

Making quantum algorithms learn from data

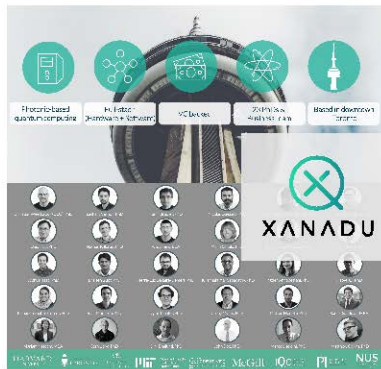
Maria Schuld

Xanadu and University of KwaZulu-Natal

APS Workshop, October 2018



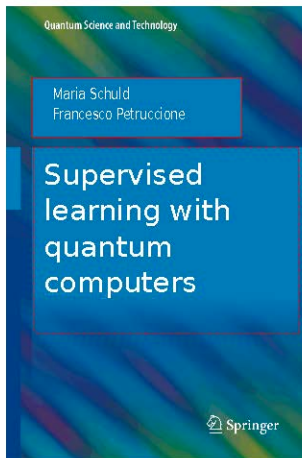
Between Toronto and Durban.



The image shows the XANADU logo, which consists of a green circle with a white 'X' inside. Below the logo, the word "XANADU" is written in a bold, sans-serif font. The background of the slide features a grid of 20 circular portraits of individuals, likely team members or researchers. Above the portraits, there are five green circular icons representing different research areas: a server rack, a molecular structure, a circuit board, an atom, and a radio tower. Below each icon is a label: "Photon-based quantum computing", "Hybrid hardware-software", "QCD devices", "Quantum simulation", and "Hybrid quantum-classical". At the bottom of the slide, there is a row of logos for various universities and research institutions, including Harvard, MIT, Stanford, UC Berkeley, Princeton, Cornell, Caltech, and others.

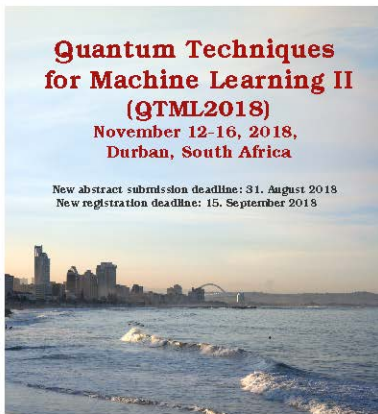


If you want to know more.



<https://www.springer.com/us/book/9783319964232>

If you want to know more.

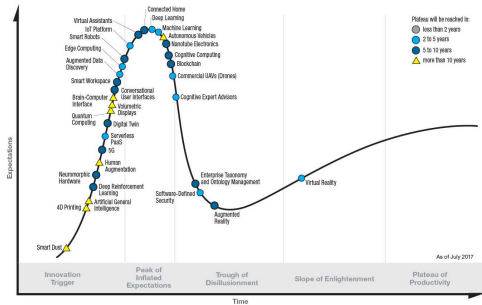


www.quantummachinelearning.org/qtml2018.html



The first generation of quantum devices is here.

Gartner **Hype Cycle** for Emerging Technologies, 2017



gartner.com/SmarterWithGartner

Source: Gartner (July 2017)
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Gartner.

The first generation of quantum devices is here.

Players

Partners



RIVER LANE



Booz | Allen | Hamilton

BraneCell



Honeywell



TOSHIBA



SIEMENS



DAIMLER

The first generation of quantum devices is here.

QUANTUM LANDSCAPE

XANADU



PHOTONICS

Squeezed states of light are entangled in a large 'cluster state'. Creation of largest entangled states over any architecture

+ PROS:

- Fast to scale
- Stable
- Long coherence times
- Room temperature computation

- CONS:

- Increase squeezing levels



XANADU



SUPERCONDUCTING LOOPS

+ PROS:

- Built on existing semiconductors

- CONS:

- Less stable + cold computing

G rigetti IBM



SILICON QUANTUM DOTS

+ PROS:

- Stable
- Built on existing semiconductors

- CONS:

- Few entangled + cold computing



TRAPPED IONS

+ PROS:

- Stable
- High gate fidelities

- CONS:

- Slow operation
- Scalability issues

ION



TOPOLOGICAL QUBITS

+ PROS:

- Naturally more fault tolerant

- CONS:

- Scalability issues



Confidential

Quantum light the most practical approach

The first generation of quantum devices is here.

The screenshot displays the Qasm Editor interface. At the top, the experiment ID is "Experiment #20180821220844" with an edit icon. To its right is a link to "Add a description". Further right are three buttons: "New", "Save", and "Save as". Below this header, a toolbar contains a "Switch to Qasm Editor" button, a status bar showing "Backend: ibmqx4", "My Units: 18", and "Experiment Units: 3", and a "Run" button. To the right of the "Run" button are "Simulate" and "Advanced" buttons. The main workspace shows a quantum circuit with five horizontal lines representing qubits, labeled $q[0]$ through $q[4]$. Each line starts with a $|0\rangle$ state. Below the qubit lines is a slider control for a parameter, currently set to 0.5 . On the right side, there is a "GATES" panel with a grid of gate icons: "id" (orange), "X" (green), "Y" (green), "Z" (green), "H" (blue), "S" (blue), "S[†]" (blue), and a plus sign (blue). Below the gates are "BARRIER" and "OPERATIONS" sections, each with a corresponding icon.

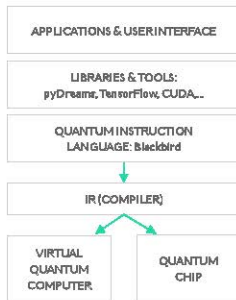
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STRAWBERRY FIELDS

Xanadu software stack



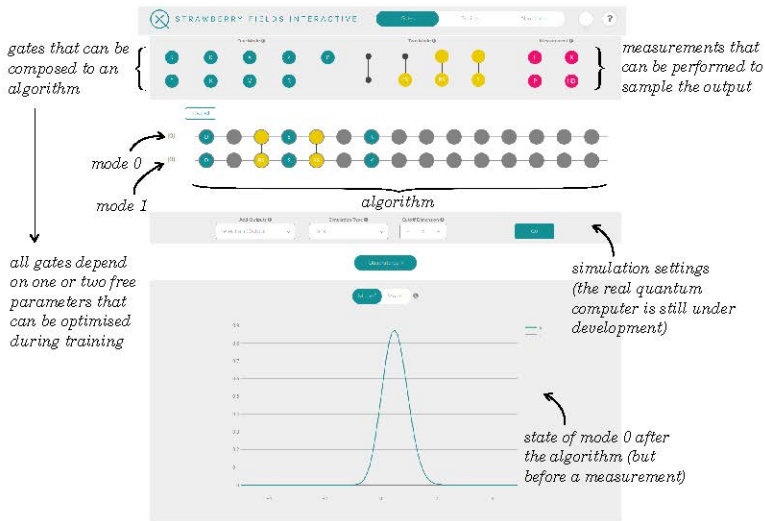
XANADU



Our programming environment **Strawberry Fields** is designed to seamlessly integrate with current Python workflows

Confidential

The first generation of quantum devices is here.



The first generation of quantum devices is here.

TRAINING QUANTUM CIRCUITS

XANADU

With StrawberryFields

```
1 #!/usr/bin/env python3
2 import strawberryfields as sf
3 from strawberryfields.ops import *
4 import tensorflow as tf
5
6 eng, q = sf.Engine(1)
7
8 alpha = tf.Variable(0.1)
9 with eng:
10     Dgate(alpha) | q[0]
11 state = eng.run('tf', cutoff_dim=7, eval=False)
12
13 # loss is probability for the Fock state n=1
14 prob = state.fock_prob([1])
15 loss = -prob # negative sign to maximize prob
16
17 # Set up optimization
18 optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.1)
19 minimize_op = optimizer.minimize(loss)
20
21 # Create Tensorflow Session and initialize variables
22 sess = tf.Session()
23 sess.run(tf.global_variables_initializer())
24
25 # Carry out optimization
26 for step in range(50):
27     prob_val, _ = sess.run([prob, minimize_op])
28     print("Value at step {}: {}".format(step, prob_val))
29
30
```

```
eng, q = sf.Engine(1)
```

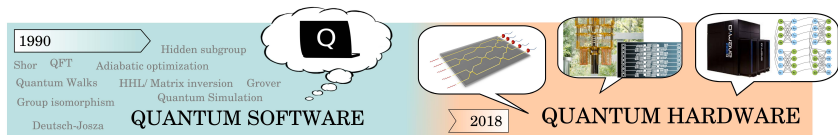
```
alpha = tf.Variable(0.1)
```

```
with eng:
```

```
    Dgate(alpha) | q[0]
```

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state = eng.run('tf', cutoff_dim=7, eval=False)
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The first generation of quantum devices is here.



QML may offer the first commercial applications.

QUANTUM MACHINE LEARNING

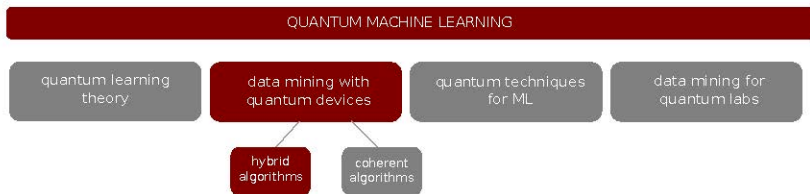
quantum learning
theory

data mining with
quantum devices

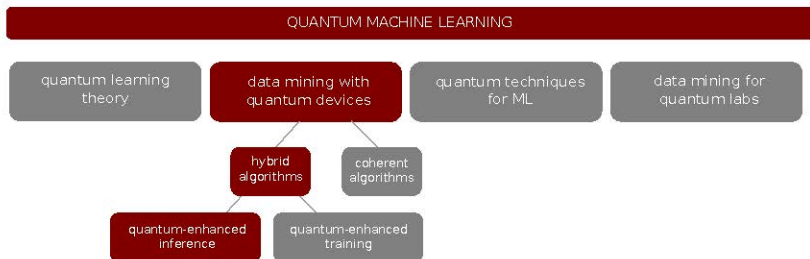
quantum techniques
for ML

data mining for
quantum labs

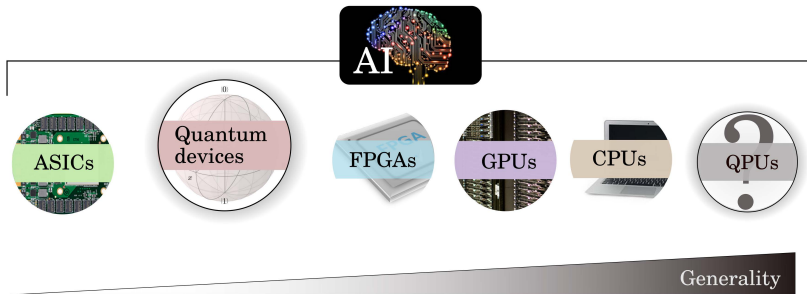
QML may offer the first commercial applications.



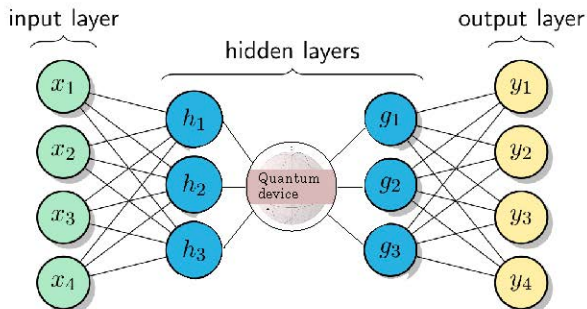
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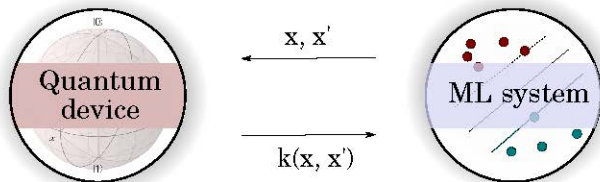
Quantum processing can enter at different levels.



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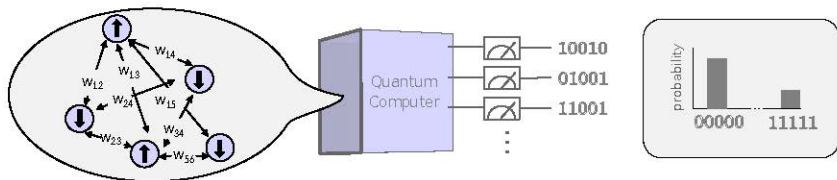


Quantum processing can enter at different levels.



Schuld and Killoran arxiv:1803.07128 (2018), Havlicek, arxiv:1804.11326 (2018)

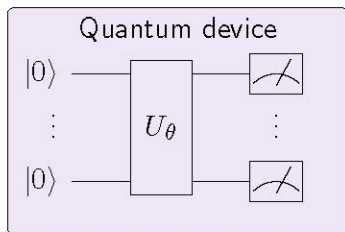
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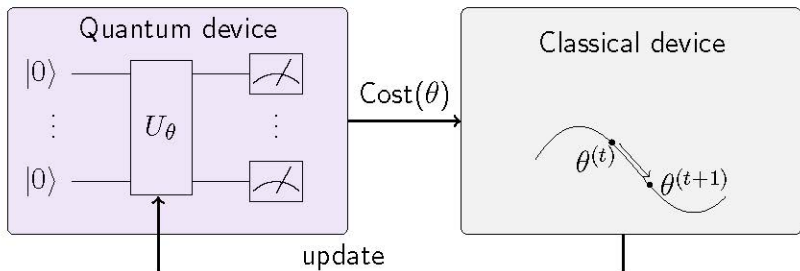
Benedetti et al. Physical Review X 7, 4 (2017), Amin et al. Physical Review X 8, 2 (2018)

VARIATIONAL CIRCUITS

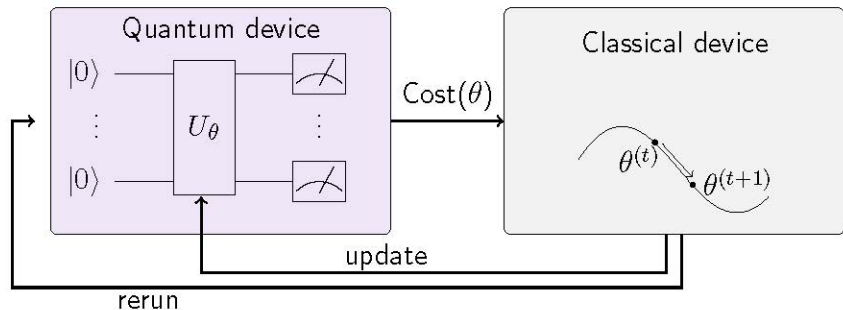
Variational circuits are adaptable quantum algorithms.



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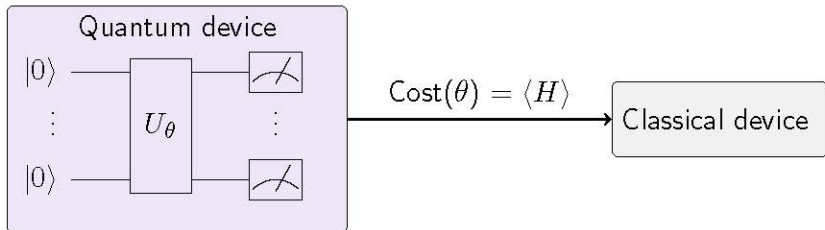


Variational circuits are adaptable quantum algorithms.



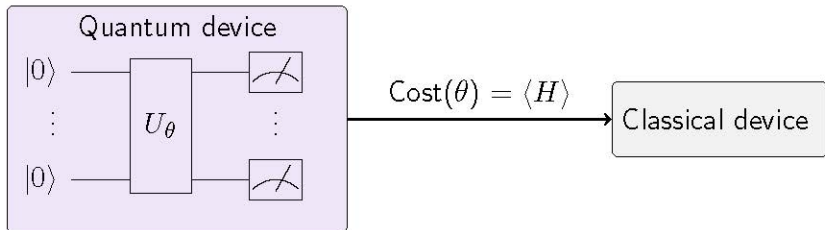
One example are variational quantum eigensolvers.

Find circuit U_θ that prepares lowest energy eigenstate with respect to Hamiltonian H .



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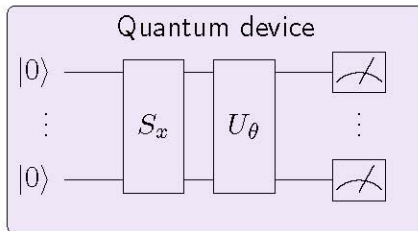
Find circuit U_θ that prepares lowest energy eigenstate with respect to Hamiltonian H .



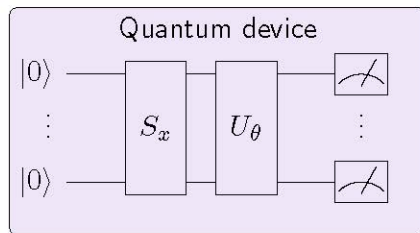
$$\langle H \rangle = \sum_{i,\alpha} h_{\alpha}^i \langle \sigma_{\alpha}^i \rangle + \sum_{\substack{i,j \\ \alpha,\beta}} h_{\alpha,\beta}^{ij} \langle \sigma_{\alpha}^i \sigma_{\beta}^j \rangle + \dots$$

LEARNING WITH VARIATIONAL CIRCUITS

We can turn the variational circuit into a classifier.

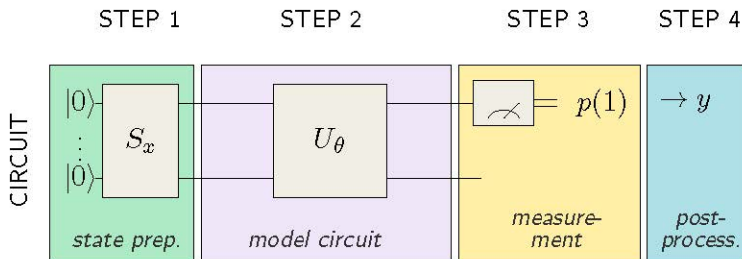


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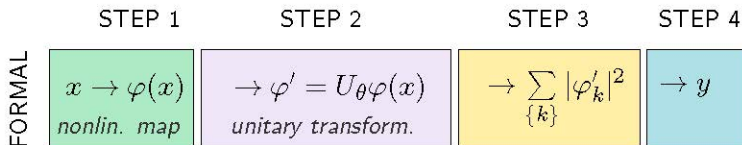
$$x \rightarrow f(x, \theta) = y$$

We can turn the variational circuit into a classifier.

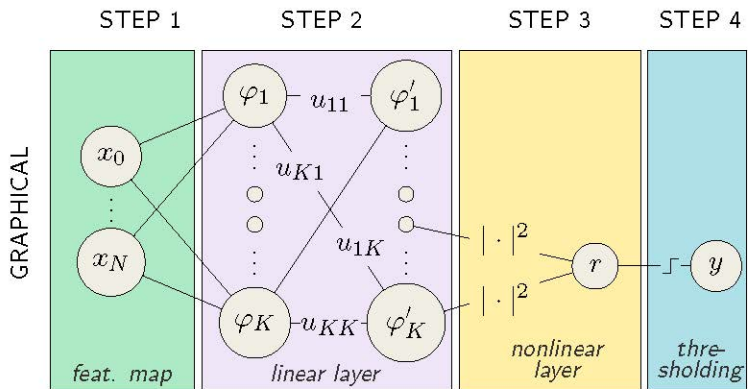


Schuld et al (2018) arxiv1804.00633

We can turn the variational circuit into a classifier.



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Schuld et al (2018) arxiv1804.00633

For training we have to compute a gradient.

Usually in supervised learning, one takes the least squares cost,

$$\text{Cost}(\theta) \propto \sum_{m=1}^M (t^m - f(x^m, \theta))^2,$$

and does gradient descent.

For training we have to compute a gradient.

Usually in supervised learning, one takes the least squares cost,

$$\text{Cost}(\theta) \propto \sum_{m=1}^M (t^m - f(x^m, \theta))^2,$$

and does gradient descent. For this one computes the gradient of the cost with regards to a parameter $w \in \theta$,

$$\partial_w \text{Cost}(\theta) \propto - \sum_{m=1}^M \frac{1}{2} (t^m - f(x^m, \theta)) \partial_w f(x^m, \theta)$$

We can compute gradients of quantum circuits.

If precision is not an issue: **Numerical optimization.**

$$\partial_w f(x, \theta) \approx \frac{f(x, \theta) + f(x, \theta + \Delta_w)}{\Delta_w}$$

Guerreschi et al (2018), Farhi and Neven (2018), Schuld et al (2018), Mitarai et al (2018)

We can compute gradients of quantum circuits.

If precision is not an issue: **Numerical optimization.**

If we are simulating the quantum device: **Automatic differentiation.**

$$f(x, \theta) = f(e(\dots b(a(w)))) \rightarrow \partial_w f(x, \theta) = \frac{df}{de} \dots \frac{db}{da} \frac{da}{dw}$$

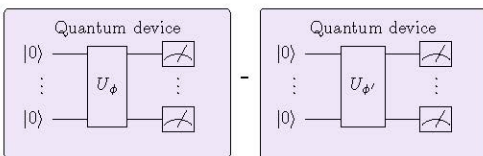
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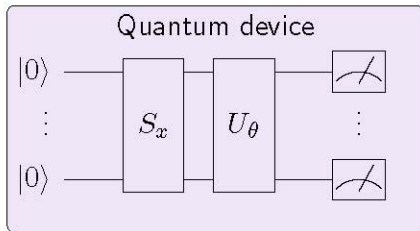
Else: **Quantum automatic differentiation.**

$$\partial_w f(x, \theta) =$$


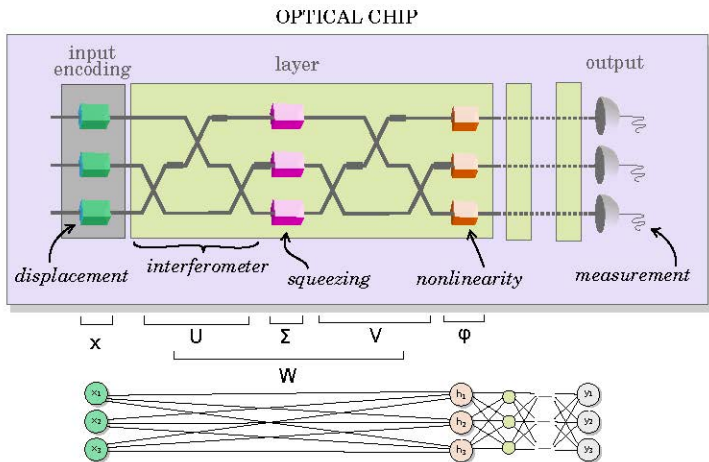
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PHOTONIC QUANTUM NEURAL NETWORK

A photonic quantum neural network



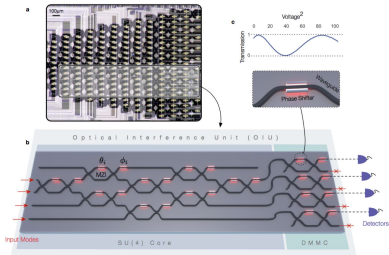
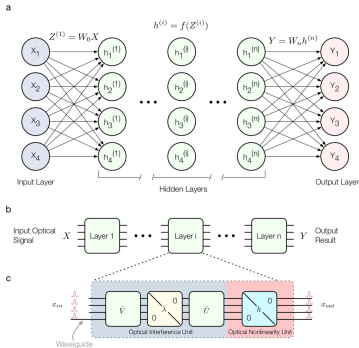
A photonic quantum neural network



Killoran et al. [arxiv1806.06871](https://arxiv.org/abs/1806.06871)

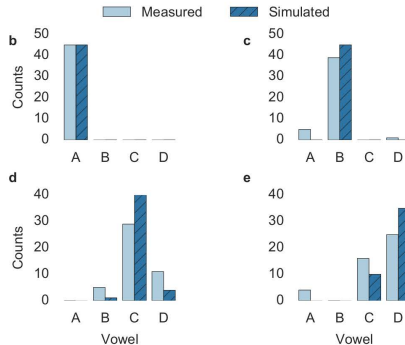
PHOTONIC QUANTUM NEURAL NETWORK

Photonic neural networks have been investigated before.



Shen et al *Deep learning with coherent nanophotonic circuits* Nature Photonics 11 (2017)

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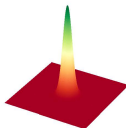
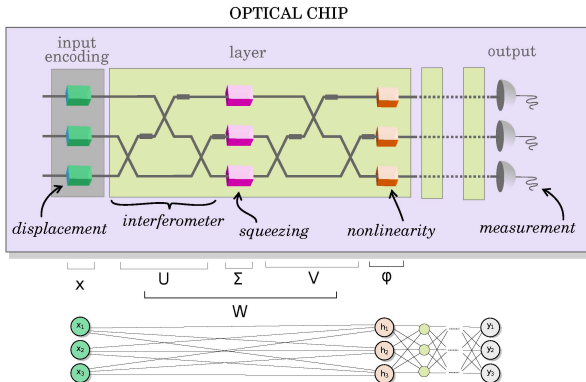


Shen et al *Deep learning with coherent nanophotonic circuits* Nature Photonics 11 (2017)

However, we are processing quantum information.

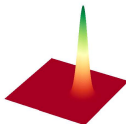
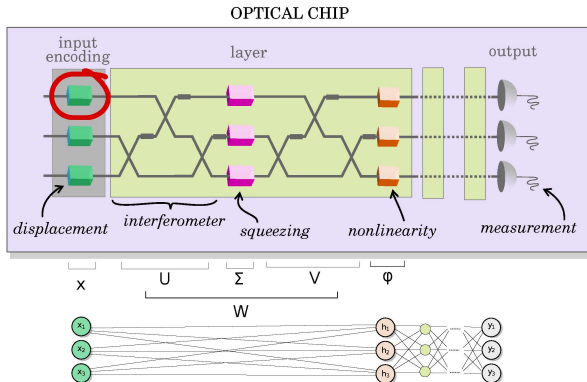
	CV	Qubit
Basic element	Qumodes	Qubits
Information unit	1 nat ($\log_2 e$ bits)	1 bit
Relevant operators	Quadrature operators $\hat{x}, \hat{p}$ Mode operators $\hat{a}, \hat{a}^\dagger$	Pauli operators $\hat{\sigma}_x, \hat{\sigma}_y, \hat{\sigma}_z$
Common states	Coherent states $ \alpha\rangle$ Squeezed states $ z\rangle$ Number states $ n\rangle$	Pauli eigenstates $ 0/1\rangle, \pm\rangle, \pm i\rangle$
Common gates	Rotation, Displacement, Squeezing, Beamsplitter, Cubic Phase	Phase Shift, Hadamard, CNOT, T Gate
Common measurements	Homodyne $\hat{x}_\phi$, Heterodyne $Q(\alpha)$, Photon-counting $ n\rangle\langle n $	Pauli-basis measurements $ 0/1\rangle\langle 0/1 , \pm\rangle\langle \pm , \pm i\rangle\langle \pm i $

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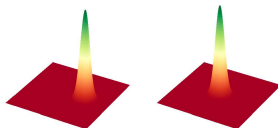
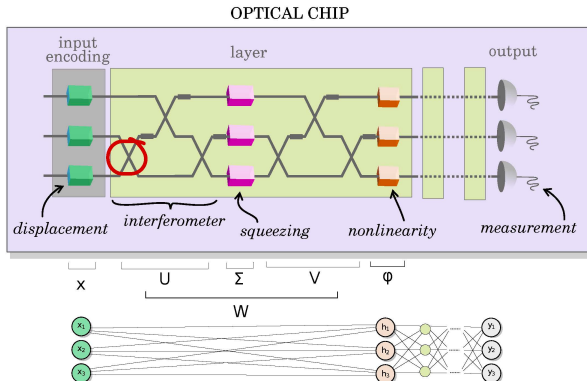
Killoran et al. arxiv1806.06871

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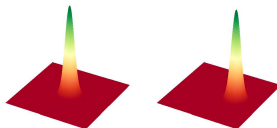
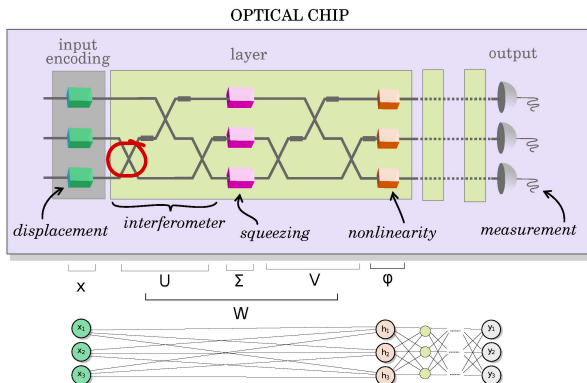
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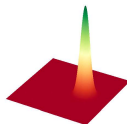
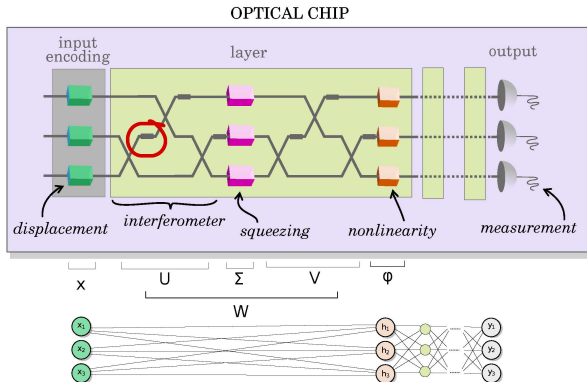
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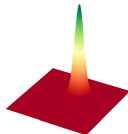
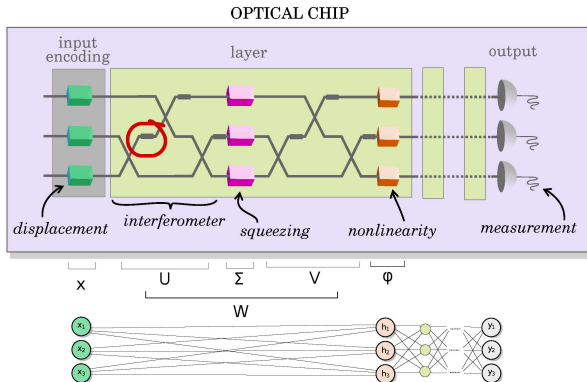
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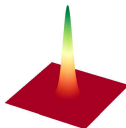
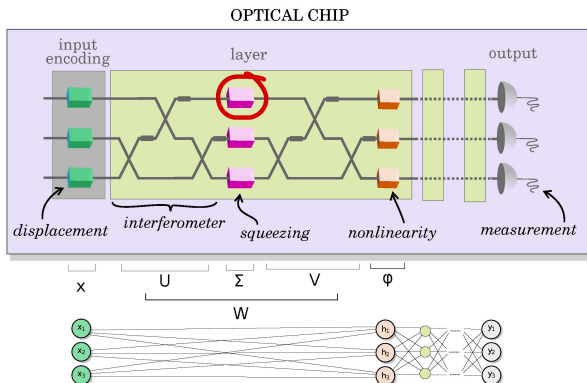
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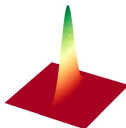
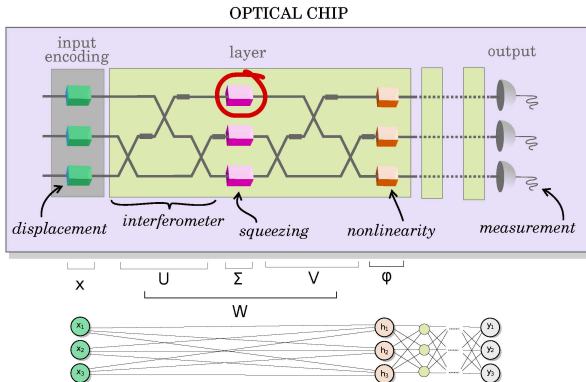
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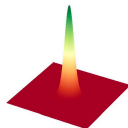
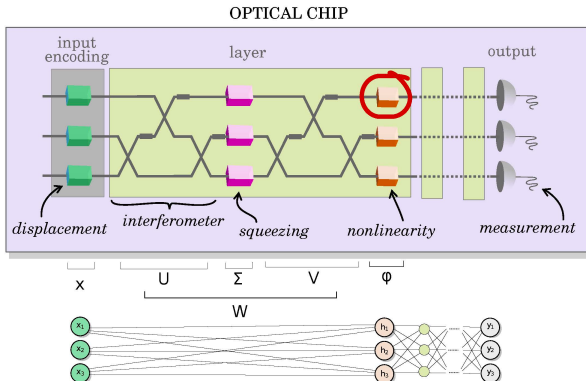
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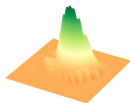
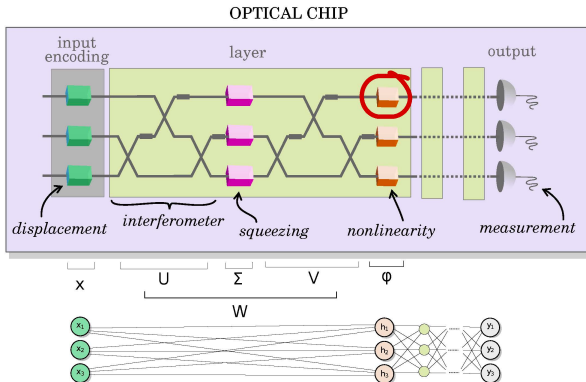
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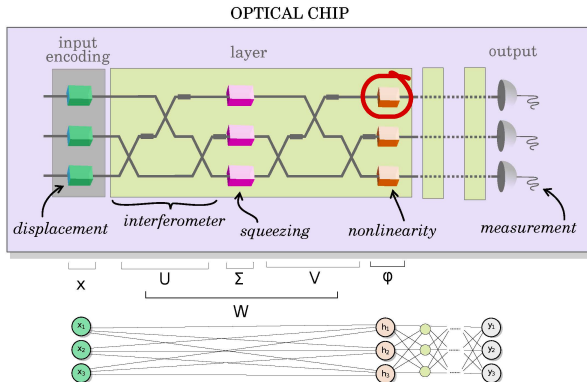
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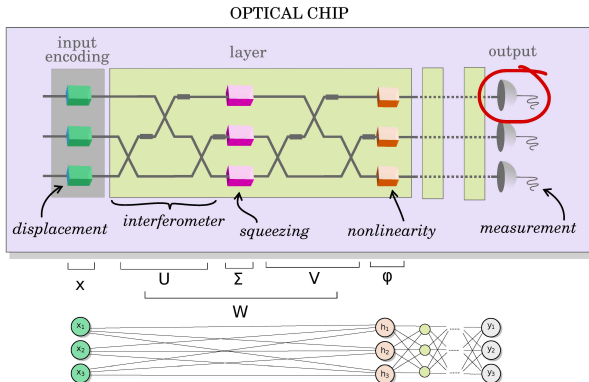
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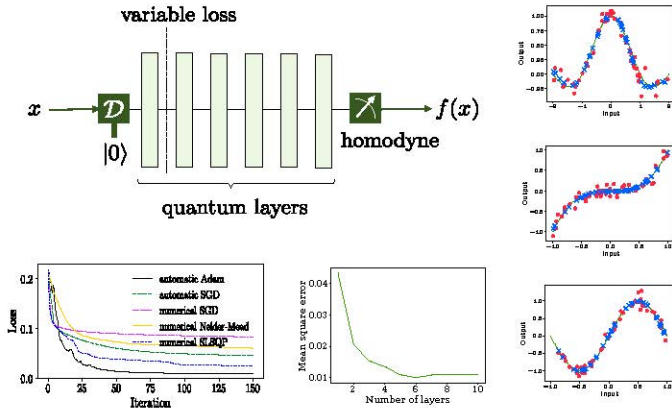
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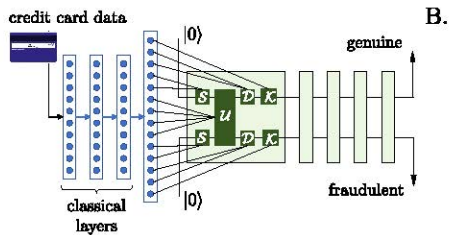


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Some results.



Some results.

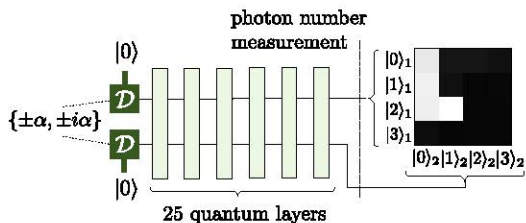


Confusion Matrix (B):

True label	Genuine	96.72	3.20
	Fraudulent	0.01	0.08
		Genuine	Fraudulent

Predicted label

Some results.



Open questions...

- ▶ What quantum advantages are to expect?
- ▶ What are good circuit architectures?
- ▶ What are good training strategies?
- ▶ Are quantum models easily trainable?

... and challenges.

- ▶ How can we benchmark these models?
- ▶ How can we simulate them?
- ▶ How can we get the machine learning community interested?
- ▶ How can we convince editors that our limited simulations are worth publishing?