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# Robust Inference for Physical Parameters with Bayesian Model Calibration

## Introduction

- Bayesian model calibration (BMC) refers to coupling of limited experimental data with an expensive computer simulator<sup>[1]</sup>.

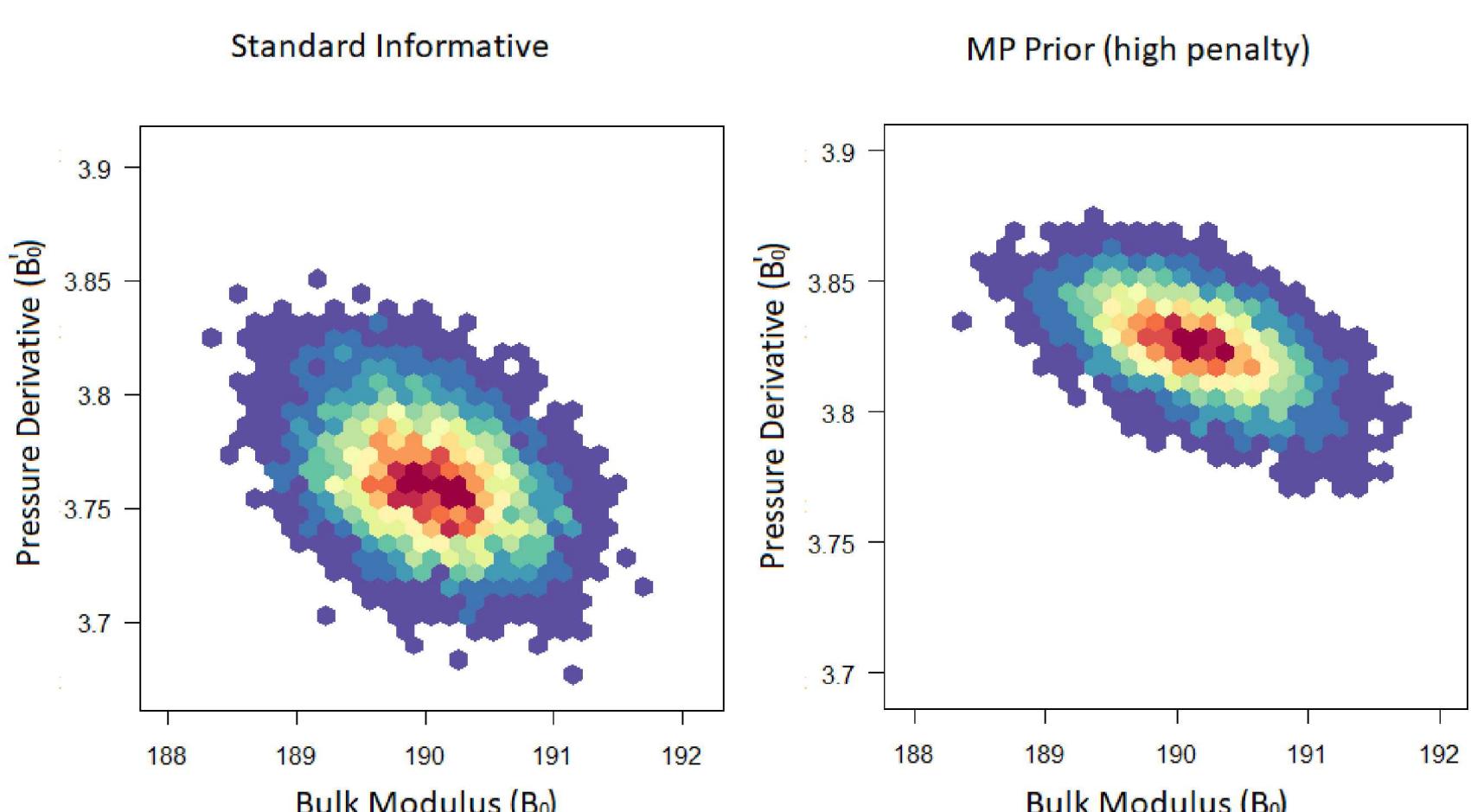
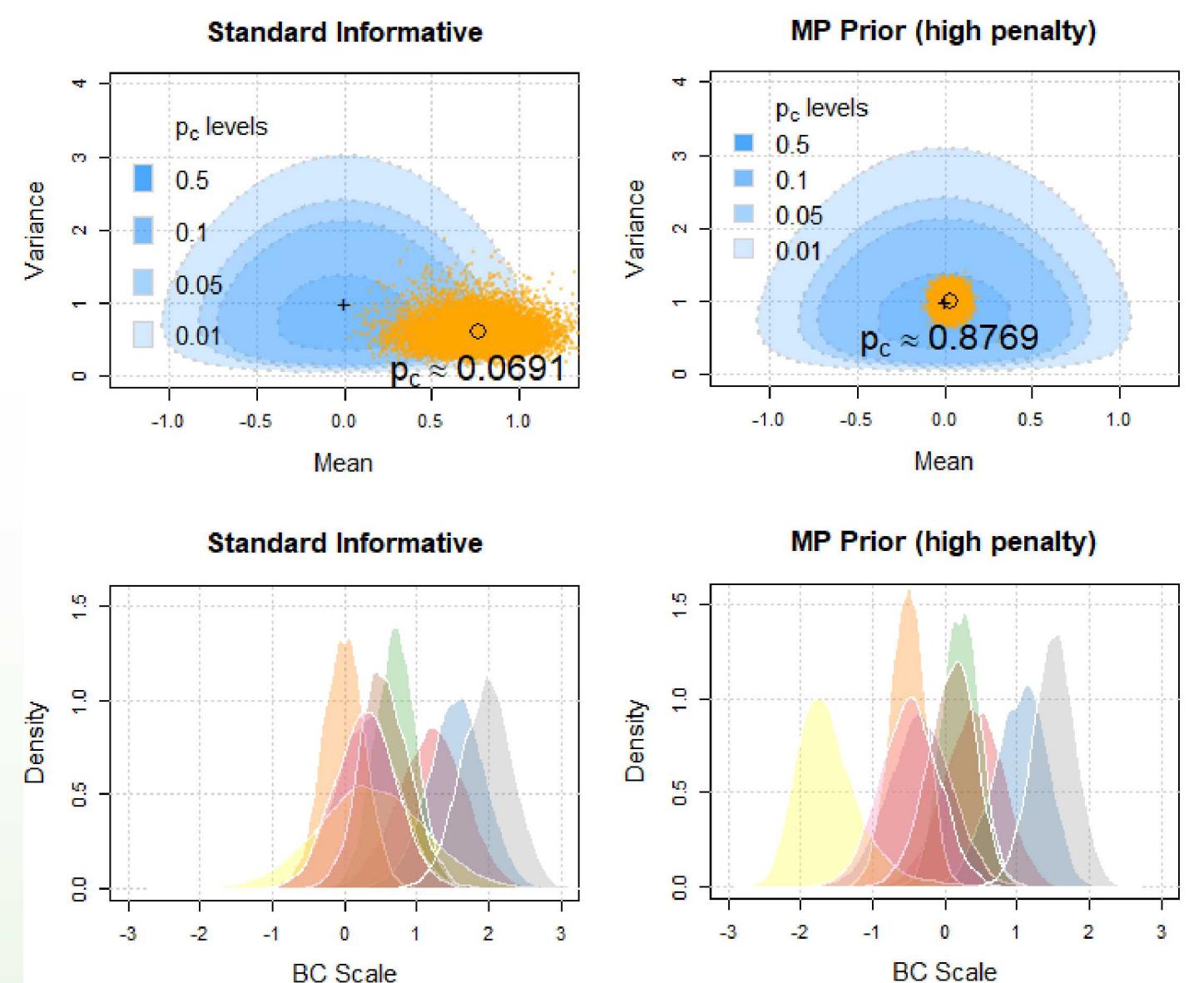
$$y(x_i) = \eta(x_i, \alpha, \gamma) + \delta(x_i) + \epsilon_i$$

- Computer simulator takes a high dimensional set of inputs known as calibration parameters.
- Modeling the discrepancy function directly leads to overfitting and unidentifiability<sup>[2]</sup>.
- Goal: Use Bayesian inference to learn the posterior distribution of the physical parameters.

## Regularization

- The addition of meaningful constraints in order to reduce overfitting.
- Example: Computer simulator takes 6 inputs, 3 of which vary across experiments.
- Some inputs represent measurement uncertainties, with known mean  $\mu$  and variance  $\nu$ .
- Overfitting can be identified with the probability of prior coherency and can be reduced or diagnosed via moment penalization<sup>[3]</sup>.

$$\pi_{\text{MP}}(\gamma) \propto \exp \left\{ -\lambda_1(M - \mu)^2 - \lambda_2(V - \nu)^2 \right\}$$



- Moment penalization leads to a shift in the posterior distribution of the physical parameters.
- More consistent with the physicists prior beliefs.

## Modularization

- Sometimes physical parameters  $\alpha$  and nuisance parameters  $\gamma$  are inherently jointly unidentifiable.
- Modularization improves identifiability by forfeiting the ability to learn about nuisance parameters, while rigorously accounting for the associated uncertainty<sup>[4]</sup>.

$$\pi_{\text{M}}(\alpha|y) = \int_{\mathbb{R}^q} \pi(\alpha|\gamma, y) \pi(\gamma) d\gamma$$

- The Modularization posterior is efficiently approximated numerically using the Sequential Gaussian Process (SGP)

