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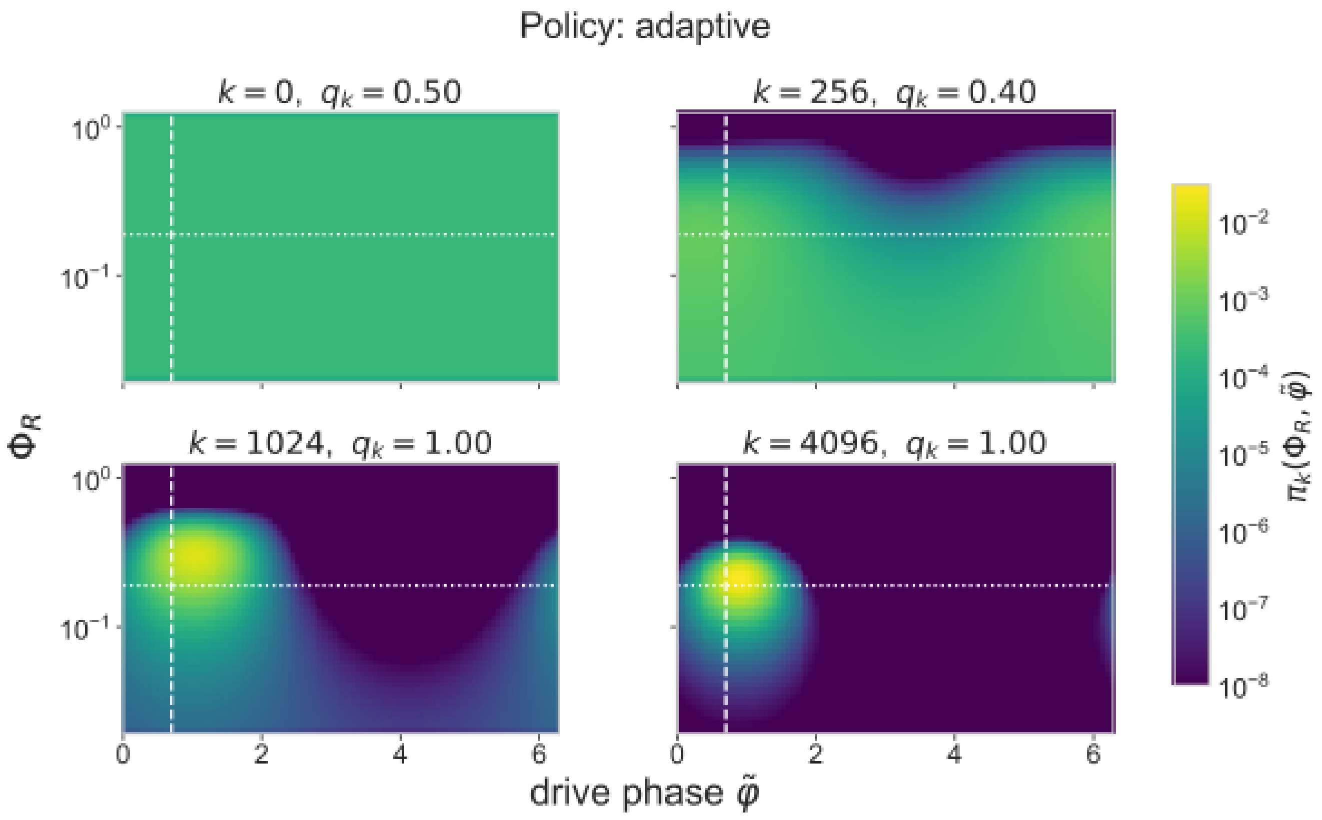
C²QA



Adaptive quantum sensing for wave-like dark matter searches

arXiv: [2609.xxxxx]
In collaboration with Codex

So Chigusa

Quantum sensing for fundamental physics institute @ CERN (4/9/2026)

Wave dark matter signals at direct detection

❖ Coherent oscillation of classical wave dark matter (DM)

$$a(t) \simeq a_0 \sin(m_{\rm DM} t - m_{\rm DM} \vec{v}_{\rm DM} \cdot \vec{x} + \delta)$$

Hajime's talk (Tue.)
Marianne's talk (Fri.)

❖ Unknown properties of DM signals

- Frequency $= m_{\rm DM}$
- Amplitude $\propto a_0$
- Oscillation phase $= \delta$
- Direction

  ex) Dark photon polarization

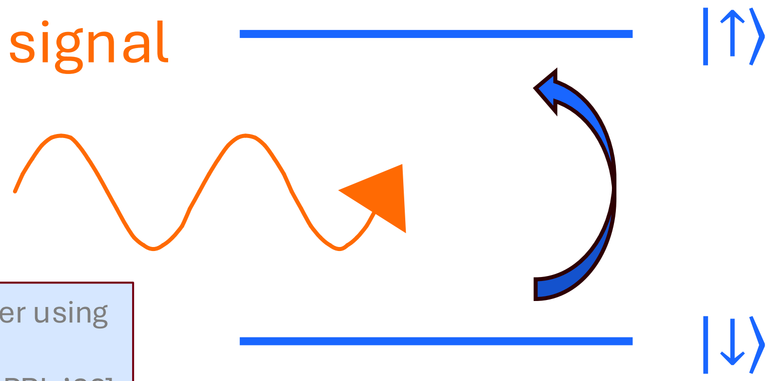
  Axion-induced $\vec{B}_{\rm eff}$

Example: "Detection of hidden photon dark matter using the direct excitation of transmon qubits"
[Chen, et al. PRL '23]

❖ Resonant drive

as example of quantum sensing

DM signal



$m_{\rm DM} = \omega_{\rm qubit}$

Detuning $\Delta = 0$ for simplicity

Population readout and projective measurements

❖ Population readout

- "DM signal flips the qubit spin at probability p"

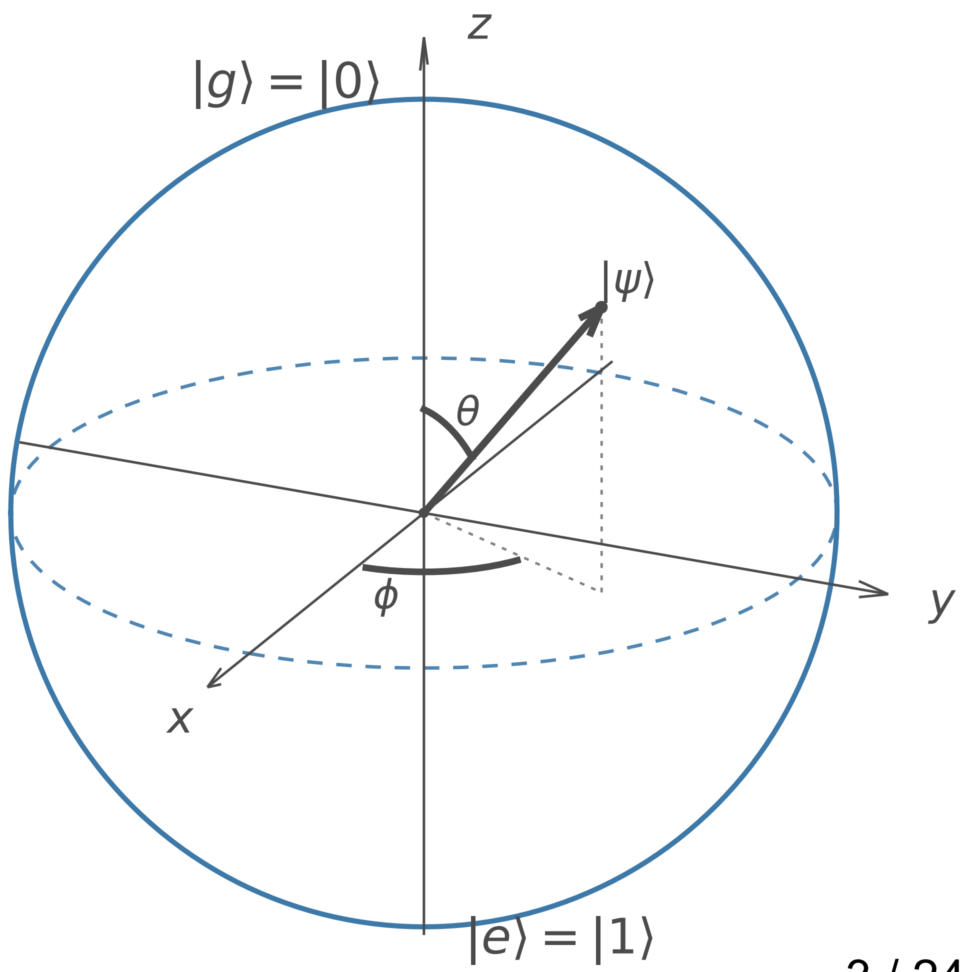
❖ Quantum description

$$|\psi\rangle = \cos\frac{\theta}{2}|\mathrm{g}\rangle + \sin\frac{\theta}{2}e^{i\phi}|\mathrm{e}\rangle$$

- $p = \sin^2\frac{\theta}{2}$
- Additional information from ϕ

❖ Projective measurement

- DOF of readout-axis choice
- "population" = z-projective measurement



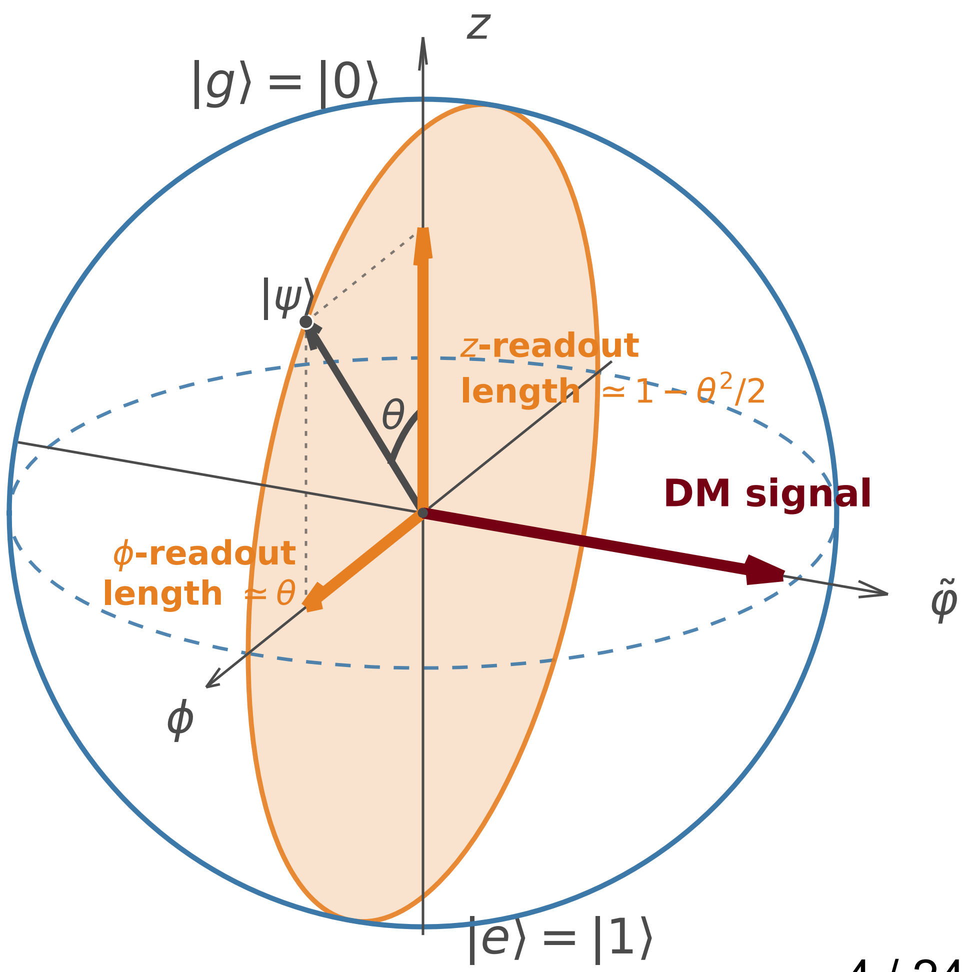
Population vs transverse readout

❖ Population readout
- Insensitive to unknown phase ϕ
- Quadratic response $2\sin^2(\theta/2) \propto \theta^2$

❖ Transverse oracle (ϕ-readout)
- Linear response $\propto \theta$
- Need to know ϕ

❖ ϕ is determined by signal direction
- For DM signal direction $\tilde{\varphi}$

  $\phi = \tilde{\varphi} - \pi/2$ is unknown $\Longrightarrow$ learn it!



Adaptive strategy

❖ During repeated measurements with n total shots,

Population readout for initial steps

- Phase-insensitive signal search

Phase learning

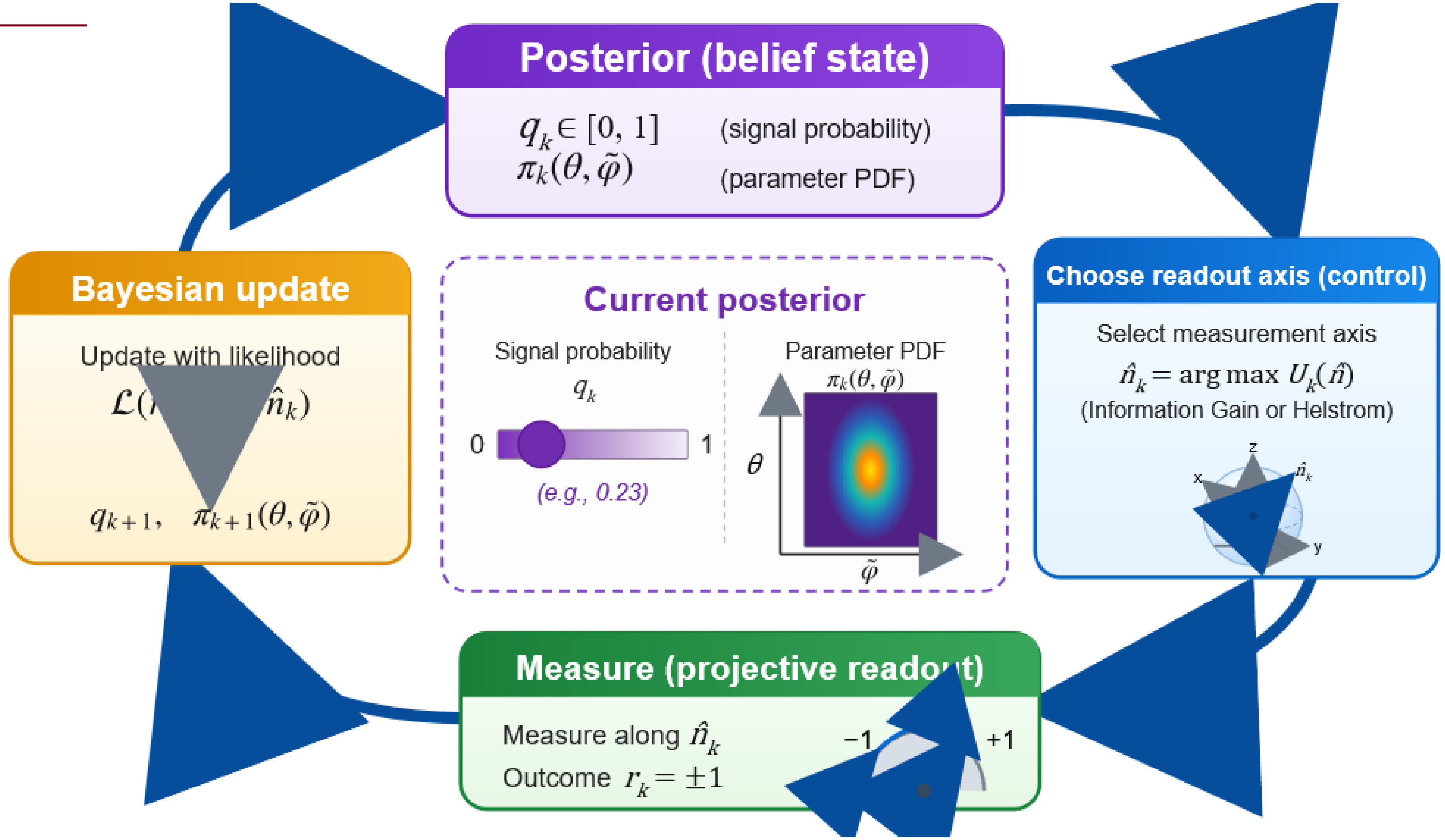
- Insert trial shots (information gain) to learn the signal phase φ

Converge to transverse oracle

- The optimal ϕ-readout for signal detection

❖ Help reject false positives/look-elsewhere effects

Bayesian adaptive readout loop



Bayesian update and final decision

❖ Bayesian update

- Start with $q_0 = \frac{1}{2}$ and $\pi_0(\theta, \tilde{\varphi})$
- If measurement along $\vec{n}_k$ results in $\mathrm{r}_k = \pm 1$

$$q_{k+1} = \frac{q_k m_k(\mathrm{r}_k|\vec{n}_k)}{(1-q_k)p_{0,k}(\mathrm{r}_k|\vec{n}_k) + q_k m_k(\mathrm{r}_k|\vec{n}_k)}$$

Similar for $\pi_k(\theta, \tilde{\varphi})$

When signal absent

Prob. of r_k

When signal exists

Prob. of r_k

❖ Final decision: frequentist test based on

$$\log B_{10,n} \equiv \log \frac{q_n}{1-q_n}$$

Utilities 1: information gain

❖ This is exploration utility to learn signal existence and parameters

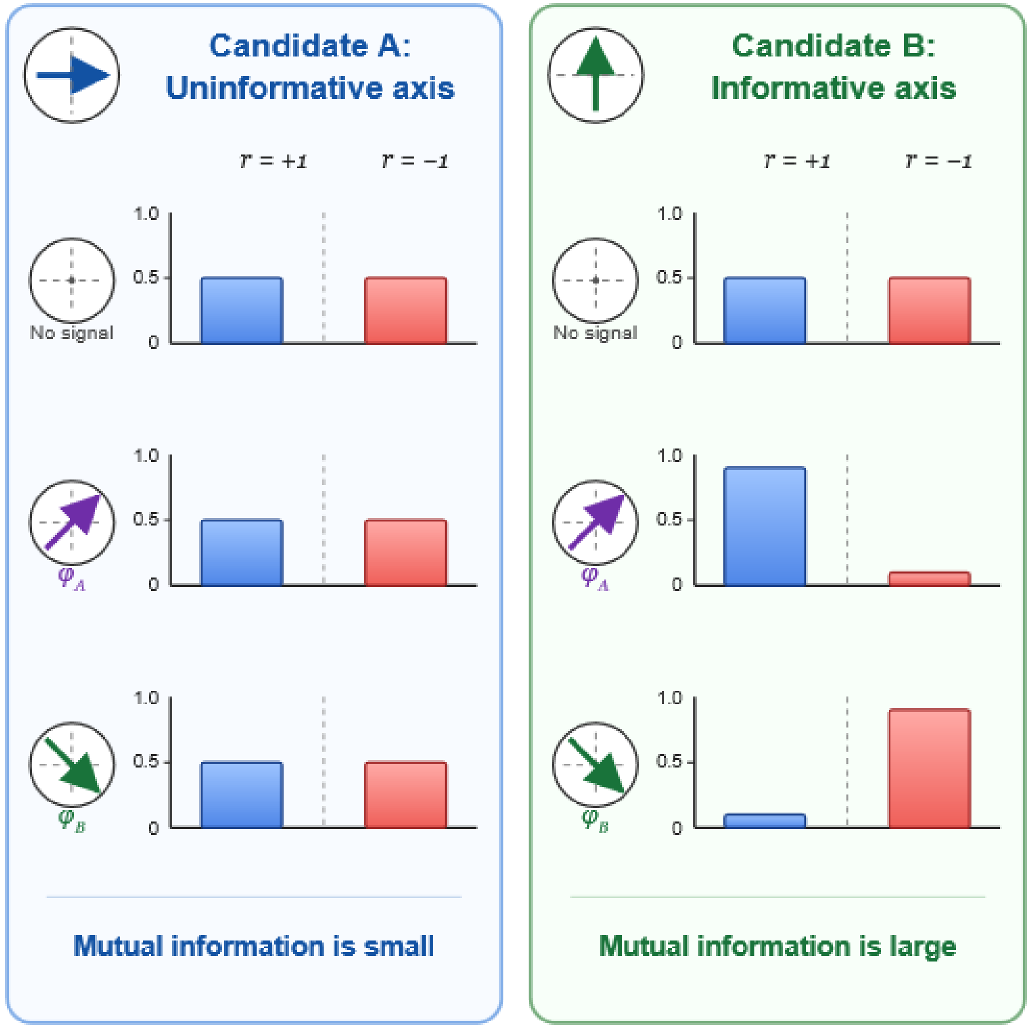
❖ Use "mutual information"

- $I(\Lambda_k; R_k)$

  $=$ How much readout $R_k \in \{\pm 1\}$ tells us about signal existence & parameters Λ_k

  $= I(\text{signal existence}; R_k) + q_k I(\theta, \tilde{\varphi}; R_k)$

Inclines to parameter learning @ $q_k \to 1$



Utilities 2: Helstrom

❖ This is detection utility to collect signal evidence

❖ Helstrom measurement:

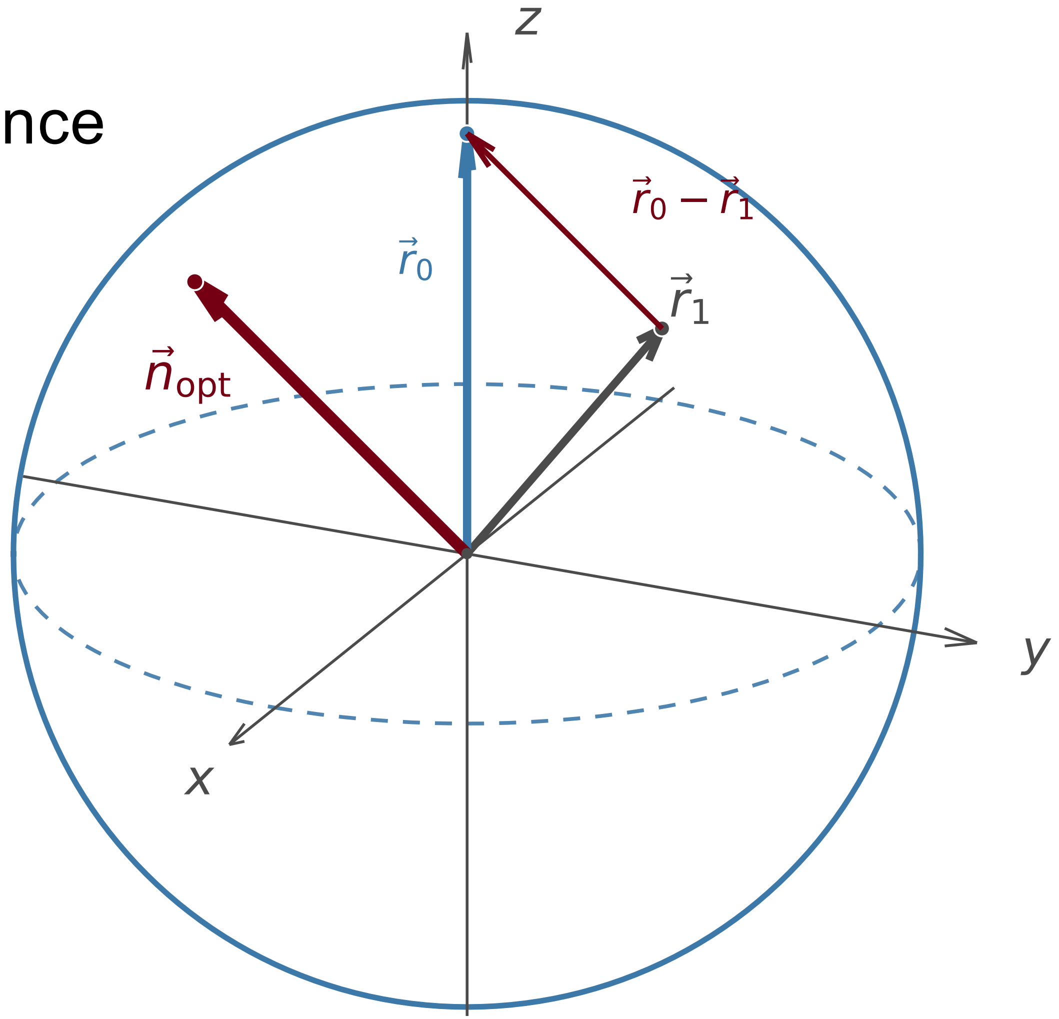
- Discrimination of ρ_0 and ρ_1
- Optimal measurement is

$$\vec{n}_{\mathrm{opt}} \propto \vec{r}_0 - \vec{r}_1$$

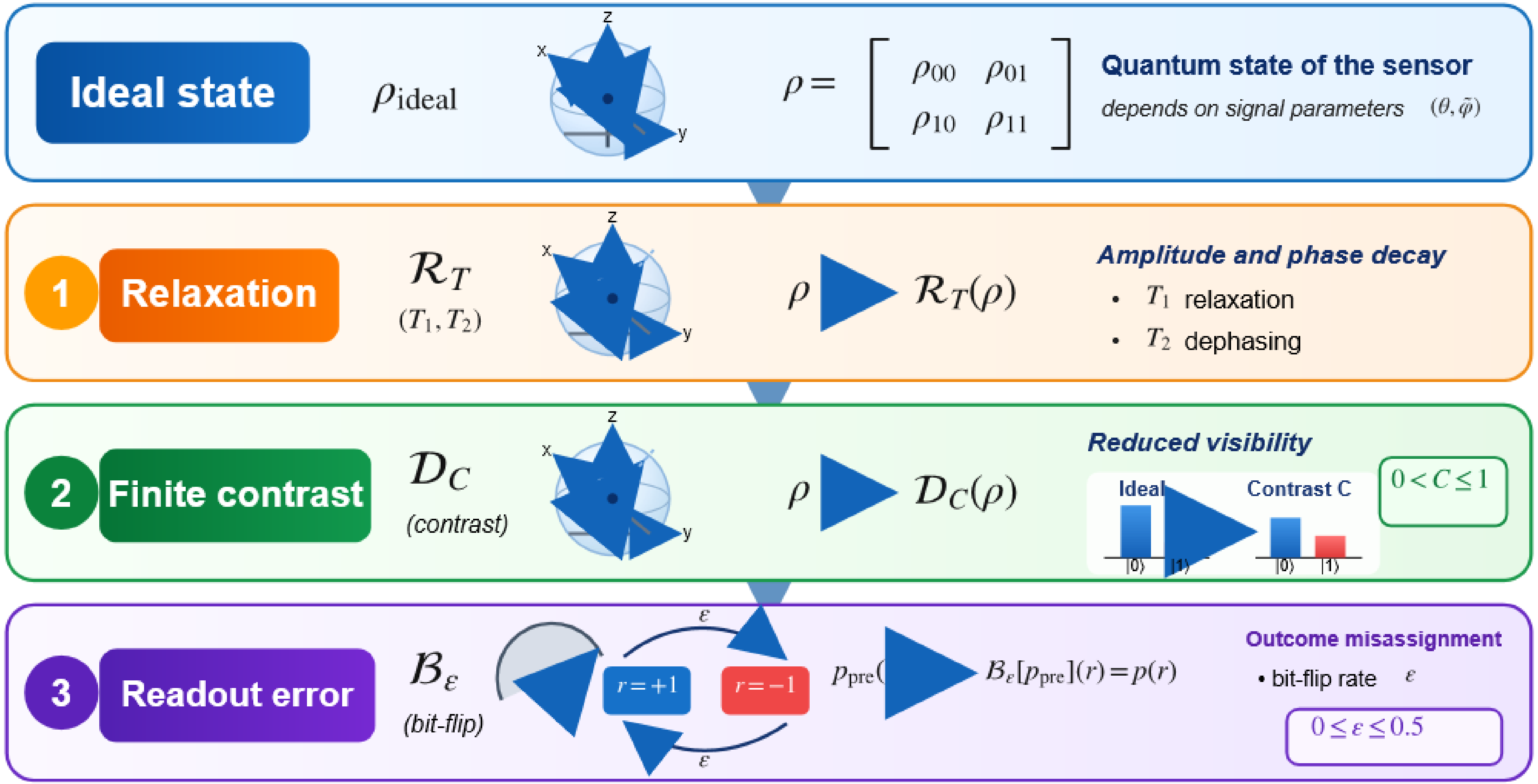
- Converges to ϕ-readout for weak signal

Challenges due to unknown ϕ

e.g. $\vec{r}_0 - \int \frac{d\phi}{2\pi}\, \vec{r}_1(\phi) \propto \vec{z}$



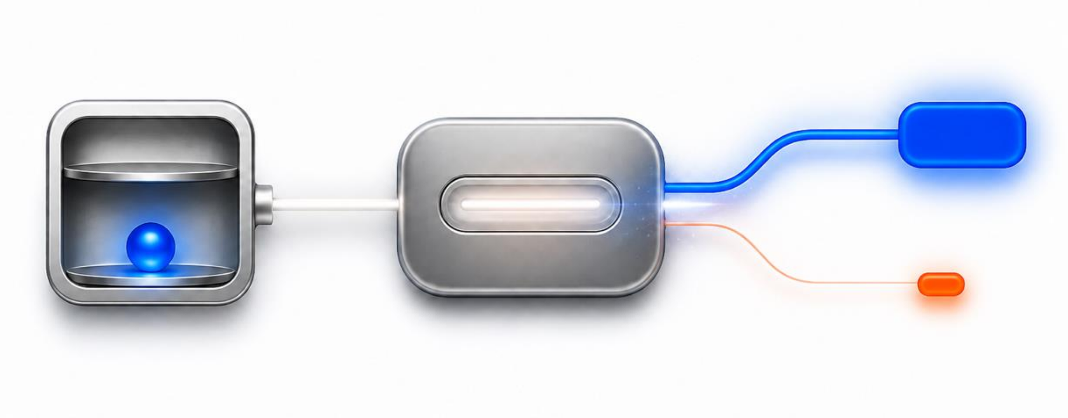
Detector imperfections enter through likelihood

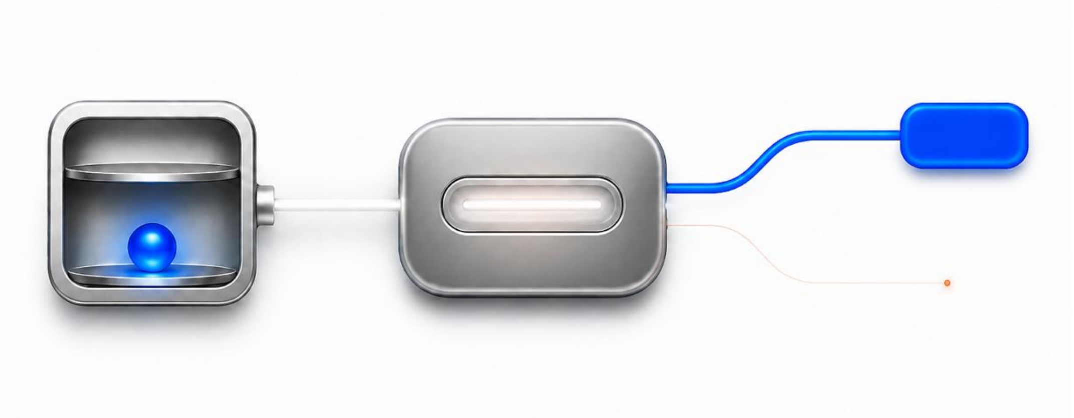


Two benchmark setups

1. Noisy baseline setup
   - $C = 0.99$
   - $\epsilon = 0.005$
   - Fake excitation rate by noise: $p_{z,0} \simeq 1\%$

2. Higher-fidelity setup
   - $C = 0.999$
   - $\epsilon = 0.0005$
   - Fake excitation rate by noise: $p_{z,0} \simeq 0.1\%$

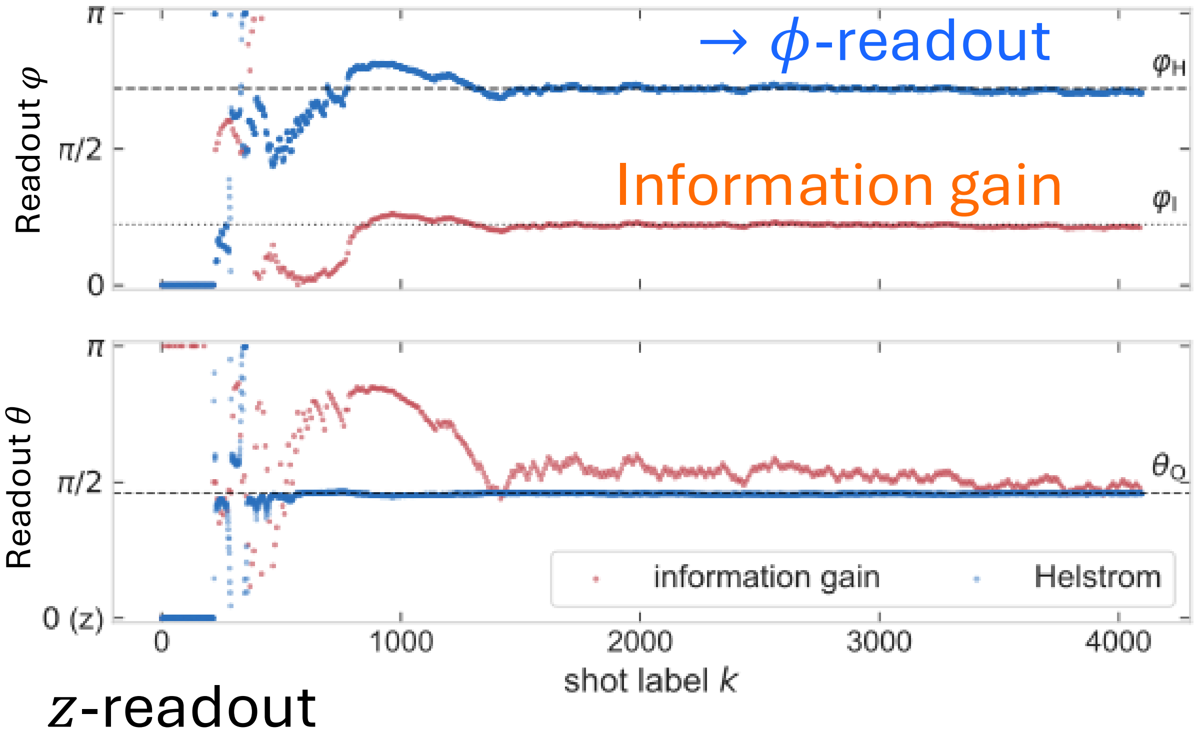


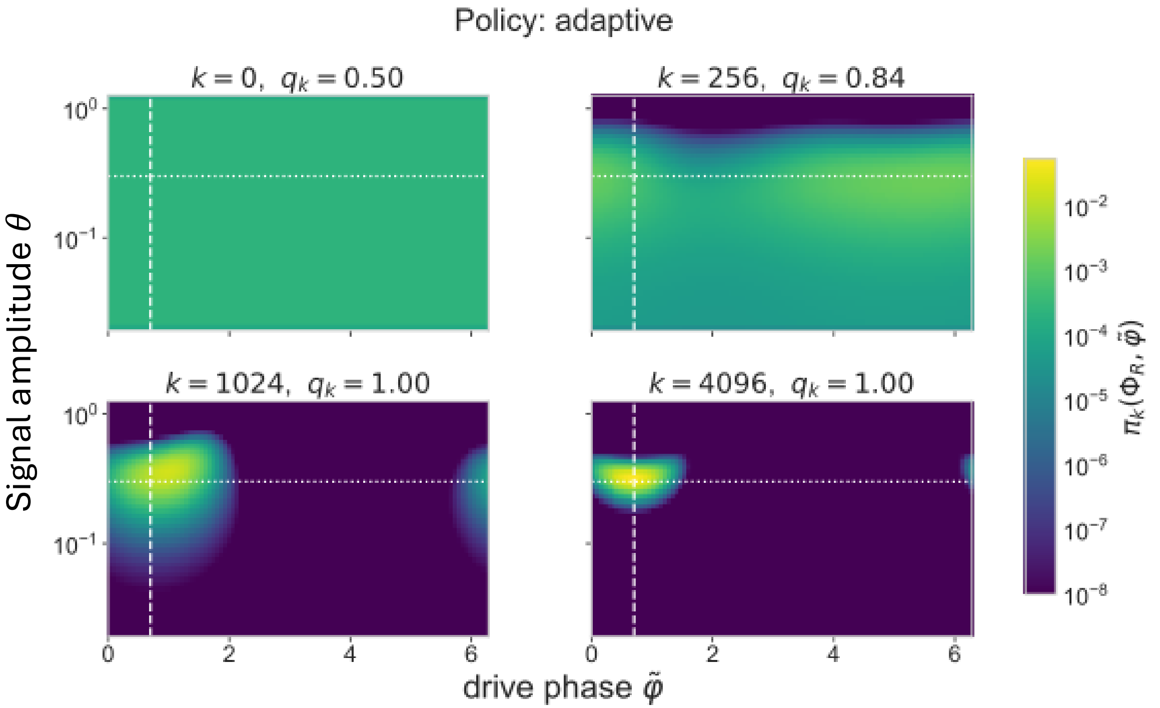


Question: How detector qualities change the optimal learning-detection balance?

Adaptive trajectory (higher-fidelity)

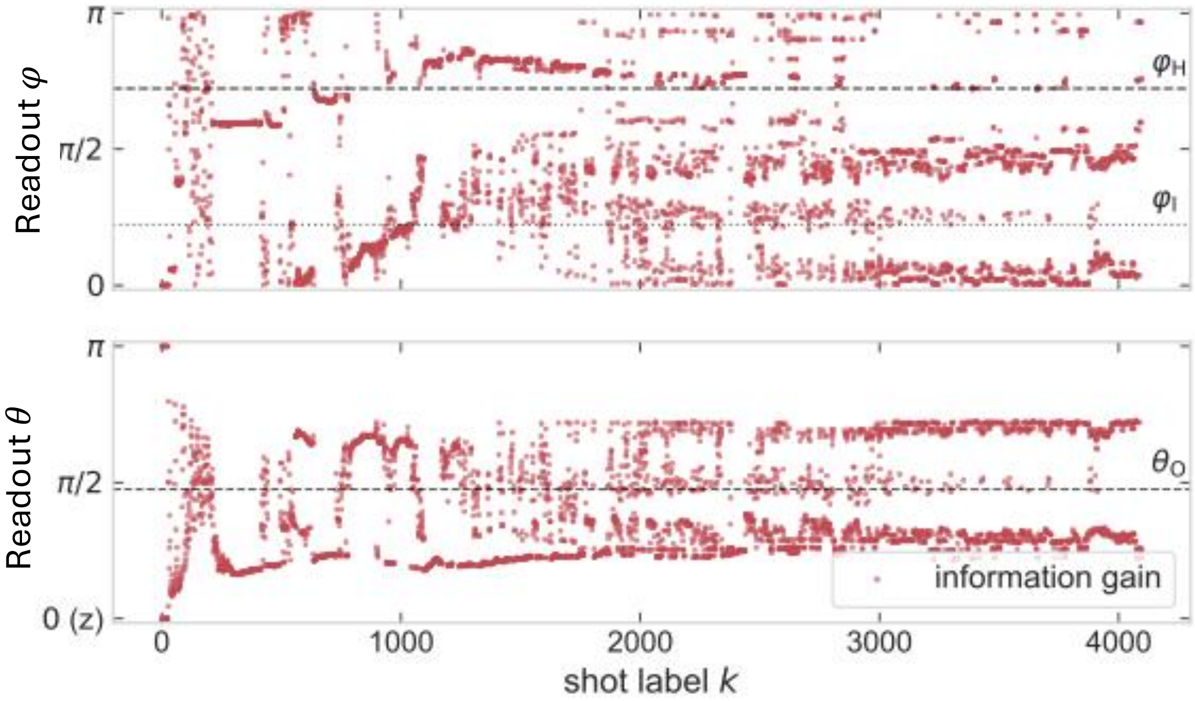
- ❖ Clear environment allows efficient localization of posterior
- ❖ Hybrid of Information gain/Helstrom is empirically the best

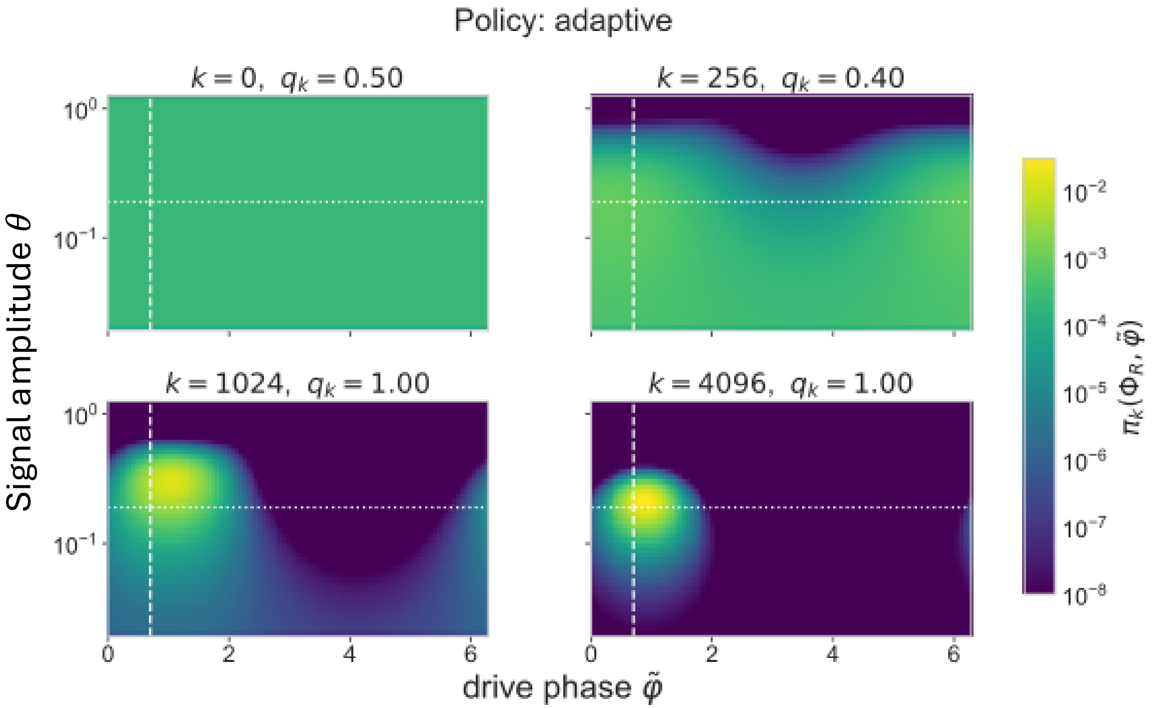




Adaptive trajectory (noisy baseline)

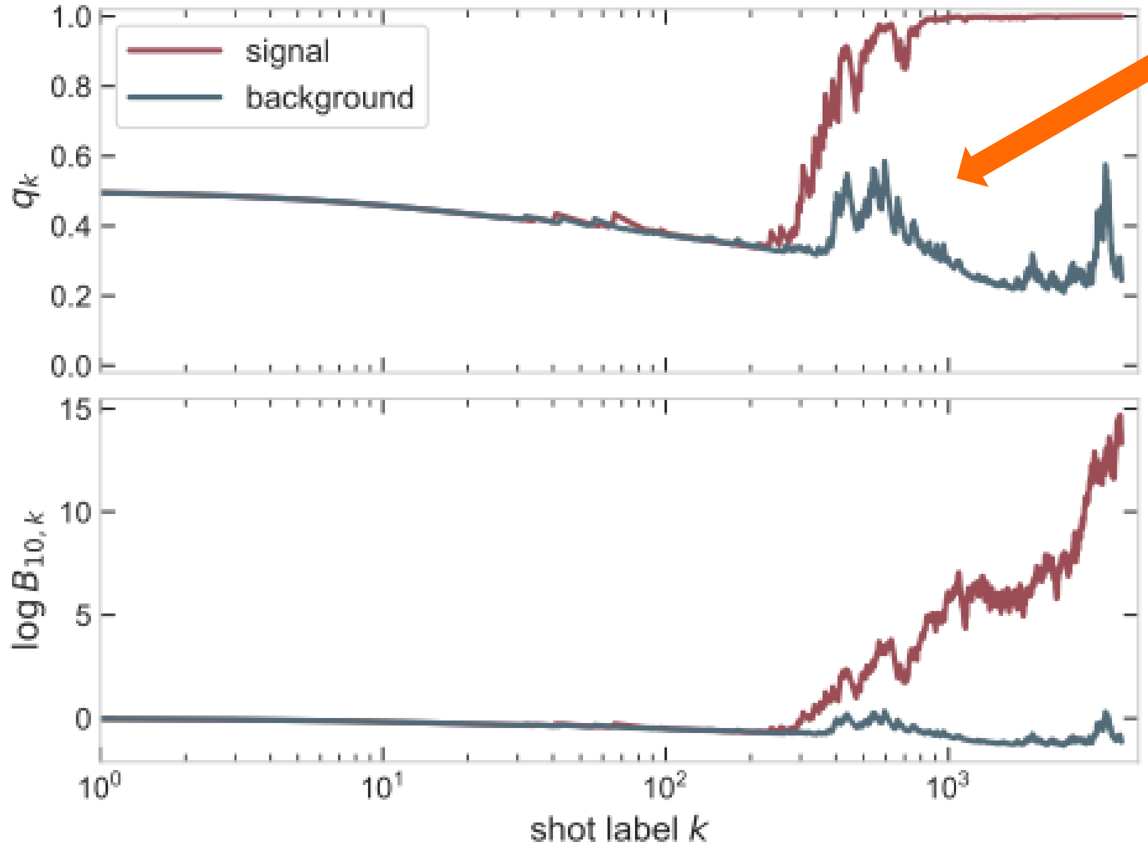
- ❖ Noisy environment makes signal learning more valuable
- ❖ Pure information gain is empirically the best

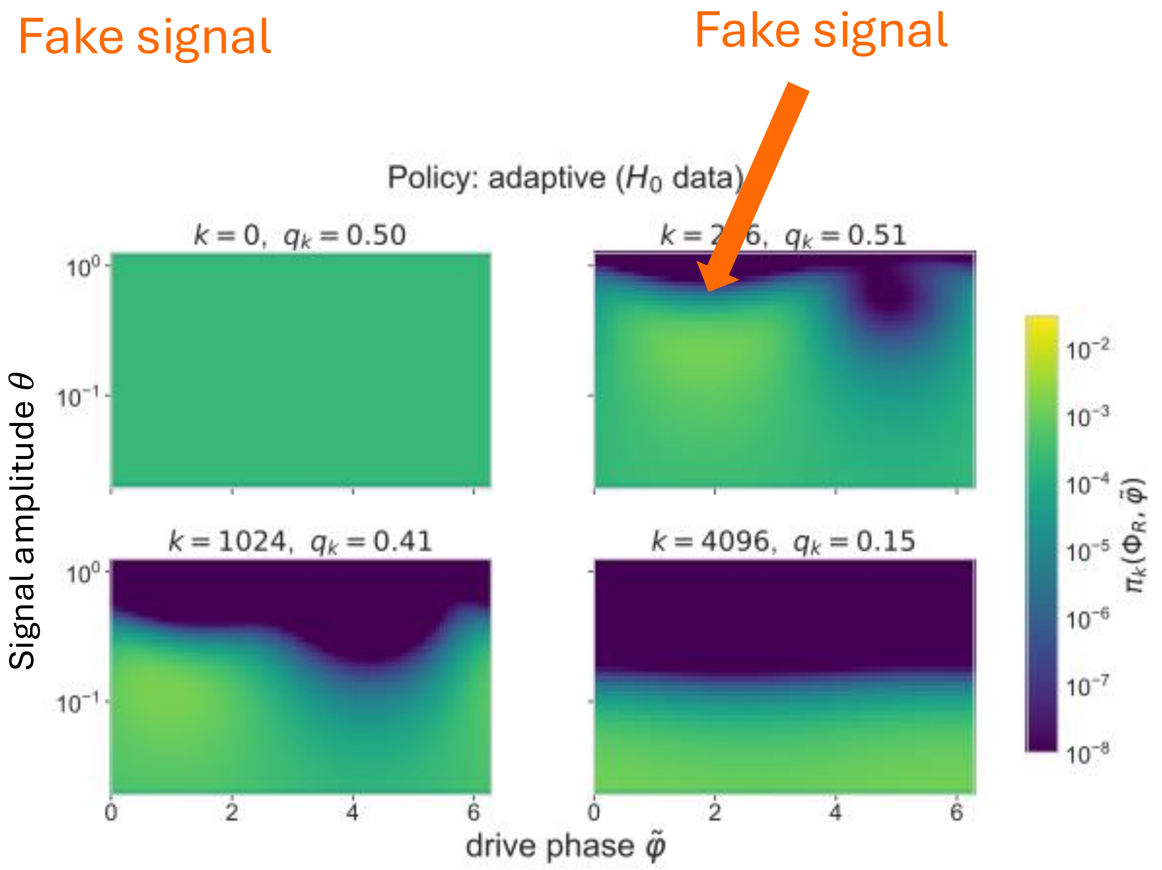




Visualizing look-elsewhere effects (noisy baseline)

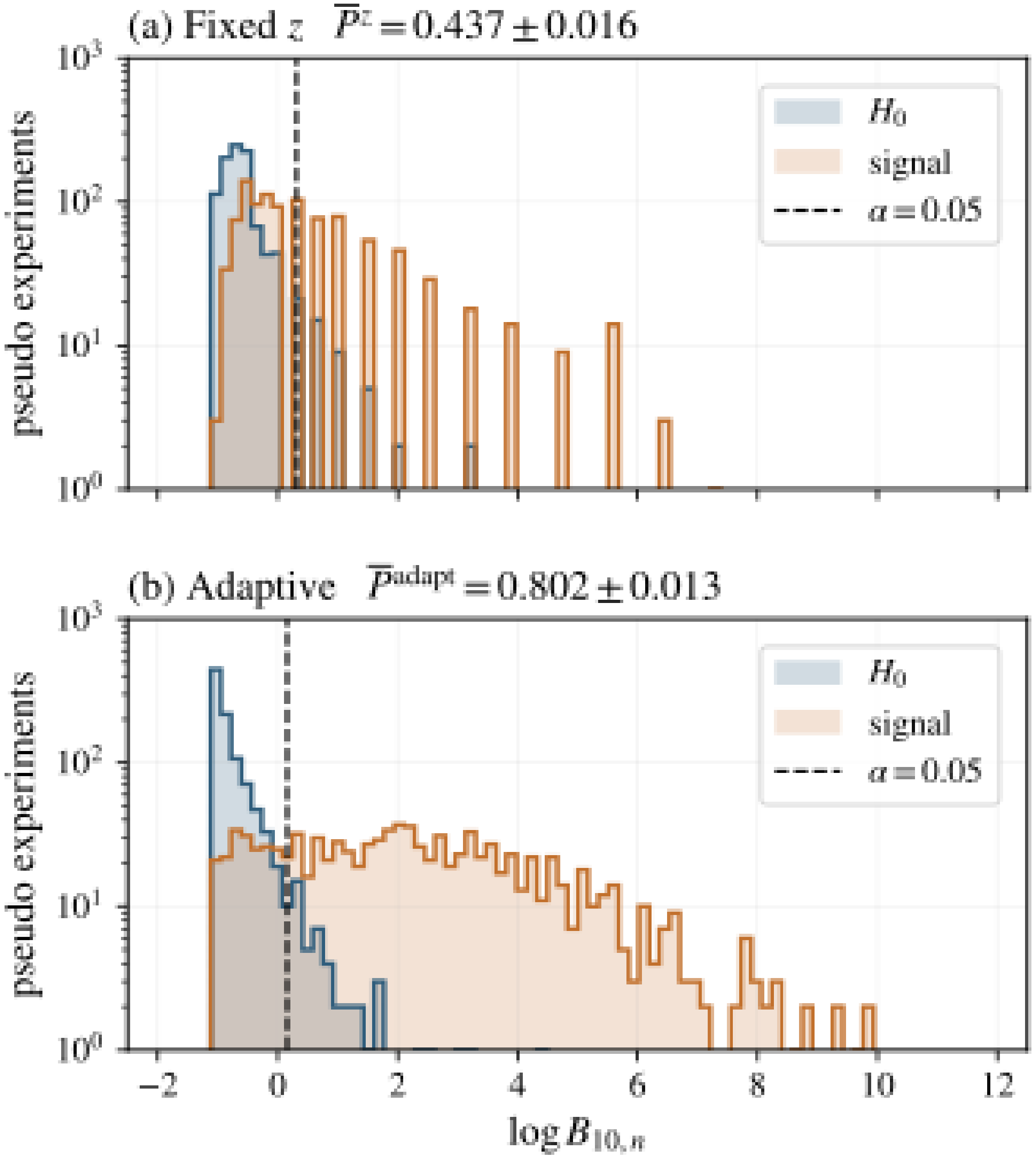
❖ Adaptive trajectory for noise-only model





Statistical treatment

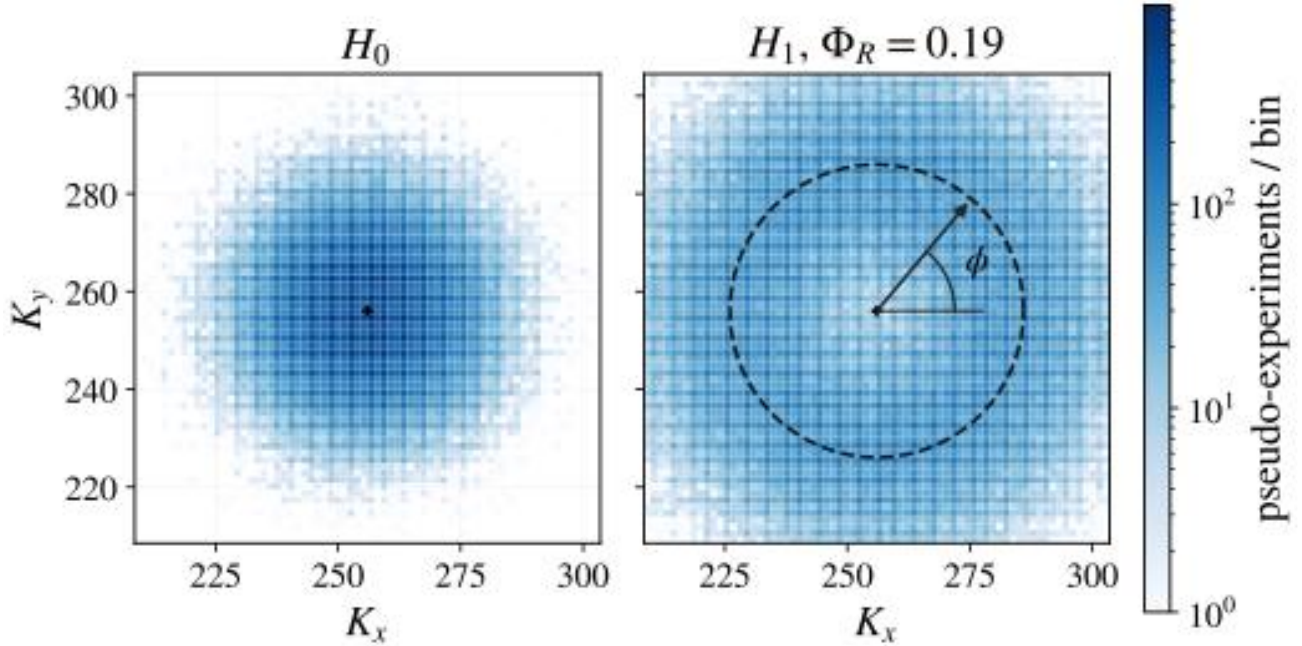
- Composite hypothesis test
  - H_0: noise only
  - H_1: noise + signal $(\theta, \tilde{\varphi})$
  - Signal marginalized by $\pi_0(\theta, \tilde{\varphi})$
- Asymmetric testing
  - Type-I error (false-positive) $\alpha < 5\%$
  - Maximize signal detection power
- Run pseudo-experiments to
  - Determine threshold from $\alpha = 5\%$
  - Evaluate detection power

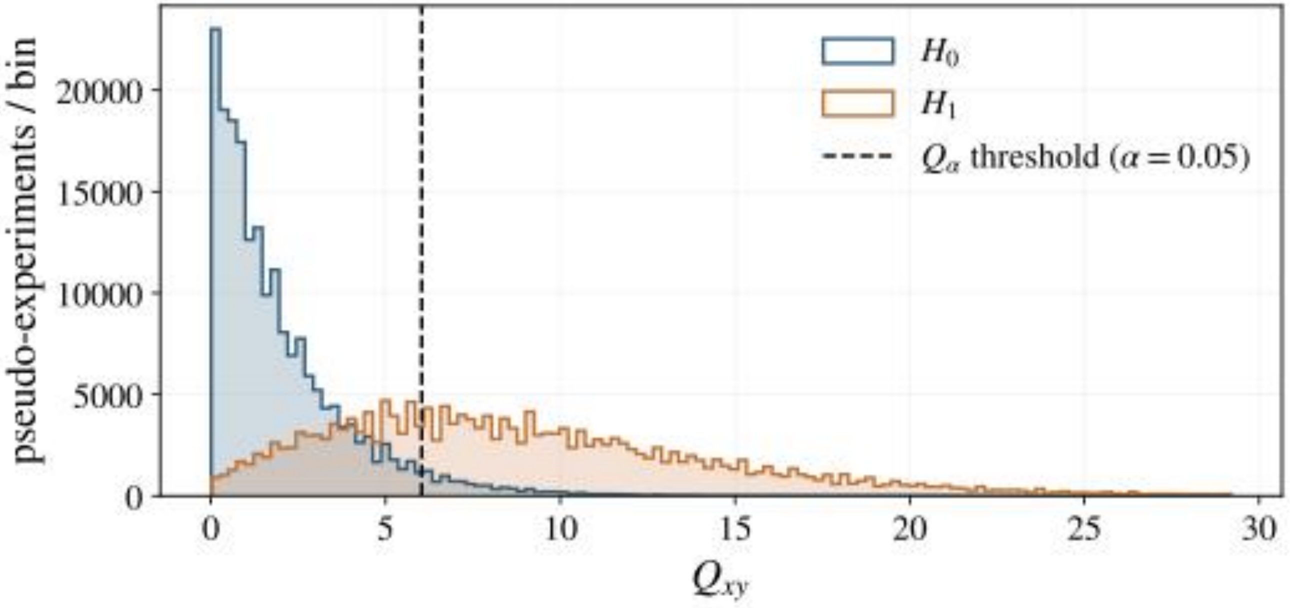


Non-adaptive baselines

- ❖ z-readout
  - Phase insensitive
  - Quadratic response
- ❖ x-readout
  - Linear response
  - Has a blind spot $\hat{n}_{\rm sig} \simeq \hat{x}$
- ❖ Alternative x/y-readout
  - Linear response
  - Lose ½ statistics

Also, transverse oracle with ϕ-readout

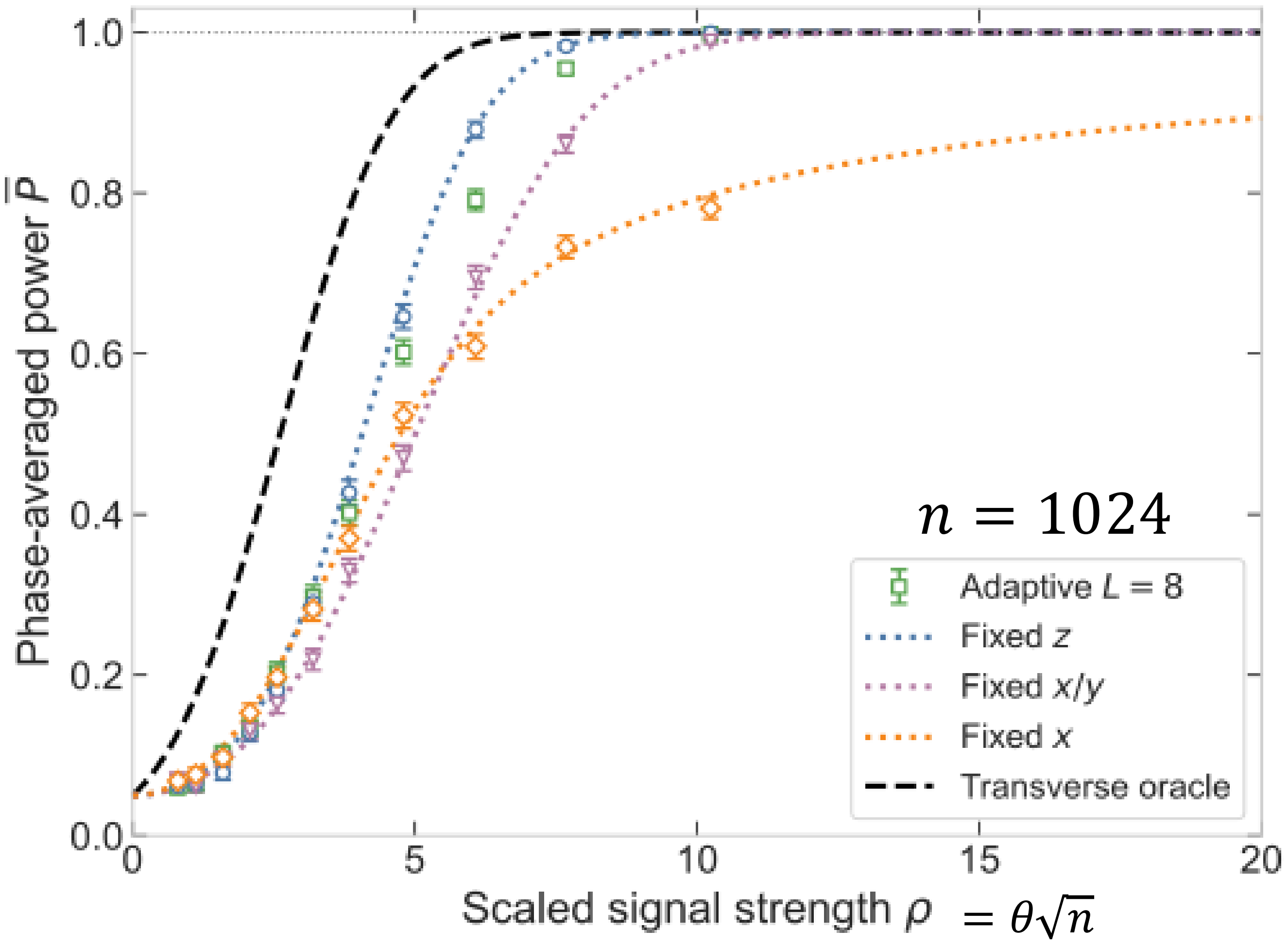




Phase-averaged detection power (higher-fidelity)

❖ Best strategy depends on n

1. z-readout for small n
2. Adaptive for large n



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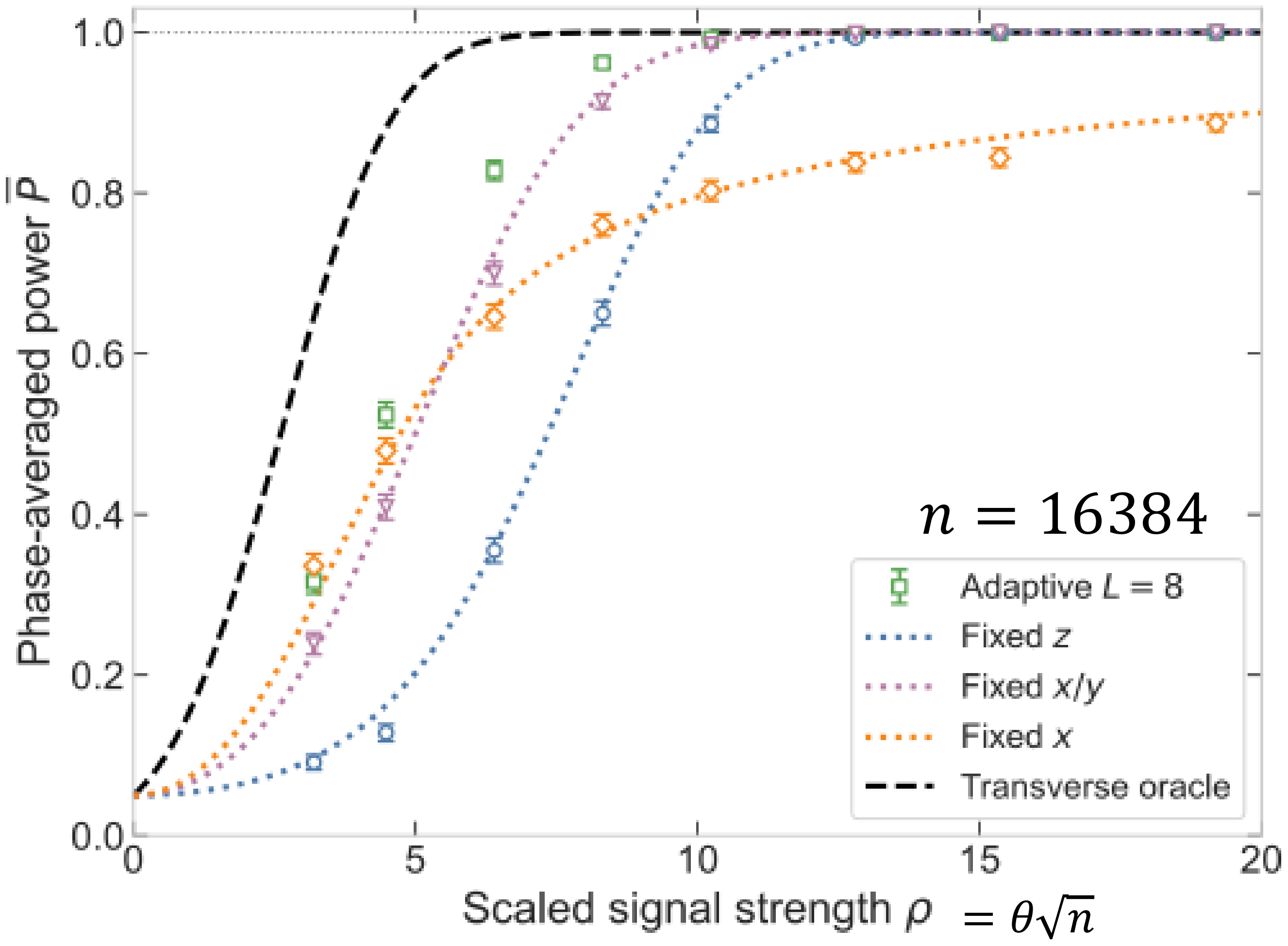
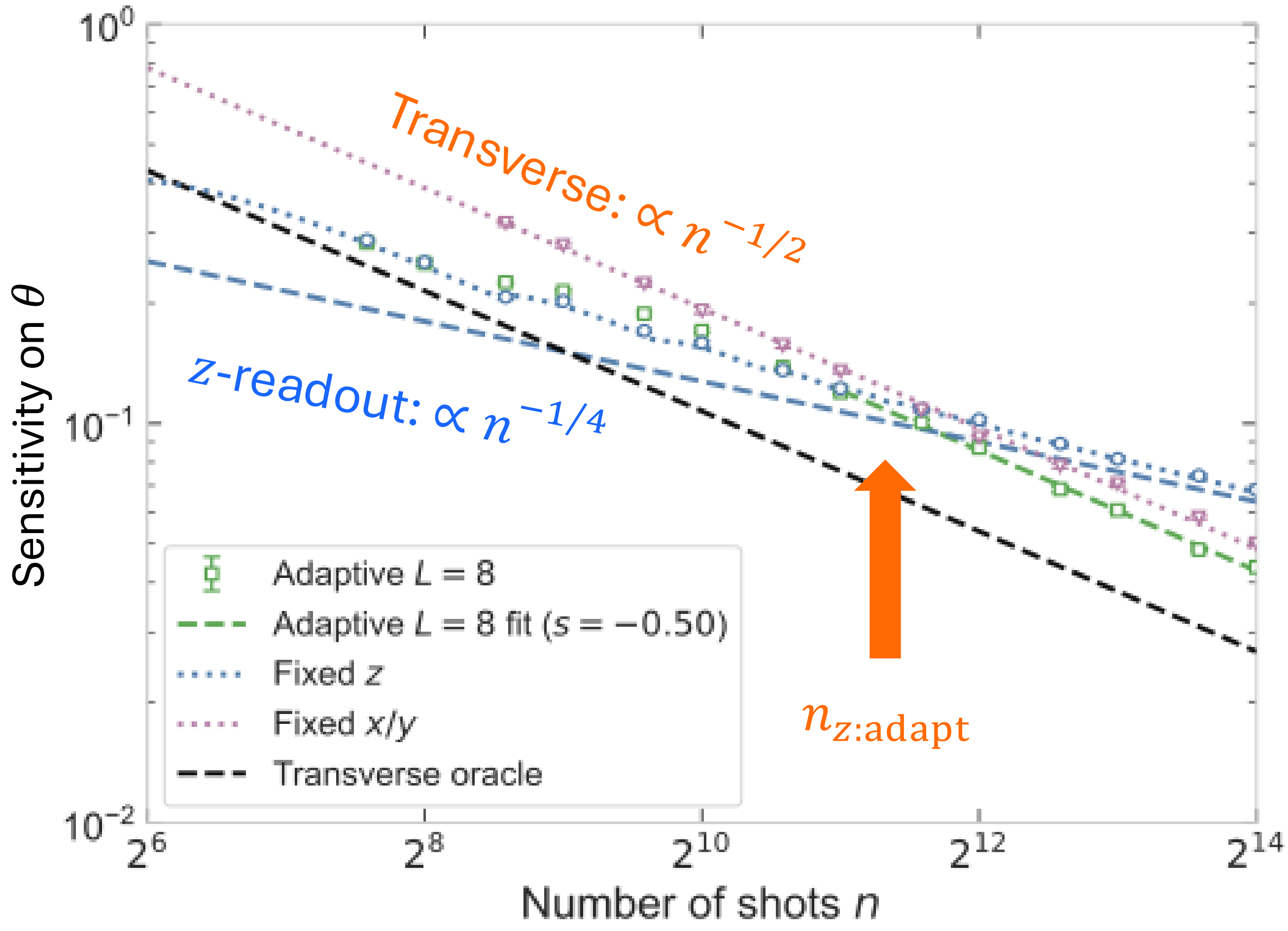


Transverse wins z-readout (higher-fidelity)

- Best strategy is
  1. z-readout for $n < n_{z:\text{adapt}}$
  2. Adaptive for $n > n_{z:\text{adapt}}$
- Crossings due to different scaling

P	$n_{z:O_\perp}$	$n_{z:x}$	$n_{z:xy}$	$n_{z:\text{adapt}}$
0.50	2.97×10^2	3.20×10^3	3.99×10^3	1.53×10^3
0.70	5.17×10^2	9.50×10^3	5.54×10^3	1.99×10^3
0.90	9.41×10^2	3.21×10^5	8.22×10^3	3.12×10^3

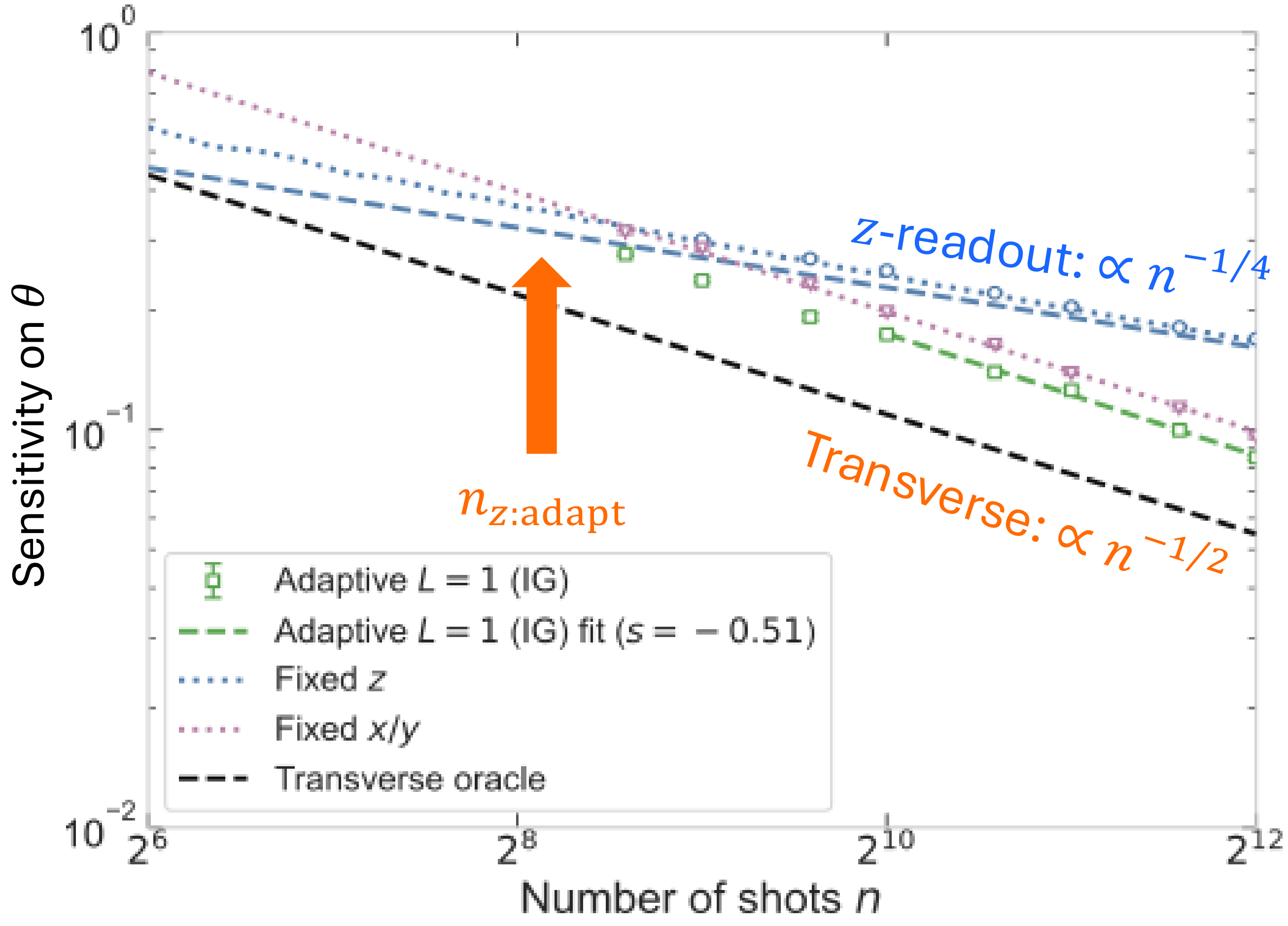


Transverse wins z-readout (noisy baseline)

- ❖ Best strategy is
  1. z-readout for $n < n_{z:\mathrm{adapt}}$
  2. Adaptive for $n > n_{z:\mathrm{adapt}}$
- ❖ Crossings due to different scaling

P	$n_{z:\mathrm{O}_\perp}$	$n_{z:x}$	$n_{z:xy}$	$n_{z:\mathrm{adapt}}$
0.50	7.88	2.32×10^2	3.03×10^2	1.47×10^2
0.70	7.90	7.20×10^2	3.77×10^2	2.12×10^2
0.90	7.50	3.08×10^4	4.89×10^2	2.86×10^2

- ❖ Adaptive sensing more important for noisy environments



Some information theory of asymmetric testing

❖ Stein's lemma tells type-II error (false negative rate) $\beta \to \exp[-\xi n + o(n)]$

- For non-adaptive approaches

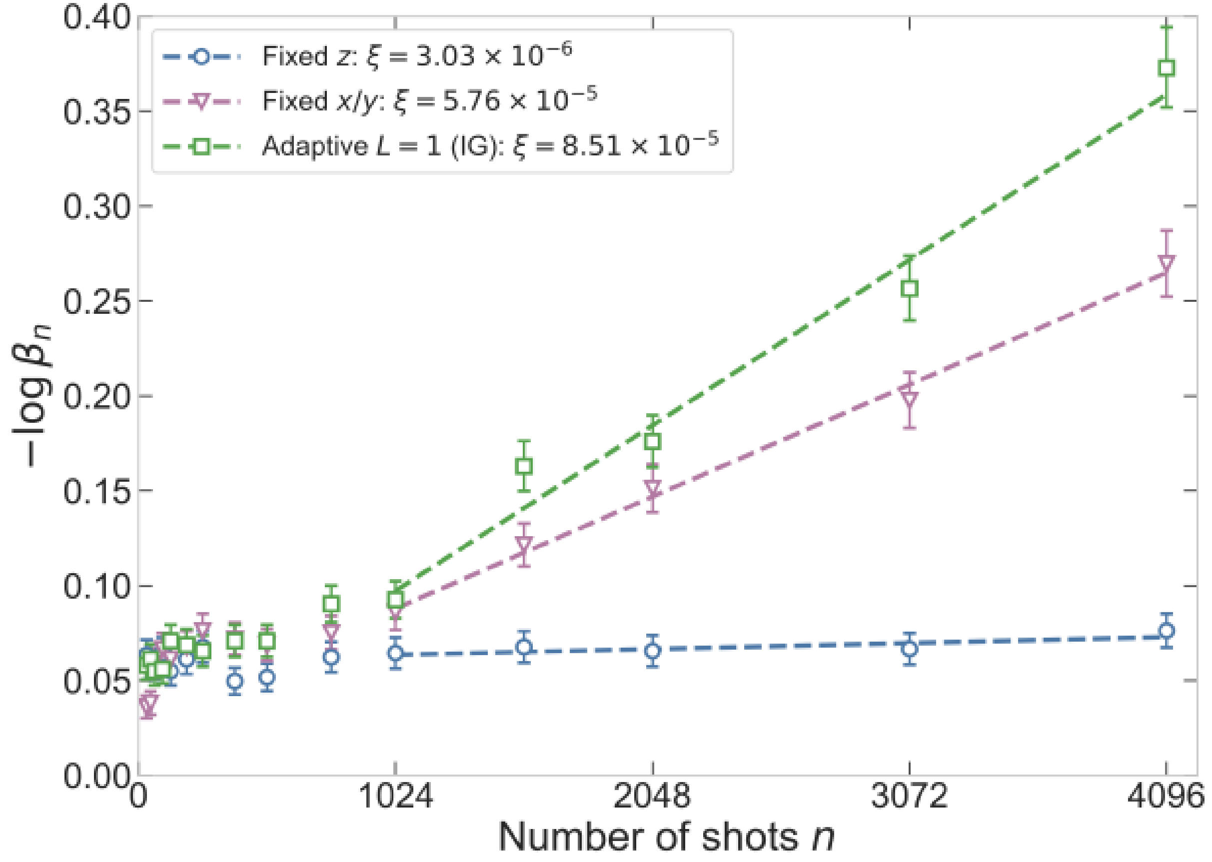
Setting	Exponent ξ	ξ for small signals
Classical	$D_{\mathrm{KL}}(P_0 \| \| P_1)$	$\propto$ Fisher information F_C
Quantum with qubit resets	$D_{\mathrm{meas}}(\rho_0 \| \| \rho_1)$	$\propto$ Fisher information F_Q
Quantum with collective meas.	$D(\rho_0 \| \| \rho_1)$	$\propto$ Fisher information F_{BKM}

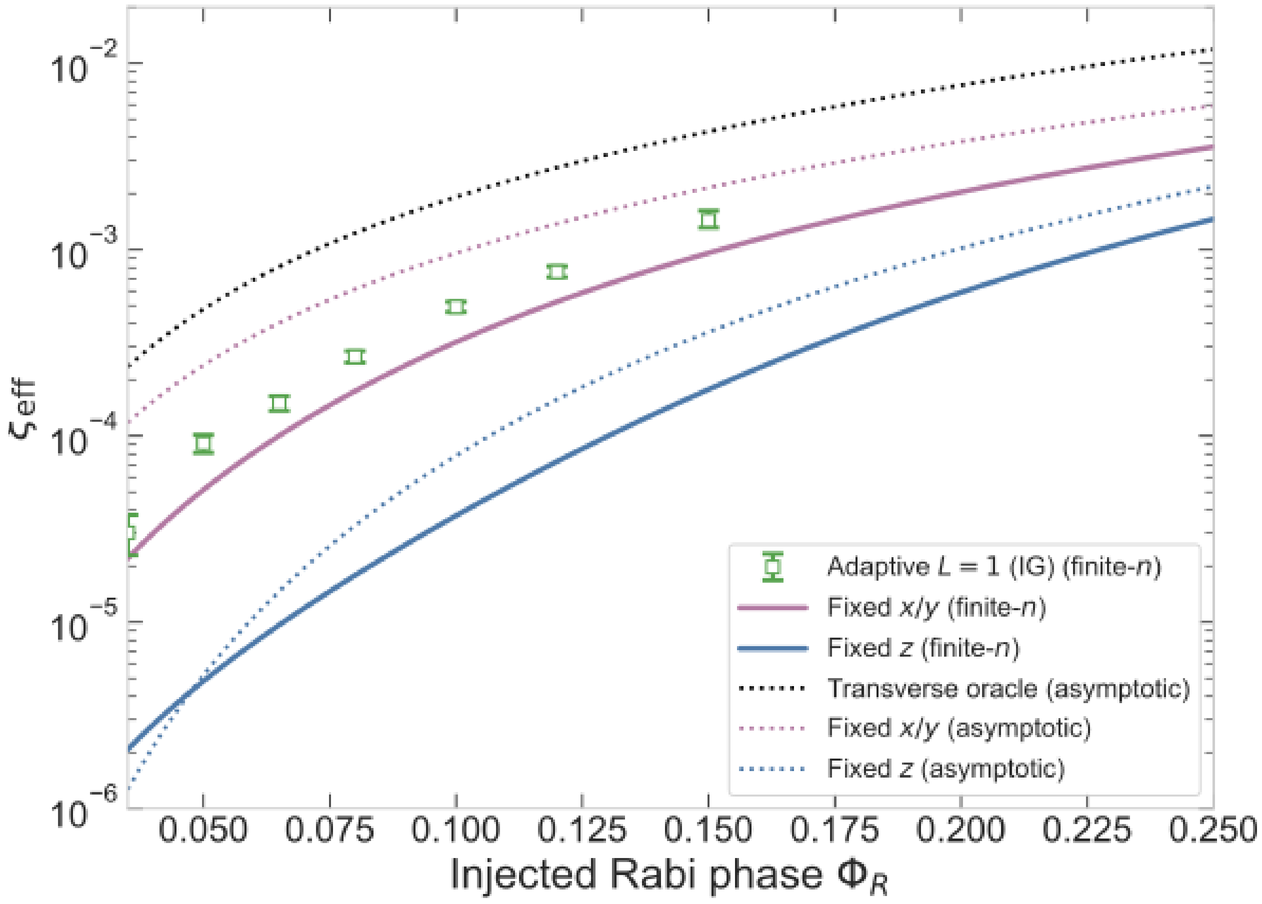
❖ Adaptive advantage proven for subset of composite problems [Bergh, et al. '23]

- Problems with non-convex set of classical channels
- Problems with non-convex set of quantum channels (convex is open)

An evidence for adaptive advantage (noisy baseline)

❖ Adaptive strategy gives the best Stein exponent





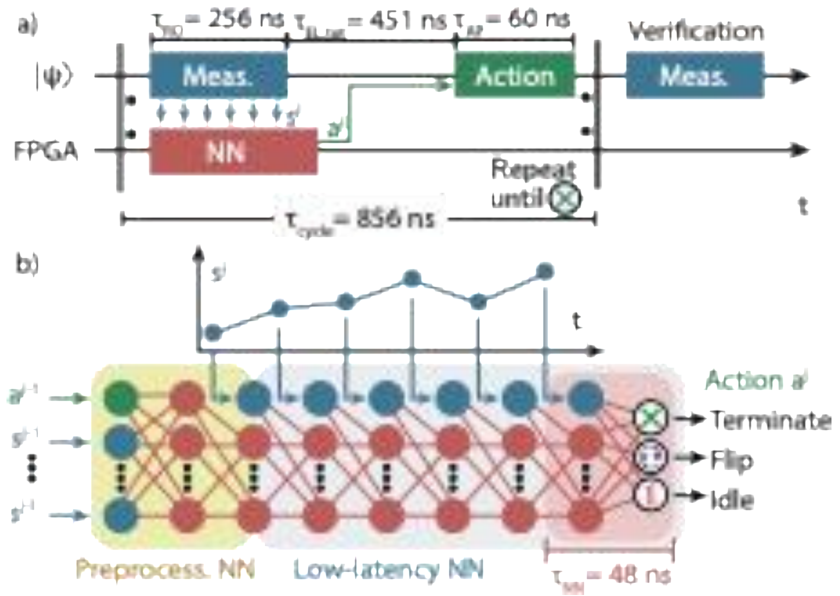
Experimental implications and next steps

❖ Implication to decision making

- Adaptive is best for $n \gtrsim n_{z:\mathrm{adapt}}$
- $n_{z:\mathrm{adapt}}$ is determined by detector properties

❖ Online update, NOT offline analysis

- Info discarded by measurement never recovered



"Realizing a deep reinforcement learning agent discovering real-time feedback control strategies for a quantum system"
[Reuer, et al. Nat. Comm. '23]

❖ Next steps

- Finite signal coherence time
- Global optimization $\Longrightarrow$ DRL
- Optimize initial state, interrogation time, etc. $\Longrightarrow$ VQA

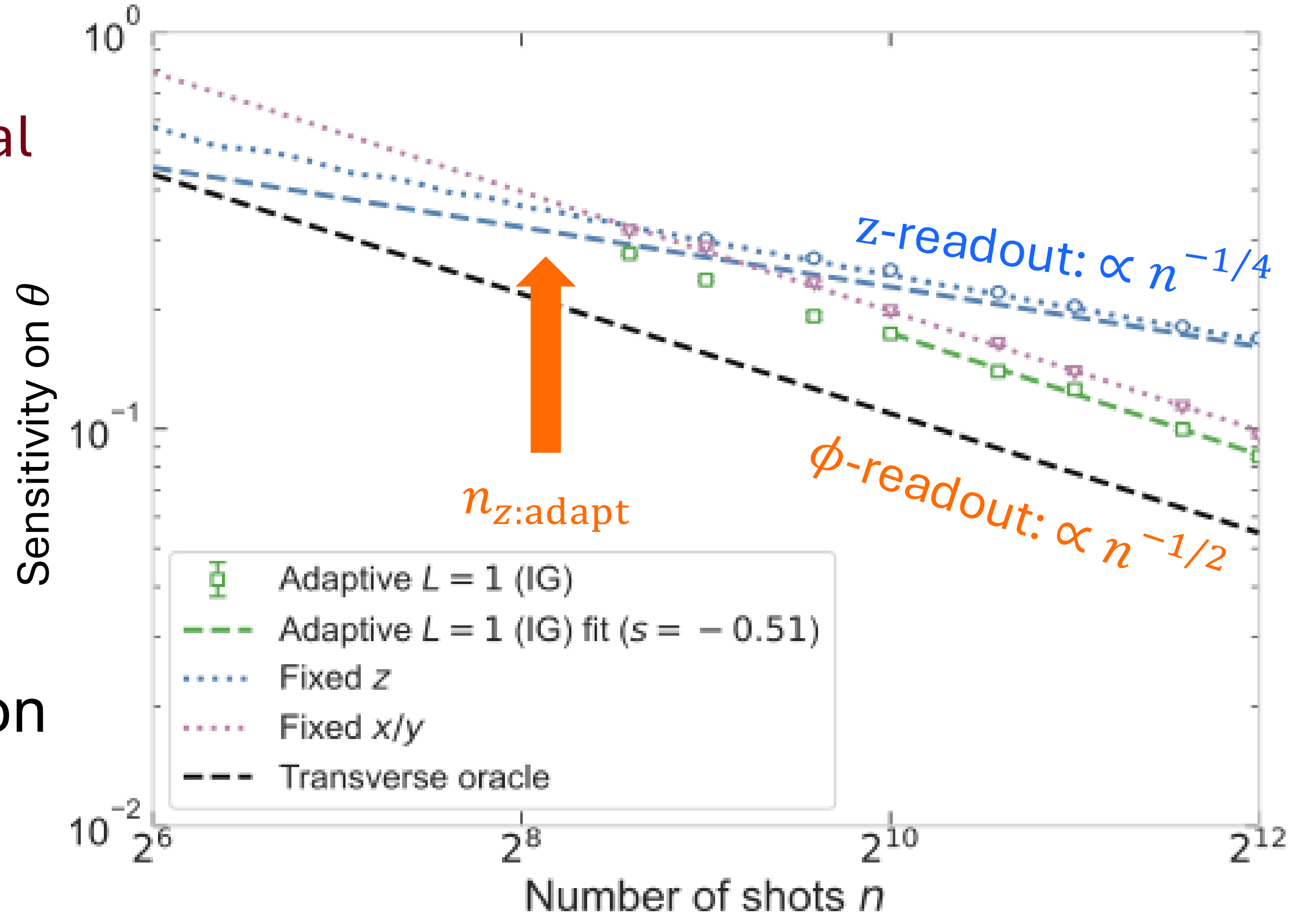
Conclusion

❖ Main message

- Adaptive strategy can be beneficial for DM searches
- The best search strategy determined by detector setups; deserves consideration during experimental design

❖ Fascinating interdisciplinary direction

Particle × Quantum × ML



Backup slides

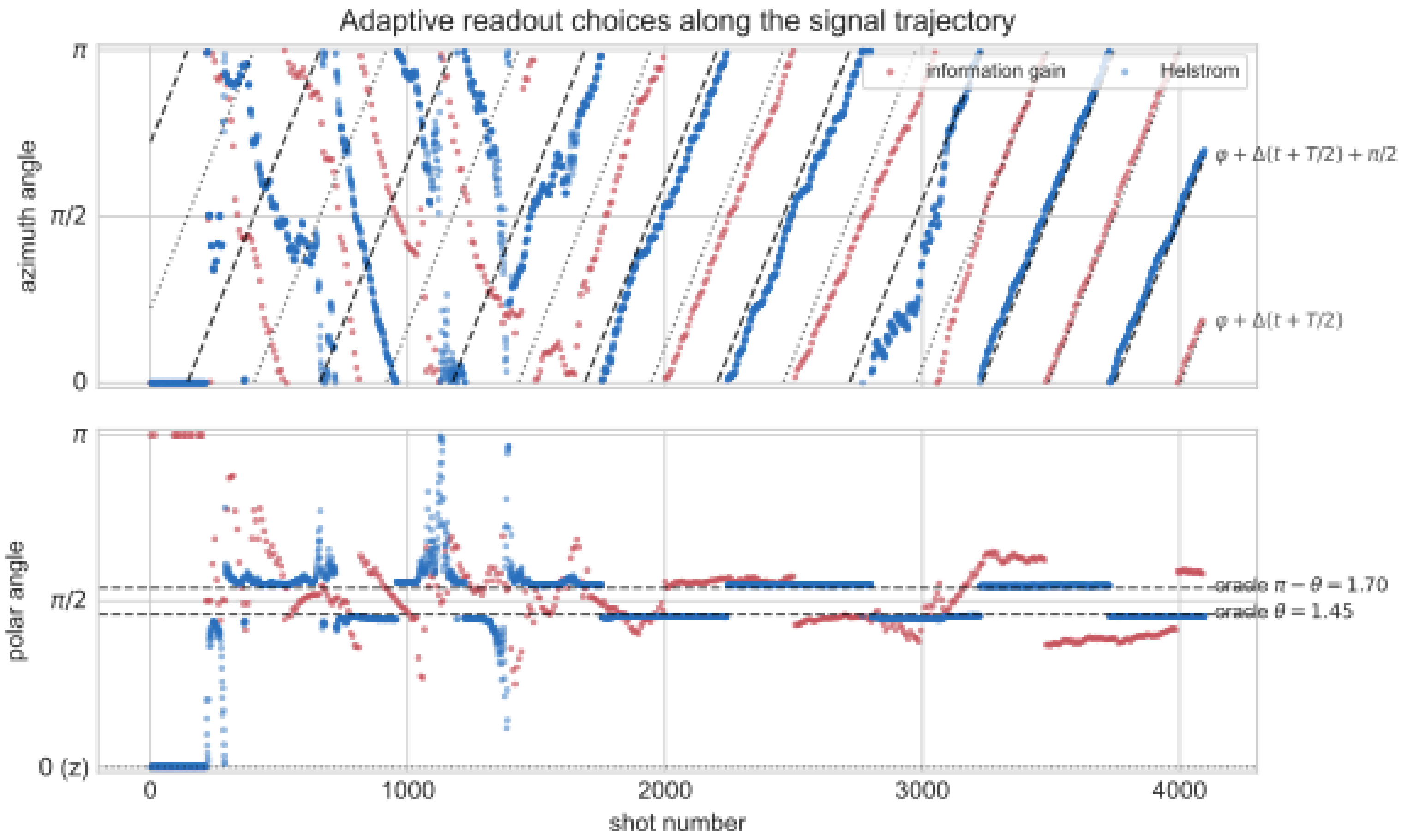
Imperfection channels

❖ Let $\rho = \frac{1}{2}(1_2 + \vec{\mathrm{r}} \cdot \vec{\sigma})$ be the ideal quantum state

1. Relaxation
   - $\mathcal{R}_T(\rho) = \frac{1}{2}\left[1_2 + \eta_2(T)\left(r_x\sigma_x + r_y\sigma_y\right) + \{1 - \eta_1(T)(1 - r_z)\}\sigma_z\right]$
   - For $T_1 = T_2 = T, \eta_2(T) \simeq 0.63, \eta_1(T) \simeq 0.53$
2. Finite contrast
   - $\mathcal{D}_C(\rho) = C\rho + \frac{(1-C)}{2}1_2 \quad (0 \leq C \leq 1)$
3. Readout error rate
   - $\mathcal{B}_\epsilon(r|r')\& = (1 - \epsilon)\delta_{r,r\prime} + \epsilon\delta_{r,-r\prime} \quad \left(0 \leq \epsilon \leq \frac{1}{2}\right)$

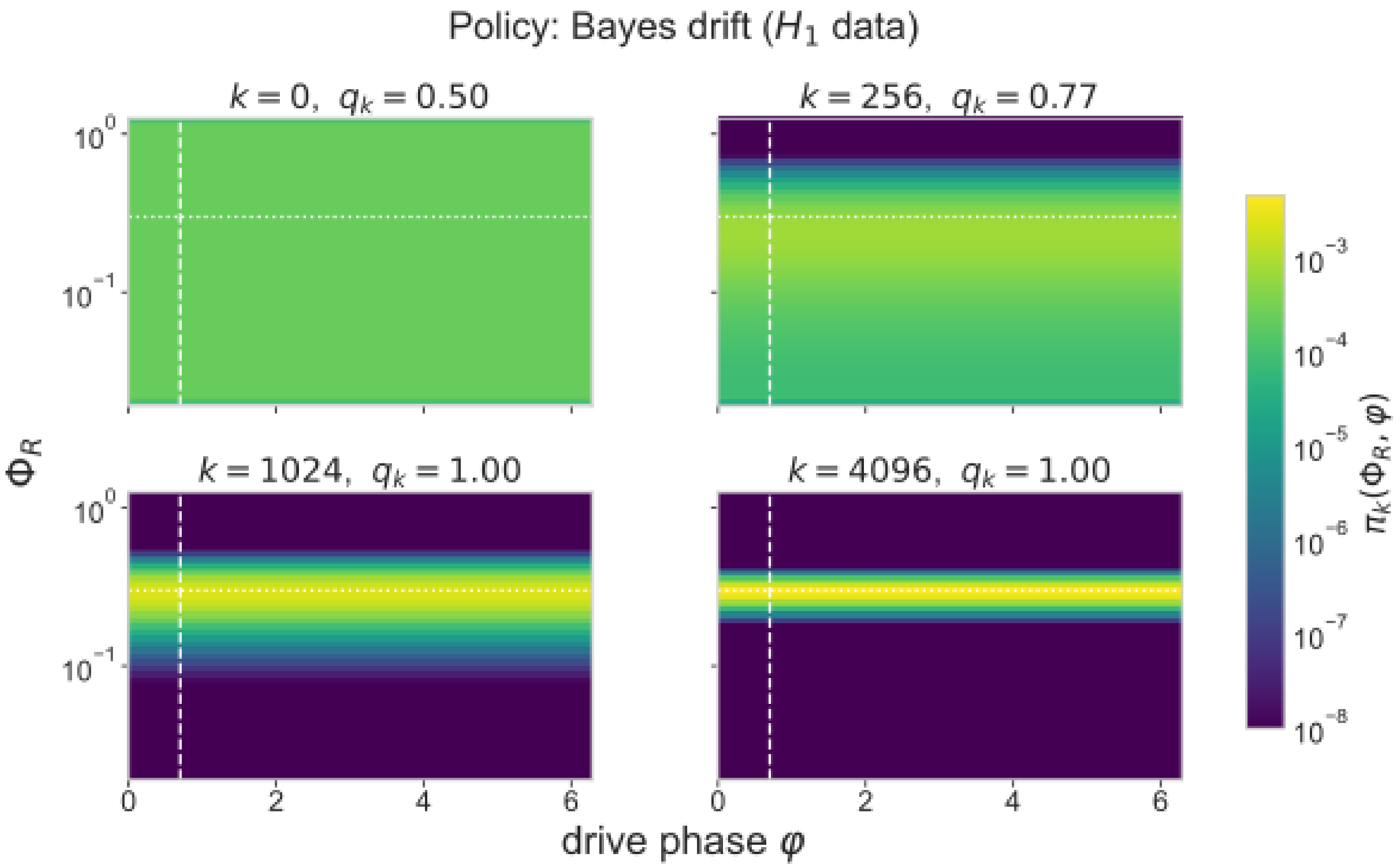
Detuning effects

❖ Detuning Δ makes optimal readout time-dependent: $\phi(\mathrm{t}) = \varphi + \pi/2 + \Delta\,\mathrm{t}$



Repeated myopic optimization ≠ global optimization

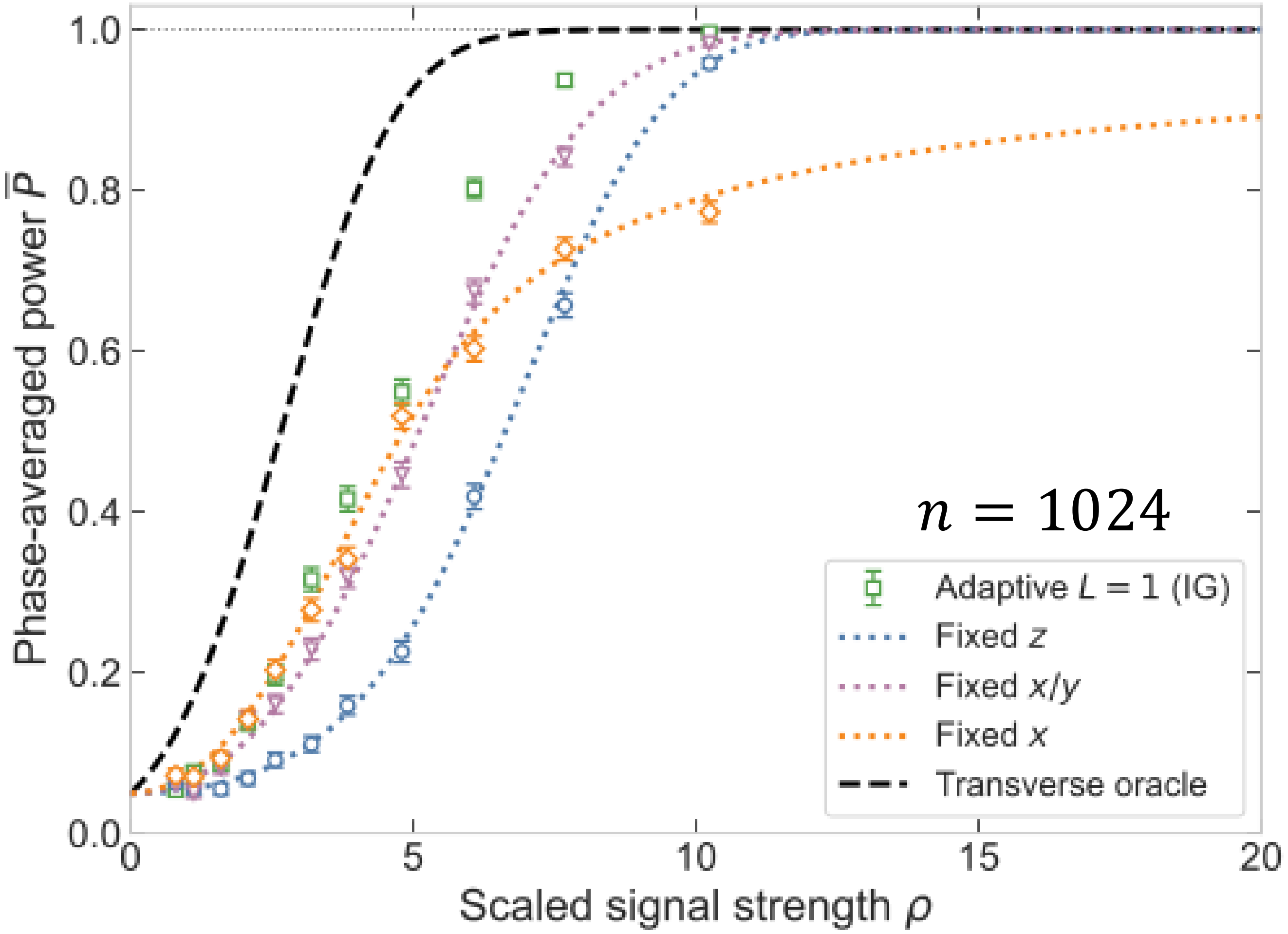
❖ Fixed-z is the best with unknown phase ⟺ No phase information is learned



Phase-averaged detection power (noisy baseline)

❖ Best strategy for increasing n_{shots}

1. z-readout for small n_{shots}
2. Adaptive for large n_{shots}



Geometric polarization diagnostic

❖ Phase information efficiency

- $f_{\mathrm{pol}} \equiv 2\left\langle \left\{ \hat{n}_{\mathrm{meas}} \cdot \left(\hat{z} \times \hat{n}_{\mathrm{sig}} \right) \right\}^2 \right\rangle$

$$= \begin{cases} 0 & (\text{fixed-}z) \\ 1 & (\text{fixed-x/y}) \\ 2 & (\text{oracle}) \end{cases}$$

- Parameterizes how efficiently phase information was used