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Paving the Way to Practically Relevant Quantum Computing

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Quantum computing is expected to be disruptive across industries

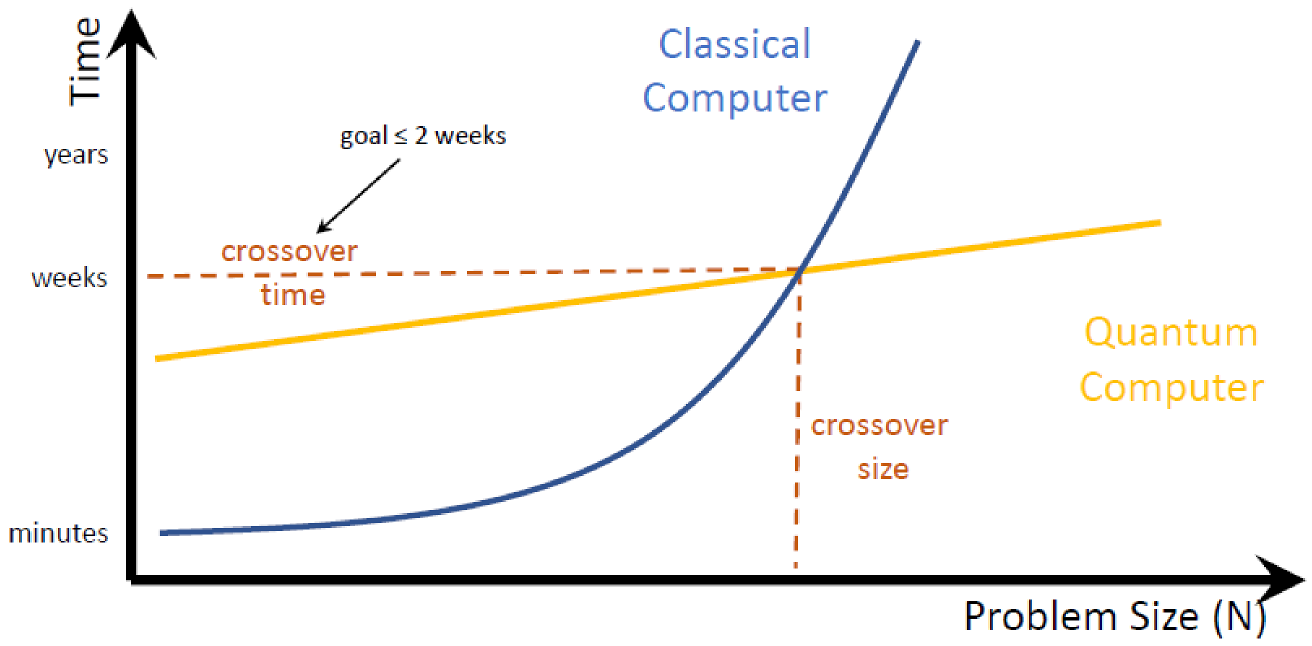
Quantum computing (QC) promises to be useful in many application areas and therefore industries:

- **Simulation** of quantum mechanical systems (Development of new drugs, chemical sector with battery development,…)
- **Solving linear systems of equations** (Fluid dynamics, e.g., in aerospace)
- **Optimization** problems (Logistics, production, pharma,…)
- **Quantum machine learning** (Computer vision, mobility,…)

But how do we really get there?

Which application categories are promising?

[T. Hoefler, T. Haener, M. Troyer, Disentangling Hype from Practicality: On Realistically Achieving Quantum Advantage, arXiv:2307.00523 [quant-ph]]



- For a **practical quantum speedup** a quantum computer needs to be faster in real time than a classical computer – not just assymptotically
- Possibly a specific **cross-over point** for every application/algorithm
- Even a perfect, fault-tolerant quantum computer will likely **execute less operations in a given time** (slower I/O rate by a factor of 10000)
- Algorithms with only a **weak (e.g. quadratic) speedup** will have a **long crossover time point** (e.g. weeks?)

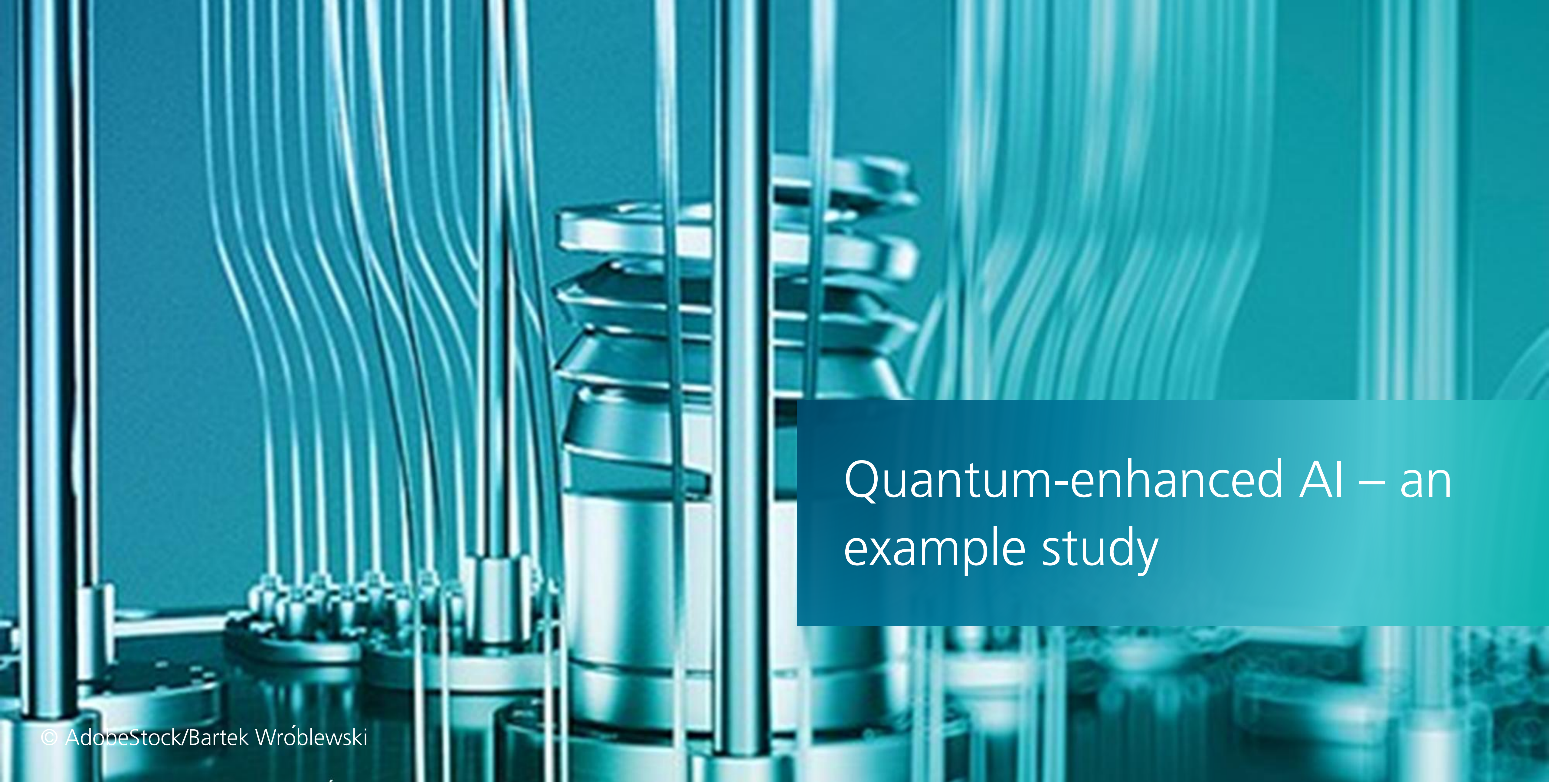
Which application categories are promising?

Lessons learned

Note: Quantum computers are generally <u>no</u> big data machines (yet).

We need

- ***„Big“* problems** on ***„small“* data**
- Ideally an **exponential or at least super-polynomial speed-up** (Shor, HHL, etc.)
- Additionally, **efficient classical-quantum workflows**
- **…**to consider **sampling overhead**



Quantum-enhanced AI – an example study

Reliable QC-assisted AI for medical classification tasks

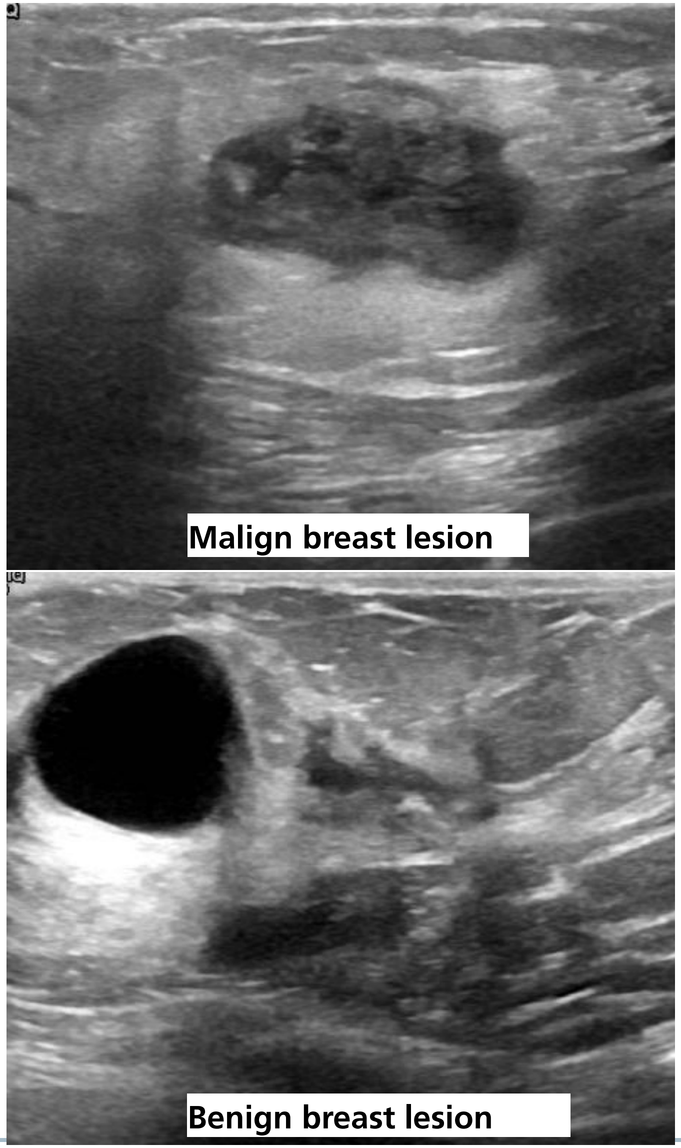
Context: Artificial intelligence increases in importance in the medical diagnosis process (e.g. in imaging).

Challenges: Image data is expensive, complex and only available in small numbers (10^2 -10^3),

The decision process needs to be comprehensible and reliable.
→ Classical methods need large training datasets.
→ Desirable to propagate uncertainties of data.

Possibilities on the quantum side to tackle these challenges:

- Quantum Convolutional Neural Networks
- Quantum Bayesian Neural Networks
- …



Source: W. Al-Dhabyani, et al, "Dataset of breast ultrasound images". Data Brief, vol 28, pp 104863, 2020

Hybrid quantum-classical convolutional neural networks

[Quantum-classical convolutional neural networks in radiological image classification, A. Matic, M. Monnet, J.M. Lorenz, B. Schachtner, T. Messerer, QCE 2022, arXiv:2204.12390, 2022]

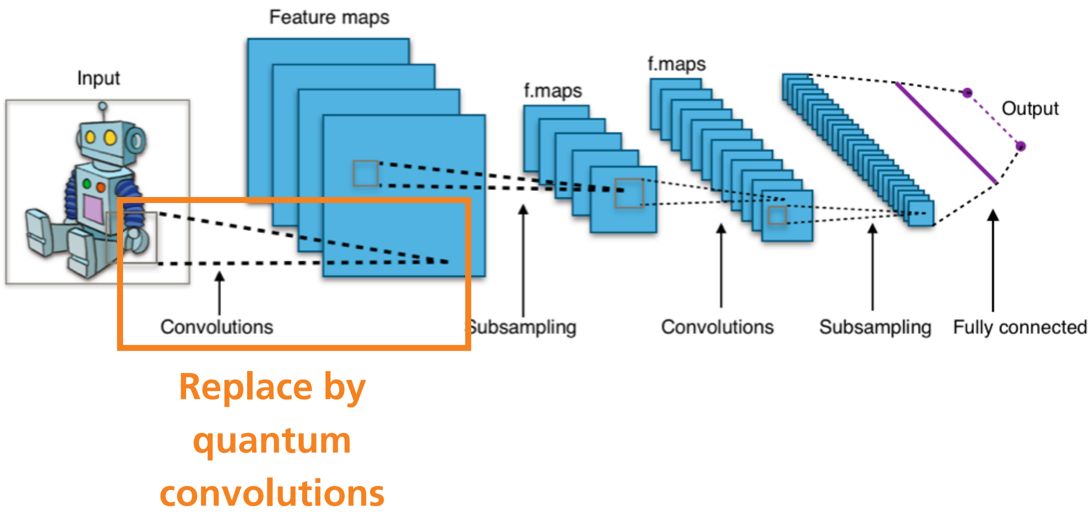
Convolutional neural networks very successful in image classification tasks.

Improvement: Hybrid quantum(-classical) convolutional neural networks promise to be better suited for situations with little training data, potentially leading to a more precise and faster training convergence.

Idea: Replace some of the classical convolutional layers by quantum convolutional layers – also replacement of pooling layers would be possible.

Hybrid ansatz, since only a few classical layers replaced → also possible to execute on the current or soon-available NISQ quantum computers (theoretically).

Classical convolutional neural network



Source: https://upload.wikimedia.org/wikipedia/commons/6/63/Typical_cnn.png, Aphex34, CC BY-SA 4.0 <https://creativecommons.org/licenses/by-sa/4.0>, via Wikimedia Commons

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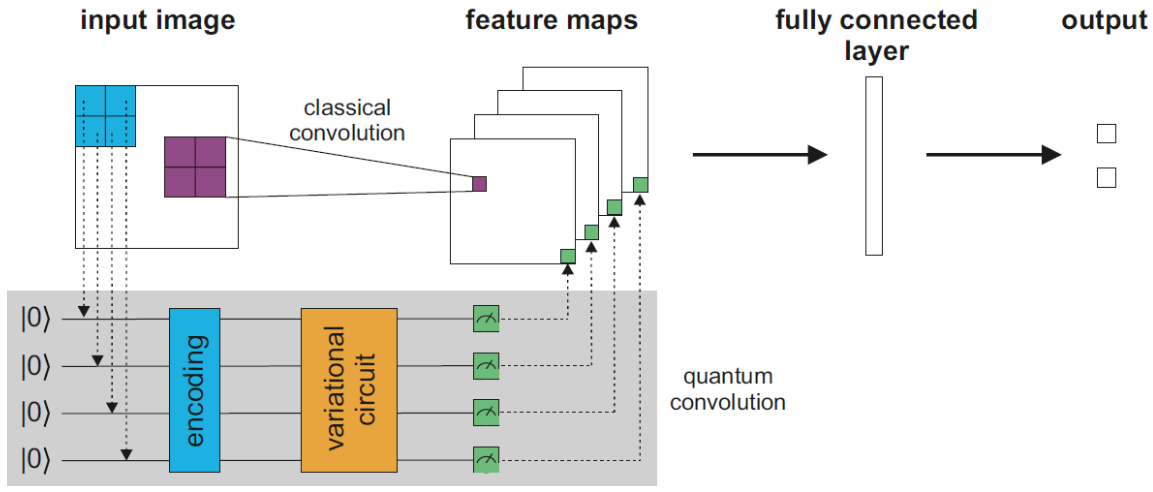

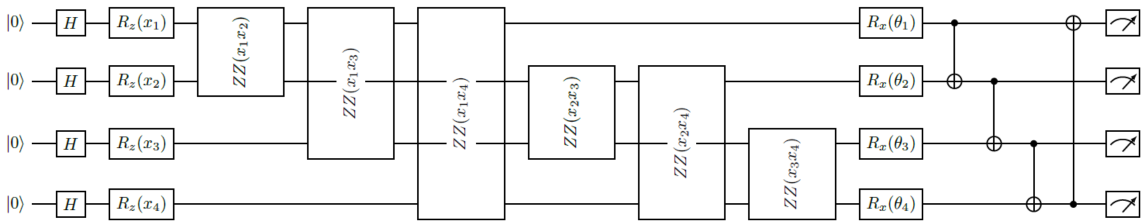

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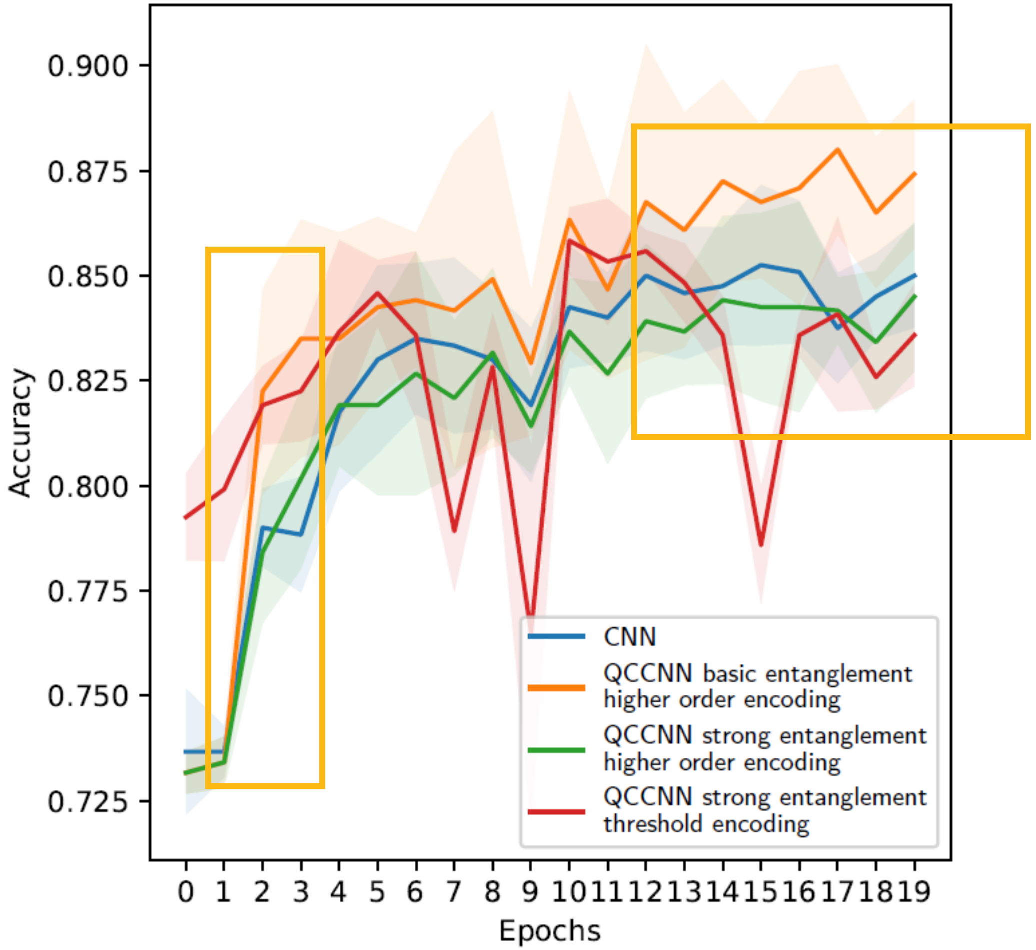


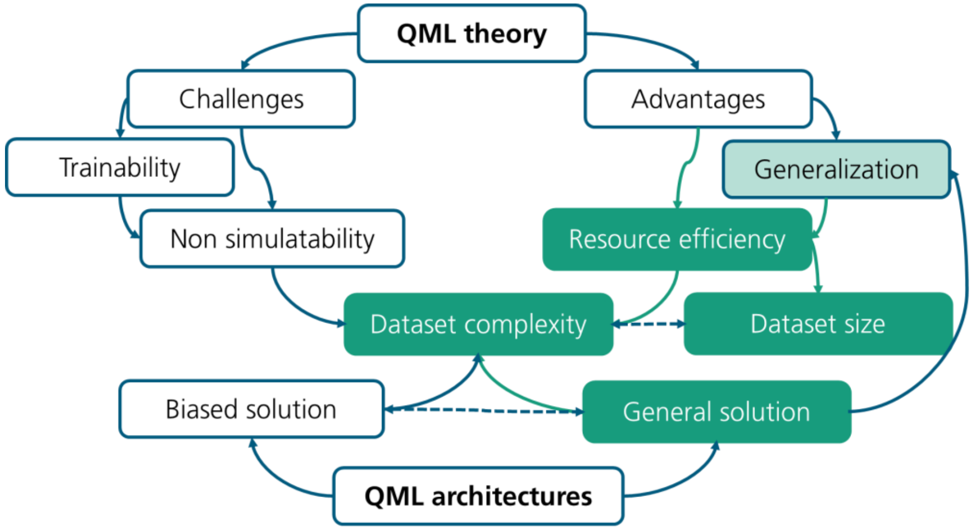
Is data-efficient learning feasible with quantum models?

[Alona Sakhnenko, Christian Mendl, Jeanette Miriam Lorenz, Is data-efficient learning feasible with quantum models?, arXiv:2508.19437]

Non-trivial datasets (+ encoding) seem to be essential for the performance of QML, but which properties does a dataset need to have?

Approach:

- Demonstrate that quantum models can generalize data-efficiently and effectively; despite previous studies indicating poor predictive accuracy of generalization metrics and speculations in the literature;
- Seek to enable characterization of datasets for which data-efficiency is possible, on the case of quantum kernel methods (which are connected to quantum neural networks);
- Use generalization metrics based on a target-alignment measure to create artificial (classical) datasets by creating artificial labels.



Is data-efficient learning feasible with quantum models?

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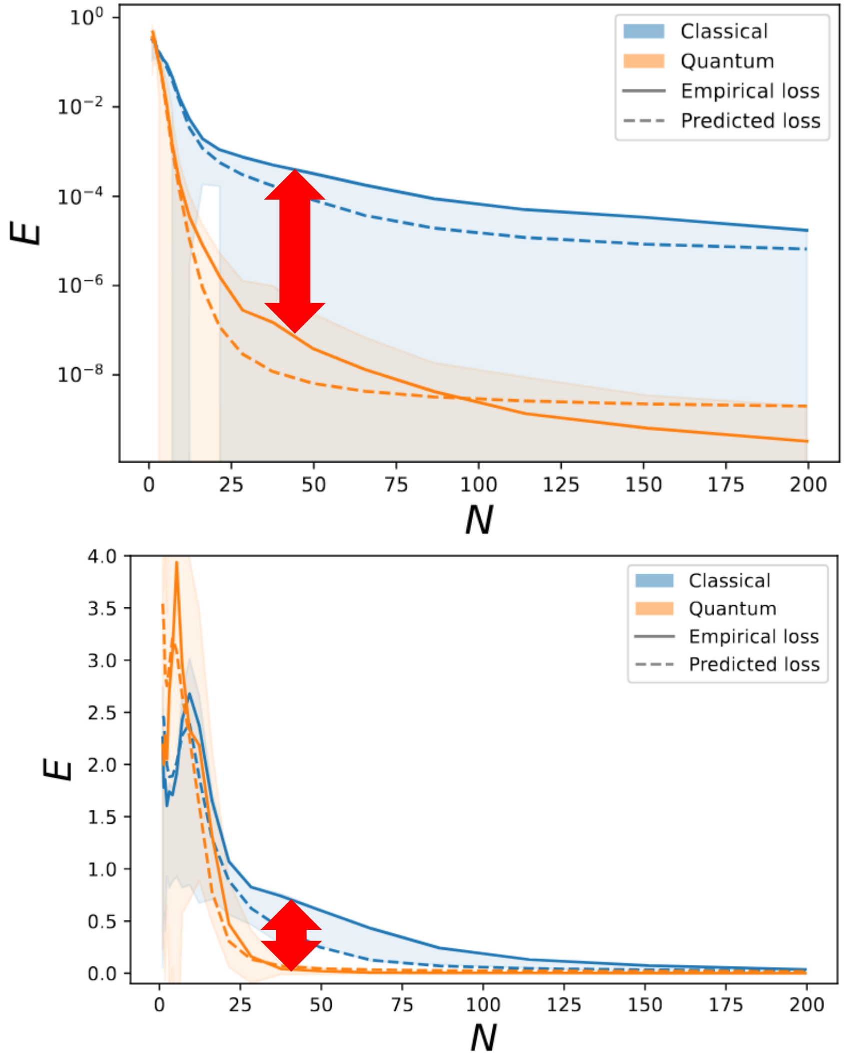
(First) empirical evidence that QKMs can achieve a low error with less data. Meaning, they can be **data-efficient.**

The method to generate different datasets is favorable for QKMs and hence to **study their properties.**

With essential tools at hand, we can now pursue important questions for future work:

- How can we characterize these datasets, and hence what are the requirements for real-world datasets where quantum models demonstrate data efficiency?
- What are the essential requirements for a generalization gap between quantum and classical models?



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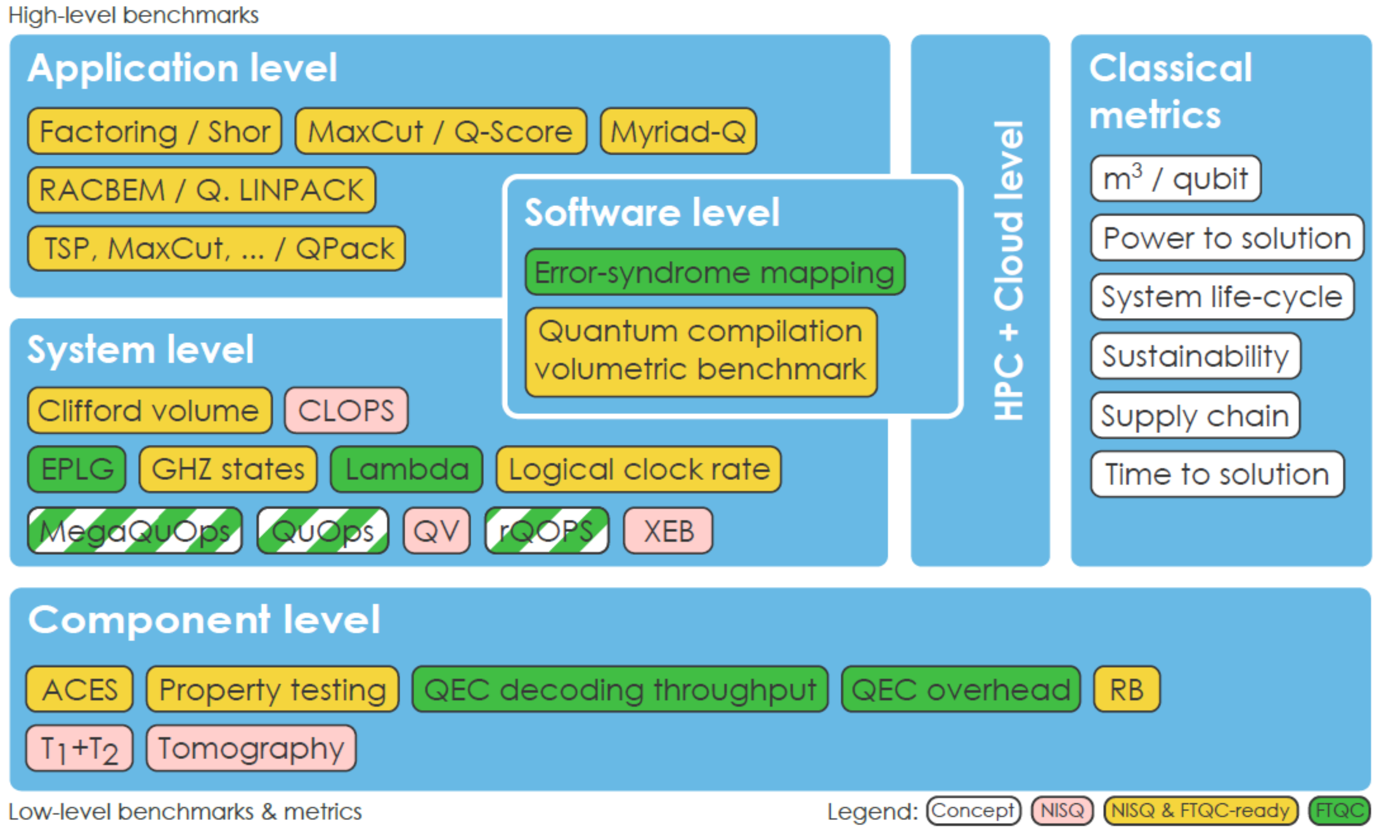
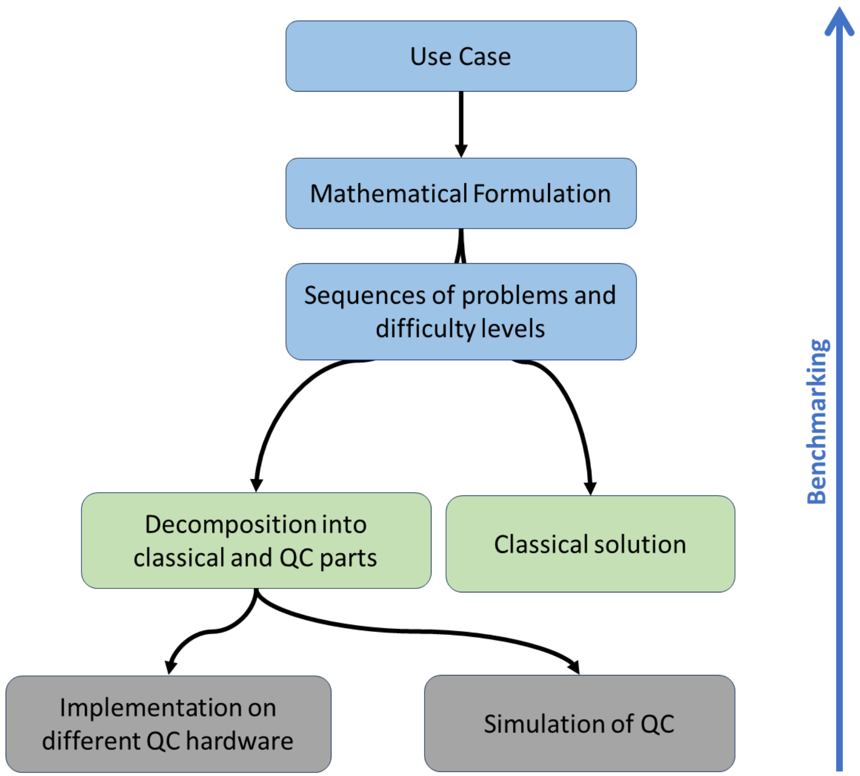
Benchmarking

Revisited

Lorenz et al., 2025, [2503.04905] [Systematic benchmarking of quantum computers: status and recommendations]
Geissler et al., 2025, [2504.11204] [BenchQC -- Scalable and modular benchmarking of industrial quantum computing applications]

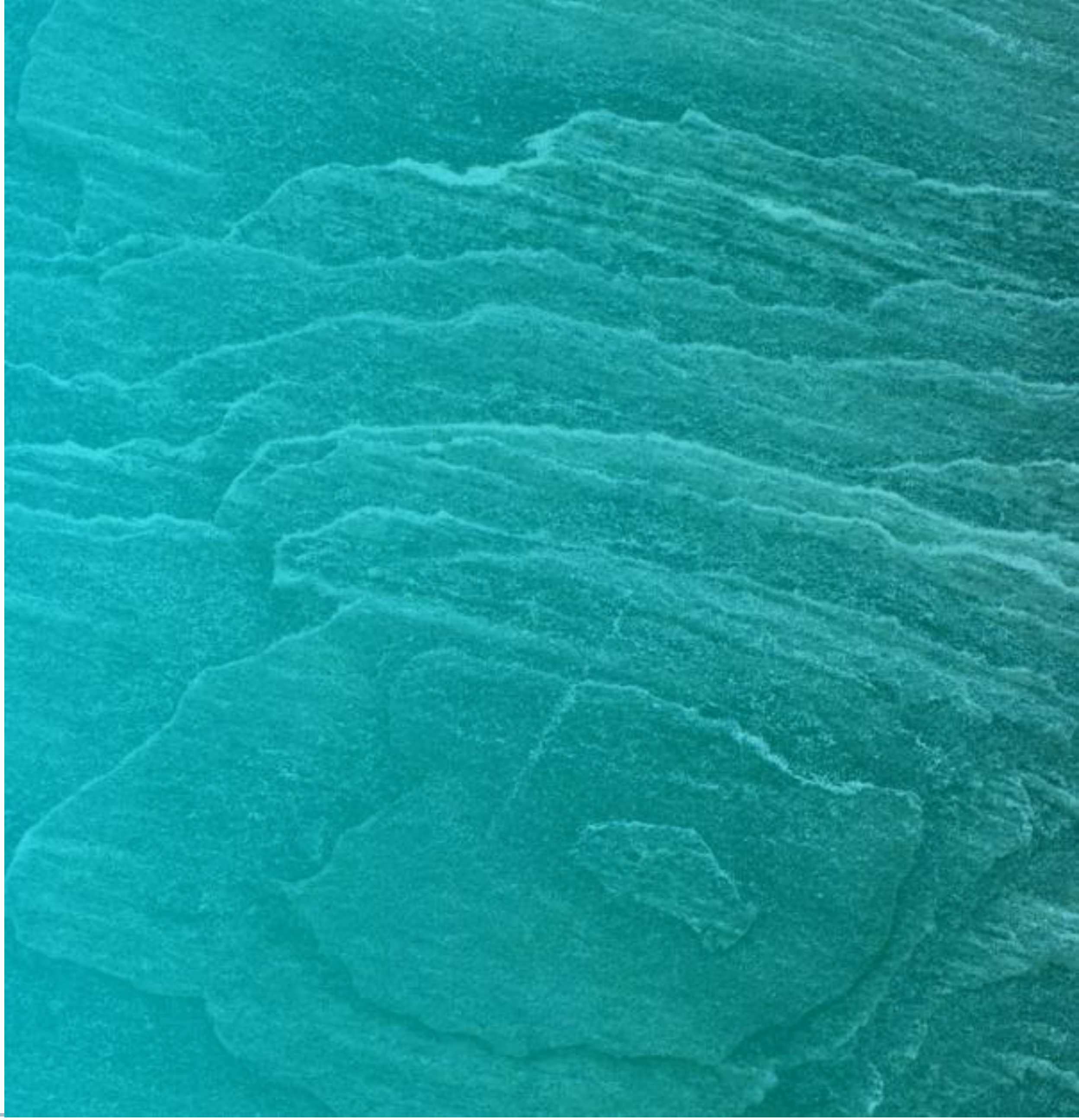




+ Tools (Quark, MQT, …)

Summary

- The question on a potential, practically relevant **quantum advantage gets more and more nuanced**, while classical algorithms and powerful modern AI continue improving.
- (Hybrid) QCNNs show promising aspects in **generalization and data efficiency**, at least empirically.
- Significant question is: What are the **data (or problem) properties** that are useful for quantum computing/are not easily simulatable classically?
- Application-centric/-driven **benchmarking** will be essential to provide a holistic quantitativ assessment.



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