Lesson 15. The Multiple Linear Regression Model - Part 1

Note. In Part 2 of this lesson, you can run the R code that generates the plots and outputs in here Part 1.

1 Overview

- We still want to study or predict the behavior of a response variable *Y*...
- But now, we will use <u>multiple</u> explanatory variables X_1, X_2, \dots, X_k

2 Choosing a multiple linear regression model

- We need:
 - 1. One quantitative response variable
 - 2. Multiple explanatory variables (quantitative or categorical)
- Suppose we have *n* observations of *k* explanatory variables (X_1, \ldots, X_k) and a response variable *Y*

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- The estimated coefficient $\hat{\beta}_i$ describes the estimated <u>average</u> relationship between the response variable Y and the explanatory variable X_i when all the other explanatory variables are fixed
- o Interpretation:

On average, an increase/decrease of 1 unit in the explanatory variable is associated with an increase/decrease of $|\hat{\beta}_i|$ in the response variable, holding all other explanatory variables fixed.

The underlined parts above should be rephrased to correspond to the context of the problem

• Let y_i be the observed value of the response variable Y for observation i
• Let x_{ji} be the observed value of the explanatory variable X_j for observation i
ullet The predicted value of the response variable Y for observation i is:
• The residual of observation <i>i</i> is still defined as:
ullet The estimated standard error of the multiple regression model with k predictors is:

4 Assessing a multiple linear regression model

• The conditions and assumptions are analogous to those in simple linear regression

Condition	Where to check	What we want		
Linearity	Residuals vs. fitted values plot	Points randomly and evenly distributed above and below residual = 0 line, moving from left to right		
Independence	Description of data collection	No indication that the errors influence each other		
Normality	Normal Q-Q plot of residuals	Points in approximately straight line		
Equal variance	Residuals vs. fitted values plot	Points span constant vertical width, moving from left to right		
Randomness	Description of data collection	Data obtained using a random process, such as random sampling from a population or randomization in an experiment		

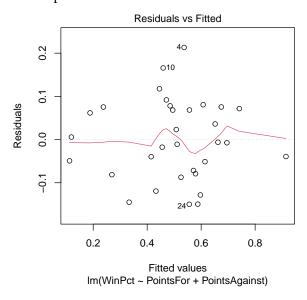
 $[\]circ~$ This is still interpreted as the size of a "typical" prediction error

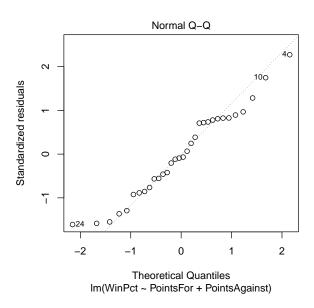
Example 1. How is an NFL team's winning percentage related to its offensive and defensive performance? The dataset NFLStandings2016 from Stat2Data contains the records for all NFL teams during the 2016 regular season. WinPct is the winning percentage, PointsFor is the total number of points scored, and PointsAgainst is the total number of points allowed. a. What is the response variable? What are the explanatory variables? b. Write the population-level model; that is, the model we will fit. Include the distribution of the error term. c. We can fit the multiple regression using R with the following code: fit <- lm(WinPct ~ PointsFor + PointsAgainst, data = NFLStandings2016)</pre> summary(fit) We get the following output: Call: lm(formula = WinPct ~ PointsFor + PointsAgainst, data = NFLStandings2016) Residuals: 1Q Median 3Q Max -0.149898 -0.073482 -0.006821 0.072569 0.213189 Coefficients: Estimate Std. Error t value Pr(>|t|)(Intercept) 0.7853698 0.1537422 5.108 1.88e-05 *** PointsFor 0.0016992 0.0002628 6.466 4.48e-07 *** PointsAgainst -0.0024816 0.0003204 -7.744 1.54e-08 *** Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1 Residual standard error: 0.09653 on 29 degrees of freedom Multiple R-squared: 0.7824, Adjusted R-squared: 0.7674 F-statistic: 52.13 on 2 and 29 DF, p-value: 2.495e-10 Write the fitted model.

d. Assess whether the conditions for multiple regression appear to be met. The code below should look familiar to you – it creates a residuals vs. fitted values plot and a Normal Q-Q plot of the residuals:

```
plot(fit, which=1)
plot(fit, which=2)
```

The output is below:





Linearity			
Independence			
Normality			
Equal variance			
Randomness			

	sider the Baltimore Ravens who scored 343 points while allowing 321 points during the 2016 season. What is their predicted winning percentage?				
ii.	Their winning percentage was actually 0.500. What is the corresponding residual?				
f. Wha	t is the estimated regression standard error?				
g. Inter	rpret the estimated coefficient of <i>PointsFor</i> .				
n. Wha	t is the predicted increase in <i>WinPct</i> associated with a 7 point increase in <i>PointsFor</i> (holding <i>PointsAgainst</i>)?				