

Tensor Renormalization Group (TRG)

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11th JICFuS Seminar on Non-perturbative Physics

Outline

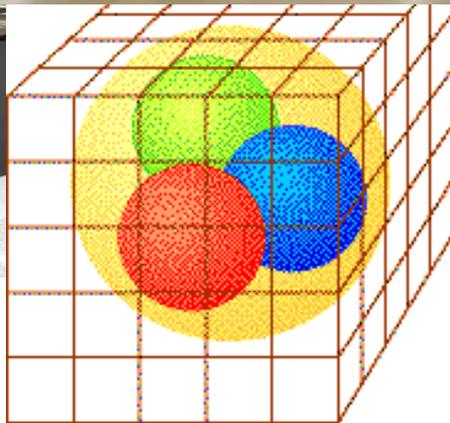
- Introduction
- TRG for 2D Ising model
- Summary & Future prospects
- Application to finite fermion density system:
Gross-Neveu model
= 2D four-fermion interaction

if time
allows

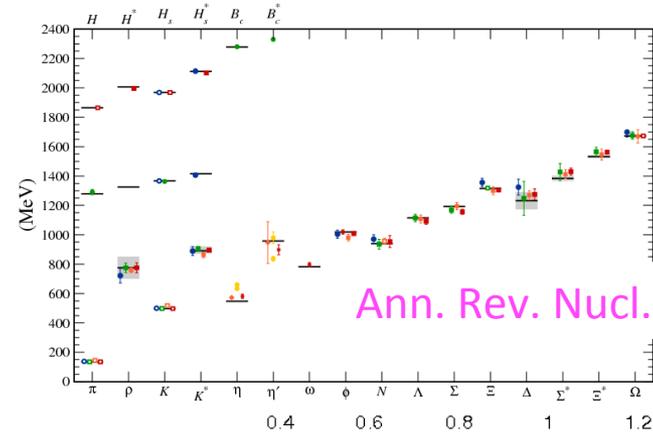
Introduction

Why **Tensor renormalization group**
instead of **Monte Carlo method**?

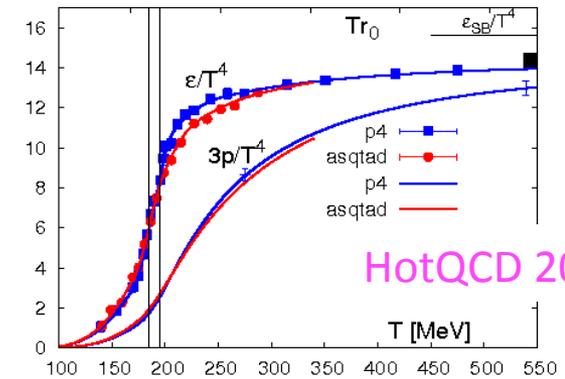
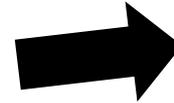
Lattice QCD by MC simulations



筑波大学素粒子論研究室



Ann. Rev. Nucl. 2012



HotQCD 2009

play crucial role in Hadron spectrum and $T \neq 0$ QCD

Limitations and problems in MC

- Light quark mass simulation **Solved!**
new algorithm & improvement of action
- Critical slowing down
continuum limit = critical point
- **Sign problem (complex action problem)**
MC cannot be applied if Boltzmann weight is complex number

$$\frac{1}{Z} \det D[U] e^{-S_G[U]} \in \mathbb{C}$$

Examples facing the sign problem

- QCD with finite quark density
 - EOS in core of compact stars
- Lattice chiral gauge theory
 - Simulation of weak interaction (SM)
- Lattice SUSY
 - not sure it exists but may be interesting
 - Dynamics of SUSY breaking
- θ term
 - Strong CP problem: Dynamics in the presence of θ -term is important

Approaches within MC framework

- Taylor expansion

Can capture phase transition (non-analytic phenomena)?

- Phase-reweighting

harder for larger volume

- Pure imaginary parameter (imaginary μ , θ)

applicable range of analytic continuation

- Complex Langevin

Convergence ?

- Lefschetz thimble

Difficult! (at least for me)

Approaches within MC framework

- Taylor expansion

Can capture phase transition (non-analytic phenomena)?

- Phase-reweighting

harder for larger volume

- Pu

app

Go beyond Monte Carlo method!

of analytic continuation

- Complex Langevin

Convergence ?

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Difficult! (at least for me)

Tensor Renormalization Group (TRG)

Levin & Nave 2007

Algorithm to compute partition function of lattice model approximately w/o relying on probability

for classical statistical system or quantum system in path-integral representation

- **Good** : No sign problem
- **Bad** : Higher dimensional system is still hard

see later

TRG for 2D Ising model

Procedures of TRG

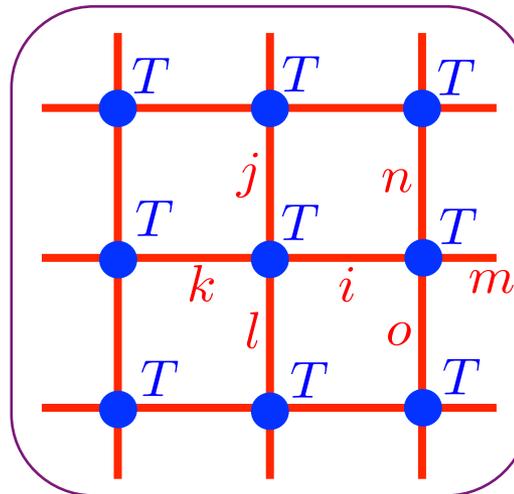
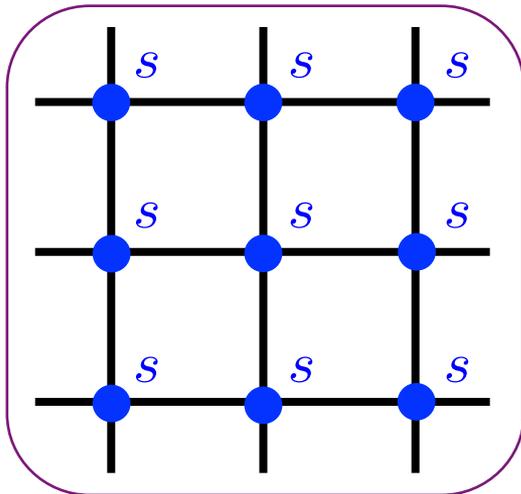
① Rewrite Z in **tensor network representation**

$$Z \equiv \sum_{\{s\}} e^{-\beta H[s]} = \sum_{i,j,k,l,\dots} \dots T_{ijkl} T_{mnop} \dots$$

Spins Tensor

- Analytic
- exact

will be explained soon New degrees of freedom

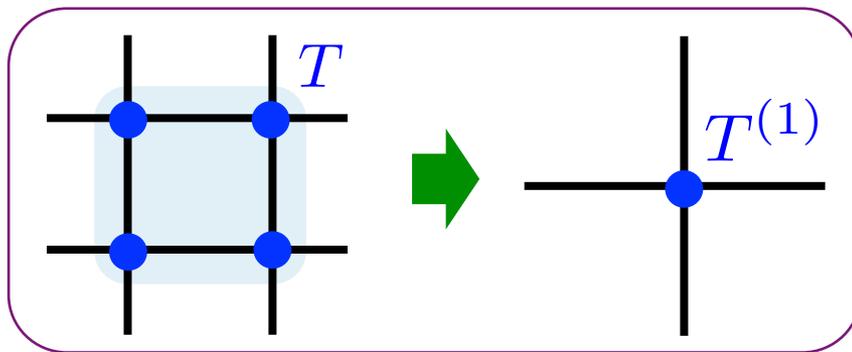


site: Tensor T
bond: index i,j,k,l,\dots

Procedures of TRG

- ① Rewrite Z in **tensor network representation**
- ② **Coarse graining Tensor**

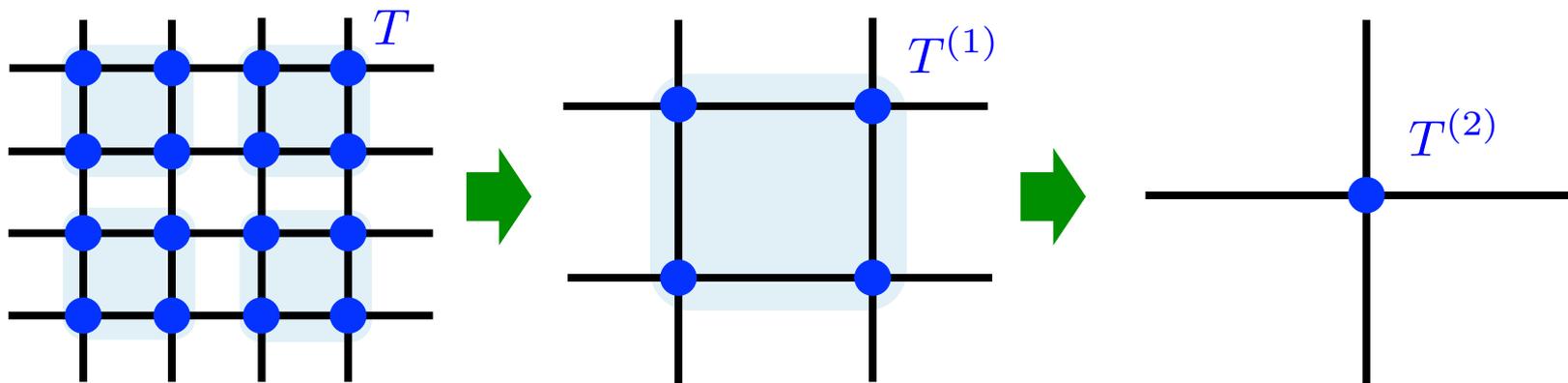
Blocking of Tensor (like spin-blocking)



- extracting important information **numerically**
- selection of information introduces **approximation**

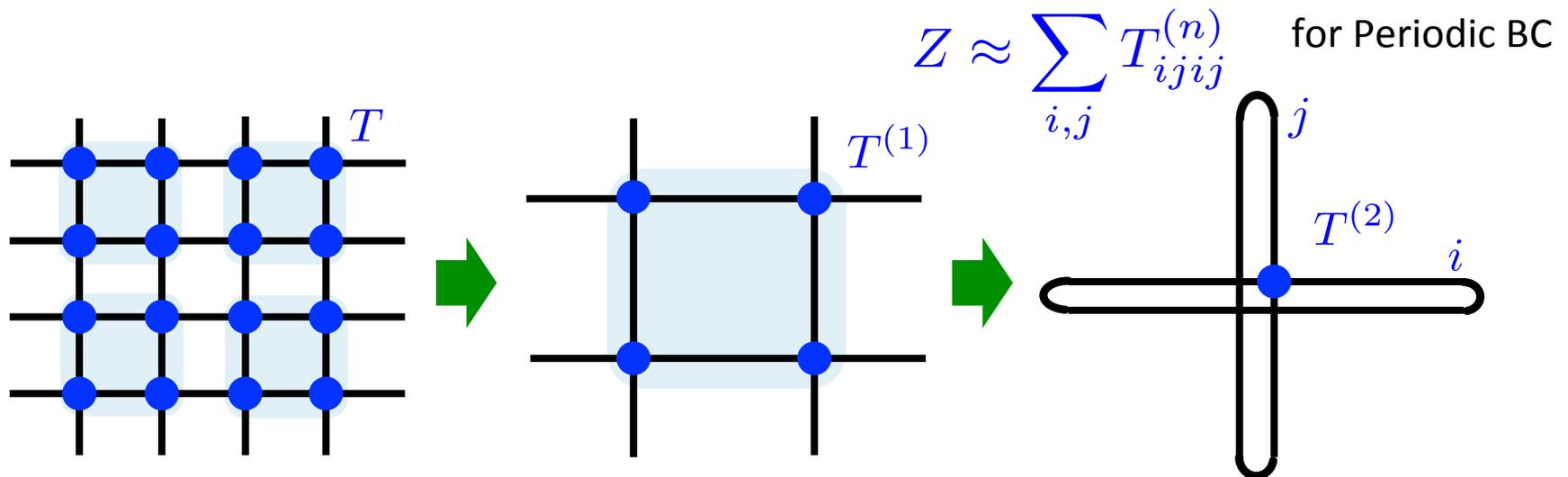
Procedures of TRG

- ① Rewrite Z in **tensor network representation**
- ② **Coarse graining Tensor**
- ③ Repeat the coarse graining and then reduce the number of tensors, finally compute Z by contraction



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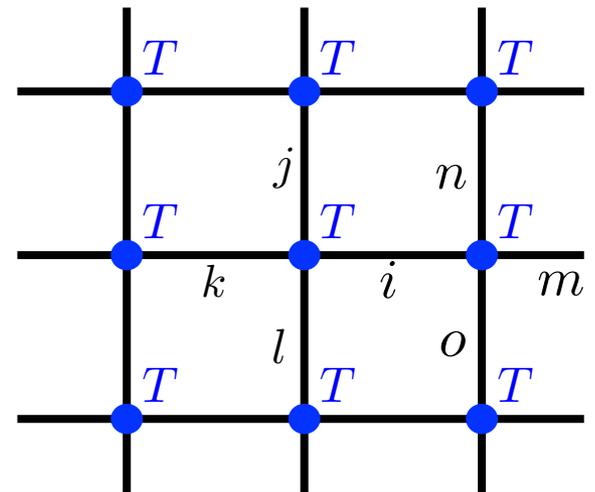


① Tensor network rep.

Direction

$$Z \equiv \sum_{\{s\}} e^{-\beta H[s]} = \sum_{i,j,k,l,\dots} \dots T_{ijkl} T_{mno} \dots$$

- 1) Expand Boltzmann weight as in High-T expansion
- 2) Identify **integer**, which appears in the expansion, as **new d.o.f.** \rightarrow index of tensor
- 3) Integrate out **old d.o.f.**
(spin variable s)
- 4) Get tensor network rep. !

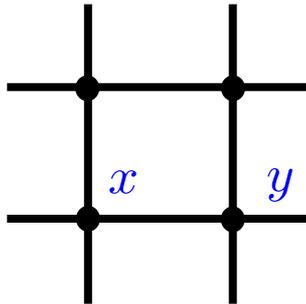


Basic procedure is common to fermion/gauge system

① Tensor network rep.

$$Z = \sum_{\{s\}} \exp \left(\sum_{\langle x,y \rangle} \beta s_x s_y \right) = \sum_{\{s\}} \prod_{\langle x,y \rangle} \exp(\beta s_x s_y)$$

nearest neighbor pair



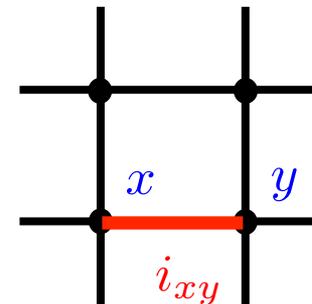
① Tensor network rep.

$$\begin{aligned} \mathcal{Z} &= \sum_{\{s\}} \exp\left(\sum_{\langle x,y \rangle} \beta s_x s_y\right) = \sum_{\{s\}} \prod_{\langle x,y \rangle} \exp(\beta s_x s_y) \\ &= (\cosh \beta)^{2V} \sum_{\{s\}} \prod_{\langle x,y \rangle} \sum_{i_{xy}=0}^1 (s_x s_y \tanh \beta)^{i_{xy}} \end{aligned}$$

$V = \#$ of lattice sites

$$\begin{aligned} \exp(\beta s_x s_y) &= \cosh(\beta s_x s_y) + \sinh(\beta s_x s_y) \\ &= \cosh \beta + s_x s_y \sinh \beta \\ &= \cosh \beta (1 + s_x s_y \tanh \beta) \\ &= \cosh \beta \sum_{i_{xy}=0}^1 (s_x s_y \tanh \beta)^{i_{xy}} \end{aligned}$$

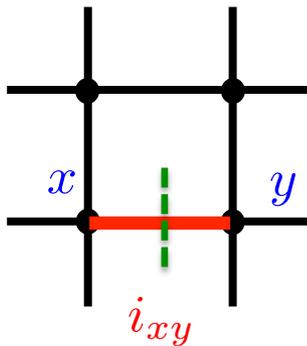
$$s_x = \pm 1$$



New d.o.f.

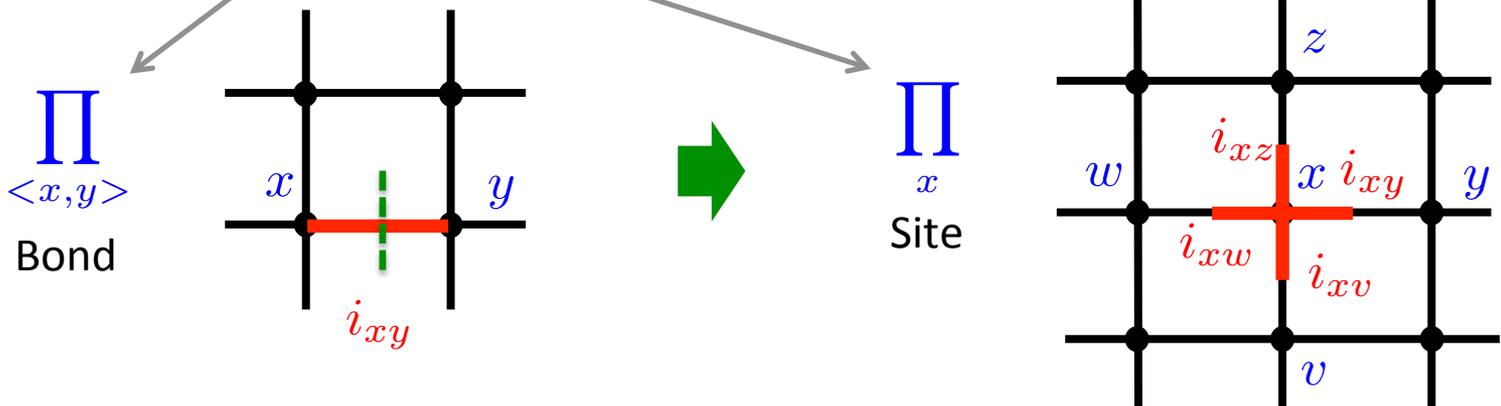
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① Tensor network rep.

$$\begin{aligned}
 \mathcal{Z} &= \sum_{\{s\}} \exp \left(\sum_{\langle x,y \rangle} \beta s_x s_y \right) = \sum_{\{s\}} \prod_{\langle x,y \rangle} \exp(\beta s_x s_y) \\
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 &= (\cosh \beta)^{2V} \sum_{\{i\}} \sum_{\{s\}} \prod_{\langle x,y \rangle} (s_x \sqrt{\tanh \beta} \cdot s_y \sqrt{\tanh \beta})^{i_{xy}} \\
 &= (\cosh \beta)^{2V} \sum_{\{i\}} \sum_{\{s\}} \prod_x (s_x \sqrt{\tanh \beta})^{i_{xy}} (s_x \sqrt{\tanh \beta})^{i_{xz}} (s_x \sqrt{\tanh \beta})^{i_{xw}} (s_x \sqrt{\tanh \beta})^{i_{xv}}
 \end{aligned}$$



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 &= (\cosh \beta)^{2V} \sum_{\{i\}} \sum_{\{s\}} \prod_x (s_x \sqrt{\tanh \beta})^{i_{xy} + i_{xz} + i_{xw} + i_{xv}} (s_x \sqrt{\tanh \beta})^{i_{xy} + i_{xz} + i_{xw} + i_{xv}} \\
 &= (\cosh \beta)^{2V} \sum_{\{i\}} \sum_{\{s\}} \prod_x (\sqrt{\tanh \beta})^{i_{xy} + i_{xz} + i_{xw} + i_{xv}} s_x^{i_{xy} + i_{xz} + i_{xw} + i_{xv}} \\
 &= (\cosh \beta)^{2V} \sum_{\{i\}} \prod_x (\sqrt{\tanh \beta})^{i_{xy} + i_{xz} + i_{xw} + i_{xv}} \sum_{s_x = \pm 1} s_x^{i_{xy} + i_{xz} + i_{xw} + i_{xv}} \quad \text{Spin sum can be done} \\
 &= (\cosh \beta)^{2V} \sum_{\{i\}} \prod_x (\sqrt{\tanh \beta})^{i_{xy} + i_{xz} + i_{xw} + i_{xv}} 2\delta(\text{mod}(i_{xy} + i_{xz} + i_{xw} + i_{xv}, 2)) \\
 &= T_{i_{xy} i_{xz} i_{xw} i_{xv}} \quad \text{New d.o.f. : index of tensor}
 \end{aligned}$$

① Tensor network rep.

$$\mathcal{Z} = 2^V (\cosh \beta)^{2V} \sum_{\dots, i, j, k, l, m, n, o, \dots} \cdots T_{ijkl} T_{mnio} \cdots$$

$$T_{ijkl} = (\sqrt{\tanh \beta})^{i+j+k+l} \delta(\text{mod}(i + j + k + l), 2)$$

$$\begin{bmatrix} T_{0000} & T_{0001} & T_{0010} & T_{0011} \\ T_{0100} & T_{0101} & T_{0110} & T_{0111} \\ T_{1000} & T_{1001} & T_{1010} & T_{1011} \\ T_{1100} & T_{1101} & T_{1110} & T_{1111} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \tanh \beta \\ 0 & \tanh \beta & \tanh \beta & 0 \\ 0 & \tanh \beta & \tanh \beta & 0 \\ \tanh \beta & 0 & 0 & (\tanh \beta)^2 \end{bmatrix}$$

Contents of tensor depend on model

① Tensor network rep.

$$\mathcal{Z} = 2^V (\cosh \beta)^{2V} \sum_{\dots, i, j, k, l, m, n, o, \dots} \dots T_{ijkl} T_{mnop} \dots$$

Key points

translational invariance

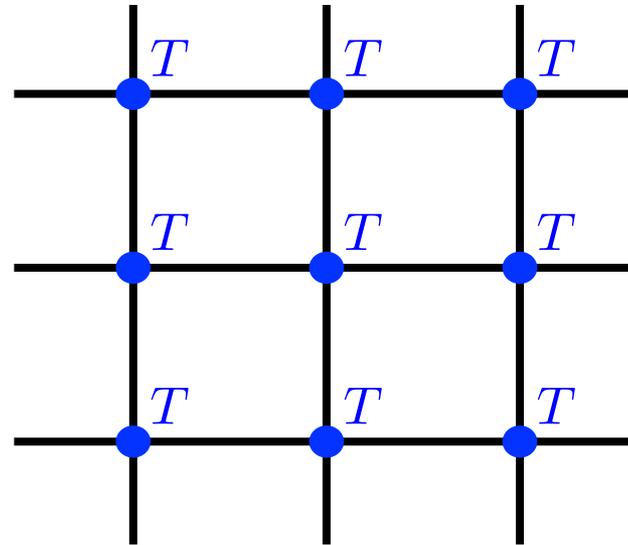


all tensors are common

local interaction
(nearest neighbor)



network (nearest neighbor)



① Tensor network rep.

$$Z = \sum_{\dots, i, j, k, l, m, n, o, \dots} \cdots T_{ijkl} T_{mno} \cdots$$

- So far, we have just rewritten Z
- Next step is to carry out the summation
- But, naïve approach costs $\propto 2^{2V}$
- One has to reduce the cost and introduce approximation but wants to keep an efficiency by summing **important part** in Z

① Tensor network rep.

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Coarse graining (renormalization, blocking)

② Coarse graining

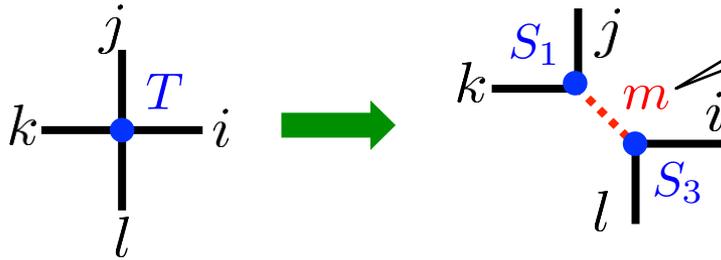
Direction

assuming translational invariance & local interaction

- Decompose tensor & extract important part = **compression of information & emergence of new d.o.f.**
- Making new tensor by combining the compact tensors = **contracting old d.o.f.**
- By repeating the **decomposition** and **contraction**, # tensors can be reduced
- After decreasing # of tensors, Z can be computed easily = ③

② Coarse graining

Decomposition of tensor

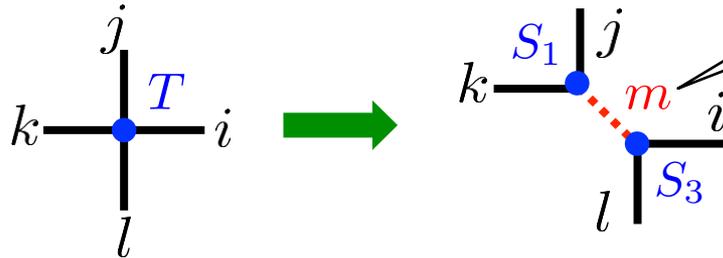


New d.o.f.

$$T_{ijkl} = \sum_m (S_1)_{jk m} (S_3)_{li m}$$

② Coarse graining

Decomposition of tensor



$$T_{ijkl} = \sum_m (S_1)_{jkm} (S_2)_{lim} (S_3)_{lim}$$

Singular value decomposition (SVD)

u, v : orthogonal matrix

$$M_{ab} = \sum_m u_{am} \sigma_m (v^T)_{mb}$$

$\sigma_1 \geq \sigma_2 \geq \dots \geq 0$: singular value

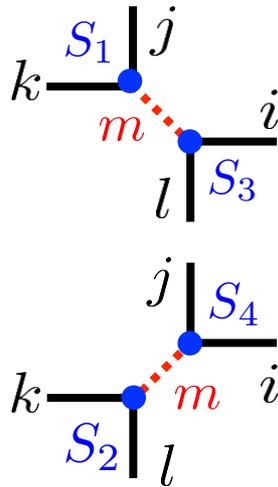
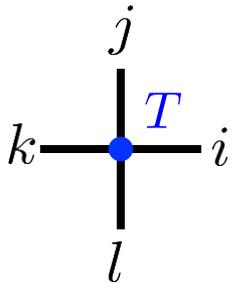
$$T_{ijkl} = M_{(kj),(il)} = \sum_m \underbrace{u_{(kj),m} \sqrt{\sigma_m}}_{\text{approx.}} \cdot \underbrace{\sqrt{\sigma_m} v_{m,(il)}^T}_{\text{approx.}} \underbrace{\sum_{m=1}^{D_{\text{cut}}} (S_1)_{jkm} (S_3)_{lim}}_{\text{approx.}}$$

D_{cut} -truncated matrix is the best approximation among all rank- D_{cut} matrices

Tensor (matrix) is approximated by low-rank tensor = **information compression**

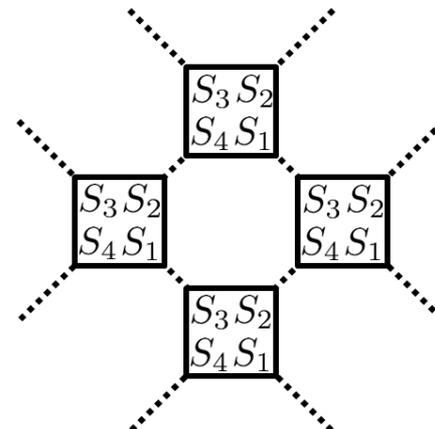
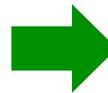
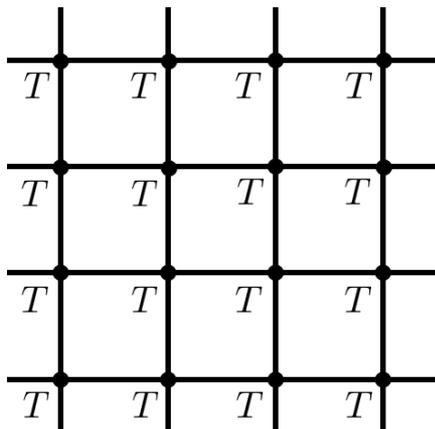
② Coarse graining

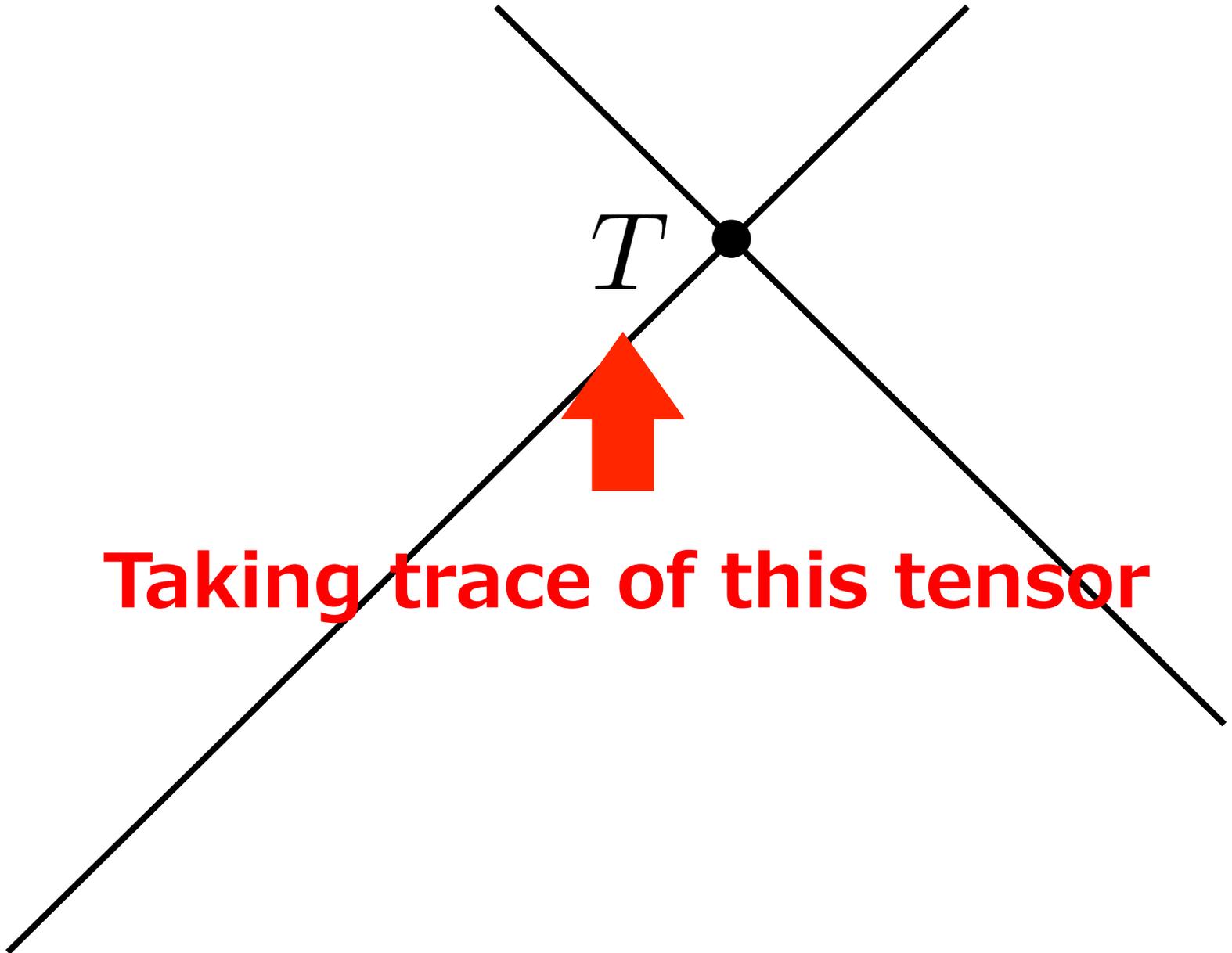
Decomposition



$$T_{ijkl} \approx \sum_{m=1}^{D_{\text{cut}}} (S_1)_{jkm} (S_3)_{lim}$$

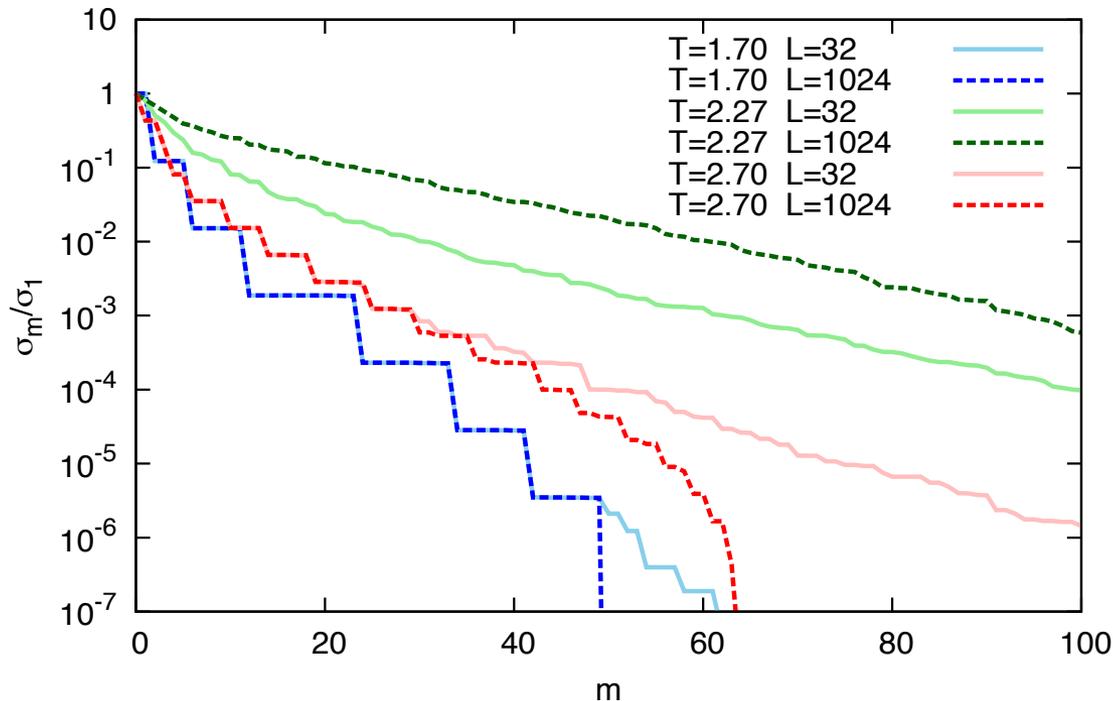
$$T_{ijkl} \approx \sum_{m=1}^{D_{\text{cut}}} (S_2)_{klm} (S_4)_{ijm}$$





Hierarchy of singular value

2D Ising model



$$D_{\text{cut}} = 32$$

$$T_c = 2 / [\ln(1 + \sqrt{2})]$$

$$= 2.269\dots$$

Entanglement entropy

$$S = - \sum_i \tilde{\sigma}_i \ln \tilde{\sigma}_i$$

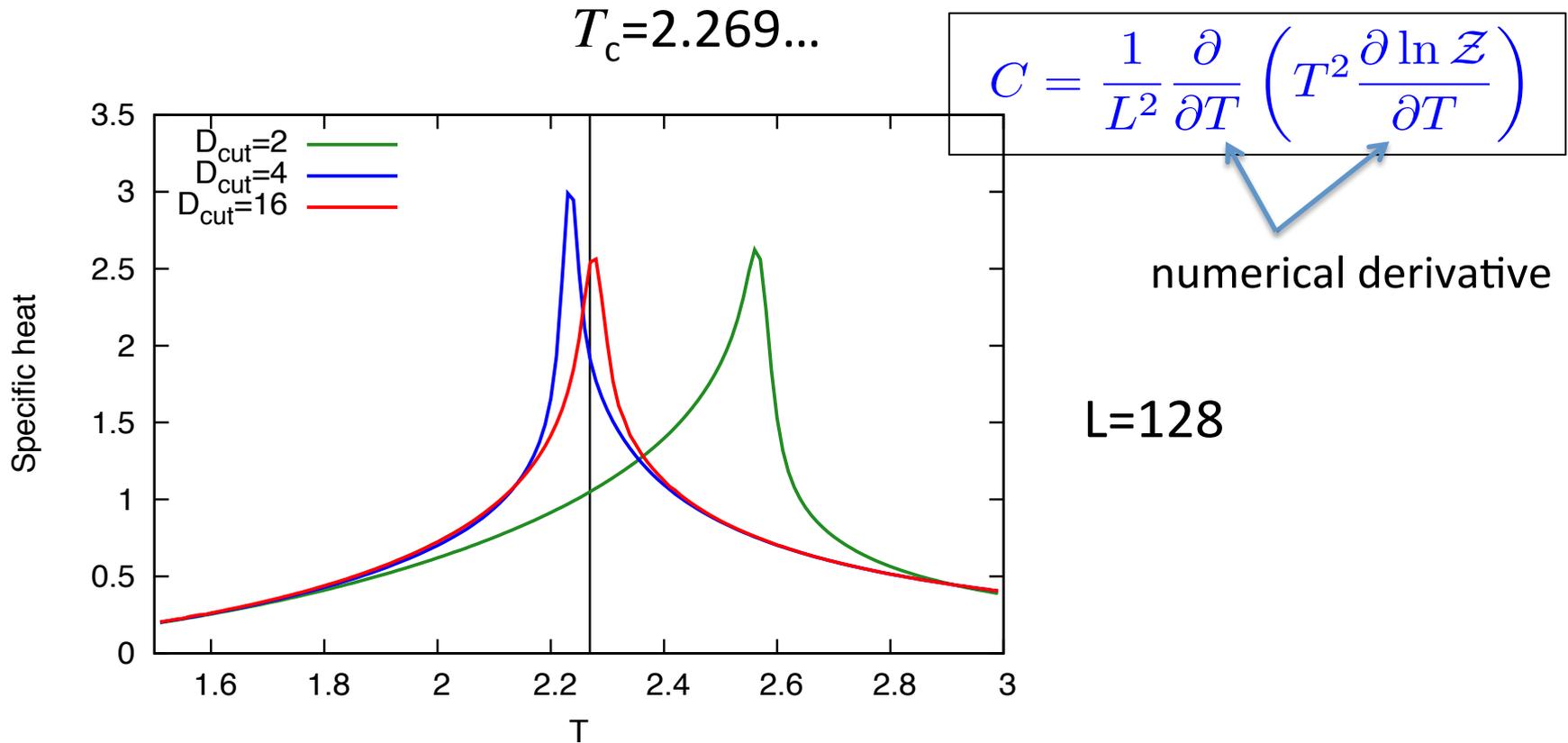
normalized singular value

- Off criticality: good hierarchy (small S)
- Near criticality: hierarchy gets worse (large S)

like critical slowing down in MC

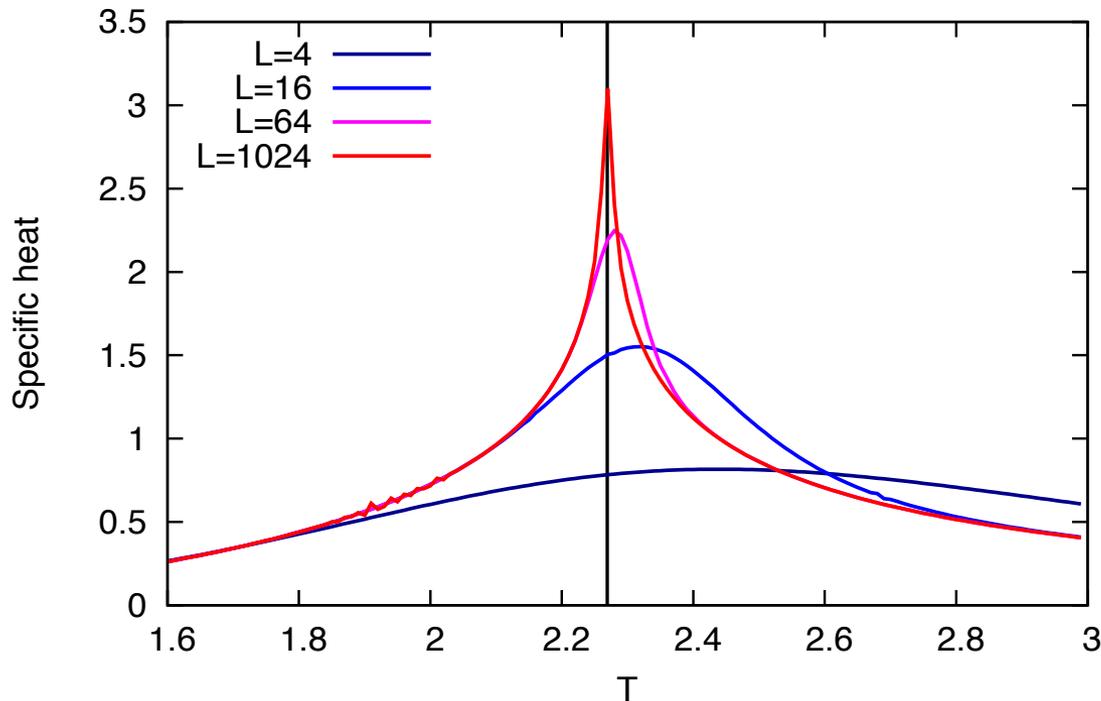
Tensor network renormalization (TNR) [Evenbly&Vidal 2014](#) can cure the situation

D_{cut} -dependence of Specific heat



For larger D_{cut} , transition T is closer to the exact T_c

Large volume



$$D_{\text{cut}} = 32$$

$$T_c = 2 / [\ln(1 + \sqrt{2})]$$
$$= 2.269\dots$$

one-day work by using this MacBook Air

$$\text{Cost} \propto \log(\text{Lattice size}) \times (D_{\text{cut}})^6 \times [\# \text{ temperature mesh}]$$

Status of numerical study of TRG

- 2D system
 - Spin: Ising model [Levin & Nave 2007](#), X-Y model [Yu et al. 2013](#), $O(3)$ [Judah et al. 2014](#)
 - Scalar: ϕ^4 theory [Shimizu 2012](#)
 - Gauge + Fermion: QED_2 [Shimizu & Kuramashi 2013](#)
 - $QED_2 + \theta$: [Shimizu & Kuramashi 2014](#)
 - Finite density: Gross-Neveu model [ST & Yoshimura 2014](#)
- Higher dimensional system
 - Higher order TRG(HOTRG): new coarse graining method applicable for any dimensional system
 - 3D Ising : [Xie et al. 2012](#), 4D Ising: [Yoshimura et al., 2015](#)
- Specialized to Gauge theory
 - Decorated tensor network renormalization: [Wittrich et al. 2014](#)

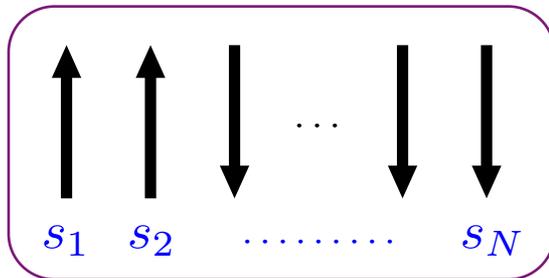
Historical background

- Density matrix renormalization group (DMRG) [White 1992](#)
 - Variational method to obtain ground state in 1D quantum sys.
 - By selecting GOOD basis using SVD, one can drastically reduce the # of data $O(2^N) \rightarrow O(N)$, N :# sites (**information compression**)
 - Target: Wave function (in Tensor network representation)
 - Before this appears, limited to $N=30$. But DMRG enables $N=100$

$$|\psi\rangle = \sum_{s_1, s_2, \dots, s_N} \underbrace{\psi_{s_1, s_2, \dots, s_N}}_{2^N \text{ elements}} |s_1\rangle \otimes |s_2\rangle \otimes \dots \otimes |s_N\rangle$$

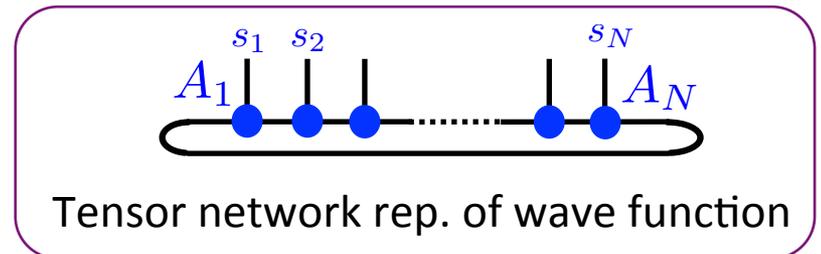
$$\text{tr} [A_1^{s_1} A_2^{s_2} \dots A_N^{s_N}]$$

$A^s : d \times d$ matrix



Matrix product state (MPS)

$2Nd^2$ elements



Tensor network rep. of wave function

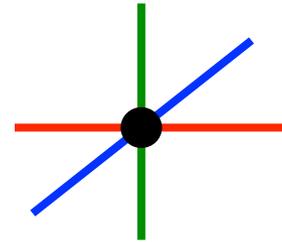
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 - Target: Wave function (in Tensor network representation)
 - Before this appears, limited to $N=30$. But DMRG enables $N=100$
- Tensor renormalization group (TRG) [Levin & Nave 2007](#)
 - Target: Partition function of classical Stat. system
 - Express partition function in terms of tensor network rep., **compress tensor by using SVD** and coarse graining tensor
 - Very powerful in 2D system. Comparable to MC or more

MC	TRG
Boltzmann weight is interpreted as probability	Tensor network rep. of partition function (no probability interpretation)
Importance sampling	Compression of tensor by SVD
Statistical errors	Systematic errors
Sign problem may appear	No sign problem ∴ no probability
Critical slowing down	Efficiency of compression gets worse around criticality

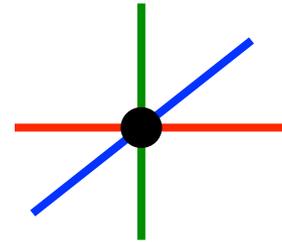
Numerical aspect of TRG and Task

- Main computation (For HOTRG, n-dim system)
 - Decomposition \Rightarrow SVD(EVD): $O(D_{\text{cut}}^6)$
 - Contraction \Rightarrow matrix-matrix product: $O(D_{\text{cut}}^{4n-1})$ **Hot spot**
- Memory
 - # elements of tensor: $O(D_{\text{cut}}^{2n})$
 - internal d.o.f. \Rightarrow more memory



Numerical aspect of TRG and Task

- Main computation (For HOTRG, n-dim system)
 - Decomposition \Rightarrow SVD(EVD): $O(D_{\text{cut}}^6)$
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 - internal d.o.f. \Rightarrow more memory



- matrix-matrix product: Level 3 BLAS \gg SVD
- Better coarse graining with small D_{cut} (highly compression)?

Improvement of Coarse graining

- Tensor Entanglement Filtering Renormalization

Gu et al. 2009

- Removing short range correlation (partially)
- works in off-criticality but not near criticality

- Second TRG Xie et al. 2009

- Optimization including environment (TRG: locally optimal)
- works in off-criticality but not near criticality

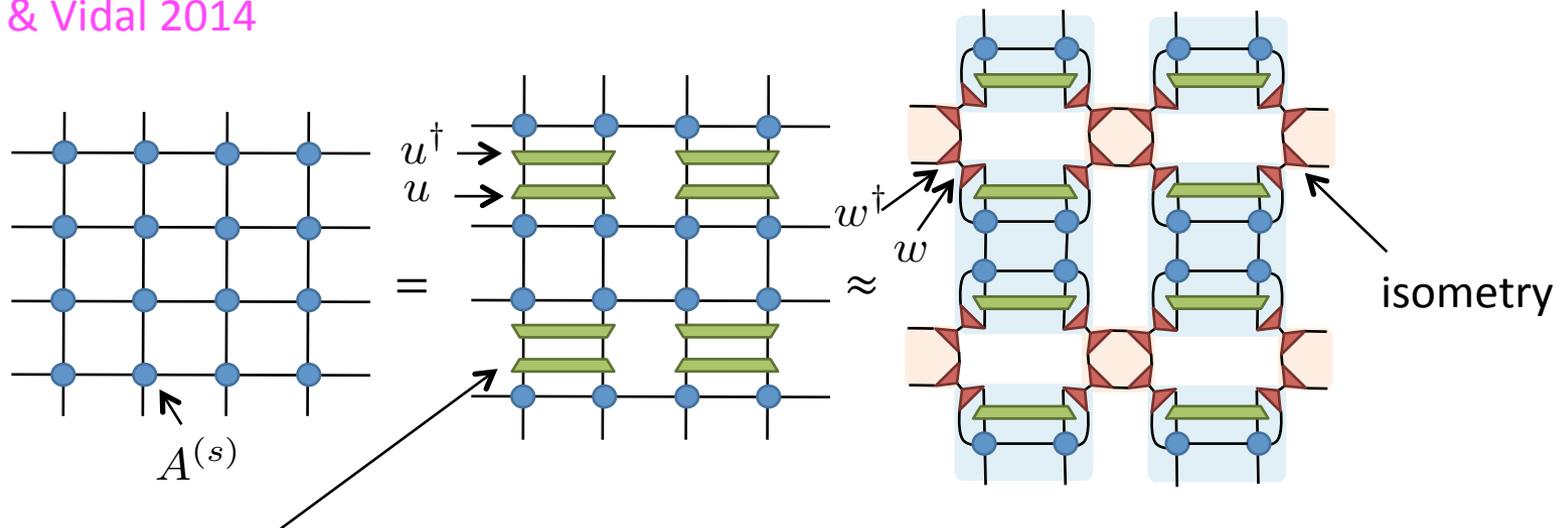
- Tensor Network Renormalization (TNR)

Evenbly & Vidal 2014

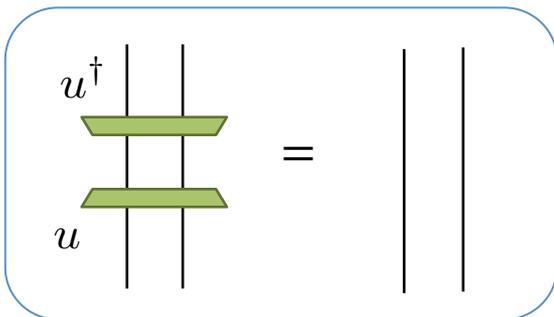
- First remove short correlation (entanglement) by using disentangler, and then coarse graining is performed
- Even around criticality, sustainable coarse graining is realized

Tensor Network Renormalization

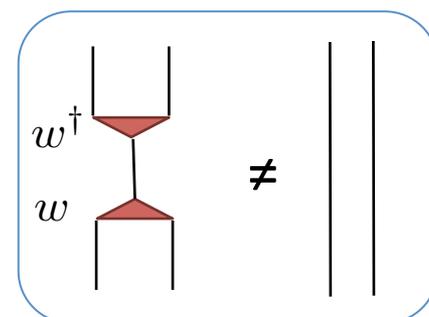
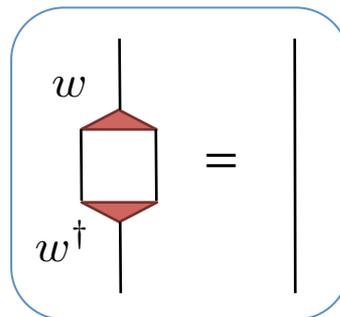
Evenbly & Vidal 2014



disentangler (unitary matrix)

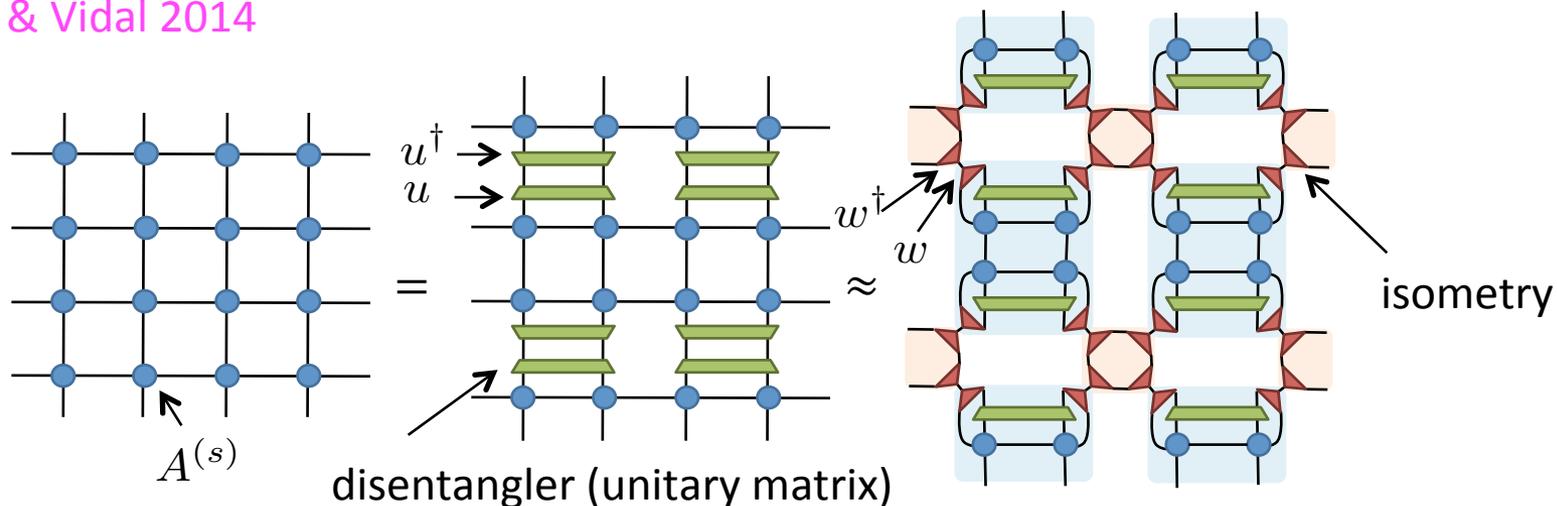


isometry



Tensor Network Renormalization

Evenbly & Vidal 2014



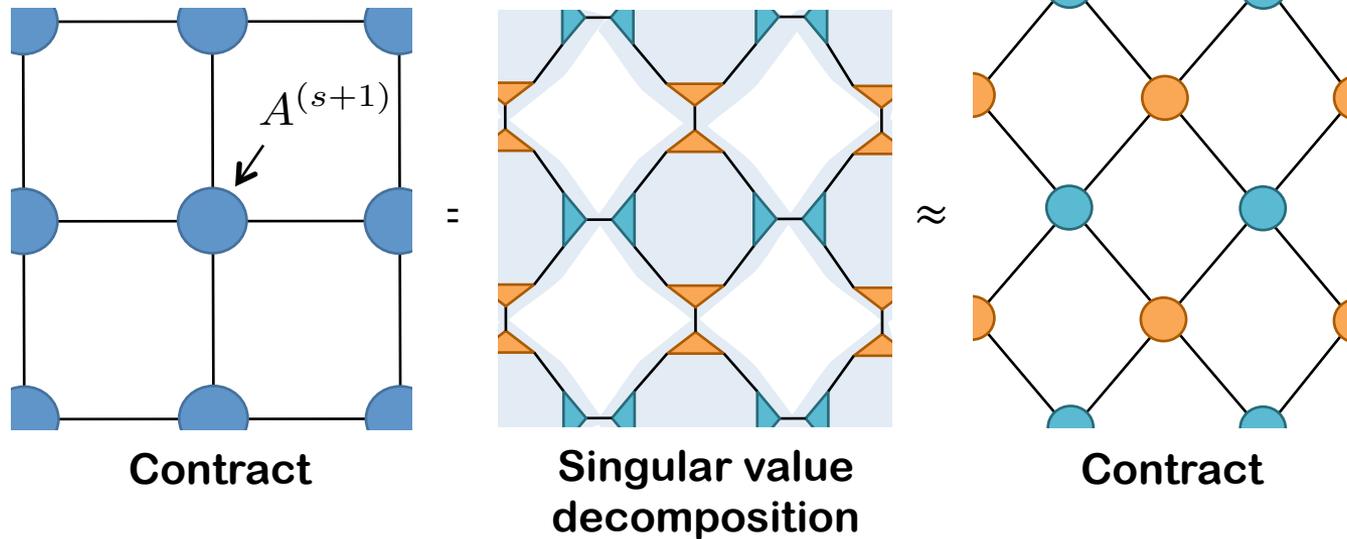
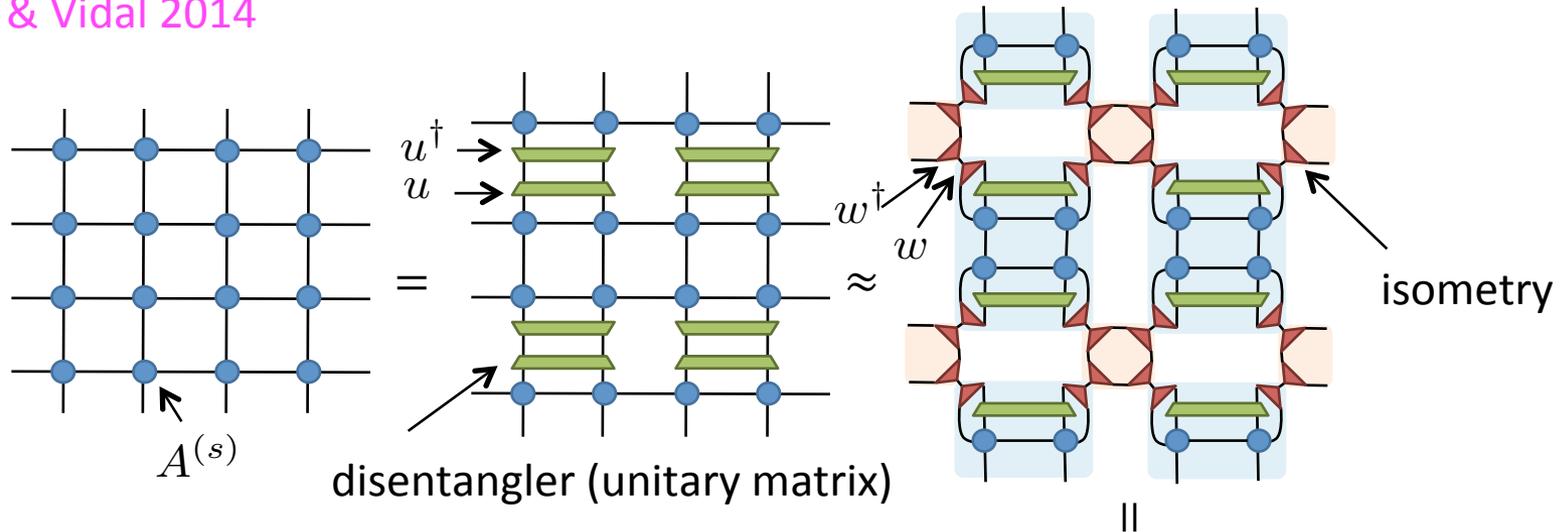
u & w are determined
such that δ is minimized

$$\delta = \left\| \begin{array}{c} u \\ \hline A \quad A \end{array} - \begin{array}{c} w^\dagger \quad w \\ \hline u \\ \hline v \quad v^\dagger \end{array} \right\|$$

Cost: $O(D_{\text{cut}}^7)$ for TNR
 $O(D_{\text{cut}}^6)$ for TRG

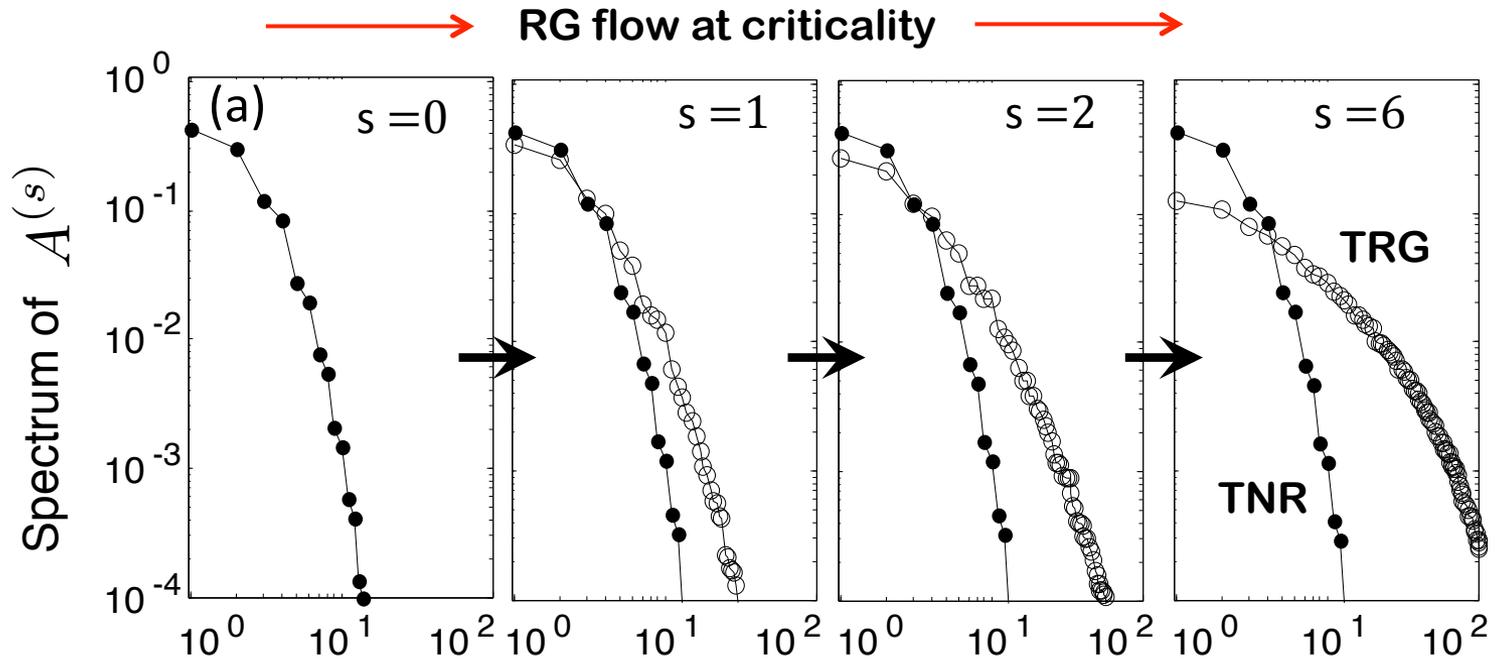
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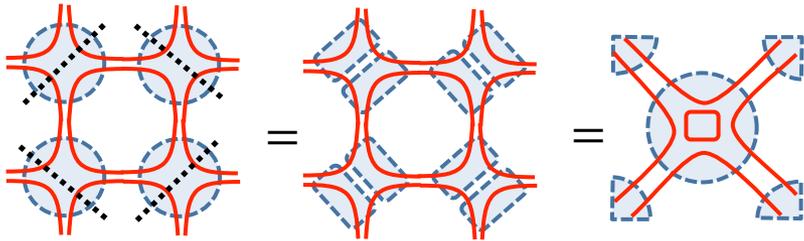


Hierarchy for TNR is robust even after several iterations:
TNR is a sustainable coarse graining

Why TNR works

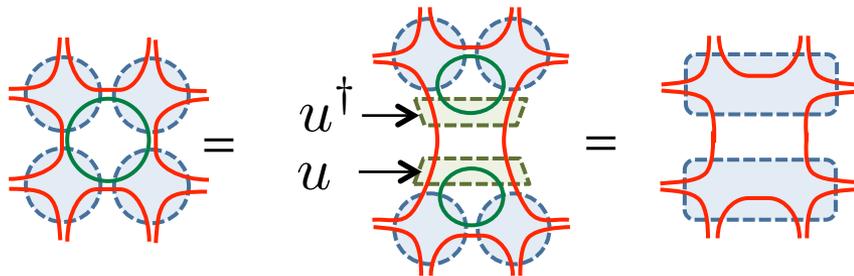
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TRG with Corner Double Line tensor

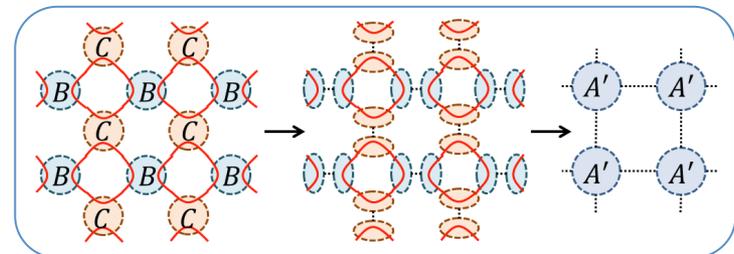
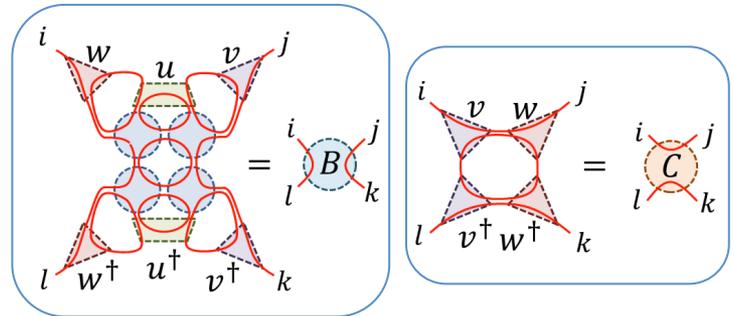
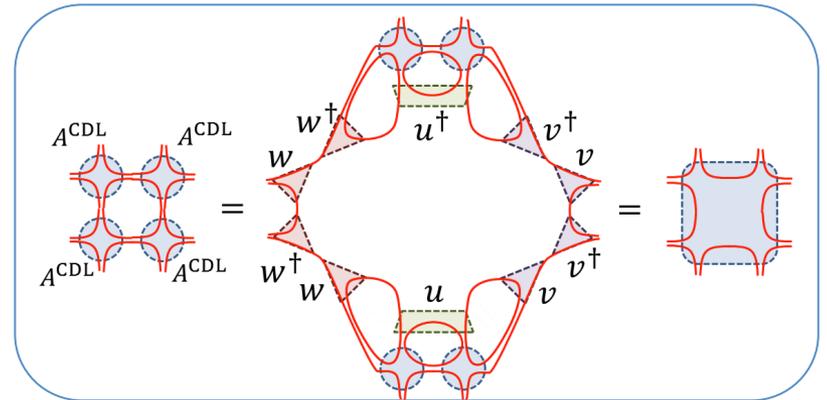


short-correlation represented by CDL remains

A role of disentangler



short-correlation can be removed



Summary

- No sign problem in TRG
- Key of TRG: information compression using SVD
- Inefficient around criticality
- But, Tensor Network Renormalization (TNR) can solve the problem. An extension to higher dimensional system is still missing
- In any case, TRG is very powerful in low (2D) dimensional system

Future prospects

- Long way to 4D QCD (+ μ & θ)
 - Higher dimensional system (4D system)
 - Cost: $O(D_{\text{cut}}^{15})$, Memory: $O(D_{\text{cut}}^8)$
 - efficient parallelization?
 - TNR?
 - Non-Abelian gauge theory
 - Character expansion \Rightarrow Tensor network rep. is OK but internal d.o.f. is huge
- Low dim. system suffering from the sign problem ?
 - 2D $CP(N-1) + \theta$: Strong CP problem 2015 Kawauchi&ST
 - Lattice SUSY, Lattice chiral gauge theory

Application to finite fermion density
system: Gross-Neveu model

2D Gross-Neveu model

Continuum

$$\mathcal{L} = \bar{\psi}(\not{\partial} + m)\psi - \frac{g^2}{2} [(\bar{\psi}\psi)^2 + (\bar{\psi}i\gamma_5\psi)^2]$$

$$\not{\partial} = \partial_\nu \gamma_\nu$$

$\bar{\psi} = (\bar{\psi}_1, \bar{\psi}_2)$ 2 components in spinor space

$$N = 1$$

2D Gross-Neveu model

Continuum

$$\mathcal{L} = \bar{\psi}(\not{\partial} + m)\psi - \frac{g^2}{2} [(\bar{\psi}\psi)^2 + (\bar{\psi}i\gamma_5\psi)^2]$$

$$\not{\partial} = \partial_\nu \gamma_\nu$$

$\bar{\psi} = (\bar{\psi}_1, \bar{\psi}_2)$ 2 components in spinor space

$$N = 1$$

Lattice

$$\not{\partial} \rightarrow \frac{\Delta^f + \Delta^b - \Delta_\nu^b \Delta_\nu^f}{2}$$

Wilson fermions

site

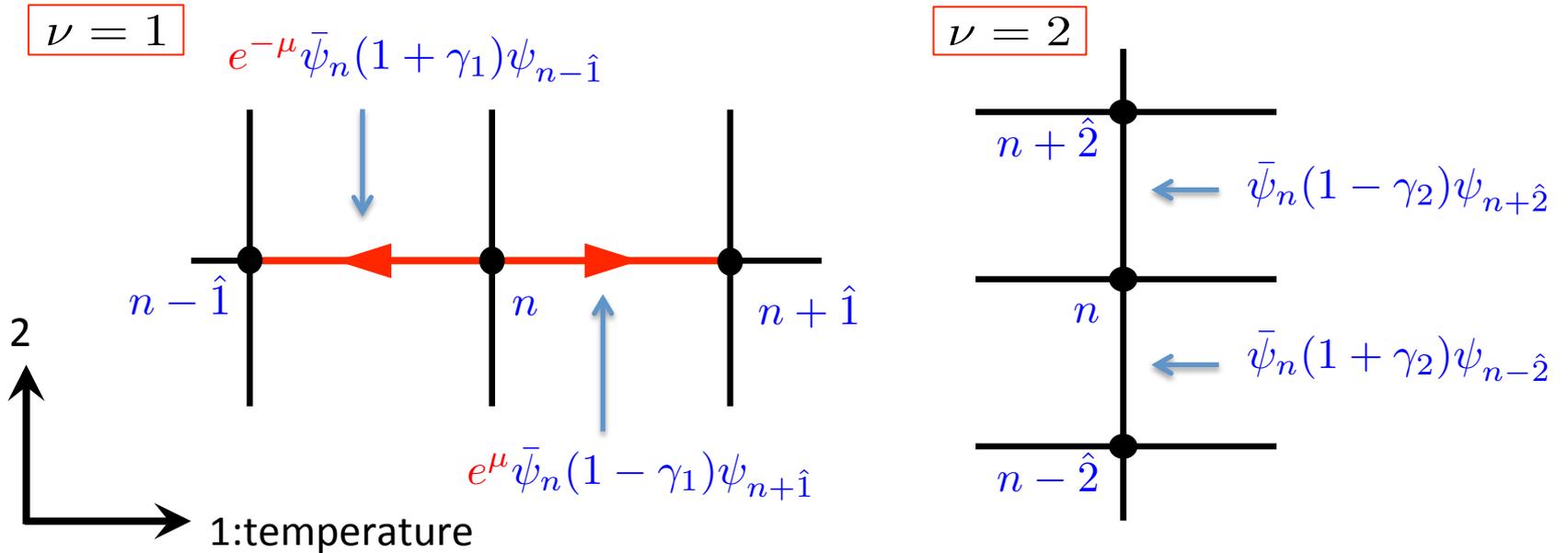
chemical potential

$$\Delta_\nu^{f/b} \psi_n = \pm (e^{\pm \mu \delta_{\nu,1}} \psi_{n \pm \hat{\nu}} - \psi_n)$$

$\nu=1$: temperature direction

$$\begin{aligned} \mathcal{L} = & -\frac{1}{2} \sum_{\nu=1}^2 [e^{\mu \delta_{\nu,1}} \bar{\psi}_n (1 - \gamma_\nu) \psi_{n+\hat{\nu}} + e^{-\mu \delta_{\nu,1}} \bar{\psi}_n (1 + \gamma_\nu) \psi_{n-\hat{\nu}}] \\ & + (m + 2) \bar{\psi}_n \psi_n - \frac{g^2}{2} [(\bar{\psi}_n \psi_n)^2 + (\bar{\psi}_n i \gamma_5 \psi_n)^2] \end{aligned}$$

2D Gross-Neveu model



$$\mathcal{L} = -\frac{1}{2} \sum_{\nu=1}^2 \left[e^{\mu\delta_{\nu,1}} \bar{\psi}_n(1-\gamma_{\nu})\psi_{n+\hat{\nu}} + e^{-\mu\delta_{\nu,1}} \bar{\psi}_n(1+\gamma_{\nu})\psi_{n-\hat{\nu}} \right]$$

Hopping term : Energy term in Ising model

$$+ (m+2)\bar{\psi}_n\psi_n - \frac{g^2}{2} [(\bar{\psi}_n\psi_n)^2 + (\bar{\psi}_ni\gamma_5\psi_n)^2]$$

mass term and interaction term : magnetic term in Ising model

Grassmann TRG

- Formulation :

Gu et al., 2010, Gu 2011

- 2D relativistic system

Shimizu & Kuramashi 2013

For fermion system, procedure is similar to that of Ising model. **But, one has to make tensor for the model by oneself.**

How to make tensor

- 1) Expand BW, and then **new d.o.f. (bosonic)** appears

$$e^{-\sum_n \mathcal{L}} = \prod_n \cdots \exp \left[\frac{1}{2} e^{-\mu} \bar{\psi}_{n+\hat{1}} (1 + \gamma_1) \psi_n \right] \cdots$$

Hopping term for **1st** direction

How to make tensor

- 1) Expand BW, and then **new d.o.f. (bosonic)** appears

$$\begin{aligned} e^{-\sum_n \mathcal{L}} &= \prod_n \cdots \exp \left[\frac{1}{2} e^{-\mu} \bar{\psi}_{n+\hat{1}} (1 + \gamma_1) \psi_n \right] \cdots \\ &= \prod_n \cdots \exp \left[e^{-\mu} \bar{\psi}_{n+\hat{1},1} \psi_{n,1} \right] \cdots \end{aligned} \quad \begin{array}{c} \curvearrowright \\ \curvearrowleft \end{array} \quad \gamma_1 = \sigma_3 = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

How to make tensor

1) Expand BW, and then **new d.o.f. (bosonic)** appears

$$e^{-\sum_n \mathcal{L}} = \prod_n \cdots \exp \left[\frac{1}{2} e^{-\mu} \bar{\psi}_{n+\hat{1}} (1 + \gamma_1) \psi_n \right] \cdots$$

$$= \prod_n \cdots \exp \left[e^{-\mu} \bar{\psi}_{n+\hat{1},1} \psi_{n,1} \right] \cdots$$

Finite expansion
due to Grassmann

$$= \prod_n \cdots \sum_{t_{n,1}=0}^1 \left(e^{-\mu} \bar{\psi}_{n+\hat{1},1} \psi_{n,1} \right)^{t_{n,1}} \cdots$$

$$= \sum_{\{t\}} \prod_n \cdots \left(e^{-\mu} \bar{\psi}_{n+\hat{1},1} \psi_{n,1} \right)^{t_{n,1}} \cdots$$

the same goes for

- ✧ other hopping terms
- ✧ mass term
- ✧ interaction term

new d.o.f. (bosonic)

How to make tensor

- 1) Expand BW, and then **new d.o.f. (bosonic)** appears
- 2) Integrate out **old d.o.f. (Grassmann)** and then one obtains tensor network rep.

$$\begin{aligned}
 \mathcal{Z} = & \sum_{\{t,x,s\}=0,1} \int \left(\prod_n d\psi_n d\bar{\psi}_n \right) \\
 & \times \prod_n \left[e^{-\mu} \bar{\psi}_{n+\hat{1},1} \psi_{n,1} \right]^{t_{n,1}} \left[e^{\mu} \bar{\psi}_{n,2} \psi_{n+\hat{1},2} \right]^{t_{n,2}} \quad \text{hopping term for 1}^{\text{st}} \text{ direc.} \\
 & \times [\dots]^{x_{n,1}} [\dots]^{x_{n,2}} \quad \text{hopping term for 2}^{\text{nd}} \text{ direc.} \\
 & \times \left[-(m+2) \bar{\psi}_{n,1} \psi_{n,1} \right]^{s_{n,1}} \left[-(m+2) \bar{\psi}_{n,2} \psi_{n,2} \right]^{s_{n,2}} \quad \text{mass term} \\
 & \times \left[2g^2 \bar{\psi}_{n,1} \psi_{n,1} \bar{\psi}_{n,2} \psi_{n,2} \right]^{s_{n,3}} \quad \text{4-fermion interaction term}
 \end{aligned}$$

New d.o.f.

How to make tensor

- 1) Expand BW, and then **new d.o.f. (bosonic)** appears
- 2) Integrate out **old d.o.f. (Grassmann)** and then one obtains tensor network rep.
- 3) However, before/after the integration, sign factor originating from Grassmann nature may appear “Randomly” → “Sign problem”?

How to make tensor

- 1) Expand BW, and then **new d.o.f. (bosonic)** appears
- 2) Integrate out **old d.o.f. (Grassmann)** and then one obtains tensor network rep.
- 3) However, before/after the integration, sign factor originating from Grassmann nature may appear “Randomly” → “Sign problem”?
- 4) To deal with the sign factor better, introduce **new Grassmann variables**

New Grassmann variable

Say

$$\left(e^{-\mu\bar{\psi}_{n+\hat{1},1}\psi_{n,1}}\right)^{t_{n,1}} = \int \underbrace{(d\xi_{n,1}\xi_{n,1})^{t_{n,1}}}_{=1} \left(e^{-\mu\bar{\psi}_{n+\hat{1},1}\psi_{n,1}}\right)^{t_{n,1}}$$

same exponent



New Grassmann variable



New Grassmann variable

Say

$$\begin{aligned} \left(e^{-\mu} \bar{\psi}_{n+\hat{1},1} \psi_{n,1} \right)^{t_{n,1}} &= \int (d\xi_{n,1} \xi_{n,1})^{t_{n,1}} \left(e^{-\mu} \bar{\psi}_{n+\hat{1},1} \psi_{n,1} \right)^{t_{n,1}} \\ &= \int \left(e^{-\mu} \psi_{n,1} d\xi_{n,1} \bar{\psi}_{n+\hat{1},1} \xi_{n,1} \right)^{t_{n,1}} \end{aligned} \quad \text{“shuffle”}$$

New Grassmann variable

Say

$$\begin{aligned} \left(e^{-\mu} \underline{\bar{\psi}_{n+\hat{1},1}} \underline{\psi_{n,1}} \right)^{t_{n,1}} &= \int (d\xi_{n,1} \xi_{n,1})^{t_{n,1}} \left(e^{-\mu} \bar{\psi}_{n+\hat{1},1} \psi_{n,1} \right)^{t_{n,1}} \\ &= \int \left(e^{-\mu} \psi_{n,1} d\xi_{n,1} \bar{\psi}_{n+\hat{1},1} \xi_{n,1} \right)^{t_{n,1}} \\ &= \int \left(e^{-\mu/2} \underline{\psi_{n,1}} d\xi_{n,1} \right)^{t_{n,1}} \left(e^{-\mu/2} \underline{\bar{\psi}_{n+\hat{1},1}} \xi_{n,1} \right)^{t_{n,1}} \end{aligned}$$

separate ψ_n $\bar{\psi}_{n+\hat{1}}$

By introducing new Grassmann variable and pairing it with old d.o.f., one can avoid an awkward manipulation of sign factors and can easily integrate out the old d.o.f.

Introduce new Grassmann variable for other hopping terms as well

Tensor network rep.

$$\mathcal{Z} = \sum_{\{t,x\}} \int \prod_n \mathcal{T}_{t_n x_n t_{n-\hat{1}} x_{n-\hat{2}}}$$

$$t_n = (t_{n,1}, t_{n,2})$$

$$x_n = (x_{n,1}, x_{n,2})$$

$$\mathcal{T}_{t_n x_n t_{n-\hat{1}} x_{n-\hat{2}}}$$

$$= \mathcal{T}_{t_n x_n t_{n-\hat{1}} x_{n-\hat{2}}}$$

fermionic part

bosonic part

$$\begin{aligned} & \times d\bar{\xi}_{n,2}^{t_n,2} d\xi_{n,1}^{t_n,1} d\bar{\eta}_{n,2}^{x_n,2} d\eta_{n,1}^{x_n,1} d\xi_{n,2}^{t_{n-\hat{1}},2} d\bar{\xi}_{n,1}^{t_{n-\hat{1}},1} d\eta_{n,2}^{x_{n-\hat{2}},2} d\bar{\eta}_{n,1}^{x_{n-\hat{2}},1} \\ & \times (\bar{\xi}_{n+\hat{1},1} \xi_{n,1})^{t_{n,1}} (\bar{\xi}_{n,2} \xi_{n+\hat{1},2})^{t_{n,2}} (\bar{\eta}_{n+\hat{2},1} \eta_{n,1})^{x_{n,1}} (\bar{\eta}_{n,2} \eta_{n+\hat{2},2})^{x_{n,2}} \end{aligned}$$

$$\mathcal{T}_{t_n x_n t_{n-\hat{1}} x_{n-\hat{2}}}$$

$$= \exp \left[\frac{\mu}{2} (-t_{n,1} - t_{n-\hat{1},1} + t_{n,2} + t_{n-\hat{1},2}) \right]$$

$$\times \sum_{s_{n,1}, s_{n,2}, s_{n,3}=0}^1 \int d\psi_n d\bar{\psi}_n (2g^2 \bar{\psi}_{n,1} \psi_{n,1} \bar{\psi}_{n,2} \psi_{n,2})^{s_{n,3}}$$

$$\times (-(m+2) \bar{\psi}_{n,1} \psi_{n,1})^{s_{n,1}} (-(m+2) \bar{\psi}_{n,2} \psi_{n,2})^{s_{n,2}}$$

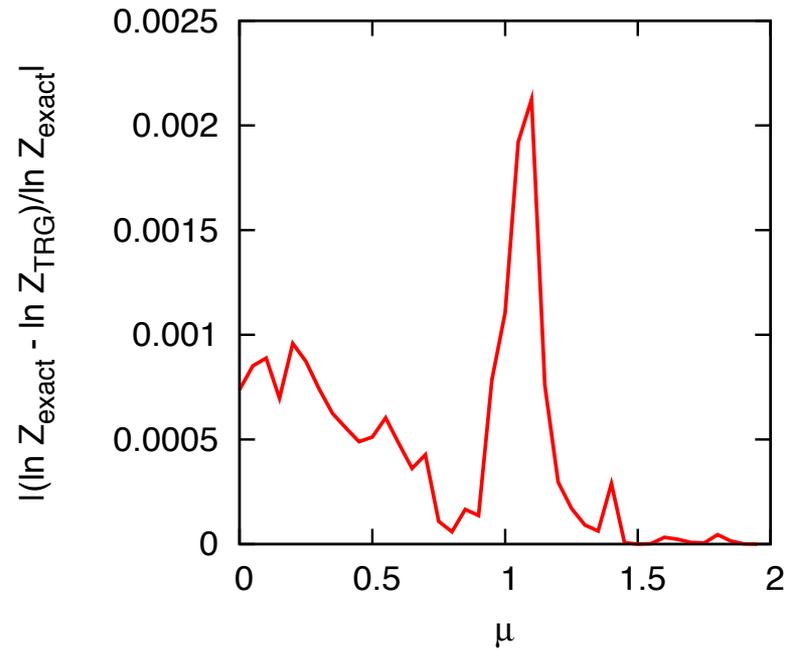
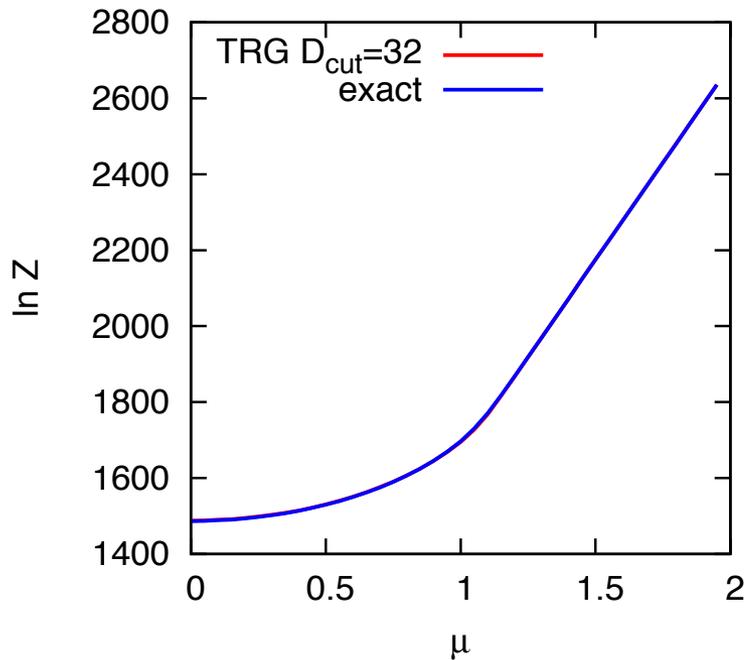
$$\times \bar{\chi}_{n,1}^{x_{n-\hat{2},1}} \chi_{n,2}^{x_{n-\hat{2},2}} \bar{\psi}_{n,1}^{t_{n-\hat{1},1}} \psi_{n,2}^{t_{n-\hat{1},2}} \bar{\chi}_{n,2}^{x_n,2} \chi_{n,1}^{x_n,1} \psi_{n,1}^{t_{n,1}} \bar{\psi}_{n,2}^{t_{n,2}}$$

Other issues

- **Coarse-graining** can be done with some care about the fermionic part of tensor
- **For finite temperature system, anti-periodic BC is imposed for fermions.** This can be taken into account by inserting another tensor (matrix) in one-time slice
- If you want more flavors N , the number of index of tensor increases N times.

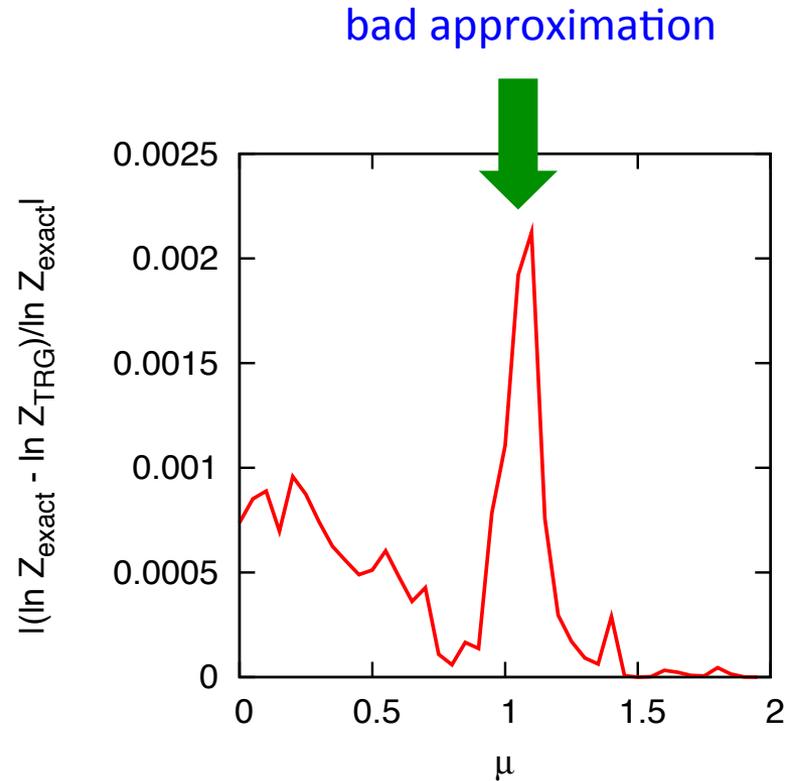
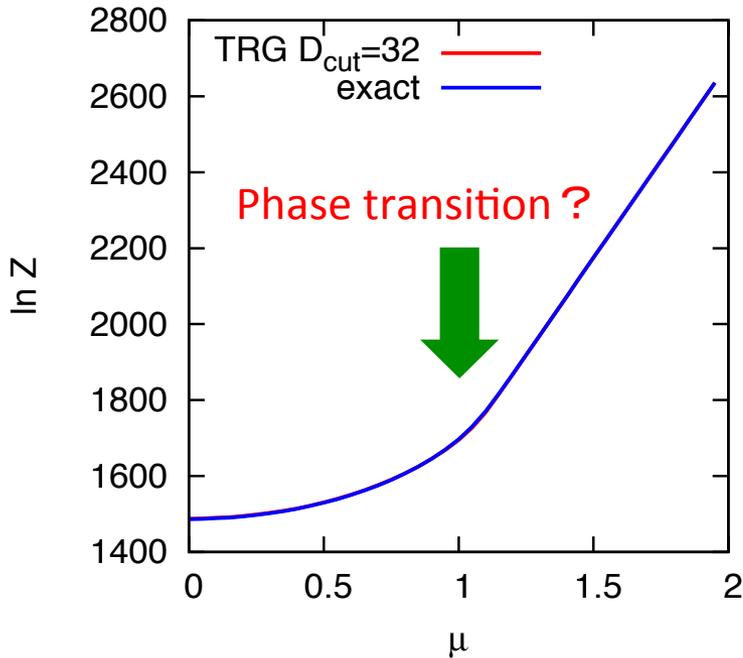
Numerical results: $\ln Z$

$$32^2 \quad g = m = 0$$



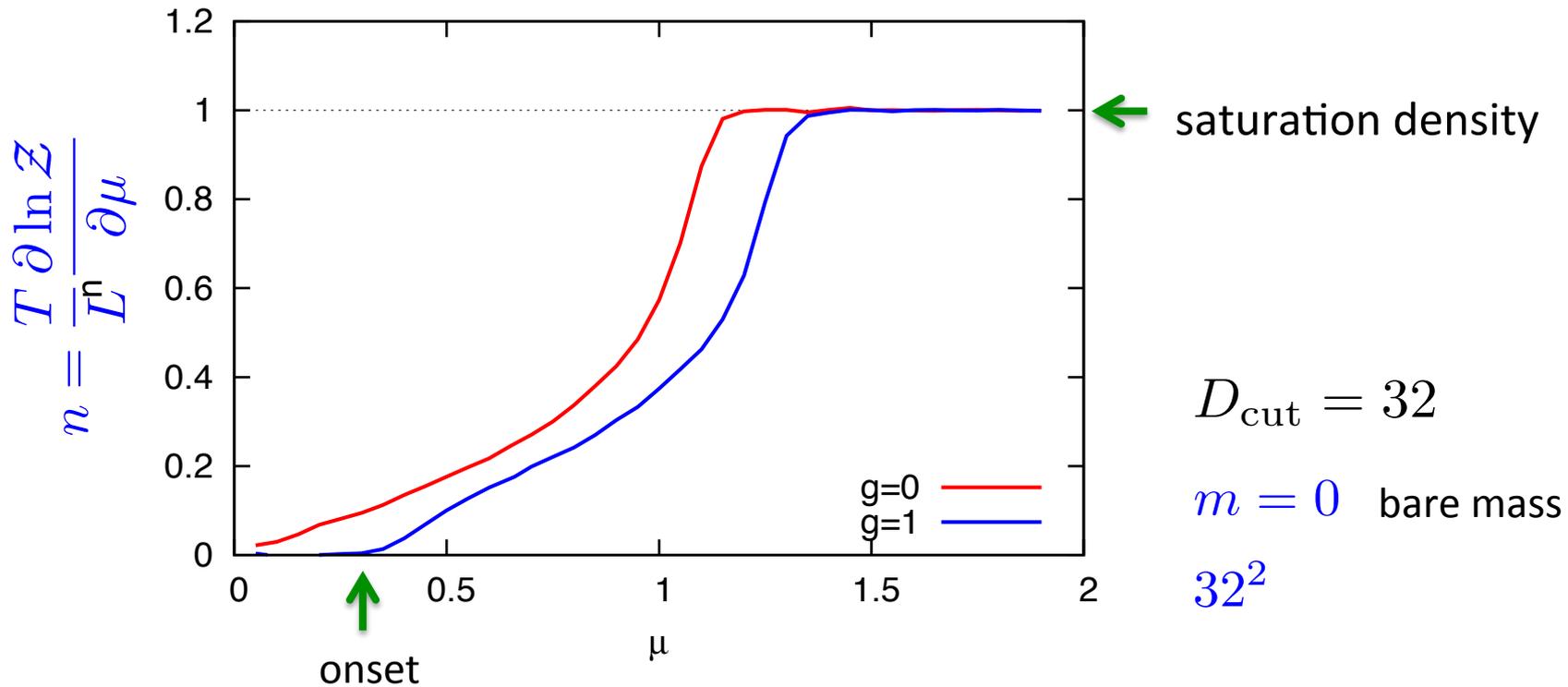
Numerical results: $\ln Z$

$$32^2 \quad g = m = 0$$



Truncation error gets larger around PT?

Fermion number density



Summary

■ Grassmann TRG

- Introduce new Grassmann variables to deal with “new sign problem”
- Demonstrate an extension to finite density in GN model

■ Outlook

- Extension to Higher dimensional system
 - Higher order Grassmann TRG *Sakai & ST in progress*
 - 2+1D Wilson Fermions = Domain wall Fermions in 2D
- Lattice SUSY, Lattice chiral gauge theory