Plaquette Renormalized Tensor Network States: Application to Frustrated Systems

Ying-Jer Kao 高英哲

Department of Physics and Center for Quantum Science and Engineering National Taiwan University

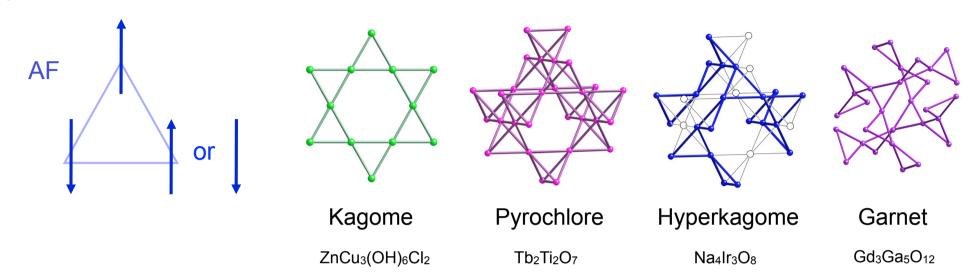
Hsin-Chih Hsiao, Ji-Feng Yu, NTU Anders W. Sandvik, Boston University Ling Wang, University of Vienna







Frustration



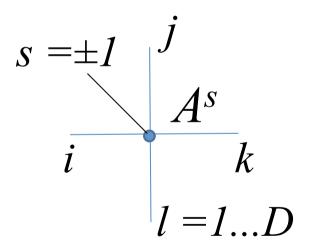
- Large number of degenerate classical ground states
- Emergence of novel spin-disordered ground states due to quantum fluctuations
- Hard to study numerically: size limitation in Exact Diagonalization, sign problem in QMC (also fermion), dimension limit for DMRG



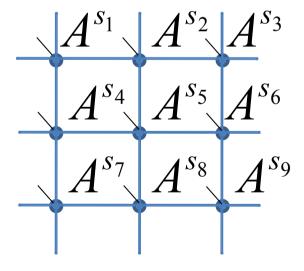
Tensor product states

 Tensor product states, projected entangled paired state (PEPS)

$$|\psi\rangle = \sum_{\{s\}} \operatorname{tTr}\{A(s_1)A(s_2)\cdots A(s_N)\}|s_1, s_2, \dots, s_N\rangle$$



 A_{ijkl} : rank-4 tensor





Tensor Contraction

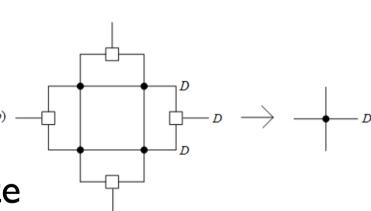
 Contracting the internal indices, the four-leg tensor can be viewed as a single tensor.

• External link dimension becomes D² after one contraction; exponential growth as we keep

contracting D⁴,D⁸.....

Computationally intensive;
 Impossible to store intermediate results.

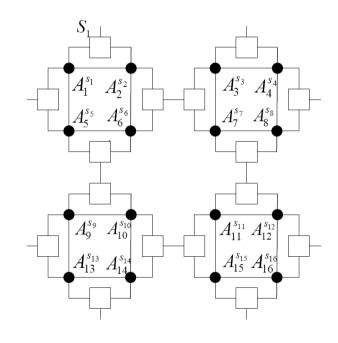
Need some RG scheme.



Plaquette renormalized trial wavefunction

$$\begin{aligned} |\psi\rangle &= \sum_{\{s\},i,j,k,l,\dots} (A_{1}^{s_{1}})_{i,j,k,l} (A_{2}^{s_{2}})_{k,m,n,o} (S_{1})_{m,j,p} (S_{2})_{q,p,r} \cdots |s_{1}s_{2} \cdots s_{N}\rangle \\ &= \sum_{\{s\}} t Tr(A_{1}^{s_{1}} \otimes A_{2}^{s_{2}} \otimes S_{1} \otimes S_{2} \otimes \cdots \otimes A_{N}^{s_{N}}) |s_{1}s_{2} \cdots s_{N}\rangle \end{aligned}$$

- We treat the elements in the A and S tensors as variational parameters, and minimize the total energy.
- Optimization: Principal axis method / random optimization, derivative-free, computationally expensive.



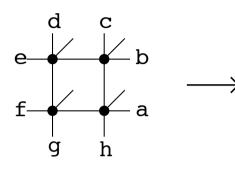


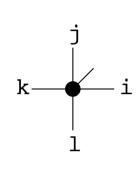
Plaquette-Renormalization

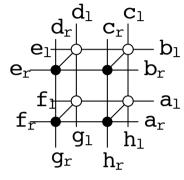
8-index tensor: D^8

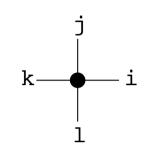
4-index tensor: D_{cut}^4 | 8-index dbl-tensor: D^{16}

4-index dbl-tensor: D_{cut}^{8}









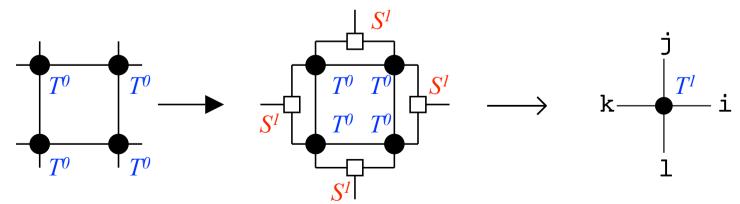
$$a,b,...g,h=1...D$$

$$i,j,k,l=1...D_{cut}$$

a,b,...g,h=1...D

$$i,j,k,l=1...D_{cut}^{2}$$

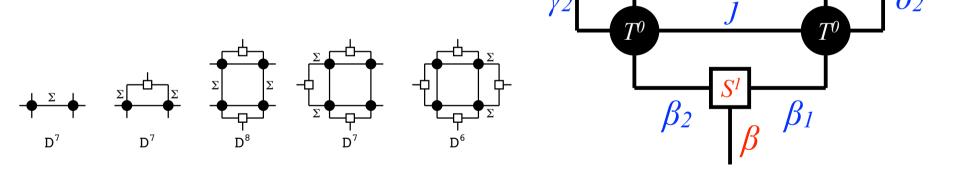
Renormalization of an 8-index plaquette tensor using auxiliary 3-index tensors S.



Building block: plaquette

• 12 internal sums. Maximum computational effort: D^8 .

 Each free index and summation contributes D.



 α_1

 α_2

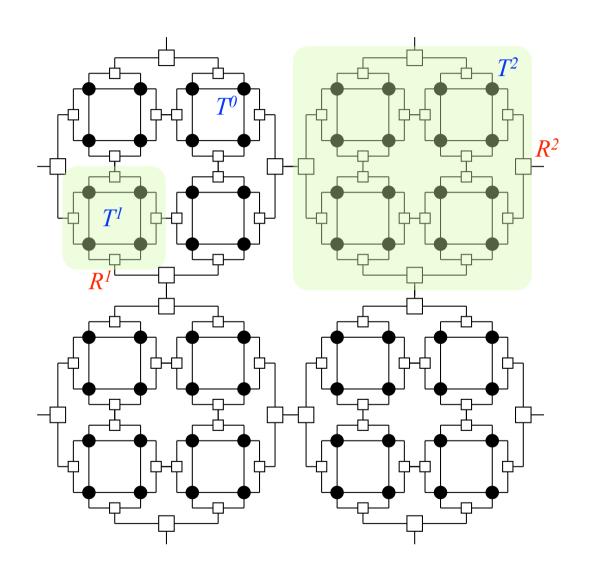
$$T^{(1),\alpha\beta}_{\ \gamma\delta} = \sum_{\alpha_1,\alpha_2,\dots,\delta_1,\delta_2,ijkl} S^{(1),\alpha}_{\alpha_1\alpha_2} S^{(1),\beta}_{\beta_1\beta_2} S^{(1),\gamma}_{\gamma_1\gamma_2} S^{(1),\delta}_{\delta_1\delta_2} T^{(0),\alpha_1l}_{\ \gamma_2i} T^{(0),\alpha_2j}_{\ i\delta_1} T^{(0),i\beta_1}_{\ k\delta_2} T^{(0),l\beta_2}_{\ \gamma_1k}$$



 δ_1

Plaquette-Renormalization of TNS

- Effective reduced tensor network for a 8x8 lattice
- Summing over all unequivalent bonds and sites
- Method is variational
- Optimize T and R globally
- Size scaling: L²Log(L)





Expectation values

$$H = \sum_{i} \hat{O}_{i}^{0} + \sum_{\langle i,j \rangle} \hat{O}_{i}^{1} \hat{O}_{j}^{2} + \sum_{\langle \langle i,j \rangle \rangle} \hat{O}_{i}^{1} \hat{O}_{j}^{2} + \cdots$$

Normalization factor:

$$\langle \psi | \psi \rangle = tTr [T_1 \otimes T_2 \otimes R_1 \otimes \cdots \otimes T_N]$$

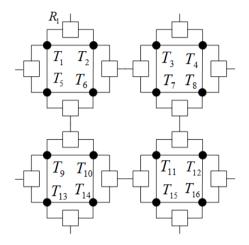
Two - body interaction:

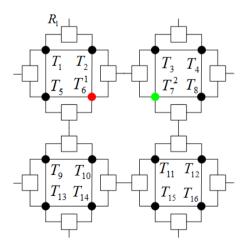
$$\left\langle \psi \left| \hat{O}_{i}^{1} \hat{O}_{j}^{2} \middle| \psi \right\rangle = t Tr \left[T_{1} \otimes T_{2} \otimes R_{1} \otimes \cdots \otimes T_{i}^{1} \otimes T_{j}^{2} \otimes \cdots \otimes T_{N} \right]$$

$$T_j = \sum_{s_j} A_j^{s_j}^* \otimes A_j^{s_j}$$

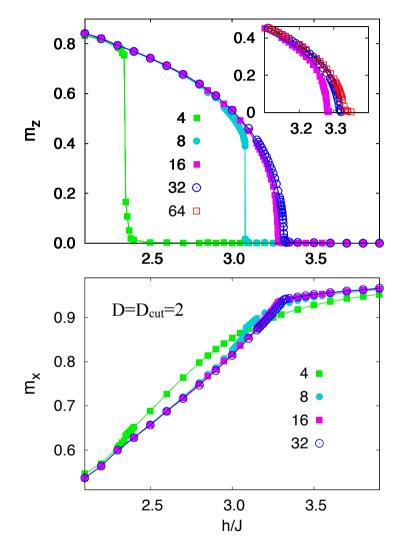
$$T_j^a = \sum_{s_j', s_j} A_j^{s_j'^*} \otimes A_j^{s_j} \langle s_j' | \hat{O}_j^a | s_j \rangle$$

$$R_i = S_i^* \otimes S_i$$





Transverse Ising Model

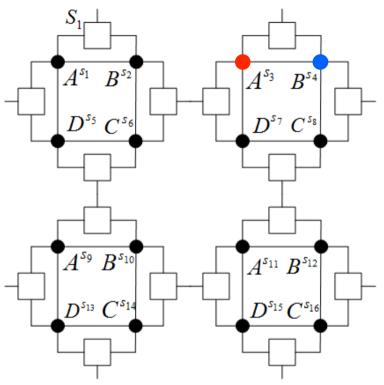


- Assume translational invariance: all initial T's are the same.
- Globally optimized T and R.
- $h_c=3.33$ (3.04,QMC)
- $m_z \sim (h-h_c)^{\beta}$, $\beta \sim 0.40$
- $h\sim h_c$, $\beta\sim 0.50$ mean-field like.

=	L	h	D	E_{var}/N	E/N	Δ_E
_	4	3.0	2	-3.1978372	-3.2155081(exact)	5.4955×10^{-3}
	8	3.0	2	-3.1717845	-3.19750(QMC)	8.0437×10^{-3}



Transverse Ising Model



- Spins at different lattice sites inside the plaquette have different environments.
- We use different tensors inside a plaquette.

L	h	D	E_{var}/N	E/N	Δ_E
				-3.2155081(exact)	
8	3.0	2	-3.1717845	-3.19750(QMC)	8.0437×10^{-3}

L	h	D	E_{var}/N	E/N	Δ_E
4	3.0	2	-3.2044358	-3.2155081(exact)	3.4434×10^{-3}
4	3.0	3	-3.2152333	-3.2155081(exact)	8.546×10^{-5}

\overline{L}	h	D	E_{var}/N	E/N	Δ_E
8	3.0	2	-3.17712	-3.19750(QMC)	6.3737×10^{-3}
8	3.044	2	-3.21404	-3.23627(QMC)	6.869×10^{-3}





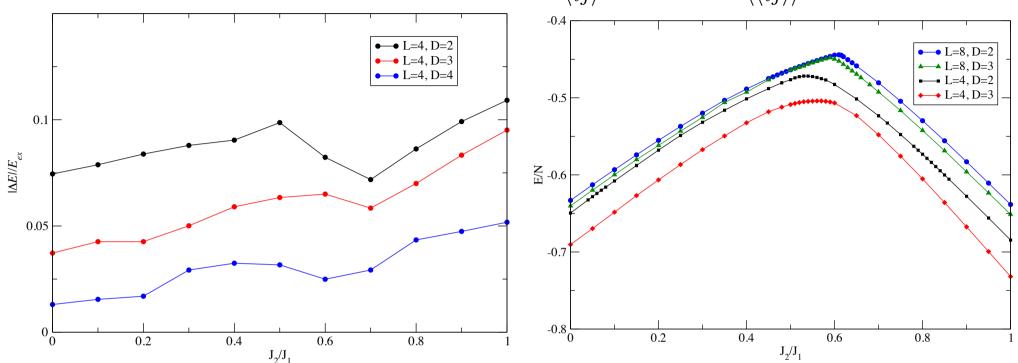
Computational Costs

- Globally optimized T and R.
- Contraction calculation is highly parallelizable.
- IBM Blue Gene/L at BU. D=2, takes weeks to optimize.
- Bottleneck: plaquette contractions.
- Take advantage of GPU (Graphic Processing Unit)
- SIMT (Single-instruction, multiple-thread) device.



J₁-J₂ Model

$$H = J_1 \sum_{\langle ij \rangle} \mathbf{S}_i \cdot \mathbf{S}_j + J_2 \sum_{\langle \langle ij \rangle \rangle} \mathbf{S}_i \cdot \mathbf{S}_j$$

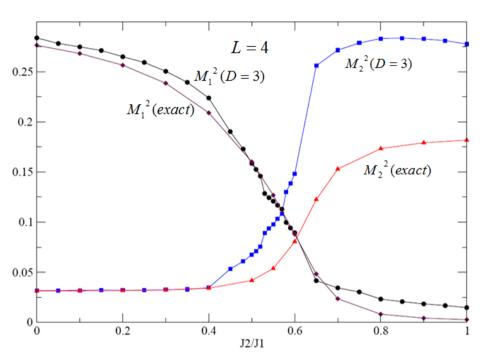


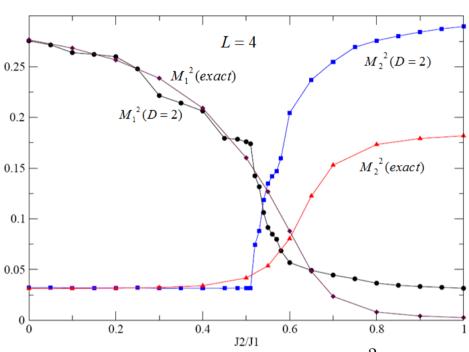
- Need large size and large D to see the real physics.
- Currently L=8, D=3 is very time consuming on CPU.





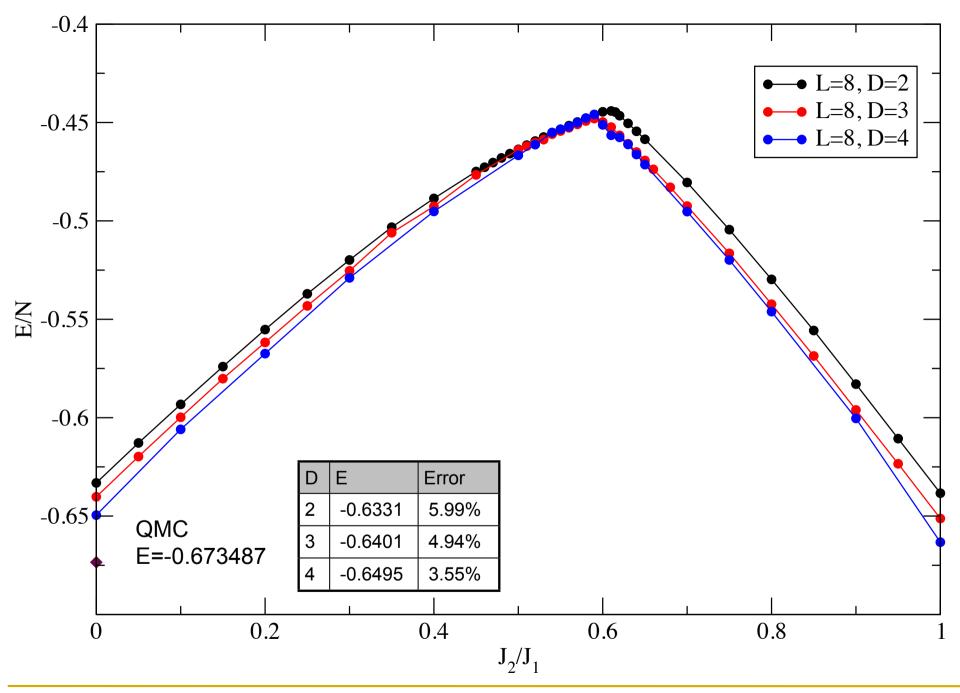
J₁-J₂ Model





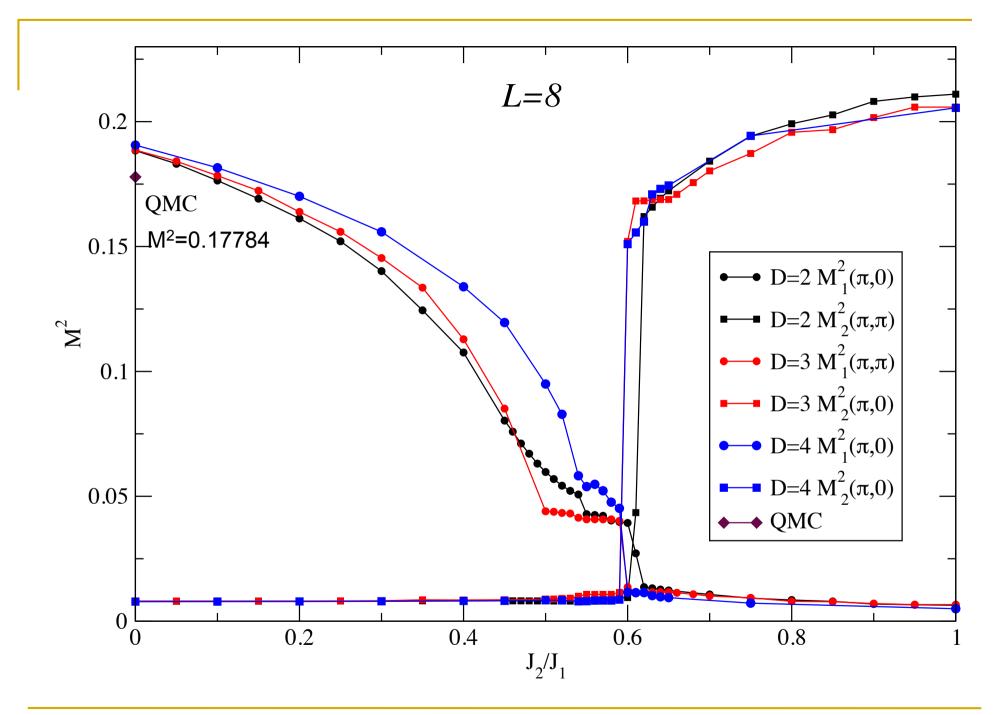
Order parameters

$$M^{2}(q_{x}, q_{y}) = \left\langle \left(\frac{1}{N} \sum_{j} e^{i(q_{x}j_{x} + q_{y}j_{y})} S_{j} \right)^{2} \right\rangle$$









Summary and Outlook

- Tensor network states are promising candidates to understand frustrated quantum spin systems.
- In plaquette renormalized tensor network representation, no approximations are made when contracting the effective renormalized tensor network.
- Non-MFT results even with the smallest possible nontrivial tensors and truncation (D = 2) in 2d transverse Ising model.
- GPU can potentially speed up the computationally intensive part of the calculation.
- GS for $J_2/J_1\sim 0.6$? VBS order?

