Multimodal Deep Representation Learning for Quantum Cross-platform Verification

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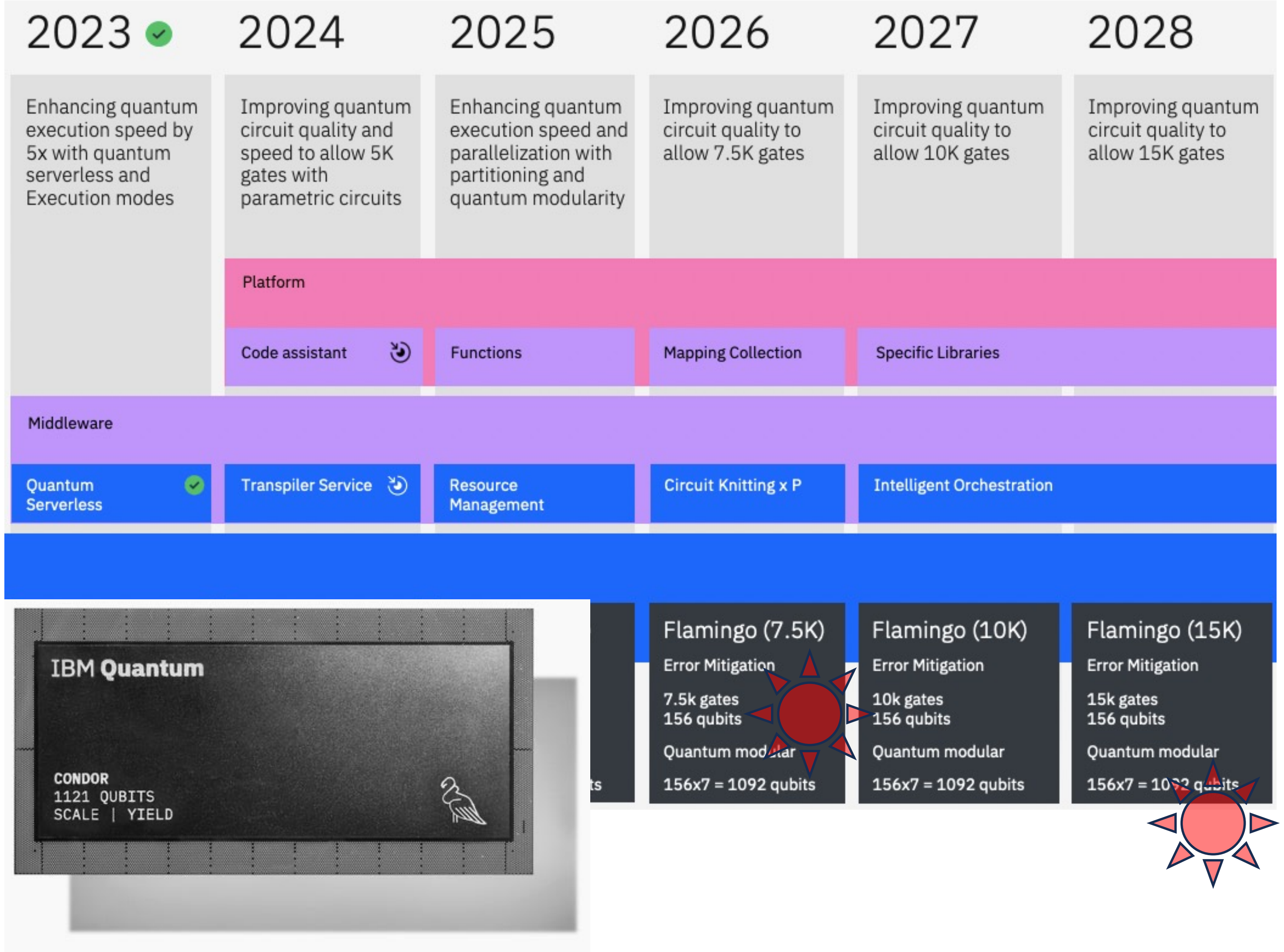
ArXiv:2311.03713

Certification of Large-qubit Quantum Devices

Progress of Quantum Hardware in 2023 (Super-conducting)

Roadmap of IBMQ with super-conducting platform



Other notable achievements

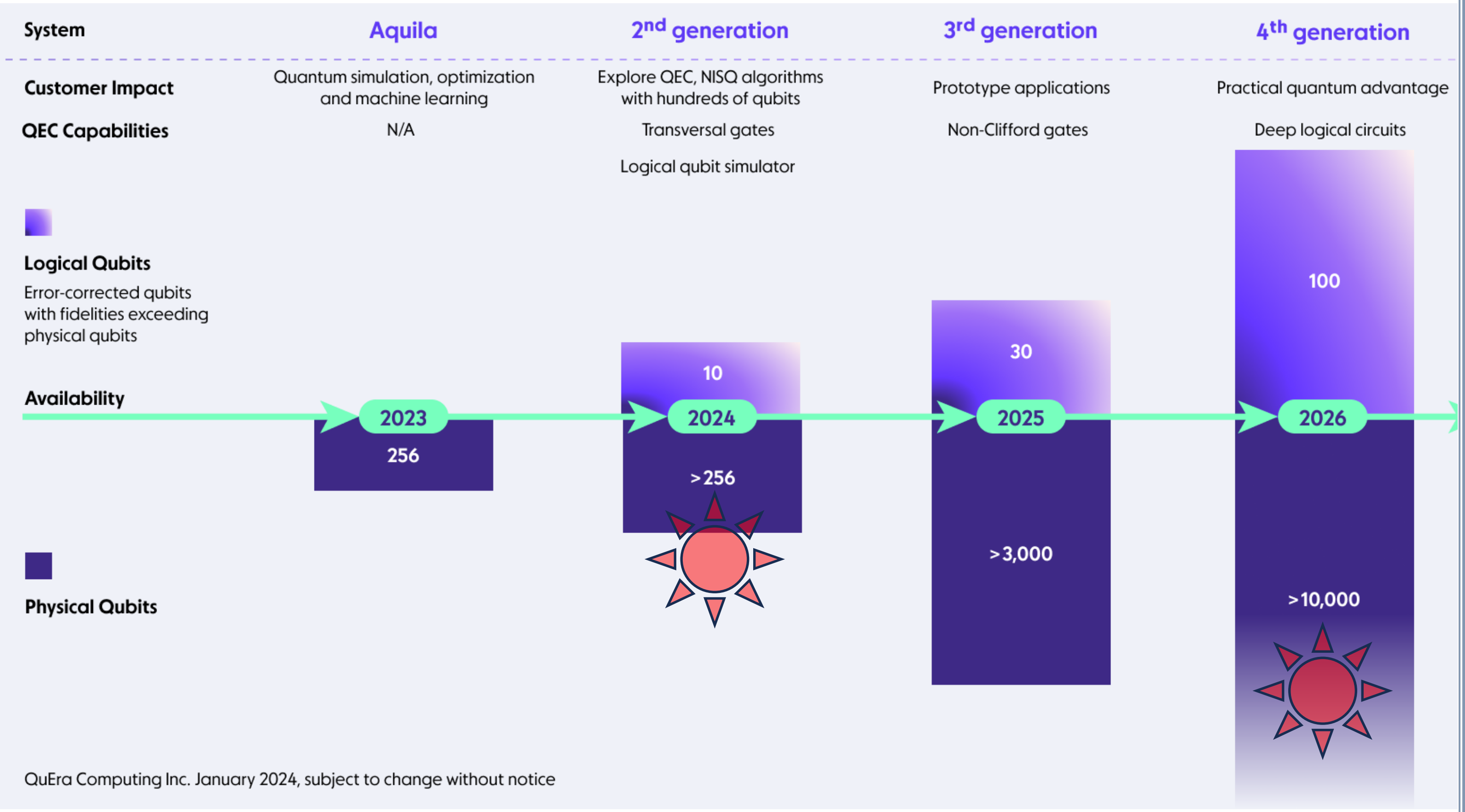
- Google Quantum AI team achieved the first-ever demonstration of a logical qubit prototype [Google Quantum AI. Suppressing quantum errors by scaling a surface code logical qubit. *Nature* **614**, 676–681 (2023)];

- SUSTech team extended the storage time of quantum information through real-time quantum error correction [Ni, Z., Li, S., Deng, X. *et al.* Beating the break-even point with a discrete-variable-encoded logical qubit. *Nature* **616**, 56–60 (2023).]

https://www.ibm.com/quantum/assets/IBM_Quantum_Development_Roadmap.pdf ; https://www.scientificamerican.com/article/ibm-releases-first-ever-1-000-qubit-quantum-chip/

Progress of Quantum Hardware in 2023 (Neutral-atom)

Roadmap of QuEra with neutral-atom platform



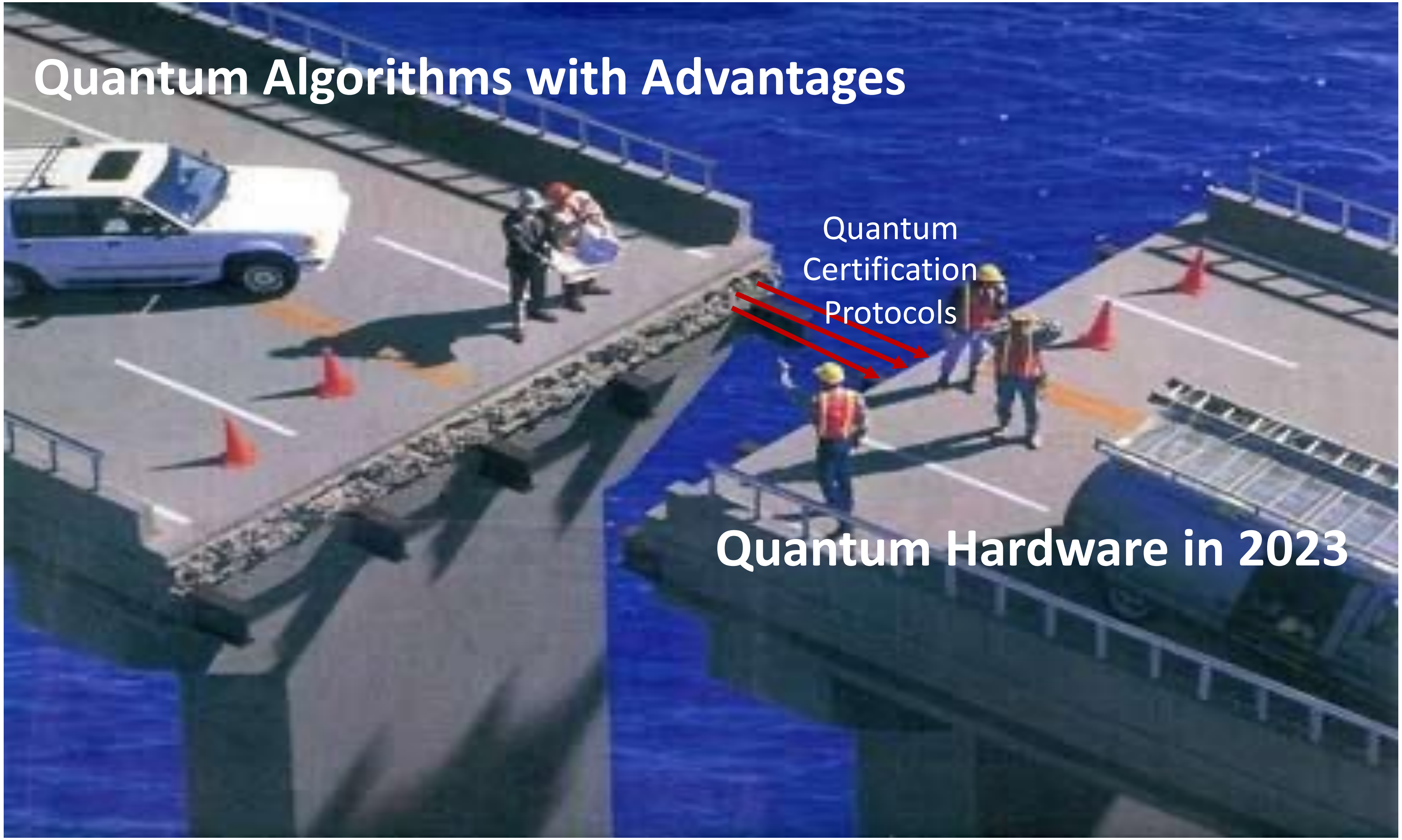
Other notable achievements

- QuEra and its collaborators successfully executed large-scale algorithms on an error-corrected quantum computer with 48 logical qubits and hundreds of entangling logical operations [Bluvstein, D., Evered, S.J., Geim, A.A. *et al.* Logical quantum processor based on reconfigurable atom arrays. *Nature* **626**, 58–65 (2024)];

- A team from Caltech achieved an important milestone using optical tweezer arrays to trap over 6100 neutral atoms [Manetsch, Hannah J., et al. "A tweezer array with 6100 highly coherent atomic qubits." *arXiv preprint arXiv:2403.12021* (2024).]

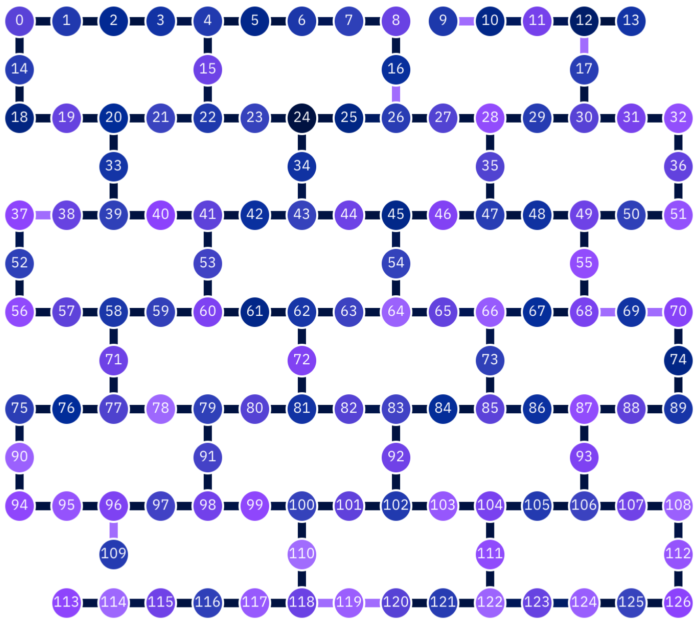
https://www.quera.com/press-releases/quera-computing-releases-a-groundbreaking-roadmap-for-advanced-error-corrected-quantum-computers-pioneering-the-next-frontier-in-quantum-innovation; https://www.nature.com/articles/s41586-023-06927-3; https://arxiv.org/pdf/2403.12021.pdf

Progress of Quantum Computing in 2023



Things change to be different with system noise

127 qubits



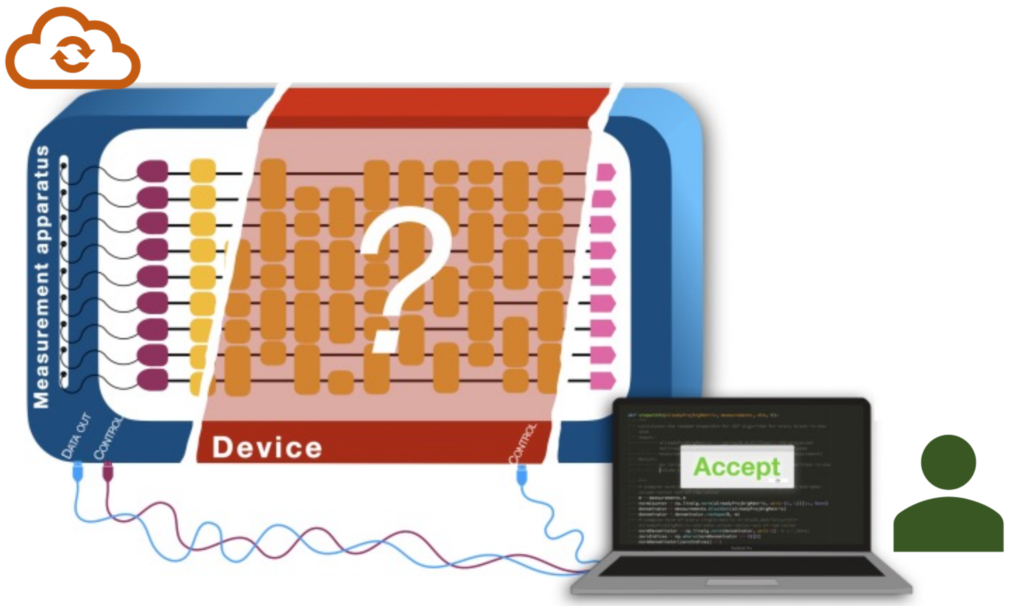
Avg. CNOT Error:	8.060e-2
Avg. Readout Error:	3.129e-2
Avg. T1:	97.1 us
Avg. T2:	96.1 us
Providers with access:	--
Supports Qiskit Runtime:	No

A circuit with 10 CNOT gates: $Fide = 0.92^{10} = 43.4\%$;

Unreliable!

https://quantum-computing.ibm.com/; https://www.rigetti.com/about-rigetti-computing

Things change to be different with system noise



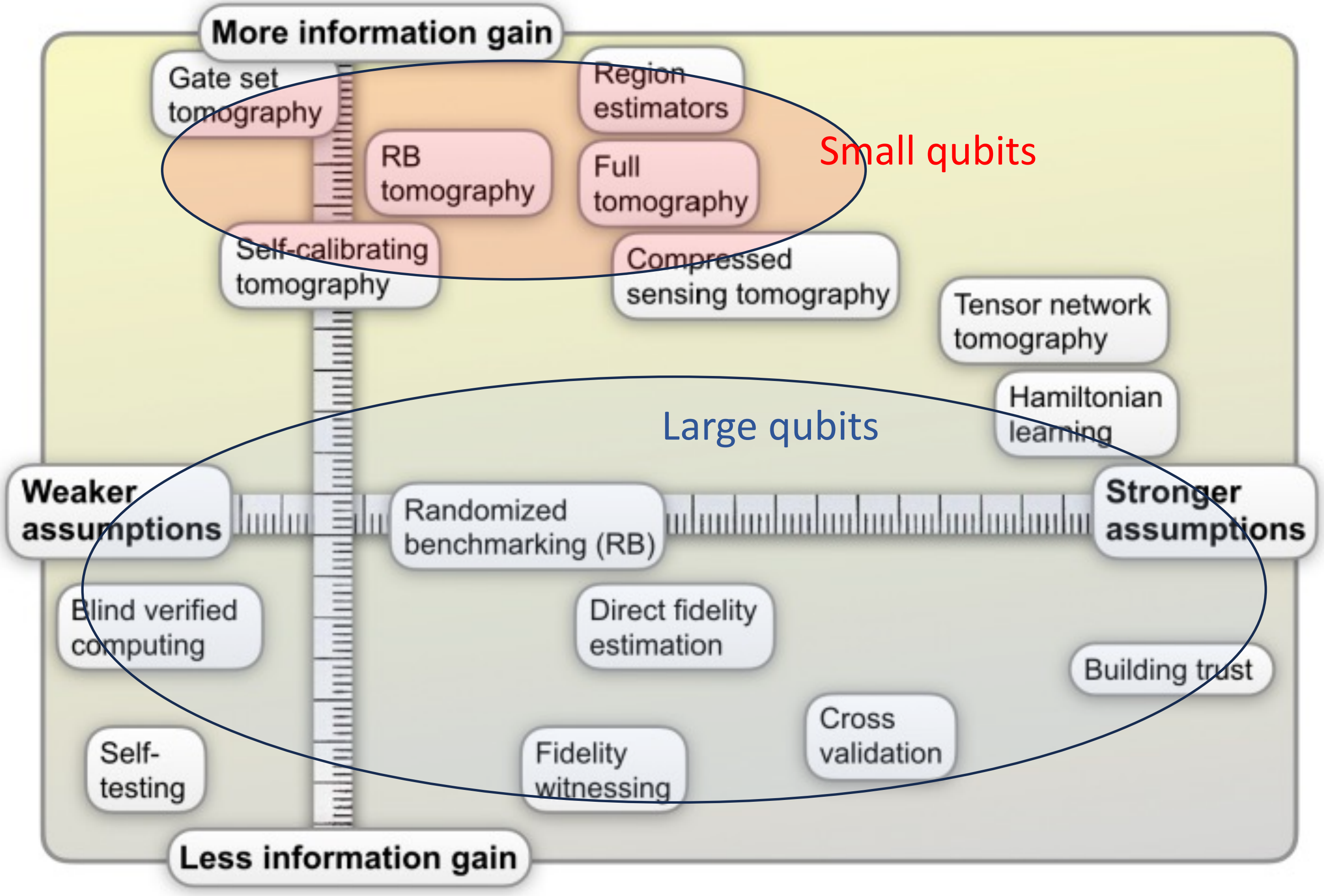
The purpose of quantum system certification (Image adapted from [Kliesch, M., & Roth, I. (2021). Theory of quantum system certification. *PRX quantum*, *2*(1), 010201.]).

Efficiently Certifying Protocols are Necessary to:

- Understand behaviors of large-qubit noisy quantum devices;
- Design reliable quantum algorithms;
- Fabricate next-generation error-corrected quantum computers.

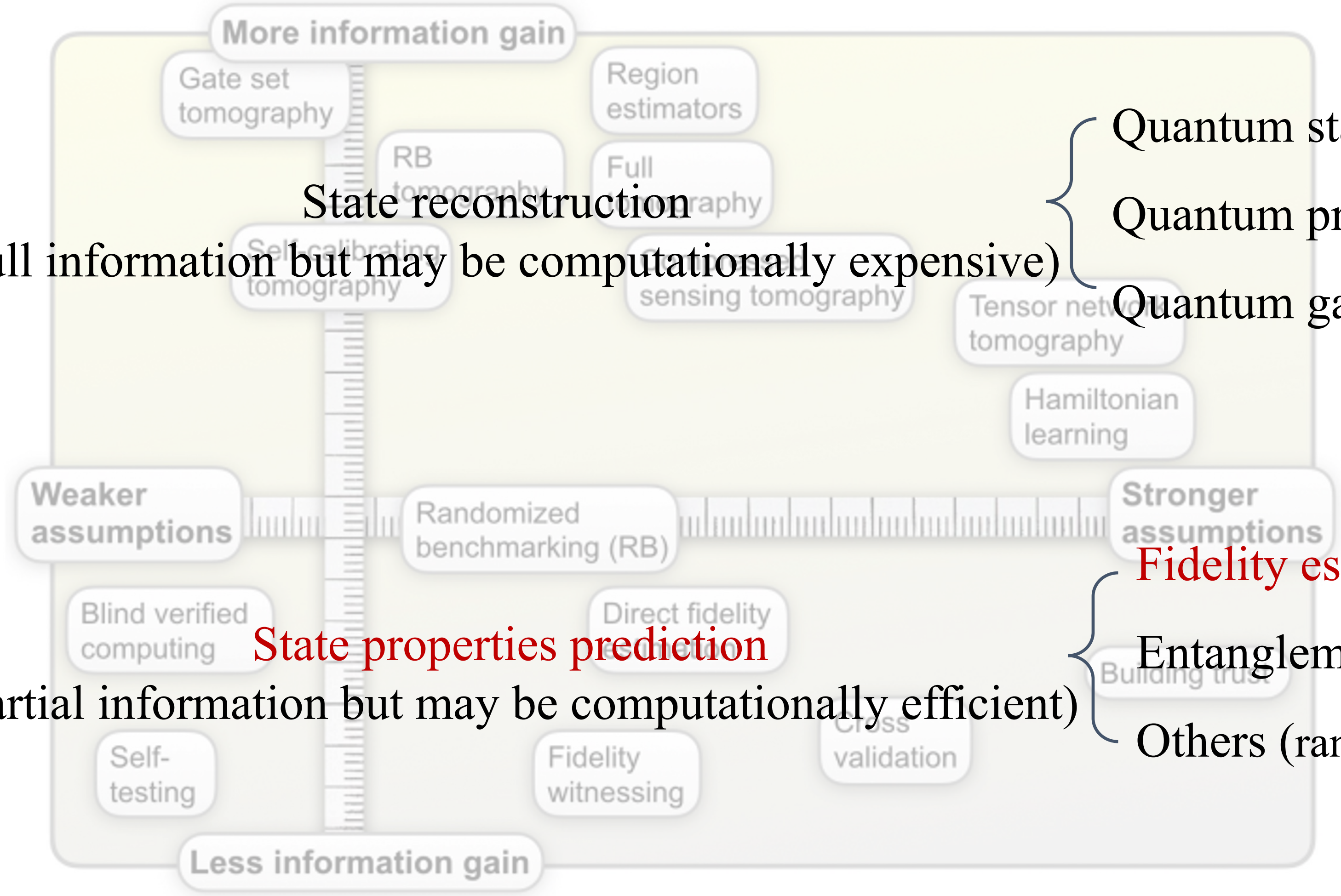
https://quantum-computing.ibm.com/; https://www.rigetti.com/about-rigetti-computing

What is quantum device certification?



Different certification protocols (Image adapted from [Eisert, Jens, et al. "Quantum certification and benchmarking." *Nature Reviews Physics* 2.7 (2020): 382-390.]),

How to certify (large-scale) quantum devices (task perspective)?



Q-Certification

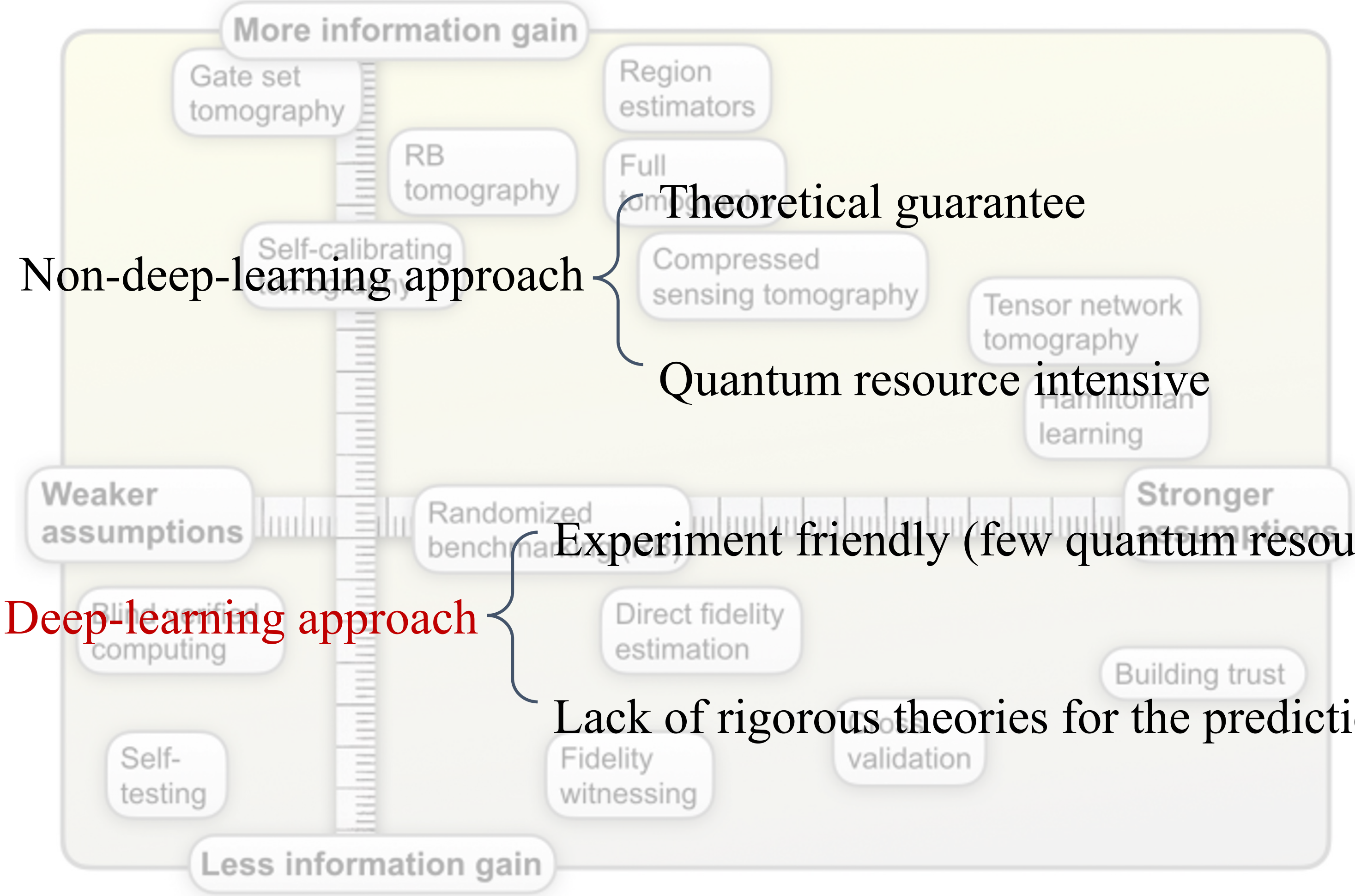
State reconstruction
(Full information but may be computationally expensive)

- Quantum state tomography
- Quantum process tomography
- Quantum gate set tomography

State properties prediction
(Partial information but may be computationally efficient)

- Fidelity estimator (Main focus here)
- Entanglement estimator
- Others (random benchmarking,…)

How to certify (large-scale) quantum devices (method perspective)?



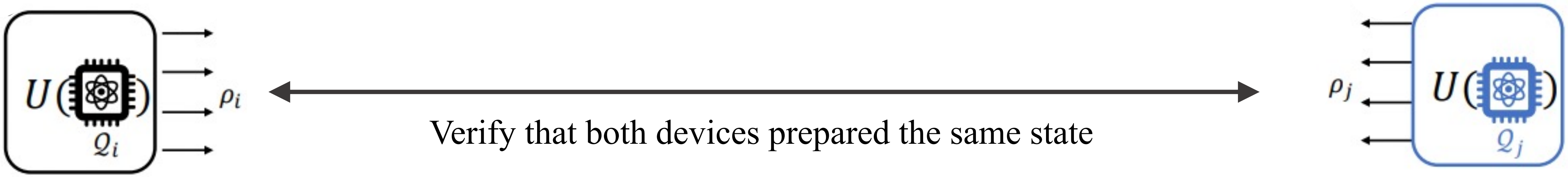
Q-Certification

- Non-deep-learning approach
  - Theoretical guarantee
  - Quantum resource intensive
- Deep-learning approach
  - Experiment friendly (few quantum resources)
  - Lack of rigorous theories for the prediction error

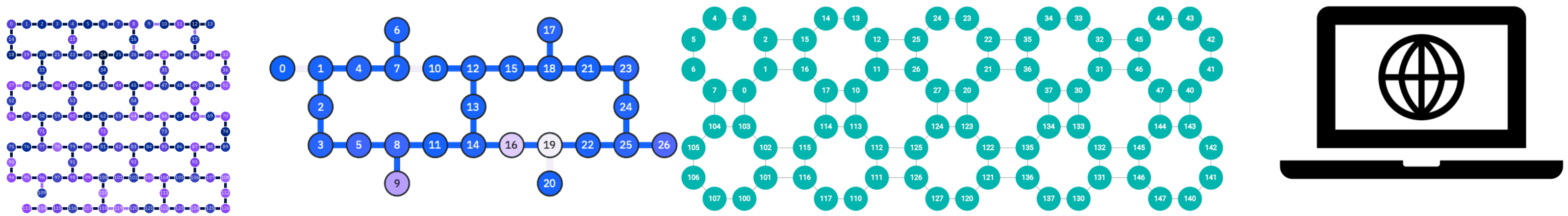
Cross-platform Quantum Circuit Verification

A Crucial Certification Task for Large-qubit Quantum Devices: Cross-platform Fidelity Estimation

<u>Intuition of the Cross-platform fidelity estimation:</u>



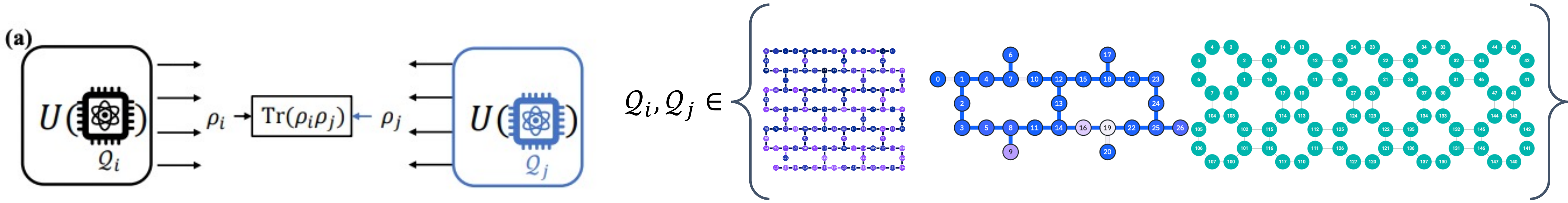
$\mathcal{Q}_i, \mathcal{Q}_j \in$



Direct fidelity estimation

[Flammia, S. T., & Liu, Y. K. (2011). *Physical review letters*, *106*(23), 230501.]

A Crucial Certification Task for Large-qubit Quantum Devices: Cross-platform Fidelity Estimation



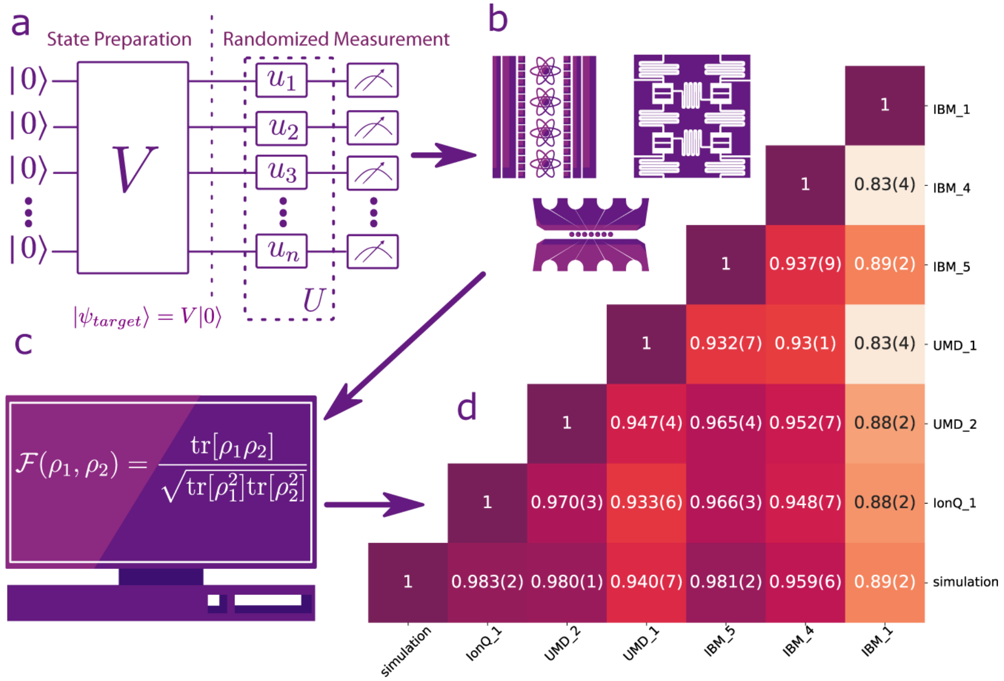
<u>Cross-platform fidelity:</u> Suppose that there are two N-qubit devices $\mathcal{Q}_i$ and $\mathcal{Q}_j$ whose noise models are described by $\mathcal{E}_i$ and $\mathcal{E}_j$, respectively. Cross-platform fidelity concerns the similarity of their output states ρ_i and ρ_j after executing *the same circuit* U, i.e.,

$$\mathcal{F}(\rho_i, \rho_j) = \frac{\mathrm{Tr}(\rho_i\rho_j)}{\sqrt{\mathrm{Tr}(\rho_i^2)\mathrm{Tr}(\rho_j^2)}} \in [0,1],$$

where $\rho_i = \mathcal{E}_i(U\rho_0 U^\top)$, $\rho_j = \mathcal{E}_j(U\rho_0 U^\top)$, and $\rho_0 = (|0\rangle\langle 0|)^{\otimes N}$.

Prior Method for Cross-platform Fidelity Estimation

<u>Classical-shadow-based cross-platform fidelity estimation</u> [Zhu, D., Cian, Z.P., Noel, C. et al. Cross-platform comparison of arbitrary quantum states. Nat Commun **13**, 6620 (2022).]:



a Load test quantum circuit (denoted by V) to two quantum platforms (the circuit V is transpiled for different platforms into their corresponding native gates);

b Apply Pauli-based classical shadow (denoted by $\{u_i\}$) to the prepared states.

c The measurement results are sent to a central data repository for processing the fidelities defined in $\mathcal{F}(\rho_i, \rho_j)$ using the classical shadow estimation state $\hat{\boldsymbol{\rho}}_{\boldsymbol{i}}$ and $\hat{\boldsymbol{\rho}}_{\boldsymbol{j}}$.

<u>Weakness:</u> When Pauli-based classical shadows are used for solving fidelity estimation tasks, $O(\exp(bN))$ measurements with b<1 are required to achieve a satisfactory estimation error. As a result, the proposed method may be impractical for certifying large-qubit quantum devices.

https://www.nature.com/articles/s41467-022-34279-5

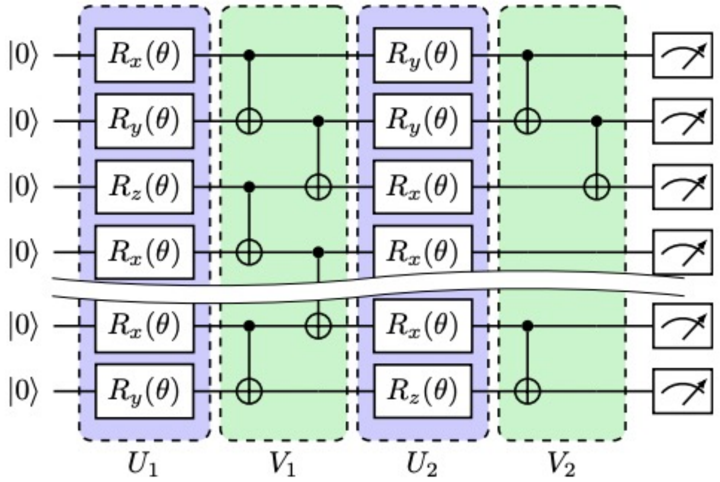
Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

Key insights:

- Prior test circuits can provide **valuable knowledge** for estimating cross-platform fidelity of the new test circuit;

Most test circuits for modern quantum devices can be categorized into the Hardware-efficient ansatz. Define the block number as L, $\boldsymbol{\theta}$ are tunable parameters, V_l is the entangled layer at each block. These circuits yield:

$$\left\{ U = \prod_{l=1}^{L} \prod_{n=1}^{N} e^{-i\theta_{l,n} H_{l,n}} V_l \middle| \theta_{l,n} \sim \mathrm{Unif}(0, 2\pi) \right\}$$

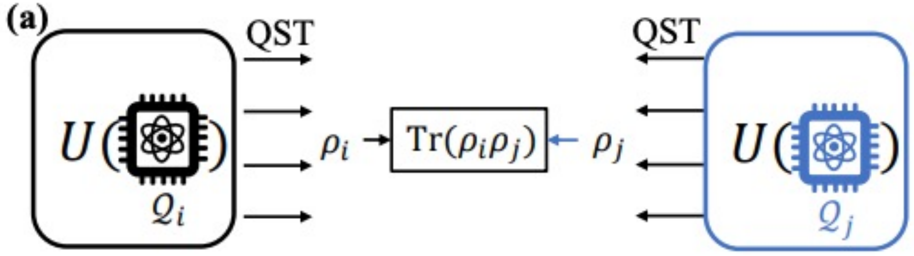


Two test circuits $\mathrm{U}(\boldsymbol{\theta})$ and $\mathrm{U}(\boldsymbol{\theta}')$ that only differ from rotation angles should have a similar a cross-platform fidelity

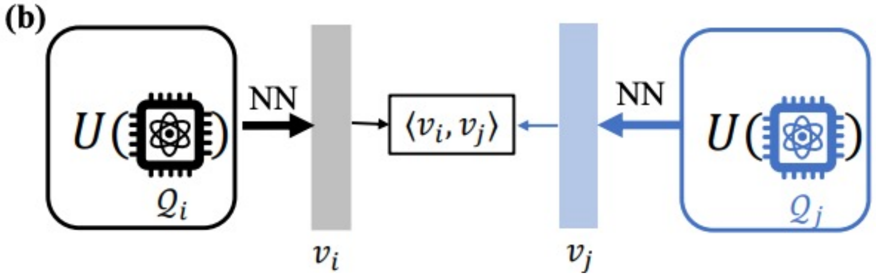
Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

Key insights:

- Prior test circuits can provide **valuable knowledge** for estimating cross-platform fidelity of the new test circuit;
    - Non-learning method **cannot** utilize these valuable knowledge;
    - Deep neural networks **can** capture these knowledge, which in turn reduces the cost for the new test circuit.



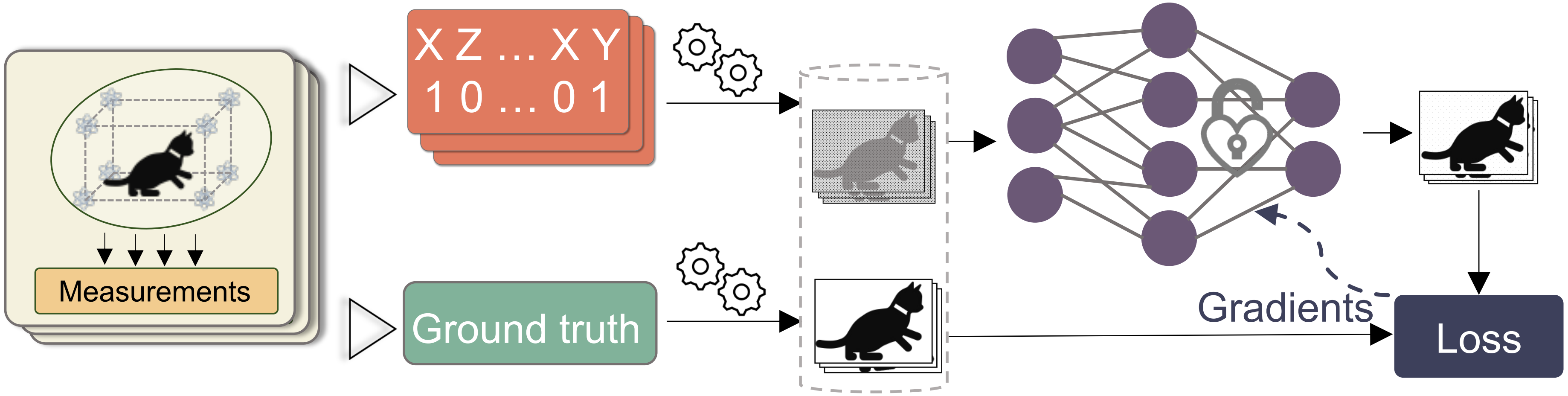
Non-learning-based CP fidelity estimation



Learning-based CP fidelity estimation

Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

Protocol: deep-learning-based quantum state property prediction



Discriminative

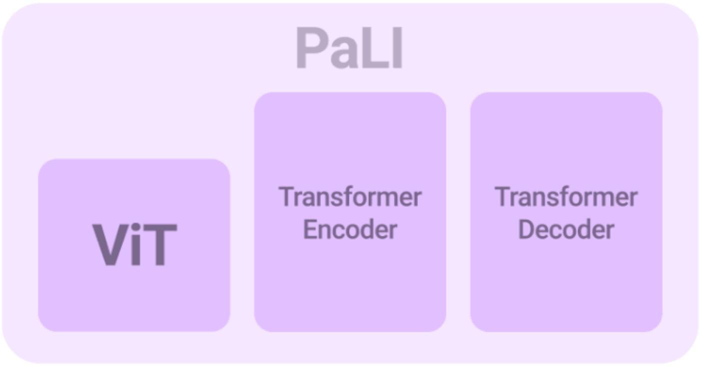
Some references

- Gao, J. et al. Experimental machine learning of quantum states. *Phys. Rev. Lett.* **120**, 240501 (2018).
- Zhu, Y., Wu, YD., Bai, G. *et al.* Flexible learning of quantum states with generative query neural networks. *Nat Commun* **13**, 6222 (2022).
- Zhang, X. et al. Direct fidelity estimation of quantum states using machine learning. *Phys. Rev. Lett.* **127**, 130503 (2021).
- Dominik Koutný *et al.*, Deep learning of quantum entanglement from incomplete measurements. *Sci. Adv.* **9**, eadd7131 (2023).

Melko, R.G., Carrasquilla, J. Language models for quantum simulation. Nat Comput Sci 4, 11–18 (2024)

Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

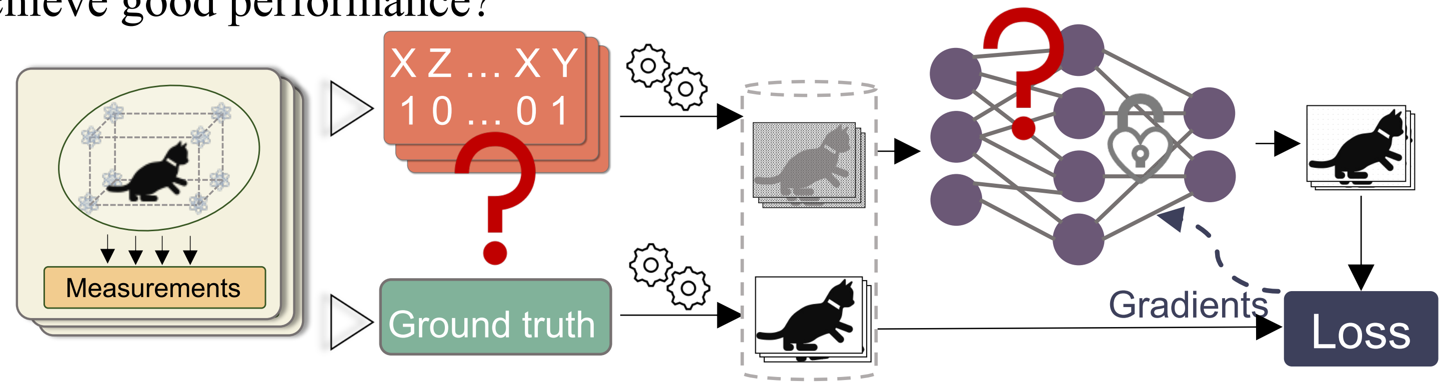
Ground-truth in modern AI: A multi-modal dataset generally enhance the performance of AI foundation models



Challenges in deep-learning-based quantum state property prediction

1. How to construct the multi-modal dataset in deep-learning-based quantum state property prediction?

2. How to design corresponding learning models to achieve good performance?

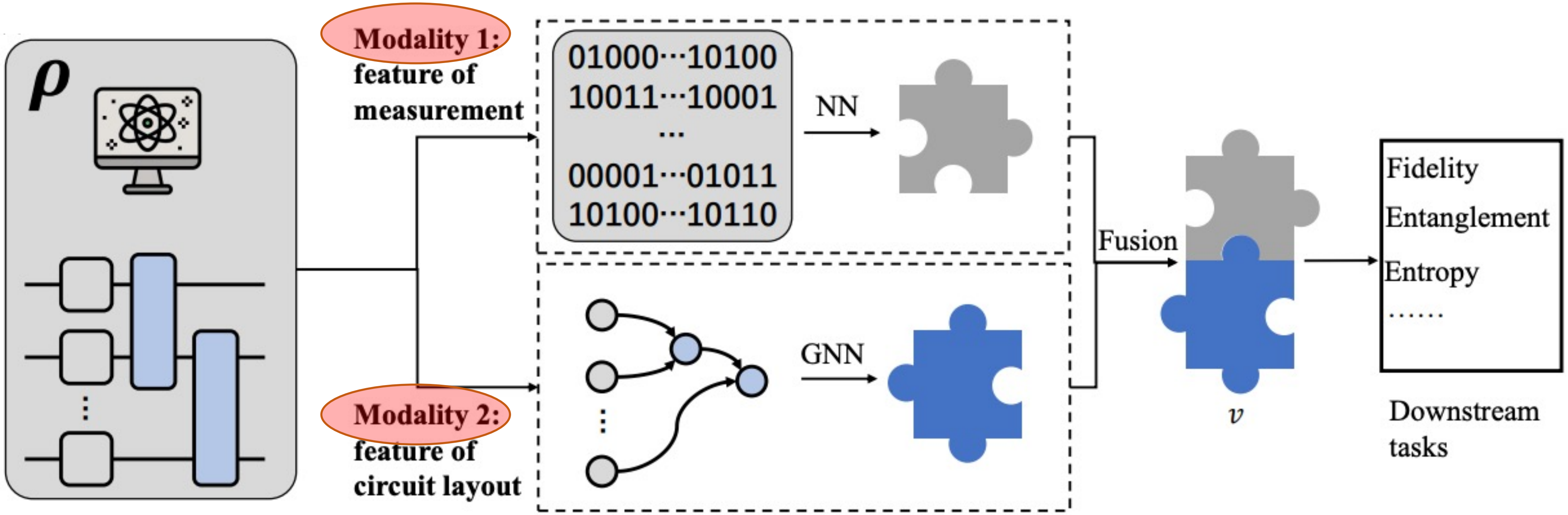


https://www.google.com/search?q=google+research+Pali&oq=google+research+Pali&gs_lcrp=EgZjaHJvbWUyBggAEEUYOTIGCAEQRRhAMgYIAhBFGEAyBggDEEUYPDIGCAQQRRg80gEINDQzOGowajeoAgCwAgA&sourceid=chrome&ie=UTF-8

Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

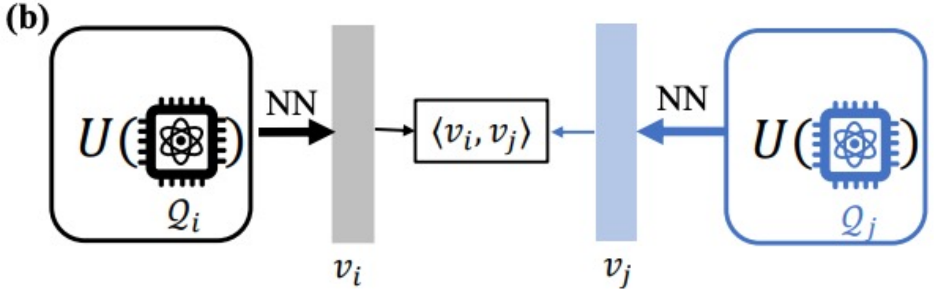
Implementation of **Measurement-Circuit Driven Neural Network** (MC-Net):

- Step 1: multimodal dataset collection
- Step 2: model implementation
- Step 3: model optimization



Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

MC-Net [Step 1]: multimodal dataset collection



$$\mathcal{D}_{\mathrm{Tr}} = \{(\boldsymbol{x}_i^{(s)}, \boldsymbol{x}_j^{(s)}, \mathcal{F}_{ij}^{(s)})\}_{s=1}^{S}$$

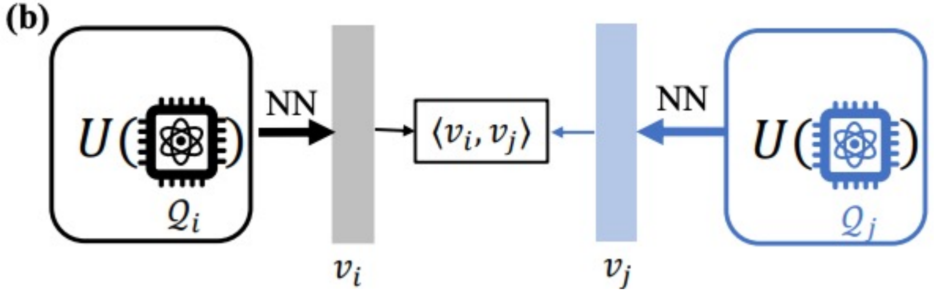
For each example $\left(\boldsymbol{x}_i^{(s)}, \boldsymbol{x}_j^{(s)}, \mathcal{F}_{ij}^{(s)}\right)$:

- $\boldsymbol{x}_i^{(s)}$ or ($\boldsymbol{x}_j^{(s)}$) represents the data features of $\rho_i^{(s)}$ or $\rho_j^{(s)}$, as the prepared state of executing the test circuit $U^{(s)}$ on $\mathcal{Q}_i$ (or $\mathcal{Q}_j$);
- $\boldsymbol{x}_i^{(s)}$ or ($\boldsymbol{x}_j^{(s)}$) contains two modalities, i.e., the measurement information and the circuit information with $\boldsymbol{x}_i^{(s)} = [\boldsymbol{x}_{i,M}^{(s)}; \boldsymbol{x}_{i,C}^{(s)}]$
- Measurement information $\boldsymbol{x}_{i,M}^{(s)}$ (Pauli-based Classical Shadow with M shots):

  1. Denote the t-th snapshot on ρ_i as $|\mathbf{b_t}\rangle = |b_{t,1}, \ldots, b_{t,N}\rangle$ and $U_t = \bigotimes_{n=1}^{N} u_{t,n}$.
  2. Compute the t-th local on the n-th qubit $\hat{\rho}_n = 3u_{t,n}^{\top}|b_n\rangle\langle b_n|u_{t,n} - I \in C^{2\times 2}$.
  3. Flatten it to the 8-dim vector, i.e., $\left[\mathrm{vec}\left(\mathrm{real}(\hat{\rho}_n)\right), \mathrm{vec}\left(\mathrm{img}(\hat{\rho}_n)\right)\right] \in R^{8\times 1}$
  4. Repeat M times (M shots) to obtain $\boldsymbol{x}_{i,M}^{(s)} \in R^{M\times 8N}$

Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

MC-Net [Step 1]: multimodal dataset collection



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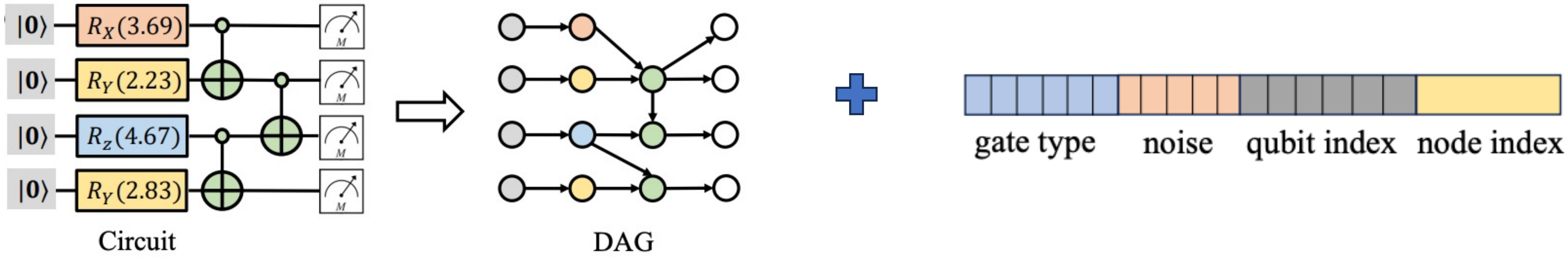
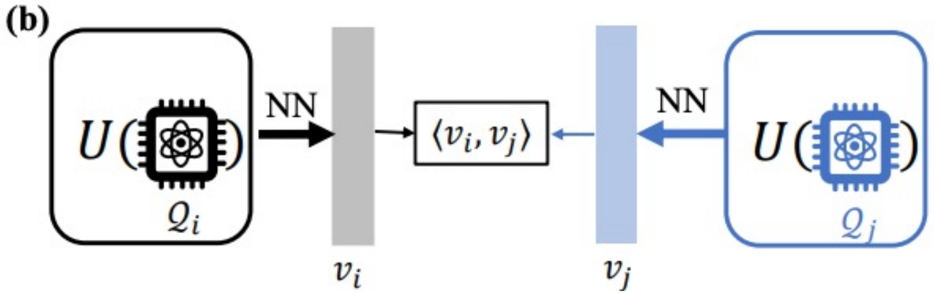
- Circuit information $\boldsymbol{x}_{i,C}^{(s)}$ (topology of the quantum circuit $U^{(s)}$ after transplilation with gate noise information):



Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

MC-Net [Step 1]: multimodal dataset collection



$$\mathcal{D}_{\mathrm{Tr}} = \{(\boldsymbol{x}_i^{(s)}, \boldsymbol{x}_j^{(s)}, \mathcal{F}_{ij}^{(s)})\}_{s=1}^{S}$$

For each example $\left(\boldsymbol{x}_i^{(s)}, \boldsymbol{x}_j^{(s)}, \mathcal{F}_{ij}^{(s)}\right)$:

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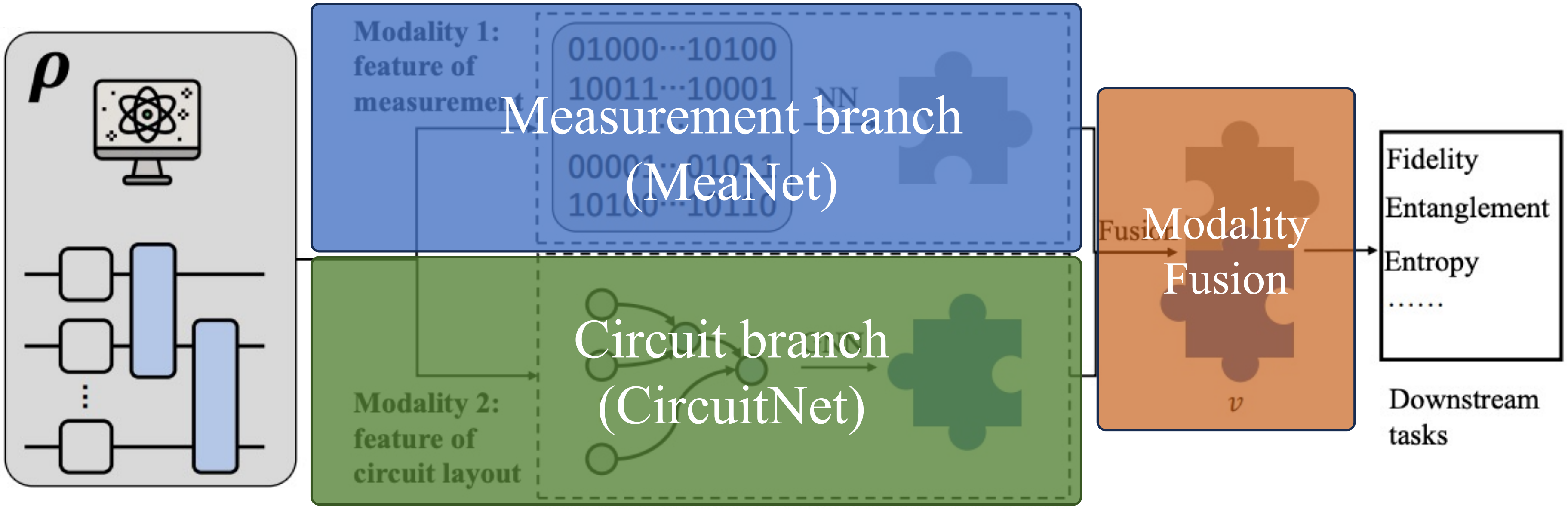
- $\mathcal{F}_{ij}^{(s)} = \mathcal{F}(\rho_i^{(s)}, \rho_j^{(s)})$ is the label of data, i.e., the cross-platform fidelity for between states $\rho_i^{(s)}$ and $\rho_j^{(s)}$;

Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

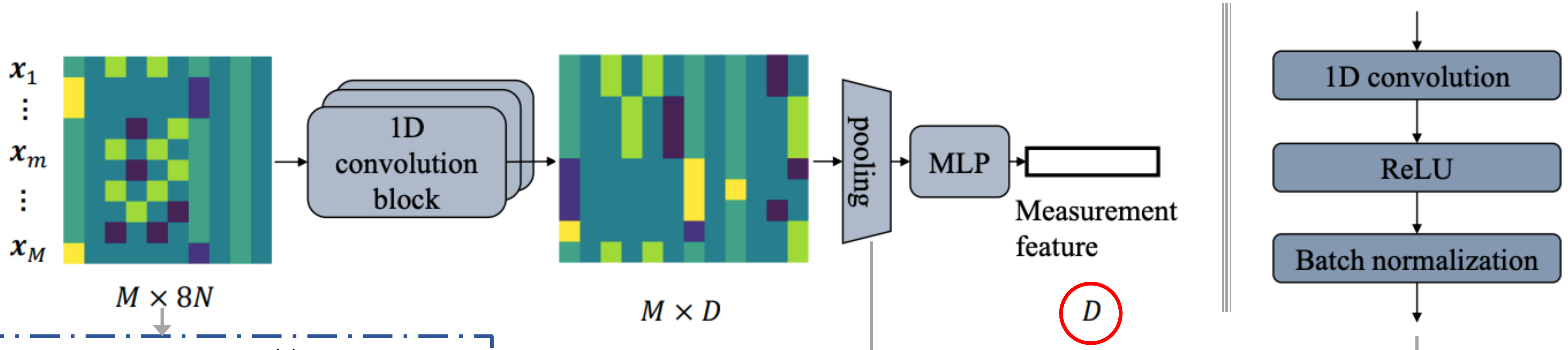
MC-Net [**Step 2**]: multimodal model implementation



$$\mathcal{D}_{\text{Tr}} = \{(\boldsymbol{x}_i^{(s)}, \boldsymbol{x}_j^{(s)}, \mathcal{F}_{ij}^{(s)})\}_{s=1}^{S}$$

Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

MC-Net [**Step 2**]: multimodal model implementation---Measurement Branch (MeaNet)



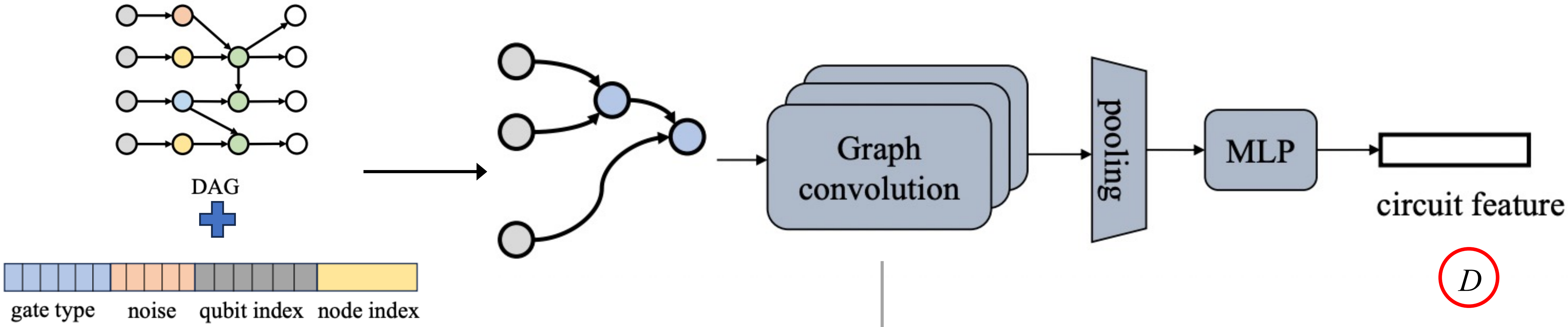
Measurement data: $\boldsymbol{x}_{i,M}^{(s)} \in R^{M \times 8N}$

This pooling operation ensures the preservation of measurement <u>permutation invariance</u>

Implementation of 1D Conv Block

Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

MC-Net [**Step 2**]: multimodal model implementation---Circuit Branch (CircuitNet)

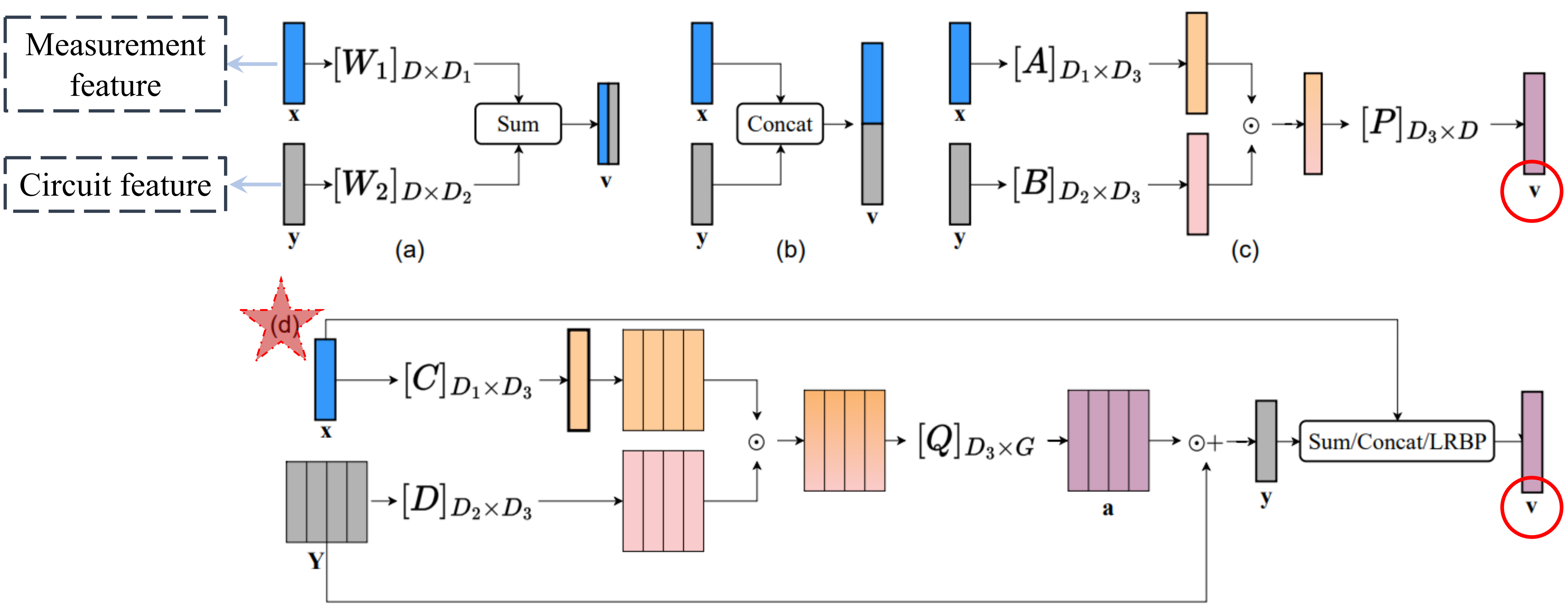


Circuit data: $\boldsymbol{x}_{i,C}^{(s)}$

Several graph convolution layers

Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

MC-Net [**Step 2**]: multimodal model implementation---Fusion Operation



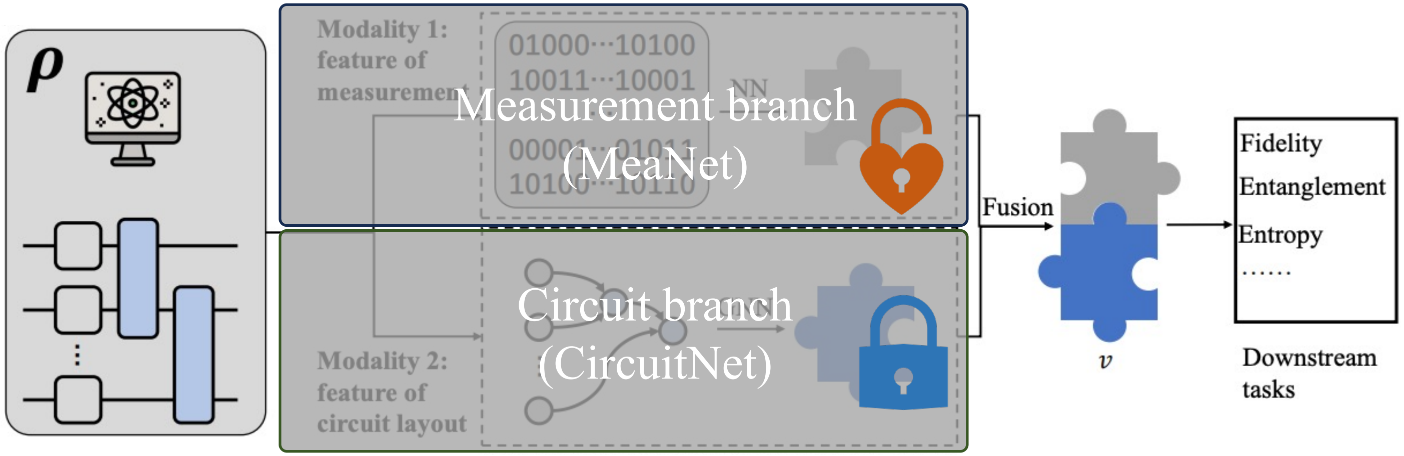
Attention-based fusion, better performance!

Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

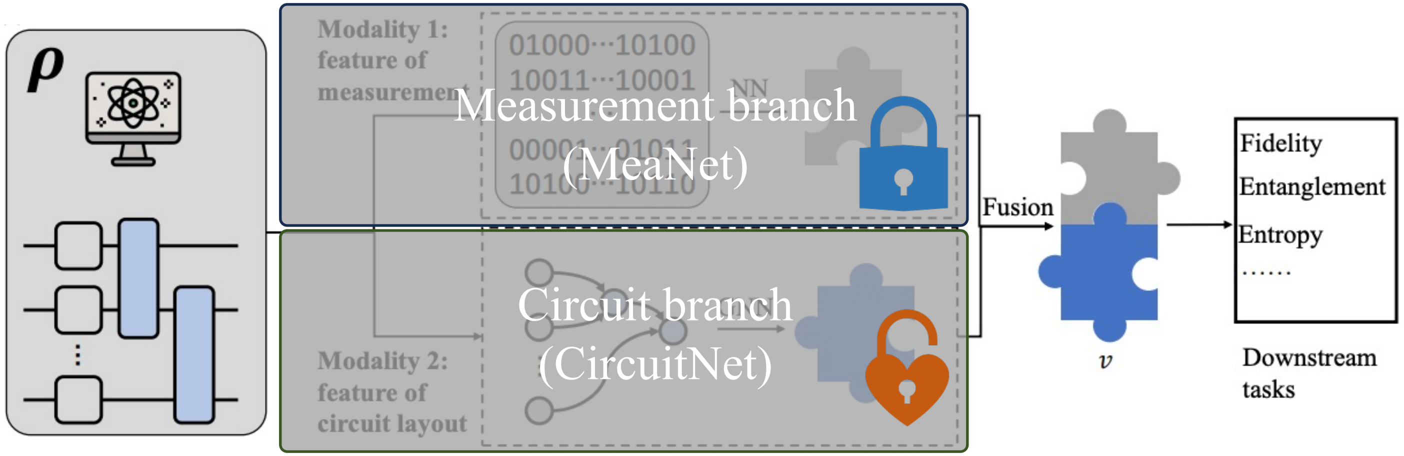
MC-Net [**Step 3**]: multimodal model optimization---Two stage training

Stage I: Independent branch training

For MeaNet



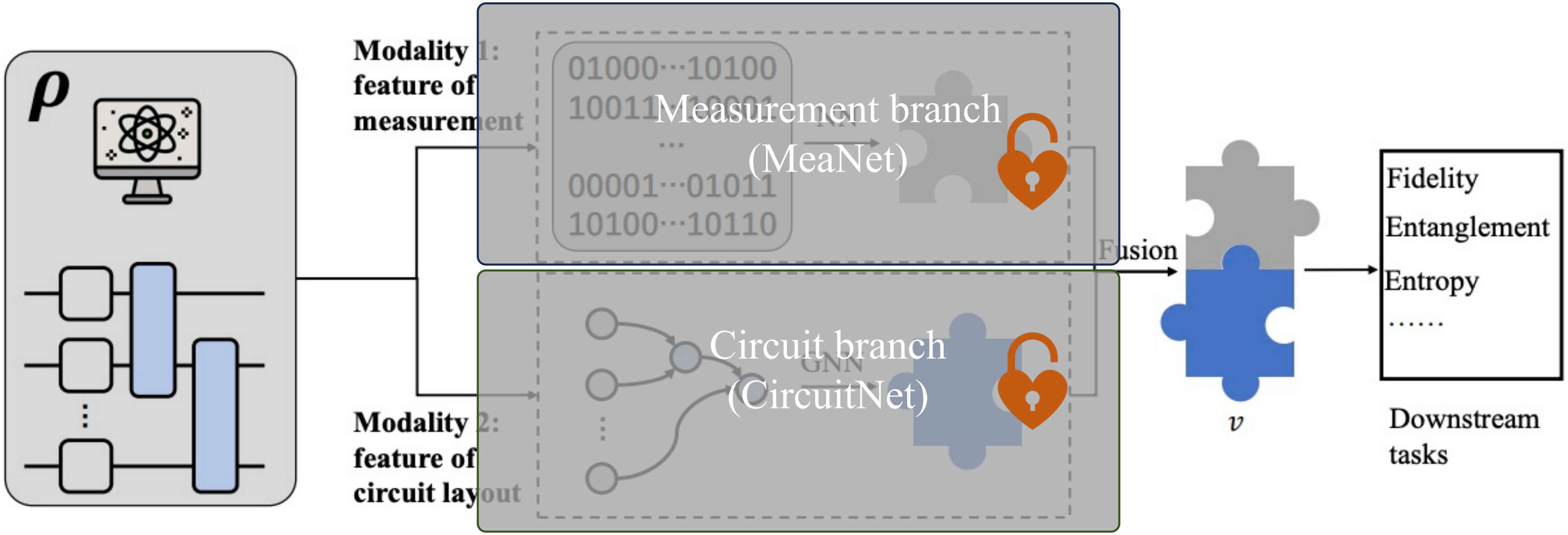
For CircuitNet



Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

MC-Net [**Step 3**]: multimodal model optimization---Two stage training

Stage II: Fine-tuning of two branches

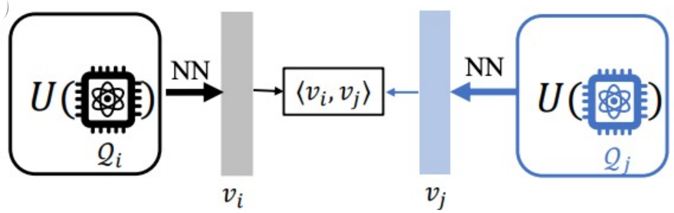


Our Solution: Measurement-Circuit Driven Neural Network for Cross-platform Fidelity Estimation

MC-Net [**Step 3**]: multimodal model optimization---Supervised learning with the objective function

$$\epsilon(\boldsymbol{w}) = \frac{1}{S}\sum_{s=1}^{S} \mathrm{D}\left(\hat{\mathcal{F}}_{ij}^{(s)}, \mathcal{F}_{ij}^{(s)}\right)$$

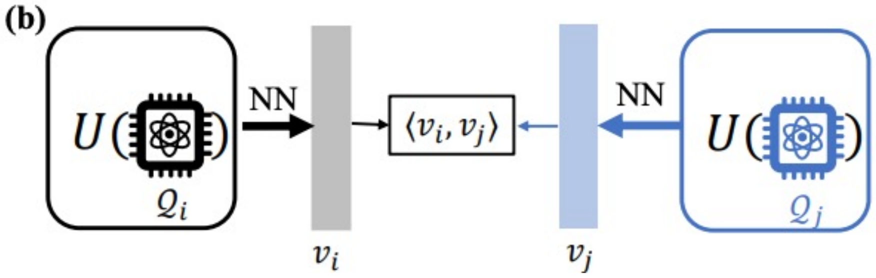
- S is the number of training examples with $\mathcal{D}_{\mathrm{Tr}} = \{(\boldsymbol{x}_i^{(s)}, \boldsymbol{x}_j^{(s)}, \mathcal{F}_{ij}^{(s)})\}_{s=1}^{S}$
- $D(\cdot,\cdot)$ is the per-sample loss, i.e., the mean squared error;
- $\mathcal{F}_{ij}^{(s)} = \mathcal{F}(\rho_i^{(s)}, \rho_j^{(s)})$ is the label of data, i.e., the cross-platform fidelity for between states $\rho_i^{(s)} and\ \rho_j^{(s)}$;
- $\hat{\mathcal{F}}_{ij}^{(s)}$ is the predicted label of the s-th test circuit with $\hat{\mathcal{F}}_{ij}^{(s)} = \frac{\left\langle \boldsymbol{v}_i^{(s)}, \boldsymbol{v}_j^{(s)} \right\rangle}{\left\| \boldsymbol{v}_i^{(s)} \right\|_2 \left\| \boldsymbol{v}_j^{(s)} \right\|_2}$.



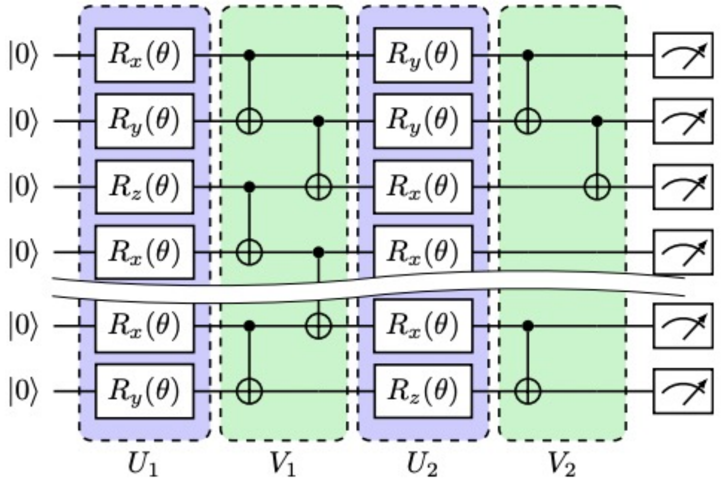
Numerical Simulations

Task 1: Performance of MC-Net for Certifying 6-qubit Quantum devices

Dataset construction



$$\left\{ U = \prod_{l=1}^{L} \prod_{n=1}^{N} e^{-i\theta_{l,n} H_{l,n}} V_l \middle| \theta_{l,n} \sim \mathrm{Unif}(0, 2\pi) \right\}$$

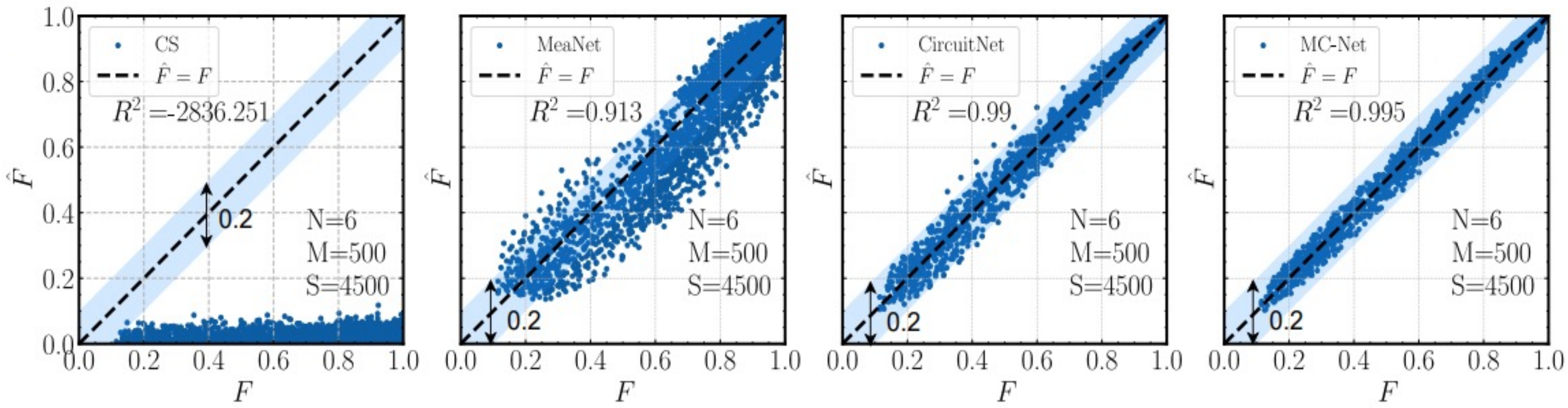


- Size of the training dataset is $S = 4500$;
- The rotation angles and CNOT gates in $\{V_l\}$ are randomly generated;
- The local depolarization noise channel is applied to Q_i and Q_j;
- Shot number for Classical Shadow is M=500.

Task 1: Performance of MC-Net for Certifying 6-qubit Quantum devices

Metric I: Coefficient of determination R^2.

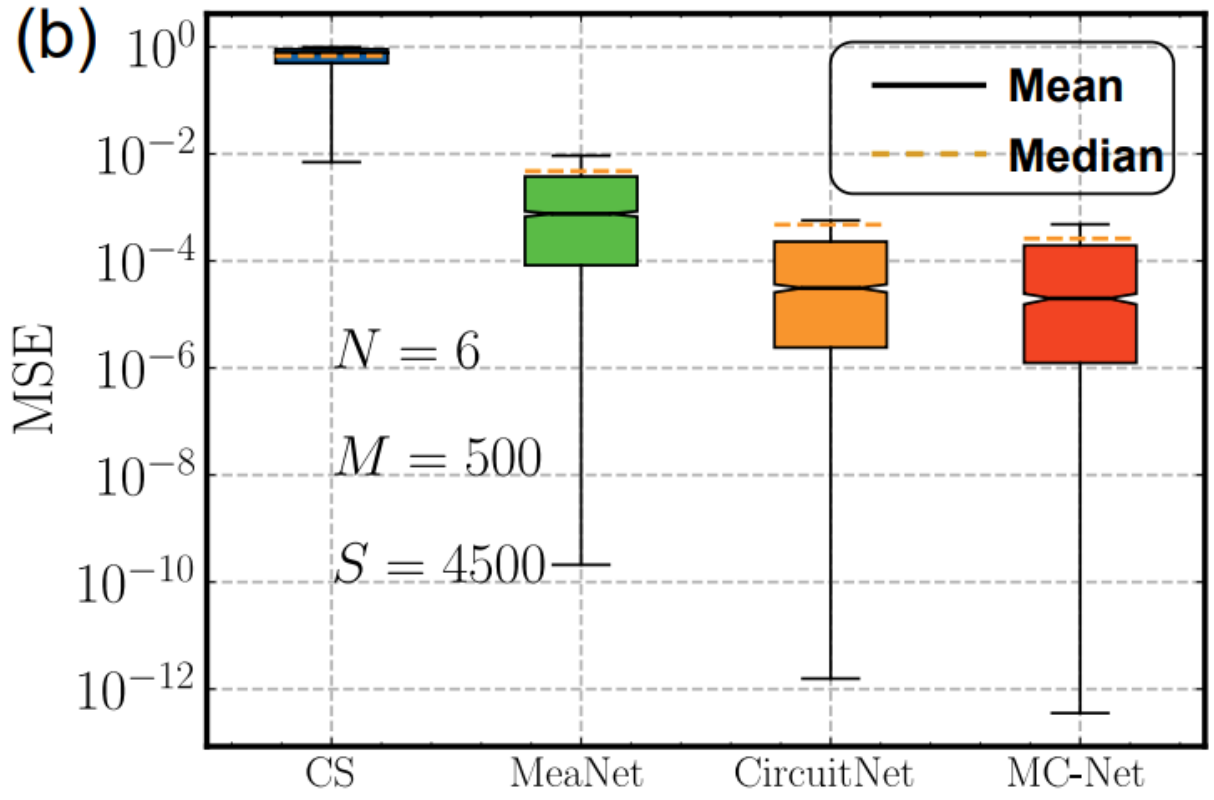
R^2 measures how well the model's estimations match the actual values, with a perfect fit having an R2 value of 1.



Task 1: Performance of MC-Net for Certifying 6-qubit Quantum devices

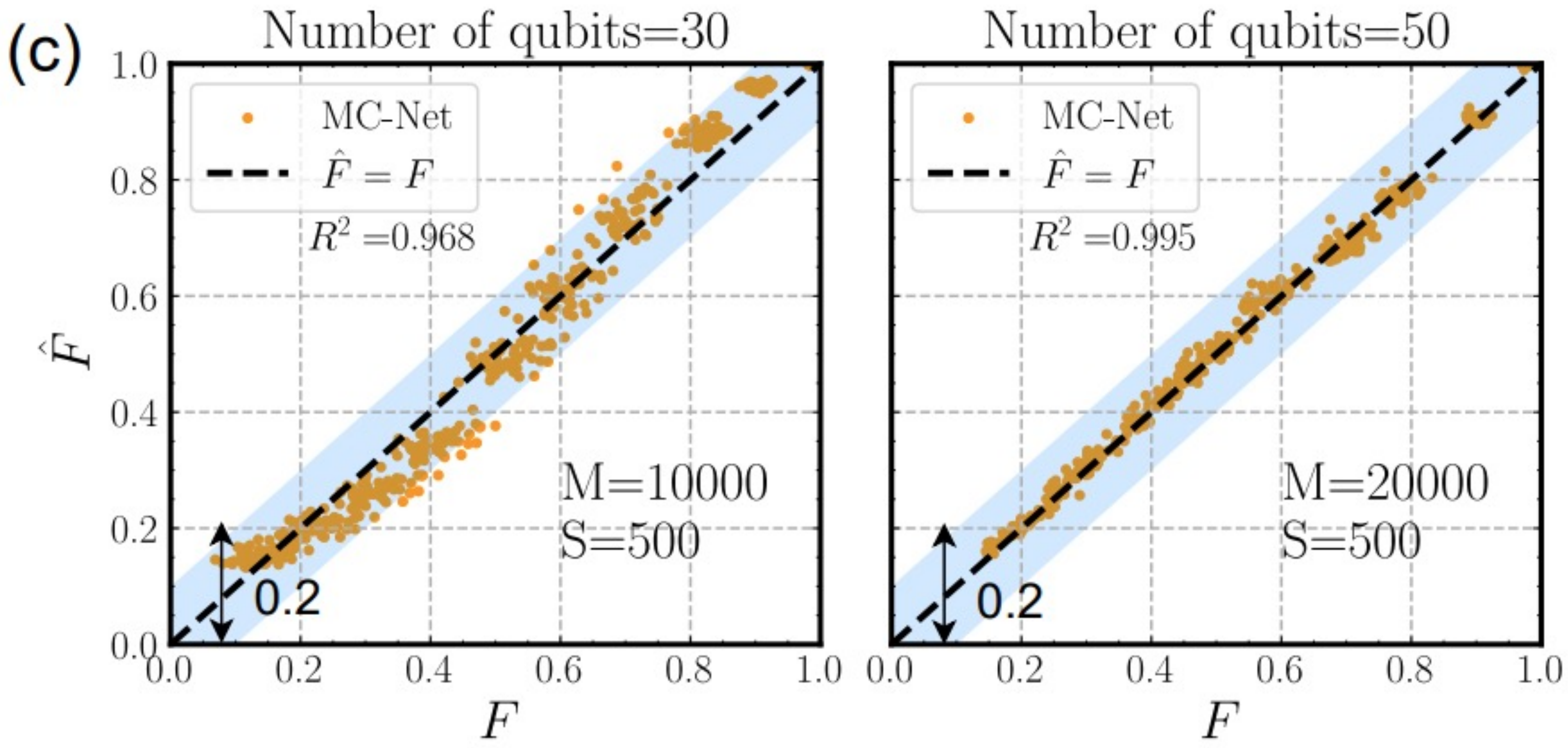
Metric II: Mean Square Error (MSE)

MSE quantifies the average squared difference between our model's predictions and the actual values.



Task II: Performance of MC-Net for Certifying 30-qubit & 50-qubit Quantum devices

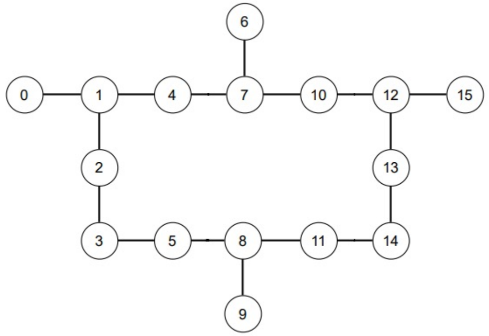
Same dataset construction rule, expect for increasing shots from M=500 to M=10000 (N=30) and M=20000 (N=50)

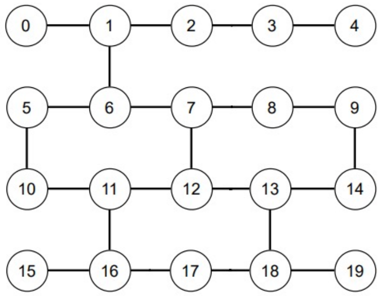


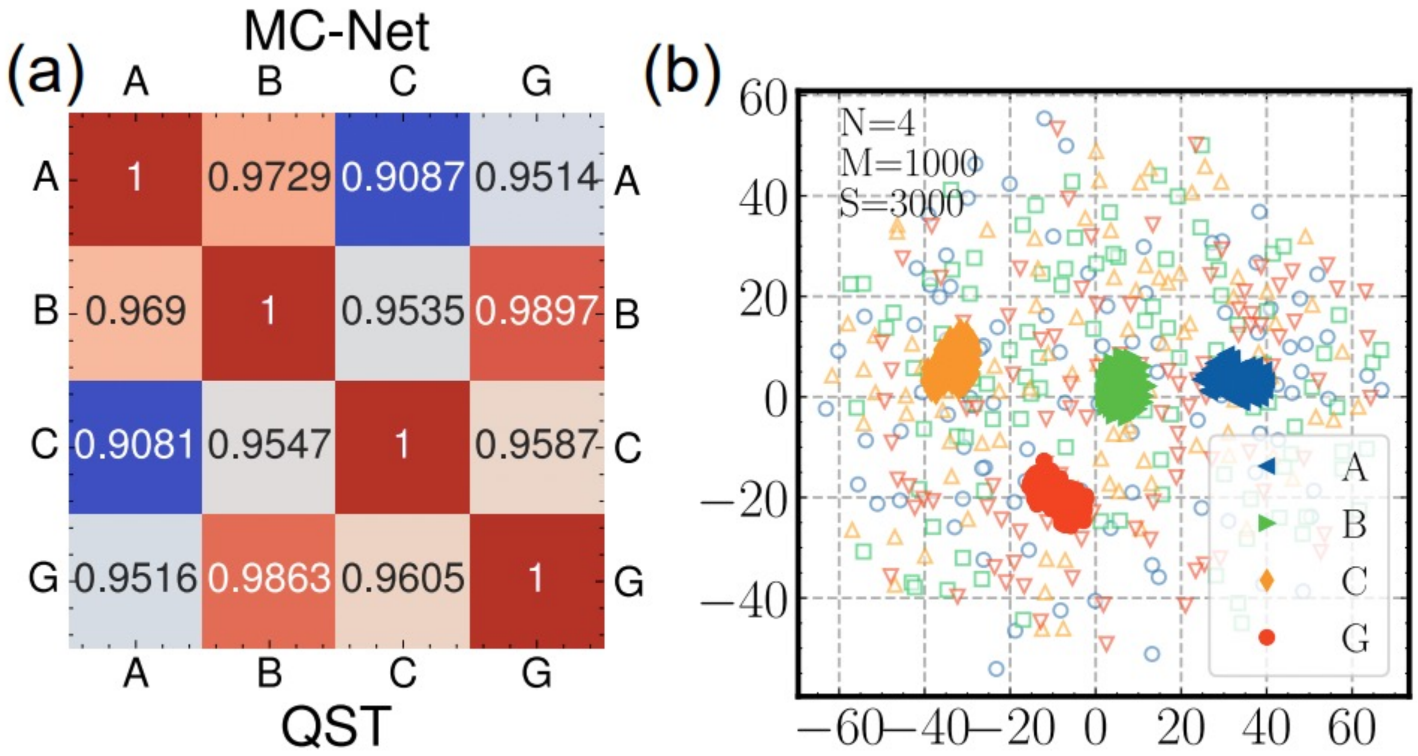
Task III: Performance of MC-Net for Certifying Real Quantum devices

Same dataset construction rule with Task 1, expect for replacing noise model by those of IBMQ devices:

- Fake_almaden (A),
- Fake_boeblingen (B),
- Fake_cambridge (C),
- Fake_guadalupe (G).



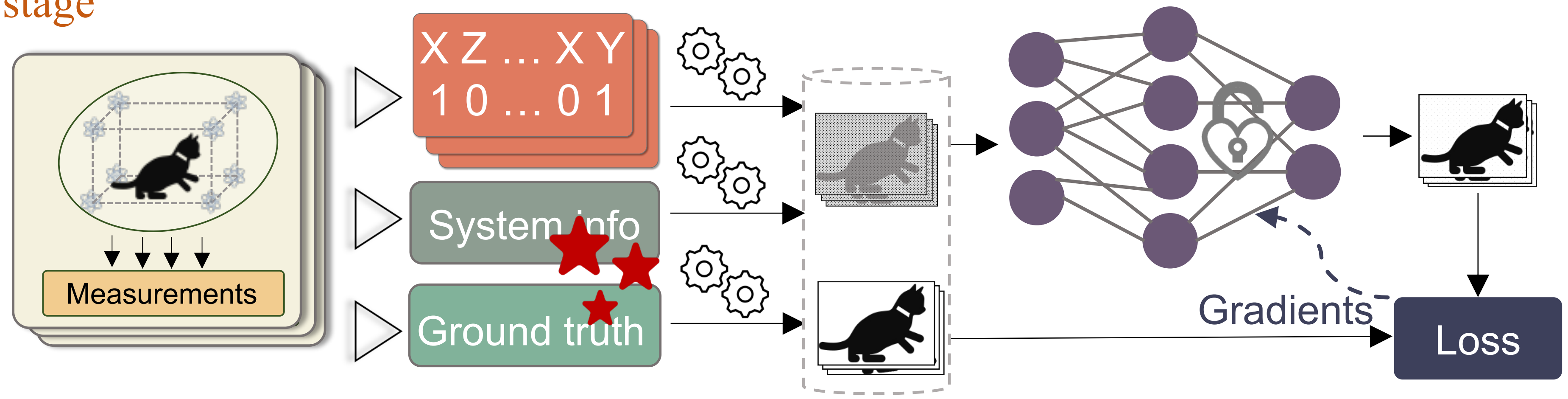




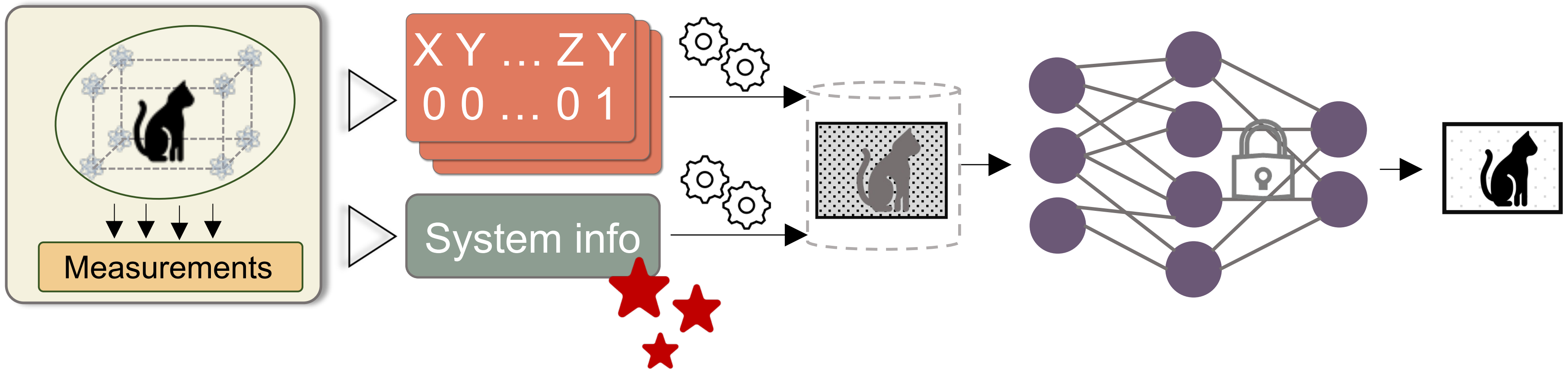
Outlook and Discussion

Data-centric quantum system learning [Du, Yuxuan, et al. *arXiv:2308.11290* (2023).]

Training stage



Inference stage



Data-centric quantum system learning [Du, Yuxuan, et al. *arXiv:2308.11290* (2023).]

System info

- Other efficient strategies to store and compute measurement and circuit modalities.
- Novel transformation methods to map the original formats to those that can be proceeded by neural networks.
- Discover other modalities that can further improve the models' performance.

Task diversities

- Apply our protocol or its variants to other quantum device certification tasks
  - Similarity Testing [Wu, Ya-Dong, et al. *Physical Review Letters* 130.21 (2023): 210601];
  - State Correlation Prediction [Tang, Yehui, et al. *ICLR* (2024)]
  - …
- Build a unified dataset to address different quantum certification tasks.

Thank You for Listening!

Q&A

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