(24742) - QML FRAMEWORK WITH QKE ALGORITHM FOR BENCHMARKING QUANTUM COMPUTER IN CONTEXT OF APPLICATION - *Sensitivity analysis of the quantum kernel estimation algorithm to different noise channels.*

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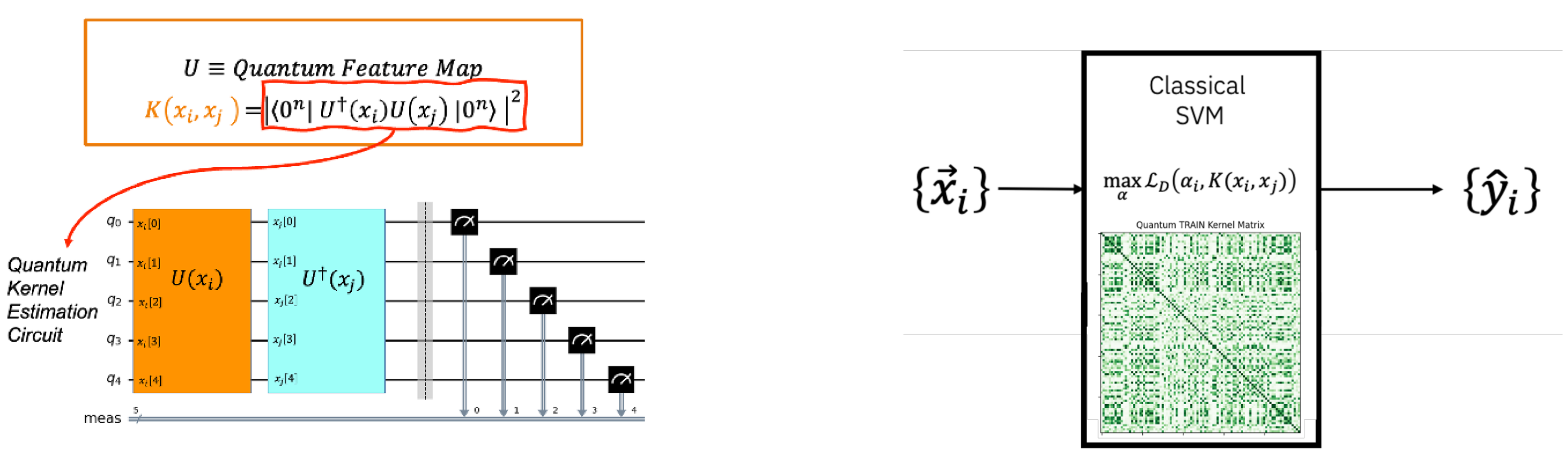
Abstract

Quantum benchmarks considering applications running in a hybrid quantum-classical environment are today an emerging field of research. In era of NISQ computing it is very likely that hybrid workloads may show first kind of advantage. Therefore, it is necessary to understand better, how certain level of noise will impact applications results in such a hybrid setup. However, today standardized benchmarks focusing on assessing the quantum hardware stack only. For assessing quality from application perspective, it is hard to estimate how these metrics will affect application results. As a first approach, we analyze the sensitivity to different noise channels of a quantum machine learning benchmark framework using quantum kernel estimation algorithm (QKE) in a standardized classification procedure with support vector classifier. We think QKE is an good candidate for such an investigation: It has a hybrid setup and needs to run over the entire classic-quantum workflow, with the most time-consuming part running on quantum. It can be easily tuned to investigate scale, quality and speed of a hybrid system in context of the accuracy of a trained model. The in ML widely used MNIST dataset delivers high accuracy results without relying on the quality of data engineering. We show the results of series of emulations on a pre-version of ParTec's quantum workbench varying number of qubits, data samples sizes, quantum feature maps and circuit depths. Our baseline work shows results without noise on a fake target device. Under same conditions different kind of noise channels have been applied to analysis its impact on the accuracy of the ML model.

Introduction

Quantum kernels have been investigated quite early as a promising method in quantum machine learning [4],[2]. When the data source is hard to recognize the intrinsic labeling patterns like it is shown in [3] the quantum kernels showed an advantage over classical machine learning methods. In analogy to the intuition with classical kernels and kernel trick [7] the resulting state fidelity can express a measure of similarity if classical data pairs are projected into quantum feature space [2][3]. Derived from the Hilbert-Schmidt product the quantum kernel estimate (QKE) can be expressed by (1):

$$K(x_i, x_j) = | < 0^n | U^\dagger(x_i) U(x_j) | 0^n > |^2 \qquad (1)$$



(a) QKE Circuit **(b)** SVM workflow

Figure 1: (a) Quantum kernel estimate circuit and (b) embedding of the quantum kernel into classical SVM workflow

QKE workflow, frameworks, and set up

QKE workflow and frameworks: The emulations were done with an early version of ParTec's quantum workbench [1]Quantum Workbench was embedded in a framework that was created following a specific workflow for the QKE experiments.

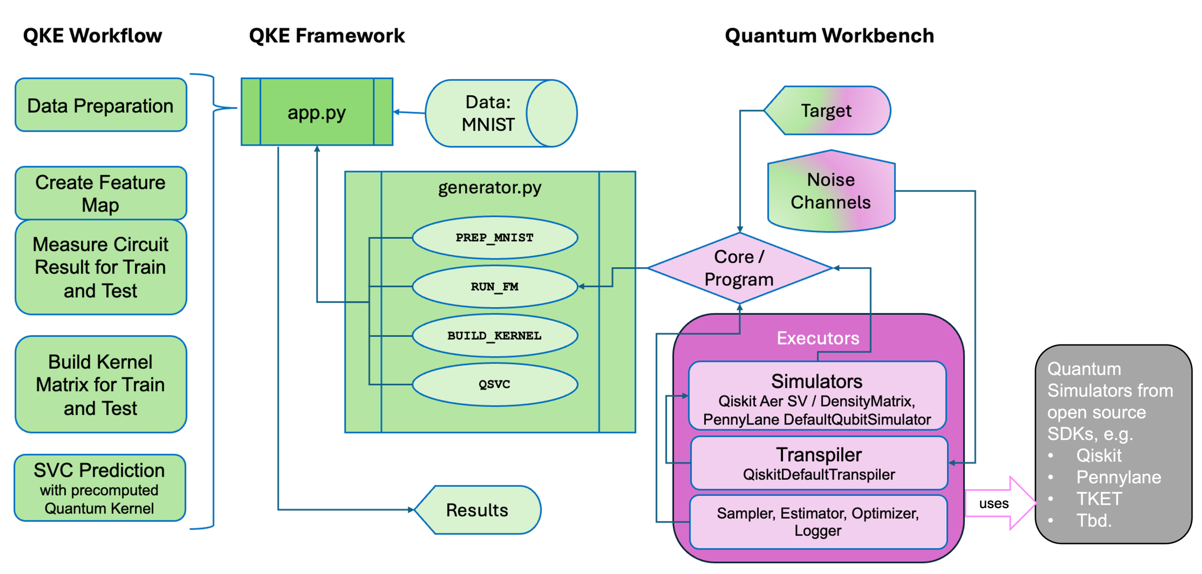


Figure 2: QKE Workflow and framework with Quantum Workbench integration

Dataset: As a simple data source MNIST data set has been used [5] provided as an nzp-file online by keras [6]:

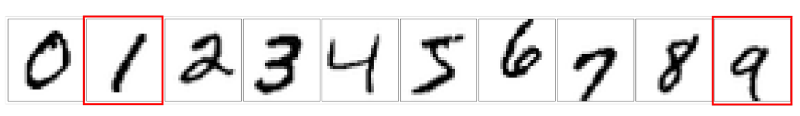


Figure 3: MNIST data - hand written numbers from 0 to 9

Quantum feature maps and defined target device: The target device is a fictive QPU with a square qubit topology and fictive, but typical basis gates. The basis gates has been defined as: R_x , R_y, R_z, P and CX. You can find this topology in many types of real devices which are build with superconductive qubits. This poster aimed to be most independent from any hardware vendor, but the authors would be very happy to enhance these emulations with real device topologies and their parameters.

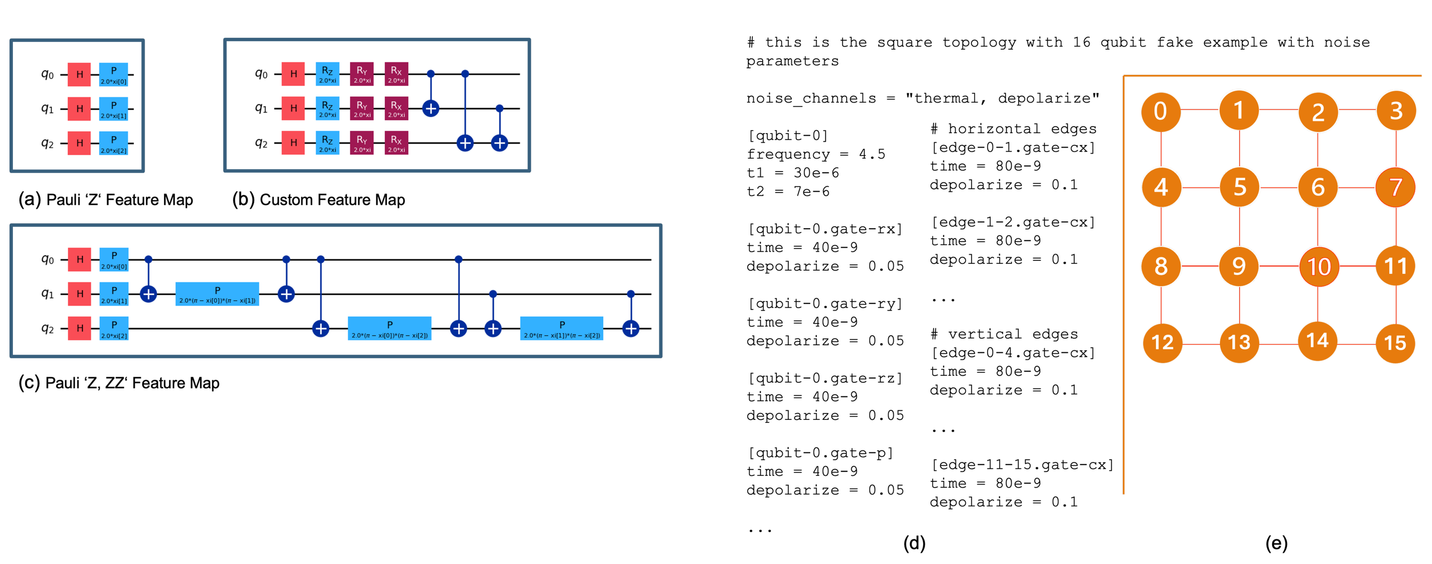


Figure 4: Used feature maps (a) Pauli-(Z), (b) Pauli(Z,ZZ), (c) custom, (d) Example of a target.toml file and (e) Square qubit topology - 16q fake device

Results

Noise-free emulations without repetitions of feature map:

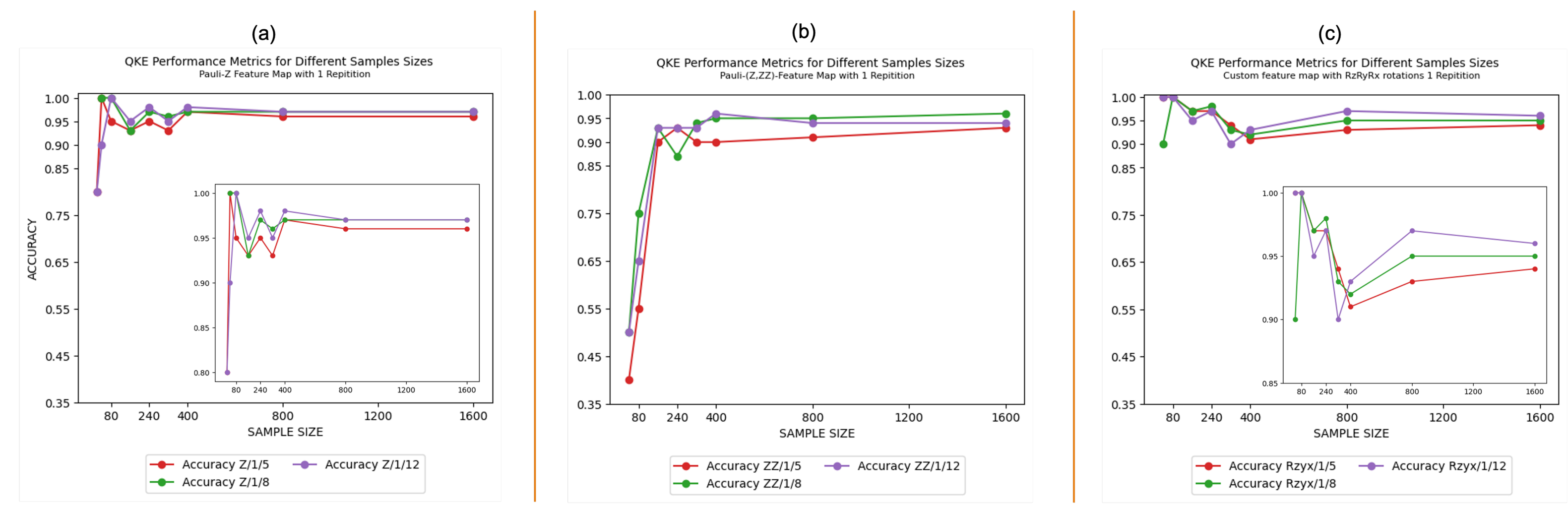


Figure 5: Accuracy at certain sample size dependent on feature map with 1 repetition only and number of qubits which are varied between 5, 8 and 12; with (a) Pauli-(Z) (b) Pauli-(Z,ZZ) (c) Custom

Noise-free emulations with repetitions of feature map:

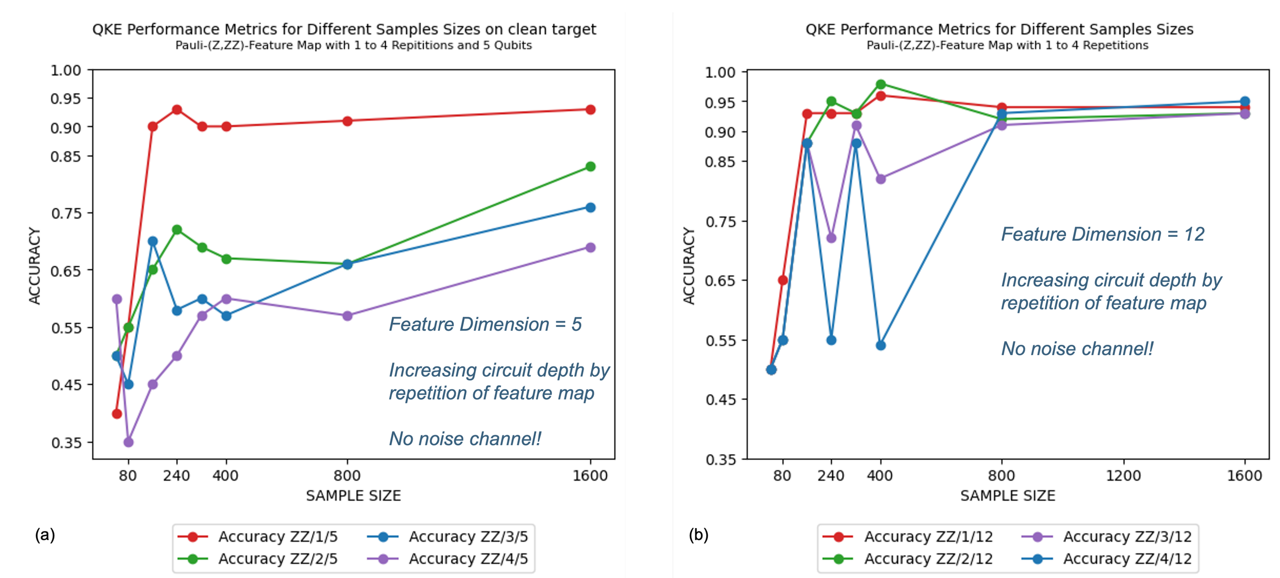


Figure 6: Accuracy at certain sample size dependent on feature map with repetitions between 1 and 4. Number of qubits are varied between 5 and 12.

Emulations with thermal and depolarizing noise channels:

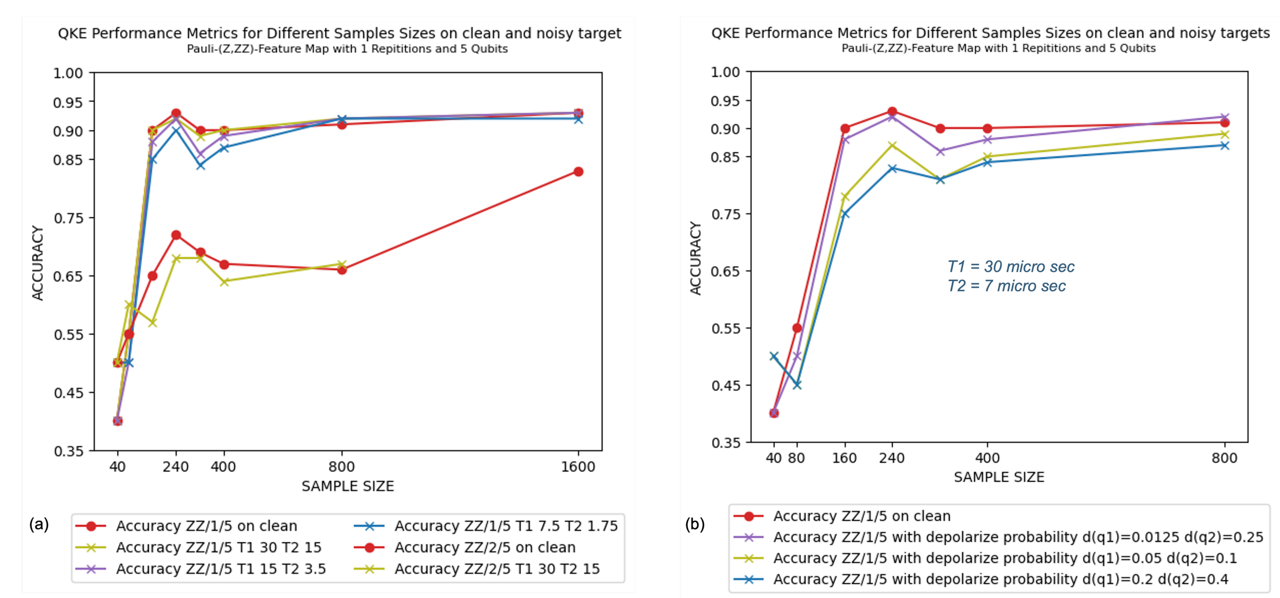


Figure 7: (a) Accuracy at certain sample sizes dependent on thermal noise for 5 qubits and Pauli-(Z,ZZ) feature map with 1 and 2 repetitions. (b) Accuracy at certain sample sizes dependent on thermal and depolarizing noise for 5 qubits and Pauli-(Z,ZZ) feature map with 1 repetitions.

Conclusions

The noise-free emulation experiments show that the accuracy of the model is sensitive to the kind of feature map, especially at smaller sample sizes. The Pauli-(Z,ZZ) feature map shows the best results over the full range of investigated sample sizes. However, with the number of repetitions of Pauli-(Z,ZZ) feature map the accuracy results are also getting worse at smaller sample sizes. This effect is increasing with a lower number of qubits which means a larger loss of information.

The accuracy of the model seems to be quite robust against thermal noise with an increasing size of samples used for the kernel matrix. This seems to be true as well for repeated feature maps, although more investigations must be done to verify this. At lower sample sizes the impact is significant on the value of accuracy. Adding additional noise sources like depolarizing noise the significance of the divergence to noise free emulations is increasing, so that even for higher sample sizes an negative impact of the result quality can not be neglected.

Further investigations with additional noise channels are work in progress and the complete results are planned to be published soon.

References

[1] E. Jennings et al. "< w|b > : a Quantum Emulation Workbench for Benchmark Construction and Application Development". In: *EuroQHPC Workshop 2024, Session C*, 2024.

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