



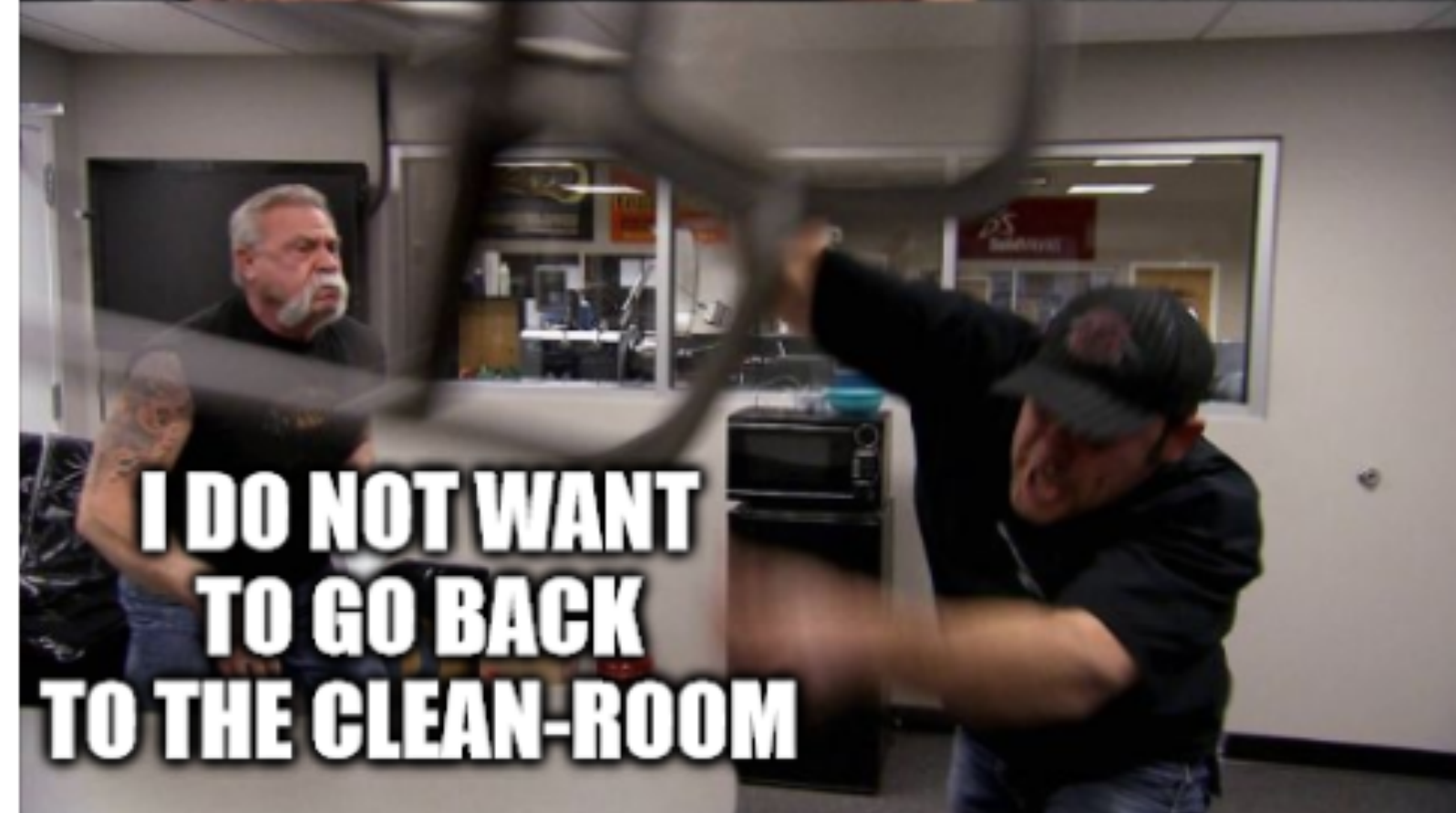
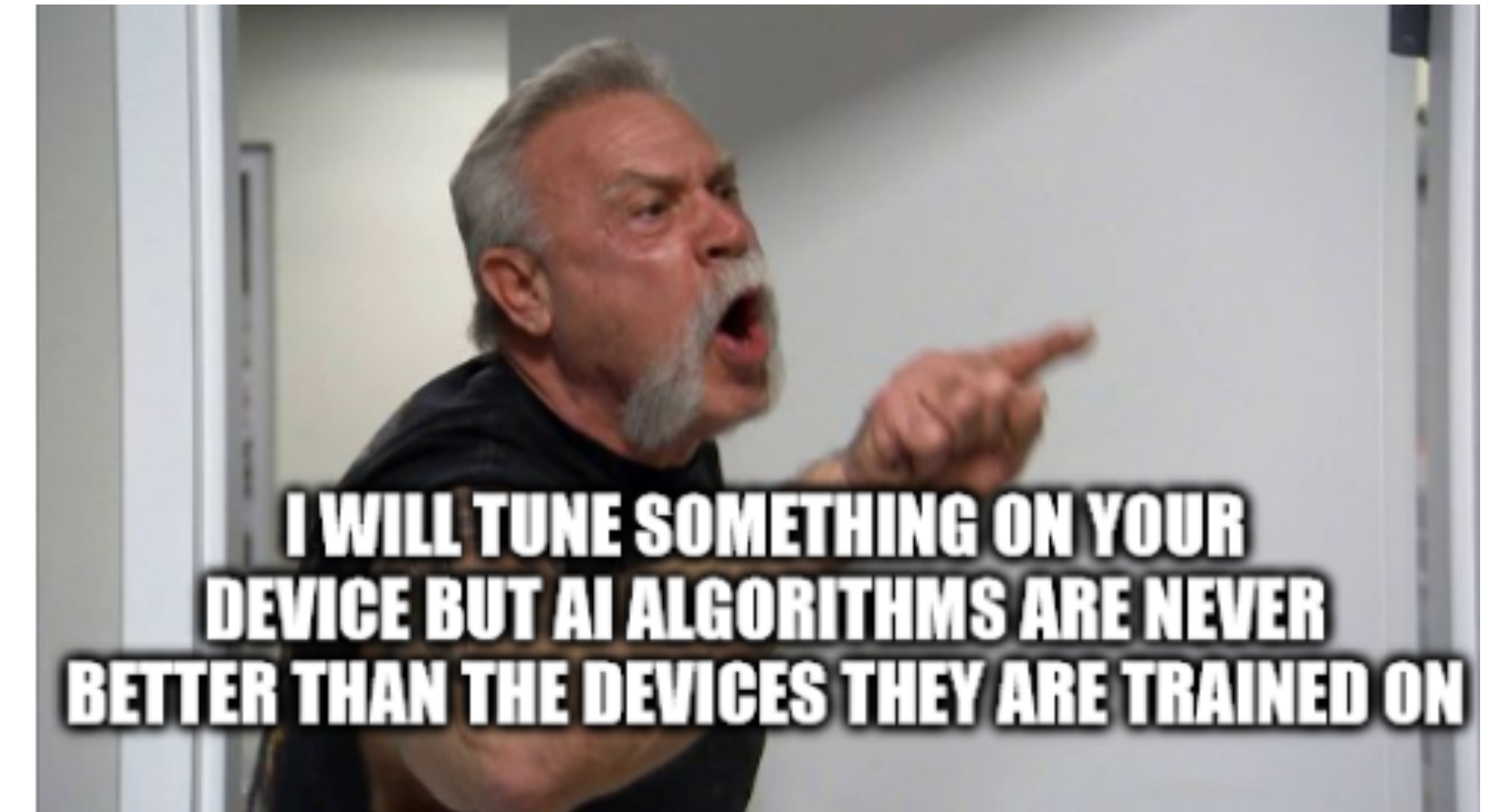
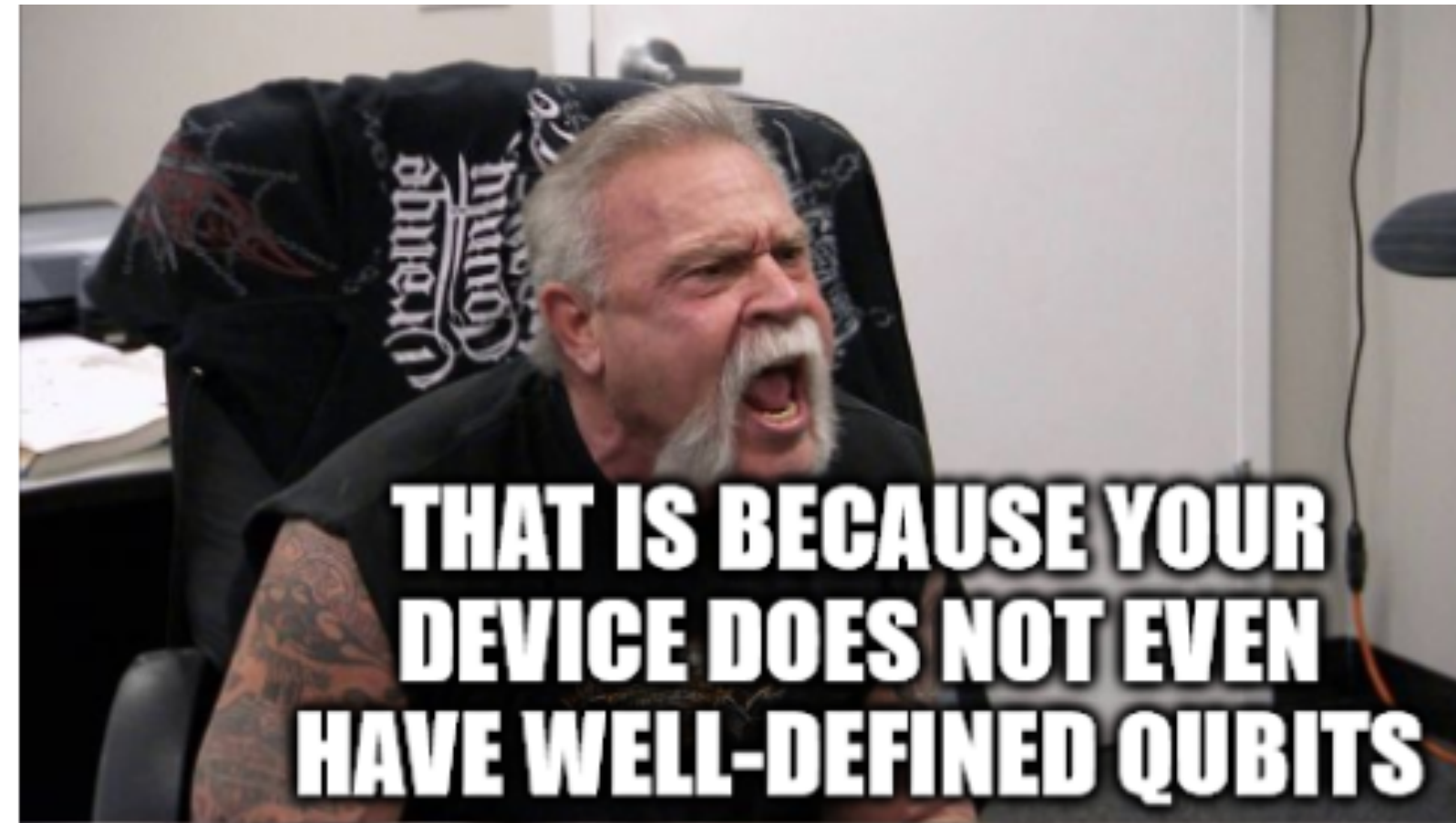
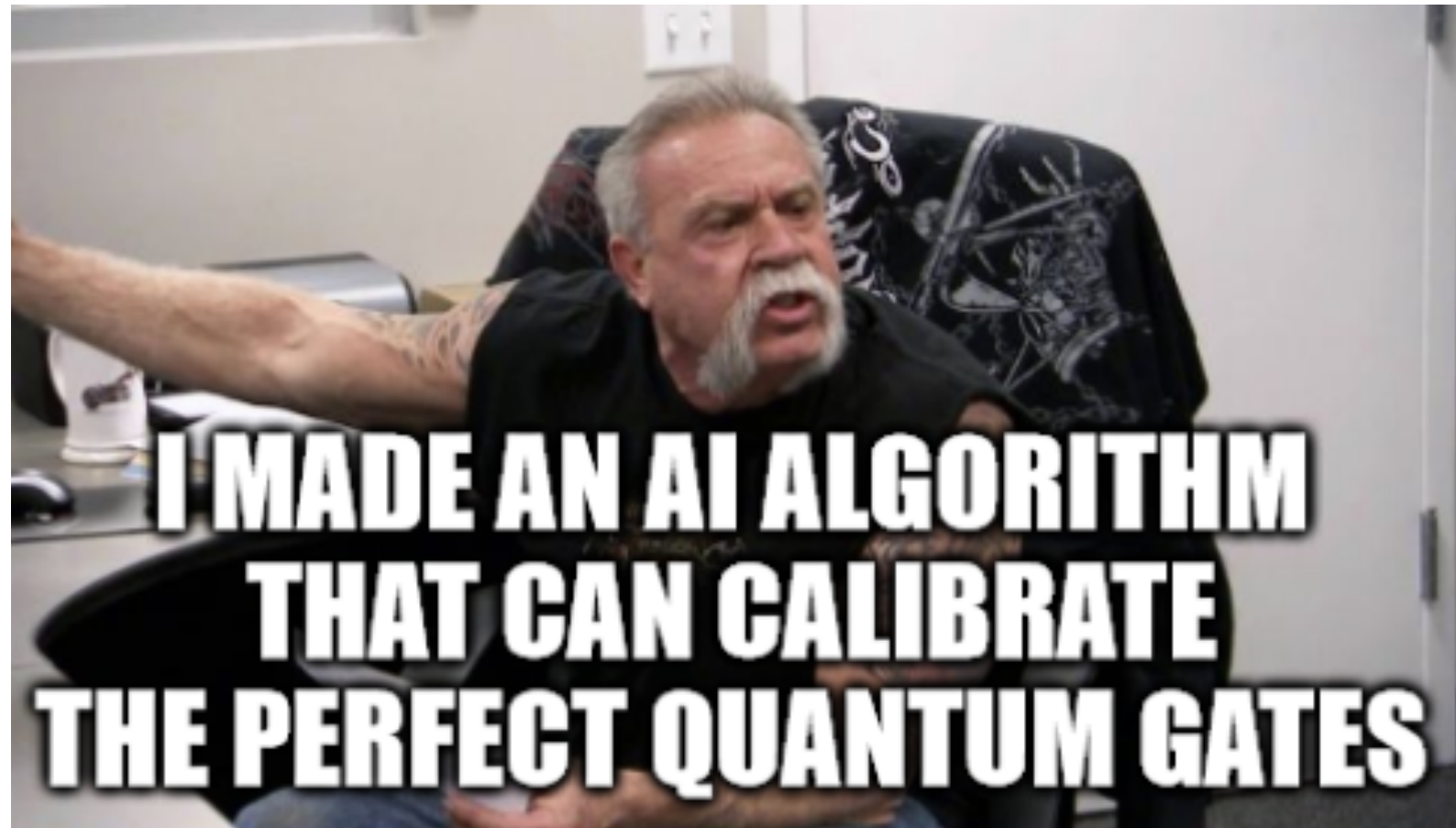
QuTech



Autonomous Quantum Control in the Age of AI

ML4QT Erlangen

Sam Katirae-Far, Joseph Rogers, Yuta Matsumoto, Valentina Gualtieri, Charles Renshaw-Whitman, Vinicius Hernandez, Brennan Undseth, Renato Durrer, Benedikt Kratochwil, Thomas Ihn, Lieven Vandersypen, and Eliska Greplova



Contemporary quantum experiments

Article | [Published: 23 October 2019](#)

Quantum simulation using a programmable superconducting processor

[Frank Arute](#), [Kunal Arya](#), [Ryan Babbush](#), [Dave Bacon](#), [Joseph C. Bardin](#), [Rami Barends](#), [Rupak Biswas](#), [Sergio Boixo](#), [Fernando G. S. L. Brandao](#), [David A. Buell](#), [Brian Burkett](#), [Yu Chen](#), [Zijun Chen](#), [Ben Chiaro](#), [Roberto Collins](#), [William Courtney](#), [Andrew Dunsworth](#), [Edward Farhi](#), [Brooks Foxen](#), [Austin Fowler](#), [Craig Gidney](#), [Marissa Giustina](#), [Rob Graff](#), [Keith Guerin](#), ... [John M. Martinis](#)  [+ Show authors](#)

[Nature](#) **574**, 505–510 (2019) | [Cite this article](#)

Article | [Open access](#) | [Published: 14 June 2023](#)

Evidence for the utility of quantum computing before fault tolerance

[Youngseok Kim](#) , [Andrew Eddins](#) , [Sajant Anand](#), [Ken Xuan Wei](#), [Ewout van den Berg](#), [Sami](#)

[Rosenblatt](#), [Hasan Nayfeh](#), [Yantao Wu](#), [Michael Zaletel](#), [Kristan Temme](#) & [Abhinav Kandala](#) 

[Nature](#) **618**, 500–505 (2023) | [Cite this article](#)

105k Accesses | **18** Citations | **947** Altmetric | [Metrics](#)

Computational simulation in quantum simulation

[Andrew D. King](#), [Alberto Nocera](#), [Marek M. Rams](#), [Jacek Dziarmaga](#), [Roeland Wiersema](#), [William Bernouidy](#), [Jack Raymond](#), [Nitin Kaushal](#), [Niclas Heinsdorf](#), [Richard Harris](#), [Kelly Boothby](#), [Fabio Altomare](#), [Andrew J. Berkley](#), [Martin Boschnak](#), [Kevin Chern](#), [Holly Christiani](#), [Samantha Cibere](#), [Jake Connor](#), [Martin H. Dehn](#), [Rahul Deshpande](#), [Sara Ejtemaee](#), [Pau Farré](#), [Kelsey Hamer](#), [Emile Hoskinson](#), [Shuiyuan Huang](#), [Mark W. Johnson](#), [Samuel Kortas](#), [Eric Ladizinsky](#), [Tony Lai](#), [Trevor Lanting](#), [Ryan Li](#), [Allison J.R. MacDonald](#), [Gaelen Marsden](#), [Catherine C. McGeoch](#), [Reza Molavi](#), [Richard Neufeld](#), [Mana Norouzpour](#), [Travis Oh](#), [Joel Pasvolosky](#), [Patrick Poitras](#), [Gabriel Poulin-Lamarre](#), [Thomas Prescott](#), [Mauricio Reis](#), [Chris Rich](#), [Mohammad Samani](#), [Benjamin Sheldan](#), [Anatoly Smirnov](#), [Edward Sterpka](#), [Berta Trullas Clavera](#), [Nicholas Tsai](#), [Mark Volkman](#), [Alexander Whiticar](#), [Jed D. Whittaker](#), [Warren Wilkinson](#), [Jason Yao](#), [T.J. Yi](#), [Anders W. Sandvik](#), [Gonzalo Alvarez](#), [Roger G. Melko](#), [Juan Carrasquilla](#), [Marcel Franz](#), [Mohammad H. Amin](#)

Quantum computers hold the promise of solving certain problems that lie beyond the reach of conventional computers. Establishing this capability, especially for impactful and meaningful problems, remains a central challenge. One such problem is the simulation of nonequilibrium dynamics of a magnetic spin system quenched through a quantum phase transition. State-of-the-art classical simulations demand resources that grow exponentially with system size. Here we show that superconducting quantum annealing processors can rapidly generate samples in close agreement with solutions of the Schrödinger equation. We demonstrate area-law scaling of entanglement in the model quench in two-, three- and infinite-dimensional spin glasses, supporting the observed stretched-exponential scaling of effort for classical approaches. We assess approximate methods based on tensor networks and neural networks and conclude that no known approach can achieve the same accuracy as the quantum annealer within a reasonable timeframe. Thus quantum annealers can answer questions of practical importance that classical computers cannot.

Subjects: [Quantum Physics \(quant-ph\)](#); [Disordered Systems and Neural Networks \(cond-mat.dis-nn\)](#); [Statistical Mechanics \(cond-mat.stat-mech\)](#)
Cite as: [arXiv:2403.00910 \[quant-ph\]](#)
(or [arXiv:2403.00910v1 \[quant-ph\]](#) for this version)

Editors' Suggestion Access by S

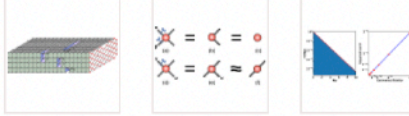
Solving the Sampling Problem of the Sycamore Quantum Circuits

Feng Pan, Keyang Chen, and Pan Zhang
Phys. Rev. Lett. **129**, 090502 – Published 22 August 2022

Article | References | Citing Articles (23) | Supplemental Material | PDF | HTML | Export Citation

ABSTRACT

We study the problem of generating independent samples from the output distribution of Google's Sycamore quantum circuits with a target fidelity, which is believed to be beyond the reach of classical supercomputers and has been used to demonstrate quantum supremacy. We propose a method to classically solve this problem by contracting the corresponding tensor network just once, and is massively more efficient than existing methods in generating a large number of *uncorrelated* samples with a target fidelity. For the Sycamore quantum supremacy circuit with 53 qubits and 20 cycles, we have generated 1×10^6 *uncorrelated* bitstrings s which are sampled from a distribution $\hat{P}(s) = |\hat{\psi}(s)|^2$, where the approximate state $\hat{\psi}$ has fidelity $F \approx 0.0037$. The whole computation has cost about 15 h on a computational cluster with 512 GPUs. The obtained 1×10^6 samples, the contraction code and contraction order are made public. If our algorithm could be implemented with high efficiency on a modern supercomputer with ExaFLOPS performance, we estimate that ideally, the simulation would cost a few dozens of seconds, which is faster than Google's quantum hardware.



Efficient tensor network simulation of IBM's Eagle kicked Ising experiment

[Joseph Tindall](#), [Matt Fishman](#), [Miles Stoudenmire](#), [Dries Sels](#)


We report an accurate and efficient classical simulation of a kicked Ising quantum system on the heavy-hexagon lattice. A simulation of this system was recently performed on a 127 qubit quantum processor using noise mitigation techniques to enhance accuracy (Nature volume 618, p.500–505 (2023)). Here we show that, by adopting a tensor network approach that reflects the geometry of the lattice and is approximately contracted using belief propagation, we can perform a classical simulation that is significantly more accurate and precise than the results obtained from the quantum processor and many other classical methods. We quantify the tree-like correlations of the wavefunction in order to explain the accuracy of our belief propagation-based approach. We also show how our method allows us to perform simulations of the system to long times in the thermodynamic limit, corresponding to a quantum computer with an infinite number of qubits. Our tensor network approach has broader applications for simulating the dynamics of quantum systems with tree-like correlations.

Comments: 18 Pages. 10 Figures. Updated to include improved BP-TNS data, simulation of the infinite system and improved error quantification

Subjects: [Quantum Physics \(quant-ph\)](#)

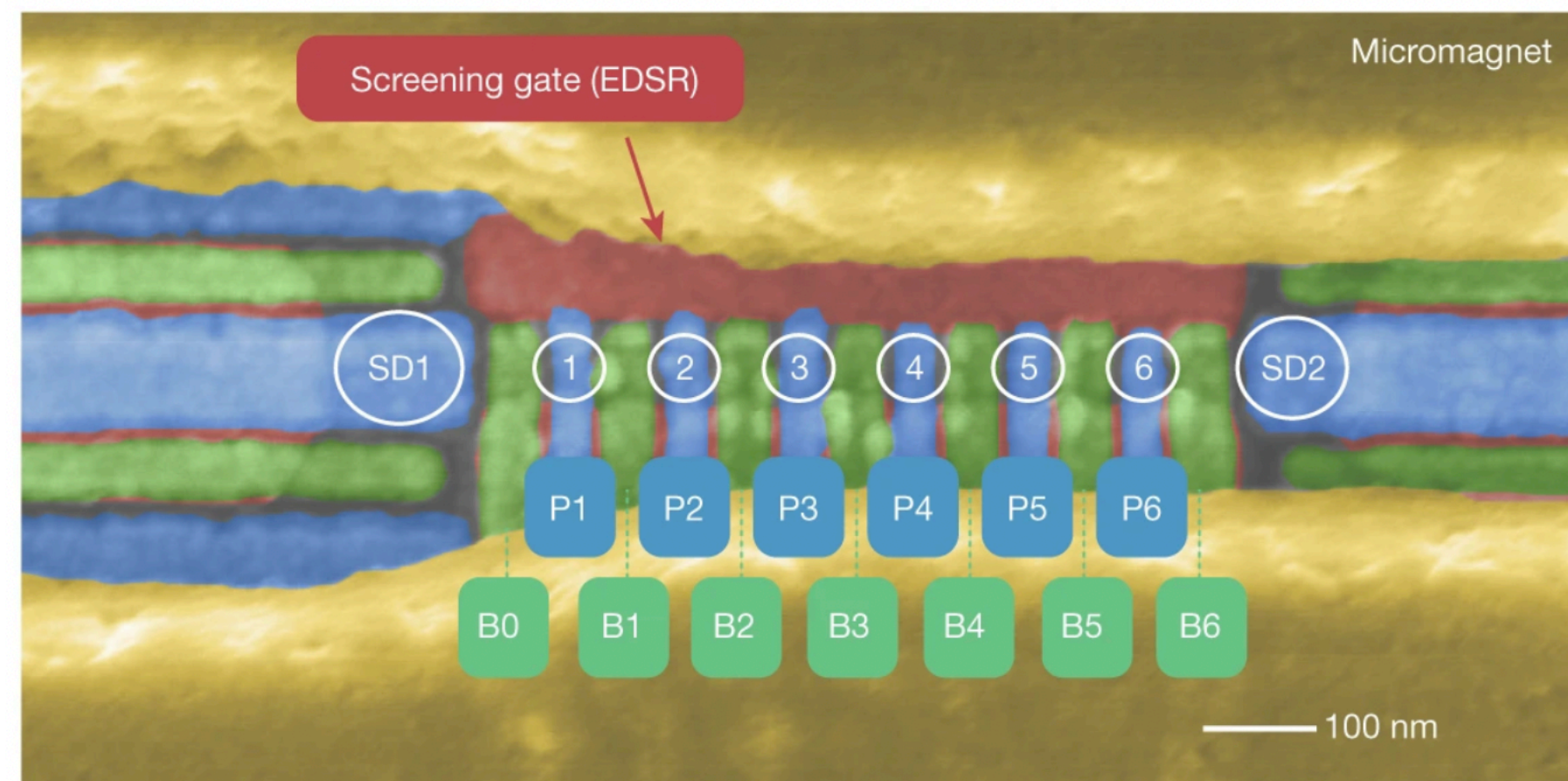
Cite as: [arXiv:2306.14887 \[quant-ph\]](#)

(or [arXiv:2306.14887v2 \[quant-ph\]](#) for this version)

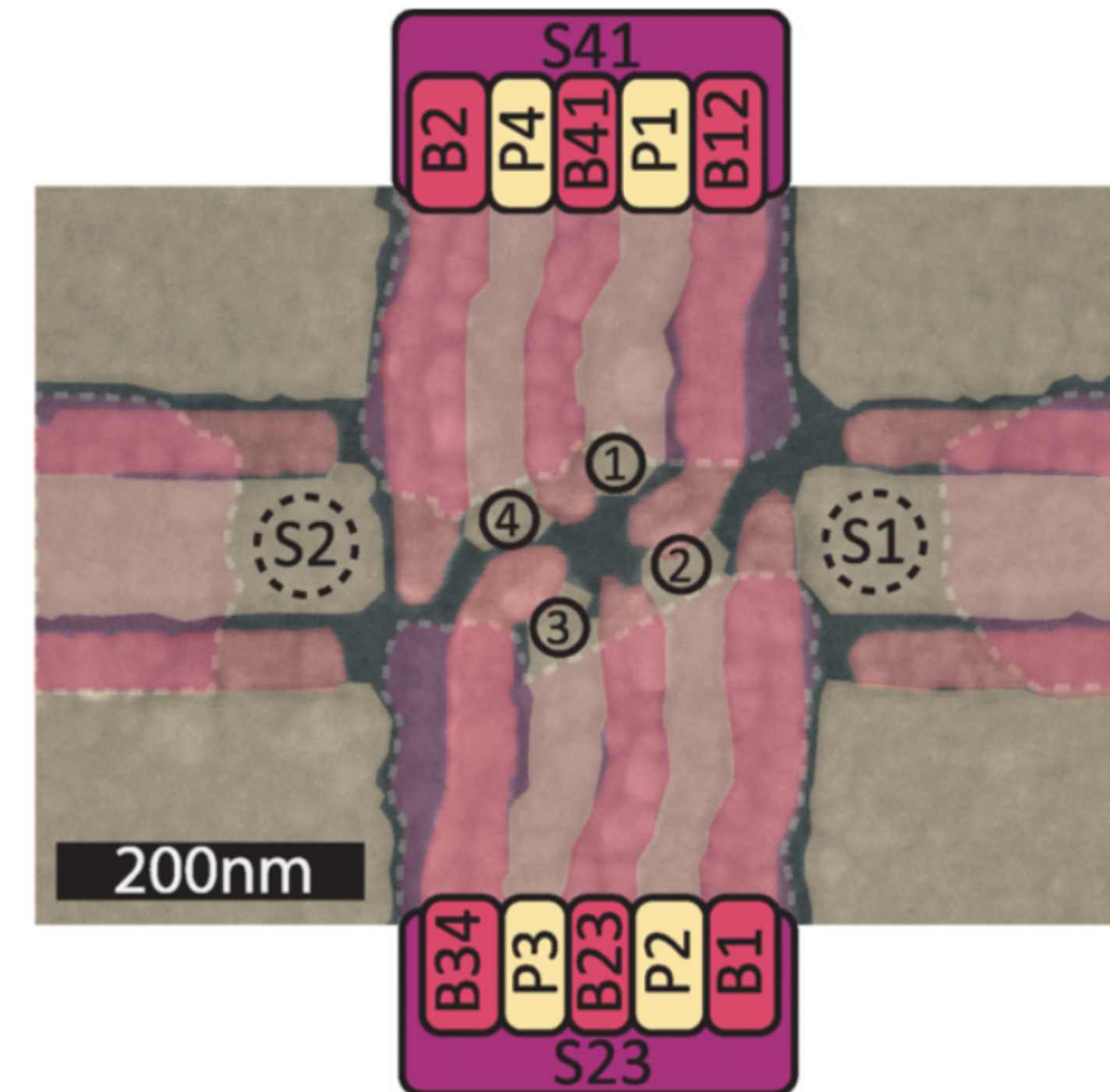
<https://doi.org/10.48550/arXiv.2306.14887> 

**"What happens if we co-design
experiments AND simulations?"**

Contemporary quantum experiments

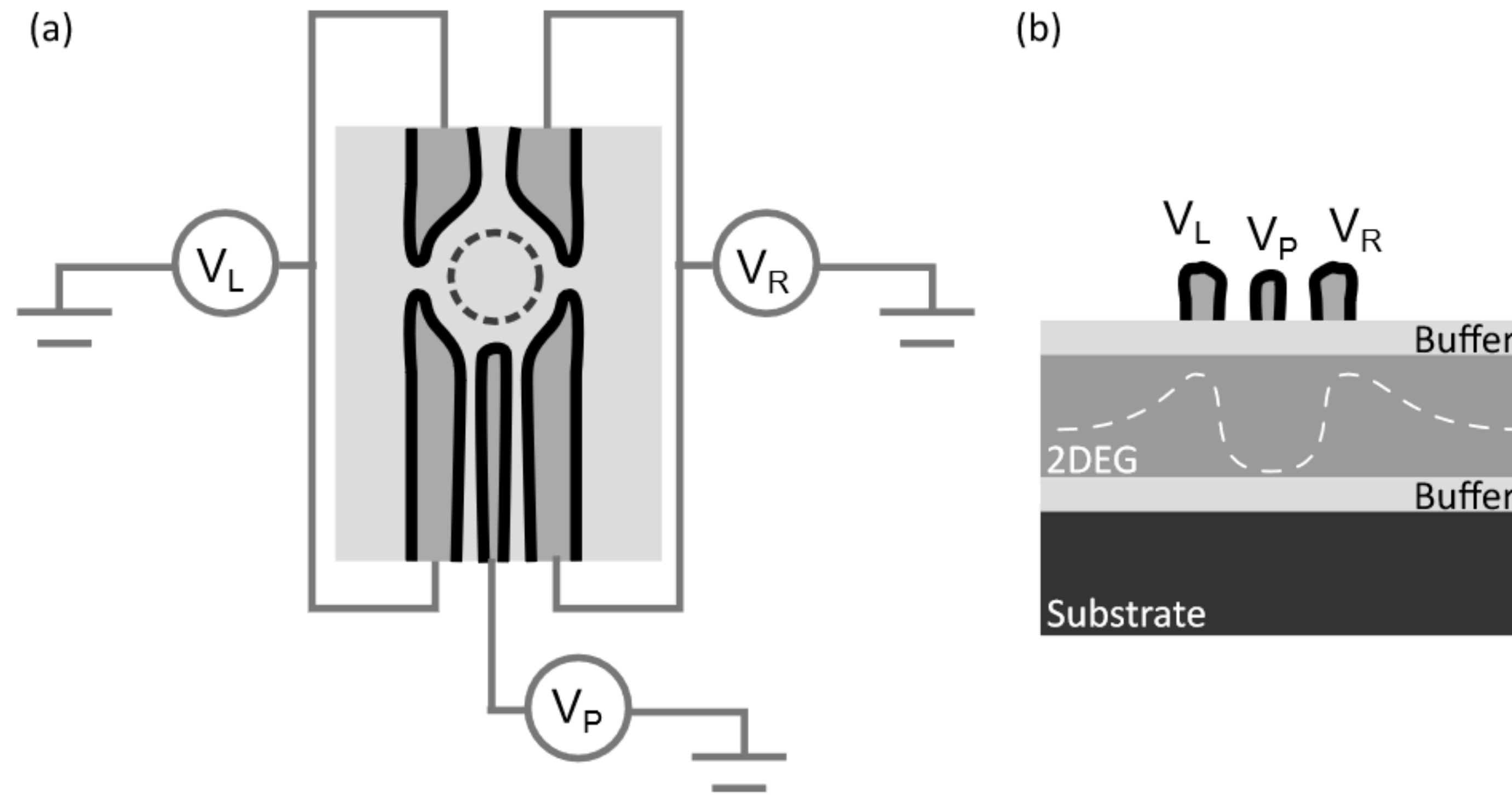


Philips, Stephan GJ, et al. "Universal control of a six-qubit quantum processor in silicon." *Nature* 609.7929 (2022): 919-924.



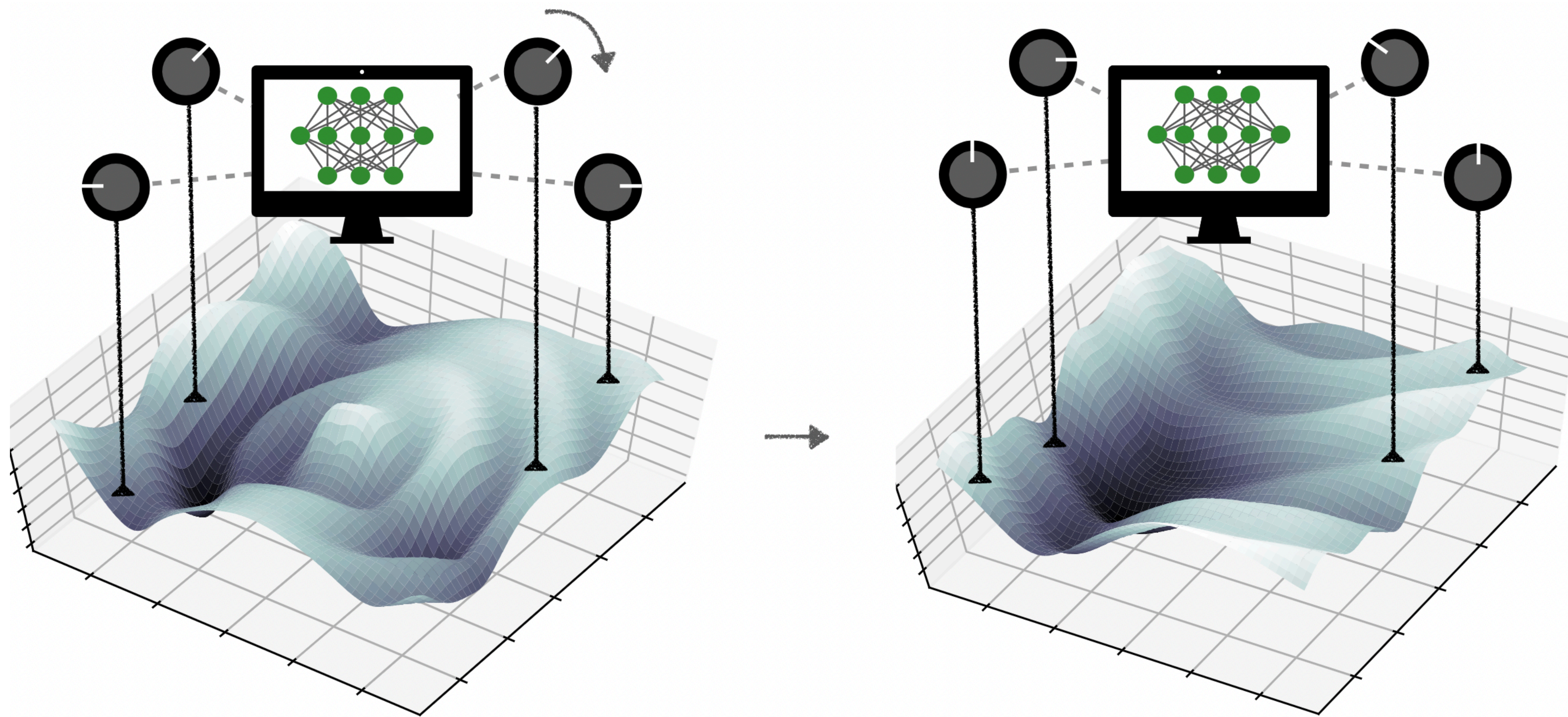
Unsel, F.K., Meyer, M., Mądzik, M.T., Borsoi, F., de Snoo, S.L., Amitonov, S.V., Sammak, A., Scappucci, G., Veldhorst, M. and Vandersypen, L.M., 2023. A 2D quantum dot array in planar $^{28}\text{Si}/\text{SiGe}$. *Applied Physics Letters*, 123(8).

Quantum Dots

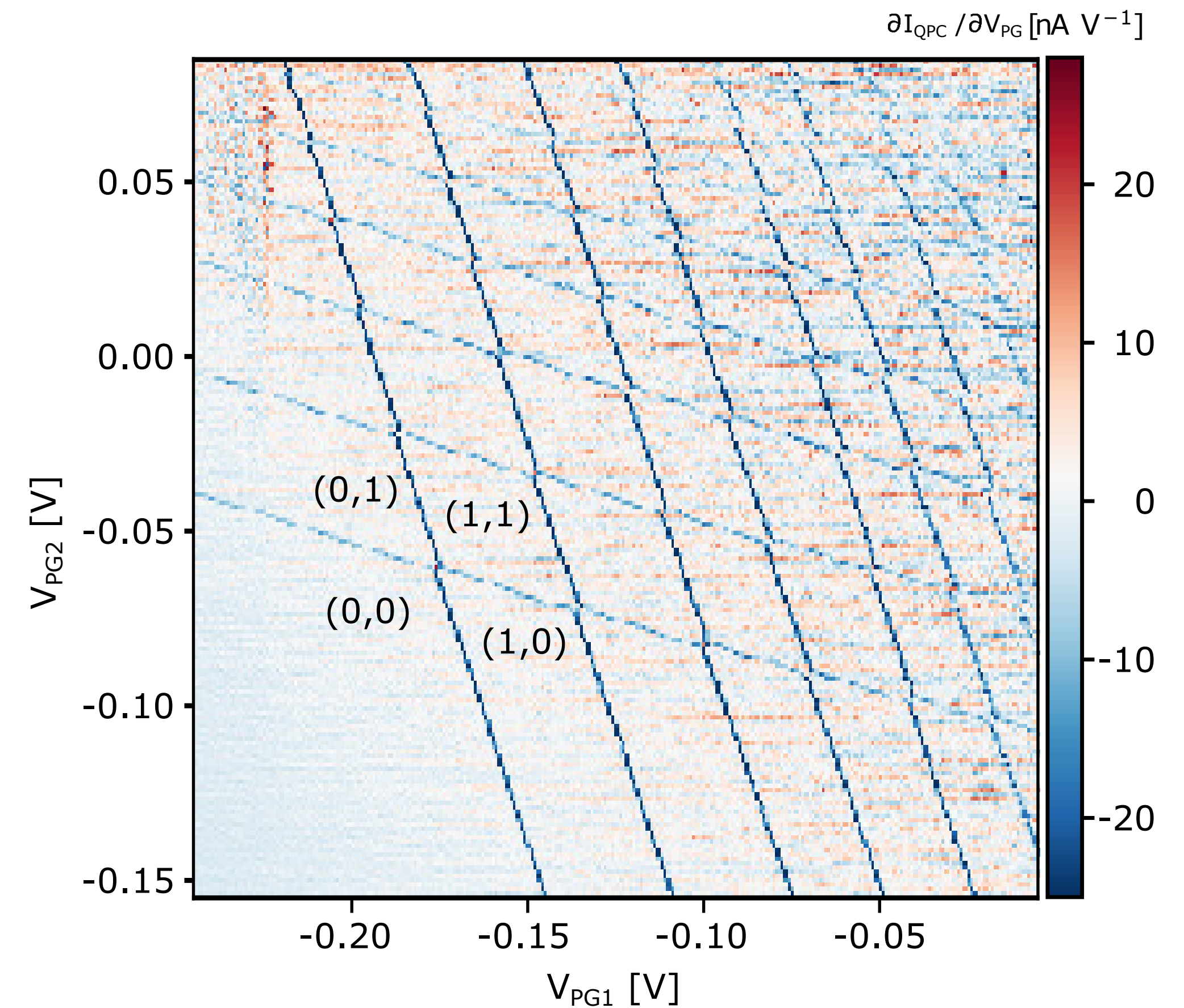
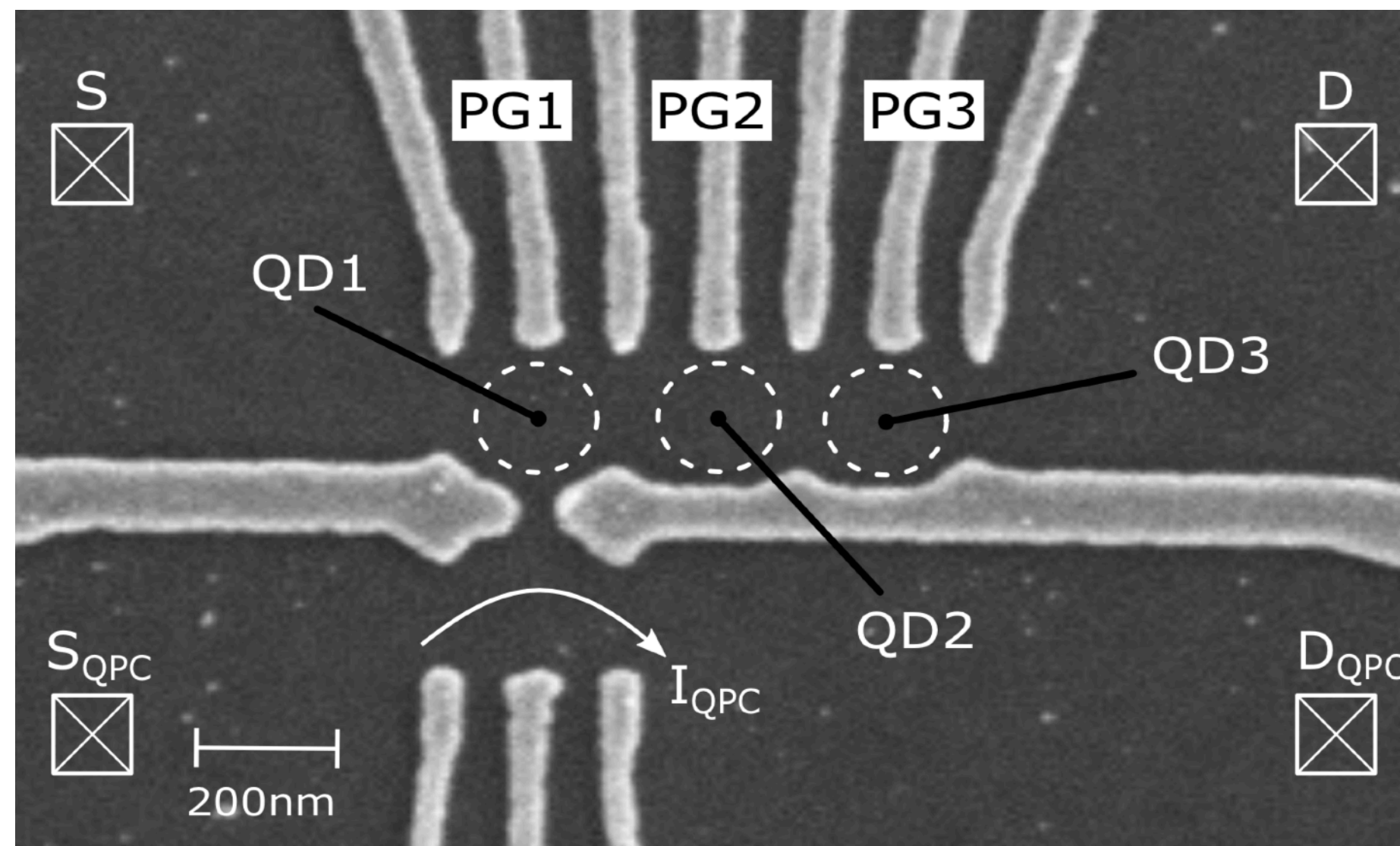


Automated calibration, control and readout of quantum systems

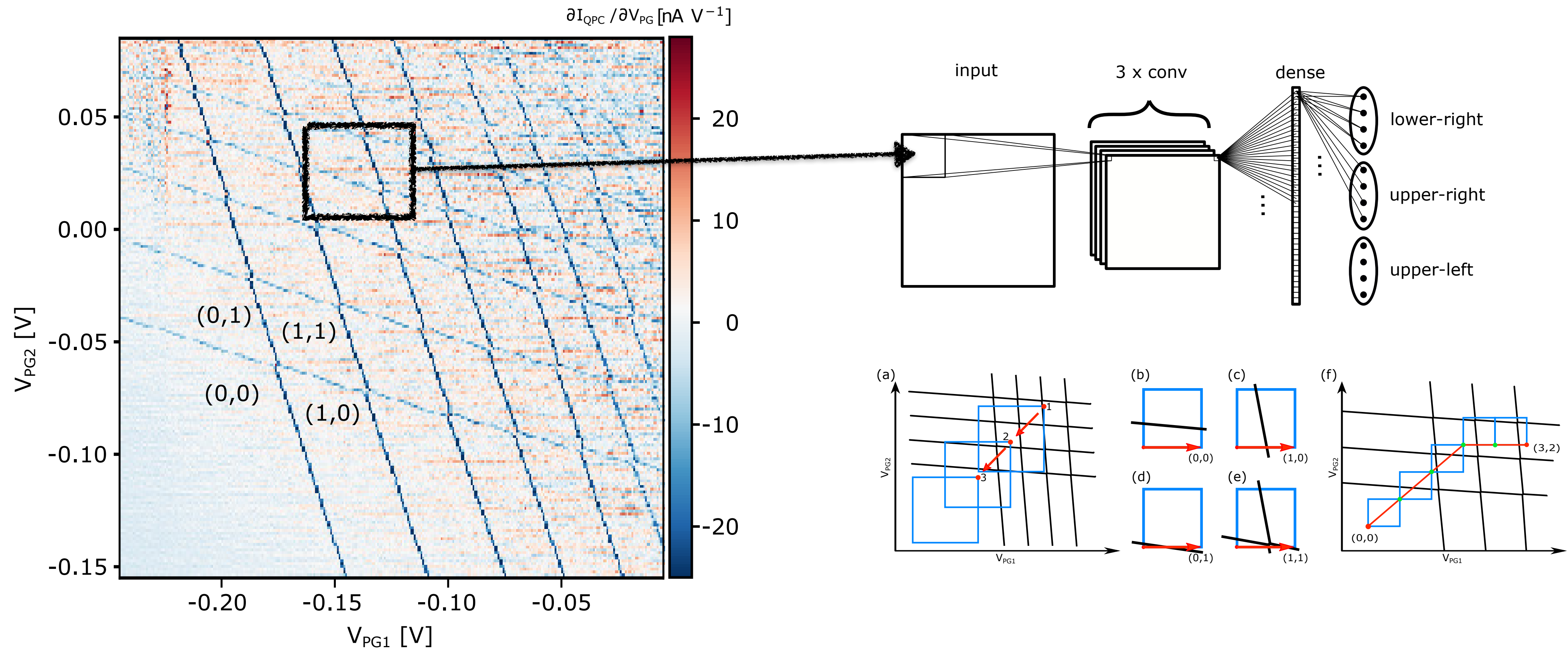
Tuning Engineered Quantum Materials



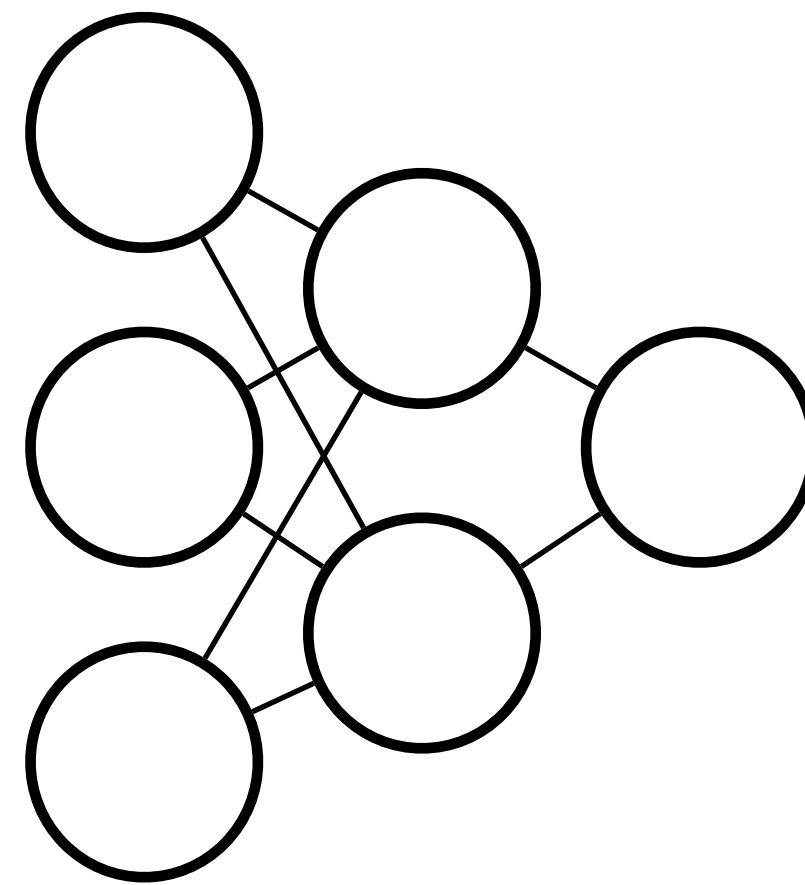
Automatic Tuning: Simple example



Preparing Specific Charge States



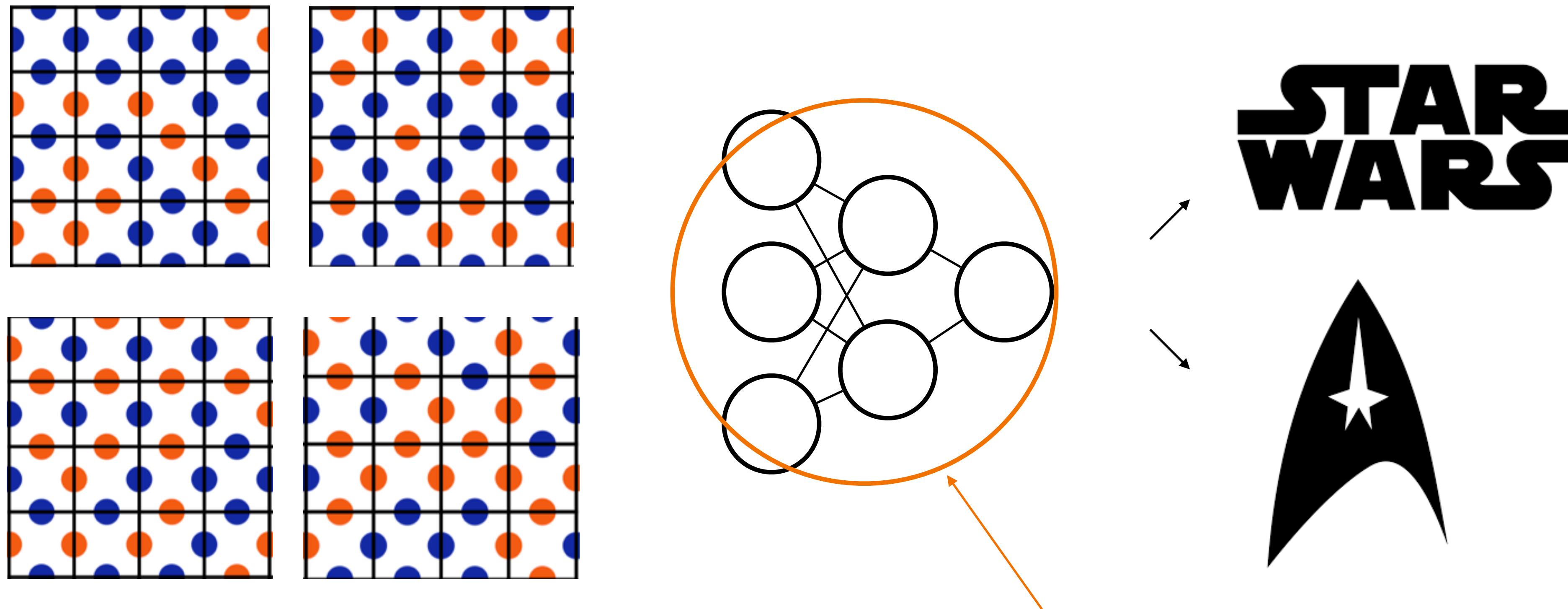
AI Image Classification



**STAR
WARS**



AI Image Classification



MACHINE LEARNING MODEL

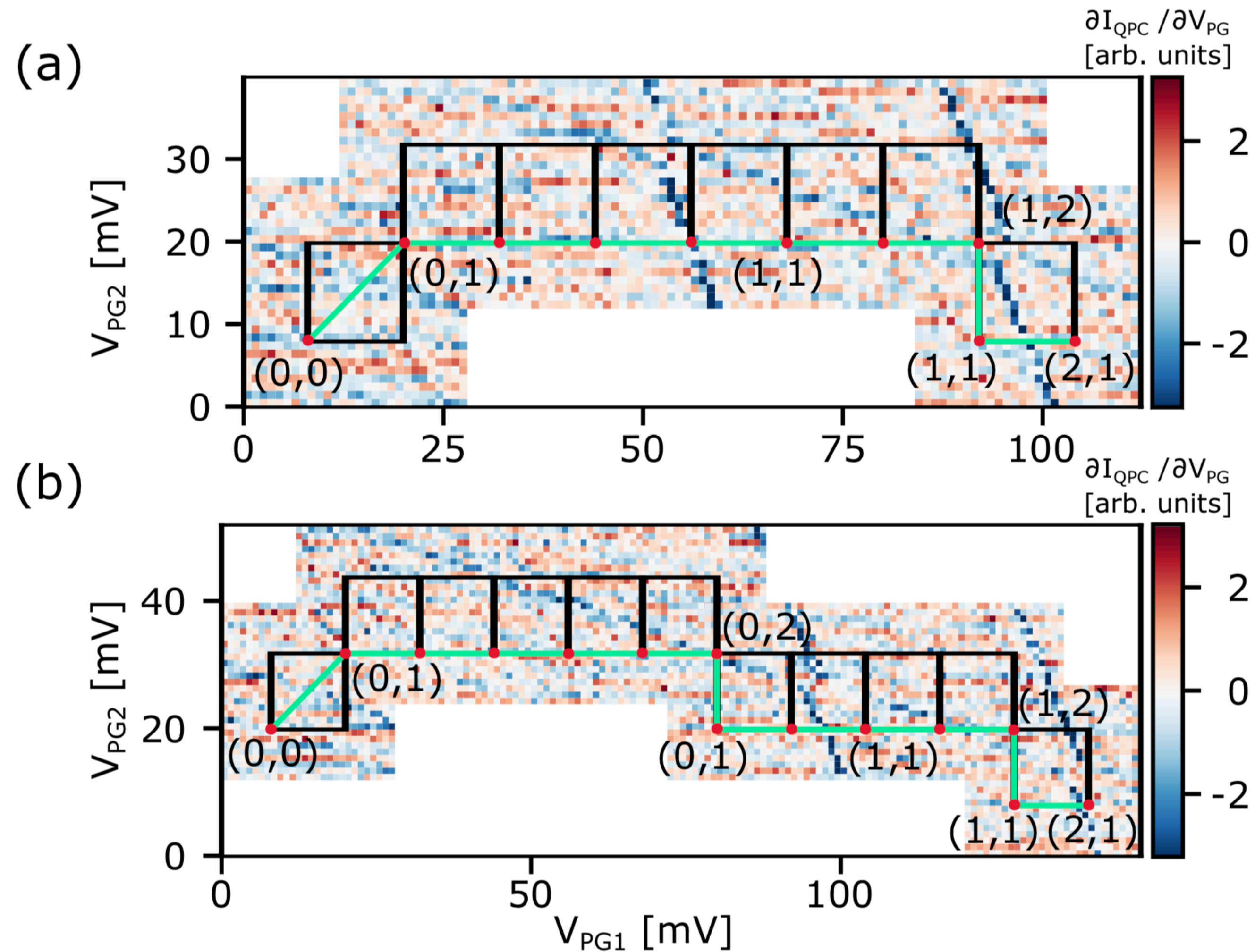
Wetzel, Sebastian J. "Unsupervised learning of phase transitions: From principal component analysis to variational autoencoders." *Physical Review E* 96.2 (2017): 022140.

Van Nieuwenburg, Evert PL, Ye-Hua Liu, and Sebastian D. Huber. "Learning phase transitions by confusion." *Nature Physics* 13.5 (2017): 435-439.

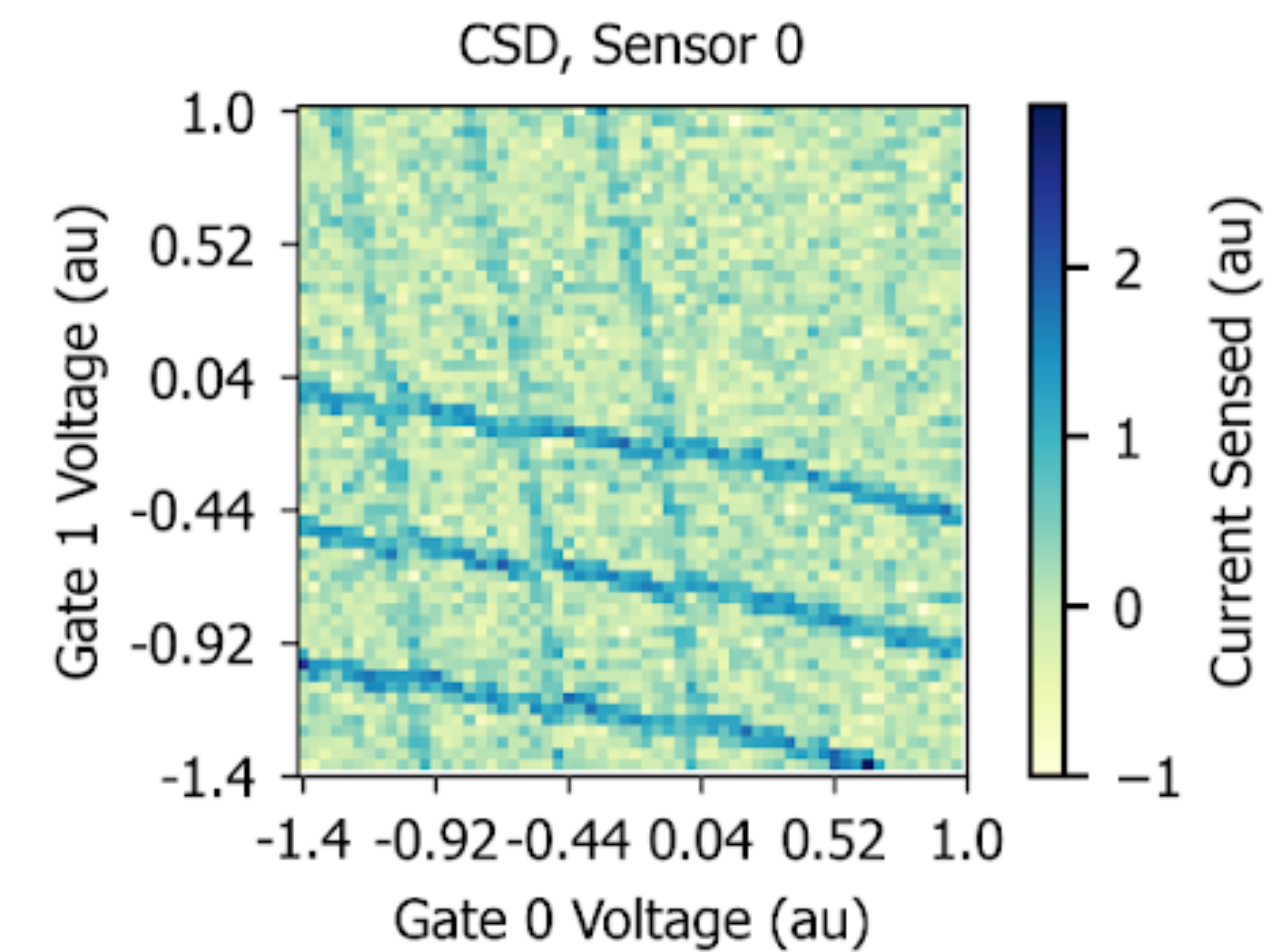
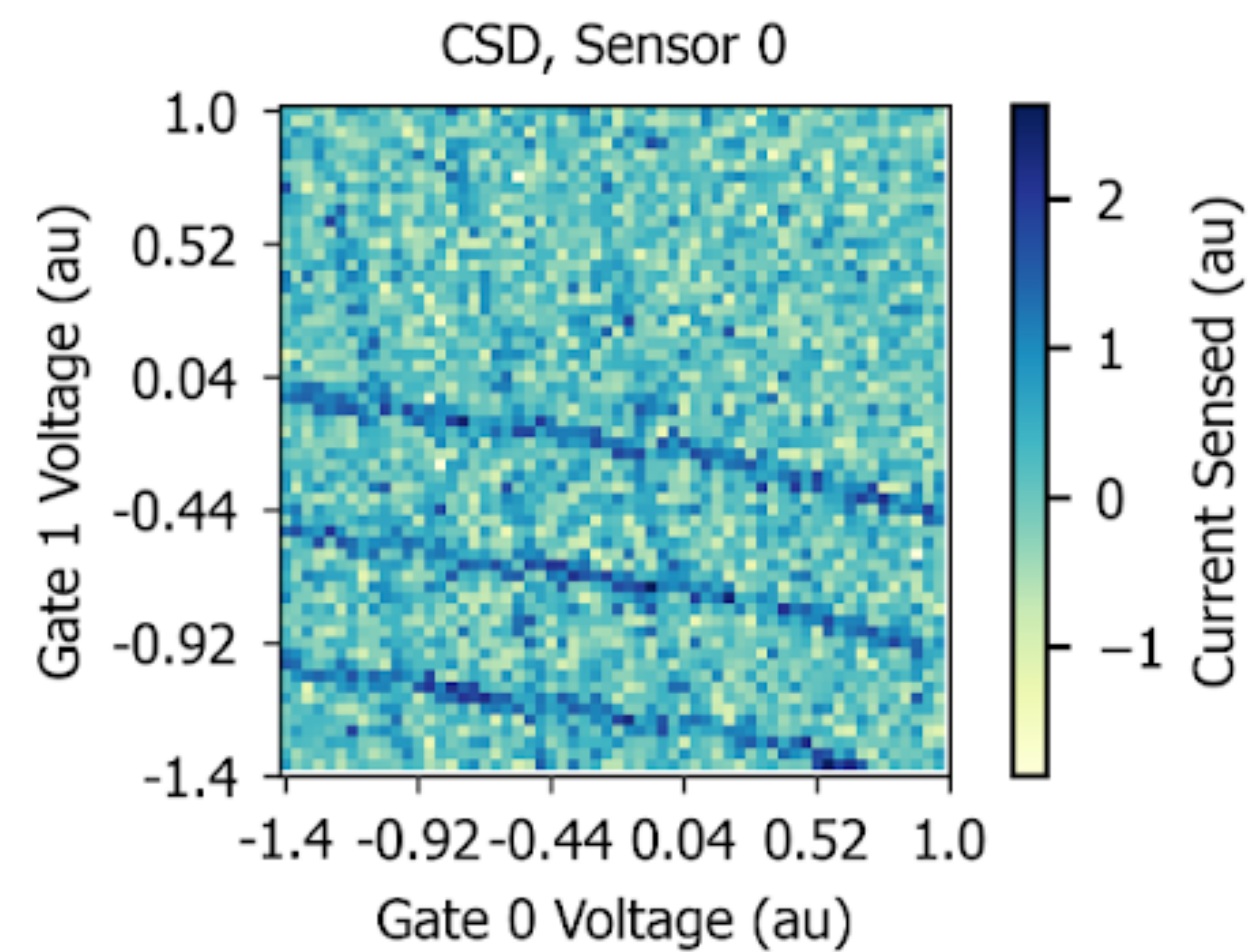
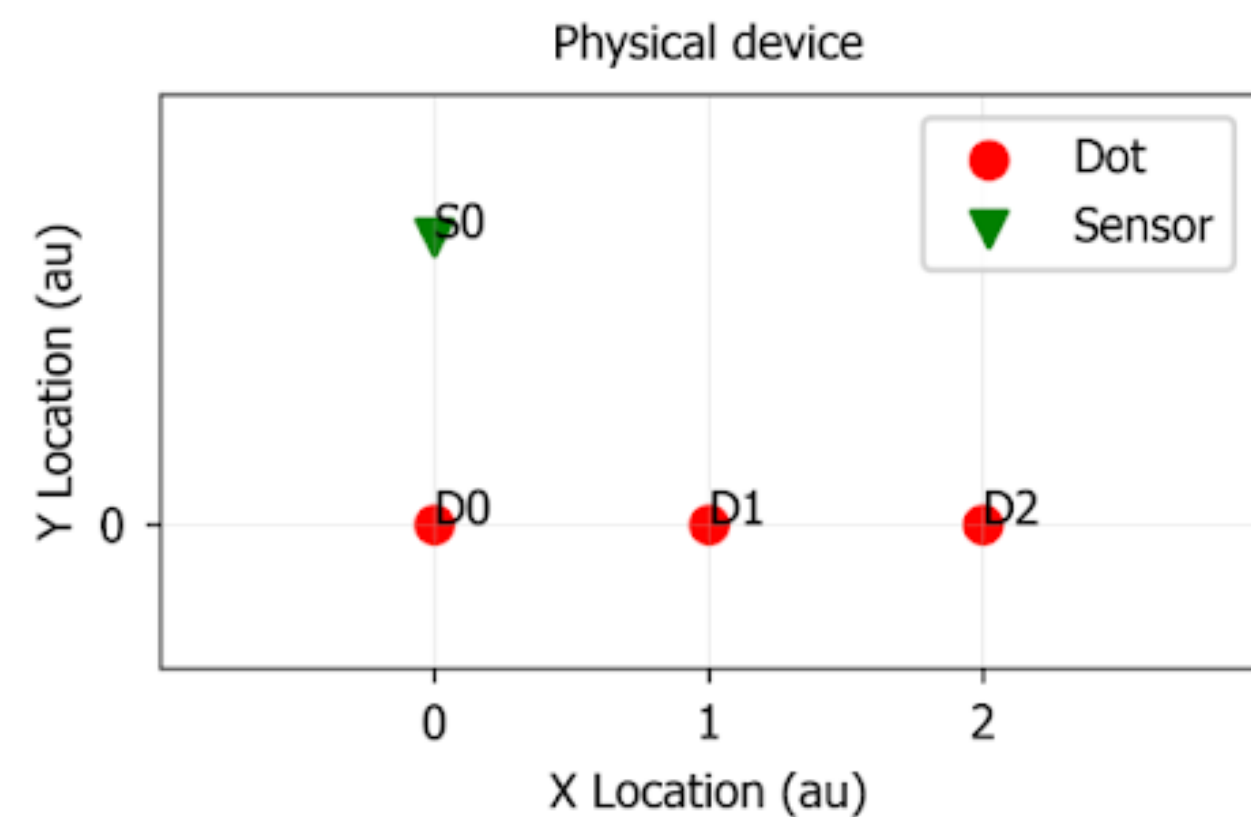
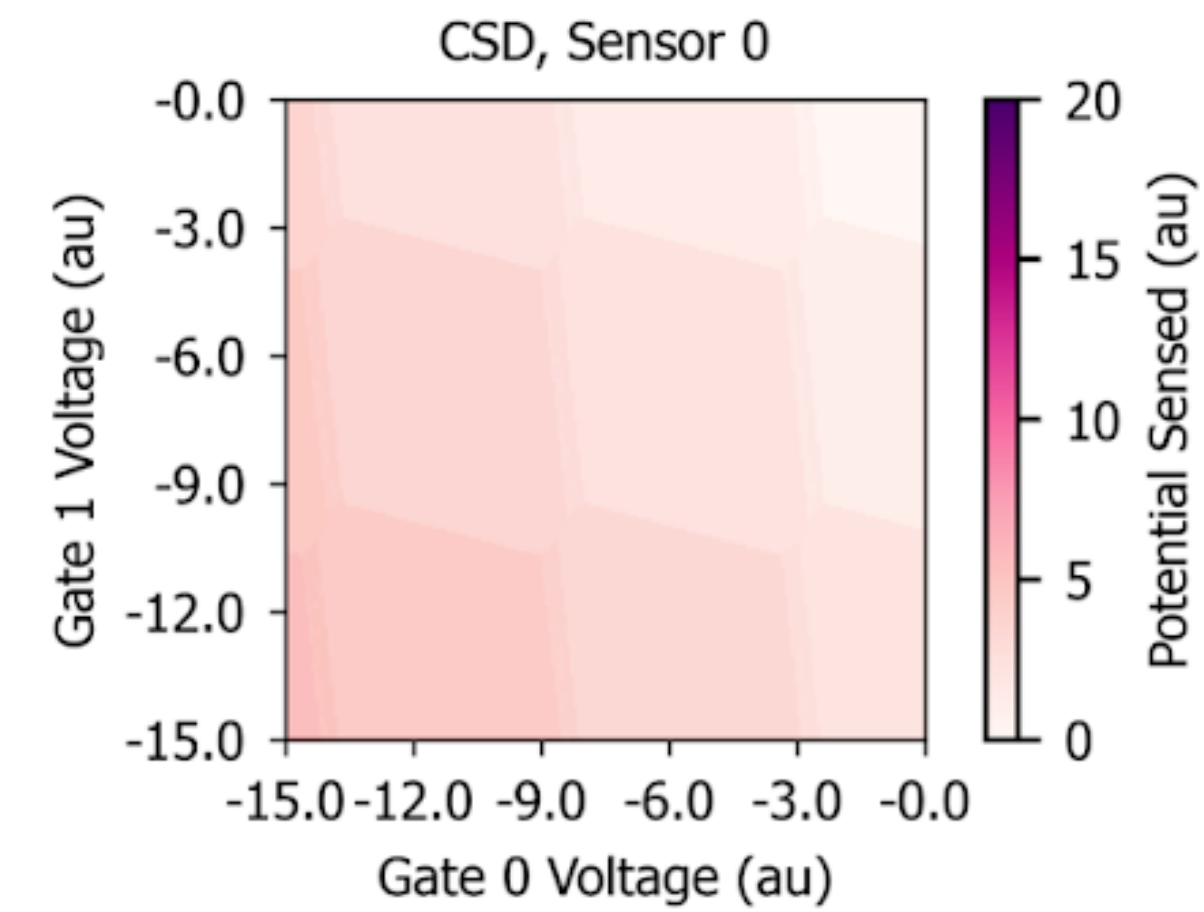
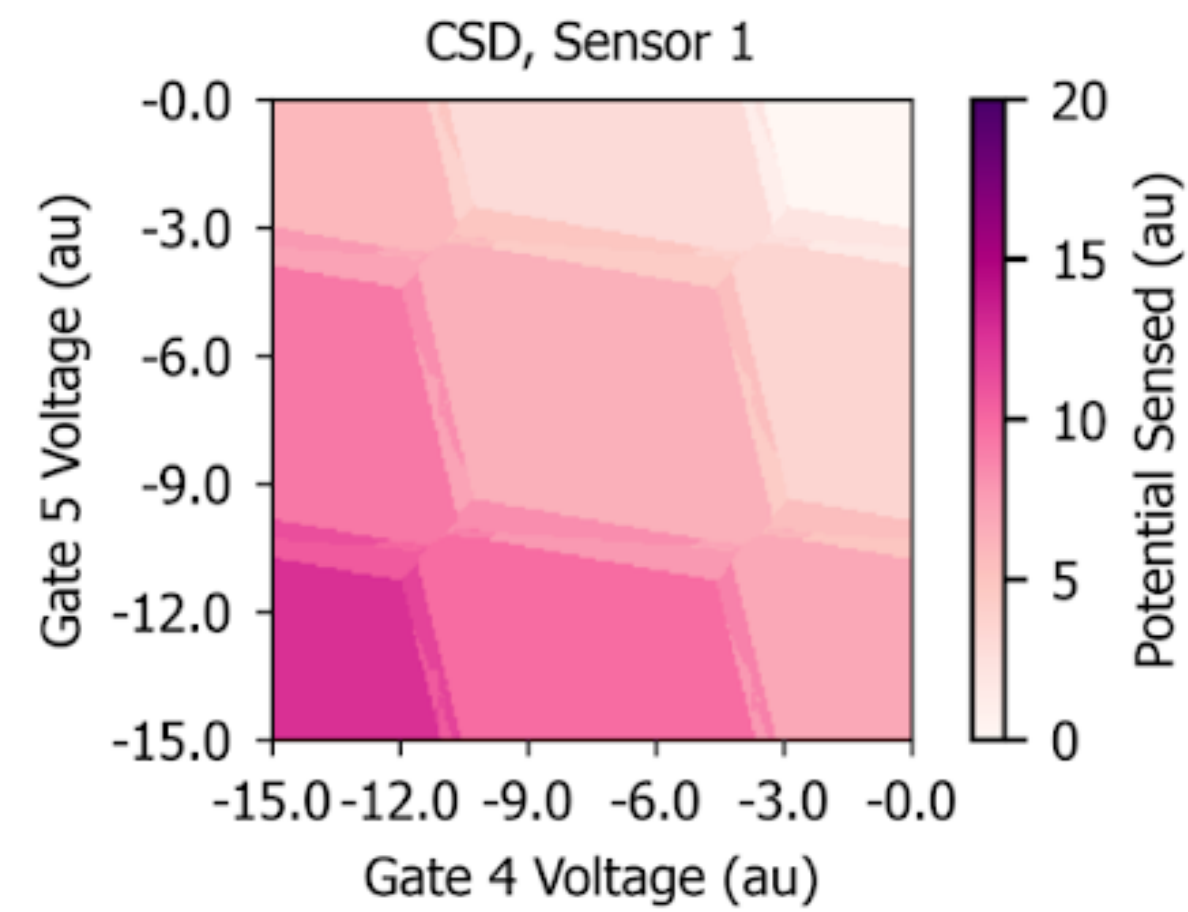
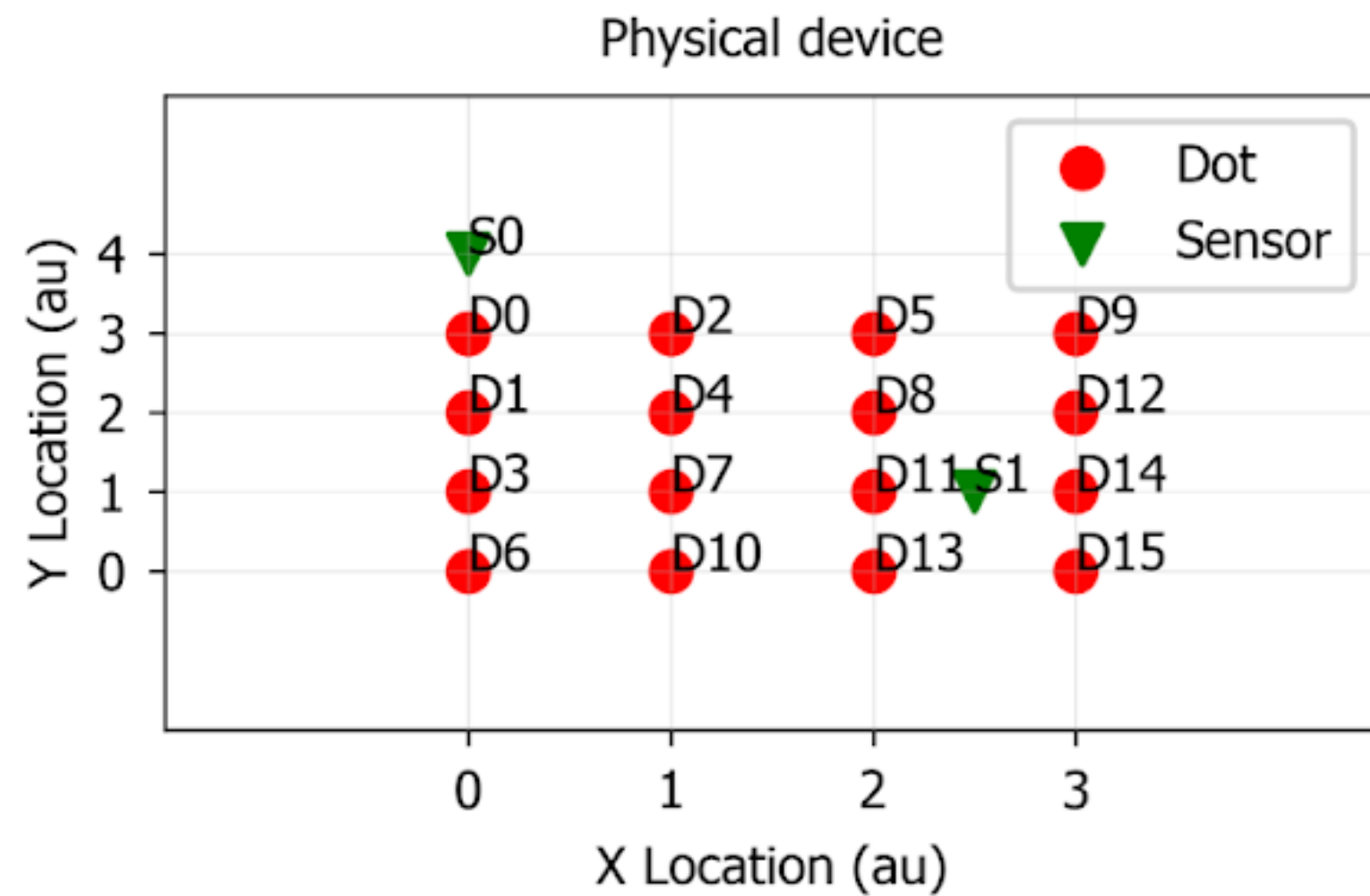
Carrasquilla, Juan, and Roger G. Melko. "Machine learning phases of matter." *Nature Physics* 13.5 (2017): 431-434.

Greplova, E., Valenti, A., Boschung, G., Schäfer, F., Lörch, N., & Huber, S. D. (2020). Unsupervised identification of topological phase transitions using predictive models. *New Journal of Physics*, 22(4), 045003.

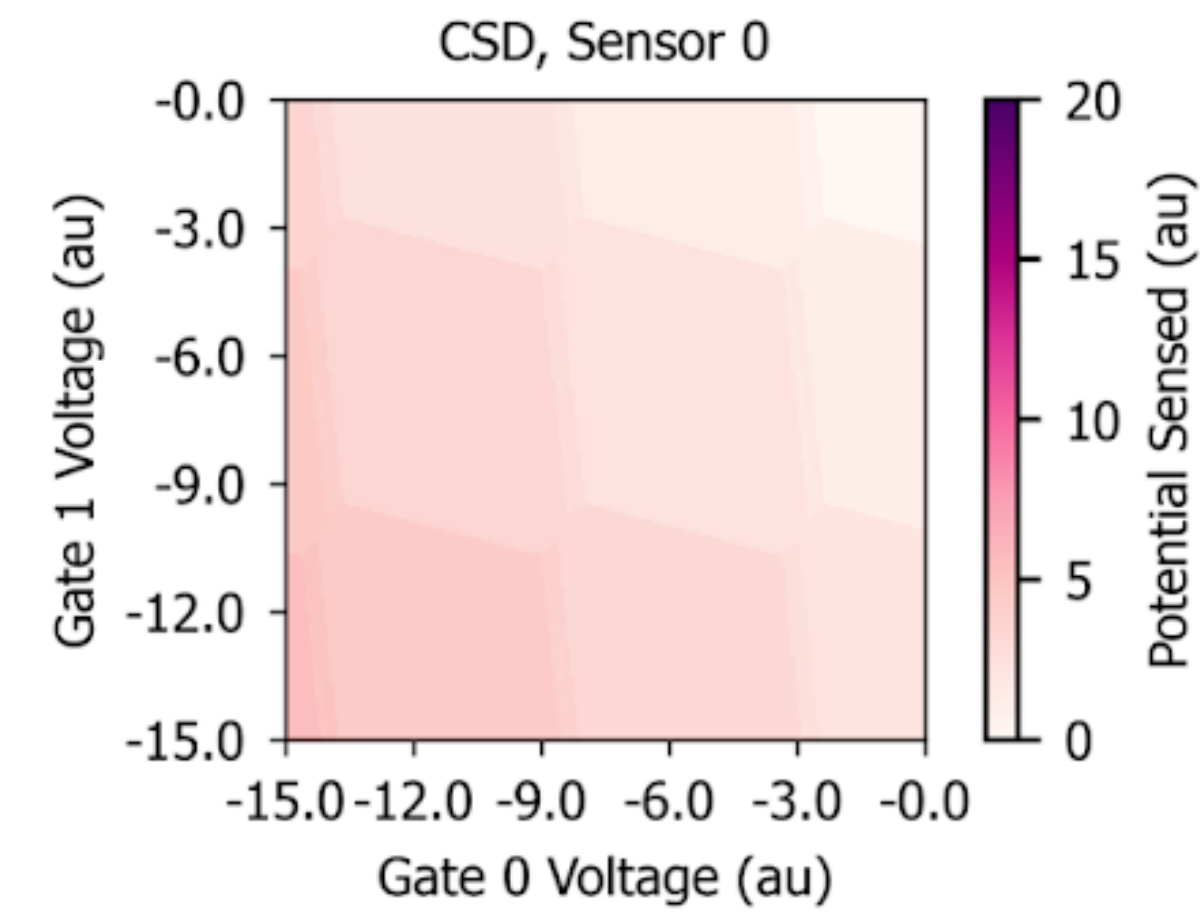
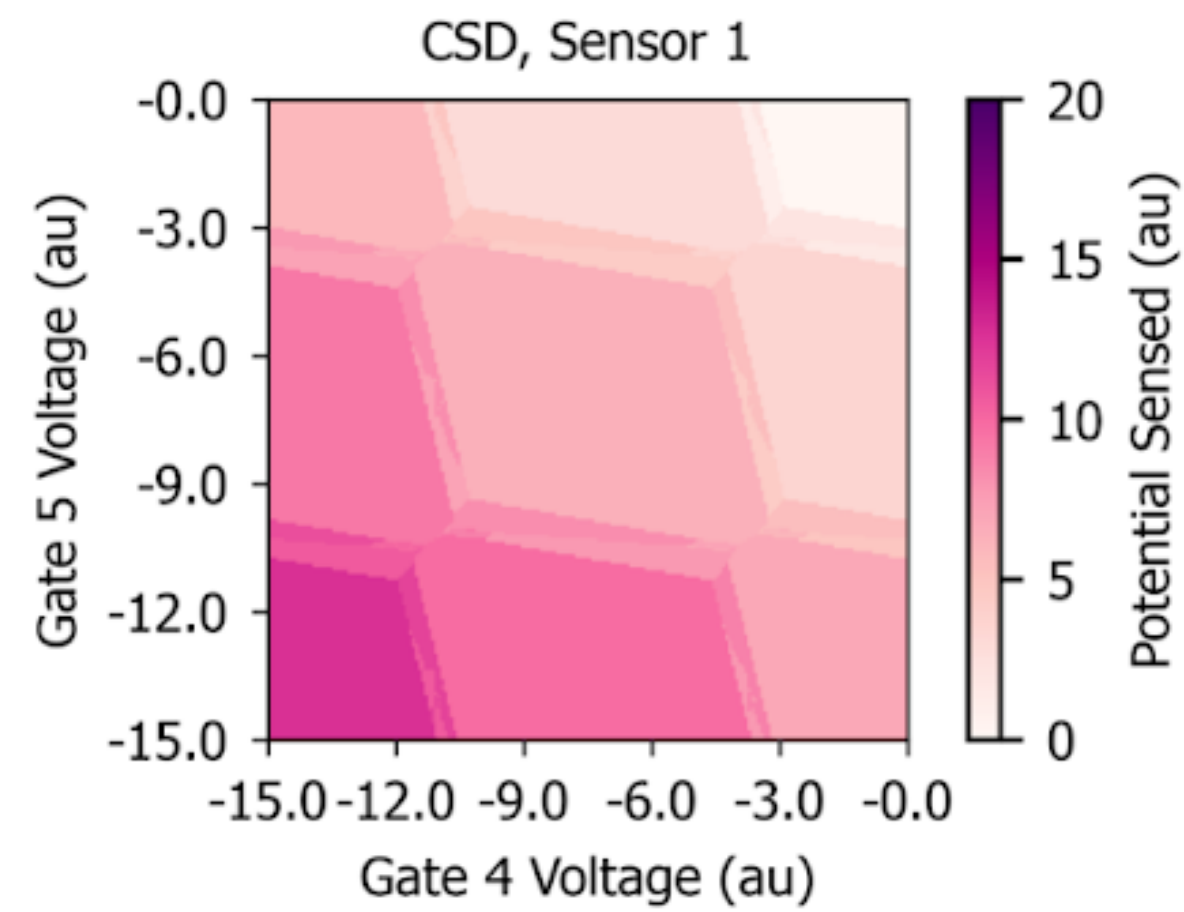
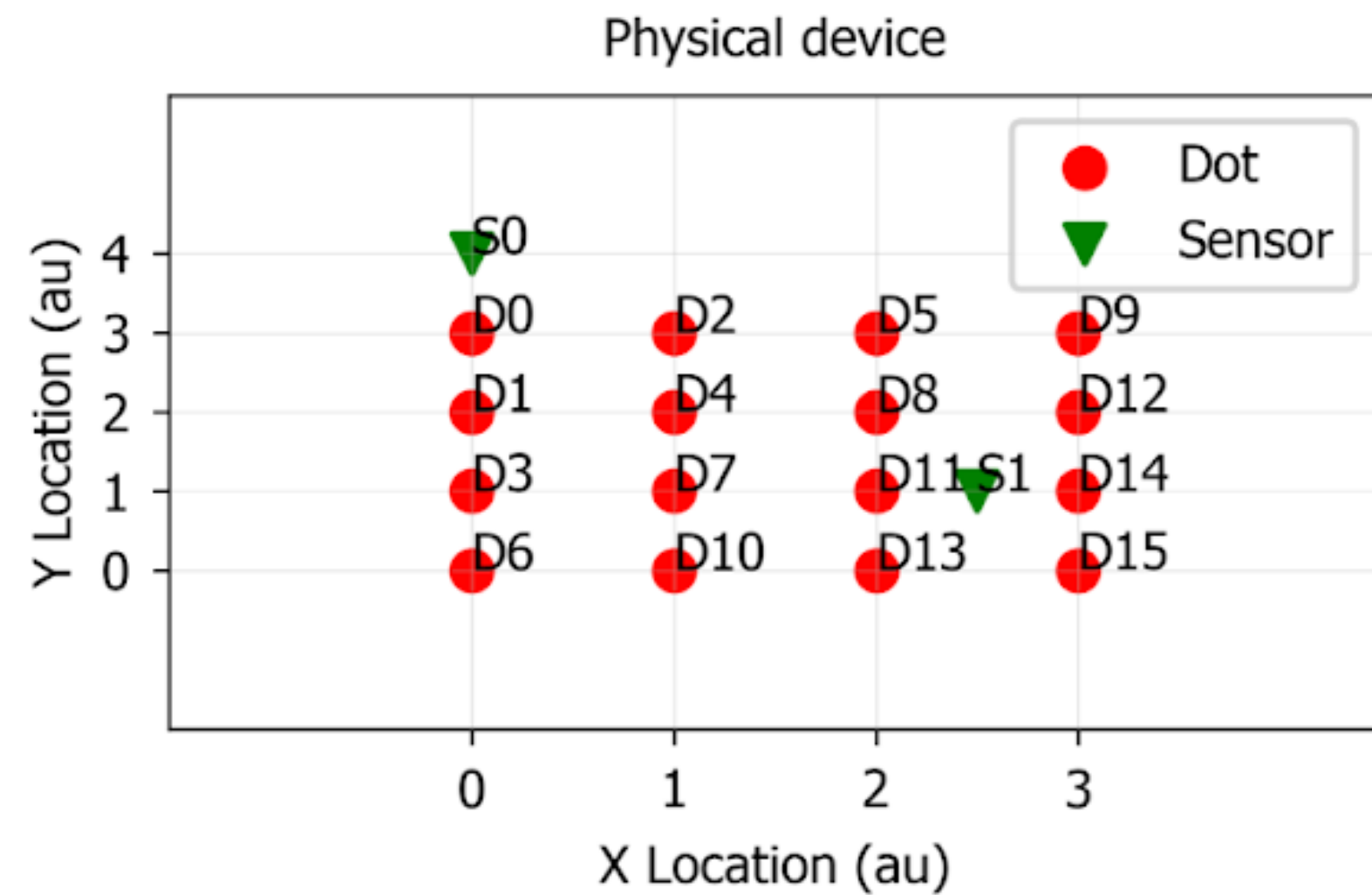
Tuning Runs on the Device



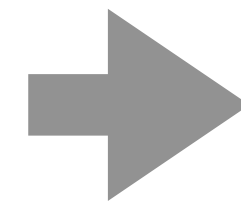
QDsim: Simulator of arbitrary geometries



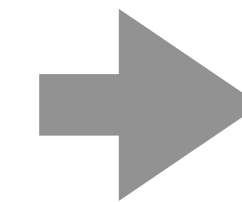
QDsim: Simulator of arbitrary geometries



CONSTANT
INTERACTION
MODEL



MINIMIZE
ENERGY



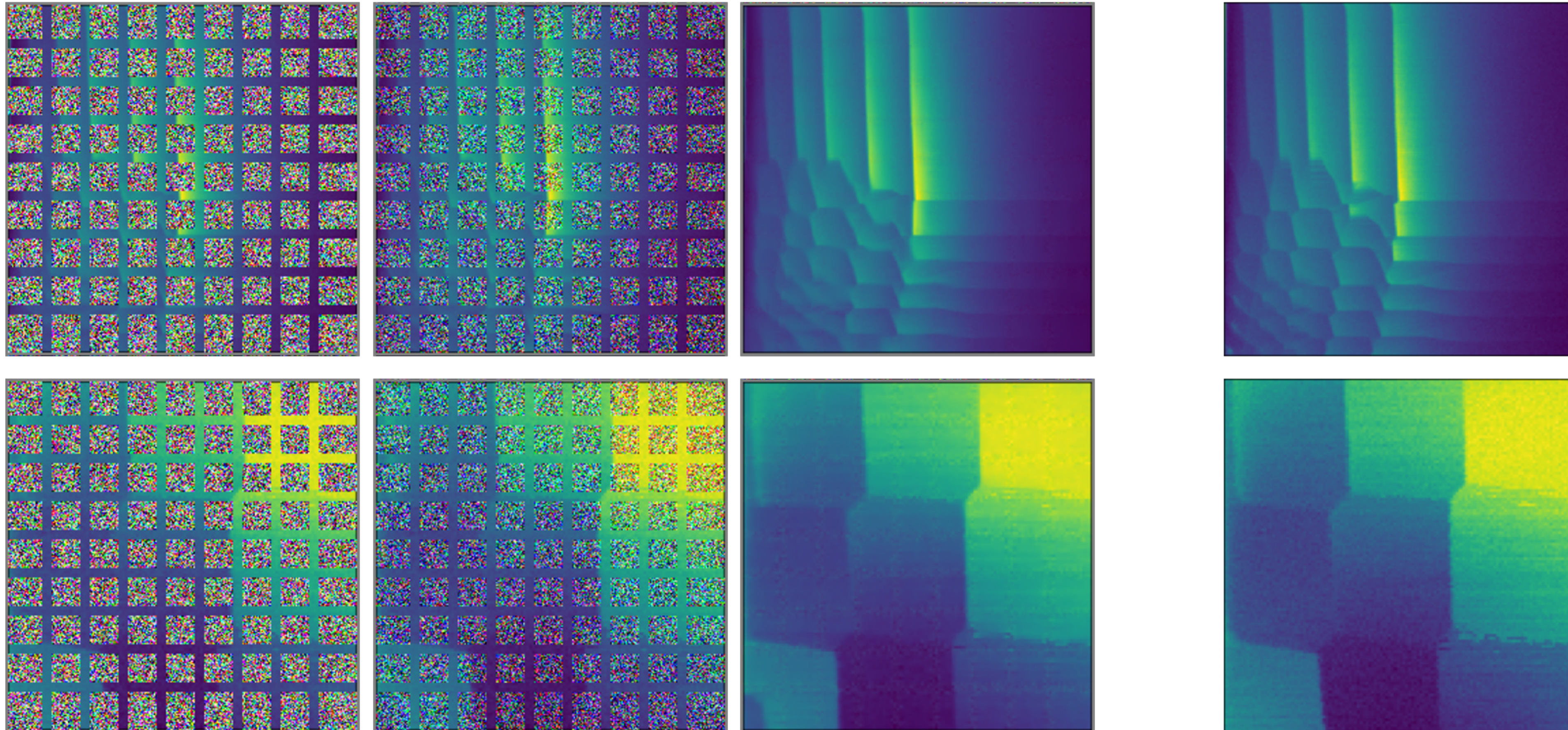
CONVEX
OPTIMIZATION
PROBLEM

`pip install qdsim`

Modern Techniques: Use diffusion and measure less! QMAI | TU Delft

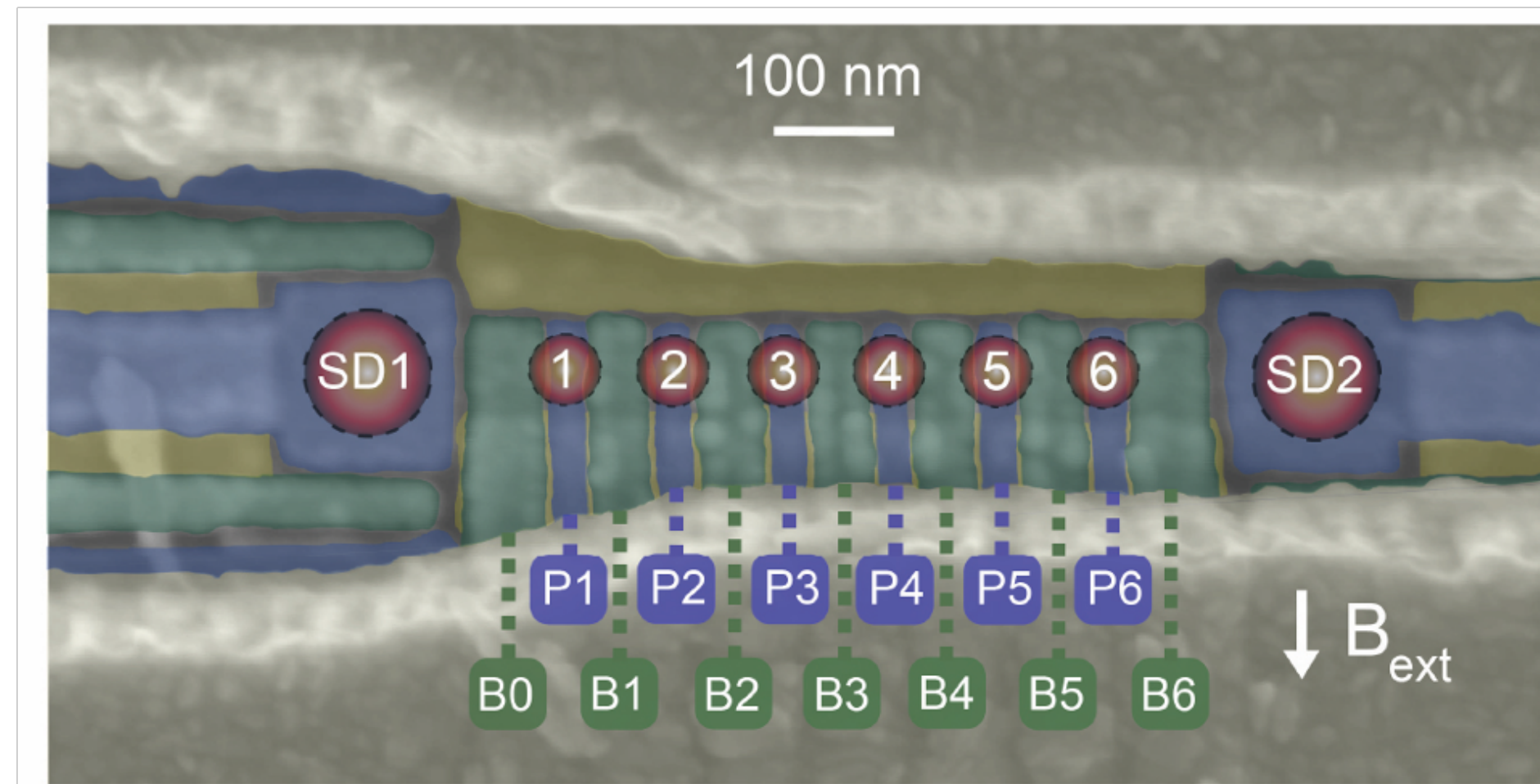
On average, 91% accuracy with 61% of the data hidden

Ground Truth

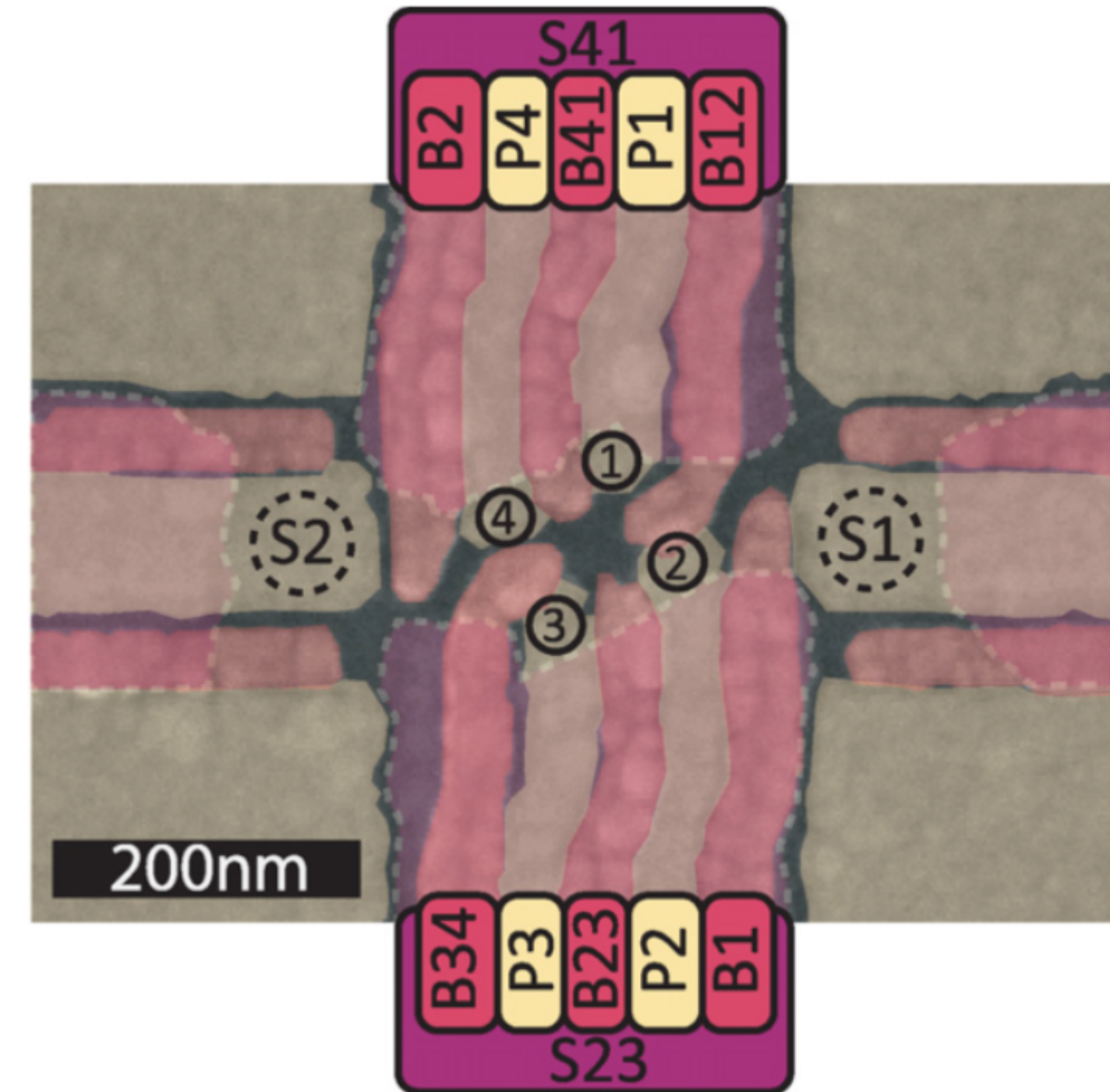


“Can we move beyond direct ML image recognition?”

Bottleneck: Readout



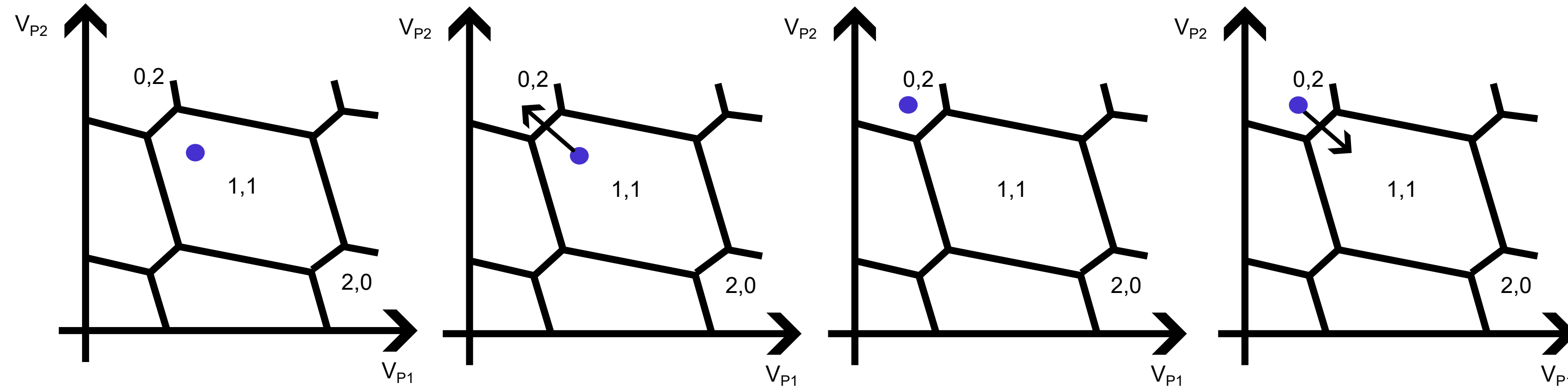
De Smet, M., Matsumoto, Y., Zwerver, A.M.J., Tryputen, L., de Snoo, S.L., Amitonov, S.V., Sammak, A., Samkharadze, N., Gül, Ö., Wasserman, R.N. and Rimbach-Russ, M., 2024. High-fidelity single-spin shuttling in silicon. *arXiv preprint arXiv:2406.07267*.



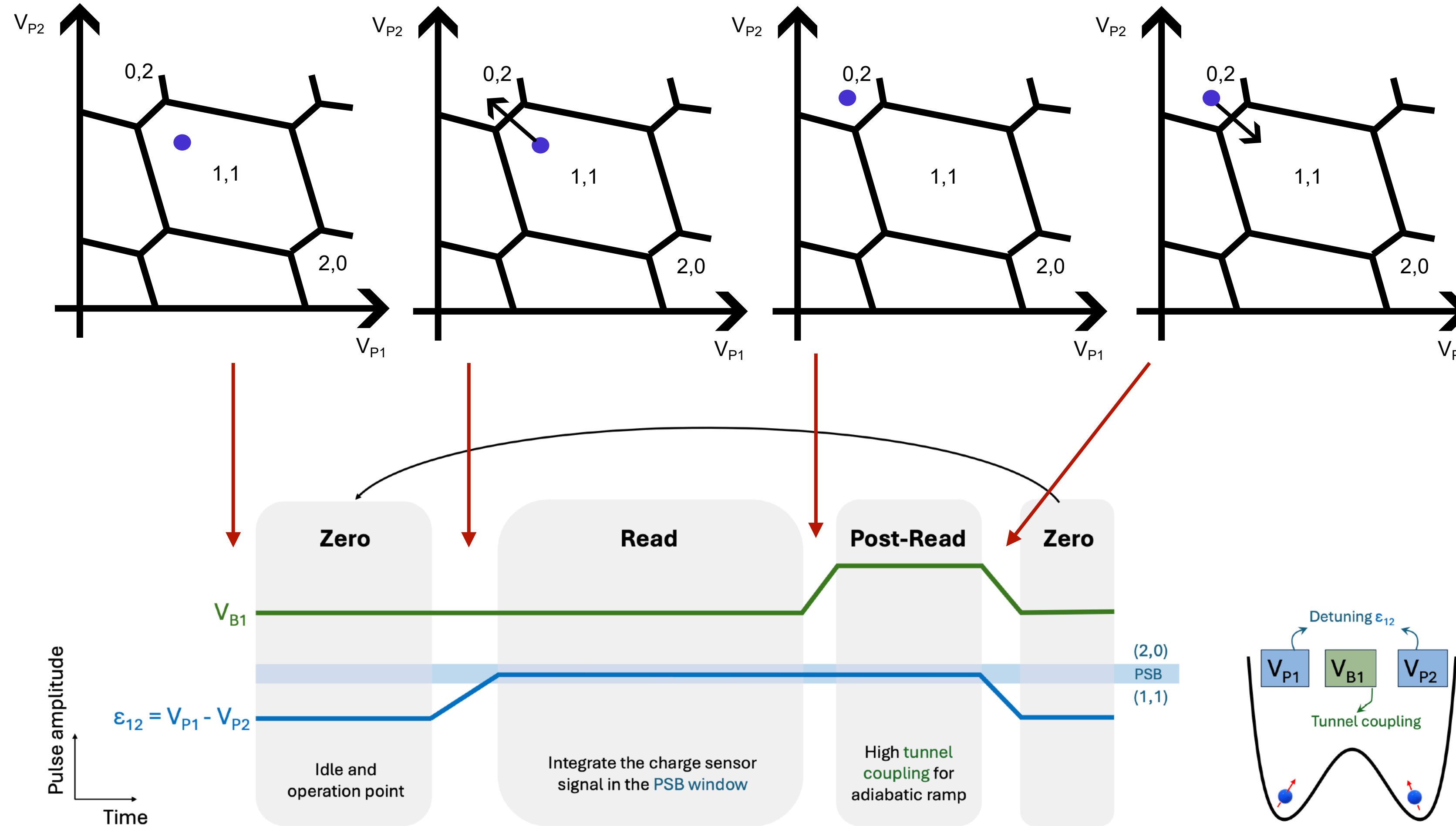
Unsel, F.K., Meyer, M., Mądzik, M.T., Borsoi, F., de Snoo, S.L., Amitonov, S.V., Sammak, A., Scappucci, G., Veldhorst, M. and Vandersypen, L.M., 2023. A 2D quantum dot array in planar 28Si/SiGe. *Applied Physics Letters*, 123(8).



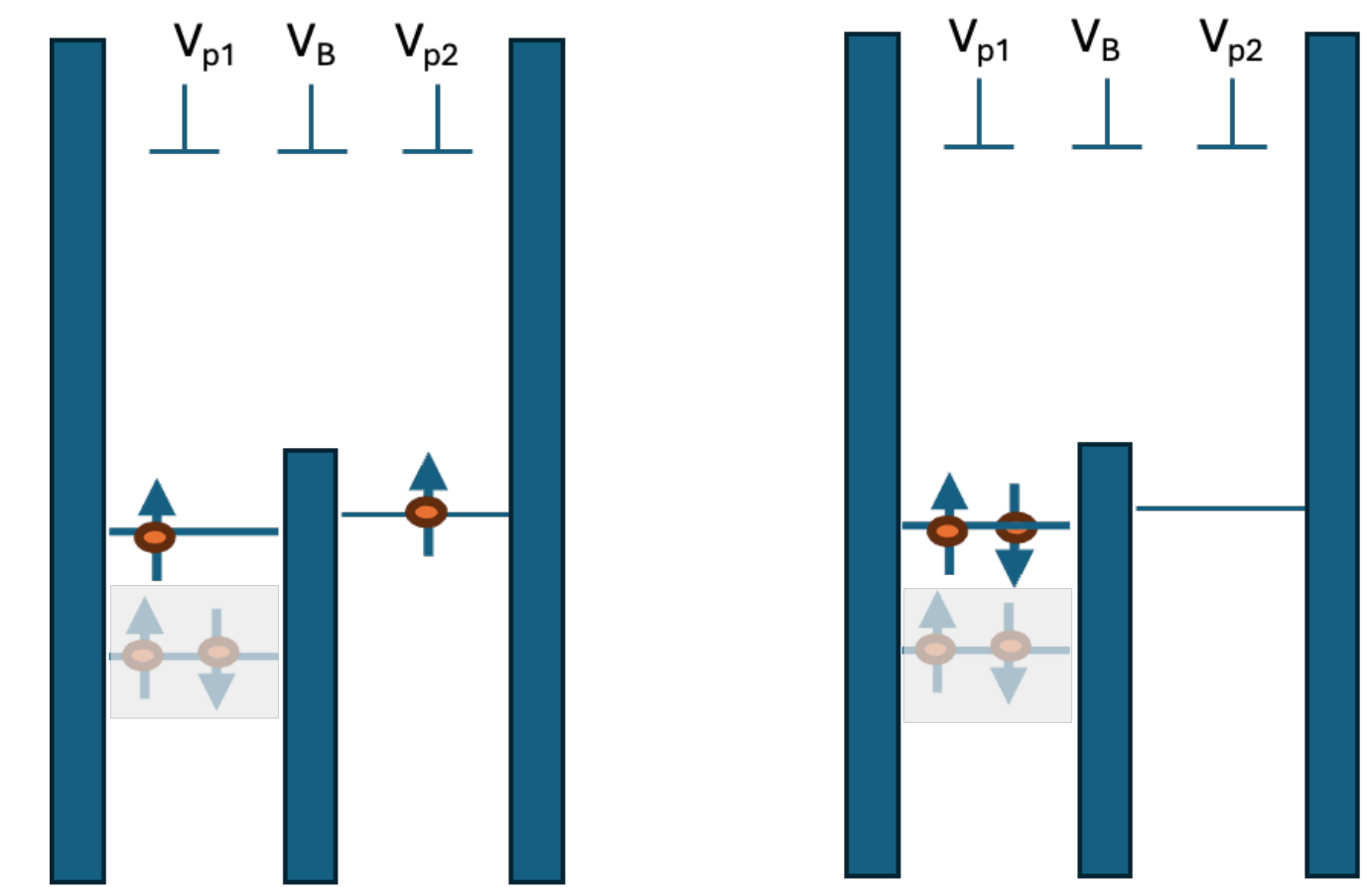
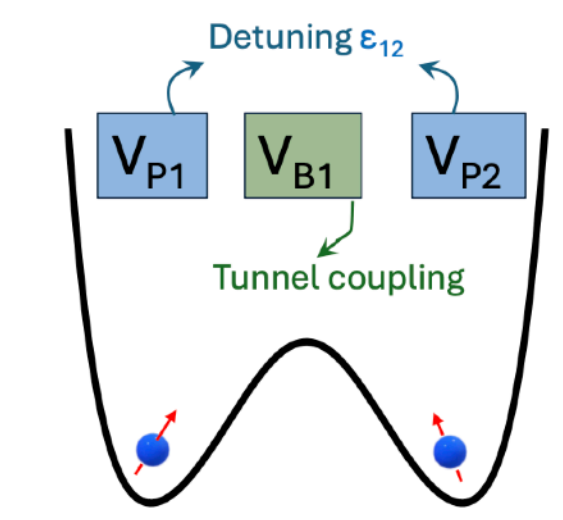
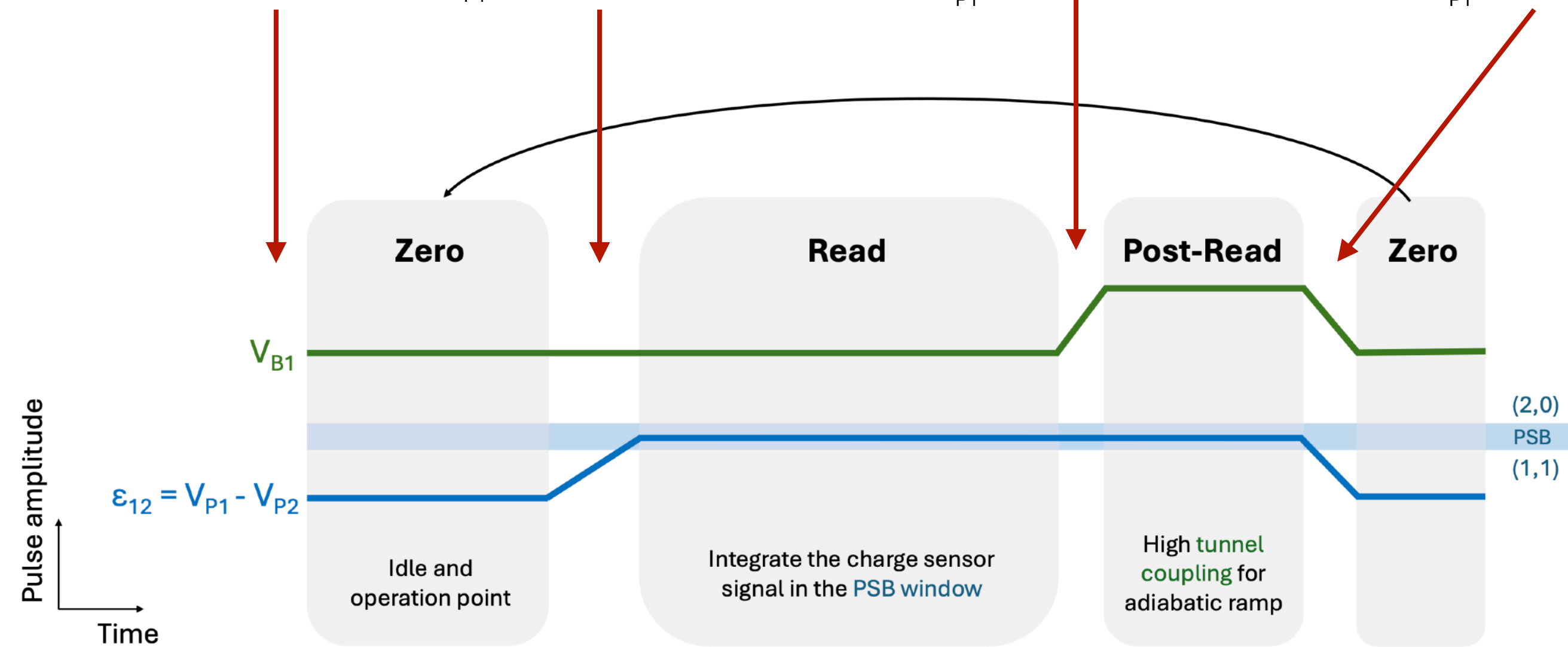
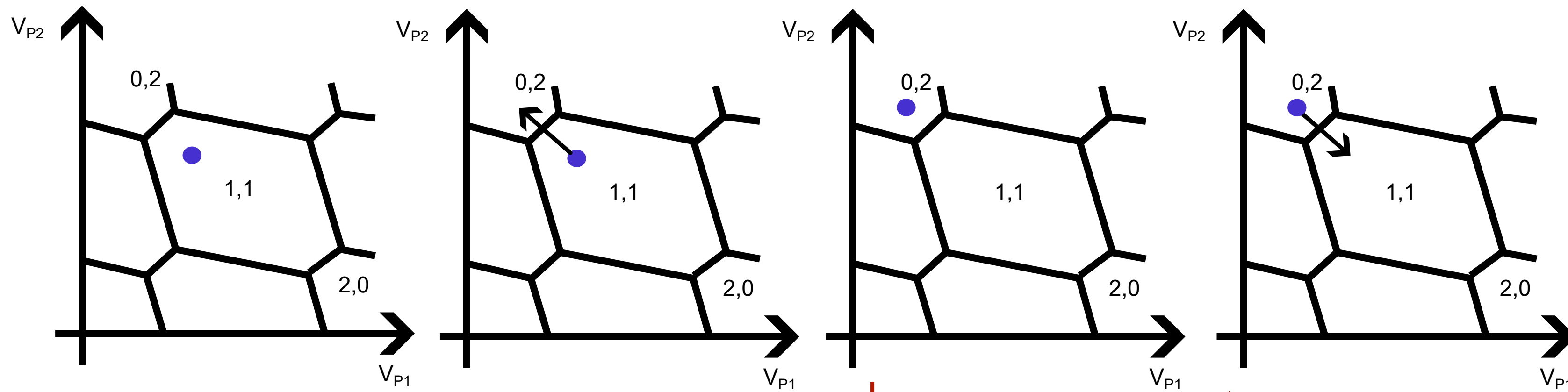
Pauli Spin Blockade readout



Pauli Spin Blockade readout

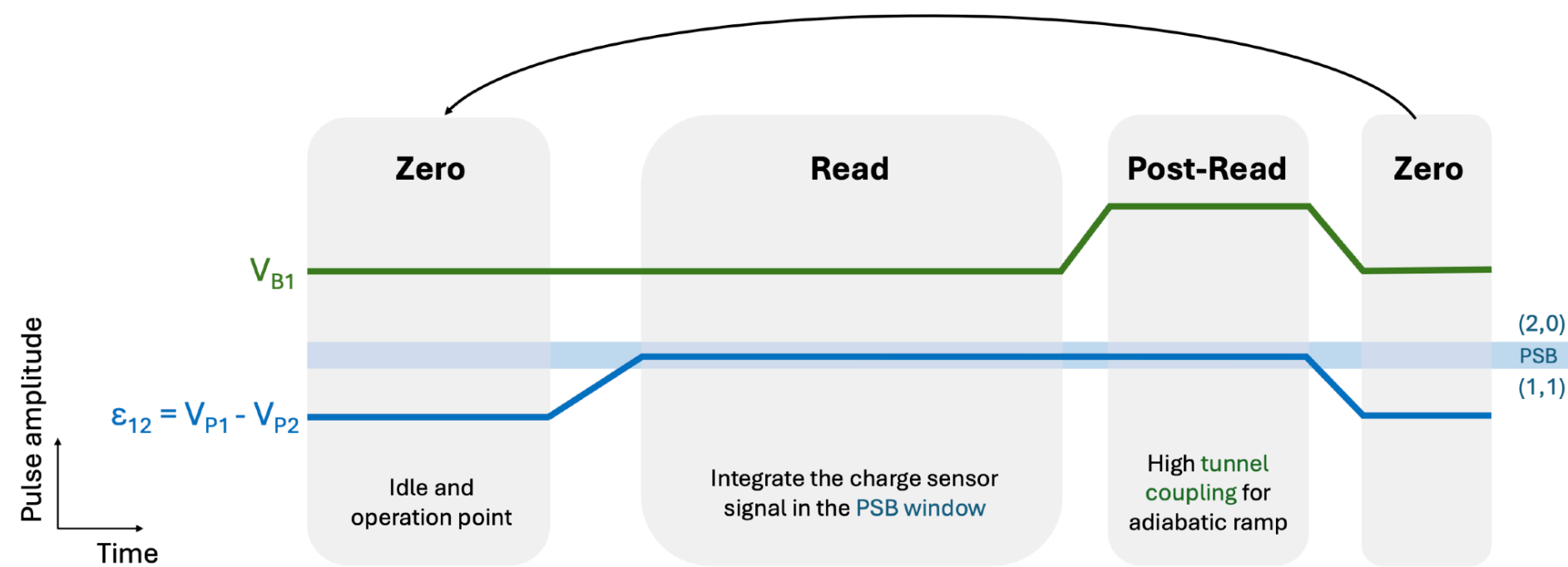


Pauli Spin Blockade readout



Optimizing the readout sequence

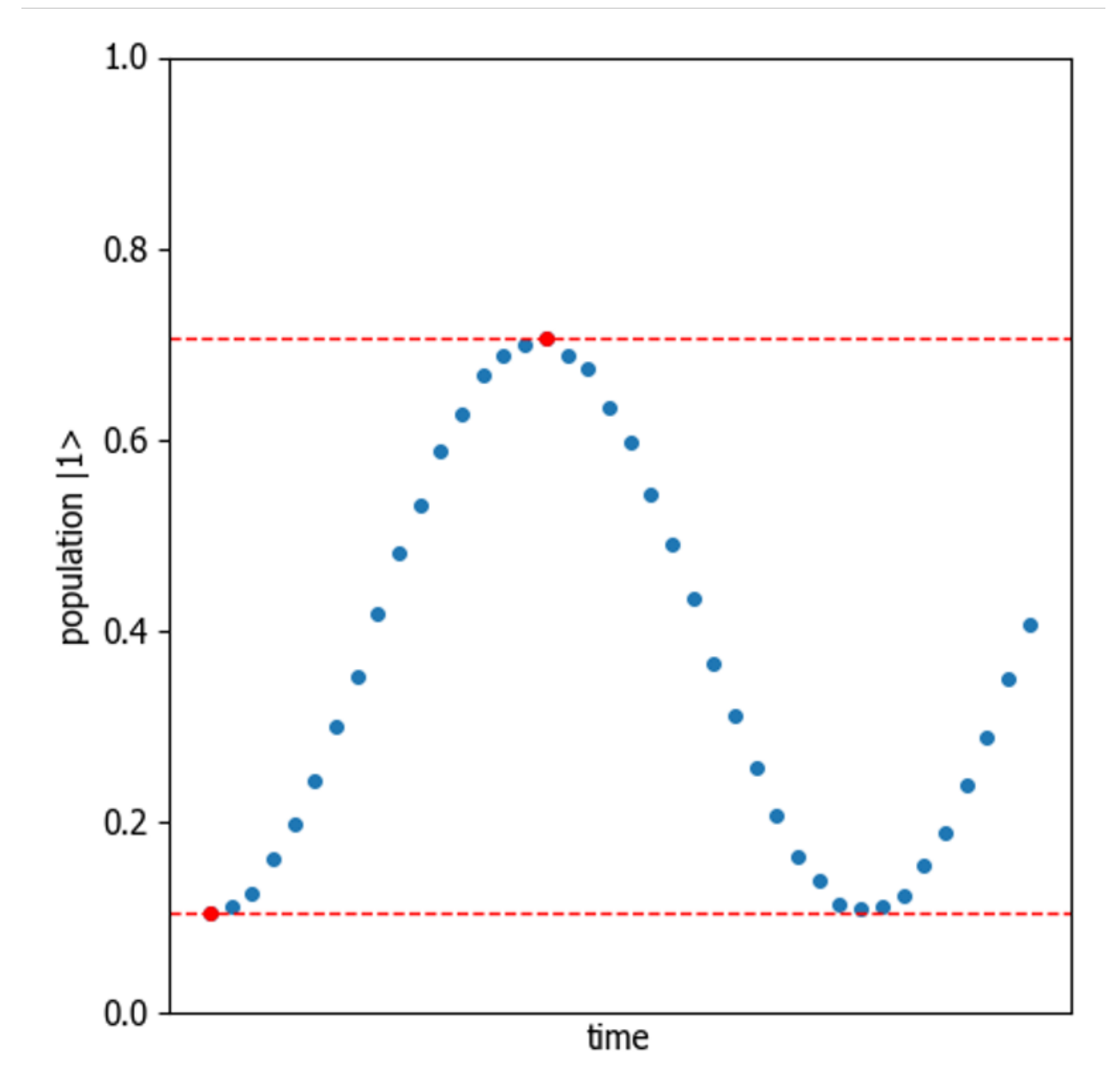
Voltages and ramp times as optimisation parameters



The Algorithm

Readout visibility

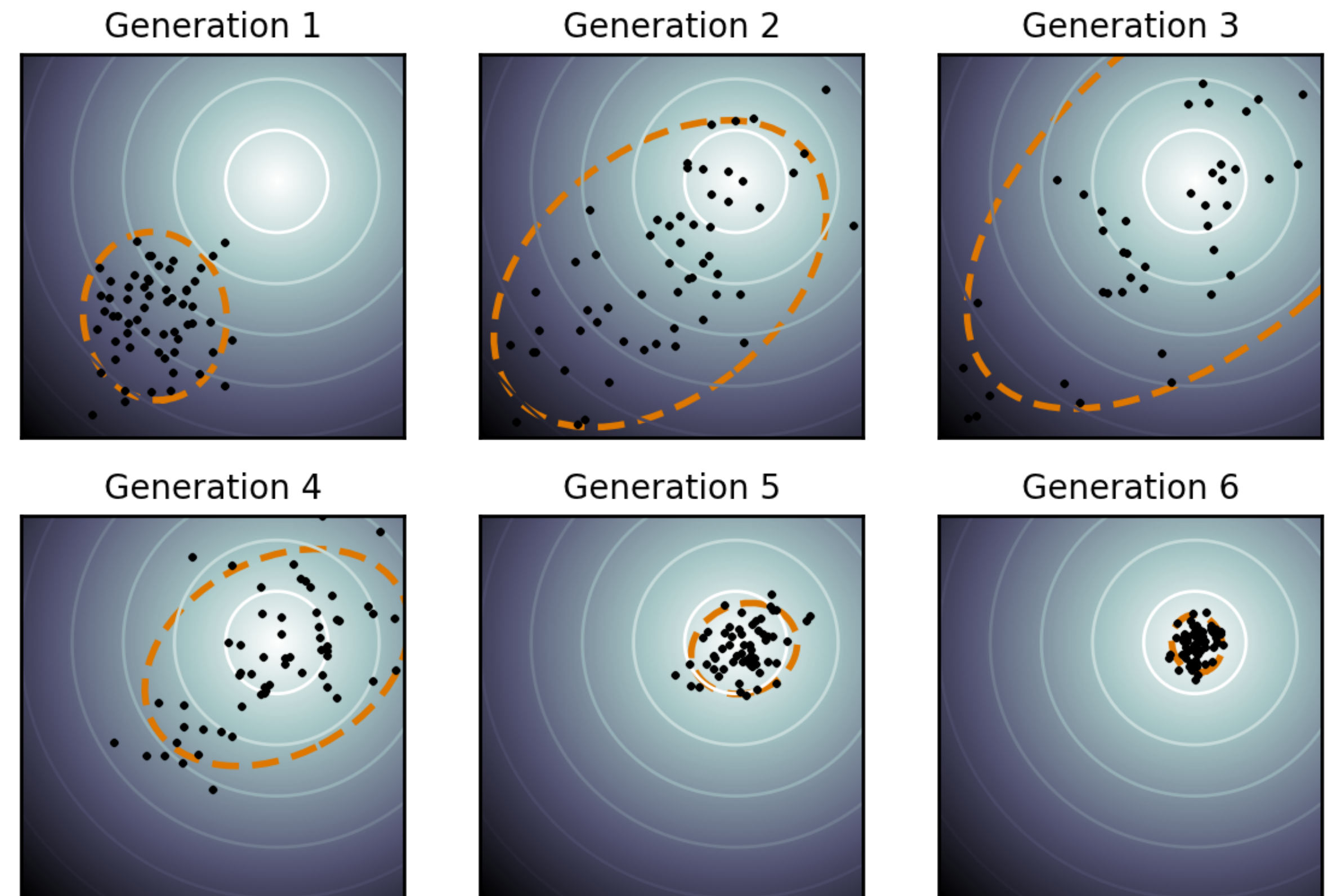
(measure $|0\rangle$ | initialize $|0\rangle$) - (measure $|0\rangle$ | initialize $|0\rangle$ + π -pulse)



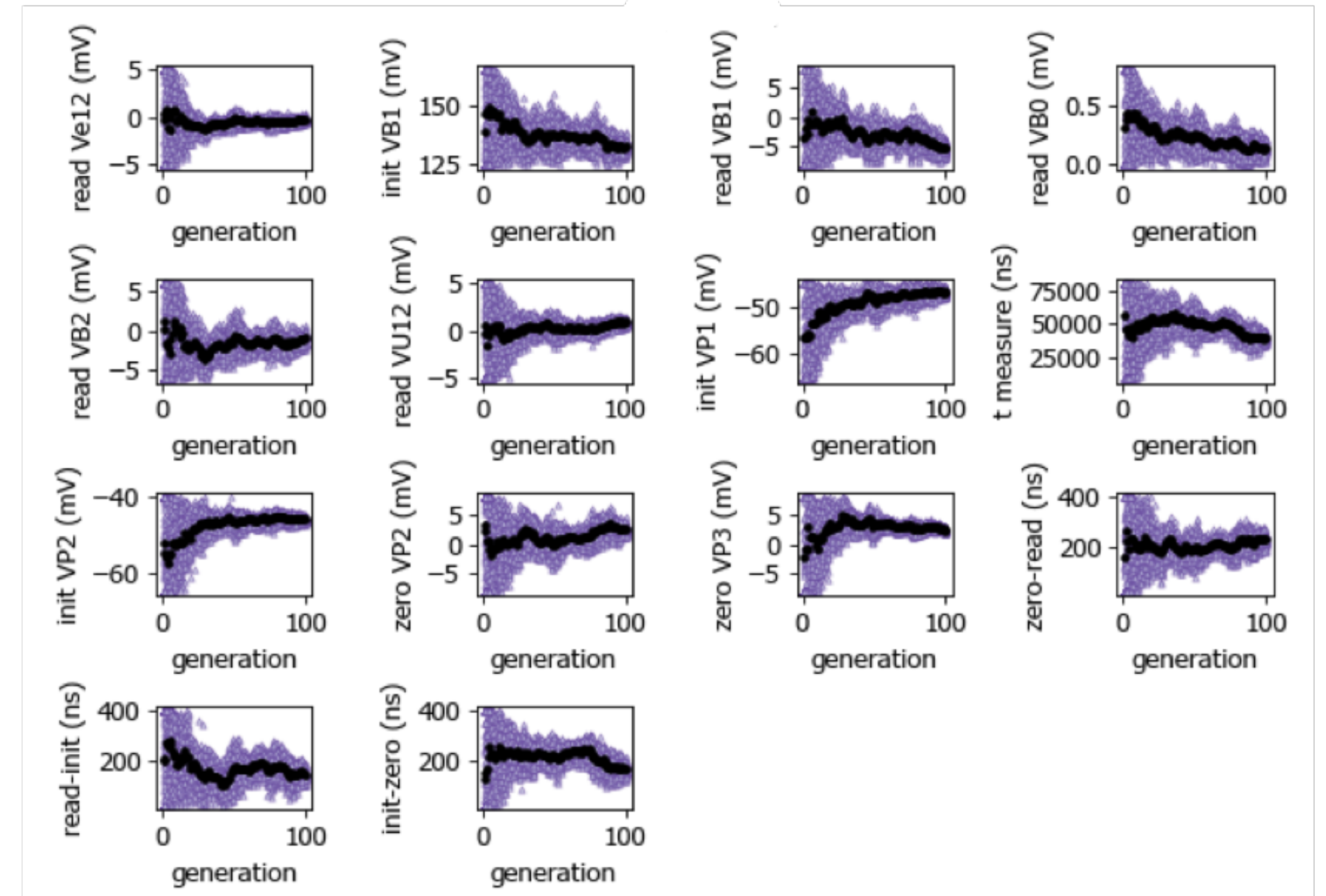
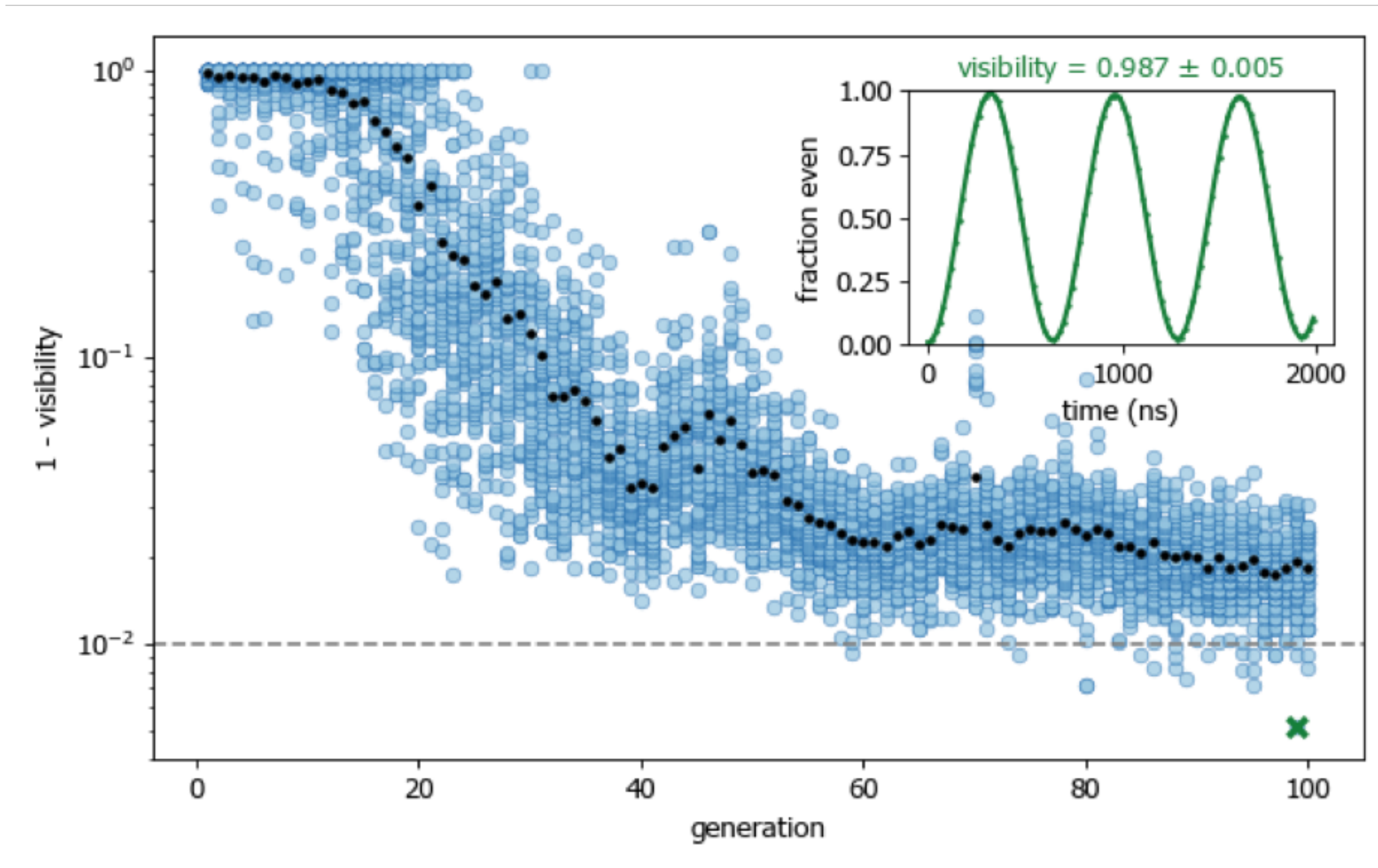
The algo: CMA-ES

Covariance matrix adaptation evolution strategy

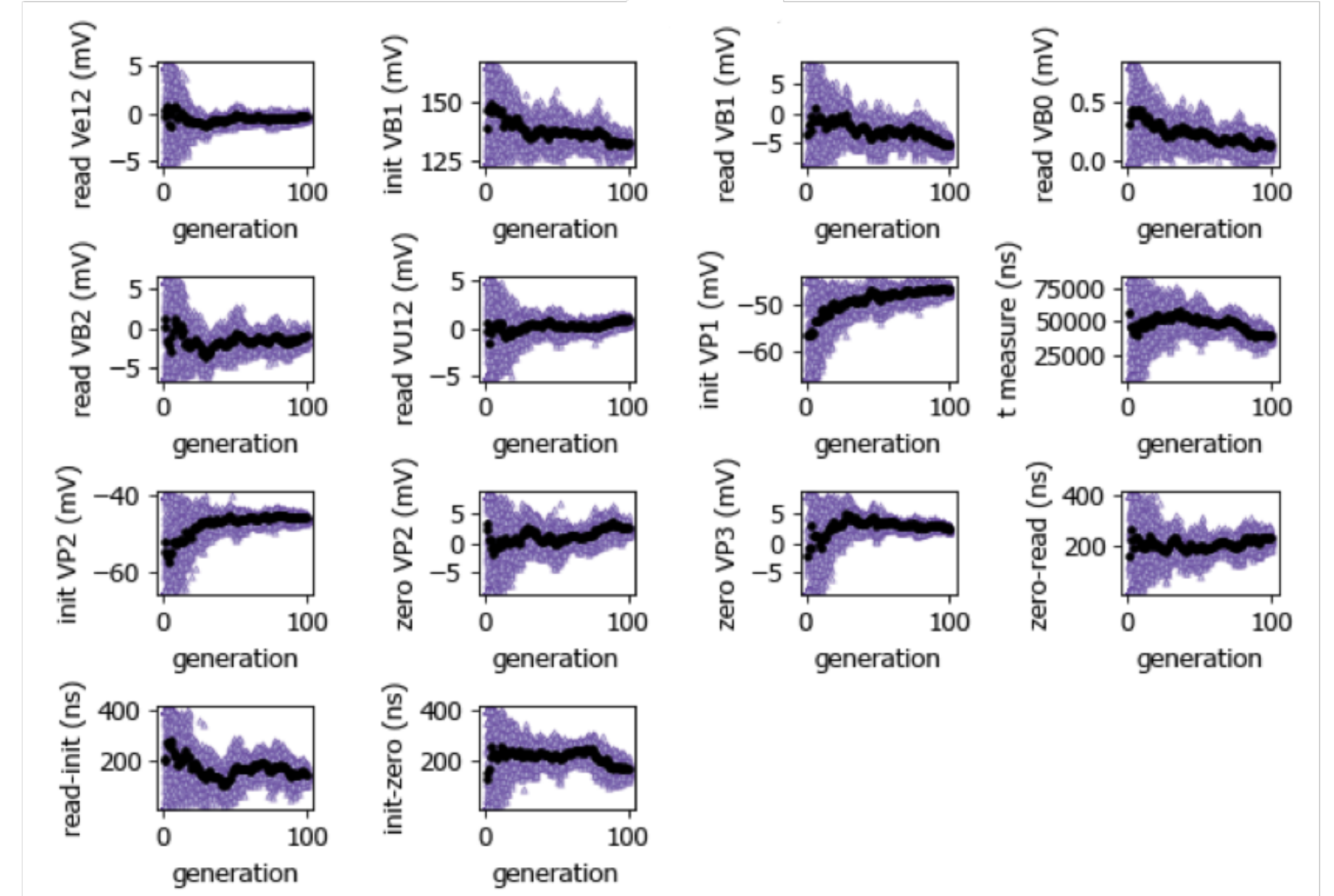
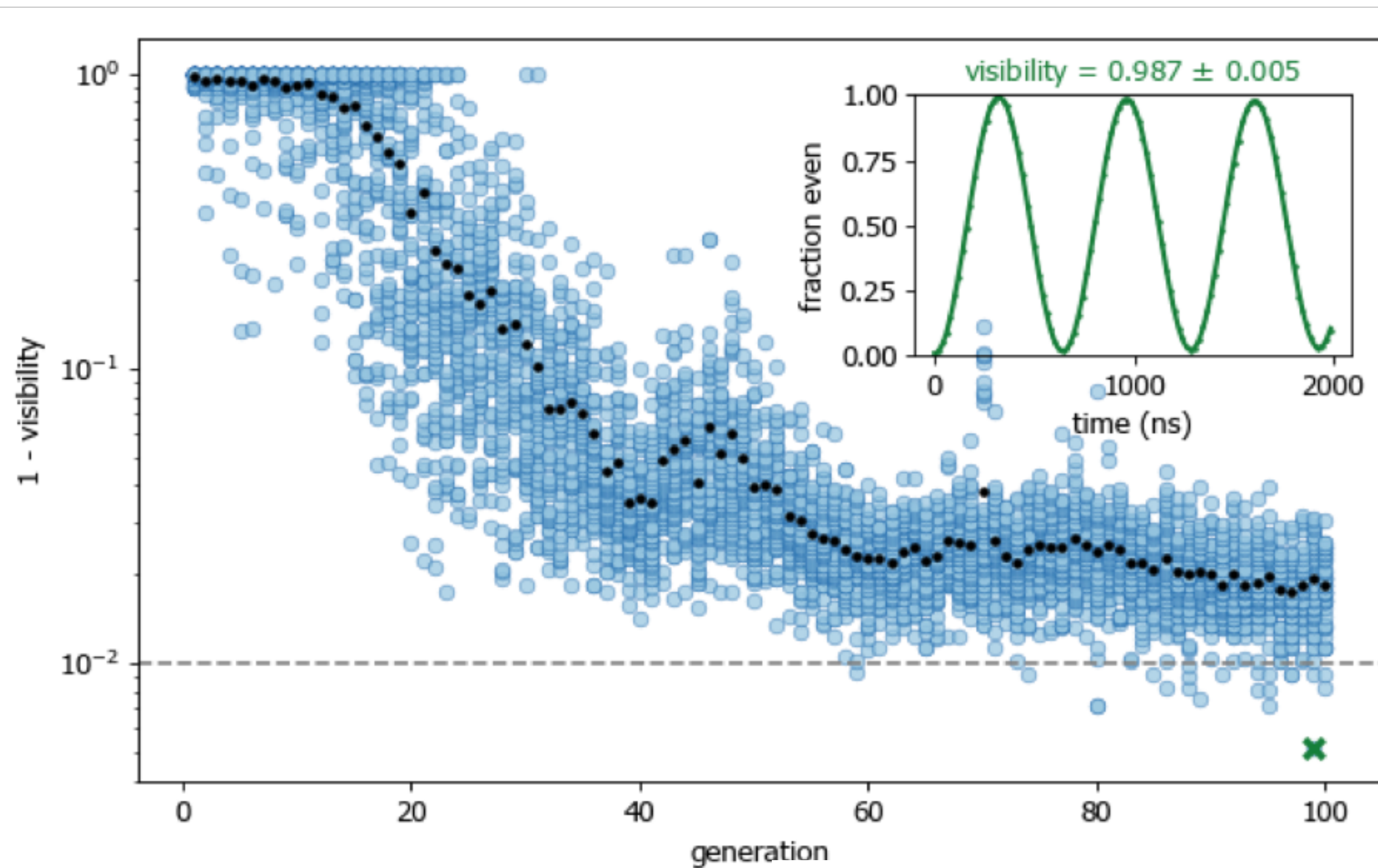
- Global optimisation
- Gradient free genetic algorithm
- Covariance matrix stores correlations



Optimising visibility

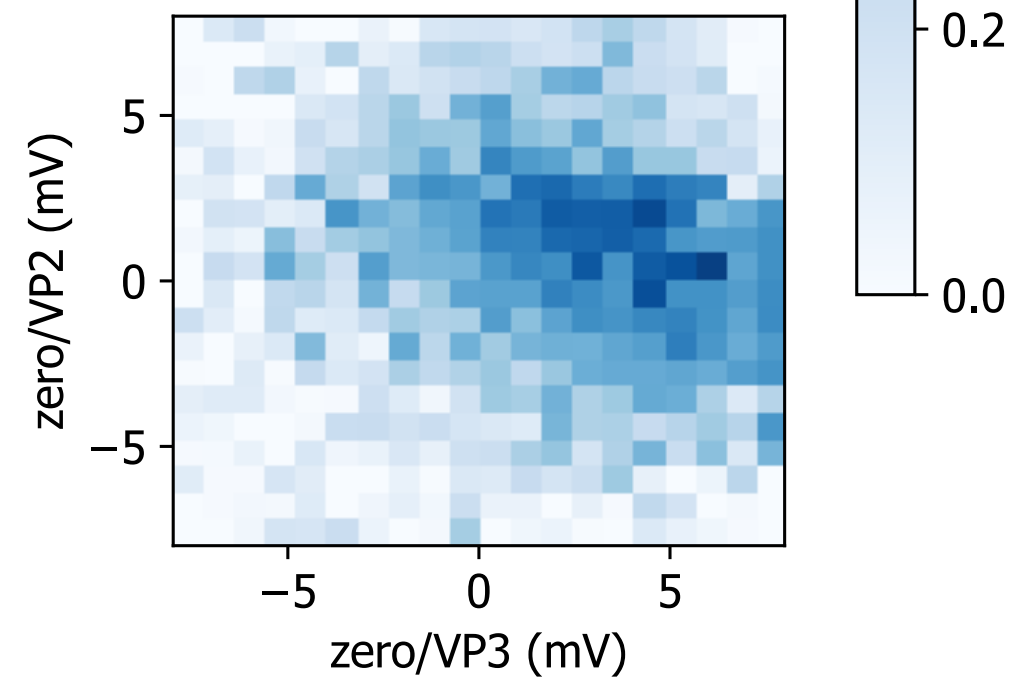
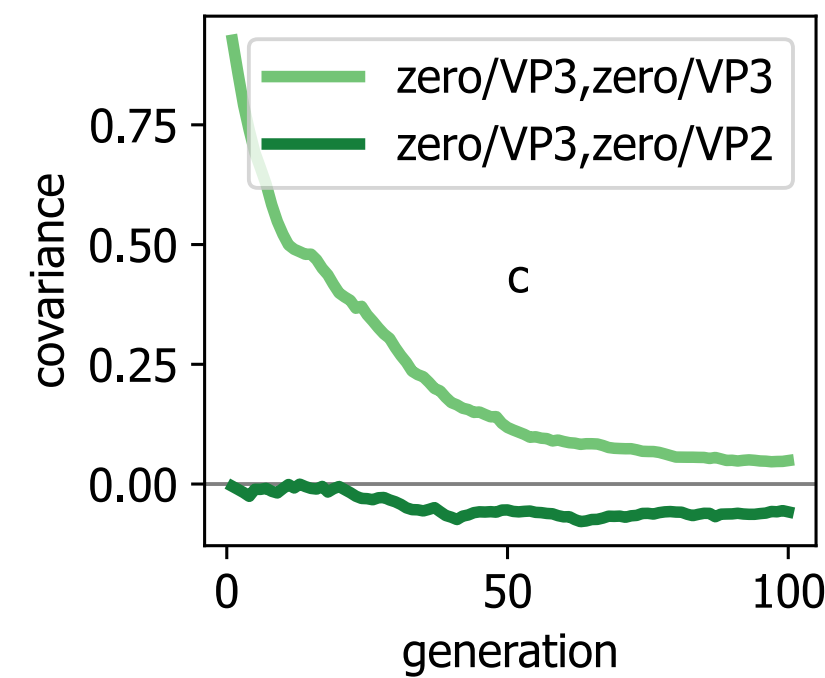
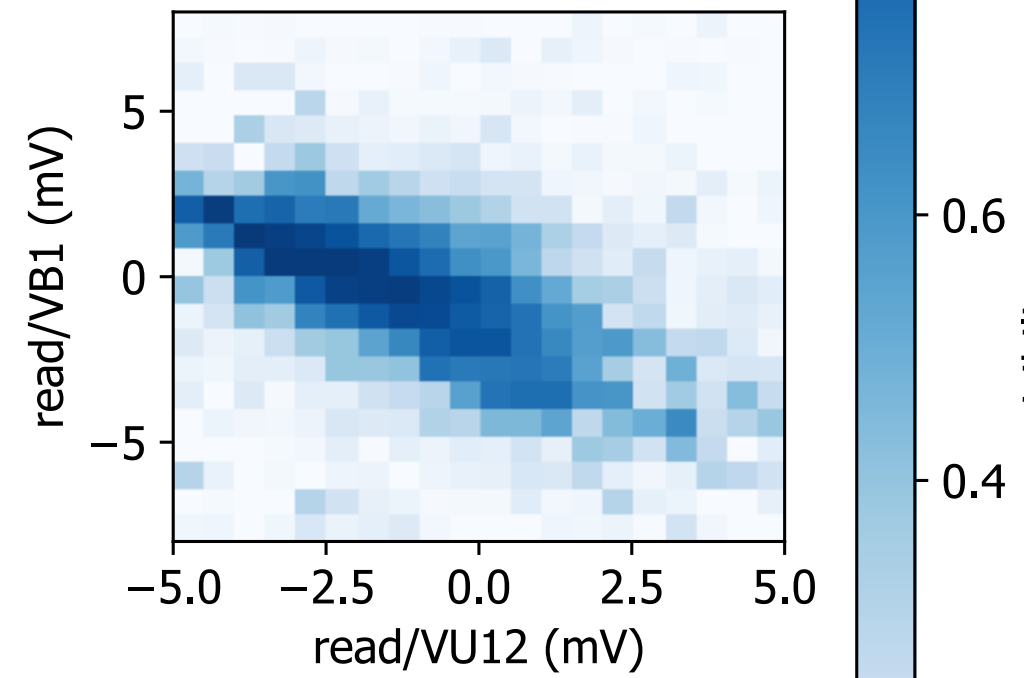
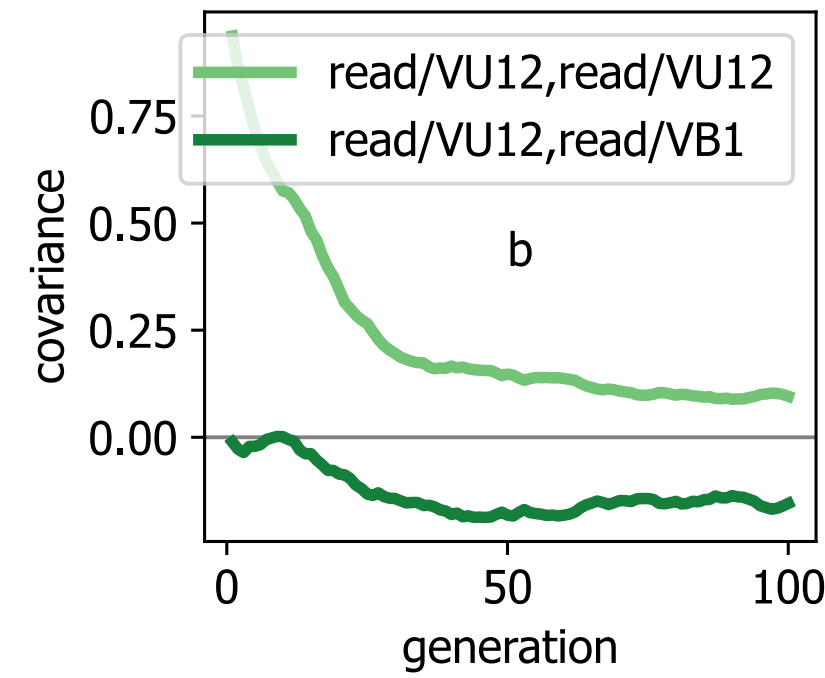
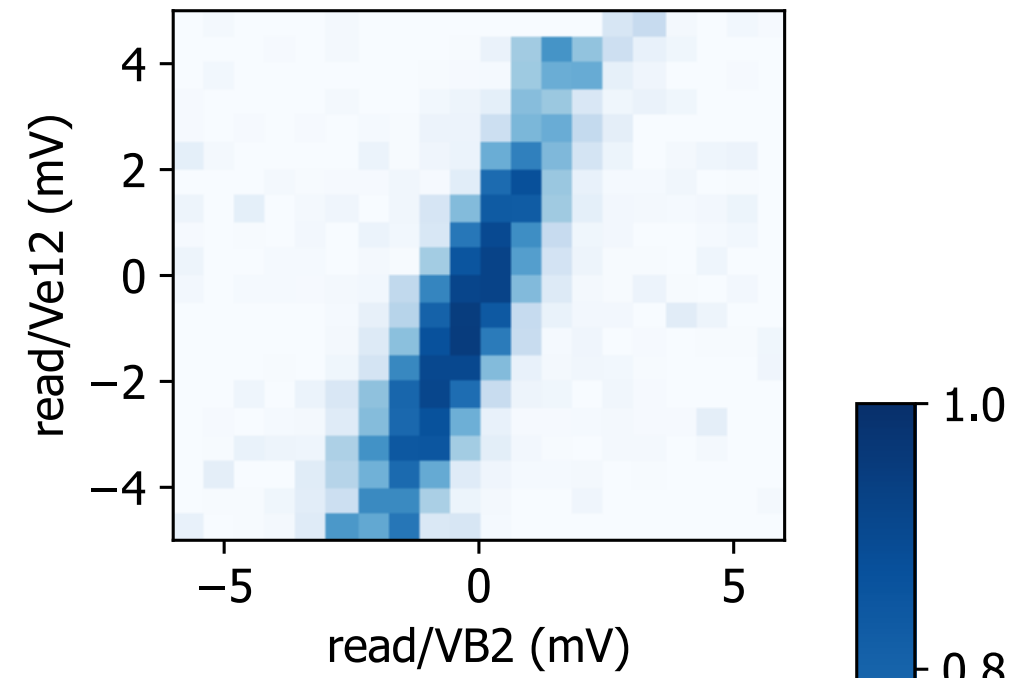
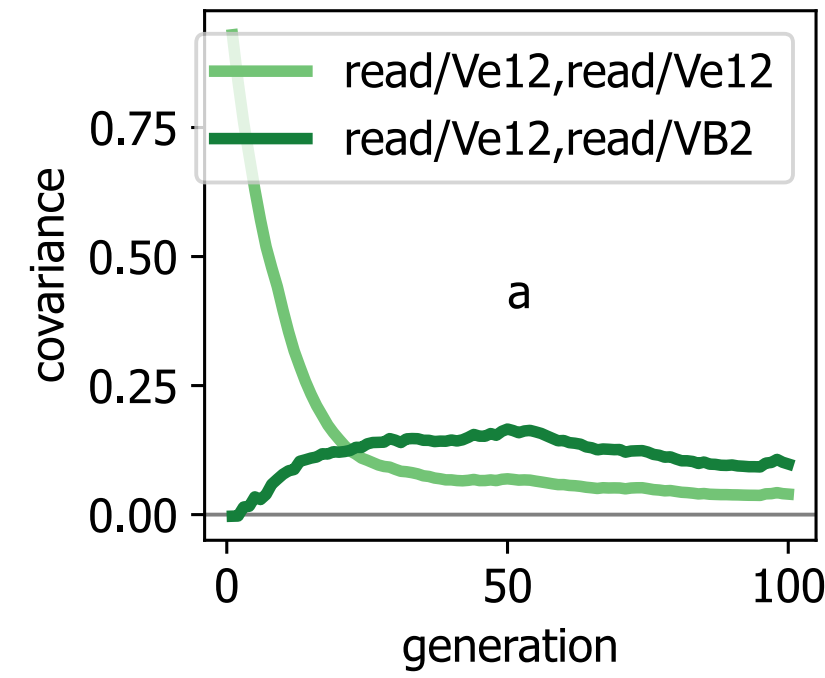
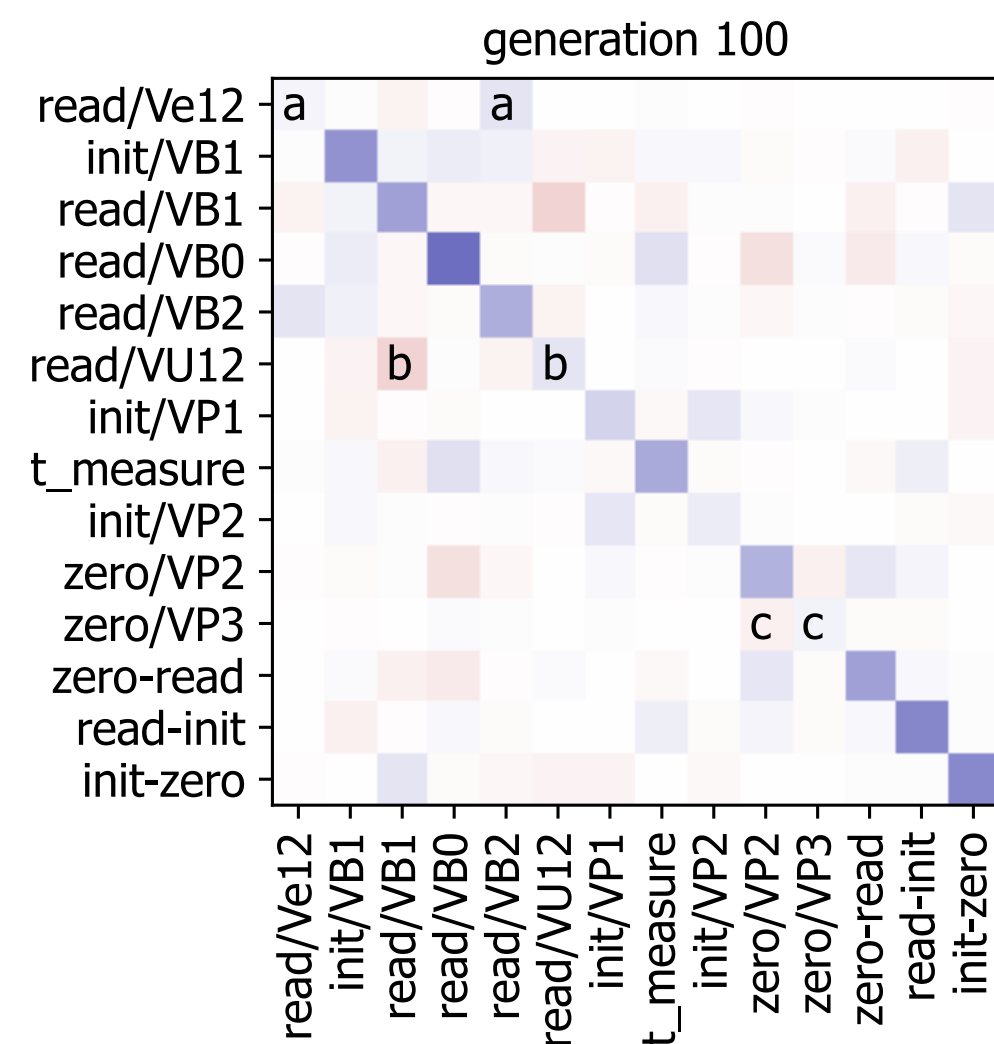
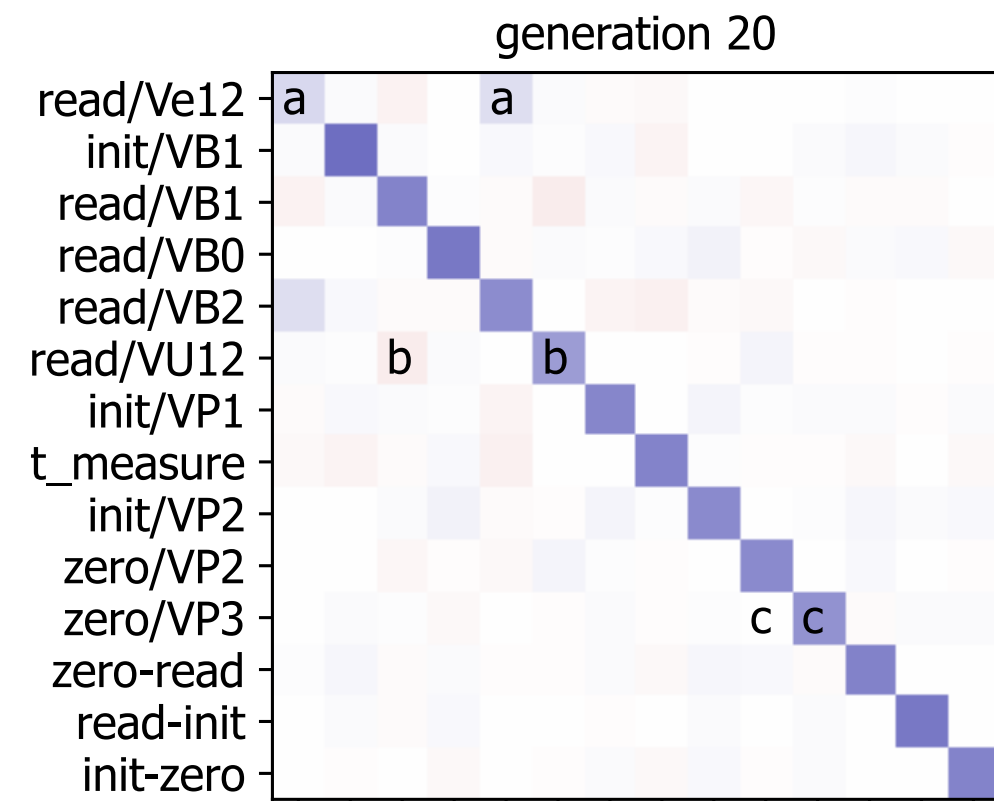


Optimising visibility

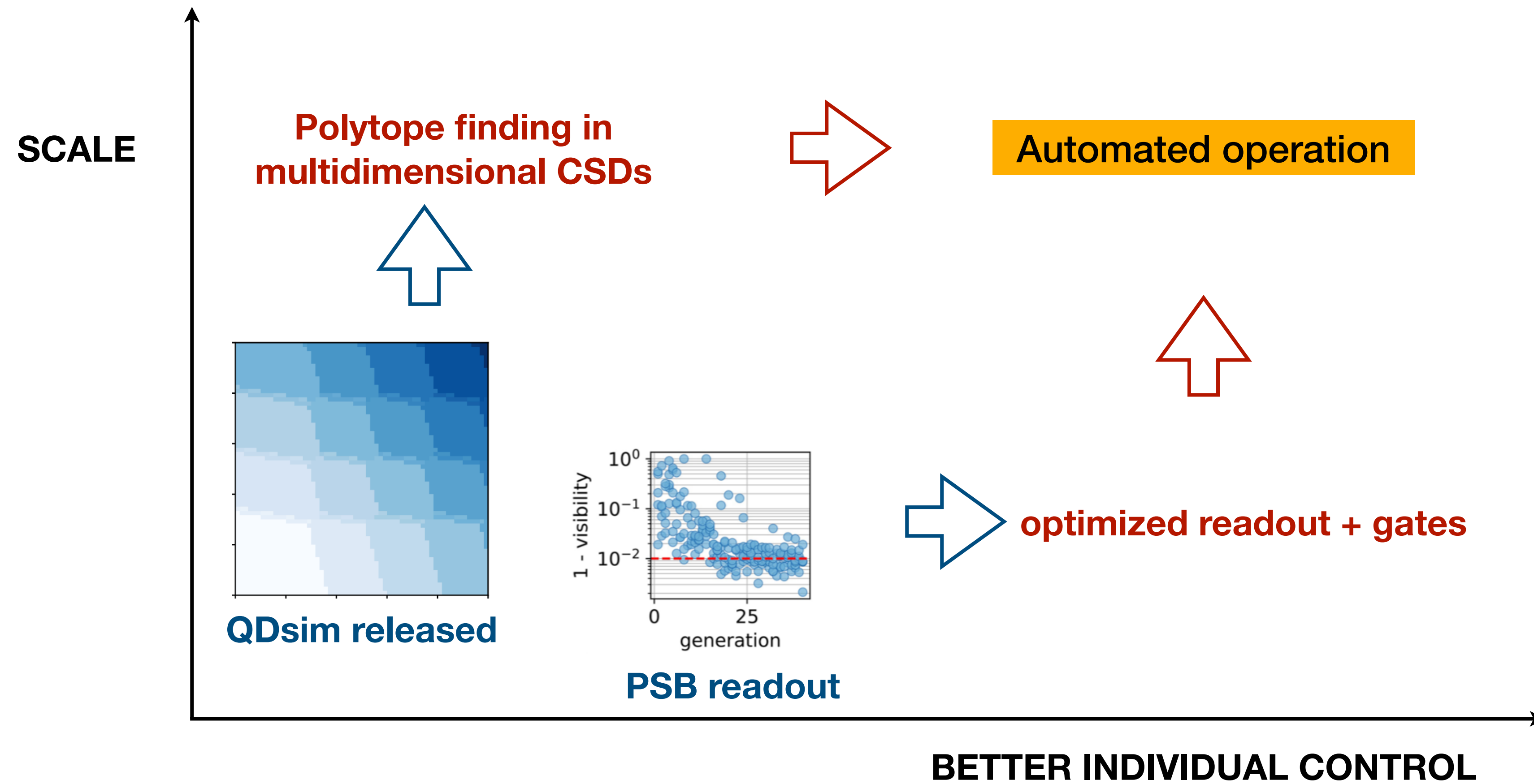


We can frequently finetune PSB readout visibility from 90% to >98% within one hour.

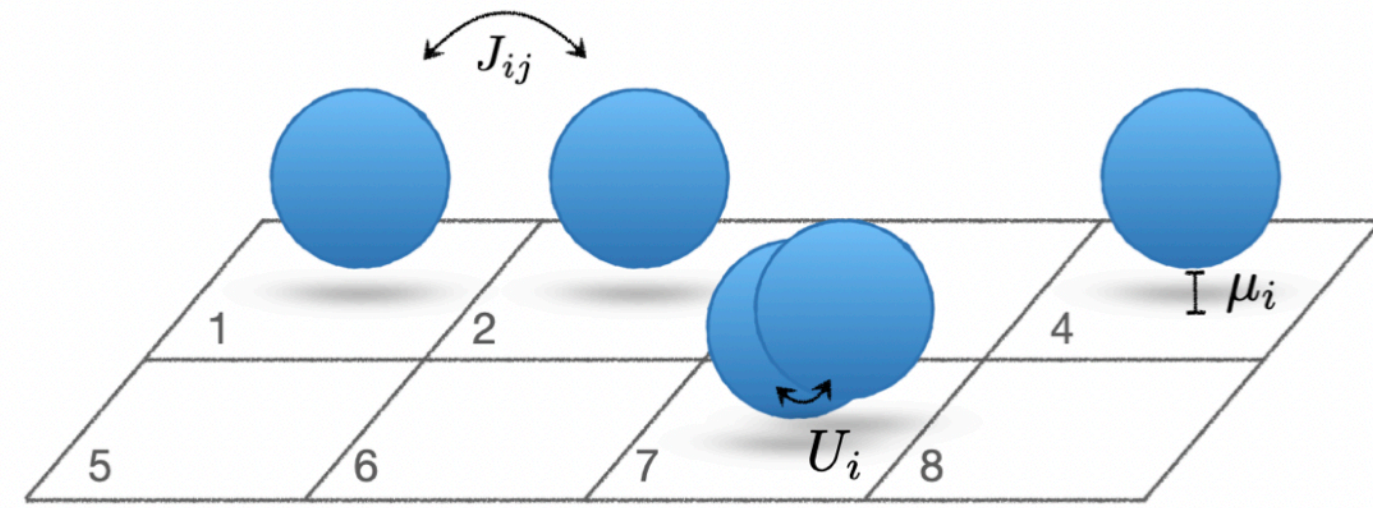
Optimising visibility: Interpretation



Going forward

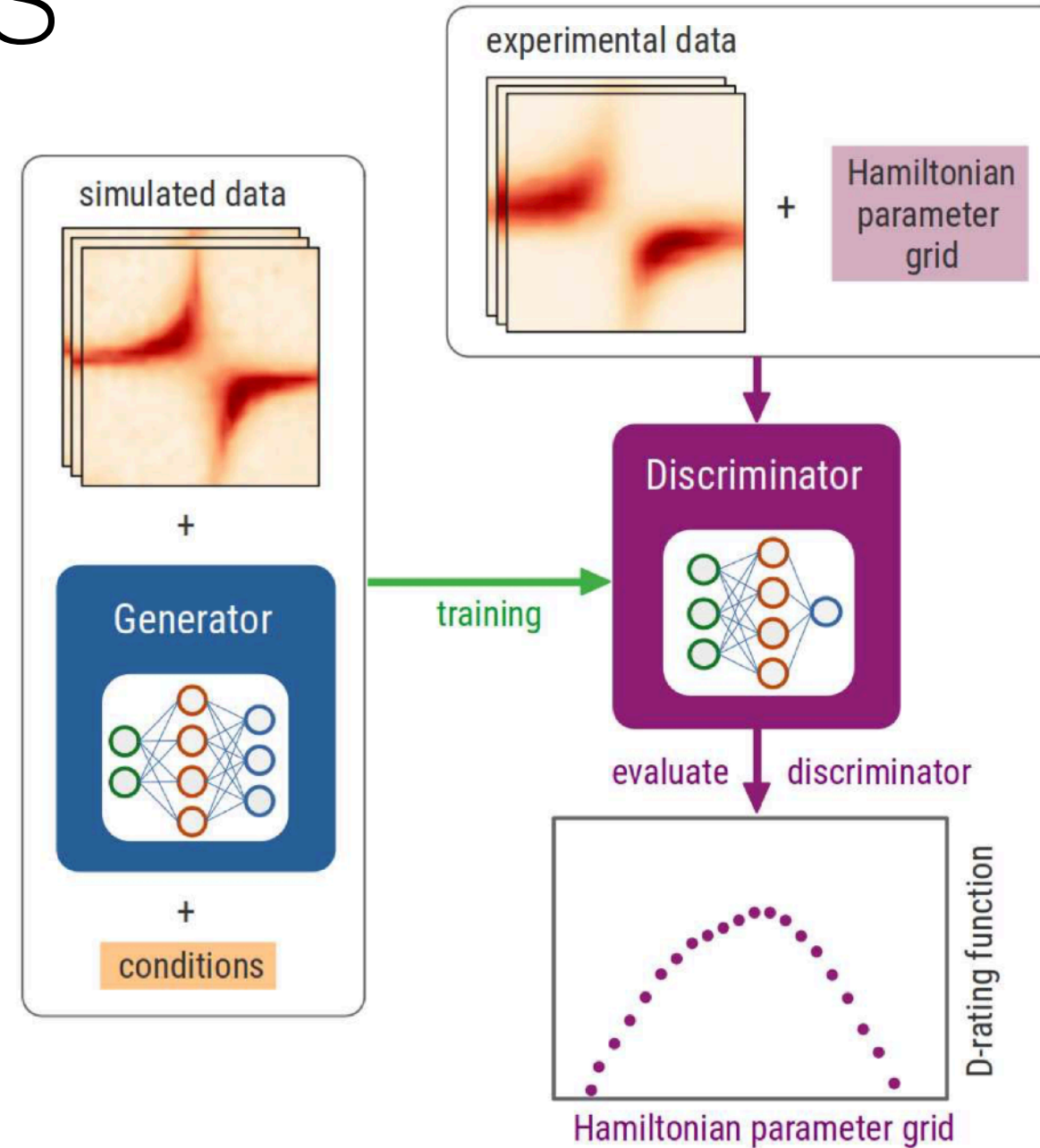


QMAI tuning applications



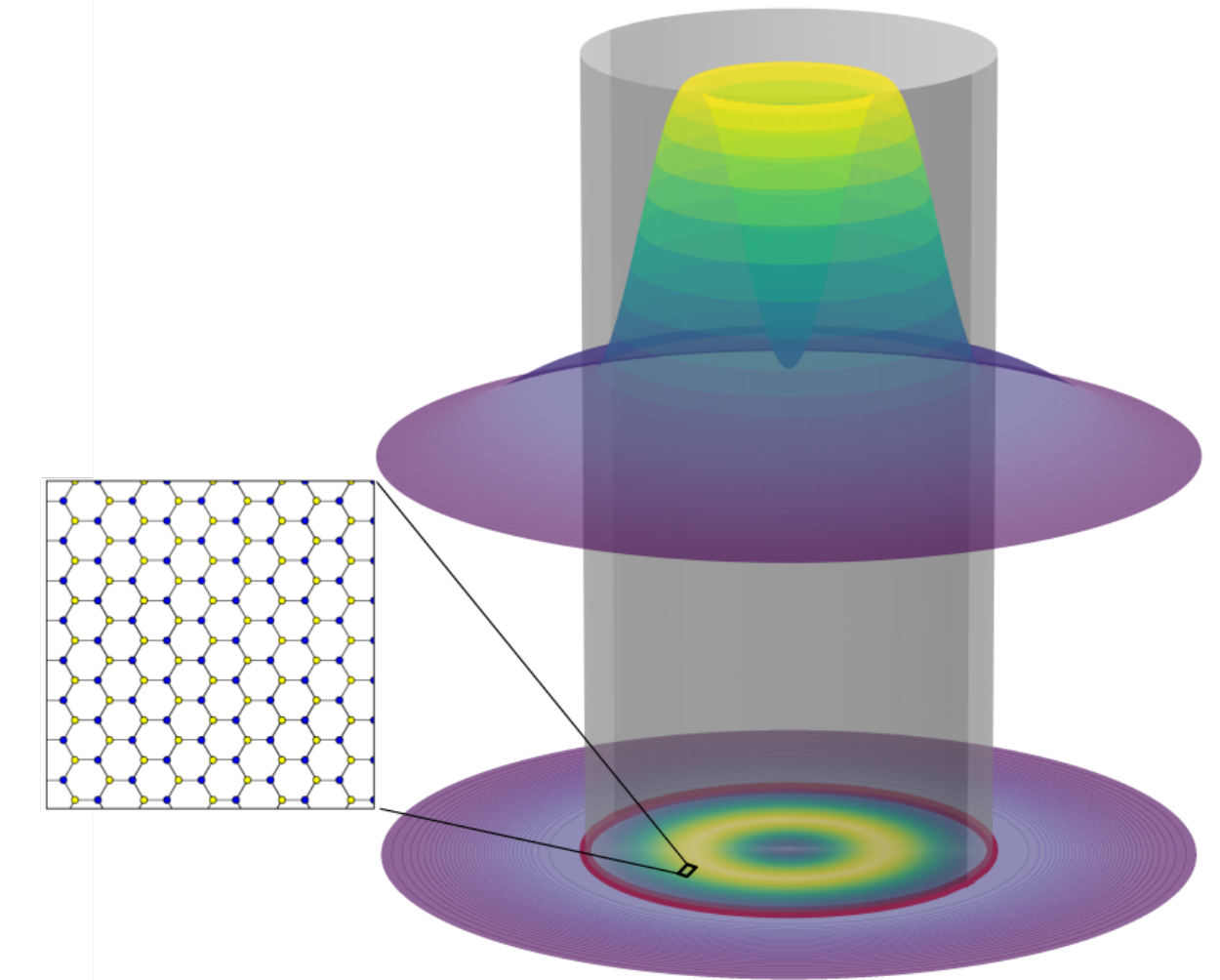
DEEP FEED-FORWARD NETWORKS

Valenti, A., Jin, G., Léonard, J., Huber, S. D., & **EG**. (2022). Scalable Hamiltonian learning for large-scale out-of-equilibrium quantum dynamics. *Physical Review A*, 105(2), 023302.



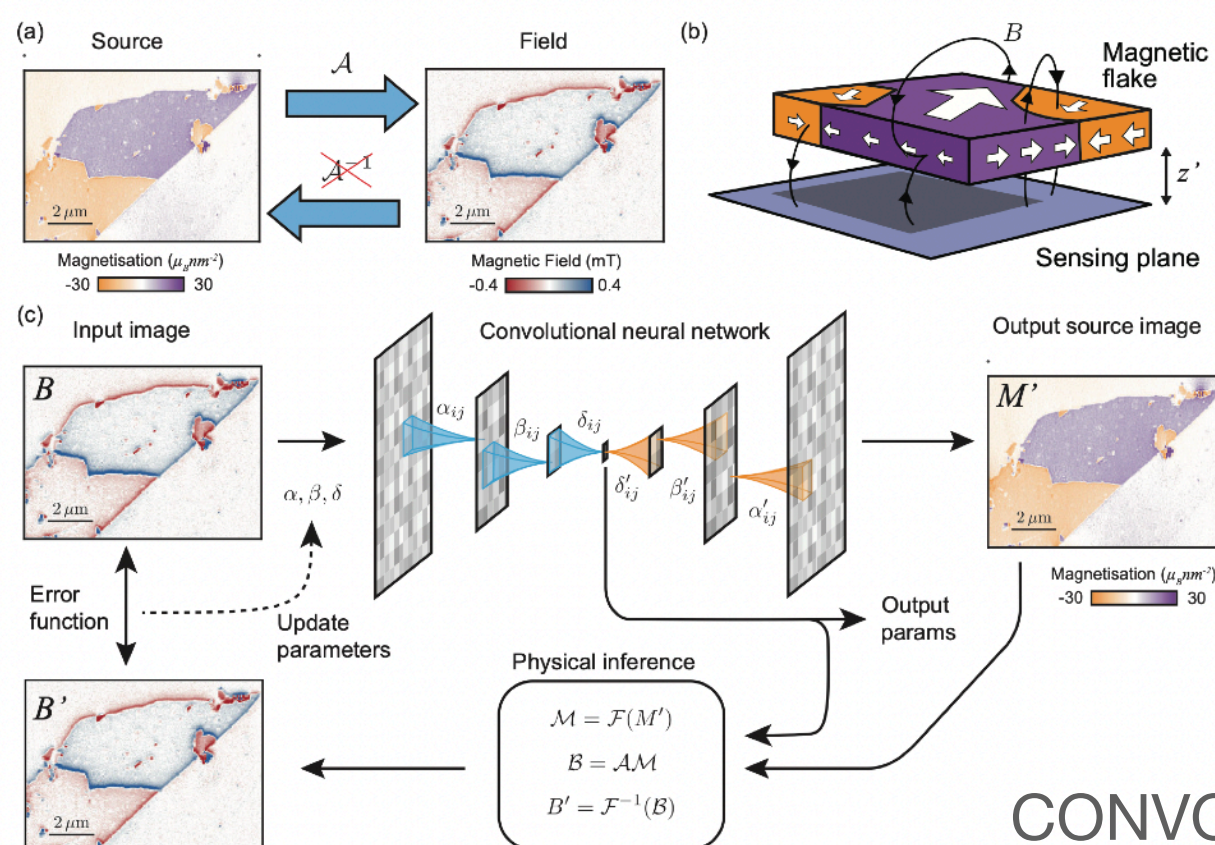
GENERATIVE MODELS

Koch, R., van Driel, D., Bordin, A., Lado, J. L., & **EG**. Adversarial Hamiltonian learning of quantum dots in a minimal Kitaev chain. *Phys. Rev. Applied* **20**, 044081 (2023)



CUSTOM OPTIMIZERS

Bucko, J., Schäfer, F., Herman, F., Garreis, R., Tong, C, Kurzmann, A, Ian T., & **EG**. (2023). Automated reconstruction of bound states in bilayer graphene quantum dots. *Physical Review Applied* 19, 024015 (2023).



CONVOLUTIONAL U-NETWORKS

Dubois, A. E. E., D. A. Broadway, A. Stark, M. A. Tschudin, A. J. Healey, S. D. Huber, J-P. Tetienne, **EG**, and P. Maletinsky. "Untrained physically informed neural network for image reconstruction of magnetic field sources." *Physical Review Applied* 18, no. 6 (2022): 064076.



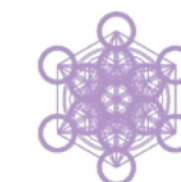
Sam Katirae-Far, Joseph Rogers, Yuta Matsumoto, Valentina Gualtieri, Charles Renshaw-Whitman, Vinicius Hernandez, Brennan Undseth, Renato Durrer, Benedikt Kratochwil, Thomas Ihn, Lieven Vandersypen.



THANK YOU!



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