

QUANT²AI:

END-TO-END QML-BENCHMARK SOFTWARE

Cristobal Corvalan M. - DLR Institute of AI Safety and Security

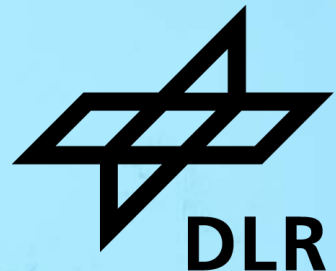
Dr. Pascal Halffmann – Fraunhofer Institute for Industrial Mathematics ITWM



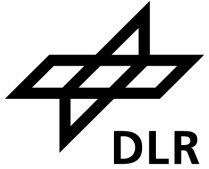
DLR
Quantum Computing
Initiative



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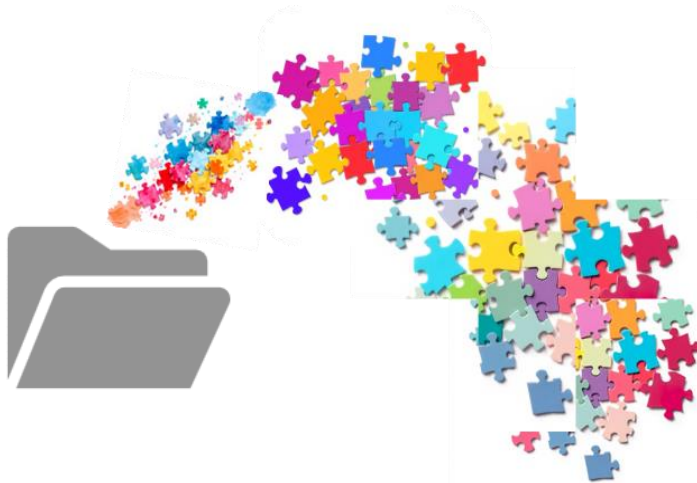
Finding a suitable solution



I have a use-case. Help me find a quantum algorithm, please.



Sure, look how many tools we have!



Quantum Circuit Learning

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(Dated: April 25, 2019)

We propose a classical-quantum hybrid algorithm for machine learning on near-term quantum

Benchmarking Quantum Reinforcement Learning

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LETTER

<https://doi.org/10.1038/s41586-019-0980-2>

Supervised learning with quantum-enhanced feature spaces

Vojtěch Havlíček^{1,2}, Antonio D. Córcoles^{1*}, Kristan Temme^{1*}, Aram W. Harrow³, Abhinav Kandala¹, Jerry M. Chow¹ & Jay M. Gambetta¹

Free Energy based QRL (FE-QRL), and Amplitude Amplification based QRL (AA-QRL). We introduce a set of metrics to evaluate the QRL algorithms on the widely applicable benchmark of gridworld games. Our results provide a detailed analysis of the strengths and weaknesses of the QRL classes, shedding light on the role of quantum principles in QRL and paving the way for future research in this field.

nature
physics

ARTICLES

<https://doi.org/10.1038/s41567-019-0648-8>

Quantum convolutional neural networks

Iris Cong¹, Soonwon Choi^{1,2,*} and Mikhail D. Lukin¹

Neural network-based machine learning has recently proven successful for many complex applications ranging from image recognition to precision medicine. However, its direct application to problems in quantum physics is challenging due to the exponential complexity of many-body systems. Motivated by recent advances in realizing quantum information processors, we

Quantum Graph Neural Networks

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Better than classical? The subtle art of benchmarking quantum machine learning models

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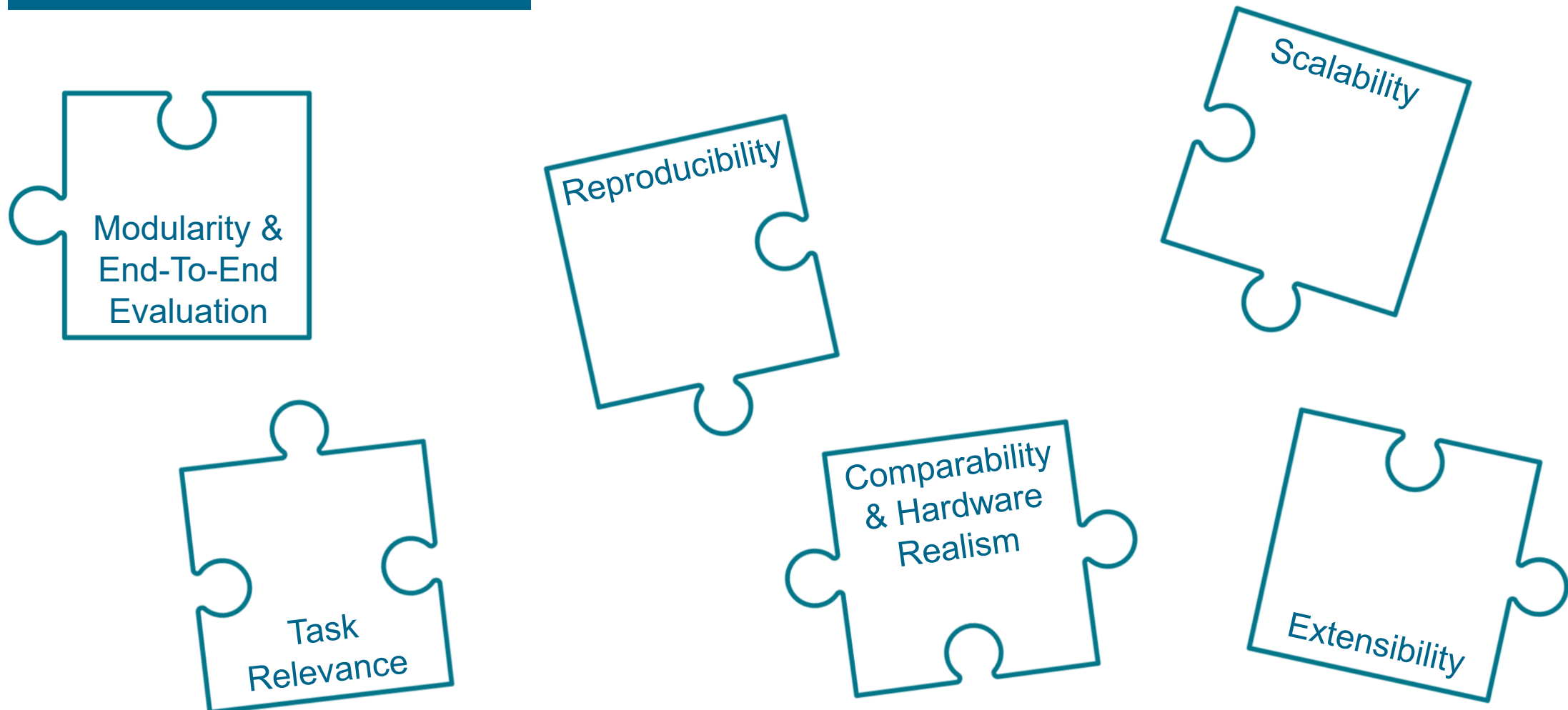
²Chalmers University of Technology

(Dated: March 15, 2024)

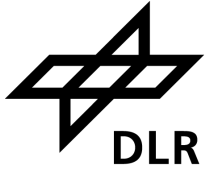
Benchmarking models via classical simulations is one of the main ways to judge ideas in quantum machine learning before noise-free hardware is available. However, the huge impact of the experimental design on the results, the small scales within reach today, as well as narratives influenced by the commercialisation of quantum technologies make it difficult to gain robust insights. To facilitate better decision-making we develop an open-source package based on the PennyLane software framework and use it to conduct a large-scale study that systematically tests 12 popular quantum machine learning models on 6 binary classification tasks used to create 160 individual datasets. We find that overall, out-of-the-box classical machine learning models outperform the quantum classifiers. Moreover, removing entanglement from a quantum model often results in as good or better performance, suggesting that “quantumness” may not be the crucial ingredient for the small learning tasks considered here. Our benchmarks also unlock investigations beyond simplistic leaderboard comparisons, and we identify five important questions for quantum model design that follow from our results.

What Defines a Good Benchmark for Quantum Machine Learning Pipelines?

Key Requirements for Credible Performance Claims



What Defines a Good Benchmark for Quantum Machine Learning Pipelines?



Key Requirements for Credible Performance Claims

A graphic of a 2x2 grid of puzzle pieces, outlined in a light blue color. The pieces are separated, with visible interlocking tabs and blanks. The text "Trustworthy Benchmarking for Research and Practice" is centered over the grid in a bold, dark blue font.

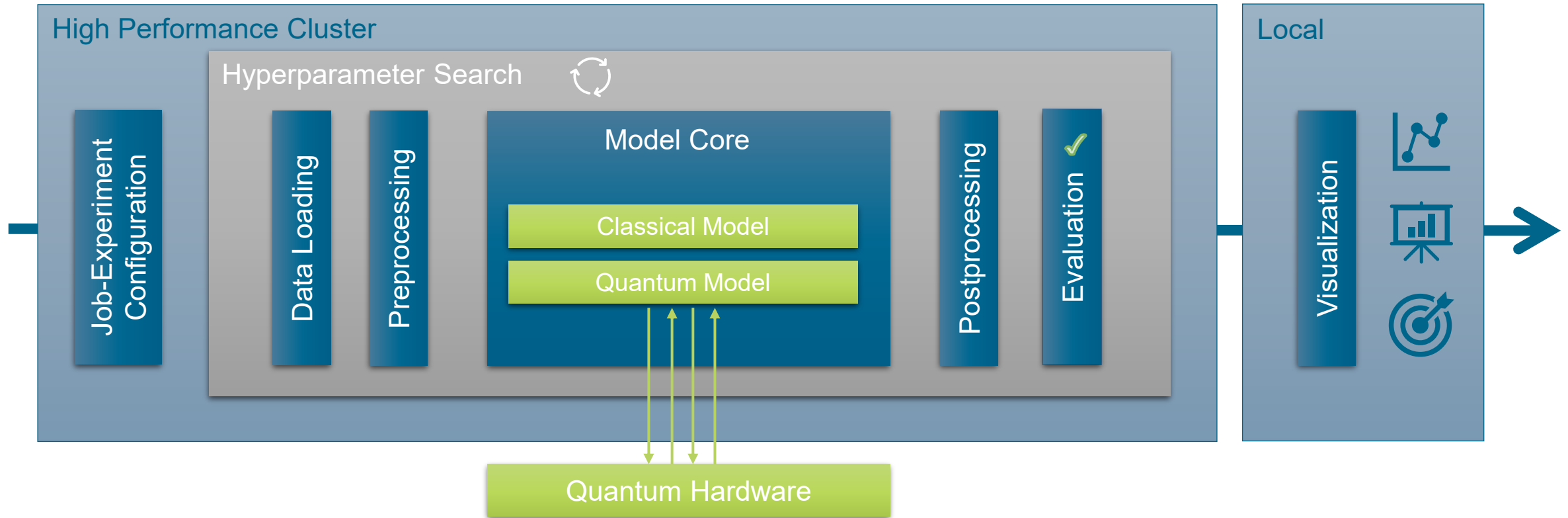
**Trustworthy
Benchmarking for
Research and Practice**

The background of the slide is a dark blue field filled with binary code (0s and 1s) falling vertically. Overlaid on this are several glowing blue and white geometric and network-like patterns. In the center, there is a series of concentric circles on a rectangular base, with a bright light beam shining down from a target-like pattern above it. To the right, there is a stylized brain shape composed of interconnected nodes and lines, resembling a neural network. At the bottom right, another network of nodes and lines is visible. Various arrows and curved lines suggest a flow or process.

QUANT²AI – QML-BENCHMARKING FRAMEWORK FOR RESEARCHERS AND PRACTITIONERS

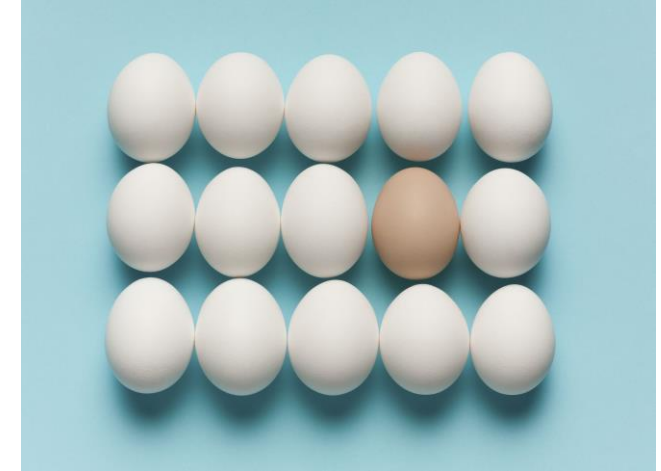
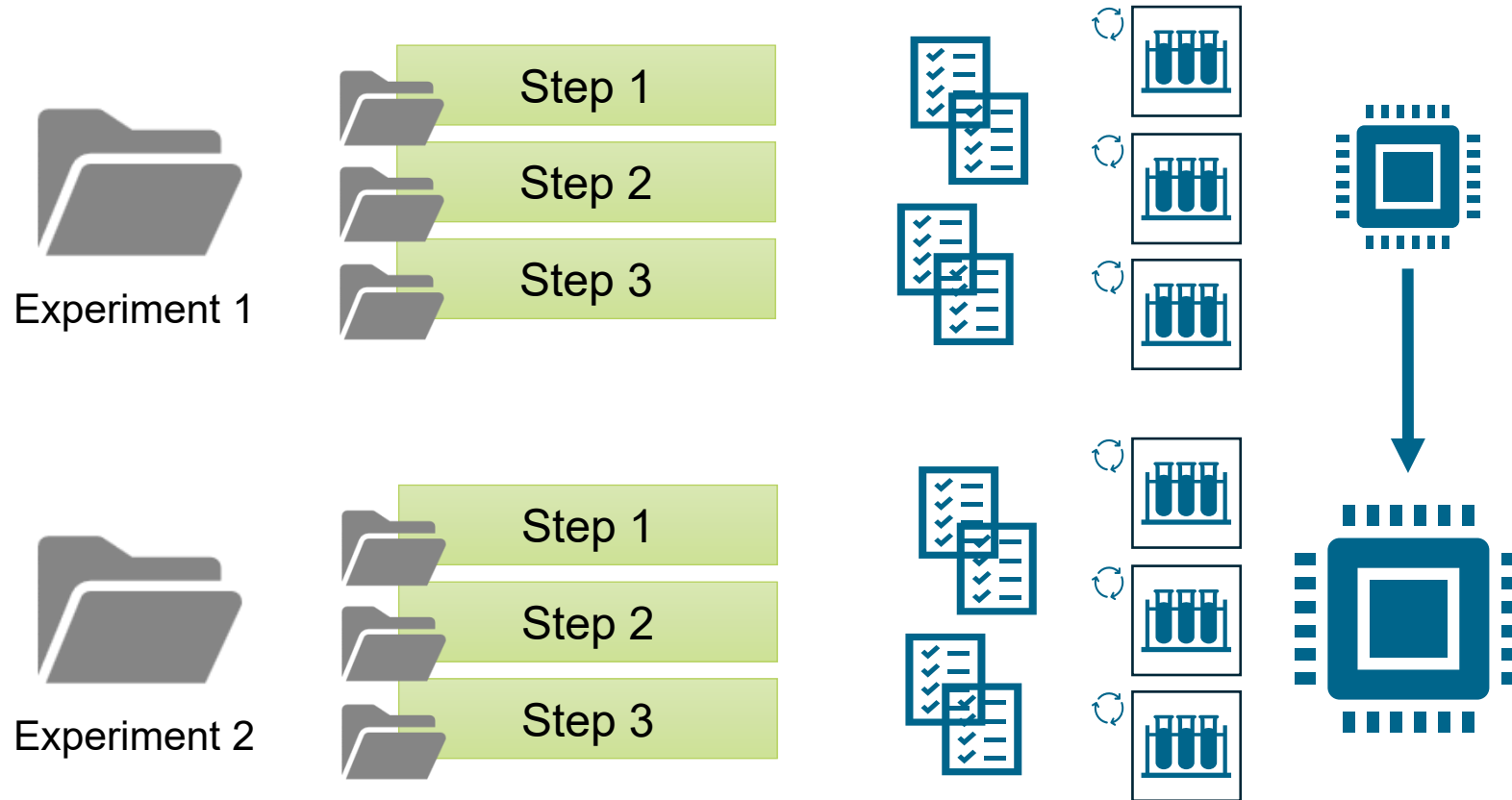
Modularity & End-to-End Evaluation

Input and Output Standardization Ensure Compatibility of Each Neighboring Block



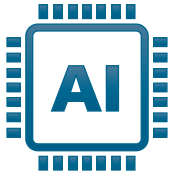
Reproducibility & Scalability

Experiments are Set Up with Same and Clean Environment
Necessary for a Fair Verification



Comparability and Hardware Realism

Metric evaluation and aggregations for scientific rigor
Statistical meaningfulness



Machine Learning
Metric



Quantum
Metric



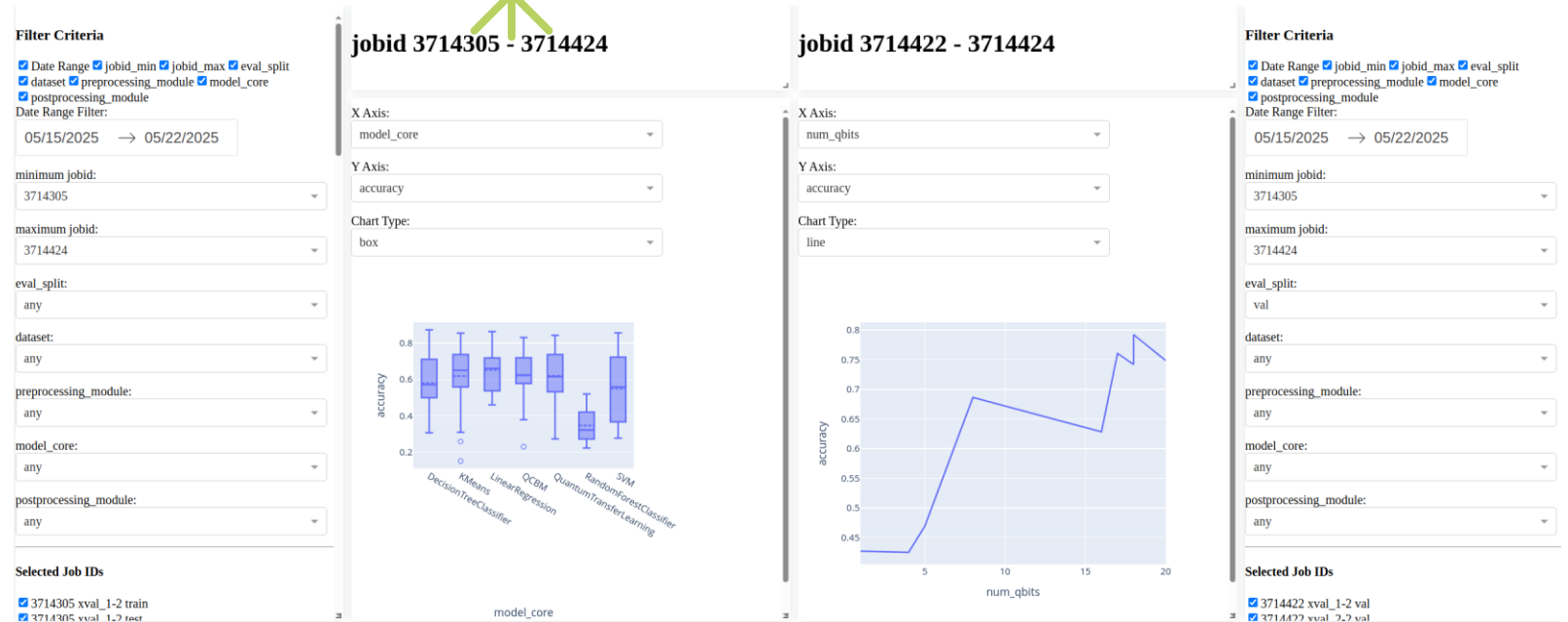
Cluster Information



Custom/ Research
Metric



Visualization Tool



LETTER

<https://doi.org/10.1038/s415>

Supervised learning with quantum-enhanced
feature spaces

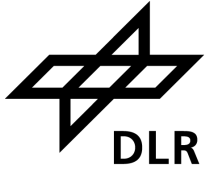
Vojtěch Havlíček^{1,2}, Antonio D. Córcoles^{1*}, Kristan Temme^{1*}, Aram W. Harrow³, Abhinav Kandala¹, Jerry M. Chow¹ & Jay M. Gambetta¹



Extensibility & Task Relevance

It Helps to Keep the Software Updated for the Upcoming Progress

Expandable Collection of Real-World Datasets, ML Tasks, and Custom Algorithms





Material Analysis Data

Iris Dataset

Additional

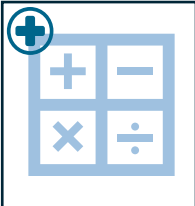




QNN

SVM

Additional





ML Metrics

Hardware Info

Additional

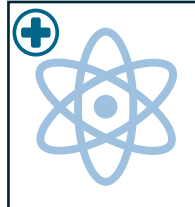


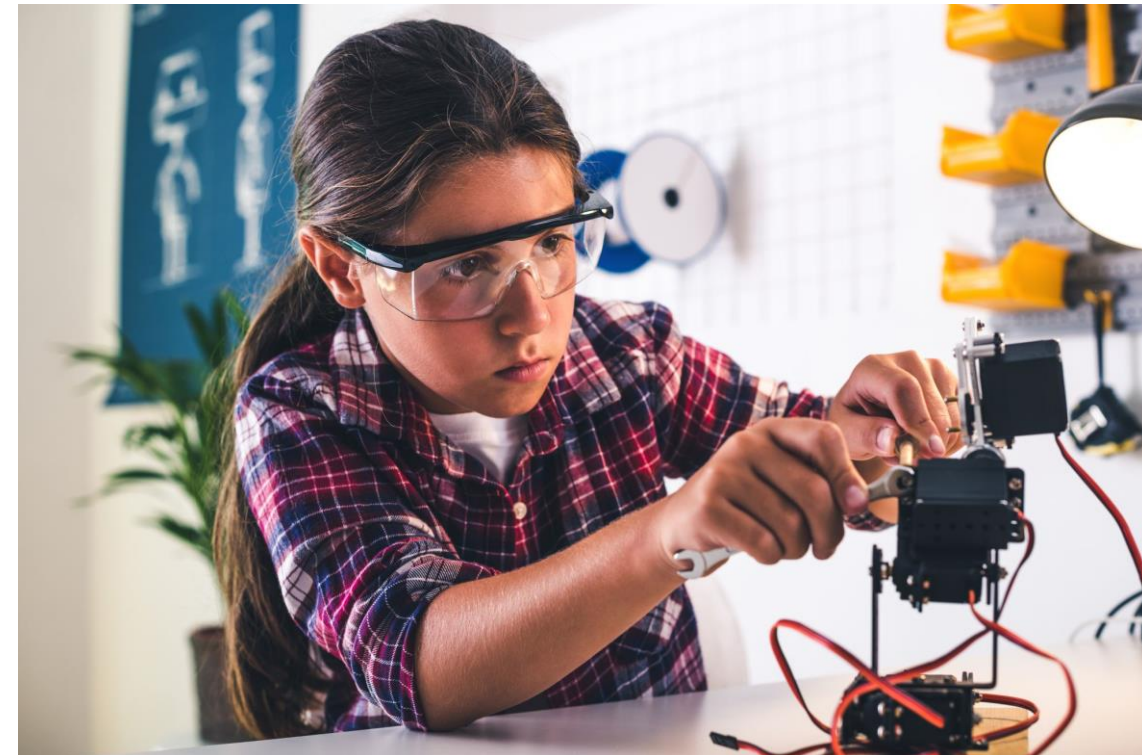


Quantum Devices

Simulations

Additional





Digest – Towards Trustworthy QML Benchmarks



- Quant²AI: A scalable, reproducible, modular benchmarking framework
- Execution on HPC with connection to quantum hardware and simulators
- Large set of datasets (both toy and real-world examples), (Q)ML models, pipeline modules, and metrics
- Both the benchmarking and the visualization provide spacious possibilities for extensions

Get Involved! Feel Free to Contact Us!



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