

# CHAPTER 3

## Multiple Regression

### 3.1 Multiple Linear Regression Model

### 3.2 Assessing a Multiple Regression Model



In chapters 1 and 2, we studied simple linear regression (SLR) with a single quantitative predictor (explanatory variable). This chapter introduce the more general case of multiple linear regression (MLR) which, allows several explanatory variables to combine in explaining a response variable.

- In example Porsche price, the price ( $Y$ ) of a used Porsche may depend on its mileage ( $X_1$ ), and also may depend on its age ( $X_2$ ).

Notice that the assumptions are the same for both simple and multiple linear regression.



## 3.1 Multiple Linear Regression:

We have  $n$  observations on  $k$  explanatory variables  $X_1, X_2, \dots, X_k$  and a response variable  $Y$ . Our goal is to study or predict the behavior of  $Y$  for the given set of the explanatory variables.

The multiple linear model is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \epsilon$$

Diagram illustrating the components of the multiple linear regression equation:

- $Y$  is labeled **Data**.
- The regression terms  $\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k$  are collectively labeled **Model**.
- $\epsilon$  is labeled **Error**.

Where,  $\epsilon \sim N(0, \sigma_\epsilon)$  and the errors are independent from one another.



# The 4 Step Process for Multiple Regression:

Collect data for the response and all predictors.

**CHOOSE** a form of the model.

Select predictors; possible transform Y.

Choose any function of predictors.

**FIT** estimate the coefficients  $\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_k$ .

Estimate the residual standard error  $\hat{\sigma}_\epsilon$  (RMSE).

**Assess** the fit.

Test the overall fit: ANOVA,  $R^2$ .

Test individual predictors: t-test.

Examine residuals.

**USE** Predications, CI's, and PI's.

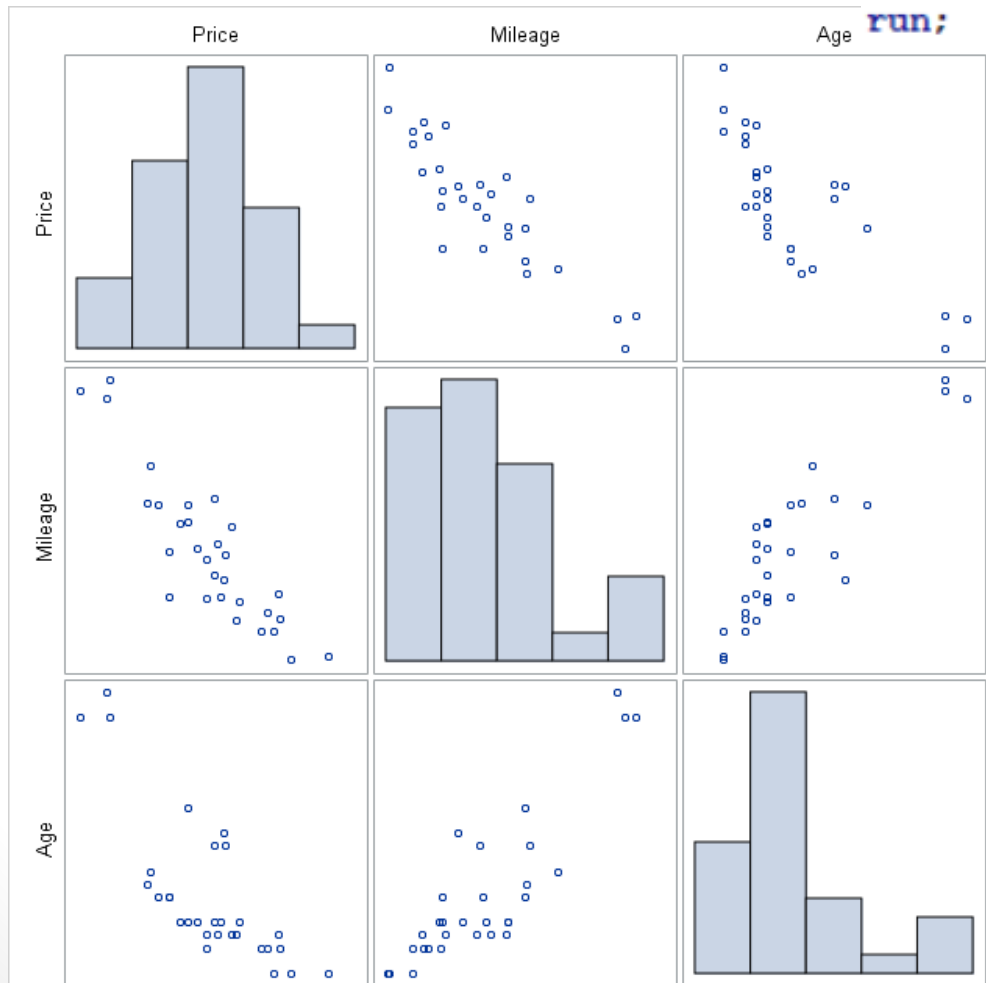


## Example 1: (*Porsche prices*)

For the same dataset *Porsche prices.csv*.

1. Using SAS, graph the scatterplot of the mileage vs. price and age.

```
proc corr plots = matrix(histogram);  
var price mileage age;  
run;
```



## 2. Using SAS, Calculate and interpret the correlation coefficients.

Pearson Correlation Coefficients, N = 30 Prob >  r  under H0: Rho=0			
	Price	Mileage	Age
Price	1.00000	-0.89135 <.0001	-0.78189 <.0001
Mileage	-0.89135 <.0001	1.00000	0.86313 <.0001
Age	-0.78189 <.0001	0.86313 <.0001	1.00000

- The correlation coefficient between the price and mileage is  $r = -0.89$ , so there is a strong negative relationship between them.
- The correlation coefficient between the price and age is  $r = -0.78$ , so there is a strong negative relationship between them.



3. State your hypotheses and interpret the p-values of the correlation coefficients.

$$H_0: \rho_{Y,X_1} = 0 \quad vs \quad H_1: \rho_{Y,X_1} \neq 0$$

$$H_0: \rho_{Y,X_2} = 0 \quad vs \quad H_1: \rho_{Y,X_2} \neq 0$$

**Decision:** Since  $p - value < 0.0001 < 0.05$  for the two predictors, so we reject  $H_0$ .

**Conclusion:** The correlation coefficient of the population doesn't equal to 0. Which means that there is a significant linear relationship between the mileage (or age) and the price.



#### 4. Fit the regression model.

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr >  t
Intercept	1	70.91916	2.48352	28.56	<.0001
Age	1	-0.13023	0.45684	-0.29	0.7778
Mileage	1	-0.56134	0.11407	-4.92	<.0001

The multiple linear regression model is:

$$\widehat{Price} = 70.92 - 0.13 \text{ Age} - 0.56 \text{ Mileage}$$





## 5. Interpret the regression coefficients.

- **Intercept:** The predicted price of a new car (0 year and 0 mile) is \$70,919.16.
- **Age coefficient:** For every additional 1 year, when the mileage held constant, the predicted price goes down by \$130.
- **Mileage coefficient:** For every additional 1000 miles, when the age held constant, the predicted price goes down by \$561.



6. What is the fitted (predicted) value of the price corresponding to 21,500 (21.5) miles and 3 years old.

$$\text{Price} = 70.91916 - 0.13023(3) - 0.56134(21.5) \\ = \$58.460$$

The predicted value of the price corresponding to 21,500 (21.5) miles and 3 years old is **\$58,460**.

7. What is the residual corresponding 21,500 (21.5) miles and 3 years old.

$$\text{residual} = \$69.4 - \$58.460 \\ = \$10.94$$



8. Using SAS, find the estimate for the standard error of the multiple regression.

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	5570.00389	2785.00195	52.39	<.0001
Error	27	1435.24577	53.15725		
Corrected Total	29	7005.24967			

*MSE*

Root MSE	7.29090	R-Square	0.7951
Dependent Mean	50.53667	Adj R-Sq	0.7799
Coeff Var	14.42695		

*$\sqrt{MSE}$*

$$\hat{\sigma}_{\epsilon} = \sqrt{MSE} = \sqrt{53.15725} = 7.29090$$

or

$$\hat{\sigma}_{\epsilon} = \sqrt{\frac{SSE}{n - k - 1}} = \sqrt{\frac{1435.24577}{30 - 2 - 1}} = \sqrt{\frac{1435.24577}{27}} = 7.29090$$



## 3.2 Assessing a Multiple Linear Regression Model:

### ANOVA for a Multiple Regression Model:

To test the effectiveness of the multiple regression linear model, the hypotheses are

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_k = 0$$

*vs*  $H_1: \text{at least one } \beta_i \neq 0$

Source of Variation	Degrees of Freedom	Sums of Squares	Mean Squares	F
Regression	k	SSR	MSR = SSR / k	MSR/ MSE
Residual	n-k-1	SSE	MSE=SSE/(n-k-1)	
Total	n-1	SST		

Number of  
predictors



## Example 2: (Porsche prices)

Interpret ANOVA table.

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	5570.00389	2785.00195	52.39	<.0001
Error	27	1435.24577	53.15725		
Corrected Total	29	7005.24967			

$$H_0: \beta_1 = \beta_2 = 0$$

*vs*  $H_1: \text{at least one } \beta_i \neq 0$

**Decision:** since  $p\text{-value} < 0.0001 < 0.05 = \alpha$ , so we reject  $H_0$

**Conclusion:** at least one of the predictors, mileage and age, has a significant effect for the explaining variability in price.



The question now is:

Do both predictor variables provide significant information about the price?

If not.

Which predictor variable is providing significant information about the price?

We can answer this question by using the individual t-test.



# Individual t-Test for Coefficients in Multiple Regression :

To test the coefficient for one of the predictors,  $X_i$ , in a multiple regression model, the hypotheses are

$$H_0: \beta_i = 0 \quad vs \quad H_1: \beta_i \neq 0, \quad i = 1, 2, \dots, k$$

and the test statistic is

$$t = \frac{\text{parameter estimate}}{\text{standard error of estimate}} = \frac{\hat{\beta}_i}{SE_{\hat{\beta}_i}}$$



### Example 3: (*Porsche prices*)

Test the hypotheses  $(\beta_1 = \beta_{age})$

$$H_0: \beta_1 = 0 \quad vs \quad H_1: \beta_1 \neq 0$$

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr >  t
Intercept	1	70.91916	2.48352	28.56	<.0001
Age	1	-0.13023	0.45684	-0.29	0.7778
Mileage	1	-0.56134	0.11407	-4.92	<.0001

**Decision:** since  $p\text{-value} = 0.7778 > 0.05 = \alpha$ , so we fail to reject  $H_0$ .

**Conclusion:** we do not have an evidence to say that the car age has a significant effect for the explaining variability in price.

**Note:** we should to drop the age from the model.





### Example 3: (*Porsche prices*)

The full model is

$$\widehat{Price} = 70.92 - 0.13 \text{ Age} - 0.56 \text{ Mileage}$$

The reduced model is

$$\widehat{Price} = 71.09 - 0.59 \text{ Mileage}$$

Note: if we fit a simple linear regression model between the price and the age, the relationship will be significant, but since the mileage by itself can fit the data well.



## Confidence Interval for a Multiple Regression Coefficients:

A confidence interval for the actual value of any multiple regression coefficient,  $\beta_i$ , has the form

$$\hat{\beta}_i \pm t^* . SE_{\hat{\beta}_i}$$

where the value of  $t^*$  is the critical value from t-table with degrees of freedom =  $n - k - 1$ .

The value of the standard error of the coefficient,  $SE_{\hat{\beta}_i}$ , is obtained from computer output.



## Example 4: (*Porsche prices*)

Find the 95% confidence interval for the population age and mileage coefficients.

Parameter Estimates							
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr >  t	95% Confidence Limits	
Intercept	1	70.91916	2.48352	28.56	<.0001	65.82341	76.01491
Age	1	-0.13023	0.45684	-0.29	0.7778	-1.06759	0.80714
Mileage	1	-0.56134	0.11407	-4.92	<.0001	-0.79538	-0.32729

The 95% confidence interval for the population age is

$$(-1.06759, 0.80714)$$

The 95% confidence interval for the population mileage is

$$(-0.79539, -0.32729)$$



## Coefficient of Multiple Determination:

The coefficient of determination,  $R^2$ , uses as a measure of the percentage of total variability in the response that is explained by the regression model.

$$R^2 = \frac{\text{Variability explained by the model}}{\text{Total variability in } Y}$$
$$= \frac{SS_{Model}}{SS_{Total}} = 1 - \frac{SSE}{SS_{Total}}$$

- In general, adding a new predictor will increase  $R^2$ .



## Adjusted Coefficient Determination :

The adjusted  $R^2$ , which helps account for the number of predictors in the model, is computed with

$$R_{adj}^2 = 1 - \frac{SSE / (n - k - 1)}{SSE / (n - 1)} = 1 - \frac{\hat{\sigma}_\epsilon^2}{S_Y^2}$$

- The  $R_{adj}^2$  value might go down when a weak predictor is added to a model.
- In general  $R_{adj}^2 \leq R^2$ .



### Example 4: (*Porsche prices*)

Find  $R^2$  and  $R_{adj}^2$  of the full model.

Root MSE	7.29090	R-Square	0.7951
Dependent Mean	50.53667	Adj R-Sq	0.7799
Coeff Var	14.42695		

$$R^2 = 0.7951 \approx 79.51\%$$

and

$$R_{adj}^2 = 0.7799 \approx 77.99\%$$

Can you explain why  $R_{adj}^2 < R^2$ ?

Because we add a weak variable to our model.



2. Determine a 95% confidence interval for the average price of Porsche with 50,000 mileage and 6 years old.

(\$37,469, \$46,673)

3. Determine a 95% prediction interval for the price of Porsche with 50,000 mileage and 6 years old.

(\$26,420, \$57,723 )



Obs	Price	Age	Mileage	predicted	Lower_Mean	Upper_Mean	Lower_Prediction	Upper_Prediction
31	.	6	50	42.0710	37.4692	46.6728	26.4195	57.7225

## Full model vs. reduced model:

- The full model contains all predictors (explanatory variables) listed in the dataset.
- The reduced model contains only the significant predictors.





# Reading Assignment

Read section 3.1 and 3.2

