Real-time error mitigation for variational optimization on quantum hardware

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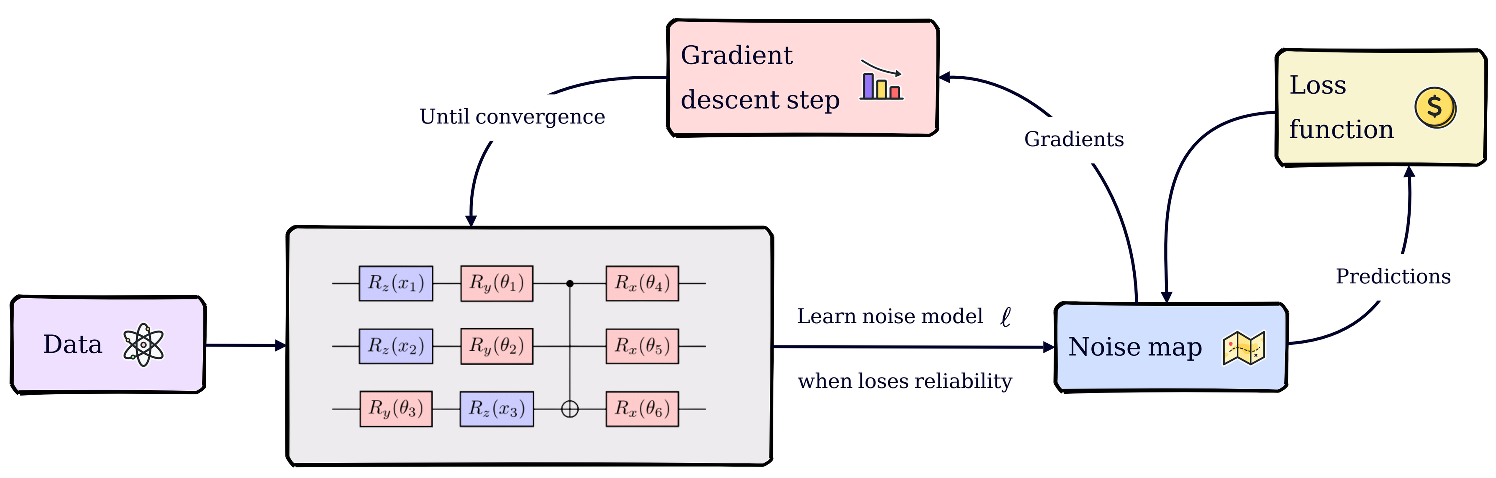
Aim

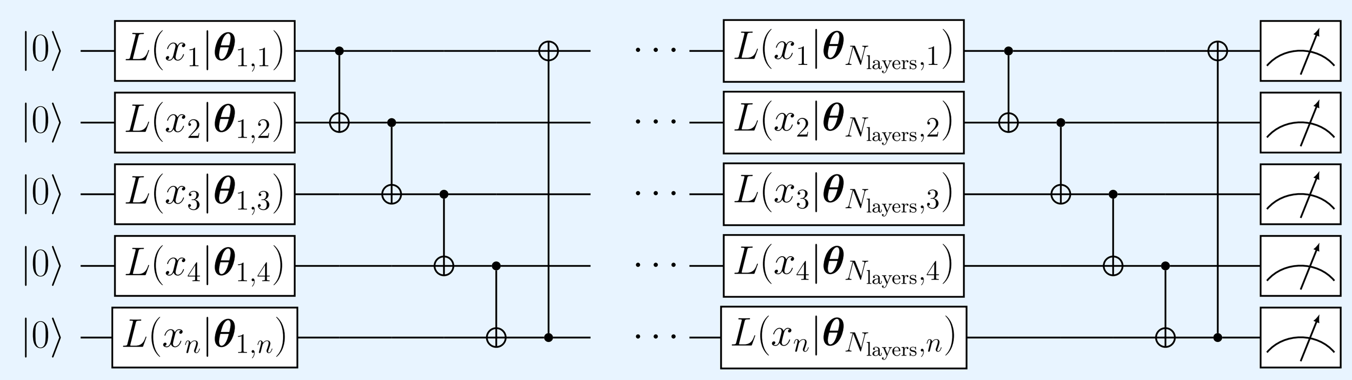
we put forward the inclusion of error mitigation routines in the process of training Variational Quantum Circuit (VQC) models. In detail, we define a Real Time Quantum Error Mitigation (RTQEM) algorithm to coadiuvate the task of fitting functions on quantum chips with VQCs.

Schematic pipeline of the RTQEM algorithm



Ansatz

We tackle multi-dimensional regression problems using a VQC as Quantum Machine Learning (QML) model. The data $\boldsymbol{x}$ are encoded into the circuit via Data Reuploading [1]:



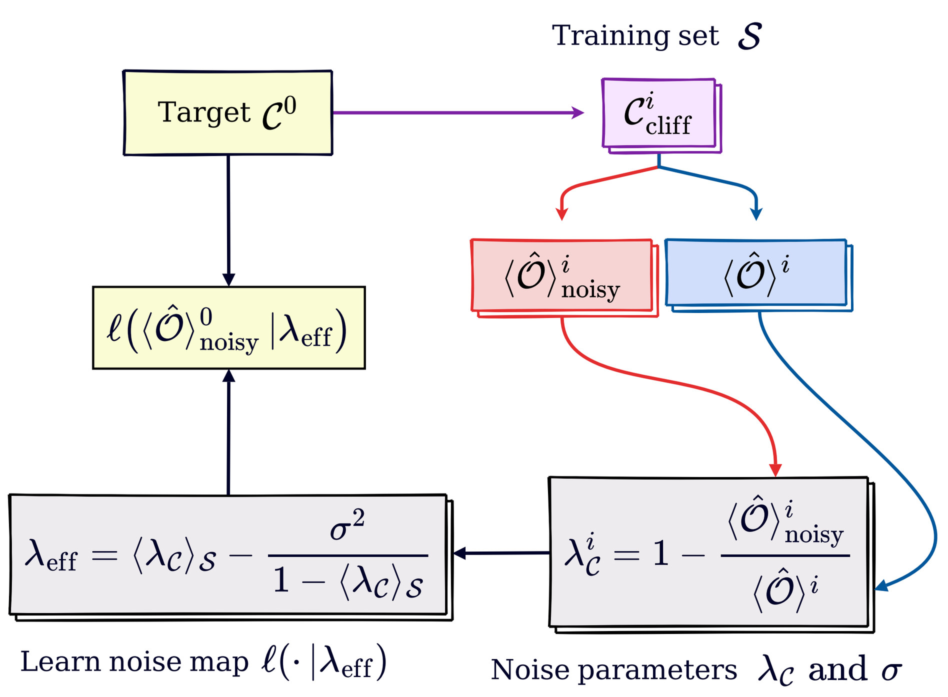
where we use the following definition of the uploading channel:

$$L(x_j|\boldsymbol{\theta}_{l,j}) = R_z(\theta_3\, x_j + \theta_4) R_y(\theta_1\, \kappa(x_j) + \theta_2)\ , \tag{1}$$

which uploads the j-th component of $\boldsymbol{x}$ at the circuit layer l.

Noise of a quantum hardware

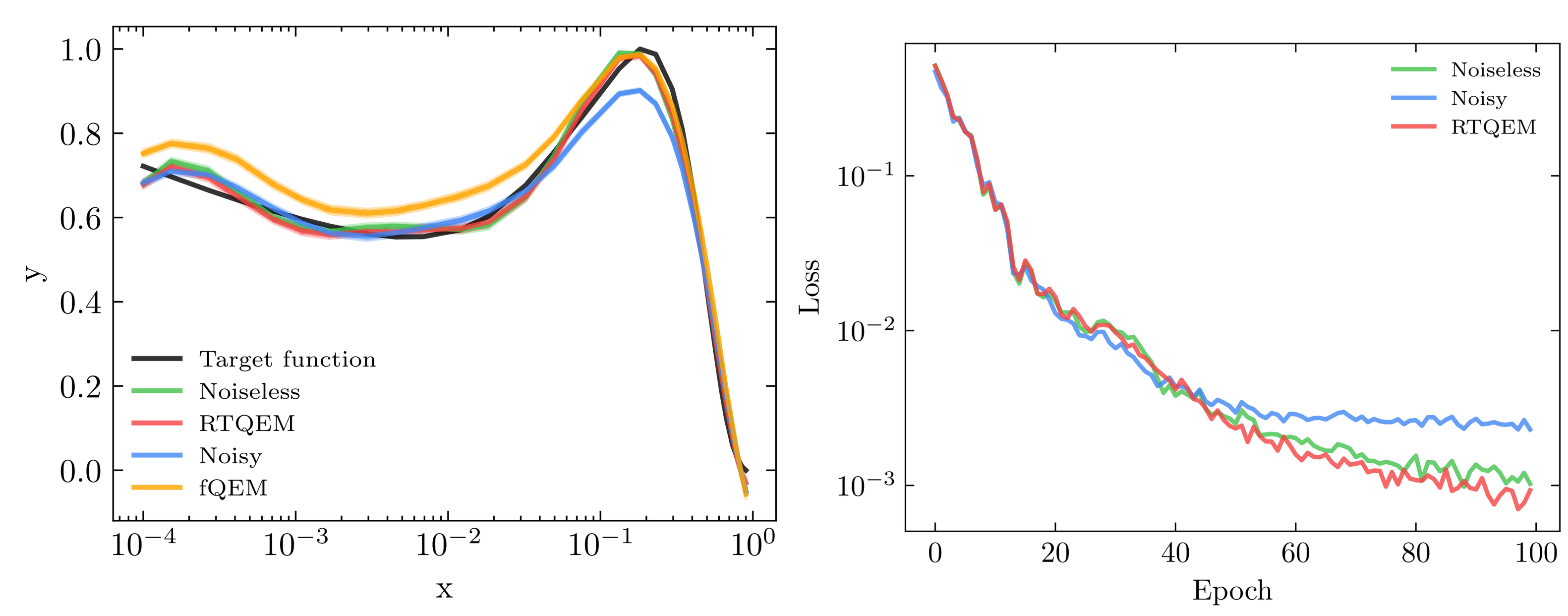
We consider a quantum system affected by local pauli noise with parameters $-1 \leq q_X, q_Y, q_Z \leq +1$ and readout noise parametrized by bit-flip probability $(1-q_M)/2$. This setup gives rise to Noise-Induced Barren Plateaus (NIBP) [2], which tend to concentrate the expectation value around 0.



To mitigate the effect of the noise, we use the Importance Clifford Sampling (ICS) [3] technique, which is a learning-based method which can be used to learn a noise map ℓ using a training set of Clifford circuits $\mathcal{S} = \{\mathcal{C}^i_{\rm cliff}\}$ built on top of the target circuit $\mathcal{C}^0$.

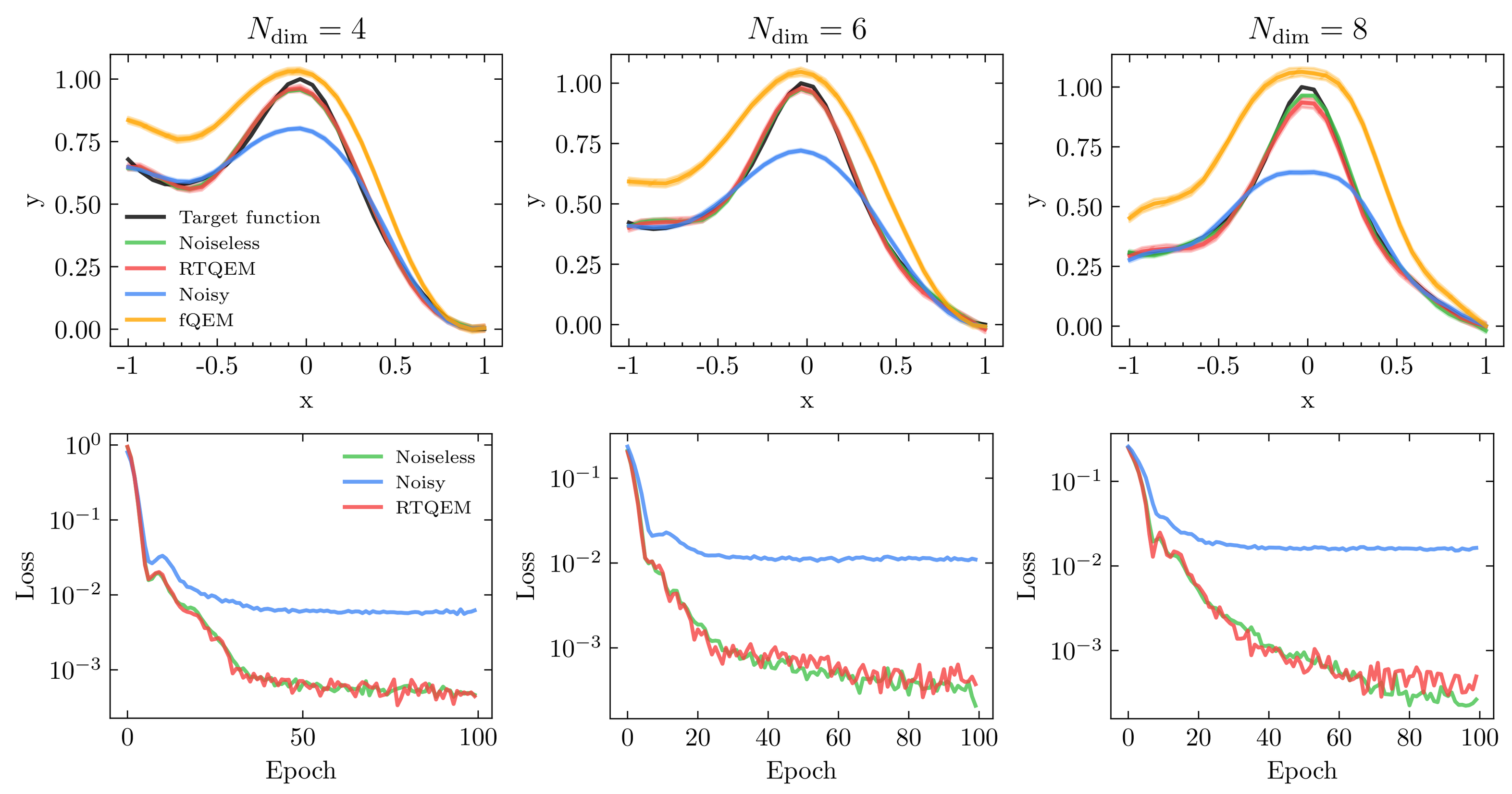
Simulation 1-dim: u-quark PDF

We firstly use a single-qubit circuit to fit the u-quark Parton Distribution Function (PDF). We set $q_M = 0.005$, $q_X = 0.007$, $q_Y = 0.003$ and $q_Z = 0.002$. We compare four configurations: noiseless, noisy unmitigated, noisy with mitigation on the final predictions (fQEM) and noisy trained with RTQEM.



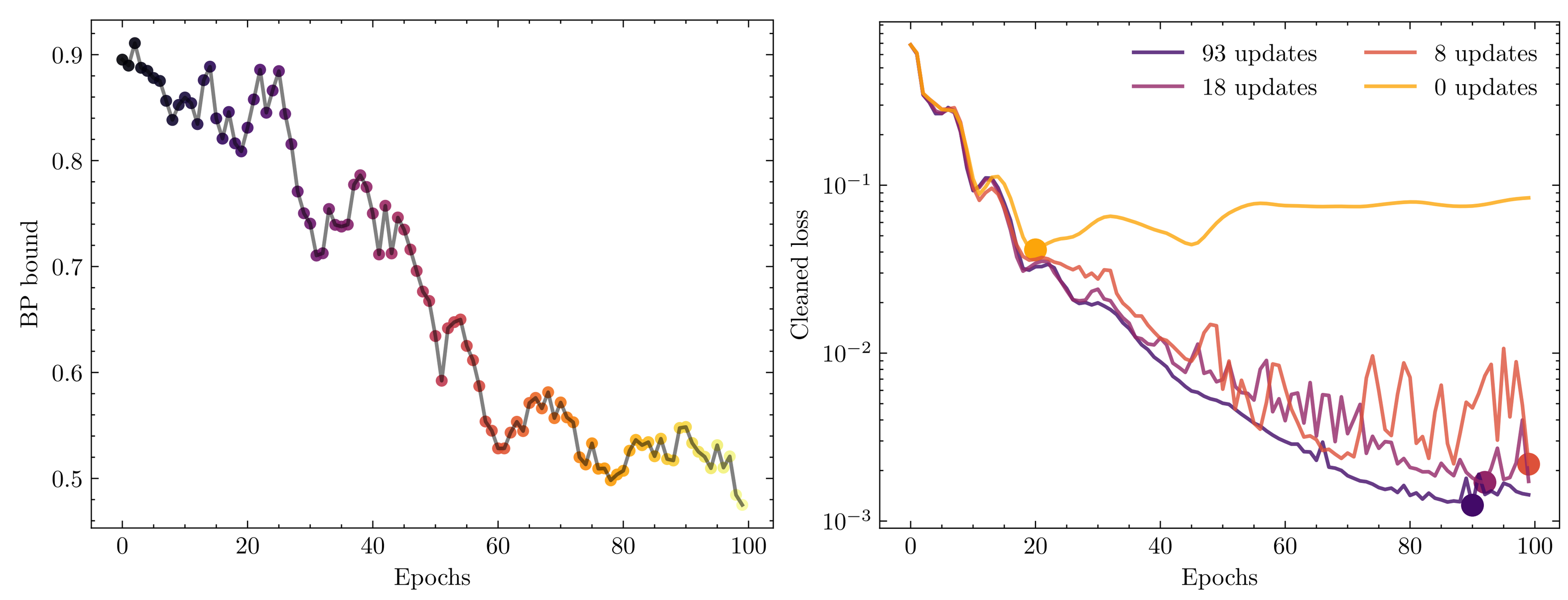
Simulation n-dim

We then tackle a simple multi dimensional target to scale up with the number of qubits.



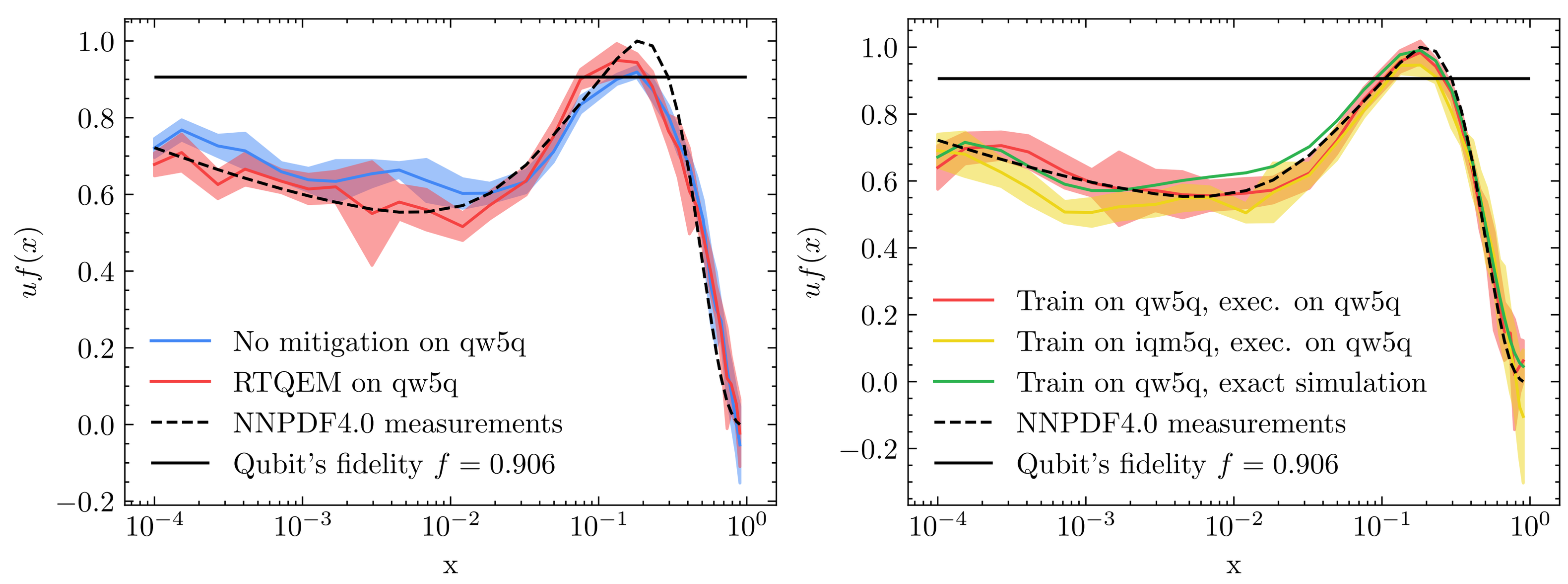
Evolving noise scenario

To study how the RTQEM procedure behave in a realistic scenario, we let the noise parameters vary following a Random Walk-like evolution.



u-quark PDF fit on superconducting devices

We finally test the RTQEM algorithm on two superconducting devices.



Simulation and hardware results

In the left Tab., simulation results, in the right one, hardware results.

Target	MSE$_{\rm noiseless}$	MSE$_{\rm noisy}$	MSE$_{\rm fqem}$	MSE$_{\rm rtqem}$
u PDF	0.008	0.018	0.023	0.008
cos 4d	0.003	0.043	0.140	0.003
cos 6d	0.002	0.083	0.214	0.002
cos 8d	0.001	0.118	0.360	0.004

Training	Predictions	Config.	$N_{\rm epochs}$	MSE
qw5q	qw5q	Noisy	50	0.0055
qw5q	qw5q	RTQEM	50	0.0042
qw5q	qw5q	RTQEM	100	0.0013
iqm5q	qw5q	RTQEM	100	0.0037
qw5q	sim	RTQEM	100	0.0016

References

[1] A. Pérez-Salinas, A. Cervera-Lierta, E. Gil-Fuster, and J. I. Latorre, "Data re-uploading for a universal quantum classifier," *Quantum*, vol. 4, p. 226, feb 2020.

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