School of
Information Technology
and Computer Science
Nile University

Advanced Quantum Machine Learning

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Dean

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Agenda

- More QML models
  - QAOA
  - Quantum Reinforcement Learning
  - Quantum LSTM
- Issues in QML
  - Barren-Plateaus
  - Effect of Noise
  - Ansatz Design
- Flooding Predication Case Study

QAOA

- The Max-Cut graph problem
- The Hamiltonian Formulation
  - $H_c = \sum_{(i,j) \in e} Z_i Z_j$
- Adiabatic Quantum Computing
  - Gama and Alpha operators
- Formulation in machine learning problem

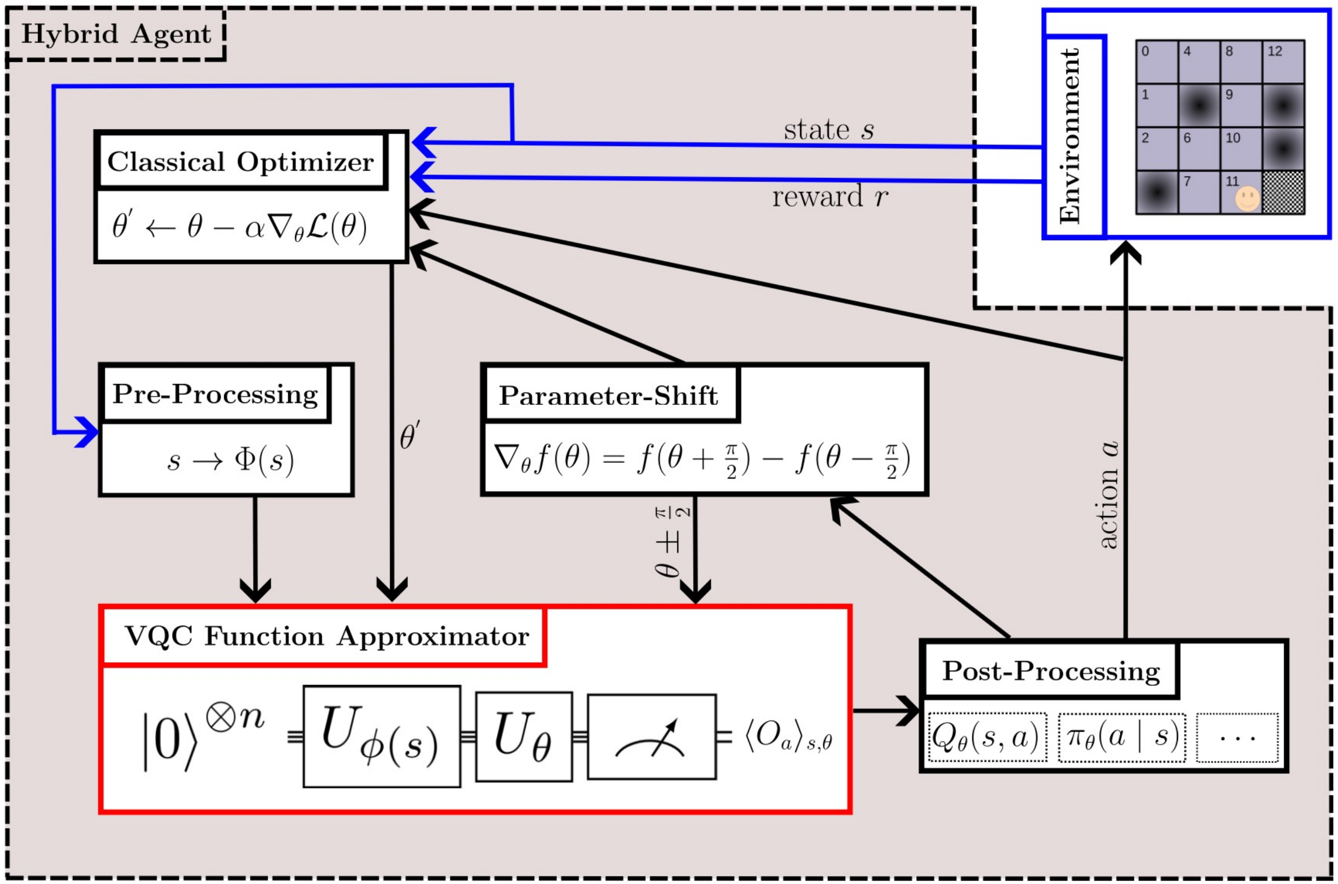
Quantum Reinforcement Learning

- Quick introduction to reinforcement learning
  - State
  - Action
  - Reward
- The goal is learning a policy:

$$\pi : \mathcal{S} \times \mathcal{A} \rightarrow [0, 1]$$
$$\pi(s, a) = \Pr(A_t = a \mid S_t = s)$$

Solution

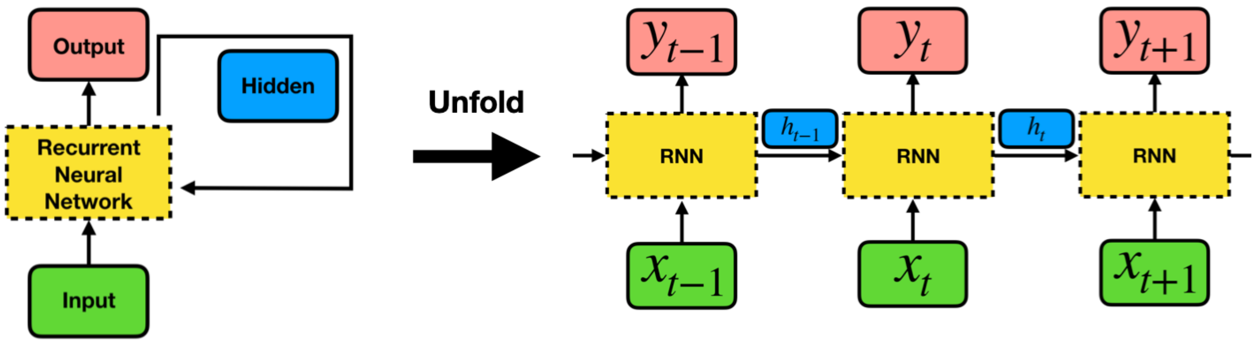
$$Q^{new}(S_t, A_t) \leftarrow (1 - \underbrace{\alpha}_{\text{learning rate}}) \cdot \underbrace{Q(S_t, A_t)}_{\text{current value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \underbrace{\left(\underbrace{R_{t+1}}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(S_{t+1}, a)}_{\text{estimate of optimal future value}} \right)}_{\text{new value (temporal difference target)}}$$



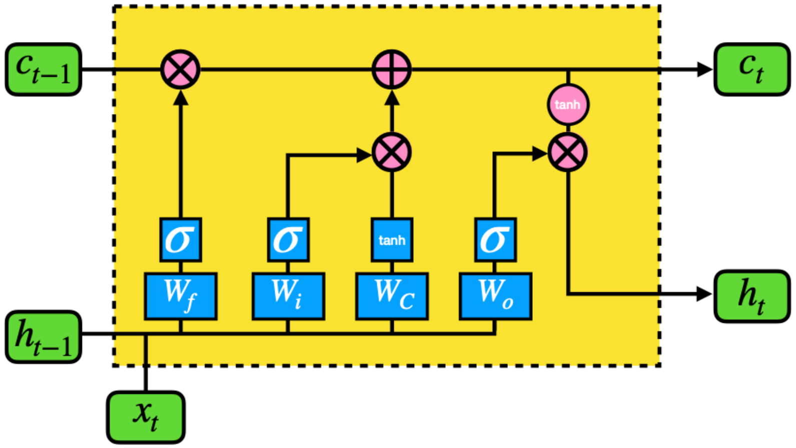
Meyer et al. 2024

Quantum LSTM

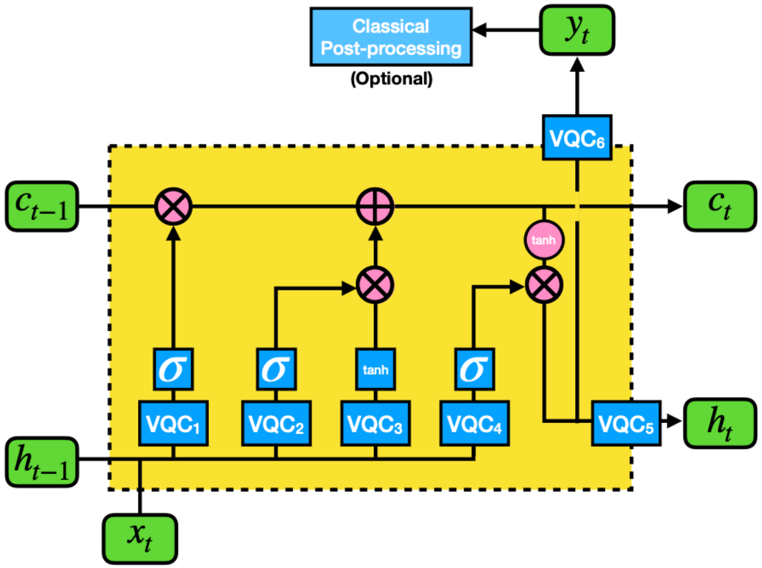
- Long Short Term Memory
- Recurrent Neural Network



QLSTM

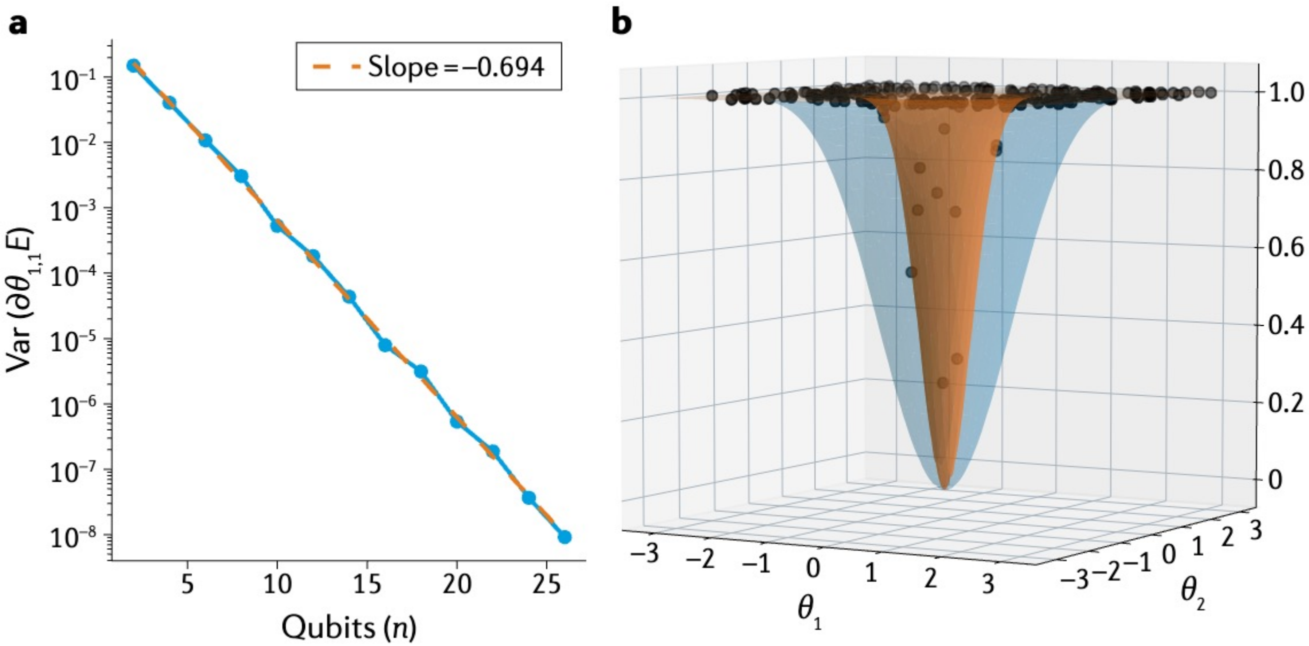


c_{t-1}
c_t
tanh
σ
σ
tanh
σ
W_f
W_i
W_C
W_o
h_t
h_{t-1}
x_t



Classical Post-processing
(Optional)
y_t
VQC_6
c_{t-1}
c_t
tanh
σ
σ
tanh
σ
VQC_1
VQC_2
VQC_3
VQC_4
VQC_5
h_t
h_{t-1}
x_t

Issues: Barren-Plateaus



Barren-Plateaus

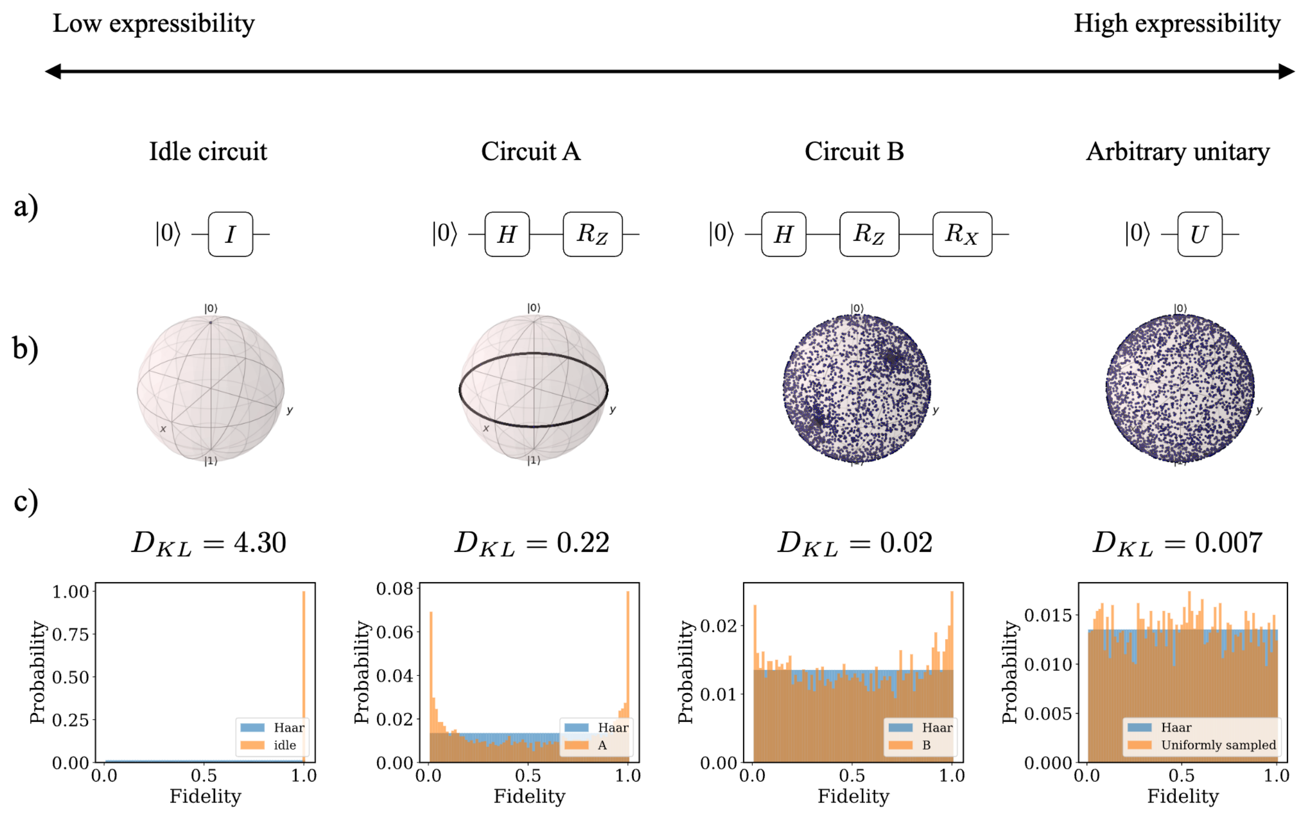
- Causes:
  - The curse of dimensionality
- Handling:
  - Avoid hardware Efficient Ansatz
  - Use shallower circuits
  - Don’t randomly initialise the model parameters

Effect of Noise

- Can cause Barren-Plateaus
- But VQA has generally
  - Noise immunisation
  - Noise mitigation
- The general strategy is again using shallow circuits
- Also error-correcting codes (fault tolerant quantum computer)

Ansatz Design

- Hardware Efficient Ansatz
- Problem Efficent Ansatz
- The Expressibility of the Ansatz
  - How uniformly do parameters explore the Hilbert Space
- The Entangling Capability of the Ansatz
  - How strong are the states entangled



Sim et al. 2019

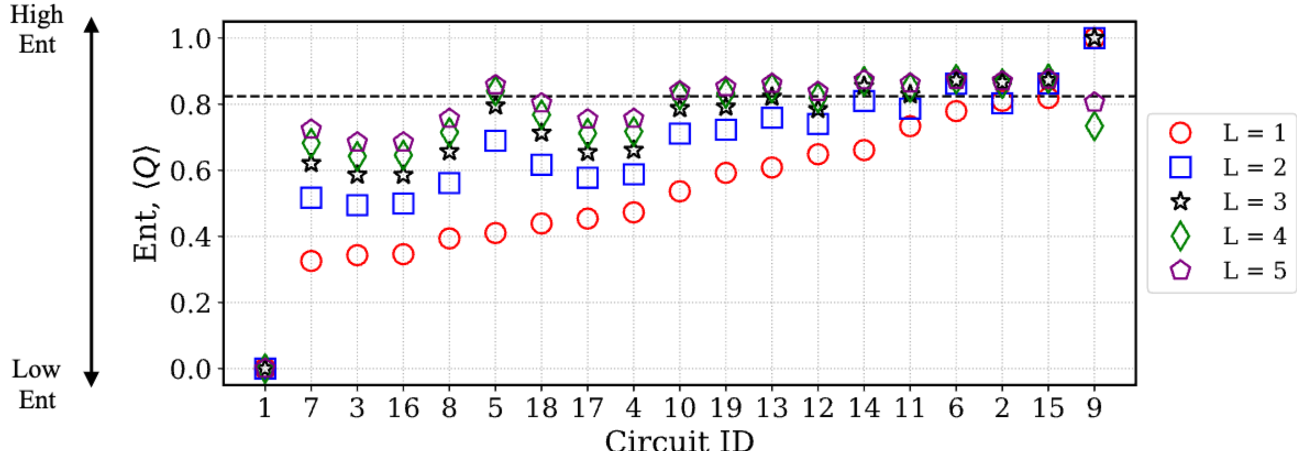
Entangling Capability

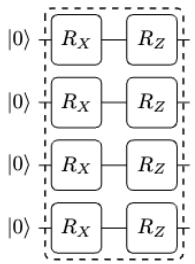
- Meyer-Wallach Measure

$$\iota_j(b)\,|b_1 \ldots b_n\rangle = \delta_{bb_j}\,|b_1 \ldots \hat{b}_j \ldots b_n\rangle$$

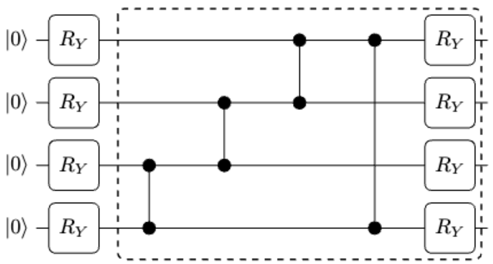
$$Q(|\psi\rangle) \equiv \frac{4}{n}\sum_{j=1}^{n} D\big(\iota_j(0)\,|\psi\rangle\,,\iota_j(1)\,|\psi\rangle\,\big),$$

Entangling Capability

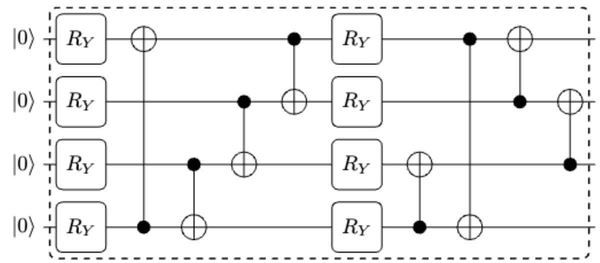




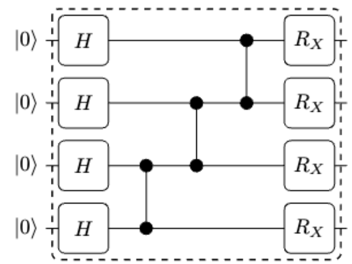
Circuit 1



Circuit 10

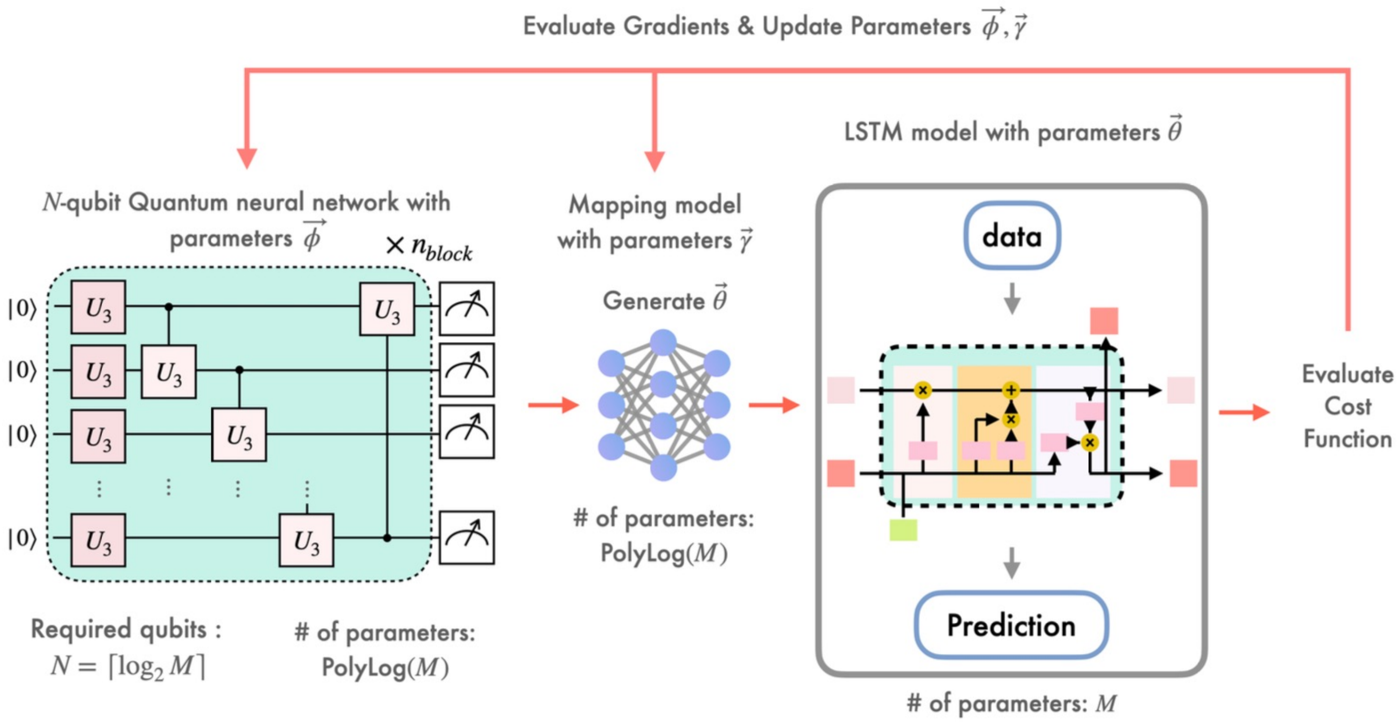


Circuit 15



Circuit 9

Flooding Prediction (Lin et al. 2024)



Flooding Prediction (Lin et al. 2024)

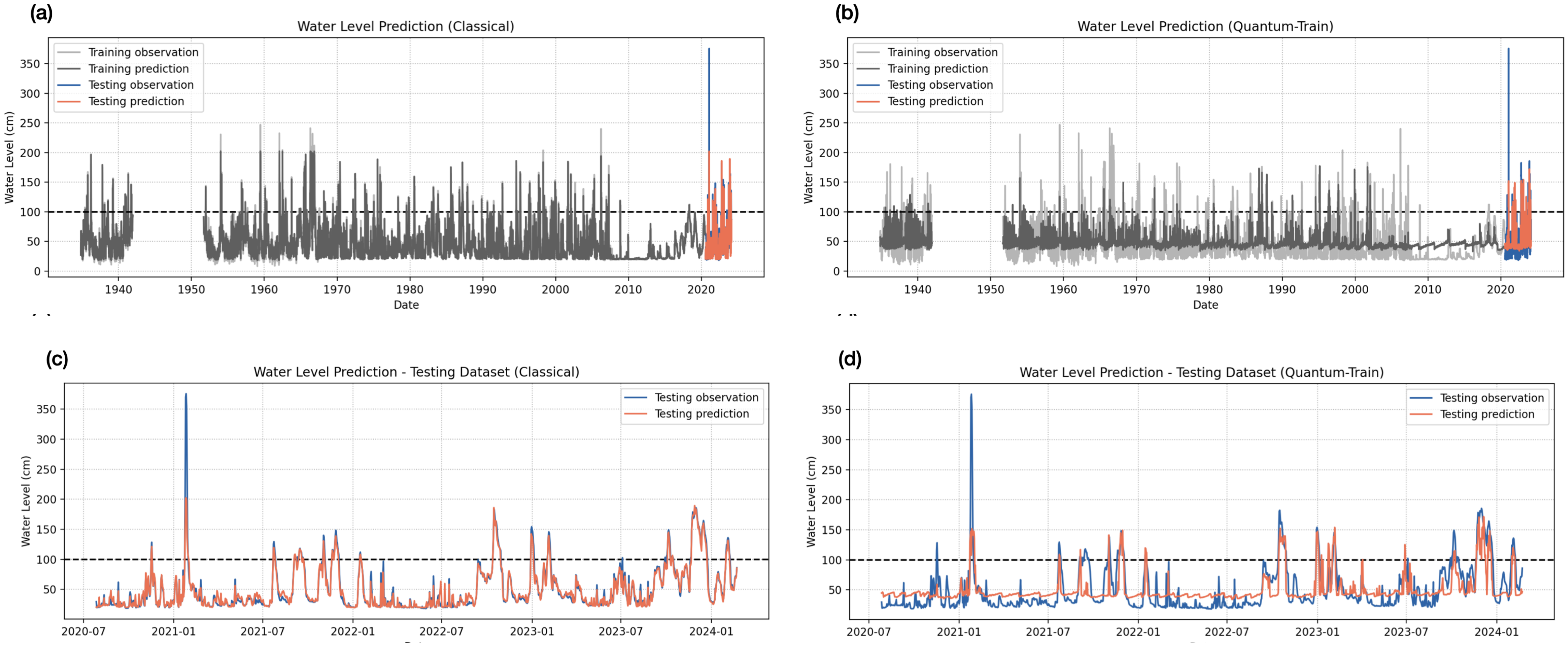
- A classical LSTM has M parameters
- The approach uses Log M qubits!
- This is done by using the fact that n qubits has 2^n probabilities
- A NN is used with feature-based, prob
- The NN maps that into the corresponding LSTM parameter

The problem

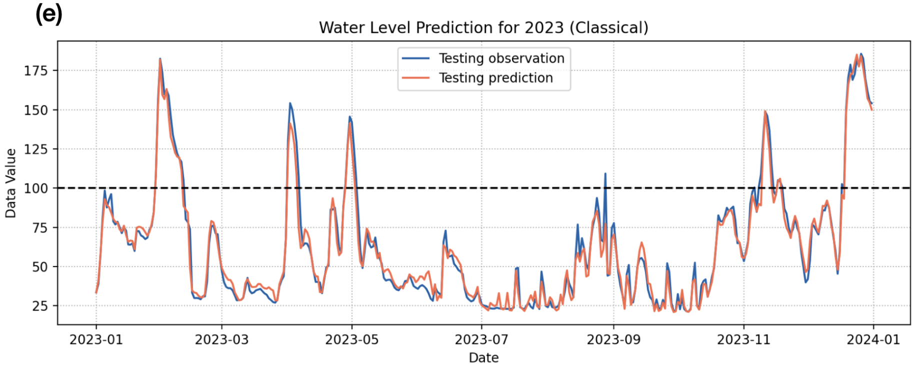
- Predict the water level on the Wupper river at a specific station
- Features:
  - Water levels and discharge rates from five river stations
  - Volume and fill levels of four water reservoirs
  - Weather data and forecast from three weather stations
  - 1 to 7 time lags points in the target station

The problem/approach

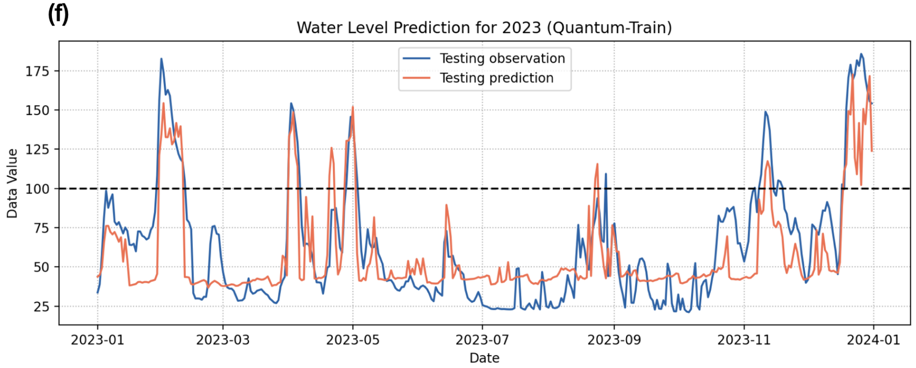
- 30 features
- Several hours to two days of input data to the LSTM
- Predict the maximum water level for the next 24 hours


(a)
Water Level Prediction (Classical)
Training observation
Training prediction
Testing observation
Testing prediction
Water Level (cm)
Date
(b)
Water Level Prediction (Quantum-Train)
Training observation
Training prediction
Testing observation
Testing prediction
Water Level (cm)
Date
(c)
Water Level Prediction - Testing Dataset (Classical)
Testing observation
Testing prediction
Water Level (cm)
(d)
Water Level Prediction - Testing Dataset (Quantum-Train)
Testing observation
Testing prediction
Water Level (cm)

(e)



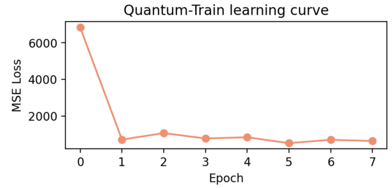
(f)



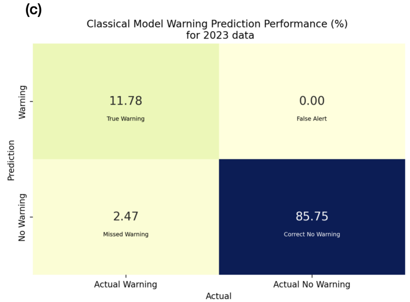
(a)

	Classical	QT (simu.)
MSE	38.02	475.91
MAE	4.19	17.44
# of training parameter	40451	18830
Training time	1.5 min	11 hr

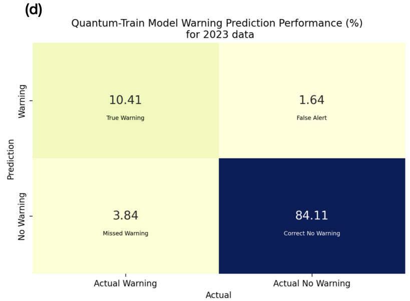
(b)



(c)



(d)



Conclusions

- QML has shown comparative results to classical ML in terms of performance
- Initial results indicate fewer parameters
- However, we still do not know how scalable the approach is

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Thank You