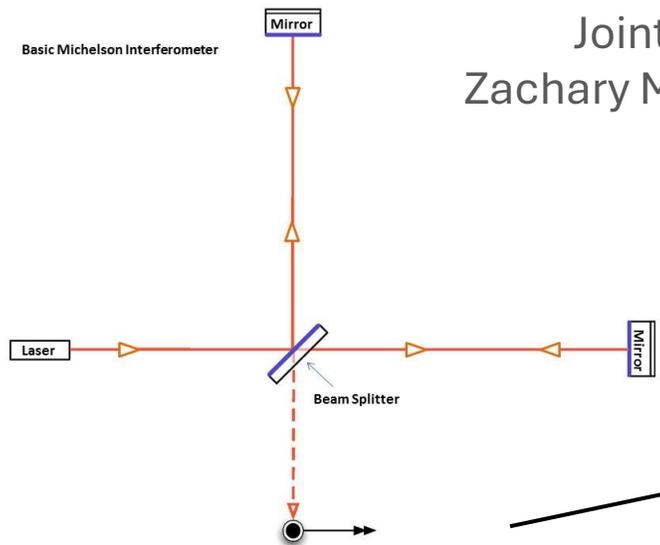# Towards sample-optimal learning of bosonic Gaussian quantum states
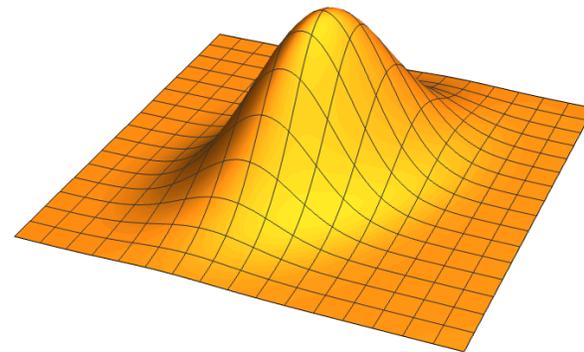
Senrui Chen (IQIM Postdoc)

IQIM Seminar, Feb 27, 2026
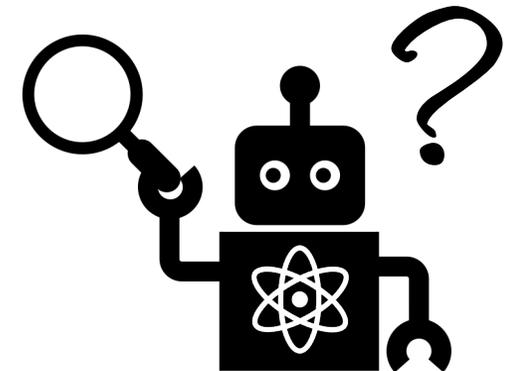
Joint work with Francesco Anna Mele, Marco Fanizza, Alfred Li, Zachary Mann, Hsin-Yuan (Robert) Huang, Yanbei Chen, and John Preskill
[arXiv 2603.18136]

Basic Michelson Interferometer

Mirror

Laser

Beam Splitter

Mirror

[Credit: Caltech/MIT/LIGO Lab]

$\rho(\mu, \Sigma)$

Bosonic Quantum Information

- Quantum information processing with continuous-variable systems
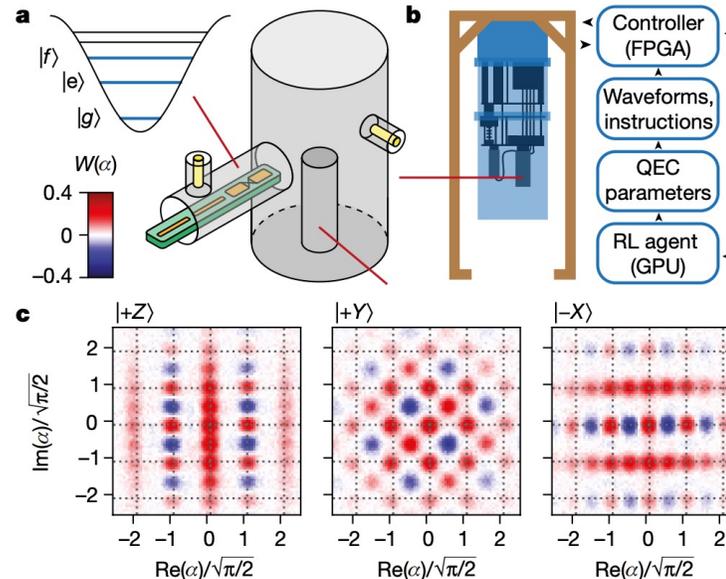
Quantum Sensing and Metrology
Gravitational wave (GW) detection
Dark matter search
Quantum imaging

Quantum Computation
Bosonic quantum error correction
Boson Sampling
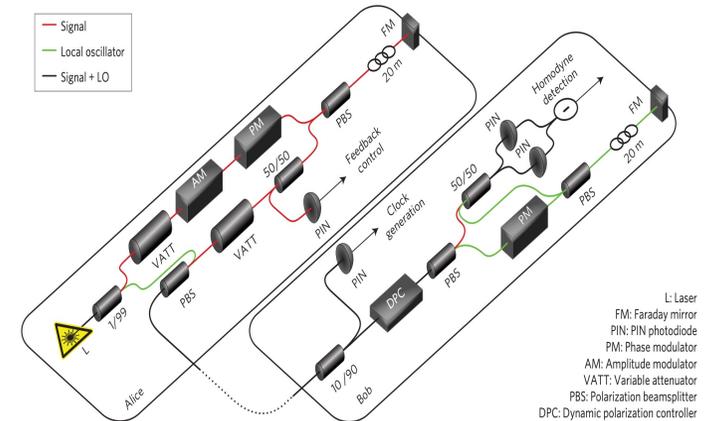
Quantum Communication
Continuous-Variable QKD

Gaussian states

- Gaussian states – a natural class of bosonic quantum states
  - Gibbs states of quadratic Hamiltonian in quadrature operators $(\hat{x}_i, \hat{p}_i)$
  - Equivalently, States with a Gaussian Wigner function

[PennyLane, Xanadu]
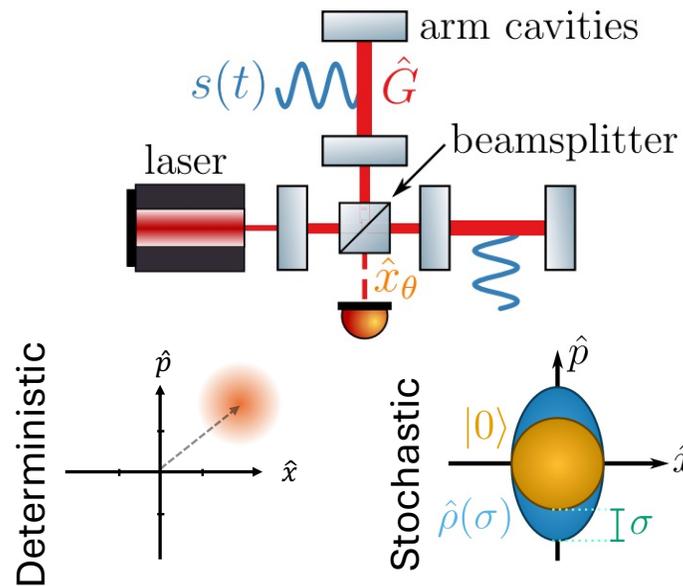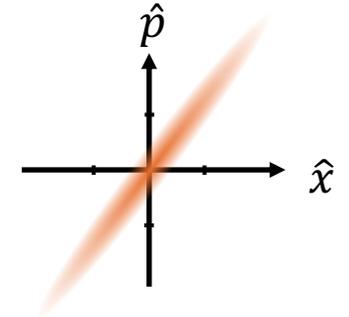
[J Gardner et al. PRL **132**, 130801 (2024)]
[J Gardner et al. PRXQ **6**, 030311 (2025)]

[Madsen et al. Nature 606, 75–81 (2022)]

[Zhong et al. Science 370, 6523 (2020)]

Gravitational wave detection in LIGO

Gaussian Boson Sampling

Learning Gaussian states

- Learning Gaussian states is important for sensing, benchmarking, etc.

- How efficiently can we learn them?

- **Formally**: How many copies are needed to learn an unknown n-mode Gaussian state ρ, with energy no more than E, to trace distance ε with probability at least 2/3?

  $$p_{\mathrm{succ}} = (1 + D_{\mathrm{tr}})/2$$

  - Trace distance: $D_{\mathrm{tr}}(\rho, \sigma) = \frac{1}{2}\mathrm{Tr}|\rho - \sigma|$, captures how good two states can be distinguished

  - For sensing broadband or time-varying signals, or benchmarking large quantum devices, the scaling with **mode number** n is important

  - We characterize energy E by the largest eigenvalues of ρ's covariance matrix.

- State-of-the-art: $N = O(n^3 \varepsilon^{-2} + n\, \mathrm{polyloglog} E)$ is sufficient[1]

  - No meaningful lower bound is known.

[1] "Energy-independent tomography of Gaussian states". Bittel, Mele, Eisert, Mele. arXiv:2508.14979

Summary of Results

Task: Learn an n-mode $\rho(\mu, \Sigma)$ to ε trace distance with probability at least 2/3.   Promise: $||\Sigma||_{\mathrm{op}} \leq \bar{E}$.

Class of states	Class of measurements	Bounds	
All Gaussian	Classical (including Gaussian)	$\widetilde{O}(n^3/\varepsilon^2)$ [BMEM25]	$\Omega(n^3/\varepsilon^2)$ Thm. 2
	Any		$\Omega(n^2/\varepsilon^2)$ Thm. 3
Pure Gaussian	Any or Gaussian	$\widetilde{\Theta}(n^2/\varepsilon^2)$ Thm. 3, 5	
Passive Gaussian	Any	$\widetilde{O}(n^2/\varepsilon^2)$ Thm. 6	Non-Gaussian Advantages
	Classical (including Gaussian)	$\Theta(n^3/\varepsilon^2)$ Thm. 2, 6	
1-mode Gaussian	Non-adaptive 1-copy Gaussian	$\widetilde{\Theta}(\bar{E}/\varepsilon^2)$ Thm. 7	

[BMEM25] Bittel, Mele, Eisert, Mele. arXiv:2508.14979 $\widetilde{\Theta}, \widetilde{O}, \widetilde{\Omega}$ suppress $\log n$, $\log \varepsilon^{-1}$, and poly $\log \log E$ factors.

Preliminaries

Basics of bosonic quantum information

- Hilbert space for n bosonic modes : $\mathcal{H}^n \cong L^2(\mathbb{R}^n; \mathbb{C})$

- Quadrature operators: $\hat{R} = [\hat{x}_1, \dots, \hat{x}_n, \hat{p}_1, \dots, \hat{p}_n]$
  - Canonical Commutation Relation (CCR): $[\hat{R}_k, \hat{R}_l] = i\Omega_{kl}$, where $\Omega = \begin{pmatrix} 0_n & -I_n \\ I_n & 0_n \end{pmatrix}$

- Mean μ and covariance Σ of a bosonic state ρ:
  - $\mu_i \coloneqq \mathrm{Tr}(\hat{R}_i \rho).$ $\Sigma_{kl} \coloneqq \frac{1}{2}\mathrm{Tr}(\{\hat{R}_k, \hat{R}_l\}\rho) - \mu_k \mu_l$

- Displacement operator: $\widehat{D}_\xi \coloneqq \exp(i\xi^\mathrm{T}\Omega\hat{R}),$ where $\xi \in \mathbb{R}^{2n}$

- **Wigner function**: $W_{\hat{O}}(r) \coloneqq \frac{1}{(2\pi)^{2n}} \int \mathrm{d}^{2n}\xi \exp(i\xi^\mathrm{T}\Omega r) \mathrm{Tr}(\widehat{D}_\xi \hat{O}),\ \ r \in \mathbb{R}^{2n}$
  - For a quantum state ρ, $\int \mathrm{d}^{2n}r\, W_\rho(r) = 1$, called **Wigner quasi-distribution**.
  - Inner product formula: $\mathrm{Tr}(\rho\hat{O}) = (2\pi)^n \int \mathrm{d}^{2n}r\, W_\rho(r)W_{\hat{O}}(r).$
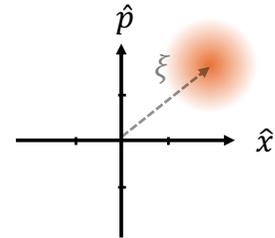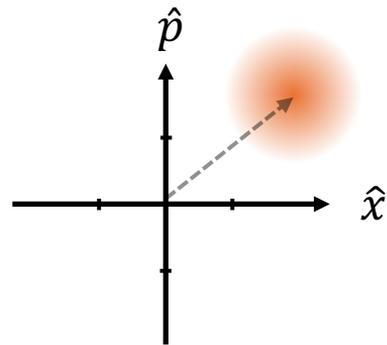
Basics of Gaussian states

- **Def**. Gaussian states are states with Gaussian Wigner distribution $W_\rho = \mathcal{N}(\mu, \Sigma)$
  - Denoted by $\rho(\mu, \Sigma)$. Note the quantum and classical moments coincide.

- **Theorem** (Uncertainty relation)[1]: $\rho(\mu, \Sigma)$ is a valid Gaussian state iff $\Sigma + i\Omega/2 \geq 0$
  - In 1-mode case, equivalent to $\lambda_1 \lambda_2 \geq \frac{1}{4}$ where λ's are eigenvalues of Σ

- Examples of 1-mode Gaussian states (in Wigner distribution):
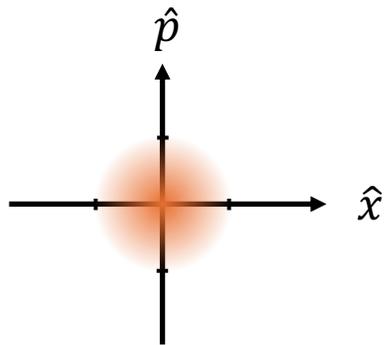
Vacuum state $|0\rangle$ Coherent state   Thermal state   Squeezed state   **NOT** a valid state!!
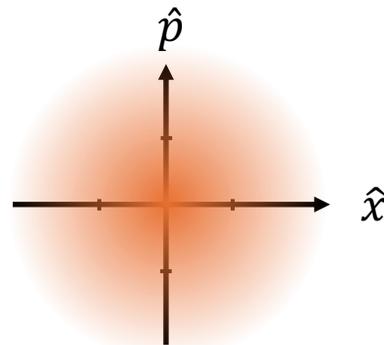
[1] Originally by Robertson and Schrödinger. See Weedbrook et al., Rev. Mod. Phys. **84**, 621 (2012)

Measurements of bosonic systems

- Measurements are POVMs: $\{E_i\}$ where $E_i \geq 0$ and $\sum_i E_i = \mathbb{I}$. $\Pr(i|\rho) = Tr(E_i \rho)$

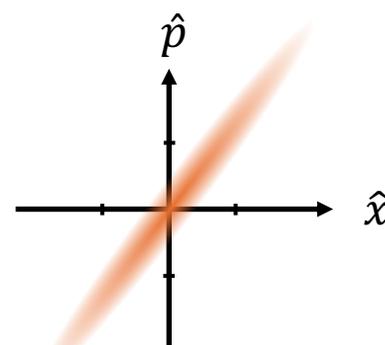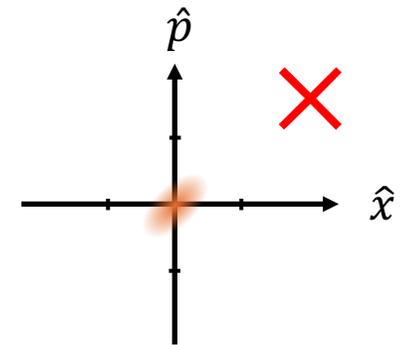1. **Classical meas.** All POVM elements E_i have **non-negative** Wigner functions
   - The most familiar instance is **Gaussian** measurements : $\left\{ E_\xi := \frac{1}{(2\pi)^n} D_\xi \rho(0, V) D_\xi^\dagger \right\}$
     where $\rho(0, V)$ is a Gaussian state called the measurement **seed**. Needs $V + i\Omega/2 \geq 0$.
   - Meas seed V on $\rho(\mu, \Sigma)$ yields $\xi \sim \mathcal{N}(\mu, \Sigma + V)$, i.e., blurred Wigner samples

   - Examples: Heterodyne (vacuum seed)   Homodyne (squeezed seed)
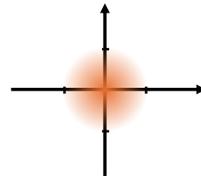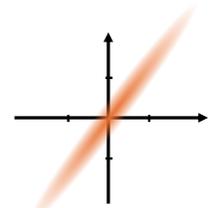
2. **Non-classical meas**.
   - Typical example: **photon number counting:** $\{E_n := |n\rangle\langle n|\}$
   - Projection to the **Fock basis**, eigen basis of $\hat{x}_i^2 + \hat{p}_i^2$ at each mode
   - Non-vacuum Fock states' Wigner functions contain <u>negative values</u>
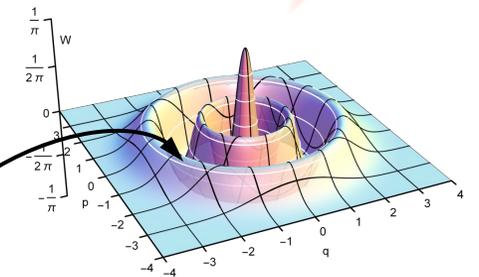
[Wigner function of $|4\rangle$, Wikipedia]

- Will Non-classical meas. help in learning Gaussian states? --- Yes, as we will see.

Learning Gaussian Wigner Distributions

Learning Gaussian Wigner distributions
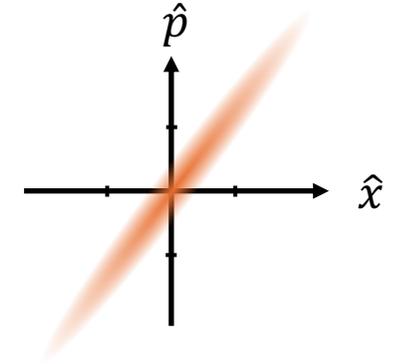
- **Warm-up question**: How many copies are needed to learn the Wigner distribution of a Gaussian states to ε TV distance?
  - $\text{TV}(p, q) := \sum_x |p(x) - q(x)|/2.$ $\text{Pr(Succ in distinguishing)} = (1 + \text{TV})/2$

- **Known**[1]: Learning classical $2n$-dim Gaussians to ε-TVD requires $\Theta(n^2 \varepsilon^{-2})$ samples

- **Thm 1**. $N = \widetilde{\Theta}(n^2 \varepsilon^{-2})$ are necessary and sufficient to learn Gaussian Wigner
  - Furthermore, this can be achieved using only **Gaussian measurements**.
  - Hide a doubly-logarithmic factor depending on energy (see next slide)

[1] Ashtiani et al. *Journal of the ACM (JACM)* 67.6 (2020): 1-42.

Learning Gaussian Wigner – upper bound

- For classical Gaussians, empirical mean & covariance estimators suffice to learn with $\Theta(n^2 \varepsilon^{-2})$ samples.

$$v_1, \cdots, v_{2m} \in \mathbb{R}^{2n} \quad \hat{\mu} := \frac{1}{m} \sum_{i=1}^{m} v_i,$$

$$\hat{\Sigma} := \frac{1}{2m} \sum_{i=1}^{m} (v_{2i} - v_{2i-1})(v_{2i} - v_{2i-1})^T$$

- For bosonic Gaussian states, there are quantum noise!
  - An adaptive Gaussian protocol can learn with $N = \Theta(n^2 \varepsilon^{-2} + n \, \text{poly} \log \log E)$ copies given that $||\Sigma||_{\text{op}} \leq E$ [BMEM25]
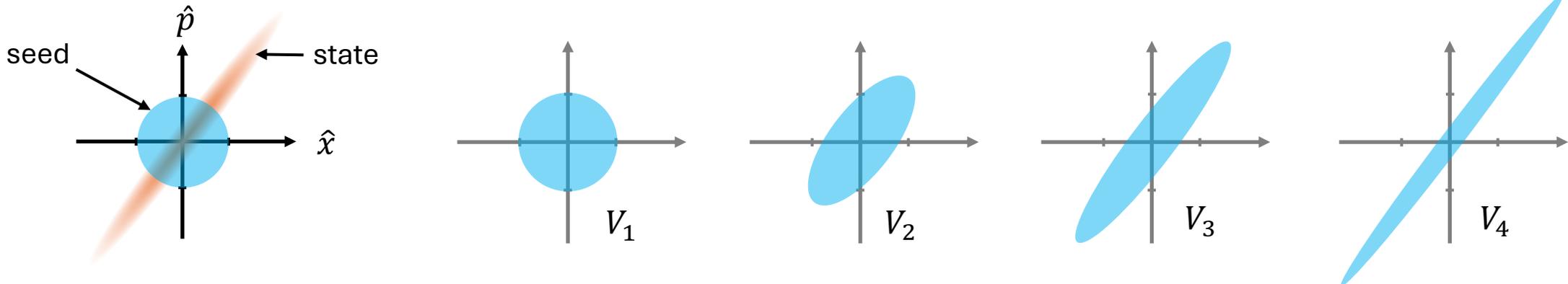
E.g. Vacuum seed overwhelms signals in highly-squeezed quadrature.

By adaptively refining seeds using $\Theta(n \cdot \text{poly} \log \log E)$ copies, one can find a good measurement seed V. Then empirical estimates suffice.

[BMEM25] "Energy-independent tomography of Gaussian states". Bittel, Mele, Eisert, Mele. arXiv:2508.14979

Learning Gaussian Wigner – lower bound

- Lower bound: $\Omega(n^2 \varepsilon^{-2})$ via an information-theoretic argument:

U_a

$\frac{n}{9}$

$\frac{8n}{9}$

ρ_a

Gaussian state ensemble of size $2^{\Omega(n^2)}$

Alice
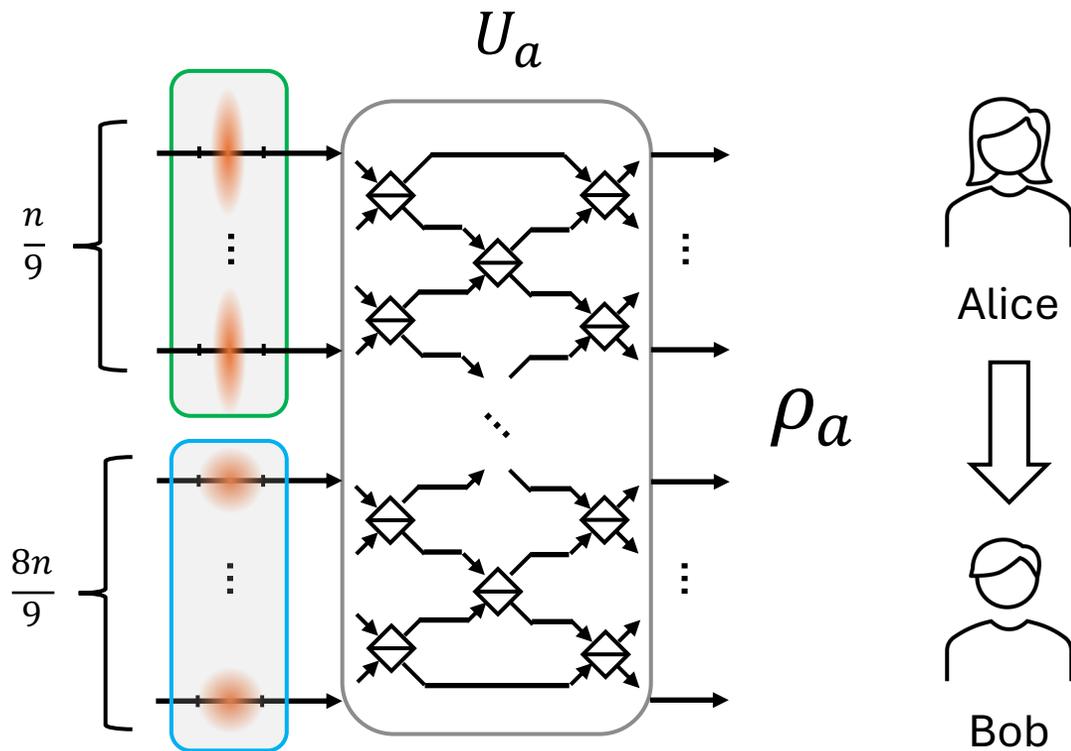
(i) Pick ρ_a at uniform random

(ii) Send N copies of ρ_a to Bob

Bob

(iii) Measure $\rho_a^{\otimes N}$ to guess a

Guarantee: $\forall\, a \neq b$,
$\mathrm{TV}\big(\mathrm{W}_{\rho_a}, \mathrm{W}_{\rho_b}\big) \geq 3\varepsilon$

If N suffices for learning,
Bob can guess a w.h.p.

Fano's inequality:
$I(A{:}B) \geq \Omega(n^2)$

Compute Holevo χ quantity
$I(A{:}B) \leq N \cdot O(\varepsilon^2)$

$N \geq \Omega(n^2 \varepsilon^{-2})$ is necessary

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Gaussian Wigner TVD $\longleftrightarrow$ Trace distance?

- We have seen $\tilde{\Theta}(n^2 \varepsilon^{-2})$ suffices to learn Gaussian Wigner to ε TVD.
  - And Gaussian measurements can achieve this.

- Is this the same as learning Gaussian states to ε trace distance?
  - $D_{\mathrm{tr}}(\rho, \sigma) := \frac{1}{2} \mathrm{Tr}|\rho - \sigma|$.

- **Lemma 1**. There exists constants $c_0, c_1, c_2 \geq 0$ such that for any n-mode Gaussian states ρ, σ satisfying $D_{\mathrm{tr}}(\rho, \sigma) \leq c_0$, it holds that
$$c_1 \mathrm{TV}(W_\rho, W_\sigma) \leq D_{\mathrm{tr}}(\rho, \sigma) \leq \sqrt{n} \cdot c_2 \mathrm{TV}(W_\rho, W_\sigma)$$
  - That is, Gaussian trace distance can be a factor of $\sim\sqrt{n}$ larger than Wigner TVD
  - Quantum samples can be more powerful than classical Wigner samples

An example of maximal separation

- Consider the following pair of n-mode Gaussian states:

$$\Sigma_0 = \frac{1}{2} I_{2n} \left(\begin{array}{c} \hat{p} \\ \longrightarrow \hat{x} \end{array} \right)^{\otimes n} \quad \text{vs.} \quad \left(\begin{array}{c} \hat{p} \\ \longrightarrow \hat{x} \end{array} \right)^{\otimes n} \Sigma_1 = \frac{1}{2}\left(1 + \frac{\varepsilon}{n}\right) I_{2n}$$

- $\text{TV}\big(\mathcal{N}(0, \Sigma_0), \mathcal{N}(0, \Sigma_1)\big) \leq \frac{1}{\sqrt{2}}||\Sigma_0^{-1/2}\Sigma_1\Sigma_0^{-1/2} - I_{2n}||_F = \varepsilon n^{-1/2}$ Wigner TV distance

- Apply **photon counting**,
  - $\text{Pr}(\text{Vacuum}|\rho_0) = 1$,
  - $\text{Pr}(\text{Vacuum}|\rho_1) = \langle 0|\rho_1|0\rangle = (1 + \varepsilon/2n)^{-n} \leq 1 - \varepsilon/4$.

- Thus $D_{\text{tr}}(\rho_0, \rho_1) \geq \varepsilon/4$, because D_{tr} is no smaller than any measured TVD

- This means $D_{\text{tr}}(\rho_0, \rho_1) \geq \sqrt{n}/4 \cdot \text{TV}(W_{\rho_0}, W_{\rho_1})$, maximal separation up to const.

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Summary, so far

- We have proven that:
  - **Thm 1.** $N = \tilde{\Theta}(n^2 \varepsilon^{-2})$ is necessary and sufficient to learn Gaussian Wigner to ε TVD
  - **Lemma 1.** $\Omega\left(\mathrm{TV}(W_\rho, W_\sigma)\right) = D_{\mathrm{tr}}(\rho, \sigma) = \sqrt{n} \cdot O\left(\mathrm{TV}(W_\rho, W_\sigma)\right)$

- This implies that, to learn a Gaussian state to ε trace distance:
  - $N = \tilde{O}(n^3 \varepsilon^{-2})$ copies are sufficient, using adaptive Gaussian measurements [BMEM25]
  - $N = \Omega(n^2 \varepsilon^{-2})$ copies are necessary, using any measurements.

- The rest of this talk
  - Can we close the n^2 vs. n^3 gap?
  - What are the roles of non-classical measurements and adaptivity?

Lower bound for classical measurements

Lower bounds for classical measurements

- **Thm 2**. $N = \Omega(n^3 \varepsilon^{-2})$ are necessary for any **classical measurements**.
  - **Recall**: Classical POVMs have non-negative Wigner functions.
  - This implies [BMEM25] is the (near-)sample optimal Gaussian scheme.
  - Thm 2 holds even if ρ is promised to be **passive** –

    $\rho(\mu, \Sigma)$ is **passive** if it can be generated via passive linear optics on thermal states.

- Learning bosonic Gaussians via classical meas. is strictly harder than learning their Wigner distribution (n^3 vs. n^2)

- Key lemma [ME12]: Classical measurements on Gaussian states can be exactly simulated by samples from their Wigner distribution.

$$\Pr(\xi|\rho) = Tr[E_\xi \rho] \propto \int d^{2n}r \, \boxed{W_{E_\xi}(r)} \cdot \boxed{W_\rho(r)}$$

Conditional
distribution $\Pr(\xi|r)$

Wigner
distribution

[BMEM25] Bittel, Mele, Eisert, Mele. arXiv:2508.14979.   [ME12] A Mari and J Eisert. PRL 109(23):230503, 2012

Lower bounds for classical measurements

- $\Omega(n^3\varepsilon^{-2})$ via an information-theoretical argument
  - Leverage the Wigner TVD – Trace distance separation in Lemma 1.

U_a

$\frac{n}{9}$

ρ_a

$\frac{8n}{9}$
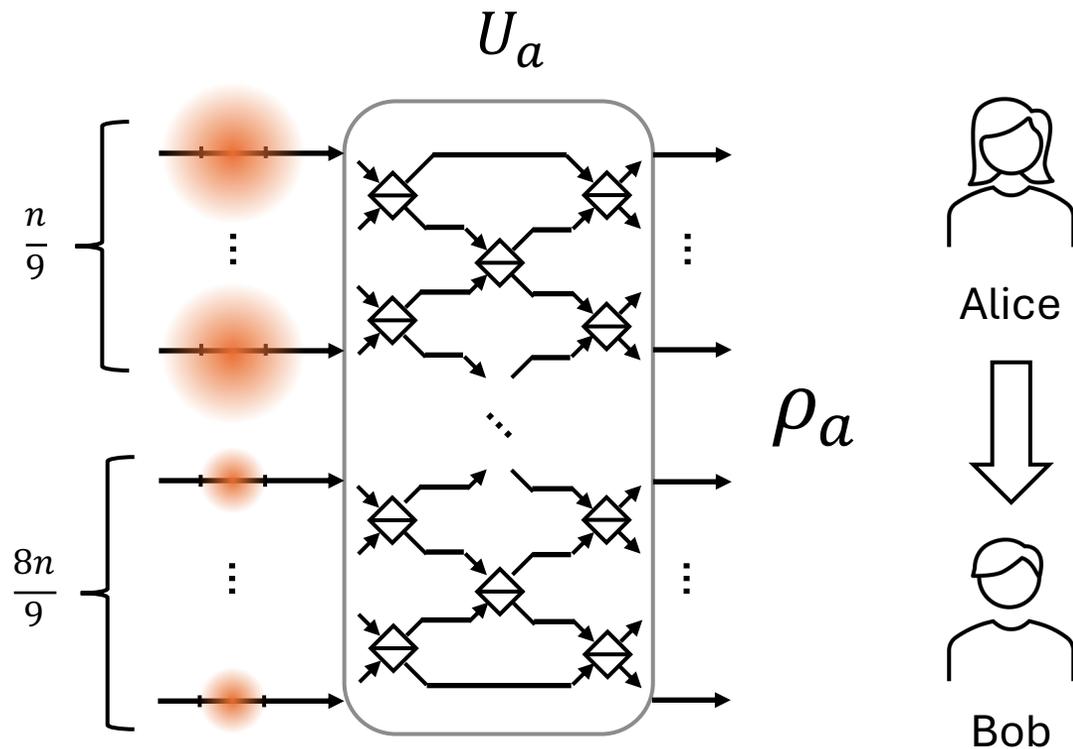
Passive Gaussian state ensemble of size $2^{\Omega(n^2)}$

Alice

(i) Pick ρ_a at uniform random

(ii) Send N **classical samples** from W_ρ to Bob.

(iii) Processing the classical samples to guess a

Bob

Guarantee: $\forall\, a \neq b$, $D_{\mathrm{tr}}(\rho_a, \rho_b) \geq 3\varepsilon$

[ME12]

If N suffices for learning, Bob can guess a w.h.p.

Fano's inequality: $I(A:B) \geq \Omega(n^2)$

Obtain mutual info upper bound: $I(A:B) \leq N \cdot O(\varepsilon^2/n)$

$N \geq \Omega(n^3\varepsilon^{-2})$ is necessary

Upper bounds

Learning Pure Gaussian states

- When can we do better than $\tilde{O}(n^3 \varepsilon^{-2})$?

- **Thm 5**. With the promise that $\rho(\mu, \Sigma)$ is **pure** and $||\Sigma||_{\mathrm{op}} \leq E$,

  $N = \tilde{O}(n^2 \varepsilon^{-2}) = O(n^2 \varepsilon^{-2} + n \operatorname{poly} \log \log E)$ suffices using Gaussian meas.

  - We also show a matching lower bound of $\widetilde{\Omega}(n^2 \varepsilon^{-2})$ for pure states with **any** meas.

- **Lemma**: $D_{\mathrm{tr}}(\rho, \sigma) = \Theta(\mathrm{TV}(W_\rho, W_\sigma))$ for pure Gaussian states ρ and σ

  - Proof: Use $D_{\mathrm{tr}}^2 = 1 - F$ for pure states and pure Gaussian fidelity formula.

- **Algorithm** using $\tilde{O}(n^2 \varepsilon^{-2})$ samples:
  1. Uses [BMEM25] to learn Wigner to ε TVD
  2. Project the estimator to a nearby pure state
  3. Convert from Wigner TV to trace distance.

- No non-Gaussian advantages for learning Pure Gaussian states!

[BMEM25] Bittel, Mele, Eisert, Mele. arXiv:2508.14979.

Learning Passive Gaussian states

- **Thm 6**. With the promise that $\rho(\mu, \Sigma)$ is **passive** and $||\Sigma||_{\mathrm{op}} \leq E$,

1. $O(n^2 \varepsilon^{-2} + n \, \mathrm{poly} \log \log E)$ copies suffices using a non-classical scheme

2. In contrast, any classical measurements require $\Omega(n^3 \varepsilon^{-2})$ copies.

- Thus, non-classical measurements provide advantages in learning!

- **Techniques**: Passive Random purification channels [MGC+25]

Learning Passive Gaussian states

- **Techniques**: Passive Random purification channels [MGC+25]

$$\mathcal{H}_A \qquad \mathcal{H}_A \otimes \mathcal{H}_B \qquad \mathcal{H}_A$$

N copies

ρ is any passive Gaussian state
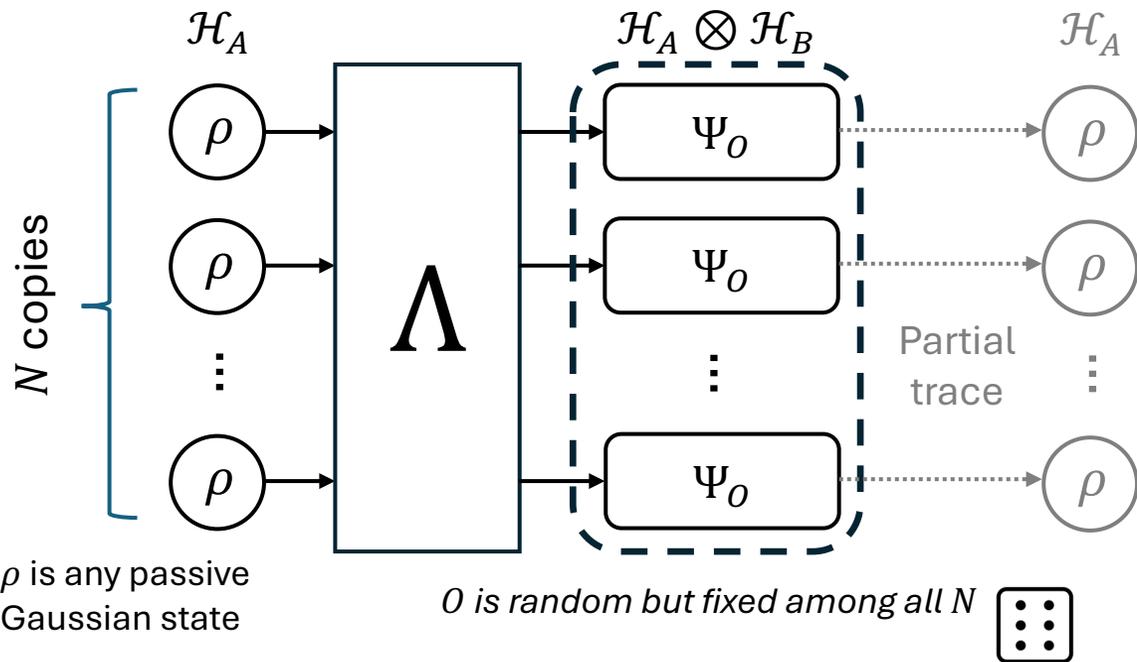
O is random but fixed among all N

- There exists a quantum channel Λ that maps N copies of any passive Gaussian states $\rho^{\otimes N}$ to N copies of a random purification $\Psi_O^{\otimes N}$

- Furthermore, Ψ_O are **pure** $2n$-mode Gaussian states with $||\Sigma_\Psi||_{op} \leq 4||\Sigma_\rho||_{op}$

- **Algorithm**: First purify, then runs pure Gaussian state learning using $\tilde{O}(n^2 \varepsilon^{-2})$ copies (**Thm. 5**)

Facts:

- Λ is an **entangling** and **non-Gaussian** channel

- Experimental implementation of Λ is unclear
  - Open problem: Find an experimentally feasible scheme

$$\Lambda^{(n,N)}\left(\rho_A^{\otimes N}\right) = \mathbb{E}_O\left[|\Psi_O\rangle\langle\Psi_O|^{\otimes N}\right] = \mathbb{E}_O\left[\left((I_A \otimes U_O)|\Psi\rangle\langle\Psi|(I_A \otimes U_O)^\dagger\right)^{\otimes N}\right]$$

Conjectures for general Gaussian states

- **Proposition**: If there exists a random purification channel for any Gaussian states, such that the purified states are Gaussian whose covariance matrices satisfy $||\Sigma_\Psi||_{op} \leq \text{poly}(||\Sigma||_{op})$, then $N = \tilde{\Theta}(n^2 \varepsilon^{-2})$ suffices to learn any Gaussian states, and there are non-Gaussian advantages.

- **Conjecture**: There exist such random purification channels
  - Similar concepts of random purification for any n-qubit states are known [PSTW25]

- **Difficulty**: Symplectic group is not compact. Need careful analysis

[PSTW25] Pelecanos, Spilecki, Tang, Wright. arXiv: 2511.15806

On the role of adaptivity

Adaptive learning

- [BEME25]'s upper bounds has $O(\text{poly} \log \log E)$ energy dependence
  - $\Pr(x|\rho, V) = \mathcal{N}(\mu, \Sigma + V)$. We want V small in highly-squeezed directions of Σ
  - This is achieved by adaptively choosing a good seed V in Gaussian measurements
  - Use $\Theta(n \text{ polyloglog } E)$ copies to find a good V. Then measure $\Theta(n^2 \varepsilon^{-2})$ copies with V

Unknown ρ Seed V_1 Seed V_2 ...   Seed $V_{\Theta(\text{polylog} \log E)}$
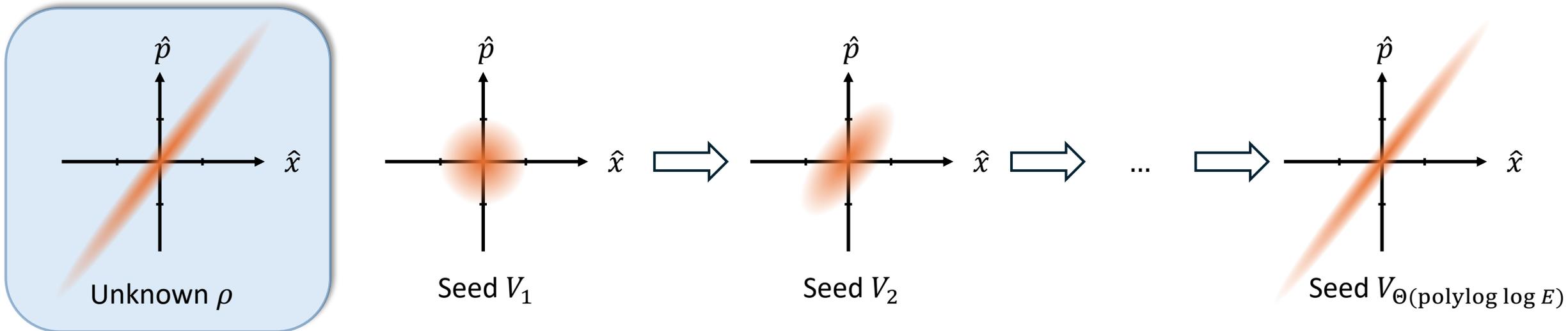
- Is adaptivity necessary? How efficient can a non-adaptive scheme be?

[BMEM25] Bittel, Mele, Eisert, Mele. arXiv:2508.14979.

Non-adaptive lower bounds

- **Thm 7**. Consider learning 1-mode Gaussian state using single-copy Gaussian meas., for any **non-adaptive** schemes, $N = \Omega(E/\varepsilon^2)$ is needed to learn ρ such that $||\Sigma||_{op} \leq E$

- **Proof ideas**: Distinguishing $\rho_{0,\theta}$ with $\rho_{1,\theta}$ for random $\theta \sim \text{Unif}[0,\pi)$, where
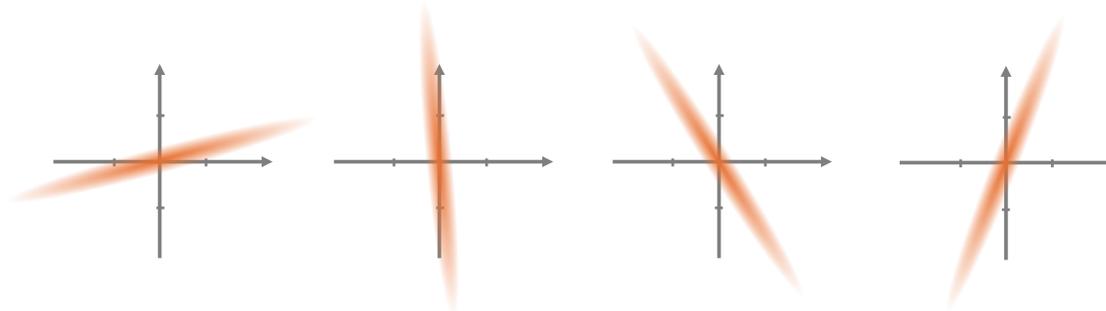

$$\Sigma_{0,\theta} = \frac{1}{2} R_\theta \begin{pmatrix} E & 0 \\ 0 & E^{-1} \end{pmatrix} R_\theta^{\mathrm{T}}$$

$$\Sigma_{1,\theta} = \frac{1}{2} R_\theta \begin{pmatrix} E & 0 \\ 0 & E^{-1} + 2\varepsilon \end{pmatrix} R_\theta^{\mathrm{T}}$$

- No fixed seed V can distinguish $\rho_{0,\theta}$ vs. $\rho_{1,\theta}$ well in average over θ

- Adaptivity is necessary for energy-independent scaling (for Gaussian meas.)
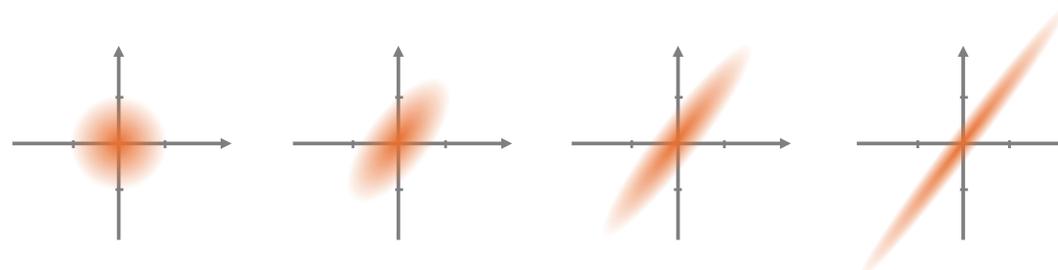
Learning 1-mode Gaussians - Comparison

V_1 V_2 V_3 V_4

(a) Heterodyne $N = \Theta(\bar{E}^2/\varepsilon^2)$

$\hat{p}$

$\hat{x}$

Unknown ρ
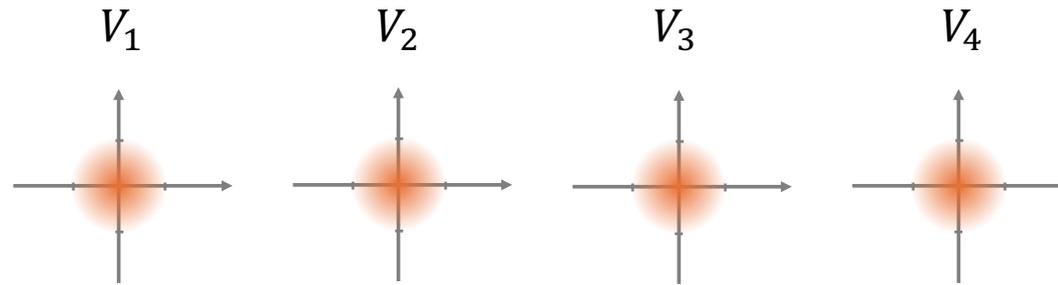
(b) Random Homodyne $N = \widetilde{\Theta}(\bar{E}/\varepsilon^2)$

(c) Adaptive General-dyne $N = \widetilde{\Theta}(1/\varepsilon^2)$

- We also obtain the following nearly-tight bounds for learning 1-mode Gaussian states with $||\Sigma||_{\mathrm{op}} \leq E$:

- Heterodyne: $\Theta(E^2\varepsilon^{-2})$

- Random-angle Homodyne $\widetilde{\Theta}(E\varepsilon^{-2})$
  - Near-optimal non-adaptive Gaussian schemes
  - Upper bound not previously known

- Adaptive [BMEM25]
  $O(\mathrm{poly}\log\log E \cdot \varepsilon^{-2}) = \widetilde{\Theta}(\varepsilon^{-2})$

Summary

Summary of Results

Task: Learn an n-mode $\rho(\mu, \Sigma)$ to ε trace distance with probability at least 2/3. Promise: $||\Sigma||_{\mathrm{op}} \leq \bar{E}$.

Class of states	Class of measurements	Bounds	
All Gaussian	Classical (including Gaussian)	$\widetilde{O}(n^3/\epsilon^2)$ [BMEM25]	$\Omega(n^3/\varepsilon^2)$ Thm. 2
	Any		$\Omega(n^2/\varepsilon^2)$ Thm. 3
Pure Gaussian	Any or Gaussian	$\widetilde{\Theta}(n^2/\varepsilon^2)$ Thm. 3, 5	
Passive Gaussian	Any	$\widetilde{O}(n^2/\varepsilon^2)$ Thm. 6	Non-Gaussian Advantages
	Classical (including Gaussian)	$\Theta(n^3/\varepsilon^2)$ Thm. 2, 6	
1-mode Gaussian	Non-adaptive 1-copy Gaussian	$\widetilde{\Theta}(\bar{E}/\varepsilon^2)$ Thm. 7	Adaptivity is helpful

$\widetilde{\Theta}, \widetilde{O}, \widetilde{\Omega}$ suppress $\log n$, $\log \varepsilon^{-1}$, and $\log \log E$ factors.

Outlook

- Can we achieve $\tilde{O}(n^2\varepsilon^{-2})$ for all Gaussian states?

- Experimentally-friendly non-classical learning scheme?

- Applications to concrete quantum sensing and benchmarking tasks?

- Learning other bosonic objects: Gaussian processes, non-Gaussian states?

Thank you!
Questions and comments are welcome