Simple Linear Regression: Model Assumptions & Inferences



Residual Analysis

Intervals

Hypothesis Test

Lecture 25

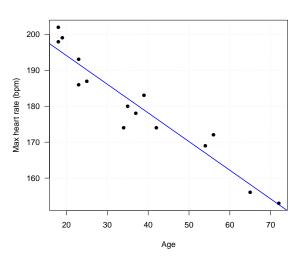
Simple Linear Regression: Model Assumptions & Inferences

Text: Chapter 11

STAT 8010 Statistical Methods I November 24, 2020

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Linear Regression Fit



Question: Is linear relationship between max heart rate and age reasonable? \Rightarrow Residual Analysis

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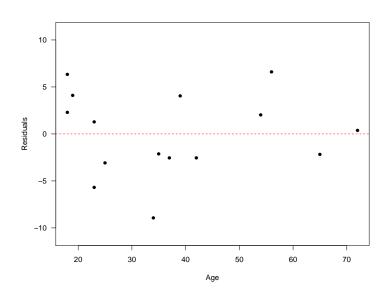


Residual Analysis

Confidence/Prediction Intervals

- The residuals are the differences between the observed and fitted values:
 - $e_i = Y_i \hat{Y}_i,$
 - where $\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i$
- e_i is NOT the error term $\varepsilon_i = Y_i \mathrm{E}[Y_i]$
- Residuals are very useful in assessing the appropriateness of the assumptions on ε_i . Recall
 - $E[\varepsilon_i] = 0$
 - $Var[\varepsilon_i] = \sigma^2$
 - $Cov[\varepsilon_i, \varepsilon_j] = 0, \quad i \neq j$

Maximum Heart Rate vs. Age Residual Plot: ε vs. X



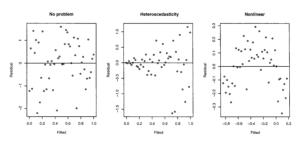
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Confidence/Prediction Intervals

Interpreting Residual Plots



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Intervals

Interpreting Residual Plots

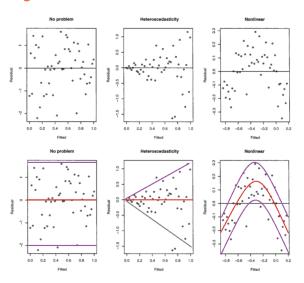


Figure: Figure courtesy of Faraway's Linear Models with R (2005, p. 59).

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Residual Analysis

Intervals

Regression: Model
Assumptions &
Inferences

Simple Linear

Residual Analysis

Intervals

Hypothesis Testin

 In SLR we assume there is a linear relationship between X and Y:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i,$$

where $E(\varepsilon_i) = 0$, and $Var(\varepsilon_i) = \sigma^2$, $\forall i$. Furthermore, $Cov(\varepsilon_i, \varepsilon_j) = 0$, $\forall i \neq j$

Least Squares Estimation:

$$\operatorname{argmin}_{\beta_0,\beta_1} \sum_{i=1}^n (Y_i - (\beta_0 + \beta_1 X_i))^2 \Rightarrow$$

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

$$\bullet \ \hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X}$$

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

• **Residuals**: $e_i = Y_i - \hat{Y}_i$, where $\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i$

Recap: Residual Analysis

- Residual Analysis: To check the appropriateness of SLR model
 - Is the regression function linear?
 - Do ε_i 's have constant variance σ^2 ?
 - Are ε_i 's independent to each other?

We plot residuals e_i 's against X_i 's (or \hat{Y}_i 's) to assess these aspects

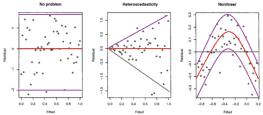


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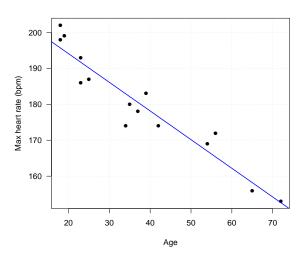
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Intervals

How (Un)certain We Are?



Can we formally quantify our estimation uncertainty? \Rightarrow We need additional (distributional) assumption on ε

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Hypothesis Testing

Recall

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

- Further assume $\varepsilon_i \sim N(0, \sigma^2) \Rightarrow Y_i \sim N(\beta_0 + \beta_1 X_i, \sigma^2)$

$$\bullet \quad \frac{\hat{\beta}_1 - \beta_1}{\hat{\sigma}_{\hat{\beta}_1}} \sim t_{n-2}, \quad \hat{\sigma}_{\hat{\beta}_1} = \frac{\hat{\sigma}}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2}}$$

$$\bullet \ \frac{\hat{\beta}_0 - \beta_0}{\hat{\sigma}_{\hat{\beta}_0}} \sim t_{n-2}, \quad \hat{\sigma}_{\hat{\beta}_0} = \hat{\sigma} \sqrt{\left(\frac{1}{n} + \frac{\bar{X}^2}{\sum_{i=1}^n (X_i - \bar{X})^2}\right)}$$

where t_{n-2} denotes the Student's t distribution with n-2 degrees of freedom



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• Recall $\frac{\hat{\beta}_1 - \beta_1}{\hat{\sigma}_{\hat{\beta}_1}} \sim t_{n-2}$, we use this fact to construct **confidence intervals (CIs)** for β_1 :

$$\left[\hat{\beta}_1 - t_{\alpha/2,n-2}\hat{\sigma}_{\hat{\beta}_1}, \hat{\beta}_1 + t_{\alpha/2,n-2}\hat{\sigma}_{\hat{\beta}_1}\right],\,$$

where α is the **confidence level** and $t_{\alpha/2,n-2}$ denotes the $1-\alpha/2$ percentile of a student's t distribution with n-2 degrees of freedom

• Similarly, we can construct CIs for β_0 :

$$\left[\hat{\beta}_0 - t_{\alpha/2, n-2}\hat{\sigma}_{\hat{\beta}_0}, \hat{\beta}_0 + t_{\alpha/2, n-2}\hat{\sigma}_{\hat{\beta}_0}\right]$$

 We often interested in estimating the mean response for a particular value of predictor, say, X_h. Therefore we would like to construct CI for E[Y_h]

• We need sampling distribution of \hat{Y}_h to form CI:

$$\bullet \quad \frac{\hat{Y}_h - Y_h}{\hat{\sigma}_{\hat{Y}_h}} \sim t_{n-2}, \quad \hat{\sigma}_{\hat{Y}_h} = \hat{\sigma} \sqrt{\left(\frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum_{i=1}^n (X_i - \bar{X})^2}\right)}$$

CI:

$$\left[\hat{Y}_h - t_{\alpha/2,n-2}\hat{\sigma}_{\hat{Y}_h},\hat{Y}_h + t_{\alpha/2,n-2}\hat{\sigma}_{\hat{Y}_h}\right]$$

• **Quiz:** Use this formula to construct CI for β_0

- Suppose we want to predict the response of a future observation given $X = X_h$
- We need to account for added variability as a new observation does not fall directly on the regression line (i.e., $Y_{h(new)} = E[Y_h] + \varepsilon_h$)
- Replace $\hat{\sigma}_{\hat{Y_h}}$ by $\hat{\sigma}_{\hat{Y}_{h(new)}} = \hat{\sigma} \sqrt{\left(1 + \frac{1}{n} + \frac{(X_h \bar{X})^2}{\sum_{i=1}^n (X_i \bar{X})^2}\right)}$ to construct CIs for $Y_{h(new)}$

The maximum heart rate MaxHeartRate (HR_{max}) of a person is often said to be related to age Age by the equation:

$$HR_{max} = 220 - Age.$$

Suppose we have 15 people of varying ages are tested for their maximum heart rate (bpm)

- Construct the 95% CI for β_1
- Compute the estimate for mean MaxHeartRate given Age = 40 and construct the associated 90% CI
- Construct the prediction interval for a new observation given Age = 40

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Assumptions &
Inferences



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Intervals

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Hypothesis Testing

- **1** $H_0: \beta_1 = 0$ vs. $H_a: \beta_1 \neq 0$
- ② Compute the **test statistic**: $t^* = \frac{\hat{\beta}_1 0}{\hat{\sigma}_{\hat{\beta}_1}} = \frac{-0.7977}{0.06996} = -11.40$
- **Outpute** P-value: $P(|t^*| \ge |t_{obs}|) = 3.85 \times 10^{-8}$
- **(a)** Compare to α and draw conclusion:

Reject H_0 at α = .05 level, evidence suggests a negative linear relationship between MaxHeartRate and Age

Hypothesis Testing

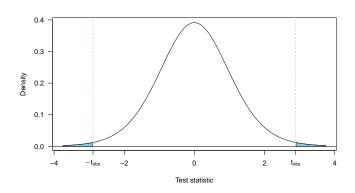
- **1** $H_0: \beta_0 = 0$ vs. $H_a: \beta_0 \neq 0$
- ② Compute the **test statistic**: $t^* = \frac{\hat{\beta}_0 0}{\hat{\sigma}_{\beta_0}} = \frac{210.0485}{2.86694} = 73.27$
- **Our Compute P-value:** $P(|t^*| \ge |t_{obs}|) \simeq 0$
- **1** Compare to α and draw conclusion:

Reject H_0 at α = .05 level, evidence suggests evidence suggests the intercept (the expected MaxHeartRate at age 0) is different from 0

Hypothesis Tests for $\beta_{age} = -1$

$$H_0: \beta_{age} = -1 \text{ vs. } H_a: \beta_{age} \neq -1$$

Test Statistic:
$$\frac{\hat{\beta}_{age}-(-1)}{\hat{\sigma}_{\hat{\beta}_{age}}} = \frac{-0.79773-(-1)}{0.06996} = 2.8912$$



P-value: $2 \times \mathbb{P}(t^* > 2.8912) = 0.013$, where $t^* \sim t_{df=13}$

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Residual Analysis

Intervals

In this lecture, we learned

- Residual Analysis for checking model assumptions
- Normal Error Regression Model and statistical inference for β_0 and β_1
- Confidence/Prediction Intervals & Hypothesis Testing

Next time we will talk about

- Analysis of Variance (ANOVA) Approach to Regression
- Orrelation (r) & Coefficient of Determination (R^2)