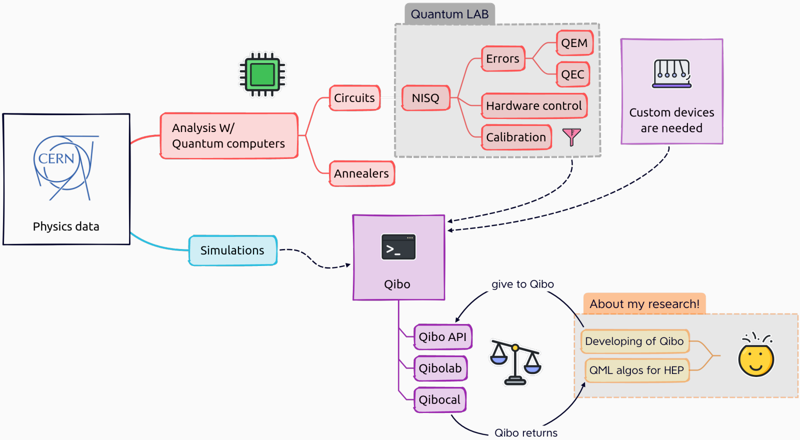
Doing full stack QML using `qibo`

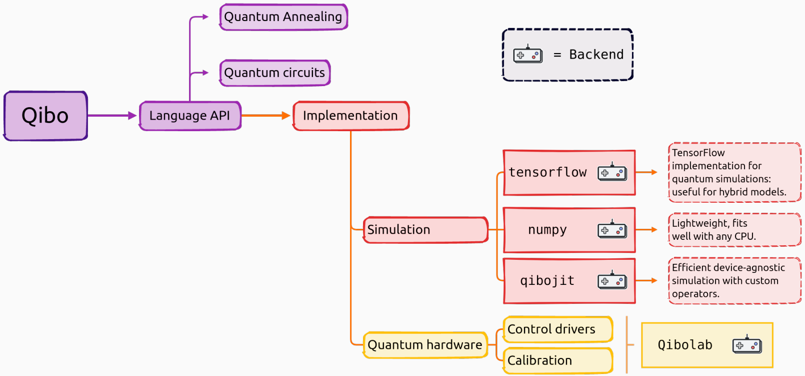
Matteo Robbiati **feat.** Alejandro Sopena

24 May 2023

Working in the NISQ era



The `qibo` ecosystem



Two snapshots

Adiabatic Evolution

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```python
# with qibo we can implement an Adiabatic Evolution via trotter formula
from qibo import models, hamiltonians, callbacks

# problem's parameters
nqubits = 1
h0 = hamiltonians.X(nqubits)
h1 = hamiltonians.Z(nqubits)
target_observable = h1

# we track the energy of h1 on the evolved ground state
energies = callbacks.Energy(target_observable)
evolution = models.AdiabaticEvolution(
    h0=h0, h1=h1, s = lambda t : t, dt=0.1, callbacks = [energies])

# calculate the evolved final state at time t=final_time
evolved_state = evolution(final_time = final_time)
```

Quantum Machine Learning - doing ML using QC

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

Quantum Computation
$\mathcal{Q}$: qubits;
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Quantum Machine Learning - operating on qubits

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Quantum Machine Learning!

Optimizer $\mathcal{O}$

</> hybrid-strategy?

on hardware?

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

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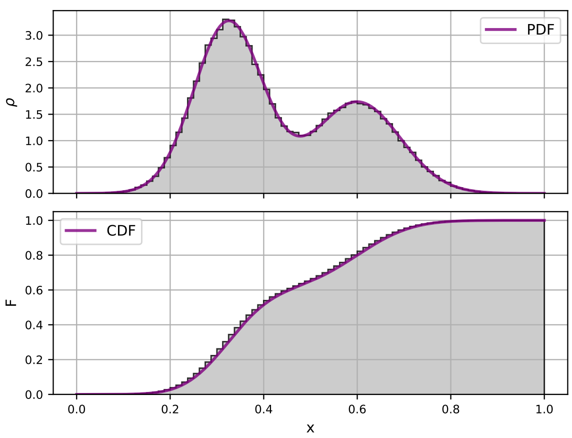
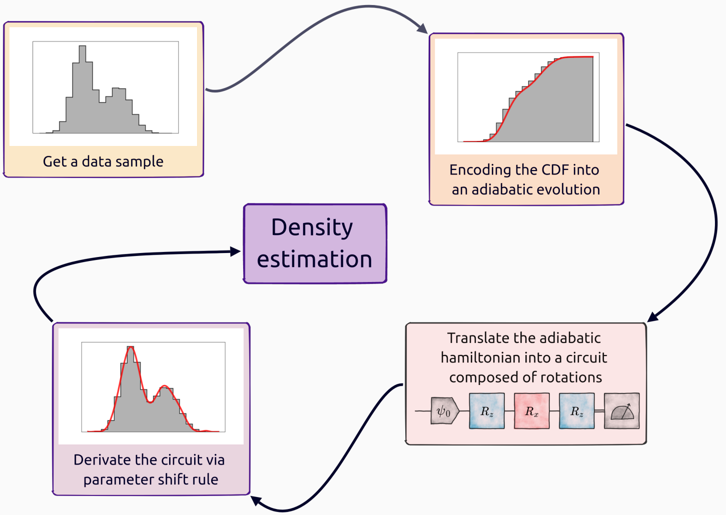
Full stack algorithms using `qibo`

STEP 0: the goal

- Let's consider a sample of data $\{x\}_{k=1}^{N_{\mathrm{data}}}$.
- We can calculate the Cumulative Density Function (CDF) values $F(x)$,
- which are related to the Probability Density Function (PDF) via $\rho(x) = \mathrm{d}F(x)/\mathrm{d}x$.



STEP 0: the idea



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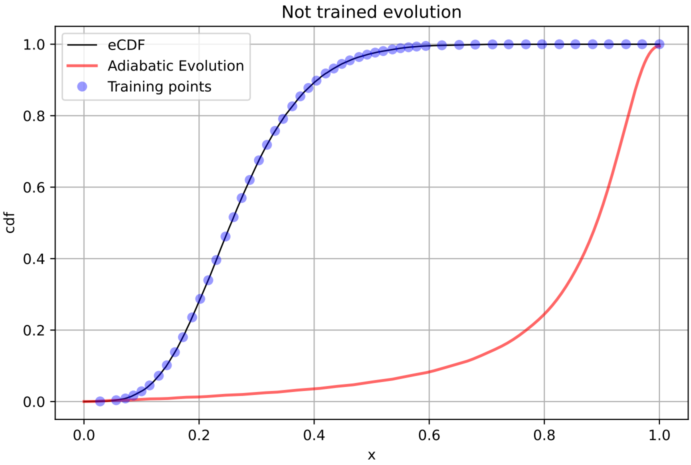
4. we choose an optimizer to find $\boldsymbol{\theta}_{\rm best}$ which minimizes $J_{\rm mse}$.

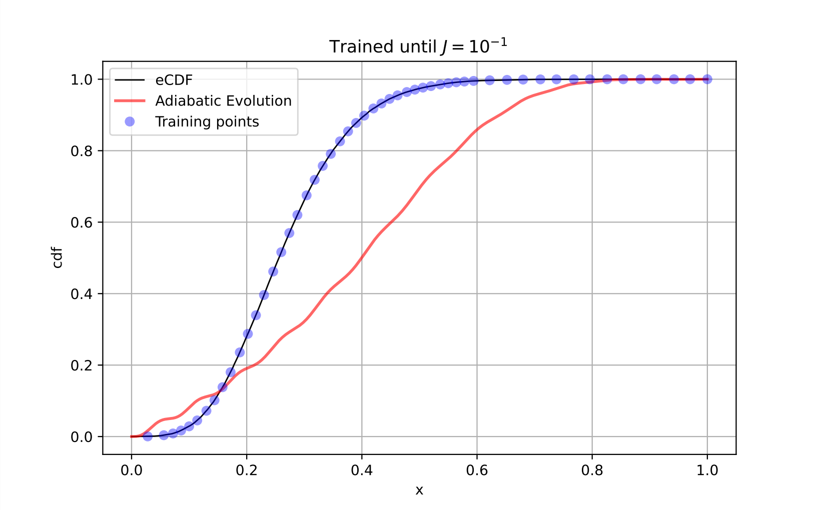
A toy example with `nqubits=1` - starting point

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



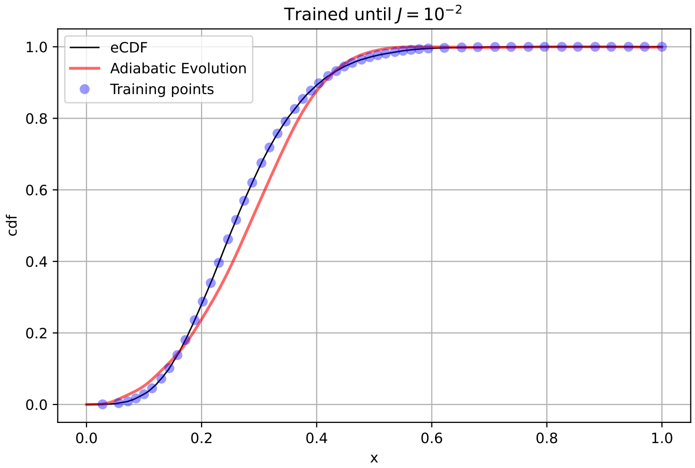
A toy example - until $J_{\mathrm{MSE}} = 10^{-1}$

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



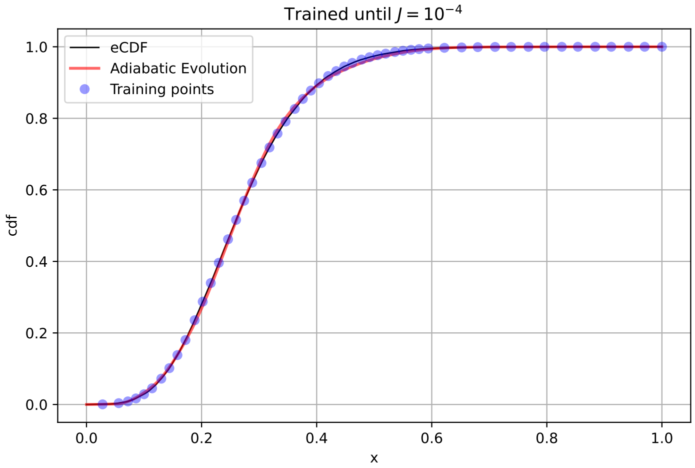
A toy example - until $J_{\text{MSE}} = 10^{-2}$

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



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

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



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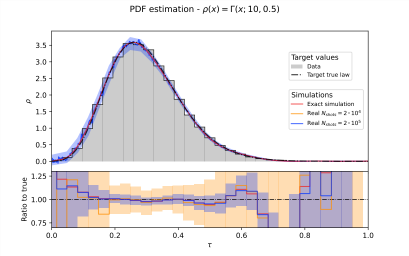

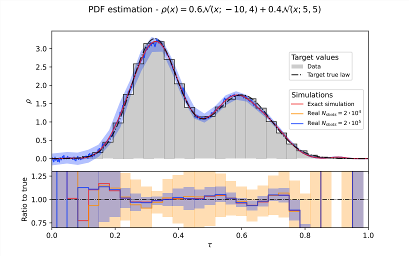

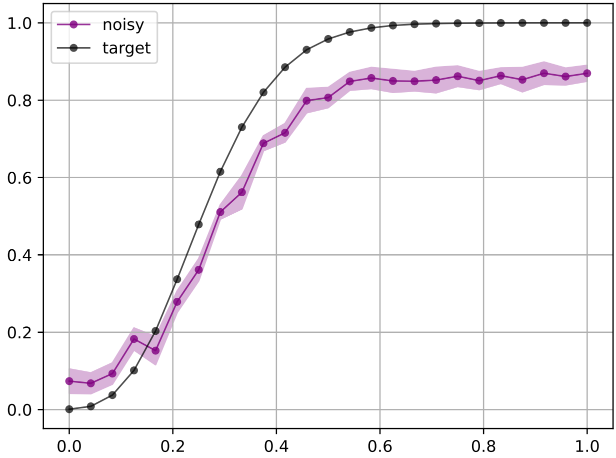

Figure 1: $N_{\text{runs}} = 10$ evaluations of CDF predictions for $N_{\text{data}} = 25$ using $N_{\text{shots}} = 1000$.

Ball to qw5q_gold

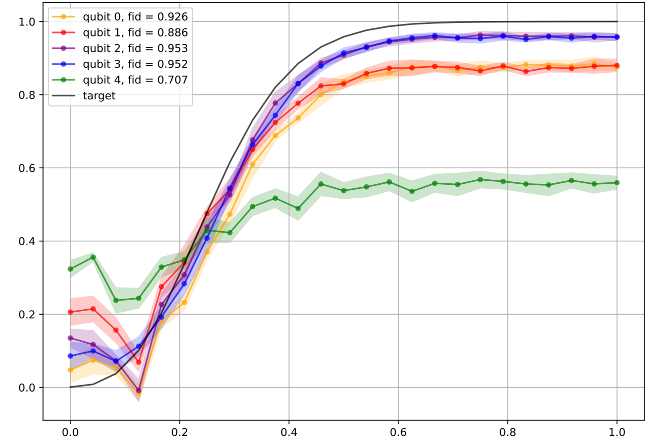

Figure 2: $N_{\text{runs}} = 10$ evaluations of CDF predictions for $N_{\text{data}} = 25$ using $N_{\text{shots}} = 1000$ and each qubit of `qw5q_gold`.

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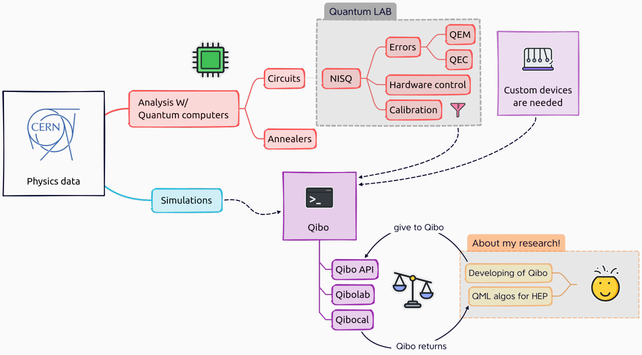

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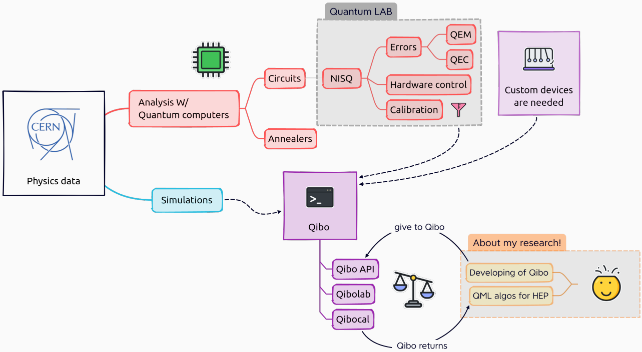

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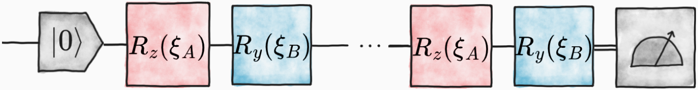

Figure 3: Here $\xi_A = \theta_1 x + \theta_2$ and $\xi_B = \theta_3 x + \theta_4$.

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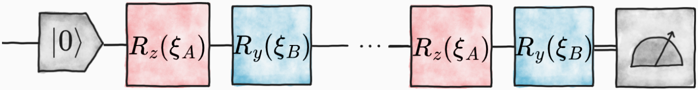

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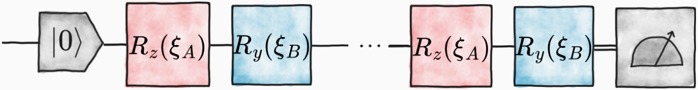

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- Using the parameter-shift rule, we can perform a gradient descent on `tii1q_b1`.

Running on `tii1q_b1`

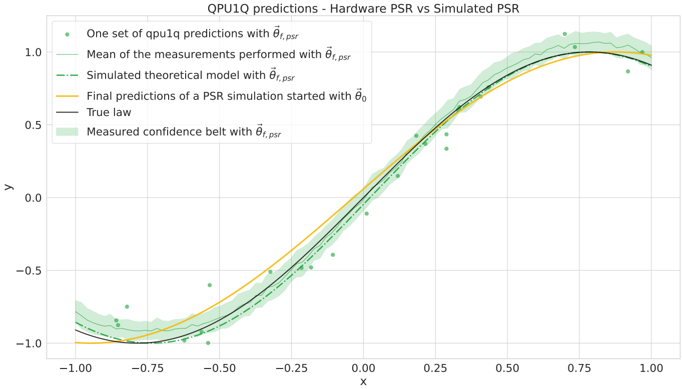


Figure 4: Batch Gradient Descent on the hardware, with gradients evaluated via Parameter-Shift Rule. We take 100 points $\{x_j\}$ in the range $[-1, 1]$ and we make 100 predictions for each x_j. Mean and standard deviation are used for determining the estimations and the confidend belt.

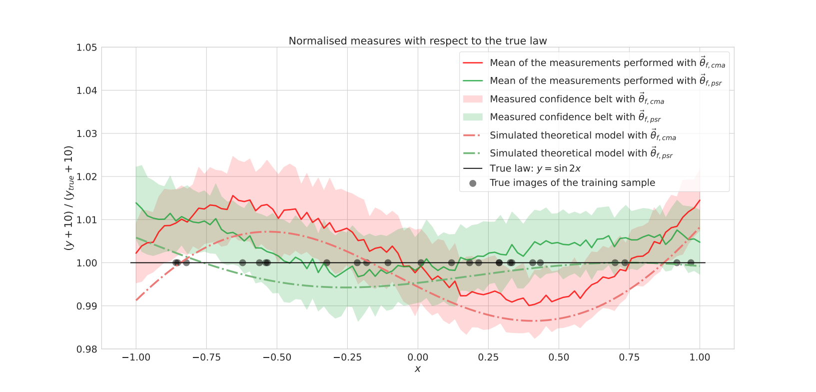
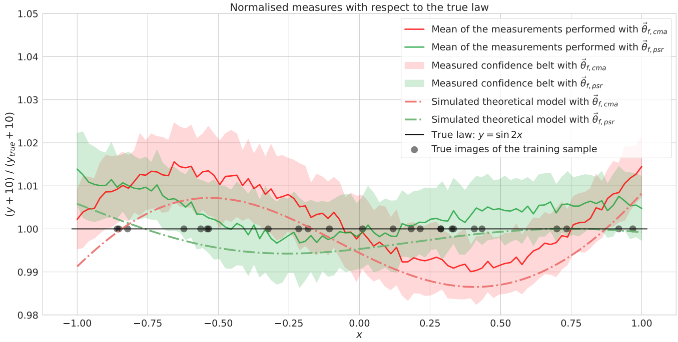


Figure 5: Normalised results of the SGD (green line) compared with true law and a genetic optimizer (red line).

Normalised results



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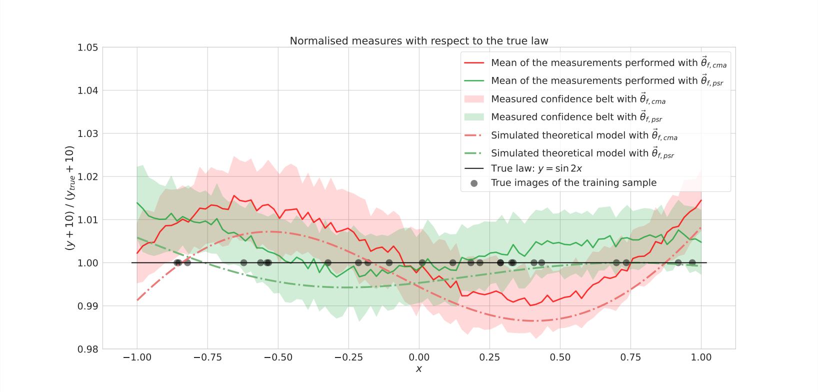

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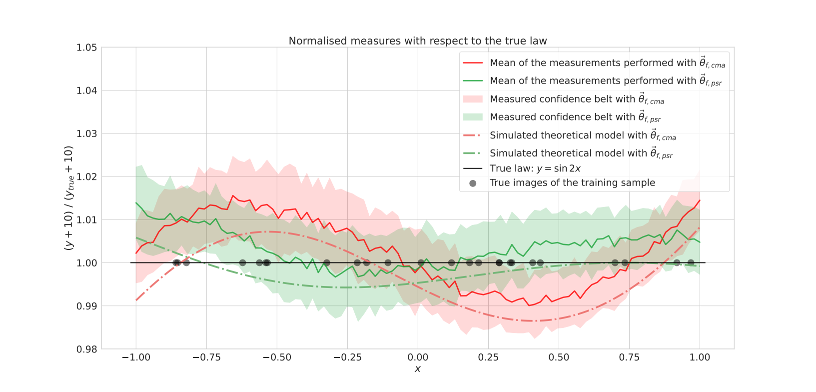

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- we can tackle only easy problems: it is slow;
- no mitigation: have been the errors absorbed into the optimization?

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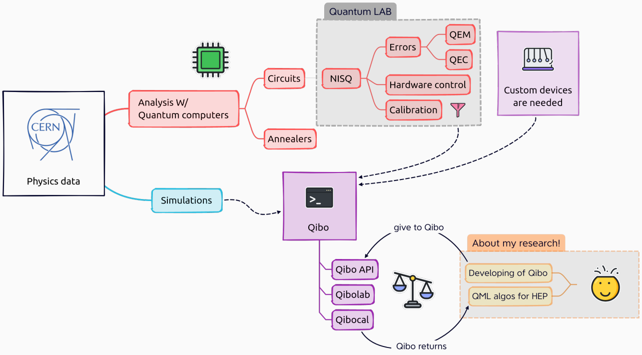

Mitigated prediction of the PDF

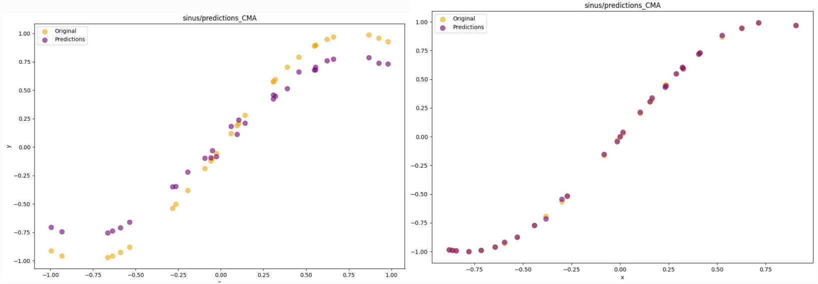

Figure 6: Predictions of a sinus function performed on `tii1q_b1` without and with CDR mitigation.

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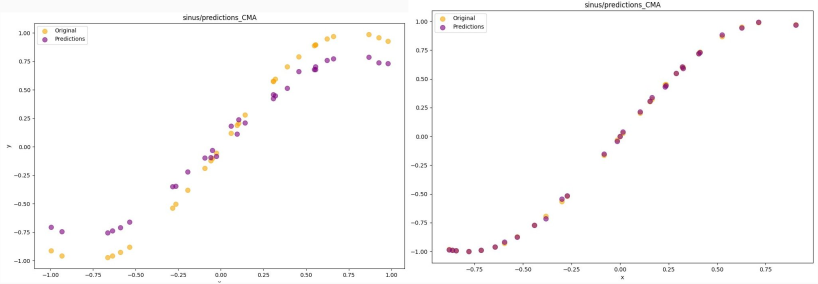

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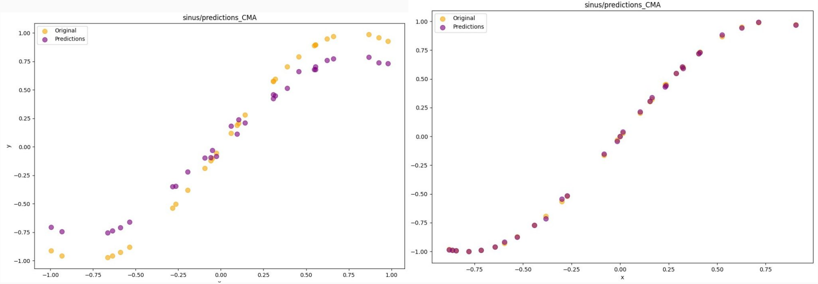

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- what's the right balance between error absorption and QEM?

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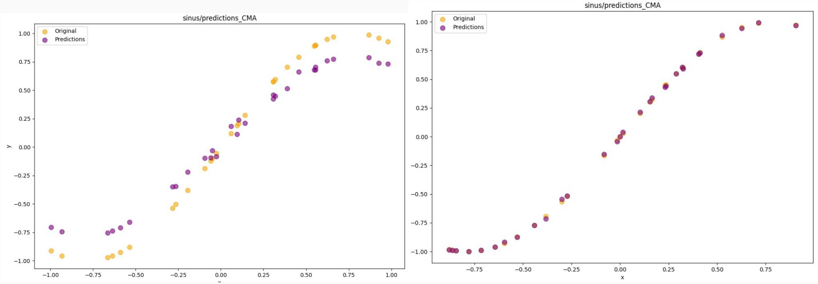


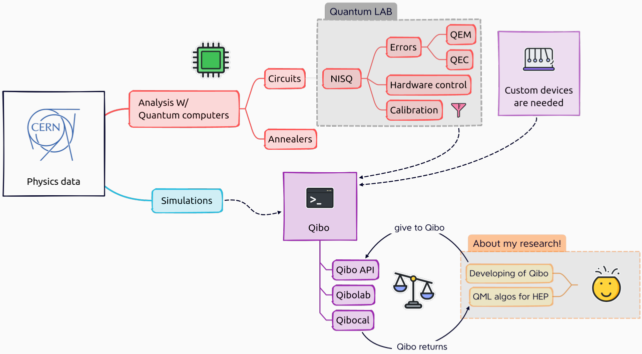
Figure 6: Predictions of a sinus function performed on `tii1q_b1` without and with CDR mitigation.

➔ These results open to new questions!

- can QEM help the training with a faster convergence?
- what's the right balance between error absorption and QEM?
- can we train the unmitigated hardware to be self-resistent?

The importance of the `qiboteam`

- These first results open several questions:
  - are these errors compatible with transmon SoA?
  - which relationship between my results' error and hardware ones?
  - where are the execution time bottlenecks?
  - what if we train the entire process on the hardware?
  - what if we apply error mitigation on predictions?
  - **what if we apply real-time error mitigation?**



Real-time error mitigation

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

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

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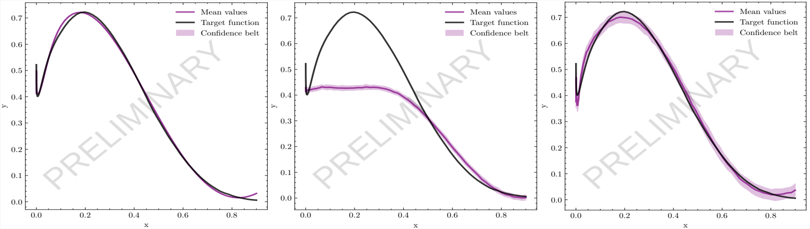

Figure 7: PDF fit performed with different levels of noisy simulation. From left to right, exact simulation, noisy simulation, noisy simulation applying error mitigation to the predictions.

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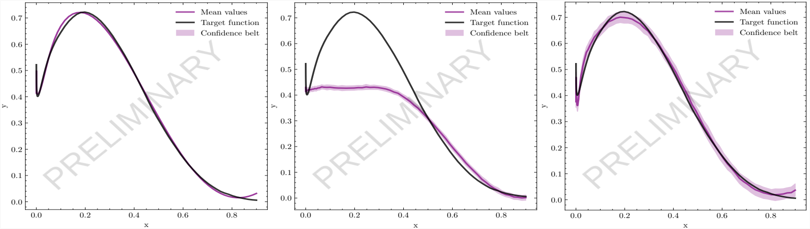

Figure 7: PDF fit performed with different levels of noisy simulation. From left to right, exact simulation, noisy simulation, noisy simulation applying error mitigation to the predictions.

- **But on the hardware?**

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

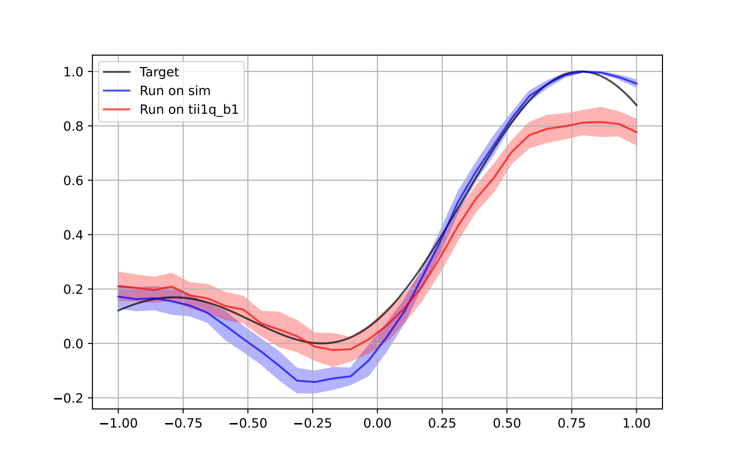

Figure 8: Full training is here performed on `tii1q_b1`. We then used the $\boldsymbol{\theta}_{\text{best}}$ to make statistics on 30 points and 30 runs with simulation (blue line) and on the device (red line).

Conclusions

qibo as research network!

`qibo` as research network!

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  - we have resources deputed to the research;

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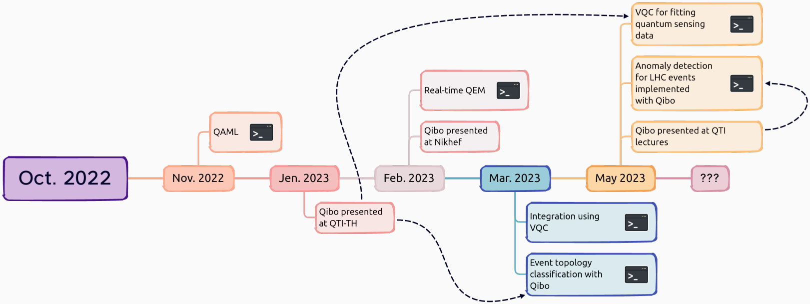
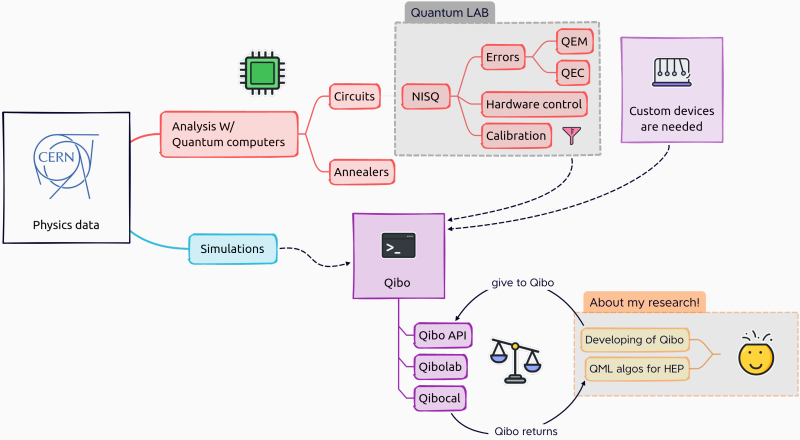


Thanks!



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