

Class 5 : PWF 2021 - QML 12/03/2021

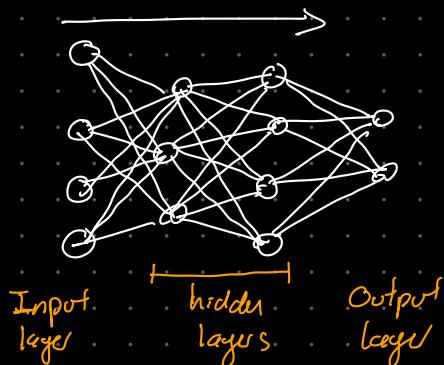
GNN = parametrized quantum circuit

As such, it needs an ansatz?

### \* Dissipative GNN

Beer Nat. Commun. 11, 808 (2020) arxiv 1902.10845

It naturally generalizes the famous, and widely used feed-forward neural network.



○ = neuron

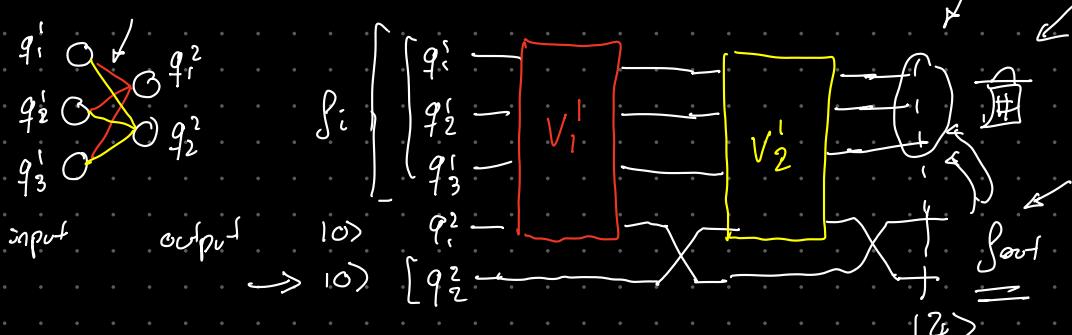
— = perception

layer-to-layer information transmission.

We are going to generalize to GML

○ = neuron  $\rightarrow$  qubit

— = perception  $\rightarrow$  unitaries acting on the qubits



Sharma arxiv 2005.12458  
always has barren plateaus.  
maybe they can be avoided

$$f_{\text{out}} = \text{Tr}_{\text{in}, \text{hid}} [ U(\vec{\theta}) (f^{\text{in}} \otimes I \otimes I)_{\text{hid}, \text{out}} U(\vec{\theta}) ]$$

PRO: Can carry out universal QC &

CON: creates big entangled states of information. requires a lot of qubits.

## $\star$ Quantum Convolutional Neural Network Cong Before Phys IS, 1273 (2019)



arXiv 1810.03739

The idea is to reduce the dimension of the data & keep the relevant features.

given an  $n$ -qubit quantum state



$\hookrightarrow \langle 8 \rangle$   
Convolutional layers:  
parametrized gates  
acting on the  
system

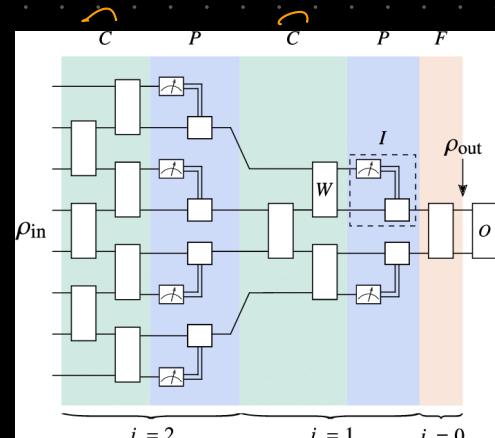
Pooling: reduce the  
dimension of data

PRO: shown to work for classification tasks

CON: shallow  $O(\log(n))$

not obvious how general  
its applicability is.

Big PRO  $\Rightarrow$  NEVER HAS A BARREN PLATEAU



Pesah PRX 11, 041011 (2020)

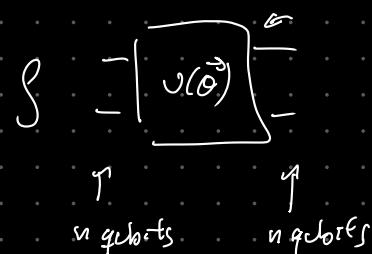
arXiv 2011.02966

$\star$  Parametrized Quantum Circuit QNN

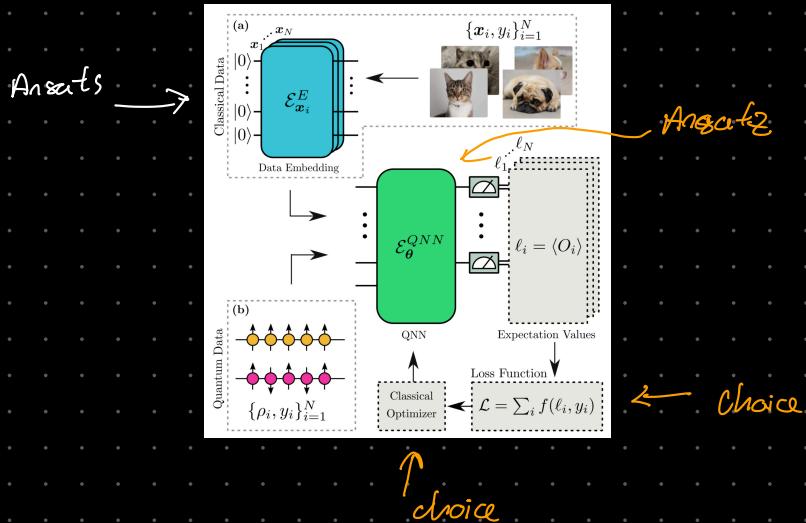
PRO: maybe more general than QCNN  
CON:

$\rightarrow$  not obvious what the ansatz should be

- hardware efficient ansatz



# Benchmarking a QML model



Benchmarking should be done with Quantum Data.

Quantum Data:

- outputs of some physical process
- synthetic quantum data: well characterized  
easy to prepare  
Good quality

$$\begin{array}{c} \text{Phase I} \quad \text{Phase II} \\ \xrightarrow{\quad} \quad \xrightarrow{\quad} \\ g_c \quad \quad H(g) \end{array}$$

a) VQE randomly pick a field  $g$

$$\begin{array}{c} |\vec{\phi}\rangle \xrightarrow{\quad} \boxed{U(\vec{\phi})} \xrightarrow{\quad} |\Psi(\vec{\phi})\rangle \\ \vdots \\ |\vec{\phi}\rangle \end{array} \quad \langle H(g) \rangle = C(\vec{\phi})$$

$|\Psi(\vec{\phi})\rangle$  = ground state of  $H(g)$

if  $g > g_c$  we assign label  $1 = g_c$

$- g < g_c \quad - \quad - \quad - \quad -1 = g_c$

once we finish VQE  $\{|\Psi_i\rangle, g_i\}$



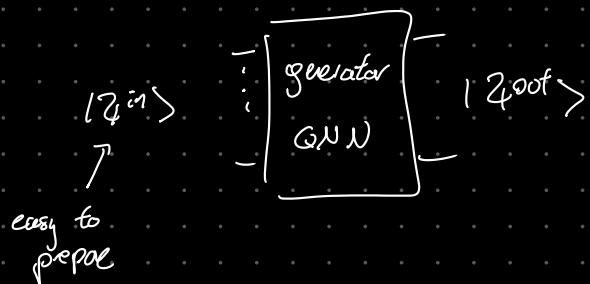
for a dataset of  $N$  points  
we need to run  $N$  VQE experiments.

2) We train a generative model to create the data set

We take the data preparation task and we apply the QML learning methodology

Train a QML model → generates data on demand

Schafzki arXiv 2109:03400 ↗



easy to prepare

we measure a quantity one  $|2^{out}\rangle$  that characterizes the dataset

- level of entanglement in  $|2^{out}\rangle$

- Order parameter (superconducting gap)

Framework Let  $\mathcal{P}$  be a probability distribution of Quantum States

sample  $|2^{in}\rangle \sim \mathcal{P}$

$$E \left[ M(|2^{out}\rangle) \right] = \eta$$

$|2^{in}\rangle \sim \mathcal{P}$

$$\text{we can use a loss: } \mathcal{L}(\vec{\theta}) = \frac{1}{|S|} \sum_{i=1}^{|S|} (M(|2^{out}\rangle) - \eta)^2$$

success if

$$M(|2^{out}\rangle) \in [\eta - \delta, \eta + \delta]$$

For binary classification: we have 2 optimization.

# Challenges for near-term Quantum Computing

## Barren Plateau:

- The cost or loss function landscape becomes, in average, exponentially flat with the problem size.
- The partial derivatives of the cost/loss vanish, in average, exponentially with the problem size.



McClean Nat. Com 9, 4812 (2018) arxiv 1803.11173

Cerezo Nat. Com 12, 1791 (2021) arxiv 2001.00550

Arrasmith arxiv 2104.05868

$$\rightarrow \Delta C \in O\left(\frac{1}{2^n}\right) \quad \frac{\partial C}{\partial \theta_a} \in O\left(\frac{1}{2^n}\right)$$

$n=4$

$$\Delta C \sim 3.0625 \rightarrow N = 256 \text{ shots}$$

Statistical Error

$$O\left(\frac{1}{\sqrt{N}}\right)$$

$\hat{t}_{\text{shots}}$

$n=20$

$$\Delta C \sim 9.5 \cdot 10^{-7} \rightarrow N = 1,1 \cdot 10^{12} \text{ shots}$$

$$\frac{1}{\sqrt{N}} \sim \frac{1}{2^n} \rightarrow \boxed{N = 2^{2n}}$$

A TRILLION

if we have a

Barren Plateau, we have  
no hope of a  
Quantum Advantage

## Mathematical definition of Barren Plateau

$C(\vec{\theta})$  has a Barren Plateau in parameter  $\theta_a$  if

$$\text{Var}\left[\frac{\partial C(\vec{\theta})}{\partial \theta_a}\right] \leq F(u) \quad F(u) \in O\left(\frac{1}{b^u}\right) \quad b > 1$$

## Chebychev's Inequality

$$P(|X - \langle X \rangle| \geq c) \leq \frac{\text{Var}(X)}{c^2} < \frac{\partial \text{Var}(X)}{\partial c_a} = 0$$

$$P\left(\left|\frac{\partial C(\vec{\alpha})}{\partial \alpha_n}\right| > c\right) \leq \frac{\text{Var} \left[\frac{\partial C(\vec{\alpha})}{\partial \alpha_n}\right]}{c^2} \leq \frac{F(u)}{c^2}$$

## Alternative definition

$$\bigcup_{\vec{Q}_A} \left[ C(\vec{Q}_B) - C(\vec{Q}_A) \right] \leq F(n)$$

Narrow gorges: valley that contains the minimum

The volume of parameters that lead to the valley, vanishes exponentially.

Example of a cost that has a Barrier Plateau:

Consider a problem of fixed state compilation:

$$103 \quad \begin{array}{c} \text{we want } U(\vec{\phi}) |\vec{\phi}\rangle \\ \vdots \\ (\omega) \leftarrow \underbrace{V}_{\text{P}} \left[ - \underbrace{U(\vec{\phi})}_{\text{P}} \right] D \end{array} \quad \begin{array}{c} \text{to be the same as } V|\vec{\phi}\rangle \\ \text{C}(\vec{\phi}) = [ - \text{Tr}[i\vec{\phi} \times \vec{\sigma}] \cdot U(\vec{\phi}) V[i\vec{\phi} \times \vec{\sigma}] V^T U^T(\vec{\phi}) ] \\ = 1 - p(0 \dots 0) \end{array}$$

$$\begin{array}{ll}
 \text{U} = \boxed{1} & \text{we know that} \\
 \text{Tug model} & \\
 U(\vec{\phi}) = \boxed{\frac{R_0}{2}} & Q_i = 0 \quad \forall i \\
 & C(\vec{\phi}) = 0 \\
 & \vdots \\
 & \boxed{\frac{R_0}{2}} \leftarrow
 \end{array}$$

$$|0\rangle = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$|\psi\rangle = |\psi_1\rangle - |\psi_2\rangle = \cos\left(\frac{\Omega_i}{2}\right)|0\rangle + \sin\left(\frac{\Omega_i}{2}\right)|1\rangle$$

$$|0\rangle = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$|\psi\rangle = \bigotimes_{i=1}^n |\psi_i\rangle = \bigotimes_{i=1}^n \left( \cos\left(\frac{\Omega_i}{2}\right)|0_i\rangle + \sin\left(\frac{\Omega_i}{2}\right)|1_i\rangle \right)$$

|2>

$$\Rightarrow C(\vec{\Omega}) = 1 - |\langle \vec{0} | \vec{\psi} \rangle|^2$$

$$\boxed{C(\vec{\Omega}) = 1 - \prod_{i=1}^n \cos^2\left(\frac{\Omega_i}{2}\right)}$$

compares 2 objects

living in an exponentially

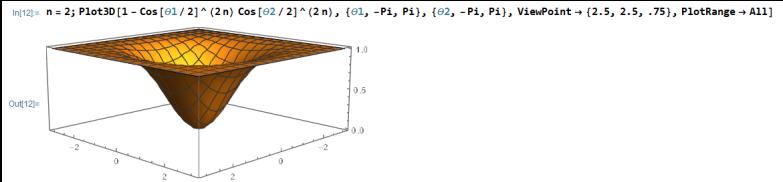
large Hilbert-Space

for visualization purpose

$$\Omega_i = \Omega_1 \quad \text{if} \quad i \leq \frac{n}{2}$$

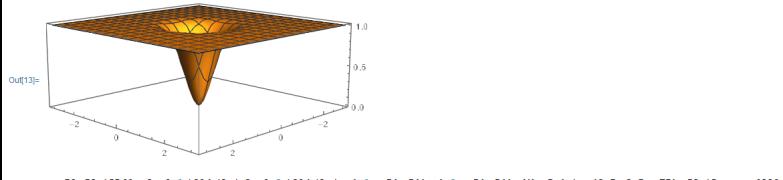
$$\Omega_i = \Omega_2 \quad \text{if} \quad i > \frac{n}{2}$$

4



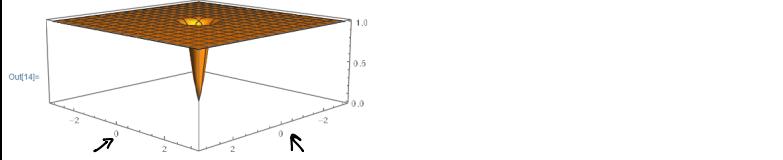
In[12]:= n = 2; Plot3D[1 - Cos[\theta1/2]^(2 n) Cos[\theta2/2]^(2 n), {\theta1, -Pi, Pi}, {\theta2, -Pi, Pi}, ViewPoint -> {2.5, 2.5, .75}, PlotRange -> All]

20



In[13]:= n = 10; Plot3D[1 - Cos[\theta1/2]^(2 n) Cos[\theta2/2]^(2 n), {\theta1, -Pi, Pi}, {\theta2, -Pi, Pi}, ViewPoint -> {2.5, 2.5, .75}, PlotRange -> All]

100



In[14]:= n = 50; Plot3D[1 - Cos[\theta1/2]^(2 n) Cos[\theta2/2]^(2 n), {\theta1, -Pi, Pi}, {\theta2, -Pi, Pi}, ViewPoint -> {2.5, 2.5, .75}, PlotRange -> All]

... General: 0.000224624<sup>100</sup> is too small to represent as a normalized machine number; precision may be lost.

... General: 0.000224624<sup>100</sup> is too small to represent as a normalized machine number; precision may be lost.

$$\frac{\partial C(\vec{\Omega})}{\partial \Omega_n} = -\cos\left(\frac{\Omega_n}{2}\right) \sin\left(\frac{\Omega_n}{2}\right) \pi \underset{\delta \neq k}{\cancel{\sum}} \cos^2\left(\frac{\Omega_j}{2}\right)$$

$$\langle \frac{\partial C(\vec{\Omega})}{\partial \Omega_n} \rangle_{\vec{\Omega}} = 0$$

$$\langle \dots \rangle_{\vec{\Omega}} = \frac{1}{2\pi} \int_{-\pi}^{\pi} d\Omega_1 \frac{1}{2\pi} \int_{-\pi}^{\pi} d\Omega_2 \dots \frac{1}{2\pi} \int_{-\pi}^{\pi} d\Omega_n$$

$$\left\langle \frac{\partial C(\vec{\phi})}{\partial \phi_a} \right\rangle = \left( \prod_{j \neq k} \frac{1}{2\pi} \int d\phi_j \cos^2 \left( \frac{\phi_j}{2} \right) \right) \left( \frac{1}{2\pi} \int \cos \left( \frac{\phi_a}{2} \right) \sin \left( \frac{\phi_a}{2} \right) d\phi_a \right)$$

$$\text{Var} \left[ \frac{\partial C(\vec{\phi})}{\partial \phi_a} \right] = \left\langle \left( \frac{\partial C(\vec{\phi})}{\partial \phi_a} \right)^2 \right\rangle - \underbrace{\left\langle \frac{\partial C(\vec{\phi})}{\partial \phi_a} \right\rangle^2}_{=0}$$

$\text{Var}[X] = \langle X^2 \rangle - \langle X \rangle^2$

$$\begin{aligned} \text{Var} \left[ \frac{\partial C(\vec{\phi})}{\partial \phi_a} \right] &= \left( \prod_{j \neq k} \frac{1}{2\pi} \int d\phi_j \cos^4 \left( \frac{\phi_j}{2} \right) \right) \left( \frac{1}{2\pi} \int \cos^2 \left( \frac{\phi_a}{2} \right) \sin^2 \left( \frac{\phi_a}{2} \right) d\phi_a \right) \\ &\quad \downarrow \quad \downarrow \\ &\quad \frac{3}{8} \quad \frac{1}{8} \\ &= \left( \frac{3}{8} \right)^{n-1} \frac{1}{8} \end{aligned}$$

Barrier Plateaus depend on the locality

Local cost function compare objects at the small problem size  
or even probit size

$$C_L = 1 - \text{Tr} [U(\vec{\phi}) | \vec{\phi} \times \vec{\phi} | U^\dagger(\vec{\phi})] B_L]$$

$$\begin{aligned} B_G &= |\vec{\phi} \times \vec{\phi}| = 1 - \frac{1}{n} \sum_{j=1}^n P_j(\vec{\phi}) \\ O_L &= \frac{1}{n} \sum_{j=1}^n |\phi \times \phi_j| \otimes \frac{1}{\phi_j} \end{aligned}$$

n times

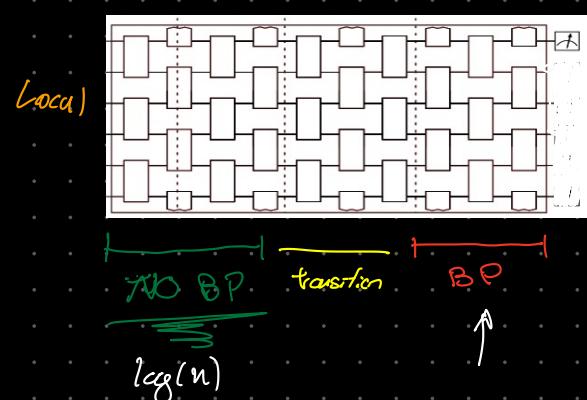
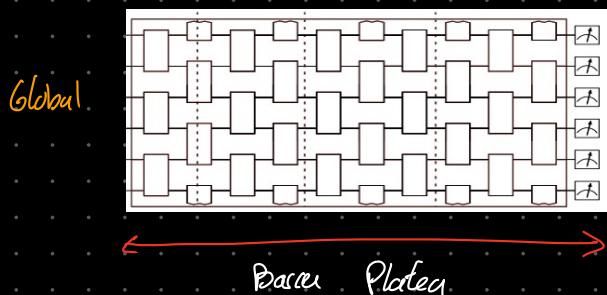
$$\text{Var} \left[ \frac{\partial C_L(\vec{\phi})}{\partial \phi_a} \right] = \frac{1}{8n^2}$$



Not all cost functions are the same

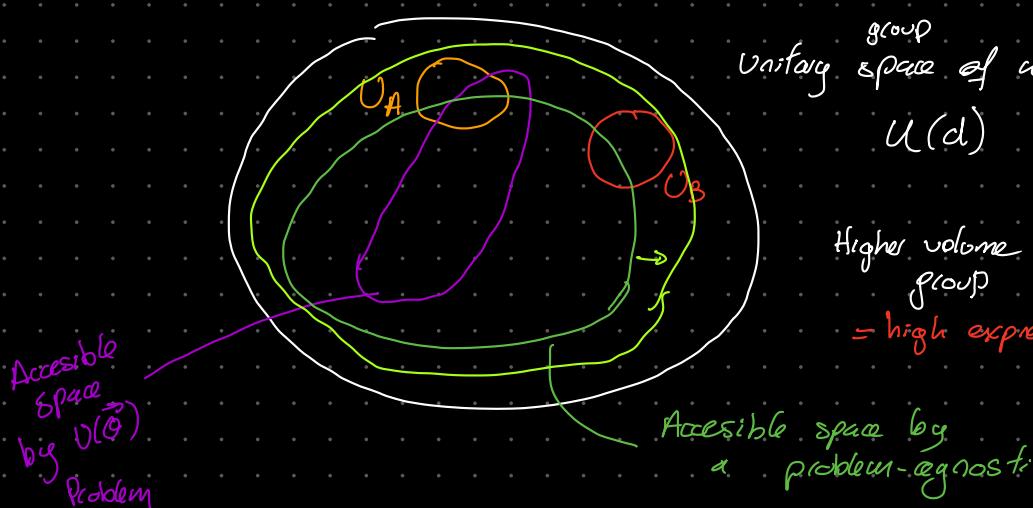
Global  $\times$   
Local  $\checkmark$

$$A(u) \rightarrow \frac{\partial \mathcal{L}}{\partial u}$$



There multiple sources of Barren Plateaus

- Locality
- Expressibility



Hardware efficient, have the property that their expressibility increases with the depth

Expressibility [non-mathematical definition]: a measure of how uniformly the circuit creates unitaries over the unitary group

A circuit with expressibility  $A(U)$  is small

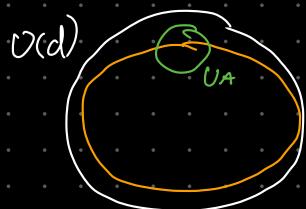
$A(U) = \text{distance to the uniform distribution of unitaries}$   
(haar measure)

Holmes arxiv 2101.02138 (2021)

$$\text{Var}\left[\frac{\partial C(\vec{\theta})}{\partial \theta_i}\right] \leq A(U) \cdot c$$

The more expressible the circuit, the smaller the gradients, and thus the more shots we need to train.

Highly expressible circuits

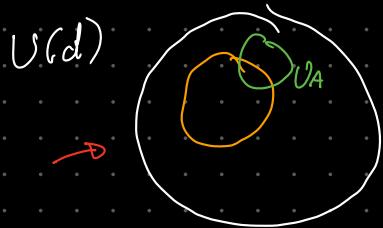


will have

Barren plateaus



Low expressibility circuits



might not have a  
Barren Plateau



does not guarantee absence of Barren plateaus (e.g. global cost function)

Larocca arxiv 2105.14377

LS Problem inspired ansatz (QAOA, DCC, HVA, QOC...) are not immune to barren plateaus.

The way to analyze if an architecture has barrier plateaus is by a principled analysis of computing

$$\text{Var} \left[ \frac{\partial C(\theta)}{\partial \theta_a} \right]$$

Other sources: Entanglement

If  $U(\theta)$  generates too much entanglement between "visible" qubits (that we measure) and "hidden" qubits, due to the quantum correlations, the reduced state of the visible qubits is exponentially close to being maximally mixed

Mareco arXiv 2010.15968

Patt. PRR 3, 023090 (2021)  
arXiv 2012.12688

$$S_C = -\left( GNN \right) - \langle \chi \rangle$$

$$S_{\text{Visible}} \sim \frac{1}{2^{n_{\text{Visible}}}}$$

Causes of Barrier Plateaus:-

- Globality

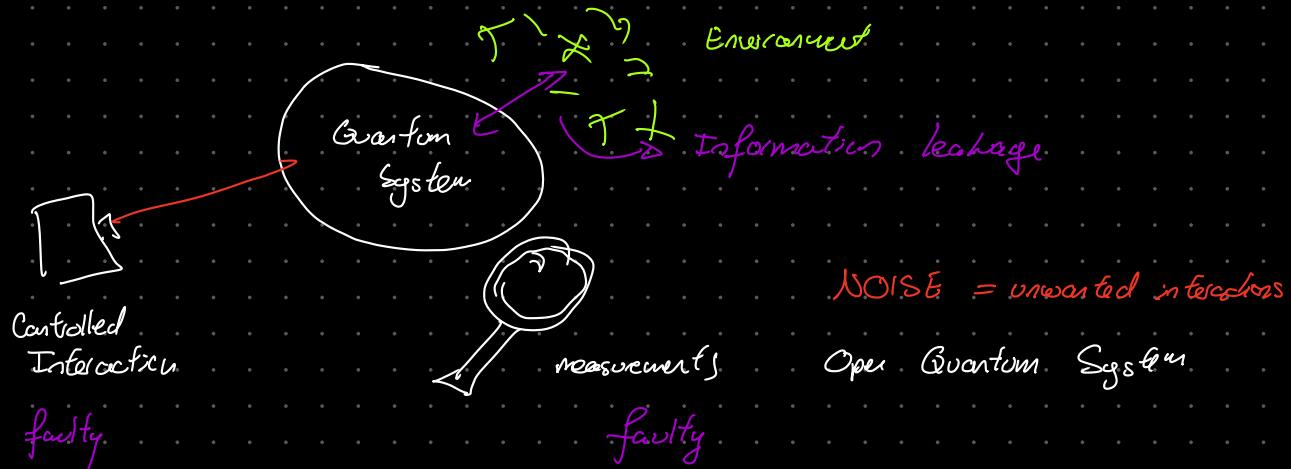
- Expressiveness

- Entanglement

# Quantum Noise

So far we have considered near-term QC for closed quantum systems that is, systems that suffer no unwanted interactions with the environment.

In reality, there is no way to perfectly isolate quantum systems (HARD)  
 → unwanted interactions of the environments



$$|\psi\rangle \longrightarrow |\tilde{\psi}\rangle$$

state was pure in a closed system

state is now mixed

## Quantum Operator Formalism

Describes transformations between quantum states

$$|\psi\rangle \rightarrow |\tilde{\psi}\rangle = \mathcal{E}(|\psi\rangle)$$

$$\mathcal{E}_U(|\psi\rangle) = U|\psi\rangle U^\dagger$$

$$\mathcal{E}_M(|\psi\rangle) = M_{\mu\nu}|\psi\rangle M^{\dagger}_{\mu\nu}$$

$$\mathcal{E}(|\psi\rangle) = \sum_k E_k |\psi\rangle E_k^\dagger$$

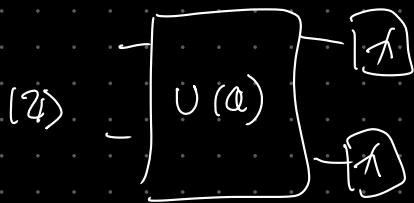
$\mathcal{E}$  = quantum operation  
 quantum channel

$$\mathcal{E}: \mathcal{H}_A \rightarrow \mathcal{H}_B$$

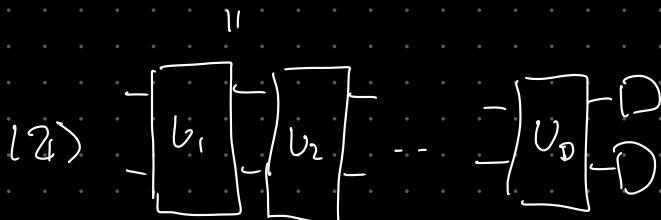
$E_k$  = Krauss operation

## Global depolarizing channel

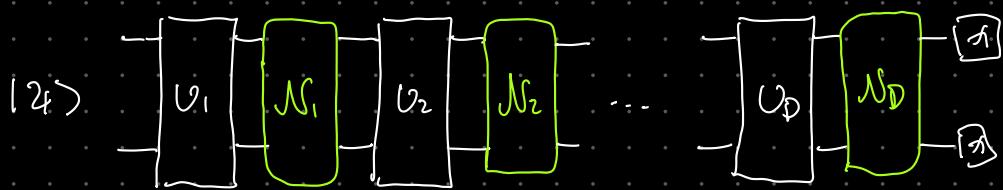
$$E(\rho) = p\rho + (1-p)\frac{I}{2^n}$$



we model noise as a noisy channel acting after every set of parallel gates.



$$U(a) = \prod_{i=1}^D U_i(a_i)$$



we can model the action of noise in the circuit

$\mathcal{N}$  = global depolarizing

$$\tilde{\rho}^{out} = U_D \dots U_2 U_1 (4 \times 4) U_1^\dagger U_2^\dagger \dots U_D^\dagger$$

$$\tilde{\rho}^{out} = \mathcal{N} \left[ U_D \mathcal{N} \left\{ \dots \mathcal{N} \left[ U_2 \mathcal{N} \left[ U_1 \mathcal{P} U_1^\dagger \right] U_2^\dagger \right] \dots \right] U_D^\dagger \right]$$

$$\boxed{\tilde{\rho}^{out} = P^D \tilde{\rho}^{out} \uparrow + (1-P^D) \frac{I}{2^n}}$$

$$C(\tilde{\rho}) = T_1 [U(4 \times 4) U^\dagger]$$

the noisy cost

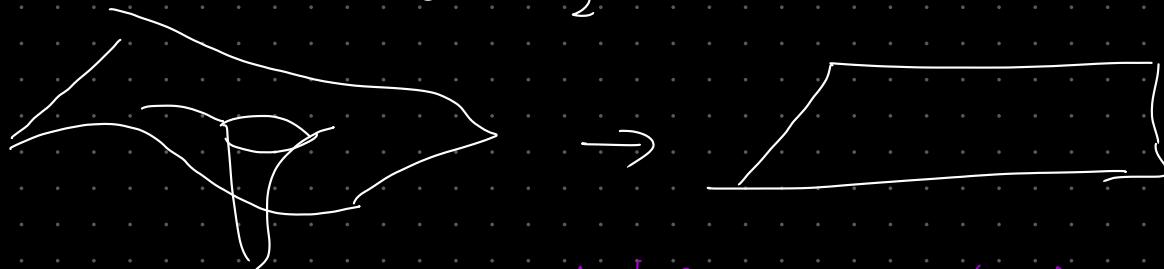
$$\tilde{C}(\tilde{\rho}) = T_1 [\tilde{\rho}^{out}]$$

$$\begin{aligned}\tilde{C}(\vec{\theta}) &= p^D \text{Tr}[\tilde{S}^{\text{out}}(\vec{\theta})] + (1-p^D) \text{Tr}\left[\frac{\mathbb{I}_{\{0\}}}{2^n}\right] \\ &= p^D C(\vec{\theta}) + \underbrace{(1-p^D) \text{Tr}[\mathbb{I}]}_{2^n} \quad \text{constant and independent of } D \\ &\quad \text{Rescale factor}\end{aligned}$$

$p^D$  is a number that decreases exponentially with the depth.

In the limit  $D \rightarrow \infty$

$$\tilde{S}^{\text{out}} = \frac{\mathbb{I}}{2^n}, \quad \tilde{C}(\vec{\theta}) = \text{constant} \quad (\star)$$



wang Nat Com 12, 6961 (2021)

arxiv 2007.14384

Noise-induced Boxer Plateau

- Solutions:
- Build better devices with smaller noise-probability  $(p \sim 1)$
  - Use shallow circuits

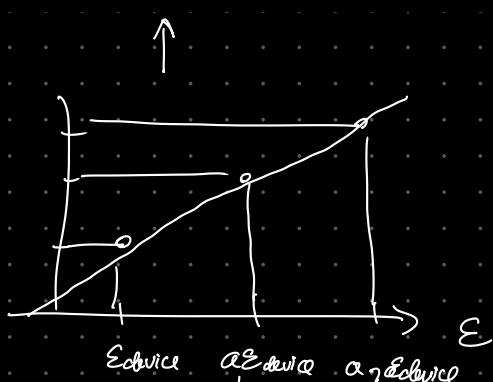
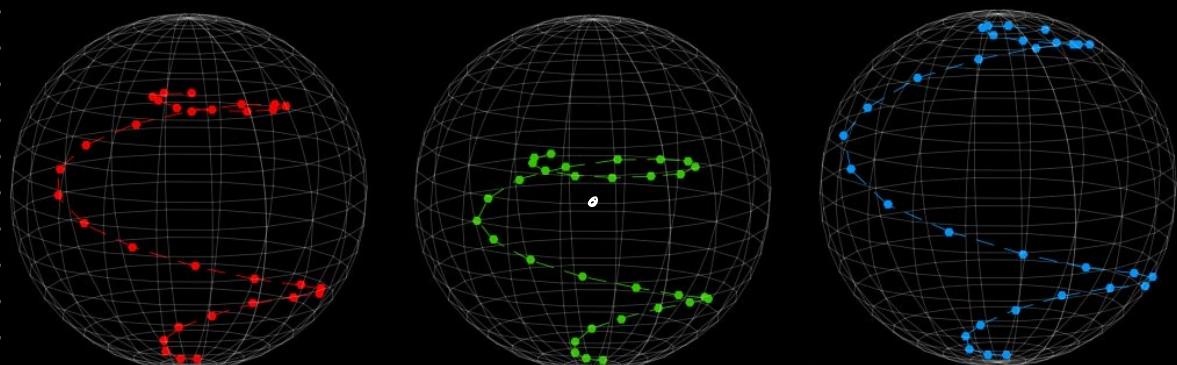
$$\underline{D \sim O(\log(n))} \rightarrow \text{the suppression is } p^D$$

$p^{\log(n)} \sim \text{poly}(n)$

# Error mitigation

How do we deal with noise, to recover noiseless expectation values.

Hope: we can train a VQA, QMC with noise, and use error mitigators to recover correct and noiseless information



Tenmei PRB 119, 180509 (2019)  
arXiv 1812.02008

Wang arXiv 2109.01081 (2021)

