

# Analysis of Residuals<sup>1</sup>

STA302 Fall 2017

---

<sup>1</sup>See last slide for copyright information.

## Residual means left over: $e_i = y_i - \hat{y}_i$

- Vertical distance of  $y_i$  from the regression hyper-plane
- An error of “prediction.”
- Big residuals merit further investigation.
- Big compared to what?
- They are normally distributed.
- Consider standardizing.
- Maybe detect outliers.
- Plots can also be informative.

## Residuals are like estimated error terms

$$e_i = y_i - \hat{y}_i \Leftrightarrow y_i = \hat{y}_i + e_i$$

$$\begin{aligned} y_i &= \hat{y}_i + e_i \\ &= b_0 + b_1 x_{i,1} + \cdots + b_k x_{i,k} + e_i \\ &= \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_k x_{i,k} + \epsilon_i \end{aligned}$$

Normal distribution of  $\epsilon_i$  implies normal distribution of  $e_i$ , but the  $e_i$  are not independent, and they do not have equal variance.

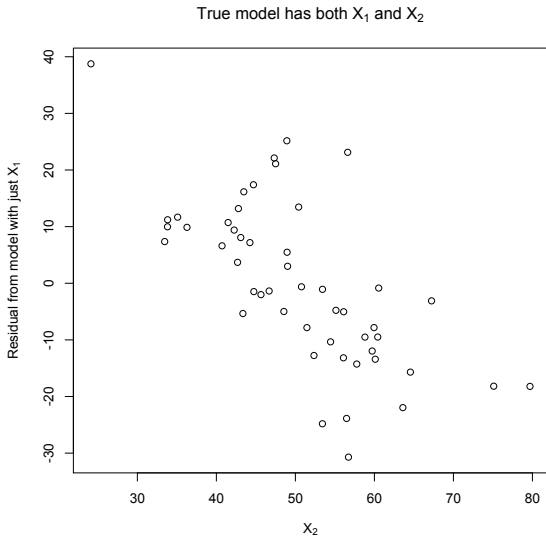
Data = Fit + Residual

$$y_i = \hat{y}_i + e_i$$

## Plotting residuals can be helpful

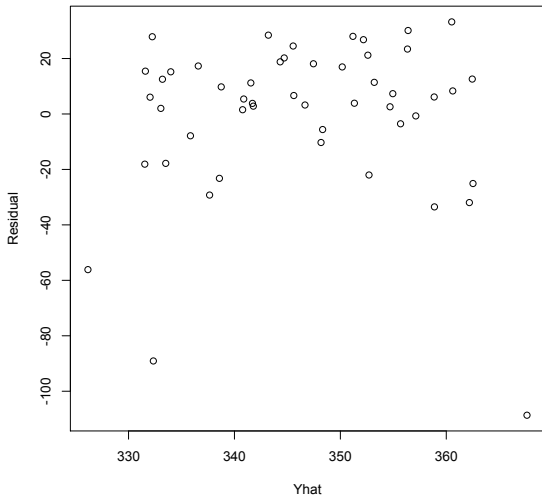
- Against predicted  $y$ .
- Against explanatory variables not in the equation.
- Against explanatory variables in the equation.
- Look for serious departures from normality.

# Plot Residuals Against Explanatory Variables Not in the Equation



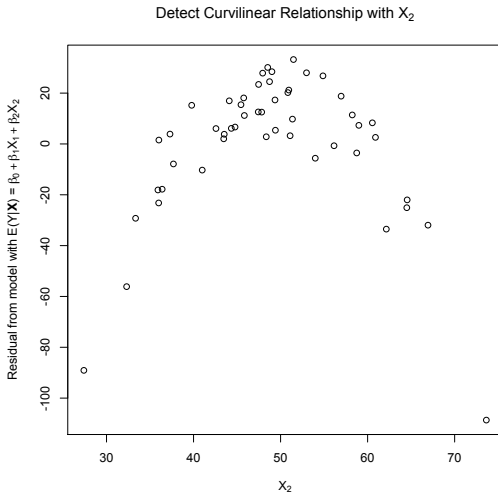
# Plot Residuals Against $\hat{y}$

Suspect Curvilinear Relationship with one or more X variables



# Plot Residuals Against Explanatory Variables in the Equation

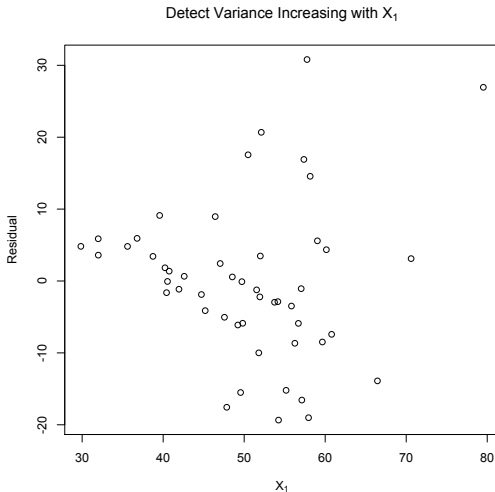
Plot versus  $X_1$  showed nothing





# Plot Residuals Against Explanatory Variables in the Equation

Can show non-constant variance



# Outlier detection

- Big residuals may be outliers. What's "big?"
- Consider standardizing.
- Could divide by square root of sample variance of  $e_1, \dots, e_n$ .
- Semi-Studentized: Estimate  $Var(e_i)$  and divide by square root of that:  $\frac{e_i}{\sqrt{s^2(1-h_{i,i})}}$
- In R, this is produced with `rstandard`.

# Studentized deleted residuals

## The idea

- An outlier will make  $s^2$  big.
- In that case, the standardized (Semi-Studentized) residual will be too small – less noticeable.
- So calculate  $\hat{y}$  for each observation based on all the other observations, but not that one.
- Predict each observed  $y$  based on all the others, and assess error of prediction (divided by standard error).
- Big values suggest that the expected value of  $y_i$  is not what it should be.

## Apply prediction interval technology

$$t = \frac{y_0 - \mathbf{x}'_0 \mathbf{b}}{\sqrt{s^2(1 + \mathbf{x}'_0(X'X)^{-1}\mathbf{x}_0)}} \sim t(n - k - 1)$$

- Note that  $y_i$  is now being called  $y_0$ .
- If the “prediction” is too far off there is trouble.
- Use  $t$  as a test statistic.
- Need to change the notation.

## Studentized deleted residual

$$e_i^* = \frac{y_i - \mathbf{x}_i' \mathbf{b}_{(i)}}{\sqrt{s_{(i)}^2 (1 + \mathbf{x}_i' (X'_{(i)} X_{(i)})^{-1} \mathbf{x}_i)}} \sim t(n - k - 2)$$

- In R, this is produced with `rstudent`.
- There is a more efficient formula.
- Use  $e_i^*$  as a test statistic of  $H_0 : E(y_i) = \mathbf{x}_i' \boldsymbol{\beta}$ .
- If  $H_0$  is rejected, investigate.
- We are doing  $n$  tests.
- Type I errors are very time consuming and disturbing.
- If independent, probability of no false positives would be  $(1 - \alpha)^n \rightarrow 0$ .
- But they are not independent.
- How about a Bonferroni correction?

## Bonferroni Correction for Multiple Tests

- The curse of a thousand  $t$ -tests.
- If the null hypotheses of a collection of tests are all true, hold the probability of rejecting one or more to less than  $\alpha = 0.05$ .
- Based on Bonferroni's inequality:

$$Pr \left\{ \bigcup_{j=1}^r A_j \right\} \leq \sum_{j=1}^r Pr \{ A_j \}$$

- Applies to any collection of  $r$  tests.
- Assume all  $r$  null hypotheses are true.
- Event  $A_j$  is that null hypothesis  $j$  is rejected.
- Do the tests as usual, obtaining  $r$  test statistics.
- For each test, use the significance level  $\alpha/r$  instead of  $\alpha$ .

# Use the significance level $\alpha/r$ instead of $\alpha$

## Bonferroni Correction for $r$ Tests

Assuming all  $r$  null hypotheses are true, probability of rejecting at least one is

$$\begin{aligned}Pr\left\{\bigcup_{j=1}^r A_j\right\} &\leq \sum_{j=1}^r Pr\{A_j\} \\ &= \sum_{j=1}^r \alpha/r \\ &= \alpha\end{aligned}$$

Just use critical value(s) for  $\alpha/r$  instead of  $\alpha$ .

# Advantages and disadvantages of the Bonferroni correction

- Advantage: Flexibility — Applies to any collection of hypothesis tests.
- Advantage: Easy to do.
- Disadvantage: Must know what all the tests are before seeing the data.
- Disadvantage: A little conservative; the true joint significance level is less than  $\alpha$ .



## Application to Studentized deleted residuals

- There are  $r = n$  tests, one for each observed  $i = 1, \dots, n$ .
- Use the critical value  $t_{\frac{\alpha}{2n}}(n - k - 2)$ .
- Even for large  $n$  it is not overly conservative.

This slide show was prepared by **Jerry Brunner**, Department of Statistics, University of Toronto. It is licensed under a **Creative Commons Attribution - ShareAlike 3.0 Unported License**. Use any part of it as you like and share the result freely. The  $\text{\LaTeX}$  source code is available from the course website:  
<http://www.utstat.toronto.edu/~brunner/oldclass/302f17>