



Reinforcement Learning in Bayesian Hamiltonian Tracking for Noise-Driven Coherent Rotation of a Spin Qubit



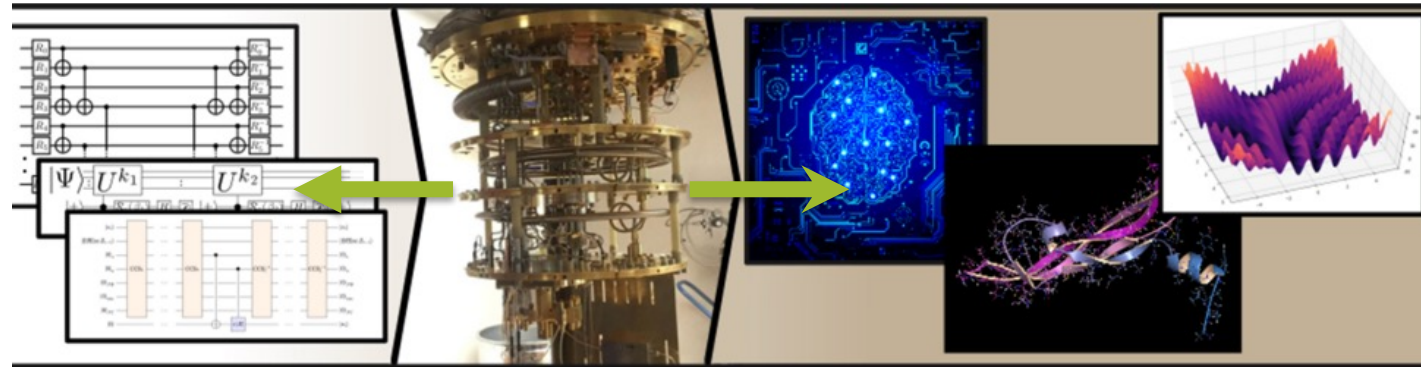
Evert van Nieuwenburg

Jan A. Krzywda | Budapest 20.06.2024

$\langle aQa^L \rangle$



Universiteit
Leiden
The Netherlands





$$S_z = -\frac{1}{2}h$$

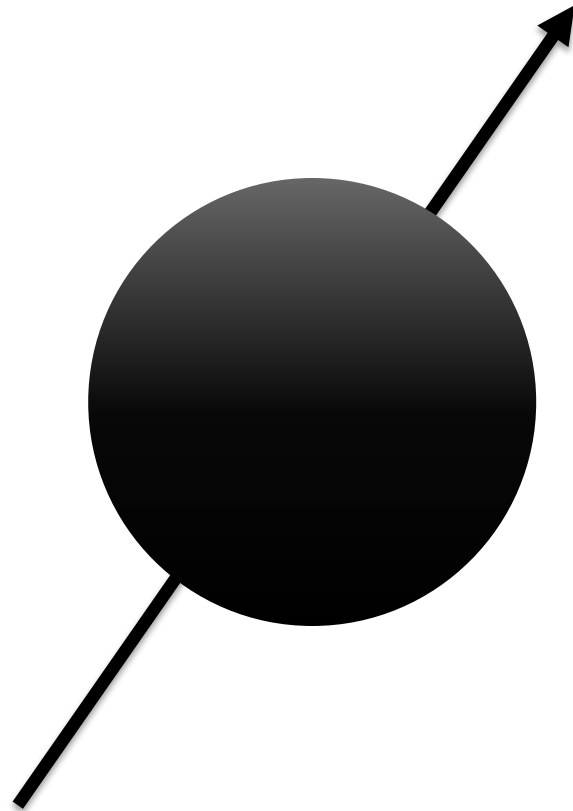
Een sikkten draait linksom of...
KUNST IN LINDEN 2001-2002



$$S_z = +\frac{1}{2}h$$

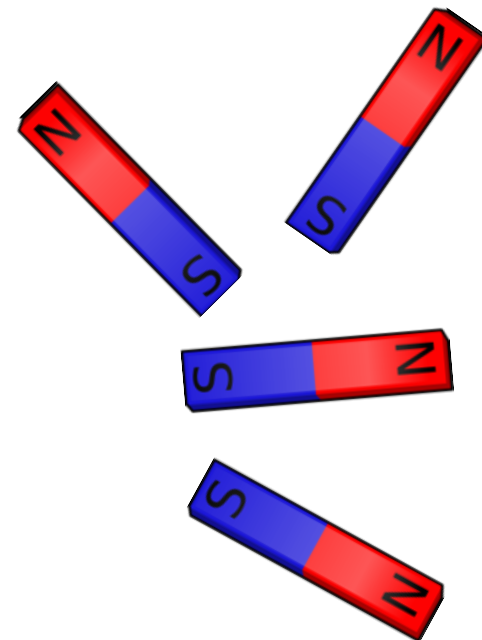
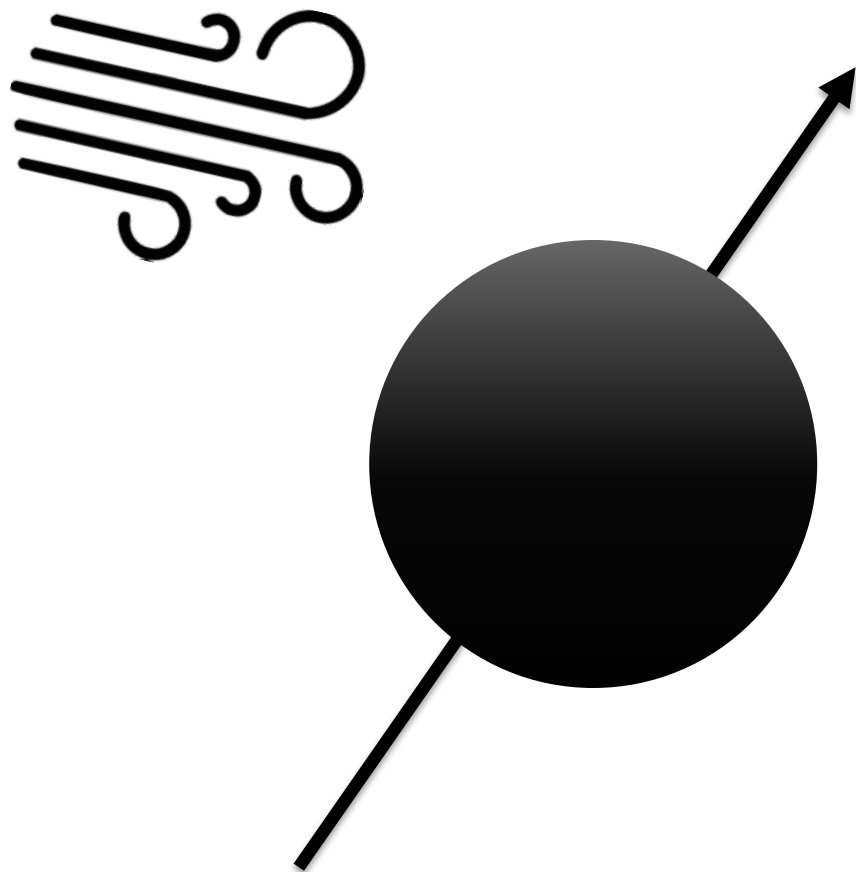
..... het draait rechtsom
SAMUEL JOHNSON (1791-1850)
i. v. v.

Idea



$$H = \omega S_z$$

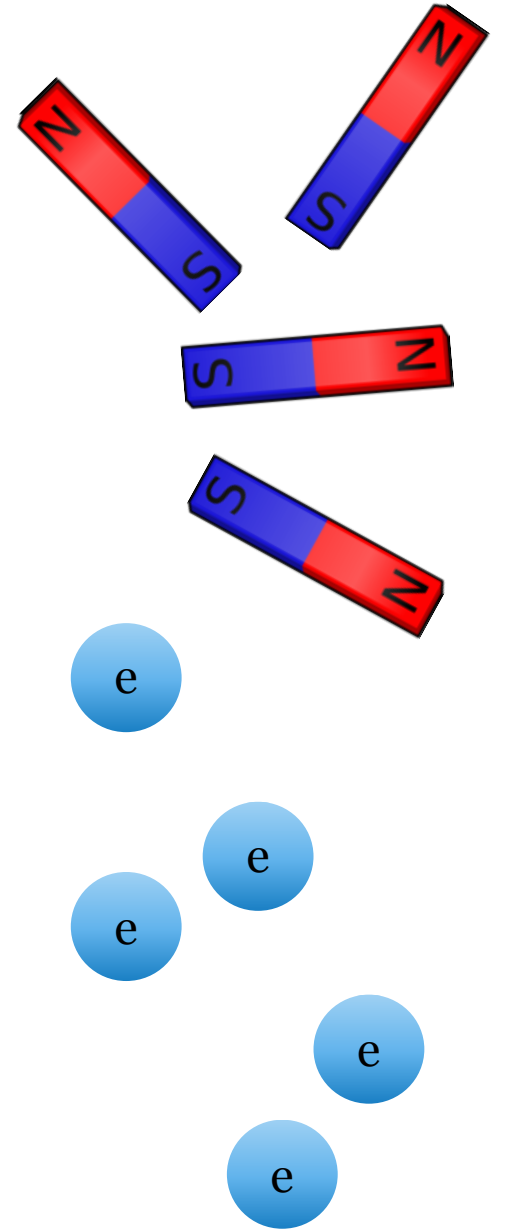
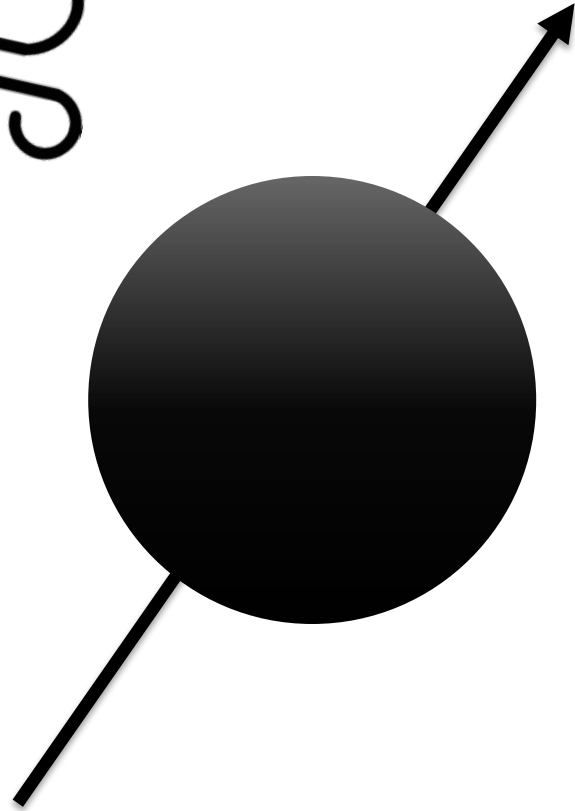
Idea



$$H = [\omega + \delta\omega(t)]S_z$$

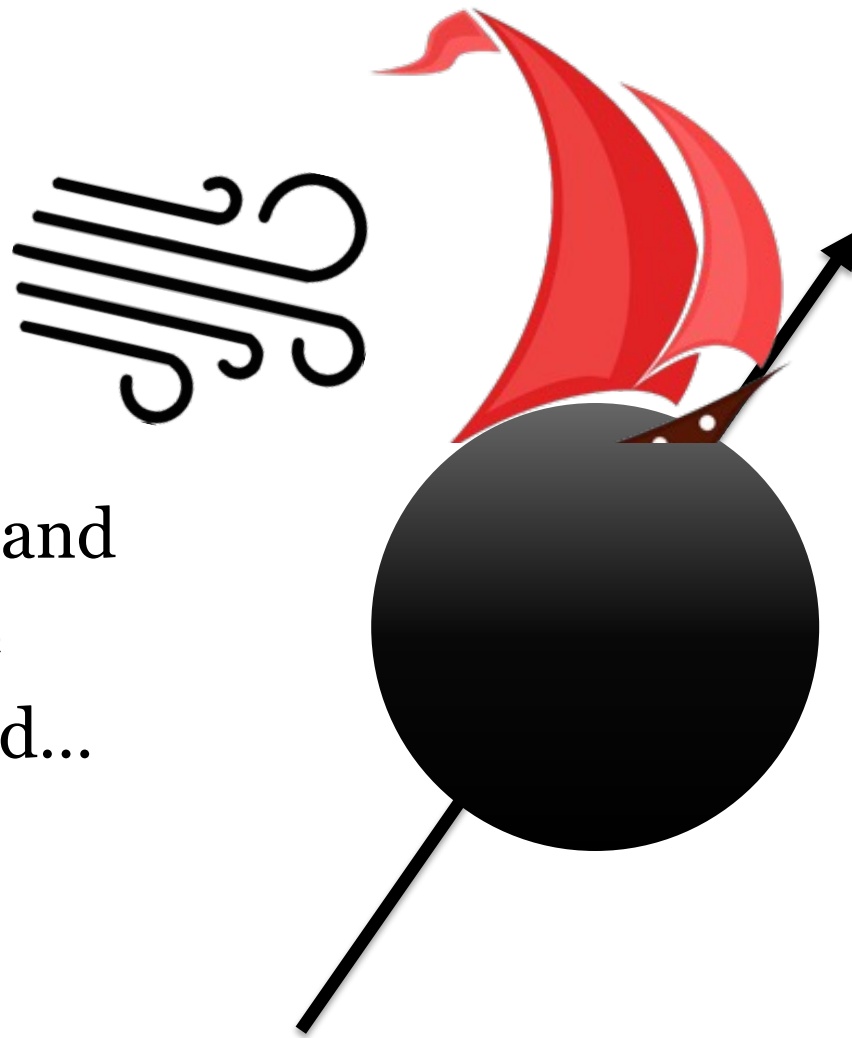
Idea

Because noise and control are interconnected...



$$H = [\omega + \delta\omega(t)]S_z$$

Idea



Because noise and control are interconnected...

...why not use the noise for coherent control?

$$H = [\omega + \delta\omega(t)]S_z$$

A blue-tinted photograph of a sailboat on the ocean. The sailboat is white with three sails and is positioned in the middle-right of the frame. The ocean is dark blue with white-capped waves. The sky is a lighter shade of blue. The overall mood is serene and calm.

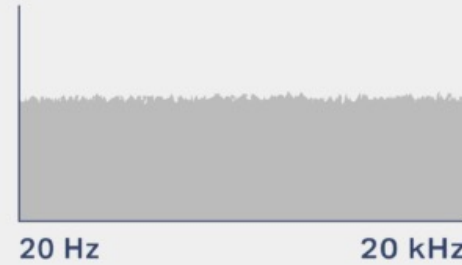
**| Theory of stochastic processes
and why do we care (3 min)**

Colors of Noise

Markovian
(Quantum optimal control,
Master equation, QEC, QEM)

White Noise

White noise equally contains all frequencies across the spectrum of audible sound.



Fans



Television Static



Vacuum Humming



$$\rho(t + s) = e^{Ls} \rho(t)$$

Colors of Noise

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Television Static



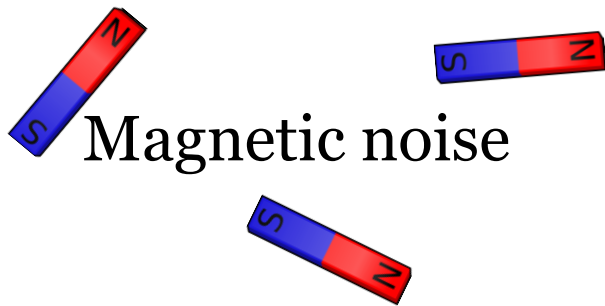
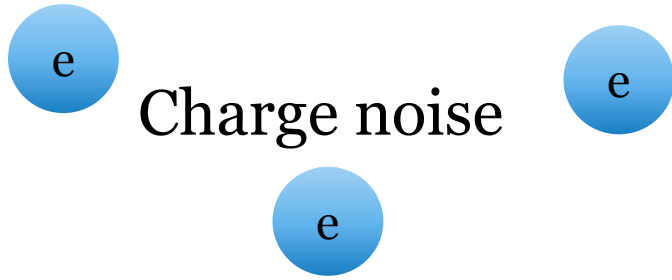
Vacuum Humming

At the level of specific open challenges, the **question how reachability differs for non-Markovian compared to Markovian dynamics remains largely unexplored**

Koch, Christiane P., et al. "Quantum optimal control in quantum technologies. Strategic report on current status, visions and goals for research in Europe." *EPJ Quantum Technology* 9.1 (2022): 19.

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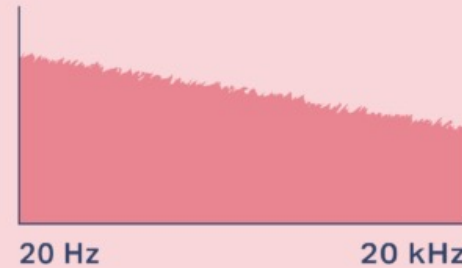
Television Static



Vacuum Humming

Pink Noise

Pink noise frequencies decrease in power with each higher octave to create a lower pitch.



Light Rain



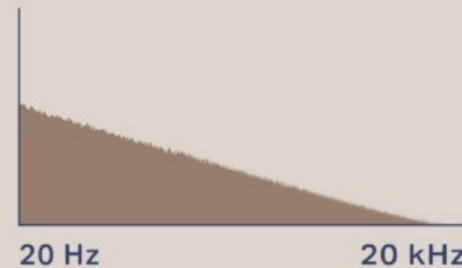
River



Wind

Brown Noise

Brown noise is deep pitched, and the power behind frequencies decreases twice as much as pink noise.



Rumbling Thunder



Waterfall

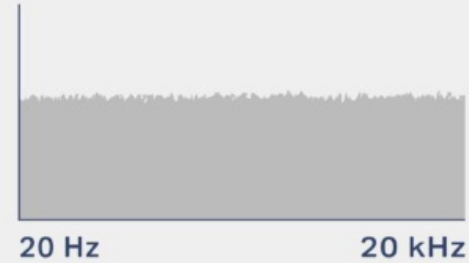


Heavy Rainfall

Colors of Noise

White Noise

White noise equally contains all frequencies across the spectrum of audible sound.



Fans



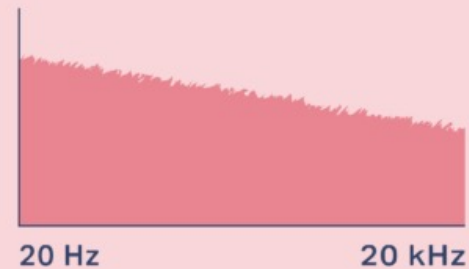
Television Static



Vacuum Humming

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Light Rain



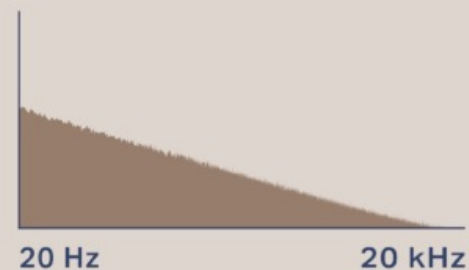
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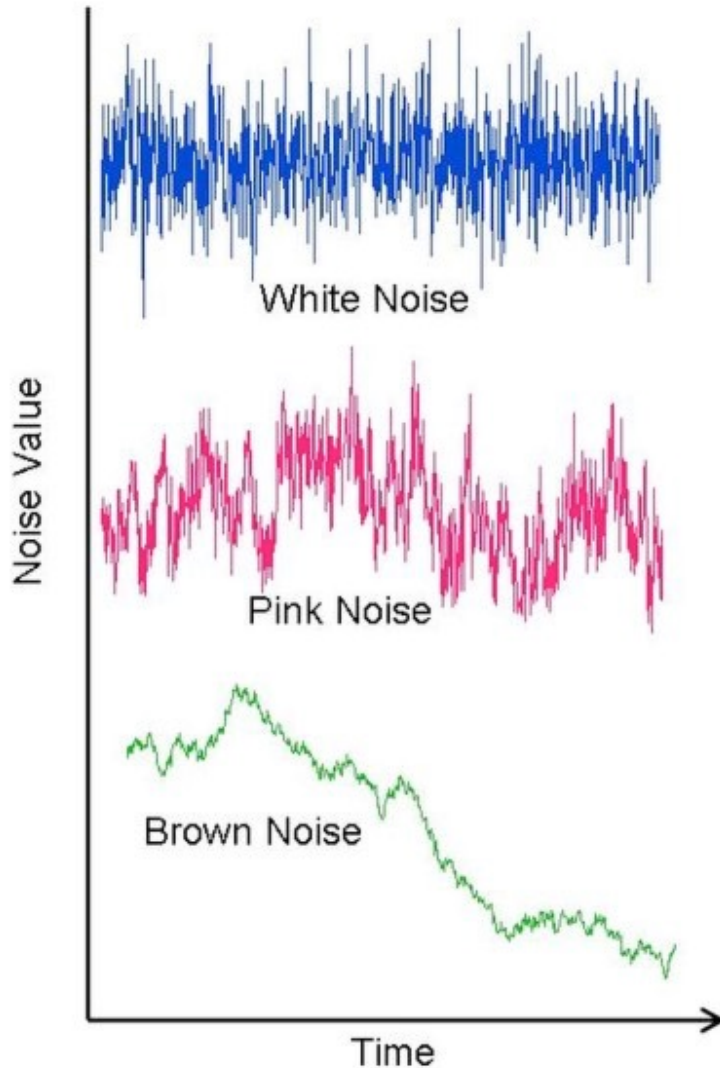
Rumbling Thunder



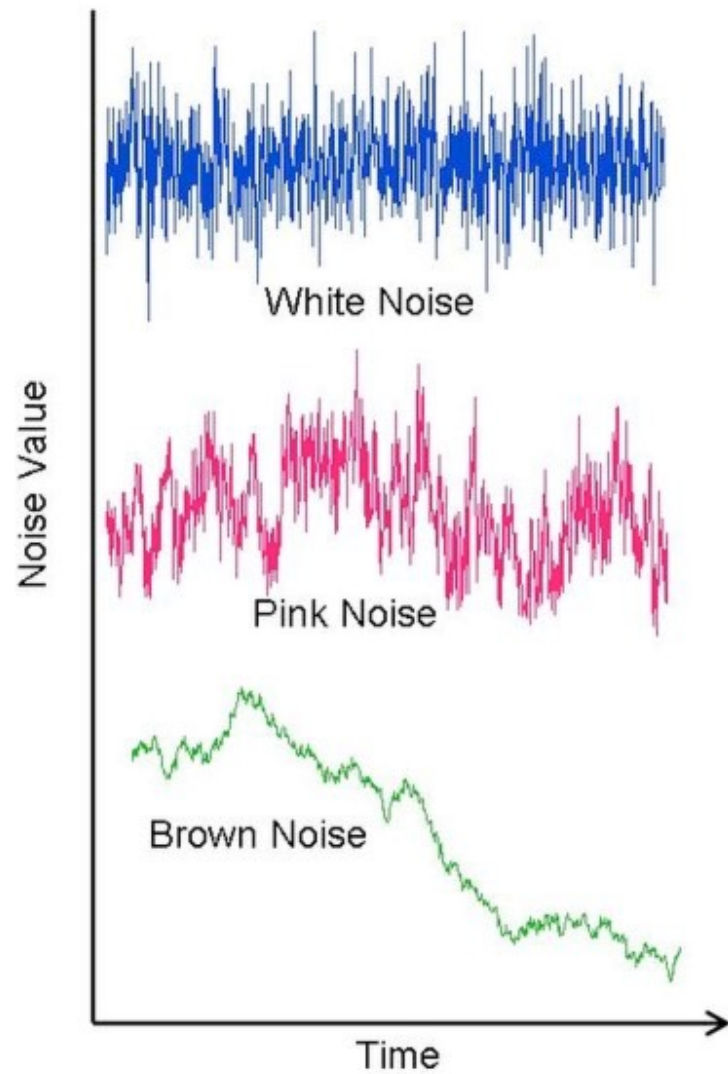
Waterfall



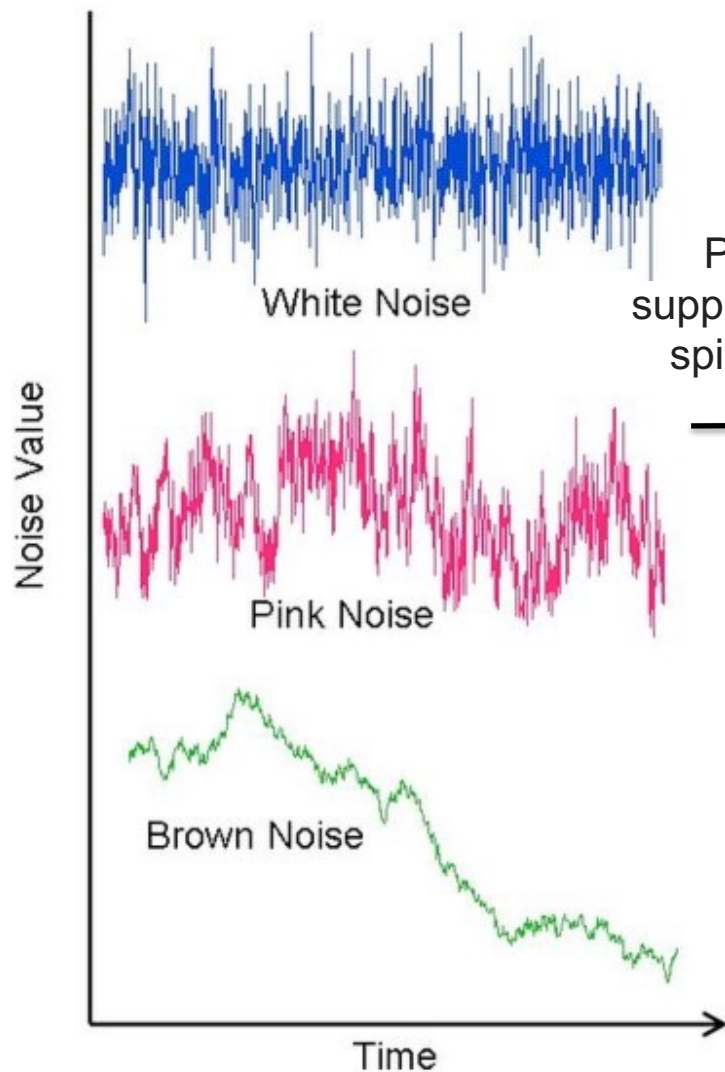
Heavy Rainfall



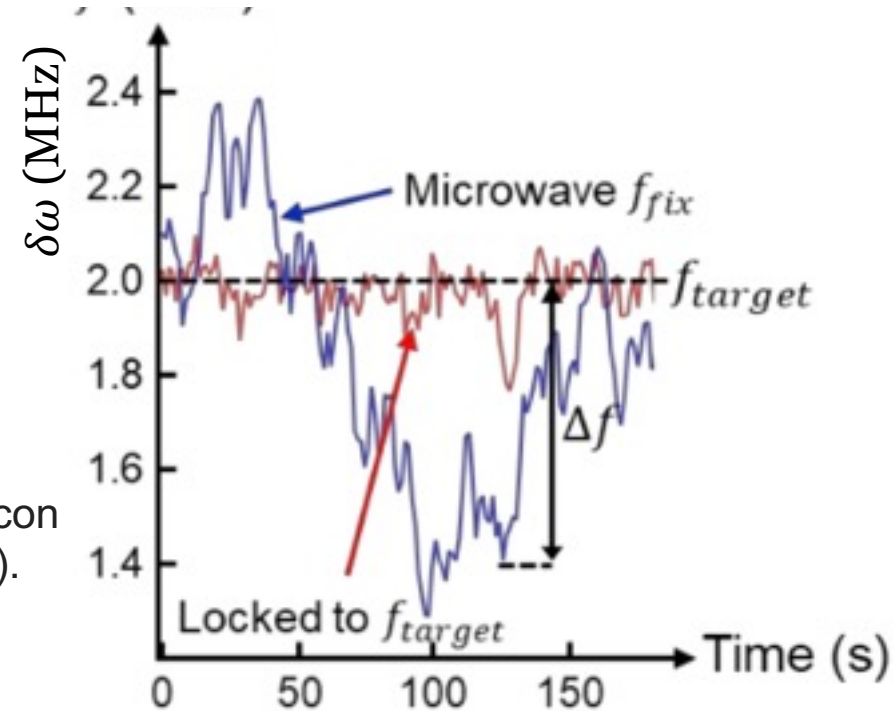
We rely on the trajectory



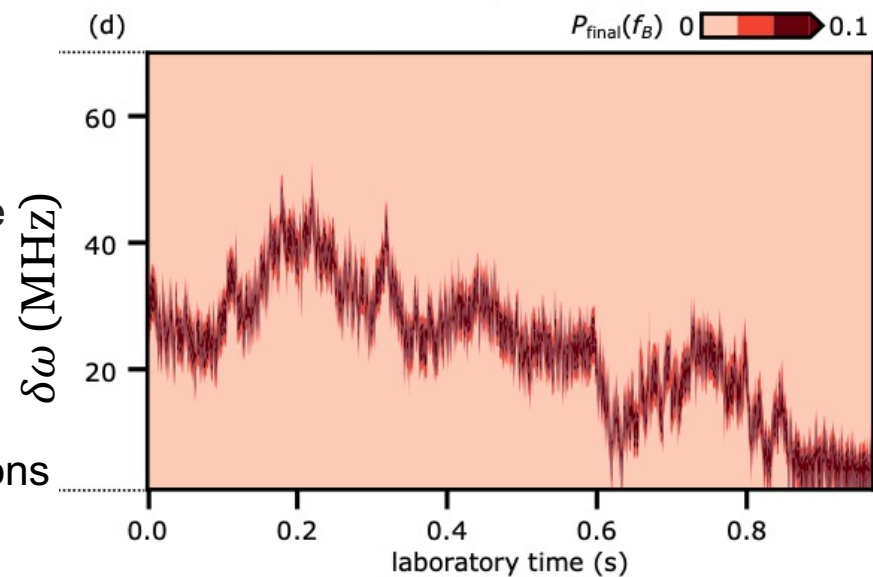
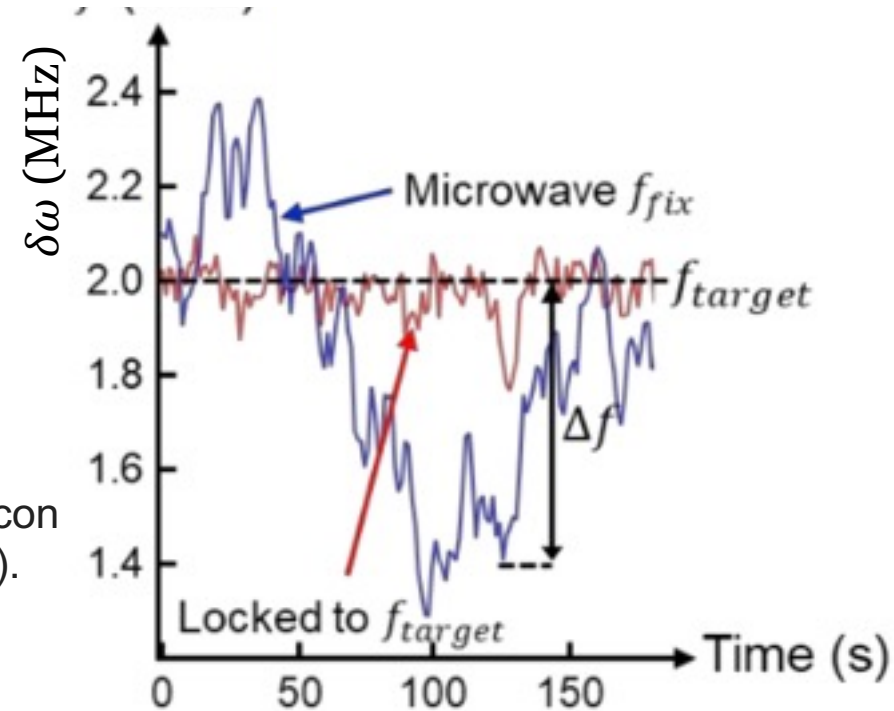
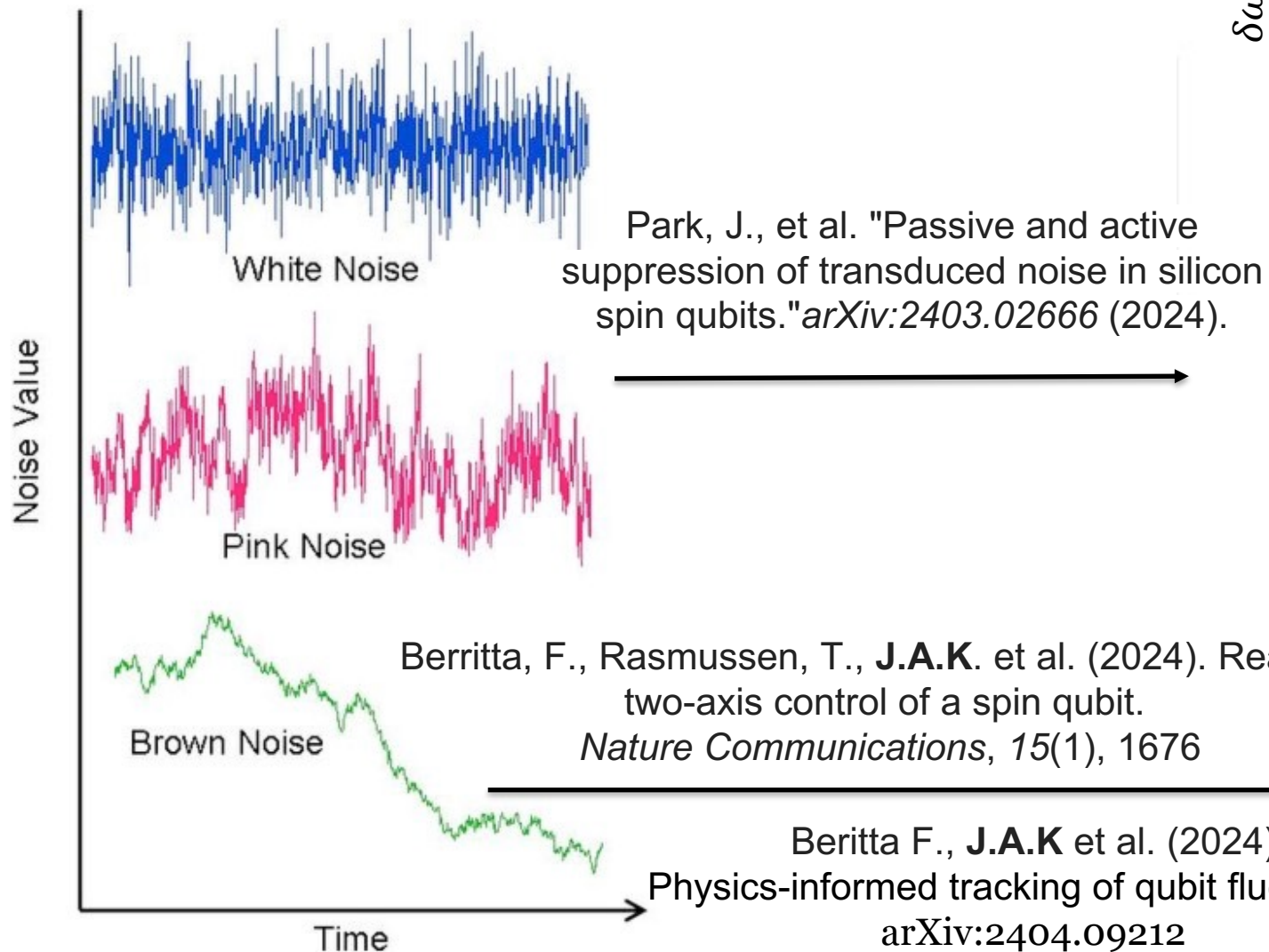
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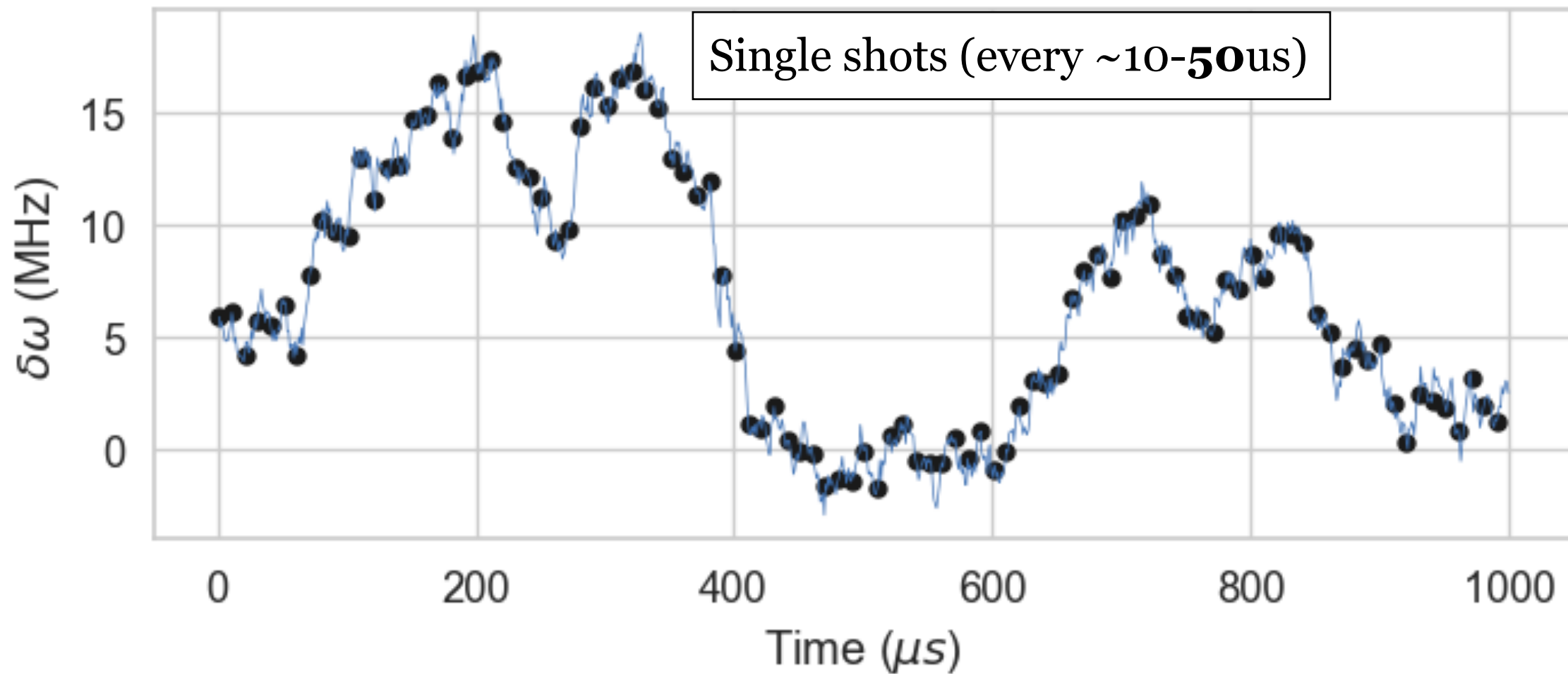
Park, J., et al. "Passive and active suppression of transduced noise in silicon spin qubits." *arXiv:2403.02666* (2024).



We rely on the trajectory



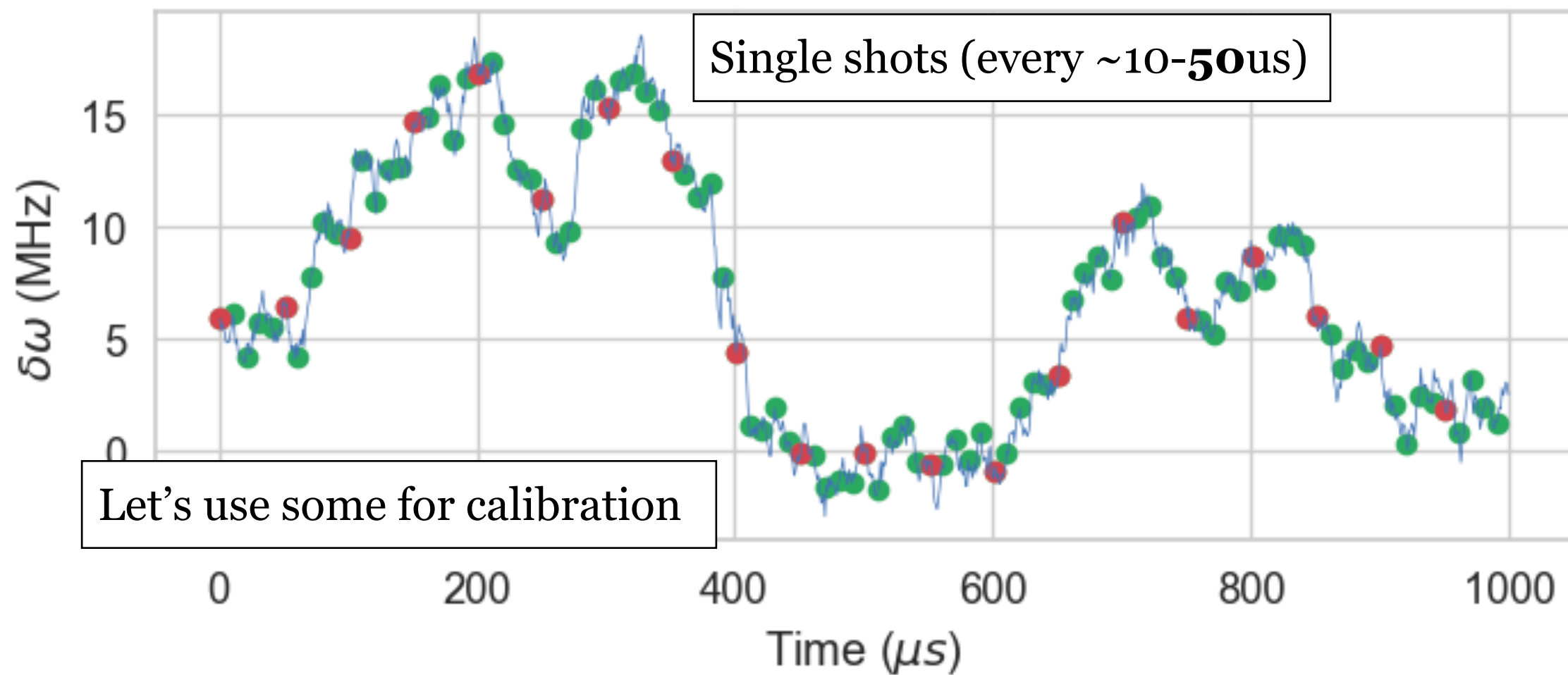
Research strategy – there is plenty of time



Quasistatic approximation

$$H_n = [\omega + \delta\omega_n]S_z$$

... to correct for the noise.

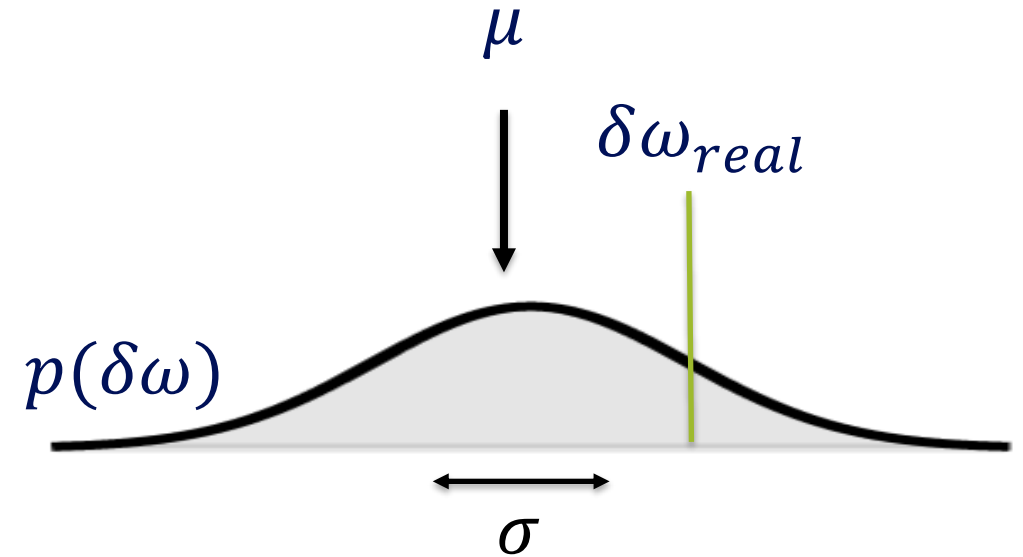
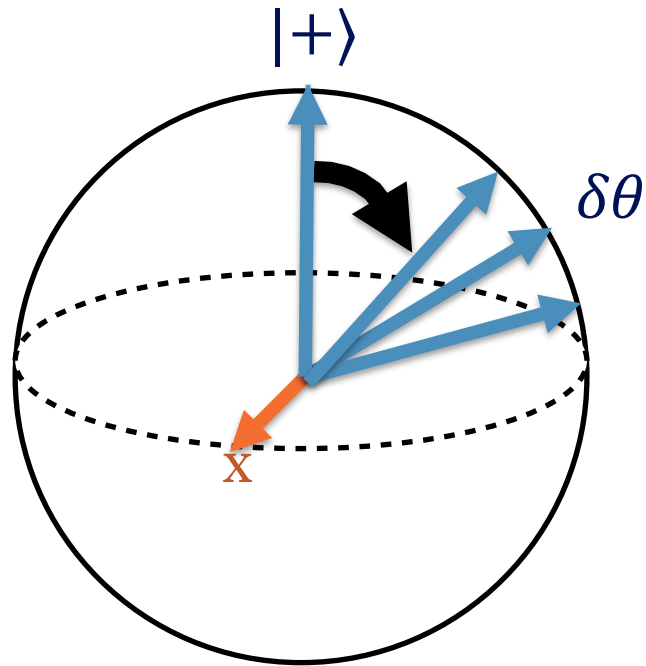


$$H_n = [\omega + \delta\omega_n]S_z$$



Bayesian estimation (2 min)

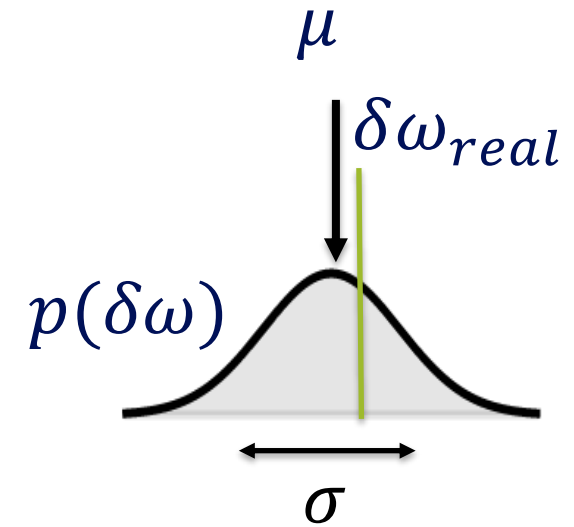
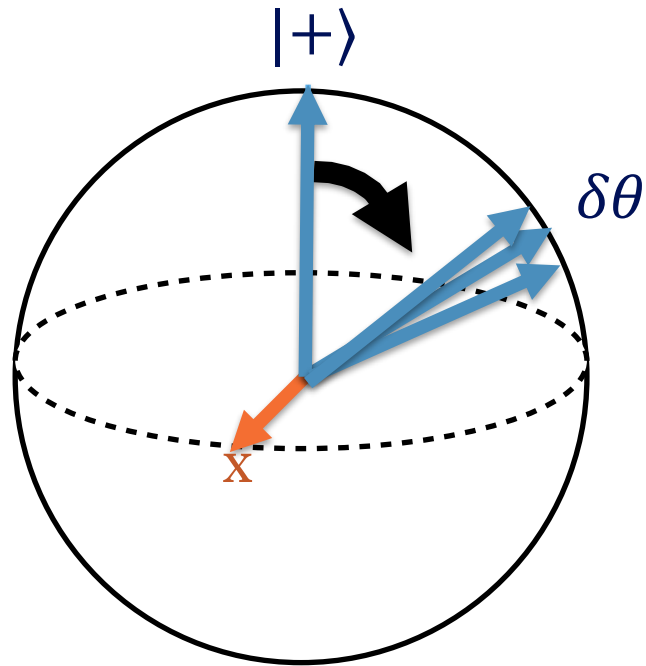
Phase gate



Gate infidelity

$$1 - F \propto \langle \delta\theta^2 \rangle \propto \sigma^2 \theta^2 / \mu^2$$

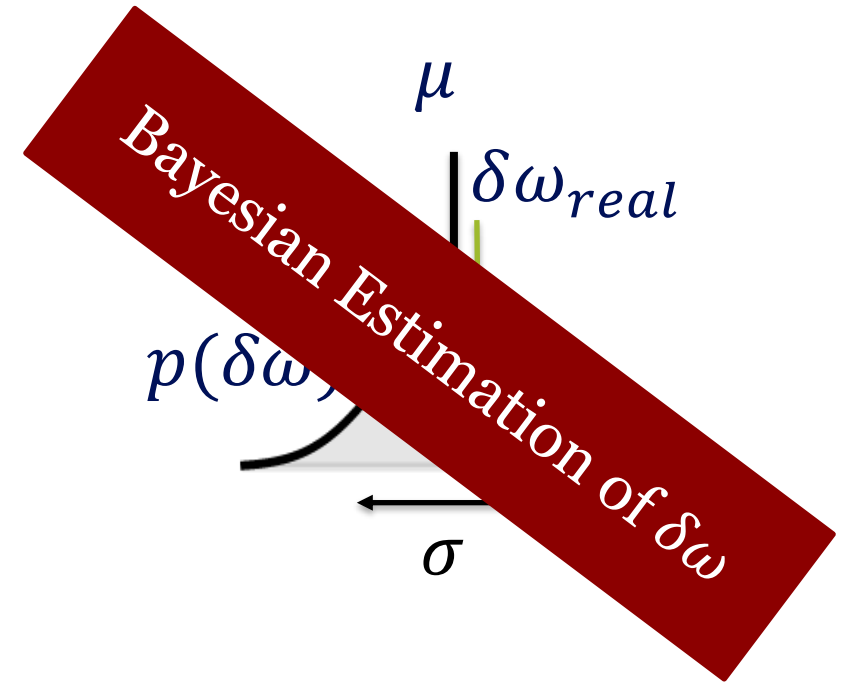
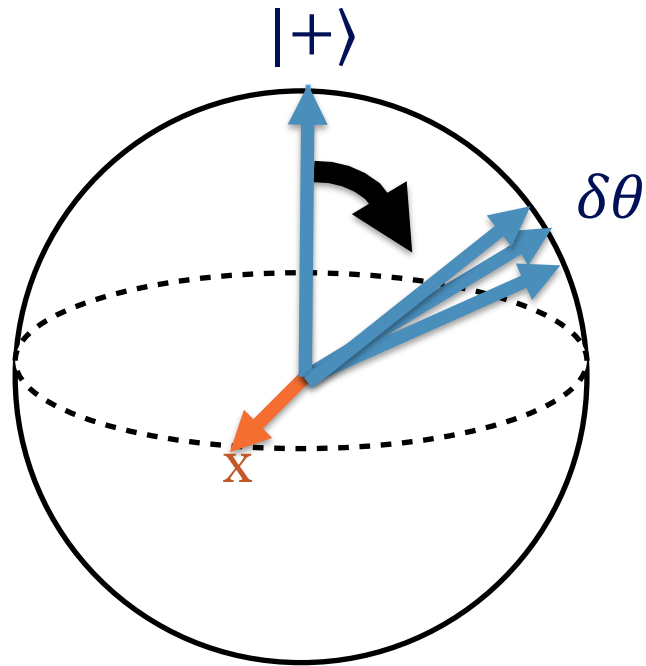
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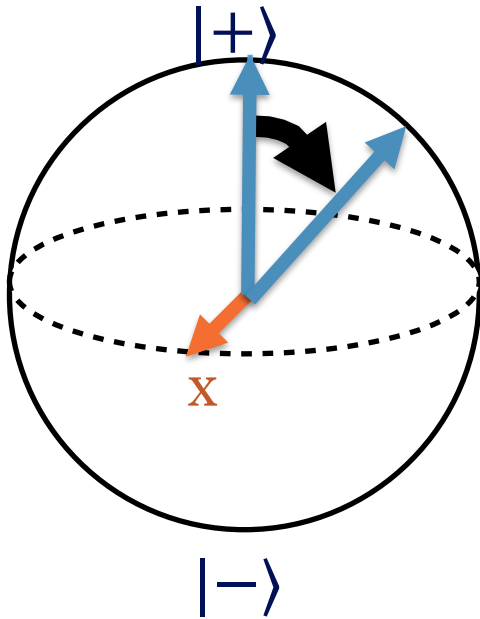
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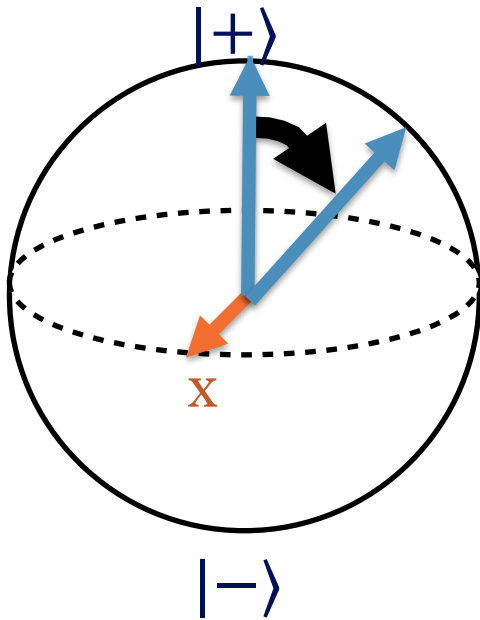
Bayesian estimation



1. Find likelihood function

$$p(x|\delta\omega, \tau) \propto 1 + x \cos(\delta\omega \tau)$$

Bayesian estimation



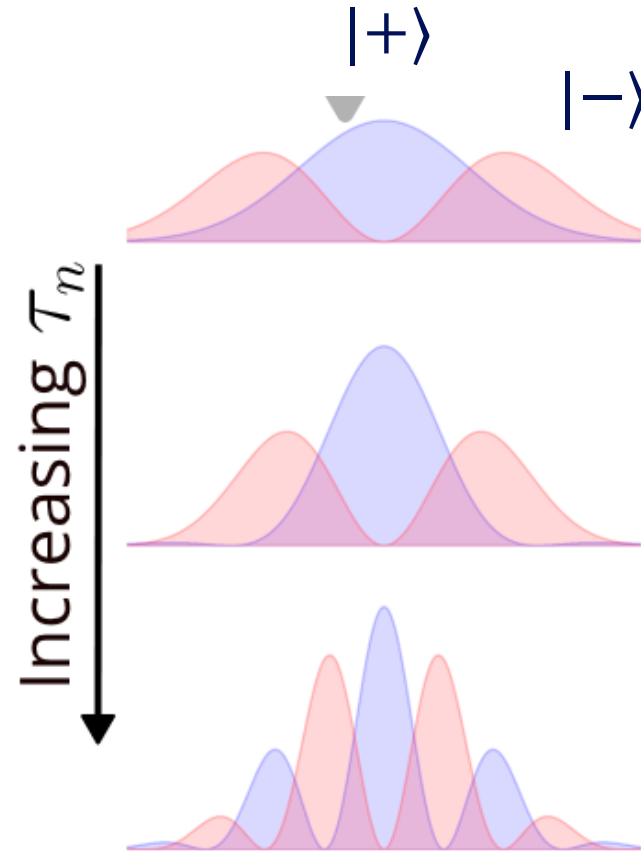
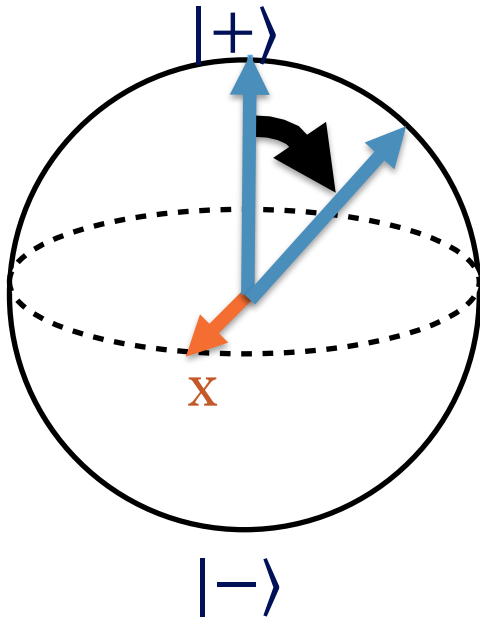
1. Find likelihood function

$$p(x|\delta\omega, \tau) \propto 1 + x \cos(\delta\omega \tau)$$

2. Use Bayesian formula


$$p(\delta\omega|x_1, \tau) \propto p(x_1|\delta\omega, \tau)p_0(\delta\omega)$$


Bayesian estimation



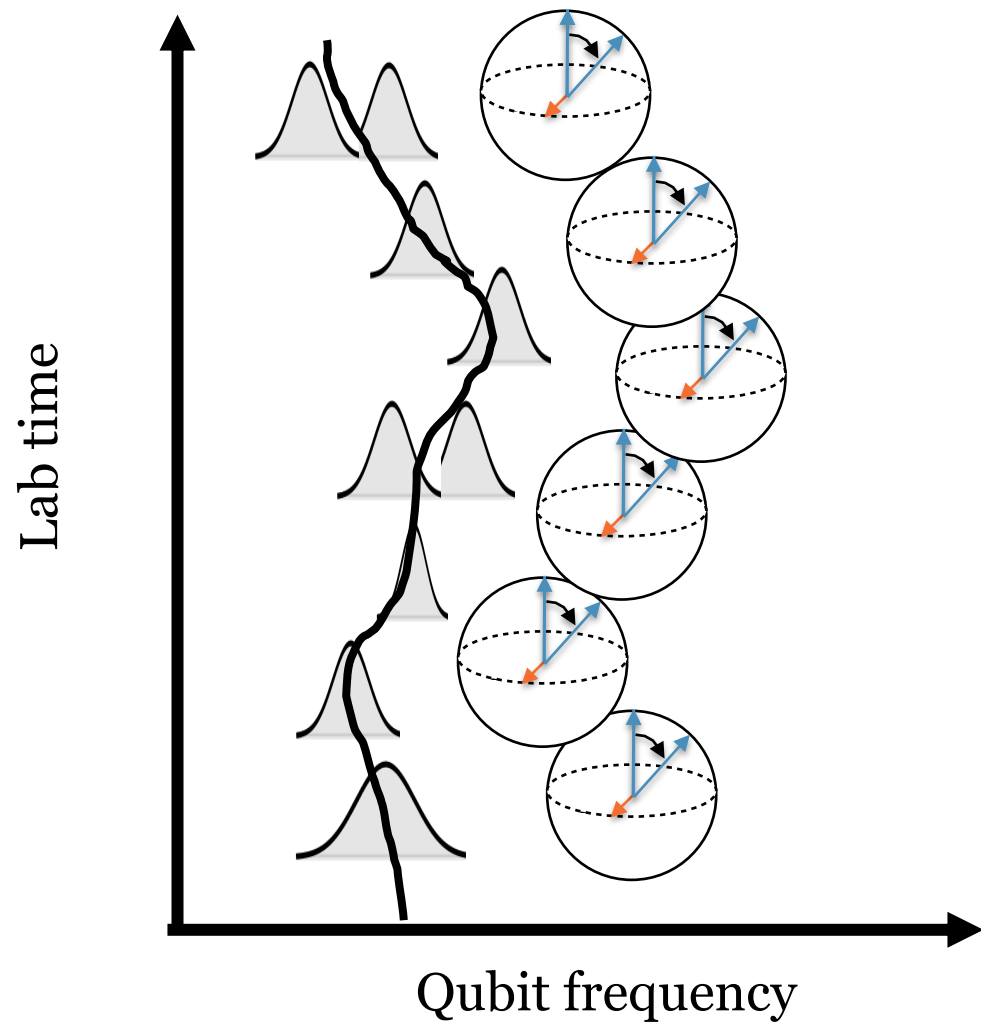
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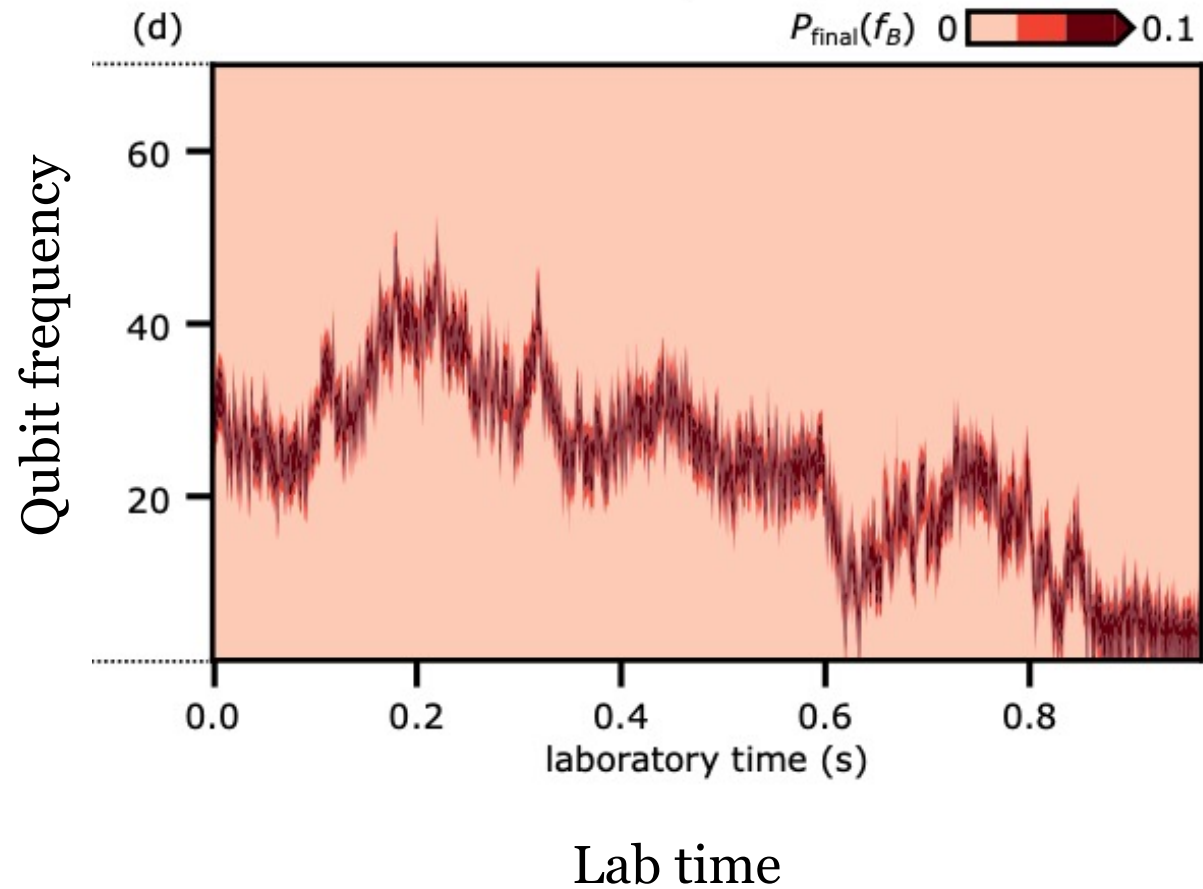
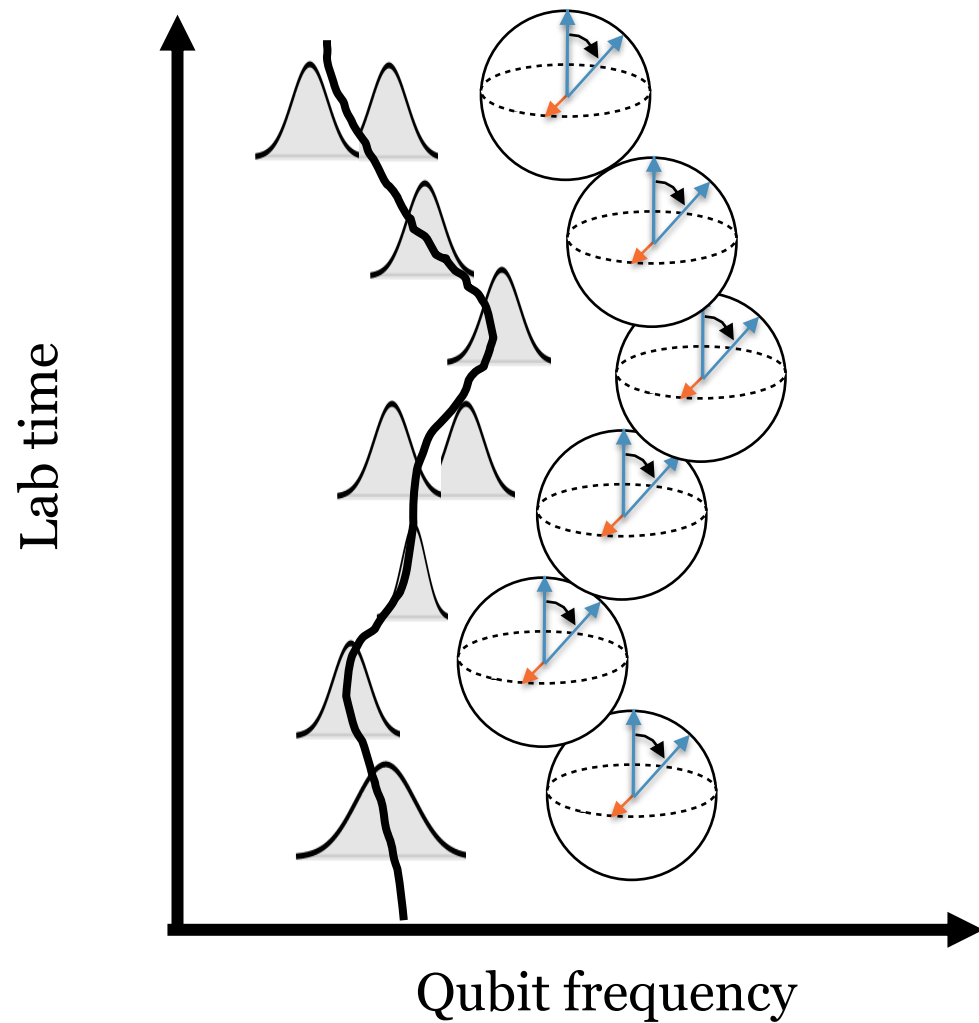
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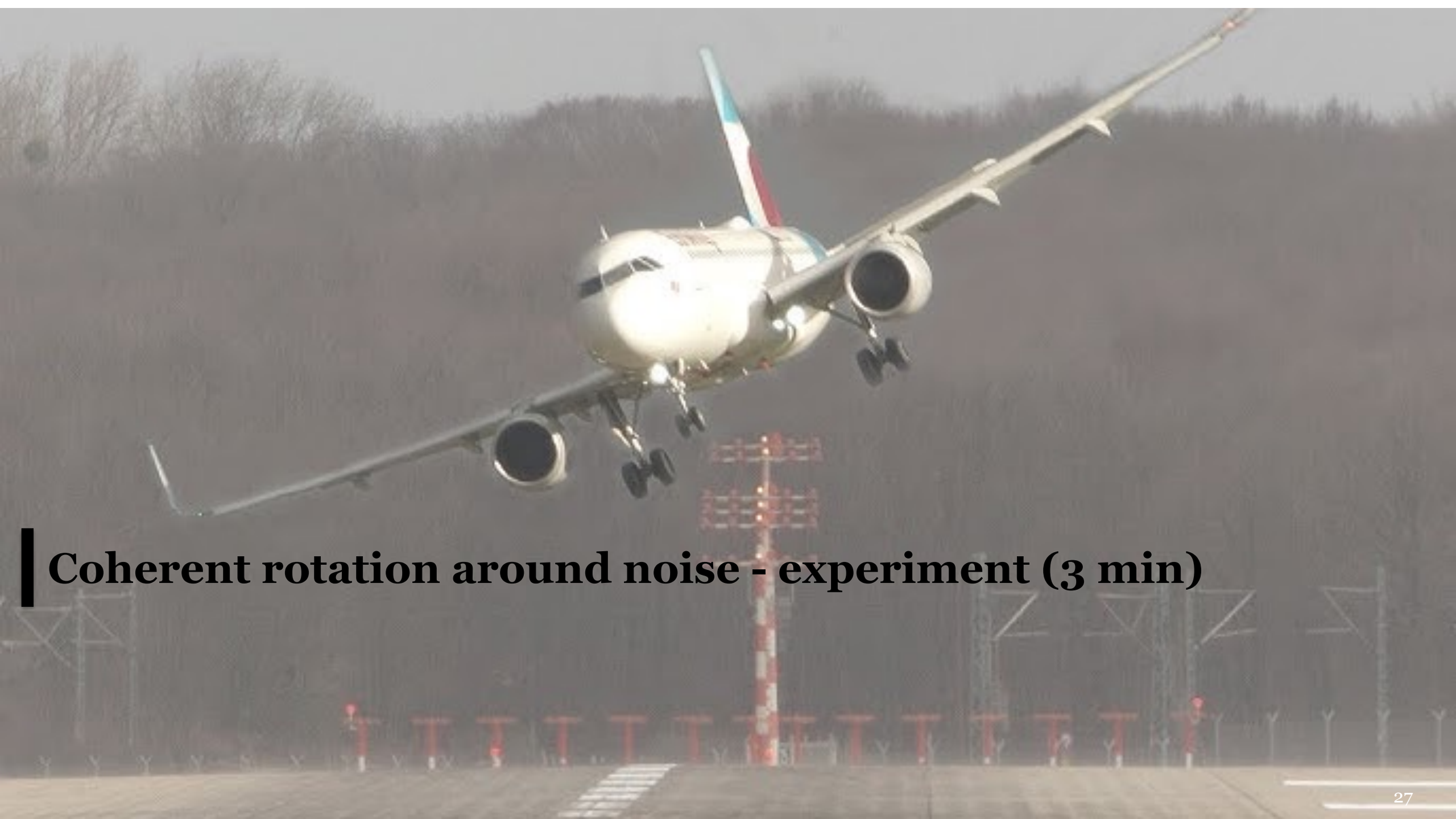
$$p(\delta\omega|x_1, \tau) \propto p(x_1|\delta\omega, \tau)p_0(\delta\omega)$$

Bayesian tracking



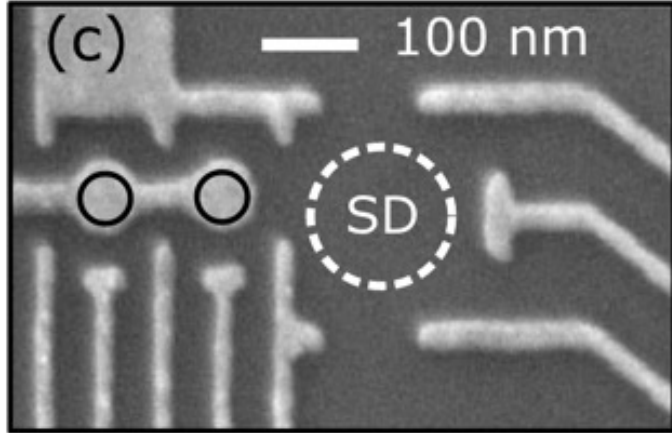
Bayesian tracking



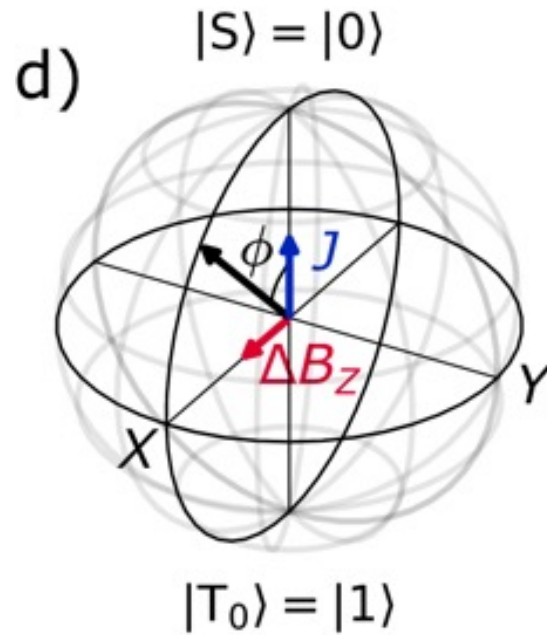


Coherent rotation around noise - experiment (3 min)

Experiment



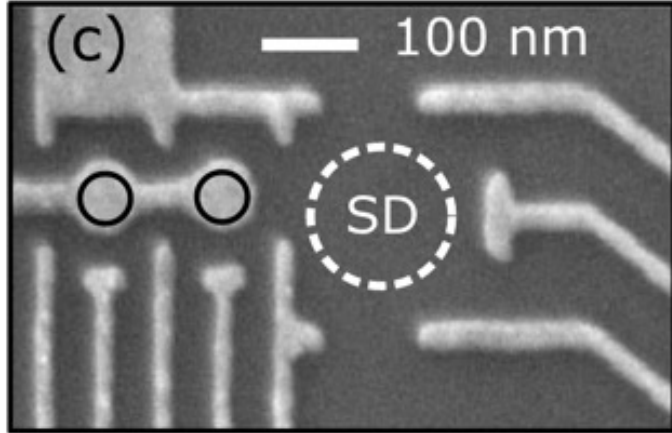
GaAs spin qubit



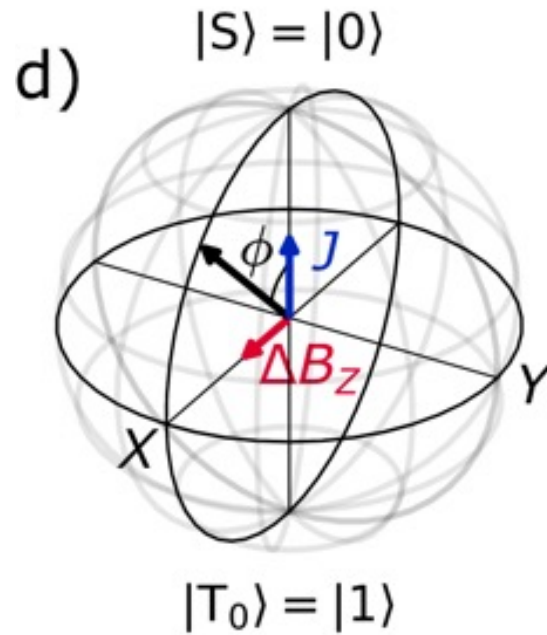
S-T subspace

$$H(\epsilon) = \delta\omega(t)S_x + J(\epsilon)S_z$$

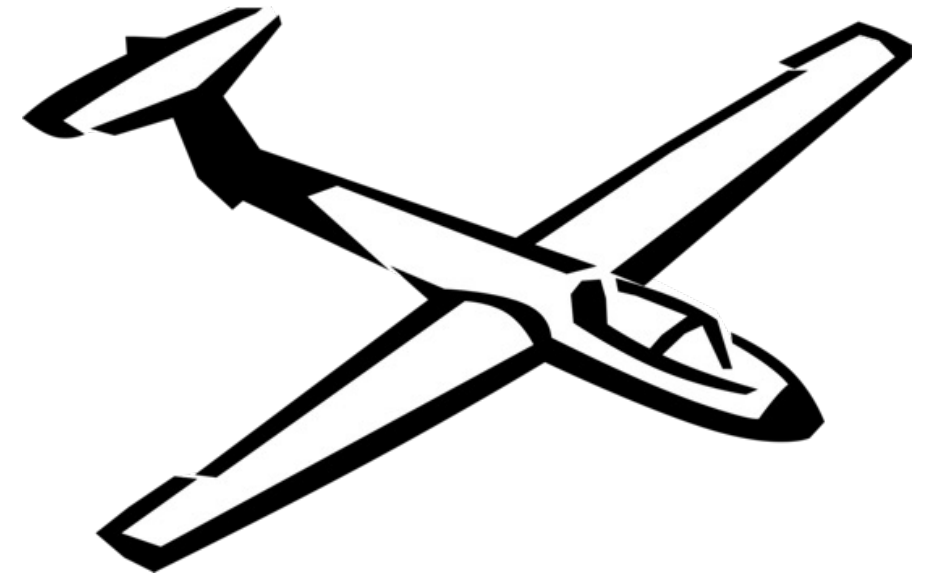
Experiment



GaAs spin qubit

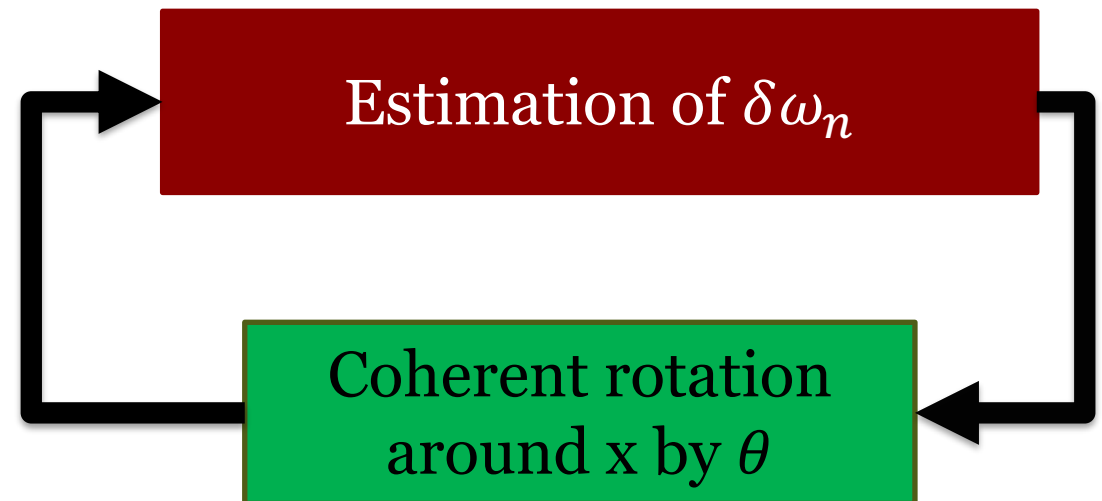


S-T subspace



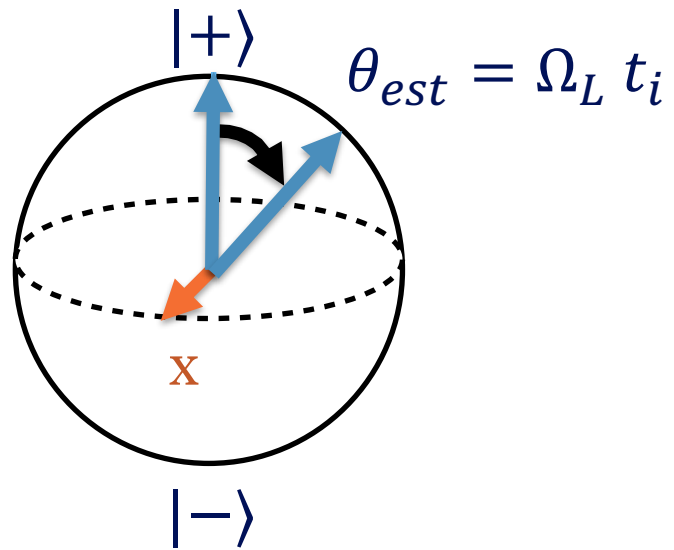
$$H(\epsilon_{11}) = \delta\omega(t)S_x$$

Zero-average



Experiment

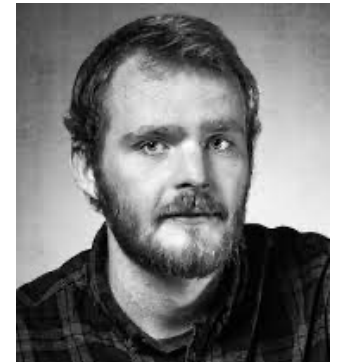
$$H(\epsilon) = \Omega_L S_x$$



Center for Quantum Devices
Niels Bohr Institute



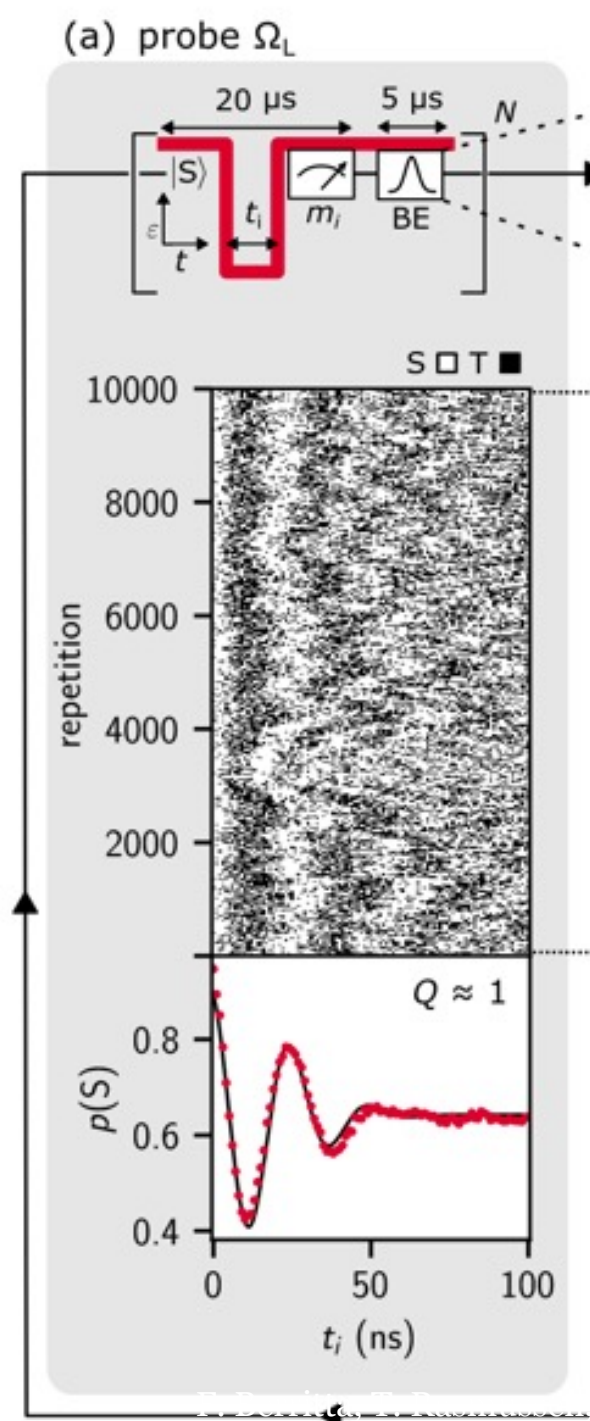
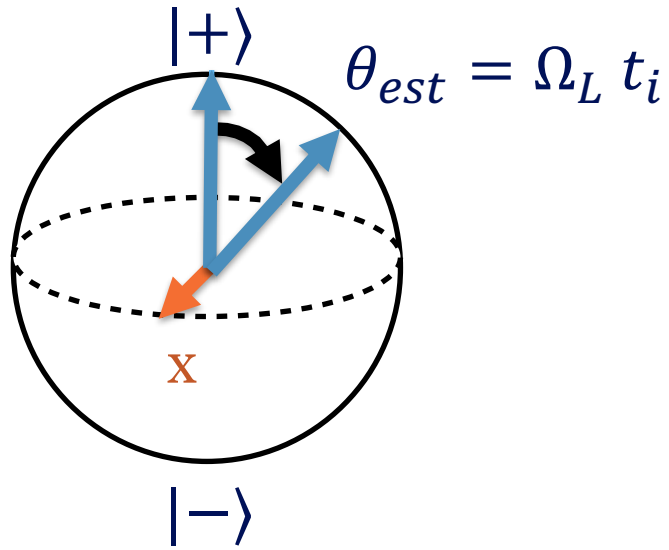
Fabrizio Berritta
TALK PAS 2.4
(yesterday)



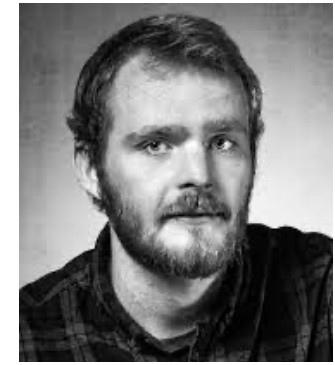
Torbjørn Raasø
Rasmussen

Experiment

$$H(\epsilon) = \Omega_L S_x$$



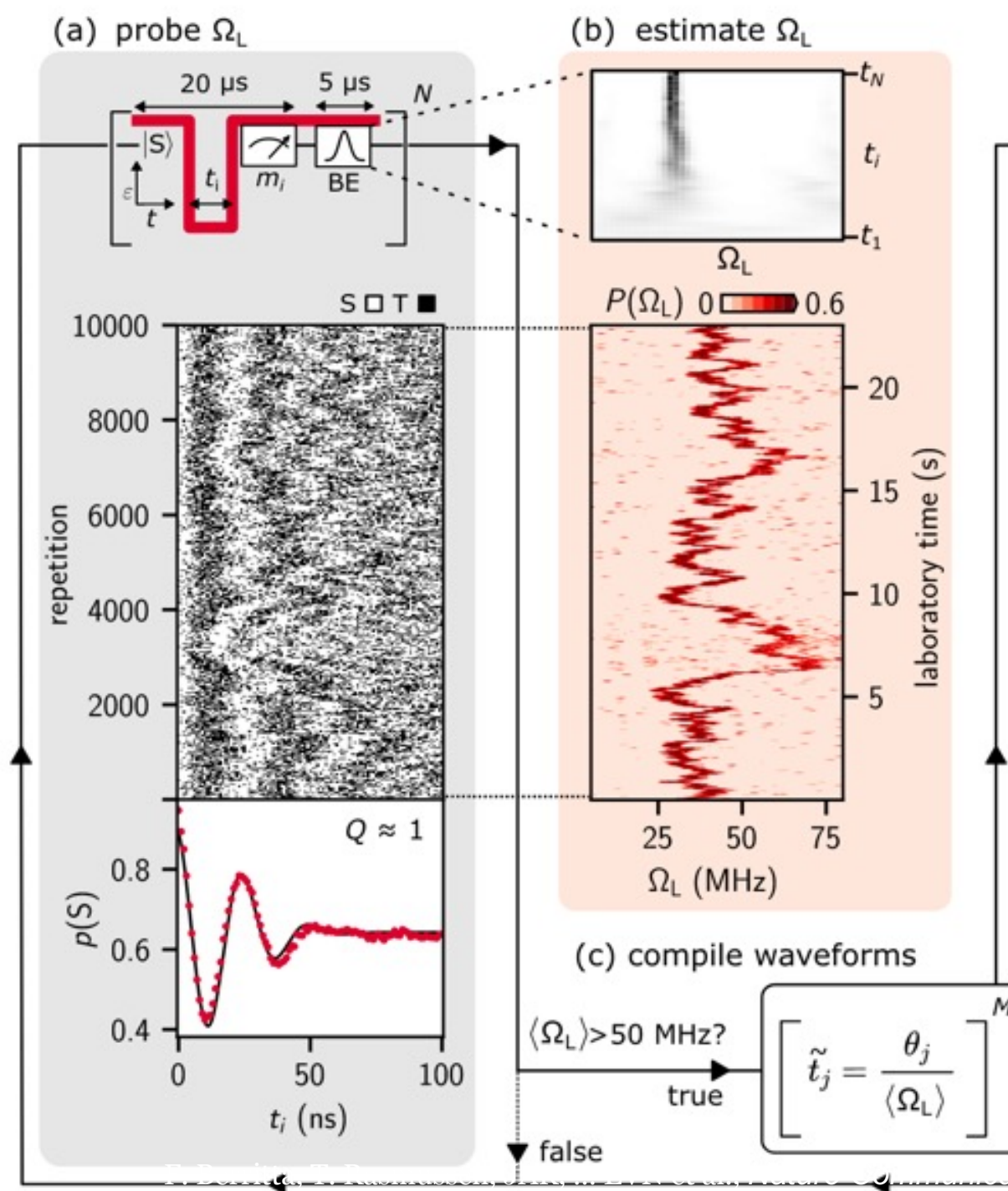
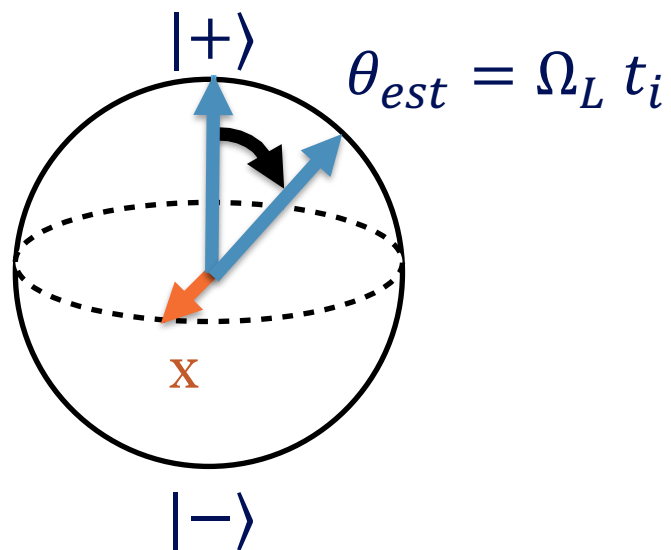
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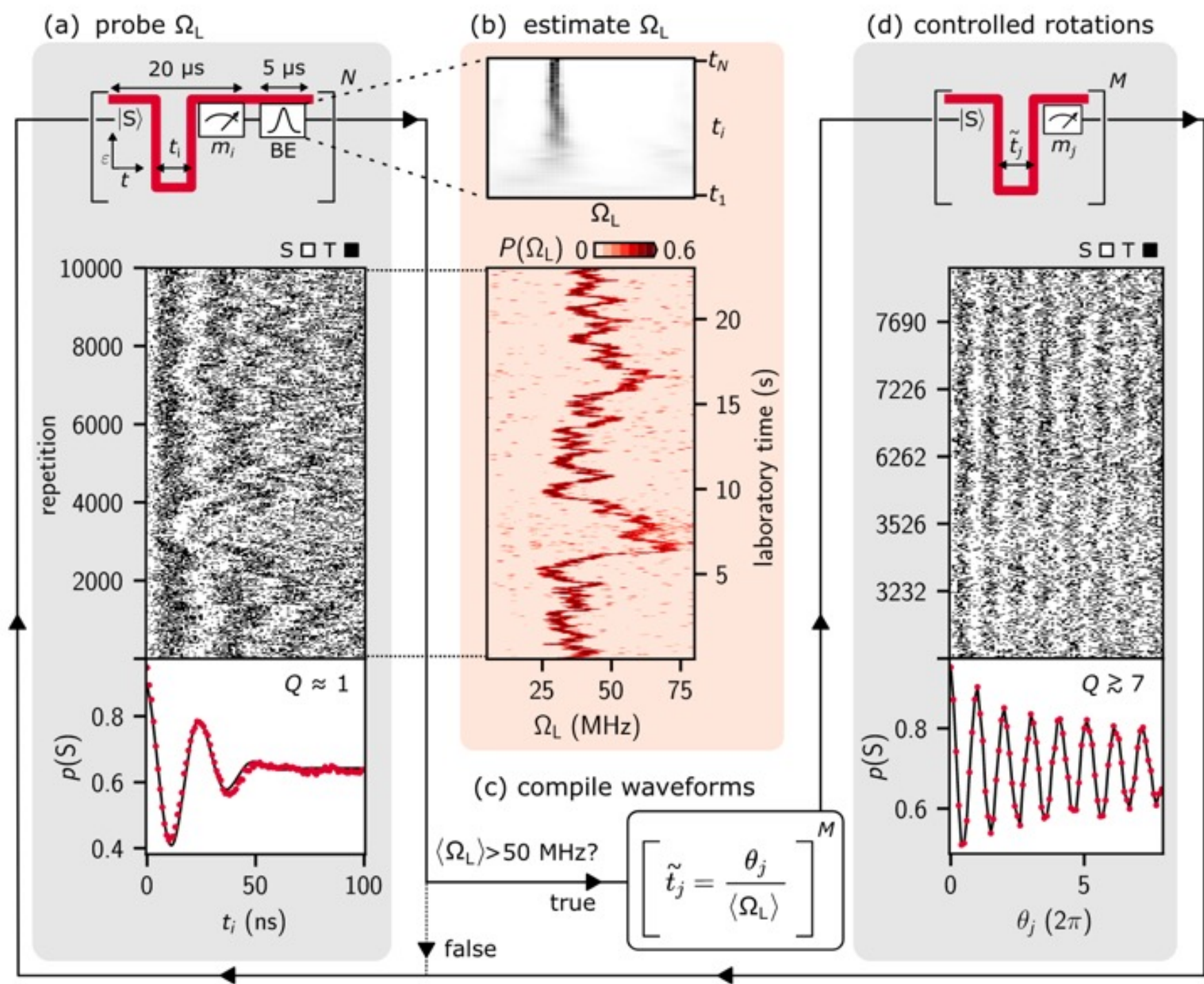
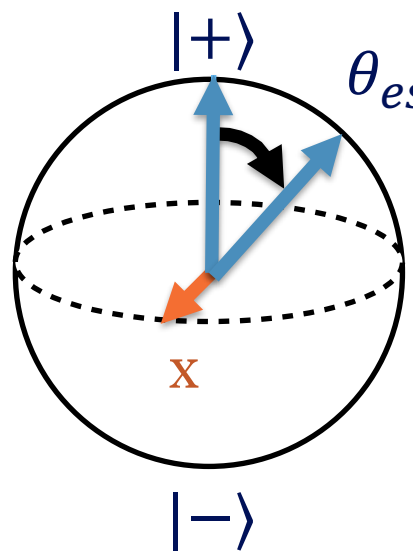
Experiment

$$H(\epsilon) = \Omega_L S_x$$



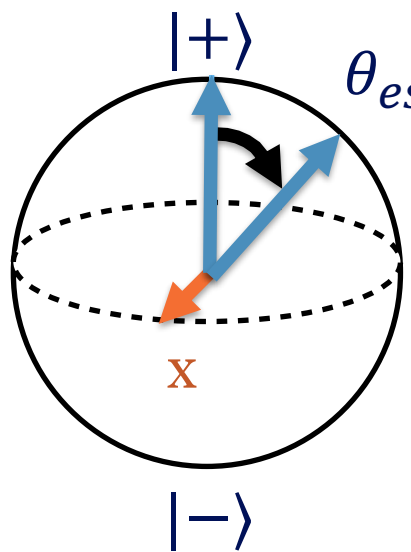
Experiment

$$H(\epsilon) = \Omega_L S_x$$



Experiment

$$H(\epsilon) = \Omega_L S_x$$

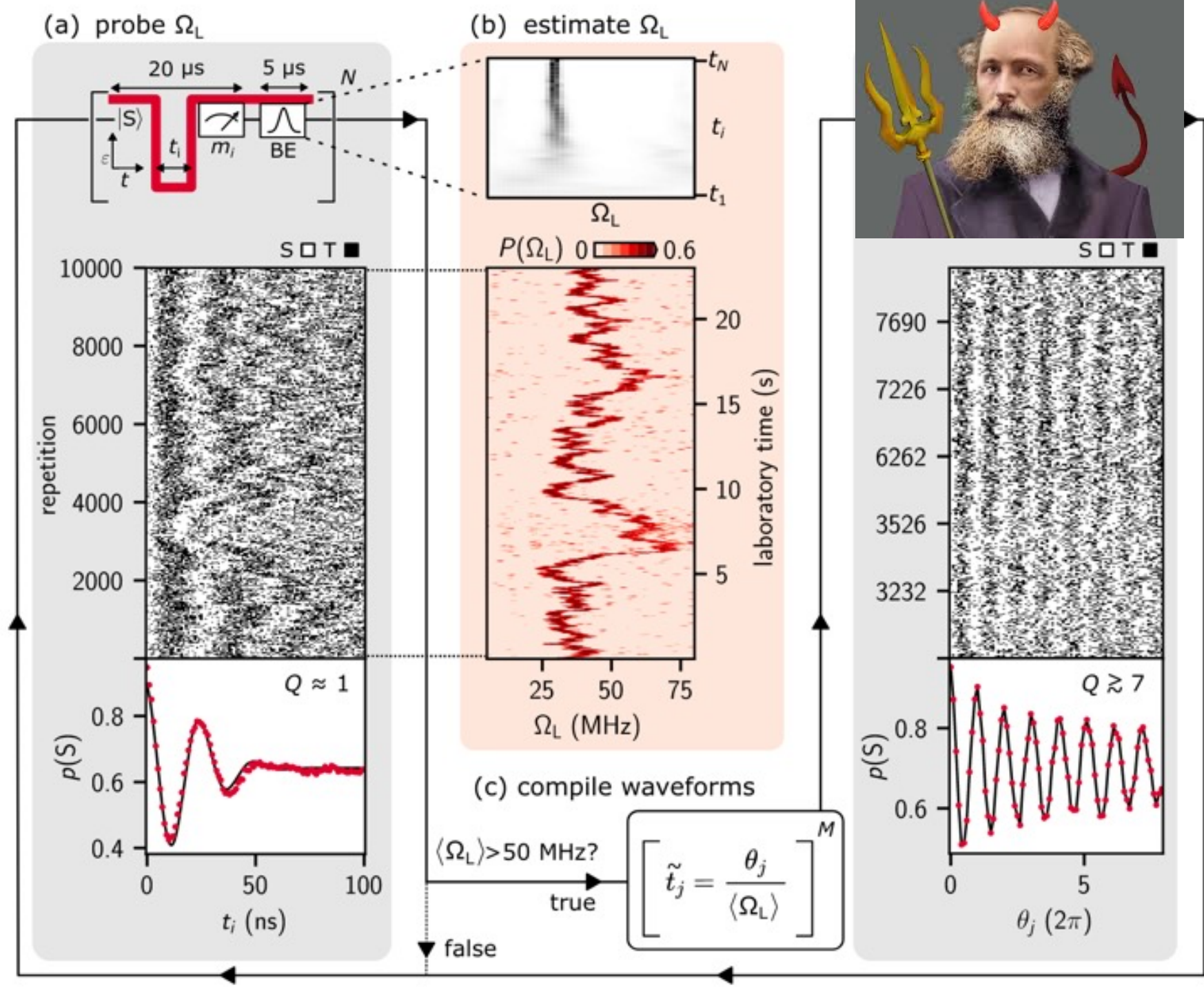


If $\Omega_L > 50$ MHz

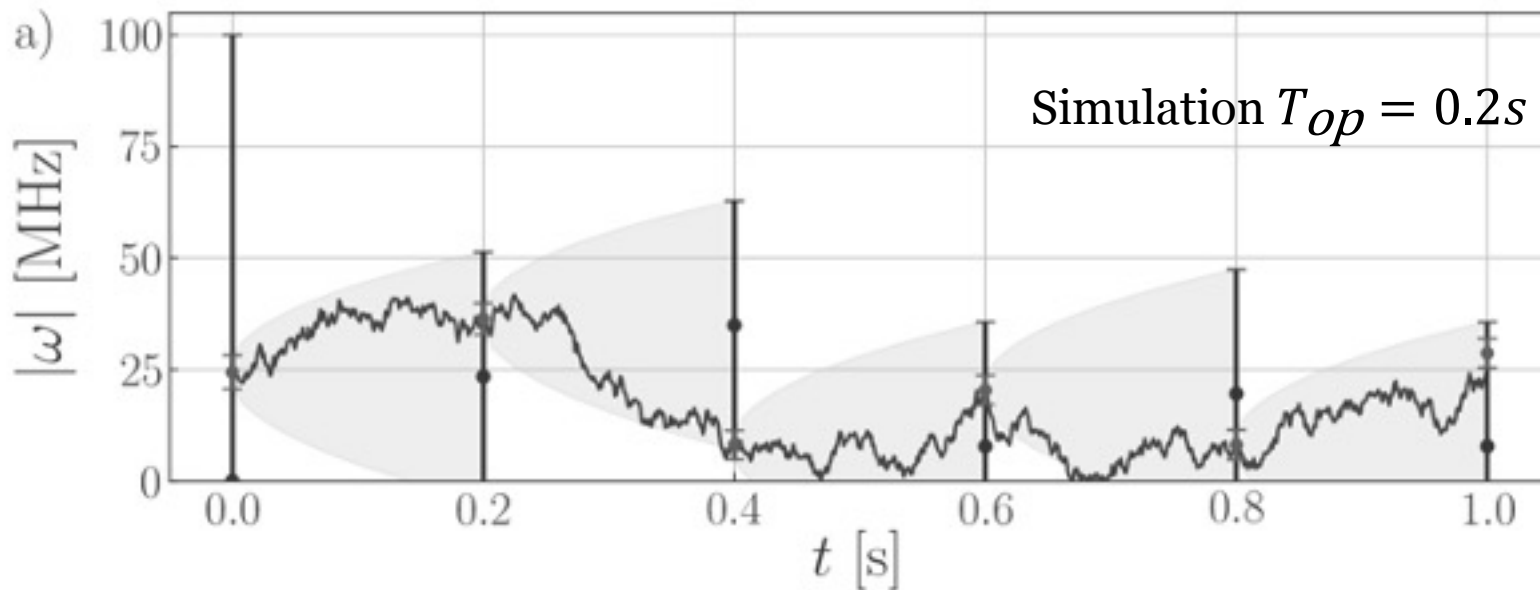
Rotate by θ , using time

$$\tau = \frac{\theta}{\widehat{\Omega}_L}$$

$\langle aQa^\dagger \rangle$



Our progress



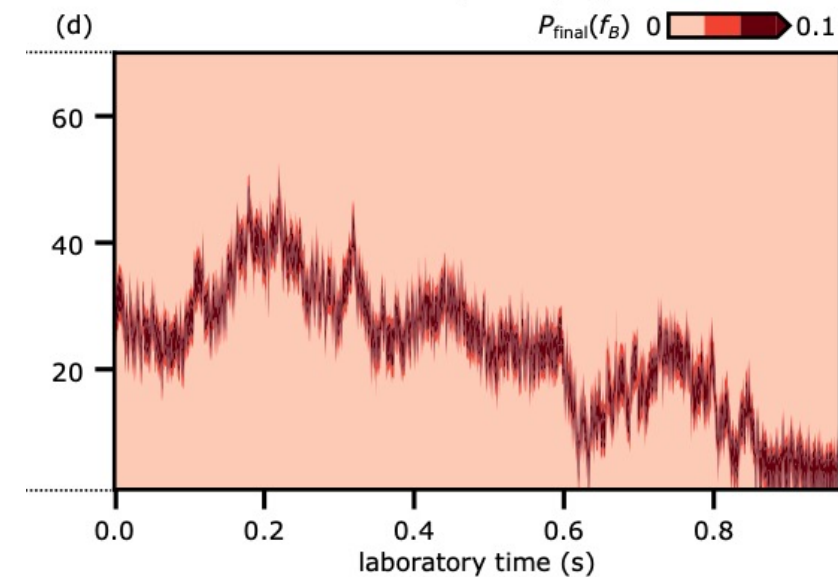
Fabrizio Berritta



Jacob Benestad

1. Physics-informed estimation
(No outliers)

$$P(\delta\omega' t | \delta\omega, 0)$$



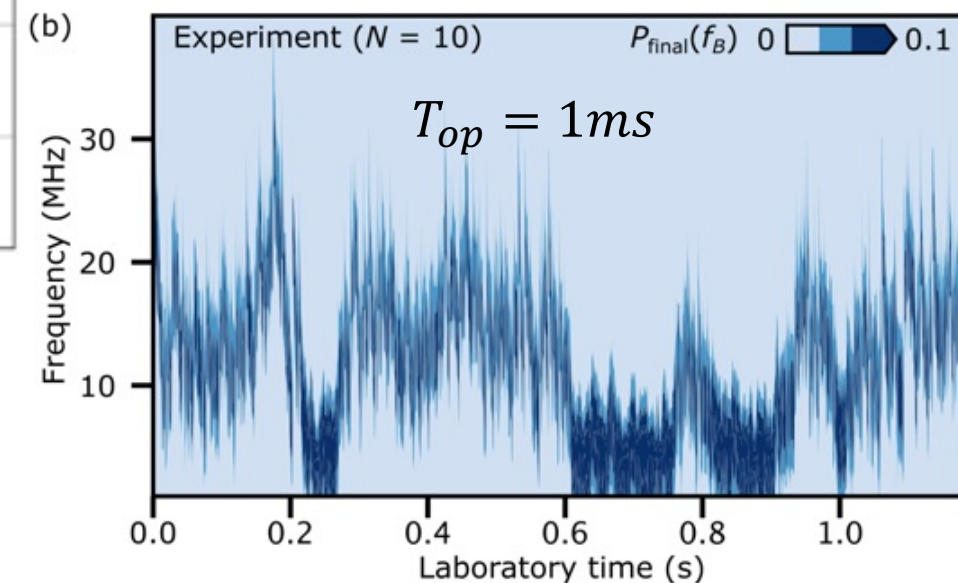
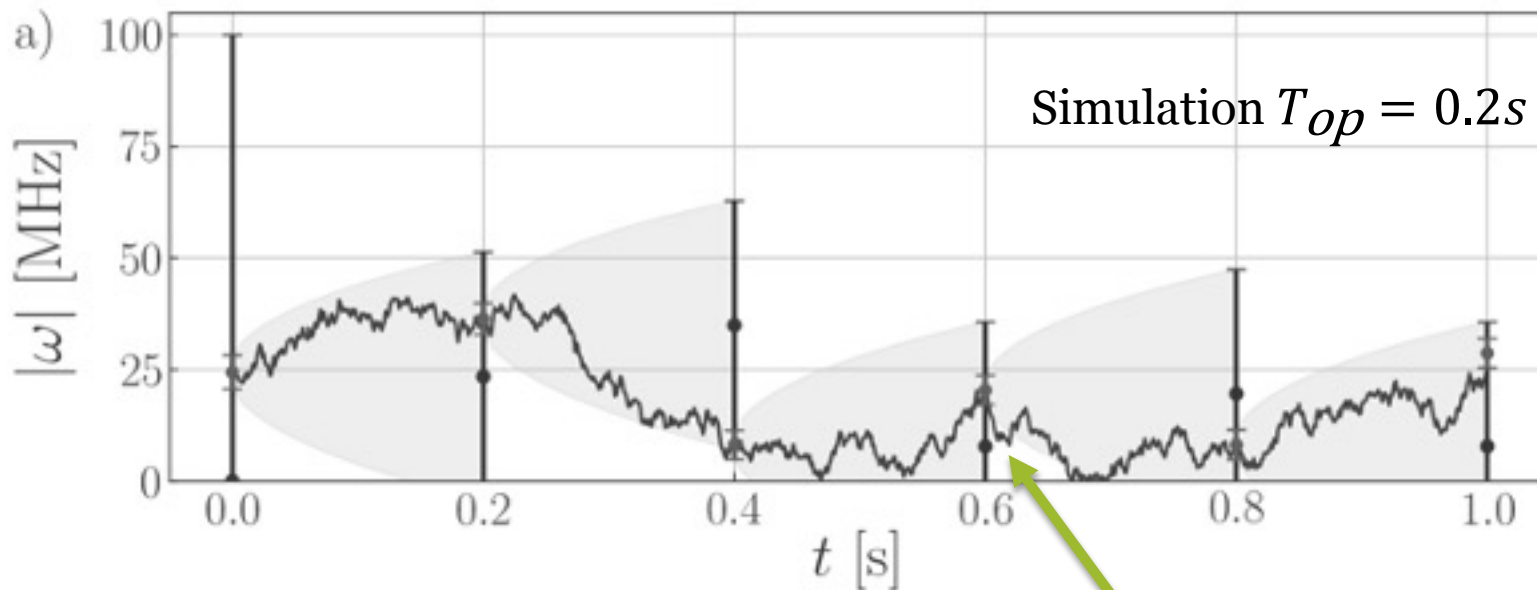
Our progress



Fabrizio Berritta



Jacob Benestad



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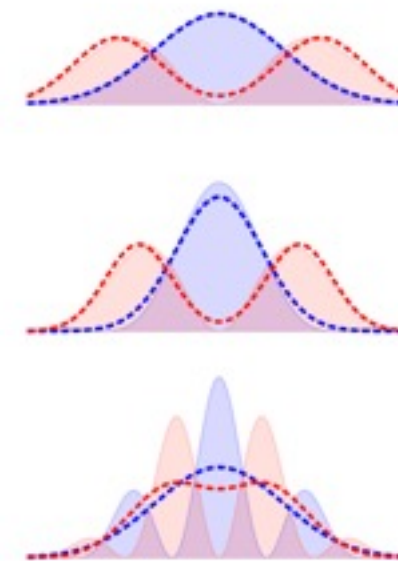
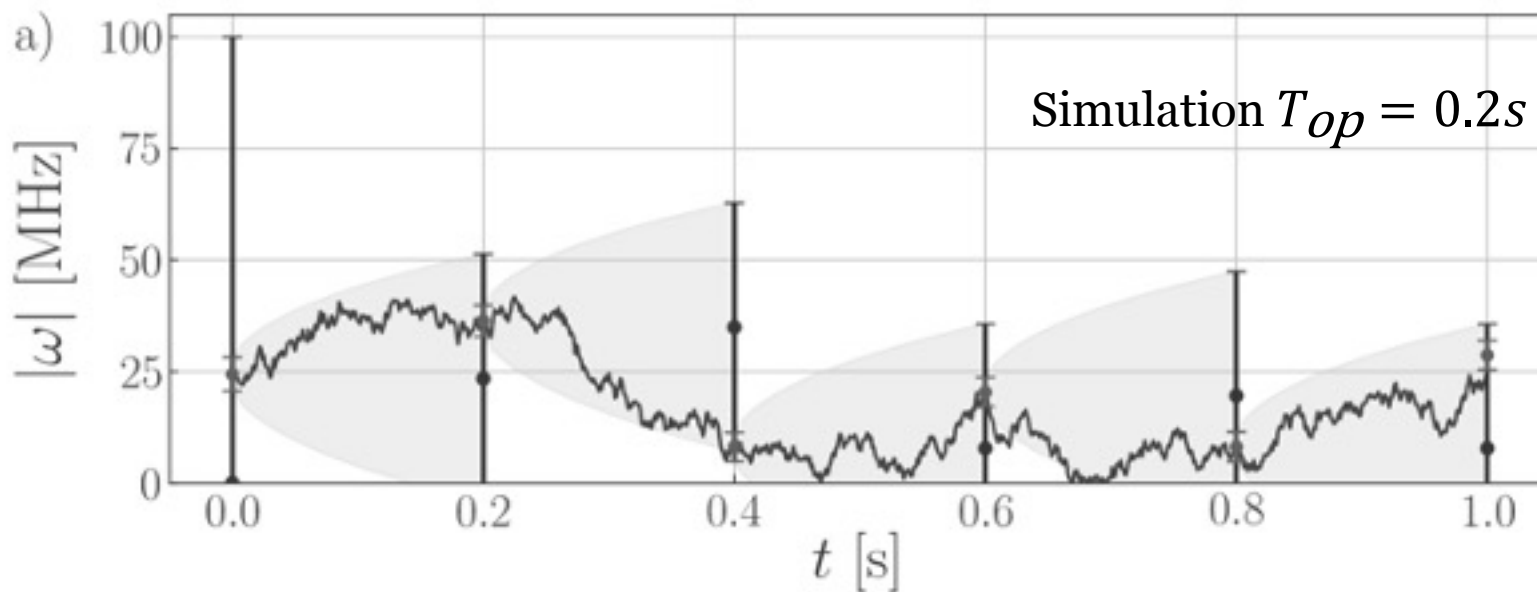
2. Adaptive time
(Few shots)

$$\tau_n = \frac{c}{\sigma_{n-1}}$$

Our progress



Jacob Benestad



Gaussian fit

1. Physics-informed estimation
(No outliers)

$$P(\delta\omega' t | \delta\omega, 0)$$

2. Adaptive time
(Few shots)

$$t_n = \frac{c}{\sigma_{n-1}}$$

3. Method of moments
(Low memory)

$$\mu_{n+1} = f(\mu_n, \sigma_n)$$

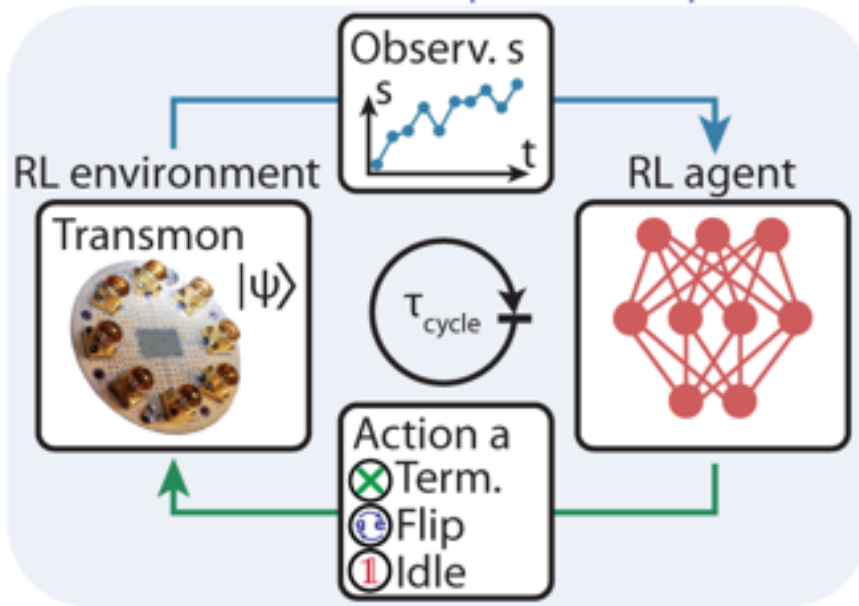
$$\sigma_{n+1} = g(\mu_n, \sigma_n)$$



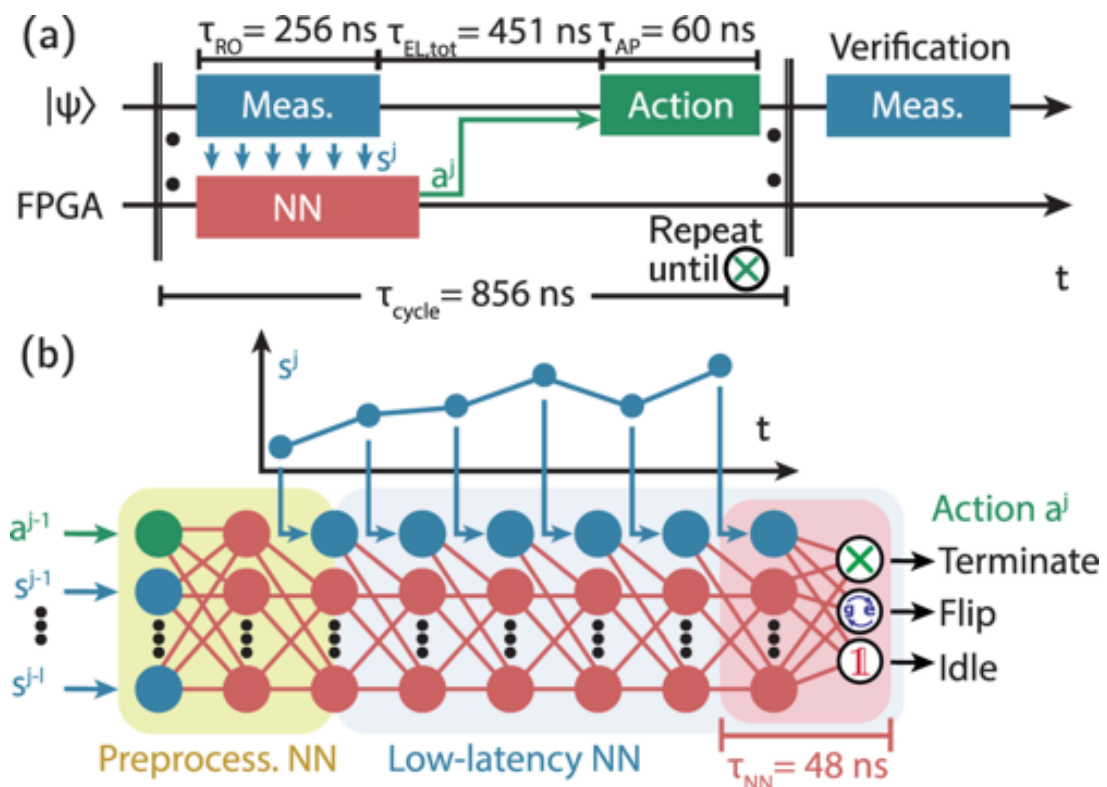
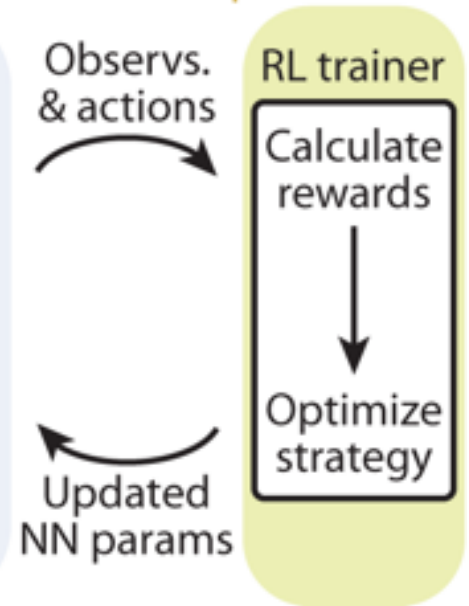
The game and its heuristics (2 min)

Reinforcement learning on the FPGA

Real-time feedback in quantum experiment



Update on PC



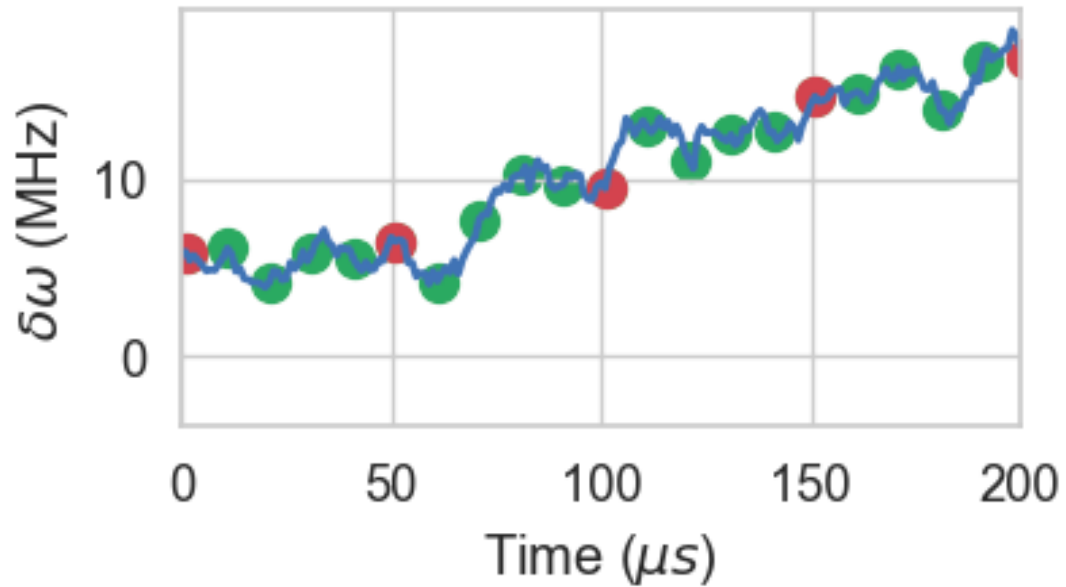
1. Hybrid optimisation method

2. Improved initialisation

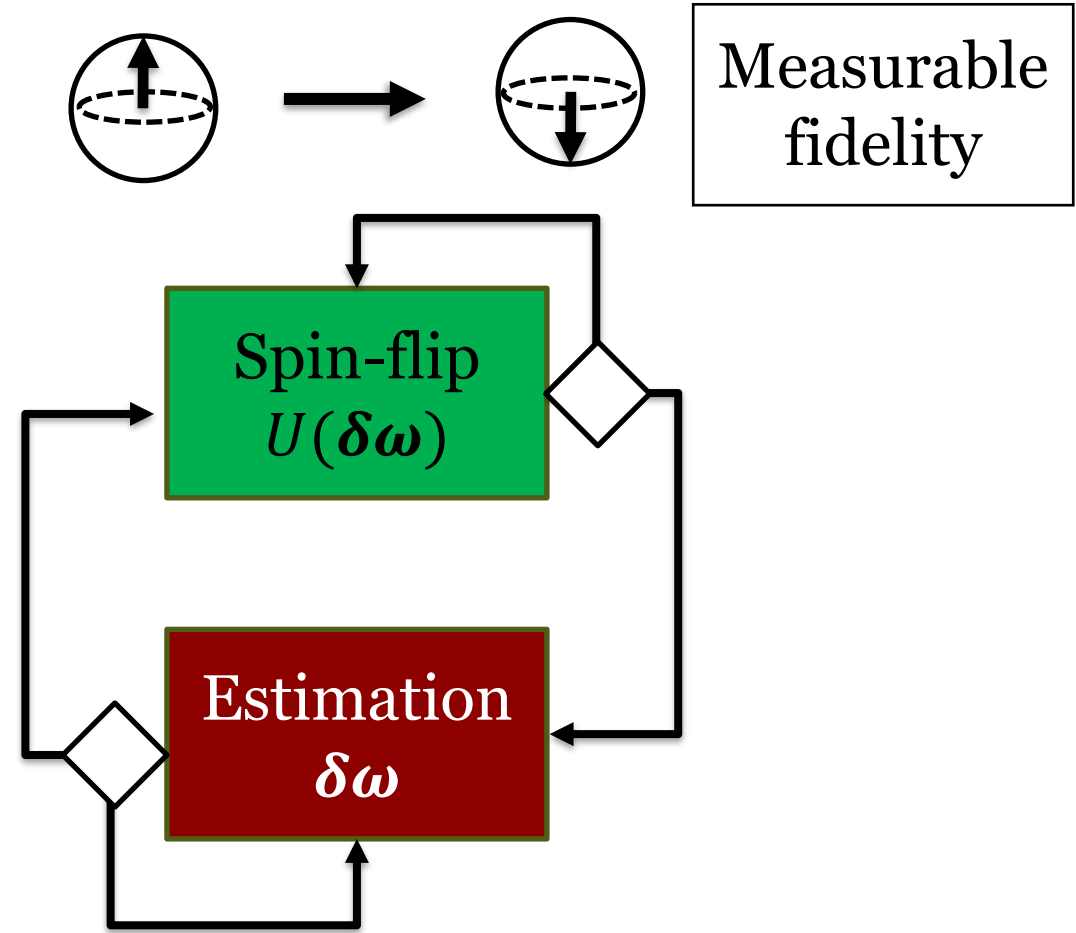
3. Markovian approach

Reuer, Kevin, et al. "Realizing a deep reinforcement learning agent for real-time quantum feedback." *Nature Communications* 14.1 (2023): 7138.

The game



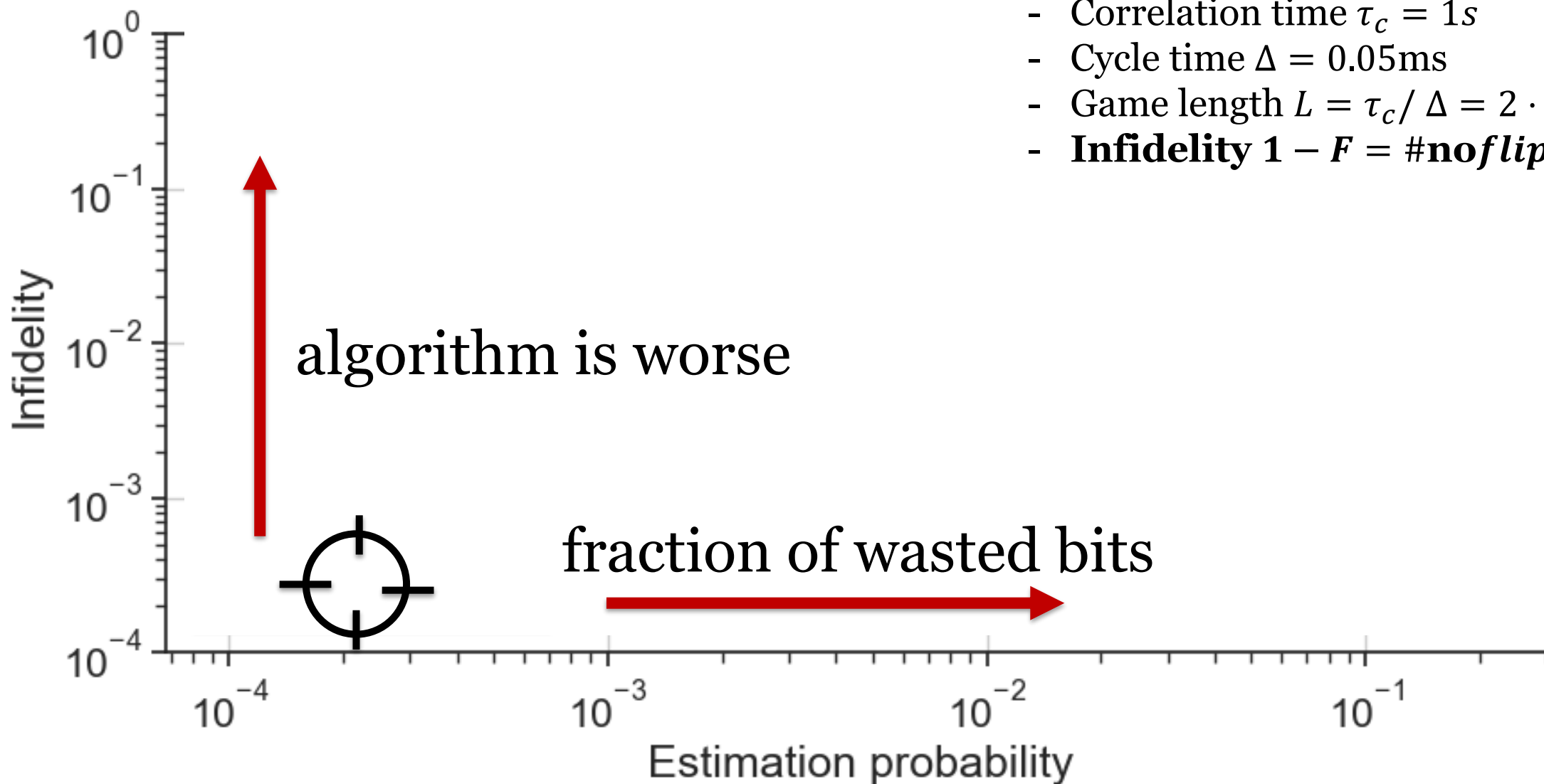
1. Resource allocation



2. Actions

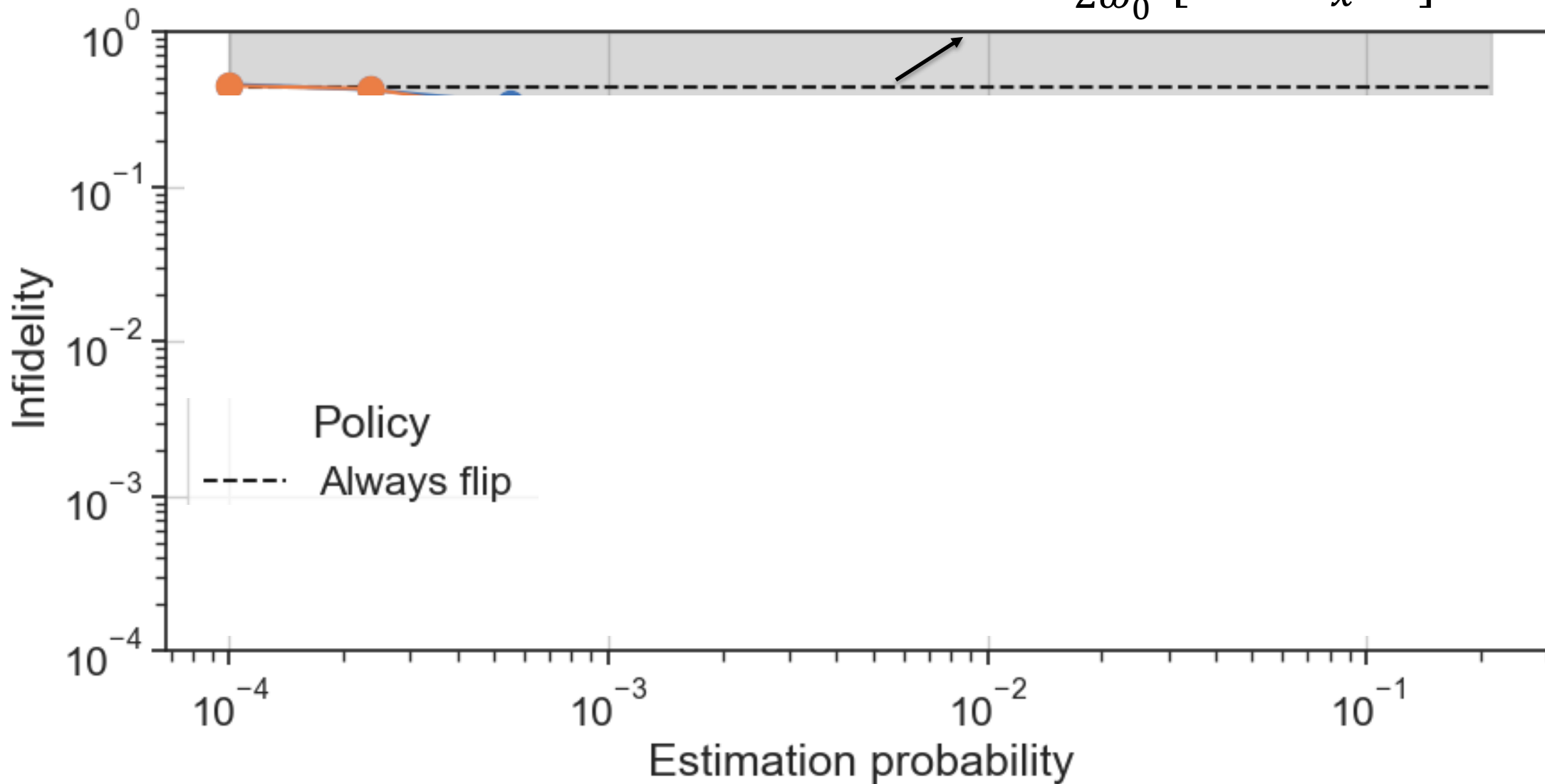
Heuristics to beat

- Noise amplitude 2MHz
- Target frequency 10MHz
- Initial error 0.5MHz
- Correlation time $\tau_c = 1s$
- Cycle time $\Delta = 0.05ms$
- Game length $L = \tau_c / \Delta = 2 \cdot 10^4$
- **Infidelity $1 - F = \#noflip / \#x$**

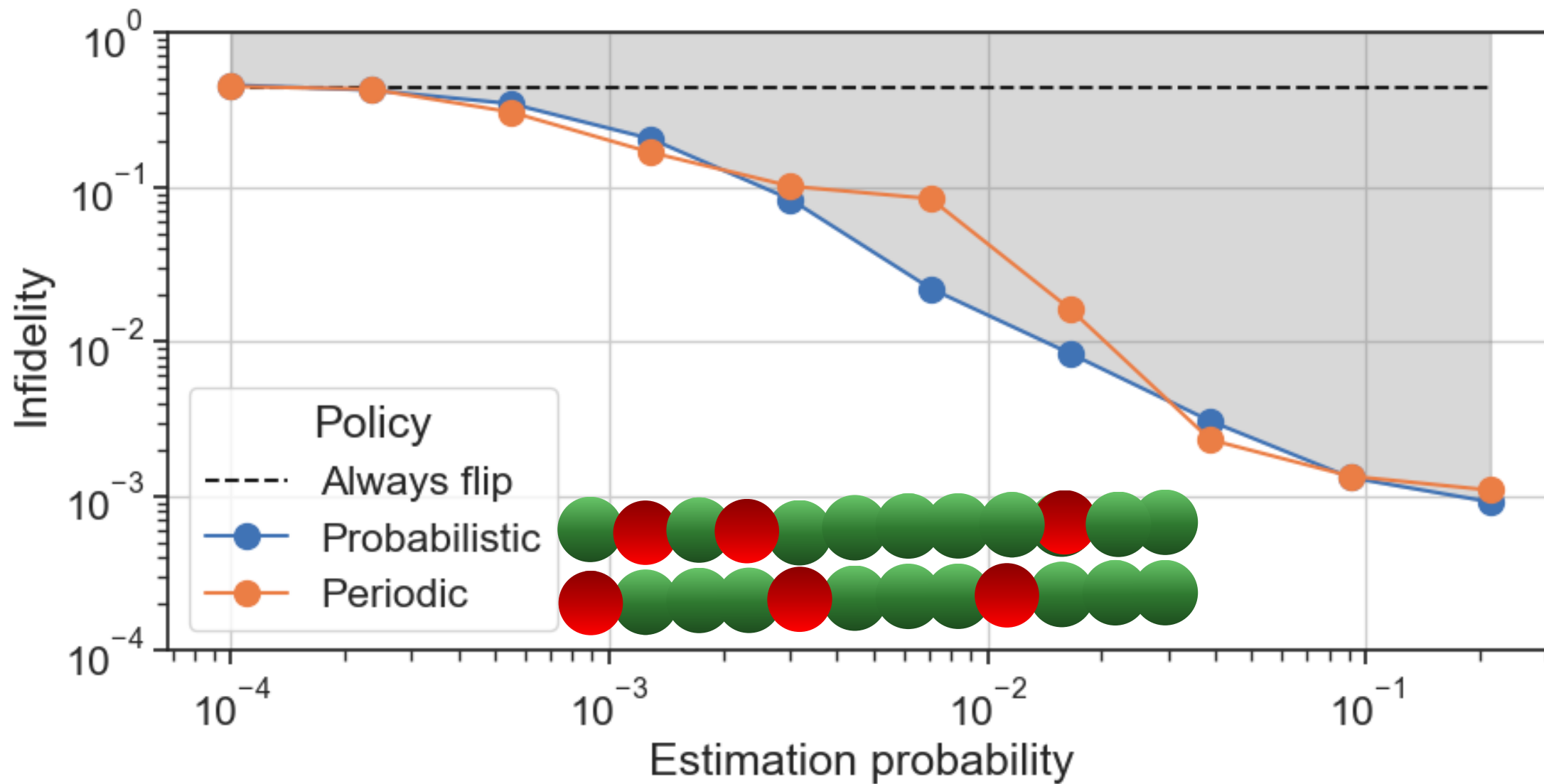


Heuristics to beat

$$\langle P(0) \rangle_{\delta\omega} \approx \frac{A^2 \pi^2}{2\omega_0^2} \left[1 - \frac{1 - e^{-x}}{x} \right] \quad x = \frac{N\Delta t}{\tau_c} = 1$$



Heuristics to beat

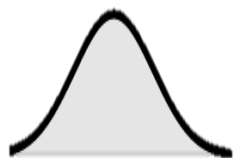




Bringing the agent – Reinforcement learning (PPO) (5min)

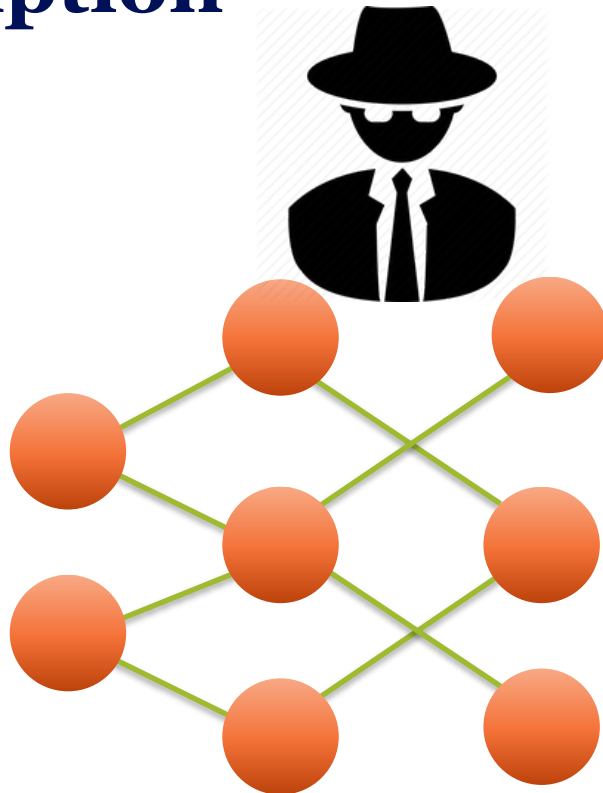
The agent description

$$H(t) = \delta\omega S_x$$



μ_n

σ_n

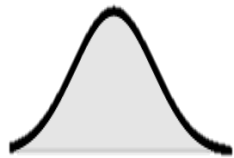


1. Observations

μ_n, σ_n

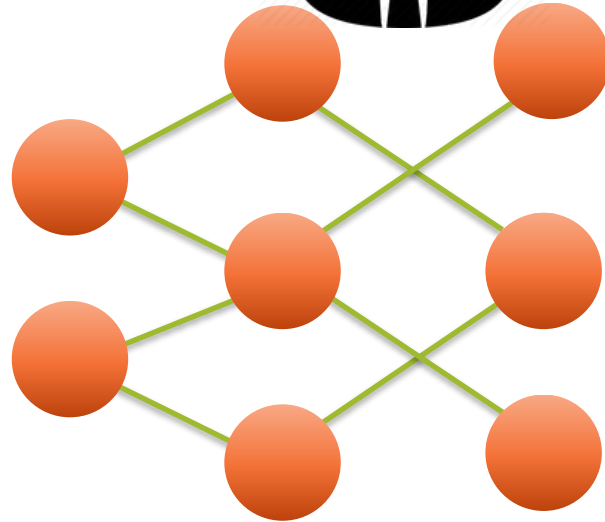
The agent description

$$H(t) = \delta\omega S_x$$



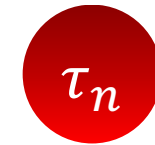
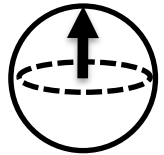
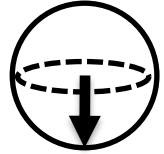
μ_n

σ_n



$$\tau = \pi / \mu_n$$

Reward



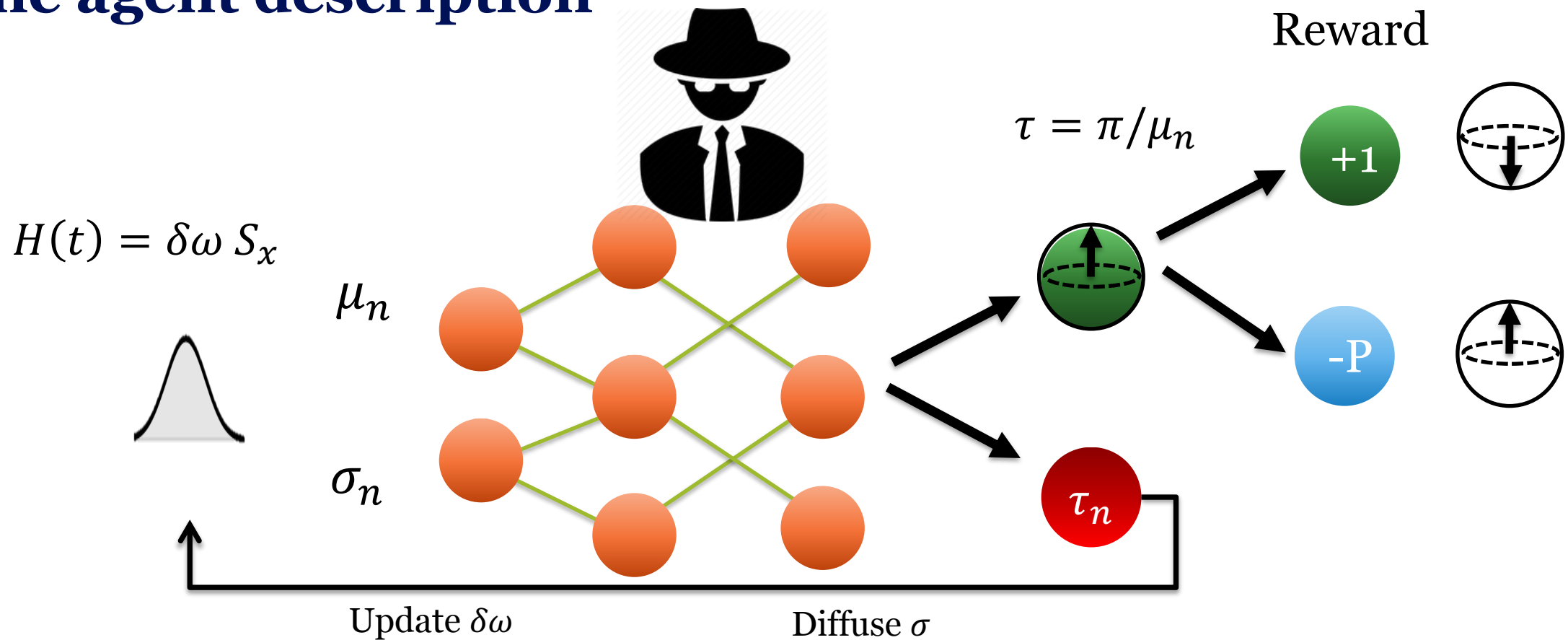
1. Observations

2. Actions

μ_n, σ_n

 Run algorithm  Estimate

The agent description



1. Observations

2. Actions

3. Bayesian update

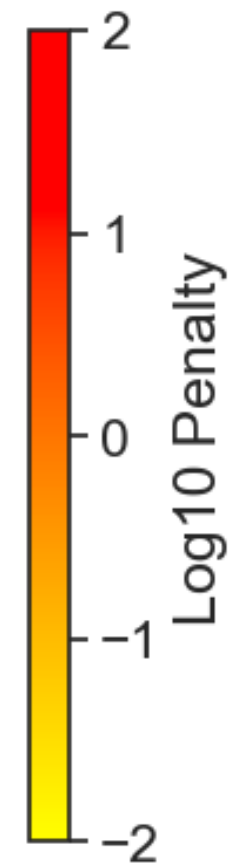
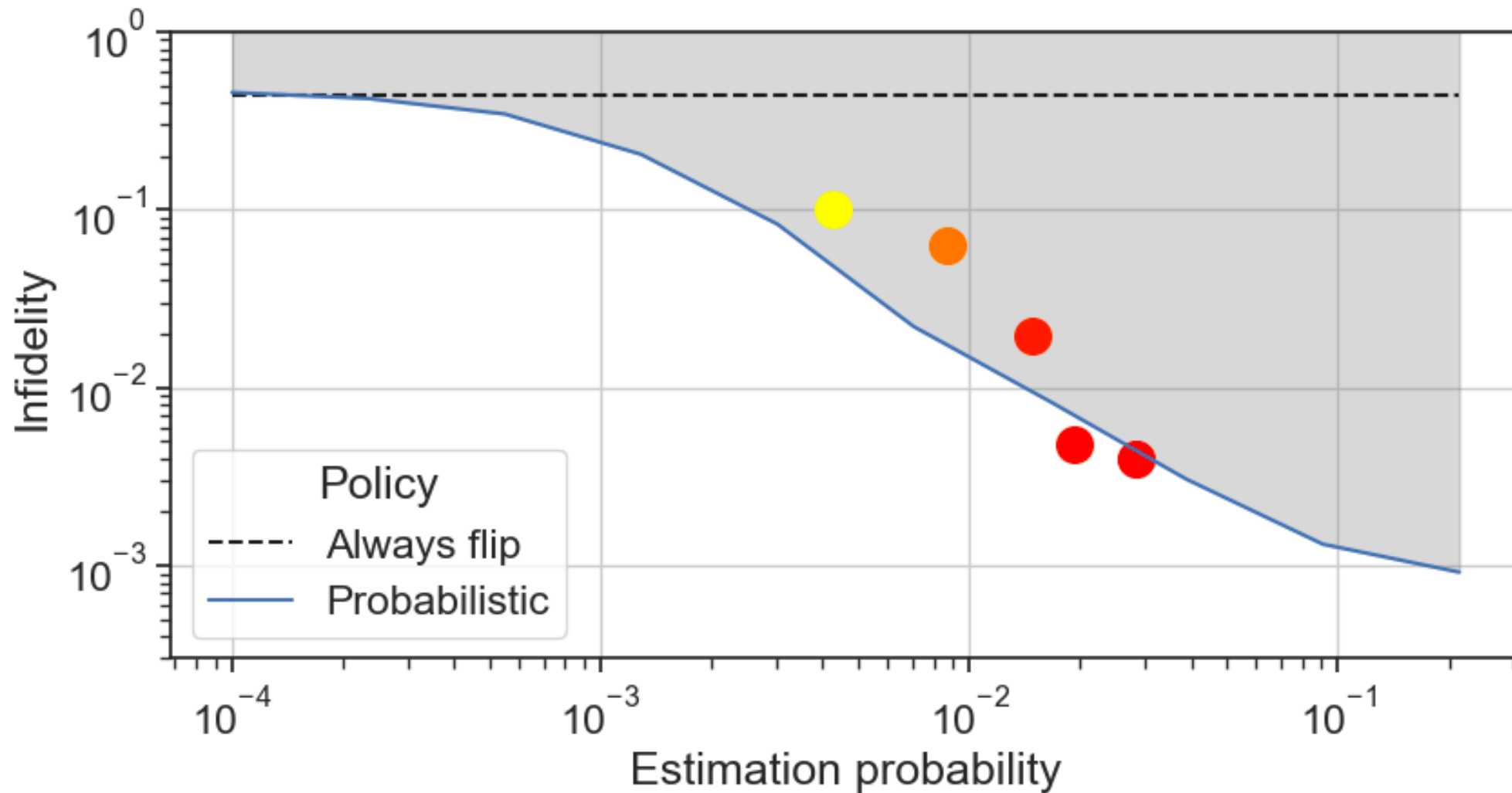
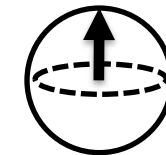
μ_n, σ_n

● Run algorithm ● Estimate

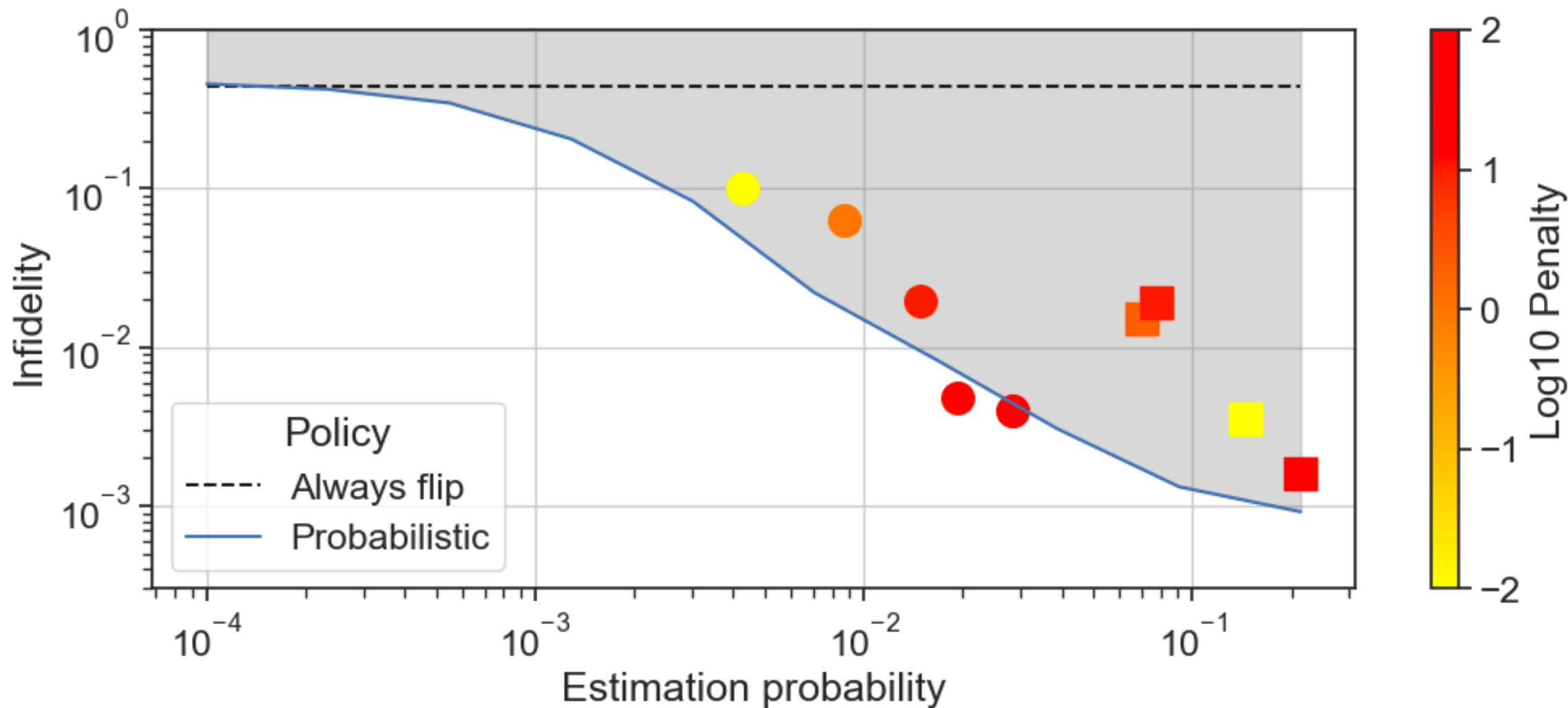
$$P(\delta\omega' t | \delta\omega, 0)$$

$$\mu_{n+1}, \sigma_{n+1} = g(\mu_n, \sigma_n, x_n, \tau_n)$$

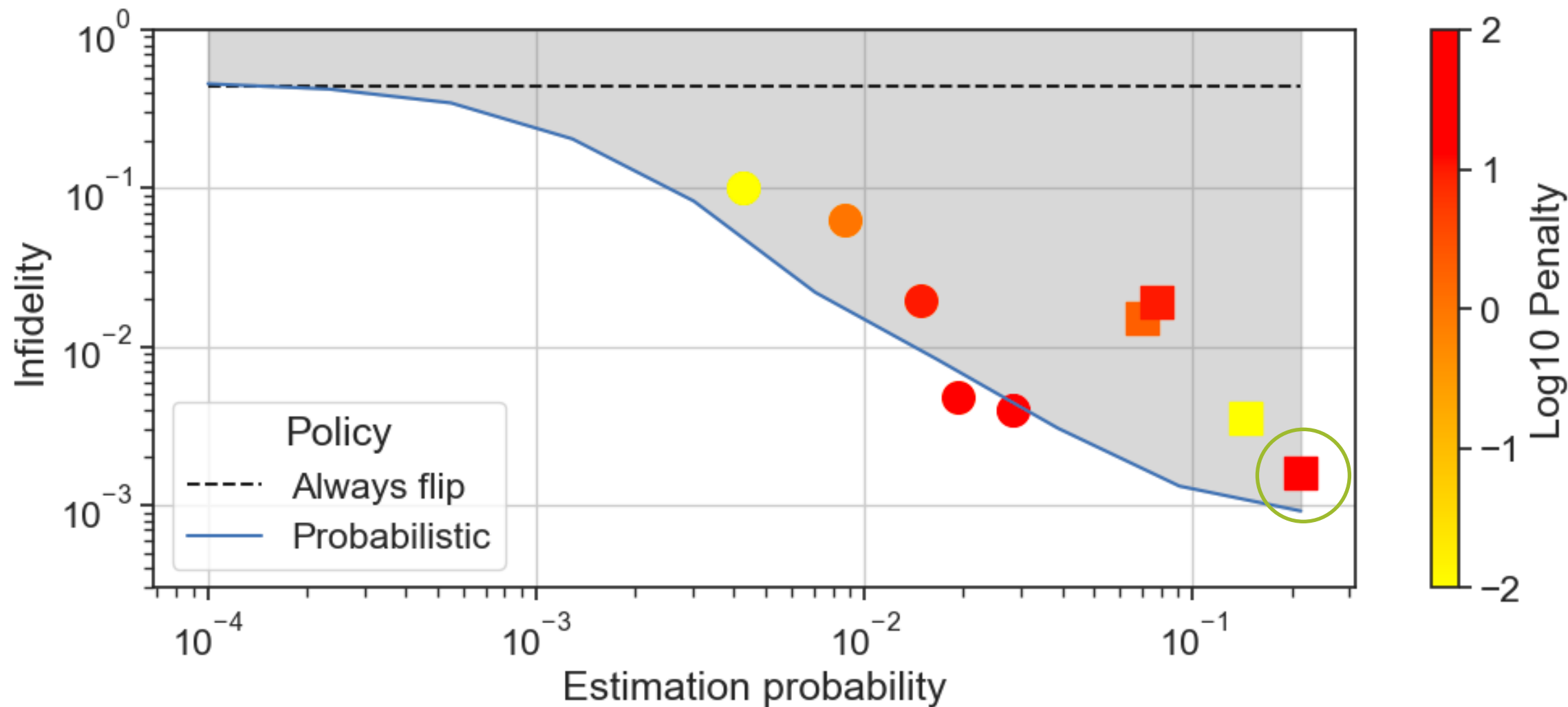
Agent cannot control time, $\tau_n = 1/c\sigma_{n-1}$



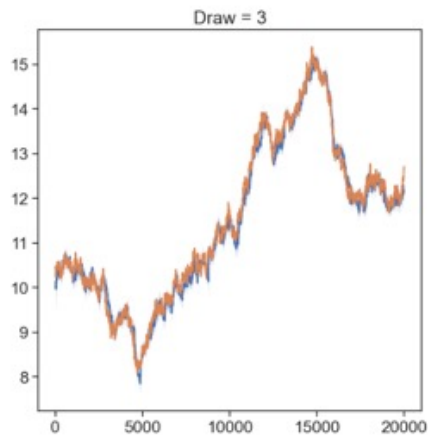
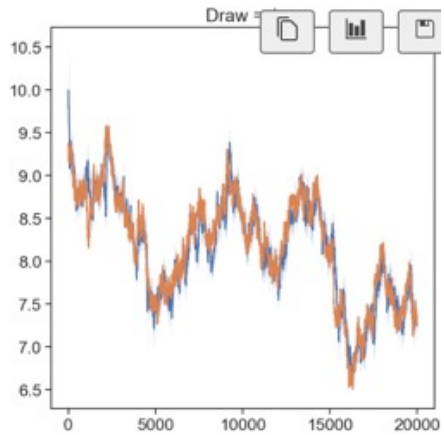
Agent can control time



Agent can control time

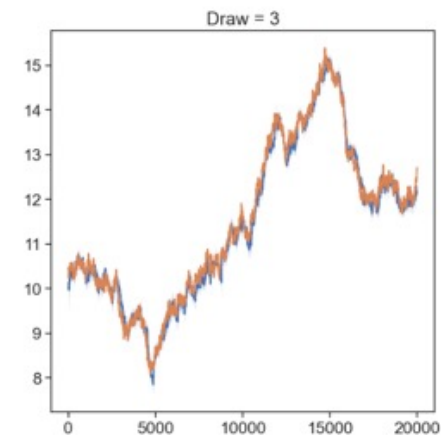
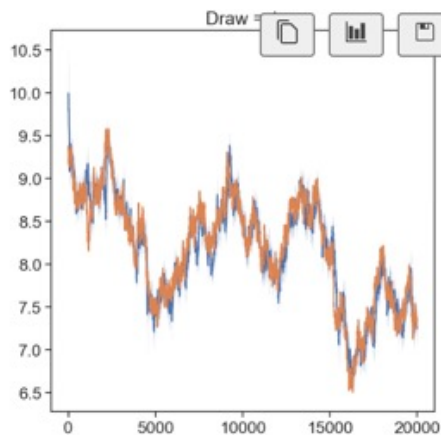


Understanding the best agent

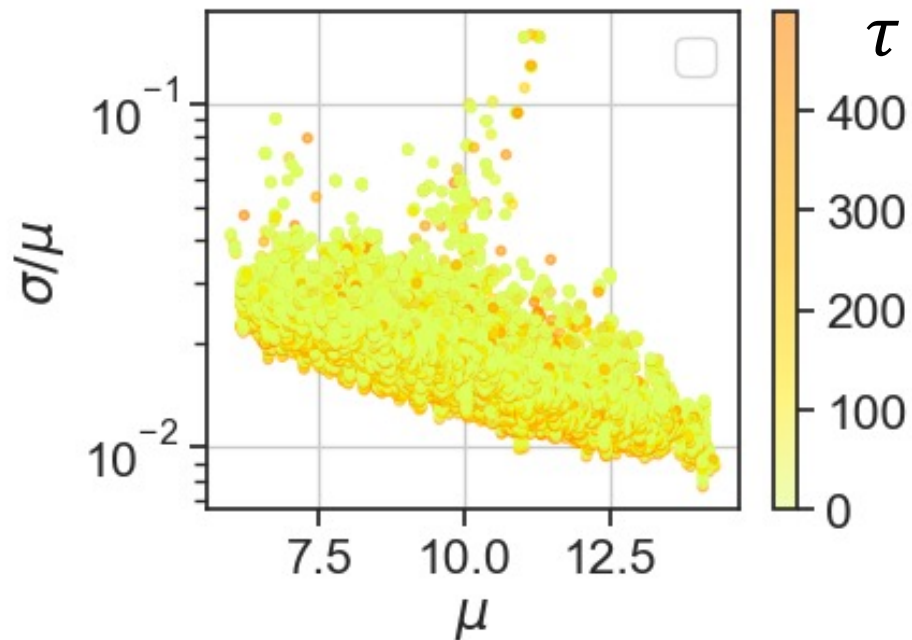


1. Tracks
trajectories

Understanding the best agent

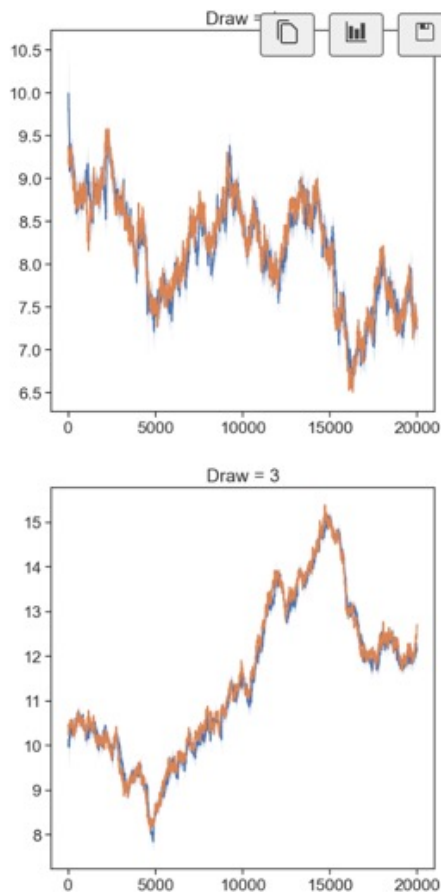


1. Tracks trajectories

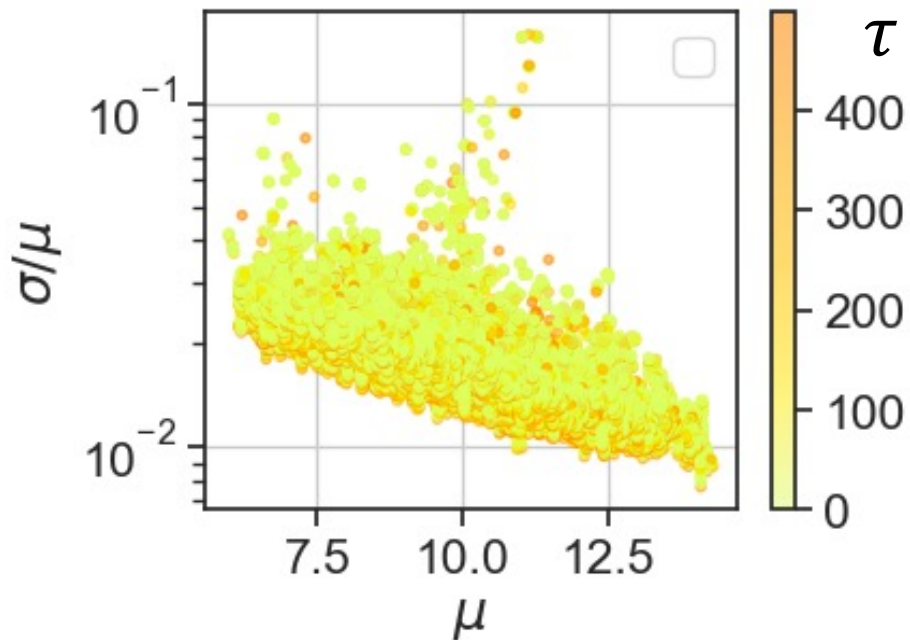


2. Applies $\frac{1}{\sigma}$ strategy

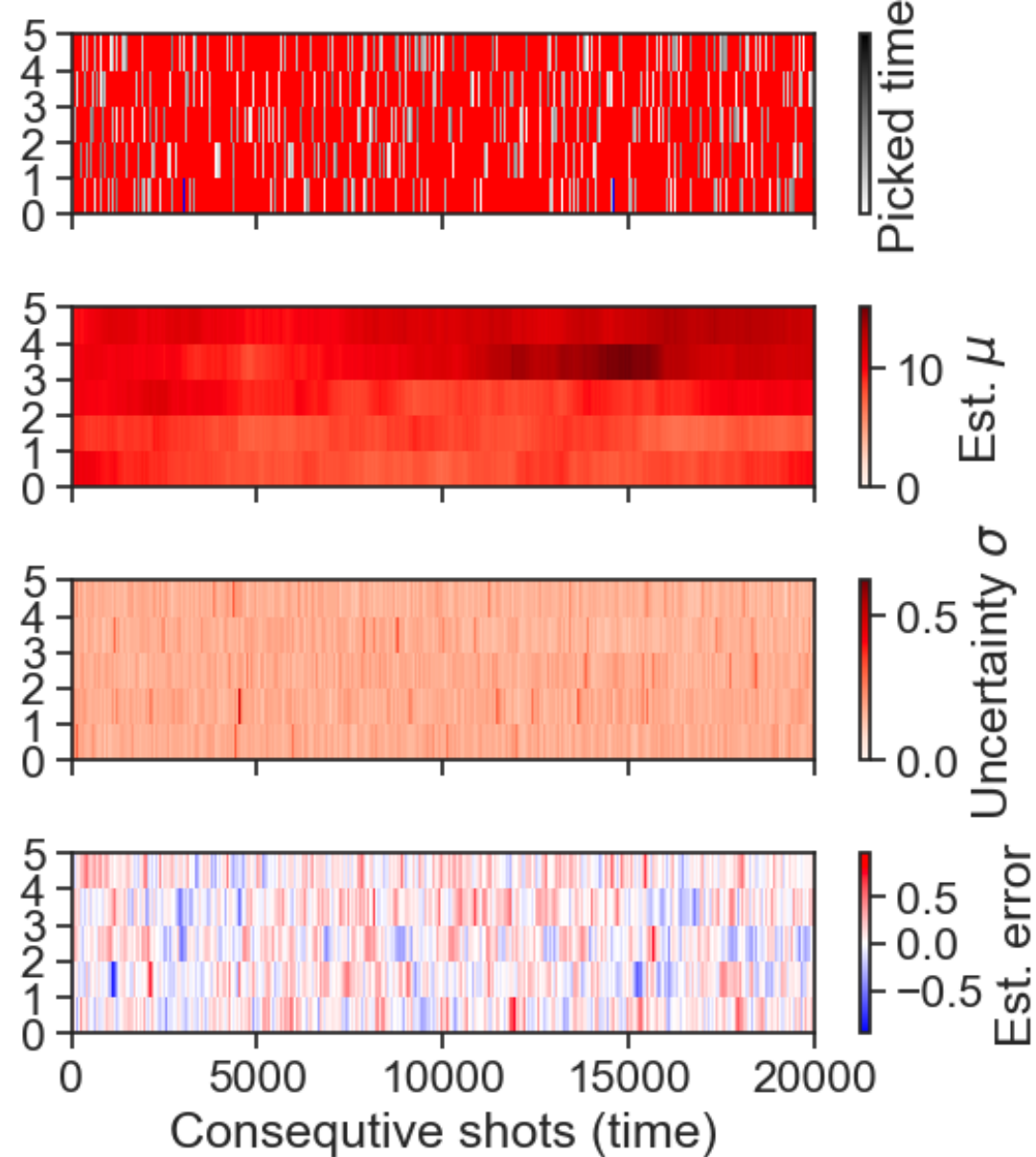
Understanding the best agent



1. Tracks trajectories

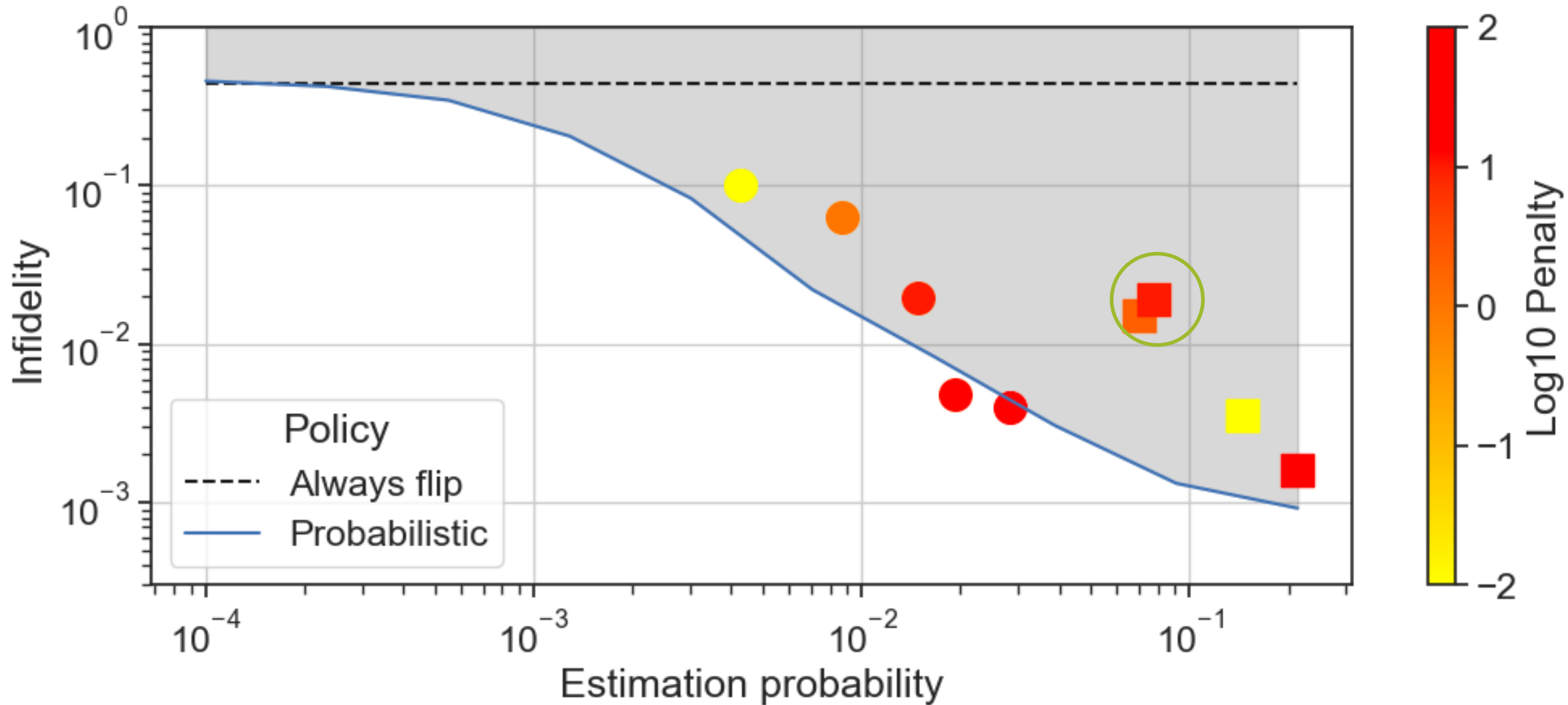


2. Applies $\frac{1}{\sigma}$ strategy

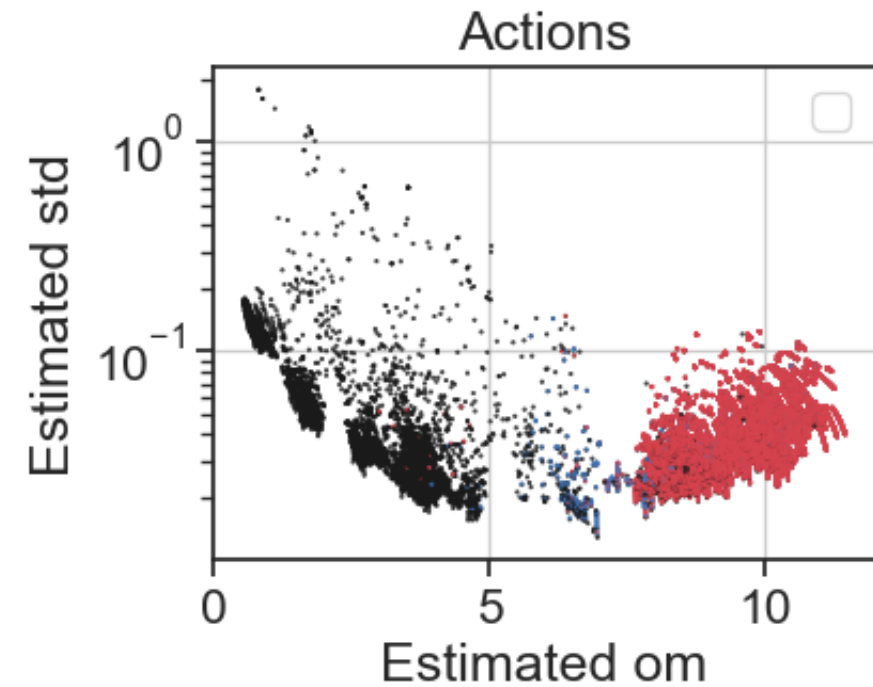


3. Behaves

But there is a more clever one

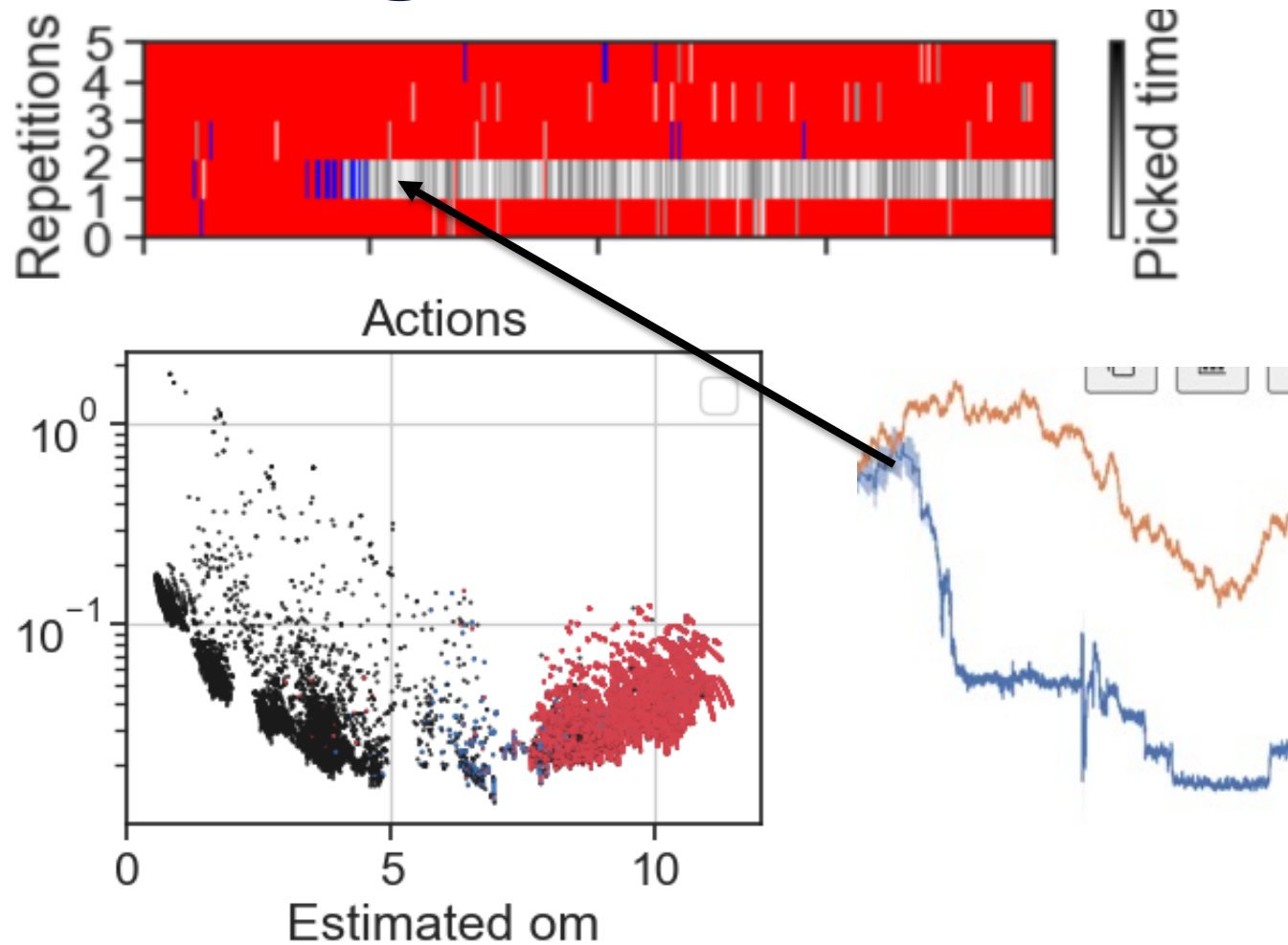


Smart agent (but not efficient)



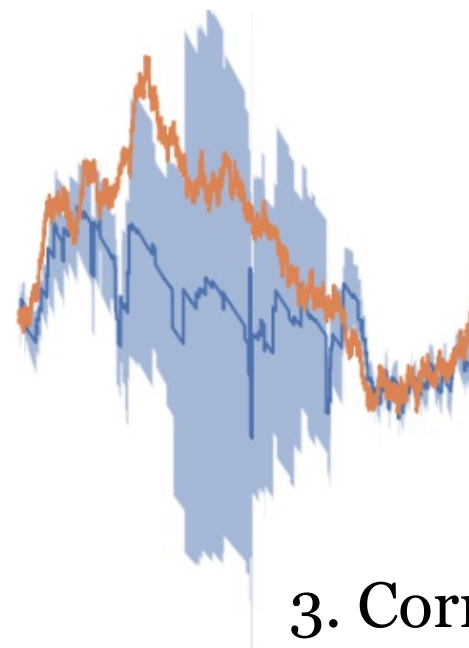
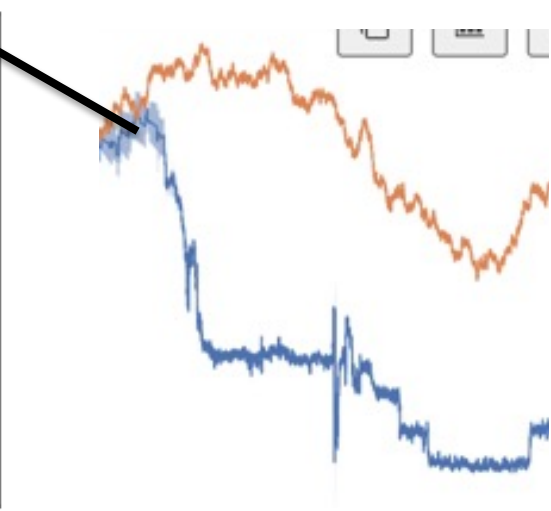
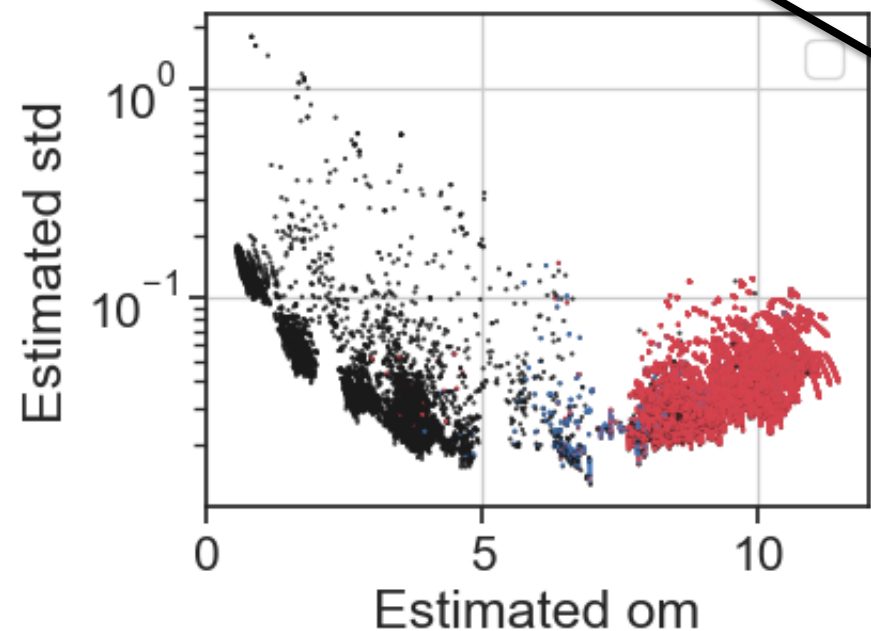
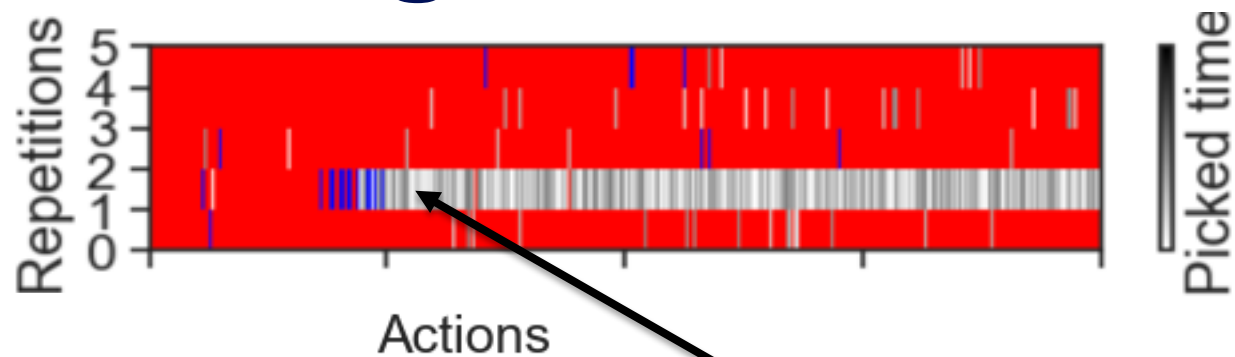
1. Waits for large field

Smart agent (but not efficient)



1. Waits for large field
2. Knows when its lost

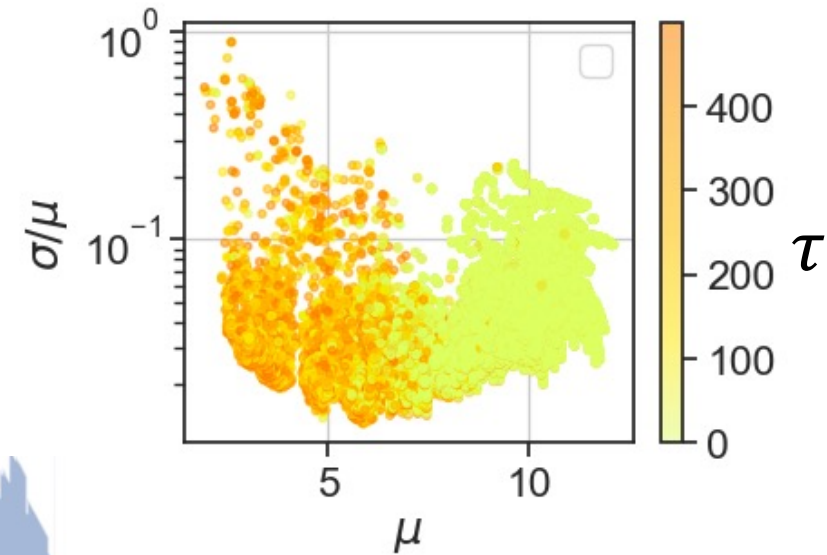
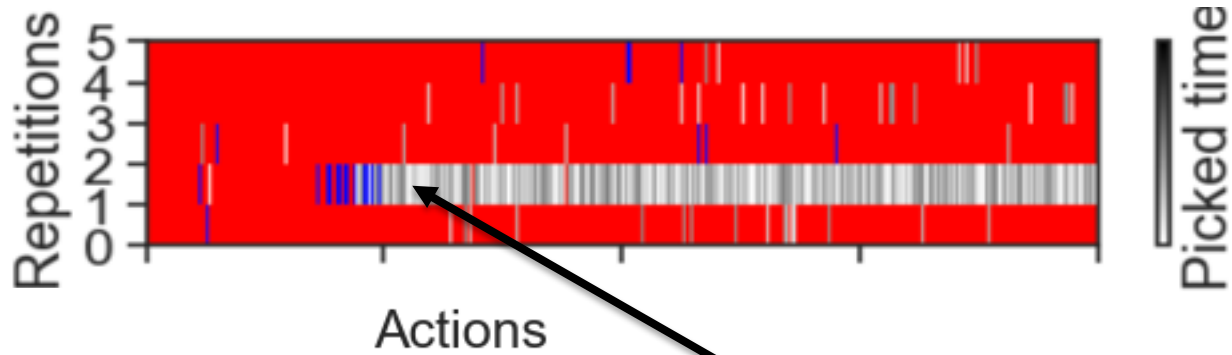
Smart agent (but not efficient)



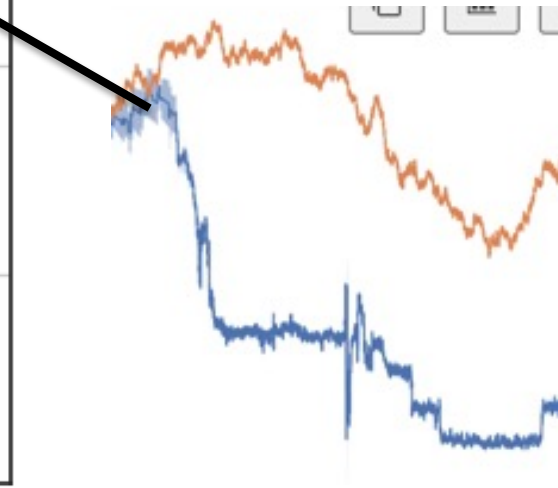
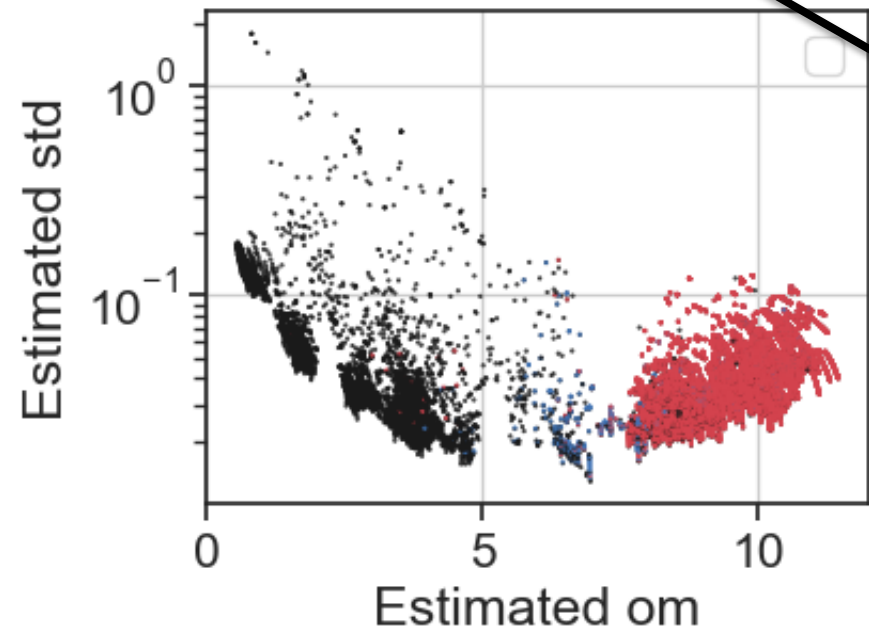
3. Correlates σ with error

1. Waits for large field
2. Knows when its lost

Smart agent (but not efficient)



4. Uses large τ
For small fields



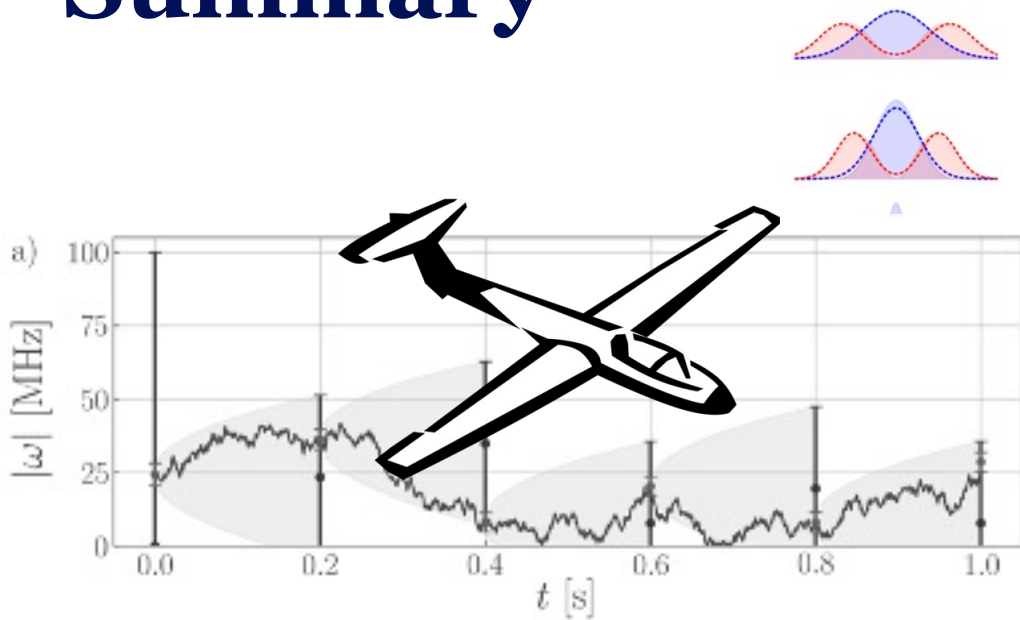
3. Correlates
 σ with error

1. Waits for large field 2. Knows when its lost

Summary



Summary



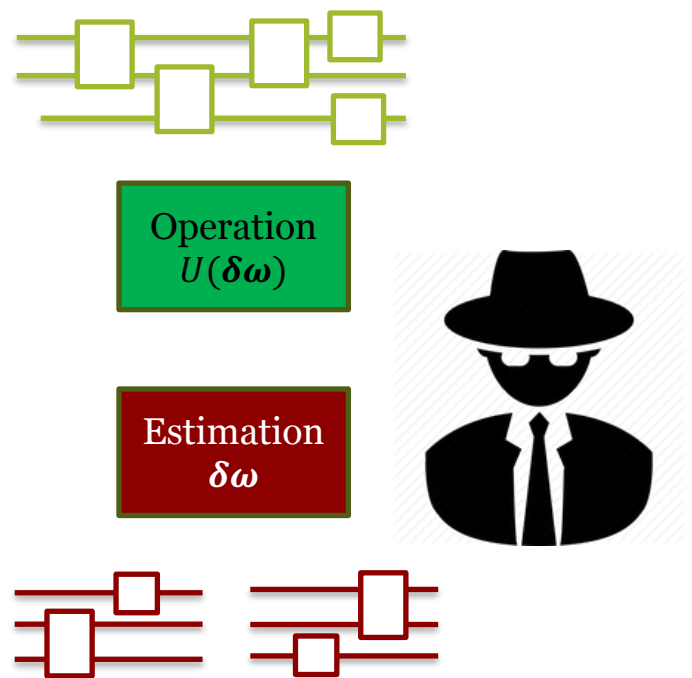
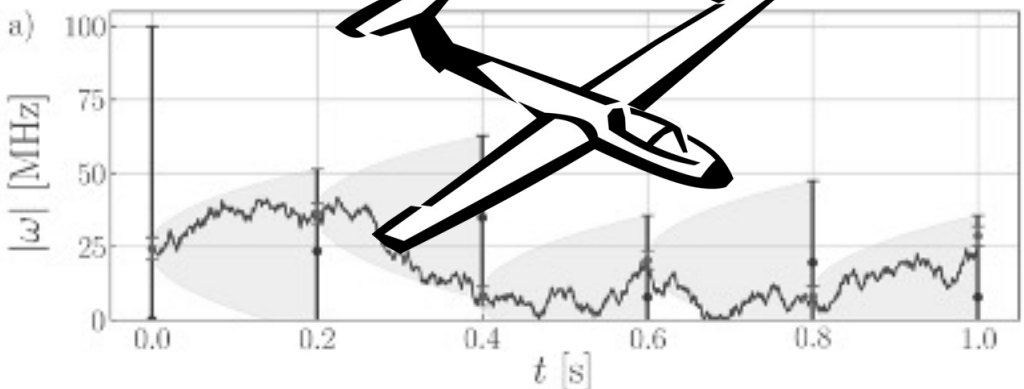
Summary

We developed methods
of fast, resource-efficient
field estimation

Outlook

Can we generalize to
arbitrary noise source?

Summary



Summary

We developed methods of fast, resource-efficient field estimation

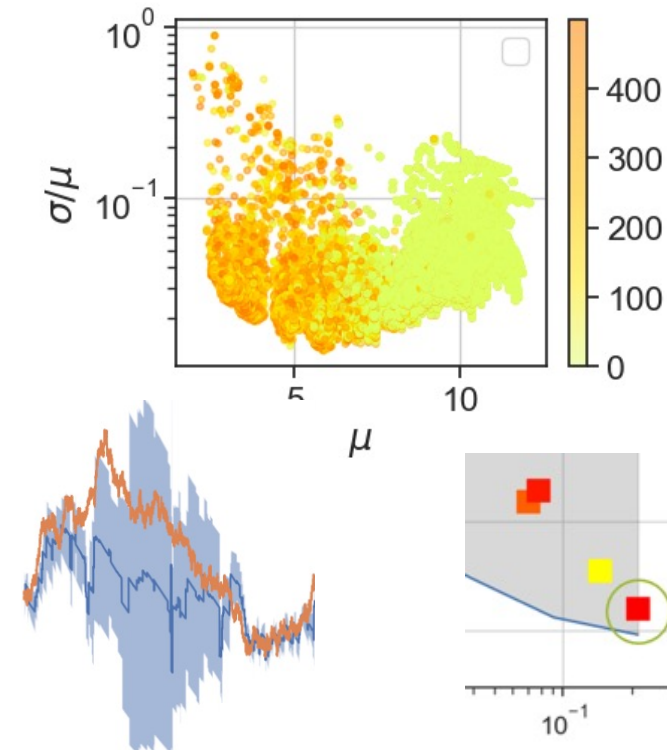
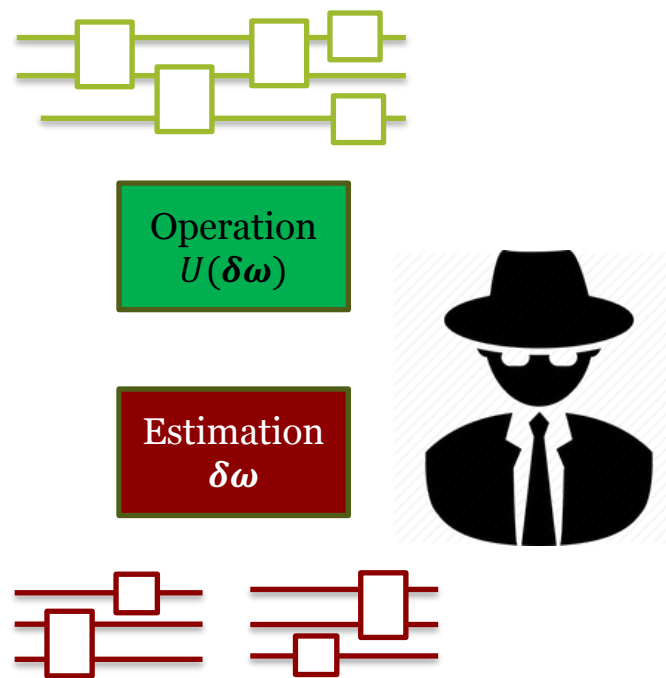
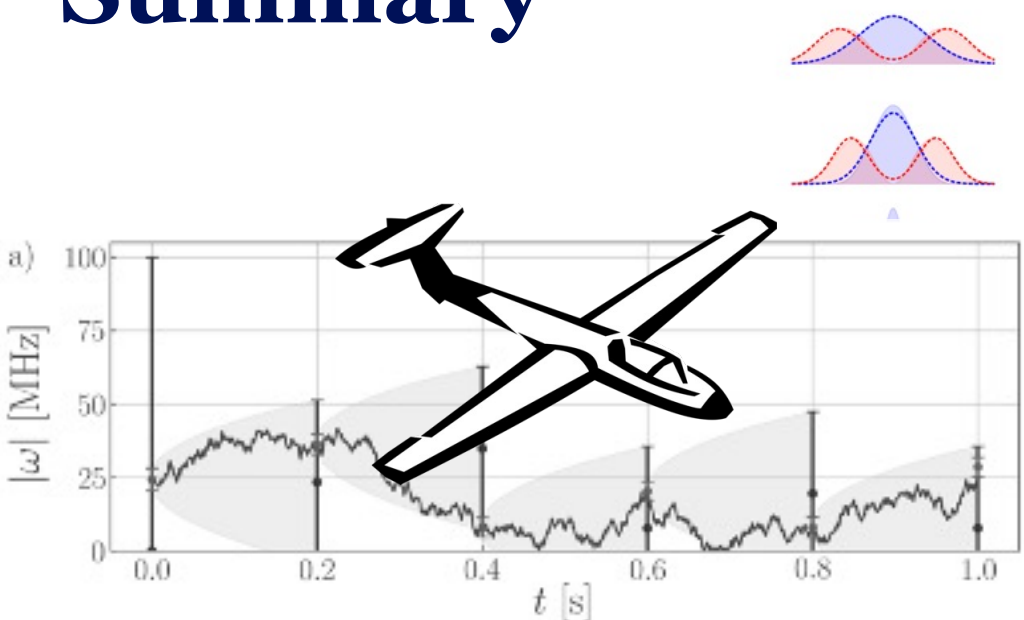
We employed a RL agent to dynamically change between estimation and operation modes

Outlook

Can we generalize to arbitrary noise source?

Can we do online learning (FPGA?)
Can we use it for two-qubit gates?

Summary



Summary

We developed methods of fast, resource-efficient field estimation

We employed a RL agent to dynamically change between estimation and operation modes

The agent developed non-trivial strategies and matched best-known heuristics

Outlook

Can we generalize to arbitrary noise source?

Can we do online learning (FPGA?)
Can we use it for two-qubit gates?

Can we beat the heuristics?
Can we use the learned strategy to improve heuristics?

Hadamard gate

$$J(\epsilon^*) = \Delta B_z$$

- For each shot, we performed two estimations:

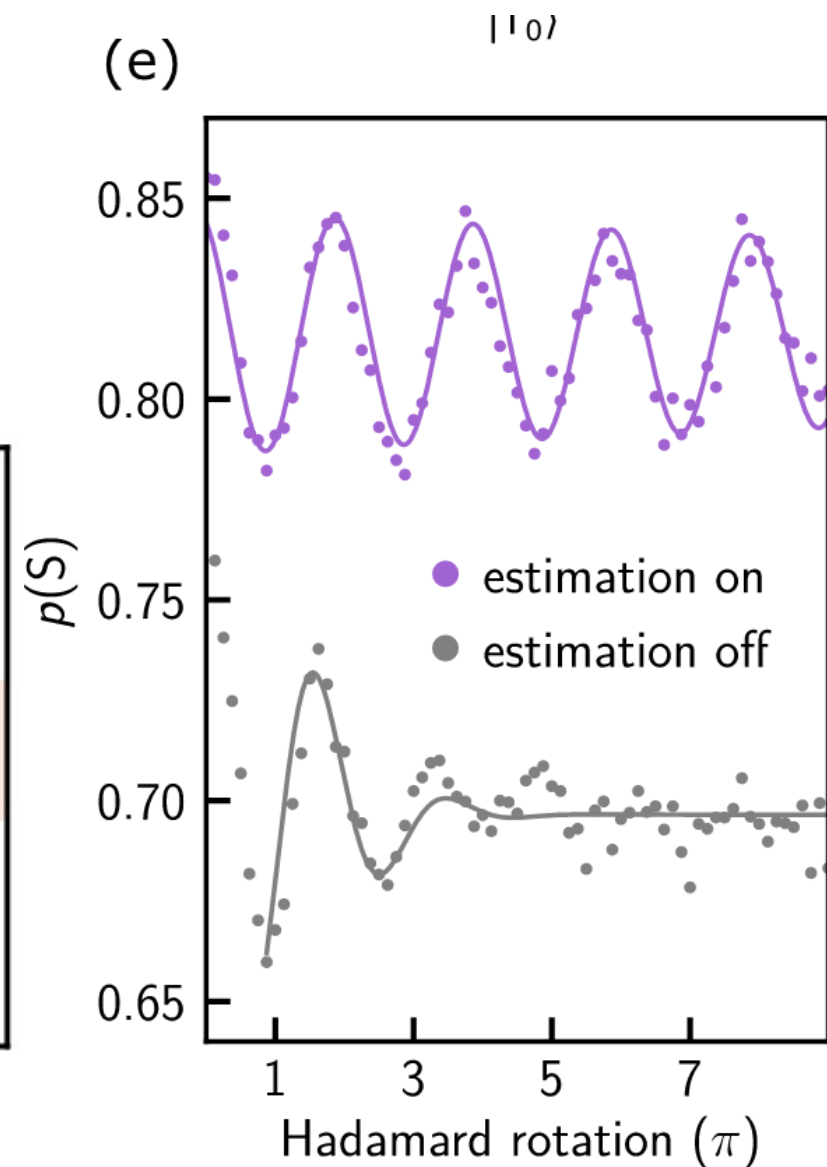
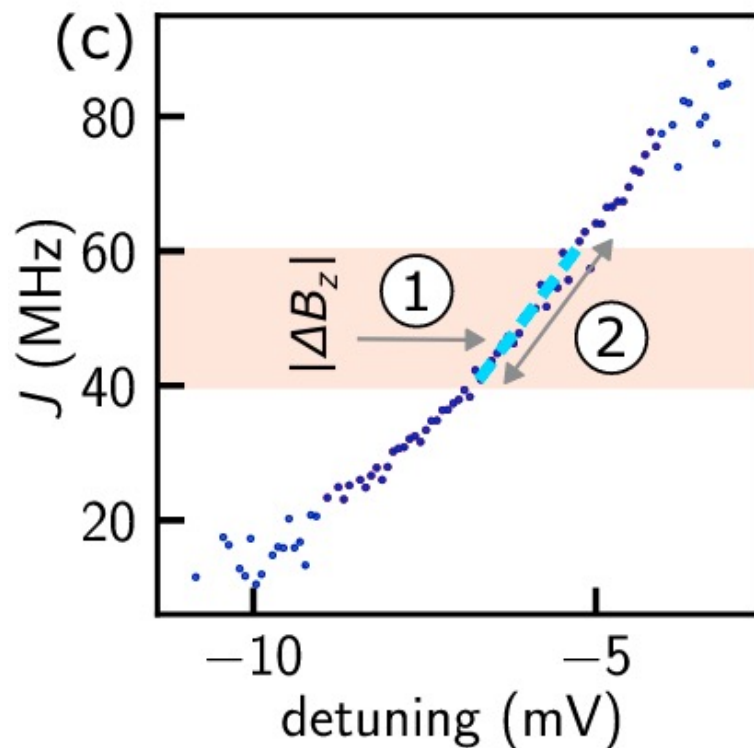
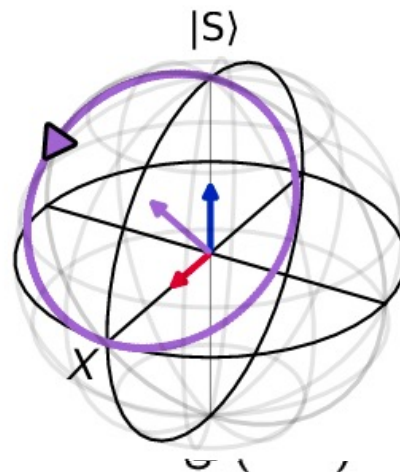
1. Estimation of ΔB_z

2. Estimation of $\Omega(\epsilon)$, at ϵ

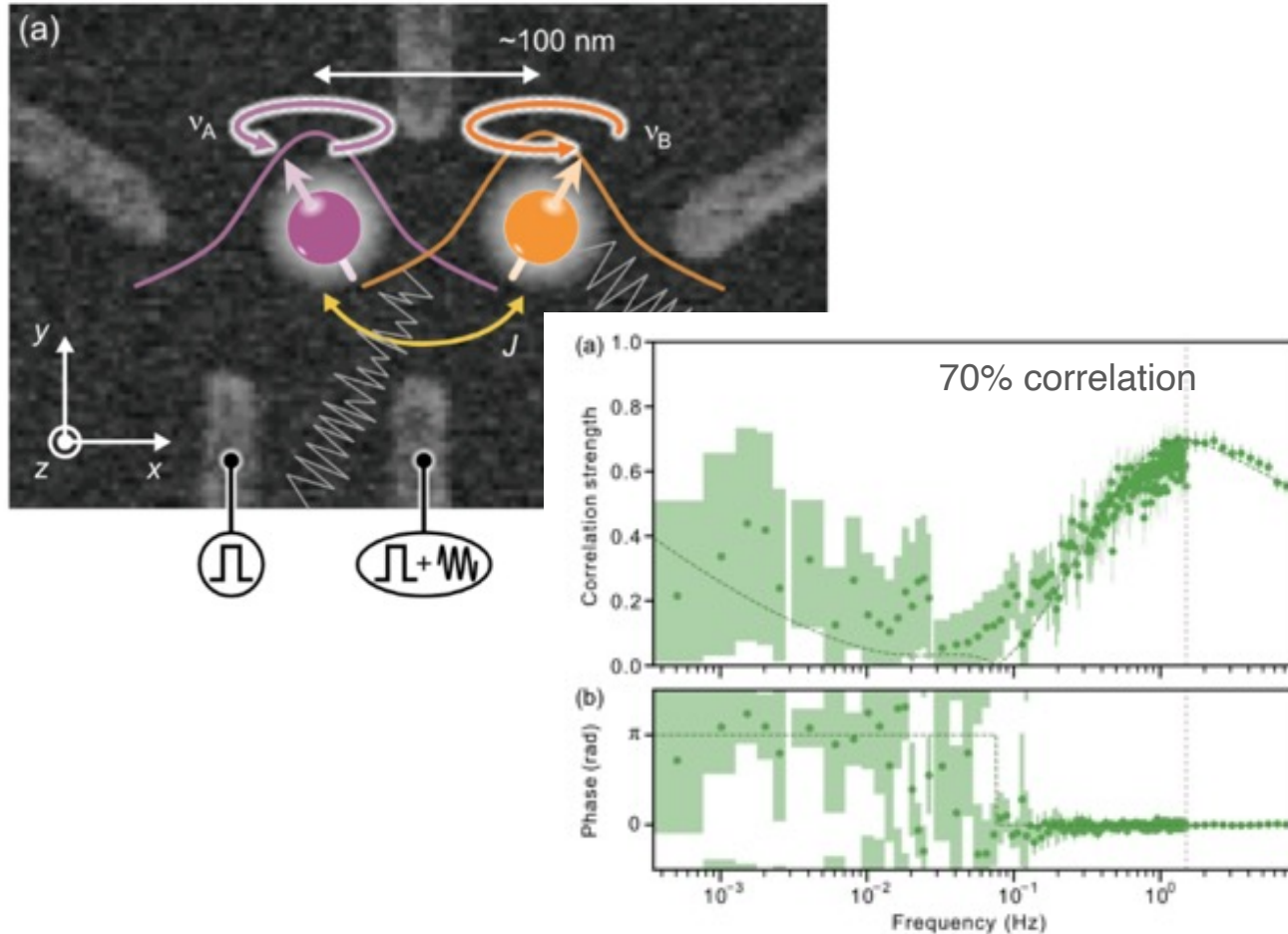
where $J(\epsilon) = \Delta B_z$

- Based on $\Delta\Omega$:

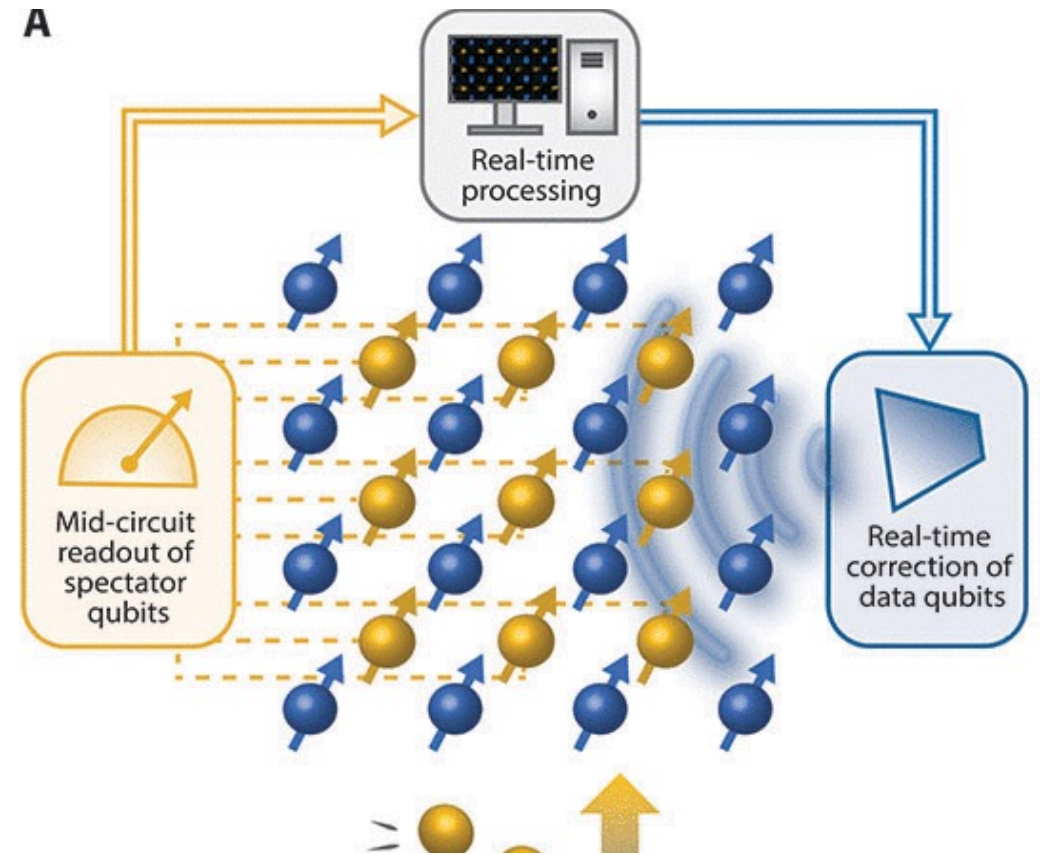
$$\Delta\epsilon = \epsilon - \epsilon^*$$



Investigate utility of spatial correlations



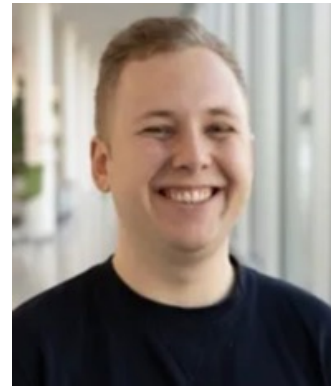
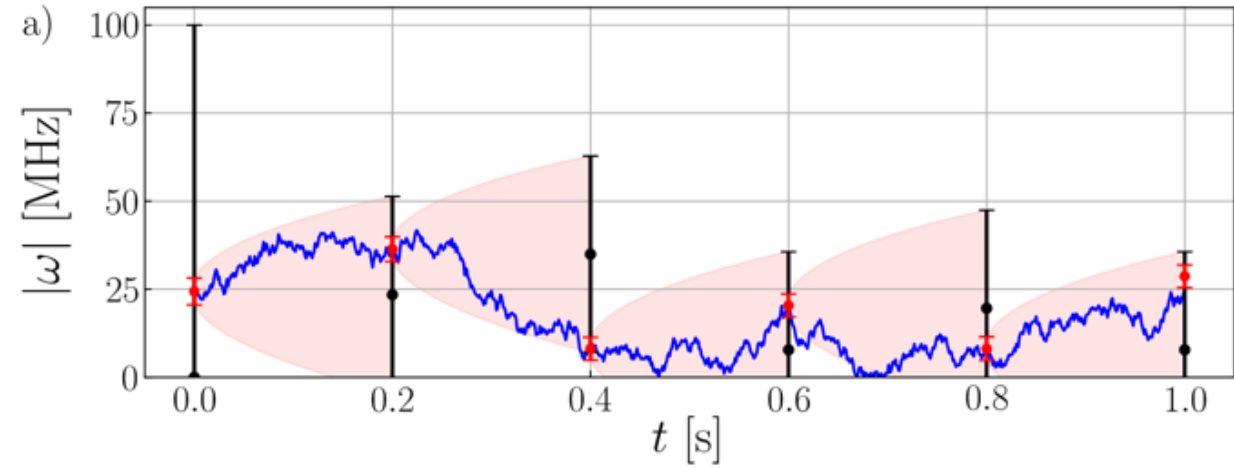
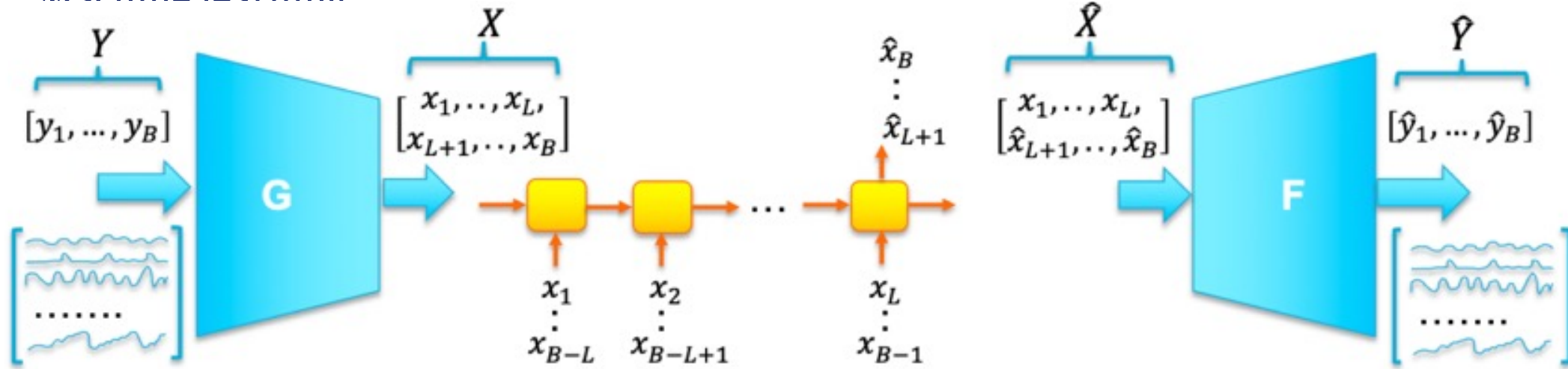
Y. Yoneda et al., arXiv:2208.14150 (2023)



K. Singh *et al.*, Mid-circuit correction of correlated phase errors using an array of spectator qubits *Science* **380**,1265-1269 (2023).

Trajectory analysis and prediction

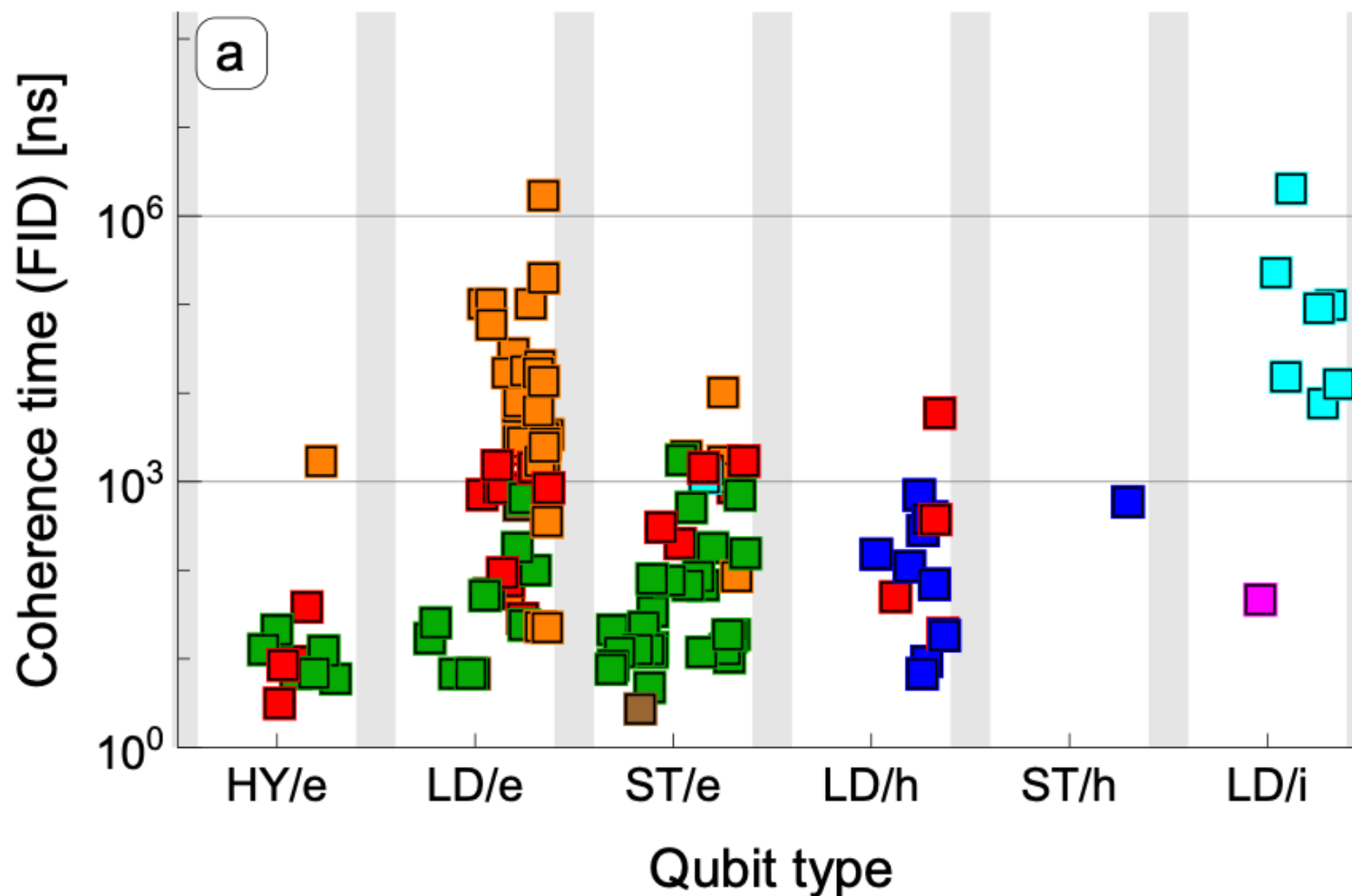
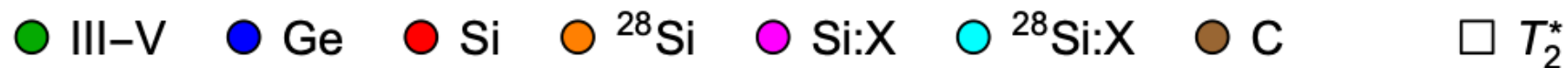
- Representing the sequential estimation and field broadening in the language of functional integral
- Process identification and prediction enabled by Machine learning



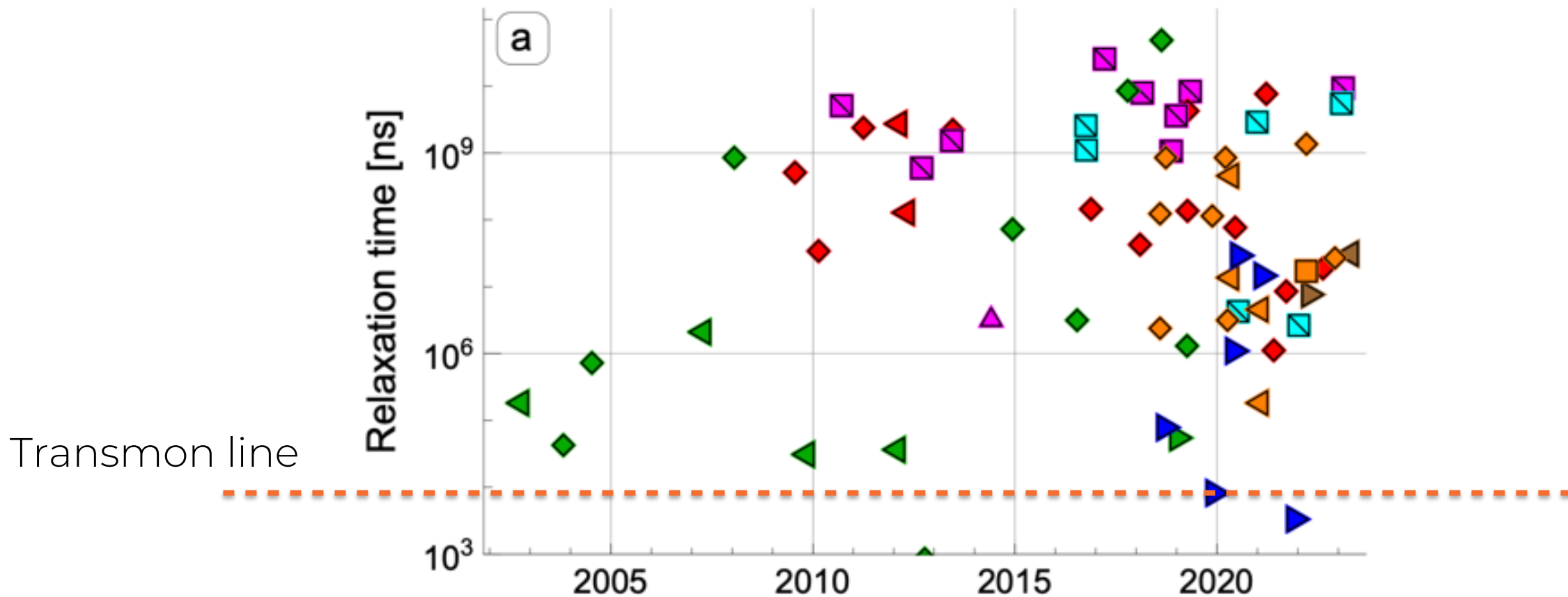
Felix Frohnert

N. Nguyen, B. Quanz, Temporal Latent Auto-Encoder: A Method for Probabilistic Multivariate Time Series Forecasting, arXiv:2101.10460 (2021)

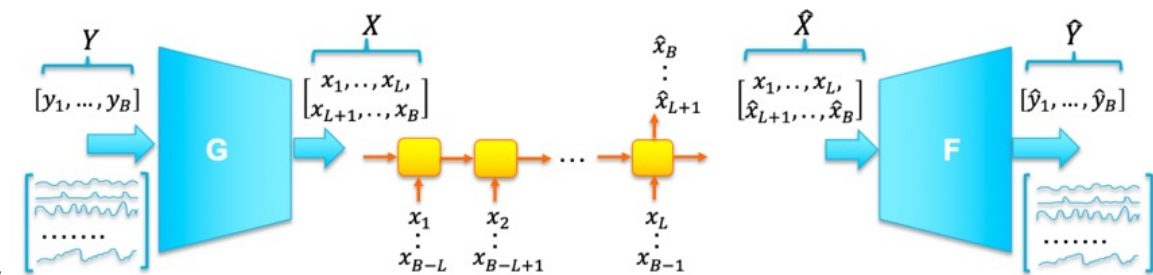
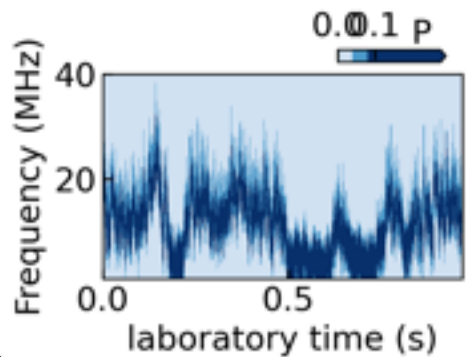
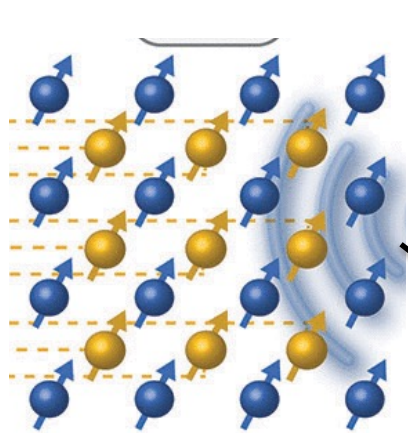
Spin qubits are limited by inhomogeneous broadening...



... and we can forget about relaxation times T_1

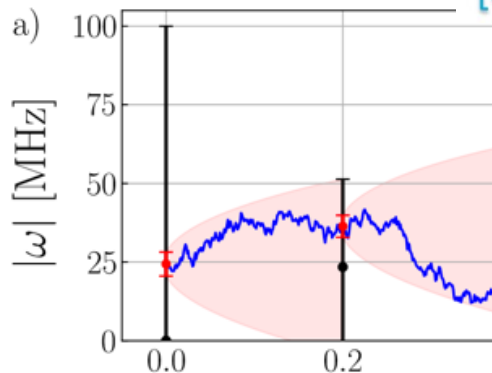
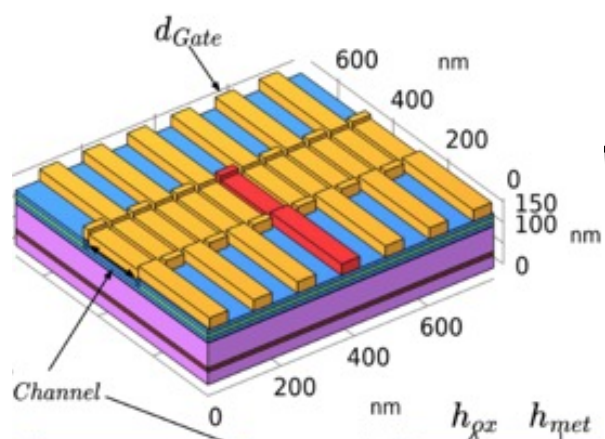


Anyway the Wind Blows: Bayesian Estimation and Feedback for Correlated

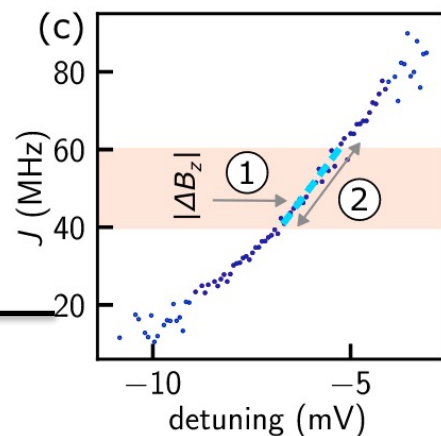


Future quantum computer

PLAN: Use ML, filtering and Bayesian tools

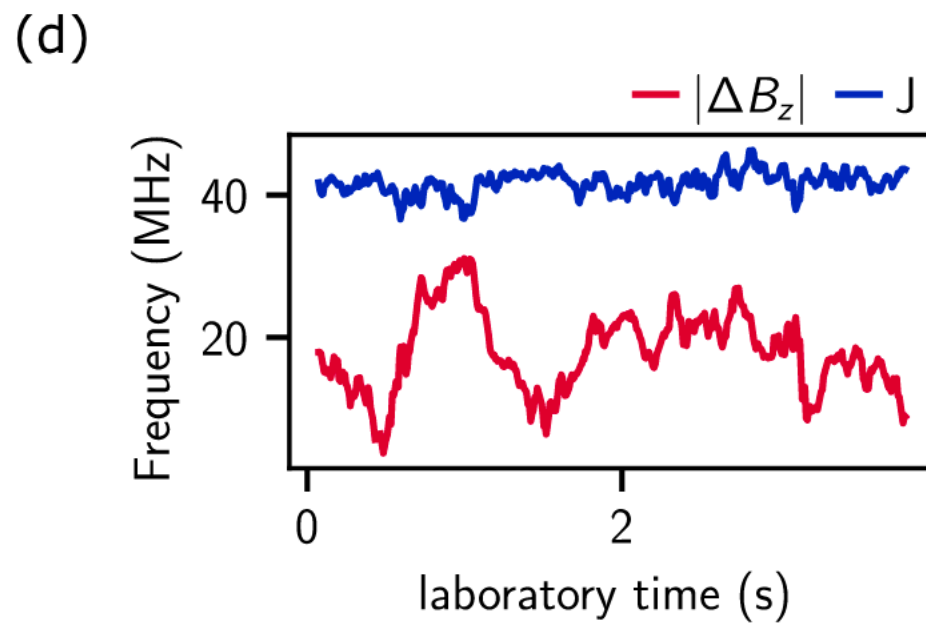
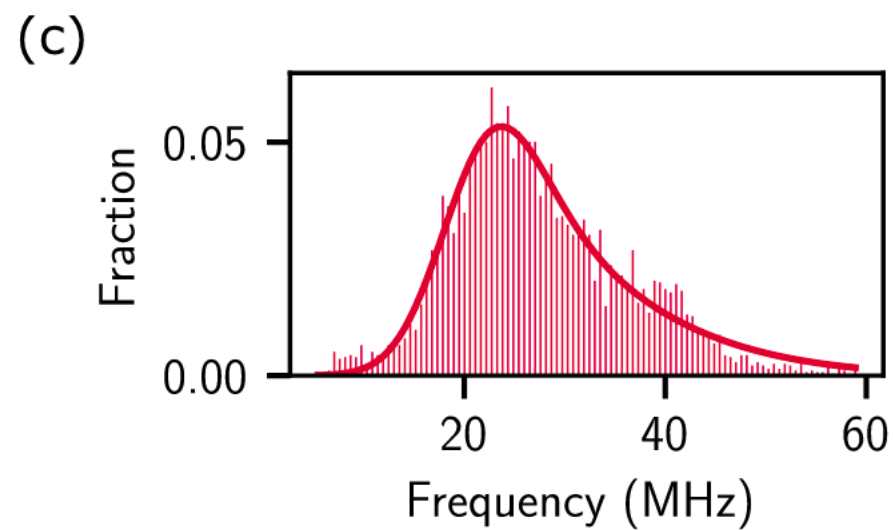
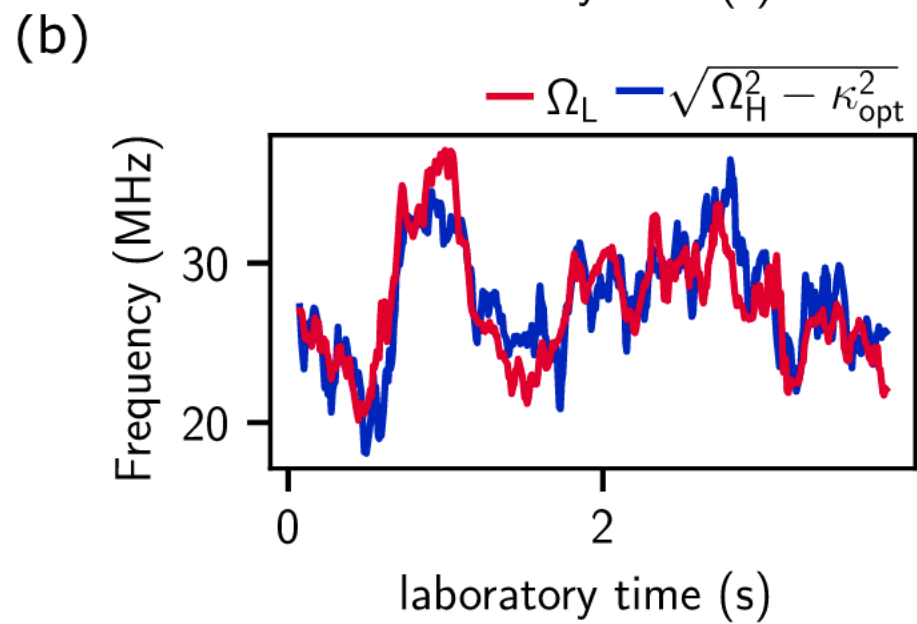
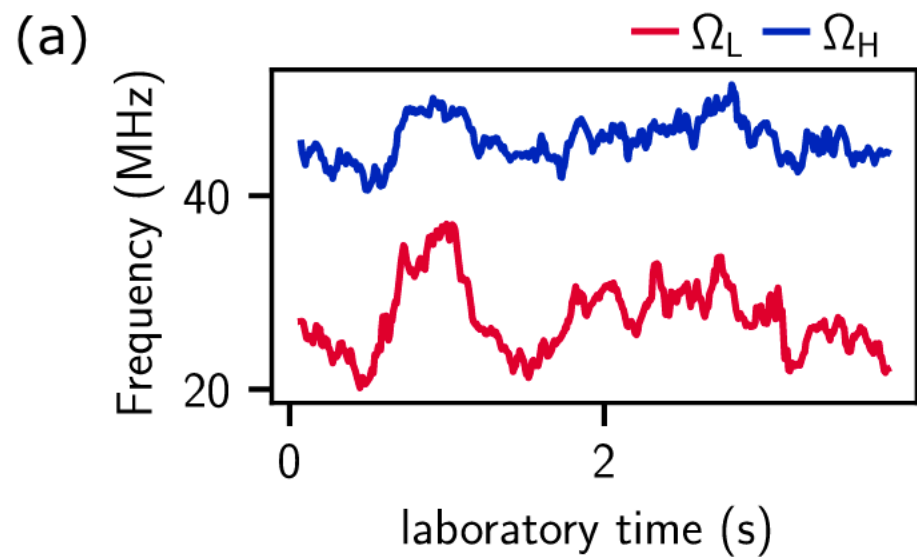


Tracking Hamiltonian Parameters



Feedback for Hadamard gate

Model of charge noise
And spatial correlations

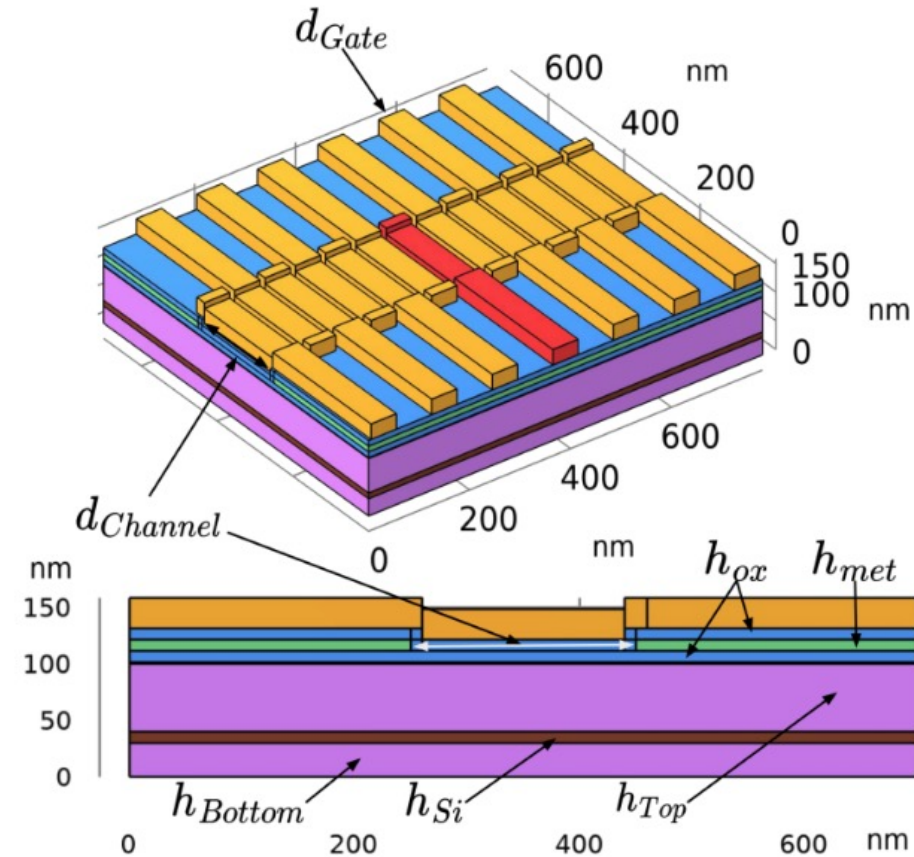
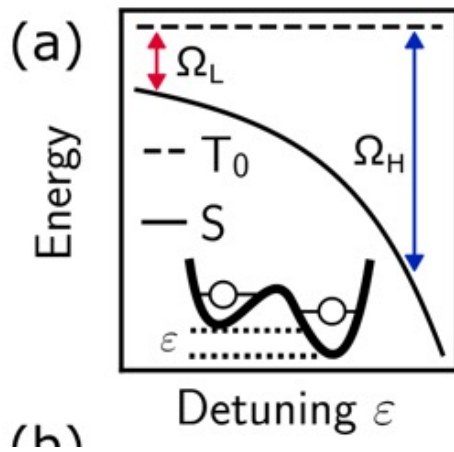


Charge noise

- Charge noise limits almost all spin qubits. For S-T we have

$$J(\epsilon + \delta\epsilon) = J(\epsilon) + \partial_{\epsilon}J(\epsilon)\delta\epsilon$$

- It is believed to originate at the isolated chargers at the oxide-semiconductor interface

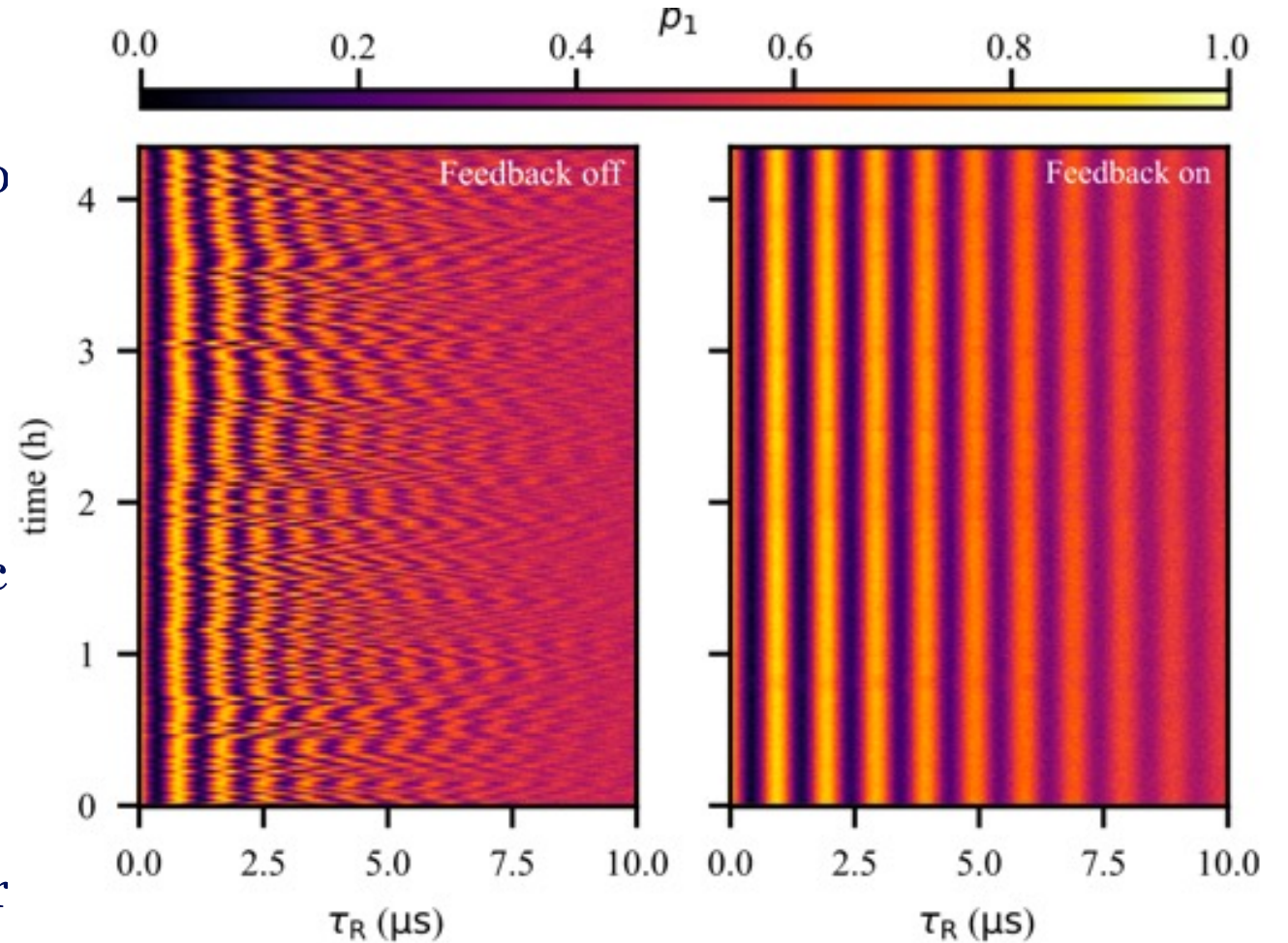


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$$J(\epsilon + \delta\epsilon) = J(\epsilon) + \partial_{\epsilon}J(\epsilon)\delta\epsilon$$

- It is believed to originate at the isolated chargers at the oxide-semiconductor interface
- Each defect is a source of telegraph noise, which result in $1/f$ spectral density
- In comparison to ΔB_z charge noise have more weight at finite frequency.



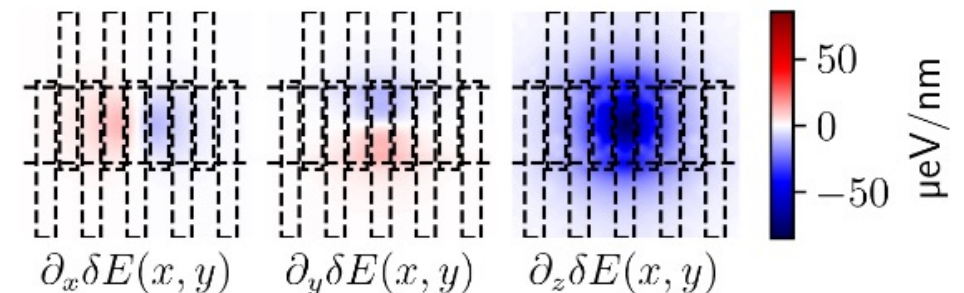
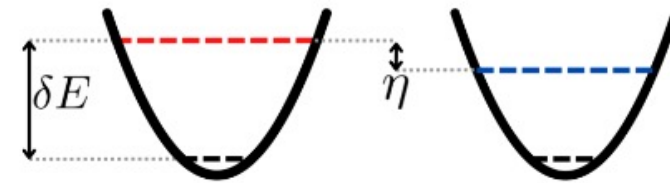
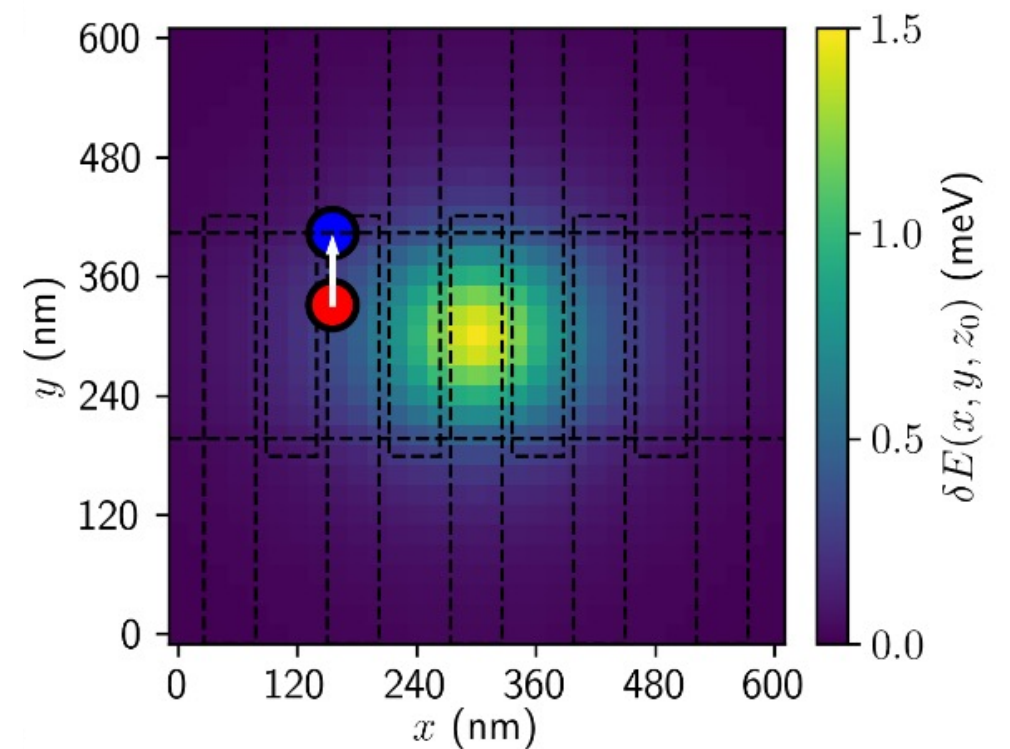
Model of charge noise

- Noise come from the sum of TLF

$$\sigma^2 = \sum_n \eta_n^2$$

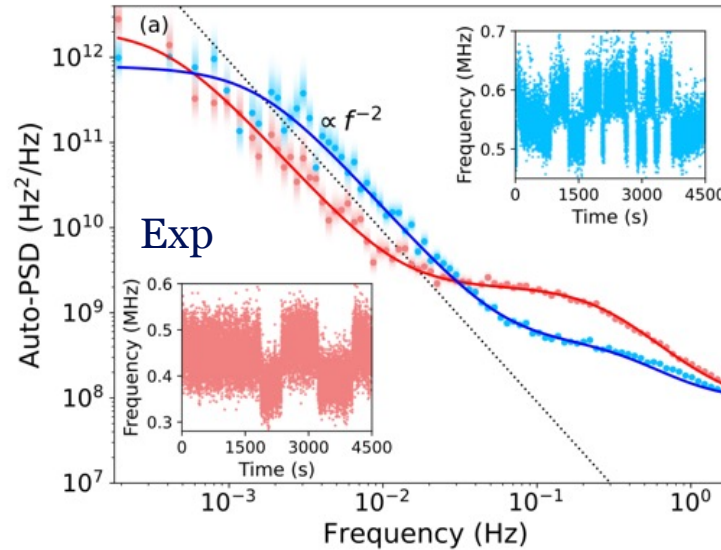
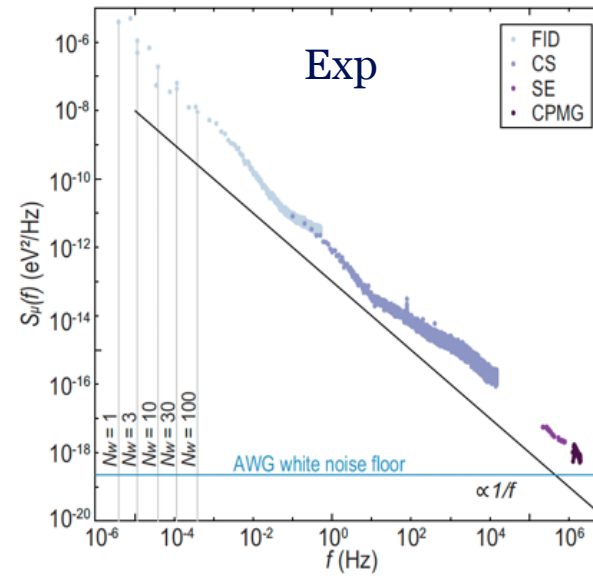
- Each defect charge can physically move by random vector $\delta \mathbf{r}_n$
- Use finite-element method (COMSOL) to compute shift of dots energy $\delta E(x, y, z_0)$ due to defect at (x, y, z_0)
- We compute the contribution from charge movement using spatial derivatives:

$$\eta_n = \nabla \delta E \cdot \delta \mathbf{r}_n$$

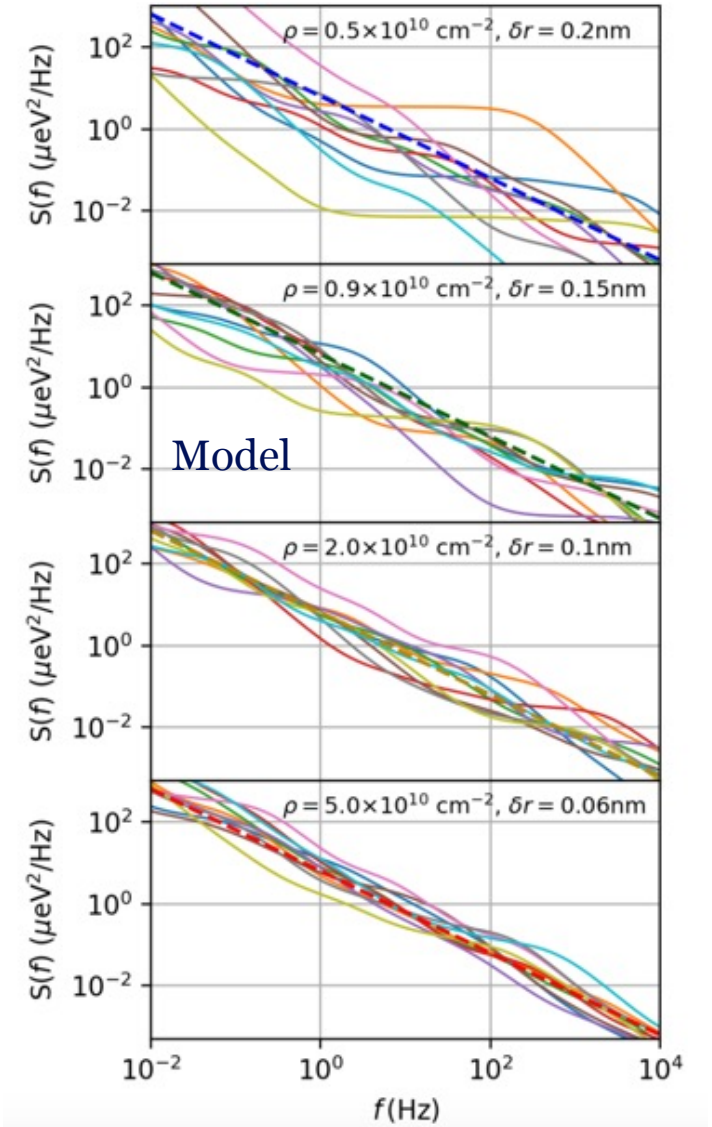


Spectral density

- Compared against experimentally measured spectra
- Adjusted two free parameters
 - Defect density ρ
 - Typical size of the displacement δr



arXiv 2302.11717 (2023)



Planar motion of the charges?

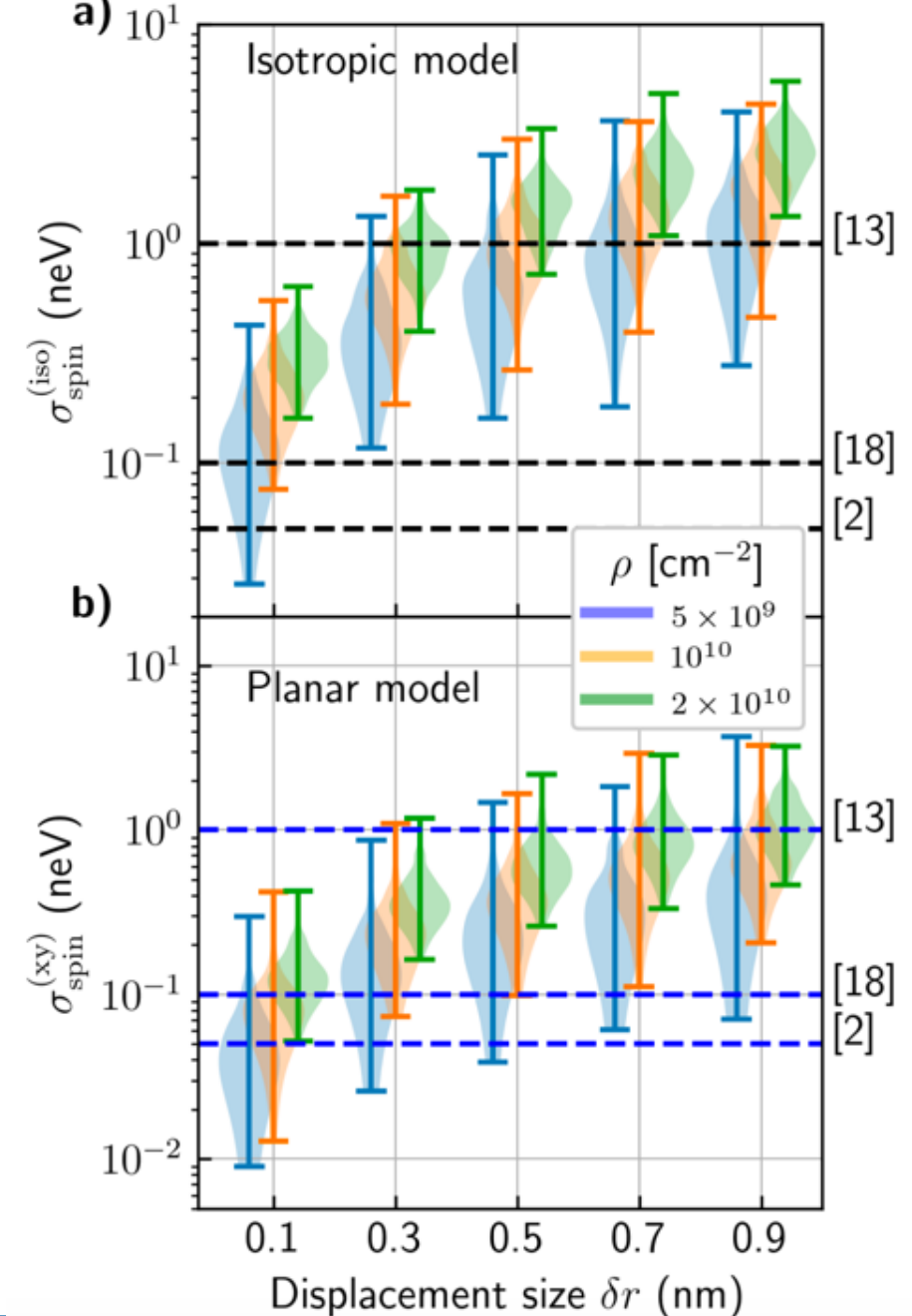
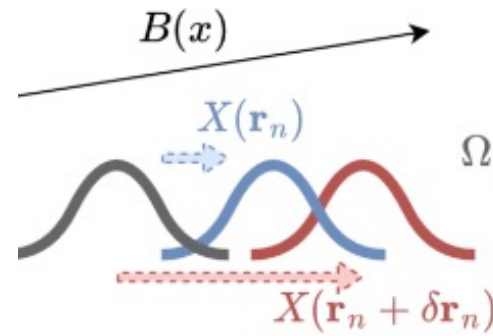
- Charge noise induces spin splitting noise(SOI)

$$H = \mathbf{B}_{\parallel} \cdot \boldsymbol{\sigma} = \Omega \hat{\sigma}'_z$$

- It is caused by shaking of wavefunction in presence of mag. field gradient

$$\delta\Omega(\mathbf{r}_n) = g\mu_B \Delta B_{\parallel} \cdot \delta R(\mathbf{r}_n)$$

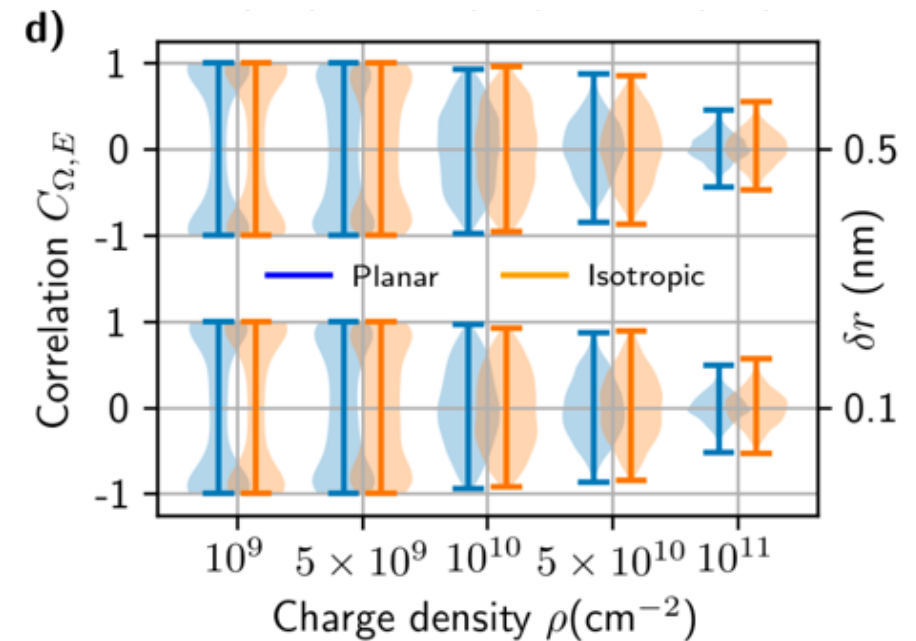
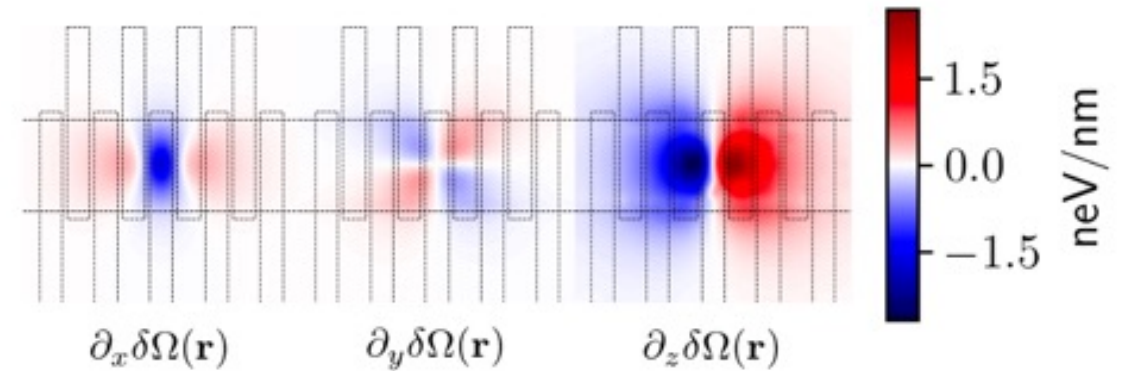
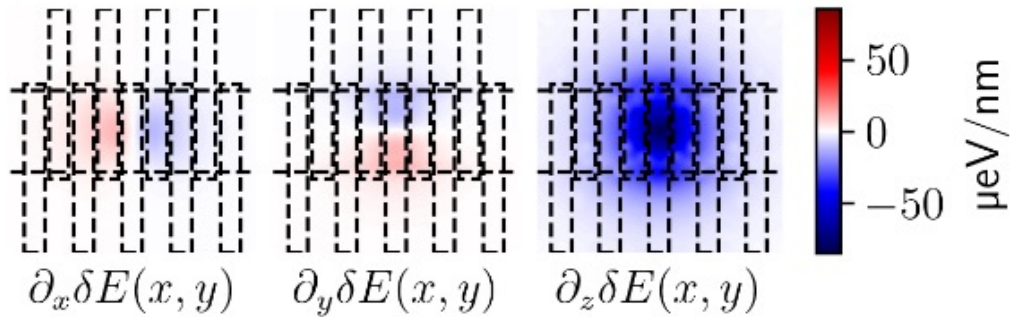
- From this analysis we made a hypothesis that charges move in the planar direction
- We predict $\rho \approx 10^{10} \text{ cm}^{-2}$, $\delta r = 0.5 \text{ nm}$



Orbital noise and spin splitting noise are (spatially) correlated

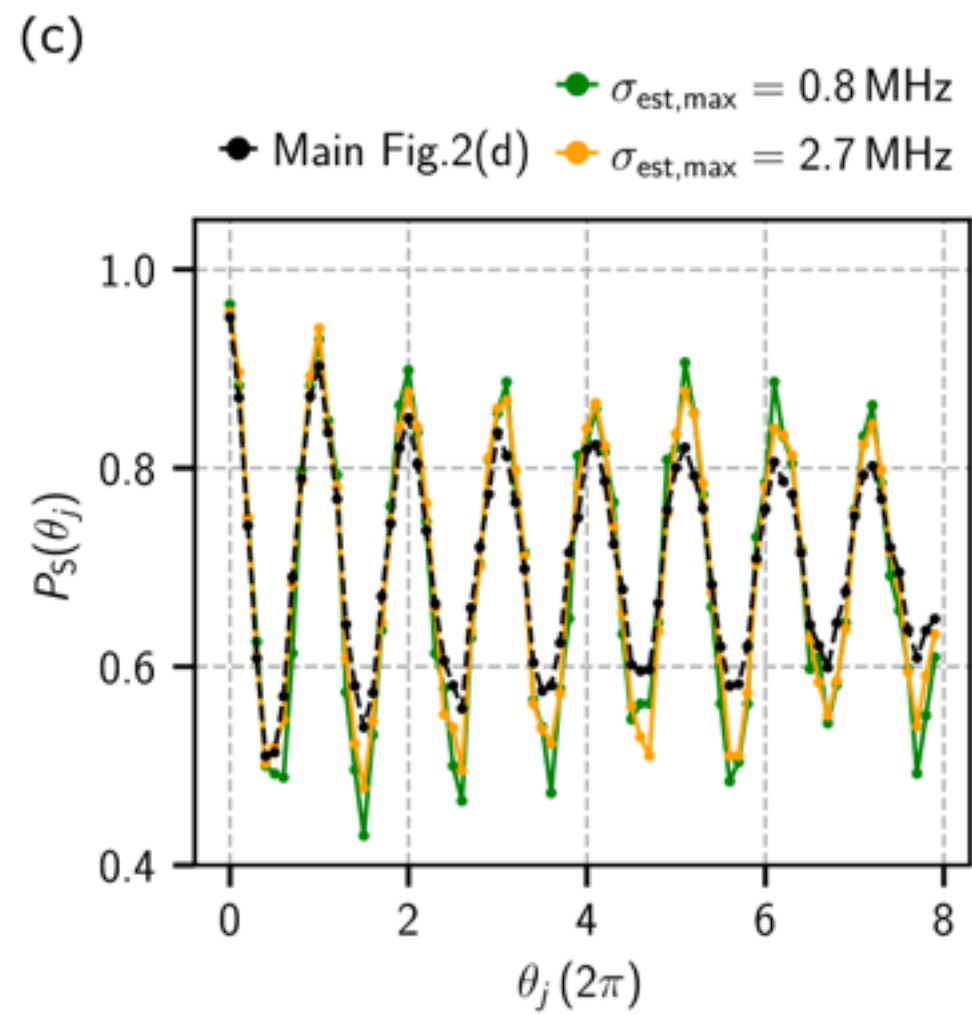
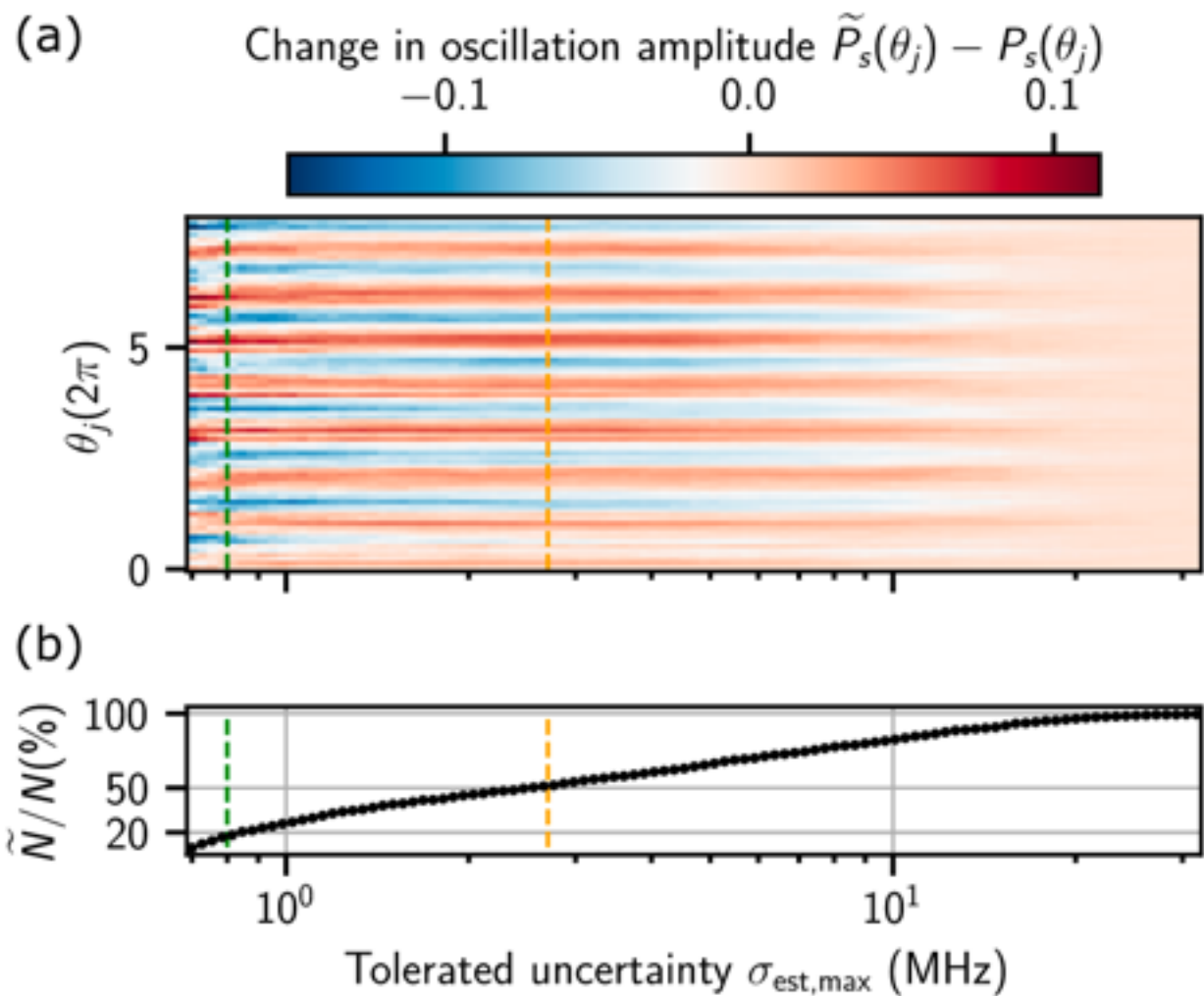
- We found that both orbital noise and spin-splitting noise can lead to spatial correlations

$$\langle \epsilon_L \epsilon_R \rangle \neq 0, \langle \Omega_L \Omega_R \rangle \neq 0$$



- Apart from that non-zero correlations between them is also expected.

- This means that $\langle \delta \epsilon \delta \Delta B_z \rangle \neq 0$



Time scales

- Correlation time $T_c = 1s$
- Relaxation time $T_1 \approx 1ms$
- Estimation time $T_{est} = 100\mu s$
- Qubit cycle $T_{cycle} = 10\mu s$
- Effective dephasing time $T_2' = 1/MHz = 1\mu s$
- Dephasing time $T_2^* = 20ns$

$$T_1 = 10^{-3}T_c$$

$$T_{est} = 10^{-4}T_c$$

$$T_{cycle} = 10^{-5}T_c$$

$$T_2' = 10^{-6}T_c$$

$$T_2^* = 10^{-8}T_c$$

Time

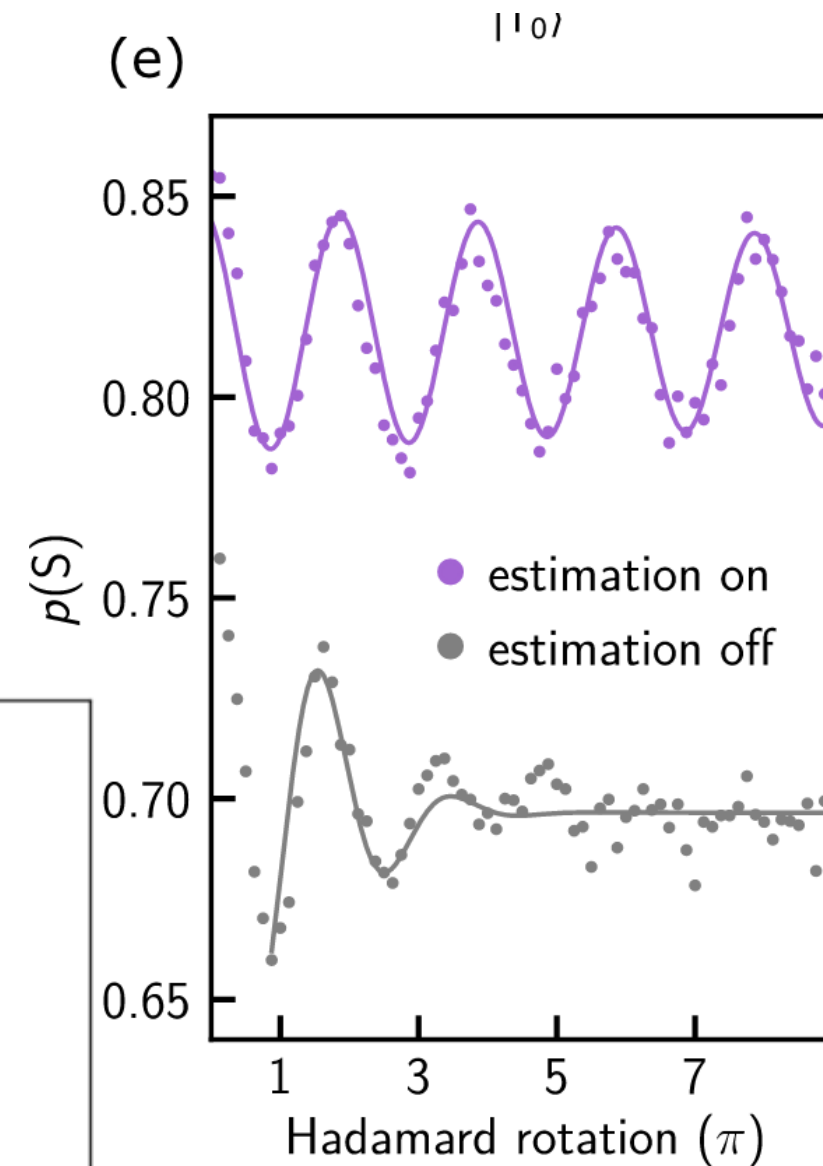
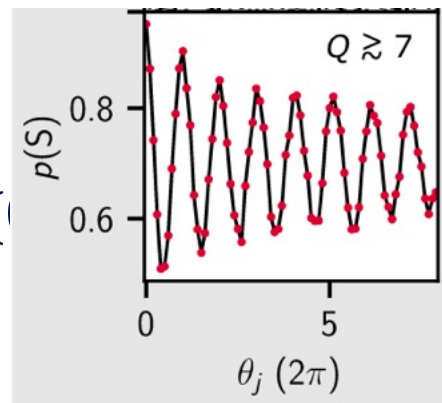
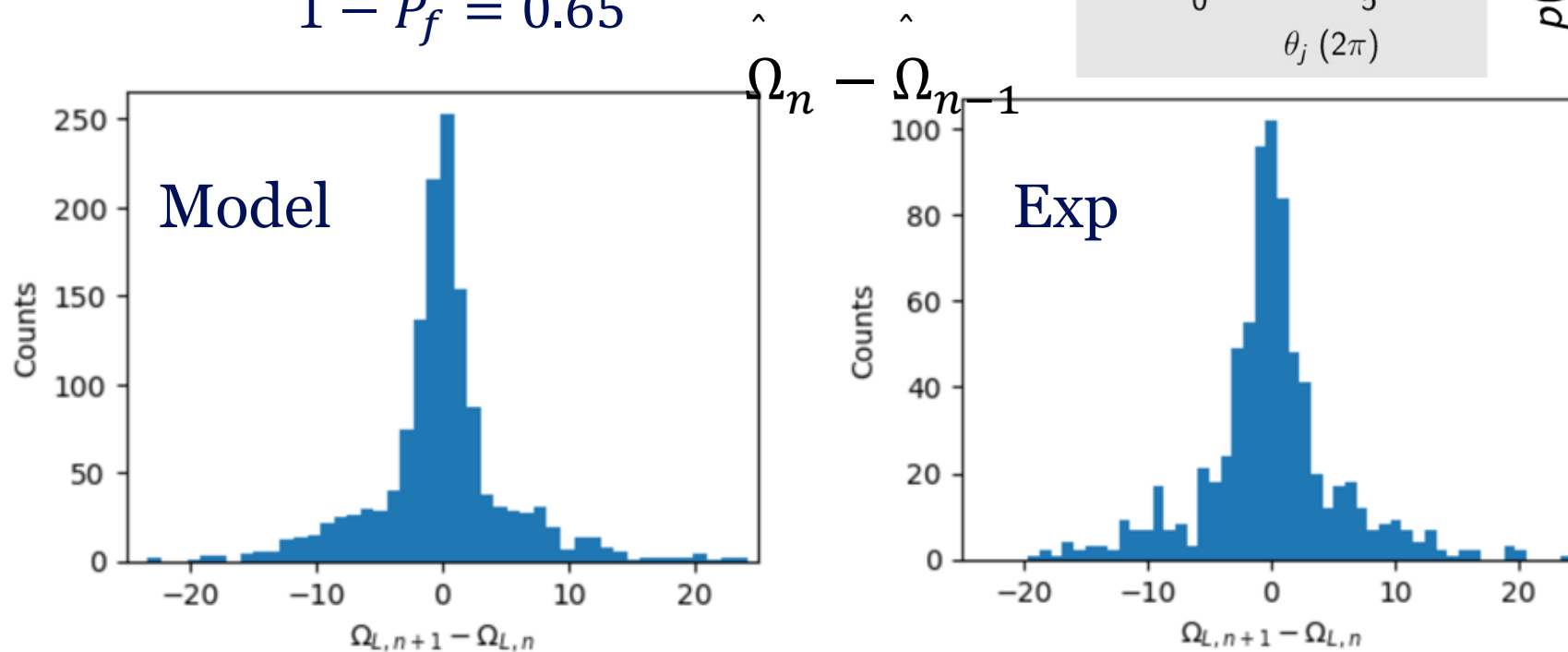
- 10^4 single shots in $0.1T_c = 0.1s$. During this time:
 - 0.1% estimation
 - 10% coherent evolution
 - 90% readout

Hadamard gate synthetisation

- Stable oscillations are achieved with feedback,
- Lack of contrast due to outliers:

$$\delta\Omega \sim P_f \mathcal{N}(0, \sigma_{out}^2) + (1 - P_f) \mathcal{N}(0, \sigma_{in}^2)$$

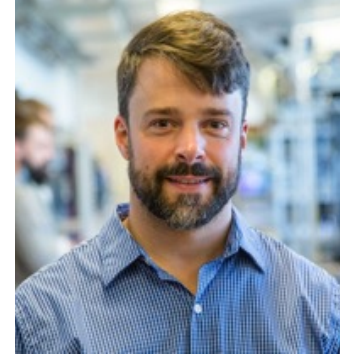
$$1 - P_f = 0.65$$



Outline (Different outline)



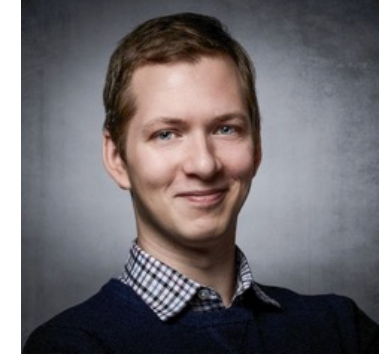
Anasua Chattejee



Ferdinand Kuemmeth



Jeroen Danon



Evert van Nieuwenburg

Experiment (NBI Copenhagen)

Theory (NTNU)

Machine learning (Leiden)

1. Spin qubit Quantum
Computer

2. Correlated noise

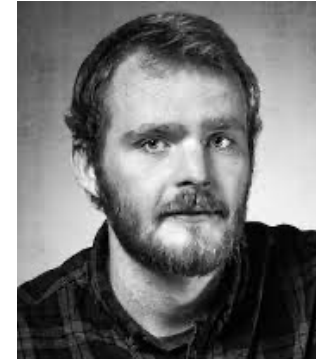
3. Gates driven by noise

4. Perspective and outlook

ConSpiQuOS



Fabrizio Berritta



Torbjørn Raasø
Rasmussen

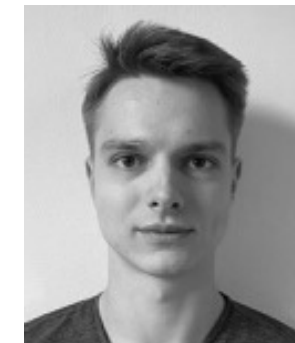


Jacob Benestad

Etiuda
Preludium

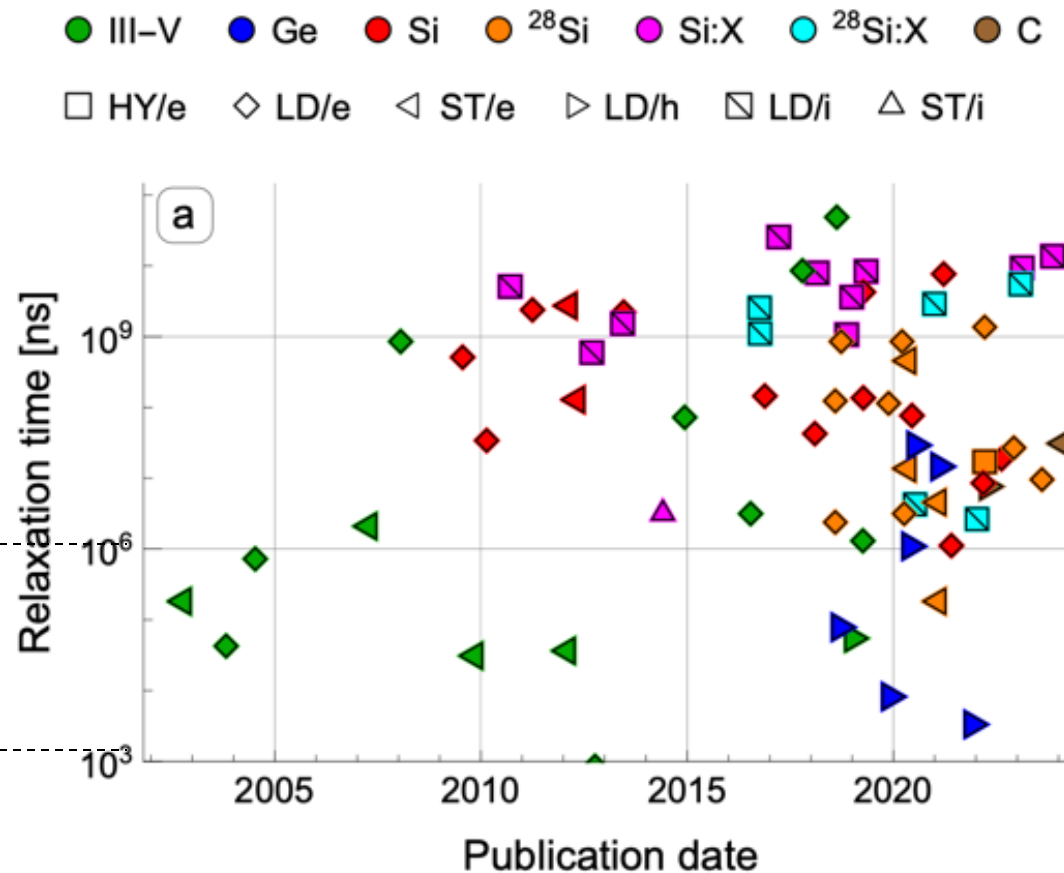
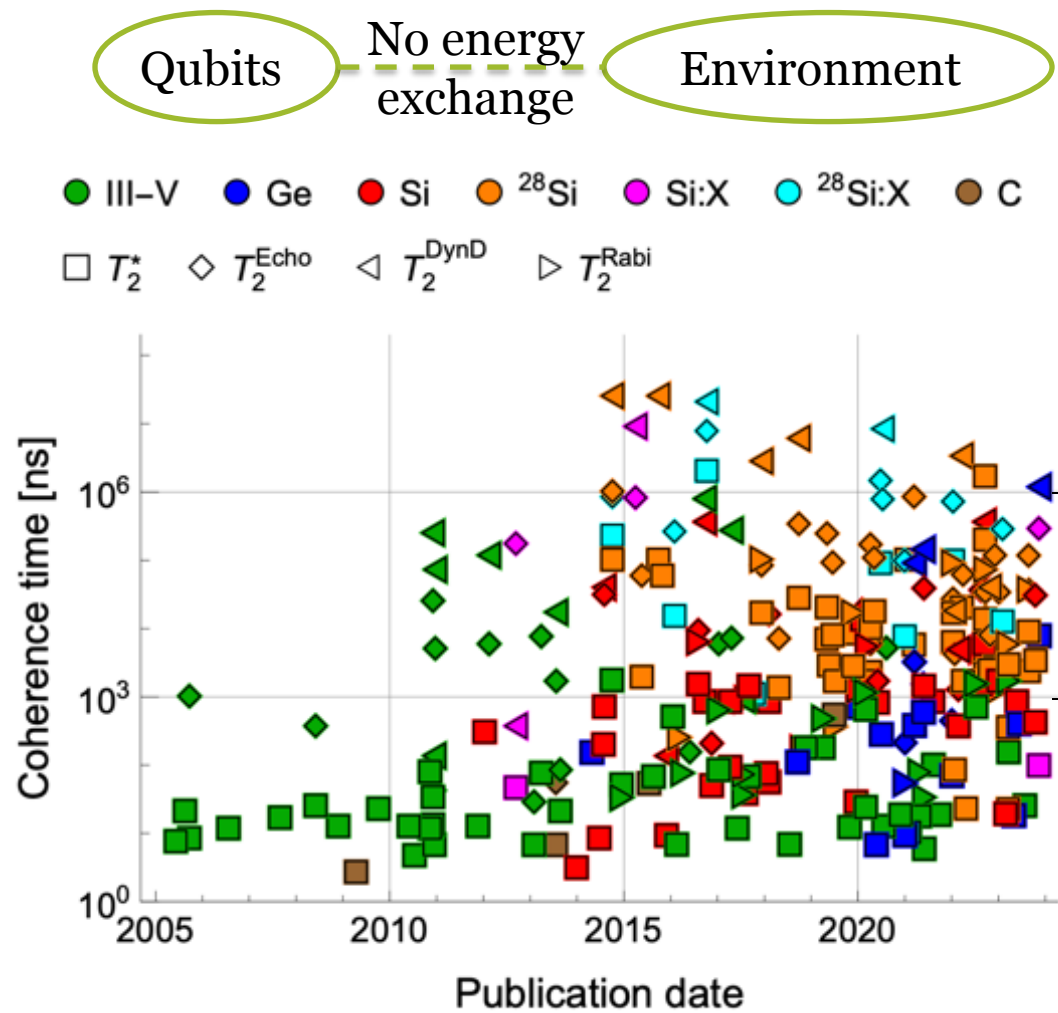


Łukasz Cywiński



Marcin Kępa

Because the noise is classical...

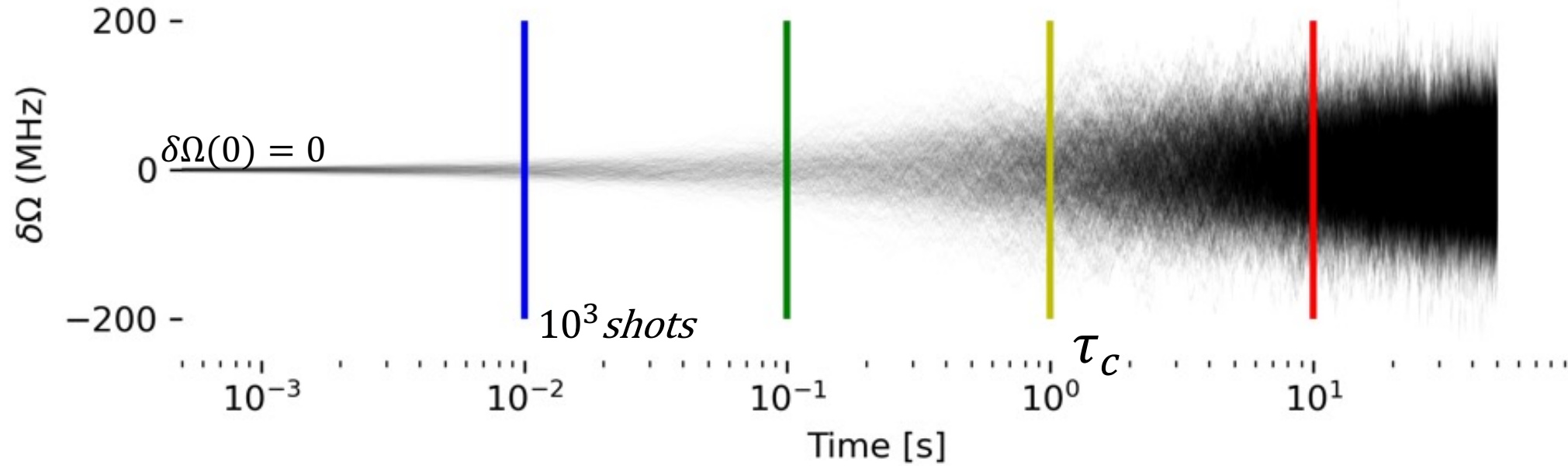


$$T_2 \gg T_1$$

Example: Nuclear noise

$$\sigma^2(t) = \sigma_f^2 - [\sigma_f^2 - \sigma^2(0)]e^{-2t/\tau_c}$$

$$\mu(t) = \delta\Omega(0)e^{-t/\tau_c}$$



$$\delta W = \frac{1}{2N} \langle\langle \delta\Omega_n^2 \rangle\rangle \tau^2 = \frac{\sigma_f^2 \tau^2}{2} \left(1 - \frac{1}{N} \sum_n e^{-n\Delta t/\tau_c}\right) = \frac{\sigma_f^2 \tau^2}{2} \left(1 - \frac{1 - e^{-N\Delta t/\tau_c}}{e^{\Delta t/\tau_c} - 1}\right)$$