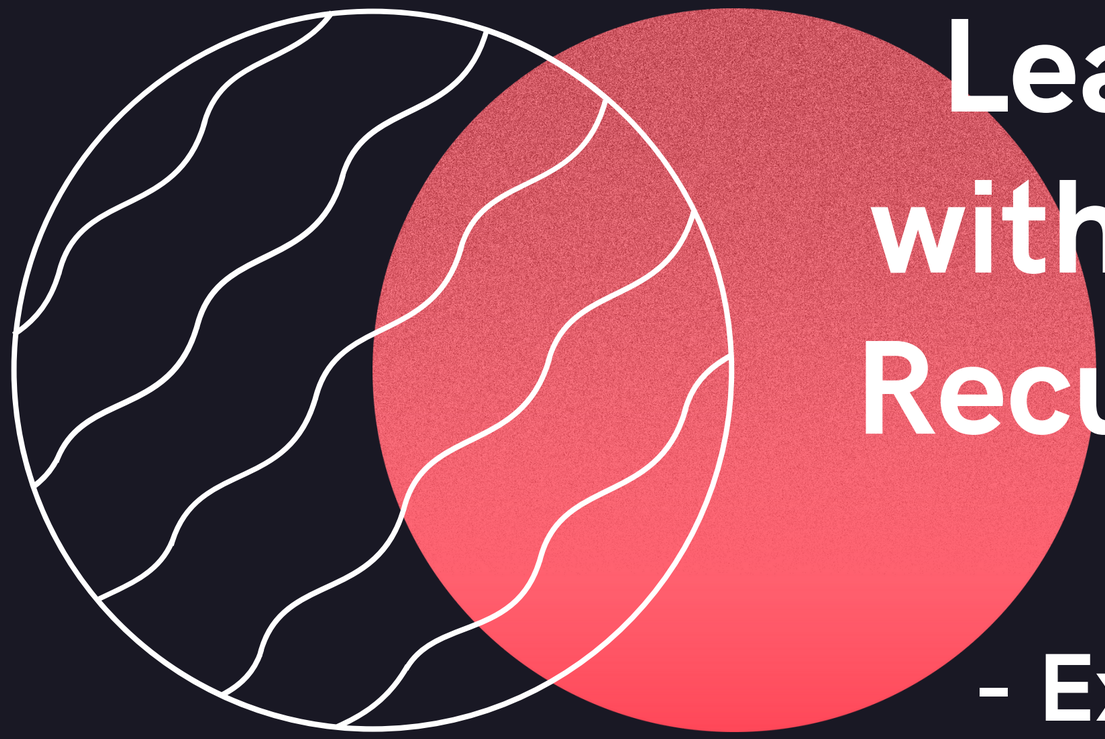


Learning Temporal Data with Variational Quantum Recurrent Neural Network

- Exploring QRNN with PennyLane

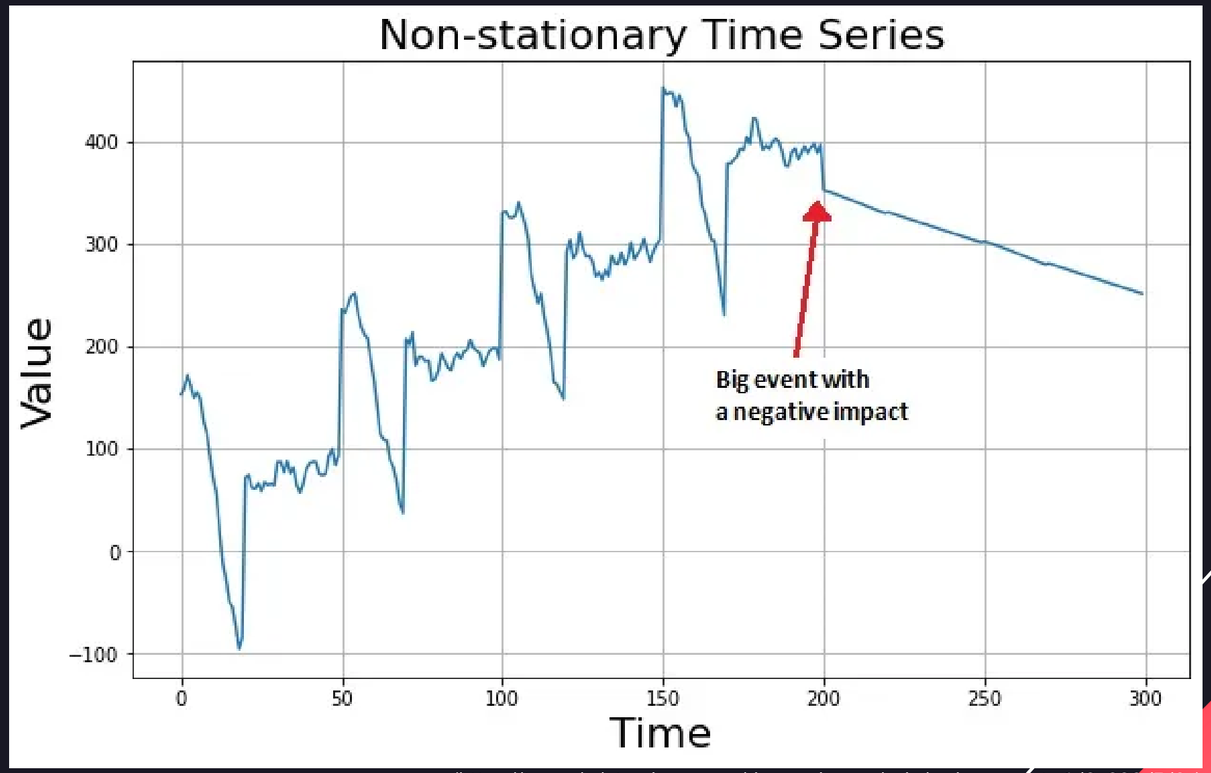
Jason Bai, Eva Wang, Jane Shi, Bobby Zou

AGENDA

1. Introduction of QRNN
2. Novel Results from the Paper
3. The Underlying Theory of the Paper
4. Software Architecture and Implementation
5. Significance
6. Limitations and Open Questions
7. Future Directions
8. Live Demo

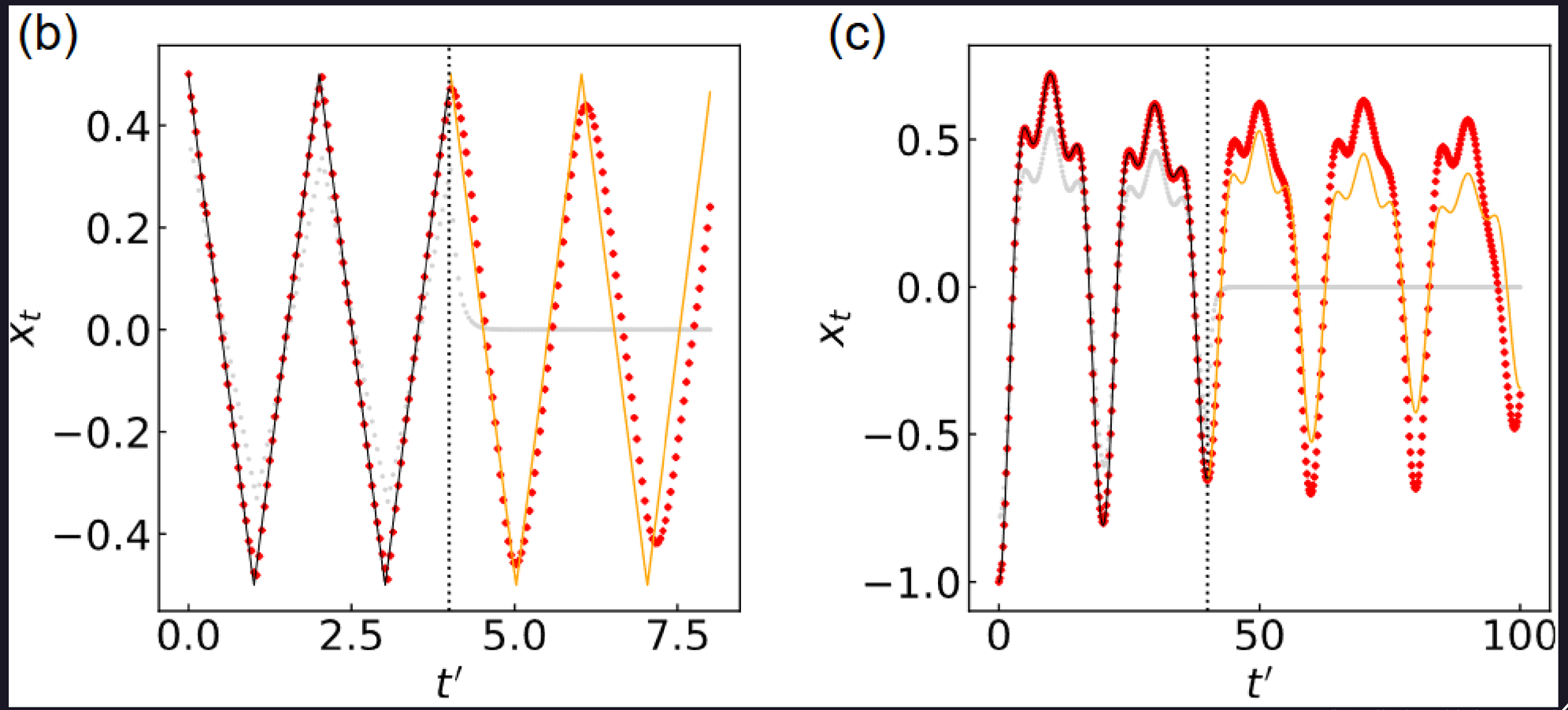
What Does Variational Quantum Recurrent Neural Network (QRNN) Do

- Quantum Approach to the classical RNN
  - RNN: Recurrent Neural Network
- **Time-Series** Analysis and Predictions
  - Predict future values based on past data
- Application Examples
  - Weather data
  - Stock Price
  - Natural Language Processing
  - Speech Recognition



(https://towardsdatascience.com/time-series-analysis-basic-concepts-1d9a090d7d8c)

Paper Results on a Triangular Wave and Three-spin Lindblad Dynamics

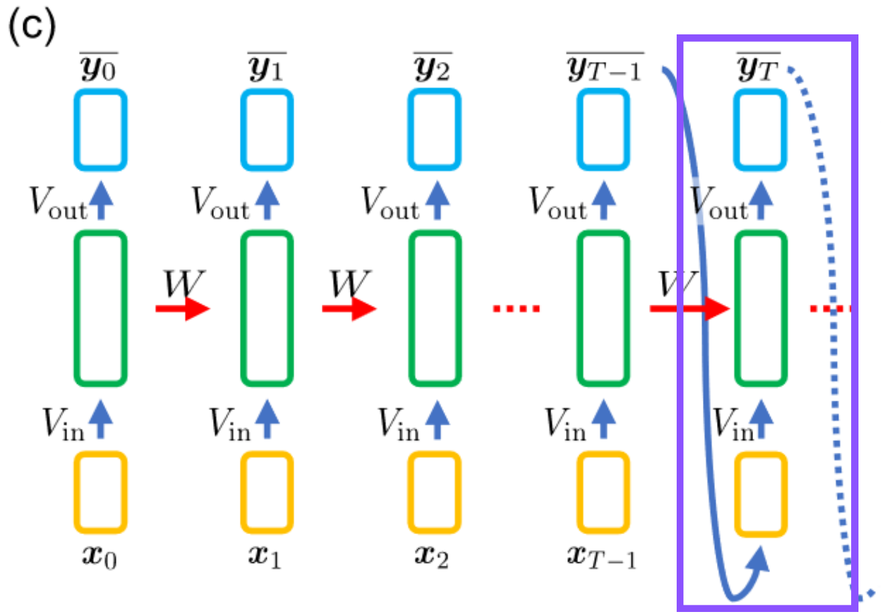


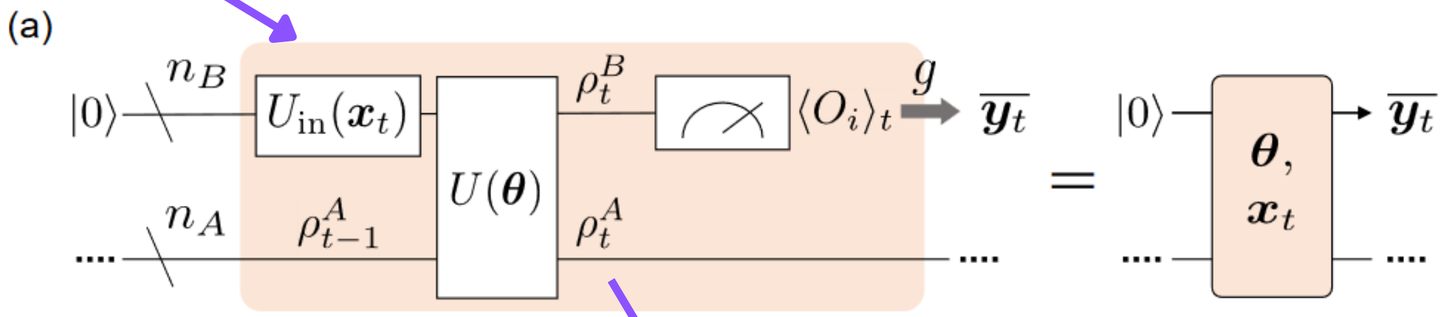
(https://arxiv.org/abs/2012.11242)

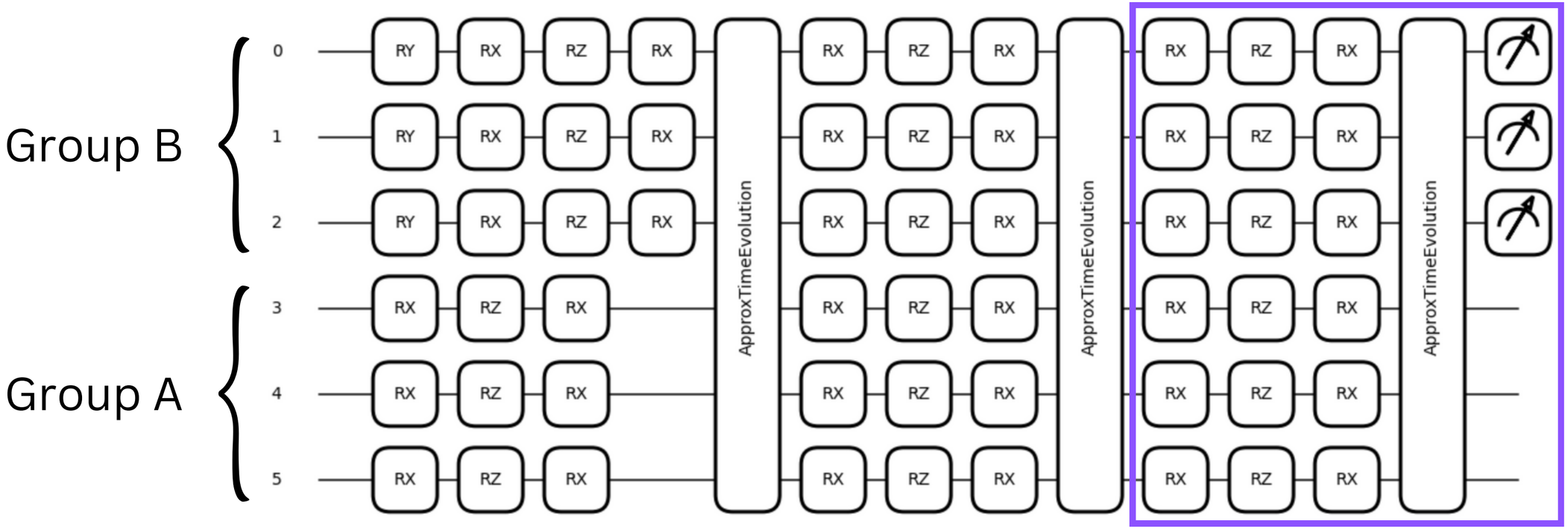
Why PennyLane?

	D-Wave Leap	IBM	Strawberry Fields	PennyLane
Gradient Decent Optimizer ↘	External	Built-In (limited), Automatic	Built-In (limited), Automatic	Built-In, Automatic
Simulation VS. Real HW	Both Available	Both Available	Both Available	Both Available
Mid Circuit Measurement	Not Possible	Possible	Possible (Continuous Variable)	Possible via Another Device
Documentation	High level, arbitrary	Detailed	Super Detailed	Super Detailed

Theory


(c)
$\overline{y_0}$
$\overline{y_1}$
$\overline{y_2}$
$\overline{y_{T-1}}$
$\overline{y_T}$
V_{out}
W
V_{in}
x_0
x_1
x_2
x_{T-1}


(a)
n_B
$|0\rangle$
$U_{\text{in}}(\boldsymbol{x}_t)$
ρ_t^B
$\langle O_i \rangle_t$
g
$\overline{\boldsymbol{y}_t}$
n_A
ρ_{t-1}^A
$U(\boldsymbol{\theta})$
ρ_t^A
$=$
$\boldsymbol{\theta}$,
$\boldsymbol{x}_t$


Group B
Group A
0
1
2
3
4
5
RY
RX
RZ
ApproxTimeEvolution

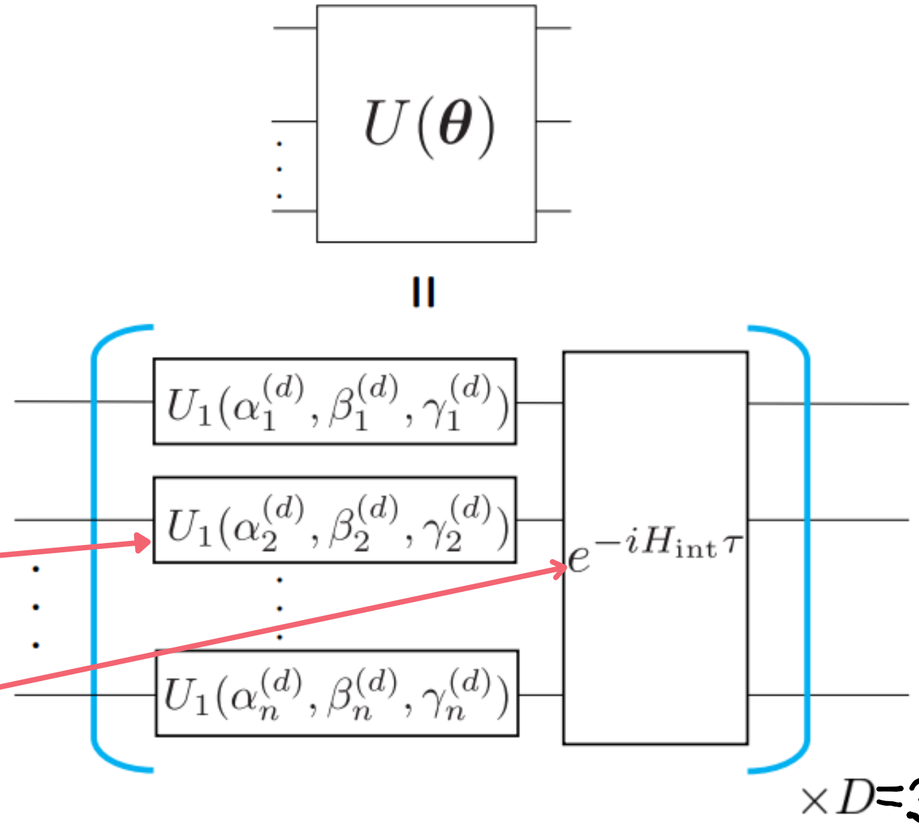
Software Architecture and Implementation

$$U_{\text{in}}(x_t) = R_y(\arccos x_t)$$

- Start by encoding input using *qml.RY*
- U1 rotations using training parameters
- *qml.ApproxTimeEvolution* uses Hamiltonian to evolve the system
  - Smaller tau: less info passed
  - bigger tau makes info too complex for rotations to extract

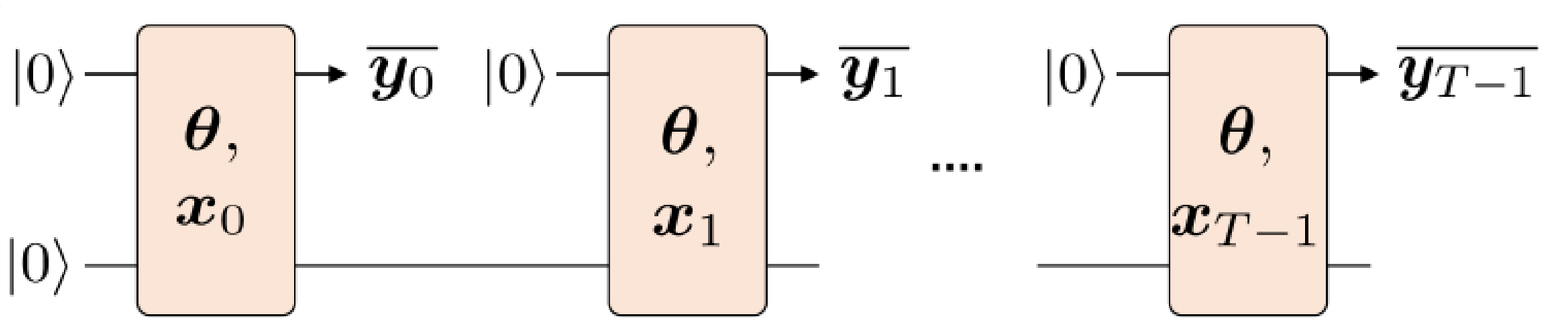
$$U_1(\alpha, \beta, \gamma) = R_x(\alpha) R_z(\beta) R_x(\gamma)$$

$$H_{\text{int}} = \sum_{j=1}^{n} a_j X_j + \sum_{j=1}^{n} \sum_{k=1}^{j-1} J_{jk} Z_j Z_k,$$

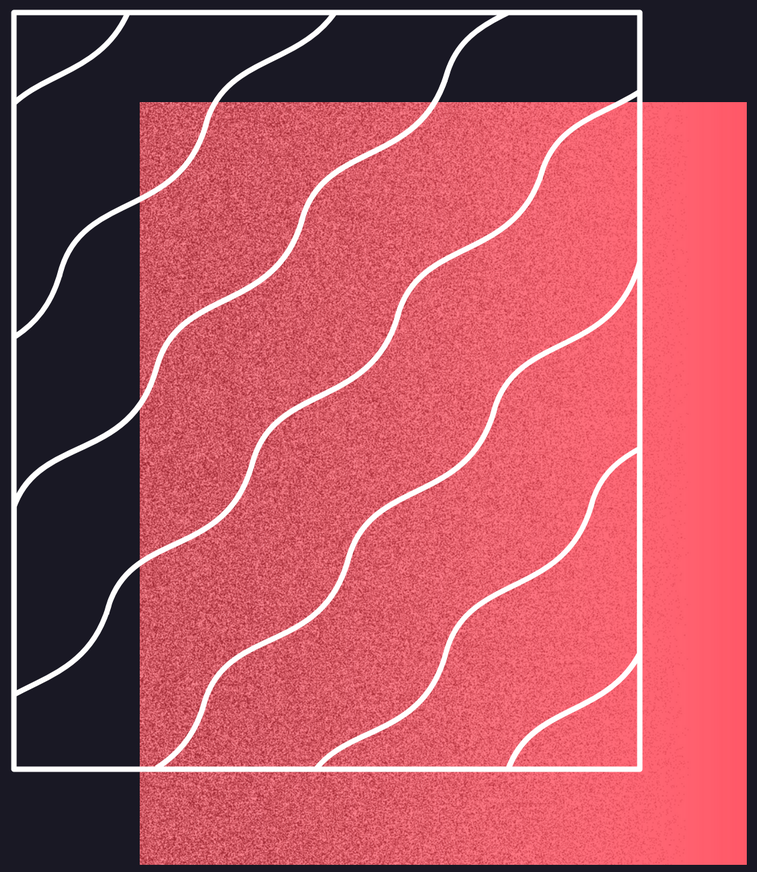


Software Architecture and Implementation (cont...)

- *qml.GradientDescentOptimizer*
  - Same Step and Cost function (and helper functions for computing loss and accuracy) from Lecture 8 demos
    - What's different: accuracy computed using absolute difference between predictions and true value
- Extra device stores previous density matrix so neural network can be trained with past information

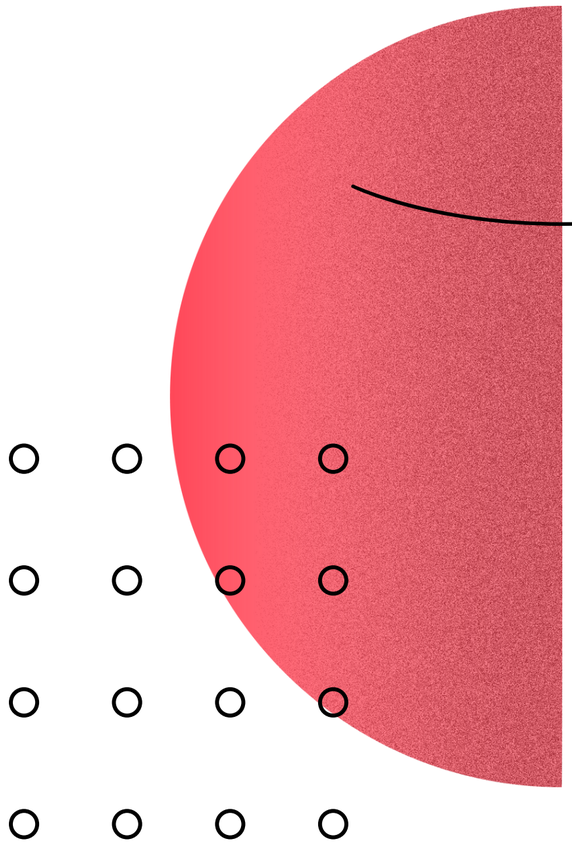


Significance of QRNN



- Utilization of Quantum over classical computer
  - PennyLane
  - Allowed QVA to perform ML tasks - Big step!
- Future application of predicting Quantum Phenomena
- Easy to setup, almost no installment cost
- QRC (Quantum Reservoir Computing) showed promising quantum advantage
  - QRC has similar structure as QRNN

Limitations and Open Questions



- Performance of QRNN vs. RNN?
  - No proof of Quantum advantage yet
- Limitation of Training Data?
  - Triangular wave, cosine wave, and three-spin Lindblad dynamics
- Architectural Challenges
  - Need to measure and reset some Qubit as it runs
    - Some architectures may not support this
  - Time-driven Hamiltonian
    - Needs to keep the state for 0.2 seconds, which is a challenge in real quantum hardware

Future Directions of Exploration

- Display of Quantum Advantage over classical RNN
  - Using real data sets
- Initializing parameters
- Variations on non-periodic but recurring data sets?
- Make tau another trainable parameter?
  - The paper varied tau from 0-10 and performed training of QRNN, then drew a plot of MSE vs. tau