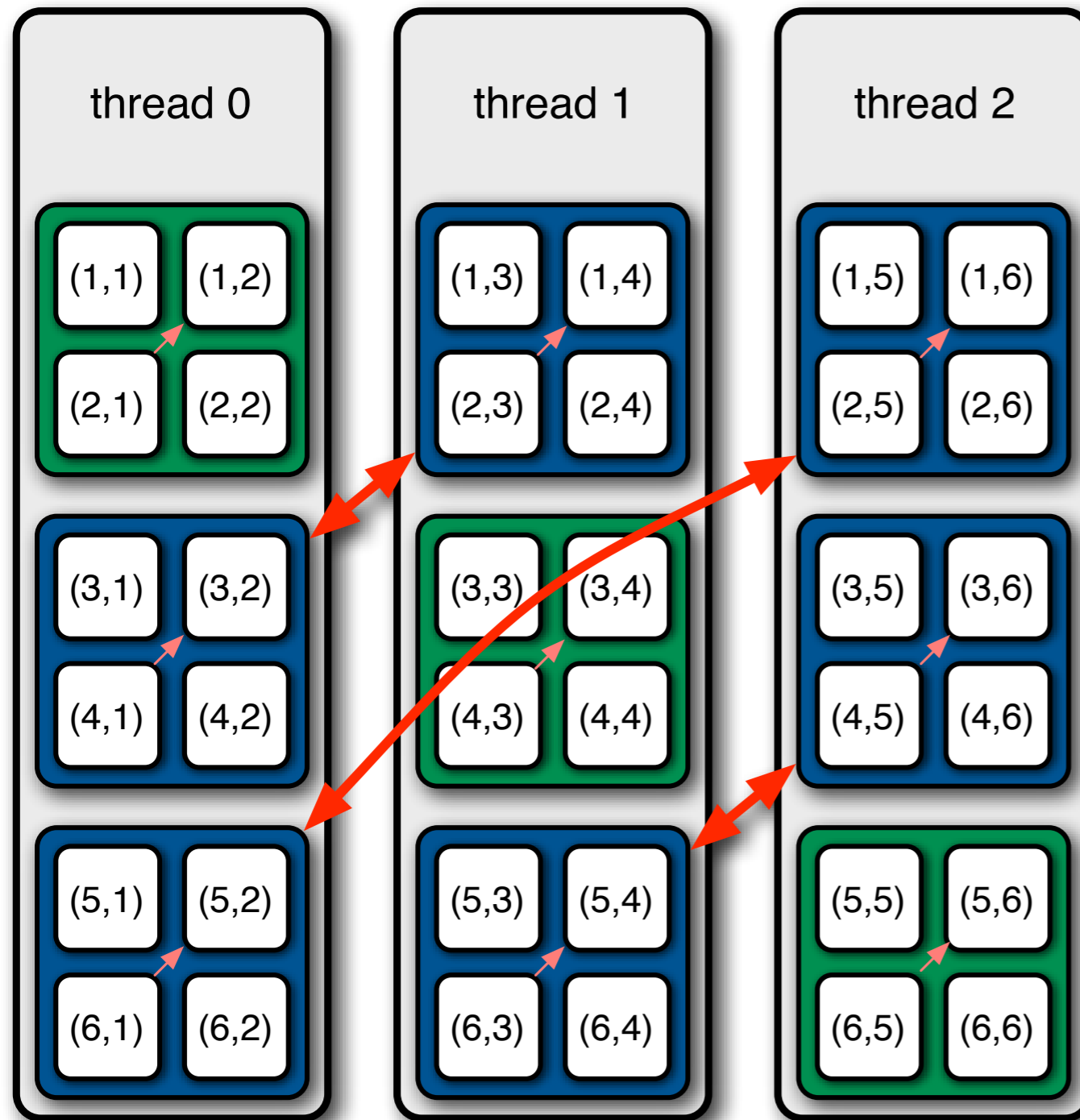


interaction diagonal



1	—	↑	↑↓	(1,1)
2	↑	—	↑↓	(1,2)
3	↑	↑	↓	(1,3)
4	—	↑↓	↑	(2,1)
5	↑	↓	↑	(2,2)
6	↑	↑↓	—	(2,3)
7	↓	↑	↑	(3,1)
8	↑↓	—	↑	(3,2)
9	↑↓	↑	—	(3,3)

Idea: matrix transpose of $v(i_{\downarrow}, i_{\uparrow})$



Lanczos-vector as matrix:
 $v(i_{\downarrow}, i_{\uparrow})$

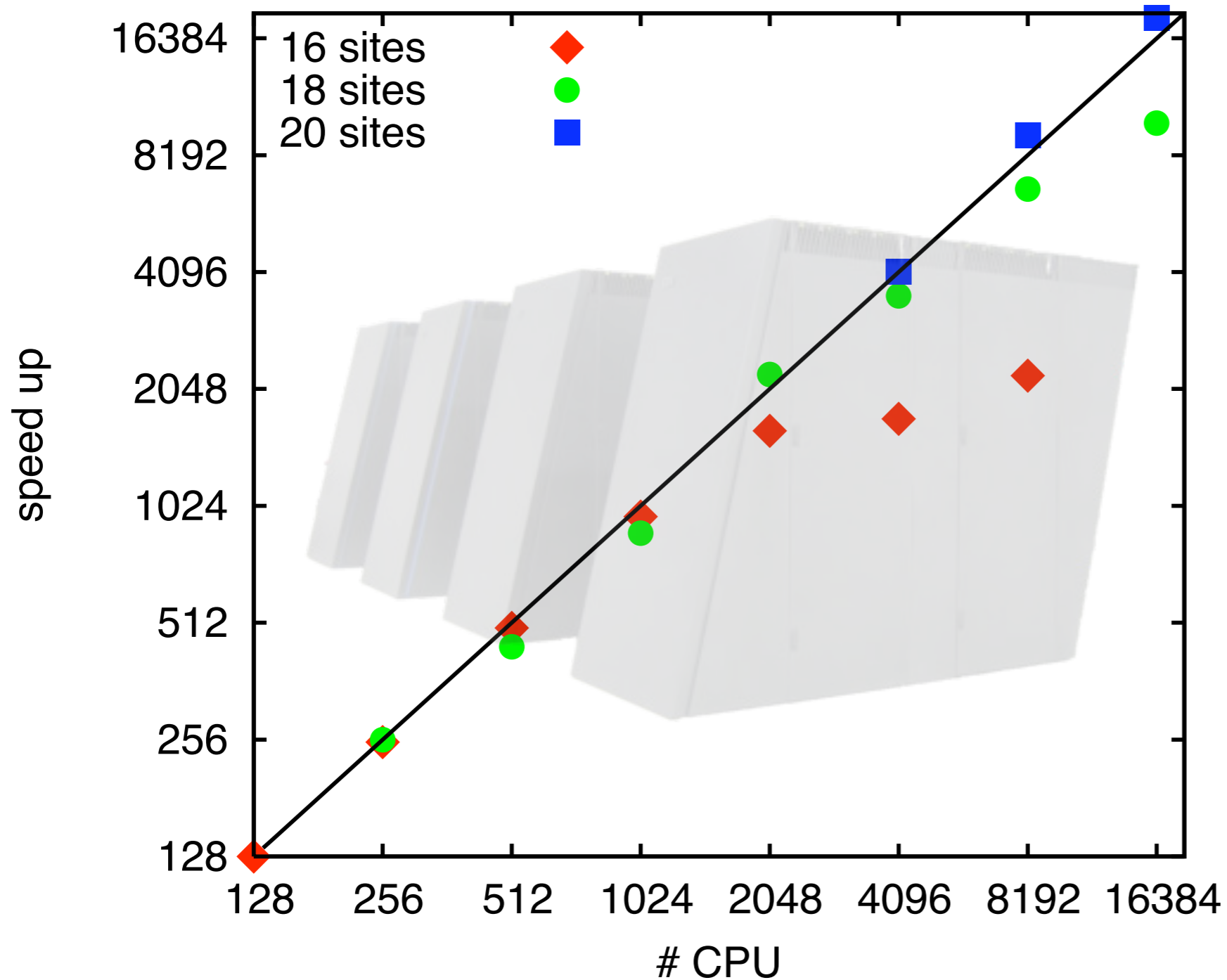
before transpose: \downarrow -hops local
after transpose: \uparrow -hops local

implementation:

`MPI_alltoall` ($N_{\downarrow} = N_{\uparrow}$)

`MPI_alltoallv` ($N_{\downarrow} \neq N_{\uparrow}$)

Implementation on IBM BlueGene/P



sites	memory
16	1 GB
18	18 GB
20	254 GB

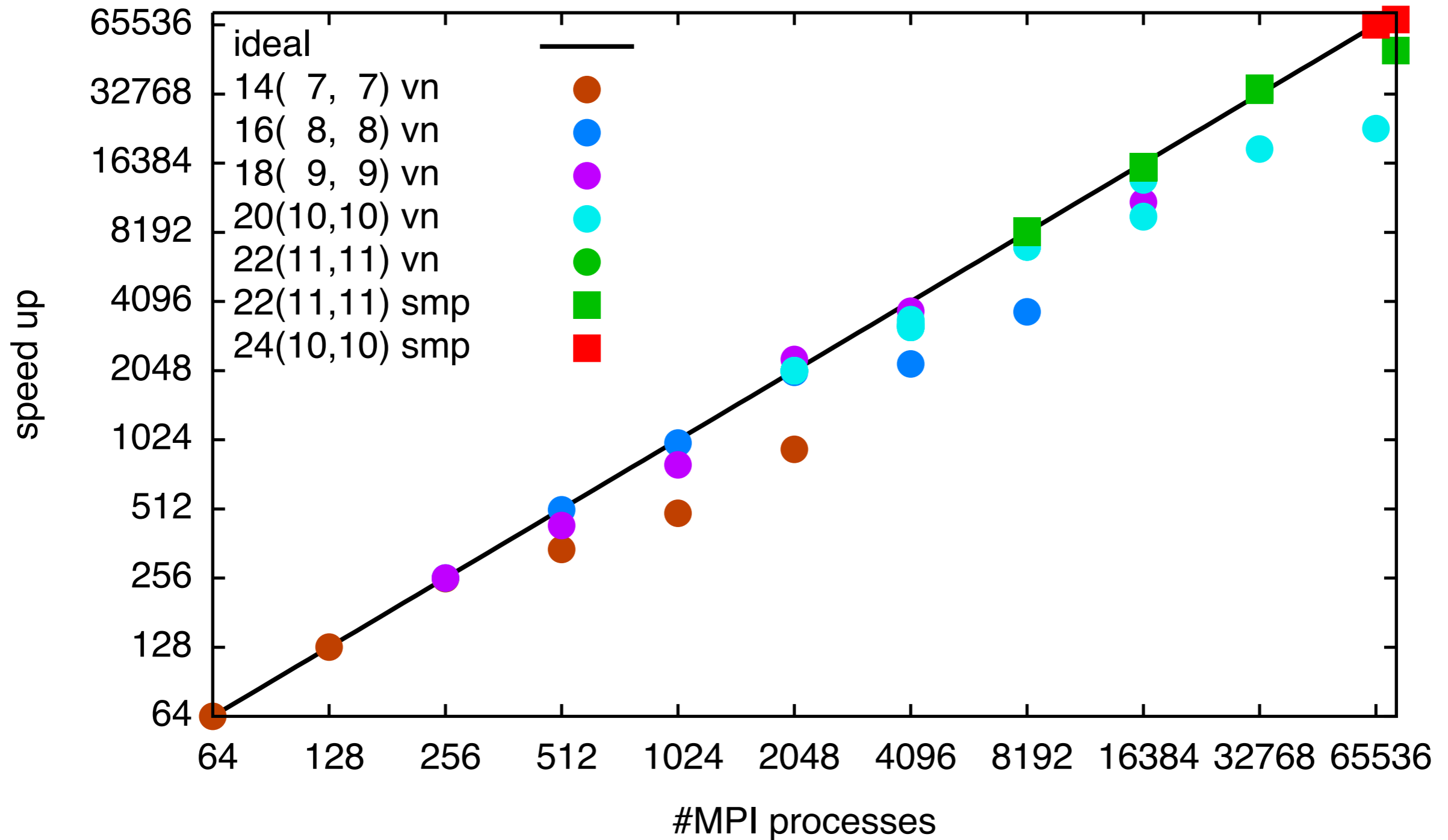
performance on full Jugene?

The screenshot displays a job scheduler interface with the following components:

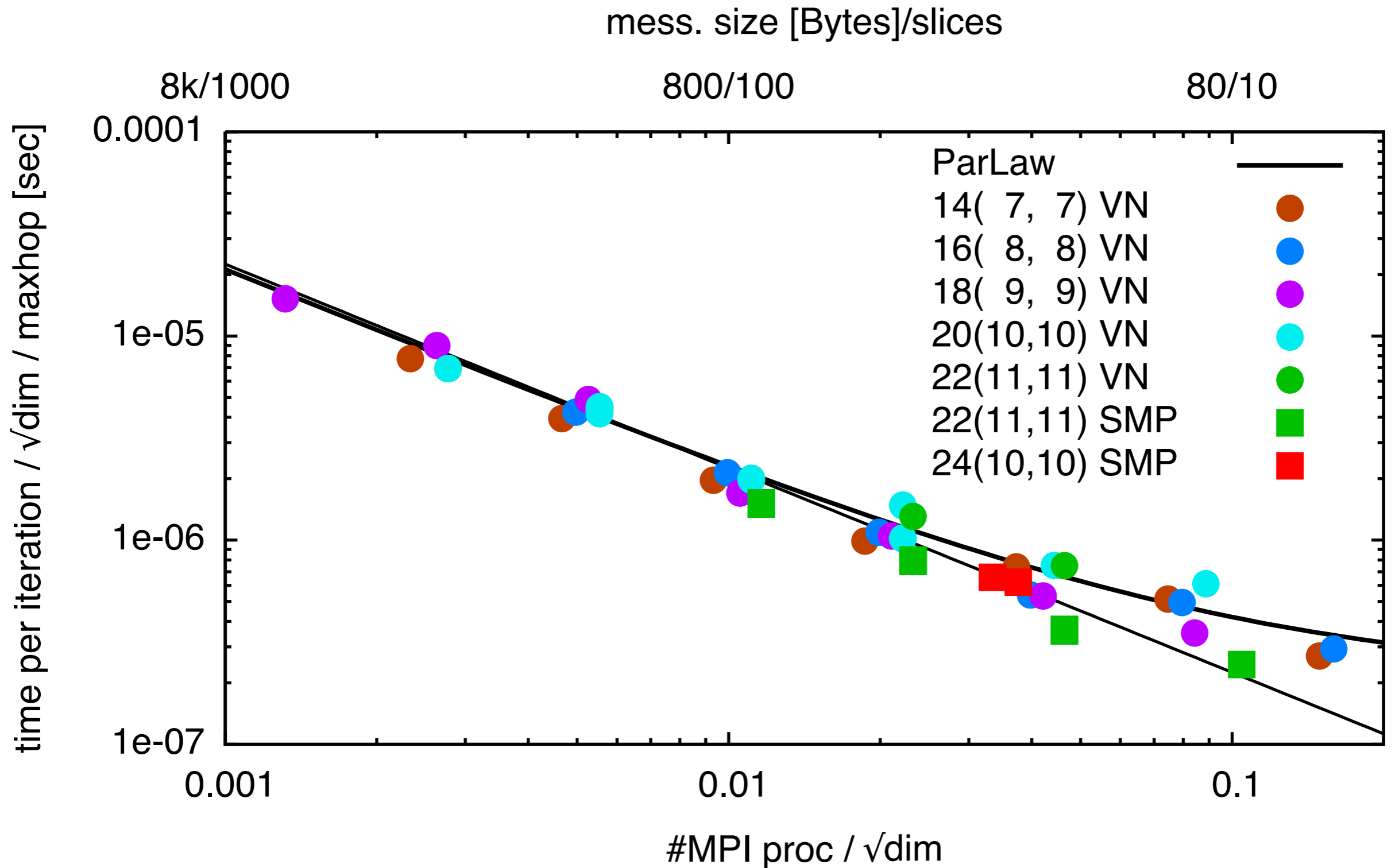
- Top Bar:** File Options Step 60 s active Search grs30002 Last Update 02/10/11-10:16:26 next in 47 s Source WWW Help
- Nodes:** A grid of 100 nodes (10x10) with status indicators (green for running, yellow for waiting).
- Progress Bar:** A horizontal bar showing 100% usage (294912 CPUs used, 0 free).
- Table:** A table with columns: CPU, Userid, Class, booknode, tasks, nodetorus, cpus, wall, TEnd. A row is highlighted in red: 1. 294912 grs30002 m144 2304 73728 294912 8.
- Charts:** A line chart showing job counts over time and a bar chart showing job distribution (large vs small jobs).
- Job Info:** Info for Jobstep jugene3b.125768.0 [sparla_big] (jug) showing user (grs30002), CPUs (294912), and time (0.1h of 1:25).
- Job Scheduling:** A Gantt chart showing job execution times for grs30002 and 125768.

#8 updates, started at Thu Feb 10 10:10:34 2011

performance on full Jugene!



performance on full Jugene!



Spin-Systems

pairwise interaction

$$\sum_{\langle j,k \rangle} J_{jk} \mathbf{S}_j \mathbf{S}_k$$

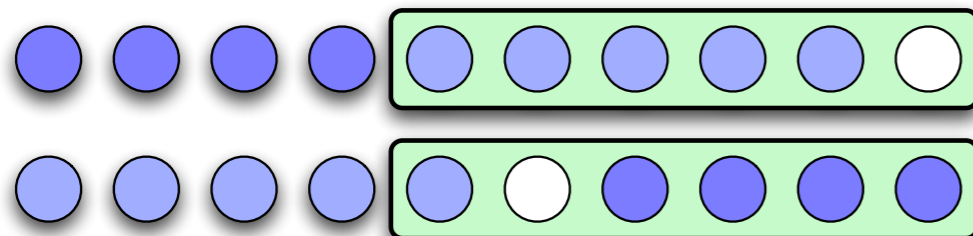
spin configurations

$$\underbrace{100100}_{i>} \quad \underbrace{1100111}_{i<}$$

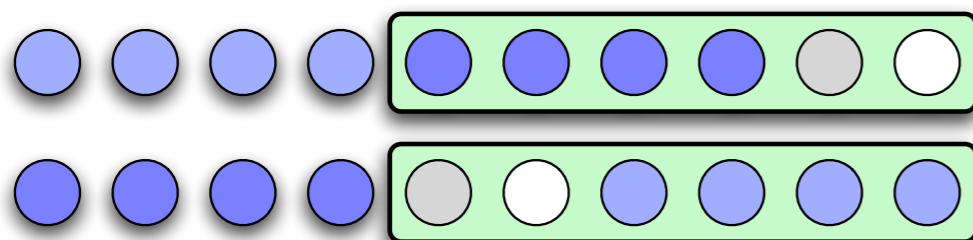
matrix transpose via
MPI_alltoallv or
systolic algorithm

decoherence: single spin

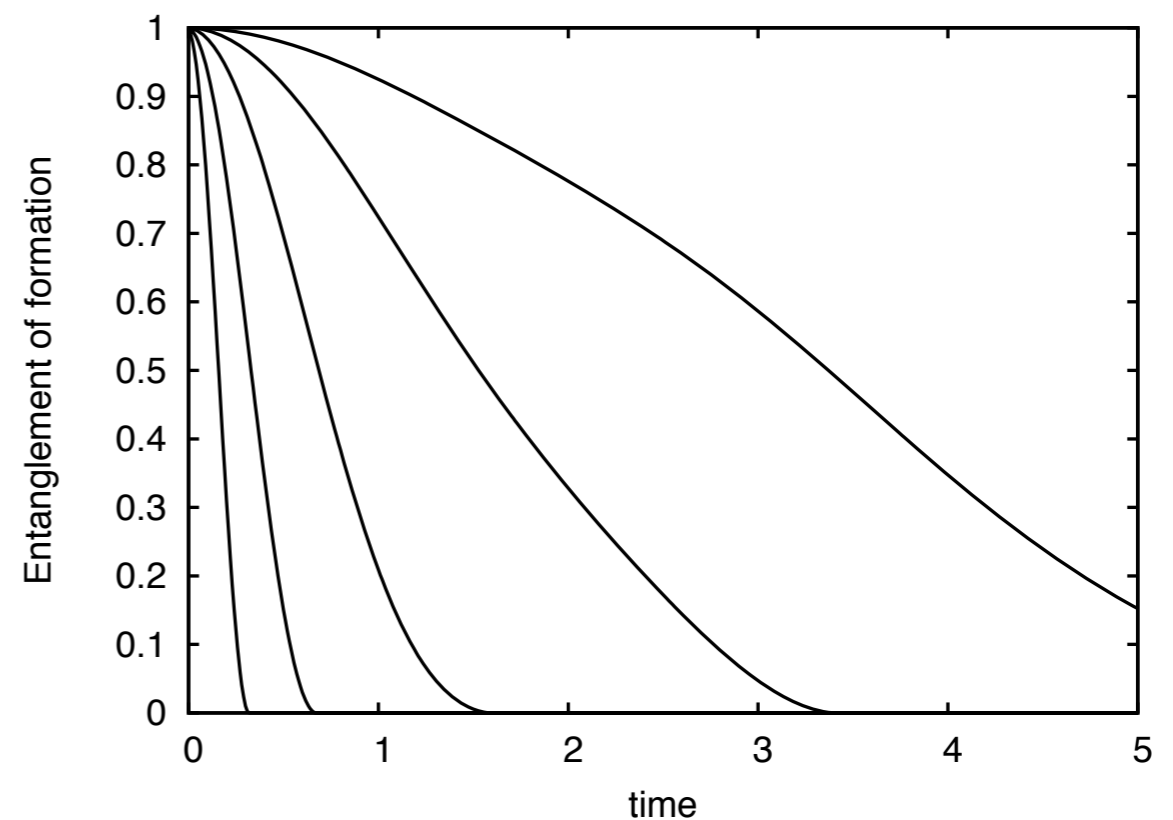
$$H = \mu_B B_0 S_0^Z + \sum_k A_k \mathbf{S}_k \mathbf{S}_0$$



decoherence: entanglement
fidelity of 2-qubit gates



Sudden Death of Entanglement



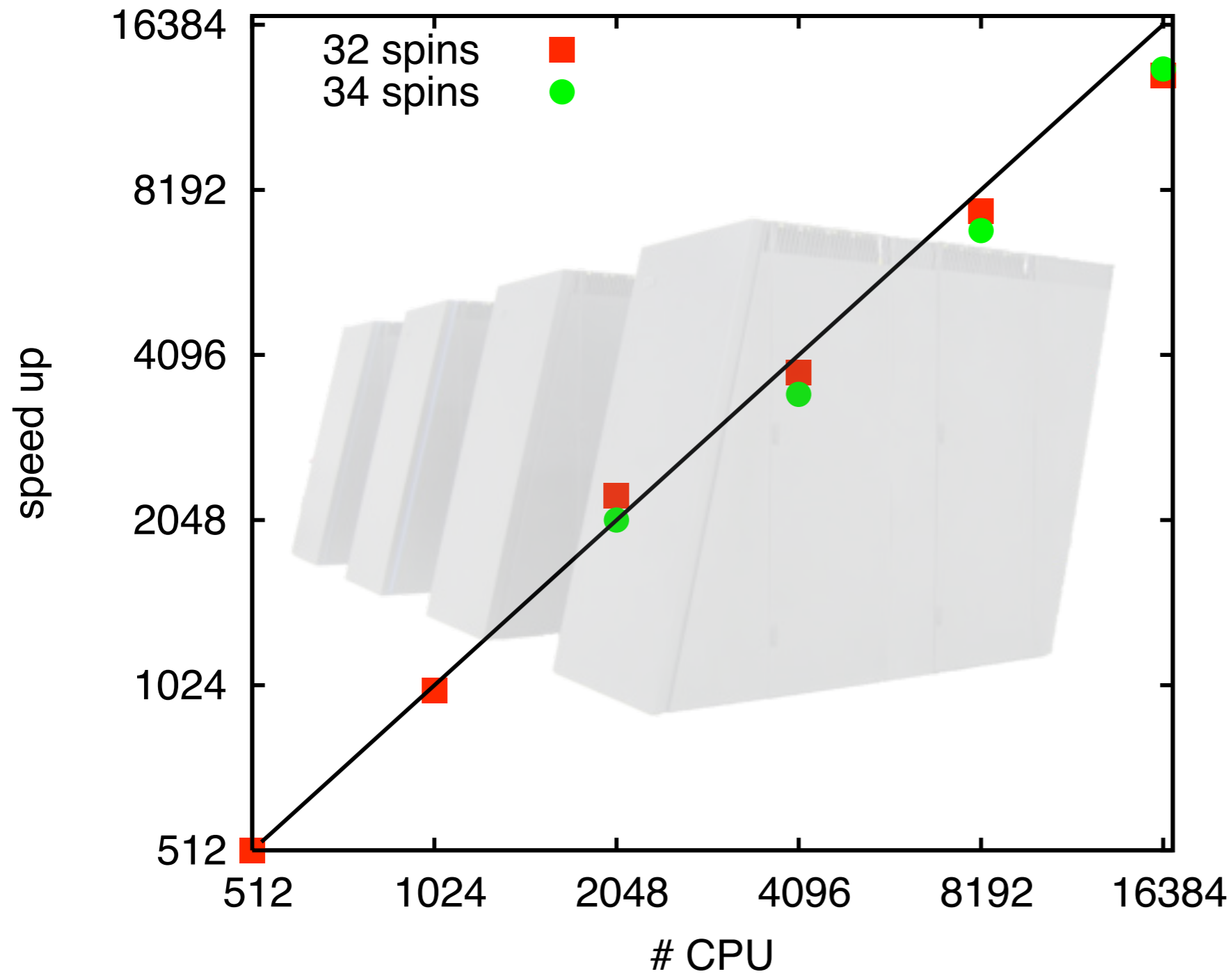
transpose for spins

43	210	43	210	43	210	43	210				
00	000	01	000	10	000	11	000	0	8	16	24
00	001	01	001	10	001	11	001	1	9	17	25
00	010	01	010	10	010	11	010	2	10	18	26
00	011	01	011	10	011	11	011	3	11	19	27
00	100	01	100	10	100	11	100	4	12	20	28
00	101	01	101	10	101	11	101	5	13	21	29
00	110	01	110	10	110	11	110	6	14	22	30
00	111	01	111	10	111	11	111	7	15	23	31

												MPI_alltoall
21	043	21	043	21	043	21	043					
00	000	01	000	10	000	11	000	0	2	4	6	
00	100	01	100	10	100	11	100	1	3	5	7	
00	001	01	001	10	001	11	001	8	10	12	14	
00	101	01	101	10	101	11	101	9	11	13	15	
00	010	01	010	10	010	11	010	16	18	20	22	
00	110	01	110	10	110	11	110	17	19	21	23	
00	011	01	011	10	011	11	011	24	26	28	30	
00	111	01	111	10	111	11	111	25	27	29	31	

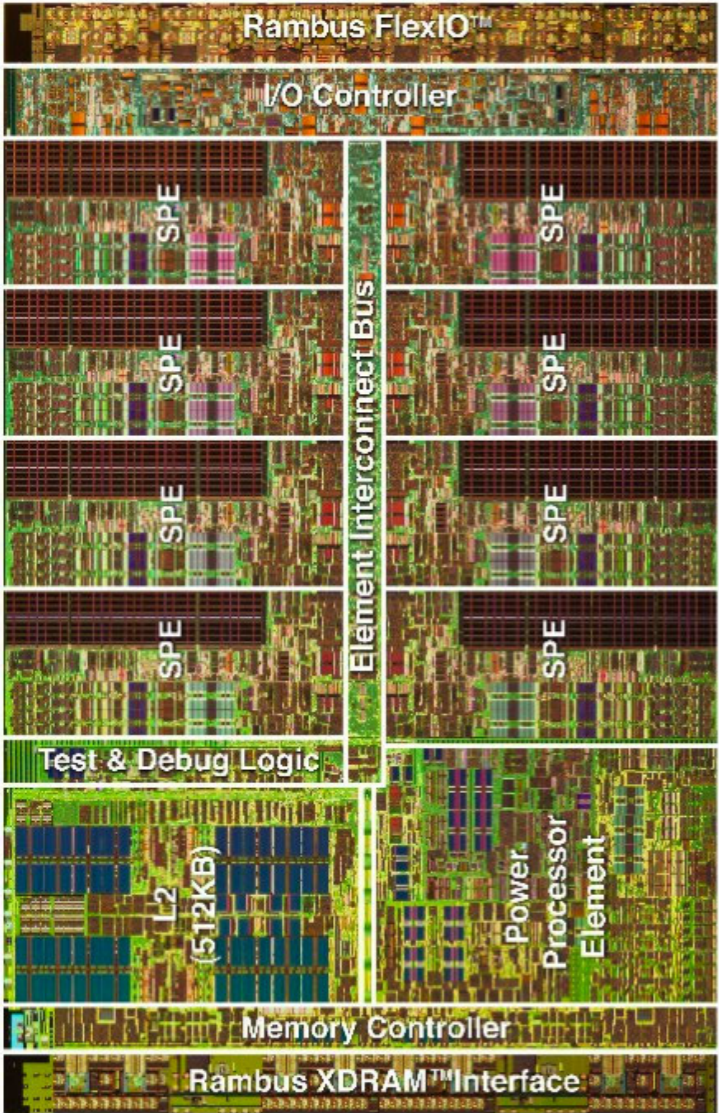
bit reordering: 43 210 ---> 21 034 -> 21 430 (mirror i<)

Heisenberg model on IBM BlueGene/P



spins	memory
32	32 GB
34	256 GB

Cell Broadband Engine



spin models

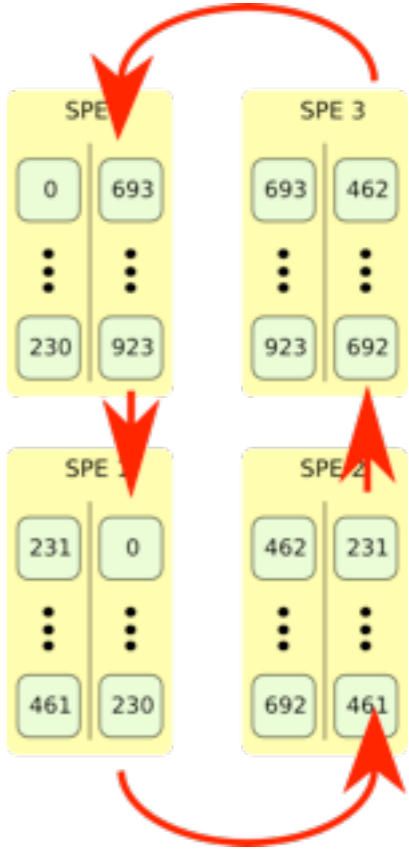
additional partitioning
of local memory

spin configurations

$$\underbrace{100100}_{i_{\text{distr}}} \quad \underbrace{1100111}_{i_{\text{cell}}} \quad \underbrace{101001}_{i_{\text{SPE}}}$$

Lanczos on Cell

rotate spin-slice
through local store



1 Power Processor
8 SPE with 256 kB
fast local store each

DMFT and optimal bath-parametrization

reminder: single-site DMFT

Hubbard model

$$H = - \sum_{ij\sigma} t_{ij} c_{i\sigma}^\dagger c_{j\sigma} + U \sum_i n_{i\uparrow} n_{i\downarrow}$$

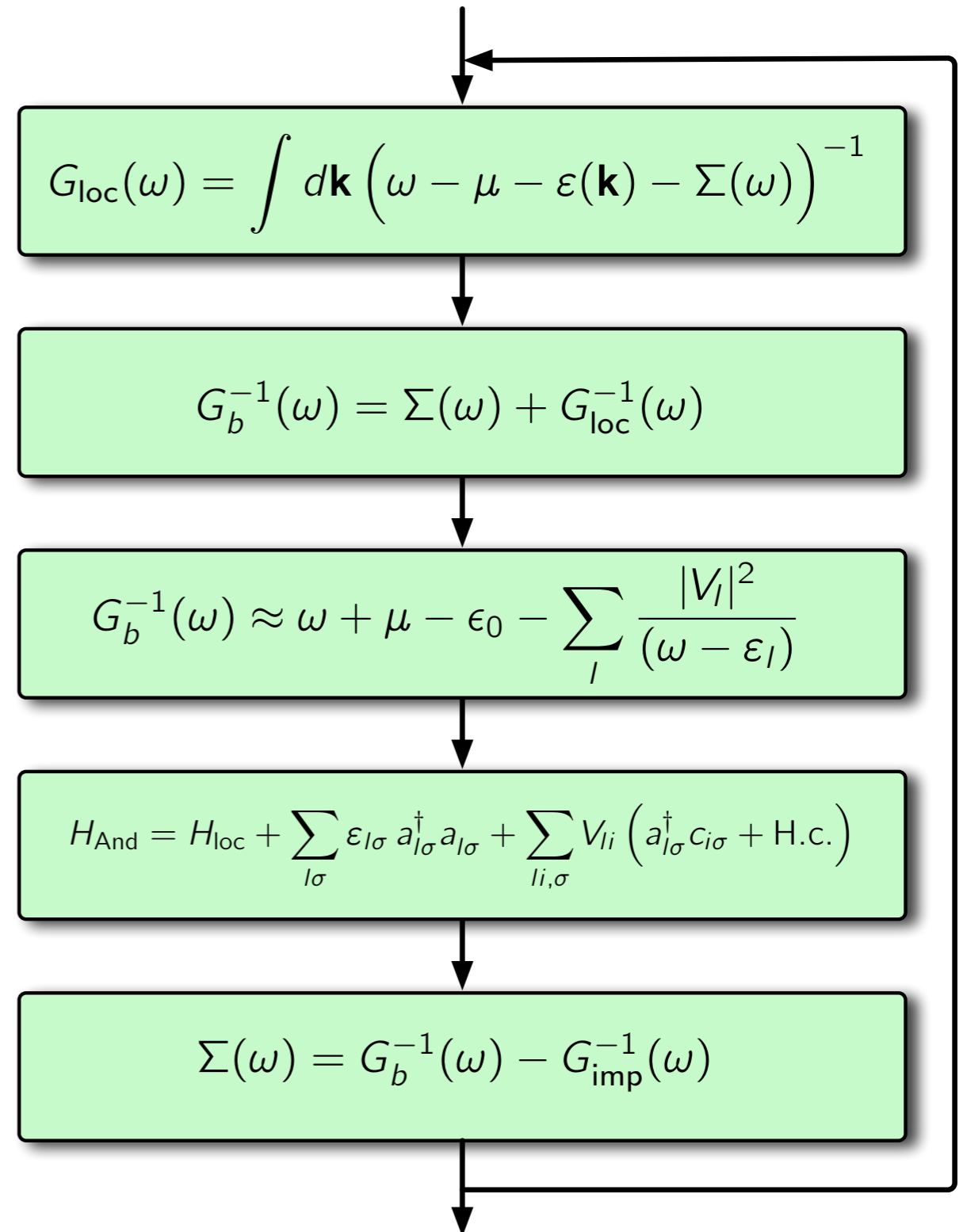


Bloch: $e^{-ik} \quad 1 \quad e^{ik} \quad e^{2ik} \quad e^{3ik} \quad e^{4ik}$

$$c_{k\sigma}^\dagger = \sum e^{ikr_i} c_{i\sigma}^\dagger \Rightarrow H(\mathbf{k}) = \epsilon(\mathbf{k})$$

project to single site: $\int d\mathbf{k} H(\mathbf{k}) = \epsilon_0$

$$H_{\text{loc}} = \epsilon_0 + U n_{\uparrow} n_{\downarrow}$$



bath parametrization

$$G_b^{-1}(\omega) = G_{\text{loc}}^{-1}(\omega) + \Sigma(\omega) = \omega + \mu - \int_{-\infty}^{\infty} d\omega' \frac{\Delta(\omega')}{\omega - \omega'}$$

$$G_{\text{And}}^{-1}(\omega) = \omega + \mu - \sum_{l=1}^{N_b} \frac{V_l^2}{\omega - \varepsilon_l}$$

how to determine bath parameters ε_l and V_l ?

$$H_{\text{And}}^0 = \begin{pmatrix} 0 & V_1 & V_2 & V_3 & \cdots \\ V_1 & \varepsilon_1 & 0 & 0 & \\ V_2 & 0 & \varepsilon_2 & 0 & \\ V_3 & 0 & 0 & \varepsilon_3 & \\ \vdots & & & & \ddots \end{pmatrix}$$

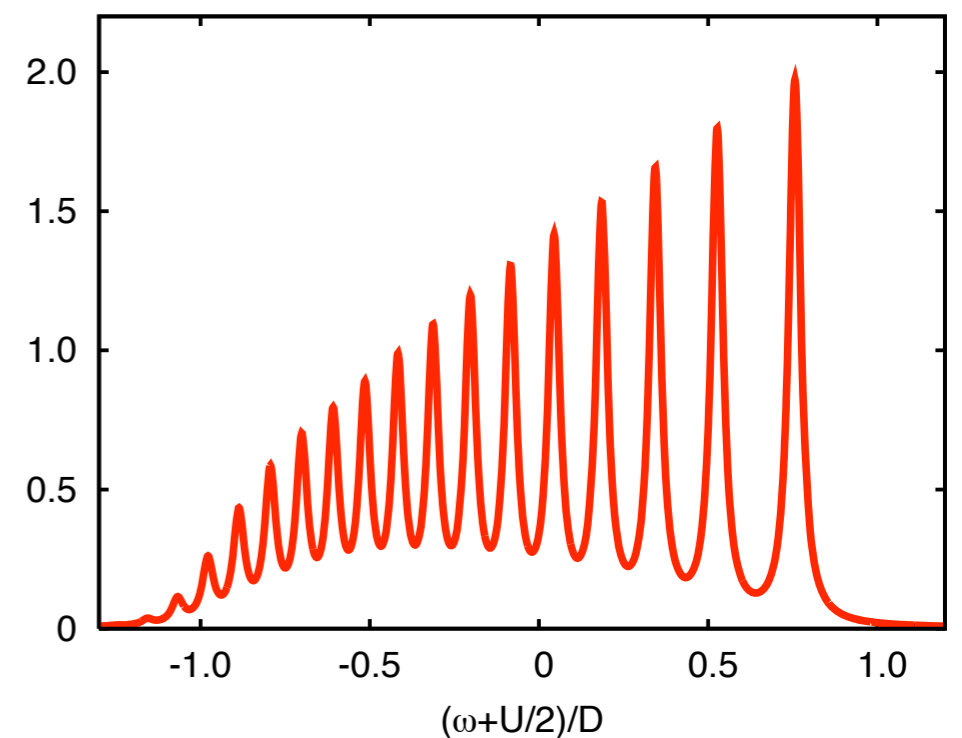
$$H_{\text{And}} = \varepsilon_0 \sum_{\sigma} n_{\sigma} + U n_{\uparrow} n_{\downarrow} + \sum_{\sigma} \sum_{l=1}^{N_b} \left(\varepsilon_l n_{l\sigma} + V_l \left(a_{l\sigma}^{\dagger} c_{\sigma} + c_{\sigma}^{\dagger} a_{l\sigma} \right) \right)$$

use Lanczos parameters

Bethe lattice: $\int d\omega' \frac{\Delta(\omega')}{\omega - \omega'} = t^2 G_{\text{imp}}(\omega)$

$$t^2 G^<(\omega) + t^2 G^>(\omega) = \frac{t^2 b_0^{<2}}{\omega + a_0^{<} - \frac{b_1^{<2}}{\omega + a_1^{<} - \dots}} + \frac{t^2 b_0^{>2}}{\omega - a_0^{>} - \frac{b_1^{>2}}{\omega - a_1^{>} - \dots}}$$

$$H_{\text{And}}^0 = \begin{pmatrix} 0 & t^2 b_0^{<} & & \dots & t^2 b_0^{>} \\ t^2 b_0^{<} & -a_0^{<} & b_1^{<} & & \\ & b_1^{<} & -a_1^{<} & b_2^{<} & \\ & & b_2^{<} & -a_2^{<} & \ddots \\ \vdots & & & \ddots & \ddots \\ t^2 b_0^{>} & & & & a_0^{>} & b_1^{>} & b_2^{>} & \dots \\ & & & & b_1^{>} & a_1^{>} & b_2^{>} & \dots \\ & & & & & b_2^{>} & a_2^{>} & \ddots \\ & & & & & & \ddots & \ddots \end{pmatrix}$$



fit on imaginary axis

fictitious temperature: Matsubara frequencies

$$\chi^2(\{V_l, \varepsilon_l\}) = \sum_{n=0}^{n_{\max}} w(i\omega_n) \left| \mathcal{G}^{-1}(i\omega_n) - \mathcal{G}_{\text{And}}^{-1}(i\omega_n) \right|^2$$

weight function $w(i\omega_n)$:

- emphasize region close to real axis
- make sum converge for $n \rightarrow \infty$ (sum rule)

reminder: single-site DMFT

Hubbard model

$$H = - \sum_{ij\sigma} t_{ij} c_{i\sigma}^\dagger c_{j\sigma} + U \sum_i n_{i\uparrow} n_{i\downarrow}$$

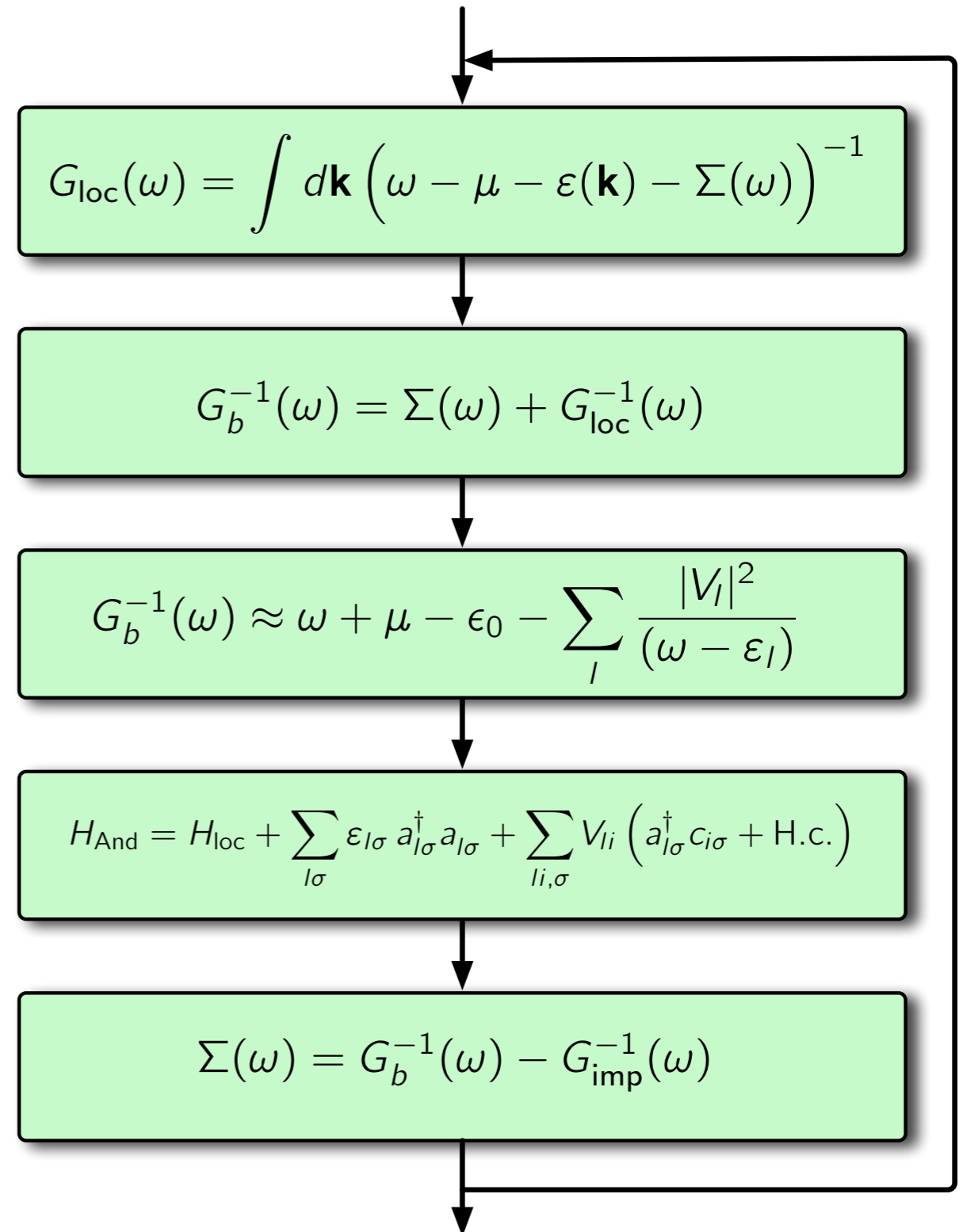


Bloch: $e^{-ik} \quad 1 \quad e^{ik} \quad e^{2ik} \quad e^{3ik} \quad e^{4ik}$

$$c_{k\sigma}^\dagger = \sum e^{ikr_i} c_{i\sigma}^\dagger \Rightarrow H(\mathbf{k}) = \epsilon(\mathbf{k})$$

project to single site: $\int d\mathbf{k} H(\mathbf{k}) = \epsilon_0$

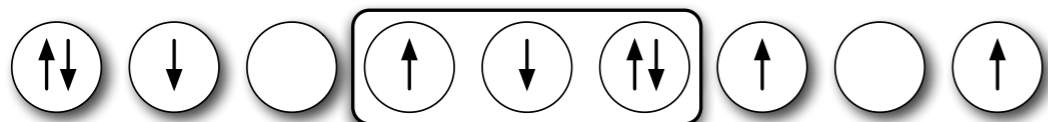
$$H_{\text{loc}} = \epsilon_0 + U n_{\uparrow} n_{\downarrow}$$



DMFT for clusters

Hubbard model

$$H = - \sum_{ij\sigma} t_{ij} c_{i\sigma}^\dagger c_{j\sigma} + U \sum_i n_{i\uparrow} n_{i\downarrow}$$

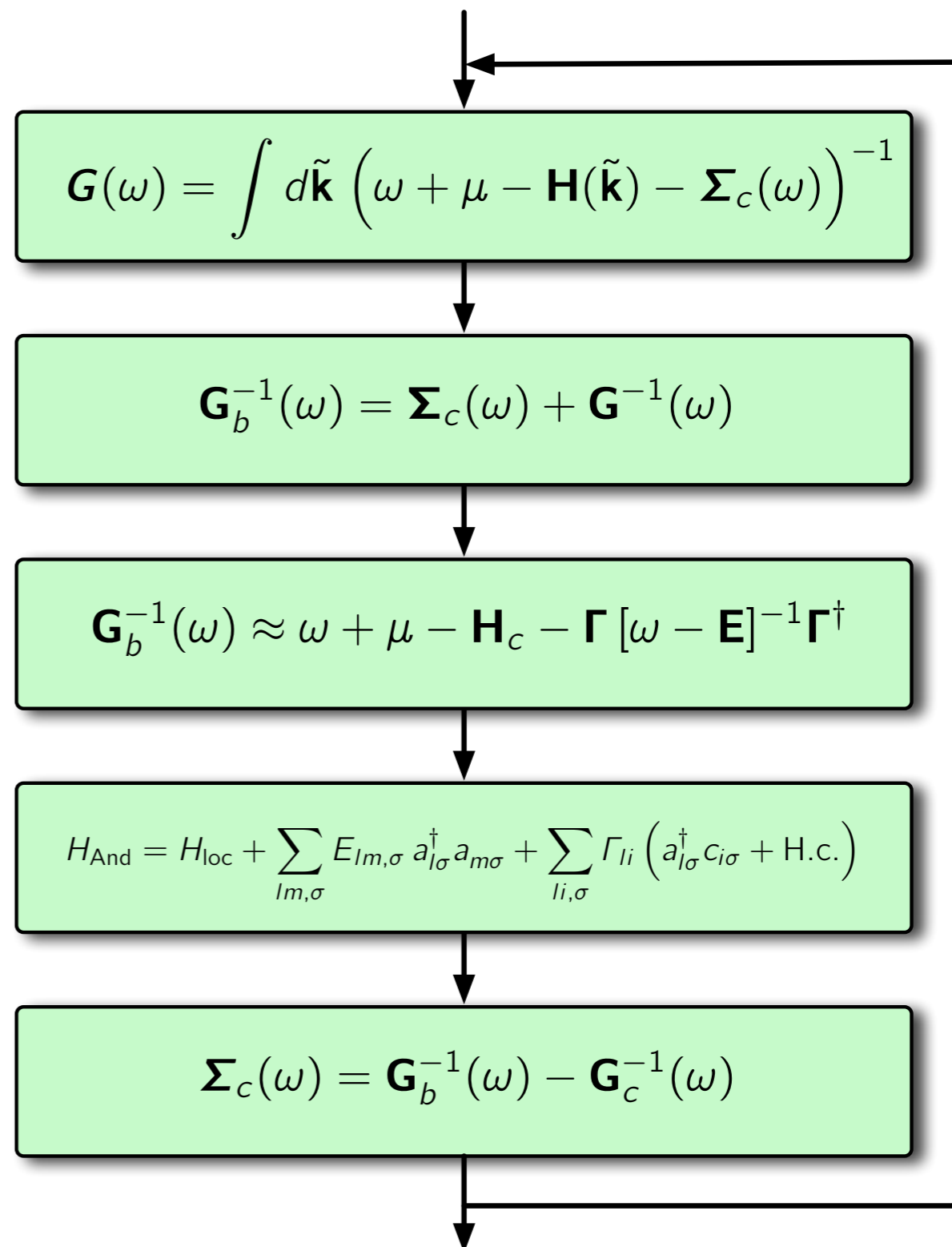
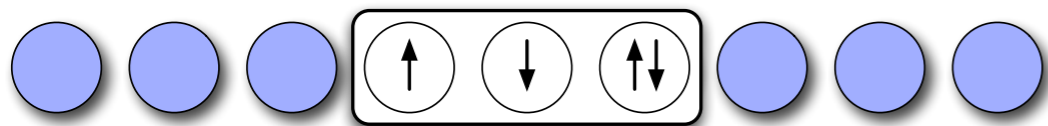


Bloch: e^{-ik} 1 e^{ik} e^{2ik} e^{3ik} e^{4ik}

$$c_{\tilde{\mathbf{k}}\sigma}^\dagger = \sum e^{i\tilde{\mathbf{k}}r_i} c_{i\sigma}^\dagger \Rightarrow \mathbf{H}(\tilde{\mathbf{k}})$$

project to cluster: $\int d\tilde{\mathbf{k}} \mathbf{H}(\tilde{\mathbf{k}}) = \mathbf{H}_c$

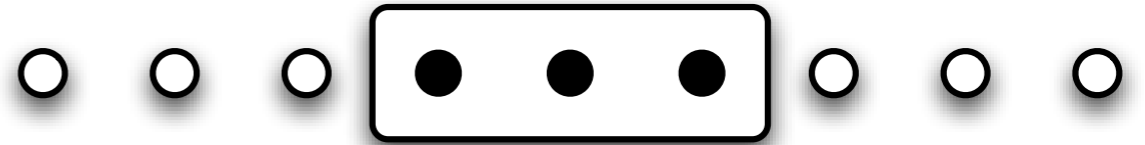
$$H_{\text{loc}} = \mathbf{H}_c + U \sum_i n_{i\uparrow} n_{i\downarrow}$$



DCA

3-site cluster

$$\mathbf{H}(\tilde{k}) = -t \begin{pmatrix} 0 & e^{i\tilde{k}} & e^{-i\tilde{k}} \\ e^{-i\tilde{k}} & 0 & e^{i\tilde{k}} \\ e^{i\tilde{k}} & e^{-i\tilde{k}} & 0 \end{pmatrix}$$



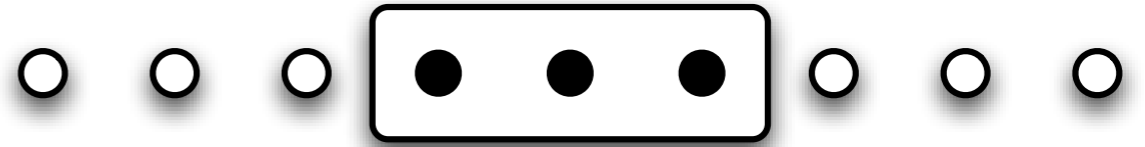
$$\mathbf{H}_c = \frac{3}{2\pi} \int_{-\pi/3}^{\pi/3} d\tilde{k} \mathbf{H}(\tilde{k}) = -\frac{3\sqrt{3}}{2\pi} t \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix}$$

translation symmetry
coarse-grained Hamiltonian

DCA

CDMFT

$$\mathbf{H}(\tilde{k}) = -t \begin{pmatrix} 0 & e^{i\tilde{k}} & e^{-i\tilde{k}} \\ e^{-i\tilde{k}} & 0 & e^{i\tilde{k}} \\ e^{i\tilde{k}} & e^{-i\tilde{k}} & 0 \end{pmatrix}$$



$$\mathbf{H}_c = \frac{3}{2\pi} \int_{-\pi/3}^{\pi/3} d\tilde{k} \mathbf{H}(\tilde{k}) = -\frac{3\sqrt{3}}{2\pi} t \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix}$$

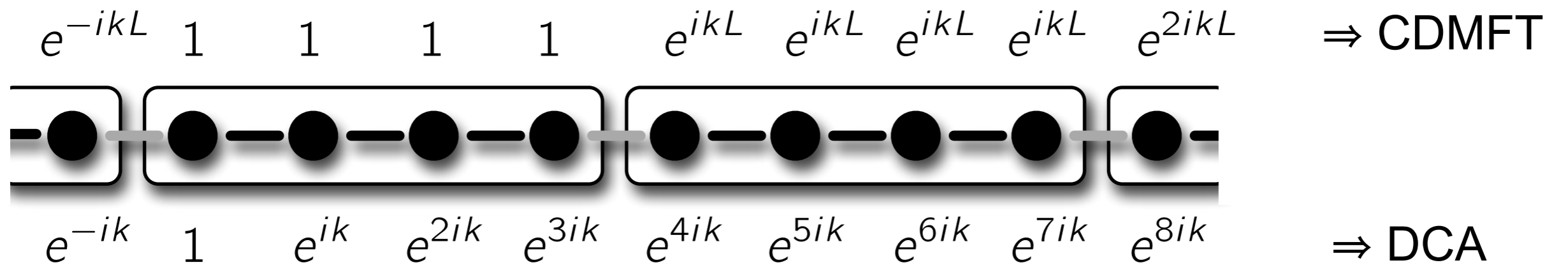
translation symmetry
coarse-grained Hamiltonian

no translation symmetry
original Hamiltonian on cluster

$$\mathbf{H}(\tilde{k}) = -t \begin{pmatrix} 0 & 1 & e^{-3i\tilde{k}} \\ 1 & 0 & 1 \\ e^{3i\tilde{k}} & 1 & 0 \end{pmatrix}$$

$$\mathbf{H}_c = \frac{3}{2\pi} \int_{-\pi/3}^{\pi/3} d\tilde{k} \mathbf{H}(\tilde{k}) = -t \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

DCA – CDMFT



$$\tilde{C}_{R_i\sigma}^{\text{CDMFT}}(\tilde{\mathbf{k}}) = \sum_{\tilde{r}} e^{-i\tilde{\mathbf{k}}\tilde{r}} C_{\tilde{r}+R_i,\sigma}$$

$$\tilde{C}_{R_i\sigma}^{\text{DCA}}(\tilde{\mathbf{k}}) = \sum_{\tilde{r}} e^{-i\tilde{\mathbf{k}}(\tilde{r}+R_i)} C_{\tilde{r}+R_i,\sigma}$$

gauge determines
cluster method:

$$\tilde{C}_{R_i\sigma}(\tilde{\mathbf{k}}) = \sum_{\tilde{r}} e^{-i(\tilde{\mathbf{k}}\tilde{r} + \varphi(\tilde{\mathbf{k}}; R_i))} C_{\tilde{r}+R_i,\sigma}$$

bath for cluster

$$H_{\text{And}} = H_{\text{clu}} + \sum_{l\sigma} \varepsilon_{l\sigma} a_{l\sigma}^\dagger a_{l\sigma} + \sum_{li,\sigma} \left(V_{l,i} a_{l\sigma}^\dagger c_{i\sigma} + \text{H.c.} \right)$$

$$\mathbf{G}_b^{-1}(\omega) \approx \omega + \mu - \mathbf{H}_c - \sum_l \frac{\mathbf{v}_l \mathbf{v}_l^\dagger}{\omega - \varepsilon_l}$$

$$\mathbf{G}_b^{-1}(\omega) = \mathbf{\Sigma}_c(\omega) + \left(\int d\tilde{\mathbf{k}} \left(\omega + \mu - \mathbf{H}(\tilde{\mathbf{k}}) - \mathbf{\Sigma}_c(\omega) \right)^{-1} \right)^{-1}$$

expand up to $1/\omega^2$: **sum-rule**

$$\sum_l \mathbf{v}_l \mathbf{v}_l^\dagger = \int d\tilde{\mathbf{k}} \mathbf{H}^2(\tilde{\mathbf{k}}) - \left(\int d\tilde{\mathbf{k}} \mathbf{H}(\tilde{\mathbf{k}}) \right)^2$$

hybridization sum-rules: single-site

H with hopping t_n to the z_n n^{th} -nearest neighbors

$$\sum_l V_l^2 = \frac{1}{(2\pi)^d} \int_{-\pi}^{\pi} d^d \mathbf{k} \varepsilon_{\mathbf{k}}^2 = \sum_n z_n t_n^2$$

special case: Bethe lattice of coordination z with hopping t/\sqrt{z}

$$\sum_l V_l^2 = t^2$$

hybridization sum-rules: DCA

hybridizations diagonal in the cluster-momenta \mathbf{K} :

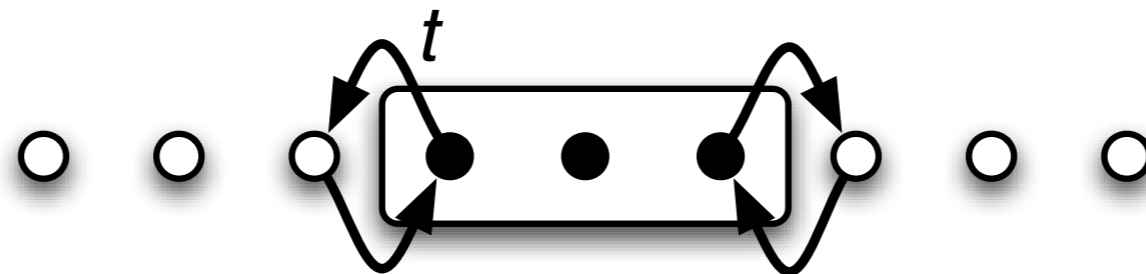
$$\sum_I |V_{I,\mathbf{K}}|^2 = \int d\tilde{\mathbf{k}} \varepsilon_{\mathbf{K}+\tilde{\mathbf{k}}}^2 - \left(\int d\tilde{\mathbf{k}} \varepsilon_{\mathbf{K}+\tilde{\mathbf{k}}} \right)^2$$

all terms $V_{I,\mathbf{K}} V_{I,\mathbf{K}'}$ mixing different cluster momenta vanish

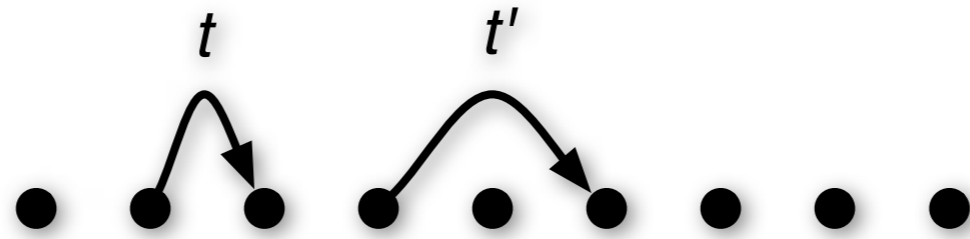
hybridization sum-rules: CDMFT

$$\mathbf{H}(\tilde{k}) = -t \begin{pmatrix} 0 & 1 & e^{-3i\tilde{k}} \\ 1 & 0 & 1 \\ e^{3i\tilde{k}} & 1 & 0 \end{pmatrix}$$

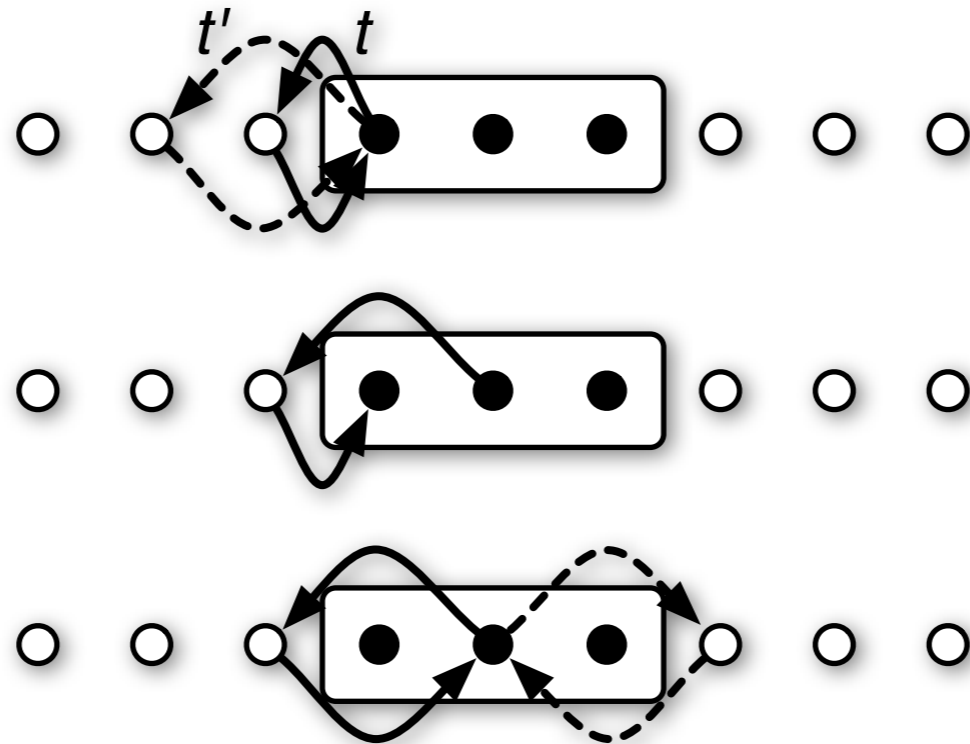
$$\sum_I \mathbf{v}_I \mathbf{v}_I^\dagger = \int d\tilde{\mathbf{k}} \mathbf{H}^2(\tilde{\mathbf{k}}) - \left(\int d\tilde{\mathbf{k}} \mathbf{H}(\tilde{\mathbf{k}}) \right)^2 = \begin{pmatrix} t^2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & t^2 \end{pmatrix}$$



hybridization sum-rules: CDMFT

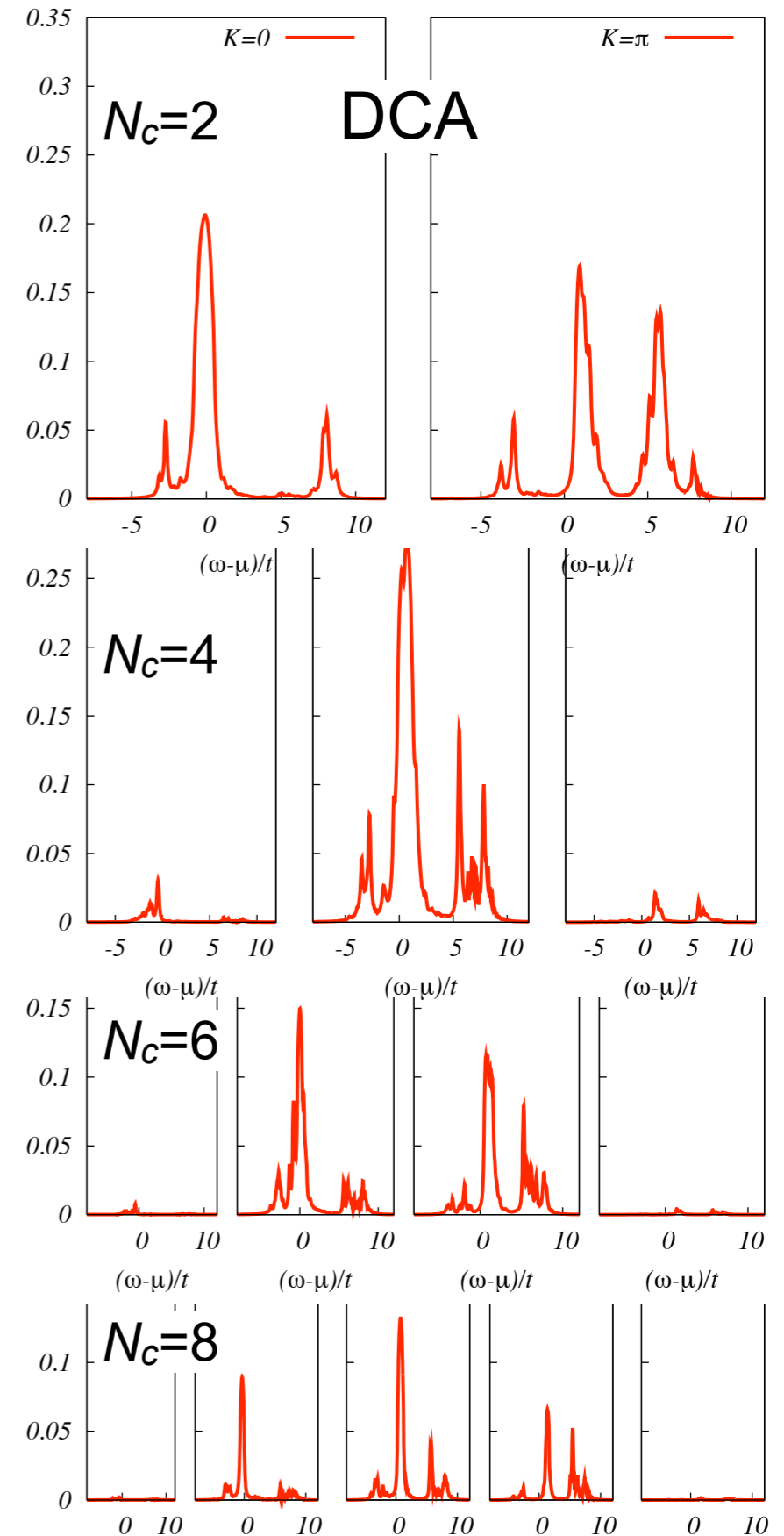
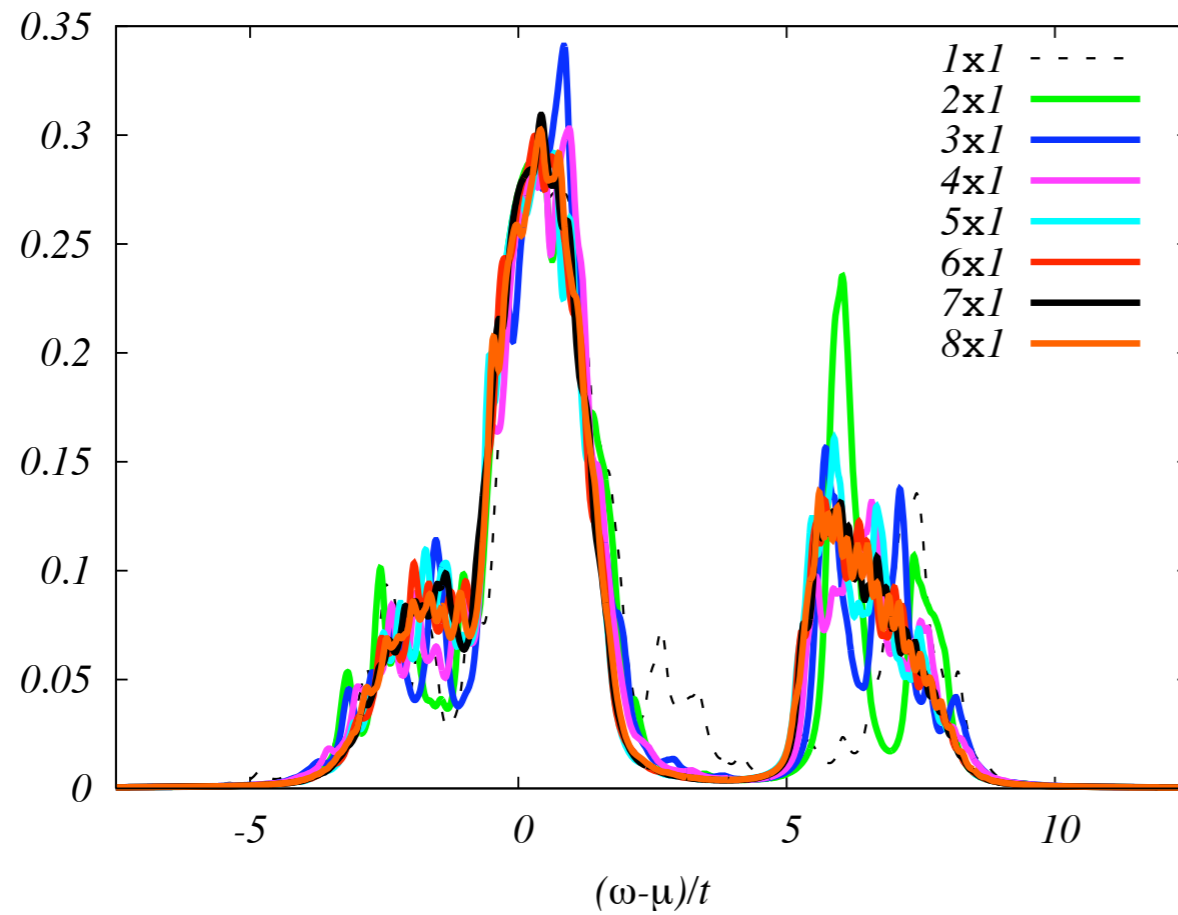


$$\left(\sum_l V_{l,i} \bar{V}_{l,j} \right) = \begin{pmatrix} t^2 + t'^2 & t t' & 0 \\ t t' & 2t'^2 & t t' \\ 0 & t t' & t^2 + t'^2 \end{pmatrix}$$



example: 1-d clusters

CDMFT



	CDMFT	DCA
hybridize	only surface	full cluster
strength	const.	$1/N_c^{2/d}$

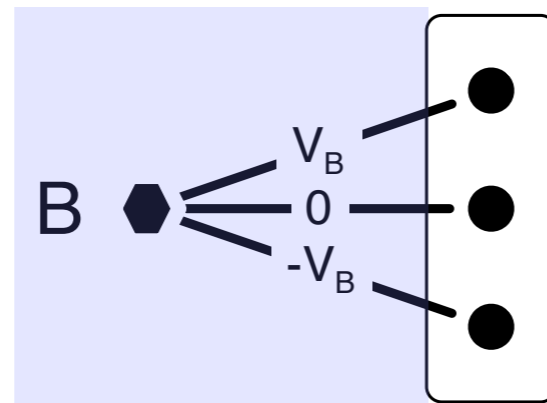
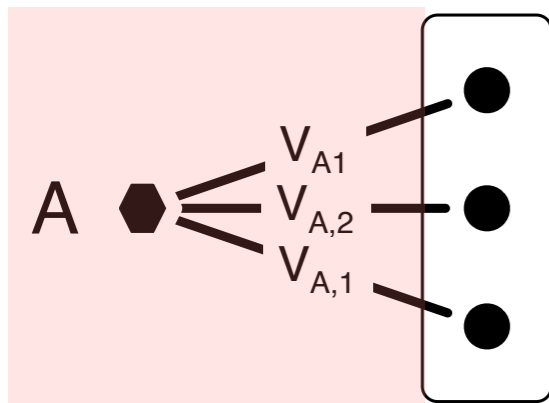
symmetry of bath

$$\mathbf{W} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 0 & 1 \\ 0 & \sqrt{2} & 0 \\ 1 & 0 & -1 \end{pmatrix}$$

irreducible representations: A (even), B (odd)

$$\mathbf{W}^\dagger \mathbf{G}_b^{-1} \mathbf{W} = \begin{pmatrix} G_{b,11}^{-1} + G_{b,13}^{-1} & \sqrt{2} G_{b,12}^{-1} & 0 \\ \sqrt{2} G_{b,21}^{-1} & G_{b,22}^{-1} & 0 \\ 0 & 0 & G_{b,11}^{-1} - G_{b,13}^{-1} \end{pmatrix}$$

block-diagonal



symmetry of bath

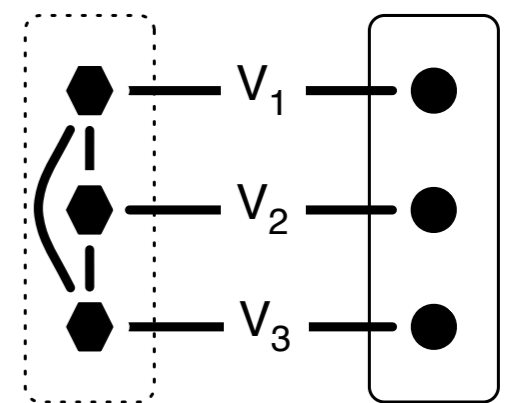
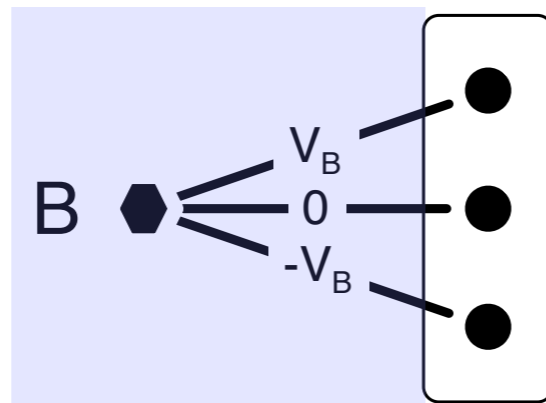
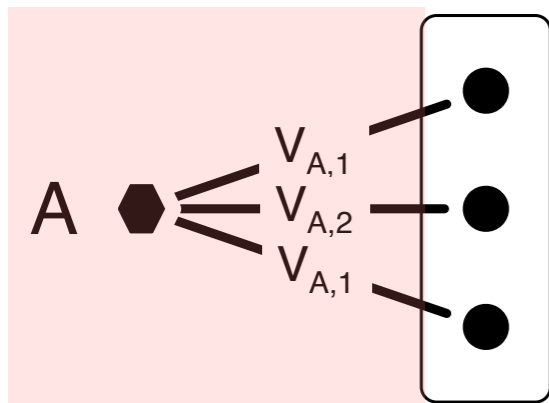
$$\mathbf{W} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 0 & 1 \\ 0 & \sqrt{2} & 0 \\ 1 & 0 & -1 \end{pmatrix}$$

irreducible representations: A (even), B (odd)

$$\mathbf{W}^\dagger \mathbf{G}_b^{-1} \mathbf{W} = \begin{pmatrix} G_{b,11}^{-1} + G_{b,13}^{-1} & \sqrt{2} G_{b,12}^{-1} & 0 \\ \sqrt{2} G_{b,21}^{-1} & G_{b,22}^{-1} & 0 \\ 0 & 0 & G_{b,11}^{-1} - G_{b,13}^{-1} \end{pmatrix}$$

block-diagonal

cluster replica: 2A+B



$$V_{A,1} = (V_1 + V_3)/\sqrt{2}$$

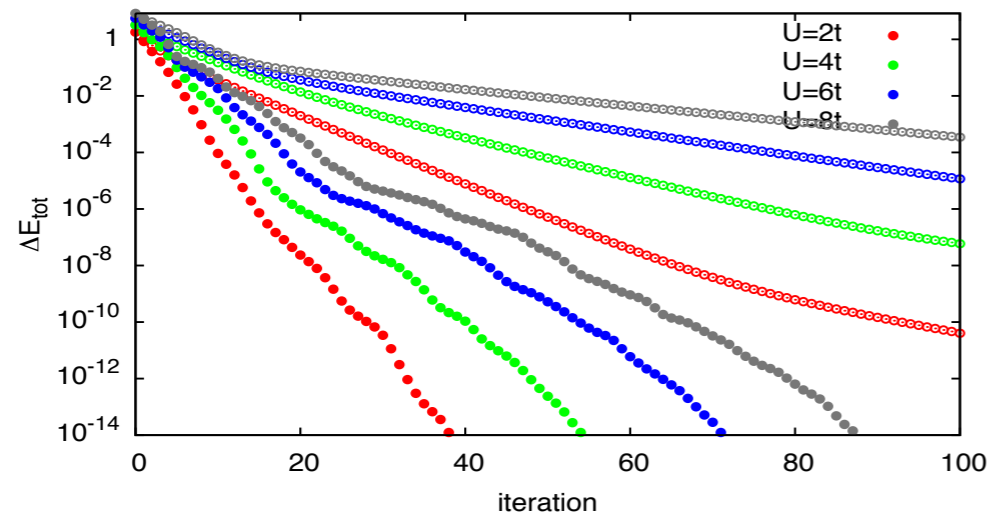
$$V_{A,2} = V_2$$

$$V_B = (V_1 - V_3)/\sqrt{2}$$

summary

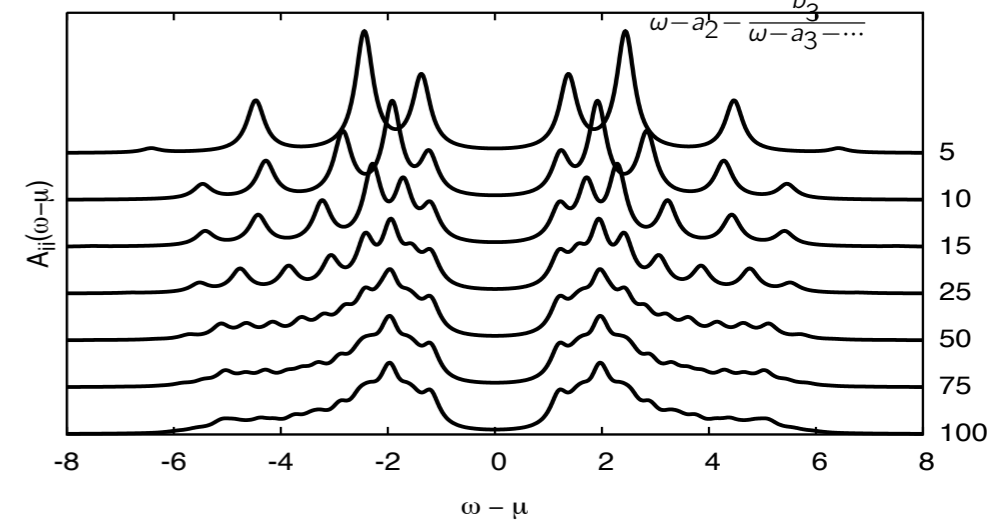
steepest descent \Rightarrow Krylov space

$$\frac{\delta E[\Psi]}{\delta \langle \Psi |} = \frac{H|\Psi\rangle - E[\Psi]|\Psi\rangle}{\langle \Psi | \Psi \rangle} = |\Psi_a\rangle \in \text{span}(|\Psi\rangle, H|\Psi\rangle)$$

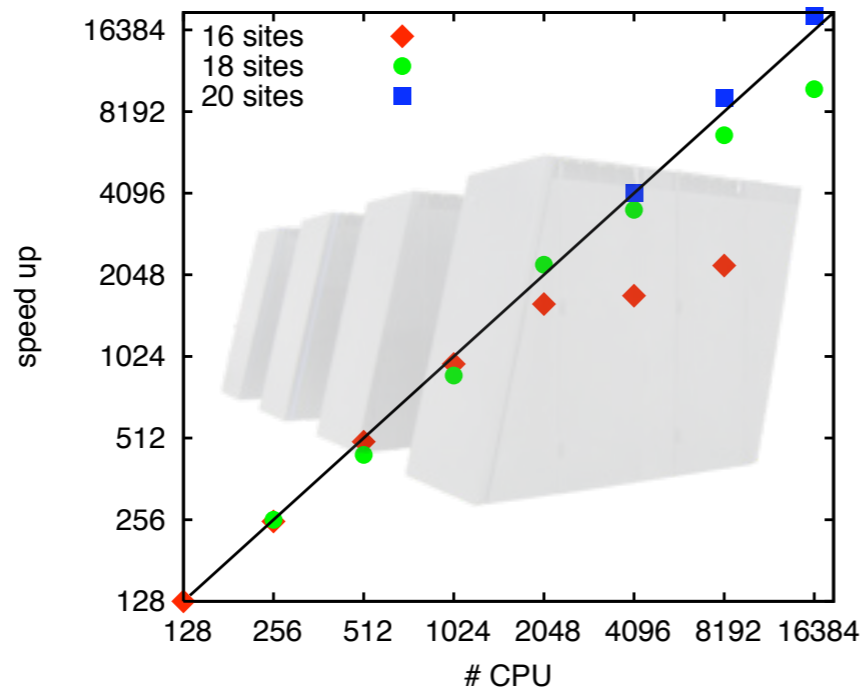
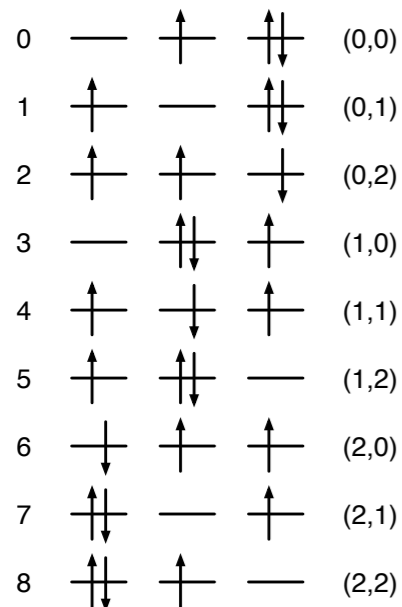


spectral function: moments

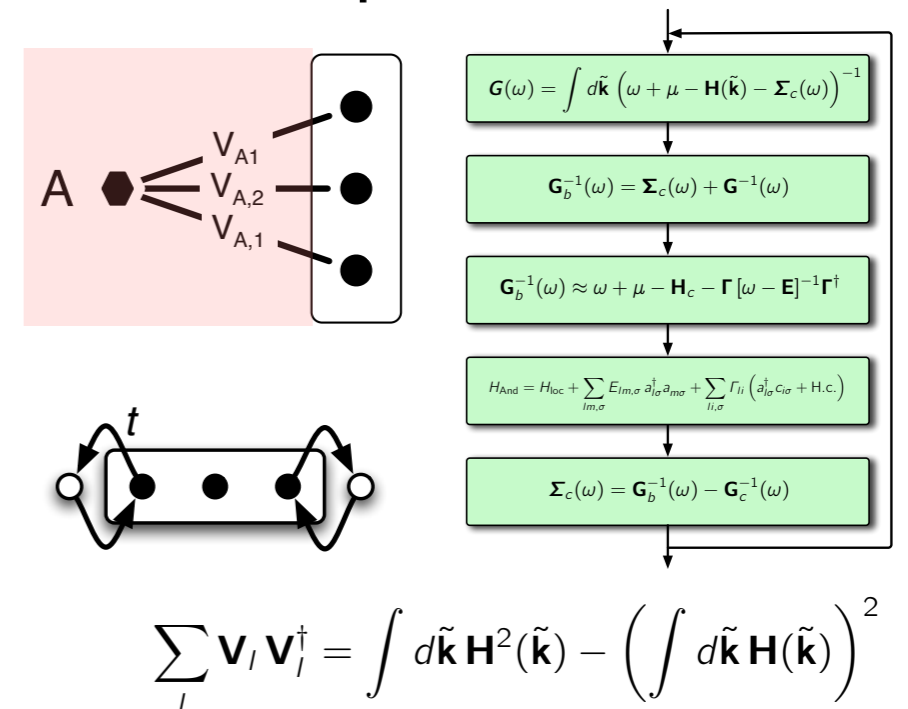
$$G_k(\omega) = \frac{b_0^2}{\omega - a_0 - \frac{b_1^2}{\omega - a_1 - \frac{b_2^2}{\omega - a_2 - \frac{b_3^2}{\omega - a_3 - \dots}}}}$$



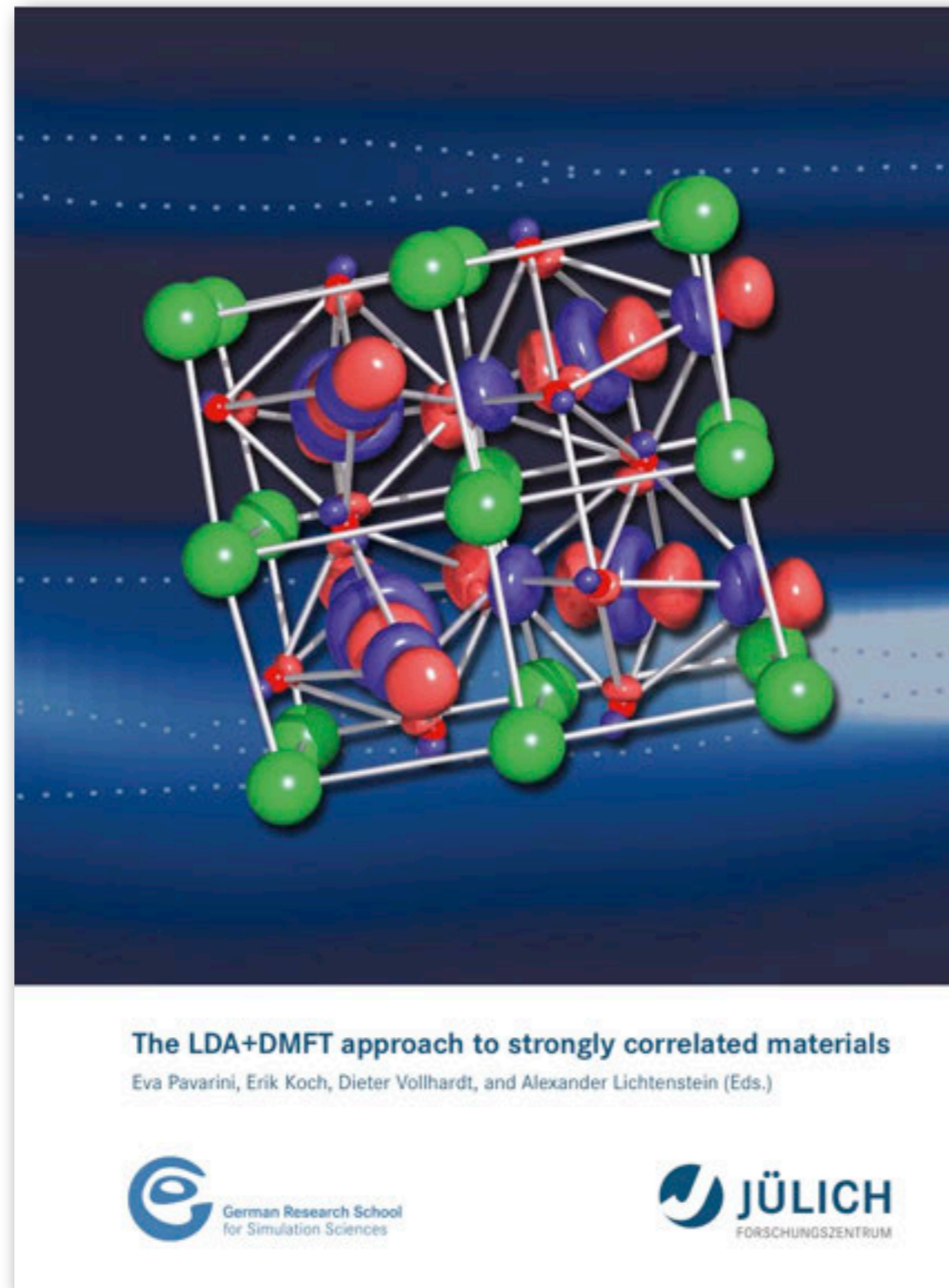
sparse Hamiltonian in Wannier representation



bath parametrization



reference



The LDA+DMFT approach to strongly correlated materials

Eva Pavarini, Erik Koch, Dieter Vollhardt, and Alexander Lichtenstein (Eds.)



