Simulate Quantum Computers with Matrix Product States

Department of Physics and Astronomy
Università degli Studi di Padova

Marco Ballarin
marco.ballarin.6@studenti.unipd.it
Classical bit $b \in \{0,1\}$

quantum qubit $|\psi\rangle \in \mathcal{H}$, $\dim(\mathcal{H}) = 2$

$|\psi\rangle = \cos \theta |0\rangle + e^{i\phi} \sin \theta |1\rangle$
Problem: $\dim(\mathcal{H})$

$\dim(\mathcal{H}) = 2^6 = 64$
Problem: $\dim(\mathcal{H})$

In general, we have:

$$\dim(\mathcal{H}) = 2^n$$

Complex numbers  \(	o\) Double precision

GB $(|\psi\rangle) = \frac{2 \cdot 64}{8} \cdot \dim(\mathcal{H}) \cdot 10^{-9}$

bit $\to$ byte  \(\to\) byte $\to$ Gigabytes

10 000 TB
Classical simulations

- Checks on Experiments
- Quantum Supremacy
- Exact simulation
- Qiskit

Fault-tolerant threshold

Quantum Algorithms (QFT)

Future development

- Quantum Machine Learning
- Scaling Behaviour

Classical Simulations of Quantum Computers

- Tensor network methods
- Efficient Information Compression
- Bounded Entanglement

Exact simulation

Fault-tolerant threshold
Tensors

- $\alpha$ = order-0 tensor = **scalar**
- $\vec{v}$ = order-1 tensor = **vector**
- $U$ = order-2 tensor = **matrix**
- $T$ = order-3 tensor = **tensor**

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

\[ v_\alpha = \begin{pmatrix} v_0 \\ v_1 \\ v_2 \\ v_3 \end{pmatrix} \quad \text{Reshape} \quad v_{\alpha\beta} = \begin{pmatrix} v_0 & v_1 \\ v_2 & v_3 \end{pmatrix} \]

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

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:

\[
\begin{pmatrix}
\overrightarrow{v}
\end{pmatrix}^* = \overrightarrow{v}
\]
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:

  \[
  \langle \psi | \phi \rangle = \sum_i \psi_i^* \phi_i = \langle \psi | \rangle \langle \rangle = \langle \psi | \phi \rangle
  \]

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

  \[
  (AB)_{ik} = \sum_j a_{ij} b_{jk} = = AB
  \]
TO: Contraction

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:

\[ T_3 = \sum_{\alpha\beta\gamma} T_{1,\alpha\beta\gamma} T_{2,\alpha\beta\gamma\mu\nu} = \]

\[ T_1 \quad T_2 \quad = \quad T_3 \]

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

\[ T_1 \quad \text{Reshape} \quad T_2 \quad \text{Matrix mult} \quad \text{Reshape} \quad T_3 \]
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:

\[ T_3 = USV^\dagger \]
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 $V^\dagger$. We thus end up with two matrices:

$$U S V^\dagger = U S V^\dagger$$

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

$$U S V^\dagger = T_1 T_2$$
SVD: RECAP

\[ T_3 \xrightarrow{\text{Reshape}} T_3 \xrightarrow{\text{SVD}} U S V^\dagger \]

\[ \xrightarrow{\text{Contraction}} \xrightarrow{\text{Reshape}} \]

\[ U S V^\dagger \xrightarrow{\text{Reshape}} T_1 \xrightarrow{\text{Reshape}} T_2 \]
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.

\[ |\psi\rangle = \sum_{s_1, s_2, \ldots, s_n = 0}^{1} c_{s_1, s_2, \ldots, s_n} |s_1, s_2, \ldots, s_n\rangle \]

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

We can finally come back to the quantum computation framework. We will so consider an $n$-qubits state $|\psi\rangle \in \mathcal{H}$, with $\dim(\mathcal{H}) = 2^n$. 
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- We end up with a network of $n - 2$ order-3 tensor and 2 order-2 tensor at the boundaries:

![Diagram of tensors and indices]

- But it does not seem to give us a significant advantage. So we do an approximation during this procedure, in particular in the separation.
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 $\chi_{\text{max}}$ bond dimension of the system, and denote with $s_1$ the greatest eigenvalue of $S$. Then:

$$S' = \begin{cases} s_i & \text{if } \frac{s_i}{s_1} \leq \epsilon_1 \text{ and } i \leq \chi_{\text{max}} \\ 0 & \text{otherwise} \end{cases}$$

We then truncate the $0$ term.

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 $\chi_{\text{max}}$ 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 \( \chi_{max} \times \chi_{max} \times 2 \).

**Bond dimension**

It controls the entanglement of the system

Number of coefficients scales as \( O(nd\chi^2) \)
State Evolution

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 $|00\ldots0\rangle$. 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:

\[
M_1 \quad M_2 \quad \cdots \quad M_n
\]

\[s_1 \quad s_n\]

\[H\]

• They do not introduce entanglement in the system, and thus do not change the bond dimension \(\chi\).
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 $\chi$ might increase after the application of a two-bit gate, up to $\chi_{max}$
• 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.
Operations on MPS

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

- The expectation value of any observable (gate):
  \[
  \langle \psi | G_i | \psi \rangle = \langle \psi | G_i | \psi \rangle
  \]

- The entanglement entropy between two partition of the system:
  \[
  S_V = \sum_{i=1}^{\min(\chi_{\text{max}},N)} s_i \ln s_i
  \]
Operations on MPS

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

- **Scalar product between quantum state (Fidelity)**

\[
\langle \psi | \phi \rangle = M_3 M_2 A N_3 N_2 B
\]

- **Perform projective measurements**

\[
\frac{1}{\sqrt{2}} (|00\rangle + |11\rangle)
\]

\[
\begin{cases} 
|00\rangle & \text{with prob } \frac{1}{2} \\
|11\rangle & \text{with prob } \frac{1}{2}
\end{cases}
\]
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.
Marconi 100 Supercomputer
Nodes: 980
Cores: 32/node
RAM: 256 GB/node
Future development

Quantum Supremacy

Quantum computational advantage using photons

Han-Sen Zhong,1,2,3, Hui Wang,1,2,3, Yu-Hao Deng,1,2,3, Ming-Cheng Chen,1,2,3, Li-Chao Peng,1,2,3, Yi-Han Luo,1,2,3, Jian Qin,1,2,3, Dian Wu,1,2,3, Xing Ding,1,2,3, Yi Hu,1,2,3, Peng Hu,1,2,3, Xiaoyan Yang,1,2,3, Wei-Jun Zhang,1,2,3, Hao Li,1,2,3, Yuxuan Li,1,2,3, Xiao Jiang,1,2,3, Lin Gan,1,2,3, Guangwen Yang,1,2,3, Lixing You,1,2,3, Zhen Wang,1,2,3, Li Li,1,2,3, Nai-Le Liu,1,2,3, Chao-Yang Lu,1,2,3, Jian-Wei Pan1,2,3

Quantum Machine Learning

The power of quantum neural networks

Machine learning of high-dimensional data on a noisy quantum processor

QUANTUM COMPUTING

Fault-tolerant threshold
Questions?
Try it yourself!

Jupyter
Thank you for your attention