

# Higher moment theory and learnability of bosonic states

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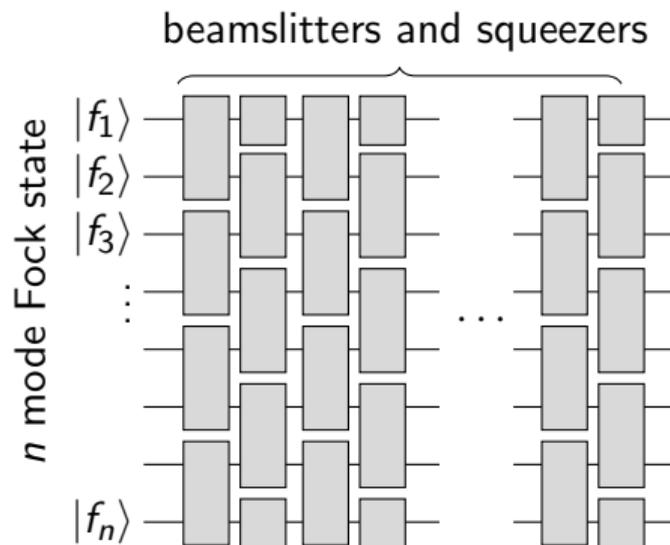
*UT Austin QI seminar, March 2, 2026*

# Introduction

- Learning (properties of) quantum states as efficiently as possible is a fundamental task in quantum information
- There is a lot of recent work on learning continuous variable (CV) states (eg. Mele, Mele, et al. 2024; Zhao, Liao, et al. 2024; Bittel, Mele, et al. 2025; Fanizza, Iyer, et al. 2025)
- Most *sample and time efficient* learning algorithms work for **Gaussian** or **near-Gaussian** states
- Learning a generic  $n$ -mode CV state requires  $\sim (\text{energy})^n$  samples (Mele, Mele, et al. 2024)

# Our goal

- Our goal is to find interesting, **highly non-Gaussian** classes of CV states with *sample and time efficient* learning algorithms
- Motivated by an open problem proposed in Aaronson and Grewal 2023, we start with **BosonSampling states**



# Overview

- 1 Introduction
- 2 First, we solve a concrete problem
  - Background
  - Problem statement
  - Solution in perfect knowledge case
  - Error analysis
  - Final theorem statement
- 3 Why did our solution work?  $G_t$  states
- 4 Outlook

# Background I

- A bosonic system of  $n$  modes is described by the creation and annihilation operators  $a_1, \dots, a_n, a_1^\dagger, \dots, a_n^\dagger$
- Equivalently, by position and momentum operators  $\mathbf{r} = (x_1, \dots, x_n, p_1, \dots, p_n)$
- These obey the CCR  $[r_i, r_j] = i\Omega_{ij}$ , with

$$\Omega = \begin{pmatrix} 0 & \mathbb{I} \\ -\mathbb{I} & 0 \end{pmatrix}$$

- A unitary transformation must preserve the CCR

$$[\mathcal{U}r_i\mathcal{U}^\dagger, \mathcal{U}r_j\mathcal{U}^\dagger] = \mathcal{U}[r_i, r_j]\mathcal{U}^\dagger = i\mathcal{U}\Omega_{ij}\mathcal{U}^\dagger = i\Omega_{ij}$$

## Background II

- A unitary transformation is called *Gaussian* if it acts affinely on  $\mathbf{r}$

$$\mathcal{U}_{S,\mathbf{d}}^\dagger r_i \mathcal{U}_{S,\mathbf{d}} = d_i + \sum_j S_{ij} r_j$$

- To preserve the CCR,  $S$  must satisfy  $S\Omega S^T = \Omega$

$$S \in \text{Sp}(2n, \mathbb{R}) := \left\{ S \in \text{GL}(2n, \mathbb{R}) \mid S\Omega S^T = \Omega \right\}$$

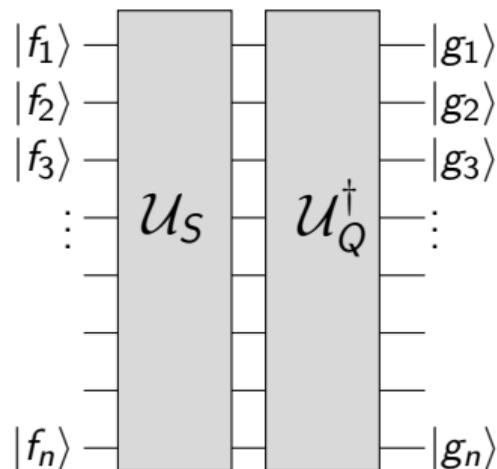
- Easy to see the composition  $\mathcal{U}_{S,\mathbf{d}}\mathcal{U}_{R,\mathbf{e}} = \mathcal{U}_{SR,R\mathbf{d}+\mathbf{e}}$
- Thus, **the group of Gaussian unitaries is**  $\text{Sp}(2n, \mathbb{R}) \ltimes \mathbb{R}^{2n}$

## Problem statement (Aaronson and Grewal 2023)

- Let  $|\mathbf{f}\rangle$  denote an unknown Fock state on  $n$  modes,  
 $\mathbf{f} = (f_1, \dots, f_n) \in \mathbb{N}_0^n$
- Let  $\mathcal{U}_S$  denote a Gaussian unitary specified by an unknown matrix  $S \in \text{Sp}(2n, \mathbb{R})$
- Let  $|\psi\rangle = \mathcal{U}_S |\mathbf{f}\rangle$

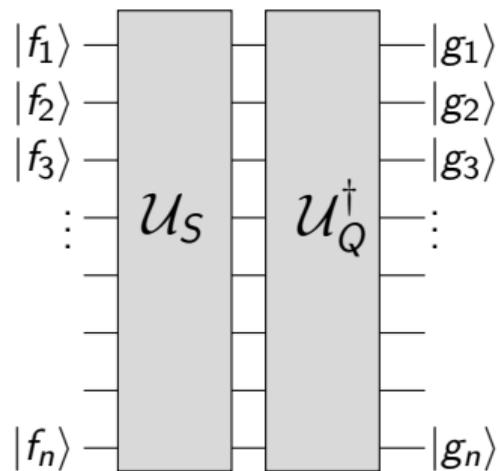
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- Given  $N$  copies of  $\psi$ , we want to learn  $\psi$  to  $\epsilon$  precision
- Find a  $\mathbf{g}$  and  $Q$  such that  $|\langle \mathbf{g} | \mathcal{U}_Q^\dagger \mathcal{U}_S | \mathbf{f} \rangle| \geq 1 - \epsilon$



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- How large must  $N$  be? *Want it be  $\leq \text{poly}(\text{energy})$*
- What is the measurement scheme?
- How hard is the classical postprocessing? *Want it be  $\leq \text{poly}(n)$*

# Analogous fermionic problem

- The analogous fermionic problem was solved in Aaronson and Grewal 2023
- Crucial difference: fermionic Fock states are Gaussian, bosonic Fock states are highly non-Gaussian

- We will solve this problem with *moments*

$$\Lambda_{i_1, \dots, i_t; j_1, \dots, j_t}^{(2t)} = \langle \psi | r_{i_1} \dots r_{i_t} r_{j_1} \dots r_{j_t} | \psi \rangle ,$$
$$(\Lambda_0^{(2t)})_{i_1, \dots, i_t; j_1, \dots, j_t} = \langle \mathbf{f} | r_{i_1} \dots r_{i_t} r_{j_1} \dots r_{j_t} | \mathbf{f} \rangle .$$

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- How do you measure moments? For the purposes of this talk, the upshot is that **poly(1/ε) copies suffice to learn the moments to ε precision** (Welsch, Vogel, et al. 1999)

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- How do you measure moments? For the purposes of this talk, the upshot is that **poly(1/ε) copies suffice to learn the moments to ε precision** (Welsch, Vogel, et al. 1999)
- For the rest of this section, we will assume that *the moments are known perfectly*

# Moment transformations

- Recall  $S \in \text{Sp}(2n, \mathbb{R})$  acts as

$$\mathcal{U}_S^\dagger r_i \mathcal{U}_S = \sum_j S_{ij} r_j$$

- How do moments transform under **arbitrary** Gaussian unitaries?

$$\begin{aligned}\Lambda_{i_1, \dots, i_t; j_1, \dots, j_t}^{(2t)} &= \langle \mathbf{f} | \mathcal{U}_S^\dagger r_{i_1} \dots r_{i_t} r_{j_1} \dots r_{j_t} \mathcal{U}_S | \mathbf{f} \rangle \\ &= \sum_{k, \ell} S_{i_1, k_1} \dots S_{i_t, k_t} S_{j_1, \ell_1} \dots S_{j_t, \ell_t} \langle \mathbf{f} | r_{k_1} \dots r_{k_t} r_{\ell_1} \dots r_{\ell_t} | \mathbf{f} \rangle \\ &= (S^{\otimes t} \Lambda_0^{(2t)} S^{T \otimes t})_{i_1, \dots, i_t; j_1, \dots, j_t}\end{aligned}$$

# Passive moment transformations

- Recall  $W \in U(n)$  acts as

$$\mathcal{U}_W^\dagger a_i \mathcal{U}_W = \sum_j W_{ij} a_j$$

- How do moments transform under **passive** Gaussian unitaries?

$$\begin{aligned}\sigma_{i_1, \dots, i_t; j_1, \dots, j_t}^{(2t)} &= \langle \psi | a_{i_1} \dots a_{i_t} a_{j_1}^\dagger \dots a_{j_t}^\dagger | \psi \rangle \\ (\sigma_0^{(2t)})_{i_1, \dots, i_t; j_1, \dots, j_t} &= \langle \mathbf{f} | a_{i_1} \dots a_{i_t} a_{j_1}^\dagger \dots a_{j_t}^\dagger | \mathbf{f} \rangle \\ \sigma^{(2t)} &= W^{\otimes t} \sigma_0^{(2t)} W^{\dagger \otimes t}\end{aligned}$$

## Reducing the problem

- By using **second moments** and linear algebra, we can reduce the problem to when the Gaussian unitary is **passive** and the Fock state is  $|b, \dots, b\rangle$
- If we were dealing with Gaussian states, this would be sufficient

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- But for us **second moments are now useless** — easy to check that for  $\mathbf{f} = (b, \dots, b)$ ,  
 $\sigma_0^{(2)} = (b + 1)\mathbb{I}$
- Therefore,  $\sigma^{(2)} = W\sigma_0^{(2)}W^\dagger = \sigma_0^{(2)}$ , so we learn nothing about  $W$  by measuring second moments

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- So now we use **fourth moments**,  $\sigma^{(4)}$

## Learning algorithm

Given the fourth moments  $\sigma^{(4)} = W^{\otimes 2} \sigma_0^{(4)} W^{\dagger \otimes 2}$  for the state  $\mathcal{U}_W |b, \dots, b\rangle$ , determine  $W$

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- Because  $\sigma_0^{(4)}$  is a matrix on  $(\mathbb{C}^n)^{\otimes 2}$ , we can represent it in bra-ket notation using the standard basis  $|1\rangle, \dots, |n\rangle$  of  $\mathbb{C}^n$

$$\sigma_0^{(4)} = (b+1)^2 (\mathbb{I} + U_{\text{SWAP}}) - b(b+1) \sum_{i=1}^n |i, i\rangle \langle i, i|,$$

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- Denote the  $i^{\text{th}}$  column vector of  $W$  by  $|w_i\rangle$ . Given access to  $\sigma^{(4)}$ , we can thus form the matrix

$$\begin{aligned} A &= \frac{1}{b(b+1)} \left( (b+1)^2(\mathbb{I} + U_{\text{SWAP}}) - \sigma^{(4)} \right) \\ &= \sum_{i=1}^n (|w_i\rangle \otimes |w_i\rangle)(\langle w_i| \otimes \langle w_i|), \end{aligned}$$

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Given access to a matrix  $A = \sum_{i=1}^n (|w_i\rangle \otimes |w_i\rangle)(\langle w_i| \otimes \langle w_i|)$ , learn  $|w_i\rangle$  (up to phases and permutations)

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- Unitarily diagonalize  $A$  and take the  $+1$  eigenvalues — we learn the eigenspace  $\text{span}\{|w_i\rangle \otimes |w_i\rangle \mid i = 1, \dots, n\}$

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- A numerical diagonalization routine will return the vectors

$$|\tilde{w}_i\rangle = \sum_{j=1}^n U_{ij} |w_j\rangle \otimes |w_j\rangle = \sum_{j=1}^n |U_{ij}| e^{i\phi_{ij}} |w_j\rangle \otimes |w_j\rangle$$

- The unitary  $U$  is totally arbitrary and unpredictable

# Learning algorithm

Given access to the vectors  $|\tilde{w}_i\rangle = \sum_{j=1}^n |U_{ij}| e^{i\phi_{ij}} |w_j\rangle \otimes |w_j\rangle$  with  $U, \phi$  unknown and arbitrary, learn  $|w_j\rangle$  (up to phases and permutations)

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- Schmidt decomposition theorem: once we have  $|\tilde{w}_i\rangle$ , the  $|U_{ij}|$  are unique up to reordering
- So we can perform the Schmidt decomposition (via SVD) to learn all the  $|w_i\rangle$  up to phases

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Subtlety: see Slide 42

# Learning algorithm

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- Schmidt decomposition theorem: once we have  $|\tilde{w}_i\rangle$ , the  $|U_{ij}|$  are unique up to reordering
- So we can perform the Schmidt decomposition (via SVD) to learn all the  $|w_j\rangle$  up to phases
- We define  $V$  to be the unitary matrix whose columns are precisely these learned vectors
- By construction,  $V$  is equal to  $W$  up to a permutation of its columns and global phases applied to the columns

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Subtlety: see Slide 42

# Learning algorithm

- In other words, we have learned the matrix  $V = W\Phi P$ , where  $\Phi$  is some arbitrary diagonal unitary matrix, and  $P$  is some arbitrary permutation matrix
- It follows that the state  $\mathcal{U}_V |b \dots b\rangle$  is the same as  $\mathcal{U}_W |b \dots b\rangle$  up to an irrelevant global phase, thereby completing the learning algorithm

# Error bounds

- Thus far, we have assumed perfect knowledge of the moments
- In practice, because we have a finite number of samples to measure, there will be an error

$$\begin{aligned}\sigma^{(2t)'} &= \sigma^{(2t)} + \varepsilon_{2t} E^{(2t)} & \|E^{(2t)}\| &\leq 1 \\ \Lambda^{(2t)'} &= \Lambda^{(2t)} + \varepsilon_{2t} F^{(2t)} & \|F^{(2t)}\| &\leq 1\end{aligned}$$

- How do we deal with this?
- Lots of perturbation theory and linear algebra
- A few interesting parts

# Passive theorem

## Theorem

- Let  $|\psi\rangle = \mathcal{U}_W |\mathbf{f}\rangle$  for an unknown unitary  $W \in \mathbb{U}(n)$  specifying an arbitrary **passive Gaussian unitary** and an arbitrary unknown Fock state  $|\mathbf{f}\rangle$
- Suppose our measurements  $\sigma^{(2)'} , \sigma^{(4)'}$  of the moment matrices  $\sigma^{(2)}, \sigma^{(4)}$  satisfy  $\|\sigma^{(2t)'} - \sigma^{(2t)}\| \leq \varepsilon_{2t}$
- Then we can **efficiently** find a  $V \in \mathbb{U}(n)$  and  $\mathbf{g}$  such that

$$|\langle \mathbf{f} | \mathcal{U}_W^\dagger \mathcal{U}_V | \mathbf{g} \rangle| \geq 1 - \frac{\gamma \|\mathbf{f}\|_\infty n}{1 - \gamma \|\mathbf{f}\|_\infty n}$$

with

$$\gamma = \varepsilon_2 \left( 32\sqrt{5}n^2(3\|\mathbf{f}\|_\infty^2 + 5\|\mathbf{f}\|_\infty + 2) + 4n \right) + 2\sqrt{5}\varepsilon_4 n$$

# General theorem

## Theorem

- Let  $|\psi\rangle = \mathcal{U}_S |\mathbf{f}\rangle$  for an unknown symplectic matrix  $S \in \text{Sp}(2n, \mathbb{R})$  specifying an **arbitrary Gaussian unitary** and an arbitrary Fock state  $|\mathbf{f}\rangle$
- Suppose our measurements  $\Lambda^{(2)'} , \Lambda^{(4)'}$  of the moment matrices  $\Lambda^{(2)}, \Lambda^{(4)}$  satisfy  $\|\Lambda^{(2t)'} - \Lambda^{(2t)}\| \leq \varepsilon_{2t}$
- Then we can efficiently find a  $Q \in \text{Sp}(2n, \mathbb{R})$  and  $\mathbf{g}$  such that

$$|\langle \mathbf{f} | \mathcal{U}_S^\dagger \mathcal{U}_Q | \mathbf{g} \rangle| \geq 1 - \mathcal{O}(\gamma e^s n \|\mathbf{f}\|_\infty)$$

with

$$\gamma = \mathcal{O}\left(\varepsilon_2^{1/8} n^{3+1/2} \|S\|^{6+1/4} \|\mathbf{f}\|_\infty^5 + \varepsilon_4 n \|S\|^5 \|\mathbf{f}\|_\infty^{2+1/2}\right)$$

## Number of measurements

- Recall that moments can be measured to precision  $\varepsilon$  with  $\text{poly}(1/\varepsilon)$  measurements (Welsch, Vogel, et al. 1999)
- From this and our theorems:

### Theorem

Let  $|\psi\rangle = \mathcal{U}_S |\mathbf{f}\rangle$  for an unknown symplectic matrix  $S \in \text{Sp}(2n, \mathbb{R})$  specifying an arbitrary Gaussian unitary and an arbitrary Fock state  $|\mathbf{f}\rangle$ .

Using  $\text{poly}(n, \|\mathbf{f}\|_\infty, \|S\|)$  copies of  $|\psi\rangle$ , with probability at least  $1 - \frac{1}{\text{poly}(n)}$  our algorithm learns  $|\psi\rangle$  to fidelity at least  $1 - \frac{1}{\text{poly}(n)}$

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Using **poly(energy)** copies of  $|\psi\rangle$ , with probability at least  $1 - \frac{1}{\text{poly}(n)}$  our algorithm learns  $|\psi\rangle$  to fidelity at least  $1 - \frac{1}{\text{poly}(n)}$

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# Gaussian states

## Definition

A Gaussian state is a thermal or ground state of a Hamiltonian that is quadratic in the quadrature operators

## Theorem

*Gaussian states are fully specified by their first two moments*

## Proof.

Let  $\rho$  be an arbitrary state and let  $\rho_G$  be a Gaussian state whose first and second moments match those of  $\rho$ . Then  $S(\rho_G) \geq S(\rho)$  with equality iff  $\rho = \rho_G$ . □

**Gaussian states are maximum entropy states subject to constraints on their first two moments**

### Definition

a  $G_t$  state is a thermal (or ground) state of a (non-degenerate) Hamiltonian that is degree  $t$  in the quadrature operators

- A  $G_t$  state is fully specified by its first  $t$  moments
- The proof of this in the mixed state case is totally analogous to the Gaussian ( $t = 2$ ) proof
- How about the pure state case?

## Pure $G_t$ states

- Suppose  $\psi$  is a  $G_t$  state; it is the ground state of  $H = \sum_i \alpha_i \hat{M}_i$  where  $\hat{M}_i$  are degree  $\leq t$  operators

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$$\begin{aligned}\langle \psi | H | \psi \rangle &= \min_{\phi} \sum_i \alpha_i \langle \phi | \hat{M}_i | \phi \rangle \\ &= \min_{m_1, m_2, \dots} \sum_i \alpha_i m_i \quad \text{st } \exists \phi, \langle \phi | \hat{M}_i | \phi \rangle = m_i\end{aligned}$$

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- Because  $H$  is non-degenerate, any state with the matching moments is  $\psi$

## Relevance to the learning algorithm

- A Fock state  $|\mathbf{f}\rangle$  is a  $G_4$  state; it is the ground state of

$$H = \sum_i (\hat{a}_i^\dagger \hat{a}_i - f_i)^2$$

- The set of  $G_t$  states is closed under the action of Gaussian unitaries (because they act affinely)
- Therefore,  $\mathcal{U}_S |\mathbf{f}\rangle$  is a  $G_4$  state
- The **first four moments suffice** to learn the state

## Learning $G_t$ states

- There is some way of learning a  $G_t$  state by measuring only the first  $t$  moments (for bosons, fermions, and qudits)
- If  $t$  is constant, there is only  $\text{poly}(n)$  numbers to measure — can this give efficient algorithms to learn arbitrary constant  $t$   $G_t$  states?

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- If  $t$  is constant, there is only  $\text{poly}(n)$  numbers to measure — can this give efficient algorithms to learn arbitrary constant  $t$   $G_t$  states?
- Main difficulty: if the moments are known to  $\varepsilon$  precision, what is the error  $f(\varepsilon)$  in the reconstructed state?
- For our algorithm we showed  $f(\varepsilon) \sim \text{poly}(1/\varepsilon)$ ; can we show this to be generally true?

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# Summary

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- Solves open problem left by Aaronson and Grewal 2023
- We construct an infinite set of Gaussian invariants for generic bosonic states using classical invariant theory of the action of symplectic group on moments, relevant for state conversion (Chabaud, Markham, et al. 2020; Hahn, Ferrini, et al. 2024)
- Lots of possible extensions!

# Extensions

- Our algorithm generalizes to a slightly larger class of states, and fails interestingly in other places
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- Can we make our algorithm have more favorable scaling with energy?
  - Our algorithm requires  $N \sim \text{poly}(n, \|\mathbf{f}\|_\infty, \|S\|)$  samples

# Extensions

- Our algorithm generalizes to a slightly larger class of states, and fails interestingly in other places
- Certain classes of states *hide information* from lower moments
- Invariants and generalizations of Wick's theorem
- Can we make our algorithm have more favorable scaling with energy?
  - Our algorithm requires  $N \sim \text{poly}(n, \|\mathbf{f}\|_\infty, \|S\|)$  samples
  - Applying (Bittel, Mele, et al. 2025), I *think* we get  $N \sim \text{poly}(n, \|\mathbf{f}\|_\infty, \log \|S\|)$

Additional slides

- 5 Additional slides
  - Theorem statements
  - Algorithm
  - Error analysis
  - Generalization of Wick's theorem

# Constant Fock theorem

## Theorem

Suppose  $\mathbf{f} = (b, \dots, b)$  for some nonnegative integer  $b$  and let  $|\psi\rangle = \mathcal{U}_W |\mathbf{f}\rangle$  for an unknown unitary  $W \in \mathbb{U}(n)$  specifying an arbitrary passive Gaussian unitary. If our measurement  $\sigma^{(4)'} of the moment matrix  $\sigma^{(4)}$  for  $|\psi\rangle$  satisfies  $\|\sigma^{(4)'} - \sigma^{(4)}\| \leq \varepsilon$ , then we can efficiently find a  $V \in \mathbb{U}(n)$  such that$

$$\|V - W\Phi P\| \leq \frac{4\sqrt{5}\varepsilon n}{b(b+1)}$$

for some (irrelevant) diagonal unitary matrix  $\Phi$  and permutation matrix  $P$ . In particular,

$$|\langle b^n | \mathcal{U}_W^\dagger \mathcal{U}_V | b^n \rangle| \geq 1 - \frac{4\sqrt{5}\varepsilon n^2 / (b+1)}{1 - 4\sqrt{5}\varepsilon n^2 / (b+1)}$$

as long as  $\varepsilon \leq \frac{b+1}{4\sqrt{5}n^2}$ .

# Passive theorem

## Theorem

Let  $|\psi\rangle = \mathcal{U}_W |\mathbf{f}\rangle$  for an unknown unitary  $W \in \mathbb{U}(n)$  specifying an arbitrary passive Gaussian unitary and an arbitrary Fock state  $|\mathbf{f}\rangle$ . If our measurements  $\sigma^{(2)'} , \sigma^{(4)'}$  of the moment matrices  $\sigma^{(2)}, \sigma^{(4)}$  satisfy  $\|\sigma^{(2t)'} - \sigma^{(2t)}\| \leq \varepsilon_{2t}$ , then we can efficiently find a  $V \in \mathbb{U}(n)$  and  $\mathbf{g}$  such that  $\|V - W\Phi P\| \leq \gamma$ , with

$$\gamma = \varepsilon_2 \left( 32\sqrt{5}n^2(3f_{\max}^2 + 5f_{\max} + 2) + 4n \right) + 2\sqrt{5}\varepsilon_4 n$$

for some diagonal unitary matrix  $\Phi$  and a permutation matrix  $P$ , and  $f_{\max} = \max_i f_i$ . Specifically,  $\mathbf{g}$  is some permutation of  $\mathbf{f}$  and  $P$  performs this permutation along with other (irrelevant) permutations within blocks of equal  $g_i$ . In particular,

$$|\langle \mathbf{f} | \mathcal{U}_W^\dagger \mathcal{U}_V | \mathbf{g} \rangle| \geq 1 - \frac{\gamma f_{\max} n}{1 - \gamma f_{\max} n}$$

as long as  $\gamma f_{\max} n < 1$ .

# General theorem

## Theorem

Let  $|\psi\rangle = \mathcal{U}_S |\mathbf{f}\rangle$  for an unknown symplectic matrix  $S \in \text{Sp}(2n, \mathbb{R})$  specifying an arbitrary Gaussian unitary and an arbitrary Fock state  $|\mathbf{f}\rangle$ . If our measurements  $\Lambda^{(2)'} , \Lambda^{(4)'}$  of the moment matrices  $\Lambda^{(2)}, \Lambda^{(4)}$  satisfy  $\|\Lambda^{(2t)'} - \Lambda^{(2t)}\| \leq \varepsilon_{2t}$ , then we can efficiently find a  $Q \in \text{Sp}(2n, \mathbb{R})$  and  $\mathbf{g}$  such that  $\|Q - S\Phi P\| \leq \gamma$ , where

$$\gamma = \mathcal{O}\left(\varepsilon_2^{1/8} e^{25s/4} n^{3+1/2} f_{\max}^5 + \varepsilon_4 e^{5s} n f_{\max}^{2+1/2}\right)$$

for some symplectic matrices  $\Phi$  and  $P$  that implement global phases and mode permutations,  $f_{\max} = \max_i f_i$ , and  $s$  is the maximum magnitude of squeezing in  $S$  (that is,  $e^s$  is the largest singular value of  $S$ ). Specifically,  $\mathbf{g}$  is some permutation of  $\mathbf{f}$  and  $P$  performs this permutation along with other (irrelevant) permutations within blocks of equal  $g_i$ . In particular,

$$|\langle \mathbf{f} | \mathcal{U}_S^\dagger \mathcal{U}_Q | \mathbf{g} \rangle| \geq 1 - \mathcal{O}(\gamma e^s n f_{\max}).$$

- 5 Additional slides
  - Theorem statements
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## Reducing the problem

- Easy to check that  $\text{Re } \Lambda_0^{(1)} = \begin{pmatrix} \frac{1}{2}\mathbb{I} + P_f & 0 \\ 0 & \frac{1}{2}\mathbb{I} + P_f \end{pmatrix}$  where  $P_f = \text{diag}\{f_1, \dots, f_n\}$
- Suppose we know  $\Lambda^{(2)}$  and  $\Lambda^{(4)}$  perfectly. Note that  $\Lambda^{(2)} = S\Lambda_0^{(1)}S^T$
- We can *symplectically diagonalize*  $\text{Re } \Lambda^{(2)}$  to yield

$$\text{Re } \Lambda^{(2)} = \text{Re } S\Lambda_0^{(1)}S^T = \text{Re } R\Lambda_0^{(1)}R^T$$

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- Note that  $R \neq S$ , however  $R^{-1}S$  is passive,  $R^{-1}S \in \operatorname{Sp}(2n, \mathbb{R}) \cap \operatorname{O}(2n) \cong \operatorname{U}(n)$

## Reducing the problem, putting it together

- $\Lambda^{(2)} = S\Lambda_0^{(2)}S^T$  and  $\Lambda^{(4)} = (S \otimes S)\Lambda_0^{(4)}(S \otimes S)^T$
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- From  $\Lambda^{(2)}$ , we learn  $R$  such that  $R^{-1}S$  is a passive Gaussian unitary
- Therefore,  $R^{-1}\Lambda^{(2)}R^{-1T}$  and  $(R^{-1} \otimes R^{-1})\Lambda^{(4)}(R^{-1} \otimes R^{-1})^T$  correspond to the state  $\mathcal{U}_W |\mathbf{f}\rangle$  for a passive  $W$
- If we can solve the passive problem to learn  $W$ , then we reapply  $R$  and we will have  $S \sim RW$

## Reducing the passive problem

- Now we just need to solve the passive problem
- Assume we know the moments  $\sigma^{(2)}$  and  $\sigma^{(4)}$  for  $\mathcal{U}_W |\mathbf{f}\rangle$  where  $\mathcal{U}_W$  is a passive Gaussian unitary

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- If we unitarily diagonalize, we will find a  $U$  such that  $\sigma^{(2)} = W \sigma_0^{(1)} W^\dagger = U \sigma_0^{(1)} U^\dagger$

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- Note  $U \neq W$ , but  $U^\dagger W$  is block diagonal,  $[U^\dagger W, P_{\mathbf{f}}] = 0$
- The passive Gaussian unitary  $U^\dagger W$  does not mix modes with different initial Fock numbers

## Reducing the passive problem, putting it together

### Example

Suppose that  $\mathbf{f} = (1, 1, 2, 2, 2)$ ; then  $U^\dagger \sigma^{(2)} U$  and  $U^{\dagger \otimes 2} \sigma^{(4)} U^{\otimes 2}$  correspond to a state

$$(\mathcal{U}_{W_1} |1, 1\rangle) \otimes (\mathcal{U}_{W_2} |2, 2, 2\rangle), \quad U^\dagger W = \begin{pmatrix} W_1 & 0 \\ 0 & W_2 \end{pmatrix}$$

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Thus, if we can solve the learning problem for each state  $\mathcal{U}_{W_i} |f_i, \dots, f_i\rangle$ , then we can reapply  $U$  to learn  $W$

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Thus, if we can solve the learning problem for each state  $\mathcal{U}_{W_i} |f_i, \dots, f_i\rangle$ , then we can reapply  $U$  to learn  $W$

- We have therefore reduced learning  $\mathcal{U}_S |\mathbf{f}\rangle$  to learning  $\mathcal{U}_W |b, \dots, b\rangle$  for unknown  $W \in \mathbb{U}(n)$  and known  $b \in \mathbb{N}_0$

## Applying higher moments

- We have so far only used second moments ( $\Lambda^{(2)}$  and  $\sigma^{(2)}$ )
- Note that  $\Lambda$  is only necessary for active Gaussian unitaries;  $\sigma$  contains all the information for passive
- If we were dealing with Gaussian states, this would be sufficient

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 $\sigma_0^{(2)} = (b + 1)\mathbb{I}$
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- Therefore,  $\sigma^{(2)} = W\sigma_0^{(2)}W^\dagger = \sigma_0^{(2)}$ , so we learn nothing about  $W$  by measuring second moments
- So now we use fourth moments,  $\sigma^{(4)}$

## Learning algorithm

Given the fourth moments  $\sigma^{(4)} = W^{\otimes 2} \sigma_0^{(4)} W^{\dagger \otimes 2}$  for the state  $\mathcal{U}_W |b, \dots, b\rangle$ , determine  $W$

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- Because  $\sigma_0^{(4)}$  is a matrix on  $(\mathbb{C}^n)^{\otimes 2}$ , we can represent it in bra-ket notation using the standard basis  $|1\rangle, \dots, |n\rangle$  of  $\mathbb{C}^n$

$$\sigma_0^{(4)} = (b+1)^2 (\mathbb{I} + U_{\text{SWAP}}) - b(b+1) \sum_{i=1}^n |i, i\rangle \langle i, i|,$$

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- Denote the  $i^{\text{th}}$  column vector of  $W$  by  $|w_i\rangle$ . Given access to  $\sigma^{(4)}$ , we can thus form the matrix

$$\begin{aligned} A &= \frac{1}{b(b+1)} \left( (b+1)^2 (\mathbb{I} + U_{\text{SWAP}}) - \sigma^{(4)} \right) \\ &= \sum_{i=1}^n (|w_i\rangle \otimes |w_i\rangle) (\langle w_i| \otimes \langle w_i|), \end{aligned}$$

## Learning algorithm

Given access to a matrix  $A = \sum_{i=1}^n (|w_i\rangle \otimes |w_i\rangle)(\langle w_i| \otimes \langle w_i|)$ , learn  $|w_i\rangle$  (up to phases and permutations)

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- Unitarily diagonalize  $A$  and take the  $+1$  eigenvalues — we learn the eigenspace  $\text{span}\{|w_i\rangle \otimes |w_i\rangle \mid i = 1, \dots, n\}$
- A numerical diagonalization routine will return the vectors

$$|\tilde{w}_i\rangle = \sum_{j=1}^n U_{ij} |w_j\rangle \otimes |w_j\rangle = \sum_{j=1}^n |U_{ij}| e^{i\phi_{ij}} |w_j\rangle \otimes |w_j\rangle$$

- The unitary  $U$  is totally arbitrary and unpredictable

# Learning algorithm

Given access to a vector  $|\tilde{w}_i\rangle = \sum_{j=1}^n |U_{ij}| e^{i\phi_{ij}} |w_j\rangle \otimes |w_j\rangle$  with  $U, \phi$  unknown and arbitrary, learn  $|w_j\rangle$  (up to phases and permutations)

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- Schmidt decomposition theorem: once we have  $|\tilde{w}_i\rangle$ , the  $|U_{ij}|$  are unique up to reordering
- So we can perform the Schmidt decomposition (via SVD) to learn all the  $|w_j\rangle$  up to phases

---

Subtlety: see Slide 42

## Learning algorithm

Given access to a vector  $|\tilde{w}_i\rangle = \sum_{j=1}^n |U_{ij}| e^{i\phi_{ij}} |w_j\rangle \otimes |w_j\rangle$  with  $U, \phi$  unknown and arbitrary, learn  $|w_j\rangle$  (up to phases and permutations)

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- So we can perform the Schmidt decomposition (via SVD) to learn all the  $|w_i\rangle$  up to phases
- We define  $V$  to be the unitary matrix whose columns are precisely these learned vectors
- By construction,  $V$  is equal to  $W$  up to a permutation of its columns and global phases applied to the columns

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Subtlety: see Slide 42

# Learning algorithm

## From Slide 14

Given access to a vector  $|\tilde{w}_i\rangle = \sum_{j=1}^n U_{ij} |w_j\rangle \otimes |w_j\rangle$  with  $U, \phi$  unknown and arbitrary, learn  $|w_j\rangle$  (up to phases and permutations)

- I had said we just perform the Schmidt decomposition
- This only gives us the true  $|w_i\rangle$  if there is no degeneracy in the  $|U_{ij}|$
- Draw  $O \in U(n)$  Haar randomly, define  $|c_i\rangle = \sum_j O_{ij} |\tilde{w}_j\rangle = \sum_j (OU)_{ij} |w_j\rangle \otimes |w_j\rangle$
- $OU$  is also Haar random, so with probability 1 the Schmidt basis is unique up to phases
- Alternatively, we show that by taking the intersection of the Schmidt decompositions of all  $|\tilde{w}_i\rangle$ , you uniquely get each  $|w_i\rangle$

# Learning algorithm

- In other words, we have learned the matrix  $V = W\Phi P$ , where  $\Phi$  is some arbitrary diagonal unitary matrix, and  $P$  is some arbitrary permutation matrix
- It follows that the state  $\mathcal{U}_V |b \dots b\rangle$  is the same as  $\mathcal{U}_W |b \dots b\rangle$  up to an irrelevant global phase, thereby completing the learning algorithm

# Summary

## Task

Using the moment matrices  $\Lambda^{(2)}$  and  $\Lambda^{(4)}$ . learn  $Q, \mathbf{g}$  such that  $\mathcal{U}_Q |\mathbf{g}\rangle = \mathcal{U}_S |\mathbf{f}\rangle$

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- **Step 1:** Symplectic diagonalization of covariance matrix  $\Lambda^{(2)}$ , learn  $R$  such that  $R^{-1}S$  is passive, thereby represented by  $W \in \mathbb{U}(n)$
- Create  $\sigma^{(2)}$  and  $\sigma^{(4)}$  from the moments  $R^{-1}\Lambda^{(2)}R^{-1T}$  and  $(R^{-1})^{\otimes 2}\Lambda^{(4)}(R^{-1T})^{\otimes 2}$

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- For each block, create  $\sigma^{(2,i)}$  from that relevant block of  $U^{\dagger \otimes 2} \sigma^{(4)} U^{\otimes 2}$

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- For each block, create  $\sigma^{(2,i)}$  from that relevant block of  $U^{\dagger \otimes 2} \sigma^{(4)} U^{\otimes 2}$
- **Step 3:** Apply the learning algorithm to each  $\sigma^{(2,i)}$ , therefore learning  $V = V_1 \oplus \dots \oplus V_k$
- Let  $Q$  be the symplectic matrix corresponding to the passive Gaussian unitary  $UV$
- Set  $Q \rightarrow RQ$

- 5 Additional slides
  - Theorem statements
  - Algorithm
  - **Error analysis**
  - Generalization of Wick's theorem

## Error in symplectic diagonalization

- A positive definite matrix  $M$  can be symplectically diagonalized  $M = SDS^T = RDR^T$
- Let  $M' = M + E = R'D'R'^T$
- One can bound  $\|D - D'\|$  in terms of  $\|E\|$
- Of course it does not make sense to bound  $\|S - R'\|$  or  $\|R - R'\|$
- Eg  $\|S - R\|$  is not bound by  $\|E\|$
- However,  $SS^T = RR^T$ ;  $\|SS^T - R'R'^T\|$  can be bound
- Using the bound on  $\|SS^T - R'R'^T\|$ , we need to bound how far  $R'^{-1}S$  is from a passive Gaussian unitary
- Bound how far  $(R'^{-1})^{\otimes 2} \Lambda^{(4)'} (R'^{-T})^{\otimes 2}$  is from error-free passive moments, send into the passive moments algorithm error analysis

## Error in passive diagonalization

- $U$  and  $W$  unitarily diagonalize the ideal  $\sigma^{(2)}$ ,  $U'$  diagonalizes  $\sigma^{(2)'$
- Need to determine how far away  $U'^{\dagger}W$  is from *any* block diagonal matrix
- This can be bound by  $\|[U'^{\dagger}W, \sigma_0^{(2)}]\|$
- Then bound how far  $U'^{\dagger \otimes 2} \sigma^{(4)'} U'^{\otimes 2}$  is from error-free block diagonal moments, send into the constant Fock algorithm error analysis

# Error in constant Fock algorithm

- Track error in matrix diagonalization
- Track error in Schmidt decomposition

- 5 Additional slides
  - Theorem statements
  - Algorithm
  - Error analysis
  - Generalization of Wick's theorem

# Wick's theorem

- Let  $\langle A \rangle \equiv \text{Tr}[\rho A]$
- If  $\rho$  is a Gaussian state with zero first moments, then Wick's theorem says eg

$$\langle x_1 x_2 x_3 x_4 \rangle = \langle x_1 x_2 \rangle \langle x_3 x_4 \rangle + \langle x_1 x_3 \rangle \langle x_2 x_4 \rangle + \langle x_1 x_4 \rangle \langle x_2 x_3 \rangle$$

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- Consider the following “algorithm” to compute sixth moments from the first four moments
  - ▶ Given the first four moments, learn the corresponding unique state, then compute the sixth moments
- Can we do better? Some generalization of Wick’s theorem?

## “Deriving” Wick’s theorem

- Because centered Gaussian states are fully specified by their second moments  $\sigma^{(2)}$ , their fourth moment must be a function of the second,  $\Sigma^{(4)}(\sigma^{(2)})$

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- Of course it must be an equivariant function,  $\Sigma^{(4)}(\mathcal{S}^{\otimes 2}\sigma^{(4)}) = \mathcal{S}^{\otimes 4}\Sigma^{(4)}(\sigma^{(4)})$
- Such functions are of the form

$$\Sigma^{(4)}(\sigma^{(4)}) = \sum_{\sigma \in \mathcal{S}_4} f_{\sigma}(\sigma^{(4)}) P_{\sigma} \sigma^{(4)} \otimes \sigma^{(4)}$$

$P_{\sigma}$  are permutations, and  $f_{\sigma}(\mathcal{S}^{\otimes 2}\sigma^{(4)}) = f_{\sigma}(\sigma^{(4)})$

## “Deriving” Wick’s theorem

- Because centered Gaussian states are fully specified by their second moments  $\sigma^{(4)}$ , their fourth moment must be a function of the second,  $\Sigma^{(4)}(\sigma^{(4)})$
- Of course it must be an equivariant function,  $\Sigma^{(4)}(S^{\otimes 2}\sigma^{(4)}) = S^{\otimes 4}\Sigma^{(4)}(\sigma^{(4)})$
- Such functions are of the form

$$\Sigma^{(4)}(\sigma^{(4)}) = \sum_{\sigma \in S_4} f_{\sigma}(\sigma^{(4)}) P_{\sigma} \sigma^{(4)} \otimes \sigma^{(4)}$$

$P_{\sigma}$  are permutations, and  $f_{\sigma}(S^{\otimes 2}\sigma^{(4)}) = f_{\sigma}(\sigma^{(4)})$

- For  $\langle x_1 x_2 x_3 x_4 \rangle$ , must be permutation symmetric, so that

$$\langle x_1 x_2 x_3 x_4 \rangle = f(\sigma^{(4)}) (\langle x_1 x_2 \rangle \langle x_3 x_4 \rangle + \langle x_1 x_3 \rangle \langle x_2 x_4 \rangle + \langle x_1 x_4 \rangle \langle x_2 x_3 \rangle)$$

- How do we find  $f(\sigma^{(4)})$ ?

## “Deriving” Wick’s theorem II

- I don’t know how to determine it from this argument alone
- For  $\sigma^{(4)}$ , the only invariants are the symplectic eigenvalues
- For a pure state, these are all 1
- Thus, this simple argument *almost* gives us Wick’s theorem for pure Gaussian states:

$$\langle x_1 x_2 x_3 x_4 \rangle \propto \langle x_1 x_2 \rangle \langle x_3 x_4 \rangle + \langle x_1 x_3 \rangle \langle x_2 x_4 \rangle + \langle x_1 x_4 \rangle \langle x_2 x_3 \rangle$$

- Can we generalize this type of argument to  $G_t$  states beyond  $t = 2$ ?
- The difficulty appears to be determining the invariant functions
- For  $t = 2$ , there are very few invariants and they are easily understood (symplectic eigenvalues)
- For larger  $t$ , there are more (this is something we characterize)

# Guess

- The guess that comes from this argument is: eg for  $G_4$  states,

$$\langle x_1 x_2 x_3 x_4 x_5 x_6 \rangle = \left[ \begin{aligned} & f_1(\sigma^{(4)}, \Sigma^{(3)}, \Sigma^{(4)}) (\langle x_1 x_2 \rangle \langle x_3 x_4 \rangle \langle x_5 x_6 \rangle + \text{permutations}) \\ & + f_2(\sigma^{(4)}, \Sigma^{(3)}, \Sigma^{(4)}) (\langle x_1 x_2 x_3 x_4 \rangle \langle x_5 x_6 \rangle + \text{permutations}) \\ & + f_3(\sigma^{(4)}, \Sigma^{(3)}, \Sigma^{(4)}) (\langle x_1 x_2 x_3 \rangle \langle x_4 x_5 x_6 \rangle + \text{permutations}) \end{aligned} \right],$$

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