

# Testing Quantum States for Purity

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& Statistics**

# 1 Quantum State Estimation

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- Basics of State Estimation
- Likelihood Analysis

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- These probabilities are parameterized by a parameter which is called a state.



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- Day-to-day, if we want to know how long an object is, we simply use a ruler, measuring tape, etc.
- In experiments, we recognize that our measuring devices and techniques are not perfect, so we append estimated uncertainties to our measurements.

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- In the situation where we can repeatedly produce and test states created with the same experimental settings, we can circumvent this restriction.
- Combining the results of multiple measurements lets us produce an **estimate** of the full state

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- Repeated measurement of identical quantum states will, in general, result in different outcomes.
- Clearly, we cannot simply measure a property *once*, pack-up and go home!!!!

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- Denote the set of measurement operators by  $\{X_1 \dots X_m\}$ , where each is a Hermitian matrix.
- Born's rule tells us that the probability of observing a particular outcome when measuring a system is given by

$$p_i(\theta) = \text{Tr}(X_i \rho(\theta))$$

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- The probability of observing  $y_i$  detections for each measurements  $X_i$  is then the product of Poisson distributions, treating the counts as independent

$$p(y_1 \dots y_m | \theta) = \prod_{i=1}^m \frac{(\lambda \text{Tr}(X_i \rho(\theta)))^{y_i}}{y_i!} e^{-\lambda \text{Tr}(X_i \rho(\theta))}.$$

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- The above is the probability of observing the counts  $\{y_1 \dots y_m\}$  given the parameter  $\theta \in \Theta$ .

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- Letting  $y_1 + \dots + y_m = n$ , by conditioning on  $n$
- multinomial distribution

$$P(Y_1 = y_1, \dots, Y_m = y_m | n; \theta) = \frac{n!}{y_1! \dots y_s!} p_1(\theta)^{y_1} \dots p_s(\theta)^{y_s}$$

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- the log-likelihood

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- a generalized linear model with a linear link function!

# Some Properties of MLE

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- the interior of  $\Theta$  are the positive definite matrices
- the boundaries consist of disjoint union of rank 1 to rank  $d - 1$  matrices.
- Again the pure states are rank 1 matrices.

# Parametrization

$\hat{\rho}$  and  $\tilde{\rho}$  MLE estimates under all states and pure states respectively

$$D(\hat{\rho}, \tilde{\rho}) = 2 \{ \ell(\hat{\rho}; y_1, \dots, y_s) - \ell(\tilde{\rho}; y_1, \dots, y_s) \}.$$

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$\theta = (\theta^{(1)}, \theta^{(2)})$  for which the pure states is given by  $\theta^{(2)} = 0$ .

The score statistic for testing for purity is

$$S(\tilde{\theta}) = \left( \frac{\partial \ell}{\partial \theta^{(2)}} \Big|_{\theta=\tilde{\theta}} \right) \mathcal{I}_{22,1}^{-1}(\tilde{\theta}) \left( \frac{\partial \ell}{\partial \theta^{(2)}} \Big|_{\theta=\tilde{\theta}} \right)',$$

$$\mathcal{I}_{22,1}(\theta) = \mathcal{I}_{22}(\theta) - \mathcal{I}_{21}(\theta) \mathcal{I}_{11}^{-1}(\theta) \mathcal{I}_{12}(\theta)$$

$$\mathcal{I}(\theta) = \begin{pmatrix} \mathcal{I}_{11}(\theta) & \mathcal{I}_{12}(\theta) \\ \mathcal{I}_{21}(\theta) & \mathcal{I}_{22}(\theta) \end{pmatrix}.$$

# Large sample theory

The score statistic for testing for purity has the result

$$S(\tilde{\theta}) \sim \chi_{(d-1)^2}^2,$$

as  $n \rightarrow \infty$  provided we “enlarge” our parameter space to

$$\mathcal{S} = \{\rho = \rho(\theta) : \rho^* = \rho \text{ Tr } \rho = 1 \text{ Tr } X_j \rho > 0 \text{ } j = 1, \dots, m\}$$

# 1 Qubit Case

In order to provide some clarity, let us consider the simplest case.  
If our parameters are  $\theta = (a_{12}, b_{12}, a_{22})$ , let

$$\rho(\theta) = \begin{pmatrix} 1 - a_{2,2} & a_{1,2} + ib_{1,2} \\ a_{1,2} - ib_{1,2} & a_{2,2} \end{pmatrix}.$$

The following new parameters are defined:

$$\alpha_{1,2} = a_{1,2}$$

$$\beta_{1,2} = b_{1,2}$$

$$\alpha_{2,2} = a_{2,2}(1 - a_{2,2}) - (a_{1,2}^2 + b_{1,2}^2).$$

# 1 Qubit Case ctd.

We have:

$$a_{1,2} = \alpha_{1,2}$$

$$b_{1,2} = \beta_{1,2}$$

$$a_{2,2} = \frac{1 \pm \sqrt{1 - 4(\alpha_{2,2} + \alpha_{1,2}^2 + \beta_{1,2}^2)}}{2}.$$

Thus

$$\rho(\alpha_{1,2}, \beta_{1,2}, \alpha_{2,2}) = \begin{pmatrix} \frac{1 \mp \sqrt{1 - 4(\alpha_{1,2}^2 + \beta_{1,2}^2 + \alpha_{2,2})}}{2} & \frac{\alpha_{1,2} + i\beta_{1,2}}{1 \pm \sqrt{1 - 4(\alpha_{1,2}^2 + \beta_{1,2}^2 + \alpha_{2,2})}} \\ \alpha_{1,2} - i\beta_{1,2} & \frac{1 \pm \sqrt{1 - 4(\alpha_{1,2}^2 + \beta_{1,2}^2 + \alpha_{2,2})}}{2} \end{pmatrix}.$$

# Control Over Rank and Uniqueness

$$\rho(\alpha_{1,2}, \beta_{1,2}, \alpha_{2,2}) = \begin{pmatrix} \frac{1 \mp \sqrt{1 - 4(\alpha_{1,2}^2 + \beta_{1,2}^2 + \alpha_{2,2})}}{2} & \frac{\alpha_{1,2} + i\beta_{1,2}}{1 \pm \sqrt{1 - 4(\alpha_{1,2}^2 + \beta_{1,2}^2 + \alpha_{2,2})}} \\ \alpha_{1,2} - i\beta_{1,2} & \frac{1 \pm \sqrt{1 - 4(\alpha_{1,2}^2 + \beta_{1,2}^2 + \alpha_{2,2})}}{2} \end{pmatrix}$$



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These properties extend beyond the single-qubit case.

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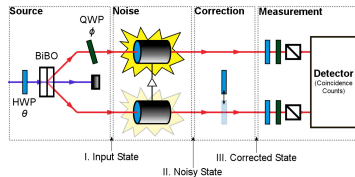


Figure: Schematic diagram of two-qubit experiment.





# Two Qubit Experiments

**Table:** Deviances, score statistics, and purities of qubit pairs.

	Data set								
	I	II	III	IV	V	VI	VII	VIII	IX
Deviance, $D$	25,146	892	3,958	148	9,835	981	199,658	4,232	205,642
Score, $S$	1,494	1,675	2,197	178	1,216	1,159	$1.85 \times 10^{13}$	$1.93 \times 10^{10}$	$2.34 \times 10^{11}$
Purity, $\hat{\gamma}$	1.527	.992	1.355	.978	1.257	.935	.668	.937	.658