

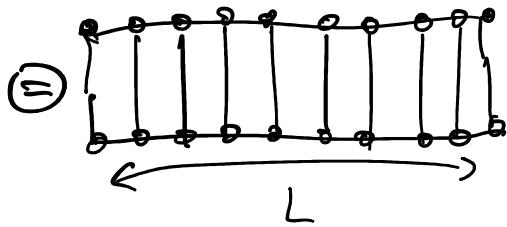
## First obstacle: Observables (I.1)

For 1D TN's (i.e. MPS) observables can be evaluated exactly at polynomial costs. For 2D TN's this is no longer true and in the absence of extra structure:

Exact contraction of 2D TN's is **Exponentially hard**

Let's observe difference between  
finite-size MPS and finite PEPS:

Cost to evaluate a norm (assuming the MPS is  
not given in the canonical form )  
 $\langle \text{MPS} | \text{MPS} \rangle \equiv$



where tensor dimensions  
are  $d$  (physical)  
 $D$   $D$  (bond dim)

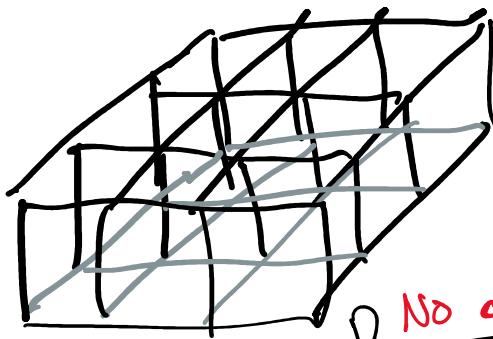
# of floating point ops  
is  $\sim L D^3 d$

i.e. linear in size & cubic in  $D$ .

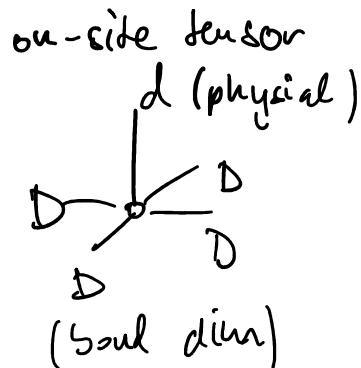
Now finite PEPS :

$$\langle \text{PEPS} | \text{PEPS} \rangle =$$

Looking at this TN  
from above :



No canonical form,  
this cannot be simplified



double-layer tensor  
by contracting over physical index

$\begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \end{array} = \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \end{array}$

permute reshape

define

$$\langle \text{PEPS} | \text{PEPS} \rangle =$$

Let's start contracting:

i)  $\begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \end{array} = \text{---} \quad \# \text{ops} : (D^2)^4$  (Product of dimensions  
of outgoing indices  
and contracted  
indices)

ii)  $\begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \end{array} = \text{---} \quad \# \text{ops} : (D^2)^5$

iii)  $\begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \end{array} = \text{---} \quad \# \text{ops} : (D^2)^3$

iv)  $\begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \end{array} = \text{---} \quad \# \text{ops} : (D^2)^6$

& continue ...

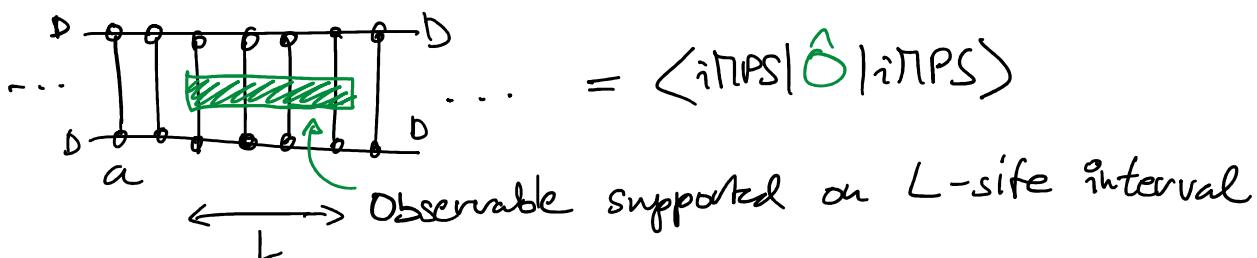
Total number of operations

$$\propto (D^2)^{\min(L_x, L_y) + 2}$$

This is Exponential(D) in width / height of the system.

\* What about infinite MPS (iMPS) ?

generated by single tensor a (i.e. 1-site translational invariant iMPS)



The boundaries of any interval are given by leading left & right eigenvectors of transfer operator

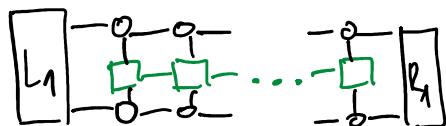
$$\begin{array}{c} D-o-D \\ | \quad | \\ o-o \\ | \quad | \\ D \end{array} = T \in \text{Matrix } D^2 \times D^2 = \sum_{i=1}^{D^2} [R_i] \Lambda_i [L_i]$$

injectivity  
of iMPS will  
guarantee  $\lambda_1 > \lambda_i > 1$   
i.e. unique leading  
eigenvalue & eigenvectors

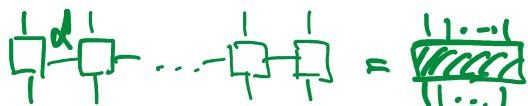
The <sup>cost of</sup> <sup>v</sup> diagonalizing  $T$  is  $O((D^2)^3)$  or to get just a few leading eigenpairs  $O((D^2)^4)$ .

With <sup>the</sup> knowledge of  $[R_1], [L_1]$  ANY observable on the interval of length  $L$  can be evaluated EXACTLY

by contracting TN:



where



i.e. MPS corresponding to  $\hat{O}$ .

with bond dimension  $d$ .

The total cost of contraction is

$$\propto L D^3 d$$

hence the diagonalization of  $T$   $O(D^4)$  dominates.

## Q: Infinite PEPS (iPEPS): How to move forward?

We work with 1-site translational invariant iPEPS (I.2)  
generated by tensor  $a$  with point-group symmetries

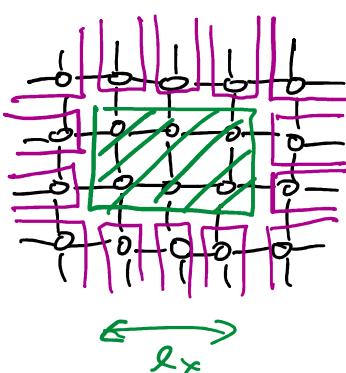
$$a_{uldr}^s = \begin{smallmatrix} u & s \\ d & r \end{smallmatrix} = \begin{smallmatrix} d & s \\ u & r \end{smallmatrix} = \begin{smallmatrix} u & s \\ d & l \end{smallmatrix} = \begin{smallmatrix} u & s \\ l & r \end{smallmatrix} = \begin{smallmatrix} d & s \\ r & l \end{smallmatrix}$$

We consider only observables with finite support, i.e.  
ones defined on a finite  $l_x \times l_y$  patch. Typical  
examples are: interaction terms of local Hamiltonian,  
local observables, correlation functions, ...

$$\langle iPEPS | \hat{O} | iPEPS \rangle =$$

$$\begin{smallmatrix} & & & & & \\ \diagup & \diagdown & & & & \\ & & & & & \end{smallmatrix} = \hat{O}$$

$l_y$



(a top view of  
double-layer  
TN)

ASSUME there exists  $C$  matrix of size  $X \times X$  and  $T$  tensor of size  $X \times X \times D^2$ , which approximate infinite parts of the above TN as

$$\dots \begin{matrix} D^2 & D^2 & D^2 \\ -\cancel{\bullet} & \cancel{\bullet} & \cancel{\bullet} \\ D^2 & D^2 & D^2 \end{matrix} D^2 \approx \frac{1^X}{T-D^2} \quad \& \quad \dots \begin{matrix} \vdots & \vdots & D^2 \\ -\cancel{\bullet} & \cancel{\bullet} & \cancel{\bullet} \\ \vdots & \vdots & D^2 \\ 0 & 0 & D^2 \\ 0 & D^2 & D^2 \end{matrix} \approx C \frac{X}{1X}$$

Then, the expectation value of  $\hat{O}$  can be approximated through  $C, T$  as

$$\langle \text{iPEPS} | \hat{O} | \text{iPEPS} \rangle \approx \begin{matrix} C & -T & -T & -T & -C \\ | & | & | & | & | \\ T & \boxed{\begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix}} & T & & T \\ | & | & | & | & | \\ C & -T & -T & -T & -C \end{matrix} = \langle \hat{O} \rangle_X$$

The error of the approximation can be controlled by increasing  $X$ , with  $X \rightarrow \infty$  limit recovering exact values

$$\lim_{X \rightarrow \infty} \langle \hat{O} \rangle_X = \langle \text{iPEPS} | \hat{O} | \text{iPEPS} \rangle$$

The contraction of approximate network  $\langle \hat{O} \rangle_X$  is still exponential in minimal linear size of the observable  $\min(l_x, l_y)$ . But for many practical use cases, i.e.

- \* Nearest neighbour interaction,  
next-nearest-neighbour interaction, ...

- \* local magnetization,  
VBS order parameter
- \* 2-point correlation functions in  
vertical or horizontal directions

the computational cost is not prohibitive,  
in particular if convergence with  $\chi$   
is fast. [generally the required  $\chi$  is  
proportional to correlation length.]

Why should such  $C, T$  exist and how  
to find them (I.3)

### TL;DR Summary

To perform approximate contraction of infinite TN  
corresponding to  $\langle i|\text{PEPS}|j\rangle \text{PEPS}$  or  $\mathbb{Z}$  of classical 2dile.  
i) pick initial  $C_0, T_0$ .

\* random initialization is also possible

\*  $C_0, T_0$  can be embedded inside larger tensors

$X \times X$ ,  $X \times X \times t$  if it's desirable to work  
with constant-size tensors for the implementation

ii) Choose environment load dimension  $X$ . Then repeat the steps 1-4 until convergence

ii.1) Contract enlarged corner

$$\begin{matrix} C_i - T_i - X \\ | & | \\ T_i - A - t \\ | & | \\ X & t \end{matrix} = C_{2 \times 2} \in \text{Matrix}(Xt) \times (Xt)$$

ii.2) Diagonalize enlarged corner by Eigenvalue decomposition

$$C_{2 \times 2} = U_i \Lambda_i U_i^+$$

ii.3) Compress enlarged corner by keeping leading  $X$  eigenvalues (by magnitude i.e.  $|\lambda_j| \geq |\lambda_k|$  for  $j < k$ ). Compress enlarged half-row/-column tensor by projectors formed from leading  $X$  eigenvectors in  $U$ .

$$C_{i+1} = \Lambda_i [ : X ]$$

(or diagonal matrix  $X \otimes X$  with  $\Lambda_{[ : X ]}$  on diagonal)

$$T_{i+1}^{\frac{t}{X}} = \begin{matrix} X \\ | \\ T_i - A - t \\ | \\ X \end{matrix}$$

Projector with leading  $X$  columns

$P = U_{Xt} \times [ : X ]$  reshaped as a rank-3 tensor with dimensions  $X \times t \times X$

$$\begin{matrix} X \\ | \\ X & t \end{matrix}$$

ii.4) Normalize tensors, for example by largest element (in magnitude)

$$C_{i+1} = C_i / \max(|C_{i+1}|) \quad \& \quad T_{i+1} = T_i / \max(|T_{i+1}|)$$

[here  $|.|$  is element-wise absolute value]

check convergence, by i.e. measuring the size of the difference of  $\Lambda_{i+1} - \Lambda_i$ .

iii) Converged tensors  $C, T$  approximate infinite

quadrant

$$\dots \begin{array}{|c|c|c|} \hline & & 1 \\ \hline & 0 & 0 \\ \hline 0 & 0 & 0 \\ \hline \end{array} \approx C$$

half-row/-column

$$\dots \begin{array}{|c|c|} \hline & 1 \\ \hline 0 & 0 \\ \hline \end{array} \approx T$$

End TL;DR summary

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Let's look at the related problem:

Partition function of 2D classical stat-mech model:

→ 2D ferromagnetic Ising model on a square lattice

$$\mathcal{H} = -\sum_{ij} \tau_i \tau_j \rightarrow Z(\beta) = \text{Tr } e^{-\beta \mathcal{H}}$$

with  $\tau \in \{-1, 1\}$  (just numbers)

$$Z = \text{Tr}_{\{\tau\}} \exp(+\beta \sum_{\langle ij \rangle} \tau_i \tau_j)$$

$$= \text{Tr}_{\{\vec{\tau}\}} \prod_{\langle i,j \rangle} \exp(\beta \tau_i \tau_j)$$

$$= \text{Tr} \prod_{\{\vec{\sigma}\}} \exp(-\beta \sigma_i \sigma_j)$$

Sum over all possible configurations of spins  $\vec{\sigma} \in \{-1, 1\}^{\otimes L^2}$  on a square lattice of size  $L \times L$



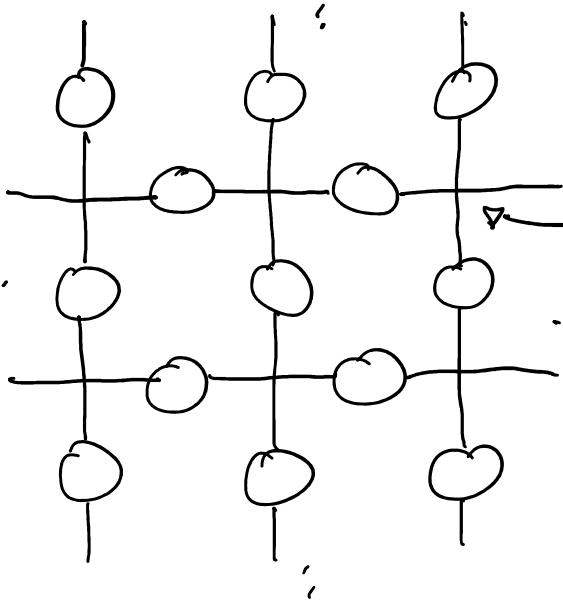
graphical interpretation

Given a configuration  $\vec{\sigma} = (\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_{L^2})$  it's Boltzmann weight  $\exp(-\beta H(\sigma))$  is expressed as a product of weights assigned to the edges of square lattice while spins  $\sigma_1, \sigma_2, \dots, \sigma_{L^2}$  sit on vertices

## Construction of $Z$ as tensor network

### Contraction (I. 3.1)

$$Z =$$



$$\overset{i}{\circ} \underset{j}{\circ} = \exp(\beta \sigma_i \sigma_j) \quad 2 \times 2 \text{ matrix}$$

$$\overset{i}{\circ} \underset{j}{+} \underset{k}{\circ} = \delta_{ijk} \quad \begin{matrix} \text{rank 4} \\ 2 \times 2 \times 2 \times 2 \\ \text{tensor} \end{matrix}$$

where only non-zero elements of delta are  $\delta_{0000} = \delta_{1111} = 1$

For any particular choice of spin states  $\Rightarrow$  configuration we get its Boltzmann weight from construction.

Let's first turn this network into familiar PEPS format where tensors sit in the vertices of the lattice, not on edges.

- i) express Boltzmann weights as a product of their square root

$$\begin{array}{c} h \\ \text{---} \bigcirc \text{---} \\ i \qquad j \end{array} = \begin{array}{c} i \qquad j \\ \sqrt{h} \qquad \sqrt{h} \\ \text{---} \nearrow \swarrow \text{---} \end{array}$$

$$h_{ij} = \exp(\beta \epsilon_i \epsilon_j)$$

$$= \cancel{\epsilon_i \epsilon_j} \begin{array}{c} \text{index} & 0 & 1 \\ \text{state} & +1 & -1 \end{array}$$

$$\begin{array}{c} \text{index state} \\ 0 \quad +1 \\ 1 \quad -1 \end{array} \begin{pmatrix} e^\beta & e^{-\beta} \\ e^{-\beta} & e^\beta \end{pmatrix}$$

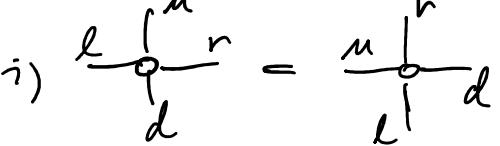
- ii) Replacing  $\text{---}$  on every edge by  $\text{---} \nearrow \swarrow \text{---}$   
 we can absorb  $\sqrt{h}$ 's symmetrically  
 into  $\delta$ 's on each vertex:

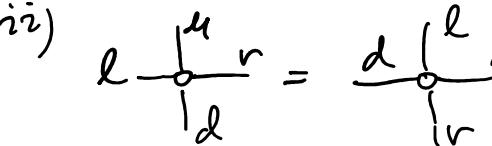
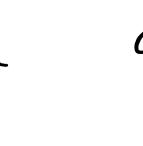
$$\begin{array}{c} \sqrt{h} \qquad \sqrt{h} \\ \text{---} \nearrow \swarrow \delta \qquad \sqrt{h} \\ \sqrt{h} \qquad \sqrt{h} \end{array} = \begin{array}{c} D \\ \text{---} \bigcirc \text{---} \\ D \qquad D \end{array} \quad \text{where } D=2$$

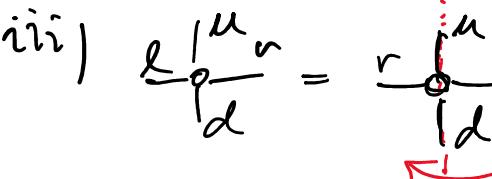
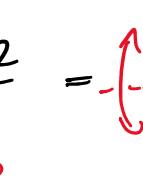
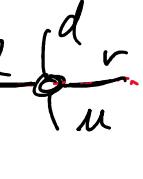
or in Einstein summation convention

$$A_{\mu l d v} = \sum_{\mu' l' d' v'} (\sqrt{h})_{\mu \mu'} (\sqrt{h})_{l l'} (\sqrt{h})_{d d'} (\sqrt{h})_{v v'} \delta_{\mu' l' d' v'}$$

Note: tensor is symmetric under the permutations of its indices corresponding to point-group symmetries of square lattice

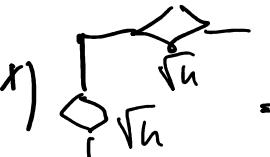
i)  =  counter-clockwise rotation by  $\pi/2$  

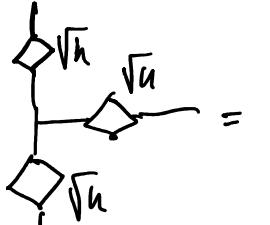
ii)  =  clockwise rotation by  $\pi/2$

iii)  =  =  reflections along y-axis and x-axis.

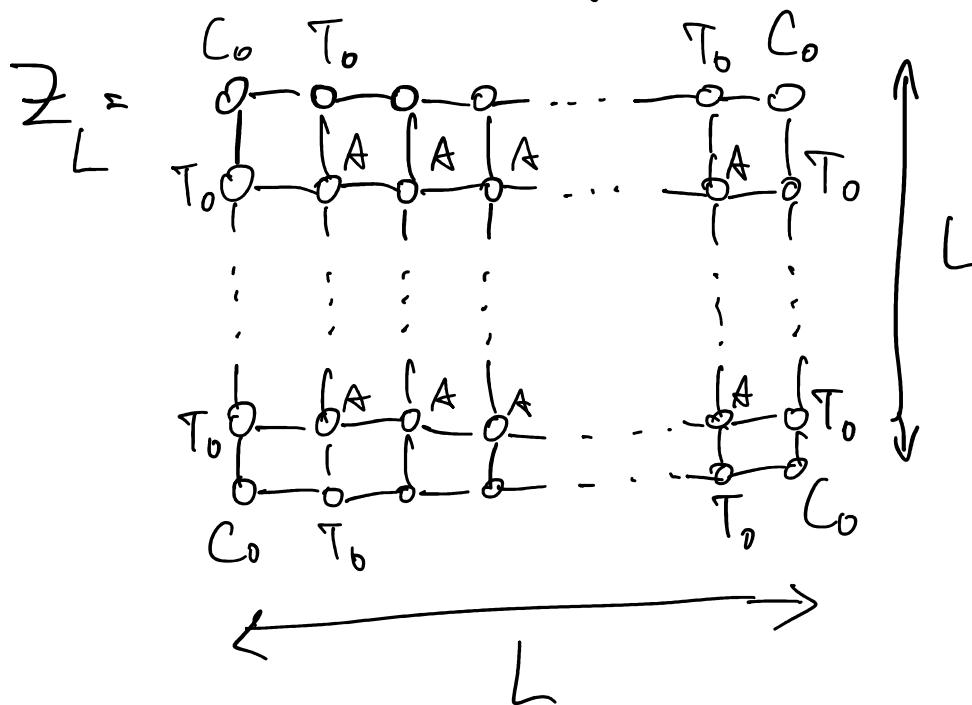
Therefore, we have expressed the partition function as a contraction of a PEPS TN generated by tensor a.

For open boundary condition, expressed through tensors:

i)  =  $C_0$  where  $T = \delta_{ij}$  with non-zero entries  $\delta_{00} = \delta_{11} = 1$   
 $C_0$  is  $D \times D$  tensor.  
&

\*)  =  where  $T = \delta_{ijk}$  with entries  $\delta_{000} = \delta_{111} = 1$   
 $T_0$  is  $D \times D \times D$  tensor

The partition function of  $L \times L$  system  
is given by the contraction of



All contracted indices (lines) have dimension  $D=2$ .

Exact contraction of such network is exponentially costly, scaling as  $\propto D^{L+2}$ .

Therefore, to move forward we have to abandon exact contraction and instead try to approximate the result

The central idea of the approach outlined below is the real-space renormalization group:

# Corner transfer matrix renormalization group

(I.3.2)

Baxter 50's, Nishino & Okanishi '96

Let's constructively perform this RG procedure.

Start with a partition function for a small system,  
say  $L=3$ :

$$Z_3 = \begin{array}{c} C_0 - T_0 - C_0 \\ | \quad | \quad | \\ T_0 - a - T_0 \\ | \quad | \quad | \\ C_0 - T_0 - C_0 \end{array} = \begin{array}{l} \text{This is a very small} \\ \text{network \& we can easily} \\ \text{contract it giving the} \\ \text{result:} \end{array}$$

Let's consider a larger network

$$Z_5 = \begin{array}{c} C_0 - T_0 - T_0 - T_0 - C_0 \\ | \quad | \quad | \quad | \quad | \\ T_0 - a - a - a - T_0 \\ | \quad | \quad | \quad | \quad | \\ T_0 - a - a - a - T_0 \\ | \quad | \quad | \quad | \quad | \\ T_0 - a - a - a - T_0 \\ | \quad | \quad | \quad | \quad | \\ C_0 - T_0 - T_0 - T_0 - C_0 \end{array}$$

Again, this network  
can be contracted  
exactly since it's  
still not too large

Let us rewrite this TN using a new set  
of tensors

i) Corner  $C_5 \xrightarrow{D_2} =$

reshape into  $D^2$  index

reshape into  $D^2$  index

which is obtained by contraction of enlarged corner of the  $T_5$  network. It's a rank-2 tensor with dimensions  $D^2 \times D^2$ .

ii) half-row/-column tensor

$$T_5 \xrightarrow{D^2} =$$

reshape to  $D^2$

reshape to  $D^2$

which is a rank-3 tensor with dimensions  $D^2 \times D^2 \times D$  (let's take this index to be the last index of  $T_5$ )

In terms of  $C_5$  &  $T_5$ , the TN  $Z_5$  can be rewritten as:

$$Z_5 = \begin{array}{c} C_5 - T_5 - C_5 \\ | \quad | \quad | \quad | \leftarrow D^2 \\ T_5 - a - T_5 \\ | \quad | \\ C_5 - T_5 - C_5 \end{array}$$

This rewriting is exact. We merely packaged/accumulated some of the contractions into a larger tensors  $C_5, T_5$  with their indices on the edge (orange) having dimension  $D^2$ .

Let's enlarge the system further, to  $L=9$  and write the TN using  $C_5, T_5$ :

$$Z_9 = \begin{array}{c} C_5 - T_5 - T_5 - T_5 - C_5 \\ | \quad | \quad | \quad | \quad | \\ T_5 - a - a - a - T_5 \\ | \quad | \quad | \quad | \quad | \\ T_5 - a - a - a - T_5 \\ | \quad | \quad | \quad | \quad | \\ T_5 - a - a - a - T_5 \\ | \quad | \quad | \quad | \quad | \\ C_5 - T_5 - T_5 - T_5 - C_5 \end{array}$$

Once again let's construct a new corner and half-row/column tensor, this time starting from an arbitrary  $C_L, T_L$

$$ii) \quad C_L \xrightarrow{D^{L/2+1}} = \boxed{\begin{matrix} C_L - T_L \\ | \\ +_L - a \end{matrix}} \xrightarrow{D^{L/2}} \left. \begin{matrix} D^{L/2} & D \\ \text{reshape} & \text{integer division} \end{matrix} \right\}$$

$D^{L/2}$        $D$   
 $\underbrace{D^{L/2} \quad D}_{\text{reshape into } D}$

$$ii) \quad \boxed{\begin{matrix} D^{L/2+1} \\ | \\ T_{L+2} - D \\ | \\ D^{L/2+1} \end{matrix}} = \boxed{\begin{matrix} D^{L/2} & D \\ | \\ T_L - a \\ | \\ D \end{matrix}} \xrightarrow{D^{L/2}} \left. \begin{matrix} D^{L/2} & D \\ \text{reshape} & \end{matrix} \right\}$$

For current system  $L=9$ ,  $C_g$  is  $D^3 \times D^3$  matrix and  $T_g$  is  $D^3 \times D^3 \times D$  rank-3 tensor.

Note: The symmetries of tensor  $a$  carry over to tensors  $C_L, T_L$ . In particular

$$\boxed{\begin{matrix} C_L - i \\ | \\ j \end{matrix}} = \boxed{\begin{matrix} C_L - j \\ | \\ i \end{matrix}}$$

$$\boxed{\begin{matrix} i_1 \\ | \\ +_L - \\ | \\ j_1 \end{matrix}} = \boxed{\begin{matrix} j_1 \\ | \\ T_L - \\ | \\ i_1 \end{matrix}}$$

$\Rightarrow C_L$  is a symmetric tensor  $\Rightarrow T_L$  is symmetric wrt. to exchange of edge indices.

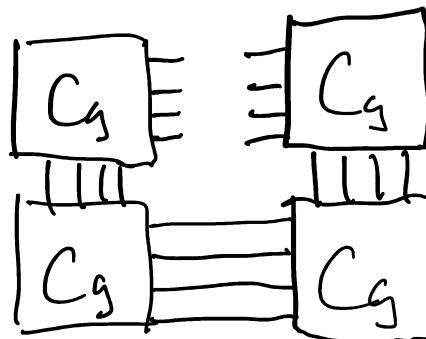
Therefore, once again  $Z_g$  can be expressed exactly as a contraction of TN with even larger tensors  $C_S, T_g$

$$Z_g = \begin{array}{c} C_g - T_g - C_S \\ | \quad | \quad | \\ T_g - D - T_g \\ | \quad | \\ C_g - T_g - C_g \end{array} \xrightarrow{D^3}$$

Continuing this process, we will eventually again hit the **exponential** wall, since the size of the  $C_L, T_L$  grows as  $\propto D^{L/2}$ .

Let's make an observation :

$$\begin{array}{c} C_g - C_g \\ | \quad | \\ C_S - C_S \end{array} = S_g =$$



$S_g$  is a density matrix

for 4 spins living on the vertical half-cut of the system.

$$\text{Then } Z_g = \text{Tr}(C_g^4)$$

or more generally

$$\begin{array}{c} C_L - C_L \\ | \quad | \\ C_L - C_L \end{array} = S_{L/2}$$

is density matrix for  $L/2$  spins on vertical half-cut.

$$\text{and } Z_{L/2} = \text{Tr}(C_L^4)$$

## Note on the observables

To measure expectation value of spin  $\tau$  sitting on side cut

$$\langle \tau \rangle = \frac{\text{Tr } \tau \exp(-\beta H)}{\text{Tr } \exp(-\beta H)}$$

we should modify the on-site kets:

$$\begin{aligned}
 & \text{Diagram showing two circles with internal nodes connected by a horizontal line. The left circle has a top node with an arrow pointing up and a bottom node with an arrow pointing down. The right circle has a top node with an arrow pointing up and a bottom node with an arrow pointing down. A bracket labeled } (\begin{matrix} 1 & -1 \\ -1 & 1 \end{matrix}) \text{ connects the two circles.} \\
 & = \sqrt{h} \\
 & = \sqrt{\begin{pmatrix} e^\beta & e^{-\beta} \\ e^{-\beta} & e^\beta \end{pmatrix}}
 \end{aligned}$$

Alternatively, we can instead transform the observables:

$$-\tau \square = \square \tau' -$$

$$\text{where } \tau' = -\square^{-1} \tau \square -$$

To evaluate physical observables on vertical half-cut, transform them by  $\tau'$  and then evaluate transformed observables on  $S_{L/2}$ .

Given that  $C_L$  is symmetric, we can simply diagonalize it :  $C_L = U_L \Lambda_L U_L^+$

$$* \boxed{S_{L/2} = U_L \Lambda_L^4 U_L^+}$$

and

$$* Z_{L-1} = \text{Tr} ([U_L \Lambda_L U_L^+]^4) = \text{Tr} (\Lambda^4)$$

since  $C_L$  is  $D^{L/2} \times D^{L/2}$  matrix,

$$\boxed{Z_{L-1} = \sum_{i=1}^{D^{L/2}} \Lambda_i^4}$$

Now we can turn back to the problem of  $C_L, T_L$  growing exponentially large with  $L$ .

(I.3.3)

Core proposition - variational compression:

To avoid exponential growth, let's **compress** the tensors  $C_L, T_L$  to size at most

$X$  - the environment (edge) dimension

$$\begin{array}{ccc} C_L & \xrightarrow{\text{compress}} & \tilde{C}_L^{(X)} \\ T_L & \xrightarrow{\quad} & \tilde{T}_L^{(X)} \end{array} \begin{array}{l} X \times X \text{ matrix} \\ X \times X \times D \text{ tensor} \end{array}$$

We want this compression to be **optimal**, such that the error on the corresponding density matrix  $\hat{\rho}_{L/2}$  and hence all observables it encodes is minimal. We define the error wrt. Frobenius norm due to  $\hat{\rho}_{L/2} = C_L^4$

$$\min_{\tilde{\rho}} \left\| \hat{\rho}_{L/2} - \tilde{\rho}_{L/2}^{(x)} \right\|_F^2 \iff \min_{\tilde{C}} \left\| C_L - \tilde{C}_L^{(x)} \right\|_F^2$$

Optimal solution of this problem (low-rank matrix approximation) is given by truncated SVD, or in this case symmetric eigen-decomposition

$$S_{L/2} = C_L^4 = U_L \Lambda_L^4 U_L^+ \quad \text{where } \lambda_{ij} \quad j > i \quad (\lambda_{ii}) \geq (\lambda_{ij})$$

$$\Rightarrow \tilde{\rho}_{L/2}^{(x)} = P \Lambda_{[::x]}^4 P^+ \quad \text{where } P = U_{[:,1:x]} \quad \text{leading } x \text{ columns}$$

This gives an error

Note: this compression preserves the symmetries of  $\tilde{C}_L^4$

$$\text{error}_C^{(x)} = \left\| C_L - \tilde{C}_L^{(x)} \right\|_F^2 = \sum_{i=1}^{D^{L/2}} \lambda_i^2 - \sum_{i=1}^x \lambda_i^2 = \sum_{i=x+1}^{D^{L/2}} \lambda_i^2$$

Hence for the partition function:

$$\text{error}_Z^{(x)} = Z_{L-1} - \tilde{Z}_{L-1} = \text{Tr}(C_L^4 - [\tilde{C}_L^{(x)}]^4) = \sum_{i=x+1}^{D^{L/2}} \lambda_i^4$$

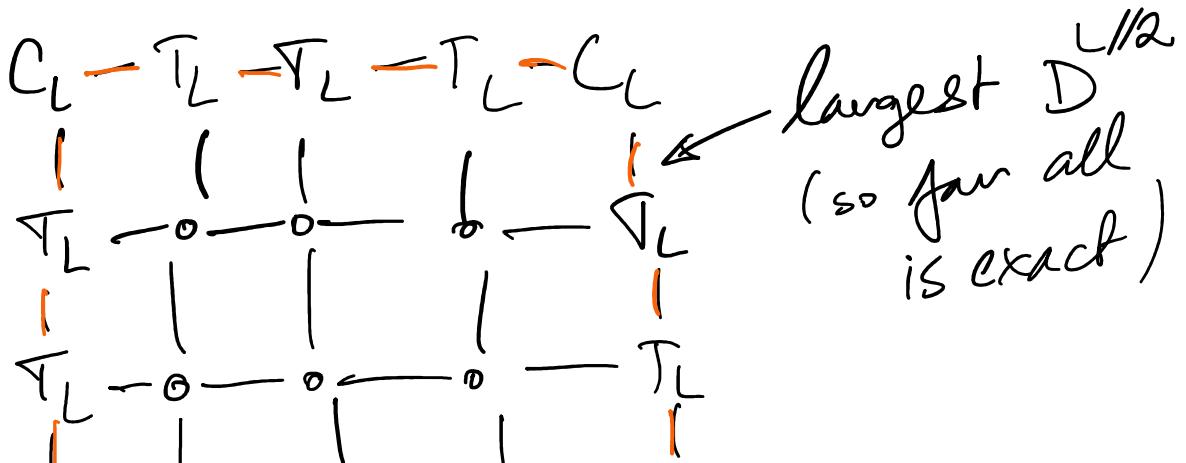
This choice is systematically improved by increasing  $x$ . It also leads to variational approximation of partition function.

Why variational?: Because  $\mathcal{F}(X, X')$  where  $X > X'$  the error  $(X') \leq \text{error}(X)$ . Given that thermodynamic free energy is  $F = -\frac{1}{k} \log Z$ , one approaches the minimal free energy from above as  $X$  is growing.

[System in thermal equilibrium at constant volume minimizes its free energy.]

### Renormalization / Compression step (I.3.4)

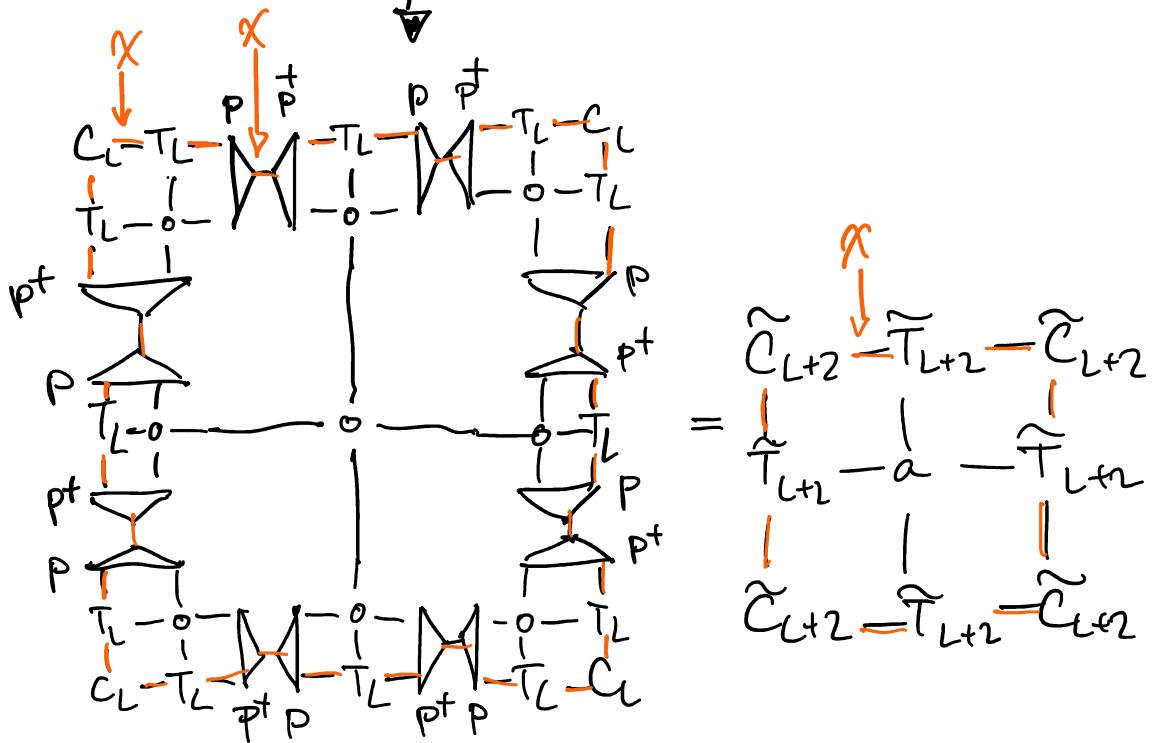
Once we have reached largest size  $L$  allowed by computational resources, we can compress the network as in the step above



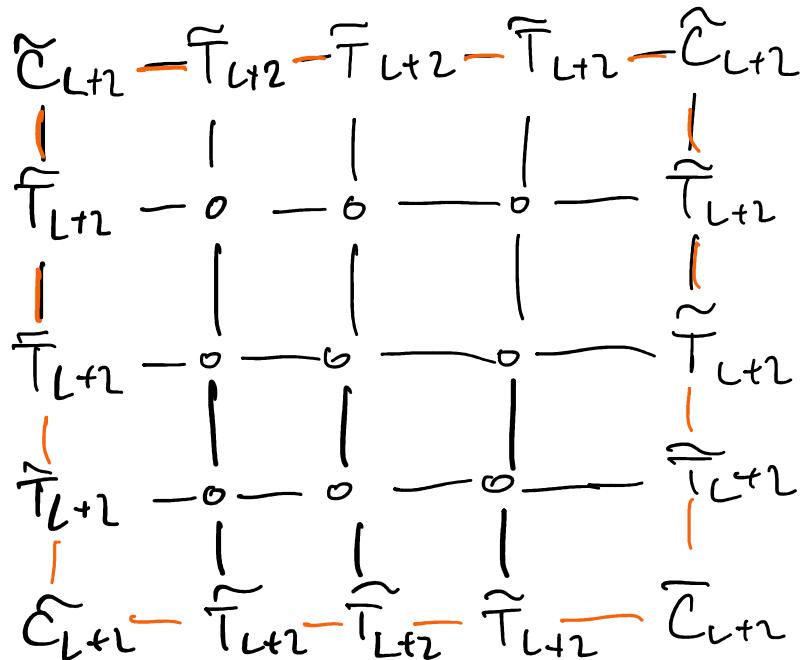
Compress



Compress



Grow



Compress

... . .

From this point onwards we just keep growing & compressing (RG step) never increasing environment dimension beyond  $X$ , until we reach fixed point  $\tilde{C}, \tilde{T}^{\infty}$ .

- \* For fixed  $X$ , the compression error depends on the decay of  $\Lambda$ 's, which in turn depends on on-site tensor  $\underline{\underline{a}}$ .

If  $X \ll D^L$  while doing error no larger than desired  $\epsilon$ , we avoided **exponential scaling**.

## Finite precision & intensive quantities I.3.5

The RG steps require controlling the magnitude of  $\tilde{C}, \tilde{T}$  i.e. by rescaling them.

Otherwise finite precision errors would follow in numerical implementations.

Such rescaling changes <sup>the</sup> value of  $Z = \text{Tr}(\tilde{C}^4)$ .  
 Still, intensive quantities such as local observables or partition function per site are unambiguous;

$$Z_L = \frac{C_L - C_L}{C_L - C_L} = : \frac{L^2}{1} \leftarrow \begin{array}{l} \text{Definition} \\ \text{of partition} \\ \text{function per site} \end{array}$$

$$Z_{L+1} = \frac{C_L - T_L - C_L}{\begin{array}{c} | \\ T_L - O - T_L \\ | \\ C_L - T_L - C_L \end{array}} = : \frac{(L+1)^2}{1}$$

$$Z_{L \times (L+1)} = \frac{C_L - C_L}{\begin{array}{c} | \\ T_L - T_L \\ | \\ C_L - C_L \end{array}} = : \frac{L \times (L+1)}{1}$$

(asymmetric system)

$$\boxed{M = \frac{Z_{L+1} \cdot Z_L}{Z_{L \times (L+1)} \cdot Z_{(L+1) \times L}}}$$

different  
in case no  $C_{4V}$   
symmetry

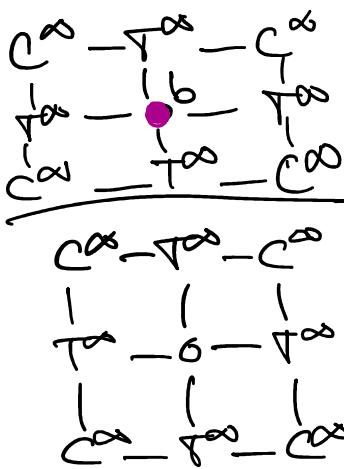
This formula remains valid even  
for compressed fixed point  $C_1^{\infty} T^{\infty}$ ,  
where strictly speaking size of the  
system is no longer well-defined.

On-site magnetization can be estimated

following its definition :

$$\langle \sigma \rangle_x = \frac{\text{Tr}(\tau \exp(-\beta H))}{\text{Tr} \exp(-\beta H)} = \frac{C^\infty - T^\infty - C^\infty}{T^\infty - b - T^\infty}$$

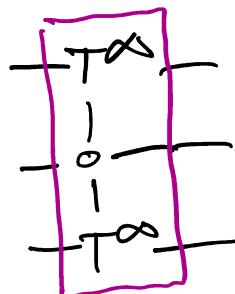
where  $b = \frac{1}{T_h} - \frac{1}{T_h} - \frac{1}{T_h}$



Correlation length is derived from 2-point correlation function or specifically its TN approximation:

$$\langle \tau_0 \tau_r \rangle = \frac{C^\infty - T^\infty - T^\infty - C^\infty}{T^\infty - b - T^\infty - \dots - T^\infty - T^\infty - C^\infty}$$

which reduces to analogous argument as for 1D MPS, here



playing the role of  $X^2 D \times X D^2$   
T - transfer matrix.

$$\text{It's gap, i.e., for } T = \sum_{i=1}^{X^2 D} \begin{bmatrix} R_i \\ L_i \end{bmatrix} \lambda_i \begin{bmatrix} R_i \\ L_i \end{bmatrix}$$

determines correlation length as  $\xi_i = -\frac{1}{\log |\lambda_i/\lambda_0|}$ .