EXTENDING QUANTUM STATE TOMOGRAPHY FOR SUPERCONDUCTING QUANTUM PROCESSORS

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ABSTRACT

Quantum State Tomography (QST):

- Reconstruction of the density matrix of a quantum state via measurements
- Critical to ensure the proper functionality of qubits and quantum operations in a quantum computer
- Necessary to fully characterize a quantum state

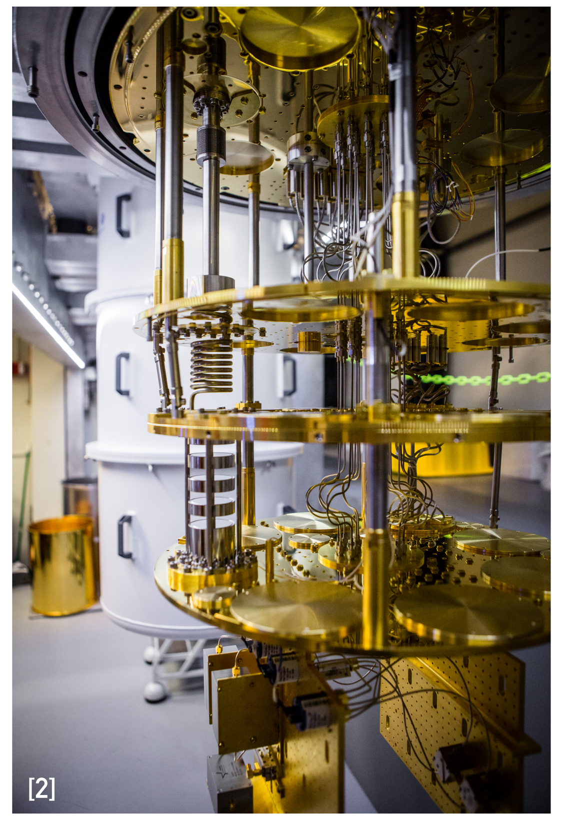
QUBIT STATE	DENSITY MATRIX
$\lvert\psi\rangle = \alpha\lvert 0\rangle + \beta\lvert 1\rangle$	$\rho = \lvert\psi\rangle\langle\psi\rvert$

Prior:

- QST implementation for 1- and 2-qubit systems in our quantum processor [1]

In this work:

- Extend QST to **n-qubit** systems
- Develop a **more scalable**, **less biased** approach to QST



[2]

MLE QUANTUM STATE TOMOGRAPHY BACKGROUND [3,4]

1 DECOMPOSE DENSITY MATRIX INTO PAULIS

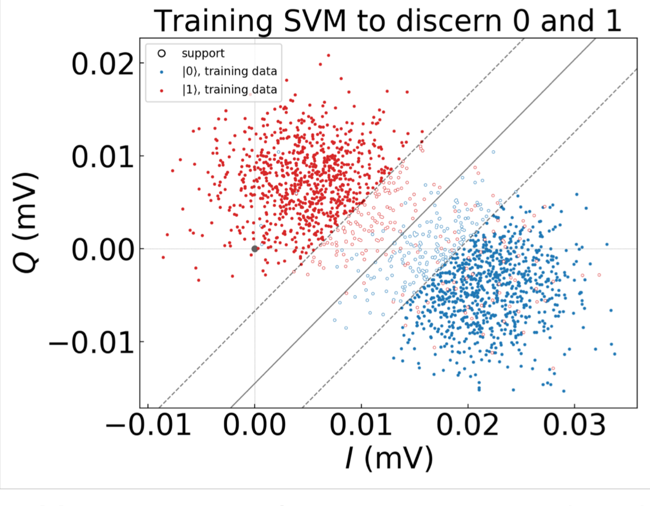
$$\rho_{1QB} = \frac{1}{2}(\langle I\rangle I + \langle\sigma_x\rangle\sigma_x + \langle\sigma_y\rangle\sigma_y + \langle\sigma_z\rangle\sigma_z) \qquad \sigma_x = \begin{bmatrix}0 & 1\\ 1 & 0\end{bmatrix}, \sigma_y = \begin{bmatrix}0 & -i\\ -i & 0\end{bmatrix}, \sigma_z = \begin{bmatrix}1 & 0\\ 0 & -1\end{bmatrix}$$

2 SOLVE FOR MEASUREMENT EXPECTATIONS

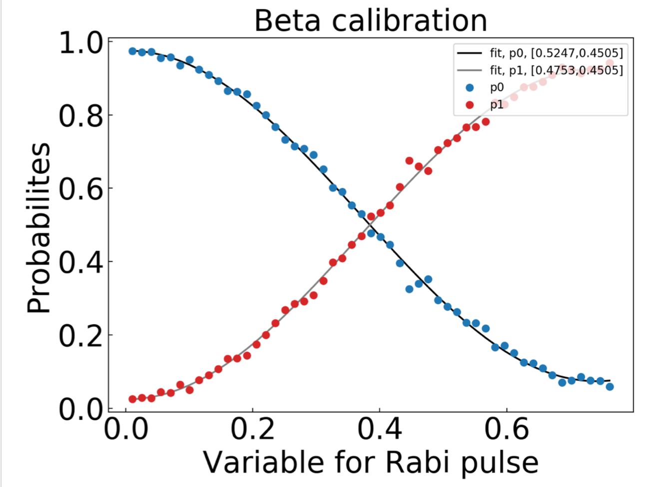
$$\begin{bmatrix}p_0\\ p_1\end{bmatrix} = \begin{bmatrix}\beta_I^{|0\rangle} & \beta_{\sigma_A}^{|0\rangle}\\ \beta_I^{|1\rangle} & \beta_{\sigma_A}^{|1\rangle}\end{bmatrix}\begin{bmatrix}\langle I\rangle\\ \langle\sigma_A\rangle\end{bmatrix}, A \in \{x,y,z\}$$

Beta parameters tell us about the bias of our system and allow us to convert probabilities of being in the ground or excited state to (unphysical) measurement expectations.

3 FIND PROBABILITIES & 'BETAS'



Measurement values are represented on the complex I-Q voltage phase plane. The ground and excited states form two separable clusters.



4 IMPOSE PHYSICALITY CONSTRAINTS

Must ensure density matrix is Hermitian.

$$\rho_t = \frac{T^\dagger T}{Tr(T^\dagger T)}, \qquad T = \begin{bmatrix}t_0 & 0\\ t_2 + it_3 & t_1\end{bmatrix}$$

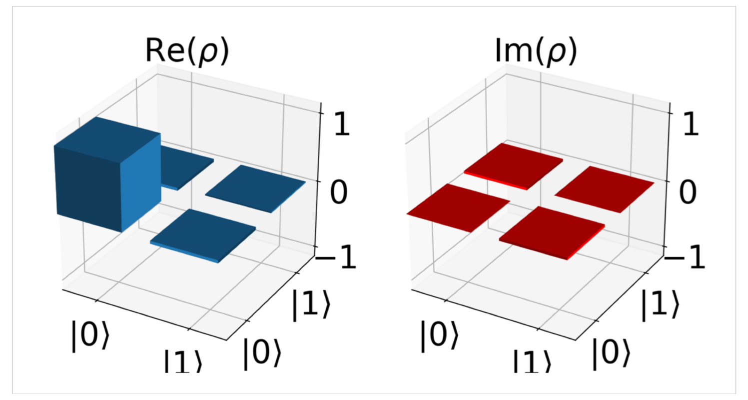
$$t_0^2 + t_1^2 + t_2^2 + t_3^2 = 1$$

5 MAXIMUM LIKELIHOOD ESTIMATION

(MLE)

$$L = \sum_{P\in\{\sigma_x,\sigma_y,\sigma_z\}} (m_{\langle P\rangle} - Tr(P\rho_t))^2$$

SAMPLE 1-QUBIT OUTPUT

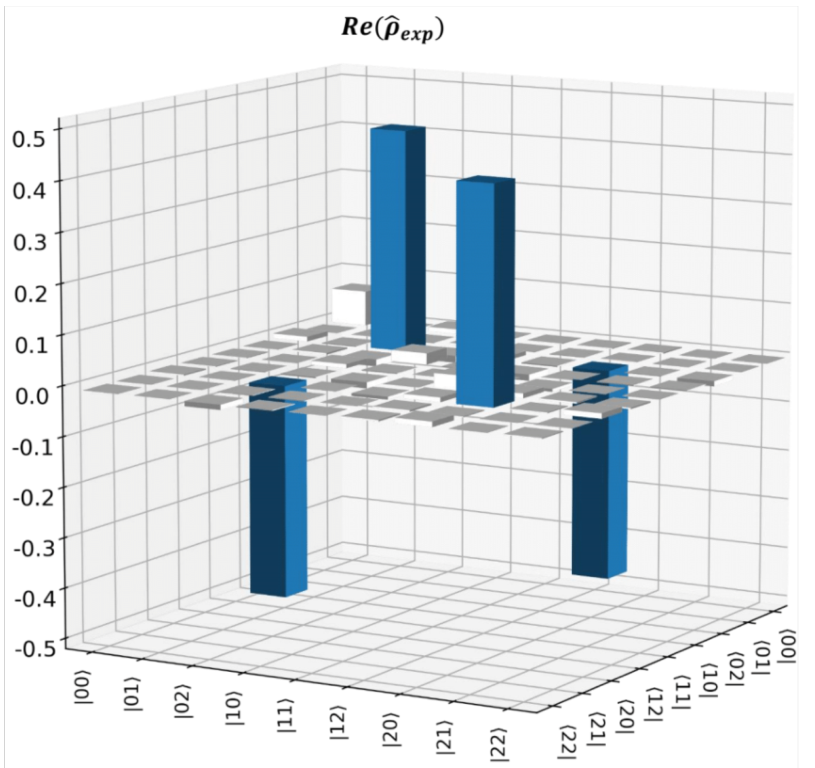


MLE N-QUBIT TOMOGRAPHY

- **Generalized** group's tomography implementation from 1- and 2-qubit systems **to n-qubit, n-level** systems
- **Improved runtime by factor of 100x**, with more efficient cost function implementation

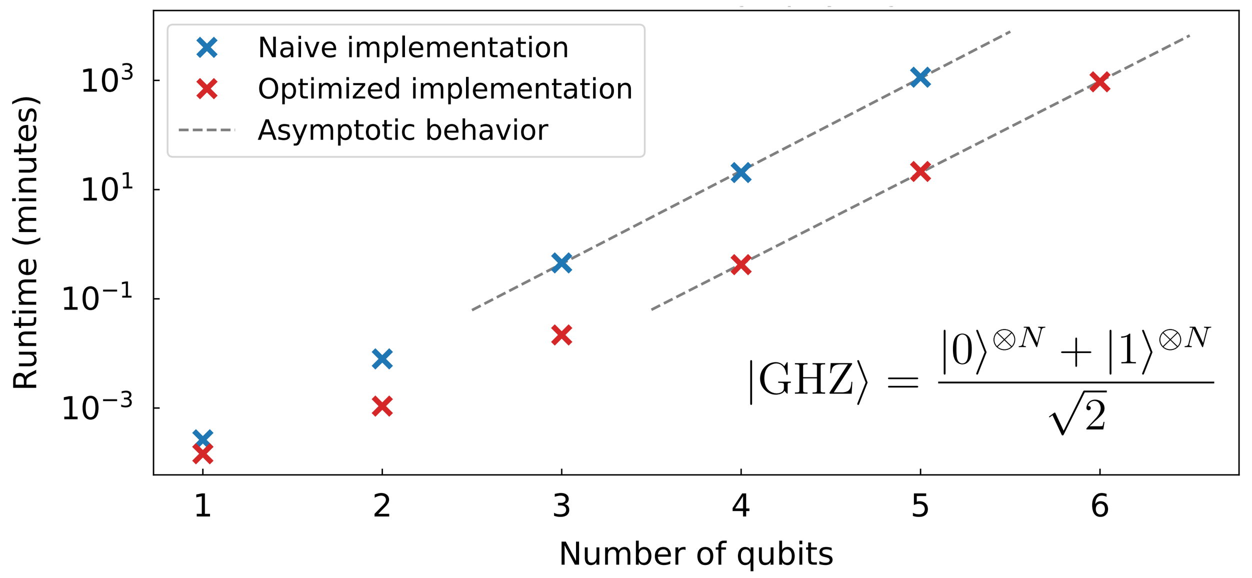
SAMPLE OUTPUT

Density matrix generated using n-qubit MLE QST code on experimental data. Used to compute fidelity of generating correlated itinerant photons in waveguide QED devices [5]. Note that the Hilbert space is truncated to 2 photons (3 states) per degree of freedom.



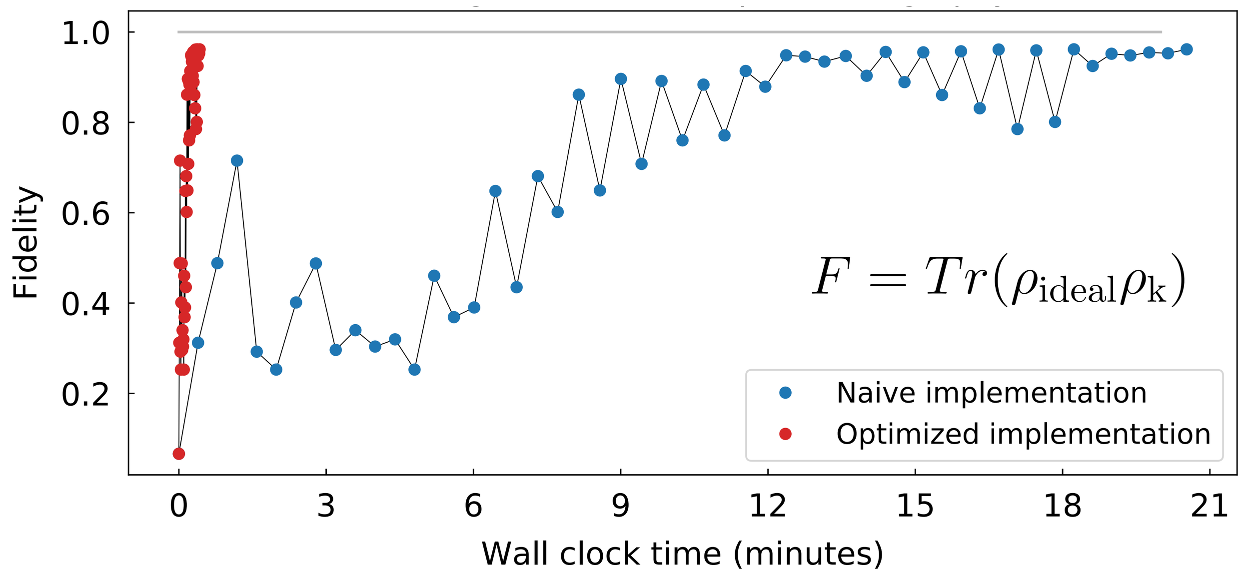
TOTAL RUNTIME OF TOMOGRAPHY ALGORITHM

with simulated noisy data



CONVERGENCE TIME OF 4-QUBIT TOMOGRAPHY

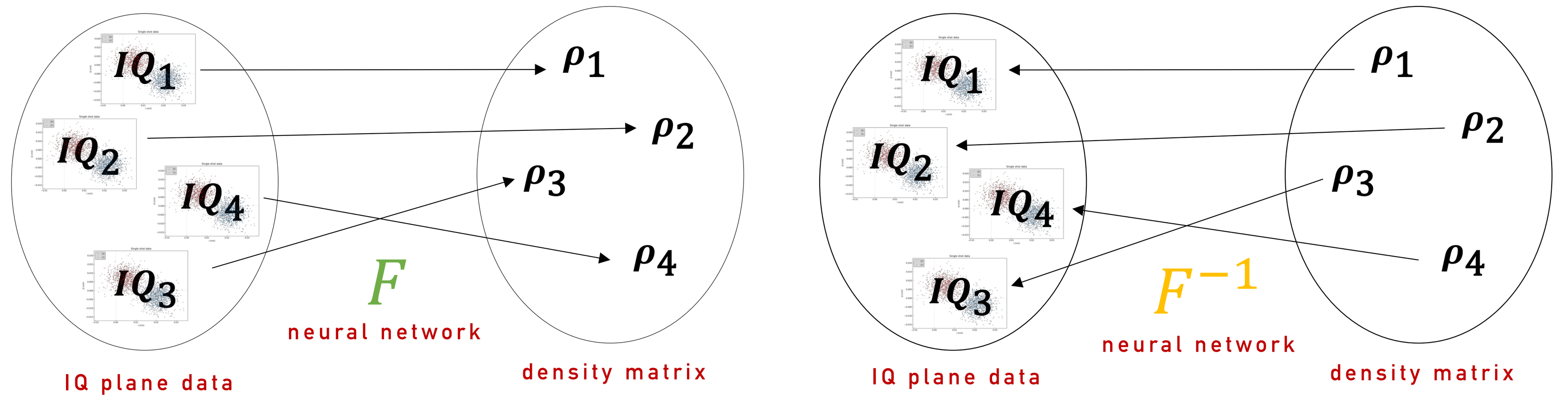
with simulated noisy data



- Limited computationally by exponential scaling of density matrix
- Maximum Likelihood Estimation known to be biased (i.e. overcalculates amount of entanglement) [6]

DEEP LEARNING FOR QST

GOAL: Use CycleGAN [7], neural net architecture, from computer vision to learn a **scalable, unbiased** mapping from measurement values to density matrices (and vice versa).



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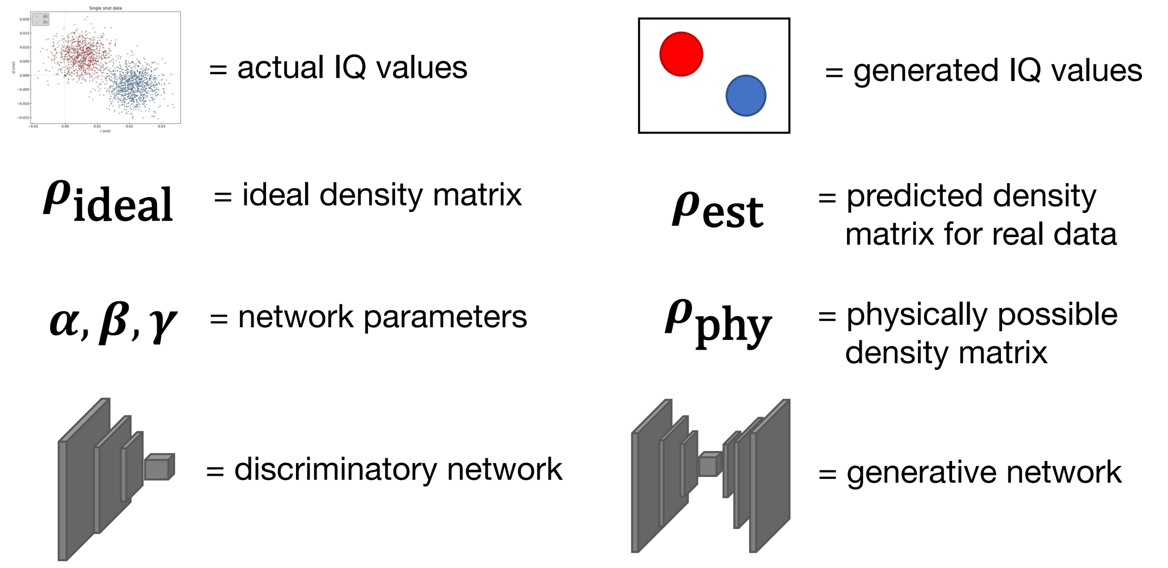
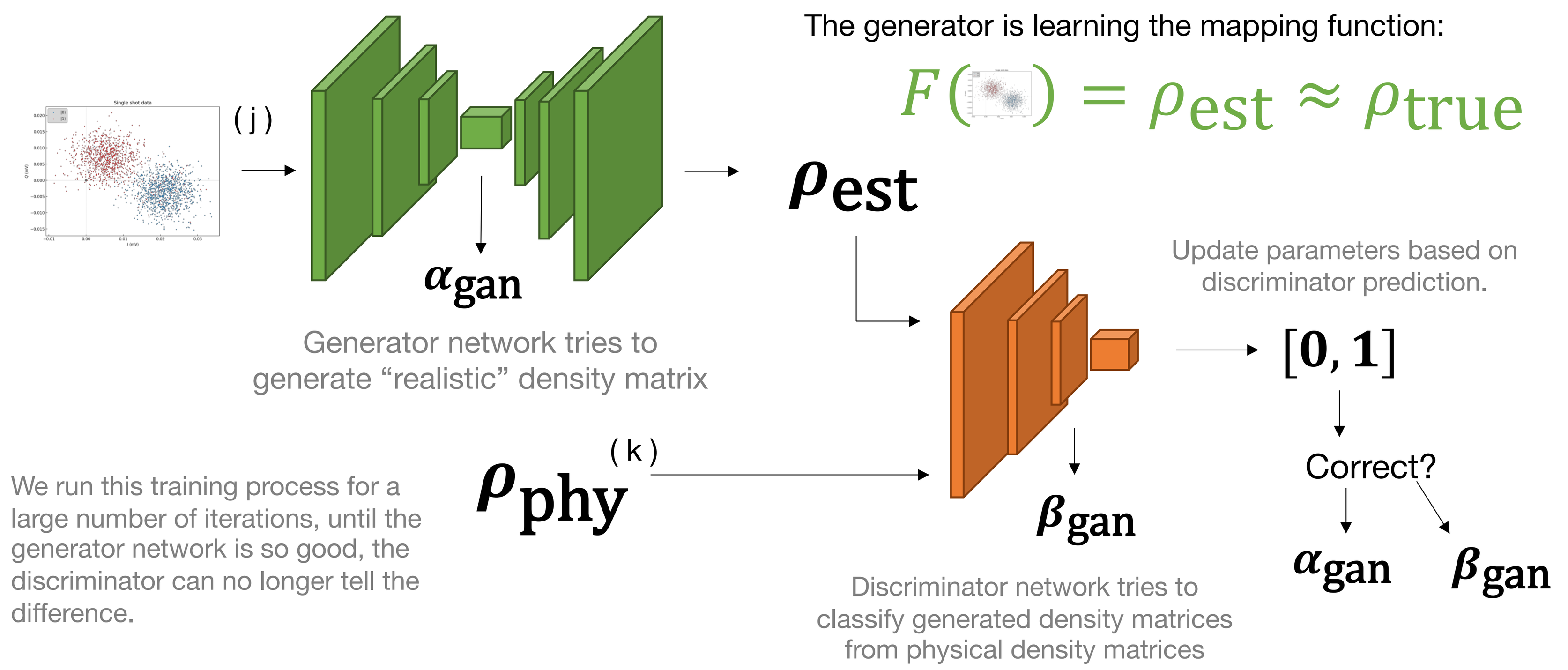


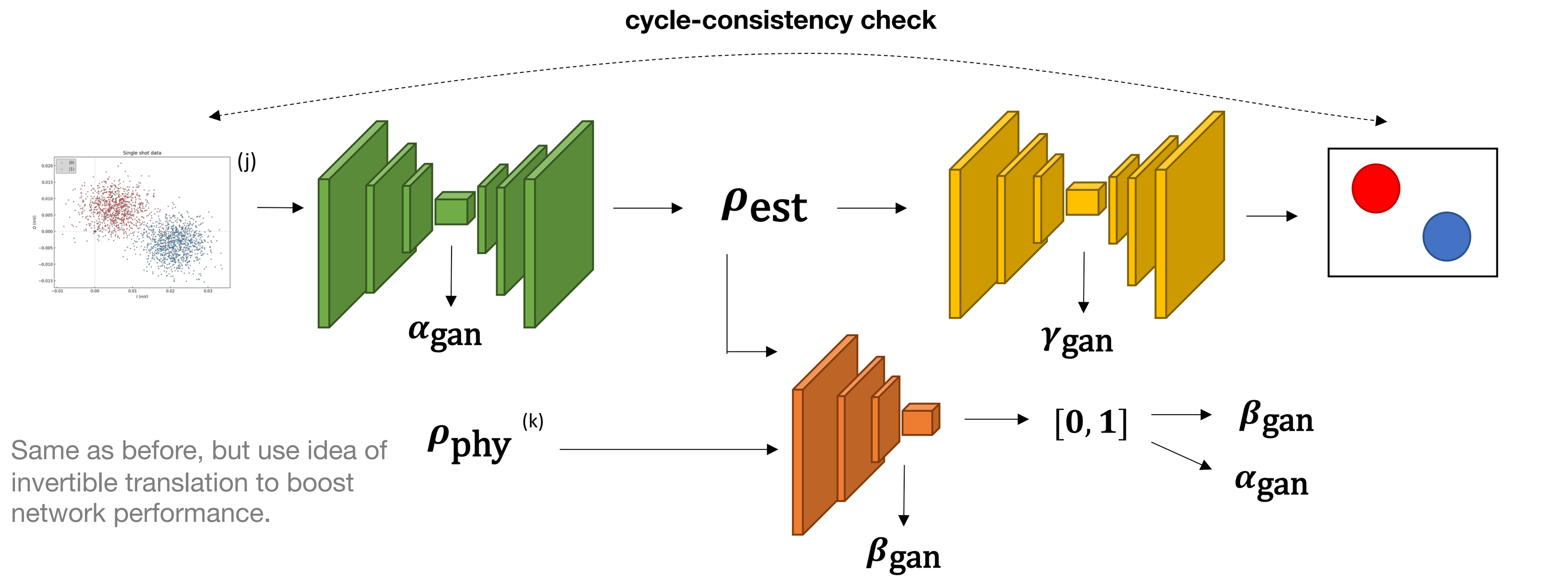
QSTGAN ARCHITECTURE DEVELOPMENT

1 GENERATIVE ADVERSARIAL NETWORK

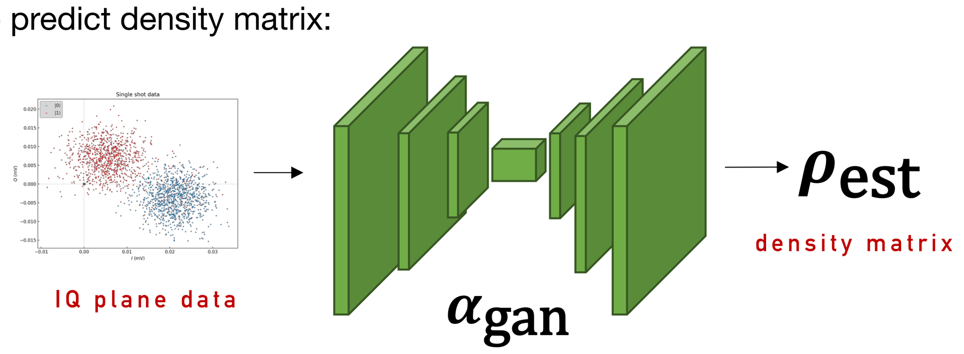


2 CYCLE-CONSISTENT GENERATIVE ADVERSARIAL NETWORK

[Data → ρ → Data]

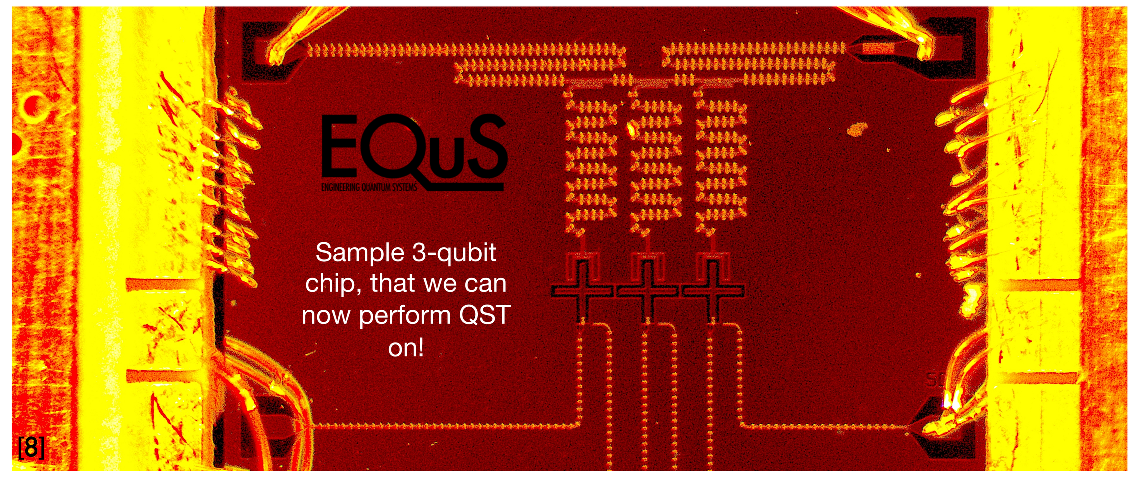


Use measurement values to predict density matrix:



SUMMARY & FUTURE WORK

- **Extended** 1-level 1- and 2- qubit MLE tomography to work on **n-level n-qubit systems**, with **100x** speed-up (implementation improvement)



- Due to **exponential complexity** of full-QST, found **MLE unfeasible for 6+** qubit systems
- **Designed novel framework for QST**, drawing inspiration from the field of computer vision
  - Approach expected to be **more scalable**, since images contain large amounts of data
  - Approach expected to be **less biased**, since the CycleGANs architecture is unsupervised
- Working to implement deep-learning architecture
  - Start with fully-supervised network, then GANs, and finally CycleGANs
  - Begin with 1-qubit data/matrices and then generalize
- Will test on real experimental data and compare results to state-of-the-art approaches, primarily based on restricted Boltzmann architectures

REFERENCES

1. Original 1- and 2- qubit EQuS tomography implementation by Morten Kjaergaard.
2. Photo by Nathan Fiske.
3. Chow, J. 2010. *Quantum Information Processing with Superconducting Qubits*. Yale University, New Haven, Connecticut.
4. Cramer, J. 2012. *Algorithmic speedup and multiplexed readout inscalable circuit QED*. Delft University of Technology, Delft, Netherlands.
5. Experimental data collected by EQuS member, Bharath Kannan.
6. *Quantum state tomography of a single qubit: comparison of methods*. Journal of Modern Optics, 63(18), 1744-1758.
7. Jun-Yan Zhu*, Taesung Park*, Phillip Isola, and Alexei A. Efros. *Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks*, in IEEE International Conference on Computer Vision (ICCV), 2017.
8. Photo by EQuS member, Youngkyu Sung.