

Noise-induced shallow circuits and absence of barren plateaus

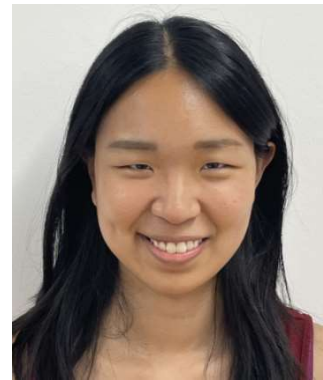
Antonio Anna Mele, **Armando Angrisani**, Soumik Ghosh, Sumeet Khatri,
Jens Eisert, Daniel Stilck França, Yihui Quek

arXiv:2403.13927



Joint work with:

Antonio Anna Mele, Soumik Ghosh, Sumeet Khatri, Jens Eisert, Daniel Stilck França, Yihui Quek



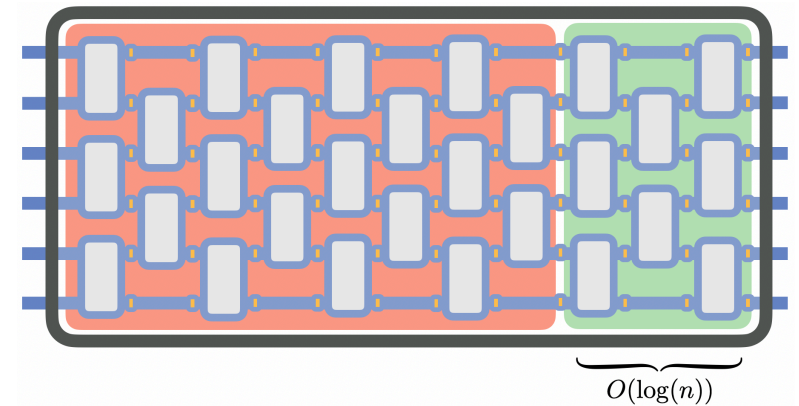
Outline

☼ Noise in quantum circuits

☼ Effective shallow circuits

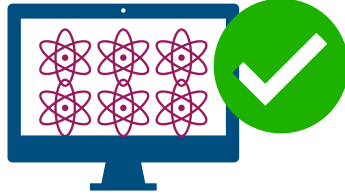
☼ Classical simulation of Pauli expectation values of noisy random circuits

☼ Barren plateaus

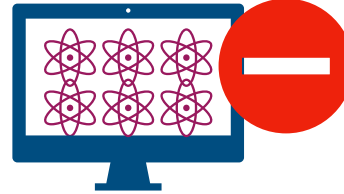


- Understanding **noise impact** in current quantum devices is important for:

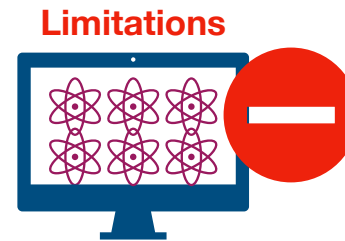
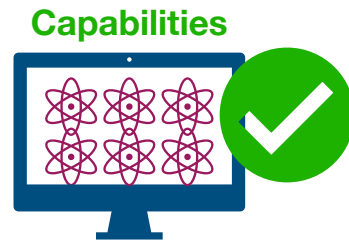
Capabilities



Limitations



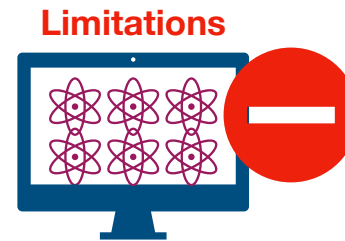
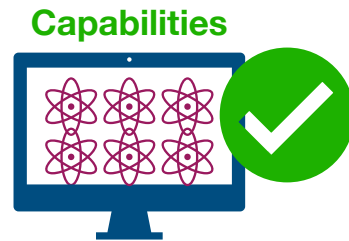
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$$\mathcal{N}(\sigma) = (1 - p)\sigma + p\frac{I}{2} \quad \text{with } p \in [0,1]$$

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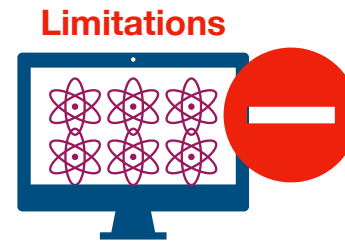
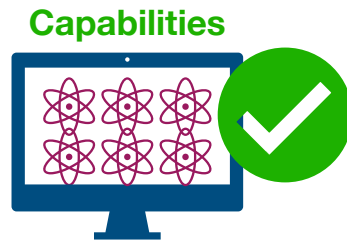


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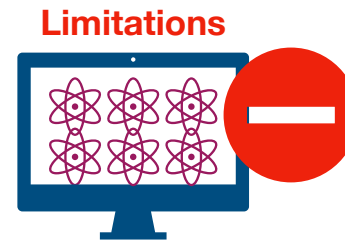
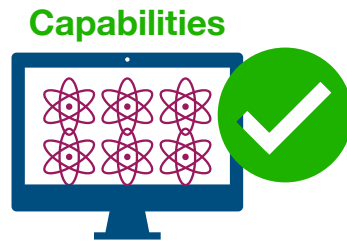
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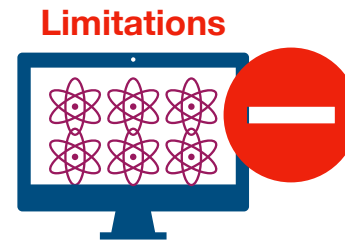
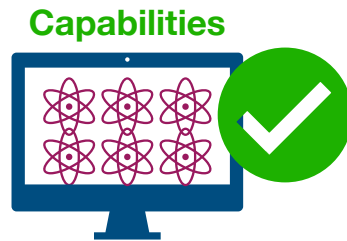
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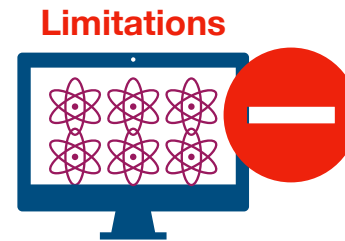
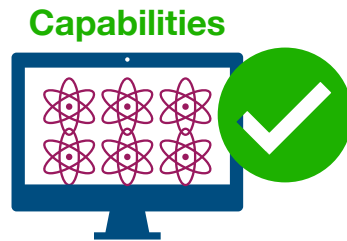
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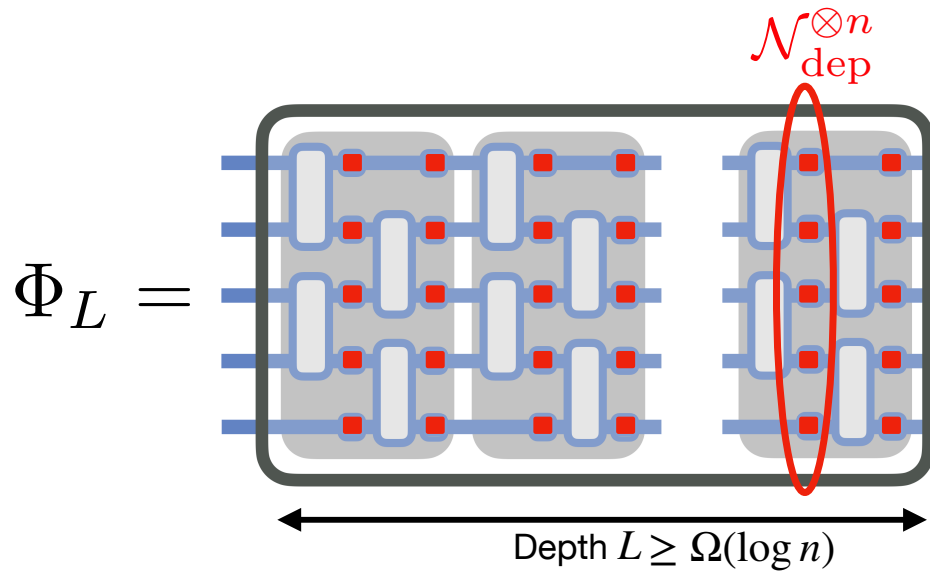
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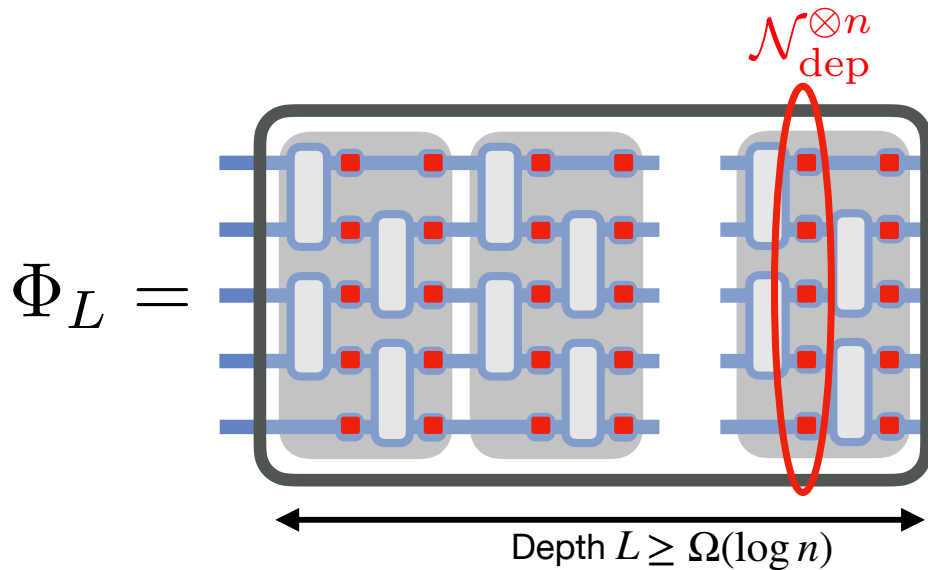
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Quantum computation possible only for $\log(n)$ depth! [6]

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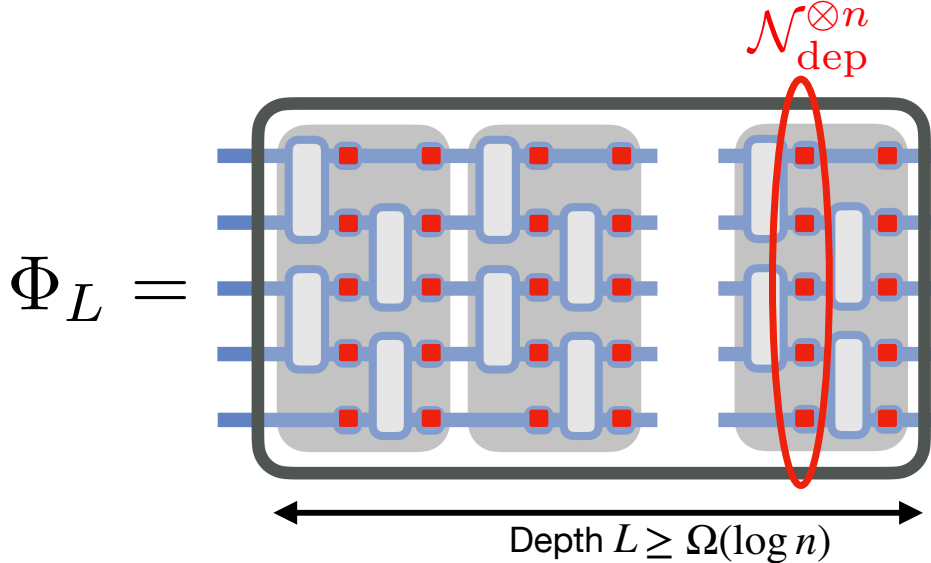
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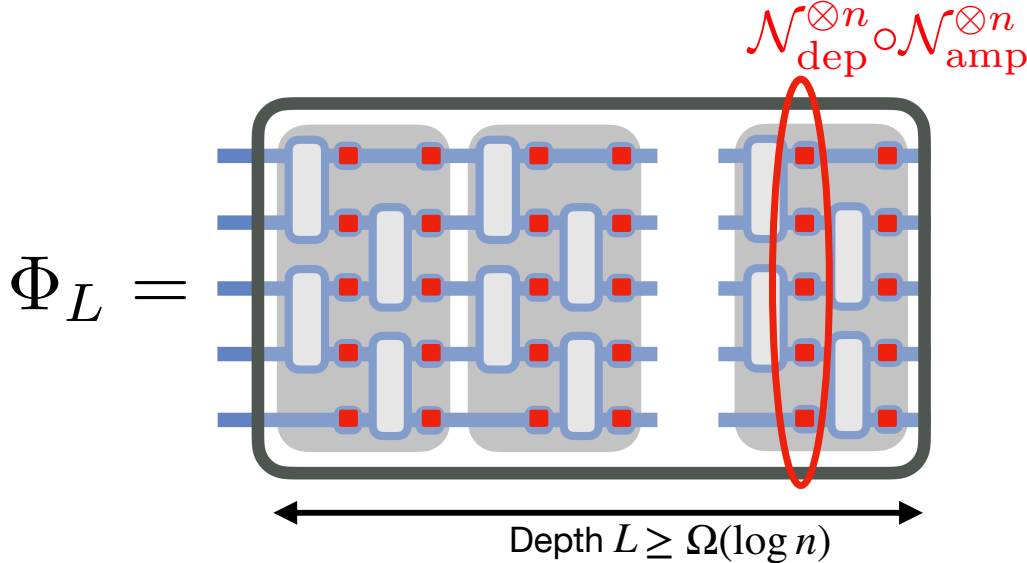
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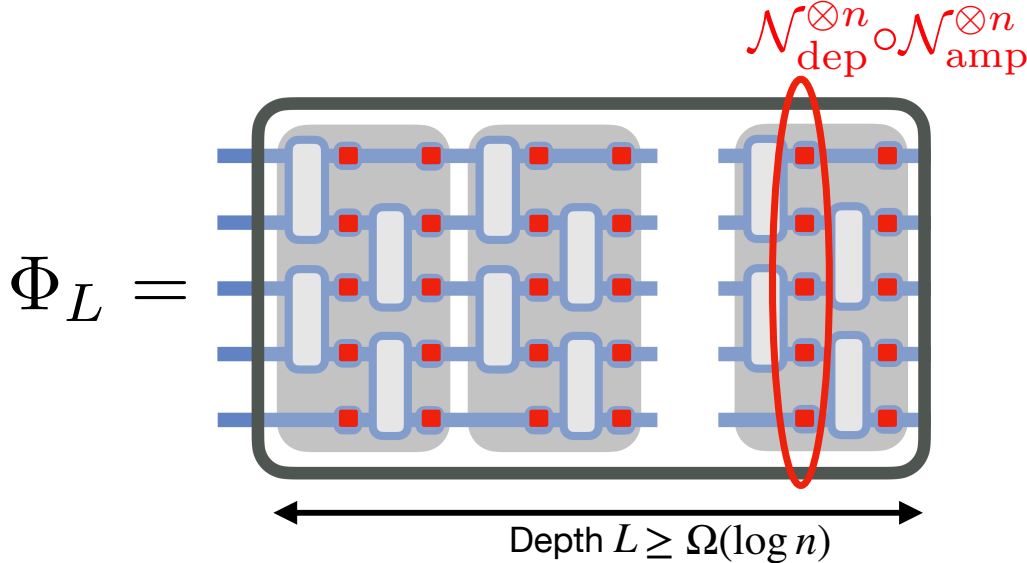
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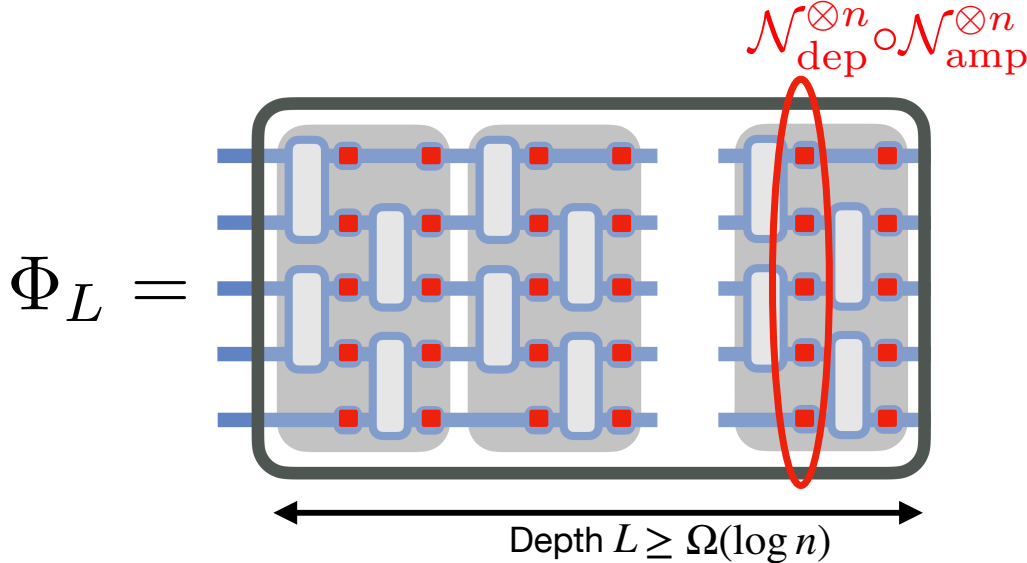
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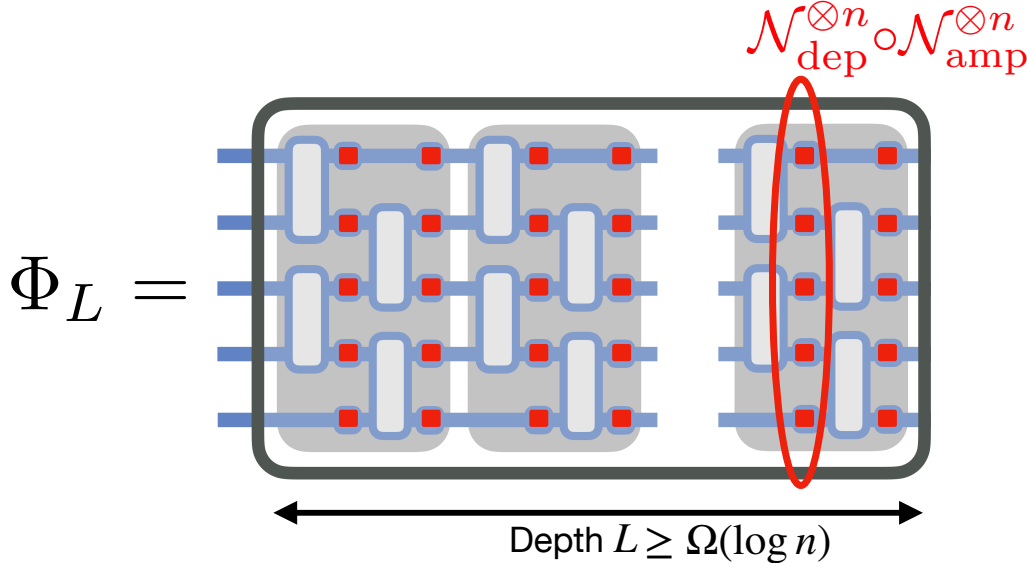
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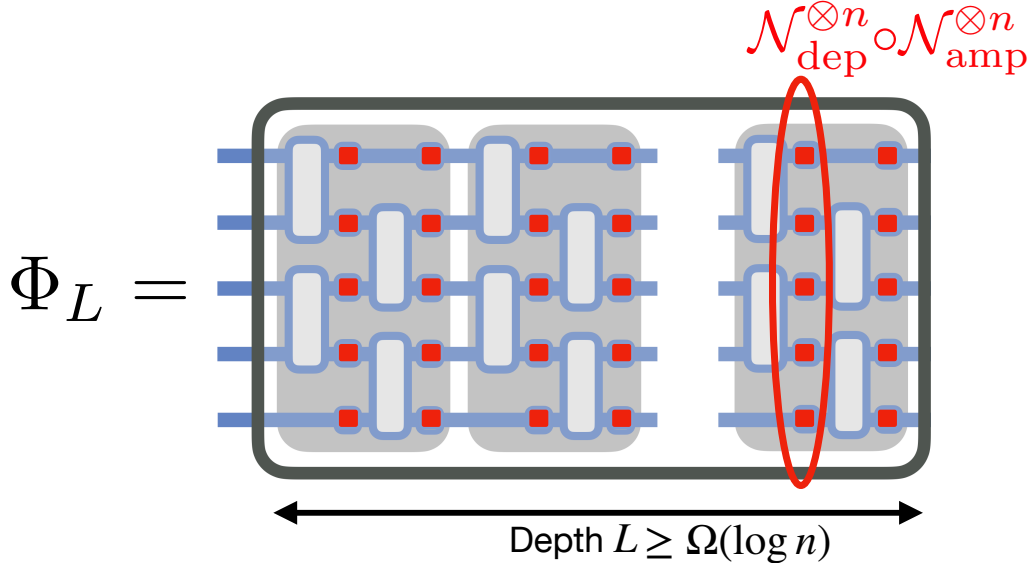
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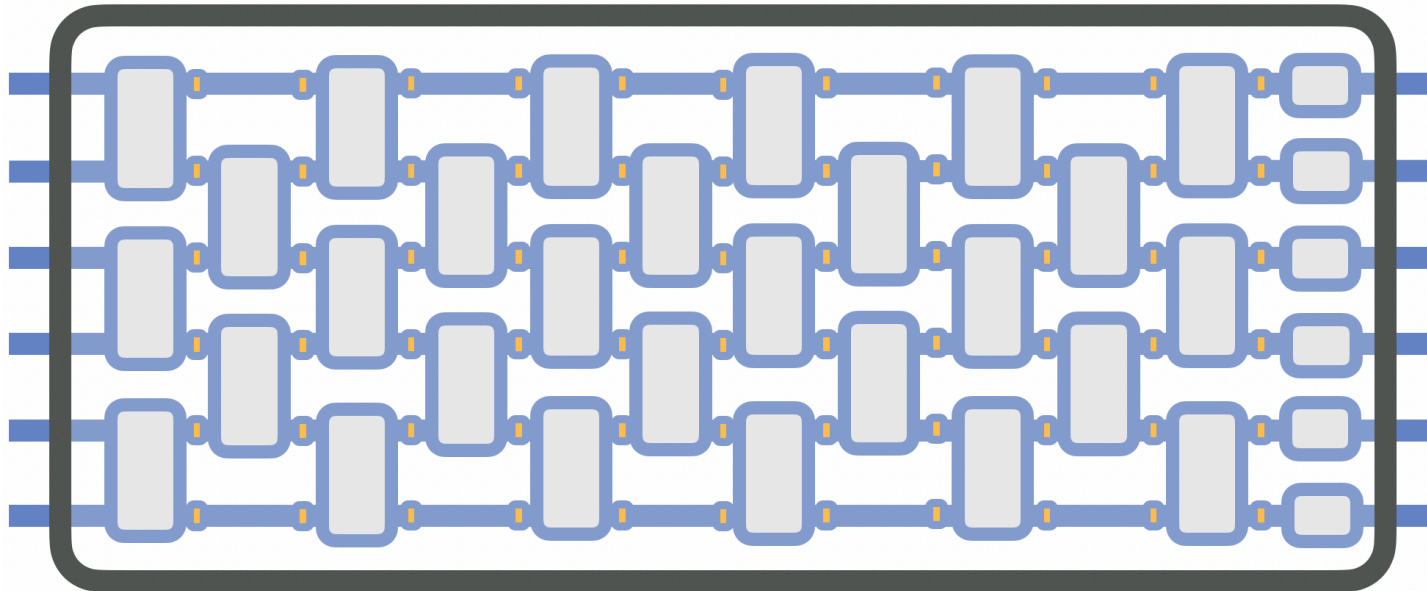
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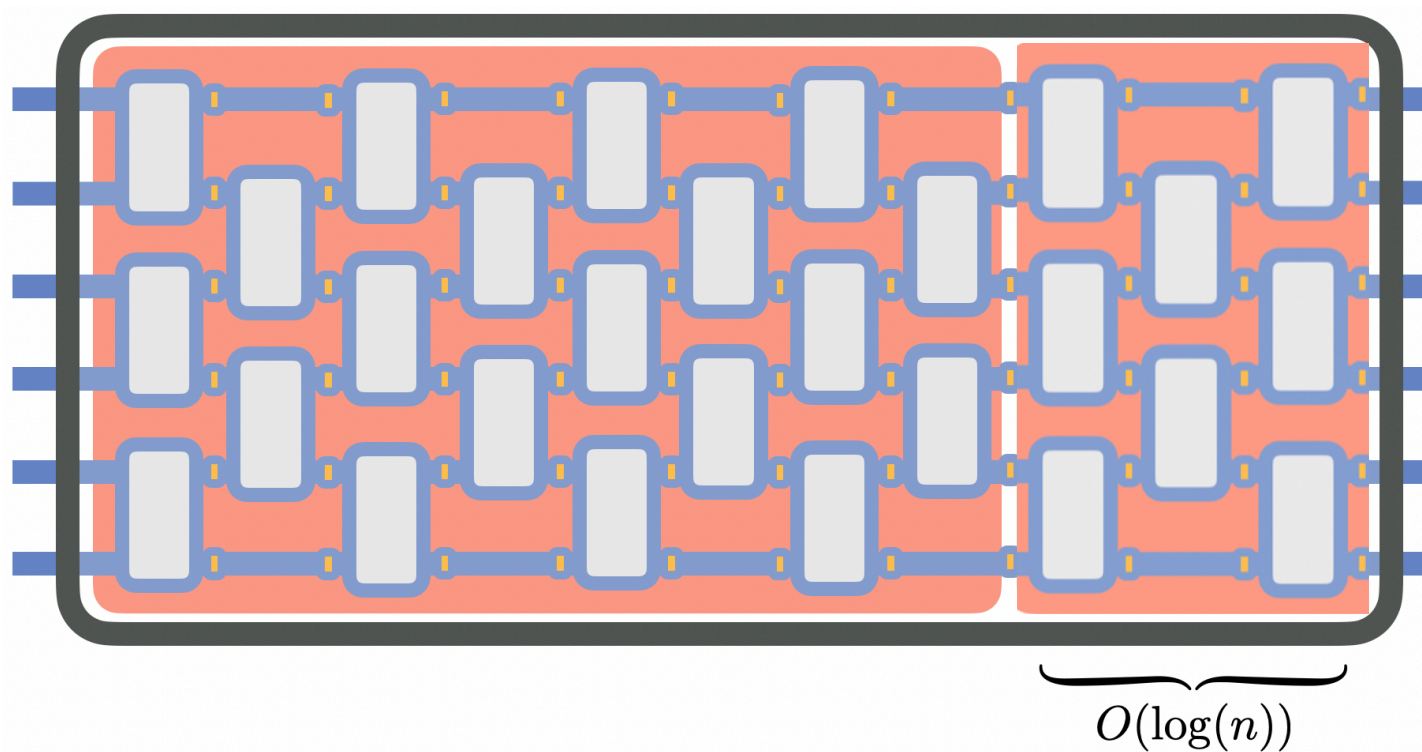
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What happens for generic noisy circuits?

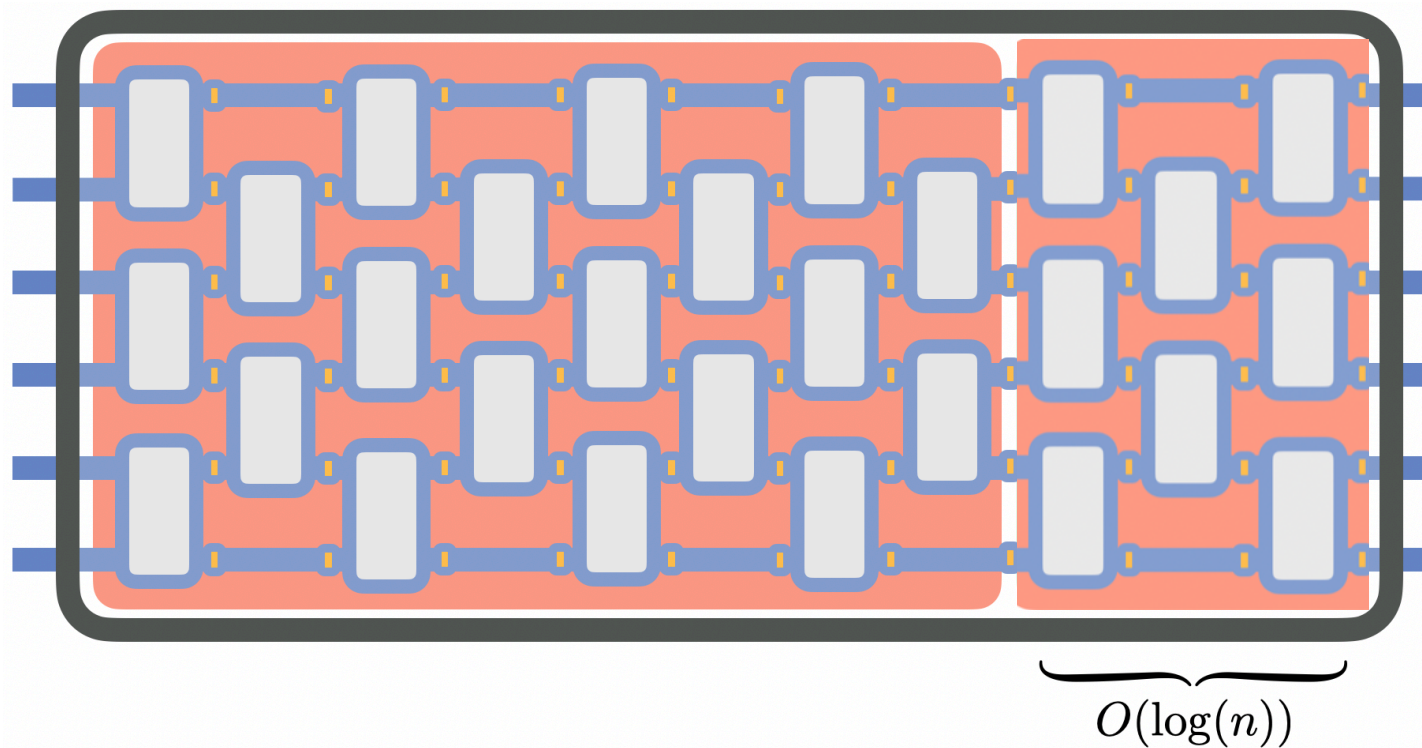


If the noise is depolarizing, no layers matter.

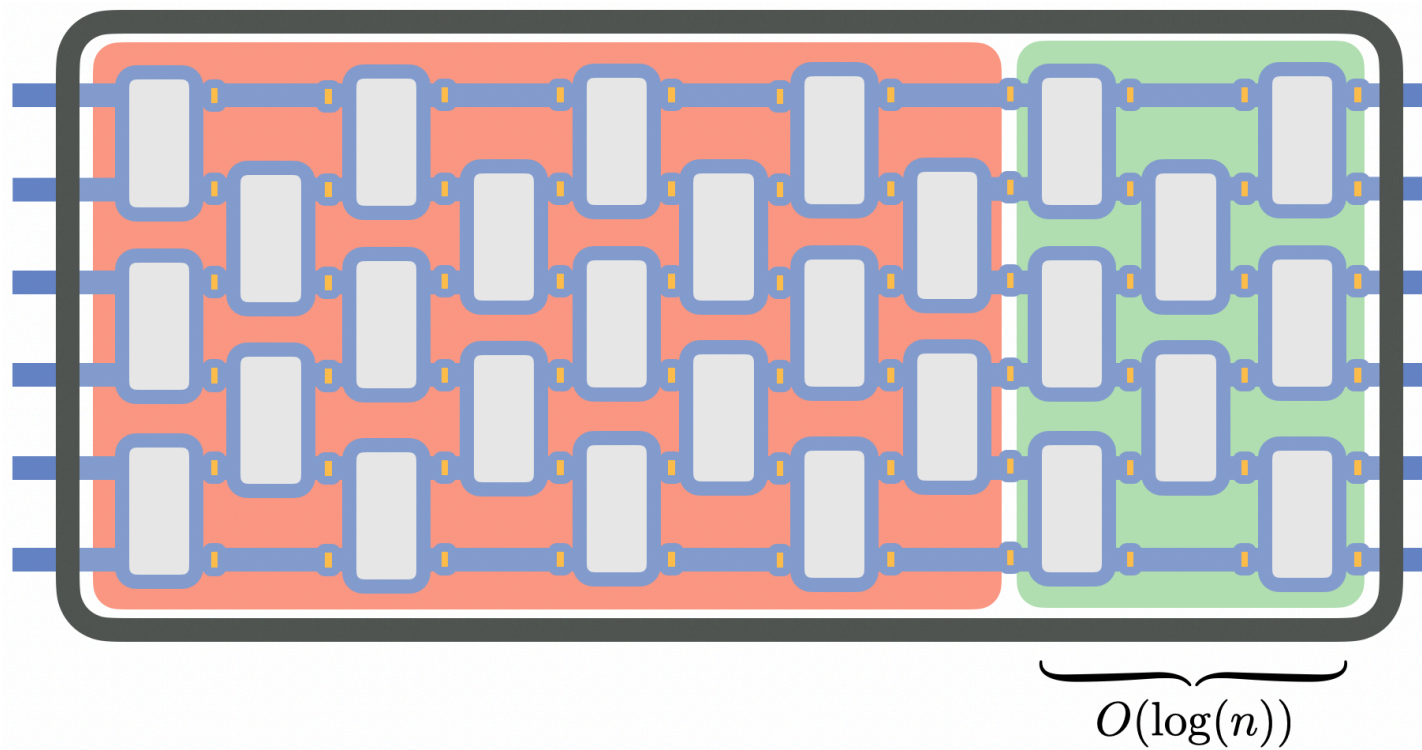


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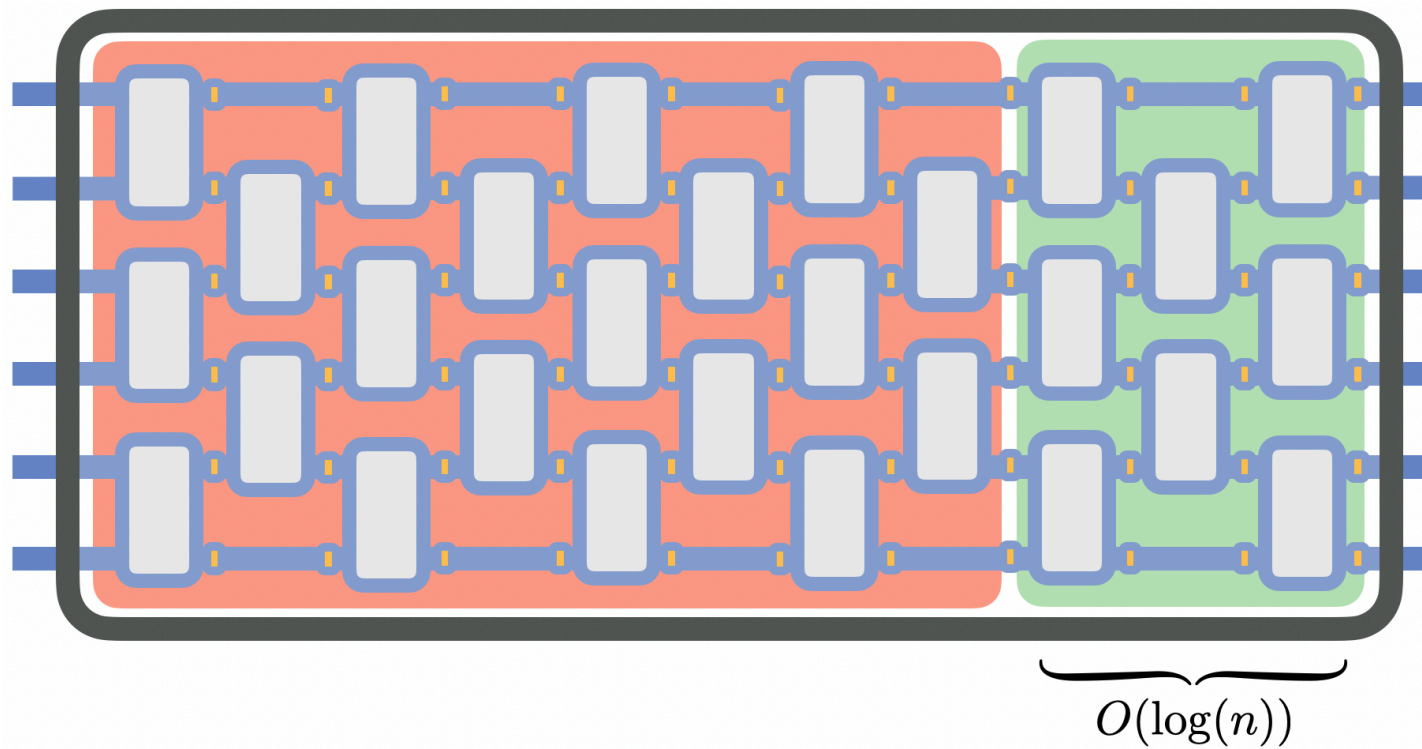
(Even for ALL circuits)



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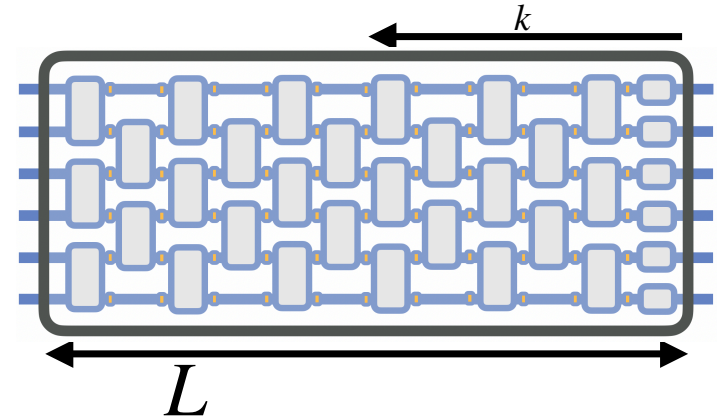


Effective shallow circuits

Proposition.

For any initial state ρ_0 (possibly complex) and observable O ,

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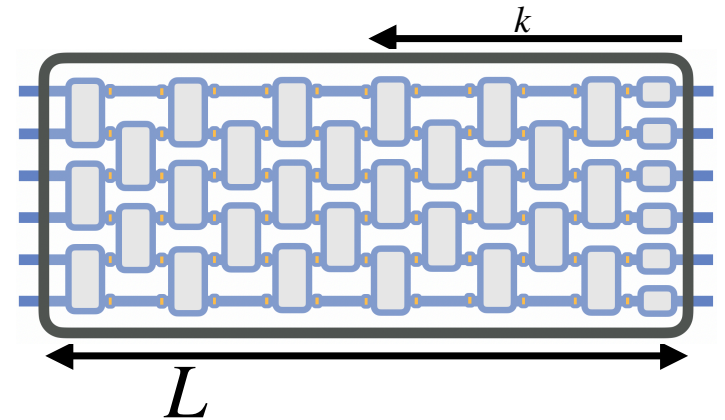
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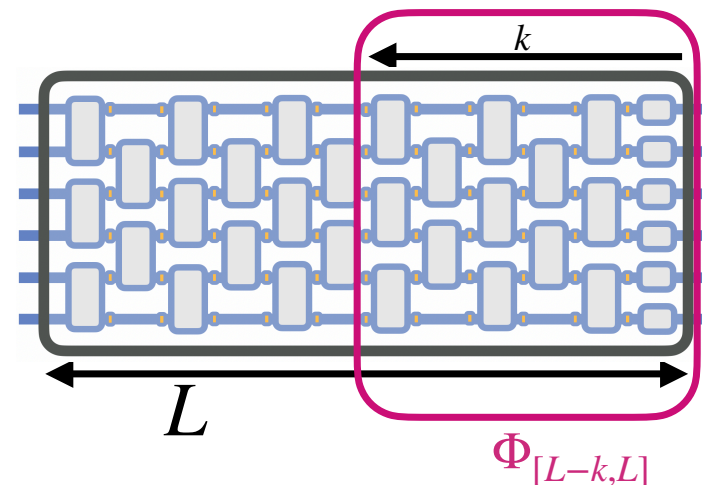
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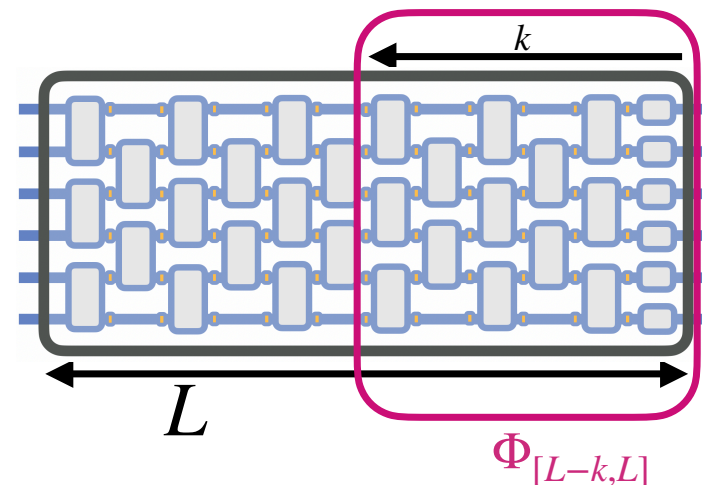
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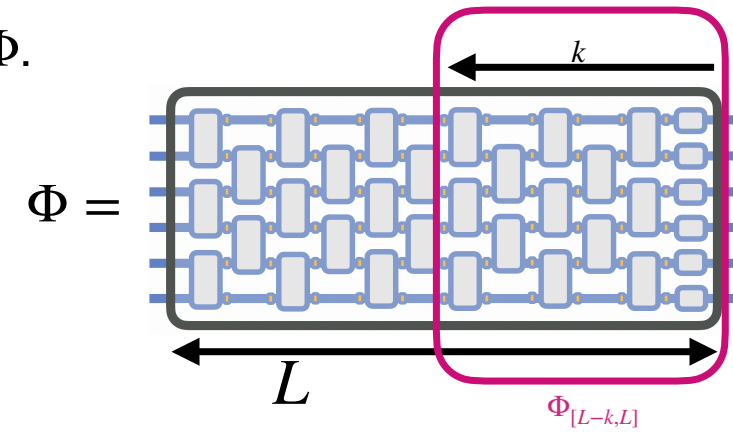
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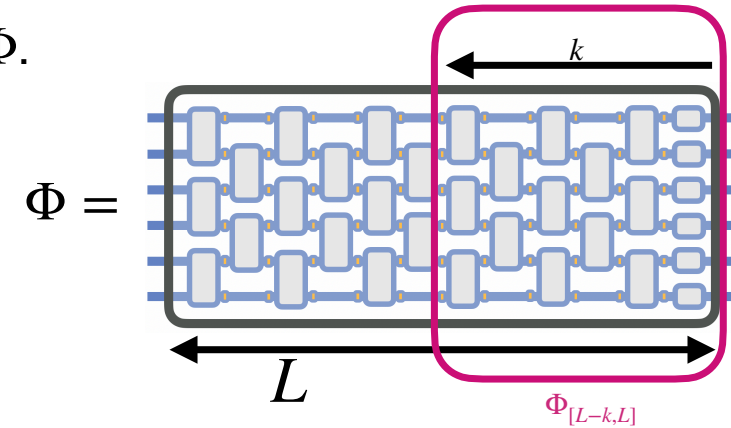
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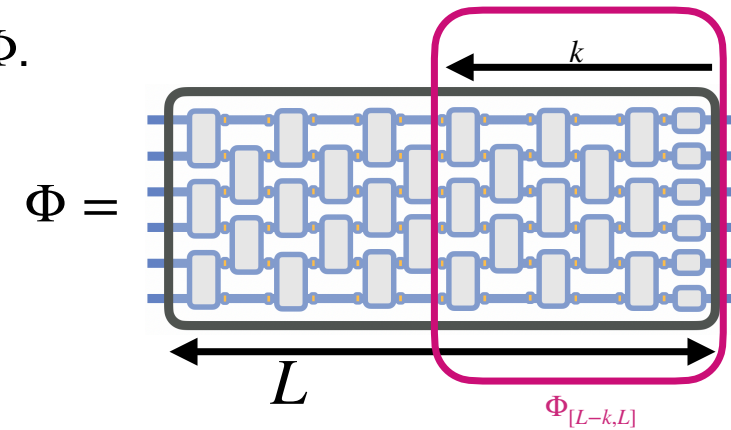
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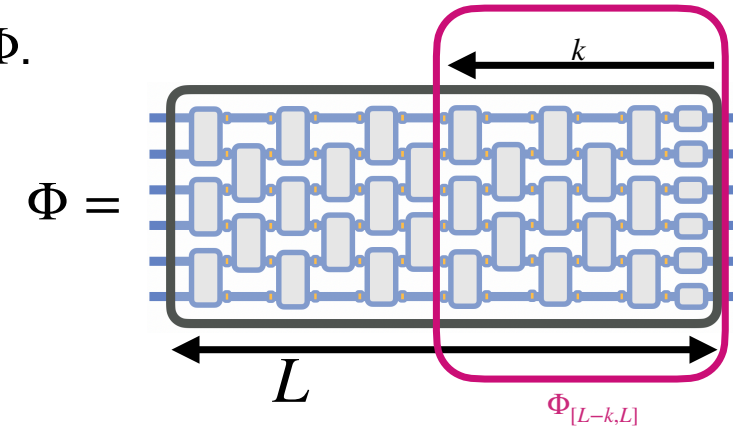
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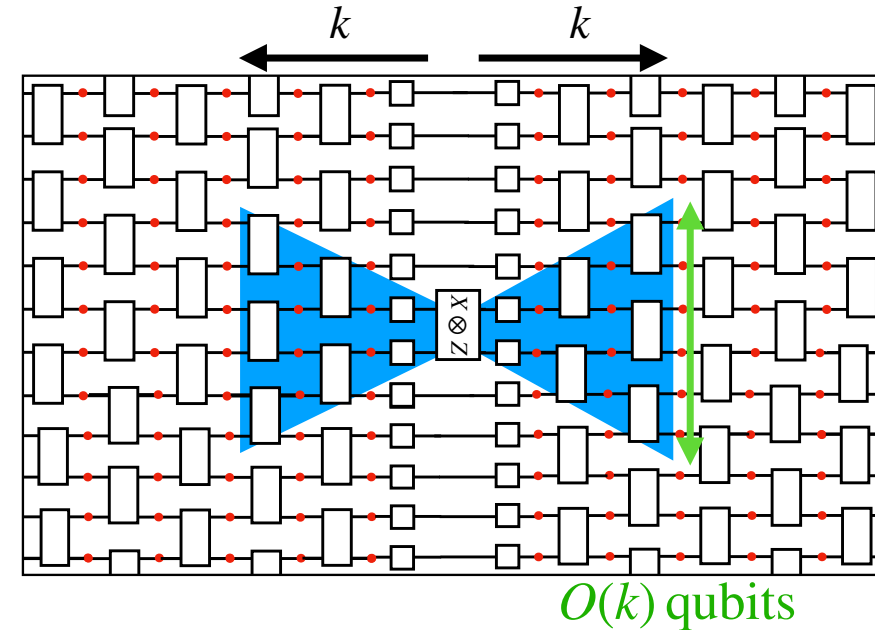
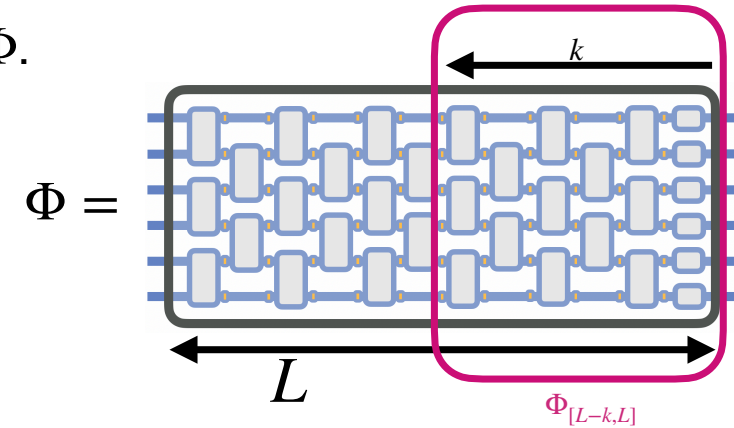
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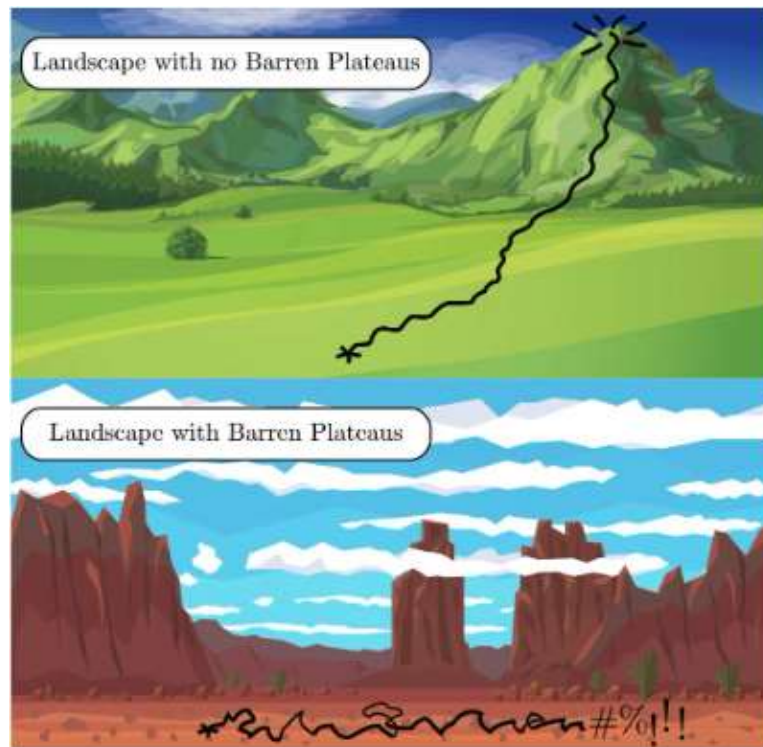
If P is local, then this is also local

- Thus, this can be computed efficiently for light-cone arguments.

Computational time (for 1D): $\exp(O(k)) = \text{poly}(\varepsilon^{-1})$



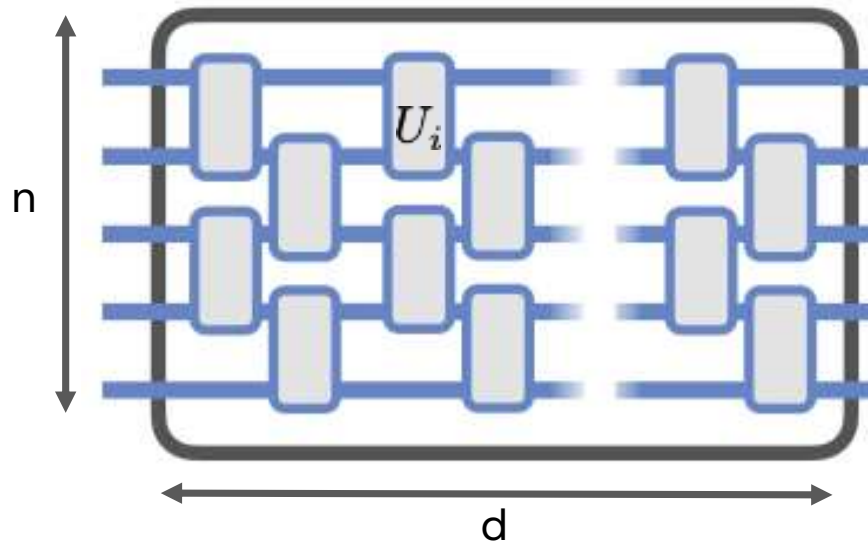
Barren plateaus are bad for variational algorithms



Gradient vanishes in all directions; can't figure out where to go!

<https://www.eurekalert.org/multimedia/739167>

Barren plateaus make optimization hard



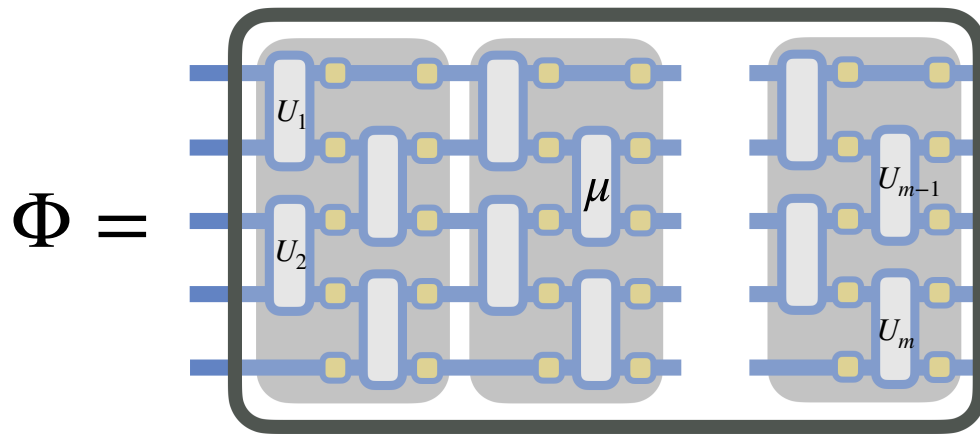
C = gradient of cost function

Math translation of 'vanishing gradient':

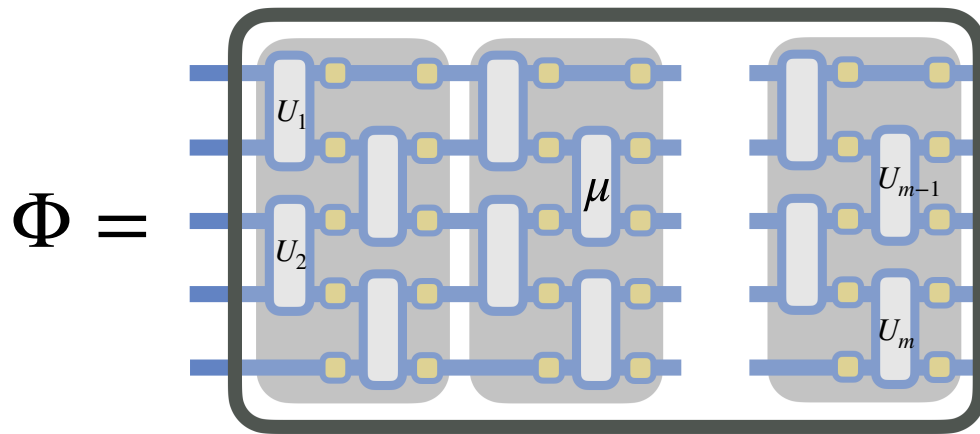
$$\text{Var}_{U_1, \dots, U_m} [C] = O(\exp(-n))$$

Recall: We are optimizing over

$$U_1, \dots, U_m$$



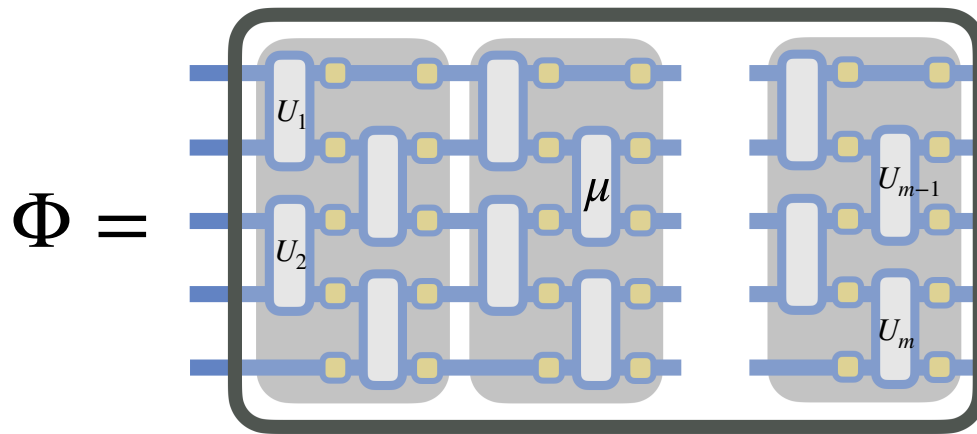
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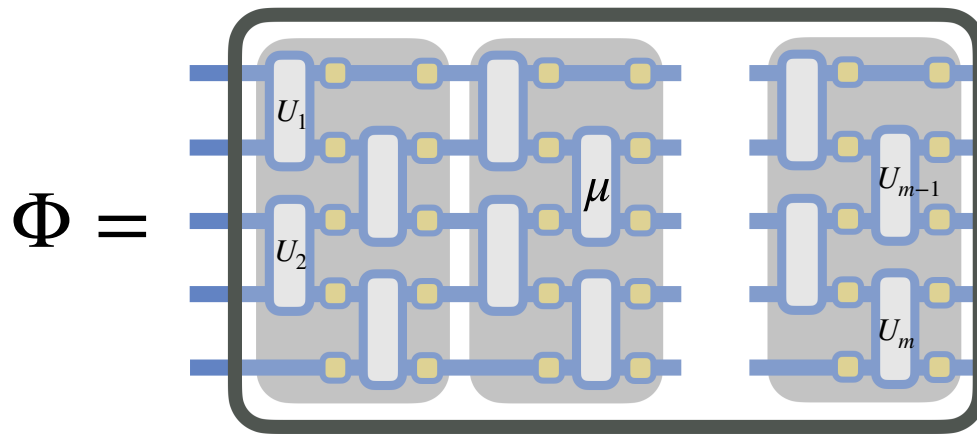
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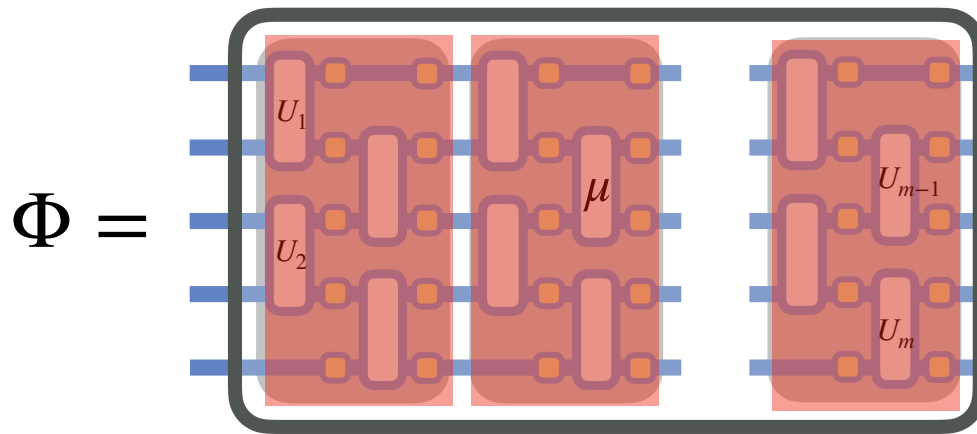
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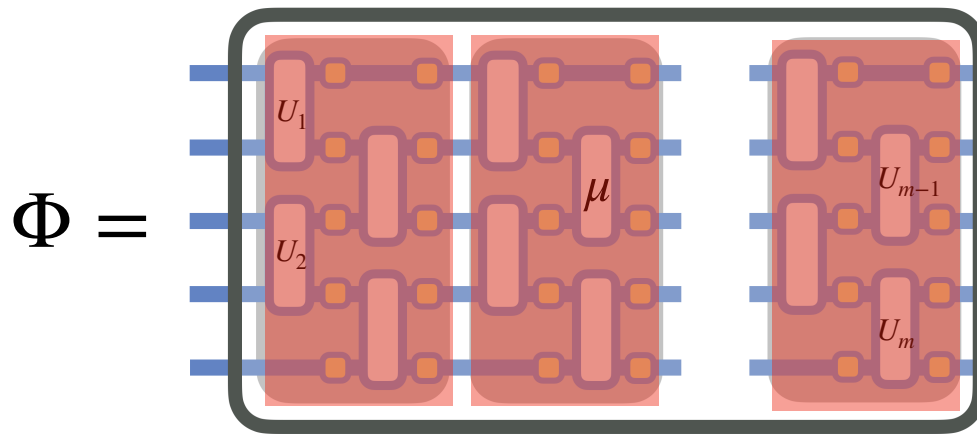
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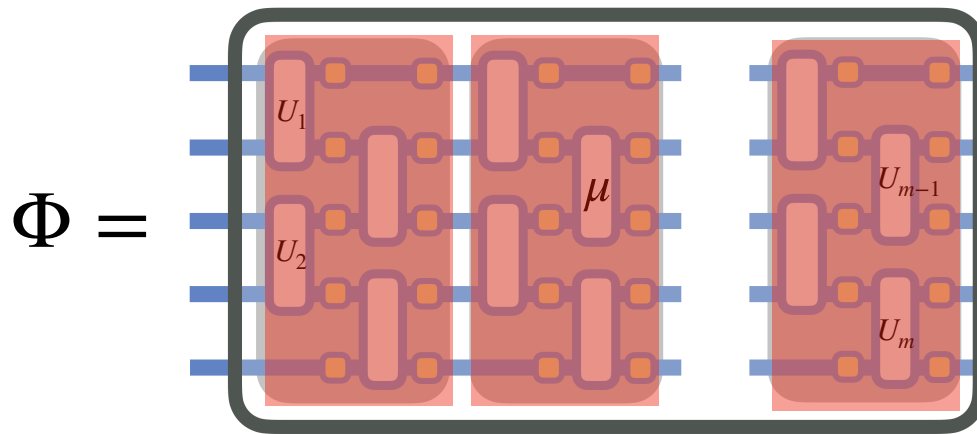
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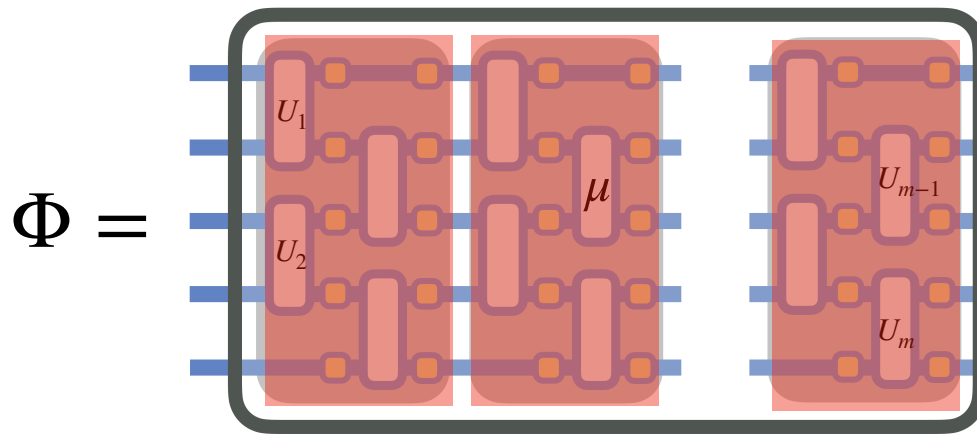
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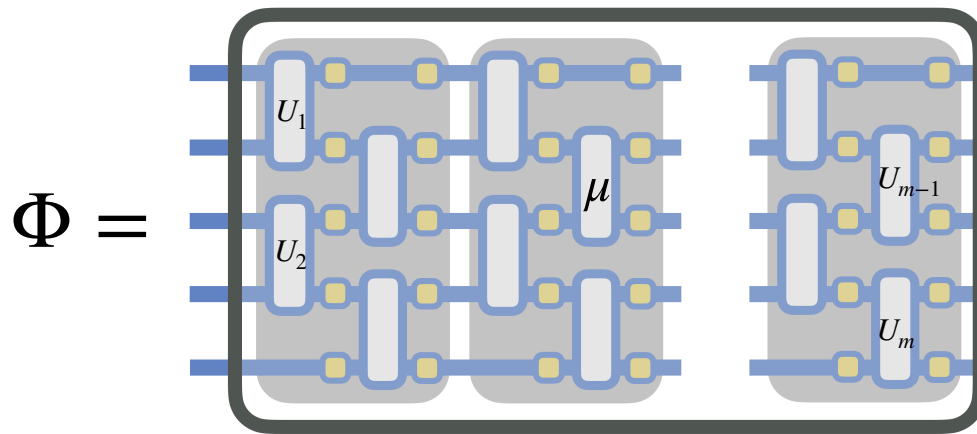
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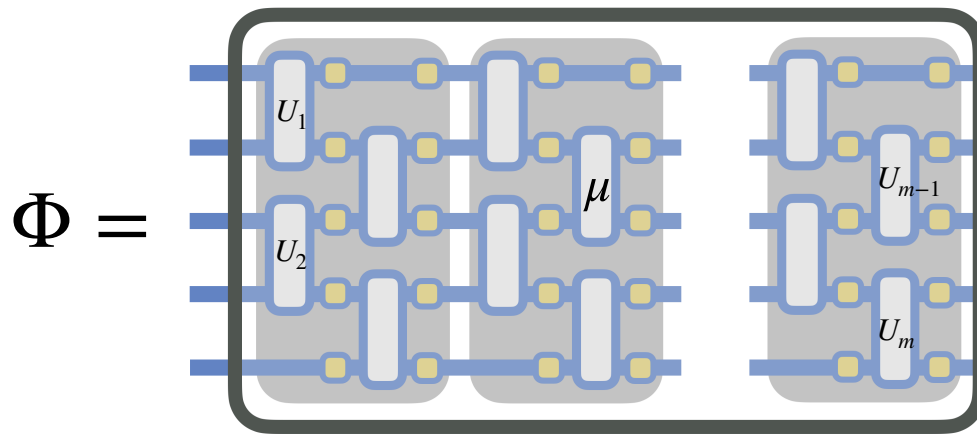
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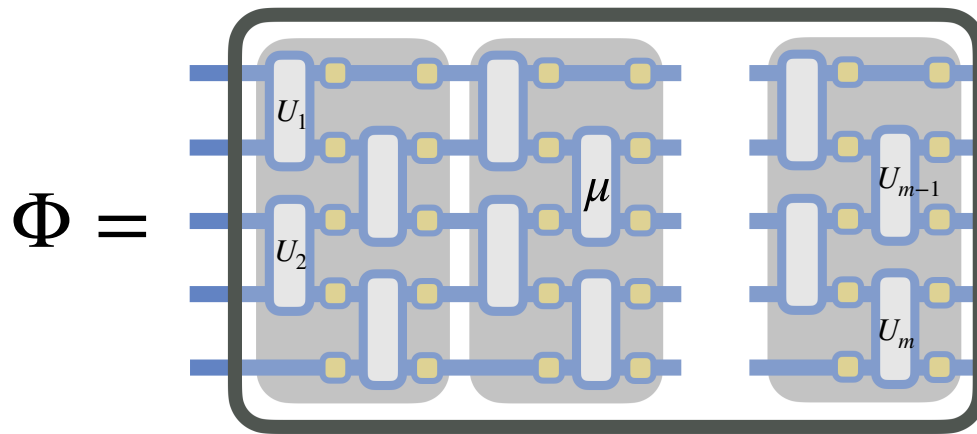


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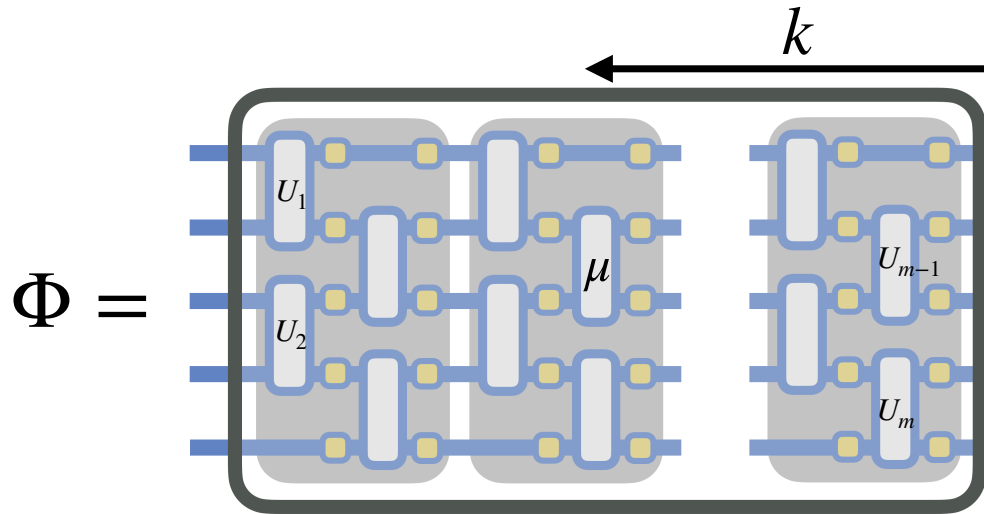
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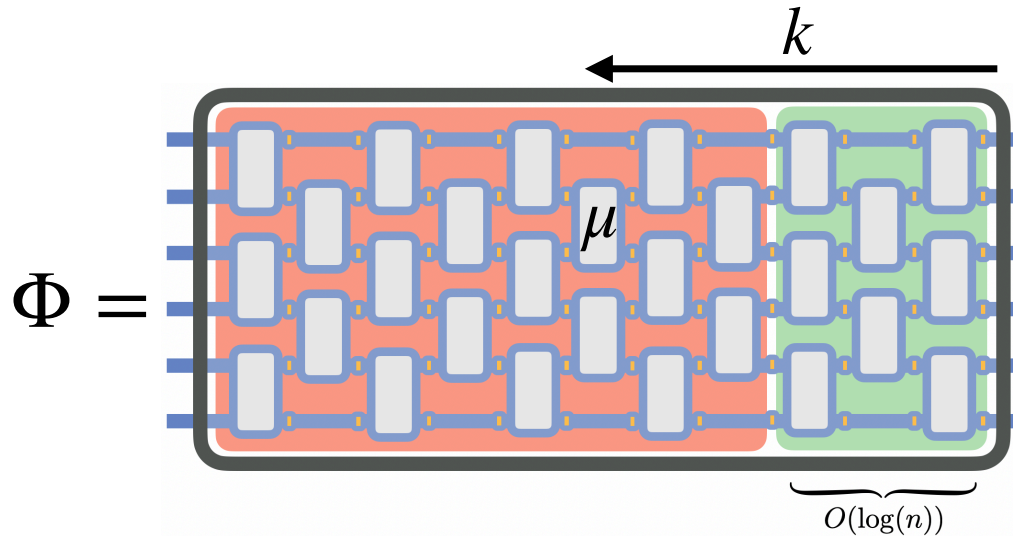
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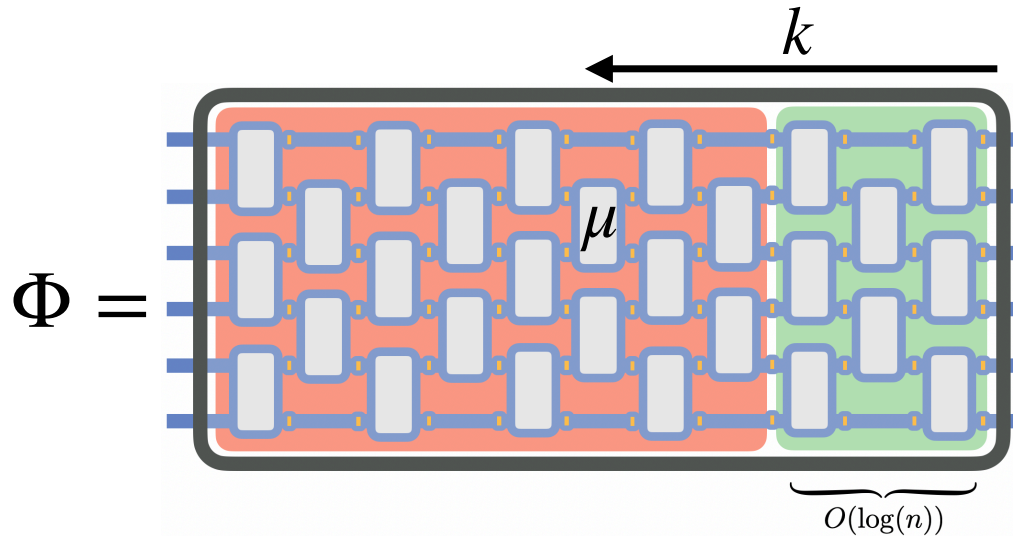
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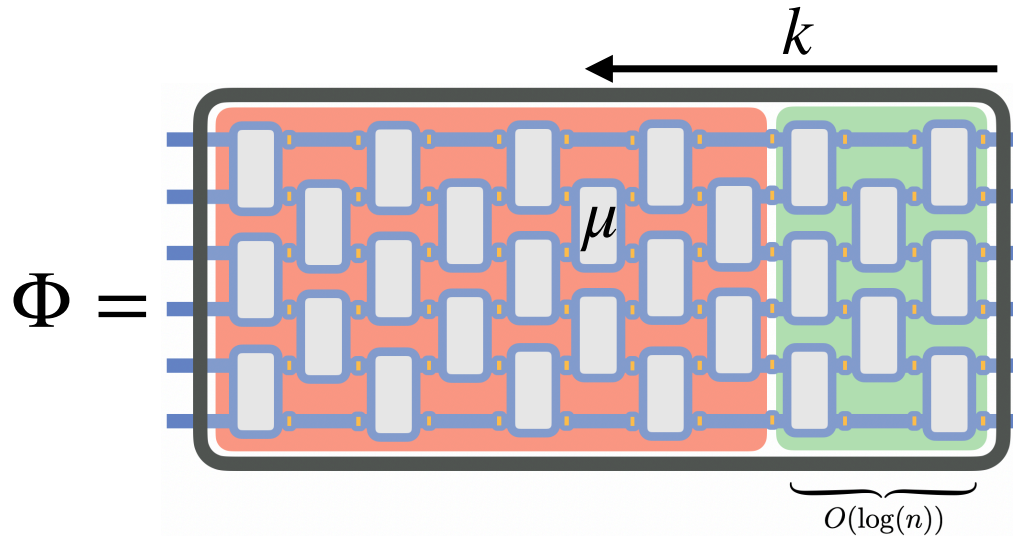
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Compare with: [3] Beyond unital noise in variational quantum algorithms: noise-induced barren plateaus and fixed points. Singkanipa *et al.*, ArXiv. (2024).

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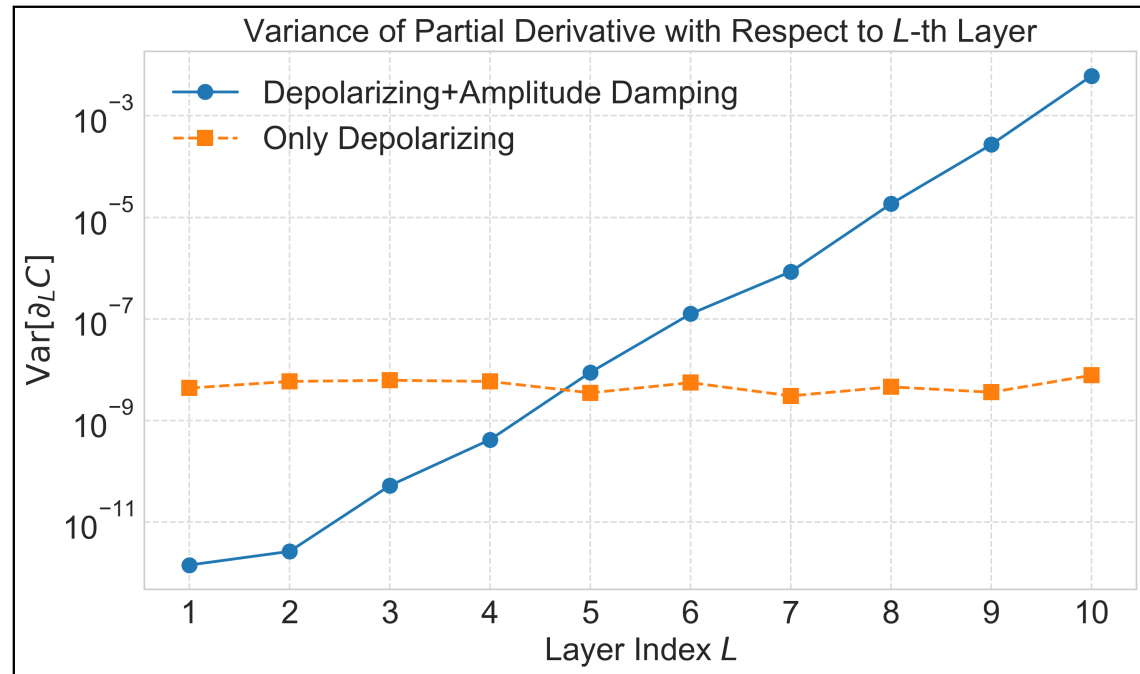
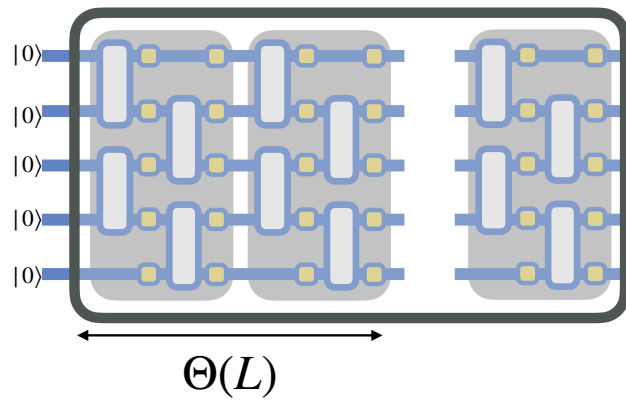
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Thanks a lot for your attention!

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