Conducting and Presenting Multiple Linear Regression Analysis Using R

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Links

Github repository https://github.com/mariarojas01/data-analysis.git

Handout (HTML website) https://mariarojas01.github.io/data-analysis

Handout (PDF) https://mariarojas01.github.io/data-analysis/Handout.pdf

Presentation (HTML) https://mariarojas01.github.io/data-analysis/Presentation.html

Presentation (PDF) https://mariarojas01.github.io/data-analysis/Presentation.pdf

What is Multiple Linear Regression

Regression analysis is used to determine the relationships between two or more variables that exhibit cause–effect patterns, and to make predictions based on those relationships.

$$Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_n X_{ni} + u_i$$

Basic Syntax in R

```
model <- lm(formula, data = dataset)
```

Usefull aplications

- Business: Demand forcasting, finantial risk modeling, market research, etc.
- Social sciences and psychology: explore how variables such as education, income, and demographics influence life satisfaction.
- In medicine: predict patient outcomes from characteristics such as age, BMI, and biomarkers.
- Machine learning and data science: serves both as a baseline predictive model for continuous outcomes and as a tool for feature importance analysis.

Assupmtions

1. Linearity: The model assumes a linear and additive relationship between each predictor.
2. Normality: The model errors are assumed to follow a normal distribution centered at zero.
3. Homoscedasticity: The errors are expected to have constant variance across all values of the predictors.
4. Independence: Errors must be independent of each other, meaning their co variances are zero.

Multicollinearity

It occurs when two or more predictor variables are highly correlated, which leads to an increase in the standard errors of the estimated coefficients.

Steps to do a multiple linear regression analysis

1. Define the research question
2. Prepare and explore the data
3. Fit the initial model with lm()
4. Perform diagnostics
5. Refine the model if necessary
6. Summarize results with broom or similar tools
7. Report and interpret results

Preparing Data and Fitting the Model in R

```r
# Load data
data(mtcars)
# Quick overview
summary(mtcars)
```


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# Quick overview
summary(mtcars)
```


```
      mpg             cyl             disp             hp       
 Min.   :10.40   Min.   :4.000   Min.   : 71.1   Min.   : 52.0  
 1st Qu.:15.43   1st Qu.:4.000   1st Qu.:120.8   1st Qu.: 96.5  
 Median :19.20   Median :6.000   Median :196.3   Median :123.0  
 Mean   :20.09   Mean   :6.188   Mean   :230.7   Mean   :146.7  
 3rd Qu.:22.80   3rd Qu.:8.000   3rd Qu.:326.0   3rd Qu.:180.0  
 Max.   :33.90   Max.   :8.000   Max.   :472.0   Max.   :335.0  
      drat             wt             qsec             vs        
 Min.   :2.760   Min.   :1.513   Min.   :14.50   Min.   :0.0000  
 1st Qu.:3.080   1st Qu.:2.581   1st Qu.:16.89   1st Qu.:0.0000  
 Median :3.695   Median :3.325   Median :17.71   Median :0.0000  
 Mean   :3.597   Mean   :3.217   Mean   :17.85   Mean   :0.4375  
 3rd Qu.:3.920   3rd Qu.:3.610   3rd Qu.:18.90   3rd Qu.:1.0000  
 Max.   :4.930   Max.   :5.424   Max.   :22.90   Max.   :1.0000  
       am              gear            carb      
 Min.   :0.0000   Min.   :3.000   Min.   :1.000  
 1st Qu.:0.0000   1st Qu.:3.000   1st Qu.:2.000  
 Median :0.0000   Median :4.000   Median :2.000  
 Mean   :0.4062   Mean   :3.688   Mean   :2.812  
 3rd Qu.:1.0000   3rd Qu.:4.000   3rd Qu.:4.000  
 Max.   :1.0000   Max.   :5.000   Max.   :8.000  
```

Fitting a multiple linear regression with lm()

Miles per gallon (mpg) is predicted by weight (wt), horsepower (hp), and number of cylinders (cyl).

```r
# Fit the model
model <- lm(mpg ~ wt + hp + cyl, data = mtcars)
# Basic summary output
summary(model)
```

Output


```r
# Fit the model
model <- lm(mpg ~ wt + hp + cyl, data = mtcars)
# Basic summary output
summary(model)
```

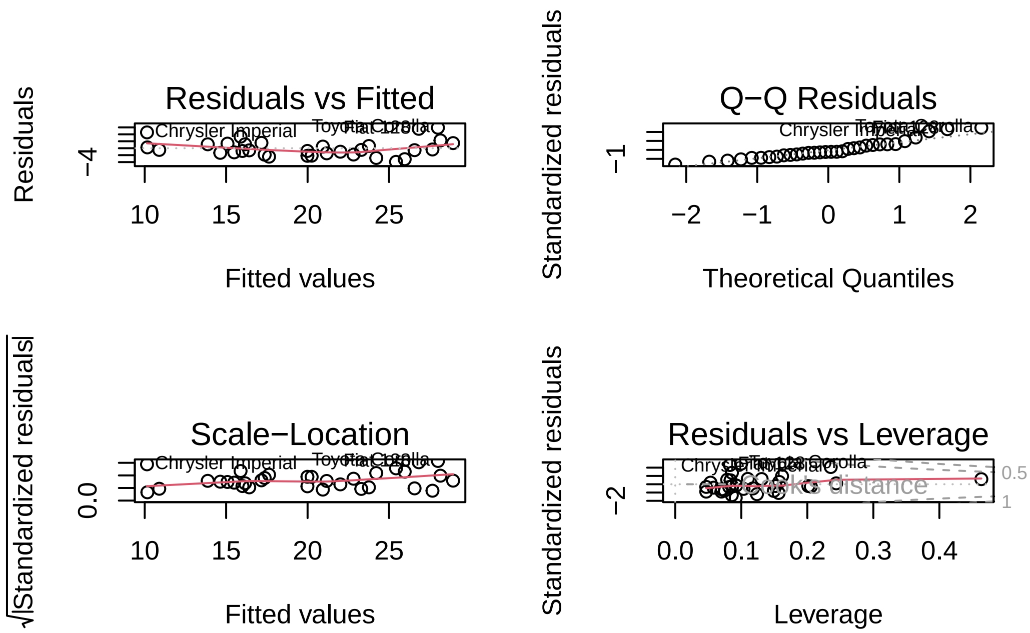

```
Call:
lm(formula = mpg ~ wt + hp + cyl, data = mtcars)

Residuals:
    Min      1Q  Median      3Q     Max
-3.9290 -1.5598 -0.5311  1.1850  5.8986

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 38.75179    1.78686  21.687  < 2e-16 ***
wt          -3.16697    0.74058  -4.276 0.000199 ***
hp          -0.01804    0.01188  -1.519 0.140015
cyl         -0.94162    0.55092  -1.709 0.098480 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.512 on 28 degrees of freedom
Multiple R-squared:  0.8431,    Adjusted R-squared:  0.8263
F-statistic: 50.17 on 3 and 28 DF,  p-value: 2.184e-11
```

Model Diagnostics in R

```r
# Basic diagnostic plots (4-panel layout)
par(mfrow = c(2, 2))
```

```r
plot(model)
par(mfrow = c(1, 1))
```

```r
# Basic diagnostic plots (4-panel layout)
par(mfrow = c(2, 2))
plot(model)
```




```r
par(mfrow = c(1, 1))
```

Checking multicollinearity with VIF

Values above about 5 are often flagged as problematic.

```r
# install.packages("car")  # run once if not installed
library(car)
vif(model)
```

```r
library(car)
```

```
Loading required package: carData
```

```r
vif(model)
```

```
      wt       hp      cyl 
2.580486 3.258481 4.757456 
```

Creating predictions

```r
# Predictions for the observed data
mtcars$pred_mpg <- predict(model)

# Create a small new data set for scenario-based predictions
new_cars <- data.frame(
  wt  = c(2.5, 3.0, 3.5),
  hp  = c(100, 150, 200),
  cyl = c(4, 6, 8)
)

predictions<- predict(model, newdata = new_cars)

cbind(new_cars, predictions) # column bind
```

```r
# Predictions for the observed data
mtcars$pred_mpg <- predict(model)

# Create a small new data set for scenario-based predictions
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  wt  = c(2.5, 3.0, 3.5),
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  cyl = c(4, 6, 8)
)

predictions<- predict(model, newdata = new_cars)

cbind(new_cars, predictions) #column bind
```

```
   wt  hp cyl predictions
1 2.5 100   4    25.26408
2 3.0 150   6    20.89545
3 3.5 200   8    16.52683
```

Present predictions

```r
# install.packages("ggplot2")  # run once
library(ggplot2)

ggplot(mtcars, aes(x = pred_mpg, y = mpg)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1, linetype = "dashed") +
  labs(
    x = "Predicted MPG",
    y = "Observed MPG",
    title = "Observed vs Predicted Fuel Efficiency"
  )
```

Output


```r
# install.packages("ggplot2")  # run once
library(ggplot2)

ggplot(mtcars, aes(x = pred_mpg, y = mpg)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1, linetype = "dashed") +
  labs(
    x = "Predicted MPG",
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    title = "Observed vs Predicted Fuel Efficiency"
  )
```

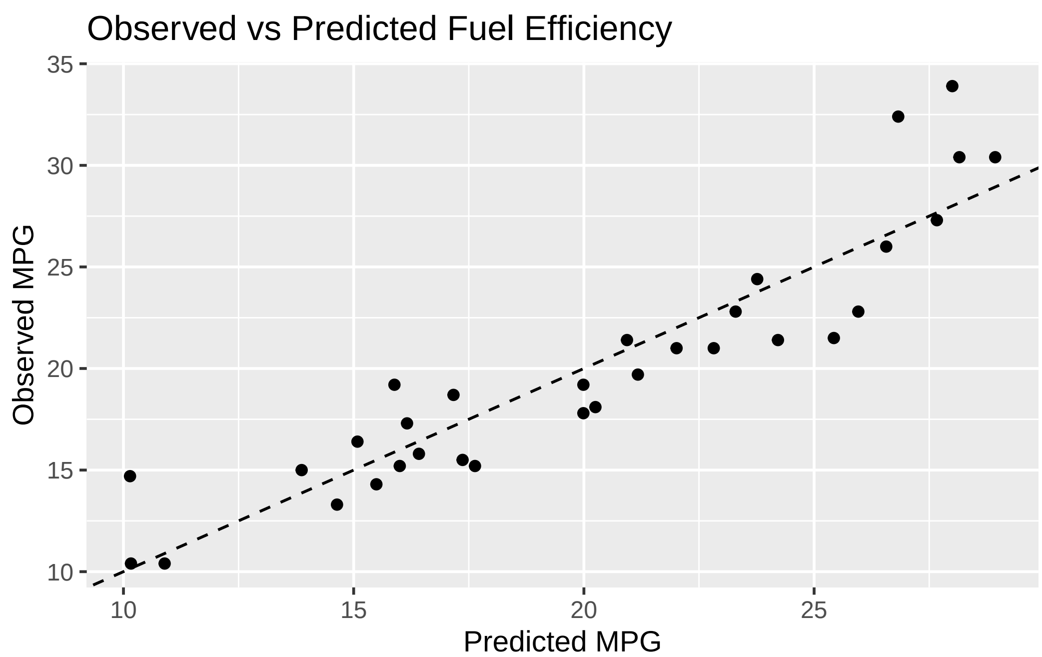

Exercise

A small company wants to understand how advertising budget and store size affect monthly sales. For this we are running a regression and predict the outcome of a new store with advertising of 28 K EUR and Store size of 185 m^2

```
sales_data <- data.frame(
  Sales = c(120, 150, 170, 200, 220, 250, 275, 300, 320, 340),
  Advertising = c(10, 15, 14, 20, 22, 25, 27, 30, 31, 33),
  StoreSize = c(100, 120, 130, 150, 160, 170, 180, 190, 200, 210)
)
```

Solution

```
# 1. Fit a multiple linear regression model

model <- lm(Sales ~ Advertising + StoreSize, data = sales_data)

# 2. Show model summary
```

```r
summary(model)

# 3. Predict sales for a new store

new_store <- data.frame(
  Advertising = 28,
  StoreSize = 185
)

predicted_sales <- predict(model, newdata = new_store)
predicted_sales
```

Solution

```r
# 1. Create a custom dataset
sales_data <- data.frame(
  Sales = c(120, 150, 170, 200, 220, 250, 275, 300, 320, 340),
  Advertising = c(10, 15, 14, 20, 22, 25, 27, 30, 31, 33),
  StoreSize = c(100, 120, 130, 150, 160, 170, 180, 190, 200, 210)
)

# 2. Fit a multiple linear regression model

model <- lm(Sales ~ Advertising + StoreSize, data = sales_data)

# 3. Show model summary

summary(model)
```

```
Call:
lm(formula = Sales ~ Advertising + StoreSize, data = sales_data)

Residuals:
    Min      1Q  Median      3Q     Max 
-11.128  -3.776   1.789   5.059  10.146 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -65.2644    38.6401  -1.689   0.1351
```

```
Advertising   2.7007     3.0055   0.899   0.3987
StoreSize     1.4811     0.6555   2.259   0.0584 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.091 on 7 degrees of freedom
Multiple R-squared:  0.9909,    Adjusted R-squared:  0.9883
F-statistic: 381.6 on 2 and 7 DF,  p-value: 7.157e-08
```

```r
# 4. Predict sales for a new store

new_store <- data.frame(
  Advertising = 28,
  StoreSize = 185
)

predicted_sales <- predict(model, newdata = new_store)
predicted_sales
```

```
       1
284.3602
```