

Real-time error mitigation for variational optimization on quantum hardware

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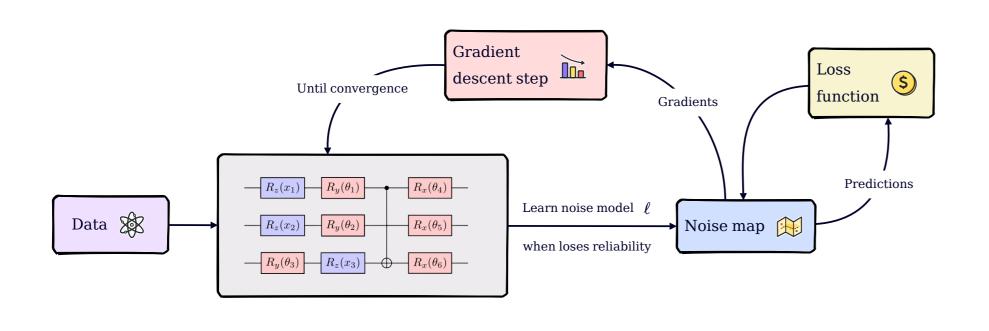


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Aim

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:

$$|0\rangle - L(x_1|\boldsymbol{\theta}_{1,1})$$

$$|0\rangle - L(x_2|\boldsymbol{\theta}_{1,2})$$

$$|0\rangle - L(x_3|\boldsymbol{\theta}_{1,3})$$

$$|0\rangle - L(x_4|\boldsymbol{\theta}_{1,4})$$

$$|0\rangle - L(x_1|\boldsymbol{\theta}_{N_{\text{layers}},2})$$

$$\cdots - L(x_1|\boldsymbol{\theta}_{N_{\text{layers}},2})$$

$$\cdots - L(x_1|\boldsymbol{\theta}_{N_{\text{layers}},3})$$

$$\cdots - L(x_1|\boldsymbol{\theta}_{N_{\text{layers}},4})$$

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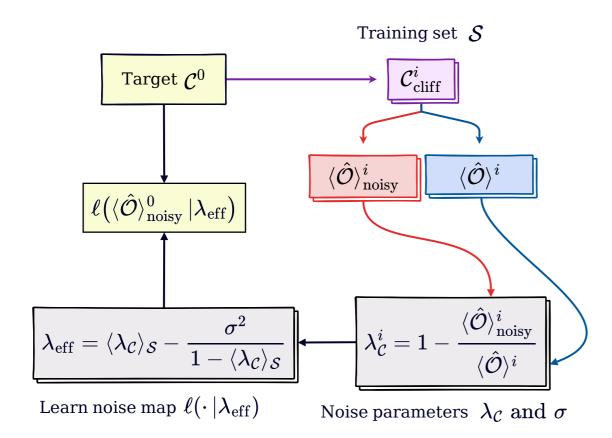
where we use the following definition of the uploading channel:

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

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

Noise of a quantum hardware

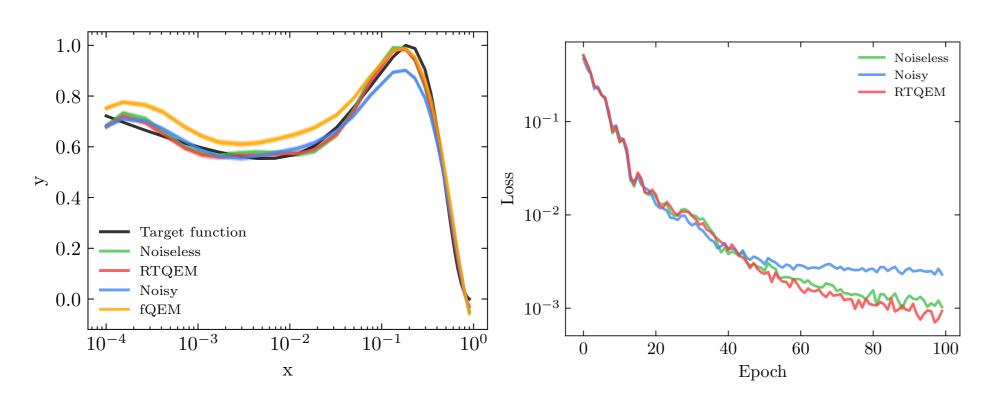
We consider a quantum system affected by local pauli noise with parameters $-1 \le q_X, q_Y, q_Z \le +1$ and readout noise parametrized by bit-flip probability $(1-q_M)/2$. This setup gives rise to Noise-Induced Barren Plateaus (NIBP), which tend to concentrate the expectation value around 0.



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

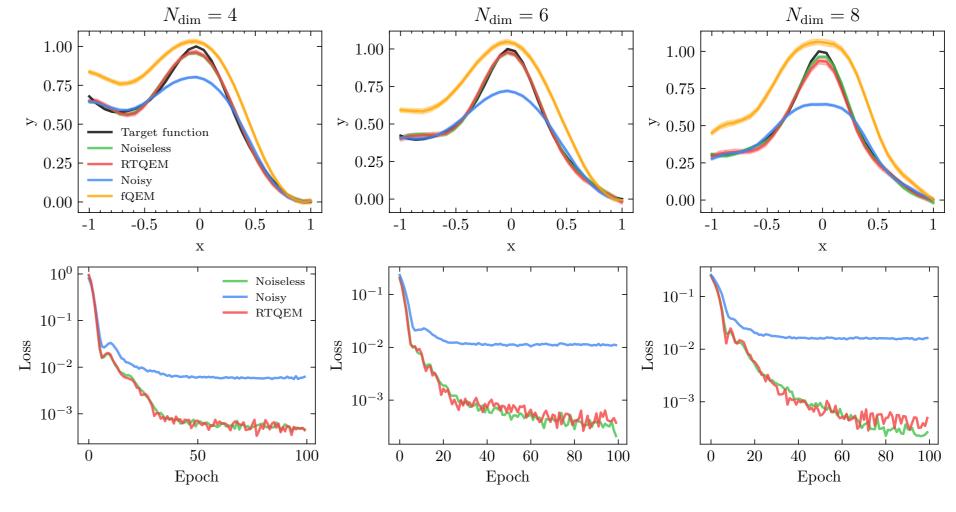
Simulation 1-dim: u-quark PDF

We firstly use a single-qubit circuit to fit the u-quark Parton Distribution Function (PDF).



Simulation n-dim

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



References

