

# Hybrid Recurrent Architectures for Quantum-Classical NLP

Stephen Clark

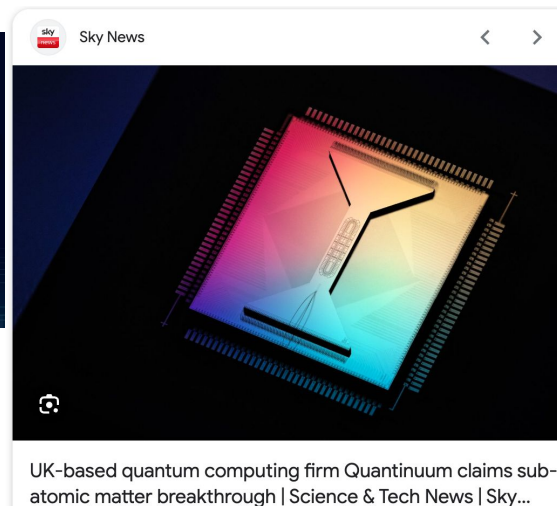
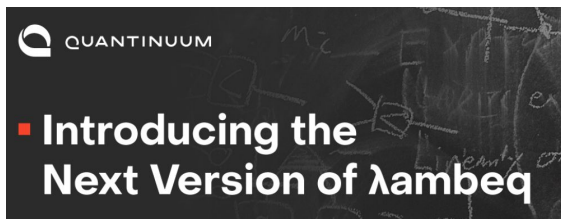
Global Software Technology Summit

University of Edinburgh

2 June 2023



# Quantum Computing



# Talk Outline

- Introduction to quantum computing / quantum circuits
- Our hybrid quantum RNN architectures
- Sentiment analysis experiments (in simulation)

# The State of a Qubit

$|\psi\rangle$

---

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad \alpha, \beta \in \mathbb{C} \quad |\psi\rangle \in \mathbb{C}^2$$

*superposition*

# The State of a Qubit

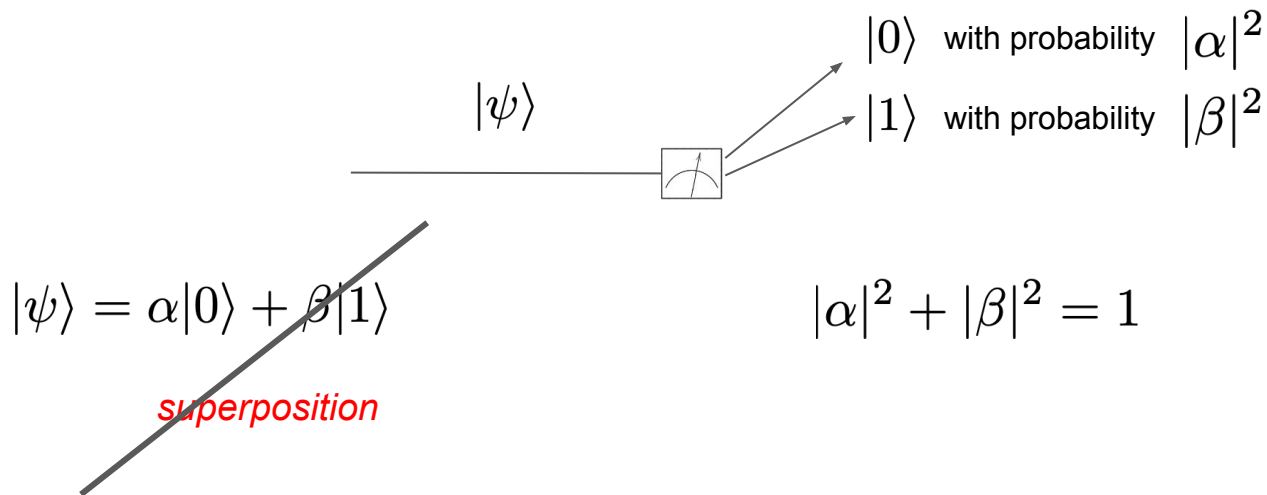
*amplitudes*

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

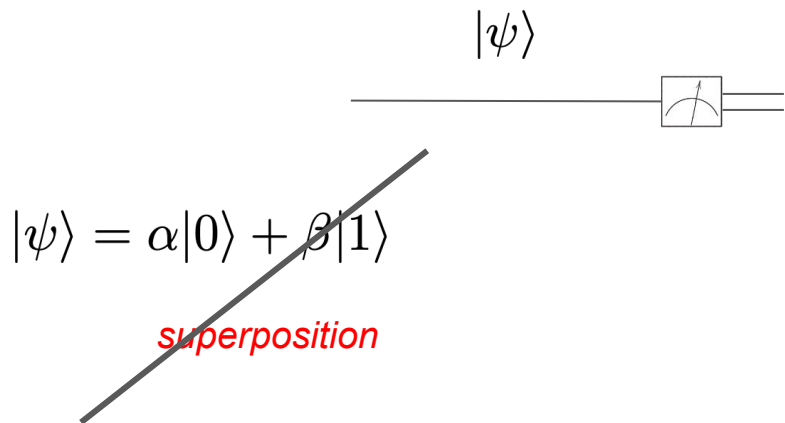
*superposition*

$$\alpha, \beta \in \mathbb{C}$$
$$|\alpha|^2 + |\beta|^2 = 1$$

# Measuring a Qubit

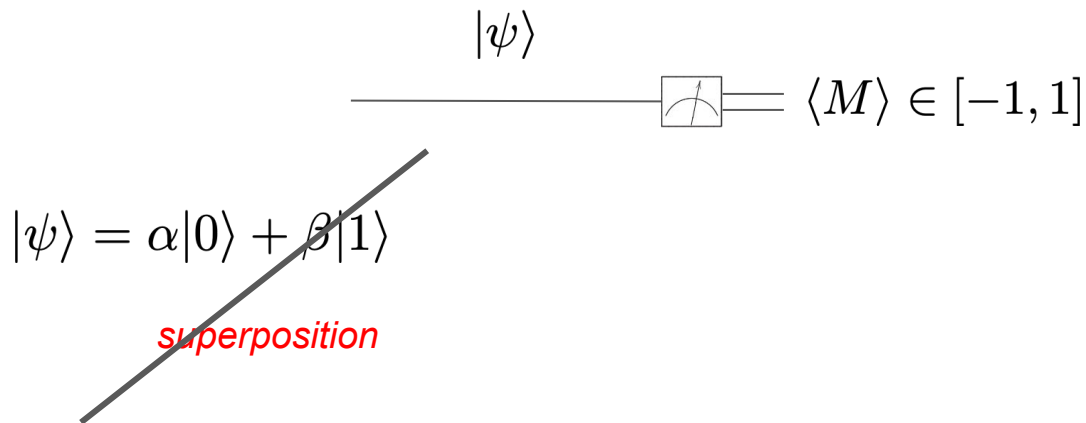


# Measuring a Qubit - Scalar Output



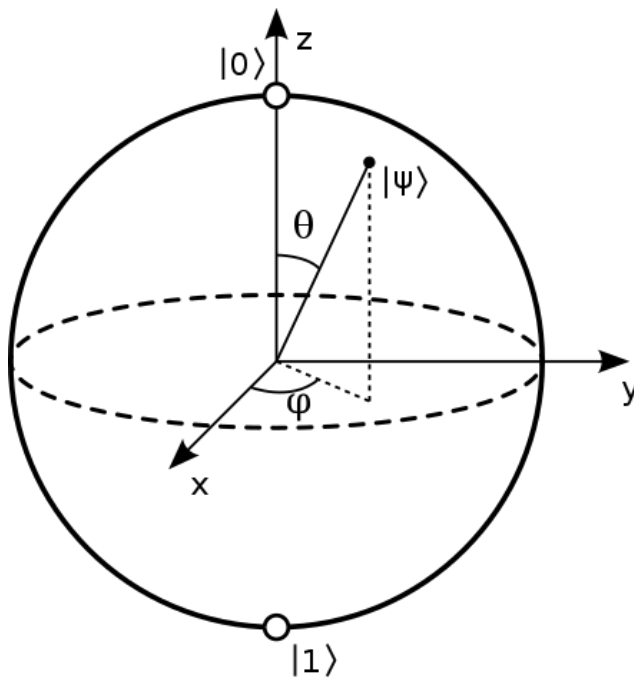
- 1 with probability  $|\alpha|^2$
- 1 with probability  $|\beta|^2$

# Measuring a Qubit - Scalar Output





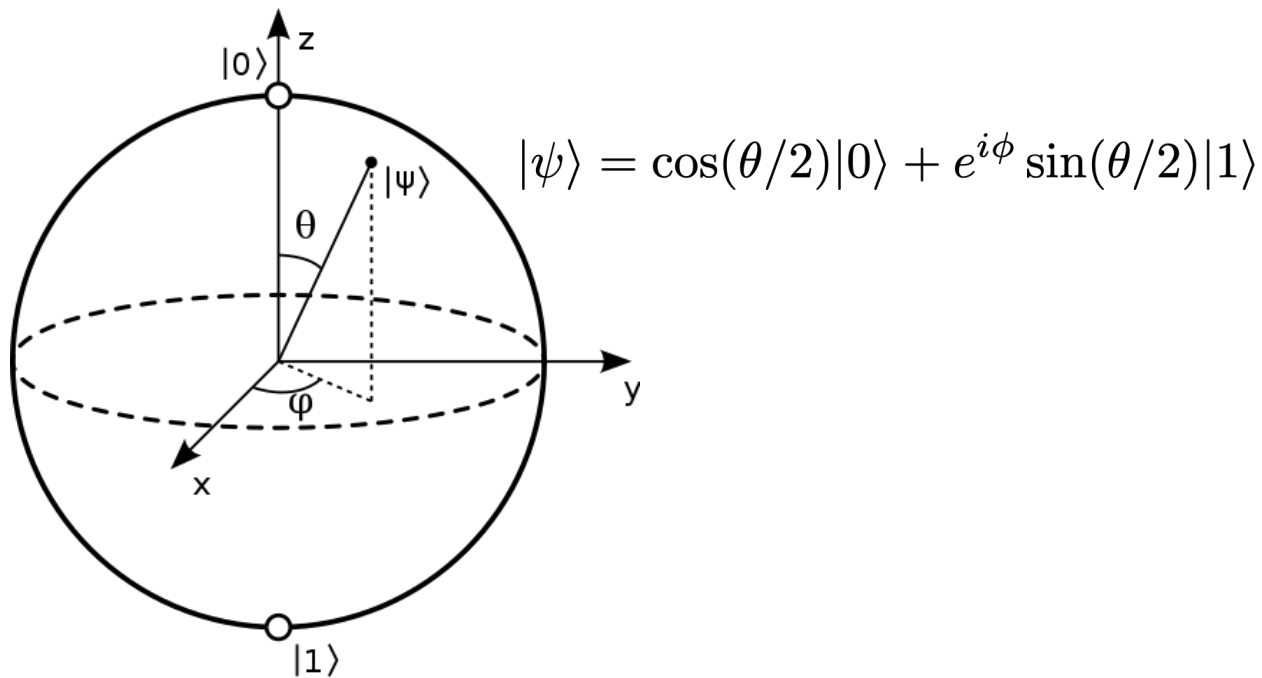
# The Bloch Sphere Representation of a Qubit



$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

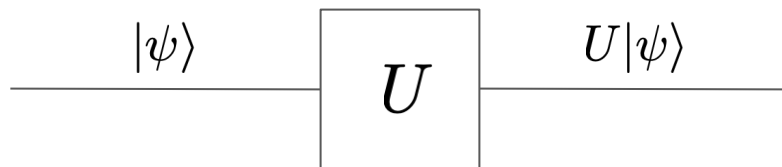
[https://en.wikipedia.org/wiki/Bloch\\_sphere](https://en.wikipedia.org/wiki/Bloch_sphere)

# The Bloch Sphere Representation of a Qubit



[https://en.wikipedia.org/wiki/Bloch\\_sphere](https://en.wikipedia.org/wiki/Bloch_sphere)

# Unitary Transformations of a Qubit

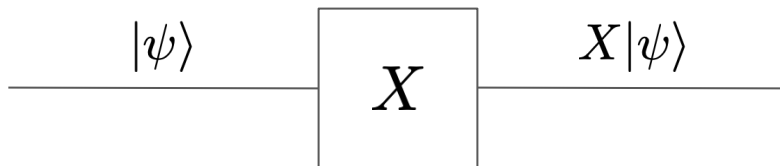


$$U : \alpha|0\rangle + \beta|1\rangle \mapsto \alpha'|0\rangle + \beta'|1\rangle$$

$$|\alpha'|^2 + |\beta'|^2 = 1$$

# 1-Qubit Quantum Gates

quantum Not gate



$$X : |0\rangle \mapsto |1\rangle$$

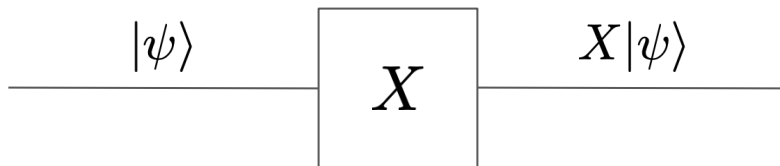
$$X : |1\rangle \mapsto |0\rangle$$



QUANTINUUM

# 1-Qubit Quantum Gates

quantum Not gate *acts linearly*



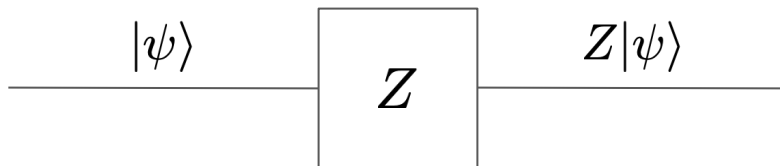
$$X : \alpha|0\rangle + \beta|1\rangle \mapsto \alpha|1\rangle + \beta|0\rangle$$



QUANTINUUM

# 1-Qubit Quantum Gates

Pauli Z Gate



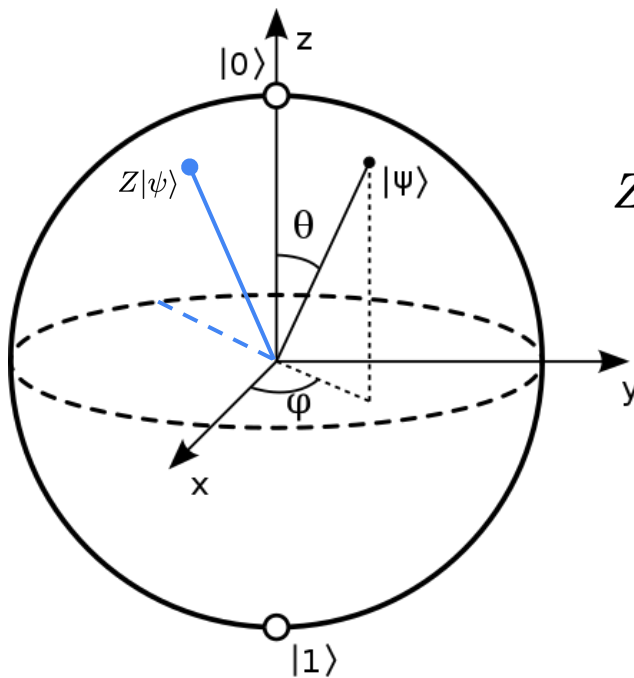
$$Z : \alpha|0\rangle + \beta|1\rangle \mapsto \alpha|0\rangle - \beta|1\rangle$$



QUANTINUUM

# 1-Qubit Quantum Gates

Pauli Z Gate *rotates about the Z axis*

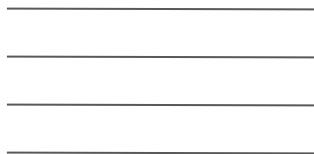


$$Z : \alpha|0\rangle + \beta|1\rangle \mapsto \alpha|0\rangle - \beta|1\rangle$$

# The State of Many Qubits

$$|\psi\rangle \in \mathbb{C}^{2^4}$$

$$|\psi\rangle$$

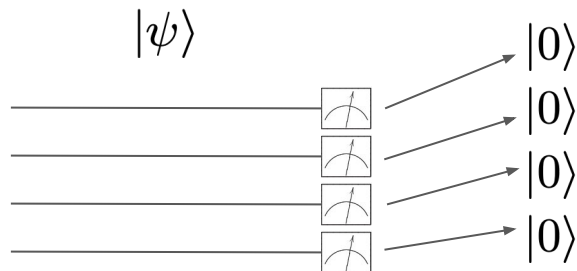


$$|\psi\rangle = \alpha_{0000}|0000\rangle + \alpha_{0001}|0001\rangle + \alpha_{0010}|0010\rangle + \dots \alpha_{1111}|1111\rangle$$



# Measuring Many Qubits

$$|\psi\rangle \in \mathbb{C}^{2^4}$$

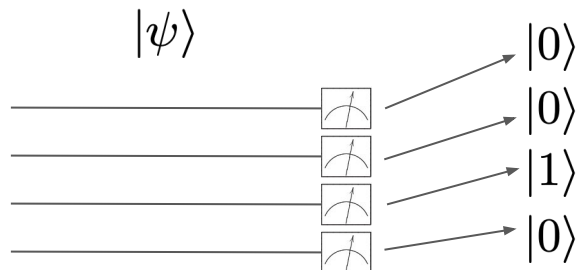


$$|\psi\rangle = \alpha_{0000}|0000\rangle + \alpha_{0001}|0001\rangle + \alpha_{0010}|0010\rangle + \dots \alpha_{1111}|1111\rangle$$

$$|\alpha_{0000}|^2$$

# Measuring Many Qubits

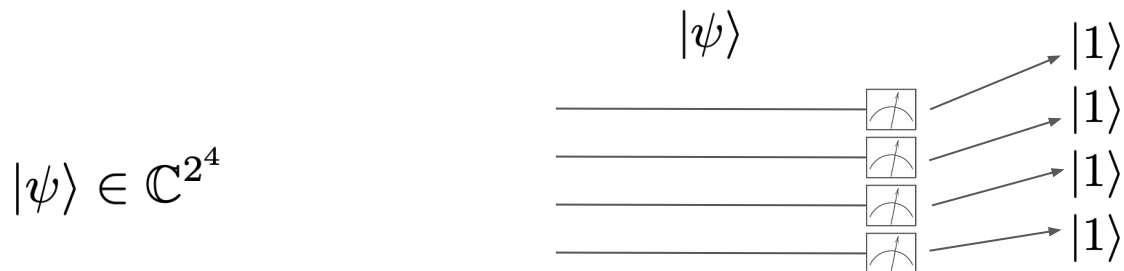
$$|\psi\rangle \in \mathbb{C}^{2^4}$$



$$|\psi\rangle = \alpha_{0000}|0000\rangle + \alpha_{0001}|0001\rangle + \alpha_{0010}|0010\rangle + \dots \alpha_{1111}|1111\rangle$$

$$|\alpha_{0010}|^2$$

# Measuring Many Qubits

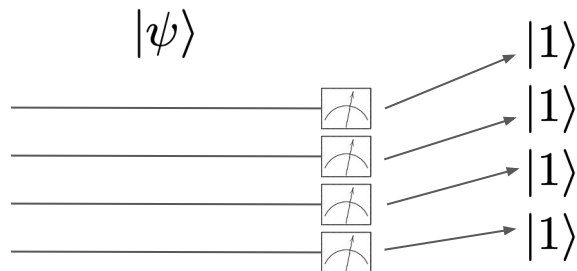


$$|\psi\rangle = \alpha_{0000}|0000\rangle + \alpha_{0001}|0001\rangle + \alpha_{0010}|0010\rangle + \dots \alpha_{1111}|1111\rangle$$

$$|\alpha_{1111}|^2$$

# Measuring Many Qubits

$$|\psi\rangle \in \mathbb{C}^{2^4}$$

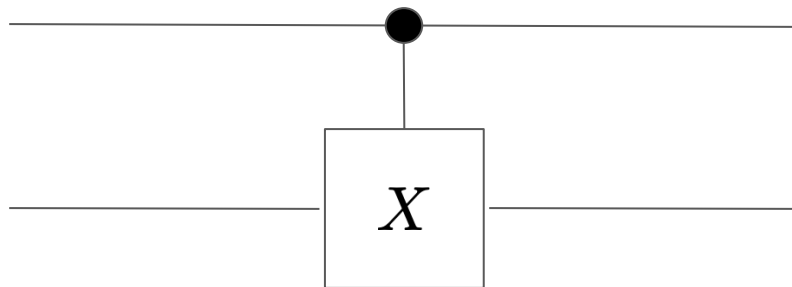


$$|\psi\rangle = \alpha_{0000}|0000\rangle + \alpha_{0001}|0001\rangle + \alpha_{0010}|0010\rangle + \dots \alpha_{1111}|1111\rangle$$

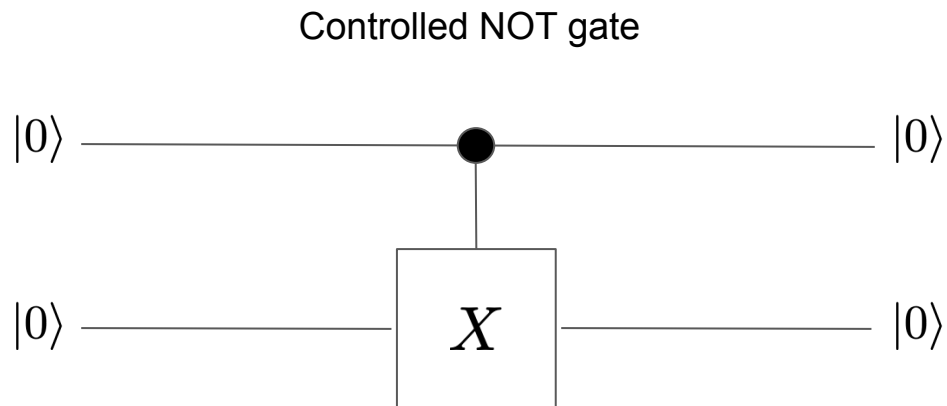
$$\sum_{b \in \{0,1\}^4} |\alpha_b|^2 = 1$$

# Entangling Qubits

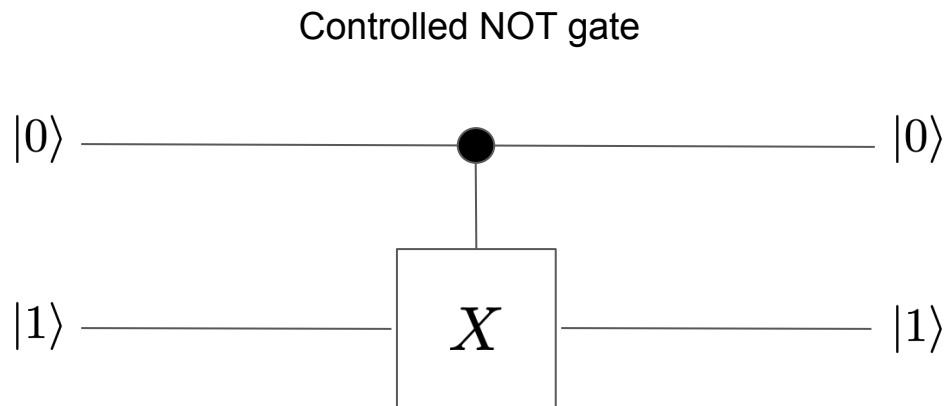
Controlled NOT gate



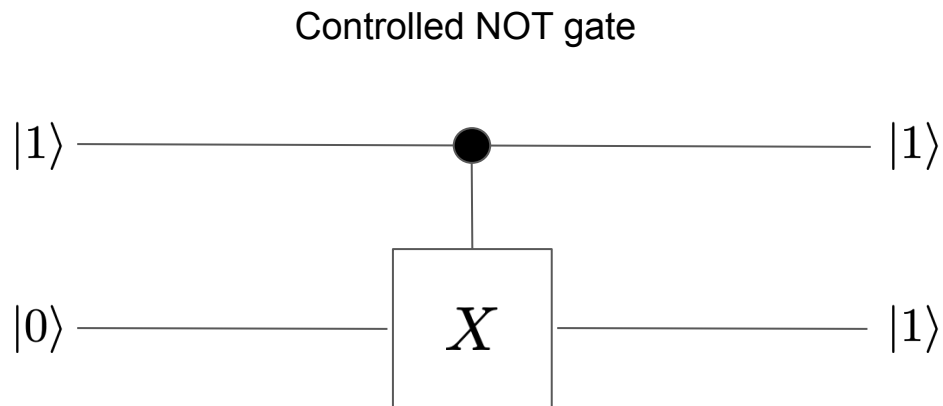
# Entangling Qubits



# Entangling Qubits

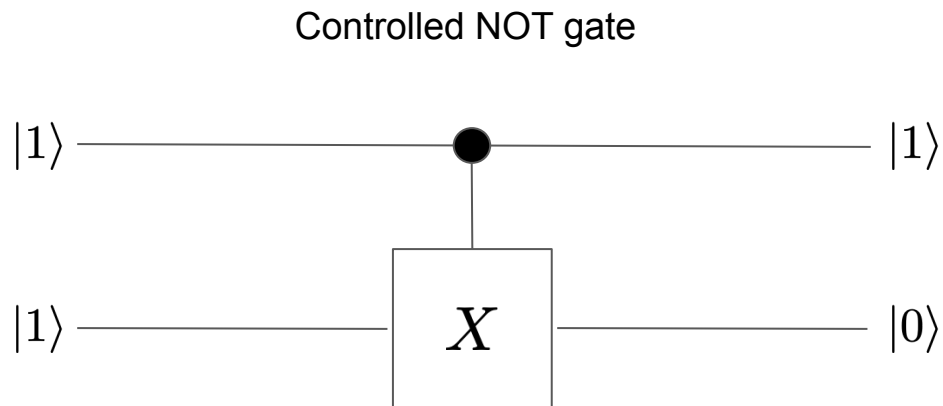


# Entangling Qubits



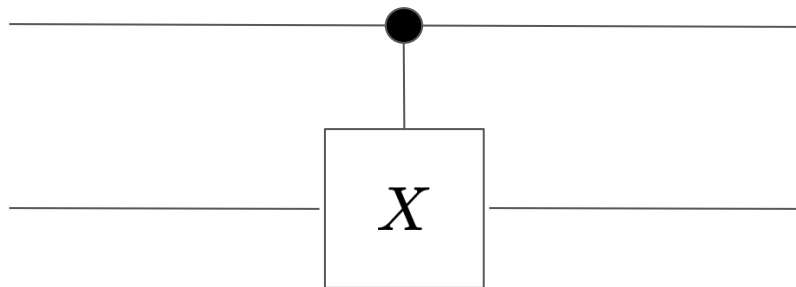


# Entangling Qubits



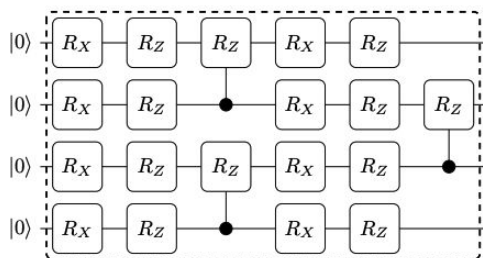
# Entangling Qubits

Controlled NOT gate *acts linearly*

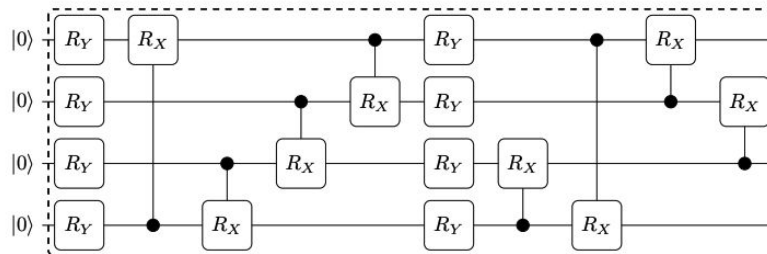


$$CX : \alpha_{00}|00\rangle + \alpha_{01}|01\rangle + \alpha_{10}|10\rangle + \alpha_{11}|11\rangle \mapsto \alpha_{00}|00\rangle + \alpha_{01}|01\rangle + \alpha_{10}|11\rangle + \alpha_{11}|10\rangle$$

# Quantum Circuits



Circuit 7

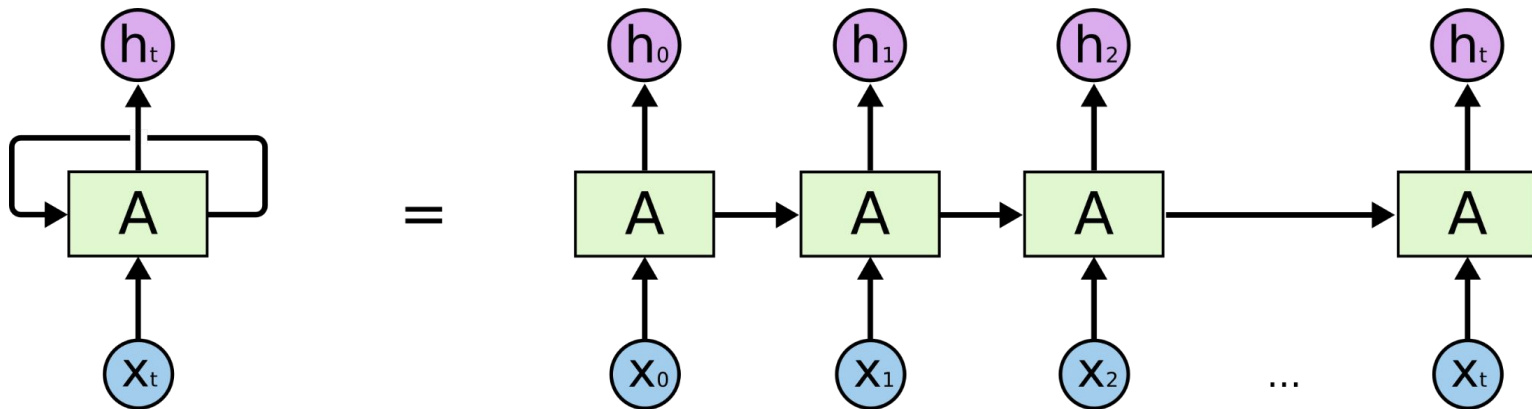


Circuit 14

Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms

Sukin Sim,<sup>1,2,\*</sup> Peter D. Johnson,<sup>2</sup> and Alán Aspuru-Guzik<sup>2,3,4,5,†</sup>

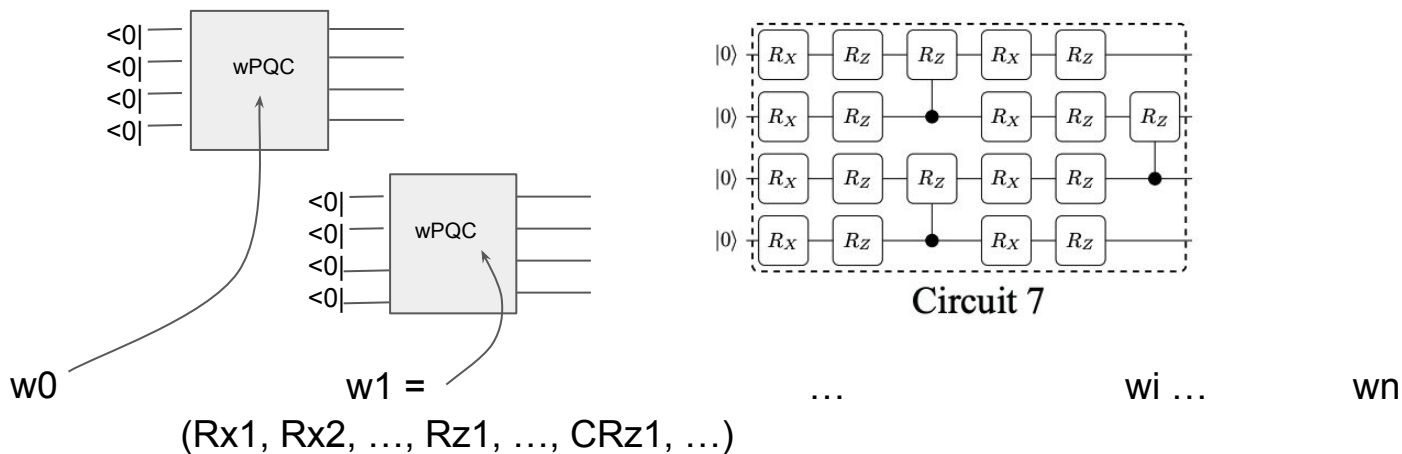
# Recurrent Neural Networks (RNNs)



$$h_t = f(x_t \mathbf{U} + h_{t-1} \mathbf{W})$$

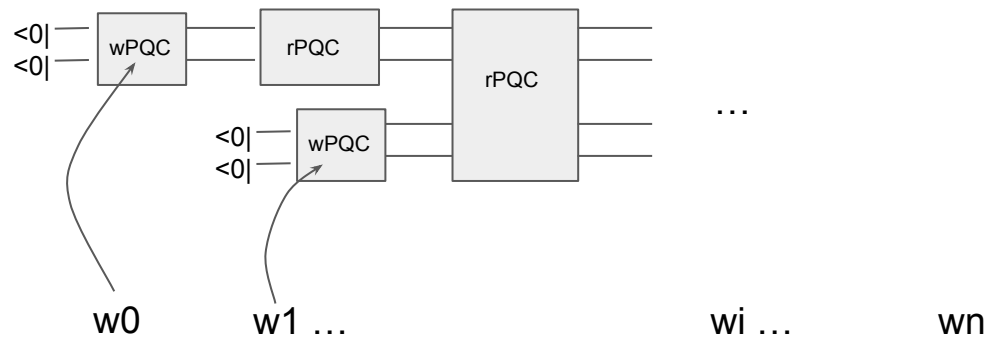
From Colah's blog: <https://colah.github.io/posts/2015-08-Understanding-LSTMs/>

# Parameterised Quantum Circuits (PQCs)

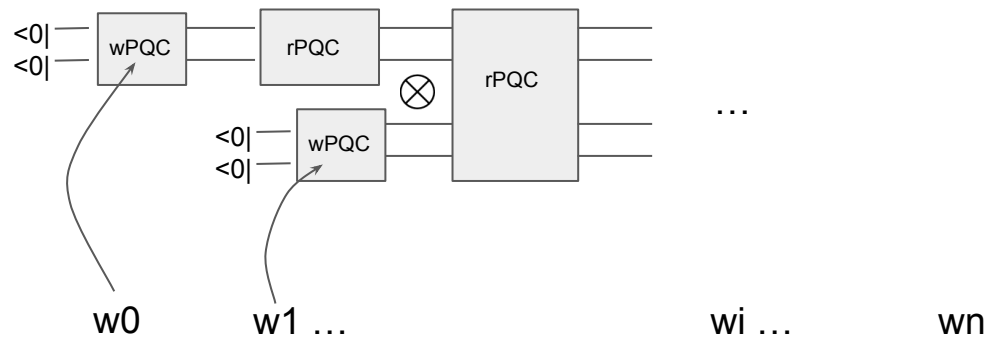


*Angle encoding*

# qRNN Take One

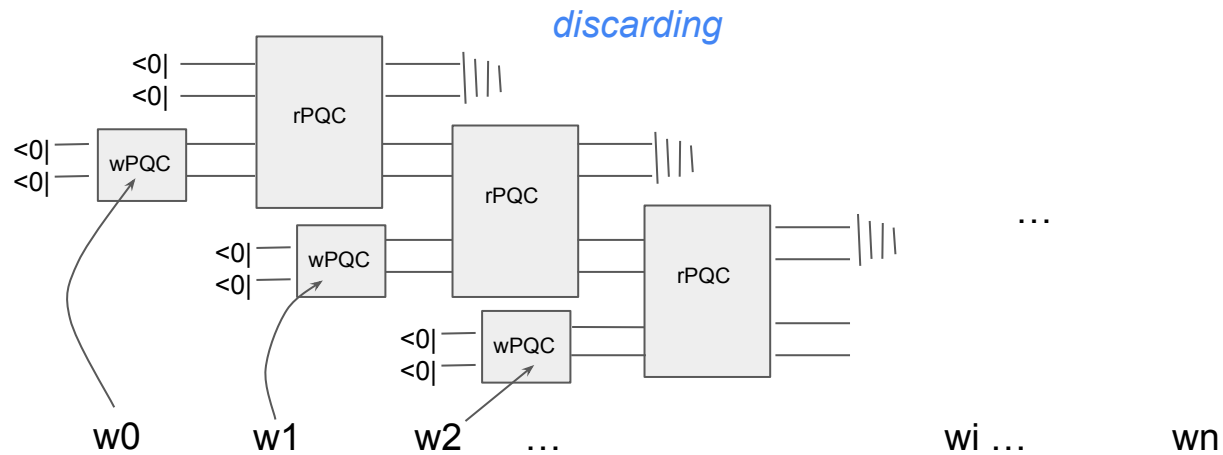


# qRNN Take One



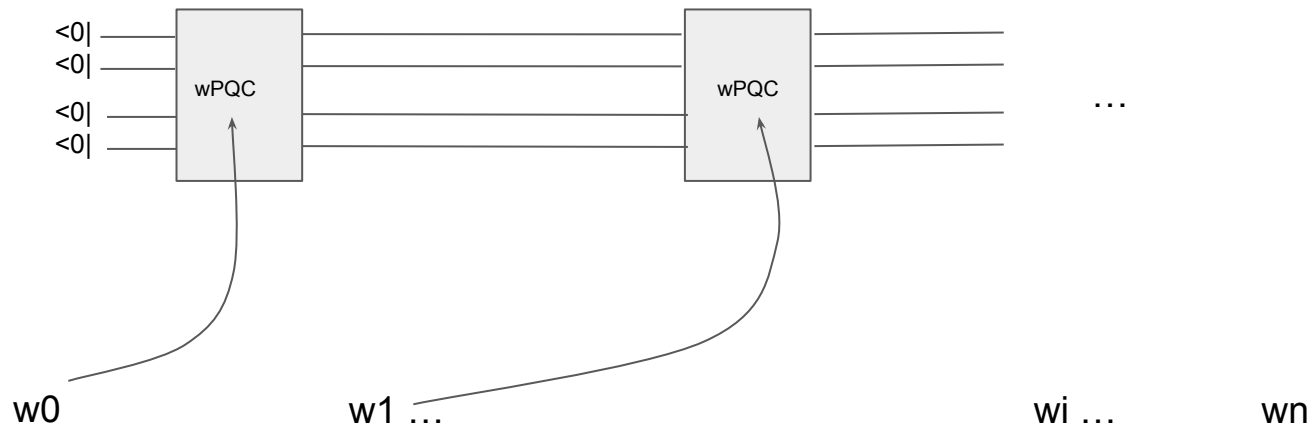
*tensor product*

# qRNN Take One

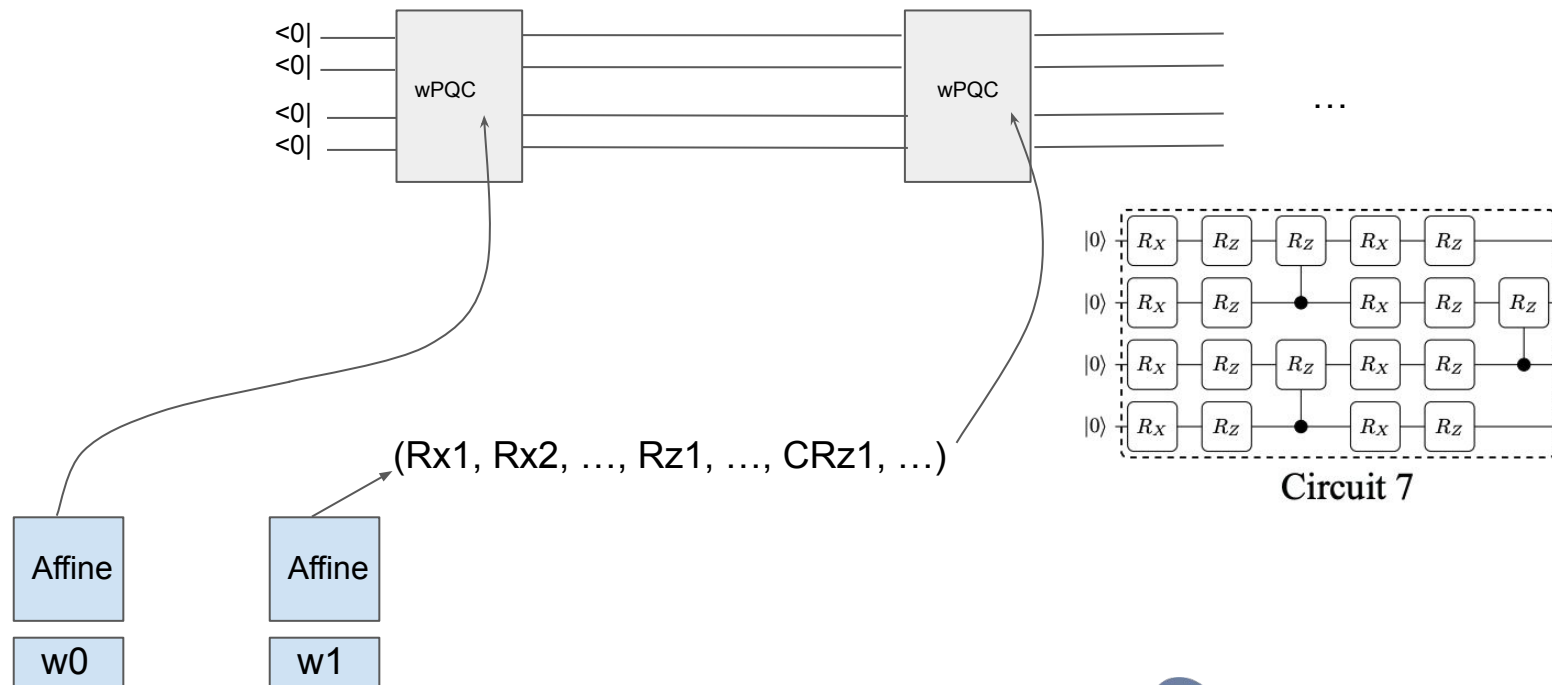




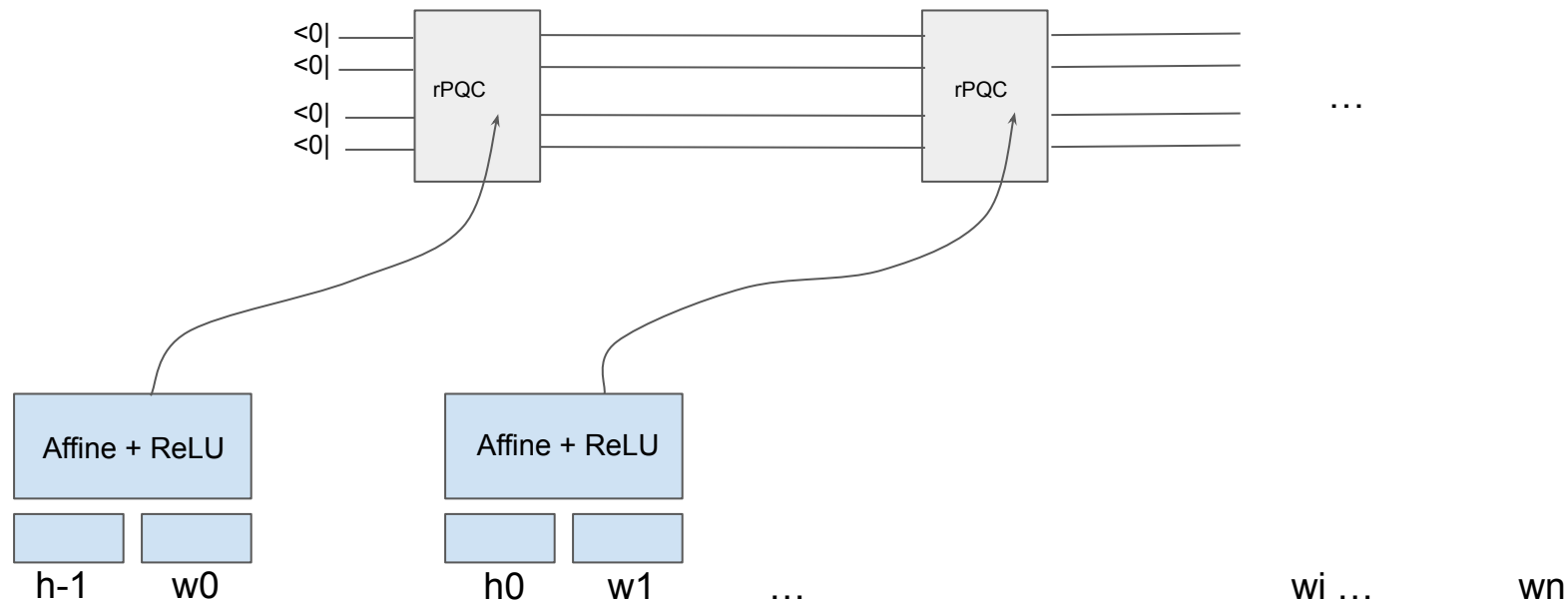
## qRNN Take Two



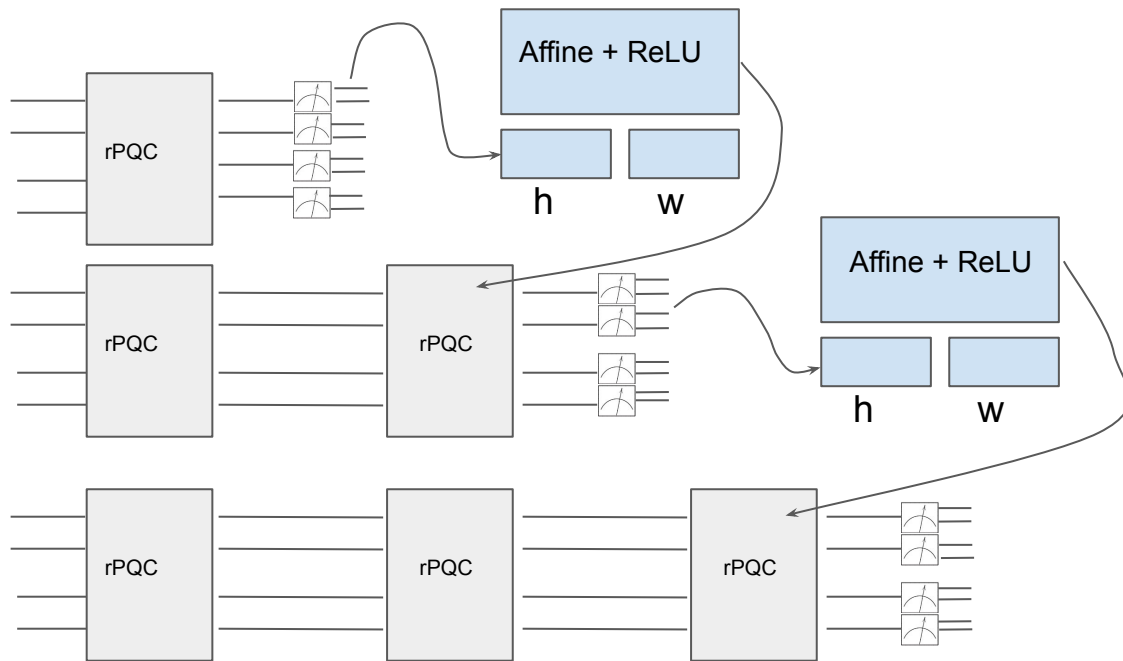
# qRNN Take Two



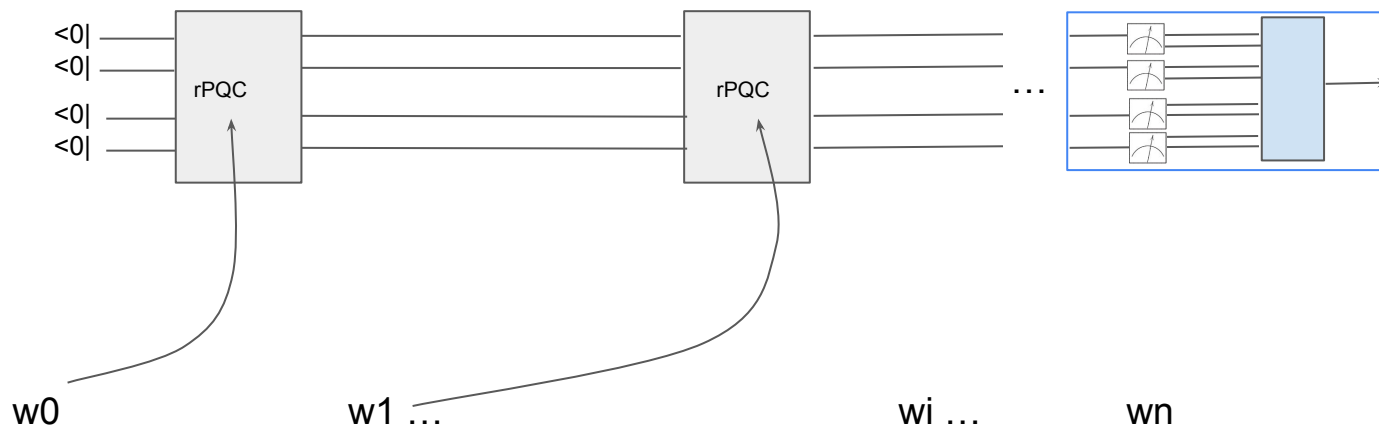
# qRNN Take Two (Variant)



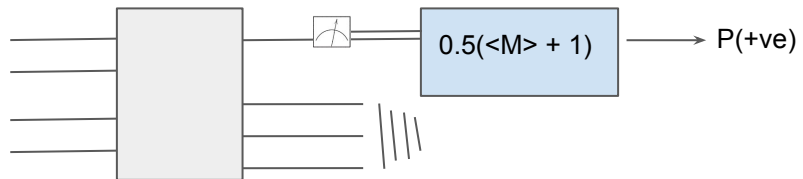
## qRNN Take Two (Variant, “Unrolled”)



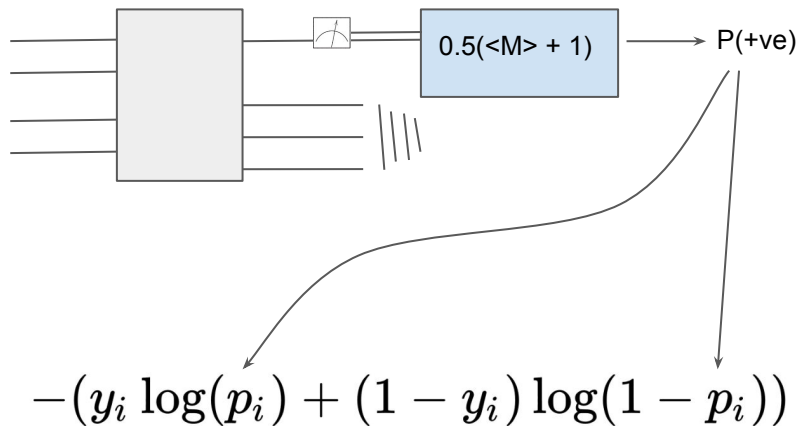
# Output



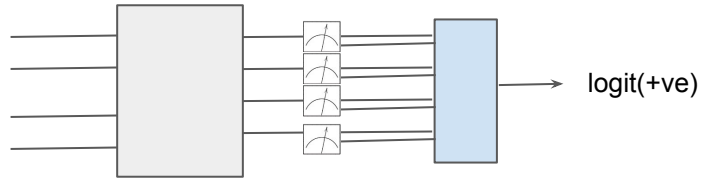
# Probabilistic Output



# Probabilistic Output for Training



# Neural Output





# The Task

- Sentiment analysis (Rotten Tomatoes dataset)
- 8,530 training examples (well balanced); 1,066 dev examples
- Simple binary classification task

if you sometimes like to go to the movies to have fun , wasabi is a good place to start .	1
emerges as something rare , an issue movie that's so honest and keenly observed that it doesn't feel like one .	1
simplistic , silly and tedious .	0
it's so laddish and juvenile , only teenage boys could possibly find it funny .	0

## Baseline / Goal

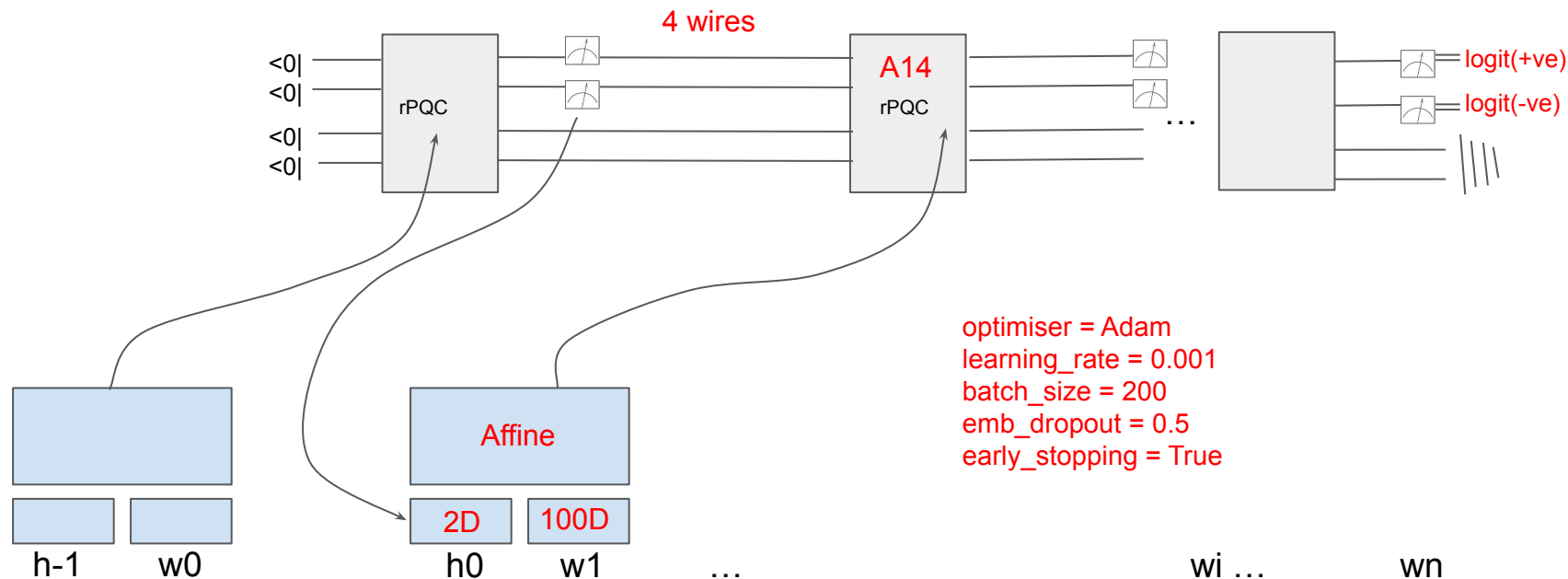
- Goal is *not* to beat the s-o-t-a
- Goal (at this stage) is to be competitive with a classical vanilla RNN

# Hybrid Toolkit

- Requirements for classical simulation:
  - easily interfaces with PyTorch (or TensorFlow, JAX, ...)
  - fast to train on real-world datasets
  - accommodates batching
  - **essentially PyTorch ML library with complex number linear algebra**



# Experimental Settings



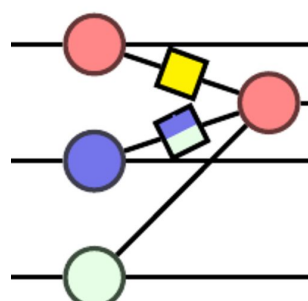
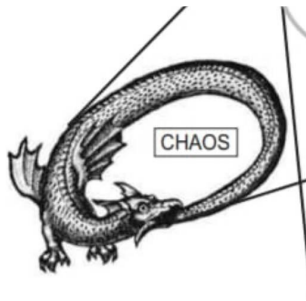
## Results on Dev Set

4 wires	Dev acc
Classical RNN	75.6
“Stairs” (w/feedback, measure 2)	76.5
“Stairs” (wo/feedback, measure 2)	75.1
“Cups” (w/feedback, measure all + affine)	76.6
“Cups” (wo/feedback, measure all + affine)	76.2

## Results (# Wires)

# wires	Dev acc “cups” w/A14 + feedback
Classical RNN	75.6
1	72.1 (rxzx)
2	75.8
4	76.6
10	77.3 (A7, +ReLU on input)

# The Oxford Hybrid NLP Team



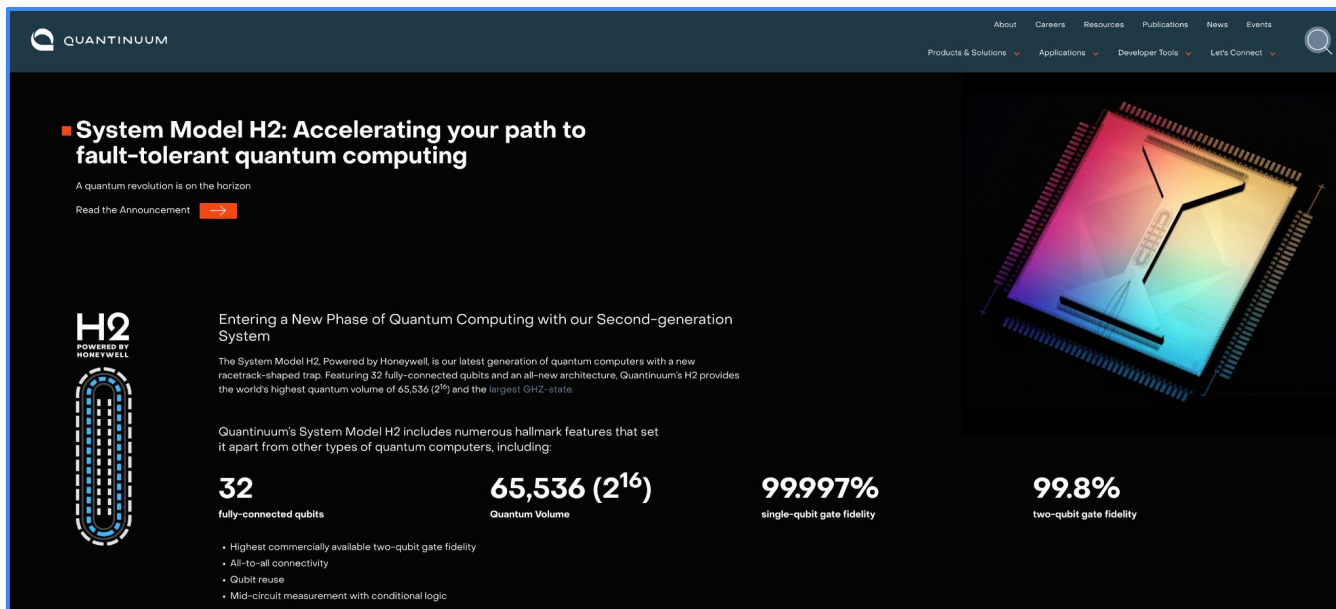
Wenduan Xu, Konstantinos Meichanetzidis, Douglas Brown, Gabriel Matos,  
Charlie London, Richie Yeung, Carys Harvey, Stephen Clark

# Future Work

- Apply the models to more tasks
  - sequence labelling, language modelling, translation, ...
- Apply pre-training / fine-tuning paradigm
- Develop more hybrid architectures
  - based on CNNs (e.g. MERA-like), transformers, ...
- Run on quantum hardware



# The Future is (Almost) Here



Quantinuum

About Careers Resources Publications News Events

Products & Solutions Applications Developer Tools Let's Connect

## System Model H2: Accelerating your path to fault-tolerant quantum computing

A quantum revolution is on the horizon

[Read the Announcement](#)

### H2

POWERED BY  
HONEYWELL

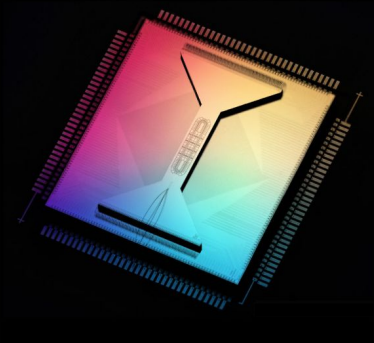
Entering a New Phase of Quantum Computing with our Second-generation System

The System Model H2, Powered by Honeywell, is our latest generation of quantum computers with a new racetrack-shaped trap. Featuring 32 fully-connected qubits and an all-new architecture, Quantinuum's H2 provides the world's highest quantum volume of 65,536 ( $2^{16}$ ) and the largest GHz state.

Quantinuum's System Model H2 includes numerous hallmark features that set it apart from other types of quantum computers, including:

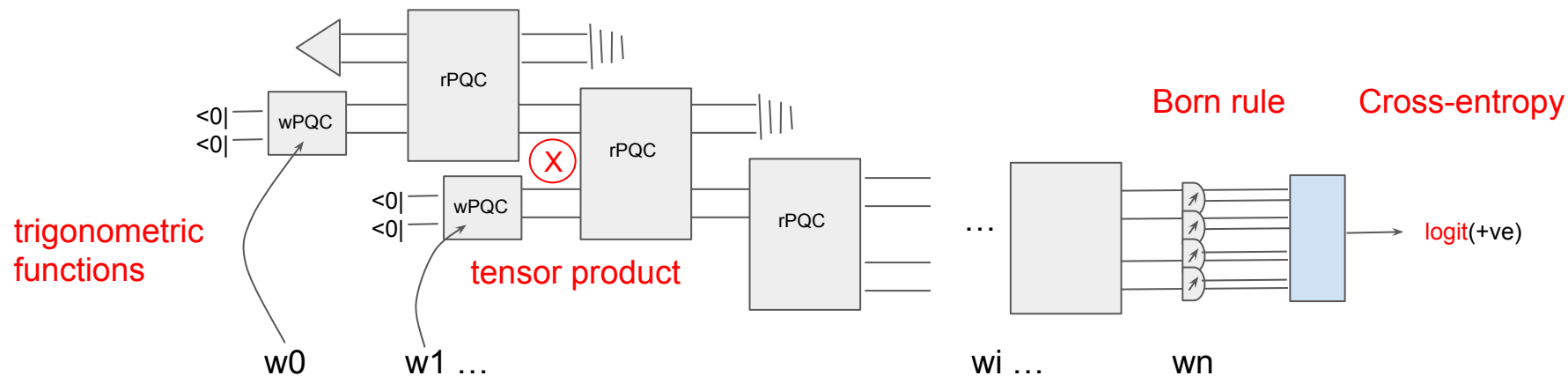
- Highest commercially available two-qubit gate fidelity
- All-to-all connectivity
- Qubit reuse
- Mid-circuit measurement with conditional logic

<b>32</b> fully-connected qubits	<b>65,536 (<math>2^{16}</math>)</b> Quantum Volume	<b>99.997%</b> single-qubit gate fidelity	<b>99.8%</b> two-qubit gate fidelity
-------------------------------------	---	--	---



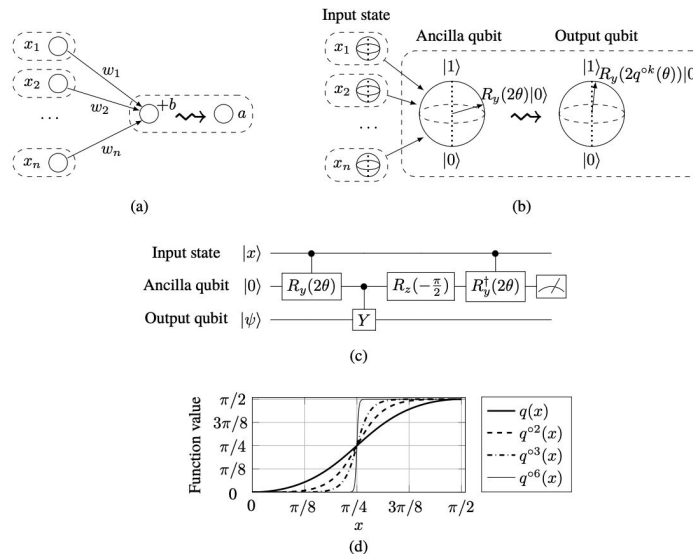
# Extra Slides

# Where are the Non-linearities?



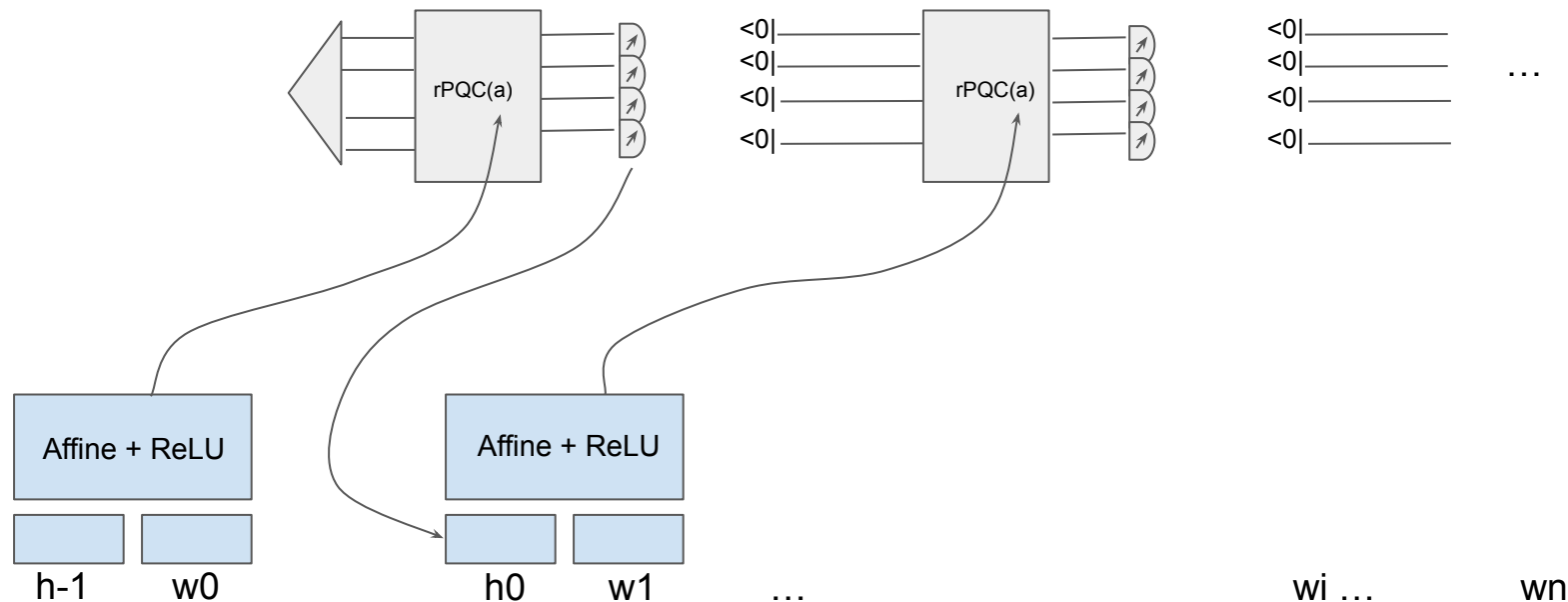
# Where are the Non-linearities?

Quantum neuron?



Quantum Neuron: an elementary building block for machine learning on quantum computers,  
Cao et al., 2017

## qRNN Take Two (Another Variant)



# Hybrid Toolkits



**lambeq**

---



Quantum



# Summary of Architectures - URNN

---

## Unitary Evolution Recurrent Neural Networks

---

**Martin Arjovsky \***

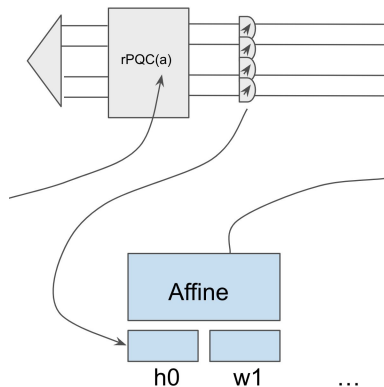
**Amar Shah \***

**Yoshua Bengio**

Universidad de Buenos Aires, University of Cambridge,  
Université de Montréal. Yoshua Bengio is a CIFAR Senior Fellow.

MARJOVSKY@DC.UBA.AR

AS793@CAM.AC.UK



Oct 2022

---

## Assessing the Unitary RNN as an End-to-End Compositional Model of Syntax

---

Jean-Philippe Bernardy

Shalom Lappin

Centre for Linguistic Theory and Studies in Probability  
Department of Philosophy, Linguistics and Theory of Science  
University of Gothenburg

---

## projUNN: efficient method for training deep networks with unitary matrices

---

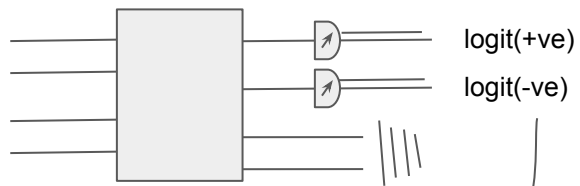
**Bobak T. Kiani**  
MIT  
bkiani@mit.edu

**Randall Balestriero**  
Meta AI, FAIR  
rbalestriero@fb.com

**Yann LeCun**  
NYU & Meta AI, FAIR  
yann@fb.com

**Seth Lloyd**  
MIT & Turing Inc.  
slloyd@mit.edu

# Logits Output



$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \quad CE = - \sum_i^C t_i \log(f(s)_i)$$

An arrow points from the  $e^{s_i}$  term in the numerator of the first equation to the 'logit(+ve)' output line in the diagram above.



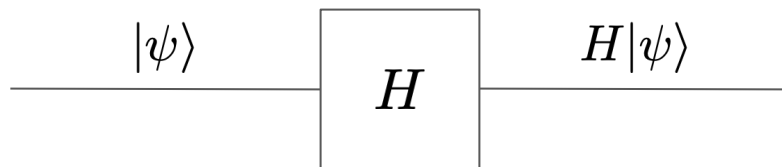
# Where does the Power Come From?

- Superposition
- Entanglement
- Interference



# 1-Qubit Quantum Gates

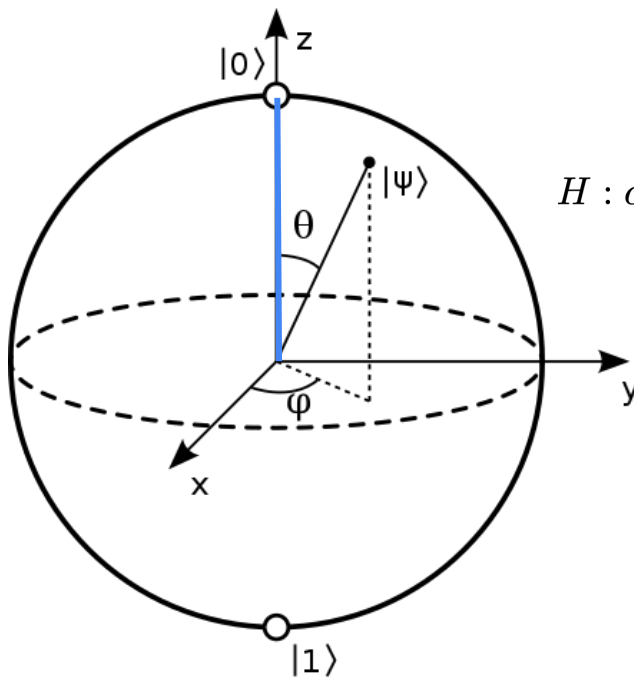
Hadamard Gate



$$H : \alpha|0\rangle + \beta|1\rangle \mapsto \alpha \frac{|0\rangle + |1\rangle}{\sqrt{2}} + \beta \frac{|0\rangle - |1\rangle}{\sqrt{2}}$$

# 1-Qubit Quantum Gates

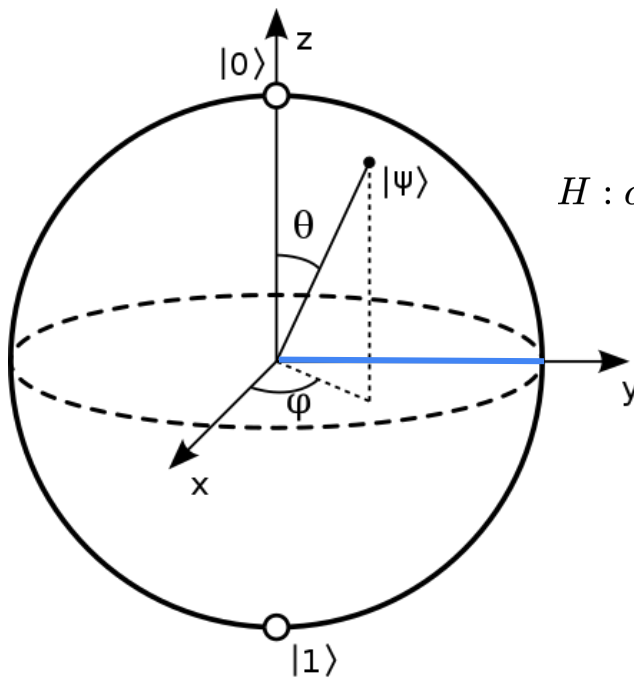
Hadamard Gate *introduces superposition*



$$H : \alpha|0\rangle + \beta|1\rangle \mapsto \alpha \frac{|0\rangle + |1\rangle}{\sqrt{2}} + \beta \frac{|0\rangle - |1\rangle}{\sqrt{2}}$$

# 1-Qubit Quantum Gates

Hadamard Gate *introduces superposition*

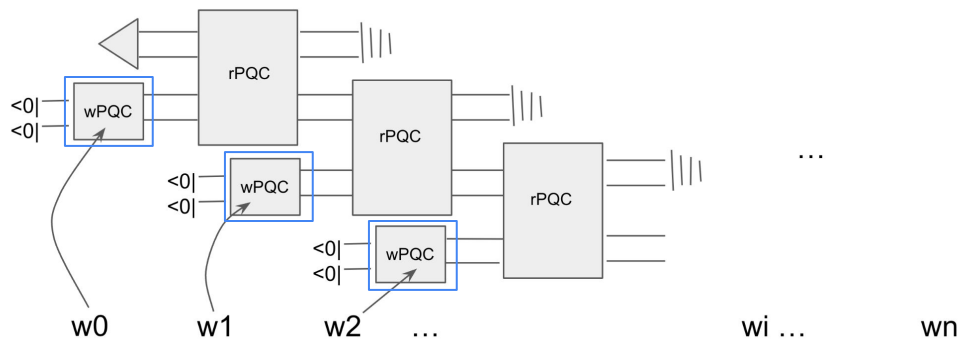


$$H : \alpha|0\rangle + \beta|1\rangle \mapsto \alpha \frac{|0\rangle + |1\rangle}{\sqrt{2}} + \beta \frac{|0\rangle - |1\rangle}{\sqrt{2}}$$

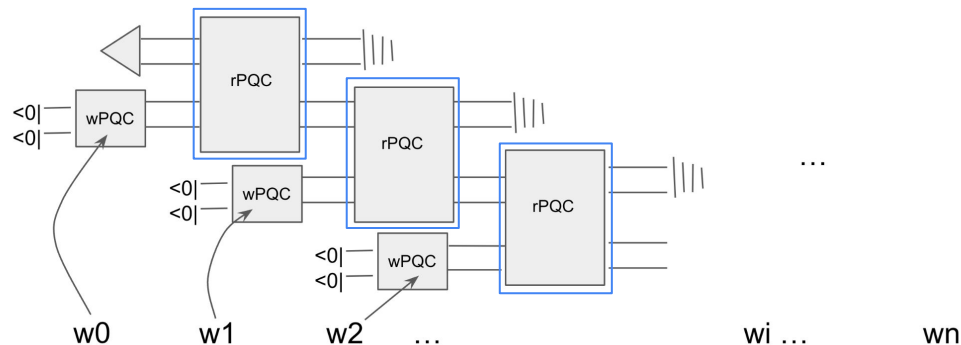
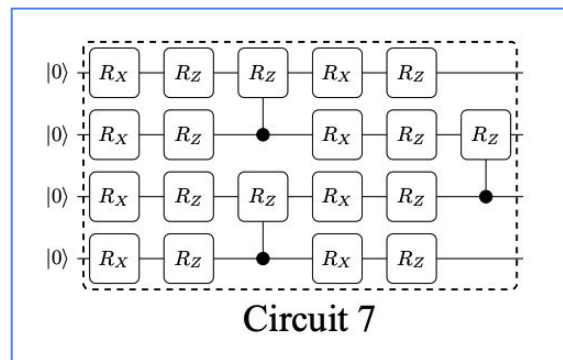
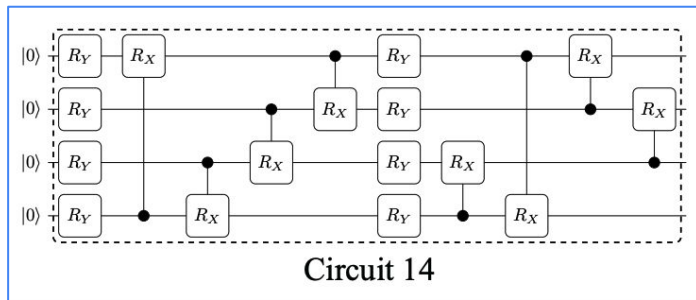
# “Stairs” Architecture in Practice

- We added density matrices to TorchQuantum
- Choice of PQC:

```
'2x4_ryzxy':  
[  
  {'input_idx': [0], 'func': 'ry', 'wires': [0]},  
  {'input_idx': [1], 'func': 'ry', 'wires': [1]},  
  {'input_idx': [2], 'func': 'rz', 'wires': [0]},  
  {'input_idx': [3], 'func': 'rz', 'wires': [1]},  
  {'input_idx': [4], 'func': 'rx', 'wires': [0]},  
  {'input_idx': [5], 'func': 'rx', 'wires': [1]},  
  {'input_idx': [6], 'func': 'ry', 'wires': [0]},  
  {'input_idx': [7], 'func': 'ry', 'wires': [1]},  
],
```



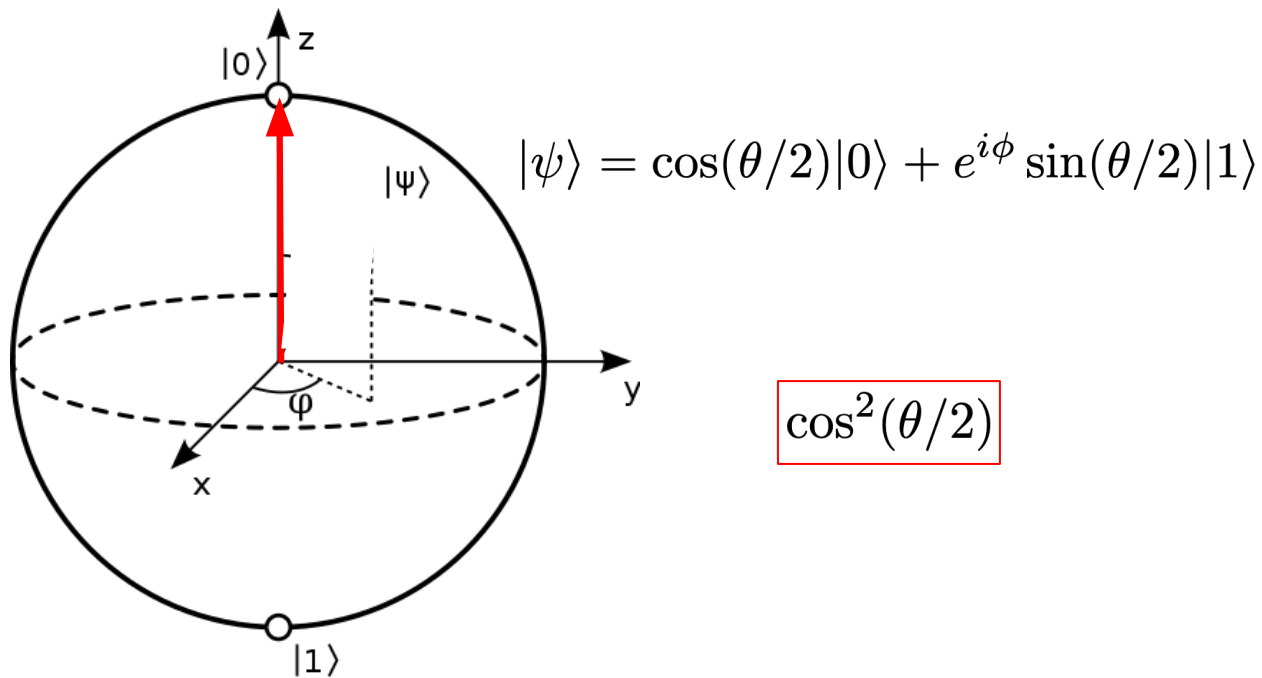
# “Stairs” Architecture in Practice



Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms

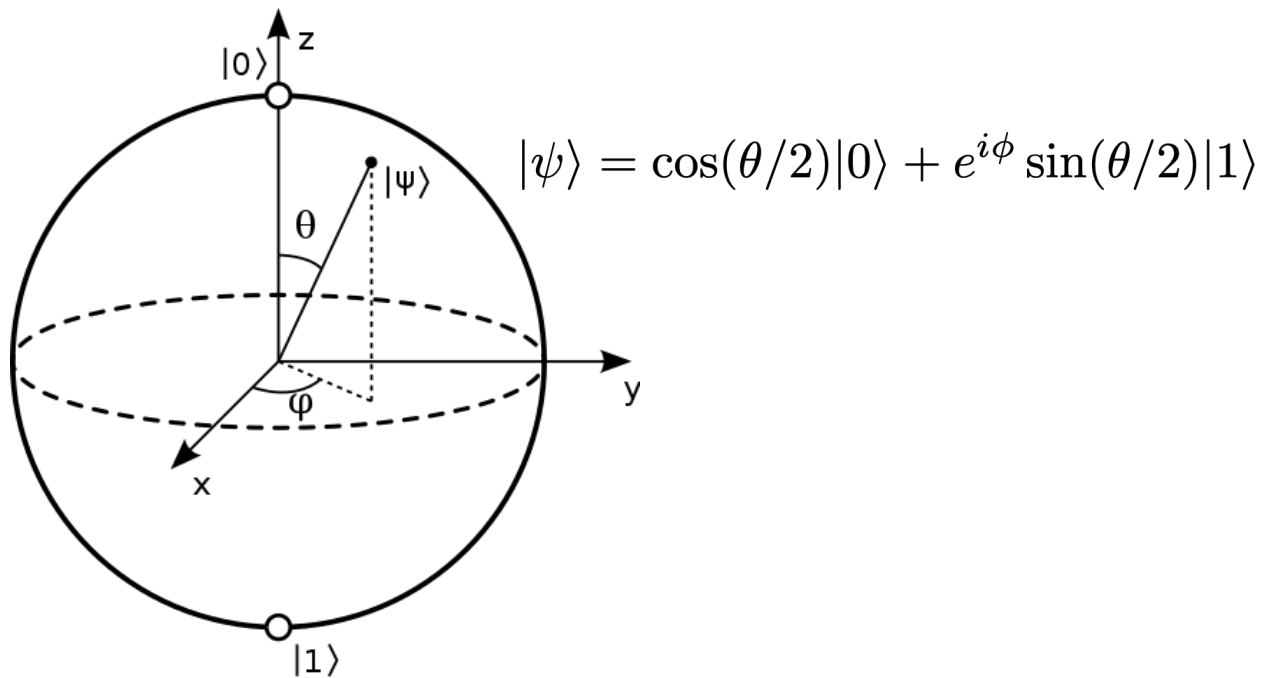
Sukin Sim,<sup>1,2,\*</sup> Peter D. Johnson,<sup>2</sup> and Alán Aspuru-Guzik<sup>2,3,4,5,†</sup>

# “The Collapse of the Wave Function”



[https://en.wikipedia.org/wiki/Bloch\\_sphere](https://en.wikipedia.org/wiki/Bloch_sphere)

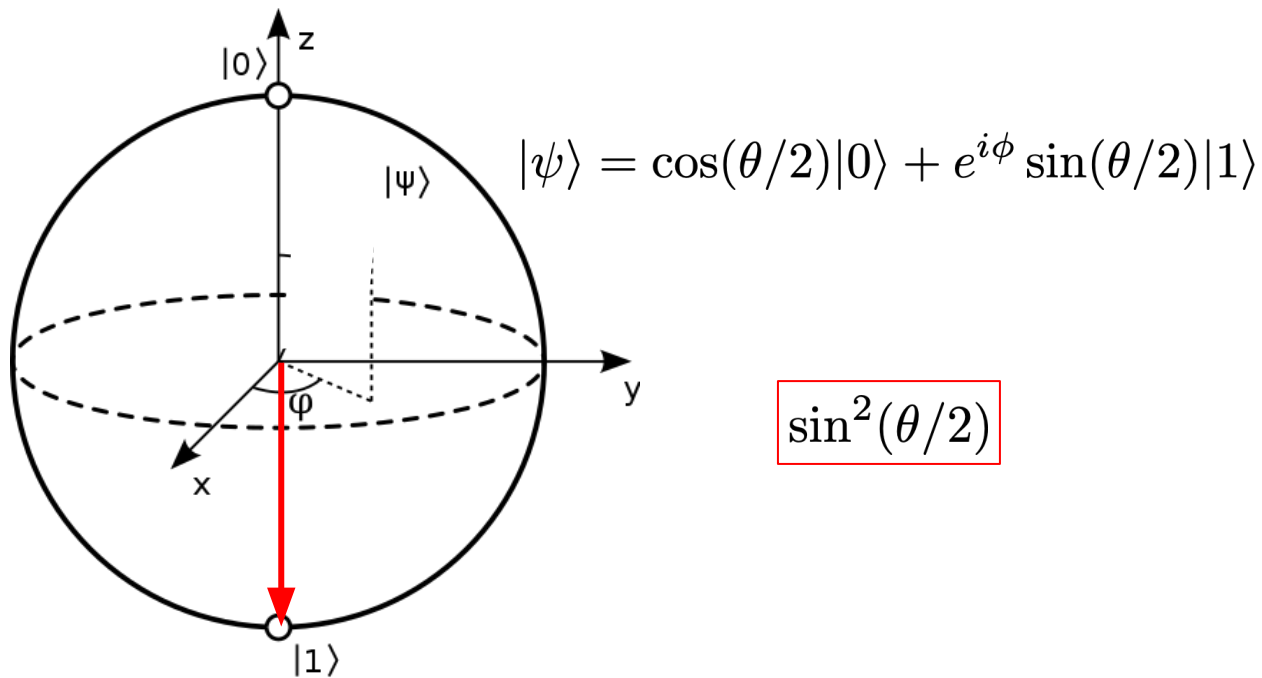
# The Bloch Sphere Representation of a Qubit



[https://en.wikipedia.org/wiki/Bloch\\_sphere](https://en.wikipedia.org/wiki/Bloch_sphere)

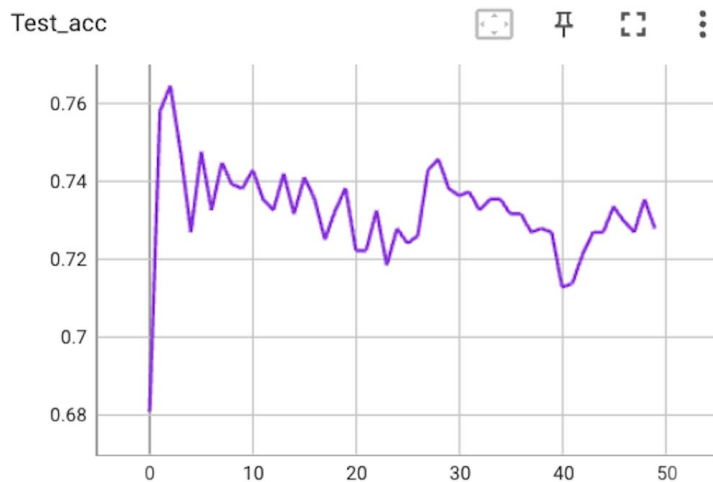


# “The Collapse of the Wave Function”



[https://en.wikipedia.org/wiki/Bloch\\_sphere](https://en.wikipedia.org/wiki/Bloch_sphere)

# Learning Curve



NVidia A30 GPU, PyTorch 1.12:

- ~5 secs / epoch for 1 wire (pure state)
- ~11 secs / epoch for 2 wires (pure state)
- ~14 secs / epoch for 4 wires (pure state)
- ~26 secs / epoch for 8 wires (pure state)