

Characterizing and Propagating Model Discrepancy in PDE-Constrained Optimization

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Want to solve:

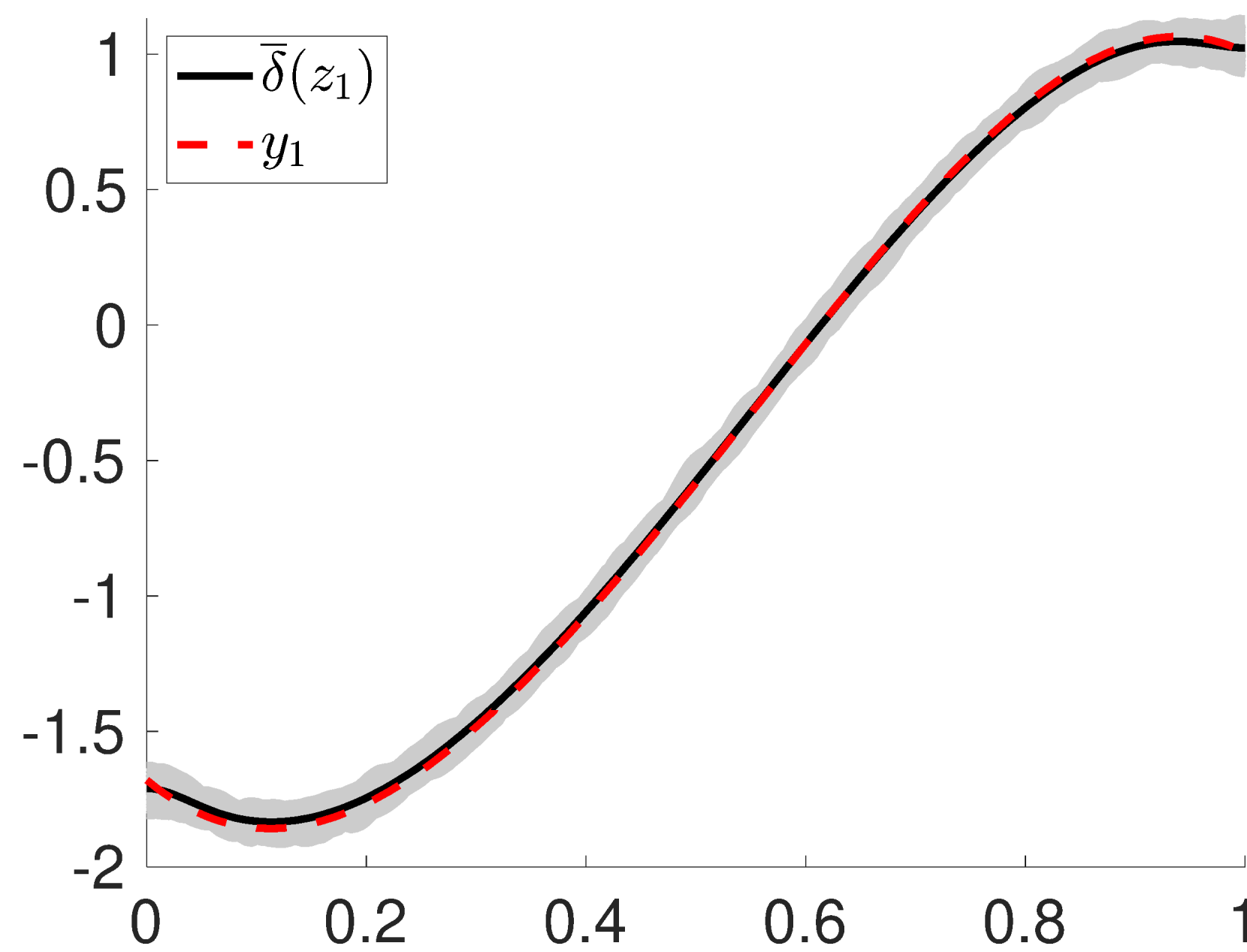
$$\min_z J(S(z), z)$$

Actually solve:

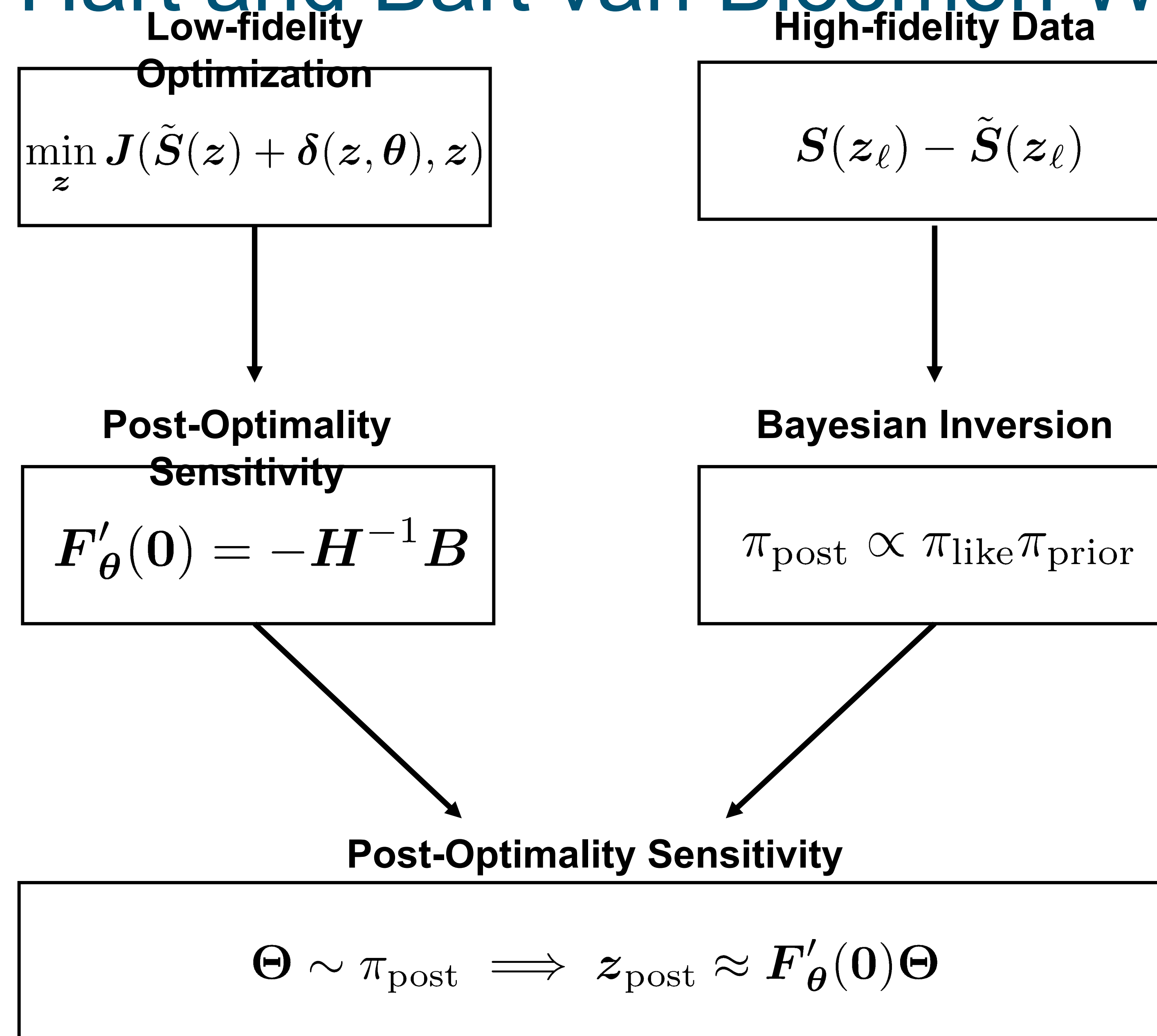
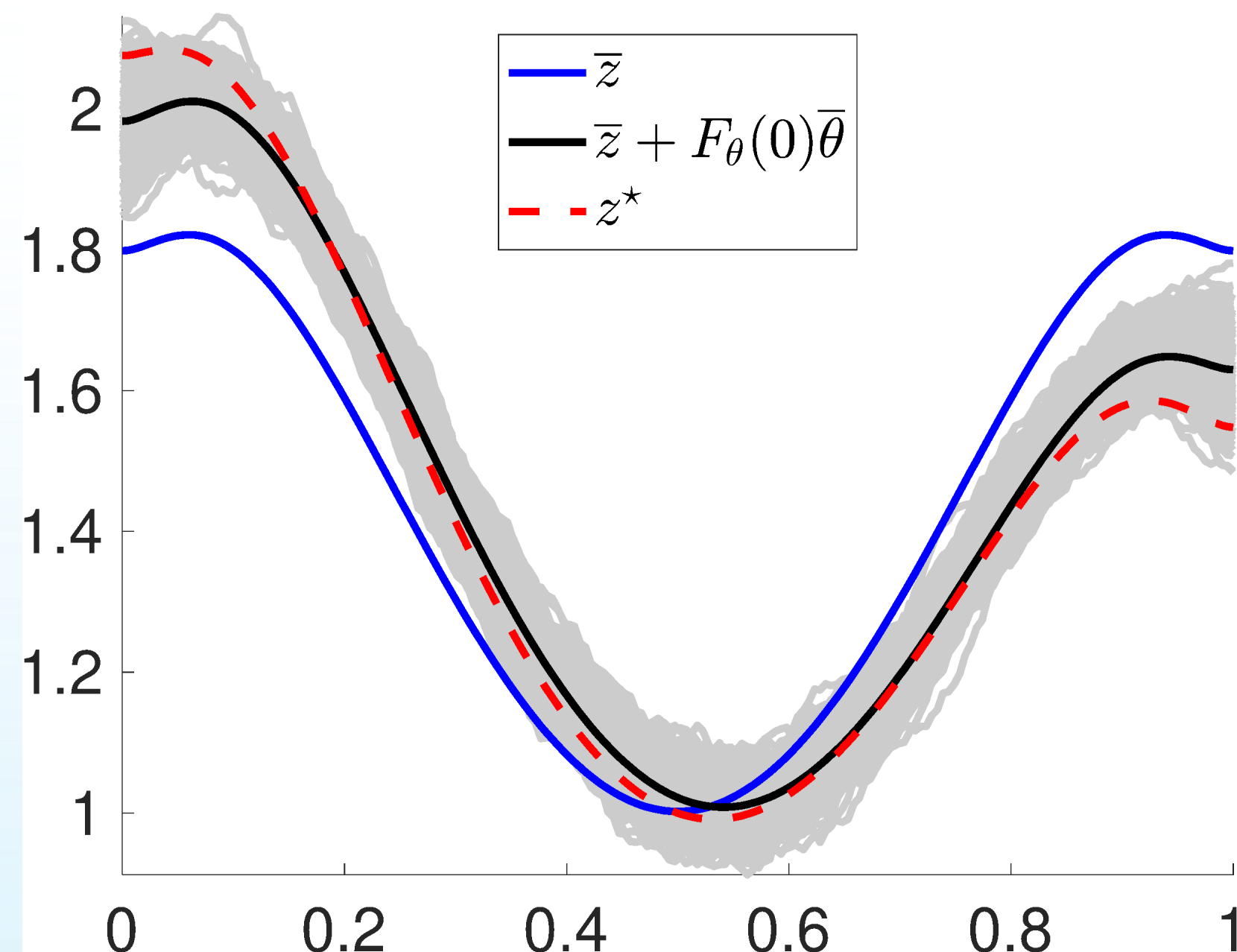
$$\min_z J(\tilde{S}(z), z)$$

1D Diffusion versus Advection-Diffusion

Posterior $\delta(z_1)$ samples



Posterior optimal solution samples



Posterior samples take the form

$$\bar{\theta} + \hat{\theta} + \tilde{\theta}$$

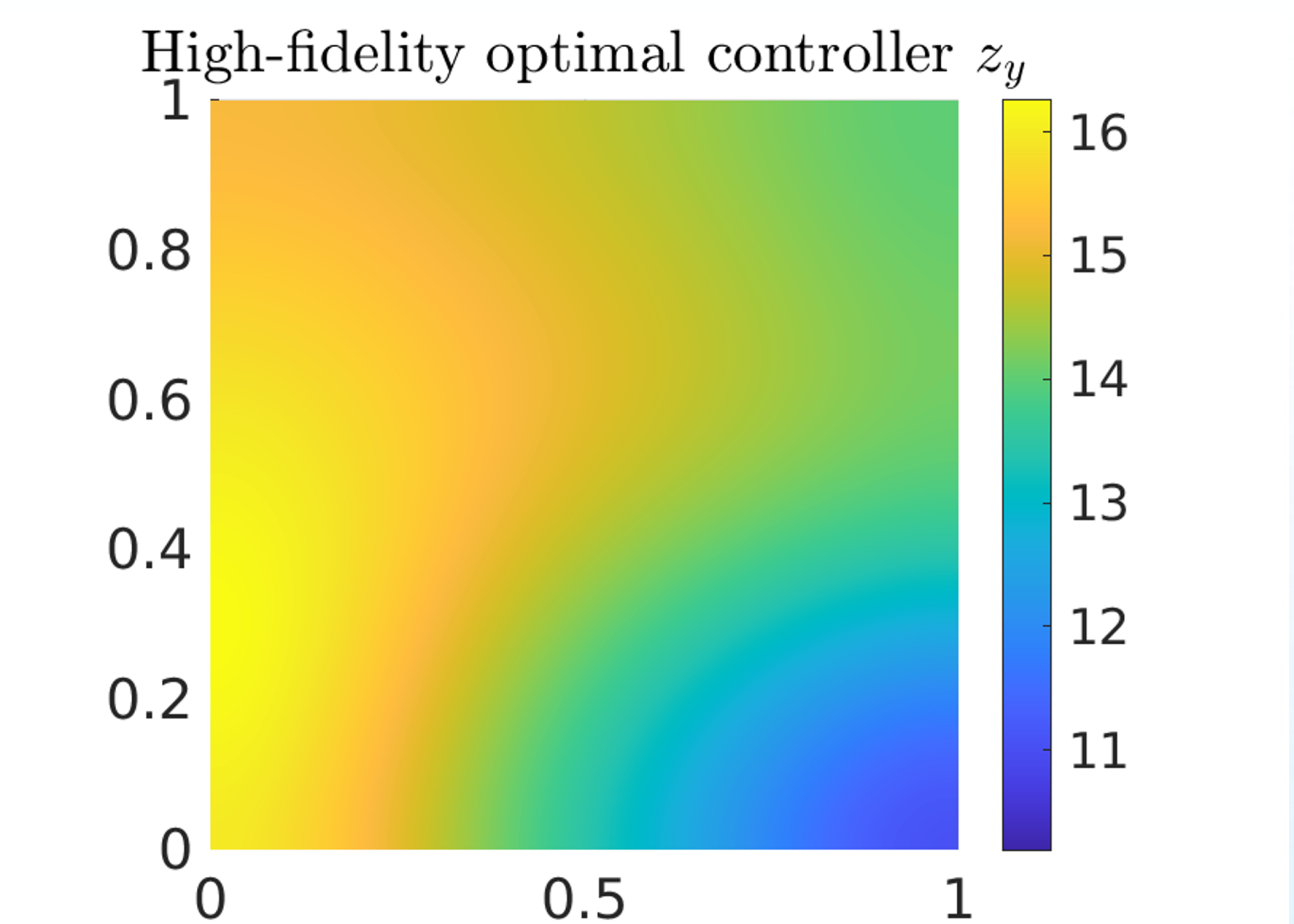
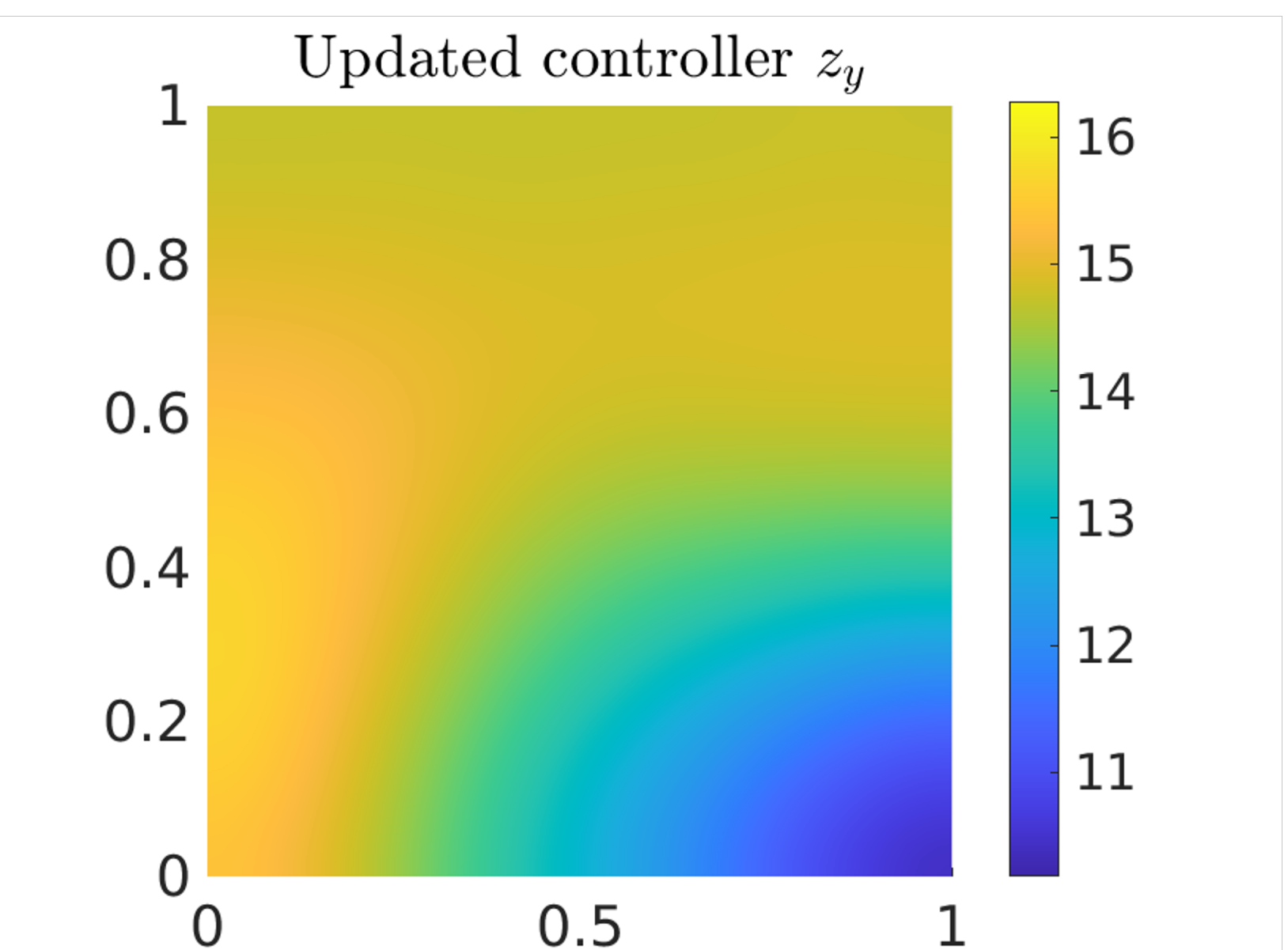
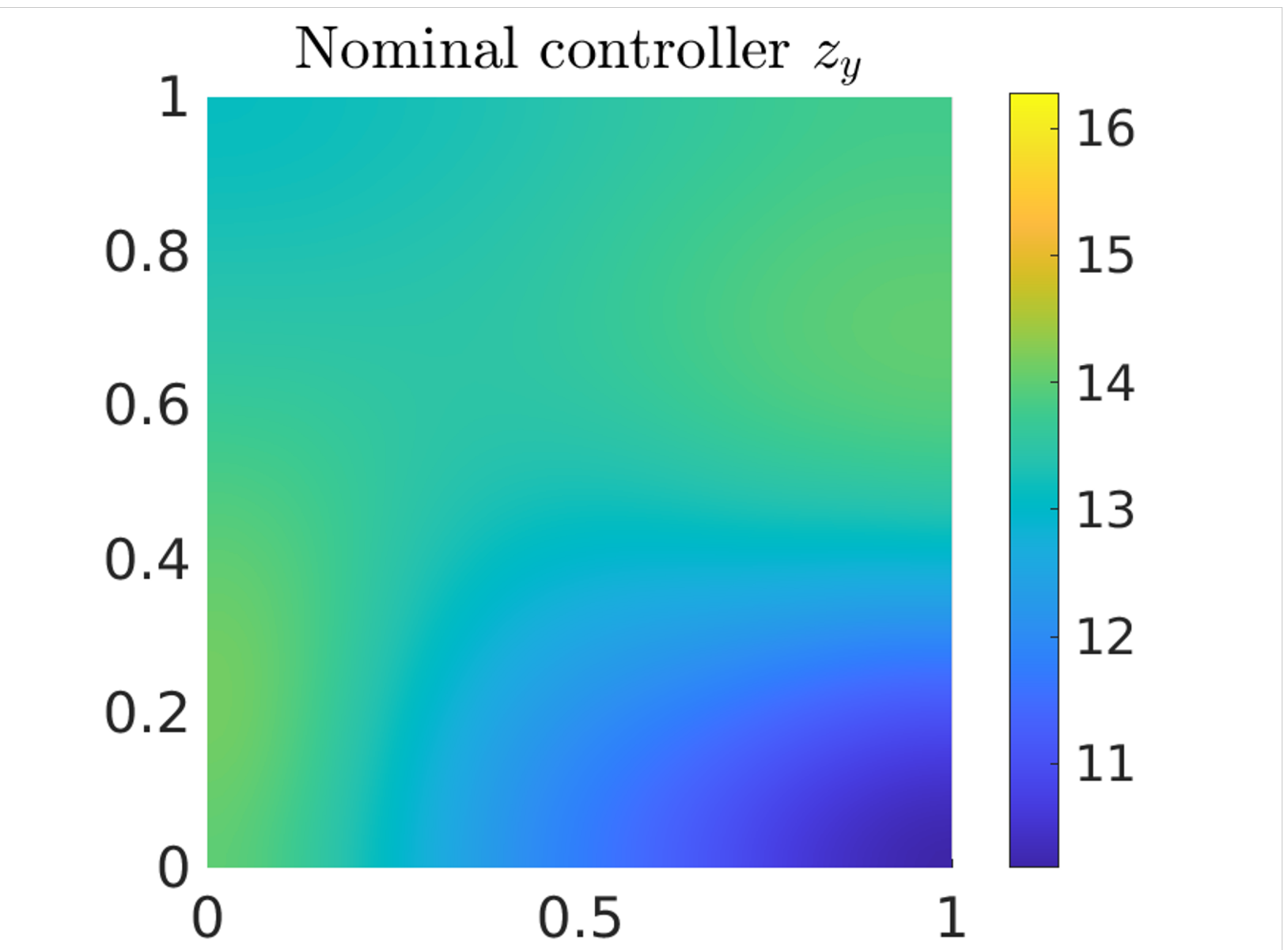
where the mean is

$$\bar{\theta} = \frac{1}{\alpha} \sum_{\ell=1}^N \left[\left(u_\ell \otimes \mathbf{M}_z^{-1} \mathbf{\Gamma}^{-1} (z_\ell - \bar{z}) \right) - \sum_{i=1}^N b_{i,\ell} \left(u_{i,\ell} \otimes \mathbf{M}_z^{-1} \mathbf{\Gamma}^{-1} w_i \right) \right]$$

and the uncertainty is modeled by

$$\hat{\theta} = \sqrt{\alpha} \sum_{i=1}^N \frac{1}{\sqrt{\lambda_i}} \left(\hat{u}_i \otimes \mathbf{M}_z^{-1} \mathbf{\Gamma}^{-1} w_i \right) \quad \text{and} \quad \tilde{\theta} = \sum_{k=1}^{n-N+1} \left(\tilde{s}_k \tilde{u}_k \otimes \tilde{w}_k \right)$$

2D Stokes versus Navier-Stokes





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$$\min_z J(S(z), z) \quad \leftarrow \text{The problem we want to solve}$$

$$\min_z J(\tilde{S}(z), z) \quad \leftarrow \text{The problem we actually solve}$$

- J is the objective
- z is a design, control, or inversion parameter
- $S(z)$ is an high-fidelity model
- $\tilde{S}(z)$ is an approximate model

Assume that we can

- solve the optimization problem constrained by \tilde{S}
- evaluate a high-fidelity model $S(z)$ at a small number of inputs z

Our goals are:

- Use the limited high-fidelity evaluations to improve the solution
- Characterize uncertainty in the optimal solution due to $S - \tilde{S}$

Posterior optimal solution samples

