Learning quantum states of continuous variable systems



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Learning quantum states of continuous variable systems, <u>arXiv:2405.01431</u> (2024)



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+ Continuous Variable Systems → Our work



Extensively developed for finite-dimensional systems





Extensively developed for finite-dimensional systems

Quantum state tomography = Learning unknown quantum states





Extensively developed for **finite**-dimensional systems

Quantum state tomography = Learning unknown quantum states

Despite many (heuristic) tomography methods in quantum optics, the literature lacks "*rigorous performance guarantees*"

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Our work fills this gap



Outline

- 1. Quantum state tomography
- 2. CV systems
- 3. Quantum state tomography of CV systems:
 - A. Energy-constrained states
 - **B.** Gaussian states
 - C. t-doped Gaussian states

Quantum state tomography = Learning unknown quantum states

Experiment

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Unknown quantum state ρ





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Tomography algorithm

Classical computer

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Tomography algorithm

Classical computer

 $\tilde{\rho} \approx \rho$

$$d_{\rm tr}(\tilde{\rho},\rho) := \frac{1}{2} \|\tilde{\rho} - \frac{1}{2}\|\tilde{\rho} - \frac{1}{2}\|\tilde{\rho}\|\tilde{\rho} - \frac{1}{2}\|\tilde{\rho}\|\tilde{\rho}\|_{2} + \frac{1}{2}\|\tilde{\rho}\|_{2} + \frac{1}{2}\|$$

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Tomography ñ algorithm **Classical computer**

$$\Pr\left[d_{\mathrm{tr}}(\tilde{\rho},\rho) \leq \varepsilon\right] \geq 1 - \delta$$
$$d_{\mathrm{tr}}(\tilde{\rho},\rho) := \frac{1}{2} \|\tilde{\rho} - \rho\|_{1}$$

$\rho \in \mathcal{S}$ = some subset of the set of quantum states

$$\Pr[d_{tr}(\tilde{\rho},\rho) \leq \varepsilon] \geq 1$$

Problem 1 (Quantum state tomography)

Given N copies of the (unknown) state $\rho \in S$, the goal is to output $\tilde{\rho}$ such that $\Pr\left[d_{\mathrm{tr}}(\tilde{\rho},\rho) \leq \varepsilon\right] \geq 1-\delta$

Problem 1 (Quantum state tomography)

Given N copies of the (unknown) state $\rho \in \mathcal{S}$, the goal is to output $\tilde{\rho}$ such that $\Pr[d_{tr}(\tilde{\rho},\rho) \leq \varepsilon] \geq 1-\delta$

Definition

The sample complexity $N(\mathcal{S}, \boldsymbol{\varepsilon}, \boldsymbol{\delta})$ is the minimum N satisfying Problem 1

$$(\varepsilon, \delta) = \tilde{\Theta}\left(\frac{D^2}{\varepsilon^2}\right)$$

$$f(\mathcal{S}, \boldsymbol{\varepsilon}, \boldsymbol{\delta}) = \tilde{\Theta}\left(\frac{D}{\boldsymbol{\varepsilon}^2}\right)$$

$$,\varepsilon,\delta$$
) = $\tilde{\Theta}\left(\frac{D^2}{\varepsilon^2}\right)$

$$\left(\mathcal{S}, \boldsymbol{\varepsilon}, \boldsymbol{\delta}\right) = \tilde{\Theta}\left(\frac{D}{\boldsymbol{\varepsilon}^2}\right)$$

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CV systems

Quantum optical systems

1 *mode* 1 qudit with $d = \infty$

Hilbert space = Span{ $|0\rangle$, $|1\rangle$, \cdots , $|d\rangle$, $|d+1\rangle$, \cdots }

A **CV** system consists in *n* modes (i.e. *n* qu*d* its with $d = \infty$)

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Fock states

Vacuum state (0 photons)

(d photons)

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Without any additional prior assumption, tomography is **impossible** (*dimension*= ∞)

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In lab, CV systems have bounded energy

 $\hat{E} | k_1 \rangle \otimes | k_2 \rangle$

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 $\hat{E} = \text{energy observable}$

$$b \otimes \ldots \otimes |k_n\rangle = \left(\sum_{i=1}^n k_i\right) |k_1\rangle \otimes |k_2\rangle \otimes \ldots \otimes |k_n\rangle$$

Total number of photons

 $|k_n\rangle$

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Assumption:

The unknown state ρ satisfies $|\operatorname{Tr}[\rho \hat{E}] \leq nE$ for some known E

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Total number of photons

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Tomography of energy-constrained states

$S(n, E) := \{n \text{ mode pure state } \psi : \operatorname{Tr}[\psi \hat{E}] \leq nE \}$

Sample complexity ?

Tomography of energy-constrained states

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Sample complexity ?

Theorem

Let $\psi \in \mathcal{S}(n, E)$ be an **unknown** state.

copies of ψ are both **necessary** and **sufficient** to output $\tilde{\psi}$ such that

$$\Pr[d_{tr}(\tilde{\psi},\psi) \leq \varepsilon] \geq 1-\delta$$

Then, a number
$$N = \tilde{\Theta}\left(\frac{E^n}{\epsilon^{2n}}\right)$$
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Tomography of energy-constrained states

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CV tomography is 'extremely inefficient'

'Extreme inefficiency' of CV tomography: $N = \tilde{\Theta} \begin{pmatrix} E^n \\ \overline{\epsilon^{2n}} \end{pmatrix}$

$\varepsilon = 0.1, \ \delta t = 1 \text{ ns}$

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n-mode state with energy per mode $\leq E$

CV tomography: n = 10, E = 1

Total time = 3000 years

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• $m(\rho)$ (first moment)

• $V(\rho)$ (covariance matrix)

Fact

A Gaussian state ρ is *uniquely* identified by $m(\rho)$ and $V(\rho)$.

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Fact

A Gaussian state ρ is *uniquely* identified by $m(\rho)$ and $V(\rho)$.

(covariance matrix) • $V(\rho)$

Fundamental question

what is the resulting trace distance error on the state?

Learning quantum states of continuous variable systems, <u>arXiv:2405.01431</u> (2024)

If we estimate $m(\rho)$ and $V(\rho)$ of an unknown Gaussian state ρ with precision ε ,

Fundamental question

what is the resulting trace distance error on the state?

$\rho_{m,V} := Gaussian state$

Learning quantum states of continuous variable systems, <u>arXiv:2405.01431</u> (2024)

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If we estimate $m(\rho)$ and $V(\rho)$ of an unknown Gaussian state ρ with precision ε ,

$$||v - t||_2 + \sqrt{2||V - W||_1}$$



what is the resulting trace distance error on the state?



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If we estimate $m(\rho)$ and $V(\rho)$ of an unknown Gaussian state ρ with precision ε ,

$$|-t||_2 + \sqrt{2||V - W||_1}$$

$$\left(1, \frac{\|\mathbf{m} - \mathbf{t}\|_2}{\sqrt{4E+1}}\right), \min\left(1, \frac{\|V - W\|_2}{4E+1}\right)$$

 \leq Trace distance Error $\leq O(\sqrt{\varepsilon})$



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AS Holevo - arXiv preprint arXiv:2408.11400, 2024





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If we estimate $m(\rho)$ and $V(\rho)$ of an unknown Gaussian state ρ with precision ε ,



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[Bittel L., Mele F.A., Mele A.A., Tirone S., Lami L., *Optimal estimates of trace distance* Theorem (*Tight* inequality) between bosonic Gaussian states and applications to learning (arXiv:2411.02368)] $\frac{1}{2} \|\rho_{\mathsf{m},V} - \rho_{\mathsf{t},W}\|_{1} \le \frac{1 + \sqrt{3}}{8} \operatorname{Tr} \left\| \|V - W\| \Omega^{\mathsf{T}} \right\|_{1}$

Learning quantum states of continuous variable systems, <u>arXiv:2405.01431</u> (2024)

If we estimate $m(\rho)$ and $V(\rho)$ of an unknown Gaussian state ρ with precision ε ,

$$\left[\left(\frac{V+W}{2}\right)\Omega\right] + \sqrt{\frac{\min(\|V\|_{\infty}, \|W\|_{\infty})}{2}} \|m-t\|_{2}$$



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Learning quantum states of continuous variable systems, <u>arXiv:2405.01431</u> (2024)

If we estimate $m(\rho)$ and $V(\rho)$ of an unknown Gaussian state ρ with precision ε ,

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$$\frac{\left(\frac{V+W}{2}\right)\Omega}{2} \sqrt{\frac{\min(\|V\|_{\infty}, \|W\|_{\infty})}{2}} \|m-t\|_{2}$$

$$\frac{+\|W\|_{\infty}}{2} \|V-W\|_{1}$$





TheoremTomography of Gaussian states is efficientLet
$$\rho$$
 be an unknown n mode Gaussian state with $\operatorname{Tr}[\rho \hat{E}] \leq nE$. Then, number $N = O\left(\frac{n^7 E^4}{\varepsilon^4} \log\left(\frac{n^2}{\delta}\right)\right) = \operatorname{poly}(n)$ of state copies suffices to output $\tilde{\rho}$ such that $\Pr\left[d_{\mathrm{tr}}(\tilde{\rho}, \rho) \leq \varepsilon\right] \geq 1 - \delta$

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Improvements in our new paper!

[Bittel L., Mele F.A., Mele A.A., Tirone S., Lami L., Optimal estimates of trace distance between bosonic Gaussian states and applications to learning (arXiv:2411.02368)]

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, a



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C. t-doped Gaussian states







Definition

An *n*-mode state $|\psi\rangle$ is a "*t*-doped Gaussian state" if it is of the form





$$\cdots (G_1 W_1 G_0 | 0)^{\otimes n}$$



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Analogous results available in different settings:

- Fermionic setting [Mele A. A., Herasymenko Y., \bullet Efficient learning of quantum states prepared with few fermionic non-Gaussian gates (2024)]
- Clifford setting [Leone L., Oliviero S.F.E., Hamma A., Learning t-doped stabilizer states (2023)] [Grewal S., Iyer V., Kretschmer W., Liang D., Efficient Learning of Quantum States Prepared With Few Non-Clifford Gates (2023)]

2t-mode (non-Gaussian) unitary



Idea of the tomography algorithm (part 1)

By estimating m($|\psi \rangle \langle \psi |$) and $V(|\psi \rangle \langle \psi |)$, one can learn and undo G



Idea of the tomography algorithm (part 2)



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Perform full-state tomography on the first 2*t* modes

~ /

Theorem

If t = O(1), tomography of *t*-doped Gaussian states is efficient.







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- Sample-complexity for energy-constrained states:
 - "*Extreme inefficiency*" of CV tomography, due to the scaling: $\sim \frac{1}{\epsilon^{2n}}$;

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$$\sim \frac{1}{\varepsilon^{2n}};$$

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 - "*Extreme inefficiency*" of CV tomography, due to the scaling:
- Tomography of Gaussian states is efficient;
- Trade-off between "efficiency in tomography" and "non-Gaussianity": *t*-doped Gaussian states)
- Technical tools of independent interest:
 - Bounds on the trace distance between Gaussian states;
 - Effective dimension and effective rank of energy-constrained states;
 - Decomposition of t-doped Gaussian unitaries/states.

$$\sim \frac{1}{\varepsilon^{2n}};$$

Open problems

- Optimal sample-complexity for energy-constrained mixed states;
- Optimal sample-complexity for Gaussian states;
- Property testing of Gaussian states
- Bosonic channels:
 - A. Tomography of arbitrary bosonic channels;
 - B. Tomography of bosonic Gaussian channels.
- Classical simulability of t-doped Gaussian states

Thank you!

Backup slides

 $\hat{\mathsf{R}} := (\hat{x}_1, \hat{p}_1, \dots, \hat{x}_n, \hat{p}_n)^t$ (quadrature operator vector)

$$\hat{\mathsf{R}} := (\hat{x}_1, \hat{p}_1, \cdots, \hat{x}_n, \hat{p}_n)^{\mathsf{t}}$$
 (quadrature

Definition (Informal)

ρ is a "Gaussian state" if

for some $\beta \in (0,\infty]$ and some (quadratic) Hamiltonian \hat{H} of the form

$$\hat{H} := (\hat{\mathsf{R}} -$$

where $h \in \mathbb{R}^{2n,2n}$ is symmetric positive definite and $m \in \mathbb{R}^{2n}$.

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e operator vector)

$$e^{-\beta \hat{H}}$$

- $\rho = \frac{1}{\text{Tr}[e^{-\beta \hat{H}}]}$

 - $-m)^{t}h(\hat{R}-m),$



• $m(\rho) := Tr[\rho \hat{R}]$ (first moment)

• $V(\rho)$ (covariance matrix)

$$V_{ij}(\rho) := \operatorname{Tr} \left[\rho \left\{ \hat{R}_i - m_i(\rho) \mathbf{1}, \hat{R}_i \right\} \right]$$

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 $\hat{R}_j - m_j(\rho) \mathbf{1} \bigg\} \qquad \forall i, j \in [2n]$

 $\{A, B\} = AB + BA$

• $m(\rho) := Tr[\rho \hat{R}]$ (first moment)

(covariance matrix) • $V(\rho)$

$$V_{ij}(\rho) := \operatorname{Tr}\left[\rho\left\{\hat{R}_i - m_i(\rho)\mathbf{1}, \hat{R}_j - m_j(\rho)\mathbf{1}\right\}\right] \quad \forall i, j \in [2n]$$
$$\{A, B\} = AB + BA$$

Fact
A Gaussian state
$$\rho$$
 is *uniquely* identified





• $m(\rho) := Tr[\rho \hat{R}]$ (first moment)

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$$\{A, B\} = AB + BA$$
Estimation of ρ
Estimated in lab via Homodese Fact

A Gaussian state (ρ) is uniquely identified by (m(ρ)) and (V(ρ)).





• $m(\rho) := Tr[\rho \hat{R}]$ (first moment)

• $V(\rho)$ (covariance matrix)

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Fact
A Gaussian state
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 $\hat{R}_j - m_j(\rho) \mathbf{1} \bigg\} \qquad \forall i, j \in [2n]$

AB + BA

ed by m(ρ) and V(ρ).



n mode pure states

$\mathcal{S}(n, E)$

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 $\left(\frac{E^n}{\epsilon^{2n}} \right)^n$ **Proof sketch of** "Any tomography algorithm must satisfy $N \ge \tilde{\Theta}$ (

$\mathcal{S}(n, E) := \left\{ n \text{ mode pure state } \psi : \operatorname{Tr}[\psi \hat{E}] \le nE \right\}$





n mode pure states

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Proof sketch of "Any tomography algorithm must satisfy $N \ge \tilde{\Theta}\left(\frac{E^n}{\epsilon^{2n}}\right)$ "

E-packing net:

We construct *M* energy-constraint states

$$\{\psi_1, \psi_2, \cdots, \psi_M\} \subseteq \mathcal{S}(n, E)$$

such that

 $d_{tr}(\psi_i, \psi_j) > 2\varepsilon \quad \forall i \neq j \in [M]$

Alice



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Proof sketch of "Any tomography algorithm must satisfy $N \ge \tilde{\Theta}\left(\frac{E^n}{\varepsilon^{2n}}\right)$ "

Alice $i \in [M]$





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Proof sketch of "Any tomography algorithm must satisfy $N \ge \tilde{\Theta}\left(\frac{E^n}{\varepsilon^{2n}}\right)$ "



Proof sketch of "Any tomography algorithm must satisfy $N \geq \tilde{\Theta}$

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Proof sketch of "Any tomography algorithm must satisfy $N \geq \tilde{\Theta}$

Alice $i \in [M]$



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 E^n \sum_{ϵ} "

Bob





Proof sketch of "There is a tomography algorithm with $N = \tilde{\Theta}$

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 ϵ^{2n}

n mode states

"

$\operatorname{Tr}[\rho \hat{E}] \leq nE$



$$\dim \mathscr{H}_{\text{eff}} = \tilde{\Theta}\left(\left(\frac{E}{\varepsilon^2}\right)^n\right)$$

Hence, quantum state tomography is achievable with

$$N = \tilde{\Theta}\left(\frac{\dim \mathscr{H}_{\text{eff}}}{\varepsilon^2}\right) = \tilde{\Theta}\left(\left(\frac{E}{\varepsilon^2}\right)^n\right)$$

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Proof sketch of "There is a tomography algorithm with $N = \tilde{\Theta}\left(\frac{E^n}{\epsilon^{2n}}\right)$ "







Proof sketch of "There is a tomography algorithm with $N = \tilde{\Theta}$

Lemma

$$\mathscr{H}_{\text{eff}} := \text{Span} \left\{ |k_1\rangle \otimes |k_2\rangle \otimes \cdots \otimes |k_n\rangle : \sum_{i=1}^n k_i \le 1 \right\}$$

Let ρ such that ${\rm Tr}[\rho \hat{E}] \leq nE$. Then, the projection $\rho_{\rm eff}$ of ρ onto $\mathscr{H}_{\rm eff}$ satisfies

$$d_{\rm tr}(\rho, \rho_{\rm eff}) \leq \varepsilon$$

Hence, quantum state tomography is achievable with

$$N = \tilde{\Theta} \left(\frac{\dim \mathcal{H}_{eff}}{\varepsilon^2} \right)$$













Hence, quantum state tomography is achievable with

$$N = \tilde{\Theta}\left(\frac{r_{\text{eff}} \dim \mathscr{H}_{\text{eff}}}{\varepsilon^2}\right) = \tilde{\Theta}\left(\frac{E^{2n}}{\varepsilon^{3n}}\right).$$



 $\dim \mathscr{H}_{\text{eff}} = \tilde{\Theta} \left(\left(\frac{E}{\varepsilon^2} \right)^n \right)$

$$= \tilde{\Theta}\left(\left(\frac{E}{\varepsilon}\right)^n\right)$$



[R. O'Donnell and J. Wright, Efficient quantum tomography (2015)][J. Haah, A. W. Harrow, Z. Ji, X. Wu, and N. Yu, Sample-optimal tomography of quantum states (2017)][R. Kueng, H. Rauhut, and U. Terstiege, Low rank matrix recovery from rank one measurements (2014)]

$$(\varepsilon, \delta) = \tilde{\Theta}\left(\frac{D^2}{\varepsilon^2}\right)$$

$$(\mathcal{S}, \boldsymbol{\varepsilon}, \boldsymbol{\delta}) = \tilde{\Theta}\left(\frac{D}{\boldsymbol{\varepsilon}^2}\right)$$

$$\blacktriangleright N(\mathcal{S}, \varepsilon, \delta) = \tilde{\Theta}\left(\frac{Dr}{\varepsilon^2}\right)$$





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$$(\varepsilon, \delta) = \tilde{\Theta}\left(\frac{D^2}{\varepsilon^2}\right)$$

$$\left(\mathcal{S}, \boldsymbol{\varepsilon}, \boldsymbol{\delta}\right) = \tilde{\Theta}\left(\frac{D}{\boldsymbol{\varepsilon}^2}\right)$$

•
$$N(\mathcal{S}, \varepsilon, \delta) = \tilde{\Theta}\left(\frac{Dr}{\varepsilon^2}\right)$$

Tomography is inefficient





The term "tomography" was first introduced in Quantum Physics in the context of optical systems [Smithey, D. T. et al "Measurement of the Wigner distribution and the density matrix of a light mode using optical homodyne tomography: Application to squeezed states and the vacuum" (1993)

Despite many (heuristic) approaches validated in quantum optics labs, the literature lacks "rigorous performance guarantees"

We give guarantees wrt trace distance



Our work fills this gap

Improvement for pure Gaussian states

Theorem

Then:

$$d_{\rm tr}(\psi,\tilde{\rho}) \le \sqrt{E_{\rm tot} + \frac{n}{2}} \left(2\|\mathsf{m}(\psi) - \mathsf{m}(\tilde{\rho})\|_2^2 + \|V(\psi) - V(\tilde{\rho})\|_{\infty} \right)^{1/2}$$

Theorem

number

$$N = O\left(\frac{n^5 E^4}{\varepsilon^4} \log\left(\frac{n^2}{\delta}\right)\right)$$

of state copies suffices to output $\tilde{\rho}$ such that $\Pr[d_{tr}(\tilde{\rho}, \rho) < \varepsilon] > 1 - \delta$

Let ψ be a pure Gaussian state, let $\tilde{\rho}$ be **any** state, with $\mathrm{Tr}[\psi \hat{E}], \mathrm{Tr}[\tilde{\rho} \hat{E}] \leq E_{\mathrm{tot}}$.

Let ρ be an **unknown** *n* mode pure Gaussian state with $Tr[\rho \hat{E}] \leq nE$. Then, a



Proof idea of the sufficient condition:

_emma

$$\mathcal{H}_{\text{eff}} := \text{Span} \left\{ \left| k_1 \right\rangle \otimes \left| k_2 \right\rangle \otimes \cdots \otimes \left| k_n \right\rangle : \sum_{i=1}^n k_i \le \right| \right\}$$

Let ρ such that $\operatorname{Tr}[\rho \hat{E}] \leq nE$. Then, the projection $\rho_{\rm eff}$ of ρ onto $\mathscr{H}_{\rm eff}$ satisfies

$$d_{\rm tr}(\rho, \rho_{\rm eff}) \leq \varepsilon.$$

In addition, $\rho_{\rm eff}$ is $4\varepsilon\text{-close}$ to a state of $\mathscr{H}_{\rm eff}$ with rank

$$r_{\rm eff} = \tilde{\Theta}\left(\left(\frac{E}{\varepsilon}\right)^n\right)$$



Fundamental question

If we estimate $m(\rho)$ and $V(\rho)$ of an unknown Gaussian state ρ with precision ε , what is the resulting trace distance error on the state?

Theorem

Let $\rho, \tilde{\rho}$ be Gaussian states with $Tr[\rho E$

 $d_{\rm tr}(\rho,\tilde{\rho}) \leq \sqrt{2(E_{\rm tot}+1)} \left(\|\mathsf{m}(\rho) - \mathsf{m}(\rho)\| \right)$

Not proved via fidelity

$$\hat{E}_{j}, \operatorname{Tr}[\tilde{\rho}\hat{E}] \leq E_{\text{tot}}. \text{ Then:}$$

$$\| (\tilde{\rho}) \|_{2} + \sqrt{2 \| V(\rho) - V(\tilde{\rho}) \|_{1}}$$



Fundamental question

If we estimate $m(\rho)$ and $V(\rho)$ of an unknown Gaussian state ρ with precision ε , what is the resulting trace distance error on the state?

Theorem

Let
$$\rho, \tilde{\rho}$$
 be Gaussian states with $\operatorname{Tr}[\rho \hat{E}], \operatorname{Tr}[\tilde{\rho} \hat{E}] \leq E_{\text{tot}}$. Then:
$$d_{\text{tr}}(\rho, \tilde{\rho}) \leq \sqrt{2(E_{\text{tot}} + 1)} \left(\|\mathsf{m}(\rho) - \mathsf{m}(\tilde{\rho})\|_2 + \sqrt{2\|V(\rho) - V(\tilde{\rho})\|_1} \right)$$

Not proved via fidelity

$$\mathcal{F}(\hat{\rho}_1, \hat{\rho}_2) = \mathcal{F}_0(V_1, V_2) \exp\left[-\frac{1}{4}\delta_u^T(V_1 + V_2)^{-1}\delta_u\right]$$

$$\mathcal{F}_{0}(V_{1}, V_{2}) = \frac{F_{\text{tot}}}{\sqrt[4]{\det [V_{1} + V_{2}]}},$$

$$F_{\text{tot}}^{4} = \det \left[2 \left(\sqrt{1 + \frac{(V_{\text{aux}}\Omega)^{-2}}{4}} + 1 \right) V_{a} \right]$$

$$V_{\text{aux}} = \Omega^{T} (V_{1} + V_{2})^{-1} \left(\frac{\Omega}{4} + V_{2}\Omega V_{1} \right)$$





Notation

Hilbert space of one mode = Span $\{ |0\rangle, |1\rangle, \dots, |d\rangle, |d+1\rangle, \dots \}$ (0 photons)

$$\hat{a} := \sum_{k=1}^{\infty} \sqrt{k} |k-1\rangle \langle k|$$
 (annihilatio

$$\hat{x} := \frac{\hat{a} + \hat{a}^{\dagger}}{\sqrt{2}}$$
 (position operator)

$$\hat{p} := \frac{\hat{a} - \hat{a}^{\dagger}}{\sqrt{2}i}$$
 (momentum operator)

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Vacuum state (*d* photons)

n operator)

Definition

\hat{G} is a **Gaussian unitary** if it is a composition of $e^{-i\hat{H}_{quad}}$, where \hat{H}_{quad} is a (quadratic) Hamiltonian:

$$\hat{H}_{\text{quad}} := (\hat{R})$$

where $h \in \mathbb{R}^{2n,2n}$ is symmetric and $m \in \mathbb{R}^{2n}$.



Any pure Gaussian state $|\psi\rangle$ is of the form $|\psi\rangle = \hat{G}|0\rangle$, for some Gaussian unitary G

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 $(-m)^{t}h(\hat{R}-m),$



