(7) Bayesian linear regression

ST440/540: Applied Bayesian Statistics

Spring, 2018

Bayesian linear regression

- Linear regression is by far the most common statistical model
- It includes as special cases the t-test and ANOVA
- The multiple linear regression model is

$$Y_i \sim \text{Normal}(\beta_0 + X_{i1}\beta_1 + ... + X_{ip}\beta_p, \sigma^2)$$

  independently across the $i = 1, ..., n$ observations
- As we'll see, Bayesian and classical linear regression are similar if $n >> p$ and the priors are uninformative.
- However, the results can be different for challenging problems, and the interpretation is different in all cases

Review of least squares

- The least squares estimate of $\boldsymbol{\beta} = (\beta_0, \beta_1, ..., \beta_p)^T$ is

$$\hat{\beta}_{OLS} = \underset{\boldsymbol{\beta}}{\text{argmin}} \sum_{i=1}^{n} (Y_i - \mu_i)^2$$

where $\mu_i = \beta_0 + X_{i1}\beta_1 + ... + X_{ip}\beta_p$

- $\hat{\beta}_{OLS}$ is unbiased even if the errors are non-Gaussian
- If the errors are Gaussian then the likelihood is proportional to

$$\prod_{i=1}^{n} \exp\left[-\frac{(Y_i - \mu_i)^2}{2\sigma^2}\right] = \exp\left[-\frac{\sum_{i=1}^{n}(Y_i - \mu_i)^2}{2\sigma^2}\right]$$

- Therefore, if the errors are Gaussian $\hat{\beta}_{OLS}$ is also the MLE

Review of least squares

- Linear regression is often simpler to describe using linear algebra notation
- Let $\mathbf{Y} = (Y_1, ..., Y_n)^T$ be the response vector and $\mathbf{X}$ be the $n \times (p+1)$ matrix of covariates
- Then the mean of $\mathbf{Y}$ is $\mathbf{X}\beta$ and the least squares solution is

$$\hat{\beta}_{OLS} = \underset{\beta}{\operatorname{argmin}}(\mathbf{Y} - \mathbf{X}\beta)^T(\mathbf{Y} - \mathbf{X}\beta) = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}$$

- If the errors are Gaussian then the sampling distribution is

$$\hat{\beta}_{OLS} \sim \text{Normal}\left[\beta, \sigma^2(\mathbf{X}^T\mathbf{X})^{-1}\right]$$

- If the variance σ^2 is estimated using the mean squared residual error then the sampling distribution is multivariate t

Bayesian regression

- The likelihood remains

$$Y_i \sim \text{Normal}(\beta_0 + X_{i1}\beta_1 + ... + X_{ip}\beta_p, \sigma^2)$$

independent for $i = 1, ..., n$ observations

- As with a least squares analysis, it is crucial to verify this is appropriate using qq-plots, added variable plots, etc.

- A Bayesian analysis also requires priors for $\boldsymbol{\beta}$ and σ

- We will focus on prior specification since this piece is uniquely Bayesian.

Priors

- For the purpose of setting priors, it is helpful to standardize both the response and each covariate to have mean zero and variance one.

- Many priors for β have been considered:
  1. Improper priors
  2. Gaussian priors
  3. Double exponential priors
  4. Many, many more...

Improper priors

- The Jeffreys' prior is flat $p(\beta) = 1$
- This is improper, but the posterior is proper under the same conditions required by least squares
- If σ is known then

$$\beta|\mathbf{Y} \sim \text{Normal}\left[\hat{\beta}_{OLS}, \sigma^2(\mathbf{X}^T\mathbf{X})^{-1}\right]$$

- See "Post beta" in `http://www4.stat.ncsu.edu/~reich/ABA/Derivations7.pdf`
- Therefore, the results should be similar to least squares
- How are they different?

Improper priors

- Of course we rarely know σ
- Typically the error variance follows an InvGamma(a, b) prior with a and b set to be small, say $a = b = 0.01$.
- In this case the posterior of β follows a multivariate t centered on $\hat{\beta}_{OLS}$
- Again, the results are similar to OLS
- The objective Bayes Jeffreys prior for $\boldsymbol{\theta} = (\boldsymbol{\beta}, \sigma)$ is

$$p(\boldsymbol{\beta}, \sigma^2) = \frac{1}{\sigma^2}$$

which is the limit as $a, b \to 0$

Multivariate normal prior

- Another common prior for is Zellner's g-prior

$$\boldsymbol{\beta} \sim \text{Normal}\left[0, \frac{\sigma^2}{g}(\mathbf{X}^T\mathbf{X})^{-1}\right]$$

- This prior is proper assuming $\mathbf{X}$ is full rank
- The posterior mean is

$$\frac{1}{1+g}\hat{\boldsymbol{\beta}}_{OLS}$$

- This shrinks the least estimate towards zero
- g controls the amount of shrinkage
- $g = 1/n$ is common, and called the unit information prior

Univariate Gaussian priors

- If there are many covariates or the covariates are collinear, then $\hat{\boldsymbol{\beta}}_{OLS}$ is unstable
- Independent priors can counteract collinearity

$$\beta_j \sim \text{Normal}(0, \sigma^2/g)$$

  independent over j

- The posterior mode is

$$\underset{\boldsymbol{\beta}}{\text{argmin}} \sum_{i=1}^{n} (Y_i - \mu_i)^2 + g \sum_{j=1}^{p} \beta_j^2$$

- In classical statistics, this is known as the ridge regression solution and is used to stabilize the least squares solution

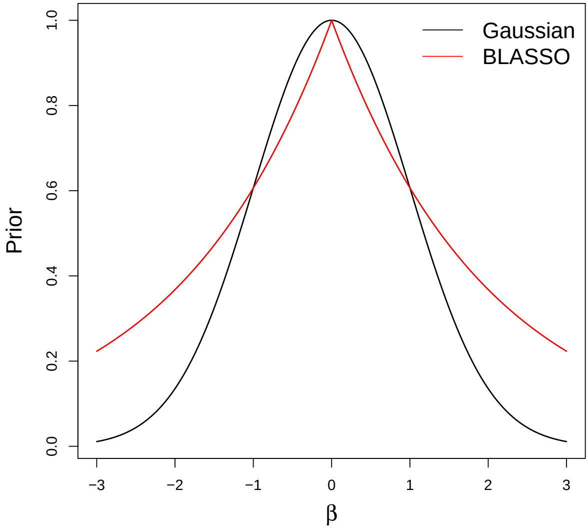
BLASSO

- An increasingly-popular prior is the double exponential or Bayesian LASSO prior
- The prior is $\beta_j \sim \text{DE}(\tau)$ which has PDF

$$f(\beta) \propto \exp\left(-\frac{|\beta|}{\tau}\right)$$

- The square in the Gaussian prior is replaced with an absolute value
- The shape of the PDF is thus more peaked at zero (next slide)
- The BLASSO prior favors settings where there are many β_j near zero and a few large β_j
- That is, p is large but most of the covariates are noise

BLASSO



BLASSO

- The posterior mode is

$$\underset{\boldsymbol{\beta}}{\text{argmin}} \sum_{i=1}^{n} (Y_i - \mu_i)^2 + g \sum_{j=1}^{p} |\beta_j|$$

- In classical statistics, this is known as the LASSO solution
- It is popular because it adds stability by shrinking estimates towards zero, and also sets some coefficients to zero
- Covariates with coefficients set to zero can be removed
- Therefore, LASSO performs variables selection and estimation simultaneously

Computing

- With flat or Gaussian (with fixed prior variance) priors the posterior is available in closed-form and Monte Carlo sampling is not needed
- With normal priors all full conditionals are Gaussian or inverse gamma, and so Gibbs sampling is simple and fast
- JAGS works well, but there are R (and SAS and others) packages dedicated just to Bayesian linear regression that are preferred for big/hard problems
- `BLR` is probably the most common
- `http://www4.stat.ncsu.edu/~reich/ABA/code/regJAGS`

Computing for the BLASSO

- For the BLASSO prior the full conditionals are more complicated
- There is a trick to make all full conditional conjugate so that Gibbs sampling can be used
- Metropolis sampling works fine too
- `BLR` works well for BLASSO and is super fast
- JAGS can handle this as well,
- `http://www4.stat.ncsu.edu/~reich/ABA/code/BLASSO`

Summarizing the results

- The standard summary is a table with marginal means and 95% intervals for each β_j
- This becomes unwieldy for large p
- Picking a subset of covariates is a crucial step in a linear regression analysis.
- We will discuss this later in the course.
- Common methods include cross-validation, information criteria, and stochastic search.

Logistic regression

- Other forms of regression follow naturally from linear regression
- For example, for binary responses $Y_i \in \{0, 1\}$ we might use logistic regression

$$\text{logit}[\text{Prob}(Y_i = 1)] = \eta_i = \beta_0 + \beta_1 X_{i1} + ... + \beta_p X_{ip}$$

- The logit link is the log-odd $\text{logit}(x) = \log[x/(1-x)]$
- Then β_j represents the increase in the log odds of an event corresponding to a one-unit increase in covariate j
- The expit transformation $\text{expit}(x) = \exp(x)/[1 + exp(x)]$ is the inverse, and

$$\text{Prob}(Y_i = 1) = \text{expit}(\eta_i) \in [0, 1]$$

Logistic regression

- Bayesian logistic regression requires a prior for β
- All of the prior we have discussed for linear regression (Zellner, BLASSO, etc) apply
- Computationally the full conditional distributions are no longer conjugate and so we must use Metropolis sampling
- The `R` function `MCMClogit` does this efficiently
- It is fast in JAGS too, for example `http://www4.stat.ncsu.edu/~reich/ABA/code/GLM`

Predictions

- Say we have a new covariate vector $\mathbf{X}_{new}$ and we would like to predict the corresponding response Y_{new}
- A plug-in approach would fix β and σ at their posterior means $\hat{\beta}$ and $\hat{\sigma}$ to make predictions

$$Y_{new}|\hat{\beta}, \hat{\sigma} \sim \text{Normal}(\mathbf{X}_{new}\hat{\beta}, \hat{\sigma}^2)$$

- However this plug-in approach suppresses uncertainty about β and σ
- Therefore these prediction intervals will be slightly too narrow leading to undercoverage

Posterior predicitive distribution (PPD)

- We should really account for all uncertainty when making predictions, including our uncertainty about β and σ
- We really want the PPD

$$
\begin{aligned}
p(Y_{new}|\mathbf{Y}) &= \int f(Y_{new}, \boldsymbol{\beta}, \sigma|\mathbf{Y}) d\boldsymbol{\beta} d\sigma \\
&= \int f(Y_{new}|\boldsymbol{\beta}, \sigma) f(\boldsymbol{\beta}, \sigma|\mathbf{Y}) d\boldsymbol{\beta} d\sigma
\end{aligned}
$$

- Marginalizing over the model parameters accounts for their uncertainty
- The concept of the PPD applies generally (e.g., logistic regression) and means the distribution of the predicted value marginally over model parameters

Posterior predicitive distribution (PPD)

- MCMC naturally gives draws from Y_{new}'s PPD
  - For MCMC iteration t we have $\beta^{(t)}$ and $\sigma^{(t)}$
  - For MCMC iteration t we sample
$$Y_{new}^{(t)} \sim \text{Normal}(\mathbf{X}\beta^{(t)}, {\sigma^{(t)}}^2)$$
  - $Y_{new}^{(1)}, ..., Y_{new}^{(S)}$ are samples from the PPD
- This is an example of the claim that "Bayesian methods naturally quantify uncertainty"
- `http://www4.stat.ncsu.edu/~reich/ABA/code/Predict`