Quantum Machine Learning - doing ML using QC

Machine Learning

$\mathcal{M}$: model;

$\mathcal{O}$: optimizer;

$\mathcal{J}$: loss function.

(x, y): data

Quantum Computation

$\mathcal{Q}$: qubits;

$\mathcal{S}$: superposition;

$\mathcal{E}$: entanglement.

Quantum Machine Learning - operating on qubits

Machine Learning

$\mathcal{M}$: model;

$\mathcal{O}$: optimizer;

$\mathcal{J}$: loss function.

(x, y): data

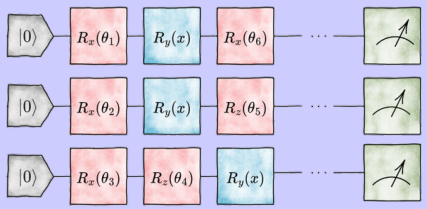
Quantum Computation

$\mathcal{Q}$: qubits;

$\mathcal{S}$: superposition;

$\mathcal{E}$: entanglement.

VQC execution



Quantum Machine Learning - natural randomness

Machine Learning

$\mathcal{M}$: model;

$\mathcal{O}$: optimizer;

$\mathcal{J}$: loss function.

(x, y): data

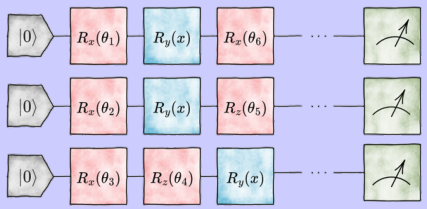
Quantum Computation

$\mathcal{Q}$: qubits;

$\mathcal{S}$: superposition;

$\mathcal{E}$: entanglement.

VQC execution



Expected values

$y_{est} \equiv \langle q_f | B | q_f \rangle$

Quantum Machine Learning - encoding the problem

Machine Learning

$\mathcal{M}$: model;

$\mathcal{O}$: optimizer;

$\mathcal{J}$: loss function.

(x, y): data

Expected values

$y_{est} \equiv \langle q_f | B | q_f \rangle$

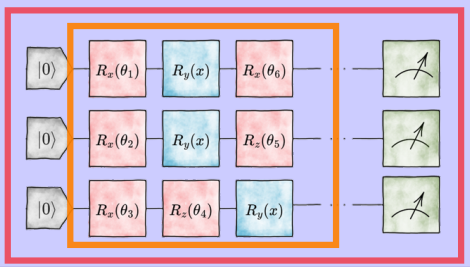
Quantum Computation

$\mathcal{Q}$: qubits;

$\mathcal{S}$: superposition;

$\mathcal{E}$: entanglement.

VQC execution



Quantum Machine Learning!

Optimizer $\mathcal{O}$
Hybrid-strategy

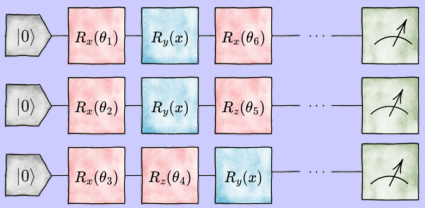
Machine Learning
$\mathcal{M}$: model;
$\mathcal{O}$: optimizer;
$\mathcal{J}$: loss function.
(x, y): data

loss function $\mathcal{J}$
$\mathcal{J}(y_{meas}, y_{est})$

Expected values
$y_{est} \equiv \langle q_f | B | q_f \rangle$

Quantum Computation
$\mathcal{Q}$: qubits;
$\mathcal{S}$: superposition;
$\mathcal{E}$: entanglement.

VQC execution



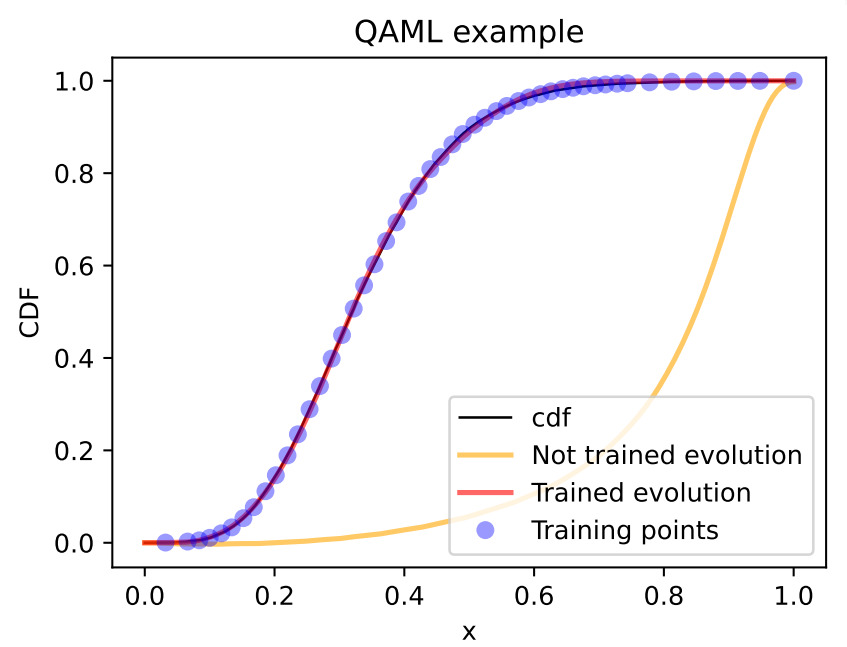
Density estimation with adiabatic QML

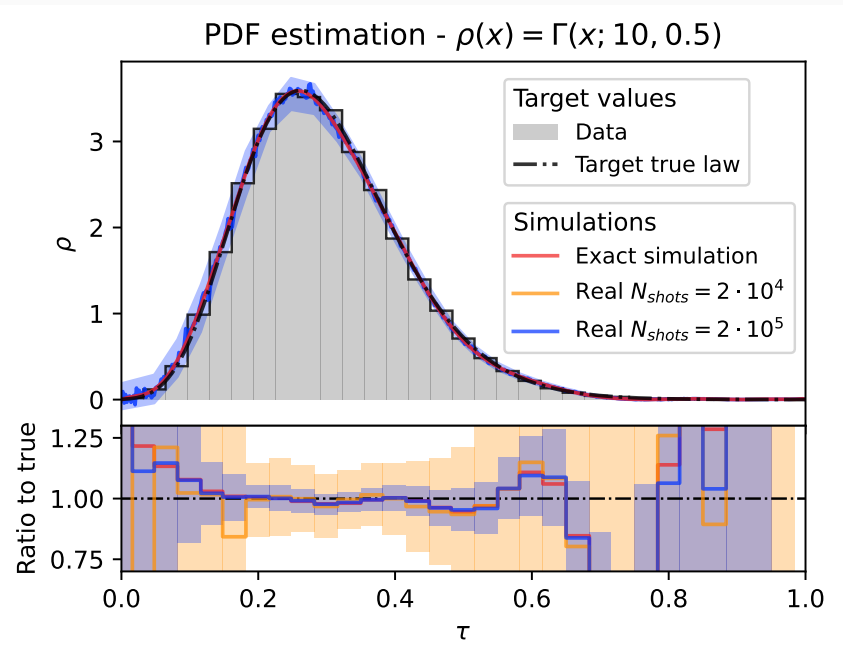
arXiv:2303.11346

Determining Probability Density Functions (PDF) by fitting the corresponding Cumulative Density Function (CDF) using an adiabatic QML ansatz.

Algorithm's summary:

1. we optimize the parameters $\boldsymbol{\theta}$ of the following adiabatic evolution:
$$H_{\mathrm{ad}}(\tau;\boldsymbol{\theta}) = [1 - s(\tau;\boldsymbol{\theta})]\hat{X} + s(\tau;\boldsymbol{\theta})\hat{Z} \tag{1}$$
in order to approximate some target CDF values with $\hat{F}(x_k \equiv \tau) = \langle\psi(\tau)|\hat{Z}|\psi(\tau)\rangle$;
2. we derivate from H_{ad} a circuit $\mathcal{C}(\tau;\boldsymbol{\theta})$ whose action on the GS of $\hat{X}$ returns $|\psi(\tau)\rangle$;
3. the circuit at step 2. can be used to calculate the CDF;
4. we compute the PDF by derivating $\mathcal{C}$ with respect to τ using the Parameter Shift Rule.





Multi-variable integration with VQCs

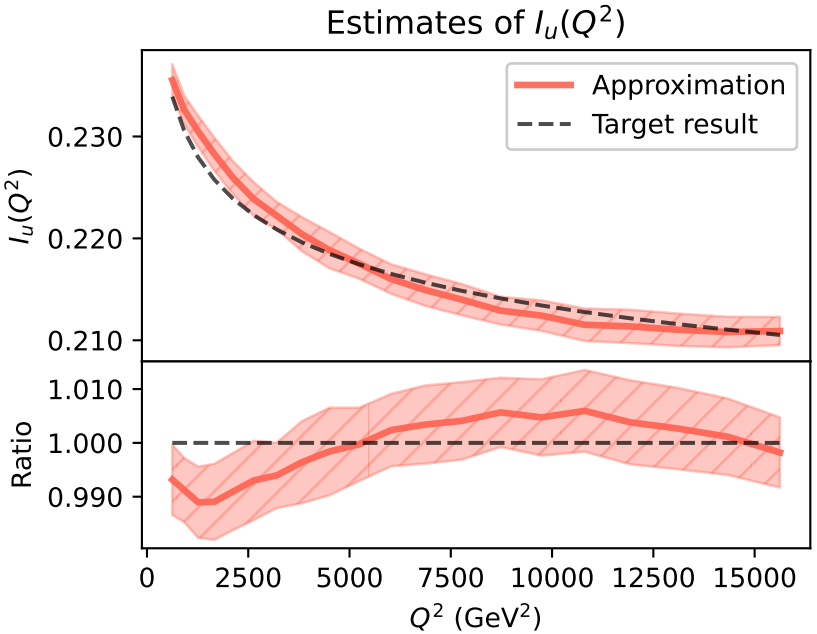
arXiv:2308.05657

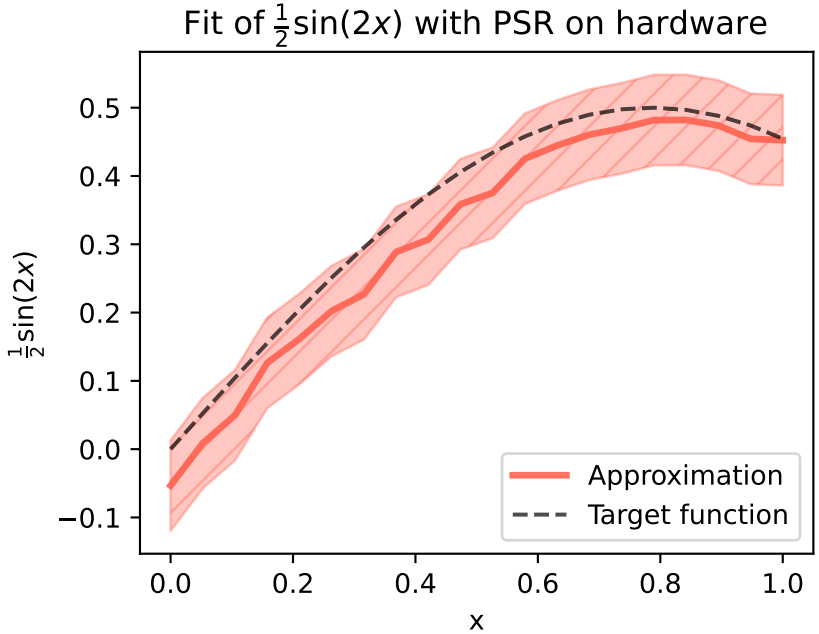
- Use Variational Quantum Circuits to calculate multi-dimensional integrals of the form:

$$I(\alpha) = \int_{x_a}^{x_b} g(\alpha; \boldsymbol{x}) \mathrm{d}^n \boldsymbol{x}. \tag{2}$$

- Algorithm's summary:

1. inspired by arXiv:2211.02834, we train the derivative of a VQC with respect to the integral variables $\boldsymbol{x}$ to approximate the integrand $g(\boldsymbol{x})$;
2. the derivatives are computed using the Parameter Shift Rule and this allows the same circuit $\mathcal{C}$ to be used for approximating any integrand marginalisation and the primitive!
3. thanks to 2., it's much more convenient to compute Eq. (2) when varying α.





Real time error mitigation in QML trainings

Coming soon!

Cleaning up the parameters space with a real time error mitigation strategy in order to overcome Noise-Induced Barren Plateaus (NIBP) when training a QML model.

Algorithm's summary:

1. we mitigate all the expected values E through Clifford Data Regression (CDR):

$$E_{\text{mit}} = \alpha_{\text{cdr}} E_{\text{noisy}} + \beta_{\text{cdr}}; \tag{3}$$

2. reduced CDR computational cost by updating $(\alpha, \beta)_{\text{cdr}}$ periodically during the training;
3. the mitigation removes the bounds and accelerate the training process.