Automated extraction of capacitive coupling for quantum dot systems

Joint Journal Club

Lisa Sommer | IBM Research Europe, Zurich | lisa.sommer@ibm.com

Motivation

Automated extraction of capacitive coupling for quantum dot systems

Joshua Ziegler,[1,*] Florian Luthi,[2] Mick Ramsey,[2] Felix Borjans,[2] Guoji Zheng,[2] and Justyna P. Zwolak[1,†]

[1] *National Institute of Standards and Technology, Gaithersburg, MD 20899, USA*

[2] *Intel Components Research, Intel Corporation, 2501 NW 229th Avenue, Hillsboro, Oregon 97124, USA*

(Dated: January 23, 2023)

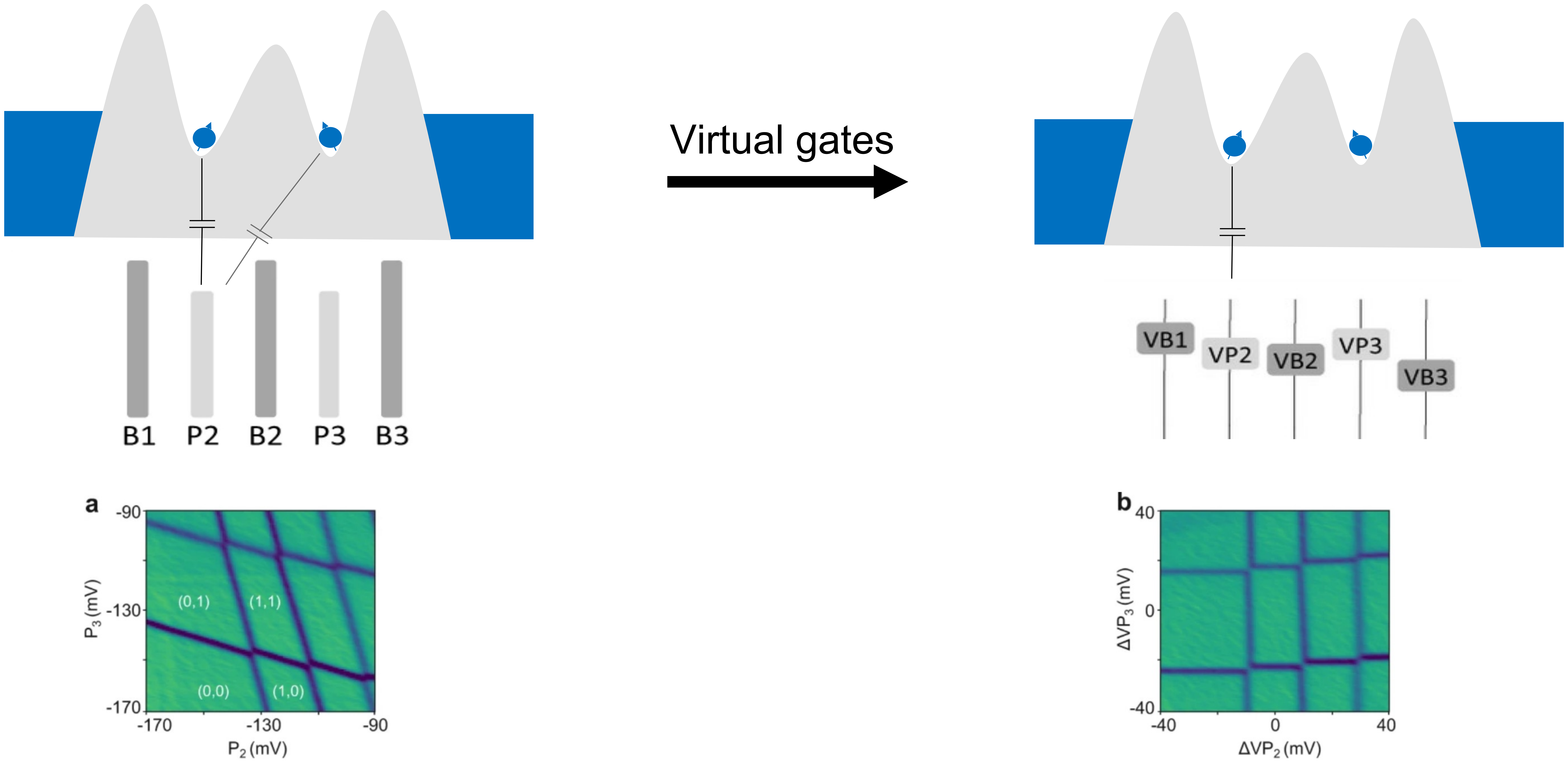
arXiv:2301.08654v1, Accepted from Phys. Rev. Applied (12.04.23)

Topic: Enable targeted control of specific quantum dots for complex QD arrays

Novelty: Reliable automated capacitive coupling identification with identification of spurious dots near operating regime

Capacitive Cross-Talk

virtual gates



Linear combination of gate voltage - mapped to onsite energy differences

Adapted from C. Volk et al. *Quantum Inf* **5**, 29 (2019).

Method of autonomous detection

Until now: autonomous identification in device use conventional fitttting and machine learning techniques

Problem: Rely on least-square fitting procedures or Hough transform

– Unreliable if data imperfect
– Sensitive to noise
– Complex to analyse

Conventional fitting

+ More flexible

– Susceptible to local minima
– Time-consuming

Convolutional neural networks

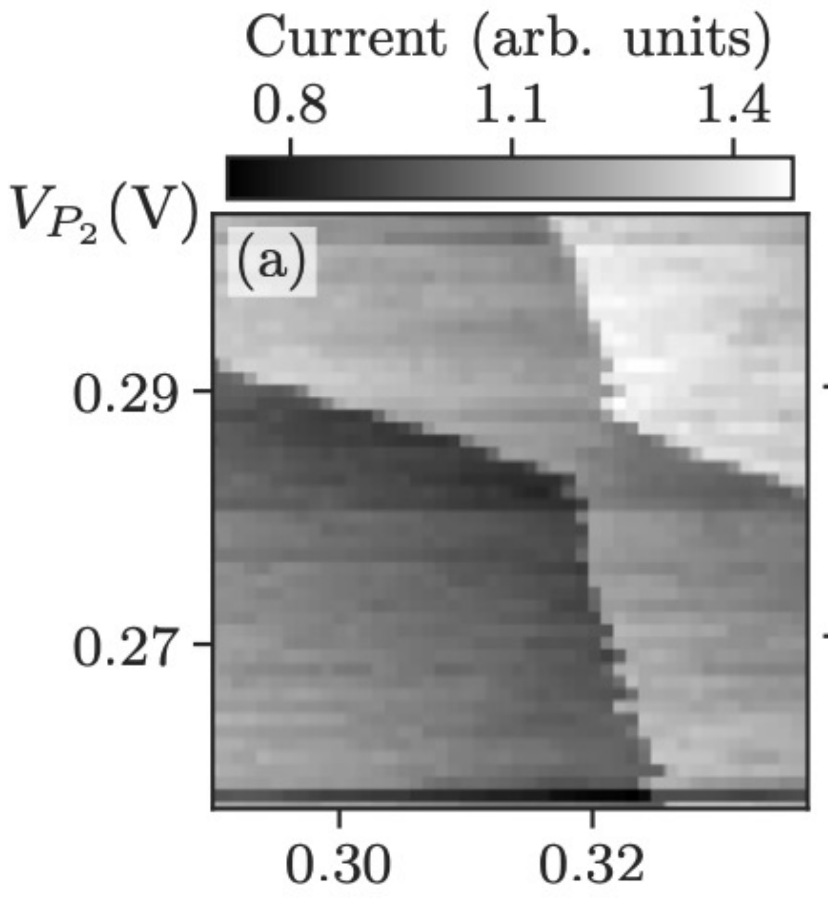
+ Suited for high-level feature

– Identify data outside of training distribution

but: simplified data with high-level representation + conventional fitting

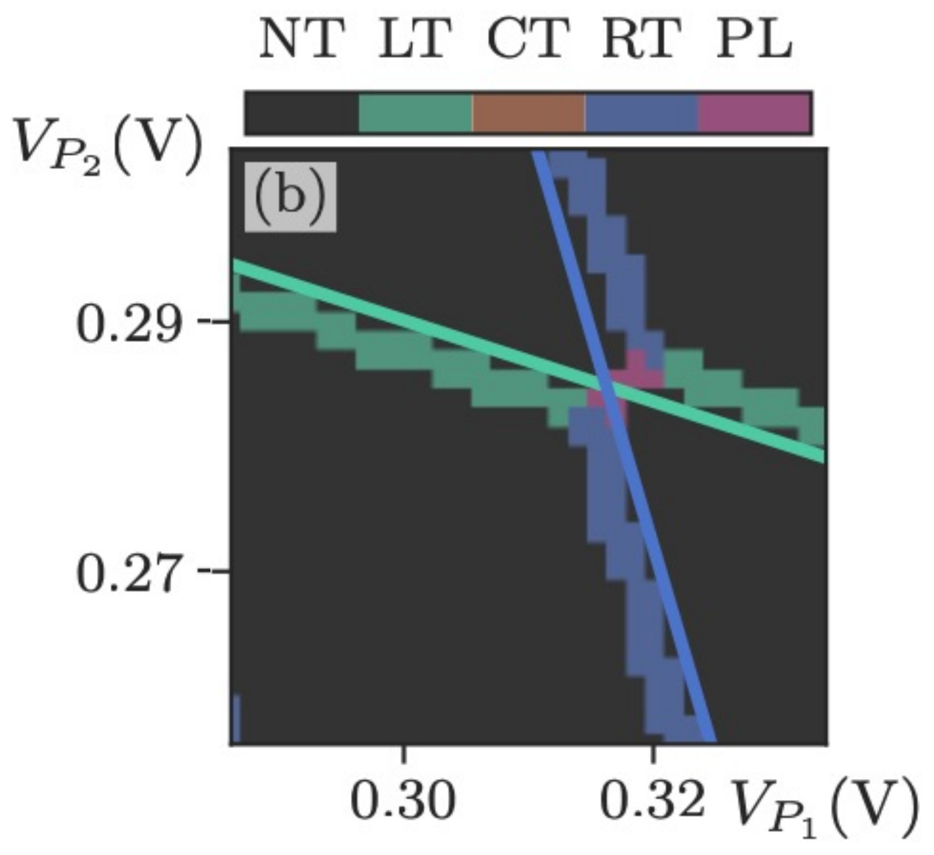
→ more targeted to key information (efficient and quick)

Data processing



Low-level QD data

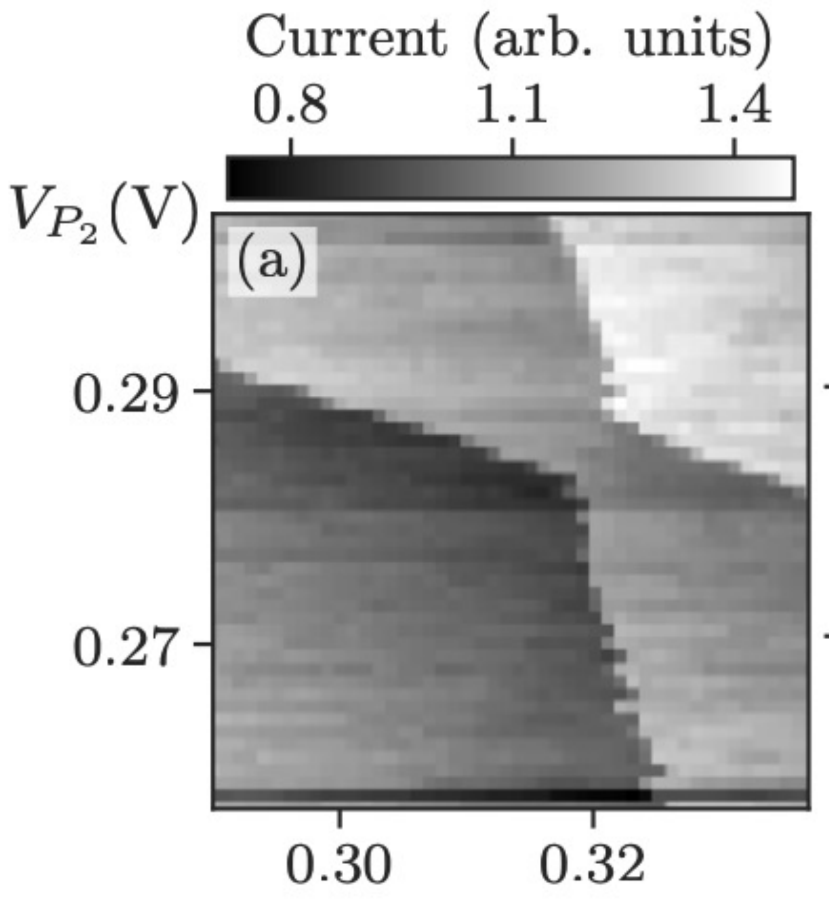
Pixel classifier



High-level QD data

Use neighboring pairs of gates

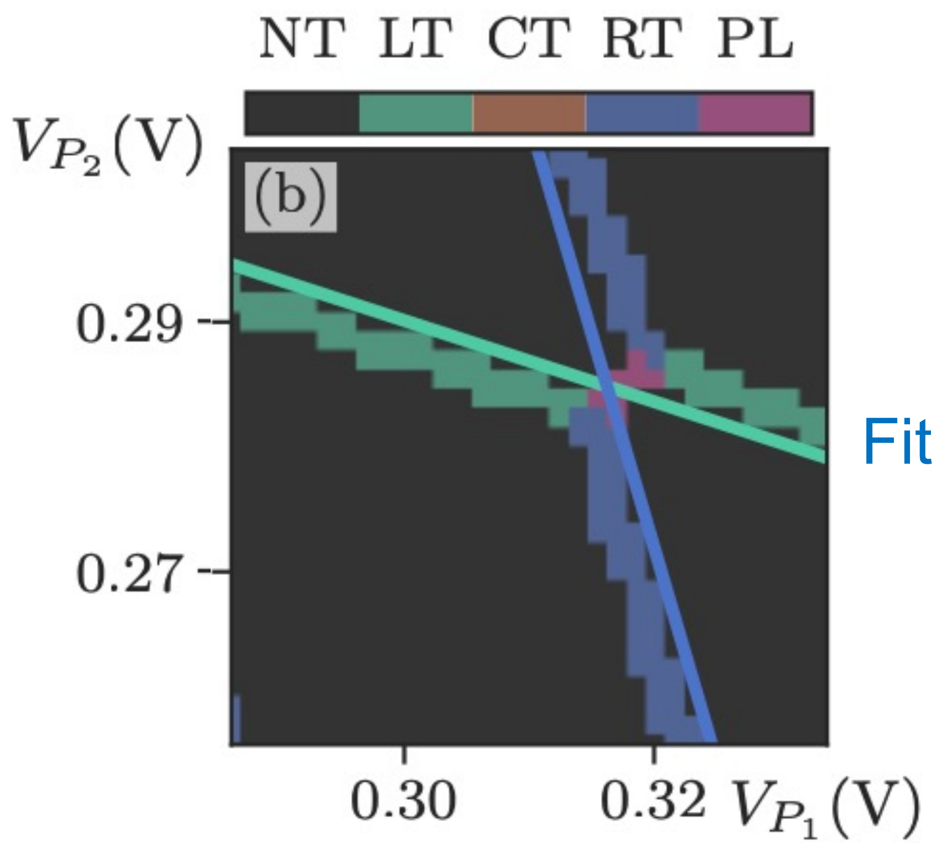
Data processing



Low-level QD data

Use neighboring pairs of gates

Pixel classifier



High-level QD data

Extract classes

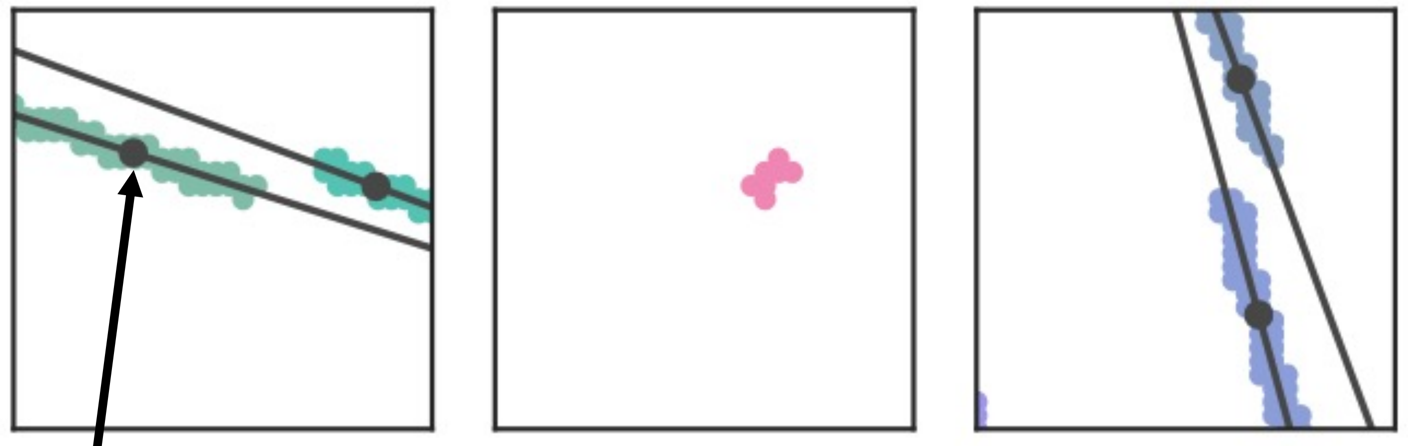
Fit via linear regression

Different classes

left-dot transition

inter-dot transition

right-dot transition



Center of pixel region

Capacitive coupling: average slope of fitted lines (weighted by standard deviations of each fit)

$$\mathbf{G}^{\text{virt}} \equiv \begin{pmatrix} V_{P_1'} \\ V_{P_2'} \end{pmatrix} = \begin{pmatrix} 1 & \alpha_{12} \\ \alpha_{21} & 1 \end{pmatrix} \begin{pmatrix} V_{P_1} \\ V_{P_2} \end{pmatrix}$$

Training the ML tool

Using simulation of QD device

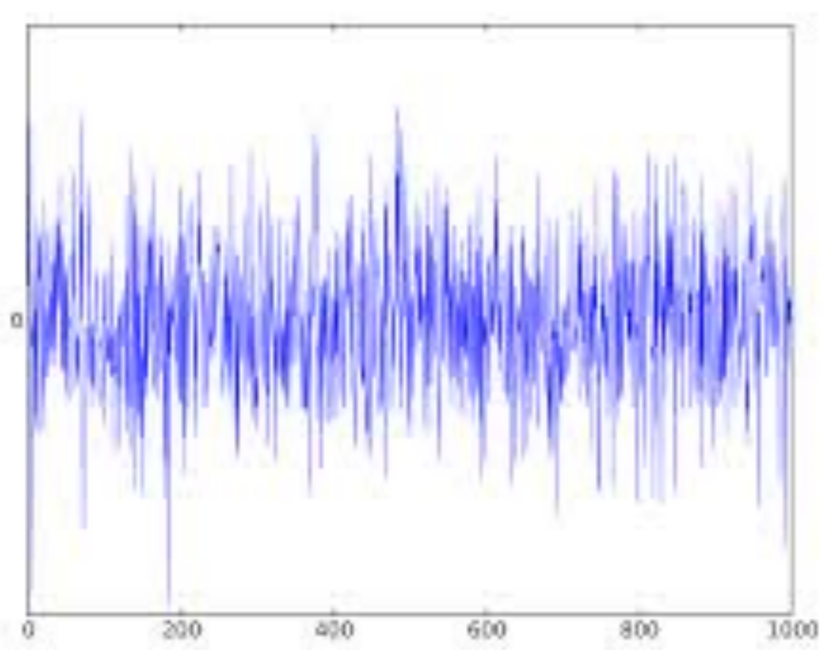
- Improve Robustness: add noise
- Improve Performance for various data: Change effect of strongly coupled QD charge sensor to plunger gates

Training: 1.6×10^5 devices 10 small scans per device

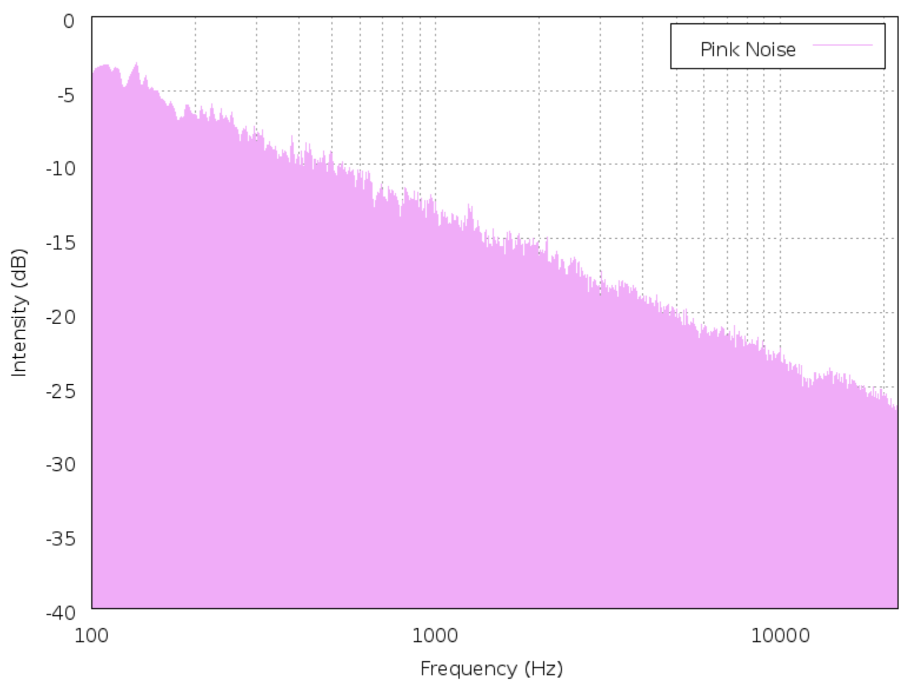
(Use pixel classification, extract slopes of transition lines)

Test data: 8 simulated devices with variations: screening length, device pitch, positions of one plunger gate -> 50 small scans (use increasing noise)

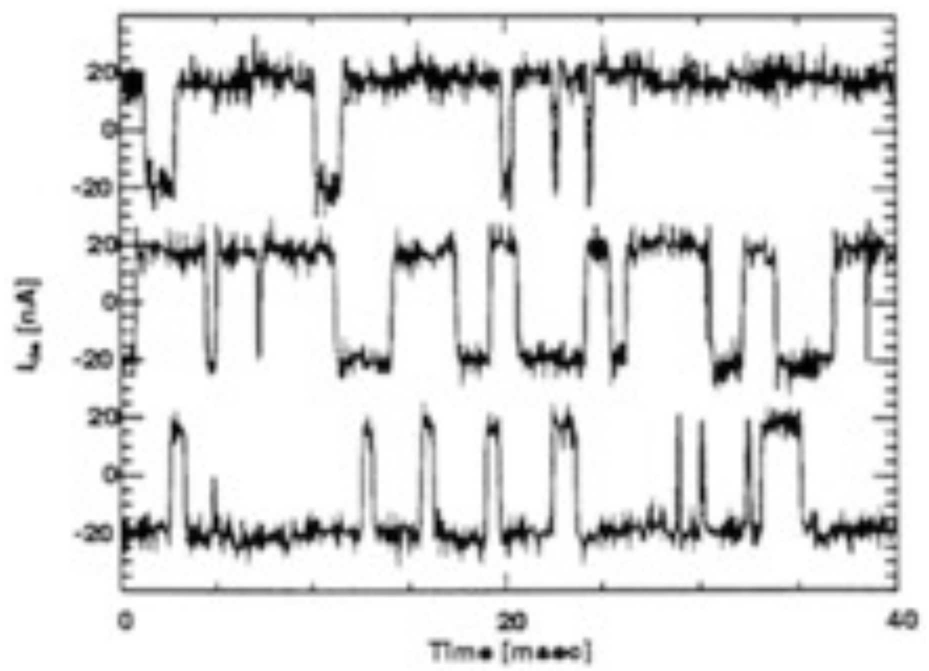
Test with large experimental measurements with spurious QDs



"White noise." *Wikipedia.*



“White Noise Definintion Vs. Pink Noise”. *Wacoustic Fields.com*



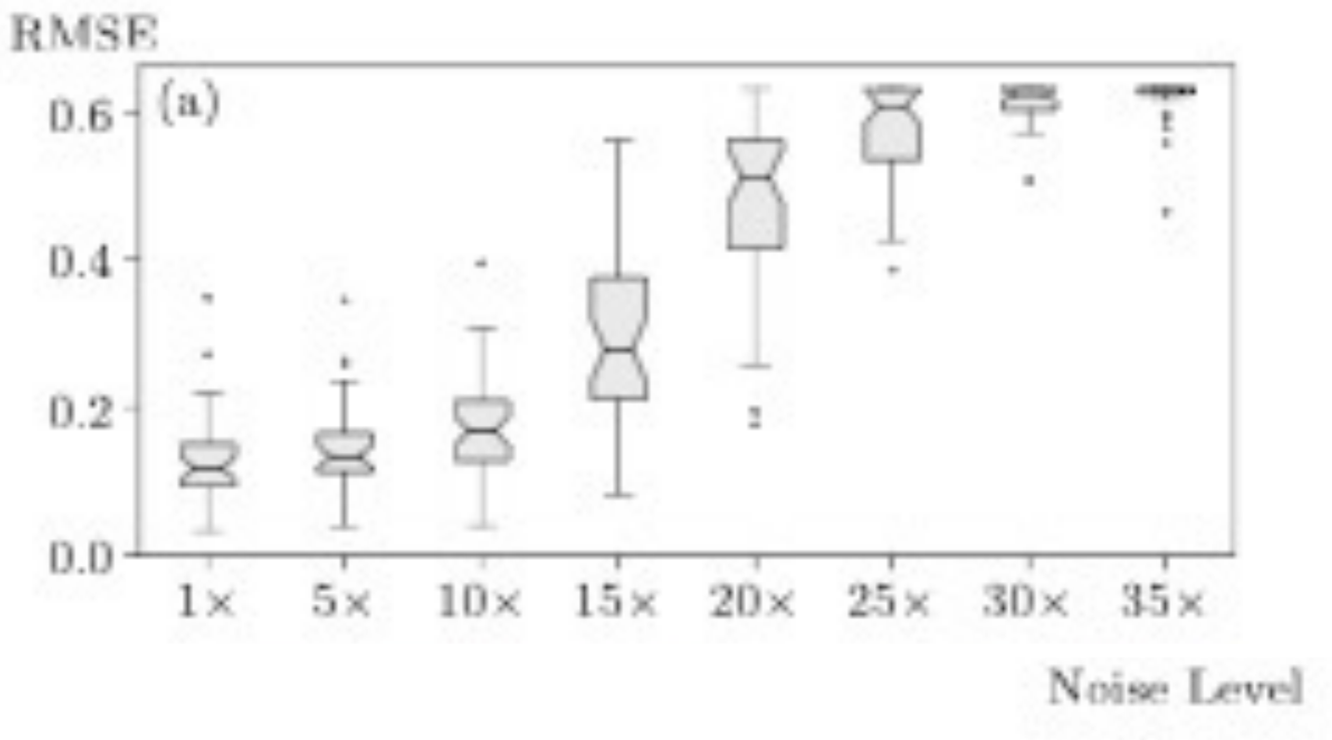
"Burst noise." *Wikipedia,*

IBM Research Zurich

Performance of the algorithm

Pixel classifier:

- Error: defined as fraction of pixels with true transitions, not contained in line segment in output
- Dependent on noise level

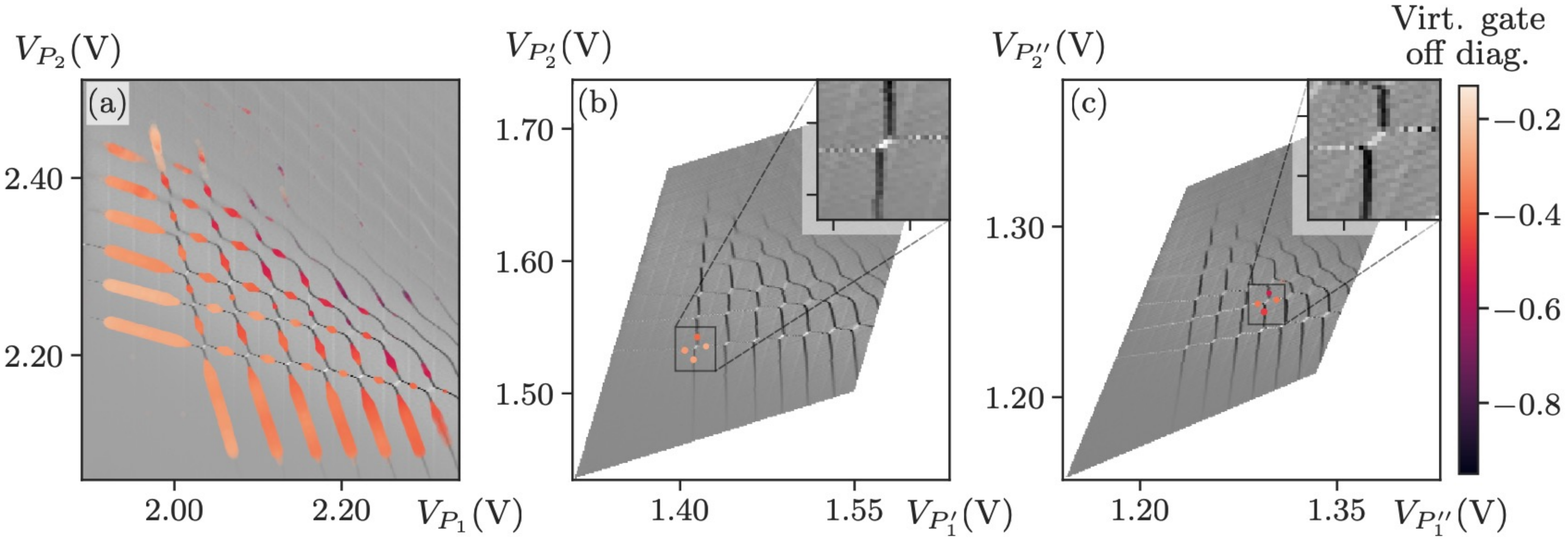


Slope extractions

- Use 8 large scans -> window 1.5 x charging energy + cropped output by one pixel
- Group in distinct clusters, if more than 5 pixel with individual fit -> error from fitted line

Virtualized gates

Experiment

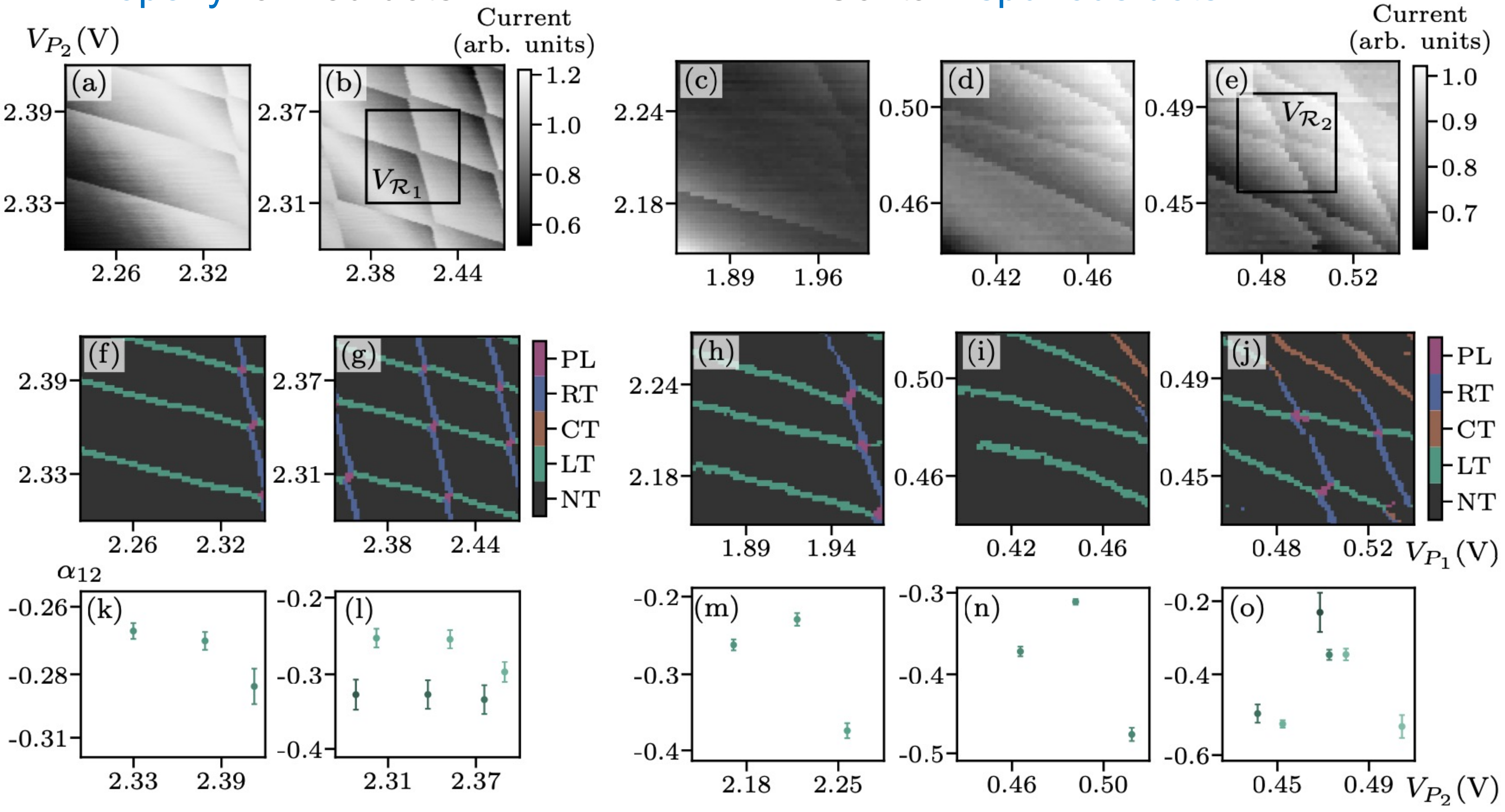


$$\mathbf{G}^{\mathrm{virt}} \equiv \begin{pmatrix} V_{P_1'} \\ V_{P_2'} \end{pmatrix} = \begin{pmatrix} 1 & \alpha_{12} \\ \alpha_{21} & 1 \end{pmatrix} \begin{pmatrix} V_{P_1} \\ V_{P_2} \end{pmatrix}$$

→ Confirmation that pixel classifier and fit work

Spurious dots detection

Properly formed dots | Contain spurious dots



Magnitude of α_{12} increases **monotonically** **non-monotonically** by added charges

Recap & Outlook

– Increasing in device size and complexity → need reliable and automated tune-up

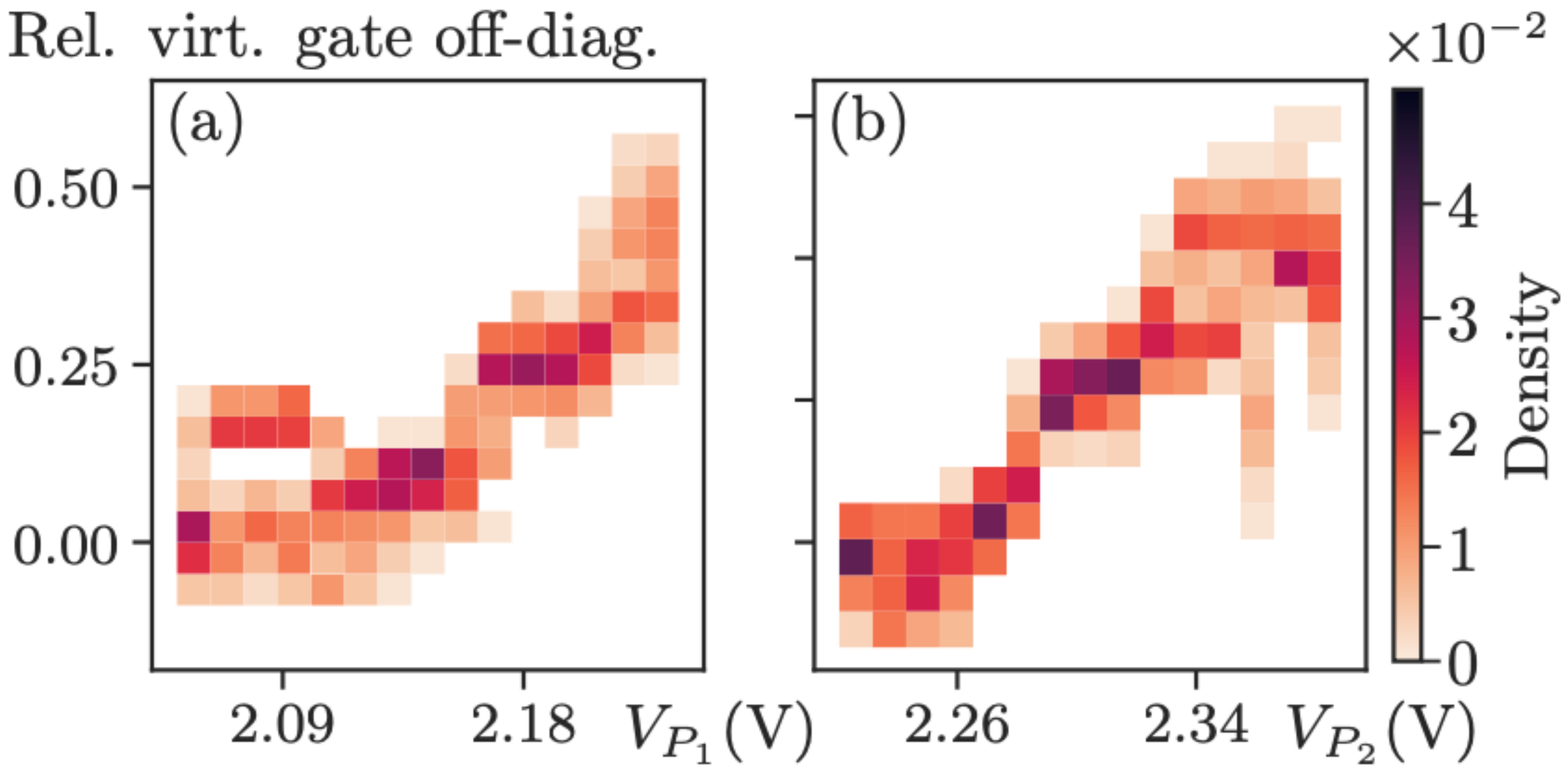
– Established orthogonal control is needed for tune-up of larger QD arrays

– Use ML based pixel-classification with curve fitting → showed reliable output

– Shown detection of spurious dots

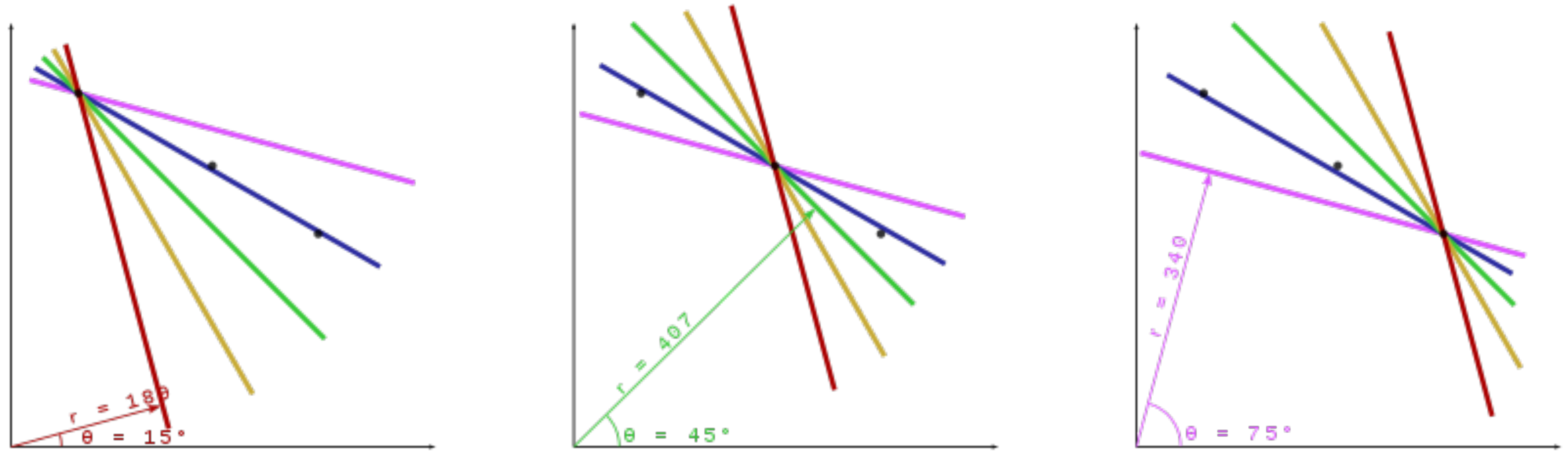
→ Automated navigation of voltage space for targeted measurement

Spatial relevance of virtual gates



effectively capture variation across charge stability diagram

Hough transform



θ	r
15	189.0
30	282.0
45	355.7
60	407.3
75	429.4

θ	r
15	318.5
30	376.8
45	407.3
60	409.8
75	385.3

θ	r
15	419.0
30	443.6
45	438.4
60	402.9
75	340.1

"Hough transform." *Wikipedia,*