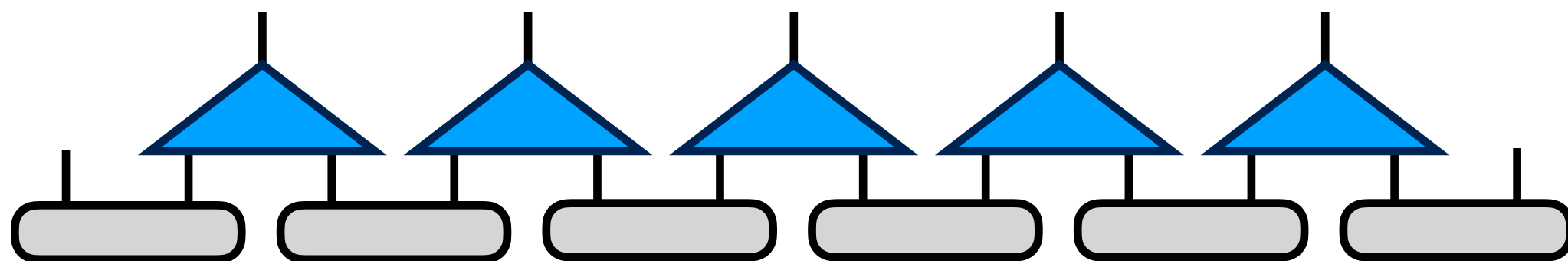


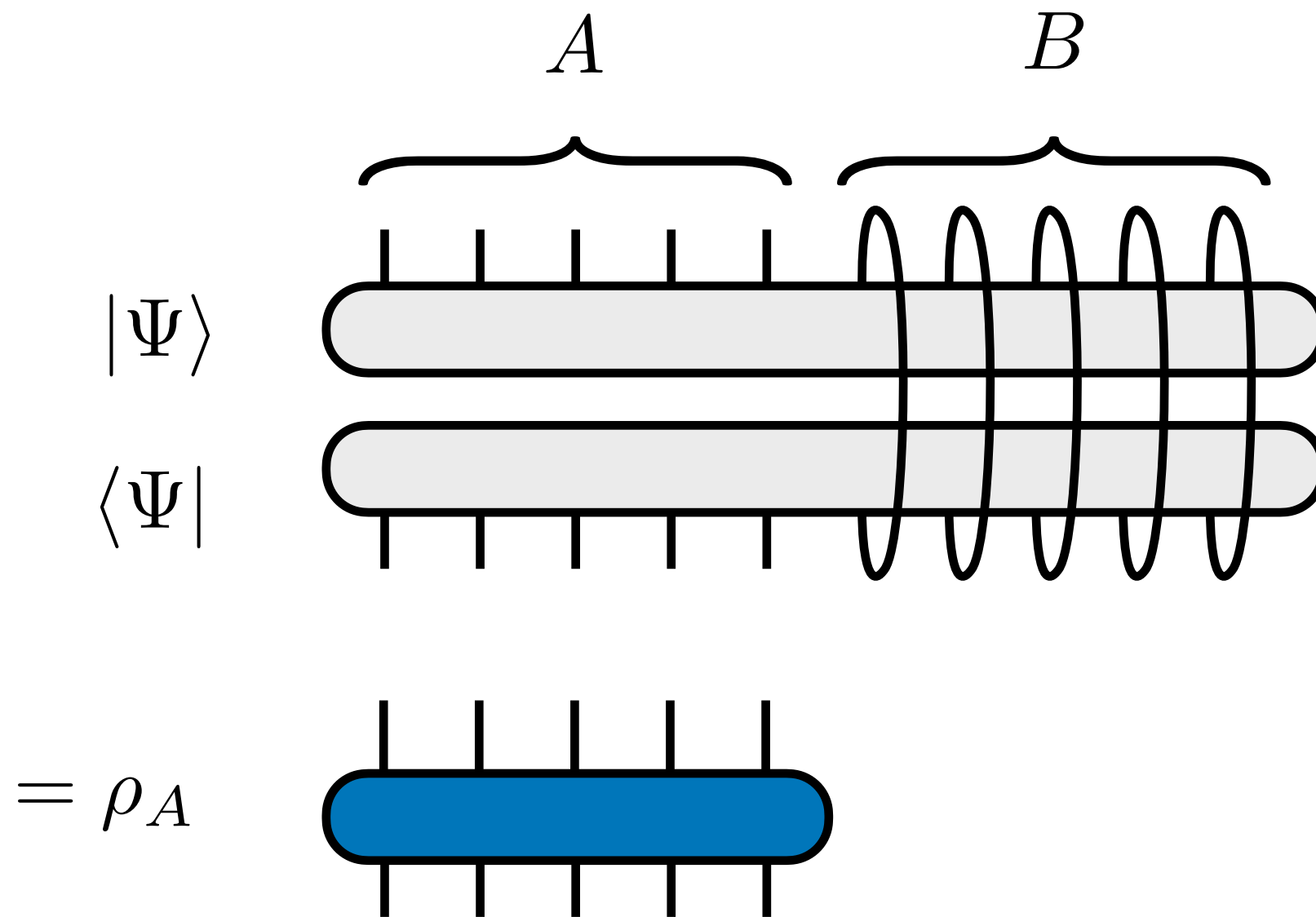
# Tensor Networks and Applications



# **Review of Previous Lecture**

# Reduced density matrix

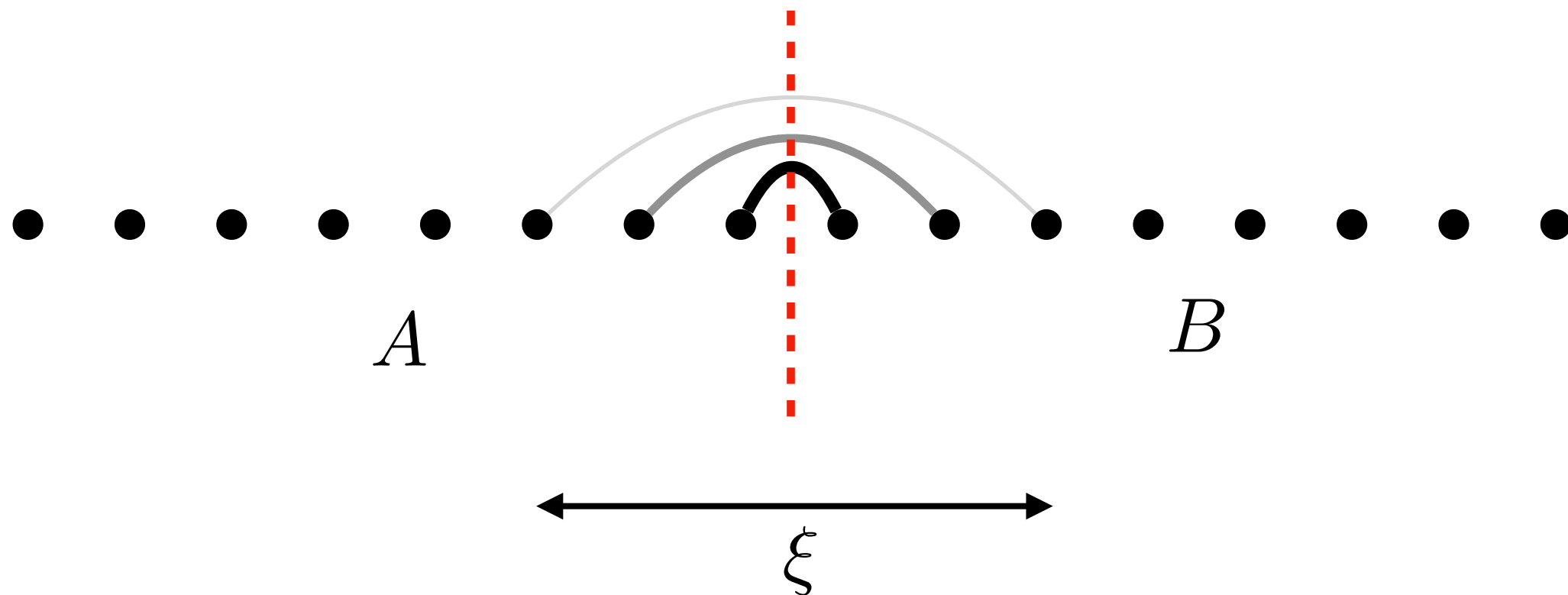
Trace over region B to get reduced density matrix of A



Eigenvalues of  $\rho_A$  define entanglement between A and B

# Boundary law implies limited entanglement of ground states

Entanglement between A and B due to spins near boundary  
(for ground state of gapped, local Hamiltonian)



Local  $H$  and gap implies a correlation length  $\xi$

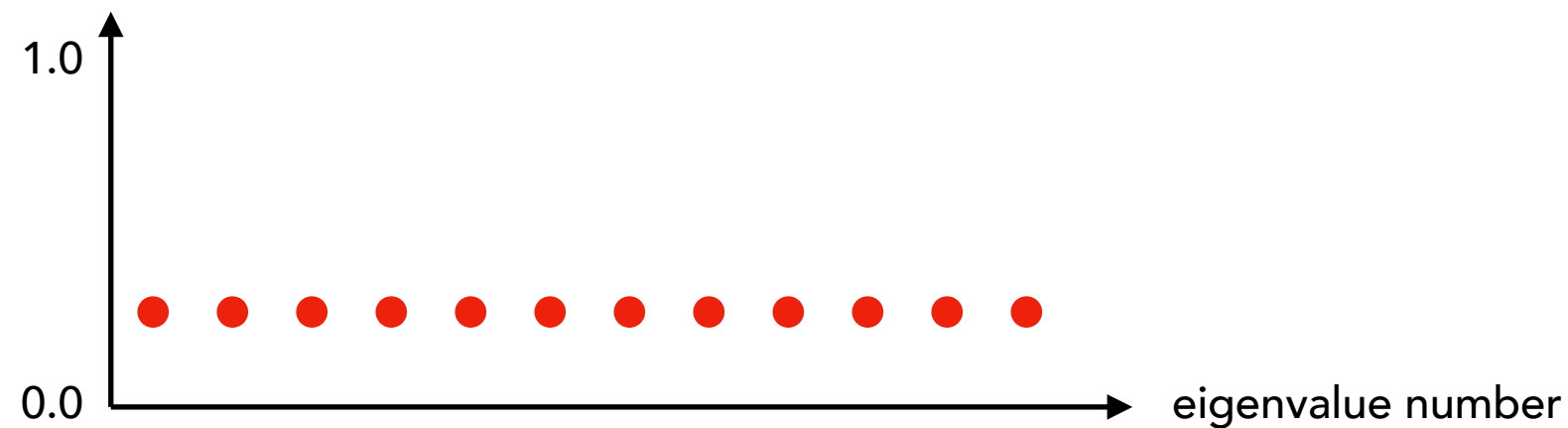


# Truncating Wavefunctions

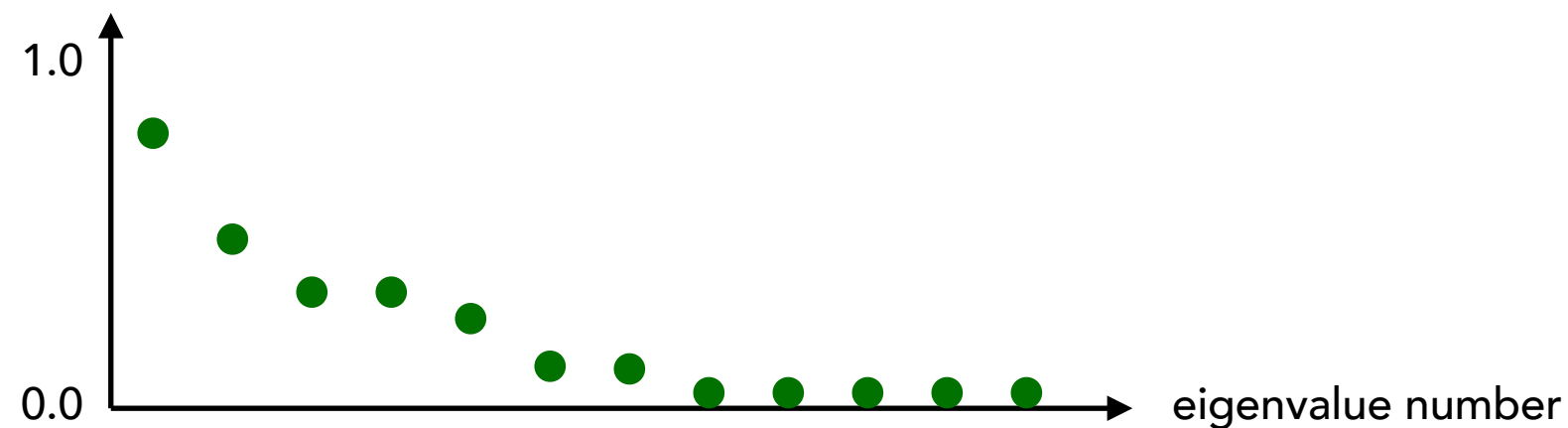
Boundary law means entanglement much less than it could be

So density matrix eigenvalues fall quickly...

Random  
state:

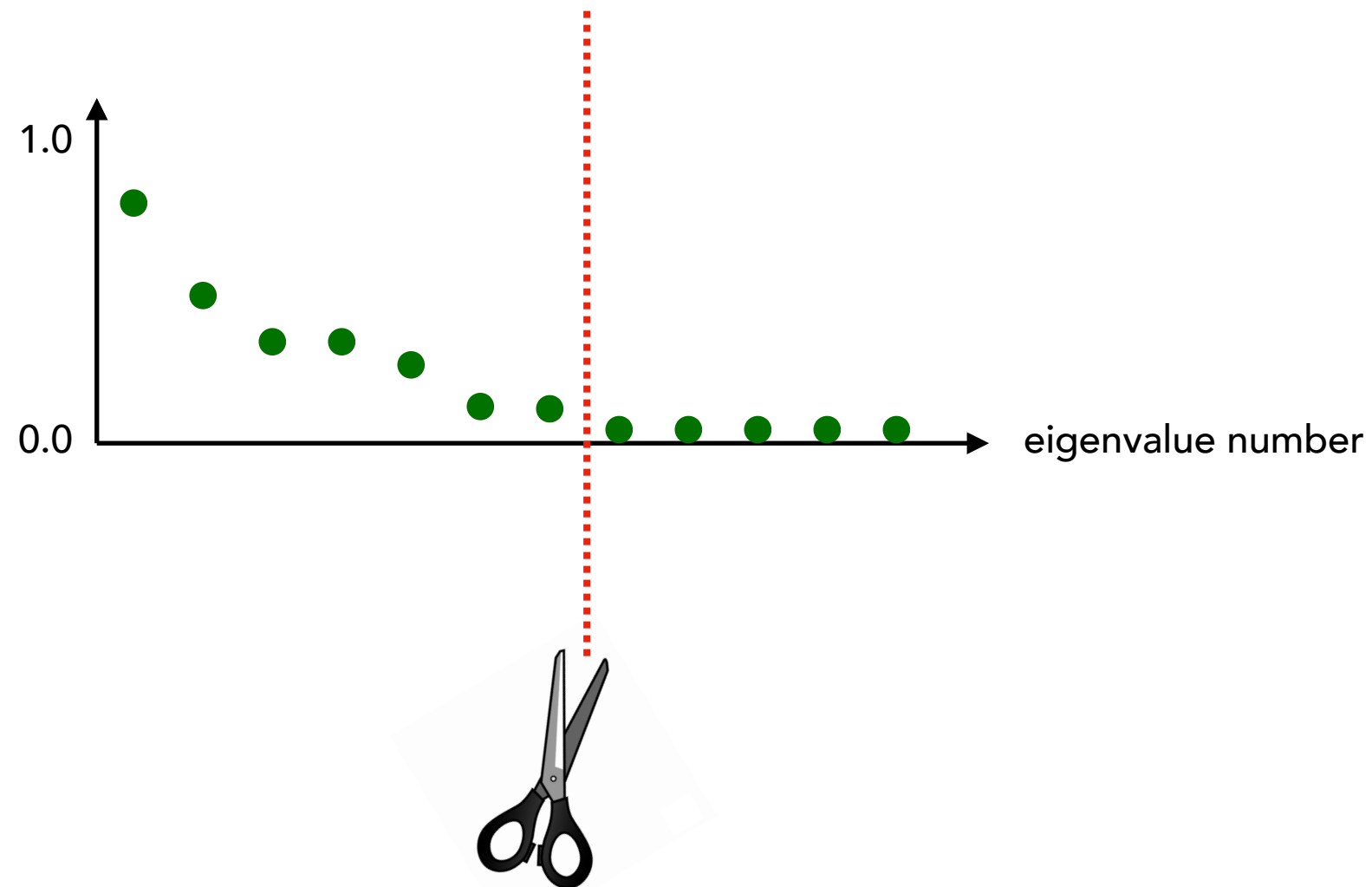


Ground  
state:



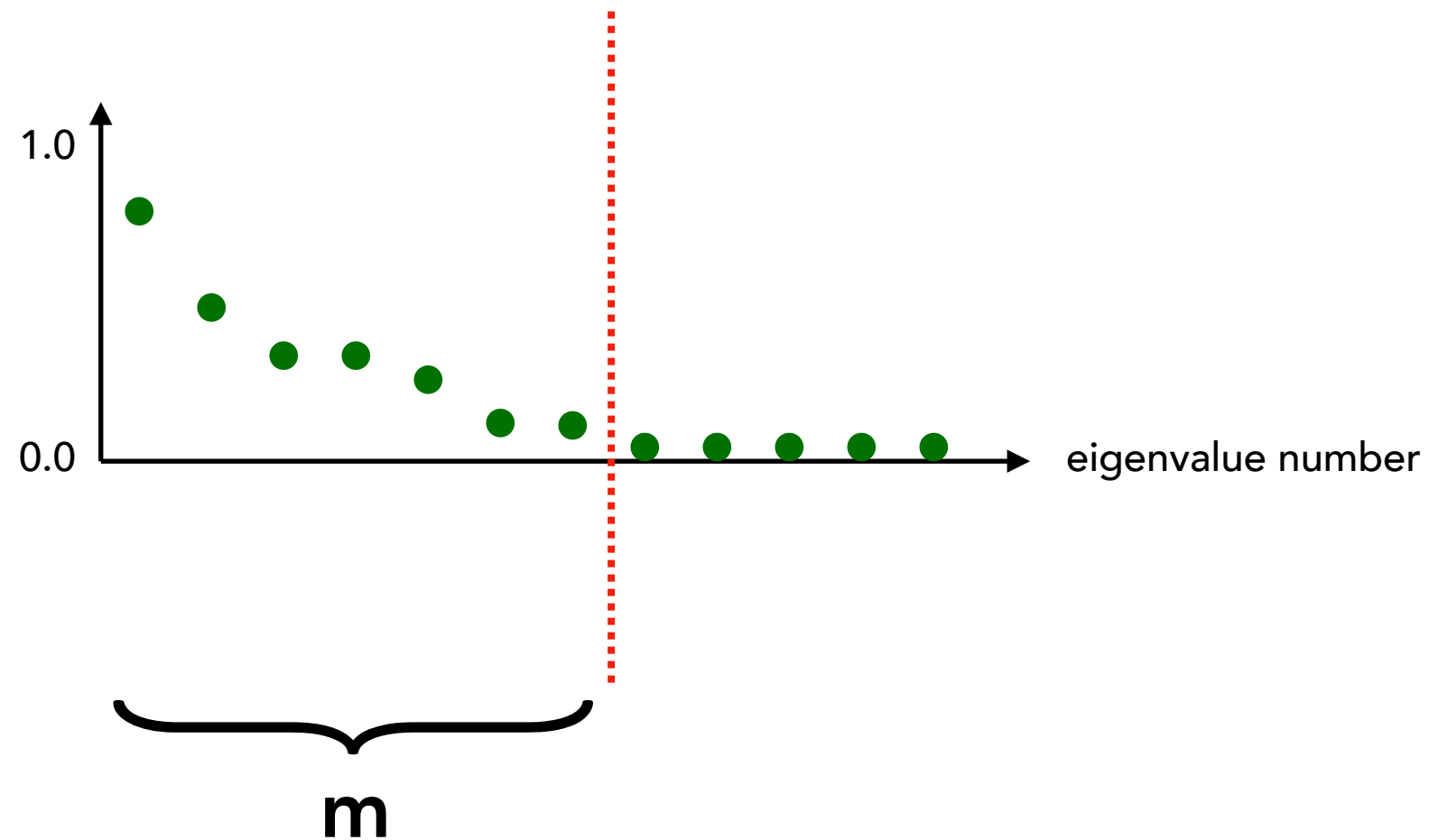
Suggests an approximation

Idea of **truncating** density matrix spectrum



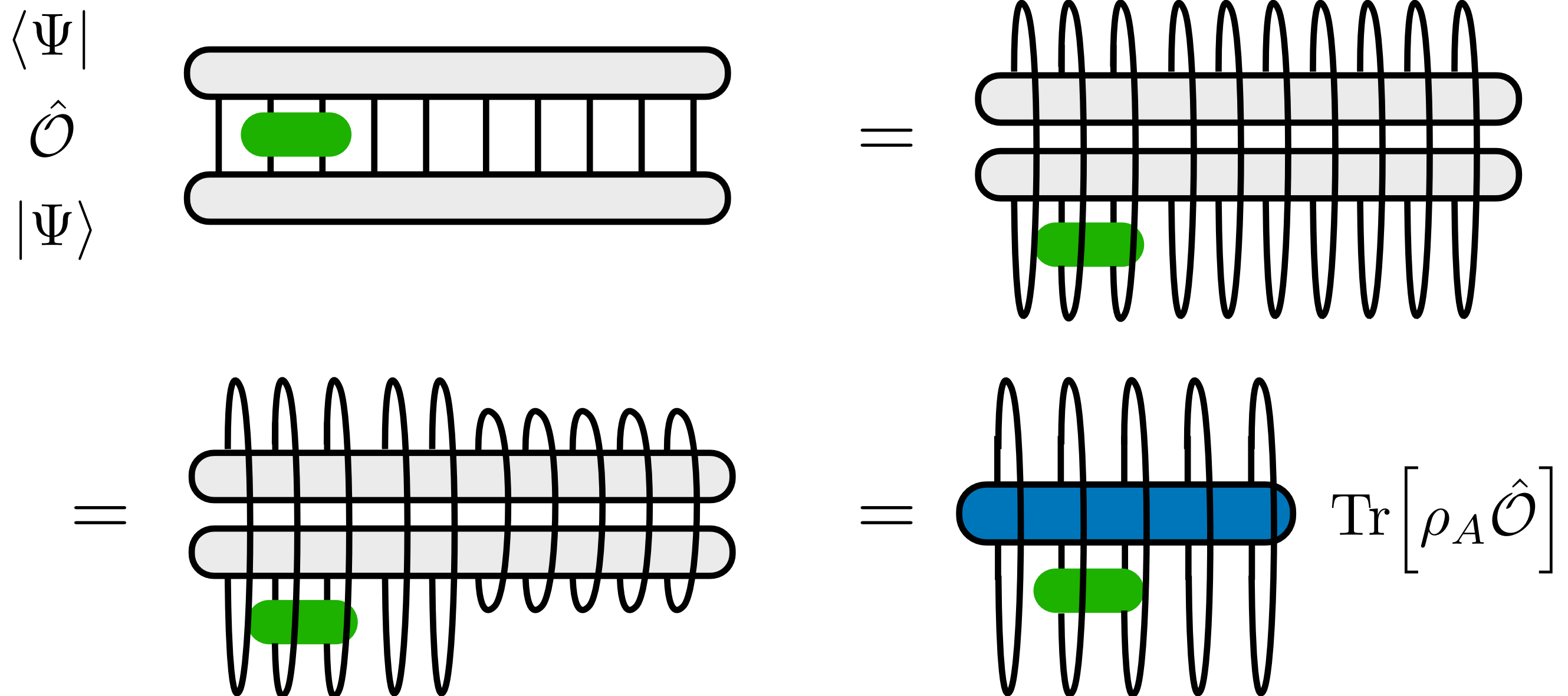
Implication of **boundary law** (= area law):

Number of eig. vals  $m$  needed for accuracy  
doesn't grow with  $N$



# Why approximate density matrix?

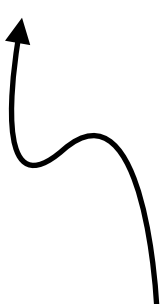
Reduced density matrix determines all observables in region A



Any observable in region A can be written as

$$\langle \hat{O} \rangle = \langle \Psi | \hat{O} | \Psi \rangle = \text{Tr} [\rho_A \hat{O}]$$

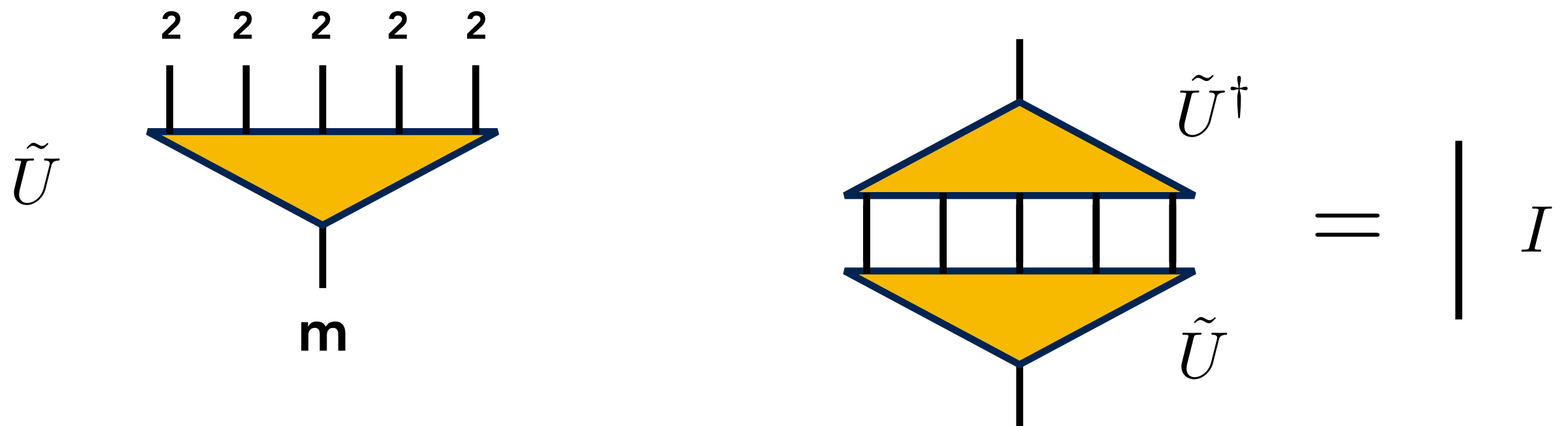
If we diagonalize  $\rho_A = \sum_n p_n |n\rangle \langle n|$

$$\langle \hat{O} \rangle = \text{Tr} [\rho_A \hat{O}] = \sum_n p_n \langle n | \hat{O} | n \rangle$$


*discarding small  $p_n$  means small error in  $\langle \hat{O} \rangle$*

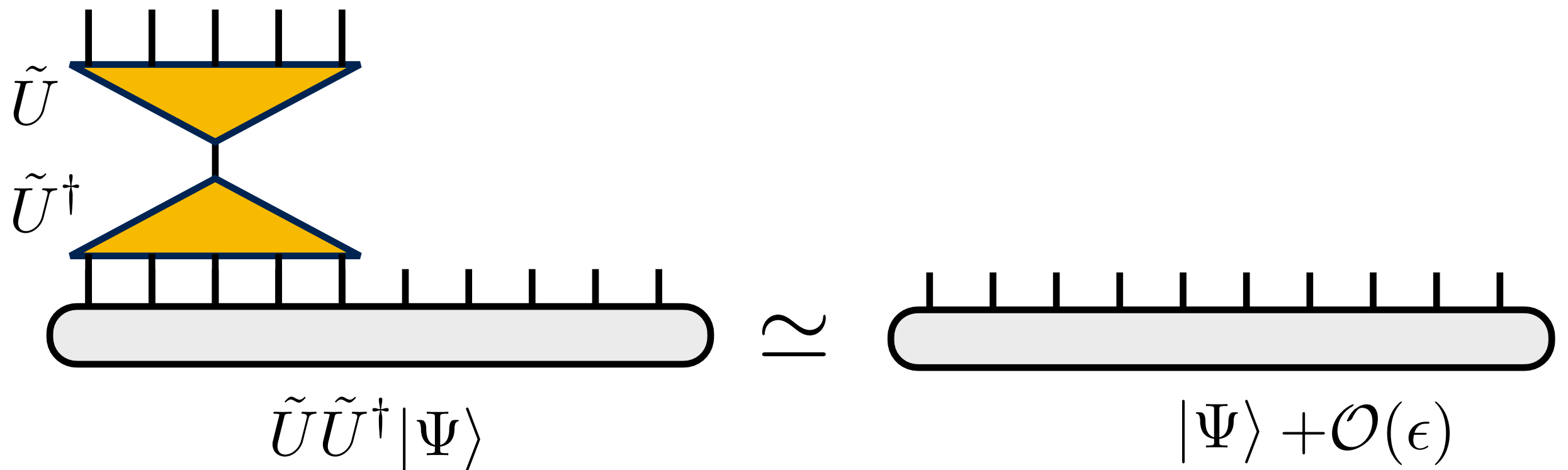
Ability to truncate  $\rho_A$  means the following

There is an isometry (rotation + projection) from sites of  $A$  to truncated basis of  $\rho_A$



$\tilde{U}$  is first  $m$  columns of unitary diagonalizing  $\rho_A$

Proposition: following approximation holds

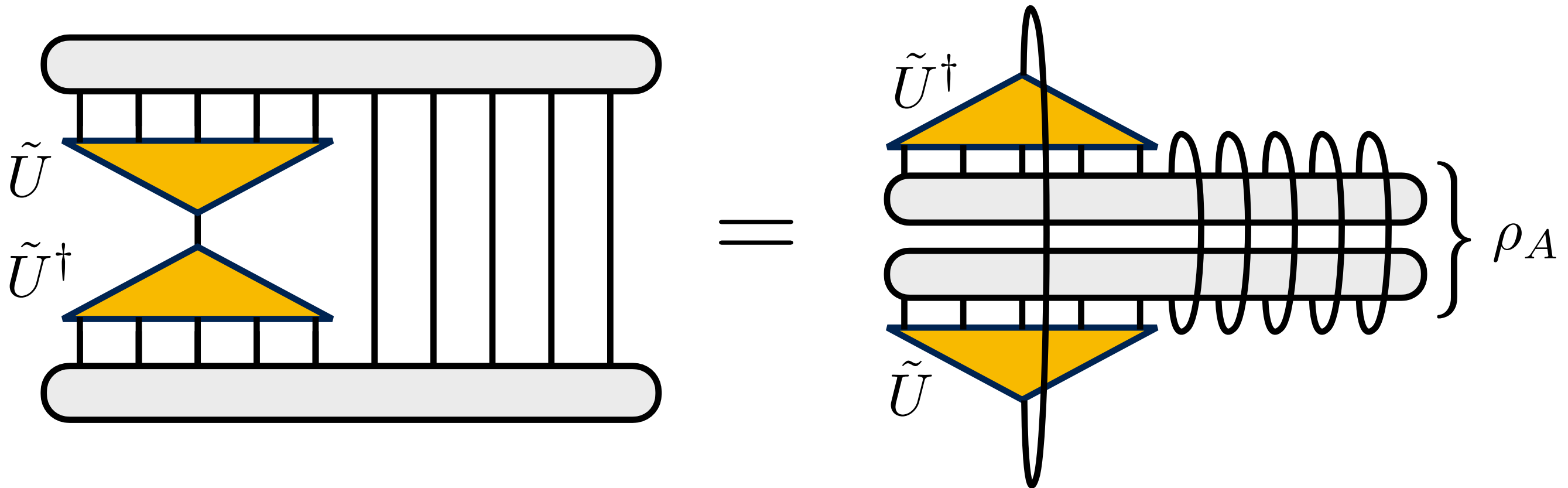


Where  $\epsilon = \sum_{n=m+1}^{d_A} p_n$  is the sum of discarded eigenvalues of  $\rho_A$

**Why?**

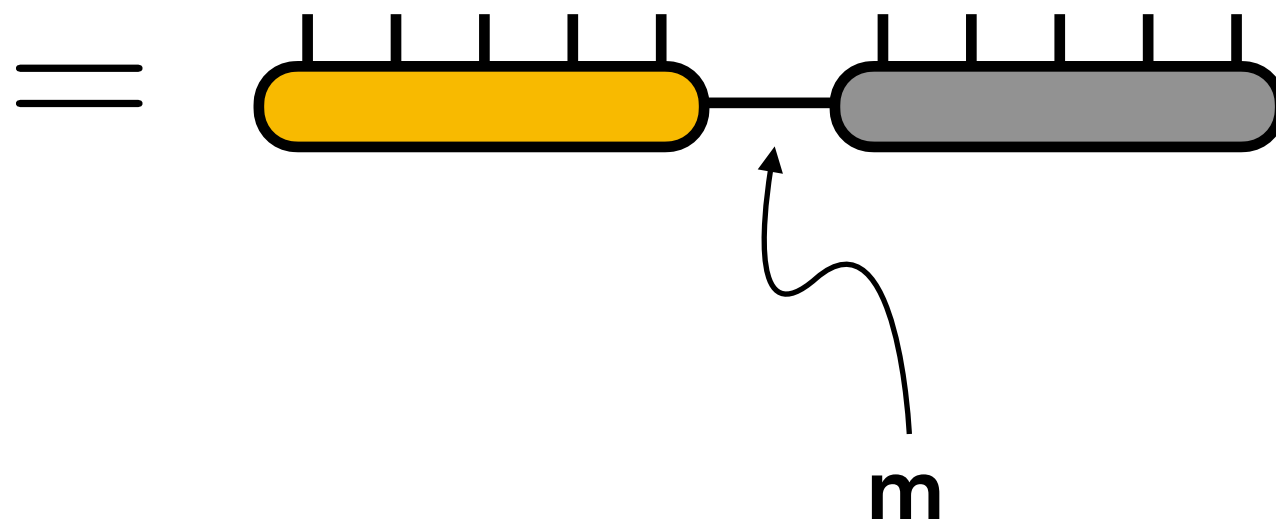
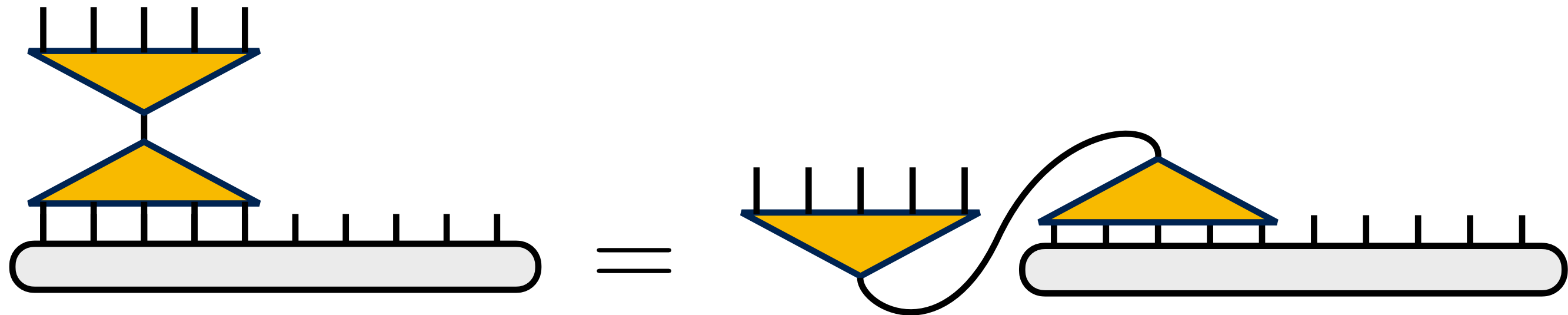


To prove, compute overlap  $\langle \Psi | \left( \tilde{U} \tilde{U}^\dagger | \Psi \rangle \right)$



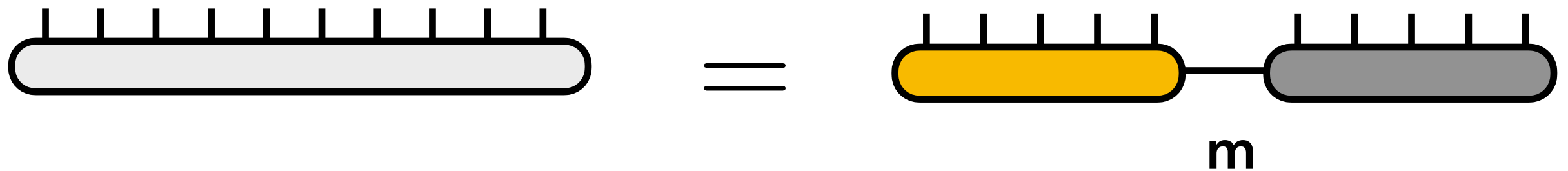
$$= \tilde{U}^\dagger \rho_A \tilde{U} = \sum_{n=1}^m p_n = \boxed{1 - \epsilon}$$

Can approximately rewrite  $|\Psi\rangle$  as follows



$$(m \ll 2^{N/2})$$

The upshot is we can factorize any ground state



$2^N$  dimensional 'vector'

two  $(2^{N/2} \times m)$  'matrices'

huge reduction in  
parameters!

Density matrix approach is "roundabout" however

Simpler approach is singular value decomposition (SVD)

Recall, for any rectangular matrix:

$$\begin{bmatrix} \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \end{bmatrix} = \begin{bmatrix} \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet \end{bmatrix} \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \lambda_3 & \\ & & & \lambda_4 \end{bmatrix} \begin{bmatrix} \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \end{bmatrix}$$

$M$   $U$   $\Lambda$   $V$

$U$  and  $V$  are unitary, and singular values  $\lambda_n$  are real & positive

Consider a numerical SVD example:

$$M = \begin{bmatrix} 0.435839 & 0.223707 & 0.10 \\ 0.435839 & 0.223707 & -0.10 \\ 0.223707 & 0.435839 & 0.10 \\ 0.223707 & 0.435839 & -0.10 \end{bmatrix}$$

Can decompose as

$$\begin{bmatrix} 1/2 & -1/2 & 1/2 \\ 1/2 & -1/2 & -1/2 \\ 1/2 & 1/2 & 1/2 \\ 1/2 & 1/2 & -1/2 \end{bmatrix} \begin{bmatrix} 0.933 & 0 & 0 \\ 0 & 0.300 & 0 \\ 0 & 0 & 0.200 \end{bmatrix} \begin{bmatrix} 0.707107 & 0.707107 & 0 \\ -0.707107 & 0.707107 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Keep fewer and fewer singular values:

$$\begin{array}{c}
 \mathbf{U} \\
 \left[ \begin{array}{ccc} 1/2 & -1/2 & 1/2 \\ 1/2 & -1/2 & -1/2 \\ 1/2 & 1/2 & 1/2 \\ 1/2 & 1/2 & -1/2 \end{array} \right]
 \end{array}
 \begin{array}{c}
 \mathbf{\Lambda} \\
 \left[ \begin{array}{ccc} 0.933 & 0 & 0 \\ 0 & 0.300 & 0 \\ 0 & 0 & 0.200 \end{array} \right]
 \end{array}
 \begin{array}{c}
 \mathbf{V} \\
 \left[ \begin{array}{ccc} 0.707107 & 0.707107 & 0 \\ -0.707107 & 0.707107 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{array} \right]
 \end{array}$$

$$= M = \left[ \begin{array}{ccc} 0.435839 & 0.223707 & 0.10 \\ 0.435839 & 0.223707 & -0.10 \\ 0.223707 & 0.435839 & 0.10 \\ 0.223707 & 0.435839 & -0.10 \end{array} \right]$$

$$||M - M||^2 = 0$$

Keep fewer and fewer singular values:

$$\begin{array}{c}
 \mathbf{U} \\
 \left[ \begin{array}{ccc} 1/2 & -1/2 & 1/2 \\ 1/2 & -1/2 & -1/2 \\ 1/2 & 1/2 & 1/2 \\ 1/2 & 1/2 & -1/2 \end{array} \right]
 \end{array}
 \begin{array}{c}
 \mathbf{\Lambda} \\
 \left[ \begin{array}{ccc} 0.933 & 0 & 0 \\ 0 & 0.300 & 0 \\ 0 & 0 & 0 \end{array} \right]
 \end{array}
 \begin{array}{c}
 \mathbf{V} \\
 \left[ \begin{array}{ccc} 0.707107 & 0.707107 & 0 \\ -0.707107 & 0.707107 & 0 \\ 0 & 0 & 1 \end{array} \right]
 \end{array}$$

$$= M_2 = \left[ \begin{array}{ccc} 0.435839 & 0.223707 & 0 \\ 0.435839 & 0.223707 & 0 \\ 0.223707 & 0.435839 & 0 \\ 0.223707 & 0.435839 & 0 \end{array} \right]$$

$$||M_2 - M||^2 = 0.04 = (0.2)^2$$

Keep fewer and fewer singular values:

$$\begin{array}{c}
 \mathbf{U} \\
 \left[ \begin{array}{ccc} 1/2 & -1/2 & 1/2 \\ 1/2 & -1/2 & -1/2 \\ 1/2 & 1/2 & 1/2 \\ 1/2 & 1/2 & -1/2 \end{array} \right]
 \end{array}
 \begin{array}{c}
 \mathbf{\Lambda} \\
 \left[ \begin{array}{ccc} 0.933 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{array} \right]
 \end{array}
 \begin{array}{c}
 \mathbf{V} \\
 \left[ \begin{array}{ccc} 0.707107 & 0.707107 & 0 \\ -0.707107 & 0.707107 & 0 \\ 0 & 0 & 1 \end{array} \right]
 \end{array}$$

$$= M_3 = \left[ \begin{array}{ccc} 0.329773 & 0.329773 & 0 \\ 0.329773 & 0.329773 & 0 \\ 0.329773 & 0.329773 & 0 \\ 0.329773 & 0.329773 & 0 \end{array} \right]$$

Truncating SVD =

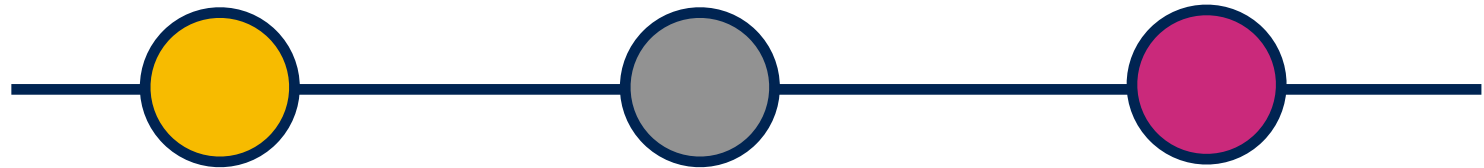
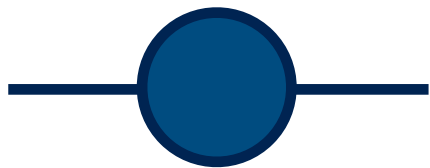
Controlled approximation for M

$$||M_3 - M||^2 = 0.13 = (0.3)^2 + (0.2)^2$$



Diagrammatically, SVD looks like:

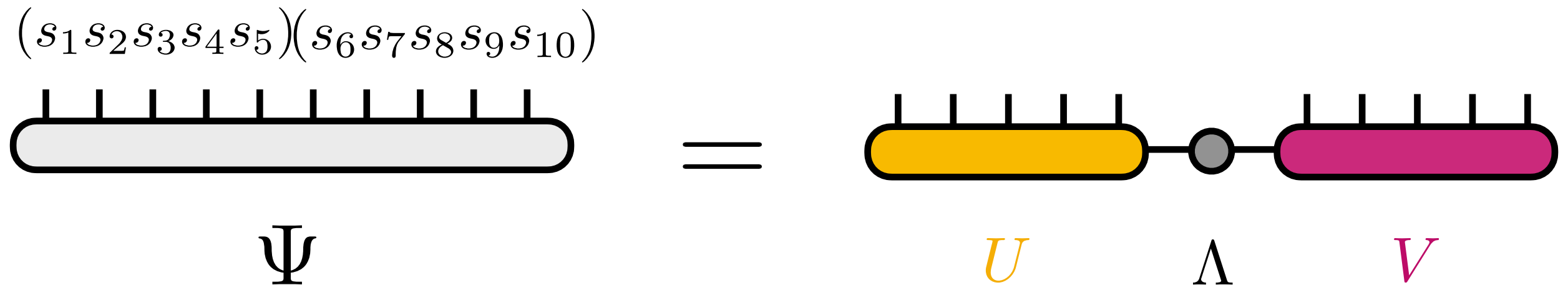
$$\begin{array}{c}
 \left[ \begin{array}{cccccc} \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \end{array} \right] \\
 M
 \end{array}
 =
 \begin{array}{c}
 \left[ \begin{array}{cccc} \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet \end{array} \right] \\
 U
 \end{array}
 \begin{array}{c}
 \left[ \begin{array}{c} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{array} \right] \\
 \Lambda
 \end{array}
 \begin{array}{c}
 \left[ \begin{array}{cccccc} \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \end{array} \right] \\
 V
 \end{array}$$



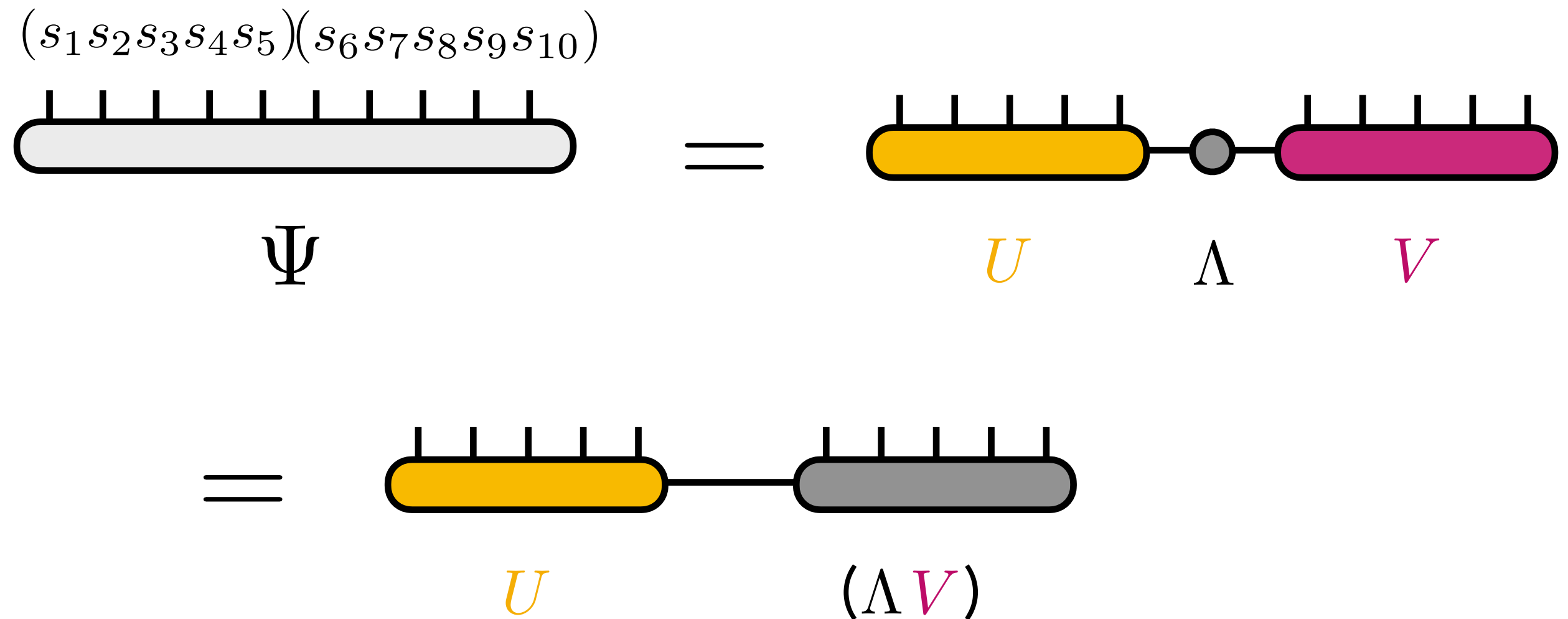
Let's apply it to our wavefunction

Treat wavefunction as matrix by grouping indices

$$\Psi(s_1 s_2 s_3 s_4 s_5)(s_6 s_7 s_8 s_9 s_{10}) = \sum_n U_n^{(s_1 s_2 s_3 s_4 s_5)} \Lambda_n V_n^{(s_6 s_7 s_8 s_9 s_{10})}$$



Multiplying singular vals into V, get same factorization as before

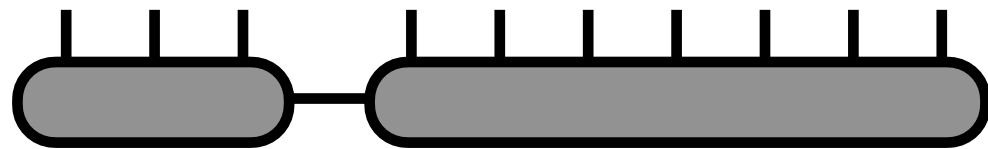
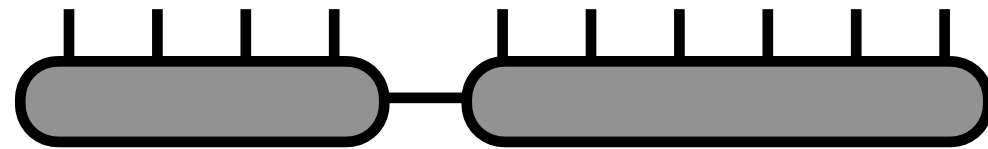
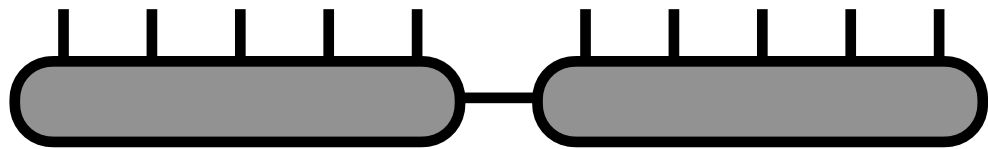


Matrix  $U$  is the *same* as from diagonalizing density matrix

Central idea of tensor networks:

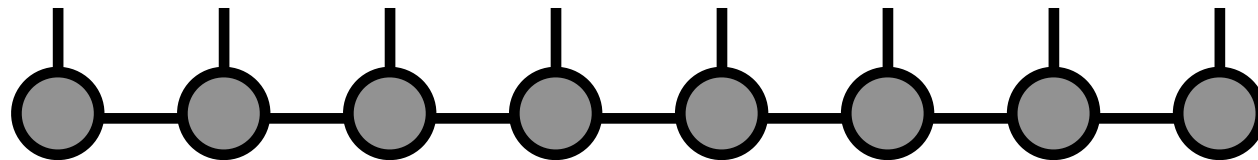
can factorize  $(s_1 \ s_2 \ s_3) \ (s_4 \ s_5 \ s_6)$ , but what is special about this bond or partition?

why not factorize all partitions at once?



etc.

Motivates following factorization



Known as *matrix product state*

Key example of a tensor network

# Matrix Product States

Wavefunction just a rule to  
map spin configurations to numbers

$$\Psi^{s_1 s_2 s_3 s_4 s_5 s_6 s_7 s_8}$$

↑ ↓ ↑ ↑ ↑ ↑ ↑ ↑



$$\Psi^{\uparrow \downarrow \uparrow \uparrow \uparrow \uparrow \uparrow \uparrow}$$

↑ ↓ ↑ ↓ ↑ ↑ ↑ ↑



$$\Psi^{\uparrow \downarrow \uparrow \downarrow \uparrow \uparrow \uparrow \uparrow}$$

↑ ↑ ↑ ↑ ↓ ↑ ↓ ↑



$$\Psi^{\uparrow \uparrow \uparrow \uparrow \downarrow \uparrow \downarrow \uparrow}$$

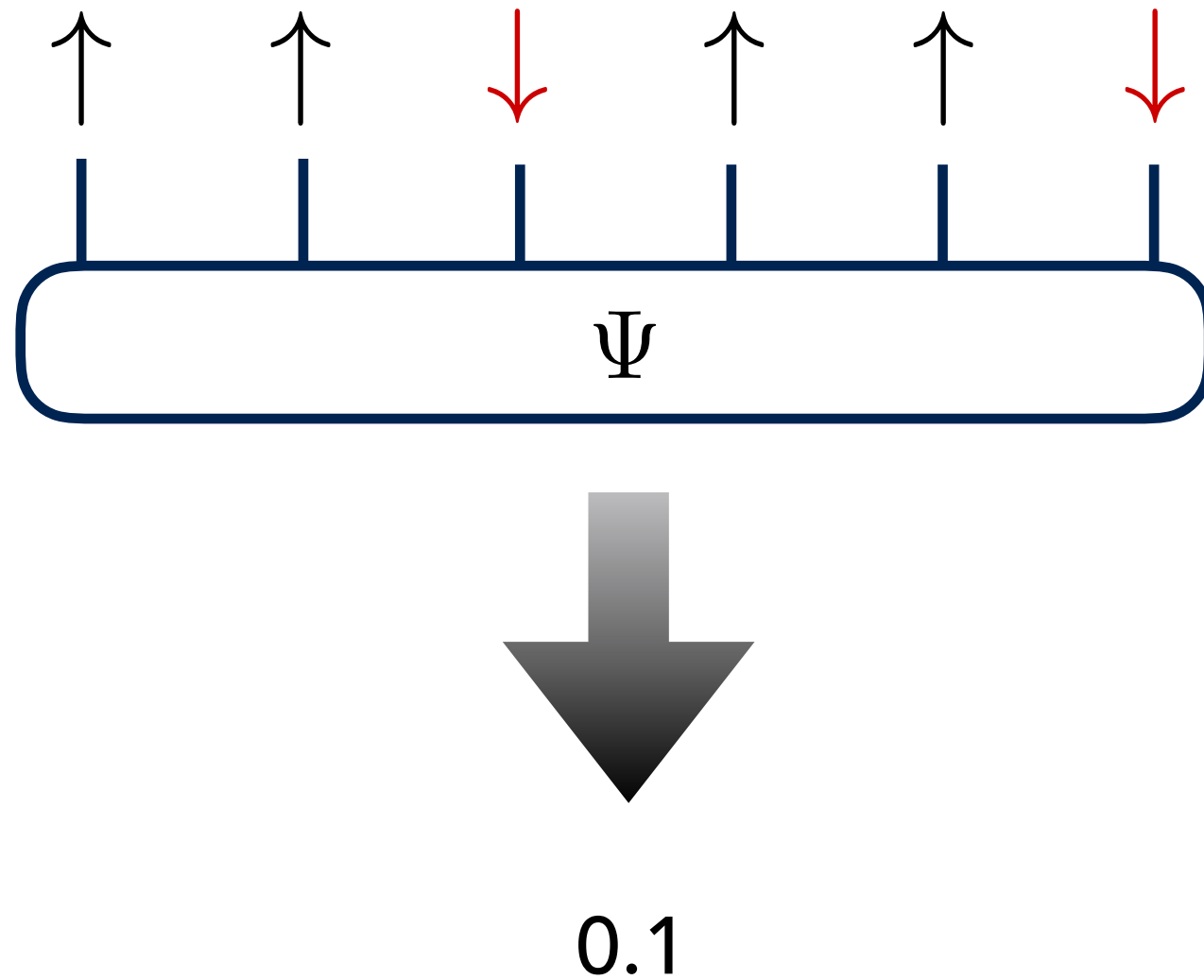
↑ ↓ ↓ ↓ ↓ ↑ ↑ ↑



$$\Psi^{\uparrow \downarrow \downarrow \downarrow \downarrow \uparrow \uparrow \uparrow}$$

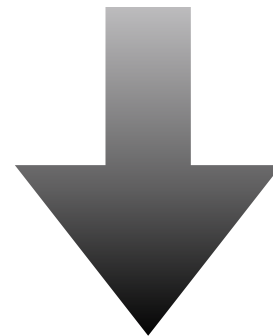
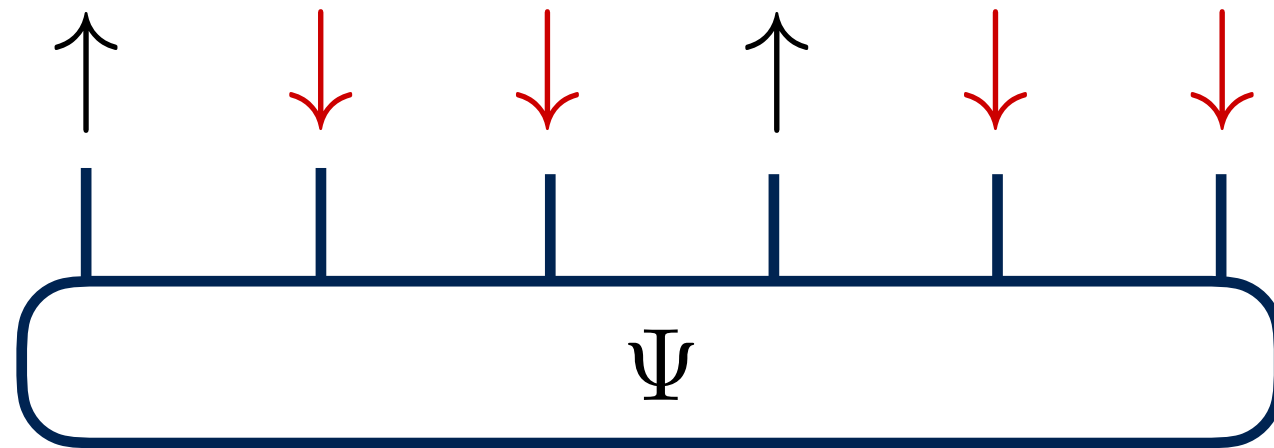
Simplest rule: store every amplitude separately

Wavefunction a "machine" mapping configurations to numbers



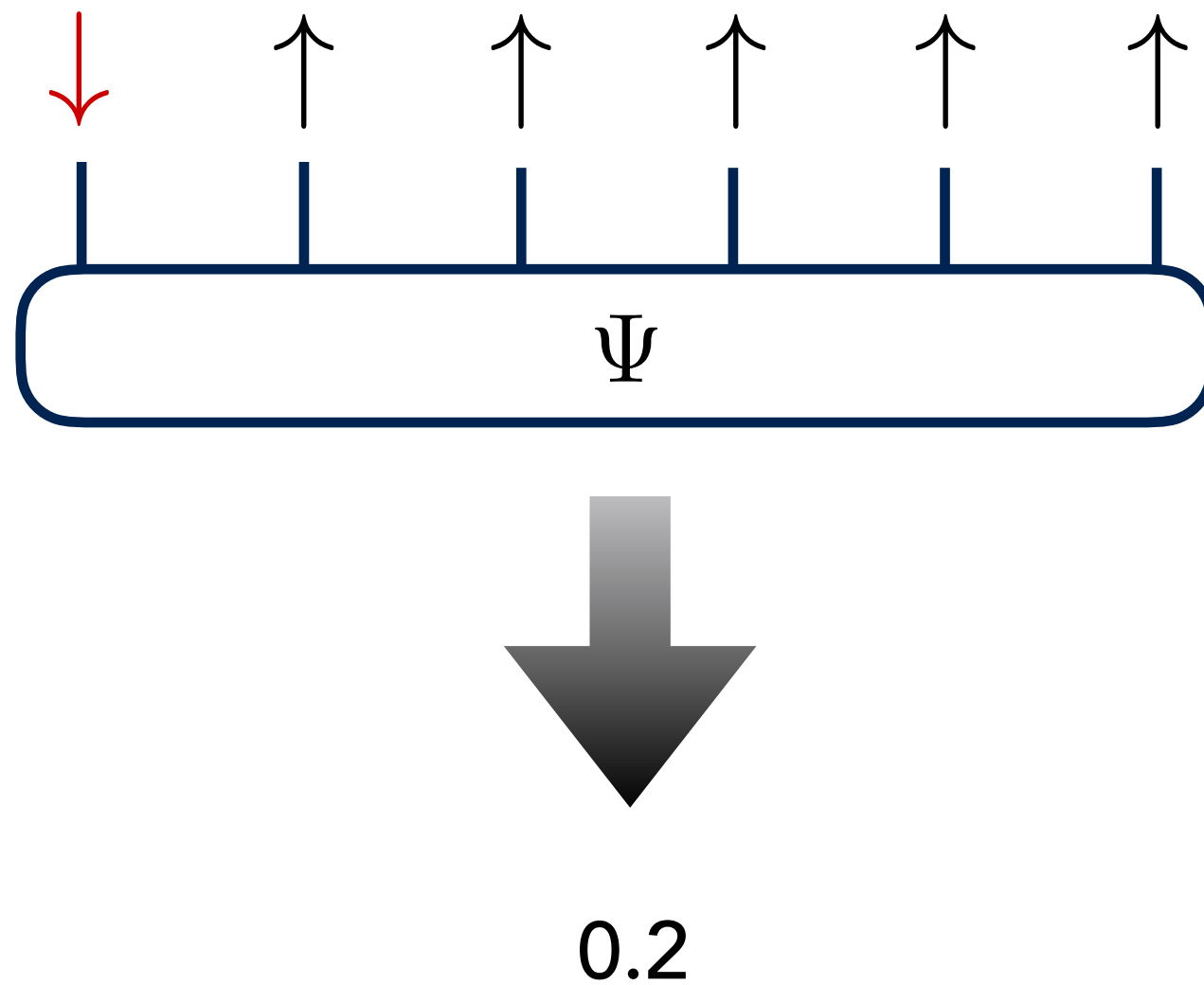


Wavefunction a "machine" mapping configurations to numbers



0.05

Can make up any rule assigning patterns to numbers



How about this rule:

- to each spin state (**up**, **down**) associate a matrix
- multiply matrices to get the probability

Pictorially:



Pictorially:

$$\uparrow \longrightarrow M^{\uparrow} = \begin{bmatrix} \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \end{bmatrix}$$

$$\downarrow \longrightarrow M^{\downarrow} = \begin{bmatrix} \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \end{bmatrix}$$

Compute wavefunction by multiplying matrices together

$$\Psi^{\uparrow \downarrow \uparrow \uparrow \downarrow} \approx$$

Compute wavefunction by multiplying matrices together

$$\Psi^{\uparrow \downarrow \uparrow \uparrow \downarrow} \approx M_1^{\uparrow}$$

Compute wavefunction by multiplying matrices together

$$\Psi^{\uparrow\downarrow\uparrow\uparrow\downarrow} \approx M_1^{\uparrow} M_2^{\downarrow}$$



Compute wavefunction by multiplying matrices together

$$\Psi^{\uparrow\downarrow\uparrow\uparrow\downarrow} \approx M_1^{\uparrow} M_2^{\downarrow} M_3^{\uparrow}$$

Compute wavefunction by multiplying matrices together

$$\Psi^{\uparrow\downarrow\uparrow\uparrow\downarrow} \approx M_1^{\uparrow} M_2^{\downarrow} M_3^{\uparrow} M_4^{\uparrow}$$

Compute wavefunction by multiplying matrices together

$$\Psi^{\uparrow\downarrow\uparrow\uparrow\downarrow} \approx M_1^{\uparrow} M_2^{\downarrow} M_3^{\uparrow} M_4^{\uparrow} M_5^{\downarrow}$$

Compute wavefunction by multiplying matrices together

$$\Psi^{\uparrow \downarrow \uparrow \uparrow \downarrow} \approx M_1^{\uparrow} M_2^{\downarrow} M_3^{\uparrow} M_4^{\uparrow} M_5^{\downarrow}$$

$$\Psi^{\uparrow \uparrow \downarrow \downarrow \downarrow} \approx M_1^{\uparrow} M_2^{\uparrow} M_3^{\downarrow} M_4^{\downarrow} M_5^{\downarrow}$$

Compute wavefunction by multiplying matrices together

$$\Psi^{\uparrow \downarrow \uparrow \uparrow \downarrow} \approx M_1^{\uparrow} M_2^{\downarrow} M_3^{\uparrow} M_4^{\uparrow} M_5^{\downarrow}$$

$$\Psi^{\uparrow \uparrow \downarrow \downarrow \downarrow} \approx M_1^{\uparrow} M_2^{\uparrow} M_3^{\downarrow} M_4^{\downarrow} M_5^{\downarrow}$$

$$\Psi^{\uparrow \downarrow \downarrow \uparrow \uparrow} \approx M_1^{\uparrow} M_2^{\downarrow} M_3^{\downarrow} M_4^{\uparrow} M_5^{\uparrow}$$

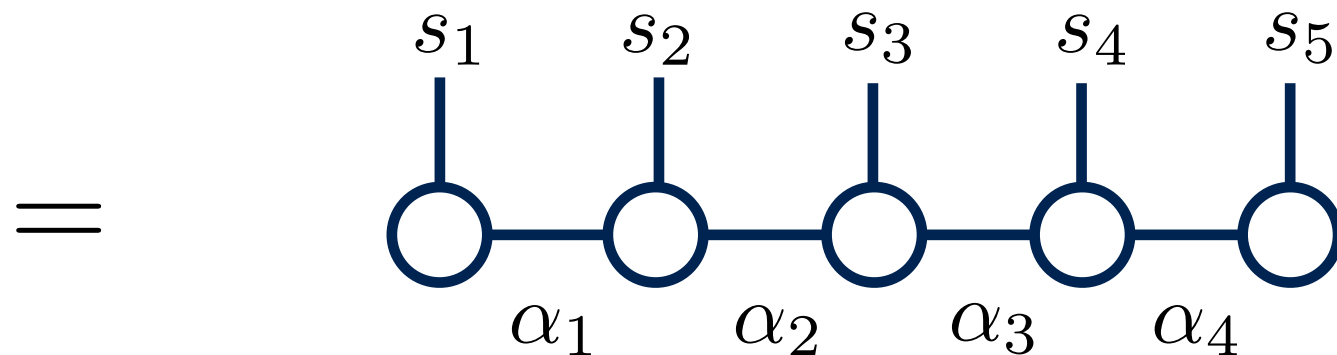
Ansatz known as *matrix product state*

$$\Psi^{s_1 s_2 s_3 s_4 s_5} = M_1^{s_1} M_2^{s_2} M_3^{s_3} M_4^{s_4} M_5^{s_5}$$

## More detail & diagrammatic form

$$\Psi^{s_1 s_2 s_3 s_4 s_5} = M_1^{s_1} M_2^{s_2} M_3^{s_3} M_4^{s_4} M_5^{s_5}$$

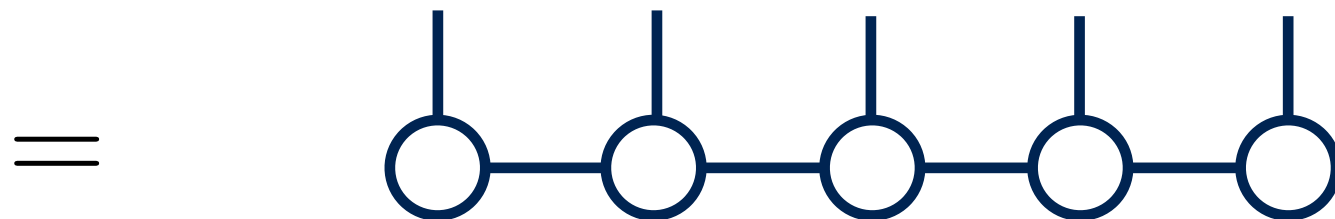
$$= \sum_{\{\alpha\}} M_{\alpha_1}^{s_1} M_{\alpha_1 \alpha_2}^{s_2} M_{\alpha_2 \alpha_3}^{s_3} M_{\alpha_3 \alpha_4}^{s_4} M_{\alpha_4}^{s_5}$$



More detail & diagrammatic form

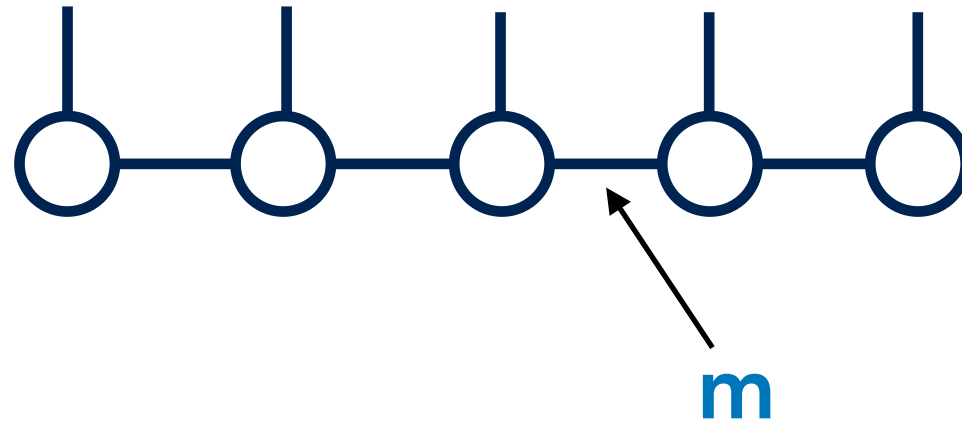
$$\Psi^{s_1 s_2 s_3 s_4 s_5} = M_1^{s_1} M_2^{s_2} M_3^{s_3} M_4^{s_4} M_5^{s_5}$$

$$= \sum_{\{\alpha\}} M_{\alpha_1}^{s_1} M_{\alpha_1 \alpha_2}^{s_2} M_{\alpha_2 \alpha_3}^{s_3} M_{\alpha_3 \alpha_4}^{s_4} M_{\alpha_4}^{s_5}$$





# Key facts about matrix product states



- linear size of matrices (dimension of bond indices) known as the *bond dimension*  $m$  (sometimes  $\chi$  or  $D$ )
- for large enough  $m$ , can represent *any state* ( $m = 2^{N/2}$ )
- entanglement of left-right cut bounded by  $\log(m)$ , so boundary law guaranteed

# Computations with Matrix Product States

Key reason to use matrix product states (MPS) is many computations become *efficient*

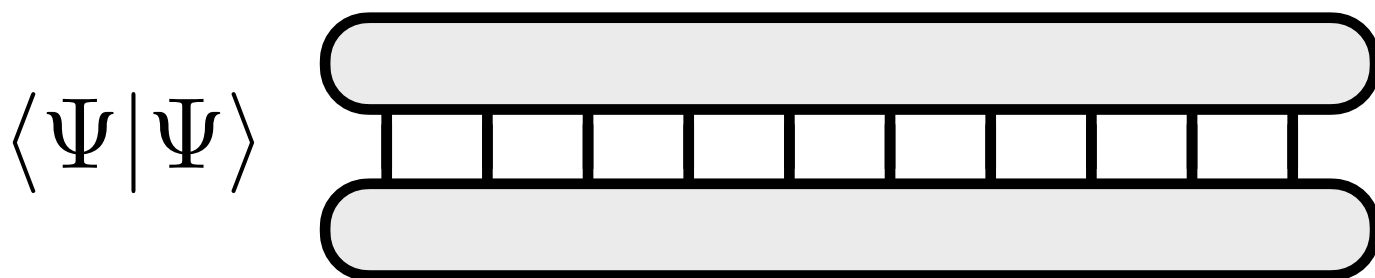
Key reason to use matrix product states (MPS) is many computations become *efficient*

By contrast, all operations with full wavefunction inefficient

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By contrast, all operations with full wavefunction inefficient

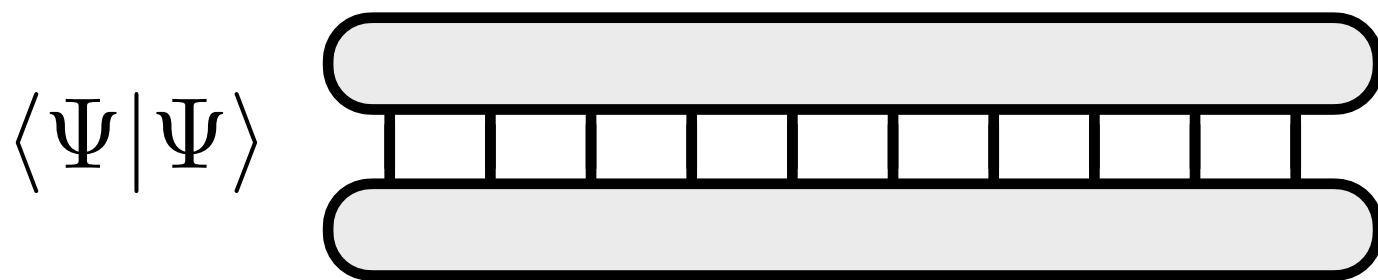
Consider computing norm of full wavefunction



Key reason to use matrix product states (MPS) is many computations become *efficient*

By contrast, all operations with full wavefunction inefficient

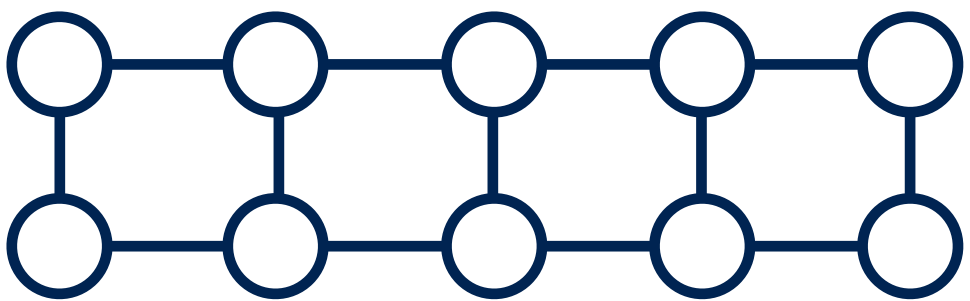
Consider computing norm of full wavefunction



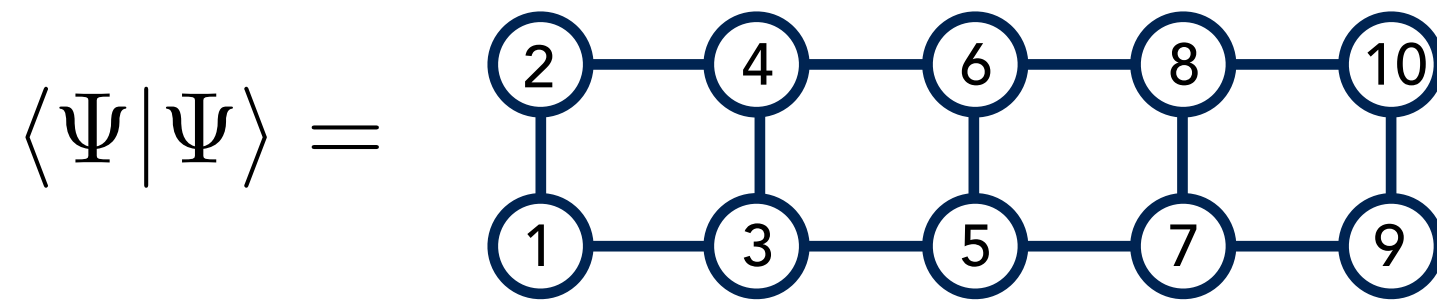
$$= \sum_{\{s\}} \Psi^{s_1 s_2 s_3 s_4 s_5 s_6 s_7 s_8 s_9 s_{10}} \bar{\Psi}_{s_1 s_2 s_3 s_4 s_5 s_6 s_7 s_8 s_9 s_{10}}$$

Requires summing  $2^{10}$  terms

Is there a more efficient strategy to compute norm of MPS?

$$\langle \Psi | \Psi \rangle =$$


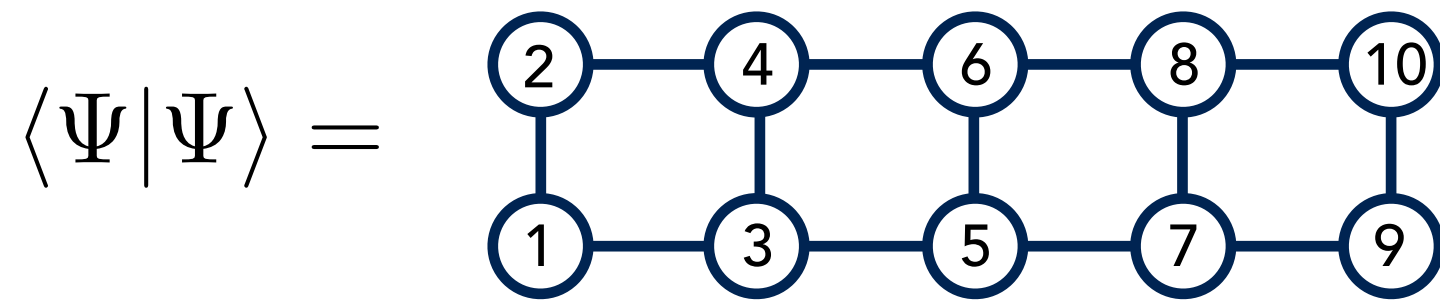
Is there a more efficient strategy to compute norm of MPS?



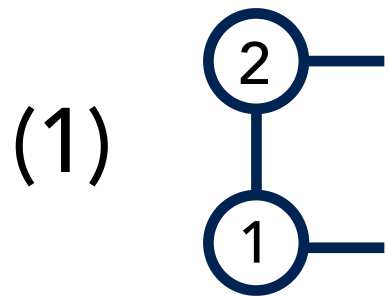
Yes!



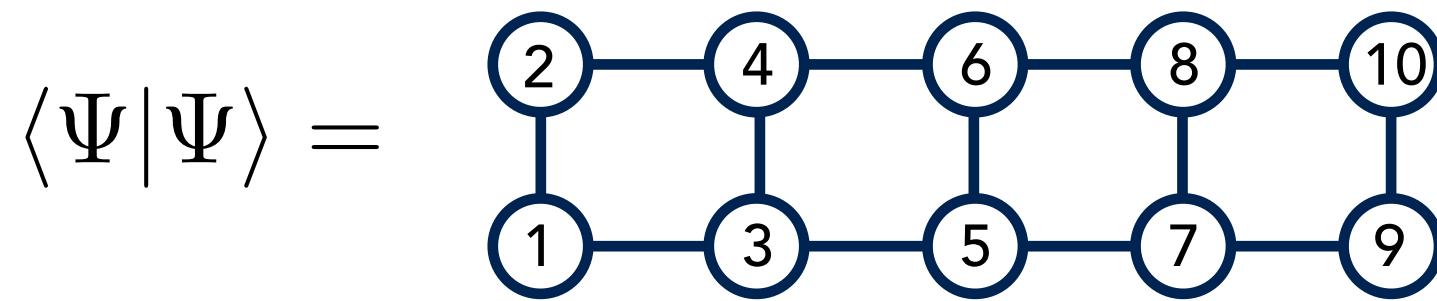
Is there a more efficient strategy to compute norm of MPS?



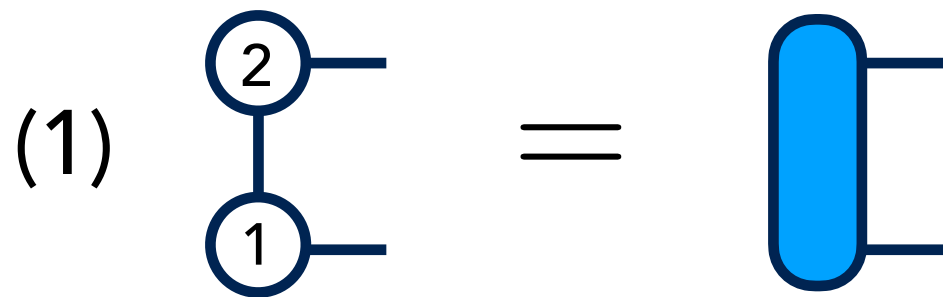
Yes!



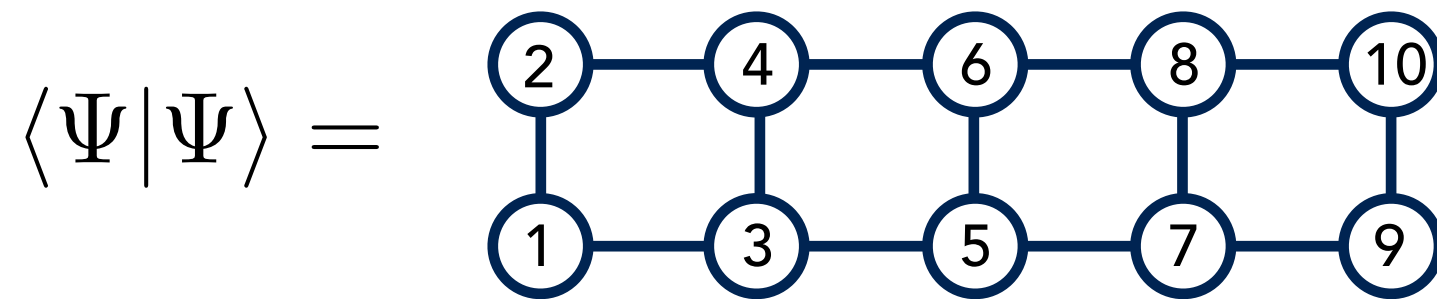
Is there a more efficient strategy to compute norm of MPS?



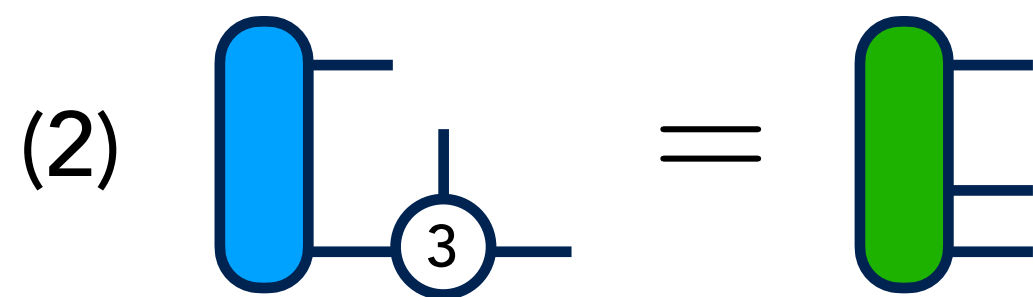
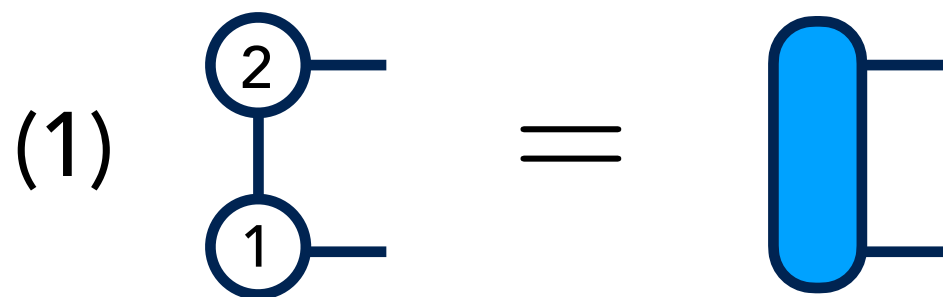
Yes!



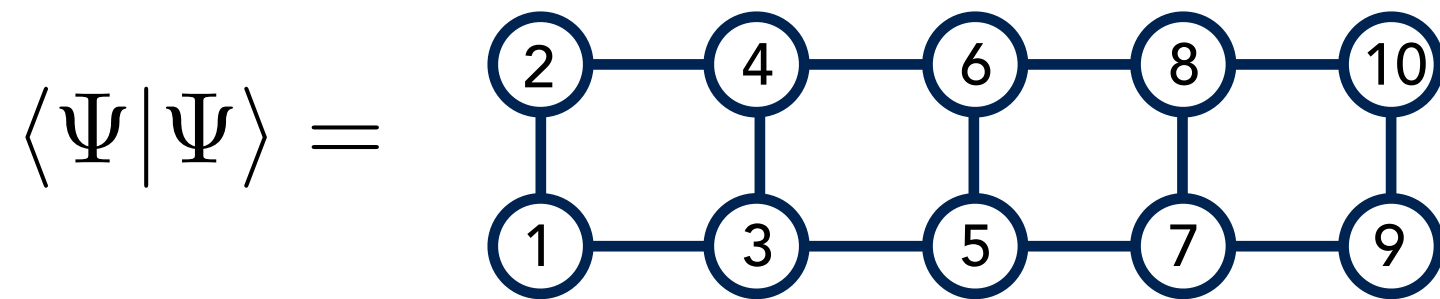
Is there a more efficient strategy to compute norm of MPS?



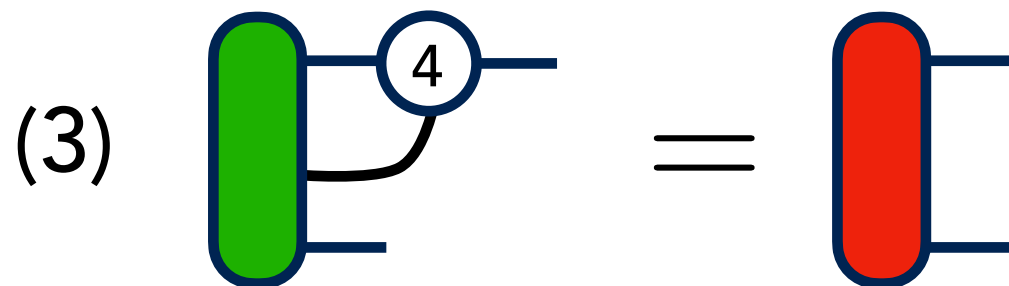
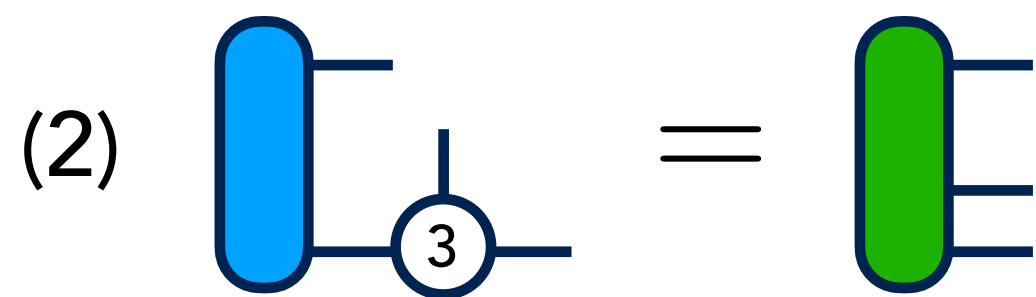
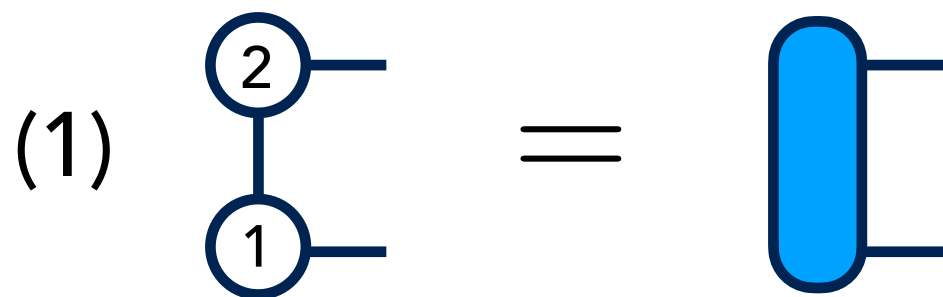
Yes!



Is there a more efficient strategy to compute norm of MPS?



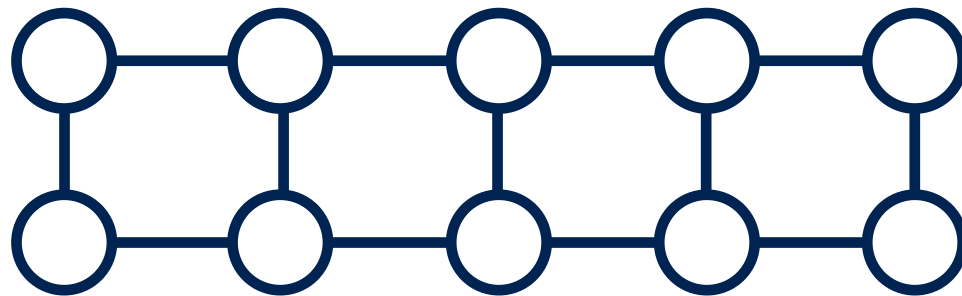
Yes!



etc. until all tensors are contracted

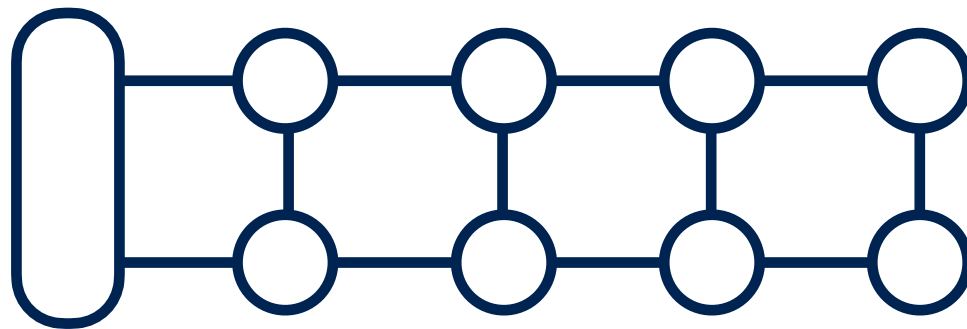
Full contraction process:

$$\langle \Psi | \Psi \rangle =$$



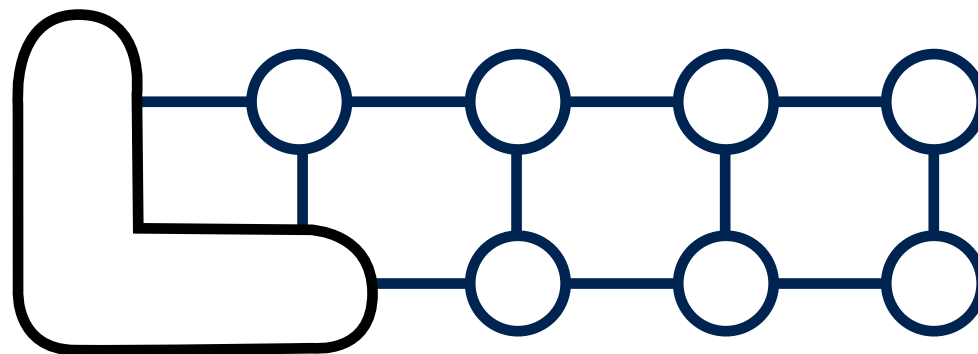
Full contraction process:

$$\langle \Psi | \Psi \rangle =$$



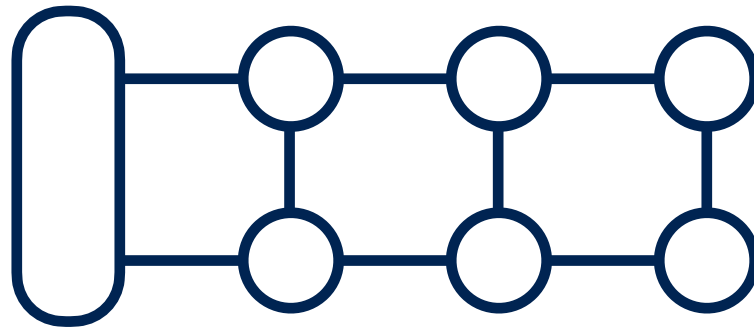
Full contraction process:

$$\langle \Psi | \Psi \rangle =$$



Full contraction process:

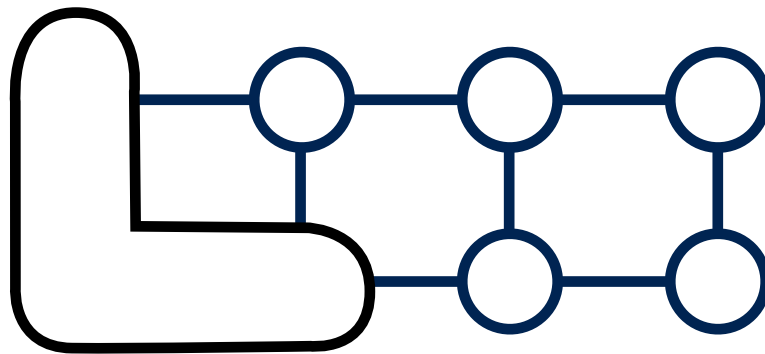
$$\langle \Psi | \Psi \rangle =$$





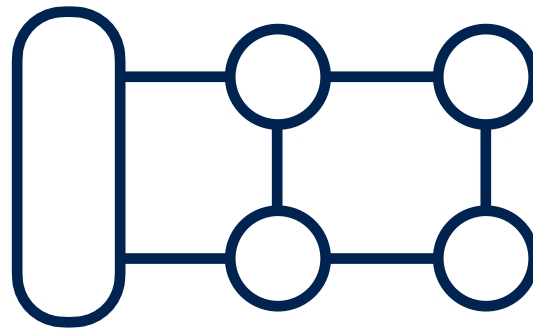
Full contraction process:

$$\langle \Psi | \Psi \rangle =$$



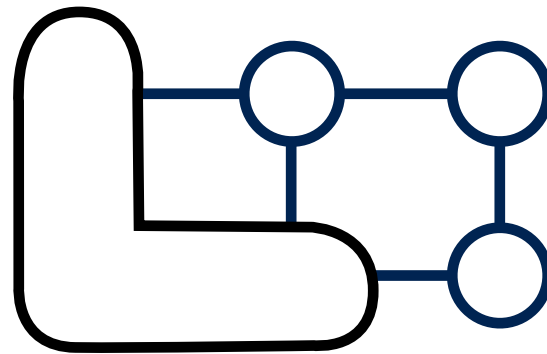
Full contraction process:

$$\langle \Psi | \Psi \rangle =$$



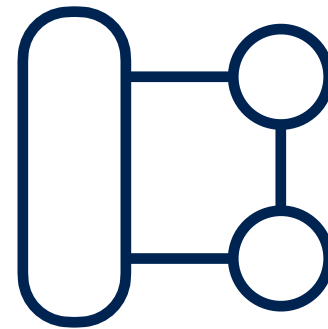
## Full contraction process:

$$\langle \Psi | \Psi \rangle =$$



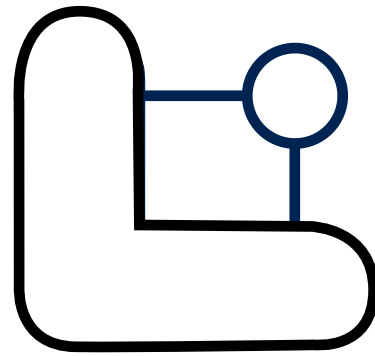
Full contraction process:

$$\langle \Psi | \Psi \rangle =$$



Full contraction process:

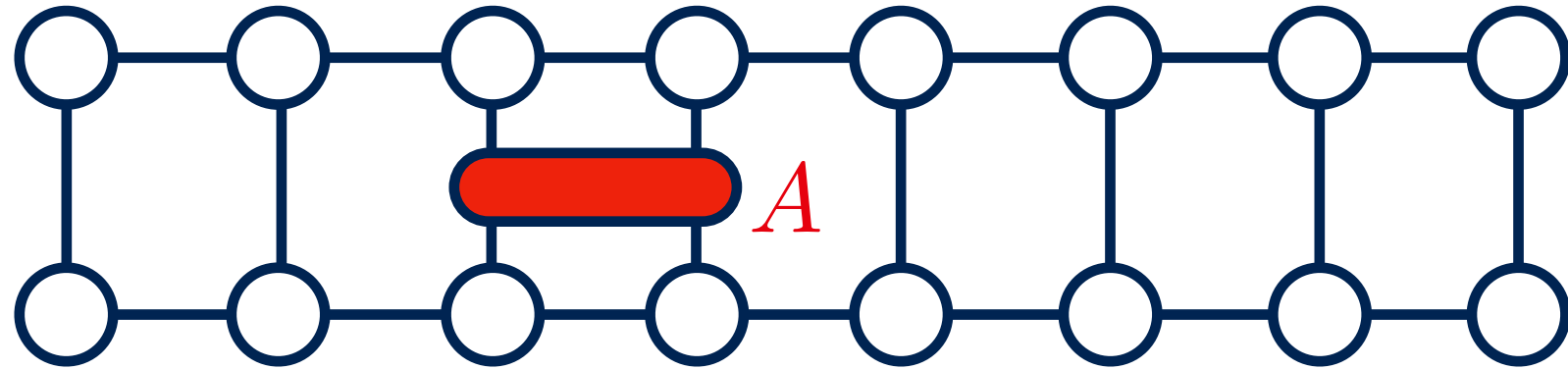
$$\langle \Psi | \Psi \rangle =$$



equals a scalar (**why?**)

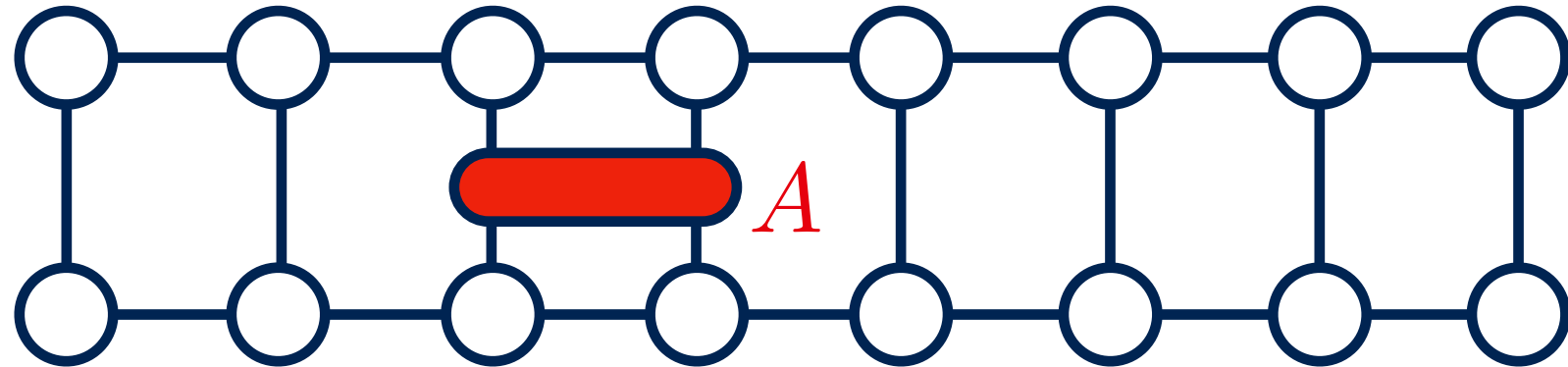
Another key computation is an **expectation value**

$$\langle \Psi | A | \Psi \rangle =$$

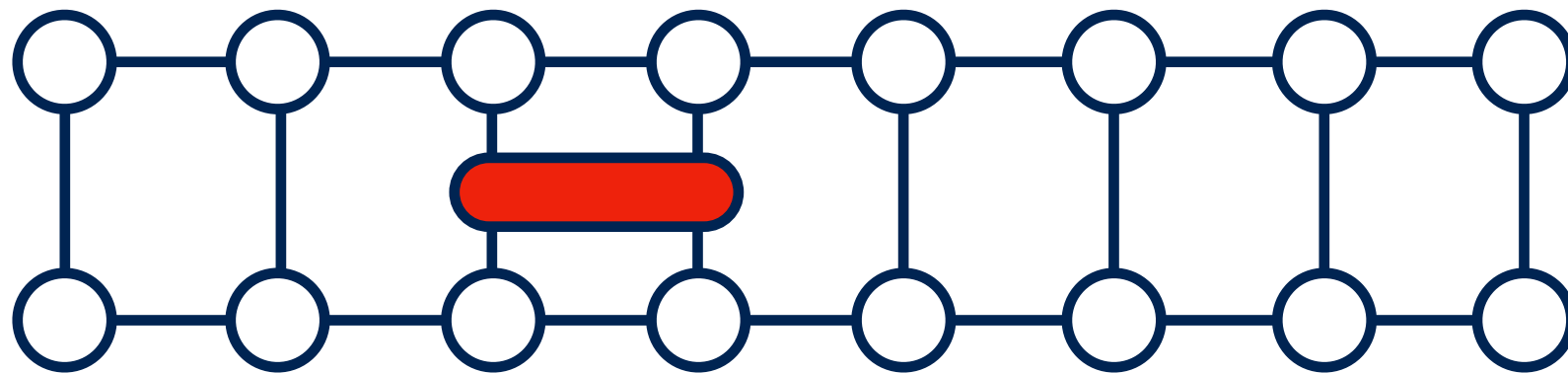


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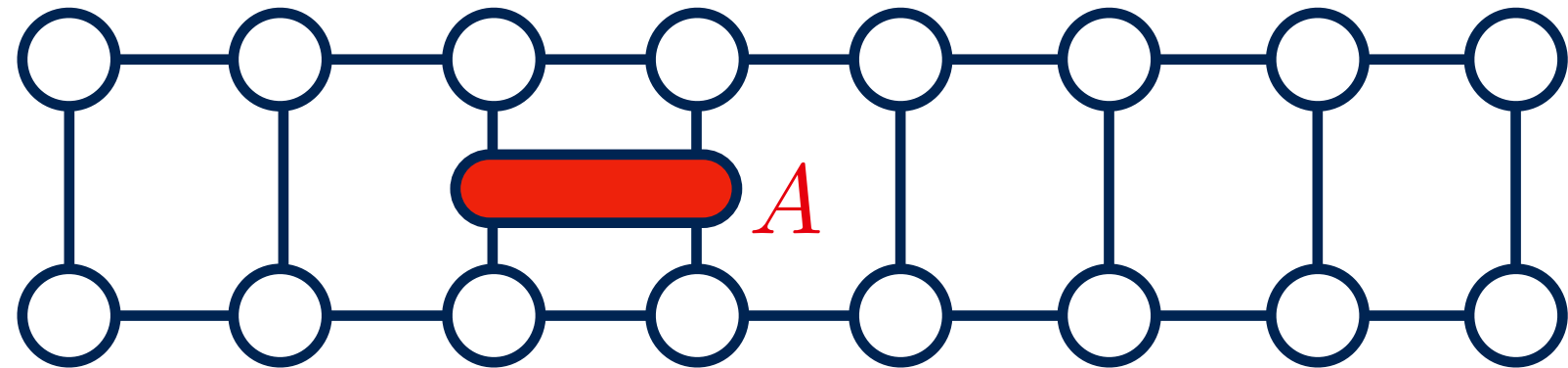


Using similar procedure as norm:

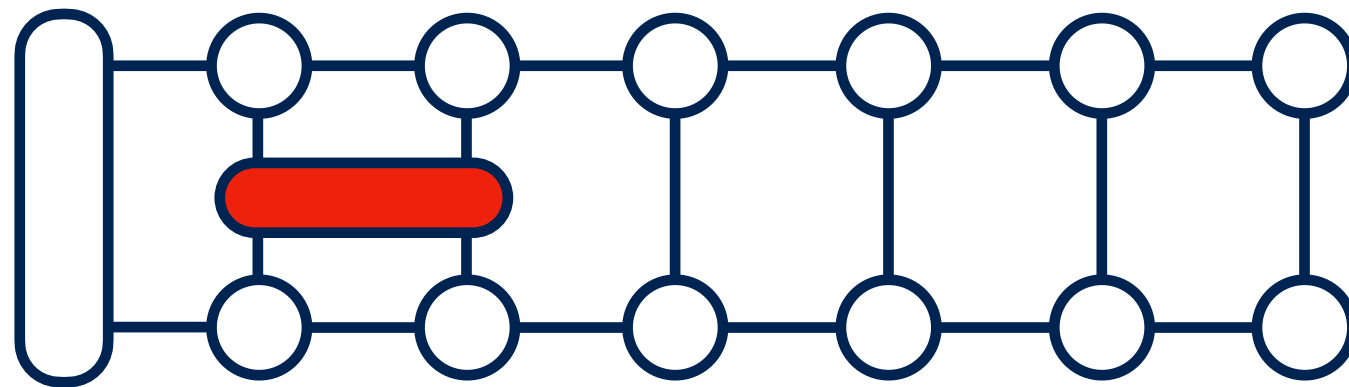


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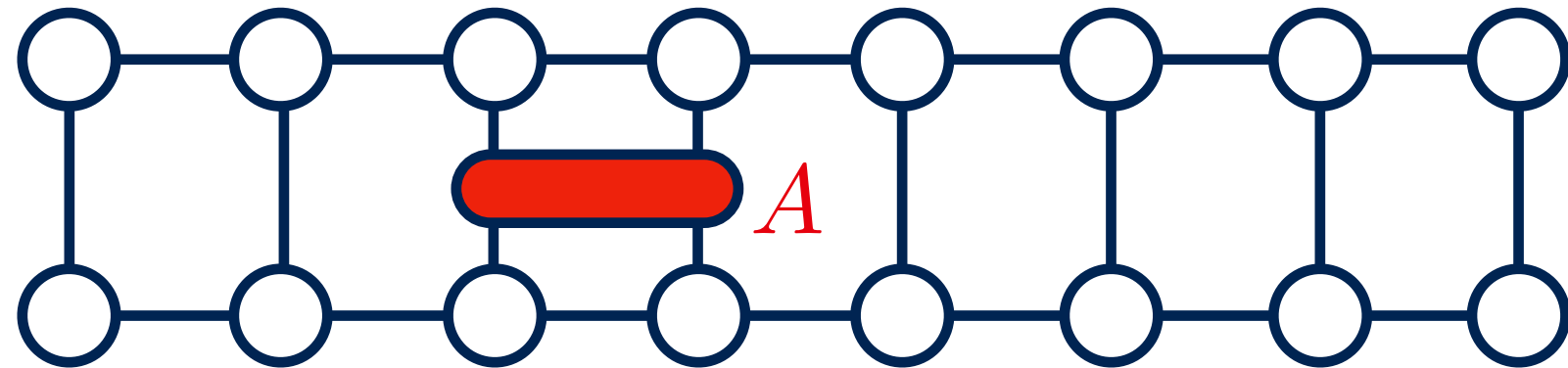
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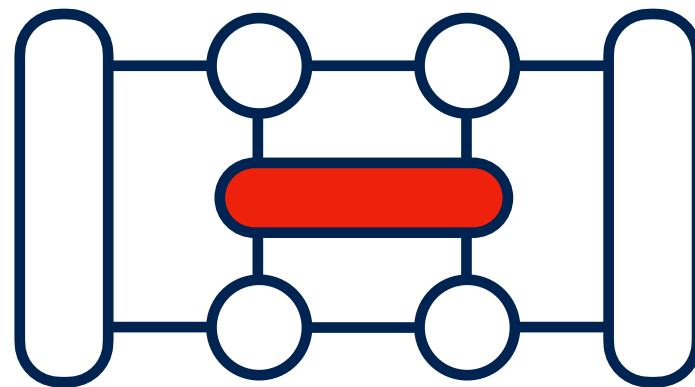


Another key computation is an **expectation value**

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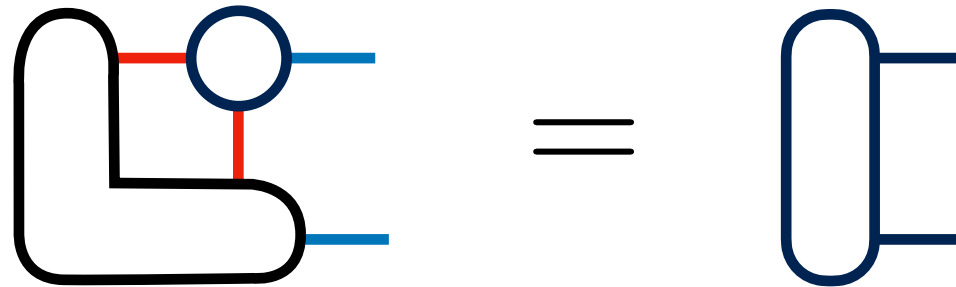


Using similar procedure as norm:



What is the **scaling** of the computational cost ?

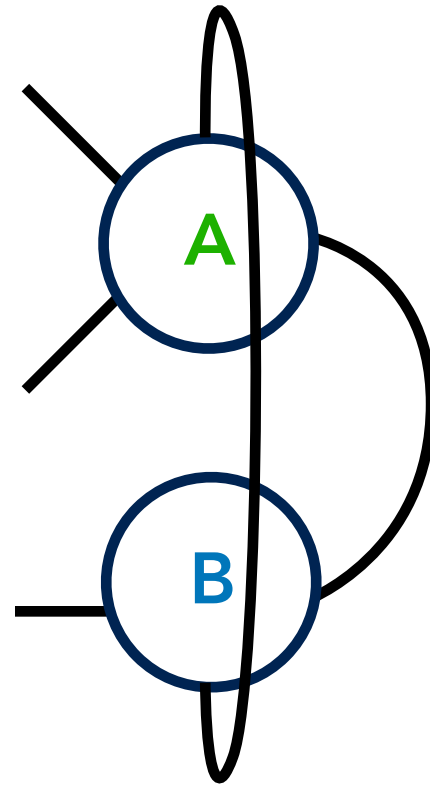
To calculate, break computation into separate steps,  
such as:



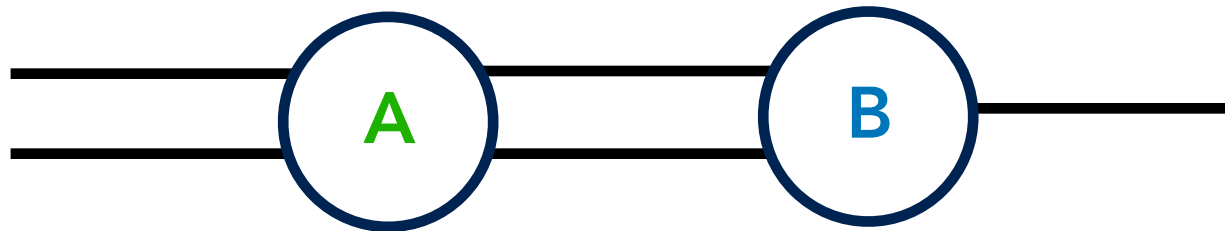
Then use rule for cost of tensor contraction:

(**dimension of contracted indices**)  
x (**dimension of uncontracted indices**)

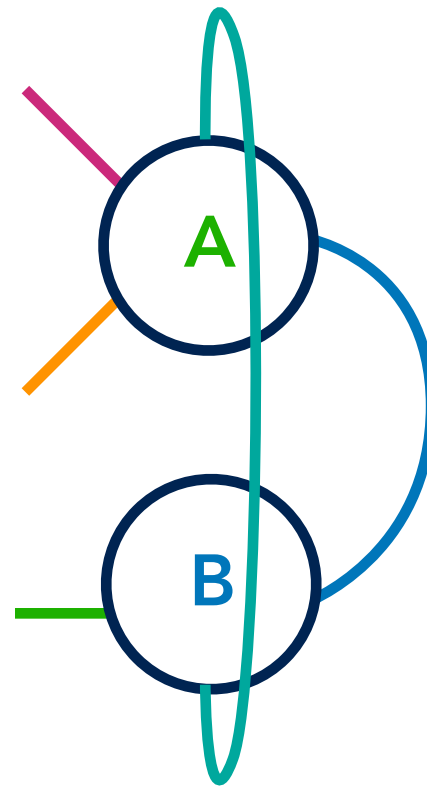
# Complicated tensor contraction



Can always be written as matrix mult. with grouped indices



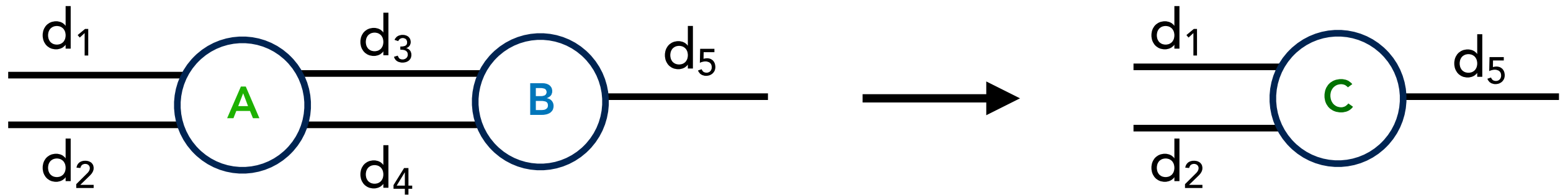
# Complicated tensor contraction



Can always be written as matrix mult. with grouped indices



To compute scaling, consider index dimensions



Computation of C equivalent to:

```
for  $i_1=1:d_1$ ,  $i_2=1:d_2$ ,  $i_5=1:d_5$ 
```

```
  for  $i_3=1:d_3$ ,  $i_4=1:d_4$ 
```

```
     $C[i_1, i_2, i_5] = A[i_1, i_2, i_3, i_4] * B[i_3, i_4, i_5]$ 
```

```
  end
```

```
end
```

Computation of C:

```
for i1=1:d1, i2=1:d2, i5=1:d5
```

```
  for i3=1:d3, i4=1:d4
```

```
    C[i1,i2,i5] = A[i1,i2,i3,i4]*B[i3,i4,i5]
```

```
  end
```

```
end
```

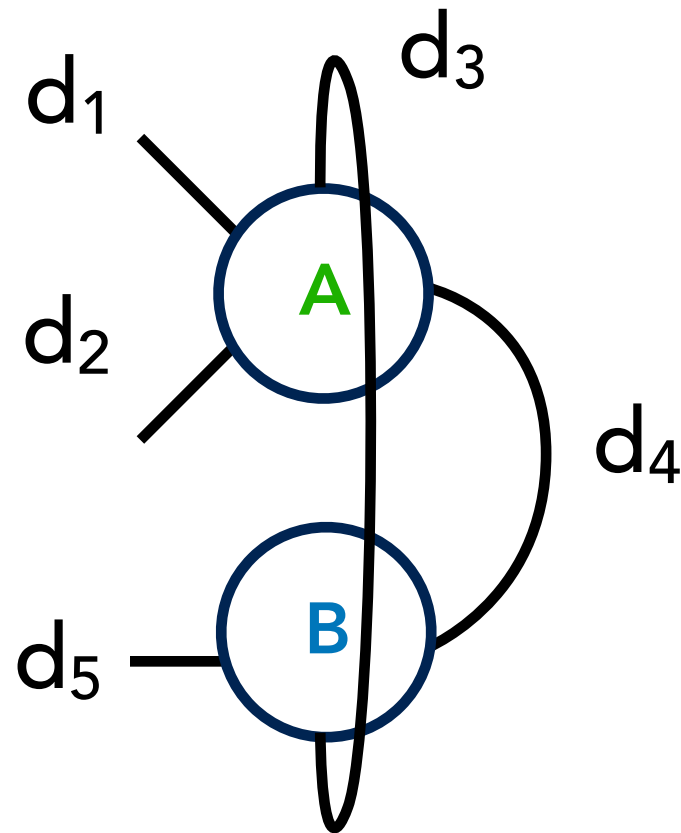
Each  $i_n$  loop takes  $d_n$  operations to complete

Overall scaling:  $(d_1 d_2 d_5) \times (d_3 d_4)$

(**dim. contracted indices**) x (**dim. uncontracted indices**)

## Summary of scaling rule

Whenever you see a tensor contraction

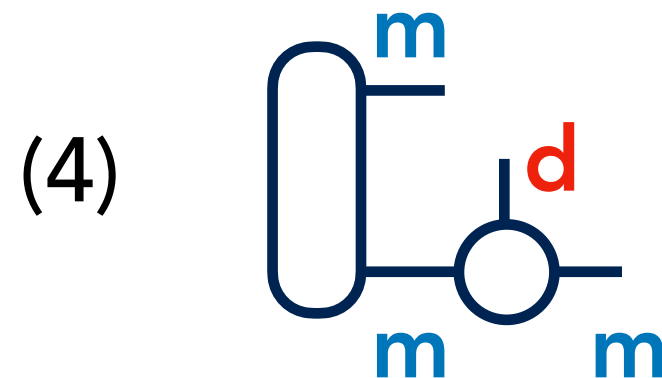
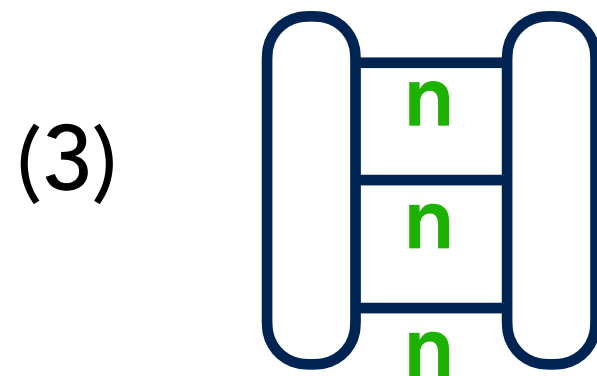
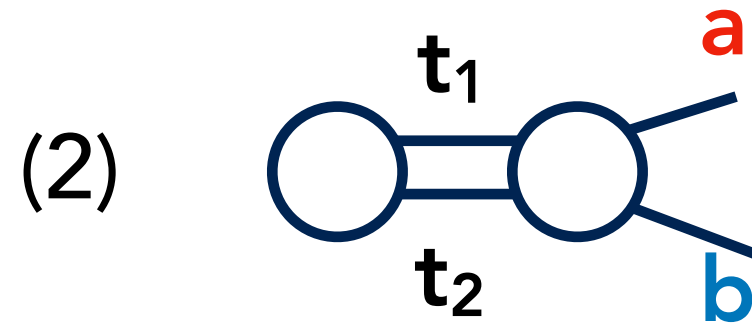


Multiply dimension of every index (just once)

$$\text{cost} = (d_1 \cdot d_2 \cdot d_3 \cdot d_4 \cdot d_5)$$

# Test Your Knowledge! 🤔

Write down the cost of the following tensor contractions (letters are index dimensions):

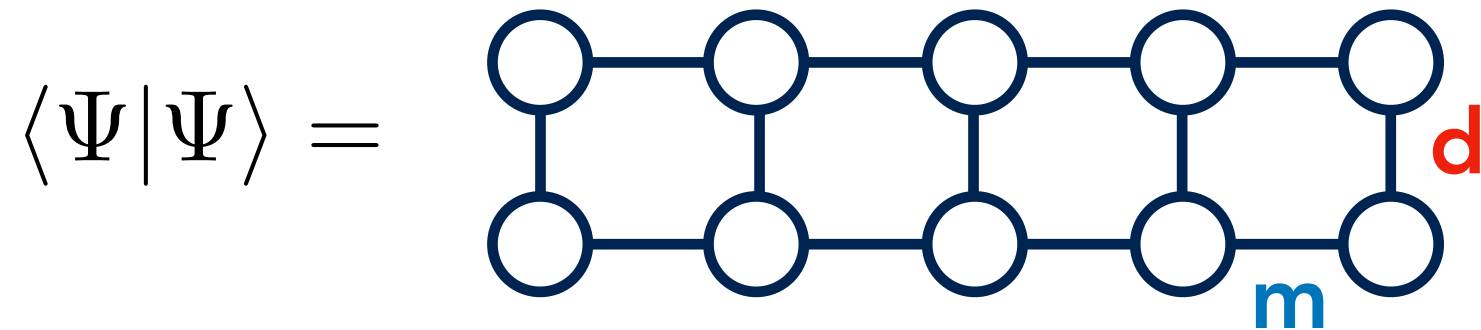




What is the **scaling** of calculations with MPS?

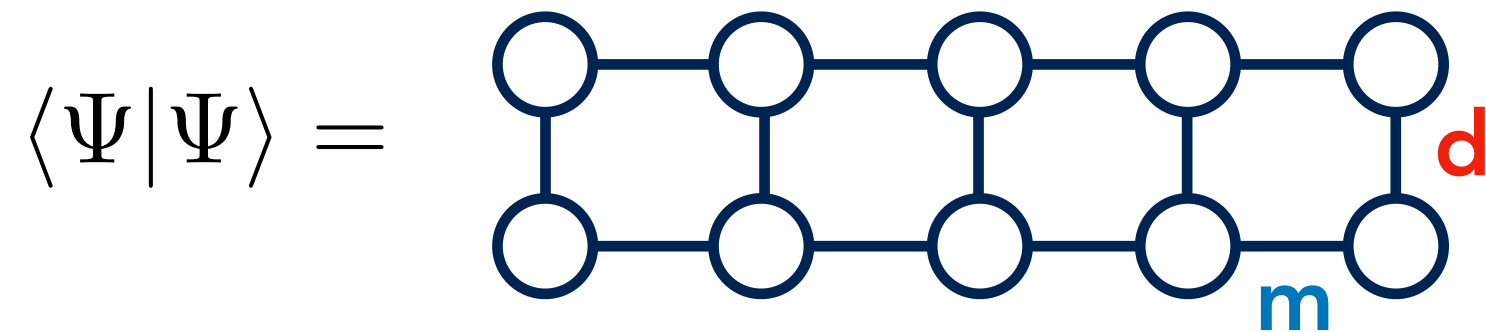
What is the **scaling** of calculations with MPS?

Consider norm of MPS bond dimension **m**, site dimension **d**



What is the **scaling** of calculations with MPS?

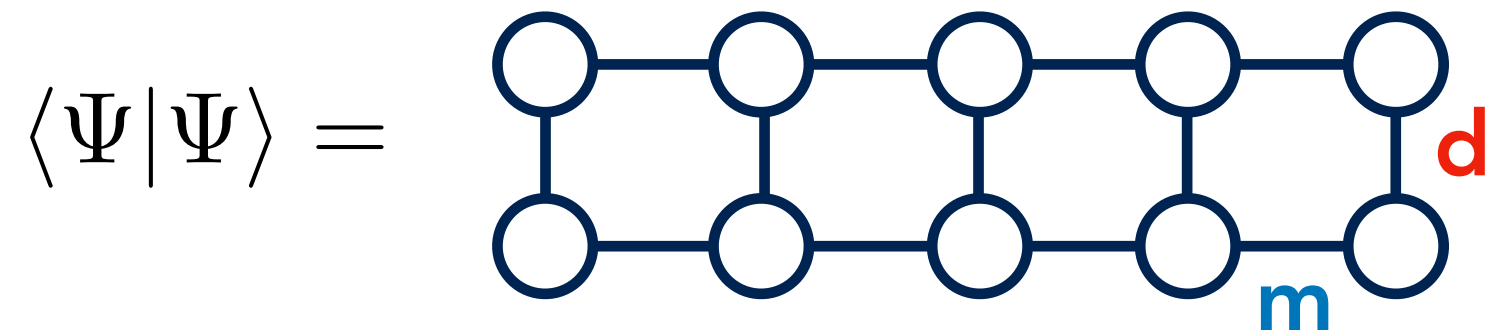
Consider norm of MPS bond dimension **m**, site dimension **d**



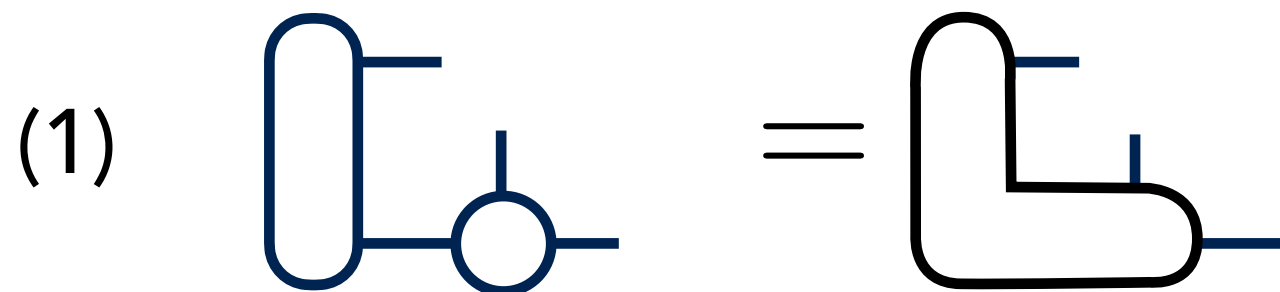
Two key operations

# What is the scaling of calculations with MPS?

Consider norm of MPS bond dimension **m**, site dimension **d**

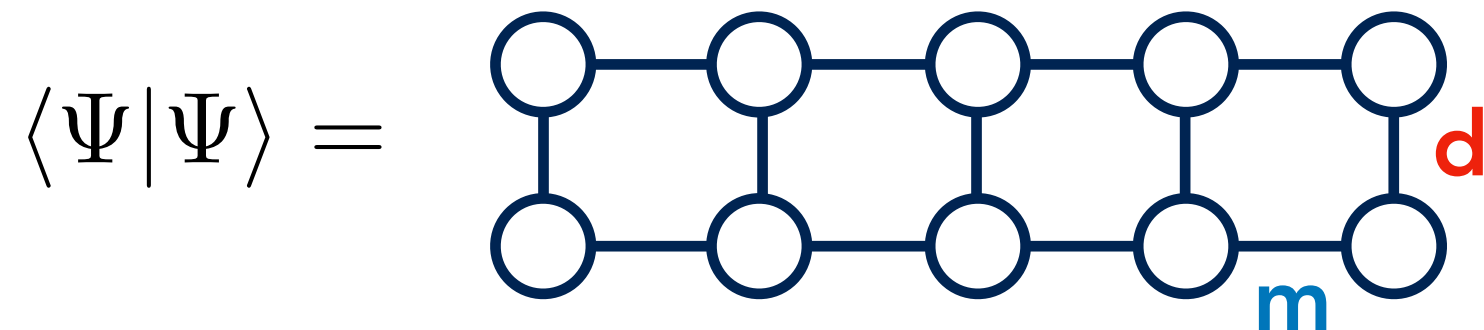


## Two key operations

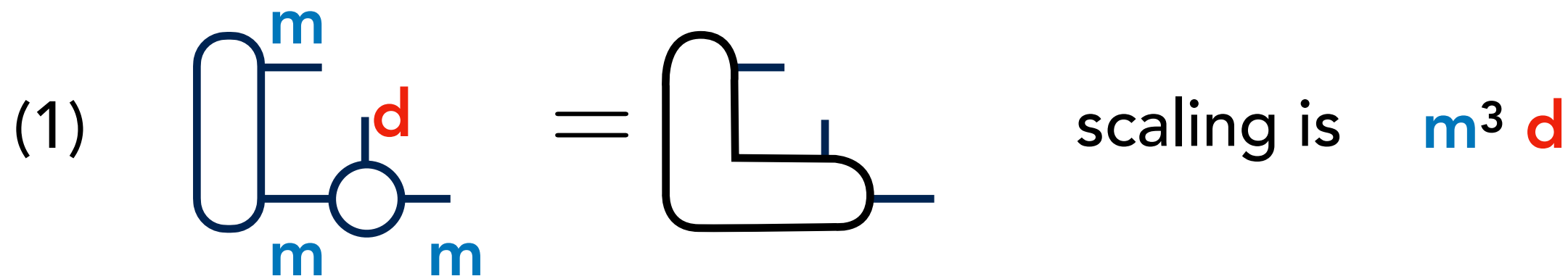


# What is the scaling of calculations with MPS?

Consider norm of MPS bond dimension  $m$ , site dimension  $d$

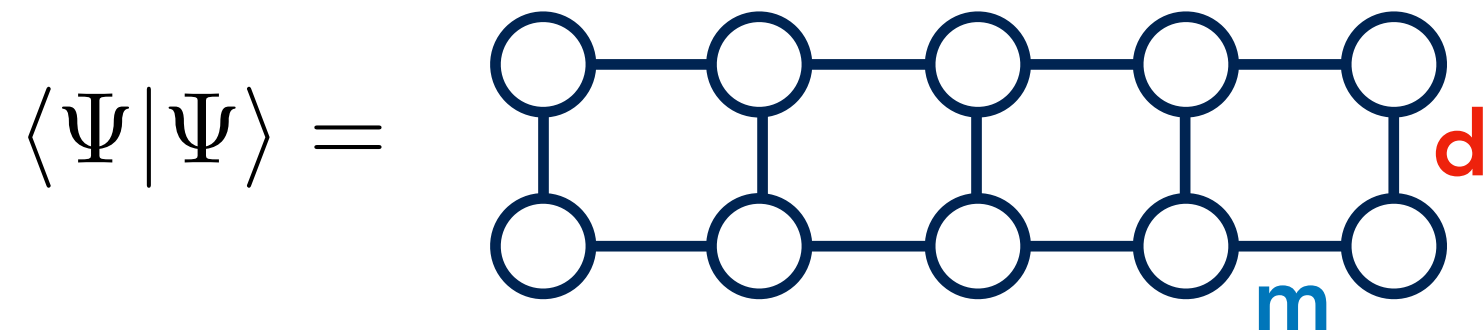


Two key operations

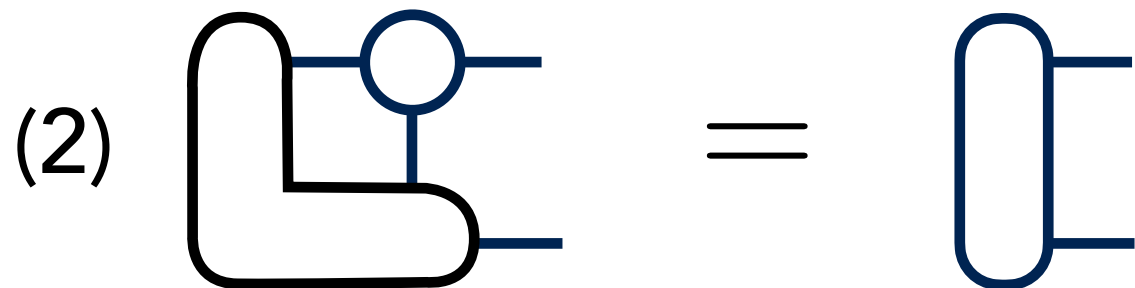


What is the **scaling** of the computational cost ?

Consider norm calculation, MPS bond dimension **m**,  
site dimension **d**

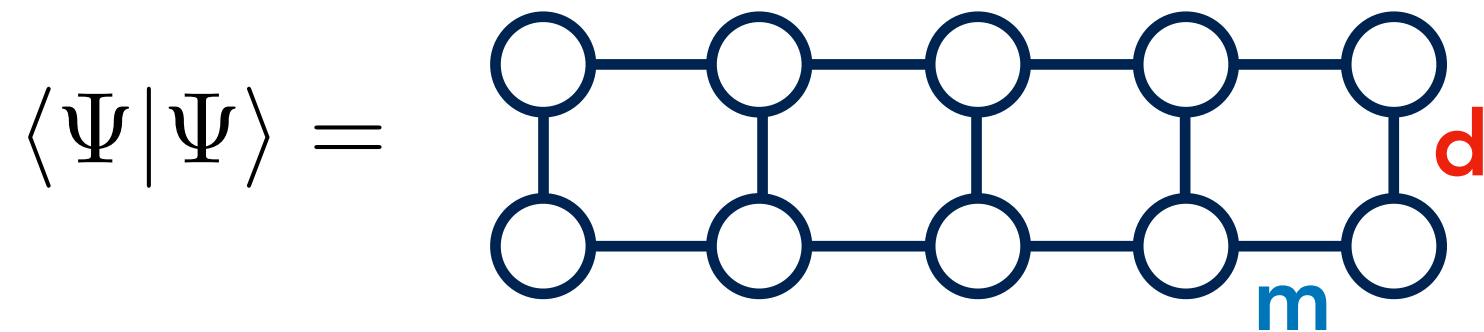


Two key operations



What is the **scaling** of the computational cost ?

Consider norm calculation, MPS bond dimension **m**,  
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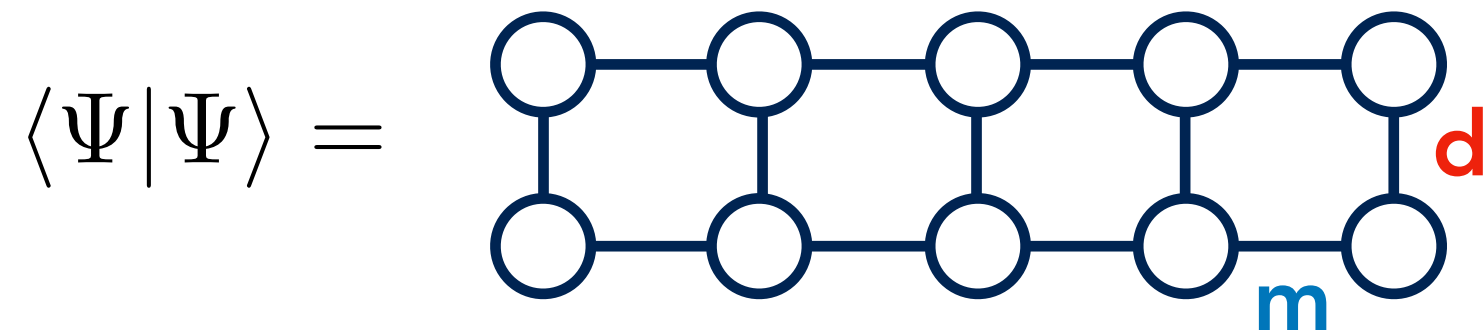


Two key operations



What is the **scaling** of the computational cost ?

Consider norm calculation, MPS bond dimension **m**,  
site dimension **d**



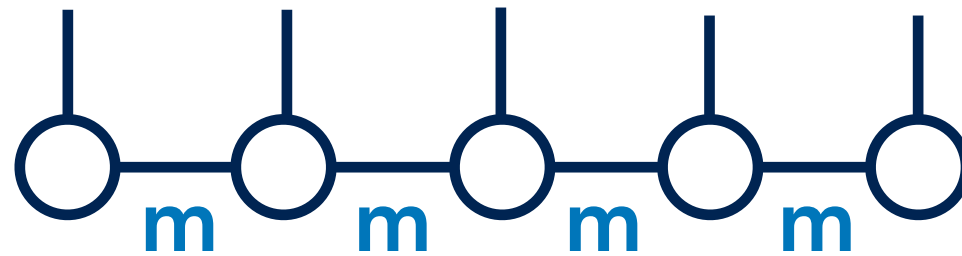
So overall scaling of norm calculation is

$$\mathbf{m}^3 \mathbf{d}$$



Rule of thumb: most every operation needed to manipulate MPS can be made to scale as

$$m^3$$



Intuition: MPS involves multiplying  $m \times m$  matrices

Scaling of  $m \times m$  matrix multiplication is  $m^3$

# **Examples of Matrix Product States**

## Example #1: singlet state

$$\begin{aligned} |\Psi\rangle &= \frac{1}{\sqrt{2}} |\uparrow\rangle |\downarrow\rangle - \frac{1}{\sqrt{2}} |\downarrow\rangle |\uparrow\rangle \\ &= \begin{bmatrix} \frac{1}{\sqrt{2}} |\uparrow\rangle & \frac{1}{\sqrt{2}} |\downarrow\rangle \end{bmatrix} \begin{bmatrix} |\downarrow\rangle \\ -|\uparrow\rangle \end{bmatrix} \end{aligned}$$

How to see this is an MPS?

$$\begin{bmatrix} \frac{1}{\sqrt{2}}|\uparrow\rangle & \frac{1}{\sqrt{2}}|\downarrow\rangle \end{bmatrix} \begin{bmatrix} |\downarrow\rangle \\ -|\uparrow\rangle \end{bmatrix} =$$

$$\begin{array}{c} |\uparrow\rangle \\ |\downarrow\rangle \end{array} \left\{ \begin{array}{c} \begin{bmatrix} \frac{1}{\sqrt{2}} & 0 \end{bmatrix} \\ \begin{bmatrix} 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \end{array} \right\} \begin{array}{c} |\uparrow\rangle \\ |\downarrow\rangle \end{array} \left\{ \begin{array}{c} \begin{bmatrix} 0 \\ -1 \end{bmatrix} \\ \begin{bmatrix} 1 \\ 0 \end{bmatrix} \end{array} \right\}$$

## Example #2: AKLT wavefunction

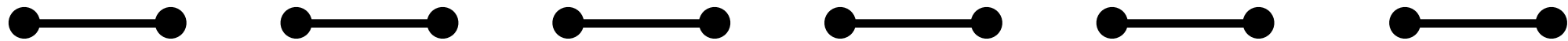
The AKLT wavefunction is the exact ground state of the following  $S=1$  Hamiltonian

$$H = \sum_j \mathbf{S}_j \cdot \mathbf{S}_{j+1} + \frac{1}{3} \sum_j (\mathbf{S}_j \cdot \mathbf{S}_{j+1})^2$$

In the same phase as  $S=1$  Heisenberg model, plus 'small' perturbation of  $(\mathbf{S} \cdot \mathbf{S})^2$  biquadratic term

Can construct AKLT wavefunction as follows

Start with  $2N$  spin  $1/2$ 's in singlet pairs



$$\bullet\text{---}\bullet = \frac{1}{\sqrt{2}}|\uparrow\rangle|\downarrow\rangle - \frac{1}{\sqrt{2}}|\downarrow\rangle|\uparrow\rangle$$

Can construct AKLT wavefunction as follows

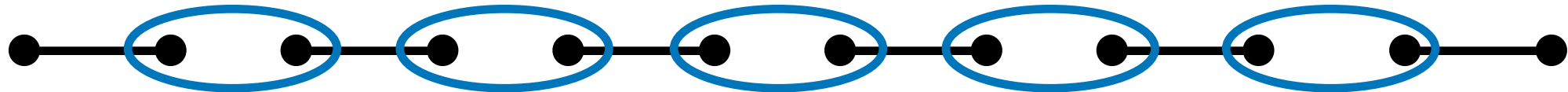
Act on pairs of  $S=1/2$ 's with projection operator  $P$



$$\text{Oval} = \hat{P} = |+\rangle\langle\uparrow\uparrow| + |0\rangle\frac{\langle\uparrow\downarrow| + \langle\downarrow\uparrow|}{\sqrt{2}} + |-\rangle\langle\downarrow\downarrow|$$

Can construct AKLT wavefunction as follows

Act on pairs of  $S=1/2$ 's with projection operator  $P$



$$\text{blue oval} = \hat{P} = |+\rangle\langle\uparrow\uparrow| + |0\rangle\frac{\langle\uparrow\downarrow| + \langle\downarrow\uparrow|}{\sqrt{2}} + |-\rangle\langle\downarrow\downarrow|$$



Can construct AKLT wavefunction as follows

After projection, blue ovals are  $S=1$  spins



Can construct AKLT wavefunction as follows

After projection, blue ovals are  $S=1$  spins



Can predict interesting properties:

- doubly degenerate entanglement spectrum
- emergent  $S=1/2$  edge spins

# Tensor approach to AKLT

$$\text{Diagram} = \frac{1}{\sqrt{2}} |\uparrow\rangle |\downarrow\rangle - \frac{1}{\sqrt{2}} |\downarrow\rangle |\uparrow\rangle$$

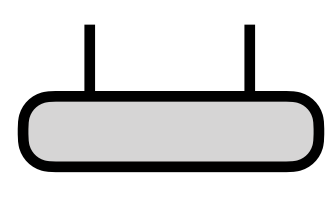
# Tensor approach to AKLT

$$\text{Diagram: a light gray rounded rectangle with two vertical lines extending upwards from its top edge} = \frac{1}{\sqrt{2}} |\uparrow\rangle |\downarrow\rangle - \frac{1}{\sqrt{2}} |\downarrow\rangle |\uparrow\rangle$$

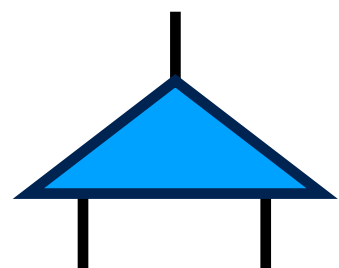
$$\text{Diagram: a light gray rounded rectangle with two vertical lines extending upwards from its top edge; the left line has an upward arrow above it, and the right line has a downward arrow above it} = \frac{1}{\sqrt{2}}$$

$$\text{Diagram: a light gray rounded rectangle with two vertical lines extending upwards from its top edge; the left line has a downward arrow above it, and the right line has an upward arrow above it} = -\frac{1}{\sqrt{2}}$$

# Tensor approach to AKLT



$$= \frac{1}{\sqrt{2}} |\uparrow\rangle |\downarrow\rangle - \frac{1}{\sqrt{2}} |\downarrow\rangle |\uparrow\rangle$$



$$= |+\rangle \langle \uparrow\uparrow| + |0\rangle \frac{\langle \uparrow\downarrow| + \langle \downarrow\uparrow|}{\sqrt{2}} + |-\rangle \langle \downarrow\downarrow|$$

# Tensor approach to AKLT

$$\begin{array}{c} \text{---} \end{array} = \frac{1}{\sqrt{2}} |\uparrow\rangle |\downarrow\rangle - \frac{1}{\sqrt{2}} |\downarrow\rangle |\uparrow\rangle$$

$$\begin{array}{c} \triangle \end{array} = |+\rangle \langle \uparrow\uparrow| + |0\rangle \frac{\langle \uparrow\downarrow| + \langle \downarrow\uparrow|}{\sqrt{2}} + |-\rangle \langle \downarrow\downarrow|$$

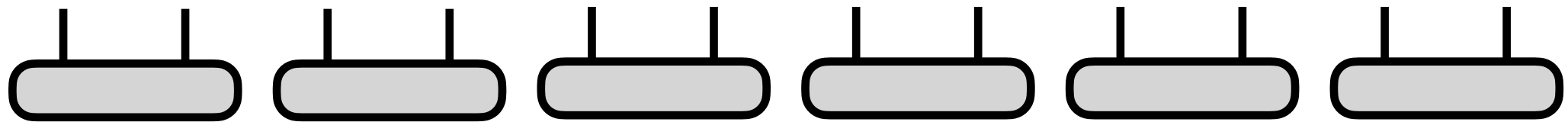
$$\begin{array}{c} + \\ \triangle \end{array} \begin{array}{c} \uparrow \\ \uparrow \end{array} = 1$$

$$\begin{array}{c} 0 \\ \triangle \end{array} \begin{array}{c} \uparrow \\ \downarrow \end{array} = \frac{1}{\sqrt{2}}$$

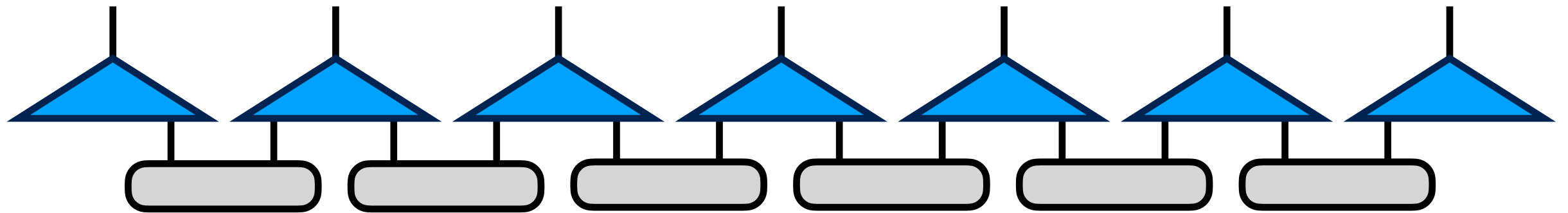
$$\begin{array}{c} 0 \\ \triangle \end{array} \begin{array}{c} \downarrow \\ \uparrow \end{array} = \frac{1}{\sqrt{2}}$$

$$\begin{array}{c} - \\ \triangle \end{array} \begin{array}{c} \downarrow \\ \downarrow \end{array} = 1$$

# Tensor approach to AKLT

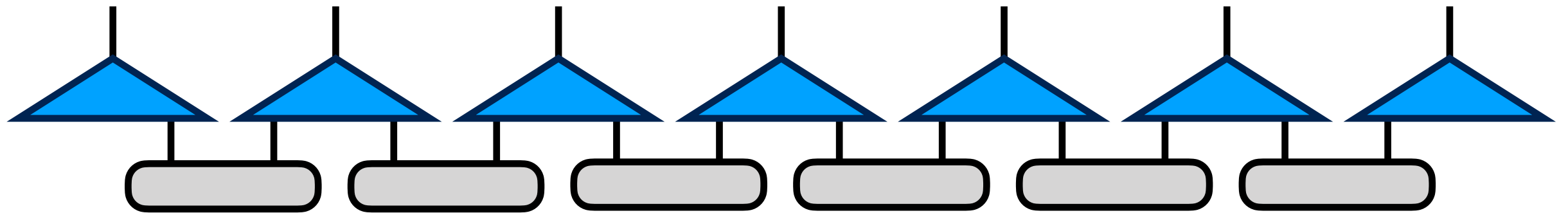


# Tensor approach to AKLT



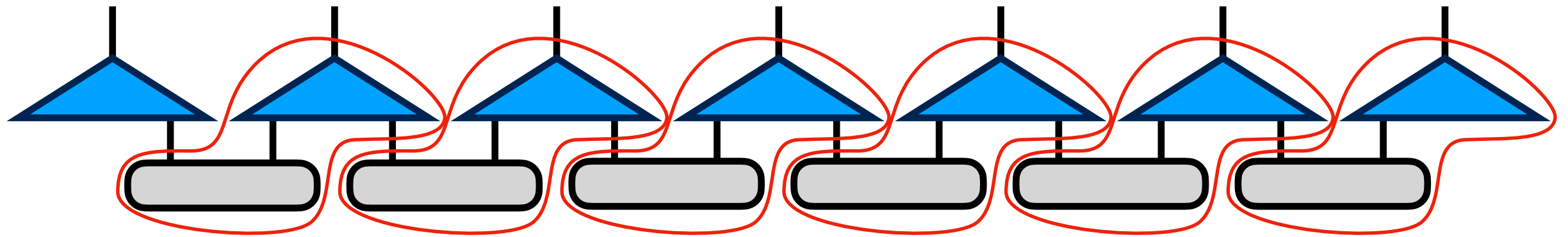


Put into MPS form



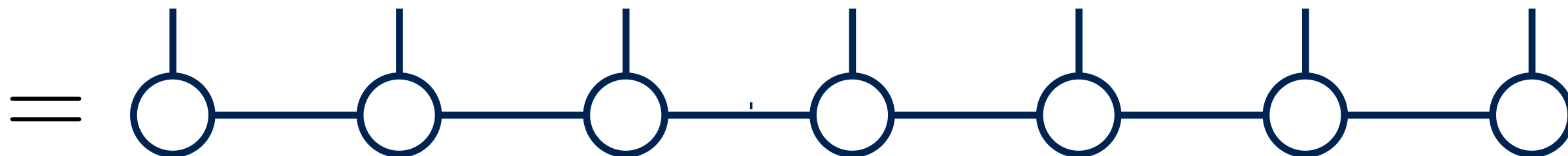
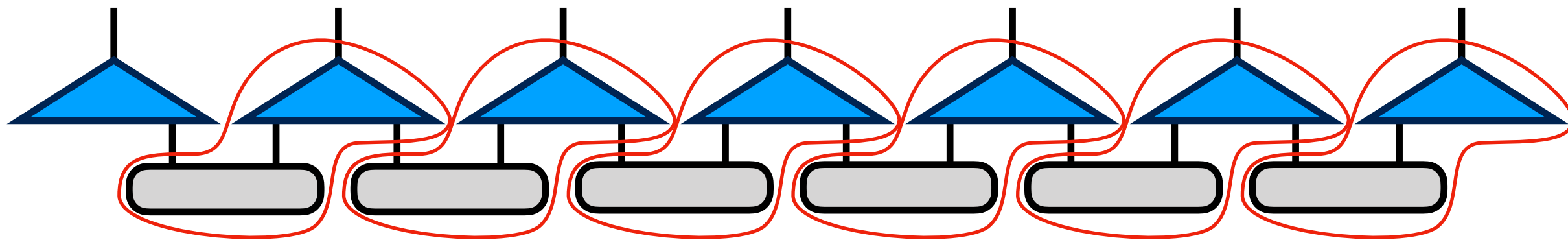
Put into MPS form

Contract pairs of tensors:



Put into MPS form

Contract pairs of tensors:



Nice form of AKLT matrix product state with periodic boundary conditions

Can actually show the following:

$$|\Psi_{\text{AKLT}}\rangle = \text{Tr} [M^{s_1} M^{s_2} M^{s_3} \dots M^{s_N}] |s_1 s_2 s_3 \dots s_N\rangle$$

where

$$M^+ = \sqrt{\frac{2}{3}} \sigma^+$$

$$M^0 = -\sqrt{\frac{1}{3}} \sigma^z$$

$$M^- = -\sqrt{\frac{2}{3}} \sigma^-$$

## Takeaway

- MPS guaranteed to obey boundary law, as do all 1D ground states (of gapped, local Hamiltonians)
- MPS can capture certain interesting states exactly
- maybe they are a useful class of wavefunction to optimize!