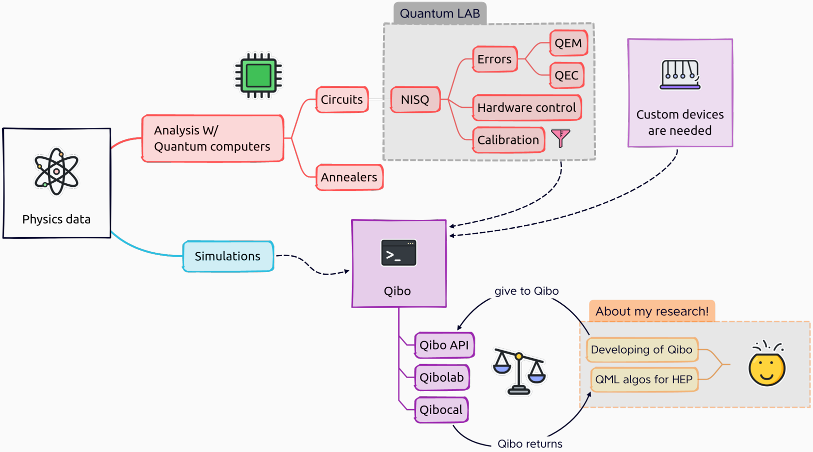
Towards a full-stack quantum operating system

Quantum simulation, control and calibration using `qibo`

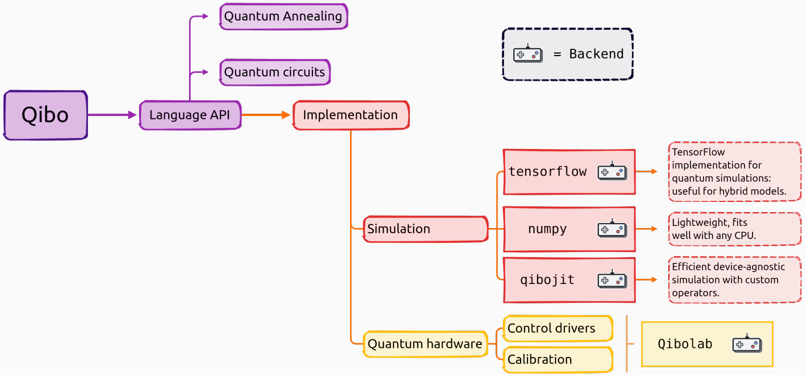
Matteo Robbiati

10 May 2023

Working in the NISQ era



What is qibo?



arXiv:2009.01845: *"Qibo: a framework for quantum simulation with hardware acceleration."*

Some features

More about `qibojit`

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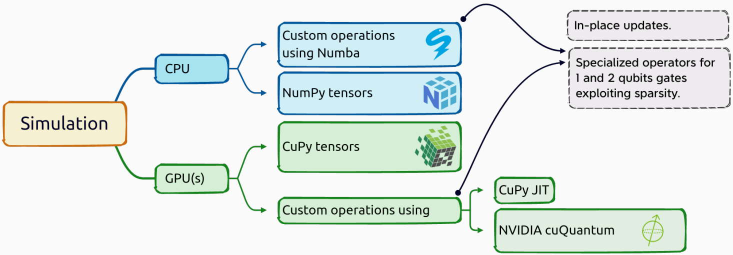
- For this reason we built `qibojit` (recommended if $N_{qubits \geq 20}$):



arXiv:2203.08826: *"Quantum simulation with just-in-time compilation."*

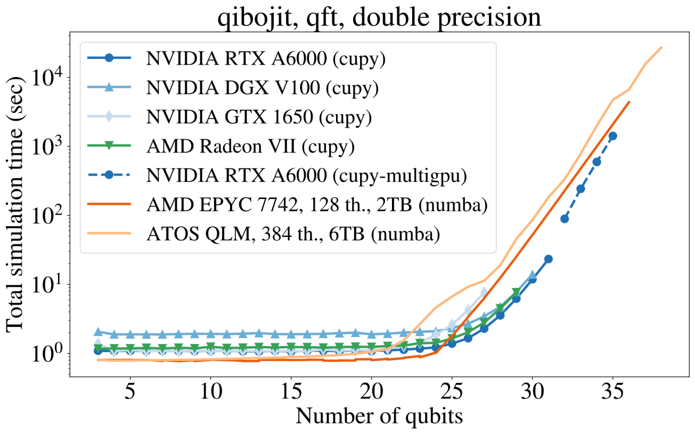


Figure 1: Quantum Fourier Transform execution with `qibojit` backend for growing number of qubits.

More about quantum annealing with `qibo`

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

$$H_{\mathrm{ad}}(\tau; \boldsymbol{\theta}) = \left[1 - s(\tau; \boldsymbol{\theta})\right] H_0 + s(\tau; \boldsymbol{\theta}) H_1. \tag{2}$$

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- If `solver=="exp"`, we use the evolutionary operator[1]:

$$|\psi(\tau = j\mathrm{d}t)\rangle = \overleftarrow{\prod_j} U_j \,|\psi(\tau = 0)\rangle \tag{3}$$

[1] Translated into a circuit form using the Trotter decomposition.

Adiabatic evolution on qibo backends

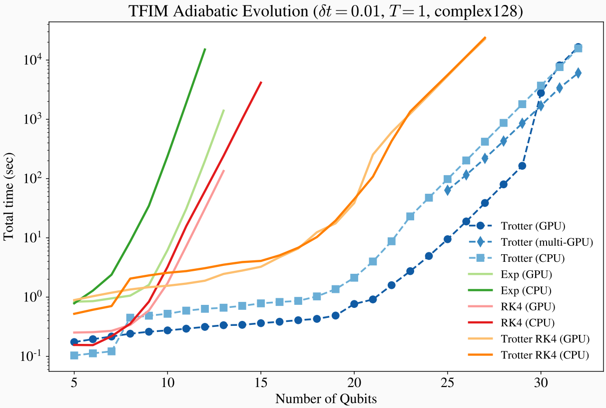
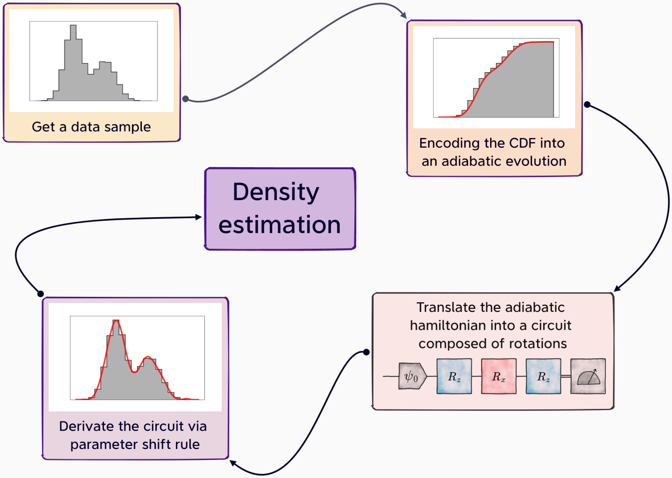


Figure 2: Adiabatic evolution execution with growing number of qubits and different solvers.

A full-stack QML algorithm

The theoretical idea



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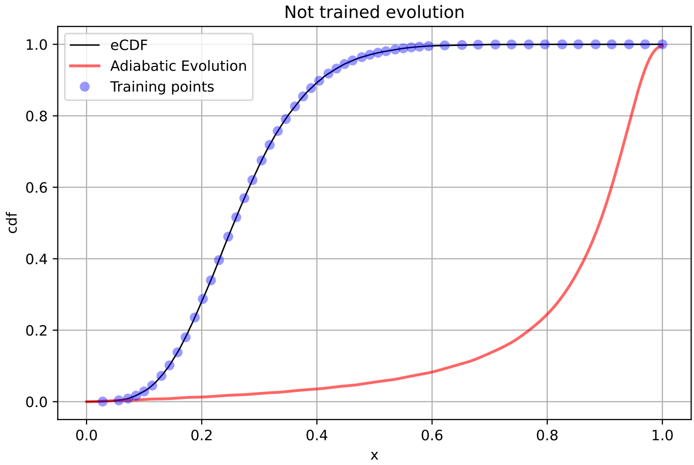
arXiv:2303.11346: *"Determining probability density functions with adiabatic quantum computing."*

A toy example with `nqubits=1` - starting point

- `nparams=20`, `dt=0.1`, `final_time=50` , `target_loss=None`



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

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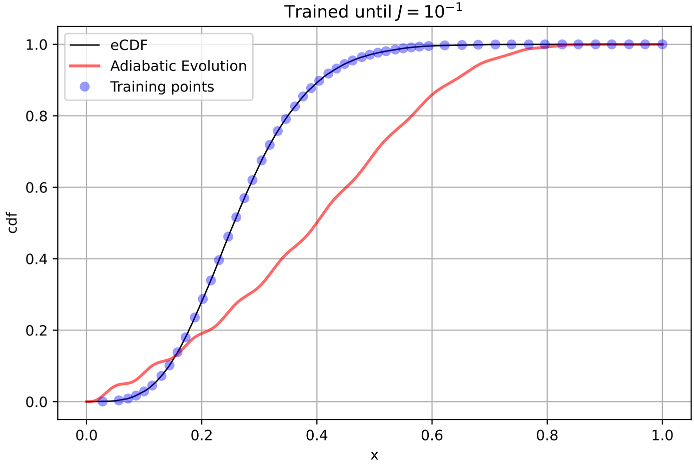
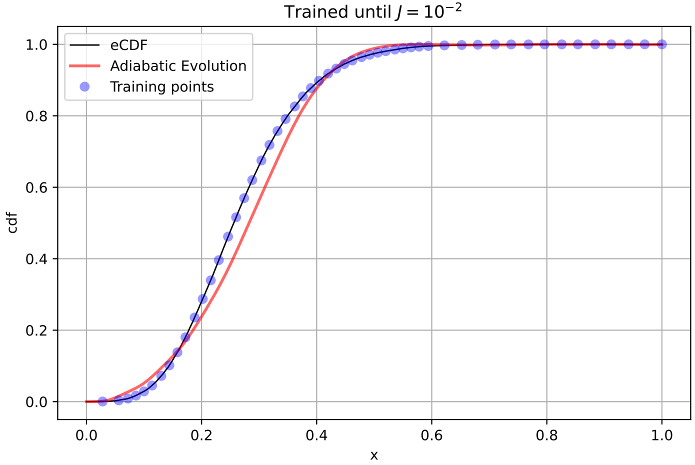


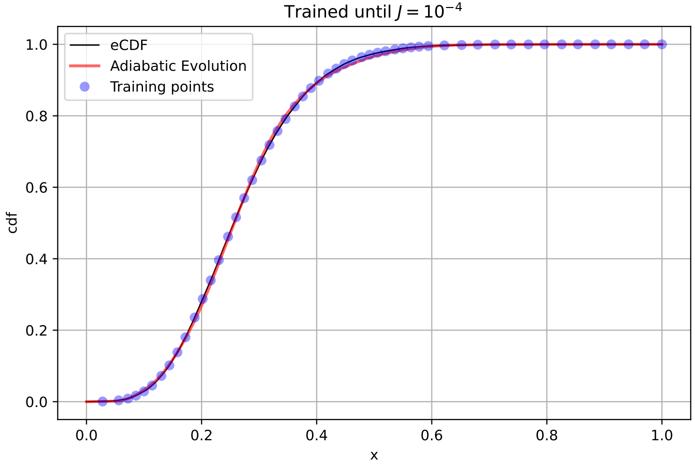
A toy example - until $J_{\mathrm{MSE}} = 10^{-2}$

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



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

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



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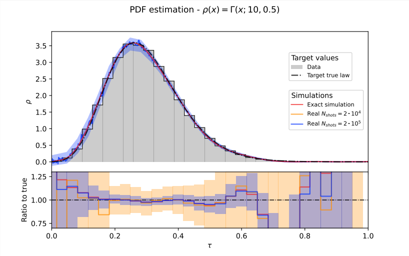

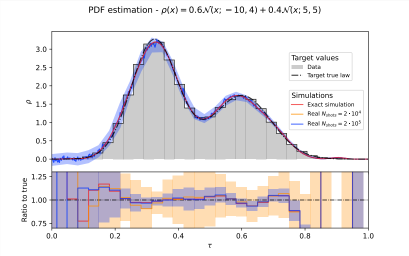

Hardware deployment

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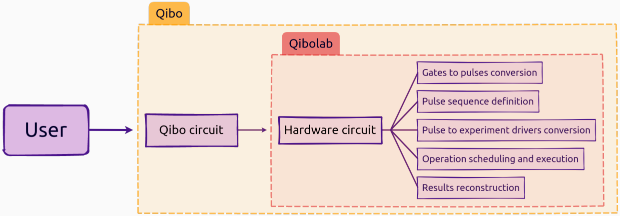

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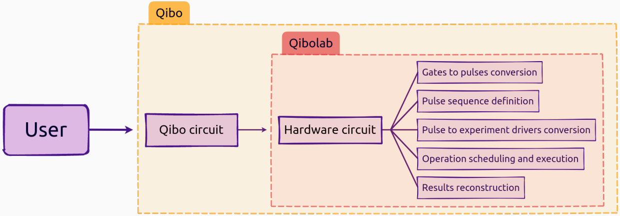

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INFN Istituto Nazionale di Fisica Nucleare

TII Technology Innovation Institute

CQT

BSC

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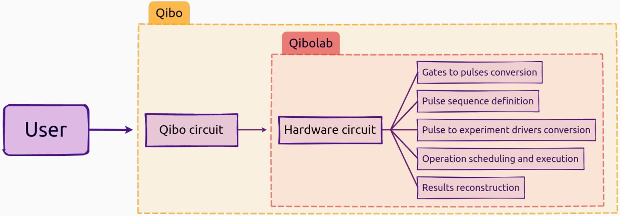

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arXiv:2202.07017: *"An open-source modular framework for quantum computing."*
arXiv:2112.02933: *"ICARUS-Q: Integrated Control and Readout Unit for Scalable Quantum Processors"*

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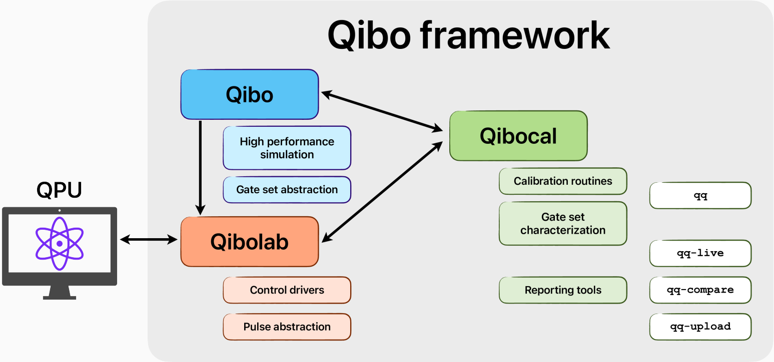

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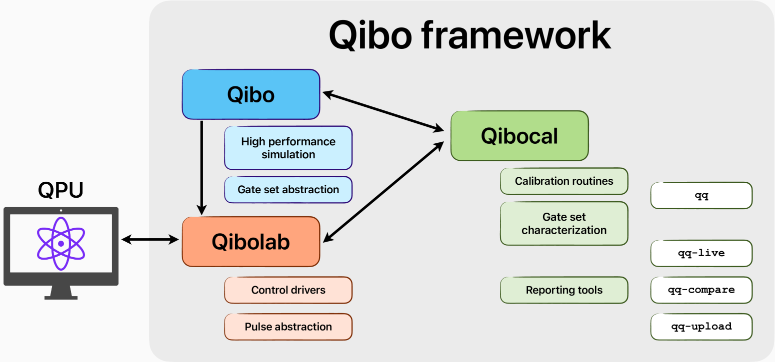


arXiv:2303.10397: *"Towards an open-source framework to perform quantum calibration and characterization."*

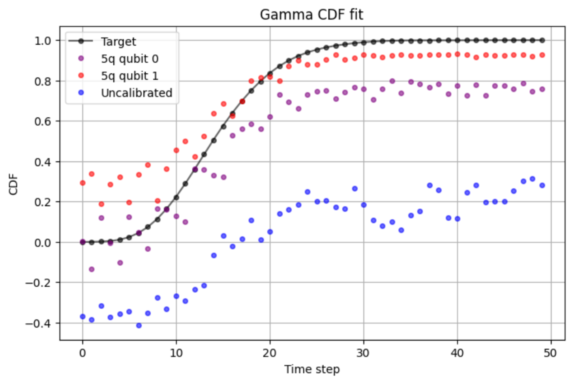
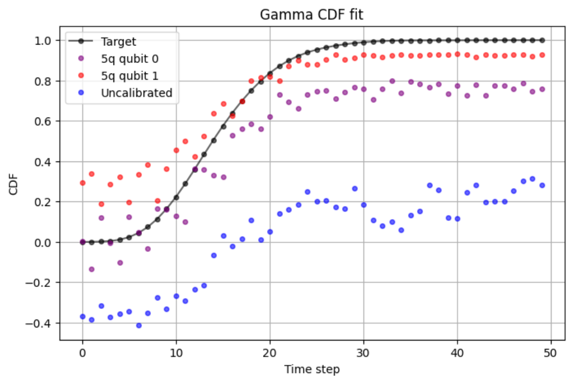


Figure 3: Different qubits requires different calibration and leads to different results.

The importance of `qibocal`



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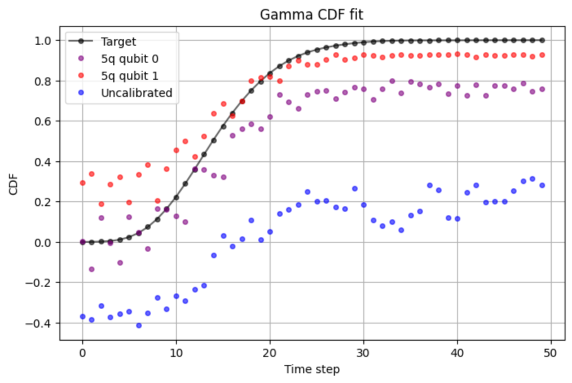

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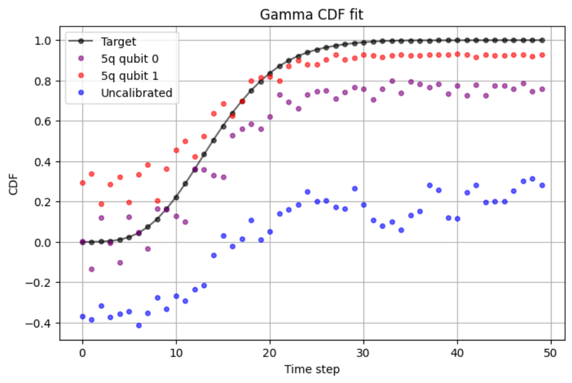

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  - what needed for improving results on the hardware?

☝: what if we train on hardware?

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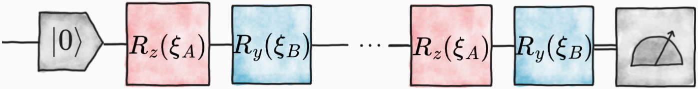

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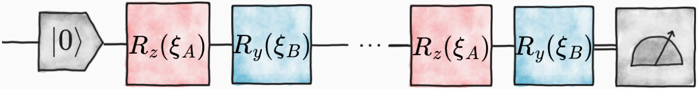

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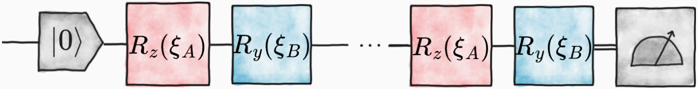

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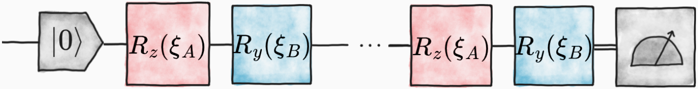

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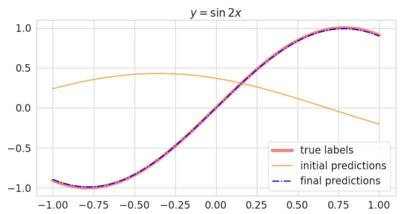
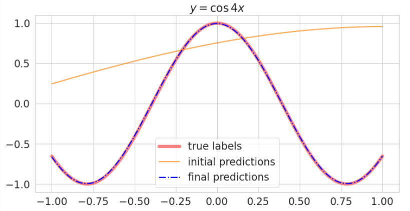
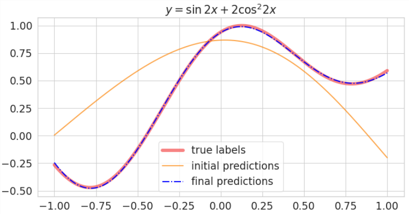
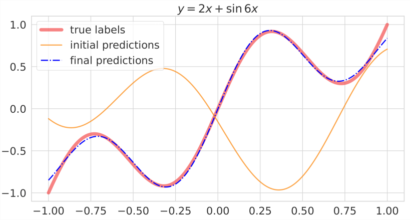
arXiv:2210.10787: *"A quantum analytical Adam descent through parameter shift rule using Qibo."*

Simulation results









Run on the hardware

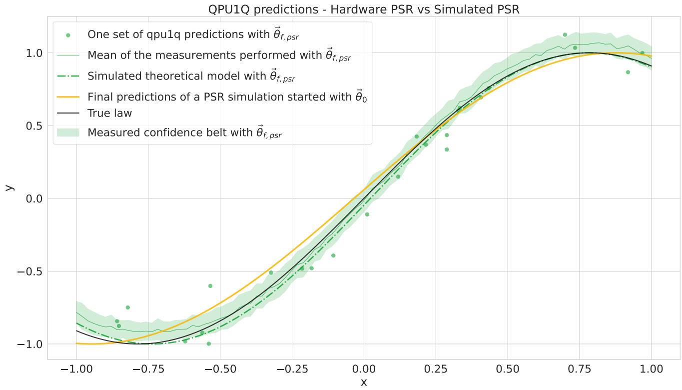


Figure 5: Batch Gradient Descent on the hardware, with gradients evaluated via Parameter-Shift Rule. We take 100 points $\{x_j\}$ in the range $[-1, 1]$ and we make 100 predictions for each x_j. Mean and standard deviation are used for determining the estimations and the confidend belt.

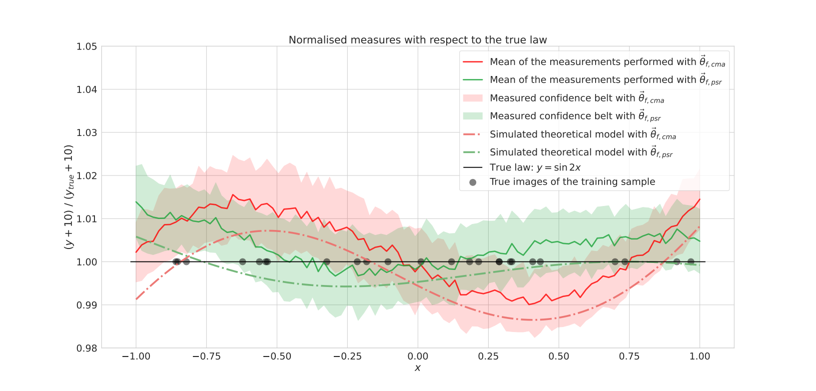
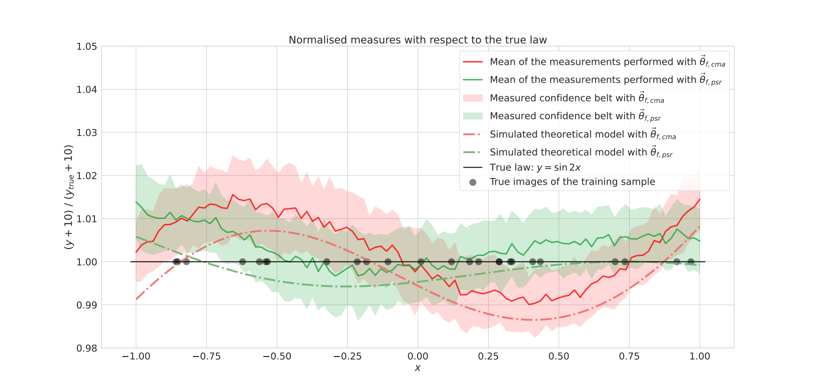


Figure 6: Normalised results of the SGD (green line) compared with true law and a genetic optimizer (red line).



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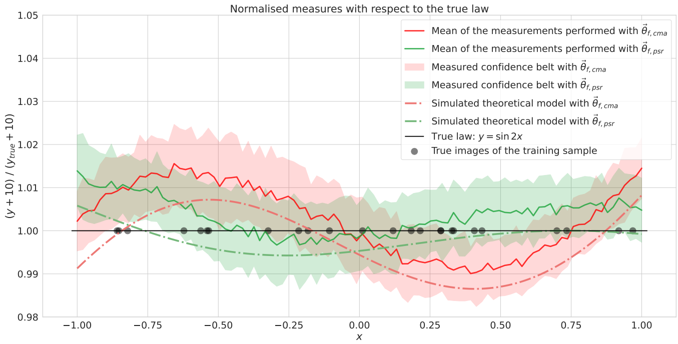

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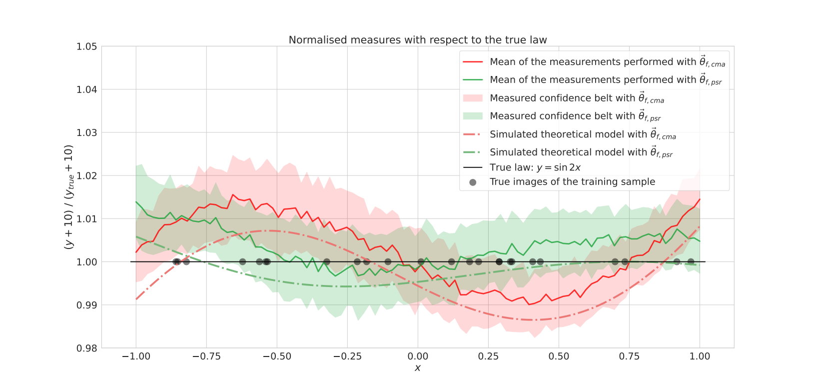

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- 👍 the full-stack framework works! comparable with a genetic algorithm;
- 👎 we can tackle only easy problems: it is slow;
- 😐 no mitigation: have been the errors absorbed into the optimization?

✌: how to get noise resistance?

- We want to reproduce the u quark PDF fit of *Pérez-Salinas et al*.

[2] We used Zero Noise Extrapolation (ZNE) and Clifford Data Regresssion (CDR).

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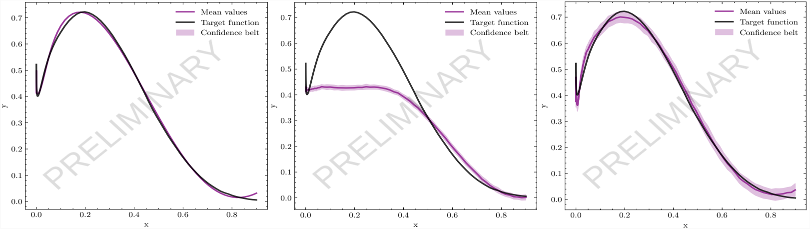

Figure 7: PDF fit performed with different levels of noisy simulation. From left to right, exact simulation, noisy simulation, noisy simulation applying error mitigation to the predictions.

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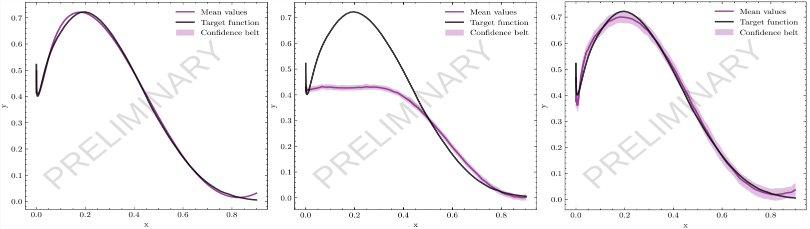

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- Run on the hardware upcoming!

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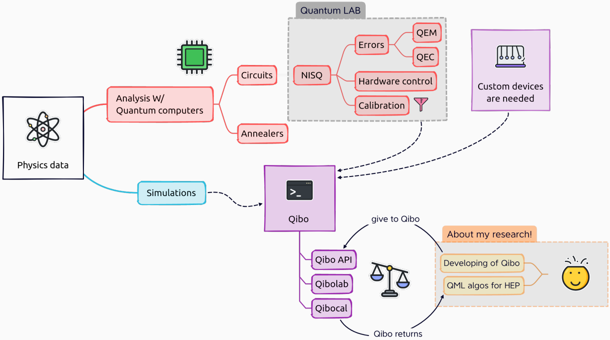

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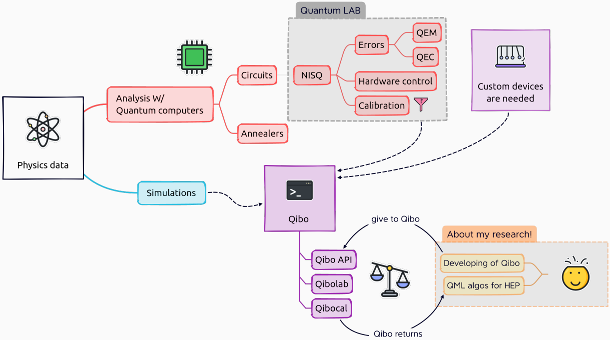

code is open-source here: feel free to make your own contribution!
Have a look to our documentation.