

Virtual Linear Map Algorithm

for classical boost in near-term quantum computing

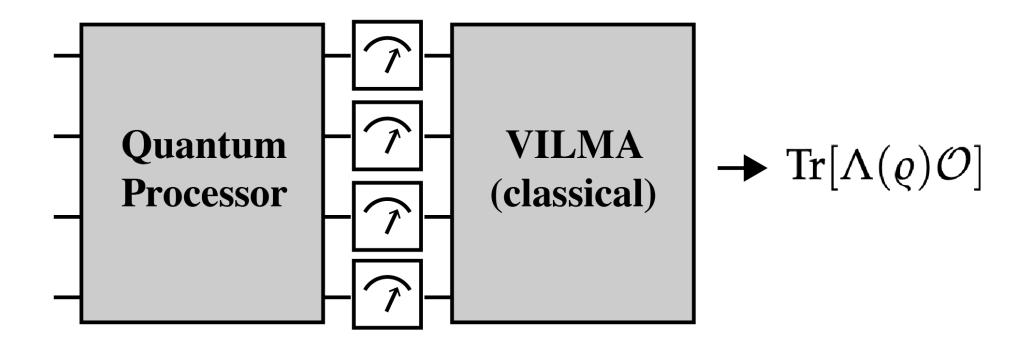
Guillermo García-Pérez CSO & co-founder, Algorithmiq | AoF Postdoctoral Researcher | Emmy Network Fellow Hiking workshop 7.2022

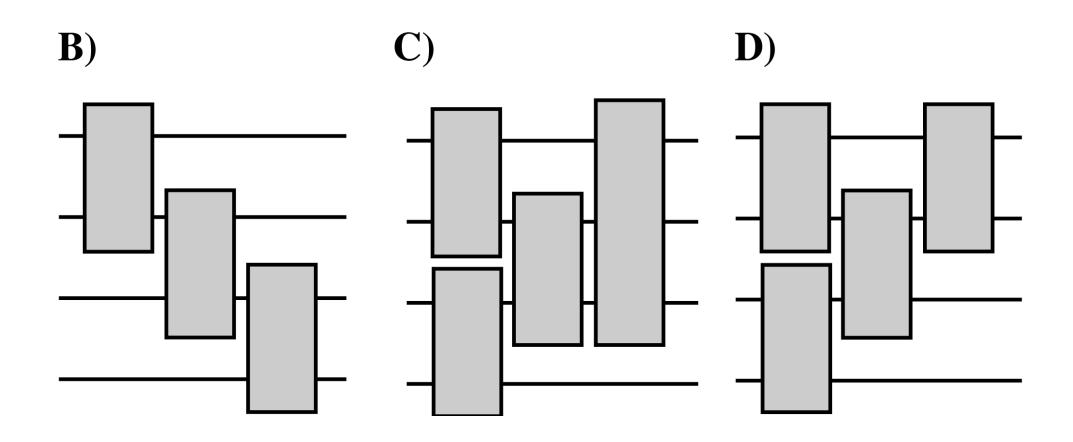
arXiv:2207.01360

GGP, Elsi-Mari Borrelli, Matea Leahy, Joonas Malmi, Sabrina Maniscalco, Matteo A. C. Rossi, Boris Sokolov, Daniel Cavalcanti

overview

A)

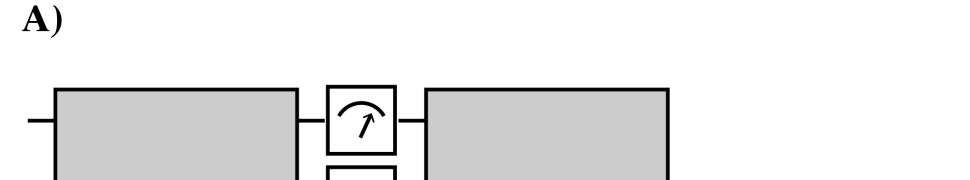


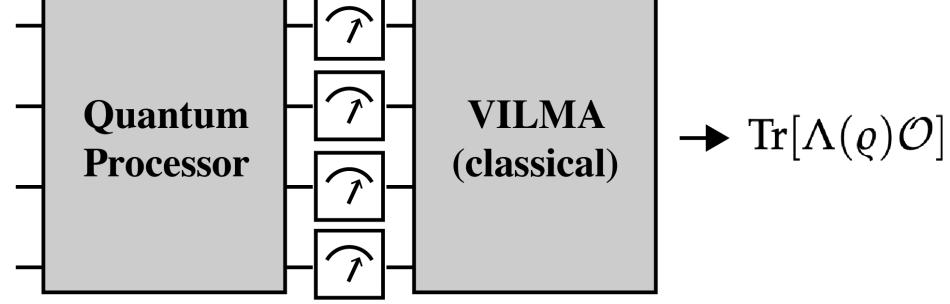


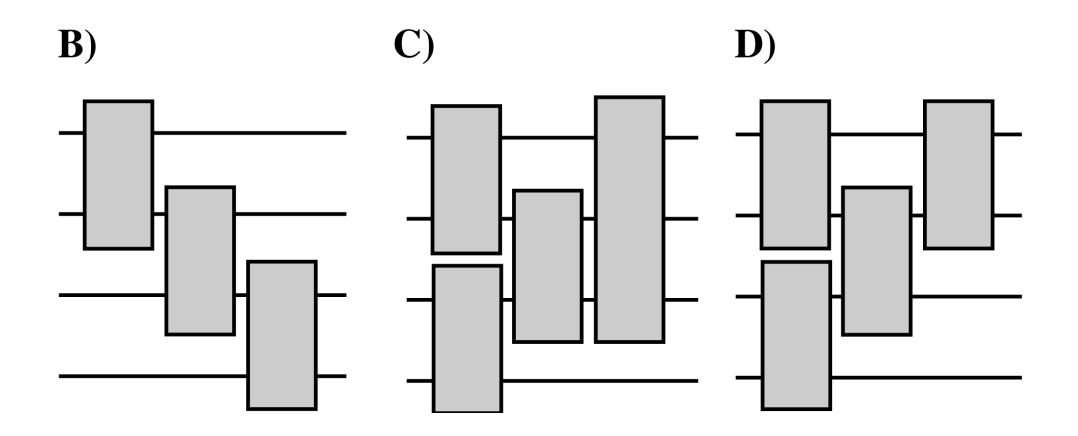
Transforming states in post-processing

- The goal is to compute expectation values of observables on the image of the physical state through some map
- We do NOT want to do full state tomography (unfeasible for large systems)
- We want the map to be circuit-like (useful for quantum computing)

operator averages on transformed states







Using IC measurement data

- Consider an IC-POVM with effects

$$\{\Pi_{\mathbf{m}} = \bigotimes^{N} \Pi_{m_i}^{(i)}\}$$

$$i=1$$

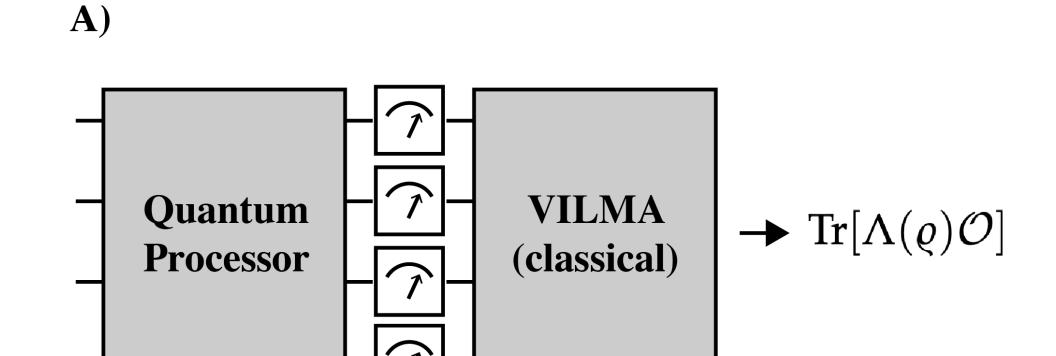
- It defines a set of dual effects such that

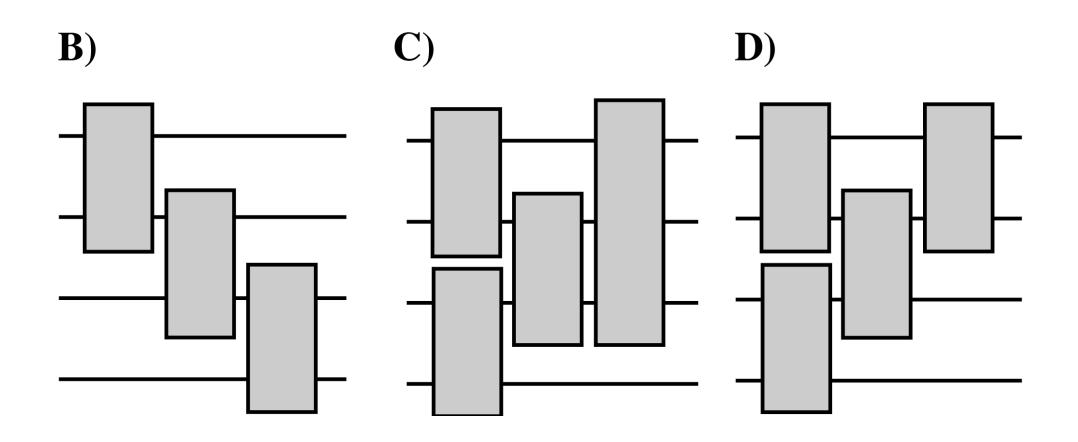
$$\mathcal{O} = \sum_{\mathbf{m}} \text{Tr}[\mathcal{O}\Pi_{\mathbf{m}}]D_{\mathbf{m}}$$
 for all \mathcal{O}

– The state of the QPU reads $\rho = \sum_{\mathbf{m}} p_{\mathbf{m}} D_{\mathbf{m}}$, with

$$D_{\mathbf{m}} = \bigotimes_{i=1}^{N} D_{m_i}^{(i)}$$
 and $p_{\mathbf{m}} = \text{Tr}[\rho \Pi_{\mathbf{m}}]$

operator averages on transformed states



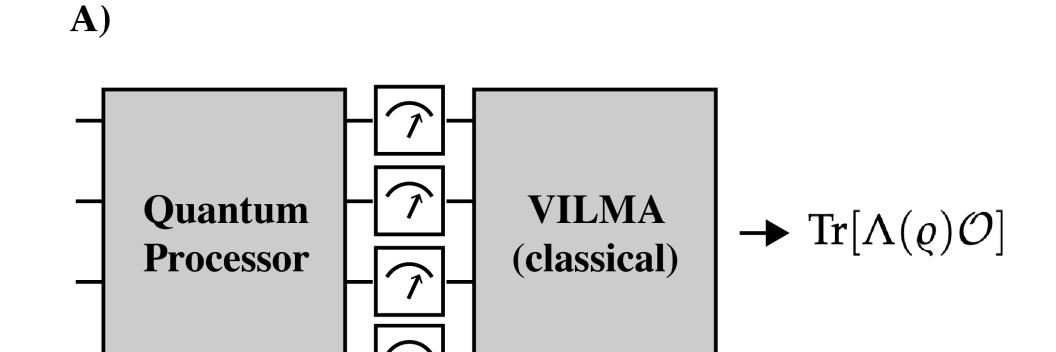


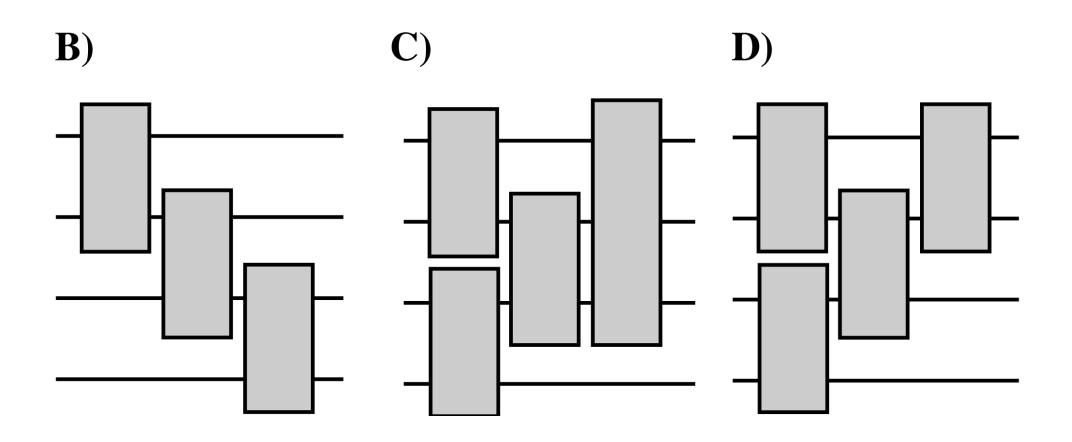
Using IC measurement data

- Let the observable be $\mathcal{O} = \sum_{\mathbf{k}} c_{\mathbf{k}} P_{\mathbf{k}}$
- For finitely many samples $S, \rho_S = \sum_{i=1}^S D_{\mathbf{m}_i}/S,$ fulfilling $\lim_{S \to \infty} \rho_S = \rho$
- Since $\operatorname{Tr}[\Lambda(\rho)\mathcal{O}] = \lim_{S \to \infty} \operatorname{Tr}[\Lambda(\rho_S)\mathcal{O}],$

$$\lim_{S \to \infty} \sum_{i=1}^{S} \frac{1}{S} \sum_{\mathbf{k}} c_{\mathbf{k}} \text{Tr}[\Lambda(D_{\mathbf{m}_{i}}) P_{\mathbf{k}}]$$

operator averages on transformed states





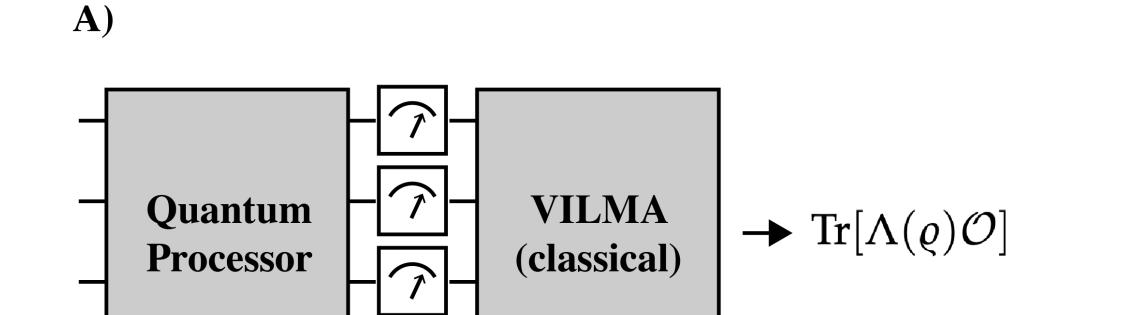
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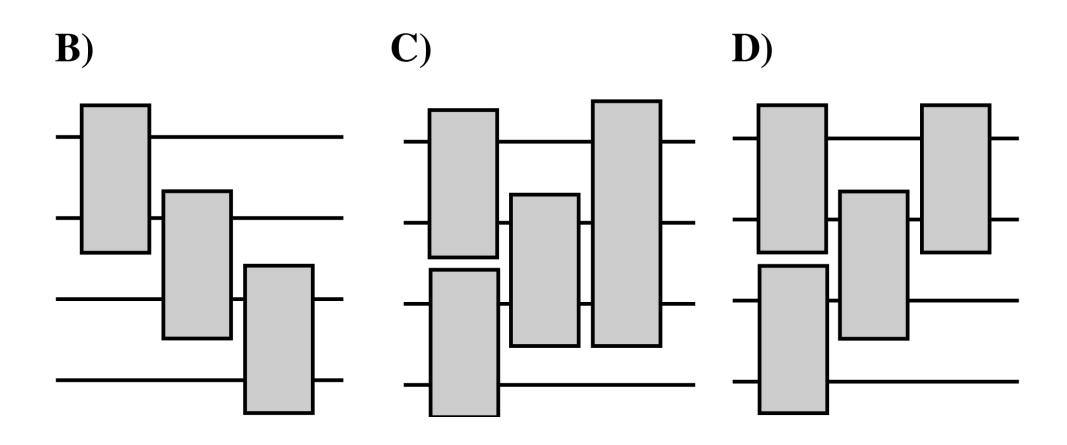
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- For finitely many samples $S, \rho_S = \sum_{i=1}^S D_{\mathbf{m}_i}/S,$ fulfilling $\lim_{S \to \infty} \rho_S = \rho$
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$$\lim_{S \to \infty} \sum_{i=1}^{S} \frac{1}{S} \sum_{\mathbf{k}} c_{\mathbf{k}} \text{Tr}[\Lambda(D_{\mathbf{m}_{i}})P_{\mathbf{k}}] \longleftarrow \omega_{\mathbf{m}_{i}}$$

- The estimator $\bar{\mathcal{O}}_{\Lambda} = \sum_{i=1}^{S} \omega_{\mathbf{m}_i} / S$ is unbiased

operator averages on transformed states





Using IC measurement data

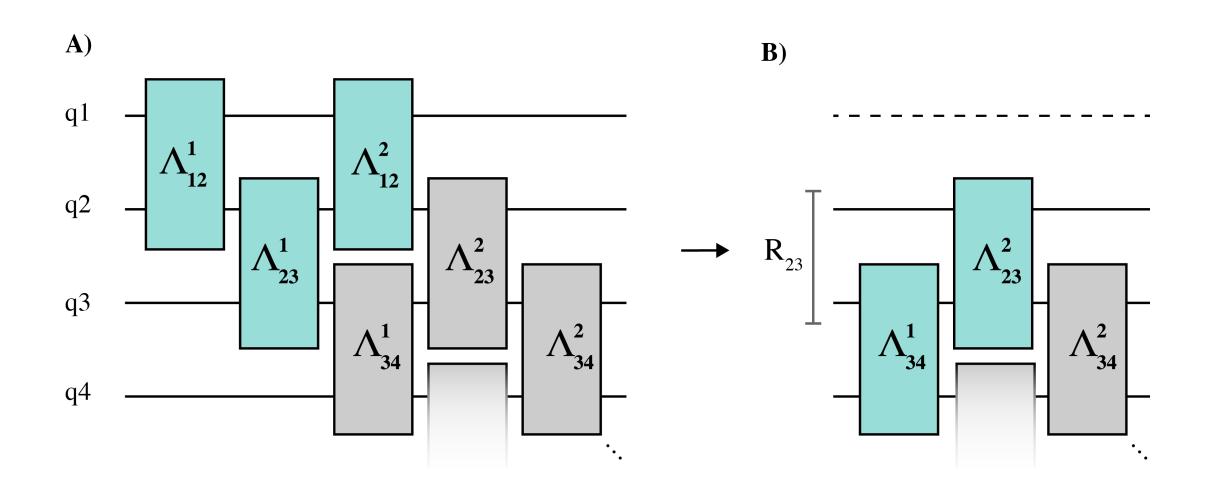
- In addition to the estimation of the mean $\bar{\mathcal{O}}_{\Lambda}$, we can estimate the statistical error of the estimation,

$$\sigma = \sqrt{\bar{V}(\mathcal{O}_{\Lambda})/S},$$

where
$$\bar{V}(\mathcal{O}_{\Lambda}) \equiv \left[\sum_{i=1}^{S} \omega_{\mathbf{m}_i}^2 / S - (\bar{\mathcal{O}}_{\Lambda})^2\right] S / (S - 1)$$
 is

an unbiased estimator of the variance of $\omega_{\mathbf{m}_i}$

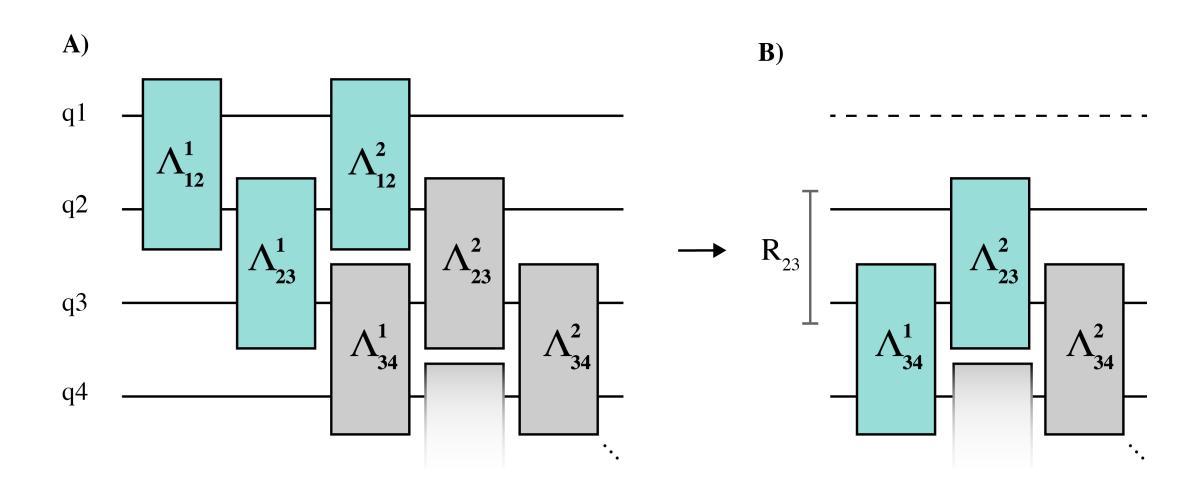
operator averages on transformed states



Traces involving mapped dual effects

- Computing the traces ${\rm Tr}[\Lambda(D_{{f m}_i})P_{f k}]$ in $\omega_{{f m}_i}$ can be challenging given the dimension of $\Lambda(D_{{f m}_i})$
- We exploit the causal cone structure of the circuit to bypass explicit high-dimensional reconstructions

operator averages on transformed states

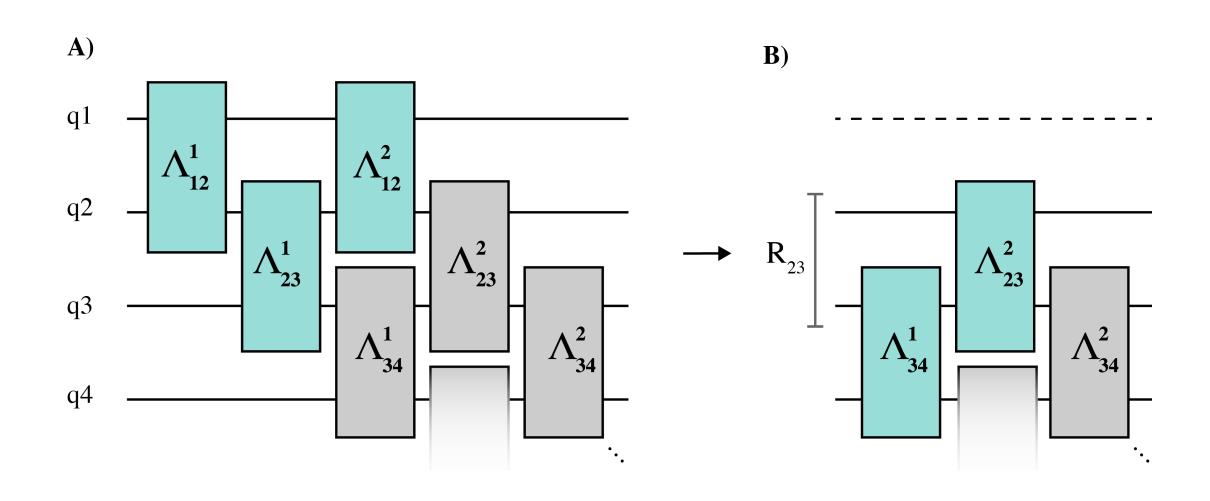


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- Compute $\Lambda^2_{12} \circ \Lambda^1_{23} \circ \Lambda^1_{12}(D_{m_1} \otimes D_{m_2} \otimes D_{m_3})$
- Compute $\Lambda^2_{23} \circ \Lambda^1_{34}(R_{2,3} \otimes D_{m_4})$
- $R_{3,4} = \text{Tr}_2[\Lambda_{23}^2 \circ \Lambda_{34}^1(R_{2,3} \otimes D_{m_4})P_{k_2} \otimes \mathbb{I}_3 \otimes \mathbb{I}_4]$

operator averages on transformed states

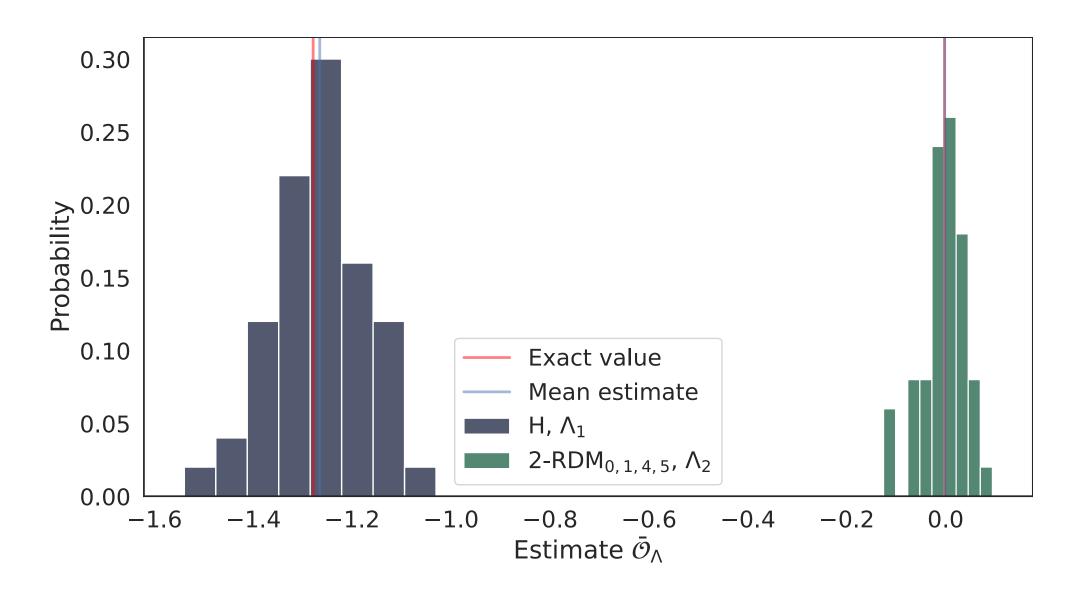


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Traces involving mapped dual effects

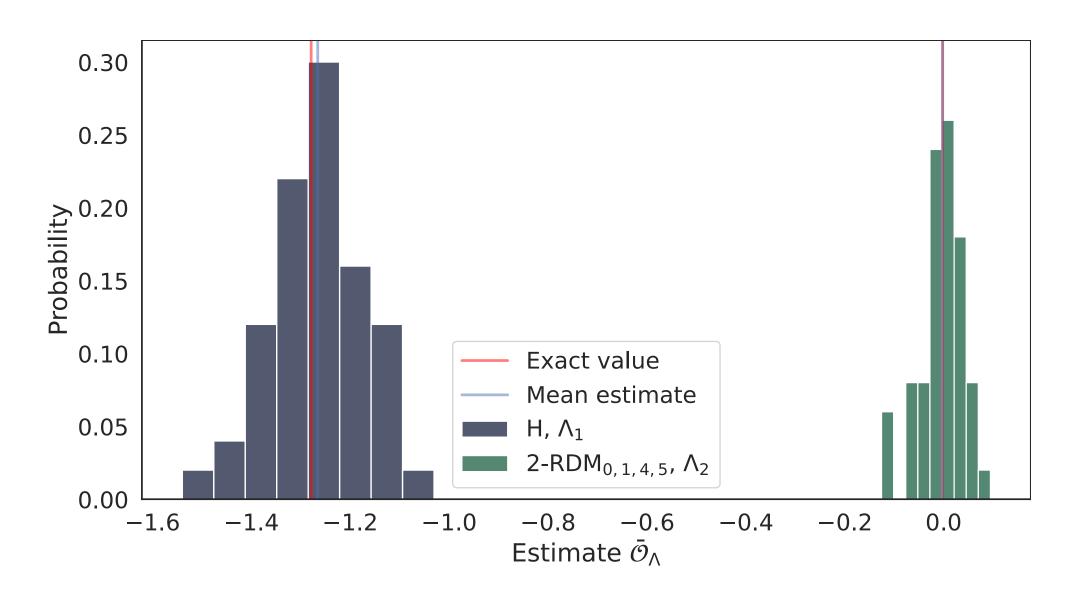
- Computing the traces ${\rm Tr}[\Lambda(D_{{f m}_i})P_{f k}]$ in $\omega_{{f m}_i}$ can be challenging given the dimension of $\Lambda(D_{{f m}_i})$
- We exploit the causal cone structure of the circuit to bypass explicit high-dimensional reconstructions
- Algorithm polynomial in system size for many circuit topologies
- Can be executed *backwards* by exchanging the roles of $D_{\mathbf{m}_i}$ and $P_{\mathbf{k}}$, and using Λ^{\dagger} , the adjoint of the map

operator averages on transformed states

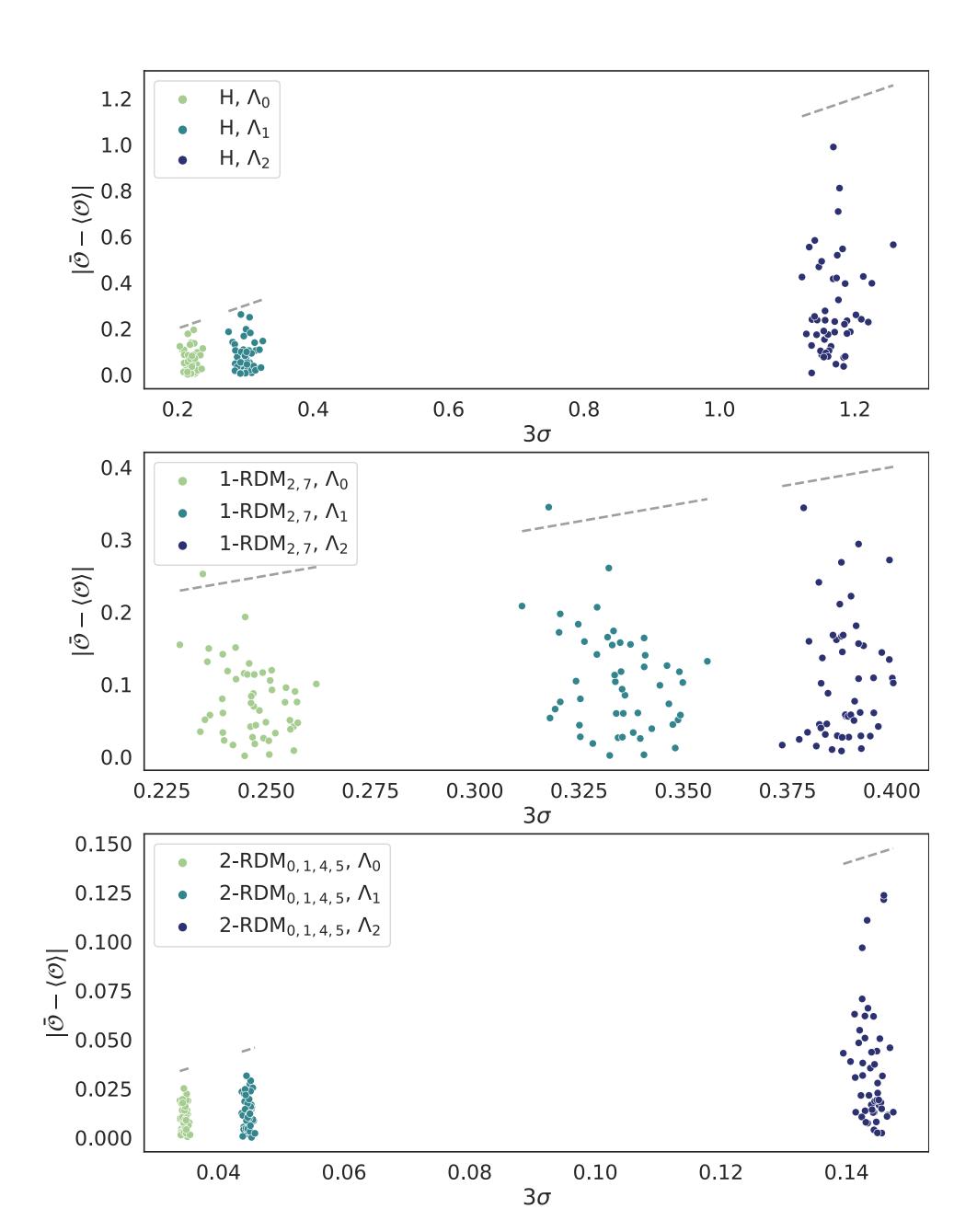


- ρ is the ground state of H_2 perturbed by a CPTP map ${\mathcal N}$
- $S = 10^4$ and we repeat the experiment 50 times
- $\Lambda_0 = \mathbb{I} | \Lambda_1 = \mathcal{N}^{-1} | \Lambda_2$ is a layer of randomly chosen unitaries
- $\bullet \quad \mathcal{O}_1 = H | \mathcal{O}_2 = \text{Re} \langle a_2^{\dagger} a_7 \rangle | \mathcal{O}_3 = \text{Re} \langle a_0^{\dagger} a_1 a_4^{\dagger} a_5 \rangle$

operator averages on transformed states

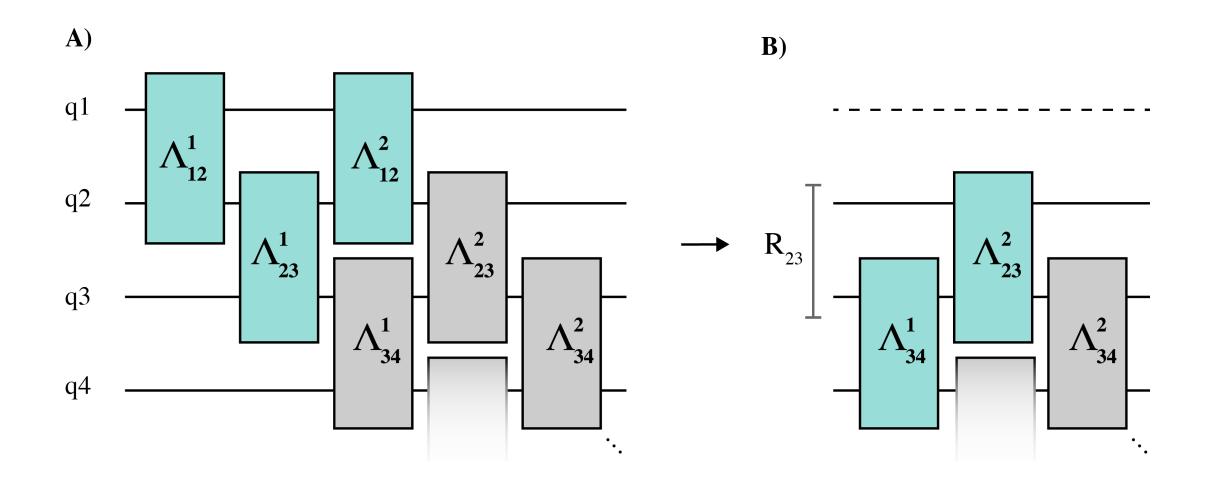


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Variational optimisation with VILMA

observable dependence on local maps



Traces algorithm revisited

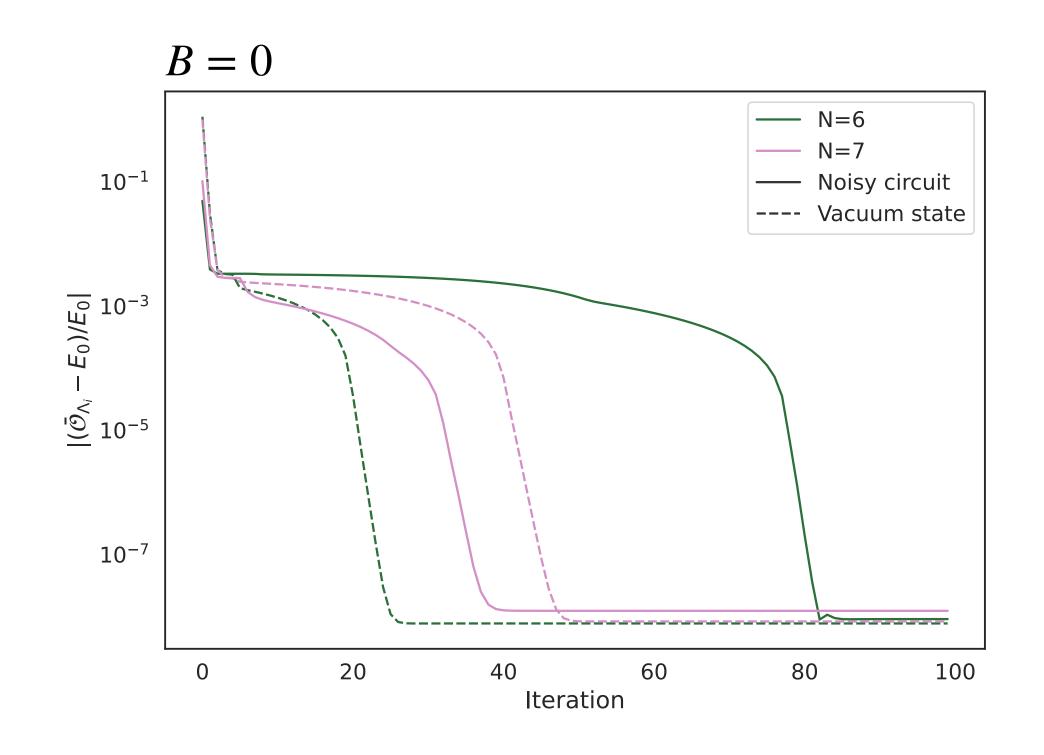
- By combining the forward and backwards algorithms, we can write an expression, linear in a singled-out map Λ^l_{ij} , that captures all the dependence of the observable average on Λ^l_{ij}

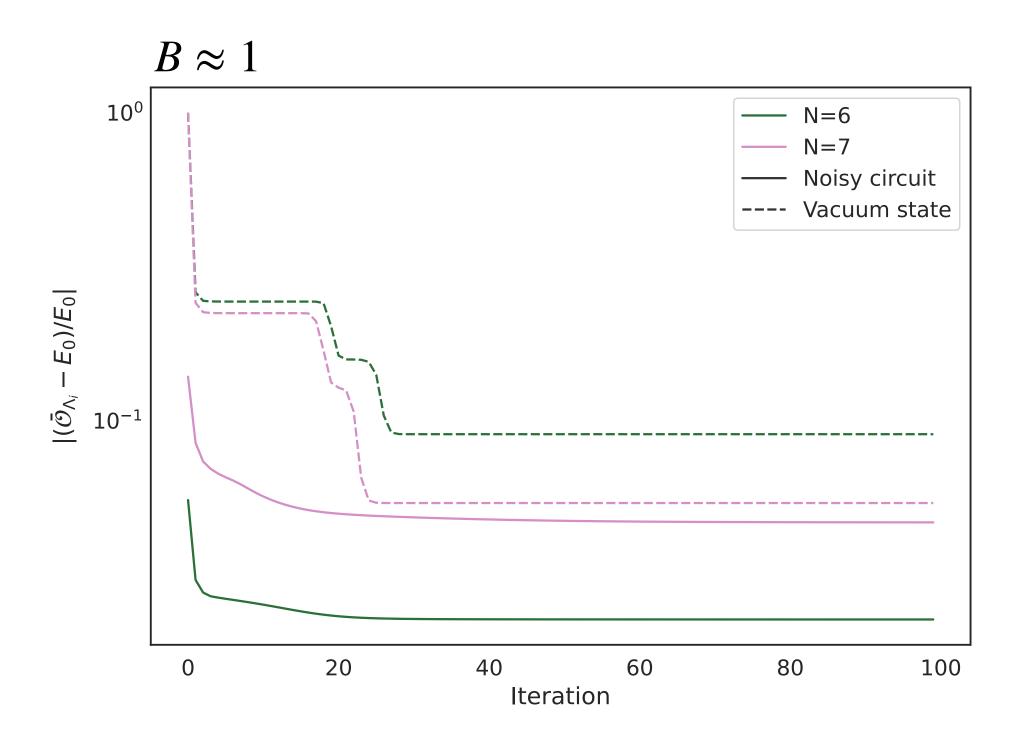
$$\bar{\mathcal{O}}_{\Lambda} = \sum_{i=1}^{S} \frac{1}{S} \sum_{\mathbf{k}} c_{\mathbf{k}} \sum_{a} \text{Tr}[\Lambda_{ij}^{l} (R_a^{(\mathbf{m}_i, \mathbf{k})}) \bar{R}_a^{(\mathbf{m}_i, \mathbf{k})}]$$

- The expression can be minimised/maximised efficiently while imposing *e.g.* positivity constraints using semi-definite programming
- In this context, it is interesting to explore "classical VILMA", in which the input data is simply $|0\rangle^{\otimes N}$

Variational optimisation with VILMA

observable dependence on local maps





- Solving for the ground state of the XX model $H = -J[\sum_i (\sigma_x^{(i)} \sigma_x^{(i+1)} + \sigma_y^{(i)} \sigma_y^{(i+1)})/2 + B\sigma_z^{(i)}]$ for B = 0 and $B \approx 1$
- Input states are a VQE circuit with noise (coherent and depolarising) in each CNOT and vacuum ($|0\rangle^{\otimes N}$)