

European Research Council  
Established by the European Commission

# Is it Gaussian?

## Testing bosonic quantum states

**Filippo Girardi**

*Scuola Normale Superiore, Pisa*

**F. Witteveen**

CWI and QuSoft



**F. Mele**

SNS, Pisa



**L. Bittel**

Freie Universität Berlin



**S.F.E. Oliviero**

Freie Universität Berlin  
SNS, Pisa



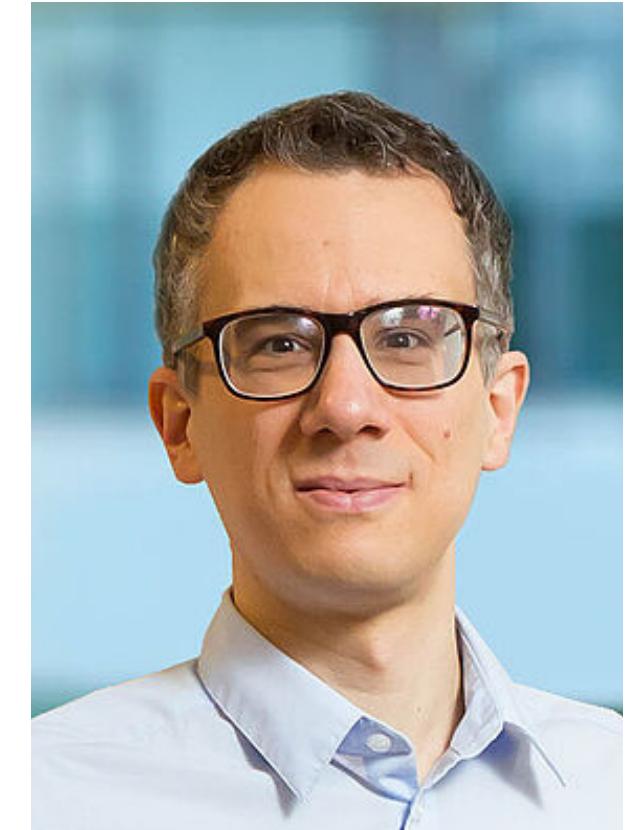
**David Gross**

University of Cologne



**Michael Walter**

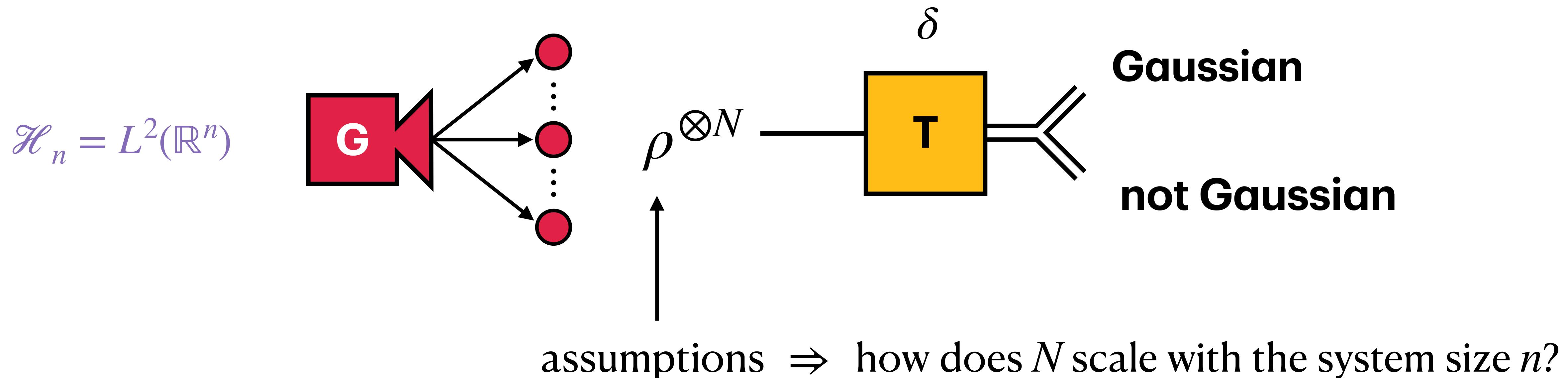
LMU München  
KdVI and QuSoft



## Quantum Physics

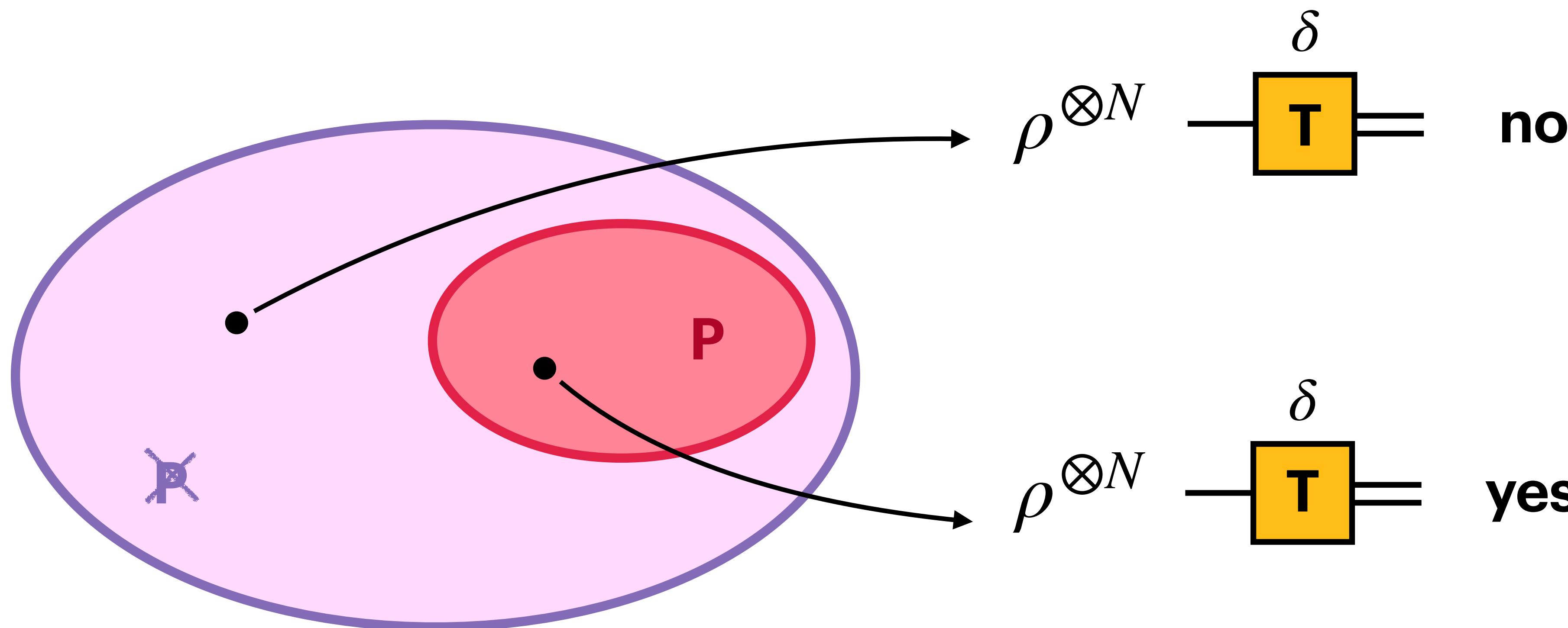
*[Submitted on 8 Oct 2025]***Is it Gaussian? Testing bosonic quantum states**

Filippo Girardi, Freek Witteveen, Francesco Anna Mele, Lennart Bittel, Salvatore F. E. Oliviero, David Gross, Michael Walter



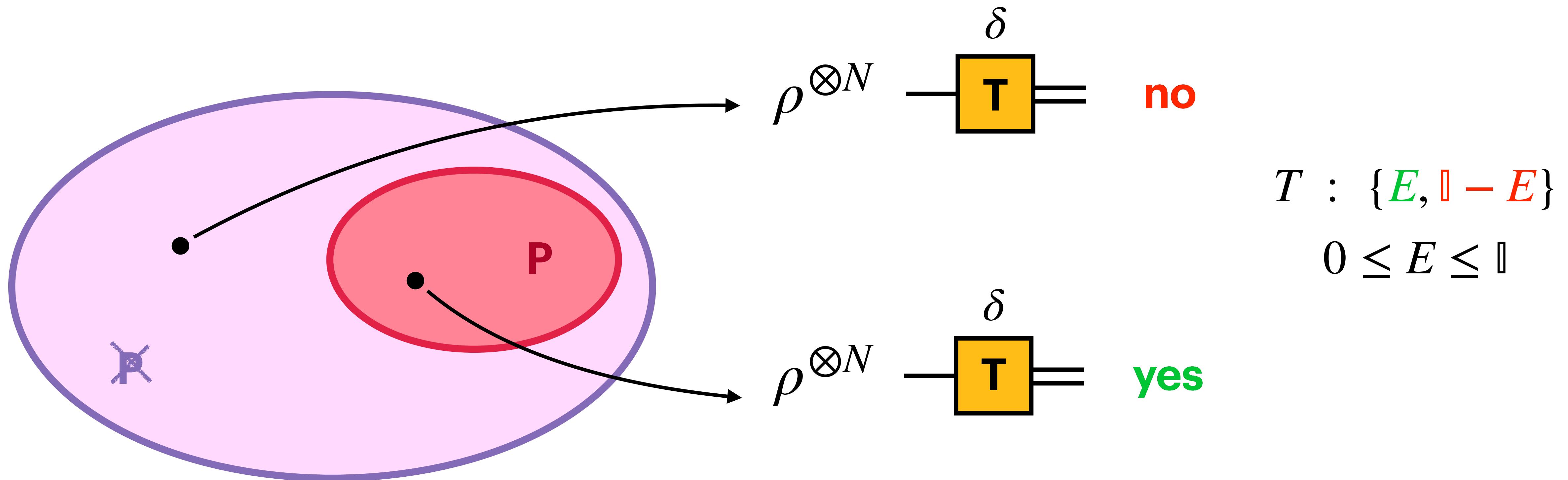
# Property testing

## General setting



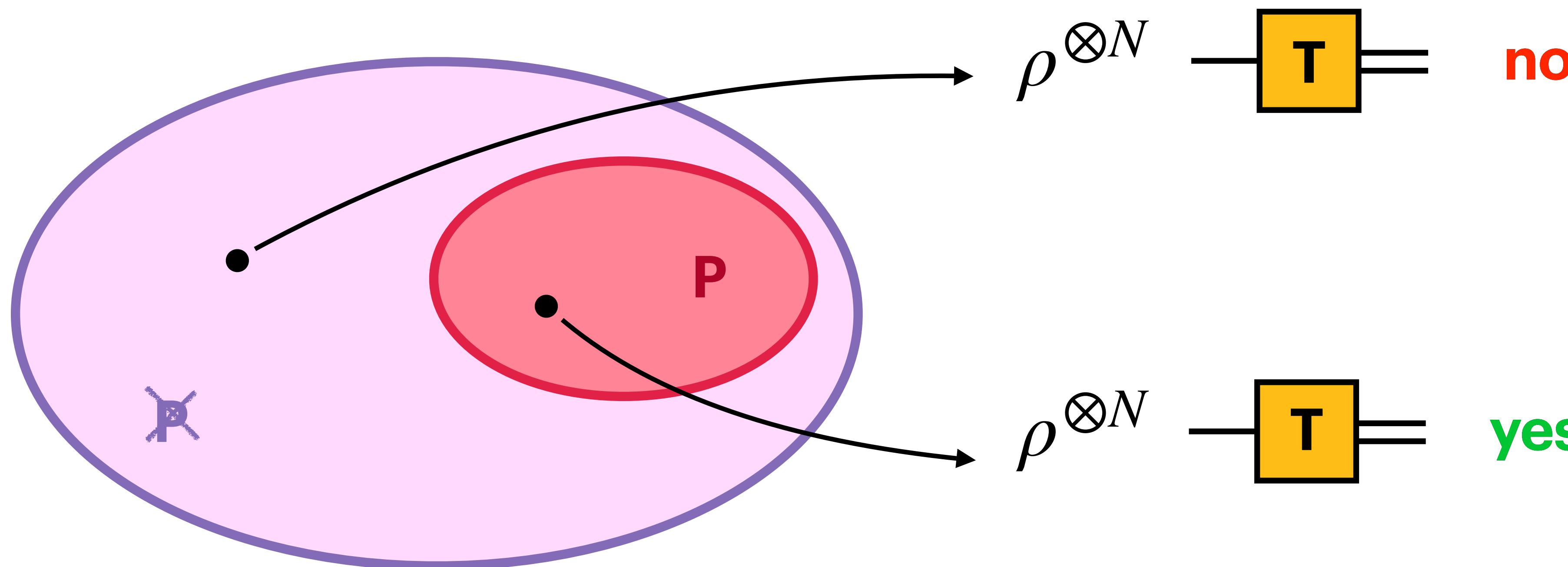
# Property testing

## General setting



# Property testing

## General setting

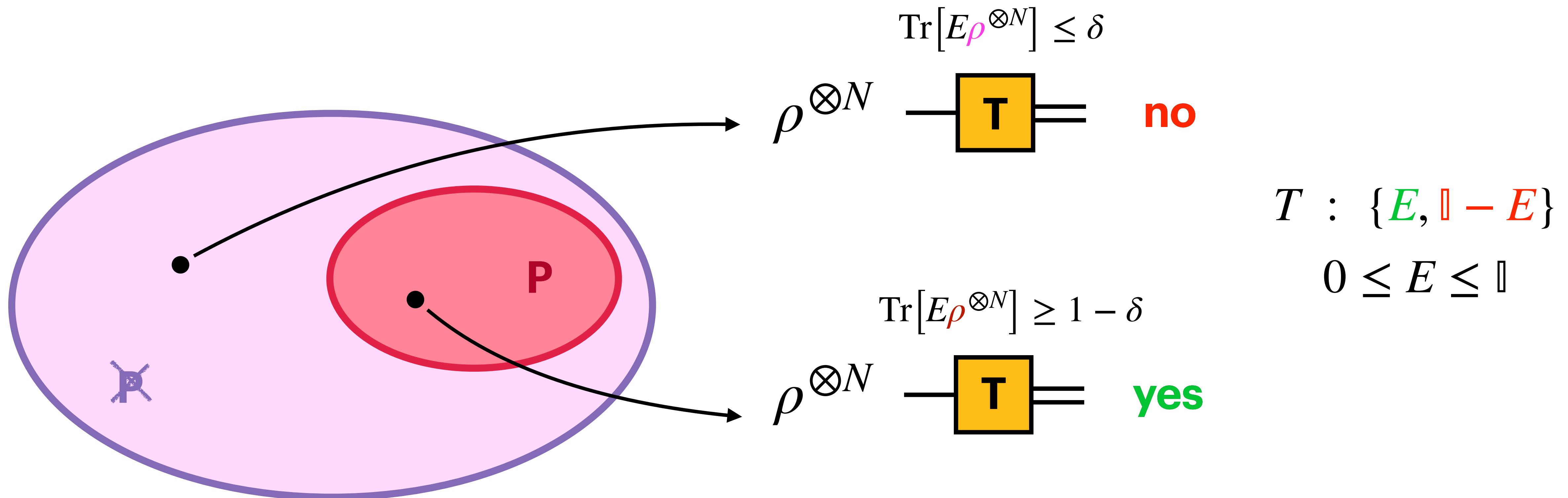


$$T : \{E, \mathbb{I} - E\}$$

$$0 \leq E \leq \mathbb{I}$$

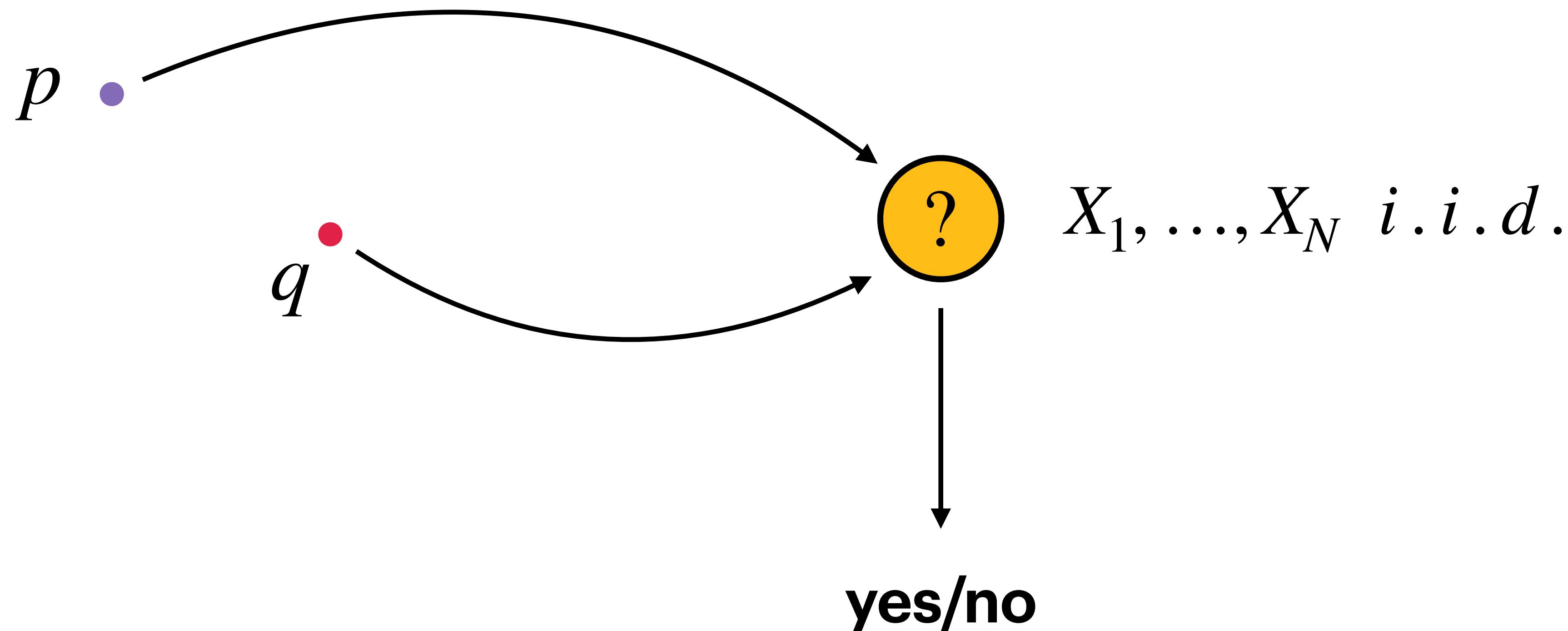
# Property testing

## General setting



# Property testing

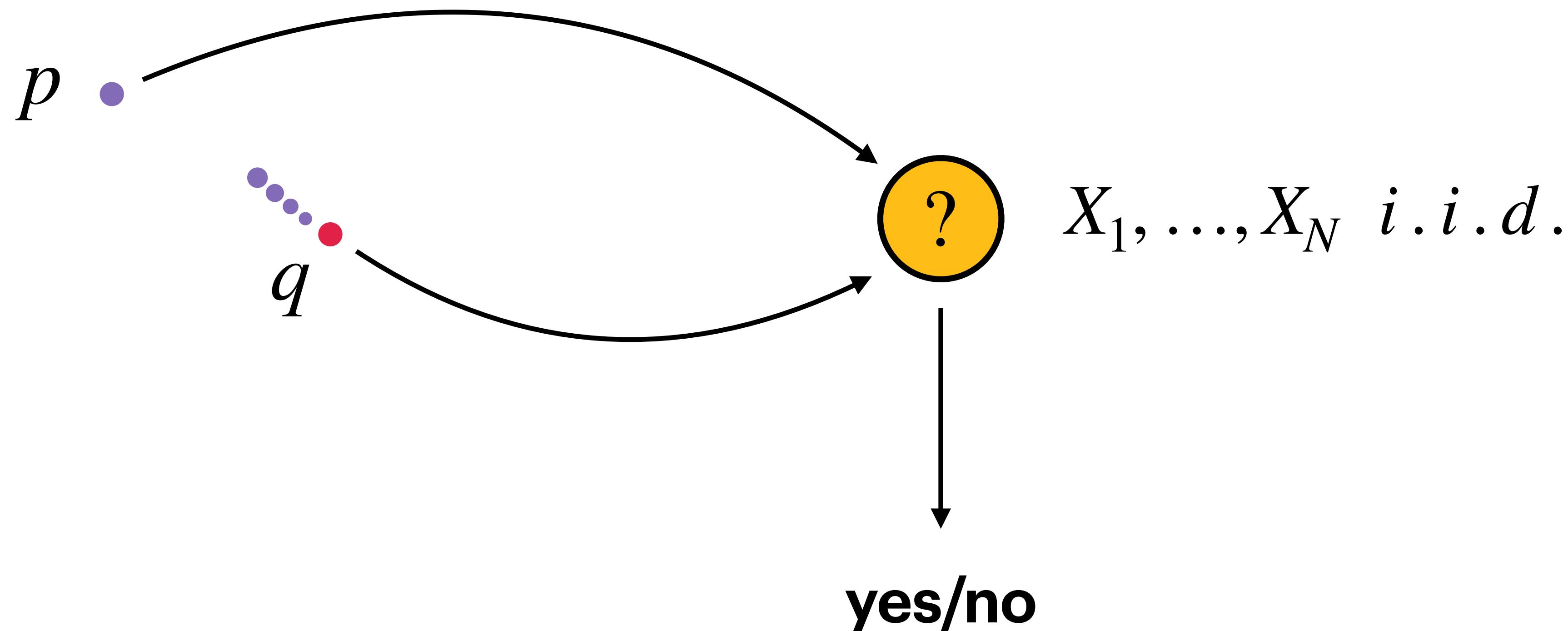
## The simple case of identity testing



L. Paninski. IEEE Tr. Inf. Th. 54 (10), 4750-4755 ,  
G&P. Valiant, FOCS, 2014,  
C. Canonne, Found. Trends Commun. Inf. Theory, Vol. 19 No. 6 pp. 1032–1198

# Property testing

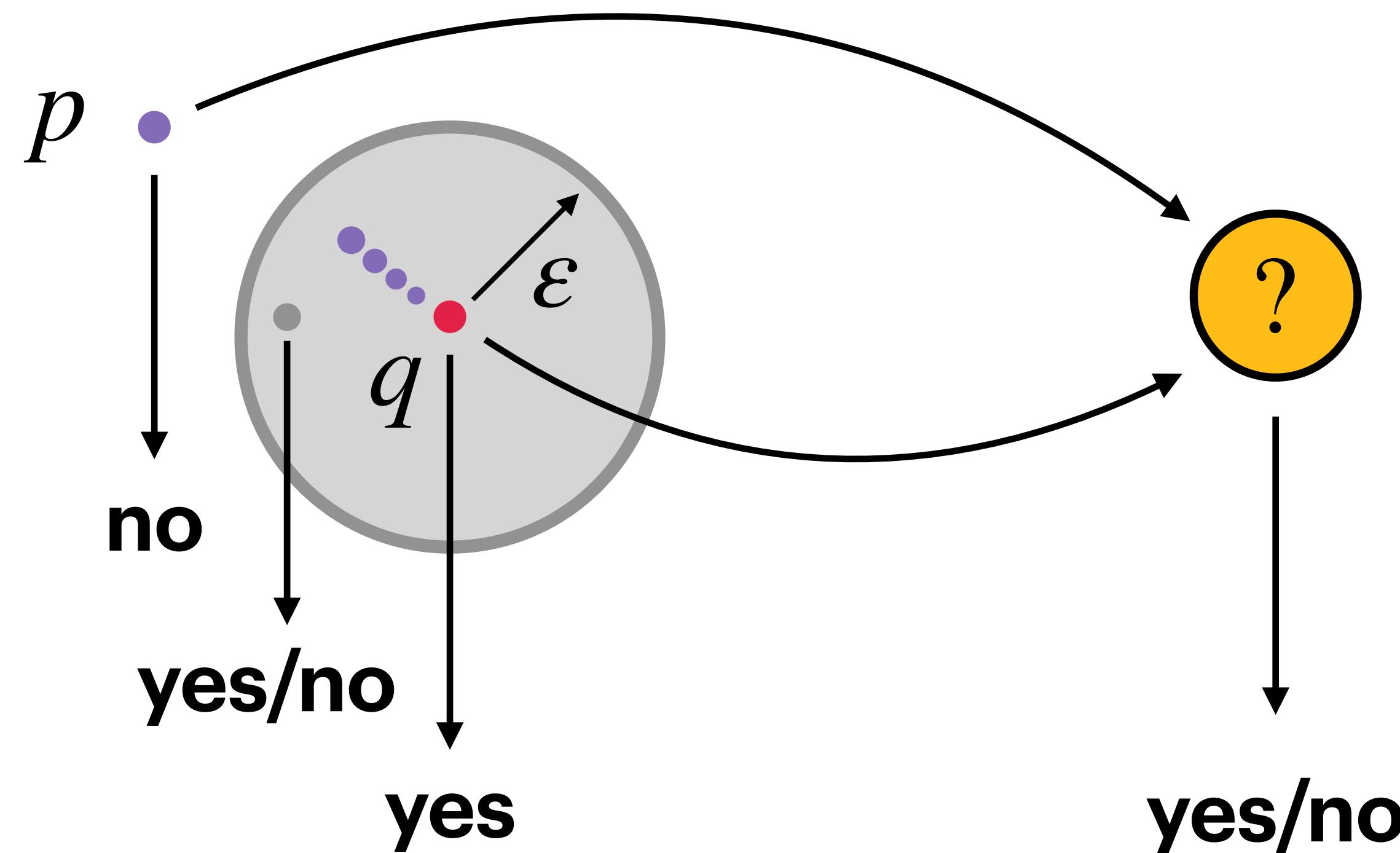
## The simple case of identity testing



L. Paninski. IEEE Tr. Inf. Th. 54 (10), 4750-4755 ,  
G&P. Valiant, FOCS, 2014,  
C. Canonne, Found. Trends Commun. Inf. Theory, Vol. 19 No. 6 pp. 1032–1198

# Property testing

## The simple case of identity testing



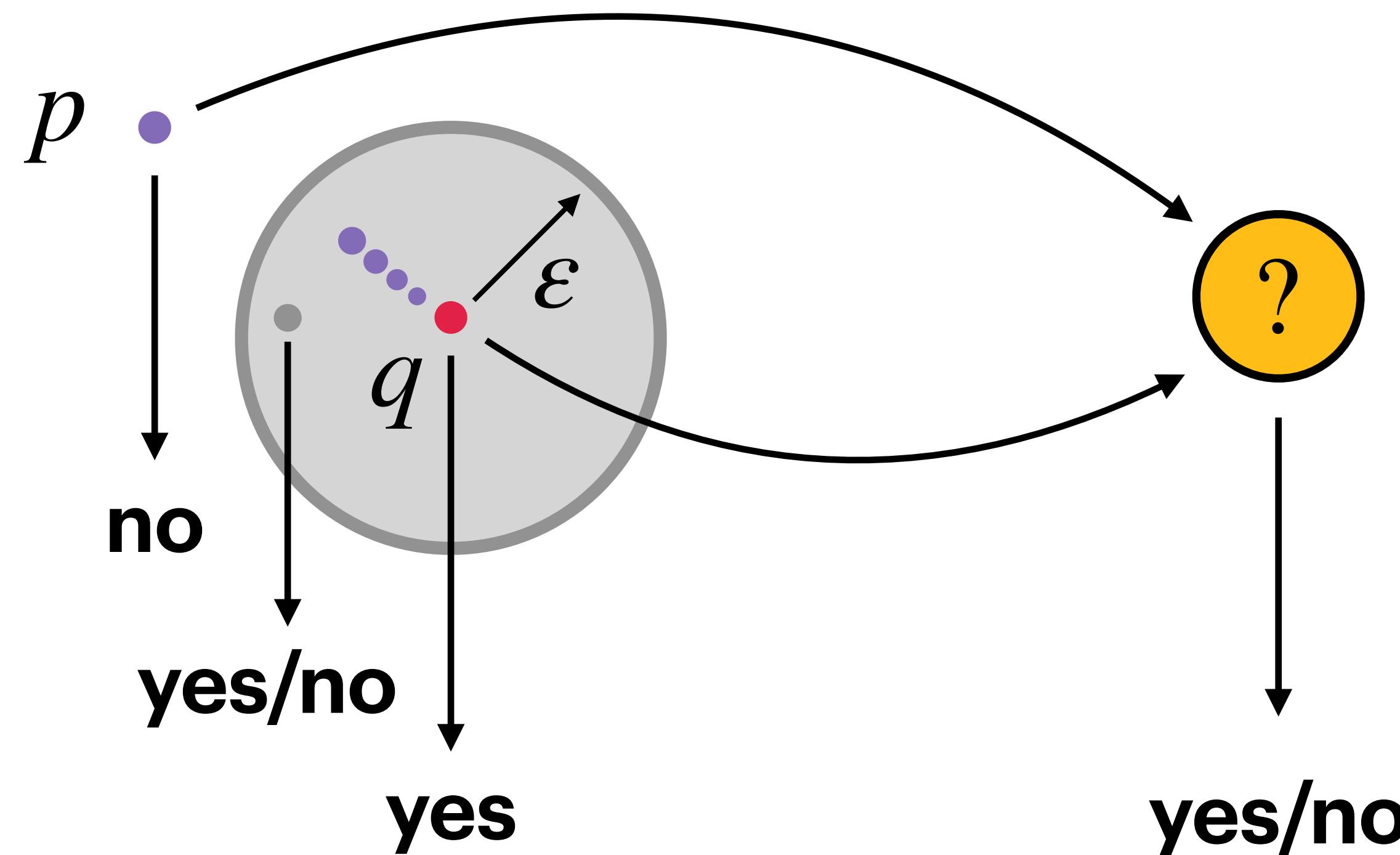
$X_1, \dots, X_N$  *i.i.d.*

**Question:** are we observing  $q$

or any other  $p$  such that  $\frac{1}{2}\|p - q\|_1 \geq \epsilon$  ?

# Property testing

## The simple case of identity testing



$X_1, \dots, X_N$  i.i.d.

**Question:** are we observing  $q$

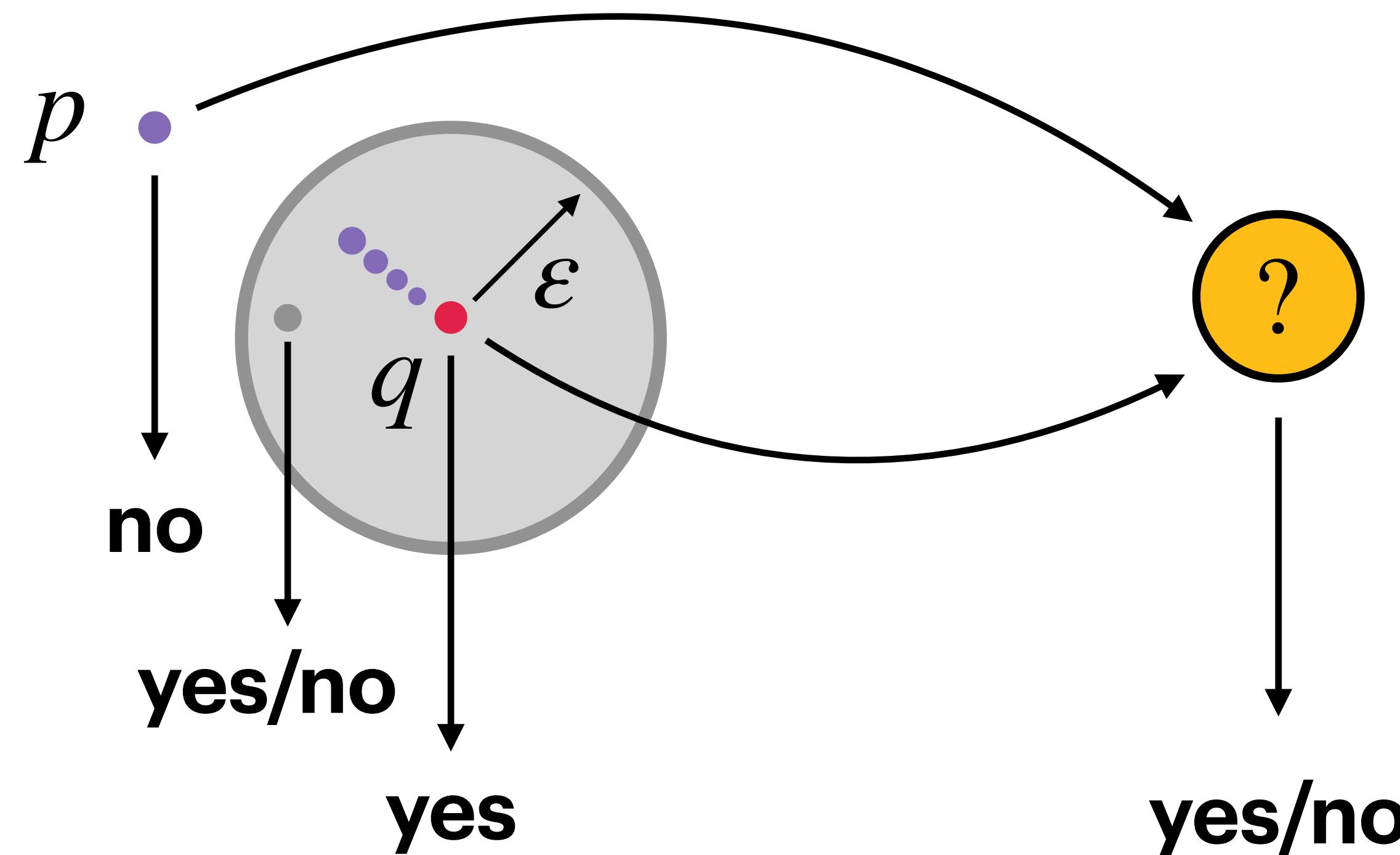
or any other  $p$  such that  $\frac{1}{2}\|p - q\|_1 \geq \varepsilon$  ?

L. Paninski. IEEE Tr. Inf. Th. 54 (10), 4750-4755 ,  
G&P. Valiant, FOCS, 2014,  
C. Canonne, Found. Trends Commun. Inf. Theory, Vol. 19 No. 6 pp. 1032–1198

$$N = \Omega\left(\frac{1}{\varepsilon^2 \|q\|_2}\right) \quad \left(\|q\|_\infty \leq \frac{1}{2}\right)$$

# Property testing

## The simple case of identity testing



$X_1, \dots, X_N$  i.i.d.

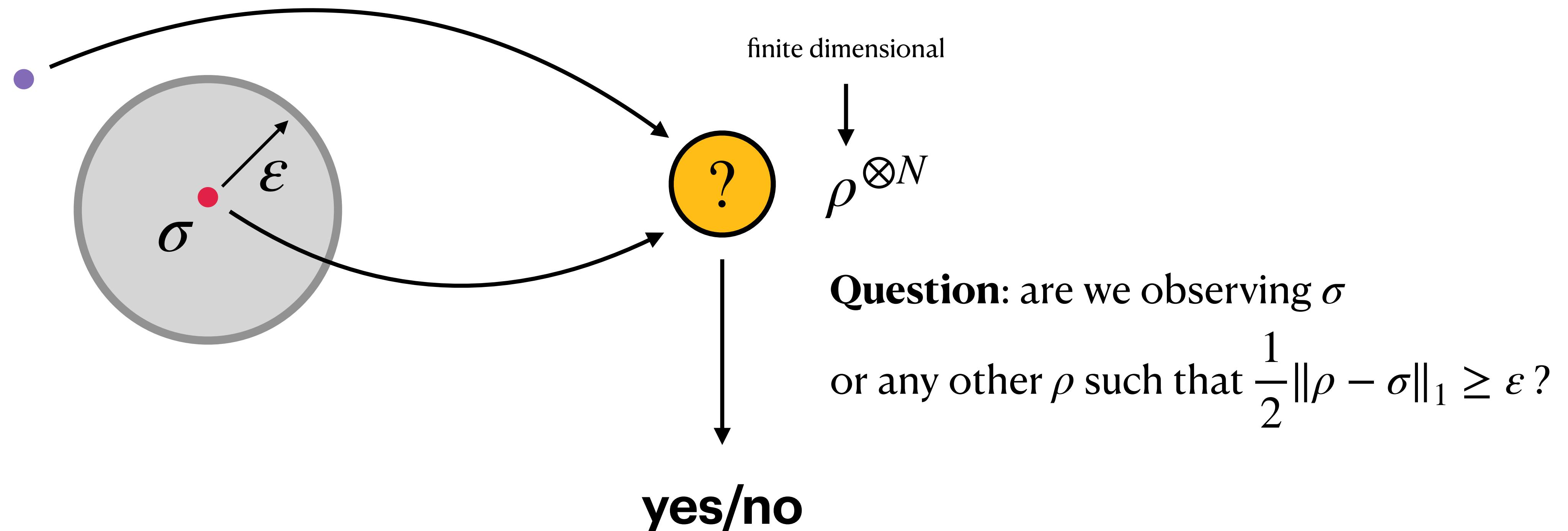
**Question:** are we observing  $q$

or any other  $p$  such that  $\frac{1}{2}\|p - q\|_1 \geq \varepsilon$ ?

$$N = \Omega\left(\frac{\sqrt{|\mathcal{X}|}}{\varepsilon^2}\right) \quad q \text{ uniform}$$

# Property testing

## The simple case of identity testing



R. O'Donnell & J. Wright, Quantum Spectrum Testing, arXiv:1501.05028

R. O'Donnell & C. Wadhwa, Instance-Optimal Quantum State Certification with Entangled Measurements, arXiv:2507.06010

# Gaussian states

## Definition

**Hilbert space:**  $\mathcal{H}_n = L^2(\mathbb{R}^n)$ , where  $n$  is the number of modes (system size).

Quadrature operator vector:  $\hat{\mathbf{R}} = (\hat{x}_1, \hat{p}_1, \dots, \hat{x}_n, \hat{p}_n)$ .

**Mean and covariance** of a state:  $\mathbf{m}(\rho) := \text{Tr}[\hat{\mathbf{R}}\rho]$ ,

$$V(\rho) := \text{Tr}[\{\hat{\mathbf{R}} - \mathbf{m}(\rho), (\hat{\mathbf{R}} - \mathbf{m}(\rho))^\top\}\rho].$$

**Energy** of a state:

$$\text{Gaussian state: } \rho = D_{\mathbf{m}} U_S \left( \bigotimes_{j=1}^m \frac{e^{-\xi_j a_j^\dagger a_j}}{\text{Tr } e^{-\xi_j a_j^\dagger a_j}}, \right) U_S^\dagger D_{\mathbf{m}}^\dagger$$

# Gaussian states

## Definition

### A dangerously oversimplified analogy (with many caveats under the carpet)

probability distributions on an infinite set

continuous-variable (CV) systems

Gaussian states

probability distributions on  $[d]$  with  $d \rightarrow \infty$

qudits with  $d = +\infty$

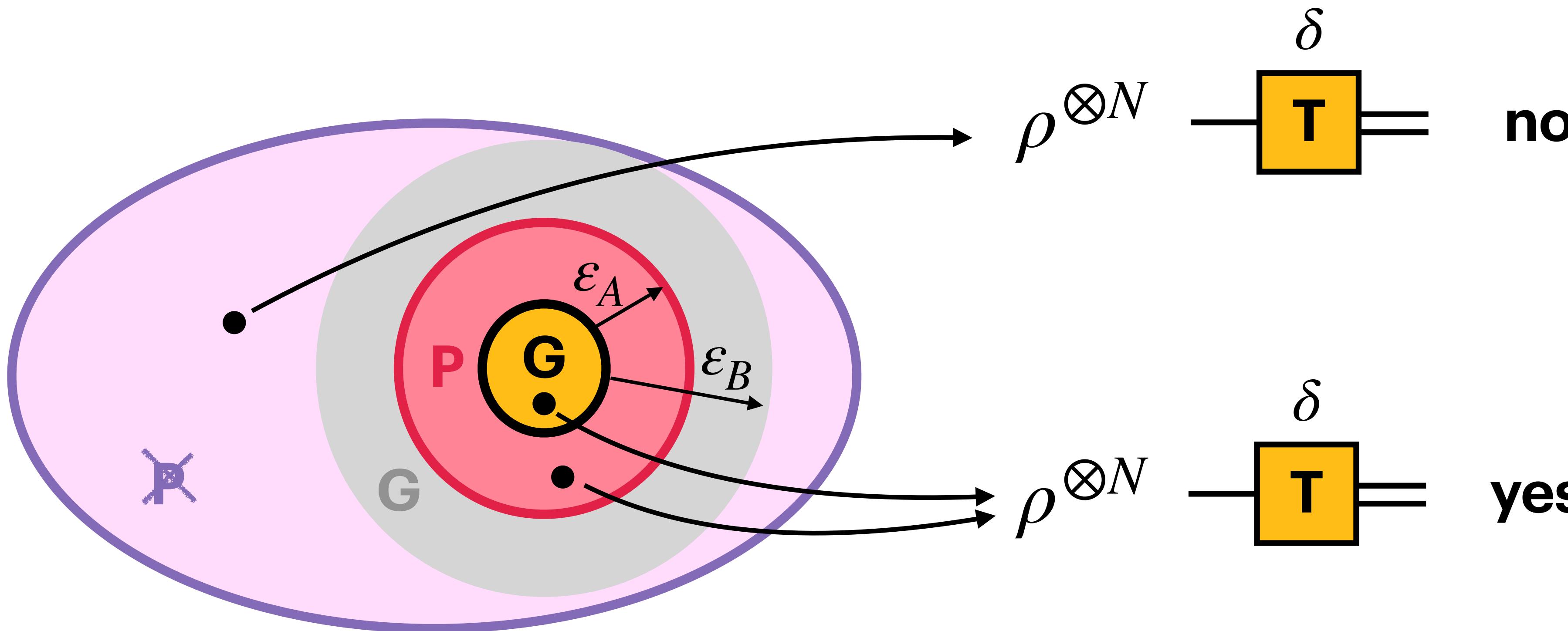
quantum generalisation of Gaussian distributions

Given a CV state, we can define its **energy**, its **mean** vector and its **covariance** matrix.

A Gaussian state is fully characterised by its mean vector and its covariance matrix.

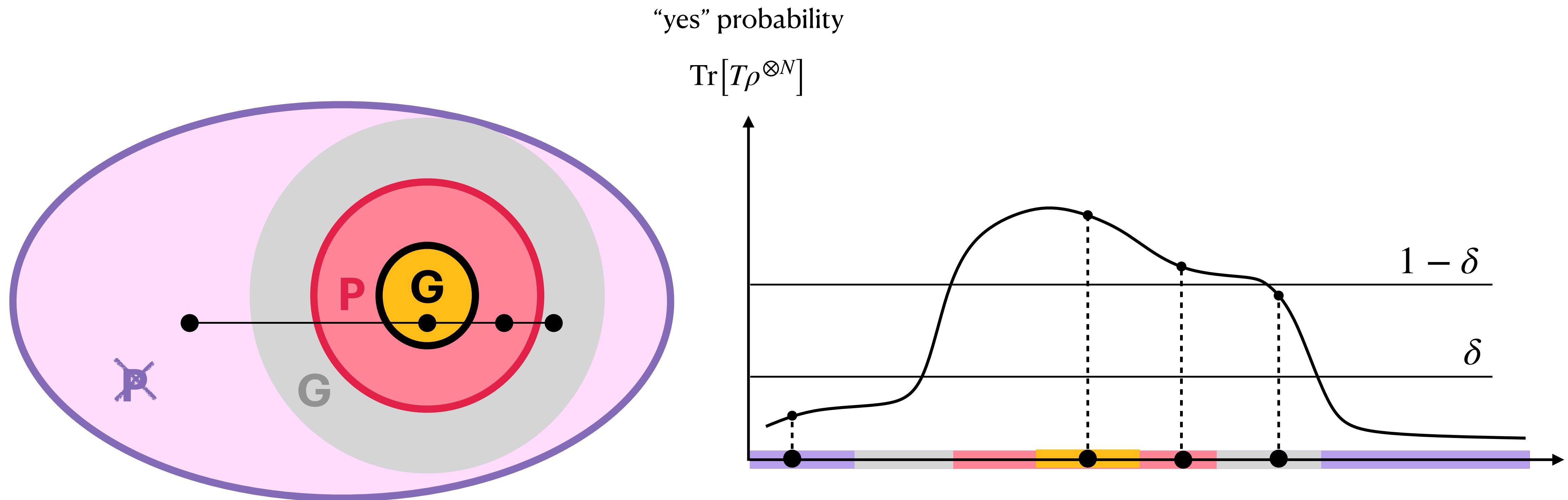
# Gaussian property testing

## Tolerant testing



# Gaussian property testing

## Tolerant testing



# Approach

- Study the properties of the subset to be tested (**symmetries**, characterisation)
- Choose the notion of distance: **trace distance** (but also relative entropy of non-Gaussianity)
- Technical tools: **trace distance bounds**
- Distinguish two regimes: testing “pure Gaussianity” and “mixed Gaussianity”

# Pure Gaussian states

## Definition of the problem

Let  $0 \leq \varepsilon_A < \varepsilon_B$ , let  $0 < \delta \leq 1$  and let

- $\mathcal{G}_E$  be the set of **pure Gaussian states** with mean energy per mode at most  $E$ .

We say that an algorithm solves the property testing problem using  $N$  samples if, for any generic state  $\rho$  such that

- A. either  $\rho$  is  $\varepsilon_A$ -close to  $\mathcal{G}_E$ , i.e.

$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \varepsilon_A$$

P

- B. or  $\rho$  is  $\varepsilon_B$ -far from  $\mathcal{G}_E$ ,

i.e.  $\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 > \varepsilon_B$ ,

NP

the algorithm can identify the underlying hypothesis A or B with failure probability at most  $\delta$ .

# Two approaches

**symmetries**  
of Gaussian states

learning  
Gaussian states

**Example.** Let  $f \in C^2(\mathbb{R})$  such that  $U_{\pi/4} f \otimes f U_{\pi/4}^\dagger = f \otimes f$ , namely

$$f\left(\frac{x+y}{\sqrt{2}}\right) f\left(\frac{x-y}{\sqrt{2}}\right) = f(x)f(y) \quad \forall x, y \in \mathbb{R}$$

Then

$$\log f\left(\frac{x+y}{\sqrt{2}}\right) + \log f\left(\frac{x-y}{\sqrt{2}}\right) = \log f(x) + \log f(y)$$

$$\Rightarrow \partial_x \partial_y \log f\left(\frac{x+y}{\sqrt{2}}\right) = - \partial_x \partial_y \log f\left(\frac{x-y}{\sqrt{2}}\right) \Rightarrow \frac{d^2}{dt^2} \log f(t) = const.$$

$f$  is Gaussian.

See, e.g., E.H. Lieb, Gaussian kernels have only Gaussian maximizers. *Invent Math* 102, 179–208 (1990).

# Two approaches

**symmetries**  
*of Gaussian states*

**learning**  
*Gaussian states*

**Proposition.** Let  $U_\theta$  be the rotation

$$(U_\theta f)(\mathbf{x}, \mathbf{y}) = f(\cos \theta \mathbf{x} + \sin \theta \mathbf{y}, -\sin \theta \mathbf{x} + \cos \theta \mathbf{y}) \quad \forall f \in L^2(\mathbb{R}^{2n}) \cong \mathcal{H}_n^{\otimes 2}.$$

For a pure state  $|\psi\rangle$  on  $\mathcal{H}_n$ , the following properties are equivalent:

1.  $U_\theta |\psi\rangle^{\otimes 2} = |\psi\rangle^{\otimes 2}$  for all  $\theta \in [0, 2\pi)$ ;
2.  $U_\theta |\psi\rangle^{\otimes 2} = |\psi\rangle^{\otimes 2}$  is a product state for some  $\theta$  which is not a multiple of  $\pi/2$ ;
3.  $|\psi\rangle$  is a pure Gaussian state with zero mean.

# Two approaches

**symmetries**  
*of Gaussian states*

**Theorem.** Take two copies of a quantum state  $\rho$  and measures whether  $\rho^{\otimes 2}$  is in the rotation-invariant subspace. Then,

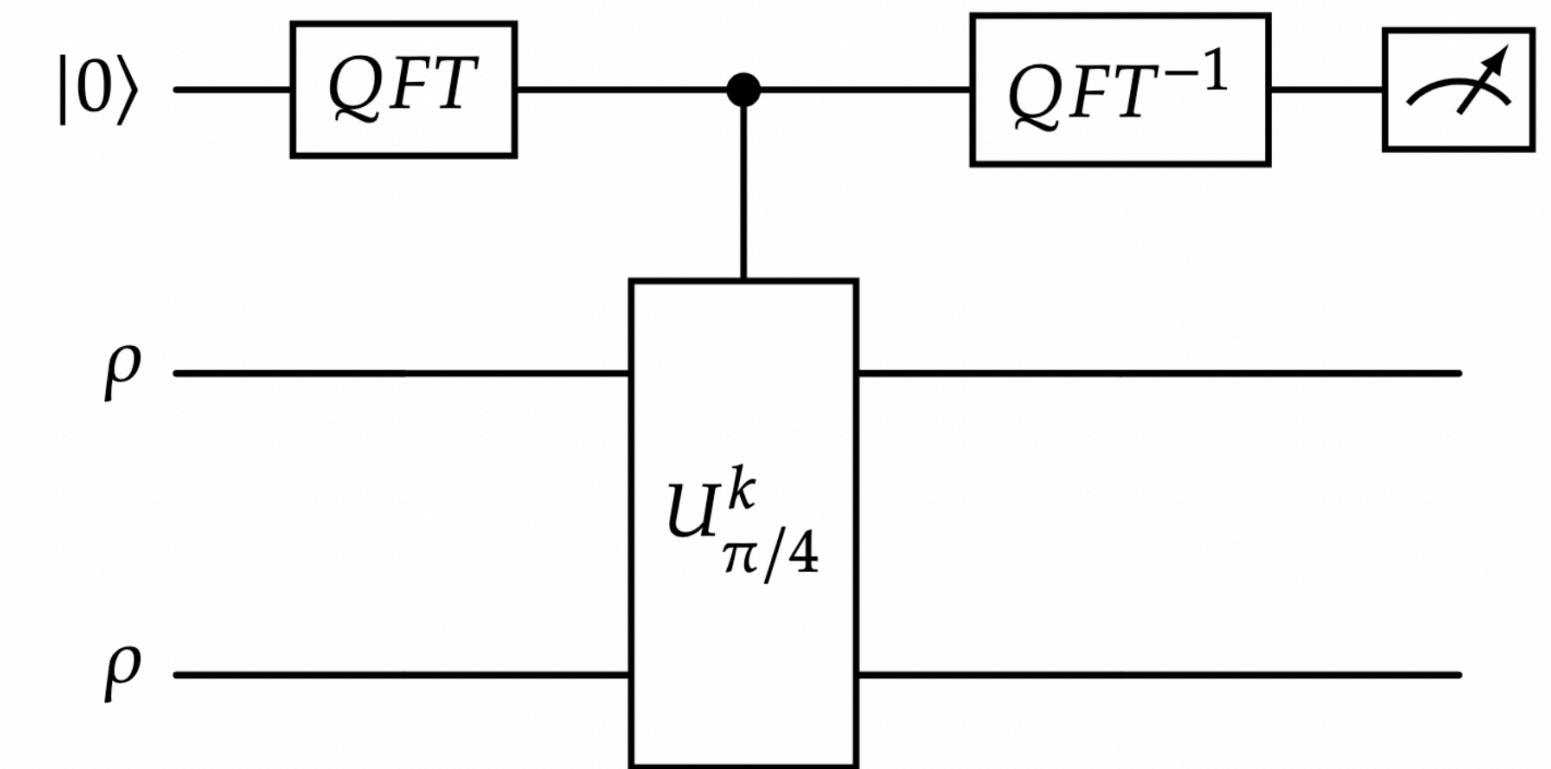
$$N = O(\varepsilon^{-2} \log(\delta^{-1})) \quad \varepsilon := \Omega\left(\min\left(\varepsilon_B^2, \frac{1}{n^4 E^4}\right) - \varepsilon_A\right)$$

copies of  $\rho$  are sufficient to test its closeness to the set of zero-mean pure Gaussian states.

**Generalisations.** Non-zero mean, smaller auxiliary systems, testing the generator of rotations  $\langle G^2 \rangle_{\rho^{\otimes 2}}$ .

**learning**  
*Gaussian states*

**Implementation.**  $\dim \mathcal{H}_A = 8$



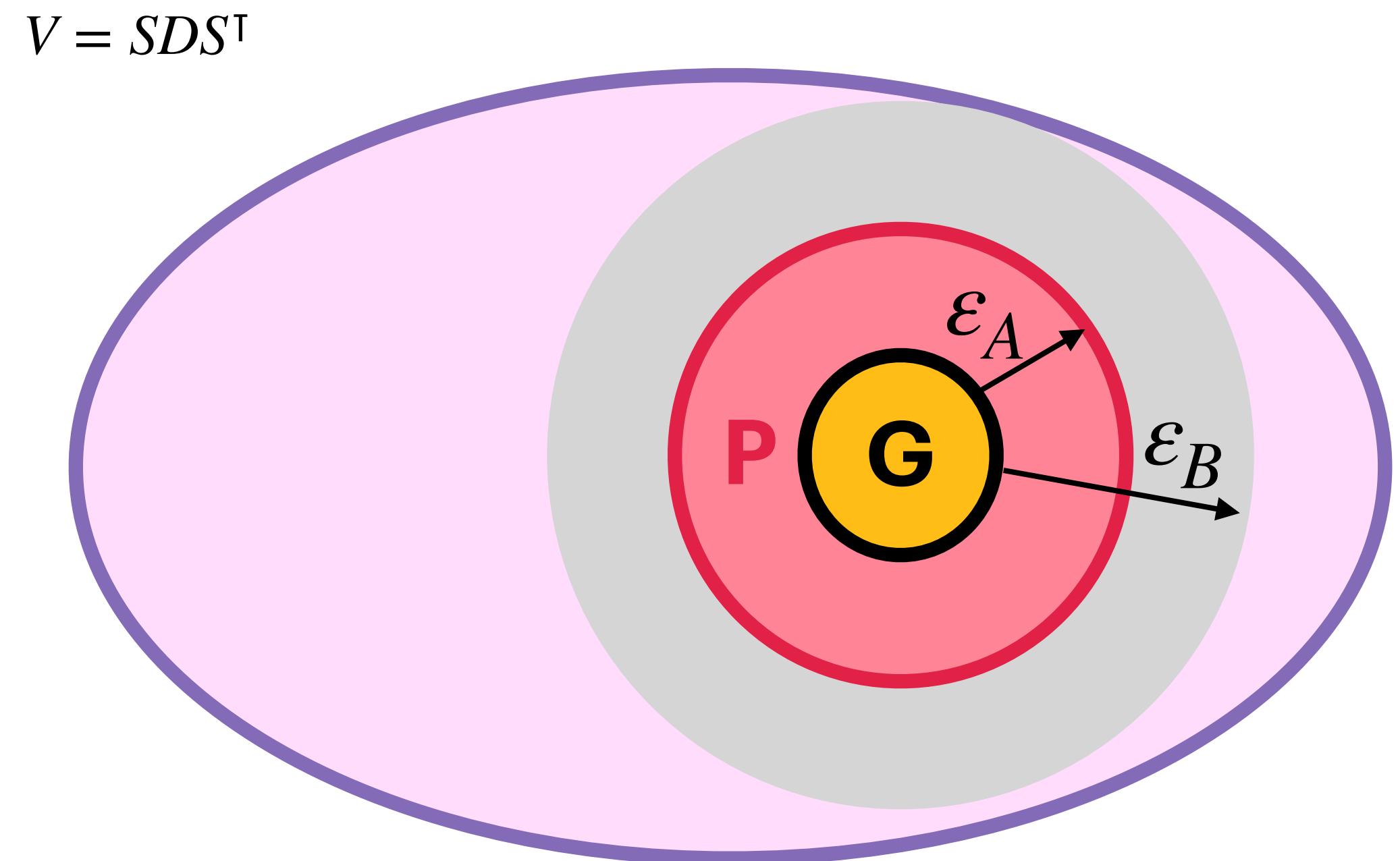
# Two approaches

symmetries  
of Gaussian states

learning  
Gaussian states

**Idea.**  $\rho$  is a pure Gaussian state iff its symplectic eigenvalues  $\{\nu_i\}$  are all equal to 1.

**Sketch of the algorithm.**



For the fermionic case,  
see Bittel & al., PRX Quantum 6, 030341 (2025)

# Two approaches

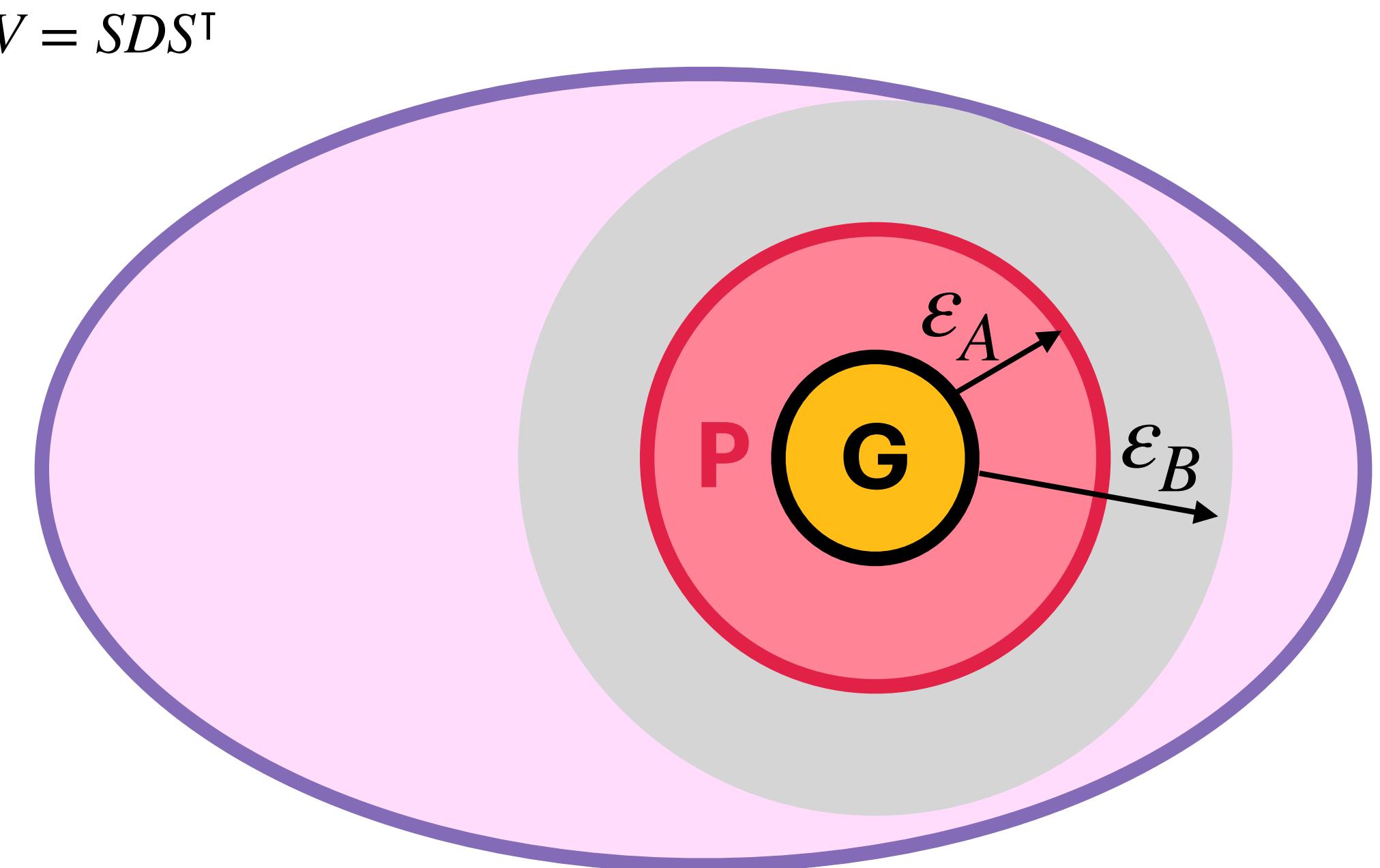
symmetries  
of Gaussian states

learning  
Gaussian states

**Idea.**  $\rho$  is a pure Gaussian state iff its symplectic eigenvalues  $\{\nu_i\}$  are all equal to 1.

**Sketch of the algorithm.**

$$\rho^{\otimes N} \longrightarrow \text{algorithm icon} = \tilde{V} = \tilde{\nu}_{\max} \text{ vs } \nu_{\text{thr}}$$



For the fermionic case,  
see Bittel & al., PRX Quantum 6, 030341 (2025)

# Two approaches

symmetries  
of Gaussian states

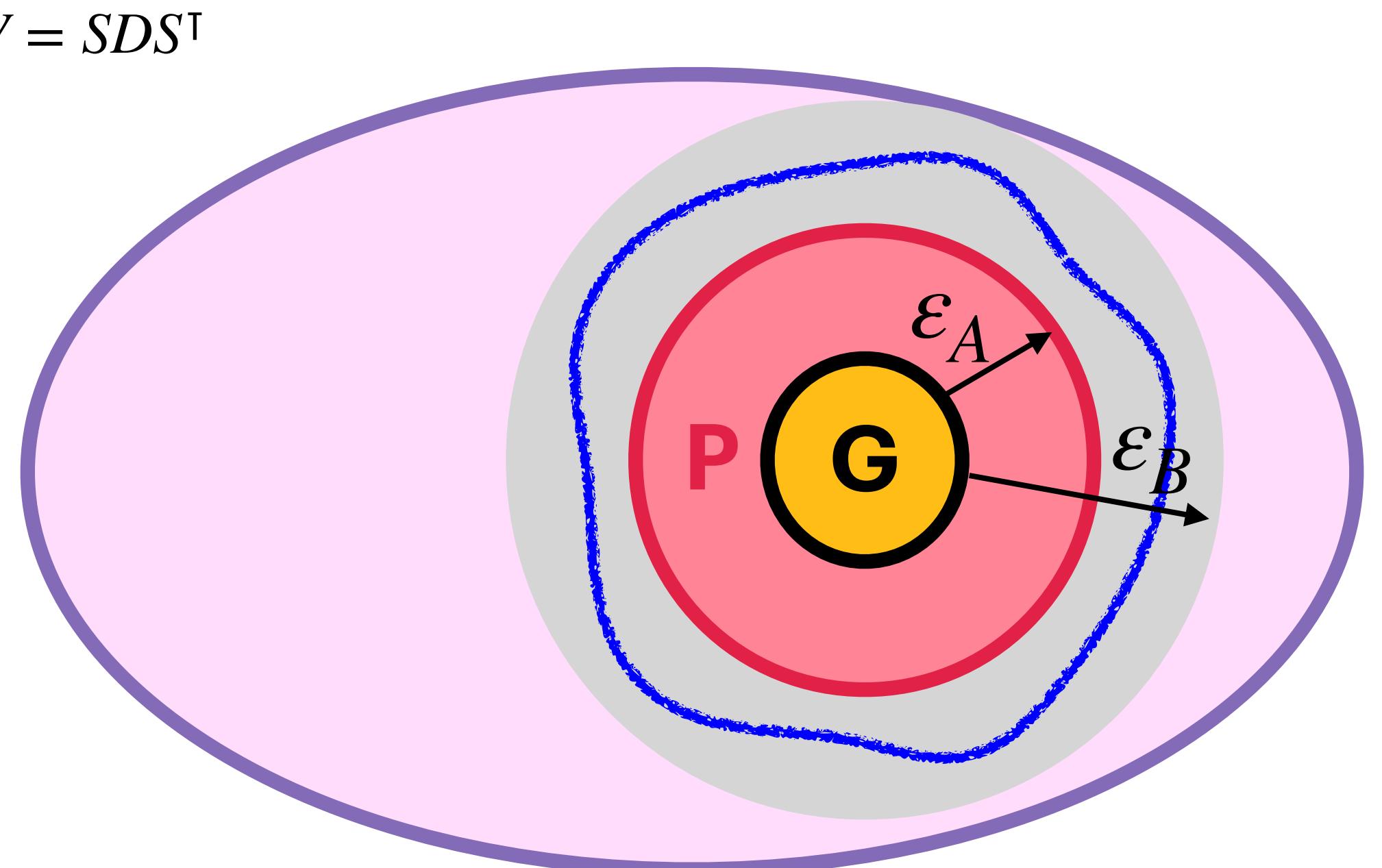
learning  
Gaussian states

**Idea.**  $\rho$  is a pure Gaussian state iff its symplectic eigenvalues  $\{\nu_i\}$  are all equal to 1.

**Sketch of the algorithm.**

$$\rho^{\otimes N} \longrightarrow \text{diagram} = \tilde{V} = \tilde{\nu}_{\max} \text{ vs } \nu_{\text{thr}}$$

$$\nu_{\text{thr}} = 1 + f(\varepsilon_A, \varepsilon_B, n, E)$$



For the fermionic case,  
see Bittel & al., PRX Quantum 6, 030341 (2025)

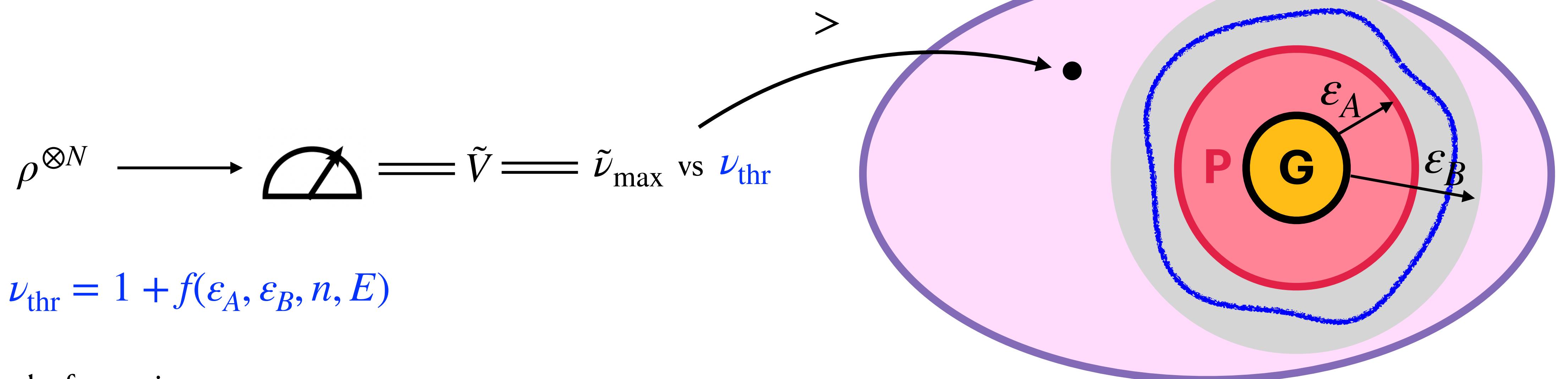
# Two approaches

symmetries  
of Gaussian states

learning  
Gaussian states

**Idea.**  $\rho$  is a pure Gaussian state iff its symplectic eigenvalues  $\{\nu_i\}$  are all equal to 1.

**Sketch of the algorithm.**



For the fermionic case,  
see Bittel & al., PRX Quantum 6, 030341 (2025)

# Two approaches

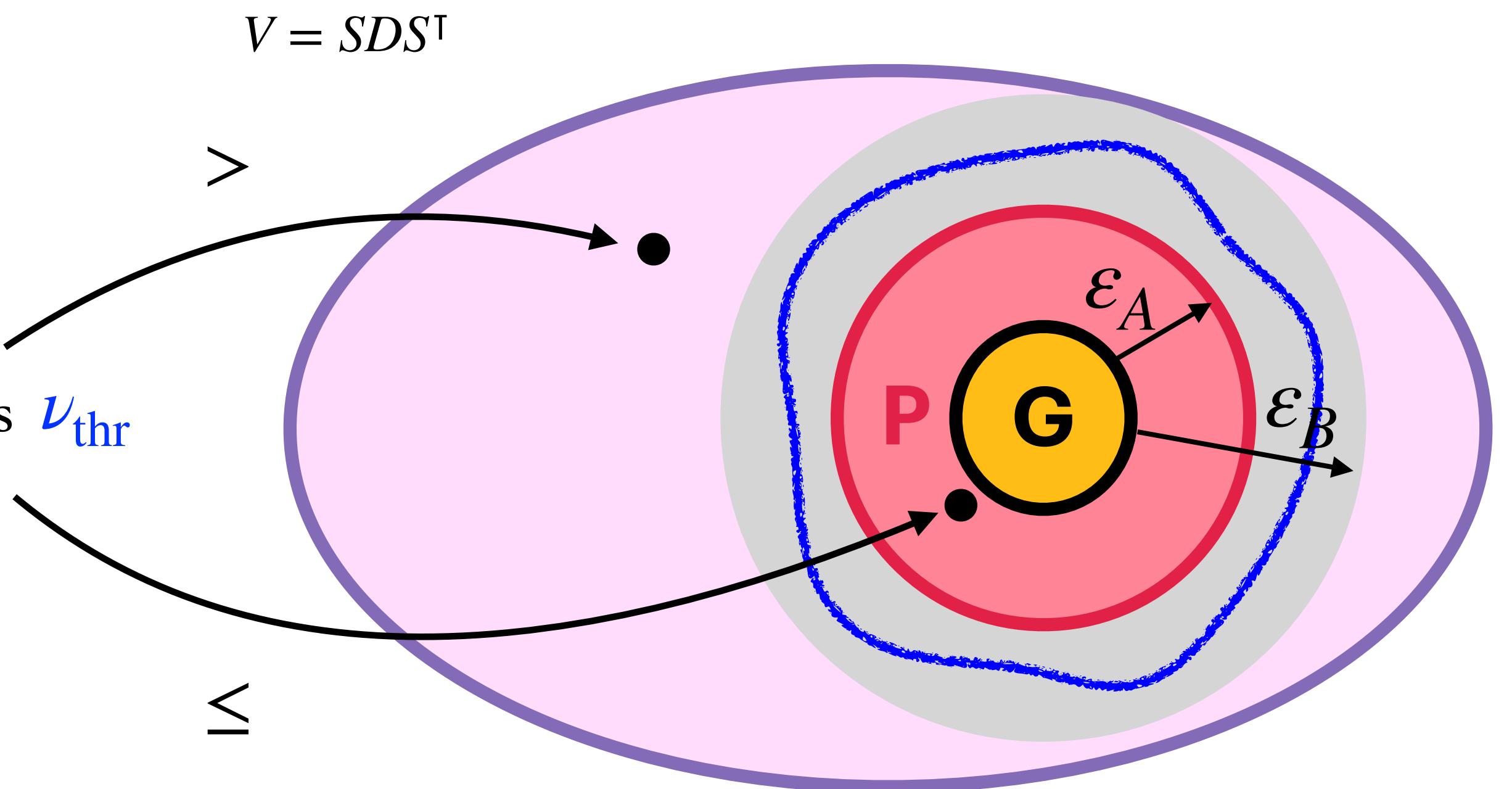
symmetries  
of Gaussian states

learning  
Gaussian states

**Idea.**  $\rho$  is a pure Gaussian state iff its symplectic eigenvalues  $\{\nu_i\}$  are all equal to 1.

**Sketch of the algorithm.**

$$\rho^{\otimes N} \longrightarrow \text{○} = \tilde{V} = \tilde{\nu}_{\max} \text{ vs } \nu_{\text{thr}}$$
$$\nu_{\text{thr}} = 1 + f(\varepsilon_A, \varepsilon_B, n, E)$$



For the fermionic case,  
see Bittel & al., PRX Quantum 6, 030341 (2025)

# Learning the covariance matrix

**Lemma 41** (Sample complexity of estimating the covariance matrix). *Let  $\varepsilon, \delta \in (0, 1)$  and  $E > 0$ . Let  $\rho$  be an  $n$ -mode quantum state satisfying with second moment of the energy upper bounded by  $nE$ , i.e.  $\sqrt{\text{Tr}[\hat{E}^2\rho]} \leq nE$ . Then, a number*

$$(n + 3) \left\lceil 68 \log\left(\frac{2(2n^2 + 3n)}{\delta}\right) \frac{200(8n^2E^2 + 3n)}{\varepsilon^2} \right\rceil = \mathcal{O}\left(\log\left(\frac{n^2}{\delta}\right) \frac{n^3E^2}{\varepsilon^2}\right), \quad (\text{C30})$$

*of copies of  $\rho$  are sufficient to build a vector  $\tilde{\mathbf{m}} \in \mathbb{R}^{2n}$  and a symmetric matrix  $\tilde{V}' \in \mathbb{R}^{2n, 2n}$  such that*

$$\Pr\left(\|\tilde{V}' - V(\rho)\|_2 \leq \varepsilon \quad \text{and} \quad \tilde{V}' + i\Omega \geq 0 \quad \text{and} \quad \|\tilde{\mathbf{m}} - \mathbf{m}(\rho)\| \leq \frac{\varepsilon}{10\sqrt{8nE}}\right) \geq 1 - \delta. \quad (\text{C31})$$

*Such procedure only requires single-copy measurements.*

# Trace distance bounds

**Lemma 10** (Upper bound on the trace distance between Gaussian states [4]). *The trace distance between two Gaussian states  $\rho(V, \mathbf{m})$  and  $\rho(W, \mathbf{t})$  can be upper bounded as follows:*

$$\frac{1}{2} \|\rho(V, \mathbf{m}) - \rho(W, \mathbf{t})\|_1 \leq \frac{1 + \sqrt{3}}{8} \max(\mathrm{Tr} V, \mathrm{Tr} W) \|V - W\|_\infty + \sqrt{\frac{\min(\|V\|_\infty, \|W\|_\infty)}{2}} \|\mathbf{m} - \mathbf{t}\|. \quad (\text{A19})$$

**Lemma 11** (Upper bound on the trace distance between an arbitrary state and a pure Gaussian state [3]). *Let  $\psi_G$  be a pure Gaussian state with covariance matrix  $V$  and first moment  $\mathbf{m}$ . Moreover, let  $\sigma$  be a (possibly non-Gaussian and possibly mixed) state with covariance matrix  $W$  and first moment  $\mathbf{t}$ . Then, it holds that*

$$\frac{1}{2} \|\psi_G - \sigma\|_1 \leq \sqrt{E} \sqrt{\|V - W\|_\infty + 2\|\mathbf{m} - \mathbf{t}\|^2}, \quad (\text{A20})$$

where  $E := \max(\mathrm{Tr}[\sigma \hat{E}], \mathrm{Tr}[\psi_G \hat{E}])$  is the maximum energy and  $\hat{E}$  denotes the energy operator.

L. Bittel, F. A. Mele, A. A. Mele, S. Tirone, L. Lami

*Optimal estimates of trace distance between bosonic Gaussian states and applications to learning*, Quantum 9, 1769 (2025)

F. A. Mele, A. A. Mele, L. Bittel, J. Eisert, V. Giovannetti, L. Lami, L. Leone, S. F. E. Oliviero,

*Learning quantum states of continuous variable systems*, Nature Physics 21, 2002-2008 (2025)

# Trace distance bounds

**Lemma 12** (Lower bound on the trace distance between Gaussian states [3]). *The trace distance between two Gaussian states  $\rho(V, \mathbf{m})$  and  $\rho(W, \mathbf{t})$  can be lower bounded in terms of the norm distance between their first moments and the norm distance between their covariance matrices as*

$$\begin{aligned} \frac{1}{2}\|\rho(V, \mathbf{m}) - \rho(W, \mathbf{t})\|_1 &\geq \frac{1}{200} \min \left\{ 1, \frac{\|\mathbf{m} - \mathbf{t}\|}{\sqrt{4 \min(\|V\|_\infty, \|W\|_\infty) + 1}} \right\}, \\ \frac{1}{2}\|\rho(V, \mathbf{m}) - \rho(W, \mathbf{t})\|_1 &\geq \frac{1}{200} \min \left\{ 1, \frac{\|V - W\|_2}{4 \min(\|V\|_\infty, \|W\|_\infty) + 1} \right\}. \end{aligned} \quad (\text{A21})$$

**Lemma 13** (Lower bound on the trace distance between arbitrary states [18]). *Let  $\rho$  be a (possibly non-Gaussian) state with first moment  $\mathbf{m}$  and covariance matrix  $V$ . Moreover, let  $\sigma$  be a (possibly non-Gaussian) state with first moment  $\mathbf{t}$  and covariance matrix  $W$ . The trace distance can be lower bounded as*

$$\frac{1}{2}\|\rho - \sigma\|_1 \geq \frac{\|\mathbf{m} - \mathbf{t}\|^2}{32 \max(\text{Tr}[\hat{E}\rho], \text{Tr}[\hat{E}\sigma])}, \quad (\text{A22})$$

$$\frac{1}{2}\|\rho - \sigma\|_1 \geq \frac{\|V - W\|_\infty^2}{3098 \max(\text{Tr}[\hat{E}^2\rho], \text{Tr}[\hat{E}^2\sigma])}, \quad (\text{A23})$$

where  $\hat{E}$  denotes the energy operator.

F. A. Mele, A. A. Mele, L. Bittel, J. Eisert, V. Giovannetti, L. Lami, L. Leone, S. F. E. Oliviero,  
*Learning quantum states of continuous variable systems*, Nature Physics 21, 2002-2008 (2025)

F. A. Mele, S. F. E. Oliviero, V. Upreti, U. Chabaud  
*The symplectic rank of non-Gaussian quantum states*, arXiv:2504.19319 [quant-ph]

# Perturbation bounds

**Lemma 36** (Perturbation on symplectic diagonalisation [71]). *Let  $V_1, V_2 \in \mathbb{R}^{2n \times 2n}$  be two covariance matrices with symplectic diagonalisations  $V_1 = S_1 D_1 S_1^\top$  and  $V_2 = S_2 D_2 S_2^\top$ , where the elements on the diagonal of  $D_1$  and  $D_2$  are arranged in descending order. Then*

$$\begin{aligned}\|D_1 - D_2\|_\infty &\leq \sqrt{K(V_1)K(V_2)}\|V_1 - V_2\|_\infty, \\ \|D_1 - D_2\|_2 &\leq \sqrt{K(V_1)K(V_2)}\|V_1 - V_2\|_2,\end{aligned}\tag{C5}$$

where  $K(V)$  is the condition number of the covariance matrix  $V$ , defined as  $K(V) := \|V\|_\infty \|V^{-1}\|_\infty$ .

# Recap

$$\rho^{\otimes N} \longrightarrow \text{Diagram} = \tilde{V} = \tilde{\nu}_{\max} \text{ vs } \nu_{\text{thr}}$$

**Learning mean and covariance.**

$$N = O\left(\log\left(\frac{n^2}{\delta}\right) \frac{n^3 E^2}{\epsilon^2}\right)$$

$$\mathbb{P}\left(\|\tilde{V}' - V(\rho)\|_2 \leq \epsilon, \tilde{V}' + i\Omega \geq 0, \|\tilde{\mathbf{m}} - \mathbf{m}(\rho)\| \leq \frac{\epsilon}{10\sqrt{8nE}}\right) \geq 1 - \delta$$

**Upper bound between Gaussian states.**

$$\begin{aligned} \frac{1}{2}\|\rho(V, \mathbf{m}) - \rho(W, \mathbf{t})\|_1 &\leq \frac{1 + \sqrt{3}}{8} \max(\text{Tr}V, \text{Tr}W) \|V - W\|_\infty \\ &\quad + \sqrt{\frac{\min(\|V\|_\infty, \|W\|_\infty)}{2}} \|\mathbf{m} - \mathbf{t}\| \end{aligned}$$

**Lower bound between Gaussian states.**

$$\begin{aligned} \frac{1}{2}\|\rho(V, \mathbf{m}) - \rho(W, \mathbf{t})\|_1 &\geq \frac{1}{200} \min\left\{1, \frac{\|\mathbf{m} - \mathbf{t}\|}{\sqrt{4\min(\|V\|_\infty, \|W\|_\infty) + 1}}\right\} \\ \frac{1}{2}\|\rho(V, \mathbf{m}) - \rho(W, \mathbf{t})\|_1 &\geq \frac{1}{200} \min\left\{1, \frac{\|V - W\|_2}{4\min(\|V\|_\infty, \|W\|_\infty) + 1}\right\} \end{aligned}$$

**Perturbation on symplectic diagonalisation.**

$$\|D_1 - D_2\|_\infty \leq \sqrt{K(V_1)K(V_2)} \|V_1 - V_2\|_\infty$$

$$\|D_1 - D_2\|_2 \leq \sqrt{K(V_1)K(V_2)} \|V_1 - V_2\|_2$$

**Upper bound between a pure Gaussian state and a generic state.**

$$\frac{1}{2}\|\psi_G - \sigma\|_1 \leq \sqrt{E} \sqrt{\|V - W\|_\infty + 2\|\mathbf{m} - \mathbf{t}\|^2}$$

**Lower bound between arbitrary states.**

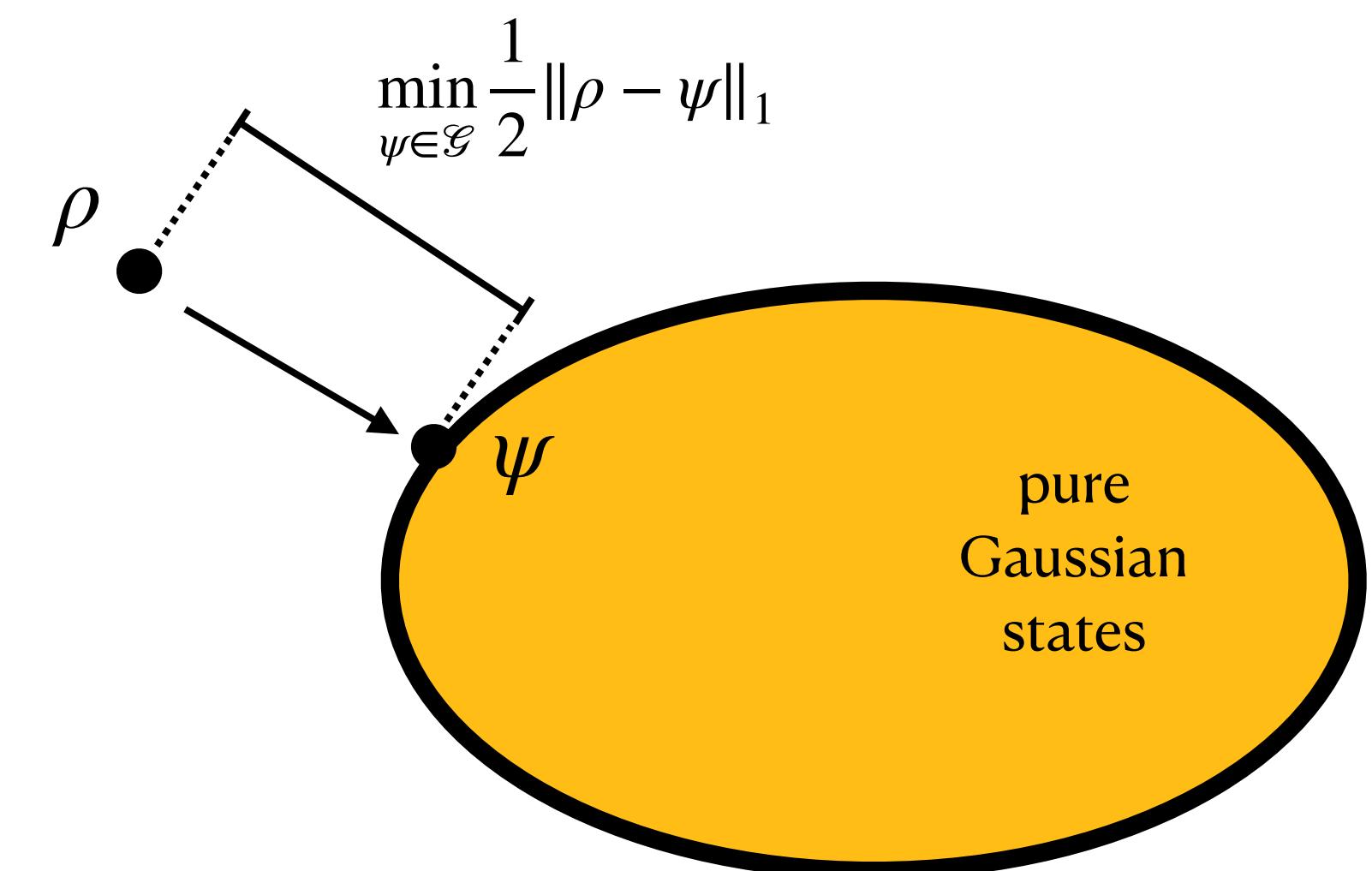
$$\begin{aligned} \frac{1}{2}\|\rho - \sigma\|_1 &\geq \frac{\|\mathbf{m} - \mathbf{t}\|^2}{32 \max(\text{Tr}[\hat{E}\rho], \text{Tr}[\hat{E}\sigma])} \\ \frac{1}{2}\|\rho - \sigma\|_1 &\geq \frac{\|V - W\|_\infty^2}{3098 \max(\text{Tr}[\hat{E}^2\rho], \text{Tr}[\hat{E}^2\sigma])} \end{aligned}$$

# Two approaches

symmetries  
of Gaussian states

learning  
Gaussian states

$\rho^{\otimes N}$

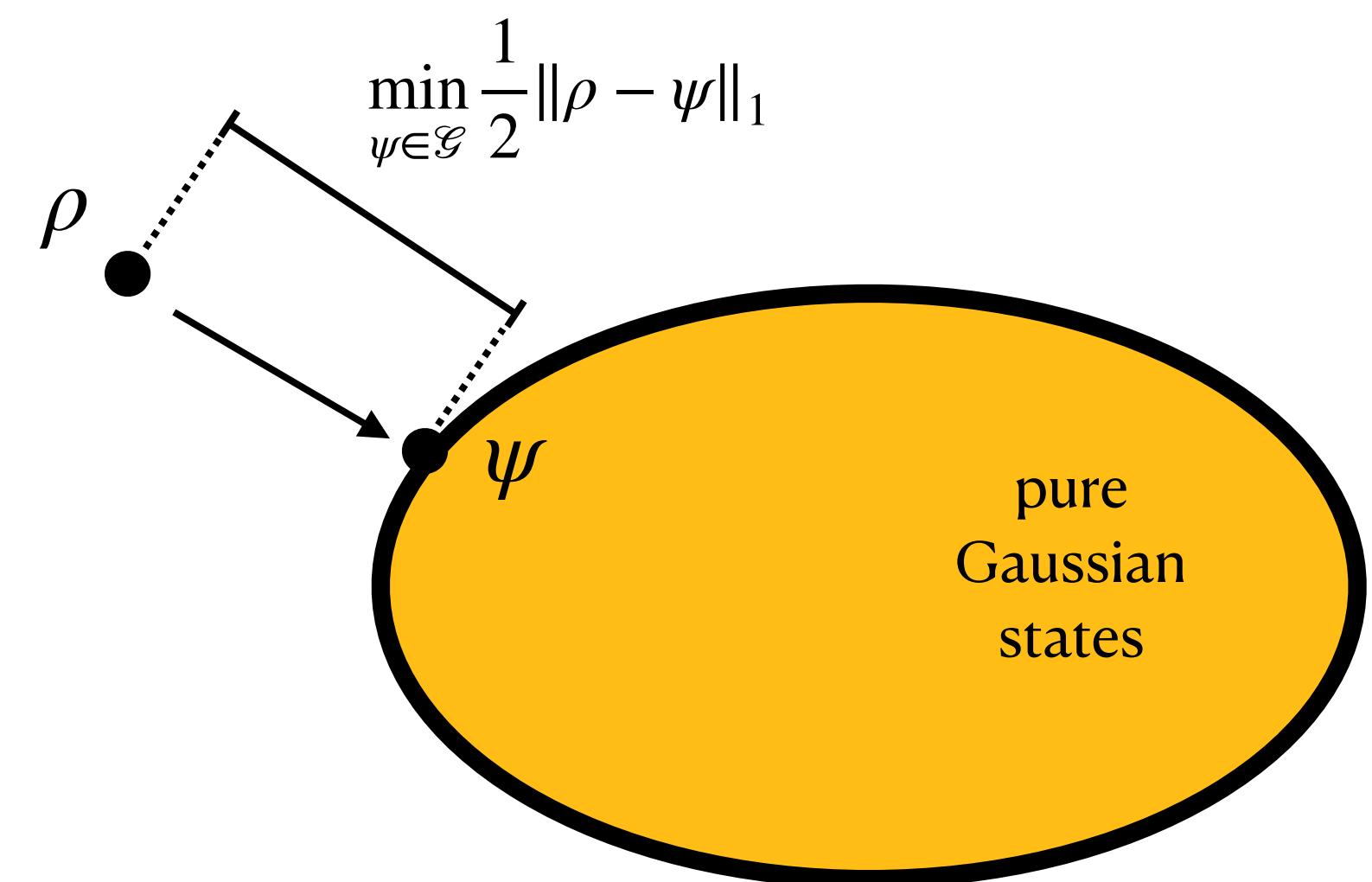


# Two approaches

**symmetries**  
of Gaussian states

**learning**  
Gaussian states

$$\begin{array}{c} \rho^{\otimes N} \\ \downarrow \\ m, V = SDS^\top \end{array}$$



# Two approaches

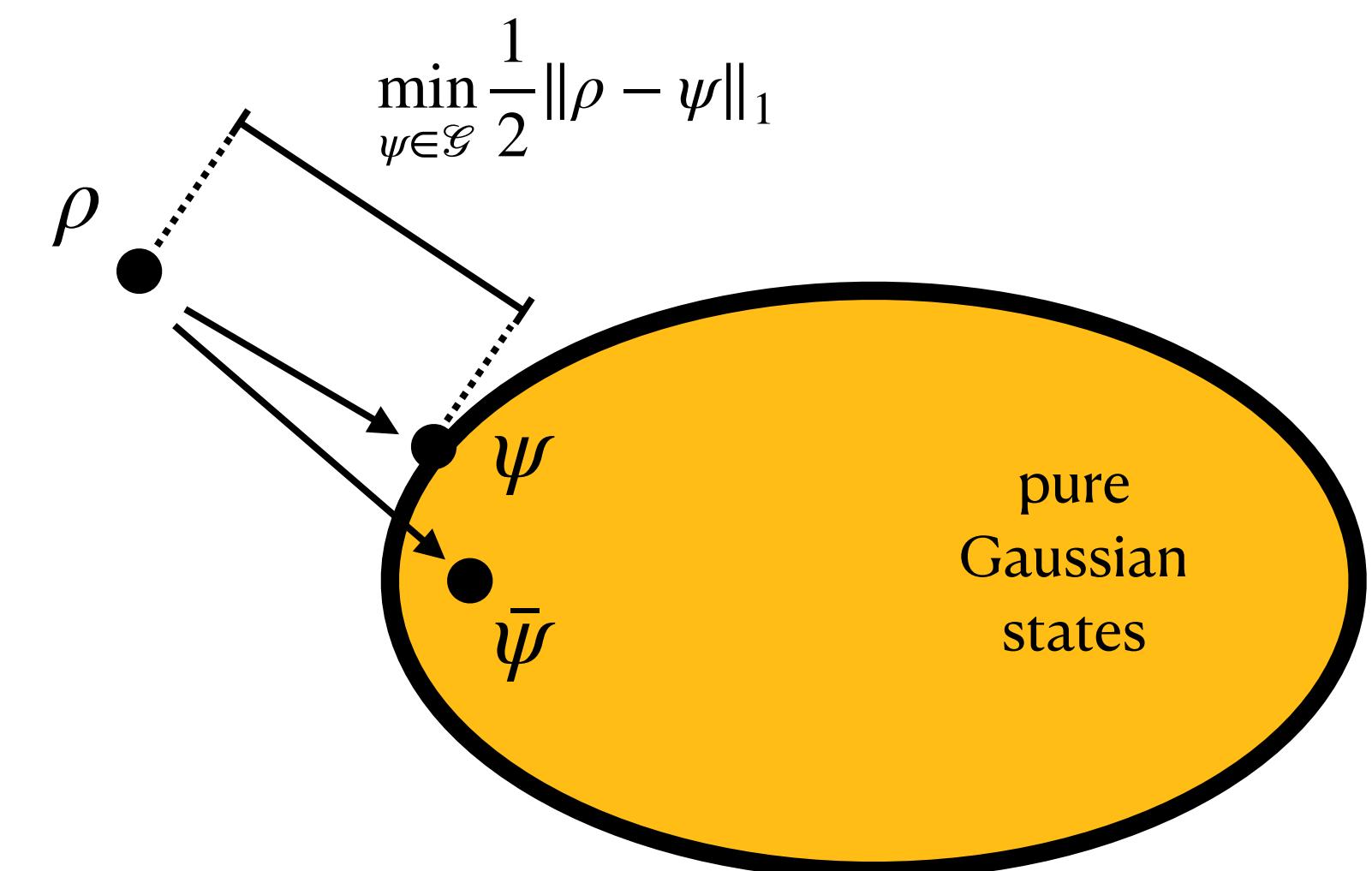
**symmetries**  
of Gaussian states

$$\rho^{\otimes N}$$

$$m, V = SDS^\top$$

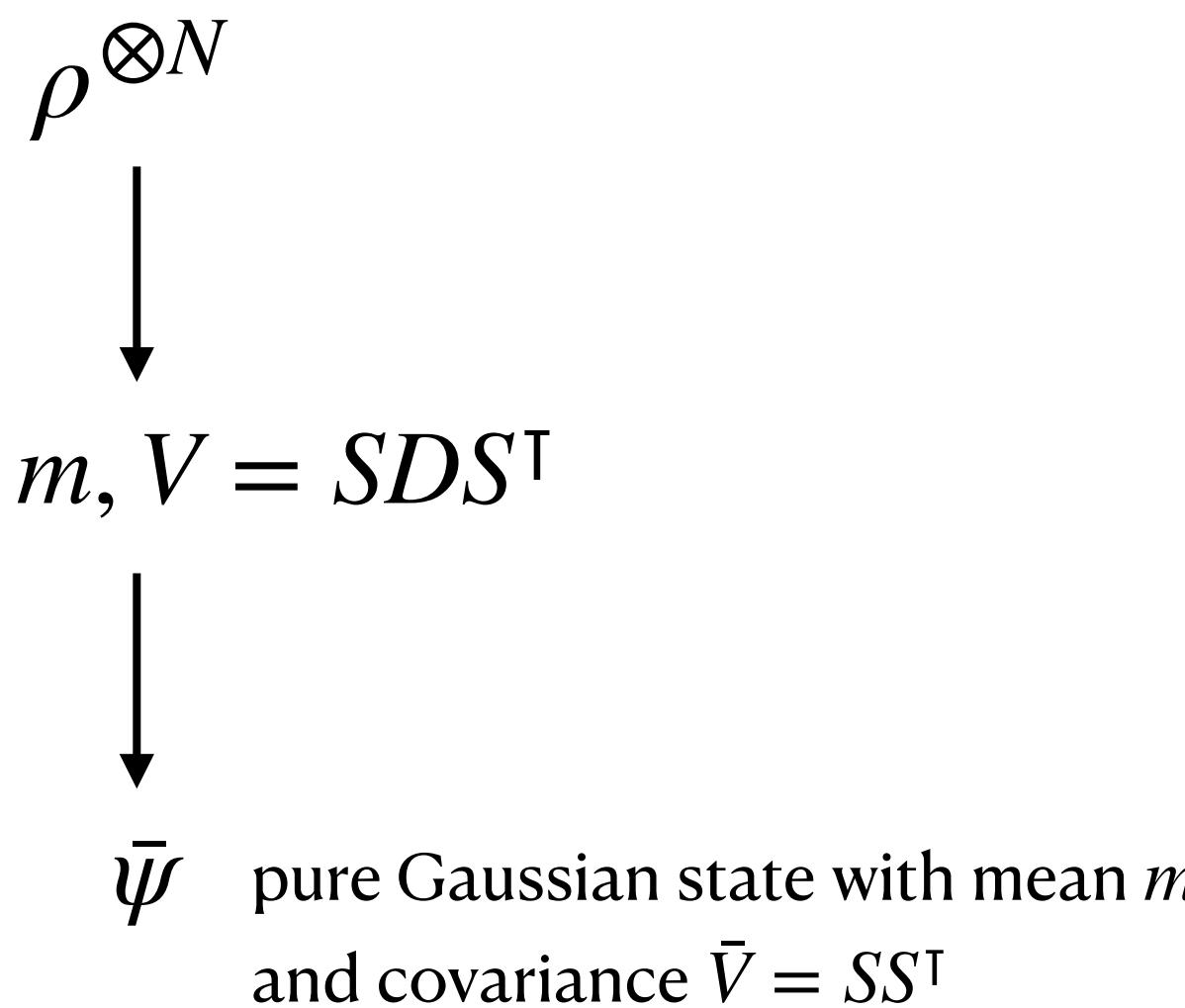
$\bar{\psi}$  pure Gaussian state with mean  $m$   
and covariance  $\bar{V} = SS^\top$

**learning**  
Gaussian states

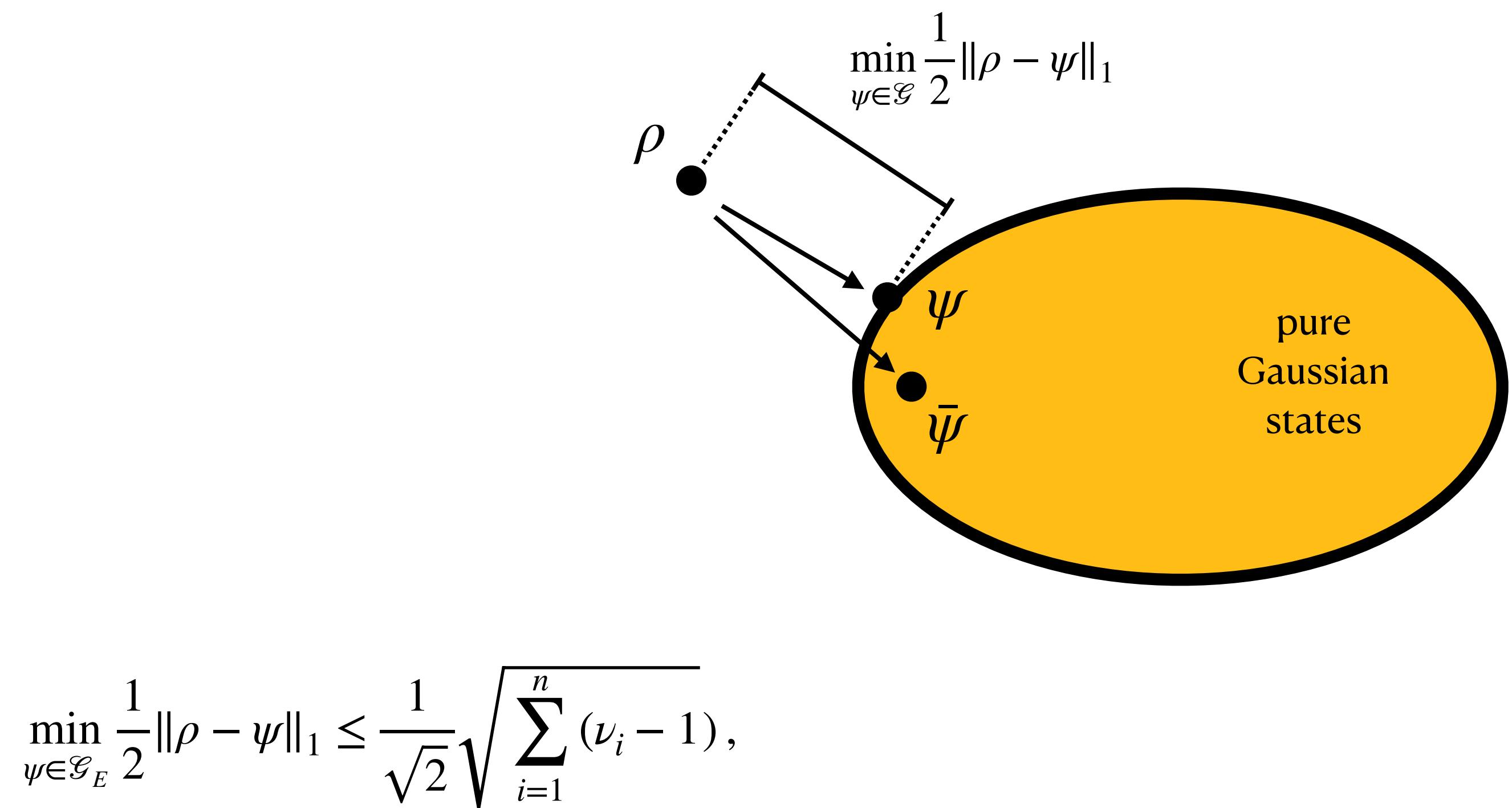


# Two approaches

**symmetries**  
of Gaussian states



**learning**  
Gaussian states



$\rho^{\otimes N}$ 

$$m, V = SDS^\top$$

$\bar{\psi}$  pure Gaussian state with mean  $m$  and covariance  $\bar{V} = SS^\top$

symmetries  
of Gaussian states

T  
←

$$\bar{\psi} = D_{m(\rho)} U_S |0\rangle\langle 0| U_S^\dagger D_{m(\rho)}^\dagger$$

$$\begin{aligned} \frac{1}{2} \|\rho - \bar{\psi}\|_1 &\stackrel{(i)}{\leq} \sqrt{1 - \text{Tr}[\rho \bar{\psi}]} \\ &= \sqrt{1 - \text{Tr}[U_S^\dagger D_{m(\rho)}^\dagger \rho D_{m(\rho)} U_S |0\rangle\langle 0|]} \\ &\stackrel{(ii)}{\leq} \sqrt{\text{Tr}[U_S^\dagger D_{m(\rho)}^\dagger \rho D_{m(\rho)} U_S \hat{N}]} \\ &\stackrel{(iii)}{=} \frac{1}{2} \sqrt{\text{Tr}[D - \mathbb{1}]} \\ &= \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^n (\nu_i - 1)}. \end{aligned}$$

$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^n (\nu_i - 1)},$$

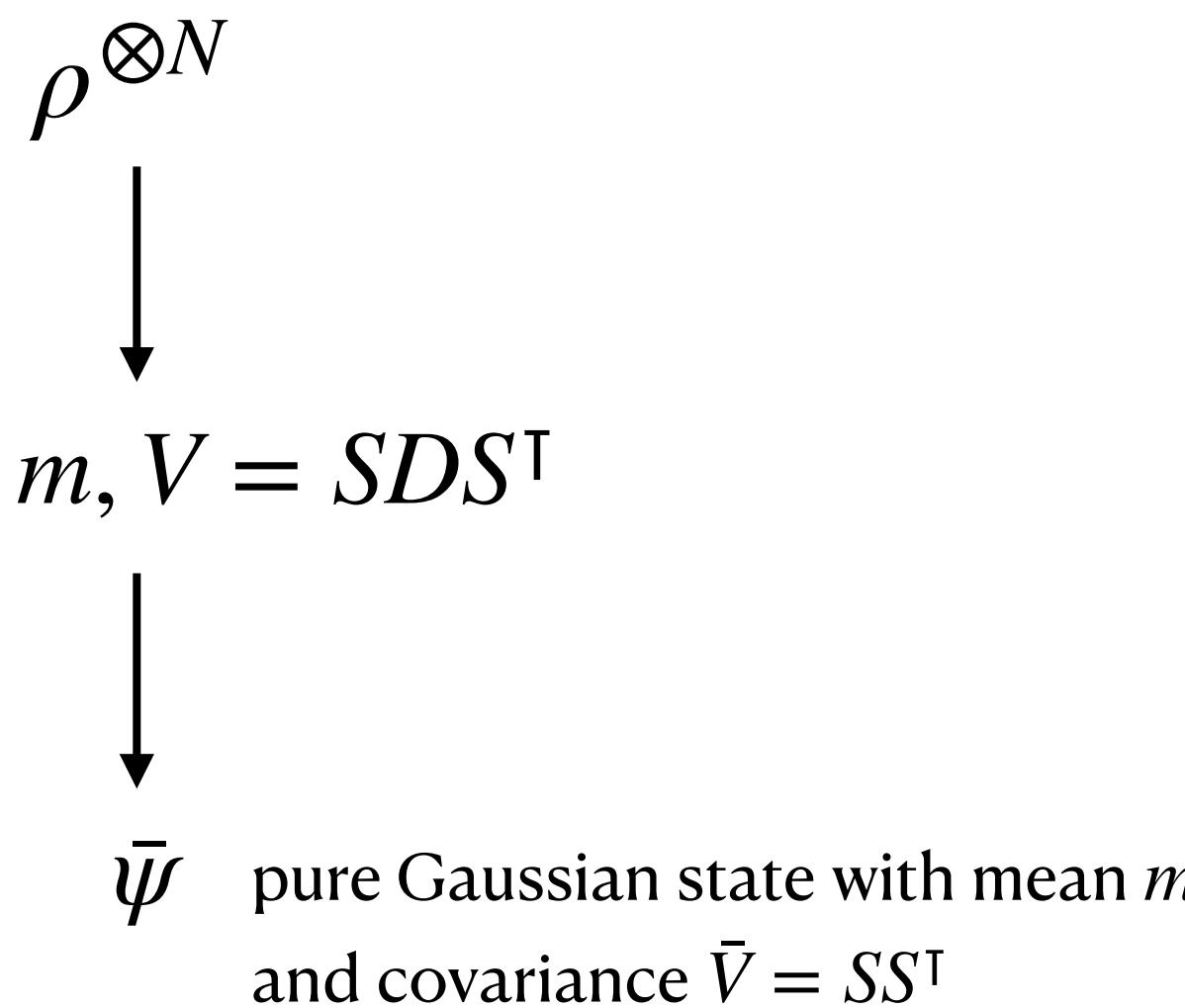
learning  
Gaussian states

$$\frac{1}{2} \|\rho - \psi\|_1$$

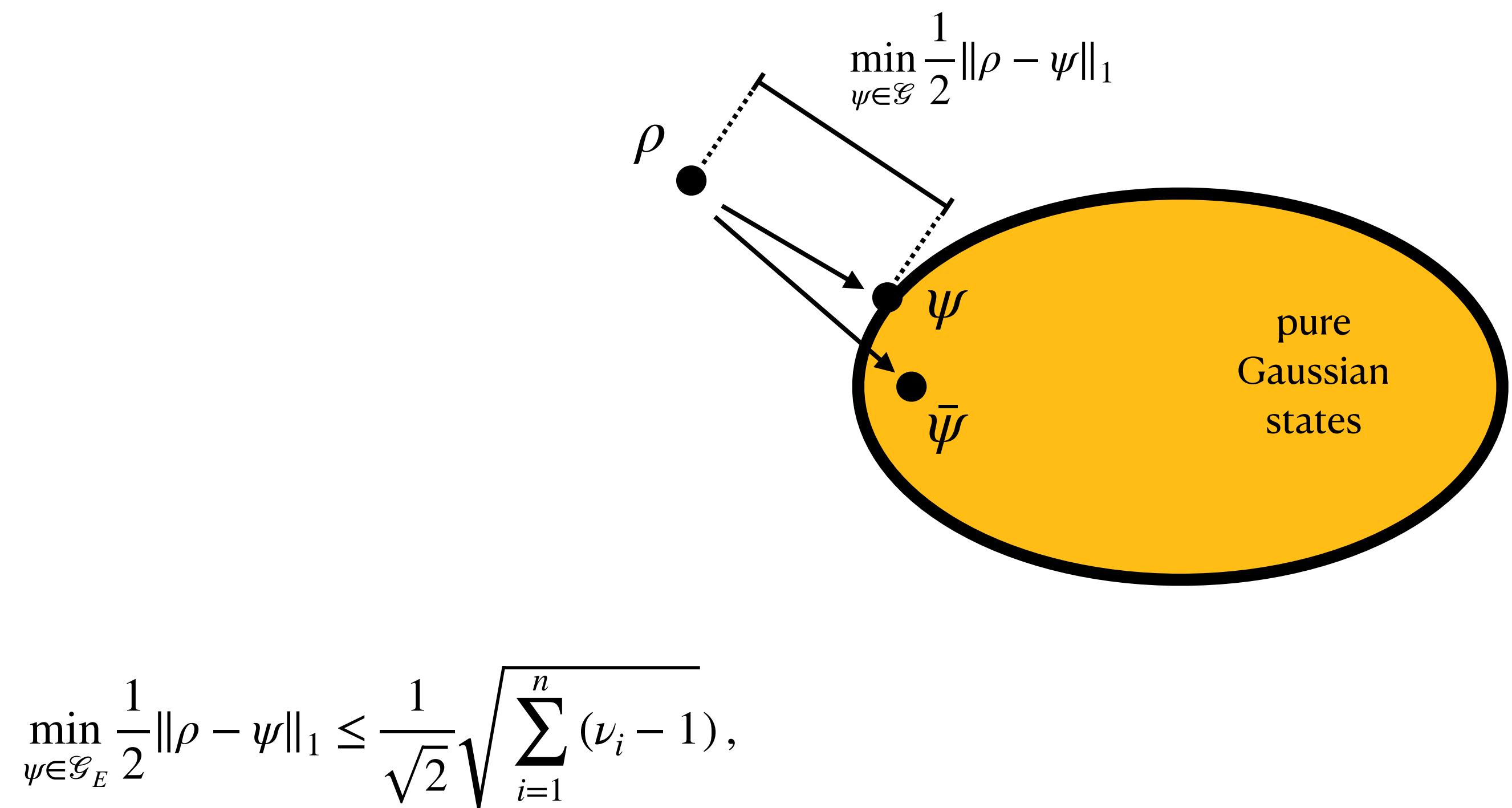


# Two approaches

**symmetries**  
of Gaussian states



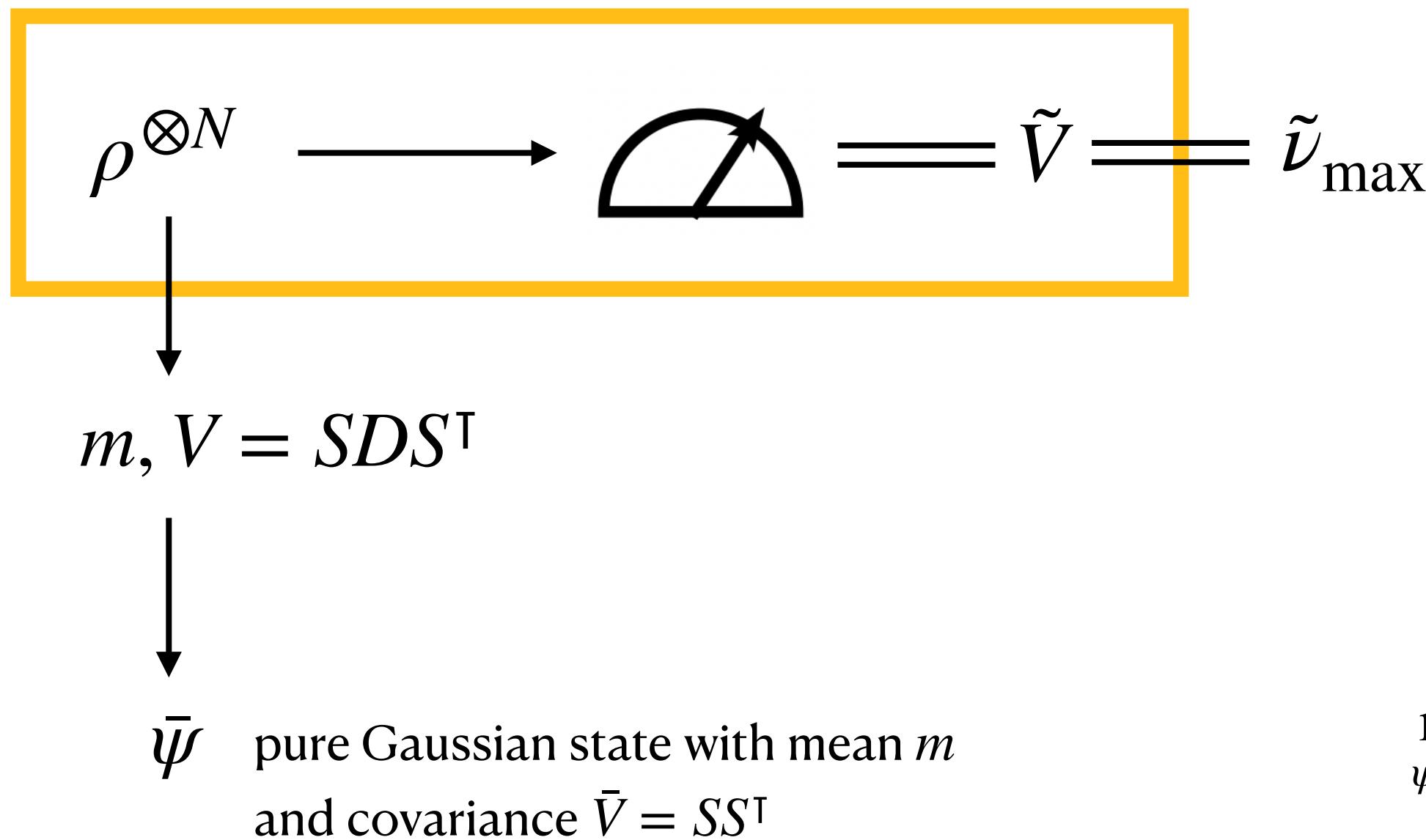
**learning**  
Gaussian states



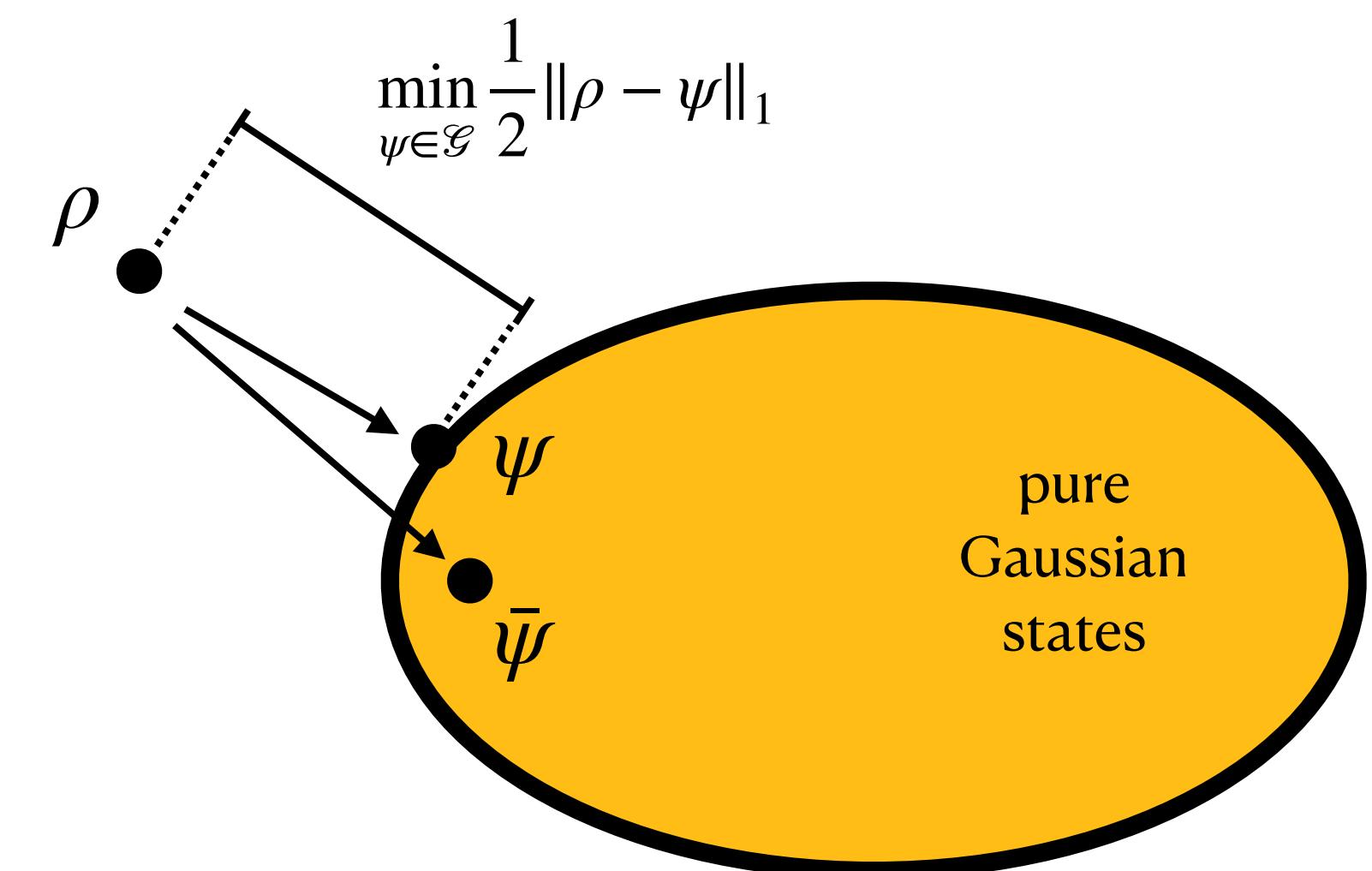
# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^n (\nu_i - 1)},$$

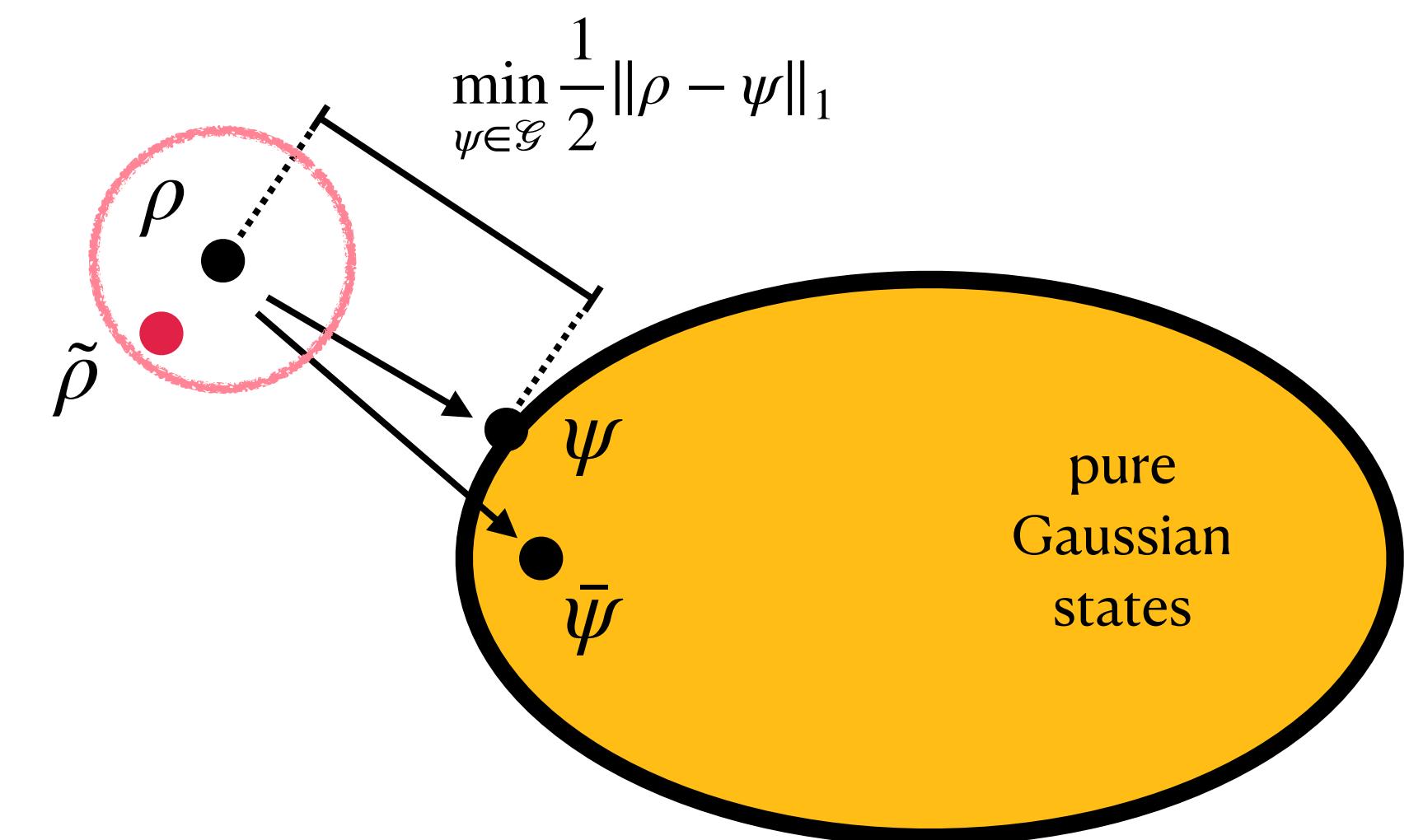
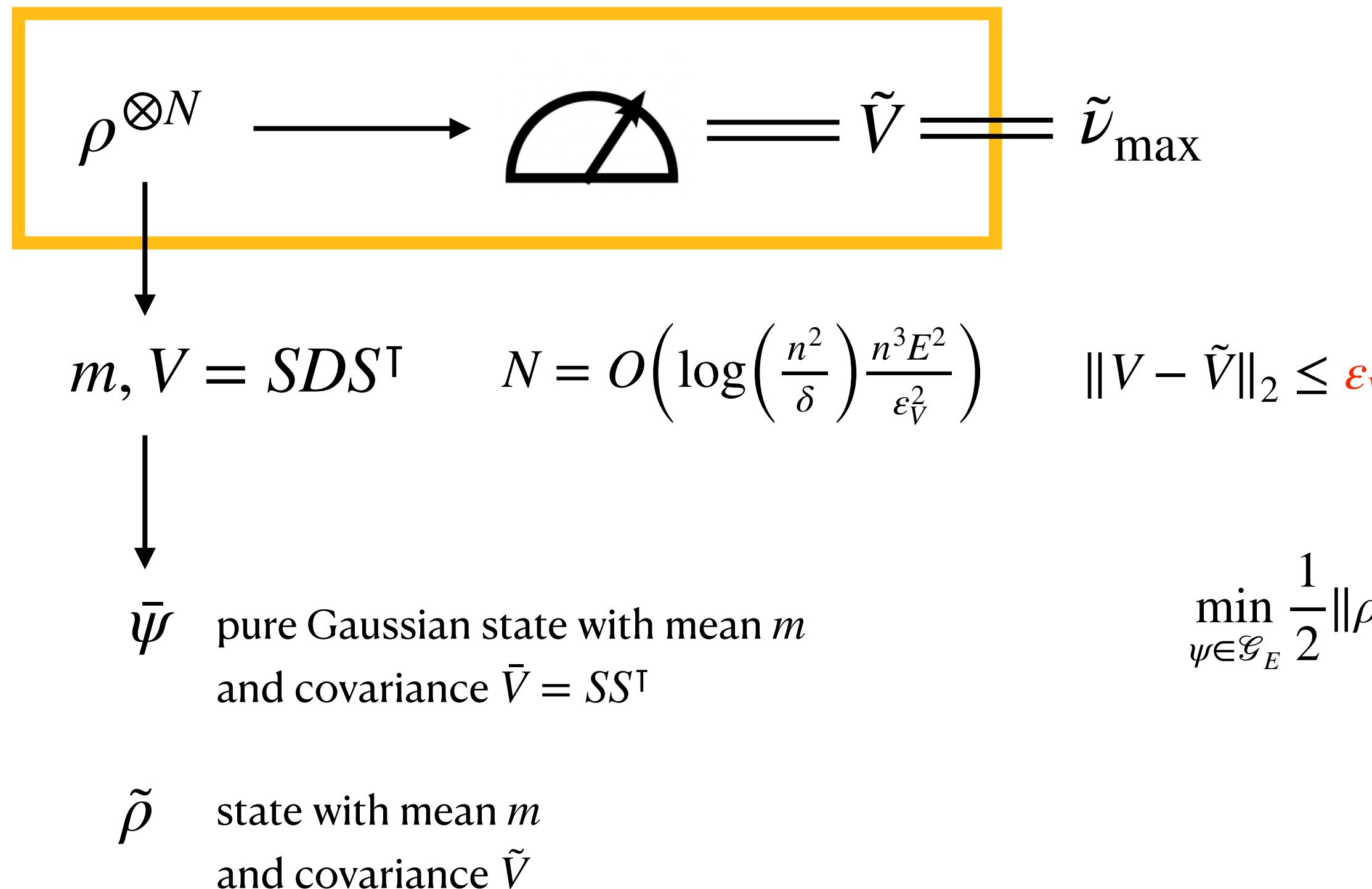


**learning**  
Gaussian states

# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.

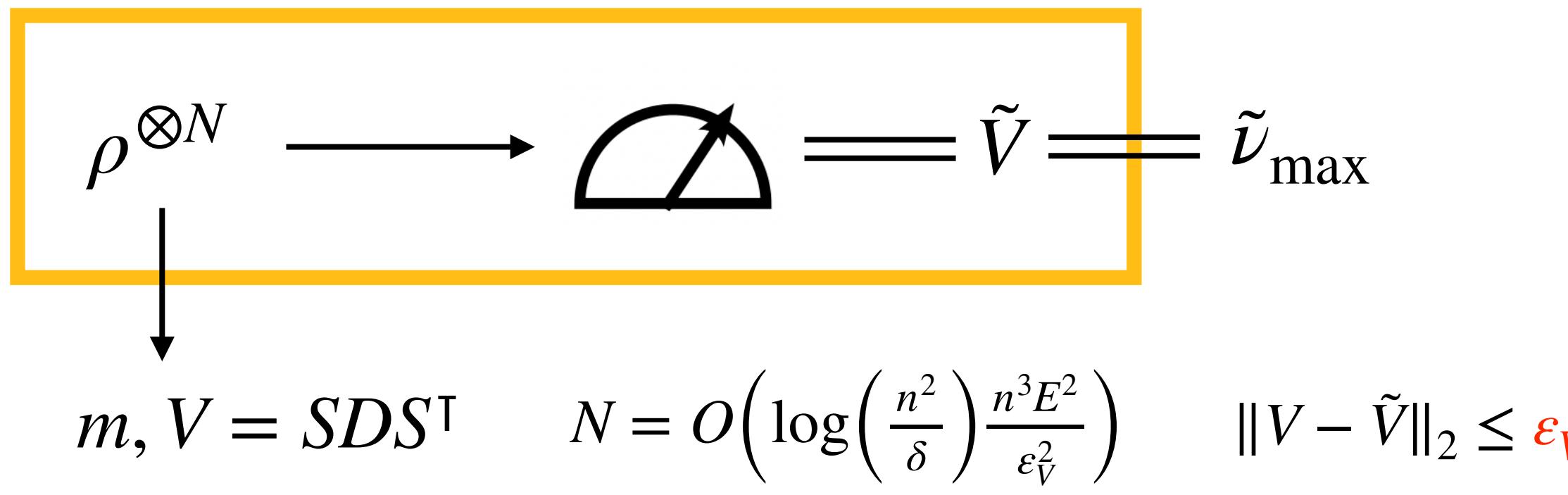


$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^n (\nu_i - 1)},$$

# Two approaches

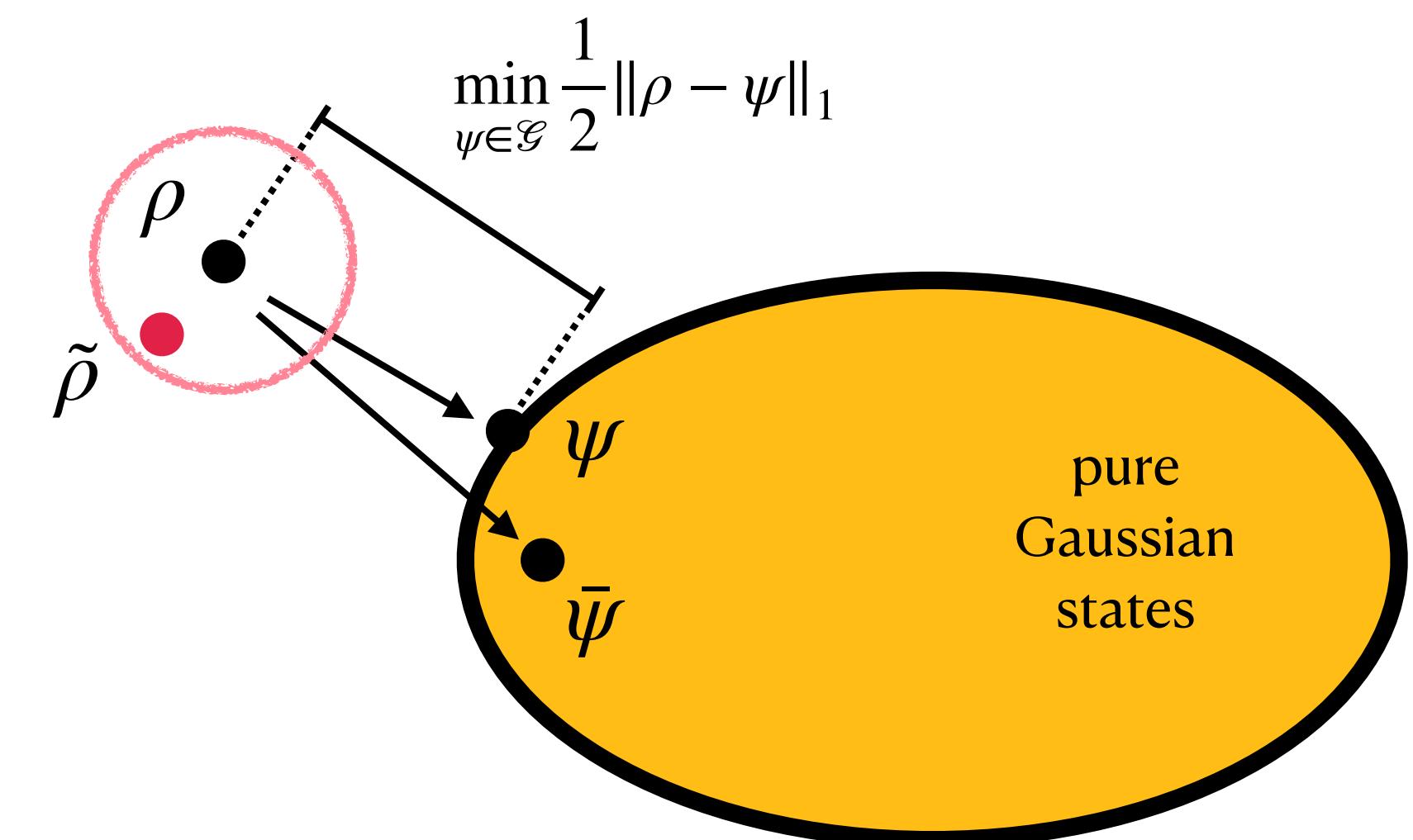
**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



$\bar{\psi}$  pure Gaussian state with mean  $m$  and covariance  $\bar{V} = SS^\top$

$\tilde{\rho}$  state with mean  $m$  and covariance  $\tilde{V}$



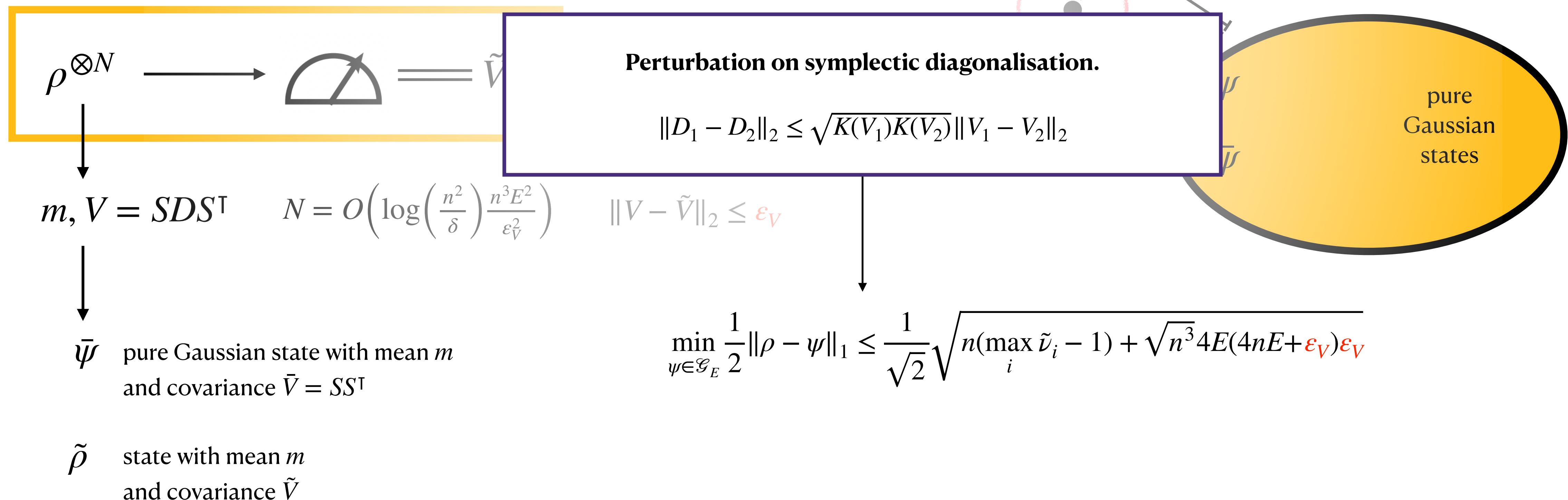
$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \varepsilon_V) \varepsilon_V}$$

# Two approaches

**symmetries**  
of Gaussian states

**learning**  
Gaussian states

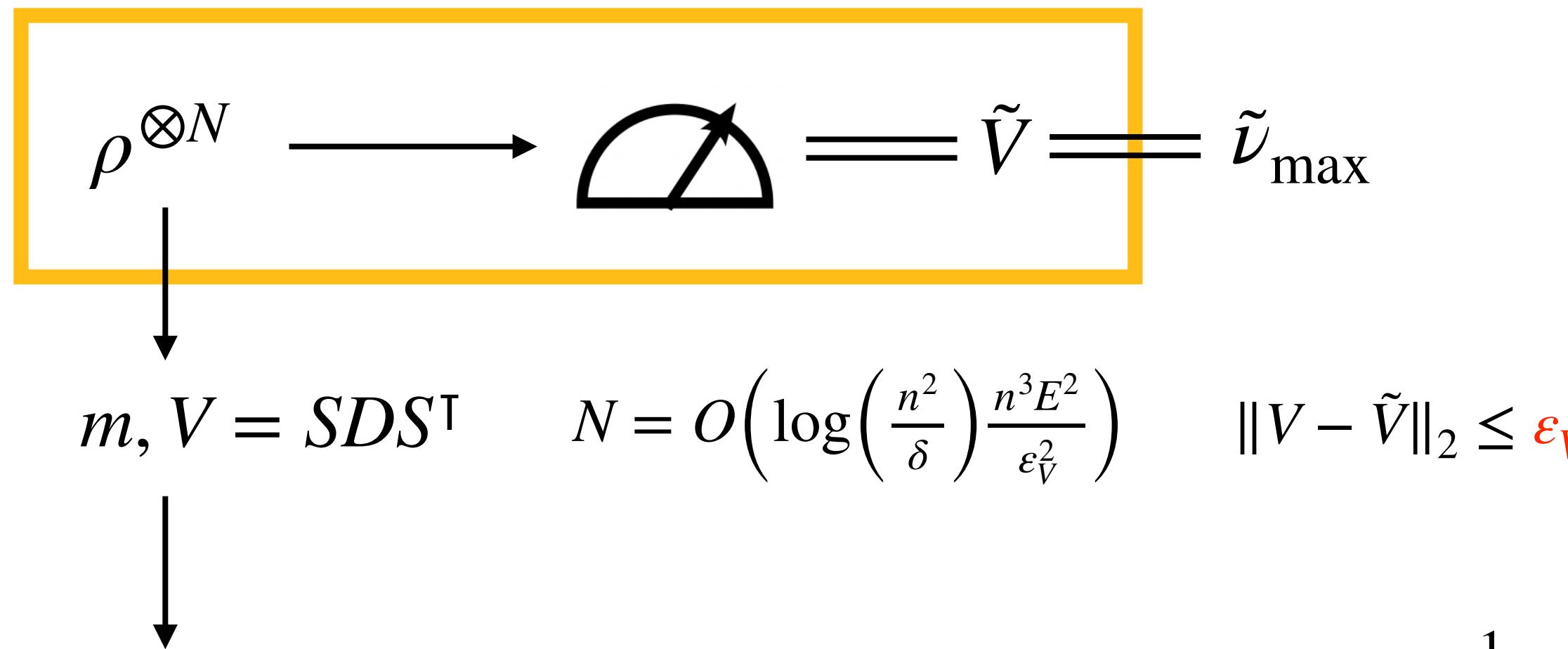
Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



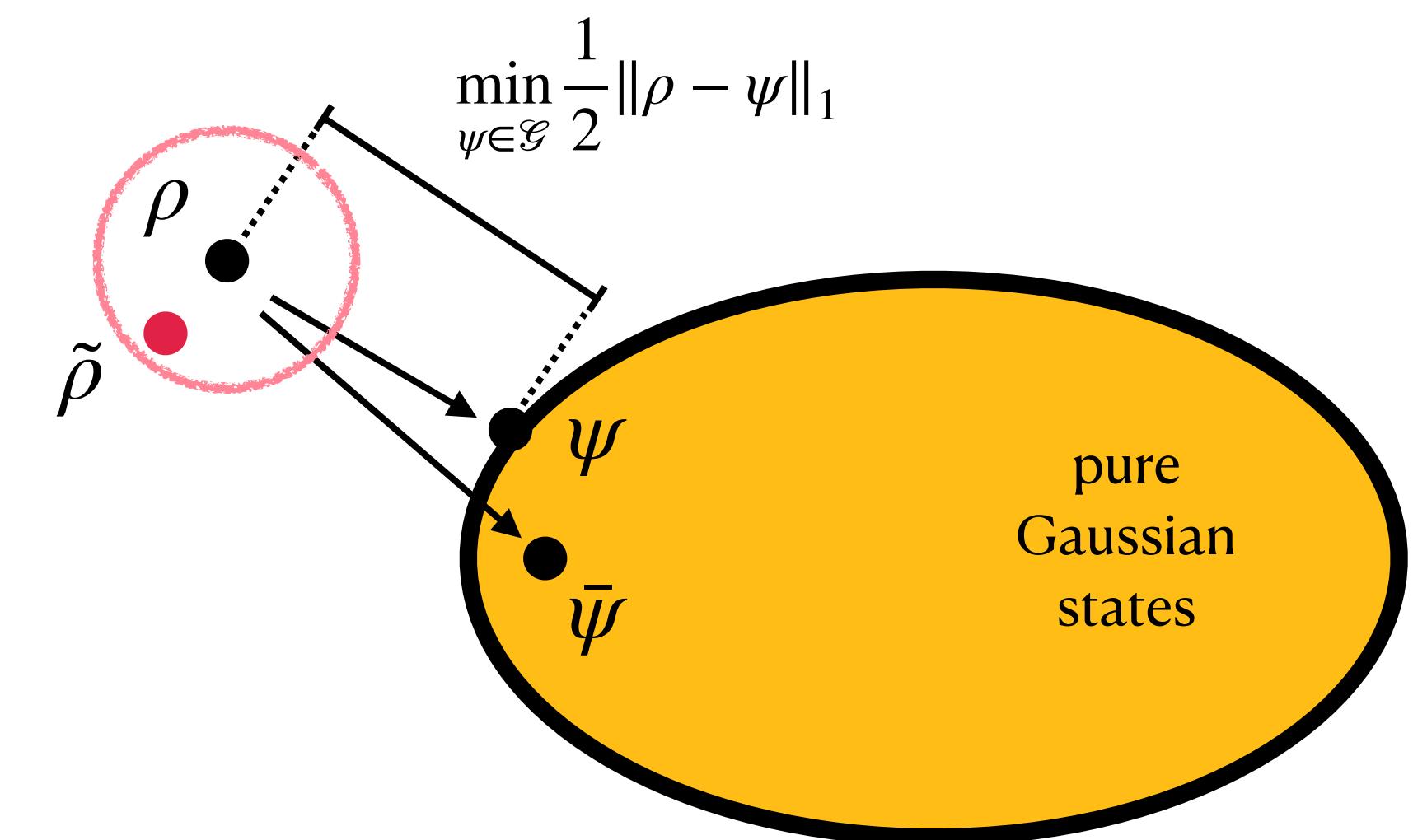
# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



$\tilde{\rho}$  state with mean  $m$  and covariance  $\tilde{V}$

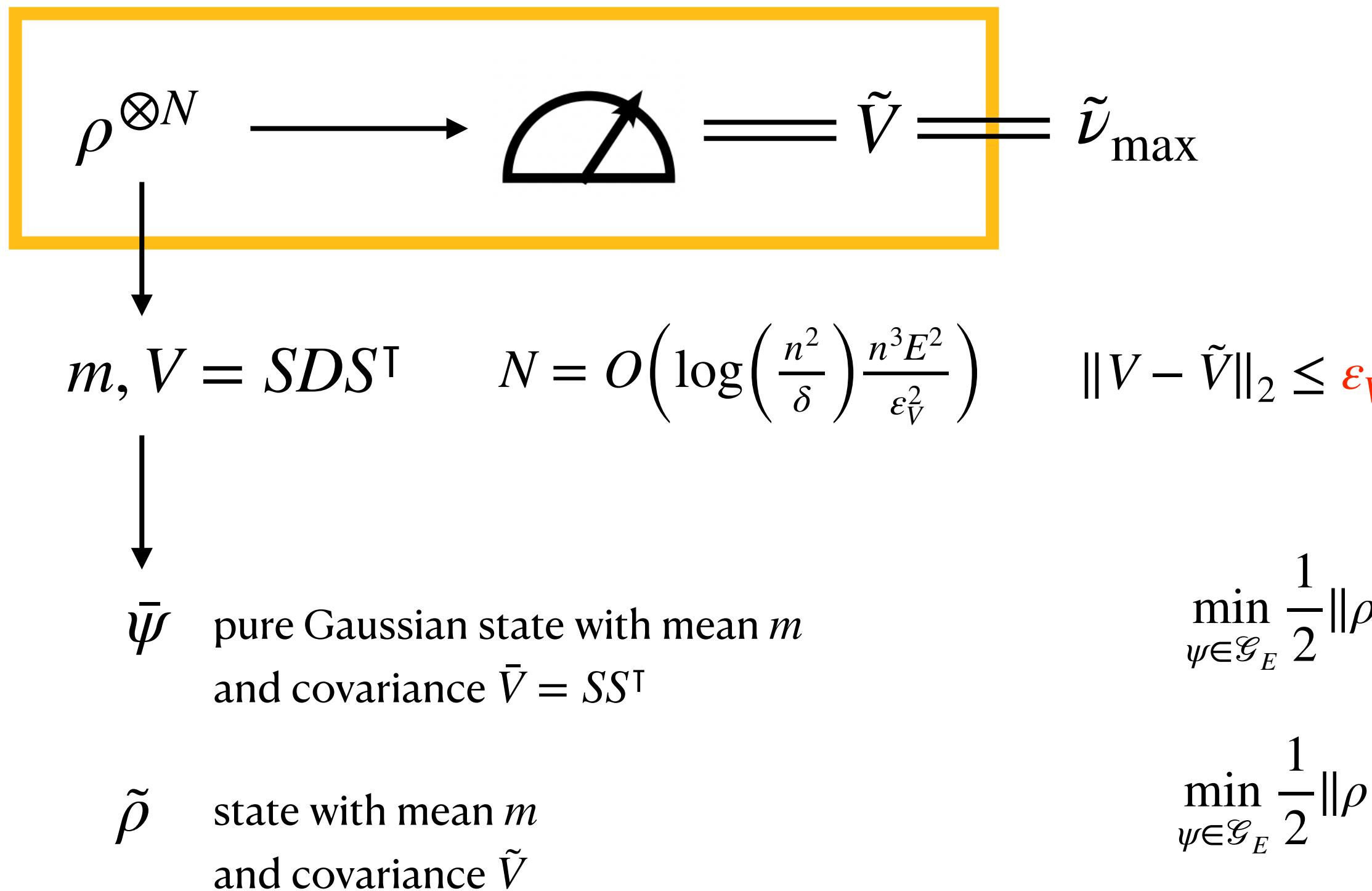


$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \varepsilon_V) \varepsilon_V}$$

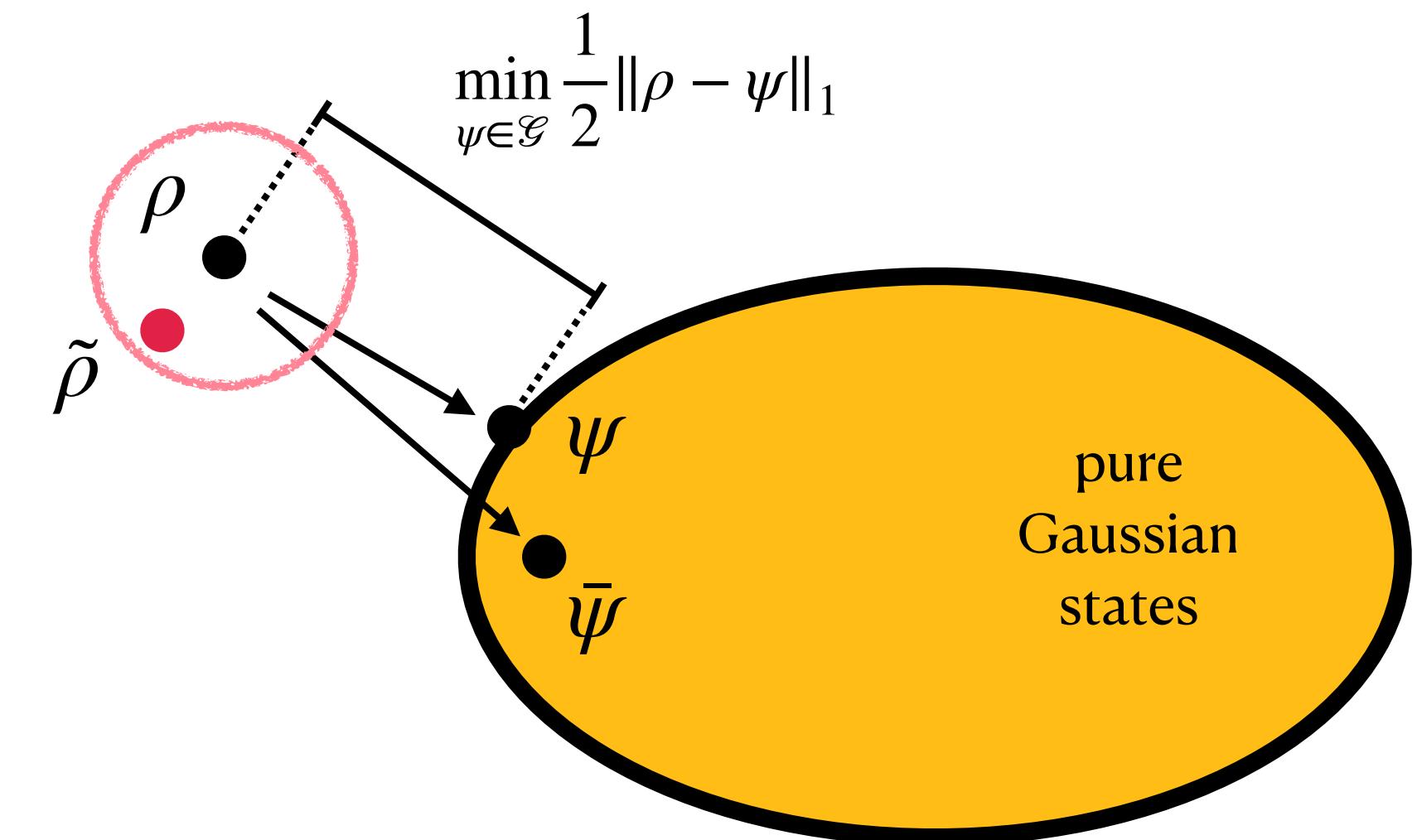
# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



**learning**  
Gaussian states



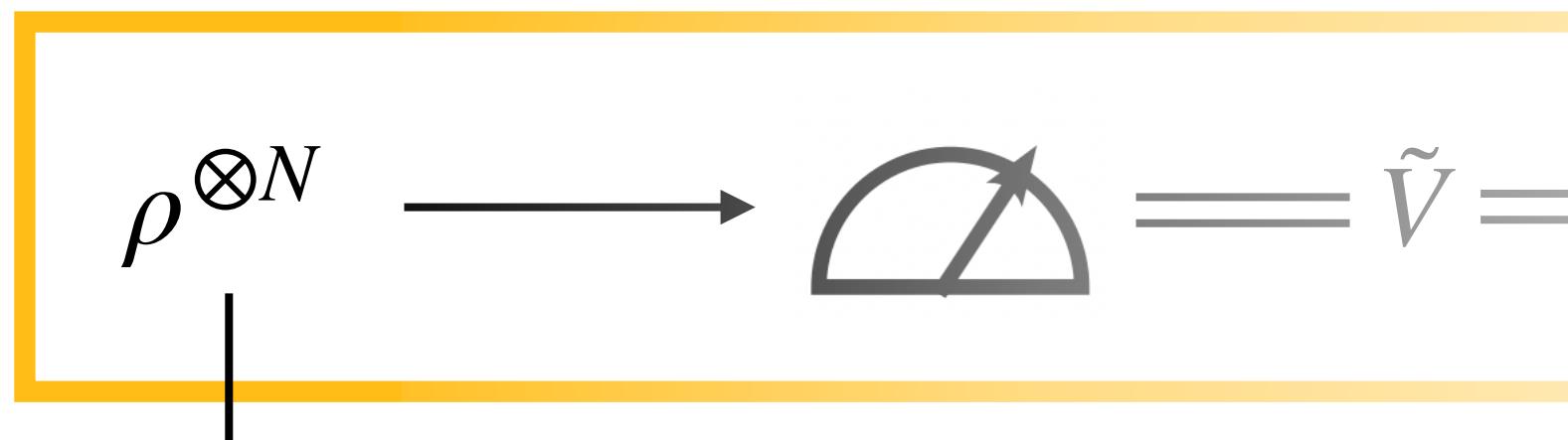
$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \varepsilon_V) \varepsilon_V}$$

$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{(\nu_{\max} - 1)^2}{c(nE)^6}$$

# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



$$N = O\left(\log\left(\frac{n^2}{\delta}\right)\frac{n^3E^2}{\varepsilon_V^2}\right)$$

$\bar{\psi}$  pure Gaussian state with mean  $m$  and covariance  $\bar{V} = SS^\top$

$\tilde{\rho}$  state with mean  $m$  and covariance  $\tilde{V}$

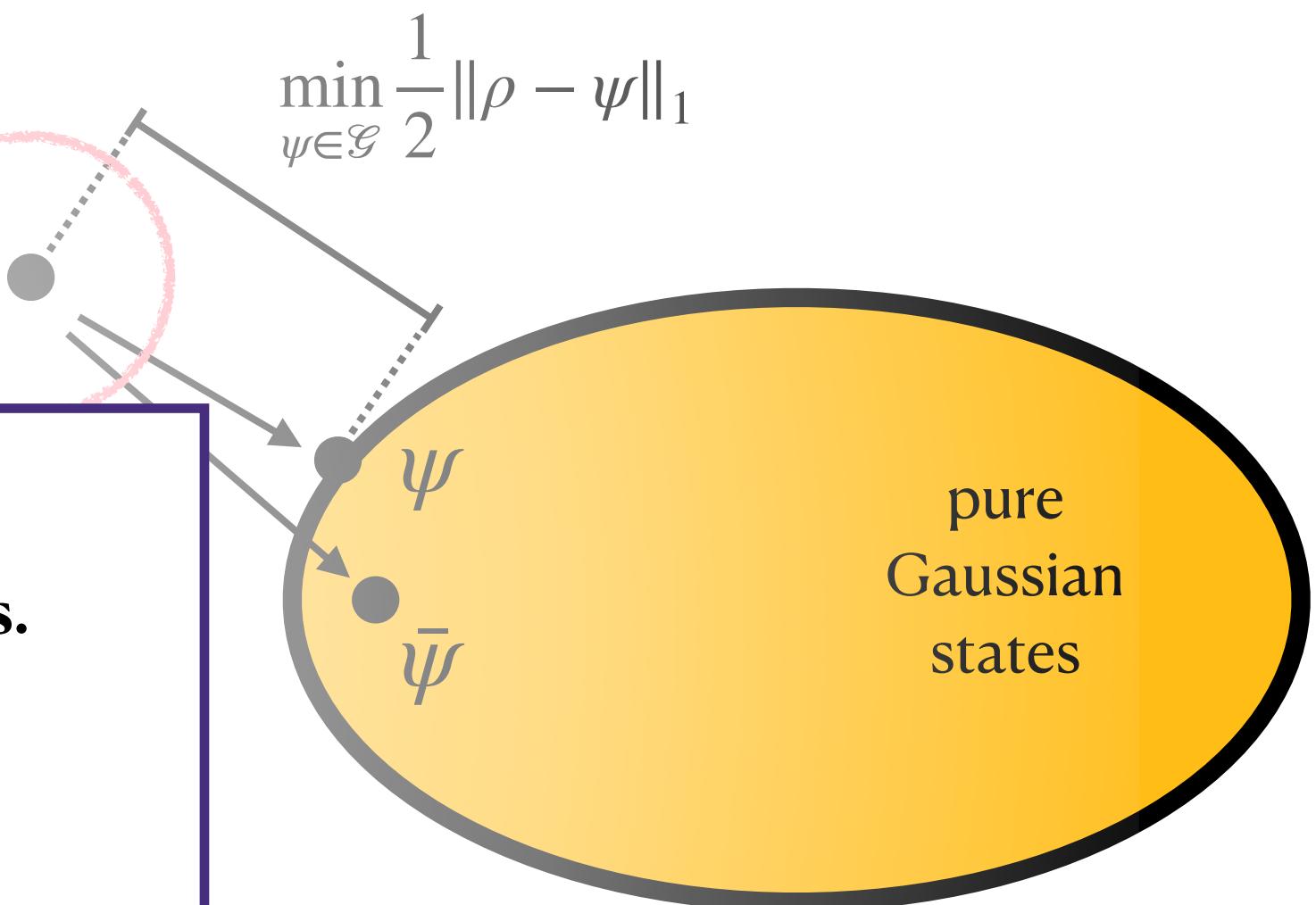
**Lower bound between arbitrary states.**

$$\frac{1}{2}\|\rho - \sigma\|_1 \geq \frac{\|V - W\|_\infty^2}{3098 \max(\text{Tr}[\hat{E}^2\rho], \text{Tr}[\hat{E}^2\sigma])}$$

$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2}\|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3}4E(4nE + \varepsilon_V)\varepsilon_V}$$

$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2}\|\rho - \psi\|_1 \geq \frac{(\nu_{\max} - 1)^2}{c(nE)^6}$$

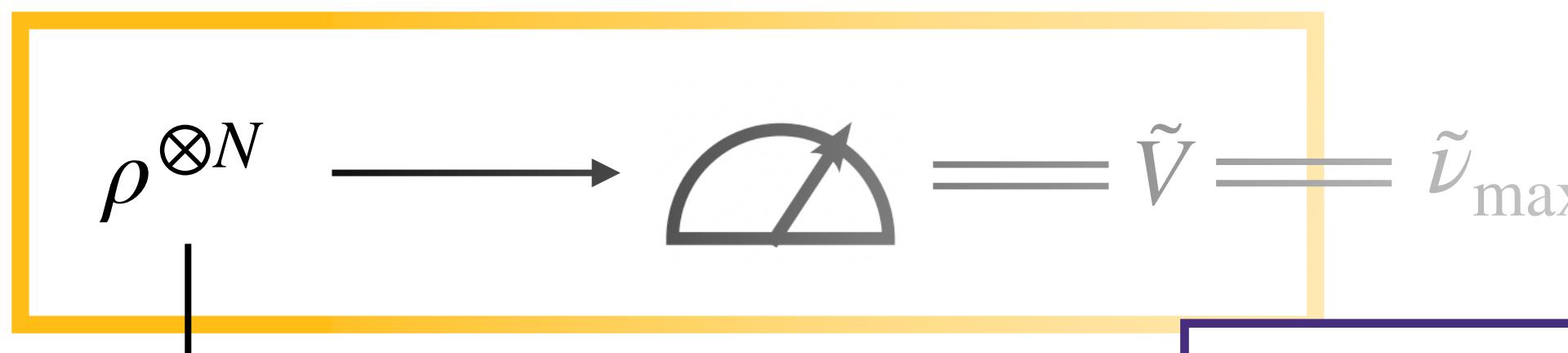
**learning**  
Gaussian states



# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.

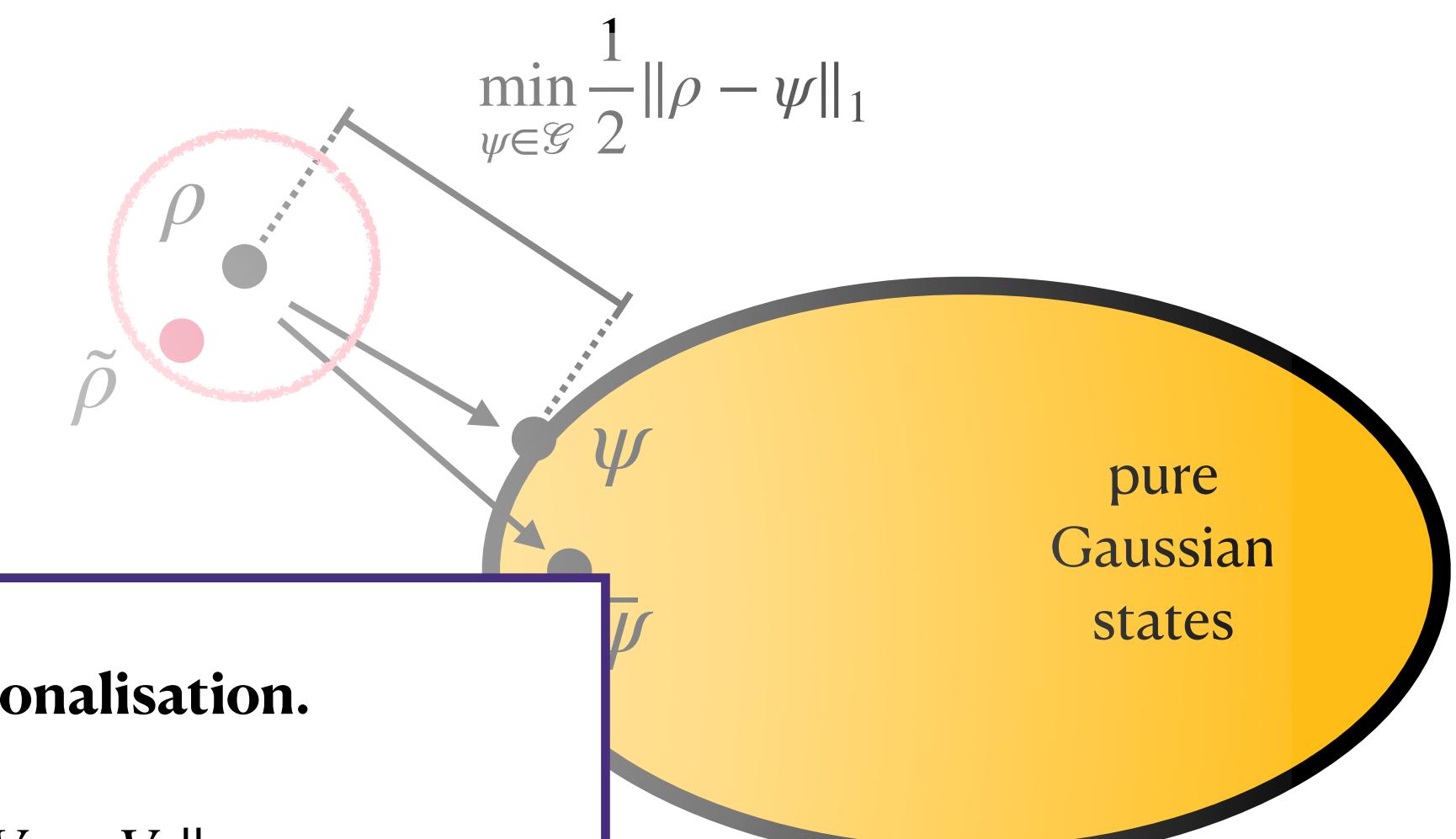


**Perturbation on symplectic diagonalisation.**

$$\|D_1 - D_2\|_2 \leq \sqrt{K(V_1)K(V_2)} \|V_1 - V_2\|_2$$

$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \epsilon_V) \epsilon_V}$$

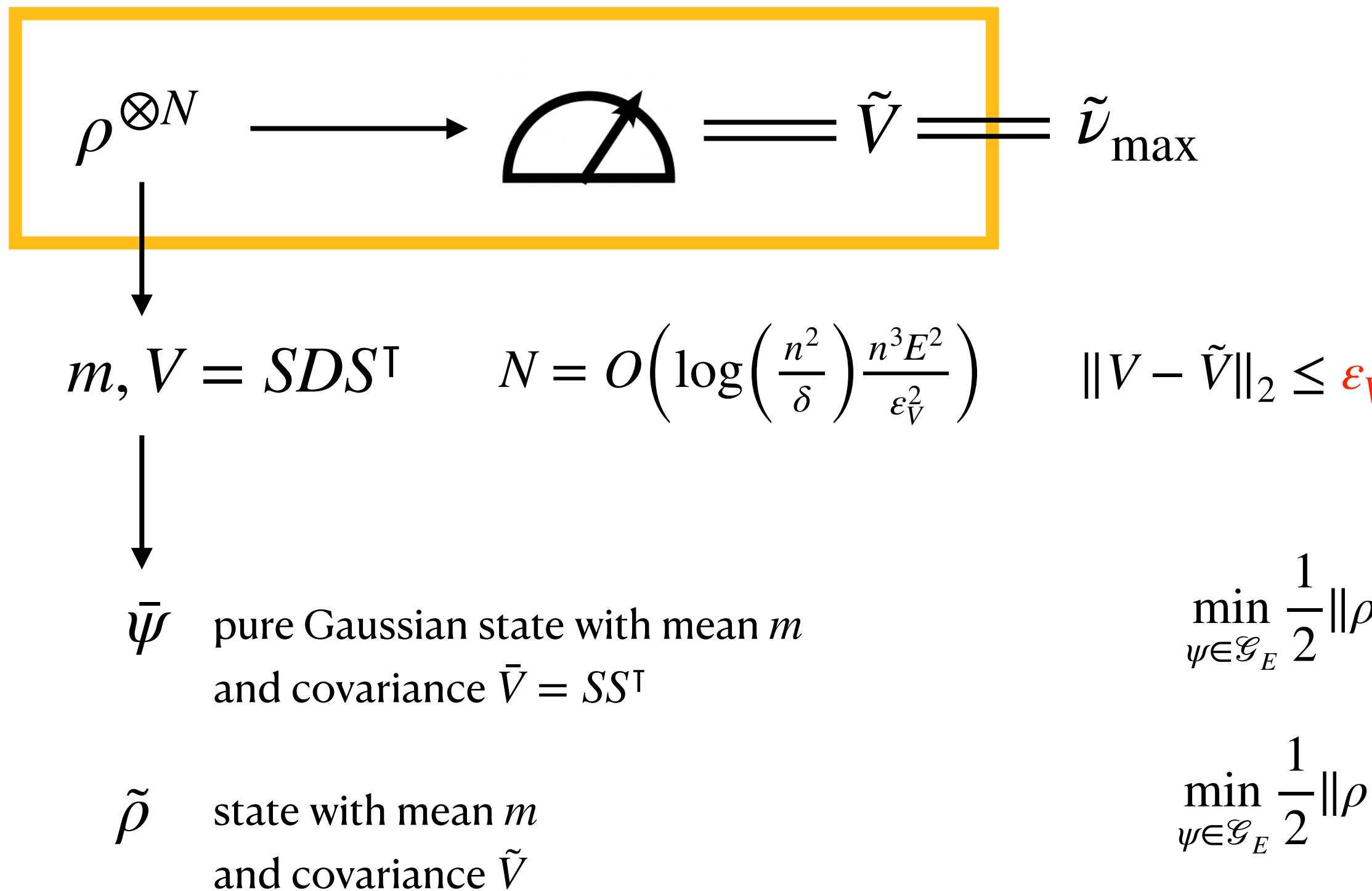
$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{(\nu_{\max} - 1)^2}{c(nE)^6}$$



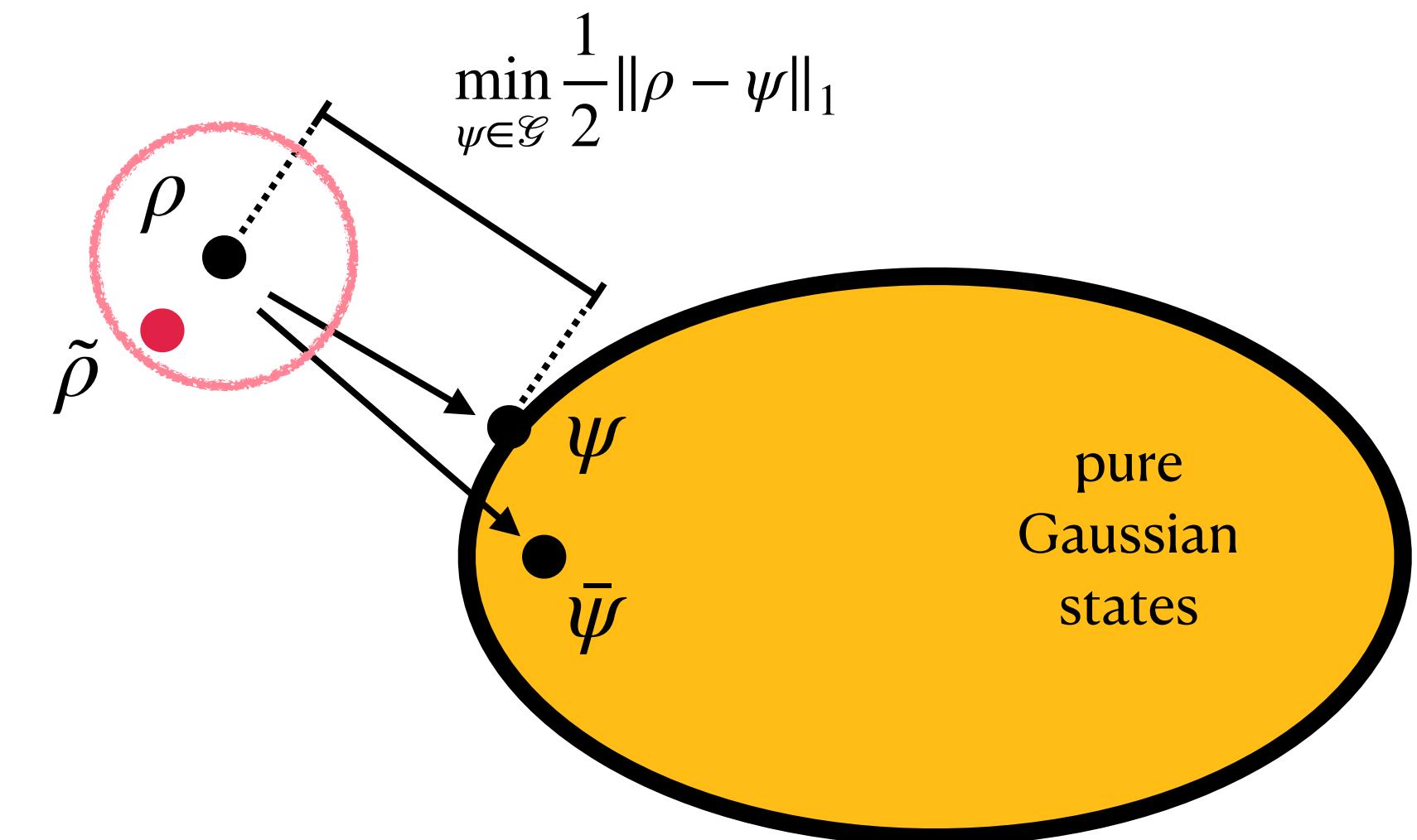
# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



**learning**  
Gaussian states



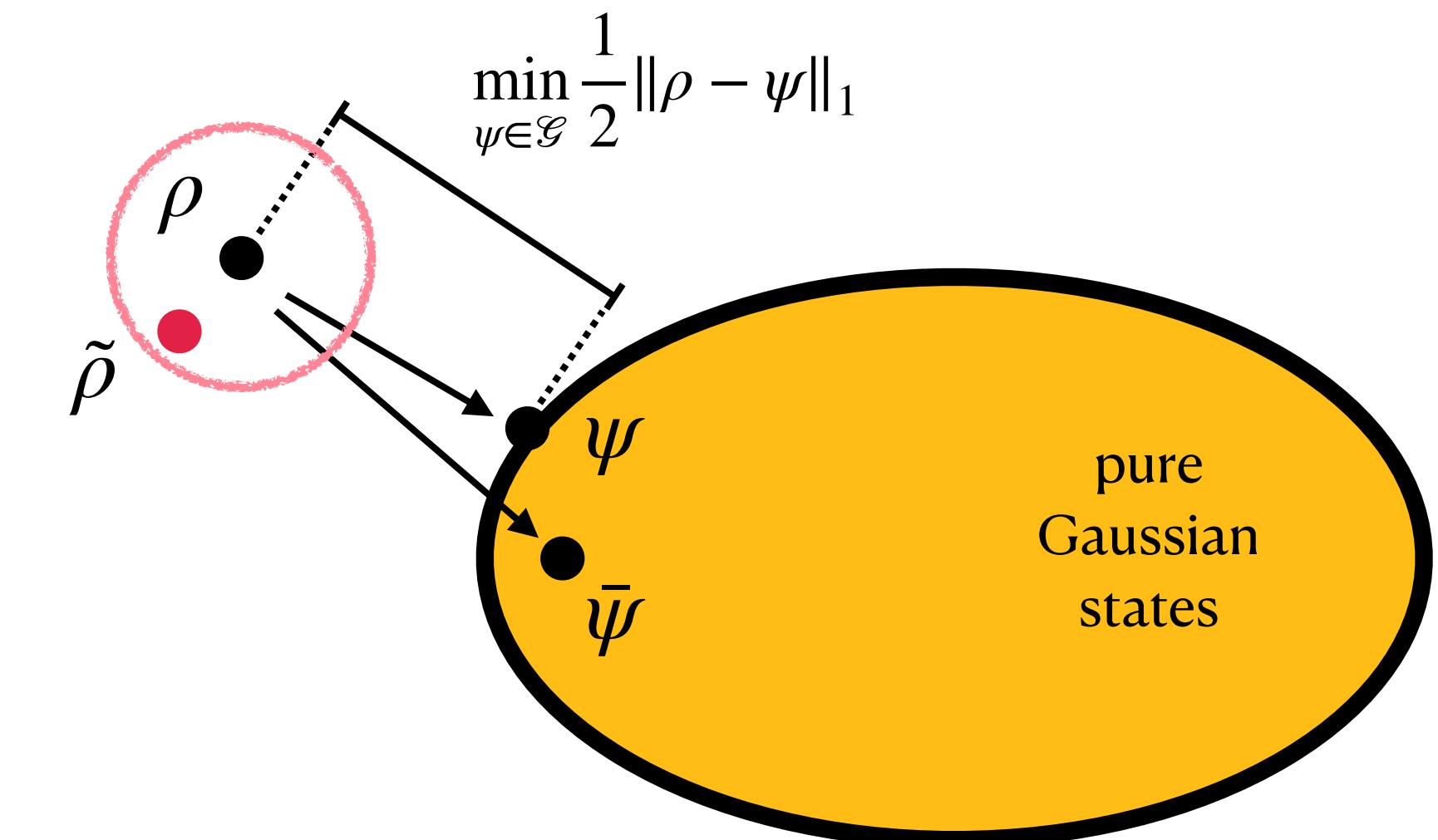
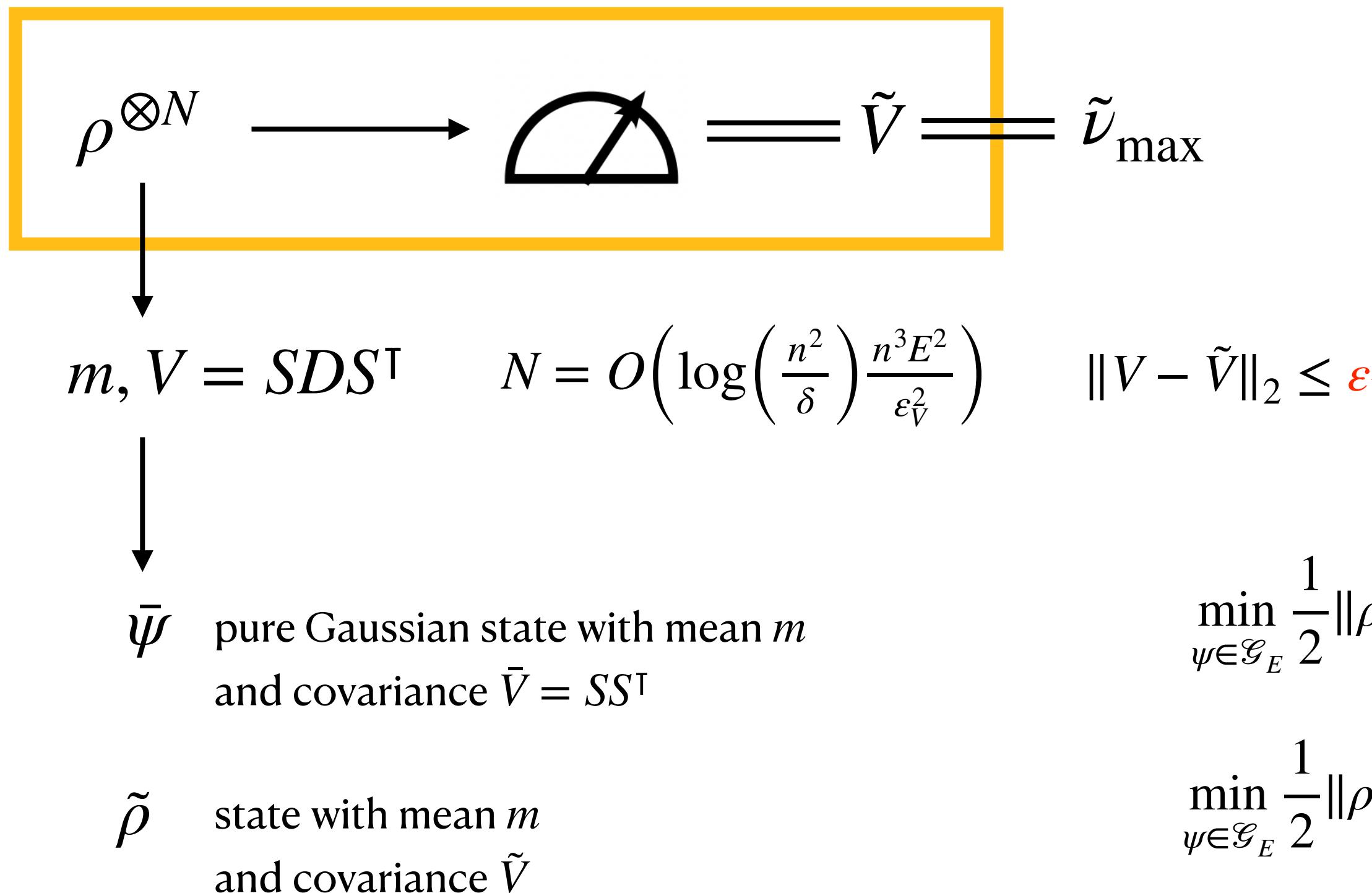
$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \varepsilon_V) \varepsilon_V}$$

$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{(\nu_{\max} - 1)^2}{c(nE)^6}$$

# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \varepsilon_V) \varepsilon_V}$$

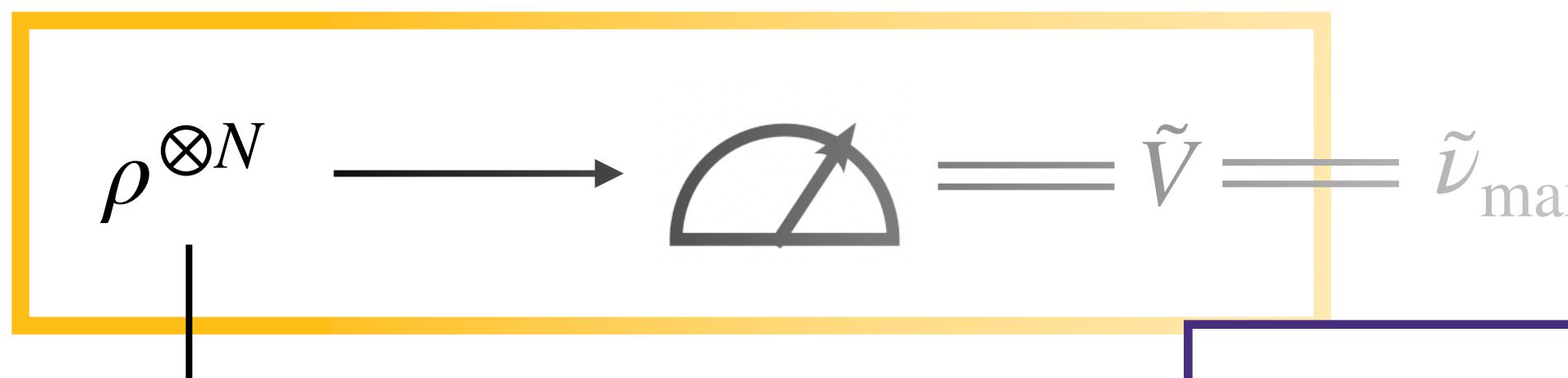
$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{1}{2c(nE)^6} [(\tilde{\nu}_{\max} - 1)^2 - 8nE(4nE + \varepsilon_V) \varepsilon_V]$$

# Two approaches

**symmetries**  
of Gaussian states

**learning**  
Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



$\bar{\psi}$  pure Gaussian state with mean  $m$  and covariance  $\bar{V} = SS^\top$

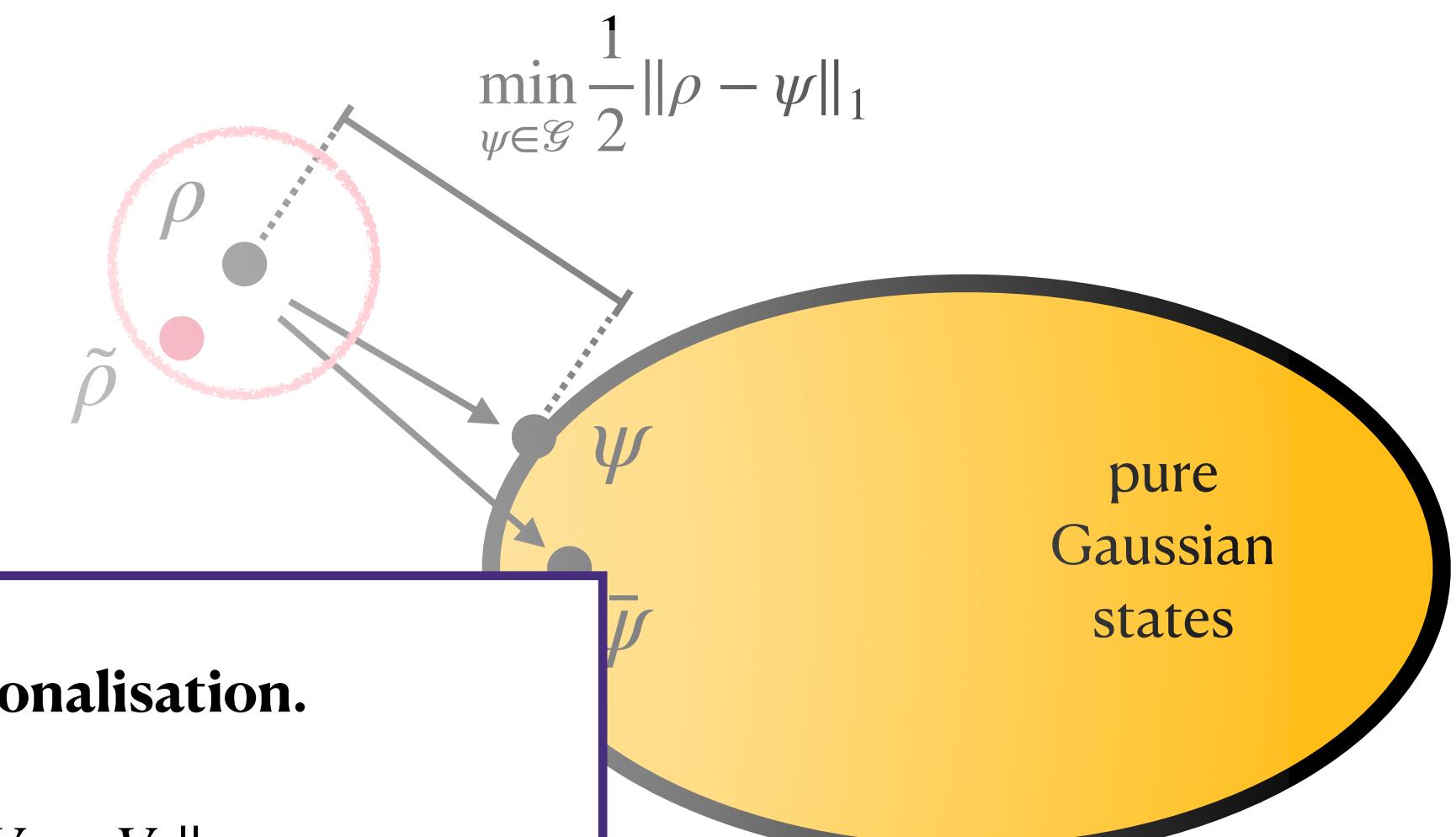
$\tilde{\rho}$  state with mean  $m$  and covariance  $\tilde{V}$

**Perturbation on symplectic diagonalisation.**

$$\|D_1 - D_2\|_2 \leq \sqrt{K(V_1)K(V_2)} \|V_1 - V_2\|_2$$

$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \epsilon_V) \epsilon_V}$$

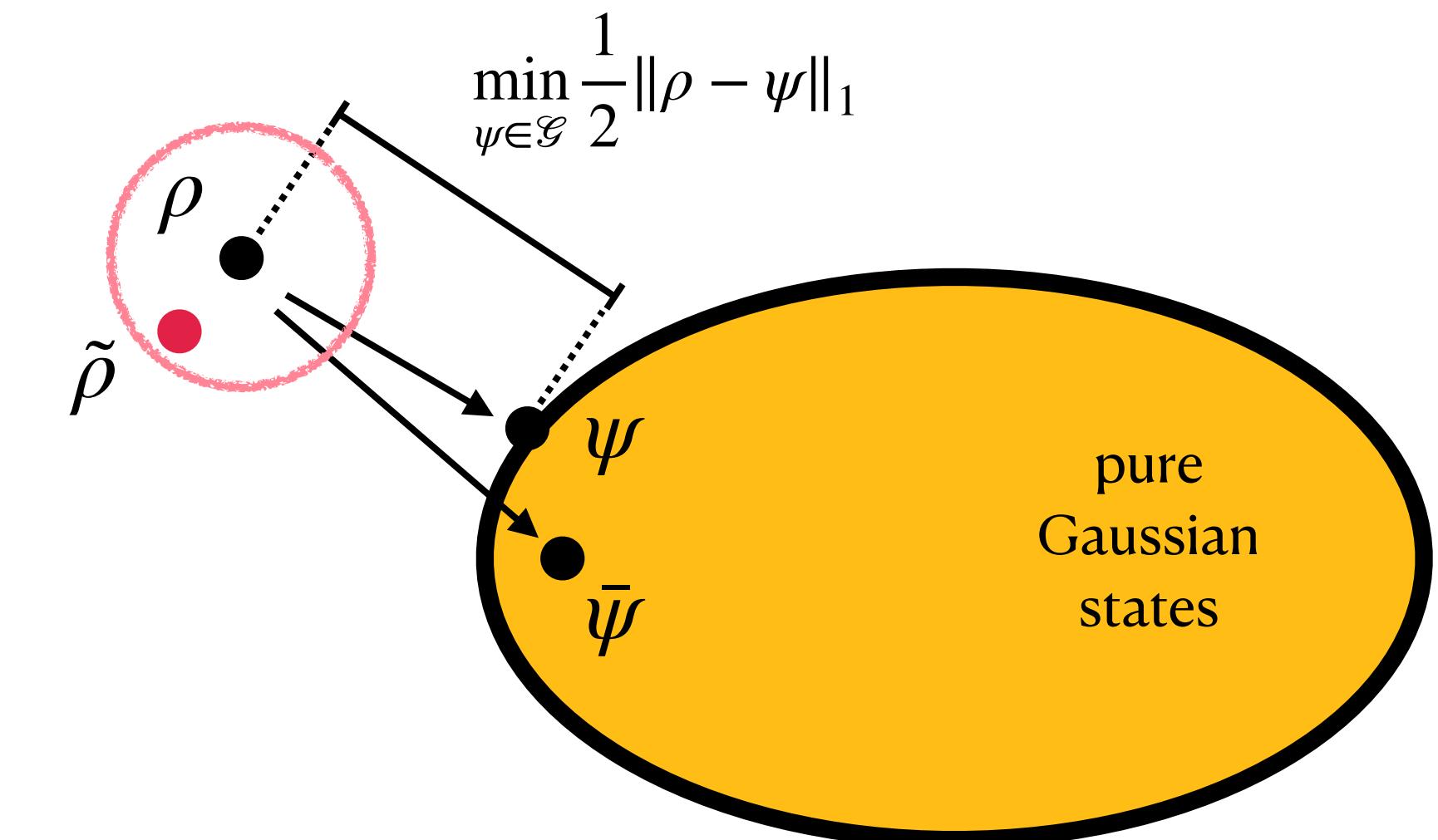
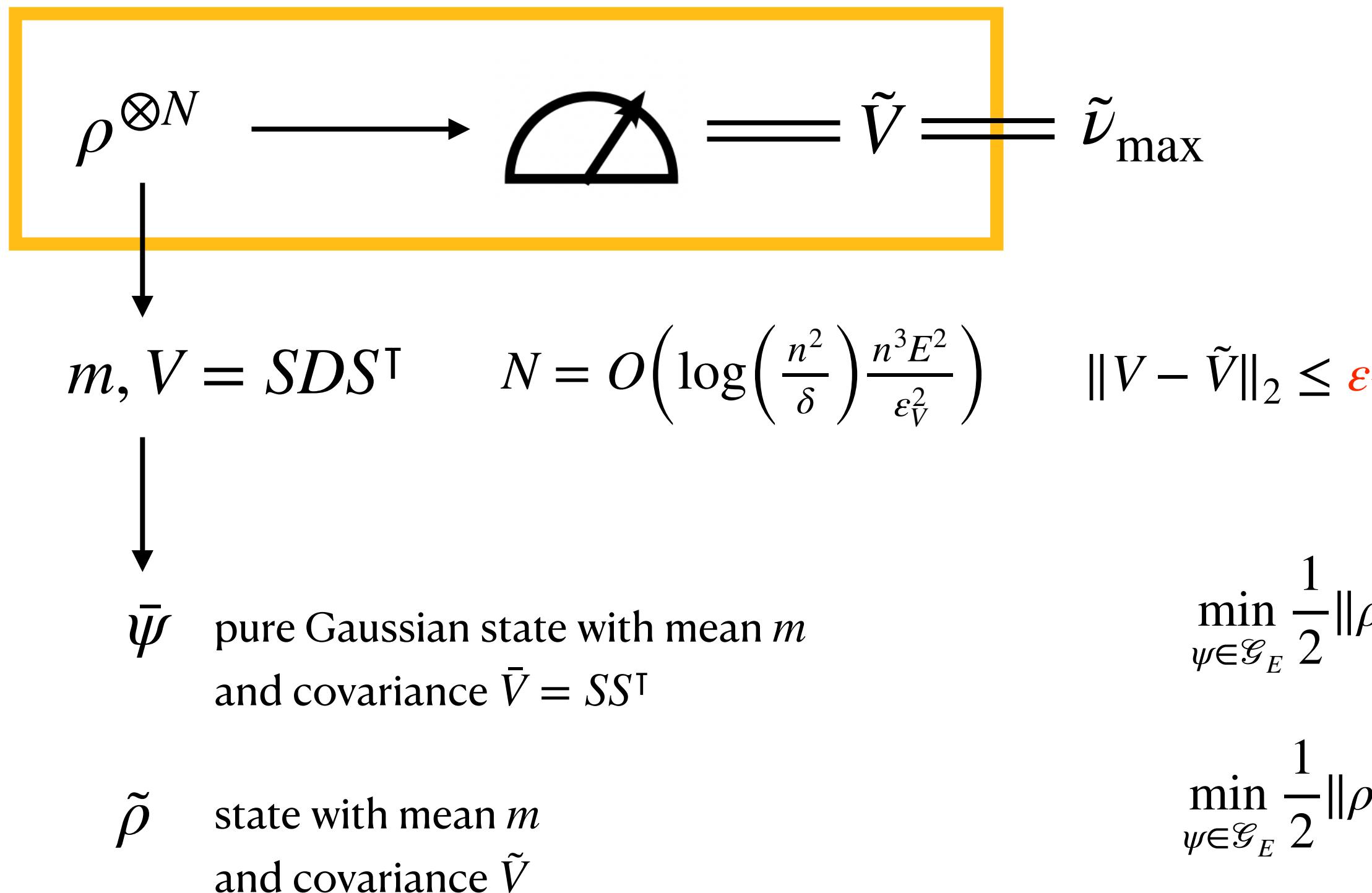
$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{1}{2c(nE)^6} [(\tilde{\nu}_{\max} - 1)^2 - 8nE(4nE + \epsilon_V) \epsilon_V]$$



# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)  
This procedure only requires single-copy measurements.



$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \varepsilon_V) \varepsilon_V}$$

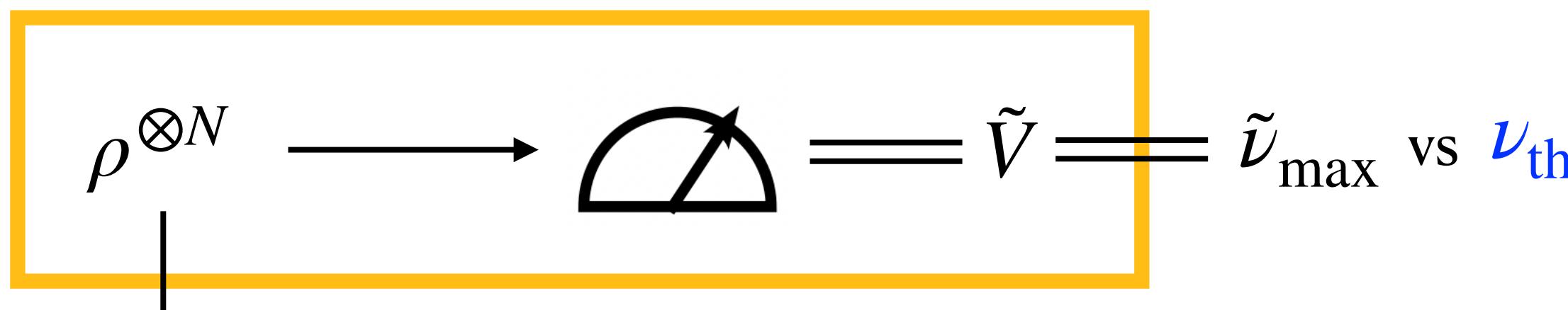
$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{1}{2c(nE)^6} [(\tilde{\nu}_{\max} - 1)^2 - 8nE(4nE + \varepsilon_V) \varepsilon_V]$$

# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)

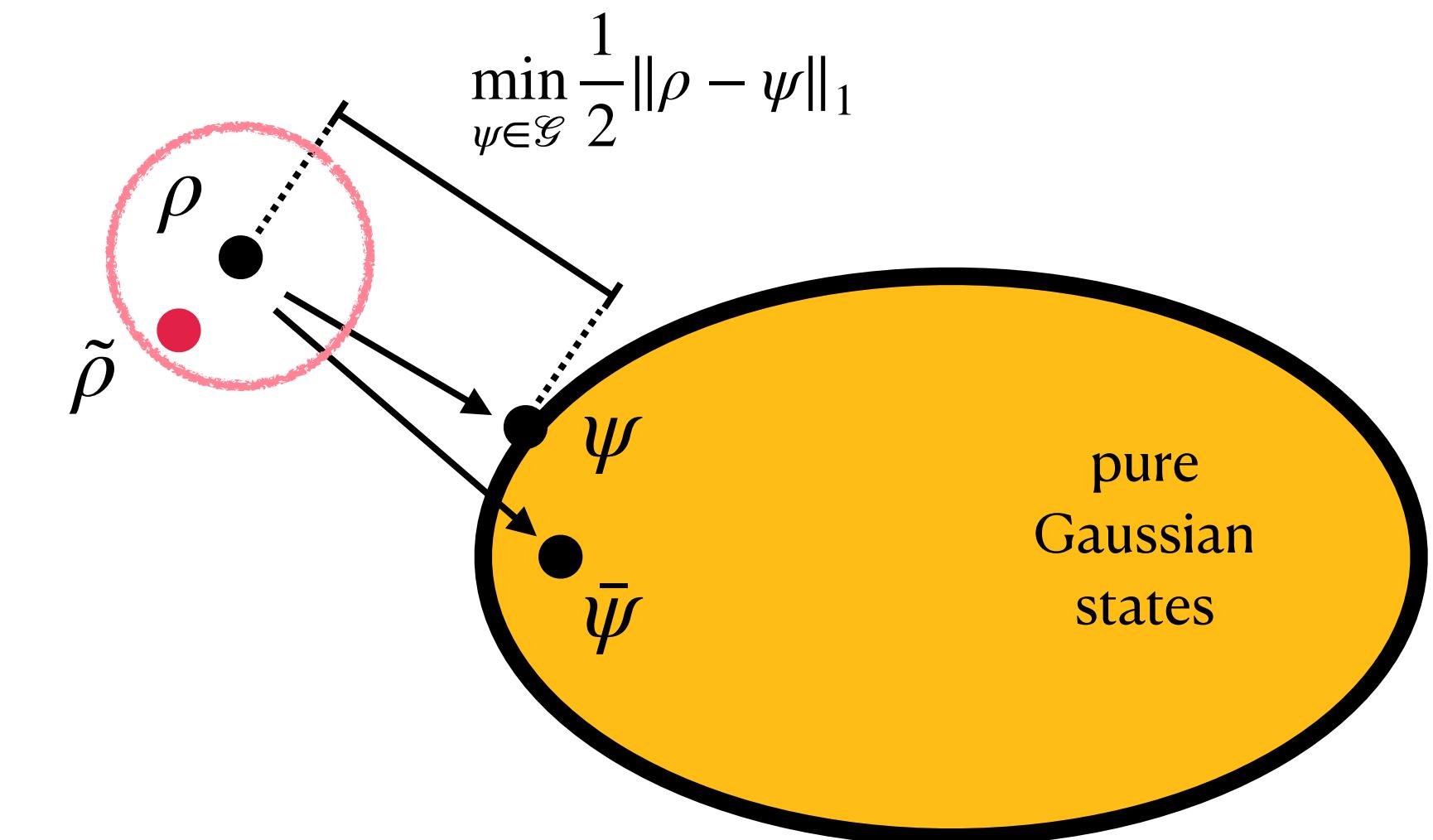
This procedure only requires single-copy measurements.



$\bar{\psi}$  pure Gaussian state with mean  $m$  and covariance  $\bar{V} = SS^\top$

$\tilde{\rho}$  state with mean  $m$  and covariance  $\tilde{V}$

**learning**  
Gaussian states



$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \varepsilon_V) \varepsilon_V}$$

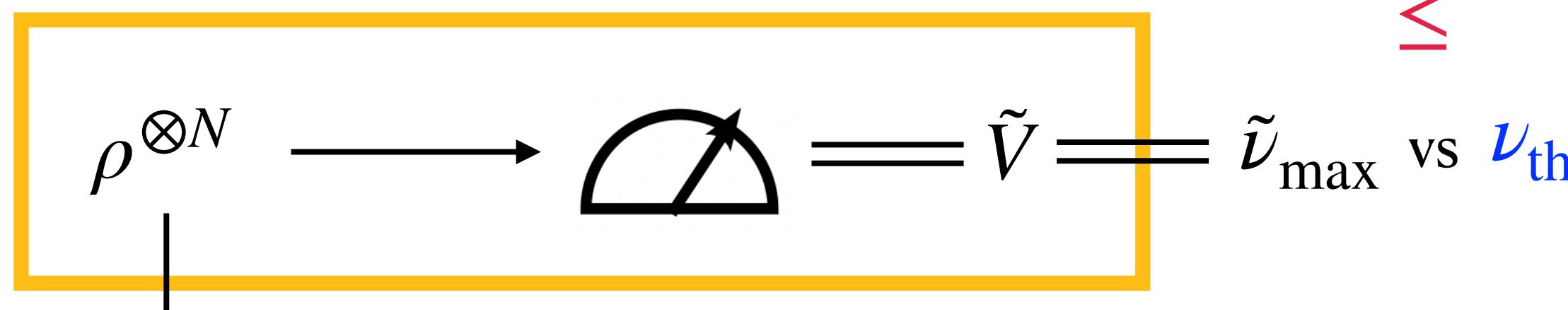
$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{1}{2c(nE)^6} [(\tilde{\nu}_{\max} - 1)^2 - 8nE(4nE + \varepsilon_V) \varepsilon_V]$$

# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)

This procedure only requires single-copy measurements.

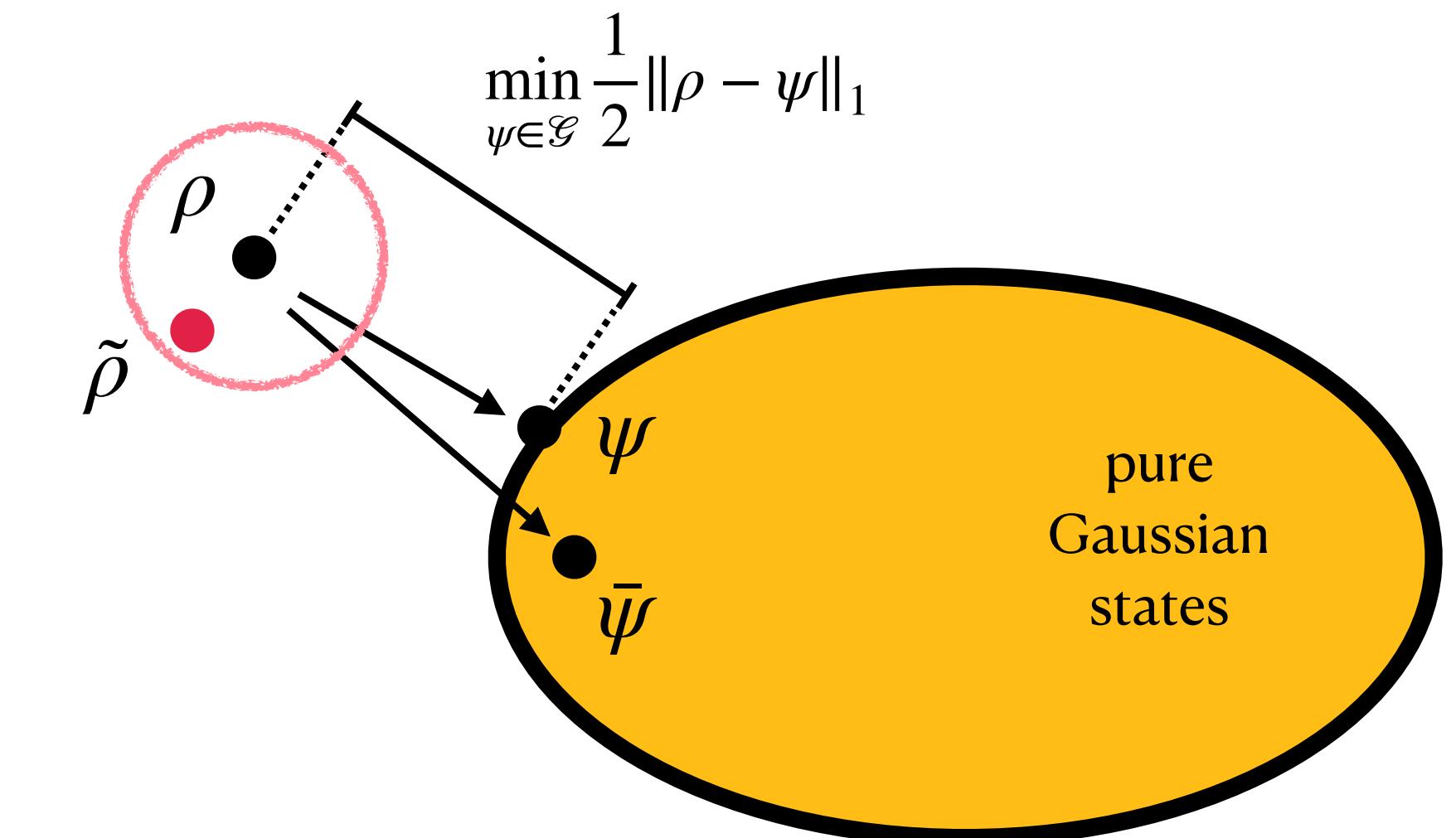


$$m, V = SDS^\top \quad N = O\left(\log\left(\frac{n^2}{\delta}\right)\frac{n^3 E^2}{\varepsilon_V^2}\right) \quad \|V - \tilde{V}\|_2 \leq \varepsilon_V$$

$\bar{\psi}$  pure Gaussian state with mean  $m$  and covariance  $\bar{V} = SS^\top$

$\tilde{\rho}$  state with mean  $m$  and covariance  $\tilde{V}$

**learning**  
Gaussian states



$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \varepsilon_V) \varepsilon_V} \leq \varepsilon_B \quad \mathbf{P} \quad \mathbf{G}$$

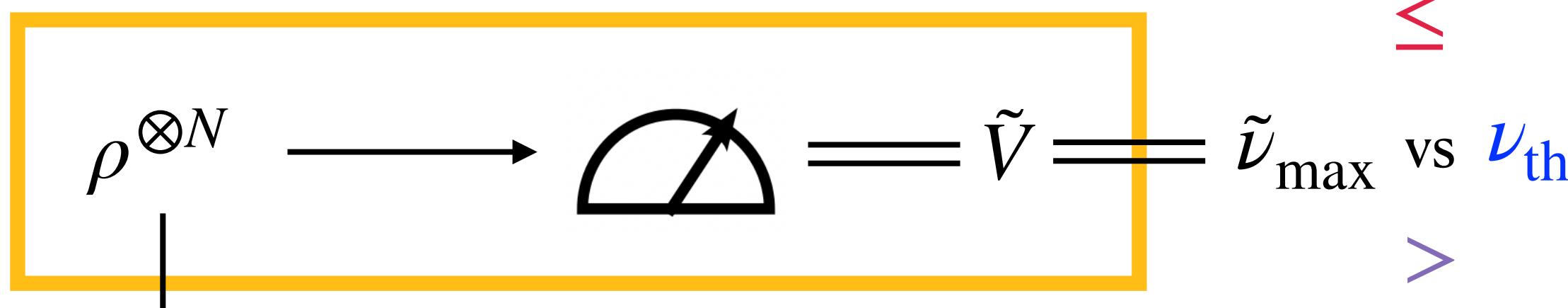
$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{1}{2c(nE)^6} [(\tilde{\nu}_{\max} - 1)^2 - 8nE(4nE + \varepsilon_V) \varepsilon_V]$$

# Two approaches

**symmetries**  
of Gaussian states

Mele & al. Nature Physics 21, 2002-2008 (2025)

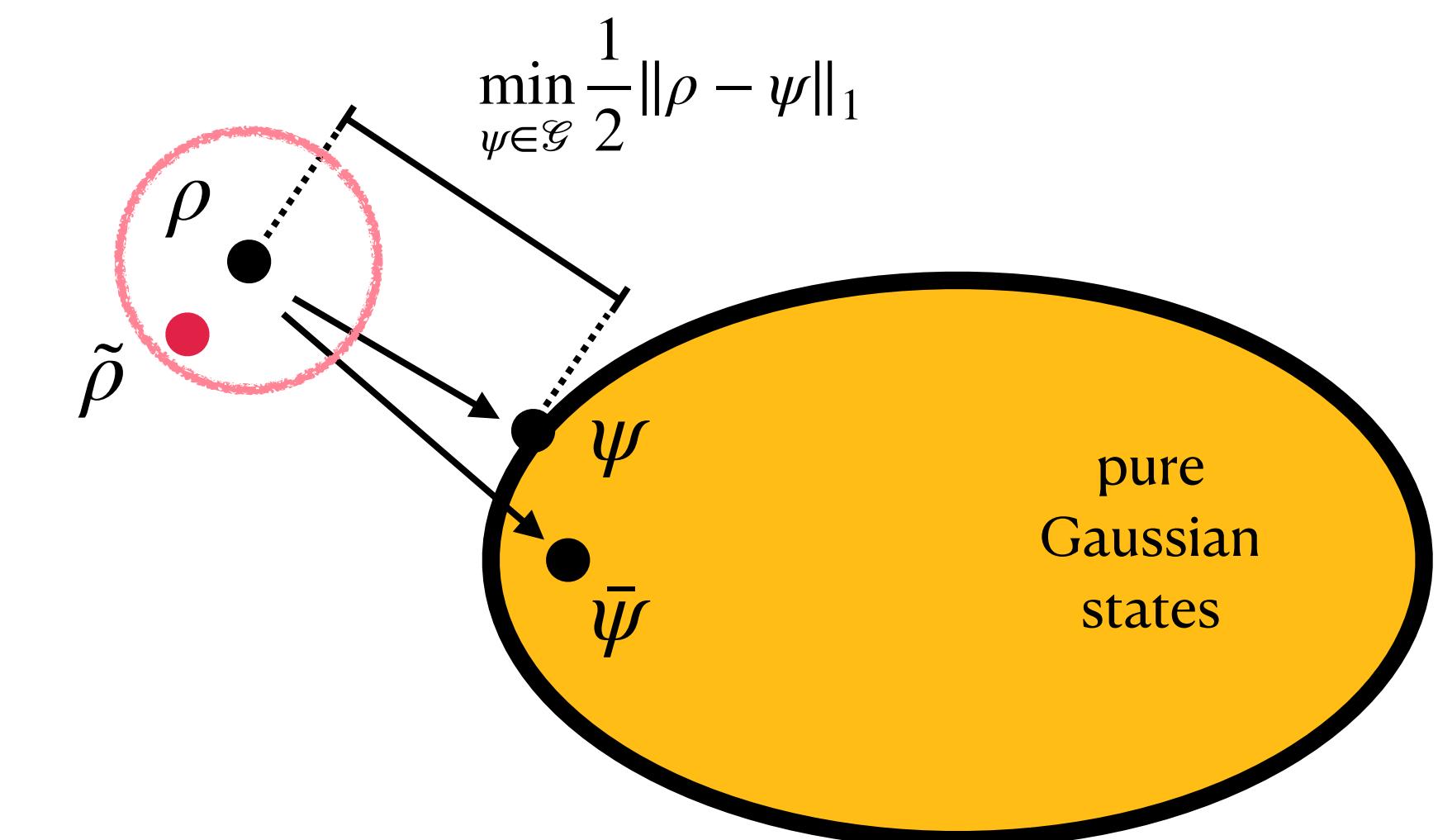
This procedure only requires single-copy measurements.



$$m, V = SDS^\top \quad N = O\left(\log\left(\frac{n^2}{\delta}\right)\frac{n^3E^2}{\varepsilon_V^2}\right) \quad \|V - \tilde{V}\|_2 \leq \varepsilon_V$$

$\bar{\psi}$  pure Gaussian state with mean  $m$  and covariance  $\bar{V} = SS^\top$

$\tilde{\rho}$  state with mean  $m$  and covariance  $\tilde{V}$



$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3} 4E(4nE + \varepsilon_V) \varepsilon_V} \leq \varepsilon_B$$

$$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{1}{2c(nE)^6} [(\tilde{\nu}_{\max} - 1)^2 - 8nE(4nE + \varepsilon_V) \varepsilon_V] > \varepsilon_A$$

P G

G P

# Two approaches

symmetries  
of Gaussian states

learning  
Gaussian states

**Theorem.** Let  $0 \leq \varepsilon_A < \varepsilon_B$  and  $\delta \in (0,1)$ . Let  $\rho$  be a possibly mixed state satisfying the energy

bound  $\sqrt{\text{Tr}[\hat{E}^2\rho]} \leq nE$ . If  $\eta := \varepsilon_B^4 - \frac{c}{2}n^8E^6\varepsilon_A > 0$ , then **single-copy measurements** on

$$N = O\left(\log\left(\frac{n}{\delta}\right) \frac{n^7E^6}{\eta^2}\right) = O(\text{poly}(n, E)) \quad \checkmark$$

copies of  $\rho$  suffice to decide whether  $\rho$  is  $\varepsilon_A$ -close or  $\varepsilon_B$ -far from  $\mathcal{G}_E$  with success probability at least  $1 - \delta$ .

# Two approaches

symmetries  
of Gaussian states

learning  
Gaussian states

**Theorem.** Let  $0 \leq \varepsilon_A < \varepsilon_B$  and  $\delta \in (0,1)$ . Let  $\rho$  be a possibly mixed state satisfying the energy

bound  $\sqrt{\text{Tr}[\hat{E}^2\rho]} \leq nE$ . If  $\eta := \boxed{\varepsilon_B^4 - \frac{c}{2}n^8E^6\varepsilon_A} > 0$ , then **single-copy measurements** on

$$N = O\left(\log\left(\frac{n}{\delta}\right) \frac{n^7E^6}{\eta^2}\right) = O(\text{poly}(n, E)) \quad \checkmark$$

copies of  $\rho$  suffice to decide whether  $\rho$  is  $\varepsilon_A$ -close or  $\varepsilon_B$ -far from  $\mathcal{G}_E$  with success probability at least  $1 - \delta$ .

# Two approaches

**Theoretical bound:**  $\tilde{V} = \tilde{\nu}_{\max}$  vs  $\nu_{\text{thr}}$

$\|V - \tilde{V}\|_2 \leq \epsilon_V$

$\left( \frac{n^3 E^2}{\epsilon_V^2} \right)$

copies at least

$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \leq \frac{1}{\sqrt{2}} \sqrt{n(\max_i \tilde{\nu}_i - 1) + \sqrt{n^3 4E(4nE + \epsilon_V)\epsilon_V}} \leq \epsilon_B$  **P** **G**

$\min_{\psi \in \mathcal{G}_E} \frac{1}{2} \|\rho - \psi\|_1 \geq \frac{1}{2c(nE)^6} [(\tilde{\nu}_{\max} - 1)^2 - 8nE(4nE + \epsilon_V)\epsilon_V] > \epsilon_A$  **G**

**Gaussian states**

$\rho$   $\tilde{\rho}$   $\psi$   $\bar{\psi}$

$\min_{\psi \in \mathcal{G}} \frac{1}{2} \|\rho - \psi\|_1$

**learning Gaussian states satisfying the energy measurements on**

success probability at

# Two approaches

symmetries  
of Gaussian states

learning  
Gaussian states

**Theorem.** Let  $0 \leq \varepsilon_A < \varepsilon_B$  and  $\delta \in (0,1)$ . Let  $\rho$  be a possibly mixed state satisfying the energy

bound  $\sqrt{\text{Tr}[\hat{E}^2\rho]} \leq nE$ . If  $\eta := \boxed{\varepsilon_B^4 - \frac{c}{2}n^8E^6\varepsilon_A} > 0$ , then **single-copy measurements** on

$$N = O\left(\log\left(\frac{n}{\delta}\right) \frac{n^7E^6}{\eta^2}\right) = O(\text{poly}(n, E)) \quad \checkmark$$

copies of  $\rho$  suffice to decide whether  $\rho$  is  $\varepsilon_A$ -close or  $\varepsilon_B$ -far from  $\mathcal{G}_E$  with success probability at least  $1 - \delta$ .

**5 minutes break**

# Mixed Gaussian states

## Definition of the problem

Let  $0 \leq \varepsilon_A < \varepsilon_B$ , let  $0 < \delta \leq 1$  and let

- $\mathcal{G}_E^{\text{mixed}}$  be the set of **mixed Gaussian states** with mean energy per mode at most  $E$ .

We say that an algorithm solves the property testing problem using  $N$  samples if, for any generic state  $\rho$  such that

A. either  $\rho$  is  $\varepsilon_A$ -close to  $\mathcal{G}_E^{\text{mixed}}$ , i.e.

$$\min_{\sigma \in \mathcal{G}_E^{\text{mixed}}} \frac{1}{2} \|\rho - \sigma\|_1 \leq \varepsilon_A$$

P

B. or  $\rho$  is  $\varepsilon_B$ -far from  $\mathcal{G}_E^{\text{mixed}}$ ,

i.e.  $\min_{\sigma \in \mathcal{G}_E^{\text{mixed}}} \frac{1}{2} \|\rho - \sigma\|_1 > \varepsilon_B$ ,

P

the algorithm can identify the underlying hypothesis A or B with failure probability at most  $\delta$ .

# Hardness result

**Theorem.** Let  $\rho$  be a state satisfying the energy bound  $\sqrt{\text{Tr}[\hat{E}^2\rho]} \leq nE$ . If  $\varepsilon_A < \varepsilon_B < O\left(\frac{1}{\text{poly}(nE)}\right)$ , deciding whether  $\rho$  is  $\varepsilon_A$ -close or  $\varepsilon_B$ -far from  $\mathcal{G}_E^{\text{mixed}}$  with success probability larger than  $2/3$  requires at least

$$N = \Omega\left(\frac{E^n}{n^4 E^4 \varepsilon_B^2}\right) \quad \times$$

copies of  $\rho$ .

**Strategy.**

# Hardness result

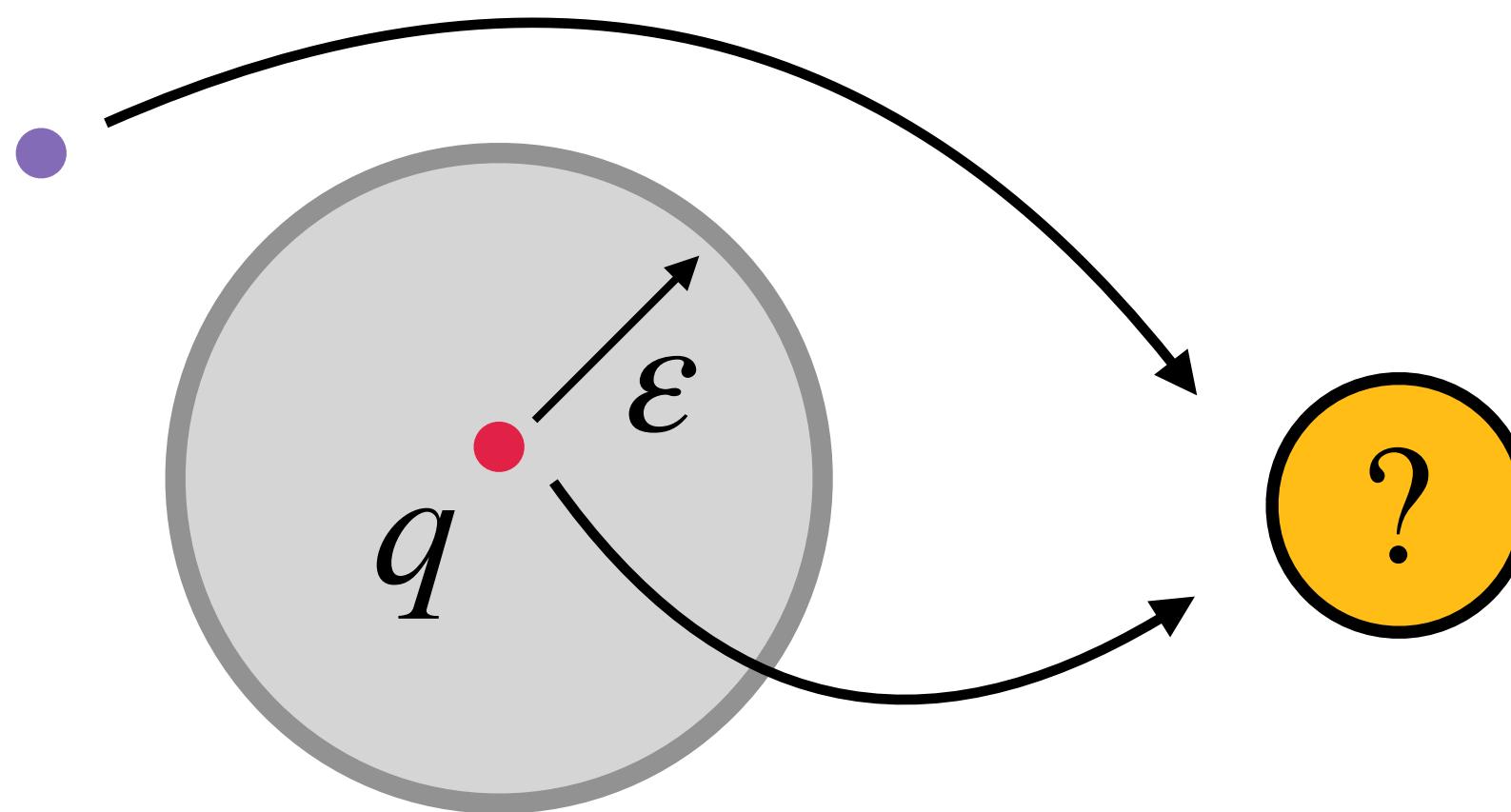
**Theorem.** Let  $\rho$  be a state satisfying the energy bound  $\sqrt{\text{Tr}[\hat{E}^2\rho]} \leq nE$ . If  $\varepsilon_A < \varepsilon_B < O\left(\frac{1}{\text{poly}(nE)}\right)$ , deciding whether  $\rho$  is  $\varepsilon_A$ -close or  $\varepsilon_B$ -far from  $\mathcal{G}_E^{\text{mixed}}$  with success probability larger than  $2/3$  requires at least

$$N = \Omega\left(\frac{E^n}{n^4 E^4 \varepsilon_B^2}\right)$$



copies of  $\rho$ .

**Strategy.**



# Hardness result

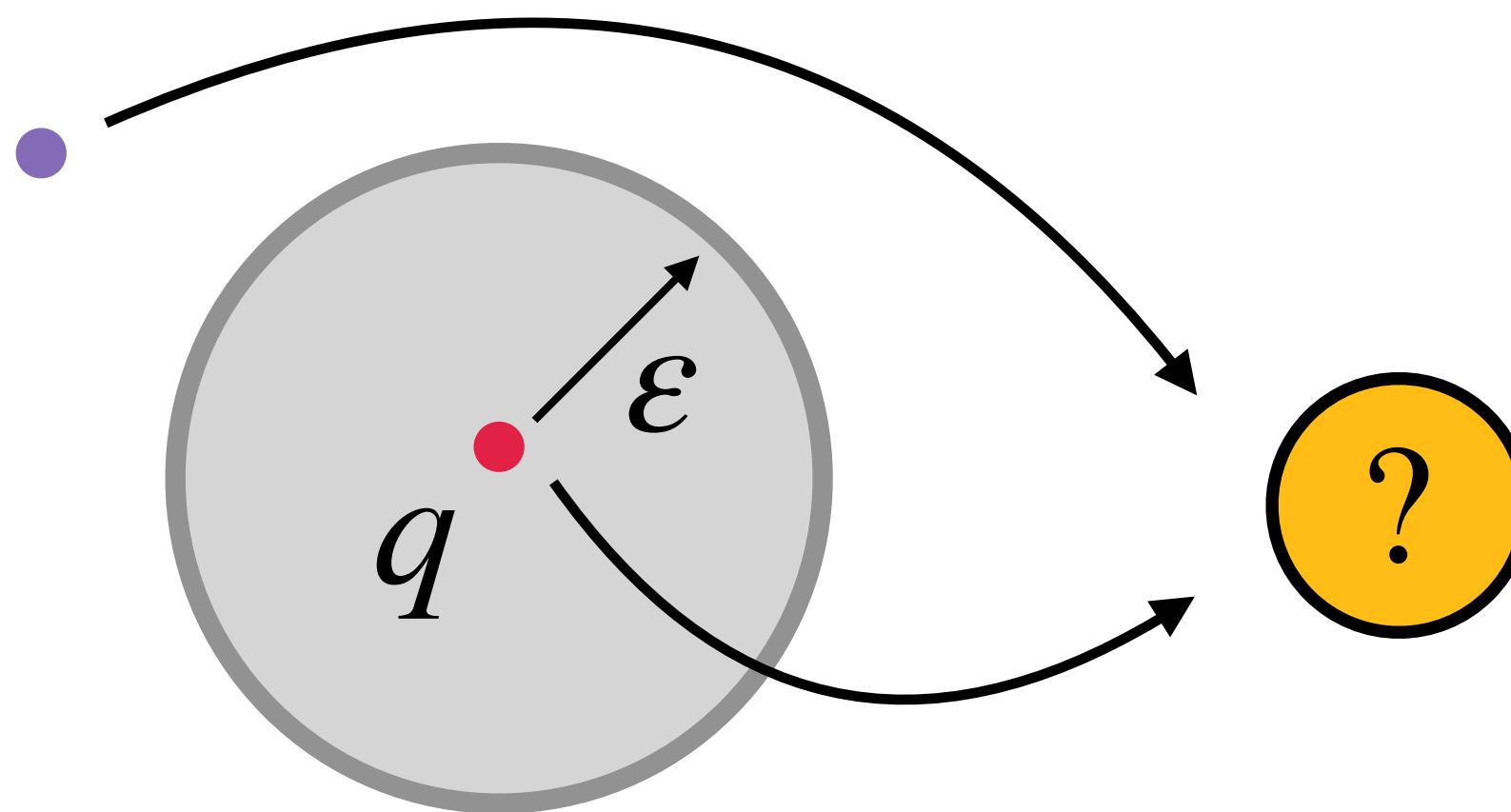
**Theorem.** Let  $\rho$  be a state satisfying the energy bound  $\sqrt{\text{Tr}[\hat{E}^2\rho]} \leq nE$ . If  $\varepsilon_A < \varepsilon_B < O\left(\frac{1}{\text{poly}(nE)}\right)$ , deciding whether  $\rho$  is  $\varepsilon_A$ -close or  $\varepsilon_B$ -far from  $\mathcal{G}_E^{\text{mixed}}$  with success probability larger than  $2/3$  requires at least

$$N = \Omega\left(\frac{E^n}{n^4 E^4 \varepsilon_B^2}\right)$$



copies of  $\rho$ .

**Strategy.**



Gaussianity  
test

# Hardness result

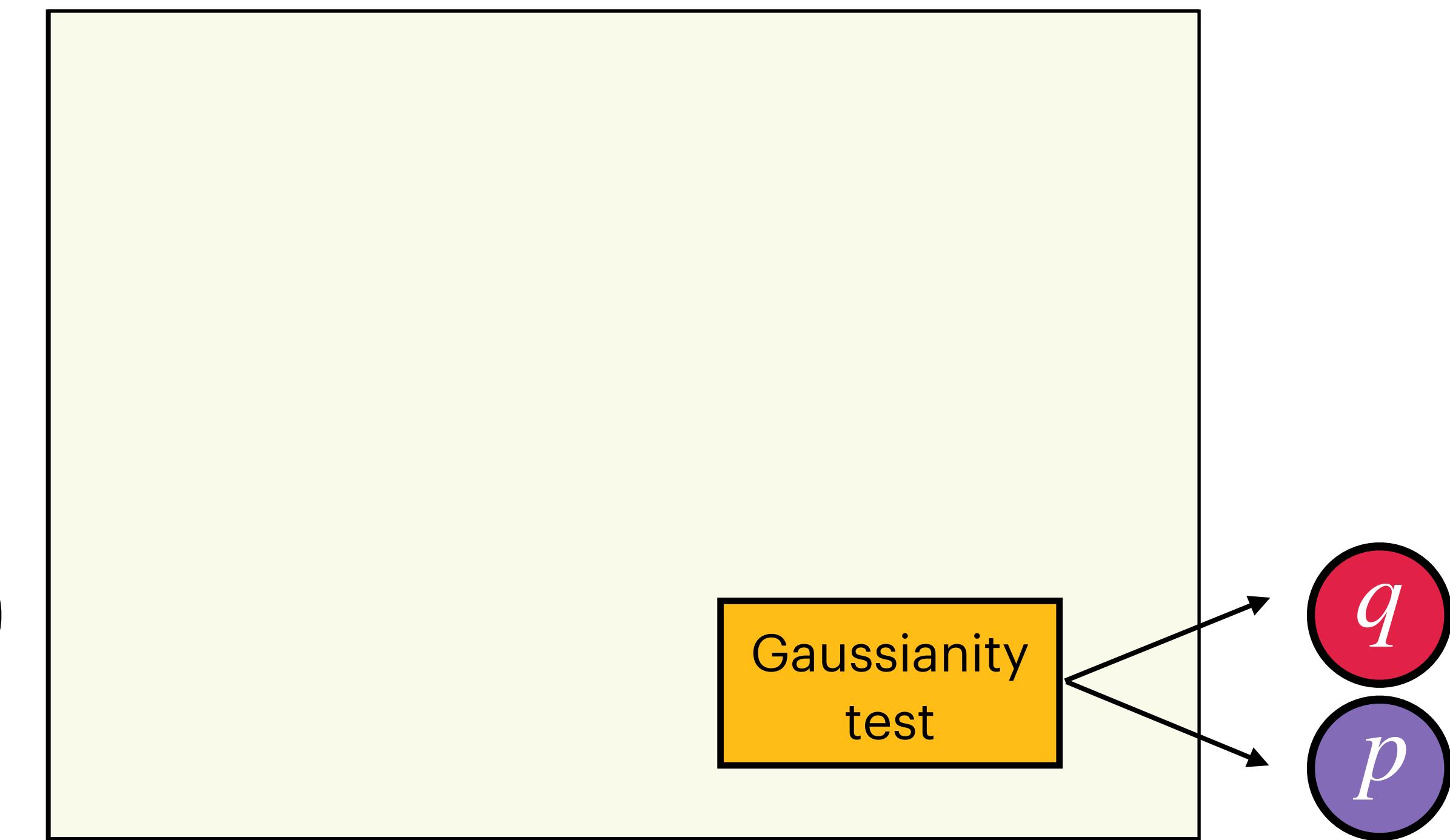
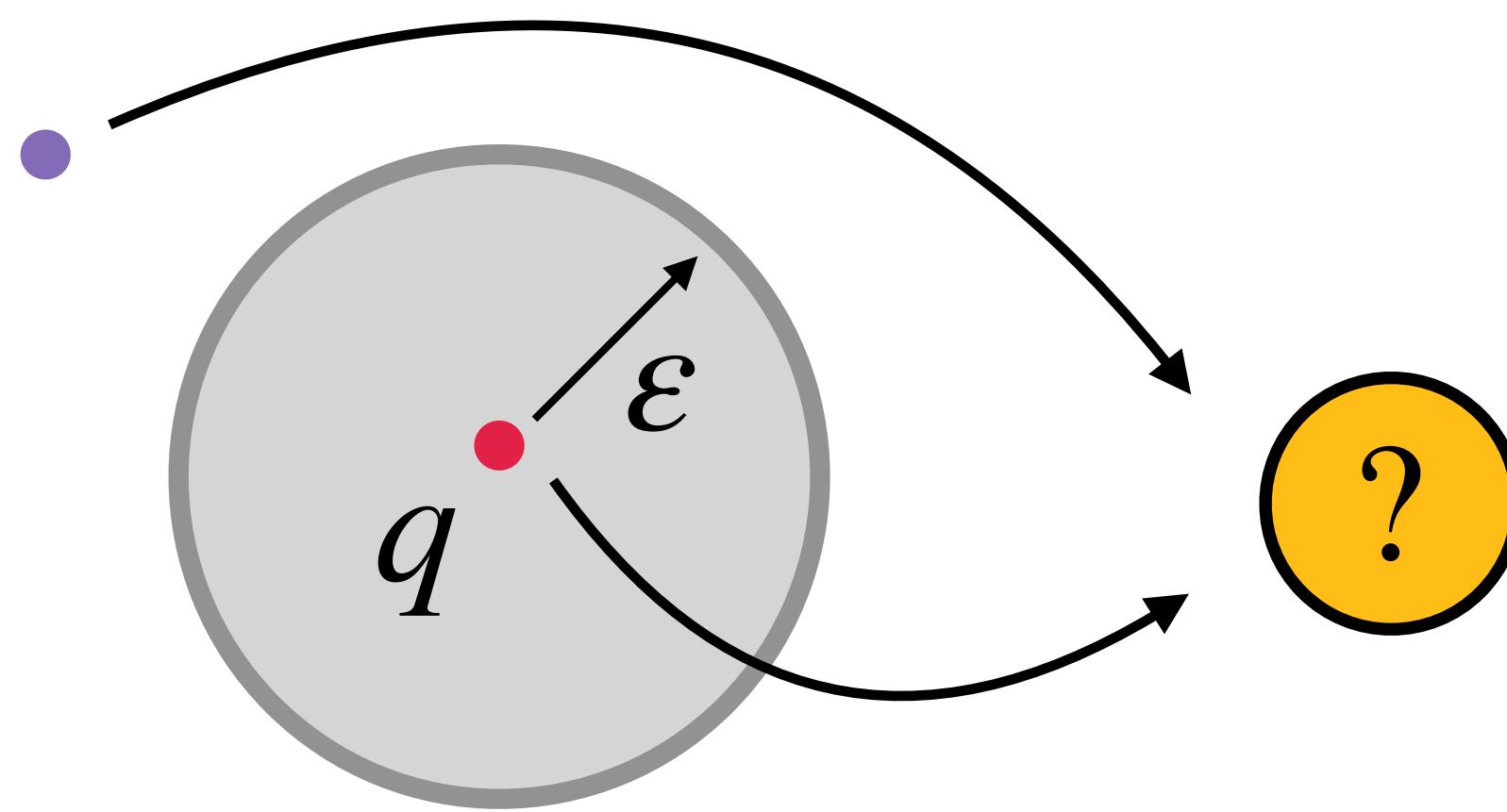
**Theorem.** Let  $\rho$  be a state satisfying the energy bound  $\sqrt{\text{Tr}[\hat{E}^2\rho]} \leq nE$ . If  $\varepsilon_A < \varepsilon_B < O\left(\frac{1}{\text{poly}(nE)}\right)$ , deciding whether  $\rho$  is  $\varepsilon_A$ -close or  $\varepsilon_B$ -far from  $\mathcal{G}_E^{\text{mixed}}$  with success probability larger than  $2/3$  requires at least

$$N = \Omega\left(\frac{E^n}{n^4 E^4 \varepsilon_B^2}\right)$$



copies of  $\rho$ .

**Strategy.**



# Hardness result

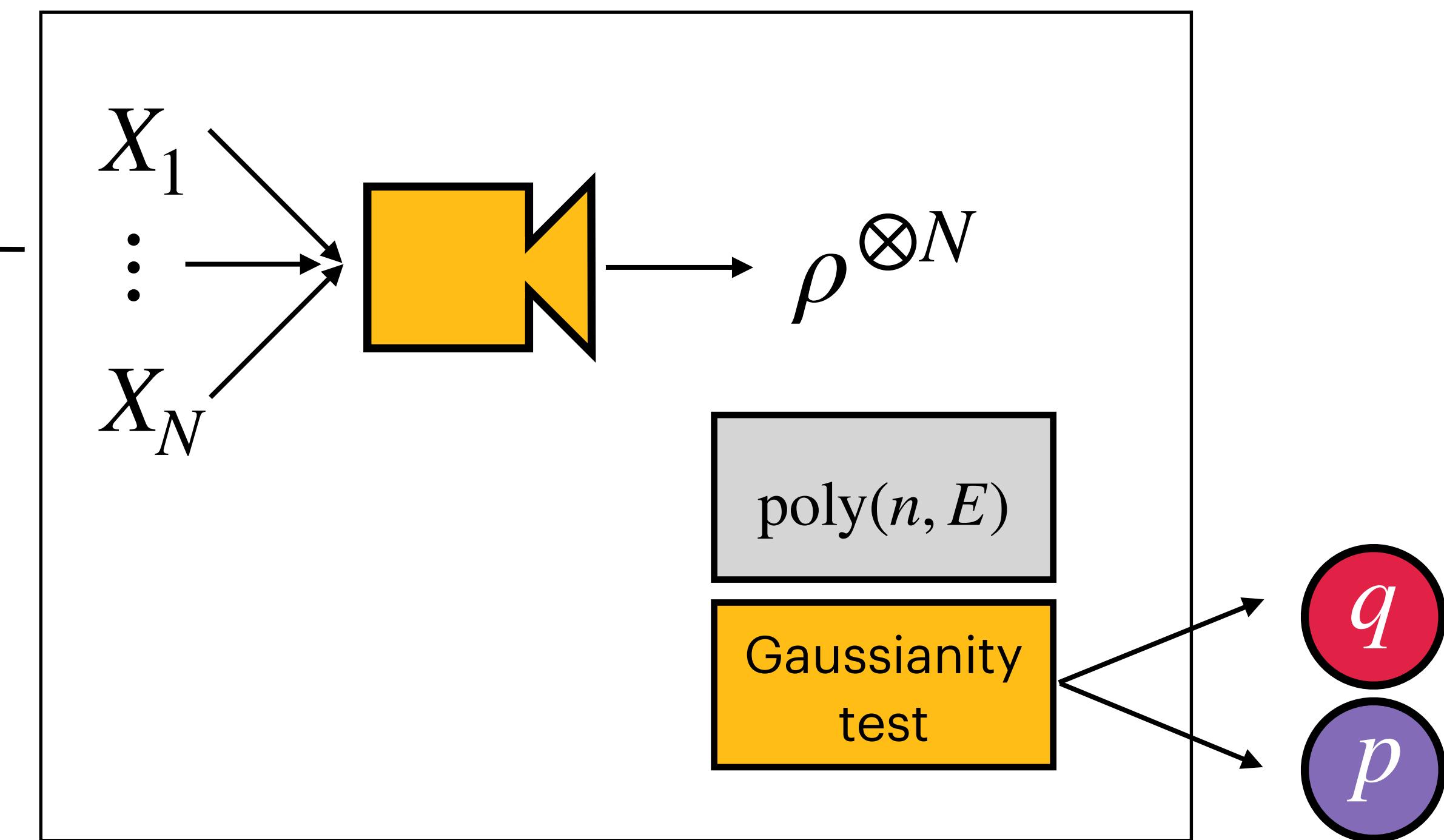
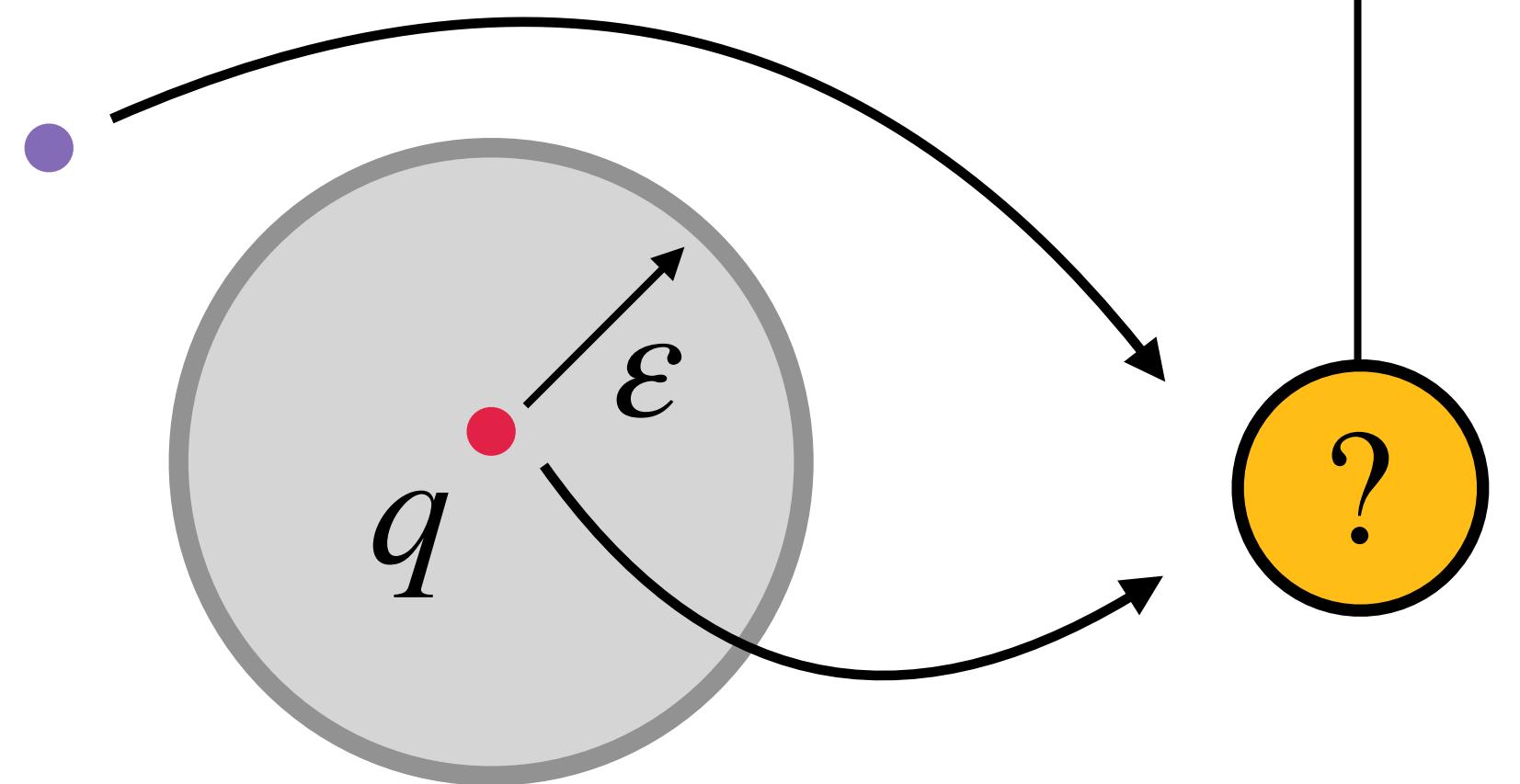
**Theorem.** Let  $\rho$  be a state satisfying the energy bound  $\sqrt{\text{Tr}[\hat{E}^2\rho]} \leq nE$ . If  $\varepsilon_A < \varepsilon_B < O\left(\frac{1}{\text{poly}(nE)}\right)$ , deciding whether  $\rho$  is  $\varepsilon_A$ -close or  $\varepsilon_B$ -far from  $\mathcal{G}_E^{\text{mixed}}$  with success probability larger than  $2/3$  requires at least

$$N = \Omega\left(\frac{E^n}{n^4 E^4 \varepsilon_B^2}\right)$$



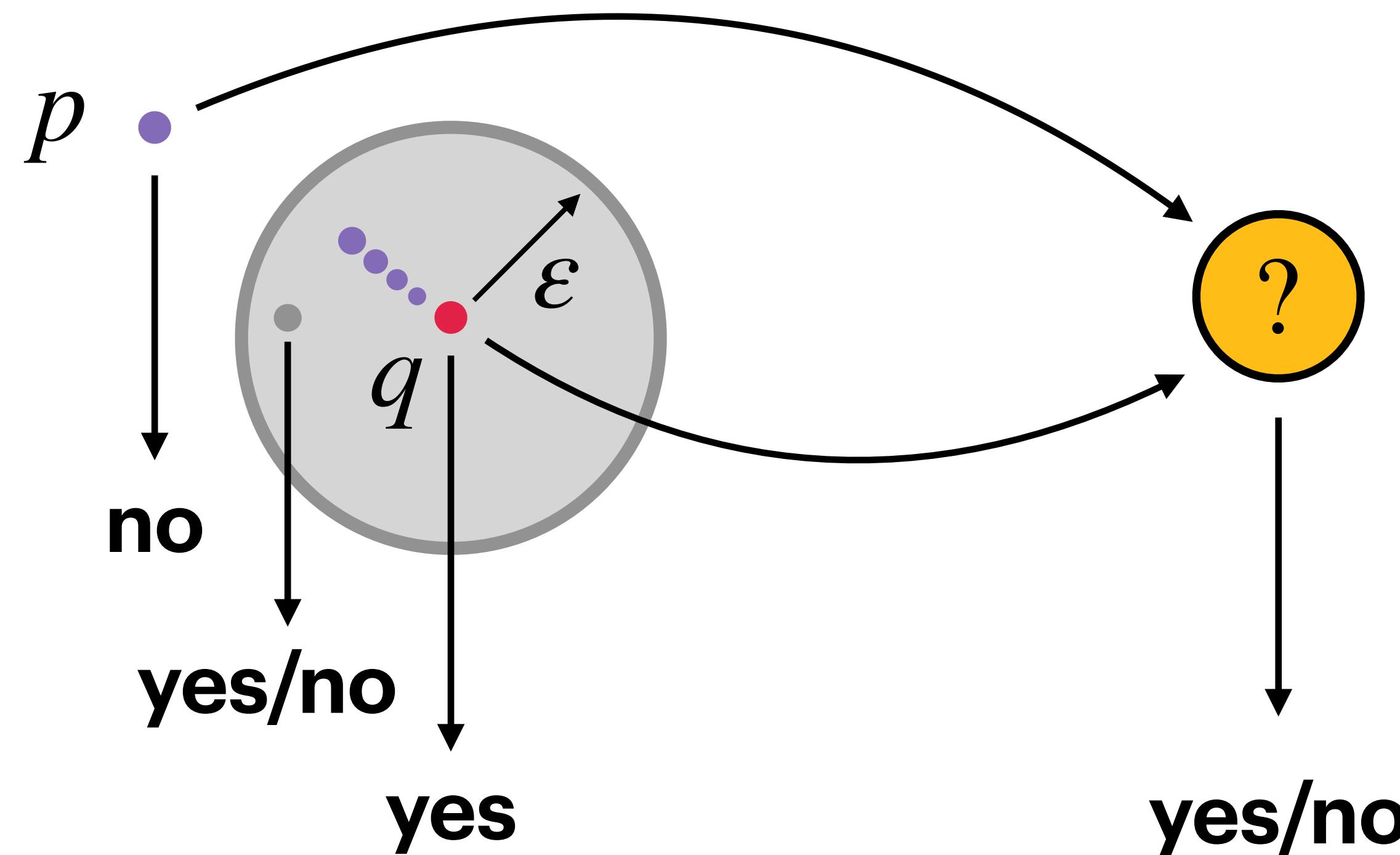
copies of  $\rho$ .

**Strategy.**



# Property testing

## The simple case of identity testing



$X_1, \dots, X_N$  i.i.d.

**Question:** are we observing  $q$

or any other  $p$  such that  $\frac{1}{2}\|p - q\|_1 \geq \varepsilon$  ?

L. Paninski. IEEE Tr. Inf. Th. 54 (10), 4750-4755 ,  
G&P. Valiant, FOCS, 2014,  
C. Canonne, Found. Trends Commun. Inf. Theory, Vol. 19 No. 6 pp. 1032–1198

$$N = \Omega\left(\frac{1}{\varepsilon^2 \|q\|_2}\right) \quad \left(\|q\|_\infty \leq \frac{1}{2}\right)$$

# A family of distributions

**Proposition.** (Classical identity testing) Let  $q$  be a probability distribution over  $\mathcal{X}$  with  $\|q\|_\infty \leq 1/2$  and let  $\varepsilon \in (0,1)$ . Then there is a family  $\mathcal{F}_{q,\varepsilon}$  of probability distributions on  $\mathcal{X}$  with the following properties:

- if  $p \in \mathcal{F}_{q,\varepsilon}$ , then there exists  $z \in \{-1, +1\}^{\mathcal{X}}$  such that

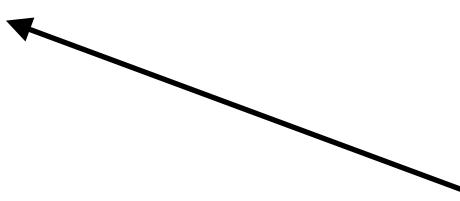
$$p(i) = \frac{(1 + 4\varepsilon z_i) q(i)}{\sum_{j \in \mathcal{X}} (1 + 4\varepsilon z_j) q(j)} \quad i \in \mathcal{X}$$

- $\frac{1}{2} \|p - q\|_1 > \varepsilon$  for any  $p \in \mathcal{F}_{q,\varepsilon}$ ;
- testing whether a distribution  $p$  is  $q$  or belongs to  $\mathcal{F}_{q,\varepsilon}$  with failure probability smaller than  $1/3$  requires at least  $\Omega\left(\frac{1}{\varepsilon^2 \|q\|_2}\right)$  samples of  $p$ .

# Encoding distributions in quantum states

$$p \rightarrow \rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$|k\rangle := |k_1 k_2 \dots k_n\rangle$



# Encoding distributions in quantum states

$$p \rightarrow \rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

↑

$$|k\rangle := |k_1 k_2 \dots k_n\rangle$$

$$q(k) := \frac{1}{(\nu+1)^n} \left( \frac{\nu}{\nu+1} \right)^{\|k\|_1} \rightarrow \rho(q) = \tau_\nu^{\otimes n} = \left( \frac{1}{\nu+1} \sum_{k_1=0}^{\infty} \left( \frac{\nu}{\nu+1} \right)^{k_1} |k_1\rangle\langle k_1| \right)^{\otimes n}$$

This  
state is  
Gaussian!

# Encoding distributions in quantum states

$$p \rightarrow \rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

↑

$$|k\rangle := |k_1 k_2 \dots k_n\rangle$$

$$q(k) := \frac{1}{(\nu + 1)^n} \left( \frac{\nu}{\nu + 1} \right)^{\|k\|_1} \rightarrow \rho(q) = \tau_\nu^{\otimes n} = \left( \frac{1}{\nu + 1} \sum_{k_1=0}^{\infty} \left( \frac{\nu}{\nu + 1} \right)^{k_1} |k_1\rangle\langle k_1| \right)^{\otimes n}$$

This state is Gaussian!

$$\text{Tr}[\tau_\nu^{\otimes n} \hat{E}^2] = n\nu(2\nu + 1) + n(n - 1)\nu^2 + n^2\nu + \frac{n^2}{4} \equiv \frac{1 - 4\varepsilon}{1 + 4\varepsilon} n^2 E^2 \rightarrow \nu = \Omega(E)$$

# Encoding distributions in quantum states

$$\text{Tr}[\rho(q)\hat{E}^2] = \frac{1 - 4\epsilon}{1 + 4\epsilon} n^2 E^2 \leq n^2 E^2$$

# Encoding distributions in quantum states

$$q \quad \rightarrow \quad \mathcal{F}_{q,\varepsilon}$$

$$p(k) = \frac{(1 + 4\varepsilon z_k) q(k)}{\sum_{j \in \mathcal{X}} (1 + 4\varepsilon z_j) q(j)} \quad k \in \mathbb{N}^k$$

$$\text{Tr}[\rho(q)\hat{E}^2] = \frac{1 - 4\varepsilon}{1 + 4\varepsilon} n^2 E^2 \leq n^2 E^2$$

# Encoding distributions in quantum states

$$q \quad \rightarrow \quad \mathcal{F}_{q,\varepsilon}$$

$$p(k) = \frac{(1 + 4\varepsilon z_k) q(k)}{\sum_{j \in \mathcal{X}} (1 + 4\varepsilon z_j) q(j)} \quad k \in \mathbb{N}^k$$

$$\text{Tr}[\rho(q)\hat{E}^2] = \frac{1 - 4\varepsilon}{1 + 4\varepsilon} n^2 E^2 \leq n^2 E^2$$

$$\text{Tr}[\rho(p)\hat{E}^2] \leq \frac{1 + 4\varepsilon}{1 - 4\varepsilon} \text{Tr}[\rho(q)\hat{E}^2] = n^2 E^2$$

# Encoding distributions in quantum states

$$q \quad \rightarrow \quad \mathcal{F}_{q,\varepsilon}$$

$$p(k) = \frac{(1 + 4\varepsilon z_k) q(k)}{\sum_{j \in \mathcal{X}} (1 + 4\varepsilon z_j) q(j)} \quad k \in \mathbb{N}^k$$

$$\text{Tr}[\rho(q)\hat{E}^2] = \frac{1 - 4\varepsilon}{1 + 4\varepsilon} n^2 E^2 \leq n^2 E^2$$

$$\text{Tr}[\rho(p)\hat{E}^2] \leq \frac{1 + 4\varepsilon}{1 - 4\varepsilon} \text{Tr}[\rho(q)\hat{E}^2] = n^2 E^2$$

$$\frac{1}{2} \|\rho(p) - \rho(q)\|_1 = \frac{1}{2} \|p - q\|_1 > \varepsilon$$

# Encoding distributions in quantum states

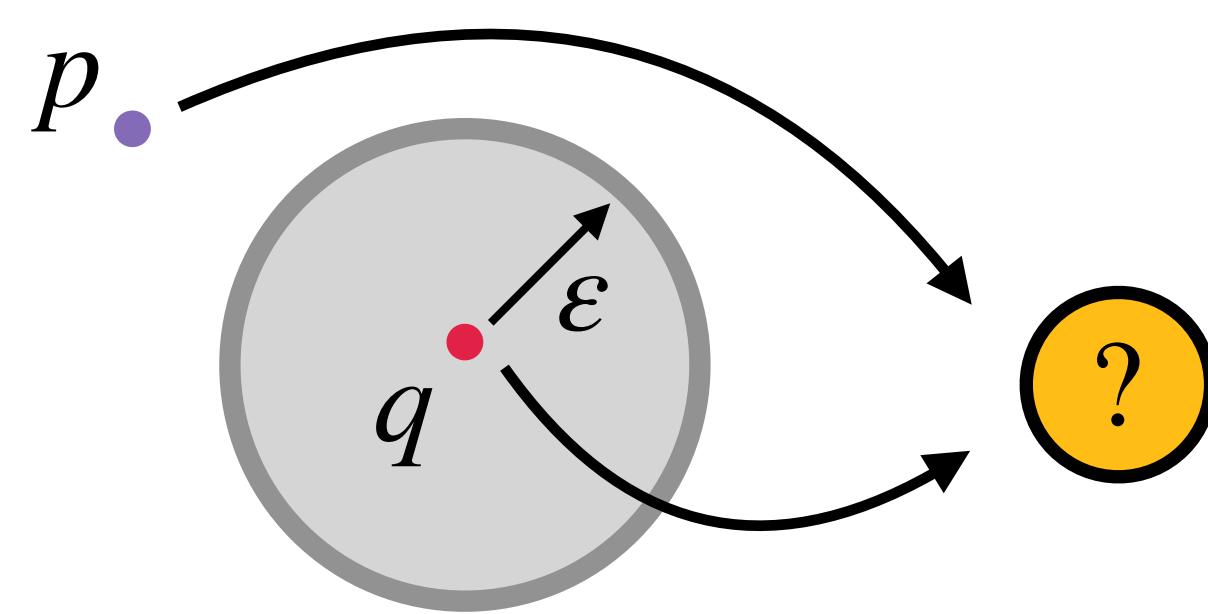
$$\mathrm{Tr}[\rho(q)\hat{E}^2] \leq n^2 E^2$$

$$\mathrm{Tr}[\rho(p)\hat{E}^2] \leq n^2 E^2$$

$$\frac{1}{2}\|\rho(p) - \rho(q)\|_1 > \varepsilon$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

# Encoding distributions in quantum states



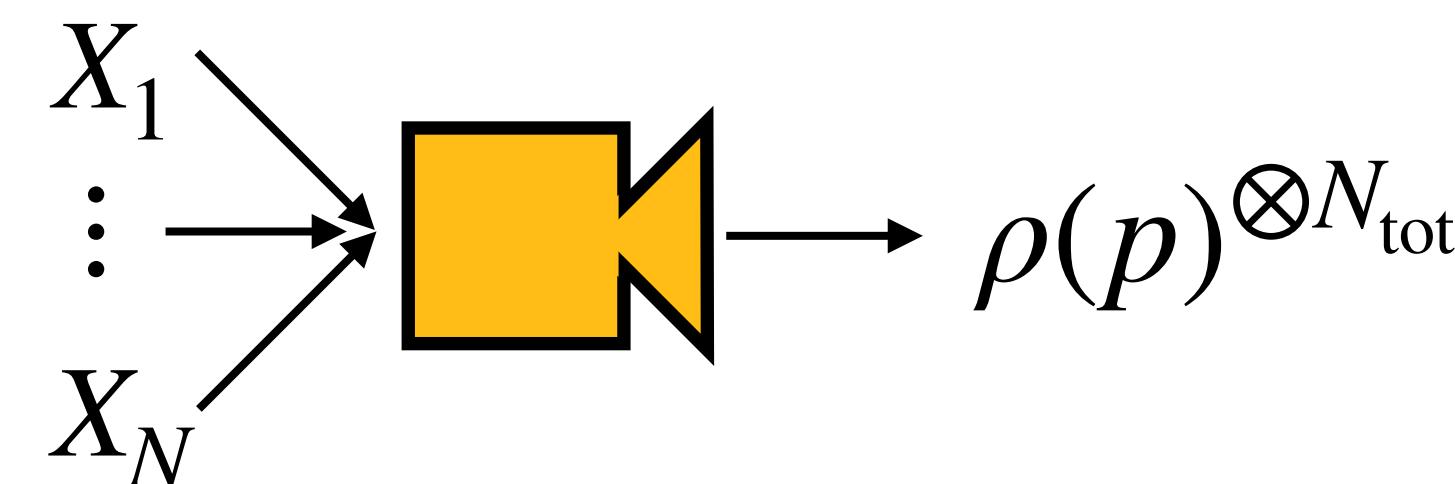
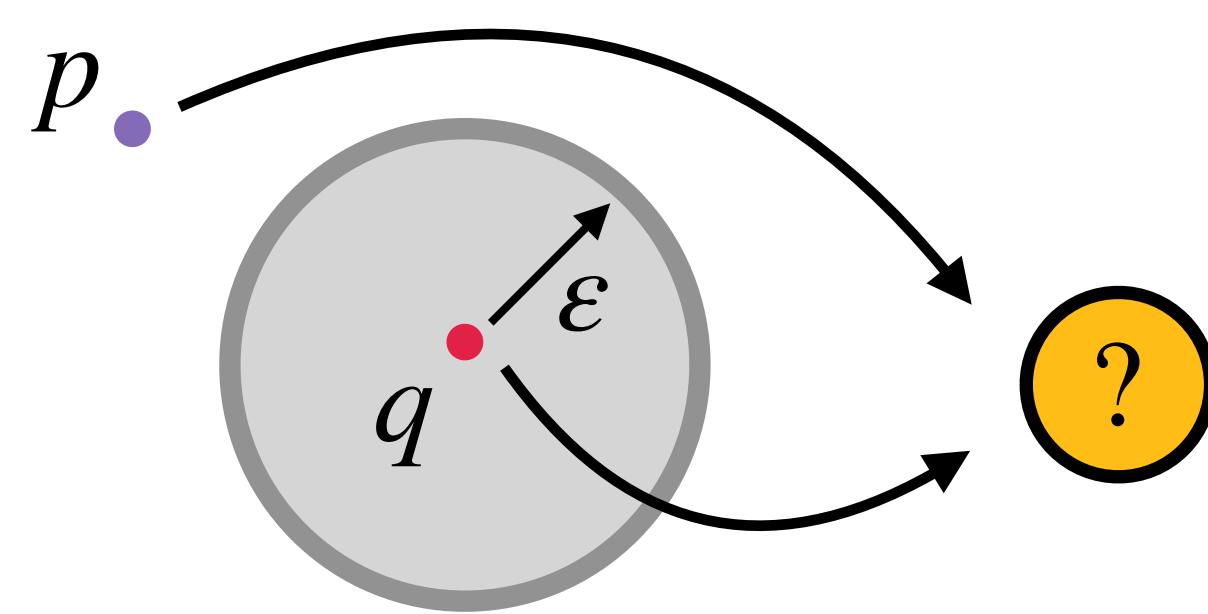
$$\mathrm{Tr}[\rho(q)\hat{E}^2] \leq n^2 E^2$$

$$\mathrm{Tr}[\rho(p)\hat{E}^2] \leq n^2 E^2$$

$$\frac{1}{2}\|\rho(p) - \rho(q)\|_1 > \varepsilon$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

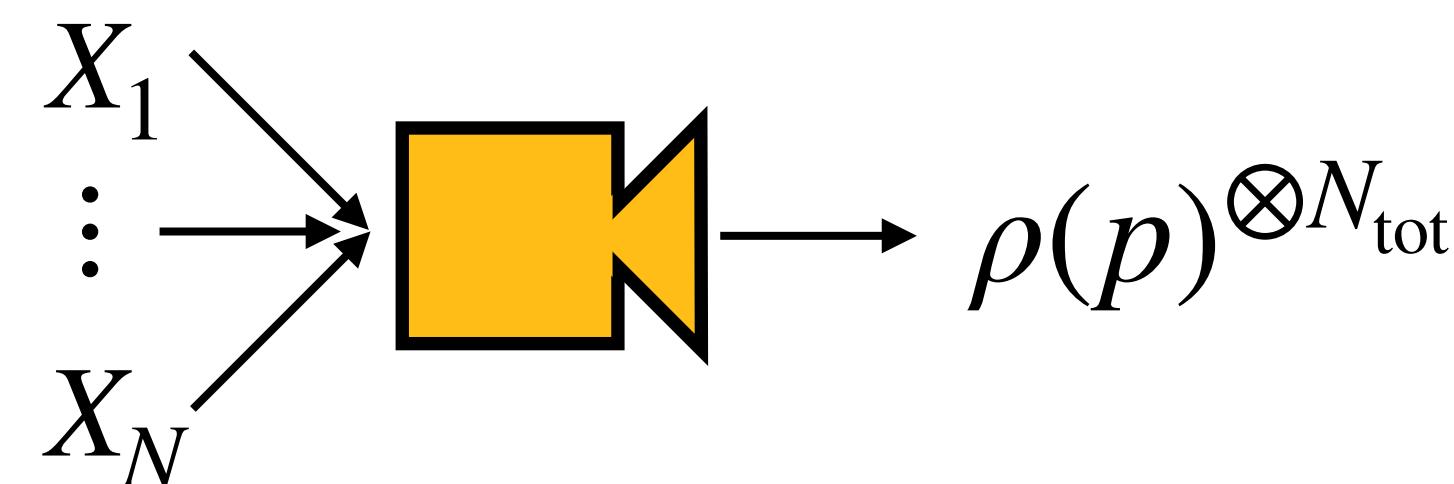
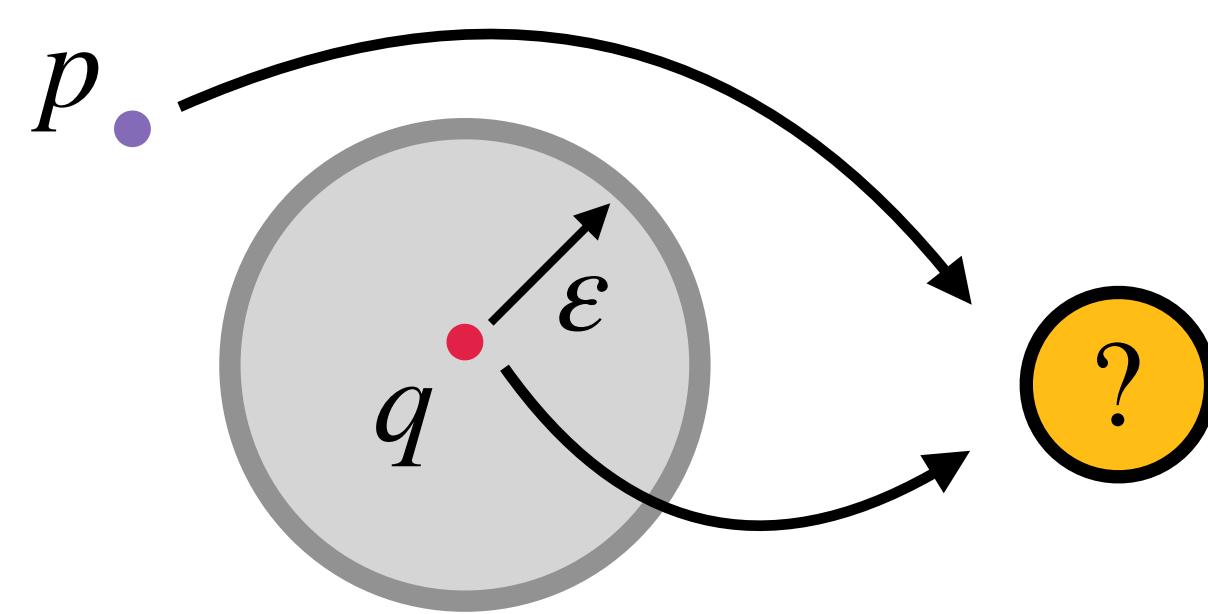
# Encoding distributions in quantum states



$$\begin{aligned}\text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon\end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

# Encoding distributions in quantum states



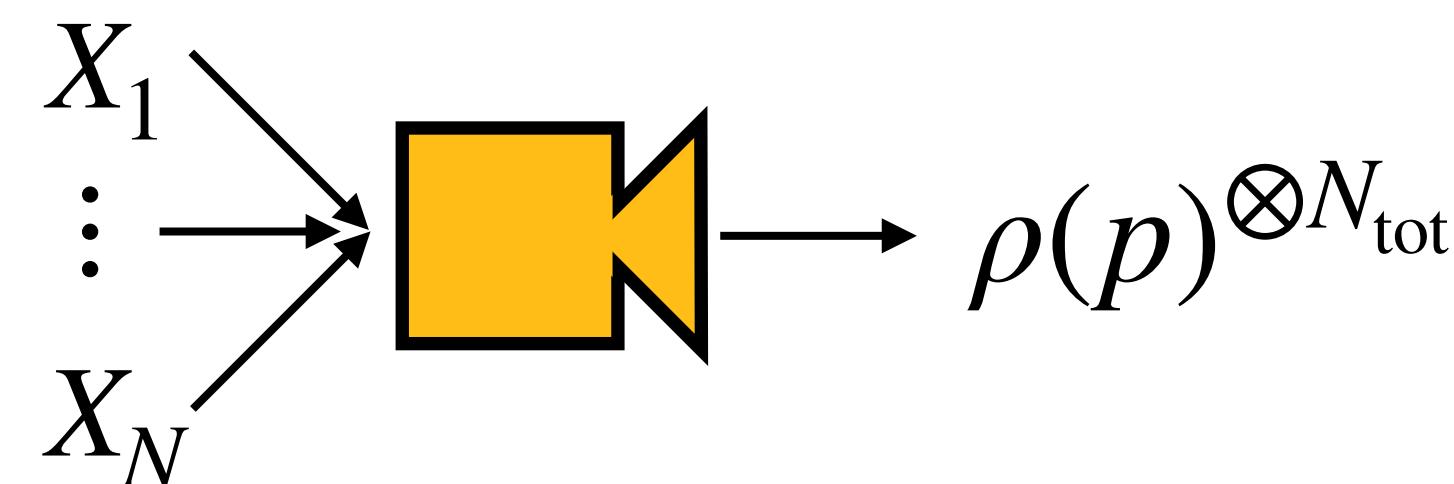
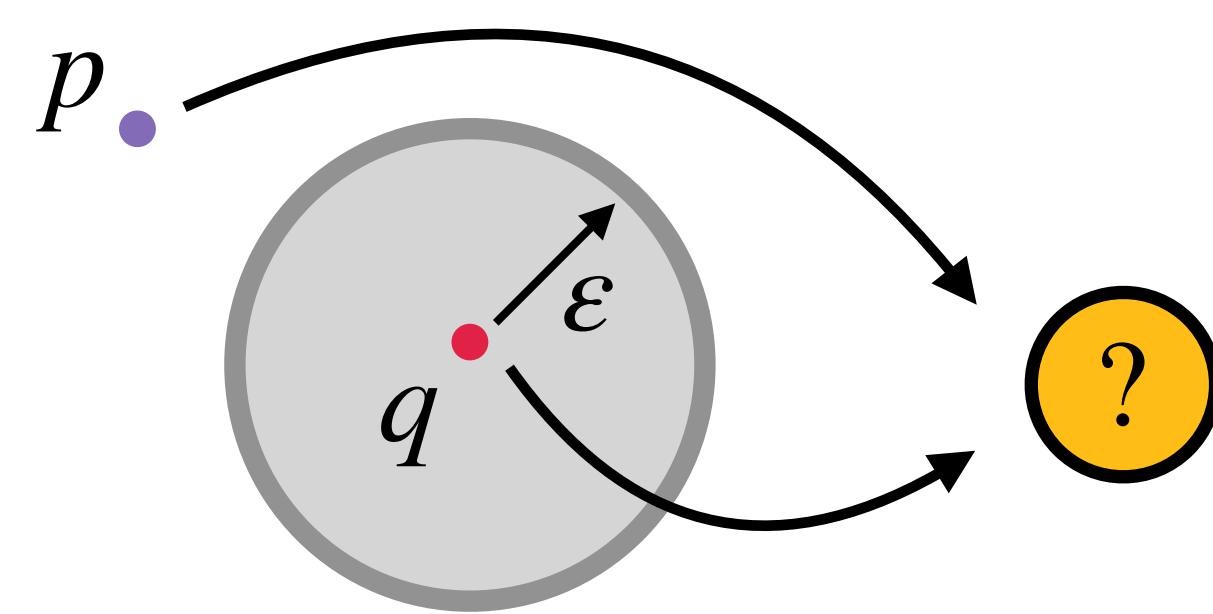
$$\begin{aligned}\text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon\end{aligned}$$

If we sample  $\{X_i = x_i\}_{i=1, \dots, N_{\text{tot}}}$ , then we prepare  $|x_1\rangle\langle x_1| \otimes \dots \otimes |x_{N_{\text{tot}}}\rangle\langle x_{N_{\text{tot}}}|$ .  
The state we obtain is exactly

$$\sum_{x_1, \dots, x_{N_{\text{tot}}} \in \mathbb{N}^n} p(x_1) \dots p(x_{N_{\text{tot}}}) |x_1\rangle\langle x_1| \otimes \dots \otimes |x_{N_{\text{tot}}}\rangle\langle x_{N_{\text{tot}}}| = \left( \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k| \right)^{\otimes N_{\text{tot}}} = \rho(p)^{\otimes N_{\text{tot}}}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

# Encoding distributions in quantum states



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

If we sample  $\{X_i = x_i\}_{i=1,\dots,N_{\text{tot}}}$ , then we prepare  $|x_1\rangle\langle x_1| \otimes \dots \otimes |x_{N_{\text{tot}}}\rangle\langle x_{N_{\text{tot}}}|$ .

The state we obtain is exactly

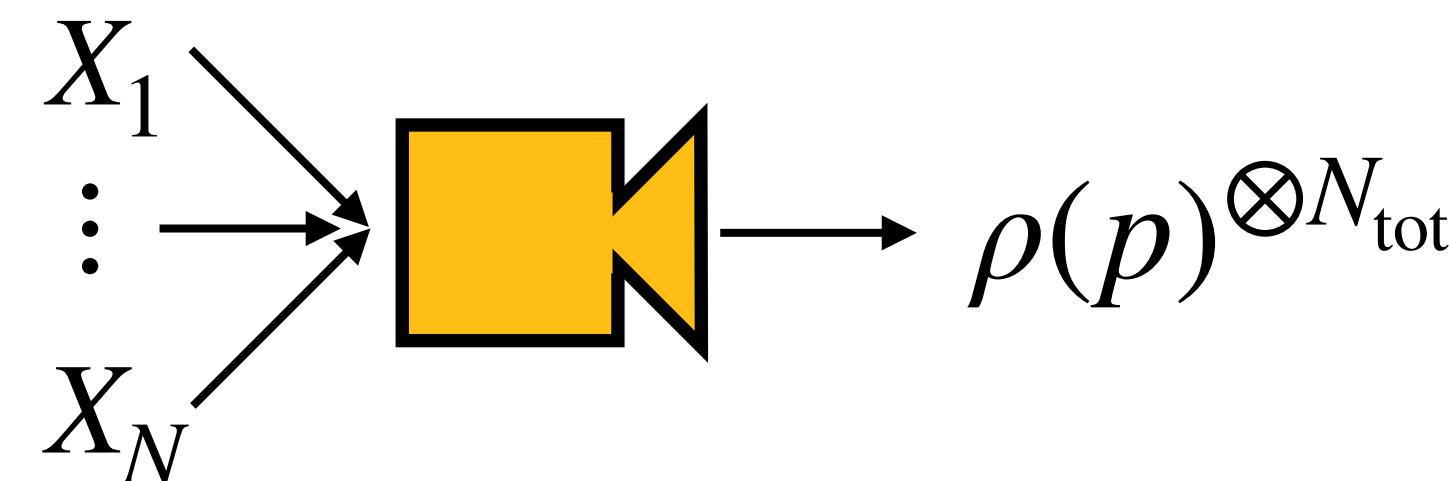
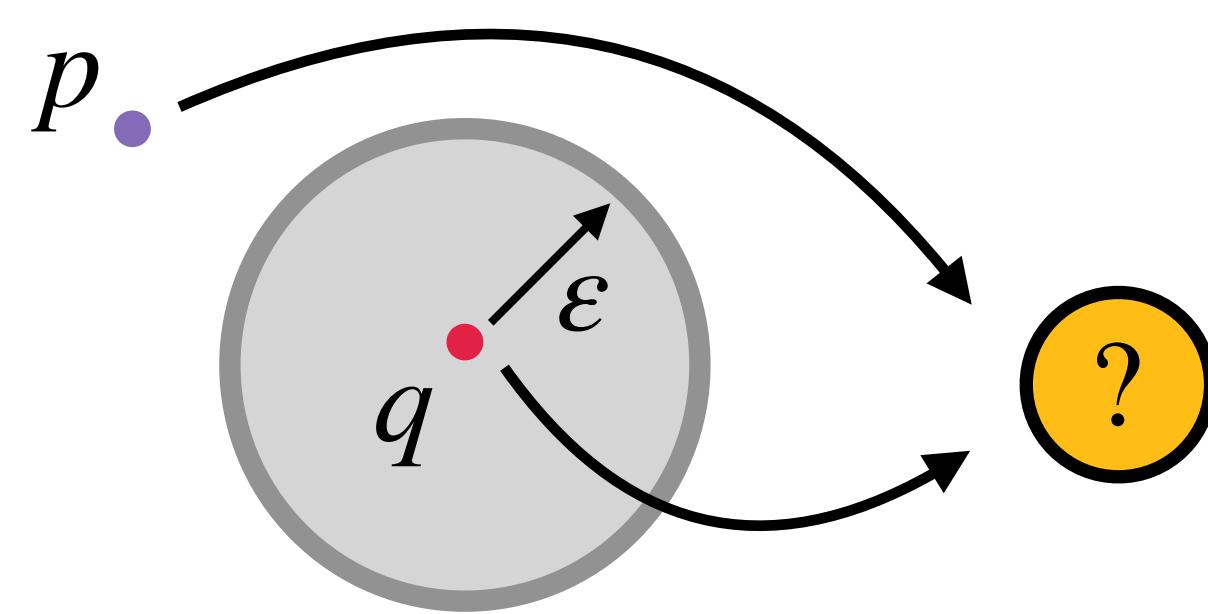
$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$\sum_{x_1, \dots, x_{N_{\text{tot}}} \in \mathbb{N}^n} p(x_1) \cdots p(x_{N_{\text{tot}}}) |x_1\rangle\langle x_1| \otimes \cdots \otimes |x_{N_{\text{tot}}}\rangle\langle x_{N_{\text{tot}}}| = \left( \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k| \right)^{\otimes N_{\text{tot}}} = \rho(p)^{\otimes N_{\text{tot}}}$$

↑

$$\mathbb{P}(\{X_i = x_i\}_{i=1,\dots,N_{\text{tot}}}) = p(x_1) \cdots p(x_{N_{\text{tot}}})$$

# Encoding distributions in quantum states



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

If we sample  $\{X_i = x_i\}_{i=1,\dots,N_{\text{tot}}}$ , then we prepare  $|x_1\rangle\langle x_1| \otimes \dots \otimes |x_{N_{\text{tot}}}\rangle\langle x_{N_{\text{tot}}}|$ .  
The state we obtain is exactly

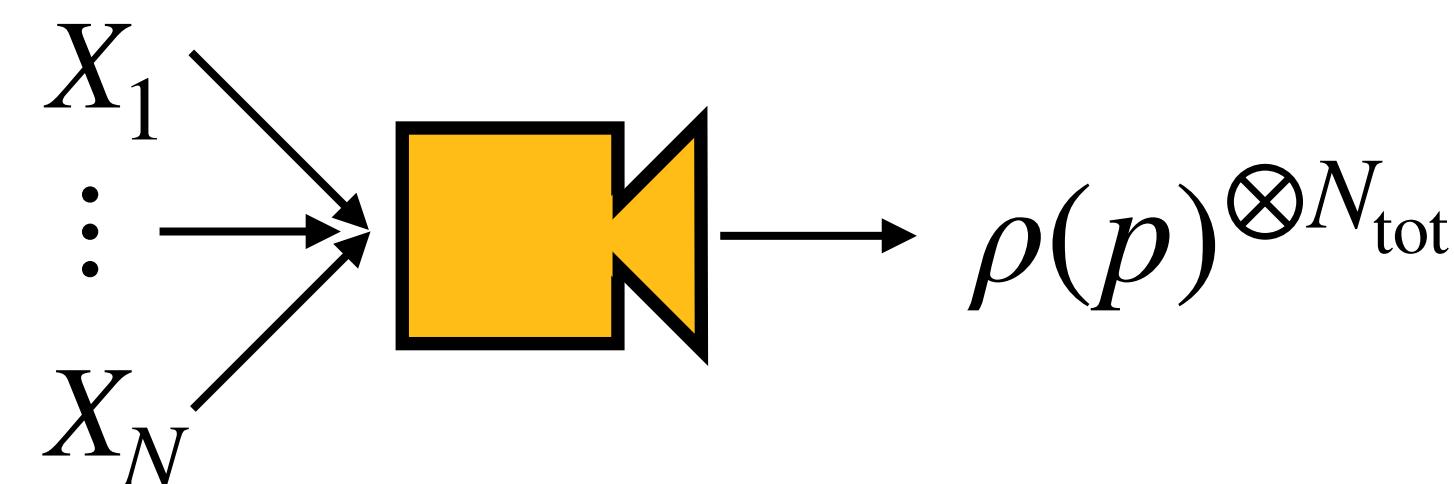
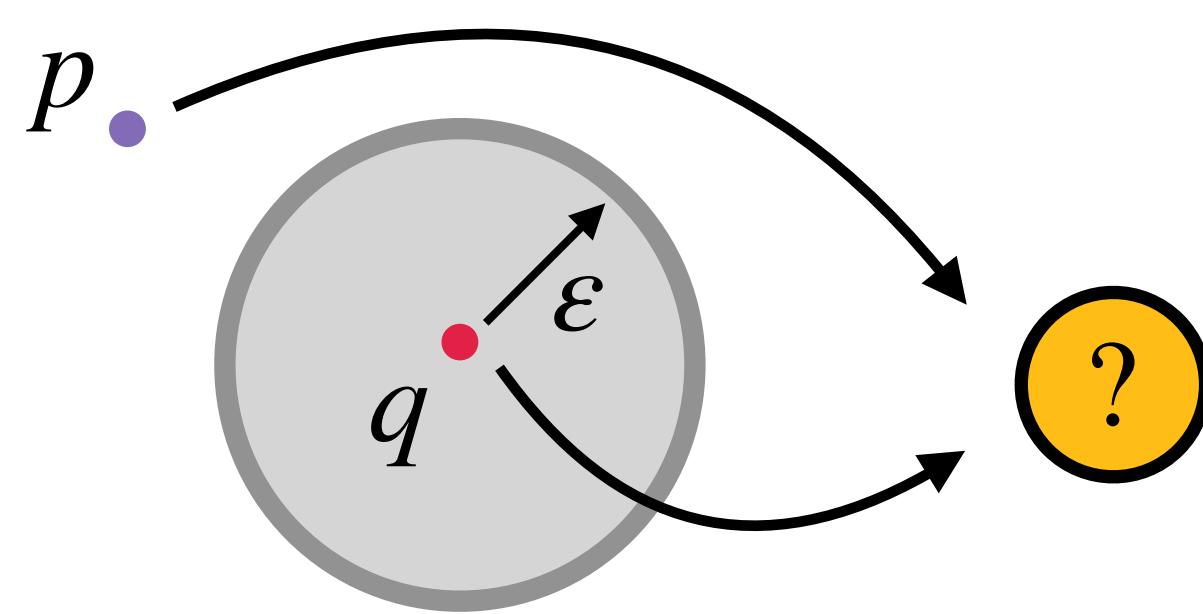
$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$\sum_{x_1, \dots, x_{N_{\text{tot}}} \in \mathbb{N}^n} p(x_1) \cdots p(x_{N_{\text{tot}}}) |x_1\rangle\langle x_1| \otimes \cdots \otimes |x_{N_{\text{tot}}}\rangle\langle x_{N_{\text{tot}}}| = \left( \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k| \right)^{\otimes N_{\text{tot}}} = \rho(p)^{\otimes N_{\text{tot}}}$$

$\uparrow$

$$\mathbb{P}(\{X_i = x_i\}_{i=1,\dots,N_{\text{tot}}}) = p(x_1) \cdots p(x_{N_{\text{tot}}})$$

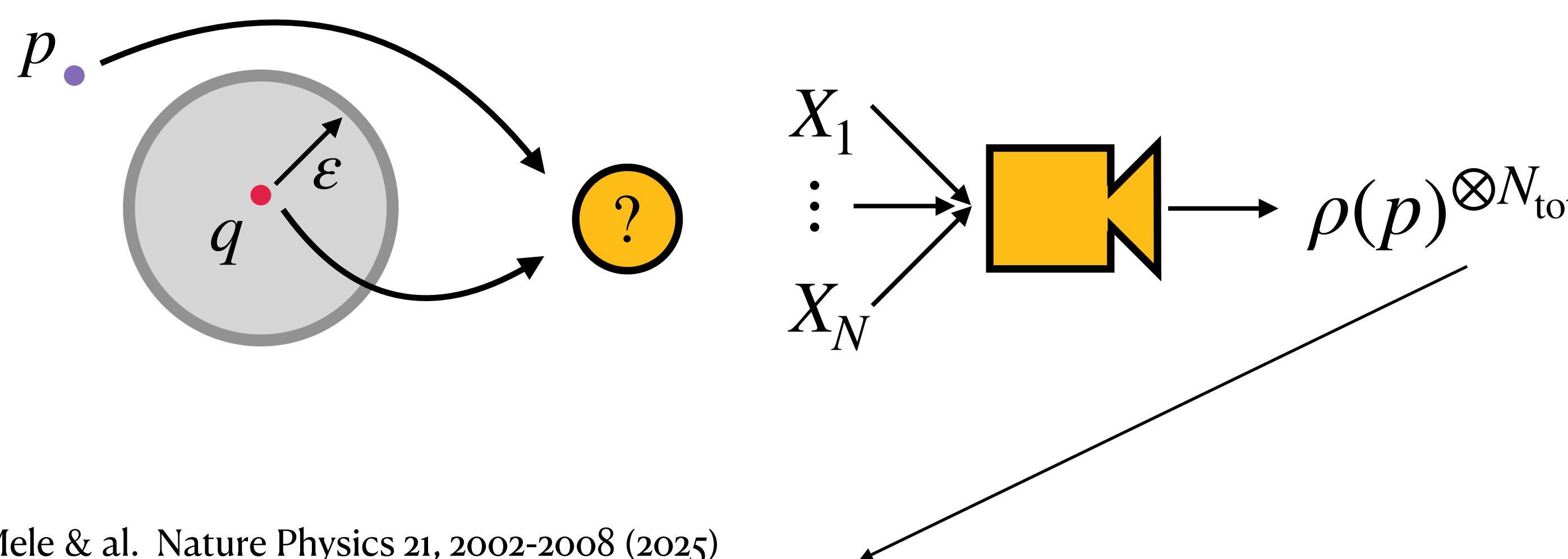
# Step 1: testing the covariance matrix



$$\begin{aligned}\text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon\end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

# Step 1: testing the covariance matrix

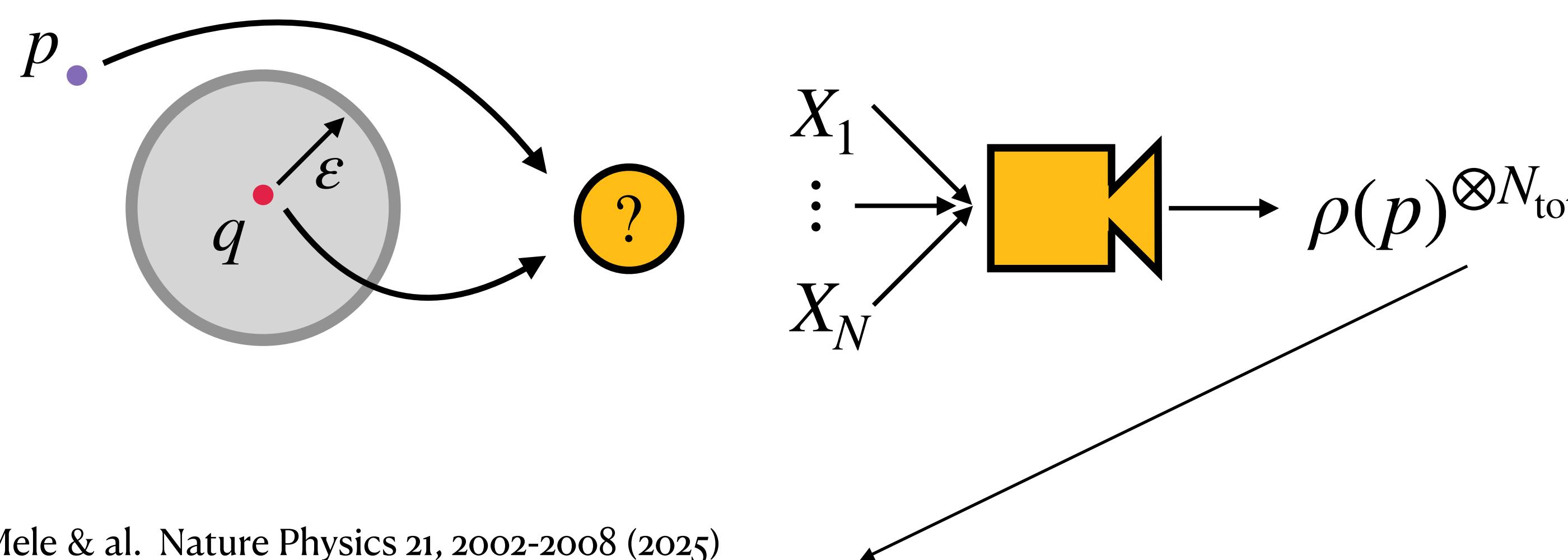


$$\begin{aligned}\text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon\end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$\rho(p)^{\otimes N_{\text{cov}}} \rightarrow \text{---} = \tilde{V}(p)$$

# Step 1: testing the covariance matrix



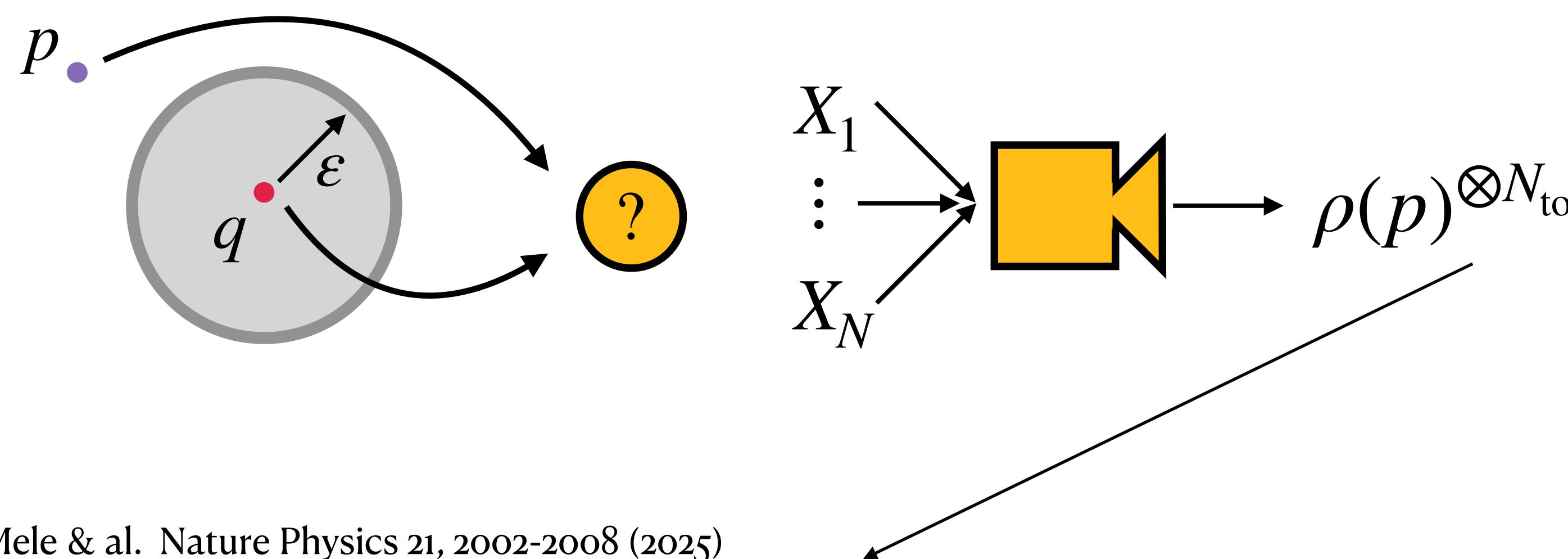
$$\begin{aligned}\text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon\end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$\rho(p)^{\otimes N_{\text{cov}}} \rightarrow \text{---} = \tilde{V}(p)$$

$$\|\tilde{V}(p) - V(p)\|_2 \leq \varepsilon_V$$

# Step 1: testing the covariance matrix



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

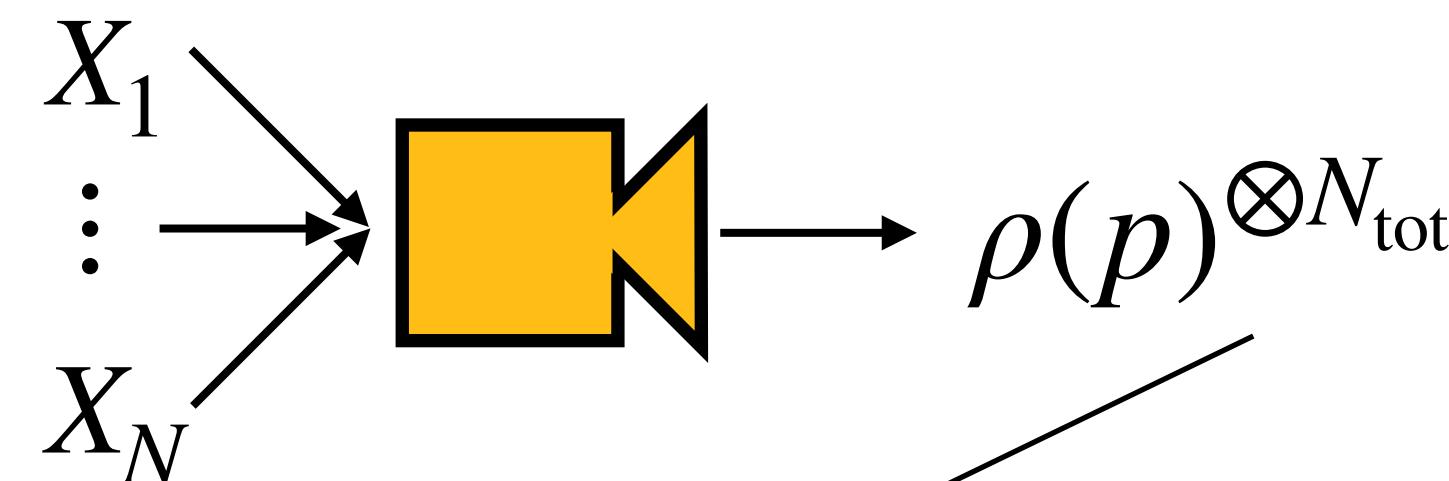
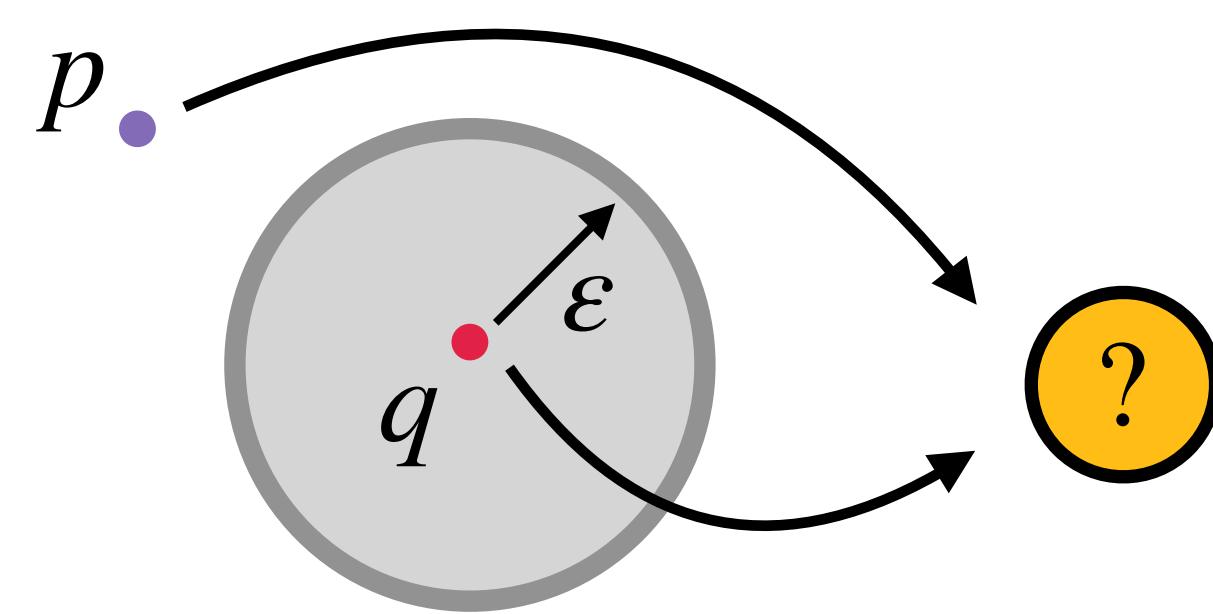
$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$\rho(p)^{\otimes N_{\text{cov}}} \rightarrow \text{---} = \tilde{V}(p)$$

$$\|\tilde{V}(p) - V(p)\|_2 \leq \varepsilon_V$$

$$\varepsilon_V = \frac{\varepsilon}{4(1 + \sqrt{3})nE}$$

# Step 1: testing the covariance matrix



Mele & al. Nature Physics 21, 2002-2008 (2025)

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

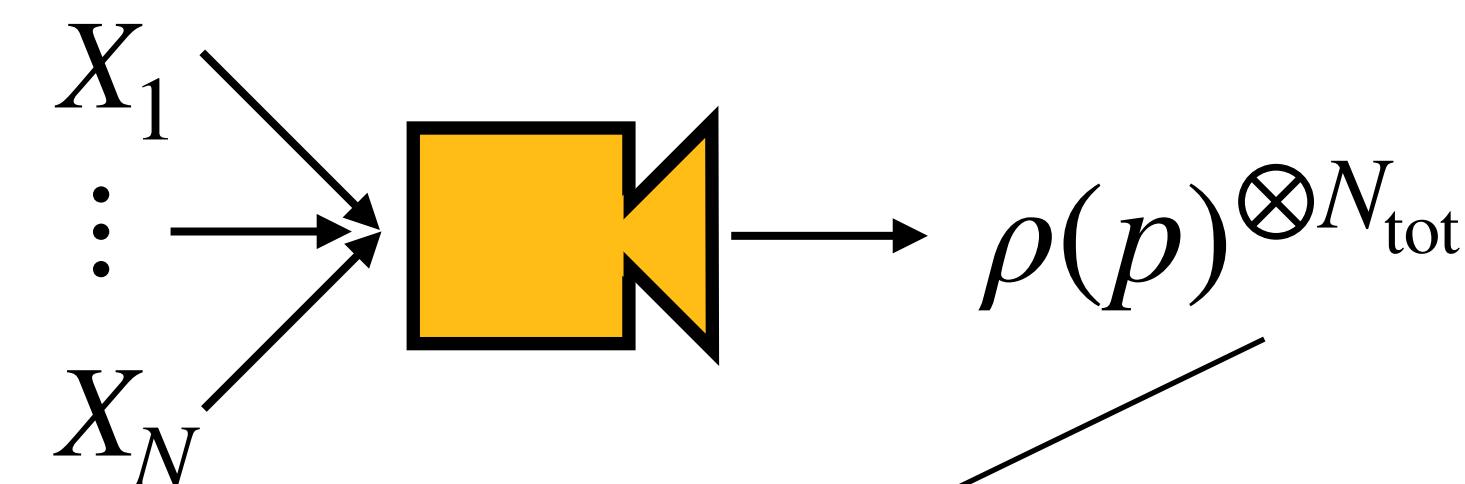
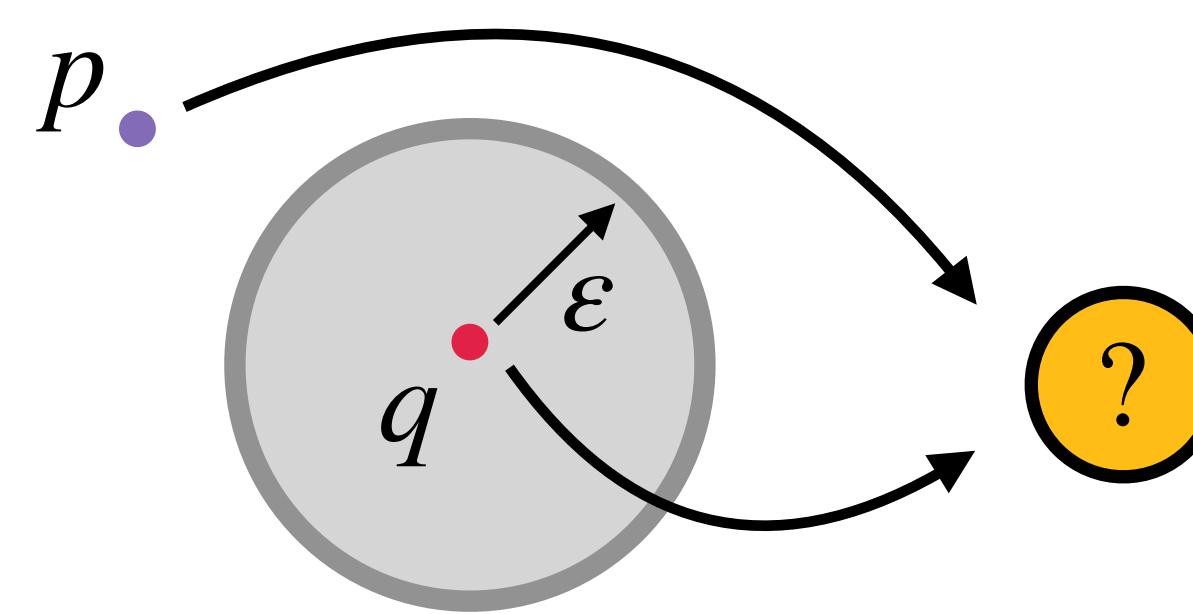
$$\boxed{\rho(p)^{\otimes N_{\text{cov}}} \rightarrow \text{○} = \tilde{V}(p)}$$

$$\|\tilde{V}(p) - V(p)\|_2 \leq \varepsilon_V$$

$$\varepsilon_V = \frac{\varepsilon}{4(1 + \sqrt{3})nE}$$

$\text{Tr}[\rho(q)\hat{E}^2] \leq n^2 E^2$
$\text{Tr}[\rho(p)\hat{E}^2] \leq n^2 E^2$
$\frac{1}{2}\ \rho(p) - \rho(q)\ _1 > \varepsilon$

# Step 1: testing the covariance matrix



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

Mele & al. Nature Physics 21, 2002-2008 (2025)

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$\rho(p)^{\otimes N_{\text{cov}}} \rightarrow \text{---} = \tilde{V}(p)$$

$$\|\tilde{V}(p) - V(p)\|_2 \leq \varepsilon_V$$

$$\varepsilon_V = \frac{\varepsilon}{4(1 + \sqrt{3})nE}$$

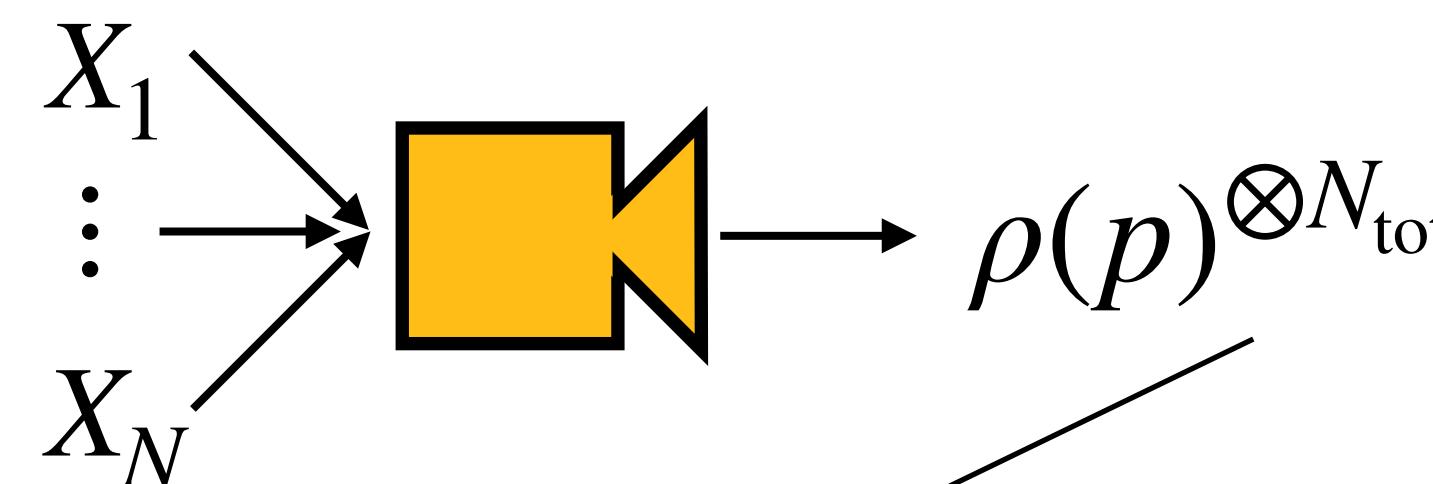
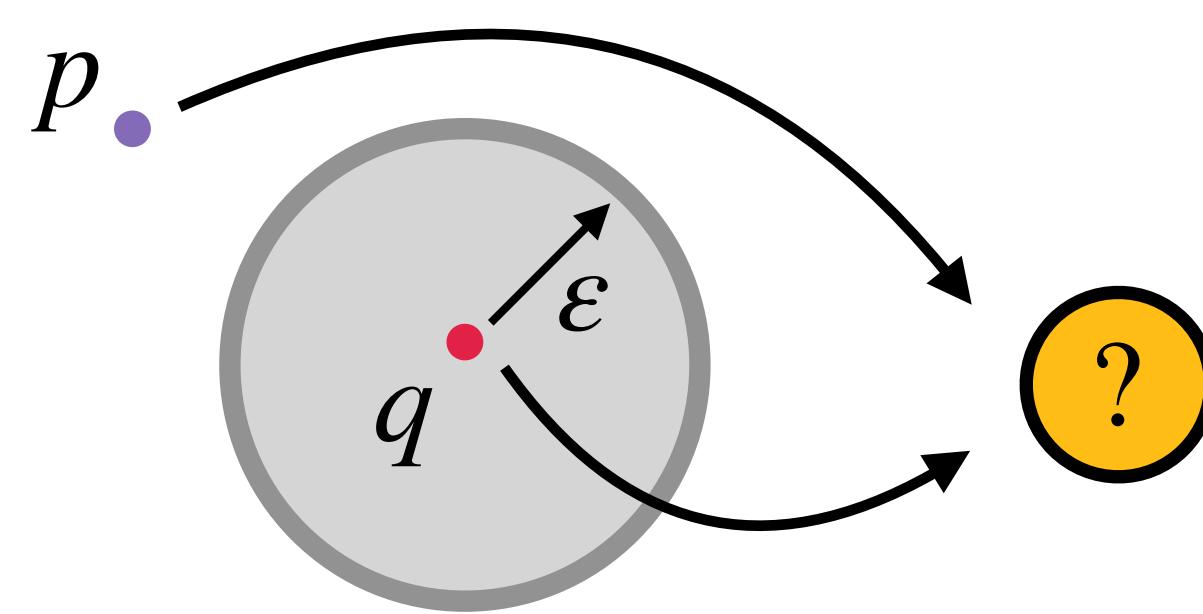
Now, if  $\|\tilde{V}(p) - V(q)\|_2 > \varepsilon_V$ ,

then  $\|V(p) - V(q)\|_2 \geq \|\tilde{V}(p) - V(q)\|_2 - \|\tilde{V}(p) - V(p)\|_2 > 0$ ,

so we output “**not**  $q$ ”, since

$$\|p - q\|_1 = \|\rho(p) - \rho(q)\|_1 > 0$$

# Step 1: testing the covariance matrix



Mele & al. Nature Physics 21, 2002-2008 (2025)

$$\rho(p)^{\otimes N_{\text{cov}}} \rightarrow \text{video camera} = \tilde{V}(p)$$

$$\|\tilde{V}(p) - V(p)\|_2 \leq \varepsilon_V$$

$$\varepsilon_V = \frac{\varepsilon}{4(1 + \sqrt{3})nE}$$

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

Now, if  $\|\tilde{V}(p) - V(q)\|_2 > \varepsilon_V$ ,

then  $\|V(p) - V(q)\|_2 \geq \|\tilde{V}(p) - V(q)\|_2 - \|\tilde{V}(p) - V(p)\|_2 > 0$ ,

so we output “not *q*”, since

$$\|p - q\|_1 = \|\rho(p) - \rho(q)\|_1 > 0$$

**Lower bound between arbitrary states.**

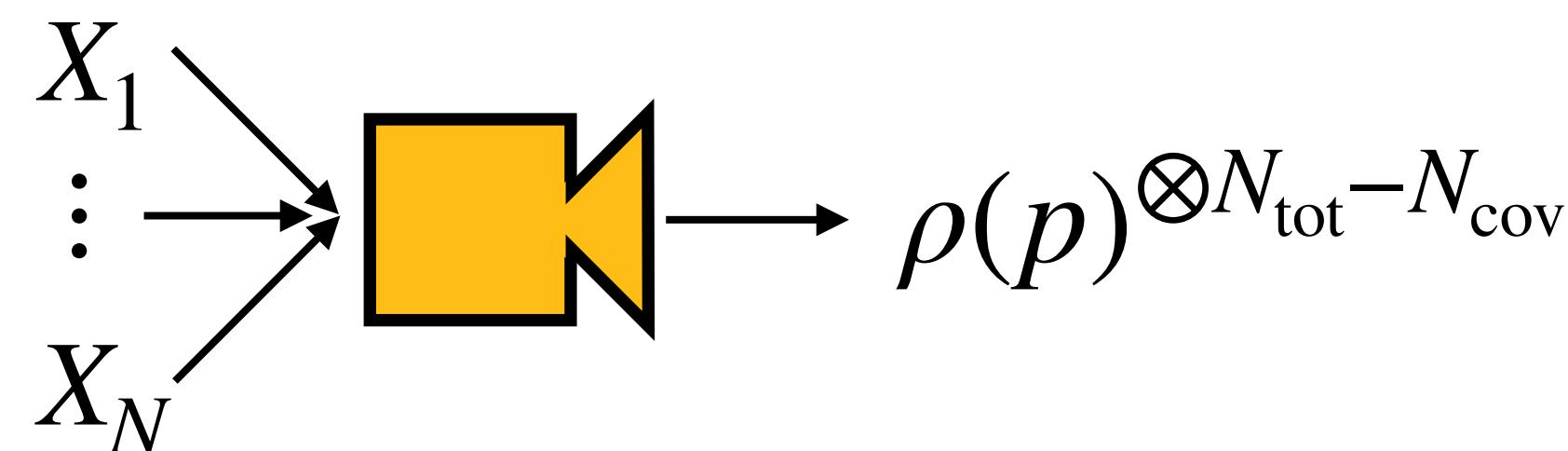
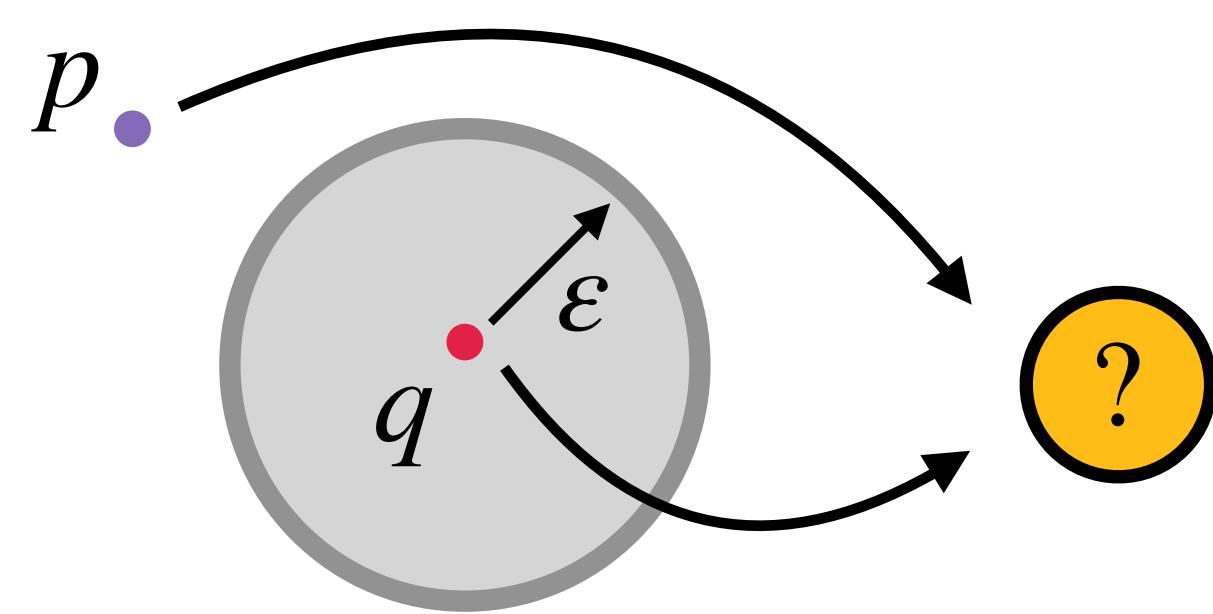
$$\frac{1}{2} \|\rho(p) - \rho(q)\|_1 \geq \frac{\|V(p) - V(q)\|_\infty^2}{3098 \max(\text{Tr}[\hat{E}^2 \rho(p)], \text{Tr}[\hat{E}^2 \rho(q)])}$$

$$\text{Tr}[\rho(q) \hat{E}^2] \leq n^2 E^2$$

$$\text{Tr}[\rho(p) \hat{E}^2] \leq n^2 E^2$$

$$\frac{1}{2} \|\rho(p) - \rho(q)\|_1 > \varepsilon$$

# Step 2: Gaussianity test



$$\boxed{\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}}$$

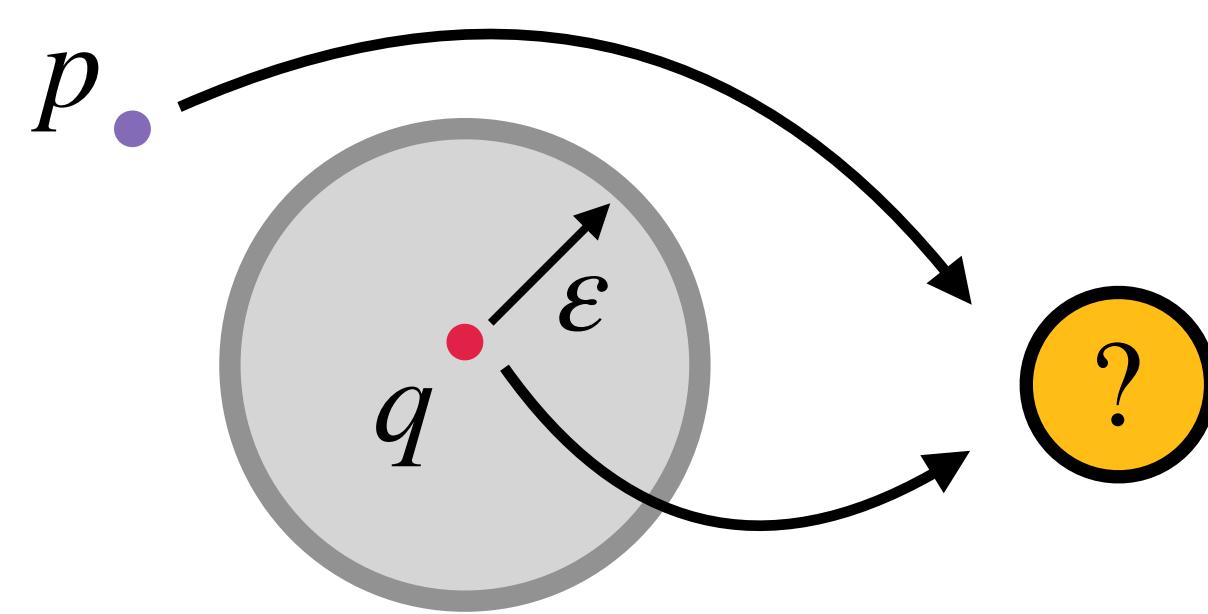
Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

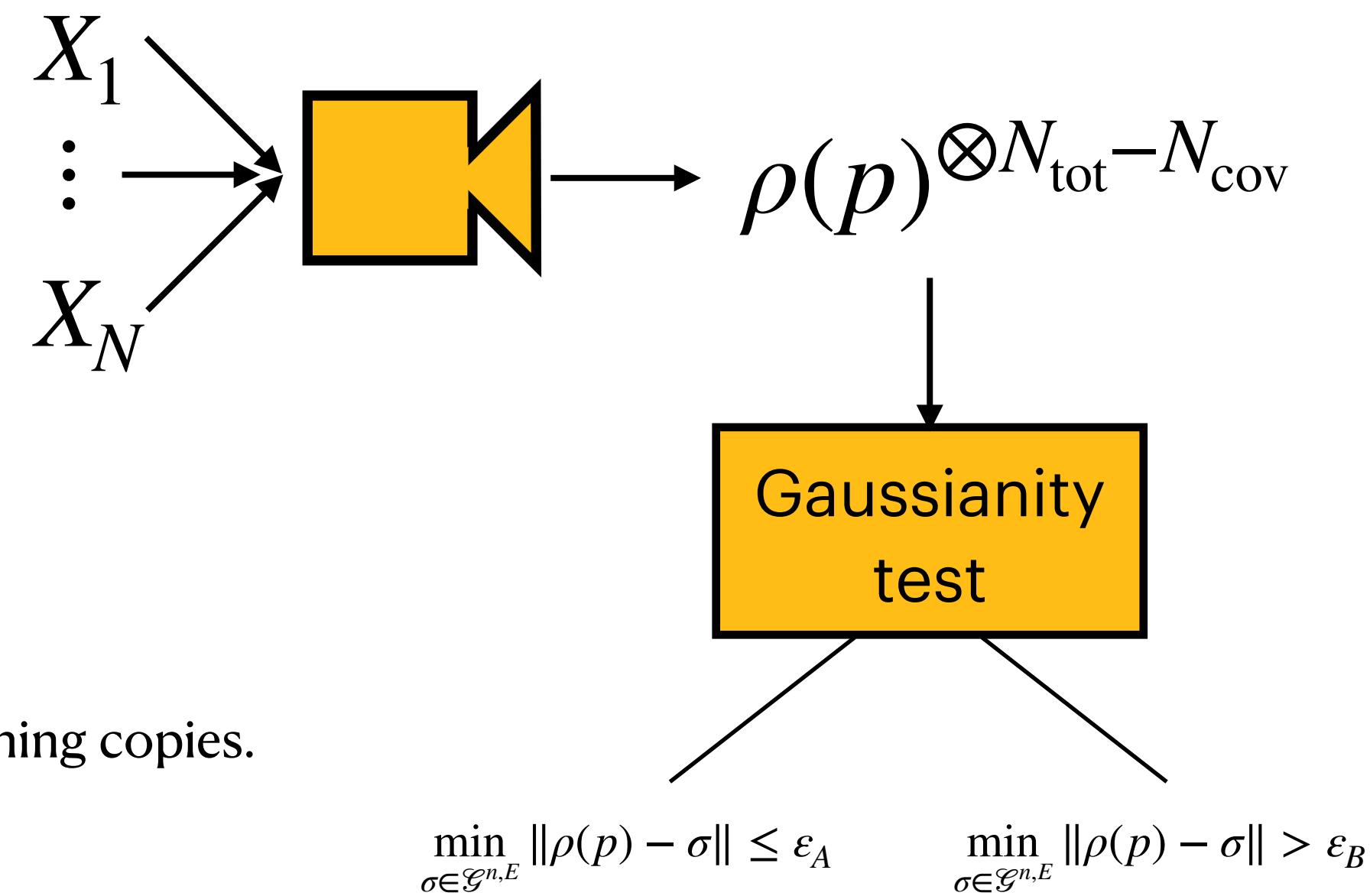
$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

# Step 2: Gaussianity test



Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

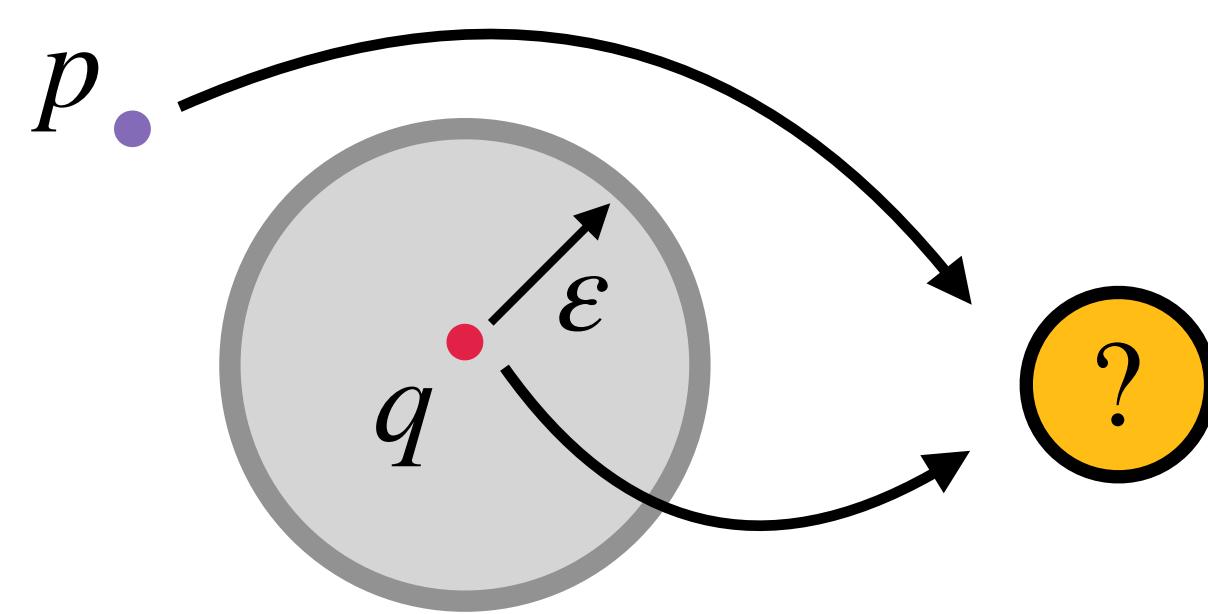


$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

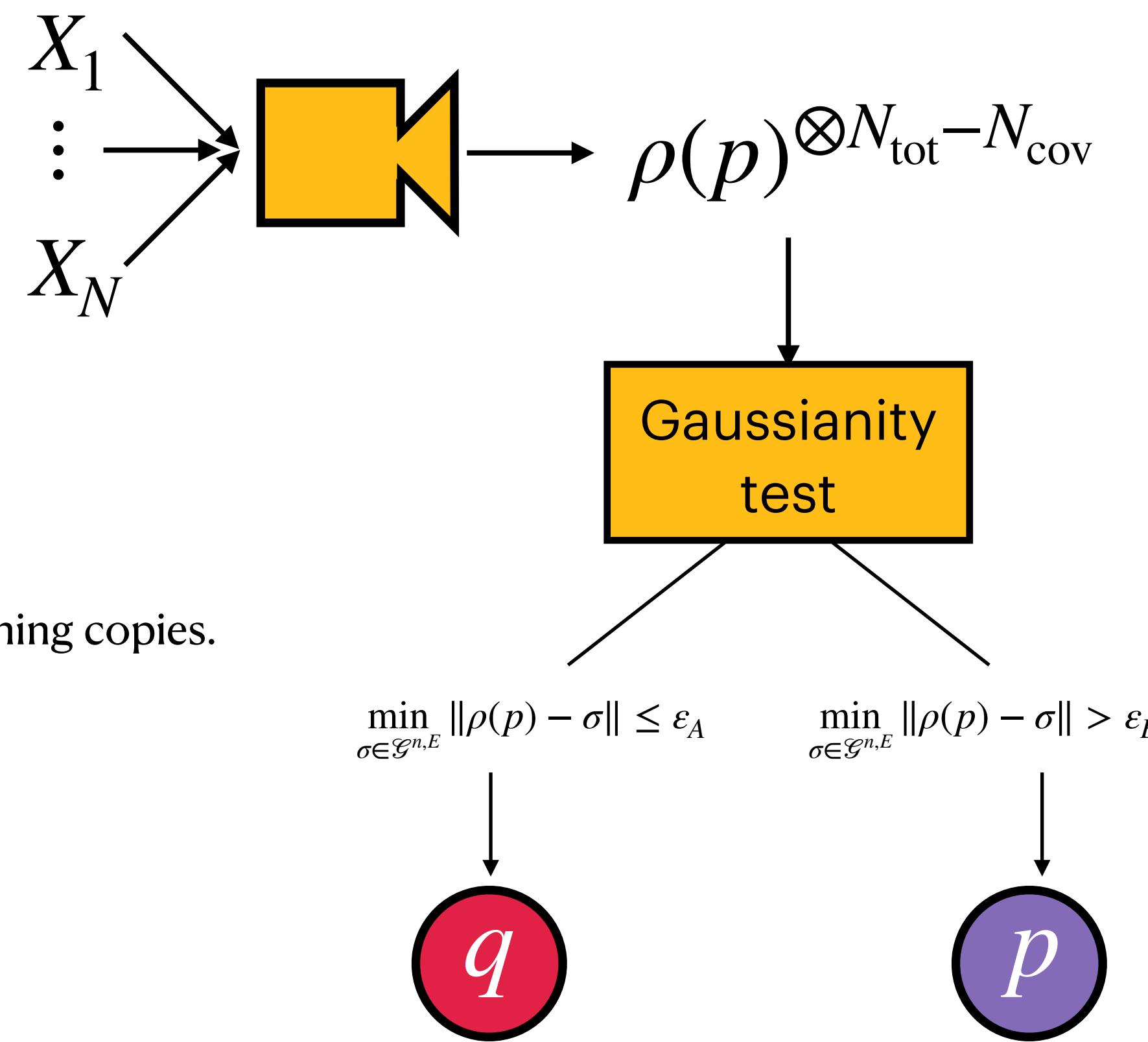
$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

# Step 2: Gaussianity test



Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

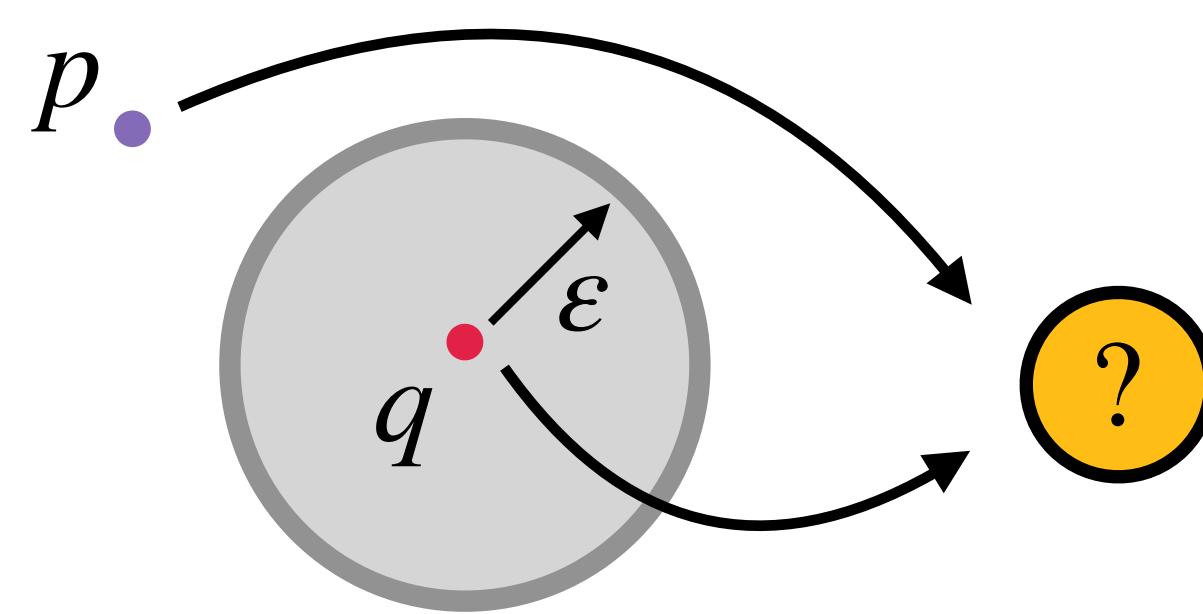


$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

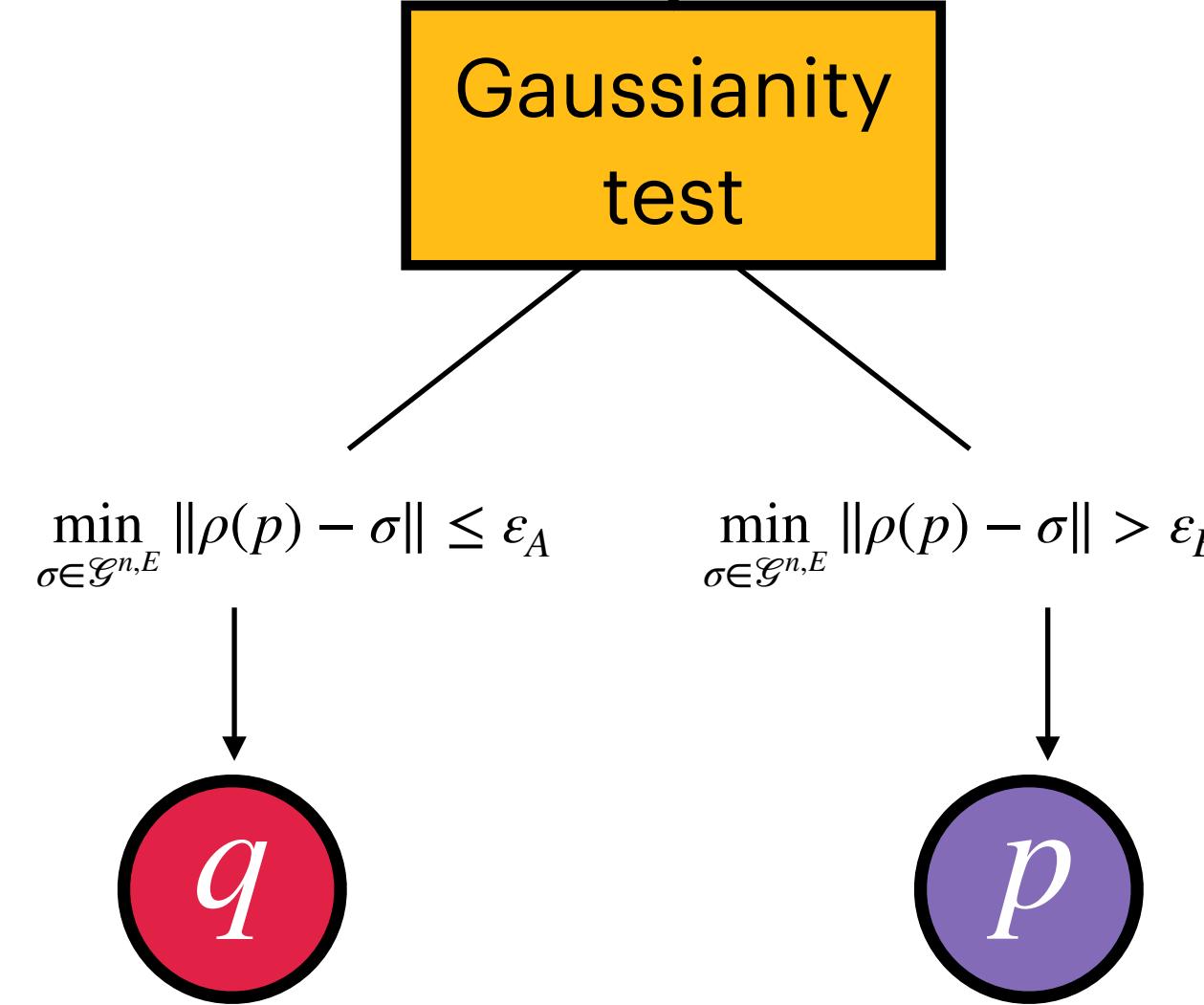
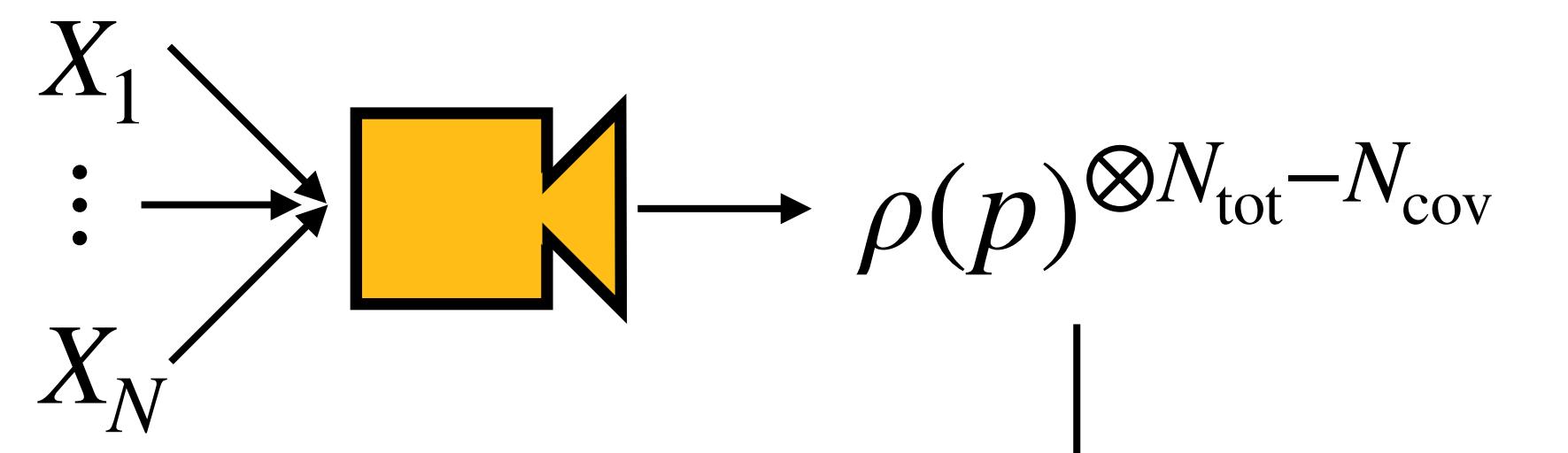
$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

# Step 2: Gaussianity test



Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.



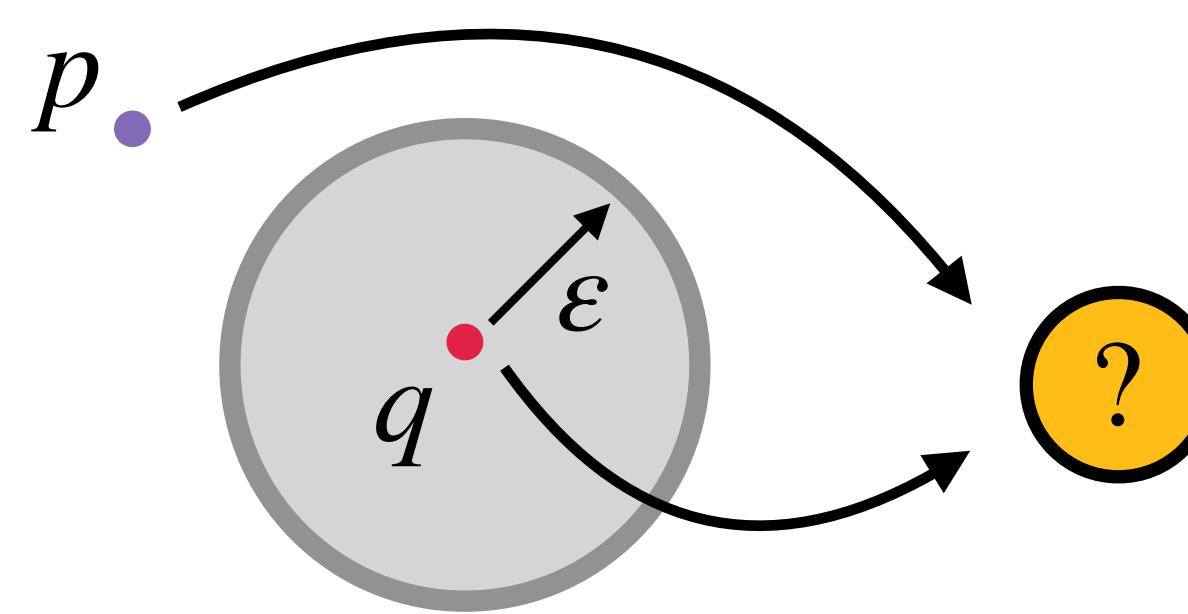
$$X_i \sim q \Rightarrow H_A$$

$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

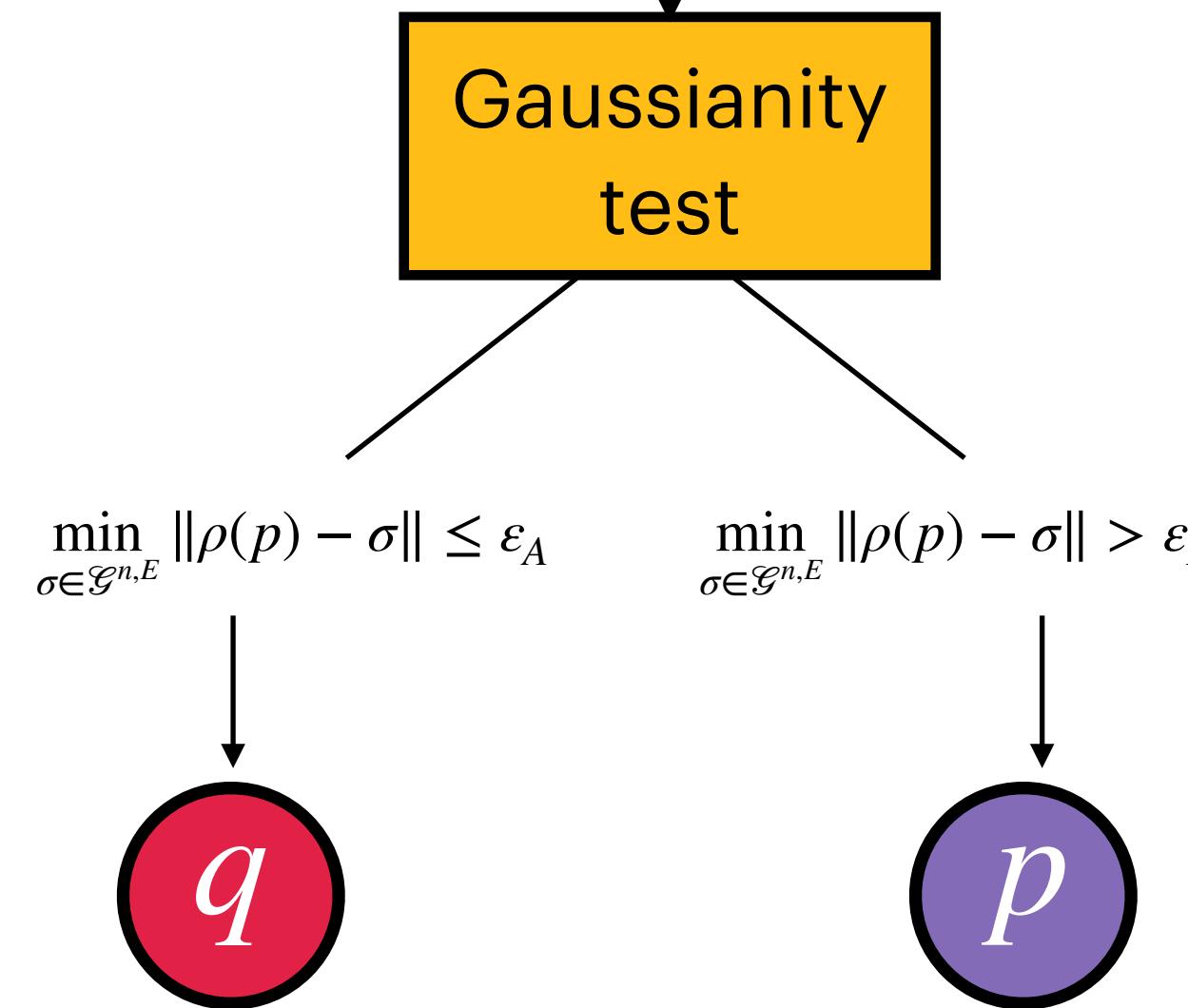
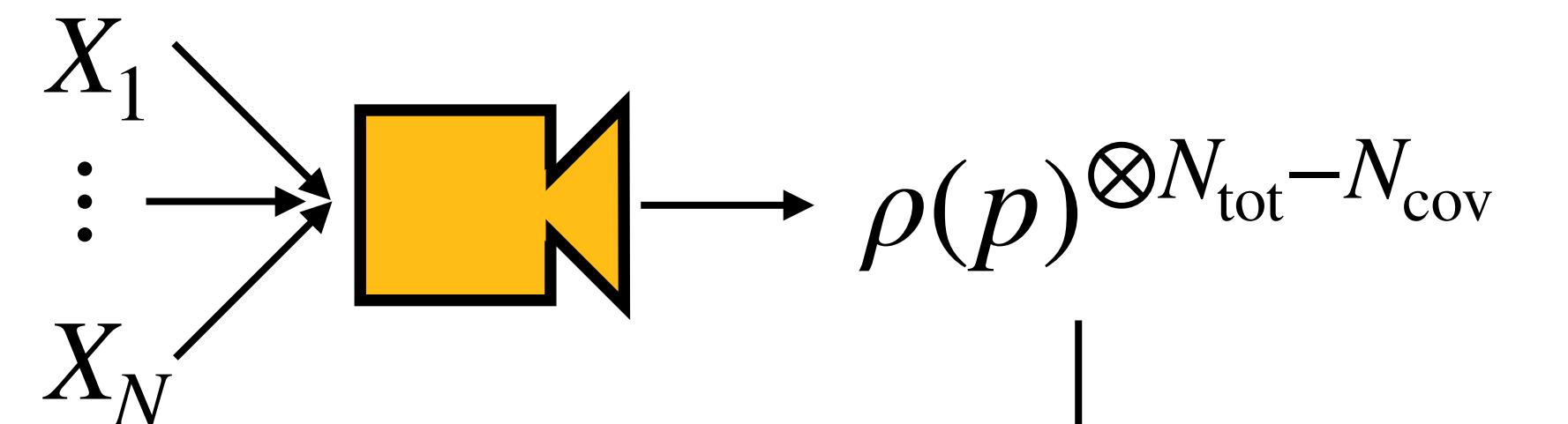
$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

# Step 2: Gaussianity test



Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.



$$X_i \sim q \Rightarrow H_A$$

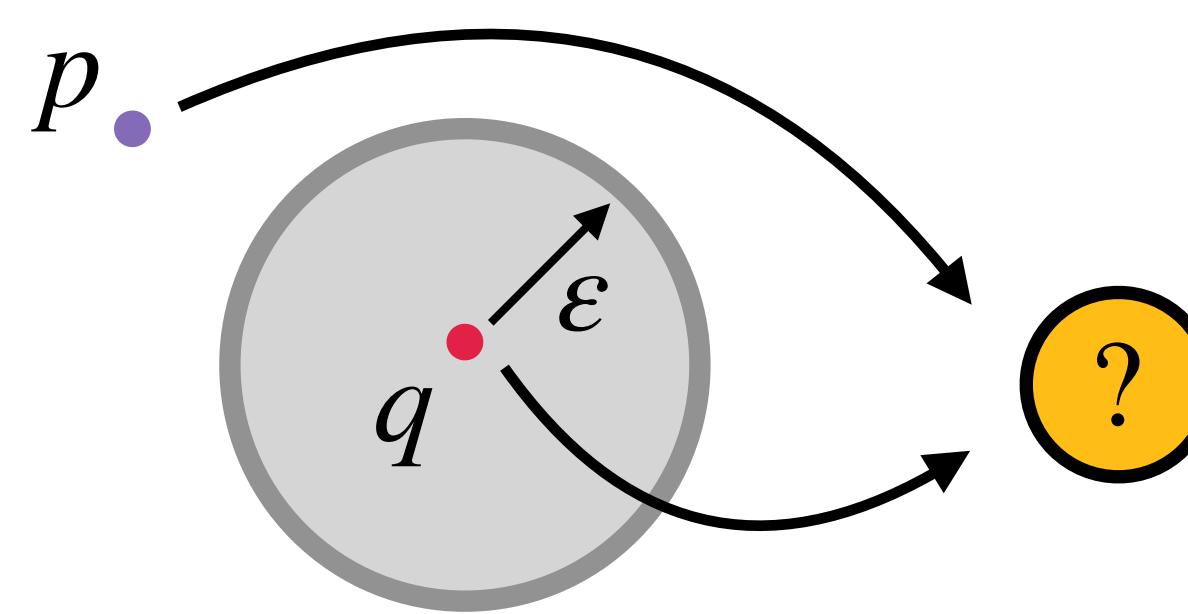
$$X_i \sim p \Rightarrow H_B$$

$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

# Step 2: Gaussianity test

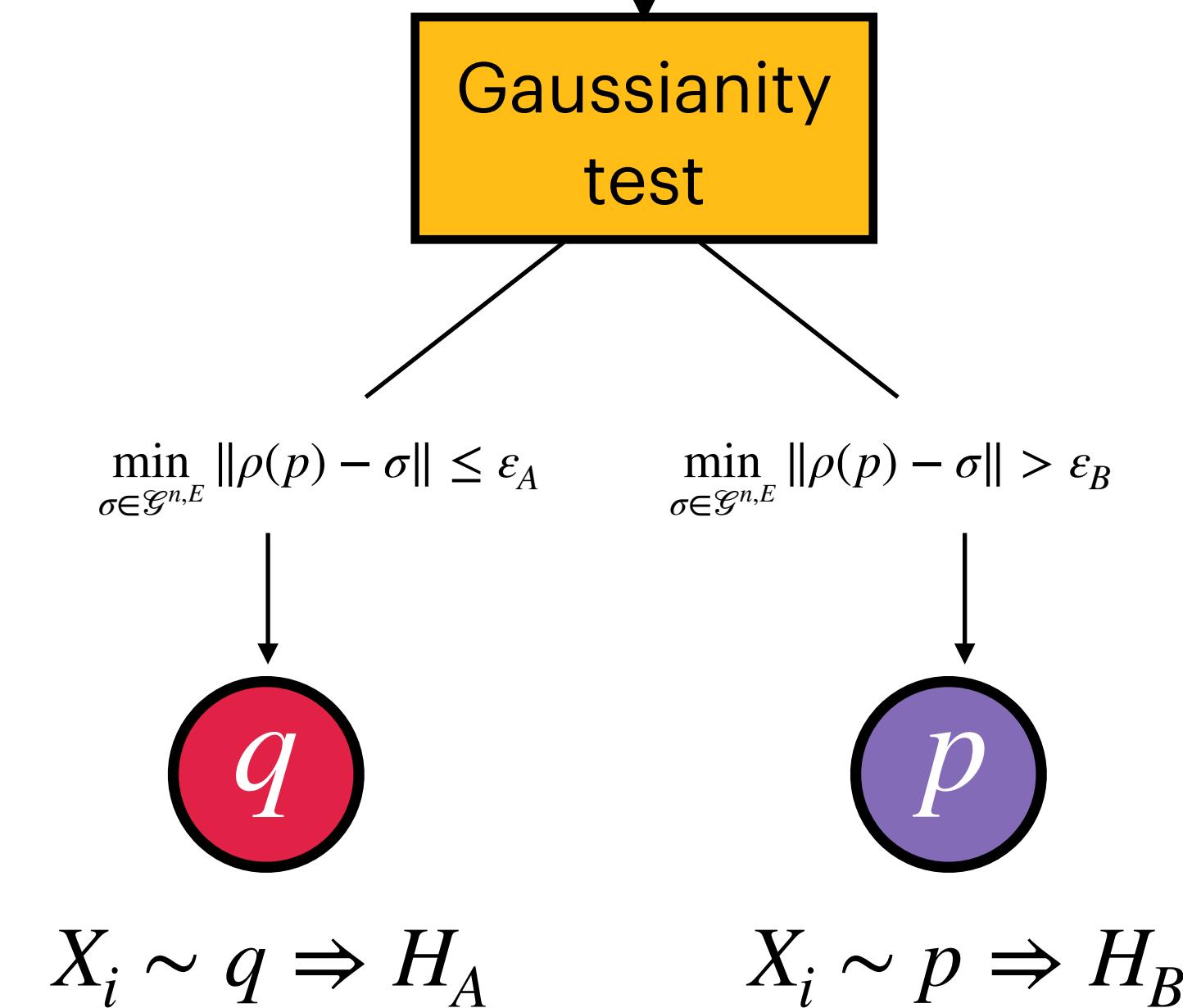
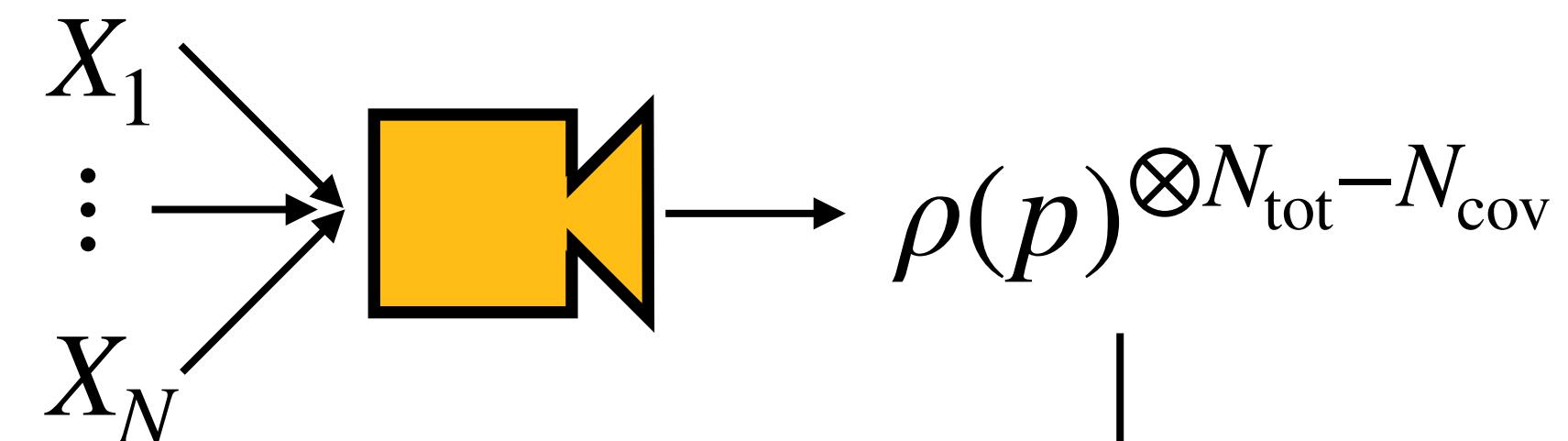


Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

$$\begin{aligned} N_{\text{Gauss}} &= N_{\text{tot}} - N_{\text{cov}} \\ &= \Omega\left(\frac{1}{\varepsilon^2 \|q\|_2}\right) - O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right) \end{aligned}$$

$$= \Omega\left(\frac{(\nu + 1)^n}{\varepsilon^2}\right) = \Omega\left(\frac{E^n}{\varepsilon^2}\right)$$



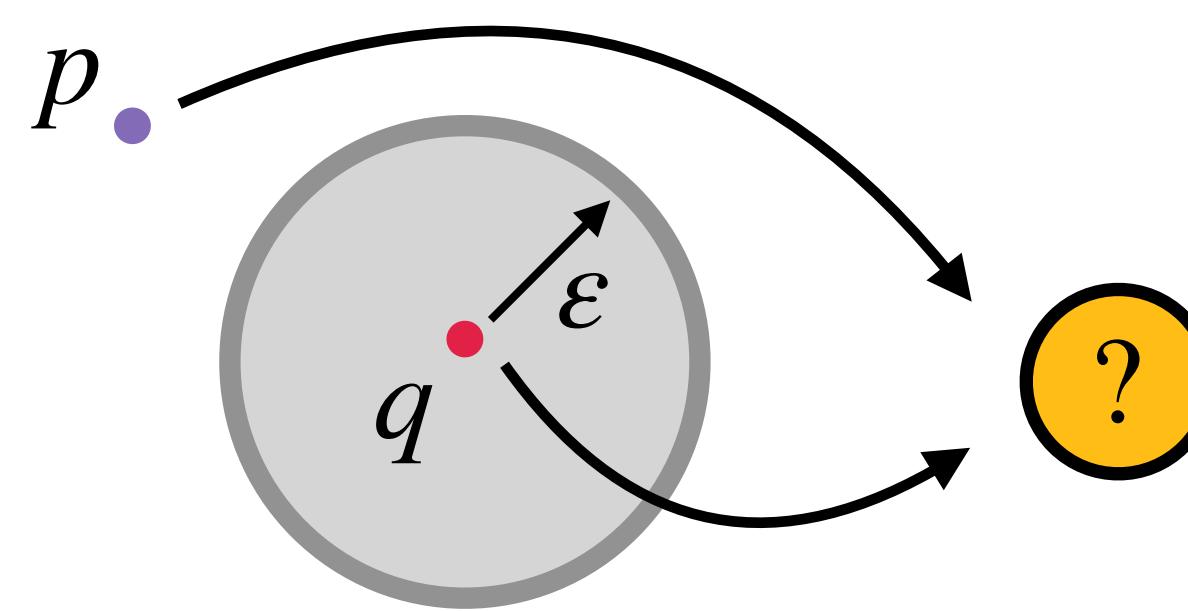
$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\nu = \Omega(E)$$

# Step 2: Gaussianity test

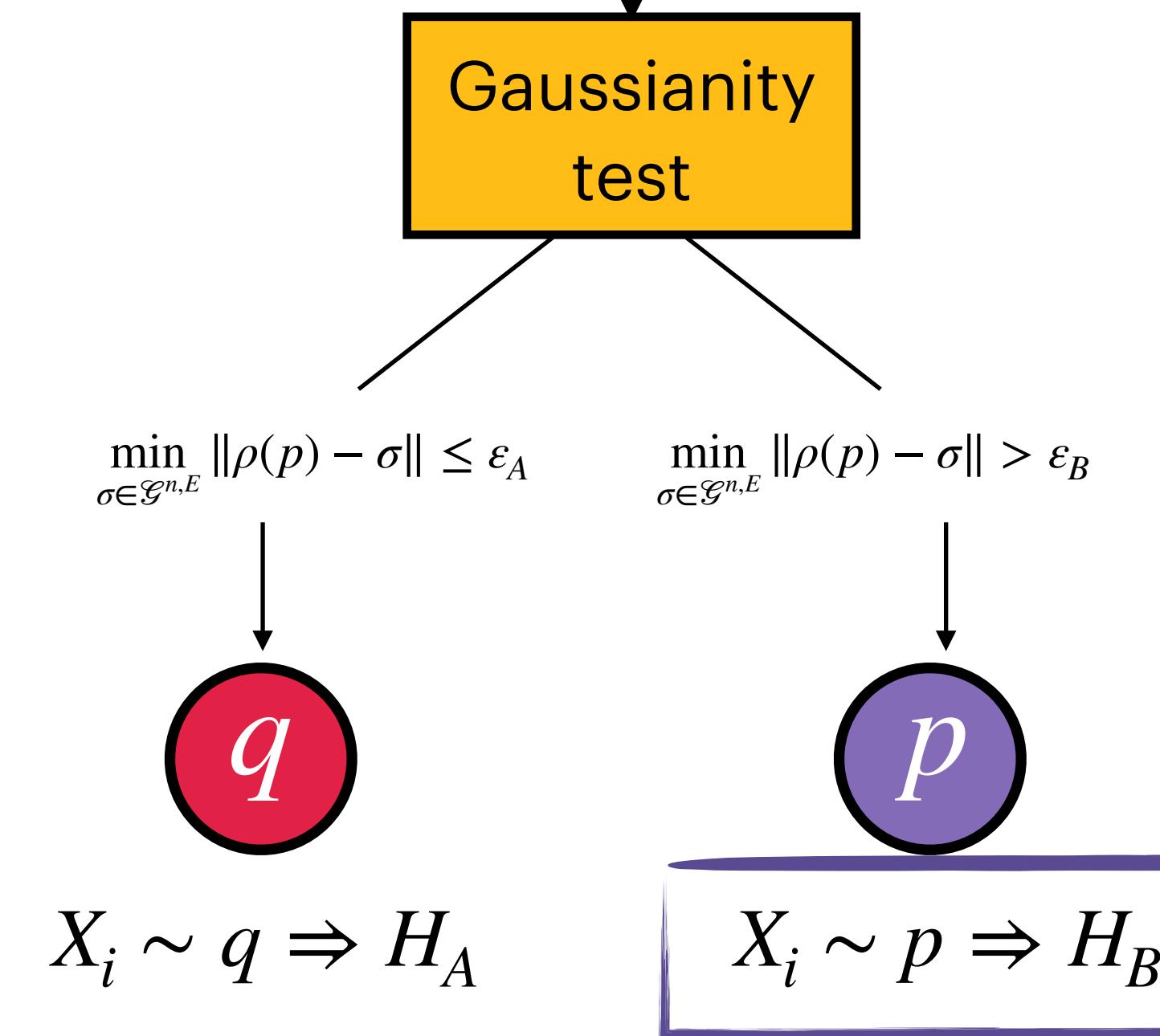
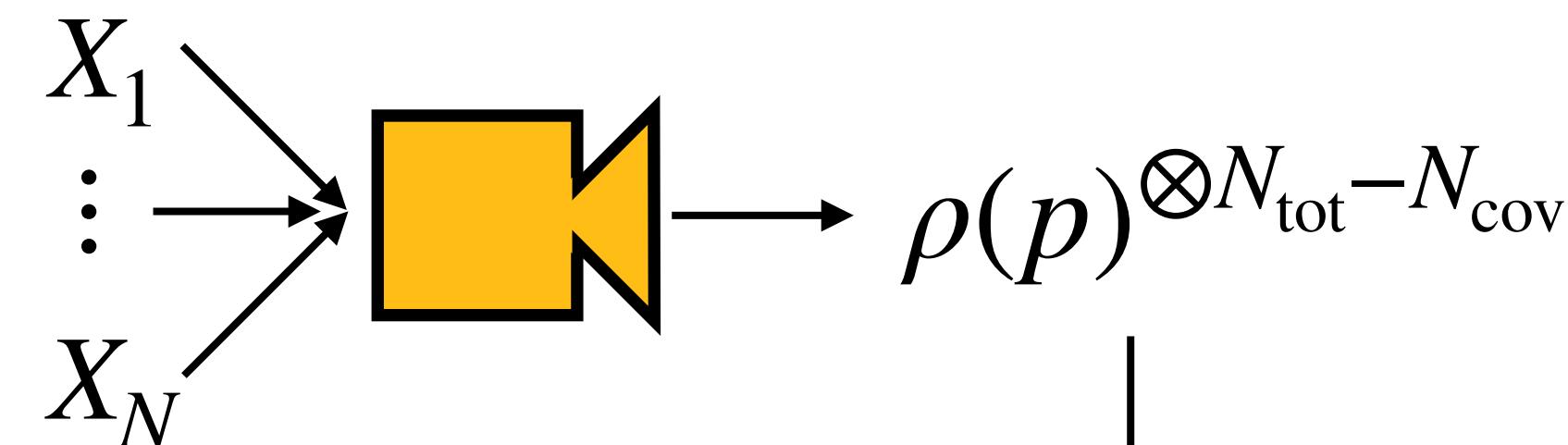


Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

$$\begin{aligned} N_{\text{Gauss}} &= N_{\text{tot}} - N_{\text{cov}} \\ &= \Omega\left(\frac{1}{\varepsilon^2 \|q\|_2}\right) - O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right) \end{aligned}$$

$$= \Omega\left(\frac{(\nu + 1)^n}{\varepsilon^2}\right) = \Omega\left(\frac{E^n}{\varepsilon^2}\right)$$



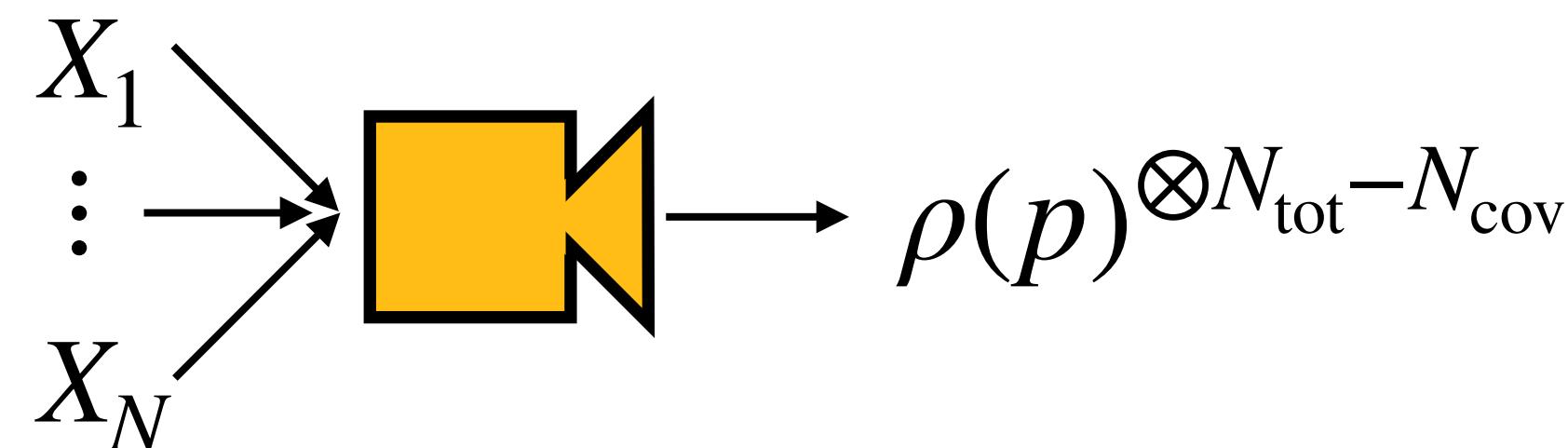
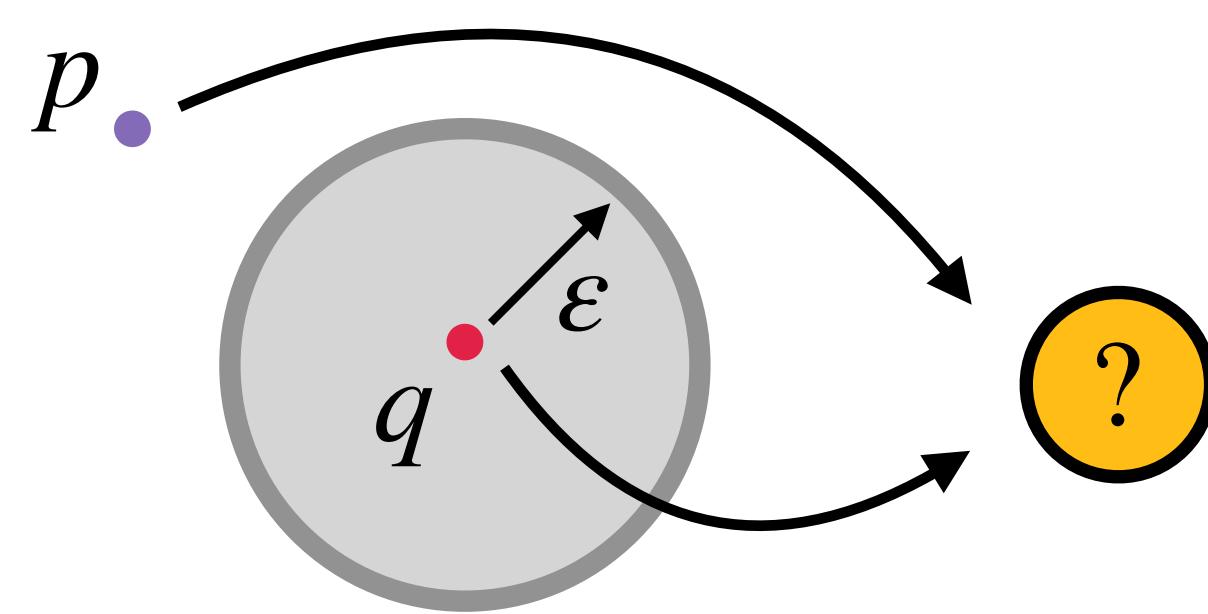
$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\nu = \Omega(E)$$

# Step 2: Gaussianity test



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

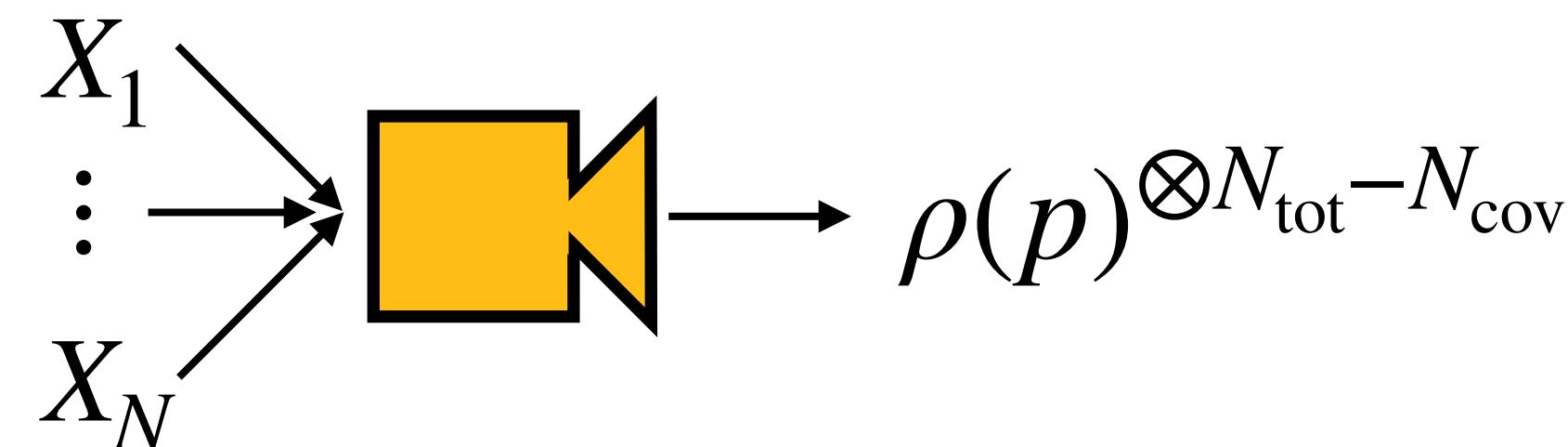
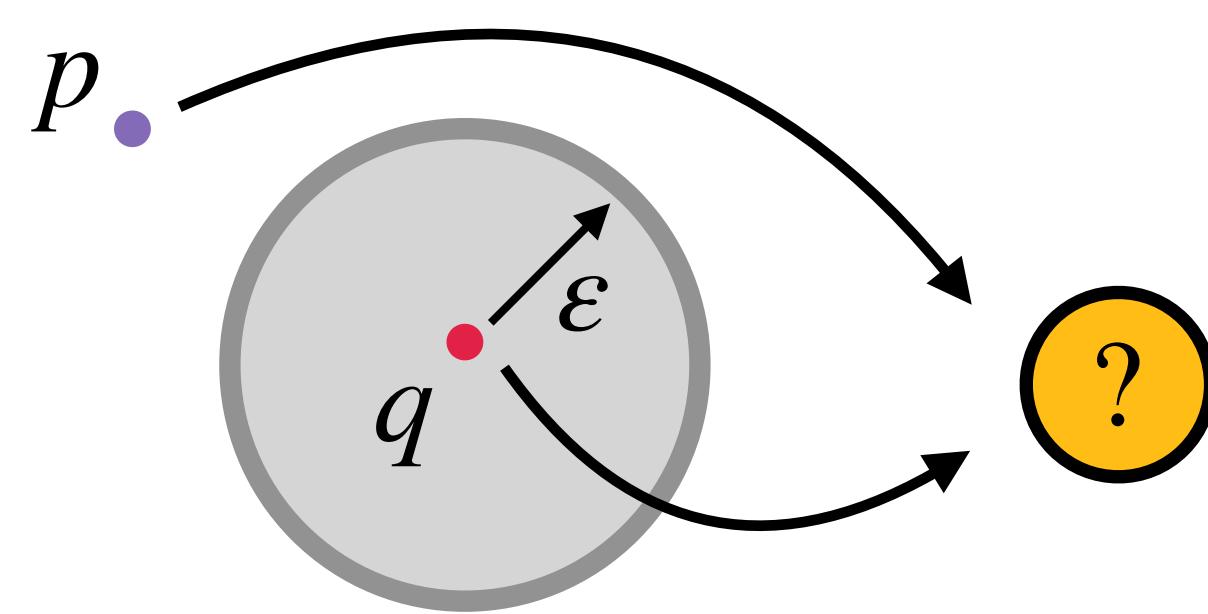
then we run the **Gaussianity test** on the remaining copies.

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\nu = \Omega(E)$$

$$X_i \sim p \Rightarrow H_B$$

# Step 2: Gaussianity test



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

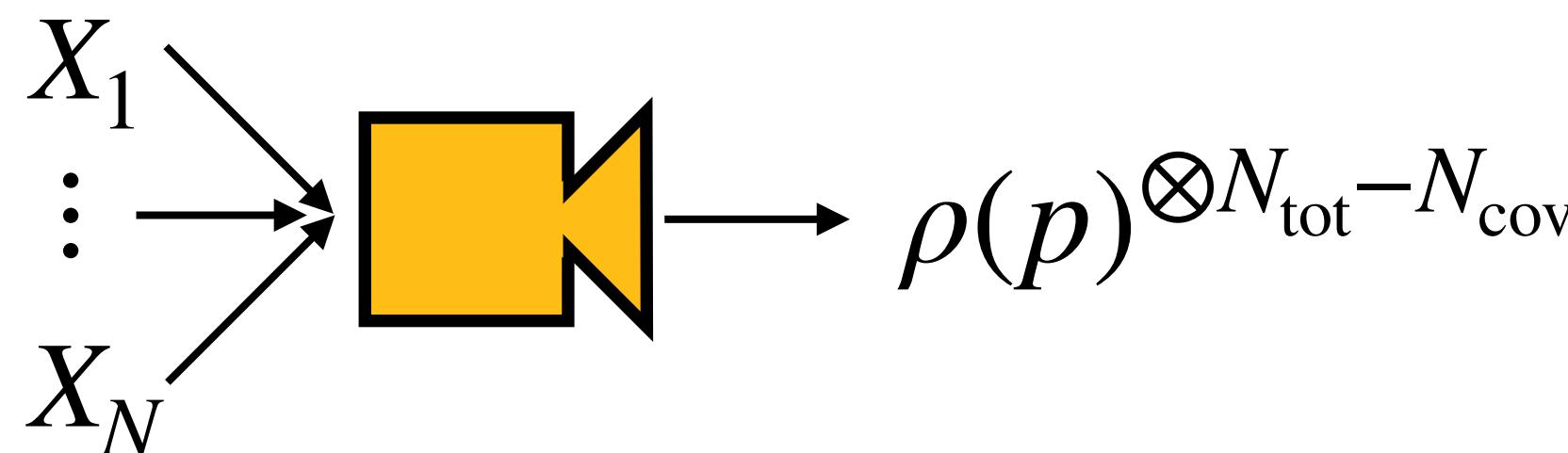
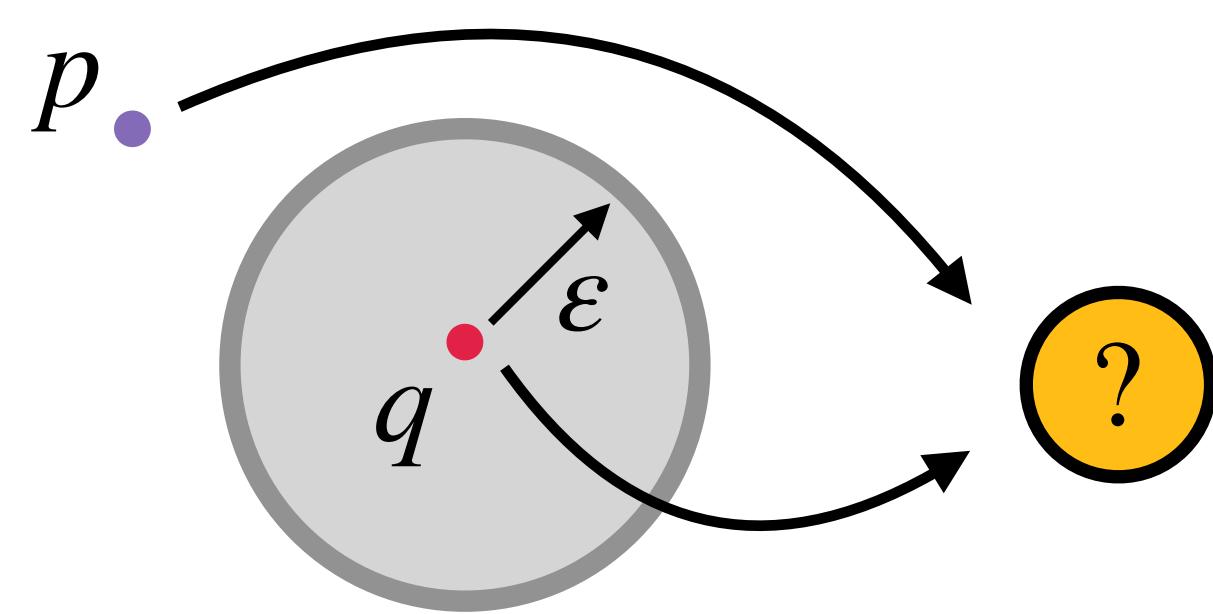
$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\nu = \Omega(E)$$

$$\neg H_B \Rightarrow \frac{1}{2}\|p - q\|_1 < \varepsilon$$

$$X_i \sim p \Rightarrow H_B$$

# Step 2: Gaussianity test



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

$$\|p - q\|_1 = \|\rho(p) - \rho(q)\|_1 \leq \|\rho(p) - G(\rho(p))\|_1 + \|G(\rho(p)) - \rho(q)\|_1$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

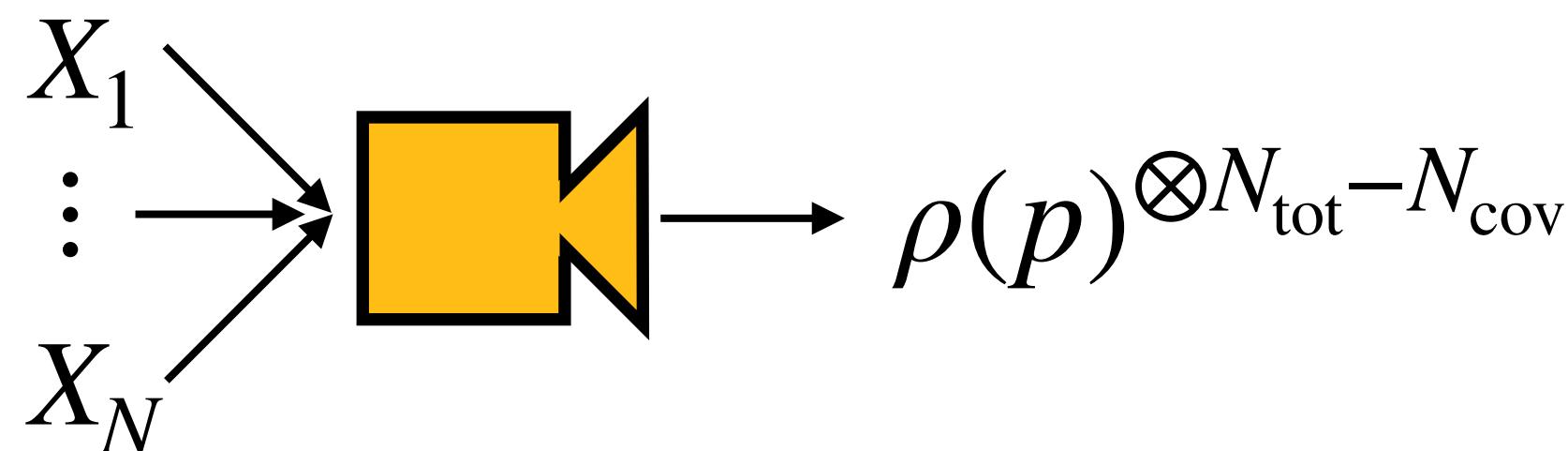
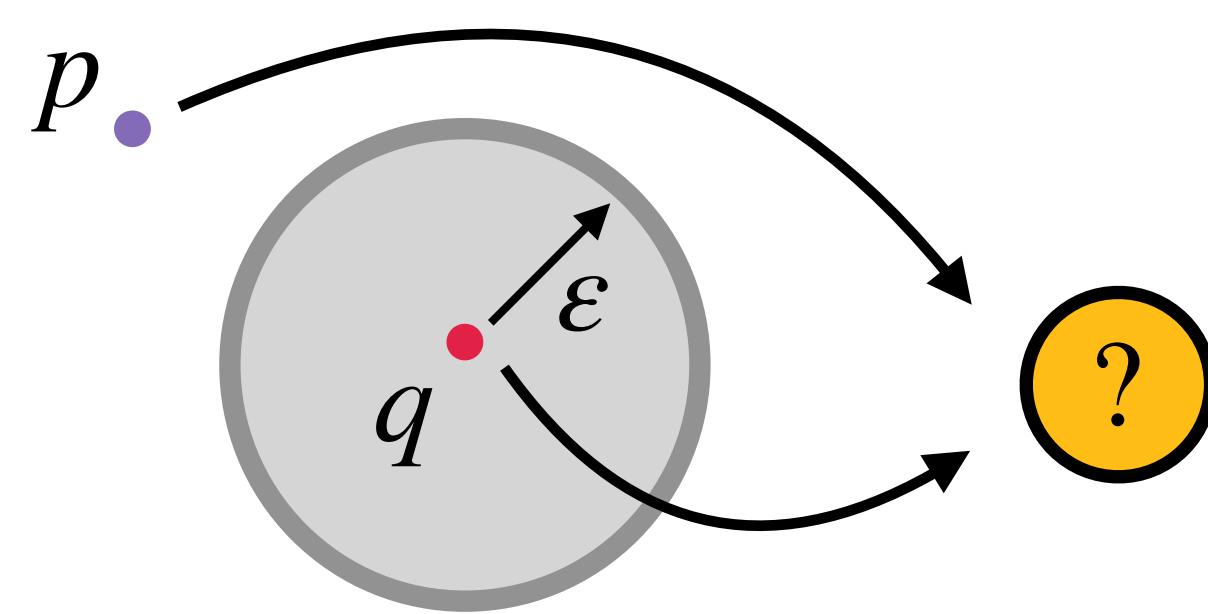
$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\nu = \Omega(E)$$

$$\neg H_B \Rightarrow \frac{1}{2}\|p - q\|_1 < \varepsilon$$

$$X_i \sim p \Rightarrow H_B$$

# Step 2: Gaussianity test



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

$$\begin{aligned} \|p - q\|_1 &= \|\rho(p) - \rho(q)\|_1 \leq \|\rho(p) - G(\rho(p))\|_1 + \|G(\rho(p)) - \rho(q)\|_1 \\ &\leq c_{nE} \left( \min_{\sigma \in \mathcal{G}_{E,\text{mixed}}} \|\rho(p) - \sigma\|_1 \right)^{1/2} + \|G(\rho(p)) - \rho(q)\|_1 \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

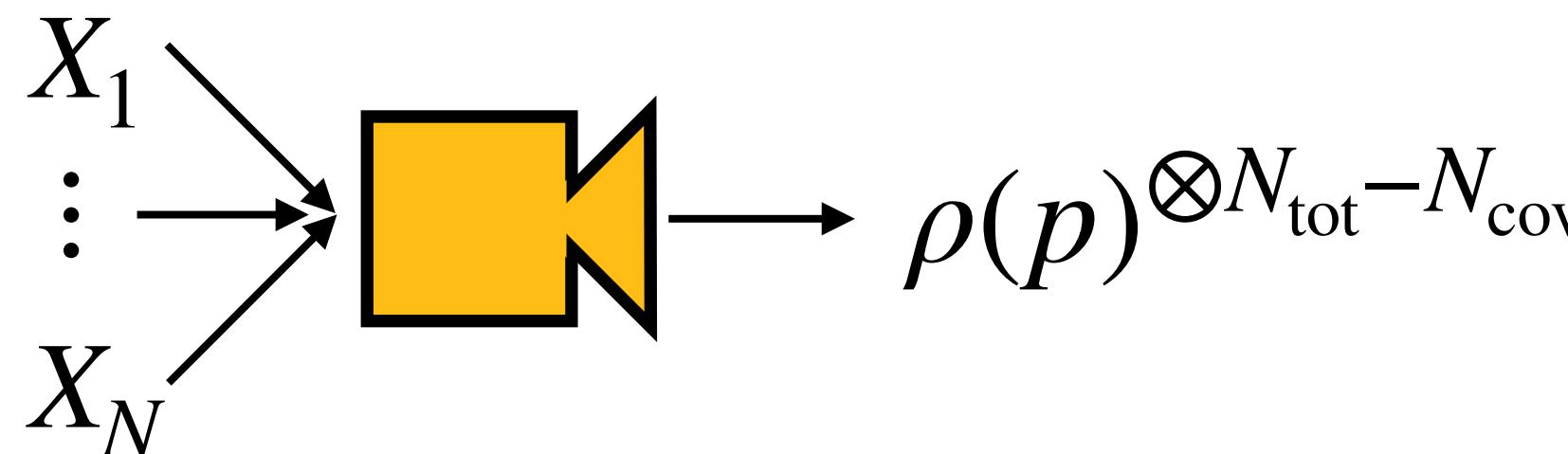
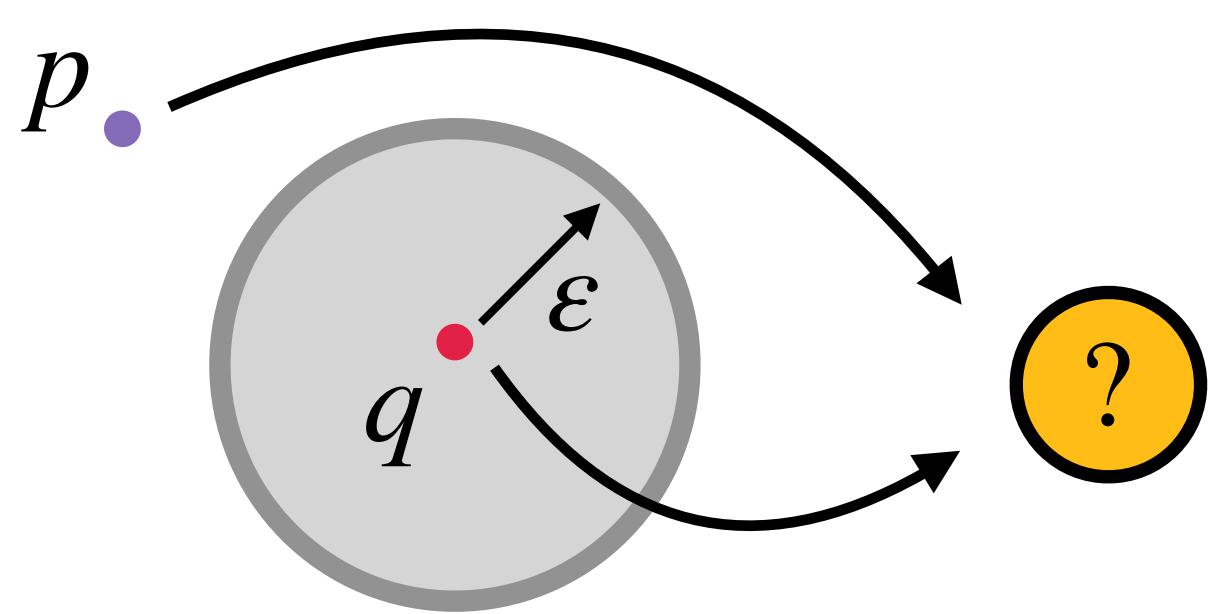
$$\nu = \Omega(E)$$

$$c_{nE} = \Theta((nE)^2)$$

$$\neg H_B \Rightarrow \frac{1}{2}\|p - q\|_1 < \varepsilon$$

$$X_i \sim p \Rightarrow H_B$$

# Step 2: Gaussianity test



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

$$\begin{aligned} \|p - q\|_1 &= \|\rho(p) - \rho(q)\|_1 \leq \|\rho(p) - G(\rho(p))\|_1 + \|G(\rho(p)) - \rho(q)\|_1 \\ &\leq c_{nE} \left( \min_{\sigma \in \mathcal{G}_{E,\text{mixed}}} \|\rho(p) - \sigma\|_1 \right)^{1/2} + \|G(\rho(p)) - \rho(q)\|_1 \\ &\leq c_{nE} \sqrt{2\varepsilon_B} + \frac{1 + \sqrt{3}}{4} \max(\text{Tr}V(p), \text{Tr}V(q)) \|V(p) - V(q)\|_\infty \end{aligned}$$

$$\neg H_B \Rightarrow \frac{1}{2}\|p - q\|_1 < \varepsilon$$

$$X_i \sim p \Rightarrow H_B$$

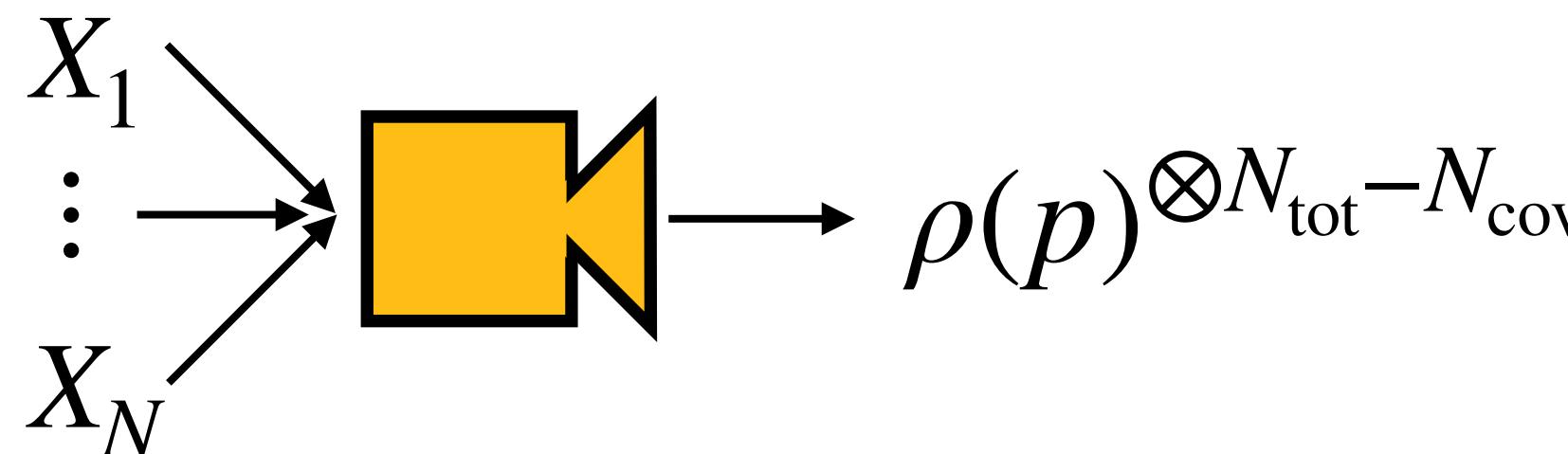
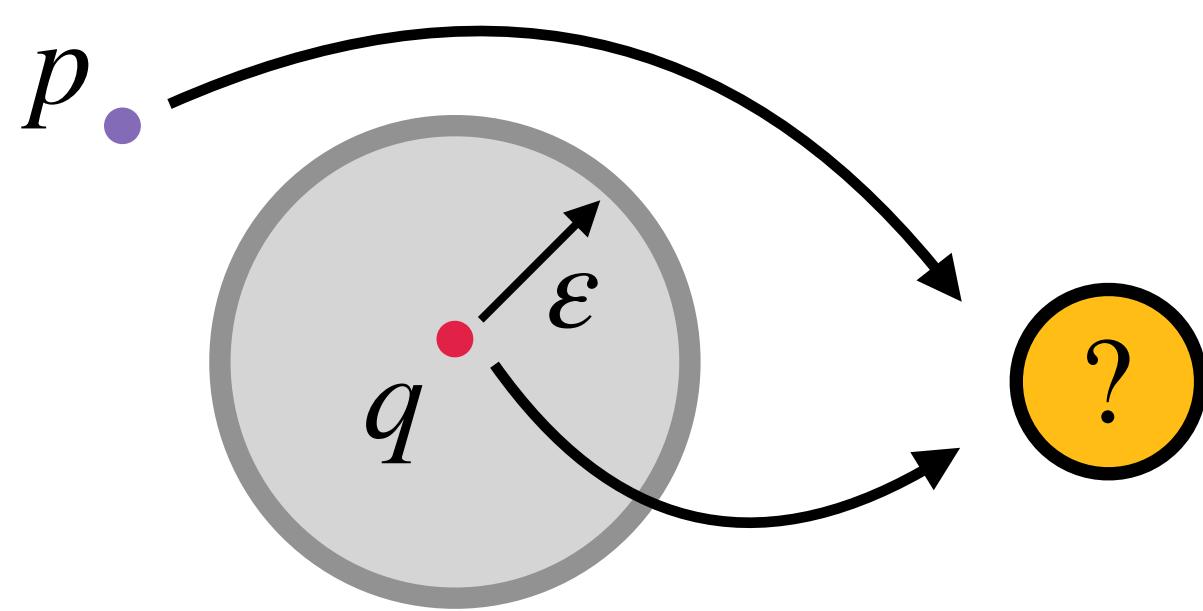
$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\nu = \Omega(E)$$

$$c_{nE} = \Theta((nE)^2)$$

# Step 2: Gaussianity test



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

**Upper bound between Gaussian states.**

$$\begin{aligned} \frac{1}{2}\|\rho(V, \mathbf{m}) - \rho(W, \mathbf{t})\|_1 &\leq \frac{1 + \sqrt{3}}{8} \max(\text{Tr}V, \text{Tr}W) \|V - W\|_\infty \quad \text{the remaining copies.} \\ \|p - q\|_1 &= \|\rho(p) - \rho(q)\|_1 \leq \|\rho(p) - G(\rho(p))\|_1 + \|G(\rho(p)) - \rho(q)\|_1 \\ &\leq c_{nE} \left( \min_{\sigma \in \mathcal{G}_{E, \text{mixed}}} \|\rho(p) - \sigma\|_1 \right)^{1/2} + \|G(\rho(p)) - \rho(q)\|_1 \\ &\leq c_{nE} \sqrt{2\varepsilon_B} + \frac{1 + \sqrt{3}}{4} \max(\text{Tr}V(p), \text{Tr}V(q)) \|V(p) - V(q)\|_\infty \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

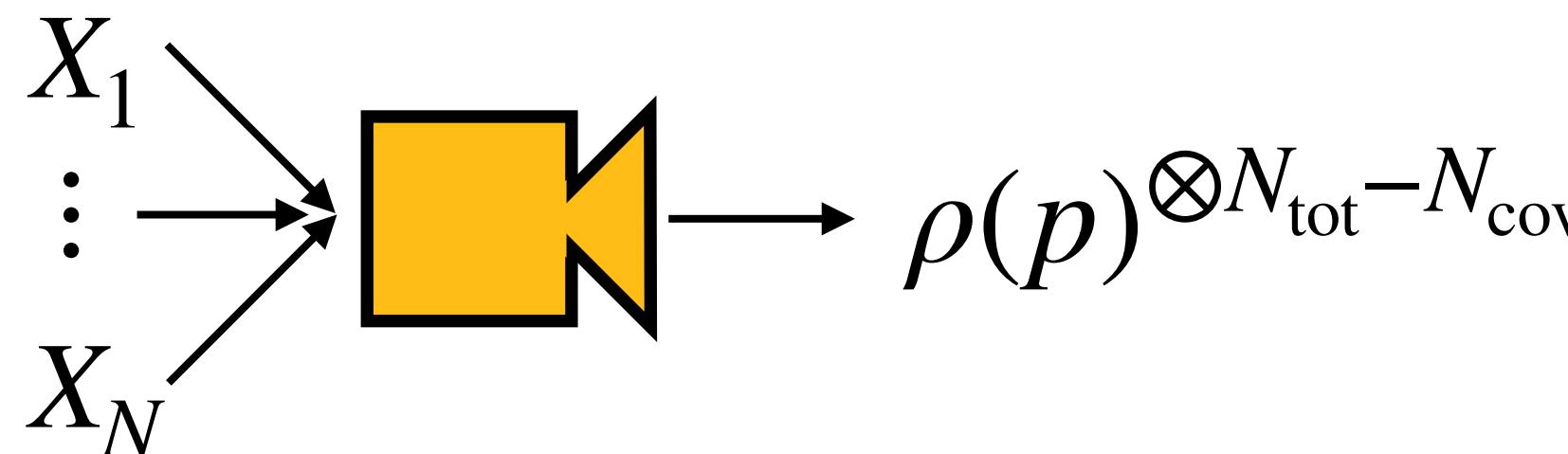
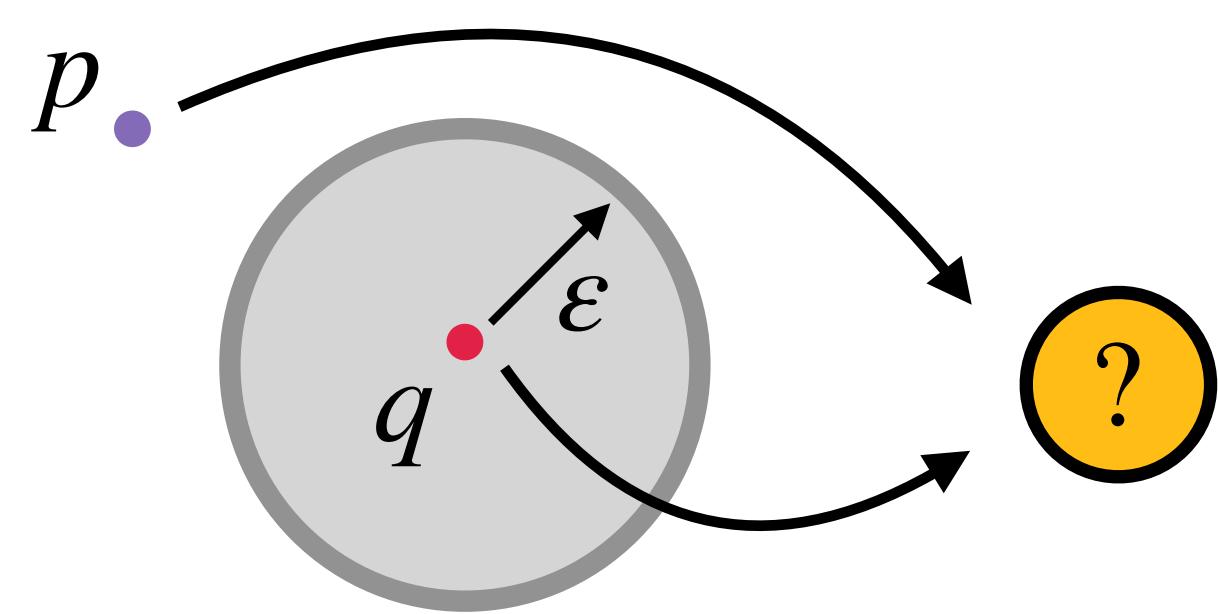
$$\nu = \Omega(E)$$

$$c_{nE} = \Theta((nE)^2)$$

$$\neg H_B \Rightarrow \frac{1}{2}\|p - q\|_1 < \varepsilon$$

$$X_i \sim p \Rightarrow H_B$$

# Step 2: Gaussianity test



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

$$\begin{aligned} \|p - q\|_1 &= \|\rho(p) - \rho(q)\|_1 \leq \|\rho(p) - G(\rho(p))\|_1 + \|G(\rho(p)) - \rho(q)\|_1 \\ &\leq c_{nE} \left( \min_{\sigma \in \mathcal{G}_{E,\text{mixed}}} \|\rho(p) - \sigma\|_1 \right)^{1/2} + \|G(\rho(p)) - \rho(q)\|_1 \\ &\leq c_{nE} \sqrt{2\varepsilon_B} + \frac{1 + \sqrt{3}}{4} \max(\text{Tr}V(p), \text{Tr}V(q)) \|V(p) - V(q)\|_\infty \end{aligned}$$

$$\neg H_B \Rightarrow \frac{1}{2}\|p - q\|_1 < \varepsilon$$

$$X_i \sim p \Rightarrow H_B$$

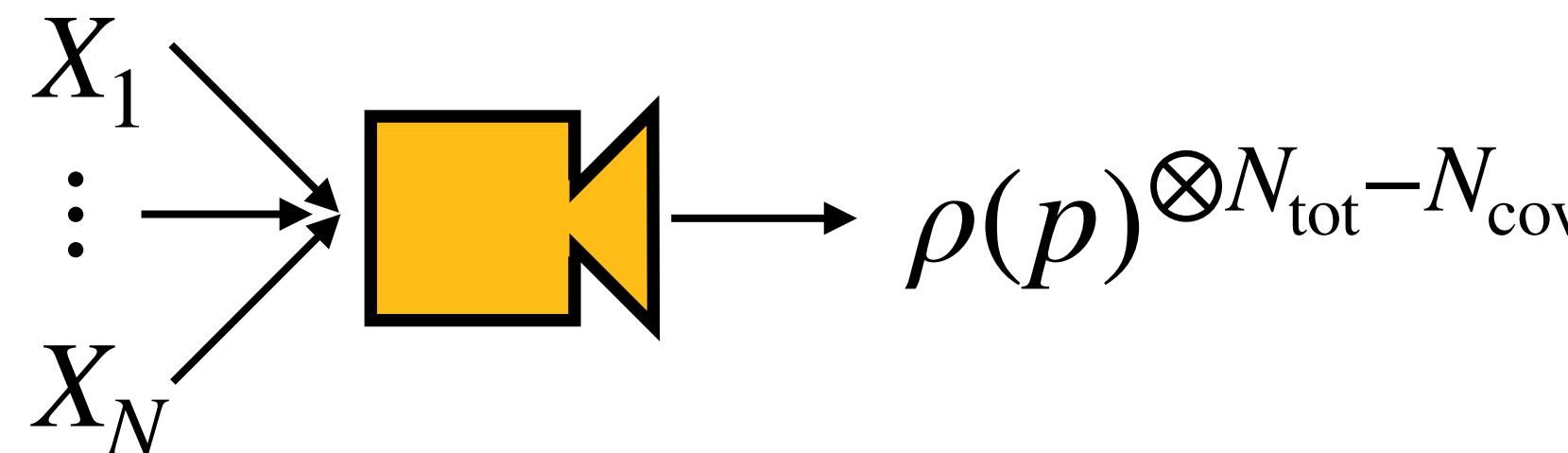
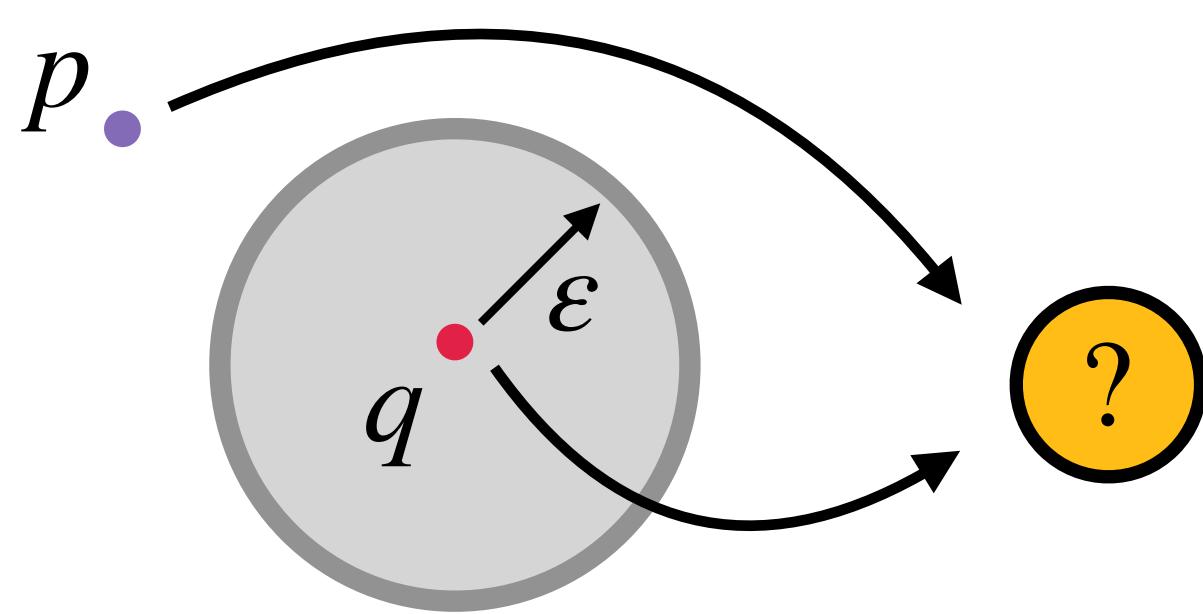
$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\nu = \Omega(E)$$

$$c_{nE} = \Theta((nE)^2)$$

# Step 2: Gaussianity test



$$\begin{aligned} \text{Tr}[\rho(q)\hat{E}^2] &\leq n^2 E^2 \\ \text{Tr}[\rho(p)\hat{E}^2] &\leq n^2 E^2 \\ \frac{1}{2}\|\rho(p) - \rho(q)\|_1 &> \varepsilon \end{aligned}$$

Otherwise, if  $\|\tilde{V}(p) - V(q)\|_2 \leq \varepsilon_V$ ,

then we run the **Gaussianity test** on the remaining copies.

$$\begin{aligned} \|p - q\|_1 &= \|\rho(p) - \rho(q)\|_1 \leq \|\rho(p) - G(\rho(p))\|_1 + \|G(\rho(p)) - \rho(q)\|_1 \\ &\leq c_{nE} \left( \min_{\sigma \in \mathcal{G}_{E,\text{mixed}}} \|\rho(p) - \sigma\|_1 \right)^{1/2} + \|G(\rho(p)) - \rho(q)\|_1 \\ &\leq c_{nE} \sqrt{2\varepsilon_B} + \frac{1 + \sqrt{3}}{4} \max(\text{Tr}V(p), \text{Tr}V(q)) \|V(p) - V(q)\|_\infty \\ &\leq \frac{1}{2}\varepsilon + (1 + \sqrt{3})nE\|V(p) - V(q)\|_2 \leq \frac{1}{2}\varepsilon + (1 + \sqrt{3})nE(2\varepsilon_V) < \varepsilon \end{aligned}$$

$$\rho(p) := \sum_{k \in \mathbb{N}^n} p(k) |k\rangle\langle k|$$

$$N_{\text{cov}} = O\left(\log(n^2) \frac{n^5 E^4}{\varepsilon^2}\right)$$

$$\nu = \Omega(E)$$

$$c_{nE} = \Theta((nE)^2)$$

$$\varepsilon \equiv 8c_{nE}^2 \varepsilon_B$$

$$\neg H_B \Rightarrow \frac{1}{2}\|p - q\|_1 < \varepsilon$$

$$X_i \sim p \Rightarrow H_B$$

# Outlook

## Results.

- two protocols to test “pure Gaussianity” (symmetry, learning) with a polynomial number of copies of  $\rho$  with respect to the system size  $n$  and with local (or even single copy) measurements;
- hardness of testing “mixed Gaussianity”, even when having access to a quantum memory.

## Open questions.

- optimal sample complexity?
- hardness even in the case  $\varepsilon_B$  constant.

（This is the case for relative entropy  $\min_{\sigma \in \mathcal{G}_E^{\text{mixed}}} D(\rho \parallel \sigma)$ .）