

Tensor networks, MPS and "Entanglement Rerouting"



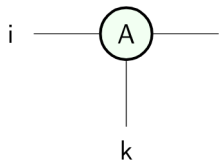
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University of Warwick

Supervisors: Matthias Caro
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$$= A_{i,j,k} \in \mathbb{C}$$

What is a tensor?

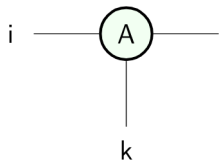


Tensor network
basics

MPS tomography

Entanglement
rerouting

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A diagram showing a light green circle labeled 'A' with three lines extending from it: one to the left labeled 'i', one to the right labeled 'j', and one downwards labeled 'k'.

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An alternative way of representing Scalars



What is a tensor? (2)



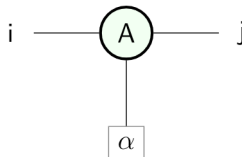
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Now for vectors.

For $i, j \in [\chi]$,


$$= \begin{pmatrix} A_{i,j,1} \\ A_{i,j,2} \\ \vdots \\ A_{i,j,\chi} \end{pmatrix} \in \mathbb{C}^\chi$$

We also denote the vector by $|A_{i,j}\rangle$

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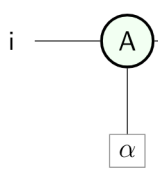
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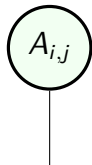
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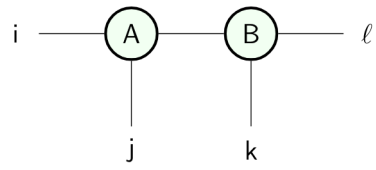

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An alternative way of representing Vectors



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 i \text{ --- } \textcircled{A} \text{ --- } \textcircled{B} \text{ --- } \ell \\
 \quad \quad \quad | \quad \quad | \\
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 \end{array}$$

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 \end{array}
 = \sum_{\alpha=1}^{\chi} A_{i,j,\alpha} B_{\alpha,k,\ell} \in \mathbb{C}$$

Connecting two tensors (2)

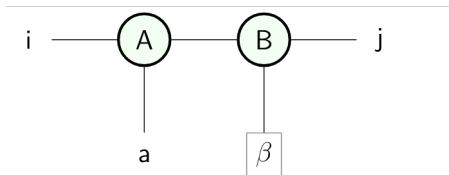


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$$\begin{aligned} &= \sum_{\gamma=1}^{\chi} A_{i,a,\gamma} B_{\gamma,\beta,j}, \forall \beta \in [\chi] \\ &= \sum_{\gamma=1}^{\chi} A_{i,a,\gamma} |B_{\gamma,j}\rangle \end{aligned}$$

Connecting two tensors (3)

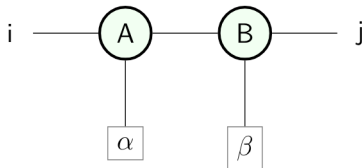


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Finally, connecting two vectors. For $i, j \in [\chi]$



Connecting two tensors (3)

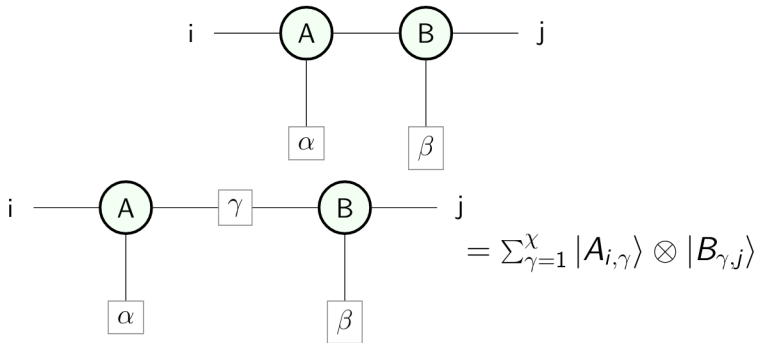


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Example of a Tensor network: MPS

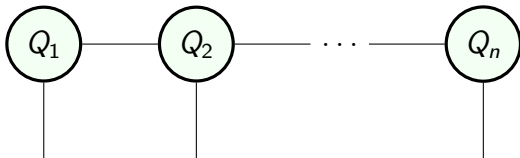


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Using tensor network notation, we can represent “states with a line entanglement structure”, called MPS, as follows



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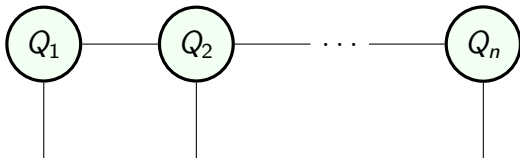


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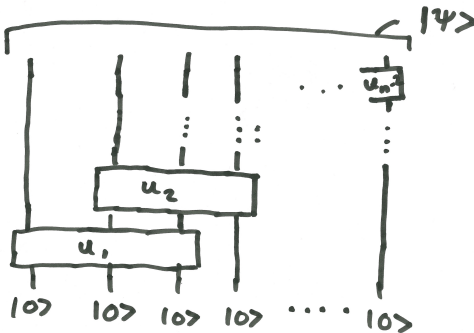
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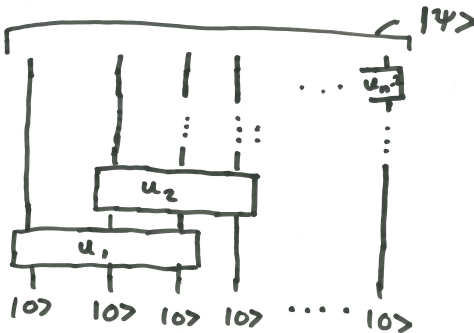
More formally, an MPS $|\psi\rangle$, with bond dimension χ , satisfies $\forall i \in [n]$, the Schmidt rank of $|\psi\rangle$ across the $\{1, \dots, i\}, \{i+1, \dots, n\}$ bipartition is at most χ . MPS have nice properties, for example they can be learnt using $\text{poly}(n, \chi)$ samples.

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where the U_i s are k -qubit unitaries, with $k = O(\log \chi)$.



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For arbitrary, rank r states, $M = \Theta(r2^n)$

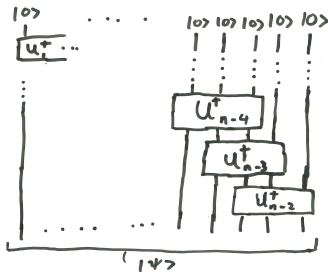
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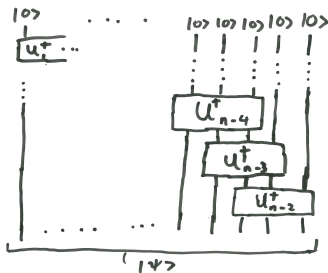
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As MPS can be prepared using these very structured circuits, we can use this to help design a tomography algorithm.

New goal: Learn $U_i^\dagger, \forall i$ as $|\phi\rangle \leftarrow U_{n-2} \dots U_1 |0\rangle$ satisfies $|\phi\rangle \approx |\psi\rangle$.



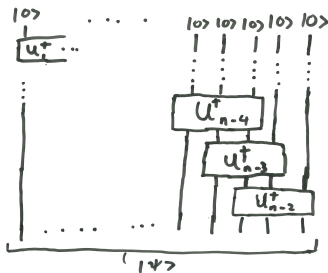
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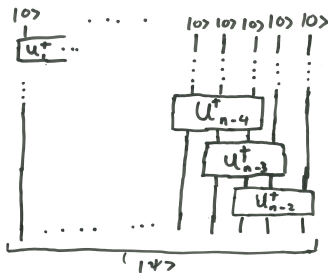
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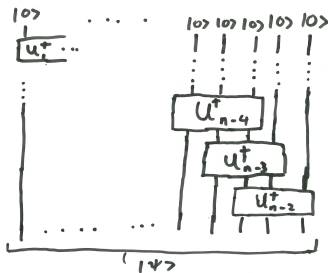
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Repeat for $U_{n-3}^\dagger, U_{n-4}^\dagger, \dots U_1^\dagger$.

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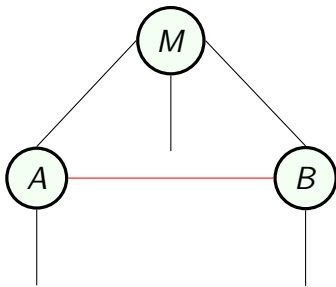


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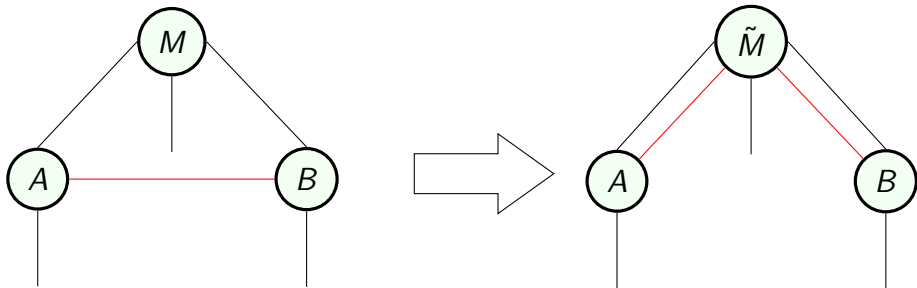


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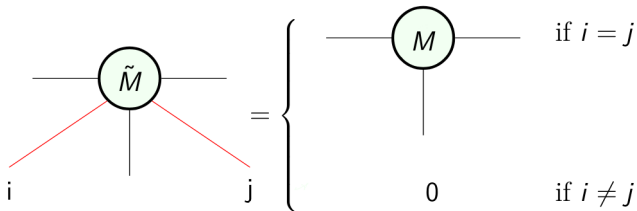
Suppose you have a tensor network that represents a state but it has some structure that is “prohibitive” e.g. the red (A, B) edge. Then we can simplify the structure as follows





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This can be extended to more than one “midpoint”.



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- ◇ Not just restricted to states, works for arbitrary tensor networks

Thanks for your attention!

Any questions?