

Title: Inference of effective quantum models in the asymptotic regime

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Abstract: <span>In this talk I will sketch a project which aims at the design of systematic and efficient procedures to infer quantum models from measured data. Progress in experimental control have enabled an increasingly fine tuned probing of the quantum nature of matter, e.g., in superconducting qubits. Such experiments have shown that we not always have a good understanding of how to model the experimentally performed measurements via POVMs. It turns out that the ad hoc postulation of POVMs can lead to inconsistencies. For example, when doing asymptotic state tomography via linear inversion, one sometimes recovers density operators which are significantly not positive semidefinite. Assuming the asymptotic regime, we suggest an alternative procedure where we do not make a priori assumptions on the quantum model, i.e., on the Hilbert space dimension, the prepared states or the measured POVMs. In other words, we simultaneously estimate the dimension of the underlying Hilbert space, the quantum states and the POVMs. We are guided by Occam's razor, i.e., we search for the minimal quantum model consistent with the data.</span>

# Inference of effective quantum models in the asymptotic regime

Cyril Stark

(based on arXiv:1209.5737, arXiv:1209.6499, arXiv:1210.1105)

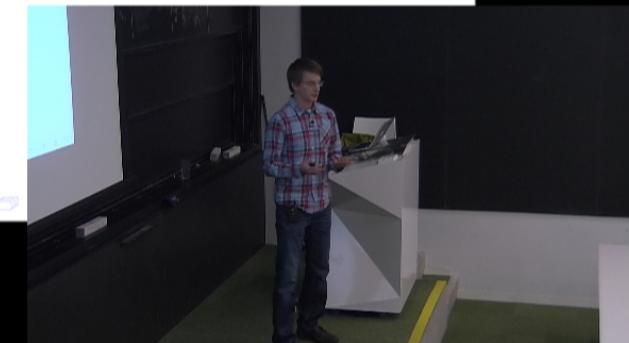
December, 2012



1. Build up quantum experiment  
Hilbert space, states, measurements **unknown**

Collect measurement data

From a quantum experiment



1. Build up quantum experiment  
Hilbert space, states, measurements **unknown**
2. Collect measurement data
3. Find a quantum model (→ this talk)



## Overview

- ▶ Setting
- ▶ Gram estimation
  - Uniqueness
  - Projective, non-degenerate measurements
  - Summary



## Overview

- ▶ Setting
  - ▶ Gram estimation
  - ▶ Uniqueness
  - ▶ Projective, non-degenerate measurements
- Summary



## Setting

- States:  $w \in \{1, \dots, W\}$
- Measurements:  $v \in \{1, \dots, V\}$
- Outcomes:  $k \in \{1, \dots, K\}$

→  $D$  is a  $V \times K$  matrix

$$D = \begin{pmatrix} \text{Probability of finding } w_1 \text{ for } v_1 & \text{Probability of finding } w_1 \text{ for } v_2 & \dots & \text{Probability of finding } w_1 \text{ for } v_K \\ \text{Probability of finding } w_2 \text{ for } v_1 & \text{Probability of finding } w_2 \text{ for } v_2 & \dots & \text{Probability of finding } w_2 \text{ for } v_K \\ \vdots & \vdots & \ddots & \vdots \\ \text{Probability of finding } w_W \text{ for } v_1 & \text{Probability of finding } w_W \text{ for } v_2 & \dots & \text{Probability of finding } w_W \text{ for } v_K \end{pmatrix}$$

→ Goal: find quantum model



## Setting

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- ▶  $f_{w,(vk)} = \frac{\#\{k|wv\}}{N_{wv}}$

D  
Data consists of triplets  $(w, v, k)$  where  $w$  is state,  $v$  is measurement,  $k$  is outcome.  
For each  $w$ ,  $v$  there is a distribution over outcomes  $k$ .  
Random variables  $w, v, k$  are jointly distributed according to  $f_{w,(vk)}$ .

Goal: find quantum model



## Setting

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Measurements:  $v \in \{1, \dots, V\}$   
Outcomes:  $k \in \{1, \dots, K\}$
- ▶  $f_{w,(vk)} = \frac{\#\{k|wv\}}{N_{wv}}$
- ▶  $\mathcal{D} = \begin{pmatrix} f_{1,(1,1)} & \cdots & f_{1,(1,K)} & \cdots & f_{1,(V,1)} & \cdots & f_{1,(V,K)} \\ f_{2,(1,1)} & \cdots & f_{2,(1,K)} & \cdots & f_{2,(V,1)} & \cdots & f_{2,(V,K)} \\ \vdots & & \vdots & & \vdots & & \vdots \\ f_{W,(1,1)} & \cdots & f_{W,(1,K)} & \cdots & f_{W,(V,1)} & \cdots & f_{W,(V,K)} \end{pmatrix}$

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- ▶ Goal: find quantum model.



## Setting

Some common approaches to find quantum models:<sup>1</sup>

- State tomography<sup>2</sup>  
(assumptions about  $\dim(\mathcal{H})$ , measurements)
- Falsification of target models, fidelity to target models<sup>3</sup>  
(relation to target model, no explicit expressions)
- Dimension witnessing<sup>4</sup>  
(lower bounds on  $\dim(\mathcal{H})$ )
- Confidence region estimators for state tomography<sup>5</sup>  
(assumptions about  $\dim(\mathcal{H})$ , measurements)
- Self-consistent quantum process tomography<sup>6</sup>  
(assumptions about  $\dim(\mathcal{H})$ , requires educated guess)

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<sup>1</sup>**Quantum model = ( $\dim(\mathcal{H})$ , states, measurements)**

Diosi et al. (2007), Brukner et al. (2009), Caves et al. (2009)

Emerson et al. (2009), Mabrook et al. (2012)

Gullans et al. (2010), Hendrickx et al. (2012)

Konstandidis-Bonner (2014), Blume-Kohout (2012)

Shankar et al. (2012)



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<sup>2</sup>[Helstrom 1976], [Hradil 1997], [Gross 2011], [Flammia et al. 2012]

• Helstrom, S. J. 1976. *Quantum Detection and Estimation Theory*. New York: Academic.

• Hradil, Z. 1997. *Quantum State Reconstruction*. Dordrecht: Kluwer.

• Gross, M., Caves, C. M., Flammia, S. T., Eisert, J., & Wolf, M. M. 2011. *Quantum tomography via linear and non-linear expectation values*. *Physical Review Letters* 107(13): 130401.

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(relation to target model; no explicit expressions)
  - Dimensional truncation  
(lower bounds on  $\dim(\mathcal{H})$ )
  - Confidence region estimators for state tomography<sup>4</sup>  
(assumptions about  $\dim(\mathcal{H})$ , measurements)
  - Self-consistent quantum process tomography<sup>5</sup>  
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<sup>3</sup>[Emerson et al. 2005], [Moroder et al. 2012]

<sup>4</sup>[Caves et al. 1996], [Caves et al. 1997]

<sup>5</sup>[Caves et al. 2002]

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<sup>4</sup>[Gallego et al. 2010], [Hendrych et al. 2012]

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<sup>6</sup>[Caves et al. 2012]



## Setting

- Our assumption: asymptotic limit, i.e.,  $N_{wv} \rightarrow \infty$ ,

$$f_{w,vk} \rightarrow p_{w,vk}$$

- Born's rule:

$$f_{w,vk} = \text{tr}(p_w E_{vk}) = \vec{p}_w^T \vec{E}_{vk}$$

- $P = (p_1 \rightarrow \vec{E}_1 \rightarrow \vec{E}_2 \rightarrow \vec{E}_3 \rightarrow \vec{E}_4 \rightarrow \cdots \vec{E}_K)$

- States-measurements Gram matrix

$$G = P^T P$$

$$\left( \begin{array}{c|c} G & D \\ \hline D & G \end{array} \right)$$

?

$$\text{rank}(D) \leq \text{rank}(G) = \text{rank}(P) = d^2$$

$$\text{rank}(P) = \text{rank}(P^T) = d^2 - \text{rank}(D) = d^2$$



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→  $P = (m_1 \cdots m_d | E_1 \cdots E_K \cdots E_{V1} \cdots E_{VK})$

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→  $\text{rank}(D) \leq \text{rank}(G) = \text{rank}(P) = d^2$

→  $\text{rank}(P) = \text{rank}(P^T) = d^2 \Rightarrow \text{rank}(D) = d^2$



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$$G = P^T P$$

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= ?

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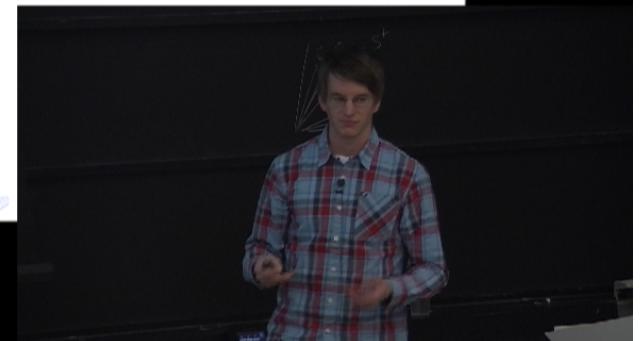
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- ▶  $\text{rank}(P_{\text{st}}), \text{rank}(P_{\text{m}}) = d^2 \Rightarrow \text{rank}(\mathcal{D}) = d^2$



## Gram estimation

- ▶ Our goal: data-compatible quantum model.
- ▶ Gigantic family of data-compatible quantum descriptions.
- ▶ Occam's razor:

$$\begin{array}{ll}\text{argmin} & \text{rank } G \\ \text{subject to} & G \in \{\text{quantum Gram matrices}\}, \\ & G = \left( \begin{array}{cc} * & \mathcal{D} \\ \mathcal{D}^T & * \end{array} \right)\end{array}$$

- NP-hard?
- Convex relaxation: hard problem → similar convex problem
- feasible set → convex feasible set
- objective function → convex objective function

---

For more information



## Gram estimation

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- ▶ NP-hard<sup>7</sup>
- ▶ Convex relaxtion: hard problem  $\mapsto$  similar convex problem
- ▶ feasible set  $\mapsto$  convex feasible set  
objective function  $\mapsto$  convex objective function

---

<sup>7</sup>[Recht, Fazel, Parillo, 2010]

## Feasible set $\mapsto$ convex feasible set

- ▶ Choose a dimension cut-off  $d_{\max}$ .

- ▶ Rough replacement

$$S_{\max} = \{\text{quantum Gram matrices}\} \subset S \cap B_{\max}(\text{quantum Gram})$$

where

$$M_{\max}(d_{\max}) := \sup\{\langle G, G \rangle : G \text{ quantum Gramian}, \dim(H) \leq d_{\max}\}$$



## Feasible set $\mapsto$ convex feasible set

- ▶ Choose a dimension cut-off  $d_{\max}$ .
- ▶ Rough replacement:

$$S^+ \supset \{\text{quantum Gram matrices}\} \mapsto S^+ \cap B_{\|\cdot\| \leq M_{QM}(d_{\max})},$$

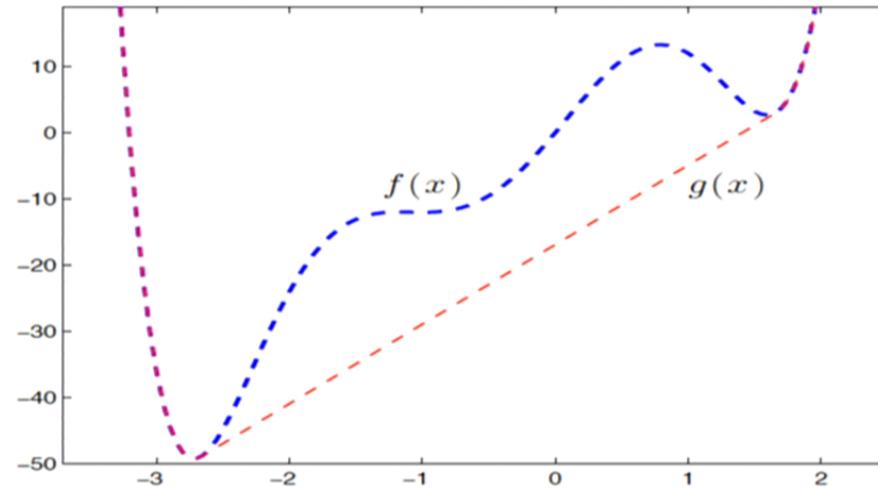
where

$$M_{QM}(d_{\max}) := \sup\{\|G - \tilde{G}\| : \tilde{G} \text{ quantum Gramian}, \dim(H) = d_{\max}\}$$



## Objective function $\mapsto$ convex objective function

- ▶  $\text{rank}(\cdot) \mapsto \text{Convex envelope of } \text{rank}(\cdot)$



## Convex relaxation

- Relaxed Gram estimation:<sup>8</sup>

$$\begin{aligned} & \operatorname{argmin} \quad \operatorname{tr} G \\ \text{subject to } & G \geq 0, \|G\| \leq M_{QM}, \\ & G = \begin{pmatrix} * & \mathcal{D} \\ \mathcal{D}^T & * \end{pmatrix} \end{aligned}$$

- Semidefinite program (SDP)

---

<sup>8</sup>See also [Fazel, Hindi, Boyd, 2001] (relaxation wrt.  $B_{\|\cdot\| \leq M_{QM}(d_{max})}$  instead of  $S^+ \cap B_{\|\cdot\| \leq M_{QM}(d_{max})}$ ).

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## Convex relaxation

- ▶ Risk:  $G_{\text{estimated}} \notin \{\text{quantum Gram matrices}\}$  possible.
  - Assume:  $\{\text{relaxed feasible}\} \subset \{\tilde{G}\}$   
 $\{\text{relaxed feasible}\} \subset \{\text{correct feasible}\}$   
because  $\emptyset \subset \{\text{correct feasible}\} \subset \{\text{relaxed feasible}\}$
  - Consequently:  $G_{\text{estimated}} \in \{\text{correct feasible}\}$ .
  - Uniqueness?  $\rightarrow$  no  
(independent of  $d$ ,  $W$ ,  $V$  and  $K$ ).

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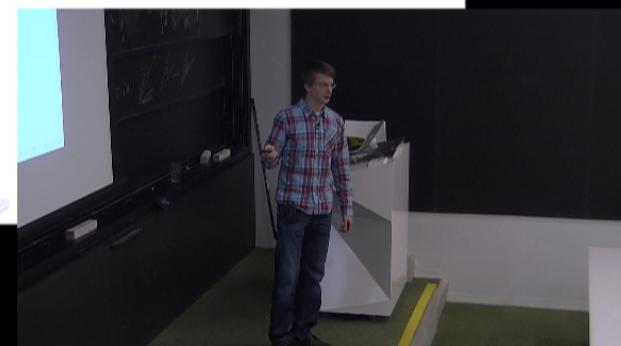
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because  $\emptyset \neq \{\text{correct feasible}\} \subseteq \{\text{relaxed feasible}\}$ .
- ▶ Consequently,  $G_{\text{estimated}} \in \{\text{correct feasible}\}$ .
- ▶ Uniqueness?  $\rightarrow$  no  
(independent of  $d$ ,  $W$ ,  $V$  and  $K$ ).



## Convex relaxation

- ▶ Risk:  $G_{\text{estimated}} \notin \{\text{quantum Gram matrices}\}$  possible.
- ▶ Assume:  $\{\text{relaxed feasible}\} = \{\tilde{G}\} \Rightarrow$ 
$$\{\text{relaxed feasible}\} = \{\text{correct feasible}\}$$
because  $\emptyset \neq \{\text{correct feasible}\} \subseteq \{\text{relaxed feasible}\}$ .
- ▶ Consequently,  $G_{\text{estimated}} \in \{\text{correct feasible}\}$ .
- ▶ Uniqueness?  $\rightarrow$  no  
(independent of  $d$ ,  $W$ ,  $V$  and  $K$ ).



## Convex relaxation

- $\exists?$  reasonable assumptions such that

$$\{\text{relaxed feasible}\} \cap \{\text{assumptions}\} = \{\tilde{G}\} \quad (*)$$

- In the remainder:  
“assumptions” = “some  $G_{ij}$ ,  $G_{ji}$ -entries are known”.

$$\begin{pmatrix} G_{ii} & P \\ P^T & G_{jj} \end{pmatrix}$$

- Known entries marked by  $\square$ .
- (\*)  $\rightarrow$  application of ideas from rigidity theory

---

The following example illustrates the application of the above ideas.



## Convex relaxation

- $\exists?$  reasonable assumptions such that

$$\{\text{relaxed feasible}\} \cap \{\text{assumptions}\} = \{\tilde{G}\} \quad (*)$$

- In the remainder:

"assumptions" = "some  $G_{st}$ ,  $G_m$ -entries are known",

$$\begin{pmatrix} G_{st} & \mathcal{D} \\ \mathcal{D}^T & G_m \end{pmatrix}$$

- Known entries marked by  $\square$
- (\*)  $\rightarrow$  application of ideas from rigidity theory

---

The following example illustrates the application of the ideas discussed so far.



## Convex relaxation

- $\exists?$  reasonable assumptions such that

$$\{\text{relaxed feasible}\} \cap \{\text{assumptions}\} = \{\tilde{G}\} \quad (*)$$

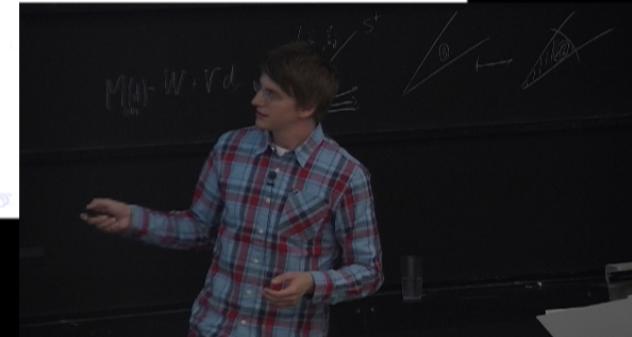
- In the remainder:

“assumptions” = “some  $G_{st}$ ,  $G_m$ -entries are known”,

$$\begin{pmatrix} G_{st} & \mathcal{D} \\ \mathcal{D}^T & G_m \end{pmatrix}$$

- Known entries marked by  $\Omega$ .

( $\Omega \subset \mathbb{N}^2$ ) → application of ideas from rigidity theory



## Convex relaxation

- $\exists?$  reasonable assumptions such that

$$\{\text{relaxed feasible}\} \cap \{\text{assumptions}\} = \{\tilde{G}\} \quad (*)$$

- In the remainder:

“assumptions” = “some  $G_{st}$ ,  $G_m$ -entries are known”,

$$\begin{pmatrix} G_{st} & \mathcal{D} \\ \mathcal{D}^T & G_m \end{pmatrix}$$

- Known entries marked by  $\Omega$ .
- $(*) \rightarrow$  application of ideas from rigidity theory<sup>9</sup>

---

<sup>9</sup>In conjunction with  $d^2 = \text{rank}(\mathcal{D})$ , or scan through  $d \leq d_{\max}$ .

## Uniqueness analysis aiming at $\{\text{relaxed feasible}\} = \{\tilde{G}\}$

- Let  $\vec{p}_1, \dots, \vec{p}_n \in \mathbb{R}^{d^2}$  arbitrary and generic.

- Set  $G_0 = \rho^T \vec{p}_0$ ,  $G = \mathbb{R}^{d^2 \times d^2}$ .

- Known entries marked by  $\Omega_0$ .

- Q: Does  $G_0$  uniquely determine  $G$ ?

- A:  $G$  unique? ...

$$\text{rank}(\nabla_{\vec{p}} G_{0,\Omega_0}(P), \dots, \nabla_{\vec{p}} G_{0,\Omega_0 \cup \Omega_1}(P)) = d^2 n - \frac{1}{2} d^2(d^2 - 1)$$

- "Asimov-Roth Theorem"

- $G_0$  unique due to additional assumptions ...

$$\text{rank}(\nabla_{\vec{p}} G_{0,\Omega_0}(P), \dots, \nabla_{\vec{p}} G_{0,\Omega_0 \cup \Omega_1}(P)) = d^2 n - \frac{1}{2} d^2(d^2 - 1)$$

## Uniqueness analysis aiming at $\{\text{relaxed feasible}\} = \{\tilde{G}\}$

- ▶ Let  $\vec{p}_1, \dots, \vec{p}_n \in \mathbb{R}^{d^2}$  arbitrary and generic.
- ▶ Set  $G_{ij} = \vec{p}_i^T \vec{p}_j$ ,  $G \in \mathbb{R}^{n \times n}$ .
- ▶ Known entries marked by  $\Omega$ .
  - Q: Does  $G_\Omega$  uniquely determine  $G$ ?
  - A:  $G$  unique?

$$\text{rank}(\nabla_{\vec{p}} G_{\Omega, \vec{p}}(P), \dots, \nabla_{\vec{p}} G_{\Omega, \vec{p}_{n-1}}(P)) = d^2 n - \frac{1}{2} d^2(d^2 - 1)$$

- ▶ "Asimov-Roth Theorem"
- ▶  $G_{\Omega, \vec{p}}$  unique due to additional assumptions

$$\text{rank}(\nabla_{\vec{p}} G_{\Omega, \vec{p}}(P), \dots, \nabla_{\vec{p}} G_{\Omega, \vec{p}_{n-1}}(P)) = d^2 n$$

---

Physical interpretation



## Uniqueness analysis aiming at $\{\text{relaxed feasible}\} = \{\tilde{G}\}$

- ▶ Let  $\vec{p}_1, \dots, \vec{p}_n \in \mathbb{R}^{d^2}$  arbitrary and generic.
- ▶ Set  $G_{ij} = \vec{p}_i^T \vec{p}_j$ ,  $G \in \mathbb{R}^{n \times n}$ .
- ▶ Known entries marked by  $\Omega$ .
- ▶ Q: Does  $G_\Omega$  uniquely determine  $G$ ?
- ▶ A:  $G$  unique<sup>10</sup>  $\Leftrightarrow$

$$\text{rank} \left( \vec{\nabla}_P G_{k_1, l_1}(P), \dots, \vec{\nabla}_P G_{k_{|\Omega|}, l_{|\Omega|}}(P) \right) = d^2 n - \frac{1}{2} d^2(d^2 - 1)$$

- ▶ "Asimov-Roth Theorem"
- ▶  $G$  unique due to additional assumptions

$$\text{rank} \left( \vec{\nabla}_P G_{k_1, l_1}(P), \dots, \vec{\nabla}_P G_{k_{|\Omega|}, l_{|\Omega|}}(P) \right) = d^2 n$$

---

<sup>10</sup>Up to discrete symmetries.



## Uniqueness analysis aiming at $\{\text{relaxed feasible}\} = \{\tilde{G}\}$

- ▶ Let  $\vec{p}_1, \dots, \vec{p}_n \in \mathbb{R}^{d^2}$  arbitrary and generic.
- ▶ Set  $G_{ij} = \vec{p}_i^T \vec{p}_j$ ,  $G \in \mathbb{R}^{n \times n}$ .
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- ▶ “Asimow-Roth Theorem”
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- ▶ “Asimow-Roth Theorem”
- ▶  $G_{\text{quantum}}$  unique due to additional assumptions  $\Leftarrow$

$$\text{rank} \left( \vec{\nabla}_P G_{k_1, l_1}(P), \dots, \vec{\nabla}_P G_{k_{|\Omega|}, l_{|\Omega|}}(P) \right) = d^2 n - \frac{1}{2} d^2(d^2 - 1)$$

---

<sup>10</sup>Up to discrete symmetries.

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---

<sup>10</sup>Up to discrete symmetries.

## Phase diagrams

- ▶ Goal: answer uniqueness-question before knowing  $P$
- ▶ Possible for generic  $P$ .<sup>11</sup>
- ▶ Universality → phase diagrams valid for generic states-measurement configurations  $P$

---

<sup>11</sup>See also [Cucuringu, Singer, 2010] (no proof)



## Phase diagrams, examples (2D)

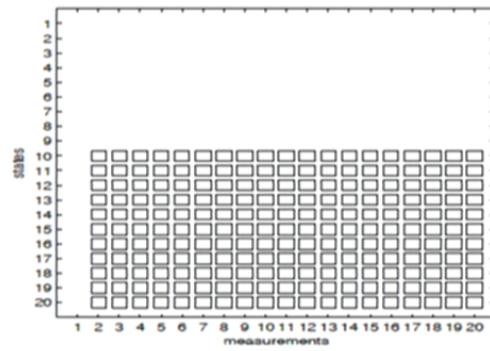


Figure: Pure states.

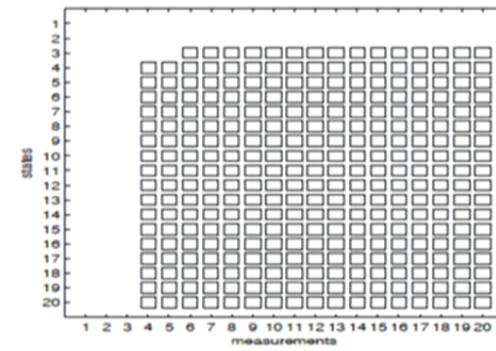


Figure: Projective measurements.



## Phase diagrams, examples (4D)

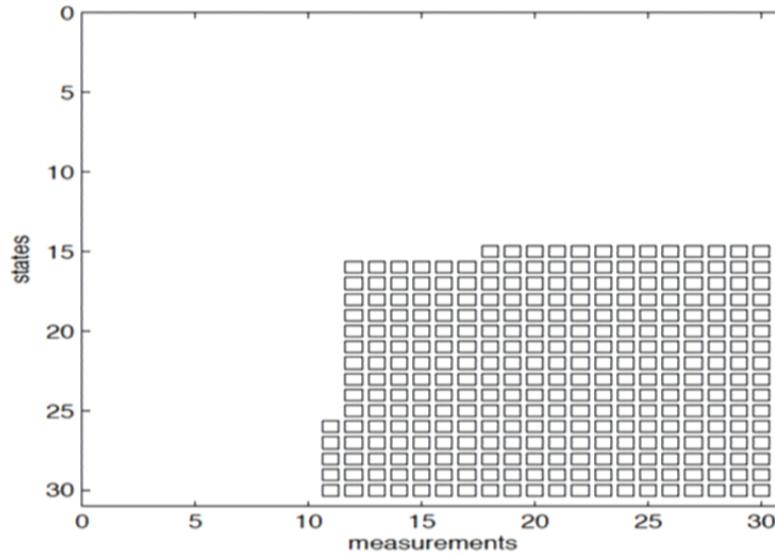
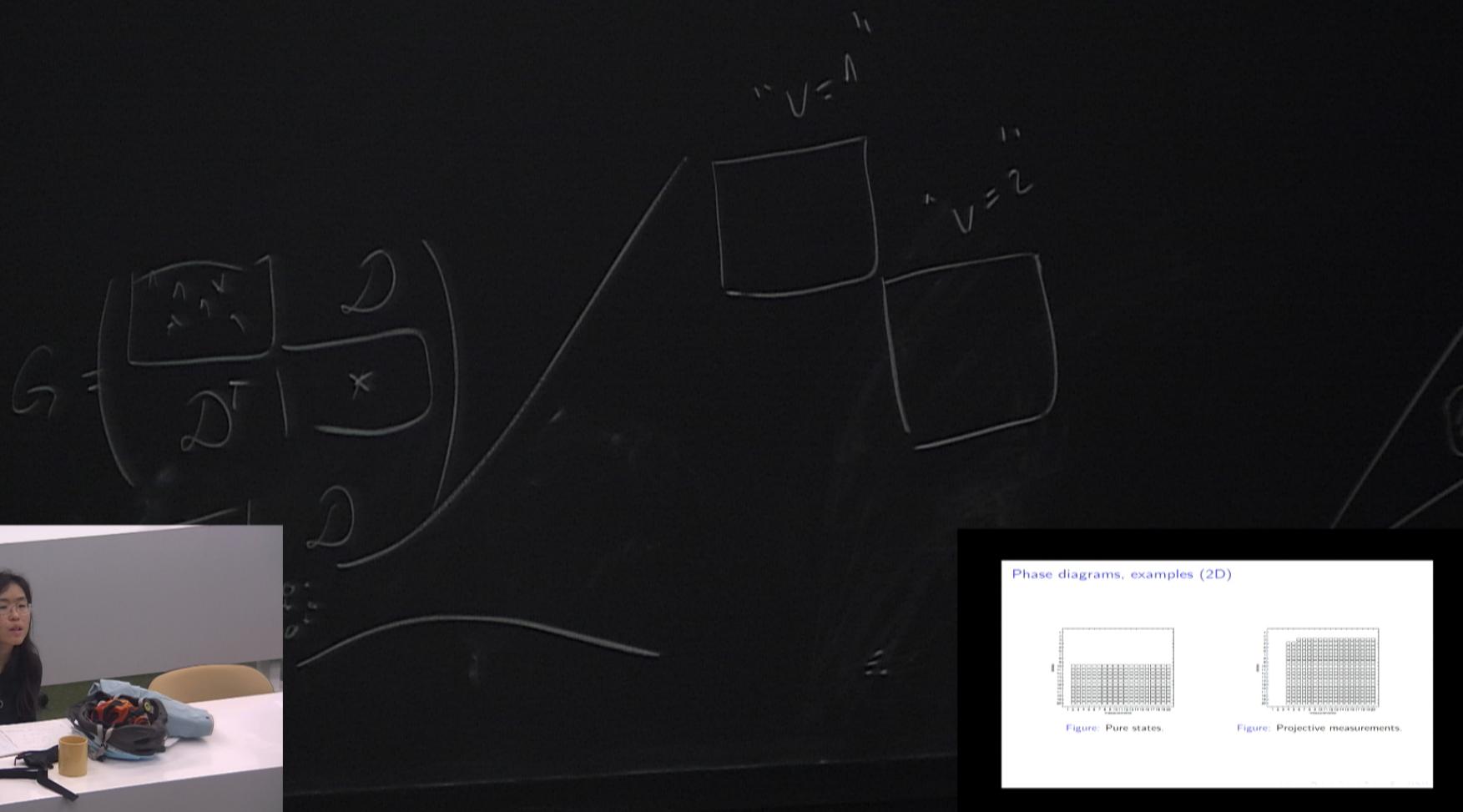


Figure: Pure states and projective, non-degenerate measurements.





Phase diagrams, examples (2D)

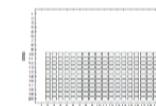


Figure: Pure states.

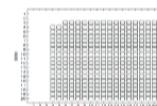


Figure: Projective measurements.

$$G = \begin{pmatrix} D & D \\ D^T & * \end{pmatrix}$$

$$G = \begin{pmatrix} * & D \\ D^T & D \end{pmatrix}$$

"V=1"

1	1	2
2	0	1
1	0	1

"V=2"



Phase diagrams, examples (2D)

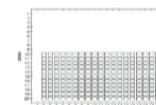


Figure: Pure states.

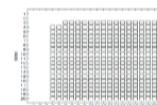


Figure: Projective measurements.

$$G = \begin{pmatrix} D & D^T \\ D^T & X \end{pmatrix}$$

"V=1"

1	1	2				
1	0	1	0	0		
2	0	0	1	0		
	0	0	0	1		
	0	0	0	0	1	

"V=2"



Phase diagrams, examples (2D)

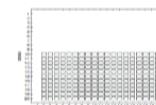


Figure: Pure states.

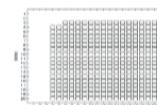


Figure: Projective measurements.

## Overview

- ▶ Setting
- ▶ Gram estimation
- ▶ Uniqueness
- ▶ Projective, non-degenerate measurements
- ▶ Summary



## Projective, non-degenerate measurements

- Recall that

$$G = \begin{pmatrix} G_{\text{st}} & \mathcal{D} \\ \mathcal{D}^T & G_m \end{pmatrix}$$

- Assume measurements are projective, non-degenerate, and states are post-measurement states.
- Then,  $\rho_{\text{st}} = E_{\text{st}}$ .

$$\mathcal{D} = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{pmatrix} \quad (\star)$$

Assume  $\dim(\mathcal{H}) = d$  and  $(\star)$ . Then,  $\rho_{\text{st}} = E_{\text{st}}$  and  $G_{\text{st}} = P = G_m$ .



## Projective, non-degenerate measurements

- ▶ Recall that

$$G = \begin{pmatrix} G_{\text{st}} & \mathcal{D} \\ \mathcal{D}^T & G_m \end{pmatrix}$$

- ▶ Assume: measurements are projective, non-degenerate, and states are post-measurement states.
- ▶ Then  $\rho_{\text{st}} = E_{\text{st}}$

$$\mathcal{D} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad (1)$$

Assume  $\dim(\mathcal{H}) = d$  and (1). Then  $\rho_{\text{st}} = E_{\text{st}}$  and  $G_{\text{st}} = P = G_m$ .



## Projective, non-degenerate measurements

- ▶ Recall that

$$G = \begin{pmatrix} G_{\text{st}} & \mathcal{D} \\ \mathcal{D}^T & G_m \end{pmatrix}$$

- ▶ Assume: measurements are projective, non-degenerate, and states are post-measurement states.
- ▶ Then,  $\rho_{vk} = E_{vk} \Rightarrow$

$$\mathcal{D} = \begin{pmatrix} \mathbb{I}_d & * & * \\ * & \ddots & * \\ * & * & \mathbb{I}_d \end{pmatrix}. \quad (*)$$

Assume  $\dim(\mathcal{H}) = d$  and  $(*)$ . Then,  $\rho_{vk} = E_{vk}$  and  $G_{\text{st}} = D = G_m$ .



## Projective, non-degenerate measurements

- ▶ Recall that

$$G = \begin{pmatrix} G_{\text{st}} & \mathcal{D} \\ \mathcal{D}^T & G_m \end{pmatrix}$$

- ▶ Assume: measurements are projective, non-degenerate, and states are post-measurement states.
- ▶ Then,  $\rho_{vk} = E_{vk} \Rightarrow$

$$\mathcal{D} = \begin{pmatrix} \mathbb{I}_d & * & * \\ * & \ddots & * \\ * & * & \mathbb{I}_d \end{pmatrix}. \quad (*)$$

### Theorem (Converse)

Assume  $\dim(\mathcal{H}) = d$  and (\*). Then,  $\rho_{vk} = E_{vk}$ , and  $G_{\text{st}} = \mathcal{D} = G_m$ .



## Representative density matrices and POVM elements

► arXiv:1210.1105



## Summary

- ▶ Gram estimation guided by Occam's razor
  - ~~ rank minimization (NP-hard)
- ▶ Convex relaxation
- ▶ Observation:  $G_{\text{estimated}} \notin \{\text{quantum Gram matrices}\}$  possible.
  - ~~ Uniqueness analysis (of independent interest)
- ▶ Special case: projective, non-degenerate measurements

Representative density matrices and POVMs via a heuristic procedure



## Summary

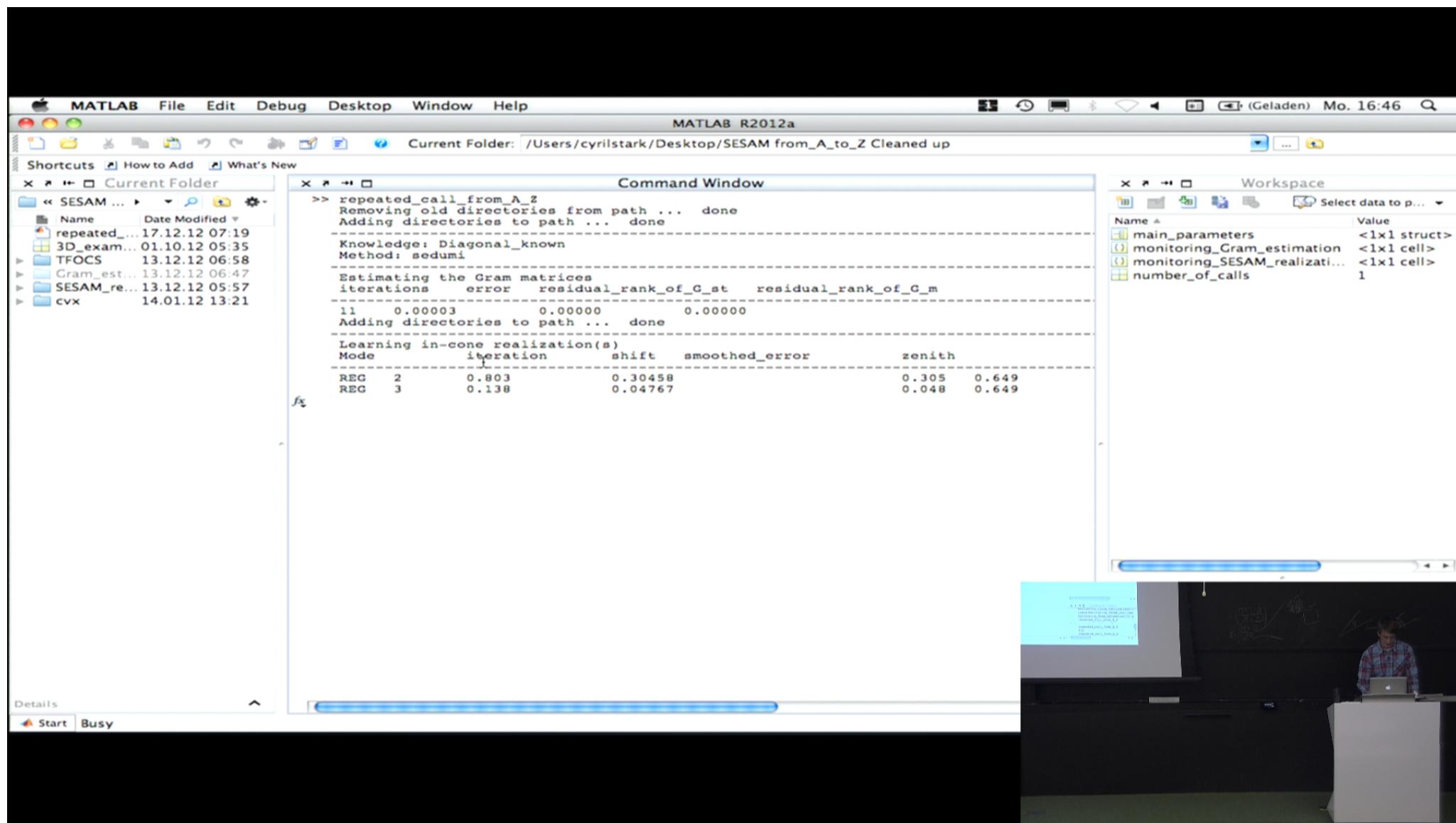
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- ▶ Representative density matrices and POVMs via a heuristic procedure.



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Thank you!



MATLAB File Edit Debug Desktop Window Help

MATLAB R2012a

Current Folder: /Users/cyrilstark/Desktop/SESAM from\_A\_to\_Z Cleaned up

Shortcuts How to Add What's New

Current Folder

Name Date Modified

- repeated... 17.12.12 07:19
- 3D\_exam... 01.10.12 05:35
- TFOCS 13.12.12 06:58
- Gram\_est... 13.12.12 06:47
- SESAM\_re... 13.12.12 05:57
- cvx 14.01.12 13:21

Command Window

```
>> repeated_call_from_A_Z
Removing old directories from path ... done
Adding directories to path ... done
Knowledge: Diagonal_known
Method: sedumi
Estimating the Gram matrices
iterations error residual_rank_of_G_st residual_rank_of_G_m
11 0.00003 0.00000 0.00000
Adding directories to path ... done
Learning in-comp realization(s)
Mode iteration shift smoothed_error zenith
REG 2 0.803 0.30458 0.305 0.649
REG 3 0.138 0.04767 0.048 0.649
REG 4 0.028 0.01109 0.011 0.649
REG 5 0.007 0.00352 0.004 0.649
REG 6 0.002 0.00127 0.001 0.649
monitoring_SESAM_realizations =
    DimHR: 2
    numberOfStates: 10
    numberOfMeas: 10
    answers: [1 2]
    random_lb_POVM: 1
    random_ub_POVM: 1
    random_lb_state: 1
    random_ub_state: 1
    used_iterations: 6
    iteration_part_one: 6
    smoothed_history: [1x160 double]
    running_time: 11.3531
    gram_corr: [30x30 double]
    gram_result: [30x30 double]
    rho_est: {1x10 cell}
    POVM_est: {10x2 cell}
    final_error: 0.0033
f8 >>
```

Workspace

Name	Type	Value
main_parameters	<1x1 struct>	
monitoring_Gram_estimation	<1x1 cell>	
monitoring_SESAM_realizati...	<1x1 cell>	
number_of_calls		1



Pirsa: 12120042

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MATLAB File Edit Debug Desktop Window Help

MATLAB R2012a

Current Folder: /Users/cyrilstark/Desktop/SESAM from\_A\_to\_Z Cleaned up

Shortcuts How to Add What's New

Current Folder

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- repeated... 17.12.12 07:19
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REG 4 0.028 0.01109 0.011 0.649
REG 5 0.007 0.00352 0.004 0.649
REG 6 0.002 0.00127 0.001 0.649
monitoring_SESAM_realizations =
DimHR: 2
numberOfStates: 10
numberOfMeas: 10
answers: [1 2]
random_lb_POVM: 1
random_ub_POVM: 1
random_lb_state: 1
random_ub_state: 1
used_iterations: 6
iteration_part_one: 6
smoothed_history: [1x160 double]
running_time: 11.3531
gram_corr: [30x30 double]
gram_result: [30x30 double]
rho_est: {1x10 cell}
POVM_est: {10x2 cell}
final_error: 0.0033
fx >> monitoring_Gram_estimation{1}.gram_corr(1,3)
```

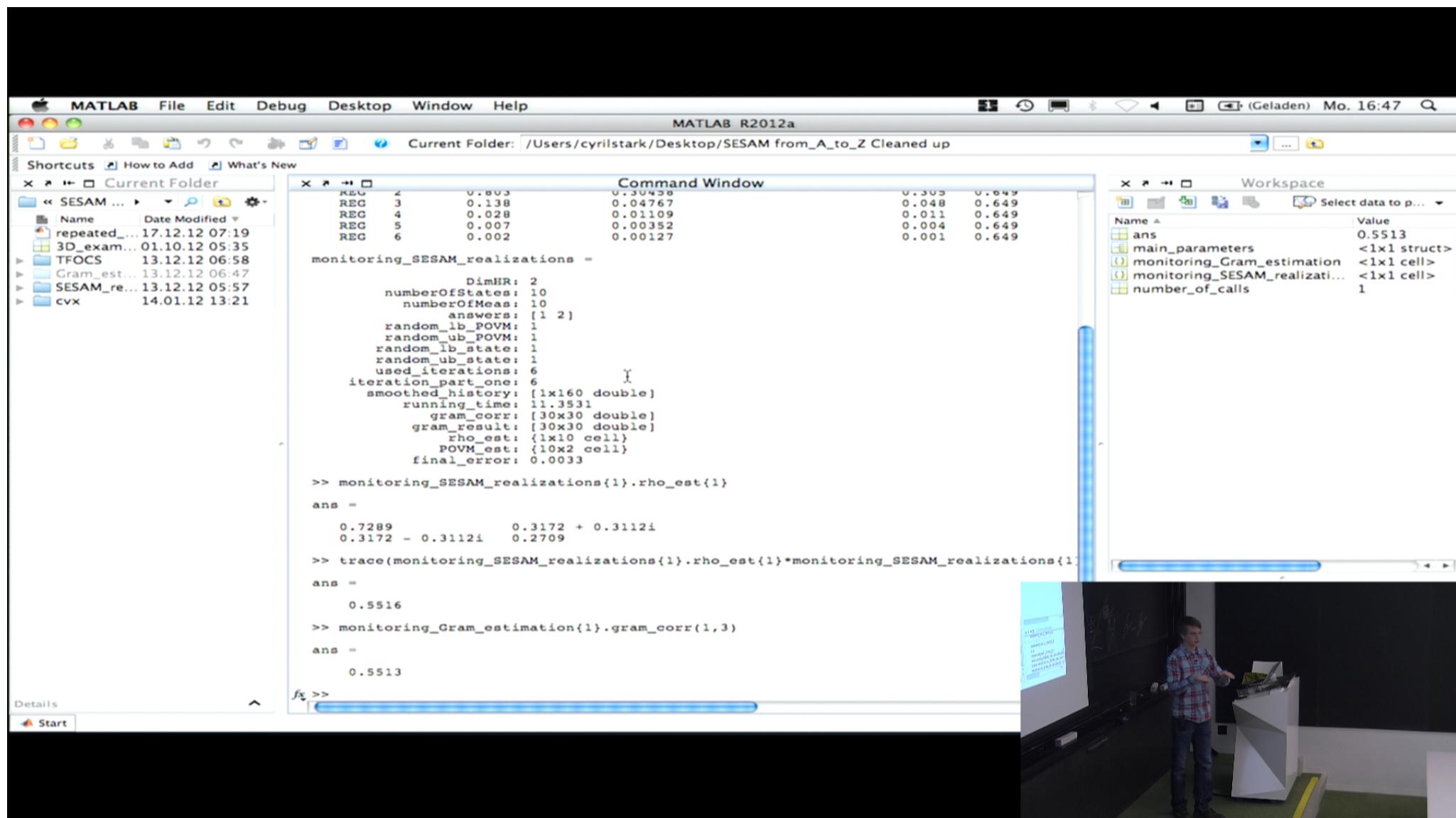
Workspace

Name	Type	Value
main_parameters	<1x1 struct>	
monitoring_Gram_estimation	<1x1 cell>	
monitoring_SESAM_realizati...	<1x1 cell>	
number_of_calls	1	



Details

Start



## Uniqueness analysis aiming at $\{\text{relaxed feasible}\} = \{\tilde{G}\}$

- ▶ Let  $\vec{p}_1, \dots, \vec{p}_n \in \mathbb{R}^{d^2}$  arbitrary and generic.
- ▶ Set  $G_{ij} = \vec{p}_i^T \vec{p}_j$ ,  $G \in \mathbb{R}^{n \times n}$ .
- ▶ Known entries marked by  $\Omega$ .
- ▶ Q: Does  $G_\Omega$  uniquely determine  $G$ ?
- ▶ A:  $G$  unique<sup>10</sup>  $\Leftrightarrow$

$$\text{rank} \left( \vec{\nabla}_P G_{k_1, l_1}(P), \dots, \vec{\nabla}_P G_{k_{|\Omega|}, l_{|\Omega|}}(P) \right) = d^2 n - \frac{1}{2} d^2(d^2 - 1)$$

- ▶ “Asimow-Roth Theorem”

$G$  is unique due to additional assumptions →

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due to symmetries.

