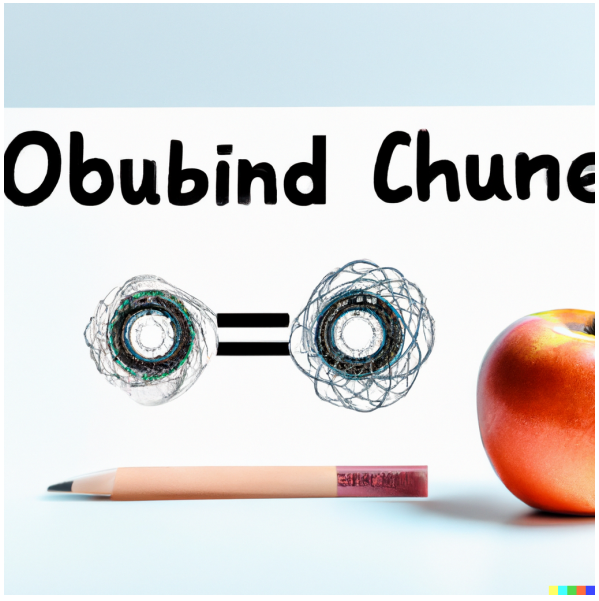
Full-stack Quantum Machine Learning using `Qibo`

SG Quantum Tech Meetup

Matteo Robbiati

25 January 2024

DALL-E 2 explaining my title



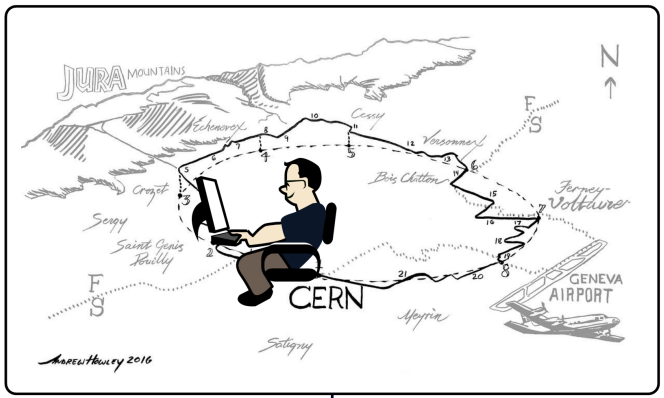
DALL-E 3 explaining my title

Me explaining my title

Me explaining my title

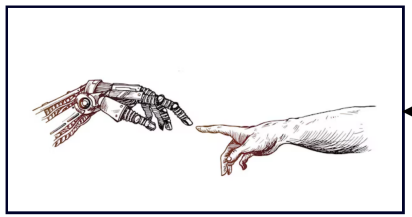
Me explaining my title

High Energy Physics

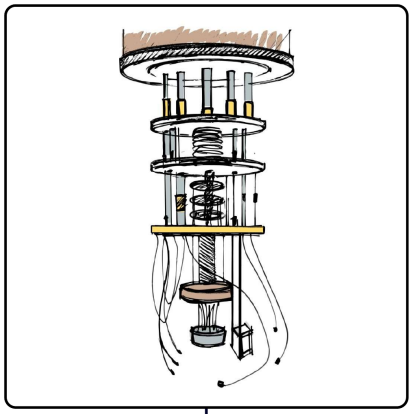


Plenty of data to analyze

Need for technological development



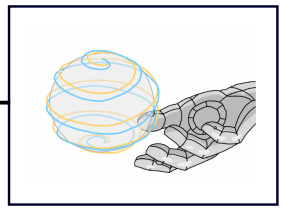
Quantum computers



Computational boost (problem specific)

Noise and limited resources

- Simulation
- Control
- Calibration



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“ Full-Stack ”

Me explaining my title

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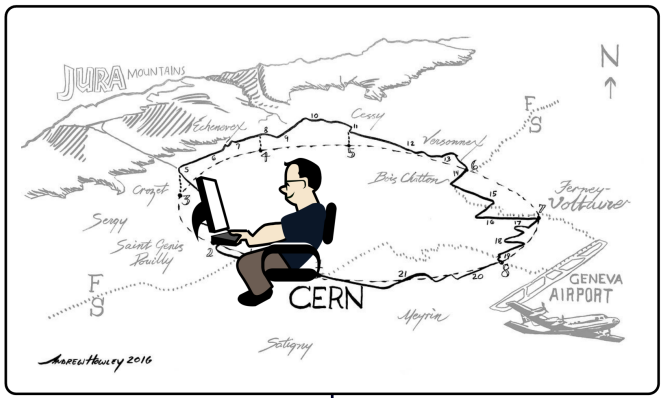

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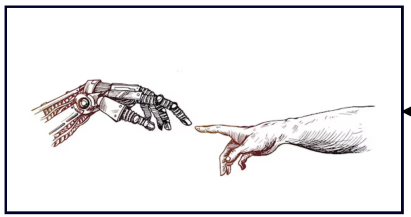

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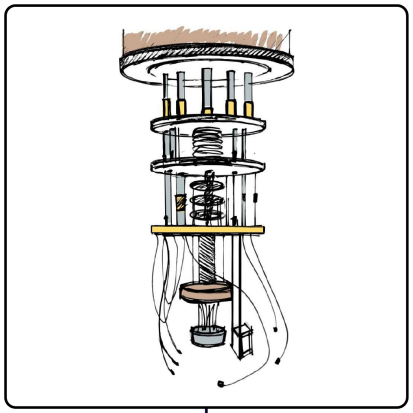

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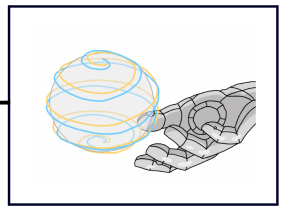
QIBO

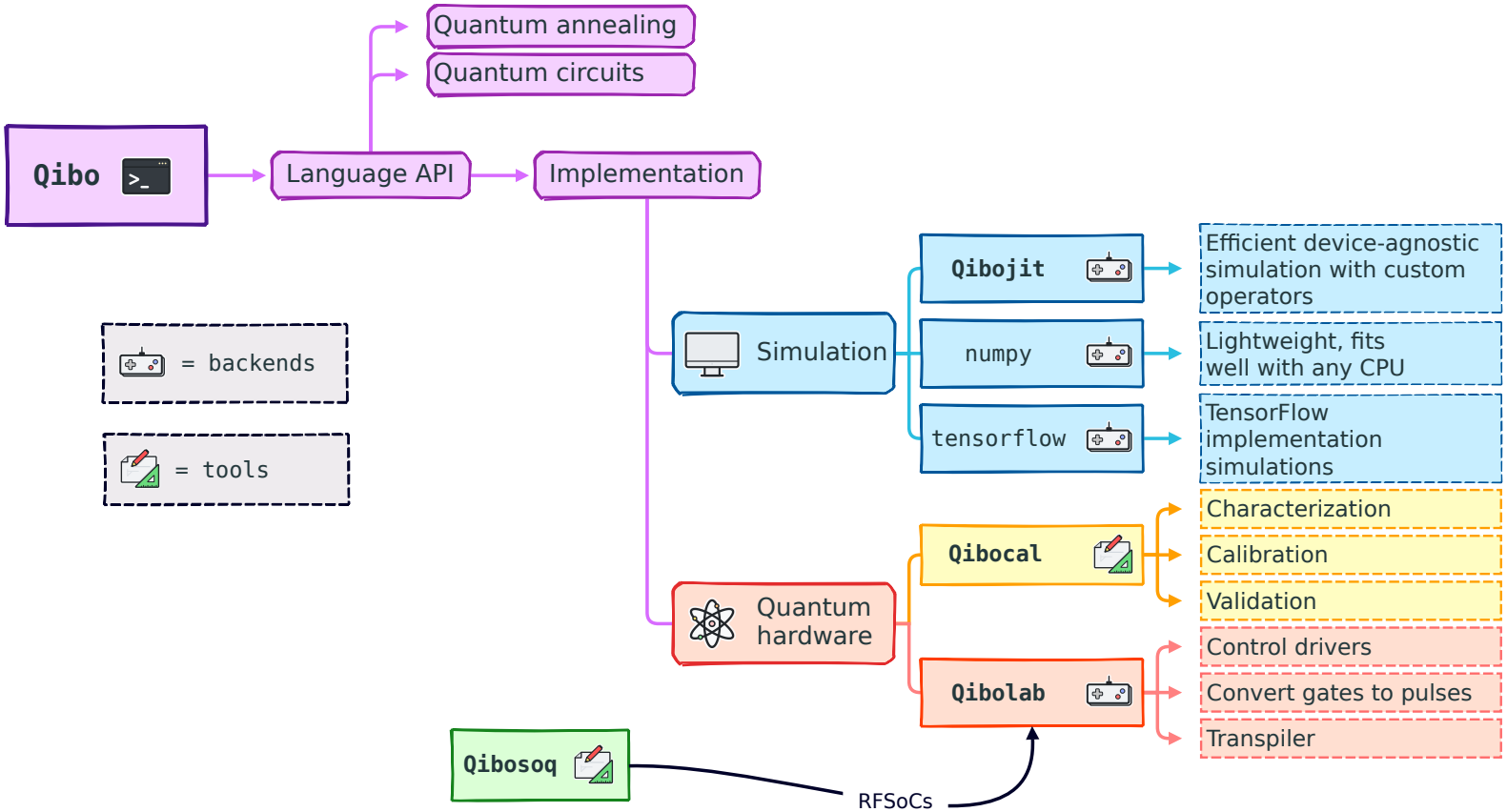


“ Quantum Machine Learning ”

“ Full-Stack ”

`Qibo` as full-stack playground

The Qibo ecosystem



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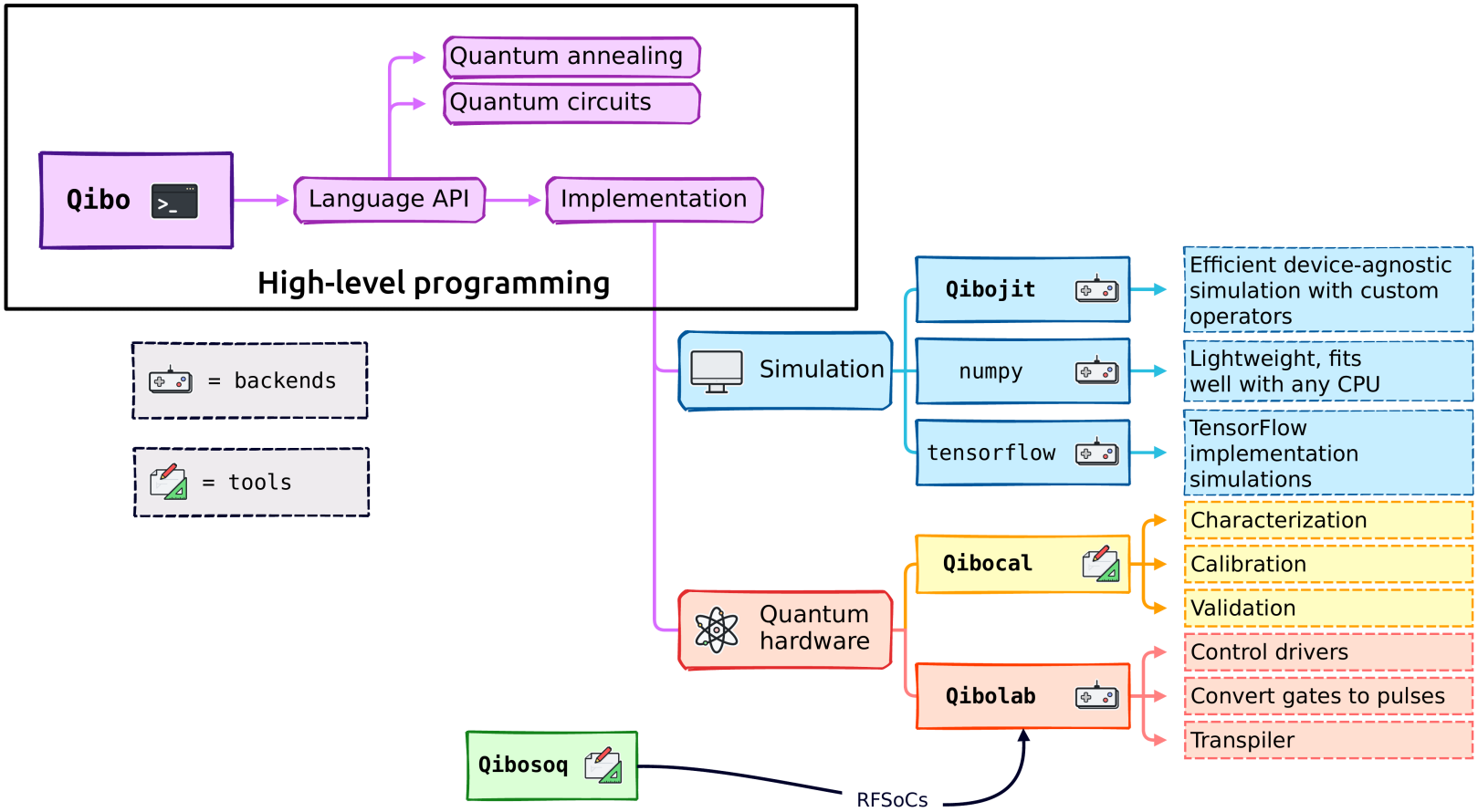

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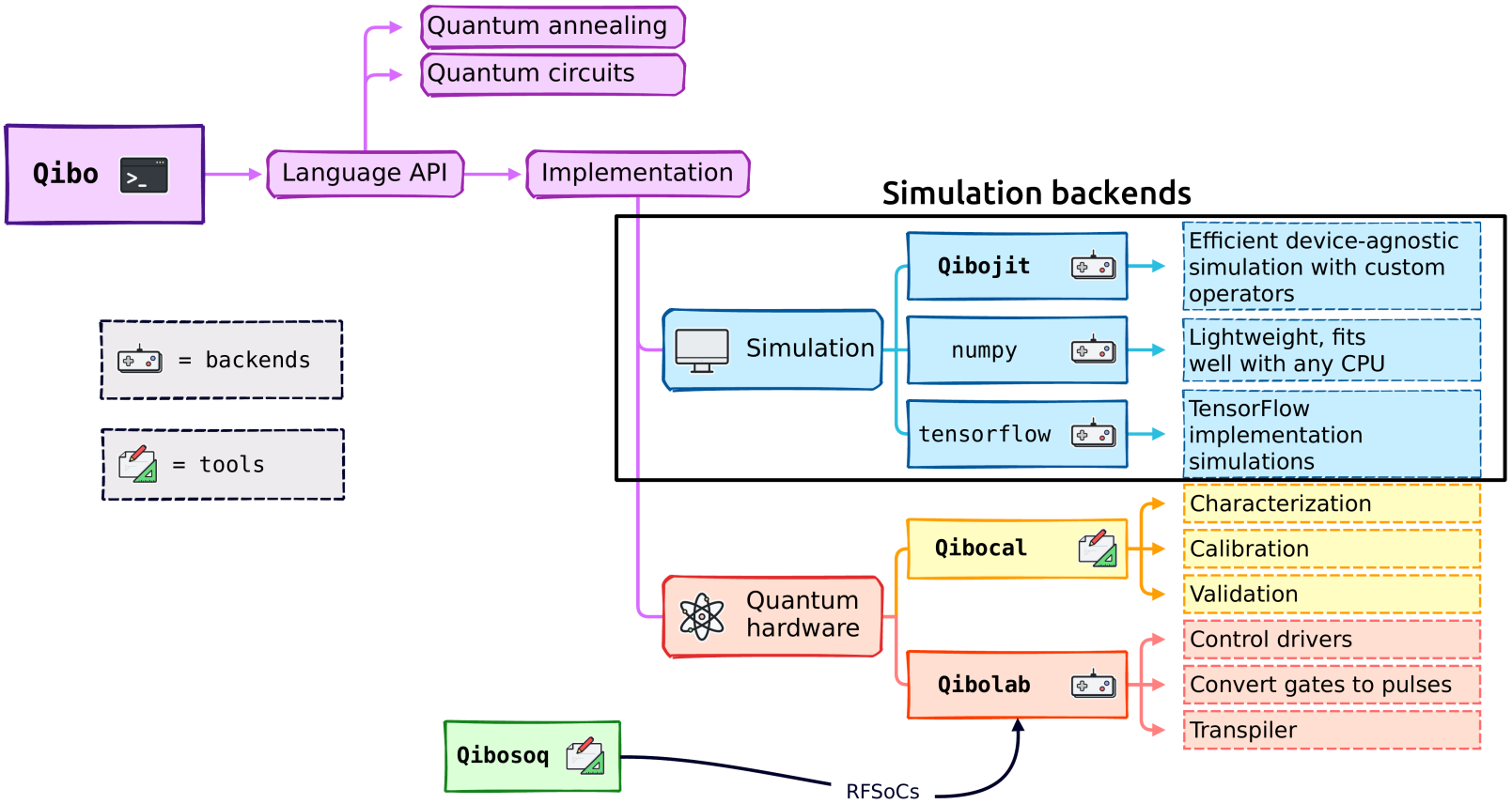

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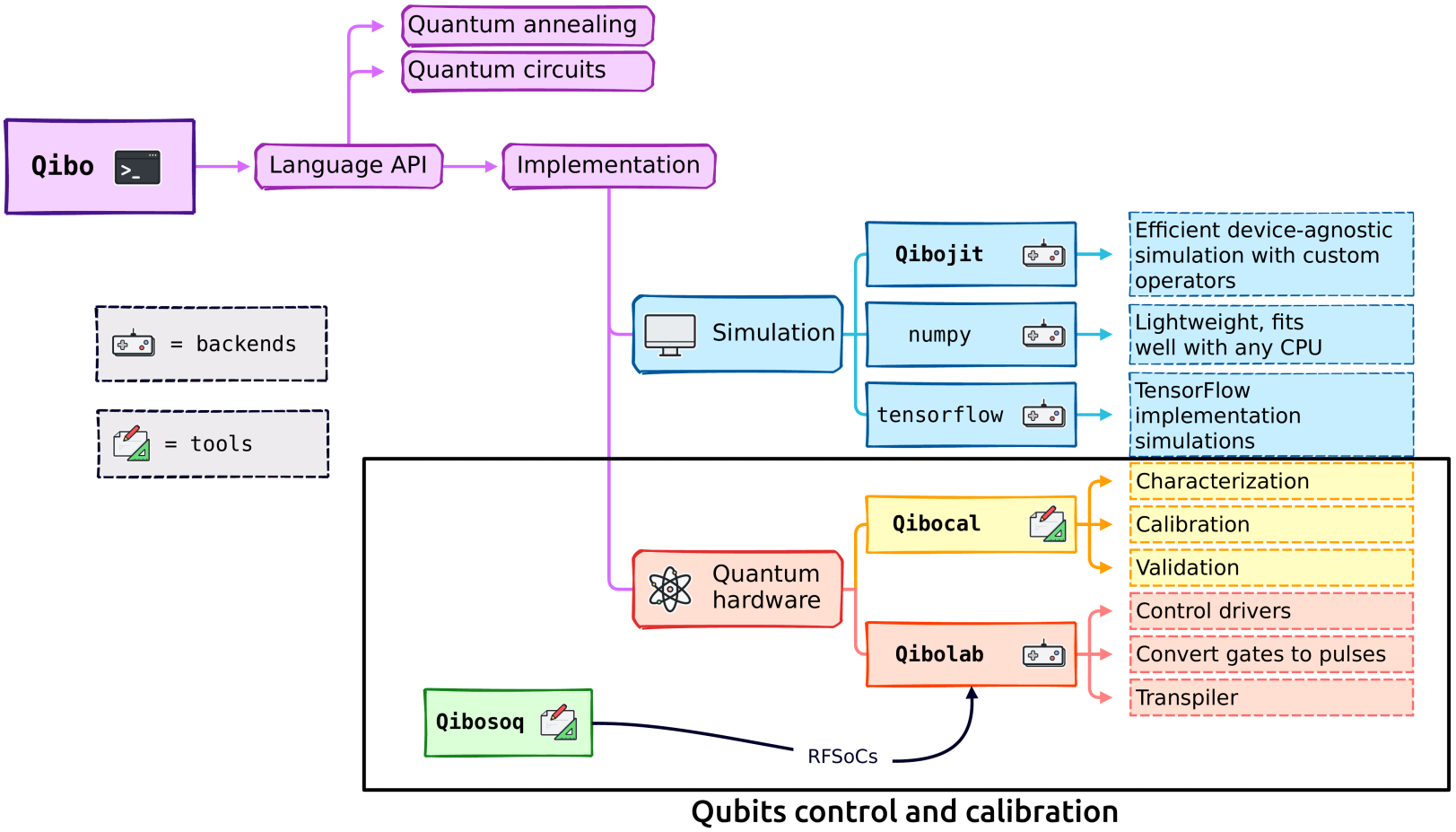

Qibo's features - modularity

Let's see a simple example of code using Qibo.

Qibo's features - modularity

Let's see a simple example of code using Qibo.

```
import qibo
from qibo import Circuit, gates

# you can set the most suitable backend
qibo.set_backend(backend="numpy")

# then you write your code, which is backend agnostic
c = Circuit(nqubits=2)
c.add(gates.H(q=0))
c.add(gates.CNOT(q0=0, q1=1))

# and execute
c(nshots=1024)
```

Qibo's features - Qibojit

- The Qibojit backend is perfect for fast and distributed simulations.

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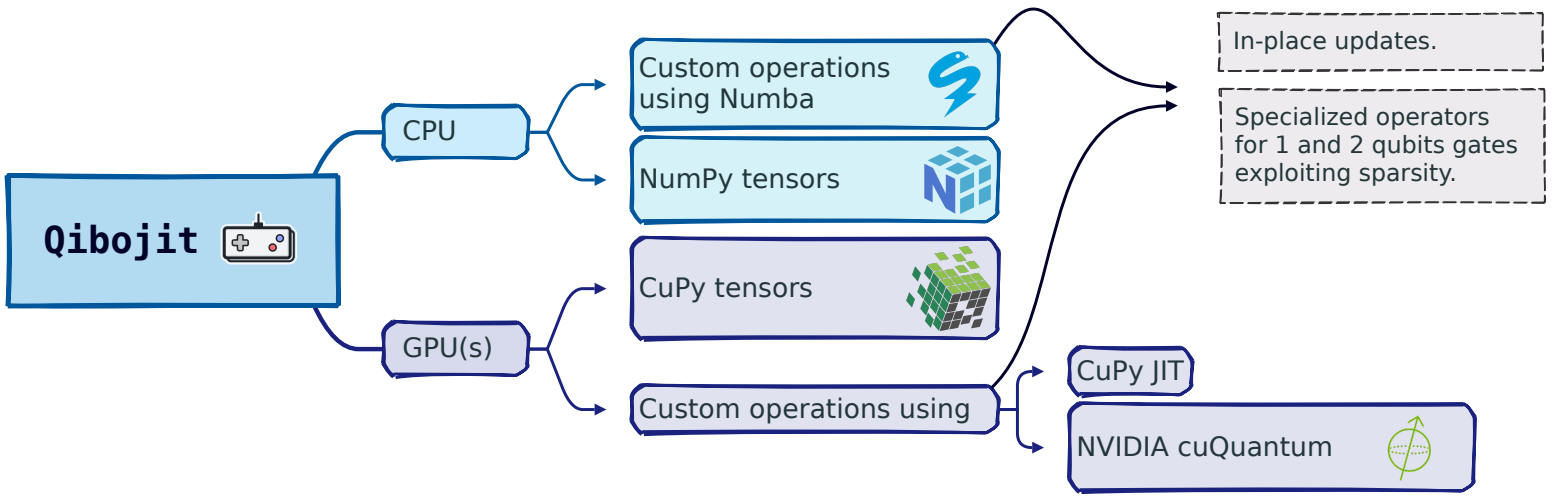

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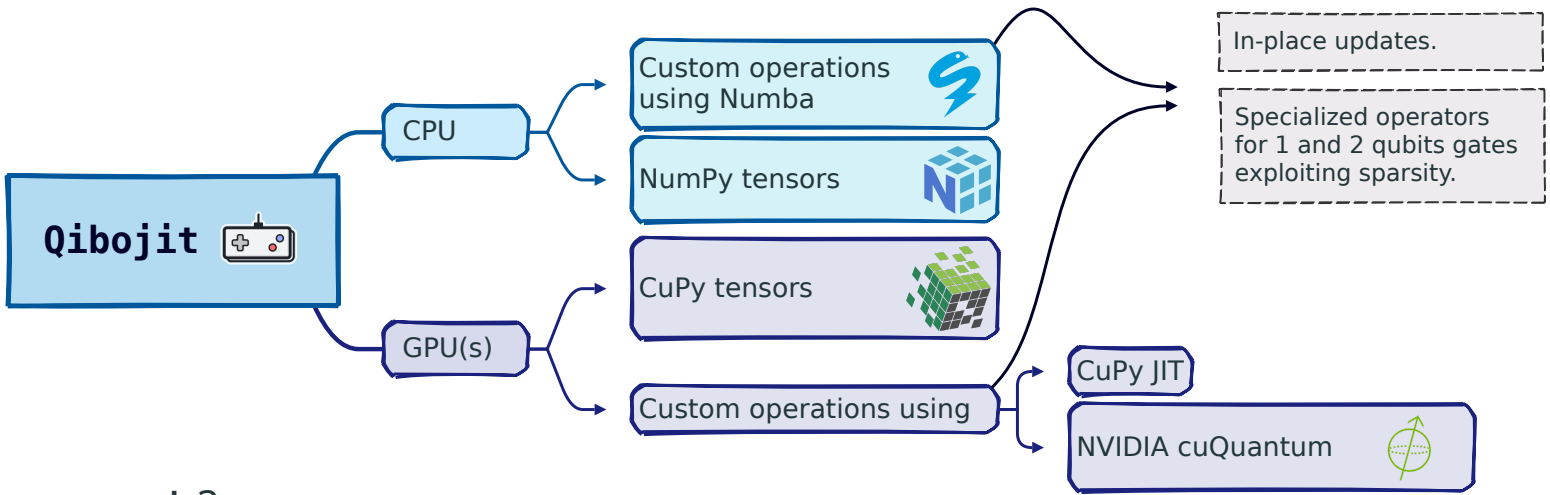

How to use it?

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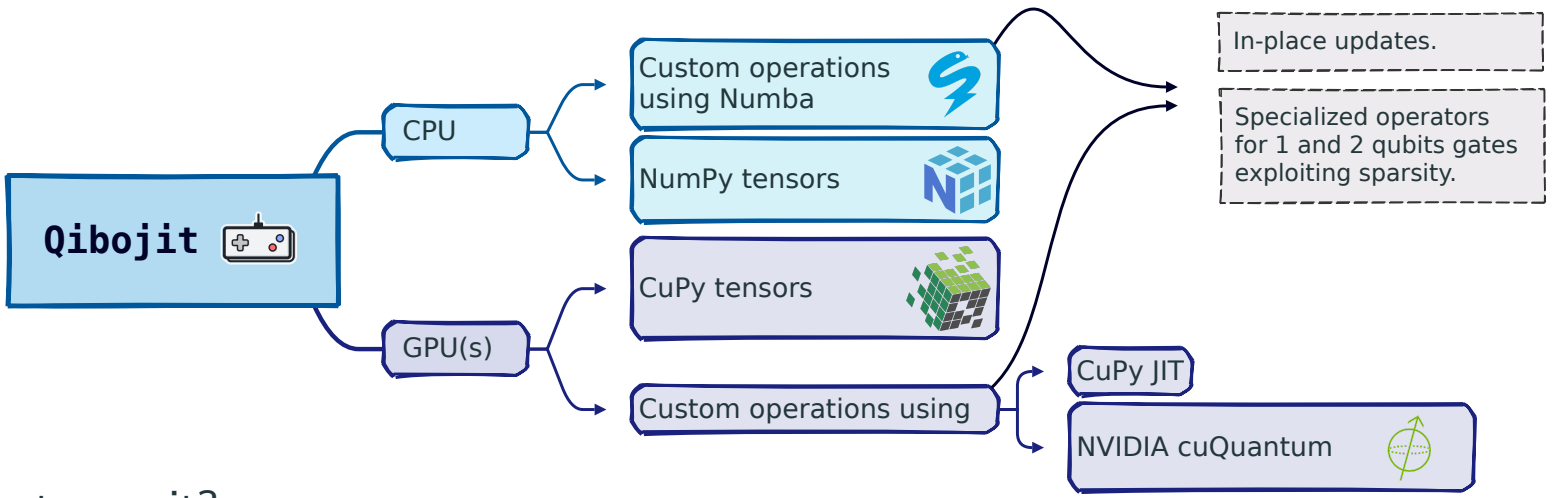
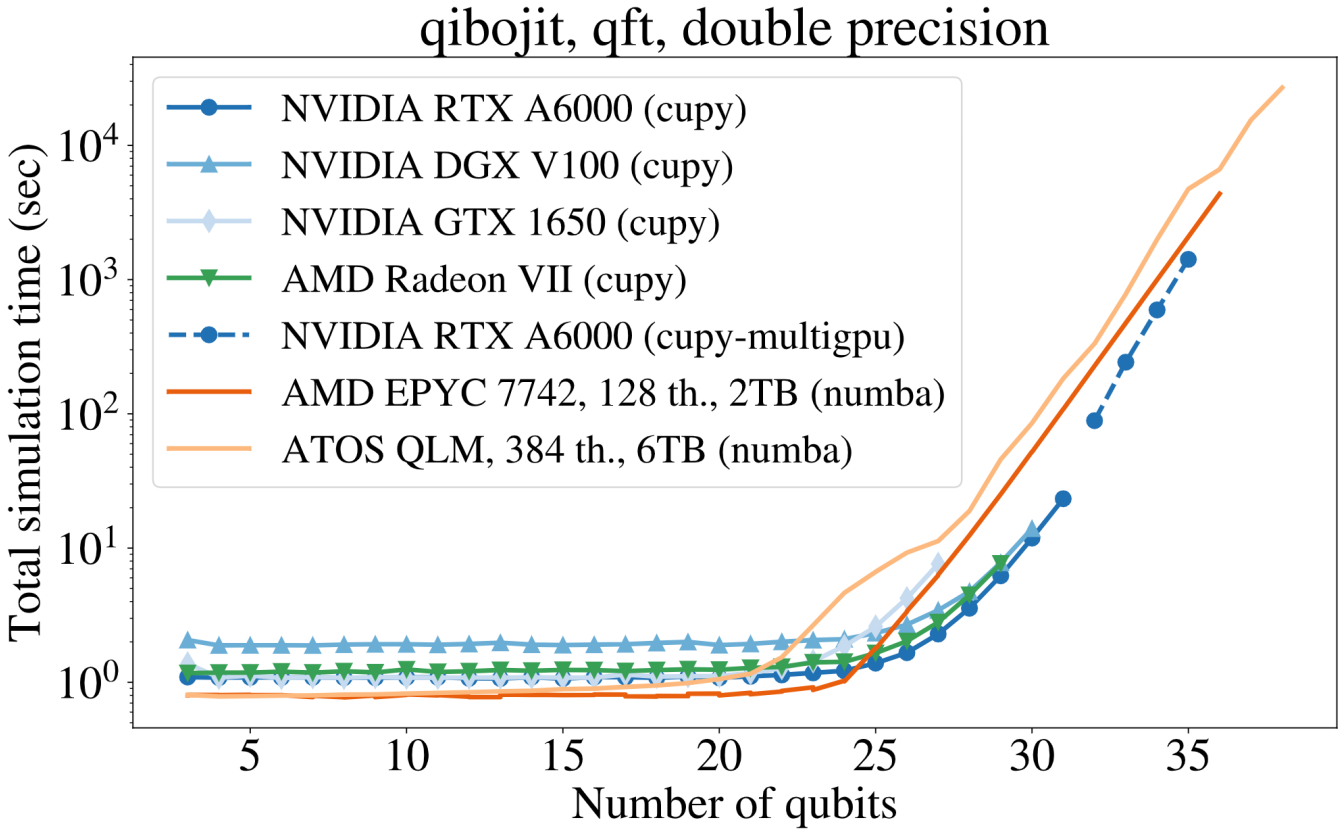


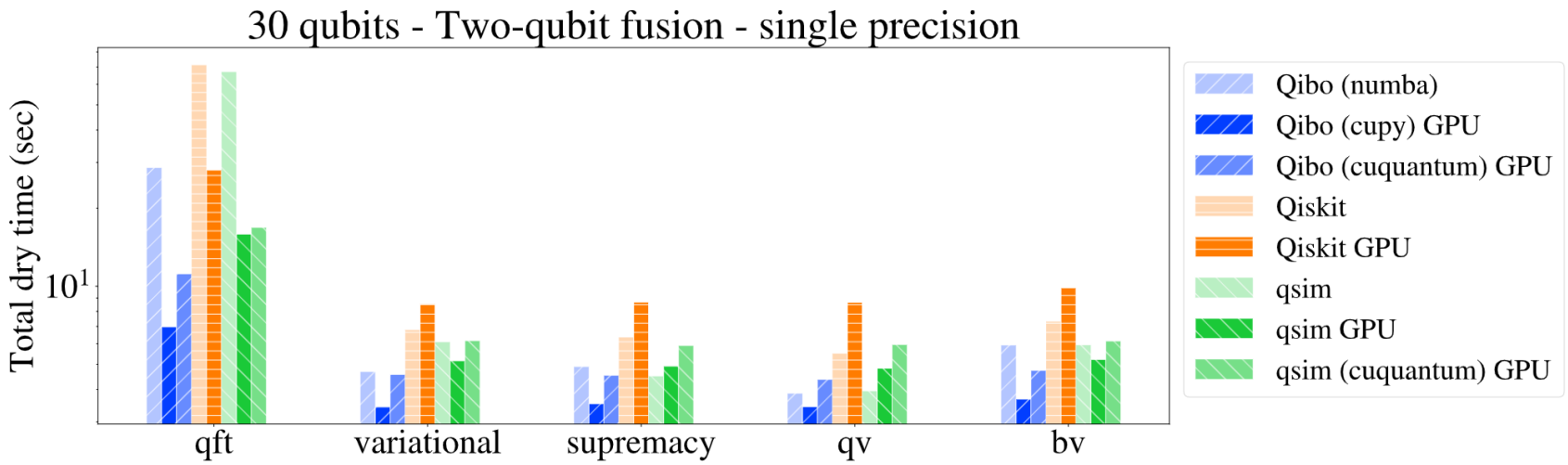
How to use it?

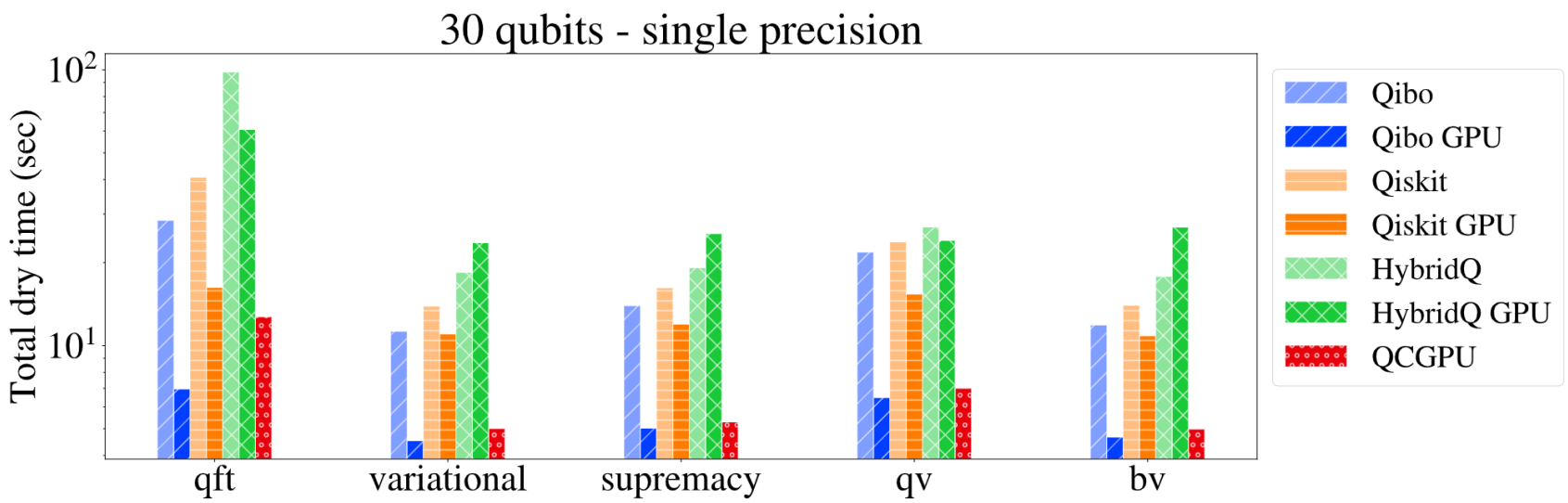
```python
import qibo
from qibo import Circuit, gates

qibo.set_backend(backend="qibojit", platform="numba")

# same code of the previous slide follows :)
```

Qibojit - **performances**



Qibojit - performances





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Qibolab

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import qibo
from qibo import Circuit, gates

qibo.set_backend(backend="qibolab", platform="qw5q")

# same code of the previous slide follows :)
```

- The same API interface can be executed on quantum hardware!

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import qibo
from qibo import Circuit, gates

qibo.set_backend(backend="qibolab", platform="qw5q")

# same code of the previous slide follows :)
```
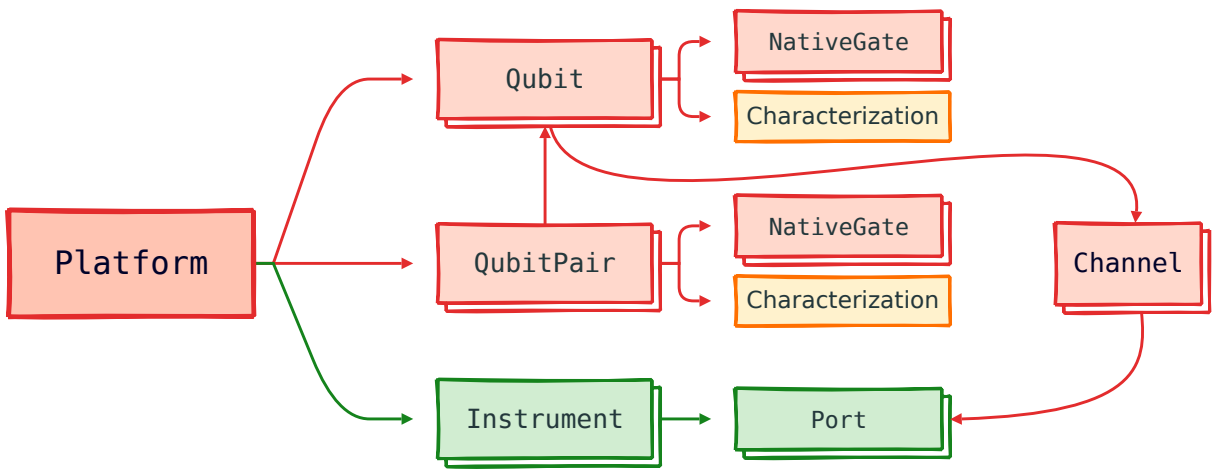
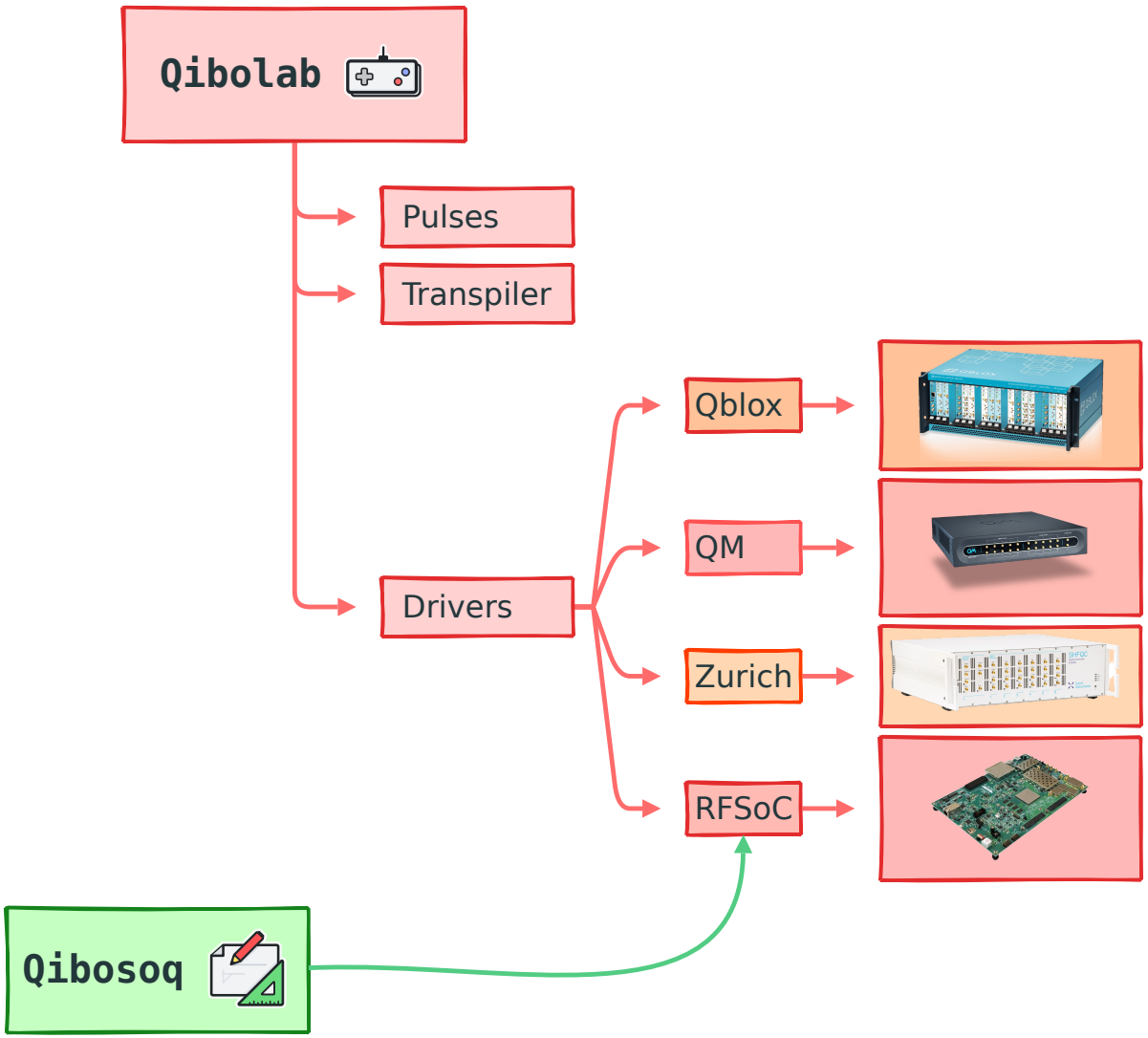
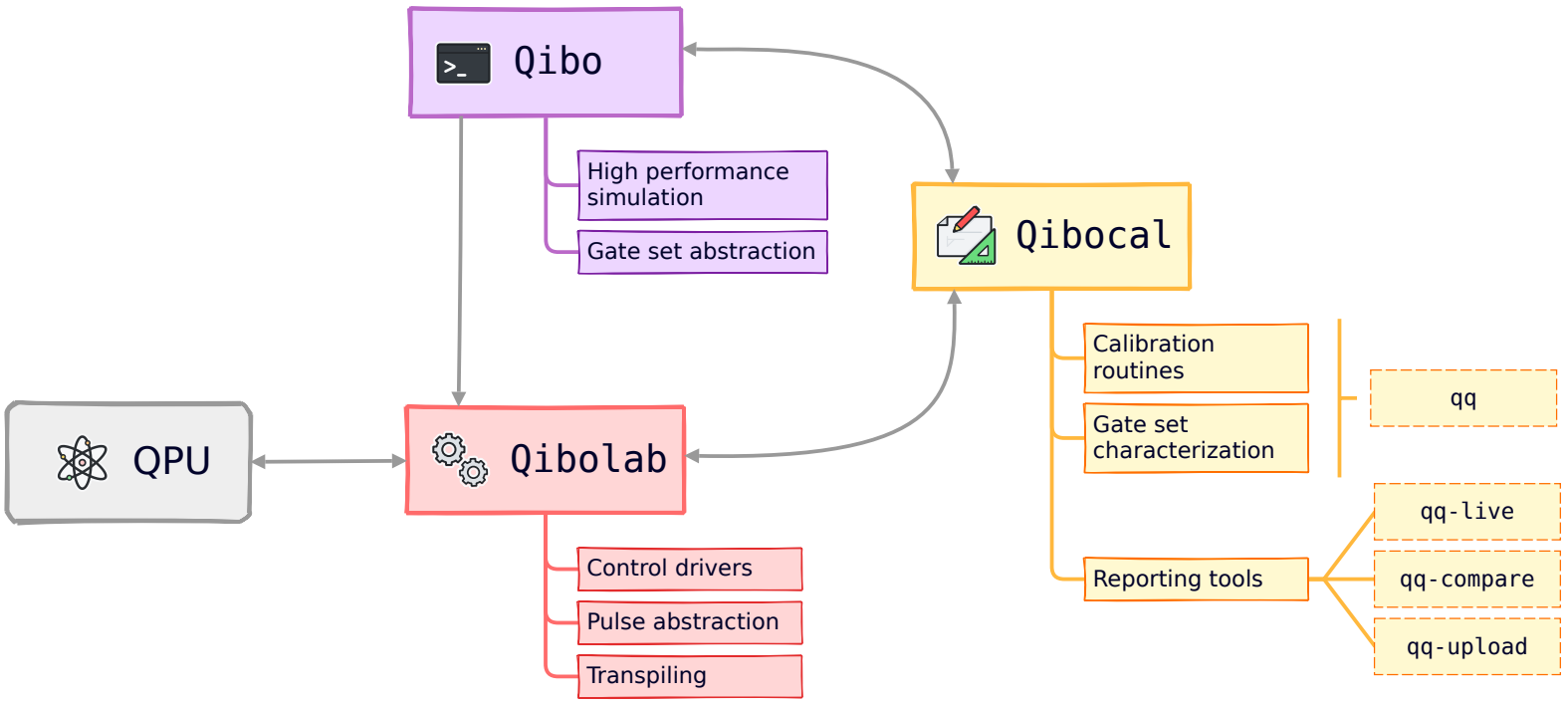

Once a proper `Platform` is written, `Qibolab` is hardware agnostic!

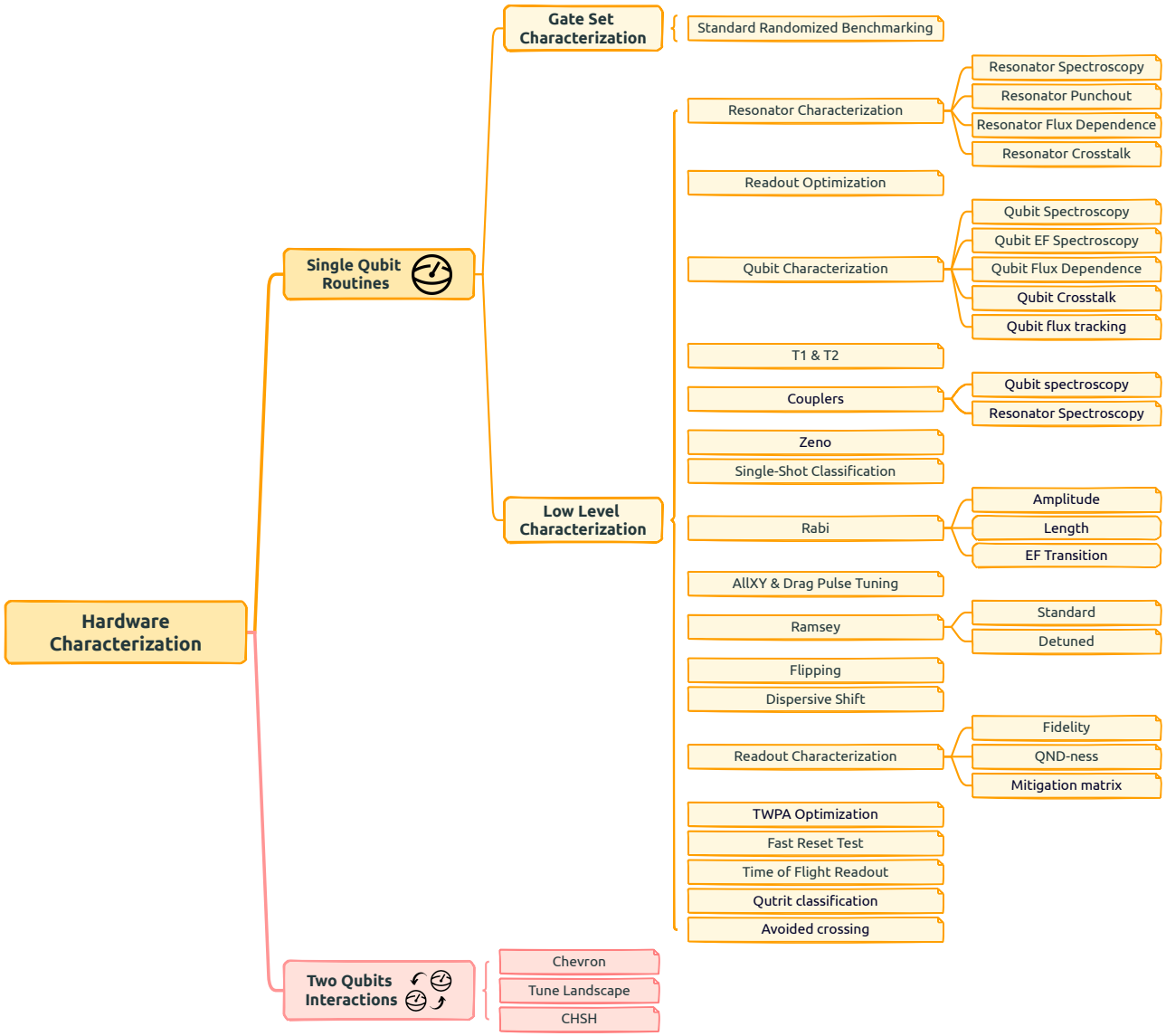


Qibolab - **current status**



Qibocal


Qibo
High performance simulation
Gate set abstraction
Qibocal
Calibration routines
Gate set characterization
qq
Reporting tools
qq-live
qq-compare
qq-upload
QPU
Qibolab
Control drivers
Pulse abstraction
Transpiling


Hardware Characterization
Single Qubit Routines
Gate Set Characterization
Standard Randomized Benchmarking
Low Level Characterization
Resonator Characterization
Resonator Spectroscopy
Resonator Punchout
Resonator Flux Dependence
Resonator Crosstalk
Readout Optimization
Qubit Characterization
Qubit Spectroscopy
Qubit EF Spectroscopy
Qubit Flux Dependence
Qubit Crosstalk
Qubit flux tracking
T1 & T2
Couplers
Qubit spectroscopy
Resonator Spectroscopy
Zeno
Single-Shot Classification
Rabi
Amplitude
Length
EF Transition
AllXY & Drag Pulse Tuning
Ramsey
Standard
Detuned
Flipping
Dispersive Shift
Readout Characterization
Fidelity
QND-ness
Mitigation matrix
TWPA Optimization
Fast Reset Test
Time of Flight Readout
Qutrit classification
Avoided crossing
Two Qubits Interactions
Chevron
Tune Landscape
CHSH

Small intro to the example

Machine Learning (ML)

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

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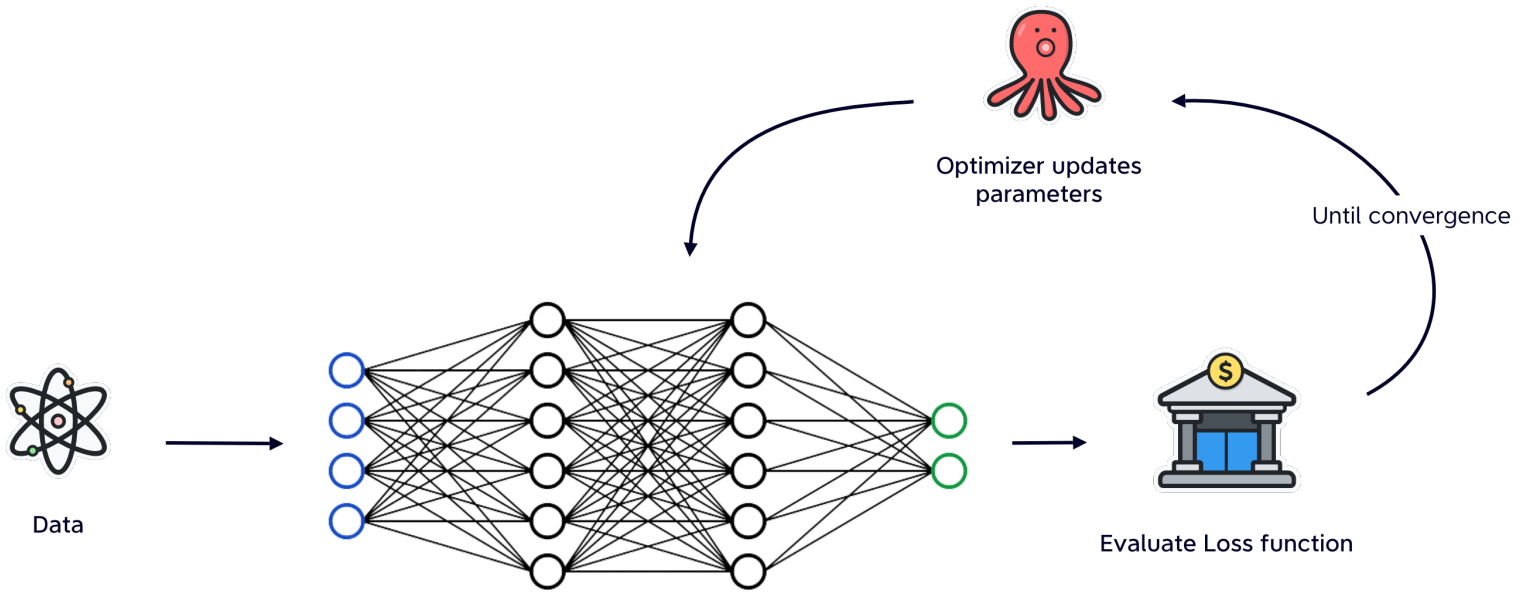

Qubits (on the Bloch sphere)

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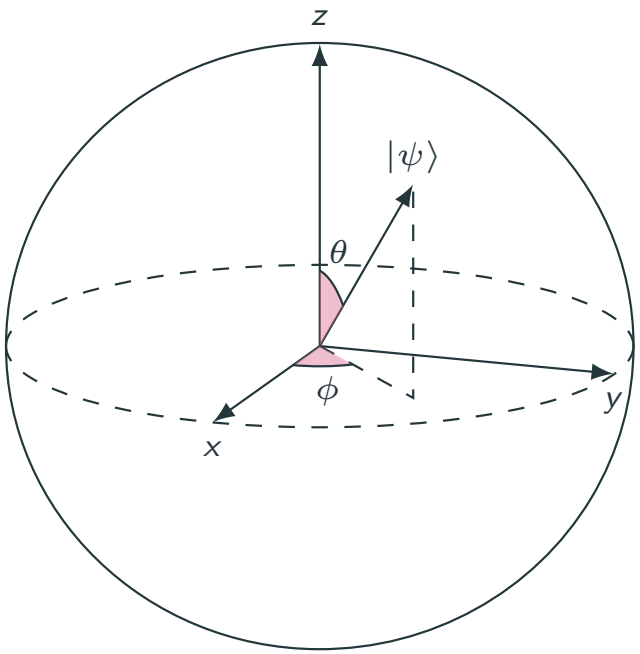
Qubits' states can be used to process information:

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



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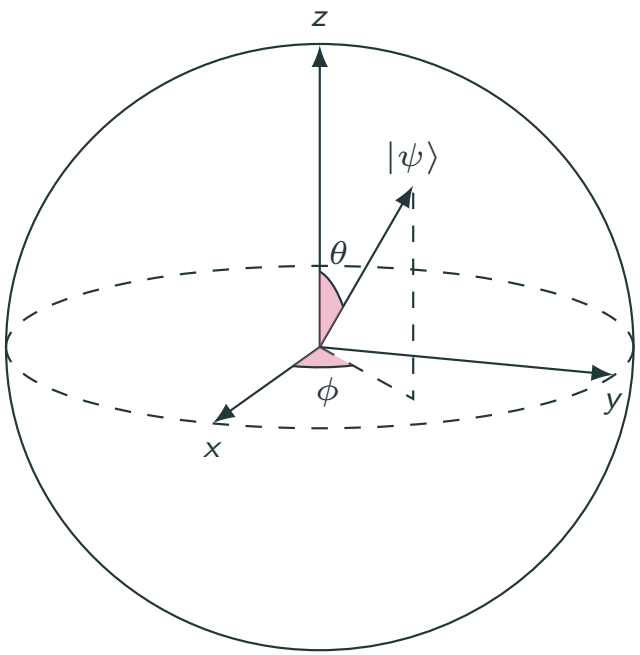

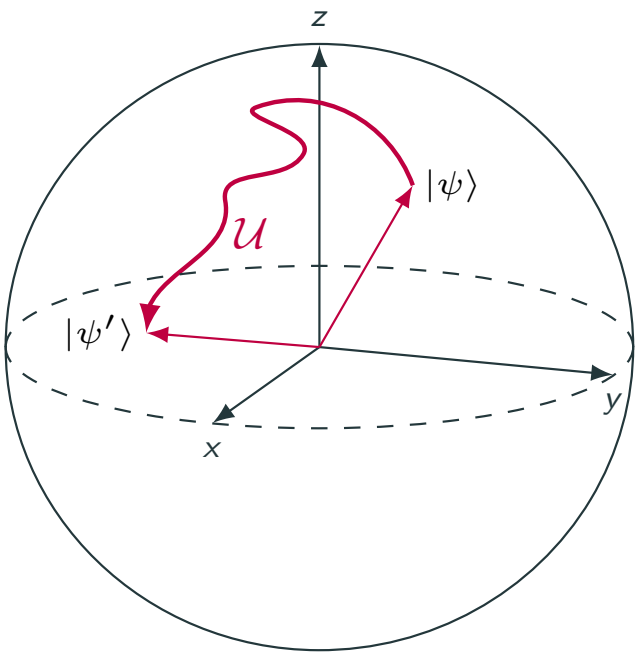

And this information can be manipulated applying unitaries $\mathcal{U}$.

Parametrized Quantum Circuits

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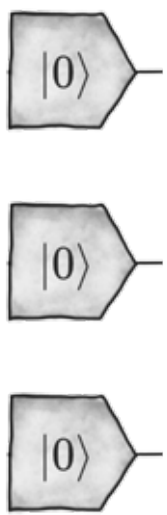
- Classical bits are replaced by **qubits**: $|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle$;



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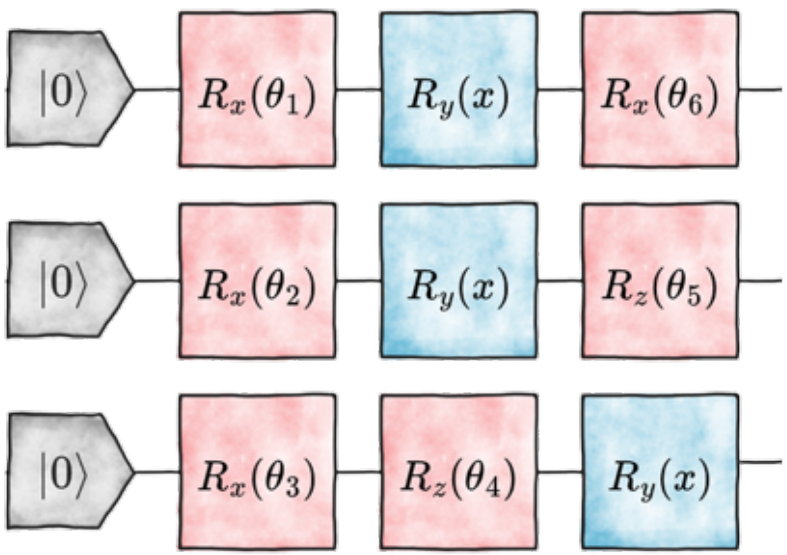

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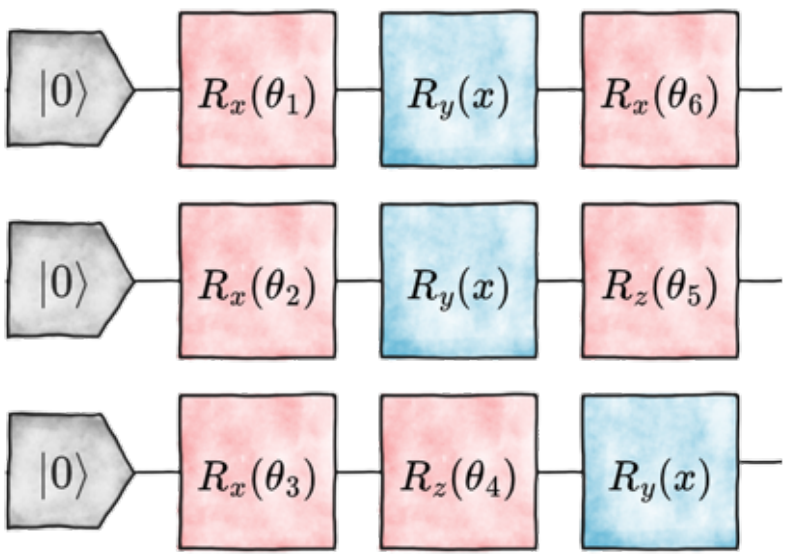

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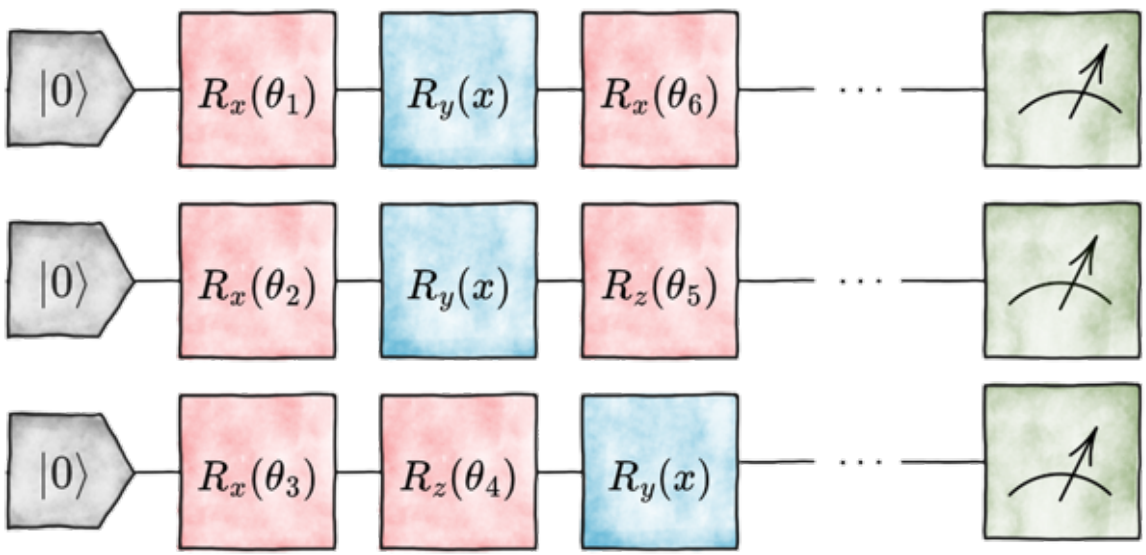
- we call the unitaries **"gates"** and many gates together **"circuit"**.
- after executing the circuit, information is accessed computing expectation values of target observables on the new qubits state.



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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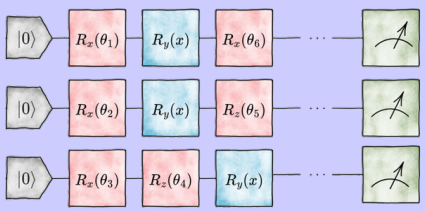
Circuit execution



Quantum Machine Learning - natural randomness

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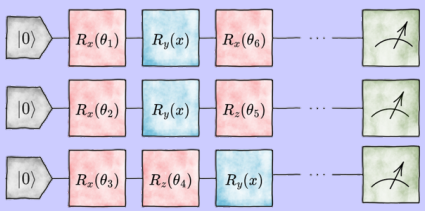

Expected values

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

Quantum Machine Learning - encoding the problem

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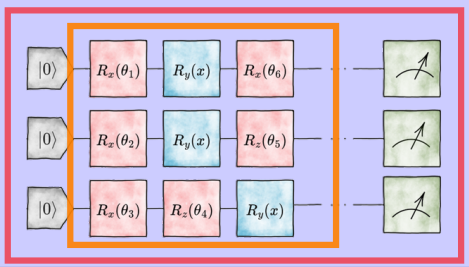

Quantum Machine Learning!

Optimizer $\mathcal{O}$
Hybrid-strategy

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

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

Expected values
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Quantum Computation
$\mathcal{Q}$: qubits;
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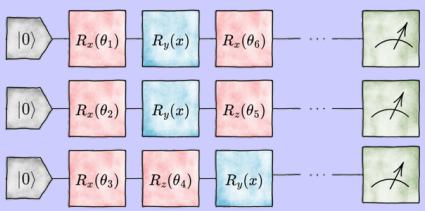
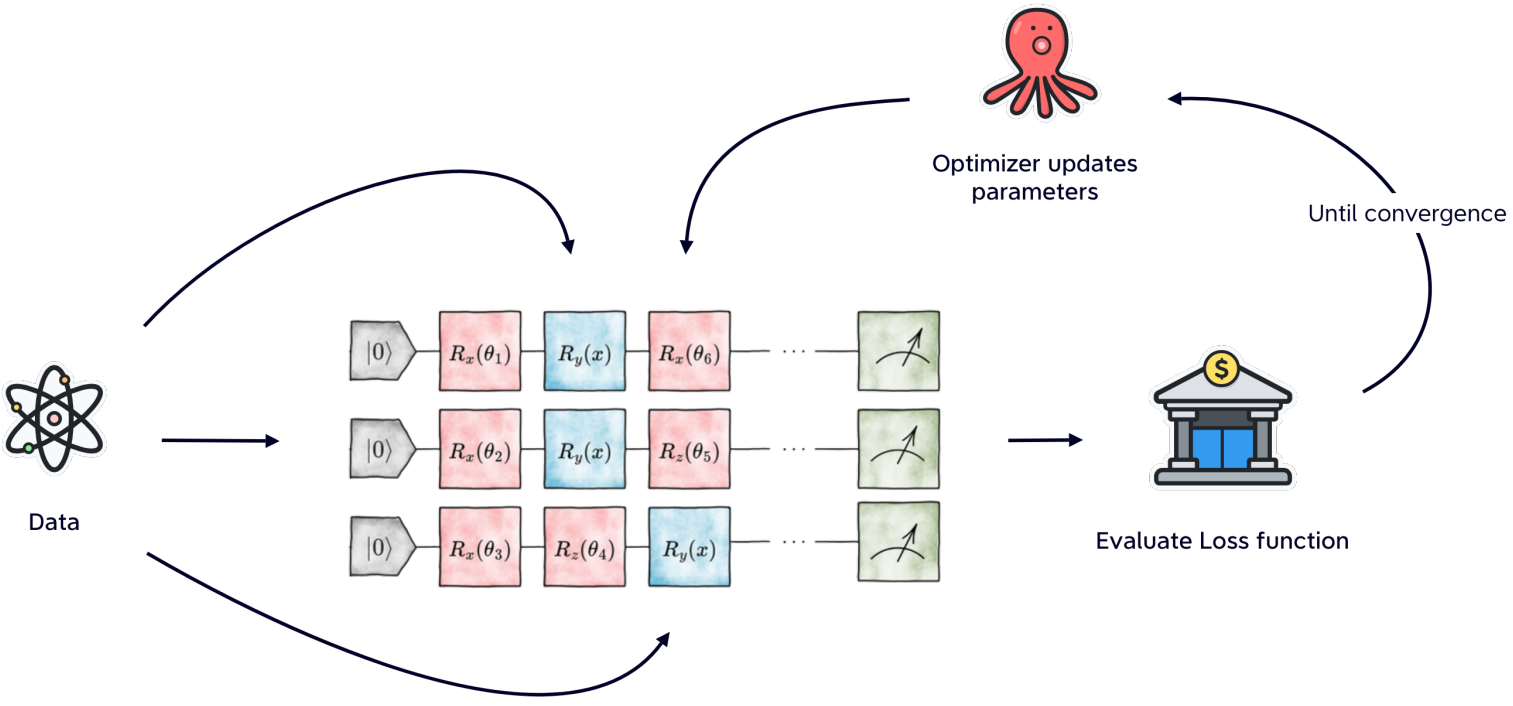


From ML to QML



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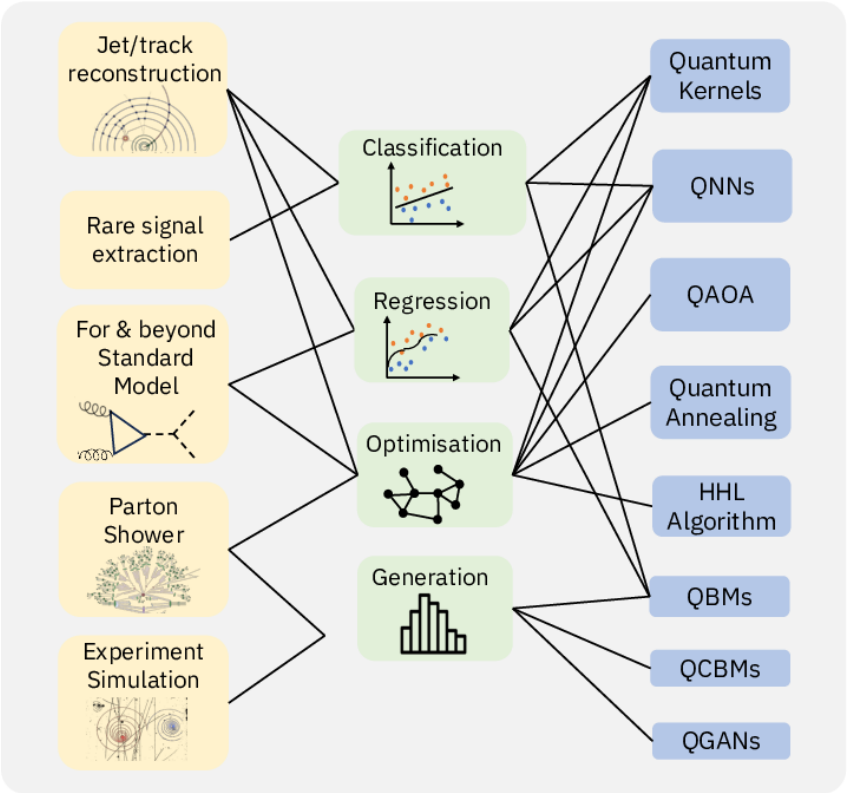

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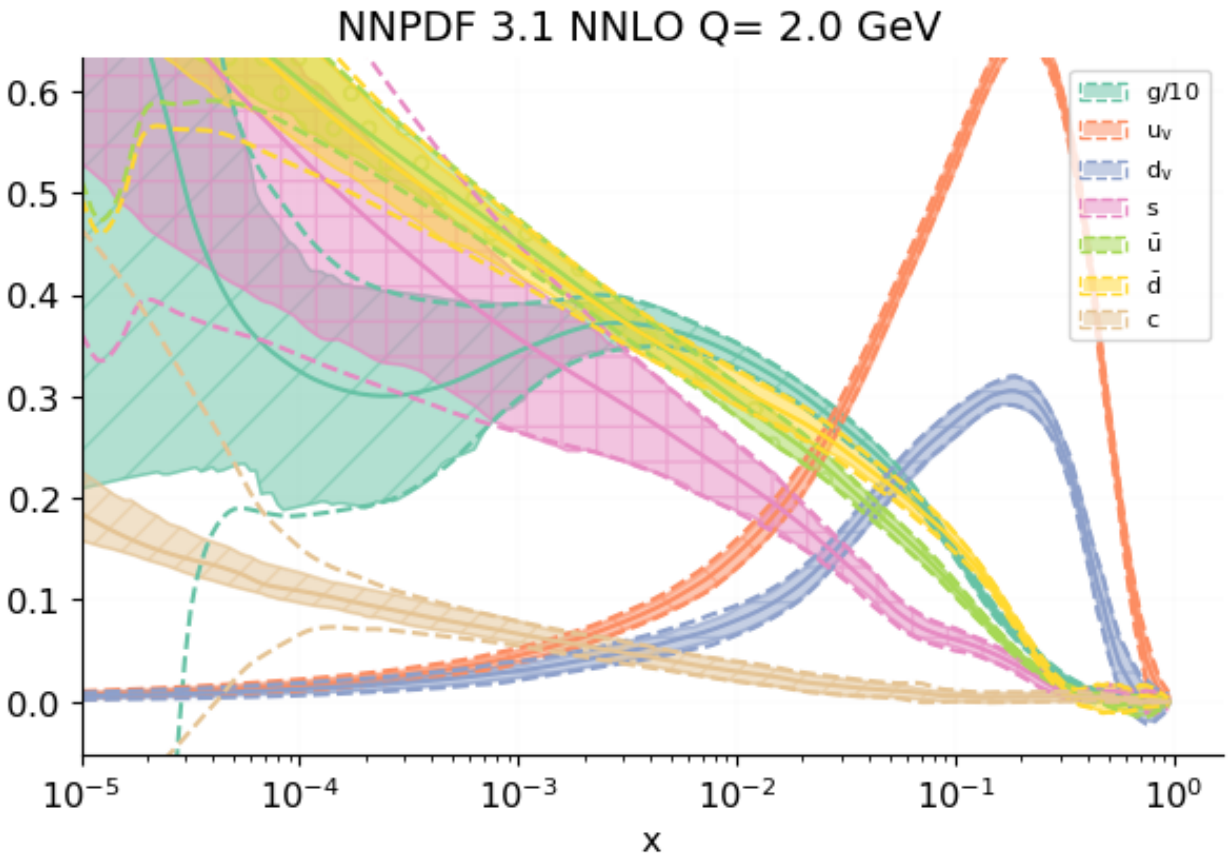
A practical example from HEP

Parton Distribution Functions as QML target

Taking one parton p_i, we can see its PDF as the probability for p_i of carring a fraction x of the momentum of the proton.

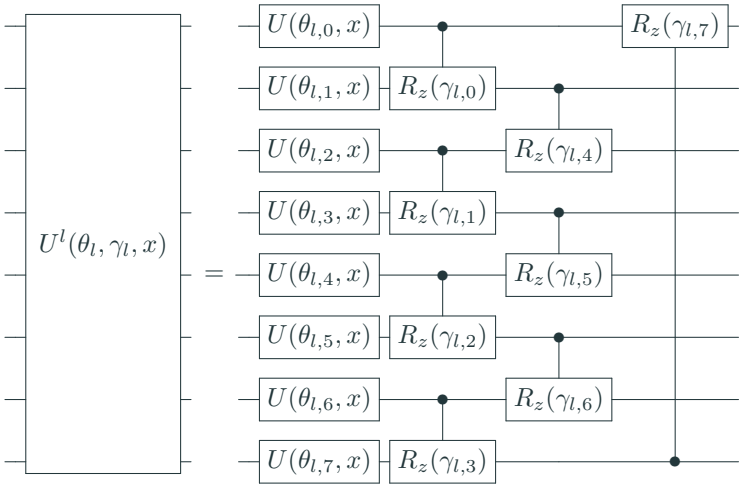


The first (algorithmic) step

arXiv:2011.13934

- Define a circuit $\mathcal{U}(\boldsymbol{x};\boldsymbol{\theta})$ using one qubit per parton p_i;
- fill gates with both x_i and $\log(x_i)$;
- Compute PDF_i prediction using expectation of $Z_i = \bigotimes_{j=0}^{n} Z^{\delta_{ij}}$:

$$\mathrm{qPDF}_i(x_i; Q_0, \boldsymbol{\theta}) = \frac{1 - \langle 0|\mathcal{U}^\dagger Z_i \mathcal{U}|0\rangle}{1 + \langle 0|\mathcal{U}^\dagger Z_i \mathcal{U}|0\rangle}$$



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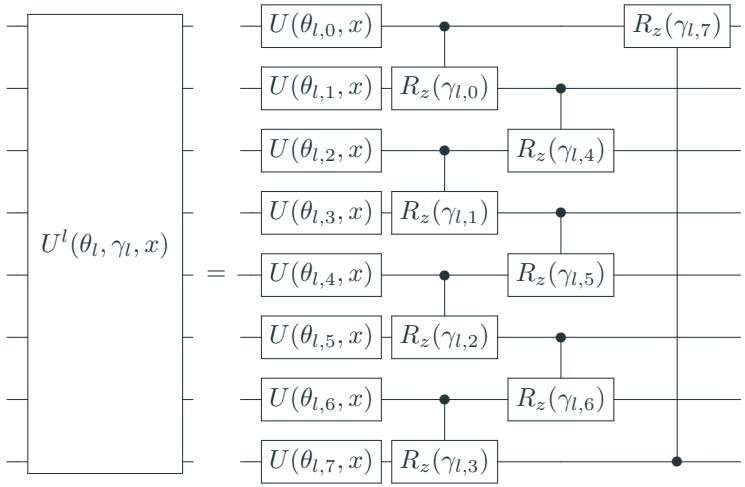

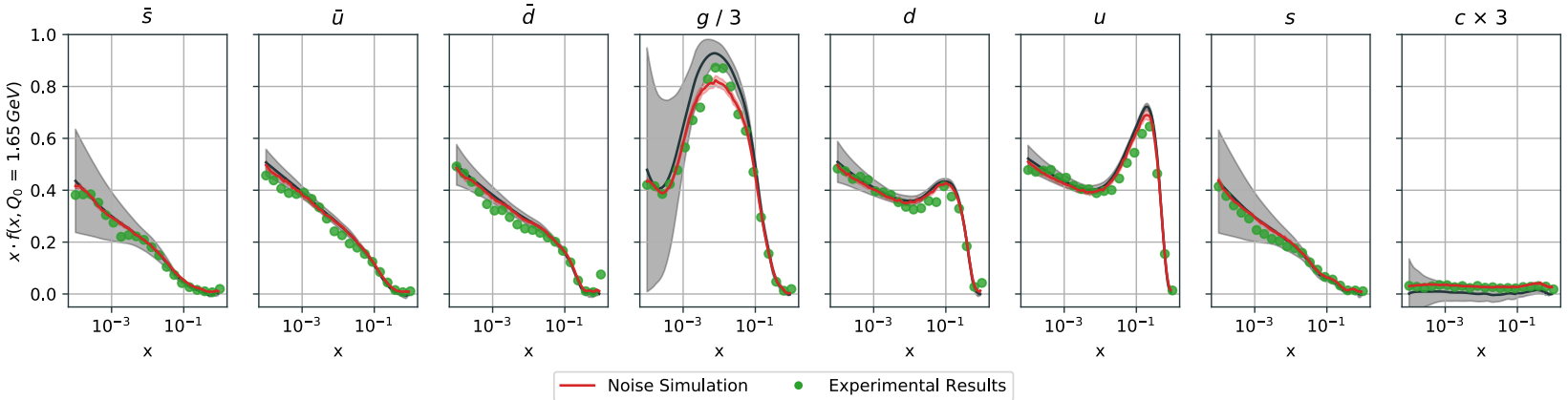

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arXiv:2308.06313

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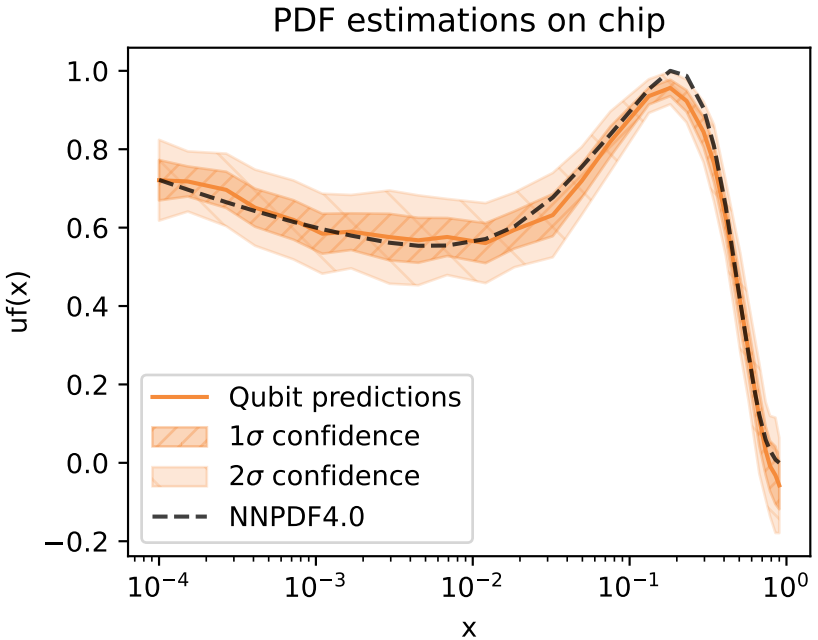

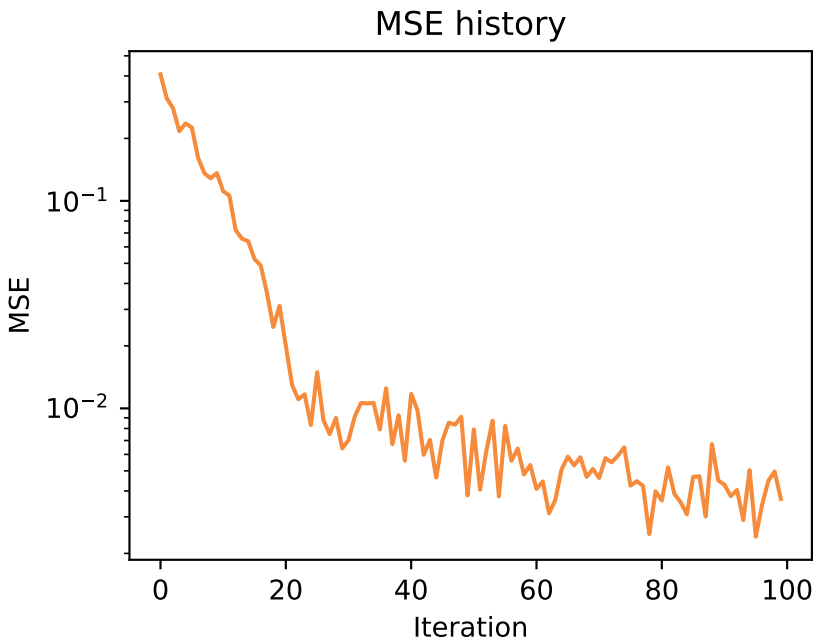

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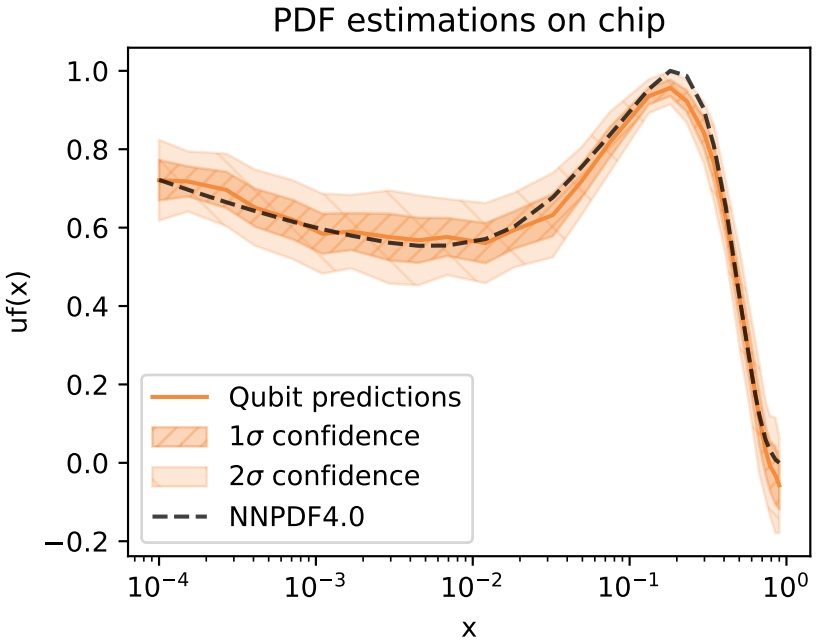

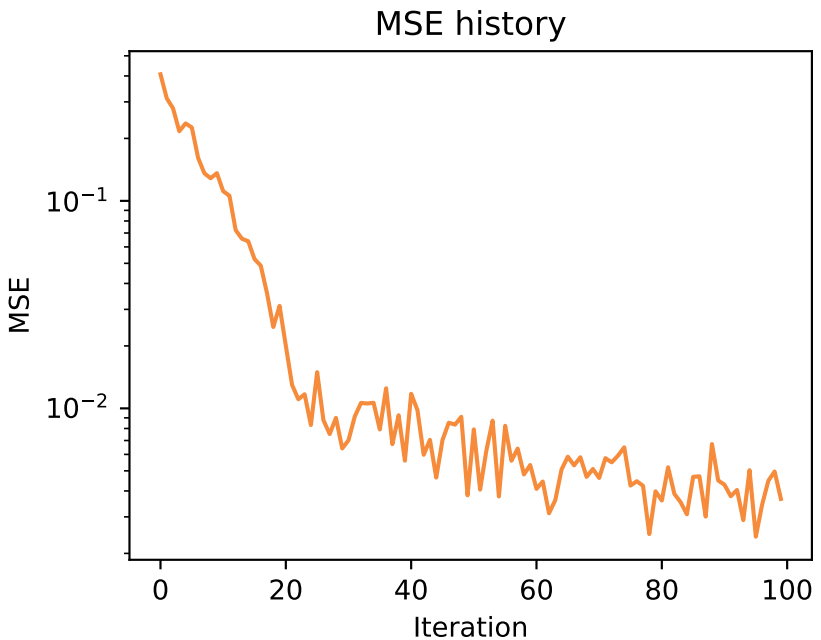

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Value	30	14	Adam	250	$3.6 \cdot 10^{-3}$	$78'$

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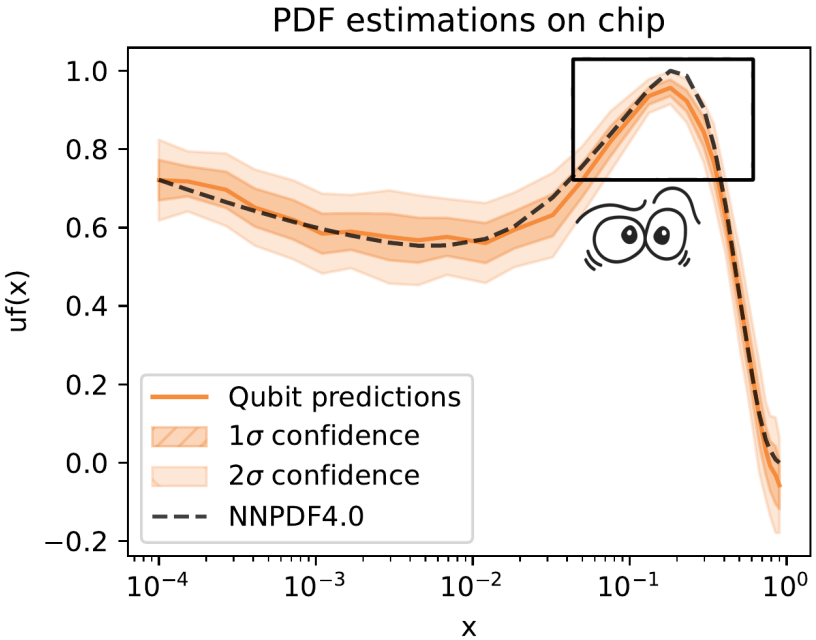

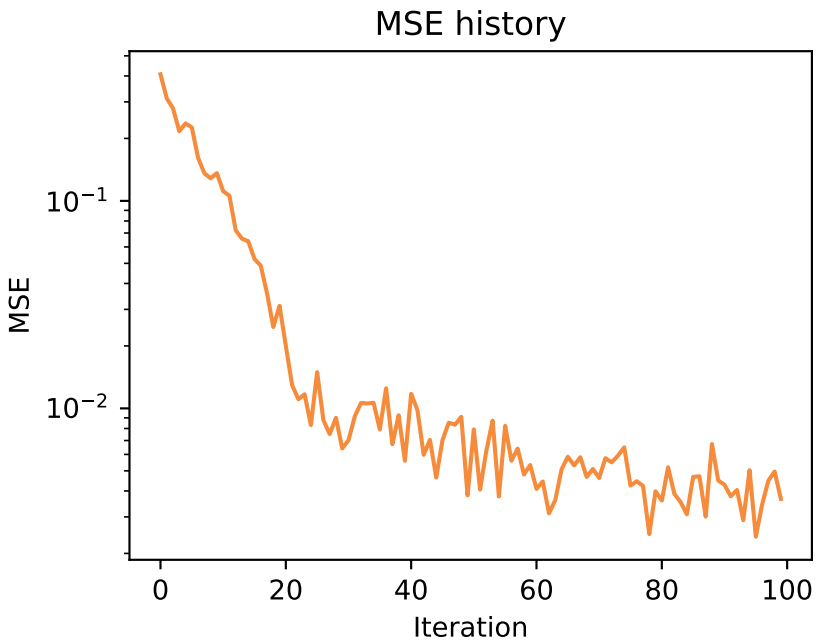

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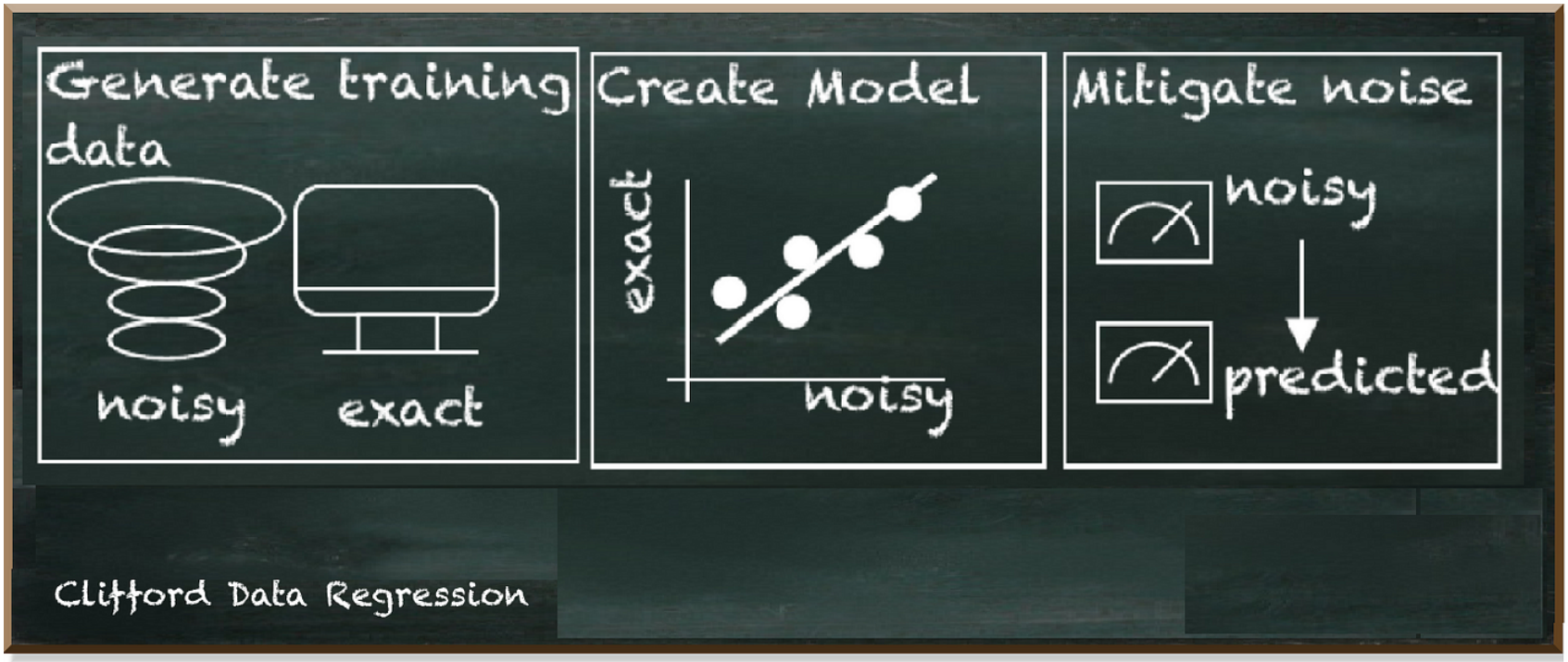

Credits: Frank Zickert.

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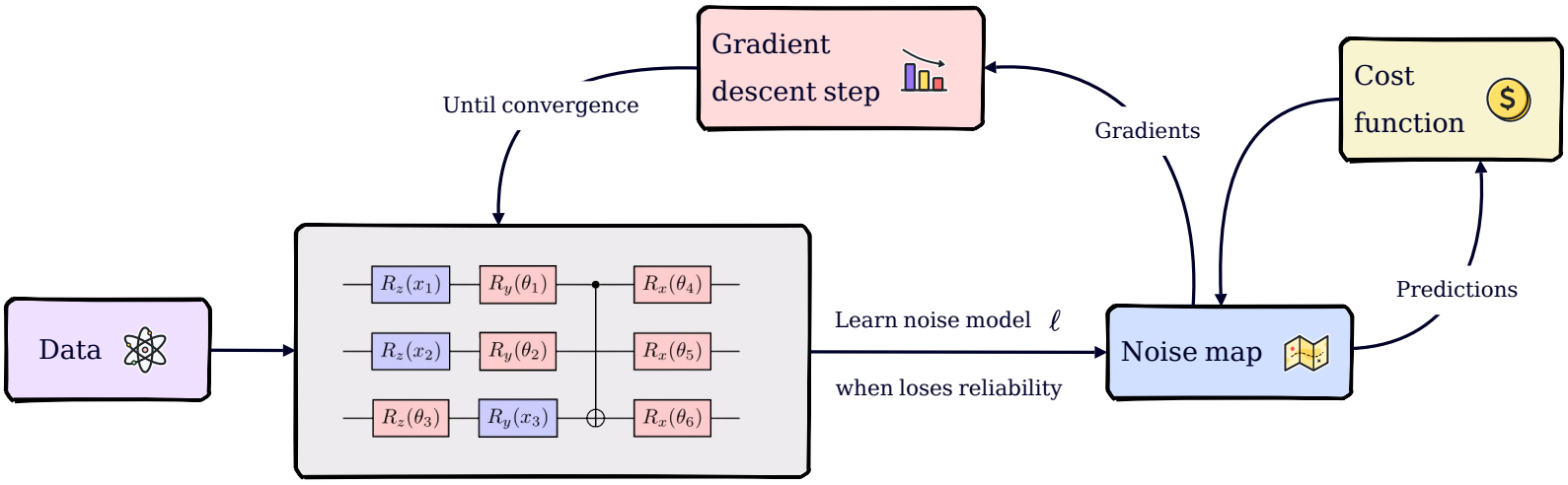

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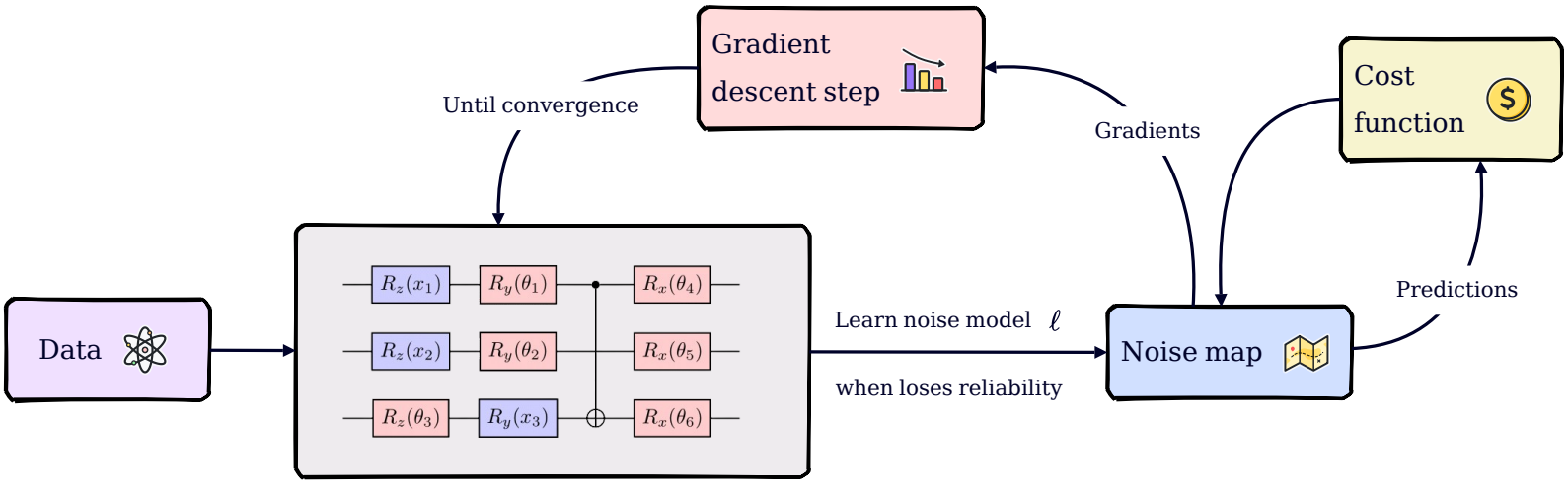

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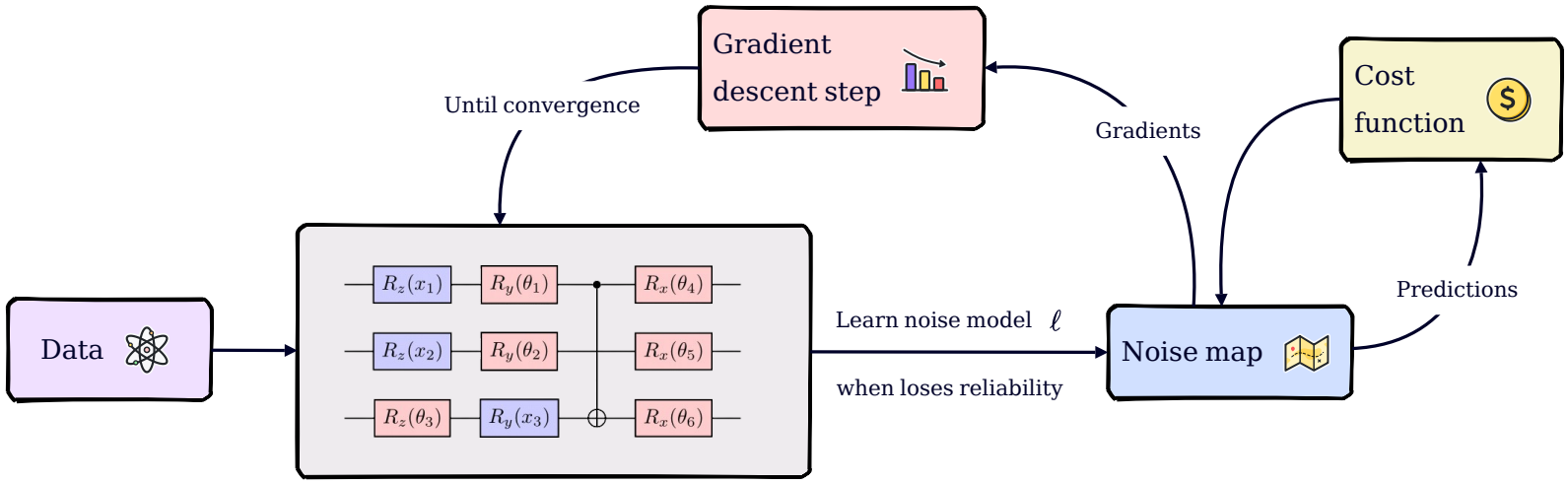
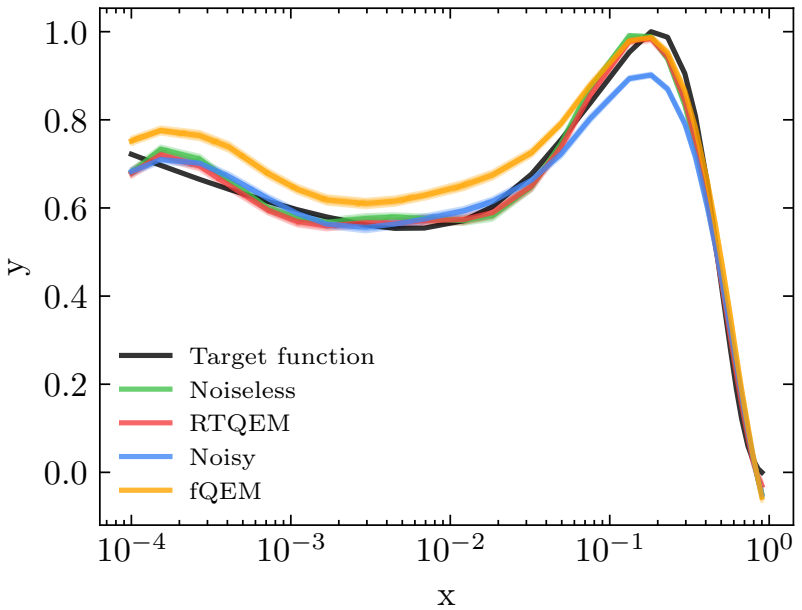
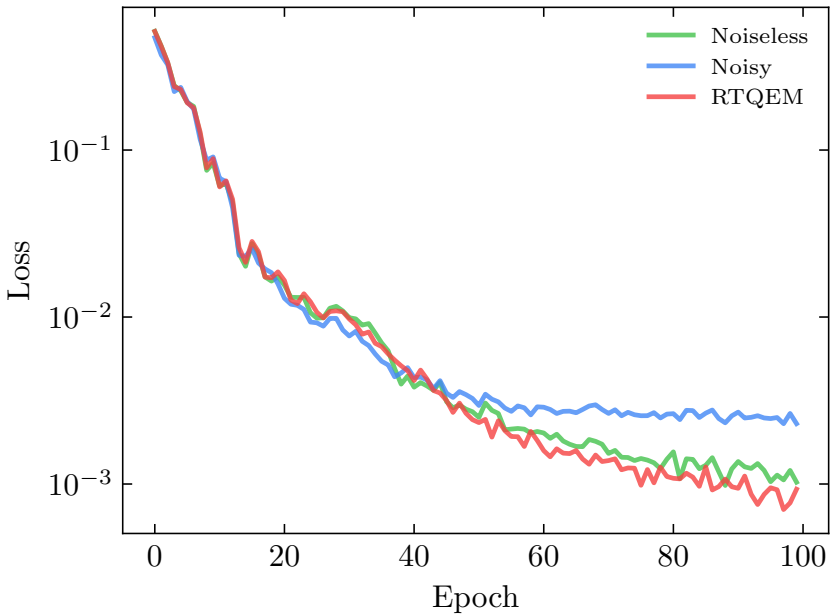


- these experiments take long execution times (but we have `Qibo`!);
- in some regimes, we aim to remove the bounds imposed by noise.

arXiv:2311.05680

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



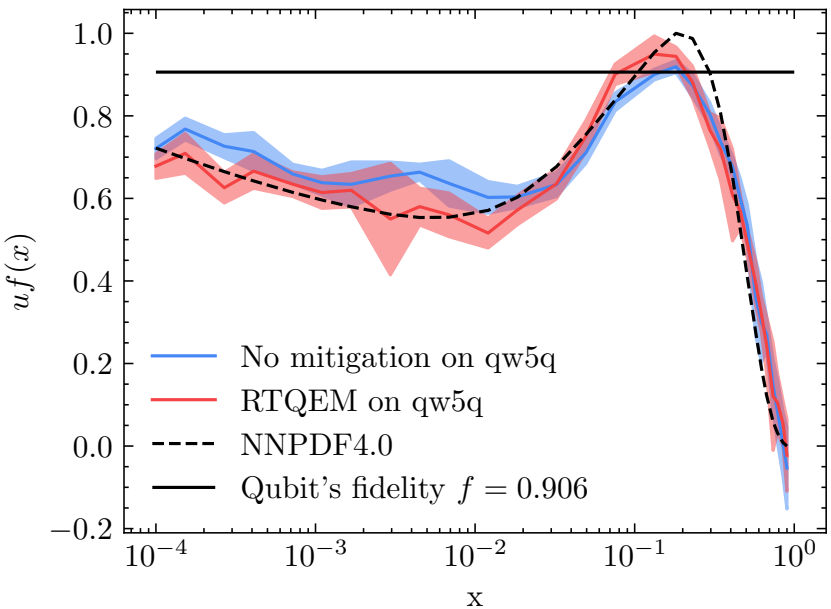


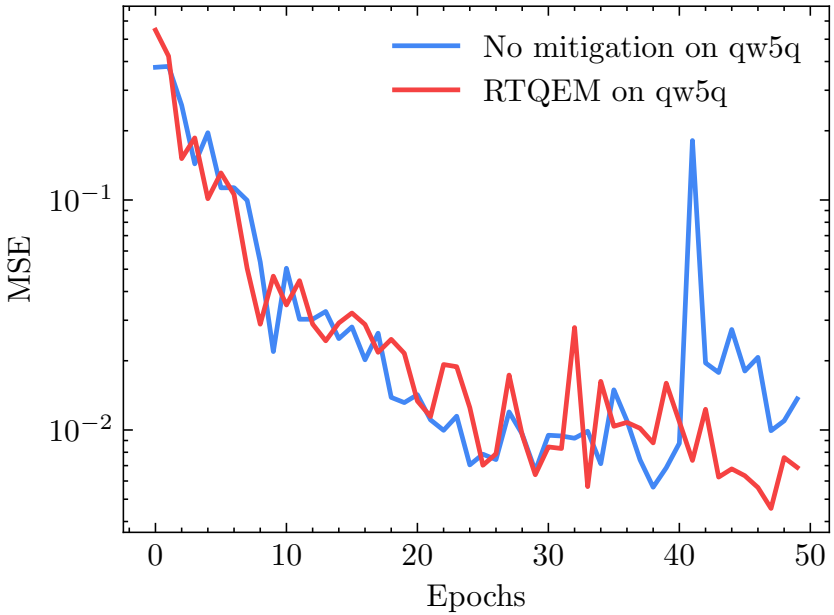
1. thanks to the RTQEM procedure, we reach a good minimum of the cost function;
2. the QEM is not effective if applied to a corrupted scenario (orange curve).

RTQEM on a superconducting qubit

arXiv:2311.05680

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





RTQEM allows exceeding the natural bound imposed by noise.

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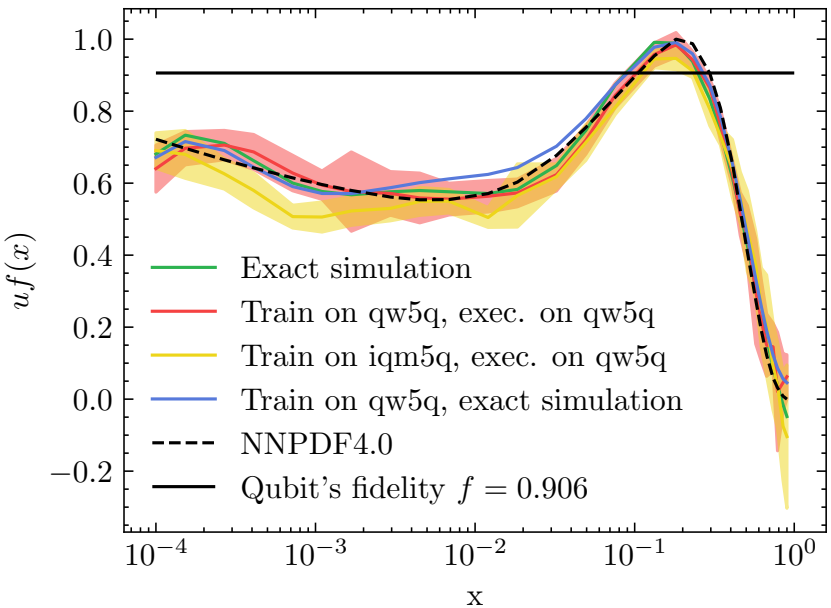

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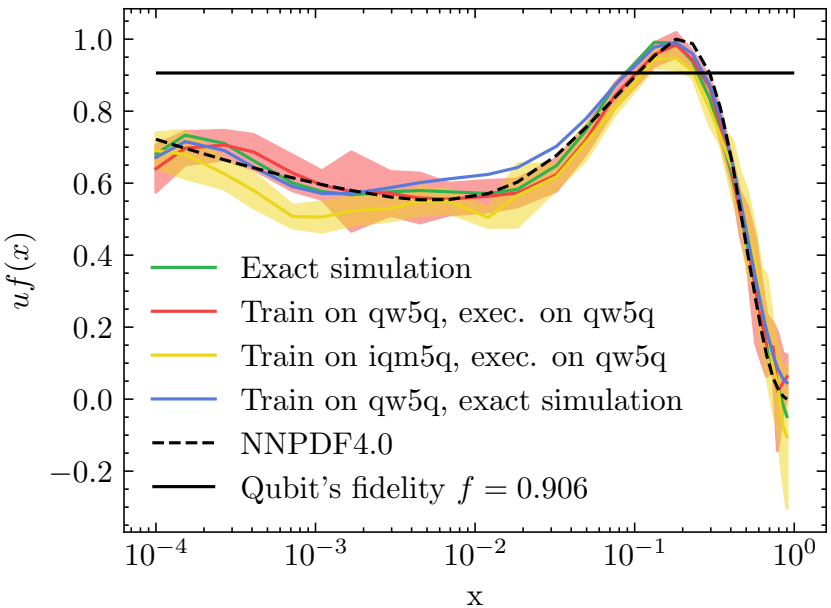

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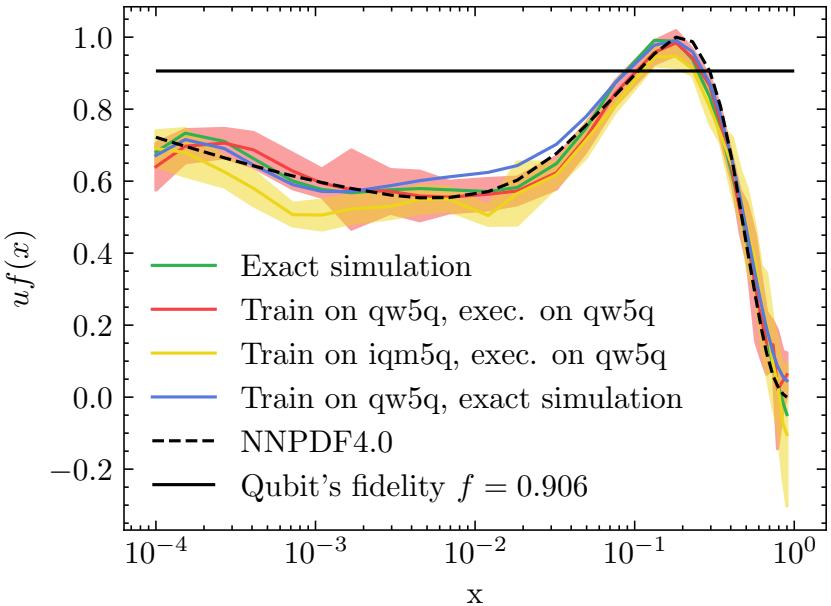

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`qw5q`	50	`qw5q`	RTQEM	0.0042
`qw5q`	100	`qw5q`	RTQEM	0.0013
`iqm5q`	100	`qw5q`	RTQEM	0.0037
`qw5q`	100	`sim`	RTQEM	0.0016

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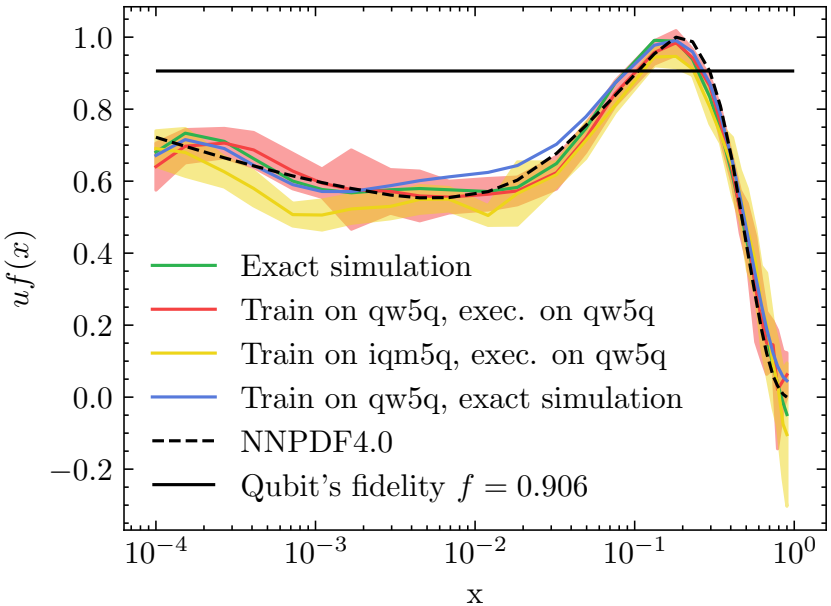

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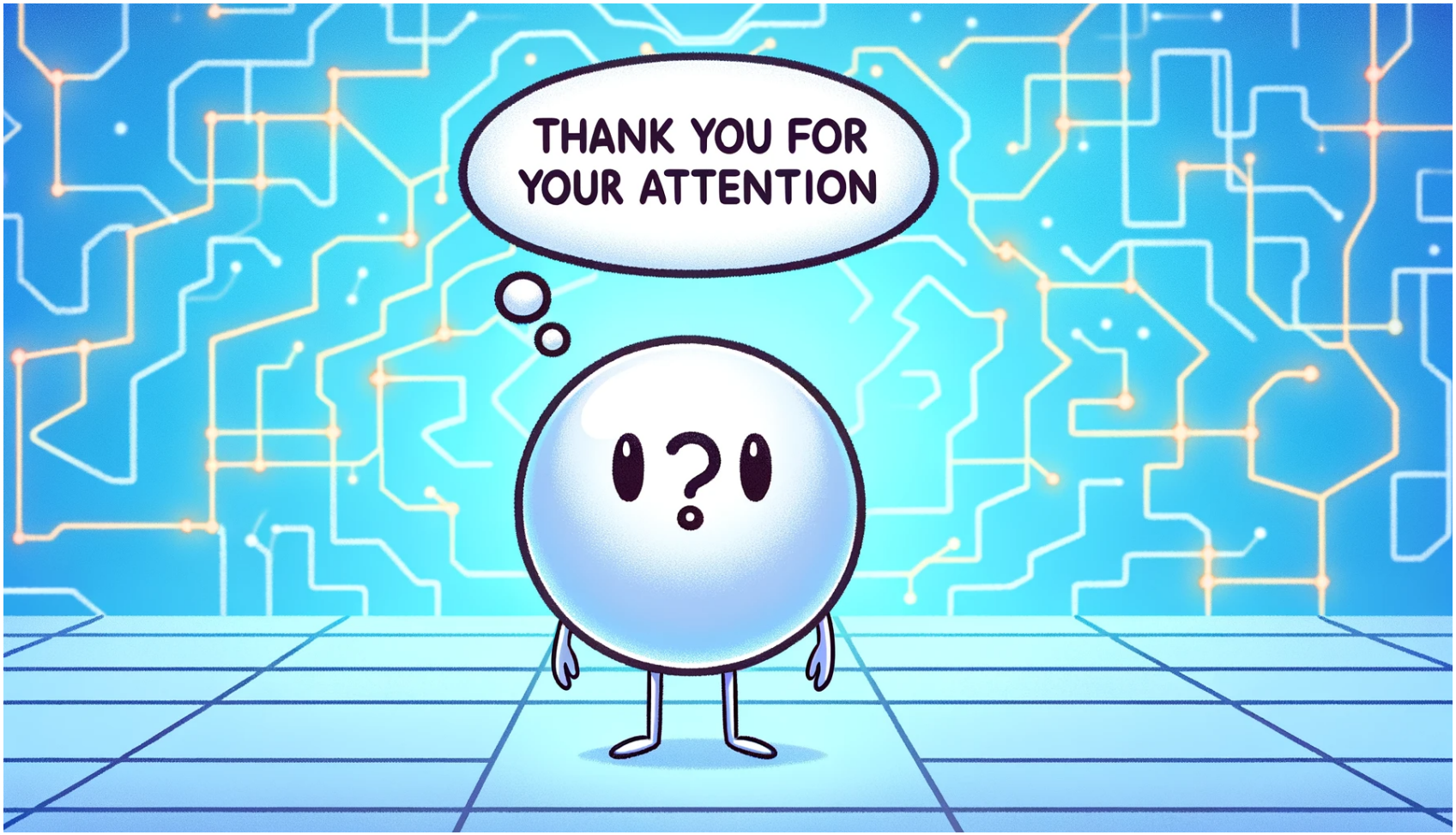
All the hardware results are obtained deploying the $\boldsymbol{\theta}_{\text{best}}$ on `qw5q`.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