

 TensorNet : A High-Performance
Tensor-Network-Based Toolkit
for Many-Body Quantum Simulations

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Outline

- Motivation
- A short introduction to TNs
- Existing Toolkits
- QTensorNet
- Decorated Square-Kagome Heisenberg Antiferromagnet
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Motivation

- **Simulation Bottleneck:**

The dimension of the Hilbert space of an N -particle quantum system grows exponentially with N , making exact diagonalization and unitary dynamics simulation infeasible for realistic system sizes.

- **Quantum Computation:**

Classical simulation of many-body quantum systems becomes crucial for the development, validation, and benchmarking of quantum algorithms and quantum hardware architectures.

- **Role of Tensor Networks (TNs):**

Tensor network approaches exploit the area law for entanglement entropy to efficiently approximate low-energy states of Hamiltonians of gapped systems with local interactions, enabling the simulation of such systems that are otherwise inaccessible to conventional methods.

TNs & Thin SVD

Matrix Product State (MPS):

$|\Psi\rangle_N = \sum_{\{s_i=1,\dots,d\}} \psi_{s_1,\dots,s_N} |s_1 \dots s_N\rangle$, where $\psi_{s_1,\dots,s_N}$ is a d^N -dimensional tensor.

$$\psi_{s_1, s_2, \dots, s_N} = A_{1, s_1, \alpha_1}^{(1)} A_{\alpha_1, s_2, \alpha_2}^{(2)} \dots A_{\alpha_{N-2}, s_{N-1}, \alpha_{N-1}}^{(N-1)} A_{\alpha_{N-1}, s_N, 1}^{(N)} \Rightarrow \begin{array}{c} \boxed{A^{(1)}} \text{---} \boxed{A^{(2)}} \text{---} \dots \text{---} \boxed{A^{(N-1)}} \text{---} \boxed{A^{(N)}} \\ \downarrow \quad \downarrow \quad \quad \quad \downarrow \quad \downarrow \\ s_1 \quad s_2 \quad \quad \quad s_{N-1} \quad s_N \end{array}$$

Number of parameters: $d^N \rightarrow dN\chi_{\max}^2$

Matrix Product Operator (MPO):

$\hat{O} = \sum_{\{s_i=1,\dots,d\}} \sum_{\{s'_i=1,\dots,d\}} o_{s_1,\dots,s_N, s'_1,\dots,s'_N} |s_1 \dots s_N\rangle \langle s'_1 \dots s'_N|$, where $o_{s_1,\dots,s_N, s'_1,\dots,s'_N}$ is a $d^N \times d^N$ -dimensional tensor.

$$o_{s_1,\dots,s_N, s'_1,\dots,s'_N} = B_{1, (s_1, s'_1), \beta_1}^{(1)} B_{\beta_1, (s_2, s'_2), \beta_2}^{(2)} \dots B_{\beta_{N-2}, (s_{N-1}, s'_{N-1}), \beta_{N-1}}^{(N-1)} B_{\beta_{N-1}, (s_N, s'_N), 1}^{(N)} \Rightarrow \begin{array}{c} \boxed{B^{(1)}} \text{---} \boxed{B^{(2)}} \text{---} \dots \text{---} \boxed{B^{(N-1)}} \text{---} \boxed{B^{(N)}} \\ \downarrow \quad \downarrow \quad \quad \quad \downarrow \quad \downarrow \\ s_1 \quad s_2 \quad \quad \quad s_{N-1} \quad s_N \\ \downarrow \quad \downarrow \quad \quad \quad \downarrow \quad \downarrow \\ s'_1 \quad s'_2 \quad \quad \quad s'_{N-1} \quad s'_N \end{array}$$

Number of parameters: $d^N \times d^N \rightarrow d^2 N \chi_{\max}^2$

Thin Singular Value Decomposition (SVD):

$$A_{n,m} = S_{n,k} V_{k,k} (D^\dagger)_{k,m}, A \in \mathbb{C}^{q \times g}, S^\dagger S = I, D^\dagger D = I.$$

Here, S is a left singular vectors,

V is a diagonal matrix of singular values,

$D^\dagger$ is a right singular vectors.

$$\begin{array}{c} \xrightarrow{g} \\ \boxed{A} \\ \xleftarrow{q} \end{array} = \begin{array}{c} \xrightarrow{r} \\ \boxed{S} \\ \xleftarrow{q} \end{array} \times_r \begin{array}{c} \xrightarrow{r} \\ \boxed{V} \\ \xleftarrow{r} \end{array} \times_r \begin{array}{c} \xrightarrow{g} \\ \boxed{D^\dagger} \\ \xleftarrow{r} \end{array}$$

Time-Dependent Variational Principle

Variational formulation of the Schrödinger equation:

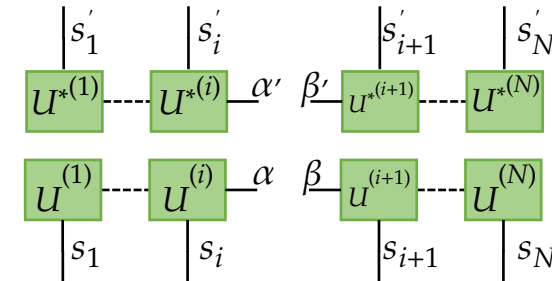
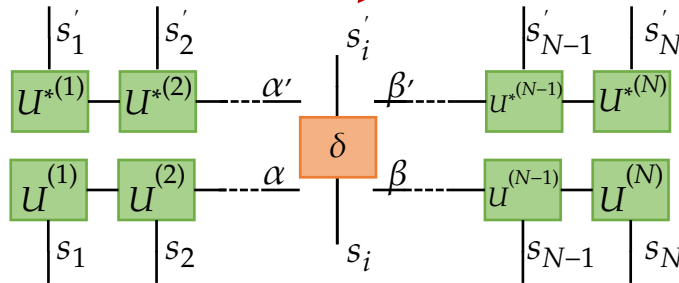
$$\min_{|\Psi^{TN}(t)\rangle} \left| \frac{d}{dt} |\Psi^{TN}(t)\rangle + \frac{i}{\hbar} \hat{H}(t) |\Psi^{TN}(t)\rangle \right|^2 \quad \forall t \in [t_{min}, t_{max}]$$

The tangent space projection operator (only loop-free TNs):

$$\frac{d}{dt} |\Psi^{TN}(t)\rangle = -\frac{i}{\hbar} \hat{P}_{|\Psi^{TN}(t)\rangle} \hat{H}(t) |\Psi^{TN}(t)\rangle$$

$$\hat{P}_{|\Psi^{TN}\rangle} = \sum_{i=1}^N \mathbb{I}^{(i)} \otimes \underbrace{\sum_{Q_i} |q_1^{[i]}, \dots, q_{r_i}^{[i]}\rangle \langle q_1^{[i]}, \dots, q_{r_i}^{[i]}|}_{\text{left part}} - \underbrace{\sum_{(i,j)_k} \sum_{q_k, q'_k} |q_k^{[j]}\rangle \langle q_k^{[j]}| \otimes |q_k^{[i]}\rangle \langle q_k^{[i]}|}_{\text{right part}}$$

Here, $|q_k^{[i]}\rangle$ is the orthonormal basis state of the TTN segment attached to site i through link q_k when the network is orthogonalized around i .



Density Matrix Renormalization Group

Variational formulation for the ground-state problem:

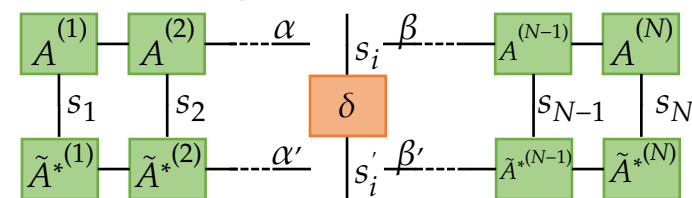
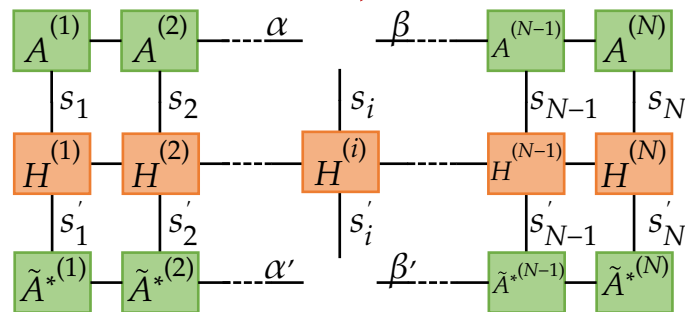
$$\min_{|\Psi^{TN}\rangle} \langle \Psi^{TN} | \hat{H} | \Psi^{TN} \rangle$$

at $\langle \Psi^{TN} | \Psi^{TN} \rangle = 1$

Lagrange multiplier method:

$$L = \langle \Psi^{TN} | \hat{H} | \Psi^{TN} \rangle - \lambda (\langle \Psi^{TN} | \Psi^{TN} \rangle - 1)$$

$$\frac{\delta L}{\delta \tilde{A}^{(i)*}} = 0 \rightarrow \hat{H}_{eff}^{(i)} \tilde{A}^{(i)} = \lambda_{min}^{(i)} \hat{N}^{(i)} \tilde{A}^{(i)}$$



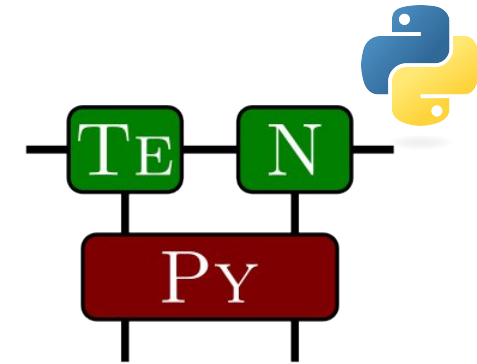
Existing Toolkits

The most widely used and functional TN toolkits are iTensor and TeNPy.

- iTensor features:
 - Utilizes a single CPU or GPU
 - Provides intuitive "smart index" algebra
 - Focuses mainly on MPS/MPO
 - Makes custom geometries hard to build
- TeNPy features:
 - Utilizes only a CPU
 - Focuses mainly on MPS/MPO
 - Makes custom geometries hard to build

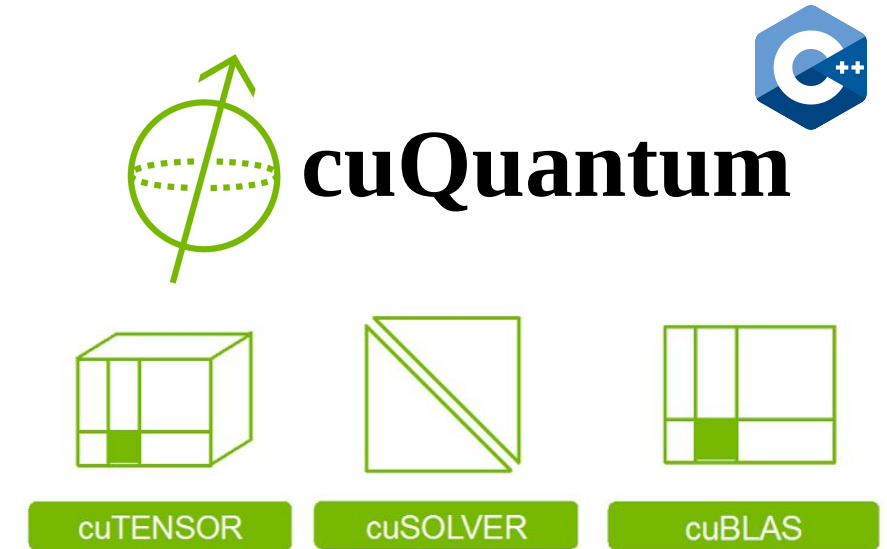
An alternative is Nvidia-developed cuQuantum package.

- cuQuantum benefits:
 - utilizes one or more GPUs via MPI
 - provides high-performance implementations of SVD/QR decomposition, tensor construction, and gradient calculation
 - Allows any tensor architecture to be built
 - Offers strong optimization of contraction paths
- cuQuantum issues:
 - Lacks ready-to-use implementations of most physical TN algorithms
 - Remains hardware-locked exclusively to NVIDIA ecosystems



TensorNet

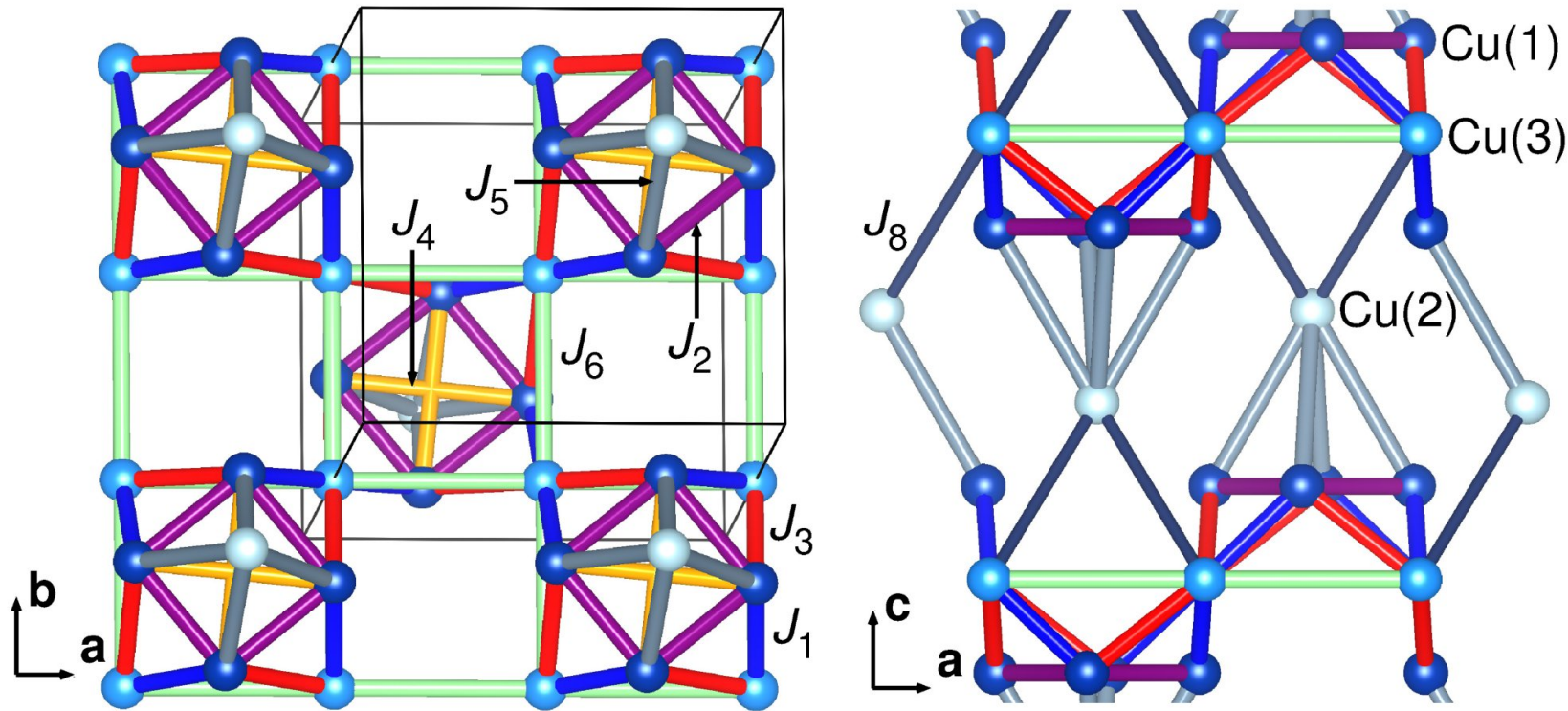
- Currently, the toolkit supports any **single-level, loop-free** tensor network.
- The toolkit utilizes a **single Nvidia GPU** (or multiple GPUs **via MPI**) for contraction of a tensor network.
- The toolkit uses **cuSOLVER**, **cuTENSOR**, and **cuBLAS** to solve linear algebra problems.
- The **TEBD**, **DMRG** & **TDVP** methods are implemented.
- Basic operations for operator algebra and Hilbert space vectors represented as TNs are implemented.



Github: <https://github.com/YauheniTalochkaN/QTensorNet>

Decorated Square-Kagome Heisenberg Antiferromagnet

Nabokoite $\text{KCu}_7\text{TeO}_4(\text{SO}_4)_5\text{Cl}$



M.G. Gonzalez, Y. Iqbal, J. Reuther, H.O. Jeschke, Field-induced spin liquid in the decorated square-kagome antiferromagnet nabokoite $\text{KCu}_7\text{TeO}_4(\text{SO}_4)_5\text{Cl}$, (2024). <https://doi.org/10.48550/arXiv.2410.10385>.

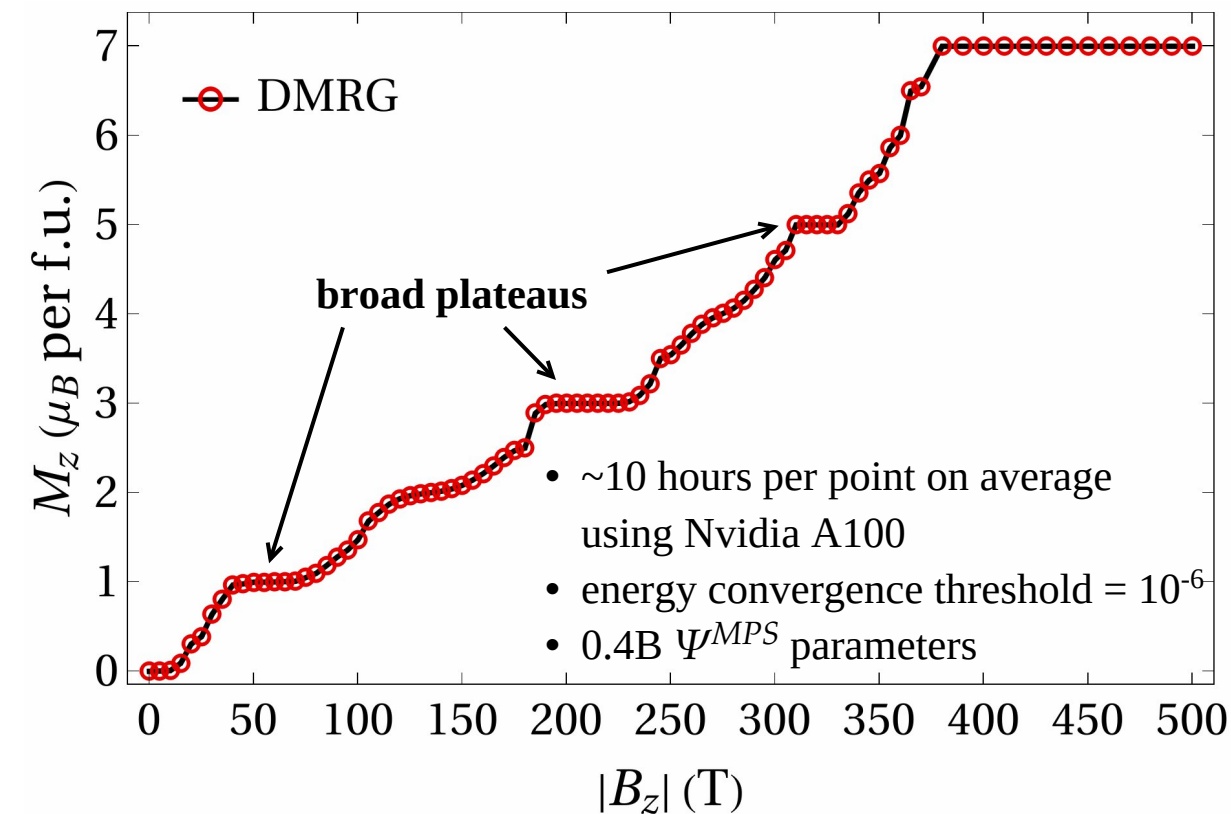
This work was carried out in collaboration with Dr. Pavel Maksimov, Bogoliubov Laboratory of Theoretical Physics, JINR.

Decorated Square-Kagome Heisenberg Antiferromagnet

$$\hat{H} = -g\mu_B \frac{\hbar}{2} \sum_{i=1}^N B_z \hat{\sigma}_{z,i} + \frac{\hbar^2}{4} \sum_{i<j} J_{ij} \hat{\sigma}_i \cdot \hat{\sigma}_j$$

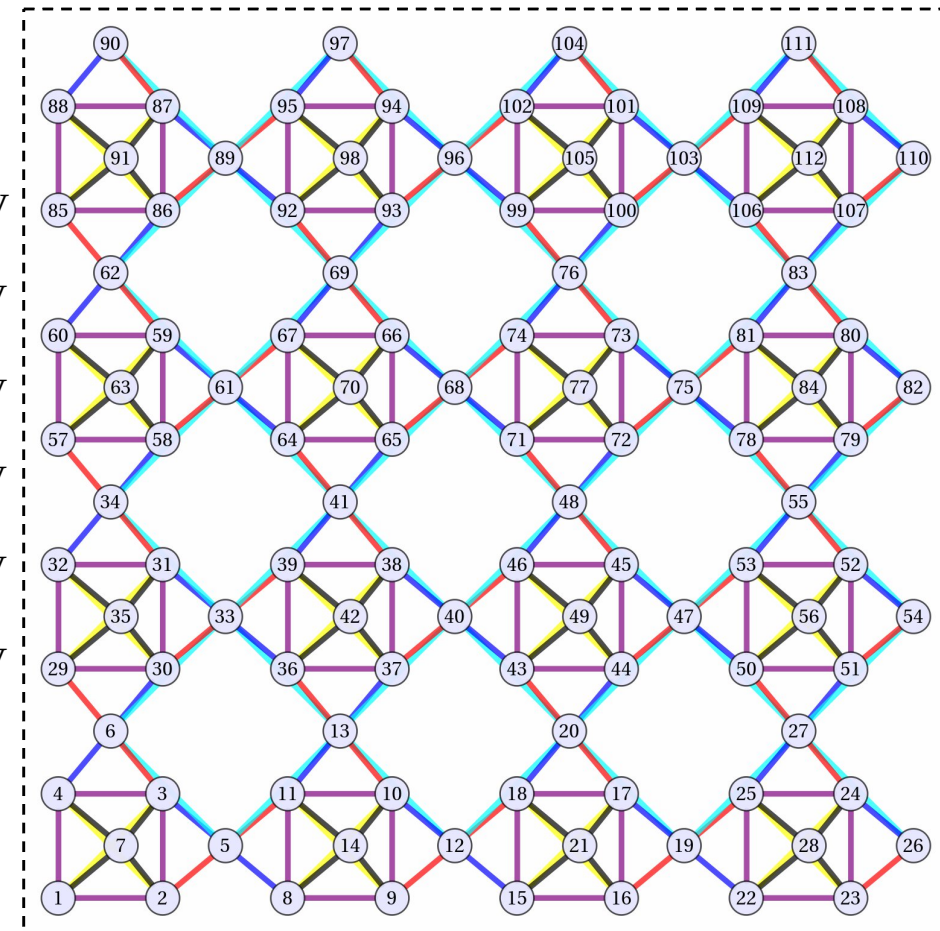
$$\begin{aligned} |\Psi\rangle &\rightarrow \Psi^{MPS} & \chi_{max}^{MPS} &= 1500 \\ \hat{H} &\rightarrow H^{MPO} & \chi_{max}^{MPO} &= 300 \end{aligned} \quad M_z = \frac{1}{16} \left\langle \Psi_{gs}^{MPS} \left| \sum_{i=1}^N \hat{\sigma}_{z,i} \right| \Psi_{gs}^{MPS} \right\rangle$$

$4 \times 4 \times 7$ cluster = 112 spins



$$\begin{aligned} J_1 &= 0.1723 \text{ meV} \\ J_2 &= 10.1685 \text{ meV} \\ J_3 &= 14.2186 \text{ meV} \\ J_4 &= 14.6495 \text{ meV} \\ J_5 &= 13.0983 \text{ meV} \\ J_6 &= 2.6714 \text{ meV} \end{aligned}$$

Periodic Boundary Conditions



Conclusions & Outlook

- QTensorNet was developed as a high-performance, GPU-accelerated toolkit for the efficient simulation of many-body quantum systems using tensor network methods.
- The ground-state magnetization dependence on the external magnetic field for a 112-spin cluster of nabokoite was calculated using QTensorNet, predicting broad plateaus at $M_z = 1, 3, \text{ and } 5 \mu_B$ per f.u.
- Neural-network-inspired optimization techniques and numerical orthogonalization methods will be integrated into QTensorNet to enable support for loopy tensor networks, such as PEPS and MERA.

Acknowledgments

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Thank you for attention!