Full-Stack Quantum Machine Learning

Matteo Robbiati

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Introduction to concepts

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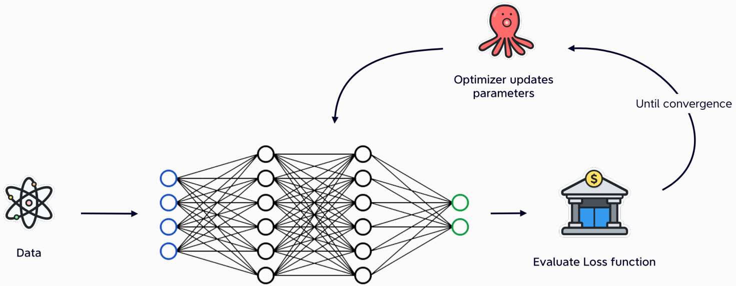

Parametric Quantum Circuits

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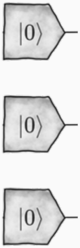

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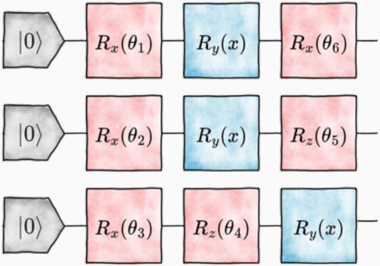

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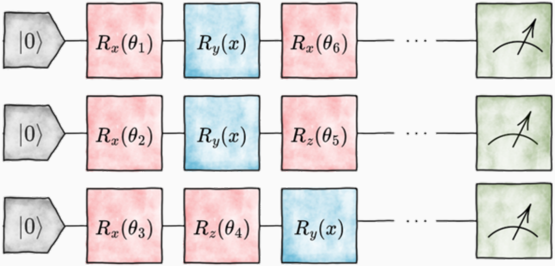
- information is accessed calculating expected values $\mathrm{E}[\hat{O}]$ of target observables $\hat{O}$ on the state obtained executing $\mathcal{C}$.



Quantum Machine Learning

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;
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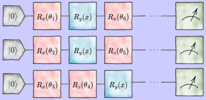

Quantum Machine Learning - natural randomness

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Expected values

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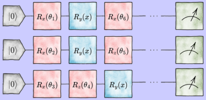

Quantum Machine Learning - encoding the problem

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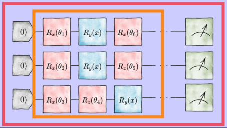

Quantum Machine Learning!

Optimizer $\mathcal{O}$
Hybrid-strategy

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

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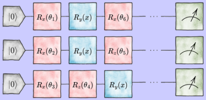
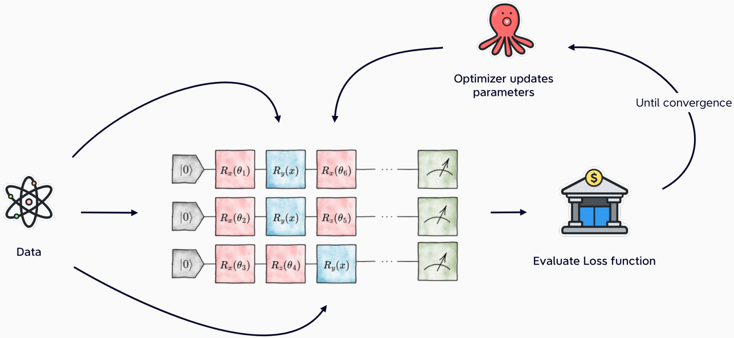


From ML to QML



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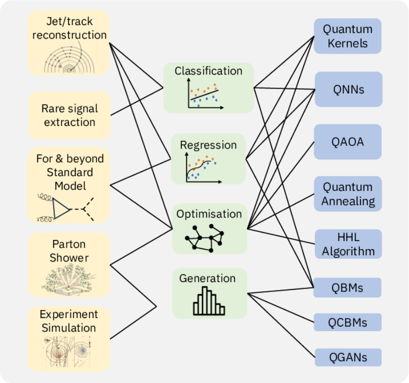

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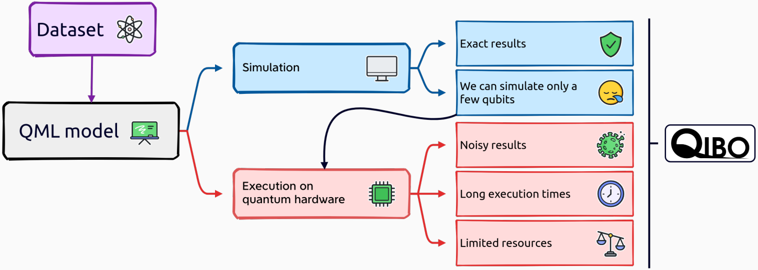
Full-stack QML



Some results

High level API: Qibo

- </> define **prototypes** and models;
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A full-stack PDF fit

arXiv:2308.06313

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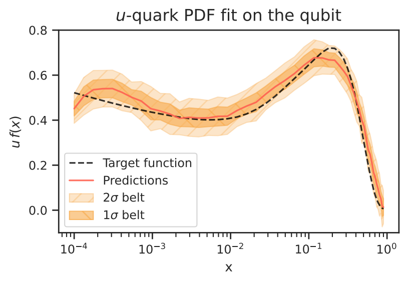

Parameter	Value
N_{data}	50
N_{shots}	500
MSE	$\sim 10^{-3}$
Electronics	Xilinx ZCU216
Training time	$\sim$ 2h

Some applications

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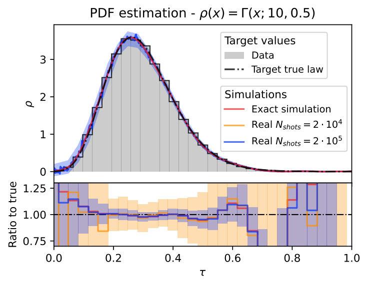

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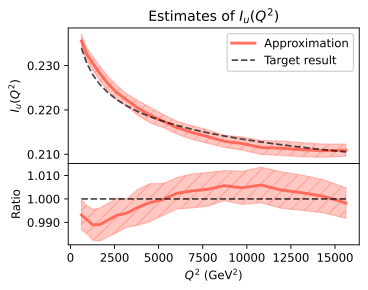
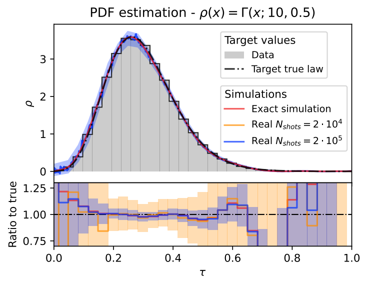
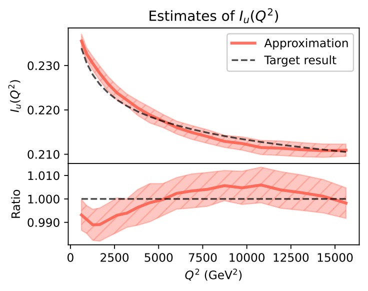
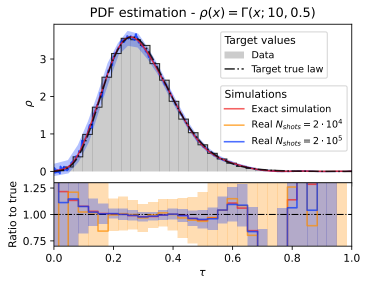
- Multi-dimensional integration using Variational Quantum Circuits, arXiv:2303.11346;

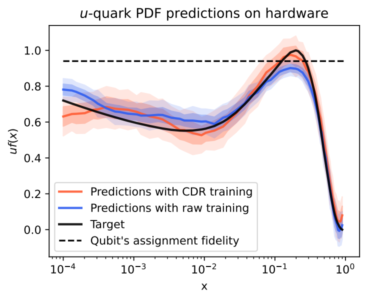




- Density estimation via Adiabatic Quantum Machine Learning, arXiv:2303.11346;
- Multi-dimensional integration using Variational Quantum Circuits, arXiv:2303.11346;
- Real-Time Quantum Error Mitigation to improve QML trainings, Coming soon!







Perspective

"One big challenge in the next three to five years is to figure out how to use the quantum hardware to improve a task in practice".

Iordanis Kerenidis.

Questions?

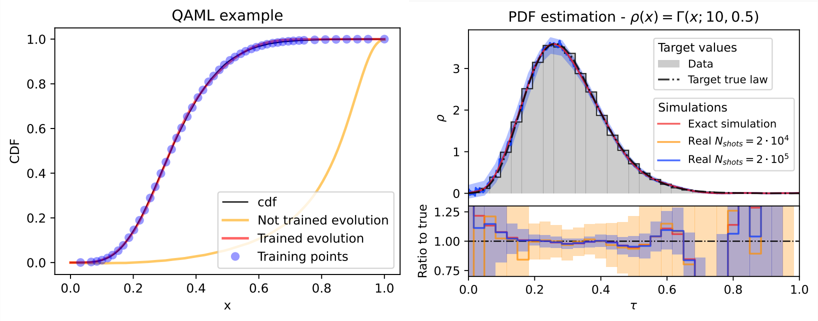
Determining PDFs with adiabatic quantum computing

- Determining Probability Density Functions (PDF).
- Algorithm's summary:

1. we optimize the parameters $\boldsymbol{\theta}$ of the following adiabatic evolution:

$$H_{\rm ad}(\tau;\boldsymbol{\theta}) = [1 - s(\tau;\boldsymbol{\theta})]\hat{\sigma}_x + s(\tau;\boldsymbol{\theta})\hat{\sigma}_z. \tag{1}$$

   we use the GS of the evolved $H_{\rm ad}$ to approximate the Cumulative Density Function (CDF);
2. we derivate from $H_{\rm ad}$ a circuit $\mathcal{C}(\tau;\boldsymbol{\theta})$ whose action on the GS of $\hat{\sigma}_x$ returns $|\psi(\tau)\rangle$;
3. we compute the PDF by derivating $\mathcal{C}$ w.r.t. τ using the Parameter Shift Rule (PSR).



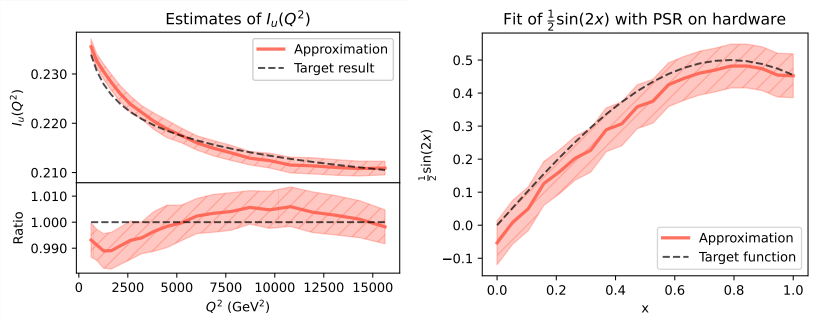
Multi-dimensional integration on hardware

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

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

- Algorithm's summary:

1. we train the derivative of a VQC w.r.t. the integral variables $\boldsymbol{x}$ to approximate $g(\boldsymbol{x})$;
2. we compute the derivatives using the PSR, which allows the same circuit $\mathcal{C}$ to be used for approximating any integrand marginalisation and the primitive! when varying α.



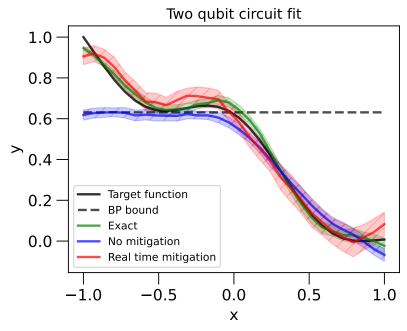
Real time error mitigation in QML trainings

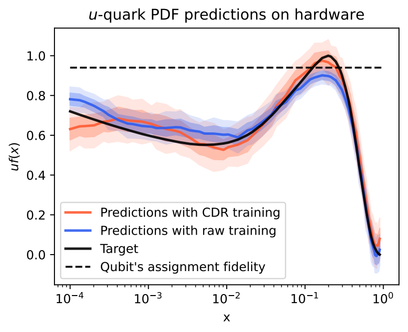
- Use Error Mitigation techniques to clean up the parameters space during the QML training.
- Algorithm's summary:

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

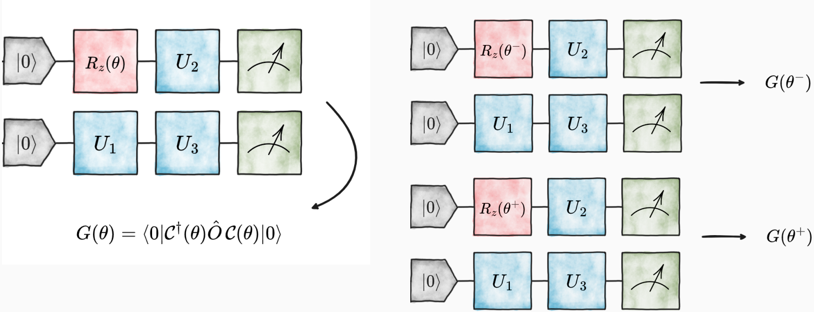
$$E_{\mathrm{mit}} = \alpha_{\mathrm{cdr}} E_{\mathrm{noisy}} + \beta_{\mathrm{cdr}}; \tag{3}$$

2. we update $(\alpha, \beta)_{\mathrm{cdr}}$ periodically during the training in order to track the noise;
3. the mitigation removes the bounds and accelerates the training process.





Parameter Shift Rule



The same circuit is executed twice with a shifted target parameter θ, then an exact evaluation of the derivative is given by:

$$\partial_\theta G = r\big[G(\theta^+) - G(\theta^-)\big].$$

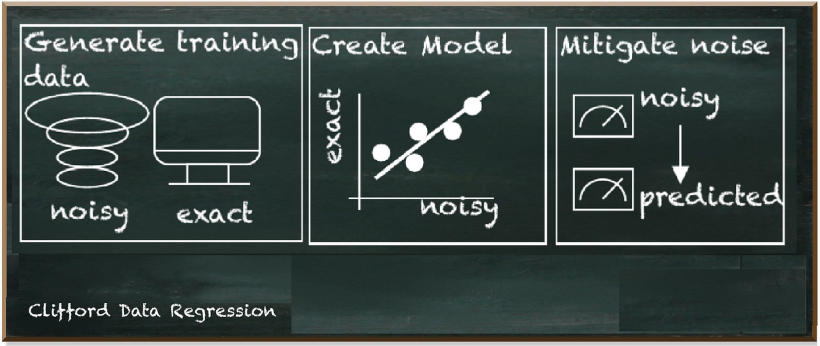


Figure 1: Credits: Frank Zickert.