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

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VQC execution
$\mathcal{M}$, $\mathcal{S}$, $\mathcal{E}$
$\mathcal{U}(\boldsymbol{\theta})\,|q_i\rangle \rightarrow |q_f\rangle$

Quantum Machine Learning - natural randomness

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Expected values
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Quantum Machine Learning!

Optimizer $\mathcal{O}$
Hybrid-strategy

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

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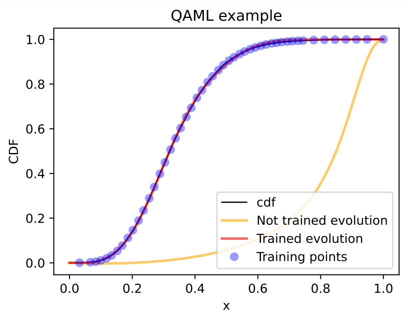
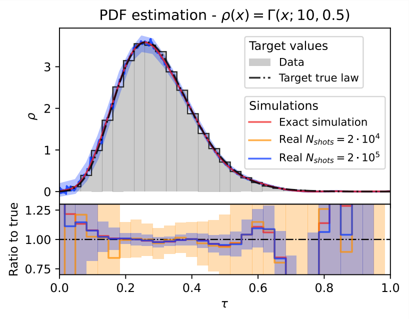
Density estimation with adiabatic QML — arXiv:2303.11346

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:
$$H_{\rm ad}(\tau;\boldsymbol{\theta}) = [1 - s(\tau;\boldsymbol{\theta})]\hat{X} + s(\tau;\boldsymbol{\theta})\hat{Z} \tag{1}$$
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 $H_{\rm ad}$ 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.



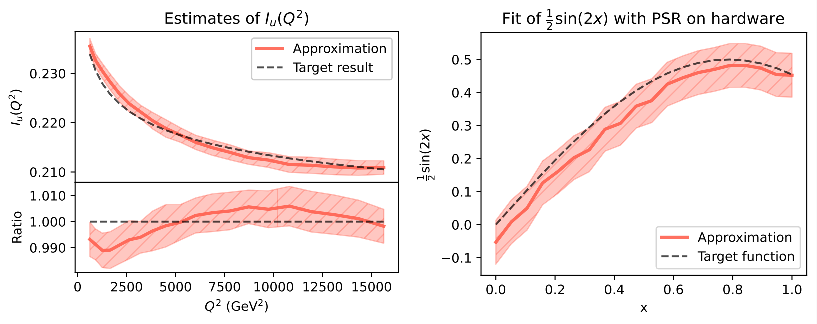


- Use Variational Quantum Circuits to calculate multi-dimensional integrals of the form:

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

- 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):

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

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