

# Net hourly wages across multiple countries McDonald's

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Nishanth

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## 1 Importing data into R

### 1.1 Viewing top rows in CSV

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```
data <- read.csv("data/BigMac-NetHourlyWage.csv")

head(data,5)
```

```
##      Country Big.Mac.Price.... Net.Hourly.Wage....
## 1 Argentina          1.78              3.3
## 2 Australia          3.84             14.0
## 3   Brazil           4.91              4.3
## 4   Britain          3.48             13.9
## 5    Canada          4.00             12.8
```

### 1.2 viewing the structure of the dataset

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```
str(data)
```

```
## 'data.frame': 27 obs. of 3 variables:
## $ Country : Factor w/ 27 levels "Argentina","Australia",...: 1 2 3 4 5 6 7
8 9 10 ...
## $ Big.Mac.Price.... : num 1.78 3.84 4.91 3.48 4 3.34 1.95 3.43 4.9 3.33 ...
## $ Net.Hourly.Wage....: num 3.3 14 4.3 13.9 12.8 3.1 3 5.1 17.7 3 ...
```

## 1.3 Basic Summary stats of dataset

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```
summary(data)
```

```
##      Country  Big.Mac.Price.... Net.Hourly.Wage....
## Argentina: 1   Min.    :1.780      Min.    : 1.300
## Australia: 1   1st Qu.:2.475      1st Qu.: 3.100
## Brazil    : 1   Median :3.330      Median : 5.100
## Britain   : 1   Mean    :3.349      Mean    : 7.726
## Canada    : 1   3rd Qu.:3.785      3rd Qu.:13.150
## Chile     : 1   Max.    :6.560      Max.    :22.600
## (Other)   :21
```

## 1.4 separating numerical and categorical variables from the dataset

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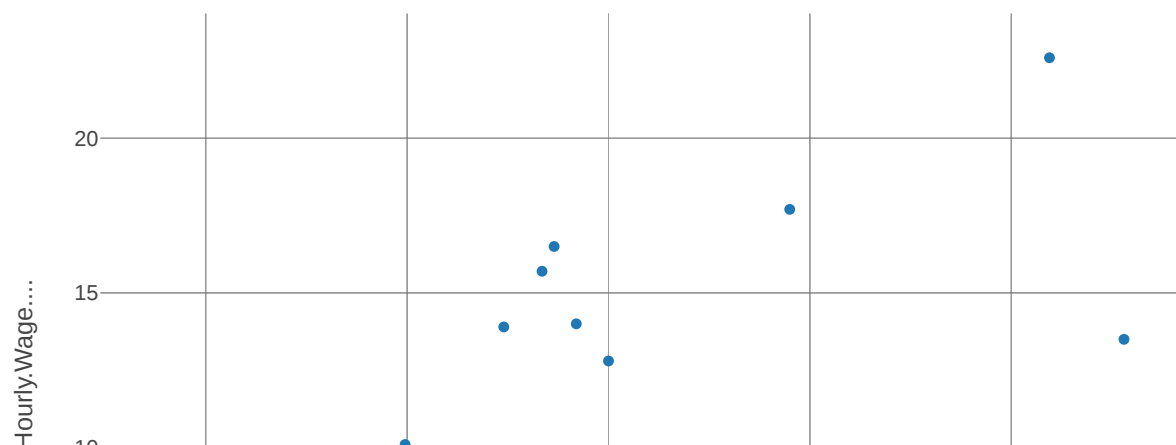
```
variable_types <- sapply(data, is.factor)
numerical_data <- data[,!(variable_types)]
categorical_data <- data[,variable_types]
```

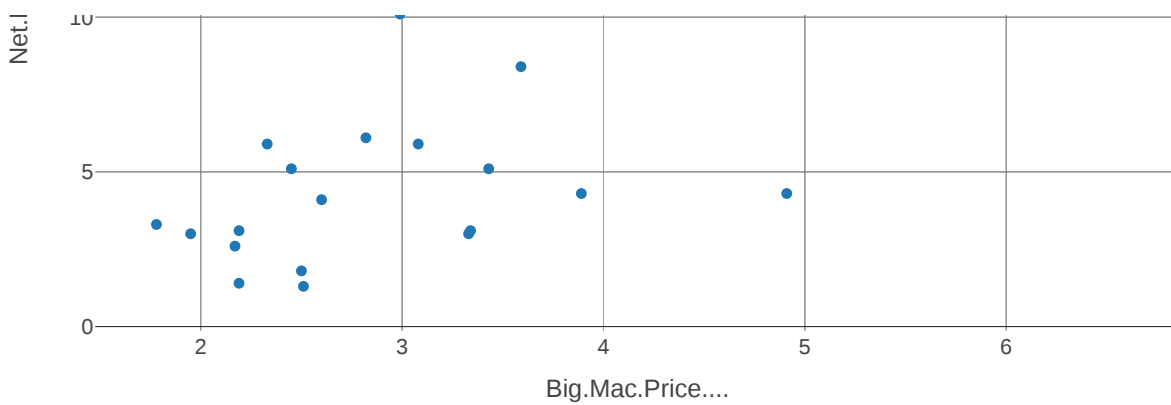
## 2 Grapical representaion of the data

### 2.1 scatter plot for net hourly wages and Big Mac price

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```
library(plotly)
p <- plot_ly(data = numerical_data, x = ~ Big.Mac.Price...., y = ~Net.Hourly.Wage....)
p
```



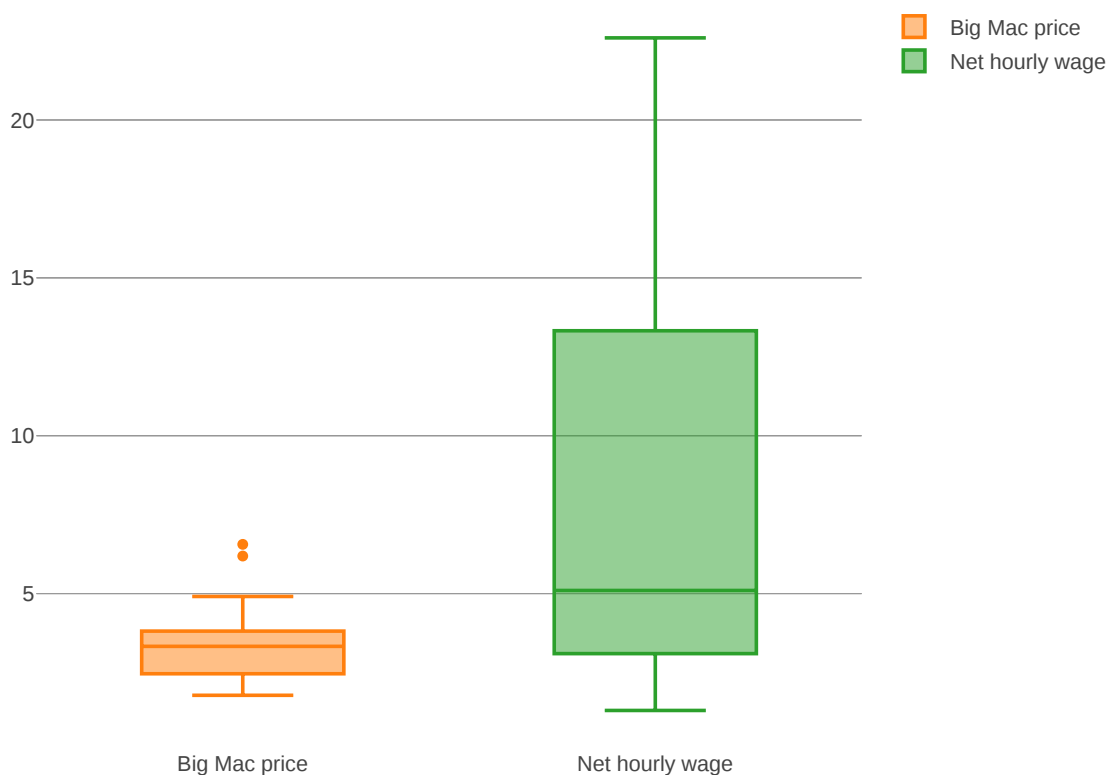


As price of the Big Mac increases net hourly wages are also increases, there is a positive relationship between Big Mac prices and Net hourly wages

## 2.2 Univariate (Box plot) analysis for Outlier analysis

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```
p <- plot_ly(type = "box") %>%
  add_boxplot(y = numerical_data$Big.Mac.Price.... , name = "Big Mac price") %>%
  add_boxplot(y = numerical_data$Net.Hourly.Wage.... , name = "Net hourly wage")
p
```



we see couple of outliers in the data for Big Mac

## 3 preprocessing

### 3.1 extracting the outlier points, rows and removing them

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```
outlier_points <- sapply(numerical_data, function(x) boxplot(x,plot=FALSE)$out)
outlier_points
```

```
## $Big.Mac.Price....
## [1] 6.56 6.19
##
## $Net.Hourly.Wage....
## numeric(0)
```

[Hide](#)

```
outlier_rows<- which(data$Big.Mac.Price....%in% outlier_points$Big.Mac.Price....)
outlier_rows
```

```
## [1] 22 23
```

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```
data_cleaned <- data[-c(outlier_rows),]
```

There are couple of outliers in Big Mac price and no outliers in net hourly wages

## 3.2 correlation between Big Mac and Net Hourly Wage

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```
cor(x = data$Big.Mac.Price...,y = data$Net.Hourly.Wage....)
```

```
## [1] 0.717055
```

correlation between Big Mac and Net Hourly wage is strong and positively correlated

## 4 Building the regression model

### 4.1 applying linear regression to the Mac Donald's data

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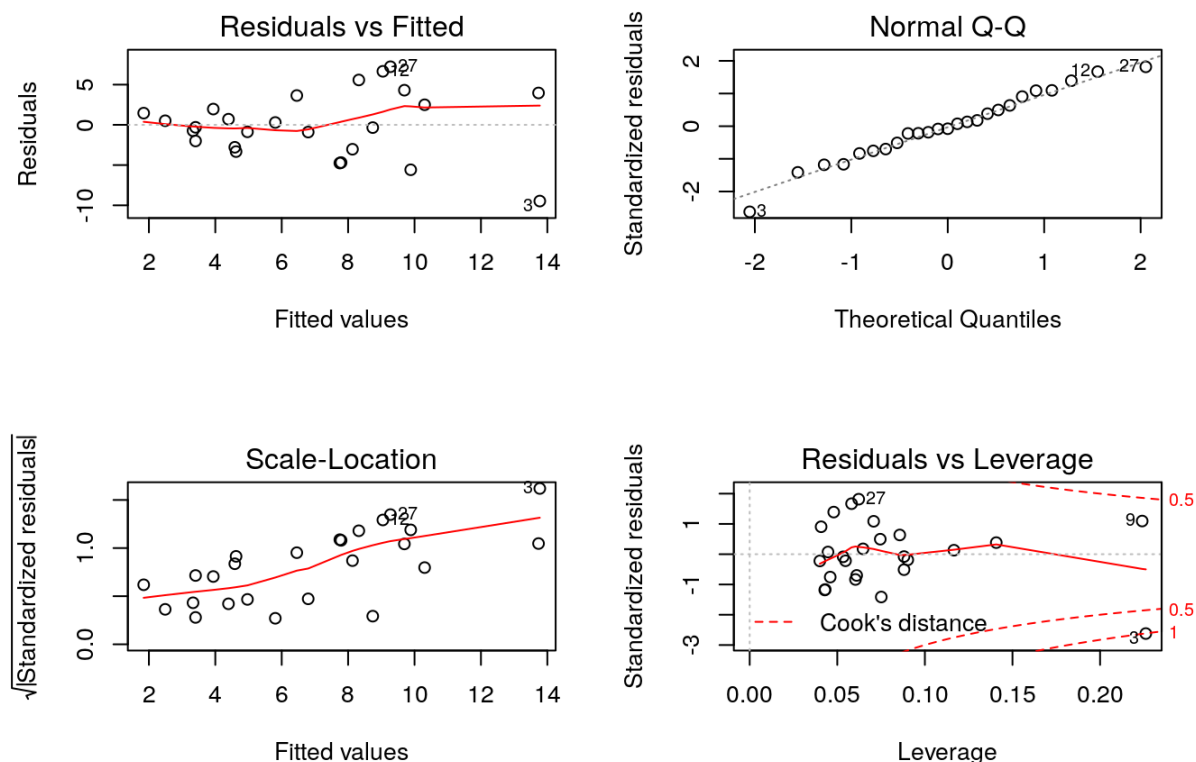
```
model.lm <- lm(Net.Hourly.Wage.... ~ Big.Mac.Price.... ,data = data_cleaned)
summary(model.lm)
```

```
##
## Call:
## lm(formula = Net.Hourly.Wage.... ~ Big.Mac.Price...., data = data_cleaned)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -9.4727 -2.7873 -0.3057  2.4957  7.2248
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -4.9411     3.1612  -1.563  0.131697
## Big.Mac.Price....  3.8114     0.9826   3.879  0.000759 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.107 on 23 degrees of freedom
## Multiple R-squared:  0.3955, Adjusted R-squared:  0.3692
## F-statistic: 15.05 on 1 and 23 DF, p-value: 0.0007594
```

## 4.2 viewing diagnostic plots of linear regression

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



## 4.3 Multivariate model approach for outliers (using cook's distance) and removal of outliers

### 4.3.1 Cook's Distance

Cook's distance is a measure computed with respect to a given regression model and therefore is impacted only by the X variables included in the model. But, what does cook's distance mean? It computes the influence exerted by each data point (row) on the predicted outcome.

The cook's distance for each observation  $i$  measures the change in  $\hat{Y}$  (fitted  $Y$ ) for all observations with and without the presence of observation  $i$ , so we know how much the observation  $i$  impacted the fitted values. Mathematically, cook's distance  $D_i$  for observation  $i$  is computed as

$$D_i = \frac{\sum_{j=1}^n (\hat{Y}_j - \hat{Y}_{j(i)})^2}{p \times MSE}$$

Cook's distance formula

where,

$\hat{Y}_j$  is the value of  $j$ th fitted response when all the observations are included.

$\hat{Y}_{j(i)}$  is the value of  $j$ th fitted response, where the fit does not include observation  $i$ .

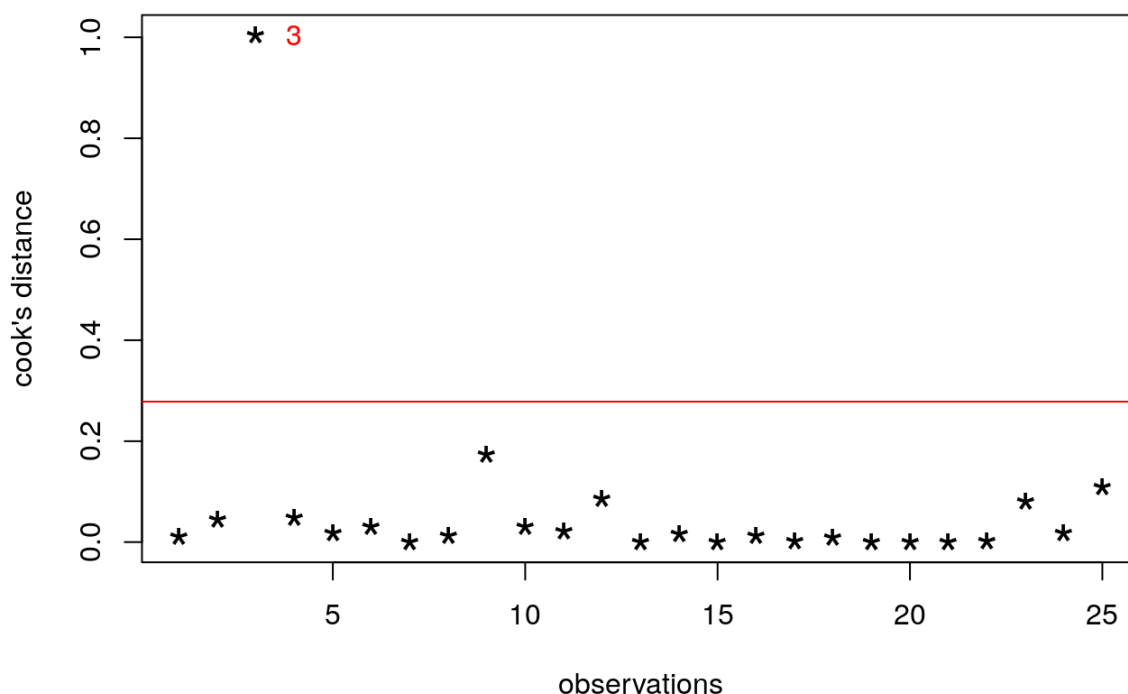
MSE is the mean squared error.

$p$  is the number of coefficients in the regression model

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```
cooks.dist<- cooks.distance(model.lm)
plot(cooks.dist, pch="*", cex=2, main="Influential Obs. by Cooks distance",xlab = "observations",ylab = "cook's distance")
abline(h = 4*mean(cooks.dist, na.rm=T), col="red")
text(x=1:length(cooks.dist)+1, y=cooks.dist, labels=ifelse(cooks.dist>4*mean(cooks.dist, na.rm=T),names(cooks.dist),""), col="red")
```

### Influential Obs. by Cooks distance



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```
data_cleaned <- data_cleaned[-c(3),]
```

## 4.4 Again applying linear regression after removal of outliers

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```
model.lm2 <- lm(Net.Hourly.Wage.... ~ Big.Mac.Price.... ,data = data_cleaned)
summary(model.lm2)
```

```
##
## Call:
## lm(formula = Net.Hourly.Wage.... ~ Big.Mac.Price...., data = data_cleaned)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -7.0640 -1.7088  0.2643  2.5001  5.9479
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -8.3760     2.9298  -2.859  0.00912 **
## Big.Mac.Price....  5.0745     0.9369   5.416 1.94e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.516 on 22 degrees of freedom
## Multiple R-squared:  0.5714, Adjusted R-squared:  0.552
## F-statistic: 29.33 on 1 and 22 DF,  p-value: 1.936e-05
```

After removal of outliers we observe p value for big mac price is more significant, adjusted R-squared increased from 36.9 to 55.2 and Multiple R squared increased from 39.5 to 57.1, overall model significance F test p - value becomes more significant.