

Real-time error mitigation for variational optimization on quantum hardware

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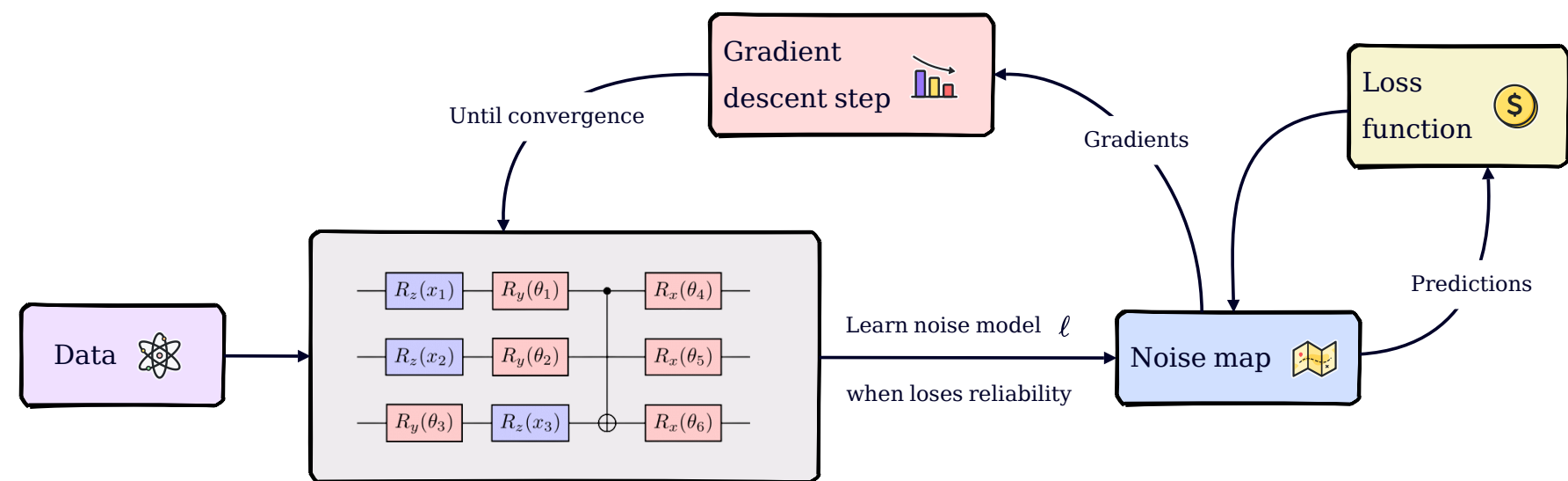
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Aim

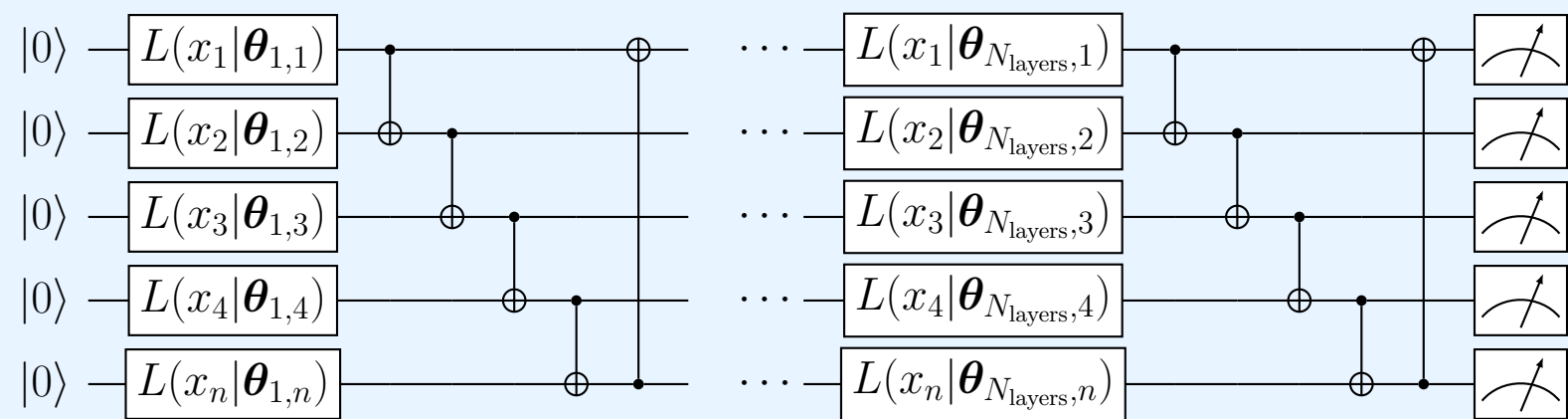
We put forward the inclusion of error mitigation routines in the process of training Variational Quantum Circuit (VQC) models. In detail, we define a Real Time Quantum Error Mitigation (RTQEM) algorithm to coadiuvate the task of fitting functions on quantum chips with VQCs.

Schematic pipeline of the RTQEM algorithm



Ansatz

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



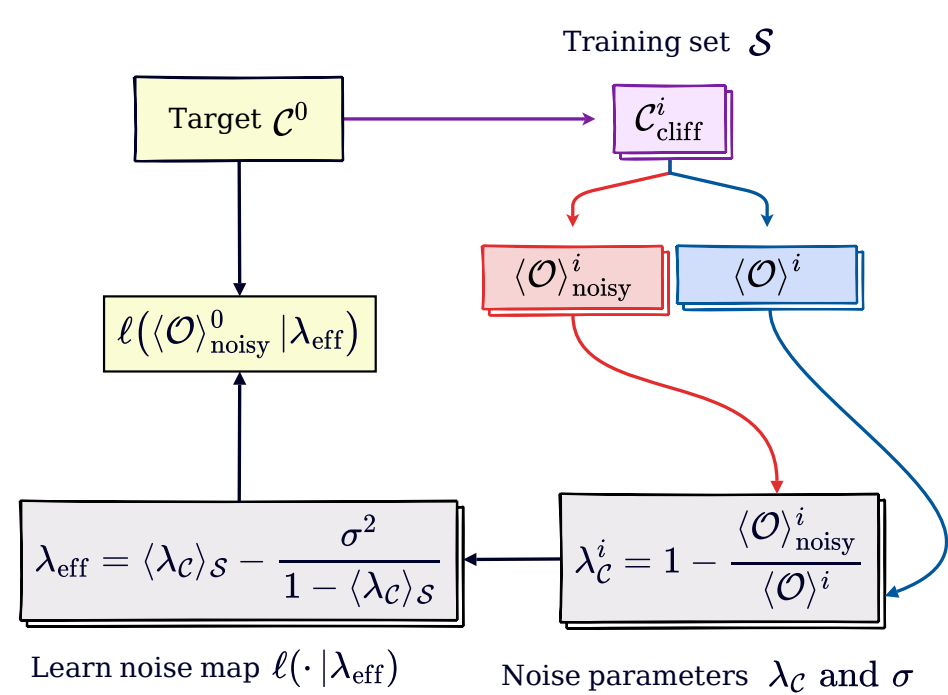
where the j -th component of x is uploaded at layer l through the channel

$$L(x_j | \theta_{1,j}) = R_z(\theta_3 x_j + \theta_4) R_y(\theta_1 \kappa(x_j) + \theta_2), \quad (1)$$

and the predictions are computed as expectation value of $Z^{\otimes n}$ over the final state.

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.



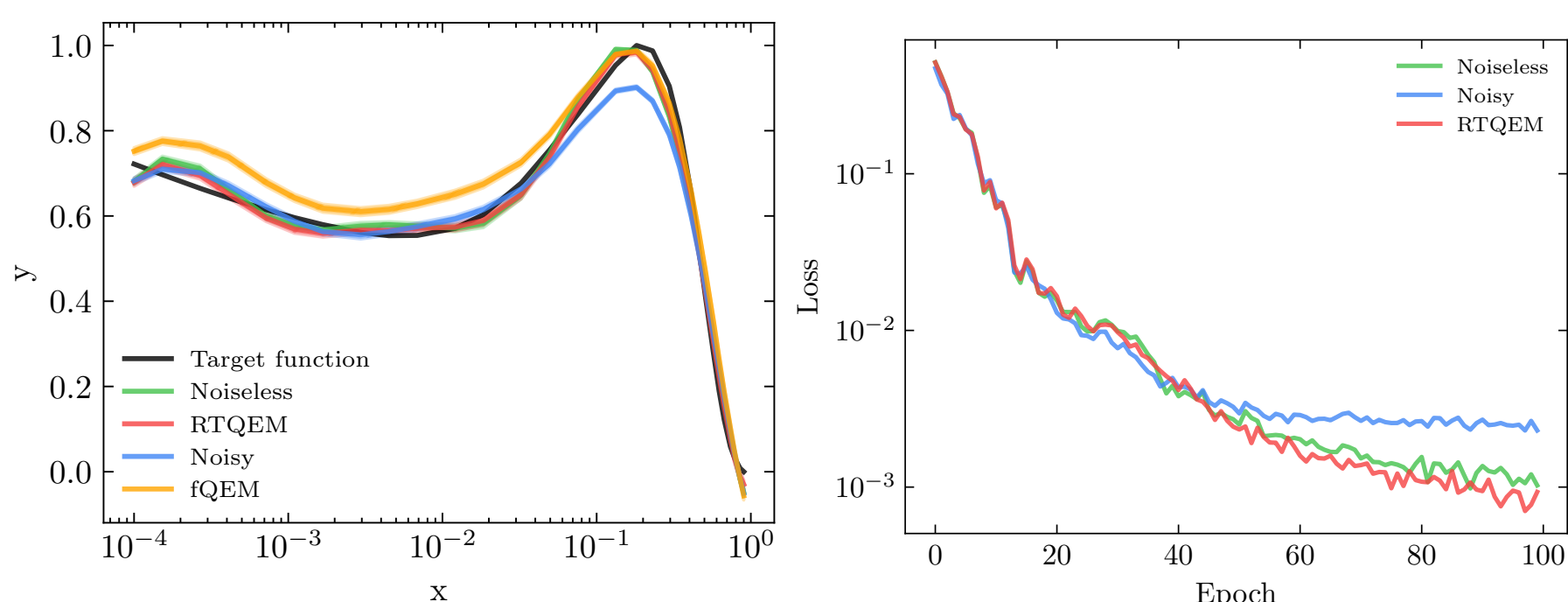
To mitigate the effect of the noise, we use the Importance Clifford Sampling (ICS) [3] technique, which is a learning-based method which can be used to learn a noise map ℓ using a training set of Clifford circuits $S = \{C_{\text{cliff}}^i\}$ built on top of the target circuit C^0 .

Update ℓ when it loses reliability

We define a metric $D(z, \ell(z))$, which quantifies the distance between a noiseless expected value z and the mitigated value $\ell(z)$. We check at each optimization iteration and, if a threshold ε_ℓ is exceeded, the map is re-learned from scratch.

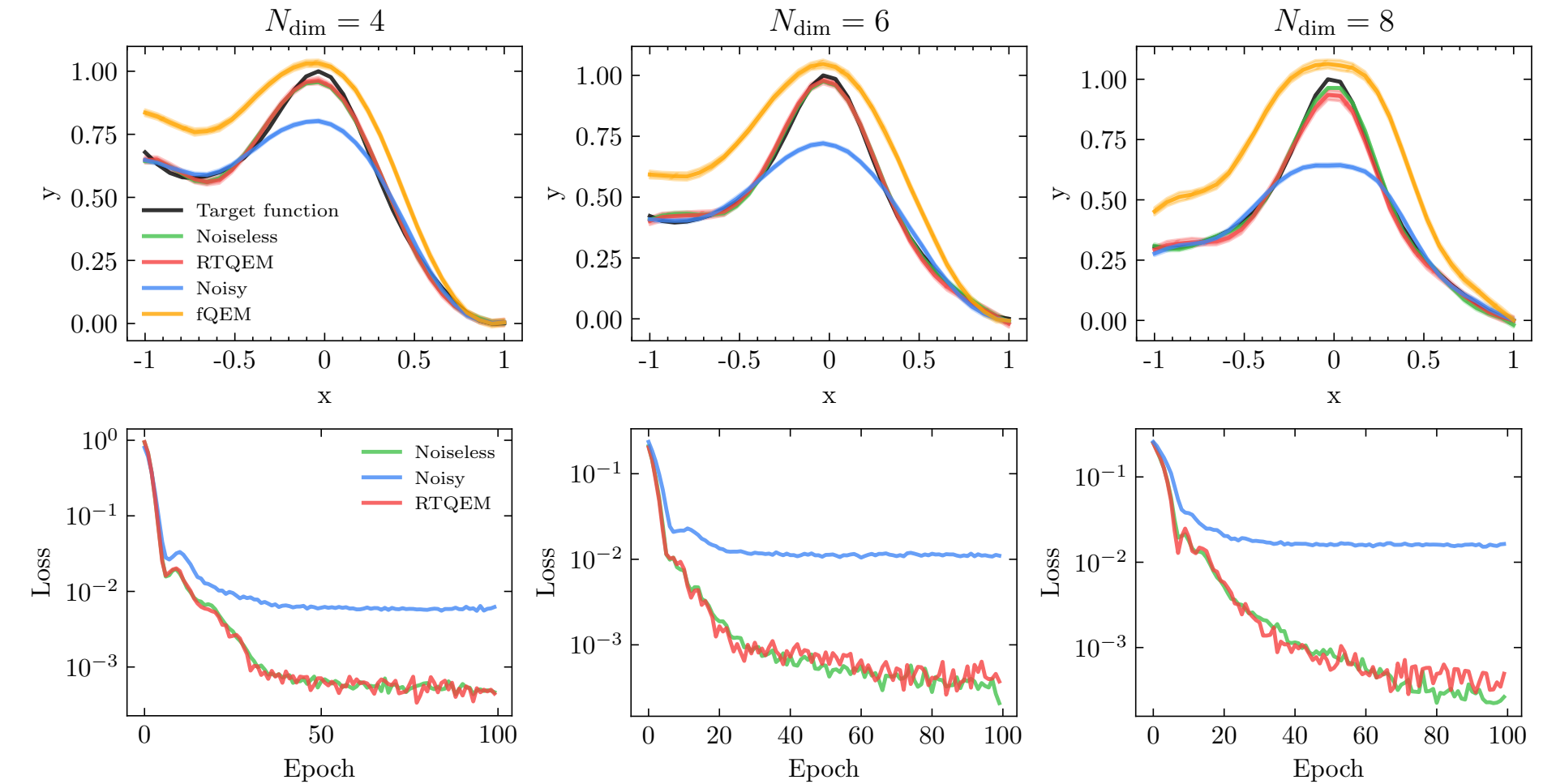
Simulation 1-dim: u -quark PDF

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.



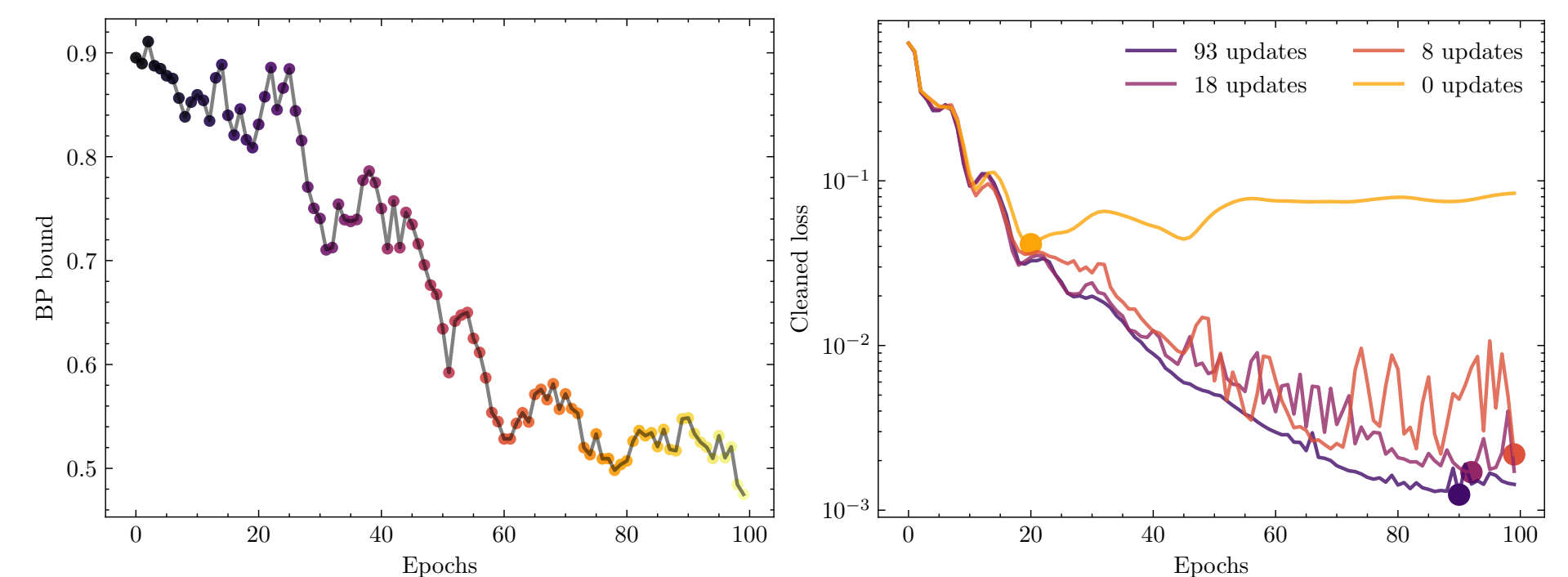
Simulation results

Mean squared error between the target labels and the predicted values.

Target	MSE _{noiseless}	MSE _{noisy}	MSE _{fqem}	MSE _{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

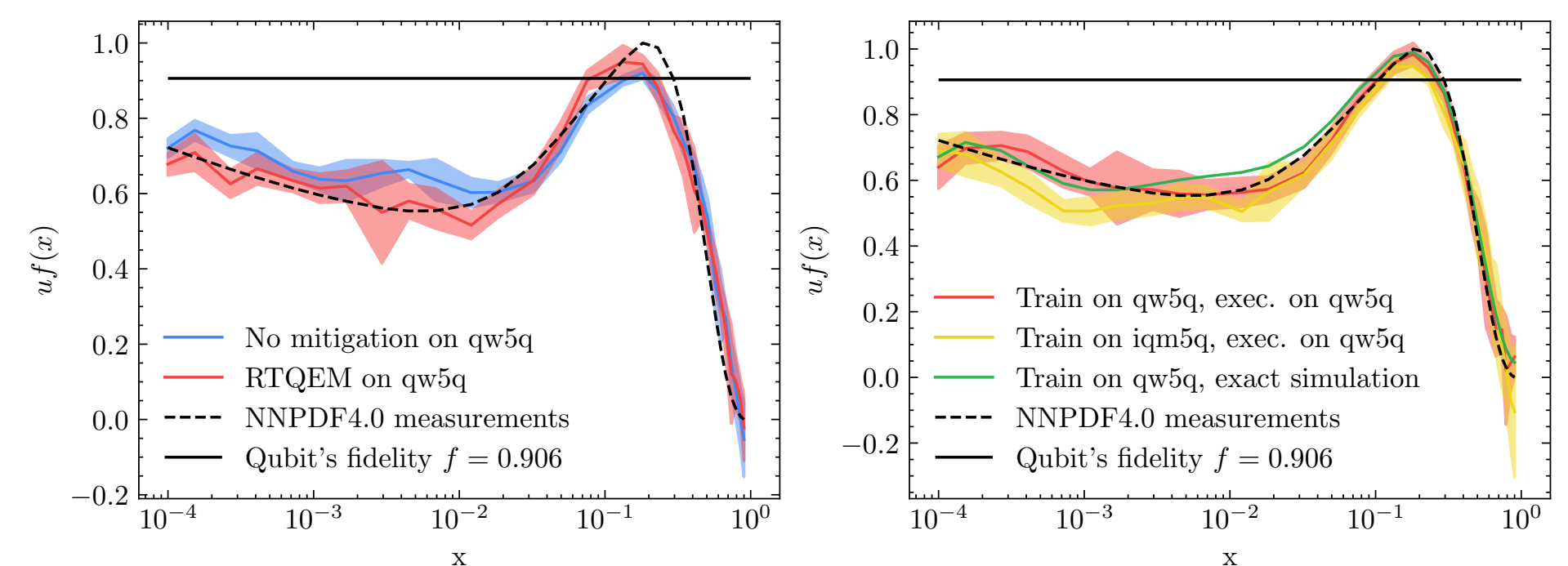
Evolving noise scenario

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.



Hardware results

We benchmark the MSE values of various prediction configurations.

Training	Predictions	Config.	N_{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.
- [2] S. Wang, E. Fontana, M. Cerezo, K. Sharma, A. Sone, L. Cincio, and P. J. Coles, "Noise-induced barren plateaus in variational quantum algorithms," *Nature Communications*, vol. 12, nov 2021.
- [3] D. Qin, Y. Chen, and Y. Li, "Error statistics and scalability of quantum error mitigation formulas," *npj Quantum Information*, vol. 9, apr 2023.