

Evaluating the performance of quantum processing units (QPUs) at large width and depth

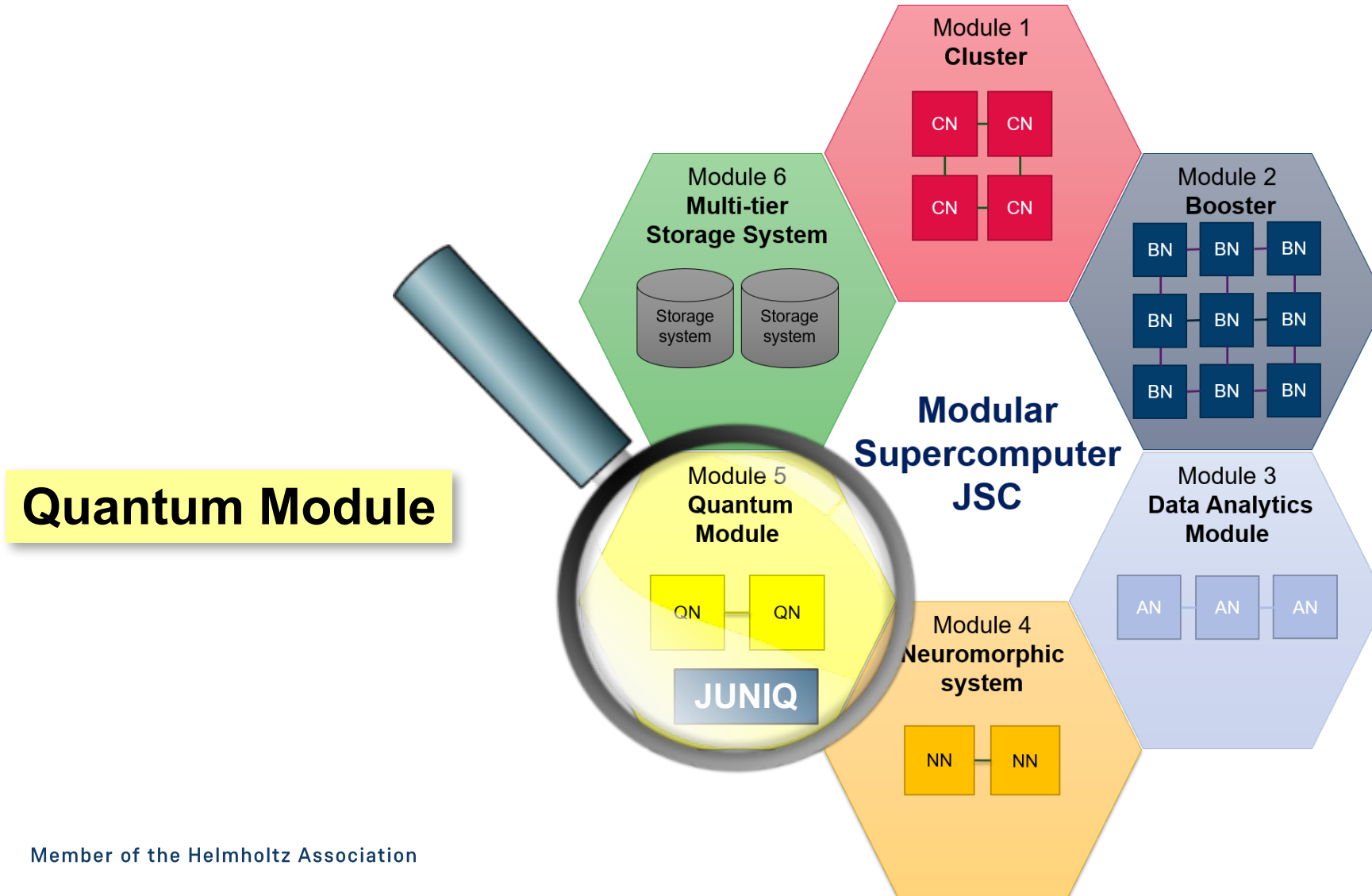
TQCI seminar dedicated to benchmarks for quantum computers

June 16, 2025 | Alejandro Montanez-Barrera | Forschungszentrum Jülich - Jülich Supercomputing Center

<https://arxiv.org/abs/2502.06471>

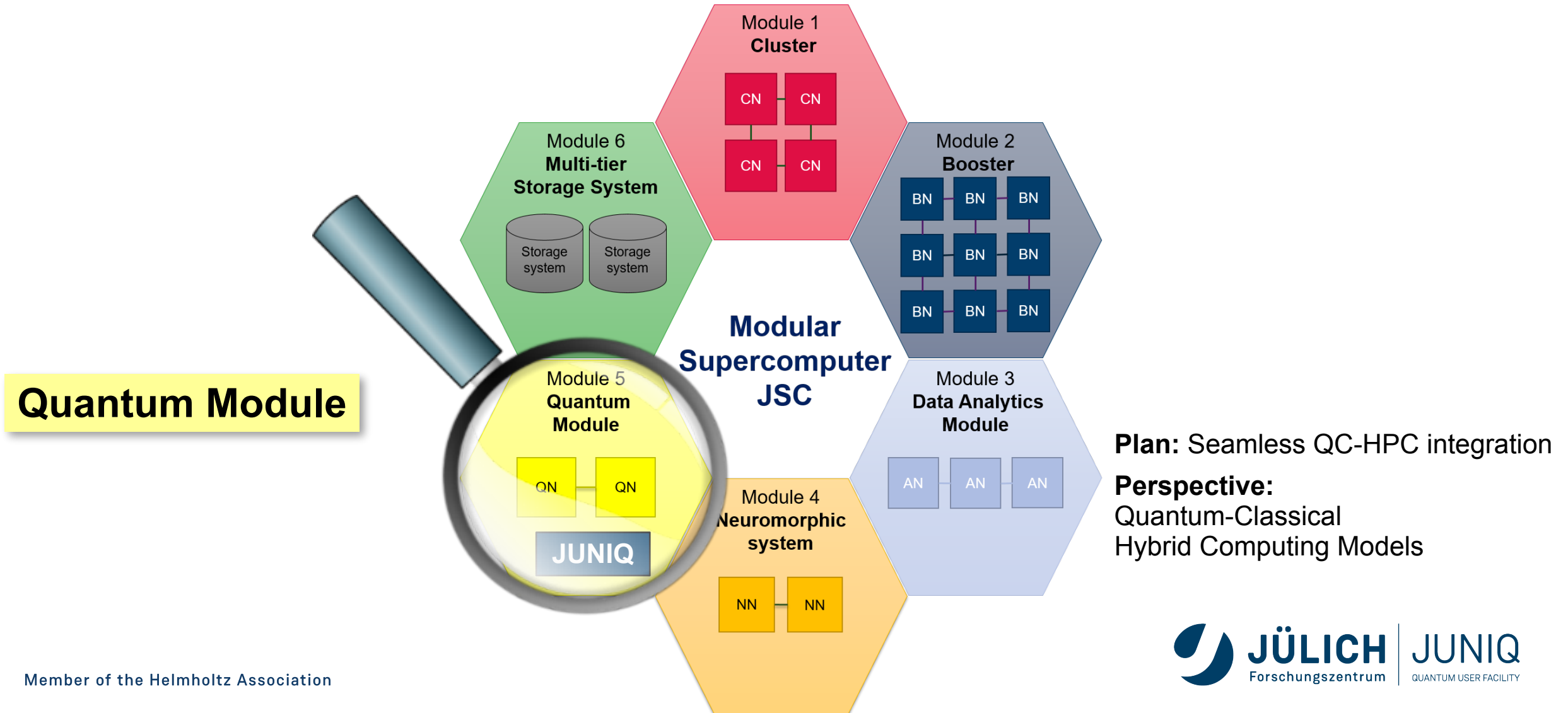
JUNIQ - Jülich UNified Infrastructure for Quantum computing

A European quantum computer user facility at the Jülich Supercomputing Centre



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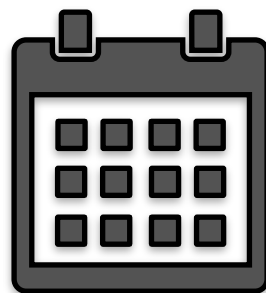
1. QC user facility for science and industry
2. Installation, operation and provision of QCs
3. Unified portal for access to QC emulators and to QC devices at different levels of technological maturity.
4. Development of algorithms and prototype applications
5. Services, training and user support
6. Modular quantum-HPC hybrid computing

Why do we do quantum benchmarking?

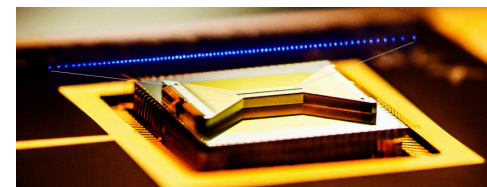
Quantum benchmarking is essential because it provides **quantitative, standardized ways to evaluate and compare quantum devices and algorithms**. In short, it tells us **how good a quantum computer really is** and whether it's improving.



Measure Device Performance



Track Progress Over Time



Compare Across Platforms

How to measure the progress of quantum processing units?

Randomized
benchmarking is
proposed by Dankert
et al

2006

[https://arxiv.org/
abs/quant-ph/
0606161](https://arxiv.org/abs/quant-ph/0606161)

How to measure the progress of quantum processing units?



Average
2Q
fidelity
(%) [Info](#)

98.720

Average 2Q fidelity
(%)



Average gate fidelities for a maximally entangling two-qubit native gate. It is regularly measured by IonQ on the device using Direct Randomized Benchmarking


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CZ fidelity (%)

IQM 99.232


CZ gate fidelities for the qubit pair measured by interleaved randomized benchmarking on 2 or 3 pairs simultaneously.


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IBM Quantum Platform

Median CZ error:

2.696e-3 99.73 %


2Q error (best): The lowest two-qubit error rate from all edges measured by isolated randomized benchmarking.




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QUANTINUUM

SYSTEMS

2-qubit gate fidelity

The 2-qubit gate fidelity is measured with 2-qubit RB

H2 – 1 : 99.89 %

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ISWAP gate fidelity (%)


Average	Median
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QUANTINUUM SYSTEMS

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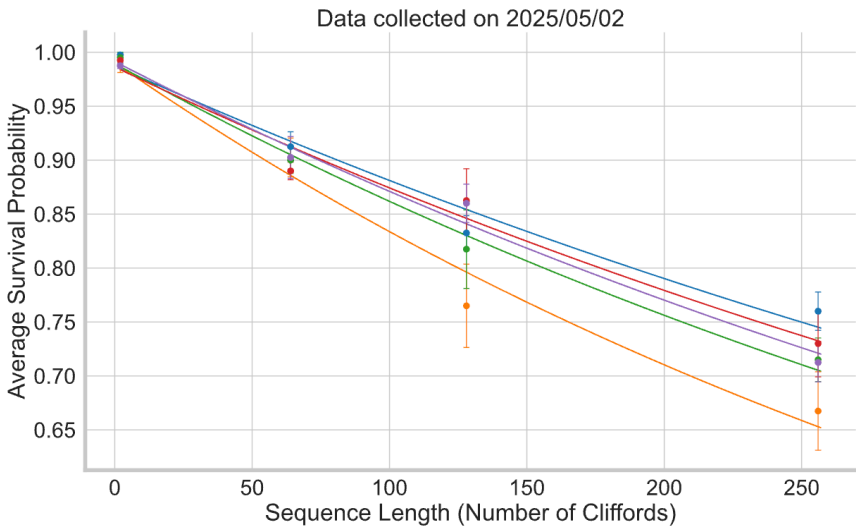
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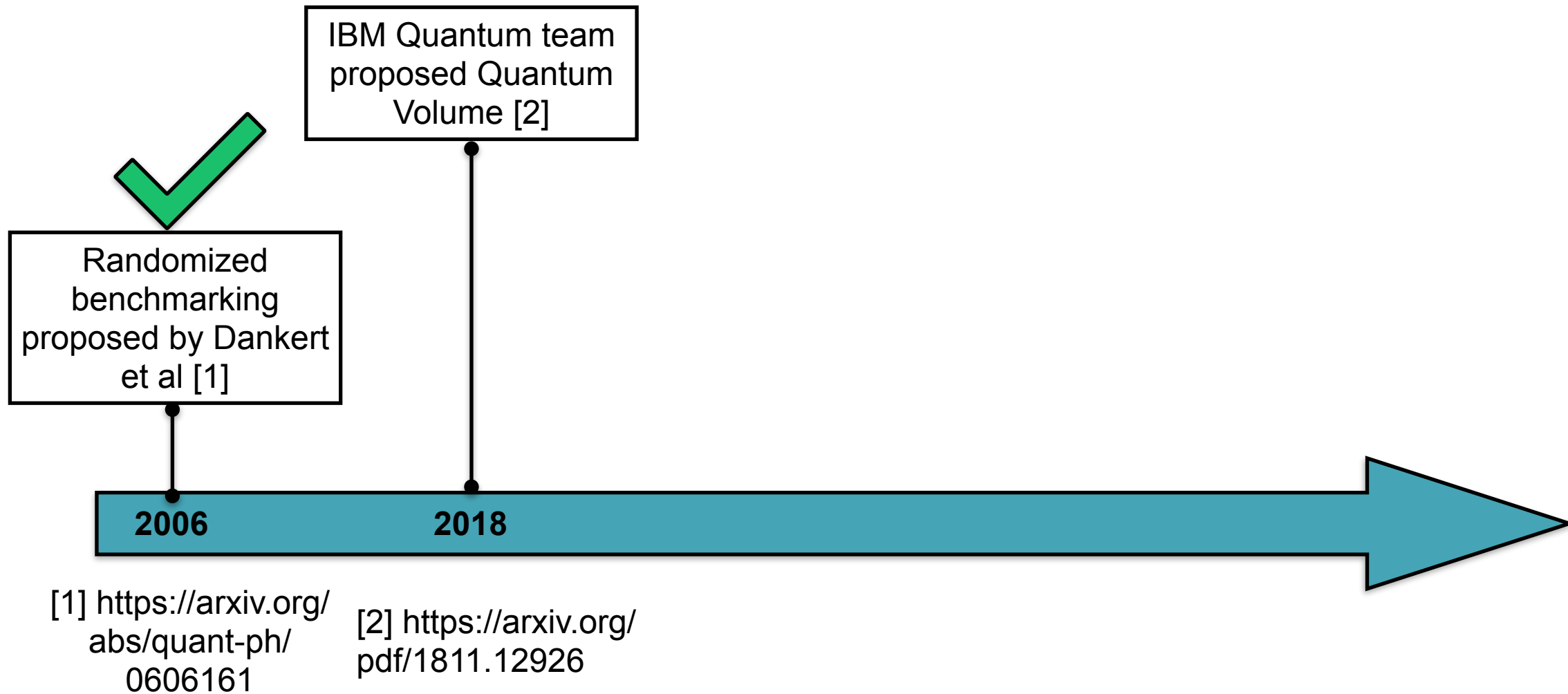
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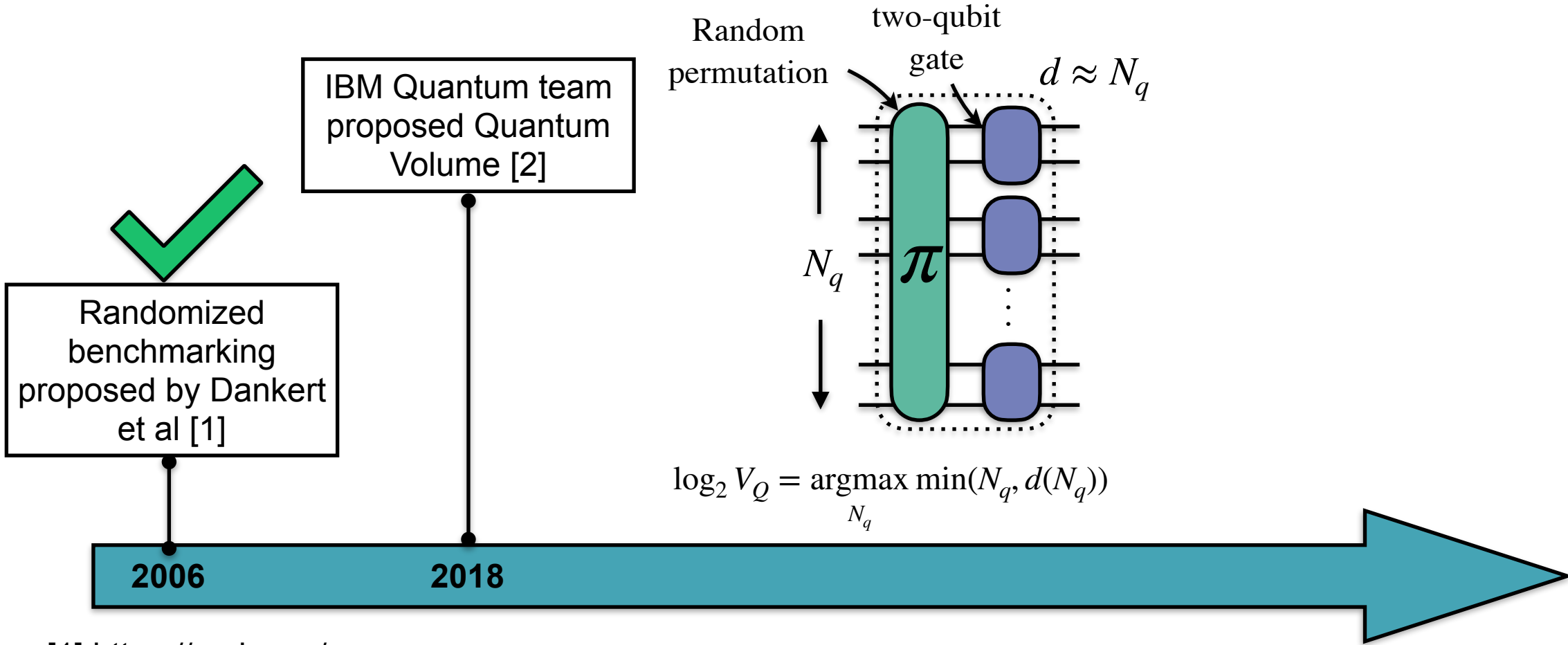
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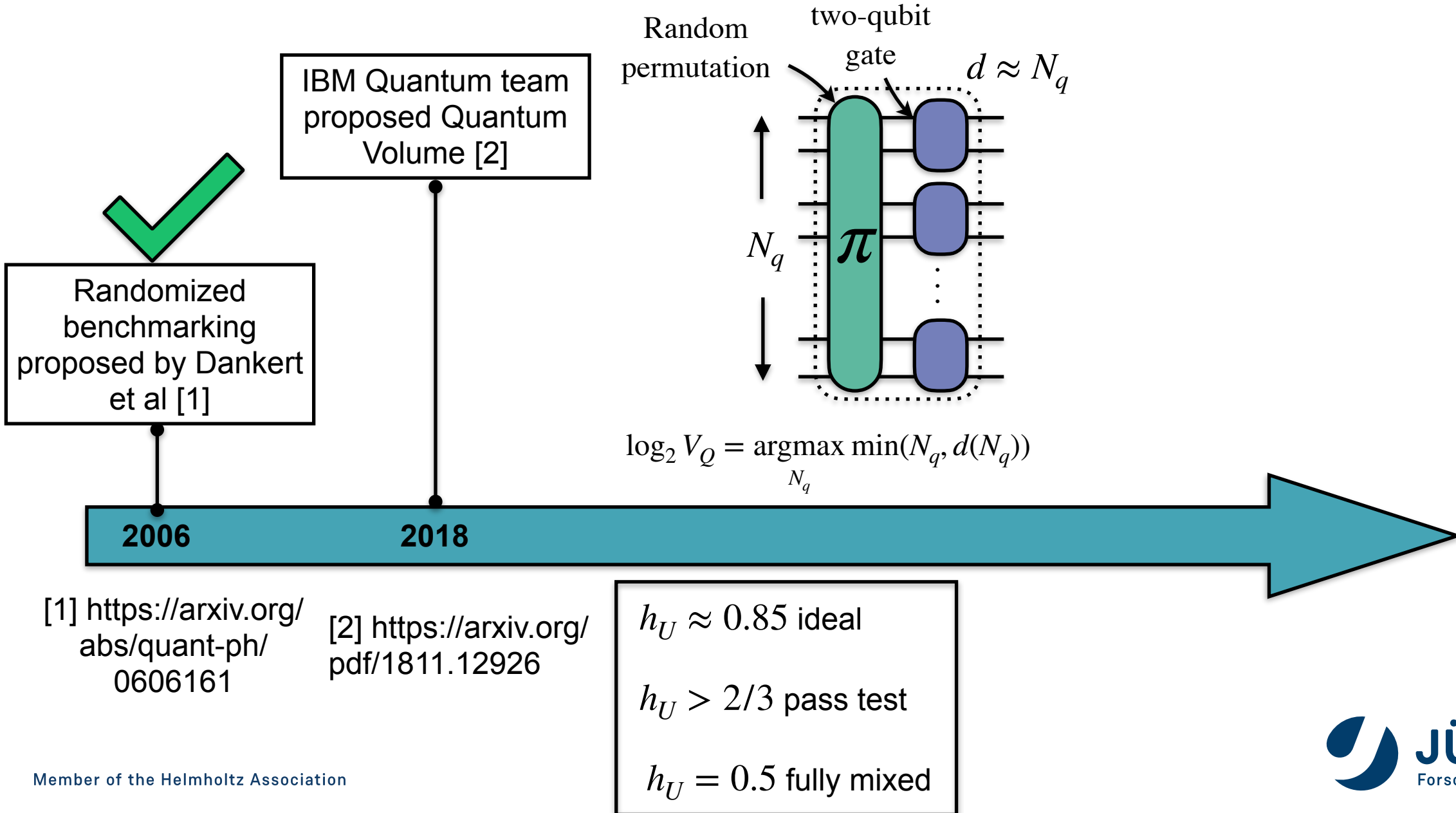
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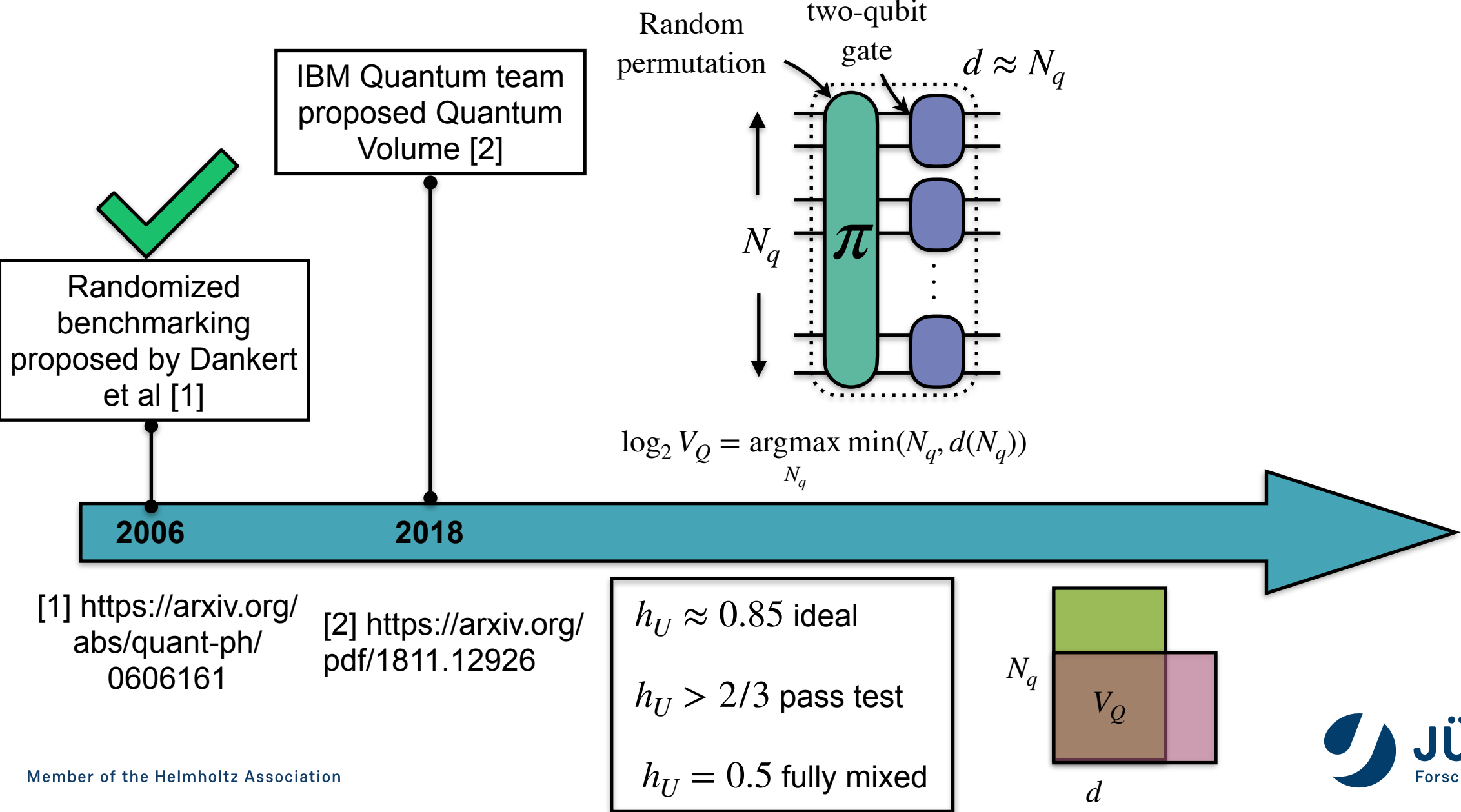
[1] <https://arxiv.org/abs/quant-ph/0606161>

[2] <https://arxiv.org/pdf/1811.12926>

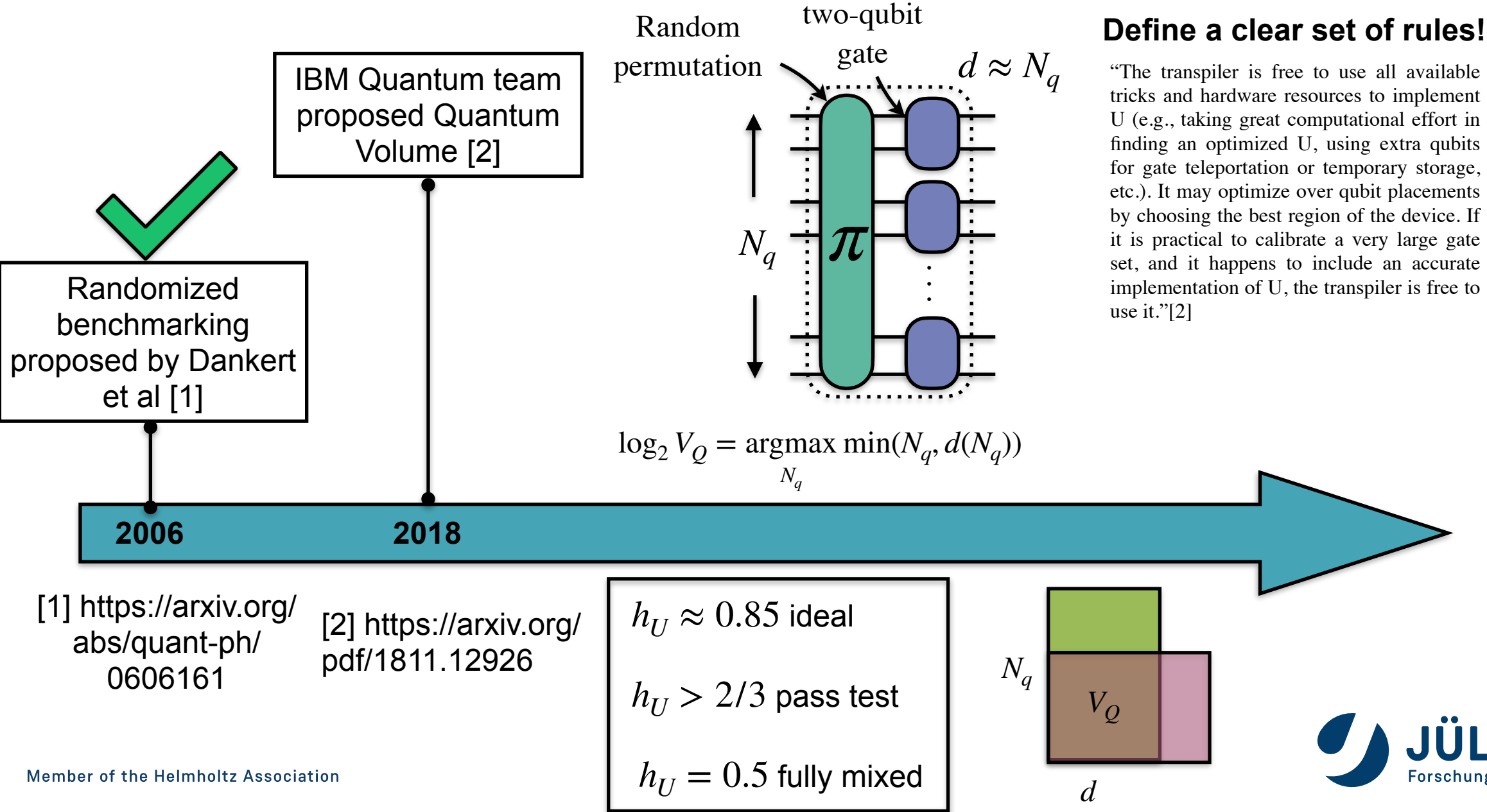
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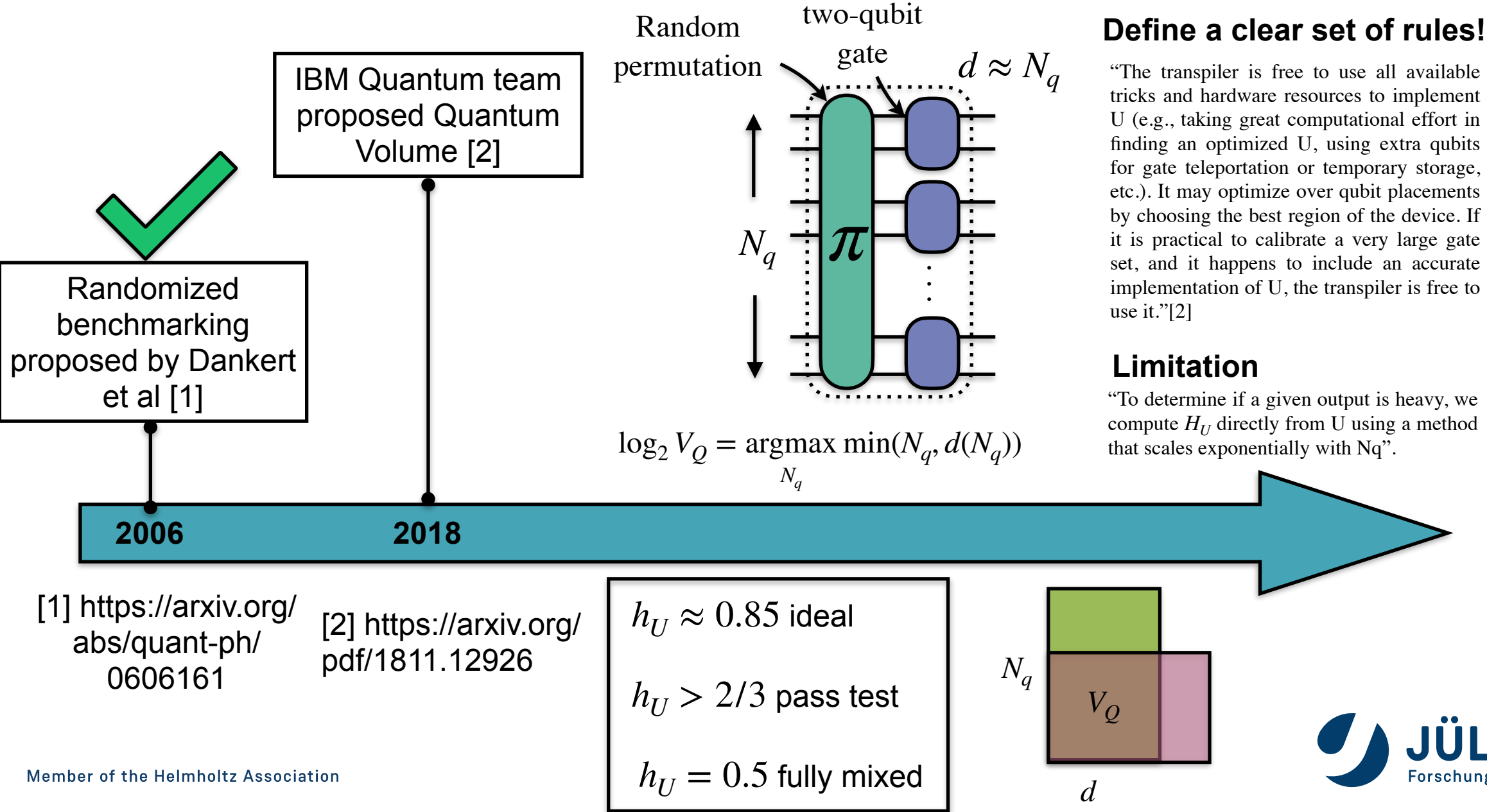
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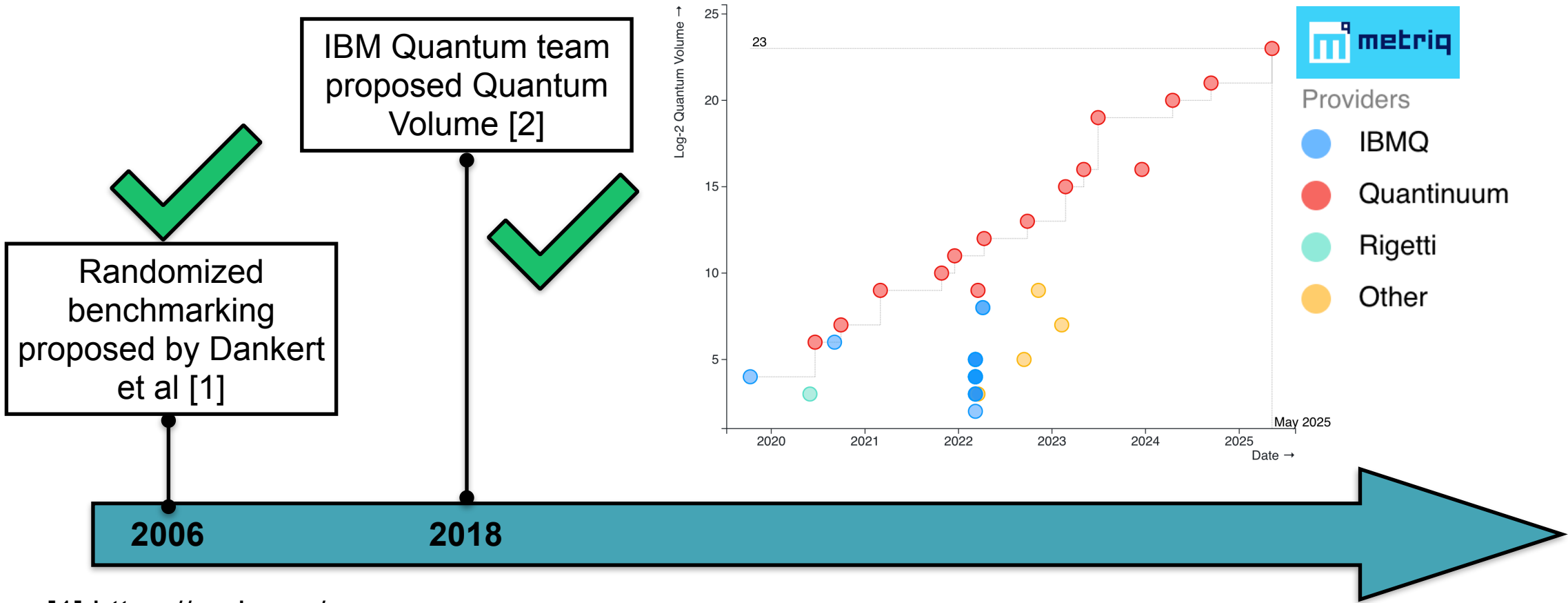
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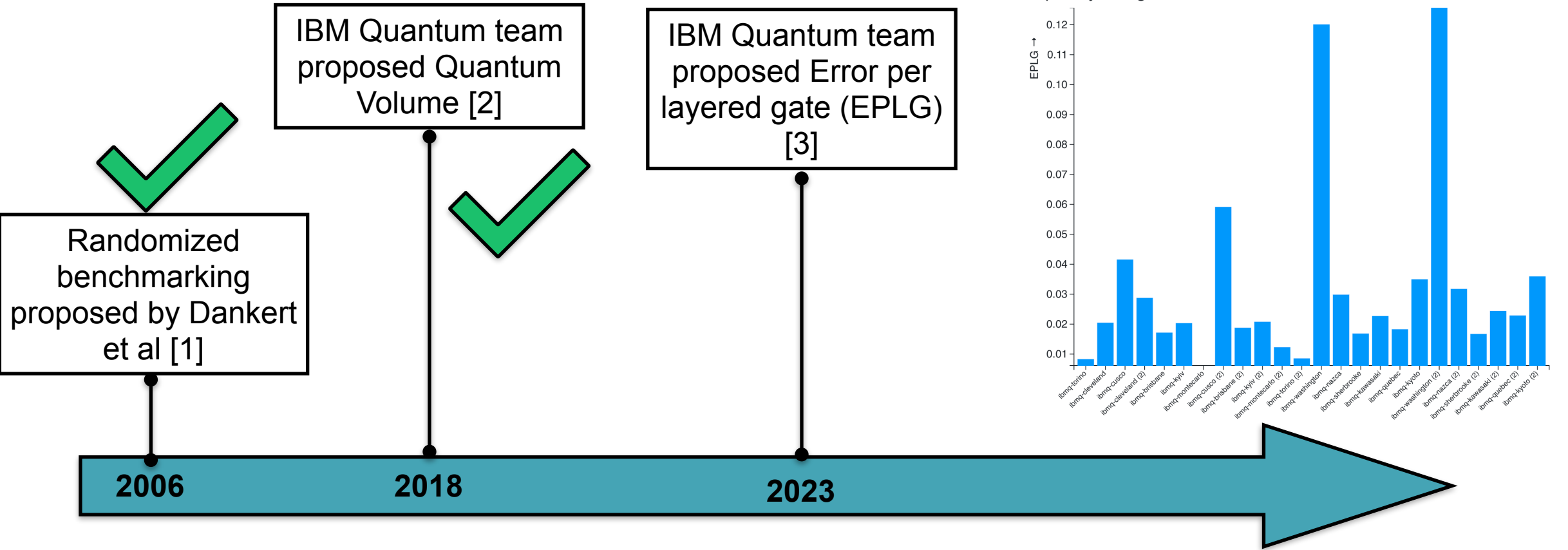
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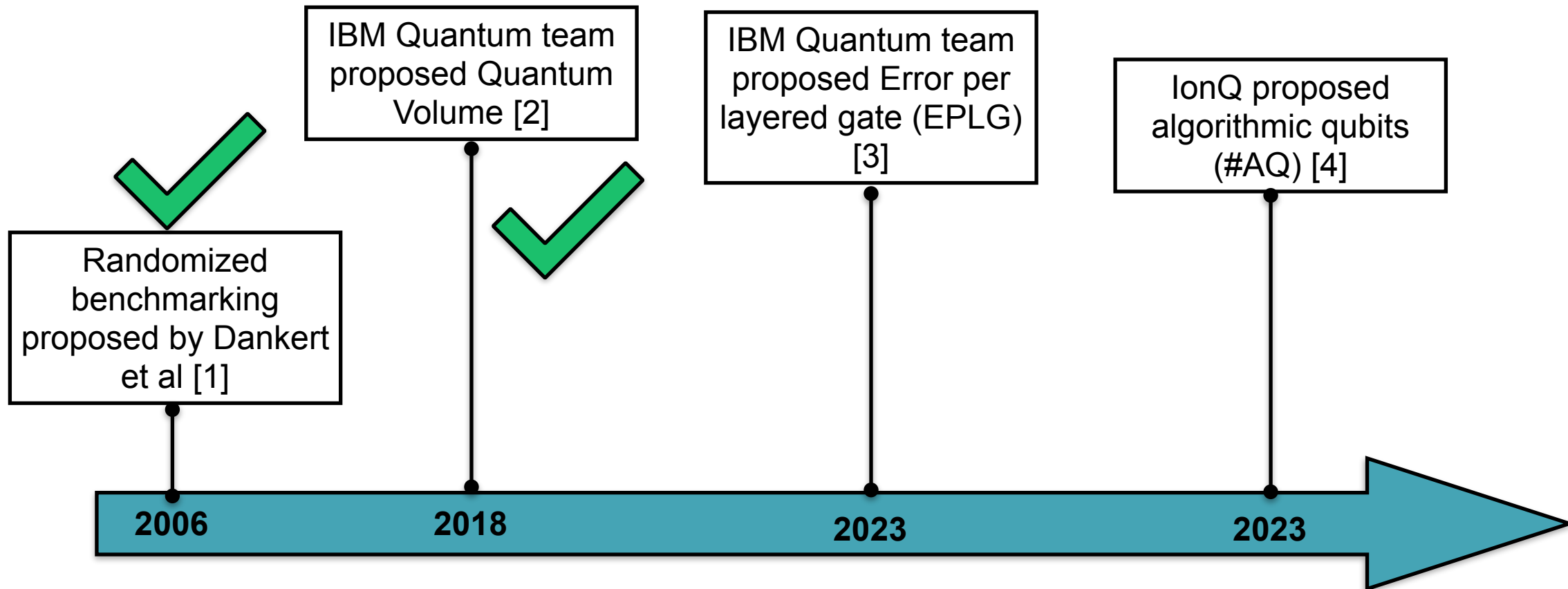
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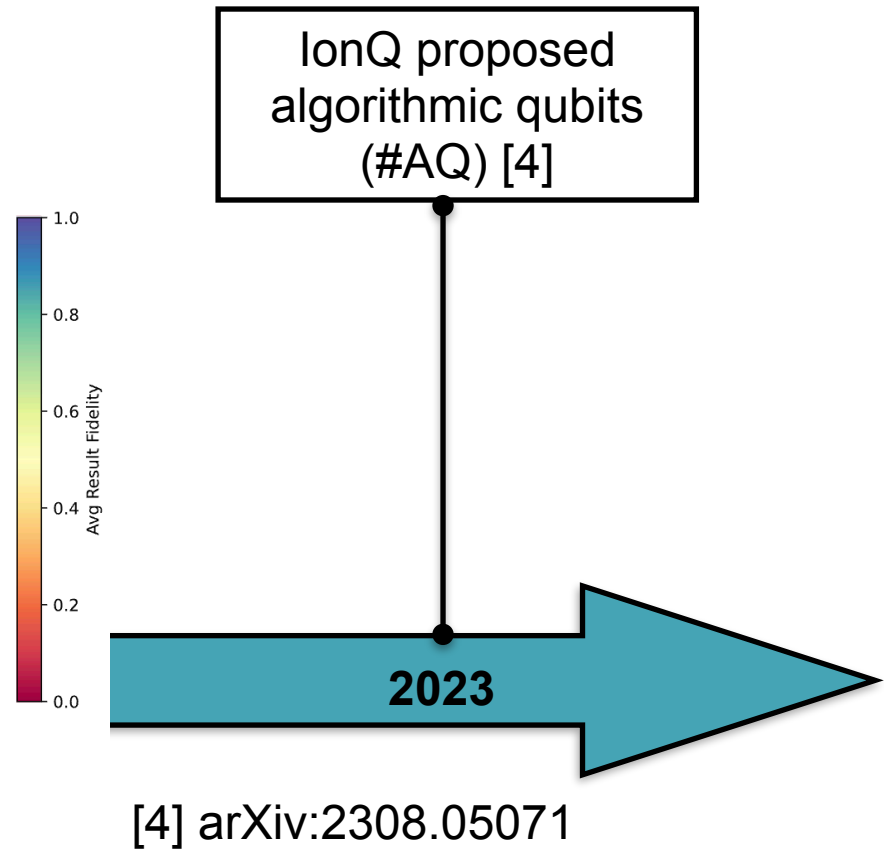
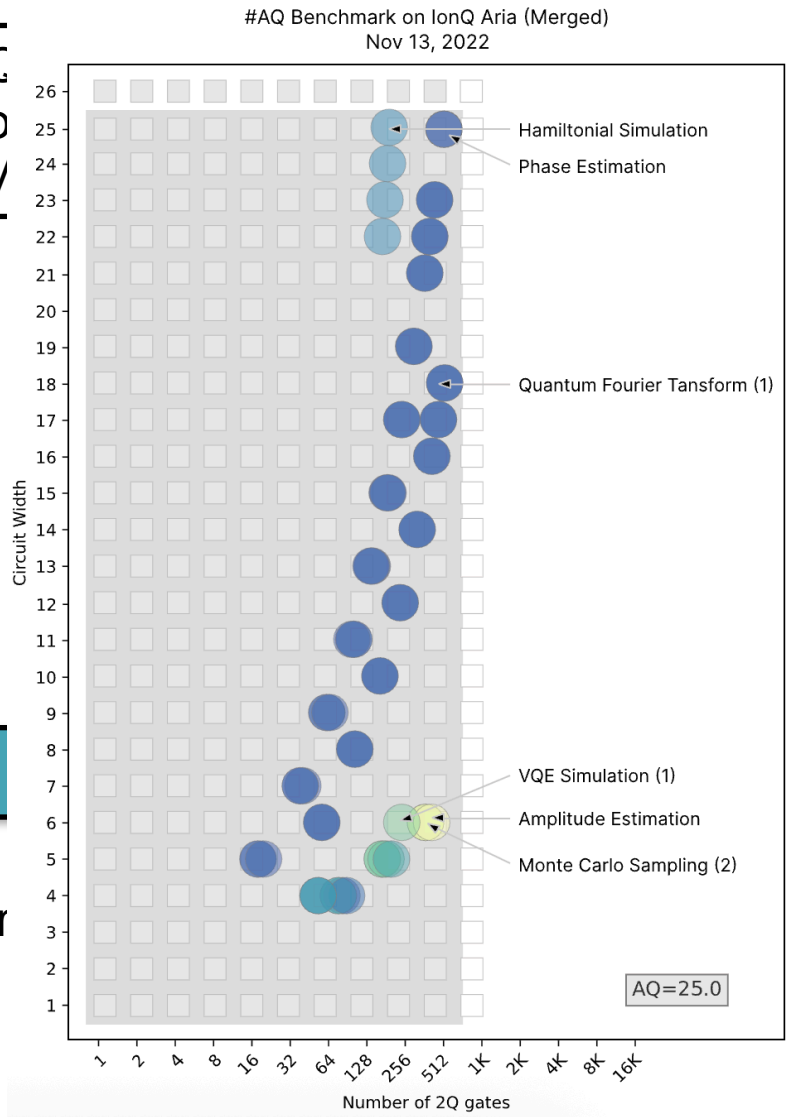
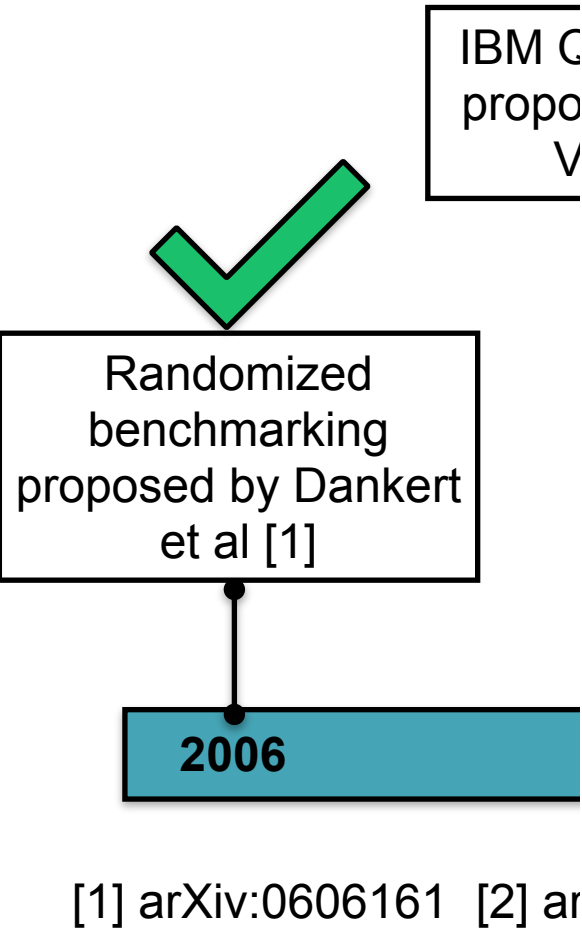
[1] arXiv:0606161 [2] arXiv:1811.12926 [3] arXiv:2311.05933

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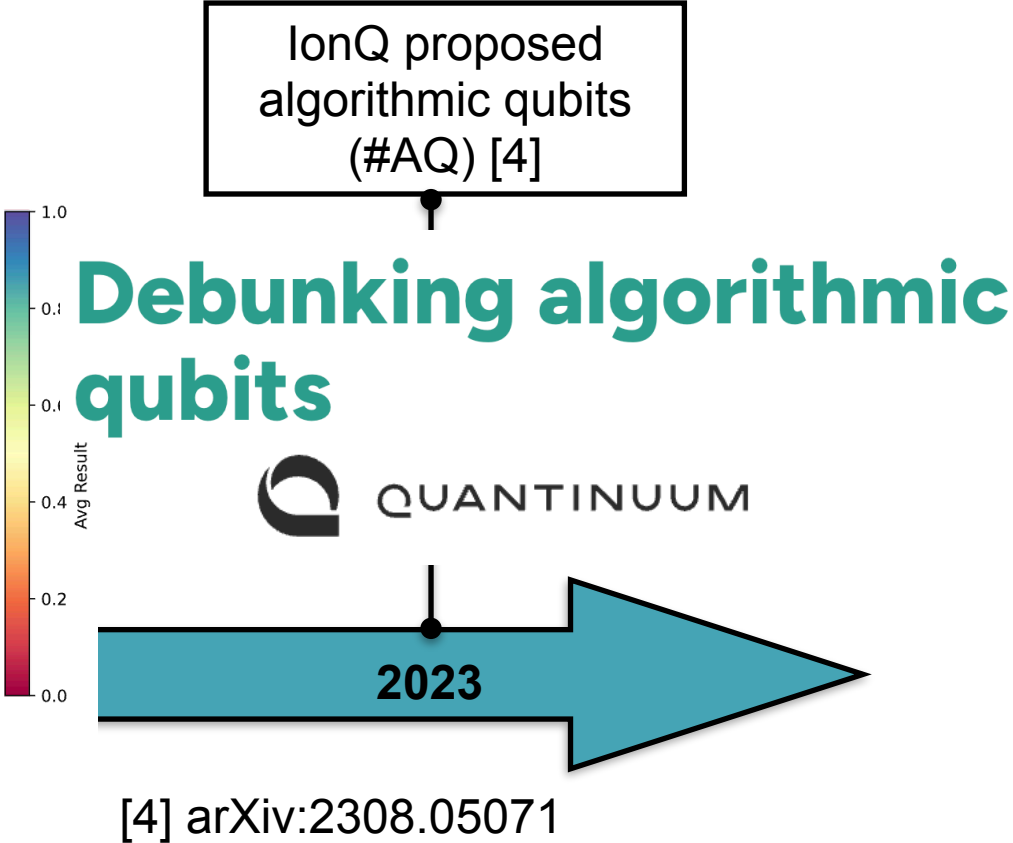
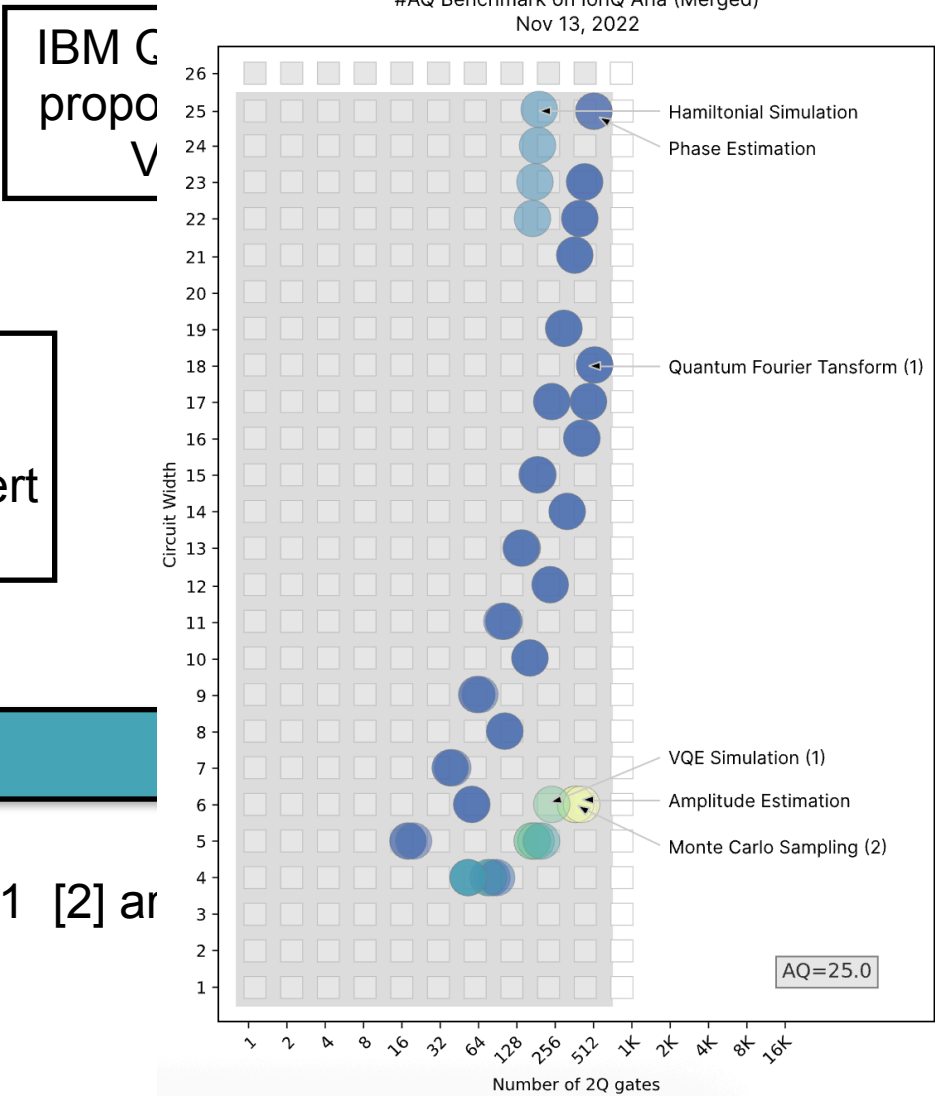
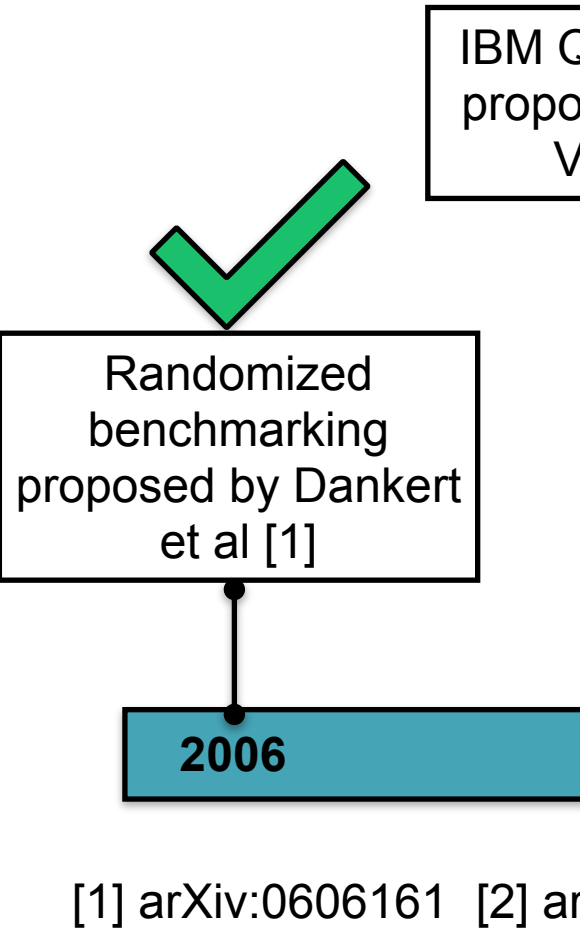


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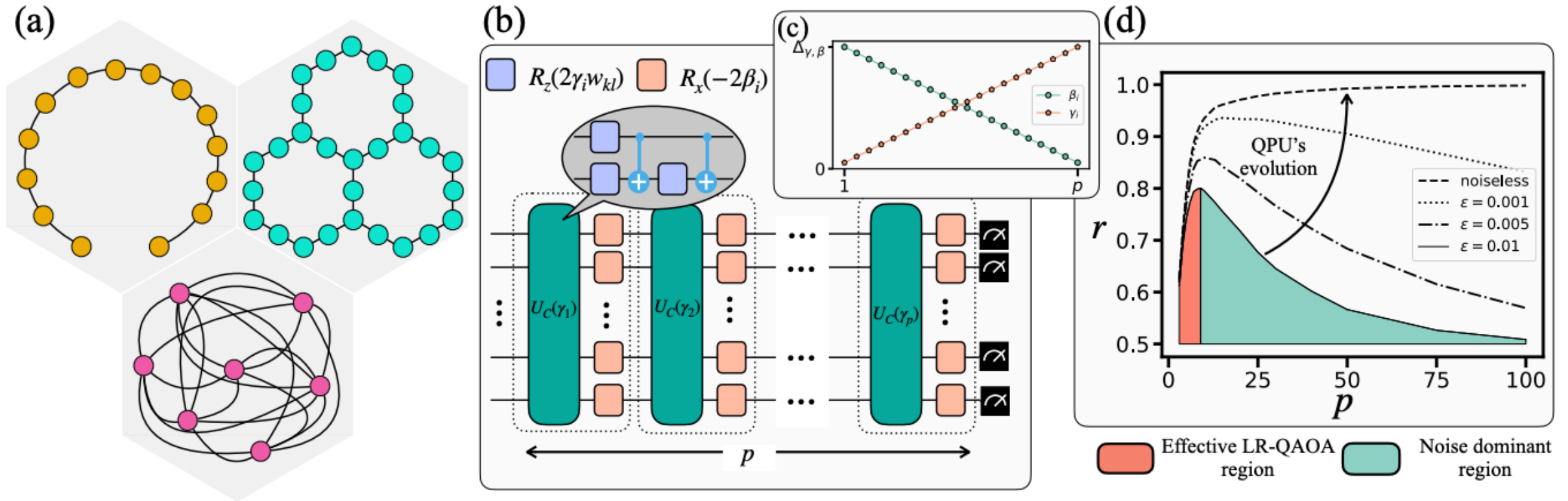
How to measure the progress of quantum processing units?



How to measure the progress of quantum processing units?



The Linear Ramp Quantum Approximate Optimization Algorithm (LR-QAOA)

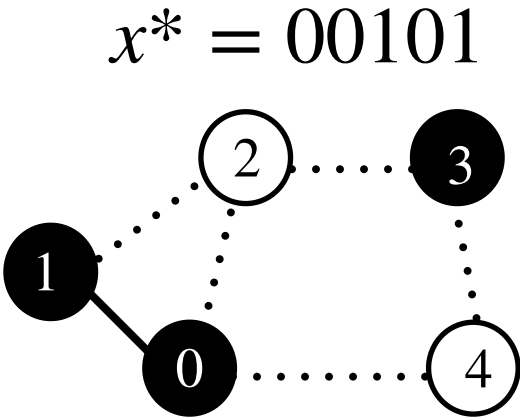
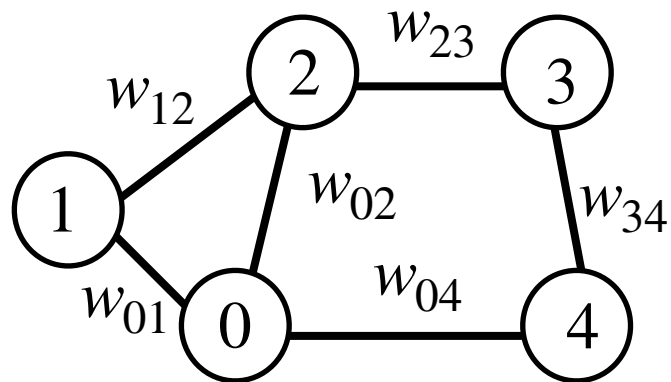


- (a) Graph topologies
- (b) QAOA algorithm
- (c) Linear ramp protocol for QAOA
- (d) Expected performance with noise

We applied this benchmark methodology to 24 different QPUs from 6 different vendors, IQM, IBM, Rigetti, IonQ, Quantinuum, and OriginQ using 5 to 156 qubits and up to $p=10,000$.

The problem behind LR-QAOA

The weighted maxcut (WMC) problem involves determining the partition of the vertices in an undirected graph so that the total weight of the edges between the two sets is maximized.



$$x^* = 00101$$

Cost function

$$C(x) = \sum_{(i,j) \in E} w_{ij}(x_i + x_j - 2x_i x_j)$$

Approximation ratio

$$r = \frac{\sum_{k=1}^n C(x^k)/n}{C(x^*)}$$

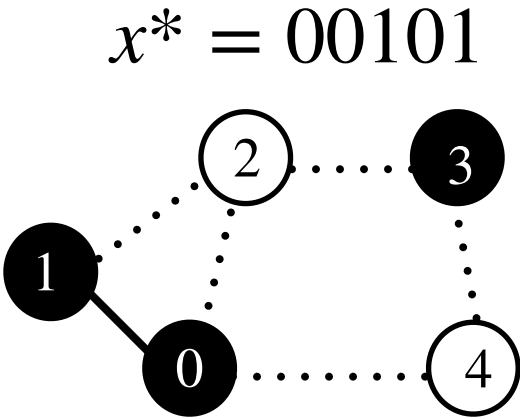
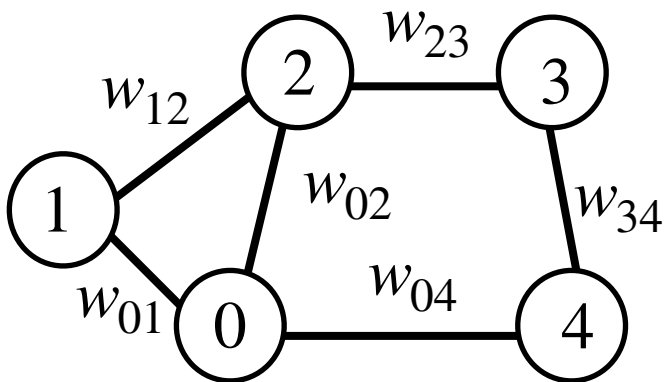
x_k sample solution

x^* optimal solution

n Samples

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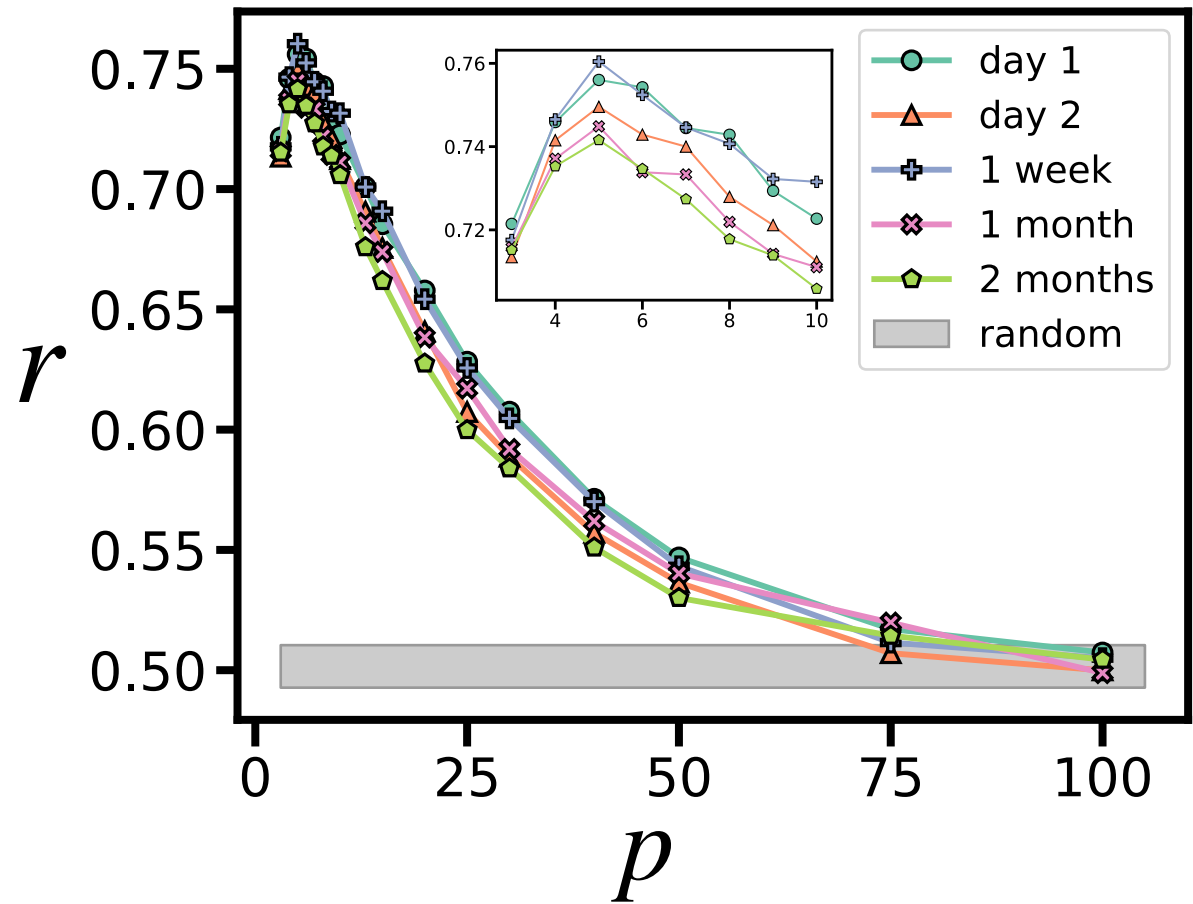
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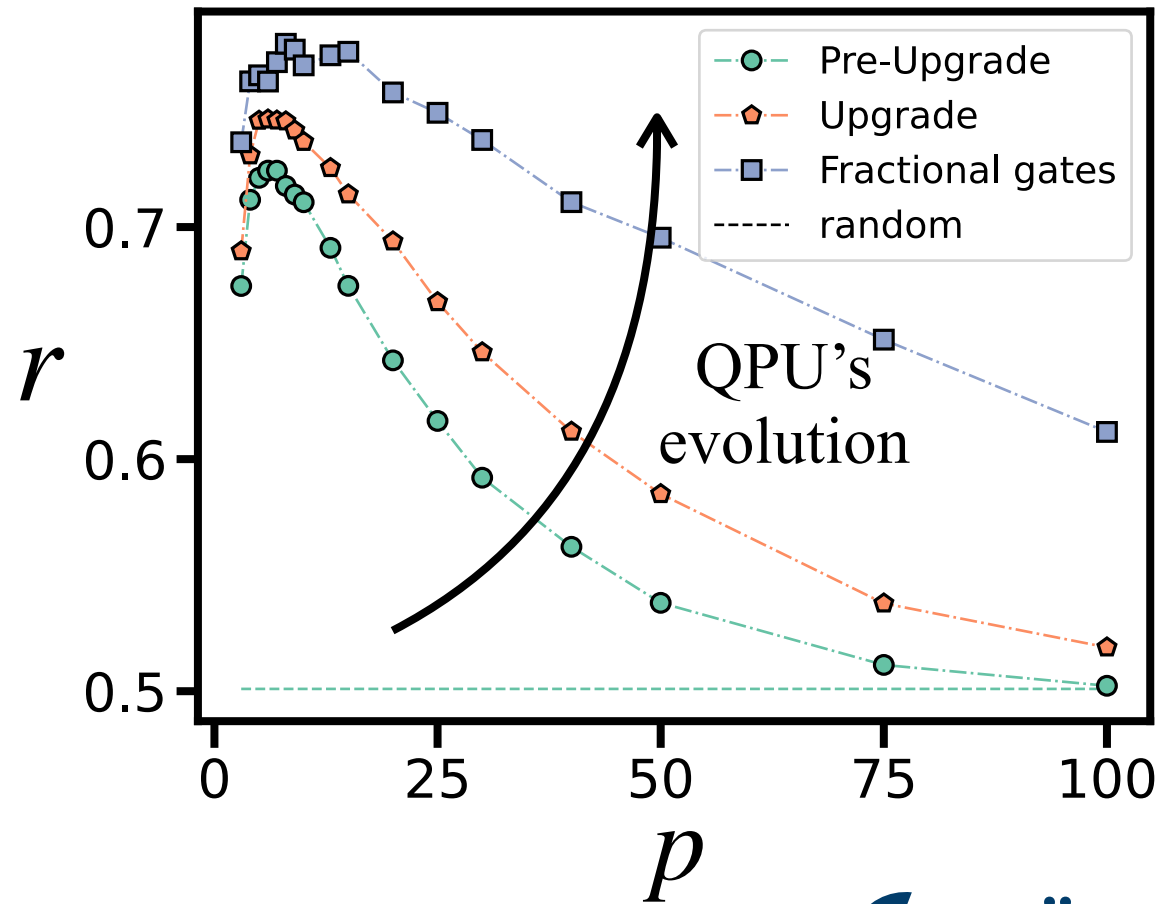
Performance metric

Tracking the evolution of real QPUs

ibm_brisbane 100 qubits

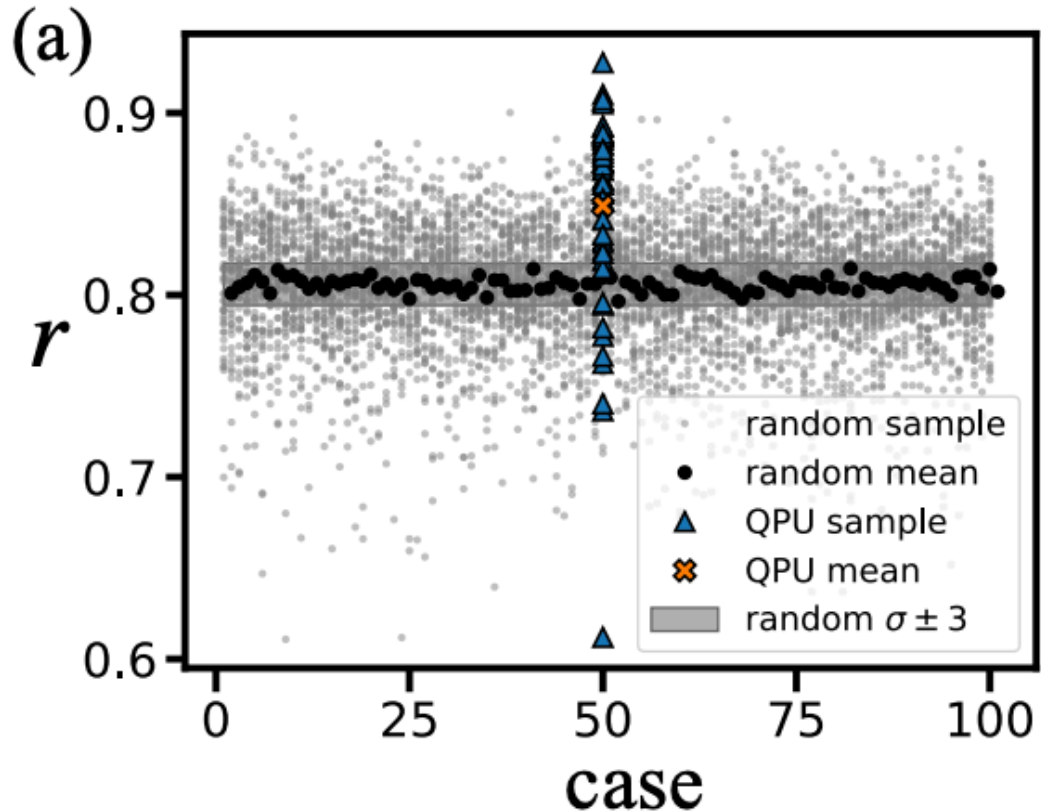


ibm_torino 133 qubits

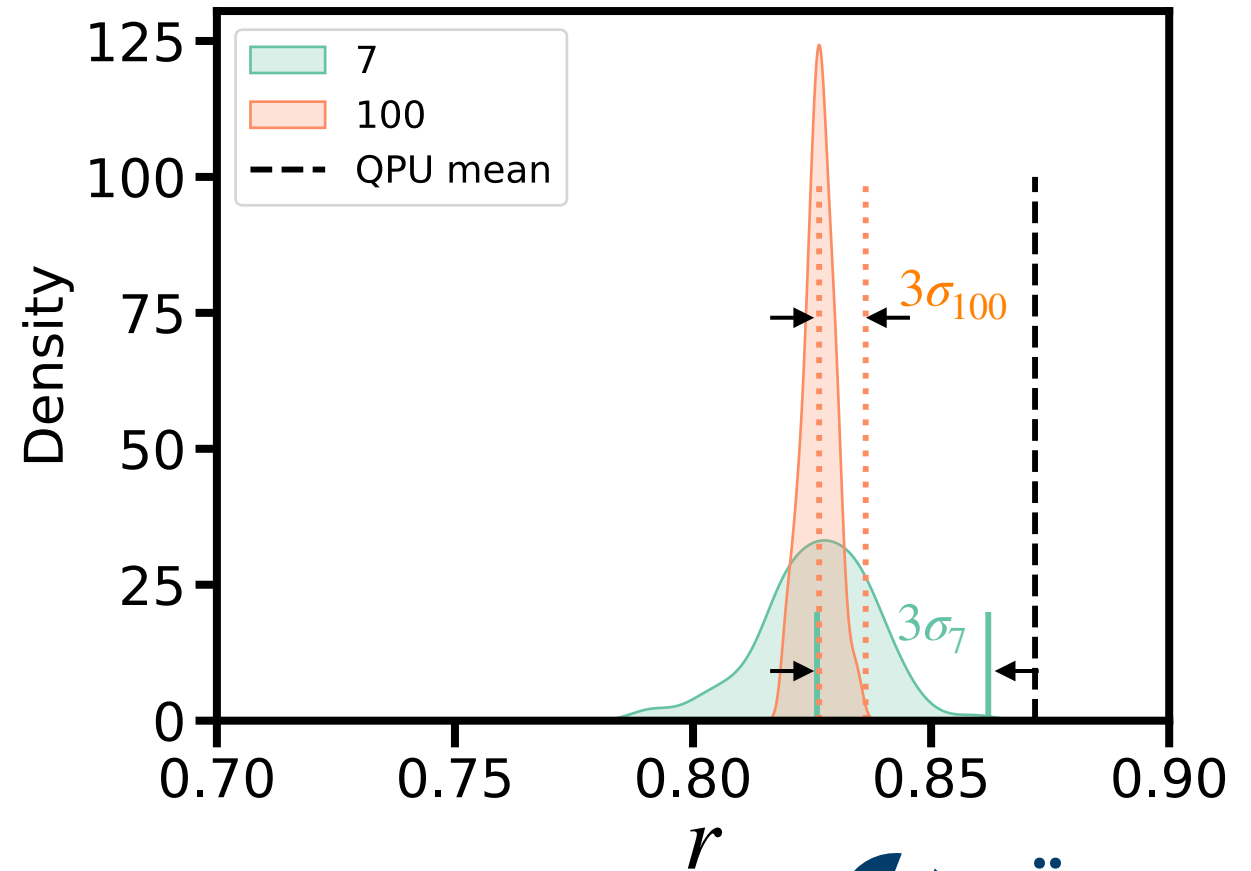


Distinguishing successful results

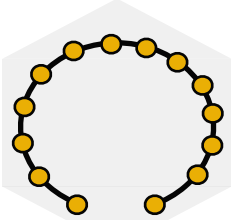
To certify if the result of a QPU is still meaningful, we compare the approximation ratio for the LR-QAOA WMC problem given by the samples of the QPU to those coming from a random sampler.



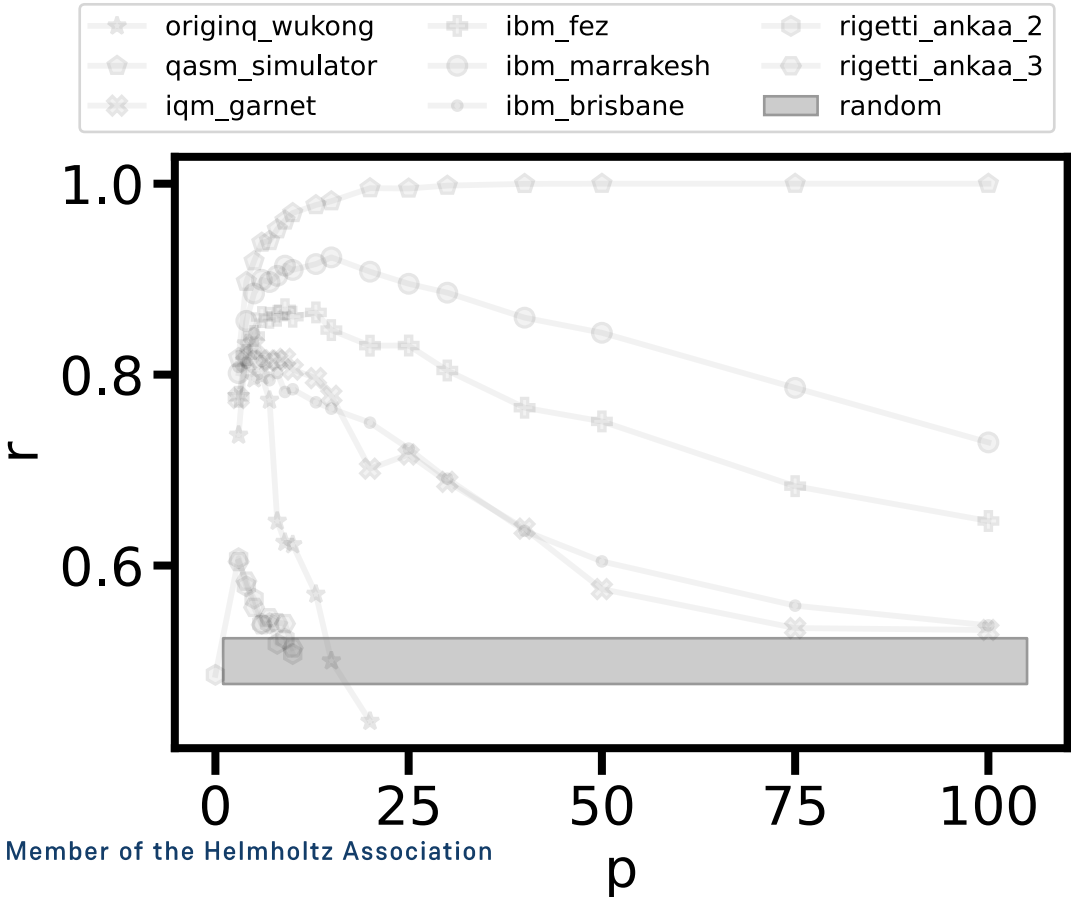
(a) H2-1 50-qubit, 50 samples, and $p=4$.



LR-QAOA on a 1D-Chain graph

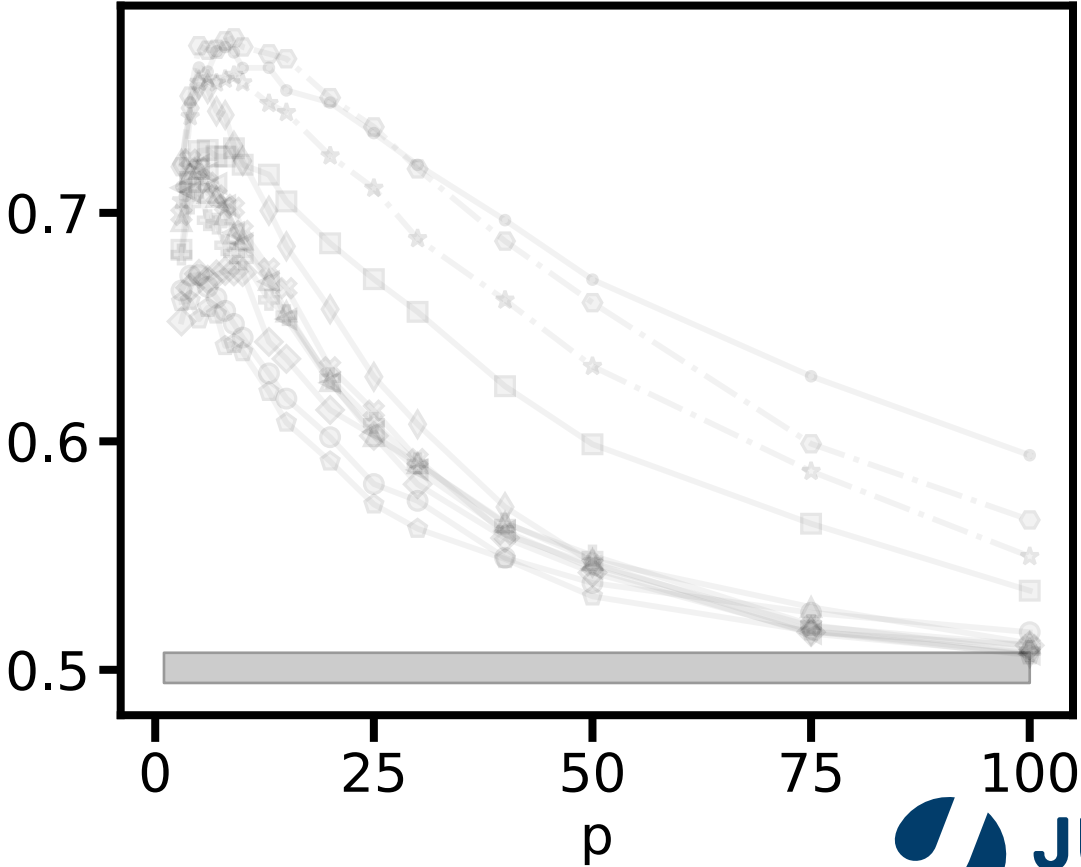


Performance on the best 5-qubit 1D chain experiment, different QPUs

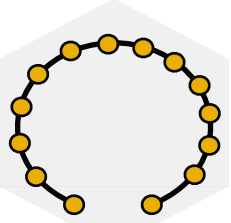


Performance on a 100-qubit 1D chain experiment. IBM QPUs (EPLG)

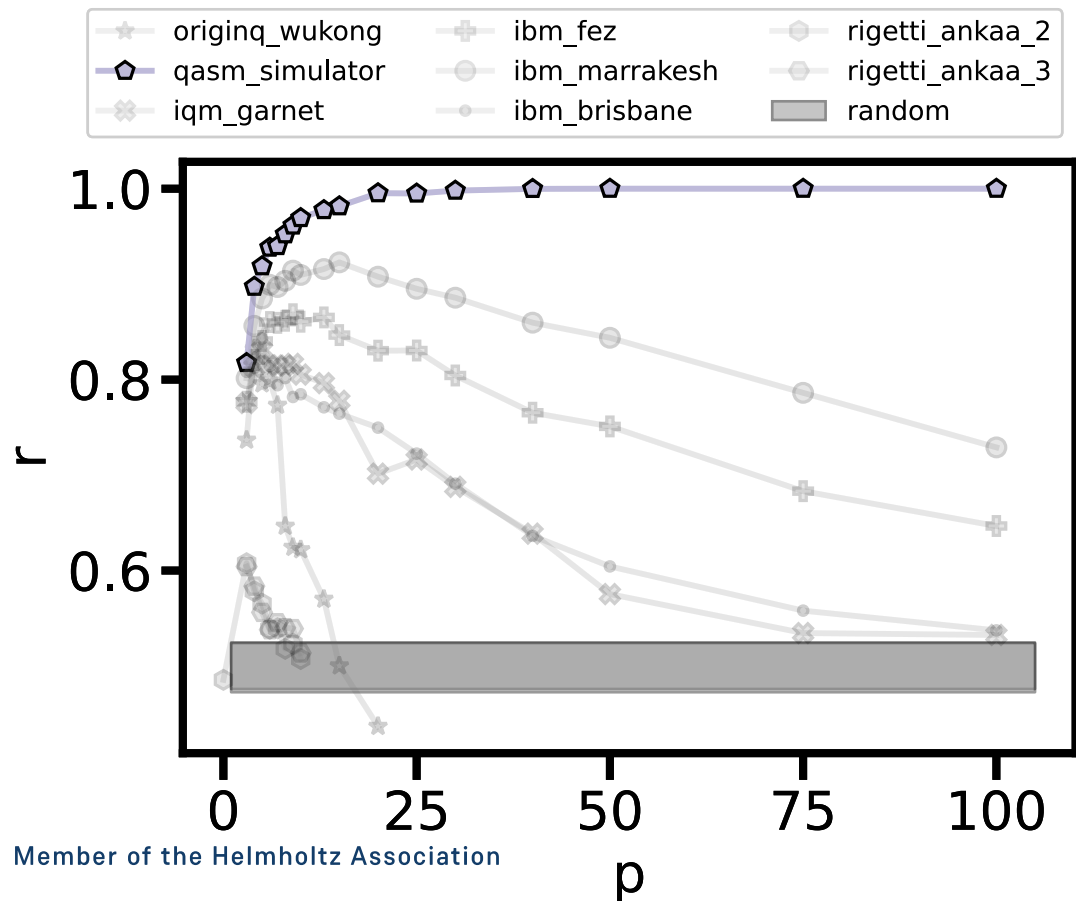
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ibm_torino-v0 (0.8)			



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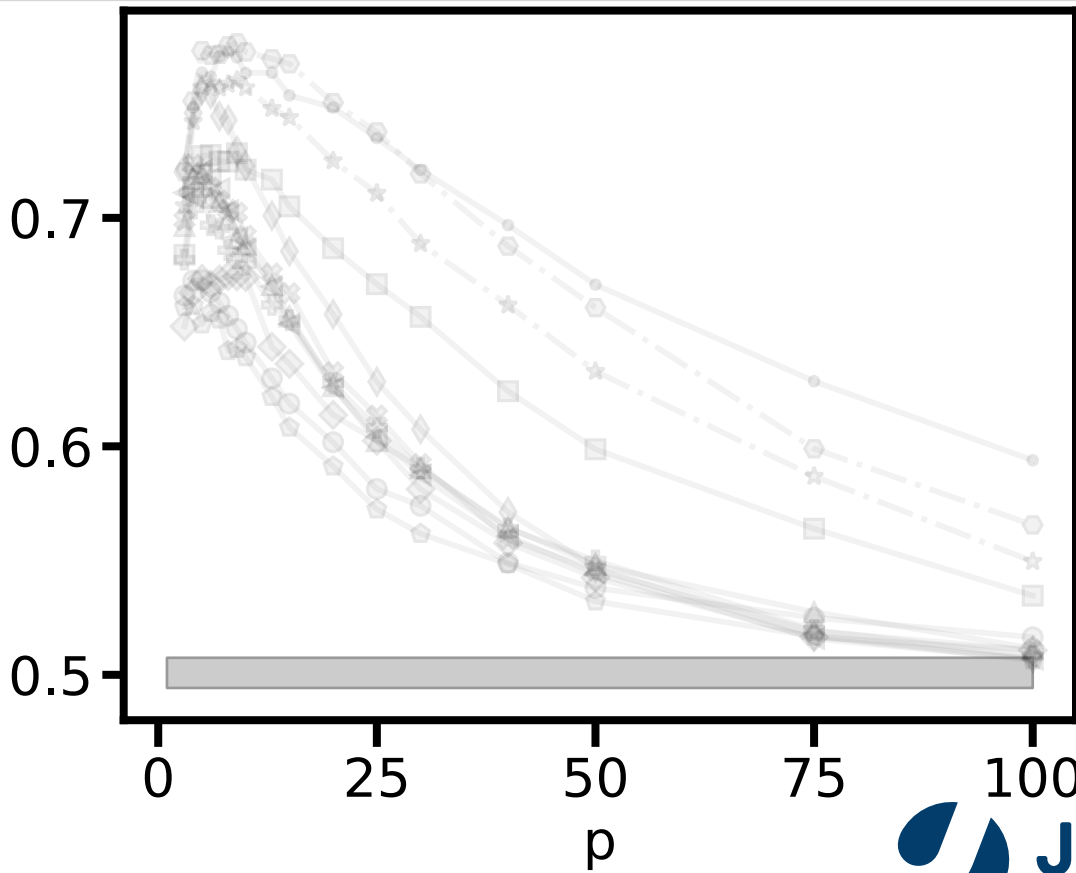


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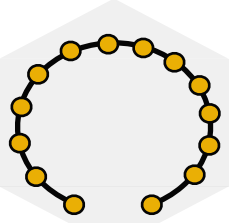


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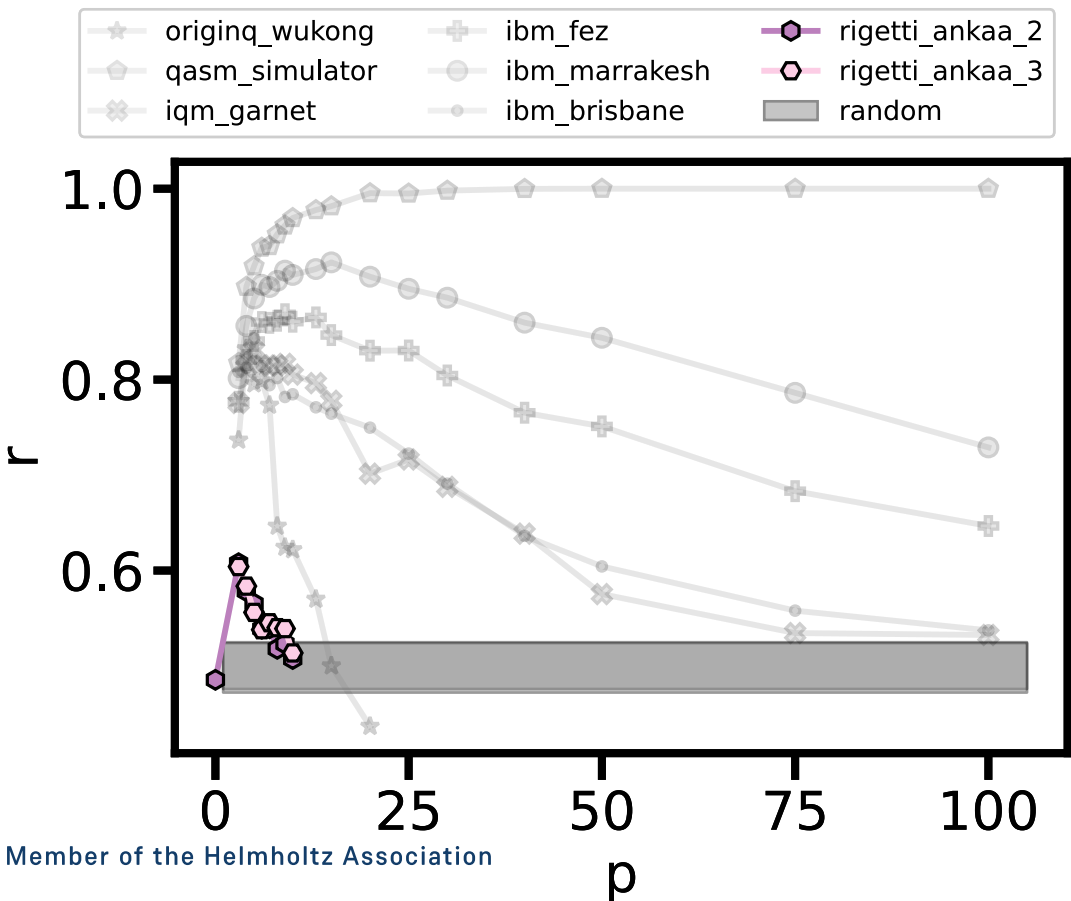
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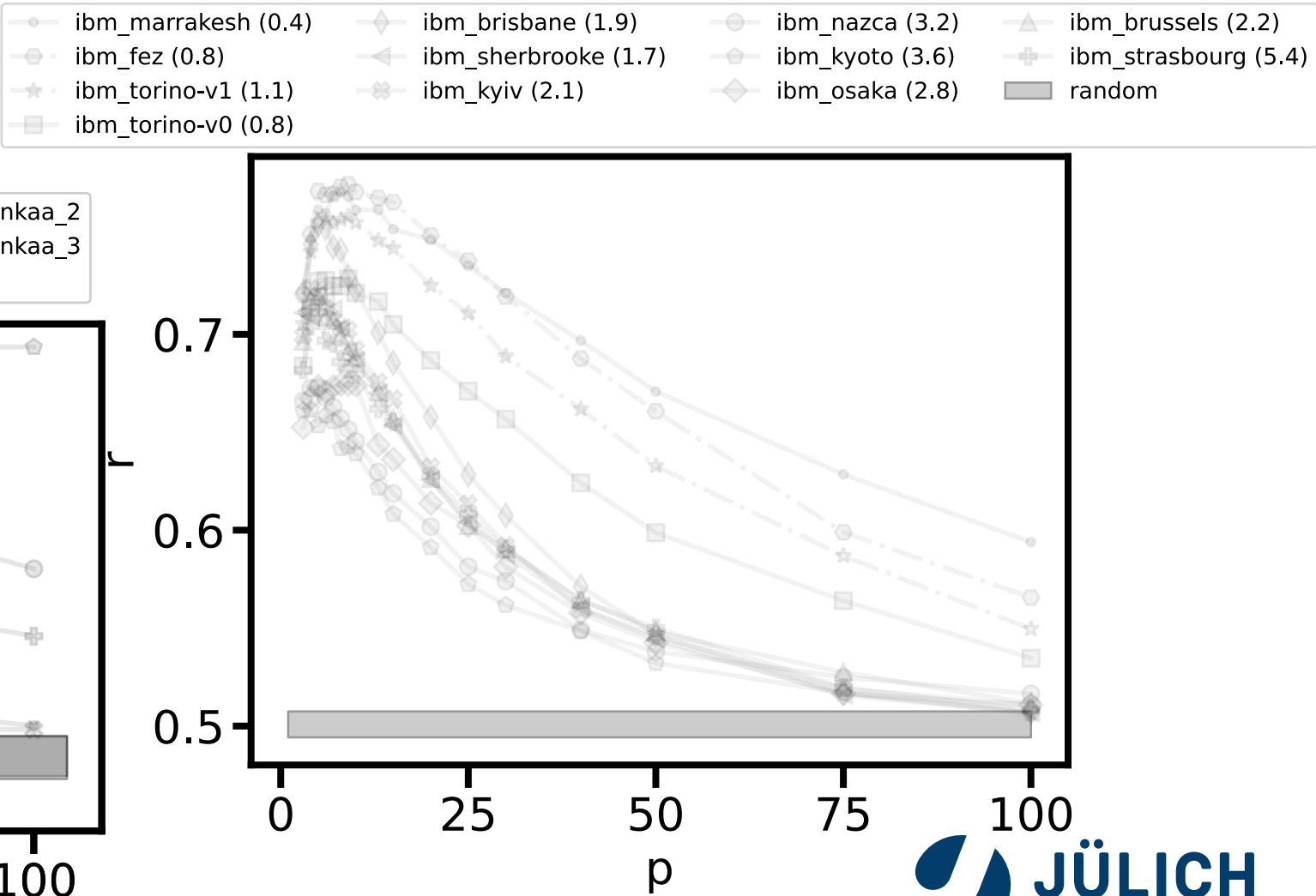
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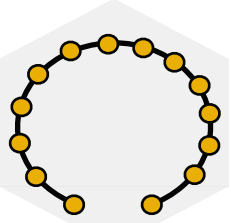
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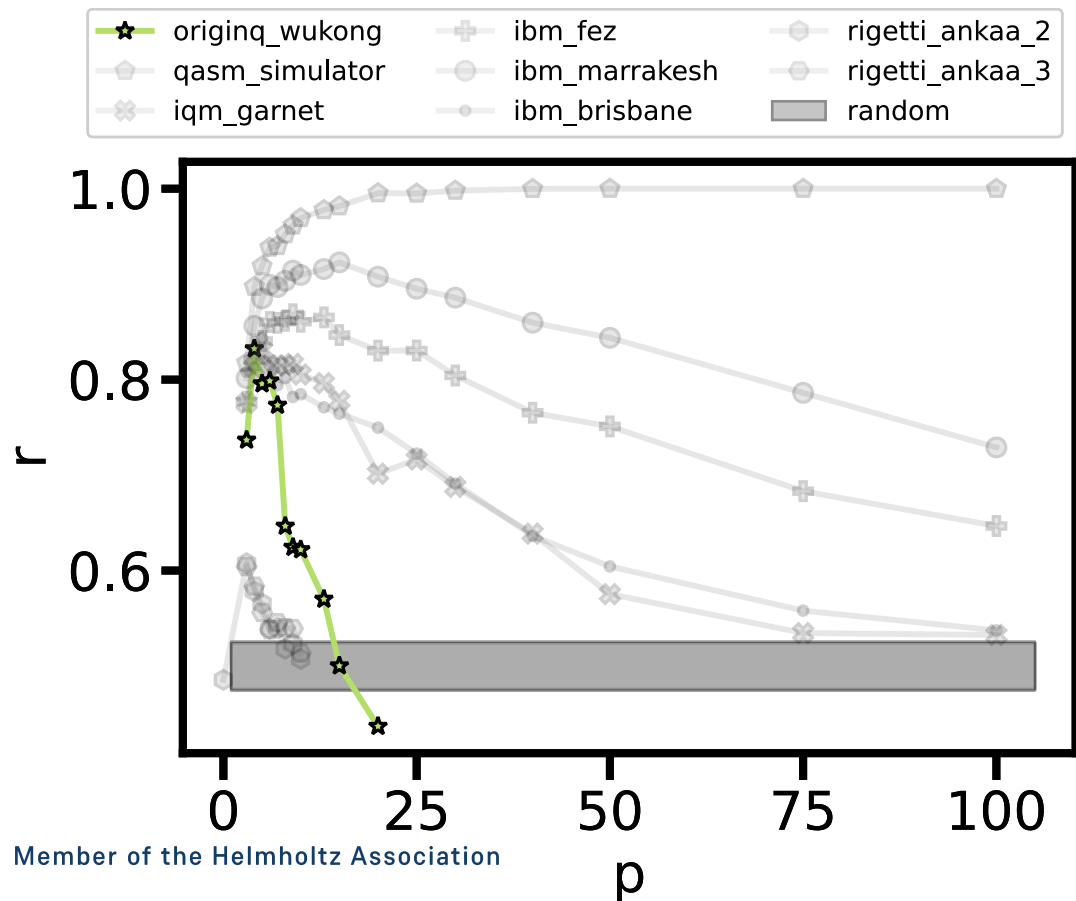
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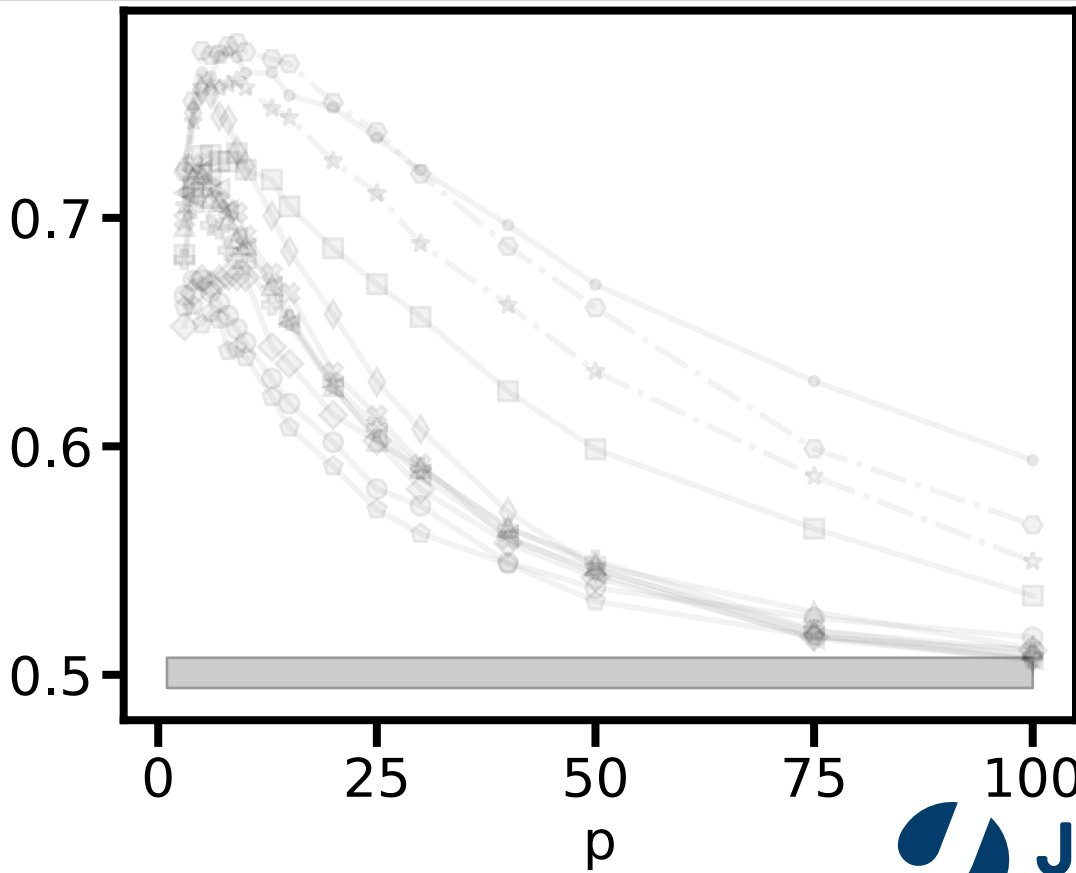


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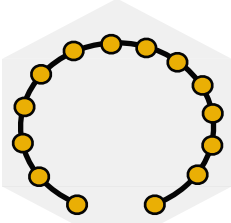


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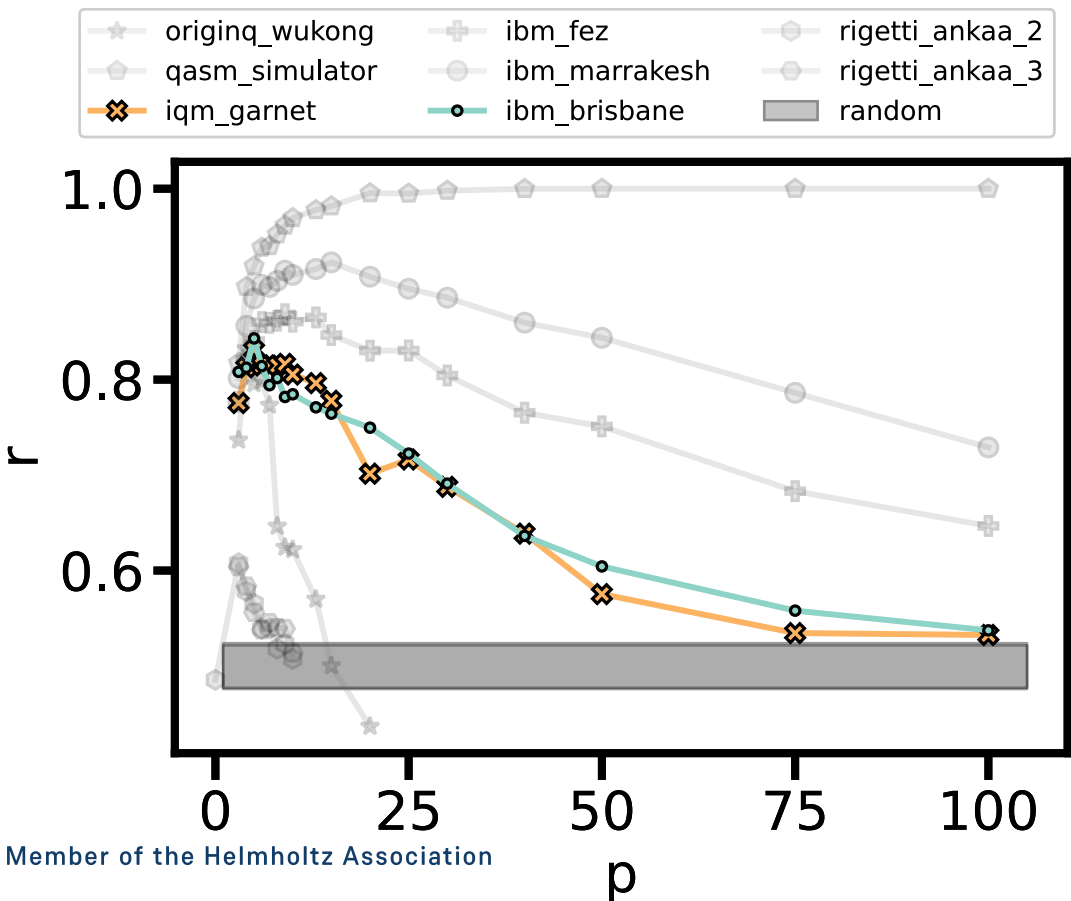
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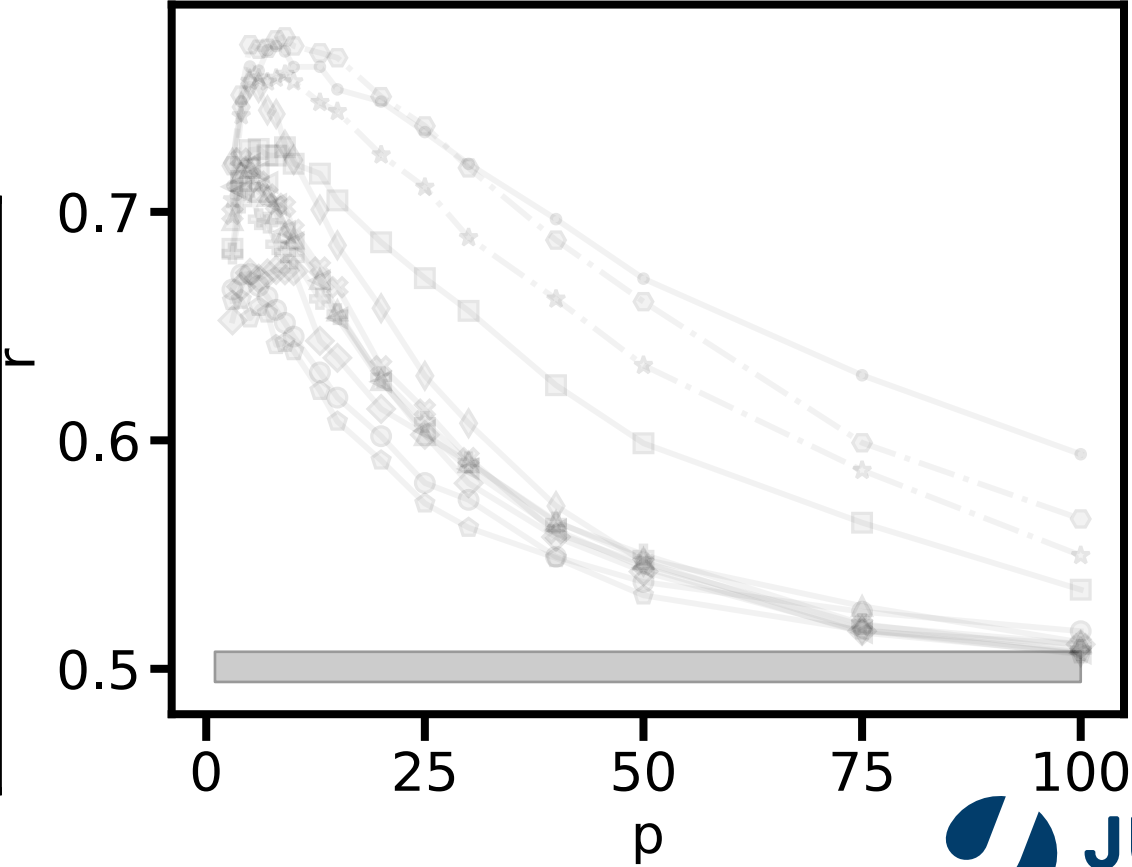
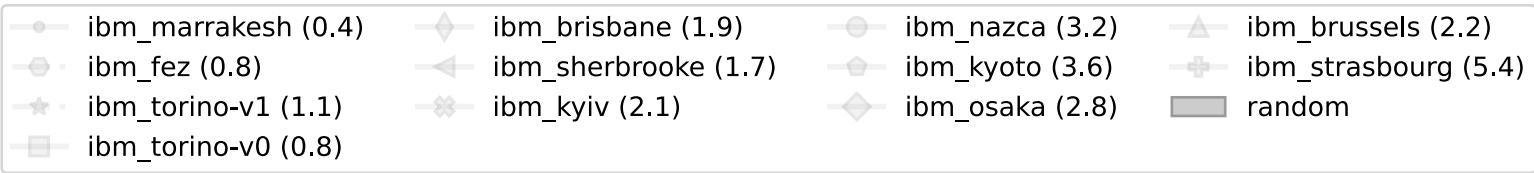
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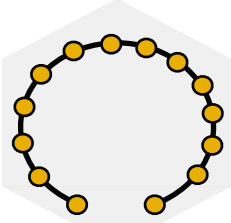
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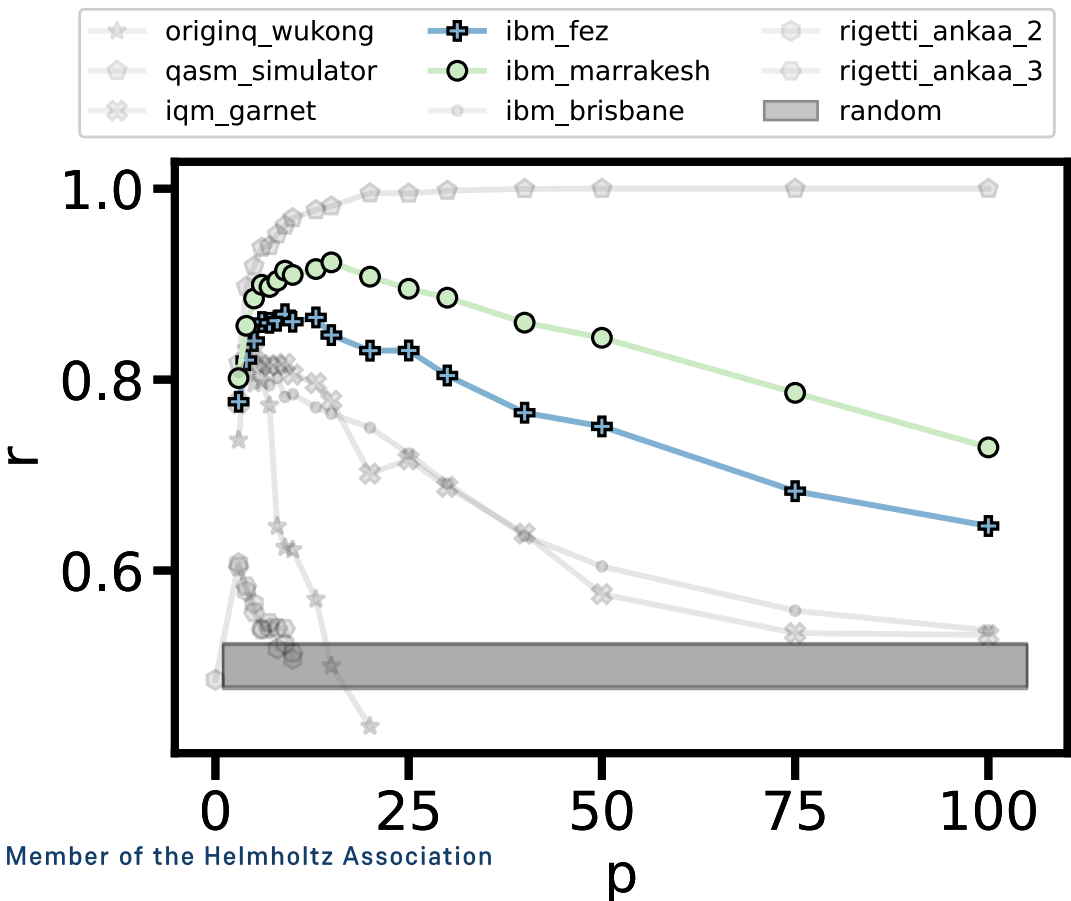
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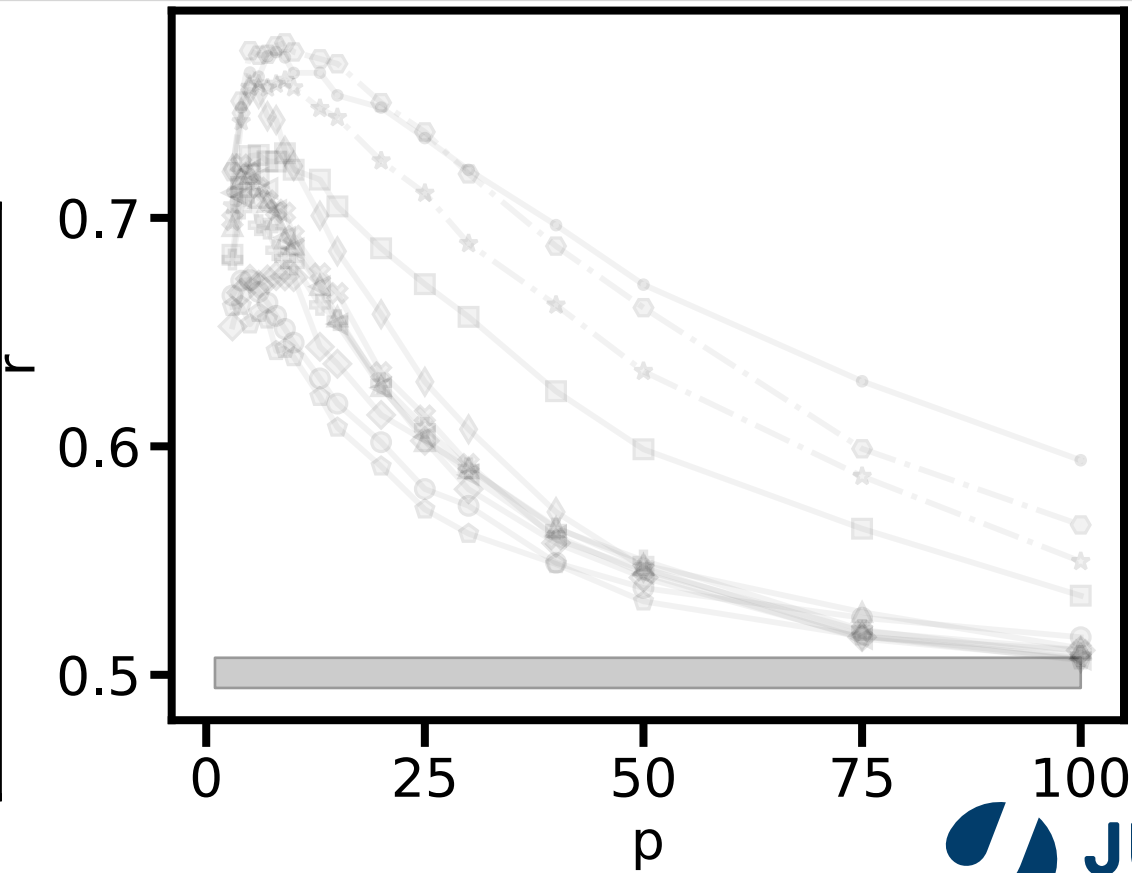


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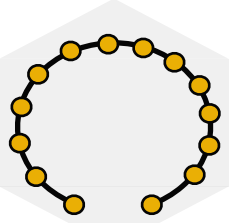


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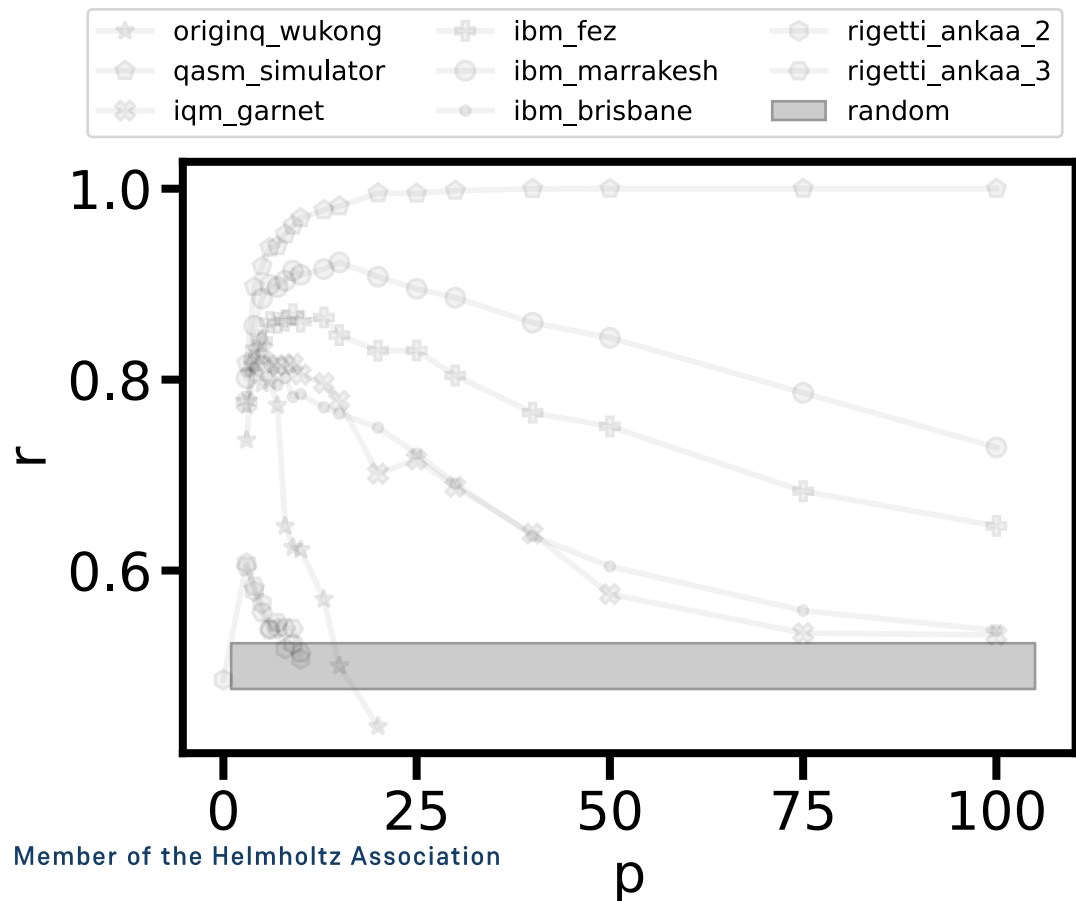
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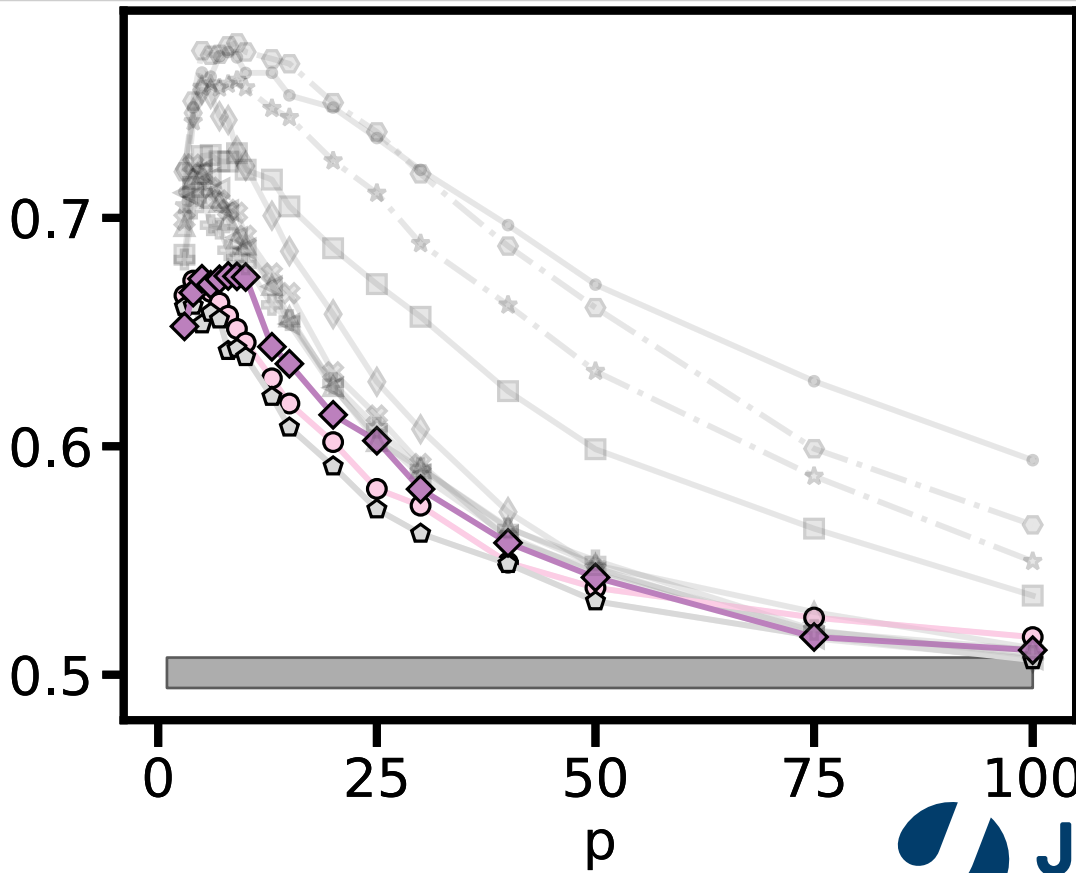


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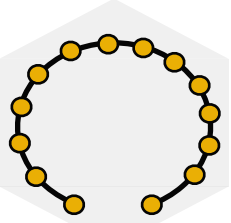


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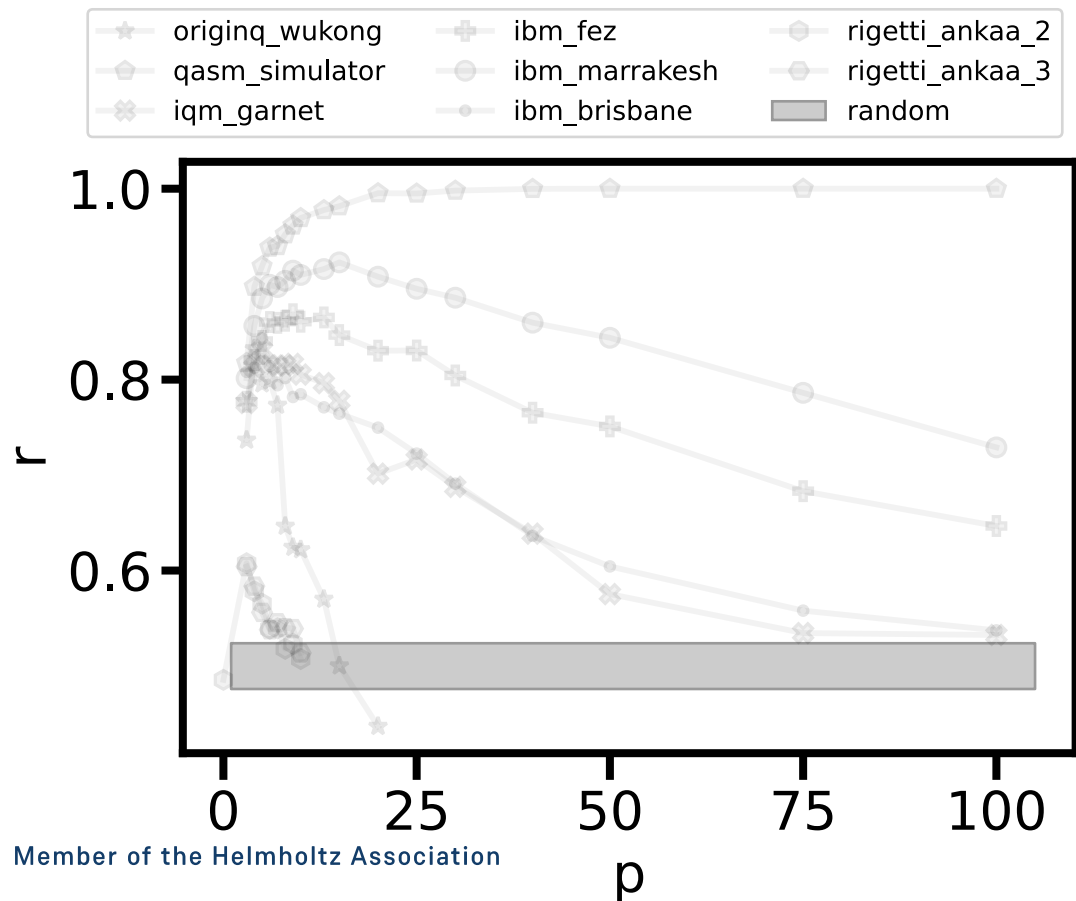
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LR-QAOA on a 1D-Chain graph

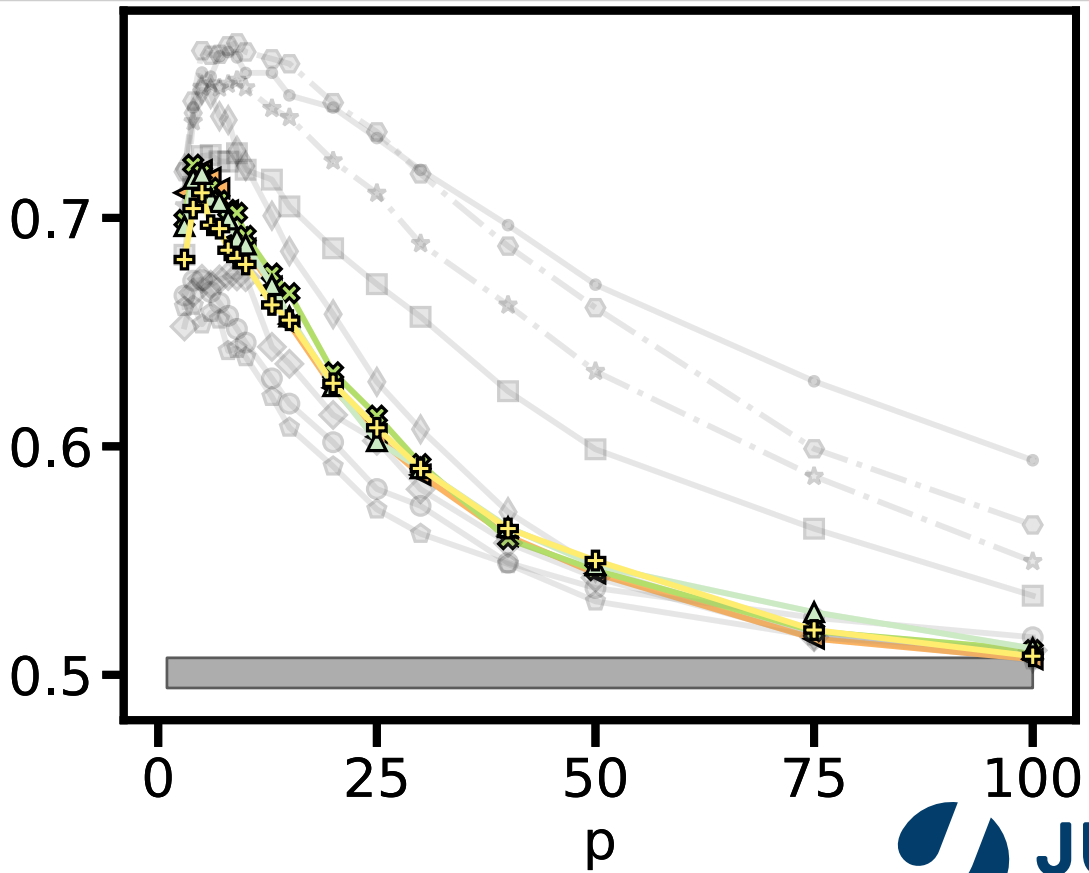


Performance on the best 5-qubit 1D chain experiment, different QPUs

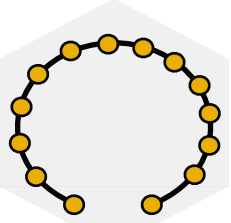


Performance on a 100-qubit 1D chain experiment. IBM QPUs (EPLG)

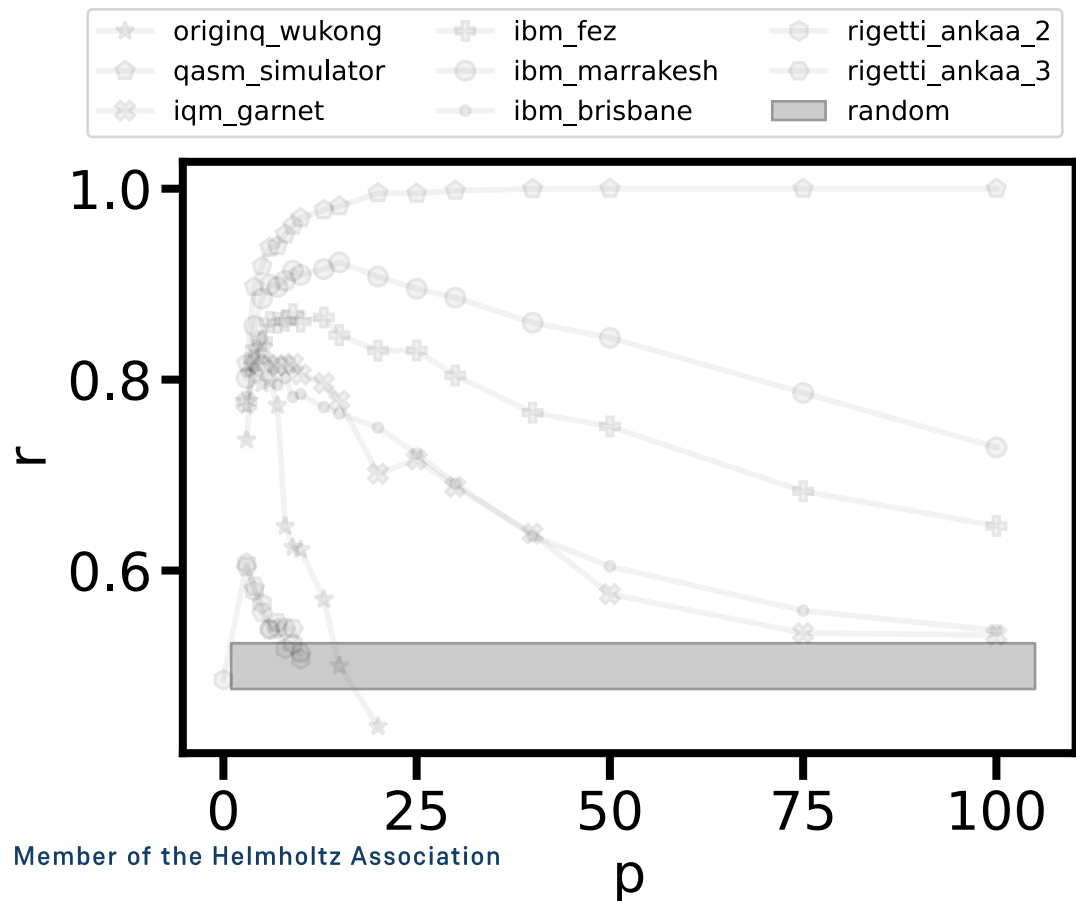
- | | | | |
|---------------------|----------------------|-----------------|----------------------|
| ibm_marrakesh (0.4) | ibm_brisbane (1.9) | ibm_nazca (3.2) | ibm_brussels (2.2) |
| ibm_fez (0.8) | ibm_sherbrooke (1.7) | ibm_kyoto (3.6) | ibm_strasbourg (5.4) |
| ibm_torino-v1 (1.1) | ibm_kyiv (2.1) | ibm_osaka (2.8) | random |
| ibm_torino-v0 (0.8) | | | |



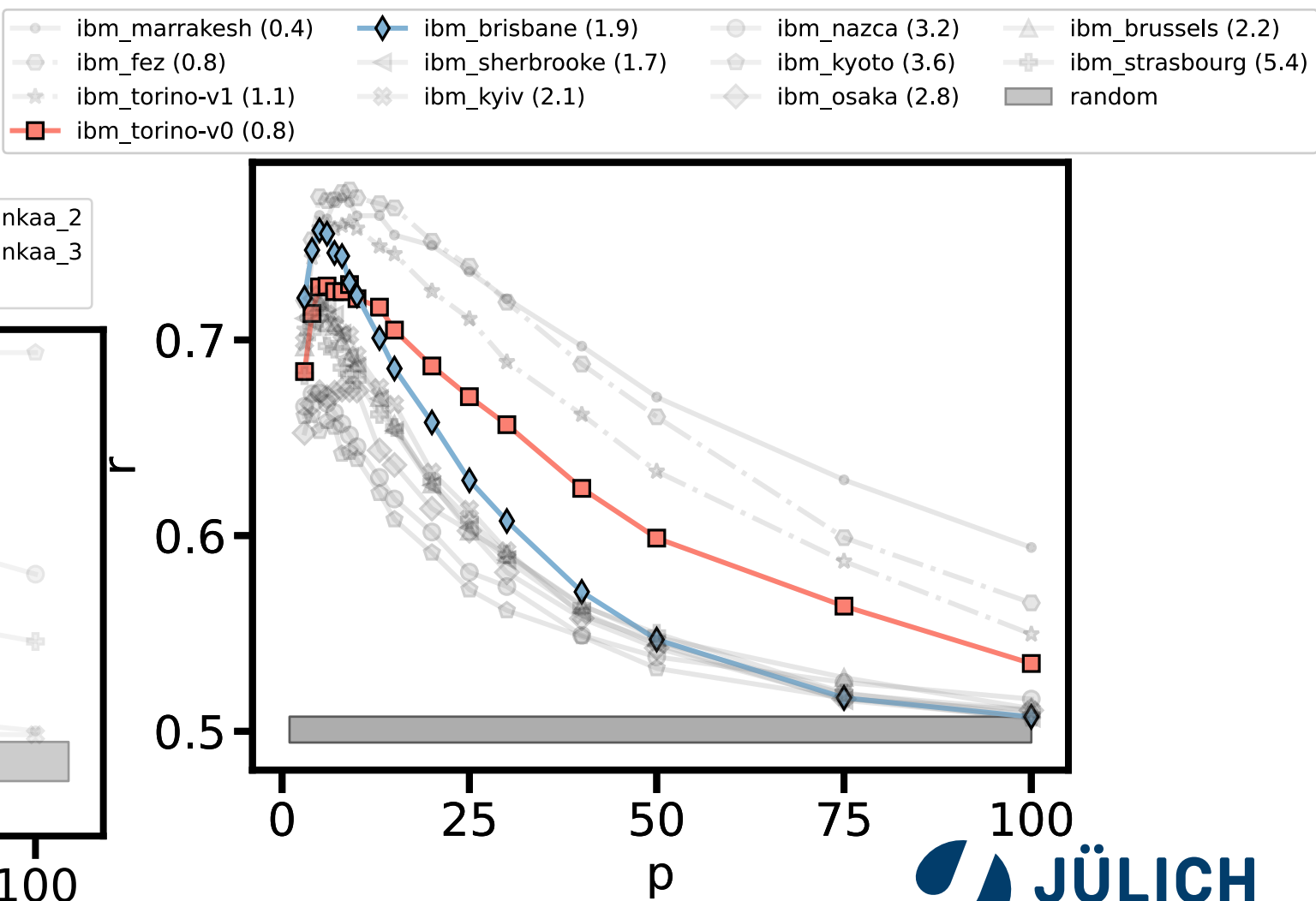
LR-QAOA on a 1D-Chain graph



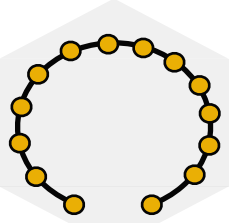
Performance on the best 5-qubit 1D chain experiment, different QPUs



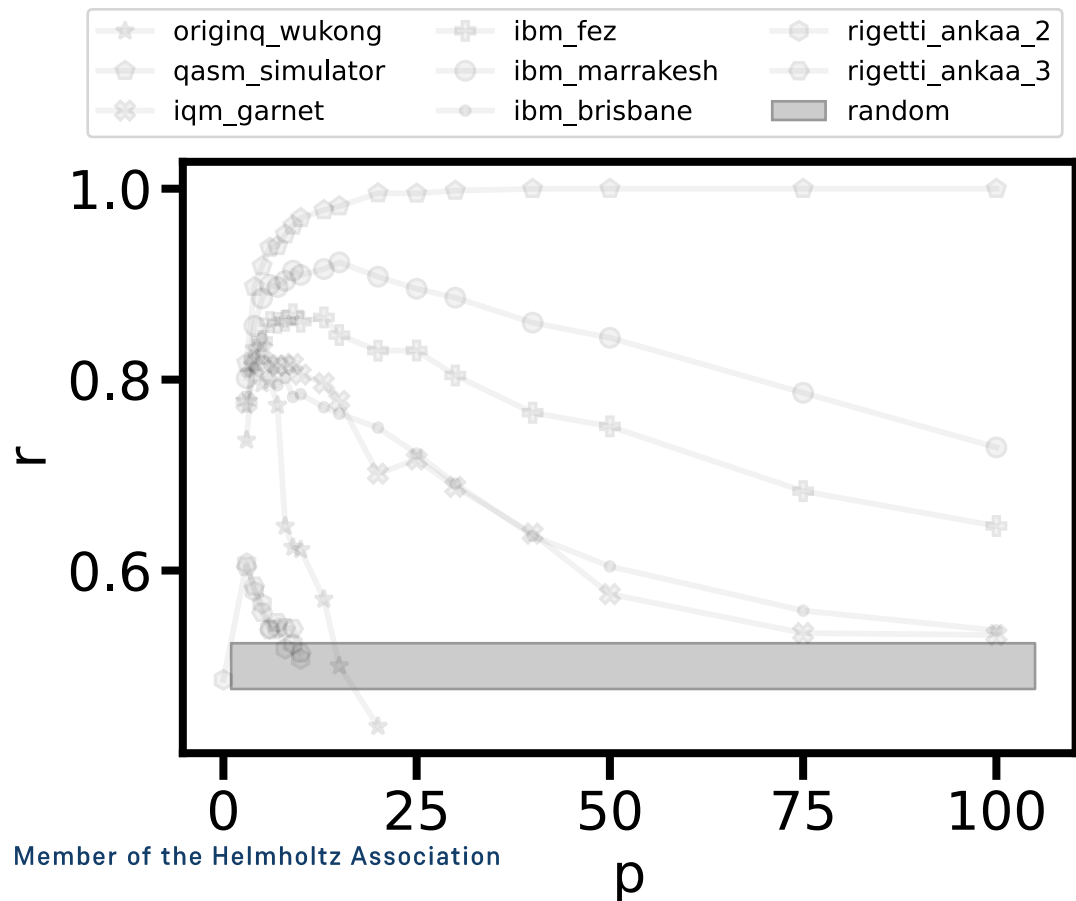
Performance on a 100-qubit 1D chain experiment. IBM QPUs (EPLG)



LR-QAOA on a 1D-Chain graph

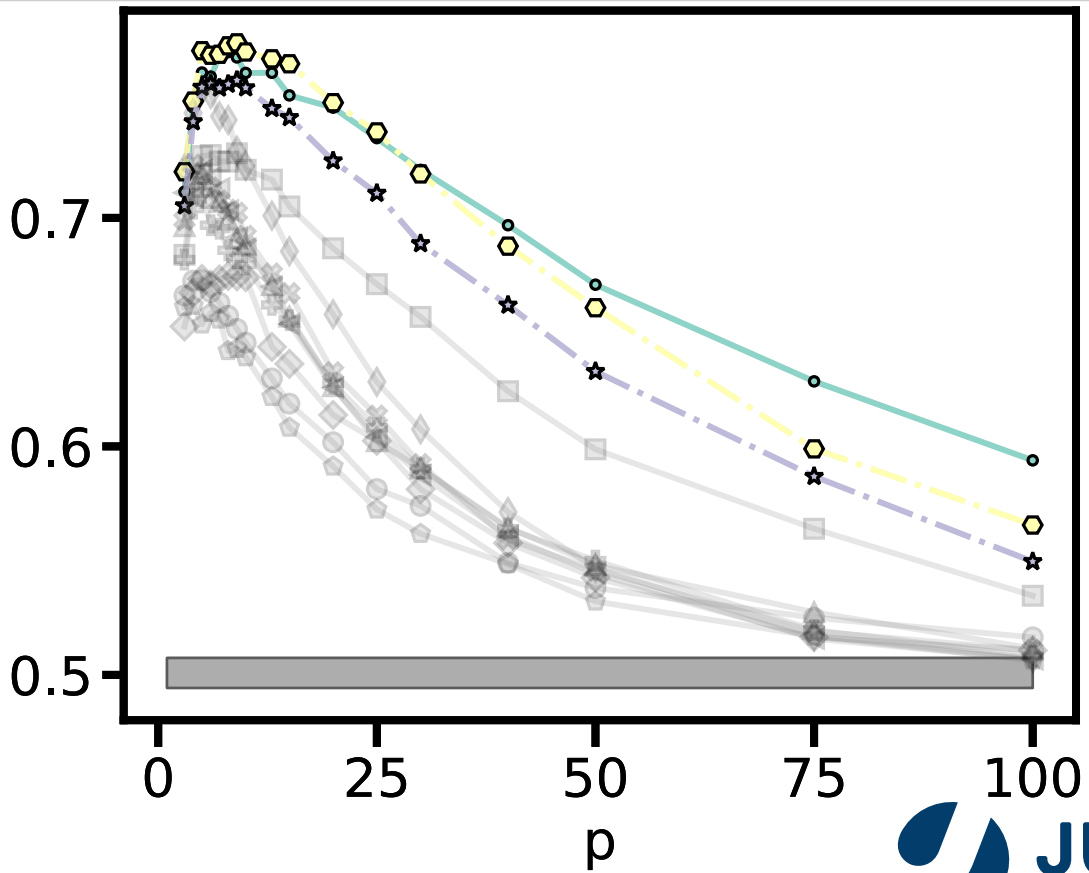


Performance on the best 5-qubit 1D chain experiment, different QPUs

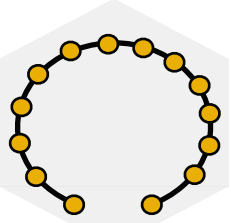


Performance on a 100-qubit 1D chain experiment. IBM QPUs (EPLG)

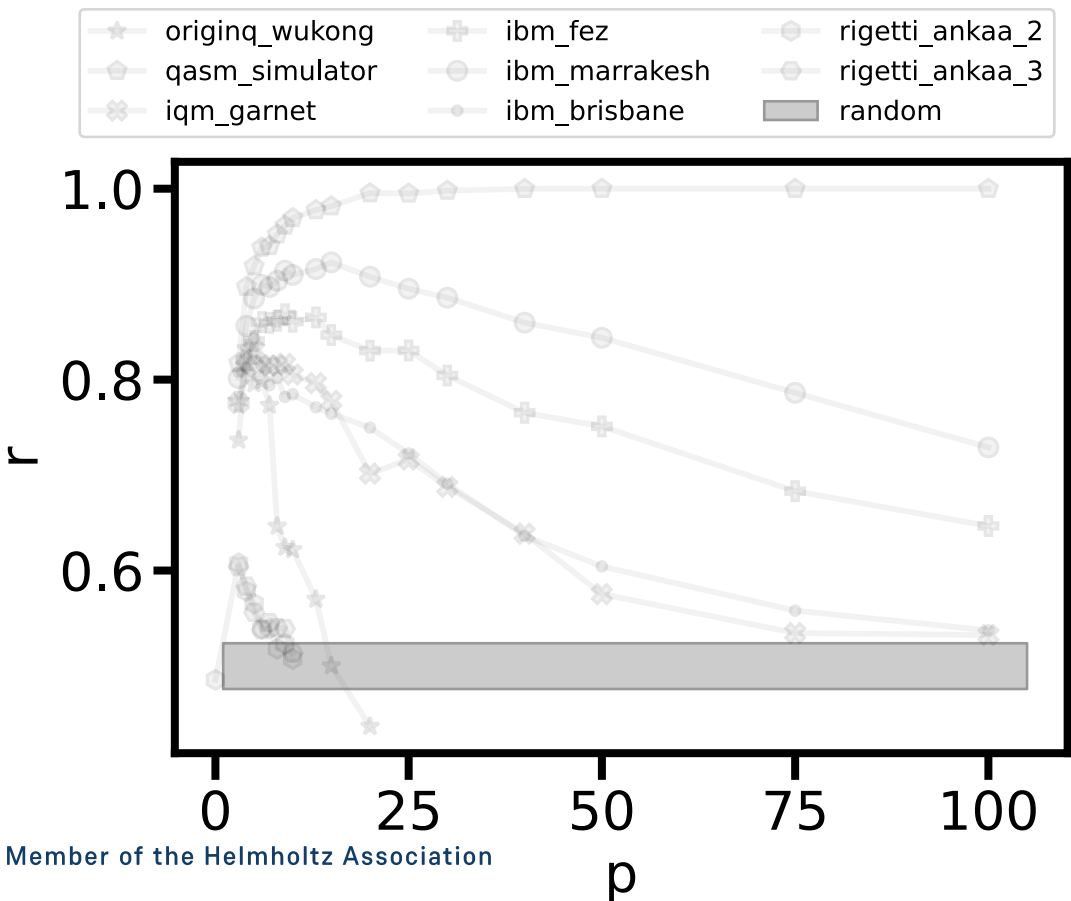
- | | | | |
|---------------------|----------------------|-----------------|----------------------|
| ibm_marrakesh (0.4) | ibm_brisbane (1.9) | ibm_nazca (3.2) | ibm_brussels (2.2) |
| ibm_fez (0.8) | ibm_sherbrooke (1.7) | ibm_kyoto (3.6) | ibm_strasbourg (5.4) |
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| ibm_torino-v0 (0.8) | | | |



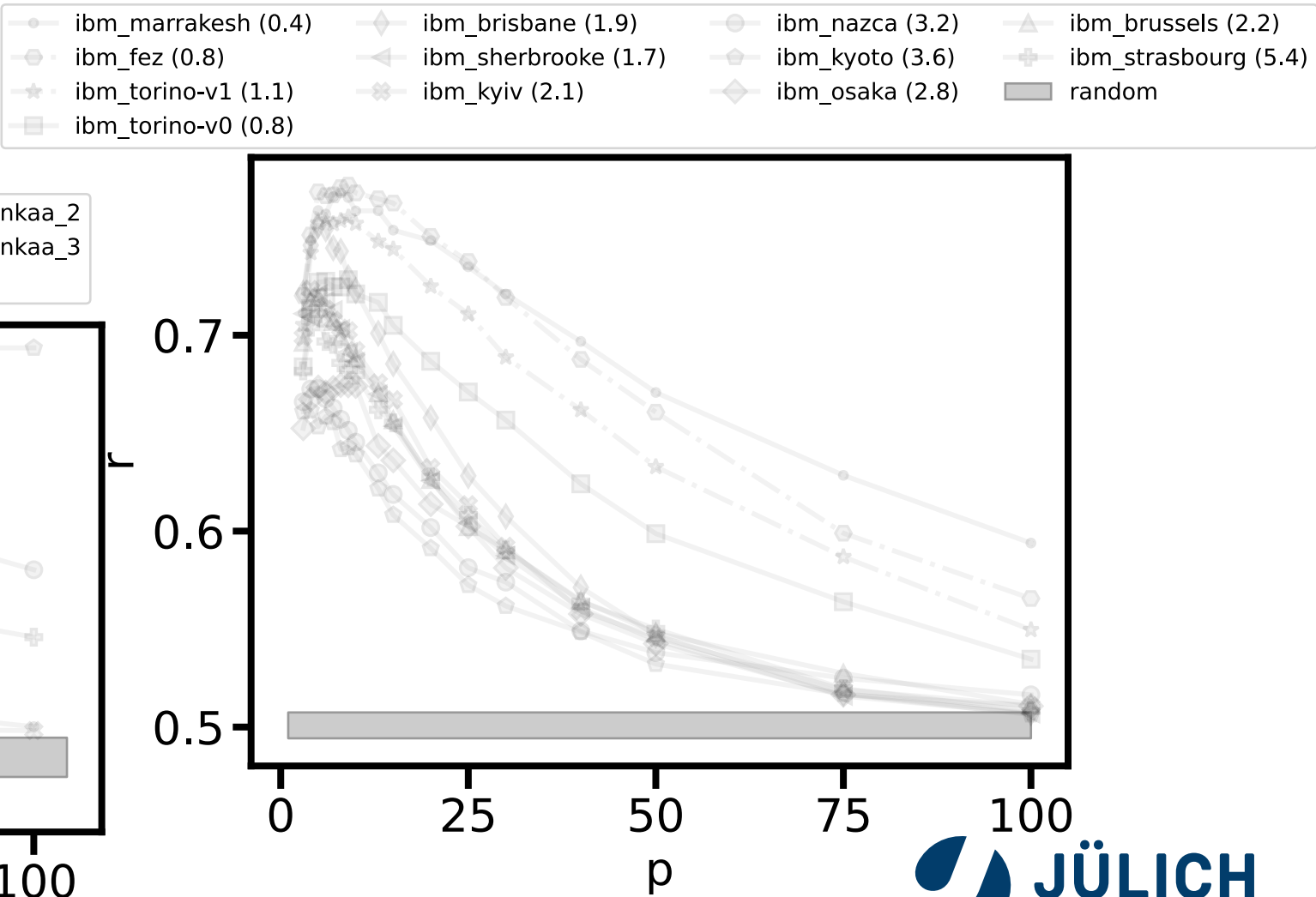
LR-QAOA on a 1D-Chain graph



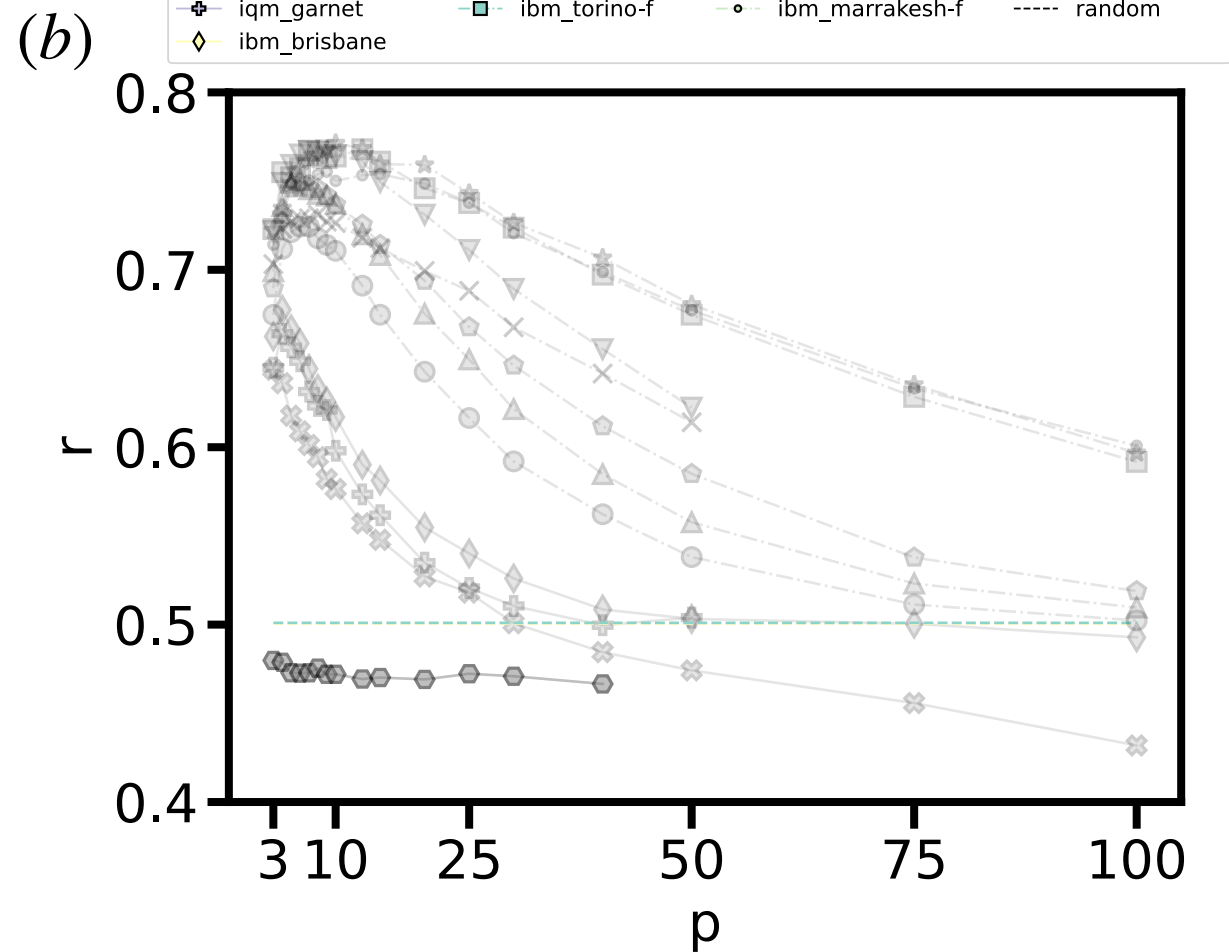
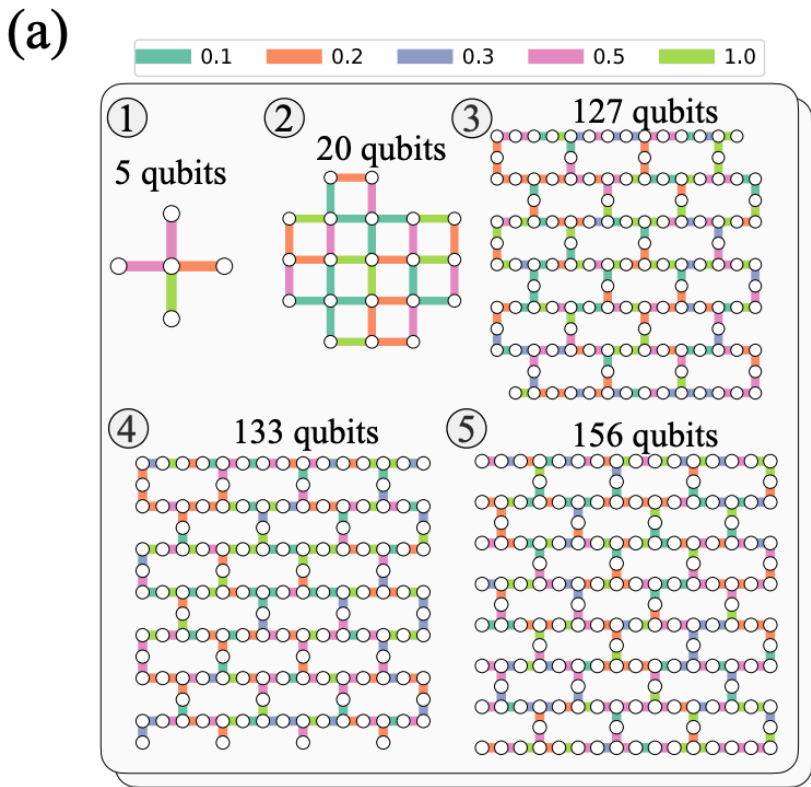
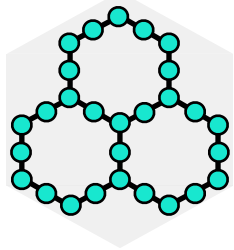
Performance on the best 5-qubit 1D chain experiment, different QPUs



Performance on a 100-qubit 1D chain experiment. IBM QPUs (EPLG)

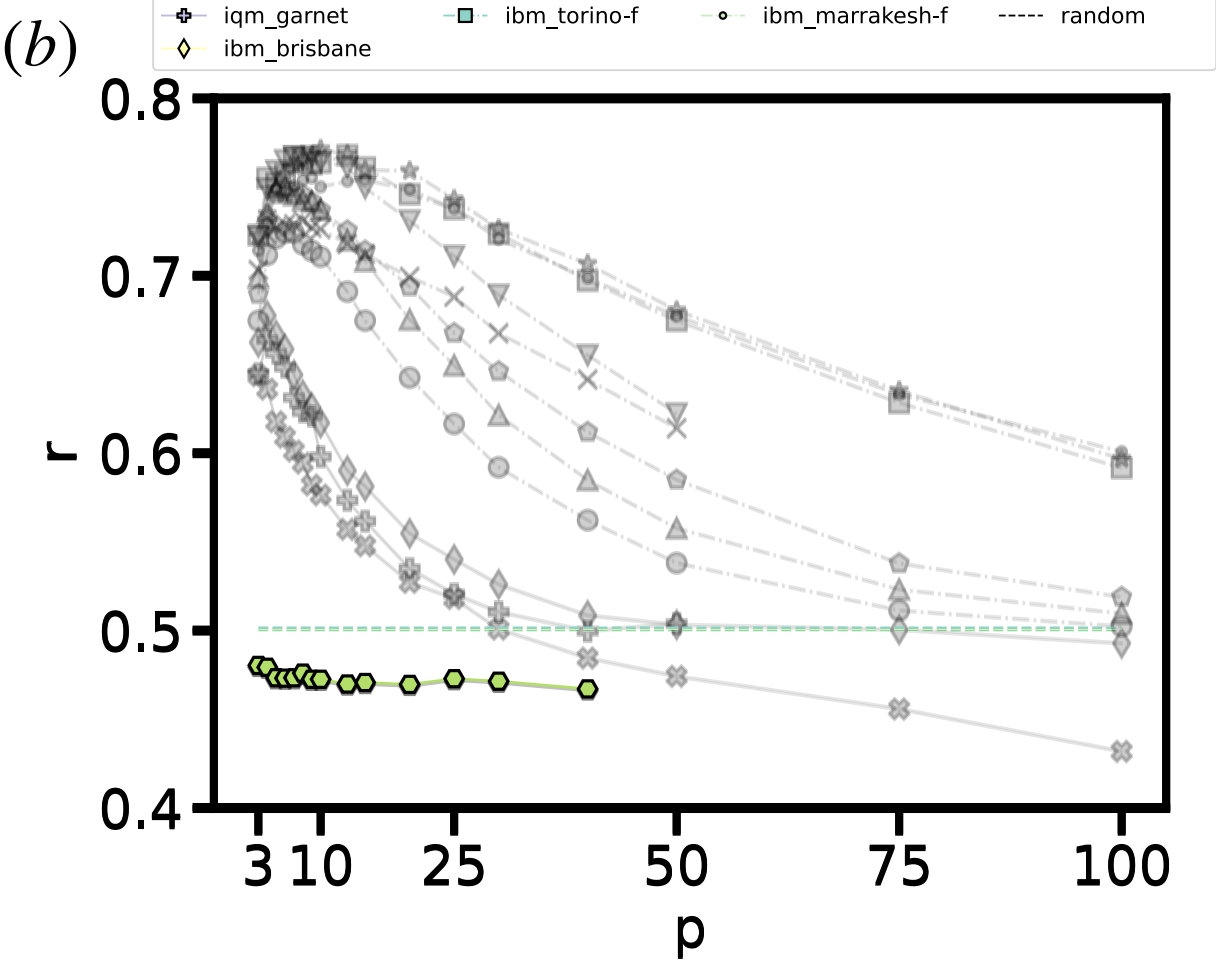
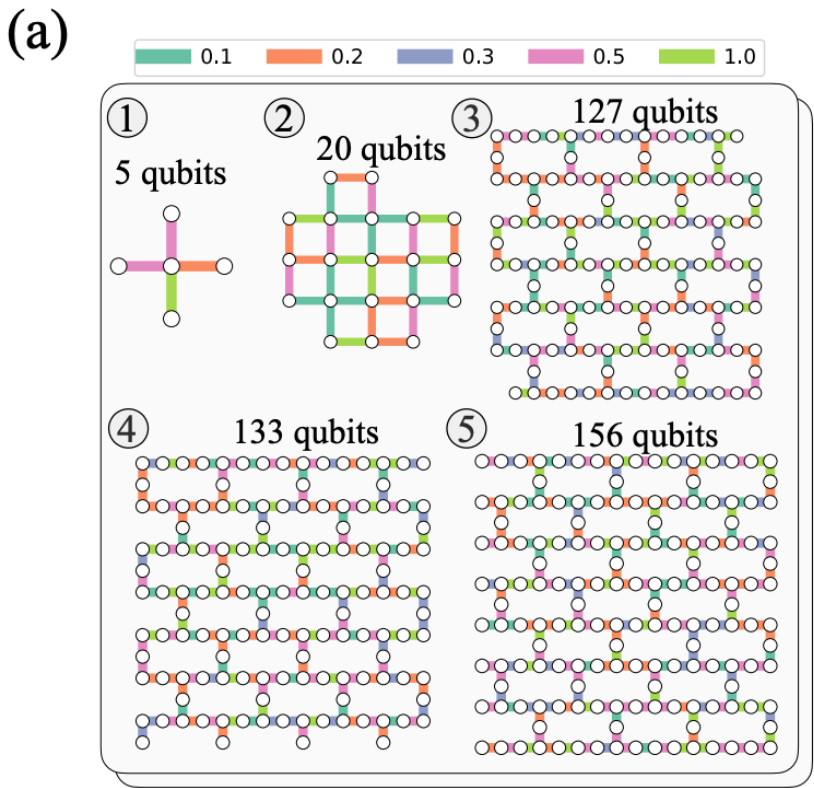
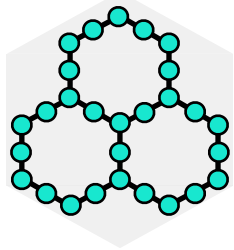


LR-QAOA on a Native layout graph



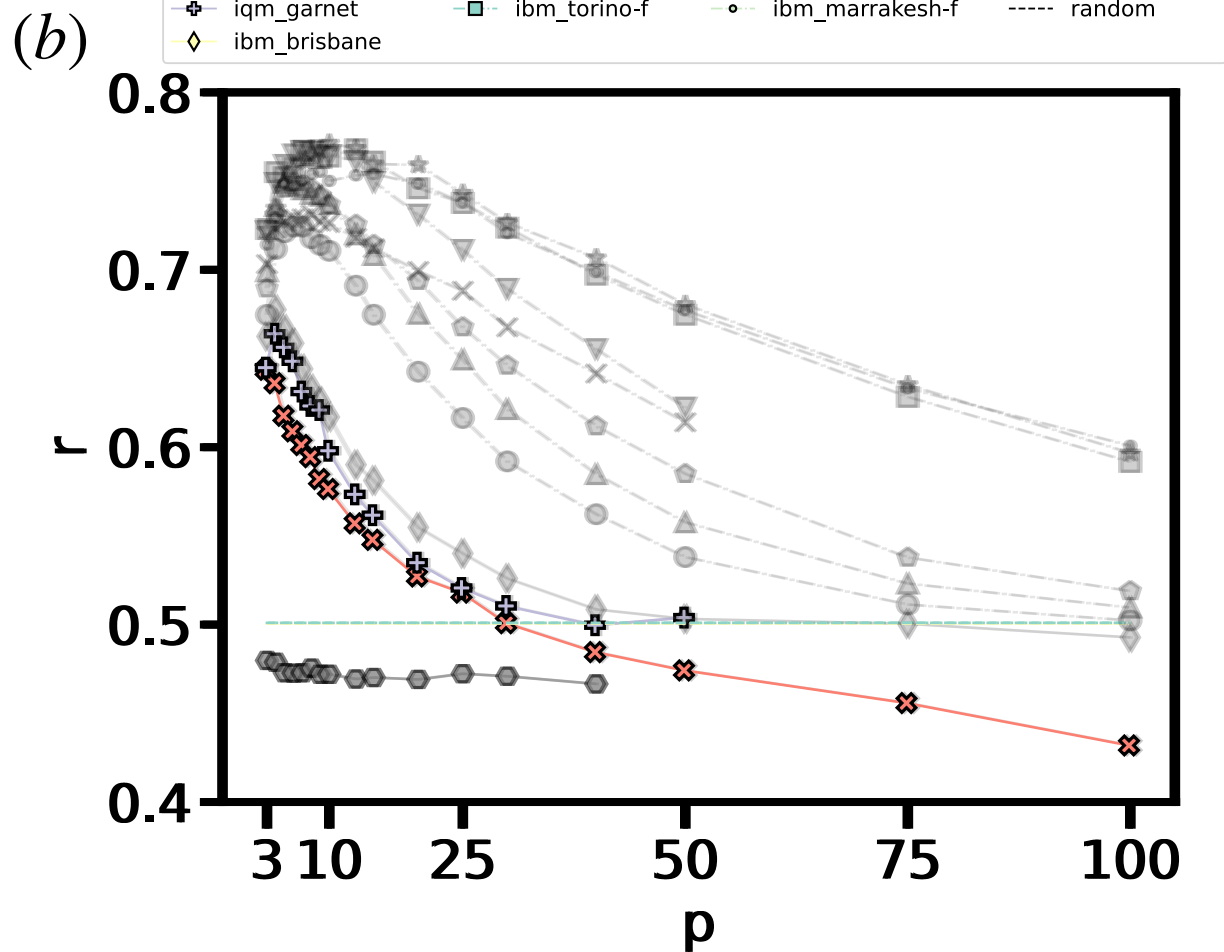
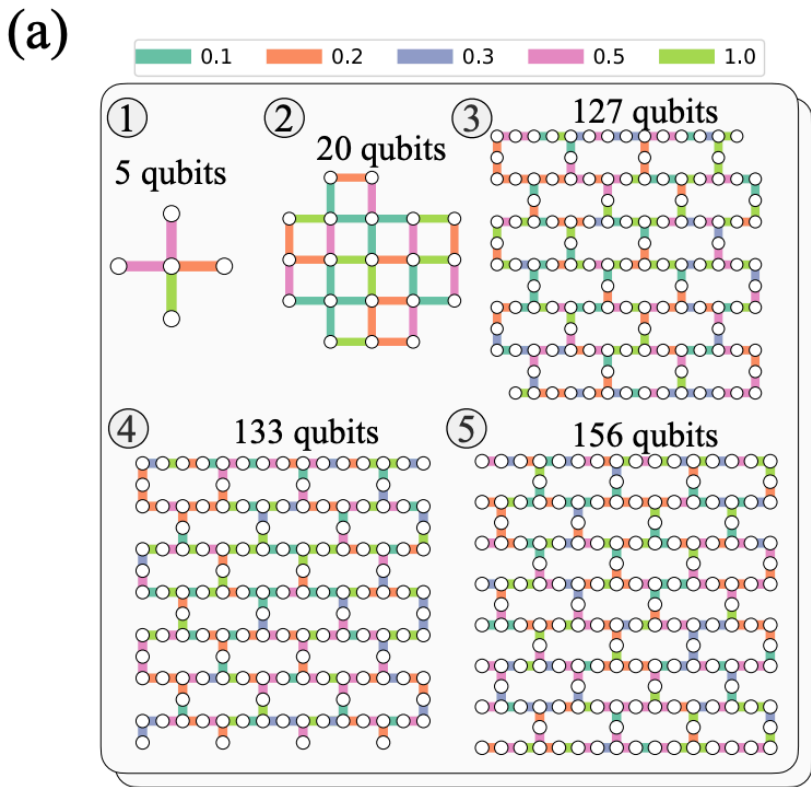
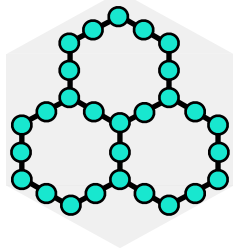
(a) Different QPUs topologies
(b) Performance on different devices

LR-QAOA on a Native layout graph



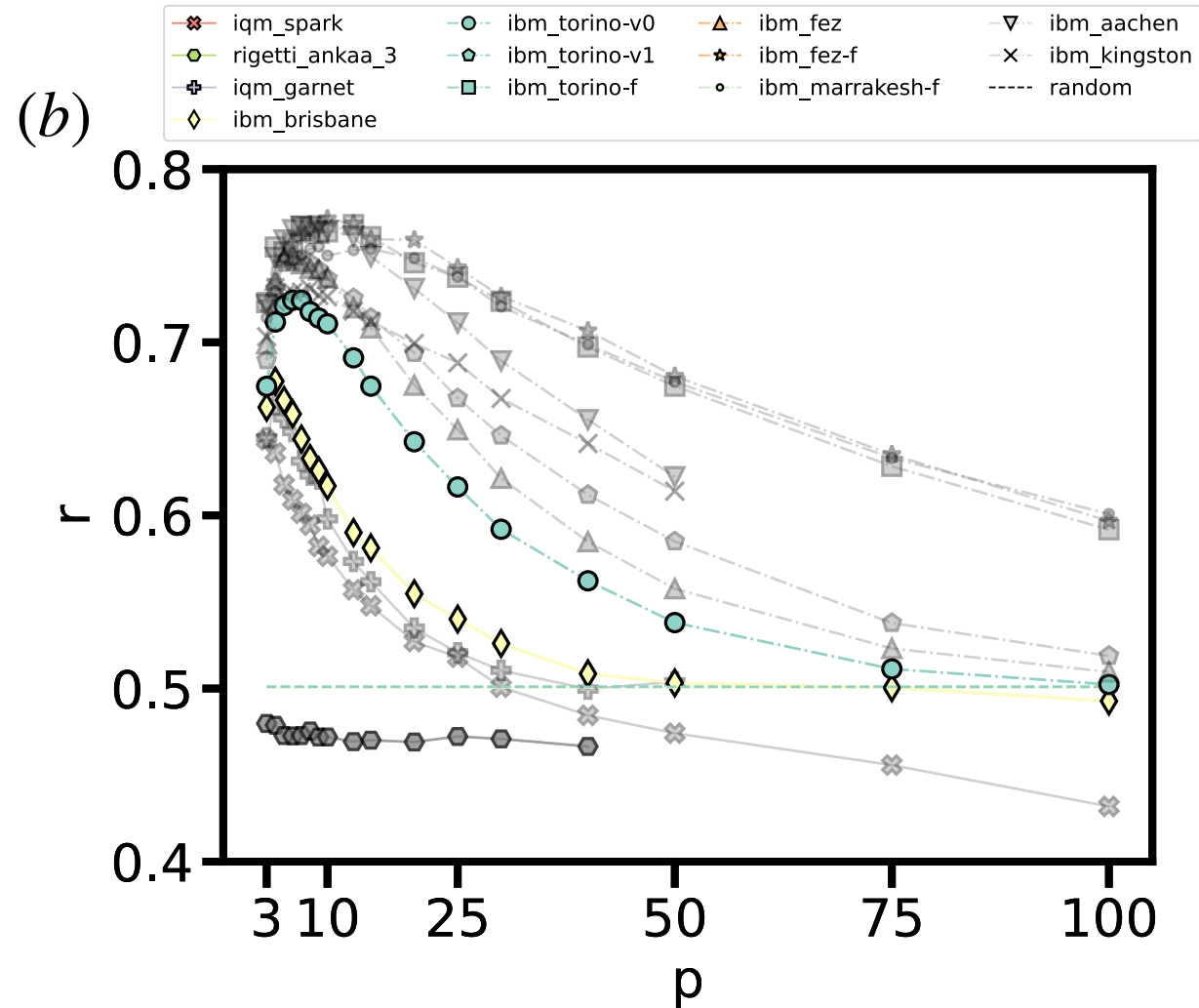
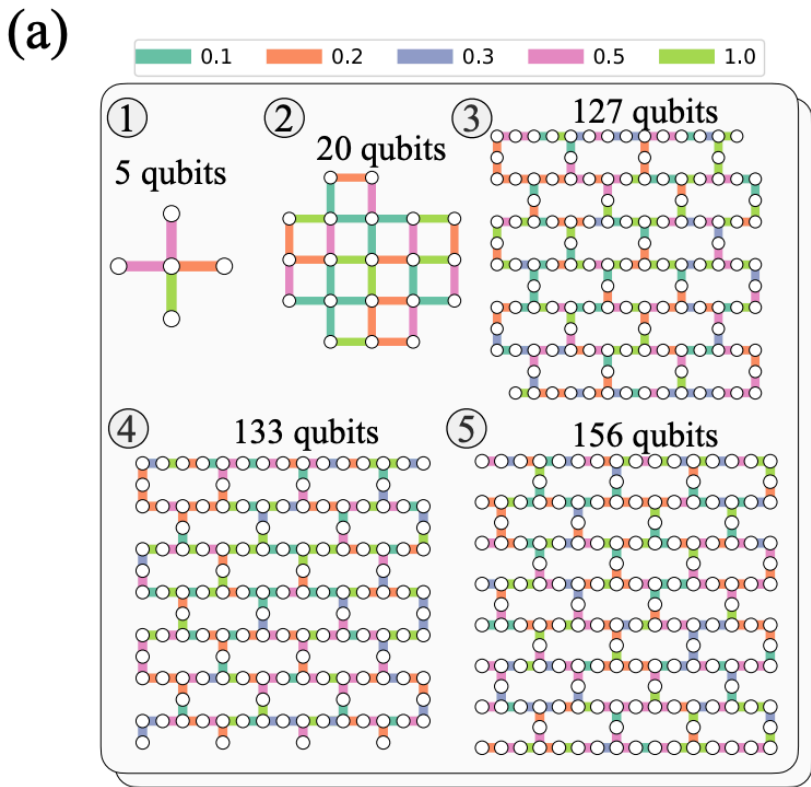
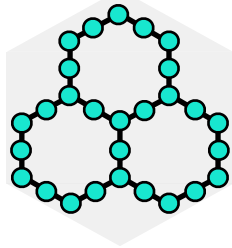
(a) Different QPUs topologies
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LR-QAOA on a Native layout graph



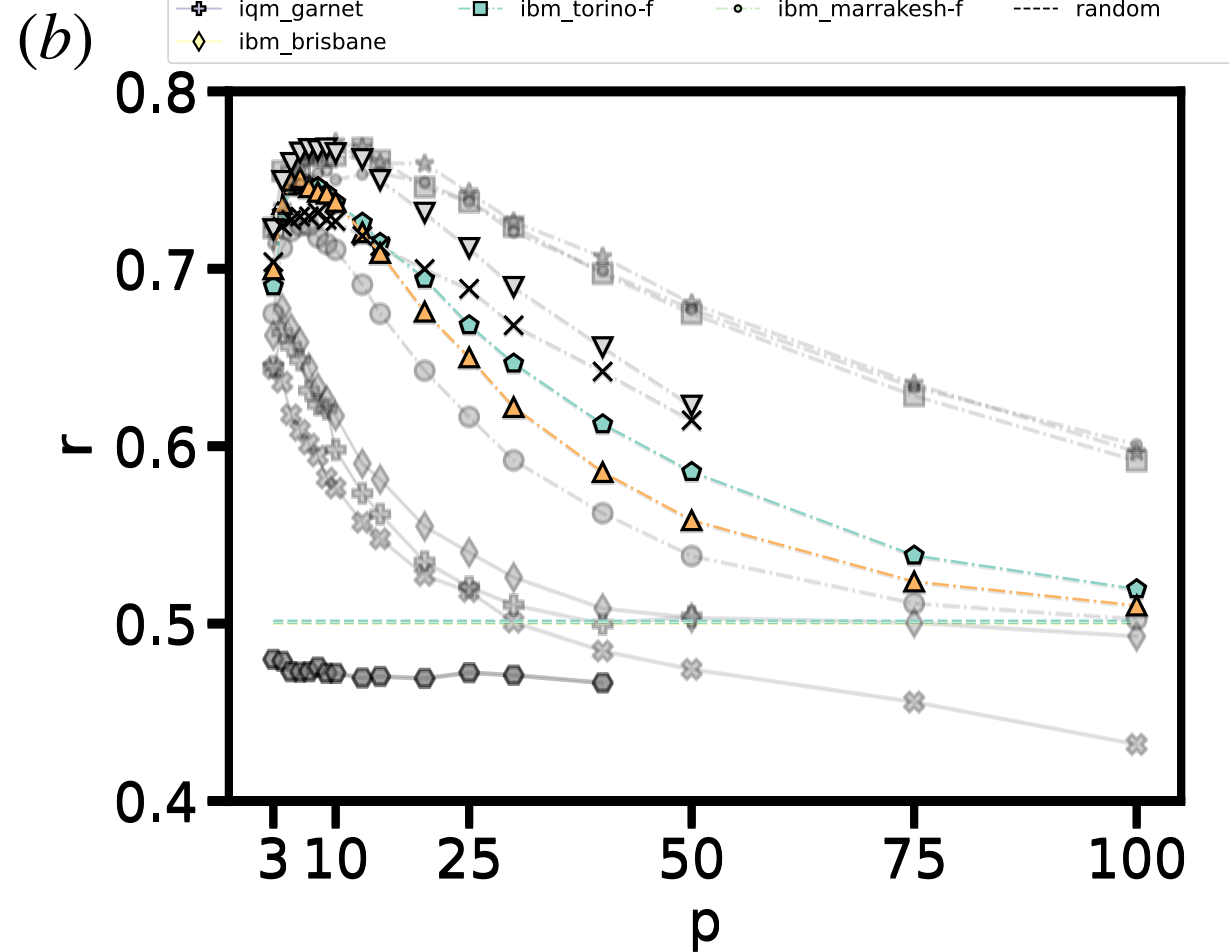
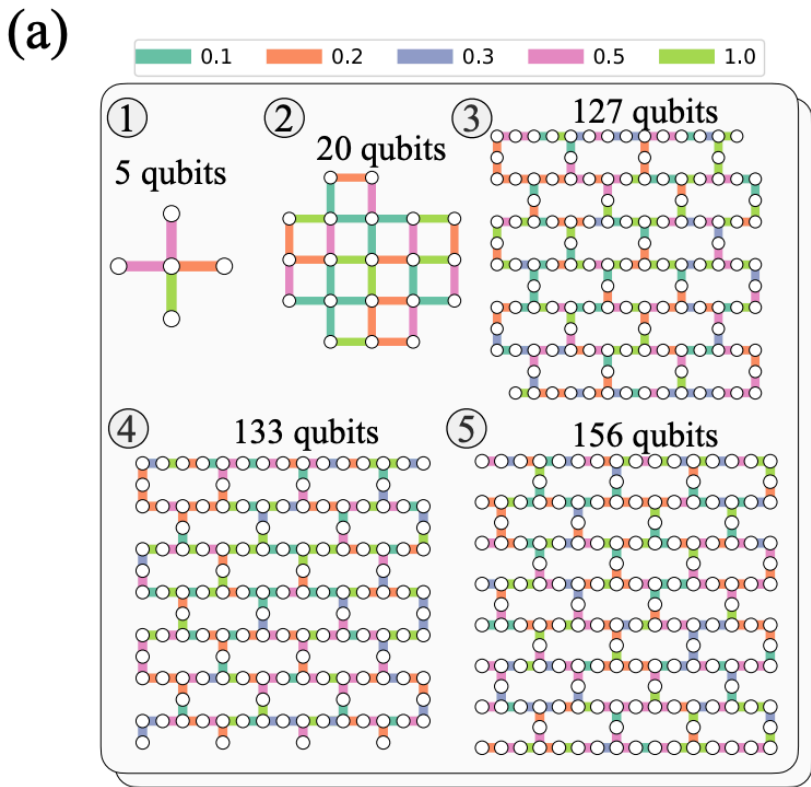
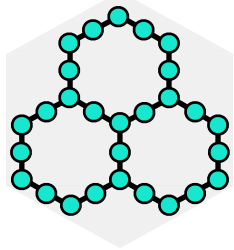
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LR-QAOA on a Native layout graph



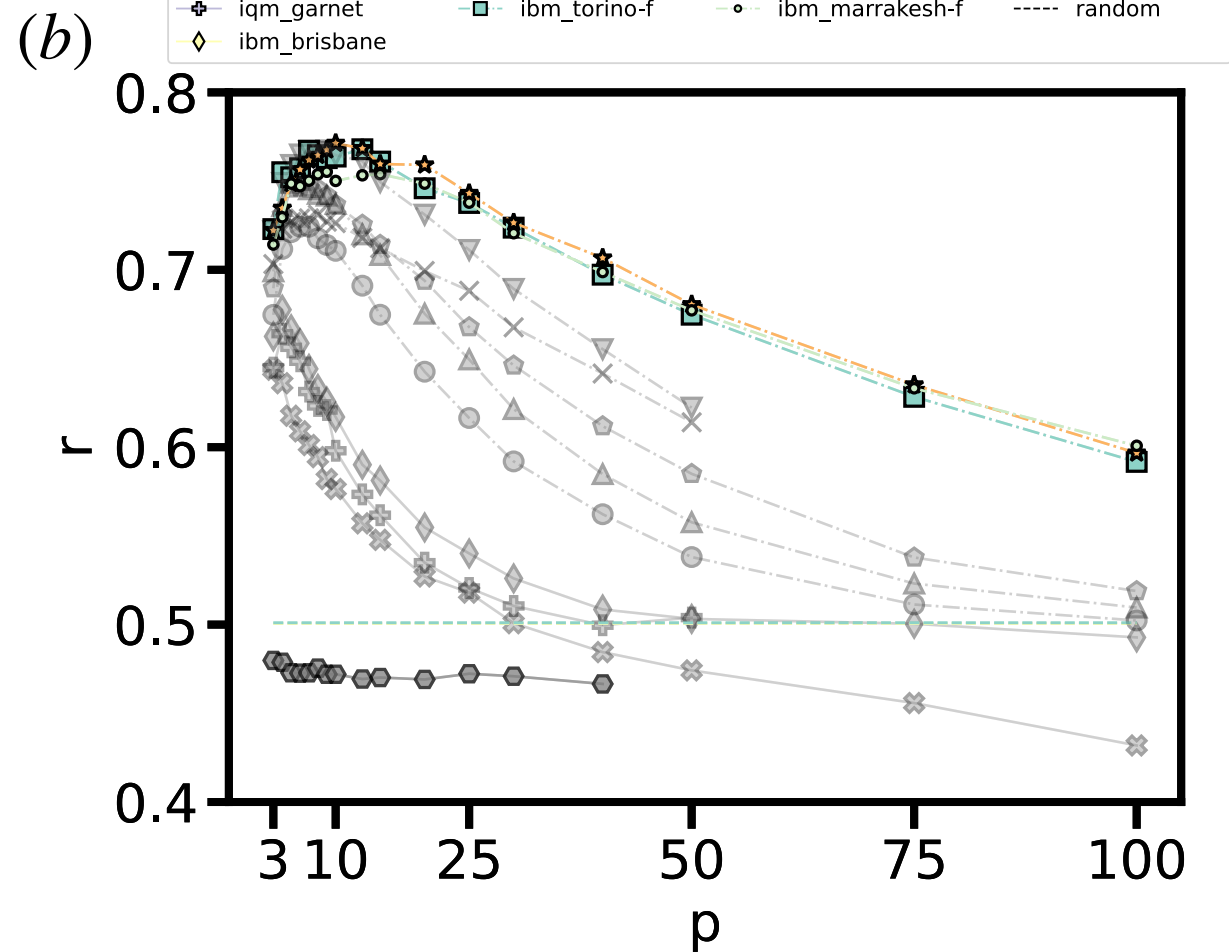
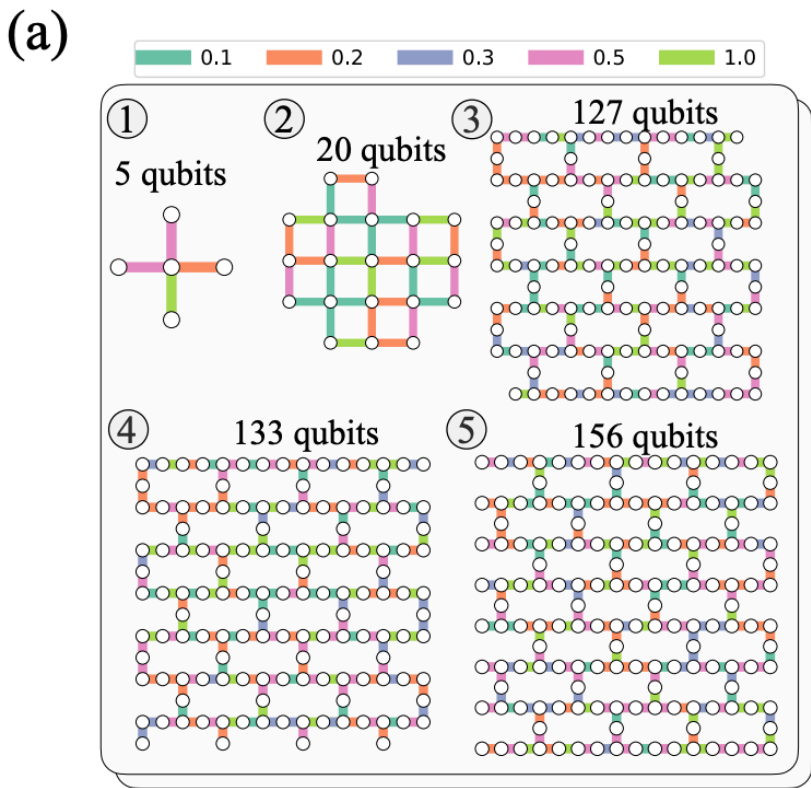
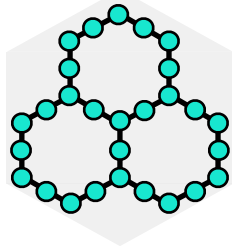
(a) Different QPUs topologies
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LR-QAOA on a Native layout graph



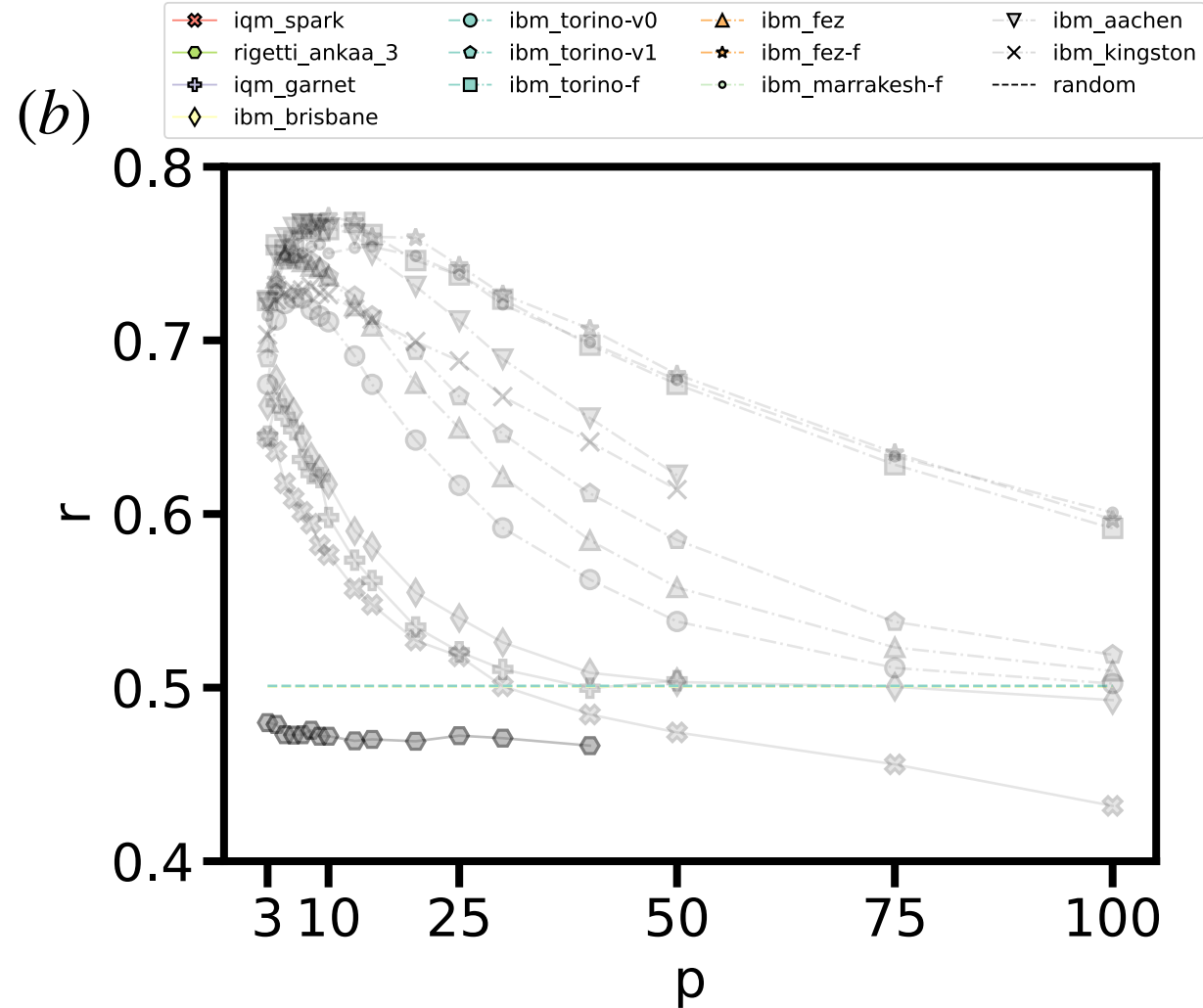
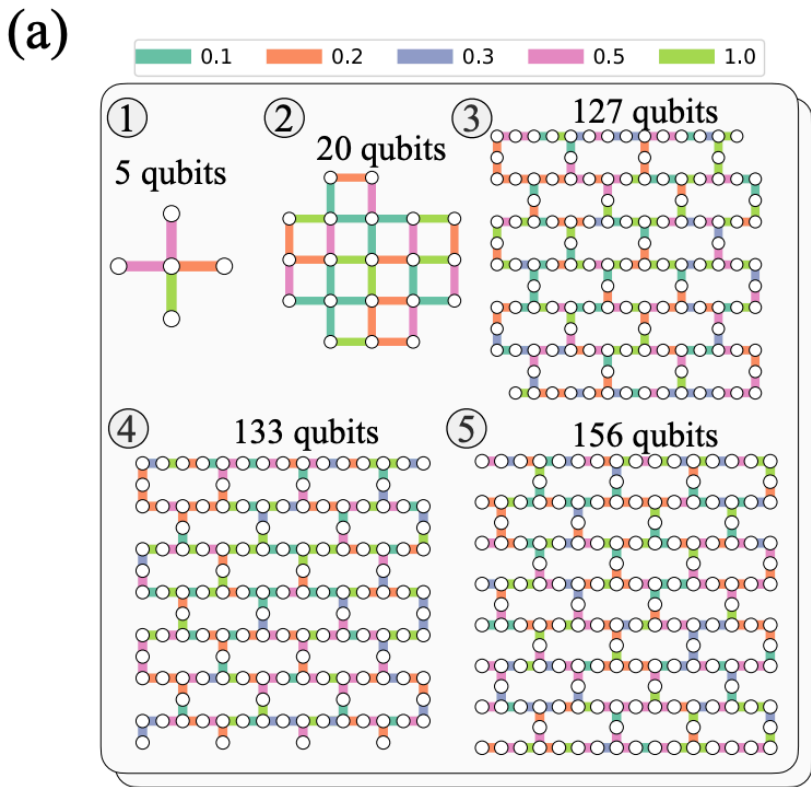
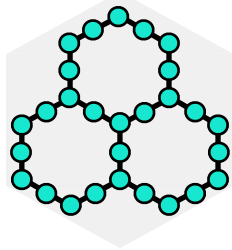
(a) Different QPUs topologies
(b) Performance on different devices

LR-QAOA on a Native layout graph



(a) Different QPUs topologies
(b) Performance on different devices

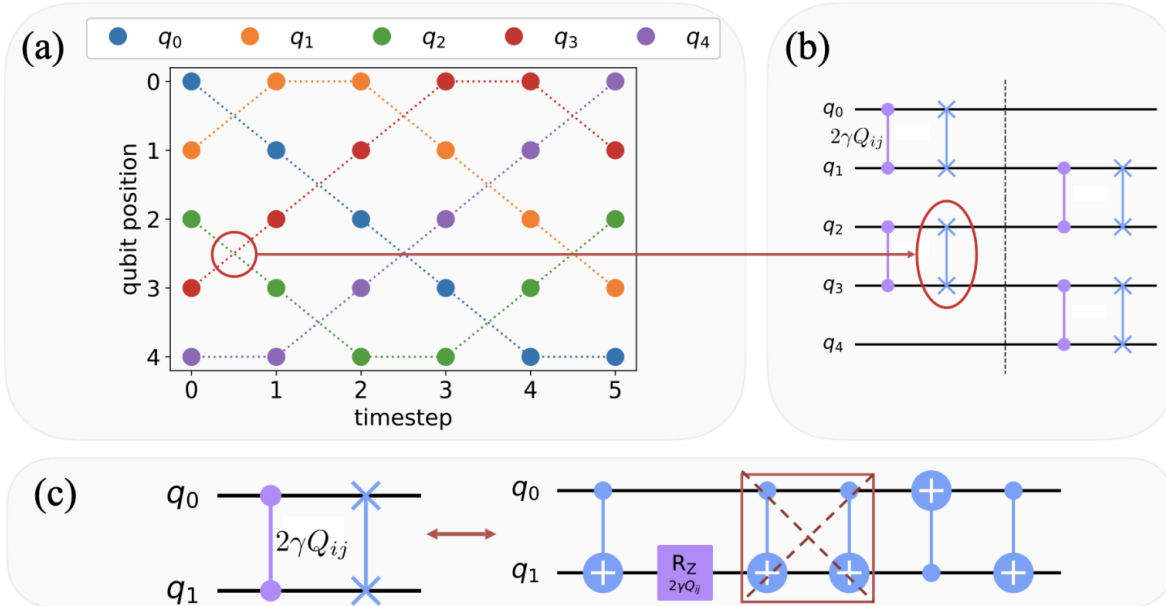
LR-QAOA on a Native layout graph



(a) Different QPUs topologies
(b) Performance on different devices

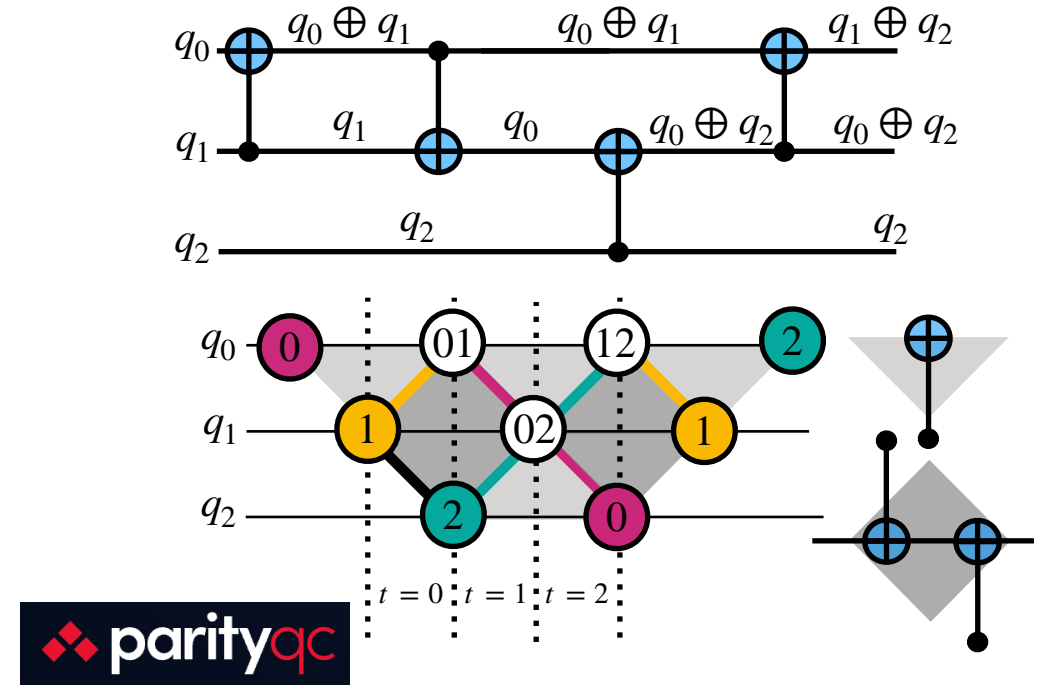
From a fixed layout to a fully connected QPUs

SWAP networks



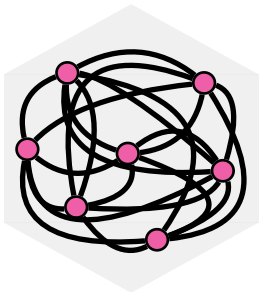
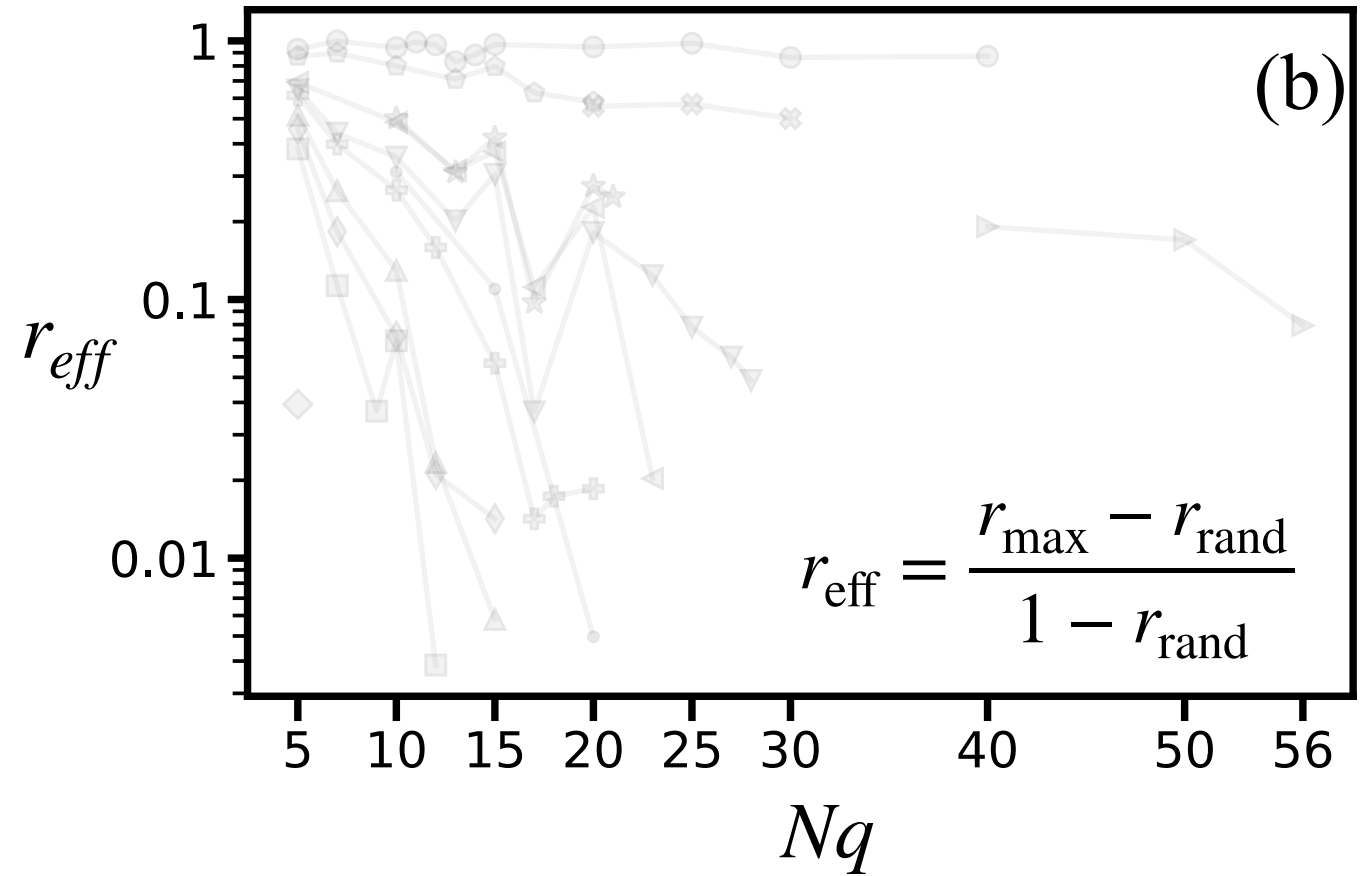
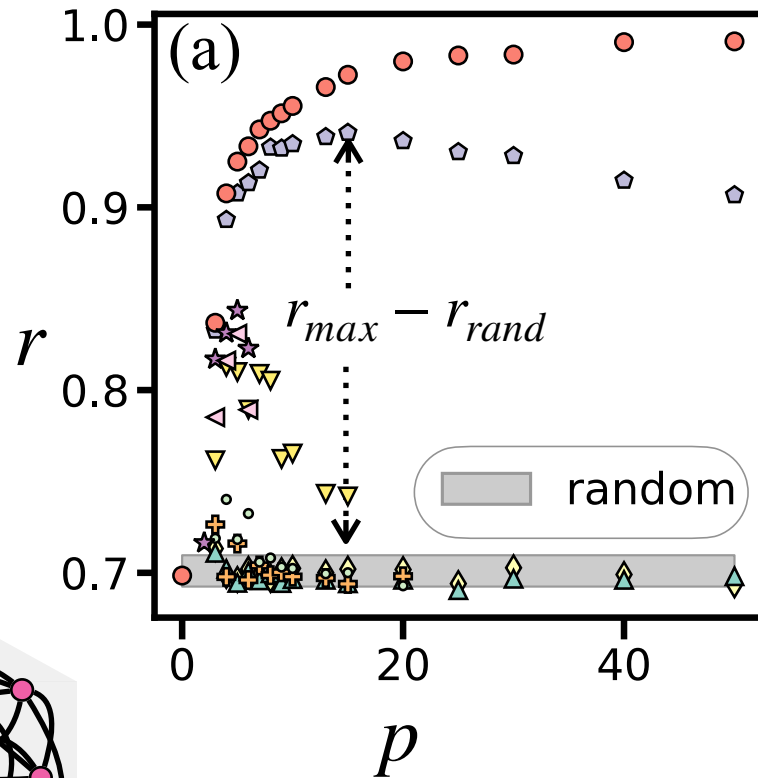
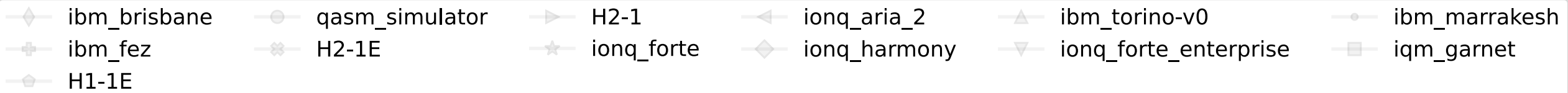
Using a swap strategy we can convert a 1D-Chain graph into a fully connected graph. We need 3 times more 2-qubit gates to implement this protocol.

Parity Twine Chain



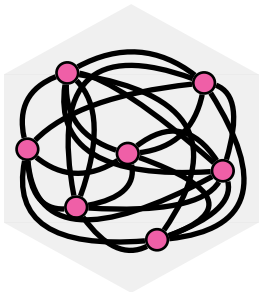
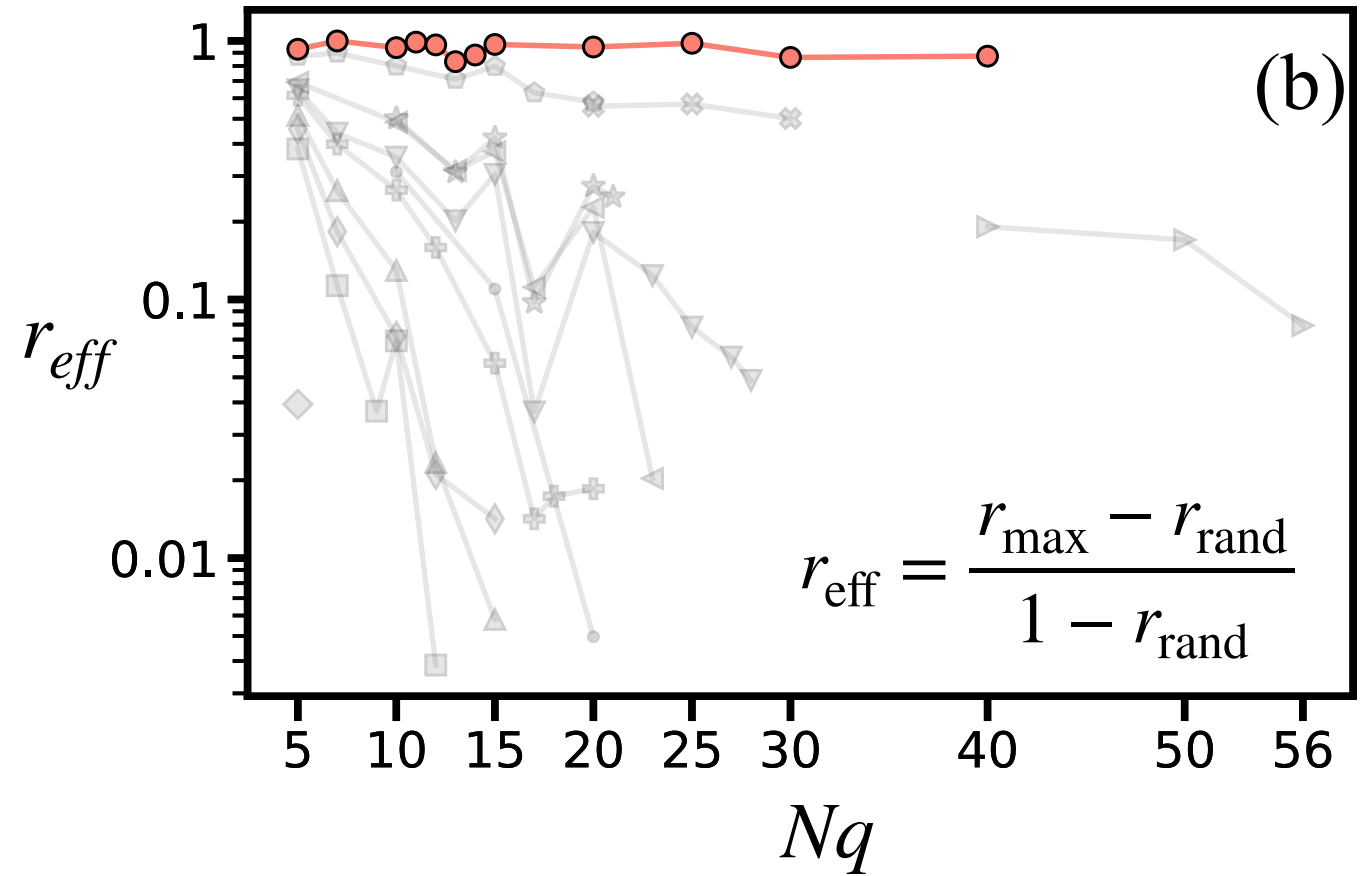
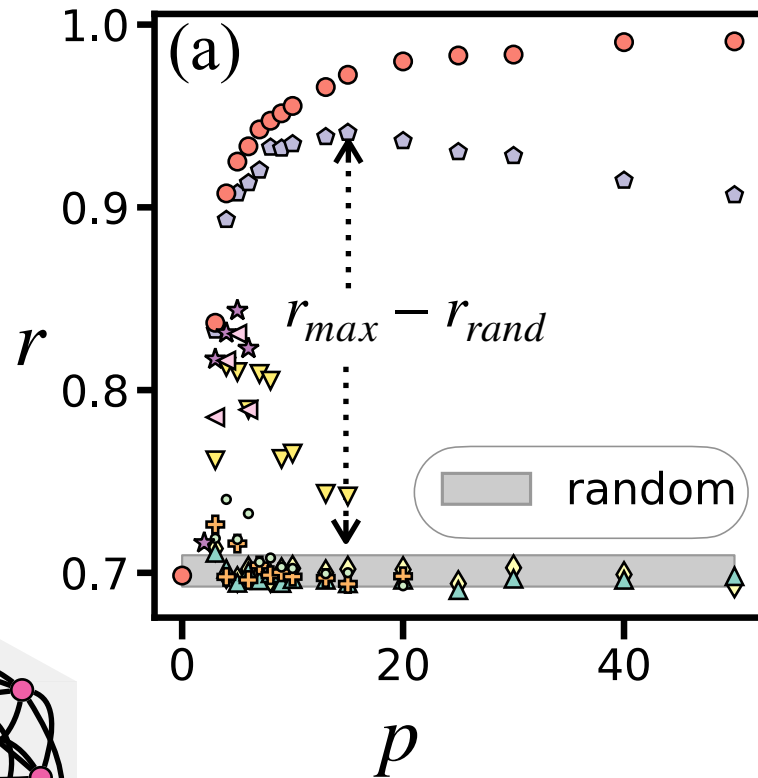
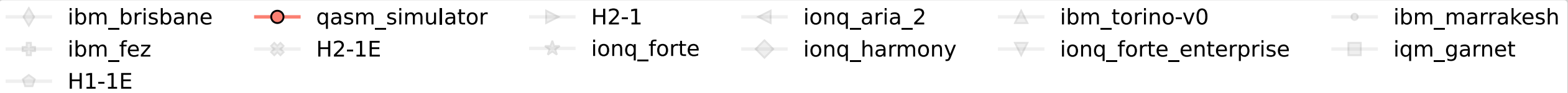
Schematic representation of the PTC encoding. (a) Circuit model to get different parities. (b) Graphic representation of the PTC in a 1D chain. Using this diagram, the equivalent building blocks for the CNOT gates are shown at the right.

LR-QAOA on Fully Connected (FC) problems



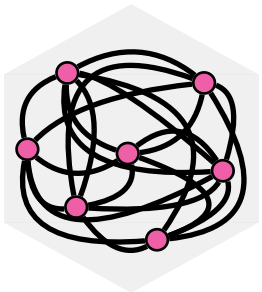
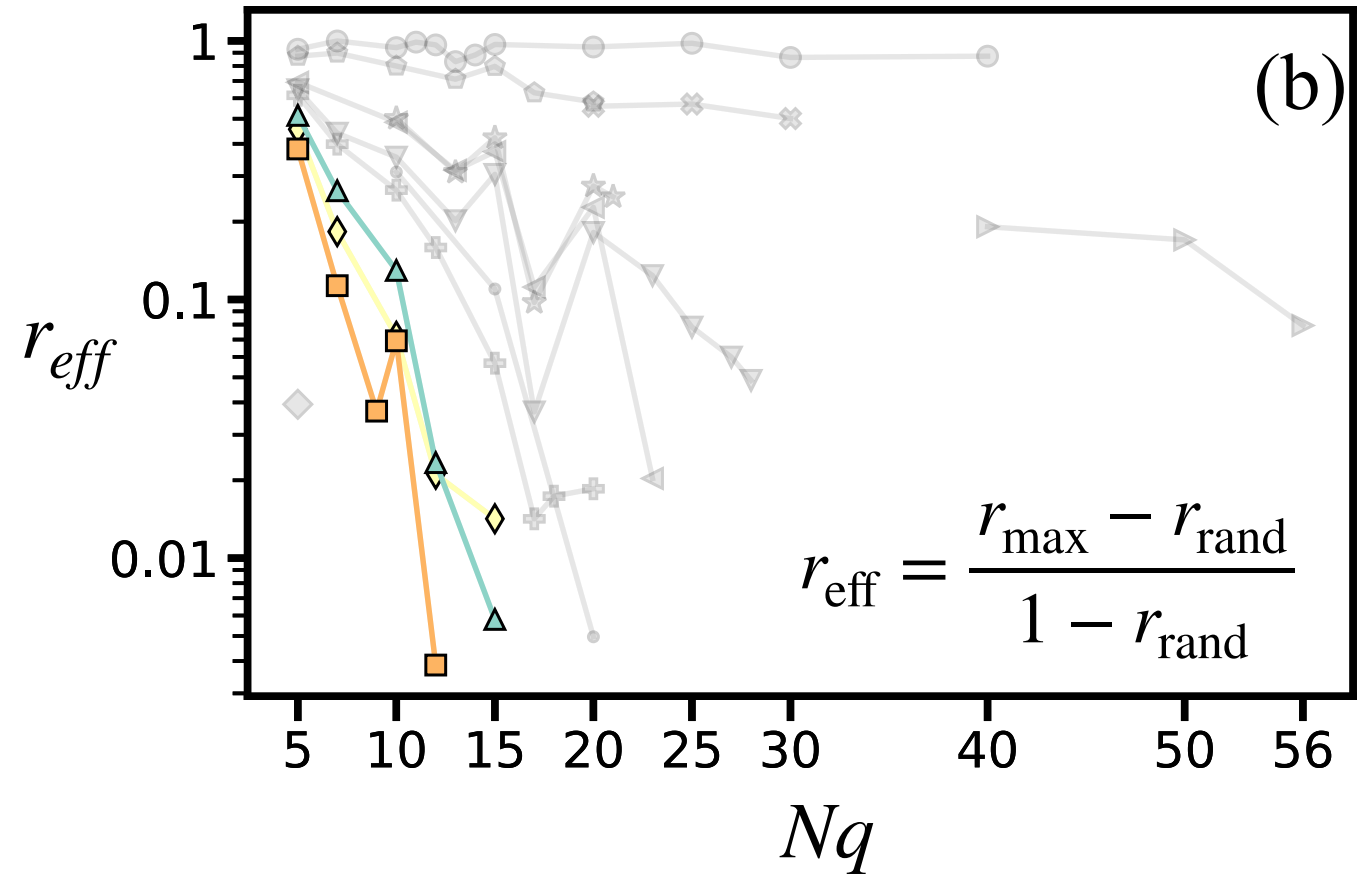
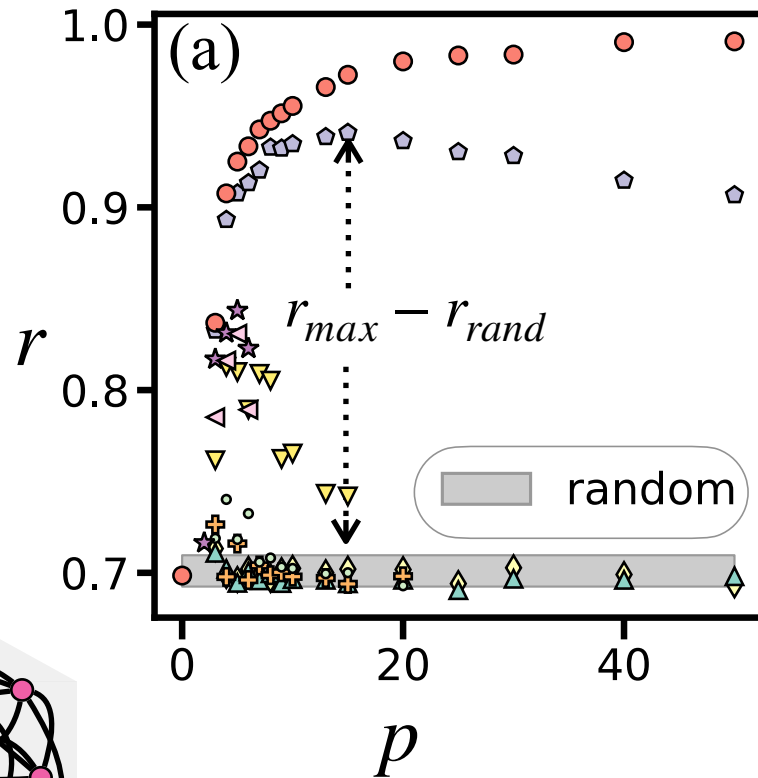
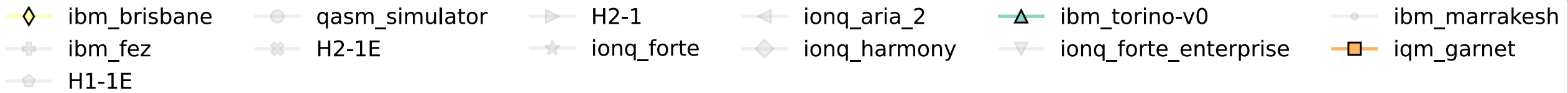
(a) FC for a 15-qubit Weighted MaxCut problem
 (b) Effective approximation ratio

LR-QAOA on Fully Connected (FC) problems



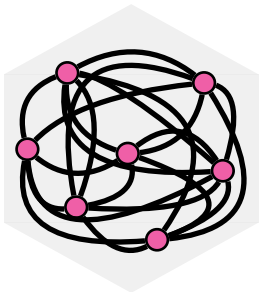
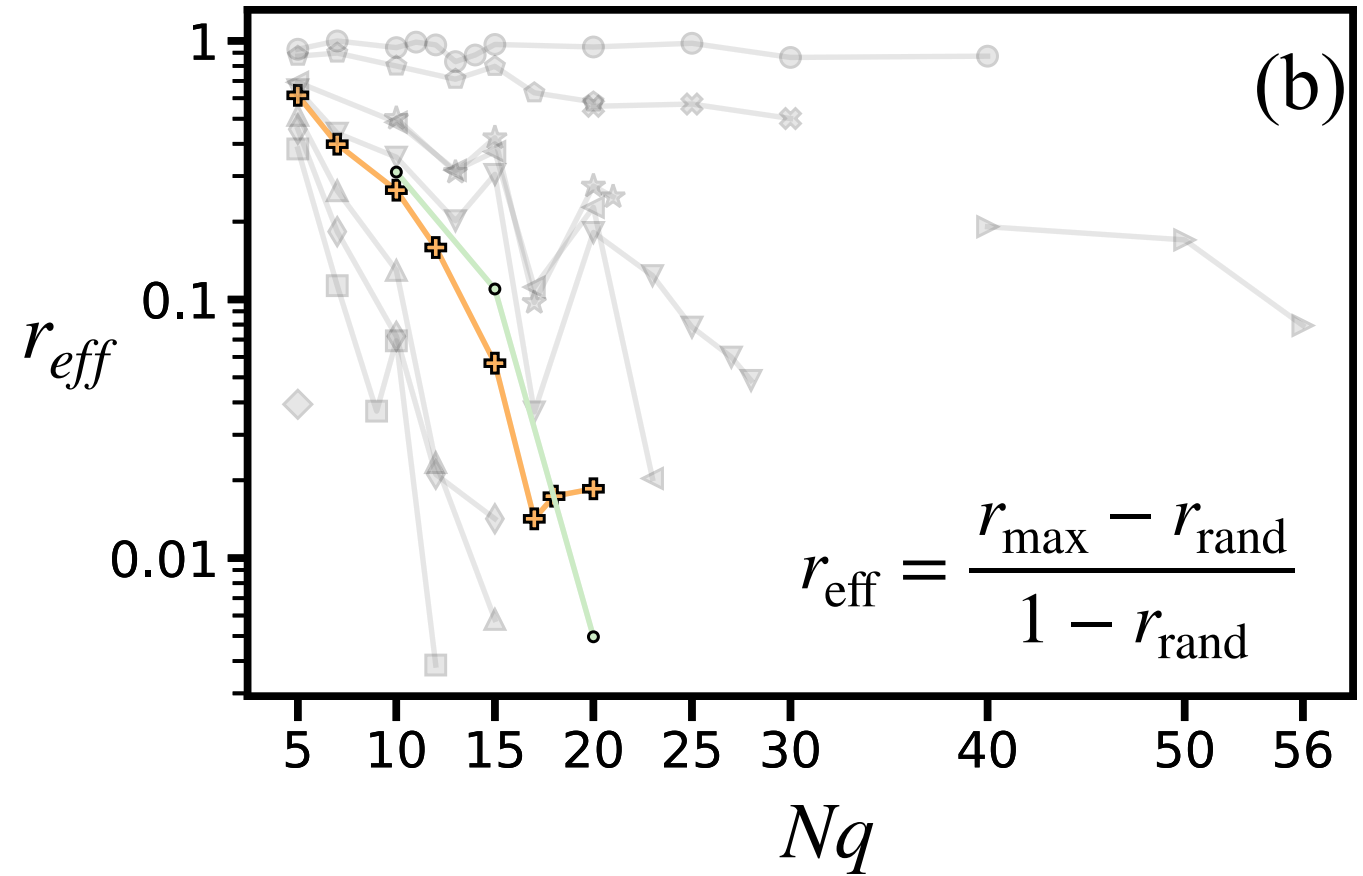
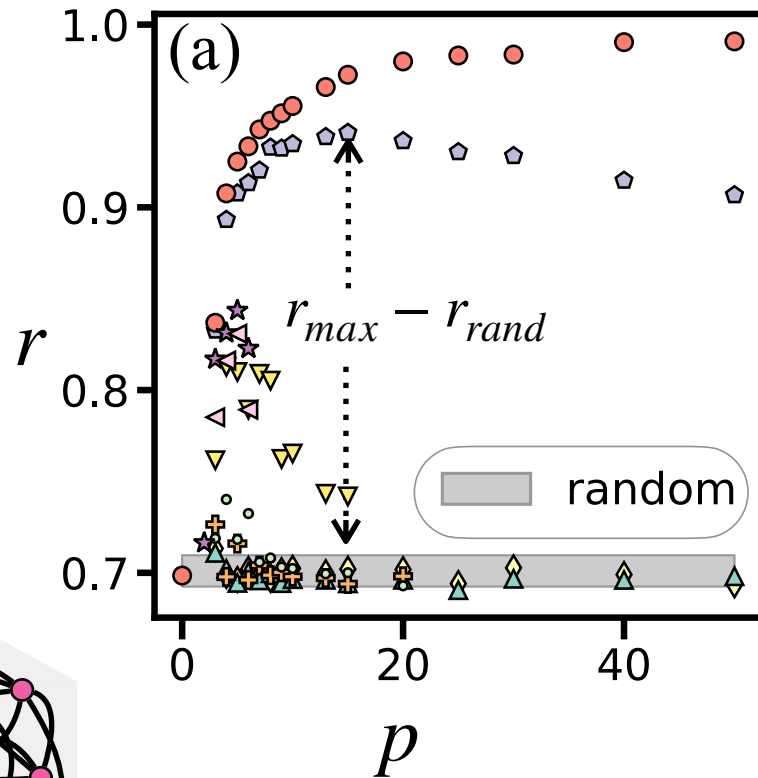
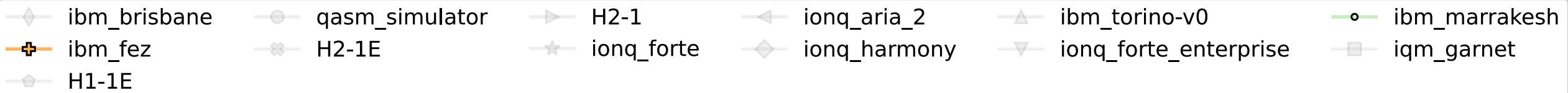
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LR-QAOA on Fully Connected (FC) problems



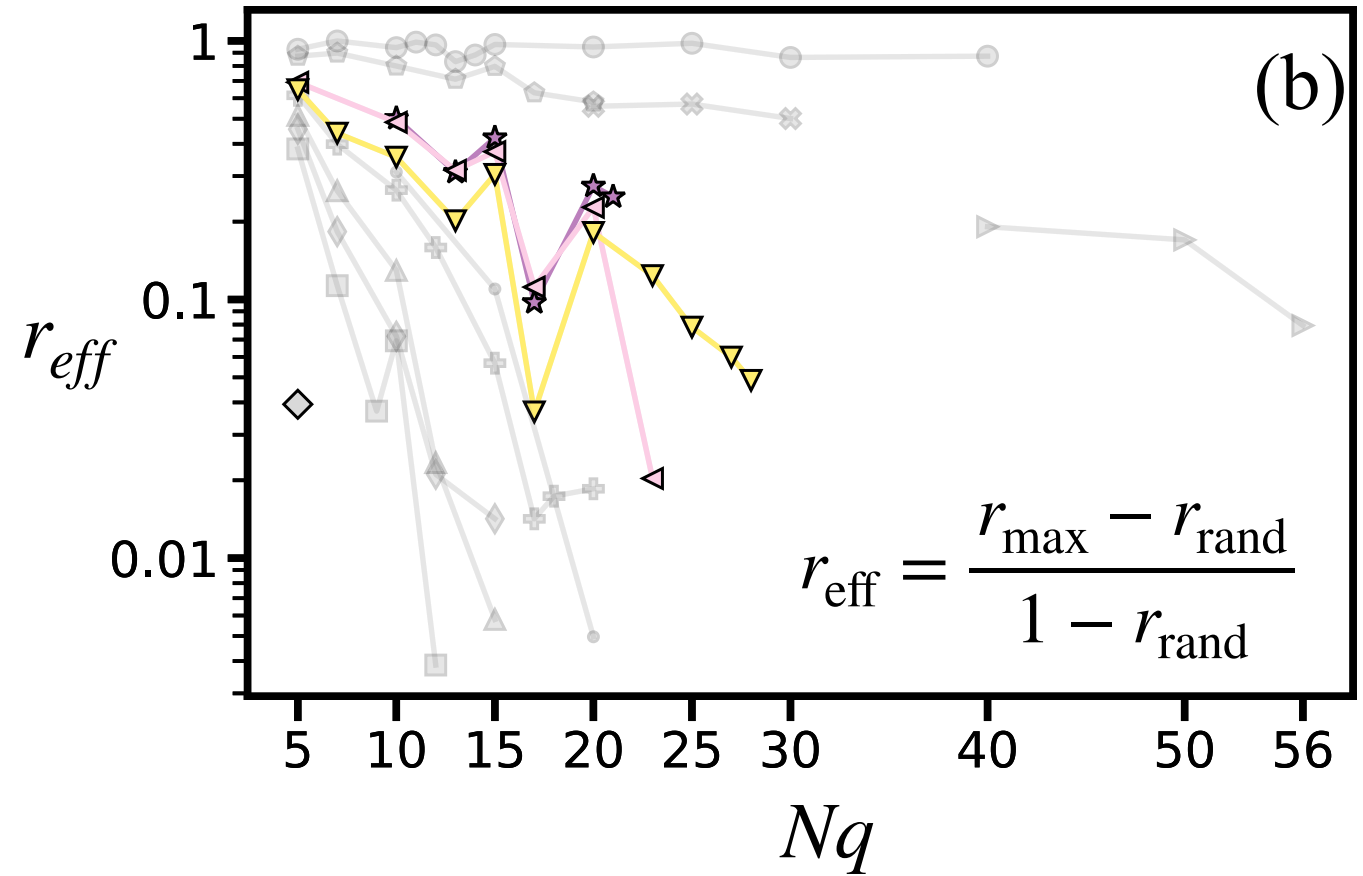
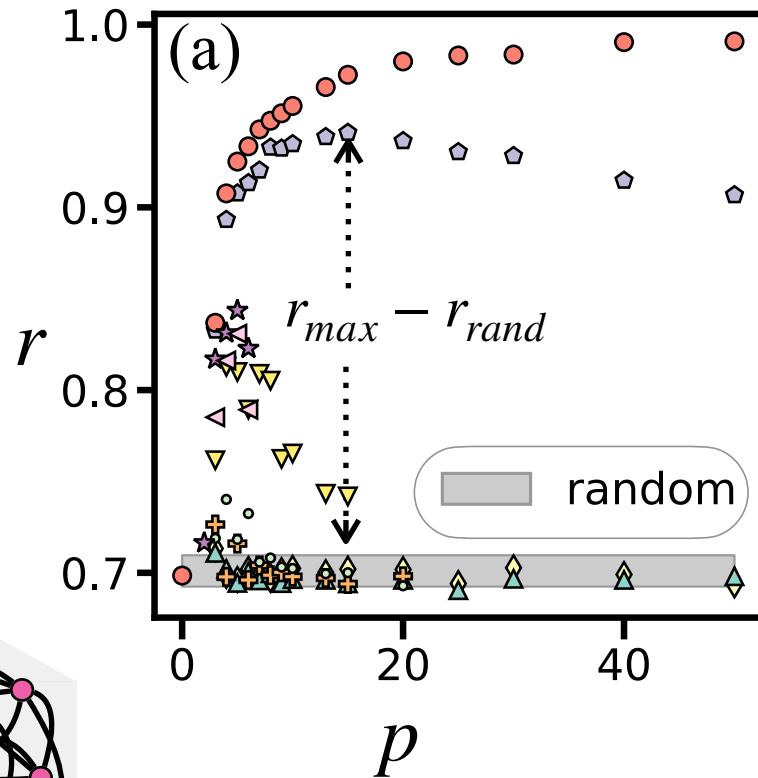
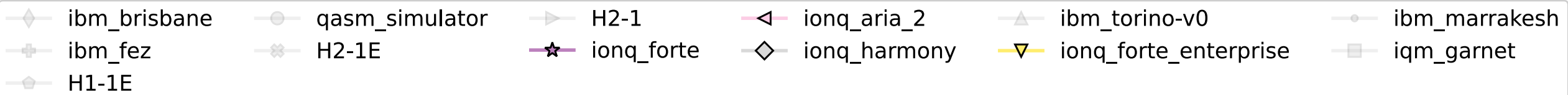
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LR-QAOA on Fully Connected (FC) problems



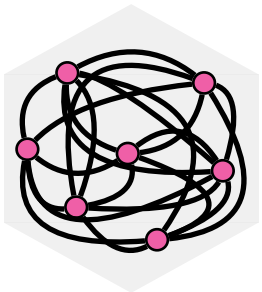
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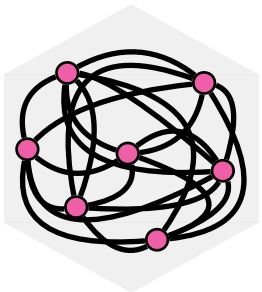
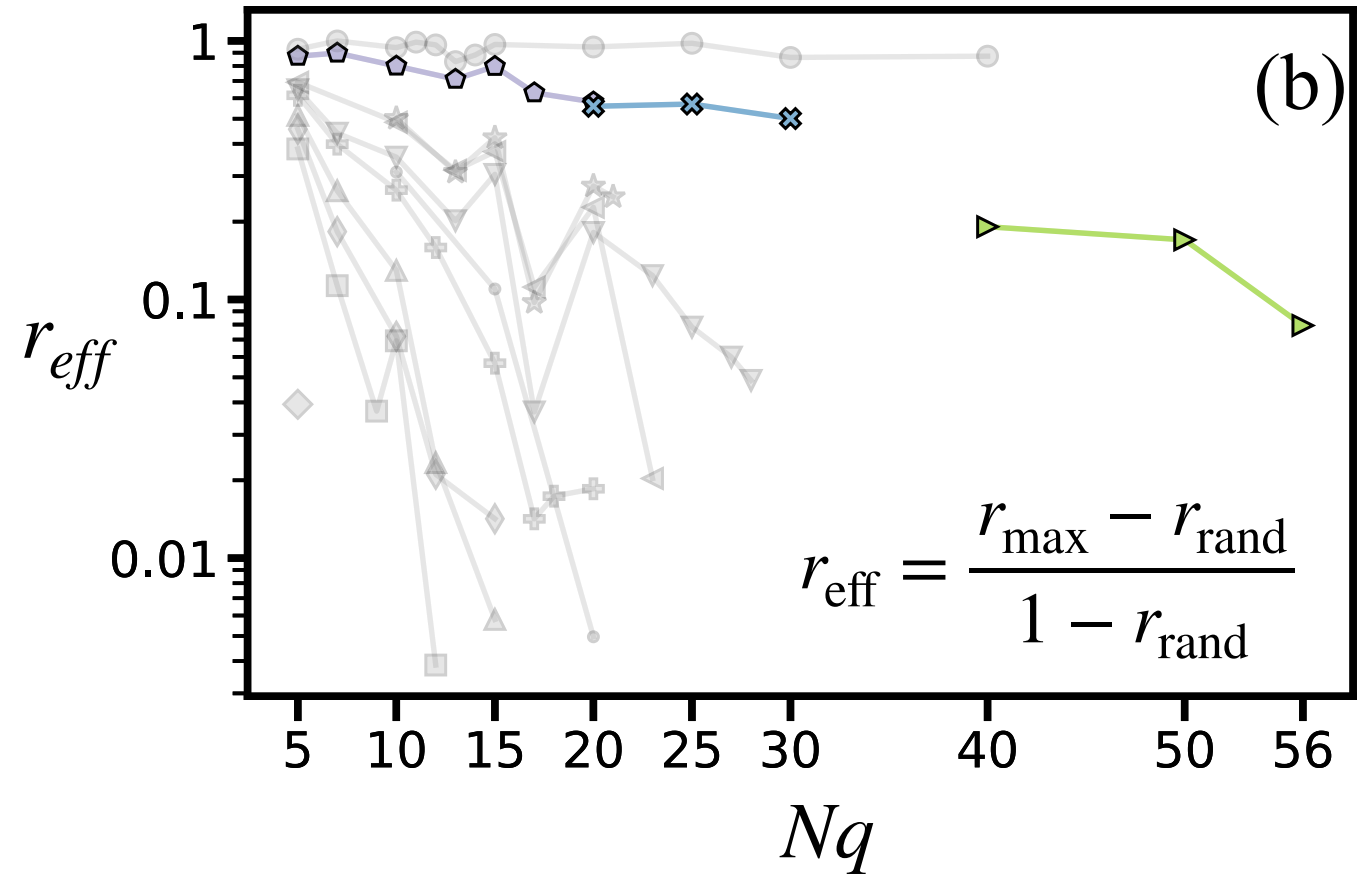
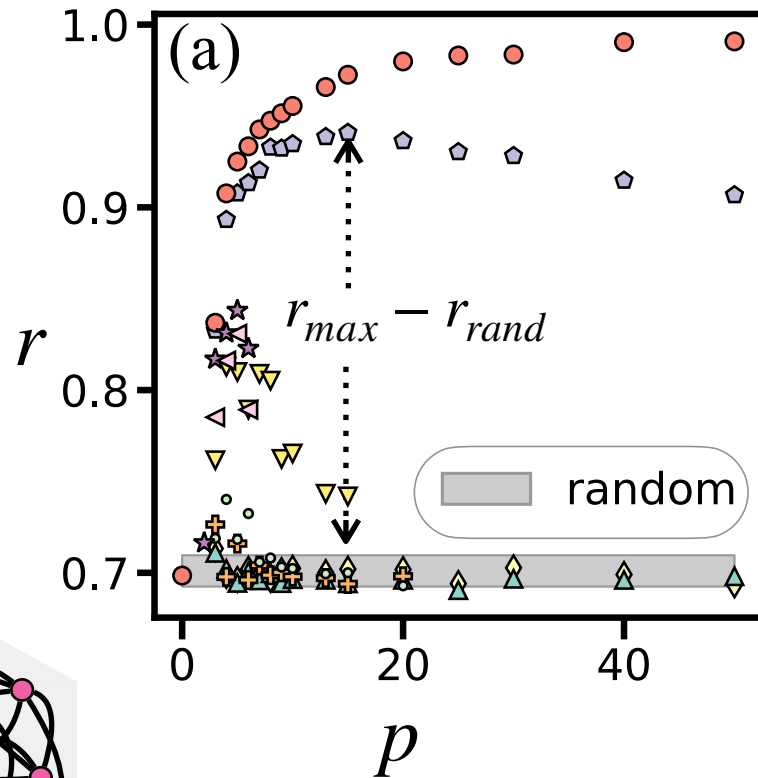
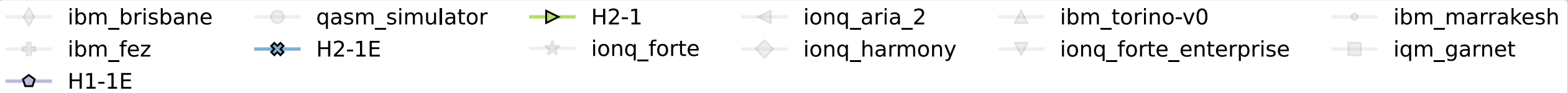


(a) FC for a 15-qubit Weighted MaxCut problem

(b) Effective approximation ratio

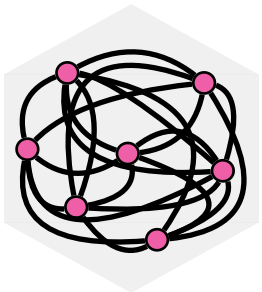
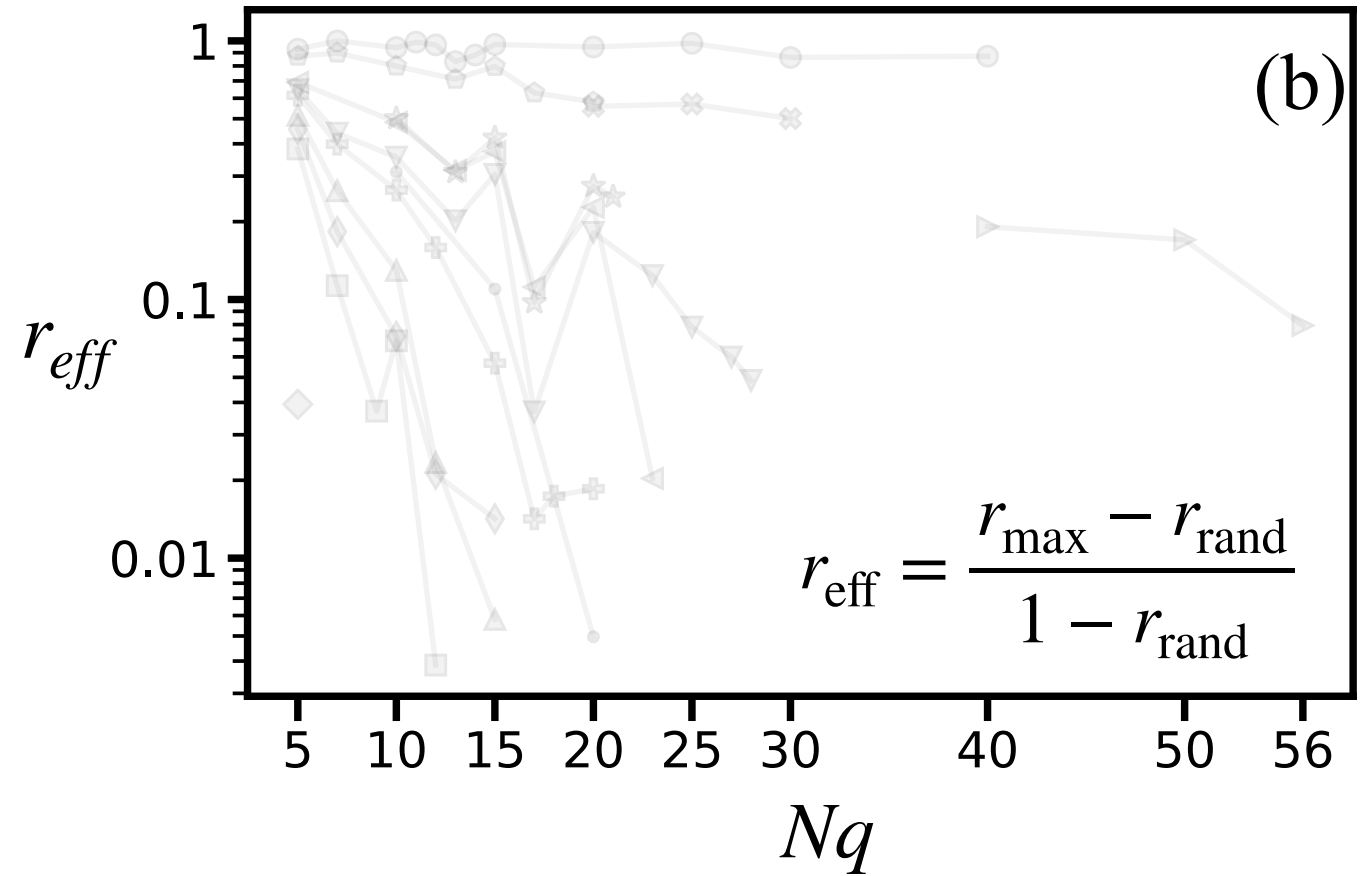
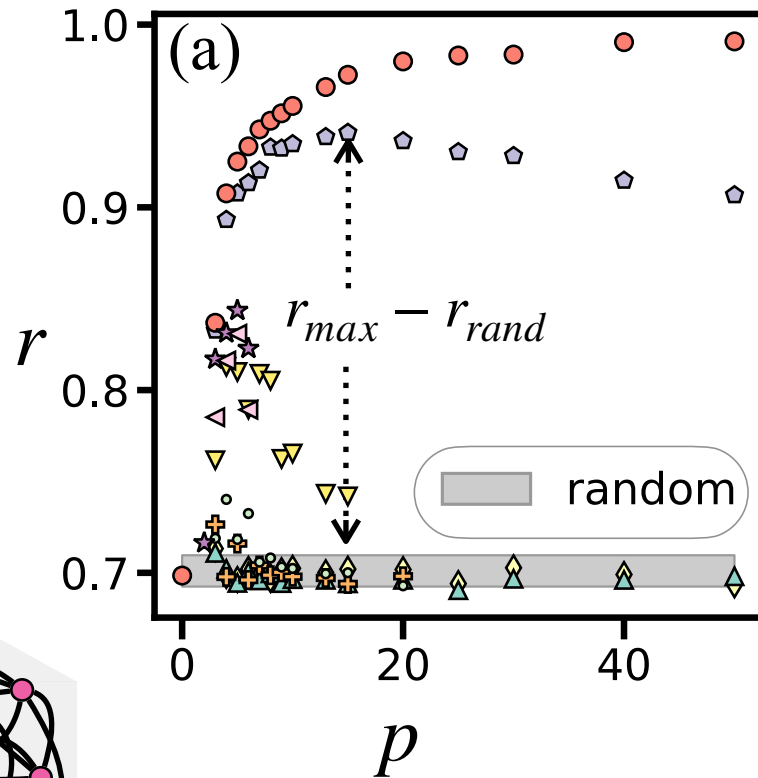
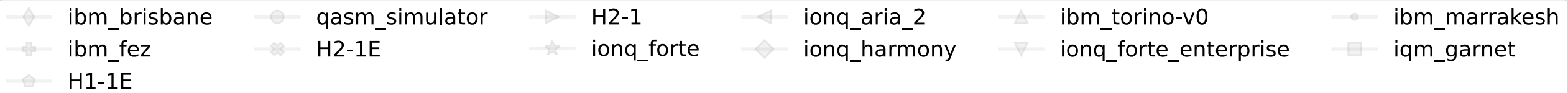


LR-QAOA on Fully Connected (FC) problems



(a) FC for a 15-qubit Weighted MaxCut problem
(b) Effective approximation ratio

LR-QAOA on Fully Connected (FC) problems



(a) FC for a 15-qubit Weighted MaxCut problem
 (b) Effective approximation ratio

Integration LR-QAOA as an open source benchmark



metriq-gym

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`metriq-gym` is a Python framework for implementing and running standard quantum benchmarks on different quantum devices by different providers.

- *Open* – Open-source since its inception and fully developed in public.
- *Transparent* – All benchmark parameters are defined in a schema file and the benchmark code is reviewable by the community.
- *Cross-platform* – Supports running benchmarks on multiple quantum hardware providers (*integration powered by [qBraid-SDK](#)*)
- *User-friendly* – Provides a simple command-line interface for dispatching, monitoring, and polling benchmark jobs (you can go on with your life while your job waits in the queue).

Conclusions

- We holistically benchmarked 24 QPUs from five vendors using LR-QAOA, evaluating their performance on different graph topologies and testing scalability in qubit count and circuit depth.
- IBM QPUs show significant improvements from Eagle to Heron generations, while IonQ and Quantinuum maintain performance through generations and offer better gate fidelity but suffer from slow execution times.
- Our results highlight key bottlenecks in quantum hardware, emphasizing the need for advancements in circuit depth, execution speed, and gate fidelity to support large-scale quantum algorithms.

Thank you