



# QBAS22 SCORE ON RIGETTI

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# Introduction to DDQCL

Data Driven Quantum Circuit Learner (DDQCL) is the hybrid quantum-classical approach that is used to assist the characterization of the quantum devices and to train shallow circuits for generative tasks.



# Our tasks

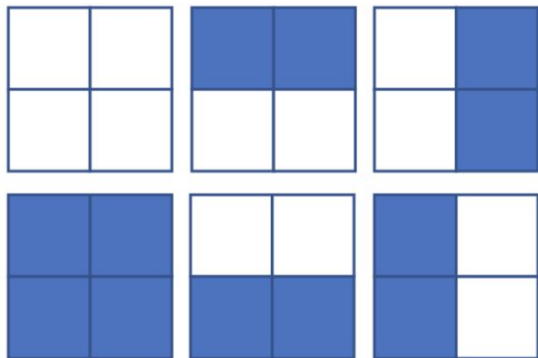
In our case of generative ML task we were given an input dataset and we output measurements.

We have a two step process:

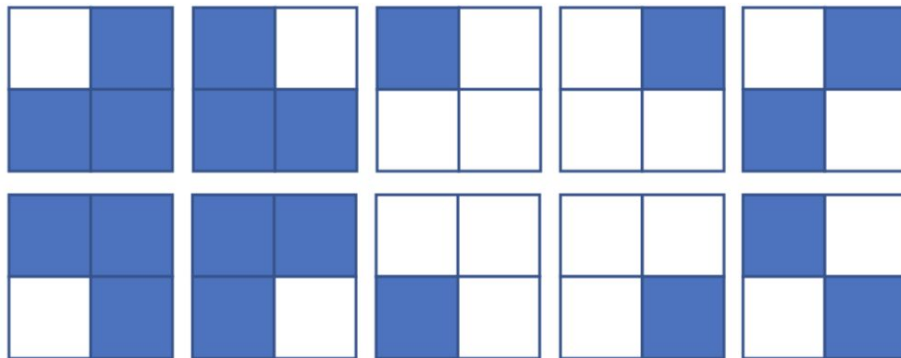
- 1) DDQCL is used to encode BAS22 (shown on next slide) in the wave function of the quantum state
- 2) The best circuits, i.e. those with lowest cost function, are compared using the qBAS22 (explained later) score

# BAS22

**BAS patterns**



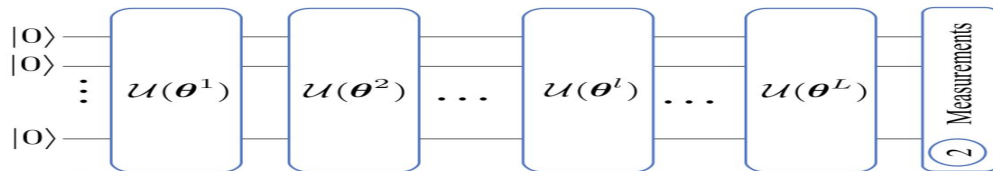
**Non-BAS pattern**



# QBAS SCORE

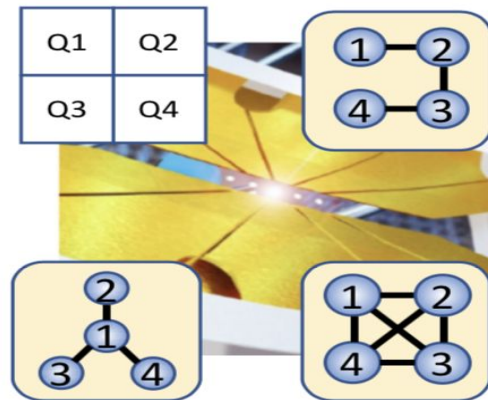
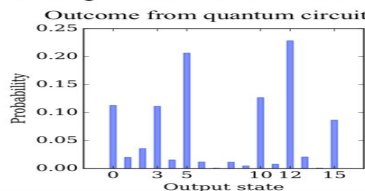
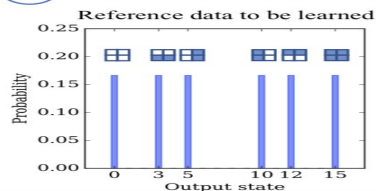
qBAS22 score for some of the possible choices of entangling layer topology (line, star, all-connected and different entangling gates YY, ZZ, CPHASE), and different number of layers.


- ① Initialize circuit with random parameters  $\theta = (\theta^1, \dots, \theta^L)$



- ④ Update  $\theta$ . Repeat 2 through 4 until convergence

- ③ Estimate mismatch between data and quantum outcomes



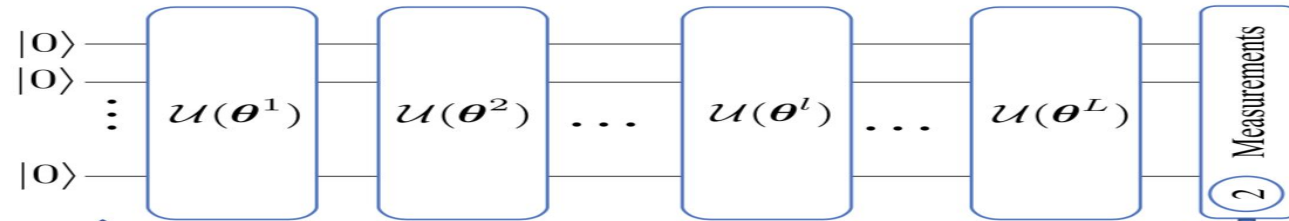


# Procedure (High-level)

- Provided with a dataset  $D$ , the goal is to obtain a good approximation to the target probability distribution for BAS22.
- The quantum circuit model is parametrized unitary gates angles, gate depths, and gate topology.
- Following the approach of generative modeling, we minimize with Kullback-Leibler function, and classically update parameters with Particle Swarm Optimization

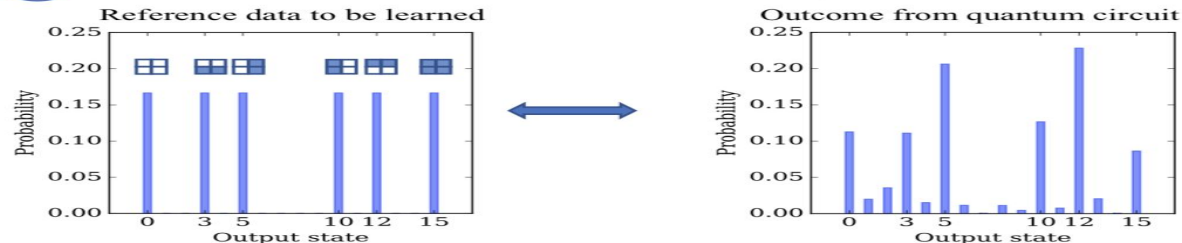
# Circuit Layout

- 1 Initialize circuit with random parameters  $\theta = (\theta^1, \dots, \theta^L)$

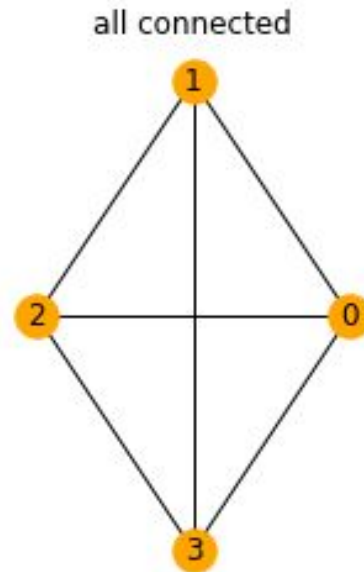
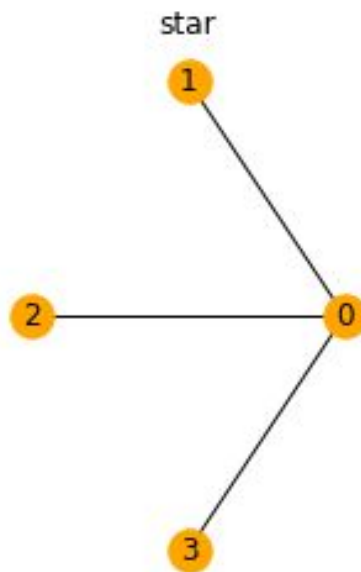
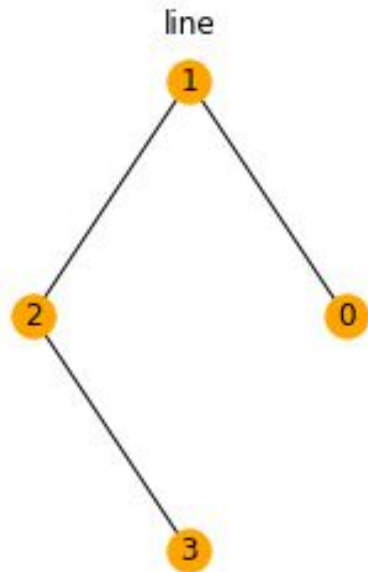


- 4 Update  $\theta$ . Repeat 2 through 4 until convergence

- 3 Estimate mismatch between data and quantum outcomes

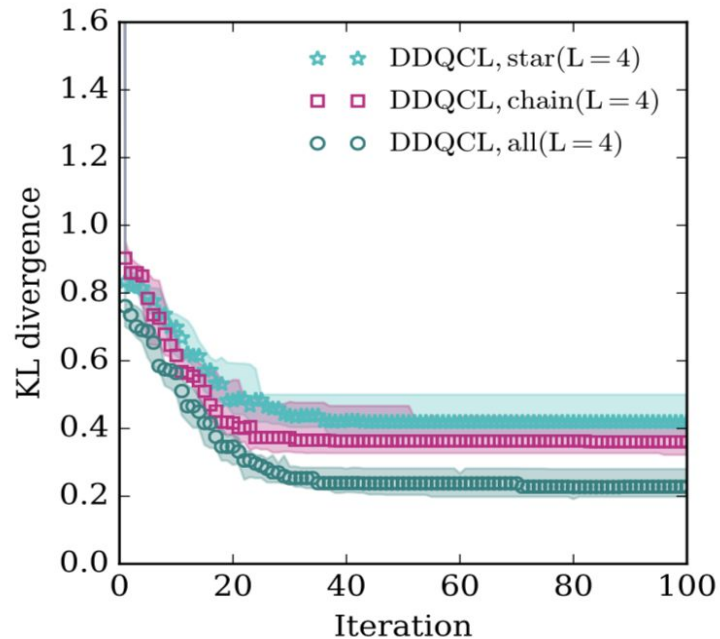
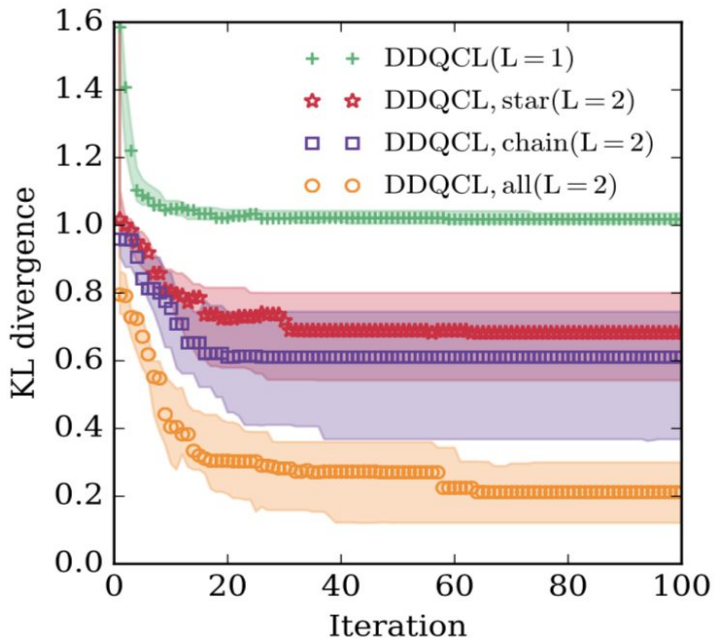


# Topology





# KL Divergence (In paper)



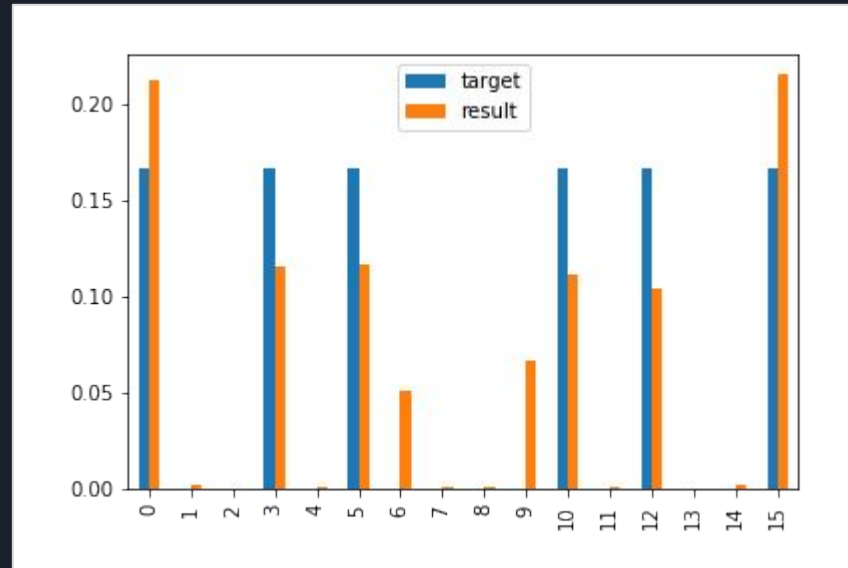


# Results

Topology	Cost function	Inst	Entangling	Layers	Gate Volume
All connected	0.18	H	YY	2	159
All connected	0.28	H	YY	3	166
Star	0.81	H	YY	2	94
Chain	0.81	H	YY	2	46

# Best performance

All connected topology, 2 layers, 0.18 cost





# Analysis

- We've replicated the experiment, but with smaller trials.
- We've also noticed that all-to-all topology outperforms all other topologies even with just 10 iterations of PSO vs 100 iterations for any other topology
- We've also noticed that YY entangling gates perform the best versus ZZ and CPHASE entangling gates even though ZZ and CPHASE have less gate volume and depth than YY
- We've also noticed that, even though other topologies have less gate volume and depth than all-to-all connected topology, all-to-all was still most optimal



# QBAS22

Next we compared qBAS scores for all-to-all topology with 2 layers (YY gates), star topology with 4 layers (YY gates), and all-to-all topology with 3 layers

- Those very different approximate solutions to the same problem can be compared at the level of qBAS22 score.

- Quantum simulations allow us to obtain the theoretical amplitudes for each of the states in the computational basis.



# FORMULA

Precision = # of measurements belonging to BAS22 / total # of measurements

Recall = # of different BAS22 in N(read) measurements / total # of BAS22 patterns

QBAS F1 score =  $(2 * \text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$

\*\*\*Goal is to score high (F1 ~ 1.0)



# OUR RESULTS

As in the case of the simulation estimation of the qBAS score, we sample 500 times from the distribution. From each of the samplings, we compute a qBAS22 score.

All-connected, 2-layers:

Precision: 0.636, Recall: 1.0, qBAS F1: 0.7775061124694376

Star, 2-layers: