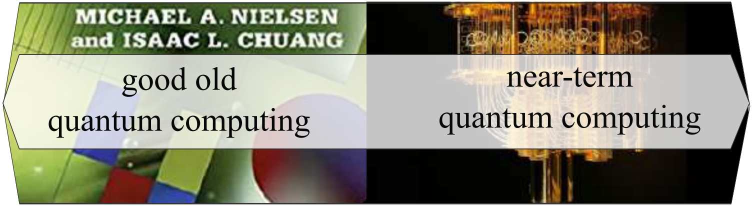
# Quantum Machine Learning

Maria Schuld

Xanadu and University of KwaZulu-Natal

SMILES, August 2020

# Quantum computing is an emerging technology.



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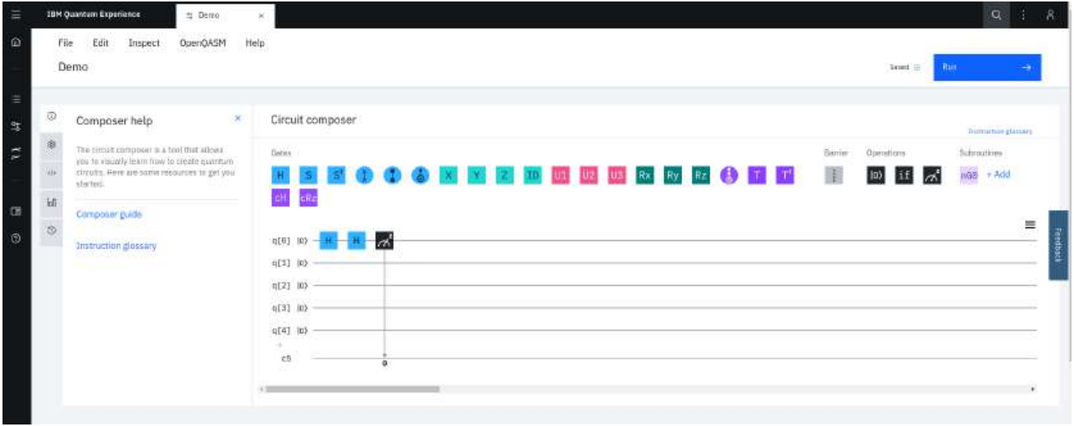

# Quantum computing is an emerging technology.

Players — Partners

# An emerging technology needs applications.

**WANTED**

Application which

- doesn't care about noise
- gives us access to multi-billion $ markets
- attracts young researchers

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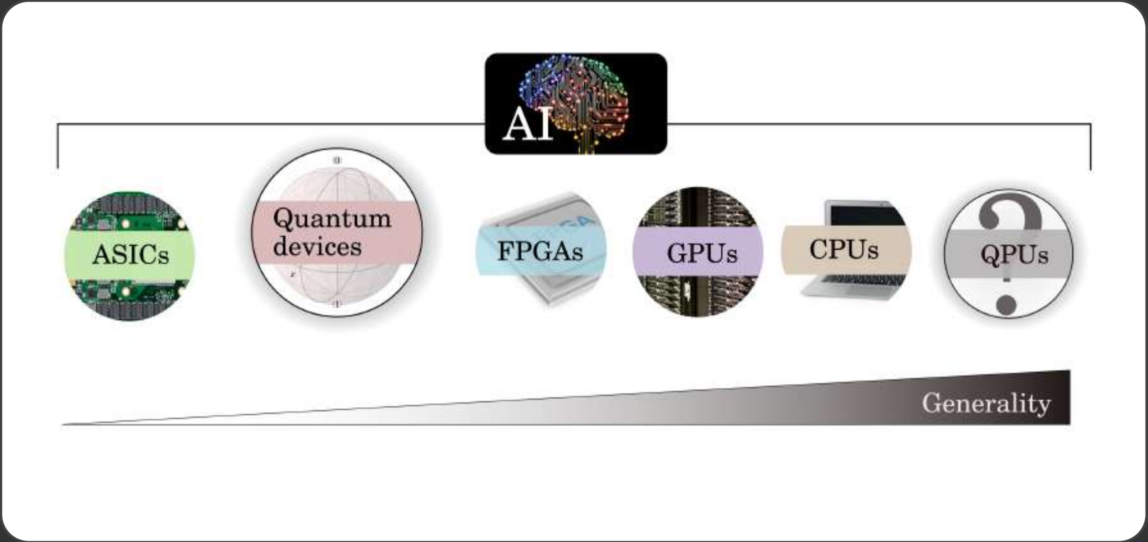
Machine Learning!

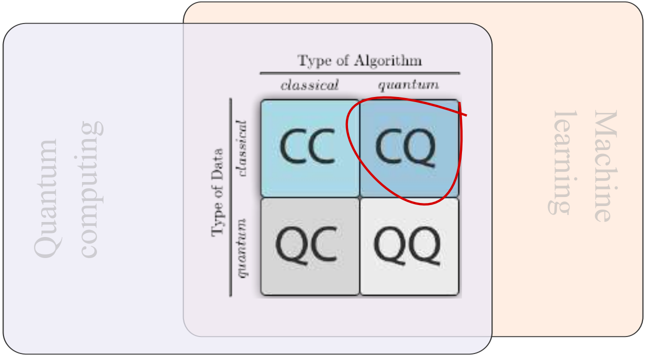
# Quantum computing could potentially enrich ML.



# Quantum computing could potentially enrich ML.

machine intelligence = data/distributions + algorithm/hardware + models

# Quantum computing could potentially enrich ML.



# Agenda

- Quantum computing
- Models
- Algorithms
- Data

# QUANTUM COMPUTING

# Quantum theory predicts expectations of measurements.

- A quantum state $|\psi\rangle$ lives in a **Hilbert space** $\mathcal{H}$ with scalar product $\langle\psi|\,\psi\rangle$.
- An **observable** is represented by a Hermitian operator $O$ on $\mathcal{H}$. The eigenvectors of $O$ form an orthonormal basis of $\mathcal{H}$ with real eigenvalues. Every $|\psi\rangle \in \mathbb{C}^N$ can hence be expressed in $O$'s eigenbasis $\{|\psi_i\rangle\}_{i=1\ldots N}$, $|\psi\rangle = \sum_{i=1}^{N} a_i|\psi_i\rangle$, where the $a_i \in \mathbb{C}$ are the **amplitudes**.
- The effect of applying $O$ to an element $|\psi\rangle \in \mathbb{C}^N$ is fully defined by the eigenvalue equations $O|\psi_i\rangle = \lambda_i|\psi_i\rangle$ with eigenvalues $\lambda_i$. **Expectation values** of the observable property are calculated by $\mathbb{E}(O) = \langle\psi|O|\psi\rangle$.
- The dynamic evolution of a quantum state is represented by a **unitary operator** $U = U(t_2, t_1)$ mapping $|\psi(t_1)\rangle$ to $U(t_2, t_1)|\psi(t_1)\rangle = |\psi(t_2)\rangle$ with $U^\dagger U = 1$. $U$ is the solution of the corresponding **Schrödinger equation** $i\hbar\partial_t|\psi\rangle = H|\psi\rangle$ with **Hamiltonian** $H$.

Schuld & Petruccione, Springer 2018

# Quantum theory predicts expectations of measurements.

1. Consider a random variable $M$ (measurement) that can take the values (observations) $\{m_1, ..., m_N\}$.
2. Assign probabilities $\{p_1, ..., p_N\}$ to these values quantifying our knowledge on how likely an observation is to occur.
3. The expectation value of the random variable is defined as

$$\langle M \rangle = \sum_{i=1}^{N} p_i m_i,$$

Schuld & Petruccione, Springer 2018

# Quantum theory predicts expectations of measurements.

Use the notation

$$q = \begin{pmatrix} \sqrt{p_1} \\ \vdots \\ \sqrt{p_N} \end{pmatrix} = \sqrt{p_1} \begin{pmatrix} 1 \\ \vdots \\ 0 \end{pmatrix} + \ldots + \sqrt{p_N} \begin{pmatrix} 0 \\ \vdots \\ 1 \end{pmatrix}, \qquad M = \begin{pmatrix} m_1 & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & m_N \end{pmatrix}.$$

The expectation value can now be written as

$$\langle M \rangle = q^T M q = \sum_{i=1}^{N} p_i m_i$$

Schuld & Petruccione, Springer 2018

# Quantum theory predicts expectations of measurements.

$$q \rightarrow \psi = \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{pmatrix} \in \mathbb{C}^N, \quad |\alpha_i|^2 = p_i$$

$$M \rightarrow O_{\text{hermitian}} \in \mathbb{C}^{N \times N}, \quad \text{eig}[\text{O}] = \{\text{m}_1, \ldots, \text{m}_\text{N}\}$$

$$\langle M \rangle = \psi^T M \psi = \langle \psi | M | \psi \rangle = \sum_{i=1}^{N} p_i m_i$$

Schuld & Petruccione, Springer 2018

# Quantum theory predicts expectations of measurements.

$$\begin{pmatrix} s_{11} & \dots & s_{1N} \\ \vdots & \ddots & \vdots \\ s_{N1} & \dots & s_{NN} \end{pmatrix} \begin{pmatrix} p_1 \\ \vdots \\ p_N \end{pmatrix} = \begin{pmatrix} p'_1 \\ \vdots \\ p'_N \end{pmatrix}, \qquad \sum_{i=1}^{N} p_i = \sum_{i=1}^{N} p'_i = 1$$

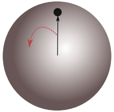
Schuld & Petruccione, Springer 2018

# Quantum theory predicts expectations of measurements.

$$\begin{pmatrix} u_{11} & \dots & u_{1N} \\ \vdots & \ddots & \vdots \\ u_{N1} & \dots & u_{NN} \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{pmatrix} = \begin{pmatrix} \alpha'_1 \\ \vdots \\ \alpha'_N \end{pmatrix}, \qquad \sum_{i=1}^{N} |\alpha_i|^2 = \sum_{i=1}^{N} |\alpha'_i|^2 = 1$$

Schuld & Petruccione, Springer 2018

# Quantum computers perform linear algebra in high-dim spaces.



PHYSICAL CIRCUIT

$$n \left[ \begin{array}{c} |0\rangle \\ \vdots \\ |0\rangle \end{array} \right.$$

MATHEMATICAL DESCRIPTION

$|1|^2 = p(0...00)$

$$2^n \left[ \boxed{\begin{array}{c} 1 + 0i \\ 0 + 0i \\ \vdots \end{array}} \right.$$

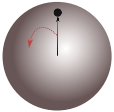
$|0|^2 = p(0...01)$

# Quantum computers perform linear algebra in high-dim spaces.

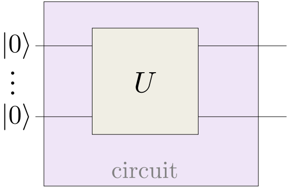
```python
from pennylane import *

dev = device('default.qubit', wires=2)

@qnode(dev)
def circuit():
    return probs(wires=[0, 1])

print(circuit()) # [1. 0. 0. 0.]
print(dev.state) # [1.+0.j 0.+0.j 0.+0.j 0.+0.j]
```

pennylane.ai

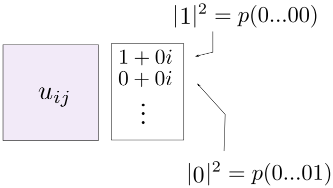
# Quantum computers perform linear algebra in high-dim spaces.



PHYSICAL CIRCUIT




MATHEMATICAL DESCRIPTION



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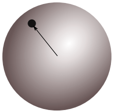
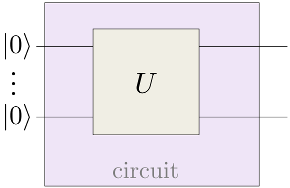


PHYSICAL CIRCUIT




MATHEMATICAL DESCRIPTION

$$|\psi_1|^2 = p(0...00)$$

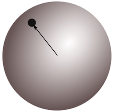
$$\begin{bmatrix} \psi_1 \\ \psi_2 \\ \vdots \end{bmatrix}$$

$$|\psi_2|^2 = p(0...01)$$

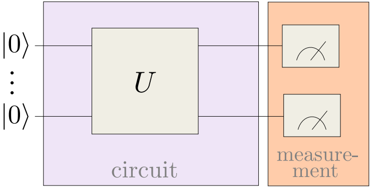
# Quantum computers perform linear algebra in high-dim spaces.

```python
from pennylane import *
import numpy as np

dev = device('default.qubit', wires=2)
U = np.array([[0.,         -0.70710678, 0.,          0.70710678],
              [0.70710678, 0.,          -0.70710678, 0.        ],
              [0.70710678, 0.,          0.70710678,  0.        ],
              [0.,         -0.70710678, 0.,          -0.70710678]])

@qnode(dev)
def circuit():
    QubitUnitary(U, wires=[0, 1])
    return probs(wires=[0, 1])

print(circuit()) # [0. 0.5 0.5 0.]
print(dev.state) # [0.+0.j 0.707+0.j 0.707+0.j 0.+0.j]
```

# Quantum computers perform linear algebra in high-dim spaces.



PHYSICAL CIRCUIT




MATHEMATICAL DESCRIPTION

$$\begin{matrix} 10110\ldots1 \\ 11010\ldots0 \\ 00001\ldots0 \\ \vdots \end{matrix} \sim \begin{bmatrix} \psi_1 \\ \psi_2 \\ \vdots \end{bmatrix}$$

$|\psi_1|^2 = p(0\ldots00)$

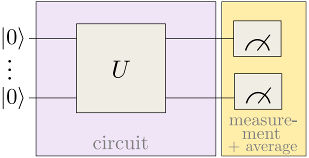
$|\psi_2|^2 = p(0\ldots01)$

# Quantum computers perform linear algebra in high-dim spaces.

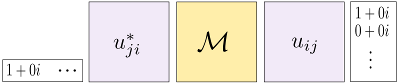
```python
from pennylane import *
import numpy as np

dev = device('default.qubit', wires=2, shots=1)
U = np.array([[0.,    -0.70710678, 0.,     0.70710678],
              [0.70710678, 0.,    -0.70710678, 0.   ],
              [0.70710678, 0.,     0.70710678, 0.   ],
              [0.,    -0.70710678, 0.,    -0.70710678]])

@qnode(dev)
def circuit():
    QubitUnitary(U, wires=[0, 1])
    return sample(PauliZ(wires=0)), sample(PauliZ(wires=1))

print(circuit()) # [[-1], [ 1]]
print(dev.state) # [0.+0.j 0.707+0.j 0.707+0.j 0.+0.j]
```

# Quantum computers perform linear algebra in high-dim spaces.

PHYSICAL CIRCUIT



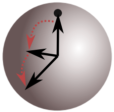

MATHEMATICAL DESCRIPTION

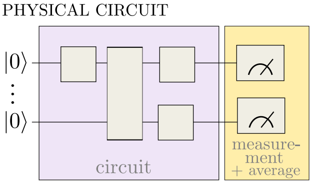


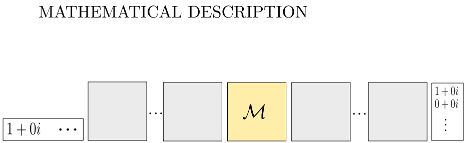
# Quantum computers perform linear algebra in high-dim spaces.

```python
from pennylane import *
import numpy as np

dev = device('default.qubit', wires=2, shots=1)
U = np.array([[0.,        -0.70710678, 0.,         0.70710678],
              [0.70710678, 0.,         -0.70710678, 0.        ],
              [0.70710678, 0.,          0.70710678, 0.        ],
              [0.,        -0.70710678, 0.,        -0.70710678]])

@qnode(dev)
def circuit():
    QubitUnitary(U, wires=[0, 1])
    return expval(PauliZ(wires=0)), expval(PauliZ(wires=1))

print(circuit()) # [0., 0.]
print(dev.state) # [0.+0.j 0.707+0.j 0.707+0.j 0.+0.j]
```

# Quantum computers perform linear algebra in high-dim spaces.



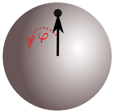


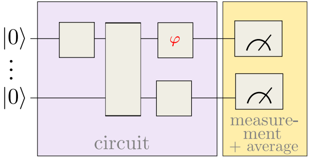
# Quantum computers perform linear algebra in high-dim spaces.

```python
from pennylane import *

dev = device('default.qubit', wires=2)

@qnode(dev)
def circuit():
    PauliX(wires=0)
    CNOT(wires=[0, 1])
    Hadamard(wires=0)
    PauliZ(wires=1)
    return expval(PauliZ(wires=0)), expval(PauliZ(wires=1))

print(circuit()) # [0., -1.]
print(dev.state) # [ 0.+0.j -0.70710678+0.j  0.+0.j  0.70710678+0.j]
```

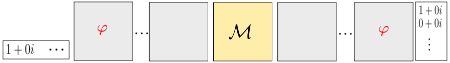
# Quantum computers perform linear algebra in high-dim spaces.




PHYSICAL CIRCUIT



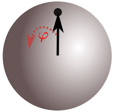

MATHEMATICAL DESCRIPTION

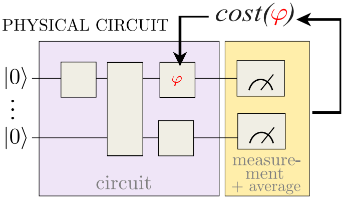


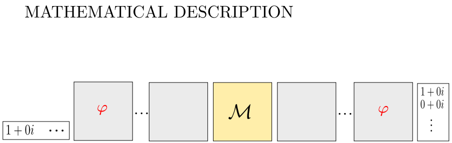
# Quantum computers perform linear algebra in high-dim spaces.

```python
from pennylane import *

dev = device('default.qubit', wires=2)

@qnode(dev)
def circuit(phi):
    RX(phi, wires=0)
    CNOT(wires=[0, 1])
    Hadamard(wires=0)
    PauliZ(wires=1)
    return expval(PauliZ(wires=0)), expval(PauliZ(wires=1))

print(circuit(0.2)) # [0. 0.98006658]
print(dev.state) # [0.70+0.j 0.+0.07j 0.70+0.j 0.-0.070j]
```

# Quantum computers perform linear algebra in high-dim spaces.



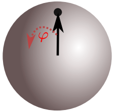



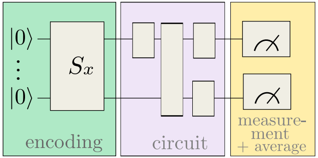
# Quantum computers perform linear algebra in high-dim spaces.

```python
from pennylane import *

dev = device('default.qubit', wires=1)

@qnode(dev)
def circuit(phi):
    Hadamard(wires=0)
    RY(phi, wires=0)
    return expval(PauliZ(wires=0))

phi = 0.2
opt = GradientDescentOptimizer(stepsize=0.2)

for i in range(5):
    phi = opt.step(circuit, phi)

    print(phi)
    # 0.39601331556824826
    # 0.5805345472544579
    # 0.7477684644009802
    # 0.8944100937922911
    # 1.0196058853338432
```

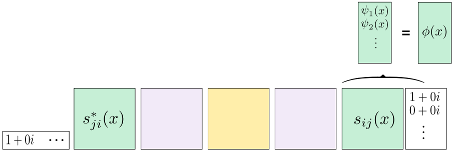
# Quantum computers perform linear algebra in high-dim spaces.




PHYSICAL CIRCUIT




MATHEMATICAL DESCRIPTION



# Quantum computers perform linear algebra in high-dim spaces.

```python
from pennylane import *

dev = device('default.qubit', wires=2)

@qnode(dev)
def circuit(phi, x=None):
    RX(x, wires=[0])
    CNOT(wires=[0, 1])
    RY(phi, wires=[1])
    return expval(PauliZ(wires=[1]))

print(circuit(0.2, x=0.1)) # 0.975
print(circuit(0.2, x=0.5)) # 0.860
```

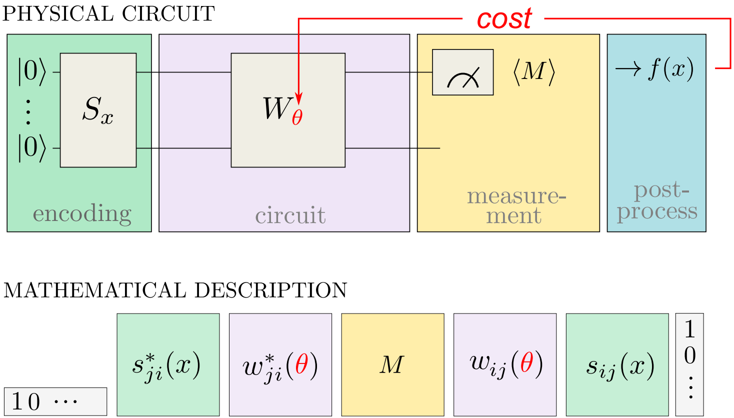
# Quantum computers perform linear algebra in high-dim spaces.

```python
import torch
from torch.autograd import Variable

data = torch.tensor([(0., 0.), (0.1, 0.1), (0.2, 0.2)])


def model(phi, x=None):
    return x*phi


def loss(a, b):
    return torch.abs(a - b) ** 2

def av_loss(phi):
    c = 0
    for x, y in data:
        c += loss(model(phi, x=x), y)
    return c

phi_ = Variable(torch.tensor(0.1), requires_grad=True)
opt = torch.optim.Adam([phi_], lr=0.02)

for i in range(5):
    l = av_loss(phi_)
    l.backward()
    opt.step()
```

```python
from pennylane import *
import torch
from torch.autograd import Variable

data = [(0., 0.), (0.1, 0.1), (0.2, 0.2)]

dev = device('default.qubit', wires=2)

@qnode(dev, interface='torch')
def circuit(phi, x=None):
    templates.AngleEmbedding(features=[x], wires=[0])
    templates.BasicEntanglerLayers(weights=phi, wires=[0, 1])
    return expval(PauliZ(wires=[1]))

def loss(a, b):
    return torch.abs(a - b) ** 2

def av_loss(phi):
    c = 0
    for x, y in data:
        c += loss(circuit(phi, x=x), y)
    return c

phi_ = Variable(torch.tensor([[0.1, 0.2],[-0.5, 0.1]]), requires_grad=True)
opt = torch.optim.Adam([phi_], lr=0.02)

for i in range(5):
    l = av_loss(phi_)
    l.backward()
    opt.step()
```

# MODELS

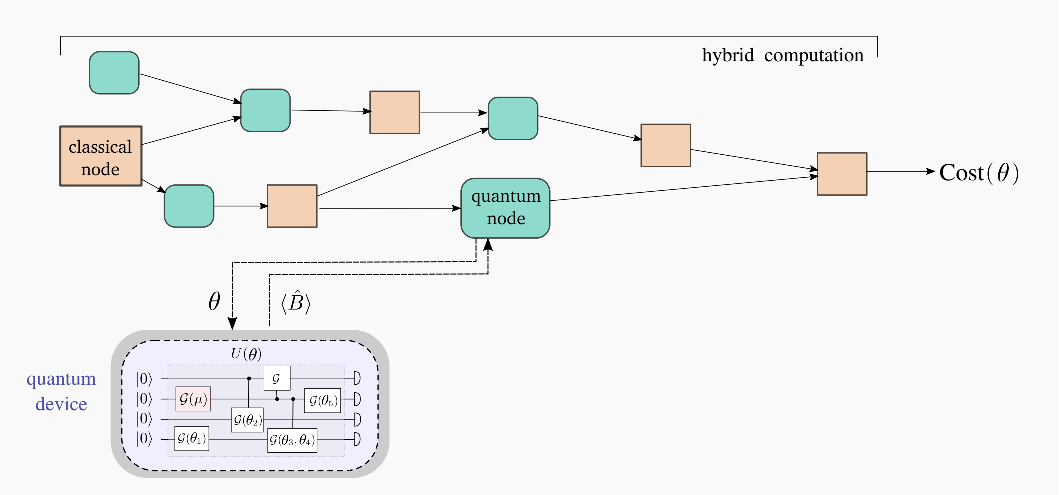
# Parametrised quantum computations can be used as ML models.




Farhi & Neven 1802.06002, Schuld et al. 1804.00633, Benedetti et al. 1906.07682

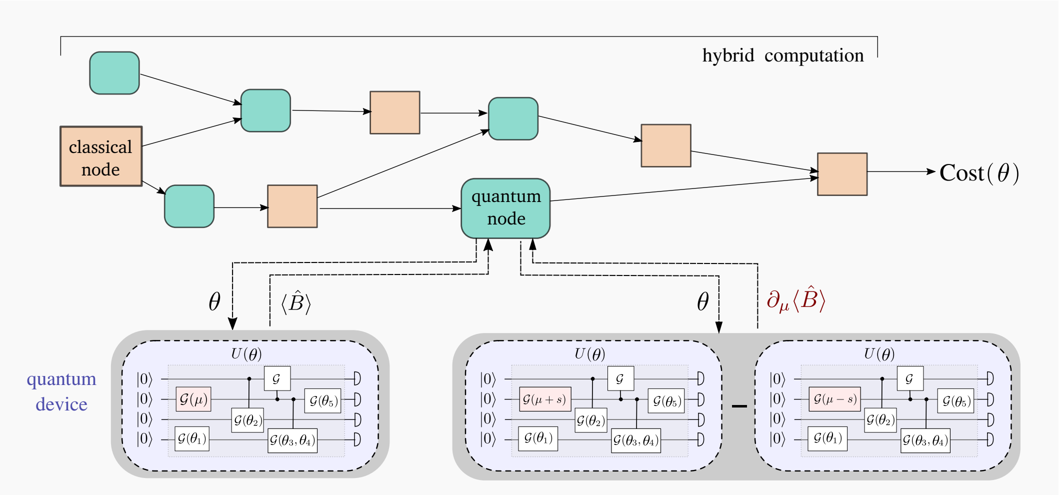
# 1. How to optimise quantum circuits?

# We can train quantum computations.



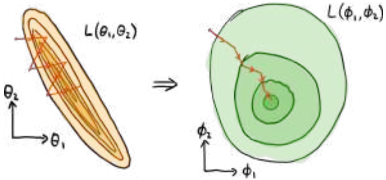

Guerreschi et al. 1701.01450, Mitarai et al. 1803.00745, Schuld et al. 1811.11184, Mari et al. 2008.06517

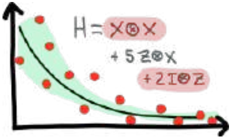
# We can train quantum computations.




Guerreschi & Smelyanskiy 1701.01450, Mitarai et al. 1803.00745, Schuld et al. 1811.11184

# We can train quantum computations.




Stokes et al. 1909.02108, Kübler et al. 1909.09083, Sweke et al. 1910.01155, Ostaszewski et al. 1905.09692, ...

# We can train quantum computations.

**Barren plateaus in quantum neural network training landscapes**

Jarrod R. McClean,[1,*] Sergio Boixo,[1,†] Vadim N. Smelyanskiy,[1,‡] Ryan Babbush,[1] and Hartmut Neven[1]
[1]*Google Inc., 340 Main Street, Venice, CA 90291, USA*
(Dated: March 30, 2018)

Many experimental proposals for noisy intermediate scale quantum devices involve training a parameterized quantum circuit with a classical optimization loop. Such hybrid quantum-classical algorithms are popular for applications in quantum simulation, optimization, and machine learning. Due to its simplicity and hardware efficiency, random circuits are often proposed as initial guesses for exploring the space of quantum states. We show that the exponential dimension of Hilbert space and the gradient estimation complexity make this choice unsuitable for hybrid quantum-classical algorithms run on more than a few qubits. Specifically, we show that for a wide class of reasonable parameterized quantum circuits, the probability that the gradient along any reasonable direction is non-zero to some fixed precision is exponentially small as a function of the number of qubits. We argue that this is related to the 2-design characteristic of random circuits, and that solutions to this problem must be studied.



Rapid developments in quantum hardware have motivated advances in algorithms to run in the so-called noisy intermediate scale quantum (NISQ) regime [1]. Many of the most promising application-oriented approaches are hybrid quantum-classical algorithms that rely on optimization of a parameterized quantum circuit [2–8]. The resilience of these approaches to certain types of errors and high flexibility with respect to coherence time and gate requirements make them especially attractive for NISQ implementations [3, 9–11].

The first implementation of such algorithms was de-

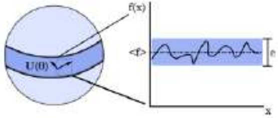


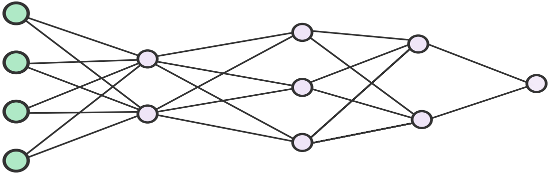

FIG. 1. A cartoon of the general geometric results from this work. The sphere depicts the phenomenon of concentration of

McClean et al. 1803.11173

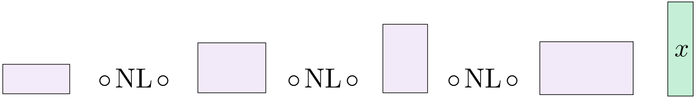
# 2. What *are* these models?

# Quantum circuits are unitary neural nets in feature space.

MODEL

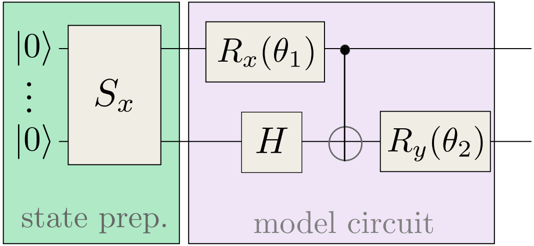


MATHEMATICAL DESCRIPTION



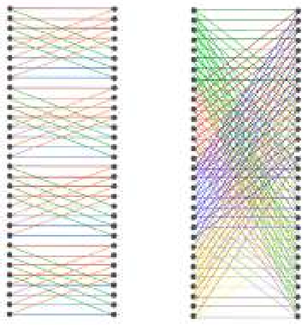
# Quantum circuits are unitary neural nets in feature space.

PHYSICAL CIRCUIT



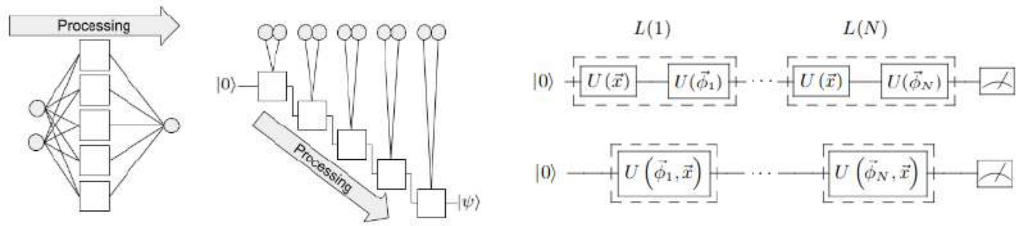

MATHEMATICAL DESCRIPTION

# Quantum circuits are unitary neural nets in feature space.



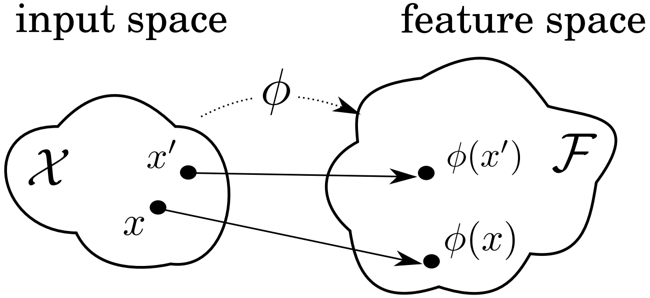
Schuld & Petruccione, Springer 2018

# Quantum circuits are unitary neural nets in feature space.




Pérez-Salinas et al. 1907.02085

# Quantum circuits are kernel methods.




$$\kappa(x, x') = \langle \phi(x), \phi(x') \rangle$$

$$f(x) = \langle \phi(x), w \rangle$$

# Quantum circuits are kernel methods.

Quantum feature map:

$$x \to \phi(x) \in \mathbb{C}^{2^{n_{\text{qubits}}}}$$

# Quantum circuits are kernel methods.

Quantum feature map:

$$x \to \phi(x) \in \mathbb{C}^{2^{n_{\text{qubits}}}}$$

Measurement:

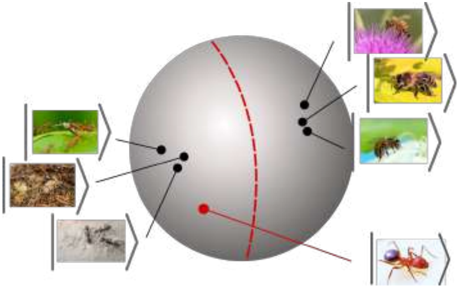
$$\phi(x)^{\dagger} M \phi(x)$$

# Quantum circuits are kernel methods.

Measurement:

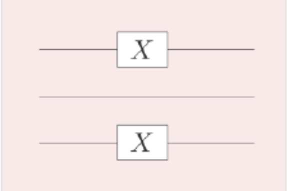
$$
\begin{aligned}
&\phi(x)^T M \phi(x) \\
&= \phi(x)^\dagger \; w w^\dagger \; \phi(x) \\
&= |\phi(x)^\dagger w|^2
\end{aligned}
$$

# Quantum circuits are kernel methods.



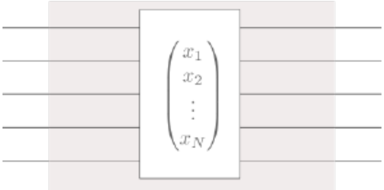
# Data encoding defines a "quantum kernel".

$$x \to \phi(x) = \begin{pmatrix} \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \end{pmatrix}$$



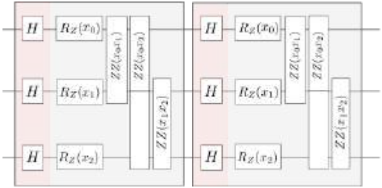
# Data encoding defines a "quantum kernel".

$$x \rightarrow \phi(x) = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \end{pmatrix}$$

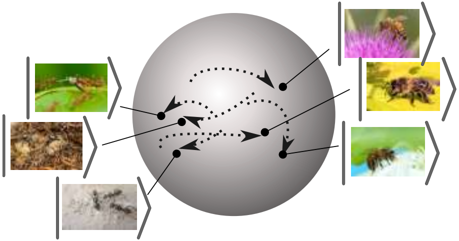


# Data encoding defines a “quantum kernel”.

$$x \rightarrow S(x) \begin{pmatrix} 1 \\ 0 \\ 0 \\ \vdots \end{pmatrix}$$



# We can engineer/train our features.



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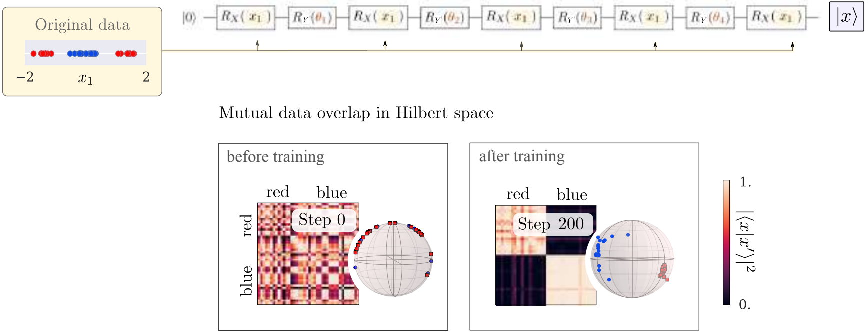


Lloyd et al. 2001.03622

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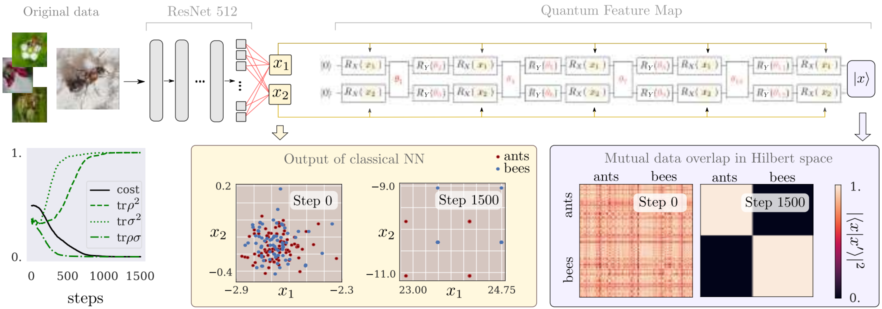
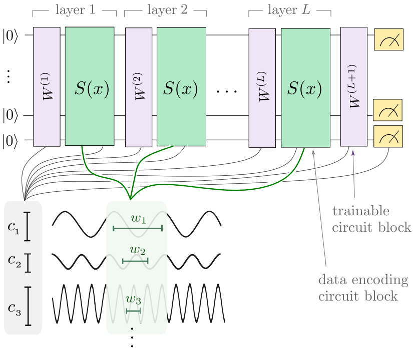


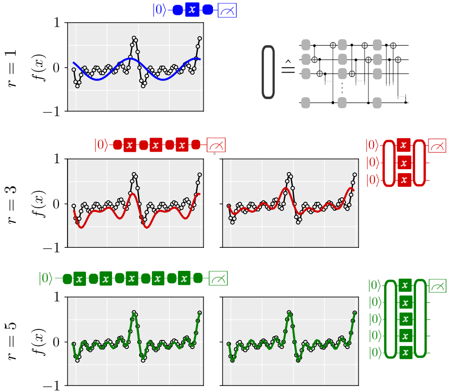

Lloyd et al. 2001.03622

# Quantum circuits are partial Fourier series.




Schuld, Sweke and Meyer 2008.XXXX

# Quantum circuits are partial Fourier series.




Schuld, Sweke and Meyer 2008.XXXX

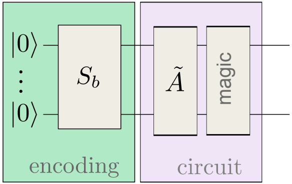
# ALGORITHMS

1. Exploit the linear algebra structure

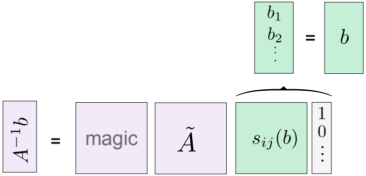
# Quantum computers can invert exponentially large matrices.*

*Assumption: the bottleneck of my ML algorithm is matrix inversion:* $Ax = b \to x = A^{-1}b$.

PHYSICAL CIRCUIT




MATHEMATICAL DESCRIPTION




Wiebe et al. 1204.5242, Rebentrost et al. 1307.0471, Zhao et al. 1803.10520, Kerenidis et al. 1603.08675, Chia et al. 1910.06151

# Quantum computers can invert exponentially large matrices.*

1. Prepare $\psi_b$.
2. Apply $\tilde{A}\ \psi_b$ (where $\tilde{A} = e^{-iA}$, but that is not so important).

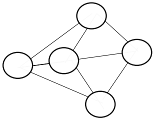
$$\begin{aligned}
\tilde{A}\psi_b &= \tilde{A}\ \left(\langle a_1, \psi_b\rangle a_1 + \cdots + \langle a_N, \psi_b\rangle a_N\right) \\
&= \langle a_1, \psi_b\rangle \lambda_1 a_1 + \cdots + \langle a_N, \psi_b\rangle \lambda_N a_N \\
&\Rightarrow \langle a_1, \psi_b\rangle \frac{1}{\lambda_1} a_1 + \cdots + \langle a_N, \psi_b\rangle \frac{1}{\lambda_N} a_N \\
&= \psi_x
\end{aligned}$$

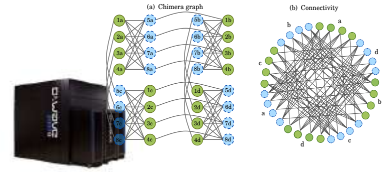
3. Use $\psi_b$ to do something interesting.

Wiebe et al. 1204.5242, Rebentrost et al. 1307.0471, Zhao et al. 1803.10520, Kerenidis et al. 1603.08675, Chia et al. 1910.06151

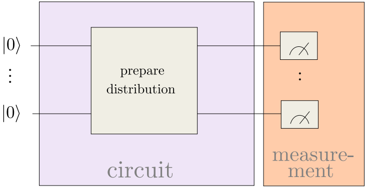
# 2. Use QC as samplers

# Quantum computers can train Boltzmann machines.*






PHYSICAL CIRCUIT




MATHEMATICAL DESCRIPTION

$|\psi_1|^2 = p(0...00)$

$$\begin{matrix} 1011 \\ 1101 \\ 0000 \\ \vdots \end{matrix} \sim \begin{bmatrix} \psi_1 \\ \psi_2 \\ \vdots \end{bmatrix}$$

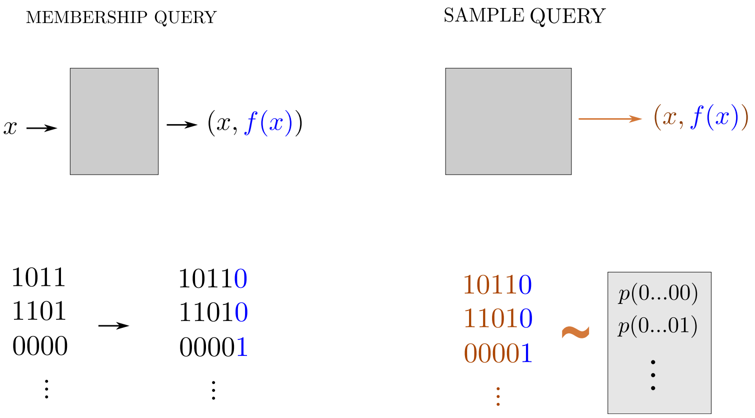
$|\psi_2|^2 = p(0...01)$

Denil & Freitas 2012(?) `https://www.cs.ubc.ca/~nando/papers/quantumrbm.pdf`

# DATA

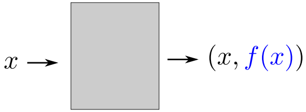
# 1. Quantum data and learnability

# Quantum computers cannot learn from "exponentially less" data.

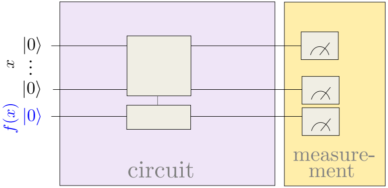


# Quantum computers cannot learn from “exponentially less” data.

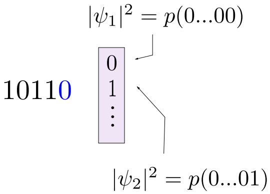
MEMBERSHIP QUERY




PHYSICAL CIRCUIT




MATHEMATICAL DESCRIPTION



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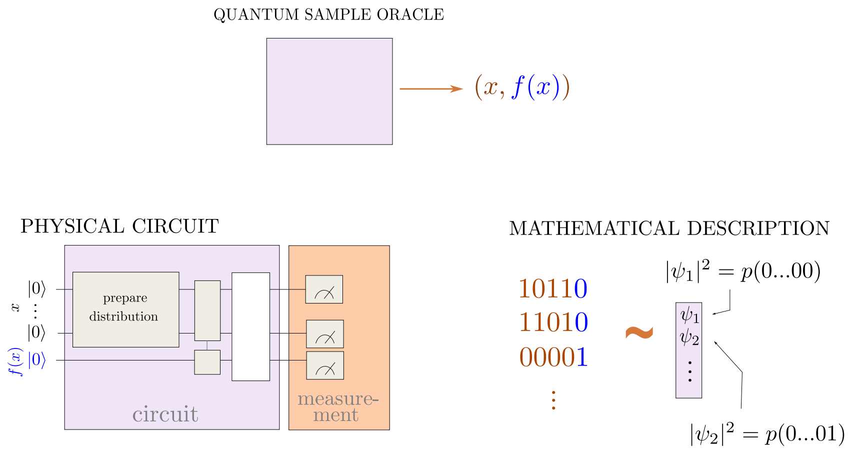

# Quantum computers cannot learn from “exponentially less” data.

## A Survey of Quantum Learning Theory

Srinivasan Arunachalam*  Ronald de Wolf†

**Abstract**

This paper surveys quantum learning theory: the theoretical aspects of machine learning using quantum computers. We describe the main results known for three models of learning: exact learning from membership queries, and Probably Approximately Correct (PAC) and agnostic learning from classical or quantum examples.

Arunachalam 1701.06806

# Quantum computers cannot learn from "exponentially less" data.

**Exact learning.** In this setting the goal is to learn a target concept from the ability to interact with it. For concreteness, we focus on learning target concepts that are Boolean functions: the target is some unknown $c : \{0,1\}^n \to \{0,1\}$ coming from a known concept class $\mathcal{C}$ of functions,[2] and our goal is to identify $c$ exactly, with high probability, using *membership queries* (which allow the learner to learn $c(x)$ for $x$ of his choice). If the measure of complexity is just the number of queries, the main results are that quantum exact learners can be polynomially more efficient than classical, but not more. If the measure of complexity is *time*, then under reasonable complexity-theoretic assumptions some concept classes can be learned much faster from quantum membership queries (i.e., where the learner can query $c$ on a superposition of $x$'s) than is possible classically.

Arunachalam 1701.06806

# Quantum computers cannot learn from "exponentially less" data.

**PAC learning.** In this setting one also wants to learn an unknown $c : \{0,1\}^n \to \{0,1\}$ from a known concept class $\mathcal{C}$, but in a more passive way than with membership queries: the learner receives several *labeled examples* $(x, c(x))$, where $x$ is distributed according to some unknown probability distribution $D$ over $\{0,1\}^n$. The learner gets multiple i.i.d. labeled examples. From this limited "view" on $c$, the learner wants to generalize, producing a *hypothesis* $h$ that probably agrees with $c$ on "most" $x$, *measured according to the same* $D$. This is the classical Probably Approximately Correct (PAC) model. In the quantum PAC model [BJ99], an example is not a random sample but a *superposition* $\sum_{x\in\{0,1\}^n} \sqrt{D(x)}|x, c(x)\rangle$. Such quantum examples can be useful for some learning tasks with a fixed distribution $D$ (e.g., uniform $D$) but it turns out that in the usual distribution-independent PAC model, quantum and classical sample complexity are equal up to constant factors, for every concept class $\mathcal{C}$. When the measure of complexity is *time*, under reasonable complexity-theoretic assumptions, some concept classes can be PAC learned much faster by quantum learners (even from classical examples) than is possible classically.

Arunachalam 1701.06806

# 2. Quantum data as quantum states

# What happens if we do QML on “quantum states”?

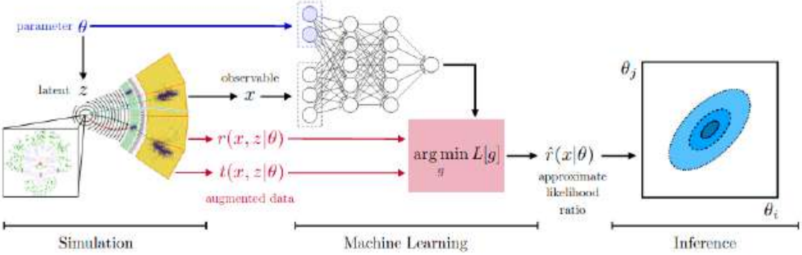


Figure 2 A schematic of machine learning based approaches to likelihood-free inference in which the simulation provides training data for a neural network that is subsequently used as a surrogate for the intractable likelihood during inference. Reproduced from (Brehmer *et al.*, 2018b).

# CONCLUSION

# Summary,...

machine intelligence = data/distributions + algorithm/hardware + models

# ...and some open questions.

- What models are quantum circuits?
- Are they actually useful?
- Will they perform well on larger problem instances?
- Will they perform well under noise?
- What problems are they good for?
- Is there a practically relevant problem for which QC are exponentially faster?
- Can QC accelerate machine learning?
- Can QC push the boundaries of what is learnable?

# Thank you!

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