Lecture 13: Ridge Regression, Lasso and Mixture Priors

STA702

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Ridge Regression

Model: $\mathbf{Y} = \mathbf{1}_n \alpha + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$

- typically expect the intercept α to be a different order of magnitude from the other predictors. Adopt a two block prior with $p(\alpha) \propto 1$
- Prior $\boldsymbol{\beta} \mid \phi \sim \textsf{N}(\mathbf{0}_b, \frac{1}{\phi\kappa}\mathbf{I}_p)$ implies the $\mathbf{b}$ are exchangable *a priori* (i.e. distribution is invariant under permuting the labels and with a common scale and mean)
- Posterior for $\boldsymbol{\beta}$

$$\boldsymbol{\beta} \mid \phi, \kappa, \mathbf{Y} \sim \textsf{N}\left((\kappa I_p + X^T X)^{-1} X^T Y, \frac{1}{\phi}(\kappa I_p + X^T X)^{-1}\right)$$

- assume that $\mathbf{X}$ has been centered and scaled so that $\mathbf{X}^T\mathbf{X} = \textsf{corr}(\mathbf{X})$ and $\mathbf{1}_n^T \mathbf{X} = \mathbf{0}_p$

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X = scale(X)/sqrt{nrow(X) - 1}
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Bayes Ridge Regression

- related to penalized maximum likelihood estimation

$$-\frac{\phi}{2}\left(\|\mathbf{Y}-\mathbf{X}\boldsymbol{\beta}\|^2+\kappa\|\boldsymbol{\beta}\|^2\right)$$

- frequentist's expected mean squared error loss for using $\mathbf{b}_n$

$$\mathsf{E}_{\mathbf{Y}\mid\boldsymbol{\beta}_*}[\|\mathbf{b}_n-\boldsymbol{\beta}_*\|^2]=\sigma^2\sum_{j=1}^{2}\frac{\lambda_j}{(\lambda_j+\kappa)^2}+\kappa^2\boldsymbol{\beta}_*^T(\mathbf{X}^T\mathbf{X}+\kappa\mathbf{I}_p)^{-2}\boldsymbol{\beta}_*$$

- eigenvalues of $\mathbf{X}^T\mathbf{X}=\mathbf{V}\boldsymbol{\Lambda}\mathbf{V}^T$ with $[\boldsymbol{\Lambda}]_{jj}=\lambda_j$
- can show that there **always** is a value of κ where is smaller for the (Bayes) Ridge estimator than MLE
- Unfortunately the optimal choice depends on "true" $\boldsymbol{\beta}_*$!
- orthogonal $\mathbf{X}$ leads to James-Stein solution related to Empirical Bayes

Choice of κ?

- fixed *a priori* Bayes (and how to choose?)
- Cross-validation (frequentist)
- Empirical Bayes? (frequentist/Bayes)
- Should there be a common κ? (same shrinkage across all variables?)
- Or a κ_j per variable? (or shared among a group of variables (eg. factors) ?)
- Treat as unknown!

Mixture of Conjugate Priors

- can place a prior on κ or κ_j for fully Bayes
- similar option for g in the g priors
- often improved robustness over fixed choices of hyperparameter
- may not have cloosed form posterior but sampling is still often easy!
- Examples:
  - Bayesian Lasso (Park & Casella, Hans)
  - Generalized Double Pareto (Armagan, Dunson & Lee)
  - Horseshoe (Carvalho, Polson & Scott)
  - Normal-Exponential-Gamma (Griffen & Brown)
  - mixtures of g-priors (Liang et al)

Lasso

Tibshirani (JRSS B 1996) proposed estimating coefficients through L_1 constrained least squares ``Least Absolute Shrinkage and Selection Operator''

- Control how large coefficients may grow

$$\min_{\boldsymbol{\beta}} \|\mathbf{Y} - \mathbf{1}_n \alpha - \mathbf{X}\boldsymbol{\beta}\|^2$$
$$\text{subject to } \sum |\beta_j| \leq t$$

- Equivalent Quadratic Programming Problem for ``penalized'' Likelihood

$$\min_{\boldsymbol{\beta}} \|\mathbf{Y} - \mathbf{1}_n \alpha - \mathbf{X}\boldsymbol{\beta}\|^2 + \lambda \|\boldsymbol{\beta}\|_1$$

- Equivaletnt to finding posterior mode

$$\max_{\boldsymbol{\beta}} -\frac{\phi}{2}\{\|\mathbf{Y} - \mathbf{1}_n \alpha - \mathbf{X}\boldsymbol{\beta}\|^2 + \lambda \|\boldsymbol{\beta}\|_1\}$$

Bayesian Lasso

Park & Casella (JASA 2008) and Hans (Biometrika 2010) propose Bayesian versions of the Lasso

$$\begin{aligned} \mathbf{Y} \mid \alpha, \boldsymbol{\beta}, \phi &\sim \mathsf{N}(\mathbf{1}_n \alpha + \mathbf{X}\boldsymbol{\beta}, \mathbf{I}_n/\phi) \\ \boldsymbol{\beta} \mid \alpha, \phi, \boldsymbol{\tau} &\sim \mathsf{N}(\mathbf{0}, \mathsf{diag}(\boldsymbol{\tau}^2)/\phi) \\ \tau_1^2 \ldots, \tau_p^2 \mid \alpha, \phi &\overset{\text{iid}}{\sim} \mathsf{Exp}(\lambda^2/2) \\ p(\alpha, \phi) &\propto 1/\phi \end{aligned}$$

- Can show that $\beta_j \mid \phi, \lambda \overset{\text{iid}}{\sim} DE(\lambda\sqrt{\phi})$

$$\int_0^\infty \frac{1}{\sqrt{2\pi s}} e^{-\frac{1}{2}\phi\frac{\beta^2}{s}} \,\frac{\lambda^2}{2} e^{-\frac{\lambda^2 s}{2}}\, ds = \frac{\lambda\phi^{1/2}}{2} e^{-\lambda\phi^{1/2}|\beta|}$$

- equivalent to penalized regression with $\lambda^* = \lambda/\phi^{1/2}$
- Scale Mixture of Normals (Andrews and Mallows 1974)

Gibbs Sampling

- Integrate out α: $\alpha \mid \mathbf{Y}, \phi \sim \textsf{N}(\bar{y}, 1/(n\phi)$
- $\boldsymbol{\beta} \mid \boldsymbol{\tau}, \phi, \lambda, \mathbf{Y} \sim \textsf{N}(,)$
- $\phi \mid \boldsymbol{\tau}, \boldsymbol{\beta}, \lambda, \mathbf{Y} \sim \mathbf{G}(,)$
- $1/\tau_j^2 \mid \boldsymbol{\beta}, \phi, \lambda, \mathbf{Y} \sim \textsf{InvGaussian}(,)$
- For $X \sim \textsf{InvGaussian}(\mu, \lambda)$, the density is

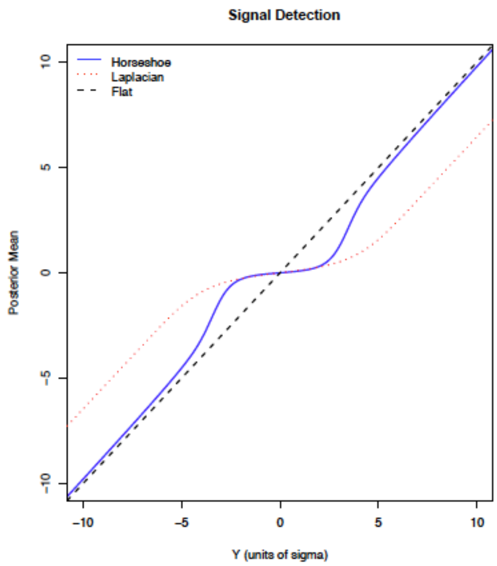
$$f(x) = \sqrt{\frac{\lambda^2}{2\pi}} x^{-3/2} e^{-\frac{1}{2}\frac{\lambda^2(x-\mu)^2}{\mu^2 x}} \qquad x > 0$$

> **Homework**
>
> Derive the full conditionals for $\boldsymbol{\beta}, \phi, 1/\tau^2$ for the model in Park & Casella

Choice of Estimator

- Posterior mode (like in the LASSO) may set some coefficients exactly to zero leading to variable selection - optimization problem (quadratic programming)
- Posterior distribution for β_j does not assign any probability to $\beta_j = 0$ so posterior mean results in no selection, but shrinkage of coeffiecients to prior mean of zero
- In both cases, large coefficients may be over-shrunk (true for LASSO too)!
- Issue is that the tails of the prior under the double exponential are not heavier than the the normal likelihood
- Only one parameter λ that controls shrinkage and selection (with the mode)
- Need priors with heavier tails than the normal!!!

Shrinkage Comparison with Posterior Mean



HS - Horseshoe of Carvalho, Polson & Scott (slight difference in CPS notation)

$$\boldsymbol{\beta} \mid \phi, \boldsymbol{\tau} \sim \mathsf{N}(\mathbf{0}_p, \frac{\mathsf{diag}(\boldsymbol{\tau}^2)}{\phi})$$

$$\tau_j \mid \lambda \overset{\text{iid}}{\sim} \mathsf{C}^+(0, \lambda^2)$$

$$\lambda \sim \mathsf{C}^+(0, 1)$$

$$p(\alpha, \phi) \propto 1/\phi)$$

- resulting prior on $\boldsymbol{\beta}$ has heavy tails like a Cauchy!

Bounded Influence for Mean

- canonical representation (normal means problem) $\mathbf{Y}^* = \mathbf{I}\boldsymbol{\beta} + \boldsymbol{\epsilon}$

$$E[\beta_i \mid \mathbf{Y}] = \int_0^1 (1 - \kappa_i) y_i^* p(\kappa_i \mid \mathbf{Y}) \, d\kappa_i = (1 - \mathsf{E}[\kappa \mid y_i^*]) y_i^*$$

- $\kappa_i = 1/(1 + \tau_i^2)$ shrinkage factor
- Posterior mean $E[\beta \mid y] = y + \frac{d}{dy} \log m(y)$ where $m(y)$ is the predictive density under the prior (known λ)
- HS has Bounded Influence: if $\lim_{|y| \to \infty} \frac{d}{dy} \log m(y) = 0$

$$\lim_{|y| \to \infty} E[\beta \mid y) \to y$$

- DE prior also has bounded influence, but bound does not decay to zero in tails

Properties for Shrinkage and Selection

Fan & Li (JASA 2001) discuss Variable selection via nonconcave penalties and oracle properties

- Model $Y = \mathbf{1}_n \alpha \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\epsilon}$ with $\mathbf{X}^T\mathbf{X} = \mathbf{I}_p$ (orthonormal) and $\boldsymbol{\epsilon} \sim N(0, \mathbf{I}_n)$
- Penalized Log Likelihood

$$\frac{1}{2}\|\mathbf{Y} + \hat{\mathbf{Y}}\|^2 + \frac{1}{2}\sum_j (\beta_j - \hat{\beta}_j)^2 + \sum_j \text{pen}_\lambda(|\beta_j|)$$

- duality $\text{pen}_\lambda(|\beta|) \equiv -\log(p(|\beta_j|))$ (negative log prior)
- Objectives:
  - Unbiasedness: for large $|\beta_j|$
  - Sparsity: thresholding rule sets small coefficients to 0
  - Continuity: continuous in $\hat{\beta}_j$

Conditions on Prior/Penalty

Derivative of $\frac{1}{2}\sum_j(\beta_j - \hat{\beta}_j)^2 + \sum_j \text{pen}_\lambda(|\beta_j|)$ is $\text{sgn}(\beta_j)\left\{|\beta_j| + \text{pen}'_\lambda(|\beta_j|)\right\} - \hat{\beta}_j$

- Conditions:
  - unbiased: if $\text{pen}'_\lambda(|\beta|) = 0$ for large $|\beta|$; estimator is $\hat{\beta}_j$
  - thresholding: $\min\left\{|\beta_j| + \text{pen}'_\lambda(|\beta_j|)\right\} > 0$ then estimator is 0 if $|\hat{\beta}_j| < \min\left\{|\beta_j| + \text{pen}'_\lambda(|\beta_j|)\right\}$
  - continuity: minimum of $|\beta_j| + \text{pen}'_\lambda(|\beta_j|)$ is at zero
- Can show that LASSO/ Bayesian Lasso fails conditions for unbiasedness
- What about other Bayes methods?

Homework

Check the conditions for the Generalized Double Pareto

Selection

- Only get variable selection if we use the posterior mode
- If selection is a goal of analysis build it into the model/analysis
  - prior belief that coefficient is zero
  - selection solved as a post-analysis decision problem