Statistics 191: Introduction to Applied Statistics

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# Statistics 191: Introduction to Applied Statistics Diagnostics for simple linear regression

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#### Outline

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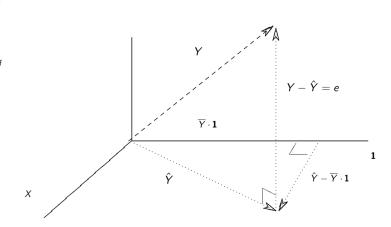
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## Diagnostics for simple regression

- Goodness of fit of regression: analysis of variance.
- *F*-statistics.
- Residuals.
- Diagnostic plots.

# Geometry of Least Squares

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## Goodness of fit

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#### Sums of squares

$$SSE = \sum_{i=1}^{n} (Y_i - \widehat{Y}_i)^2 = \sum_{i=1}^{n} (Y_i - \widehat{\beta}_0 - \widehat{\beta}_1 X_i)^2$$

$$SSR = \sum_{i=1}^{n} (\overline{Y} - \widehat{Y}_i)^2 = \sum_{i=1}^{n} (\overline{Y} - \widehat{\beta}_0 - \widehat{\beta}_1 X_i)^2$$

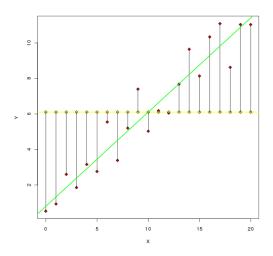
$$SST = \sum_{i=1}^{n} (Y_i - \overline{Y})^2 = SSE + SSR$$

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} = \widehat{Cor}(X, Y)^2.$$

Basic idea: if  $R^2$  is large: a lot of the variability in  $\boldsymbol{Y}$  is explained by  $\boldsymbol{X}$ .

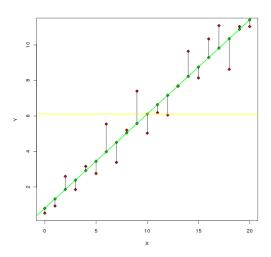
# Total sum of squares

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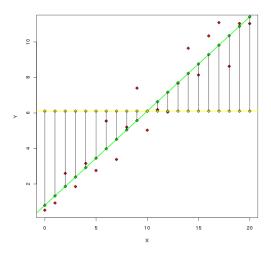
## Error sum of squares

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# Regression sum of squares

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## F-statistics

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#### What is an *F*-statistic?

- An F-statistic is a ratio of "sample variances (mean squares)": it has a numerator, N, and a denominator, D that are independent.
- Let

$$N \sim rac{\chi^2_{
m num}}{df_{
m num}}, \qquad D \sim rac{\chi^2_{
m den}}{df_{
m den}}$$

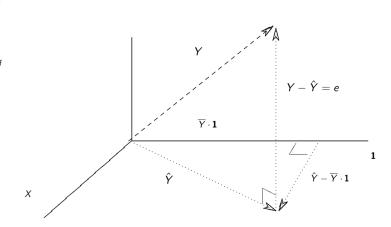
and define

$$F=\frac{N}{D}$$
.

• We say F has an F distribution with parameters  $df_{\text{num}}, df_{\text{den}}$  and write  $F \sim F_{df_{\text{num}}, df_{\text{den}}}$ .

# Geometry of Least Squares

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# F-statistic in simple linear regression

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#### Goodness of fit F-statistic

The ratio

$$F = \frac{SSR/1}{SSE/(n-2)} = \frac{MSR}{MSE}$$

can be thought of as a ratio of "variances".

• In fact, under  $H_0: \beta_1 = 0$ ,

$$F \sim F_{1,n-2}$$

because

$$SSR = \|\widehat{\mathbf{Y}} - \overline{Y} \cdot \mathbf{1}\|^2$$
$$SSE = \|\mathbf{Y} - \widehat{\mathbf{Y}}\|^2$$

and from our picture, these vectors are orthogonal.

## F and t statistics

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#### Relation between F and t

• If  $T \sim t_{\nu}$ , then

$$T^2 \sim rac{{\it N}(0,1)^2}{\chi_
u^2/
u} \sim rac{\chi_1^2/1}{\chi_
u^2/
u}.$$

- In other words, the square of a t-statistic is an F-statistic.
   Because it is always positive, an F-statistic has no direction (±) associated with it.
- In fact, (see R code)

$$F = \frac{MSR}{MSE} = \frac{\widehat{\beta}_1^2}{SE(\widehat{\beta}_1)^2}.$$

## F-statistics in regression models

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#### Interpretation of an F-statistic

- In regression, the numerator is usually a difference in "goodness" of fit of two (nested) models.
- The denominator is  $\hat{\sigma}^2$  an estimate of  $\sigma^2$ .
- Our example today: the bigger model is the simple linear regression model, the smaller is the model with constant mean (one sample model).
- If the F is large, it says that the "bigger" model explains a lot more variability in  $\mathbf{Y}$  (relative to  $\sigma^2$ ) than the smaller one.

## *F*-test in simple linear regression

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#### Example in more detail

• Full (bigger) model :

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

Reduced (smaller) model:

$$RM: Y_i = \beta_0 + \varepsilon_i$$

• The F-statistic has the form

$$F = \frac{(SSE(RM) - SSE(FM))/(df_{RM} - df_{FM})}{SSE(FM)/df_{FM}}$$

• Reject  $H_0$ : RM is correct, if  $F > F_{1-\alpha,1,n-2}$ .

## Diagnostics

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#### What are the assumptions

•

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

• Errors  $\varepsilon_i$  are assumed independent  $N(0, \sigma^2)$ .

## Diagnostics

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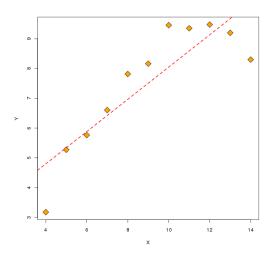
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#### What can go wrong?

- Regression function can be wrong: maybe regression function should be quadratic (see R code).
- Model for the errors may be incorrect:
  - may not be normally distributed.
  - may not be independent.
  - may not have the same variance.
- Detecting problems is more art then science, i.e. we cannot test for all possible problems in a regression model.
- Basic idea of diagnostic measures: if model is correct then residuals  $e_i = Y_i \widehat{Y}_i, 1 \le i \le n$  should look like a sample of (not quite independent)  $N(0, \sigma^2)$  random variables.

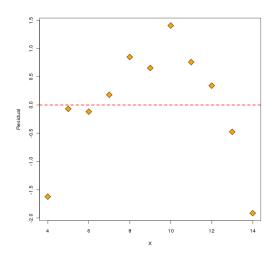
## A bad simple linear regression model

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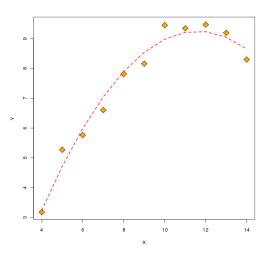
## Residuals from linear model

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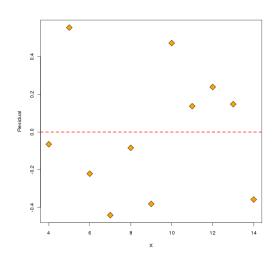
# Quadratic model

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## Residuals from quadratic model

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#### Problems with the errors

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#### Possible problems & diagnostic checks

- Errors may not be normally distributed or may not have the same variance qqnorm can help with this.
- Variance may not be constant. Can also be addressed in a plot of X vs. e: fan shape or other trend indicate non-constant variance.
- Outliers: points where the model really does not fit!
   Possibly mistakes in data transcription, lab errors, who knows? Should be recognized and (hopefully) explained.

## Non-normality

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#### qqnorm

- If  $e_i, 1 \le i \le n$  were really a sample of  $N(0, \sigma^2)$  then their sample quantiles should be close to the sample quantiles of the  $N(0, \sigma^2)$  distribution.
- Plot:

$$e_{(i)}$$
 vs.  $\mathbb{E}(\varepsilon_{(i)})$ ,  $1 \leq i \leq n$ .

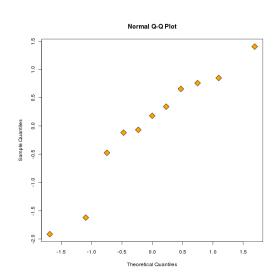
where  $e_{(i)}$  is the *i*-th smallest residual (order statistic) and  $\mathbb{E}(\varepsilon_{(i)})$  is the expected value for independent  $\varepsilon_i$ 's  $\sim N(0, \sigma^2)$ .

# QQplot of residuals from linear model

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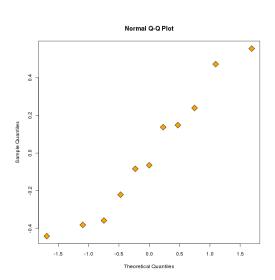
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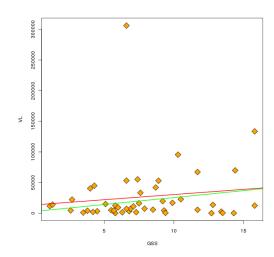
# QQplot of residuals from quadratic model

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## Outlier and nonconstant variance

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## Outlier and nonconstant variance

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