The Superiority of Quantum Machine Learning on NISQ Technology

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What's the motivation?

Quantum computers may revolutionise the technology industry. However:

I'm going to build a quantum computer.

Good luck, it's hard.

Okay, maybe one of the small ones which are easier to build.

You know, the ones that do some but not all quantum computations.

If it is not very quantum how do you know it is not just classical?

Golly, I didn't think about that.

What do you want to do with it anyway?

Break RSA!

Not likely...

We suggest:

- *IQP* as a small (*non-universal*) quantum computer to explore.
- *Machine learning* using IQP devices as a useful application.

What is this "IQP" computer and what is it good for?

There are several reasons why IQP [1] circuits are great for NISQ technology.

IQP circuits are easy enough to build.

Since they're instantaneous you don't even need any memory!

I bet circuits that simple can be simulated classically.

Think again! In general they cannot be simulated classically [2].

Even up to a reasonable error [3].

Noise isn't always reasonable man.

You're not the most reasonable either... man.

Classical hardness exists in the face of constant independent noise [4].

These aren't the only advantages either.

Average case hardness There is a family of IQP circuits, a constant fraction of which cannot be simulated classically [4]. What's more this family can be implemented on a NISQ friendly 2D lattice.

Verification There also exists efficient methods for verifying some IQP computations without classical simulation [1, 5, 6]. This is incredibly valuable within the quantum supremacy realm.

It is for these reasons that we explore this class of circuits.

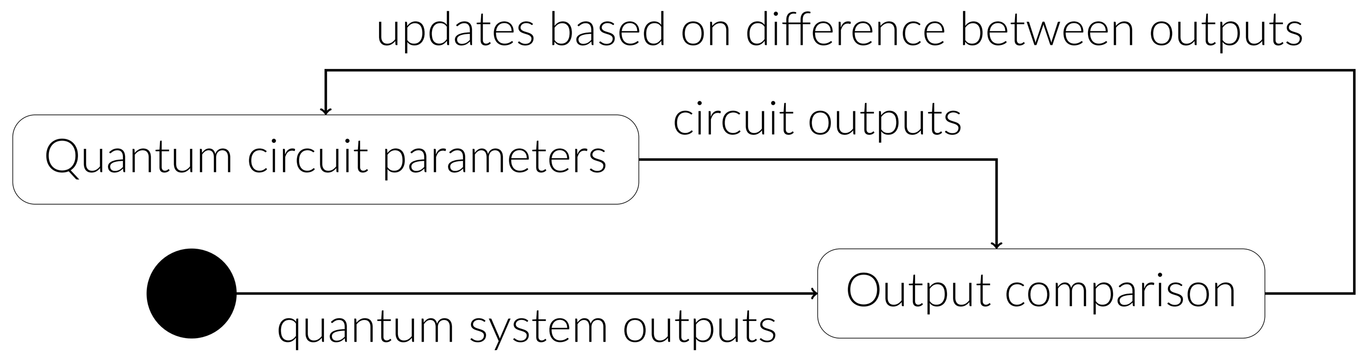
What can we do with these IQP devices?

While we have identified several nice theoretical properties of IQP circuits...

What a complicated paperweight.

Sarcasm is the lowest form of wit. Actually it's useful too!!

One key application of quantum computation will be in reproducing the outputs of natural quantum systems. 'Learning' the correct quantum circuit to reproduce the statistics of our natural quantum system is one exciting application.



Here we will consider the case where the 'quantum system outputs' are classical. The gate parameters of a quantum circuit are then trained to mimic these outputs using a classical optimiser. We call this *distribution learning*.

Superiority of machine learning

You can't put 'learning' in inverted commas and hope no one sees!

If the trained model's outputs are close to the original, you've learnt.

How can you talk about 'Quantum Learning Supremacy' then?

You haven't mentioned a distribution.

A distribution may be 'learnable' by a BQP computation but not a BPP one.

More inverted commas... are you serious?

Here we outline the formalisation of '*Quantum Learning Supremacy*', specifically for distribution learning. We model our definitions around those from the theory of classical distribution learnability [7].

Generator A generator $GEN_{D'}$ generates outputs of a distribution D'.

(d, ϵ)-Generator For a metric, d, we say $GEN_{D'}$ is a (d, ϵ)-Generator for D if $d(D, D') \leq \epsilon$.

Learnability For a complexity class C, a class of distributions $\mathcal{D}_n$ is called (d, ϵ, C)-learnable if there exists an algorithm $\mathcal{A} \in C$, called a learning algorithm for $\mathcal{D}_n$, which, given access to GEN_D for any distribution $D \in \mathcal{D}_n$, outputs $GEN_{D'}$, a (d, ϵ)-Generator for D, with high probability.

Quantum Learning Supremacy An algorithm $\mathcal{A} \in$ BQP is said to have demonstrated the supremacy of quantum learning over classical learning if there exists a class of distributions $\mathcal{D}_n$ for which there exists d, ϵ such that $\mathcal{D}_n$ is $(d, \epsilon, \text{BQP})$-Learnable, but $\mathcal{D}_n$ is not $(d, \epsilon, \text{BPP})$-Learnable.

The Ising Born Machine

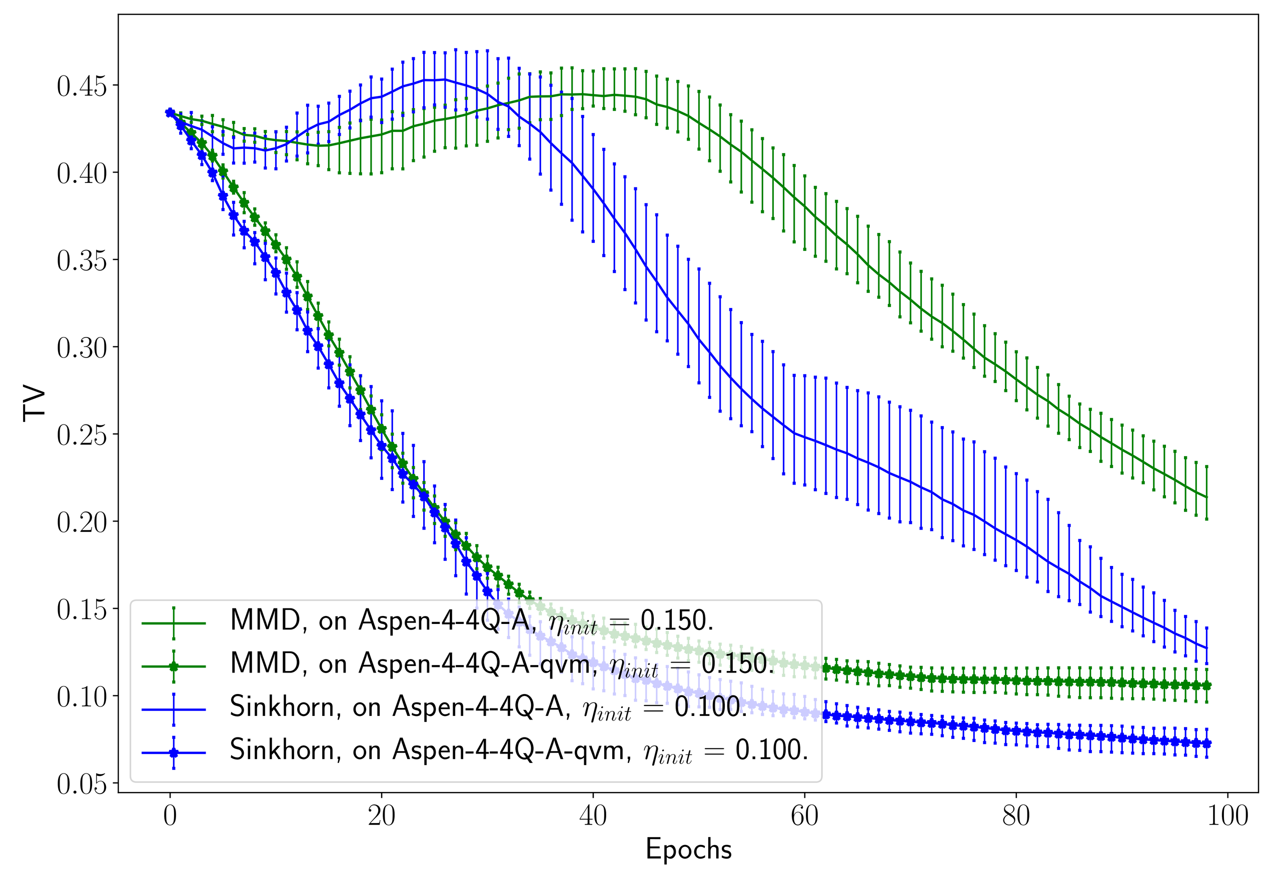
The Ising Born Machine [8] brings together the IQP class and machine learning to create an interesting aplication of quantum computation, and a route to demonstrating the supremacy of quantum machine learning.

In the case of the Ising Born Machine we have the following:

The model we train is an IQP circuit By comparing samples from a quantum systems and measurements of an IQP circuit, we train the circuit to approximate the system's outputs.

The training can be accelerated using certain cost functions While the output comparison is usually done using the '*maximum mean discrepancy*', we propose using the Sinkhorn divergence, which uses optimal transport. Using it can be shown to improve the rate of convergence, and the accuracy of the learning process.

The latter point is demonstrated below, where the Aspen-4-4Q-A is Rigetti's QPU.



We hope in the future to be able to formalise and charaterise the Ising Born Machine's capacity to demonstrate Quantum Learning Supremacy.

References

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