Linear Regression - Part 1 - Edx Analytical Edge

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This use the EDx course - Analytical Edge

Single variable regression.

The general equation for a linear regression model

$y^i = \beta_0 + \beta_1 x^i + \varepsilon^i$

where:

- y^i is the i^{th} observation of the dependent variable
- β_0 is the intercept coefficient
- β_1 is the regression coefficient for the dependent variable
- x^i is the i^{th} observation of the independent variable
- ε^i is the error term for the i^{th} observation. It basically is the difference in therm of y between the observed value and the estimated value. It is also called the residuals. A good model minimize these errors.

One way to assess how good our model is to:

1. compute the SSE (the sum of squared error)
   - SSE = $(\varepsilon^1)^2 + (\varepsilon^2)^2 + \cdots + (\varepsilon^n)^2 = \sum_{i=1}^{N} \varepsilon^i$
   - problem: SSE is dependent of N. SSE will naturally increase as N increase
2. compute the RMSE (the root mean squared error)
   - RMSE = $\sqrt{\frac{SSE}{N}}$
   - It depends of the unit of the independent variable
3. compute R^2
   - It compare the models to a baseline model
   - R^2 is **unitless** and **universaly** interpretable
   - SST is the sum of the squared of the difference between the observed value and the mean of all the observed value

$R^2 = 1 - \frac{SSE}{SST}$

In practice.

First example. Predicting wine price.

The wine.csv file is used in the class. The *AGST* is the independent variable while the *price* is the dependent variable.

Let's load it and then have a quick look at its structure.

```
wine = read.csv("wine.csv")
str(wine)
```

```
## 'data.frame':    25 obs. of  7 variables:
##  $ Year       : int  1952 1953 1955 1957 1958 1959 1960 1961 1962
1963 ...
##  $ Price      : num  7.5 8.04 7.69 6.98 6.78 ...
##  $ WinterRain : int  600 690 502 420 582 485 763 830 697 608 ...
##  $ AGST       : num  17.1 16.7 17.1 16.1 16.4 ...
##  $ HarvestRain: int  160 80 130 110 187 187 290 38 52 155 ...
##  $ Age        : int  31 30 28 26 25 24 23 22 21 20 ...
##  $ FrancePop  : num  43184 43495 44218 45152 45654 ...
```

```
head(wine)
```

```
##   Year  Price WinterRain    AGST HarvestRain Age FrancePop
## 1 1952 7.4950        600 17.1167         160  31  43183.57
## 2 1953 8.0393        690 16.7333          80  30  43495.03
## 3 1955 7.6858        502 17.1500         130  28  44217.86
## 4 1957 6.9845        420 16.1333         110  26  45152.25
## 5 1958 6.7772        582 16.4167         187  25  45653.81
## 6 1959 8.0757        485 17.4833         187  24  46128.64
```

We use the `lm` function to find our linear regression model.

```
model1 = lm(Price ~ AGST,data=wine)
summary(model1)
```

```
##
## Call:
## lm(formula = Price ~ AGST, data = wine)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.78450 -0.23882 -0.03727  0.38992  0.90318
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -3.4178     2.4935  -1.371 0.183710
## AGST          0.6351     0.1509   4.208 0.000335 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.4993 on 23 degrees of freedom
## Multiple R-squared:  0.435,  Adjusted R-squared:  0.4105
## F-statistic: 17.71 on 1 and 23 DF,  p-value: 0.000335
```

The `summary` function applied on the model is giving us a bunch of important information

- the stars next to the predictor variable indicated how significant the variable is for our regression model
- it also gives us the value of the R coefficient

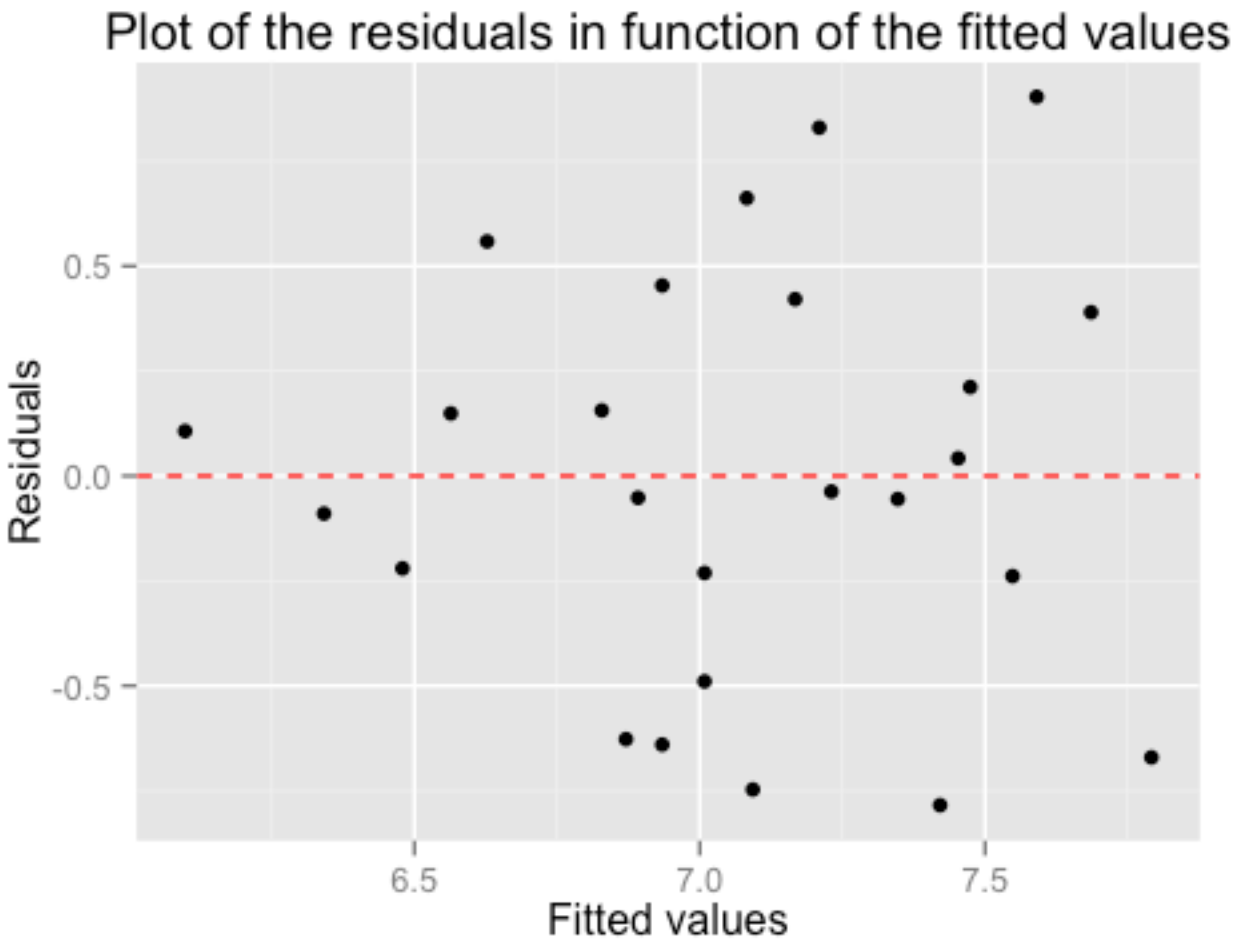
We could have calculated the R value ourselves:

```
SSE = sum(model1$residuals^2)
SST = sum((wine$Price - mean(wine$Price))^2)
r_squared = 1 - SSE/SST
r_squared
```

```
## [1] 0.4350232
```

It is always nice to see how our residuals are distributed.
We use the `ggplot2` library and the `fortify` function which transform the `summary(model1)` into a data frame usable for plotting.

```
library(ggplot2)
model1 <- fortify(model1)
ggplot(model1, aes(.fitted, .resid)) + geom_point() +
geom_hline(yintercept = 0, col = "red", linetype = "dashed") +
xlab("Fitted values") + ylab("Residuals") + ggtitle("Plot of the
residuals in function of the fitted values")
```



Multi-variables regression.

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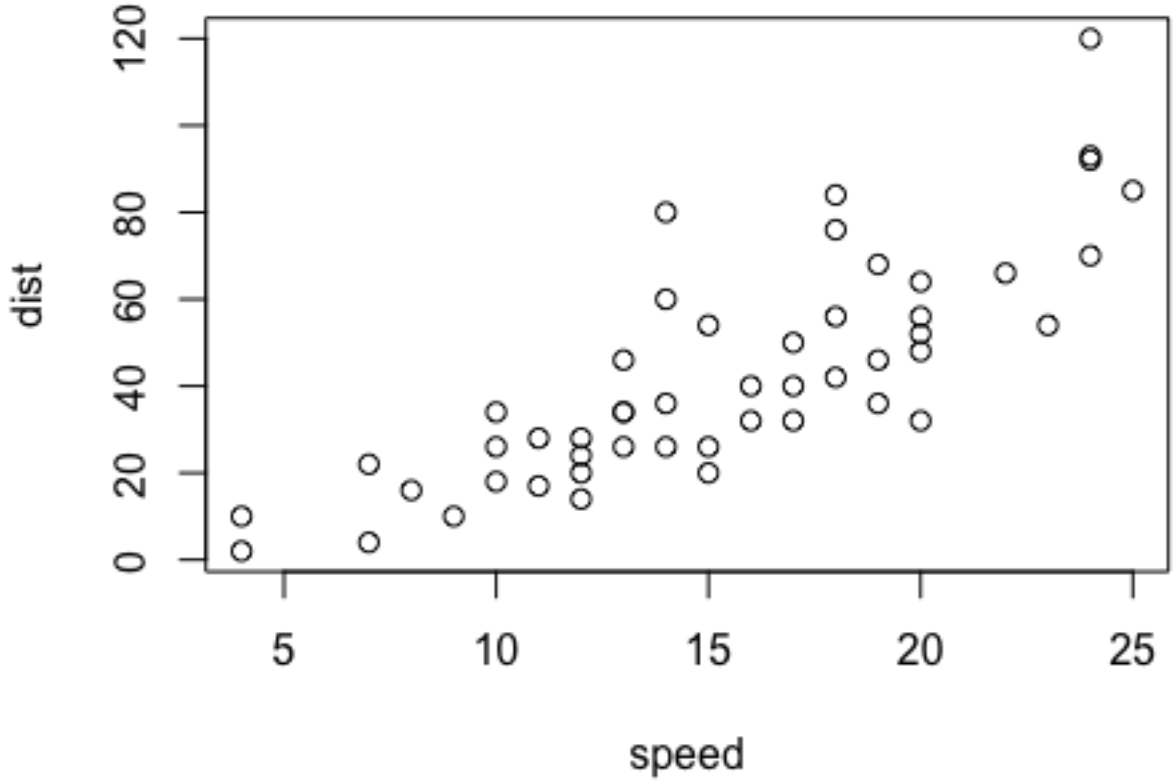
When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```
summary(cars)
```

```
##      speed           dist       
##  Min.   : 4.0   Min.   :  2.00  
##  1st Qu.:12.0   1st Qu.: 26.00  
##  Median :15.0   Median : 36.00  
##  Mean   :15.4   Mean   : 42.98  
##  3rd Qu.:19.0   3rd Qu.: 56.00  
##  Max.   :25.0   Max.   :120.00
```

You can also embed plots, for example:



Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.