Lecture 18: Outliers and Robust Regression

STA702

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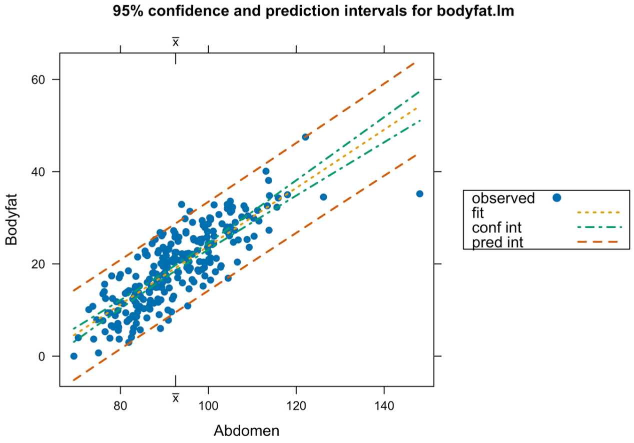
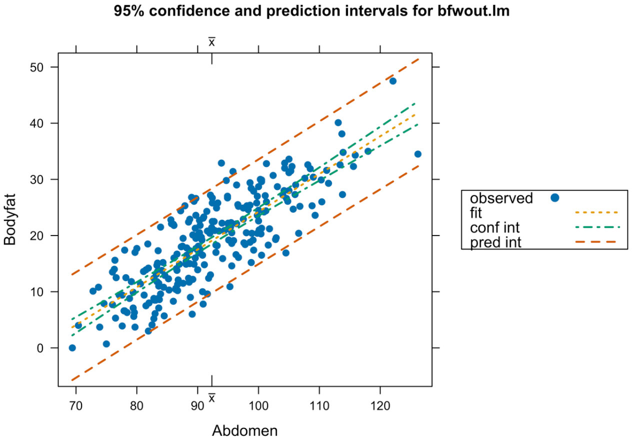
Body Fat Data

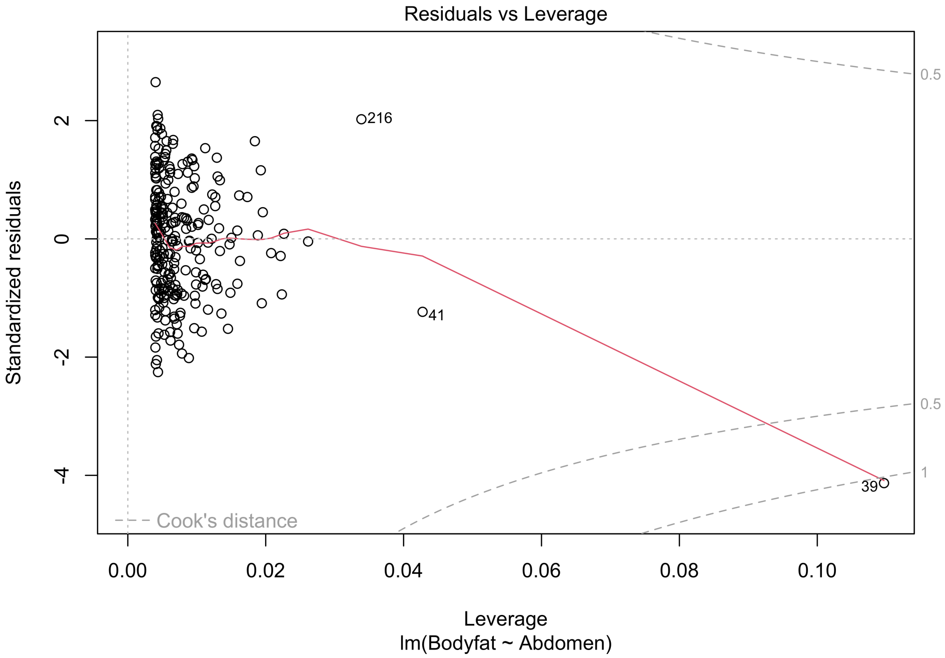




Which analysis do we use? with Case 39 or not – or something different?

Cook’s Distance

```r
plot(bodyfat.lm, which=5)
```



Options for Handling Outliers

What are outliers?

- Are there scientific grounds for eliminating the case?
- Test if the case has a different mean than population
- Report results with and without the case
- Model Averaging to Account for Model Uncertainty?
- Full model $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{I}_n\delta + \epsilon$
- δ is a $n \times 1$ vector; $\boldsymbol{\beta}$ is $p \times 1$
- All observations have a potentially different mean!

Outliers in Bayesian Regression

- Hoeting, Madigan and Raftery (in various permutations) consider the problem of simultaneous variable selection and outlier identification
- This is implemented in the package `BMA` in the function `MC3.REG`
- This has the advantage that more than 2 points may be considered as outliers at the same time
- The function uses a Markov chain to identify both important variables and potential outliers, but is coded in Fortran so should run reasonably quickly.
- Can also use `BAS` or other variable selection programs

Model Averaging and Outliers

- Full model $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{I}_n\delta + \epsilon$
- δ is a $n \times 1$ vector; $\boldsymbol{\beta}$ is $p \times 1$
- 2^n submodels $\gamma_i = 0 \Leftrightarrow \delta_i = 0$
- If $\gamma_i = 1$ then case i has a different mean ``mean shift'' outliers

Mean Shift $=$ Variance Inflation

- Model $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{I}_n \delta + \epsilon$
- Prior

$$\begin{aligned} \delta_i \mid \gamma_i &\sim N(0, V\sigma^2\gamma_i) \\ \gamma_i &\sim \textsf{Ber}(\pi) \end{aligned}$$

- Then ϵ_i given σ^2 is independent of δ_i and

$$\epsilon^*_i \equiv \epsilon_i + \delta_i \mid \sigma^2 \begin{cases} N(0, \sigma^2) & wp \quad (1 - \pi) \\ N(0, \sigma^2(1 + V)) & wp \qquad \pi \end{cases}$$

- Model $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \epsilon^*$ **variance inflation**
- $V + 1 = K = 7$ in the paper by Hoeting et al. package `BMA`

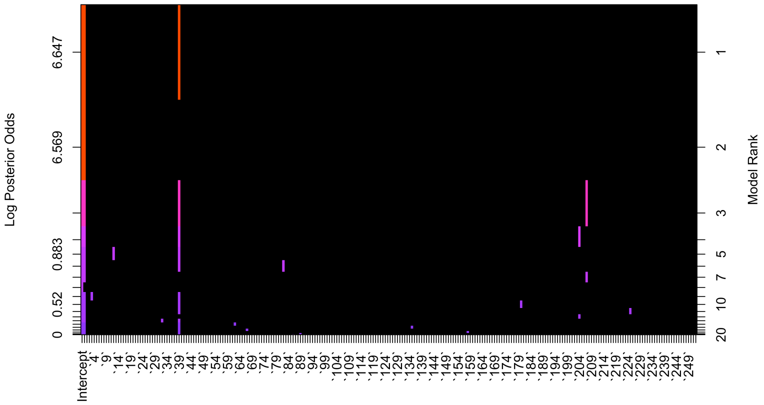
Simultaneous Outlier and Variable Selection

```r
library(BMA)
bodyfat.bma = MC3.REG(all.y = bodyfat$Bodyfat, all.x = as.matrix(b
                      num.its = 10000, outliers = TRUE)
summary(bodyfat.bma)
```

```
Call:
MC3.REG(all.y = bodyfat$Bodyfat, all.x = as.matrix(bodyfat$Abdomen),
num.its = 10000, outliers = TRUE)

Model parameters: PI = 0.02 K = 7 nu = 2.58 lambda = 0.28 phi = 2.85

  15  models were selected
 Best  5  models (cumulative posterior probability =  0.9939 ):

           prob     model 1    model 2    model 3    model 4    model 5
variables
  all.x    1          x          x          x          x          x
outliers
```

BAS with Truncated Prior

```r
bodyfat.w.out = cbind(bodyfat[, c("Bodyfat", "Abdomen")],
                      diag(nrow(bodyfat)))

bodyfat.bas = bas.lm(Bodyfat ~ ., data=bodyfat.w.out,
                     prior="hyper-g-n", a=3, method="MCMC",
                     MCMC.it=2^18,
                     modelprior=tr.beta.binomial(1,254, 50))
```



Change Error Assumptions

Use a Student-t error model

$$Y_i \overset{\text{ind}}{\sim} t(\nu, \alpha + \beta x_i, 1/\phi)$$

$$L(\alpha, \beta, \phi) \propto \prod_{i=1}^{n} \phi^{1/2} \left(1 + \frac{\phi(y_i - \alpha - \beta x_i)^2}{\nu}\right)^{-\frac{(\nu+1)}{2}}$$

- Use Prior $p(\alpha, \beta, \phi) \propto 1/\phi$
- Posterior distribution

$$p(\alpha, \beta, \phi \mid Y) \propto \phi^{n/2-1} \prod_{i=1}^{n} \left(1 + \frac{\phi(y_i - \alpha - \beta x_i)^2}{\nu}\right)^{-\frac{(\nu+1)}{2}}$$

Bounded Influence

- Treat σ^2 as given, then **influence** of individual observations on the posterior distribution of $\boldsymbol{\beta}$ in the model where $\textsf{E}[\mathbf{Y}_i] = \mathbf{x}_i^T \boldsymbol{\beta}$ is investigated through the score function:

$$\frac{d}{d\boldsymbol{\beta}} \log p(\boldsymbol{\beta} \mid \mathbf{Y}) = \frac{d}{d\boldsymbol{\beta}} \log p(\boldsymbol{\beta}) + \sum_{i=1}^n \mathbf{x}_i g(y_i - \mathbf{x}_i^T \boldsymbol{\beta})$$

- influence function of the error distribution (unimodal, continuous, differentiable, symmetric)

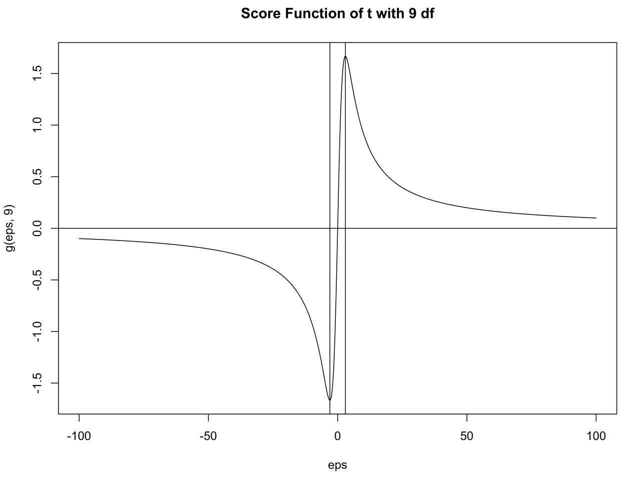
$$g(\boldsymbol{\epsilon}) = -\frac{d}{d\boldsymbol{\epsilon}} \log p(\boldsymbol{\epsilon})$$

- An outlying observation y_j is accommodated if the posterior distribution for $p(\boldsymbol{\beta} \mid \mathbf{Y}_{(i)})$ converges to $p(\boldsymbol{\beta} \mid \mathbf{Y})$ for all $\boldsymbol{\beta}$ as $|\mathbf{Y}_i| \to \infty$.
- Requires error models with influence functions that go to zero such as the Student t (O'Hagan, 1979, West 1984)

Choice of df for Student-t

Investigate the Score function

$$\frac{d}{d\boldsymbol{\beta}} \log p(\boldsymbol{\beta} \mid \mathbf{Y}) = \frac{d}{d\boldsymbol{\beta}} \log p(\boldsymbol{\beta}) + \sum_{i=1}^{n} \mathbf{x}_i g(y_i - \mathbf{x}_i^T \boldsymbol{\beta})$$



- Score function for t with α degrees of freedom has turning points at $\pm\sqrt{\alpha}$
- $g'(\boldsymbol{\epsilon})$ is negative when $\boldsymbol{\epsilon}^2 > \alpha$ (standardized errors)
- Contribution of observation to information matrix is negative and the observation is doubtful
- Suggest taking $\alpha = 8$ or $\alpha = 9$ to reject errors larger than $\sqrt{8}$ or 3 sd.

Scale-Mixtures of Normal Representation

- Latent Variable Model

$$\begin{aligned} Y_i \mid \alpha, \beta, \phi, \lambda & \overset{\text{ind}}{\sim} N(\alpha + \beta x_i, \frac{1}{\phi \lambda_i}) \\ \lambda_i & \overset{\text{iid}}{\sim} G(\nu/2, \nu/2) \\ p(\alpha, \beta, \phi) & \propto 1/\phi \end{aligned}$$

- Joint Posterior Distribution:

$$\begin{aligned} p((\alpha, \beta, \phi, \lambda_1, \ldots, \lambda_n \mid Y) \propto \ & \phi^{n/2} \exp\left\{ -\frac{\phi}{2} \sum \lambda_i (y_i - \alpha - \beta x_i)^2 \right\} \times \\ & \phi^{-1} \\ & \prod_{i=1}^n \lambda_i^{\nu/2 - 1} \exp(-\lambda_i \nu/2) \end{aligned}$$

- Integrate out ``latent'' λ's to obtain marginal t distribution

JAGS - Just Another Gibbs Sampler

```
rr.model = function() {
  df <- 9
  for (i in 1:n) {
    mu[i] <- alpha0 + alpha1*(X[i] - Xbar)
    lambda[i] ~ dgamma(df/2, df/2)
    prec[i] <- phi*lambda[i]
    Y[i] ~ dnorm(mu[i], prec[i])
  }
  phi ~ dgamma(1.0E-6, 1.0E-6)
  alpha0 ~ dnorm(0, 1.0E-6)
  alpha1 ~ dnorm(0,1.0E-6)
  beta0 <- alpha0 - alpha1*Xbar  # transform back
  beta1 <- alpha1
  sigma <- pow(phi, -.5)
  mu34 <- beta0 + beta1*2.54*34  #mean for a man w/ a 34 in waist
  y34 ~ dt(mu34,phi, df)   # integrate out lambda_34
}
```

⚠ **Warning! Normals and Student-t are parameterized in terms of precisions!**

What output to Save?

The parameters to be monitored and returned to R are specified with the variable `parameters`

```
parameters = c("beta0", "beta1", "sigma", "mu34", "y34", "lambda[3
```

- Use of `<-` for assignment for parameters that calculated from the other parameters. (See R-code for definitions of these parameters.)
- `mu34` and `y34` are the mean functions and predictions for a man with a 34in waist.
- `lambda[39]` saves only the 39th case of λ
- To save a whole vector (for example all lambdas, just give the vector name)

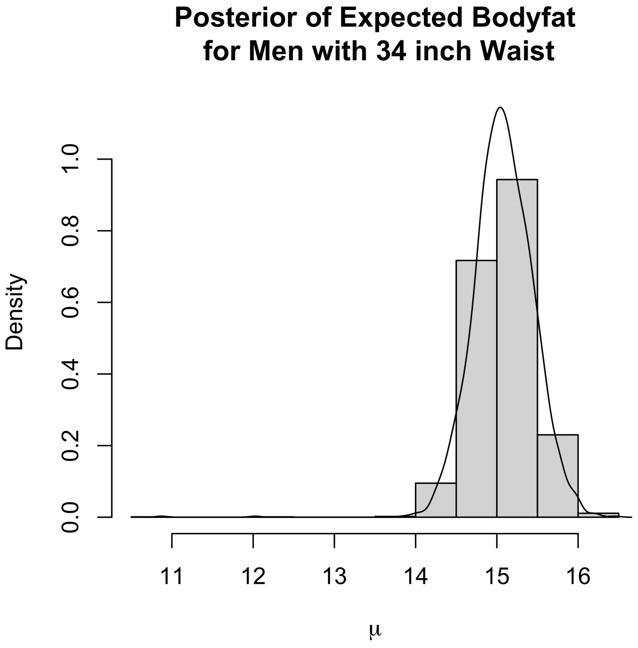
Running JAGS from R

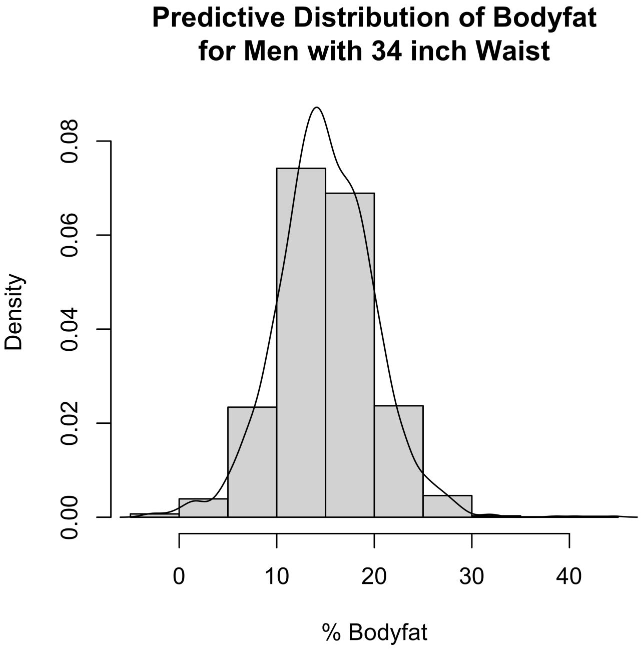
Install jags from sourceforge

```r
library(R2jags)

# Create a data list with inputs for Winpost/Jags

bf.data = list(Y = bodyfat$Bodyfat, X=bodyfat$Abdomen)
bf.data$n = length(bf.data$Y)
bf.data$Xbar = mean(bf.data$X)

# run jags
bf.sim = jags(bf.data, inits=NULL, par=parameters,
              model=rr.model, n.chains=2, n.iter=20000)
```

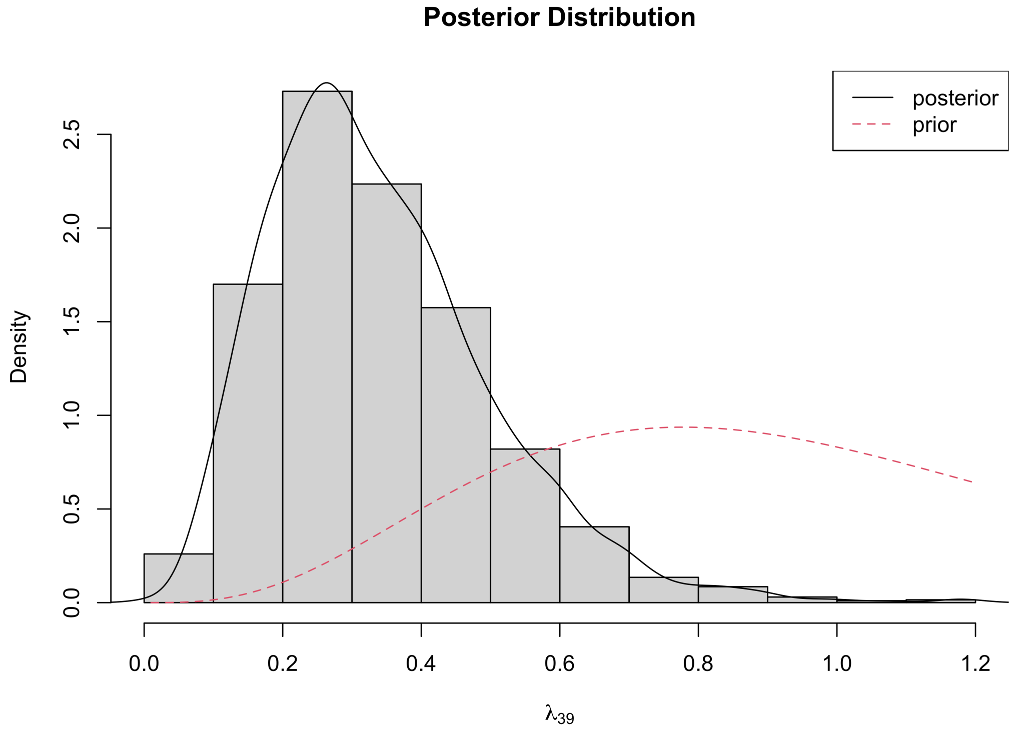
```r
# create an MCMC object
library(coda)
bf.post = as.mcmc(bf.sim$BUGSoutput$sims.matrix)
```

Posterior Distributions


Posterior of Expected Bodyfat for Men with 34 inch Waist


Predictive Distribution of Bodyfat for Men with 34 inch Waist

Posterior of λ_{39}



Comparison

95% Confidence/Credible Intervals for β

	2.5 %	97.5 %
lm all	0.5750739	0.6875349
robust bayes	0.6016984	0.7184886
lm w/out 39	0.6144288	0.7294781

- Results intermediate without having to remove any observations!
- Case 39 down weighted by λ_{39} in posterior for β
- Under prior $E[\lambda_i] = 1$
- large residuals lead to smaller λ

$$\lambda_j \mid \text{rest}, Y \sim G\left(\frac{\nu+1}{2}, \frac{\phi(y_j - \alpha - \beta x_j)^2 + \nu}{2}\right)$$

-

Prior Distributions on Parameters

- As a general recommendation, the prior distribution should have ``heavier" tails than the likelihood
- with t_9 errors use a t_α with $\alpha < 9$
- also represent via scale mixture of normals
- Horseshoe, Double Pareto, Cauchy all have heavier tails

Summary

- Classical diagnostics useful for EDA (checking data, potential outliers/influential points) or posterior predictive checks
- BMA/BVS and Bayesian robust regression avoid interactive decision making about outliers
- Robust Regression (Bayes) can still identify outliers through distribution on weights
- continuous versus mixture distribution on scale parameters
- Other mixtures (sub populations?) on scales and $\boldsymbol{\beta}$?
- Be careful about what predictors or transformations are used in the model as some outliers may be a result of model misspecification!