

# Bayesian LASSO

STA 4241

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# Introduction

Linear Regression Model:

$$y_i = \beta_0 + \sum_{j=1}^p \beta_j x_{ij} + \epsilon, \epsilon_i \sim N(0, \sigma^2)$$

OLS Estimation:

$$RSS(\beta) = \sum_{i=1}^n \left( Y_i - \beta_0 - \sum_{j=1}^p \beta_j X_{ij} \right)^2$$

LASSO

$$\hat{\beta}_{lasso} = \arg \min_{\beta} \left\{ RSS(\beta) + \lambda \sum_{j=1}^p |\beta_j| \right\}$$

# Bayesian LASSO

Bayesian Theorem:

$$p(\beta|X, Y) \propto p(Y|X, \beta)p(\beta)$$

Laplace Prior:

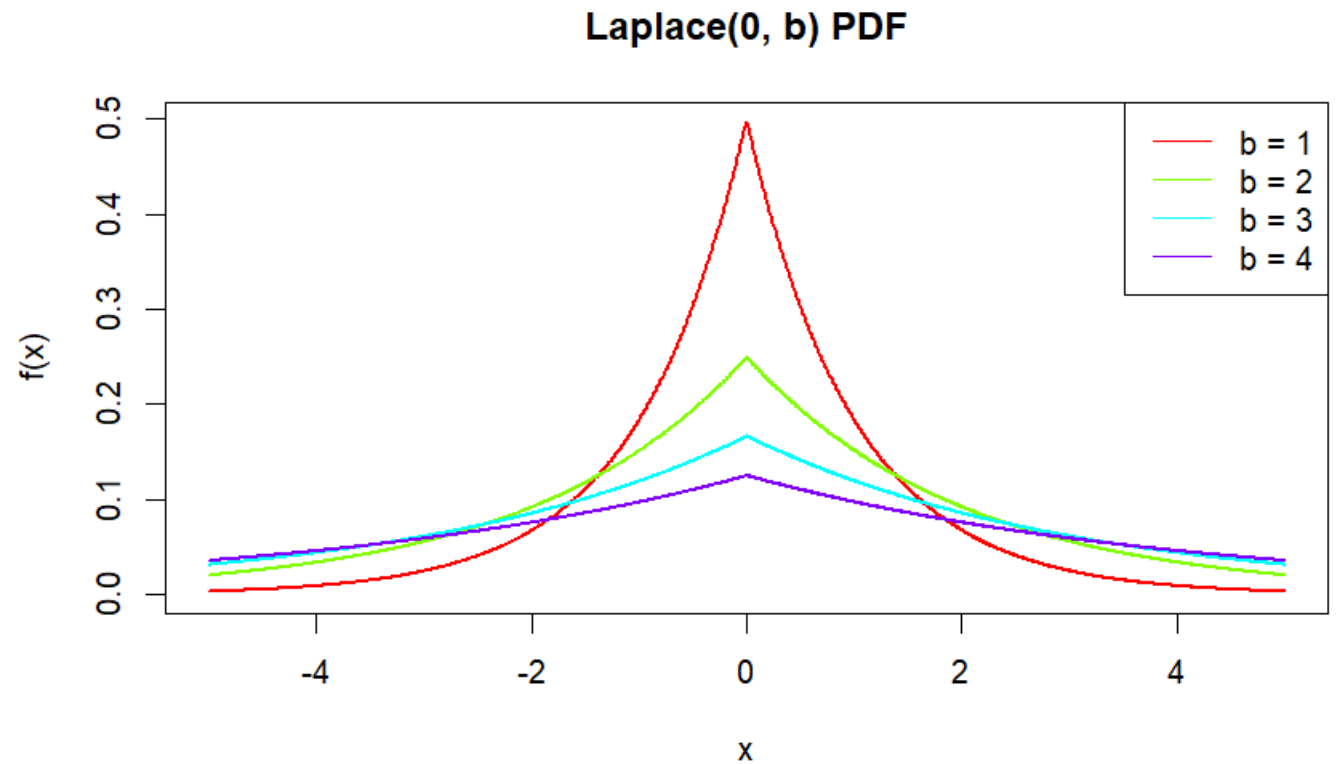
$$\beta_j \sim \text{Laplace}(0, b)$$

$$p(\beta_j) = \frac{1}{2b} \exp\left(-\frac{|\beta_j|}{b}\right)$$

Equivalence to frequentist LASSO:

$$\hat{\beta}_{MAP} = \arg \min \left\{ RSS(\beta) + \frac{b}{2\sigma^2} \sum_{j=1}^p |\beta_j| \right\}$$

with  $\lambda = \frac{2\sigma^2}{b}$



# Hierarchical Bayesian Model

$$p(\beta, \lambda, \sigma^2 | y) \propto p(y | \beta, \sigma^2) \prod_{j=1}^Y p(\beta_j | \lambda_j, \sigma^2) p(\lambda_j) p(\sigma^2)$$

Likelihood:

$$y | \beta, \sigma^2 \sim N(X\beta, \sigma^2 I_n)$$

Prior for  $\beta$ :

$$\beta_j | \lambda_j, \sigma^2$$

Prior for  $\lambda_j$ :

$$\lambda_j \sim \text{Exp}\left(\frac{\lambda^2}{2}\right)$$

Prior for  $\sigma^2$ :

$$\sigma^2 \sim IG(a_0, b_0)$$

# Gibbs Sampling Algorithm

## 1. Update $\beta$ :

1. Full conditional is Gaussian:

$$p(\beta|\lambda, \sigma^2, y) \sim N\left((X^T X + D_\lambda^{-1})^{-1} X^T y, \sigma^2 (X^T X + D_\lambda^{-1})^{-1}\right)$$

## 2. Update $\lambda$ :

1. Full conditional is Inverse-Gaussian:

$$\lambda|\beta, \sigma^2 \sim \text{InverseGaussian}\left(\sqrt{\frac{\sigma^2}{\lambda|\beta|}}, \lambda^2\right)$$

## 3. Update $\sigma^2$ :

1. Full conditional is Inverse-Gamma:

$$\sigma^2|\beta, \lambda, y \sim IG\left(a_0 + \frac{n+p}{2}, b_0 + \frac{\|y - X\beta\|^2}{2} + \frac{1}{2} \sum_{j=1}^p \frac{\beta_j^2}{\lambda_j}\right)$$

# Simulation Example

Set-up:

- $n = 500, p = 20$
- $\beta^* = (1.5, 2.5, 3.5, 0, \dots, 0)$
- $X_{ij} \sim N(0, 1), Y = X\beta^* + \epsilon \sim N(0, 1)$

Methods Compared:

1. Frequentists LASSO
  1. Bootstrap (empirical intervals)
2. Bayesian LASSO

# Simulated Example: results

## Frequentist Lasso Estimates:

```
## [1] 1.4513956897 2.4324151397 3.4355699619 0.0000000000 0.0000000000
## [6] -0.0181063290 0.0008068596 0.0413408229 0.0000000000 0.0000000000
## [11] 0.0000000000 0.0000000000 -0.0179382157 -0.0125672986 0.0000000000
## [16] 0.0080060524 0.0000000000 0.0000000000 0.0458186691 0.0000000000
```

##

## Bootstrapped Lasso Means and 95% Intervals:

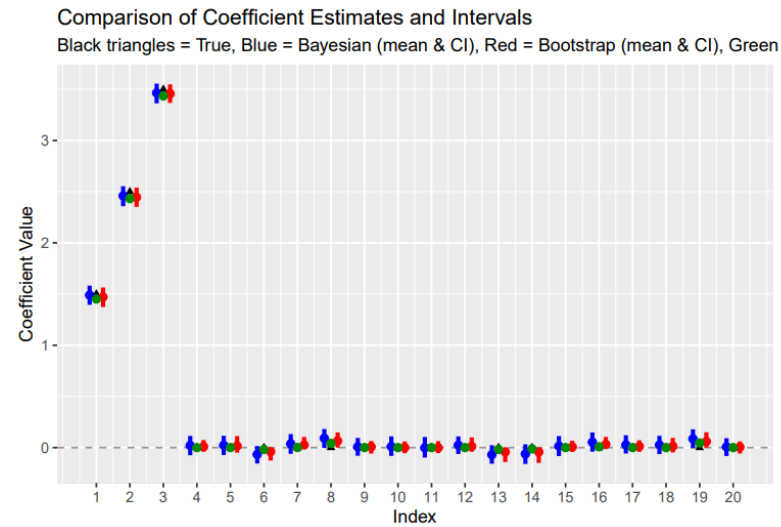
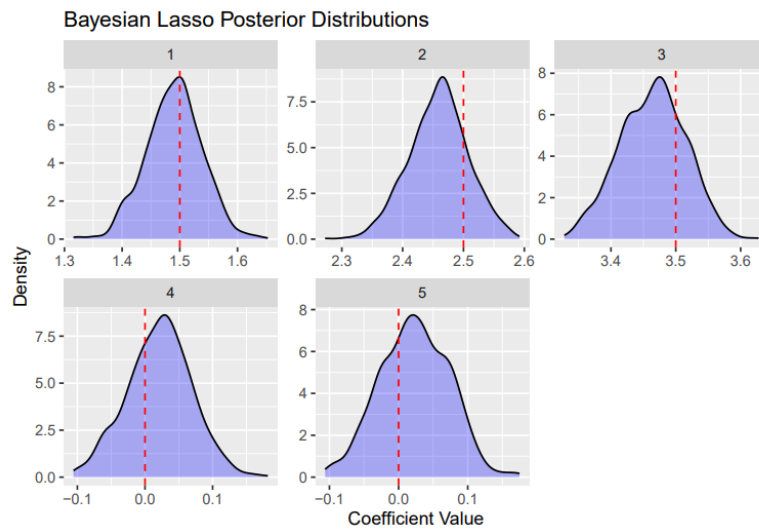
```
##          [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
## mean      1.471133 2.446005 3.457501 0.009607898 0.01613904 -0.03935249
## ci_lower  1.373514 2.352196 3.367407 -0.039184316 -0.04886426 -0.12620823
## ci_upper  1.563989 2.539126 3.548582 0.073839278 0.11288932 0.000000000
##          [,7]      [,8]      [,9]      [,10]     [,11]
## mean      0.02589403 0.06547572 0.007932695 2.642478e-05 -0.001745804
## ci_lower -0.01290876 0.00000000 -0.058153373 -5.425888e-02 -0.053470641
## ci_upper  0.10468195 0.14804731 0.064584540 5.947082e-02 0.062938355
##          [,12]     [,13]     [,14]     [,15]     [,16]
## mean      0.01161351 -0.04186976 -0.0421790768 0.00667215 0.03133238
## ci_lower -0.03995028 -0.14040612 -0.1492642160 -0.04159837 0.000000000
## ci_upper  0.10004003 0.00000000 0.0008926861 0.06717149 0.10452442
##          [,17]     [,18]     [,19]     [,20]
## mean      0.01217462 0.01348161 0.06011742 0.004675554
## ci_lower -0.04063421 -0.04715406 0.00000000 -0.057687255
## ci_upper  0.07150023 0.09498035 0.14959496 0.059895024
```

##

## Bayesian Lasso Posterior Means and 95% Credible Intervals:

```
##          [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
## mean      1.489961 2.458935 3.464444 0.02139147 0.02305214 -0.06632575
## ci_lower  1.395016 2.358254 3.363268 -0.07458665 -0.07218371 -0.15487936
## ci_upper  1.582228 2.553421 3.555510 0.11428027 0.11560833 0.01576948
##          [,7]      [,8]      [,9]      [,10]     [,11]
## mean      0.03774316 0.091826876 0.008084577 0.01041076 -0.002268714
## ci_lower -0.06027940 -0.002965315 -0.078762204 -0.08087050 -0.097045694
## ci_upper  0.13211690 0.181392104 0.095022368 0.11024738 0.103488751
##          [,12]     [,13]     [,14]     [,15]     [,16]
## mean      0.02418686 -0.06898059 -0.06154494 0.01520955 0.05280079
## ci_lower -0.06159162 -0.15712832 -0.15902972 -0.08227585 -0.03957666
## ci_upper  0.10982833 0.02381479 0.03293029 0.11291128 0.14802858
##          [,17]     [,18]     [,19]     [,20]
## mean      0.02704109 0.02560291 0.086079654 0.007602938
## ci_lower -0.05760811 -0.06307989 -0.004802462 -0.081495506
## ci_upper  0.12069999 0.11518782 0.178723196 0.092350040
```

# Simulated Example: results



```
##  
## MSE of Estimates:  
  
## Lasso: 0.000788102  
  
## Lasso (Bootstrap mean): 0.001056956  
  
## Bayesian Lasso (Posterior mean): 0.001973984  
  
##  
## Variable Selection (qualitative):  
  
## Lasso sets coefficients exactly to zero or not, Bayesian gives a probability.  
  
## Number of exact zeros (Lasso): 10  
  
## Bayesian CI containing zero (count): 17 out of 20 coefficients
```



# Conclusion

- Advantage:
  - Interpretability (probabilistic, standard error)
  - Flexibility
- Limitation:
  - Computationally intensive
  - Does not automatically zero out coefficients.

# Reference

Chen, Y. (2021). STA521: Predictive Modelling and Statistical Learning, Lecture 9: Bayesian Regression I. Duke University. Retrieved from <https://www2.stat.duke.edu/courses/Fall21/sta521.001/post/week05-1/main.pdf>

Kyung, Minjung & Gill, Jeff & Ghosh, Malay & Casella, George. (2010). Penalized Regression, Standard Errors, and Bayesian Lassos. *Bayesian Analysis*. 5. 369-412. 10.1214/10-BA607.

Park, T., & Casella, G. (2008). The Bayesian Lasso. *Journal of the American Statistical Association*, 103(482), 681–686.

Tibshirani, R. (1996). Regression shrinkage and selection via the Lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1), 267–288.

