

Pre-Verification of Quantum Processes

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Outline

1. Introduction
2. Pre-Verification
3. Chernoff & Neighbors
4. Simulation & Experiment
5. Conclusions



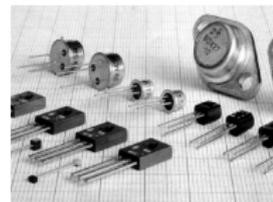
pre-verification



classical testing quantum data

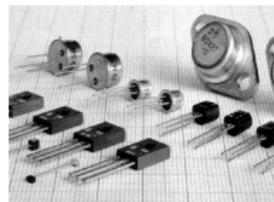
Introduction

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- Data “fidelity” checked via error control theory.



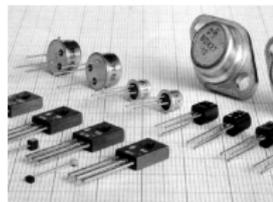
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- Device “fidelity” checked via hypothesis testing theory.



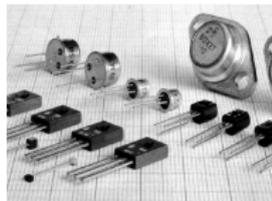
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- **Error Detection** & **Error Correction** .



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- Data and device “fidelity” .
- Data “fidelity” checked via error control theory.
- Device “fidelity” checked via hypothesis testing theory.
- **Error Detection** ☑ & **Error Correction** ☒ .
- “Naive”: Check all possible I/O combinations.



Quantum Case: States and Processes

States

- Data transmission \rightarrow State transmission.
- Density matrices have $d_s^2 - 1$ elements.

Processes

- Devices \rightarrow Processes: $\mathcal{H}_S \rightarrow \mathcal{H}_S$.
- Density matrices characterized by $d_s^2 - 1$ elements.
- Processes characterized by $d_s^4 - d_s^2$ elements.
- Costly when $d_s = 2^m$, for m qubits^a.

^a pseudo-spins are different

Process Tomography-I

Basics

- Basis ϱ_k .

- Any density matrix $\rho = \sum_{k=1}^{d_s^2} c_k \varrho_k$

- For any process Φ , measure $\tilde{\varrho}_k = \Phi(\varrho_k)$.

- From linearity, $\Phi(\rho) = \sum_{k=1}^{d_s^2} c_k \Phi(\varrho_k) = \sum_{k=1}^{d_s^2} c_k \tilde{\varrho}_k$.

- Count again : $d_s^2 - 1$ for each of the d_s^2 density matrices.

- Total $\Rightarrow d_s^4 - d_s^2$.

d_s	$d_s^4 - d_s^2$
2	12
3	72
4	240
5	600
6	1260
7	2352
8	4032
9	6480
10	9900

Process Tomography-II: EAPT

- Entanglement Assisted Process Tomography (EAPT)¹.
- Choi-Jamiołkowski: $\Phi \Leftrightarrow \varrho_\Phi$, where $\varrho_\Phi := [\Phi \otimes \mathbb{I}] (|\phi\rangle\langle\phi|)$.
- $|\phi\rangle = \frac{1}{\sqrt{d_s}} \sum_j |j\rangle|j\rangle$ is maximally entangled state in dilated space.
- Employ $|\phi\rangle$ and use state tomography to find ρ_Φ .
- **Caveat:** Production of highly entangled state $|\phi\rangle$! As many measurements!

¹Altepeter, Joseph B., et al. Physical Review Letters 90.19 (2003): 193601.

Process Tomography-III: AAPT

- Ancilla Assisted Process Tomography (AAPT)².

- $$R = \sum_k^{d_s^2} \lambda_k A_k \otimes B_k, \lambda_k > 0.$$

- maximal rank state R faithful in mapping Φ :

$$[\Phi \otimes I](R) = \sum_k^{d_s^2} \lambda_k \Phi(A_k) \otimes B_k.$$

- max rank states are “easy” to produce.
- **Caveat:** As many measurements!

²Altepeter, Joseph B., et al. Physical Review Letters 90.19 (2003): 193601.

Compressive Sensing

- Compressive Sensing: Prelude to CQPT³.
- Res.(Mbps→Gbps) \times Mult. Freq. \times (# of Sensors) \Rightarrow "Data Deluge" $|x\rangle$
- $\text{rank}(|x\rangle) = K \ll N$: Nyquist/Shannon + Throwaway + Transmit.
- Access compressible inf. $K \ll N$ directly via $M = \mathcal{O}(K \log(N))$ meas.
- Randomized measurements are universal.
- Take away: $\text{rank}(|x\rangle) = K \Rightarrow \mathcal{O}(K \log(N))$ measurements.

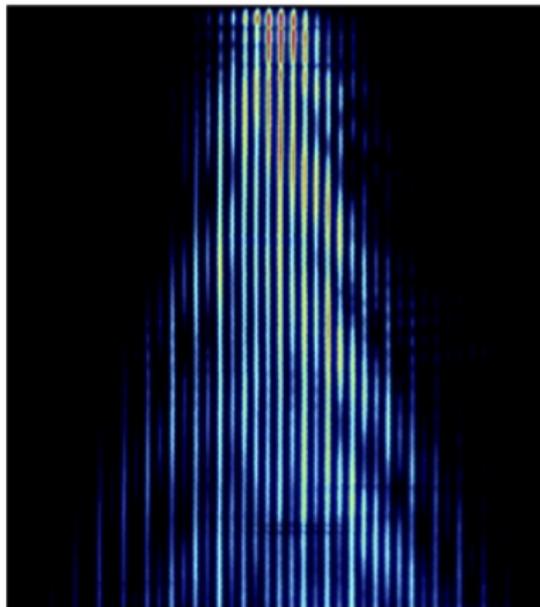
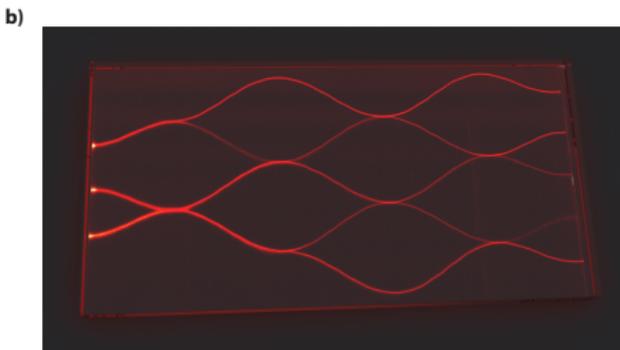
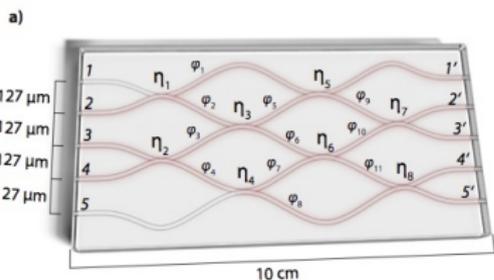
³Candes, E. J., et al., Communications on pure and applied mathematics 59.8 (2006): 1207-1223.

Process Tomography-IV: CQPT

- Compressive Quantum Process Tomography(CQPT)⁴.
- Take away: It takes $\mathcal{O}(K \log(N))$ measurements.
- Assume that the Process Matrix ρ_{Φ} is sparse.
- Small (logarithmically) number of measurements suffice.
- **Caveat:** Not \forall processes, measure zero applicability!

⁴Shabani, A., et al. Physical Review Letters 106.10 (2011): 100401.

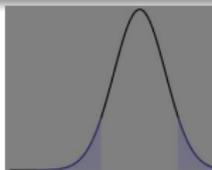
Construct, Convince & Measure



^aTillmann, Max, et al. Nature Photonics (2013),
Driesow et al., PRL 105, 143902(10)

Hoeffding's Inequality

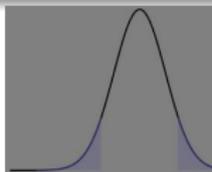
- Z_1, \dots, Z_M , independent random variables.



^a Hoeffding, Wassily. Journal of the American statistical association 58.301 (1963): 13-30.

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- Assume that $a_i \leq Z_i \leq b_i \forall i \in [1, M]$



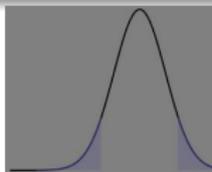
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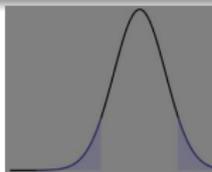
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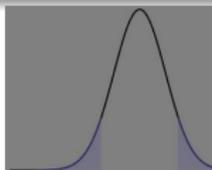
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- If $\{Z_1 \dots Z_M\}$ from the correct hypothesis, $\bar{Z} \approx \mathbb{E}(\bar{Z})^a$.



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Application to Pre-Verification

- Assume $Z_j = \text{tr}(\mathcal{E}_j \Phi(\rho_j)) + \sqrt{\eta_j} d \mathbb{W}_j$.

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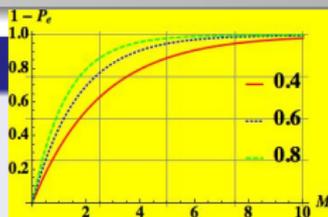
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- Distinguishing neighbors follows common sense.

Chernoff Bound for Processes

Asymptotic Error Probability

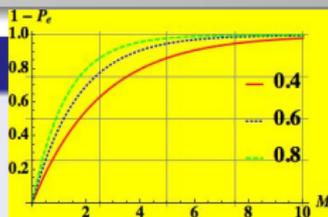
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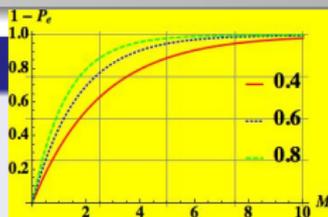
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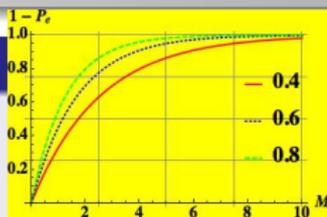
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- ξ_{qcb} is a dist. measure. Apply to ρ_Φ and $\rho_\Phi + \varepsilon d\rho_\Phi$



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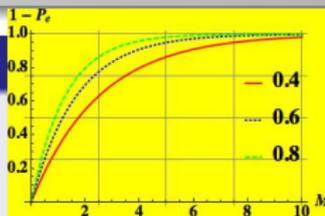
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- Spectral decomposition $\rho_\Phi = \sum_i \lambda_i |i\rangle\langle i|$



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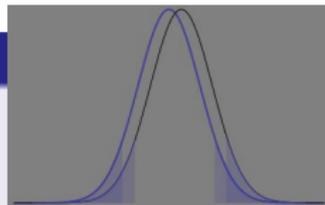
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- Spectral decomposition $\rho_\Phi = \sum_i \lambda_i |i\rangle\langle i|$
- $\xi_{qcb} = \frac{\varepsilon}{2} \sum_{i,j} \frac{|\langle i|d\rho_\Phi|j\rangle|^2}{(\sqrt{\lambda_i} + \sqrt{\lambda_j})^2} = \frac{\varepsilon}{2} d\xi$.



Distinguishing Neighbors Via Q. Chernoff & Hoeffding

Chernoff

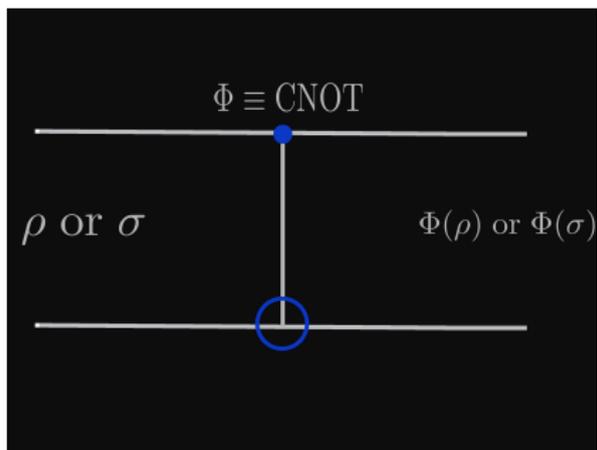
- $\mathbb{P}_e = \exp(-\frac{M\varepsilon}{2} d\xi)$
- As $\varepsilon \rightarrow 0$ for a given M , $\mathbb{P}_e \rightarrow 1$.
- $M = -\frac{2}{\varepsilon d\xi} \log(\mathbb{P}_e)$ Scales badly.



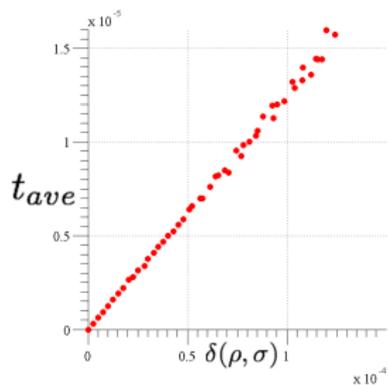
Hoeffding

- $\mathbb{E}(\bar{Z}) \rightarrow \mathbb{E}(\bar{Z}) + \varepsilon \mathbb{E}(d\bar{Z})$
- As if $\mathbb{P}(|\bar{Z} - \mathbb{E}(\bar{Z})| \geq t) \leq 2e^{-\frac{Mt^2}{\sigma^2}} \rightarrow \mathbb{P}(|\bar{Z} - \mathbb{E}(\bar{Z})| \geq t) \leq 2e^{-\frac{M(t - \varepsilon \mathbb{E}(d\bar{Z}))^2}{\sigma^2}}$
- $M = -\frac{\sigma^2}{(\varepsilon \mathbb{E}(d\bar{Z}))^2} \log\left(\frac{\mathbb{P}_e}{2}\right)$ Scales badly as well.

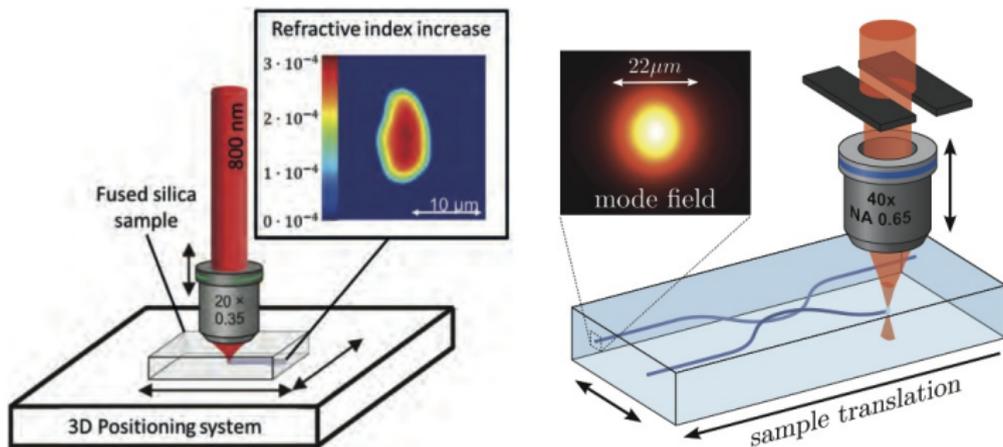
Simulation



- Choose 10 random measurements from 240.
- 10^4 random neighbors of ρ with average δ .
- Exponent increases.



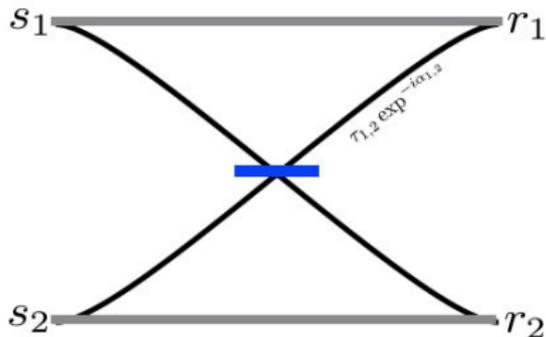
Experiment (“Construct”)



- Femtosecond Lasers used to etch waveguides.⁵
- Velocity \rightarrow n . Evanescent coupling.
- 1% errors.

⁵Szameit A. and Nolte, J. Phys. B 43, 163001 (2010)

Experiment (“Convince”)



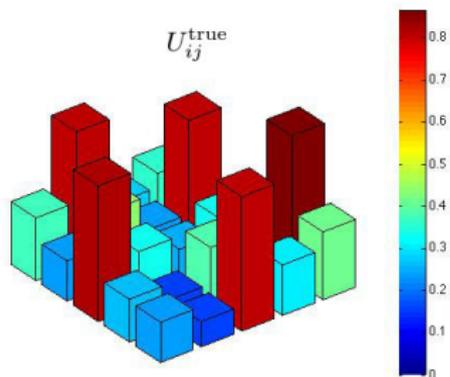
$$Q = |\text{PerP}|^2$$

$$C = \text{Per}|P|^2$$

$$V = (C - Q)/C$$

Measure these

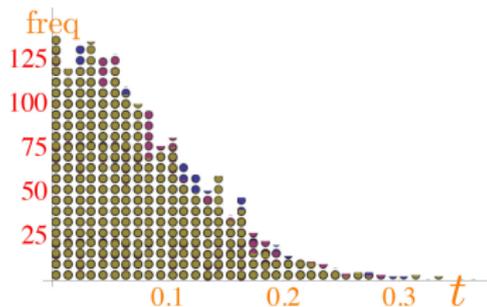
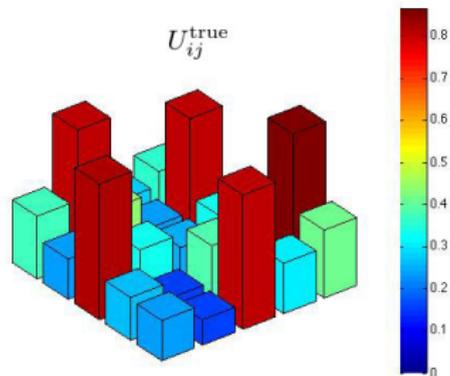
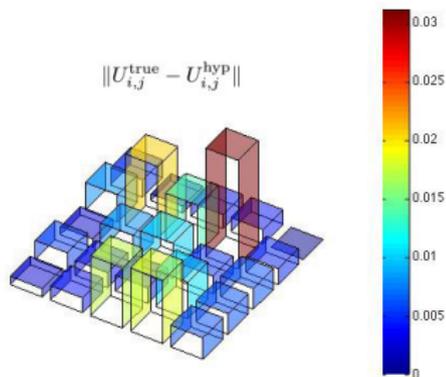
$$P_2 = \begin{pmatrix} \sqrt{r_j} & 0 \\ 0 & \sqrt{r_g} \end{pmatrix} * \begin{pmatrix} e^{i\alpha_{j,k}} \tau_{j,k} & e^{i\alpha_{j,h}} \tau_{j,h} \\ e^{i\alpha_{g,k}} \tau_{g,k} & e^{i\alpha_{g,h}} \tau_{g,h} \end{pmatrix} * \begin{pmatrix} \sqrt{s_j} & 0 \\ 0 & \sqrt{s_g} \end{pmatrix}$$



“Super Stable Tomography”^a

^aLaing, Anthony, and Jeremy L. O’Brien 1208.2868

Convince-II: Pre-Verify



- min 2% dev. 14 times the min 1% value.

Conclusions

- Mesoscopic devices are state of the art...quantum data deluge!
- Bypass “fluorescence” + “imaging” type techniques.
- Replace QPT (when possible) with confidence test.
- No requirements: sparsity , linearity...
- Can be used “alongside” QPT.
- Doesn't violate canon on undecidability⁶...

⁶Rosgen, Bill. *Th. Q. Comp., Comm., and Crypt.* Springer Berlin Heidelberg, 2011. 63-76.

The End