

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.

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

Basic Syntax in R

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

Usefull applications

- Business: Demand forecasting, financial 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

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

```
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data(mtcars)
# 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).

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

Output

```
# 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

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

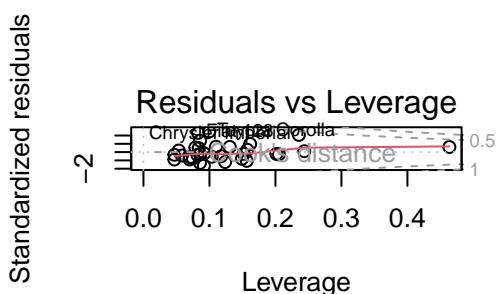
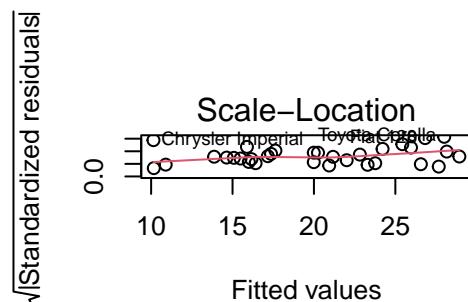
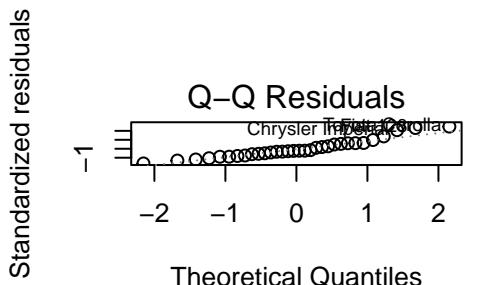
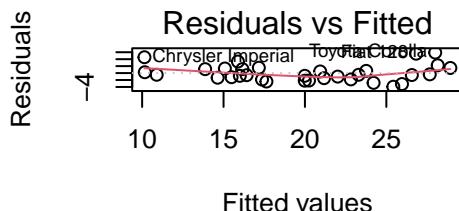
```
plot(model)
```

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

```
# Basic diagnostic plots (4-panel layout)
```

```
par(mfrow = c(2, 2))
```

```
plot(model)
```



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

Checking multicollinearity with VIF

Values above about 5 are often flagged as problematic.

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

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

```
Loading required package: carData
```

```
vif(model)
```

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

Creating predictions

```
# 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
```

```
# 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
```

```
   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

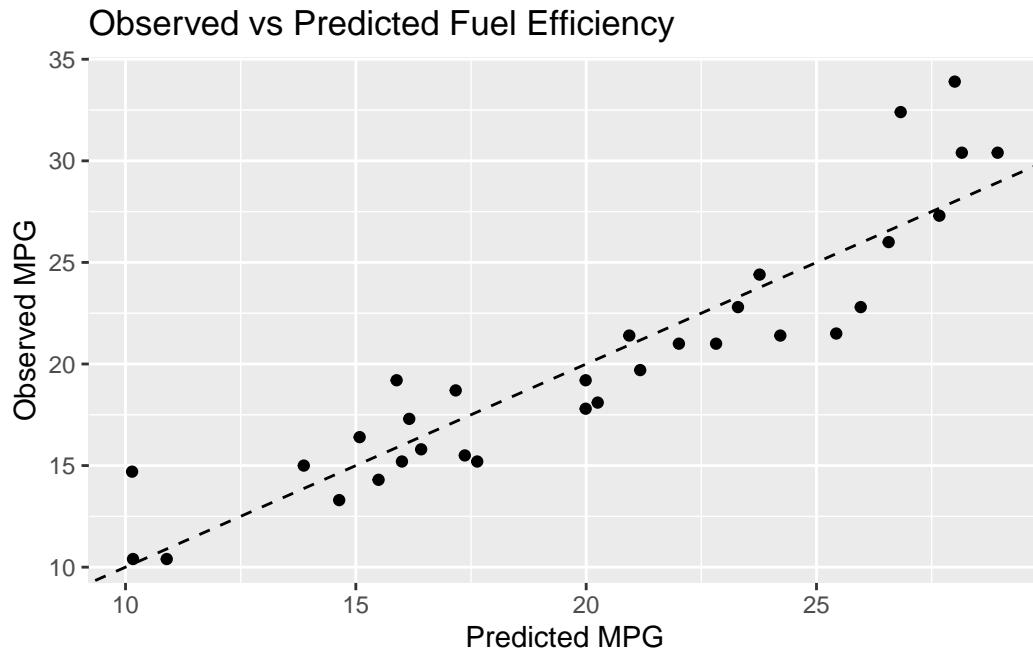
```
# install.packages("ggplot2") # run once
library(ggplot2)

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

```
# 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"
  )
```



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 128 m²

```
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
```

```

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

```

# 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
```

```
# 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
```