# Lecture 26

## Simple Linear Regression: ANOVA Approach to Regression

Text: Chapter 11

*STAT 8010 Statistical Methods I*
December 1, 2020

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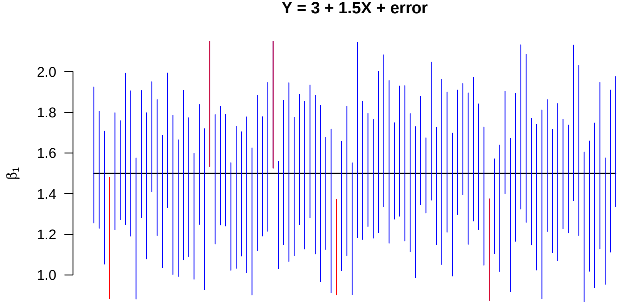
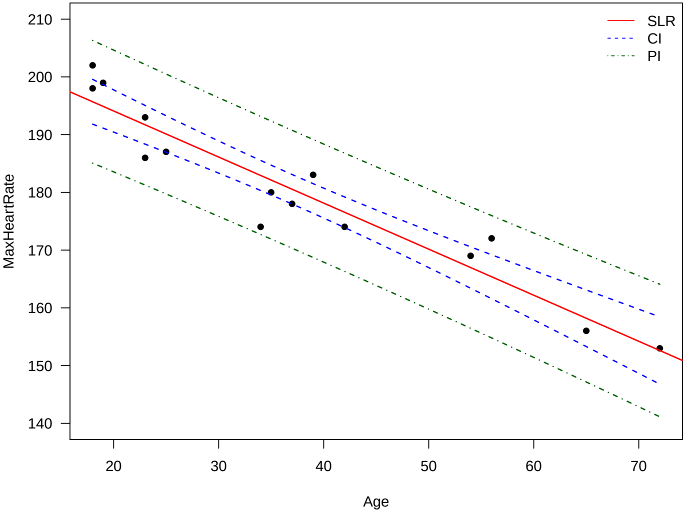
# Understanding Confidence Intervals

- Suppose $Y = \beta_0 + \beta_1 X + \varepsilon$, where $\beta_0 = 3$, $\beta_1 = 1.5$ and $\sigma^2 \sim \mathrm{N}(0, 1)$
- We take 100 random sample each with sample size 20
- We then construct the 95% CI for each random sample ($\Rightarrow$ 100 CIs)



# Confidence Intervals vs. Prediction Intervals



# Analysis of Variance (ANOVA) Approach to Regression

## Partitioning Sums of Squares

- Total sums of squares in response

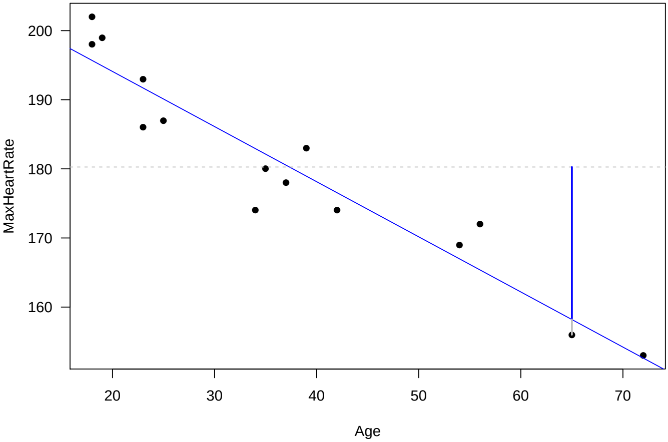
$$\text{SST} = \sum_{i=1}^{n}(Y_i - \bar{Y})^2$$

- We can rewrite SST as

$$\sum_{i=1}^{n}(Y_i - \bar{Y})^2 = \sum_{i=1}^{n}(Y_i - \hat{Y}_i + \hat{Y}_i - \bar{Y})^2$$

$$= \underbrace{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}_{\text{Error}} + \underbrace{\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2}_{\text{Model}}$$

# Partitioning Total Sums of Squares



# Total Sum of Squares: SST



- If we ignored the predictor $X$, the $\bar{Y}$ would be the best (linear unbiased) predictor

$$Y_i = \beta_0 + \varepsilon_i \tag{1}$$

- SST is the sum of squared deviations for this predictor (i.e., $\bar{Y}$)

- The **total mean square** is SST$/(n-1)$ and represents an unbiased estimate of $\sigma^2$ under the model (1).

# Regression Sum of Squares: SSR

- SSR: $\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2$
- Degrees of freedom is 1 due to the inclusion of the slope, i.e.,
$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \quad (2)$$
- "Large" MSR = SSR/1 suggests a linear trend, because
$$\mathrm{E}[MSE] = \sigma^2 + \beta_1^2 \sum_{i=1}^{n}(X_i - \bar{X})^2$$

# Error Sum of Squares: SSE



- SSE is simply the sum of squared residuals

$$\text{SSE} = \sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

- Degrees of freedom is $n - 2$ (Why?)
- SSE large when |residuals| are "large" $\Rightarrow$ $Y_i$'s vary substantially around fitted regression line
- MSE $=$ SSE$/(n-2)$ and represents an unbiased estimate of $\sigma^2$ **when taking $X$ into account**

# ANOVA Table and F test

| Source | df | SS | MS |
|---|---|---|---|
| Model | 1 | SSR = $\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2$ | MSR = SSR/1 |
| Error | $n-2$ | SSE = $\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$ | MSE = SSE/(n-2) |
| Total | $n-1$ | SST = $\sum_{i=1}^{n}(Y_i - \bar{Y})^2$ | |

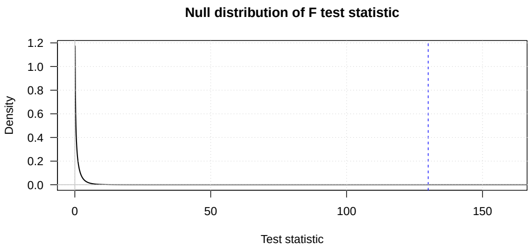
- **Goal:** To test $H_0 : \beta_1 = 0$
- Test statistics $F^* = \frac{\text{MSR}}{\text{MSE}}$
- If $\beta_1 = 0$ then $F^*$ should be near one $\Rightarrow$ reject $H_0$ when $F^*$ “large"
- We need sampling distribution of $F^*$ under $H_0 \Rightarrow F_{1,n-2}$, where $F(d_1, d_2)$ denotes a F distribution with degrees of freedom $d_1$ and $d_2$

# F Test: $H_0 : \beta_1 = 0$ vs. $H_a : \beta_1 \neq 0$

```
fit <- lm(MaxHeartRate ~ Age)
anova(fit)
```
```

```
Analysis of Variance Table

Response: MaxHeartRate
          Df  Sum Sq Mean Sq F value
Age        1 2724.50 2724.50  130.01
Residuals 13  272.43   20.96
             Pr(>F)
Age       3.848e-08 ***
```


```

# SLR: F-Test vs. T-test

## ANOVA Table and F-Test

```
Analysis of Variance Table

Response: MaxHeartRate
          Df  Sum Sq Mean Sq
Age        1 2724.50 2724.50
Residuals 13  272.43   20.96
          F value    Pr(>F)
Age        130.01 3.848e-08
```

## Parameter Estimation and T-Test

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 210.04846    2.86694   73.27  < 2e-16
Age          -0.79773    0.06996  -11.40 3.85e-08
```

# Correlation and Simple Linear Regression



- Pearson Correlation: $r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$
- $-1 \le r \le 1$ measures the strength of the **linear relationship** between $Y$ and $X$
- We can show

$$r = \hat{\beta}_1 \sqrt{\frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}},$$

this implies

$$\beta_1 = 0 \text{ in SLR } \Leftrightarrow \rho = 0$$

# Coefficient of Determination $R^2$

- Defined as the proportion of total variation explained by SLR

$$R^2 = \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} = \frac{\text{SSR}}{\text{SST}} = 1 - \frac{\text{SSE}}{\text{SST}}$$

- We can show $r^2 = R^2$:

$$\begin{aligned} r^2 &= \left( \hat{\beta}_{1,\text{LS}} \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \right)^2 \\ &= \frac{\hat{\beta}^2_{1,\text{LS}} \sum_{i=1}^n (X_i - \bar{X})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \\ &= \frac{\text{SSR}}{\text{SST}} \\ &= R^2 \end{aligned}$$

# Maximum Heart Rate vs. Age: $r$ and $R^2$

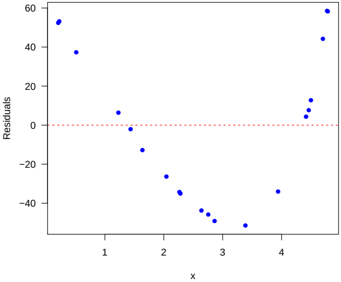


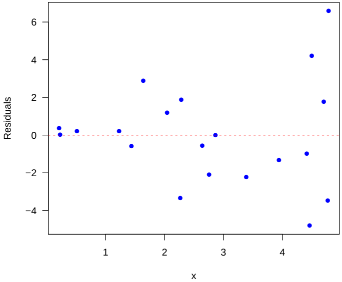
```
> summary(fit)$r.squared
[1] 0.9090967
> cor(Age, MaxHeartRate)
[1] -0.9534656
```

**Interpretation:**

There is a strong negative linear relationship between `MaxHeartRate` and `Age`. Furthermore, $\sim 91\%$ of the variation in `MaxHeartRate` can be explained by `Age`.

# Residual Plot Revisited



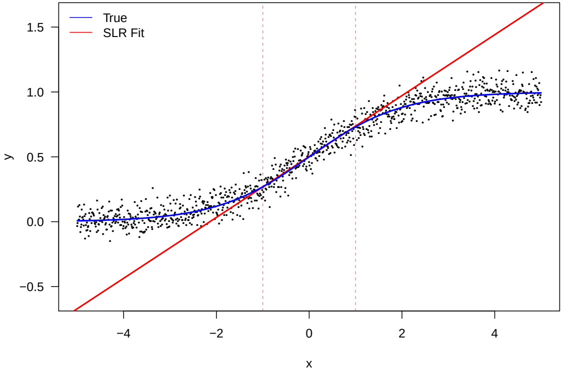

$\Rightarrow$ Nonlinear relationship

- Transform $X$
- Nonlinear regression

$\Rightarrow$ Non-constant variance

- Transform $Y$
- Weighted least squares

# Extrapolation in SLR




Extrapolation beyond the range of the given data can lead to seriously biased estimates if the **assumed relationship does not hold the region of extrapolation**

# Summary of SLR

- **Model:** $Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$
- **Estimation:** Use the method of least squares to estimate the parameters
- **Inference**
  - **Hypothesis Testing**
  - **Confidence/prediction Intervals**
  - **ANOVA**
- **Model Diagnostics and Remedies**