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Connecting the Dots in Quantum Computing: How Applications Drive Forward Developments

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Quantum computing is expected to lead to disruptive effects over different 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?

Bringing QC into application

QC hardware

QC software

QC algorithms

?

Applications in industry & academia

- Chemistry, material science
- Pharma
- Logistics
- Aerospace
- Mobility
- Machine learning
- Security
- Climate modeling
- …

For which applications is the use of QC really sensible & how to enable this?

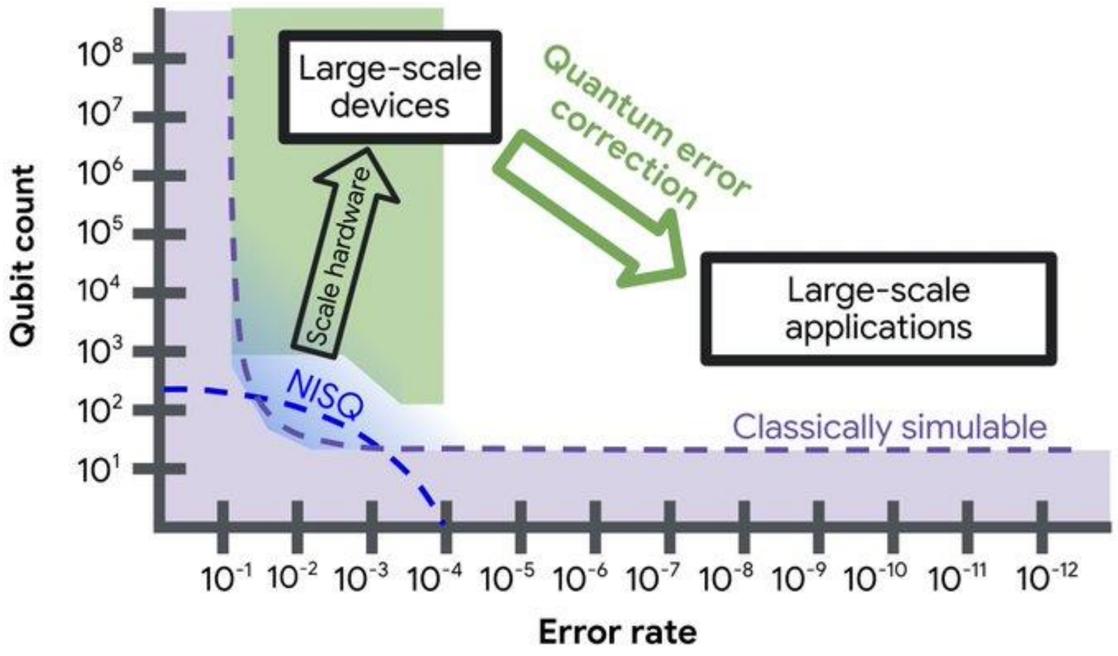
Towards practical quantum advantage

The recent years have shown clearly that current NISQ devices are not suited to result in large-scale quantum utility/ to realize a practical quantum advantage.

Certainly, central to realize this is the establishment of quantum error correction (and error mitigation will probably still be needed, see Eisert & Preskill 2025).

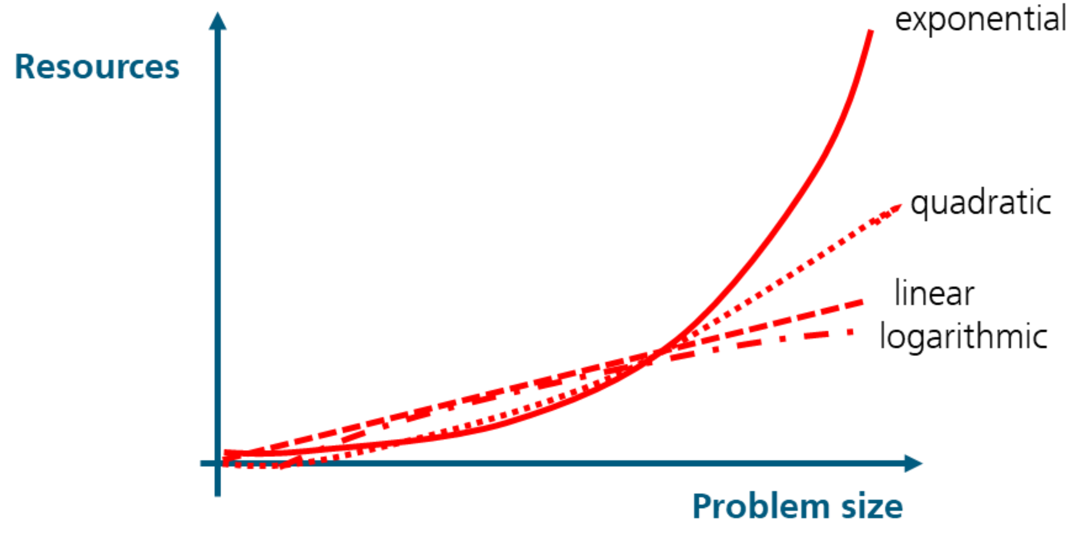
But even if we had now large fault-tolerant quantum computers available, we would not fully understand (yet) for what to use them & which quantum algorithms will result in practical quantum advantages.

Additionally, we need to establish the software (stack) to unlock the potential quantum computers offer to the wider community of users – and to allow for efficient compute workflows.



[Michael Newman, Google Quantum AI]

So, what do we need to achieve?



In QC we are interested in achieving at least a polynomial speedup with respect to classical algorithms, probably even super-polynomial required [1]

→ Complexity Theory, comparisons quantum & classical algorithms typically in ‚Big-O'-notation

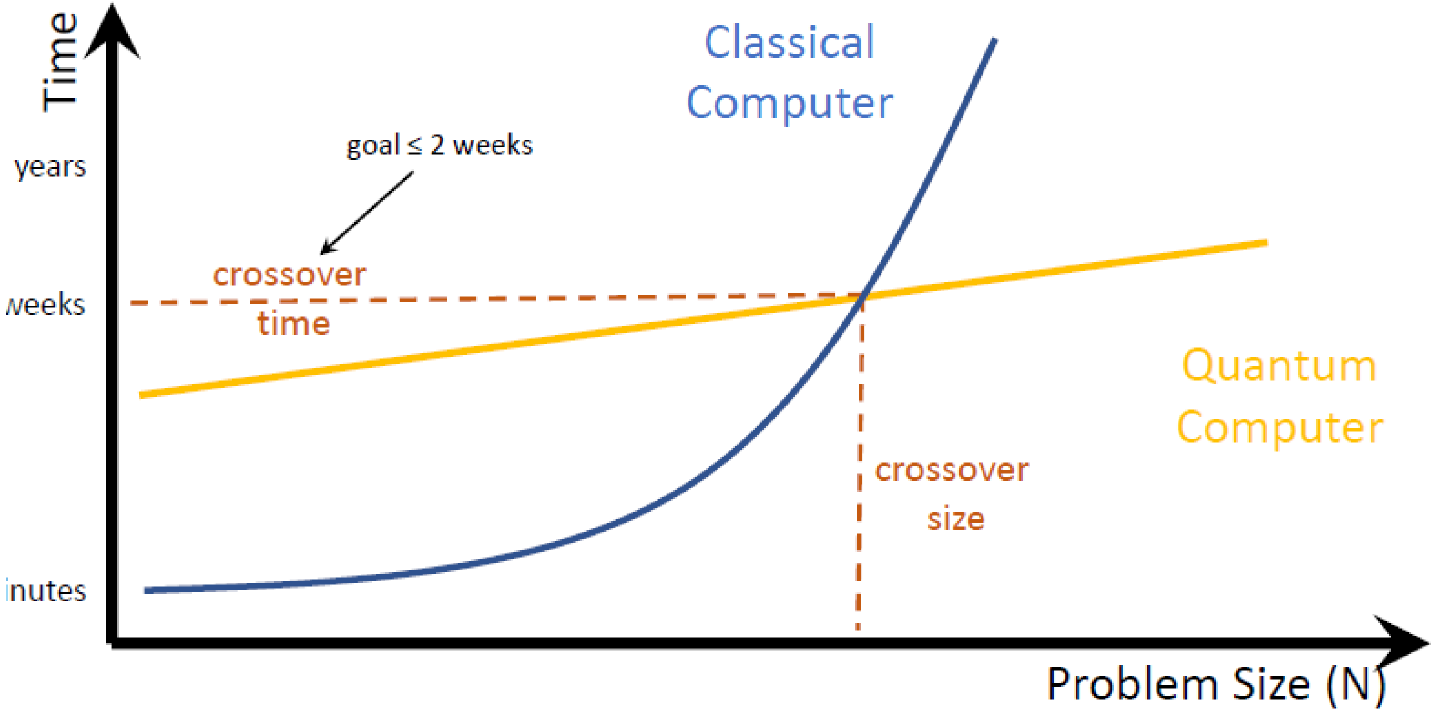
Note: simply measuring benefits in terms of computational complexity might be too short-sighted: accuracy, energy efficiency, interpreting data differently

Also tendency (need!) to go to more ‚empirical' benchmarks (like in ML)

[1] Torsten Hoefler, Thomas Haener, Matthias Troyer, Disentangling Hype from Practicality: On Realistically Achieving Quantum Advantage, arXiv:2307.00523 [quant-ph]

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]]



To achieve a **practical quantum advantage** it is required that a quantum computer is also faster in real time compared to a classical computer – this means not just asymptotically.

Possibly for every application/algorithm specific cross-over point.

But quantum computers are slower than classical computers

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

	GPU	ASIC	Future Quantum
I/O bandwidth	10,000 Gbit/s	10,000 Gbit/s	1 Gbit/s
Operation throughput			
16-bit floating point	195 Top/s	550 Top/s	10.5 kop/s
32-bit integer	9.75 Top/s	215 Top/s	0.83 kop/s
binary (boolean logical)	4,992 Top/s	77,000 Top/s	235 kop/s

- Even a perfect, fault-tolerant quantum computer will have a slower I/O rate than a classical computer, by a factor of 10000.
- This implies that a QC can execute less operations in a given time.
- **Algorithms with only a quadratic advantage will thus result in a crossover time point of multiple weeks, which is (/might be) infeasible in practice.**

What to do?

Quantum computers are generally no big data machines (yet). (See counter-proposal by J. Liu et al. 2024)

We require applications/problems with significant (‚big') compute challenges on *little* data

And ideally with an exponential or at least super-polynomial speed-up – or a different kind of advantage

Examples:

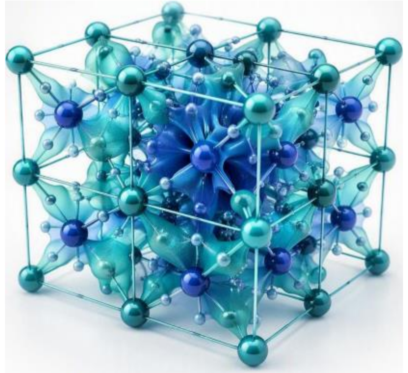
- Shor's algorithm
- Simulations in quantum chemistry, material science and quantum physics
- Solution of linear systems of equations with **highly structured data**, assuming that no loading of big data is required + the full solution cannot be sampled without losing the advantage

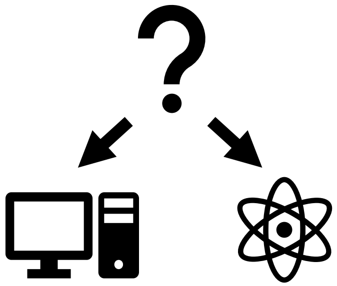
Additionally, **efficient classical-quantum workflow required** + need to **consider sampling overhead**

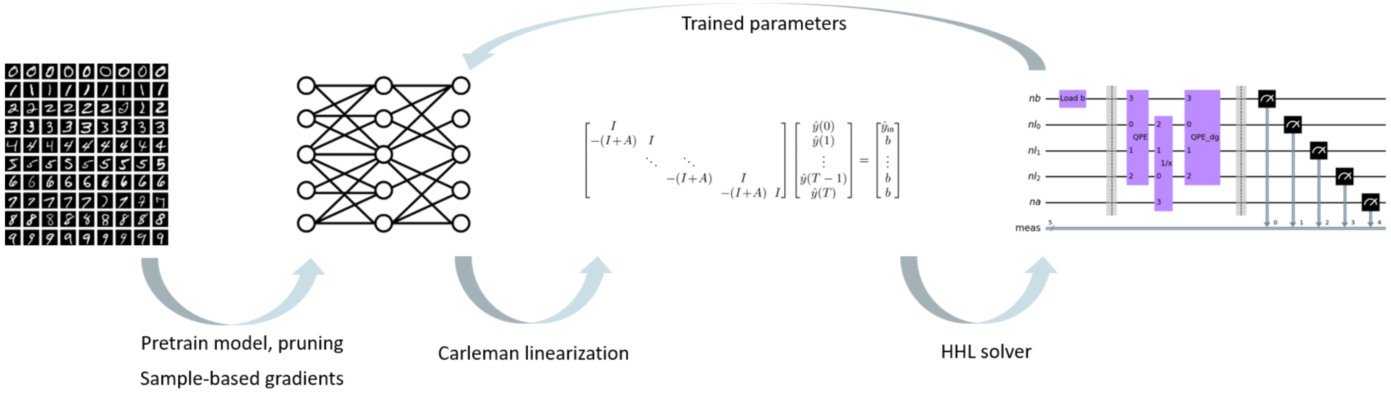
In more and more (reasonable) applications, the quantum computer enters as computational subroutine

Examples

- **Molecule simulations**
  - See recent example by IBM, Cleveland clinics, Michigan HPC center (A. Shajan et al., arXiv:2512.17130v1) – example to simulate 300 atoms in electronic structure calculations.
  - Only one very specific subroutine put to QC, heavy classical HPC load
- **Large-scale optimization problems**
  - Can sometimes be decomposed in parts more suited for QC or more suited for classical computers
- **Quantum-enhanced AI**
  - HHL can help in solving linear systems of equations as appearing in AI models/ training







Efficiency:
Providing abstractions to the user

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Quantum software stacks required to support quantum-classical workflows

Efficiently, otherwise we lose a possible quantum advantage

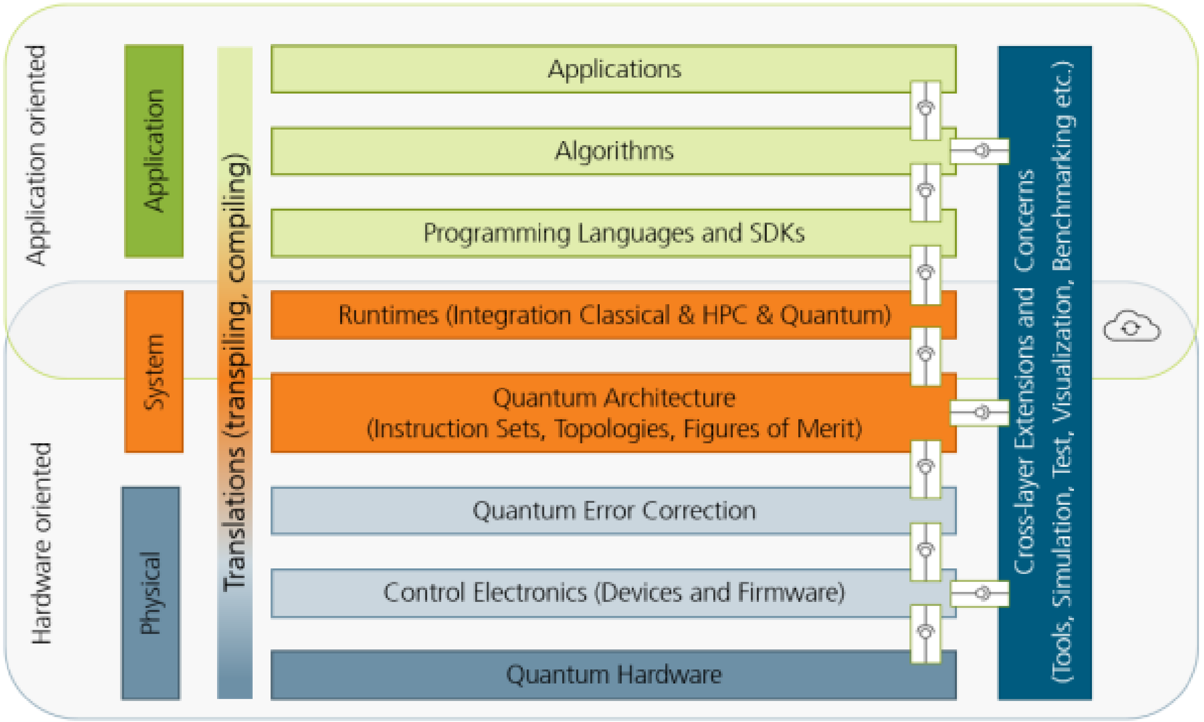
The installation and integration of quantum computers in EuroHPC centers (will) allow to do research on these kind of workflows.

In parallel, various quantum software stacks emerge – typically mainly concentrating on the hardware-closer layers, not yet concentrating on the application-close layers.

But: complicated stacks, different possibilities on how to realize it → **significant complexity for the application user in using them**!

Eventually, the use of these hybrid systems needs to be possible **without requiring in-depth hardware or algorithmic expertise** - ultimately achieving a **level of abstraction comparable to what TensorFlow and PyTorch have achieved in the AI domain**

Note: a number of European and national projects are about to start to work on these issues.



Design principle of a QSS according to the QCNext project

Supported by:
Federal Ministry for Economic Affairs and Climate Action
on the basis of a decision by the German Bundestag

An example

Infineon Loudspeaker & Microfons

Planning of efficient garbage collection routes

Infineon sensors & actuators detect fill level of containers

Task:

- Optimize routes for waste collection vehicles with QC assistance.
- Build on filling level simulation a few days in advance.
- Goal: More efficient (ecologic and economic) routes.

Even 1-2% increase of efficiency would make a great impact.

Can quantum computing come to help?

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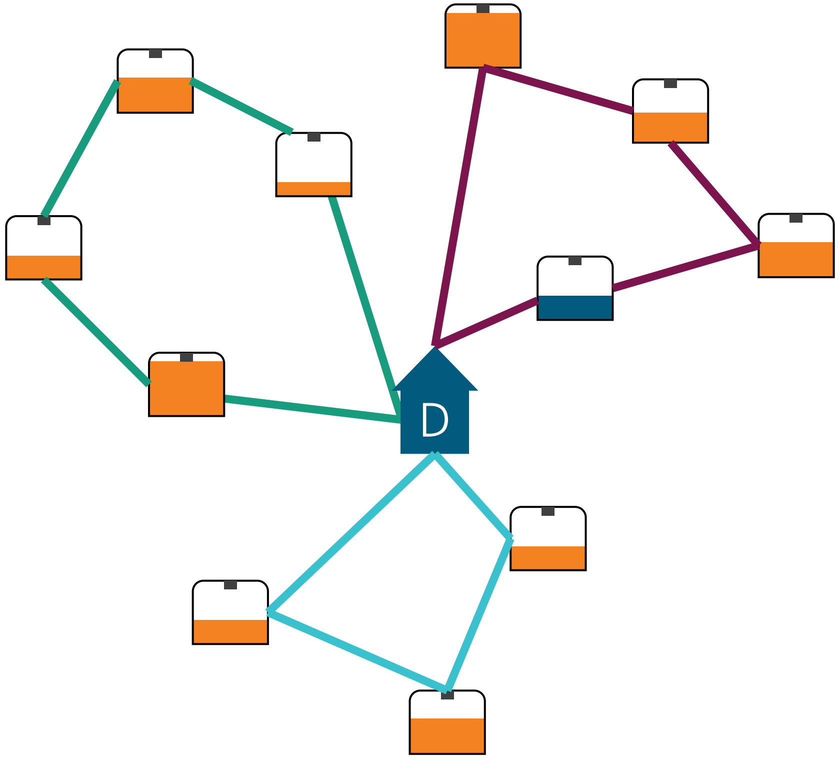
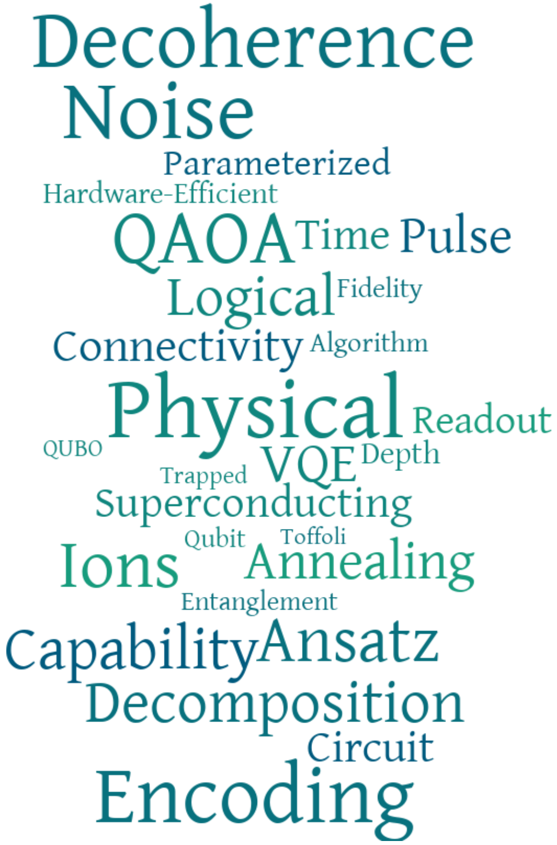
Large zoo of potential quantum algorithms:

- **Variational algorithms** (VQE, QAOA)
  - Advantage not proven
- **Fault-Tolerant algorithms**:
  - Grover, QPE, …

Which algorithm to choose & how to ensure efficiency?





An abstraction layer for QC-assisted solutions of optimization problems

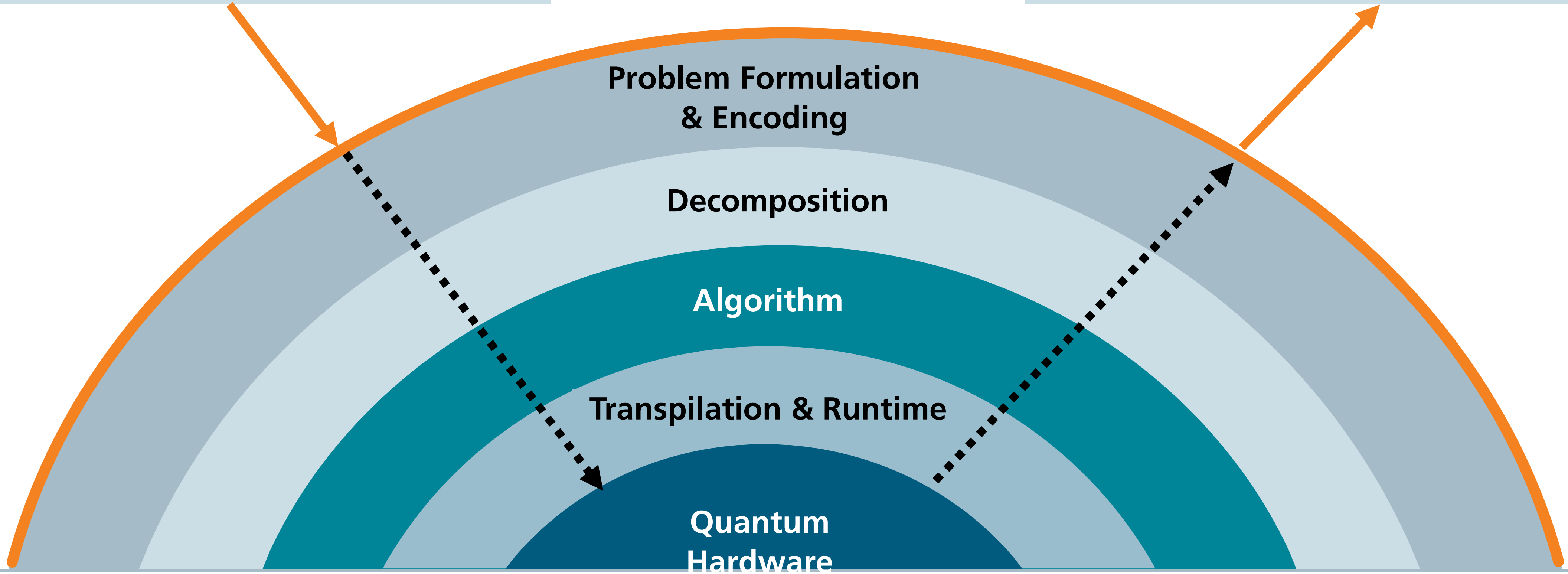
Hiding the complexity from the user

Problem

e.g. »How do I make my garbage collection more efficient?«

Solution

e.g. »These routes are 5% shorter and still collect all garbage in time«



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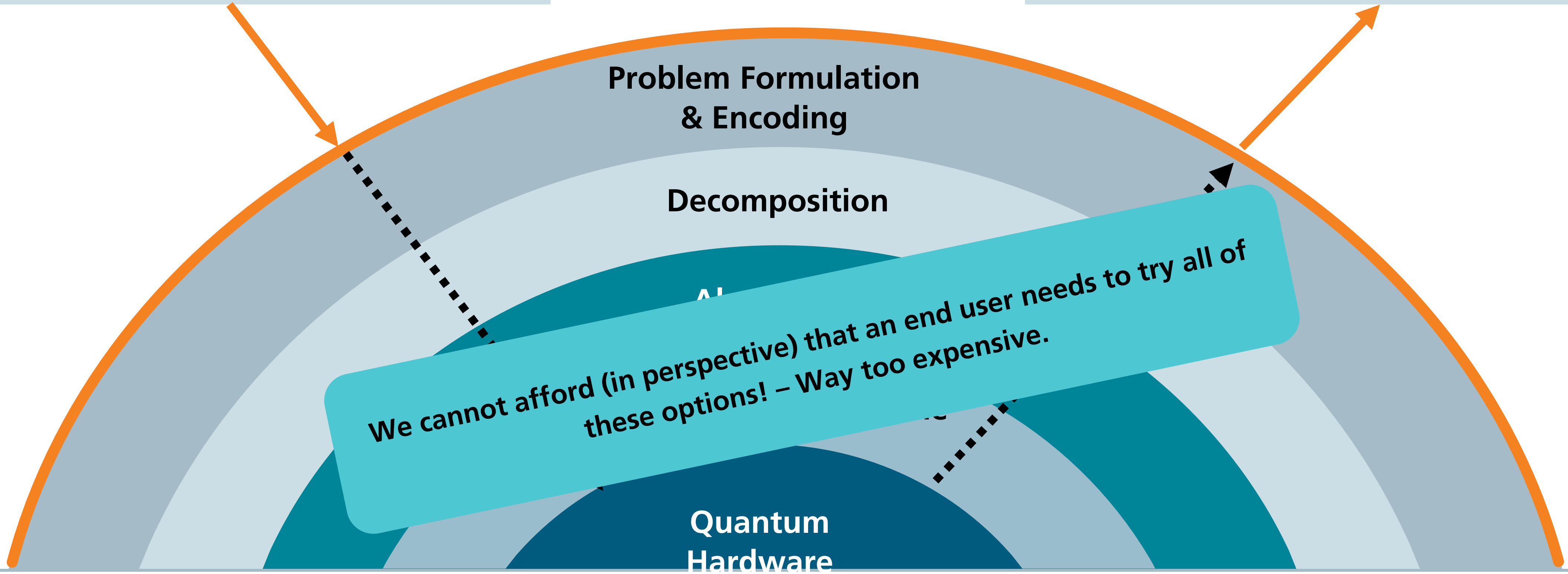


We cannot afford (in perspective) that an end user needs to try all of these options! – Way too expensive.

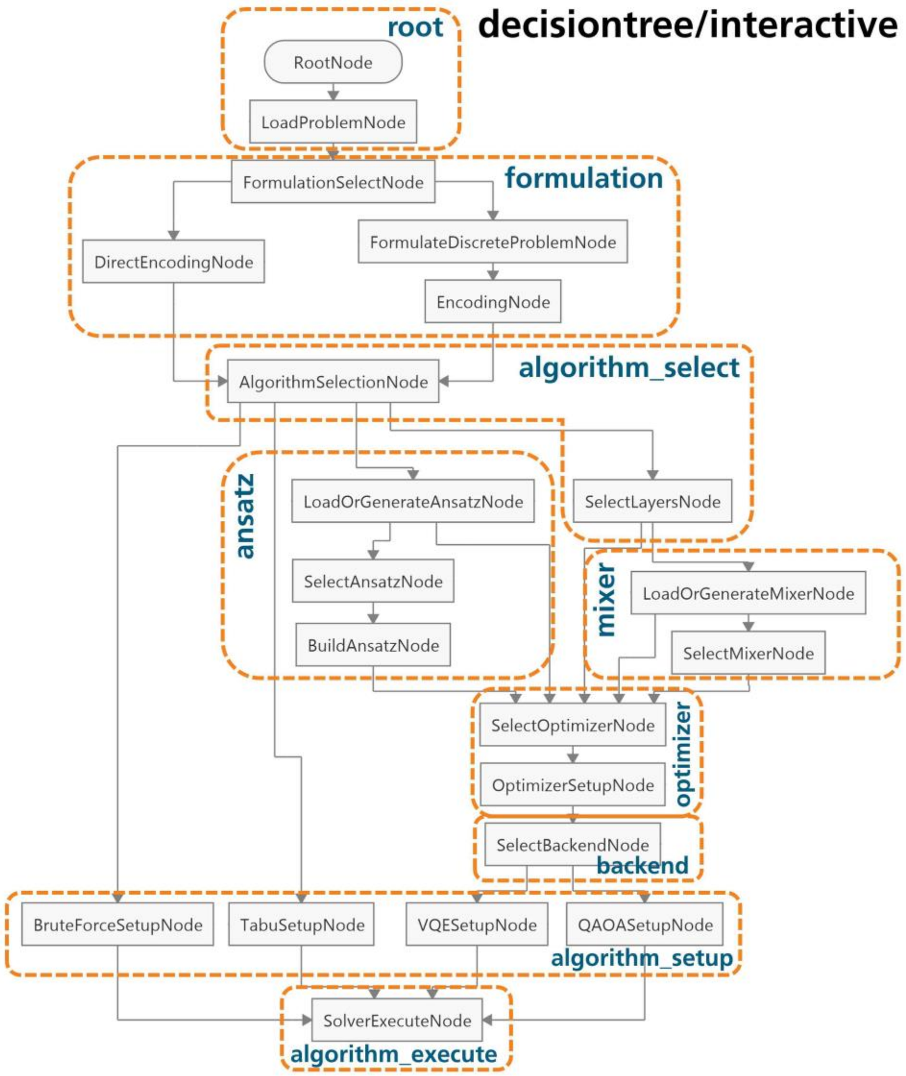
Recommened solution paths through the QuaST decision tree

Realizing quantum-assisted solutions to optimization problems requires the non-trivial connection of different algorithms & software layers.

E.g.:

- Which (quantum) algorithm to choose to obtain advantage over classical solvers?
- How to control interplay with classical optimizers?

QuaST decision tree – providing abstractions towards the end user. With easy-to-use web interface.



"Recommending Solution Paths for Solving Optimization Pro-blems with Quantum Com-puting", B. Poggel et al., QSW 2022.

"Quantum-Assisted Solution Paths for the Capacitated Vehicle Routing Problem", L. Palackal et al., QCE 2023.

"Creating Automated Quantum-Assisted Solutions for Optimization Problems", B. Poggel et al., arXiv:2409.20496 [quant-ph]

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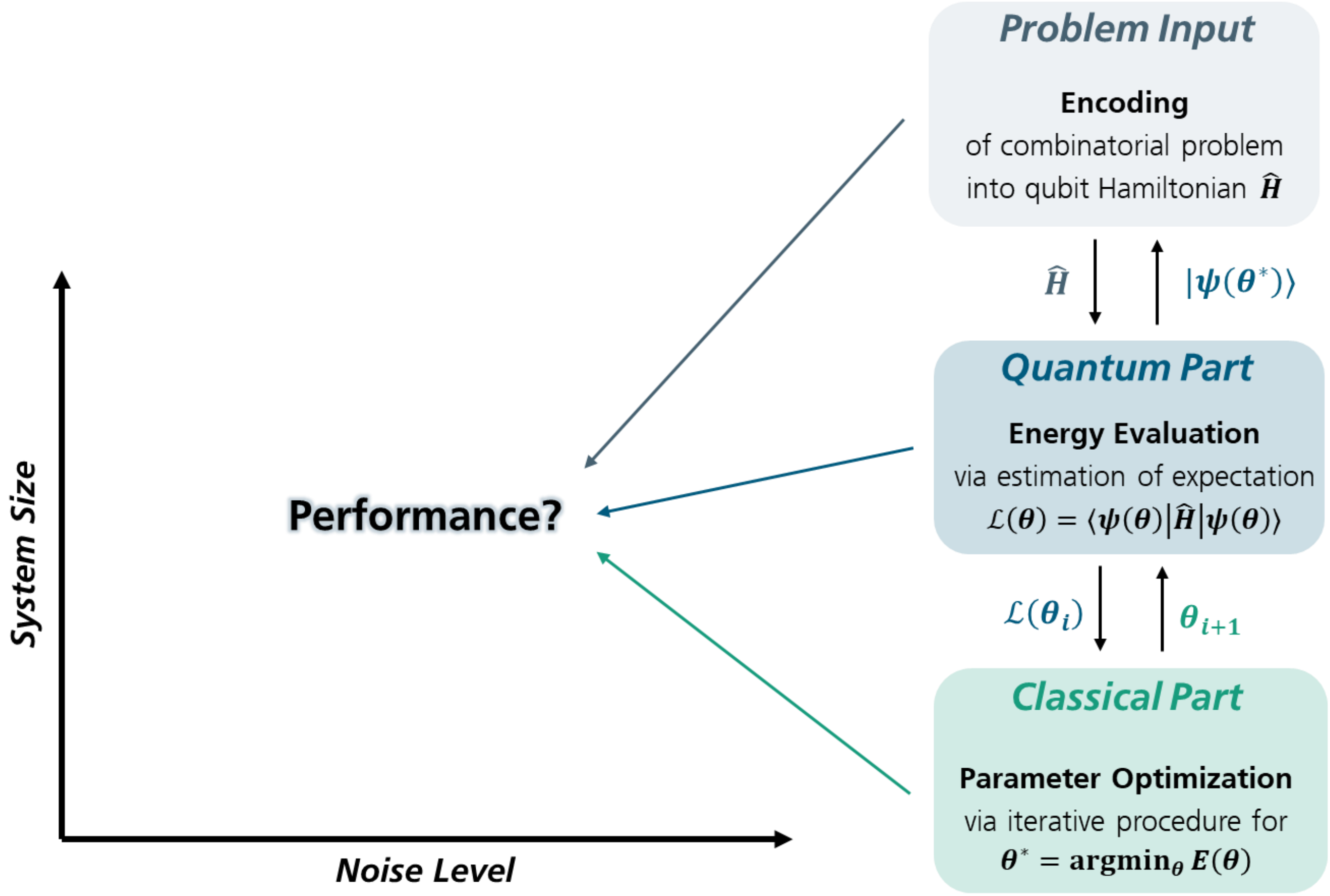
A systematic benchmarking pipeline for variational algorithms

[Scalability Challenges in Variational Quantum Optimization under Stochastic Noise, A. Bärligea, B. Poggel, J.M. Lorenz, Physical Review A 112 (3), 032407]



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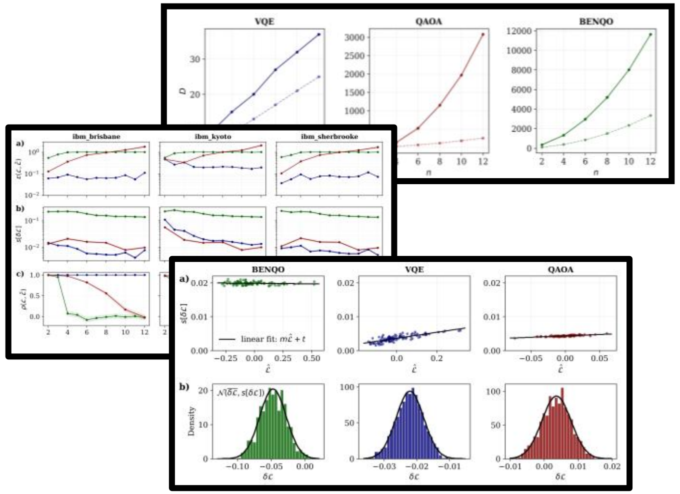
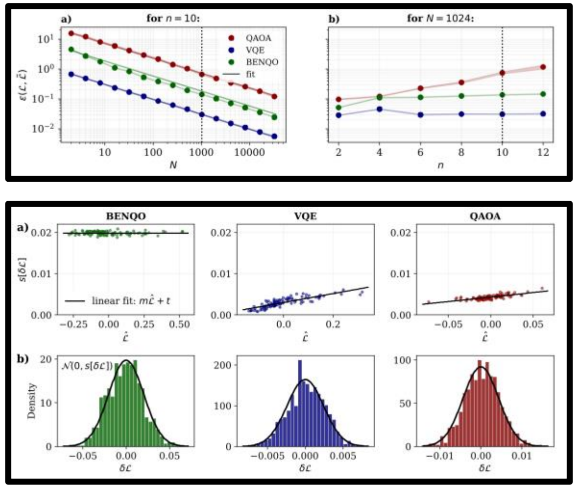
Analysis of …

… Hardware Errors

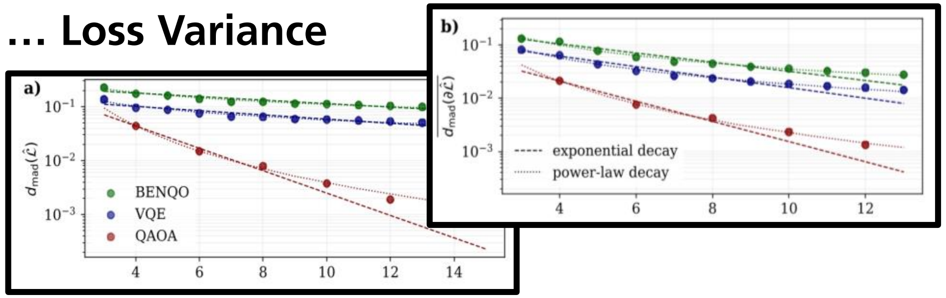


… Finite Sampling Errors

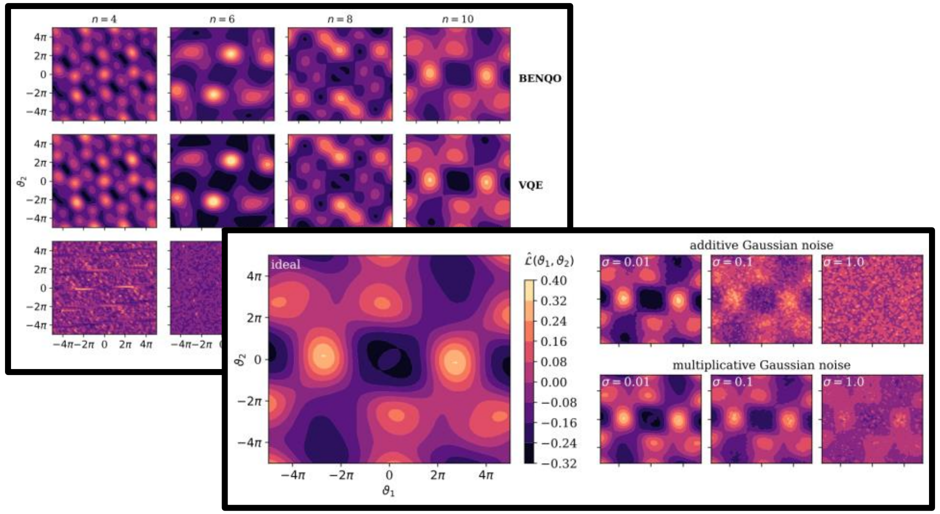


Scaling Behavior
Distribution Behavior

… Loss Variance



… Loss Landscapes



 26.2.2025 **Public information**

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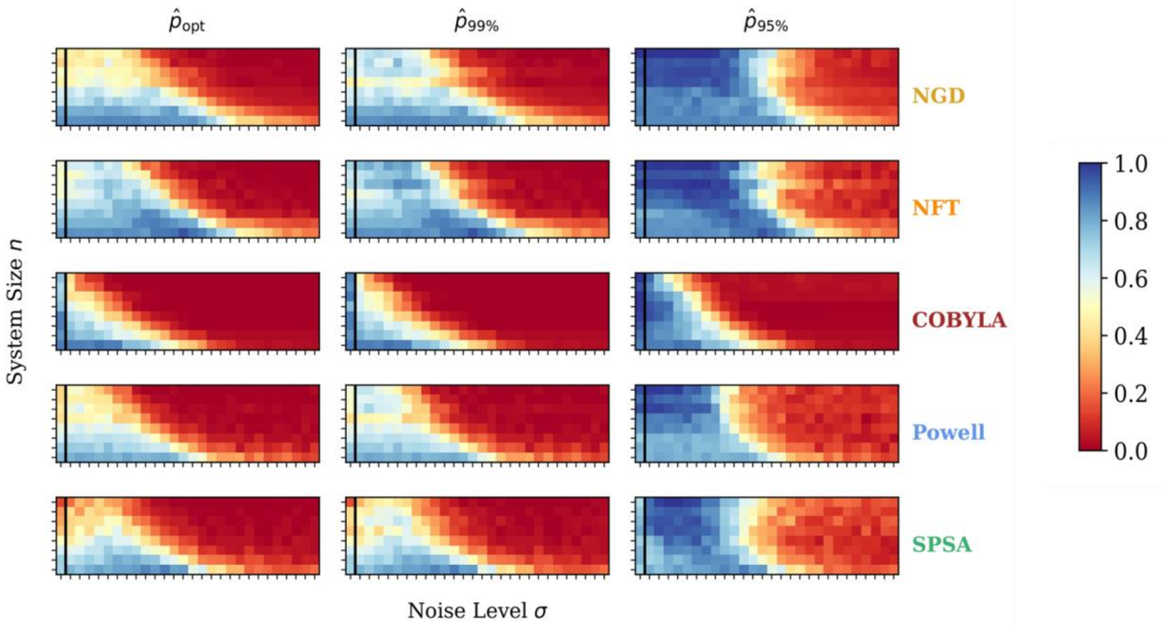
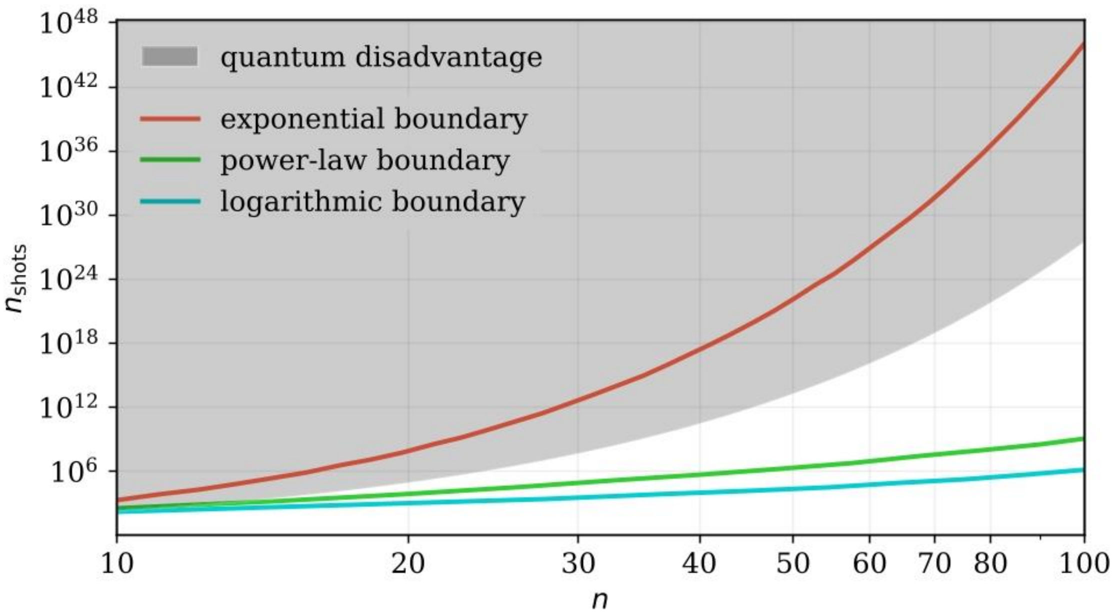
Sample probability of finding the optimal solution



How many shots do we need for classical optimizers to find useful solutions?



We can thus calculate when the sampling overhead is too high such that practically the quantum algorithm would not be useful.

Transforming and classifying the data through quantum-enhanced AI

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),

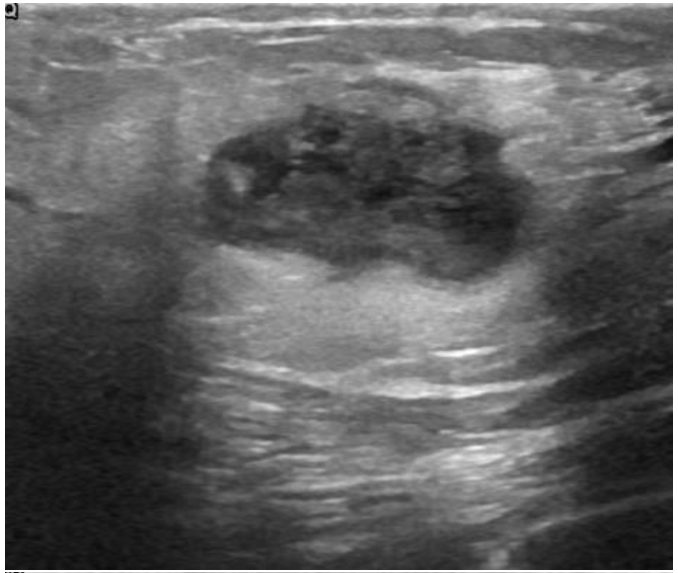
The decision process needs to be comprehensible and reliable.

→ Classical methods need large training datasets.

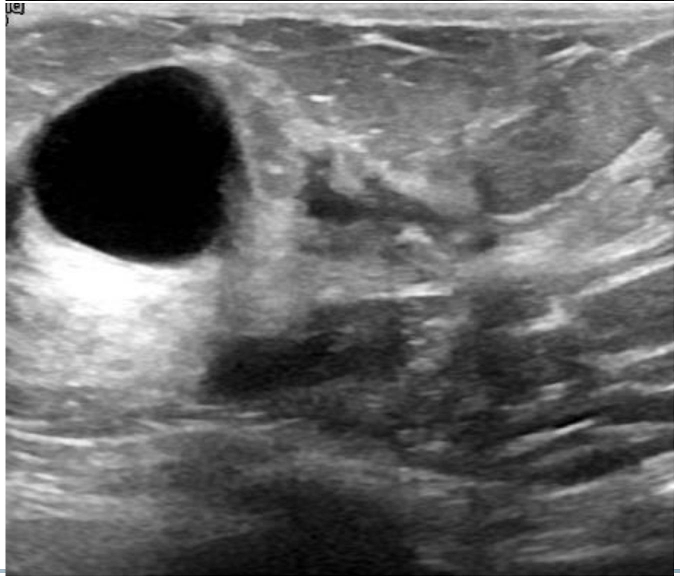
→ Desirable to propagate uncertainties of data.

Possibilities on the quantum side to tackle these challenges:

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



Malign breast lesion



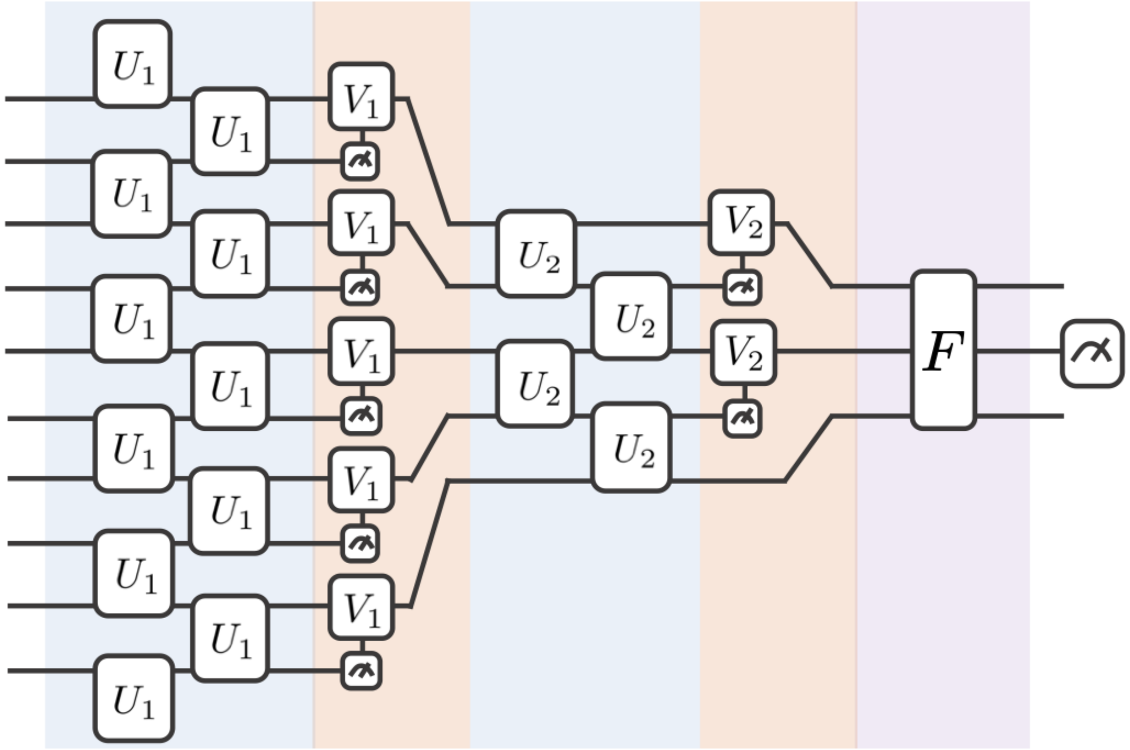
Benign breast lesion

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

Quantum convolutional neural networks

Generalization with less data (?)

Sources:
- Iris Cong, Soonwon Choi, Mikhail D. Lukin. "Quantum Convolutional Neural Networks" arxiv:1810.03787, 2018.
- Matthias C. Caro, Hsin-Yuan Huang, M. Cerezo, Kunal Sharma, Andrew Sornborger, Lukasz Cincio, Patrick J. Coles. "Generalization in quantum machine learning from few training data" arxiv:2111.05292, 2021.



Architecture of a QCNN as proposed by I. Cong et al.

Studies by M. Caro et al. have shown good generalization properties

The **generalization error** is given by the difference between the expected true loss of a (Q)ML model and the average loss over the training dataset: $gen(\alpha) = R(\alpha) - \hat{R}_S(\alpha)$

Specifically for QCNN particularly favorable: $gen(\alpha) \sim O\left(\sqrt{\frac{T \log MT}{N}}\right)$

for T parametrized local quantum channels, M gates and N the training set size.

However, the resulting generalization bounds are relatively loose.

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]

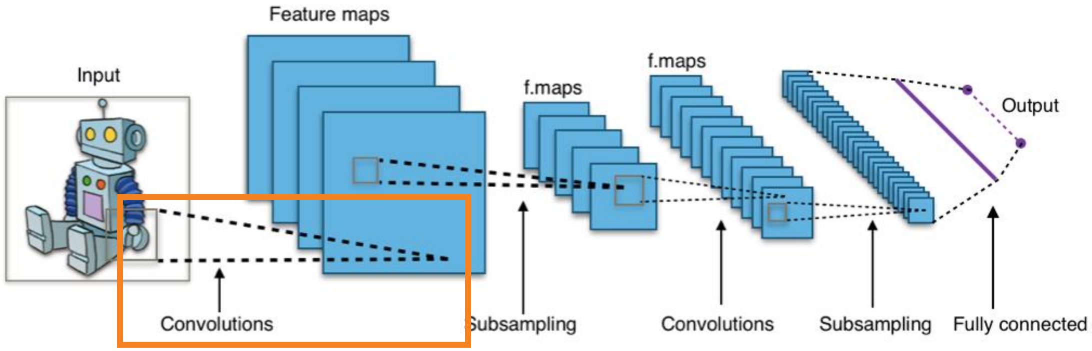
Convolutional neural networks very successful in image classification tasks.

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



Replace by quantum convolutions

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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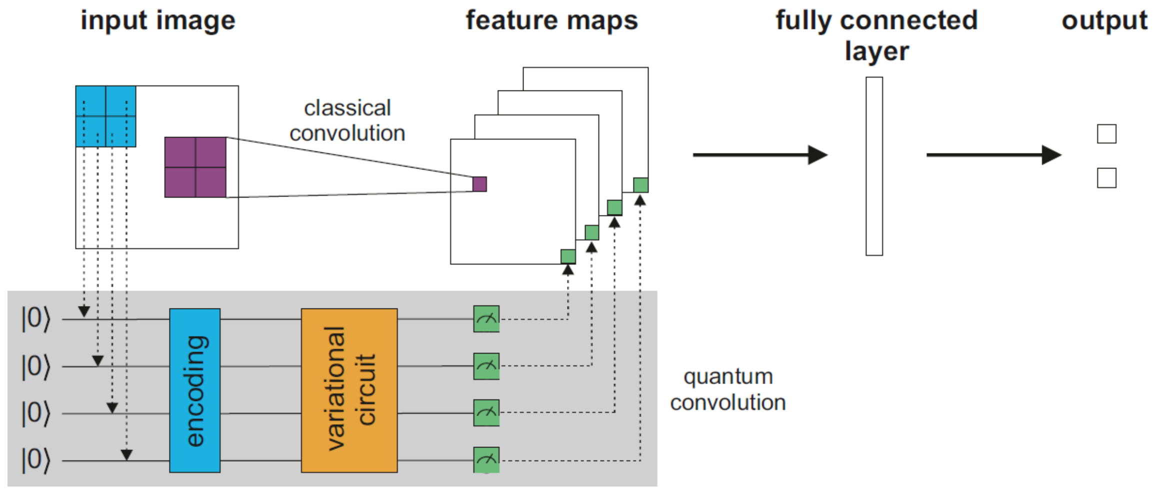

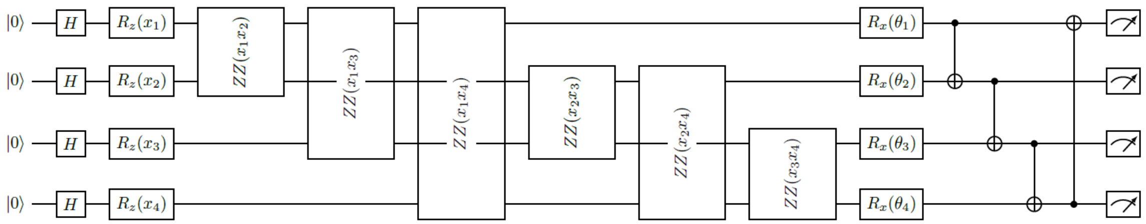

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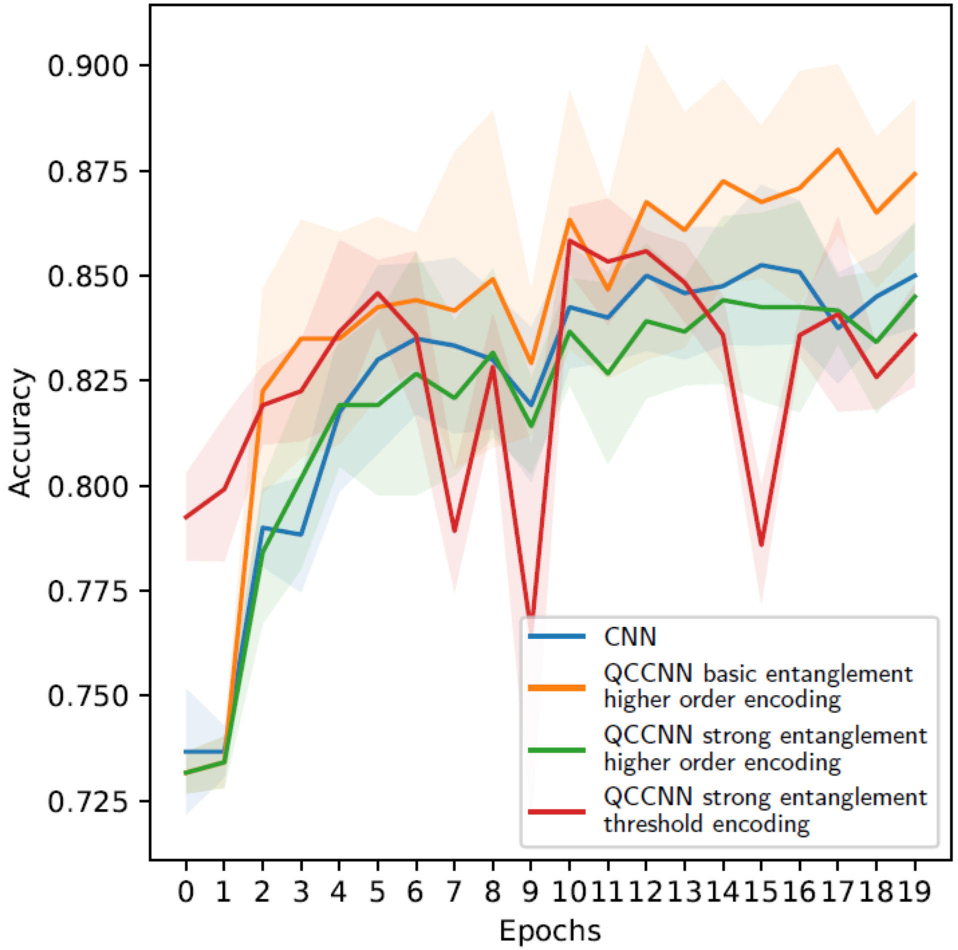
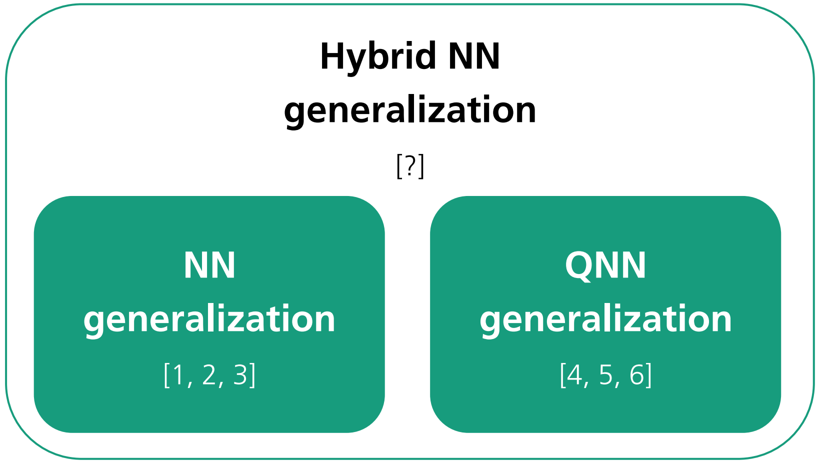


Generalization Bounds in Hybrid Quantum-Classical Machine Learning Models?

- **Generalization** is one of the most sought-after ML metrics.
- **Hybrid algorithms** are the only viable solution on the current hardware, and as the technology matures it is expected that hybrid algorithms will continue to evolve and remain relevant beyond NISQ.
- Despite the growing popularity of hybrid models, the conditions under which they generalize accurately remain **largely unexplored**.



[1] Fengxiang He and Dacheng Tao. "Recent advances in deep learning theory". 2021. arXiv: 2012.10931
[2] Amira Abbas et al. "Effective Dimension of Machine Learning Models". arXiv: 2112.04807
[3] Chiyuan Zhang et al. "Understanding deep learning (still) requires rethinking generalization". In: Commun. ACM 64.3 (Feb. 2021), pp. 107–115. ISSN: 0001-0782.
[4] Matthias C. Caro et al. "Generalization in quantum machine learning from few training data". In: Nature Communications 13.1 (2022), p. 4919. DOI: 10.1038/s41467- 022- 32550- 3.
[5] Amira Abbas et al. "The power of quantum neural networks". In: Nature Computational Science 1.6 (June 2021), pp. 403–409. ISSN: 2662-8457. DOI: 10.1038/s43588-021-00084-1.
[6] Hsin-Yuan Huang et al. "Power of data in quantum machine learning". In: Nature Communications 12.1 (May 2021). ISSN: 2041-1723. DOI: 10.1038/s41467-021-22539-9.

Generalization Bounds in Hybrid Quantum-Classical Machine Learning Models

[T. Wu, A. Bentellis, A. Sakhnenko, J.M. Lorenz, Generalization Bounds in Hybrid Quantum-Classical Machine Learning Models, Phys. Rev. A 113, 022425]

Using **covering numbers** [1] the complexity of the quantum and classical components can be quantified separately.

Number of trainable quantum gates

Bound on classical layers

Number of training data

$$\overbrace{R(h) - \hat{R}(h)}^{\text{Generalization error}} \in \tilde{\mathcal{O}}\left(\underbrace{\sqrt{\frac{T \log(T)}{N}}}_{\text{Quantum contribution}} + \underbrace{\frac{\alpha}{\sqrt{N}}}_{\text{Classical contribution}} \right)$$

This bound **decomposes cleanly into quantum and classical contributions**:

- Introducing classical layers into the architecture does not introduce significant generalization disadvantage & **a well-designed hybrid model can match the generalization capabilities of a purely quantum model**;
- **Theoretical justification for hybridization** as a strategy for improving scalability without sacrificing learning performance.

[1] Matthias C. Caro et al. “Generalization in quantum machine learning from few training data”. In: Nature Communications 13.1 (2022), p. 4919. DOI: 10.1038/s41467-022- 32550- 3.

However, Q(C)NNs easily classically simulatable (?)

So far QCNNs and QNNs mostly tested on simple/toy datasets + tests typically performed in simulation by the community

- Yielded equivalent or better results than classical models

But:

- **Issues with the trainability**, linked to barren plateaus. Specific architectures (such as QCNNs) do not present barren plateaus.
- Indications that **a wide class of models (QCNNs and QNNs) are in general easily simulatable,** see P. Bermejo et al. 2024
  - A quantum computer might not be needed for the actions in QCNNs
  - Possibly quantum computer needed to produce classical shadows from quantum data

Which properties do we need to require in the data to obtain a quantum advantage?

Benefits from quantum computing by simply using data transformation

By constructing digital-analog quantum convolutional neural networks

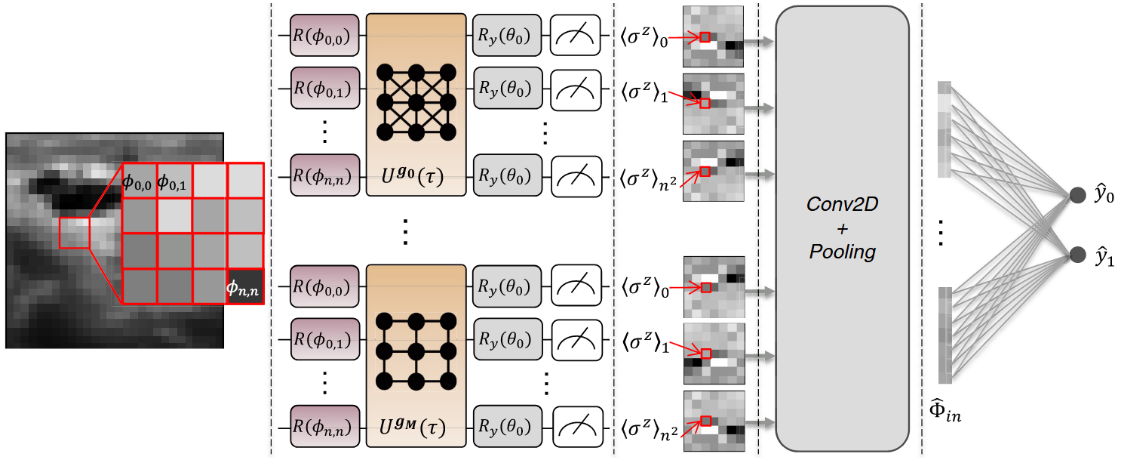
Simen et al. (2024) propose a Digital-Analog Quantum Convolutional Neural Network (DAQCNN) for image classification

Combining standard CNNs with **non-trainable** digital-analog quantum kernels

- Digital part: encoding $n \times n$ pixels into single-qubit rotations
- Analog part: highly entangled analog block
- measuring observables → generating new images → CNN

Multiple DAQ-kernels to detect more characteristics in the images

- Varying the level of entanglement of the analog block



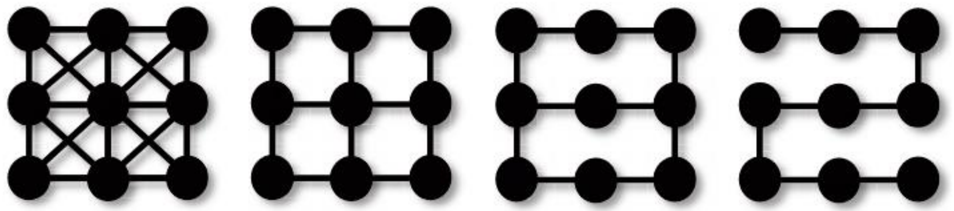


Fig. 1 and Fig. 2: adapted from Simen et al., 'Digital-analog quantum convolutional neural networks for image classification', arXiv:2405.00548, 2024.

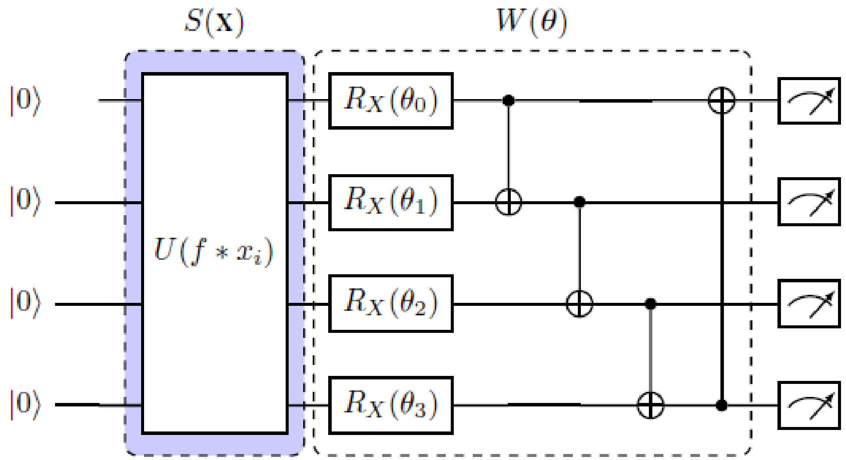
The role of data encoding

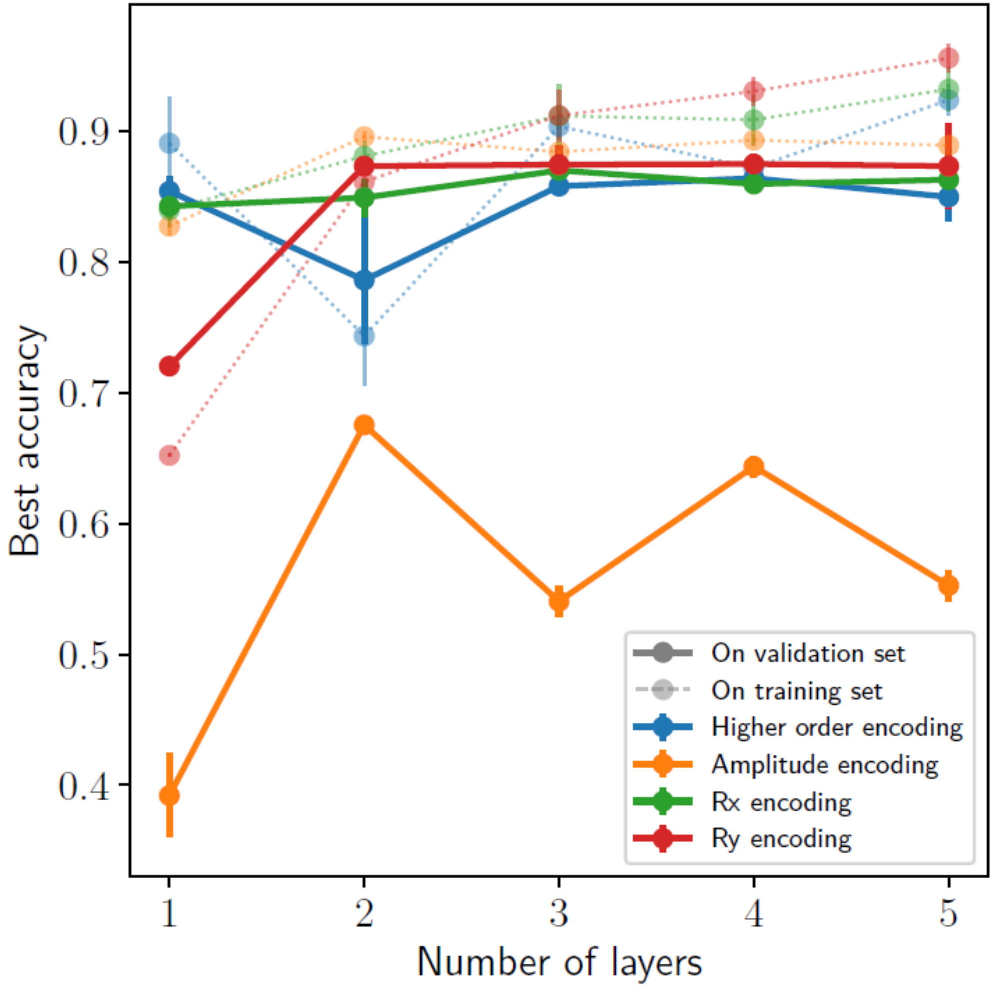
[M. Monnet,…, J.M. Lorenz, Understanding the effects of data encoding on quantum-classical convolutional neural networks, QCE 2024.]

Different indications in literature that the type of data encoding is critical for the performance.

Using again 2D ultrasound images, this can be confirmed.

Experiment: Different encoding strategies $U(f \star x_i)$ followed by PQC; this sequence can be repeated in n layers.





But which is now the right encoding, and do we need the variational part?

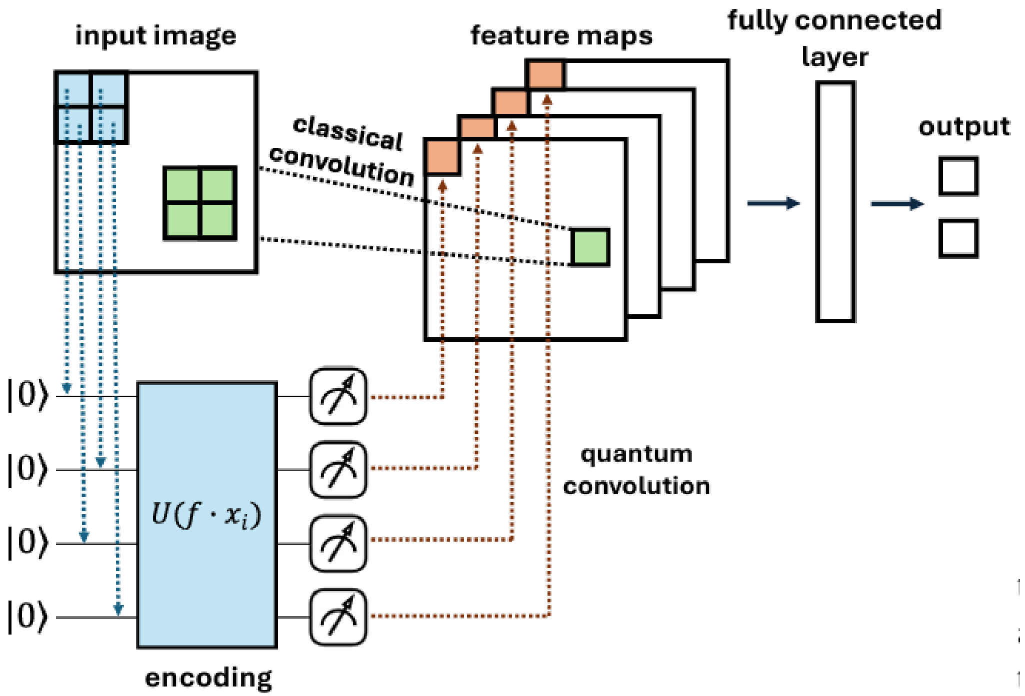
[L. Tokuhiro,…, J. M. Lorenz, Discovering Data Encoding Strategies for Quantum-Classical Neural Networks Using Monte Carlo Tree Search, QCE 2026]

QC as a simple data transformer

- Remove the trainable quantum block
- Keep the quantum circuit as a fixed feature extractor
- Only the classical layer is trained

Can we automatically find effective quantum data encodings for image classification?

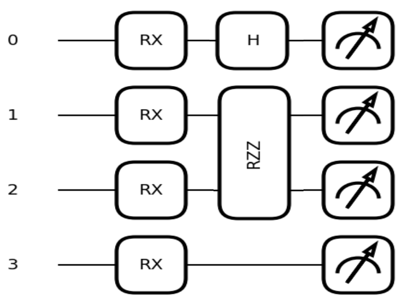
- Search over encoding circuits instead of hand-designing them
- Using Monte Carlo Tree Search (MCTS)
- Which circuit properties correlate with good performance?

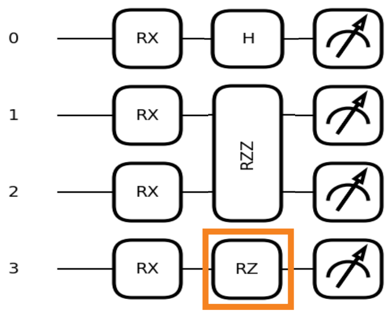


Discovering Data Encoding Circuits via Monte Carlo Tree Search

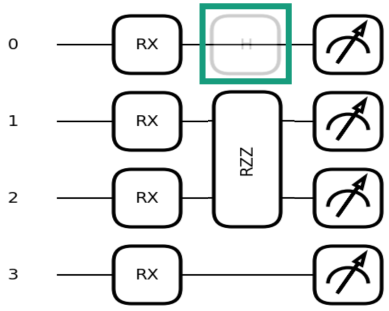
[L. Tokuhiro,…, J. M. Lorenz, Discovering Data Encoding Strategies for Quantum-Classical Neural Networks Using Monte Carlo Tree Search, QCE 2026]

Data encoding search via MCTS: gate pool $\mathcal{G} = \{R_X, R_Y, R_Z, R_{ZZ}, H, \mathrm{CNOT}\}$

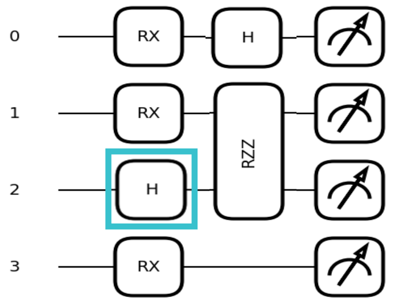




Add

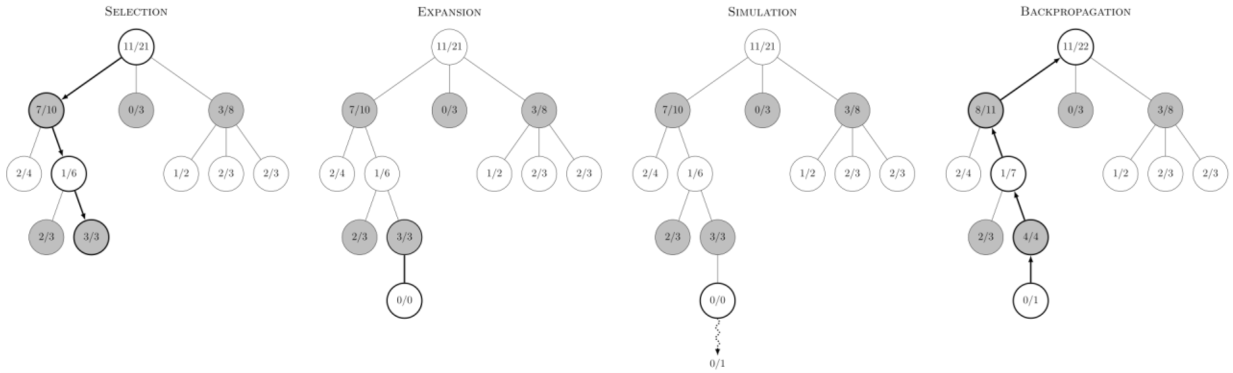


Remove



Replace

- Grow tree: each node possible encoding circuit → performance (AUC) as reward → update branch
- branches that led to good circuits become more attractive



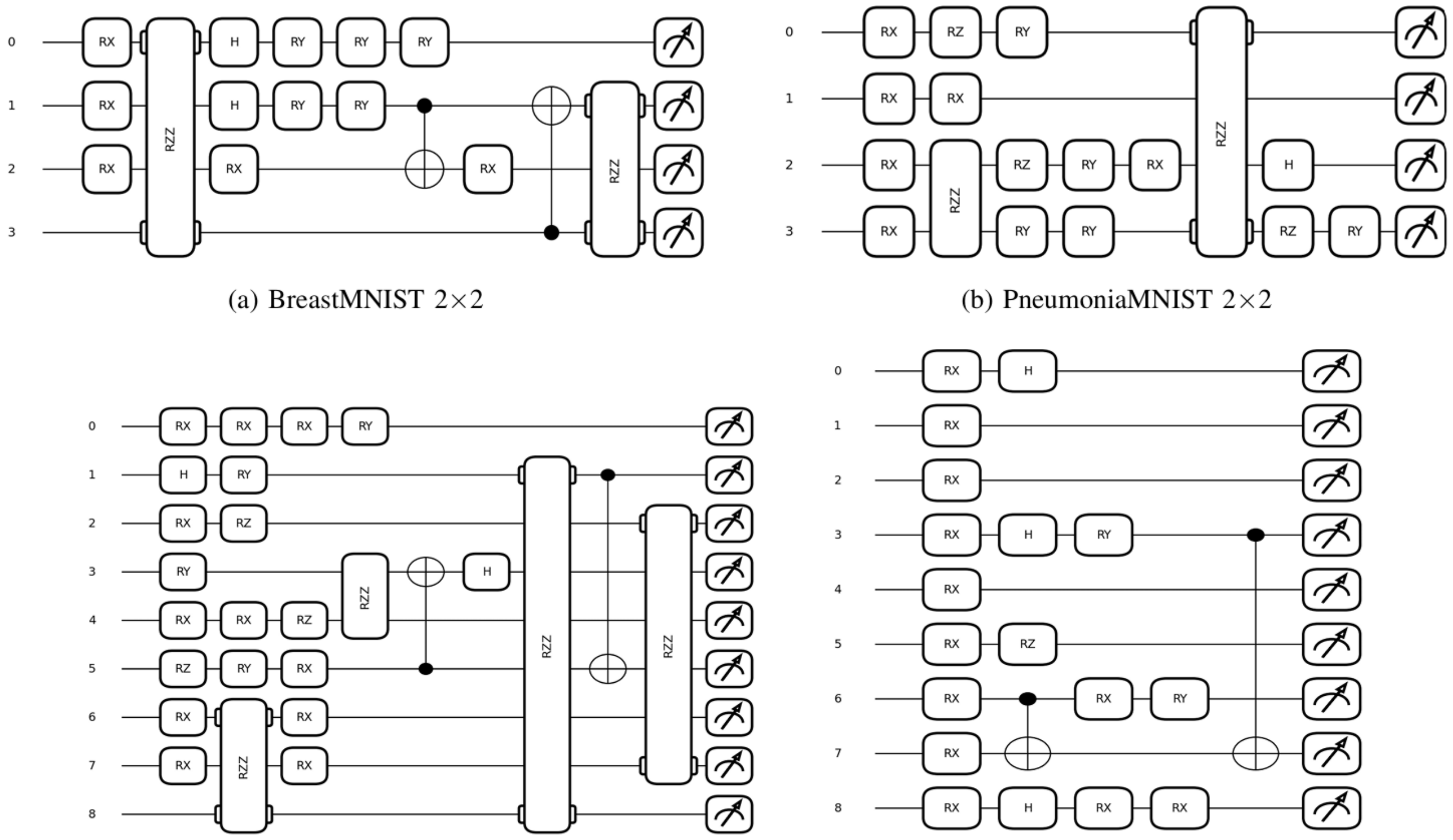
Discovering Data Encoding Circuits - Results

[L. Tokuhiro,…, J. M. Lorenz, Discovering Data Encoding Strategies for Quantum-Classical Neural Networks Using Monte Carlo Tree Search, QCE 2026]

Results validated on two datasets:

- BreastMNIST
- PneumoniaMNIST

Resulting circuits interestingly asymmetric in contrast to typical suggestions in literature.



(a) BreastMNIST 2×2

(b) PneumoniaMNIST 2×2

(c) BreastMNIST 3×3

(d) PneumoniaMNIST 3×3

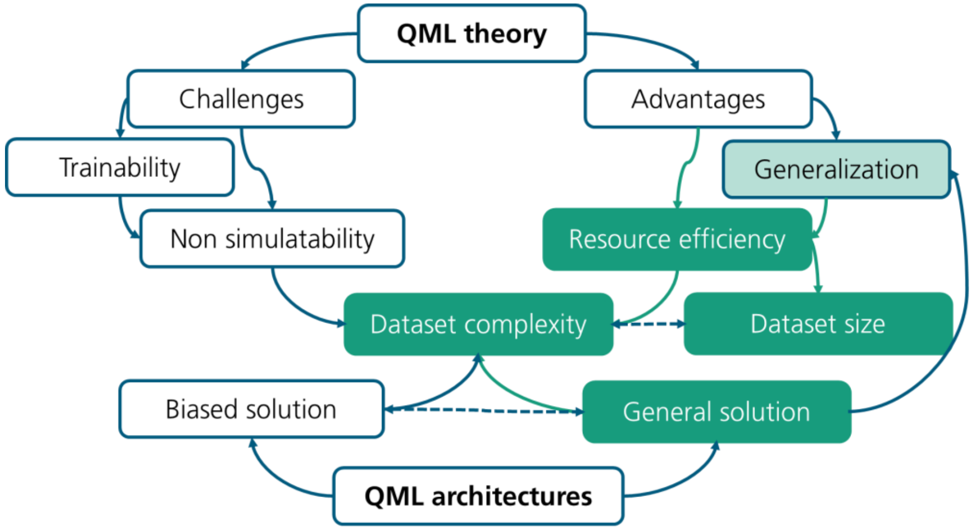
Is data-efficient learning feasible with quantum models?

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

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

Purpose and method:

- Demonstrate that **quantum models can generalize data-efficiently and effectively**;
- 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?

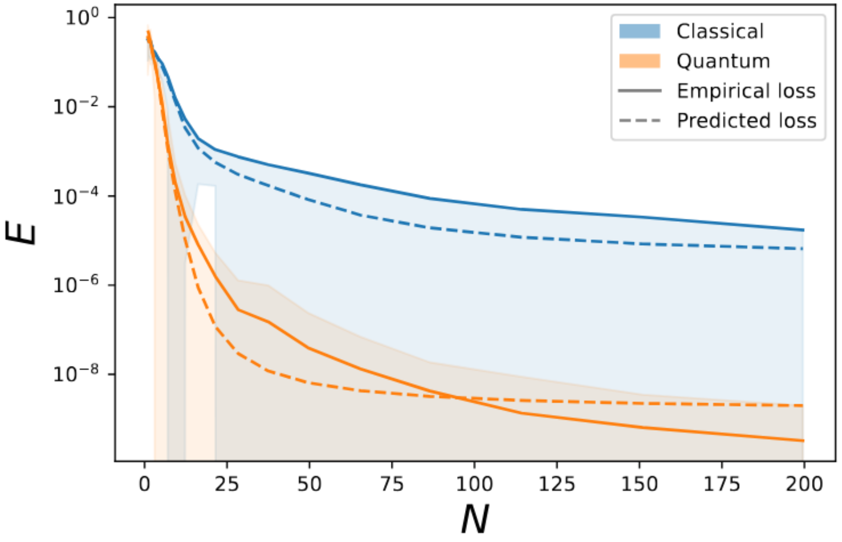
[Alona Sakhnenko, Christian Mendl, Jeanette Miriam Lorenz, Is data-efficient learning feasible with quantum models?, arXiv:2508.19437]

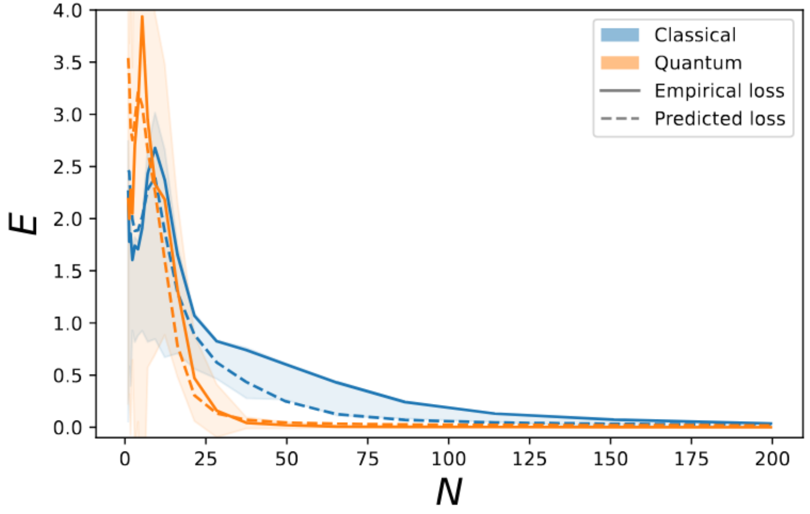
(First) empirical evidence that QKMs can achieve a low error with less data. Meaning, they can be **data-efficient.**

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?





Conclusions on QCNNs

QCNNs show good generalization properties, and this propagates to hybrid quantum-classical models.

Different works demonstrate that the data encoding step is crucial for the final performance. Have now tools at hand to analyze this systematically.

We see indications in the literature that (some) Q(C)NNs are easily classical simulatable, but this seems to depend on the data type. Is there any classical data for which they could still show benefits?

Zooming in on the presumed data efficiency aspect, it can be empirically shown that there exists at least one classical dataset that activates corresponding generalization metrics for quantum kernels.

Benchmarking & How to evaluate architecture (hardware, software, algorithms) choices systematically

Motivation

Quantum computing itself already proposed in the 1980s:

- R.P. Feynman
- D. Deutsch
- …

Key fault-tolerant algorithms proposed in the 1990's:

- Shor's algorithm
- Grover's algorithm

Despite small laboratory experiments of realizing quantum computers in the 1990s, interest in quantum computing only raised significantly in 2019 with the Google Sycamore experiment

- Since then various claims of quantum advantage, quantum utility,…
- But no practical quantum advantage achieved yet.
- One difficulty is the slowness of quantum hardware versus power of modern AI.

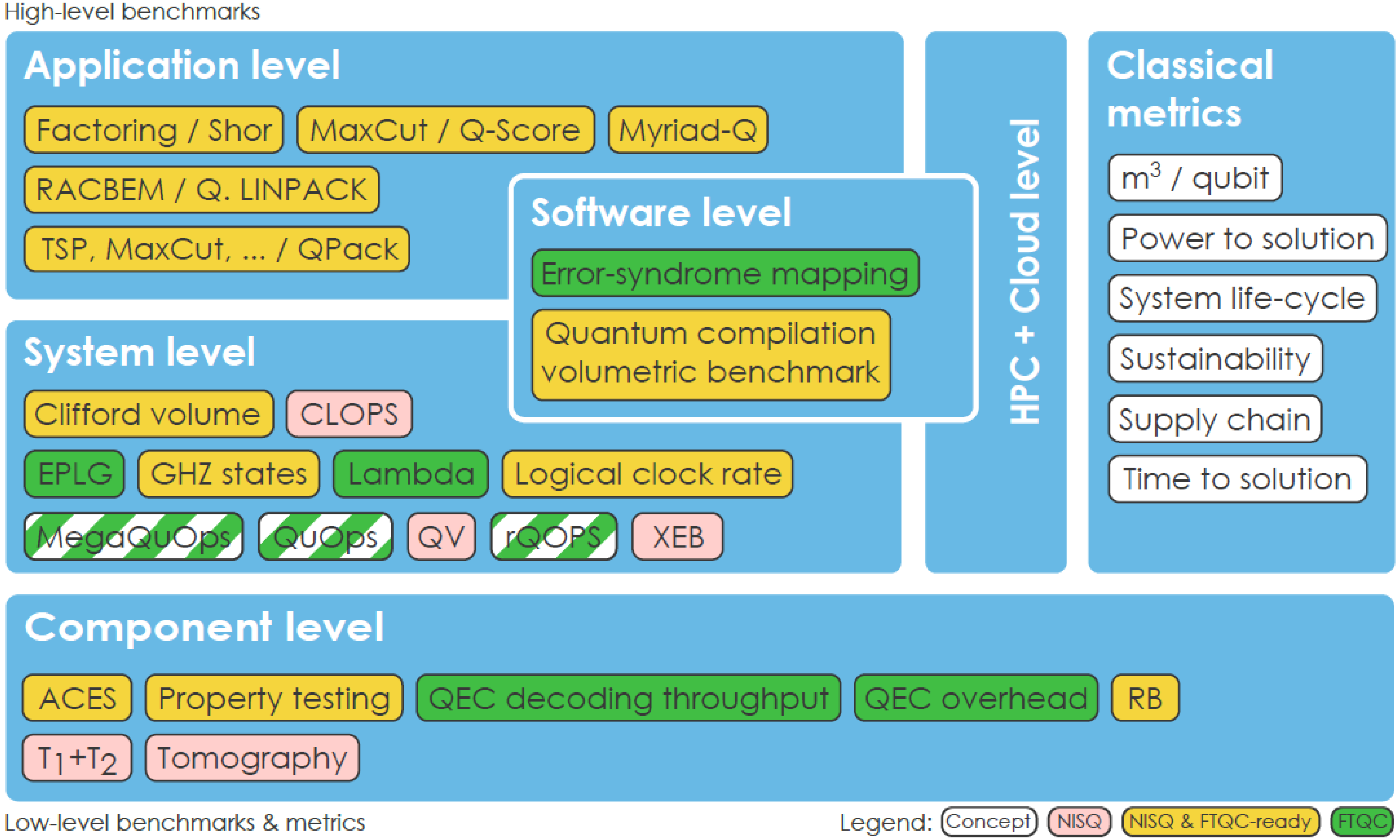
➔ **Benchmarking of all quantum hardware, software & algorithms and indeed solving use cases required.**

➔ **Different levels of benchmarks:**

- **Component-level:** benchmarks of hardware implementation of individual components
- **System-level:** benchmarks of hardware performance of entire implementations
- **Application-level:** comping from concrete use cases

+ also finer level benchmarks

Different types of benchmarks



Bench-QC: Application-driven benchmarking of quantum computers

Lighthouse project of the Munich Quantum Valley

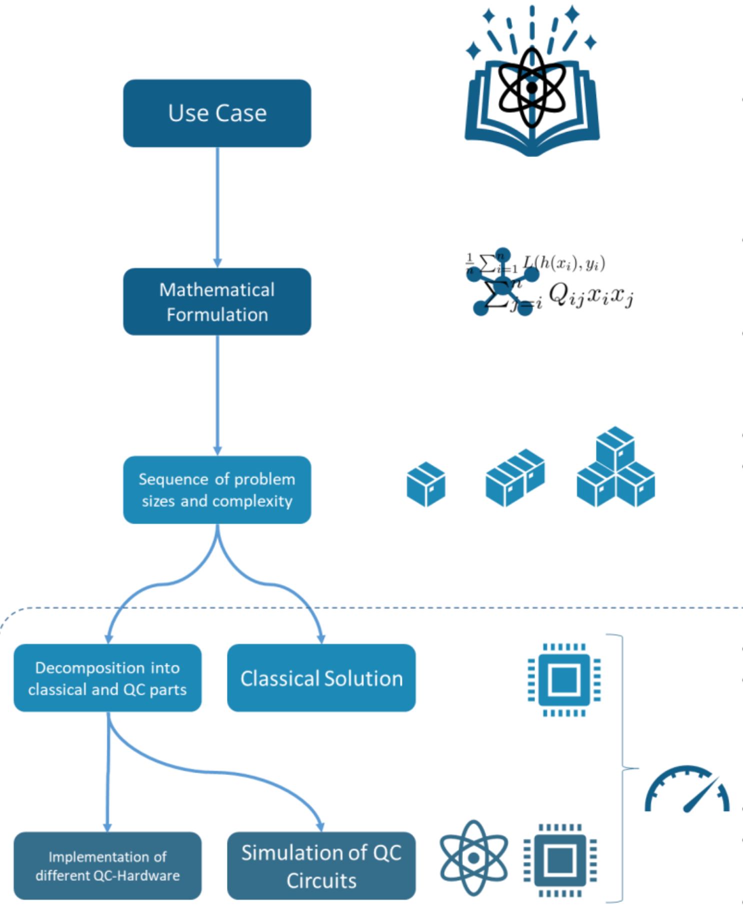
Munich Quantum Valley

Which QC-technology will be suited for which application use case and when?

→ Potential analysis and benchmarks from the application perspective

Use cases from simulation, optimization and quantum machine learning

Fraunhofer IIS
REPLY Machine Learning
BMW GROUP
OptWare
Fraunhofer IKS
QUANTINUUM



- Growing **Quantum Use-Case Catalogue**

- Mapping to graph, machine learning, (combinatorial) optimization, [...] problem
- QC compatible formulation

- Increasing problem sizes
- Increasingly more difficult problem instances

- Implementation of a **classical baseline**
- Definition and development of **application-relevant performance metric**

- Comparison of different hardware implementation
- Scaling behavior, identification of **limiting (or enabling) factors** along the stack
- Identify **co-design potential**

  Public information

Fraunhofer IKS

How to construct benchmarks

[https://arxiv.org/abs/2503.04905]

Benchmarks need to be reproducible & provide a meaningful comparison across platforms

- Defined in a **SDK-agnostic** and open (e.g., Open-QASM) format
- At least one **reference implementation** using a specific SDK including both quantum circuits + classical post-processing routines
- **Standardized evaluation** code with statistical methods defined + **sample datasets**
- Benchmarks are required to be **transparent**, e.g. error mitigation method clearly outlined
- **Classical resources** in hybrid algorithms need to be clearly defined, delineated and quantified
- **Scalable**

Systematic benchmarking of quantum computers: status and recommendations

Jeanette Miriam Lorenz[*,†], Thomas Monz[‡,§], Jens Eisert[¶,∥], Daniel Reitzner[**], Félicien Schopfer[††], Frédéric Barbaresco[‡‡], Krzysztof Kurowski[x], Ward van der Schoot[xi], Thomas Strohm[xii], Jean Senellart[xiii], Cécile M. Perrault[xiv], Martin Knufinke[xv], Ziyad Amodjee[xvi], Mattia Giardini[xvii]

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***Abstract*—Architectures for quantum computing can only be scaled up when they are accompanied by suitable benchmarking techniques. The document provides a comprehensive overview of the state and recommendations for systematic benchmarking of quantum computers. Benchmarking is crucial for assessing the performance of quantum computers, including the hardware, software, as well as algorithms and applications. The document highlights key aspects such as component-level, system-level, software-level, HPC-level, and application-level benchmarks. Component-level benchmarks focus on the performance of individual qubits and gates, while system-level benchmarks evaluate the entire quantum processor. Software-level benchmarks consider the compiler's efficiency and error mitigation techniques. HPC-level and cloud benchmarks address integration with classical systems and cloud platforms, respectively. Application-level benchmarks measure performance in real-world use cases. The document also discusses the importance of standardization to ensure reproducibility and comparability of benchmarks, and highlights ongoing efforts in the quantum computing community towards establishing these benchmarks. Recommendations for future steps emphasize the need for developing standardized evaluation routines and integrating benchmarks with broader quantum technology activities.**

***Index Terms*—Quantum computing, quantum algorithms, benchmarking, metrics.**

CONTENTS

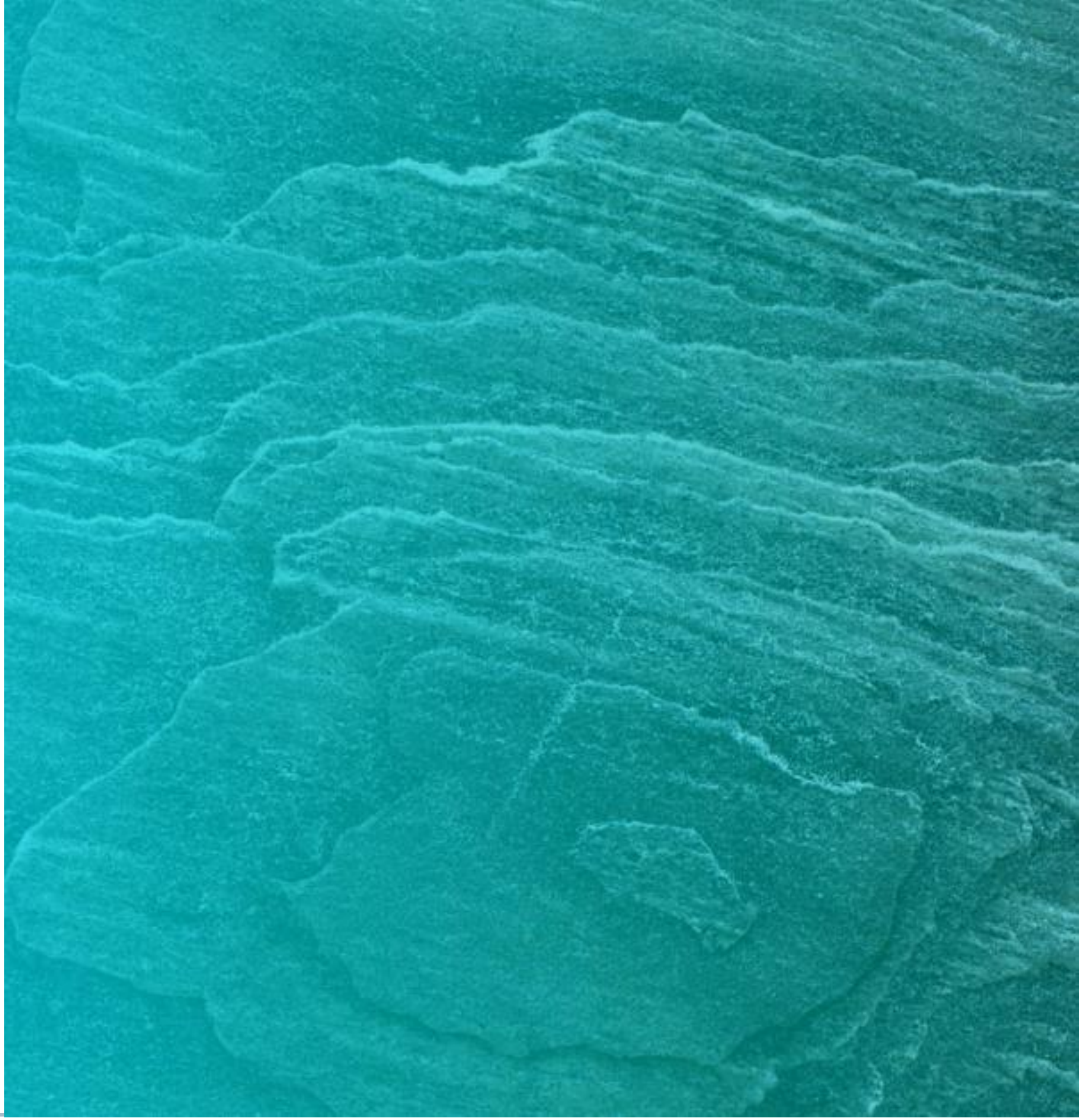
LIST OF ABBREVIATIONS

ACES *Averaged circuit eigenvalue sampling* is a component-level benchmarking method that is capable of detecting and characterising correlations.

FTQC *Fault-tolerant quantum computing* relies on careful computational instructions such that errors do not

Summary

- The question on a potential, practically relevant quantum advantage gets more and more nuanced while classical algorithms and powerful modern AI continue improving.
- Quantum computing will enter as subroutine! Thus, quantum-classical workflows are the key. Abstractions for the user required!
- This also implies that the question gets more prominent on which problem nucleus the use of quantum computing is sensible.
- This boils more and more down to the problem and/or data structure.
- Parallel to this, tensor networks turn out to be very powerful and can be regarded as alternative to using quantum computers.
- Application-centric/-driven benchmarking will be essential to provide a holistic quantitative assessment.



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