Quantum-Assisted Machine Learning in Near-Term Quantum Devices -- Part 2a: Gate-based QML

Alejandro Perdomo-Ortiz

Senior Quantum Scientist, Zapata Computing, Canada

Honorary Senior Research Associate, Computer Science Dept., UCL, UK

@aperdomoortiz, @ZapataComputing

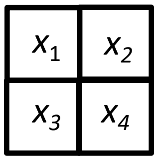
ZAPATA

Funding:

NASA USRA UCL ZAPATA

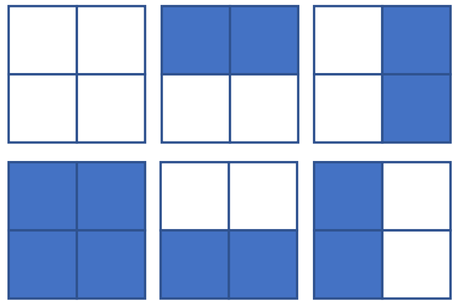
Quantum Languages Designs and Implementation, Sept 28, 2019

Unsupervised generative modeling with NISQ devices



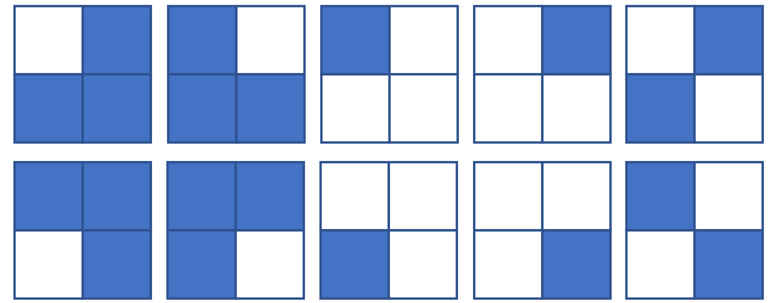
$x_1x_2x_3x_4$

BAS patterns



{0000,1100, 0101,
1111,0011,1010}

Non-BAS pattern



Ludwig Boltzmann (1844-1906)

Boltzmann machines

$$P_{Boltzman} \propto exp[-\xi(s_1, ..., s_N)/T_{eff}]$$

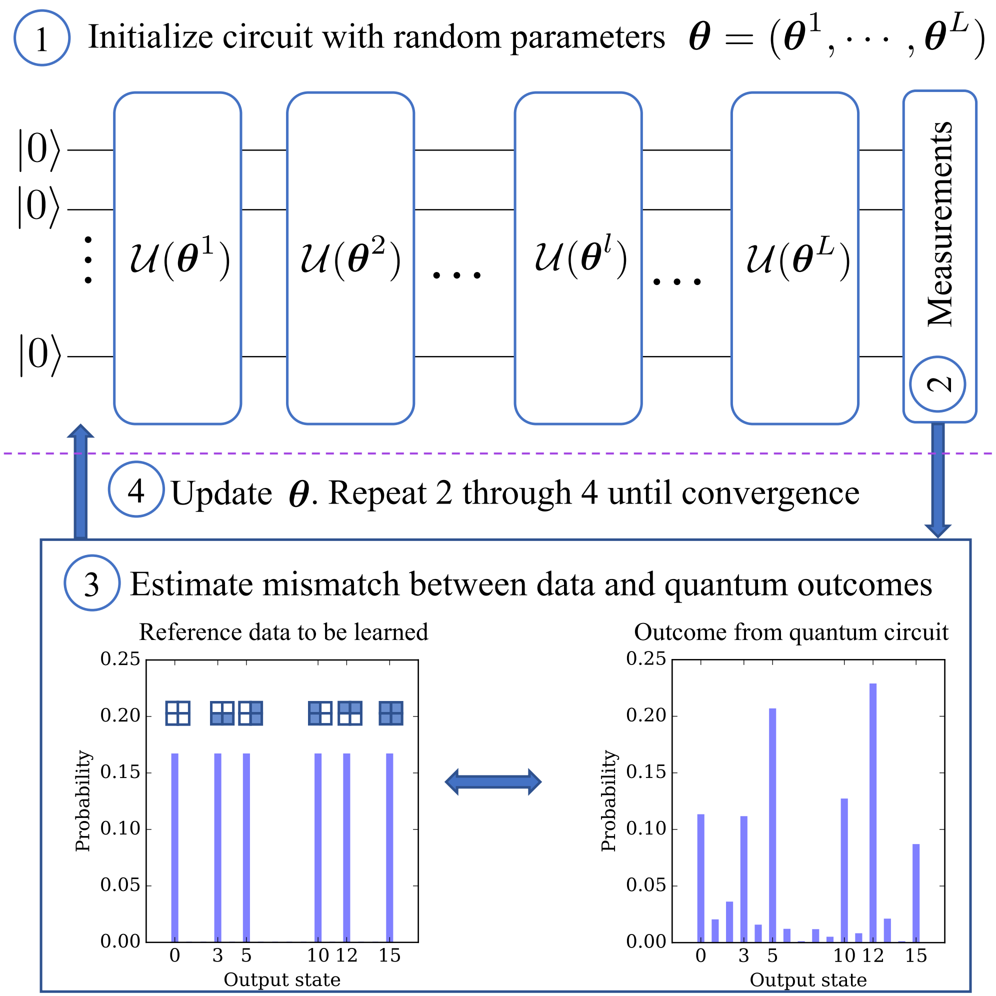
Max Born (1882-1970)

Quantum Circuit Born machines (QCBM) $P_{\boldsymbol{\theta}}(\mathbf{x}) = |\langle \mathbf{x}|\psi(\boldsymbol{\theta})\rangle|^2.$

Generative modeling with NISQ devices, beyond Boltzmann

QCBMs: Benedetti, Garcia-Pintos, Perdomo, Leyton-Ortega, Nam, and Perdomo-Ortiz. A generative modeling approach for benchmarking and training shallow quantum circuits. **npj QI, 5, 45 (2019).**

Data-Driven Quantum Circuit Learning (DDQCL)



QPU

$$P_{\boldsymbol{\theta}}(\mathbf{x}) = |\langle \mathbf{x} | \psi(\boldsymbol{\theta}) \rangle|^2.$$

QCBM

CPU

$$\mathcal{C}_{nll}(\boldsymbol{\theta}) = -\frac{1}{D} \sum_{d=1}^{D} \log \max(\epsilon, P_{\boldsymbol{\theta}}(\mathbf{x}^{(d)}))$$

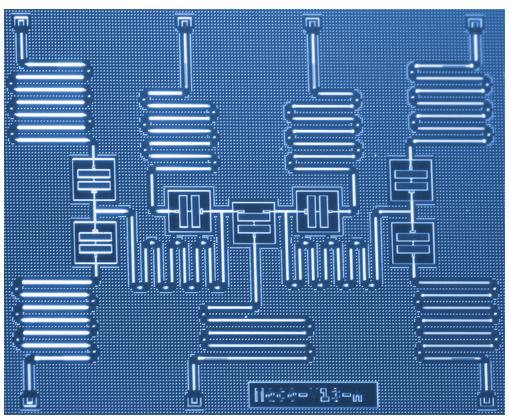
Benedetti, Garcia-Pintos, Perdomo, Leyton-Ortega, Nam, and Perdomo-Ortiz. A generative modeling approach for benchmarking and training shallow quantum circuits. **npj QI, 5, 45 (2019)**

Follow Up Work on DDQCL

Recent theoretical work:

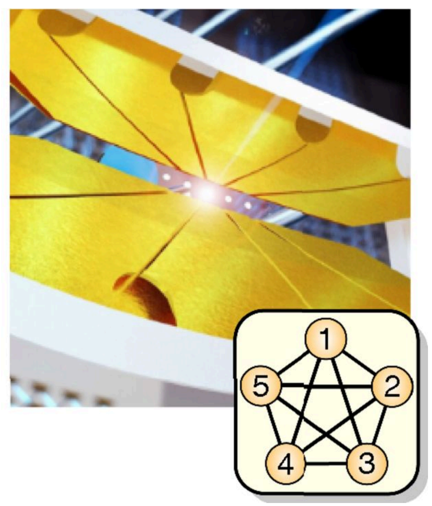
- Supervised QCL: Mitarai et al. **arXiv:1803.00745v1.**
- Differentiable QCBM: Liu, Wang. **arXiv:1804.04168v1.**
- QCBM expressive power: Du et al. **arXiv:1810.11922.**

Recent DDQCL experimental work:



IBM's Tokyo:
Hamilton et al.
arXiv:1811.09905.

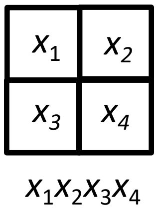
This talk!



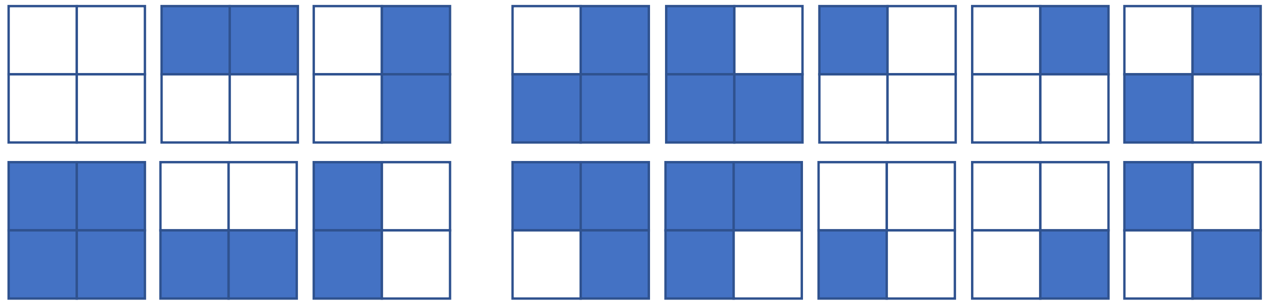
UMD trapped ions:
Zhu et al.
arXiv:1812.08862.

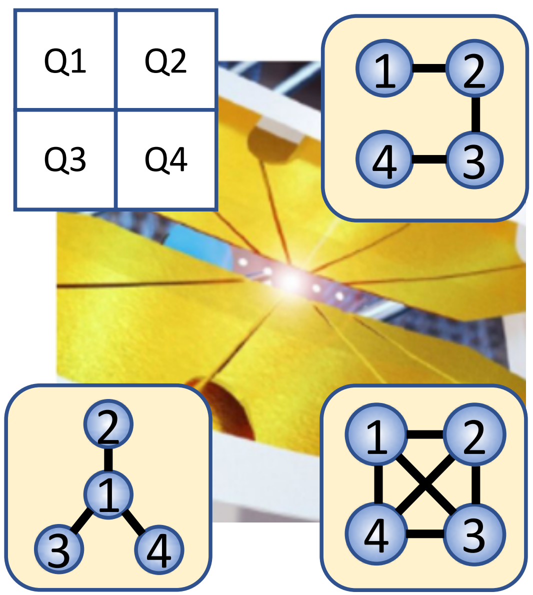
Rigetti's Aspen:
Leyton-Ortega et al.
arXiv:1901.08047

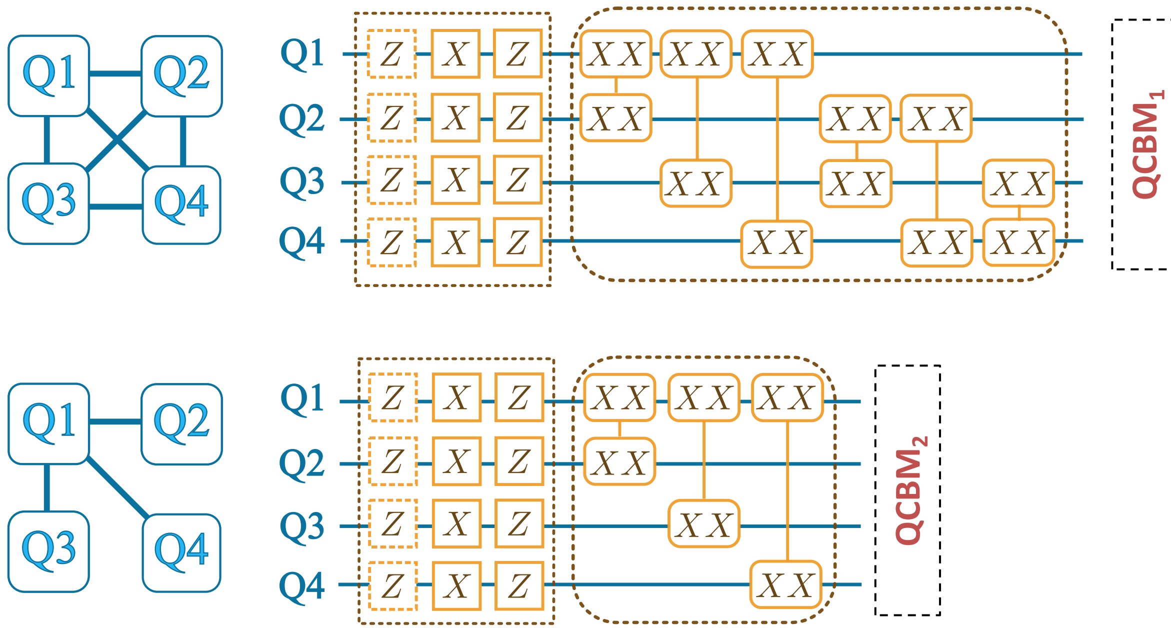
Quantum Circuit Born Machines (QCBM)



BAS patterns **Non-BAS pattern**





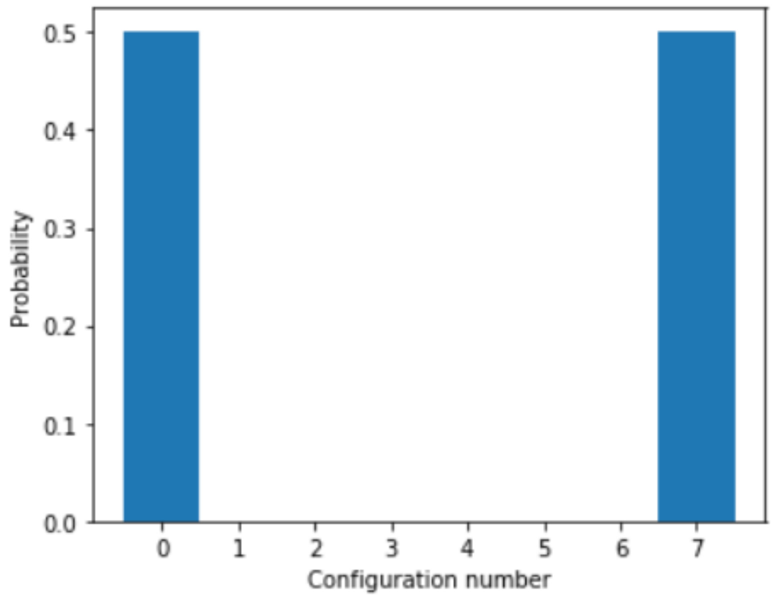


Benedetti et al. A generative modeling approach for benchmarking and training shallow quantum circuits. **npj QI, 5, 45 (2019)**.

Zhu et al. Training of Quantum Circuits on a Hybrid Quantum Computing. **arXiv:1812.08862. Science Advances. In press.**

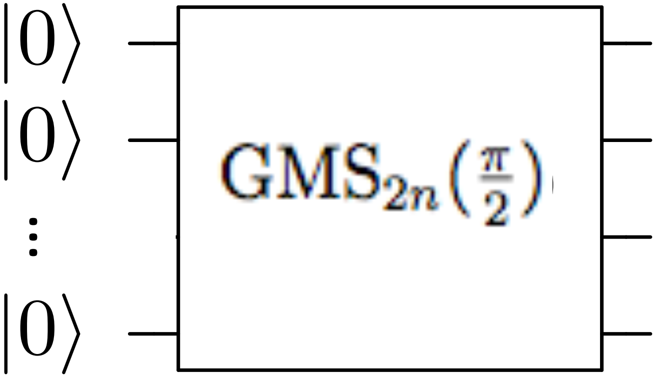
Experiment 1. "GHZ state preparation"

$$\mathcal{D} = (\mathbf{x}^{(1)}, \cdots, \mathbf{x}^{(D)})$$

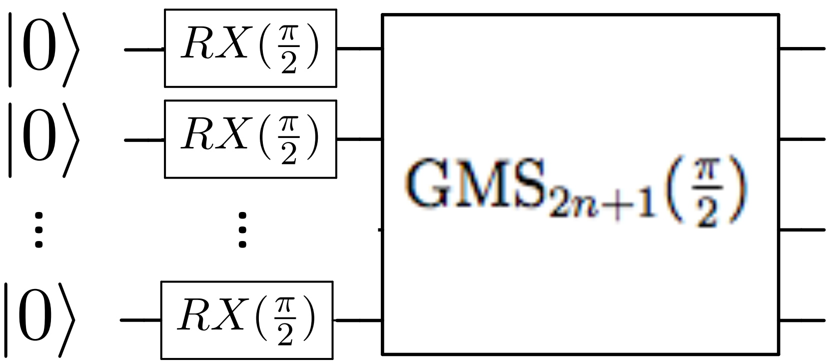


Benedetti et al. A generative modeling approach for benchmarking and training shallow quantum circuits. **npj QI, 5, 45 (2019)**.

For even N

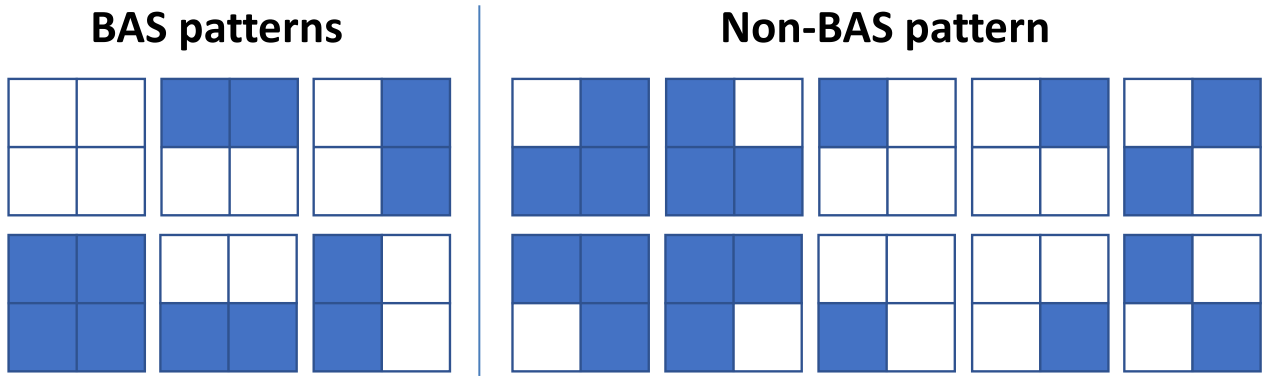


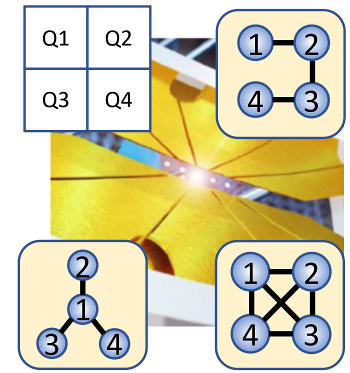
For odd N



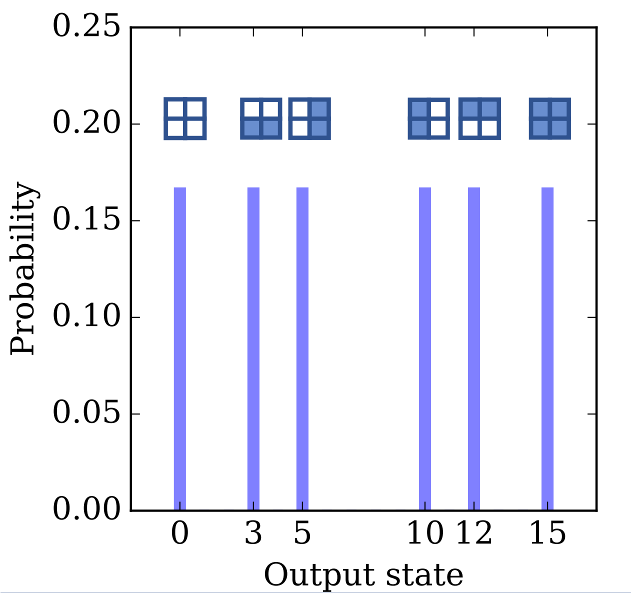
Essentially same circuit as that in: **T. Monz, et al. "14-qubit entanglement: Creation and coherence," Phys. Rev. Lett. 106, 130506 (2011).**

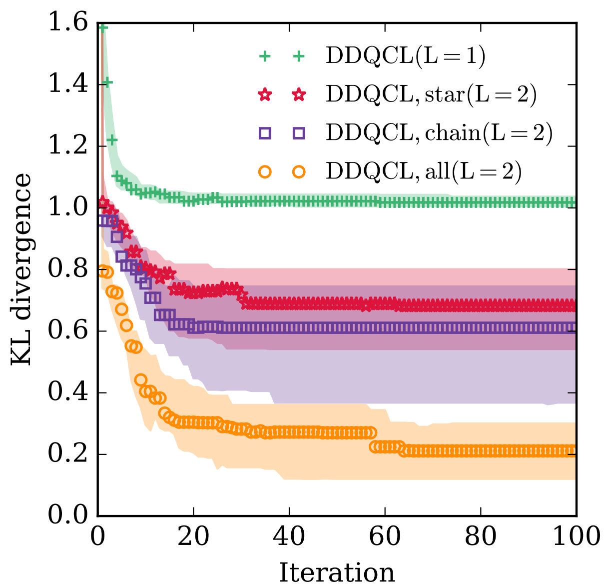
A generative approach to training shallow circuits

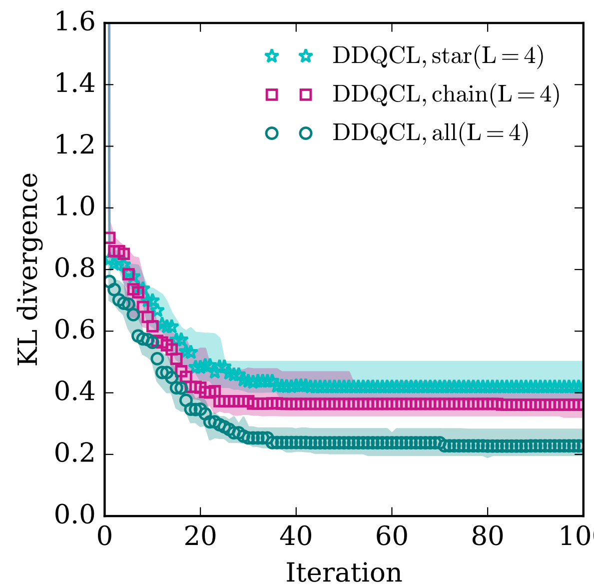




$$\mathcal{D} = (\mathbf{x}^{(1)}, \cdots, \mathbf{x}^{(D)})$$

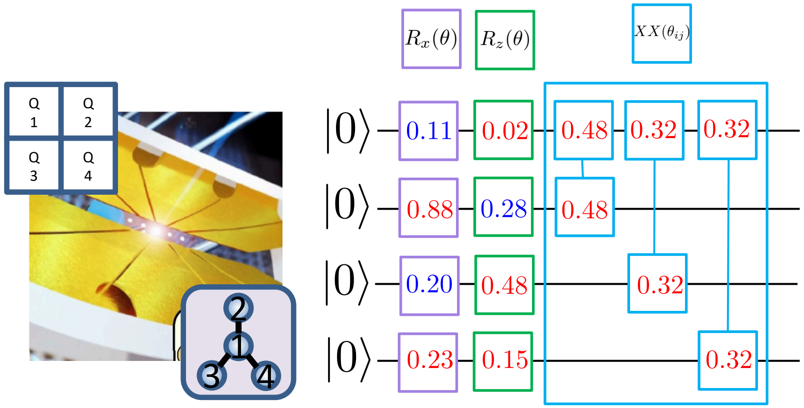






Benedetti, Garcia-Pintos, Nam, and Perdomo-Ortiz. A generative modeling approach for benchmarking and training shallow quantum circuits. **arXiv:1801.07686** (2018).

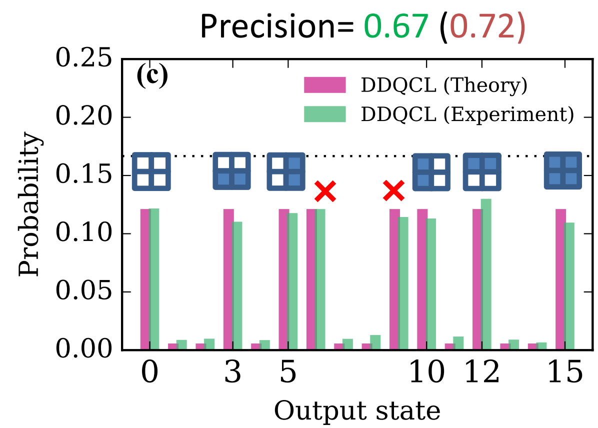
A generative approach to training shallow circuits

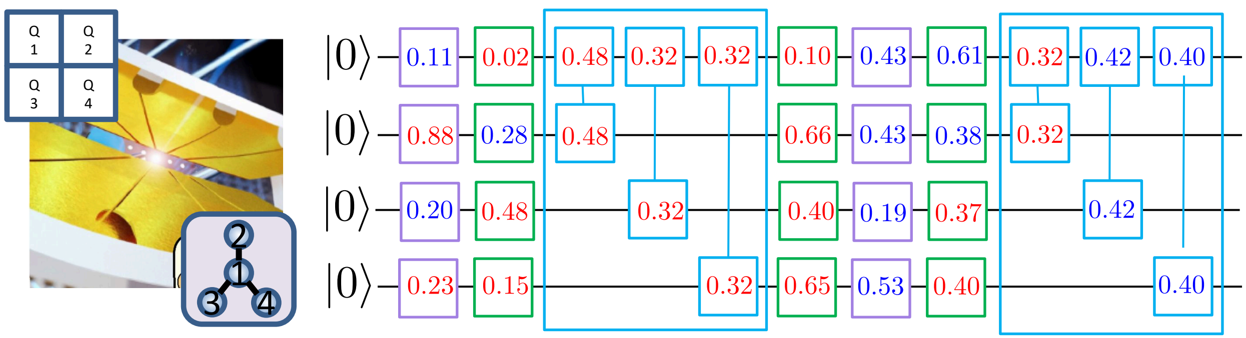


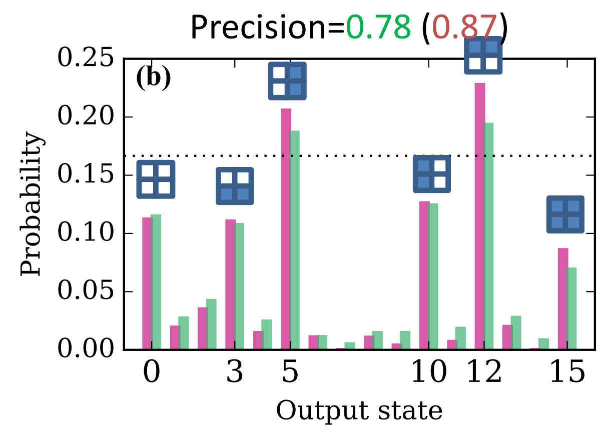
Conventions:

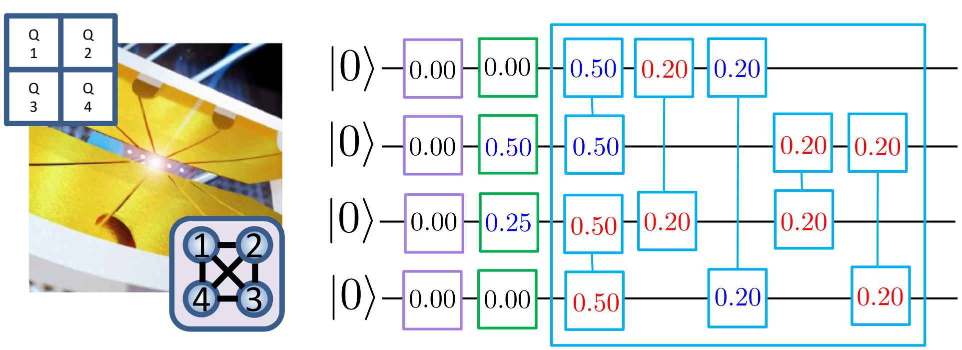
$$R_\alpha(\theta_i) = e^{-i\hat{\sigma}_i^\alpha \boldsymbol{\theta_i}\pi/2}$$

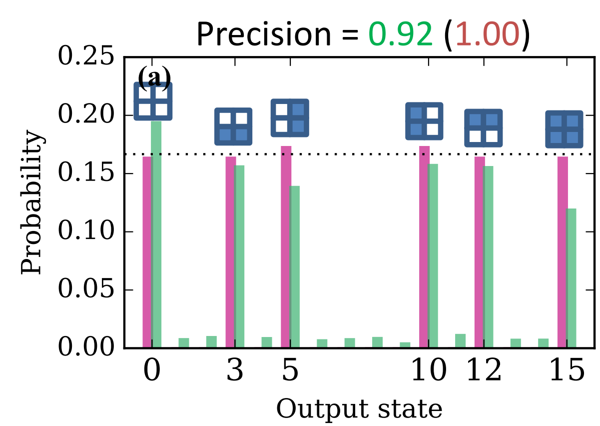
$$XX(\theta_{ij}) = e^{-i\hat{\sigma}_i^x \hat{\sigma}_j^x \boldsymbol{\theta_{ij}}\pi/2}$$







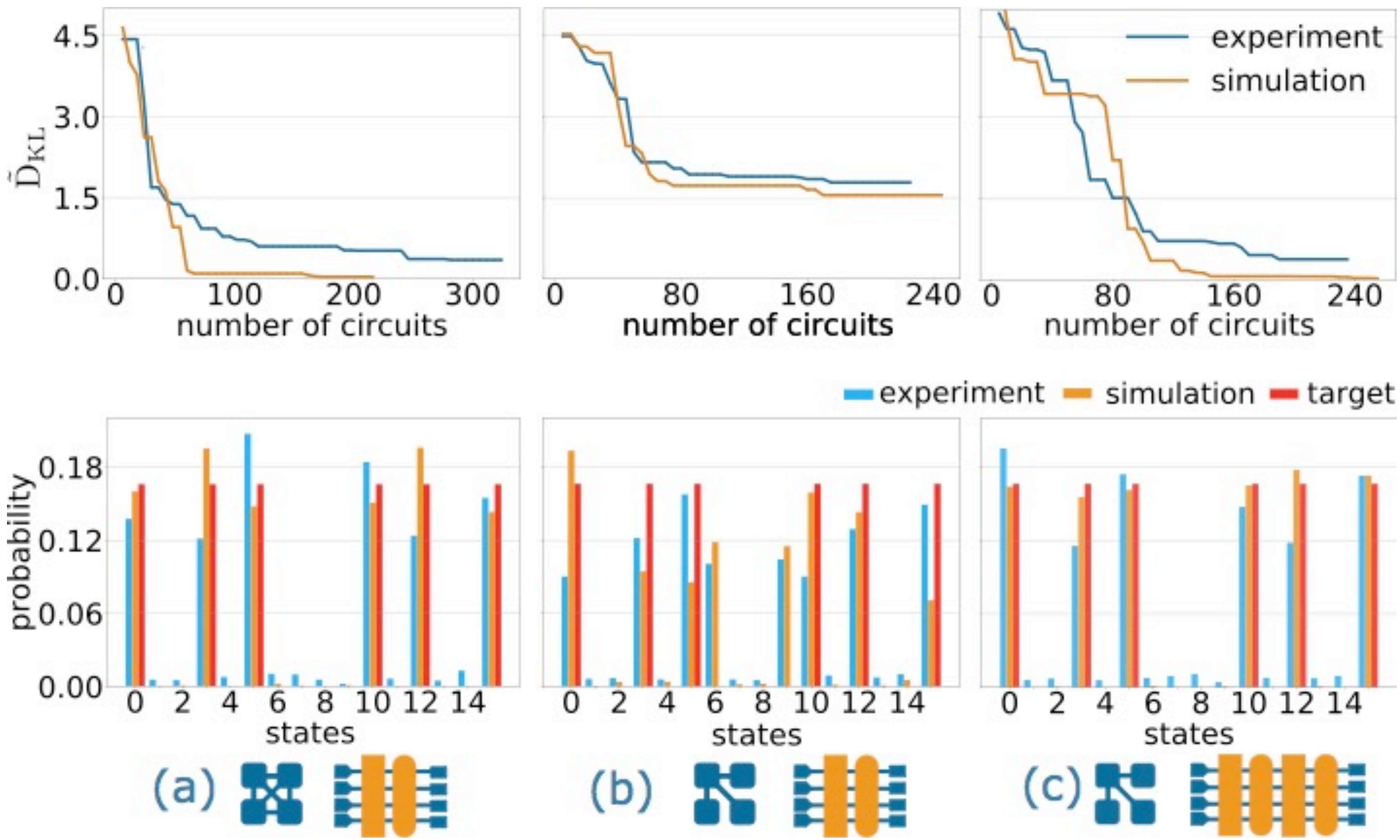




$$0.2 \to \frac{\arctan[\sqrt{2}/2]}{\pi} = 0.195913...$$

→ KL =0.0

Experimental Realization of DDQCL in a Trapped Ion QC



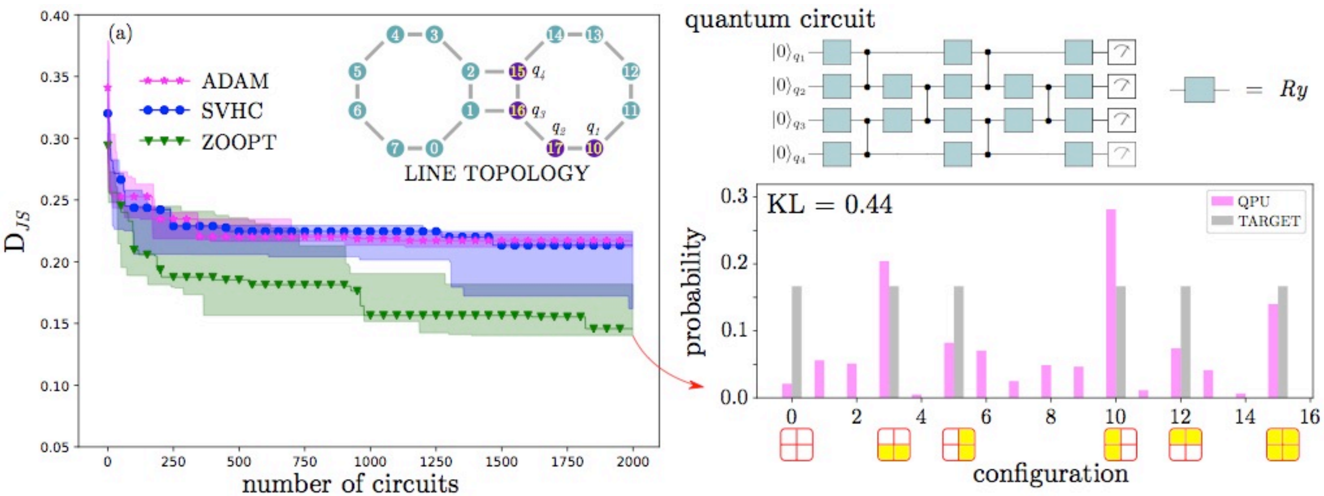
KL = 0.094, qBAS = 0.91

KL = 0.328, qBAS = 0.77

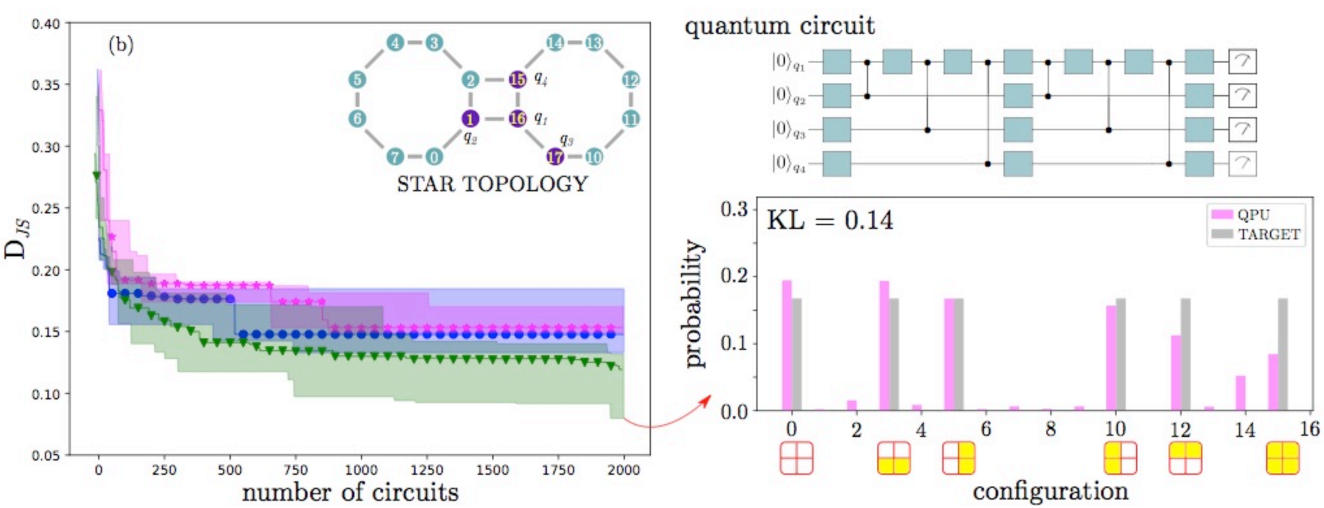
KL = 0.10, qBAS = 0.91

Zhu et al. Training of Quantum Circuits on a Hybrid Quantum Computing. **arXiv:1812.08862**

Experimental Realization in Rigetti's QPU



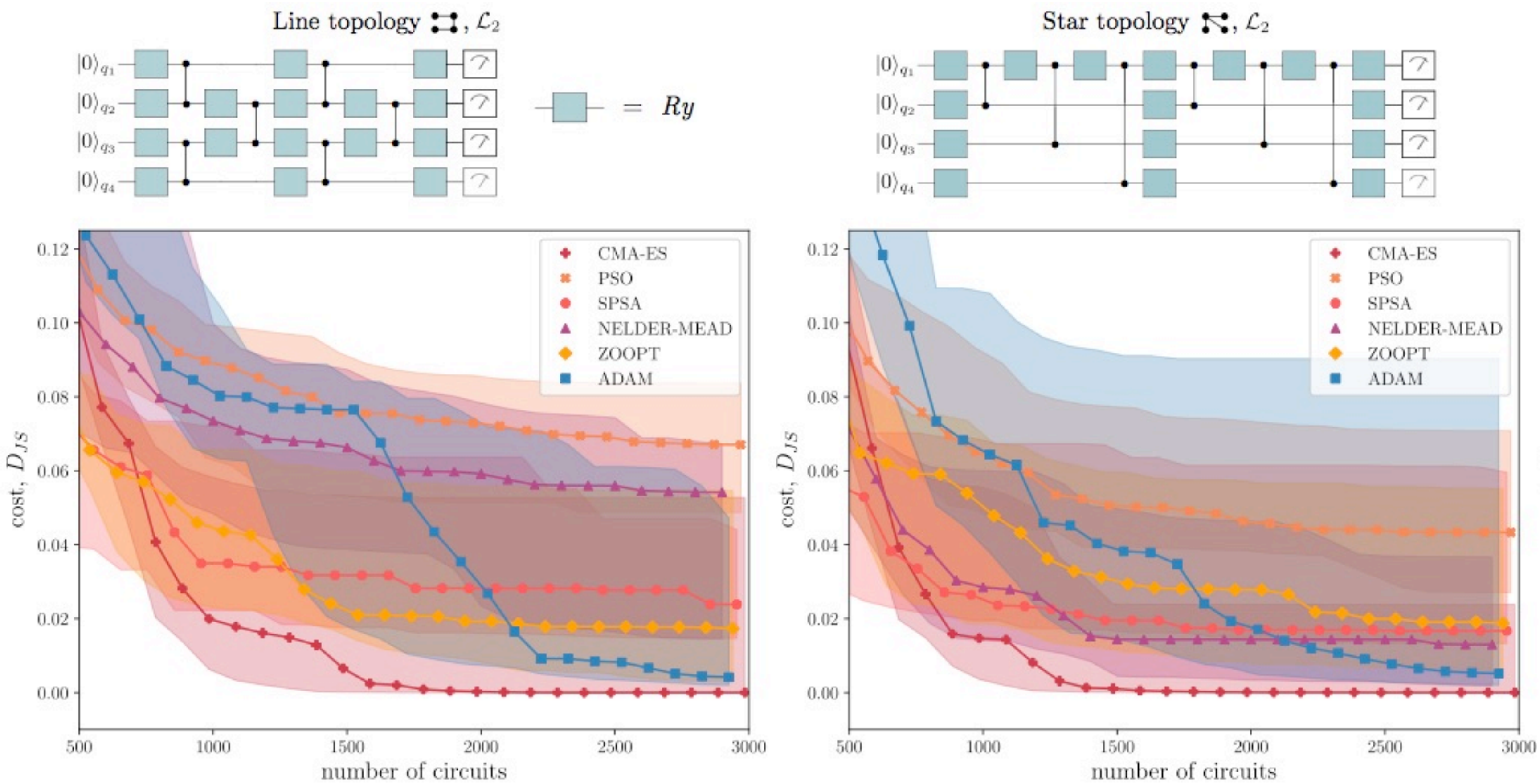
KL = 0.46
qBAS = 0.76



KL = 0.14
qBAS = 0.89

Leyton-Ortega, et al. **Robust** Implementation of Generative Modeling with Parametrized Quantum Circuits. **arXiv:1901.08047**

Benchmarking Classical Optimizers



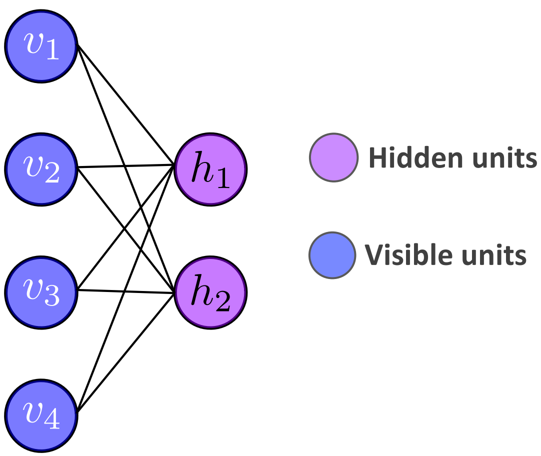
- Significant variance from initialization,
- Impact of circuit ansatz,
- Impact from solver/method (gradient-based versus gradient-free).

Leyton-Ortega and Perdomo-Ortiz.
In preparation.

Comparing Classical and Quantum ML Models

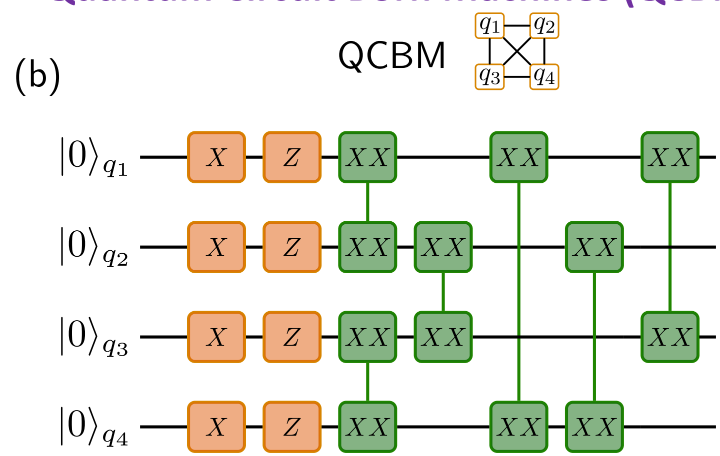
NP-hard version of portfolio optimization problem

Restricted Boltzmann Machines (RBM)



versus

Quantum Circuit Born Machines (QCBM)

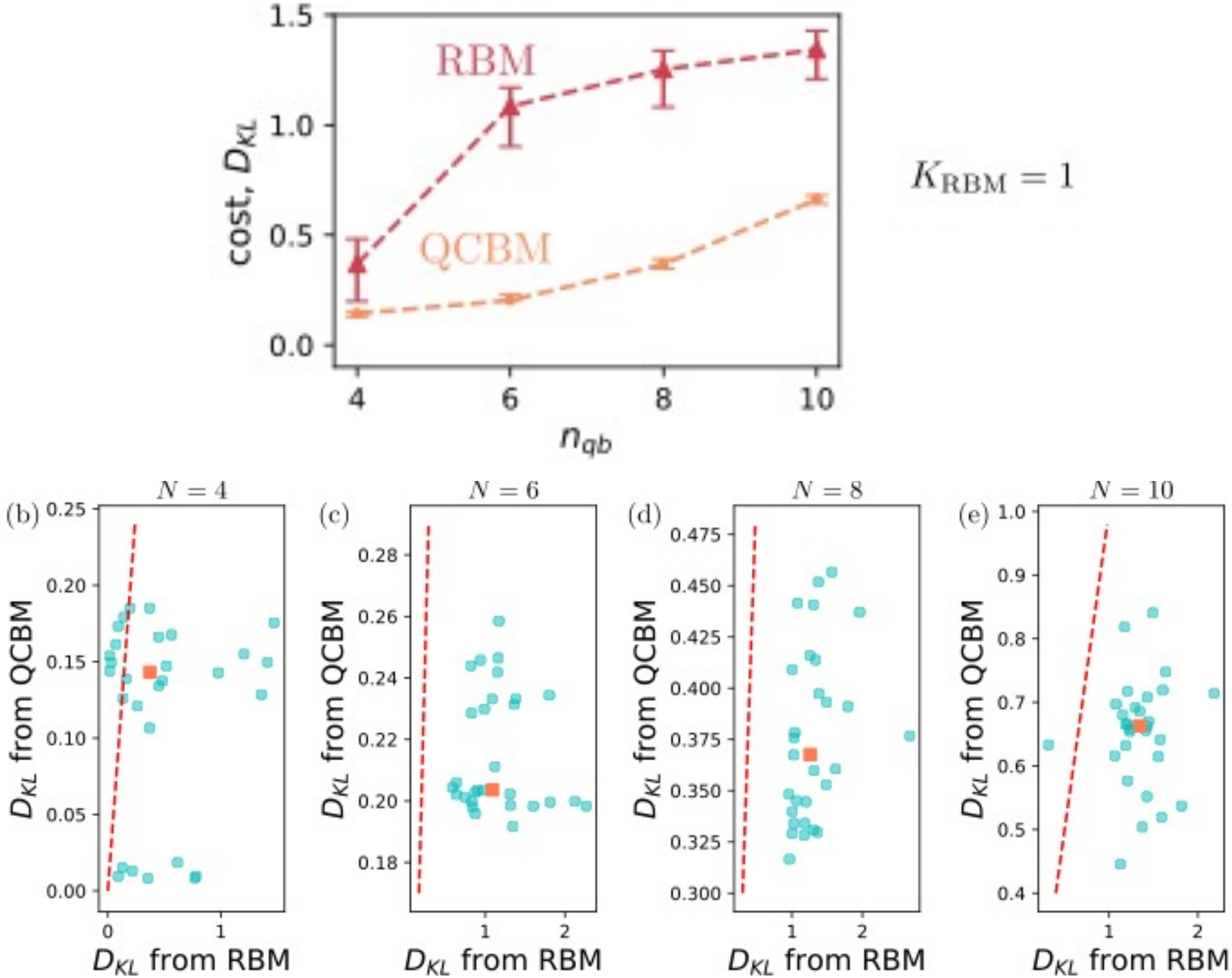


 # parameters:

Stochastic gradient descent, CD-*k*, with *k = 1,10, and 100* → $\frac{N(N+3)}{2}$ ← DDQCL with CMA-ES

Alcazar et al. Classical versus Quantum Models in ML: Insights from a Finance Application. **arXiv:1908:10778**

Classical versus Quantum Models in ML for Finance



Alcazar et al. Classical versus Quantum Models in ML: Insights from a Finance Application. **arXiv:1908:10778**

Entanglement of BAS-like quantum states

$$S_\psi = -\frac{1}{3}\Big[\mathrm{Tr}(\rho_{AB}\log_2\rho_{AB}) + \mathrm{Tr}(\rho_{AC}\log_2\rho_{AC}) + \mathrm{Tr}(\rho_{AD}\log_2\rho_{AD})\Big]$$

$$|BAS(2,2)\rangle = \frac{1}{\sqrt{6}}\left(e^{iu_1}|0000\rangle + e^{iu_2}|0011\rangle + e^{iu_3}|0101\rangle + e^{iu_4}|1010\rangle + e^{iu_5}|1100\rangle + |1111\rangle\right)$$

$$\begin{aligned} S_{BAS(2,2)} = -\tfrac{1}{9}\Big[& \tfrac{2}{\ln(2)}\sqrt{\cos^2\left(\tfrac{v_1}{2}\right)}\tanh^{-1}\left(\sqrt{\cos^2\left(\tfrac{v_1}{2}\right)}\right) \\ & + 2\cos^2\left(\tfrac{v_2}{4}\right)\log_2\left(\tfrac{2}{3}\cos^2\left(\tfrac{v_2}{4}\right)\right) + 2\cos^2\left(\tfrac{v_2-v_1}{4}\right)\log_2\left(\tfrac{2}{3}\cos^2\left(\tfrac{v_2-v_1}{4}\right)\right) \\ & + \log_2\left(4 + 2\sqrt{2}\sqrt{\cos(v_1)+1}\right) + \log_2\left(4 - 2\sqrt{2}\sqrt{\cos(v_1)+1}\right) \\ & + 2\sin^2\left(\tfrac{v_2}{4}\right)\log_2\left(\tfrac{2}{3}\sin^2\left(\tfrac{v_2}{4}\right)\right) + 2\sin^2\left(\tfrac{v_2-v_1}{4}\right)\log_2\left(\tfrac{2}{3}\sin^2\left(\tfrac{v_2-v_1}{4}\right)\right) \\ & - \log_2(31104)\Big]. \end{aligned}$$

where,

$$v_1 = u_2 - u_3 - u_4 + u_5 \text{ and } v_2 = u_1 - u_3 - u_4$$

Benedetti et al. A generative modeling approach for **benchmarking and training** shallow quantum circuits. **arXiv:1801.07686** (2018).

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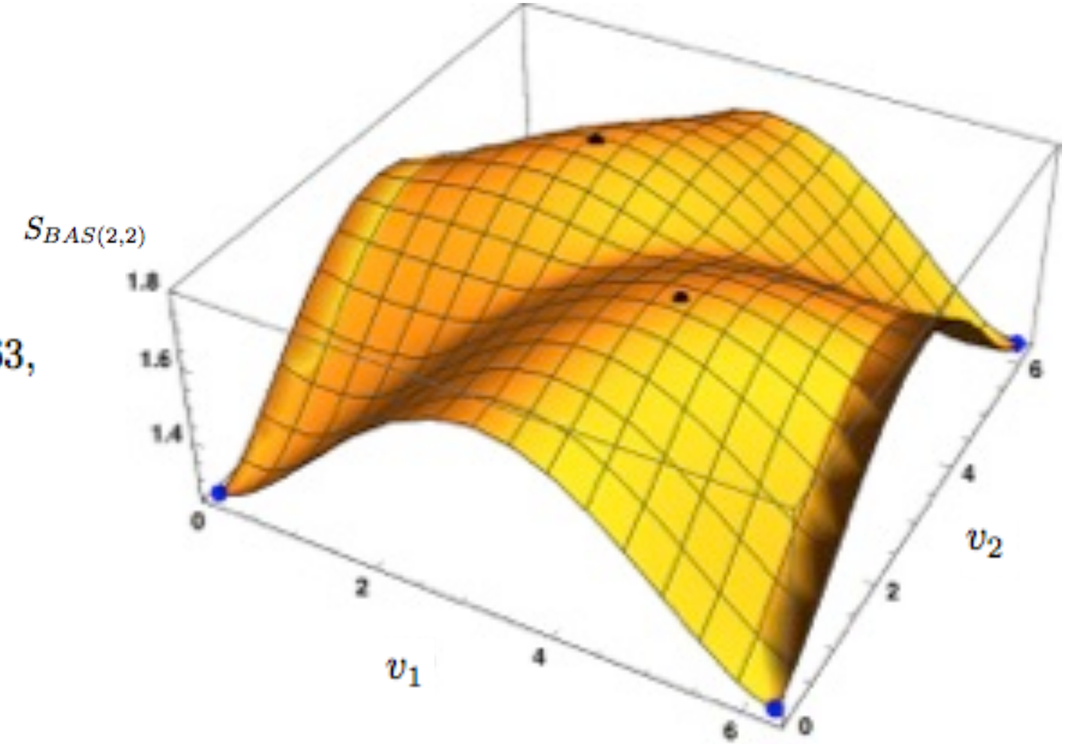
$$\min S_{BAS(2,2)} = \frac{1}{3}\log_2\left(\frac{27}{2}\right) \approx 1.25163,$$

$$\max S_{BAS(2,2)} = \frac{1}{2}\log_2(12) \approx 1.79248.$$

$$S_{GHZ} = 1.$$



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Summary

- Are there data sets and (non-obvious) real-world applications in need of quantum resources from NISQ devices?

  - Combinatorial optimization? **Machine learning?**

  Perspective: Perdomo-Ortiz, et al. Opportunities and Challenges in Quantum-Assisted Machine Learning in Near-term Quantum Computers. **Quantum Sci. Technol. 3, 030502 (2018).** Invited special issue on "What would you do with a 1000 qubit?"

- **Why** and **where** to look for **quantum advantage** in quantum-assisted ML, with NISQ devices?

- Know your hybrid quantum-classical pipeline: **mind classical optimizers**, **cost function/data set**, **circuit ansatz design**, etc.

- NISQ quantum models in a real-world setting: an example from a financial application.

Acknowledgments

Institutions/ Funding

Theory collaborators

M. Benedetti (UCL), J. Realpe-Gomez(NASA), D. Garcia-Pintos (Qubitera), V. Leyton-Ortega (Qubitera/Rigetti), O. Perdomo (Qubitera/Rigetti), Y. Nam (IonQ), and F. J. Fernandez-Alcazar (Natl. Australia Bank).

Experiments by University of Maryland team

Chris Monroe

Kevin Landsman | Norbert Linke | Caroline Figgatt

Daiwei Zhu

Thanks also to Rigetti Computing for QPU access and technical discussions with the theory team.

@aperdomoortiz, @ZapataComputing