



# Quantum-Powered Times Series Forecasting

*Lighting Talks- openlab*

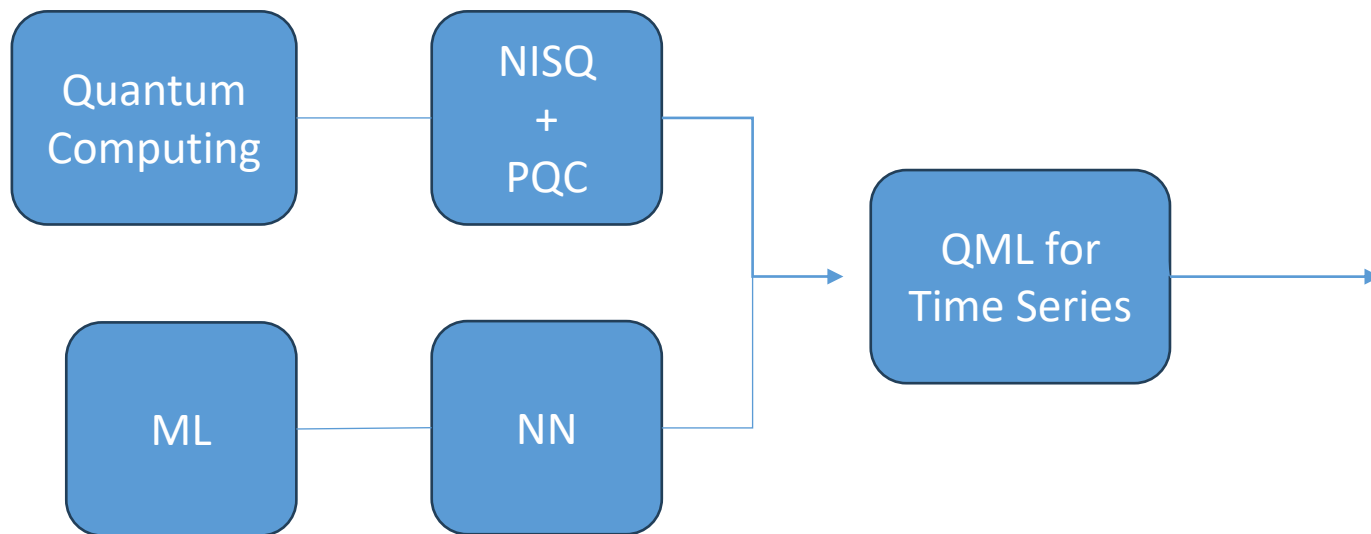
*Supervisors: Sofia Vallecorsa, Michele Grossi, Alice Barthe*

Andrew Spiro  
andrew.charles.spiro@cern.ch

16 / 08 / 2023

# Background

## Setting up QML for time series prediction



### Quantum Machine Learning in Finance: Time Series Forecasting

Dimitrios Emmanoulopoulos and Sofija Dimoska\*  
Chief Technology Office  
Barclays

February 1, 2022

#### Abstract

We explore the efficacy of the novel use of parametrised quantum circuits (PQCs) as quantum neural networks (QNNs) for forecasting time series signals with simulated quantum forward propagation. The temporal signals consist of several sinusoidal components (deterministic signal), blended together with trends and additive noise. The performance of the PQCs is compared against that of classical bidirectional long short-term memory (BiLSTM) neural networks. Our results show that for time series signals consisting of small amplitude noise variations (up to 40 per cent of the amplitude of the deterministic signal) PQCs, with only a few parameters, perform similar to classical BiLSTM networks, with thousands of parameters, and outperform them for signals with higher amplitude noise variations. Thus, QNNs can be used effectively to model time series having, at the same time, the significant advantage of being trained significantly faster than a classical machine learning model in a quantum computer.

#### 1 Introduction

In a genuine quantum computing infrastructure (i.e. an environment which performs computations using quantum phenomena such as superposition, entanglement, tunnelling etc.) quantum algorithms [22] can run significantly faster with respect to their classical equivalents. These algorithms cover many application areas such as optimisation problems, combinatorics, cryptography, solution of partial differential equations, simulations e.g. [36].

In the field of machine learning quantum enhancement can come in two different flavours e.g. [19]. The first flavour concerns the training process which can be significantly accelerated, even for classical machine learning models, using quantum optimisation algorithms. In some cases, involving complex loss functions with multiple minima, these algorithms can even yield more accurate results by localising more effectively the global minimum. The second flavour concerns the identification of complex patterns since, in a quantum computing environment, the data as they can be sampled more efficiently from probability distributions that are exponentially difficult to sample using classical methods on classical computers.

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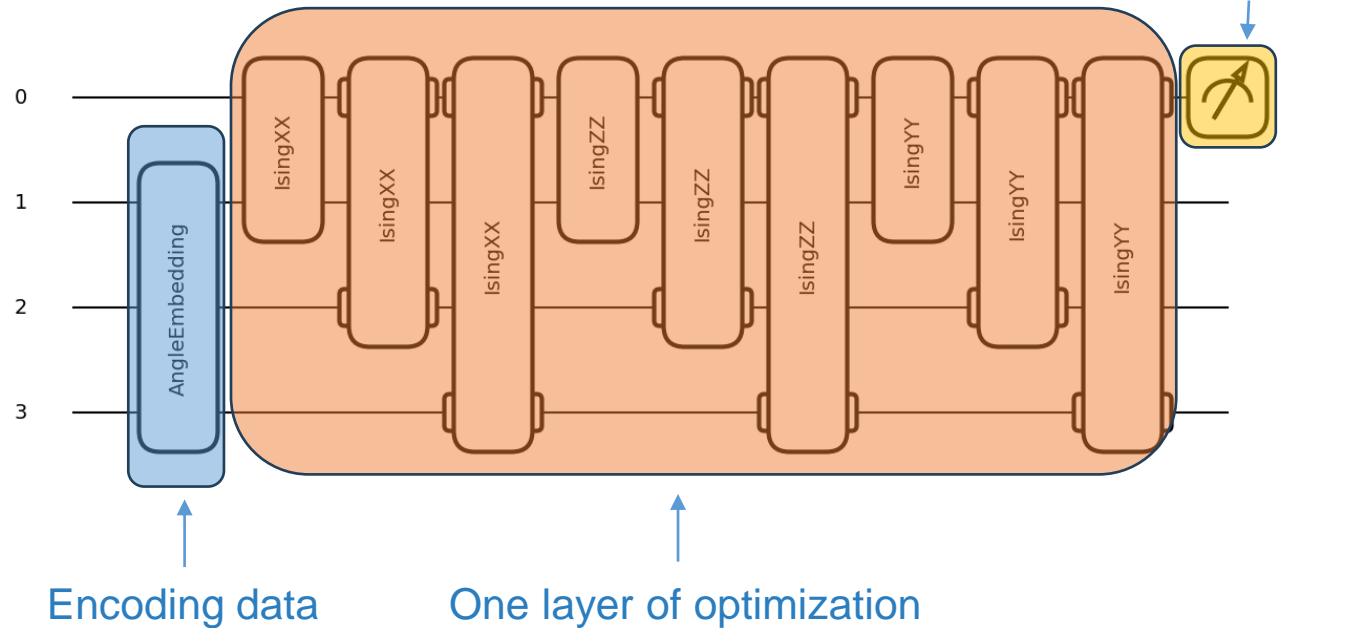
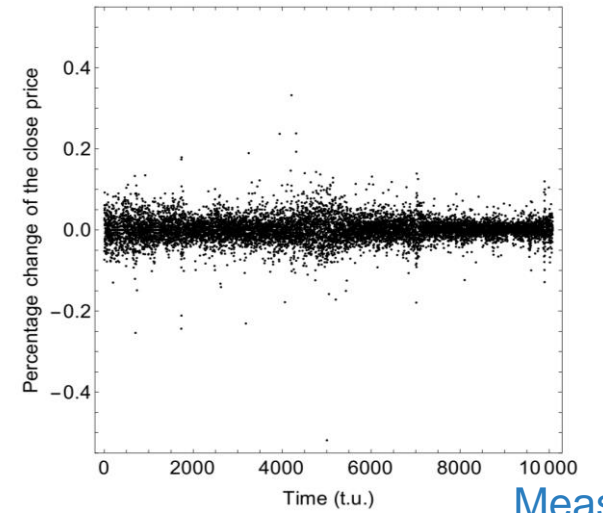
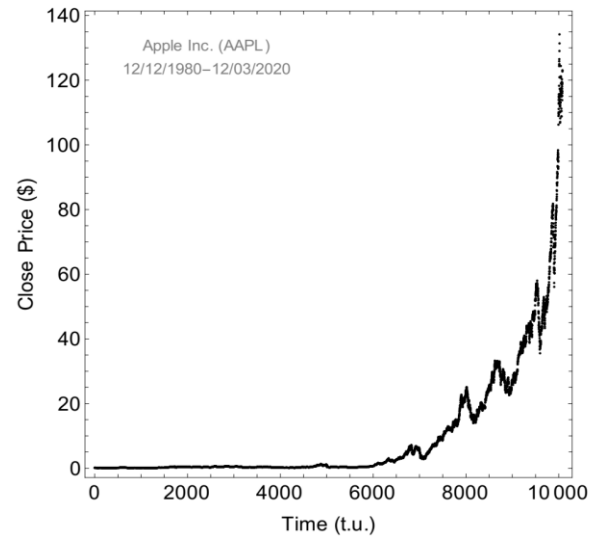
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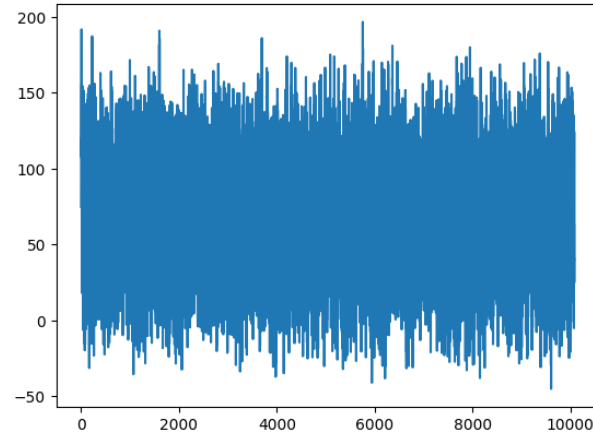
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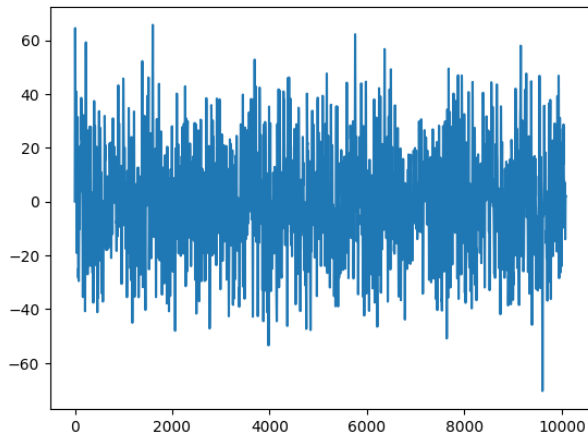
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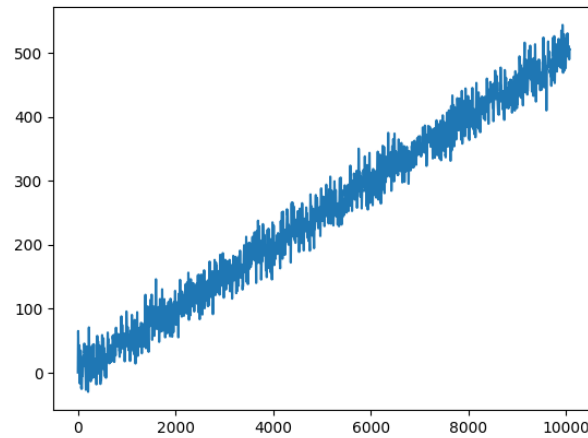
Plus, Noise



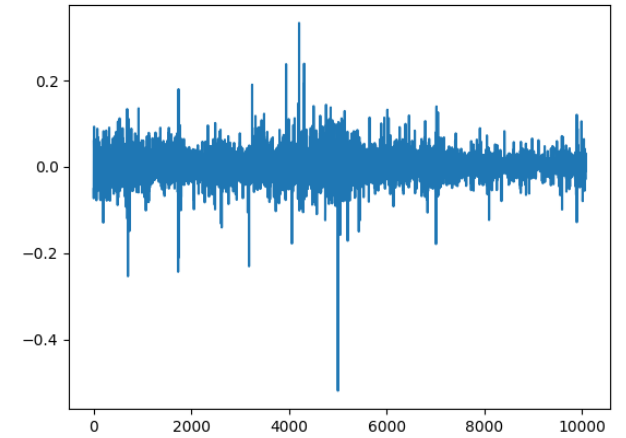
Sinusoidal Components



Plus, Linear Trends



Full Signal



Complexity

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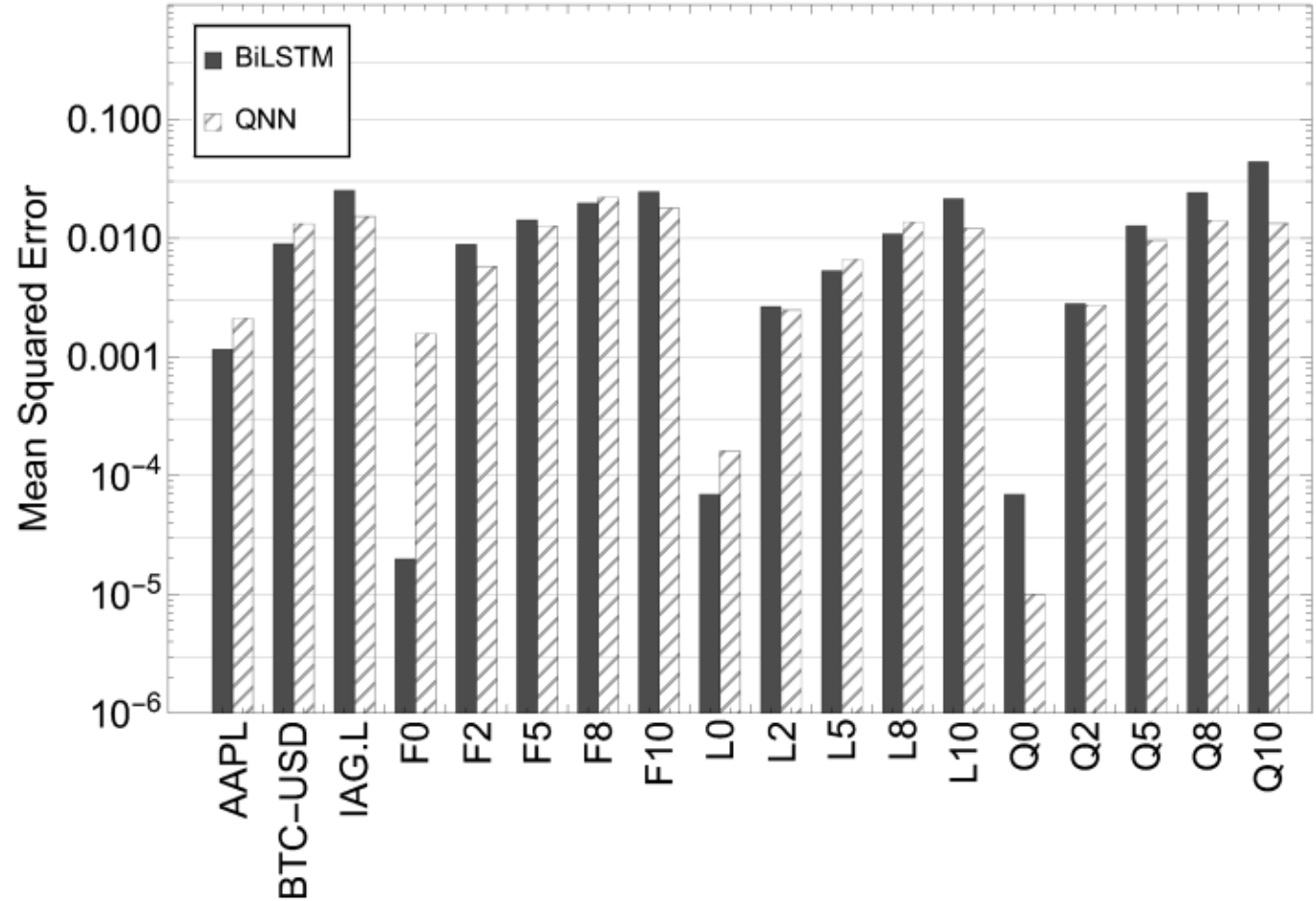
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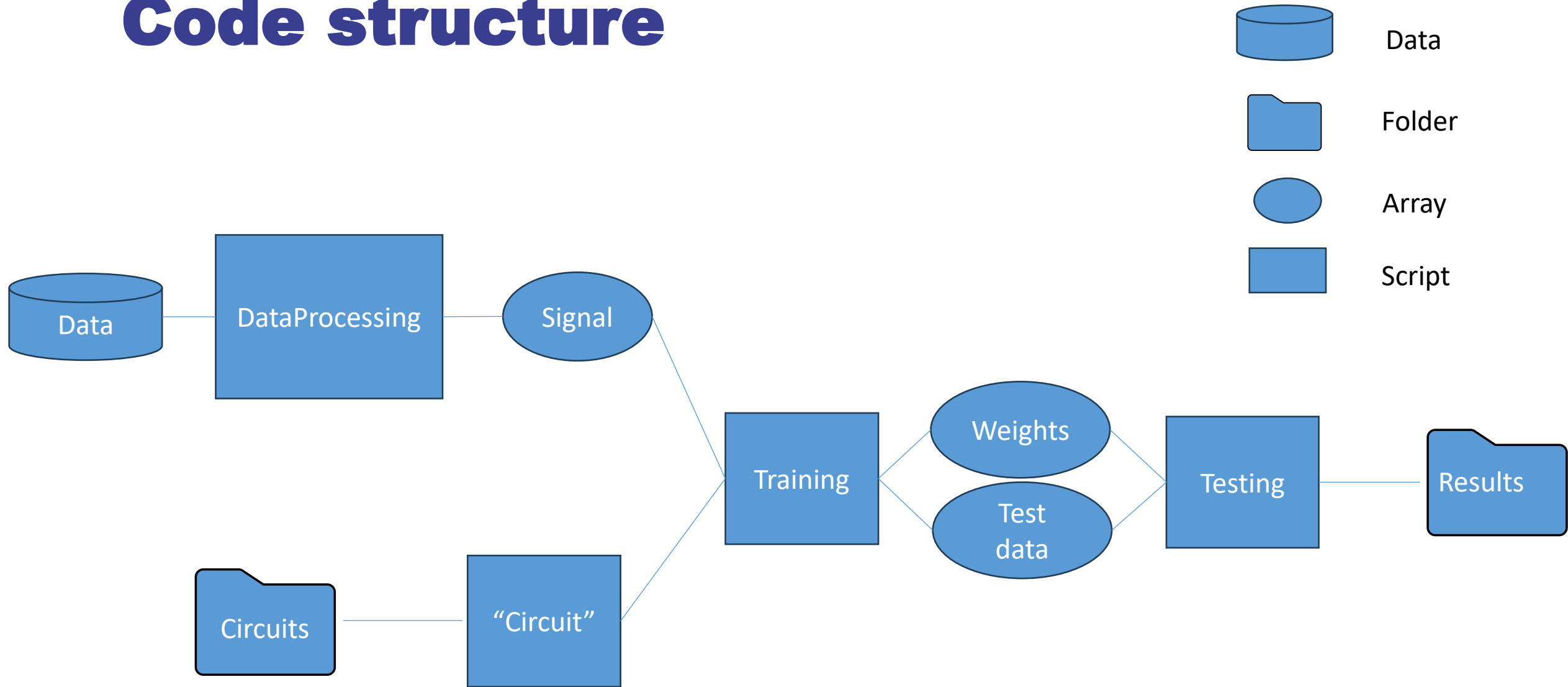
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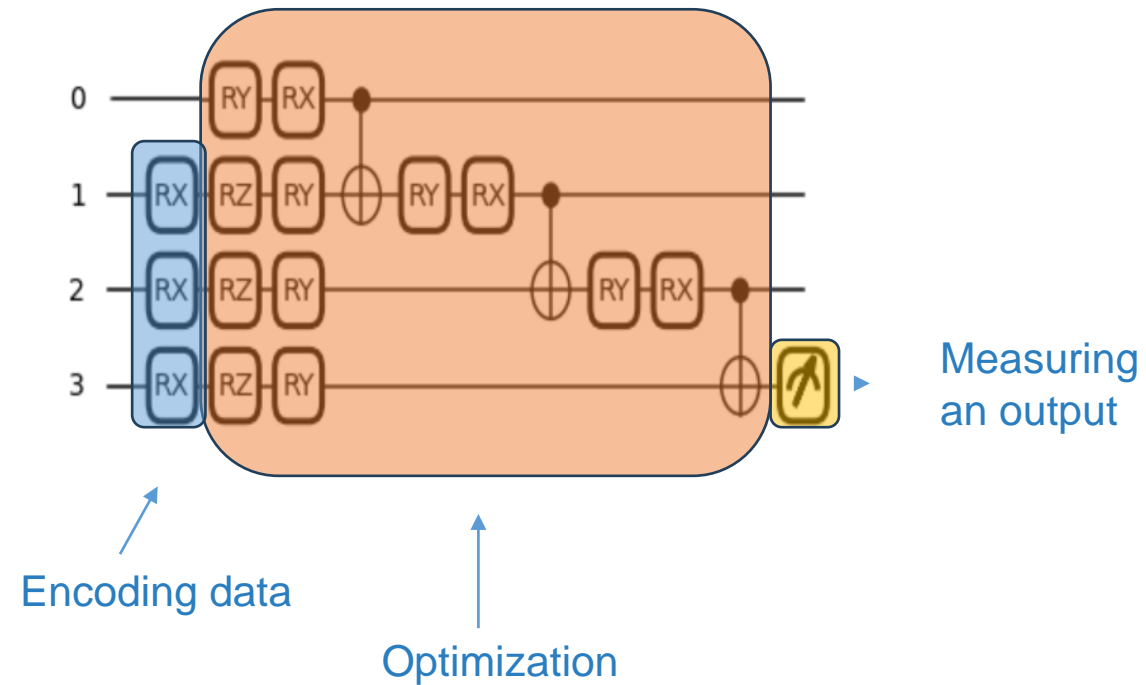


arXiv:2202.00599v1 [quant-ph] 1 Feb 2022

# Code structure

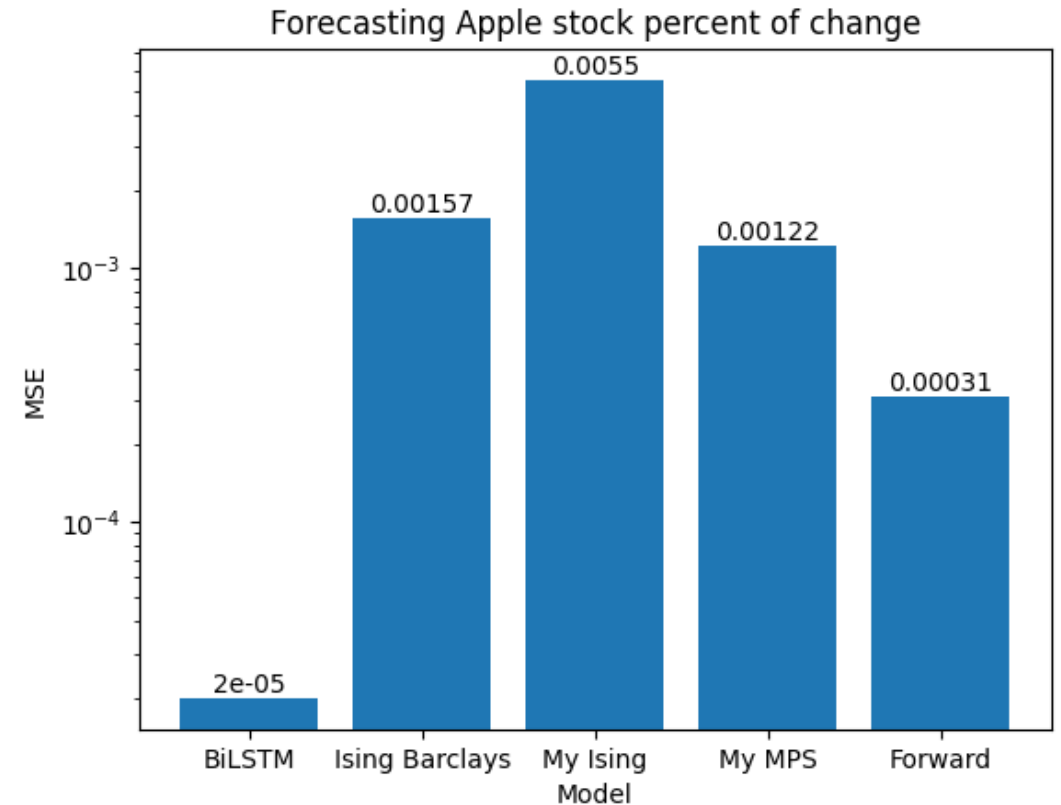
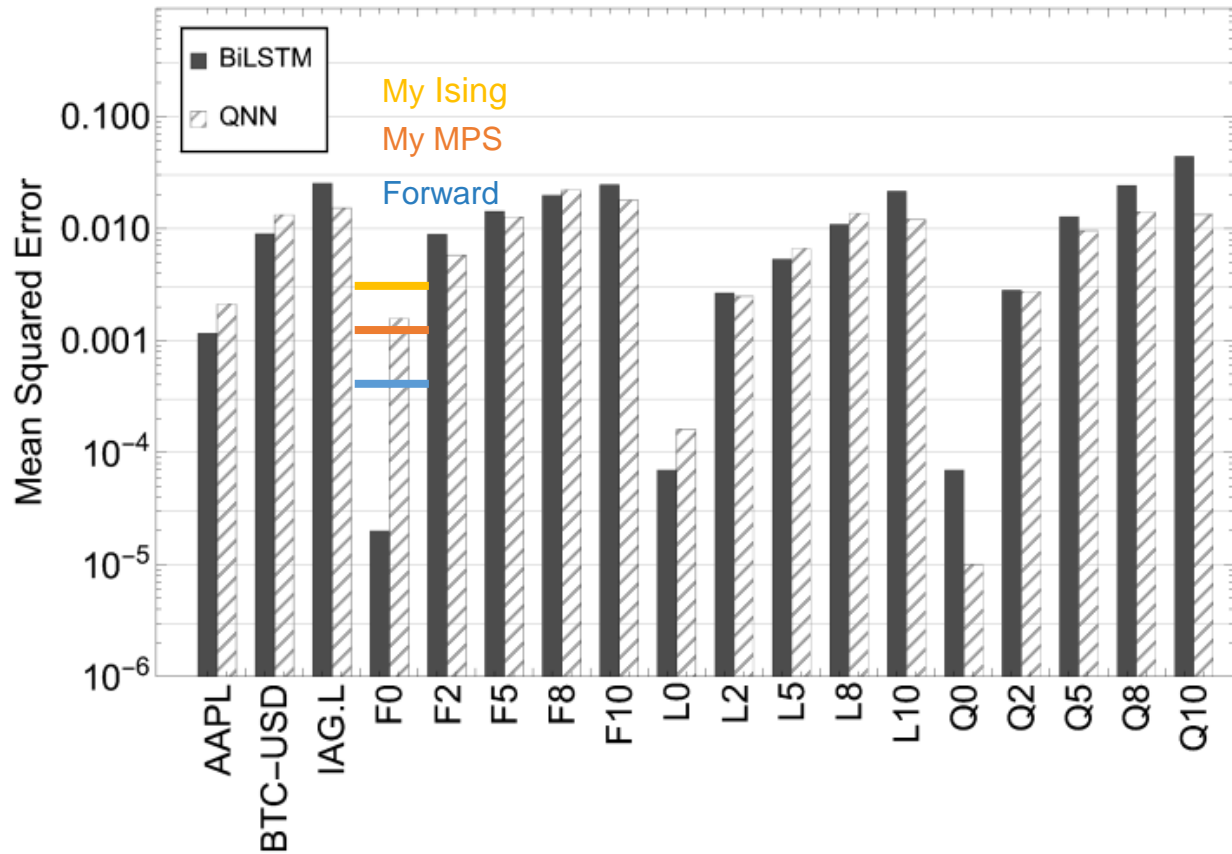


# MPS architecture



# Results

## Barclays Comparison

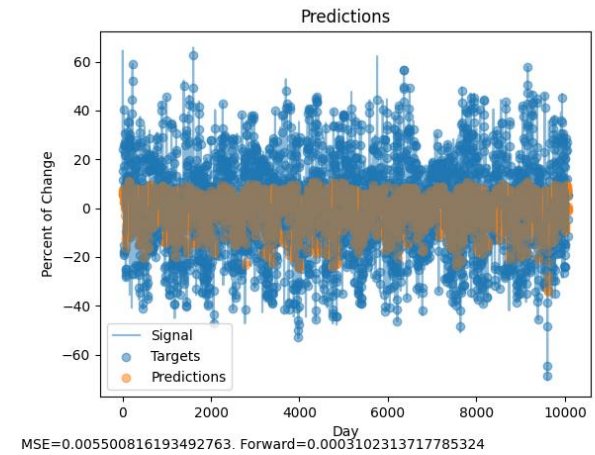
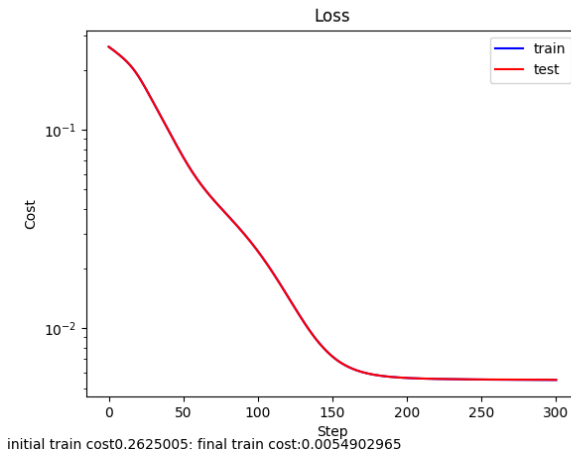




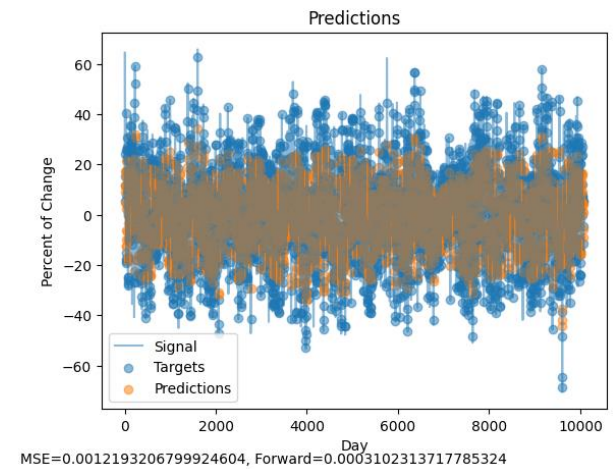
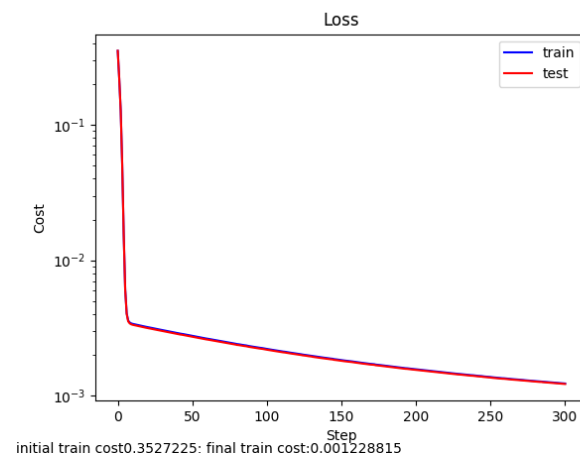
# Results

## Loss and Predictions

Ising



MPS



# Hyperparameters

## Model:

- Ising
  - Layers: 2
- MPS



## Data

- Sample size
- Threshold: 50
- Noise coefficient: 0-1
- Trend: FLQ



## Training

- Sampling strategy: random
- Max steps: 10
- Epochs: 300

# Try it yourself and Thank You!

<https://github.com/CERN-IT-INNOVATION>

