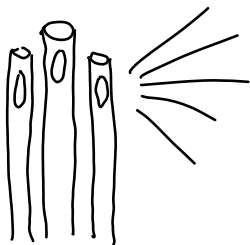


Compressed sensing and quantum state tomography

- recovering sparse objects from few measurements.



David Gross, Uni Hannover

QQQ Meeting
FU Berlin
October 2009

Outline

I will

- ▶ Motivate the problem,
- ▶ tell you our results,
- ▶ and then prove something else to you.

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The starting point

- ▶ Let ρ be an unknown density matrix on \mathbb{C}^d .
- ▶ Assume that $\text{rank } \rho = r$, with $r \ll d$.
- ▶ How many parameters are needed to specify ρ ?
 - ▶ Well, roughly rd .
- ▶ How many coefficients do I need to know to recover ρ using full tomography?
 - ▶ Well, clearly $d^2 \gg rd$.
- ▶ What a waste.

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Central question

Can we obtain complete information about an unknown quantum state using substantially fewer than d^2 measurement settings, if that state is (essentially) low-rank?

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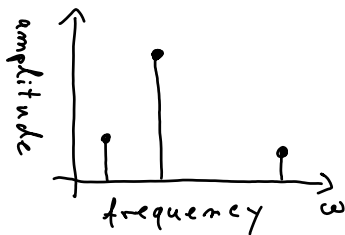
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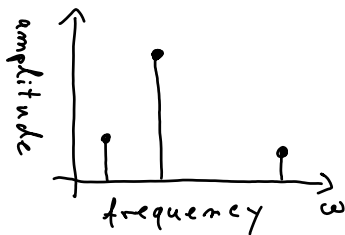
Yes, we can.

Classical analogue



- ▶ Spectrum of an organ: at any time few (r) out of many possible (d) frequencies sound.
- ▶ So spectrum essentially described by $r \ll d$ numbers.
- ▶ Task: find that spectrum using few measurements.

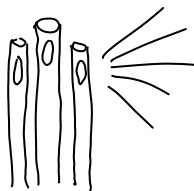
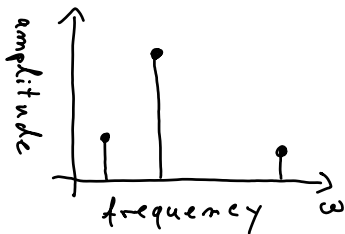
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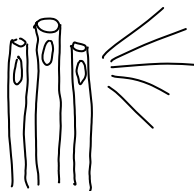
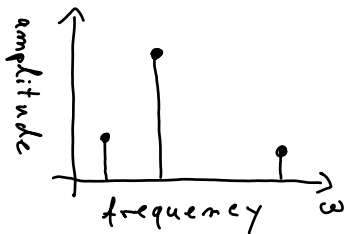
Classical analogue

- ▶ First idea: measure in frequency domain.
 - ▶ Fails. Need d sensors.
- ▶ Second idea: take few samples in time domain.
 - ▶ Nyquist would suggest that we need $f_{\max}/2$ samples. Far too many.
 - ▶ But Nyquist holds for *general* signals — hope to optimize when support is low.



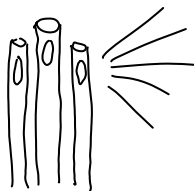
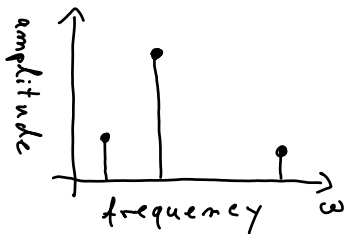
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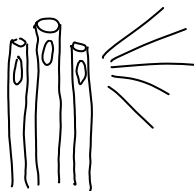
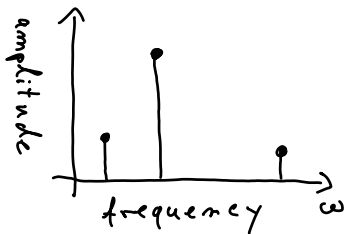
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Classical compressed sensing

Theorem [Candès, Tao, *et.al.* (2004)]

- ▶ Knowing r ($\log d$) randomly chosen time-domain amplitudes, one can recover any signal ψ composed from at most r frequencies.
- ▶ The scheme is probabilistic, and succeeds with high probability.
- ▶ The recovery is *exact*.
- ▶ It is achieved *computationally efficiently*. The signal uniquely solves the convex problem

$$\begin{aligned} & \text{minimize}_{\psi'} && \|\hat{\psi}'\|_{\ell_1} \\ & \text{subject to} && \psi'(t) = c_t \quad \forall c_t \in \Omega, \end{aligned}$$

with Ω the set of observed time-domain amplitudes

$$c_t = \psi(t).$$

Going quantum

Return to unknown rank- r density matrix ρ .

- ▶ Strong analogues to compressed sensing: want to learn *sparse object* without knowing the sparsity pattern.

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Going quantum

Indeed, previous results [Candès, Tao, *et.al.* (2008)] extend compressed sensing techniques to *matrix completion*.

- ▶ Task here: reconstruct low-rank matrix from few randomly chosen matrix elements.
- ▶ Not directly applicable to quantum case. More natural here: sample e.g. *Pauli expectation values*

$$\text{tr } \rho (\sigma_{i_1} \otimes \cdots \otimes \sigma_{i_n})$$

for n -qubit system.

- ▶ Doesn't work for all low-rank matrices, but just for certain "incoherent ones".
- ▶ Proof *very* complicated (ca. 50 pages, written by Fields Medalist).

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Quantum compressed sensing

Theorem [Gross, Liu, Flammia, Becker, Eisert (2009)].

- ▶ Knowing rd ($\log d$) randomly chosen Pauli expectation values, one can recover any rank- r density operator ρ .
- ▶ The scheme is probabilistic, and succeeds with high probability.
- ▶ The recovery is *exact*.
- ▶ It is achieved *computationally efficiently*. The density matrix ρ uniquely solves the convex problem

$$\begin{aligned} & \text{minimize} && \|\rho'\|_1 \\ & \text{subject to} && \text{tr } \rho' \sigma_{\mathbf{i}} = c_{\mathbf{i}} \quad \forall \mathbf{i} \in \Omega, \end{aligned}$$

with Ω the set of observed Pauli expectation values

$$c_{\mathbf{i}} = \text{tr } \rho(\sigma_{i_1} \otimes \cdots \otimes \sigma_{i_n}).$$

Details on blackboard

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