



Accurate Quantum State Estimation

via

Experimentalist

“Keeping the ~~Expert~~ Honest”

quant-ph/0603116

Robin Blume-Kohout (Caltech-IQI)

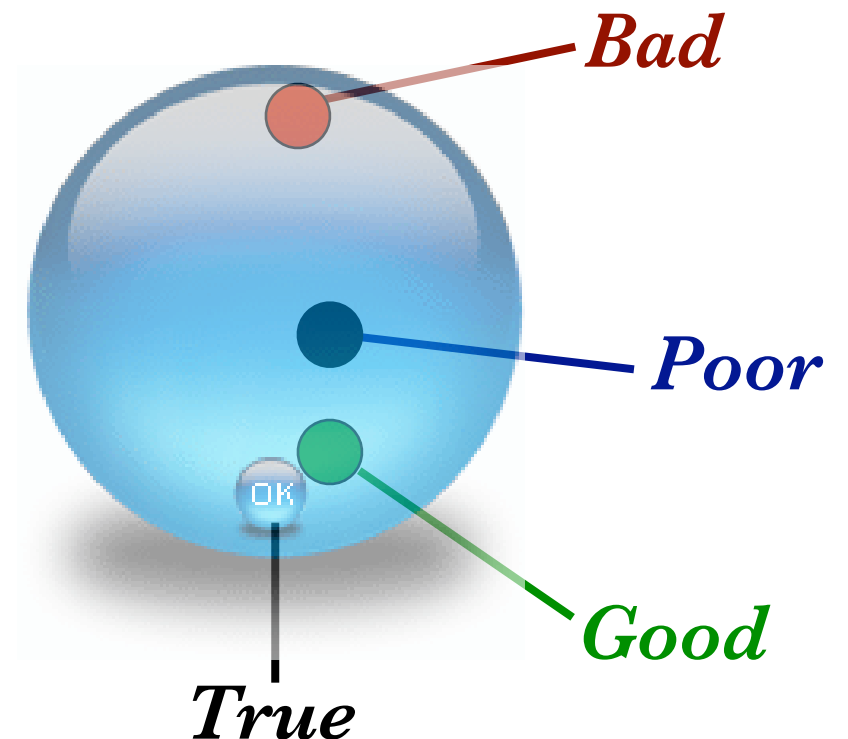
with Patrick Hayden (McGill)
and Karan Malhotra (IIT-Kanpur)

What is State Estimation?

- **Goal:** Characterize a source of quantum systems.
- You measure N identical copies.
- Measurement record:

$$\mathcal{M} = \{ \hat{E}_1, \hat{E}_2, \dots, \hat{E}_N \}$$

- Then report your best guess for ρ .
- **Key Application:** Verifying quantum hardware for fault tolerant quantum computation.
=> probabilities in $[10^{-3} \dots 10^{-5}]$ are important!



What's the Problem?

- Current technology: **Maximum Likelihood Estimation**

$$\mathcal{M} = \left\{ \hat{E}_1, \hat{E}_2, \dots, \hat{E}_N \right\} \longrightarrow \mathcal{L}(\rho) \equiv p(\mathcal{M}|\rho) \longrightarrow \rho_{\text{MLE}}$$

- ρ_{MLE} does not honestly represent the experimentalist's knowledge about the observed ensemble.
- **Why?** ρ_{MLE} typically has zero eigenvalues:

$$\lambda_i = \langle \phi_i | \rho_{\text{MLE}} | \phi_i \rangle = 0$$

- Zero eigenvalue = zero probability
 - ↳ absolute certainty
 - ↳ doesn't admit error bars!

Yes, it's a problem

PHYSICAL REVIEW A, VOLUME 64, 052312

Measurement of qubits

Daniel F. V. James,^{1,*} Paul G. Kwiat,^{2,3} William J. Munro,^{4,5} and Andrew G. White^{2,4}

¹*Theoretical Division T-4, Los Alamos National Laboratory, Los Alamos, New Mexico 87545*

²*Physics Division P-23, Los Alamos National Laboratory, Los Alamos, New Mexico 87545*

³*Department of Physics, University of Illinois, Urbana-Champaign, Illinois 61801*

⁴*Department of Physics, University of Queensland, Brisbane, Queensland 4072, Australia*

⁵*Hewlett-Packard Laboratories, Filton Road, Stoke Gifford, Bristol BS34 8QZ, United Kingdom*

(Received 20 March 2001; published 16 October 2001)

$$\hat{\rho} = \begin{pmatrix} 0.5069 & -0.0239 + i0.0106 & -0.0412 - i0.0221 & 0.4833 + i0.0329 \\ -0.0239 - i0.0106 & 0.0048 & 0.0023 + i0.0019 & -0.0296 - i0.0077 \\ -0.0412 + i0.0221 & 0.0023 - i0.0019 & 0.0045 & -0.0425 + i0.0192 \\ 0.4833 - i0.0329 & -0.0296 + i0.0077 & -0.0425 - i0.0192 & 0.4839 \end{pmatrix}$$

This matrix is illustrated in Fig. 3 (right). In this case, the matrix has eigenvalues 0.986 022, 0.013 977 7, 0, and 0; and $\text{Tr}\{\hat{\rho}^2\} = 0.972\,435$, indicating that, while the linear reconstruction gave a nonphysical density matrix, the maximum likelihood reconstruction gives a legitimate density matrix.

1. D. F. V. James et. al., “Measurement of Qubits,” *Phys. Rev. A*, 64:052312 (2001)

Yes, it's a problem

Vol 438 | 1 December 2005 | doi:10.1038/nature04279

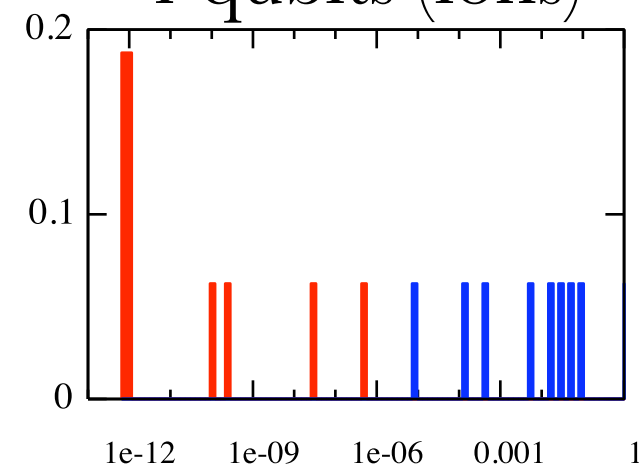
nature

LETTERS

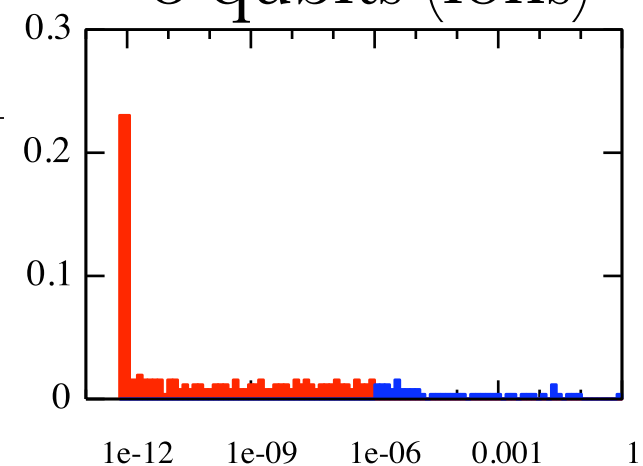
Scalable multiparticle entanglement of trapped ions

H. Häffner^{1,3}, W. Hänsel¹, C. F. Roos^{1,3}, J. Benhelm^{1,3}, D. Chek-al-kar¹, M. Chwalla¹, T. Körber^{1,3}, U. D. Rapol^{1,3}, M. Riebe¹, P. O. Schmidt¹, C. Becher^{1,†}, O. Gühne³, W. Dür^{2,3} & R. Blatt^{1,3}

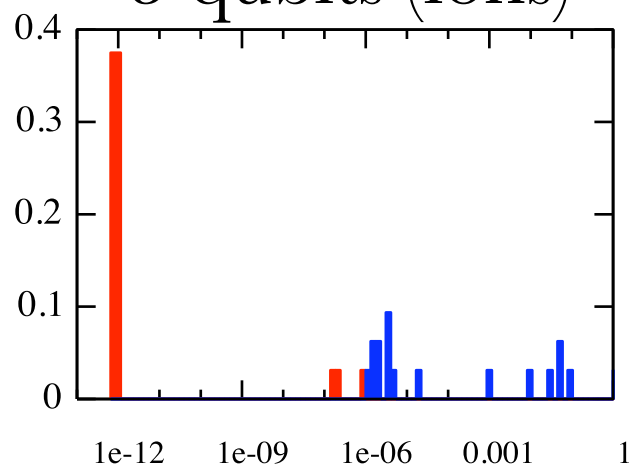
4 qubits (ions)



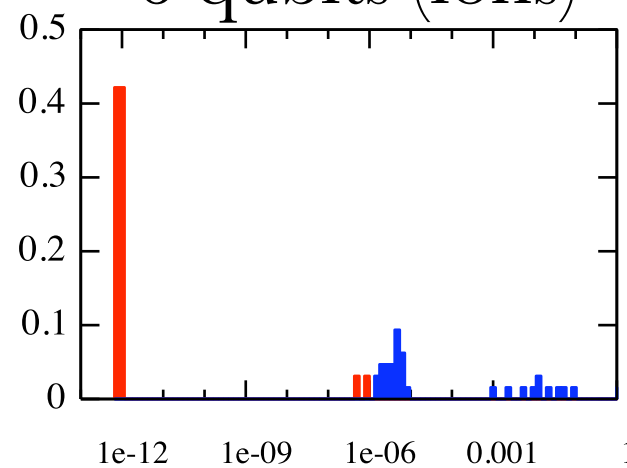
8 qubits (ions)



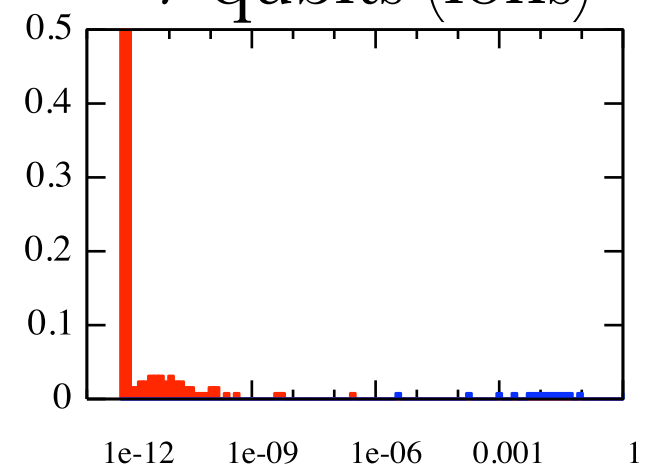
5 qubits (ions)



6 qubits (ions)



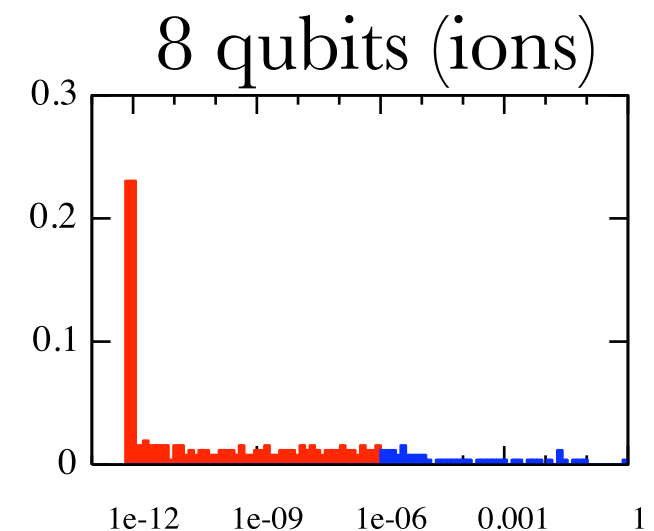
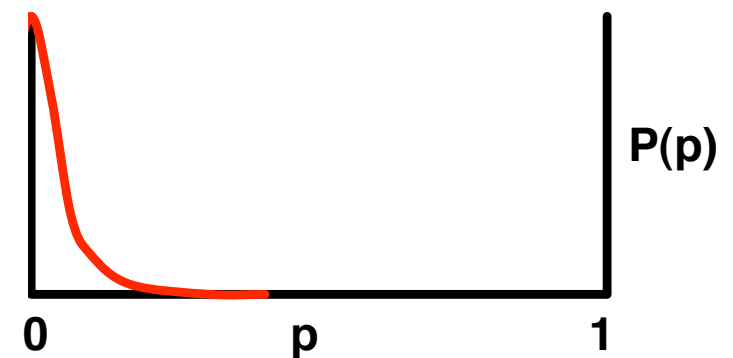
7 qubits (ions)



1. D. F. V. James et. al., "Measurement of Qubits," *Phys. Rev. A*, 64:052312 (2001)
2. Häffner et. al., "Scalable multiparticle entanglement of trapped ions," *Nature*, 438:643-6 (2005)

Error Bars?

- “But aren’t there error bars in there?”
- Not always.
- What does ~~$p = 0 \pm 0.1$~~ mean?
 $\Rightarrow p = 0.05 \pm 0.05$



States as Predictions

- Quantum states are like probability distributions: they predict the outcome of future measurements.
- Lets define a metric $f(\rho : \sigma)$ that measures how well σ predicts measurements on ρ .
 1. **The best estimate of ρ is ρ itself.**
 - i.e., $f(\rho : \rho) > f(\rho : \sigma)$ for all $\sigma \neq \rho$.
 2. **$f(\rho : \sigma)$ should correspond to an *operational* test**
 - i.e., someone's utility (reward or cost) for some practical procedure.

Quantum Strictly Proper Scoring Rules

Victor the Verifier measures a copy of ρ , and pays you $R_i(\sigma)$ if he gets outcome i .

$$1) f(\rho : \sigma) = \sum_i p(i) R_i(\sigma)$$

$$\text{Measurement} = \{E_i\} : \sum E_i = \mathbb{1}.$$

$$\begin{aligned} f(\rho : \sigma) &= \sum_i \text{Tr}[\rho E_i] R_i(\sigma) \\ &= \text{Tr}[\rho \mathcal{R}(\sigma)] \end{aligned}$$

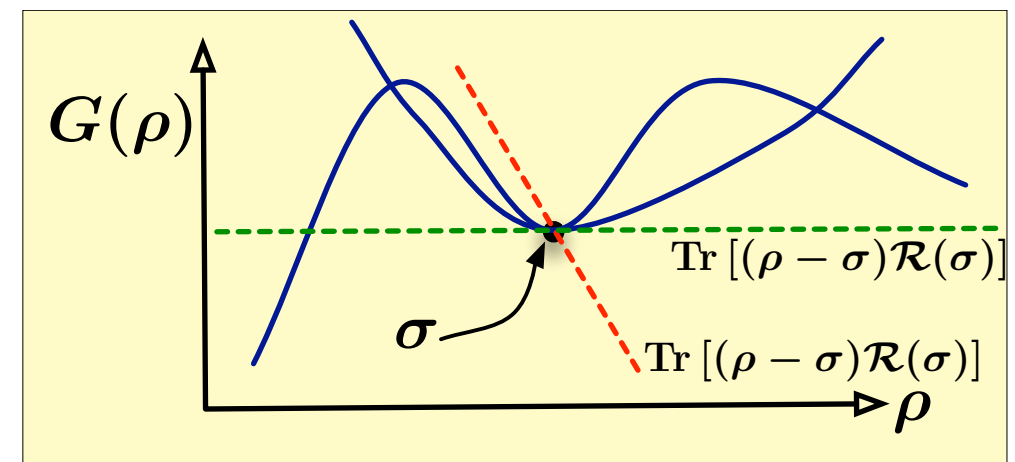
$$\text{where } \mathcal{R}(\sigma) = \sum_i E_i R_i(\sigma).$$

$$\text{Define "value": } G(\rho) \equiv f(\rho : \rho) = \text{Tr}[\rho \mathcal{R}(\rho)].$$

$$2) f(\rho : \rho) > f(\rho : \sigma) \text{ if } \sigma \neq \rho.$$

$$f(\rho : \rho) > f(\sigma : \sigma) + f(\rho : \sigma) - f(\sigma : \sigma)$$

$$G(\rho) > G(\sigma) + \text{Tr}[(\rho - \sigma)\mathcal{R}(\sigma)]$$



- $f(\rho : \sigma)$ is a subgradient to $G(\rho)$
- $G(\rho)$ must be strictly convex.

- The estimator's *expected loss* for lying is $\Delta(\rho : \sigma) \equiv G(\rho) - f(\rho : \sigma)$.
- $\Delta(\rho : \sigma)$ is an *operational divergence* = good measure of σ 's predictive accuracy.
- Operational divergences are **1 : 1** with strictly convex "entropies" $G(\rho)$.

A survey of metrics

- GOOD METRICS (OPERATIONAL DIVERGENCES)

1. L2 distance: $\text{Tr}[(\rho - \sigma)^2] \Leftrightarrow R_i = 2s_i - \text{Tr}(\sigma^2) - 1$

2. Relative entropy: $S(\rho||\sigma) = \text{Tr}\left[\rho \log \frac{\sigma}{\rho}\right] \Leftrightarrow R_i = \ln(s_i)$

- BAD METRICS

1. Overlap: $1 - \text{Tr}[\rho\sigma]$ *Improper (motivates lying)*

2. Trace-norm: $||\rho - \sigma||_1$

3. Fidelity: $1 - \left[\text{Tr}\sqrt{\sqrt{\sigma}\rho\sqrt{\sigma}}\right]^2$

Non-operational

Bayesian Mean Estimation

unconditionally optimizes every operational divergence

If you *know* ρ , the optimal estimate is $\sigma = \rho$.

But what if your knowledge is uncertain (probabilistic)?

\implies the state could be ρ_i with probability π_i .

KEY FACT: $f(\rho : \sigma) = \text{Tr}[\rho \mathcal{R}(\sigma)]$ is *linear* in ρ .

\implies *expected* utility is

$$\bar{f} = \sum \pi_i f(\rho_i : \sigma) = f\left(\sum \pi_i \rho_i : \sigma\right)$$

\implies optimal estimate is $\sigma = \bar{\rho} \equiv \sum \pi_i \rho_i$

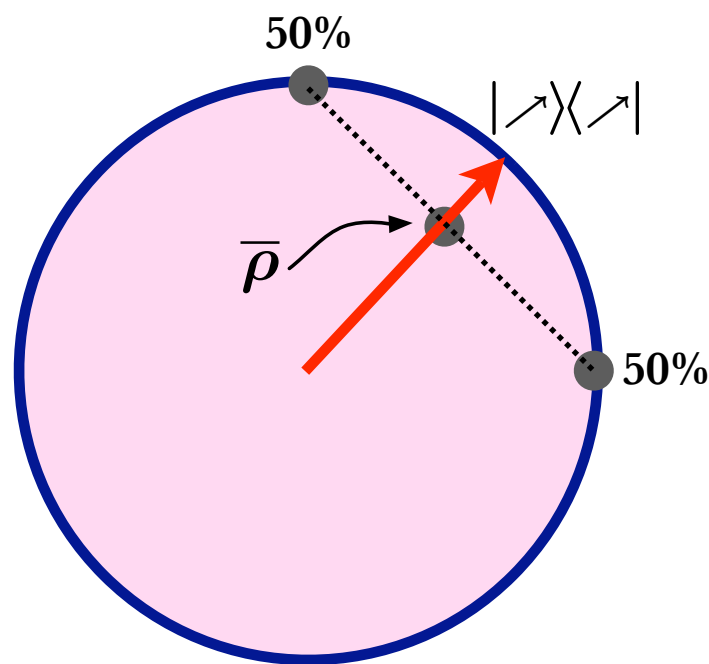
This is fairly straightforward, but tedious... see quant-ph/0603116

If unknown ρ was selected from distribution $\pi_0(\rho)d\rho$, and measurements $\mathcal{M} = \{E_1, E_2 \dots\}$ were made, then:

1. Your knowledge is $\pi(\rho)d\rho = \frac{p(\mathcal{M}|\rho)\pi_0(\rho)d\rho}{\int p(\mathcal{M}|\rho)\pi_0(\rho)d\rho}$.
2. The optimal estimate is $\bar{\rho} = \int \rho \pi(\rho)d\rho$.

But isn't this obvious? **NO**

(a) Suppose we optimize fidelity.



$$\overline{F}(\rho_i, \bar{\rho}) = \frac{3}{4}$$

$$\overline{F}(\rho_i, |\nearrow\rangle\langle\nearrow|) = \frac{3+2\sqrt{2}}{4+2\sqrt{2}} \approx 0.85$$

MORAL: fidelity measures how well σ *simulates* ρ , not how well it *estimates* ρ .

(b) Suppose we assume the future will look (statistically) just like the past.

- We know what future datasets will look like
- We can add them to measurement record
- $\mathcal{M} \longrightarrow \mathcal{M} \cup \mathcal{M} \cup \mathcal{M} \cup \dots$
- $p(\mathcal{M}|\rho) \longrightarrow p(\mathcal{M}|\rho)^\infty$
- So $\pi(\rho)d\rho \longrightarrow \delta(\rho - \rho_{\text{MLE}})$

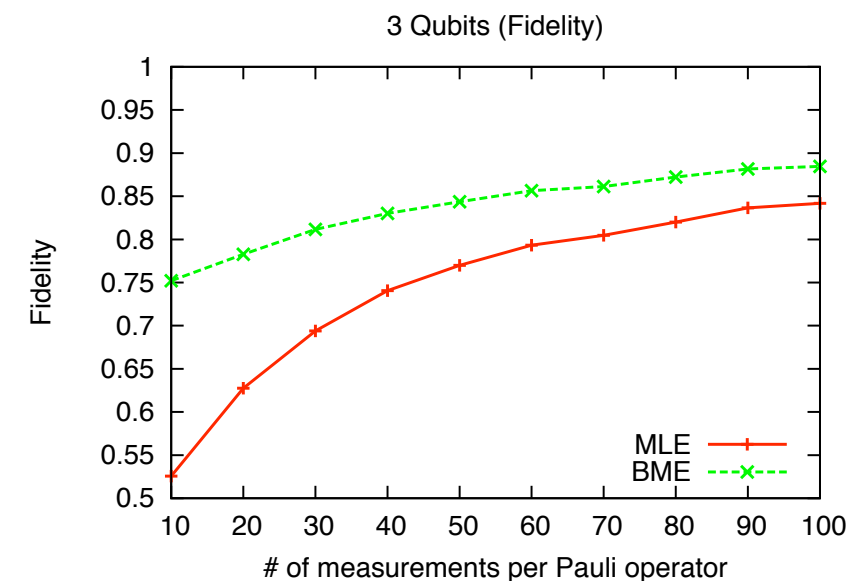
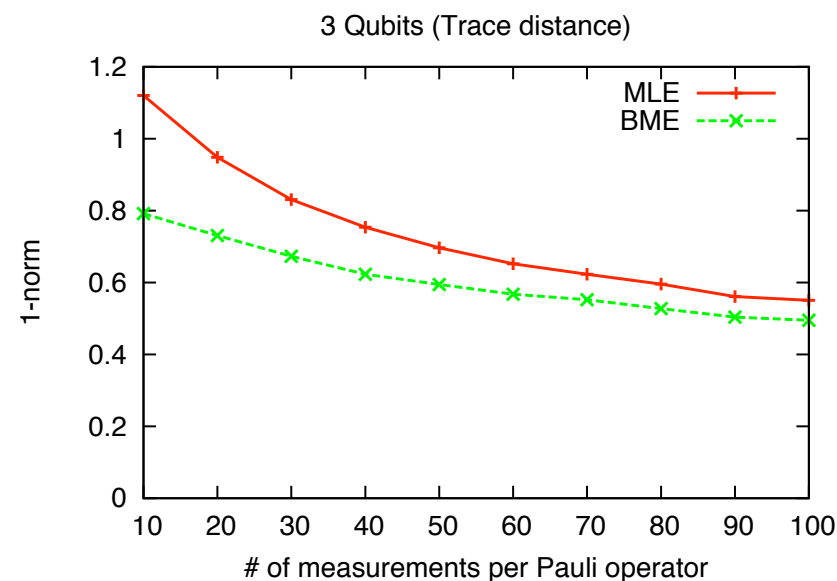
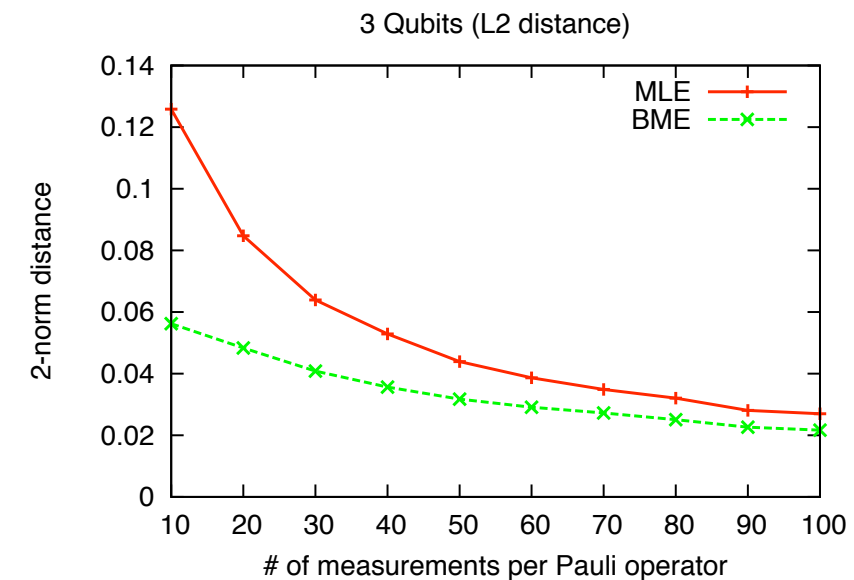
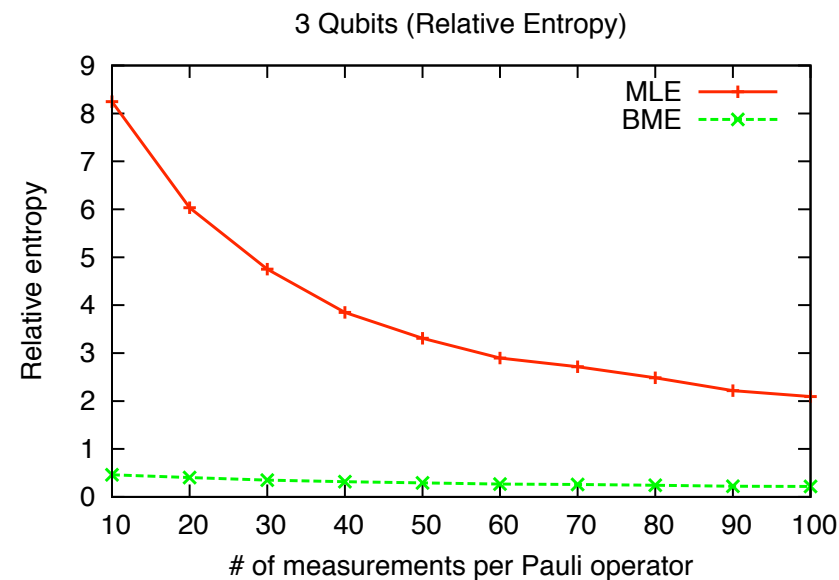
MORAL: MLE can be derived by assuming this “frequentist axiom”.

(This explains a lot...)

How good is MLE?

NUMERICS:

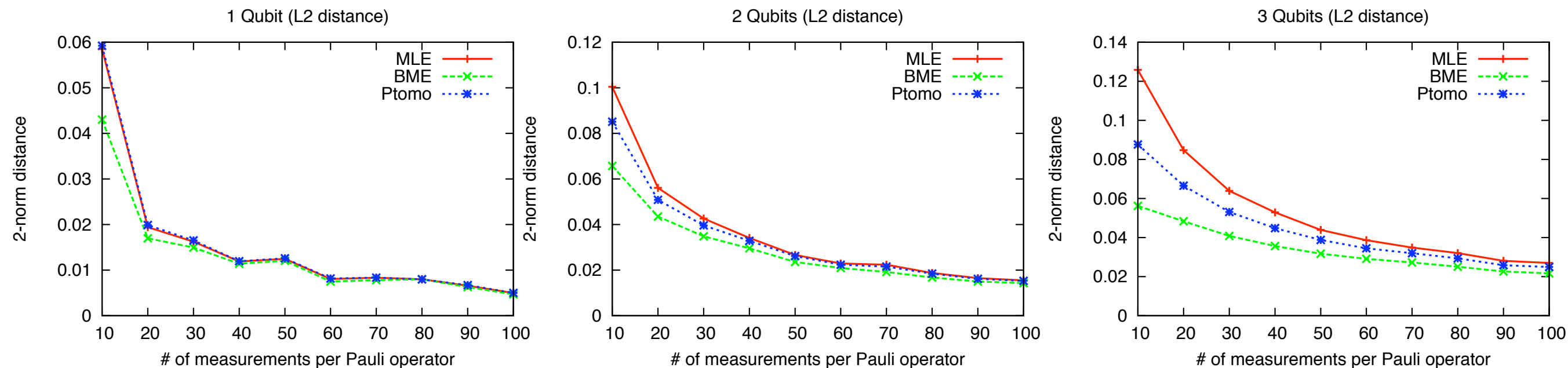
1. Generate random (Hilbert-Schmidt measure) mixed states ρ for n qubits,
2. Measure each of 4^{n-1} Pauli observables N times,
3. Analyze measurement record to get σ ,
4. Compare σ to ρ using:
 - (a) L2-norm,
 $\text{Tr} [(\rho - \sigma)^2],$
 - (b) relative entropy,
 $\text{Tr} [\rho(\ln \rho - \ln \sigma)],$
 - (c) fidelity,
 $\text{Tr} \left[\sqrt{\sqrt{\sigma} \rho \sqrt{\sigma}} \right]^2$
 - (d) L1-norm,
 $\text{Tr} [|\rho - \sigma|].$



Quick & Dirty Tomography

1. MLE gets computationally difficult for large systems.
2. BME is even harder!
3. $\frac{1}{\sqrt{3}} (|\text{D.James}\rangle + |\text{T.Havel}\rangle + |\text{P.Jessen}\rangle)$ suggested “quick 'n' dirty tomography”.

$$\sigma_{\text{tomo}} = \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & -\lambda_3 & \\ & & & -\lambda_4 \end{pmatrix} \longrightarrow \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & 0 & \\ & & & 0 \end{pmatrix} \longrightarrow \frac{1}{\lambda_1 + \lambda_2} \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & 0 & \\ & & & 0 \end{pmatrix} = \sigma.$$



Conclusions

- It's worth thinking carefully and deeply about state estimation.
- Operational divergences are a good way to evaluate the predictive accuracy of estimates.
- BME is optimal, and a baseline for evaluating other (more efficient) approaches.
- Quick & dirty methods can outperform MLE.