One-Hot Encoding Multiple Linear Regression - Exercise

October 28, 2021

One-Hot Encoding for Multiple Linear Regression - Exercise

[41]:
```
# Import necessary package
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

0.0.1 Step 1: Load the dataset

[42]:
```
# Load the dataset into pandas dataframe
df = pd.read_csv("E:\\MY LECTURES\\DATA SCIENCE\\3.Programs\\dataset\\carprices.
↪csv")
# Change this location based on the location of dataset in your machine
```

[43]:
```
# Display the first five records
df
```

[43]:

	Car Model	Mileage	Sell Price($)	Age(yrs)
0	BMW X5	69000	18000	6
1	BMW X5	35000	34000	3
2	BMW X5	57000	26100	5
3	BMW X5	22500	40000	2
4	BMW X5	46000	31500	4
5	Audi A5	59000	29400	5
6	Audi A5	52000	32000	5
7	Audi A5	72000	19300	6
8	Audi A5	91000	12000	8
9	Mercedez Benz C class	67000	22000	6
10	Mercedez Benz C class	83000	20000	7
11	Mercedez Benz C class	79000	21000	7
12	Mercedez Benz C class	59000	33000	5

[44]:
```
# Dataset shape (number of rows and columns)
df.shape
```

[44]: (13, 4)

0.0.2 Step 2: Apply EDA

You may apply univariate and bivariate analysis

0.0.3 Step 3. Pre-process and extract the features

Unique values in the dataset

[45]:
```
df.nunique()
```

[45]:
```
Car Model         3
Mileage          12
Sell Price($)    13
Age(yrs)          7
dtype: int64
```

One hot encoding

[46]:
```
dummies = pd.get_dummies(df['Car Model'])
dummies
```

[46]:
```
    Audi A5  BMW X5  Mercedez Benz C class
0         0       1                      0
1         0       1                      0
2         0       1                      0
3         0       1                      0
4         0       1                      0
5         1       0                      0
6         1       0                      0
7         1       0                      0
8         1       0                      0
9         0       0                      1
10        0       0                      1
11        0       0                      1
12        0       0                      1
```

[47]:
```
# join dummies dataframe with df dataframe
merged_df = pd.concat([df,dummies],axis='columns')
merged_df
```

[47]:
```
                  Car Model  Mileage  Sell Price($)  Age(yrs)  Audi A5  BMW X5  \
0                    BMW X5    69000          18000         6        0       1
1                    BMW X5    35000          34000         3        0       1
2                    BMW X5    57000          26100         5        0       1
3                    BMW X5    22500          40000         2        0       1
4                    BMW X5    46000          31500         4        0       1
5                   Audi A5    59000          29400         5        1       0
```

```
6                 Audi A5    52000          32000          5        1       0
7                 Audi A5    72000          19300          6        1       0
8                 Audi A5    91000          12000          8        1       0
9   Mercedez Benz C class    67000          22000          6        0       0
10  Mercedez Benz C class    83000          20000          7        0       0
11  Mercedez Benz C class    79000          21000          7        0       0
12  Mercedez Benz C class    59000          33000          5        0       0

    Mercedez Benz C class
0                       0
1                       0
2                       0
3                       0
4                       0
5                       0
6                       0
7                       0
8                       0
9                       1
10                      1
11                      1
12                      1
```

categorical feature does not work so remove "Car Model" feature from the dataset as we have one hot encoding for that variable

[48]:
```
merged_df.drop('Car Model', axis=1, inplace=True)
```

[49]:
```
merged_df.head()
```

[49]:

	Mileage	Sell Price($)	Age(yrs)	Audi A5	BMW X5	Mercedez Benz C class
0	69000	18000	6	0	1	0
1	35000	34000	3	0	1	0
2	57000	26100	5	0	1	0
3	22500	40000	2	0	1	0
4	46000	31500	4	0	1	0

To avoid multi-collinearity among three dummy columns (SK-learn does it for you, but we can do this) Dummy Variable Trap

When you can derive one variable from other variables, they are known to be multi-colinear. Here if you know values of california and georgia then you can easily infer value of new jersey state, i.e. california=0 and georgia=0. There for these state variables are called to be multi-colinear. In this situation linear regression won't work as expected. Hence you need to drop one column.

NOTE: sklearn library takes care of dummy variable trap hence even if you don't drop one of the state columns it is going to work, however we should make a habit of taking care of dummy variable trap ourselves just in case library that you are using is not handling this for you

[50]:
```
merged_df.drop('Mercedez Benz C class', axis=1, inplace=True)
```

[51]:
```
merged_df.head()
```

[51]:

	Mileage	Sell Price($)	Age(yrs)	Audi A5	BMW X5
0	69000	18000	6	0	1
1	35000	34000	3	0	1
2	57000	26100	5	0	1
3	22500	40000	2	0	1
4	46000	31500	4	0	1

[52]:
```
merged_df.shape
```

[52]: (13, 5)

Swap the price feature to last position

[53]:
```
columns_titles = ["Mileage","Age(yrs)","Audi A5","BMW X5","Sell Price($)"]
df = merged_df.reindex(columns=columns_titles)
df.head()
```

[53]:

	Mileage	Age(yrs)	Audi A5	BMW X5	Sell Price($)
0	69000	6	0	1	18000
1	35000	3	0	1	34000
2	57000	5	0	1	26100
3	22500	2	0	1	40000
4	46000	4	0	1	31500

[54]:
```
# We are going to predict price using all the other features
# Load Price feature into Y and remaining features into X
X = df.iloc[:,:4].values
Y = df.iloc[:,4].values
```

0.0.4 Step 4. Split the data for training and testing

[55]:
```
# Splitting dataset into training and testing set
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size = 0.2,␣
↪random_state = 0)
```

0.0.5 Step 5: Training phase (bulding the model)

[56]:
```
# Fitting line on two dimension on the training set
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(x_train, y_train)
```

[56]:
```
LinearRegression()
```

[57]:
```
b = model.intercept_
```

[58]:
```
coef = model.coef_
```

[59]:
```
print("The linear model is Y = ", end = " ")
counter = 0
for i in coef:
    print(np.round(i,2),"*",columns_titles[counter], "+", end= " ")
    counter = counter + 1
print(np.round(b,2))
```

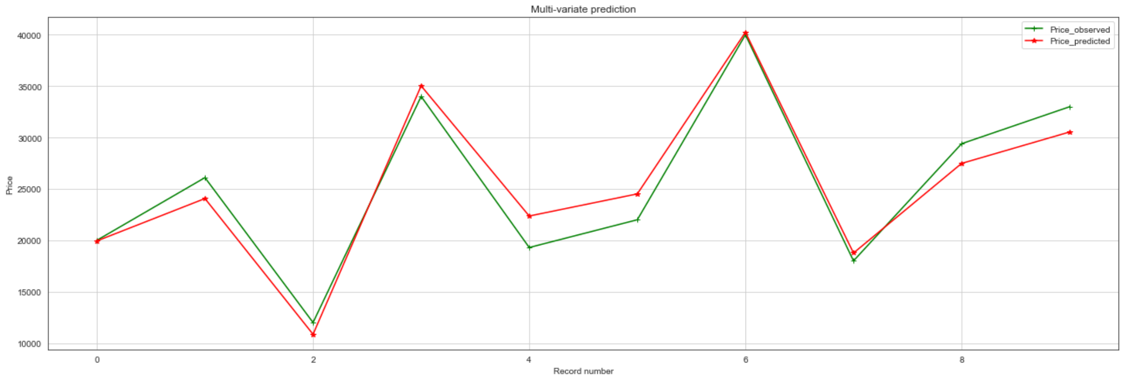
```
The linear model is Y =  0.18 * Mileage + -7474.11 * Age(yrs) + -3059.8 * Audi
A5 + -6116.02 * BMW X5 + 57232.34
```

[60]:
```
# Predicting the Training set results
y_train_pred = model.predict(x_train)
```

Visualizing the model It involves over 3 dimensions, so imagine yourself.

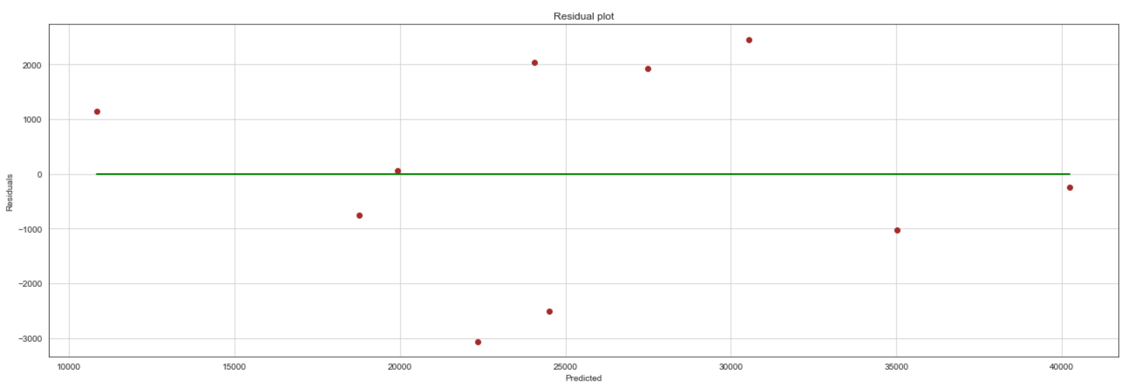
Plotting observed sale (x) and predicted sale (y) for training set

[61]:
```
# Predicting the Test set results (displaying only for 100 reocrds)
x = np.arange(len(y_train_pred))
fig = plt.figure(figsize=(22,7))
plt.plot(x,y_train[:100],"g-+",label="Price_observed")
plt.plot(x,y_train_pred[:100],"r-*",label="Price_predicted")
plt.grid(b=None)
plt.xlabel("Record number")
plt.ylabel("Price")
plt.title("Multi-variate prediction")
plt.legend()
plt.show()
```



Residual (Error) plot If the model has done good predictions, then the datapoints must be near around to horizontal line.

[62]:
```
sns.set_style(style='white')
fig = plt.figure(figsize=(22,7))
residuals = y_train-y_train_pred
zeros = y_train-y_train
plt.scatter(y_train_pred,residuals,color="brown")
plt.grid(b=None)
plt.plot(y_train_pred,zeros,"g")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.title("Residual plot")
plt.show()
```



0.0.6 Different error calculations to asses the model for training set

1. **Sum of Squared Error (SSE)**

$$SSE(m,b) = \sum_{i=1}^{n}(y_i - \hat{y})^2 = \sum_{i=1}^{n}(y_i - (m * x_i + b))^2 \tag{1}$$

[63]:
```
sum = 0
n = len(x_train)
for i in range (0,n):
  diff = y_train[i] - y_train_pred[i]
  squ_diff = diff**2
  sum = sum + squ_diff
Train_SSE = np.round(sum,2)
print("Sum of Squared Error (SSE) :",Train_SSE)
```

```
Sum of Squared Error (SSE) : 32587358.29
```

2. **Mean Squared Error (MSE)**

$$MSE(m,b) = \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n} = \frac{\sum_{i=1}^{n}(y_i - (m * x_i + b))^2}{n} \tag{2}$$

[64]:
```
Train_MSE = np.round(Train_SSE/n,2)
print("Mean Squared Error (MSE) :",Train_MSE)
```

```
Mean Squared Error (MSE) : 3258735.83
```

3. **Root Mean Squared Error (RMSE)**

$$RMSE(m,b) = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n}} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - (m * x_i + b))^2}{n}} \tag{3}$$

[65]:
```
Train_RMSE = np.round(np.sqrt(Train_MSE),2)
print("Root Mean Squared Error (RMSE) :",Train_RMSE)
```

```
Root Mean Squared Error (RMSE) : 1805.2
```

4. **Mean Absolute Error (MAE)**

$$MAE(m,b) = \frac{\sum_{i=1}^{n}|(y_i - \hat{y})|}{n} \tag{4}$$

[66]:
```
sum = 0
n = len(x_train)
for i in range (0,n):
  diff = y_train[i] - y_train_pred[i]
```

```
  sum = sum + np.abs(diff)
Train_MAE = np.round(sum/n,2)
print("Mean Absolute Error (MAE) :",Train_MAE)
```

```
Mean Absolute Error (MAE) : 1522.98
```

5. Mean Absolute Percentage Error (MAPE)

$$MAPE(m,b) = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{(y_i - \hat{y})}{y_i}\right| = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{(y_i - (m * x_i + b))}{y_i}\right| \tag{5}$$

[67]:
```
sum = 0
n = len(x_train)
for i in range (0,n):
  diff = (y_train[i] - y_train_pred[i])/y_train[i]
  sum = sum + np.abs(diff)
Train_MAPE = np.round(sum/n*100,2)
print("Mean Absolute Percentage Error (MAPE) :",Train_MAPE)
```

```
Mean Absolute Percentage Error (MAPE) : 6.68
```

0.0.7 Calculating R-Squred value (goodness of model) using SSE

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

[68]:
```
from sklearn.metrics import r2_score
out = r2_score(y_train,y_train_pred)
Train_RS = np.round(out,2)*100
print("R-Squred value (goodness of model) for training set :",Train_RS,"%")
```

```
R-Squred value (goodness of model) for training set : 95.0 %
```

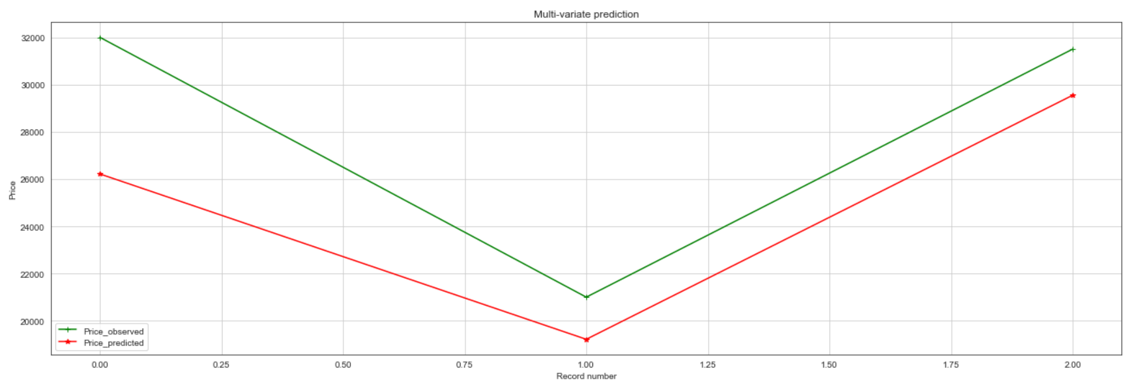
0.0.8 Step 6: Testing phase

[69]:
```
# Predicting values for test input set
y_test_pred = model.predict(x_test)
```

Visualizing the model It involves more than 3 dimensions, so imagine yourself

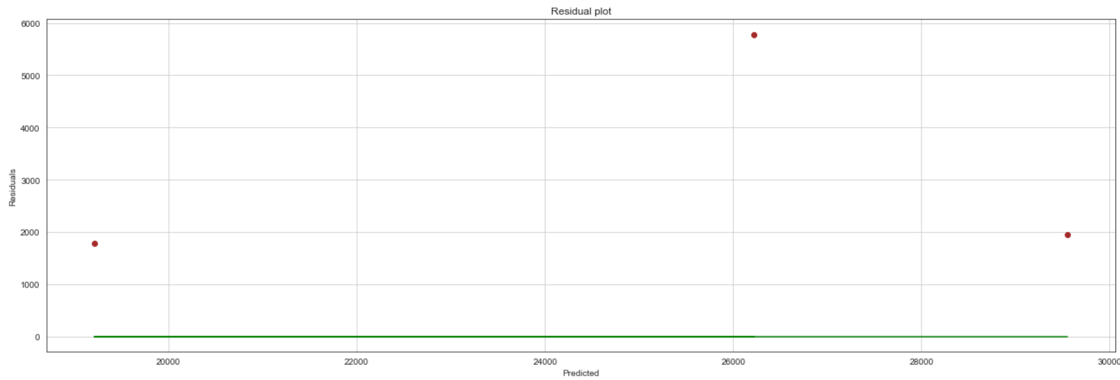
Plotting observed sale (x) and predicted sale (y) for test set

[70]:
```
# Plotting the predicted values
x = np.arange(len(y_test_pred))
fig = plt.figure(figsize=(22,7))
plt.plot(x,y_test,"g-+",label="Price_observed")
plt.plot(x,y_test_pred,"r-*",label="Price_predicted")
plt.grid(b=None)
plt.xlabel("Record number")
plt.ylabel("Price")
plt.title("Multi-variate prediction")
plt.legend()
plt.show()
```



Residual (Error) plot If the model has done good predictions, then the datapoints must be near around to horizontal line.

[71]:
```
sns.set_style(style='white')
fig = plt.figure(figsize=(22,7))
residuals = y_test-y_test_pred
zeros = y_test-y_test
plt.scatter(y_test_pred,residuals,color="brown")
plt.grid(b=None)
plt.plot(y_test_pred,zeros,"g")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.title("Residual plot")
plt.show()
```



0.0.9 Different error calculations to asses the model for the test set

1. Sum of Squared Error (SSE)

$$SSE(m,b) = \sum_{i=1}^{n}(y_i - \hat{y})^2 = \sum_{i=1}^{n}(y_i - (m * x_i + b))^2 \tag{7}$$

[72]:
```
sum = 0
n = len(x_test)
for i in range (0,n):
  diff = y_test[i] - y_test_pred[i]
  squ_diff = diff**2
  sum = sum + squ_diff
Test_SSE = np.round(sum,2)
print("Sum of Squared Error (SSE) :",Test_SSE)
```

```
Sum of Squared Error (SSE) : 40450871.58
```

2. Mean Squared Error (MSE)

$$MSE(m,b) = \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n} = \frac{\sum_{i=1}^{n}(y_i - (m * x_i + b))^2}{n} \tag{8}$$

[73]:
```
Test_MSE = np.round(Train_SSE/n,2)
print("Mean Squared Error (MSE) :",Test_MSE)
```

```
Mean Squared Error (MSE) : 10862452.76
```

3. Root Mean Squared Error (RMSE)

$$RMSE(m,b) = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n}} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - (m * x_i + b))^2}{n}} \tag{9}$$

[74]:
```python
Test_RMSE = np.round(np.sqrt(Test_MSE),2)
print("Root Mean Squared Error (RMSE) :",Test_RMSE)
```

```
Root Mean Squared Error (RMSE) : 3295.82
```

4. Mean Absolute Error (MAE)

$$MAE(m,b) = \frac{\sum_{i=1}^{n} |(y_i - \hat{y})|}{n} \tag{10}$$

[75]:
```python
sum = 0
n = len(x_test)
for i in range (0,n):
  diff = y_test[i] - y_test_pred[i]
  sum = sum + np.abs(diff)
Test_MAE = np.round(sum/n,2)
print("Mean Absolute Error (MAE) :",Test_MAE)
```

```
Mean Absolute Error (MAE) : 3173.61
```

5. Mean Absolute Percentage Error (MAPE)

$$MAPE(m,b) = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{(y_i - \hat{y})}{y_i} \right| = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{(y_i - (m * x_i + b))}{y_i} \right| \tag{11}$$

[76]:
```python
sum = 0
n = len(x_test)
for i in range (0,n):
  diff = (y_test[i] - y_test_pred[i])/y_test[i]
  sum = sum + np.abs(diff)
Test_MAPE = np.round(sum/n*100,2)
print("Mean Absolute Percentage Error (MAPE) :",Test_MAPE)
```

```
Mean Absolute Percentage Error (MAPE) : 10.92
```

0.0.10 Calculating R-Squred value (goodness of model) using SSE

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{12}$$

[77]:
```python
from sklearn.metrics import r2_score
out = r2_score(y_test,y_test_pred)
Test_RS = np.round(out,2)*100
print("R-Squred value (goodness of model) for testing set :",Test_RS,"%")
```

```
R-Squred value (goodness of model) for testing set : 48.0 %
```

0.0.11 Step 7. Underfitting and overfitting observation

[78]:
```
print("Error \t From training phase       From testing phase ")
print("====================================================")
print("SSE   \t\t",Train_SSE,"\t\t", Test_SSE)
print("MSE   \t\t",Train_MSE,"\t\t", Test_MSE)
print("RMSE   \t\t",Train_RMSE,"\t\t", Test_RMSE)
print("MAE   \t\t",Train_MAE,"\t\t", Test_MAE)
print("RS   \t\t",Train_RS,"\t\t\t", Test_RS)
```

```
Error    From training phase       From testing phase
====================================================
SSE              32587358.29             40450871.58
MSE              3258735.83              10862452.76
RMSE             1805.2                  3295.82
MAE              1522.98                 3173.61
RS               95.0                    48.0
```

0.0.12 Step 8. Let us predict for future inputs

Price of mercedez benz that is 4 yr old with mileage 45000? pass input as 45000,4,0,0 (the dropped feature (Price of mercedez benz) is taken as 1).

[79]:
```
model.predict([[45000,4,0,0]])
```

[79]:
```
array([35482.61265574])
```

Price of BMW X5 that is 7 yr old with mileage 86000? pass input as 86000,7,0,1 (the dropped feature (Price of mercedez benz) is taken as 0).

[80]:
```
model.predict([[86000,7,0,1]])
```

[80]:
```
array([14366.82569264])
```