

Towards a full-stack quantum operating system

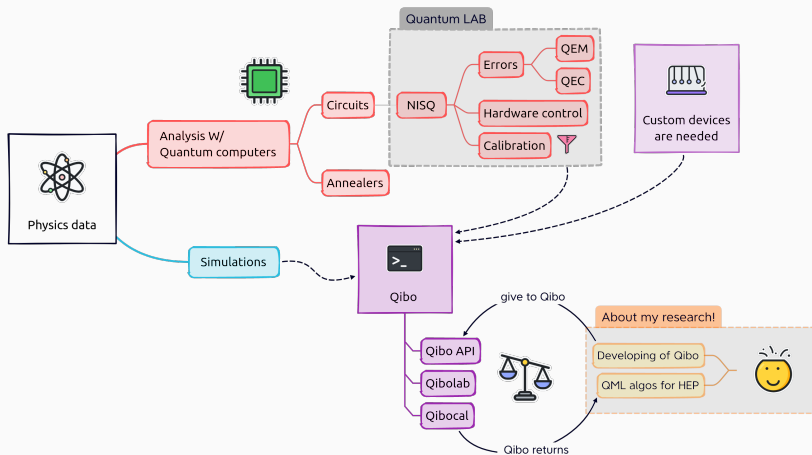
Quantum simulation, control and calibration using qibo

Matteo Robbiati

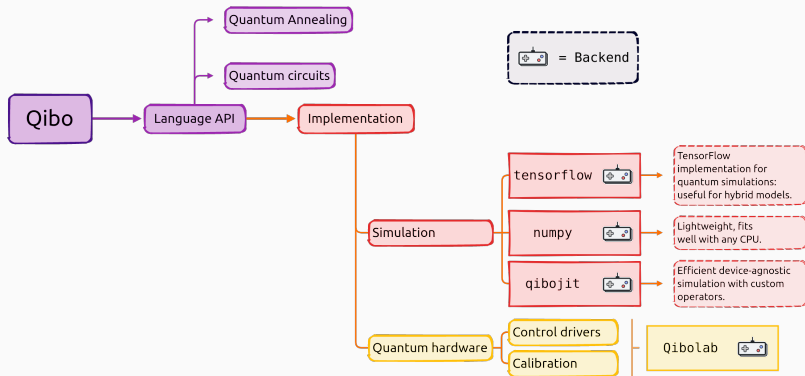
10 May 2023



Working in the NISQ era



What is qibo?



 [arXiv:2009.01845](https://arxiv.org/abs/2009.01845): "Qibo: a framework for quantum simulation with hardware acceleration."

- ➡ We do state vector simulation, which solves:

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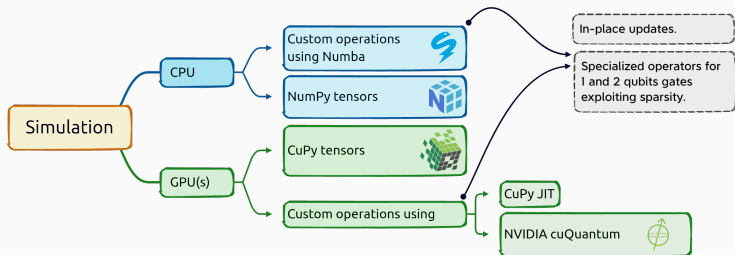
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More about qibojit

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- ➔ where the number of operations scales exponentially with N_{qubits} .
- ➔ For this reason we built qibojit (recommended if $N_{qubits} \geq 20$):



 [arXiv:2203.08826](https://arxiv.org/abs/2203.08826): "Quantum simulation with just-in-time compilation."

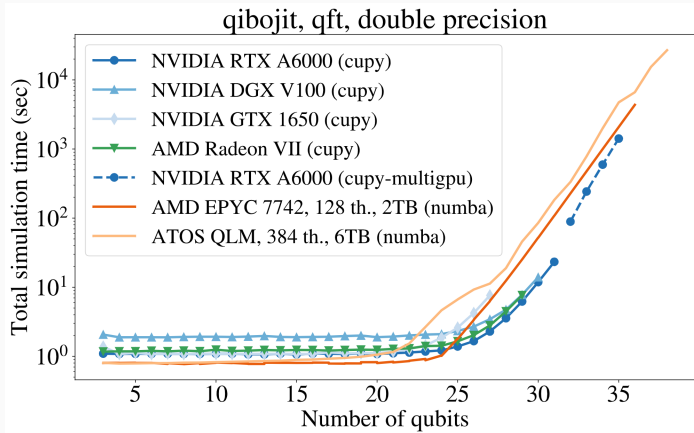


Figure 1: Quantum Fourier Transform execution with qibojit backend for growing number of qubits.

- ➡ An `AdiabaticEvolution` model is provided, which implements:

$$H_{\text{ad}}(\tau; \theta) = [1 - s(\tau; \theta)] H_0 + s(\tau; \theta) H_1. \quad (2)$$

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- ➡ If `solver=="exp"`, we use the evolutionary operator¹:

$$|\psi(\tau = jdt)\rangle = \prod_j^{\leftarrow} U_j |\psi(\tau = 0)\rangle \quad (3)$$

¹Translated into a circuit form using the Trotter decomposition.

Adiabatic evolution on qibo backends

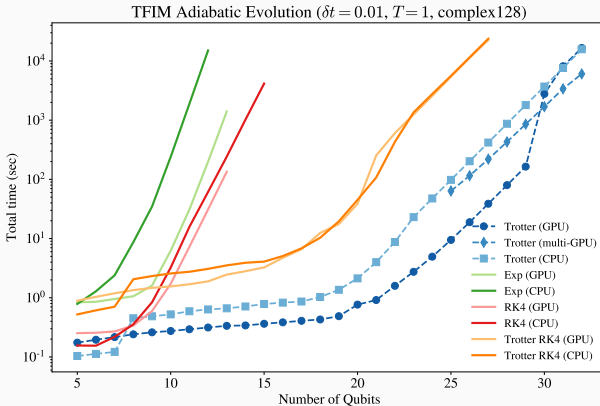
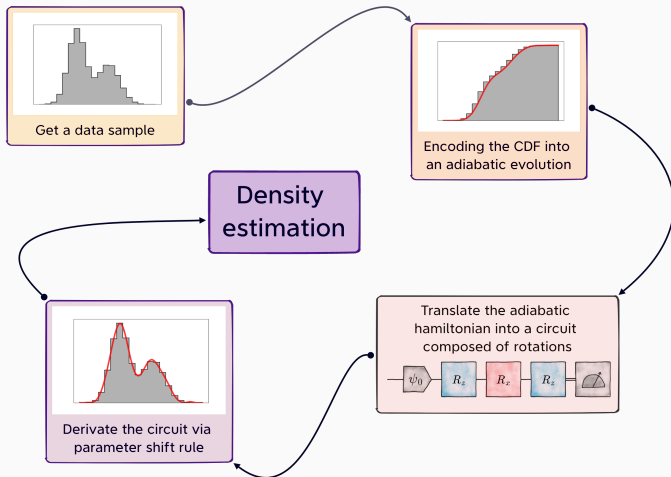


Figure 2: Adiabatic evolution execution with growing number of qubits and different solvers.

A full-stack QML algorithm

The theoretical idea



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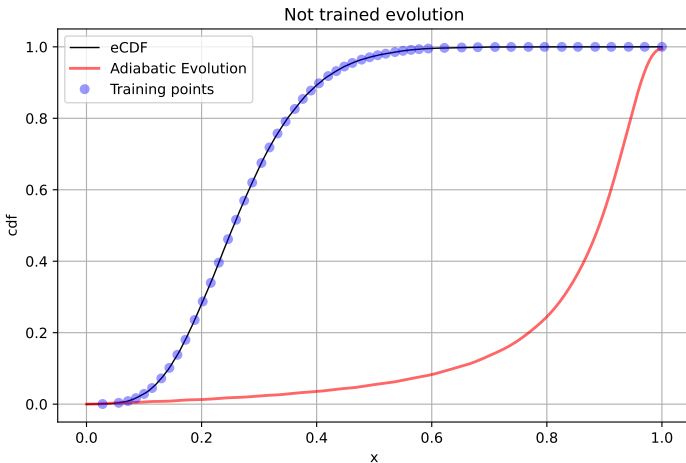
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📖 [arXiv:2303.11346](https://arxiv.org/abs/2303.11346): “Determining probability density functions with adiabatic quantum computing.”

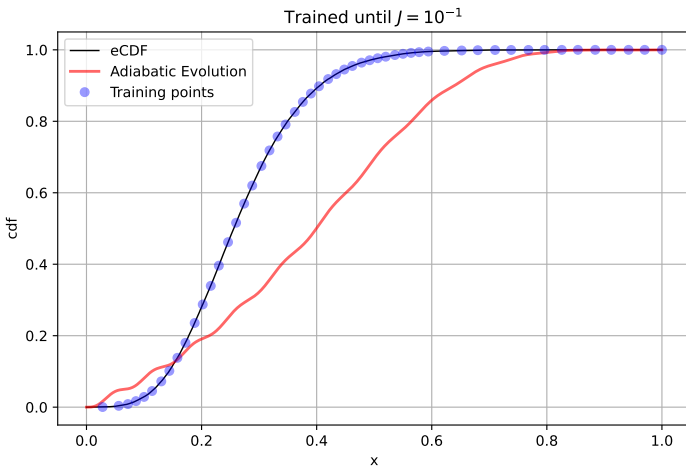
A toy example with $n_{\text{qubits}}=1$ - starting point

➔ $n_{\text{params}}=20$, $dt=0.1$, $\text{final_time}=50$, $\text{target_loss}=\text{None}$



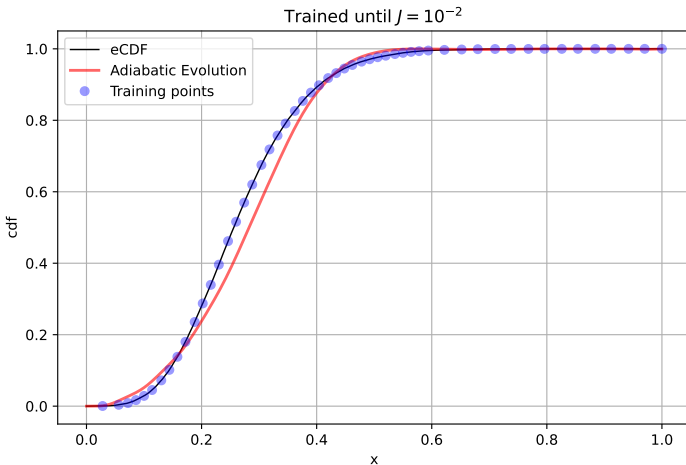
A toy example - until $J_{\text{MSE}} = 10^{-1}$

➔ `nparams=20, dt=0.1, final_time=50, target_loss=1e-1`



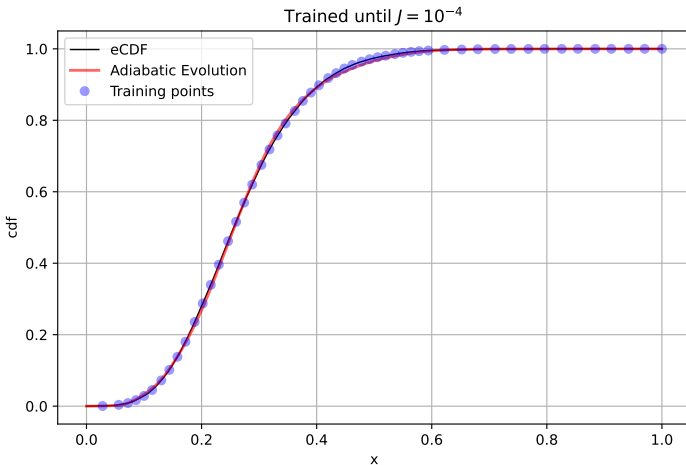
A toy example - until $J_{\text{MSE}} = 10^{-2}$

➔ `nparams=20, dt=0.1, final_time=50, target_loss=1e-2`



A toy example - ending at $J_{\text{MSE}} = 10^{-4}$

➔ `nparams=20, dt=0.1, final_time=50, target_loss=1e-4`



SIMULATION: from $\{H_{\text{ad}}\}$ to a circuit and derivate!

➡ Firstly, we did some calculations and approximations in order to:

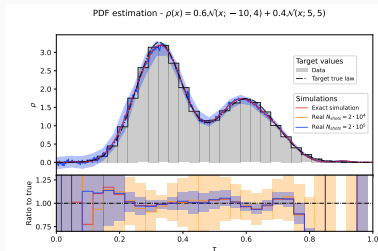
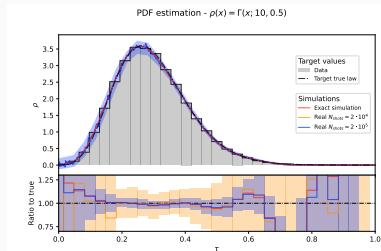
1. translate the Hamiltonians' sequence into a single unitary:

$$\prod_{j=1}^n e^{-iH_j dt} \rightarrow \mathcal{U}(t);$$

2. translate this unitary in a sequence of rotational gates:

$$\mathcal{U}(t) = R_z(\theta_1)R_x(\theta_2)R_z(\theta_3) \quad \text{with } \theta_i \equiv \theta_i(t).$$

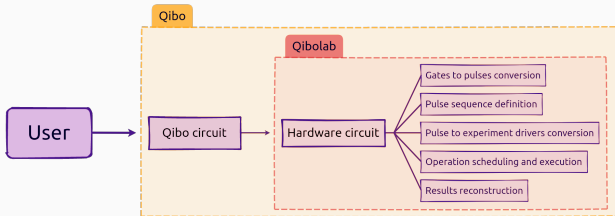
➡ Then, we derivate the expected values using parameter shift rule and chain rule.



- ➔ qibo is hardware-agnostic!

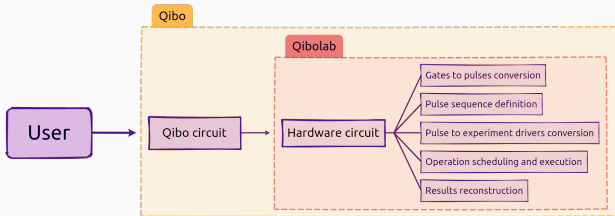
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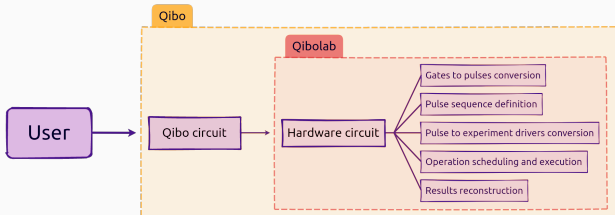


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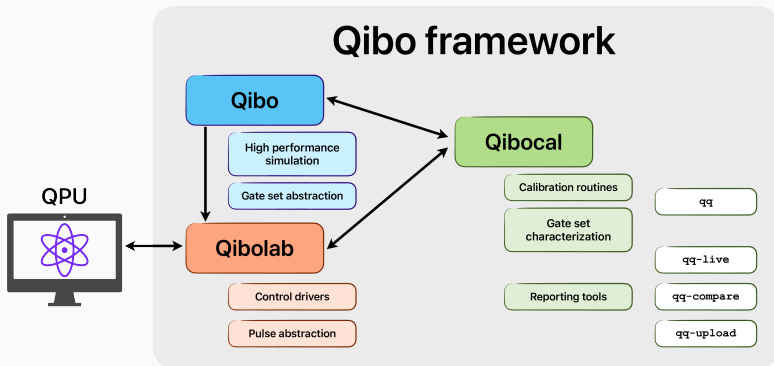
 [arXiv:2202.07017](https://arxiv.org/abs/2202.07017): “An open-source modular framework for quantum computing.”

 [arXiv:2112.02933](https://arxiv.org/abs/2112.02933): “ICARUS-Q: Integrated Control and Readout Unit for Scalable Quantum Processors”

- ➡ Each quantum control routine is useless if the sequences of pulses are not well calibrated with the single qubit.

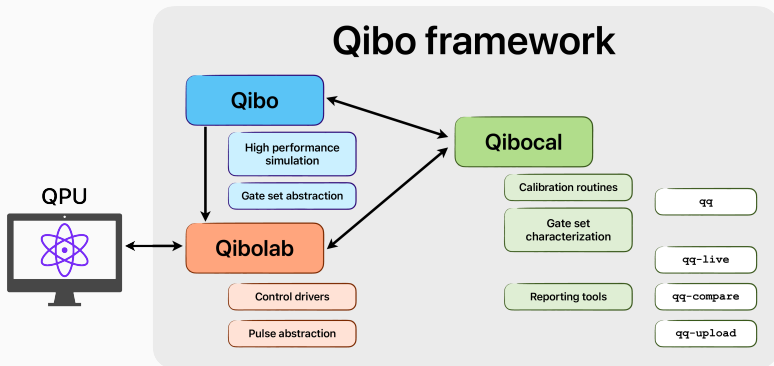
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 [arXiv:2303.10397](https://arxiv.org/abs/2303.10397): "Towards an open-source framework to perform quantum calibration and characterization."

The importance of qibocal

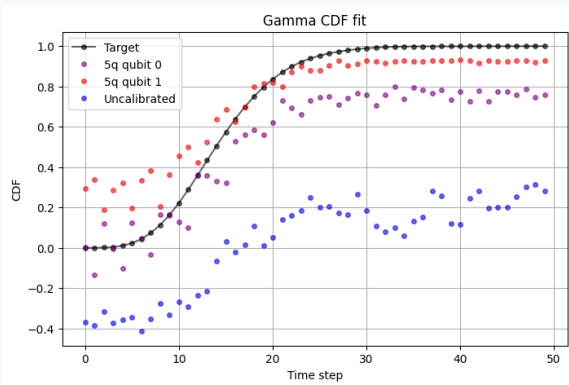


Figure 3: Different qubits requires different calibration and leads to different results.

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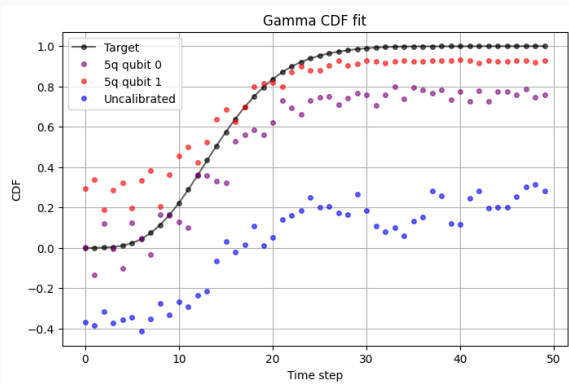


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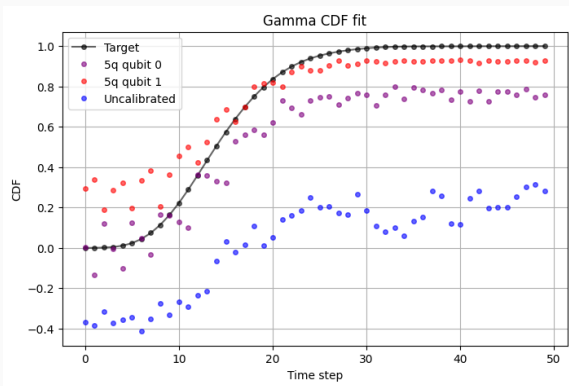


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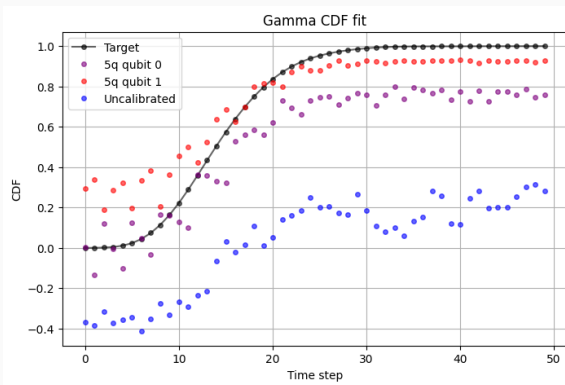


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➡ Open questions:

- 👉 what if the entire training is performed on a NISQ device? *are the results self-resistant to the noise?*
- 👉 what needed for improving results on the hardware?

: **what if we train on hardware?**

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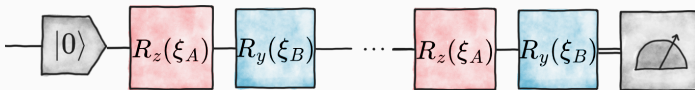


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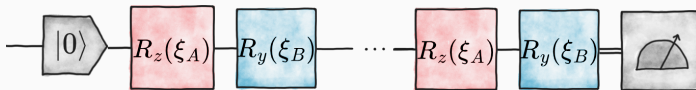


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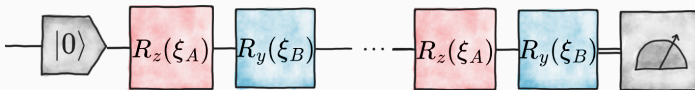


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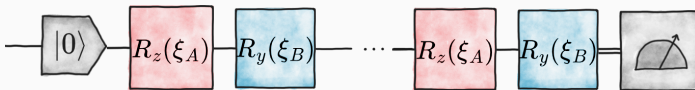


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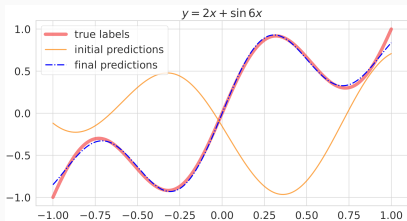
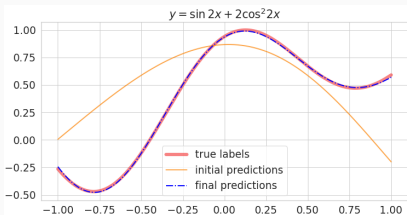
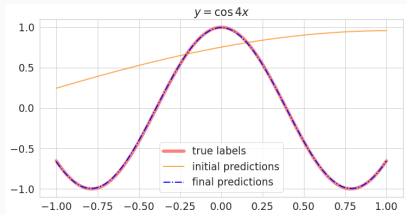
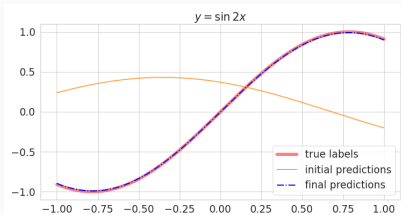
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📖 [arXiv:2210.10787](https://arxiv.org/abs/2210.10787): "A quantum analytical Adam descent through parameter shift rule using Qibo."

Simulation results



Run on the hardware

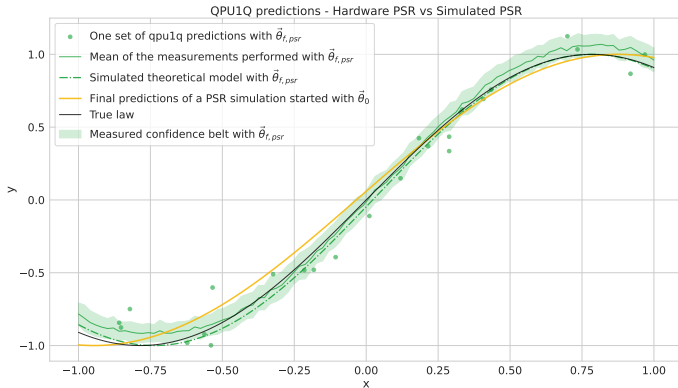


Figure 5: Batch Gradient Descent on the hardware. Gradients are evaluated via Parameter-Shift Rule.

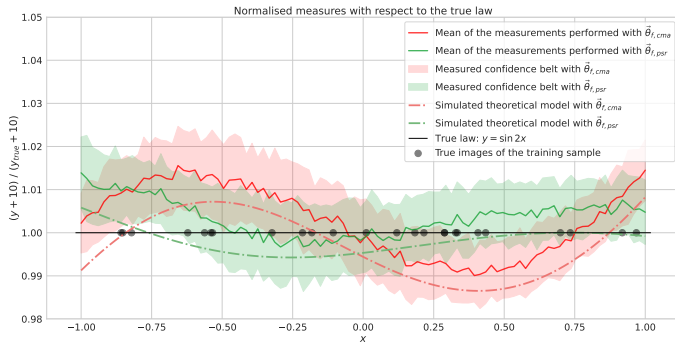


Figure 6: Normalised results of the SGD (green line) compared with true law and a genetic optimizer (red line).

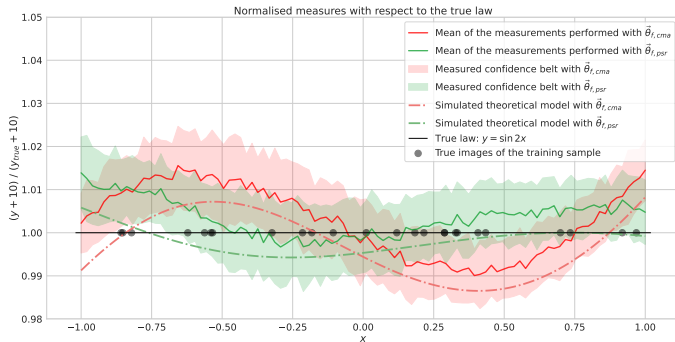


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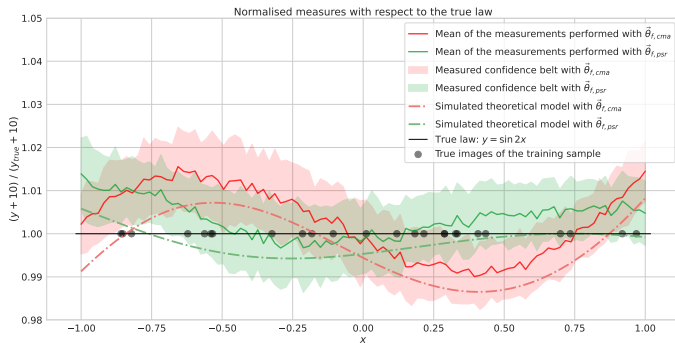


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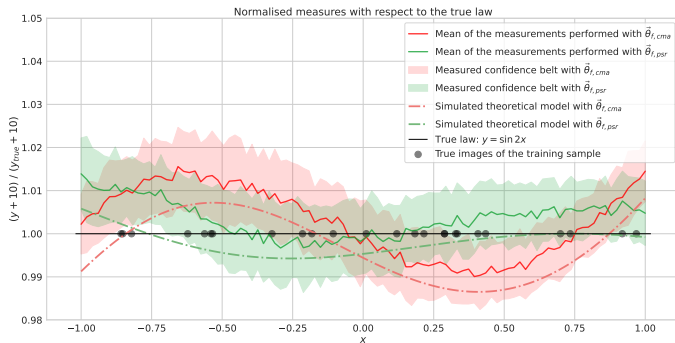


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- 👍 the full-stack framework works! comparable with a genetic algorithm;
- 🐢 we can tackle only easy problems: it is slow;
- 😬 no mitigation: have been the errors absorbed into the optimization?

✌️: how to get noise resistance?

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²We used Zero Noise Extrapolation (ZNE) and Clifford Data Regression (CDR).

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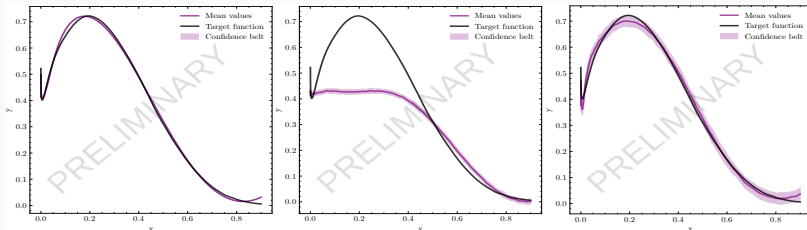


Figure 7: PDF fit performed with different levels of noisy simulation. From left to right, exact simulation, noisy simulation, noisy simulation applying error mitigation to the predictions.

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- ➔ We want to reproduce the u quark PDF fit of *Pérez-Salinas et al.*
- ➔ We apply error mitigation techniques² during a QML training!

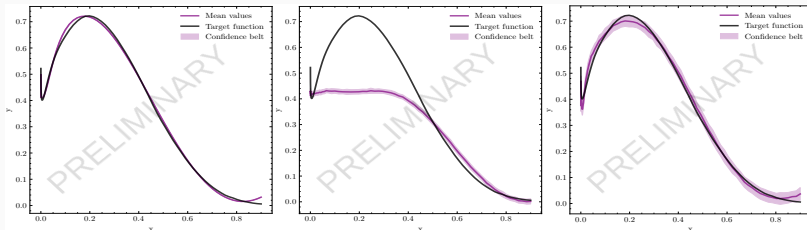


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- ➔ Run on the hardware upcoming!

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Conclusions

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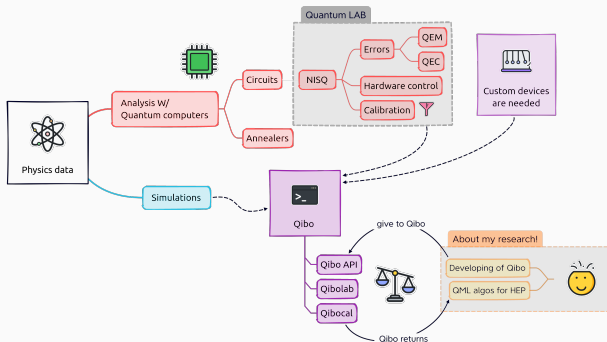
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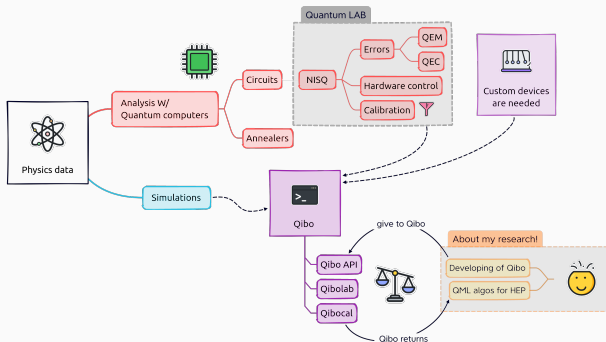
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- 🔗 code is open-source [here](#): feel free to make your own contribution!
- 📖 Have a look to our [documentation](#).