

Applying Model Selection to Quantum State Tomography: Choosing Hilbert Space Dimension

Travis L Scholten

APS March Meeting
5 March 2015

Tomography is hard

Doing so in infinite dimensional
Hilbert space is harder

Let's make it easier...



U.S. DEPARTMENT OF
ENERGY

NNSA
National Nuclear Security Administration



Sandia
National
Laboratories

Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

Tomography is hard.

We do tomography to
make the unknown knowable

State tomography

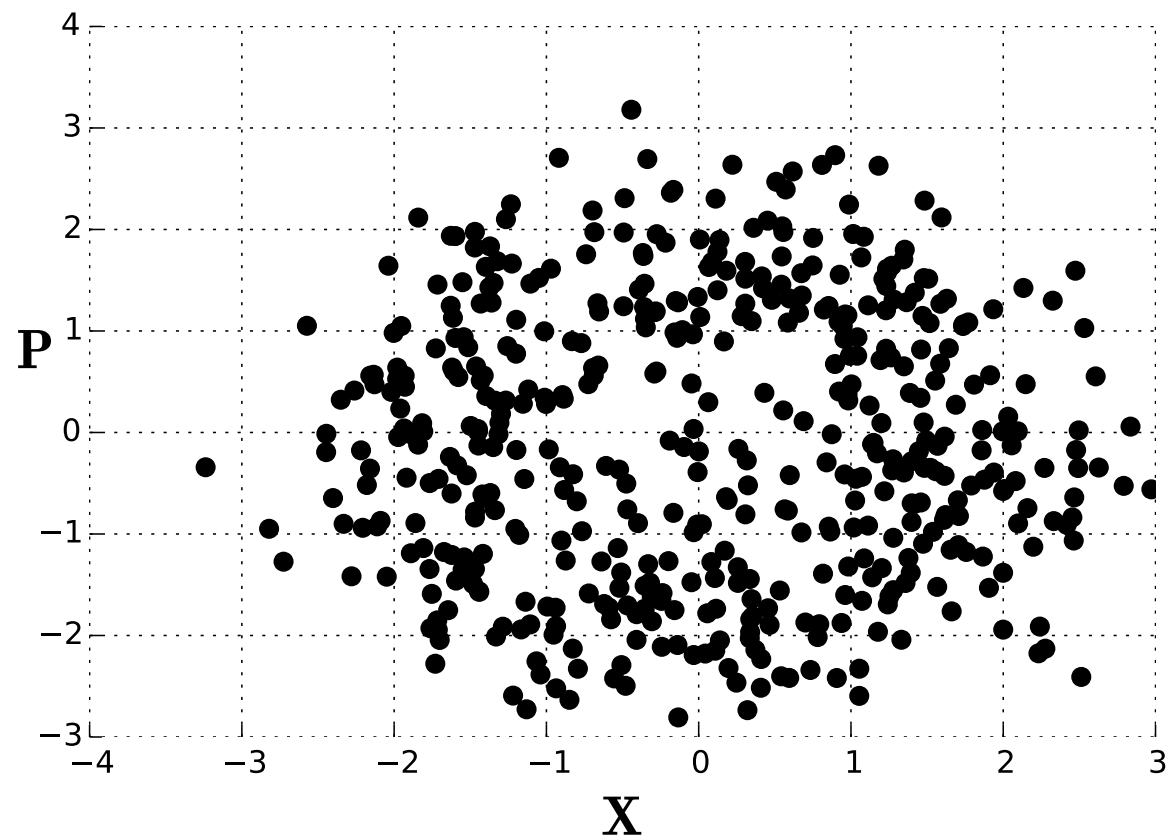
Process tomography

Gate Set tomography



Tomography in infinite dimensional Hilbert space is harder.

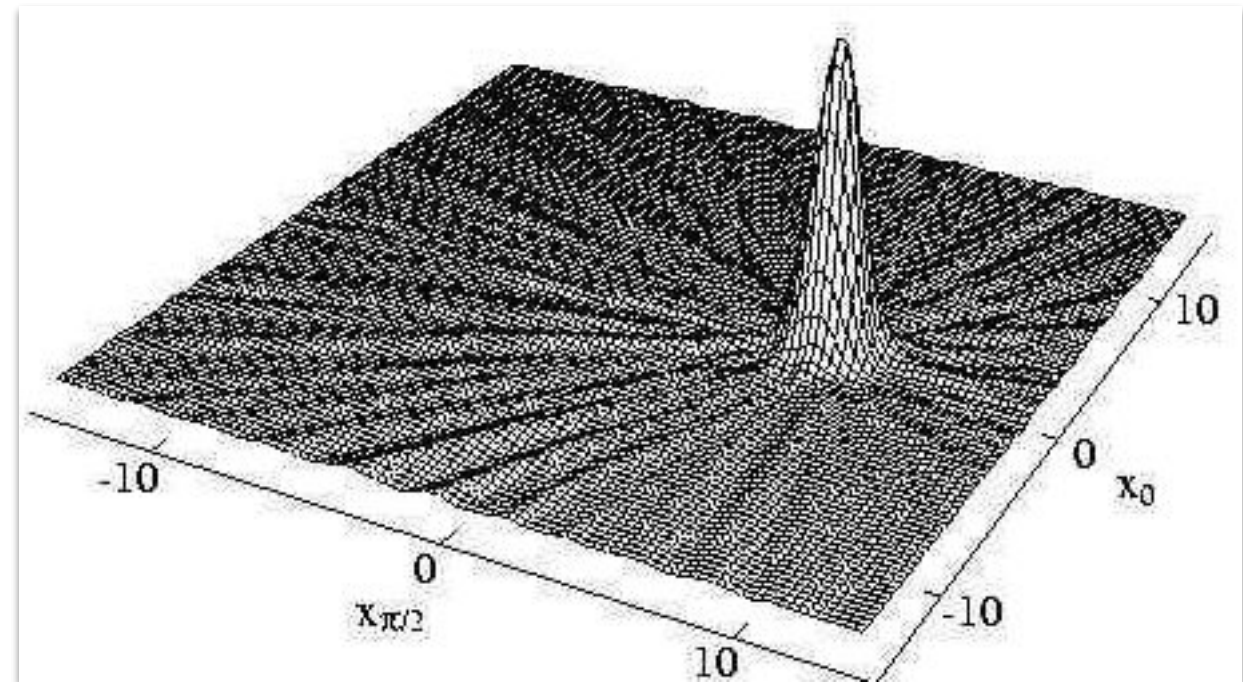
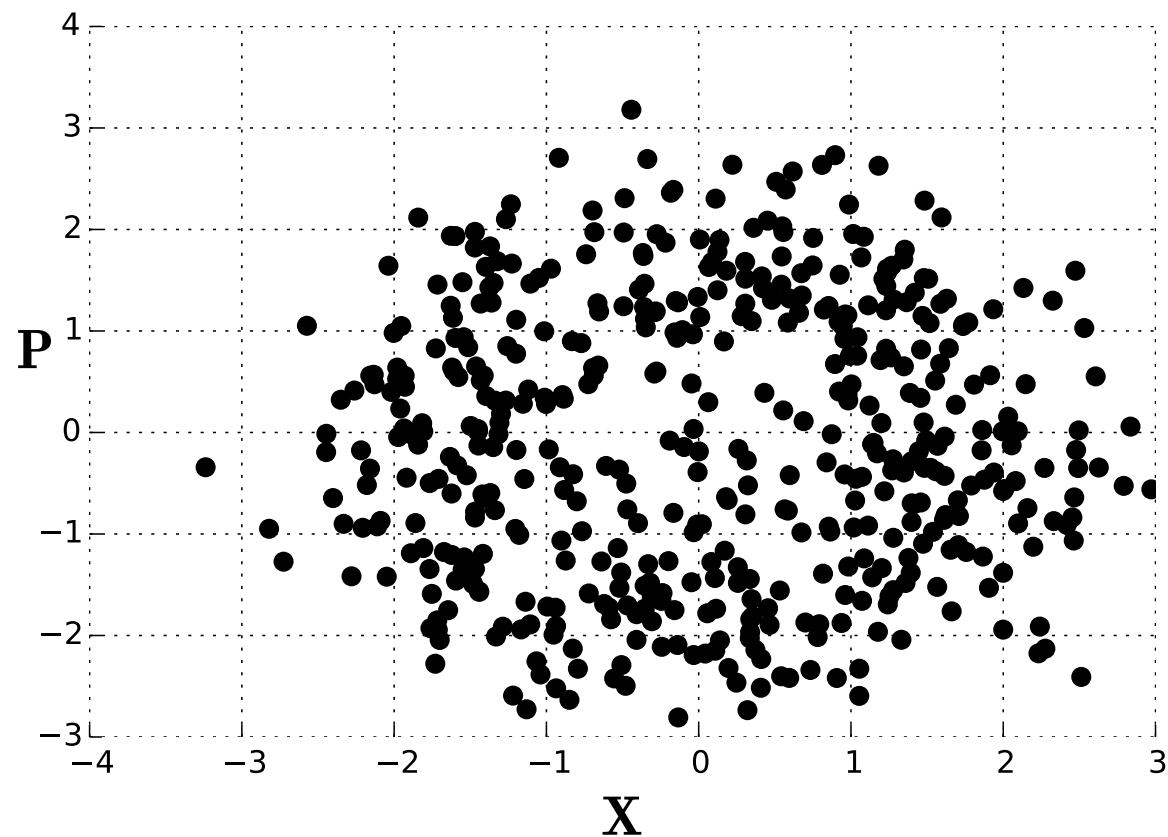
484 Simulated Heterodyne
Measurement Outcomes



From measurements on
a **continuous variable system**,
we estimate...

Tomography in infinite dimensional Hilbert space is harder.

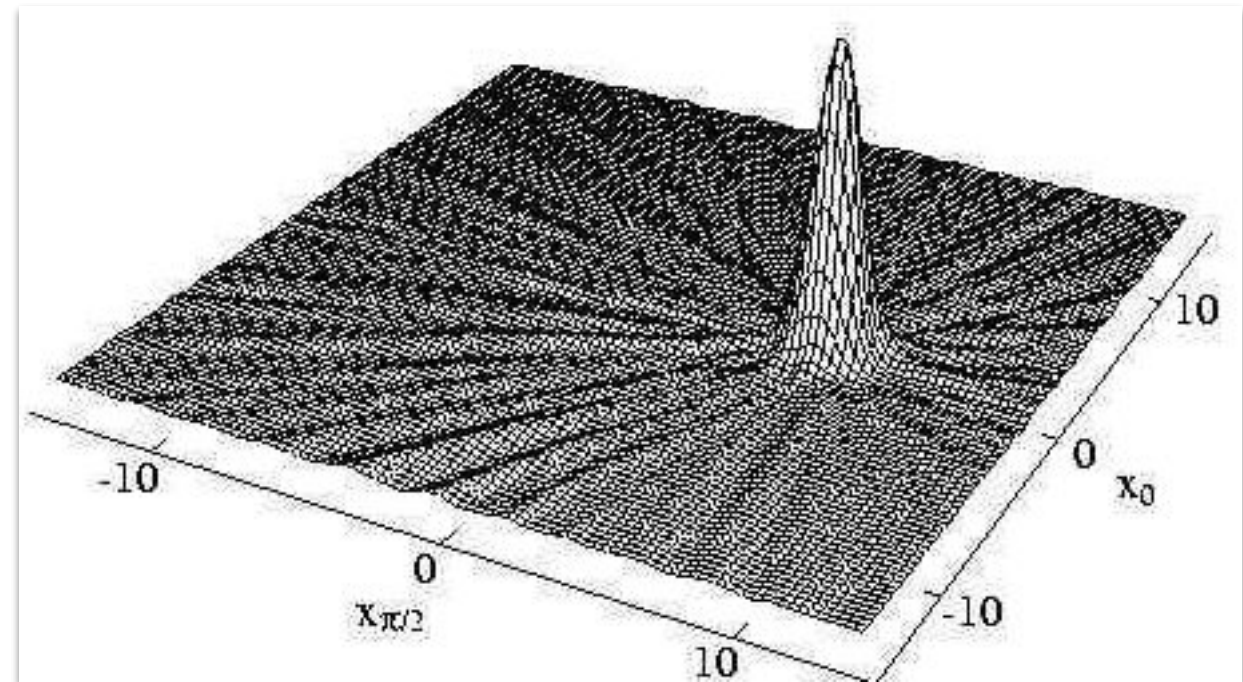
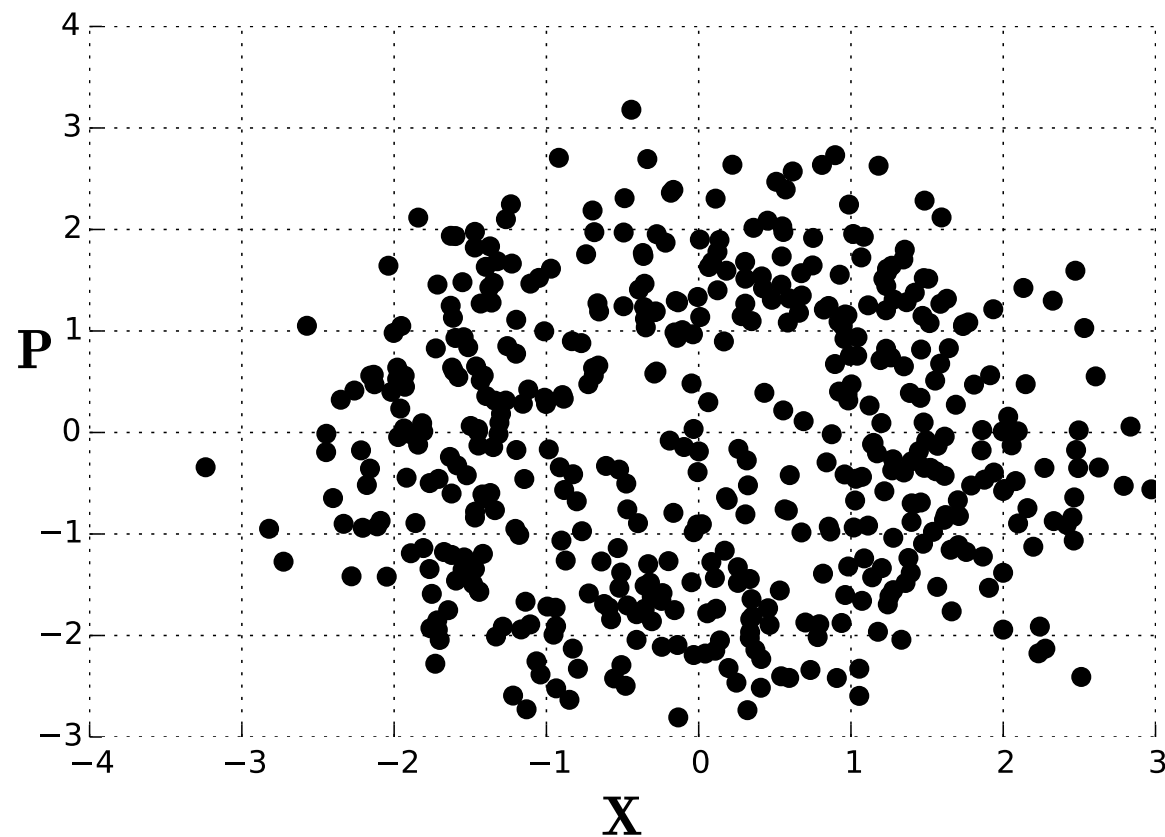
484 Simulated Heterodyne
Measurement Outcomes



...a Wigner function...

Tomography in infinite dimensional Hilbert space is harder.

484 Simulated Heterodyne Measurement Outcomes



$$\hat{\rho} = \begin{pmatrix} \rho_{00} & \rho_{01} & \cdots \\ \rho_{10} & \rho_{11} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

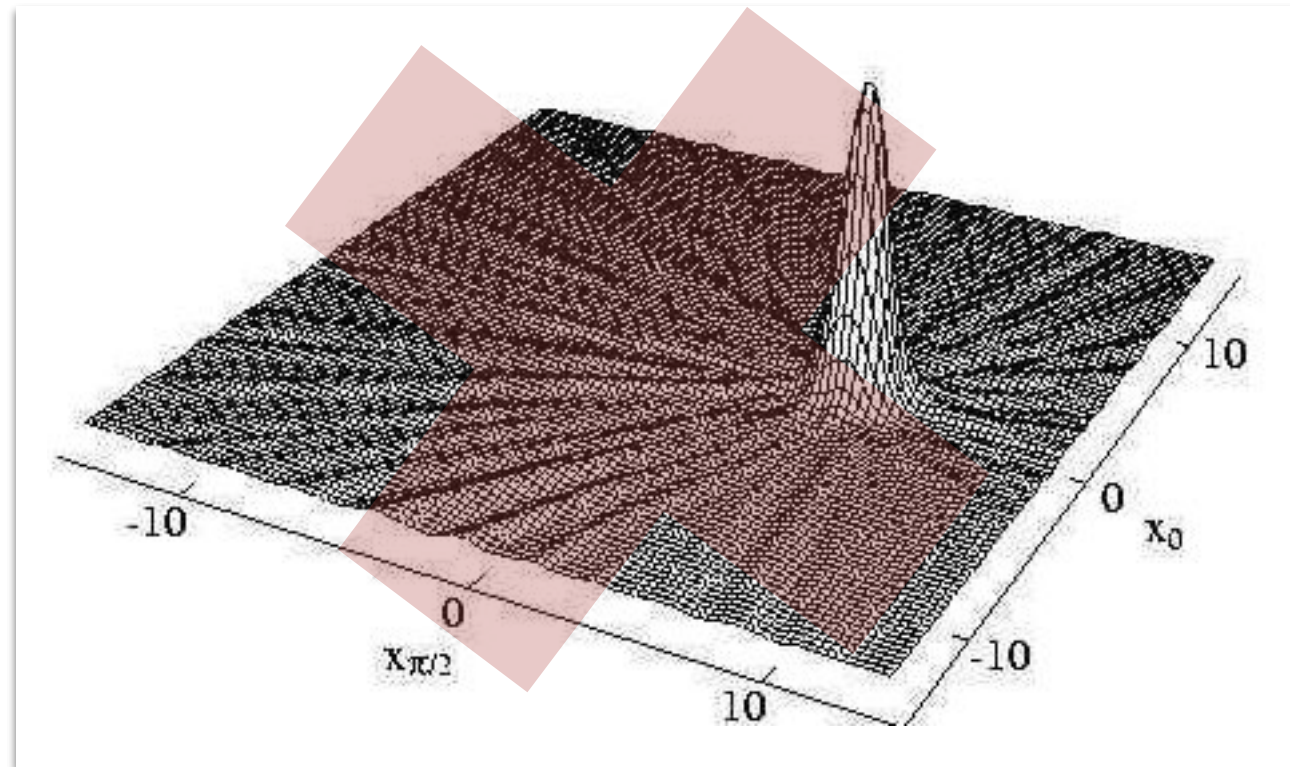
...a Wigner function...
...or a density matrix

Tomography in infinite Hilbert space is harder.

Ad-hoc smoothing/binning
not always reliable

Infinite parameters
estimated from **finite data!**

Don't use an infinite matrix



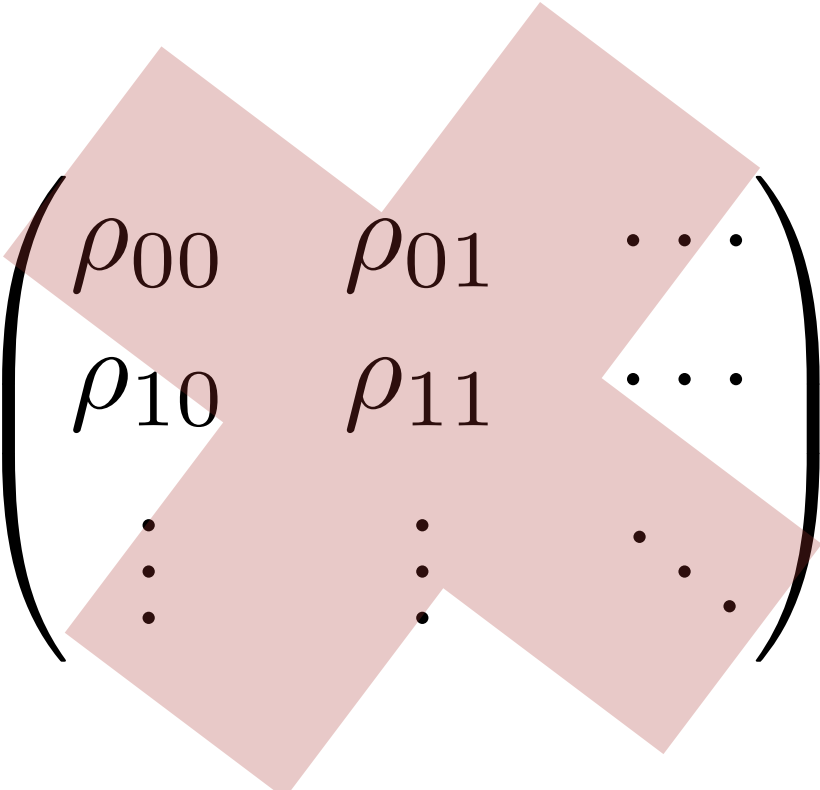
$$\hat{\rho} = \begin{pmatrix} \rho_{00} & \rho_{01} & \cdots \\ \rho_{10} & \rho_{11} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

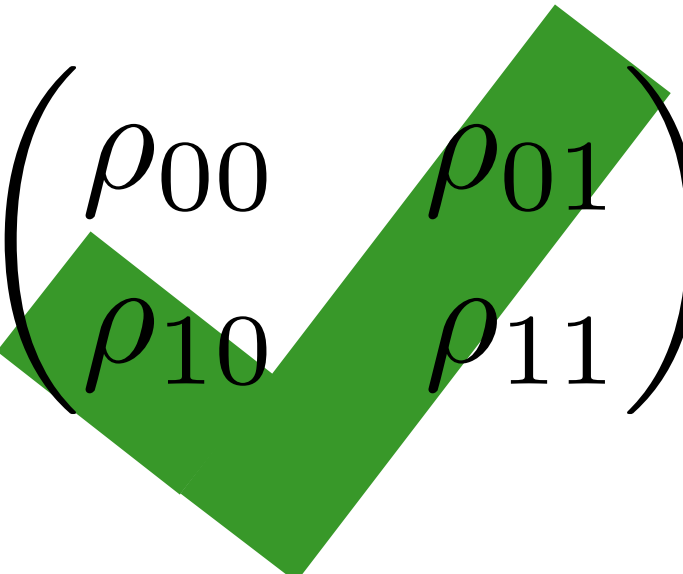
Let's make it easier.

Don't use an infinite matrix...

Finite parameters
estimated from **finite data**.

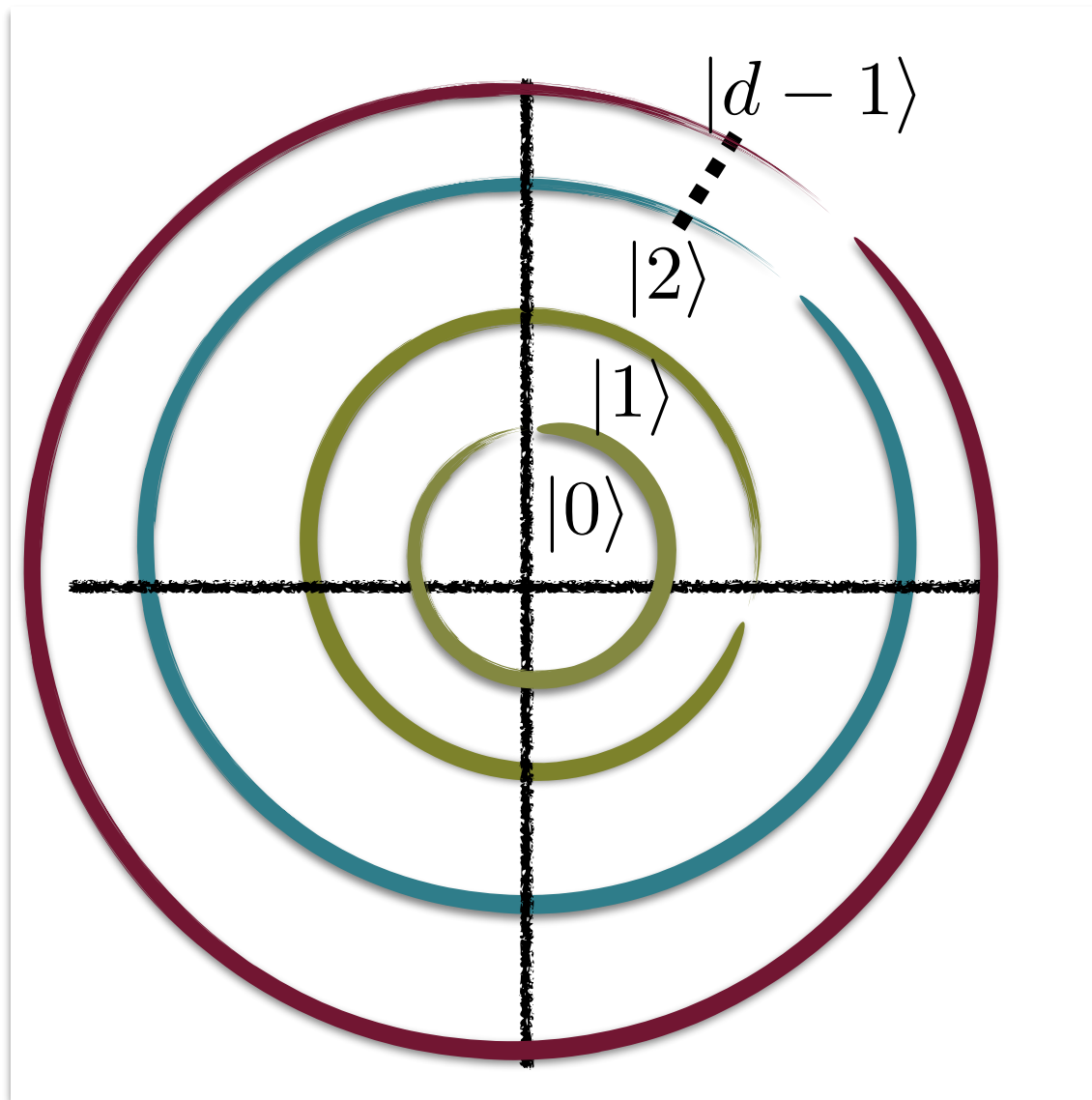
...use a smaller one instead!

$$\hat{\rho} = \begin{pmatrix} \rho_{00} & \rho_{01} & \cdots \\ \rho_{10} & \rho_{11} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}$$


$$\hat{\rho} = \begin{pmatrix} \rho_{00} & \rho_{01} \\ \rho_{10} & \rho_{11} \end{pmatrix}$$


Let's make it easier.

Low energy states can be modeled using a **truncated Fock basis**: $\mathcal{H}_d = \text{span}(|0\rangle, \dots, |d-1\rangle)$



$$\hat{\rho} = \begin{pmatrix} \rho_{00} & \rho_{01} & \rho_{02} & \cdots \\ \rho_{10} & \rho_{11} & \rho_{12} & \cdots \\ \rho_{20} & \rho_{21} & \rho_{22} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

model is $\rho \in D(\mathcal{H}_2)$
(3 parameters)

model is $\rho \in D(\mathcal{H}_3)$
(8 parameters)

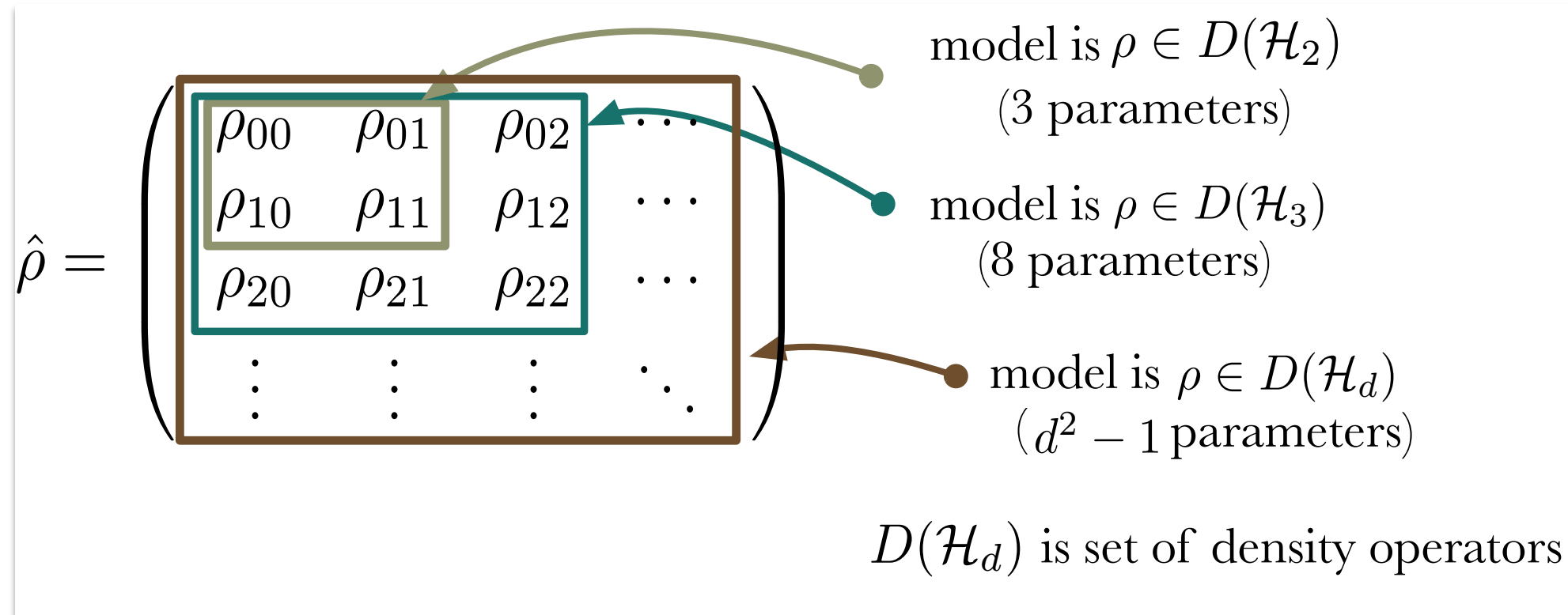
model is $\rho \in D(\mathcal{H}_d)$
($d^2 - 1$ parameters)

$D(\mathcal{H}_d)$ is set of density operators

This is where we will do tomography.

Let's make it easier.

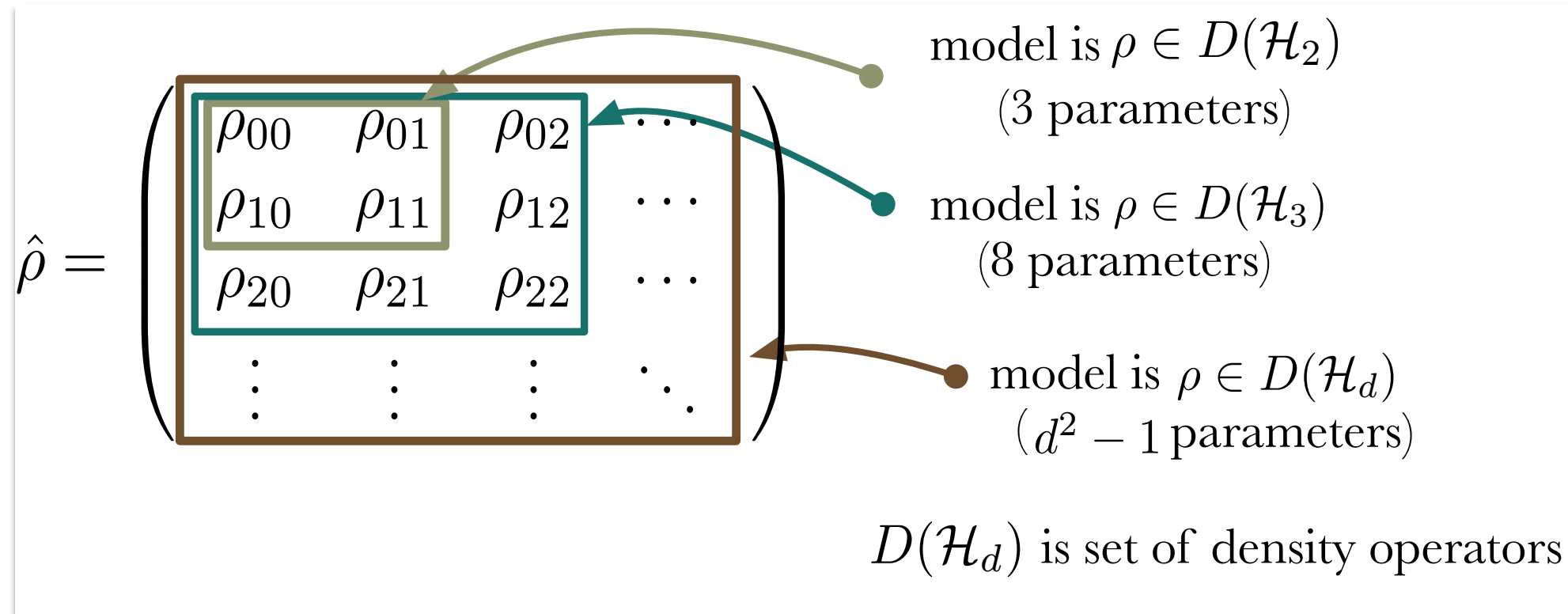
We have an **algorithm** for deciding which d is best.



- 1) Take data
- 2) For d in $[2, 3, 4, \dots]$, compare model d to $d + 1$
- 3) If model $d + 1$ fits significantly better, reject d
Otherwise, d is where we stop.

Let's make it easier.

We can **quantify** “fitting significantly better”.



Goodness of fit = loglikelihood ratio statistic:

$$\lambda(d_1, d_2) = -2 \log \left(\frac{\mathcal{L}(d_1)}{\mathcal{L}(d_2)} \right) = -2 \log \left(\frac{\max_{\rho \in D(\mathcal{H}_{d_1})} \mathcal{L}(\rho)}{\max_{\rho \in D(\mathcal{H}_{d_2})} \mathcal{L}(\rho)} \right)$$

Let's make it easier.

The **precise** algorithm for “fitting significantly better”.

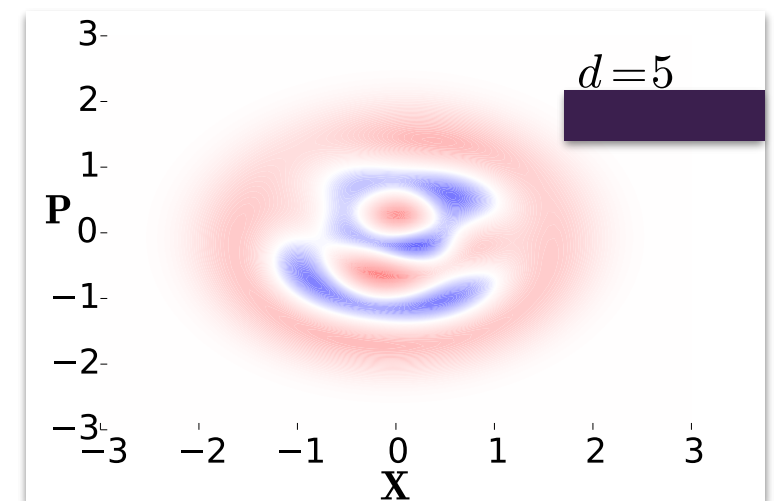
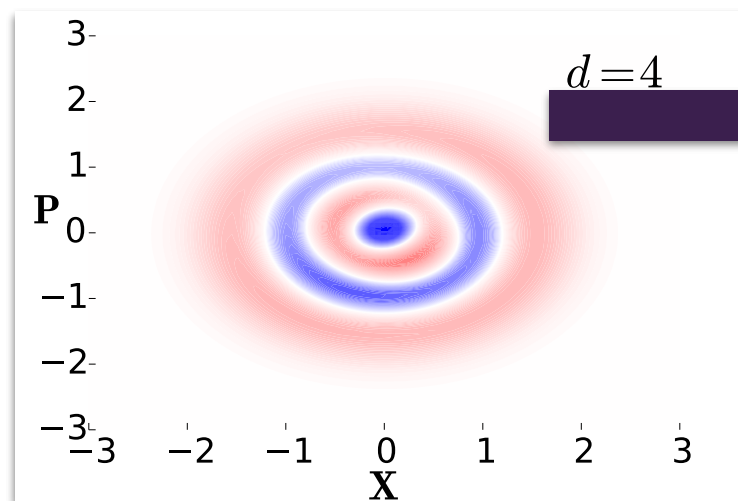
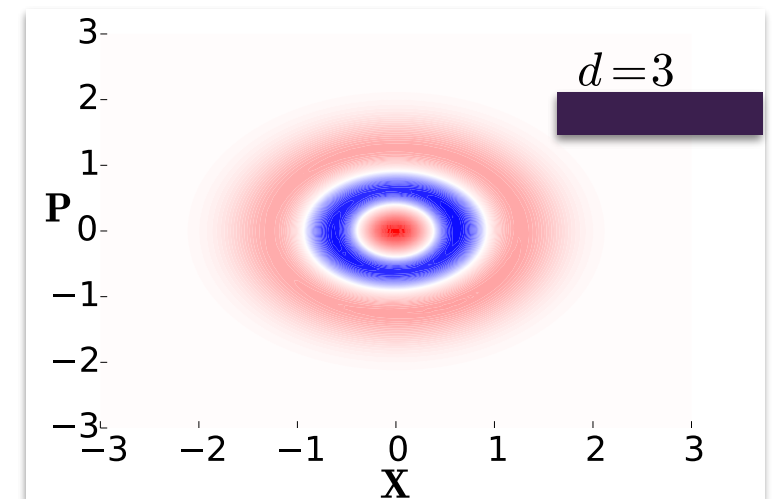
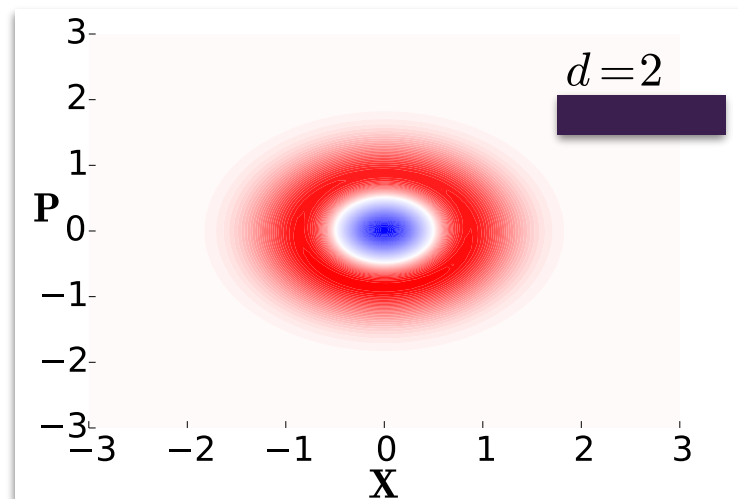
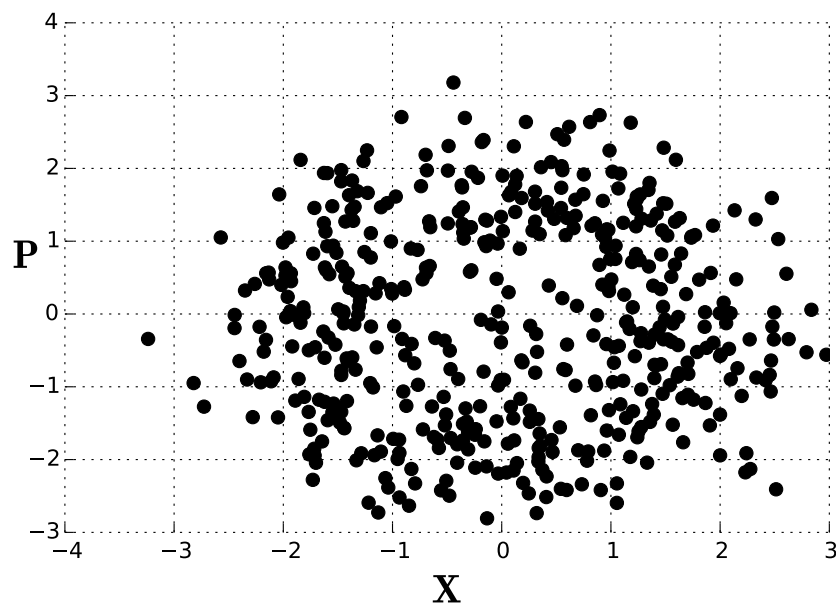
$$\lambda(d_1, d_2) = -2 \log \left(\frac{\mathcal{L}(d_1)}{\mathcal{L}(d_2)} \right) = -2 \log \left(\frac{\max_{\rho \in D(\mathcal{H}_{d_1})} \mathcal{L}(\rho)}{\max_{\rho \in D(\mathcal{H}_{d_2})} \mathcal{L}(\rho)} \right)$$

- 1) Take data
- 2) Compute $\lambda(d, d + 1)$ for d in $[2, 3, 4, \dots]$
- 3) If $\lambda(d, d + 1)$ greater than threshold, reject d
Otherwise, d is where we stop.

Let's make it easier.

An **example** demonstrates use of loglikelihood ratio statistic.

484 Simulated Heterodyne
Measurement Outcomes

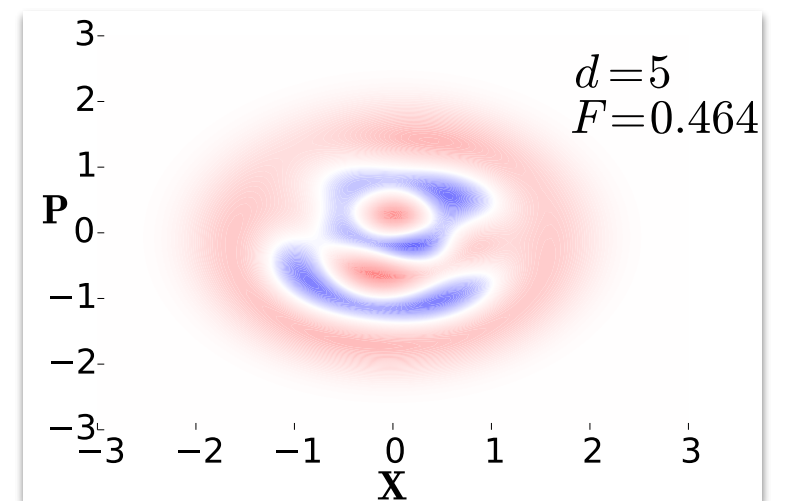
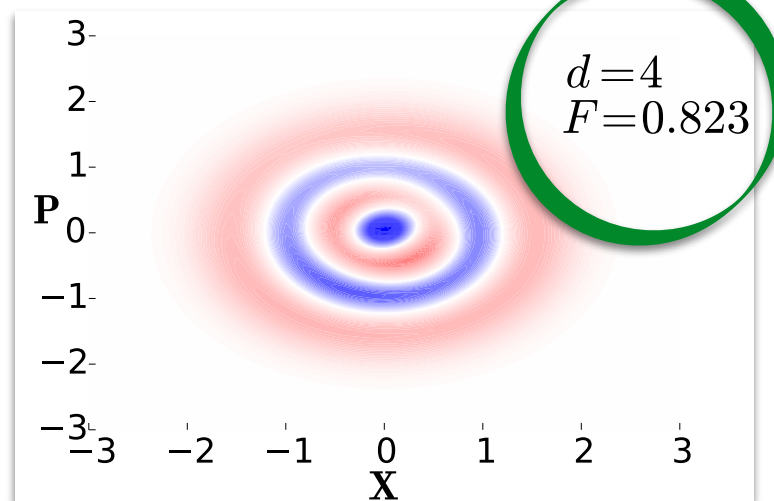
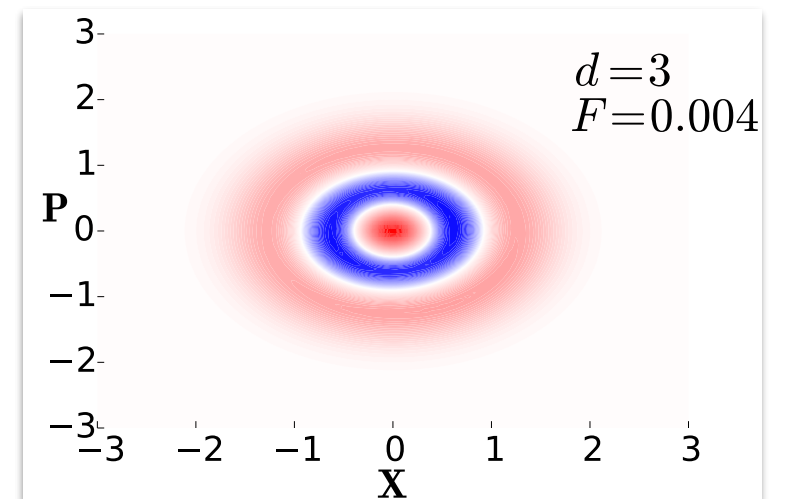
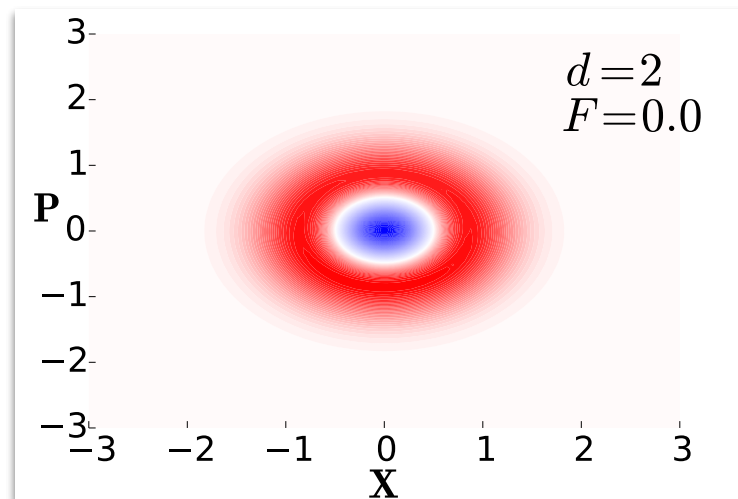
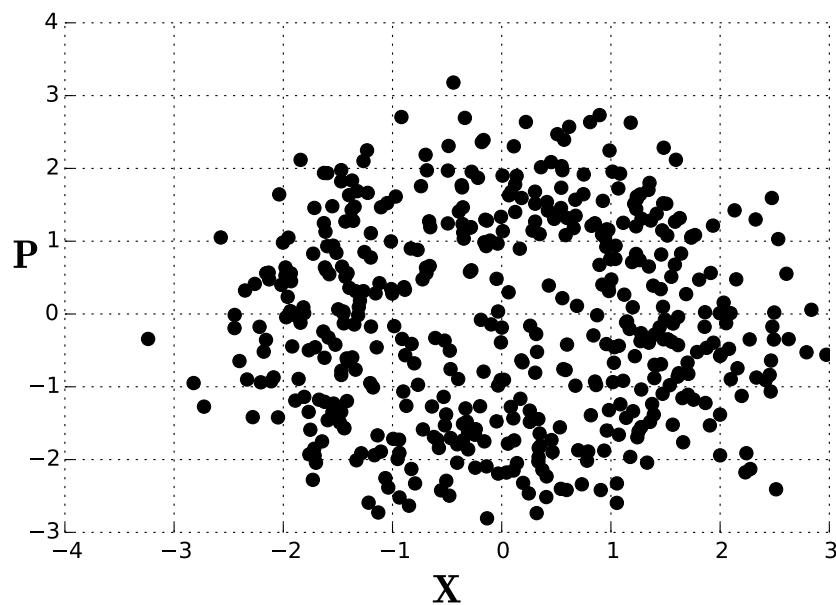


Can you tell which
model fits the best?

Let's make it easier.

An **example** demonstrates use of loglikelihood ratio statistic.

484 Simulated Heterodyne
Measurement Outcomes

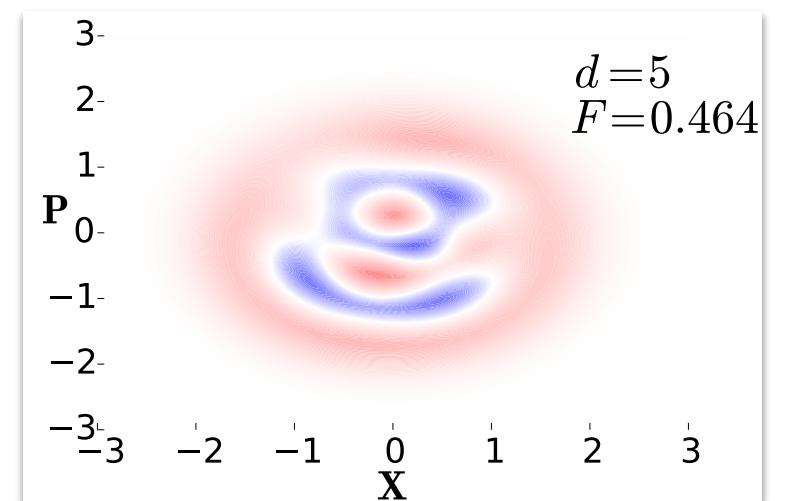
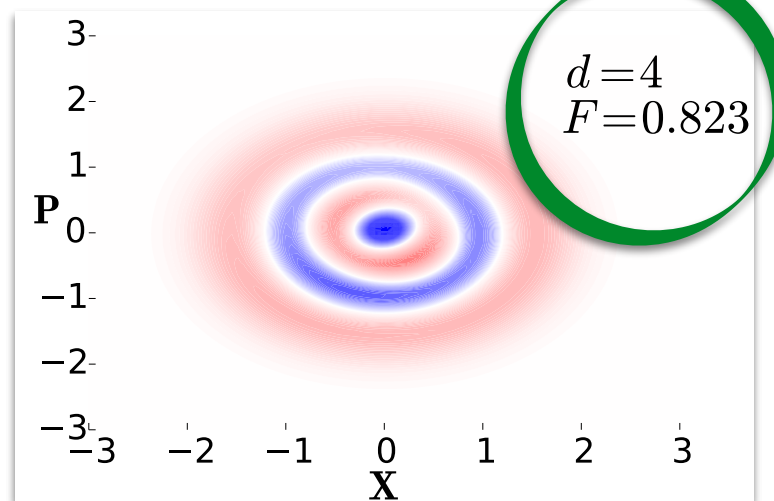
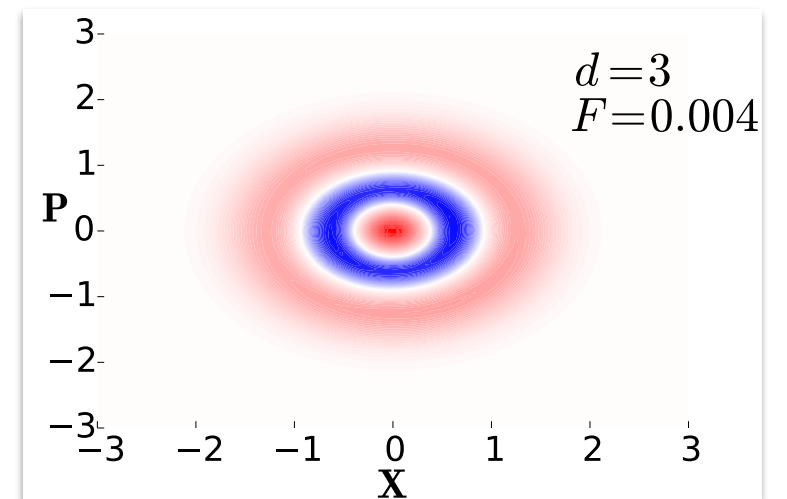
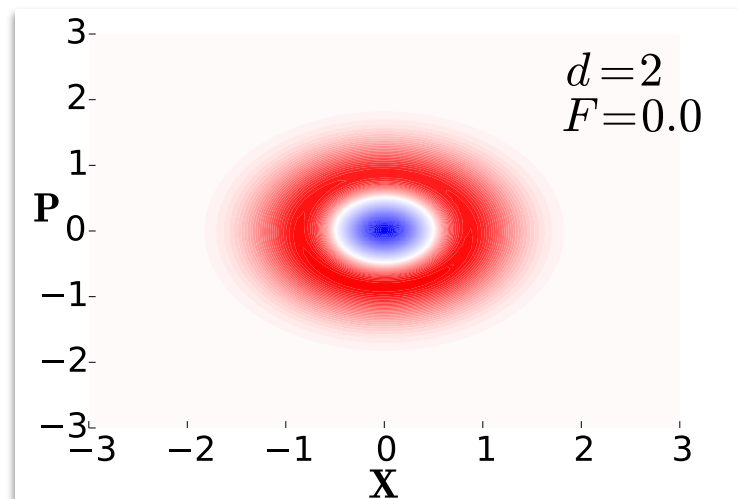
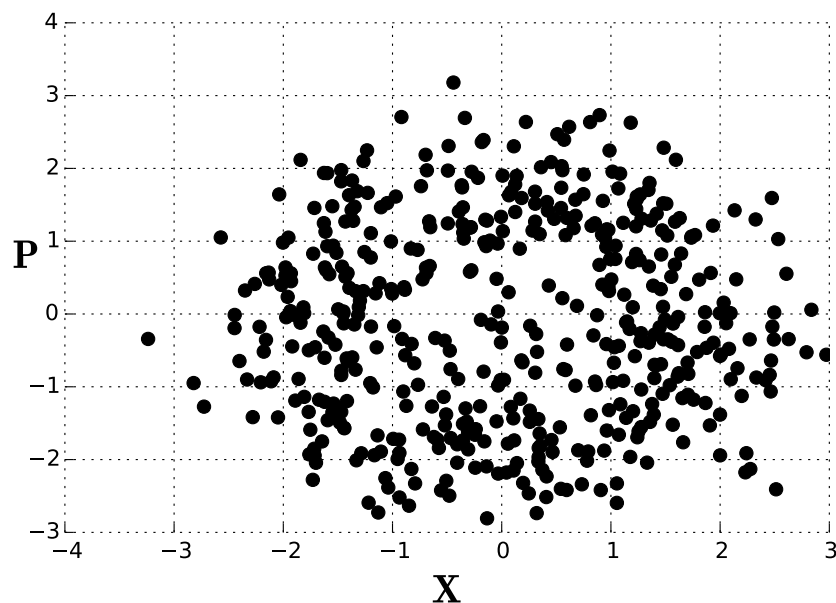


Can you tell which
model fits the best?

Let's make it easier.

An **example** demonstrates use of loglikelihood ratio statistic.

484 Simulated Heterodyne
Measurement Outcomes

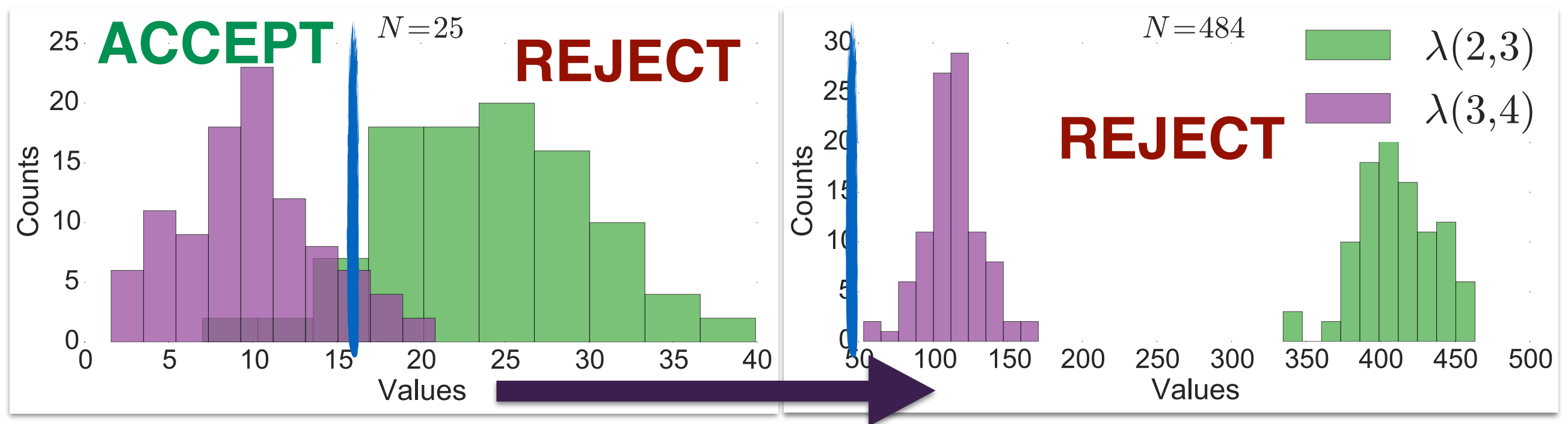


Can you tell which
model fits the best?

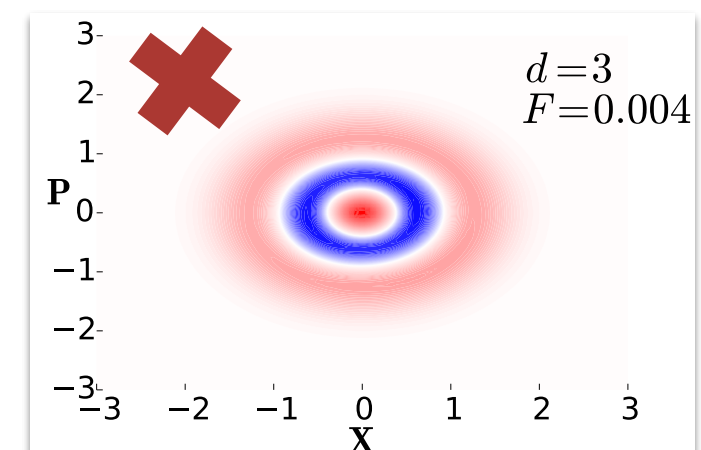
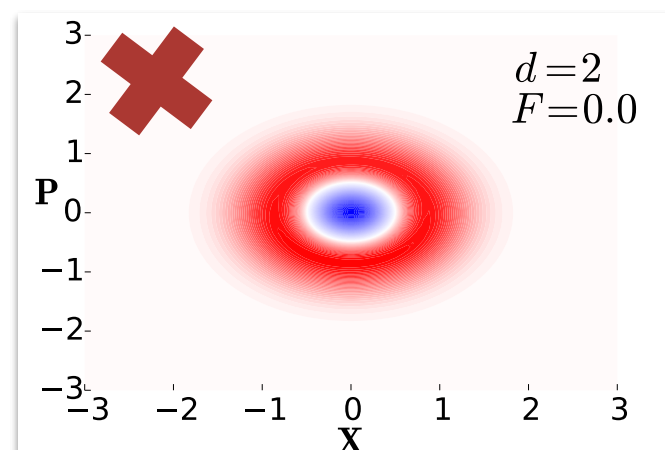
What if you did not
know the true state?

Let's make it easier.

A threshold decides when **smaller models fit worse**.

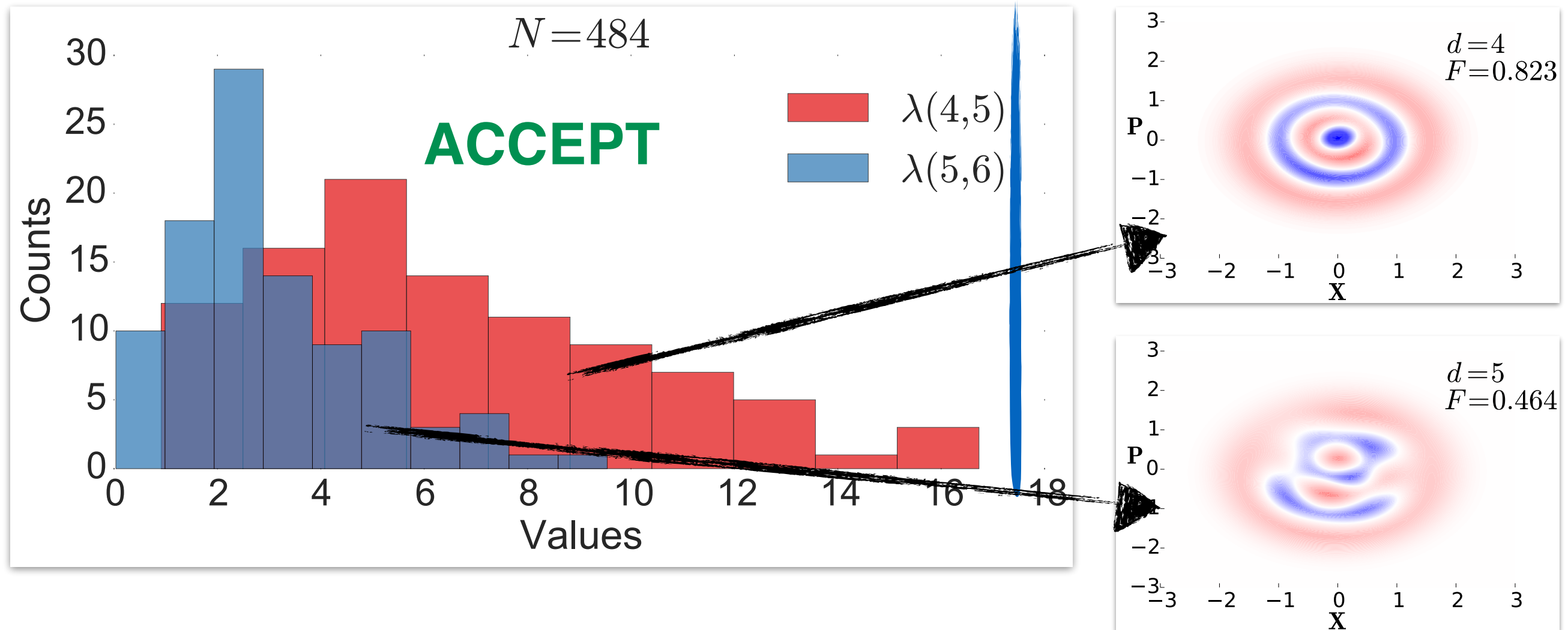


Qubit/qutrit does not well model 4 dimensional system...statistic grows with sample size.



Let's make it easier.

When smaller model **fits well**, all larger models do too.



This is the focus of my current work.

Use numerics to investigate.