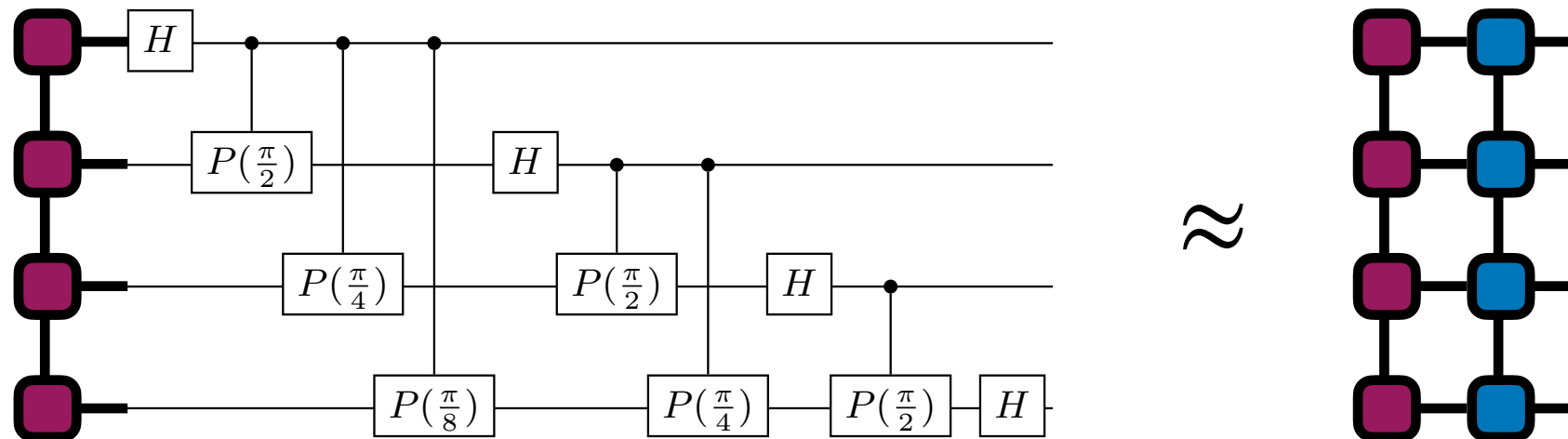


Time Evolution with Tensor Networks



Tensor Network Algorithms

An important capability is
time evolving tensor networks

$$e^{-iHt} |\psi(0)\rangle = |\psi(t)\rangle$$

Algorithms:

- Time evolving block decimation (TEBD)
- Time-dependent variational principle (TDVP)

Tensor Network Algorithms

TEBD algorithm $H = \sum_j h_{j,j+1}$

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Tensor Network Algorithms

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Tensor Network Algorithms

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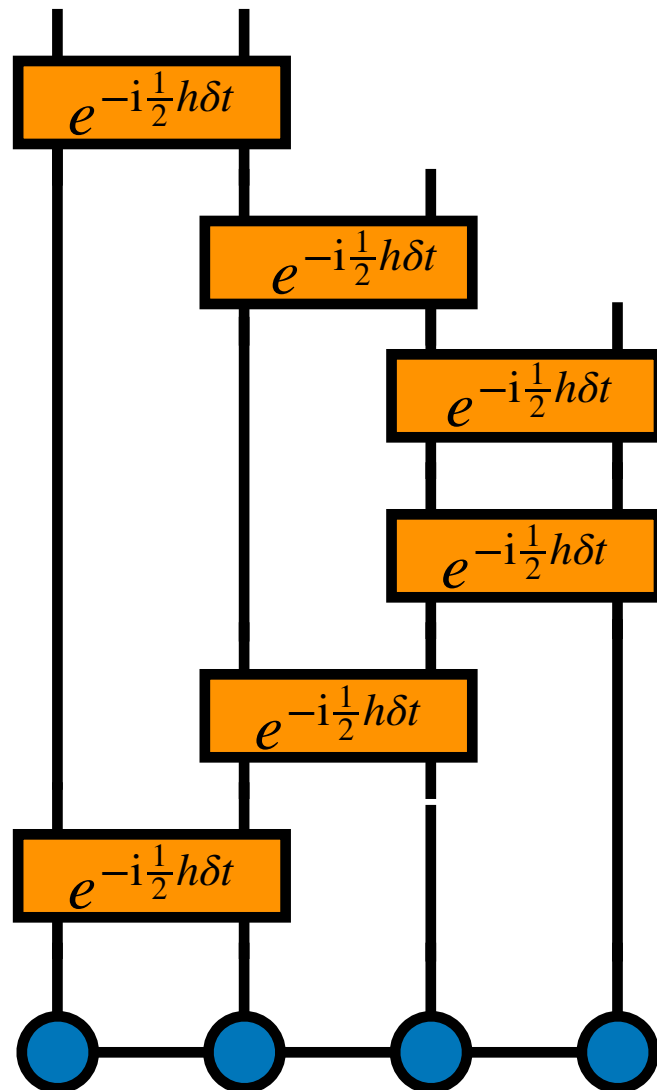
1st Order: $e^{-iH\delta t} = \prod_i e^{-ih_{i,i+1}\delta t} + \mathcal{O}(\delta t^2)$

2nd Order: $e^{-iH\delta t} = \left(\prod_{1 \leq i \leq N} e^{-\frac{1}{2}ih_{i,i+1}\delta t} \right) \left(\prod_{N \geq i \geq 1} e^{-\frac{1}{2}ih_{i,i+1}\delta t} \right) + \mathcal{O}(\delta t^3)$

Tensor Network Algorithms

TEBD algorithm

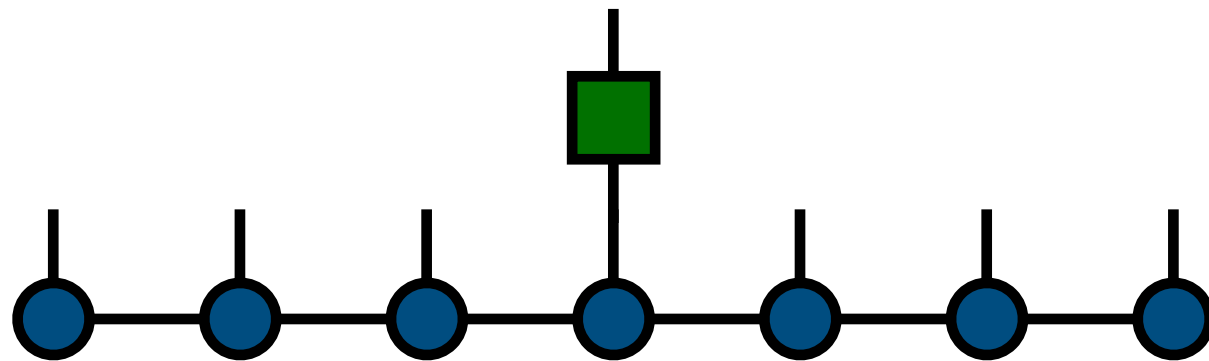
$$e^{-iH\delta t} = \left(\prod_{1 \leq i \leq N} e^{-\frac{1}{2}i h_{i,i+1} \delta t} \right) \left(\prod_{N \geq i \geq 1} e^{-\frac{1}{2}i h_{i,i+1} \delta t} \right) + \mathcal{O}(\delta t^3)$$



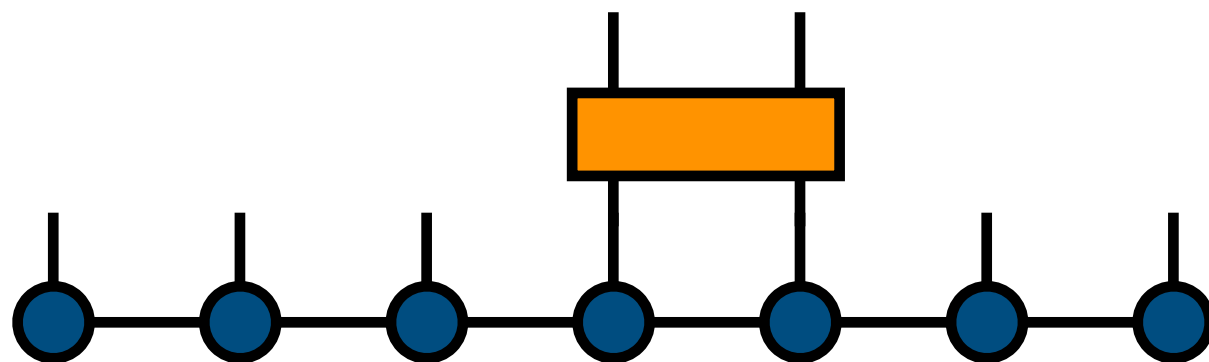
$$\approx e^{-iH\delta t} |\psi(t)\rangle = |\psi(t + \delta t)\rangle$$

Tensor Network Algorithms

TEBD = controlled application of one-qubit and two-qubit gates to an MPS



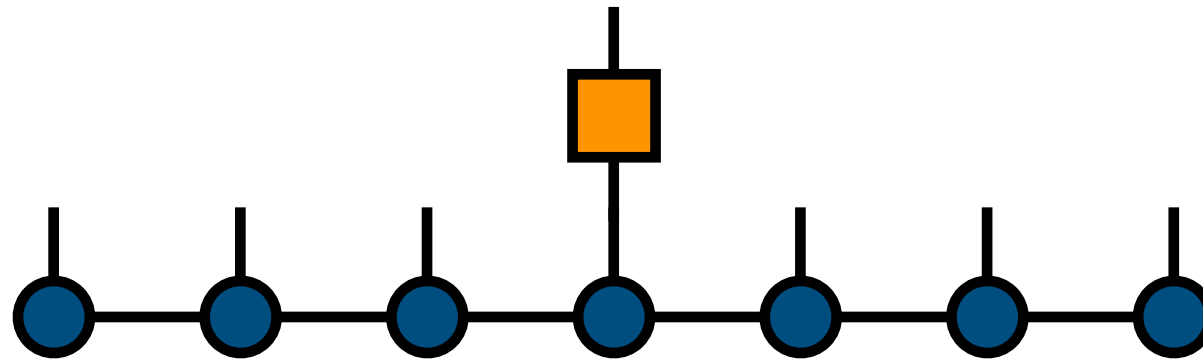
one-qubit gate is exact



two-qubit gate incurs
small error controlled
by bond-dimension χ

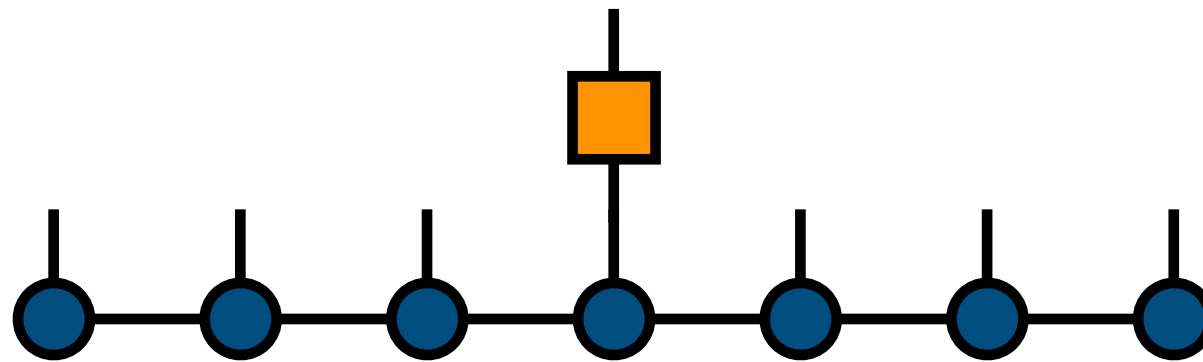
Tensor Network Algorithms

Say we want to act a single-qubit gate on a wavefunction in MPS form

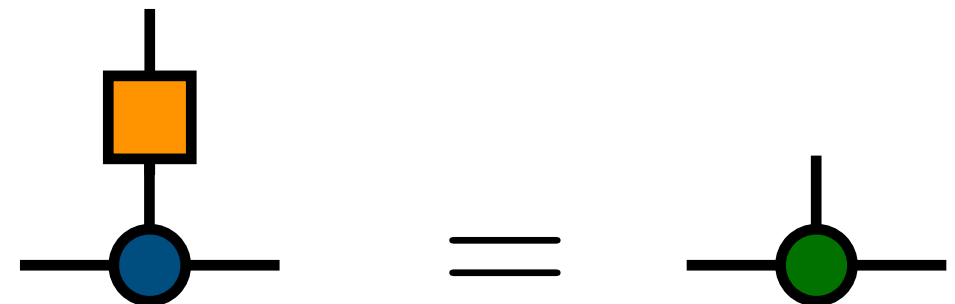


Tensor Network Algorithms

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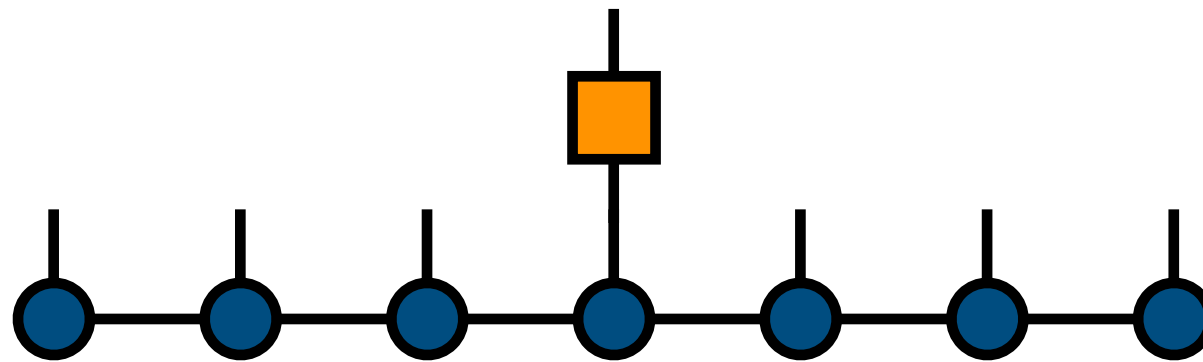


Just operate on one tensor:

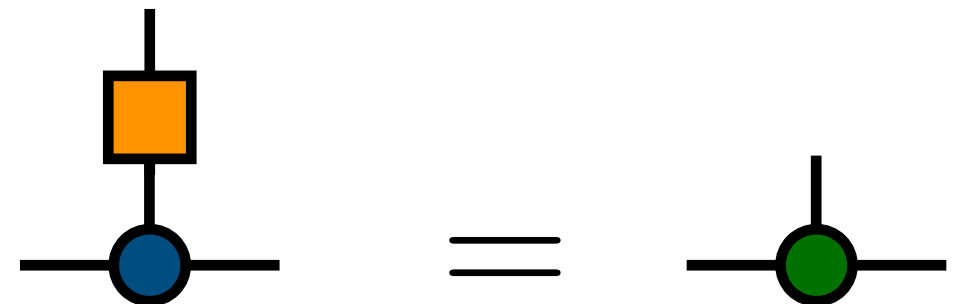


Tensor Network Algorithms

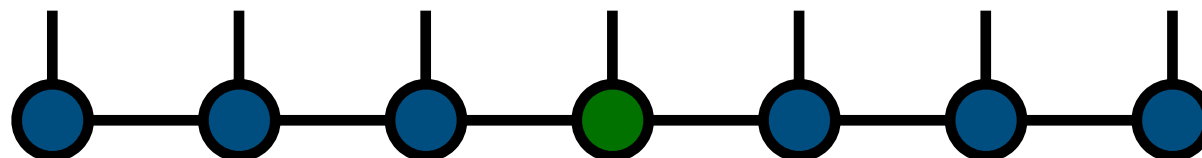
Say we want to act a single-qubit gate on a wavefunction in MPS form



Just operate on one tensor:

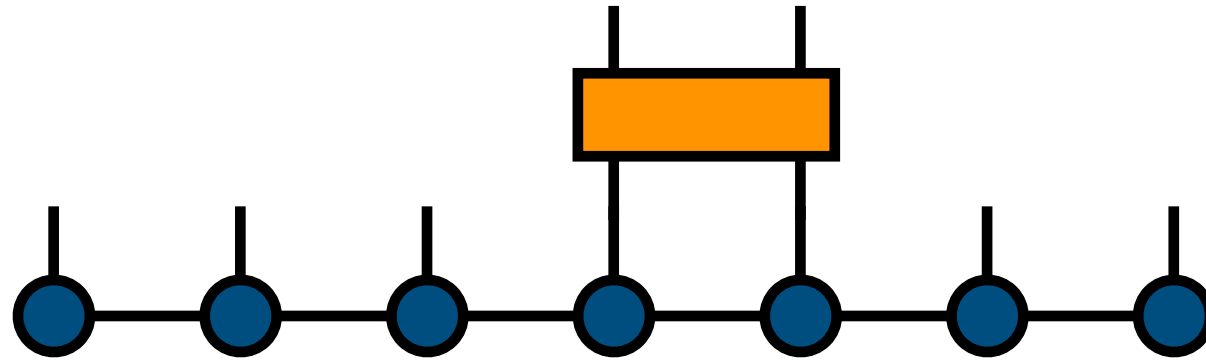


Result:

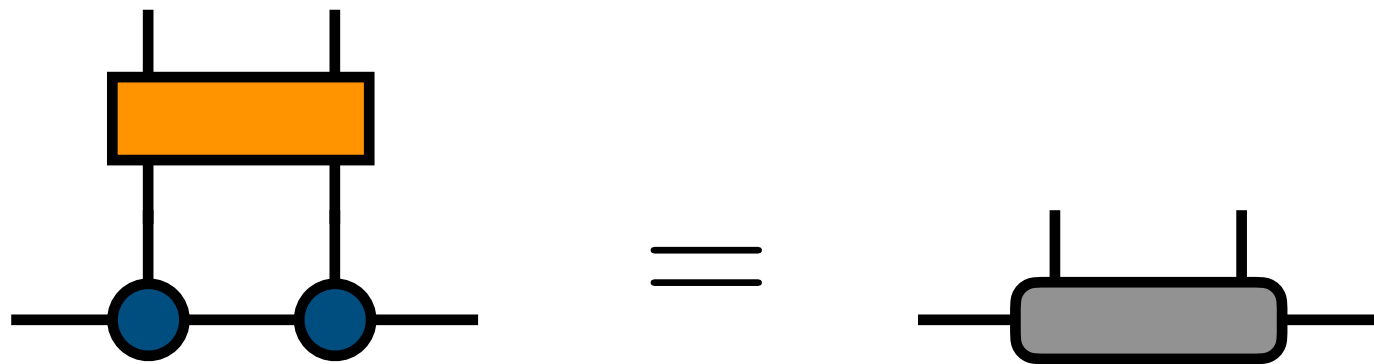


*same bond
dimension*

Say we want to act two-qubit gate on a wavefunction in MPS form

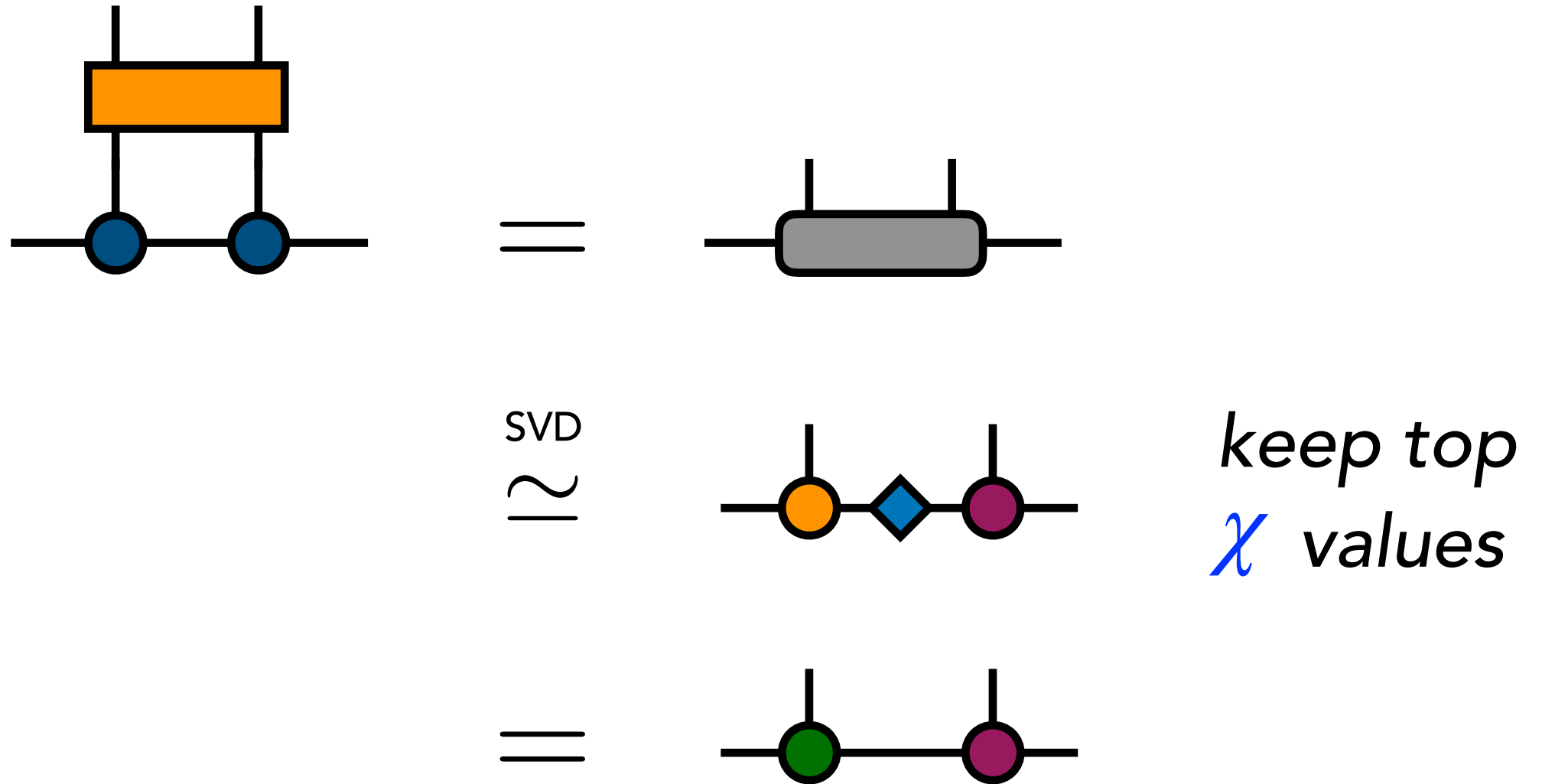


Operate on two tensors:

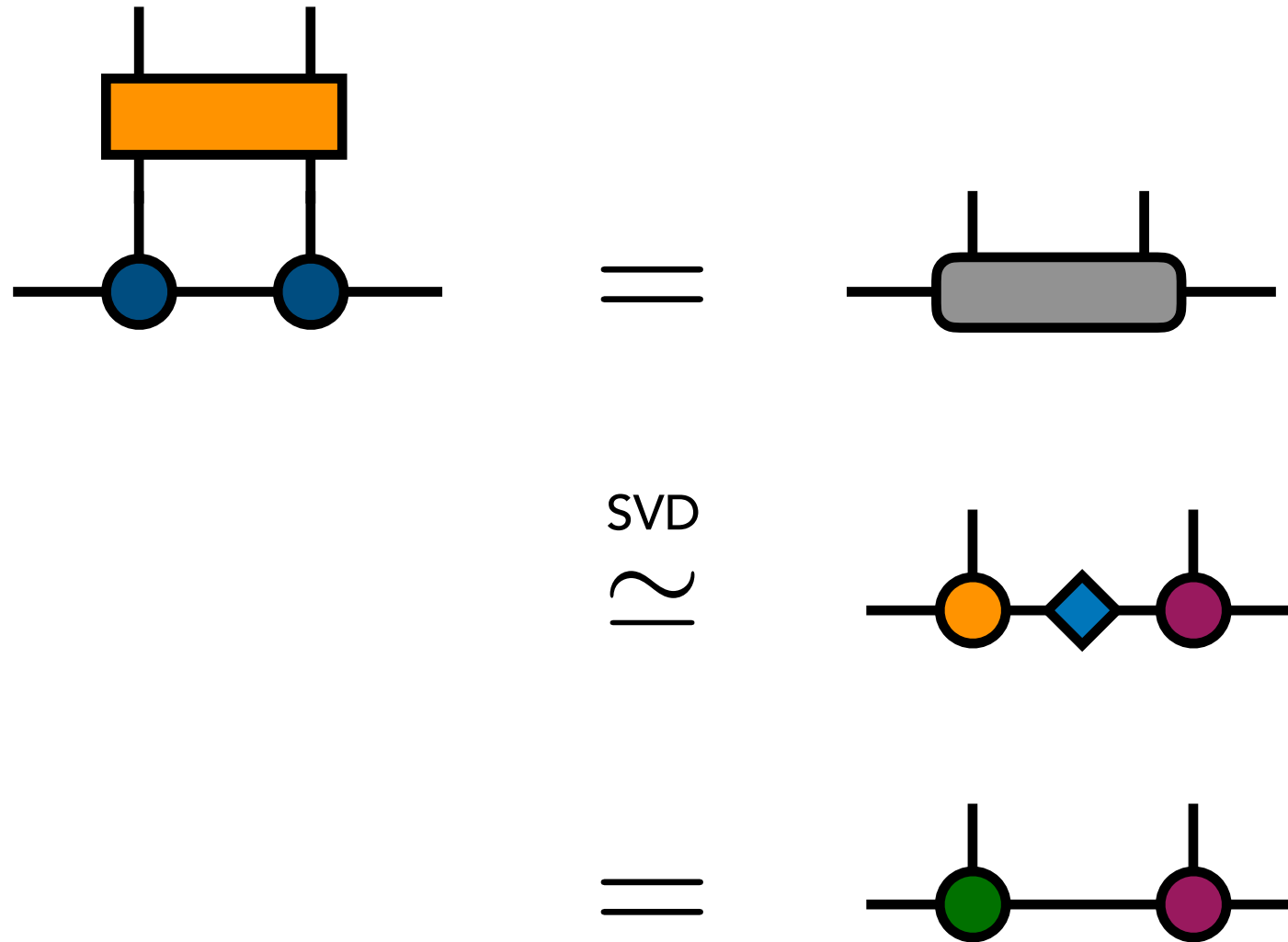


*destroy
MPS form
locally*

But can recover MPS form using truncated SVD:



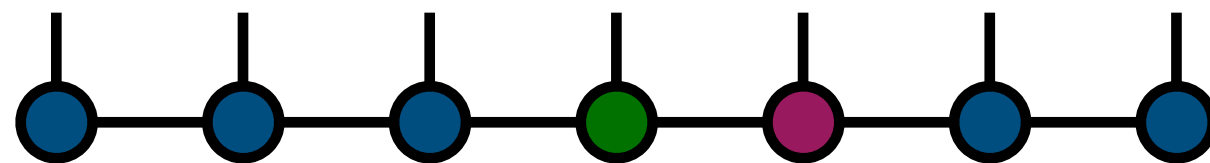
But can recover MPS form using truncated SVD:



*keep top
 χ values*

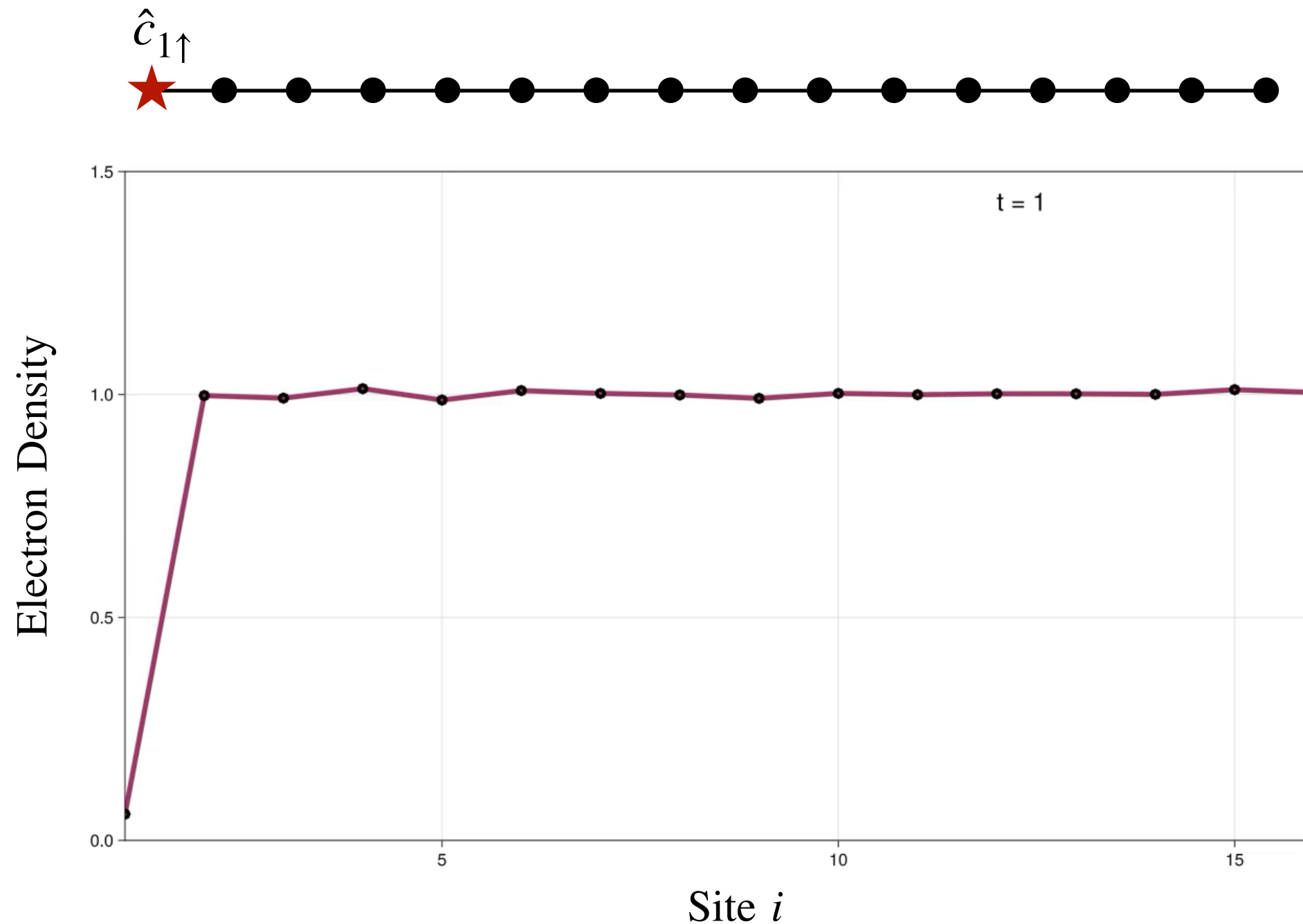
*with loss of
fidelity
dependent
on level of
truncation*

Result:



Tensor Network Algorithms

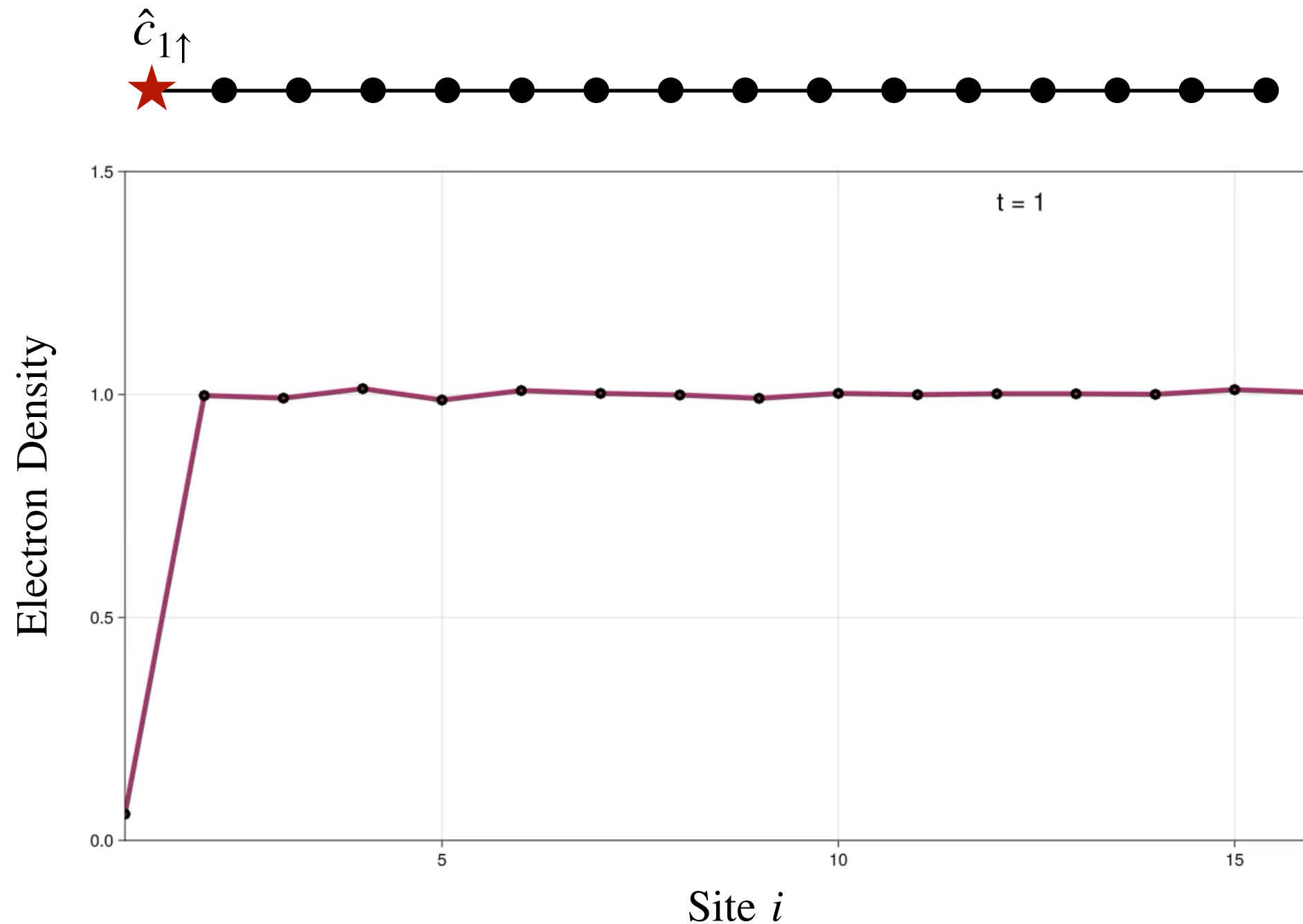
TEBD results: electron chain* after removing particle on site 1



*Impurity model with uniform hopping and $U=6$

Tensor Network Algorithms

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Tensor Network Algorithms

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Time-dependent variational principle (TDVP)

Tensor Network Algorithms

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Time-dependent variational principle (TDVP)

- Lets us handle long range interactions

Tensor Network Algorithms

TDVP algorithm

Time evolve via a DMRG-like sweeping procedure

Start with the full Hamiltonian

$$H = \text{---} \bullet \text{---} \bullet \text{---} \bullet \text{---} \bullet \text{---} \bullet \text{---} \bullet$$

Can be a local or non-local Hamiltonian now

Tensor Network Algorithms

TDVP algorithm [1]

$$H = \text{---} \bullet \text{---} \bullet \text{---} \bullet \text{---} \bullet \text{---} \bullet \text{---} \bullet$$

Solve the Schrödinger equation in the manifold of MPS of fixed bond dimension χ

$$\frac{d|\psi(t)\rangle}{dt} = -i\mathcal{P}_{|\psi(t)\rangle}H|\psi(t)\rangle$$

$\mathcal{P}_{|\psi(t)\rangle}$ is the projector onto the tangent space of this manifold for the current state

[1] J. Haegeman et al, TDVP for Quantum Lattices, PRL 107 (2011)

Tensor Network Algorithms

TDVP algorithm

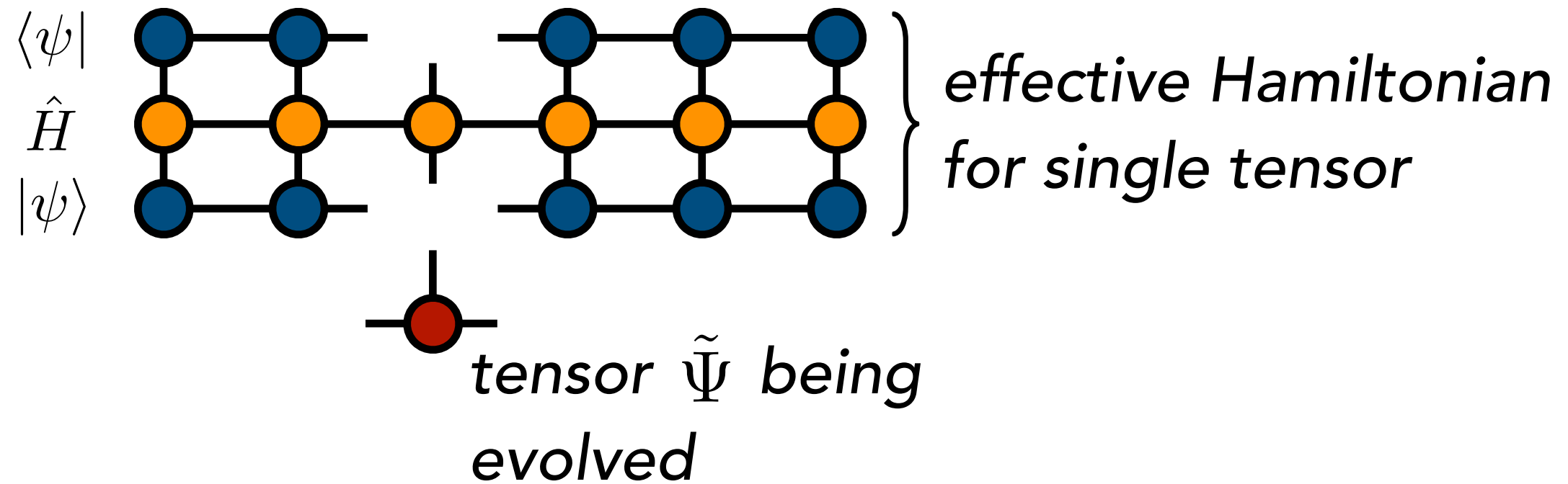
$$\frac{d|\psi(t)\rangle}{dt} = -i\mathcal{P}_{|\psi(t)\rangle}H|\psi(t)\rangle$$

$$|\psi(t + \delta t)\rangle = e^{-i\mathcal{P}_{|\psi(t)\rangle}H\delta t}|\psi(t)\rangle$$

$\mathcal{P}_{|\psi(t)\rangle}$ can be constructed exactly and we Trotterize the exponential at the level of the projector, not the Hamiltonian, solving the local integral equation that arises site by site.

Tensor Network Algorithms

TDVP algorithm



Tensor Network Algorithms

At each configuration, integrate time forward by small amount

Solving:

The diagram shows the equation $i \frac{d}{dt}$ followed by a red dot with four external lines (top, bottom, left, right). This is equal to a diagram consisting of a 3x3 grid of dots. The four corner dots (top-left, top-right, bottom-left, bottom-right) are blue, and the five central dots (top-middle, top-center, middle-left, middle-center, middle-right) are orange. The central orange dot has four external lines (top, bottom, left, right). The grid is connected by horizontal and vertical lines, with the central dot also connected to the four dots immediately surrounding it.

from $t \rightarrow t + dt$

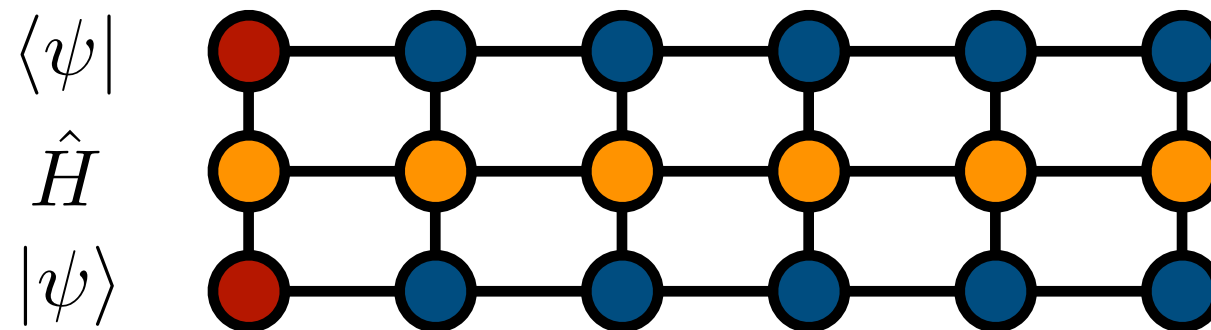
$=$

$= \hat{H}_{\text{Eff}} \cdot$

Tensor Network Algorithms

TDVP algorithm

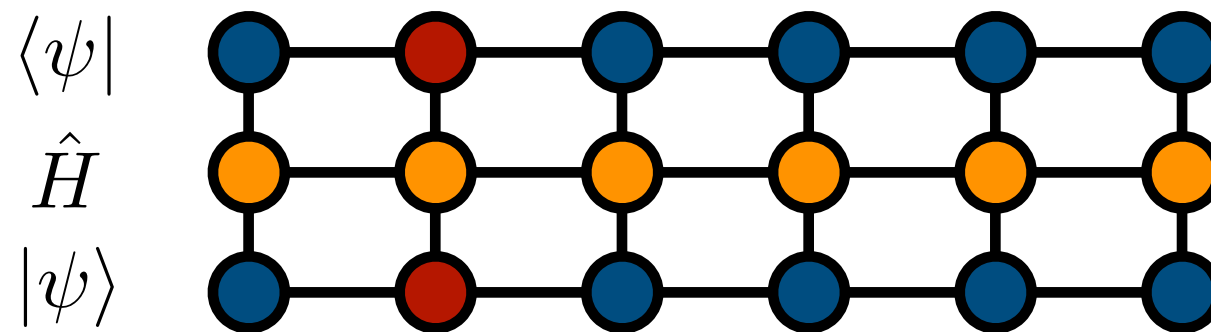
“Sweep” just like in DMRG, but solve a different local optimization problem (by integrating the local equation of motion induced by the Projected Hamiltonian $e^{-i\mathcal{P}_{|\psi(t)\rangle}H\delta t}$)



Tensor Network Algorithms

TDVP algorithm

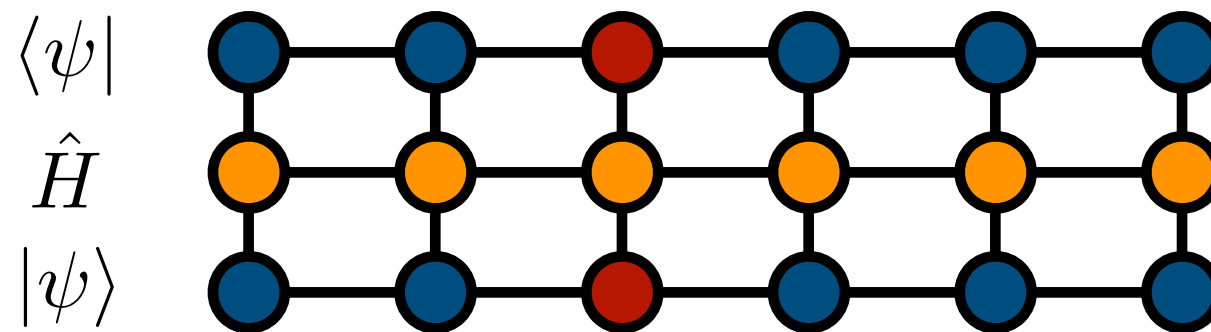
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Tensor Network Algorithms

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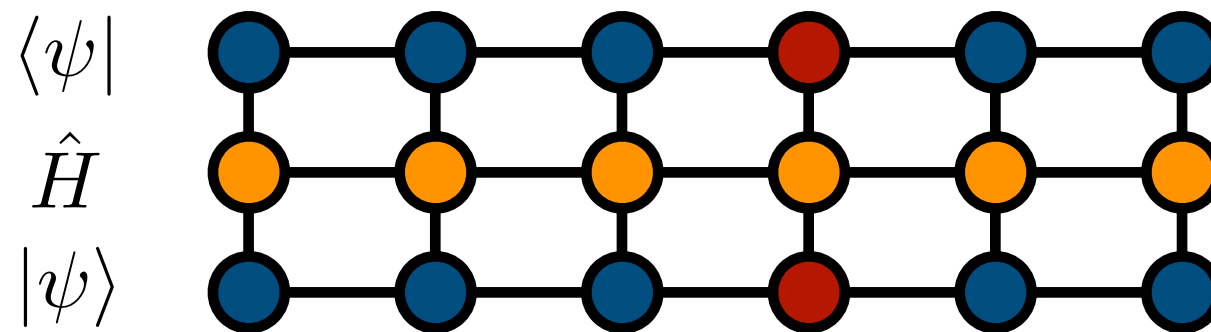
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Tensor Network Algorithms

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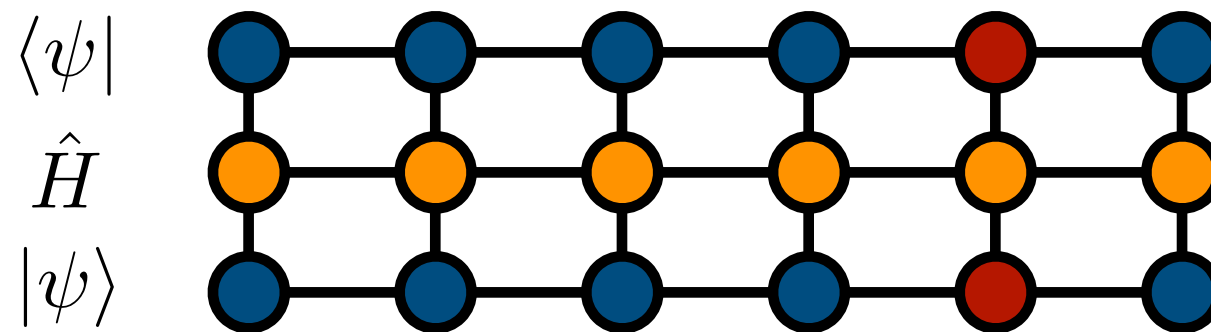
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Tensor Network Algorithms

TDVP algorithm

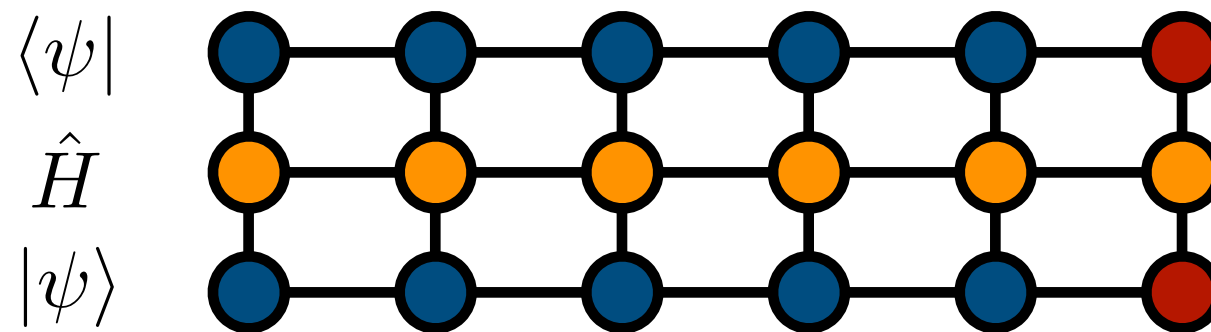
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Tensor Network Algorithms

TDVP algorithm

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Tensor Network Algorithms

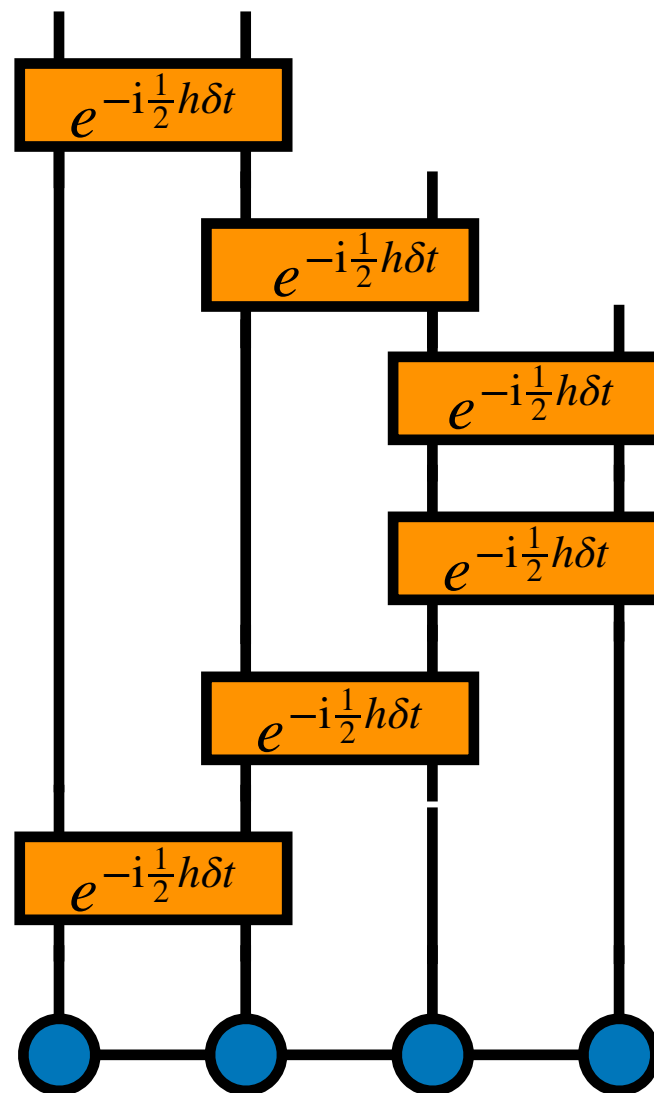
TDVP algorithm

- Sweeping algorithm, like DMRG. One-site version (fixed bond dimension) and two-site (adaptive bond dimension) versions exist.
- Scales as $\mathcal{O}(L\chi^3 t)$ for a fixed total time t , just like TEBD.
- Handles long-range interactions
- “State-of-the-art” for time evolving an MPS

TDVP and TEBD Applications

What can we do with these time-evolution algorithms?

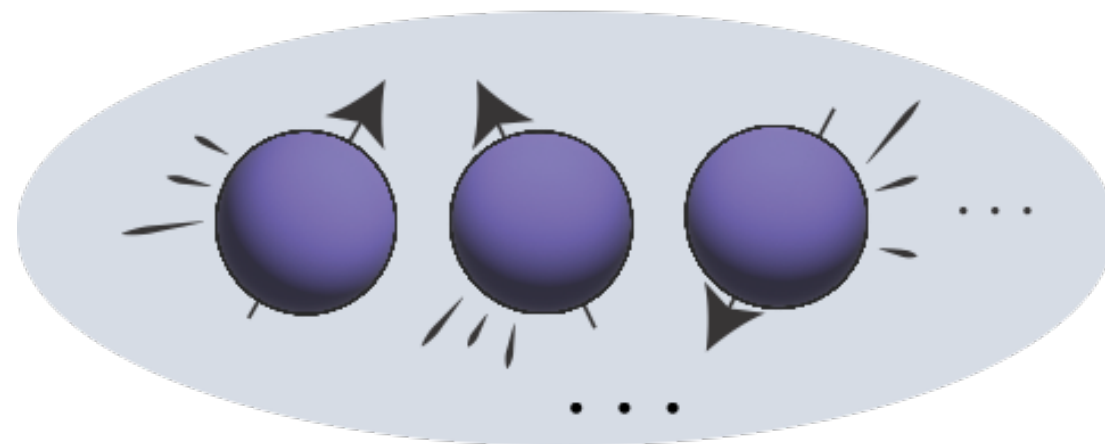
- Time evolving block decimation (TEBD)
- Time-dependent variational principle (TDVP)



TDVP and TEBD Applications

Quenches are the immediate use case of TEBD and TDVP

$$e^{-iHt} |\psi(0)\rangle = |\psi(t)\rangle$$

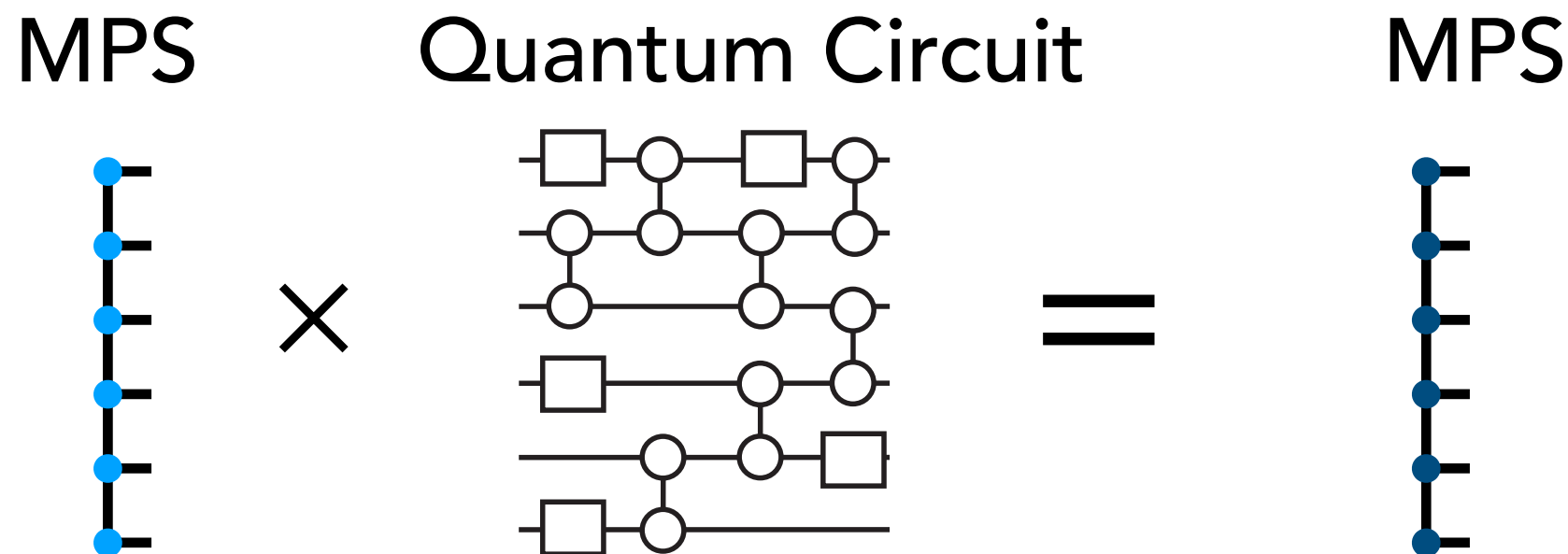


Algorithm Runtime: $\mathcal{O}(L\chi^3 t)$

Out-of-equilibrium physics is a very rich,
active research topic

TDVP and TEBD Applications

Simulating quantum circuits is possible with TEBD



Can even sample perfectly $x \sim P(x) = |\langle x | \psi \rangle|^2$ from an MPS $|\psi\rangle$ in $\mathcal{O}(L\chi^3)$ time

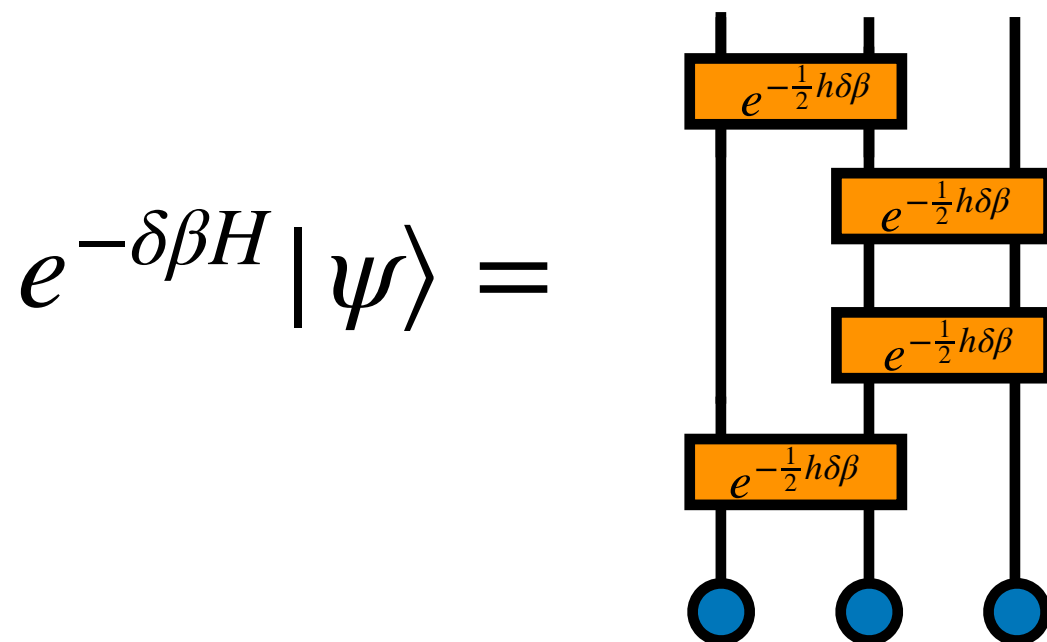
- Zhou, EMS, Waintal, "What Limits the Simulation of Quantum Computers?", [PRX 10, 041038](#) (2020)
- Ayral et al., "DMRG Algorithm for Simulating Quantum Circuits with a Finite Fidelity", [PRX Quantum 4, 020304](#) (2023)

TDVP and TEBD Applications

Imaginary time evolution (TEBD or TDVP)

We can evolve in imaginary time with $t \rightarrow i\beta$ to get ground states or even thermal states (by evolving an MPO)

$$\lim_{\beta \rightarrow \infty} e^{-\beta H} |\psi\rangle = \lim_{n \rightarrow \infty} \prod_{k=1}^n e^{-\delta\beta H} |\psi\rangle \rightarrow |\psi_{GS}\rangle$$



TDVP and TEBD Applications

We can even do finite temperature whilst staying in the pure state picture

First observe, for any basis, $\beta = \frac{1}{T}$

$$e^{-\beta \hat{H}} = \sum_i \underbrace{e^{-\frac{\beta}{2} \hat{H}} |i\rangle \langle i| e^{-\frac{\beta}{2} \hat{H}}}_{\text{Freedom to choose these}} \propto \sum_i |\phi_i\rangle \langle \phi_i|$$

Freedom to
choose these $|\phi_i\rangle \propto e^{-\frac{\beta}{2} \hat{H}} |i\rangle$

We have

$$e^{-\beta \hat{H}} = \sum_i e^{-\frac{\beta}{2} \hat{H}} |i\rangle \langle i| e^{-\frac{\beta}{2} \hat{H}} \propto \sum_i |\phi_i\rangle \langle \phi_i|$$

Obtain observables as

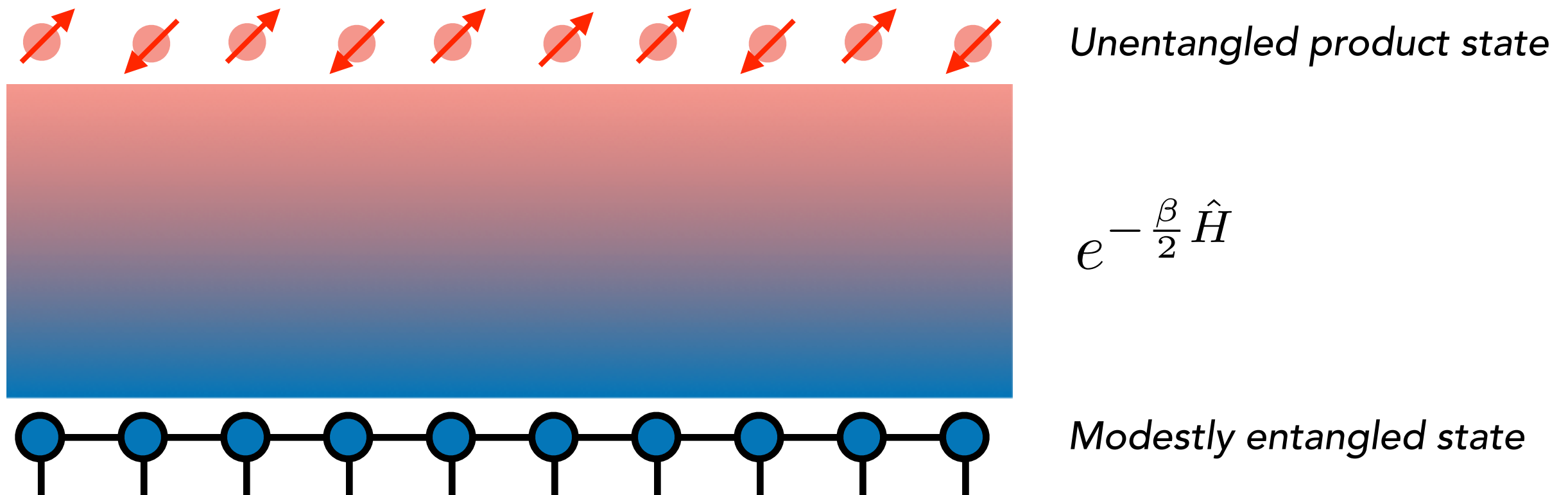
$$\langle \hat{A} \rangle = \frac{1}{\mathcal{Z}} \text{Tr} [e^{-\beta \hat{H}} \hat{A}] = \frac{1}{\mathcal{Z}} \sum_i P_i \langle \phi_i | \hat{A} | \phi_i \rangle$$

↑
an average over
pure states

Expanding $e^{-\beta \hat{H}} \propto \sum_i |\phi_i\rangle \langle \phi_i|$

To give tensor networks their best chance

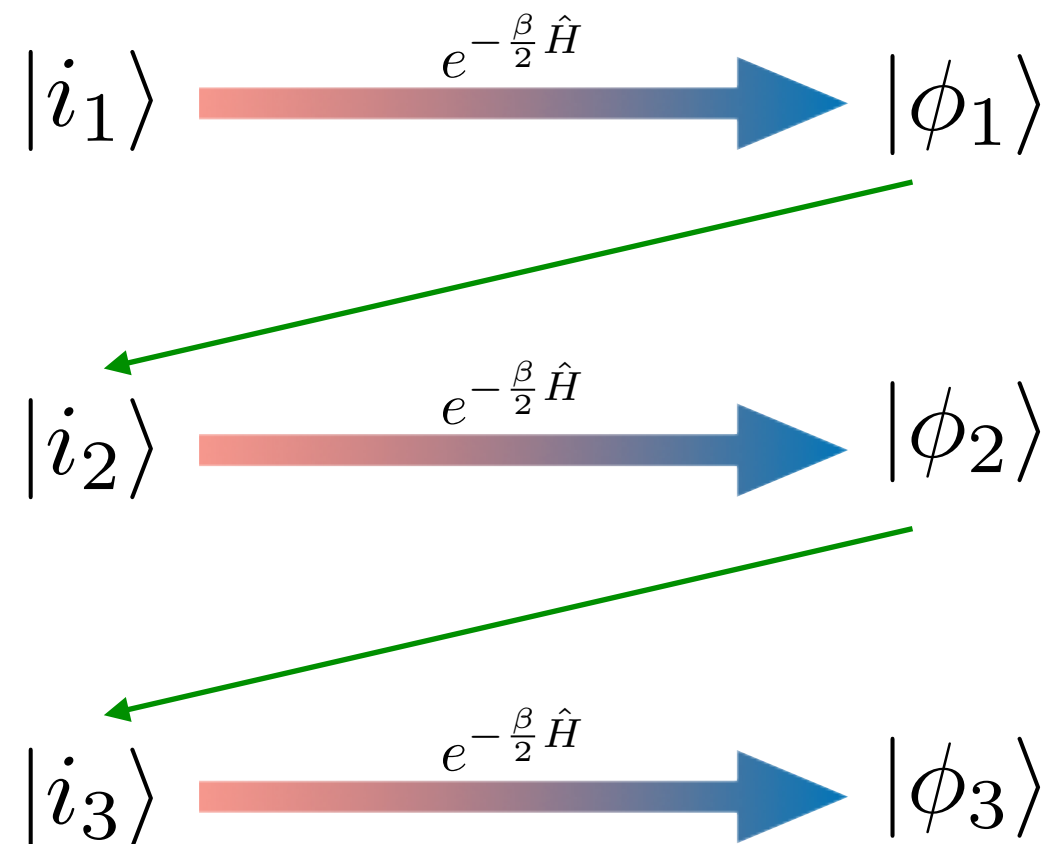
choose $|\phi_i\rangle \propto e^{-\frac{\beta}{2} \hat{H}} |i\rangle$ to "descend" from
untangled (zero-entanglement) states



- ☑ **Solved** problem of representing $|\phi_i\rangle \propto e^{-\frac{\beta}{2}\hat{H}}|i\rangle$
(choose $|i\rangle$ as product states)

One more **problem**: too many states –
there are exponentially many $|i\rangle$ and thus $|\phi_i\rangle$

- ☑ **Solution**: sample over the $|i\rangle$



$$p(\phi_1 \rightarrow i_2) = |\langle i_2 | \phi_1 \rangle|^2$$

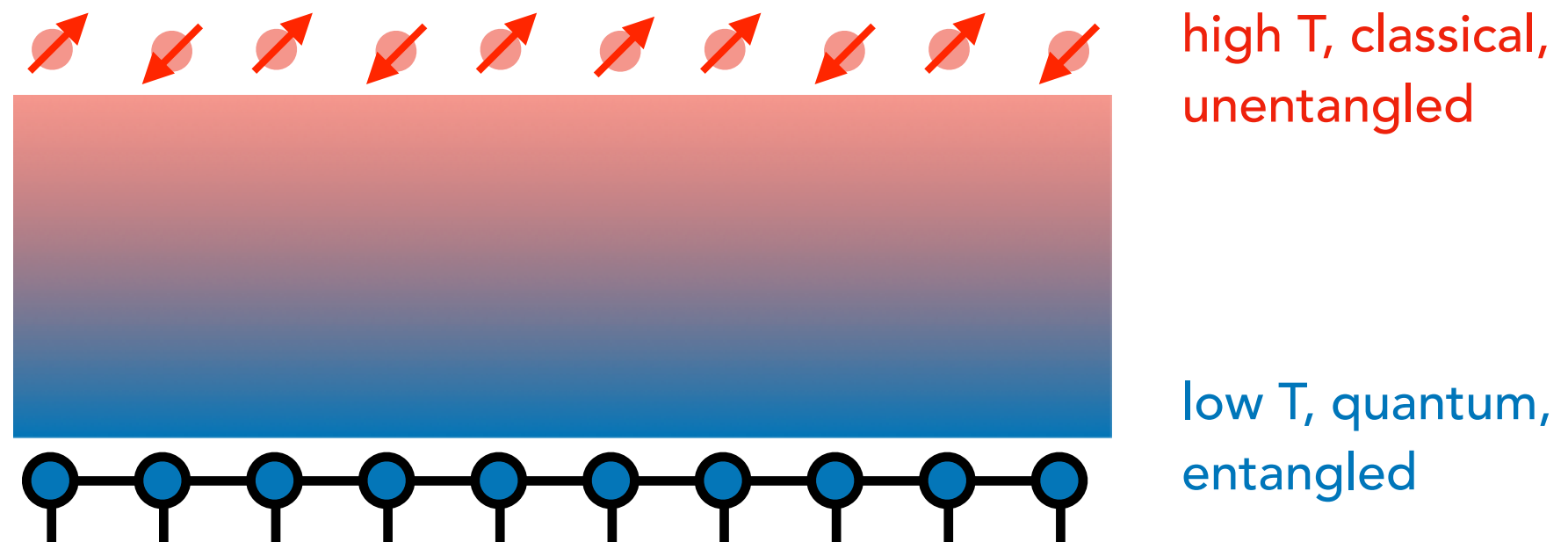
$$p(\phi_2 \rightarrow i_3) = |\langle i_3 | \phi_2 \rangle|^2$$

Algorithm just described named
minimally entangled typical thermal states (**METTS**)^{1,2}

$$|\phi_i\rangle \propto e^{-\frac{\beta}{2} \hat{H}} |i\rangle \quad \text{METTS wavefunction}$$

Quantum Monte Carlo where samples are
entangled wavefunctions, not classical configurations

Classicality of METTS depend on T

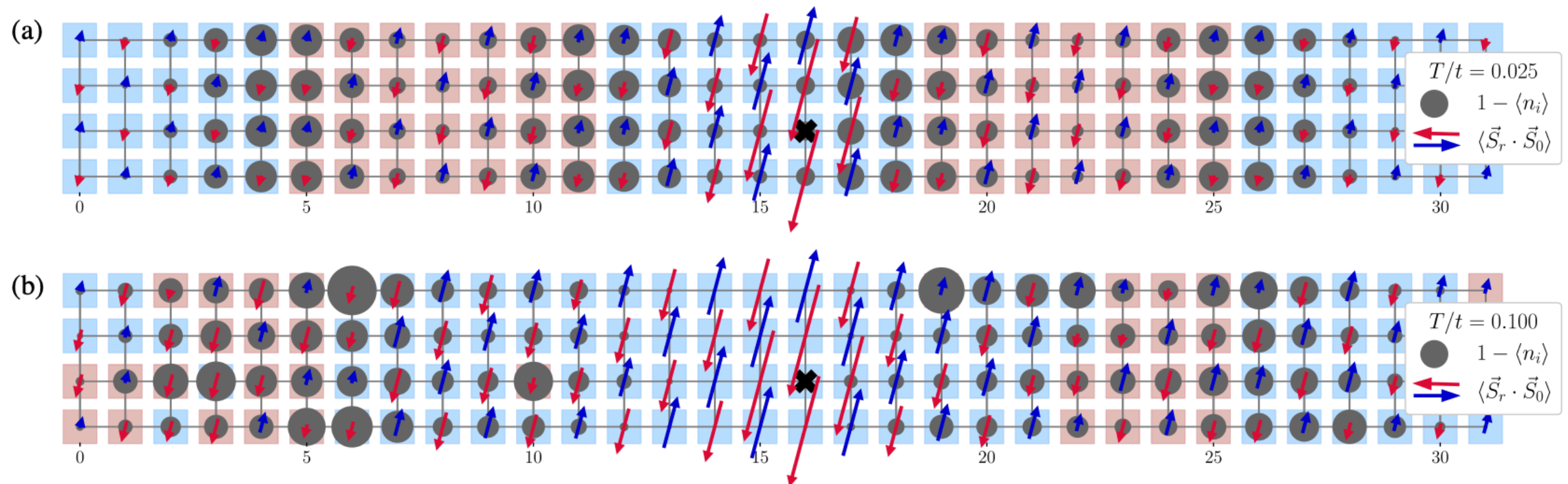


[1] S.R. White, PRL (2009)

[2] Stoudenmire, White, NJP (2010)

Minimally entangled typical thermal states (METTS)

Used by researchers here at CCQ to study finite temperature electronic systems [1]:



[1] A. Wietek et al, PRX 11 (2021)

Further Applications of TDVP and TEBD

- Open Quantum Systems $\rho(t) = \exp(\mathcal{L}t)\rho(0)$
- Green's functions
- OTOCS (Out-of-time ordered correlators)
- Many more...
- Now lets do some time evolution with [ITensorMPS.jl](#)