

Learning Across Qubit Domains

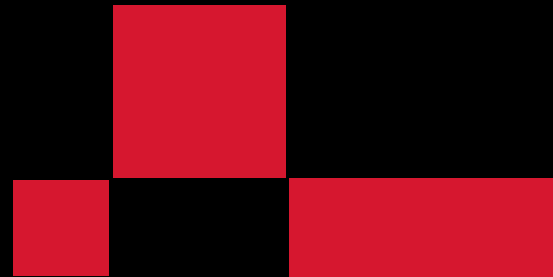
Machine Learning Techniques for
Superconducting Qubits

ILLINOIS TECH

Jehu Martinez

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Jmartinez88@hawk.illinoistech.edu



Superconducting qubits as sensitive detectors

A qubit's measured response depends on its state and its environment.

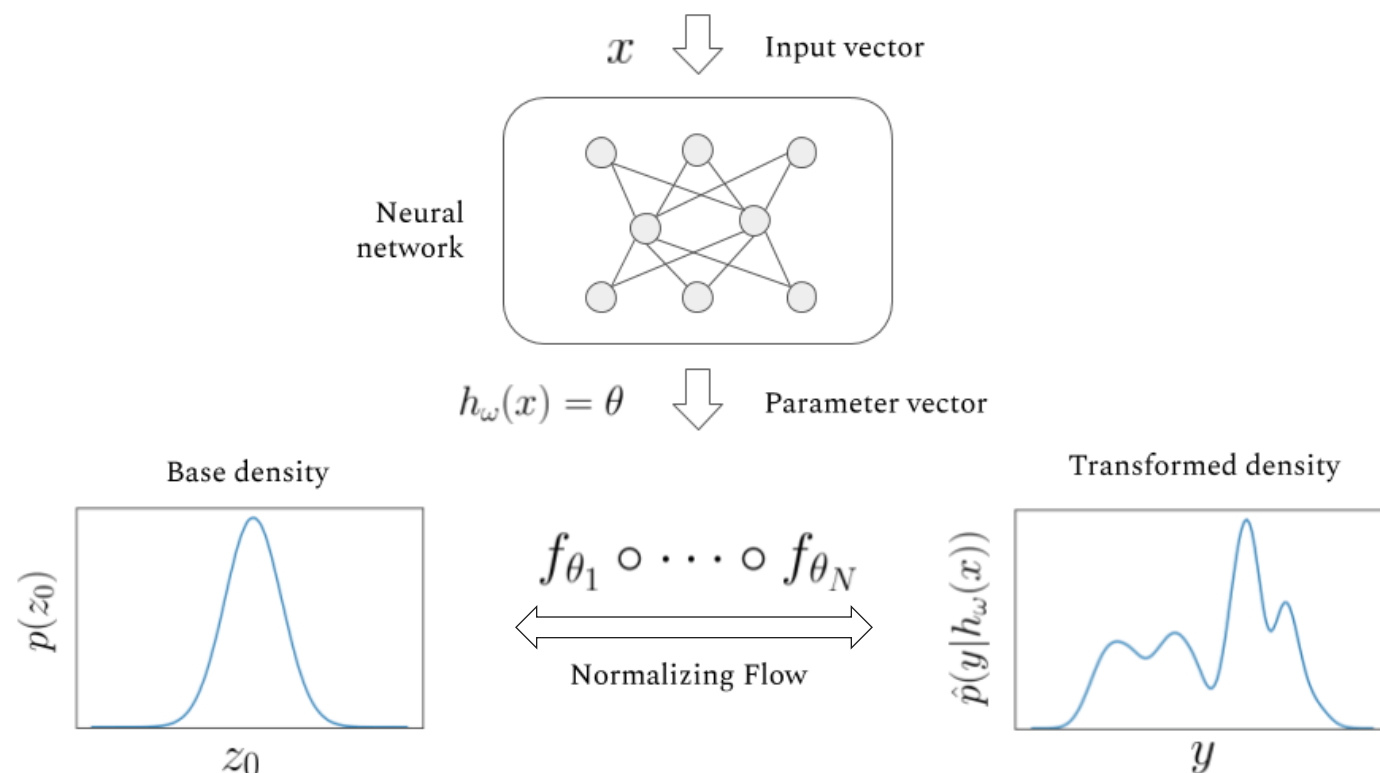
Environmental noise and device defects such as two-level systems (TLS) can change measured distributions. The same sensitivity that enables sensing also complicates the background reference.

Detector question

How can we identify an unexpected change when ordinary device behavior also varies with operating conditions?

Normalizing flows

A normalizing flow learns a reversible transformation between measured features and a simple reference distribution.



<https://siboehm.com/articles/19/normalizing-flow-network>

- Train the NF on background distribution
- Evaluate the learned density for a new measurement
- Inspect Latent coordinate for distribution changes

A likelihood score for each measurement

The change of variables accounts for the deformation of feature space:

$$p_{\theta}(x) = p_0(f_{\theta}(x)) |det(\partial f_{\theta} / \partial x)|$$

$$S(x) = -\log p_{\theta}(x)$$

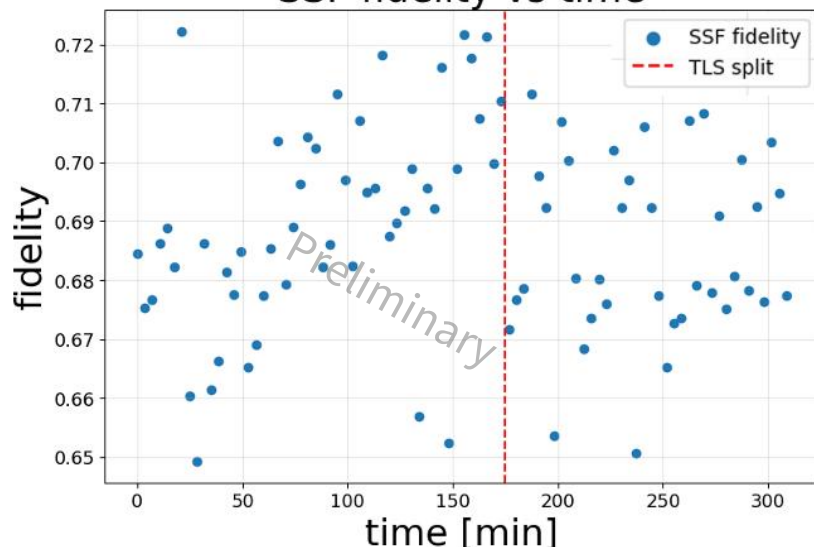
Larger negative log-likelihood (NLL) means lower density under the learned background model.

A background score distribution supplies the reference for flagging changes. Each modality needs its own calibration.

Flow likelihood: L. Dinh et al., ICLR 2017, arXiv:1605.08803. Likelihood caveats: E. Nalisnick et al., ICLR 2019, arXiv:1810.09136.

Measurements of the same device

SSF fidelity vs time

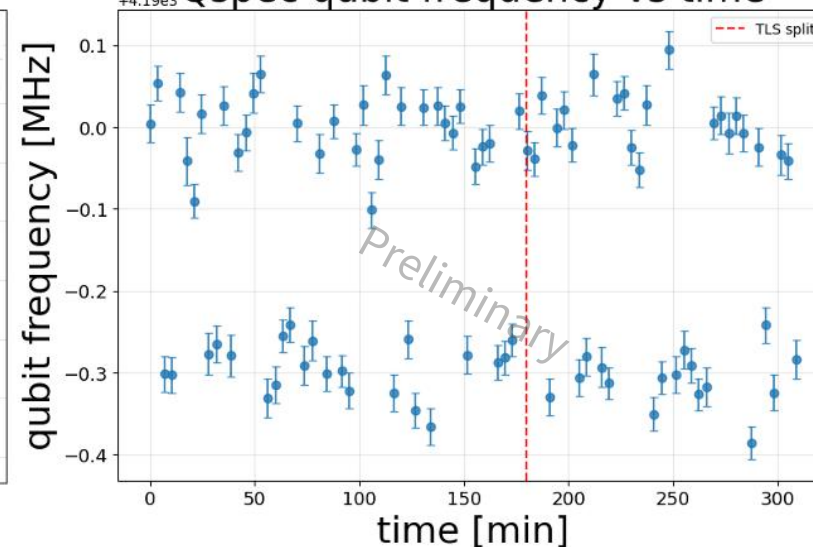


Single-shot fidelity (SSF)

State discrimination from microwave readout I, Q.

Modeling target: the background distribution within each measurement modality.

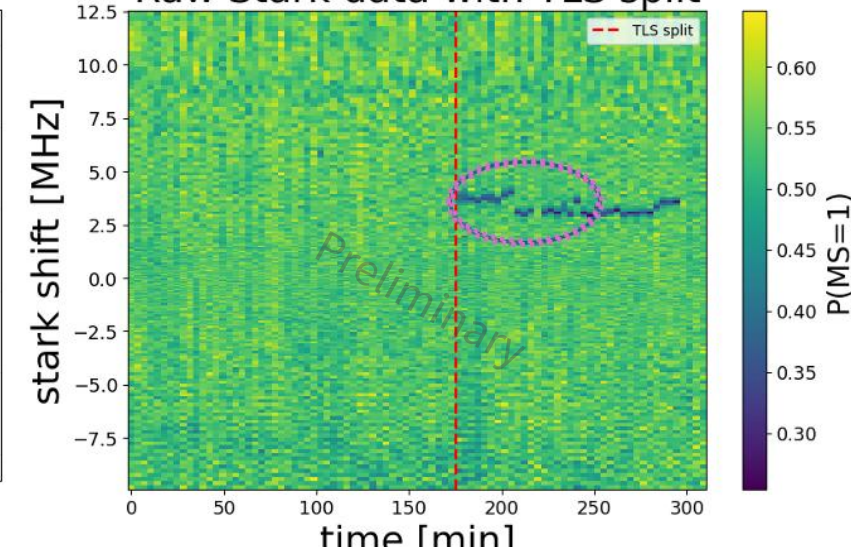
Qspec qubit frequency vs time



Qubit spectroscopy

Resonance position and spectral structure.

Raw Stark data with TLS split

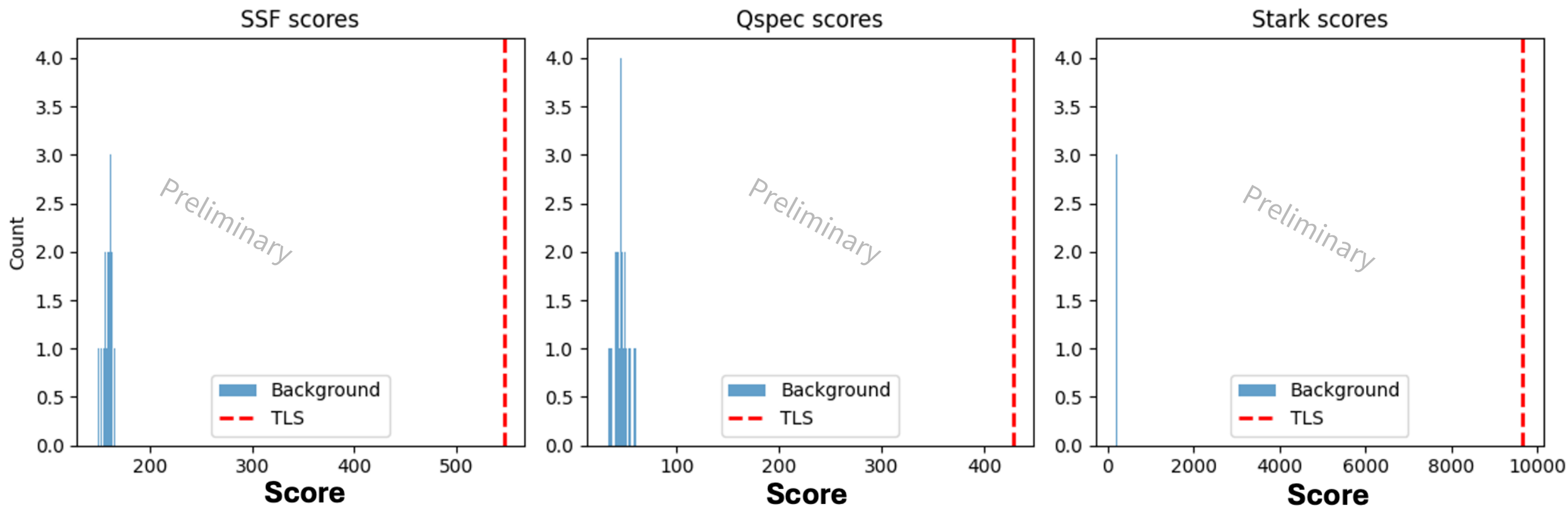


Stark spectroscopy

Drive-dependent response and defect-related features.

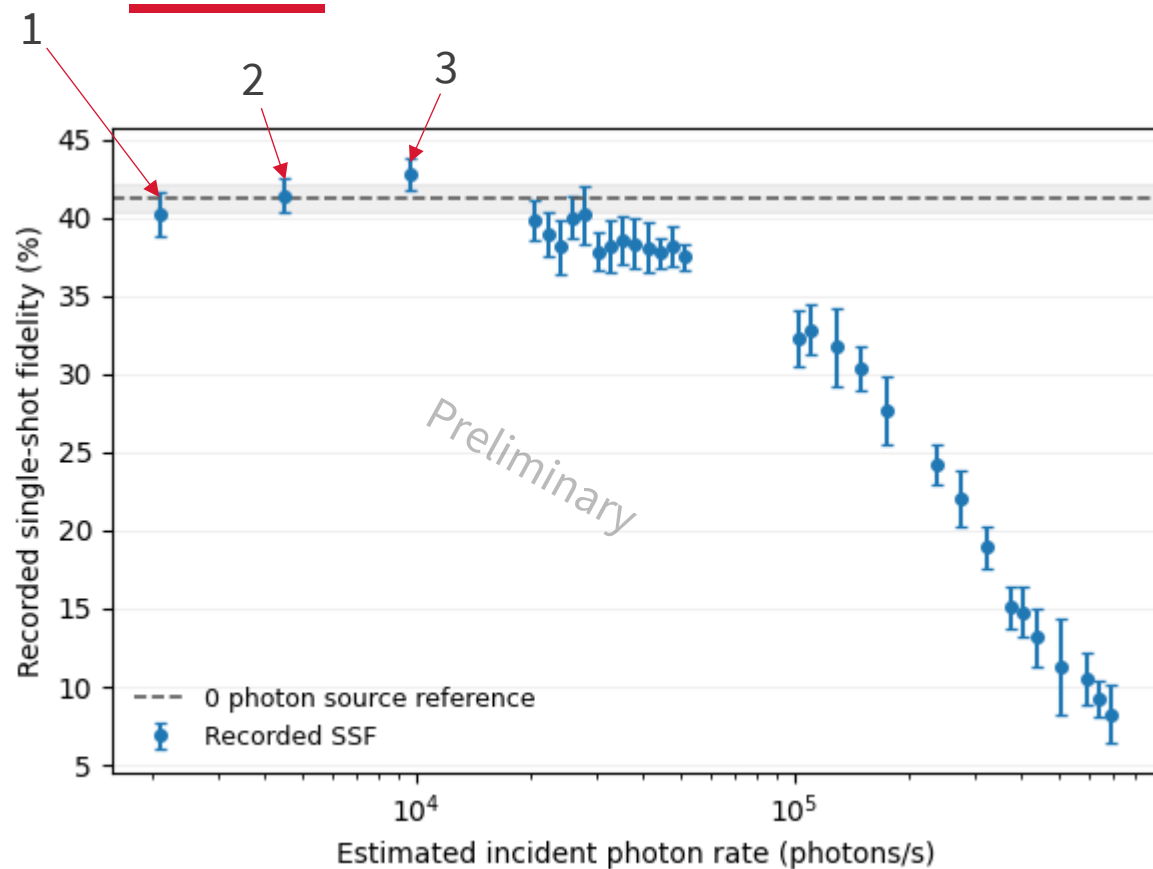
TLS data collection: Ryan Edward Linehan and Arianna.

A TLS-associated example across modalities

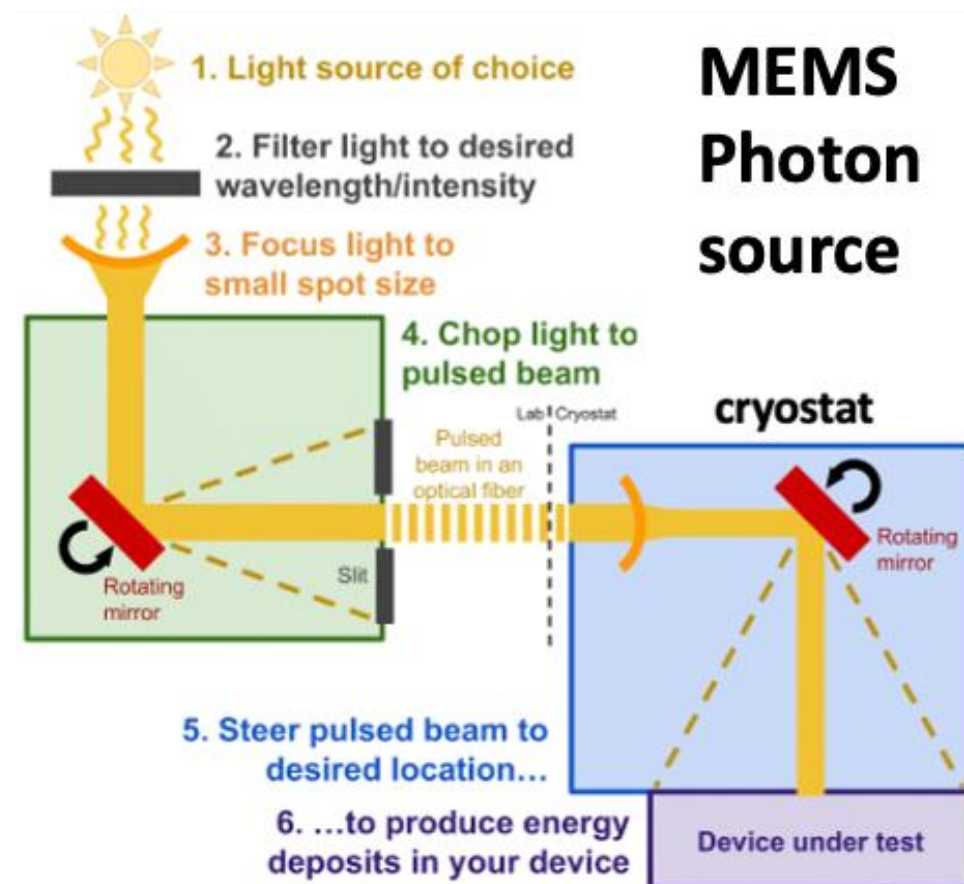


The highlighted score lies outside the displayed background scores in each modality.
This is a qualitative example.

MEMS data: controlled photon exposure

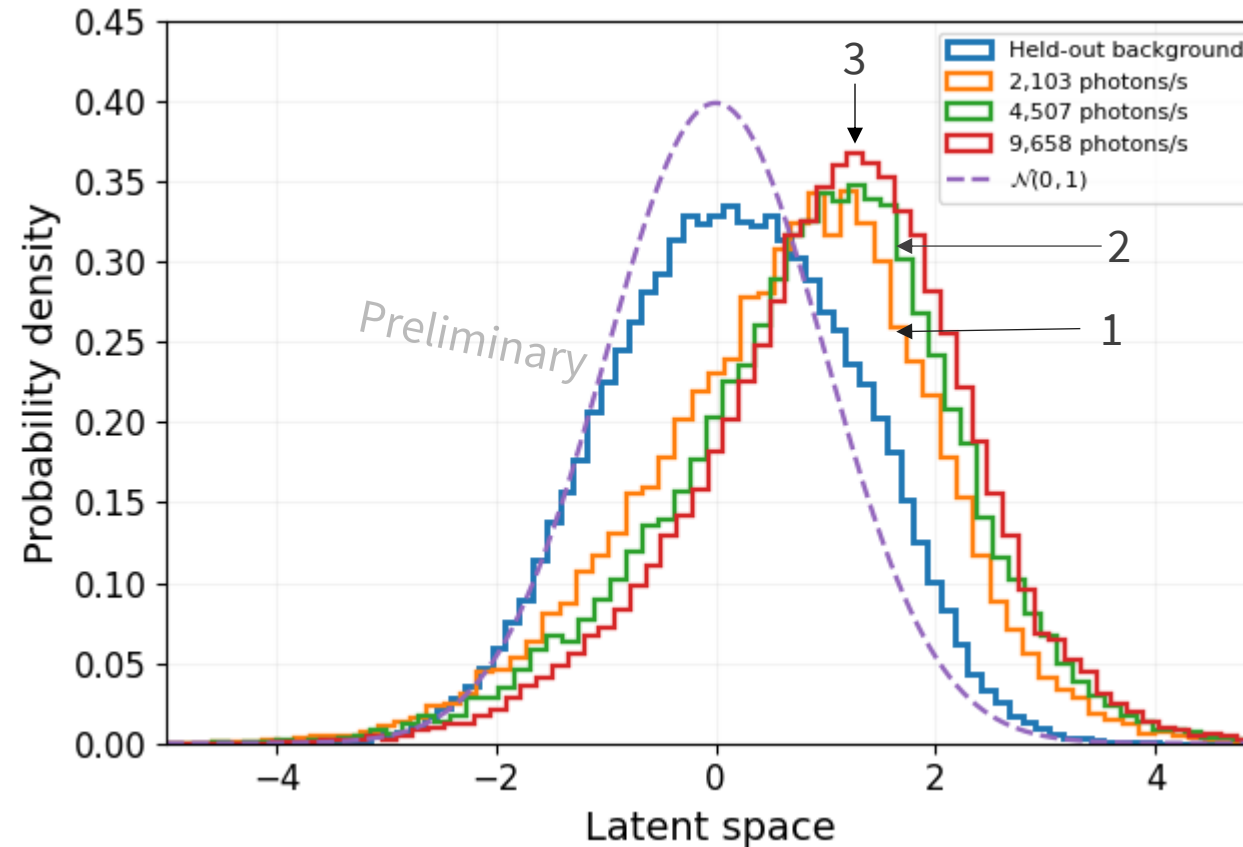


MEMS data collection: Israel Hernandez.



Question: Can the full readout distribution reveal changes that are difficult to distinguish in mean SSF?

MEMS data: looking beyond mean SSF



Learn the background

Train the normalizing flow on the reference readout distribution.

Compare photon-exposed data

At 10^3 photons/s, the latent distribution shifts relative to the held-out background.

Background changes across qubit domains

A model trained in domain A learns $p(x)$. Ordinary background in domain B may follow a different distribution $p'(x)$.

$$p_A(x) \neq p_B(x)$$

Same measurement, new conditions

A new time interval, voltage, or device.

Fine-tuning can reuse the input features.

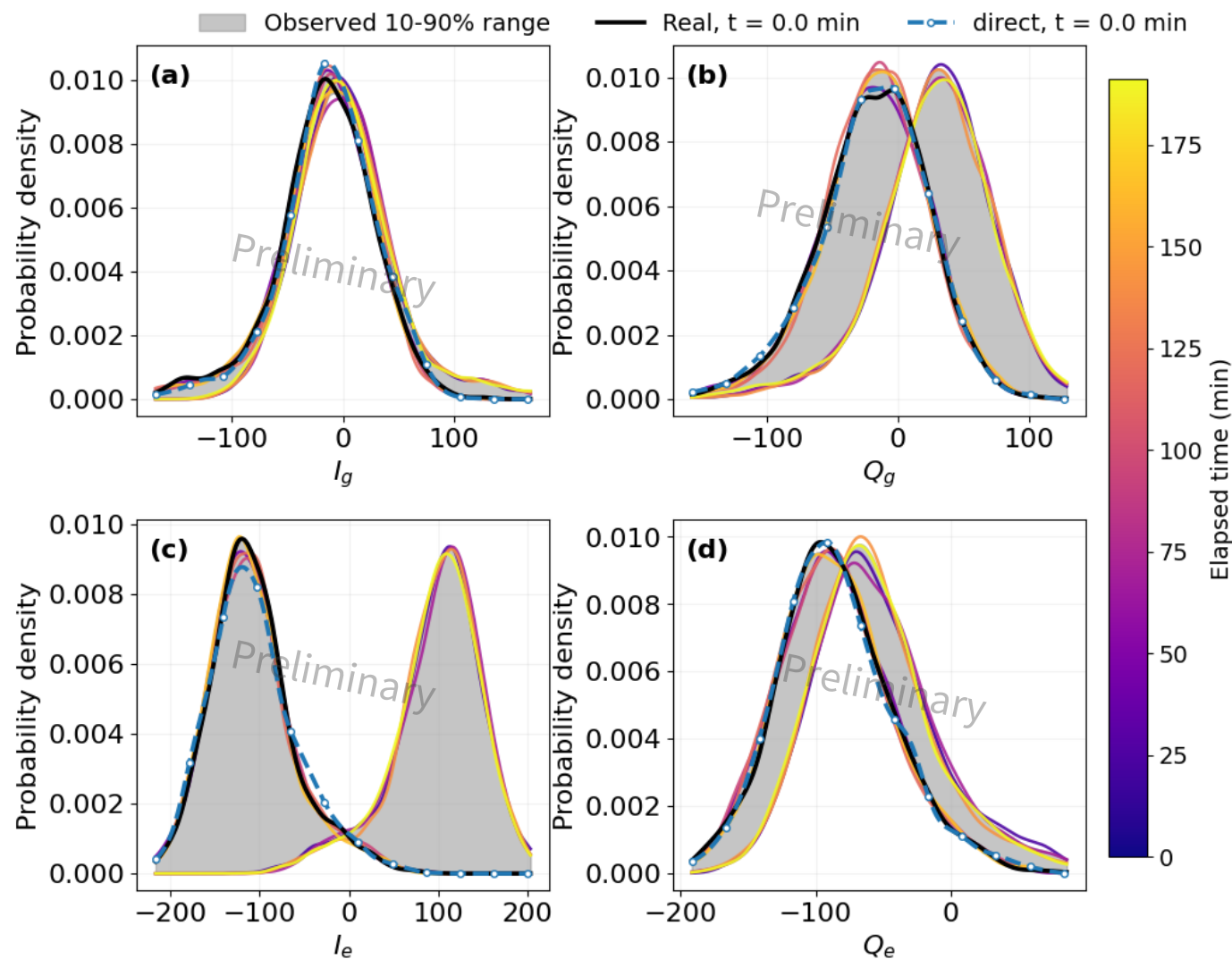
Different measurement modality

SSF readout versus spectroscopy.

A new representation or model interface may be required.

Transfer-learning question: how much new background data is needed to recover a useful reference?

Source-domain background modeling



1. Direct conditioning

Reading the comparison

Black: measured distribution at $t = 0$.

Dashed blue: model distribution at $t = 0$.

Colors: distributions at different elapsed times.

Preliminary observation

Longer training improved agreement in the runs tested so far.

Temp data collection: Arianna H. Colón Cesaní.

Adapting a learned background with limited data

Direct conditioning

Model the readout distribution as a function of elapsed time:

$$p_{\theta}(x|t).$$

Reuse the trained model

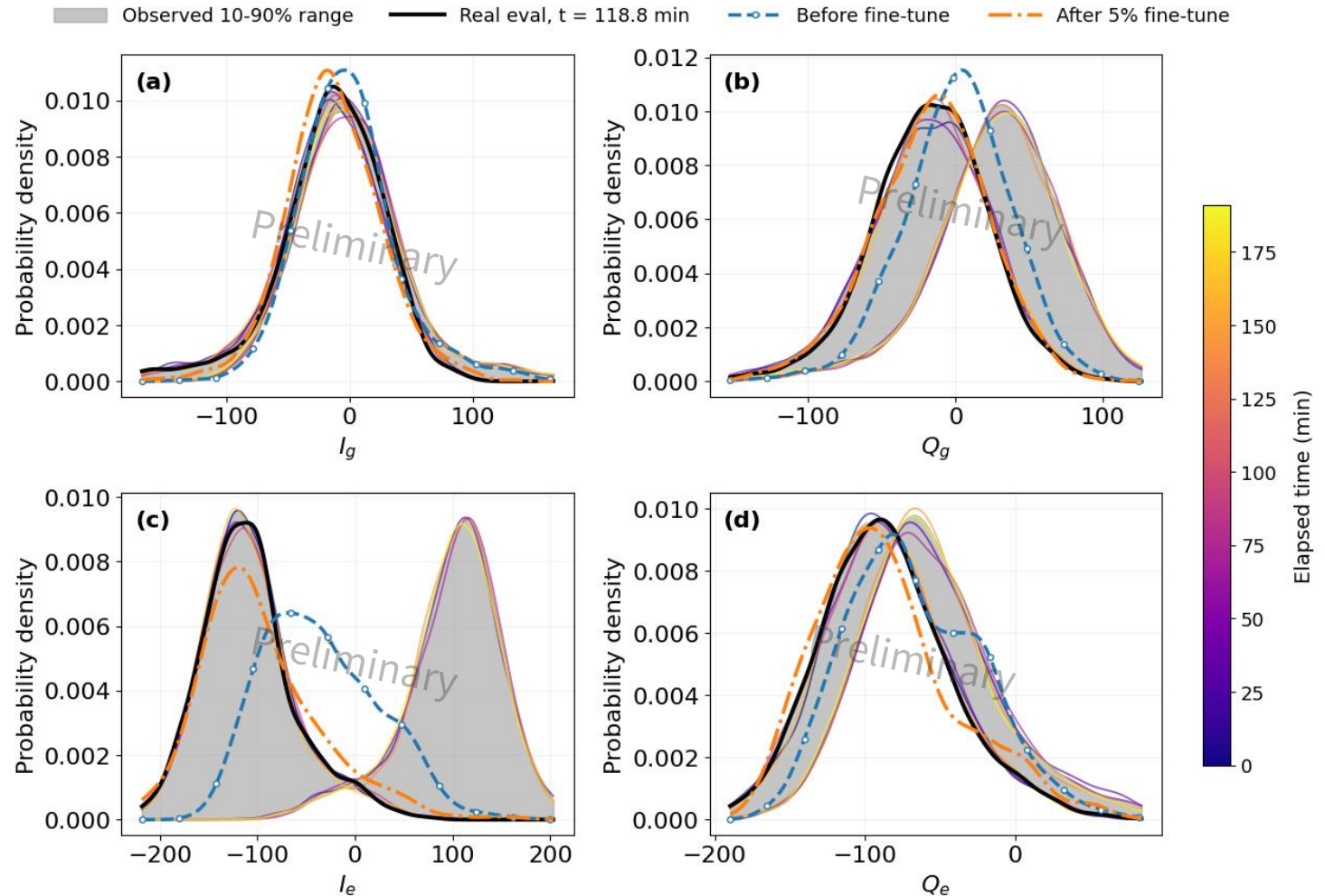
Update the learned background using the 5% fine-tuning setting.

Before and after

Black: measured data.
Blue: before fine-tuning.
Orange: after fine-tuning.

Preliminary result

Closer agreement in Q_g and I_e , with residual channel-dependent differences.



20 mK; evaluation at t = 118.8 min. Shown: before and after the 5% fine-tuning step.

Next step: transfer across temperature

Question: Can a learned background model adapt to a different temperature using limited new data?

$$p_{t_s}(x|t) \rightarrow p_{t_t}(x|t)$$

Source temperature T_s Target temperature T_t

Model comparison

Treatment at the target temperature

Frozen source model	Apply the trained model without updating its parameters.
Fine-tuned source model	Reuse the trained weights and update them using limited target background data.
Model trained from scratch	Train a new model using the same target-data budget.

Evaluate on separate target runs: distribution agreement, false-alarm control, and response to

Summary and next steps

Normalizing flows provide a learned background reference for superconducting-qubit measurements.

Current examples

These examples show shifts in model scores and latent distributions as measurement conditions change.

Ongoing direction

Test whether limited fine-tuning can preserve useful latent space as the background changes across qubit domains.

Calibrated performance on independent runs remains the benchmark.

Thank you!

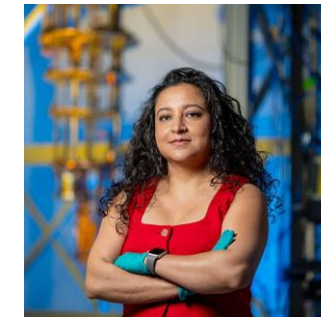
Our group



Thank you for the measurements, guidance, and collaboration.



**Israel
Hernandez**
IIT



**Rakshya
Khatiwada**
IIT / Fermilab

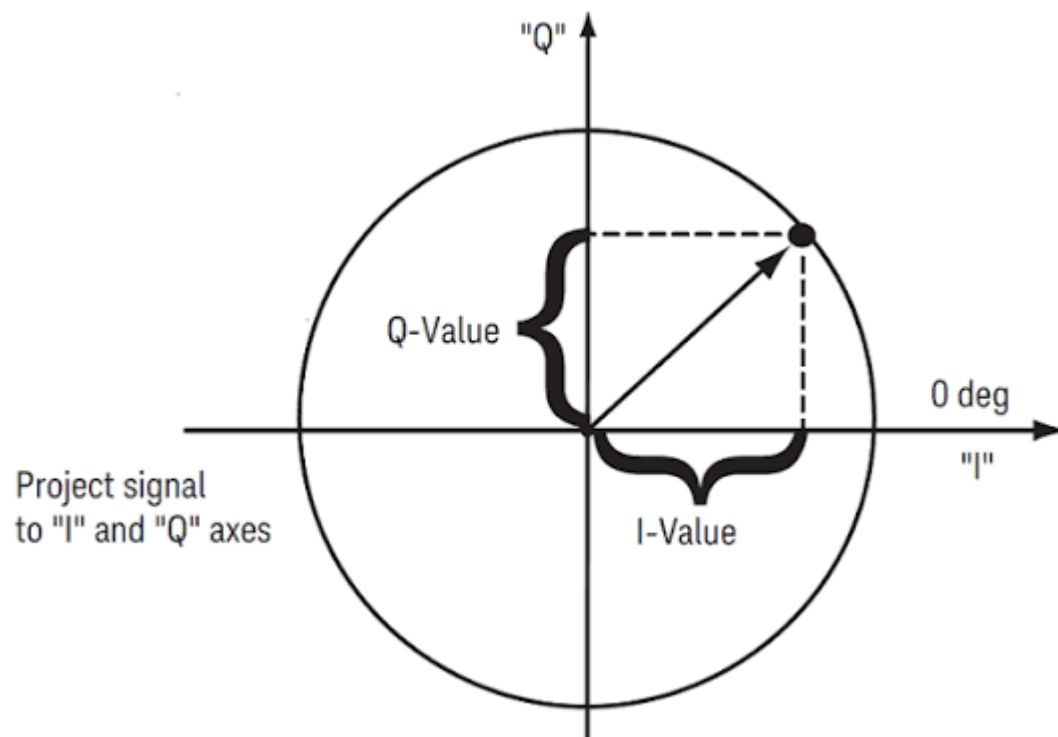


**Ajeeta
Khatiwada**
Los Alamos

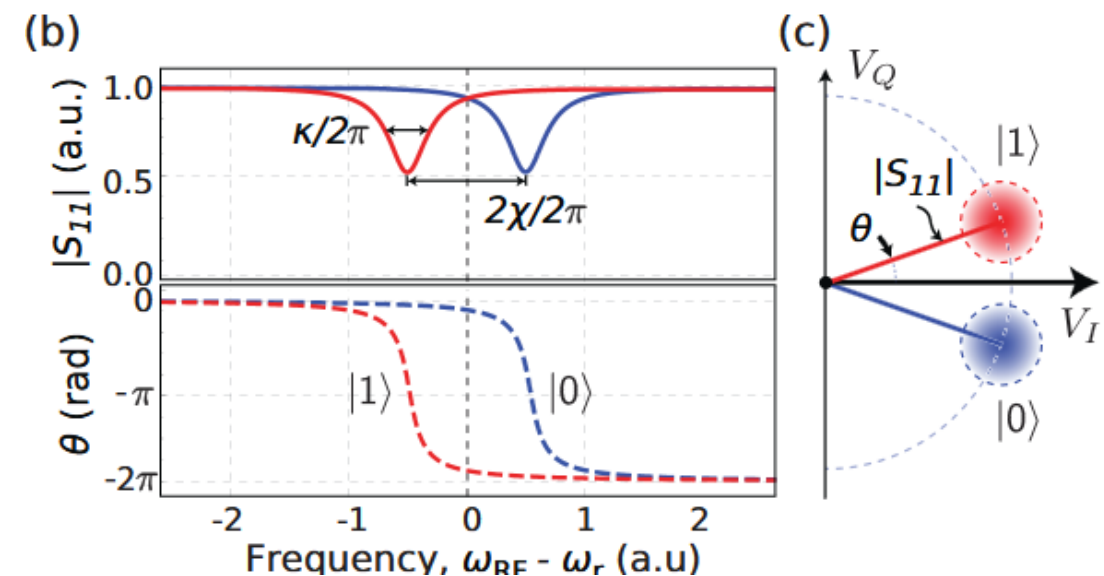


**Sara
Sussman**
Fermilab

What is I and Q? and How we measure superconducting qubits?

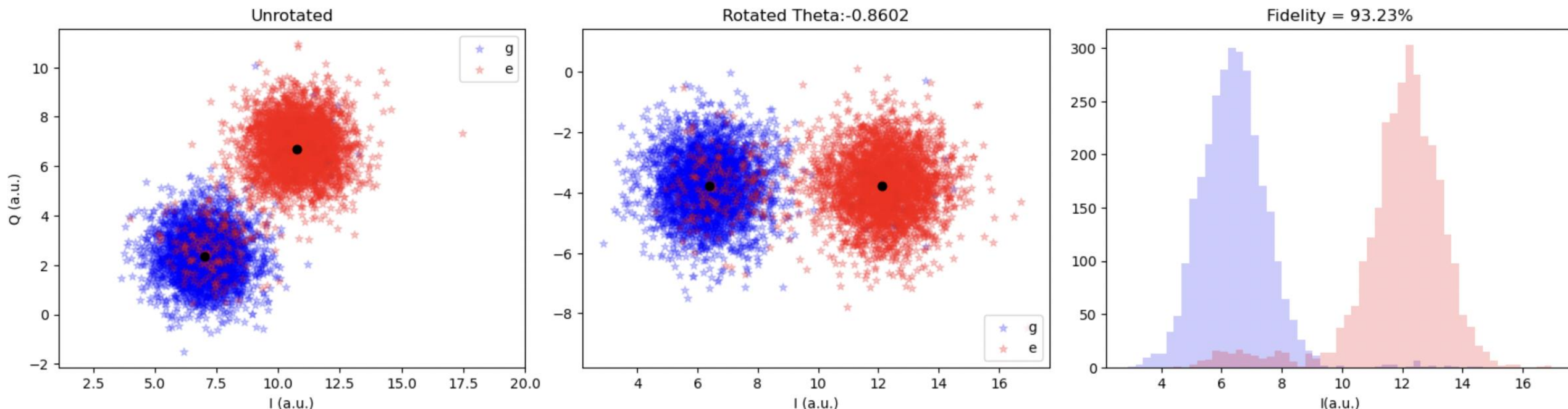


<https://arxiv.org/pdf/1904.06560>



Single Shot Fidelity

Microwave readout produces distributions of single-shot measurements.



Purpose: Determine how accurately we can distinguish the qubit's ground and excited states.

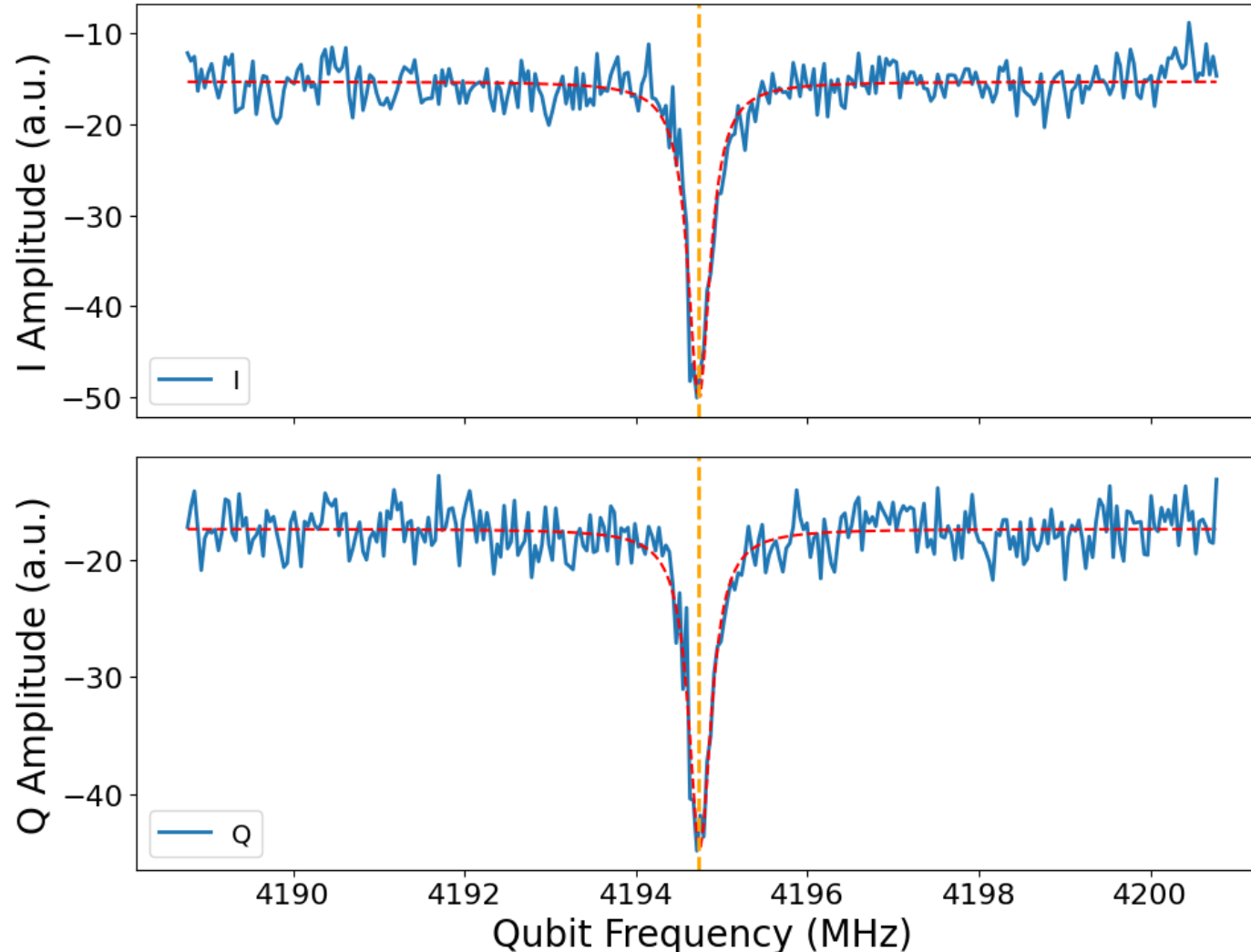
Measurement: Prepare each state and repeatedly measure the microwave readout signal (I and Q).

Rotation: Rotate the I/Q distributions to maximize their separation along one measurement axis.

Classification: Apply a threshold to distinguish ground and excited states.

Q-Spec

Qubit Spectroscopy Q1, 4194.73 MHz FWHM: -0.3, 600*1 avgs



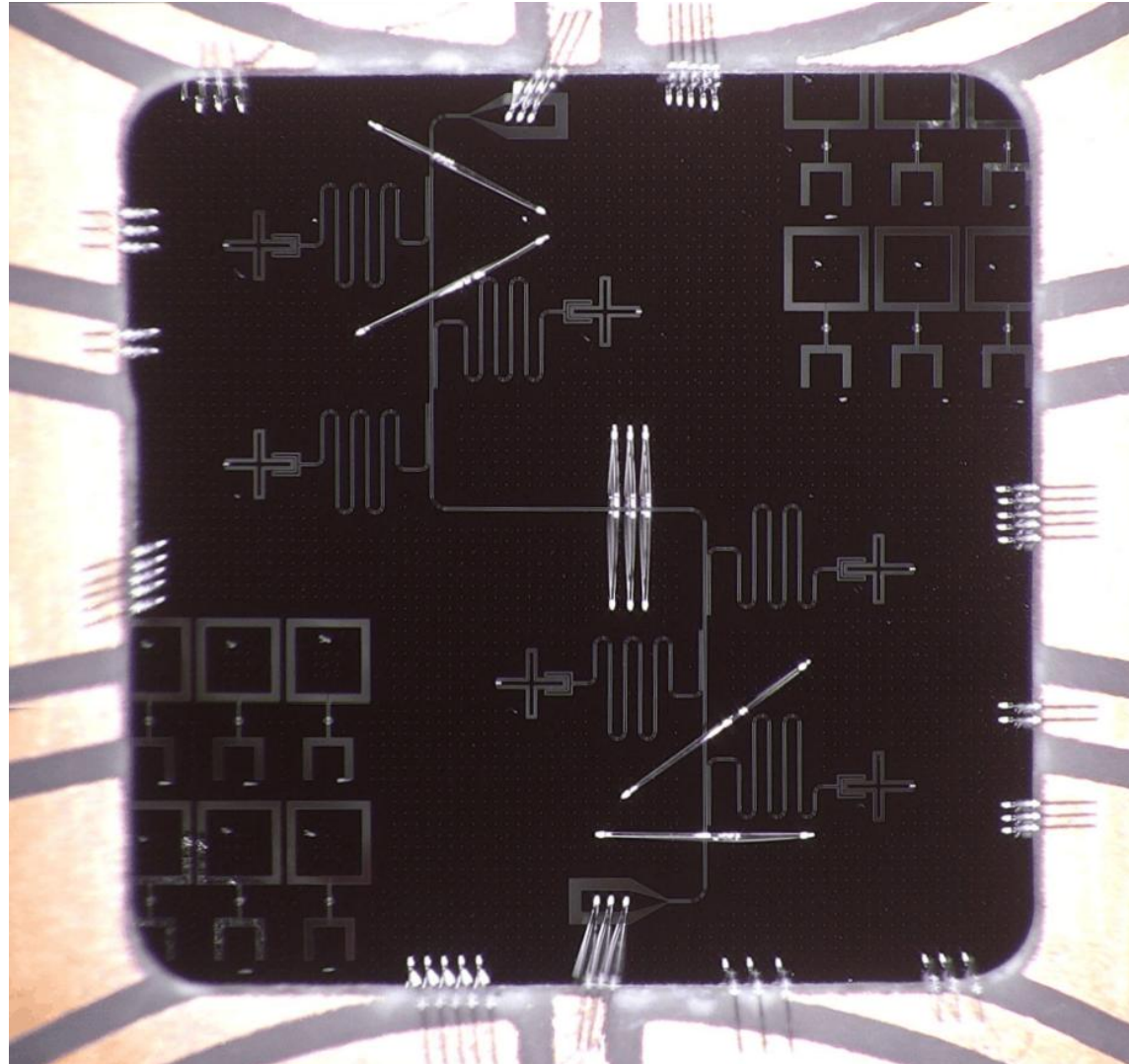
- **Purpose:** Determine the qubit's transition frequency .
- **Measurement:** Sweep the microwave drive frequency and measure the resonator response through I and Q.
- **Resonance:** When the drive matches the qubit transition frequency, the qubit is excited, changing the resonator response.

How long do these measurements take ?

Data-taking Block **source_on_substudy6**

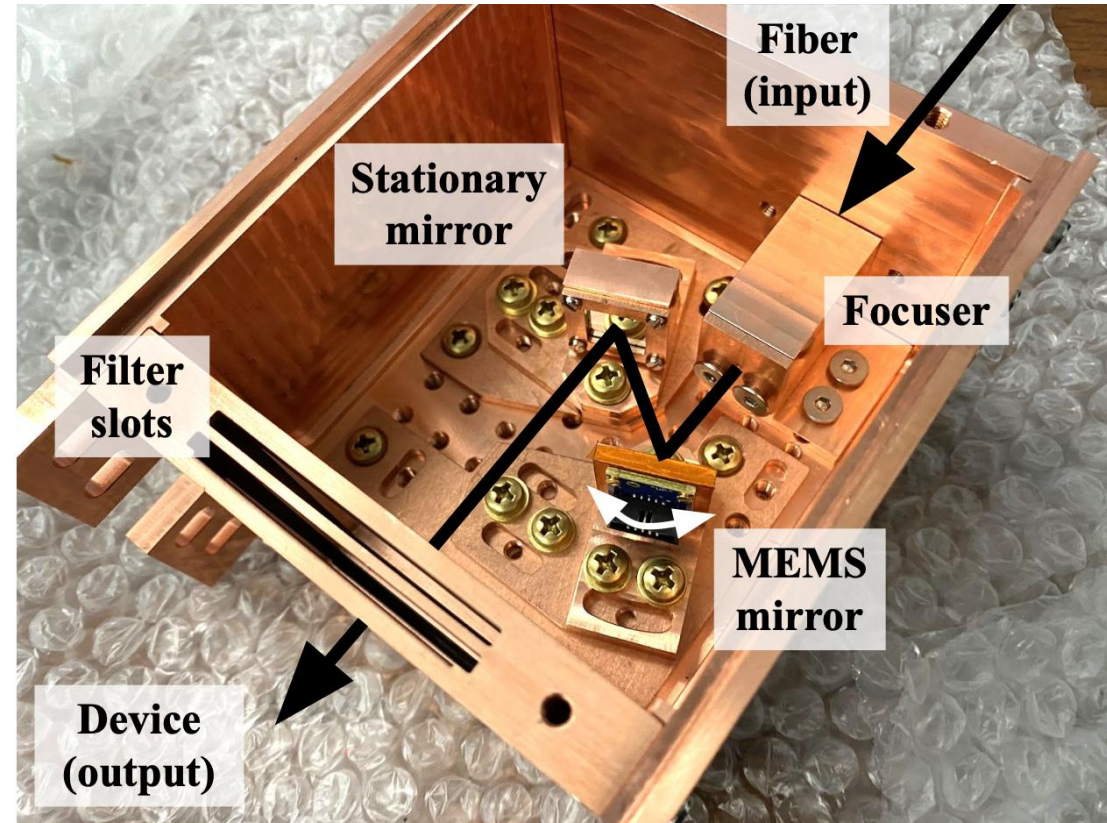
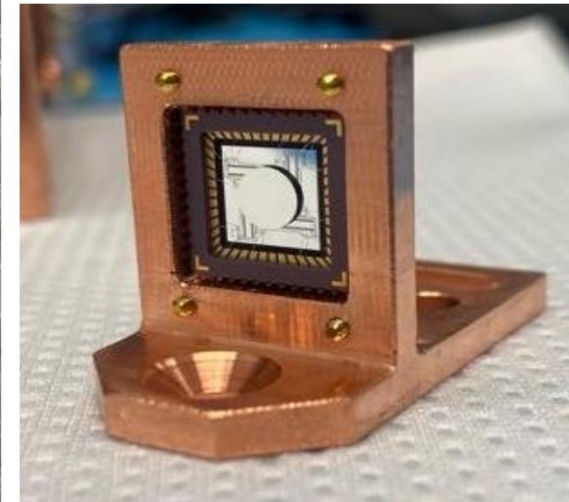
<i>program</i>	<i>gain</i>	<i>reps</i>	<i>steps</i>	<i>start</i>	<i>end</i>	<i>relax delay</i>	<i>time</i>	<i>rounds</i>
q_spec_ge	0.1	500	250	-10 MHz	+10 MHz	10 us	3.01 s	1
ssf_ge		3000	–	–	–	600 us	3.77 s	1
T1_ge		200	60	0 us	200 us	600 us	~8 s	1
high_gain_qlspec_ge	1.0	500	600	-30 MHz	+30 MHz	10 us	~8 s	1
stark_spec		500	200	0	1.0	400 us	43.5 s	1

MEMS and TEMP sweep Qubit

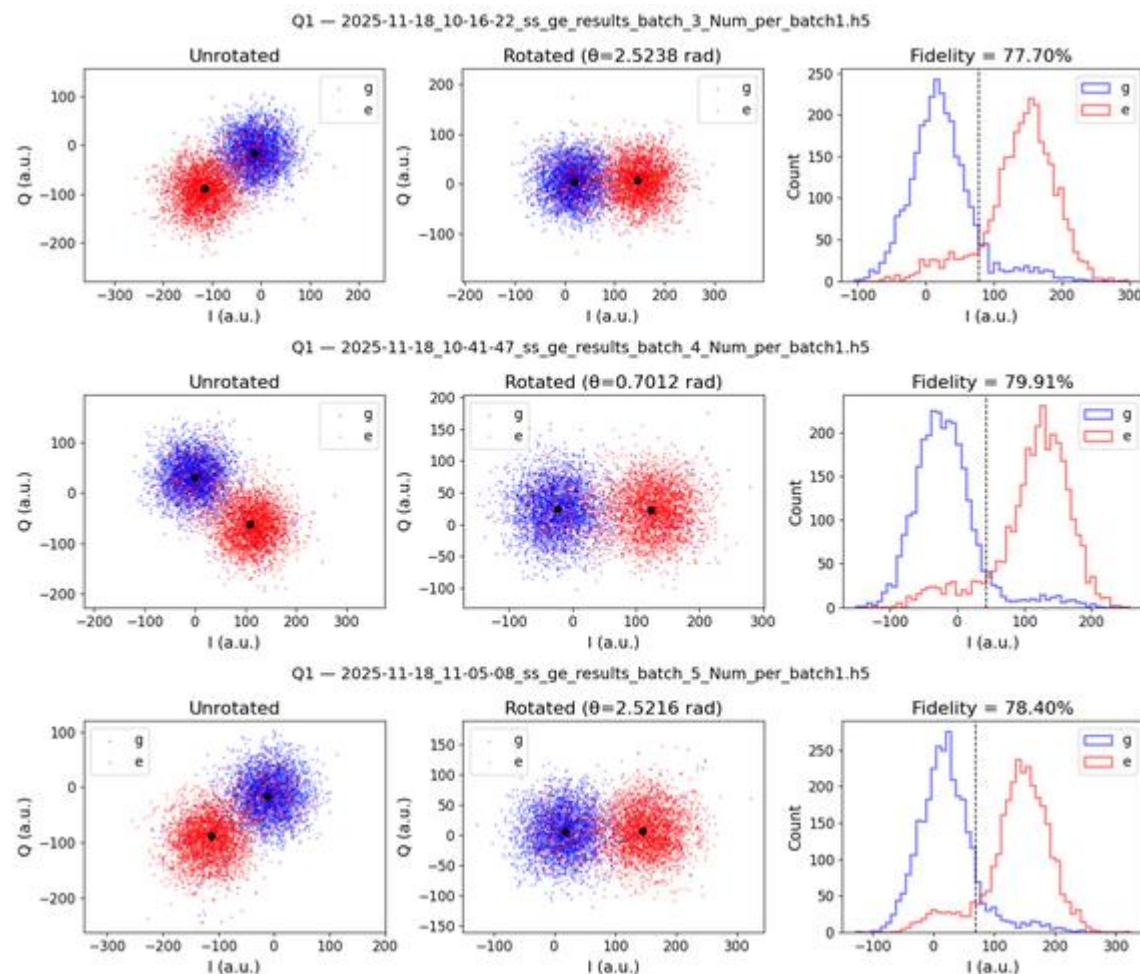


MEMS SETUP:

- **Optical input:** 475 nm light delivered through an optical fiber.
- **Beam steering:** Focuser and MEMS mirror direct light toward the device.
- **Superconducting device:** Six qubits exposed to controlled optical illumination.
- **Measurement:** Monitor qubit response using microwave readout and single-shot fidelity.



Bi-stable I/Q position of quantum states (Imperfect phase locking?)

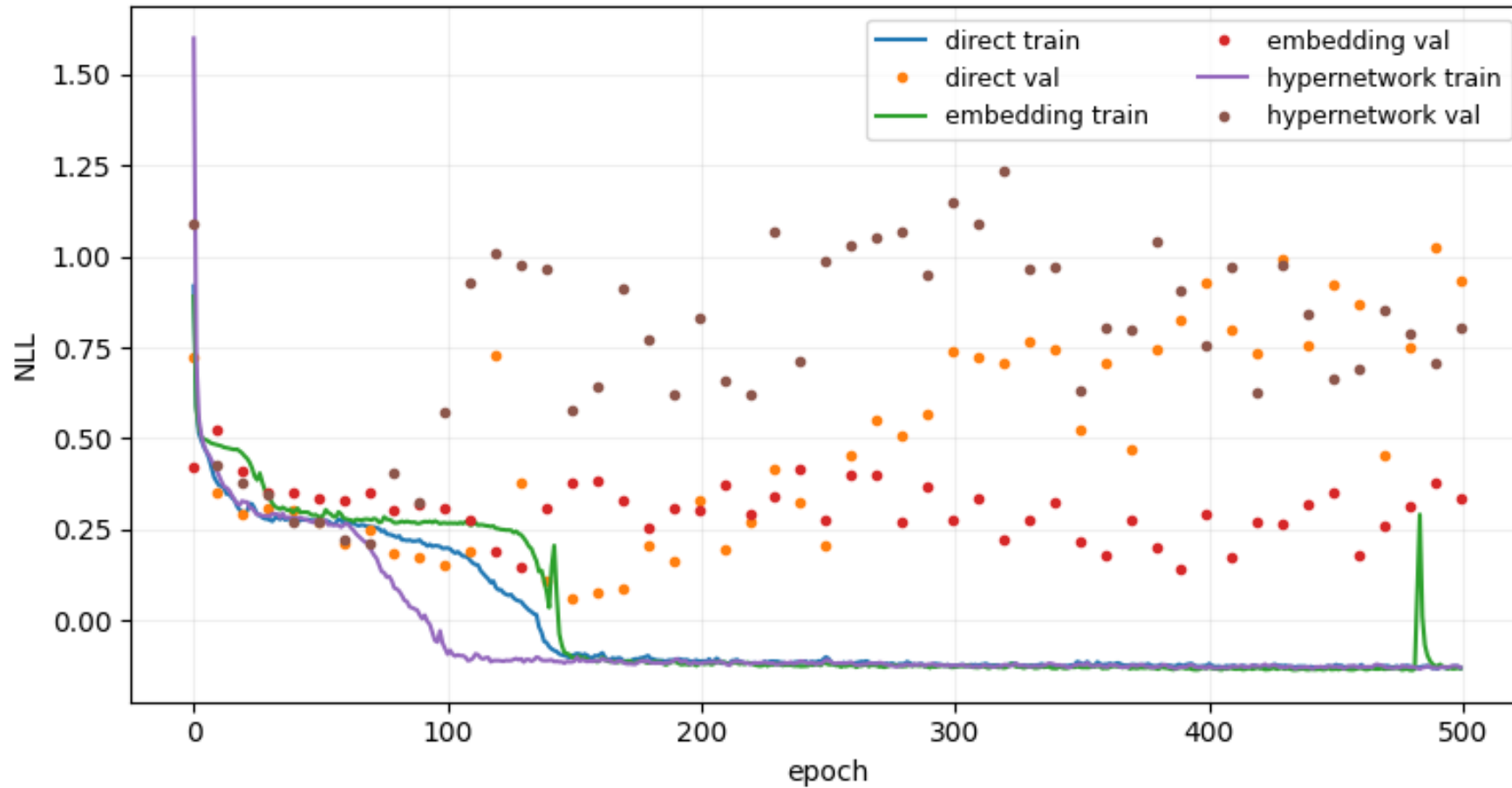


- Data-set 1 : 0 min
- Data-set2 : 23 min
- Data-set 3: 46 min
- 6,000 shots per dataset, 3,000 in ground state and 3,000 in excited state
- Trained on 75% raw shots, 25% for validation

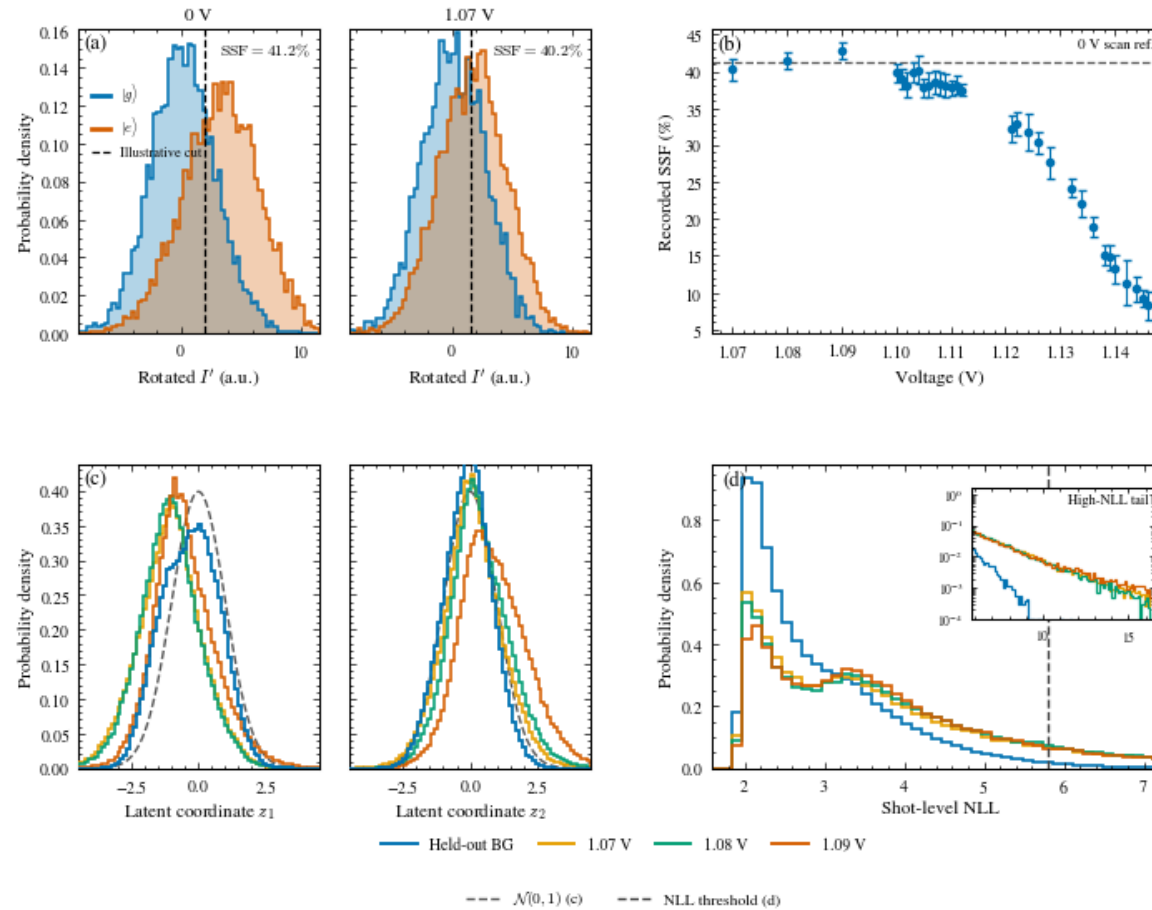
Temp data collection: Arianna H. Colón Cesaní.

Transfer Loss

20 mK conditional SSF



SSF fidelity and flow diagnostics



Readout distributions, recorded fidelity, latent marginals, and the NLL tail in an earlier shot-level analysis.

SSF inputs and independent data

One source file supplies paired Ig, Qg, Ie, Qe arrays.

$$\text{xraw} = [I_g, Q_g, I_e, Q_e, |V_g|, |V_e|, \arg V_g, \arg V_e], \quad V_s = I_s + iQ_s$$

- Concatenate complete shot arrays into one measurement vector.
- Split source files before fitting scalers and PCA.
- The current flow receives 8 retained PCA coordinates per measurement.
- Evaluate density in that retained feature space.

Independent unit: the original measurement run

Repeated rows retain their parent-run identity. Copies do not increase the independent sample size.

Selected references

Normalizing flows

G. Papamakarios et al., Normalizing Flows for Probabilistic Modeling and Inference, JMLR 22(57), 1–64 (2021).
jmlr.org/papers/v22/19-1028.html

Flow architecture

L. Dinh, J. Sohl-Dickstein, and S. Bengio, Density estimation using Real NVP, ICLR (2017).
arXiv:1605.08803

Likelihood-based anomaly detection

E. Nalisnick et al., Do Deep Generative Models Know What They Don't Know? ICLR (2019).
arXiv:1810.09136

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