



Simulate Quantum Computers with Matrix Product States

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Introduction





Problem: dim(%) CINECA









Classical simulations CINECA







Tensors







We can manipulate **Tensors** and **reshape** their indexes (legs) as we prefer:



This means that a tensor of **any order** can be mapped to a **matrix**. So, we can use linear algebra to work with tensors.





Tensor operations **CINECA**

We can perform operations on tensors, and we have to decide a notation for them, in particular using the graphical notation introduced previously.

We start by introducing the **complex conjugate** of a order-1 tensor:





Tensor operations **CINECA**

We can perform operations on tensors, and we have to decide a notation for them, in particular using the graphical notation introduced previously.

Then we introduce the **contraction** between two tensor along their **legs.**

 We start from two order-1 tensor, and it is equivalent to the scalar product between two vectors:

$$\langle \psi | \phi \rangle = \sum_{i} \psi_{i}^{*} \phi_{i} = \qquad \begin{vmatrix} \phi \rangle \\ 1 \\ \langle \psi | \end{pmatrix} = \qquad \langle \psi | \phi \rangle$$

 Then, the contraction between two order-2 tensor is simply the matrixmatrix multiplication:

$$(AB)_{ik} = \sum_{j} a_{ij}b_{jk} = \begin{bmatrix} A \\ I \\ B \end{bmatrix} = \begin{bmatrix} A \\ B \end{bmatrix}$$



TO: Contraction CINECA

We can perform operations on tensors, and we have to decide a notation for them, in particular using the graphical notation introduced previously.

• In general, we can contract any leg of an order-*n* tensor:

$$T_{3} = \sum_{\alpha\beta\gamma} T_{1,\alpha\beta\gamma\delta\eta} T_{2,\alpha\beta\gamma\mu\nu} = \begin{array}{c} & & \\ T_{1} & & \\ T_{2} & & \\ T_{3} & & \\$$

• What will be done in practice by the simulator, however, will be a little different:





TO: SVD



We can perform operations on tensors, and we have to decide a notation for them, in particular using the graphical notation introduced previously.

• Finally, we present a way to **separate** tensors. This means that we can pass from a single tensor to two tensors. First, we reshape it such that we have a matrix, dividing separating in different legs the indices that we want to divide



• Then, we use the **Singular Value Decomposition** (SVD) technique to separate the tensor. We obtain three matrices:

Unitary

$$T_3 = USV^*$$

Diagonal



TO: SVD



We can perform operations on tensors, and we have to decide a notation for them, in particular using the graphical notation introduced previously.

 Then, we contract the diagonal matrix S with V[†]. We thus end up with two matrices:



Finally, we reshape the tensors to have the original legs (2 green, 2 yellow)

$$-U - SV^{\dagger} - = T_1 - T_2$$











We can finally come back to the quantum computation framework. We will so consider an *n*-qubits state $|\psi\rangle \in \mathcal{H}$, with dim $(\mathcal{H}) = 2^n$.

• A quantum state can be represented as a vector. We can reshape that vector as an order-*n* tensor, where each leg has dimension 2.



 We can then apply iteratively the separation of the tensor, as seen previously.



Quantum State

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We end up with a network of *n* − 2 order-3 tensor and 2 order-2 tensor at the boundaries:



• But it does not seem to give us a significant advantage. So we do an approximation during this procedure, in particular in the **separation**.



Truncation



We can finally come back to the quantum computation framework. We will so consider an *n*-qubits state $|\psi\rangle \in \mathcal{H}$, with dim $(\mathcal{H}) = 2^n$.

• We call χ_{max} bond dimension of the system, and denote with s_1 the greatest eigenvalue of *S*. Then:



We keep the eigenvalues only if they are **big enough**. In this way, we are neglecting the sub-leading term for the state description. We keep only the first highest χ_{max} eigenvalues. In this way, we keep the quantum state manageable even for big number of qubits. However, this may be a strong approximation.





The Matrix Product State representation of a quantum state is particularly efficient, due to the clever truncation.

The truncation means that our tensors has at most dimensions







However, we have seen how to write an MPS starting from a state-vector. If we are not able to write the state-vector, due to RAM bounds, we cannot write the MPS? The answer is no, and it is indeed what the simulator does.

- We start by the state $|00...0\rangle$. It is the usual starting state in quantum computation. Furthermore, being a **separable** state, which means with **no entanglement**, it can be described exactly by MPS with a bond dimension $\chi = 1$.
- We then apply gates to evolve the state, bringing it into the target state $|\psi\rangle$, as we would do normally with a quantum circuit.
- However, we have two limitations:
 - We can only apply 1-qubit and 2-qubits gates;
 - We can only work with quantum circuits with a **linear topology**;





• Application of one-quit gates is easy, we simply have to contract the qubit tensor with the gate matrix:



• They do not introduce entanglement in the system, and thus do not change the bond dimension χ .





Two-qubit gates

- Application of two-qubit gates is a little more involved, but we have all the ingredients to do it.
 - First, we need to reshape the gate matrix in an order-4 tensor.
 - Then, we perform the contraction.
 - Finally, we separate the tensors back.



• They introduce entanglement in the system, and thus the bond dimension χ might increase after the application of a two-bit gate, up to χ_{max}



Orthogonality Center CINECA

- There are, however, some subtleties. The truncation induces an error, and we want to minimise that error.
- To do so, we have to set the **orthogonality center** of the tensor network on the interested qubit.
- In general, in a tensor network, if all branches connected to a tensor A form an isometry between their open indices and their indices connected to A, then A is said do be a center of orthogonality.
- Practically, A is a center of orthogonality if all the other tensors in the network are unitary, and so contract to the identity with their adjoint.







MPS are not only an efficient way of simulating quantum circuits. We can also **measure** interesting quantities:

• The expectation value of any observable (gate):



• The entanglement entropy between two partition of the system:







MPS are not only an efficient way of simulating quantum circuits. We can also **measure** interesting quantities:

Scalar product between quantum state (Fidelity)



• Perform projective measurements







MPS are restrained to be used in a **linear topology**. However, any circuit can be mapped into a linear topology using **swap gates**.



There are algorithms that **minimise** the number of swaps to map an arbitrary circuit to a linear topology.



CINECA CINECA m100

Marconi 100 Supercomputer **Nodes:** 980 Cores: 32/node RAM: 256 GB/node



Image from CINECA





OUANTUM COMPUTING

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Future development CINECA



Quantum computational advantage using photons

Hao Li³, Yuxuan Li⁴, Xiao Jiang^{1,2}, Lin Gan⁴, Guangwen Yang⁴, Lixing You³, Zhen Wang³, Li Li^{1,2},

Yi-Han Luo^{1,2}, Jian Qin^{1,2}, Dian Wu^{1,2}, Xing Ding^{1,2}, Yi Hu^{1,2}, Peng Hu³, Xiao-Yan Yang³, Wei-Jun Zhang³,

Han-Sen Zhong^{1,2}*, Hui Wang^{1,2}*, Yu-Hao Deng^{1,2}*, Ming-Cheng Chen^{1,2}*, Li-Chao Peng^{1,2},



The power of quantum neural networks Amira Abbas^{1,2}, David Sutter¹, Christa Zoufal^{1,3}, Aurelien Lucchi³, Alessio Figalli³, and Stefan Woerner^{1,*}

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Machine learning of high dimensional data on a noisy quantum processor

Quantum

Nachine Learning

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(Dated: January 26, 2021)



Fault-tolerant threshold





Questions?





Try it yourself! CINECA







Thank you for your attention

Marco Ballarin