Full-stack Quantum Machine Learnig

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A snapshot of Quantum Computing

Quantum Computing and circuits notation

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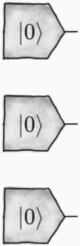

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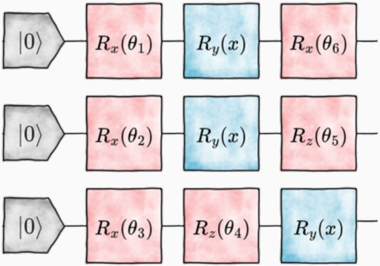

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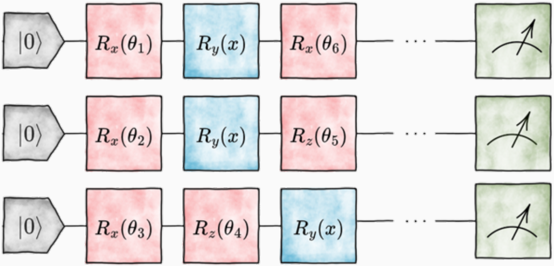
- we extract information by calculating expected values:

$$\langle q_i | \mathcal{C}^\dagger(\boldsymbol{\theta}) \hat{O}\, \mathcal{C}(\boldsymbol{\theta}) | q_i \rangle\,,$$

with $\mathcal{C}(\boldsymbol{\theta})$ parametric circuit, $|q_i\rangle$ initial qubit's state and $\hat{O}$ arbitrary observable.



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;
$\mathcal{E}$: entanglement.

Quantum Machine Learning - operating on qubits

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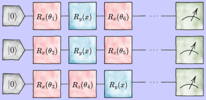

Quantum Machine Learning - natural randomness

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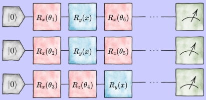

Expected values

$y_{est} \equiv \langle q_f | \hat{O} | q_f \rangle$

Quantum Machine Learning - encoding the problem

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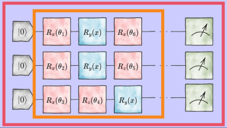

Quantum Machine Learning!

Optimizer $\mathcal{O}$
Hybrid-strategy

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

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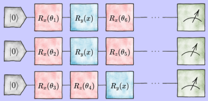
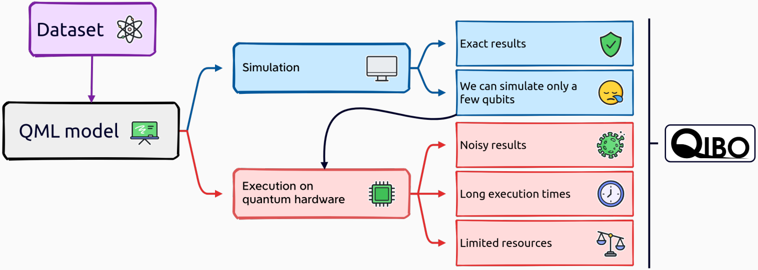


Full-stack QML



Some results

High level API: Qibo

- </> define prototypes;
- </> implement training loop;
- </> simulate training.

A full-stack PDF fit — arXiv:2308.06313

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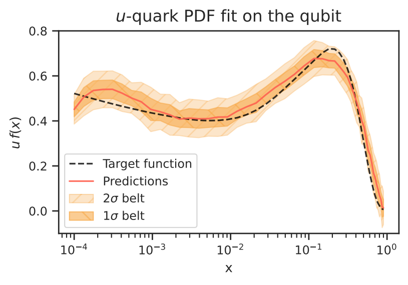
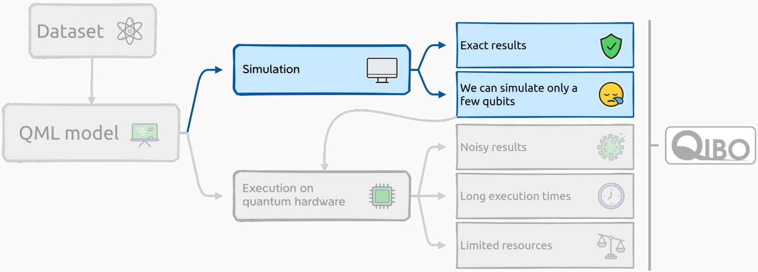


Parameter	Value
N_{data}	50
N_{shots}	500
MSE	50
Electronics	Xilinx ZCU216
Training time	2h

Simulation as first approach



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We work on the algorithmic part   arXiv:2303.11346

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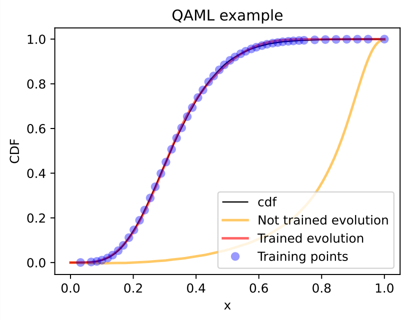

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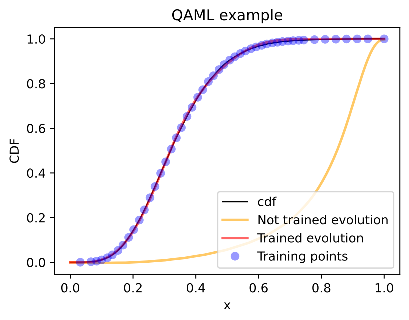
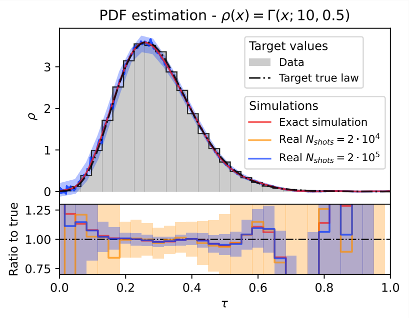
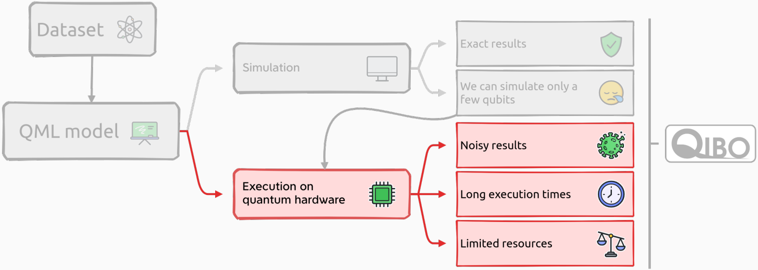




How does my algorithm perform on a real quantum computer?



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

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Multi-dimensional integration on hardware arXiv:2308.05657

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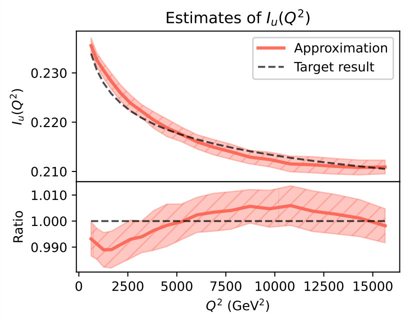

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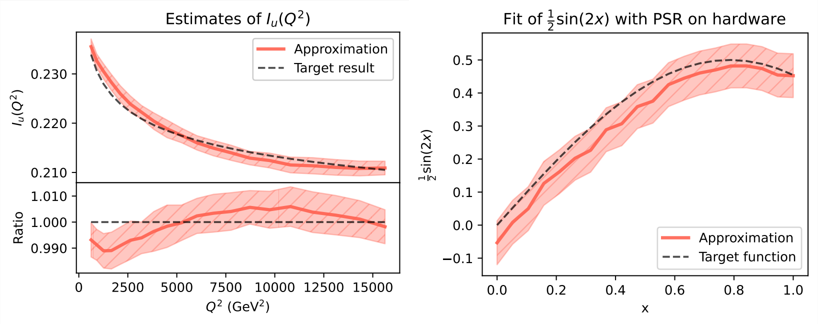
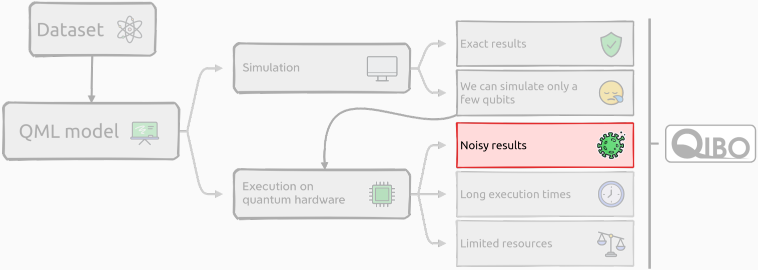


How to deal with noise?



Real time error mitigation in QML trainings

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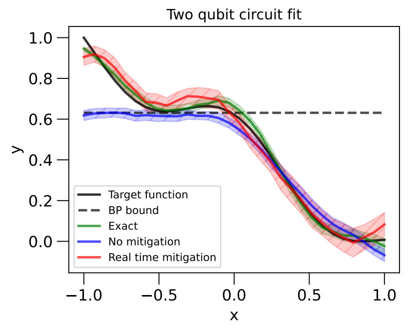

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