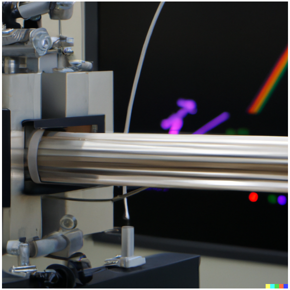
Full-stack Quantum Machine Learning for HEP

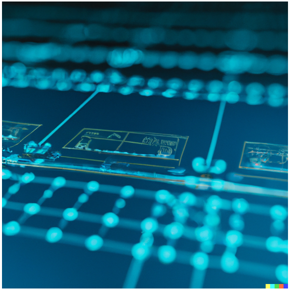
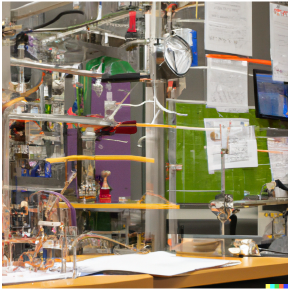
MCM23

Matteo Robbiati

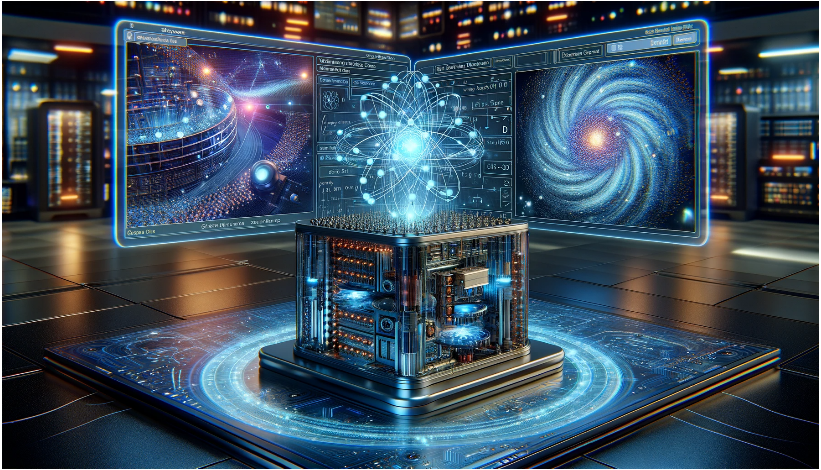
20 December 2023

DALL-E 2 explaining my title



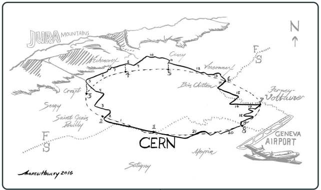



DALL-E 3 explaining my title

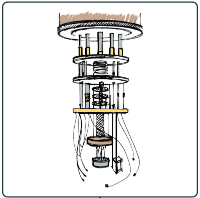


Me explaining my title

High Energy Physics



Quantum computers



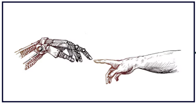
Plenty of data to analyze

Need for technological development

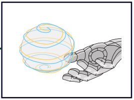
Computational boost (problem specific)

Noise and limited resources

- Simulation
- Control
- Calibration



“ For HEP! ”



“ Quantum Machine Learning ”

“ Full-Stack ”

Introductory concepts

Machine Learning (ML)

ML helps in solving statistical problems, such as data generation, classification, etc.

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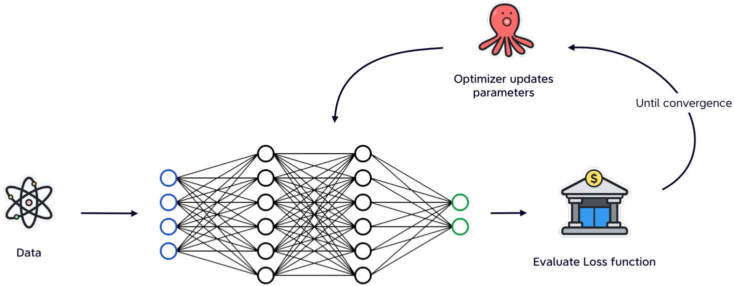

Qubits (on the Bloch sphere)

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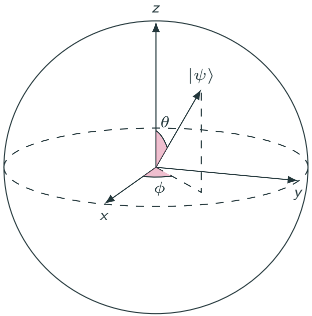
Qubits' states can be used to process information:

$$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \qquad \text{where} \qquad \alpha = \cos\frac{\theta}{2}, \quad \beta = e^{i\phi}\sin\frac{\theta}{2}.$$



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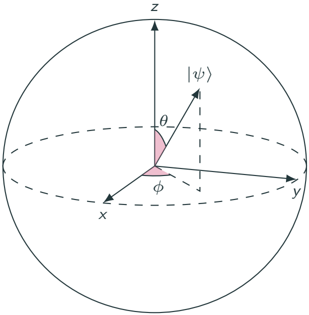

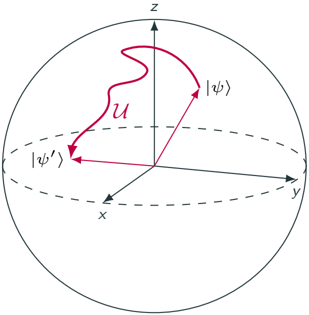

And this information can be manipulated applying unitaries $\mathcal{U}$.

Parametrized Quantum Circuits

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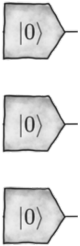

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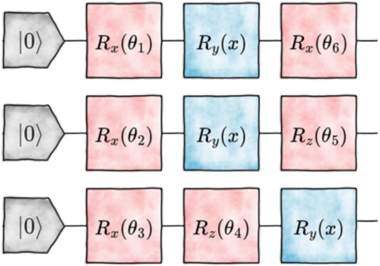

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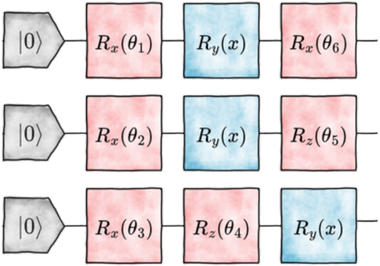

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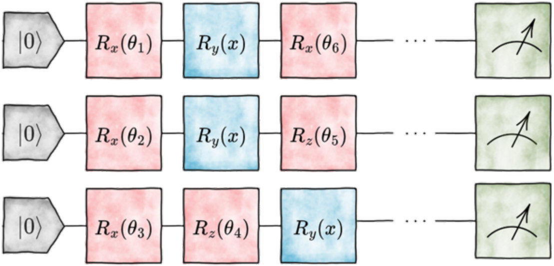
- after executing the circuit, information is accessed computing expectation values of target observables on the new qubits state.



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 - operating on qubits

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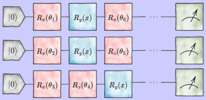

Quantum Machine Learning - natural randomness

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Expected values
$y_{est} \equiv \langle \psi' | \hat{O} | \psi' \rangle$

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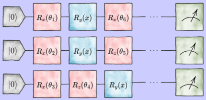

Quantum Machine Learning - encoding the problem

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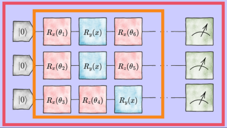

Quantum Machine Learning!

Optimizer $\mathcal{O}$
Hybrid-strategy

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

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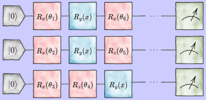
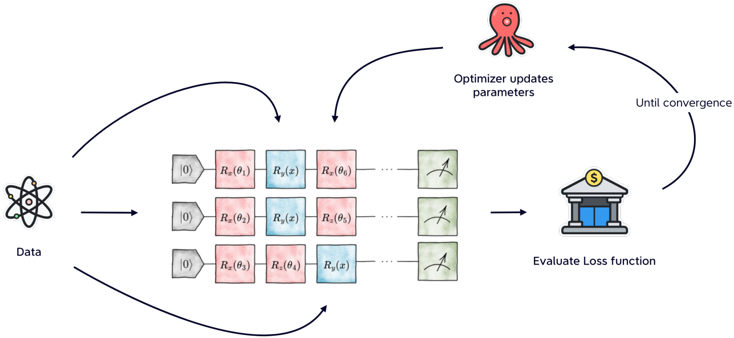


From ML to QML



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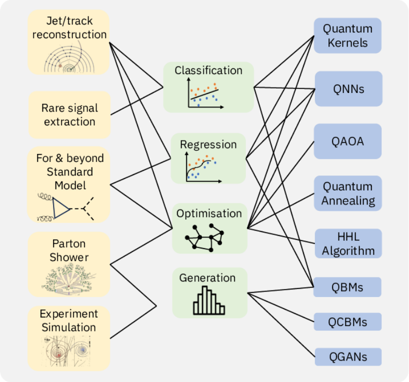

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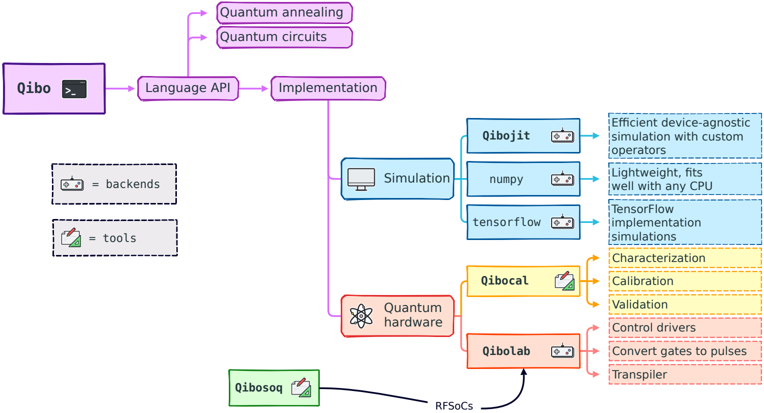
My playground: Qibo



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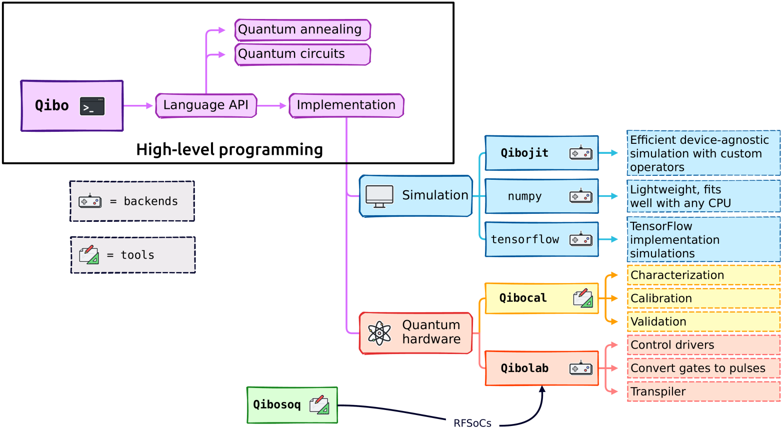

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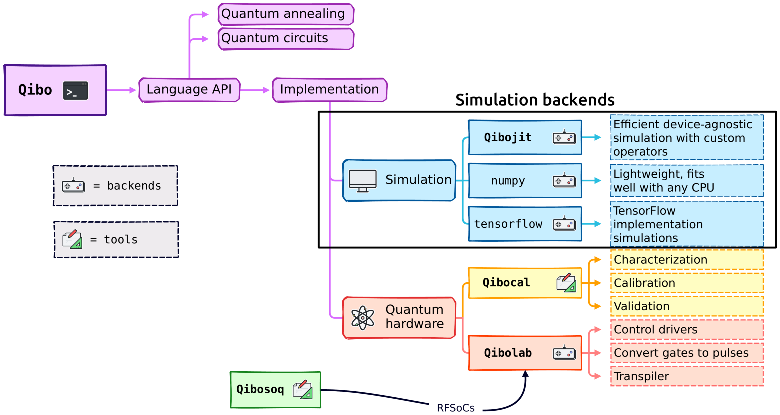

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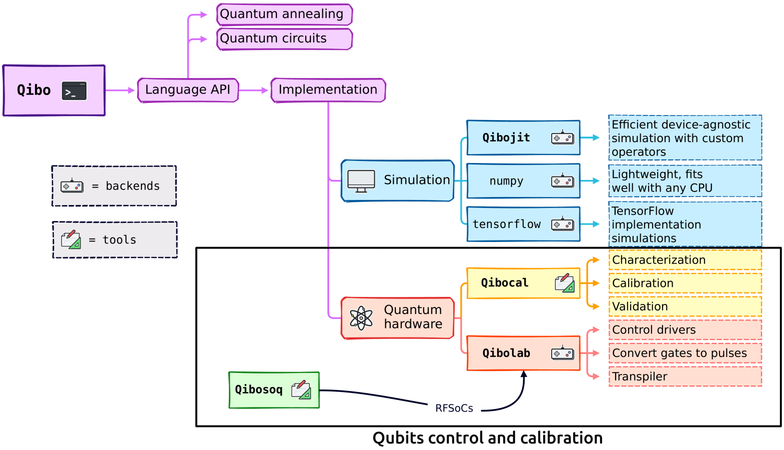

PDFs as QML target

- Define a circuit $\mathcal{U}(\boldsymbol{x};\boldsymbol{\theta})$ using one qubit per parton p_i;
- fill gates with both x_i and $\log(x_i)$;
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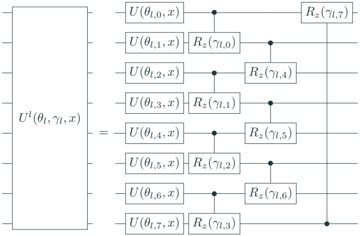

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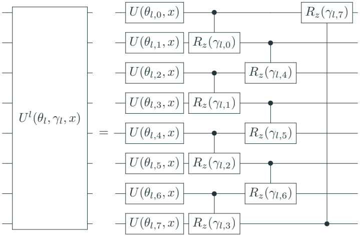

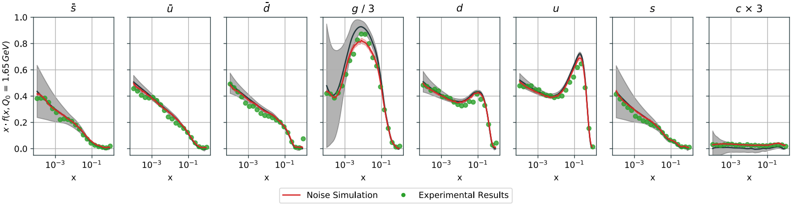

What if we run on hardware? arXiv:2308.06313

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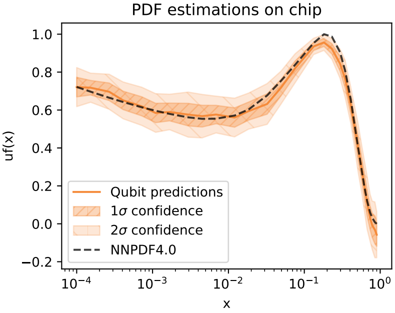

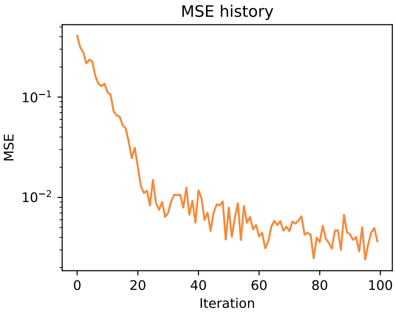

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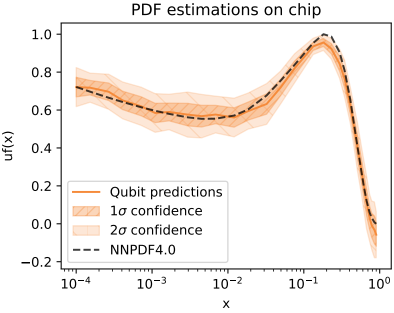

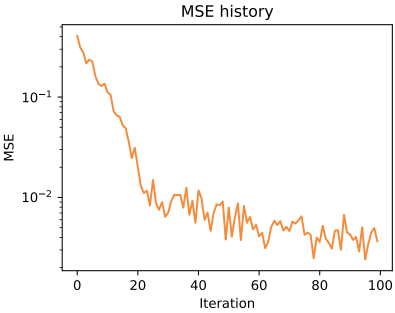

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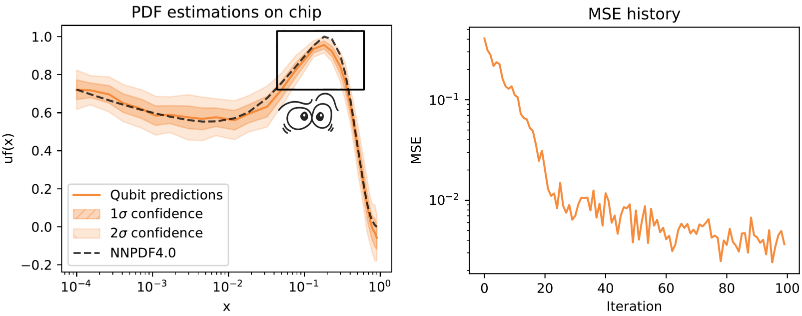

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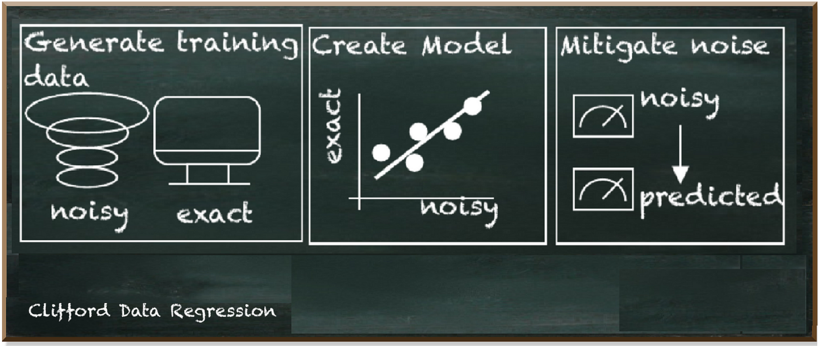

Credits: Frank Zickert.

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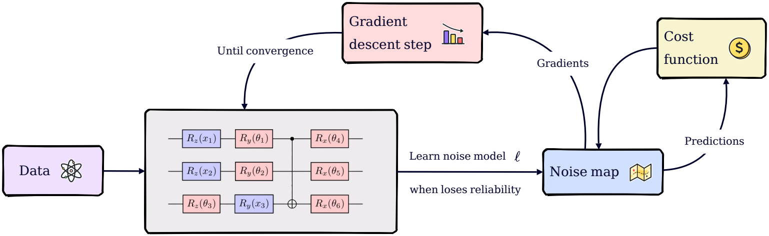

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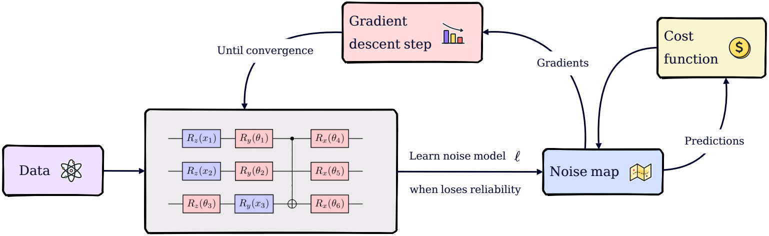

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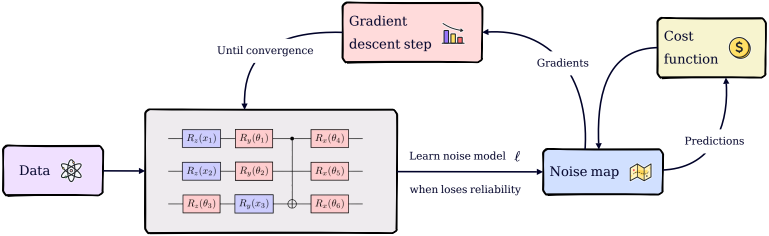
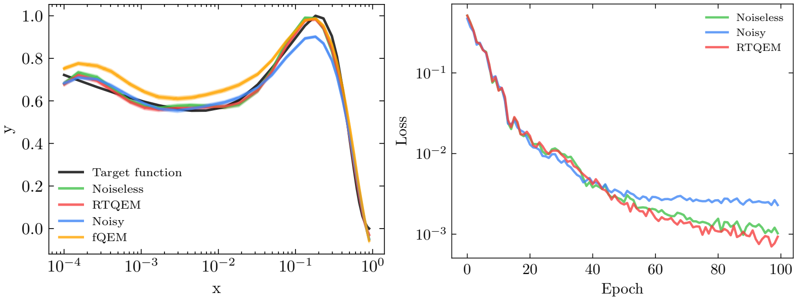


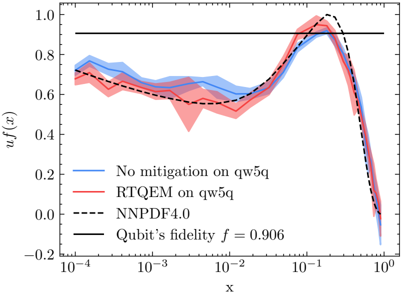
- these experiments take long execution times (but we have `Qibo`!);
- in some regimes, we aim to remove the bounds imposed by noise.

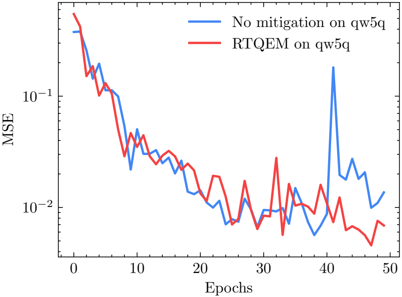
Parameter	N_{train}	N_{params}	N_{shots}	$\mathrm{MSE}_{\mathrm{rtqem}}$	$\mathrm{MSE}_{\mathrm{nomit}}$	Noise
Value	30	16	10^4	0.008	0.018	local Pauli



1. thanks to the RTQEM procedure, we reach a good minimum of the cost function;
2. the QEM is not effective if applied to a corrupted scenario (orange curve).

Parameter	N_{train}	N_{params}	N_{shots}	$\mathrm{MSE}_{\mathrm{rtqem}}$	$\mathrm{MSE}_{\mathrm{nomit}}$	Noise
Value	15	16	500	0.0042	0.0055	real noise





RTQEM allows exceeding the natural bound imposed by noise.

We perform a longer training on two different devices (and noises!) using the same initial conditions of the previous slide but $N_{\mathrm{epochs}} = 100$.

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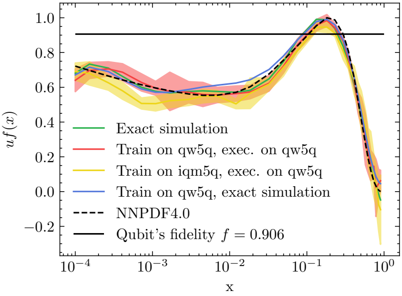

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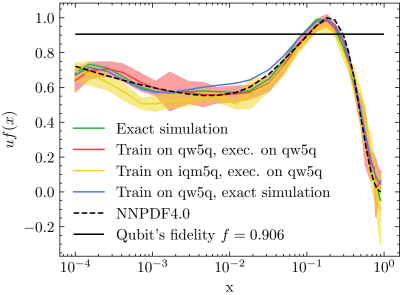
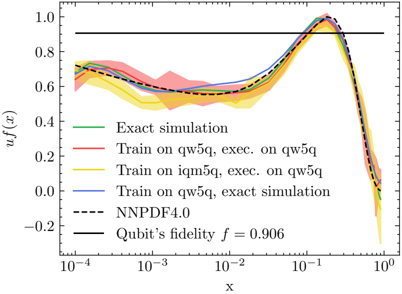


- `qw5q` from QuantWare and controlled using Qblox instruments;
- `iqm5q` from IQM and controlled using Zurich Instruments.

We perform a longer training on two different devices (and noises!) using the same initial conditions of the previous slide but $N_{\text{epochs}} = 100$.



- qw5q from QuantWare and controlled using Qblox instruments;
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Train.	Epochs	Pred.	Config.	MSE
qw5q	50	qw5q	noisy	0.0055
qw5q	50	qw5q	RTQEM	0.0042
qw5q	100	qw5q	RTQEM	0.0013
iqm5q	100	qw5q	RTQEM	0.0037
qw5q	100	sim	RTQEM	0.0016

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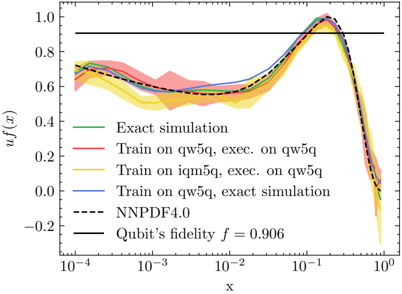

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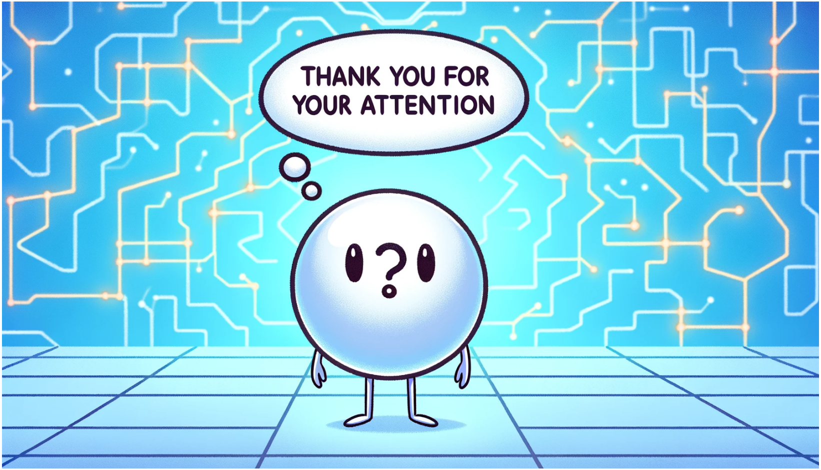
All the hardware results are obtained deploying the $\boldsymbol{\theta}_{\text{best}}$ on qw5q.


THANK YOU FOR
YOUR ATTENTION