Quantum Recurrent Neural Networks for Multivariate Time Series Prediction

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Some Machine Learning algorithms, like Recurrent Neural Networks (RNNs), analyse time series to predict unknown values of variables in a complex system. When dealing with multi-layer networks and broad series, some issues, such as overfitting or memory losses, arise. Several approaches intend to address them, for example, the Long Short-Term Memory (LSTM) cell. Despite these approaches, learning from multivariate-complex systems is still a challenge and requires networks with many non-linear terms, expensive to compute on classical devices.

Quantum Computation emerges as a promising approach to tackle complex problems more efficiently since it allows to compute non-linear terms in a high dimensional space without spending exponential resources. We propose a Quantum RNN (QRNN) model as a first step towards multivariate time series forecasting. The core of QRNN is a parameterized quantum circuit that iteratively exchanges information, but, at the same time, it keeps memory from past data.

1. Motivation

Some applications of Time Series

Finance
- Stock prices
- Financial crashes

Meteorology-geology
- Weather forecasting
- Earthquake prediction

Medicine
- Electroencephalography

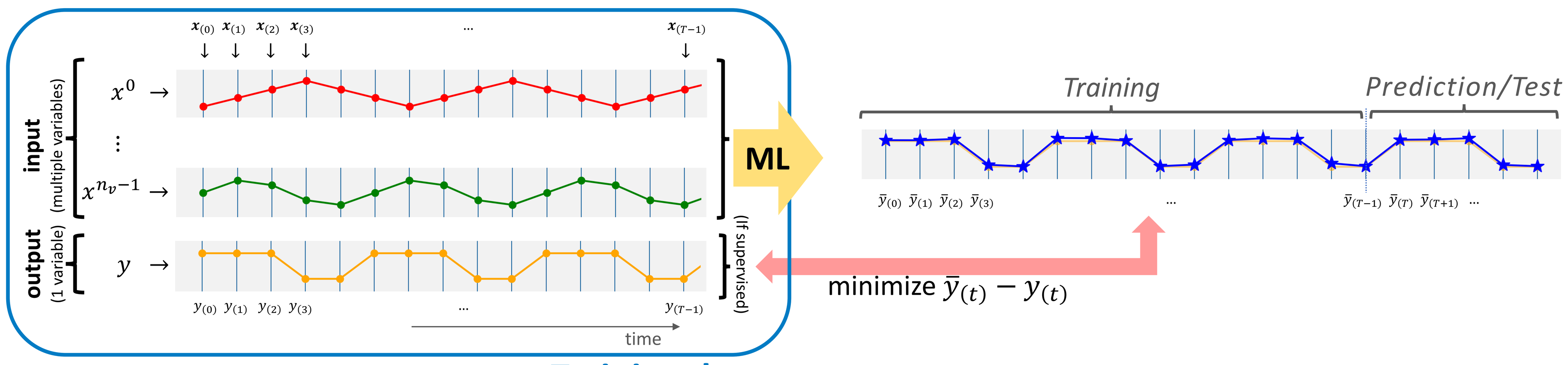
Artificial Intelligence
- Natural language
- Speech recognition

Industry
- Data from sensors

Common issues
- Large sequences
- High non-linearity
- High dimensionality

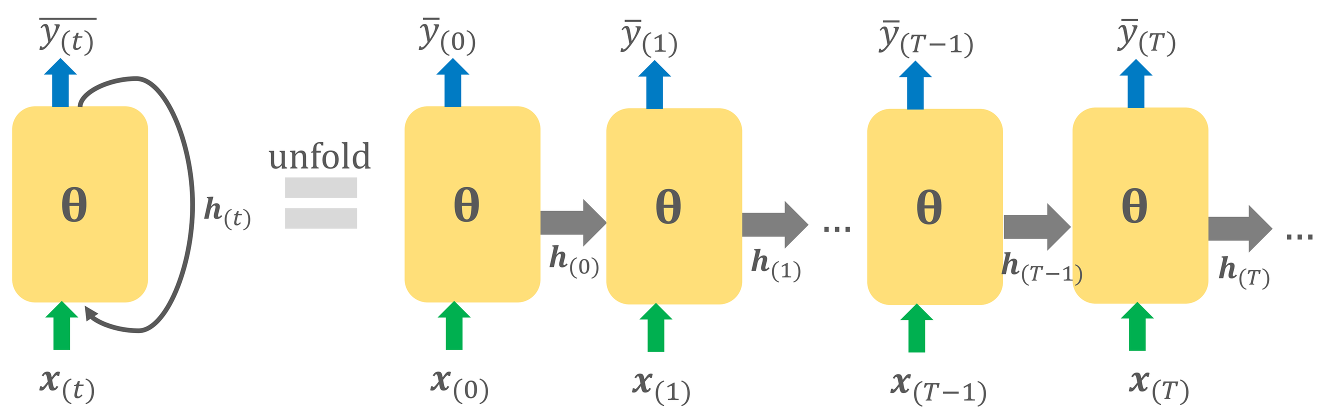
2. Multivariate time series

Our **objective** is to have a Machine Learning (ML) algorithm that models **multivariate time series**.



Training data

3. The Classical RNN model



The supervised RNN cell receives a multivariate input at each time and returns:
- an estimation as **output**, $\overline{y_{(t)}}$,
- a **hidden state**, $h_{(t)}$.

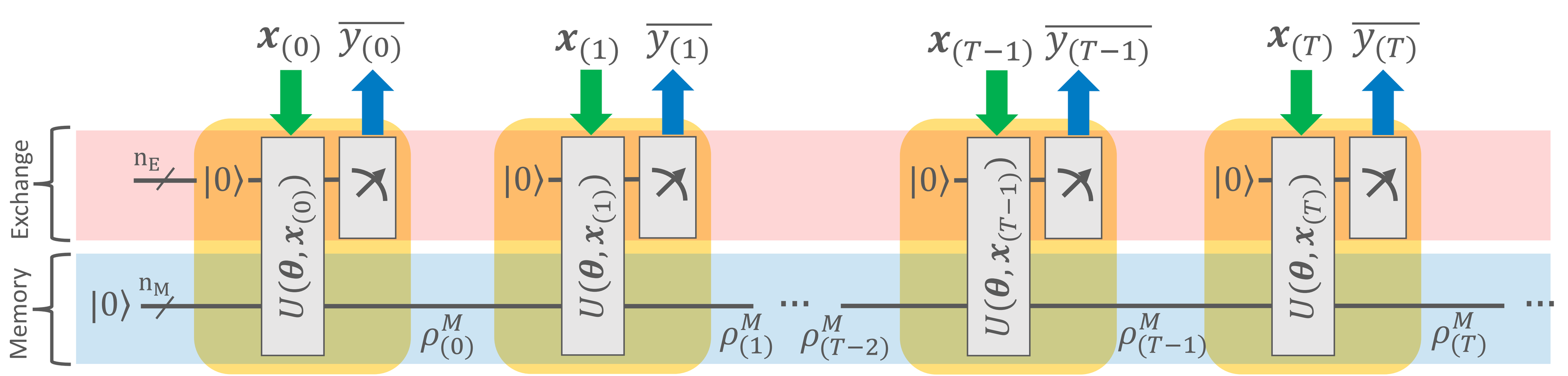
The latter is reintroduced inside the cell recurrently.

We show the cell and its unfolded representation through time [1].

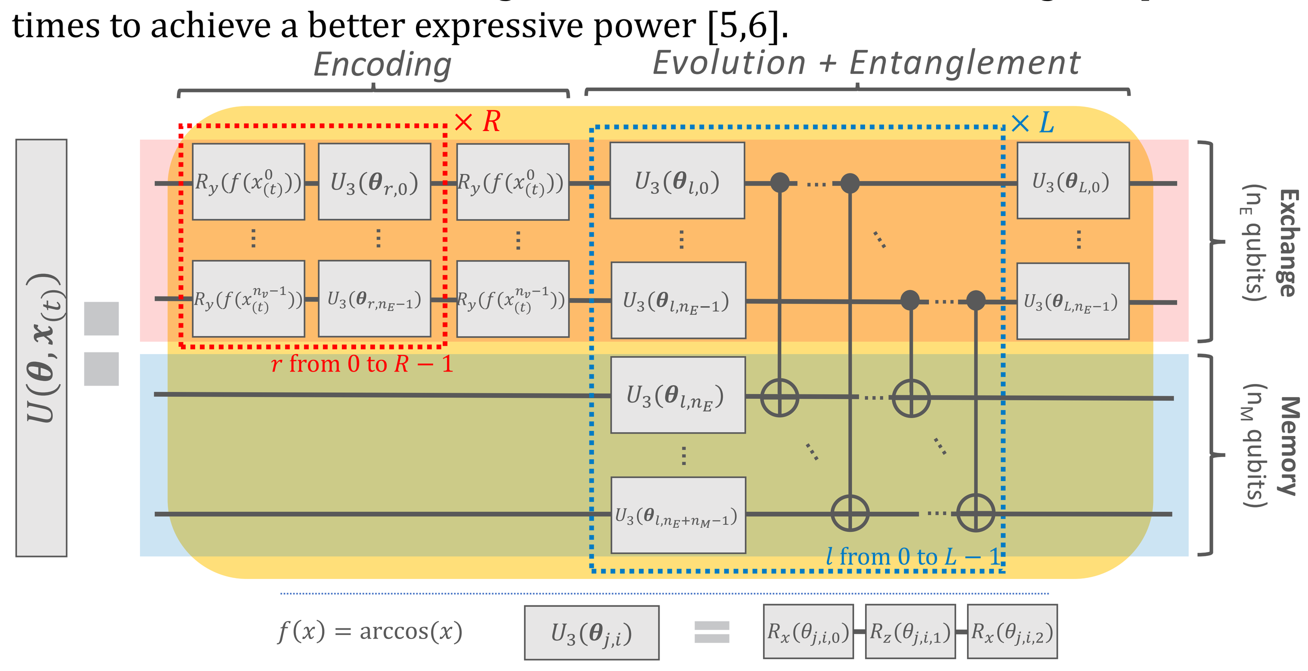
4. The QRNN circuit structure

The QRNN circuit is inspired in the classical RNN, by dividing the qubits into two groups [2,3]:
- **Exchange register (E)**: recurrently, it receives and measures classical data.
- **Memory register (M)**: it is never measured, keeping previous information.

The unitary U encodes data into the circuit, applies an evolution depending on the set of parameters $\boldsymbol{\theta}$ and entangles qubits from E to M, transporting information between the two registers.



This is the unitary U for multivariate inputs, similar to the proposal in ref. [4], a hardware-efficient ansatz for gate-based devices. Data encoding is repeated R times to achieve a better expressive power [5,6].



5. Results

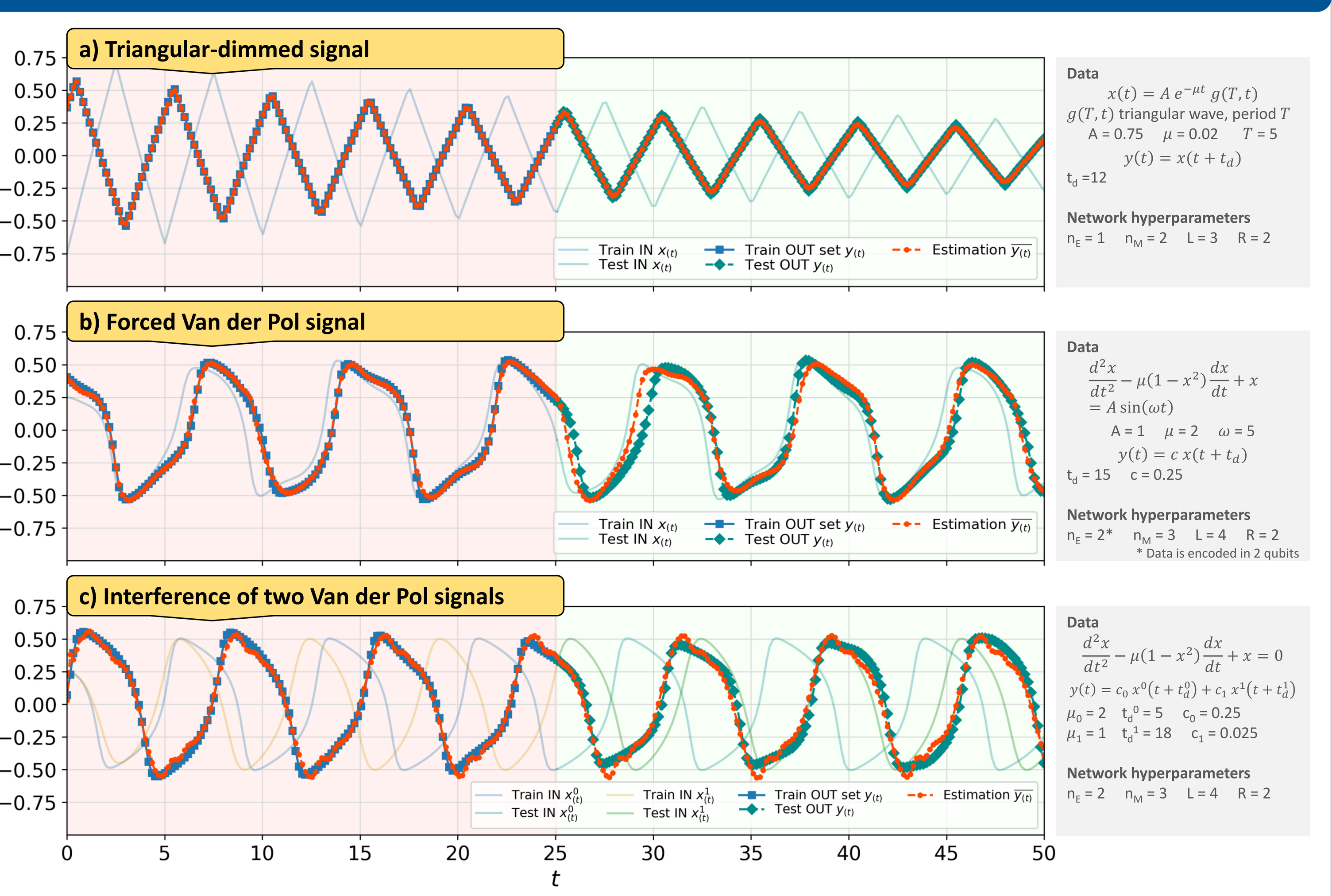
We use our QRNN model to **predict** future values from a known series. At a time t, the network takes the vector $\boldsymbol{x}_{(t)} = \left(x^0_{(t)}, \dots, x^{n_V-1}_{(t)}\right)$ and estimates a value $\overline{y_{(t)}}$, which corresponds to a magnitude that depends on the inputs with different delays.

- **Cost function**: root mean square error (RMSE) between the network's outputs $\overline{y_{(t)}}$ and the references $y_{(t)}$.
- **Parameters**: set $\boldsymbol{\theta}$ for rotation gates, scaling factor a, bias b.

$$\overline{y_{(t)}} = a \cdot \left(\langle Z^{\otimes n_E} \rangle(\boldsymbol{x}, \boldsymbol{\theta})\right)_{(t)} + b$$

- **Optimisation**: minimisation of the RMSE by **L-BFGS-B** method; random initialisation of $\boldsymbol{\theta}$.

The circuit is ideally emulated with a **density matrix emulator**.



6. Perspectives

Conclusions for this work:
- The presented QRNN model can learn a multivariate series and predict the behaviour of a univariate series that depends on it.
- With a small number of qubits we achieve a good convergence, by adding multiple entanglement layers.

Next steps:
- Simulation with noise and sampling.
- Explore other optimisation techniques: stochastic and genetic algorithms.
- Training noisy data.

References

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