Advancing Comprehension of Quantum Application Outputs: A Visualization Technique

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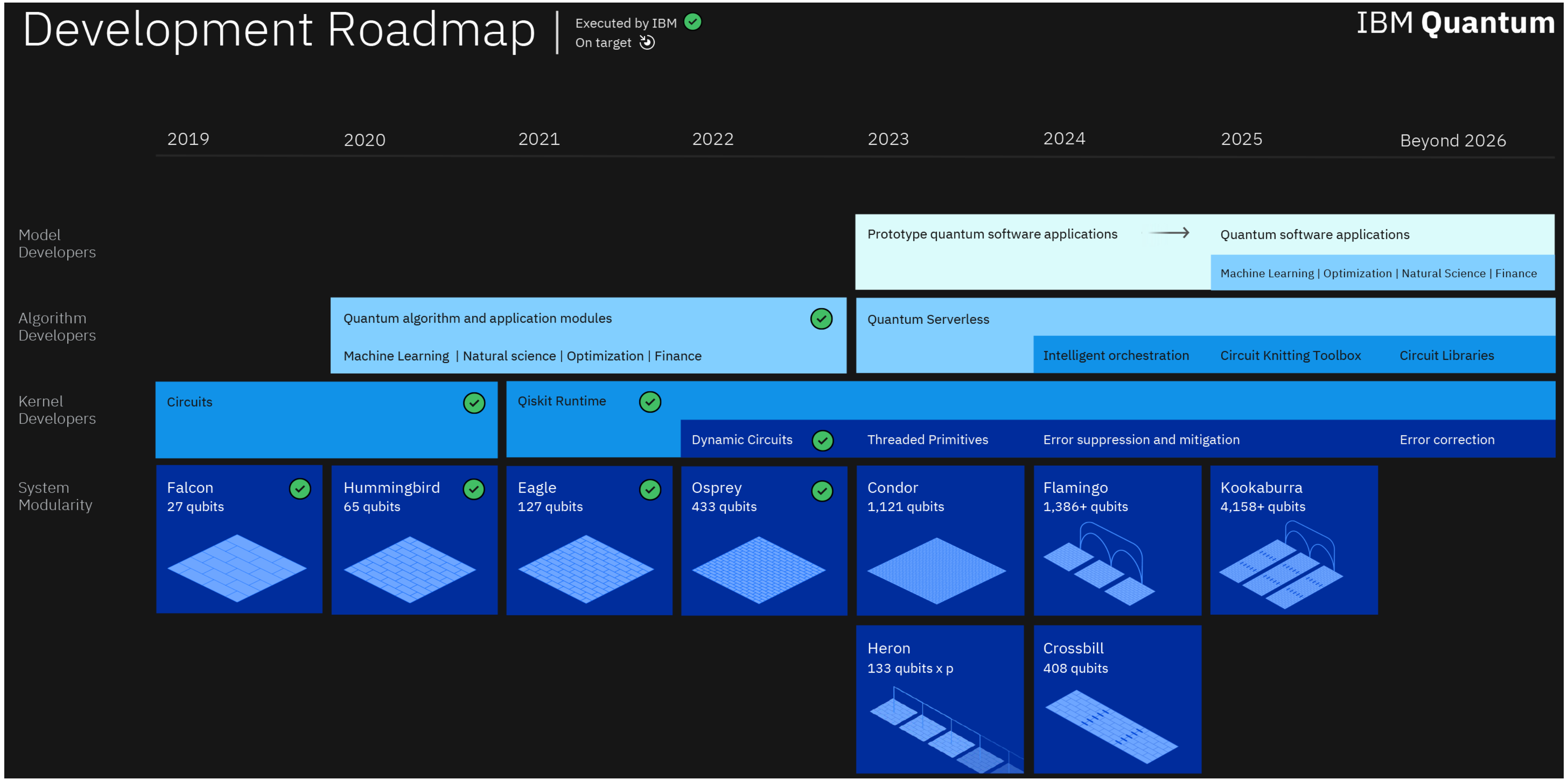
Quantum Computing Hardware Advances

We are going to see quantum computers with large number of qubits in the next few years.



IBM quantum roadmap [https://research.ibm.com/blog/ibm-quantum-roadmap-2025]

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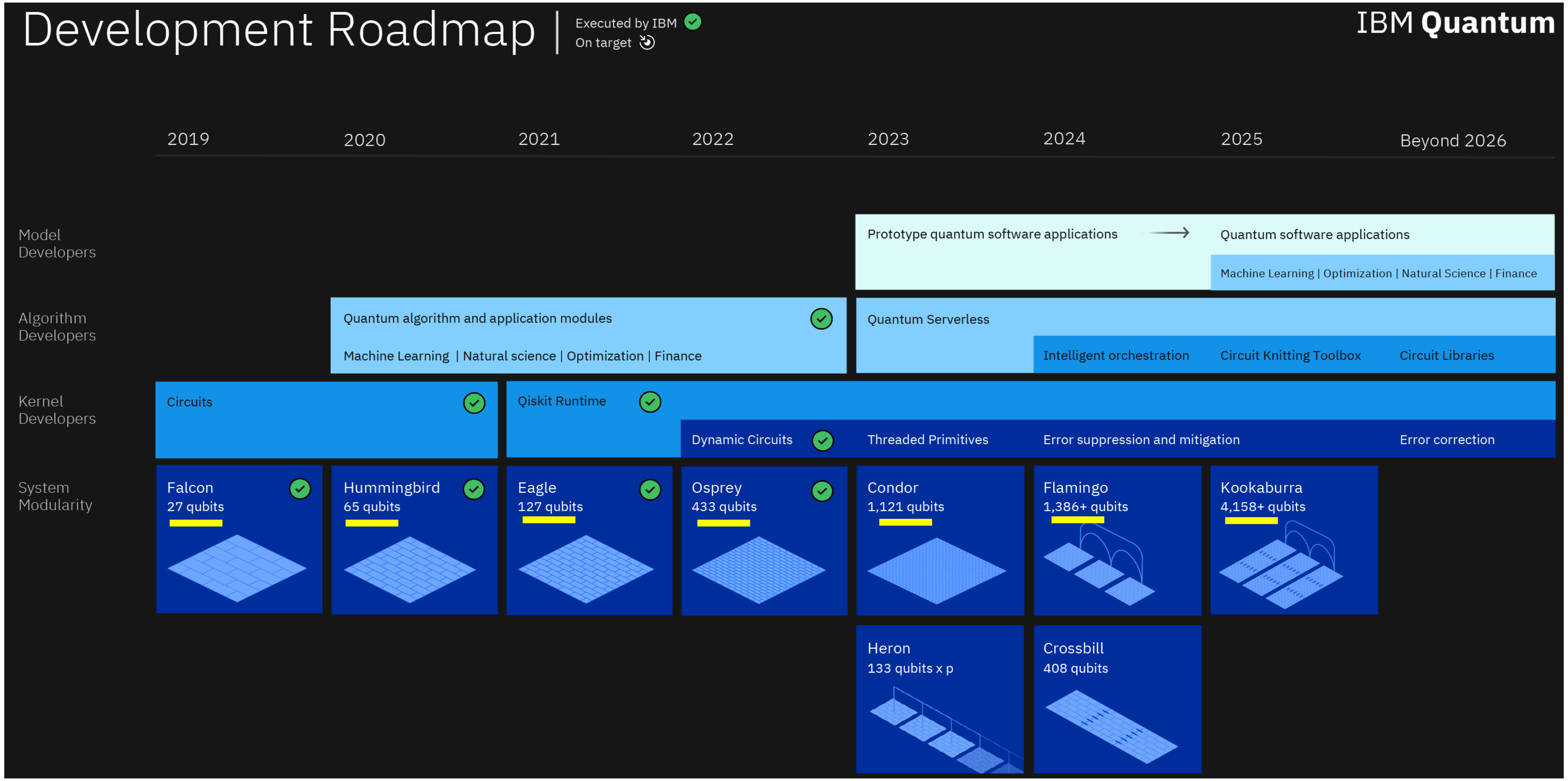

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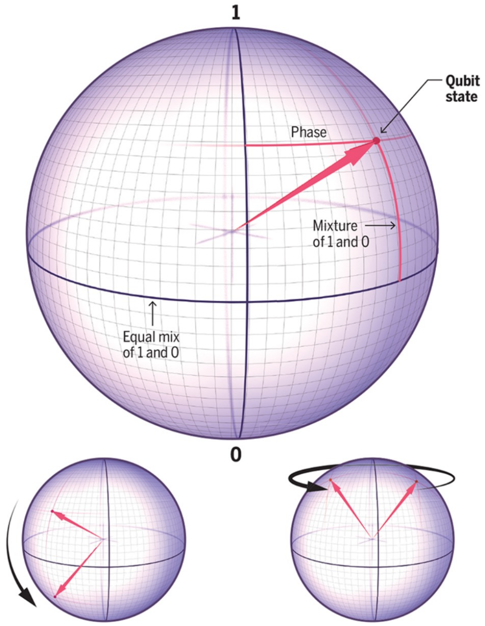
Major Challenge: Errors in Quantum Computing systems

Noise/error in quantum processors leads to issues of reproducibility and reliability of outputs



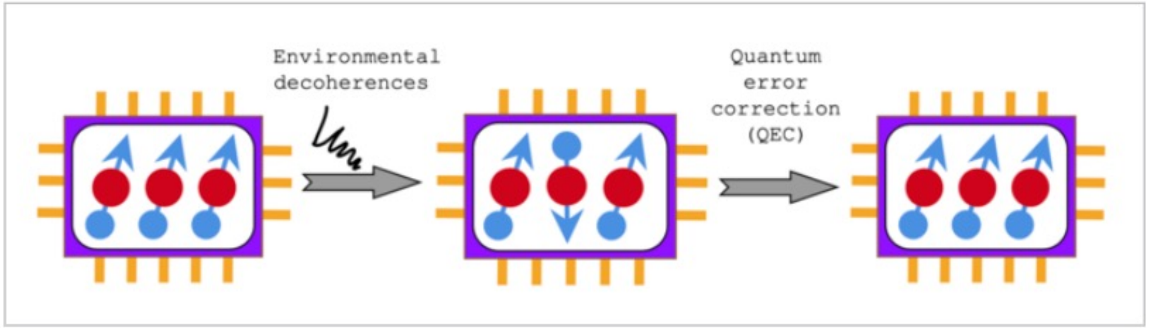
Bit-flip error **Phase-flip error**

[Cho A., 2020]

- Quantum decoherence: information loss from exposure to air molecules, electromagnetic waves etc.
- Gate errors: imperfect implementation of quantum gates
- Crosstalk error: when qubit states flip during CNOT operation on adjacent qubits.
- Measurement errors: erroneous measurement operations and the significant measurement times

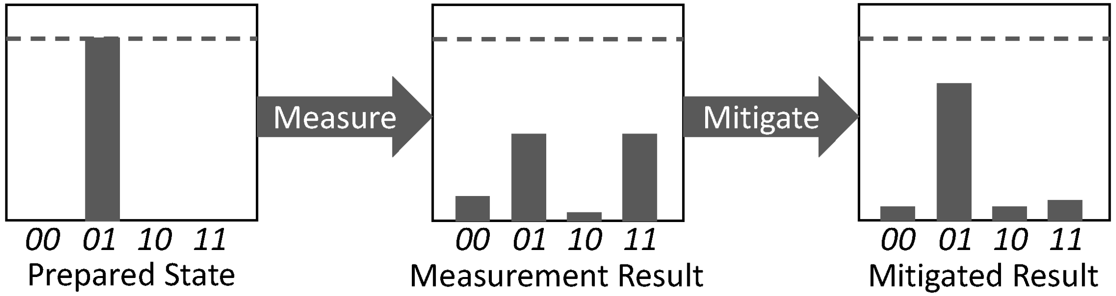
Addressing Noise in Quantum Processors

Quantum Error Correction (QEC)
- Requires larger number of qubits



[Image credits to Sangkha Borah from OIST Graduate University]

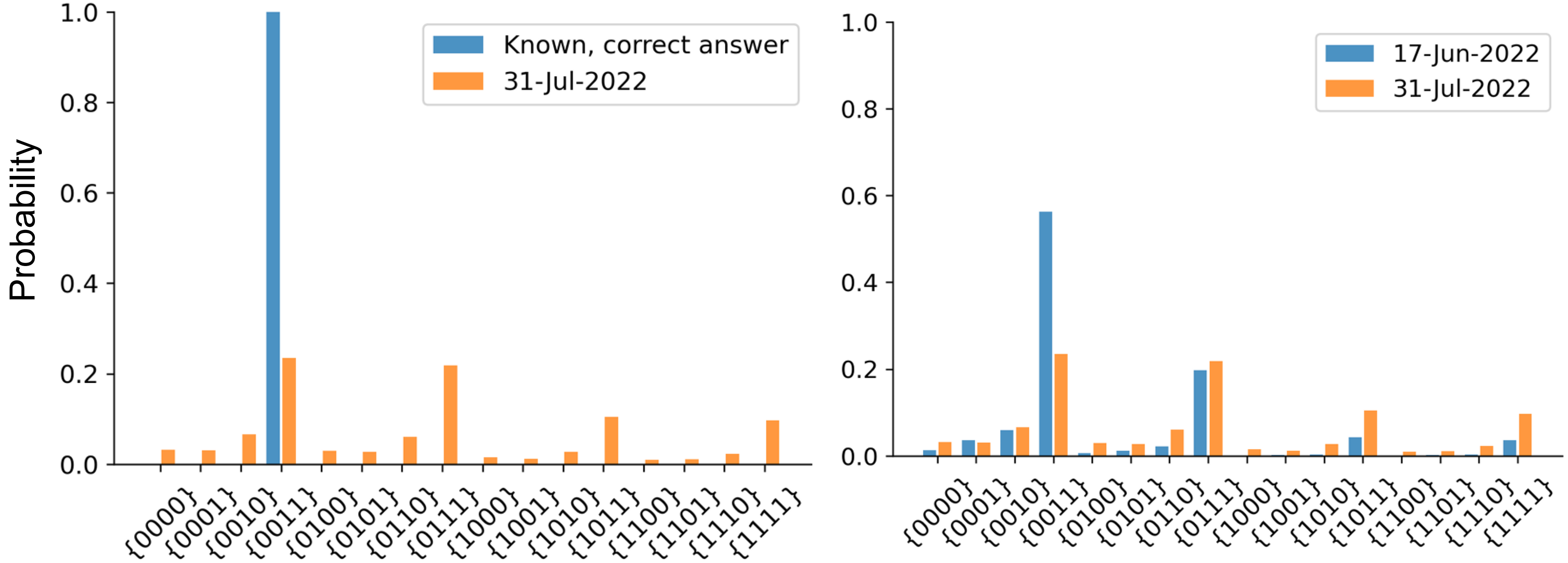
Quantum Error Mitigation (QEM)
- Postprocessing to bring measurement results closer to preparation state
- Smaller qubit overhead



[Beisel, 2022 et al.]

Visualization to Understand Output Variability

Visualizations can help us understand noise in quantum application outputs



Observed measurement distributions of a 4-qubit program

[Dasgupta and Humble, 2022]

Limitation:

These visualizations do not scale well to systems with larger number of qubits!

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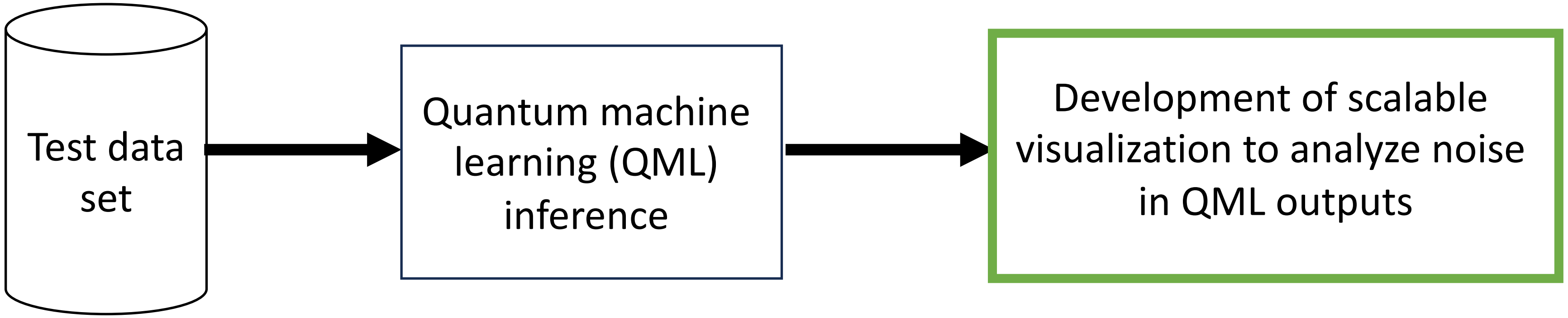
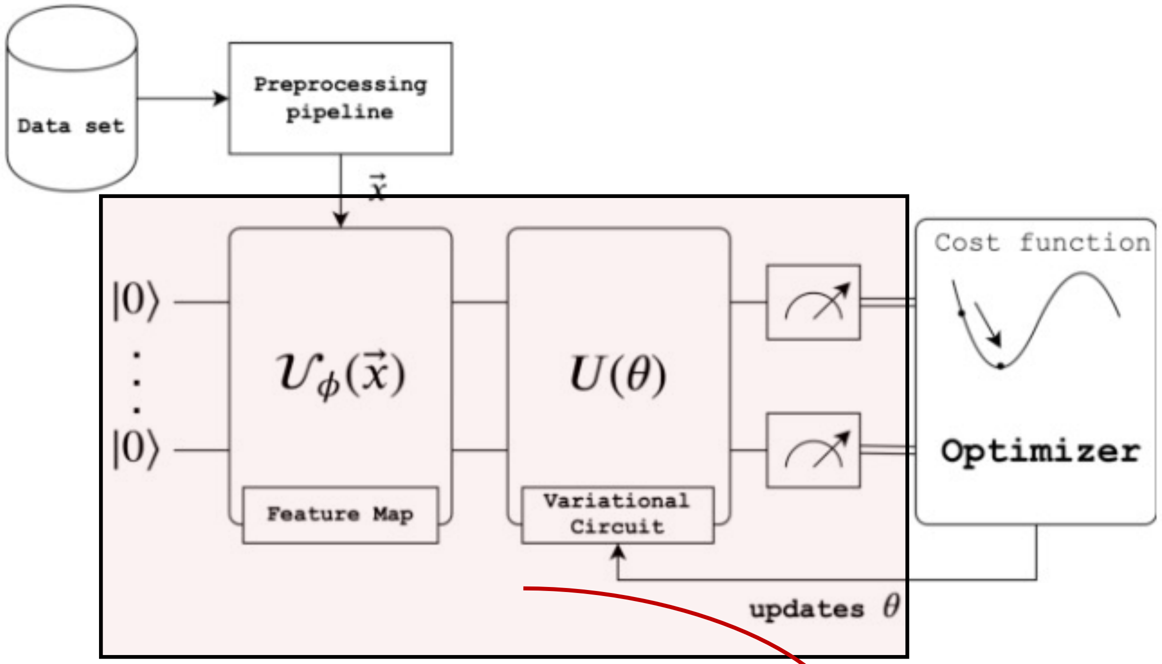
Research Contributions



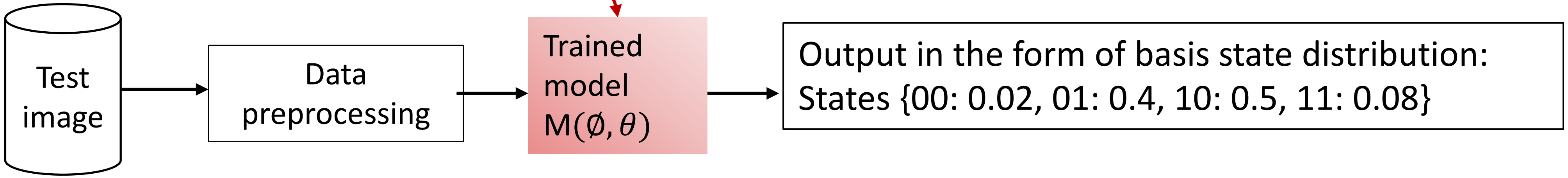
- We develop scalable visualization to distinguish between noisy and non-noisy states (falls under the category of error mitigation and error visualization)

- QML is our case study

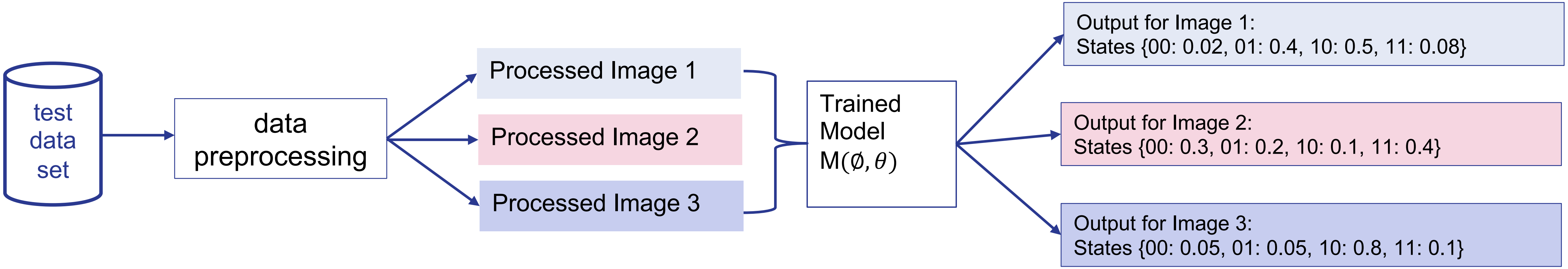
Quantum Machine Learning (QML) For Case Study



- Variational quantum circuits (VQC) can result in lower learning and inference times compared to classical computing
- QML can be used in drug discovery, image processing, and natural language processing.
- Compressed MNIST images encodes onto amplitudes of 7 qubits using amplitude encoding.



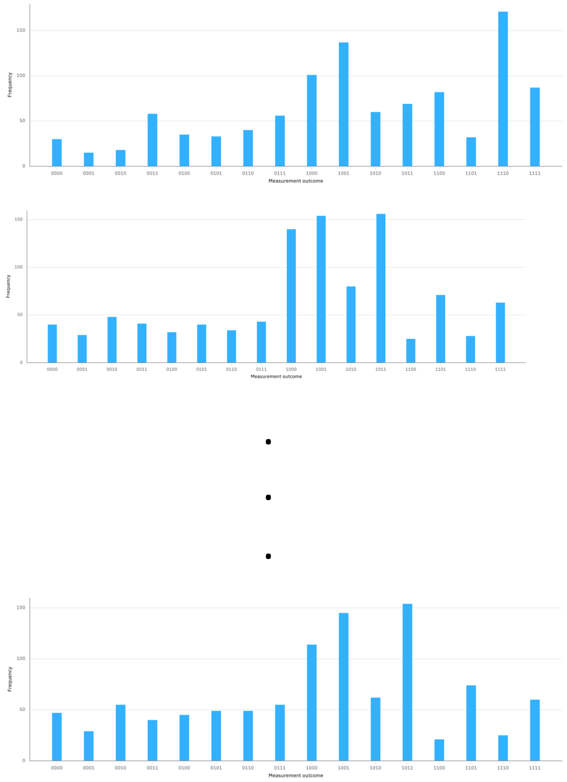
QML Inference Data For Our Analysis



- QML Inference is performed by using our existing trained QML model on unseen images.
- Each test image corresponds to one basis state distribution
- Main challenge: develop scalable visualization to understand variation across state distributions

Brute-Force Visualization Is Not Scalable

Direct/mean visualization of basis states does not reveal useful information and is not scalable



Basis state distribution for image 1

Basis state distribution for image 2

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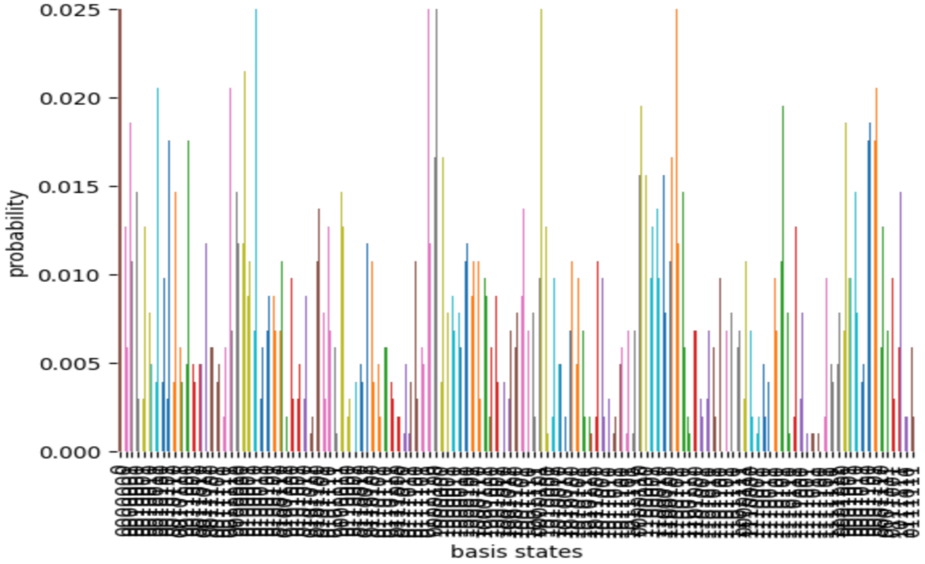
.

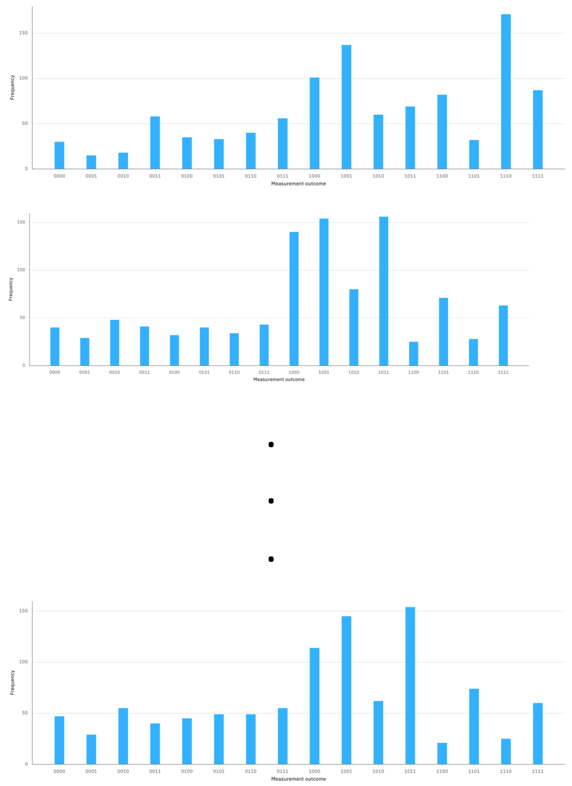
Basis state distribution for image 1000

Basis state distribution per image



Mean distribution visualization

Our Visualization Approach



Basis state distribution for image 1

Basis state distribution for image 2

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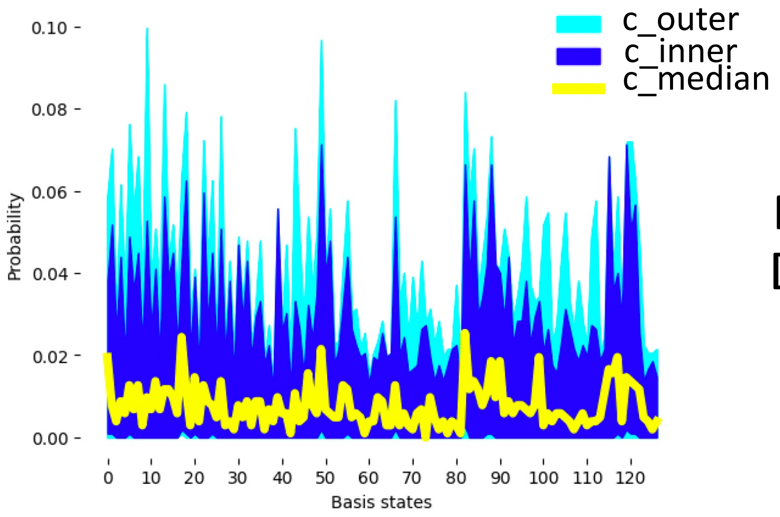
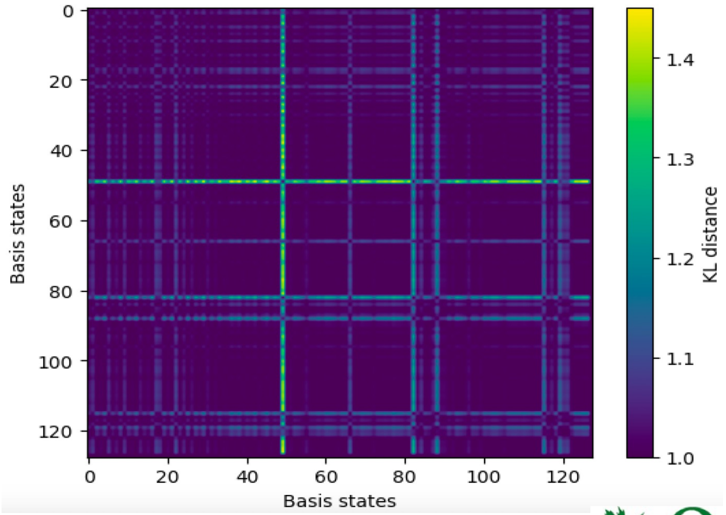
Basis state distribution for image 1000

Basis state distributions



Functional boxplot
[Sun and Genton, 2011]



Heat map of pairwise Kullback-Leibler (KL) distance of 128 basis states

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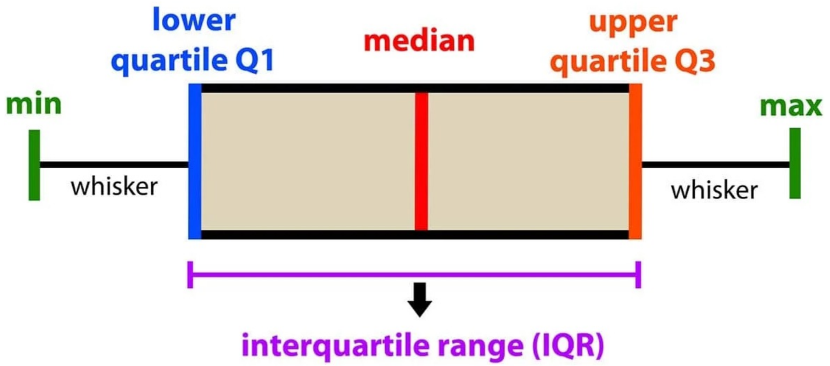
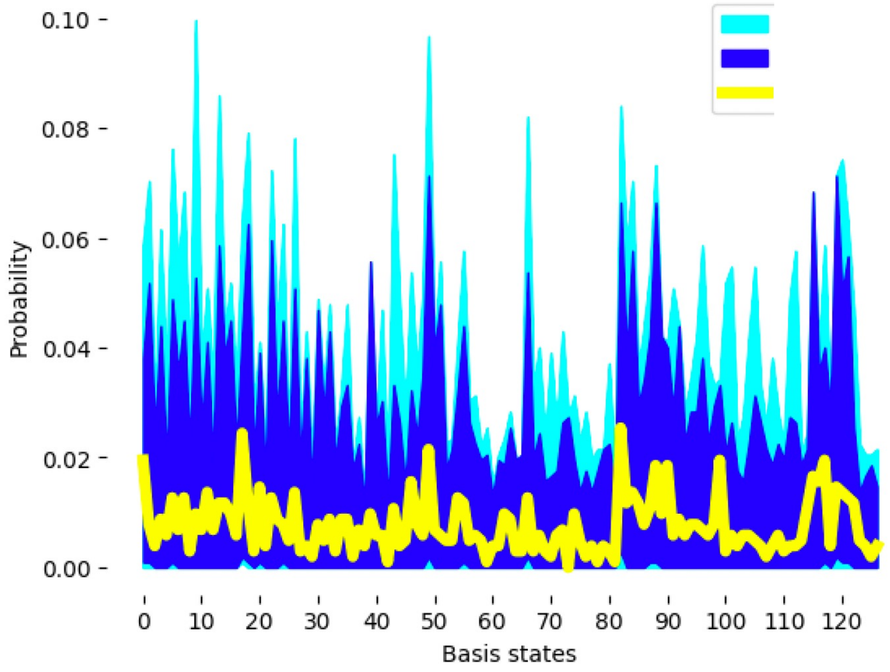
Functional Boxplot for Noise Visualization



1D boxplot
[Tukey, 1977]

Entire uncertainty range
Central 50% (IQR)
Median probability



Functional boxplot [Sun and Genton, 2011]

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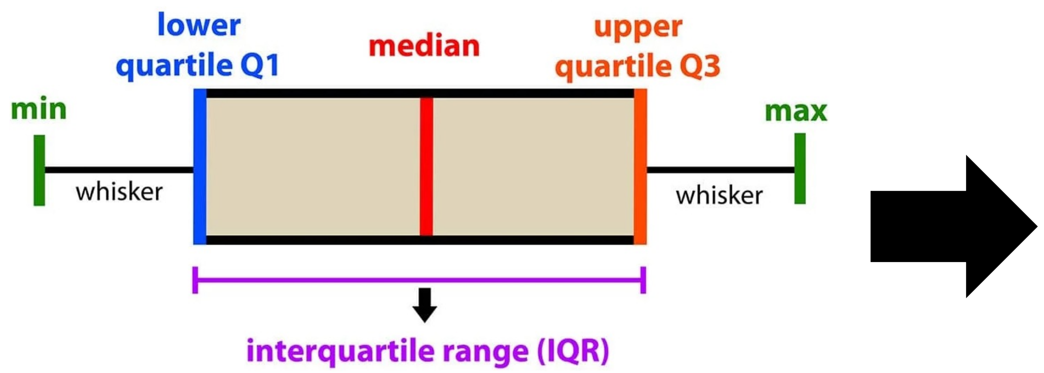

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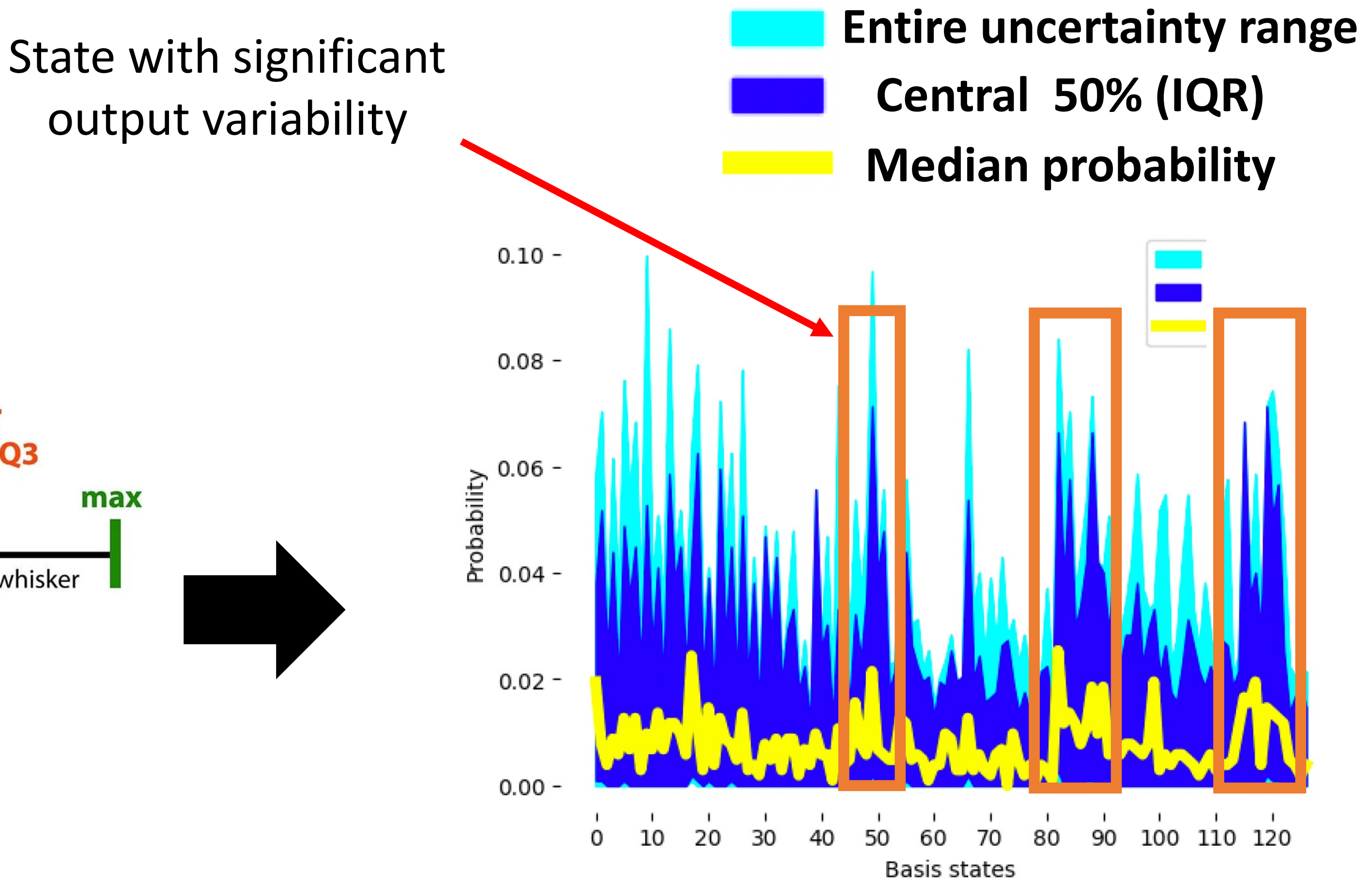
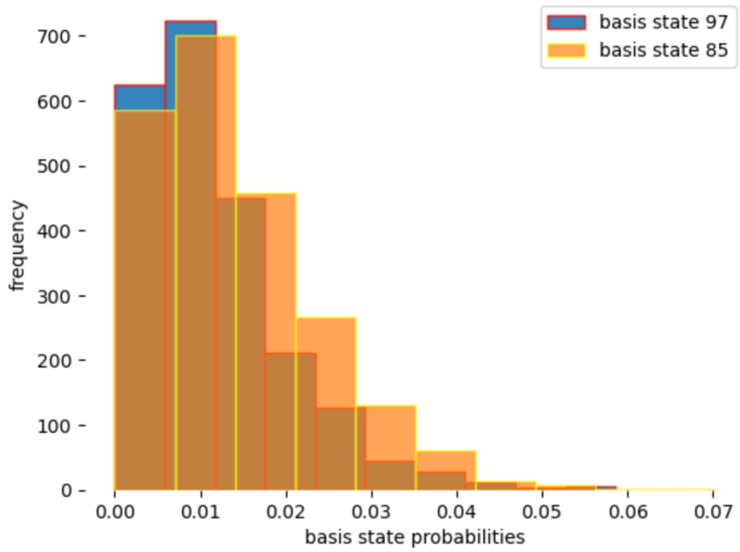


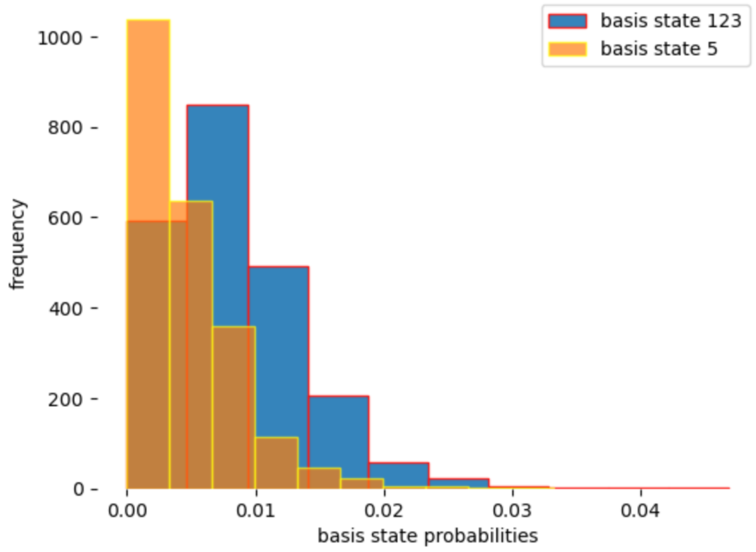
Functional boxplot [Sun and Genton, 2011]

KL Distance Visualization

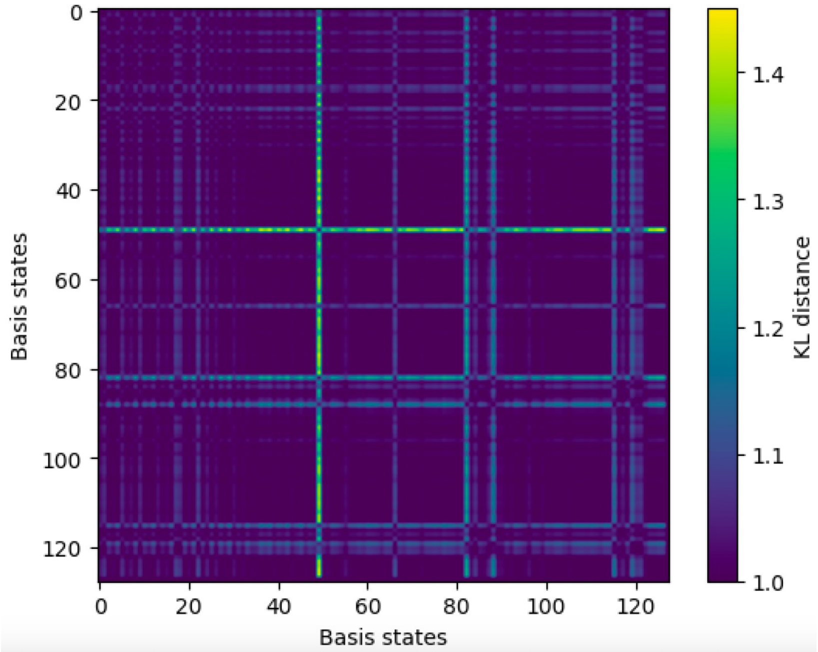
(larger KL distance corresponds to yellow lines, therefore, indicating more noise)



Lower **KL distance**



Larger **KL distance**



Visualization of pairwise **KL distance**

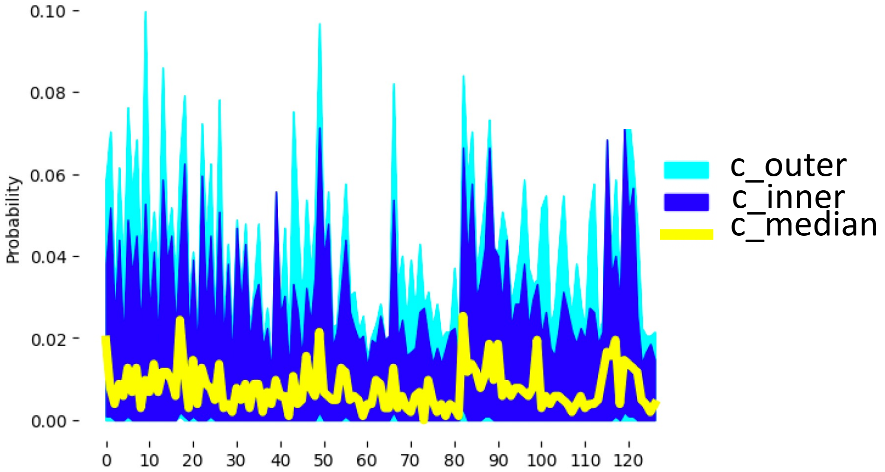
$$D_{\mathrm{KL}}(P \parallel Q) = \sum_{x \in \mathcal{X}} P(x) \log\left(\frac{P(x)}{Q(x)}\right)$$

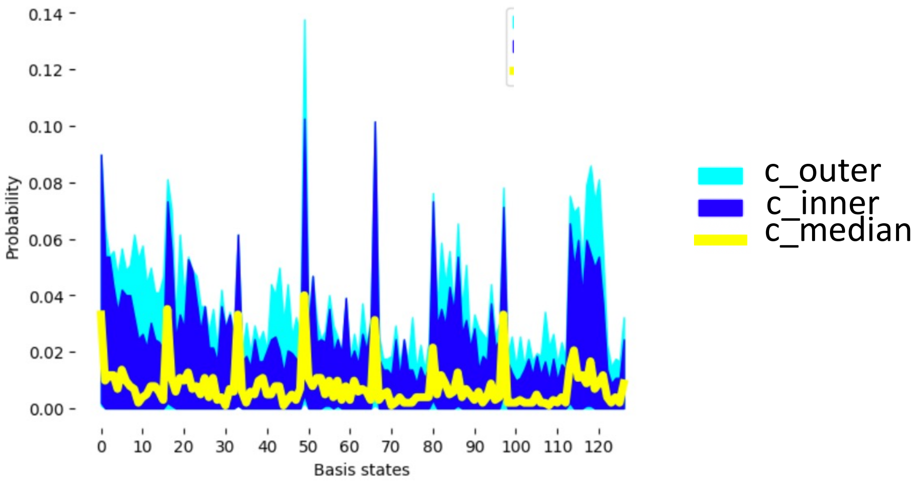
Results on 7-Qubit Quantum Machines

IBM-Q Nairobi

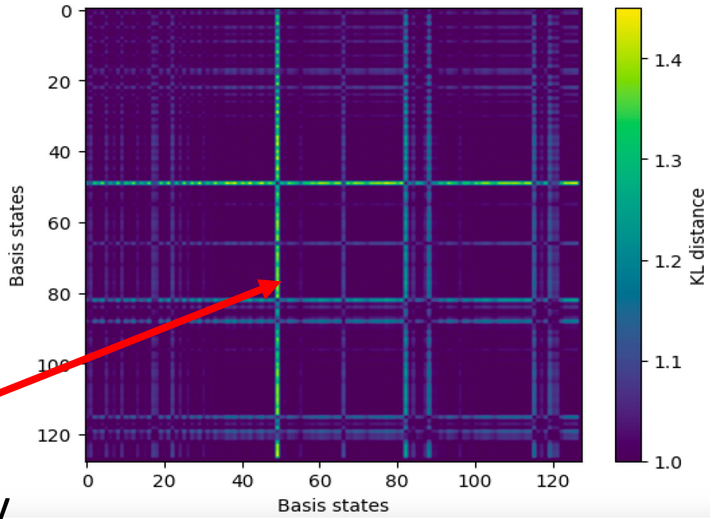
IBM-Q Oslo

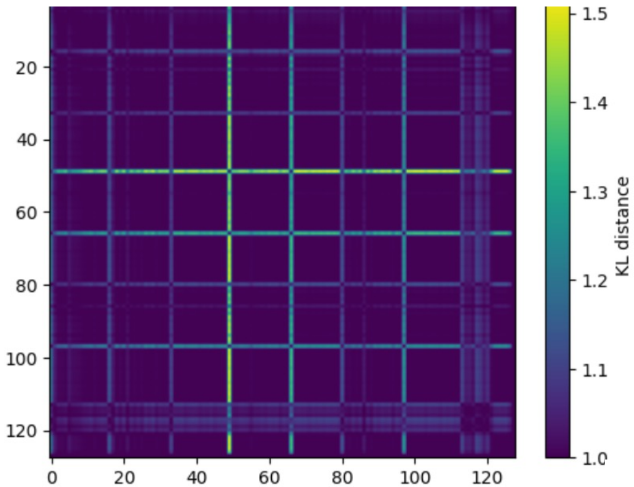
Functional boxplot





Heat map of pairwise KL distance of 128 basis states





State with significantly different distribution

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Conclusion and Future Work

- Our work (functional boxplots and KL distance) provides a ground for scalable quantum noise visualization
- Our proposed approach can help users visually identify noisy and non-noisy basis states.
- In the future, we would like to test our approach on processors with large number of qubits, e.g., 400+ qubits.
- Ultimately, we would like to investigate how our visualizations can be utilized for mitigating noise in quantum application outputs.
- Our position paper on our perspectives is accepted at the DOE ASCR workshop on Basic Research Needs in Quantum Computing and Networking.

Acknowledgements

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Thank You

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