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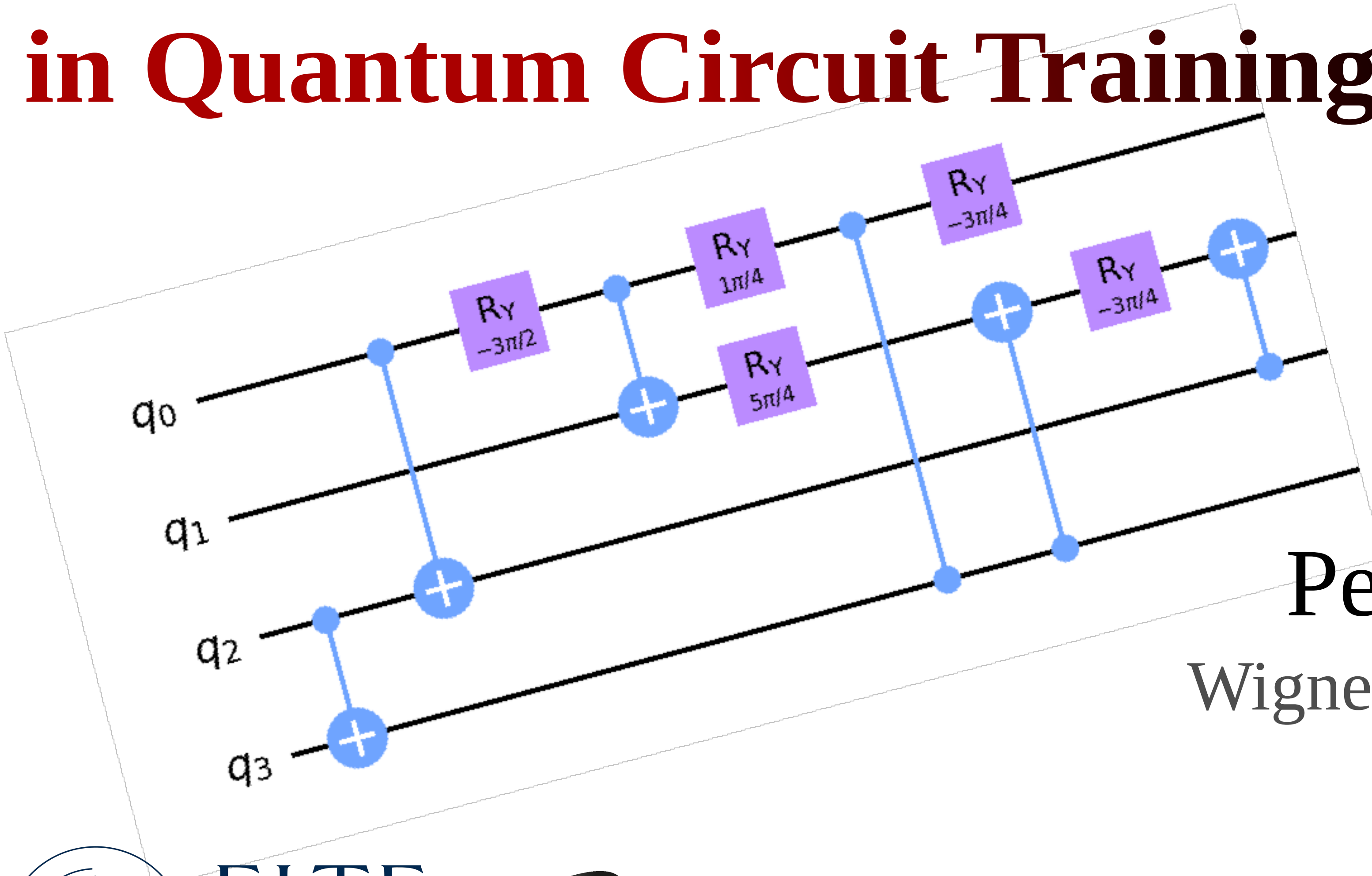
Batched Line Search Strategy for Navigating through Barren Plateaus in Quantum Circuit Training



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Qubit based architecture

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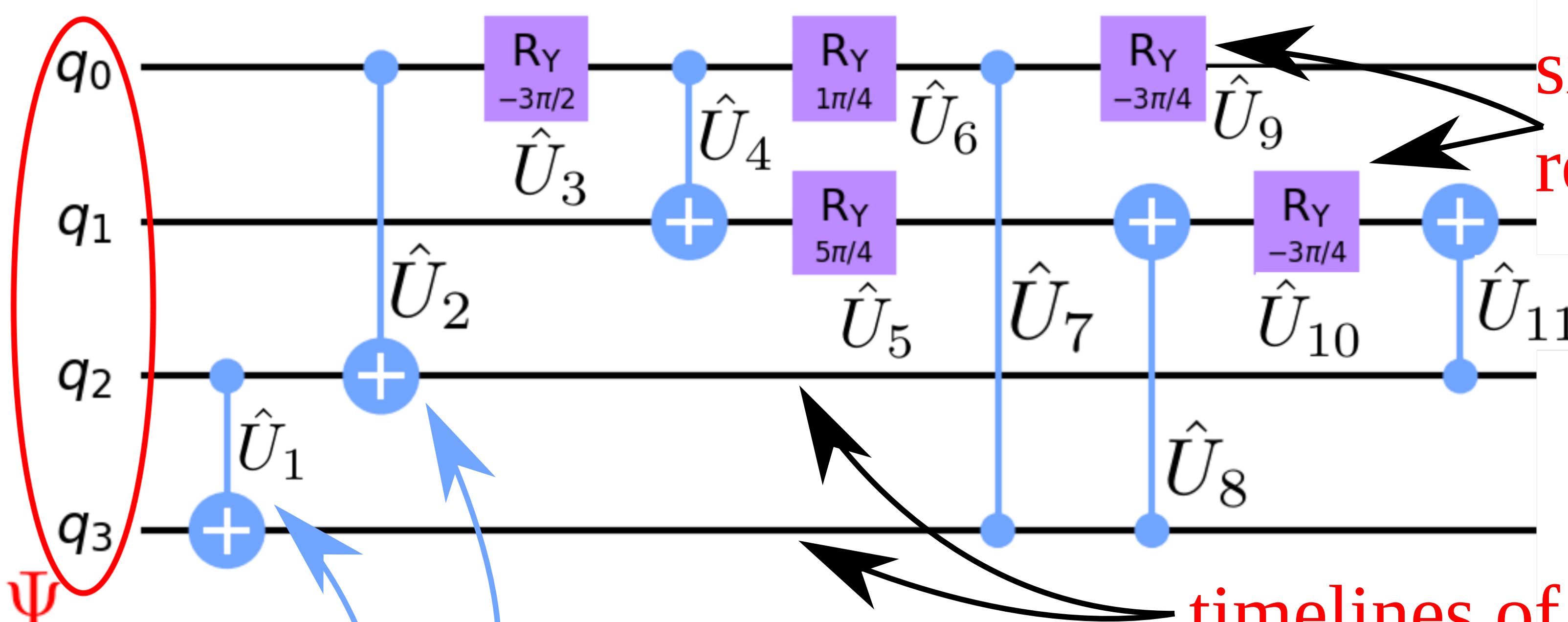
quantum program (unitary)

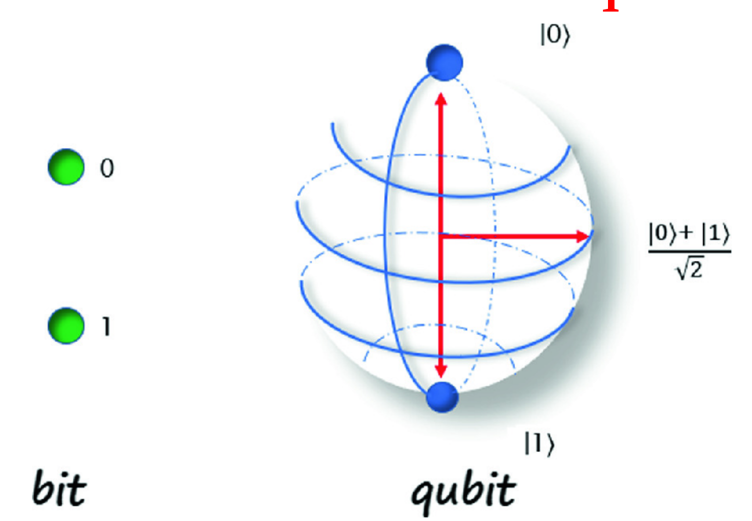
$$\hat{U} = \hat{U}_{11} \cdot \hat{U}_{10} \cdot \hat{U}_9 \cdot \hat{U}_8 \cdot \hat{U}_7 \cdot \hat{U}_6 \cdot \hat{U}_5 \cdot \hat{U}_4 \cdot \hat{U}_3 \cdot \hat{U}_2 \cdot \hat{U}_1$$



single qubit rotations

timelines of the qubits

controlled not gates



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Software toolkits to train parametric quantum circuits

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Gate decomposition utilities:

- Quantum Fast Approximate Synthesis Tool (QFAST)
- QSearch + LEAP

(Lawrence Berkeley National Laboratory)

BERKELEY LAB

QML utilities:

QISKIT

T|ket>: A Retargetable Compiler for NISQ Devices

(Cambridge Quantum Computing Ltd., University of Strathclyde

Qulacs: a fast and versatile quantum circuit simulator for research purposevices

(QunaSys, Osaka University, NTT, and Fujitsu)

QIBO a framework for quantum simulation with hardware acceleration

SQUANDER: toolkit to train quantum circuits

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- SQUANDER: Sequential Quantum Gate Decomposer

Quantum gate compilation

State preparation

gradient descend and evolutionary optimizers

Quantum ML

GitHub https://github.com/rakytap/sequential-quantum-gate-decomposer

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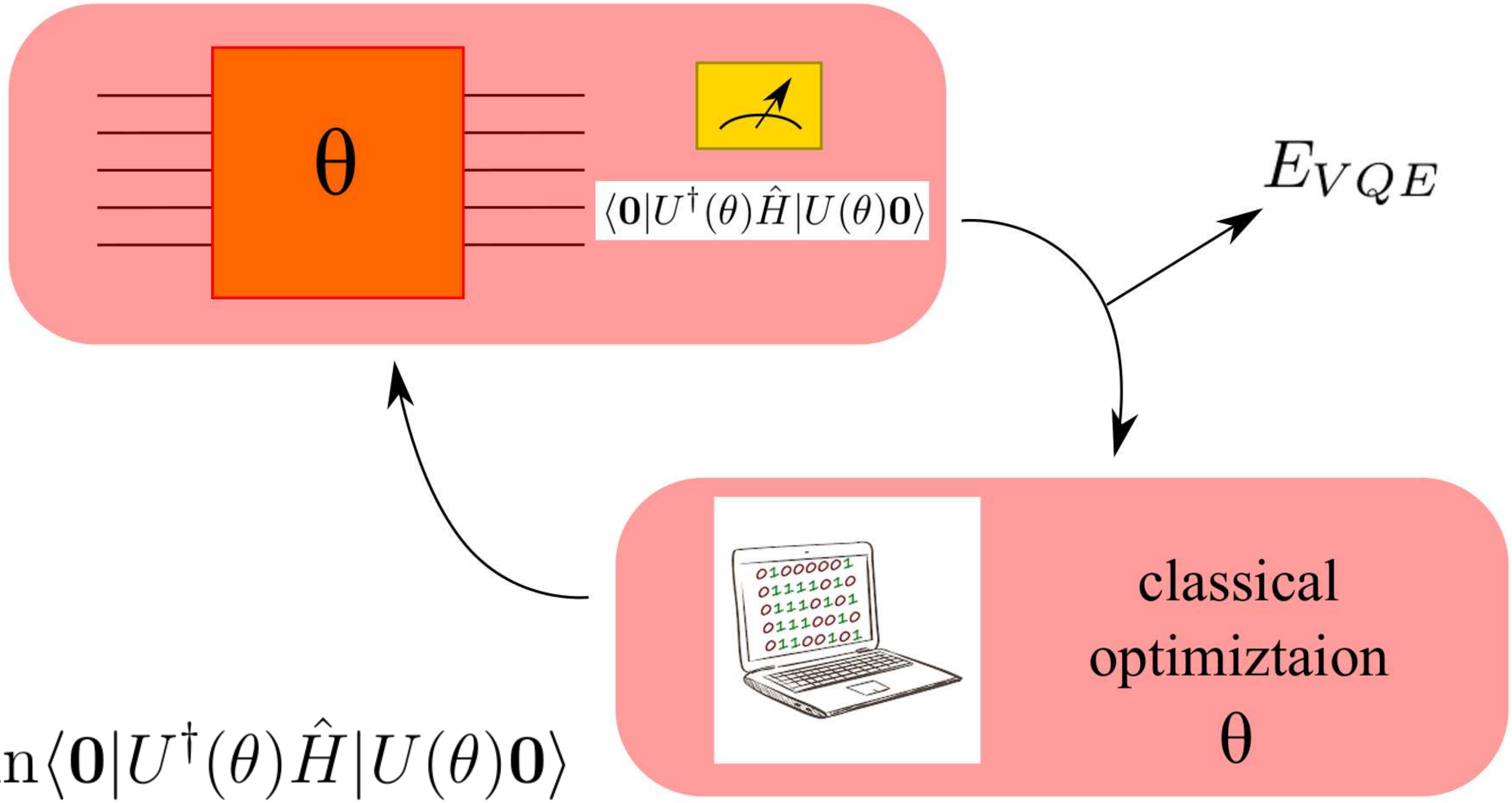
Variational quantum eigensolver



$$E_{VQE} = \min_{\theta} \langle \mathbf{0}|U^\dagger(\theta)\hat{H}|U(\theta)\mathbf{0}\rangle$$

$$\hat{H} = \sum_{\alpha}^{\mathcal{P}} w_\alpha \hat{P}_\alpha$$

ARTICLE

DOI: 10.1038/s41467-018-07090-4 OPEN

Barren plateaus in quantum neural network training landscapes

Jarrod R. McClean[1], Sergio Boixo[1], Vadim N. Smelyanskiy[1], Ryan Babbush[1] & Hartmut Neven[1]

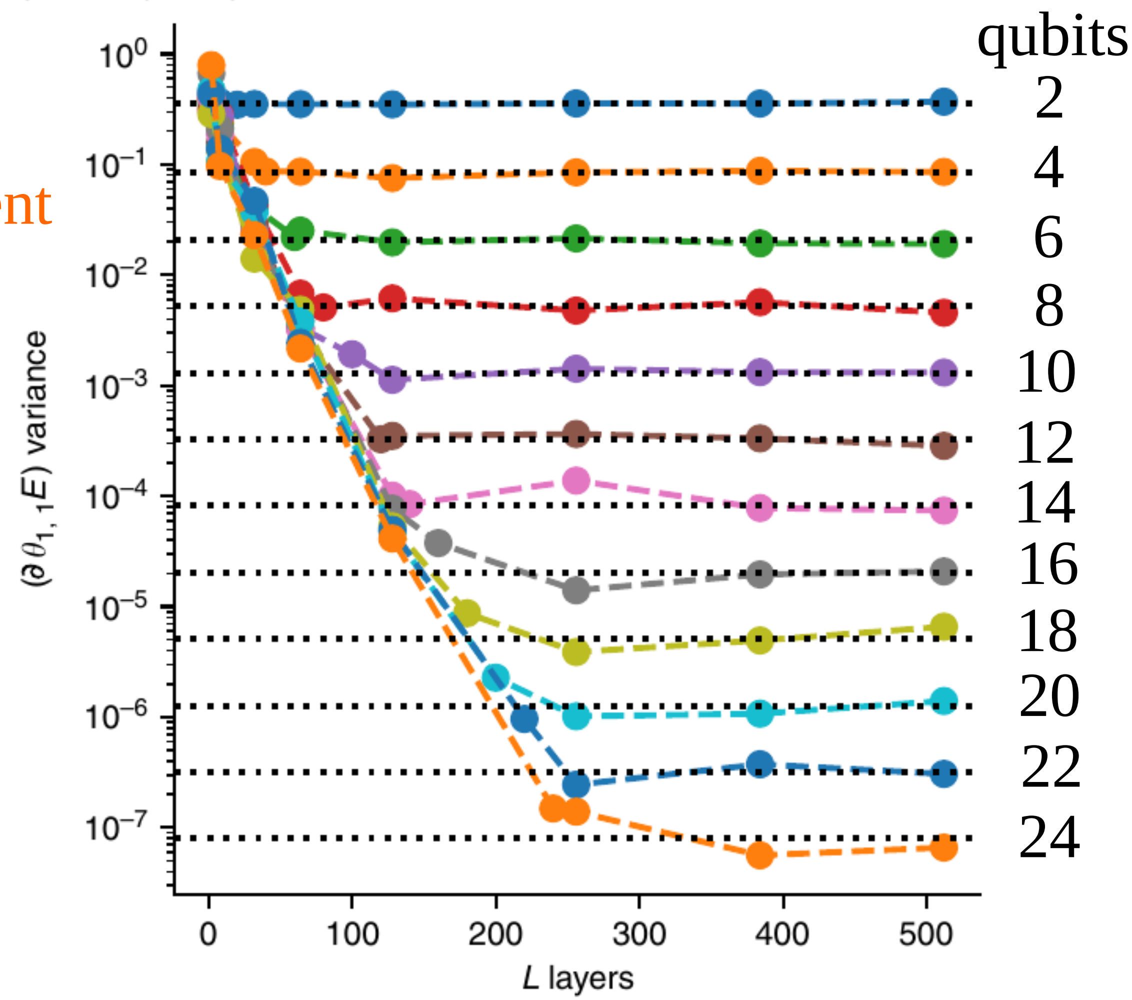
The variance of the cost function gradient

(and consequently its typical value)

vanishes exponentially

in the qubit number N

$$\mathrm{Var}[\partial_{i,l} E(\boldsymbol{\theta})] \sim \mathcal{O}\left(\frac{1}{2^{2N}}\right)$$



Barren plateau & entanglement entropy

controlling entangelement to mitigate BP?

Second Rényi entropy

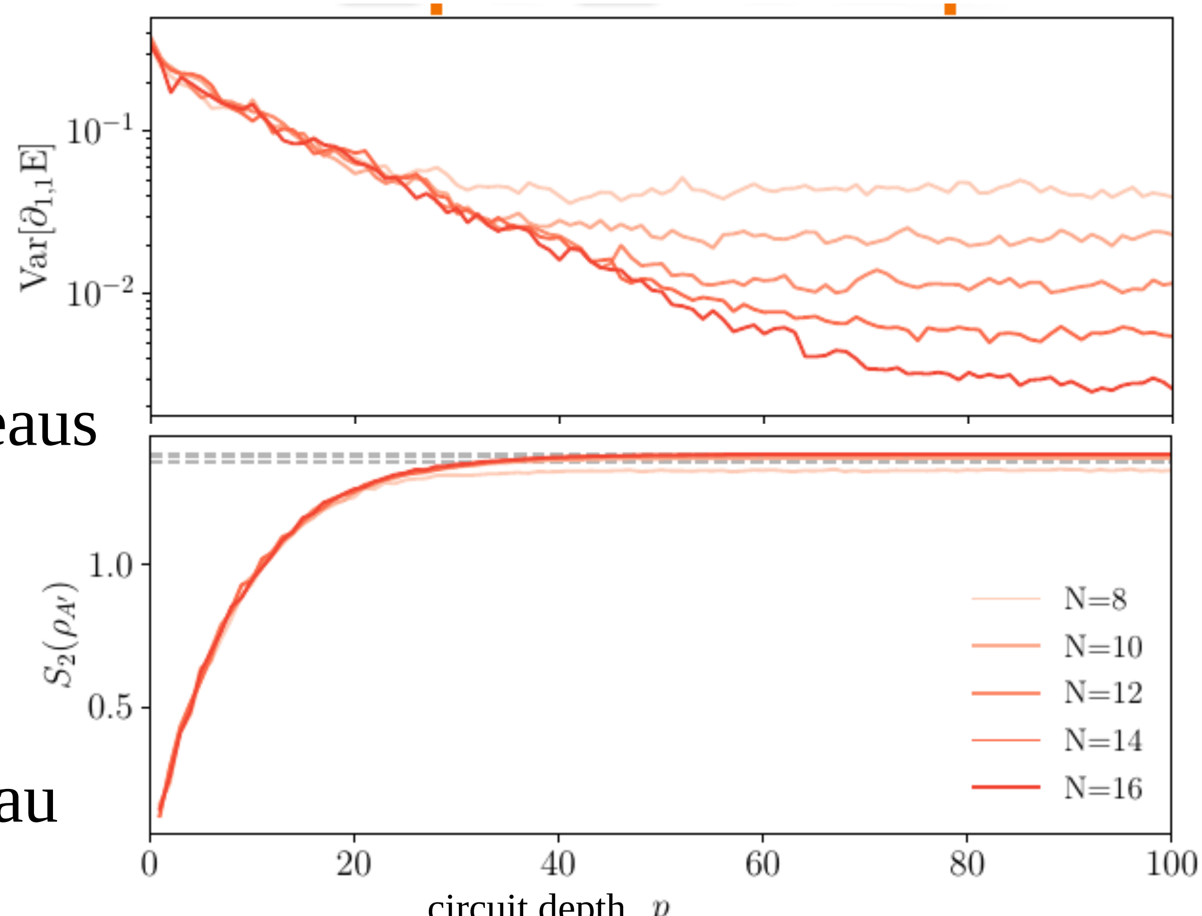
$$S_2 = -\ln \mathrm{Tr}\rho_A^2$$

subsystem

Avoiding Barren Plateaus Using Classical Shadows

Stefan H. Sack, Raimel A. Medina, Alexios A. Michailidis, Richard Kueng, and Maksym Serbyn

PRX QUANTUM 3, 020365 (2022)



Entanglement-Induced Barren Plateaus

Carlos Ortiz Marrero, Mária Kieferová, and Nathan Wiebe

PRX Quantum 2, 040316

Entanglement devised barren plateau mitigation

Taylor L. Patti, Khadijeh Najafi, Xun Gao, and Susanne F. Yelin

Phys. Rev. Research 3, 033090

Avoiding Barren Plateaus Using Classical Shadows

Stefan H. Sack, Raimel A. Medina, Alexios A. Michailidis,
Richard Kueng, and Maksym Serbyn

PRX QUANTUM 3, 020365 (2022)

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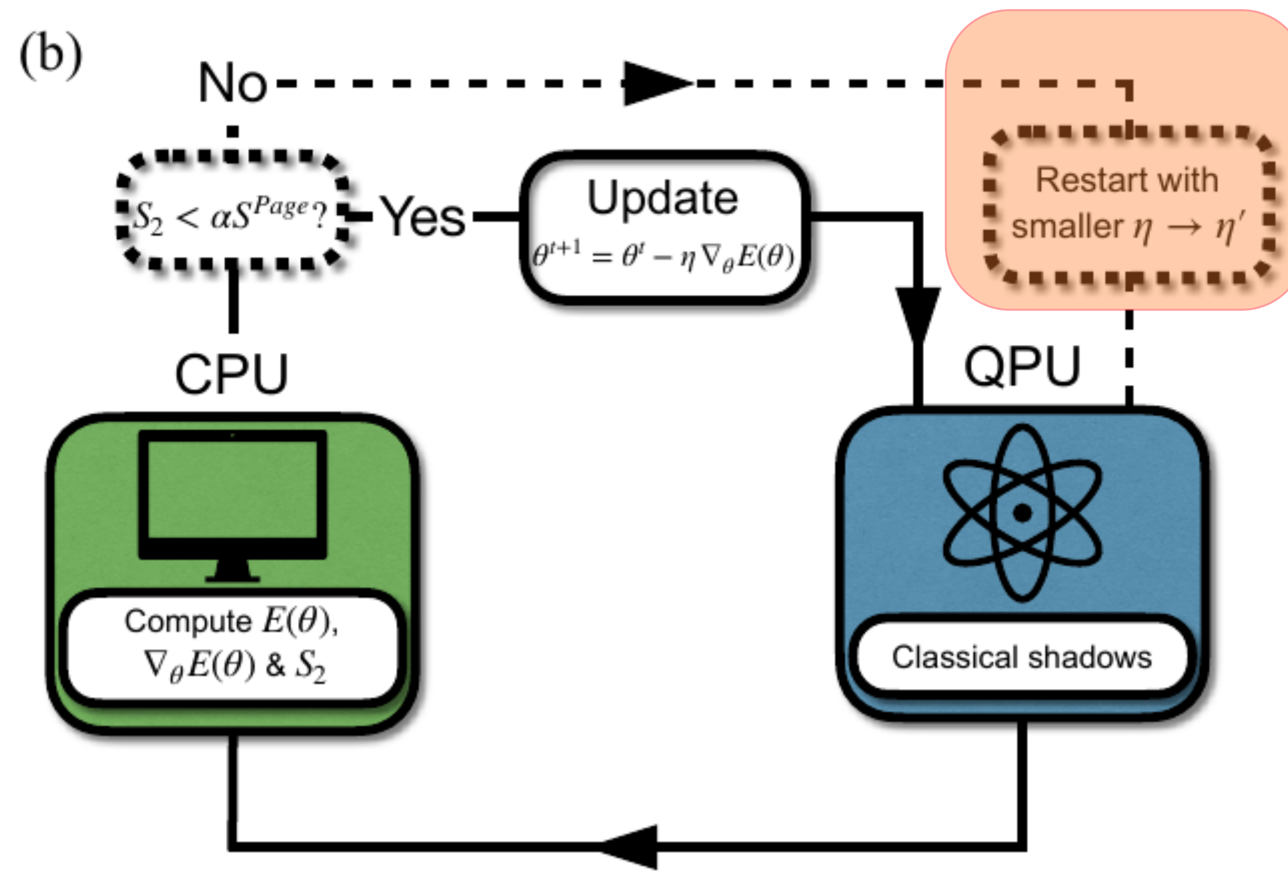
- **monitor the entropy and control the lerning rate**

$$\boldsymbol{\theta}^{t+1} = \boldsymbol{\theta}^{t} - \eta \nabla_{\boldsymbol{\theta}} E(\boldsymbol{\theta}),$$

Decreasing the learning rate!!



- parameter initialization to low entangling gates
  Quantum 3, 214 (2019), PRX Quantum 3, 010313 (2022)
- use local cost functions
  Nature Communications 12, 1791 (2021)
- use matrix product states
  PRX Quantum 3, 010313
- layer-by-layer optimization
  Quantum Mach. Intell. 3, 5 (2021)

limiting the expressiveness of the circuit

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~~Decrease~~ Increase the learning rate

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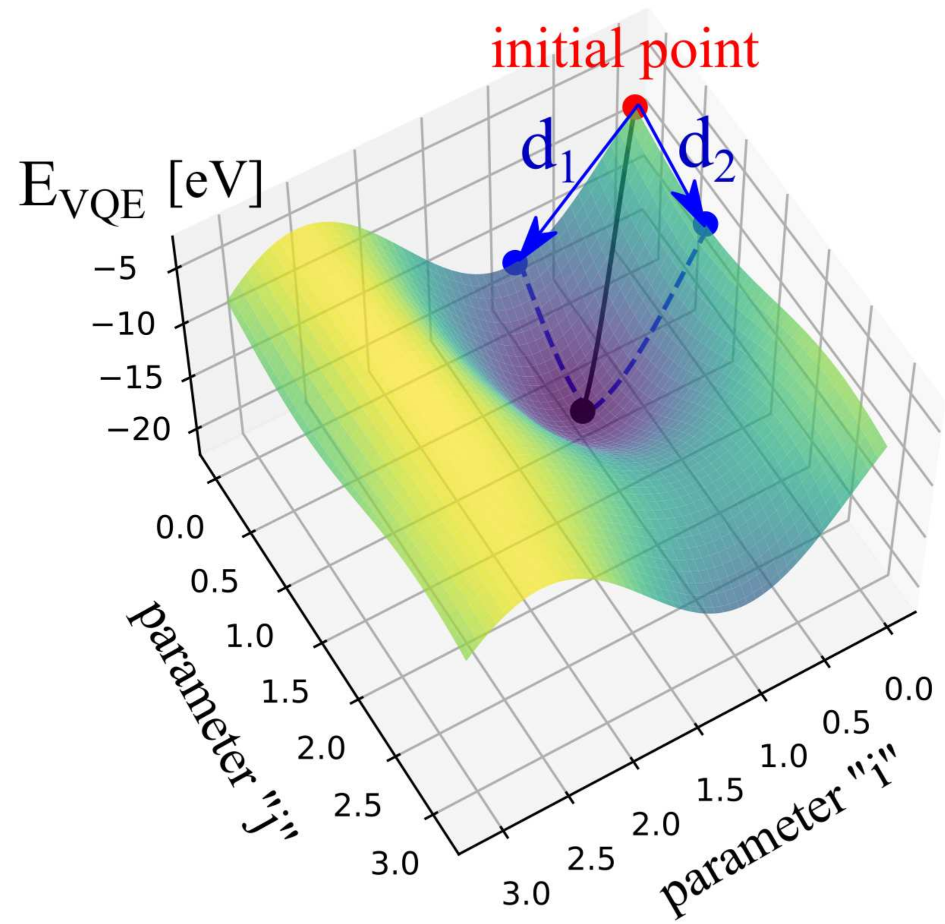
- Perform line search along a well defined direction

Search direction ⟶ line search
⟶ Search direction ⟶ line search
⟶ Search direction ⟶ line search
⟶ Search direction ⟶ line search
⟶ •••

- How to determine search direction?
- What is the range of the line search?
- layer-by-layer optimization



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Parameter dependence

gate containing parameter p_i: U_p

$$|\Psi\rangle = U_1 \cdot U_2 \cdot U_3 \ldots \overbrace{(A \cdot \cos(p_i) + B \cdot \sin(p_i) + C)}^{U_p} \ldots U_{K-2} \cdot U_{K-1} \cdot U_K |0\rangle$$

matrices

$$|\Psi\rangle = \cos(p_i)|a\rangle + \sin(p_i)|b\rangle + |c\rangle$$

scalars

$$E = \langle\Psi|H|\Psi\rangle = \kappa \cdot \sin(2p_i + \xi) + \gamma \cdot \sin(p_i + \phi) + C$$

knowing the constants, the line search becomes efficient

Gradient free search direction

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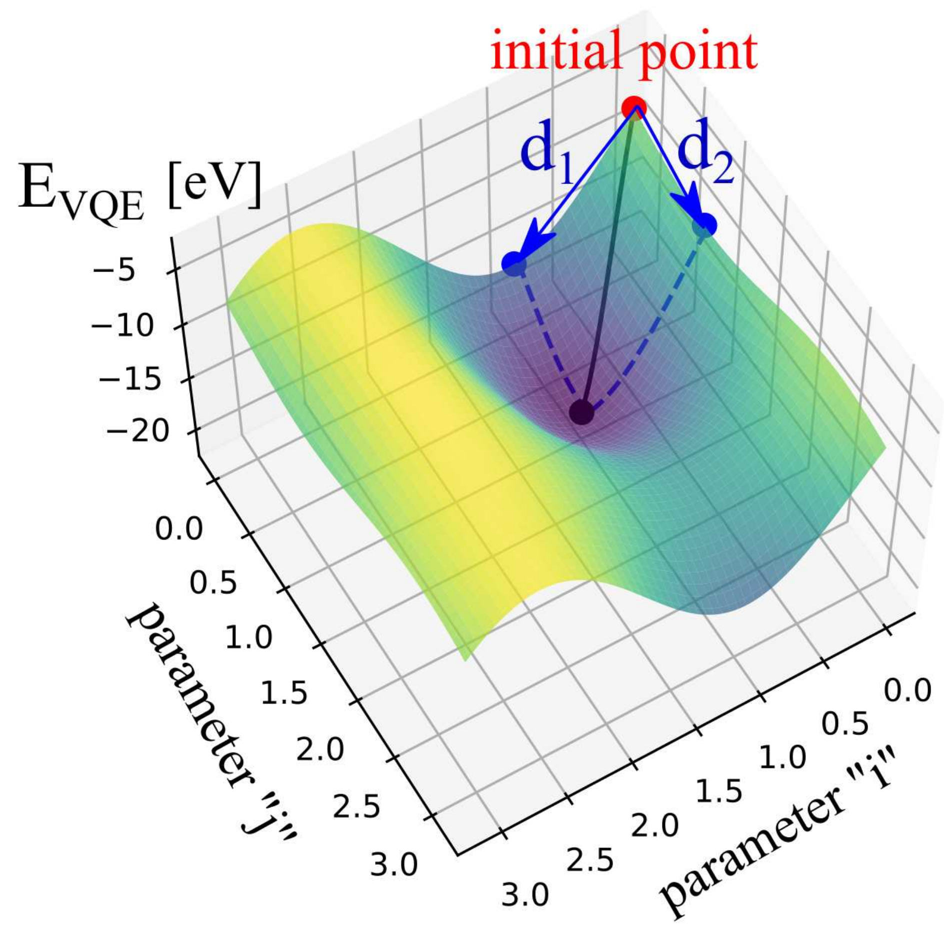
$$E_{VQE} = \kappa \cdot \sin(2\theta_i + \xi) + C$$

- randomly select a subset Λ of the parameters
- determine the parameter-wise minimum θ_i^*
- we define the search direction

$$d_i = \begin{cases} \theta_i^* - \theta_i & \text{if } i \in \Lambda \\ 0 & \text{otherwise.} \end{cases}$$

- decreasing values in E_{VQE} are automatically associated with moderate entaglement entropy.
- There are no additional hyper-parameters in the algorithm



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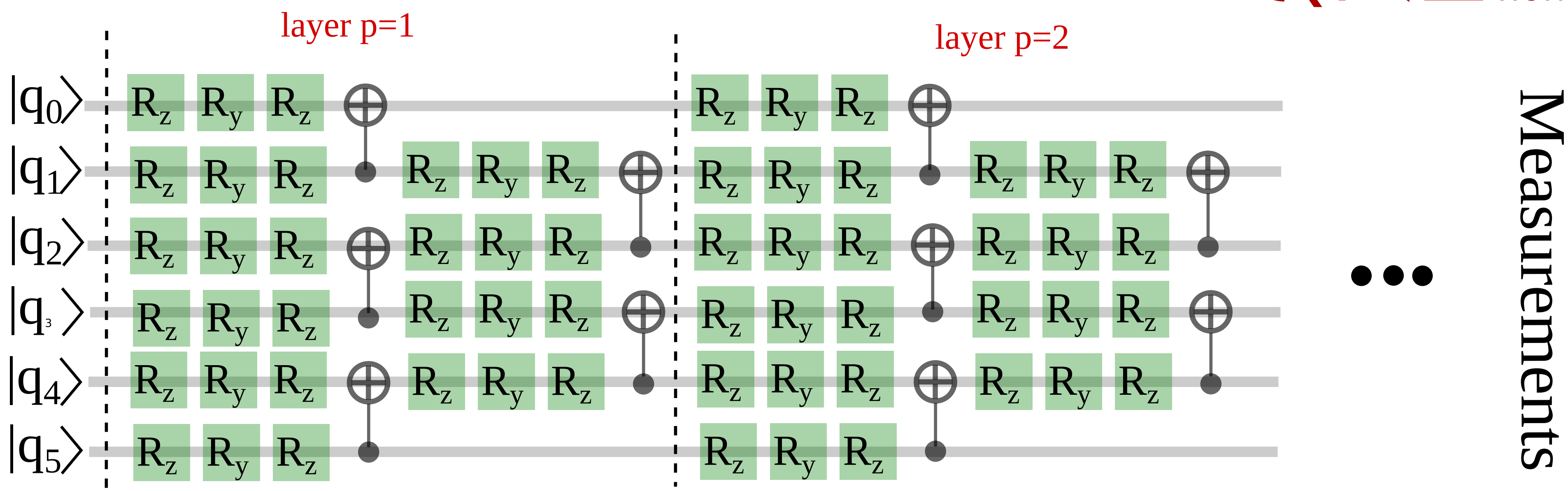
The studied VQE problem



Heisenberg XXX model

$$\hat{H}_{XXX} = \sum_{i,j \in V_{\mathcal{G}}} J\left(\hat{\sigma}_i^z \hat{\sigma}_j^z + \hat{\sigma}_i^y \hat{\sigma}_j^y + \hat{\sigma}_i^x \hat{\sigma}_j^x\right) + h_z \sum_N \hat{\sigma}_i^z$$

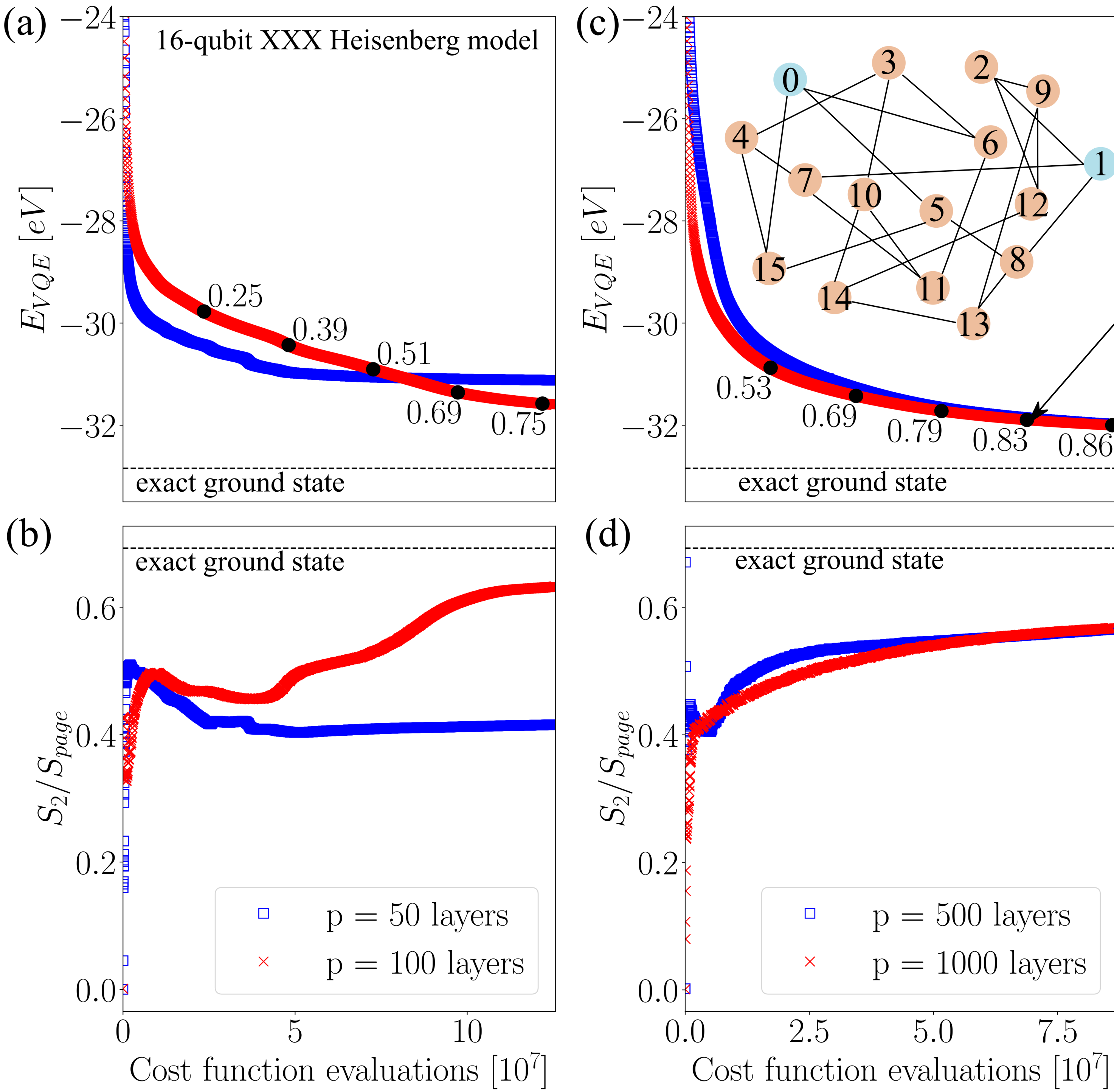
Sachdev-Ye-Kitaev (SYC) model describing Majorana fermions

$$\hat{H}_{SYC} = \sum_{1 \leq i < j < k < l \leq 2N} J_{i,j,k,l}\, \chi_i \chi_j \chi_k \chi_l$$

$$\{\chi_i, \chi_j\} = \delta_{i,j}$$

$J_{i,j,k,l}$ is taken from a Gaussioan distribution

16-qubit system VQE



$$M = |\langle \Psi_0 | \Psi(\boldsymbol{\theta}) \rangle|^2$$

16-qubit wave-function:
131070 free parameters

circuit with 100-layers:
9000 free parameters

circuit with 500-layers:
45000 free parameters

circuit with 1000-layers:
90000 free parameters

Compare optimization strategies

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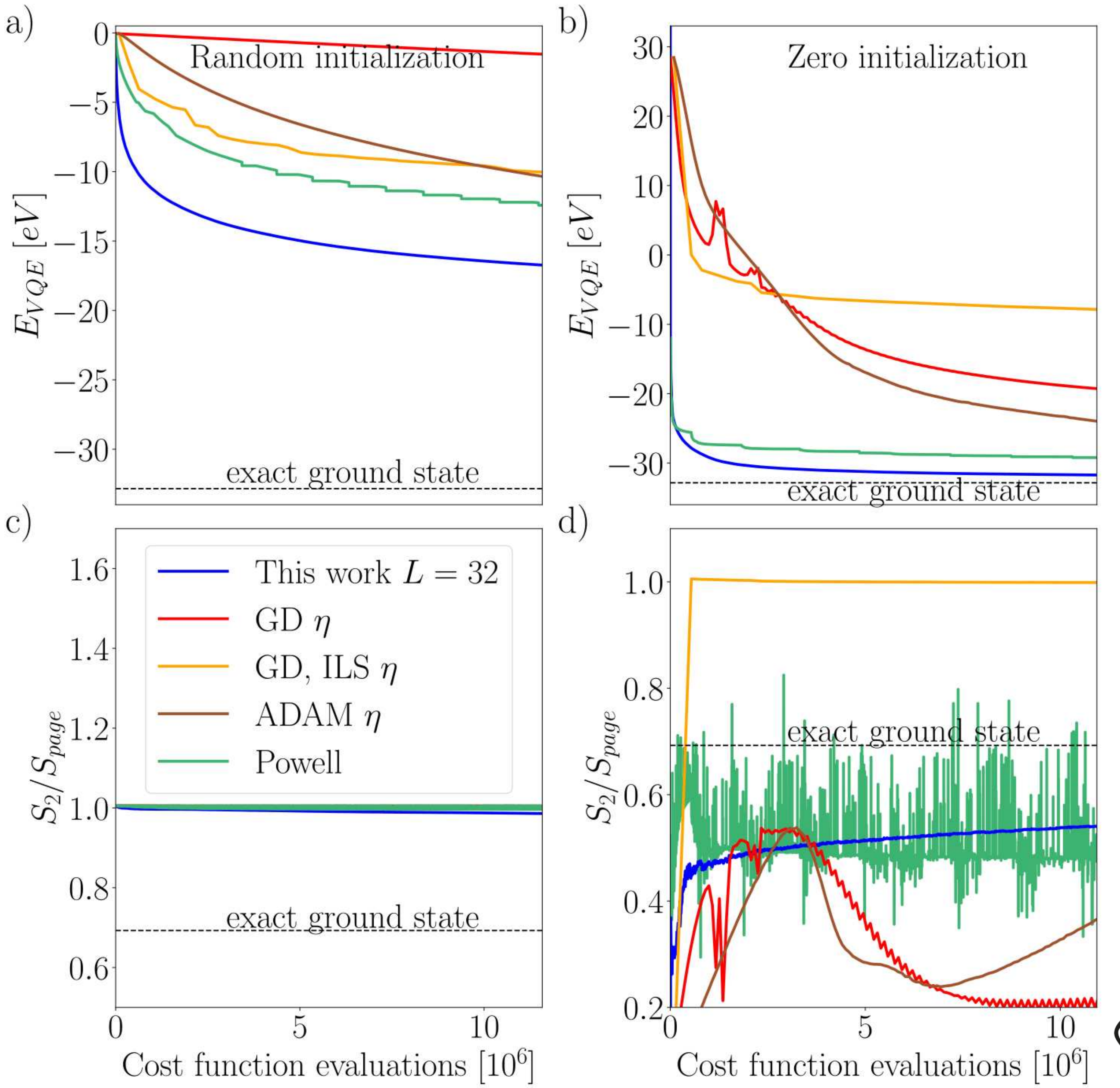

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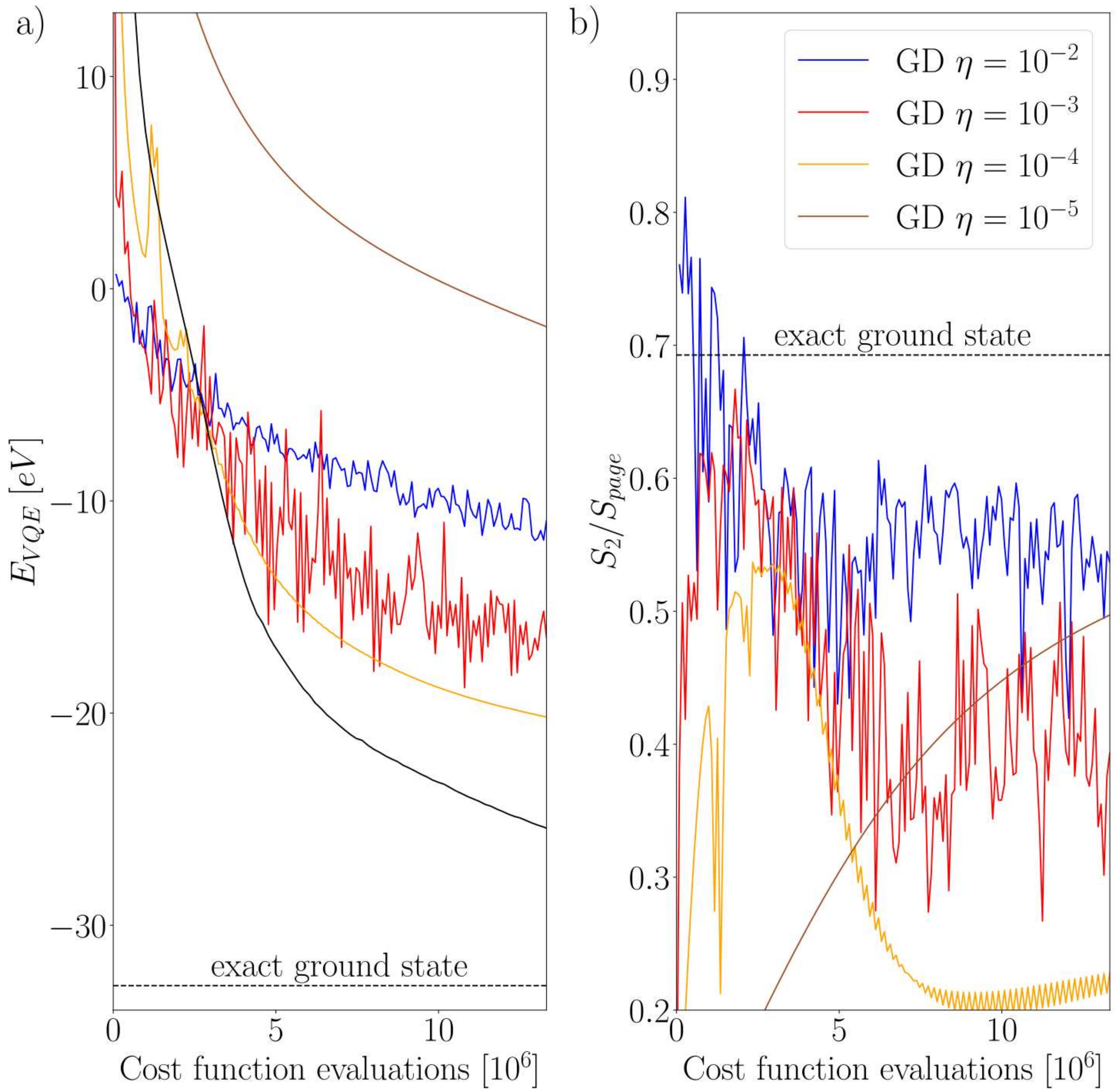
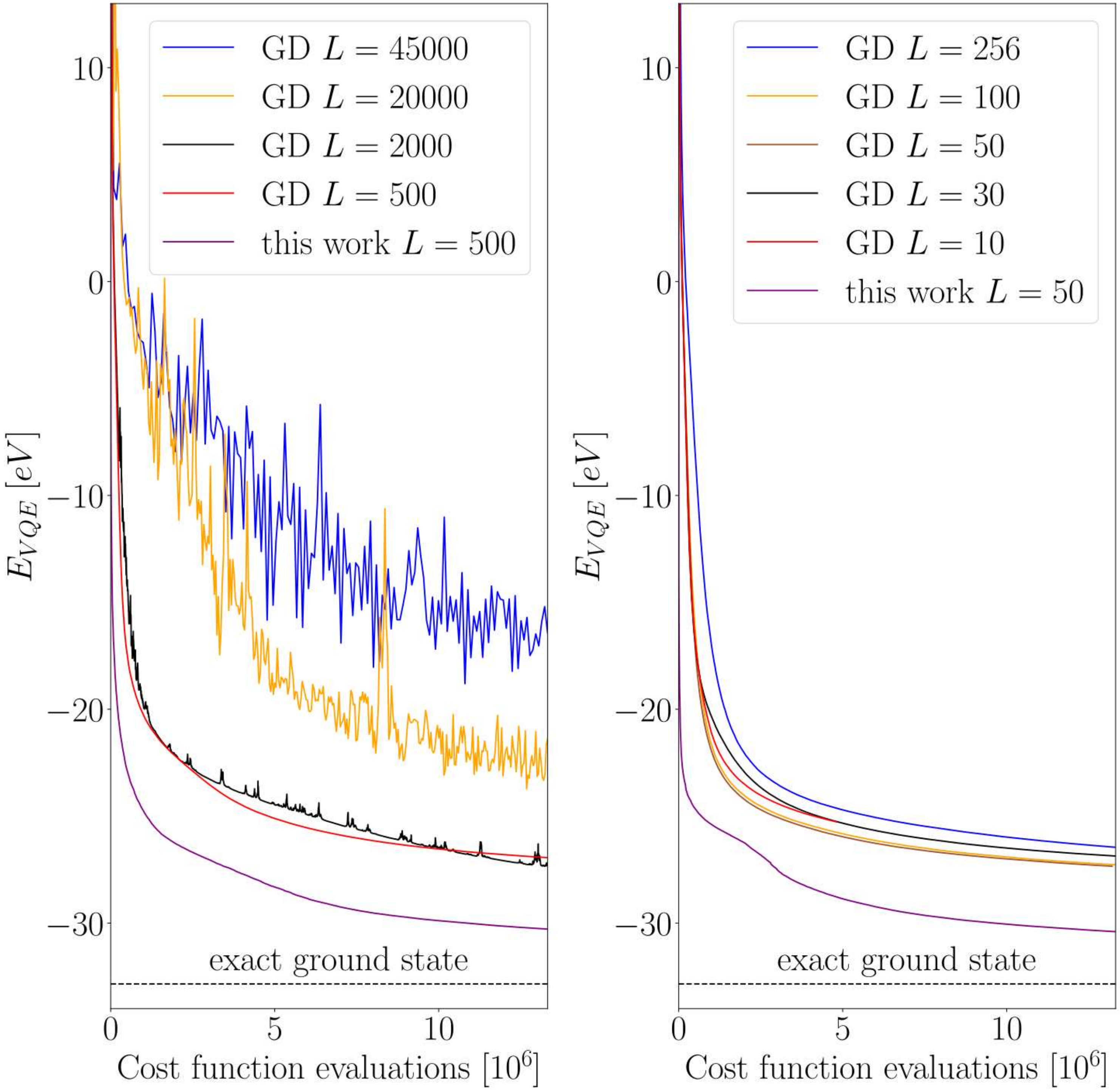
How much the learning rate influences the optimization?



Why is our method so efficient?



L... the number of parameters updated in one iteration

GD... Gradent descend

Compare optimization strategies

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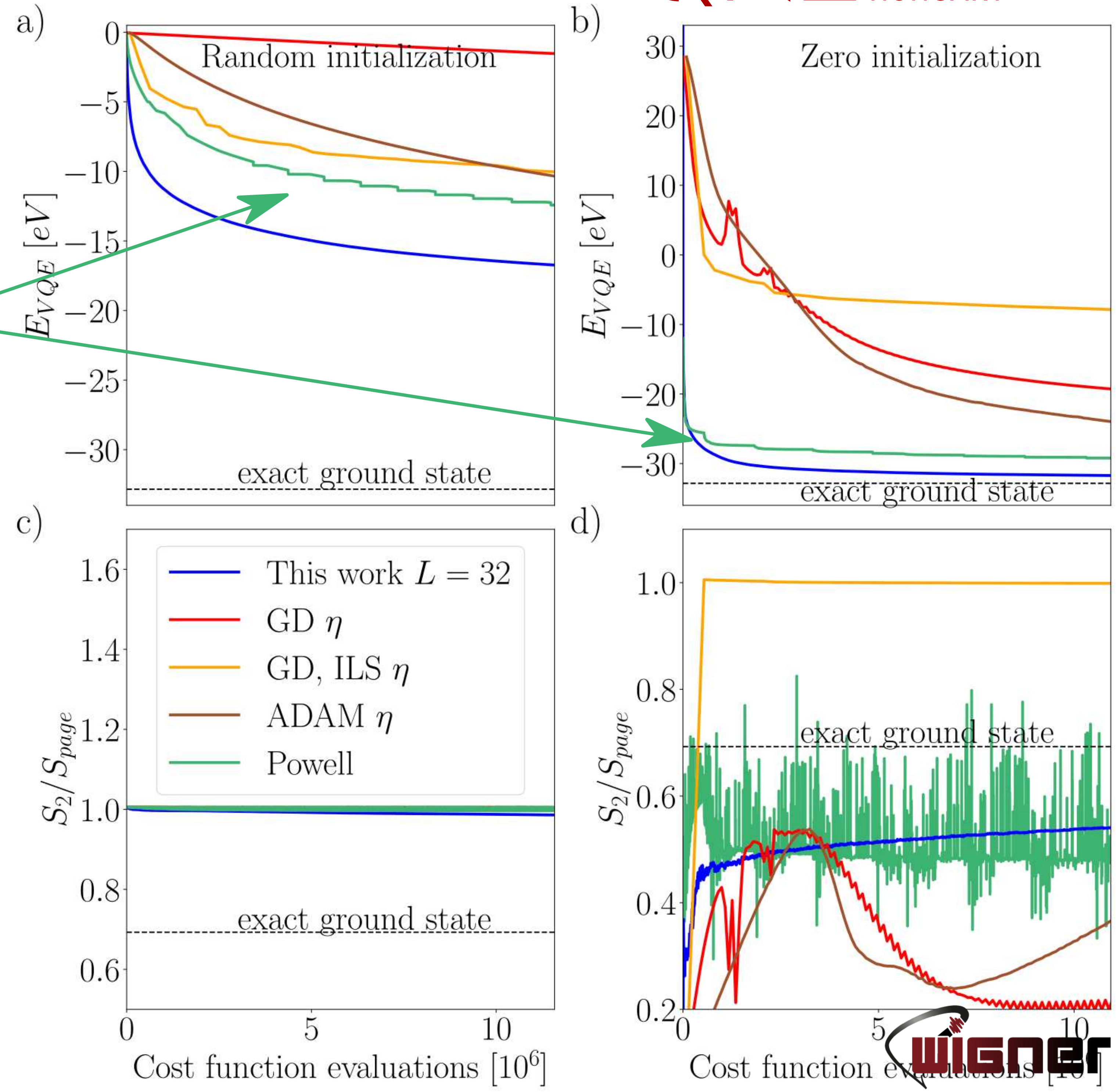
Steps in
the curve of
optimization



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Further numerical improvements to scale up VQE experiments

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- More efficient circuit ansatz adopted to
  - the coupling structure of the underlying model
  - the interaction types in the physical system
- Introducing noise into the model
- Using accelerators to evaluate the cost function

or

or

GPU

FPGA

AI data-flow chip

GPU QC simulation benchmark

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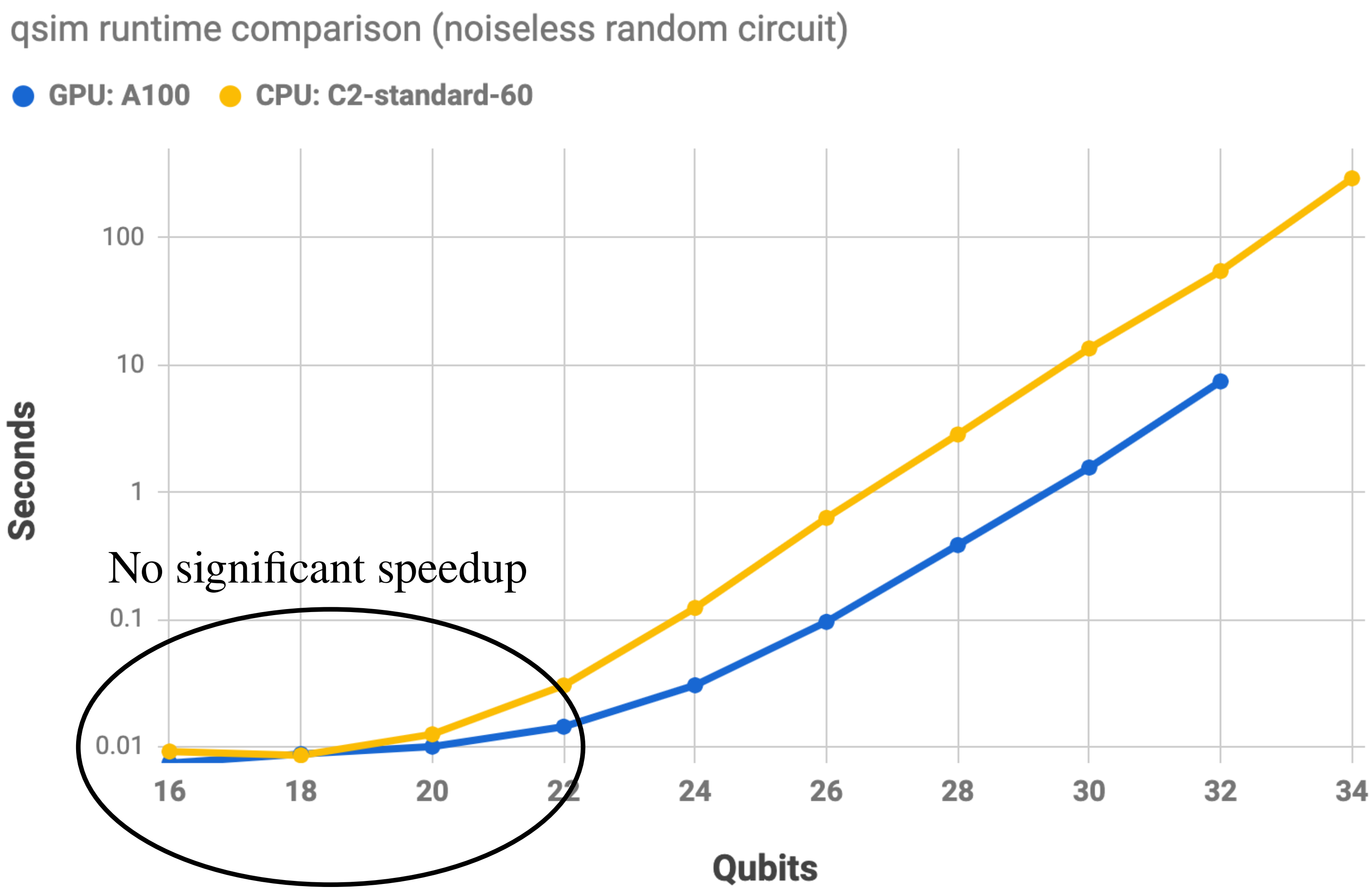

Google Quantum AI

https://quantumai.google/qsim/choose_hw

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groq

MAXELER Technologies Maximum Performance Computing

Aknowledgement

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MAXELER Technologies Maximum Performance Computing