

Optimal error regions for
quantum state estimation:
They are as hard to
compute as this title is long

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Outline

- error regions crash course
- error regions for quantum state estimation (QSE)
- complexity result for Bayesian credible regions
- comments on Frequentist's confidence regions

Error Regions

Frequentist
→ confidence regions

Bayesian
→ credible regions

Error Regions

Frequentist
→ confidence regions

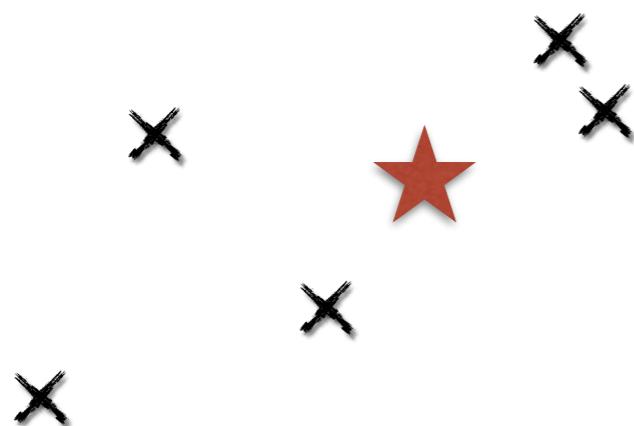
Bayesian
→ credible regions



Error Regions

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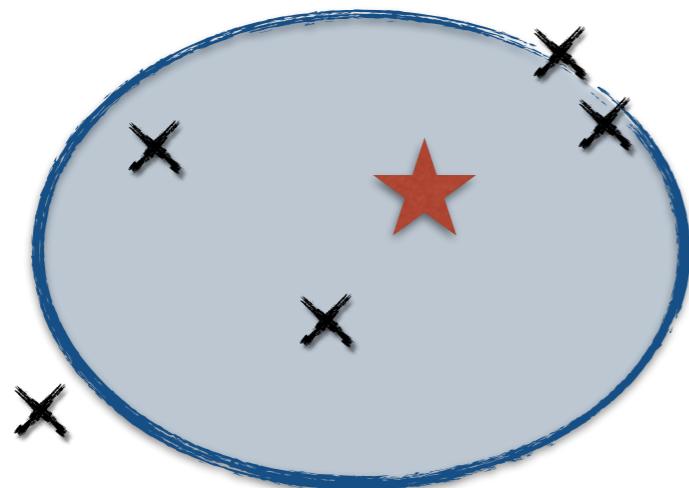
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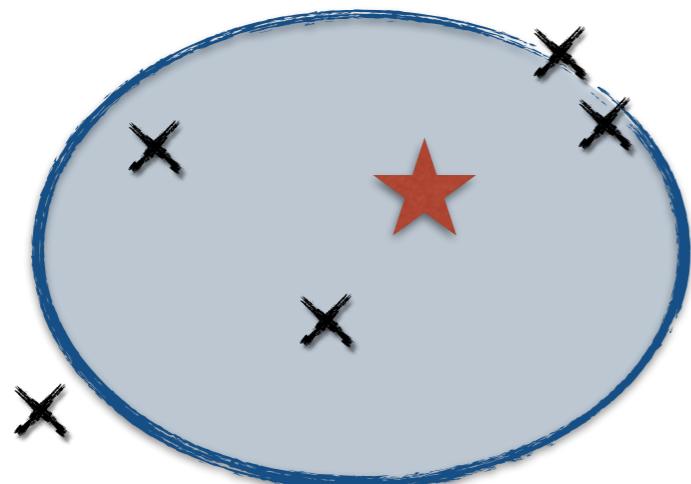


c.r. should contain
true value with
probability $\geq 1 - \alpha$

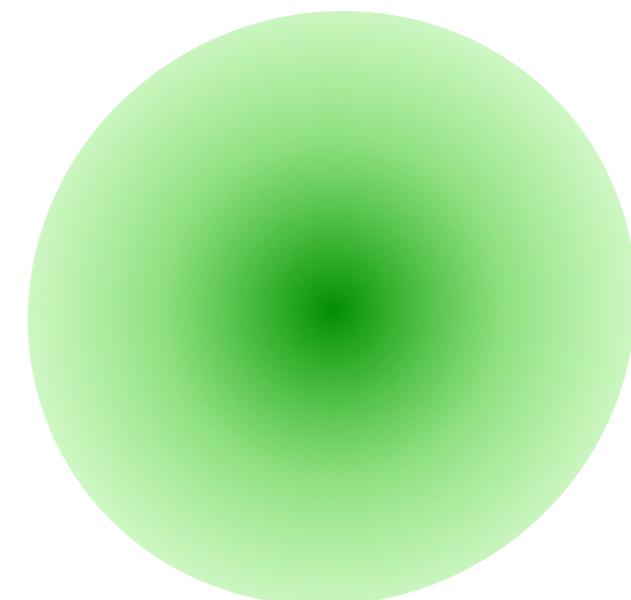
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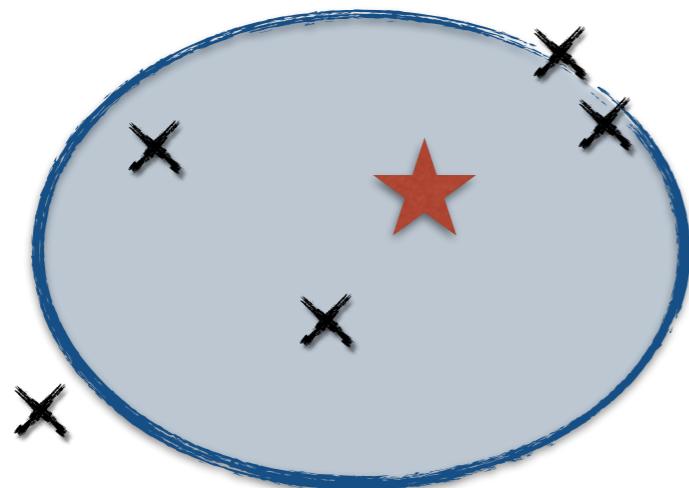


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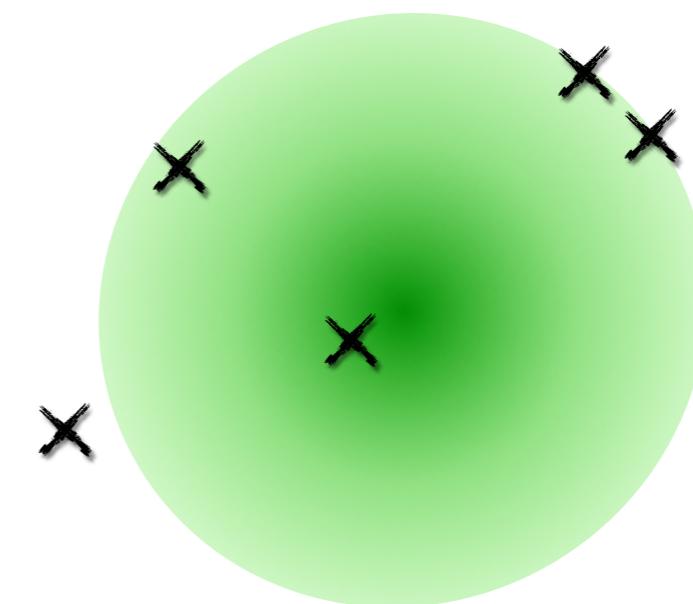
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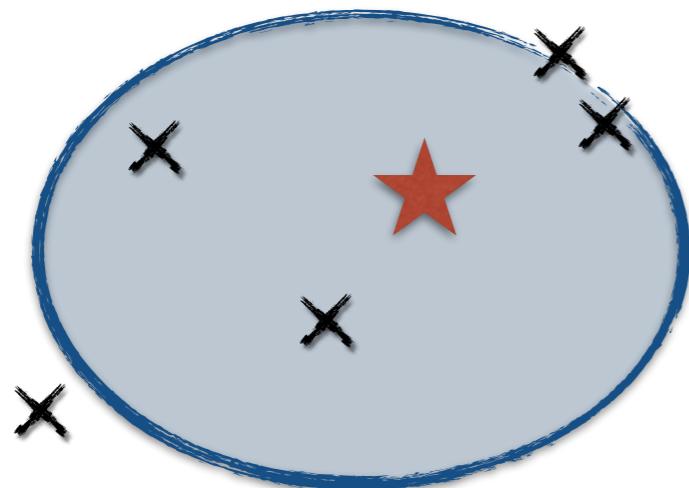


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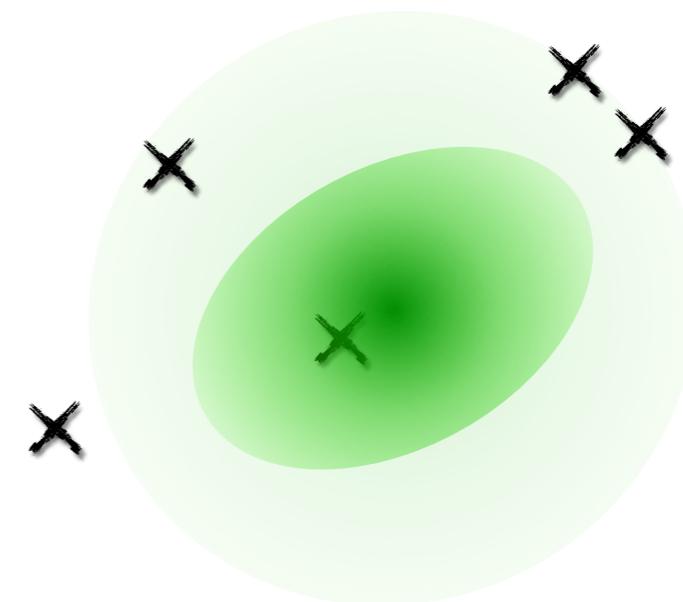
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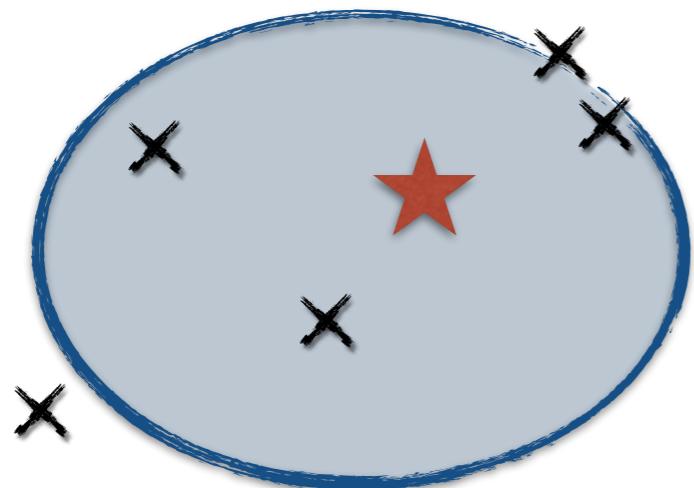
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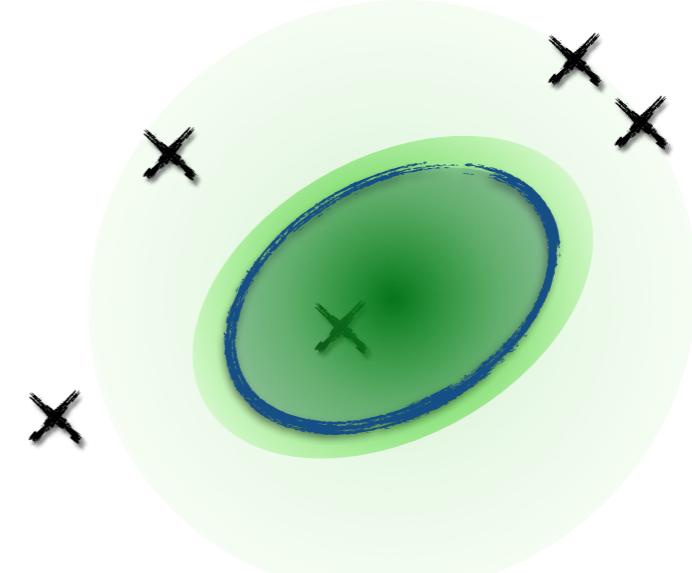
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mass of posterior
contained in c.r.
should be $\geq 1 - \alpha$

Error Regions



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c.r. should contain
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- minimal volume
(uniform, average,
or minimax)
- unbiasedness
- ...

- minimal volume

Geometric construction of Error Regions in QSE

\mathbb{R}^m

\hat{x}_y

Geometric construction of Error Regions in QSE

\mathbb{R}^m

- task: estimate state ρ
from measurement
outcomes y

$\times_{\hat{y}}$

Geometric construction of Error Regions in QSE

\mathbb{R}^m

- task: estimate state ρ from measurement outcomes y
- simplest case: linear inversion of Gaussian measurements

$\times \hat{y}$

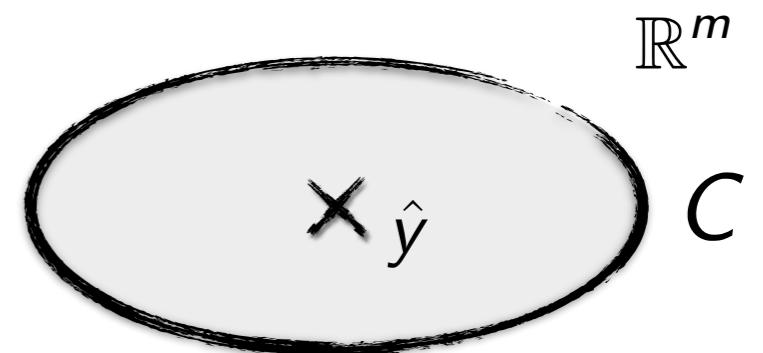
$A \uparrow \downarrow A^{-1}$

$\times \hat{\rho}$

$$\mathcal{S}^d = \{X \in \mathbb{H}^{d \times d} : \text{tr } X = 1\}$$

Geometric construction of Error Regions in QSE

- task: estimate state ρ from measurement outcomes y
- simplest case: linear inversion of Gaussian measurements

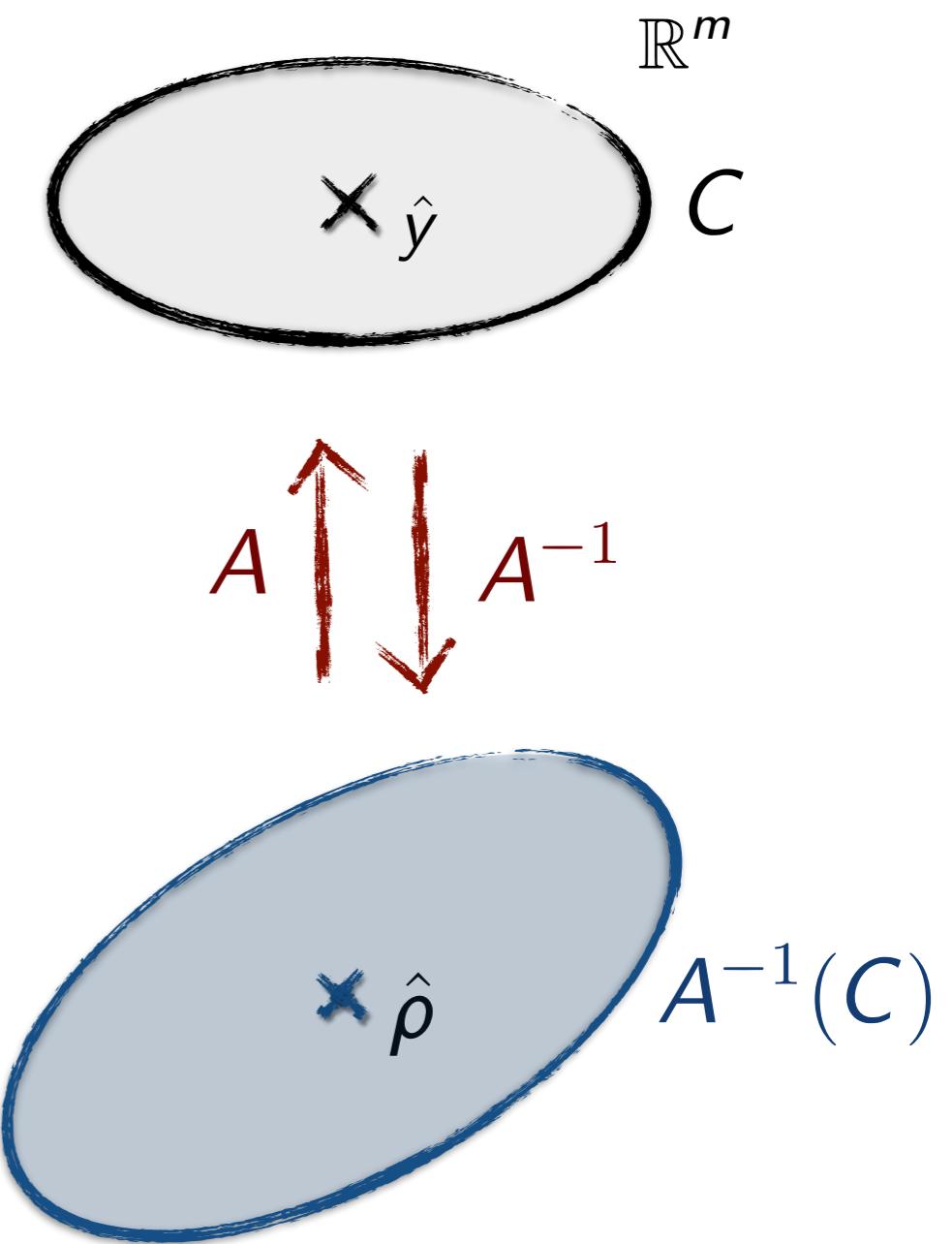


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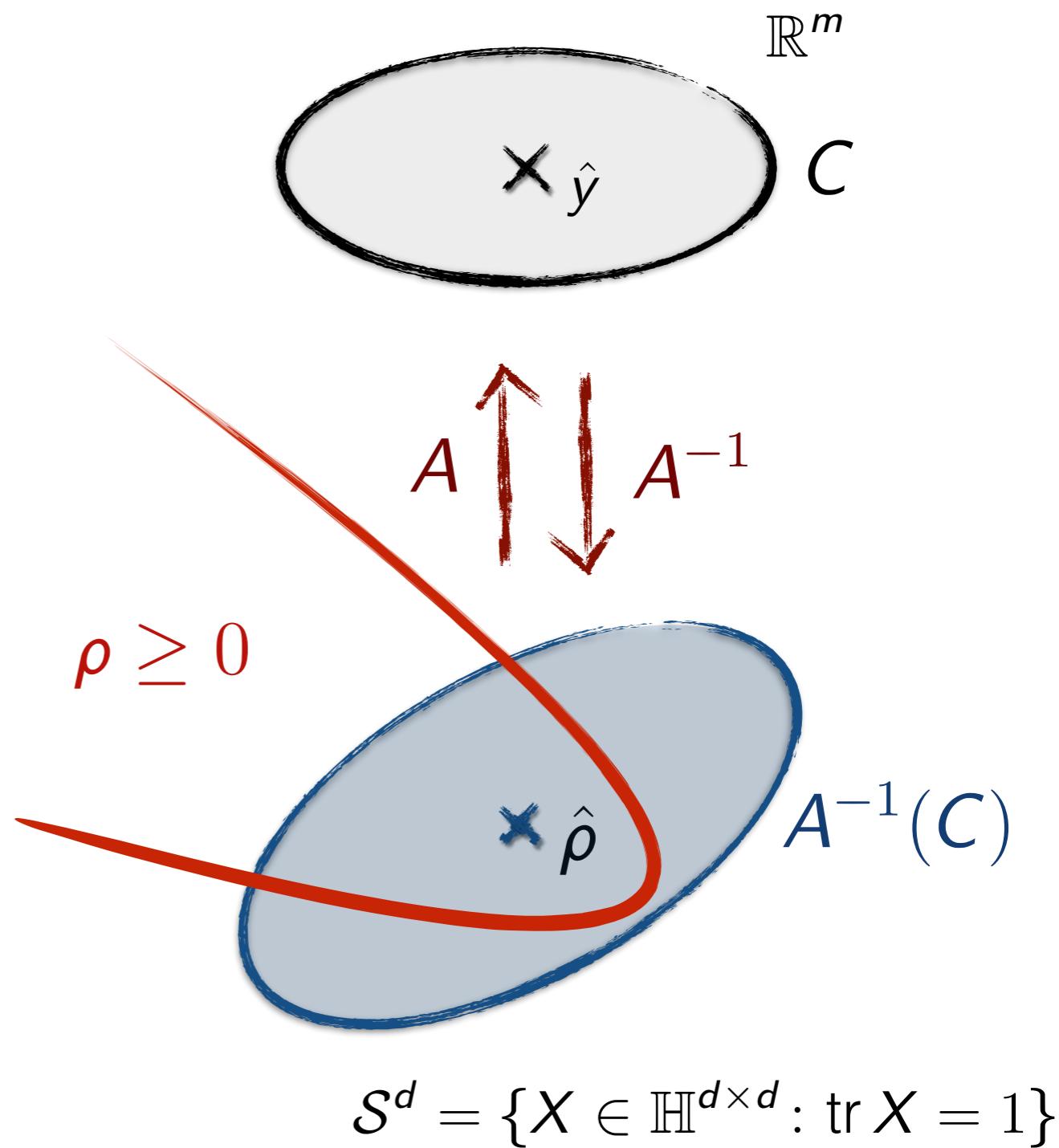
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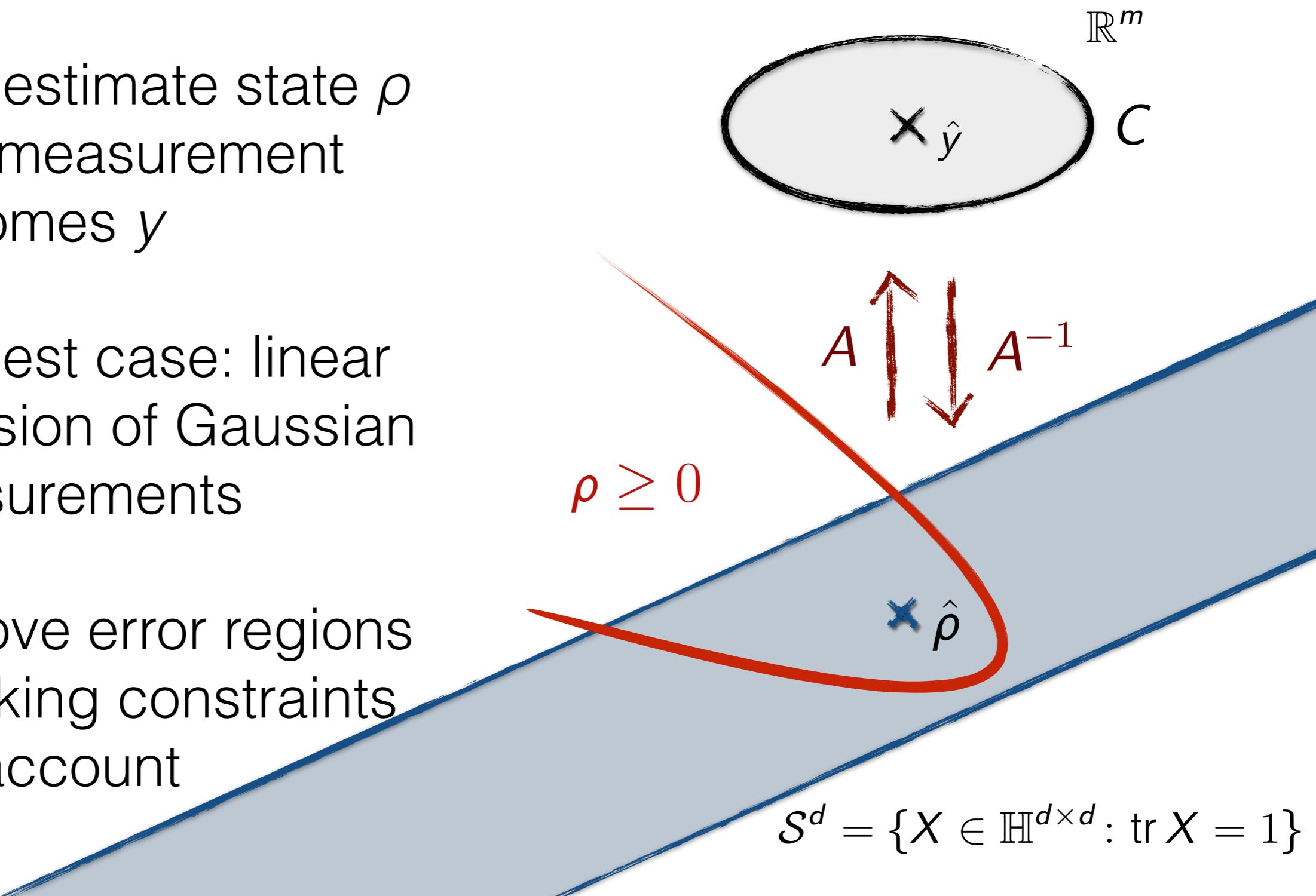
Geometric construction of Error Regions in QSE

- task: estimate state ρ from measurement outcomes y
- simplest case: linear inversion of Gaussian measurements
- improve error regions by taking constraints into account



Geometric construction of Error Regions in QSE

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Result I

Problem 1 For given ellipsoid $\mathcal{E} \subset \mathcal{S}^d$, decide whether $\mathcal{E} \subset \text{PSD}$ or $\mathcal{E} \not\subset \text{PSD}$.

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Problem 1 For given ellipsoid $\mathcal{E} \subset \mathcal{S}^d$, decide whether $\mathcal{E} \subset \text{PSD}$ or $\mathcal{E} \not\subset \text{PSD}$.

- coNP complete \Rightarrow no efficient algorithm
- **Corollary:** No efficient algorithm for computing volume of truncated ellipsoid
- statistical significance?

Bayesian POV

- Gaussian prior with mean θ and covariance matrix Σ

$$\pi_{\theta, \Sigma}(\rho) = (2\pi)^{-\frac{N}{2}} |\Sigma|^{-\frac{1}{2}} \exp\left(-\frac{1}{2} \|\rho - \theta\|_{\Sigma}^2\right)$$

- Bayesian update with Gaussian observation
 \implies Gaussian posterior $\pi_{\theta', \Sigma'}$
- minimal volume credible regions from greedy construction

$$\mathcal{E}(R_{1-\alpha}) = \left\{ \rho \in \mathcal{S}^d : \|\rho - \theta'\|_{\Sigma'} \leq R_{1-\alpha} \right\}$$

- $R_{1-\alpha}$ determined by $\int_{\mathcal{E}} \pi_{\theta', \Sigma'}(\rho) d\rho = 1 - \alpha$

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efficiently
computable

Bayesian POV: Physical Constraints

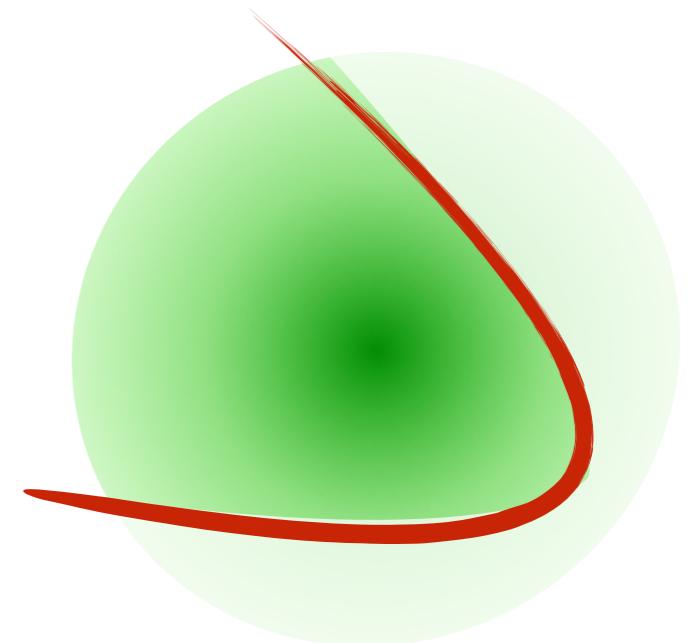
- truncated Gaussian prior

$$\pi_{\theta, \Sigma}^+(\rho) = C \times \pi_{\theta, \Sigma}(\rho) \times \chi^+(\rho)$$

\implies truncated Gaussian posterior

$$\pi_{\theta', \Sigma'}^+(\rho) = C' \times \pi_{\theta', \Sigma'}(\rho) \times \chi^+(\rho)$$

- optimal error regions: truncated ellipsoids with radius $R_{1-\alpha}^+$



Bayesian POV: Physical Constraints

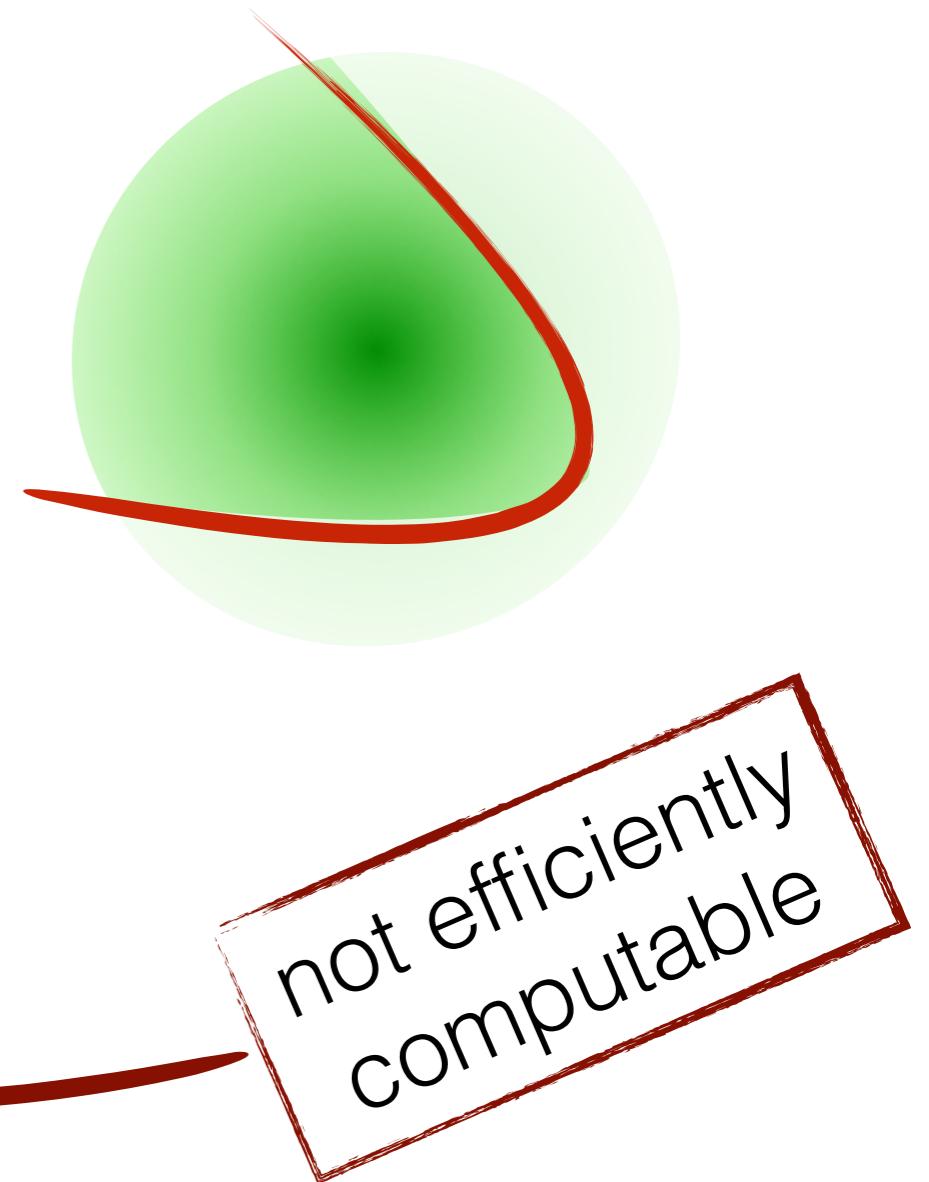
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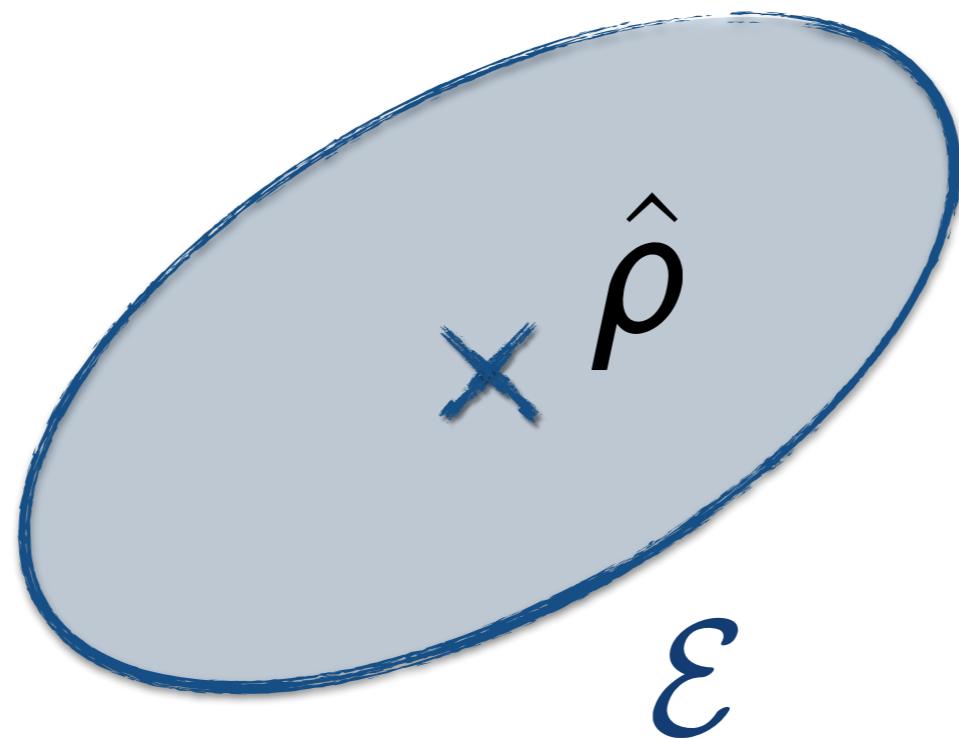
Bayesian POV: Physical Constraints

- truncated Gaussian priors

Problem 2 For given mean $\theta \in S^d$, covariance matrix Σ , credibility $1 - \alpha \in [0, 1]$, and accuracy δ with $\delta^{-1} \in \mathbb{N}$, determine the radius of the minimal-volume credible ellipsoid $R_{1-\alpha}^+$ with given accuracy.

not efficiently computable

Frequentist Optimal Confidence Region?



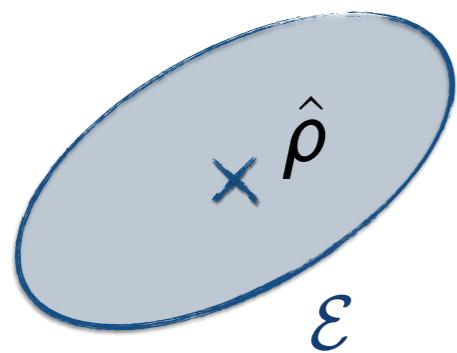
$$\hat{\rho} = \frac{1}{d} \mathbf{I} + \sum_i \langle \hat{\rho} \rangle_i \boldsymbol{\sigma}_i \quad \text{with } \langle \hat{\rho} \rangle_i := \frac{1}{N_i} \sum_{k=1}^{N_i} y_{i,k}$$

Frequentist Optimal Confidence Region?

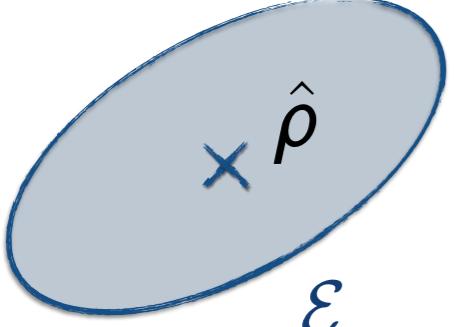
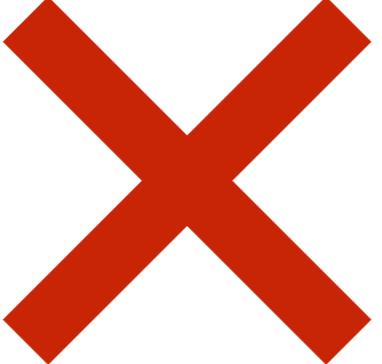
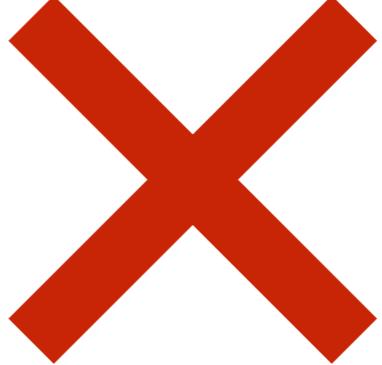
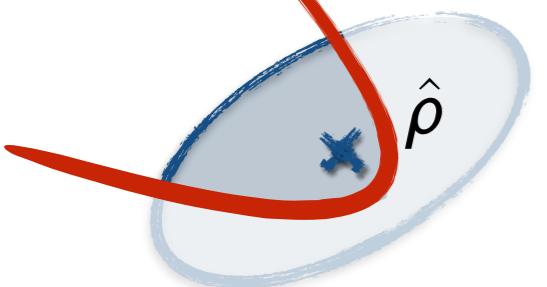
MinMax
Expected
Volume

Admissible

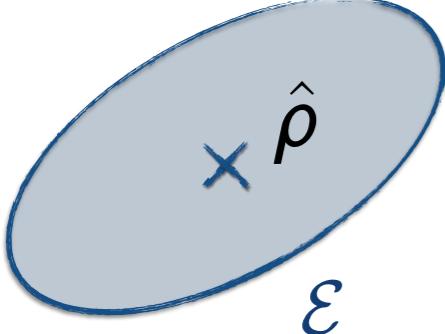
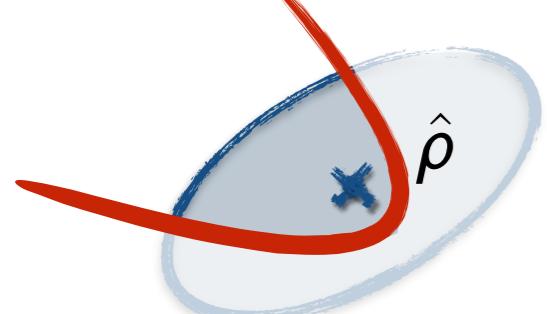
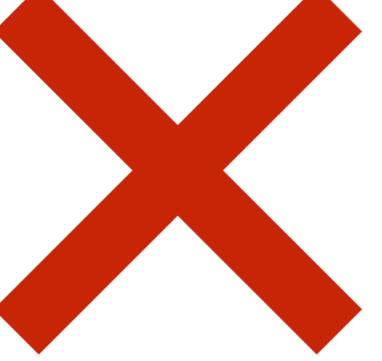
Expected
Volume
+ Unbiased



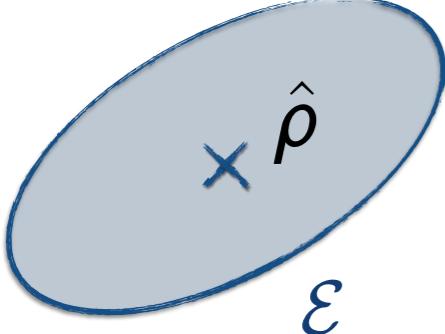
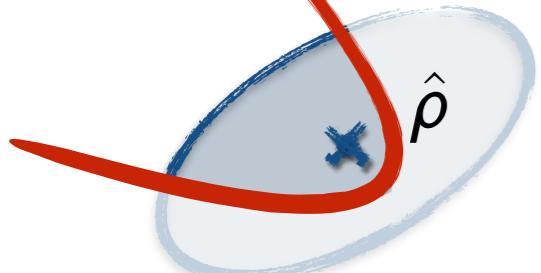
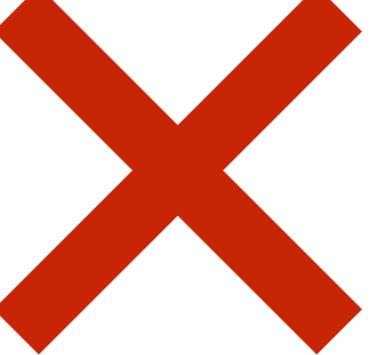
Frequentist Optimal Confidence Region?

MinMax Expected Volume	Admissible	Expected Volume + Unbiased
		
		

Frequentist Optimal Confidence Region?

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Frequentist Optimal Confidence Region?

MinMax Expected Volume	Admissible	Expected Volume + Unbiased
		
		 

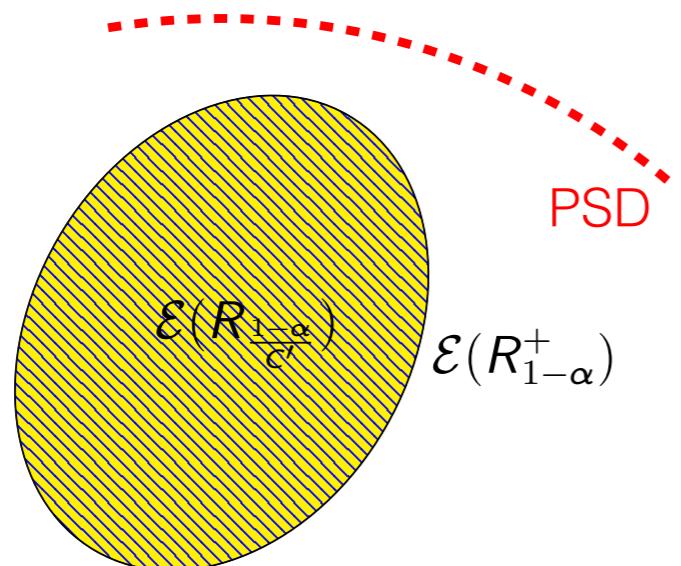
Conclusion

- truncated ellipsoids as error regions for QSE
- constitute optimal Bayesian credible regions for Gaussian posterior distribution
- computing radius computational hard problem
- application to Frequentists' confidence regions: $\text{\texttt{_}}\backslash(\backslash)\text{\texttt{_}}\text{\texttt{/}}$

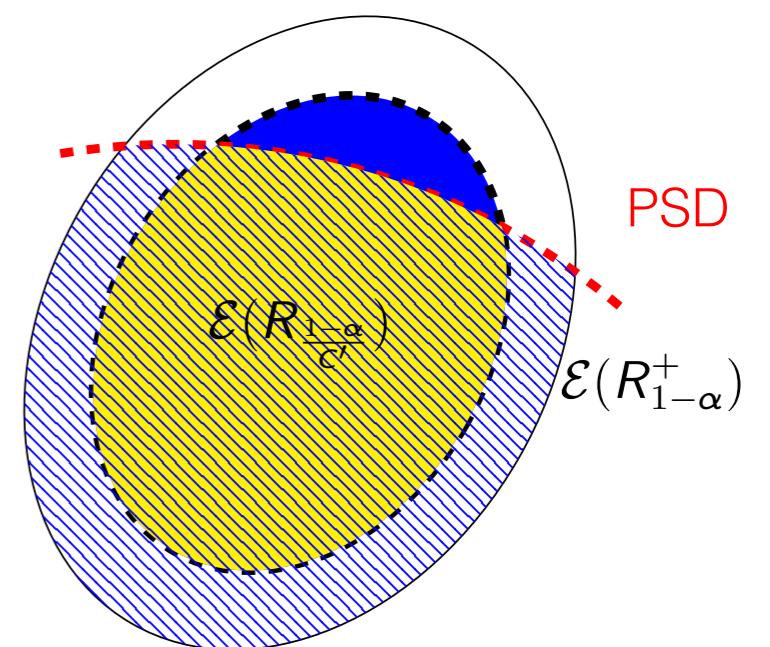
Let's look at credibility level $\frac{1-\alpha}{C'}$ & recall truncated posterior

$$\pi_{\theta', \Sigma'}^+(\rho) = C' \times \pi_{\theta', \Sigma'}(\rho) \times \chi^+(\rho)$$

$$\mathcal{E}(R_{\frac{1-\alpha}{C'}}) \subset \text{PSD}$$



$$\mathcal{E}(R_{\frac{1-\alpha}{C'}}) \not\subset \text{PSD}$$



$$\implies R_{\frac{1-\alpha}{C'}} = R_{1-\alpha}^+$$

$$\implies R_{\frac{1-\alpha}{C'}} < R_{1-\alpha}^+$$

Frequentist POV

- special case: Pauli measurements $\implies \rho = \frac{1}{d} I + \sum_i \langle \rho \rangle_i \sigma_i$
- estimate $\langle \rho \rangle_i$ by empirical mean

$$\langle \hat{\rho} \rangle_i := \frac{1}{N_i} \sum_{k=1}^{N_i} y_{i,k}$$

where $y_{i,k} \in \{\pm 1\}$... outcome of the k -th measurement of σ_i ;

- Gaussian assumption $\langle \hat{\rho} \rangle_i \sim \mathcal{N}(\langle \hat{\rho} \rangle_i, \Sigma_i) \implies$ “natural” confidence region

$$\mathcal{E} = \left\{ \hat{\rho} + \sum_i \Sigma_i u_i \sigma_i : \sum u_i^2 \leq R^2 \right\}$$