# Using Push-Forward and Pullback Measures for Parameter Identification and Distribution Estimation

# **Distribution Estimation**

# **Goal:** Obtain the Best Distribution of $\lambda$

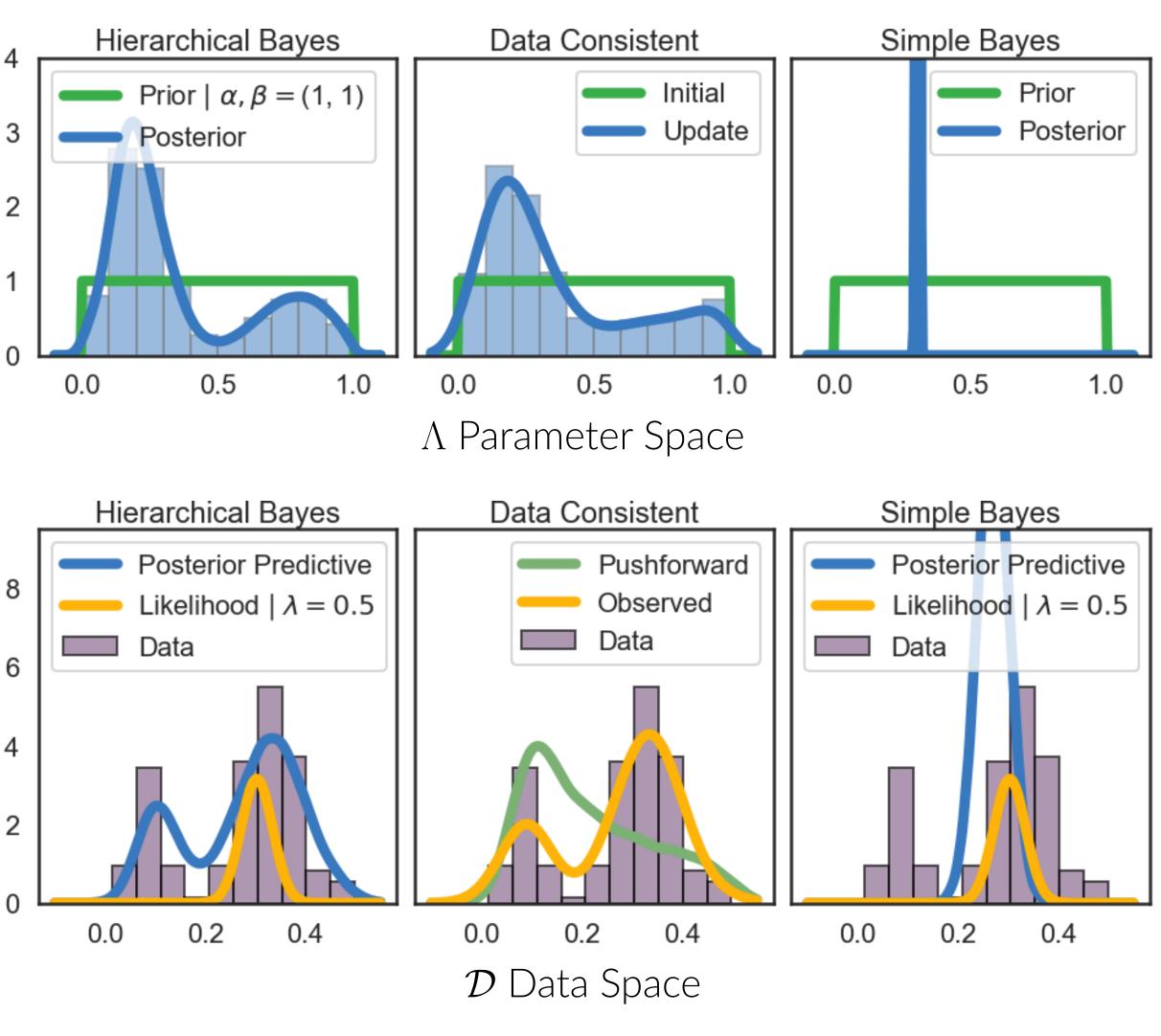
**Bayesian Context:** Simple Bayes model is insufficient, hierarchical Bayes model required.

**Data Consistent Context:** Use data to construct observed distribution.

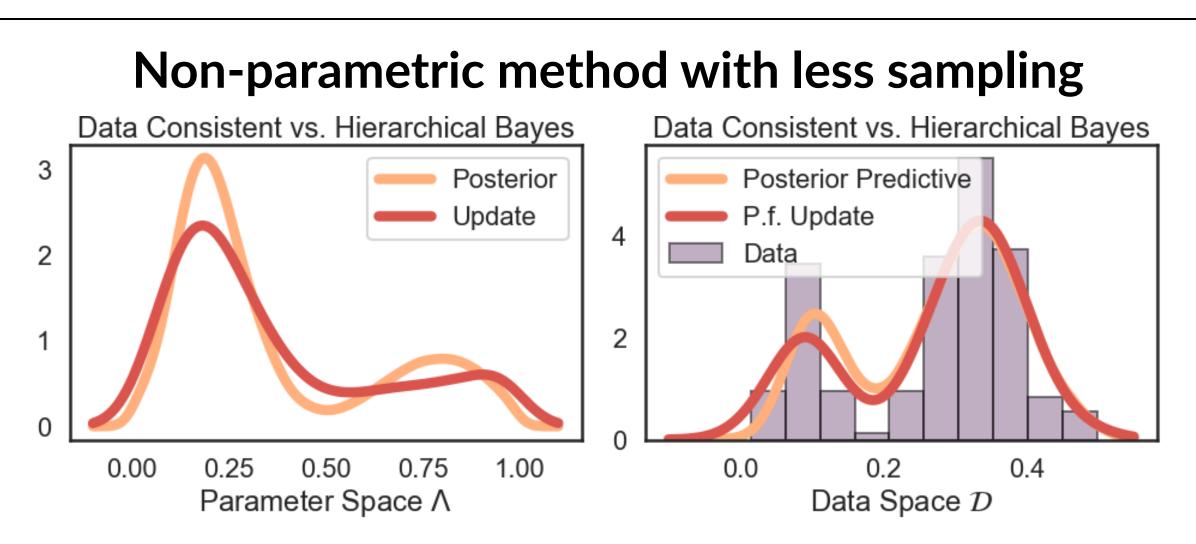
# Example

	Consider an exponential decay problem with uncertain de	
	$u(t) = u_0 \exp(-\lambda t), \ u_0 = 0.5, \ t = 2$	
	Simple Bayes	$ \begin{vmatrix} \pi_{\text{prior}} \sim U[0,1], & \pi_{\text{L}} \left( \boldsymbol{d} \mid \lambda \right) \sim N \left( Q \left( \lambda \right) \\ \pi_{\text{post}} \left( \lambda \mid \boldsymbol{d} \right) \propto \pi_{\text{prior}} \left( \lambda \right) \pi_{\text{L}} \left( \boldsymbol{d} \mid \lambda \right) \end{vmatrix} $
	Hierarchical Bayes*	$\begin{vmatrix} \pi_{\text{prior}}(\alpha,\beta) \sim \chi_{1}^{2}, & \alpha,\beta \in \Omega := [0,\infty) \\ \pi_{\text{prior}}(\lambda \mid \alpha,\beta) s \sim \text{Beta}(\alpha,\beta), & \pi_{\text{L}}(\boldsymbol{d} \mid \lambda) \sim \\ \pi_{\text{post}}(\lambda \mid \boldsymbol{d}) \propto \int_{\Omega} \pi_{\text{prior}}(\lambda,\alpha,\beta) \pi_{\text{L}}(\boldsymbol{d} \mid \lambda,\beta) \\ \end{vmatrix}$
	Data Consistent	$\pi_{\rm up}(\lambda) = \pi_{\rm in}(\lambda) \frac{\pi_{\rm obs}(Q(\lambda))}{\pi_{\rm pre}(Q(\lambda))}$

## **Plots of Concepts and Results**



## Takeaways



## Tian Yu Yen and Michael Pilosov

University of Colorado: Denver

ecay rate:

 $(\lambda), \sigma^2)$  $\times [0,\infty)$  $\sim N\left(Q\left(\lambda
ight),\sigma^{2}
ight)$  $(\alpha, \beta) d\Omega$ 

# Intro to Data Consistent Inversion

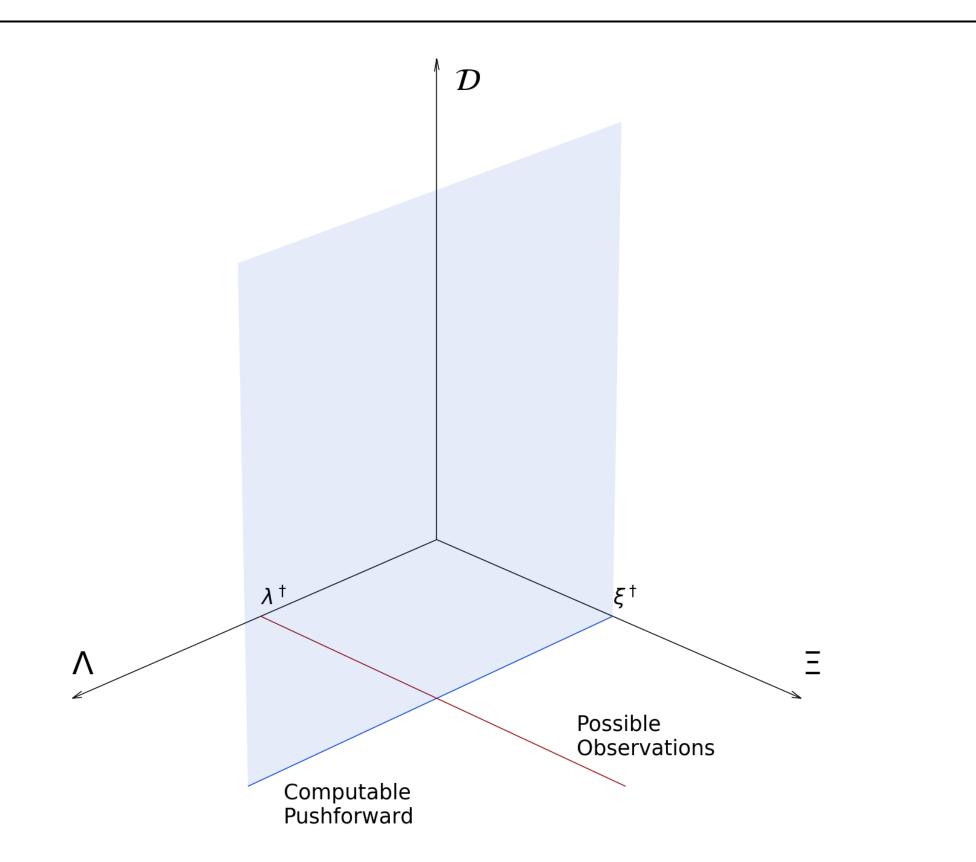
## **Solving Stochastic Inverse Problems**

**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.

## The Data Consistent Approach

 $\pi_{\mathrm{up}}\left(\lambda
ight) = \pi_{\mathrm{in}}\left(\lambda
ight) rac{\pi_{\mathrm{obs}}\left(\mathrm{Q}\left(\lambda
ight)
ight)}{\pi_{\mathrm{pre}}\left(\mathrm{Q}\left(\lambda
ight)
ight)}$ 

# Which Stochastic Inverse Problem?



Do you want to solve for a single parameter value or for a parameter distribution?

- $\lambda \in \Lambda, \xi \in \Xi$
- $oldsymbol{d}\in\mathcal{D}$
- $Q: \Lambda \to \mathcal{D}$
- $\pi_{\text{prior}}, \pi_{\text{L}}$
- $\bullet \pi_{\mathrm{in}}, \ \pi_{\mathrm{obs}}, \ \pi_{\mathrm{pre}}$
- $\pi_{\mathrm{post}}, \ \pi_{\mathrm{up}}$

# Notation

Parameter Space, Noise Space Observables Quantity of Interest Map Prior, Likelihood



Author: Michael Pilosov || Advisor: Dr. Troy Butler



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

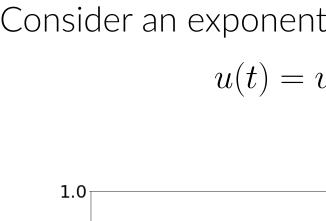
Initial, Observed, Predicted (**push-forward**) Posterior, Update (**pullback**)

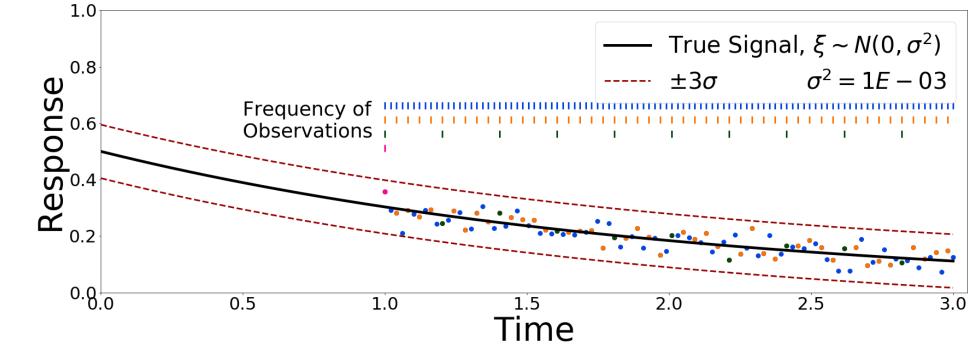
# **Parameter Identification**

## **Goal: Obtain the Best Value of** $\lambda$

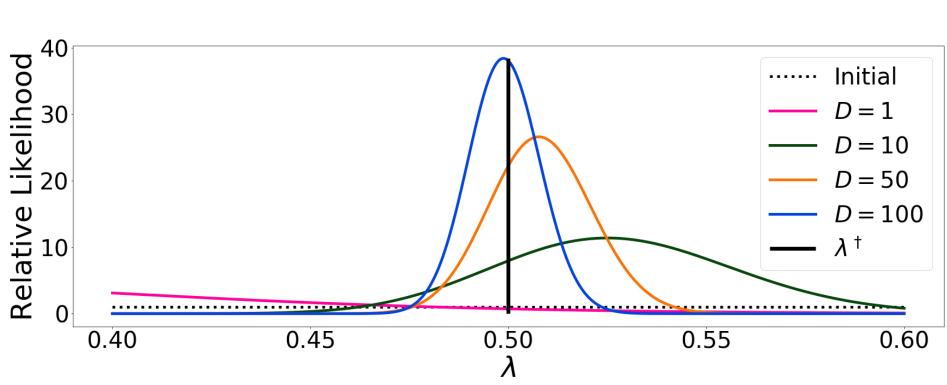
**Bayesian Context:** Simple Bayes model uses assumed likelihood function of data given  $\lambda$ .

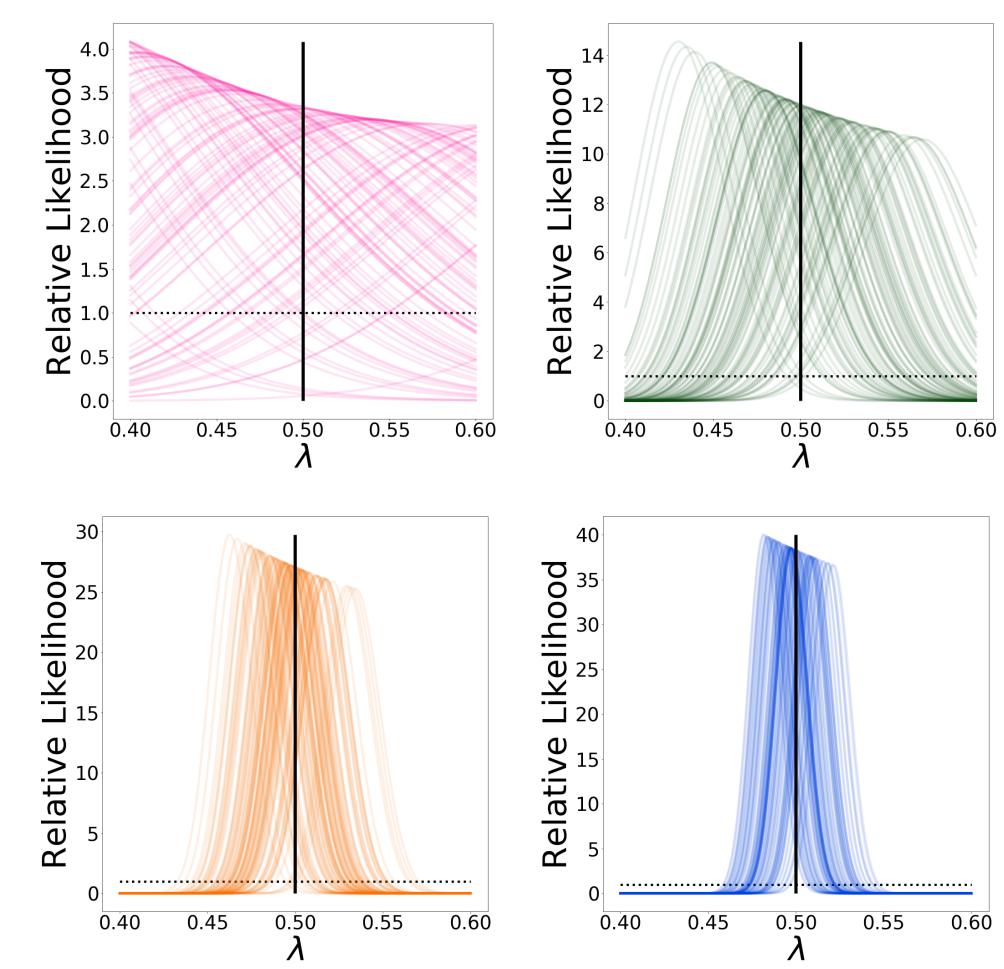
**Data Consistent Context:** Uses data to construct a predicted distribution of the average residuals given  $\lambda$ .





## **Convergence of Data Consistent Approach**





# Example

Consider an exponential decay problem with uncertain decay rate:  $u(t) = u_0 \exp(-\lambda t), \ u_0 = 0.5, \ t \in [0,3]$ 

How do solutions change with more data?

 $\lambda^{\dagger}$  and  $\pi_{\mathrm{up}}$  for D=1,10,50,100 for N=1000

## **Comparison to Bayes**

How do solutions on conditionals of  $\Xi$  compare?