Lecture 4

Multiple Linear Regression: Model Selection and Model Checking

Reading: Faraway (2014) Chapters 6 and 10 or Faraway (2002) Chapters 7 and 10

DSA 8020 Statistical Methods II
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Agenda

1. **Model Selection**
2. **Model Diagnostics**
3. **Non-Constant Variance & Transformation**

Model Selection in Multiple Linear Regression

Multiple Linear Regression Model:

$$Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{p-1} x_{p-1} + \varepsilon_i, \quad \varepsilon_i \overset{i.i.d.}{\sim} \mathrm{N}(0, \sigma^2)$$

Basic Problem: how to choose between competing linear regression models?

- Model too "small": underfit the data; poor predictions; high **bias**; low **variance**
- Model too big: "overfit" the data; poor predictions; low **bias**; high **variance**

In the next few slides we will discuss some commonly used model selection criteria to choose the "right" model

Mallows' C_p Criterion

A good model should balance **bias** and **variance** to get good predictions

$$(\hat{Y}_i - \mu_i)^2 = (\hat{Y}_i - \mathrm{E}(\hat{Y}_i) + \mathrm{E}(\hat{Y}_i) - \mu_i)^2$$
$$= \underbrace{(\hat{Y}_i - \mathrm{E}(\hat{Y}_i))^2}_{\sigma^2_{\hat{Y}_i}\ \text{Variance}} + \underbrace{(\mathrm{E}(\hat{Y}_i) - \mu_i)^2}_{\text{Bias}^2},$$

where $\mu_i = \mathrm{E}(Y_i | X_i = x_i)$

- Mean squared prediction error (MSPE): $\sum_{i=1}^n \sigma^2_{\hat{Y}_i} + \sum_{i=1}^n (\mathrm{E}(\hat{Y}_i) - \mu_i)^2$
- C_p criterion measure:

$$\Gamma_p = \frac{\sum_{i=1}^n \sigma^2_{\hat{Y}_i} + \sum_{i=1}^n (\mathrm{E}(\hat{Y}_i) - \mu_i)^2}{\sigma^2}$$
$$= \frac{\sum \text{Var}_{\text{pred}} + \sum \text{Bias}^2}{\text{Var}_{\text{error}}}$$

C_p Criterion

C_p statistic:

$$C_p = \frac{\text{SSE}}{\text{MSE}_\text{F}} + 2p - n$$

- When model is correct $\mathrm{E}(C_p) \approx p$
- When plotting models against p
  - Biased models will fall above $C_p = p$
  - Unbiased models will fall around line $C_p = p$
  - By definition: C_p for full model equals p

We desire models with small p and C_p around or less than p. See R session for an example

Adjusted R^2 Criterion

Adjusted R^2, denoted by R^2_{adj}, attempts to take account of the phenomenon of the R^2 automatically and spuriously increasing when extra explanatory variables are added to the model.

$$R^2_{\text{adj}} = 1 - \frac{\text{SSE}/(n-p-1)}{\text{SST}/(n-1)}$$

- Choose model which maximizes R^2_{adj}
- Same approach as choosing model with smallest MSE

Predicted Residual Sum of Squares $PRESS$ Criterion

- For each observation i, predict Y_i using model generated from other $n-1$ observations
- $PRESS = \sum_{i=1}^{n}(Y_i - \hat{Y}_{i(i)})^2$
- PRESS statistic is a form of cross-validation
- Want to select model with small $PRESS$

Information criteria

There are two widely used information criteria:

- Akaike's information criterion (AIC)

$$n \log(\frac{\text{SSE}_k}{n}) + 2k$$

- Bayesian information criterion (BIC)

$$n \log(\frac{\text{SSE}_k}{n}) + k \log(n)$$

Automatic Search Procedures

- Forward Selection: begins with no predictors and then adds in predictors one by one using some criterion (e.g., p-value or AIC)
- Backward Elimination: starts with all the predictors and then removes predictors one by one using some criterion
- Stepwise Search: a combination of backward elimination and forward selection. Can add or delete predictor at each stage
- All Subset Selection: Comparing all possible models using a selected criterion. Impractical for “large” number of predictors

Model Assumptions

Model:

$$Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{p-1} x_{p-1} + \varepsilon_i, \quad \varepsilon_i \overset{i.i.d.}{\sim} \mathrm{N}(0, \sigma^2)$$

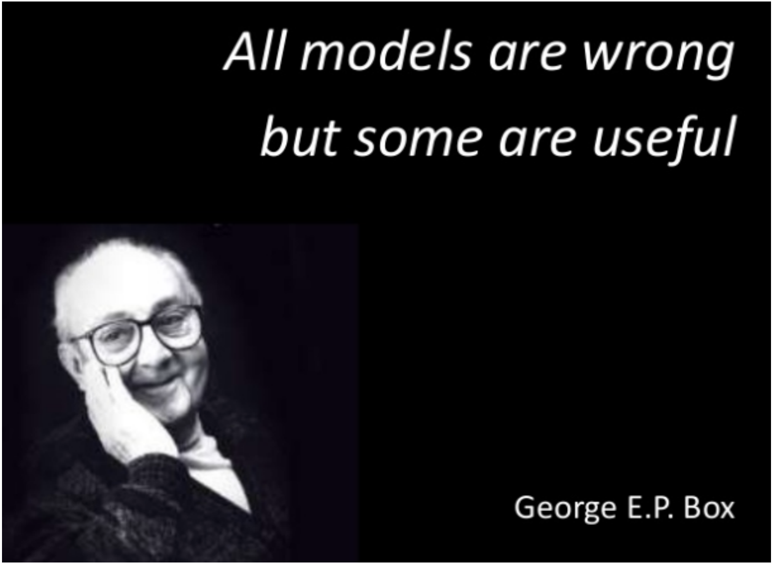
We make the following assumptions:

- Linearity:

$$\mathrm{E}(Y | x_1, x_2, \cdots, x_{p-1}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{p-1} x_{p-1}$$

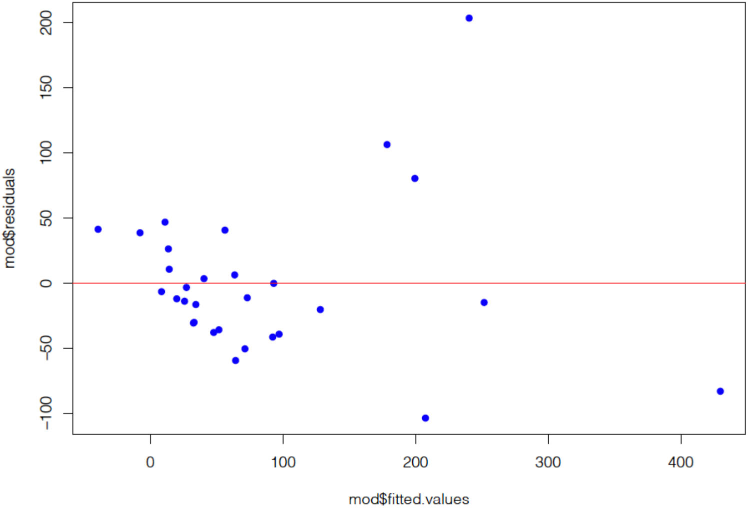
- Errors have constant variance, are independent, and normally distributed

$$\varepsilon_i \overset{i.i.d.}{\sim} \mathrm{N}(0, \sigma^2)$$


All models are wrong
but some are useful
George E.P. Box

Residuals versus Fits Plot

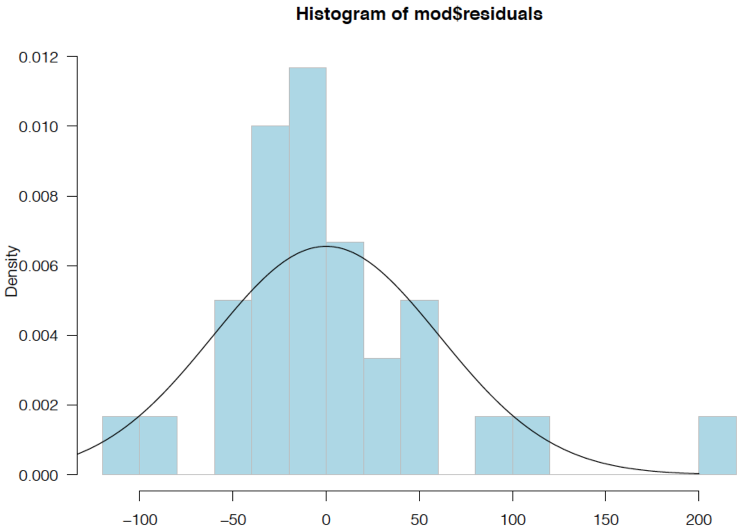
```
plot(mod$fitted.values, mod$residuals, pch = 16, col = "blue")
abline(h = 0, col = "red")
```



We will revisit this in the end of the lecture

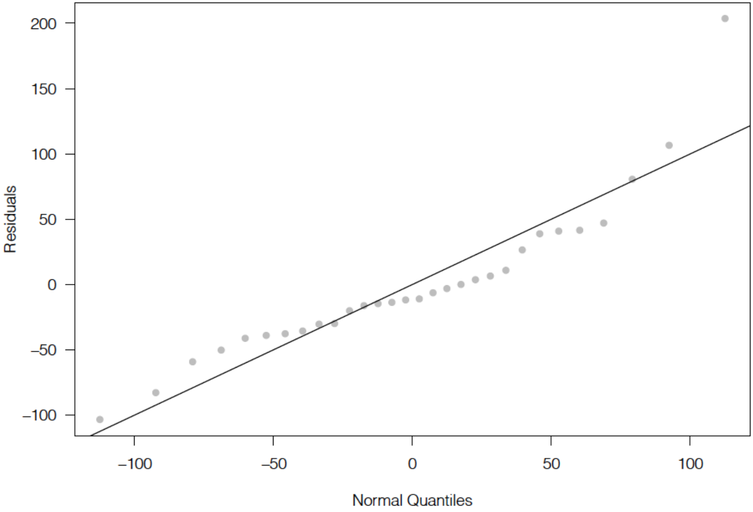
Assessing Normality of Residuals: Histogram

```
par(las = 1)
hist(mod$residuals, 12, prob = T,
     col = "lightblue", border = "gray")
xg <- seq(-200, 200, 1)
yg <- dnorm(xg, 0, 60.86)
lines(xg, yg)
```



Assessing Normality of Residuals: QQ Plot

```
plot(qnorm(1:30 / 31, 0, 60.86), sort(mod$residuals), pch = 16,
     col = "gray", xlab = "Normal Quantiles", ylab = "Residuals")
abline(0, 1)
```



Leverage: Detecting "Extreme" Predictor Values

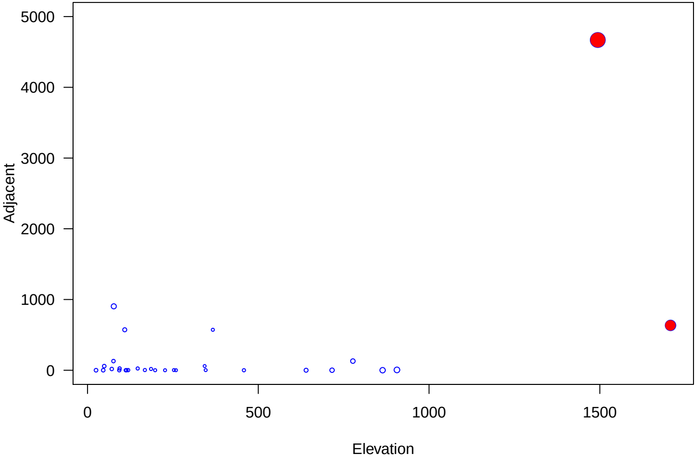
Recall in MLR that $\hat{y} = \boldsymbol{X}(\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y} = \boldsymbol{H}\boldsymbol{y}$ where $\boldsymbol{H}$ is the hat-matrix

- The leverage value for the i_{th} observation is defined as:

$$h_i = \boldsymbol{H}_{ii}$$

- Can show that Var$(e_i) = \sigma^2(1 - h_i)$, where $e_i = y_i - \hat{y}_i$ is the residual for the i_{th} observation
- $\frac{1}{n} \le h_i \le 1, \quad 1 \le i \le n$ and $\bar{h} = \sum_{i=1}^{n} \frac{h_i}{n} = \frac{p}{n} \Rightarrow$ a "rule of thumb" is that leverages of more than $\frac{2p}{n}$ should be looked at more closely

Leverage Values of `Species` ~ `Elev` + `Adj`

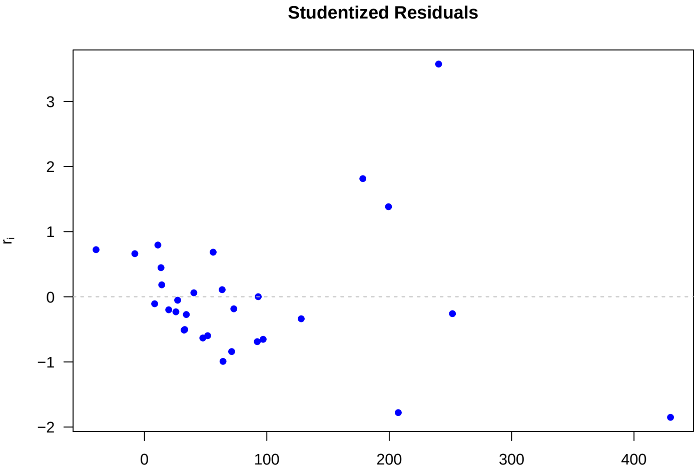


Studentized Residuals

As we have seen Var$(e_i) = \sigma^2(1 - h_i)$, this suggests the use of $r_i = \frac{e_i}{\hat{\sigma}\sqrt{(1-h_i)}}$

- r_i's are called **studentized residuals**. r_i's are sometimes preferred in residual plots as they have been standardized to have equal variance.
- If the model assumptions are correct then Var$(r_i) = 1$ and Corr(r_i, r_j) tends to be small

Studentized Residuals of `Species` ~ `Elev` + `Adj`



Studentized Deleted Residuals

- For a given model, exclude the observation i and recompute $\hat{\boldsymbol{\beta}}_{(i)}$, $\hat{\sigma}_{(i)}$ to obtain $\hat{y}_{i(i)}$

- The observation i is an outlier if $\hat{y}_{i(i)} - y_i$ is "large"

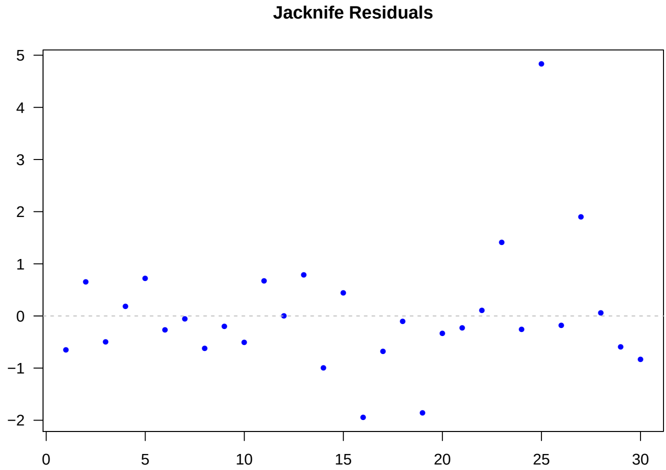
- Can show
  $\text{Var}(\hat{y}_{i(i)} - y_i) = \sigma^2_{(i)} \left(1 + \boldsymbol{x}_i^T (\boldsymbol{X}_{(i)}^T \boldsymbol{X}_{(i)})^{-1} \boldsymbol{x}_i\right) = \frac{\sigma^2_{(i)}}{1-h_i}$

- Define the **Studentized Deleted Residuals** as

$$t_i = \frac{\hat{y}_{i(i)} - y_i}{\sqrt{\hat{\sigma}^2_{(i)}(1-h_i)}} = \frac{\hat{y}_{i(i)} - y_i}{\sqrt{\text{MSE}_{(i)}(1-h_i)^{-1}}}$$

which are distributed as a t_{n-p-1} if the model is correct and $\varepsilon \sim \mathrm{N}(\mathbf{0}, \sigma^2 \boldsymbol{I})$

Jackknife Residuals of `Species` ~ `Elev` + `Adj`

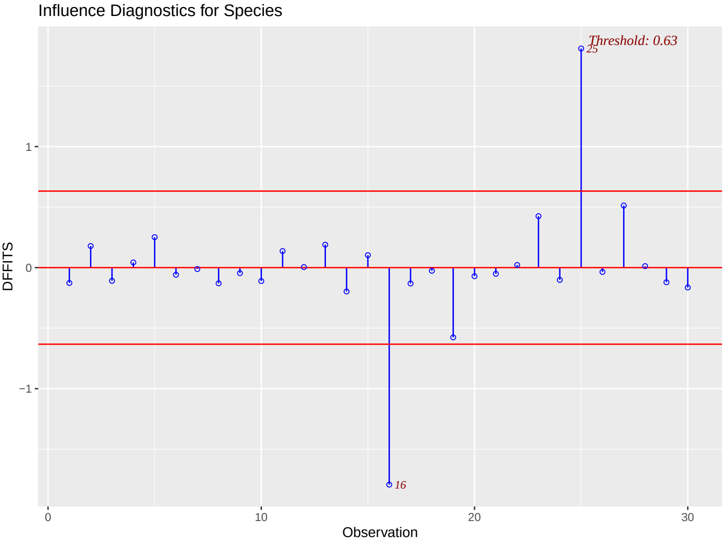


Influential Observations

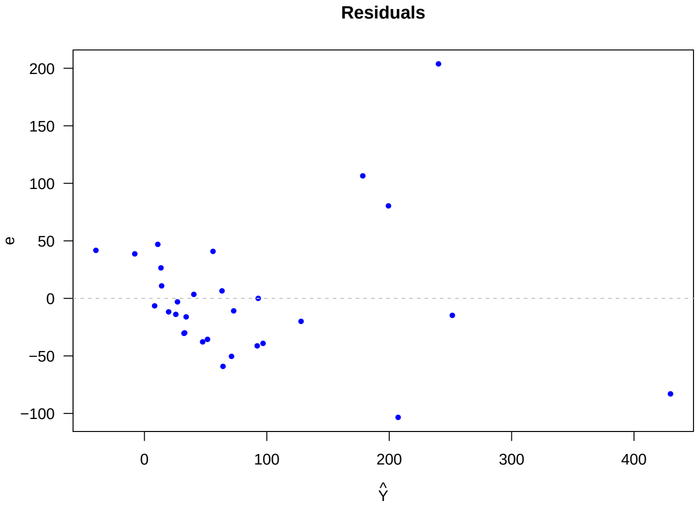
DFFITS

- Difference between the fitted values $\hat{y}_i$ and the predicted values $\hat{y}_{i(i)}$
- $\text{DFFITS}_i = \frac{\hat{y}_i - \hat{y}_{i(i)}}{\sqrt{\text{MSE}_{(i)} h_i}}$
- Concern if absolute value greater than 1 for small data sets, or greater than $2\sqrt{p/n}$ for large data sets

DFFITS of `Species` ~ `Elev` + `Adj`



Residual Plot of `Species` ~ `Elev` + `Adj`



Residual Plot After Square Root Transformation