

# Lower bound on quantum full mixed-state tomography

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①  $O_j = |j\rangle \langle j|$ , for  $j = 1, \dots, d$ .

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Given unitary access to  $|\psi\rangle$ :

$$\tilde{\Theta} \left( \min \left\{ \frac{d^{\frac{1}{q}}}{\varepsilon}, \frac{1}{\varepsilon^{\frac{1}{1-\frac{1}{q}}}} \right\} \right). \text{ [vA'21; This work]}$$

Probably many more...



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- ① *Parameters:*  $1 \leq r \leq d$ , and  $\varepsilon \in [0, 1/256]$ .
- ② *Input:*  $U : |0\rangle \mapsto |\psi\rangle = \sum_{j=1}^r \alpha_j |\psi_j\rangle_A |\chi_j\rangle_B$ .
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*Remainder of this talk:*  $\Omega(\frac{dr}{\varepsilon})$  queries are required.

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*Ingredients:*

- ① Absolute constants  $c, C \in (0, 1)$ .
- ②  $D \subseteq \{0, 1\}^{dr}$  with  $|D| \geq C \cdot 2^{dr}$ .
- ③ For all  $b \in D$ , let  $S_b \subseteq |D|$ , with  $b \in S_b$ .  
(horizontal edges)
- ④ For all  $\tilde{b} \in D$ ,  $|\{b \in D : \tilde{b} \in S_b\}| \leq 2^{cdr}$ .  
(right degree bounded by  $2^{cdr}$ )

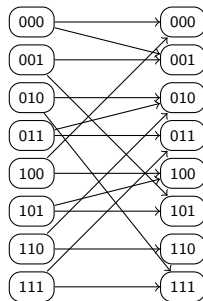
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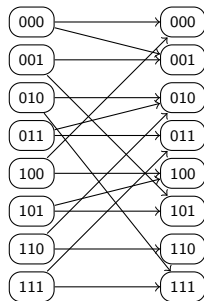
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*Approximate string recovery  $(\epsilon, D, b \mapsto S_b)$ :*

- 1 **Input:**  $O_b^{(\epsilon)} : |j\rangle \mapsto e^{2\pi i \epsilon b_j} |j\rangle$  with  $b \in D$ .
- 2 **Output:** any  $\tilde{b} \in S_b$ .

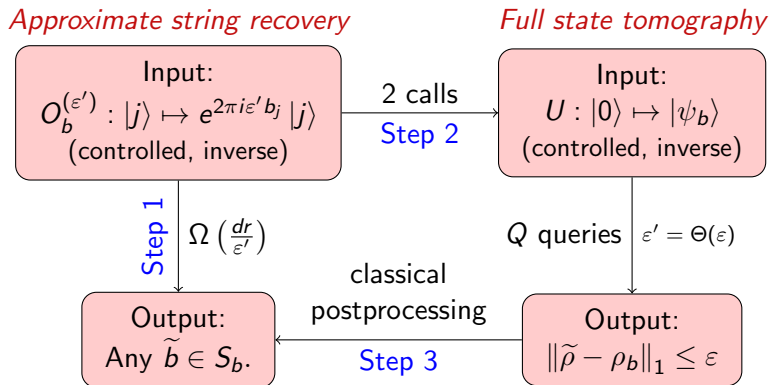
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# Lower bound – proof overview

*Idea: “Embed the approximate string recovery problem into the full state-tomography problem.”*



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- ② Algorithm:
  - ① Run the algorithm that outputs any  $\tilde{b} \in S_b$  with  $Q$  queries.
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  - ① Proof via adversary method.
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- ② Adversary method for relations: [Bel'15]
  - ① Approximate string recovery is a relation.

# Lower bound – approximate string recovery

Case:  $\varepsilon' = 1/2$

- ①  $O_b^{(\varepsilon')} : |j\rangle \mapsto e^{2\pi i b_j} |j\rangle = (-1)^{b_j} |j\rangle$ .
- ② Algorithm:
  - ① Run the algorithm that outputs any  $\tilde{b} \in S_b$  with  $Q$  queries.
  - ② Output any  $b \in D$  such that  $\tilde{b} \in S_b$  uniformly at random.
- ③ Recovers  $b$  with probability at least  $2/3 \cdot 2^{-cdr}$ .
- ④ Polynomial method: [FGGS'99]  
 $C \cdot 2^{dr} \leq |D| \leq \frac{3}{2} \cdot 2^{cdr} \cdot 2^{drH(Q/dr)}$ .

Thus,  $Q = \Omega(dr)$ .

Case:  $\varepsilon' \in (0, 1/2)$

Idea: Any problem becomes  $1/\varepsilon'$  harder when switching from  $O_b$  to  $O_b^{(\varepsilon')}$ .

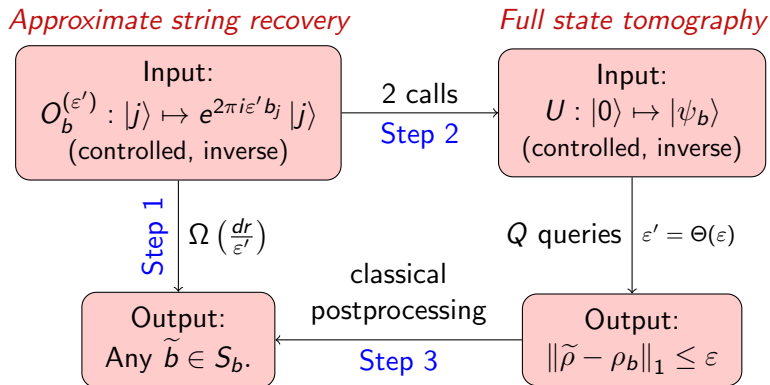
Technical difficulties:

- ① Proof for functions. [LMRŠS'11]
  - ① Proof via adversary method.
  - ② Approximate string recovery is not a function.
- ② Adversary method for relations: [Bel'15]
  - ① Approximate string recovery is a relation.
- ③ Combine both: [CJ'21].

Thus,  $Q = \Omega(\frac{dr}{\varepsilon'})$ .

# Lower bound – proof overview

*Idea: “Embed the approximate string recovery problem into the full state-tomography problem.”*



# Lower bound – embedding

*Embedding:* ( $\varepsilon < 1/256$ )

① Let  $U^{(1)}, \dots, U^{(r)} \in \mathbb{C}^{d \times d}$  unitaries.

② Let  $b \in \{0, 1\}^{dr}$ .

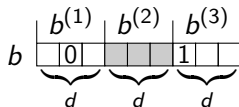
③ Define

$$|\psi_b^{(j)}\rangle = \frac{1}{\sqrt{d}} \sum_{k=1}^d \sum_{c \in \{0,1\}} \sqrt{\frac{1}{2} + 128\varepsilon(-1)^{c+b_k^{(j)}}} |c\rangle |k\rangle.$$

④ Let  $|\psi_b\rangle = \frac{1}{\sqrt{r}} \sum_{j=1}^r (I \otimes U^{(j)}) |\psi_b^{(j)}\rangle_A |j\rangle_B$

⑤ Let  $\rho_b = \text{Tr}_B[|\psi_b\rangle\langle\psi_b|]$ .

# Lower bound – embedding



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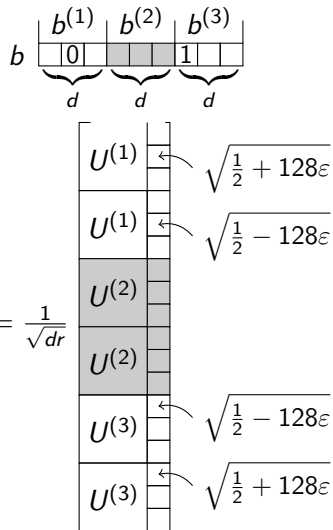
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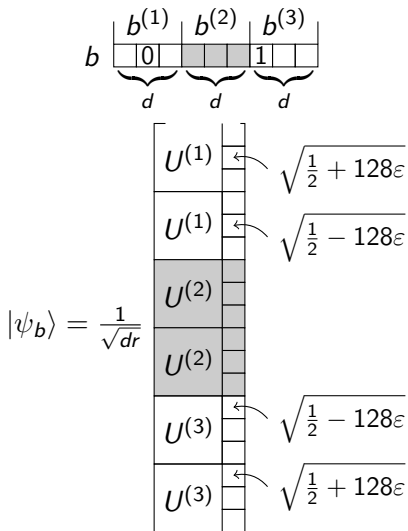
## Lower bound – embedding

For a single bit  $b \in \{0, 1\}$ , we can perform:

① Let  $\xi, \varepsilon'$  to be fixed later.

② Start with state

$$\frac{1}{\sqrt{2}} \begin{bmatrix} e^{\pi i(\xi + \varepsilon')} \\ e^{-\pi i(\xi + \varepsilon')} \end{bmatrix}$$





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Diagram illustrating the embedding of a single bit  $b$  into a quantum state  $|\psi_b\rangle$ .

The bit  $b$  is represented by a sequence of three blocks, each of size  $d$ :

- Block 1:  $b^{(1)}$  (containing 0)
- Block 2:  $b^{(2)}$  (shaded)
- Block 3:  $b^{(3)}$  (containing 1)

The quantum state  $|\psi_b\rangle$  is defined as:

$$|\psi_b\rangle = \frac{1}{\sqrt{dr}} \begin{bmatrix} U^{(1)} \\ U^{(1)} \\ U^{(2)} \\ U^{(2)} \\ U^{(3)} \\ U^{(3)} \end{bmatrix}$$

The state is composed of six entries, each of size  $d$ , grouped into three pairs:

- Pair 1:  $U^{(1)}$  and  $U^{(1)}$  (unshaded)
- Pair 2:  $U^{(2)}$  and  $U^{(2)}$  (shaded)
- Pair 3:  $U^{(3)}$  and  $U^{(3)}$  (unshaded)

The amplitudes for each pair are given by:

- Pair 1:  $\sqrt{\frac{1}{2} + 128\varepsilon}$  and  $\sqrt{\frac{1}{2} - 128\varepsilon}$
- Pair 2:  $\sqrt{\frac{1}{2} - 128\varepsilon}$  and  $\sqrt{\frac{1}{2} + 128\varepsilon}$
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## Lower bound – embedding

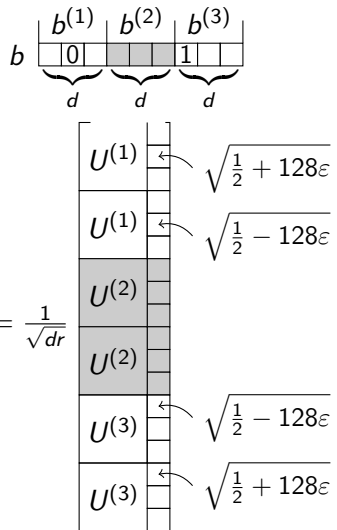
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$$\frac{1}{\sqrt{2}} \begin{bmatrix} e^{\pi i(\xi + (-1)^b \varepsilon')} \\ e^{-\pi i(\xi + (-1)^b \varepsilon')} \end{bmatrix}$$
- 4 Apply  $H$  and then  $S$

$$\begin{bmatrix} \cos(\pi(\xi + (-1)^b \varepsilon')) \\ \sin(\pi(\xi + (-1)^b \varepsilon')) \end{bmatrix} = \begin{bmatrix} \sqrt{\frac{1}{2} + (-1)^b 128\varepsilon} \\ \sqrt{\frac{1}{2} - (-1)^b 128\varepsilon} \end{bmatrix}$$



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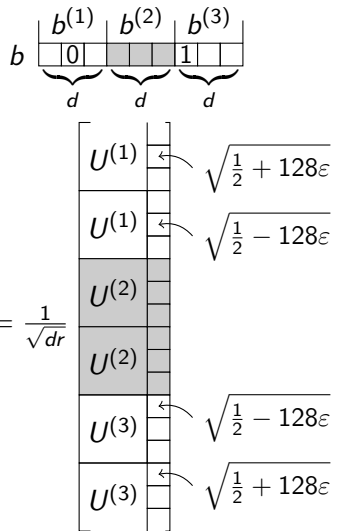
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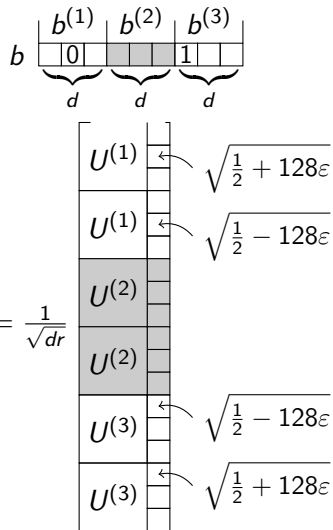
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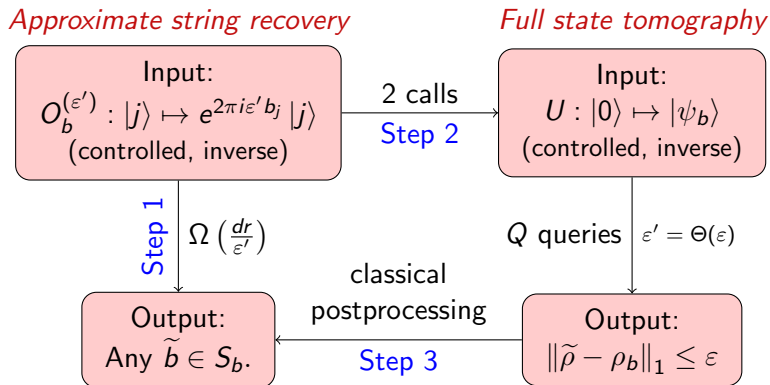
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Now perform in parallel to obtain  $|\psi_b\rangle$ .



# Lower bound – proof overview

*Idea: “Embed the approximate string recovery problem into the full state-tomography problem.”*



# Lower bound – postprocessing

# Lower bound – postprocessing

## 1 Postprocessing algorithm:

- 1 Run algorithm to obtain  $\tilde{\rho}$  s.t.  $\|\tilde{\rho} - \rho_b\|_1 \leq \varepsilon$ .
- 2 Output any  $\tilde{b} \in \{0, 1\}^{dr}$  such that  $\|\tilde{\rho} - \rho_{\tilde{b}}\|_1 \leq \varepsilon$ .

It follows that  $\|\rho_b - \rho_{\tilde{b}}\|_1 \leq 2\varepsilon$ .

# Lower bound – postprocessing

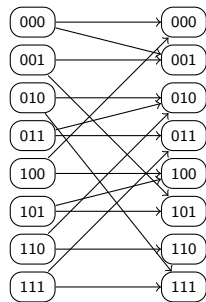
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- 2 Thus, let  $S_b = \{\tilde{b} \in \{0, 1\}^{dr} : \|\rho_b - \rho_{\tilde{b}}\|_1 \leq 2\varepsilon\}$ .

Input:  $b \in \{0, 1\}^{dr}$     Output:  $\tilde{b} \in \{0, 1\}^{dr}$



Edge when  $\|\rho_b - \rho_{\tilde{b}}\|_1 \leq 2\varepsilon$ .



# Lower bound – postprocessing

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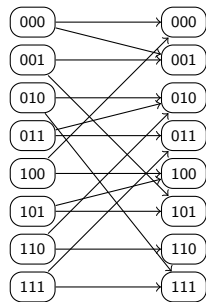
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## 3 Then $b \in S_b$ . (horizontal edges)

Input:  $b \in \{0, 1\}^{dr}$     Output:  $\tilde{b} \in \{0, 1\}^{dr}$



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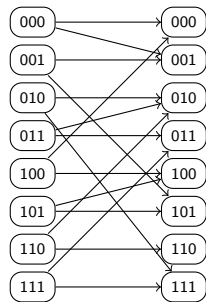
(horizontal edges)

## 4 Remains to show that $\exists c \in (0, 1)$ s.t.

$$|\{b \in \{0, 1\}^{dr} : \tilde{b} \in S_b\}| \leq 2^{cdr}.$$

(bounded right degree)

Input:  $b \in \{0, 1\}^{dr}$     Output:  $\tilde{b} \in \{0, 1\}^{dr}$

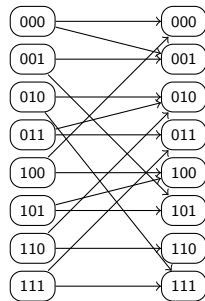


Edge when  $\|\rho_b - \rho_{\tilde{b}}\|_1 \leq 2\varepsilon$ .

## Lower bound – postprocessing

Let  $b, \tilde{b} \in \{0, 1\}^{dr}$  uniformly at random.  
Suppose that  $\exists c \in (0, 1)$  s.t.  
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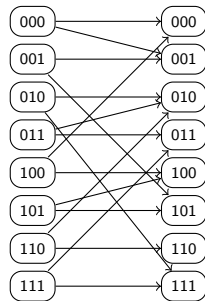
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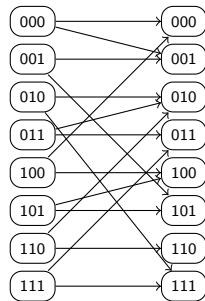
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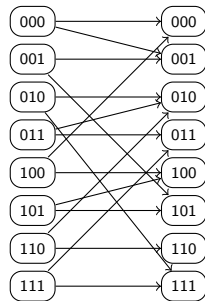
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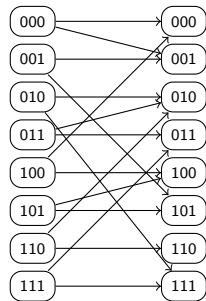
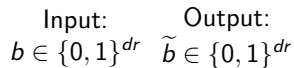
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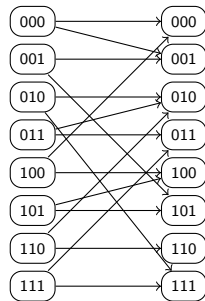
④  $|\{\tilde{b} : \deg(\tilde{b}) \leq 2^{-cdr/2} \cdot 2^{dr}\}| \geq 2^{dr}(1 - 2^{-cdr/2}).$

⑤ Let  $D \subseteq \{0, 1\}^{dr}$  be the set for all these  $\tilde{b}$ 's:  
 $|D| \geq C \cdot 2^{dr}$ , with  $C \in (0, 1)$ .

Thus it remains to show  $\exists c \in (0, 1)$  s.t.

$$\mathbb{P} \left[ \|\rho_b - \rho_{\tilde{b}}\|_1 \leq 2\varepsilon \right] \leq 2^{-cdr}.$$

Input:  $b \in \{0, 1\}^{dr}$     Output:  $\tilde{b} \in \{0, 1\}^{dr}$



Edge when  $\|\rho_b - \rho_{\tilde{b}}\|_1 \leq 2\varepsilon.$

## Lower bound – proximity probability analysis

Remains to prove:  $\exists c \in (0, 1)$  s.t.

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$$\|\rho_b - \rho_{\tilde{b}}\|_1 = \frac{32\varepsilon}{rd} \|XY^\dagger\|_1, \text{ where}$$

①  $X = [U^{(1)}\delta^{(1)} \ \dots \ U^{(r)}\delta^{(r)}],$

②  $Y = [U^{(1)}\mathbb{1} \ \dots \ U^{(r)}\mathbb{1}],$

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③ *Interpretation:* overlaying point clouds.

$$\begin{aligned} \|XY^\dagger\|_1 &= \max_{U \text{ unitary}} |\text{Tr}[Y^\dagger UX]| \\ &= \max_{U \text{ unitary}} \sum_{j=1}^r |y_j^\dagger Ux_j|. \end{aligned}$$

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$$\|\rho_b - \tilde{\rho}_b\|_1 = \frac{32\varepsilon}{rd} \|XY^\dagger\|_1, \text{ where}$$

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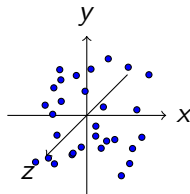
②  $Y = [U^{(1)}\mathbb{1} \dots U^{(r)}\mathbb{1}],$

③  $\delta^{(j)} = (-1)^{b^{(j)}} - (-1)^{\tilde{b}^{(j)}}.$

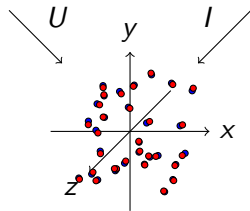
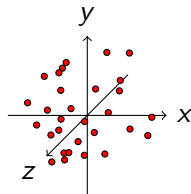
③ *Interpretation:* overlaying point clouds.

$$\begin{aligned} \|XY^\dagger\|_1 &= \max_{U \text{ unitary}} |\text{Tr}[Y^\dagger UX]| \\ &= \max_{U \text{ unitary}} \sum_{j=1}^r |y_j^\dagger Ux_j|. \end{aligned}$$

Columns of  $X$



Columns of  $Y$



Columns of  $UX$  &  $Y$

## Lower bound – proximity probability analysis II

Recall:  $Y = [U^{(1)}\mathbb{1} \ \dots \ U^{(r)}\mathbb{1}]$ .



## Lower bound – proximity probability analysis II

Recall:  $Y = [U^{(1)} \mathbb{1} \quad \dots \quad U^{(r)} \mathbb{1}]$ .

*Idea:* Let

$$U^{(1)} = \frac{1}{\sqrt{d}} \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & \omega_d & \omega_d^2 & \dots & \omega_d^{d-1} \\ 1 & \omega_d^2 & \omega_d^4 & \dots & \omega_d^{2(d-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega_d^{d-1} & \omega_d^{2(d-1)} & \dots & \omega_d^{(d-1)^2} \end{bmatrix}$$
$$U^{(2)} = \frac{1}{\sqrt{d}} \begin{bmatrix} 1 & \omega_d^{d-1} & \omega_d^{2(d-1)} & \dots & \omega_d^{(d-1)^2} \\ 1 & 1 & 1 & \dots & 1 \\ 1 & \omega_d & \omega_d^2 & \dots & \omega_d^{d-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega_d^{d-2} & \omega_d^{2(d-2)} & \dots & \omega_d^{(d-2)(d-1)} \end{bmatrix}$$

Then  $Y = \sqrt{d}I$ .

# Lower bound – proximity probability analysis II

Recall:  $Y = [U^{(1)}\mathbb{1} \ \dots \ U^{(r)}\mathbb{1}]$ .

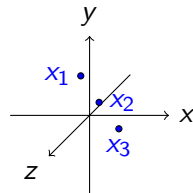
*Idea:* Let

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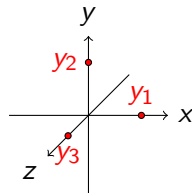
$$U^{(2)} = \frac{1}{\sqrt{d}} \begin{bmatrix} 1 & \omega_d^{d-1} & \omega_d^{2(d-1)} & \dots & \omega_d^{(d-1)^2} \\ 1 & \omega_d^{d-1} & \omega_d^{2(d-1)} & \dots & \omega_d^{(d-1)^2} \\ 1 & 1 & 1 & \dots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega_d^{d-2} & \omega_d^{2(d-2)} & \dots & \omega_d^{(d-2)(d-1)} \end{bmatrix}$$

Then  $Y = \sqrt{d}I$ .

Columns of  $X$



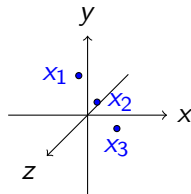
Columns of  $Y$



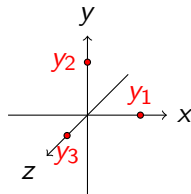
## Lower bound – proximity probability analysis II

Recall  $X = [U^{(1)}\delta^{(1)} \quad \dots \quad U^{(r)}\delta^{(r)}]$ .

Columns of  $X$



Columns of  $Y$



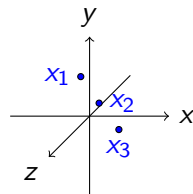
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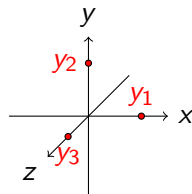
① For any unitary  $U$ :

$$\|\rho_b - \rho_{\tilde{b}}\|_1 \geq \frac{32\varepsilon}{r\sqrt{d}} \sum_{j=1}^r |e_j^\dagger U x_j|.$$

Columns of  $X$



Columns of  $Y$



## Lower bound – proximity probability analysis II

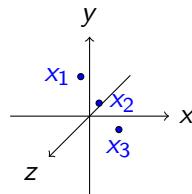
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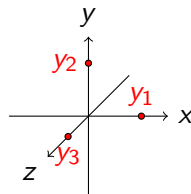
$$\|\rho_b - \rho_{\tilde{b}}\|_1 \geq \frac{32\varepsilon}{r\sqrt{d}} \sum_{j=1}^r |e_j^\dagger U x_j|.$$

② Greedy strategy to build  $U$ .

Columns of  $X$



Columns of  $Y$



## Lower bound – proximity probability analysis II

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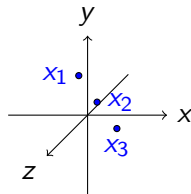
③ Let  $S_j = \text{Span}\{x_1, \dots, x_{j-1}\}$ . Then:

①  $\dim(S_j) = j - 1$ .

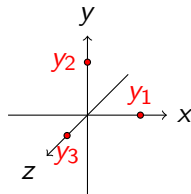
②  $|e_j^\dagger U x_j| = \|\Pi_{S_j^\perp} x_j\|$ .

③  $S_j$  is independent from  $x_j$ .

Columns of  $X$



Columns of  $Y$



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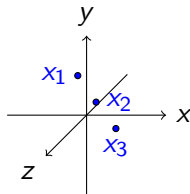
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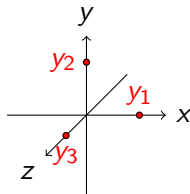
④ Since  $\delta^{(j)}$  has independent entries,  $\exists c \in (0, 1)$  s.t.

$$\mathbb{P} \left[ \left| \|\Pi_{S_j^\perp} x_j\| - \sqrt{d - j + 1} \right| \geq \frac{1}{4} \sqrt{d} \right] \leq 2^{-cd}. [\text{RV'13}]$$

Columns of  $X$



Columns of  $Y$



## Lower bound – proximity probability analysis II

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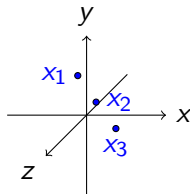
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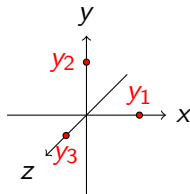
$$\mathbb{P} \left[ \left| \|\Pi_{S_j^\perp} x_j\| - \sqrt{d - j + 1} \right| \geq \frac{1}{4} \sqrt{d} \right] \leq 2^{-cd}. [\text{RV}'13]$$

⑤ If  $\|\rho_b - \rho_{\tilde{b}}\|_1 \leq 2\varepsilon$ , then the above must hold for at least  $r/4$  terms.

Columns of  $X$



Columns of  $Y$





# Lower bound – proximity probability analysis II

Recall  $X = [U^{(1)}\delta^{(1)} \quad \dots \quad U^{(r)}\delta^{(r)}]$ .

① For any unitary  $U$ :

$$\|\rho_b - \rho_{\tilde{b}}\|_1 \geq \frac{32\varepsilon}{r\sqrt{d}} \sum_{j=1}^r |e_j^\dagger U x_j|.$$

② Greedy strategy to build  $U$ .

③ Let  $S_j = \text{Span}\{x_1, \dots, x_{j-1}\}$ . Then:

①  $\dim(S_j) = j - 1$ .

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③  $S_j$  is independent from  $x_j$ .

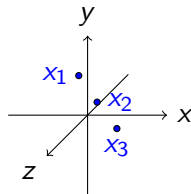
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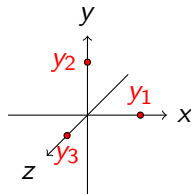
⑤ If  $\|\rho_b - \rho_{\tilde{b}}\|_1 \leq 2\varepsilon$ , then the above must hold for at least  $r/4$  terms.

⑥ Thus  $\mathbb{P} \left[ \|\rho_b - \rho_{\tilde{b}}\|_1 \leq 2\varepsilon \right] \leq 2^{-cdr/4}.$

Columns of  $X$

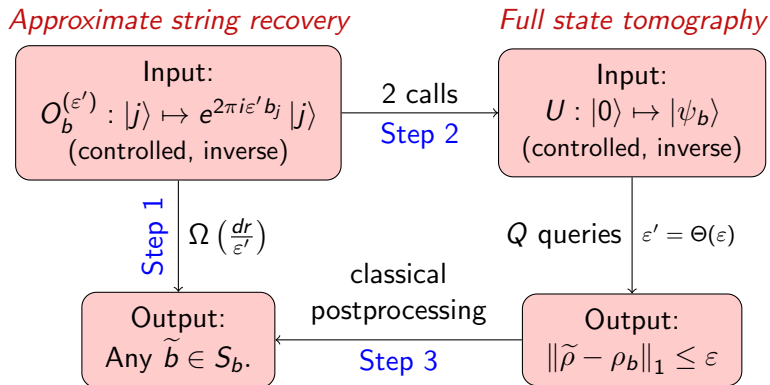


Columns of  $Y$



# Lower bound – proof overview

*Idea: “Embed the approximate string recovery problem into the full state-tomography problem.”*



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