

Push-forward Measures for Parameter Identification under Uncertainty

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Introduction

Motivation

How do we update initial descriptions of uncertainty using model predictions and data?

Data-Consistent Inversion is a novel framework that uses push-forward and pull-back measures to ensure solutions are consistent with the observed distribution of data.

Question

How do we cast a **Parameter Identification** problem in the context of **Data-Consistent Inversion**?

Framework

- \mathbb{P}, π Probability Measure, Density
- $\Lambda \subset \mathbb{R}^P$ Parameter Space
- $\mathbf{o} : \Lambda \rightarrow \mathcal{O} \subset \mathbb{R}^D$ Observables
- $\Xi \subset \mathbb{R}^D$ Noise Space
- $\lambda^\dagger \in \Lambda$ True Parameter
- $\mathbf{d}(\xi) \subset \mathbb{R}^D$ Possible Data, $d_i(\xi) = \mathbf{o}_i(\lambda^\dagger) + \xi_i$
- $\xi^\dagger \in \Xi$ Noise in Measurements
- σ^2 Variance of Noise
- $\mathbf{d}^\dagger \in \mathbb{R}^D$ Observed Data, $\mathbf{d}^\dagger = \mathbf{d}(\xi^\dagger)$
- $\mathbb{P}_{\text{in}}, \pi_{\text{in}}$ Initial
- $\mathbb{P}_{\text{obs}}, \pi_{\text{obs}}$ Observed
- $\mathbb{P}_{\text{pre}}, \pi_{\text{pre}}$ Predicted (**push-forward**)
- $\mathbb{P}_{\text{up}}, \pi_{\text{up}}$ Updated (**pull-back**)

Updating with Observations and Predictions

$$\mathbb{P}_{\text{up}} = \mathbb{P}_{\text{in}} \frac{\mathbb{P}_{\text{obs}}}{\mathbb{P}_{\text{pre}}} \quad \left| \quad \pi_{\text{up}}(\lambda) = \pi_{\text{in}}(\lambda) \frac{\pi_{\text{obs}}(Q(\lambda))}{\pi_{\text{pre}}(Q(\lambda))}$$

References & Attribution

Advisor: Dr. Troy Butler



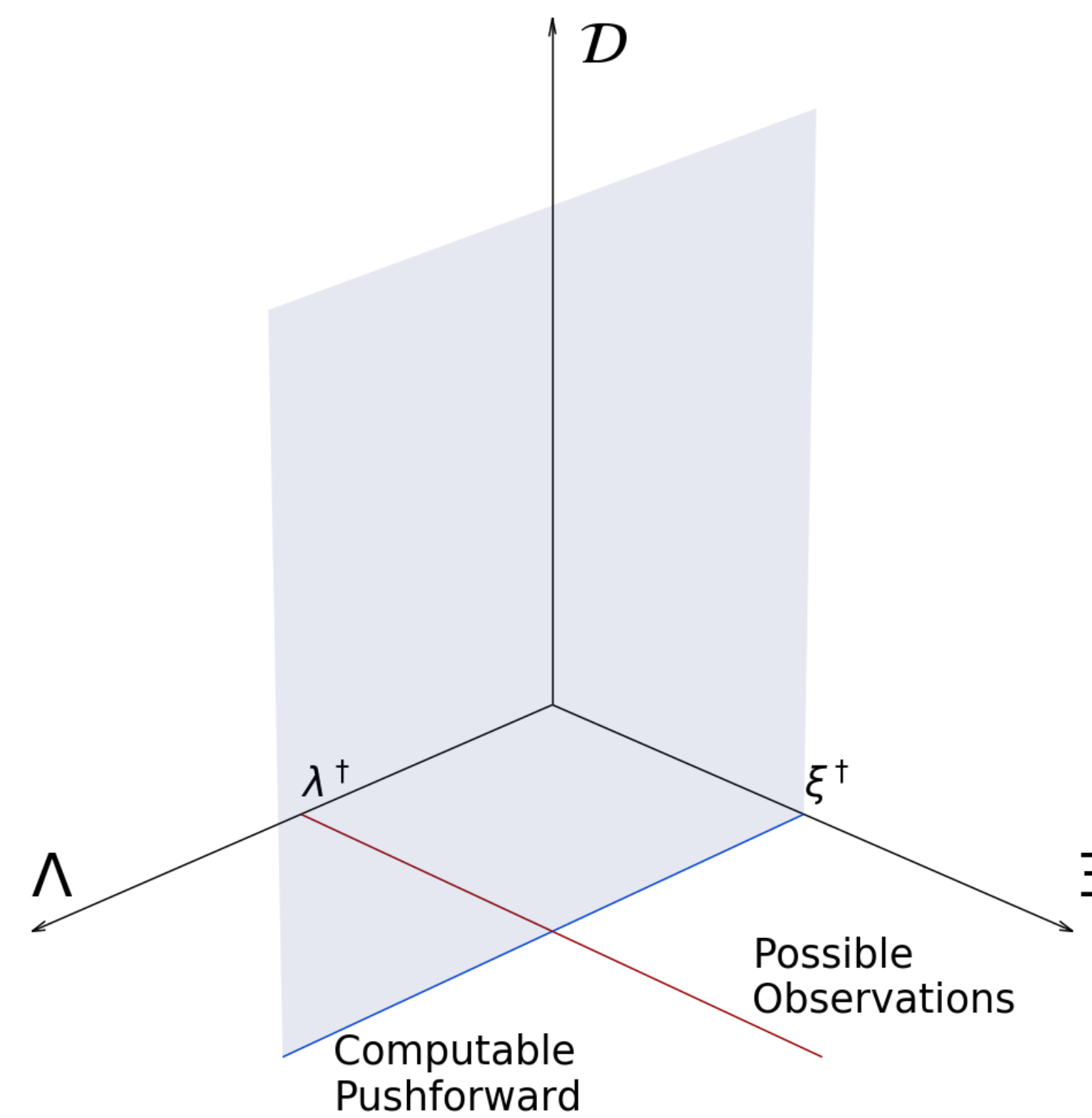
(Left to Right): Theory, Stability, BET, ConsistentBayes, Personal Website.
Funding provided by NSF DMS-1818941.

Approach

Quantity of Interest Map

A Functional Relating **Predictions** and **Data**

- Ideal $Q(\lambda, \xi) = F(\mathbf{o}(\lambda), \mathbf{d}(\xi))$
- Theoretical $Q(\Lambda, \Xi) =: \mathcal{D}_{\mathcal{T}} \subset \mathbb{R}$
- Practical $Q(\lambda) = F(\mathbf{o}(\lambda), \mathbf{d}^\dagger)$
- Computable $Q(\Lambda) =: \mathcal{D}_{\mathcal{C}} \subset \mathcal{D}_{\mathcal{T}}$



How do conditionals of Ξ compare to the joint density?

Observed Distribution

Given a functional, what measure do we invert?

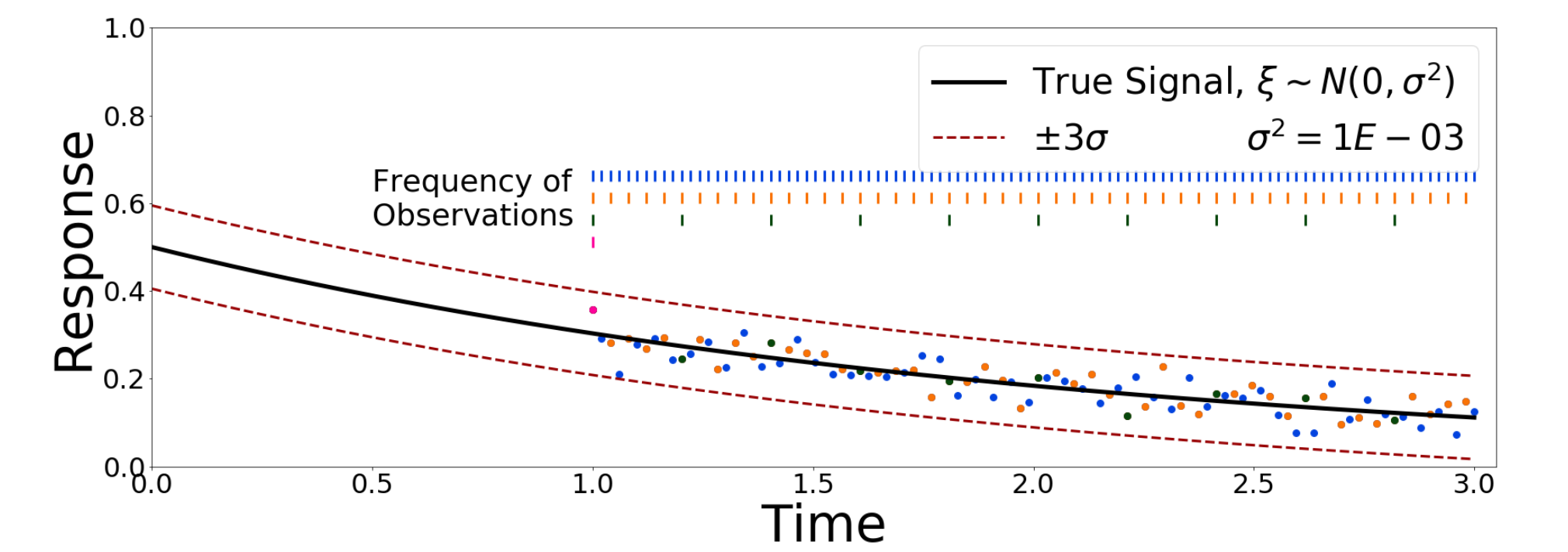
$Q(\lambda^\dagger, \xi) \sim \pi_{\text{obs}}$ when we allow ξ to vary over Ξ

$F(\mathbf{o}(\lambda), \mathbf{d}^\dagger)$	ξ	π_{obs}
$\frac{1}{\sigma\sqrt{D}} \sum (\mathbf{o}_i(\lambda) - \mathbf{d}_i^\dagger)$	$\xi \sim L^2$	$N(0, 1)$
$\frac{1}{\sigma^2} \sum (\mathbf{o}_i(\lambda) - \mathbf{d}_i^\dagger)^2$	$\xi \sim N(0, \sigma^2)$	$\chi^2(D)$
$\frac{1}{\sigma^2 D} \sum (\mathbf{o}_i(\lambda) - \mathbf{d}_i^\dagger)^2$	$\xi \sim N(0, \sigma^2)$	$\Gamma(D/2, D/2)$
\vdots	\vdots	\vdots

Choices of F and associated π_{obs} for stochastic inverse problem with $\mathbf{d}^\dagger = \mathbf{o}_i(\lambda^\dagger) + \xi_i^\dagger$

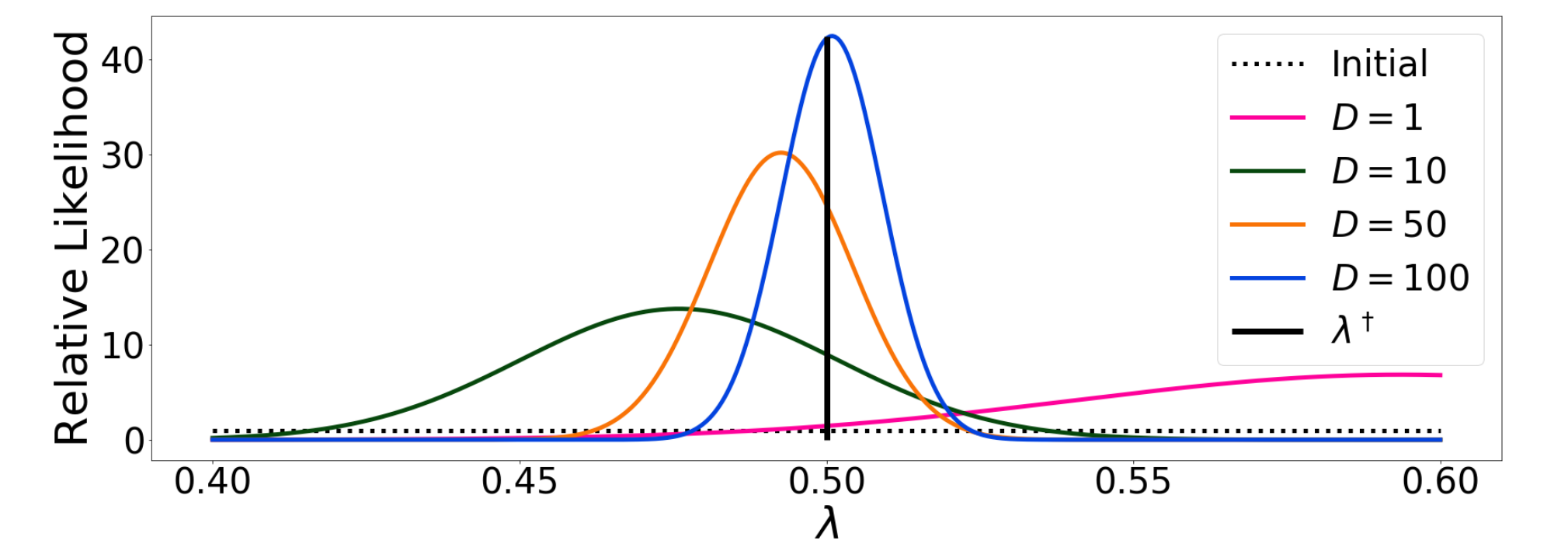
Example

Consider an exponential decay problem with uncertain initial condition:



Convergence

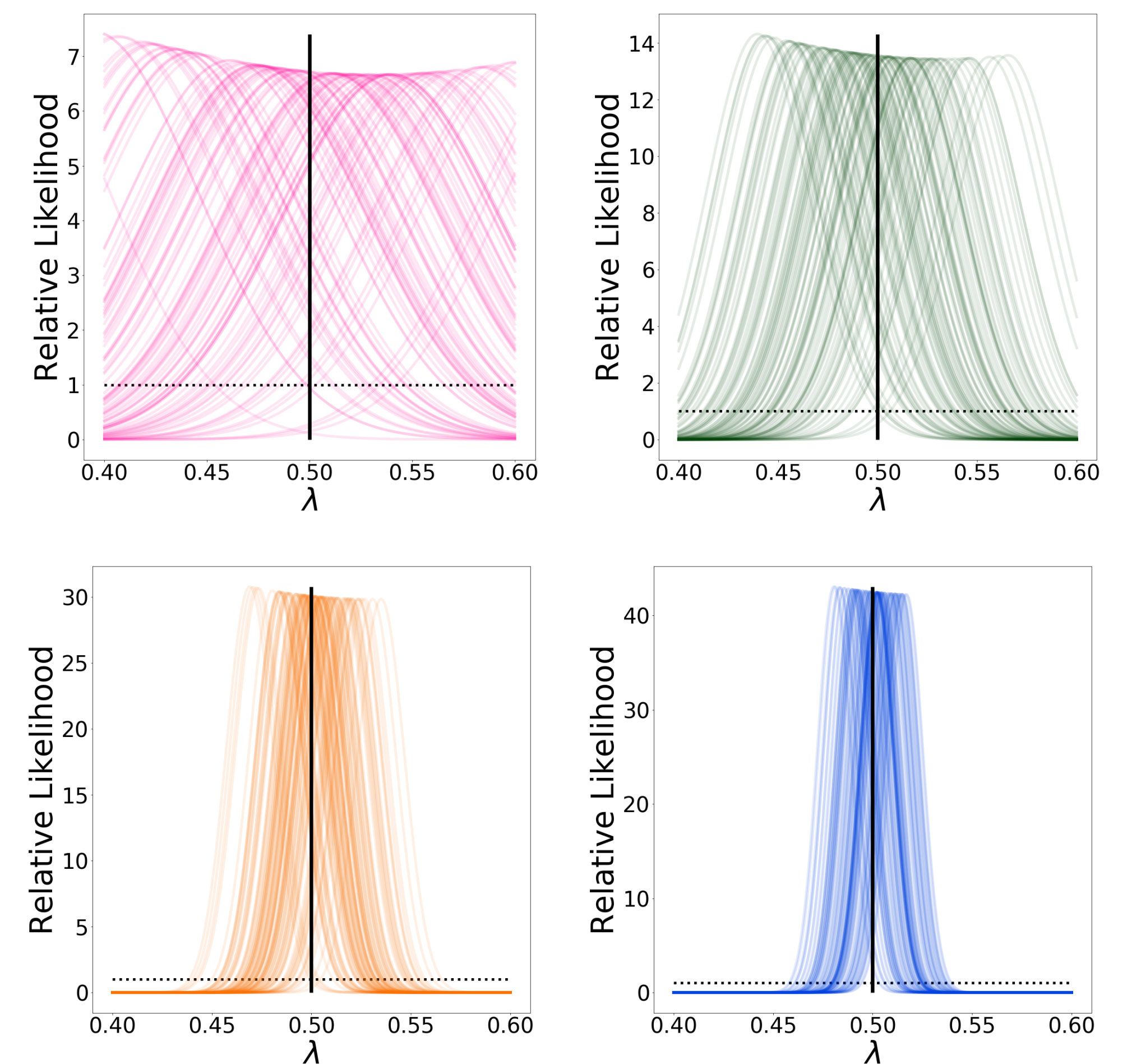
How do solutions change with more data?



λ^\dagger and π_{up} for $D = 1, 10, 50, 100$ for $N = 1000$

Stability

How do solutions on conditionals of Ξ compare?



λ^\dagger and π_{up} for one hundred realizations of ξ^\dagger for $D = 1, 10, 50, 100$