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Subdirección Académica
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## MINERÍA DE DATOS

*BDD-1703SC9A*

## "*Practice 2*"


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*"Por una juventud integrada al desarrollo de México"*

Tijuana B.C. a 26 de Noviembre del 2021

# Practica 2

In this practice we will show an example of the implementation of multiple linear regression, a machine learning model, first we have the reading of the dataset to use where the path is specified and once the dataset is identified, it is read with the read.cv method being attached to a variable in R.

```
#We already had the path at downloads
getwd()
setwd("../MachineLearning/SimpleLinearRegression")
getwd()
# Importing the dataset
dataset <- read.csv('50_Startups.csv')
```

Coding of categorical data as converting them to 1, 2 and 3 respectively.

```
# Encoding categorical data
dataset$State = factor(dataset$State,
                       levels = c('New York', 'California', 'Florida'),
                       labels = c(1,2,3))
```

We show the data obtained:

```
#Show dataset
dataset
```

Result:

```
> dataset
   R.D.Spend Administration Marketing.Spend State    Profit
1  165349.20      136897.80       471784.10     1 192261.83
2  162597.70      151377.59       443898.53     2 191792.06
3  153441.51      101145.55       407934.54     3 191050.39
4  144372.41      118671.85       383199.62     1 182901.99
5  142107.34       91391.77       366168.42     3 166187.94
6  131876.90       99814.71       362861.36     1 156991.12
7  134615.46      147198.87       127716.82     2 156122.51
8  130298.13      145530.06       323876.68     3 155752.60
...
```

Divide the data set into the training set and the test set. Using the "calTools" library, where 80% is specified for training and 20% for testing the specific dataset. Ending with two new variables with the respective data.

```
# Splitting the dataset into the Training set and Test set
# Install.packages('caTools')
library(caTools)
set.seed(123)
```

```
split <- sample.split(dataset$Profit, SplitRatio = 0.8)
training_set <- subset(dataset, split == TRUE)
test_set <- subset(dataset, split == FALSE)
```

Next, the regression variable is obtained from the use of the "lm" method that is used to fit linear models, in this case with the use of the formula parameter that uses the Profit values as constants with respect to all the other variables, all relative to the training dataset.

```
# Fitting Multiple Linear Regression to the Training set
#regressor   =   lm(formula   =   Profit   ~   R.D.Spend   +   Administration   +
Marketing.Spend + State)
regressor = lm(formula = Profit ~ .,
               data = training_set )

summary(regressor)
```

Result, we can observe the most significant variables where the lower “Pr (> | t |)” the lower the variable to be considered relevant to have a better prediction, for standardization purposes it is recommended that the value be less than 0.05.

```
Residuals:
   Min     1Q Median     3Q    Max
-33128  -4865      5   6098  18065

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      4.965e+04  7.637e+03   6.501 1.94e-07 ***
R.D.Spend        7.986e-01  5.604e-02  14.251 6.70e-16 ***
Administration  -2.942e-02  5.828e-02  -0.505    0.617
Marketing.Spend  3.268e-02  2.127e-02   1.537    0.134
State2           1.213e+02  3.751e+03   0.032    0.974
State3           2.376e+02  4.127e+03   0.058    0.954
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9908 on 34 degrees of freedom
Multiple R-squared:  0.9499,  Adjusted R-squared:  0.9425
F-statistic:   129 on 5 and 34 DF,  p-value: < 2.2e-16
```

Now a test is carried out for the model, this through making some predictions with the use of the variables of "Regressor" obtained previously and the test data as a dataset.

```
# Prediction the Test set results
y_pred = predict(regressor, newdata = test_set)
y_pred
```

Result:

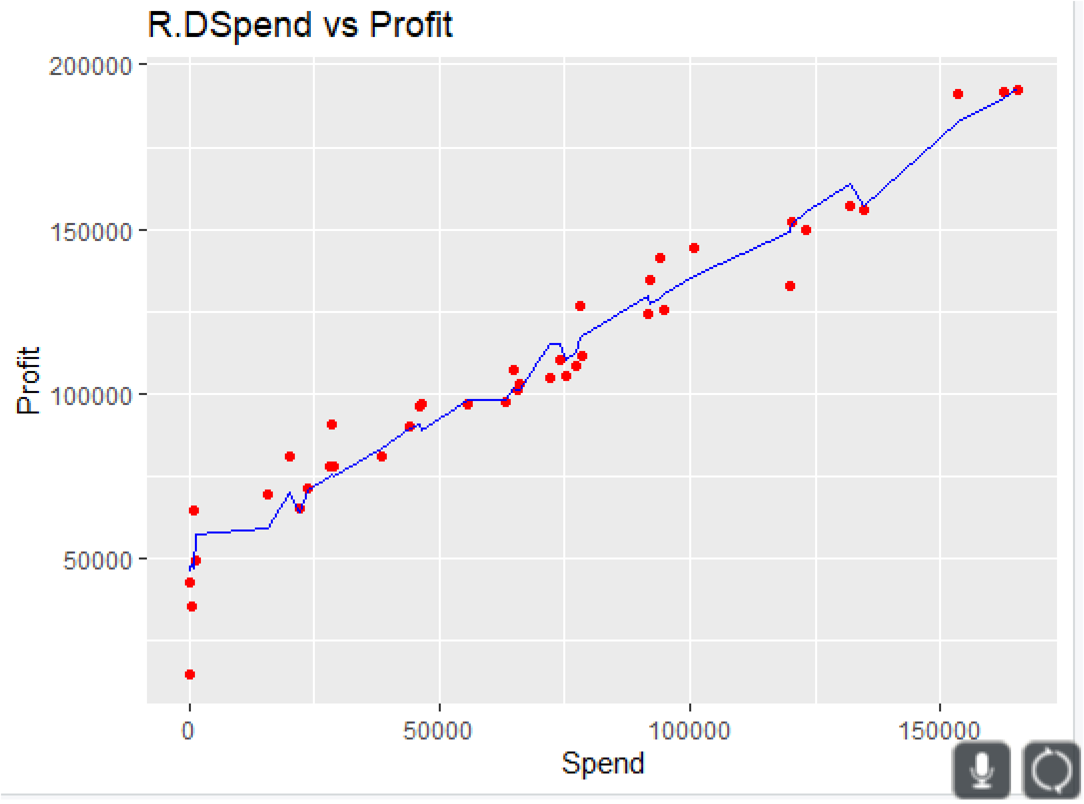
```
> y_pred
         4          5          8         11         16         20         21
24         31         32
173981.09  172655.64  160250.02  135513.90  146059.36  114151.03  117081.62
110671.31  98975.29  96867.03
```

Assignment: visualize the simple linear regression model with R.D.Spend.

For the first visualization we show the data with respect to the training dataset, to plot the points we use the “R.D.Spend” variable as “X” and the “Profit” variable as “Y”, defining red as the color. For the visualization of the line we define the "X" for the variable "R.D.Spend" and "Y" the value generated by the prediction of "Regressor" and the training data, shown in blue, ending with the definition of the titles.

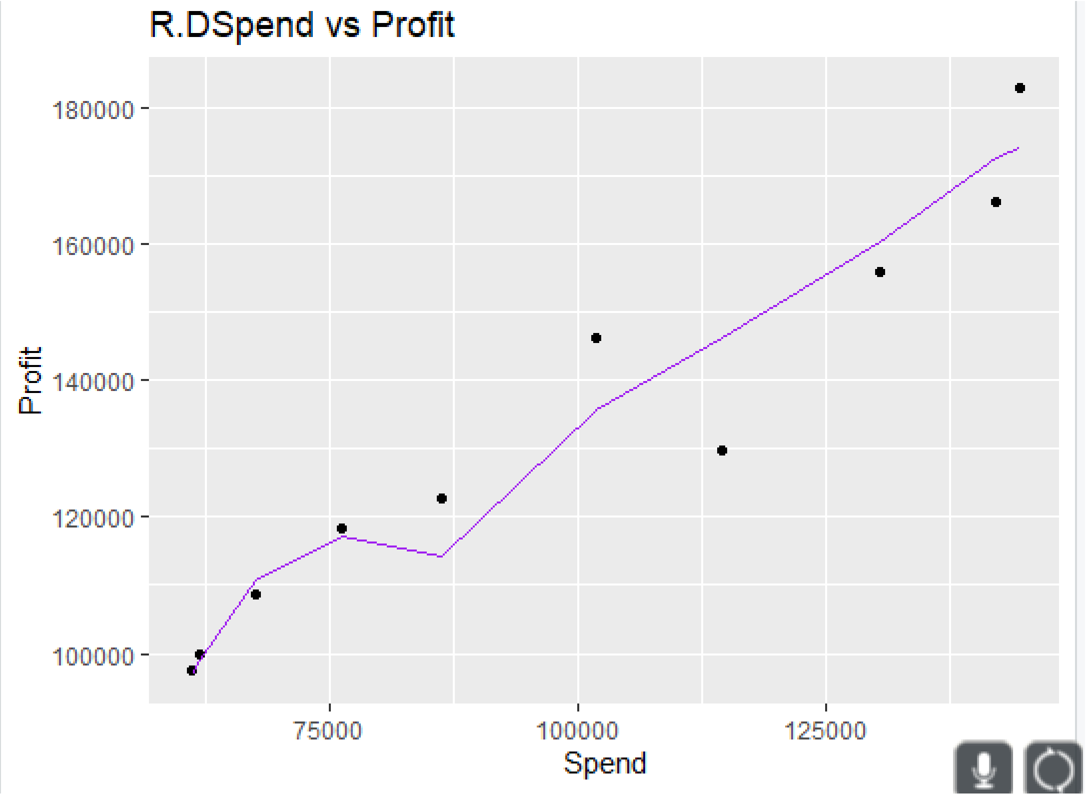
```
# Assigment: visualize the simple liner regression model with R.D.Spend

#this is the plot using the trainingset
library(ggplot2)
ggplot() +
  geom_point(aes(x=training_set$R.D.Spend, y=training_set$Profit),
             color = 'red') +
   geom_line(aes(x = training_set$R.D.Spend, y = predict(regressor, newdata =
training_set)),
            color = 'blue') +
  ggtitle('R.DSpend vs Profit') +
  xlab('Spend') +
  ylab('Profit')
```




Similarly, for the test data, it is necessary to plot the points using the “R.D.Spend” variable as “X” and the “Profit” variable as “Y”, defining black as the color. For the visualization of the line we define the "X" for the variable "R.D.Spend" and "Y" the value generated by the prediction of "Regressor" and the test data, shown in purple, ending with the definition of the titles.

```
# This is the plot using the testset
ggplot() +
  geom_point(aes(x=test_set$R.D.Spend, y=test_set$Profit),
             color = 'black') +
    geom_line(aes(x = test_set$R.D.Spend, y = predict(regressor, newdata =
test_set)),
            color = 'purple') +
  ggtitle('R.DSpend vs Profit') +
  xlab('Spend') +
  ylab('Profit')
```




The following code shows an example of how eliminating the least significant variables one by one shows better results. Until you have the ideal set that meets the aforementioned conditions.

```
# Building the optimal model using Backward Elimination
regressor = lm(formula = Profit ~ R.D.Spend + Administration + Marketing.Spend
+ State,
               data = dataset )
summary(regressor)

regressor = lm(formula = Profit ~ R.D.Spend + Administration +
Marketing.Spend,
               data = dataset )
summary(regressor)

regressor = lm(formula = Profit ~ R.D.Spend + Marketing.Spend,
               data = dataset )
summary(regressor)

regressor = lm(formula = Profit ~ R.D.Spend + Marketing.Spend,
               data = dataset )
summary(regressor)
```

Result of the significance of the values and how the prediction result is closer to what was expected.

```
Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     4.698e+04  2.690e+03  17.464   <2e-16 ***
R.D.Spend       7.966e-01  4.135e-02  19.266   <2e-16 ***
Marketing.Spend 2.991e-02  1.552e-02   1.927     0.06 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9161 on 47 degrees of freedom
Multiple R-squared:  0.9505,  Adjusted R-squared:  0.9483
F-statistic: 450.8 on 2 and 47 DF,  p-value: < 2.2e-16

> y_pred = predict(regressor, newdata = test_set)
> y_pred
        4         5         8        11        16        20        21
24        31        32
173441.31  171127.62  160455.74  135011.91  146032.72  115816.42  116650.89
109886.19  99085.22  98314.55
```

Task parses atomization tracking backward Removal function

1. Start with the declaration of backwardElimination giving the value xy sl = 0.05
2. Numvars is equal to the length of x
3. We iterate with the count of the variable numvar
4. Inside we have the MLR formula
5. Using maxvar to obtain the coefficient of the regressor summary
6. We compare the value of maxvar if it is greater than sl
7. We use backward elimination using x and j as variables
8. At the end we return a summary of the regressor

```
backwardElimination <- function(x, sl) {
  numVars = length(x)
  for (i in c(1:numVars)){
    regressor = lm(formula = Profit ~ ., data = x)
    maxVar = max(coef(summary(regressor))[c(2:numVars), "Pr(>|t|)"])
    if (maxVar > sl){
      j = which(coef(summary(regressor))[c(2:numVars), "Pr(>|t|)"] == maxVar)
      x = x[, -j]
    }
    numVars = numVars - 1
  }
  return(summary(regressor))
```

```
}

SL = 0.05
#dataset = dataset[, c(1,2,3,4,5)]
training_set
backwardElimination(training_set, SL)
```

It ends by showing the “Summary” of the best combination of variables for a better prediction, where in all the variables to be used it represents an “SL” less than 0.05.

```
Call:
lm(formula = Profit ~ ., data = x)

Residuals:
   Min     1Q Median     3Q    Max
-34334  -4894   -340   6752  17147

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 4.902e+04  2.748e+03   17.84   <2e-16 ***
R.D.Spend   8.563e-01  3.357e-02   25.51   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9836 on 38 degrees of freedom
Multiple R-squared:  0.9448,  Adjusted R-squared:  0.9434
F-statistic: 650.8 on 1 and 38 DF,  p-value: < 2.2e-16
```