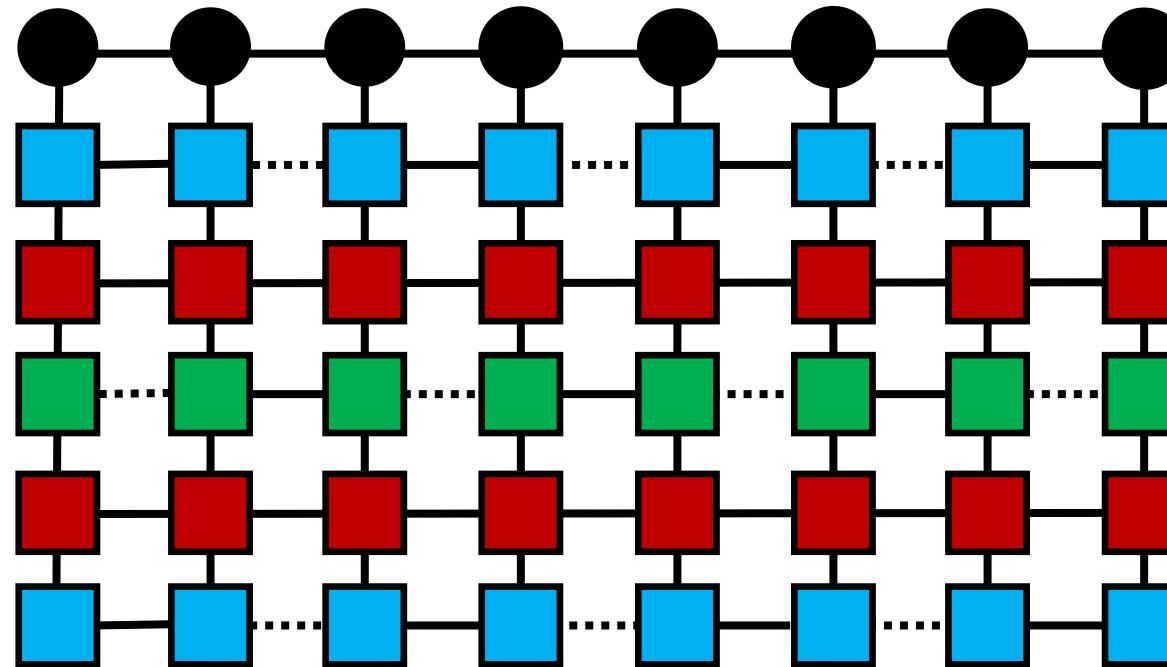


# An Introduction to Matrix Product State Algorithms

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# Matrix Product States

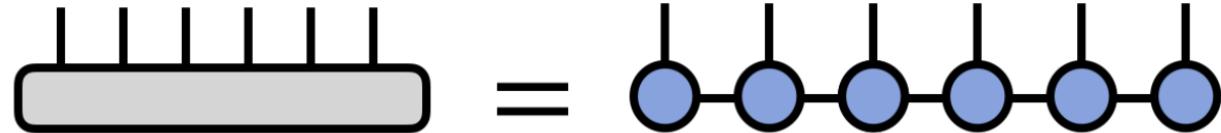
<https://tensornetwork.org>

## Tensor Networks

Matrix

$M_{ij}$

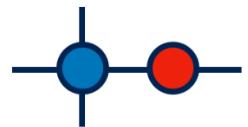
$i - \bullet - j$



3-legged Tensor

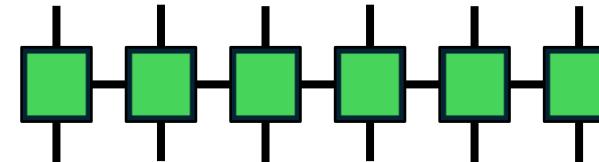
$T_{ijk}$

$i - \bullet - k$   
  |  
  j



$$= \sum_k T_{ijkl} V_{km}$$

$$T^{s_1 s_2 s_3 s_4 s_5 s_6} = \sum_{\{\alpha\}} A_{\alpha_1}^{s_1} A_{\alpha_1 \alpha_2}^{s_2} A_{\alpha_2 \alpha_3}^{s_3} A_{\alpha_3 \alpha_4}^{s_4} A_{\alpha_4 \alpha_5}^{s_5} A_{\alpha_5}^{s_6}$$



N – Length of MPS

d – size of the physical dimensions e.g. 2 for spins

D – size of largest bond dimensions

- Approximate tensor of size  $d^N$  with MPS of size  $N d D^2$
- Bond dimensions transfer information between one site to the next
- Smaller bond dimension = More compression
- Larger bond dimensions = More ‘entanglement’

# Matrix Product States

# Tensor Cross Interpolation

- Can discretise function onto a tensor
  - We can express any tensor as an MPS
  - Compression of the MPS representation for a given error threshold depends on the structure of the function
  - MPS of function allows for applications such as integration or Fourier transform

$$F_{\sigma} = f(\mathbf{x}(\sigma)) = \begin{array}{ccccccccccccc} & & & & & & & & & & & & & & \\ \hline & \sigma_{11} & \cdots & \sigma_{N1} & \sigma_{12} & \cdots & \sigma_{N2} & & \cdots & & \sigma_{1R} & \cdots & \sigma_{NR} \\ \\ & = & & & & & & & & & & & & & \\ & \sigma_1 & \sigma_2 & \cdots & & \sigma_\ell & & & & \cdots & & & & \sigma_{\mathcal{L}} \end{array}$$

$$F_{\boldsymbol{\sigma}} \approx \tilde{F}_{\boldsymbol{\sigma}} = \prod_{\ell=1}^{\mathcal{L}} M_{\ell}^{\sigma_{\ell}} = [M_1]_{1a_1}^{\sigma_1} [M_2]_{a_1 a_2}^{\sigma_2} \cdots [M_{\mathcal{L}}]_{a_{\mathcal{L}-1} 1}^{\sigma_{\mathcal{L}}}$$

$$\begin{array}{c} F \\ \hline \sigma_1 \sigma_2 \quad \cdots \quad \sigma_\ell \quad \cdots \quad \sigma_{\mathcal{L}} \end{array} \approx \begin{array}{ccccccccc} & M_1 & \chi_1 & M_2 & \chi_2 & & M_\ell & \chi_\ell & M_{\mathcal{L}} \\ \times & a_0 & \sigma_1 & a_1 & \sigma_2 & a_2 & \cdots & \sigma_\ell & a_\ell & \cdots & \sigma_{\mathcal{L}} & a_{\mathcal{L}} & \times \end{array}.$$

# Matrix Product States

<https://tensornetwork.org>

## Basic Operations

Tensor Contraction:

$$\begin{aligned} & \text{Diagram showing two ways to contract a 2D grid of red and blue circles.} \\ & \text{Top row: Direct contraction resulting in } \langle \phi | \psi \rangle. \\ & \text{Bottom row: Contracting a vertical column first, resulting in a diagram with a grey L-shaped connector.} \end{aligned}$$

Expectation values:

$$\text{Diagram showing a 2D grid of red and blue circles with green squares placed over them, representing operators. This is equated to } \langle \psi | \hat{O} | \psi \rangle.$$

Efficient contraction algorithms have time complexity  $O(dD^3N)$

Canonical Forms:

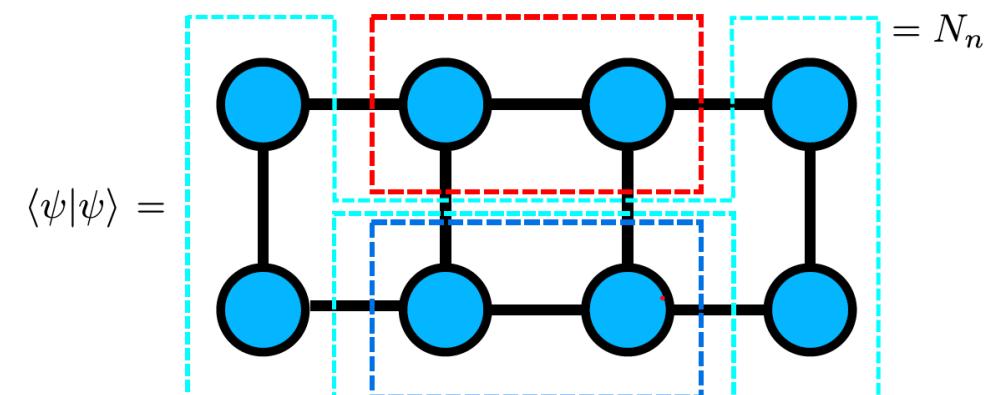
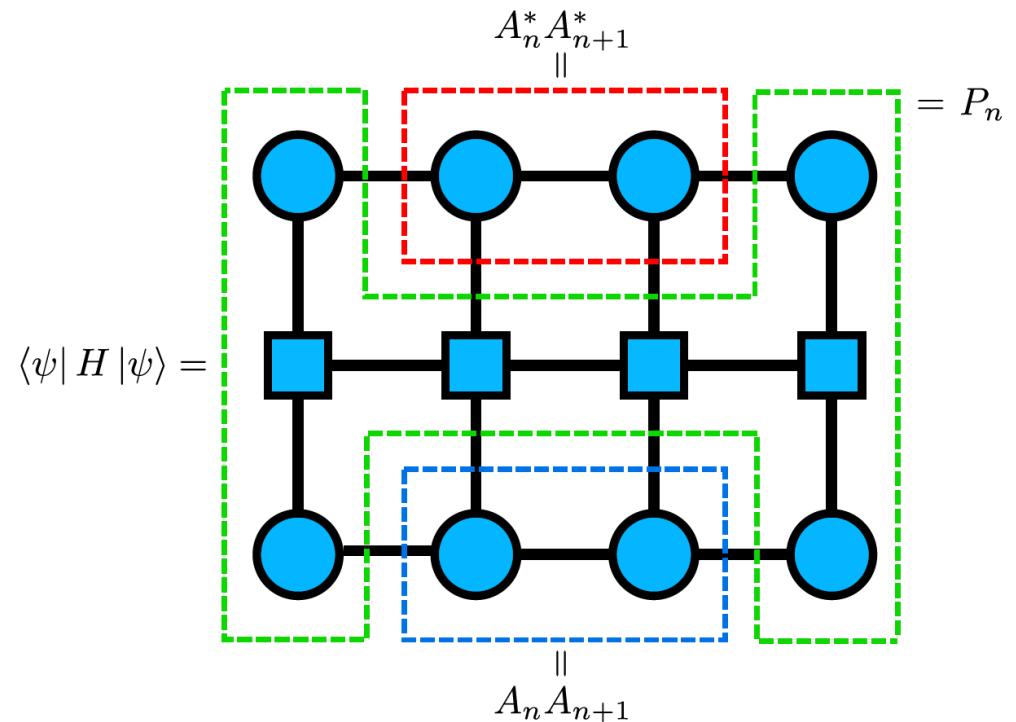
$$\text{Diagram showing a sequence of tensors: red circle - red circle, followed by } =, \text{ then } A, A^{-1}, A, A^{-1}, \text{ followed by } =, \text{ then green circle - green circle, followed by a comma.}$$

$$\text{Diagram showing a blue circle connected to a blue circle with a curved arrow above it, labeled } U^\dagger, \text{ followed by } =, \text{ then a simple black loop.}$$

# DMRG

## The Algorithm

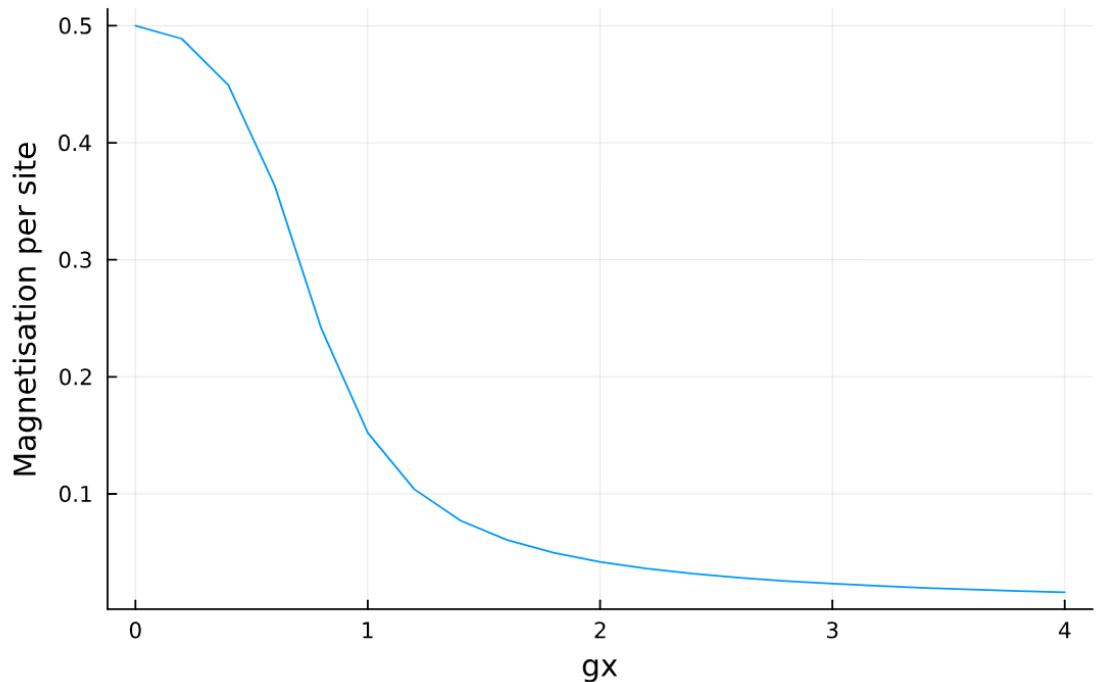
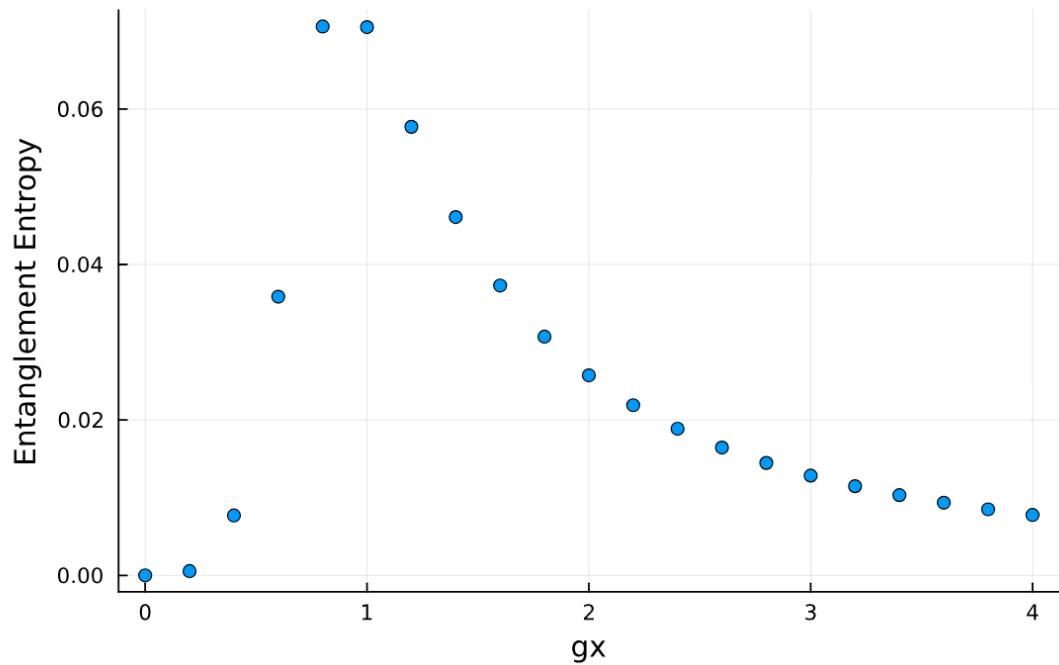
- Used to find the ground state of Hamiltonians expressed as Matrix Product Operators.
- Minimise the energy,  $E = \frac{\langle \psi | H | \psi \rangle}{\langle \psi | \psi \rangle}$  with respect to two sites at a time.
- Canonical forms simplify the calculation of  $N_n$ , at each site the equation to be solved is  
$$P_n(A_n A_{n+1}) = E(A_n A_{n+1})$$
- The algorithm sweeps left and right updating sites until the percentage change in energy is below threshold for convergence
- Improve efficiency by storing and updating  $P_n$  at each step for reuse to avoid calculating contractions



# DMRG

## Transverse Field Ising Model

$$\hat{H} = J \sum_{i=1}^{N-1} Z_i Z_{i+1} + g_x \sum_{i=1}^N X_i + g_z \sum_{i=1}^N Z_i$$



## Schwinger Model

$$\mathcal{H} = -i\bar{\psi}\gamma^1 (\partial_1 - igA_1) \psi + m\bar{\psi}\psi + \frac{1}{2} \left( \dot{A}_1 + \frac{g\theta}{2\pi} \right)^2$$

$$\Rightarrow H_W = x(r-1) \sum_{n=0}^{N-2} (\sigma_{2n}^+ Z_{2n+1} Z_{2n+2} \sigma_{2n+3}^- + \text{h.c.})$$

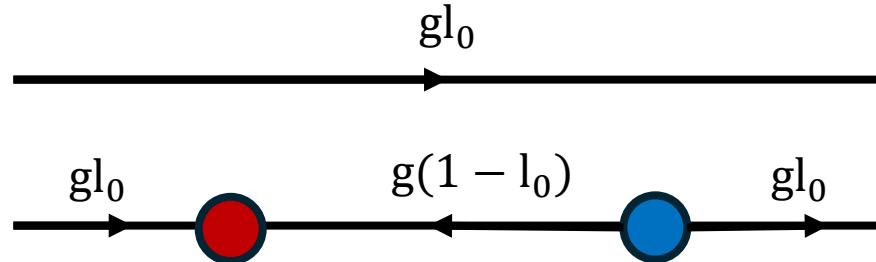
$$+ \frac{x(r+1)}{2} \sum_{n=0}^{N-2} (X_{2n+1} X_{2n+2} + Y_{2n+1} Y_{2n+2})$$

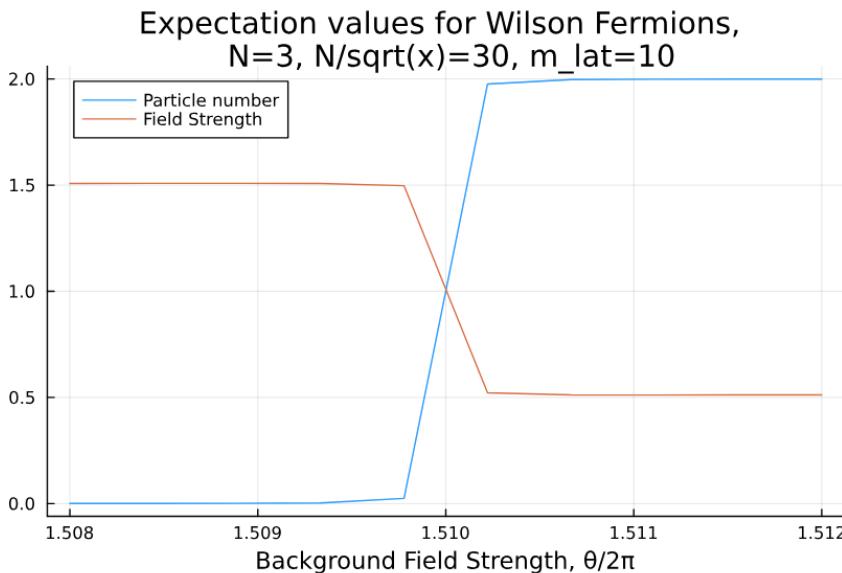
$$+ \left( \frac{m_{\text{lat}}}{g} \sqrt{x} + xr \right) \sum_{n=0}^{N-1} (X_{2n} X_{2n+1} + Y_{2n} Y_{2n+1})$$

$$+ \frac{1}{2} \sum_{n=0}^{2N-1} \sum_{k=n+1}^{2N-1} \left( N - \left\lceil \frac{k+1}{2} \right\rceil + \lambda \right) Z_n Z_k$$

$$+ l_0 \sum_{n=0}^{2N-3} \left( N - \left\lceil \frac{n+1}{2} \right\rceil \right) Z_n$$

$$+ l_0^2(N-1) + \frac{1}{4}N(N-1) + \frac{\lambda N}{2}$$



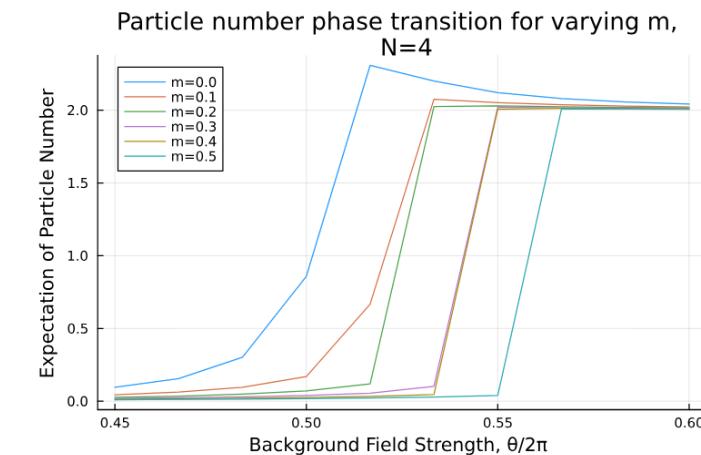
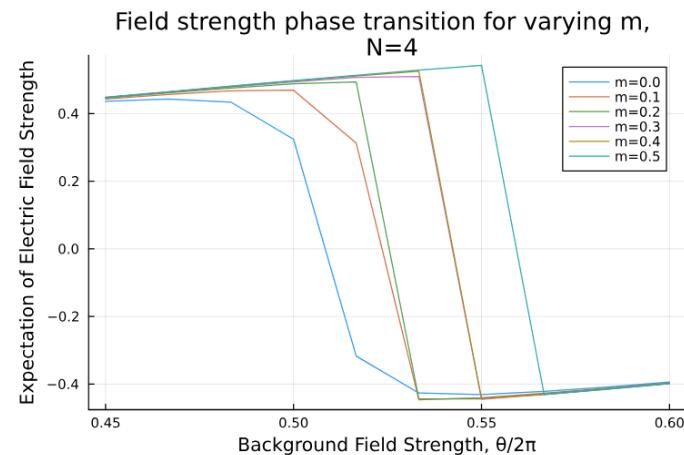


## First Order Phase Transition:

- Mass  $> 0.33$ , transition expected at  $\theta/2\pi = l_0 = 0.5$  (lattice effects change the location of the phase transition)
- Pair production: particle number jumps from 0 to 2
- Particles screen the background field: field strength drops

## Second Order Phase Transition:

- For masses below 0.33, no phase transition
- See particle number and field strength change smoothly



# TEBD

## The Algorithm

$$\begin{aligned}\hat{U}^{\text{exact}}(\delta) &= e^{-i\delta\hat{H}} \\ &= e^{-i\delta\hat{H}_{\text{even}}}e^{-i\delta\hat{H}_{\text{odd}}}e^{-i\delta^2[\hat{H}_{\text{even}}, \hat{H}_{\text{odd}}]} \\ &\approx e^{-i\delta\hat{H}_{\text{even}}}e^{-i\delta\hat{H}_{\text{odd}}} \\ &\equiv \hat{U}^{\text{TEBD1}}(\delta).\end{aligned}$$

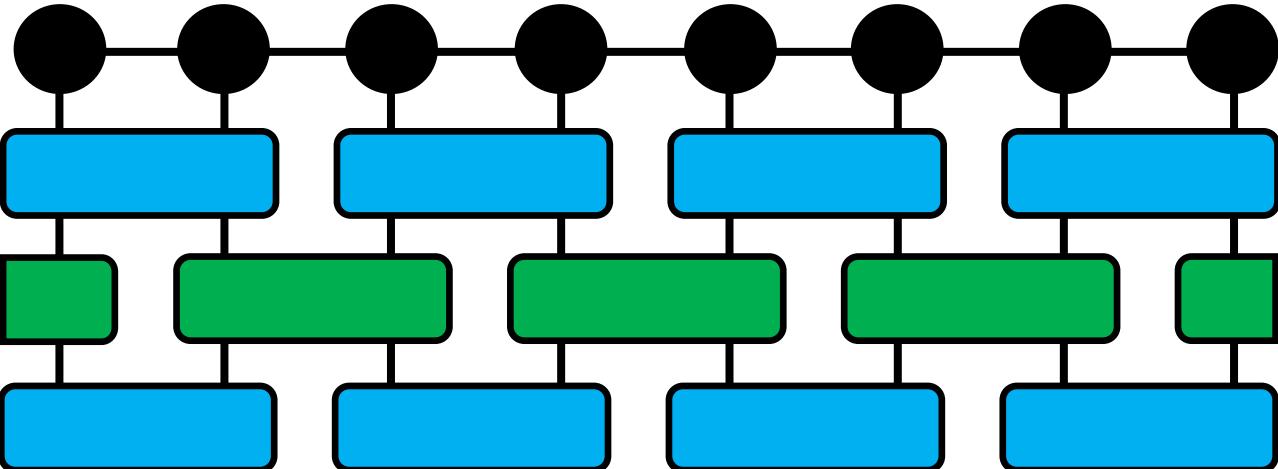
$$e^{-i\delta\hat{H}_{\text{even}}} = e^{-i\delta \sum_{j \text{ even}} \hat{h}_{j,j+1}} = \prod_{j \text{ even}} e^{-i\delta\hat{h}_{j,j+1}}$$

$$\hat{U}^{\text{TEBD2}}(\delta) \equiv e^{-i\frac{\delta}{2}\hat{H}_{\text{even}}}e^{-i\delta\hat{H}_{\text{odd}}}e^{-i\frac{\delta}{2}\hat{H}_{\text{even}}}$$

Split the Hamiltonian into internally commuting parts which have terms that can be exponentiated individually

TEBD2 has error  $O(\delta^2)$  per time step  $T/\delta$

$$\hat{H} = \sum_j \hat{h}_{j,j+1}$$

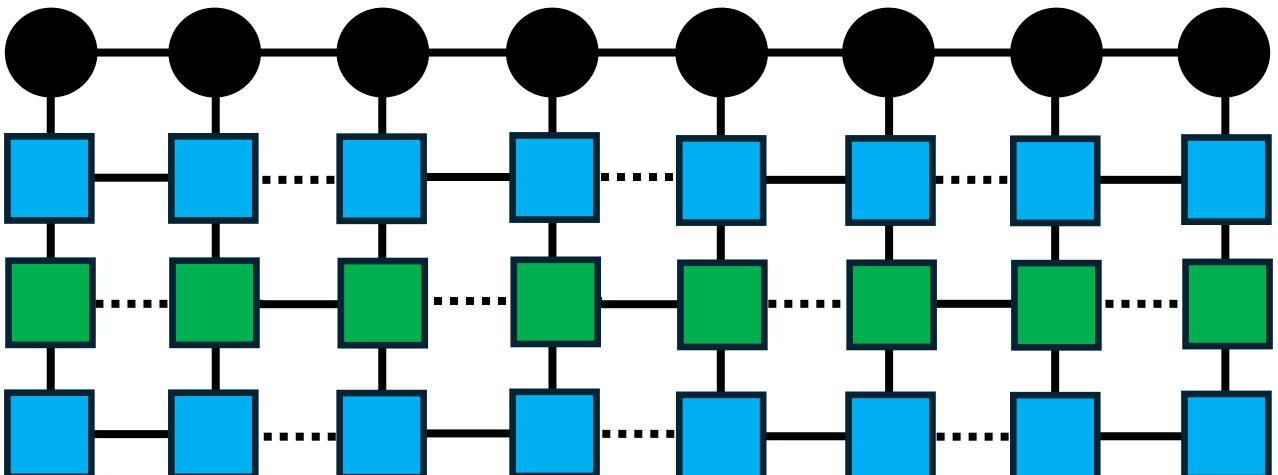


$|\psi\rangle$

$$\hat{U}_{\text{Odd}} = e^{-i\delta\hat{H}_{\text{Odd}}/2}$$

$$\hat{U}_{\text{Even}} = e^{-i\delta\hat{H}_{\text{Even}}}$$

$$\hat{U}_{\text{Odd}} = e^{-i\delta\hat{H}_{\text{Odd}}/2}$$



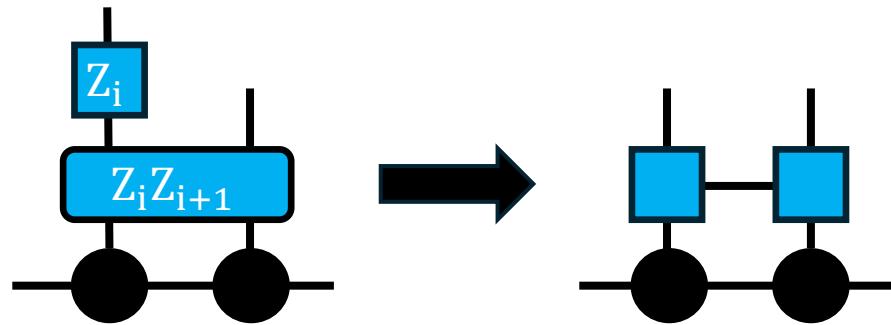
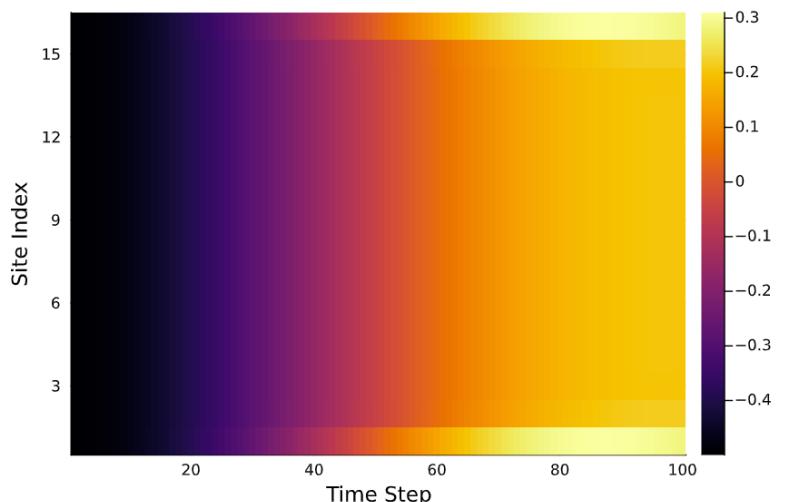
# TEBD

## Transverse Field Ising Model

Split Hamiltonian in two:  
Z terms ( $Z_i Z_{i+1}$  and  $Z_i$ ), and X (transverse)  
terms. Internally commute as same Paulis

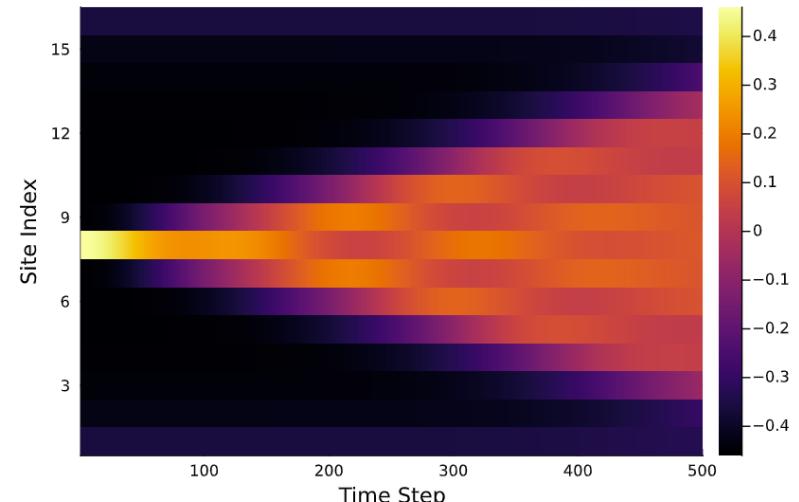
Quenches:

- Find the ground state with no external field
- Time evolve with an external field
- See how the spins change



Spinons:

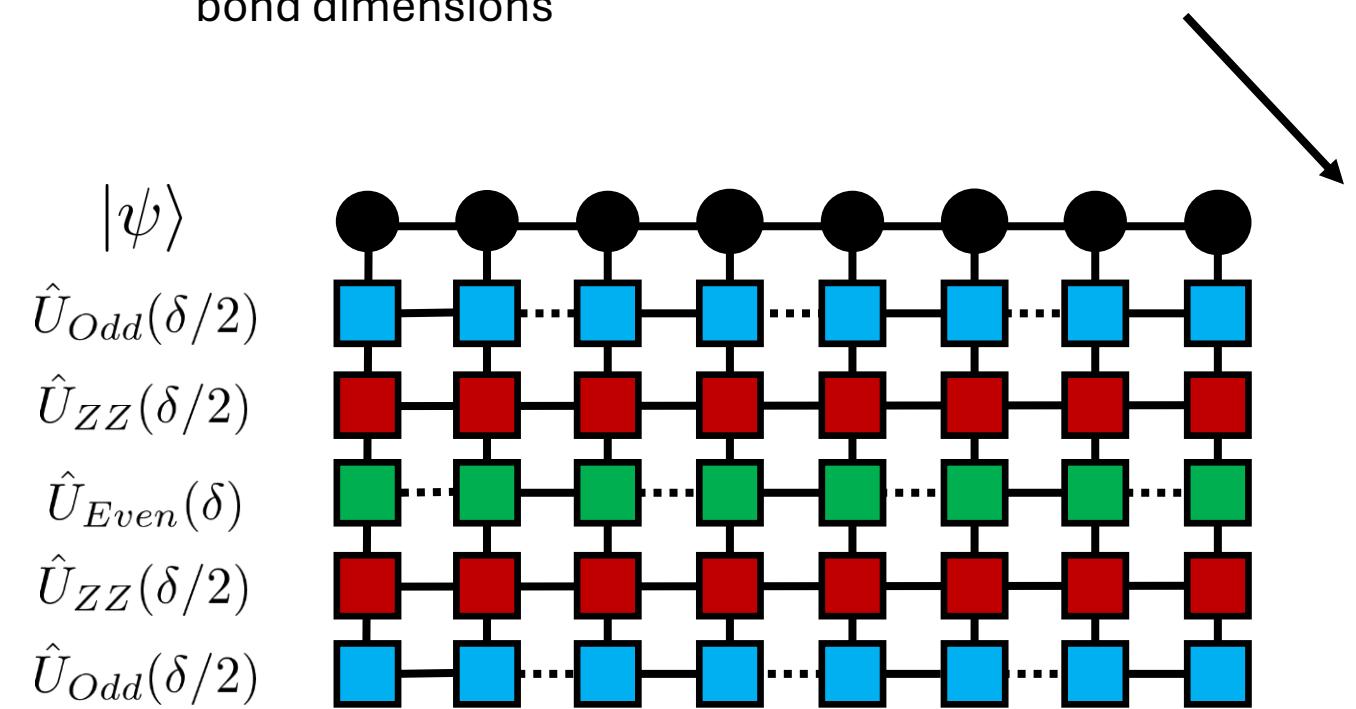
- Find the ground state with an external field
- Flip one spin in ground state
- See how the entanglement grows through the system



# TEBD

## Time Dependent Schwinger Model

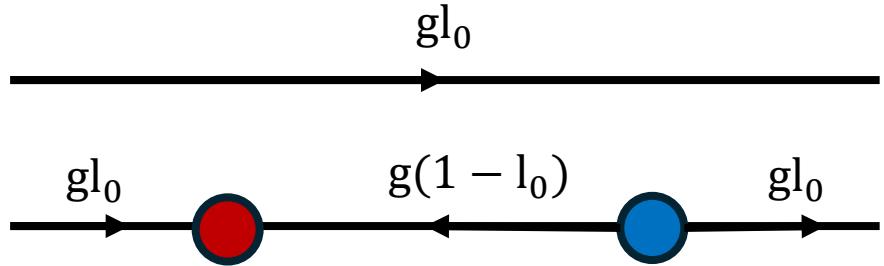
The Schwinger Hamiltonian has long range  $Z_i Z_j$  interaction terms which are inefficient to express with gates – can do it by implementing swaps but it is costly – so we separate them from the rest and approximate the terms with an MPO of truncated bond dimensions



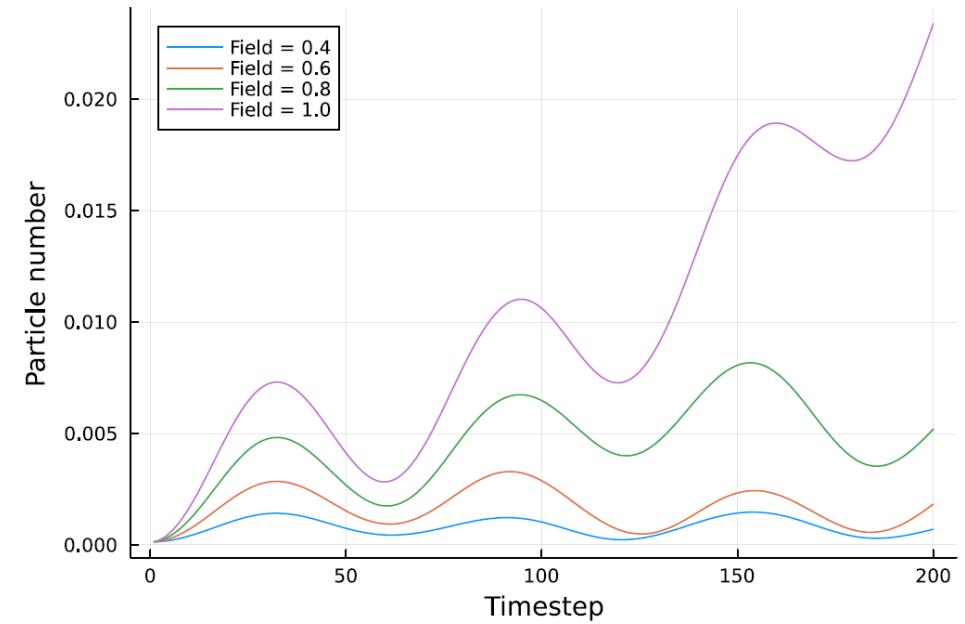
$$\begin{aligned}
 H_W = & x(r-1) \sum_{n=0}^{N-2} (\sigma_{2n}^+ Z_{2n+1} Z_{2n+2} \sigma_{2n+3}^- + \text{h.c.}) \\
 & + \frac{x(r+1)}{2} \sum_{n=0}^{N-2} (X_{2n+1} X_{2n+2} + Y_{2n+1} Y_{2n+2}) \\
 & + \left( \frac{m_{\text{lat}}}{g} \sqrt{x} + xr \right) \sum_{n=0}^{N-1} (X_{2n} X_{2n+1} + Y_{2n} Y_{2n+1}) \\
 & + \boxed{\frac{1}{2} \sum_{n=0}^{2N-1} \sum_{k=n+1}^{2N-1} \left( N - \left\lceil \frac{k+1}{2} \right\rceil + \lambda \right) Z_n Z_k} \\
 & + l_0 \sum_{n=0}^{2N-3} \left( N - \left\lceil \frac{n+1}{2} \right\rceil \right) Z_n \\
 & + l_0^2(N-1) + \frac{1}{4}N(N-1) + \frac{\lambda N}{2}
 \end{aligned}$$

# TEBD

## Time Dependent Schwinger Model



When we quench the Hamiltonian from no external field to different values, we see oscillations in particle number



# Other Applications of Matrix Product States

Thanks for Listening!

- Integrating Feynman diagrams for high energy physics
- Machine learning
- Simulating quantum Fourier transform
- Simulating and benchmarking quantum computing
- Solving PDEs

