Week 2 presentation

Quantum Machine learning beyond kernel methods

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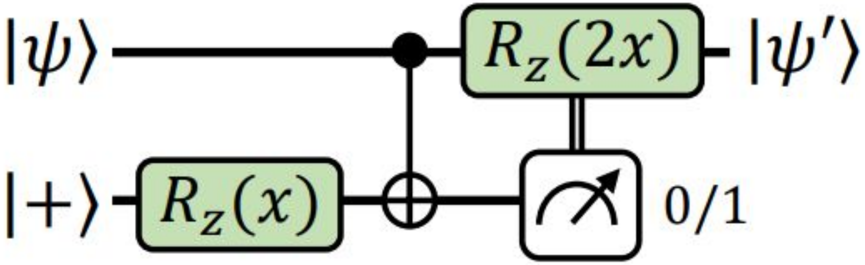
Quantum Gate-teleportation technique:

- Enables the application of quantum operations between spatially separated qubits without requiring direct interaction between the qubits.
- Leads to Drastic reductions in the communication required for distributed quantum protocols.
- We simulate the encoding gates in data-reuploading model of the form $R_z(h(\boldsymbol{x})) = e^{-\mathrm{i}h(\boldsymbol{x})Z/2}$

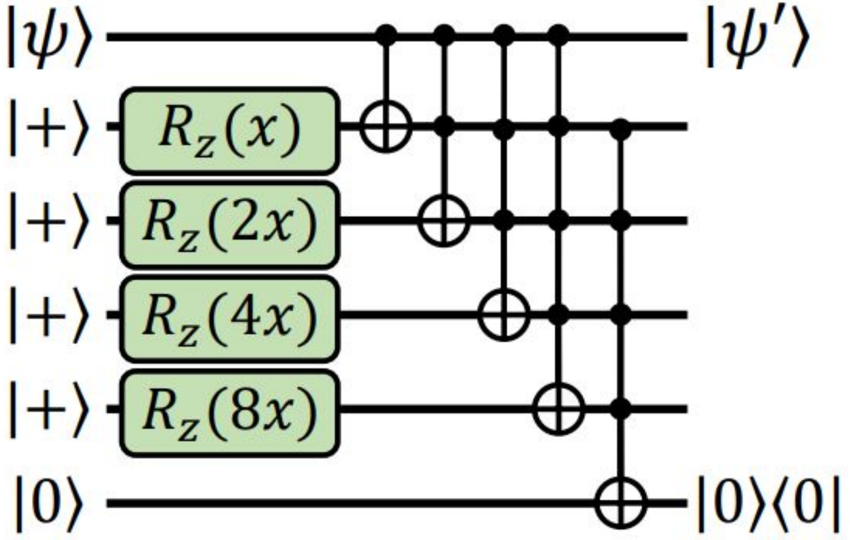
State before measurement:

$$\frac{1}{\sqrt{2}}\left(R_z(x)\left|\psi\right\rangle \otimes \left|0\right\rangle + e^{\mathrm{i}x} R_z(-x)\left|\psi\right\rangle \otimes \left|1\right\rangle\right)$$

- This gadget moves all data-dependent parts of the circuit on additional ancilla qubits, essentially turning it into an explicit mode



- Nested gadget for all D encoding gates in the circuit, the probability that all of them are implemented successfully without corrections is the $p = (1 - 2^{-N})^D$
- This gives the exact mapping from the data re-uploading to an equivalent explicit model in an exact way $\mathrm{Tr}[\rho'(\boldsymbol{x})O'_{\boldsymbol{\theta}}] = \mathrm{Tr}[\rho(\boldsymbol{x},\boldsymbol{\theta})O_{\boldsymbol{\theta}}]$



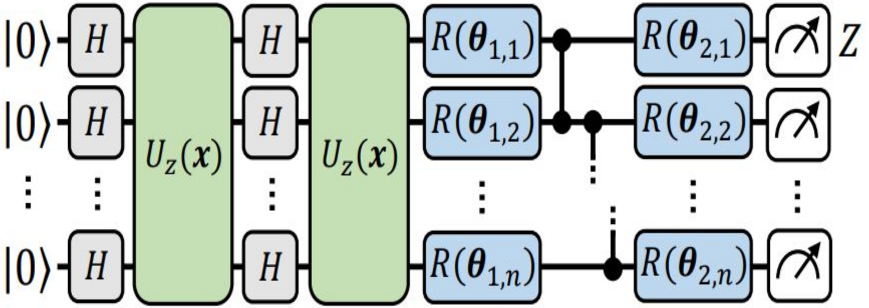
Dataset generation:

- Fashion MNIST dataset (28x28) $\longrightarrow$ PCA $\longrightarrow$ embedded onto 2≤n≤12 qubits.
- For M=1000 samples, the labels of data points are generated by an explicit model with (3nL) no. of parameters

$$U_\phi(\boldsymbol{x})\left|0^{\otimes n}\right\rangle = U_z(\boldsymbol{x}) H^{\otimes n} U_z(\boldsymbol{x}) H^{\otimes n}\left|0^{\otimes n}\right\rangle$$

for

$$U_z(\boldsymbol{x}) = \exp\left(-\mathrm{i}\pi\left[\sum_{i=1}^{n} x_i Z_i + \sum_{\substack{j=1,\\ j>i}}^{n} x_i x_j Z_i Z_j\right]\right)$$



Final labels are given by the generating function (expectation value of Z_1 observable) :

$$g(\boldsymbol{x}) = w_{\mathcal{D},\boldsymbol{\theta}} \operatorname{Tr}[\rho(\boldsymbol{x}) V(\boldsymbol{\theta})^\dagger Z_1 V(\boldsymbol{\theta})]$$

- w is a re-normalization factor that sets the standard deviation of these labels to 1 over the training set

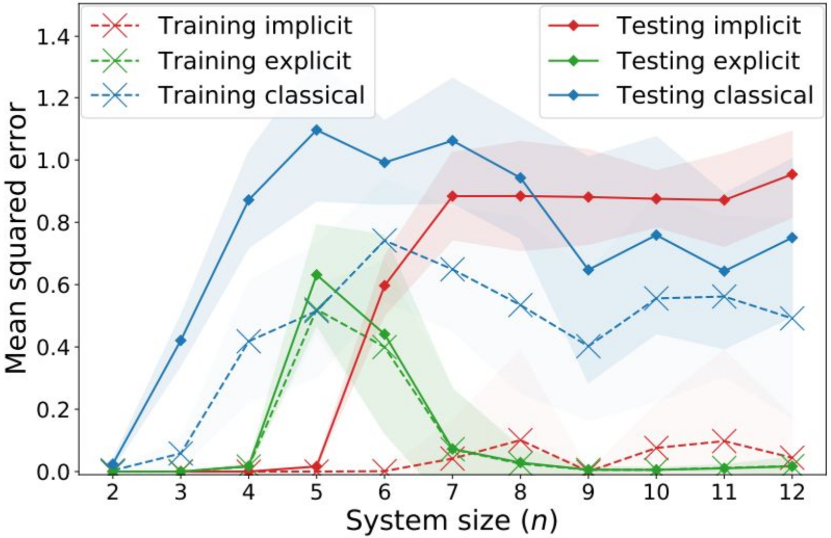


Fig: Best performance of implicit models for different regularization strengths.

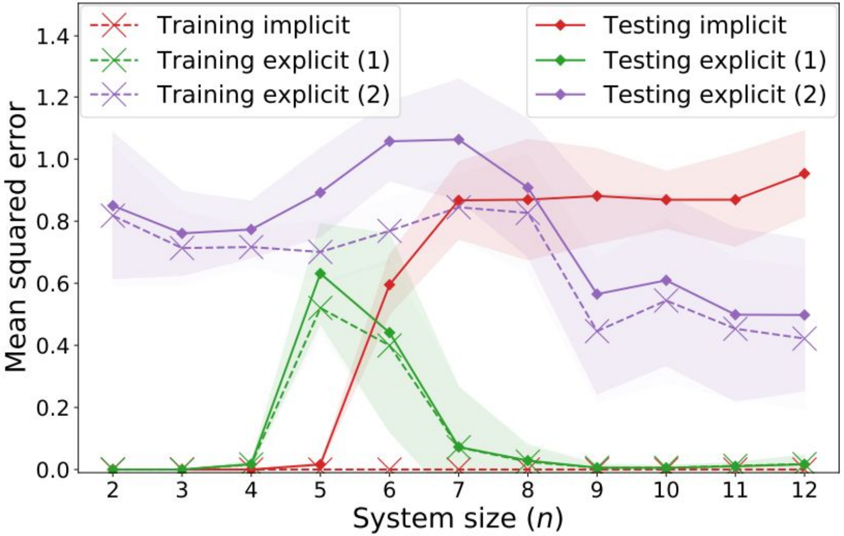


Fig: Regression performance of explicit models from the same variational family as the models generating the data labels (1) and from a different variational family (2).