CWRU DSCI351-351M-453: Week10b w10b-p-LinRegr

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Contents

10.2.1.1 Understanding simple linear regression

10.2.1.1.1 Build and use our own simple linear regression algorithm

- Create multiple linear regression models in R
- Perform diagnostic tests of such models
- Score new data using a linear regression model
- Examine how well the model predicts the new data

Regression seeks to obtain the model coefficients

- that explain the variable's relationship the best
- but such a model only seldom reflects the relationship entirely

Indeed, measurement error,

- And also attributes that are not included in the analysis
- affect also the data.

The model residuals

- express the deviation of the observed data points
- to the model.

The residual's value

- is the vertical distance from a point
- to the regression line.

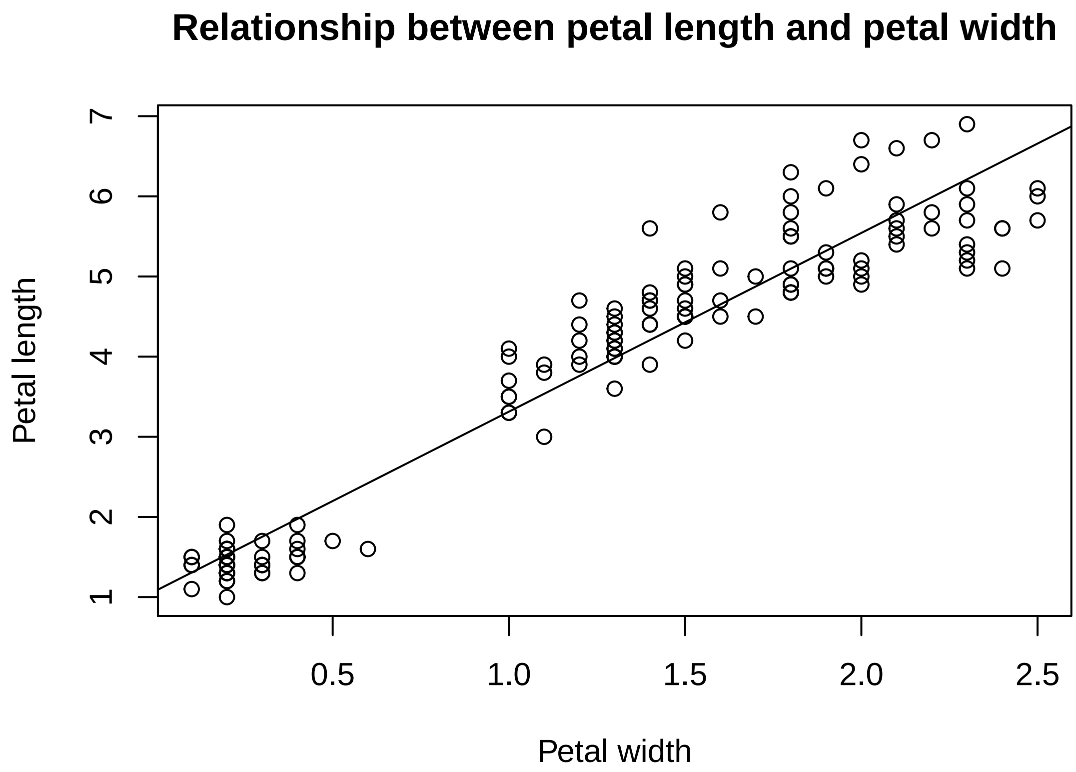
10.2.1.2 Let's examine this with an example of the iris dataset.

We have already seen that the dataset contains data about iris flowers.

For the purpose of this example,

- we will consider the petal length as the response
  - sometimes the response is referred to as the "criterion"
- and the petal width as the predictor

```r
plot(iris$Petal.Length ~ iris$Petal.Width,
     main = "Relationship between petal length and petal width",
     xlab = "Petal width", ylab = "Petal length")
iris.lm = lm(iris$Petal.Length ~ iris$Petal.Width)
abline(iris.lm)
```



10.2.1.2.1 Computing the intercept and slope coefficient

```r
SlopeCoef = cor(iris$Petal.Length,iris$Petal.Width) *
  (sd(iris$Petal.Length) / sd(iris$Petal.Width))
SlopeCoef
```

```
## [1] 2.22994
```

```r
coeffs = function(y,x) {
  ((length(y) * sum( y*x)) -
      (sum( y) * sum(x)) )  /
    (length(y) * sum(x^2) - sum(x)^2)
}

coeffs(iris$Petal.Length, iris$Petal.Width)
```

```
## [1] 2.22994
```

10.2.1.2.2 Now make your linear regression function

```r
iris.lm
```

```
##
## Call:
```

```
## lm(formula = iris$Petal.Length ~ iris$Petal.Width)
##
## Coefficients:
##      (Intercept)  iris$Petal.Width
##            1.084             2.230
```

```
regress =  function(y,x) {
  slope = coeffs(y,x)
  intercept = mean(y) - (slope * mean(x))
  model = c(intercept, slope)
  names(model) = c("intercept", "slope")
  model
}
```

10.2.1.2.3 Now perform regression on Petal Length and Petal Width

```
model = regress(iris$Petal.Length, iris$Petal.Width)
model
```

```
## intercept     slope
##  1.083558  2.229940
```

10.2.1.2.4 Obtaining the residuals

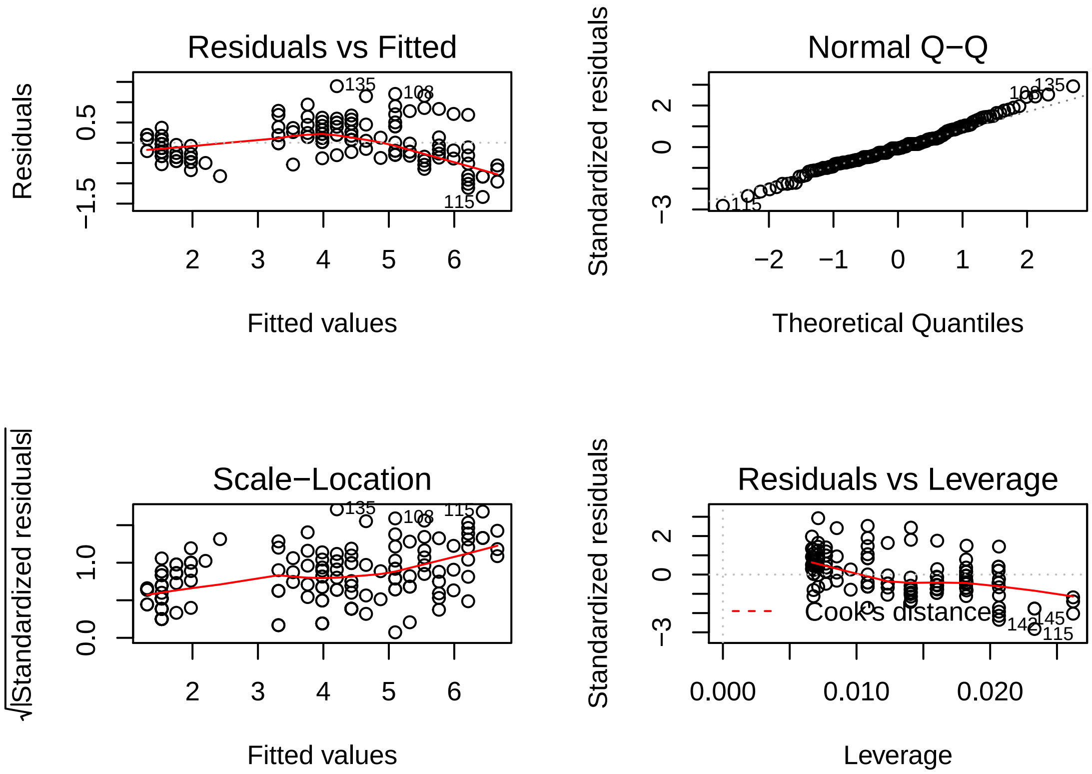
```
resids = function(y,x, model) {
  y - model[1] - (model[2] * x)
}

Residuals = resids(iris$Petal.Length, iris$Petal.Width, model)

head(round(Residuals,2))
```

```
## [1] -0.13 -0.13 -0.23 -0.03 -0.13 -0.28
```

```
par(mfrow = c(2, 2))
plot(iris.lm)
```



10.2.1.3 Computing the significance of the coefficients

This is also the uncertainty

- in your regression coefficients

```
Significance = function(y, x, model) {
  SSE = sum(resids(y,x,model)^2)
  DF = length(y) - 2
  S = sqrt( SSE / DF)
  SEslope = S / sqrt(sum( (x - mean(x))^2 ))
  tslope = model[2] / SEslope
  sigslope = 2*(1 - pt(abs(tslope),DF))
  SEintercept = S * sqrt((1/length(y) + mean(x)^2 / sum( (x - mean(x))^2)))
  tintercept = model[1] / SEintercept
  sigintercept = 2*(1 - pt(abs(tintercept),DF))
  RES = c(SEslope, tslope, sigslope, SEintercept, tintercept, sigintercept)
  names(RES) = c("SE slope", "T slope", "sig slope", "SE intercept",
               "t intercept", "sig intercept")
  RES
}

round(Significance(iris$Petal.Length,iris$Petal.Width, model), 3)
```

```
##       SE slope        T slope     sig slope  SE intercept   t intercept
##          0.051         43.387         0.000         0.073        14.850
## sig intercept
##          0.000
```

```r
summary(iris.lm)
```

```
##
## Call:
## lm(formula = iris$Petal.Length ~ iris$Petal.Width)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.33542 -0.30347 -0.02955  0.25776  1.39453
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       1.08356    0.07297   14.85   <2e-16 ***
## iris$Petal.Width  2.22994    0.05140   43.39   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4782 on 148 degrees of freedom
## Multiple R-squared:  0.9271, Adjusted R-squared:  0.9266
## F-statistic:  1882 on 1 and 148 DF,  p-value: < 2.2e-16
```

10.2.1.4 Links

Learning Predictive Analytics with R, Eric Mayor, Packtpub 2015