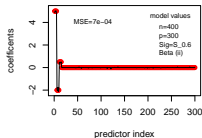
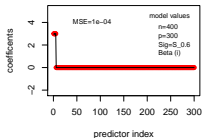
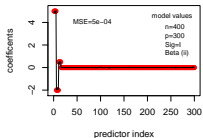
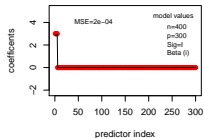
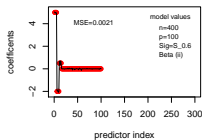
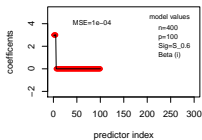
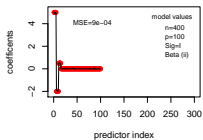
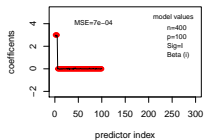
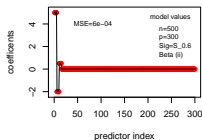
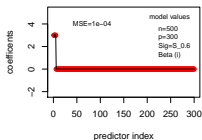
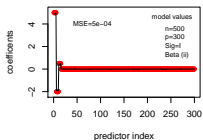
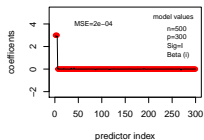
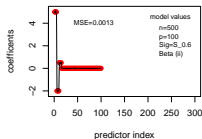
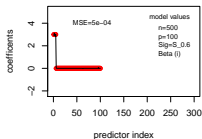
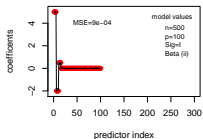
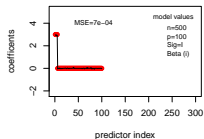


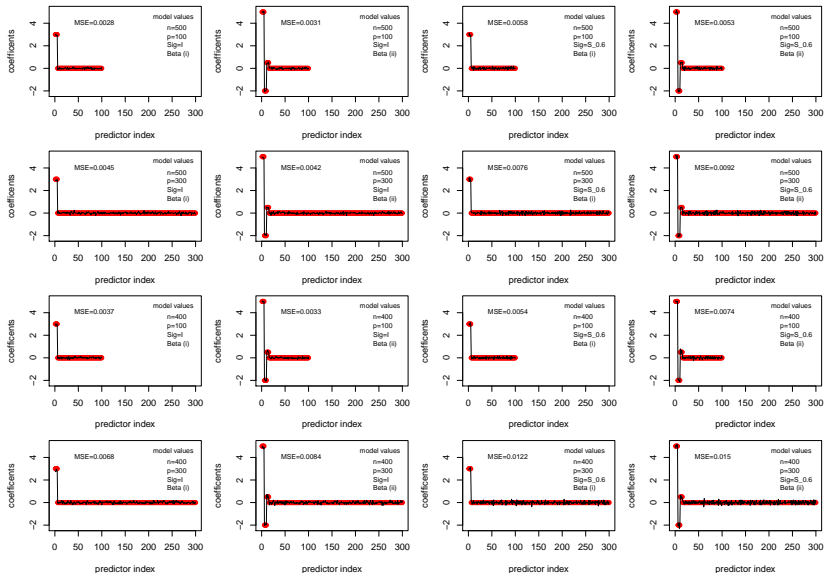
AMS 268 - HW #1

Raquel Barata

LASSO



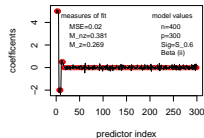
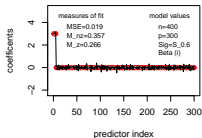
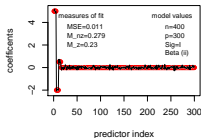
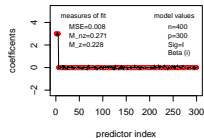
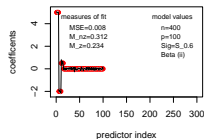
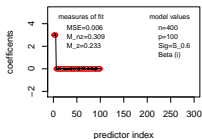
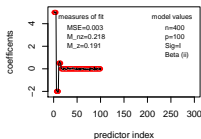
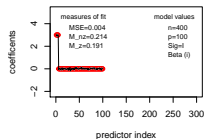
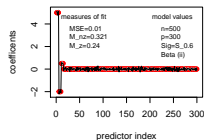
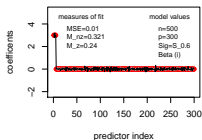
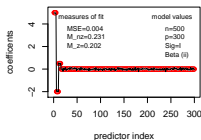
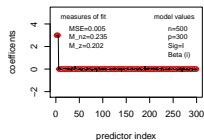
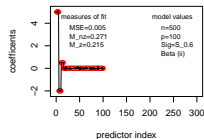
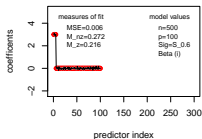
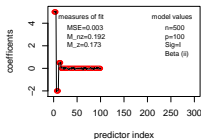
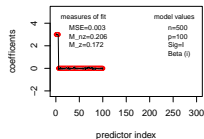
Ridge Regression



LASSO vs. Ridge Regression

- ▶ True values in red with estimates $\tilde{\beta}$ in black.
- ▶ λ_j chosen to minimize error.
- ▶ $MSE = \frac{1}{p} \sum_{i=1}^p (\beta - \tilde{\beta})^2$, where $\tilde{\beta}$ is the estimate for β , are unanimously smaller when data is fit using LASSO for all 16 combinations.
- ▶ Ridge regression coefficients $\tilde{\beta}_j$ are farther from true values when $\beta_j = 0$.

Spike and Slab



Spike and Slab

- ▶ True values β_j in red, $E(\beta_j|y)$ in black, 95% posterior intervals in grey.
- ▶ Spike and slab code written using the model in the notes with fixed $v_0 = 0.1^2$ and $v_1 = 10^2$.
- ▶ $MSE = \frac{1}{p} \sum_{i=1}^p (\beta - E(\beta_j|y))^2$.
- ▶ $M_{nz} = mean(L_j : \beta_j^0 \neq 0)$ and $M_z = mean(L_j : \beta_j^0 = 0)$ where L_j is the length of the 95% posterior interval for β_j .
- ▶ Variable selection is more straight forward for Spike and Slab than LASSO as posterior samples provide marginal inclusion probabilities $Pr(\gamma_j = 1|y, X)$ for coefficient β_j .

Posterior Prediction for $n = 500$, $p = 100$, $\Sigma = S_{0.6}$ and $\beta^{(i)}$

- ▶ 95% posterior predictive intervals for 50 new predictors in grey, $y_{est,i}$ in black, and true values $y_{pred,i}$ in red.
- ▶ $MSPE = \frac{1}{50} \sum_{i=1}^{50} (y_{pred,i} - y_{est,i})^2$.

