1.One-Hot Encoding Multiple Linear Regression

October 28, 2021

One-Hot Encoding for Multiple Linear Regression - Without SK-Learn

[46]:
```
# 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

[47]:
```
# Load the dataset into pandas dataframe
df = pd.read_csv("E:\\MY LECTURES\\DATA SCIENCE\\3.
↪Programs\\dataset\\house_price.csv")
# Change this location based on the location of dataset in your machine
```

[48]:
```
# Display the first five records
df
```

[48]:

	town	area	price
0	monroe township	2600	550000
1	monroe township	3000	565000
2	monroe township	3200	610000
3	monroe township	3600	680000
4	monroe township	4000	725000
5	west windsor	2600	585000
6	west windsor	2800	615000
7	west windsor	3300	650000
8	west windsor	3600	710000
9	robinsville	2600	575000
10	robinsville	2900	600000
11	robinsville	3100	620000
12	robinsville	3600	695000

[49]:
```
# Dataset shape (number of rows and columns)
df.shape
```

[49]: (13, 3)

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

[50]:
```
df.nunique()
```

[50]:
```
town      3
area      9
price    13
dtype: int64
```

One hot encoding

[51]:
```
dummies = pd.get_dummies(df.town)
dummies
```

[51]:

	monroe township	robinsville	west windsor
0	1	0	0
1	1	0	0
2	1	0	0
3	1	0	0
4	1	0	0
5	0	0	1
6	0	0	1
7	0	0	1
8	0	0	1
9	0	1	0
10	0	1	0
11	0	1	0
12	0	1	0

[52]:
```
# join dummies dataframe with df dataframe
merged_df = pd.concat([df,dummies],axis='columns')
merged_df
```

[52]:

	town	area	price	monroe township	robinsville	west windsor
0	monroe township	2600	550000	1	0	0
1	monroe township	3000	565000	1	0	0
2	monroe township	3200	610000	1	0	0
3	monroe township	3600	680000	1	0	0
4	monroe township	4000	725000	1	0	0
5	west windsor	2600	585000	0	0	1
6	west windsor	2800	615000	0	0	1

7	west windsor	3300	650000	0	0	1
8	west windsor	3600	710000	0	0	1
9	robinsville	2600	575000	0	1	0
10	robinsville	2900	600000	0	1	0
11	robinsville	3100	620000	0	1	0
12	robinsville	3600	695000	0	1	0

categorical feature does not work with numerical prediction. So, remove "town" feature as we have one hot encoding for that variable

[53]:
```
merged_df.drop('town', axis=1, inplace=True)
```

[54]:
```
merged_df.head()
```

[54]:

	area	price	monroe township	robinsville	west windsor
0	2600	550000	1	0	0
1	3000	565000	1	0	0
2	3200	610000	1	0	0
3	3600	680000	1	0	0
4	4000	725000	1	0	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. Therefore, 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

[55]:
```
merged_df.drop('monroe township', axis=1, inplace=True)
```

[56]:
```
merged_df.head()
```

[56]:

	area	price	robinsville	west windsor
0	2600	550000	0	0
1	3000	565000	0	0
2	3200	610000	0	0
3	3600	680000	0	0
4	4000	725000	0	0

[57]:
```
merged_df.shape
```

[57]: (13, 4)

Swap the price feature to last position

[58]:
```
columns_titles = ["area","robinsville","west windsor","price"]
df = merged_df.reindex(columns=columns_titles)
df.head()
```

[58]:

	area	robinsville	west windsor	price
0	2600	0	0	550000
1	3000	0	0	565000
2	3200	0	0	610000
3	3600	0	0	680000
4	4000	0	0	725000

[59]:
```
# We are going to predict price using all the other features
# Load Price feature into Y and remaining features into X
X = df.iloc[:,:3].values
Y = df.iloc[:,3].values
```

0.0.4 Step 4. Split the data for training and testing

[60]:
```
# 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)

[61]:
```
# Fitting line on two dimension on the training set
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(x_train, y_train)
```

[61]:
```
LinearRegression()
```

[62]:
```
b = model.intercept_
```

[63]:
```
coef = model.coef_
```

[64]:
```
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))
```

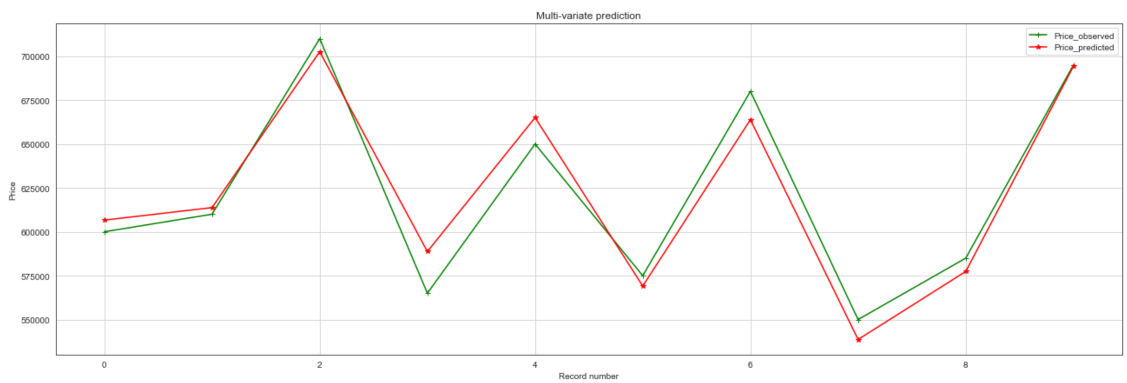
```
The linear model is Y =  125.21 * area + 30430.79 * robinsville + 38735.88 *
west windsor + 213093.22
```

[65]:
```python
# 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

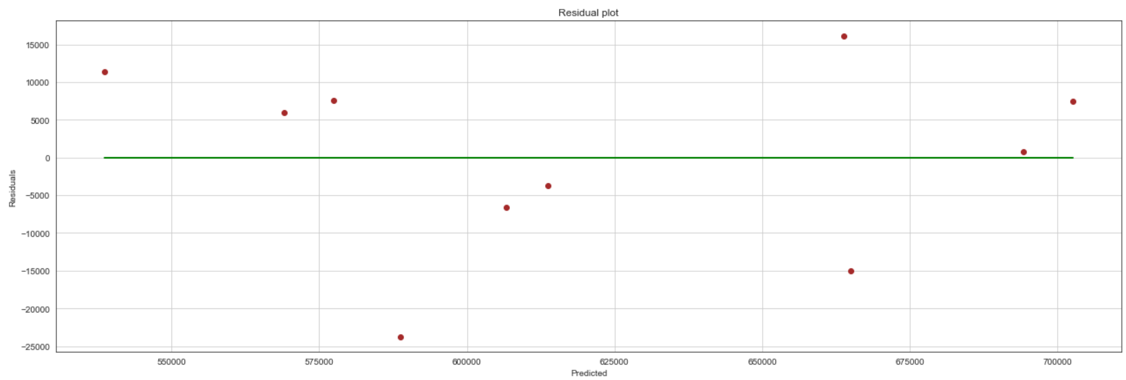
[66]:
```python
# Predicting the Test set results (displaying only for 100 reocrds)
x = np.arange(len(y_train_pred))
fig = plt.figure(figsize=(22,7))
plt.plot(x,y_train[:100],"g-+",label="Price_observed")
plt.plot(x,y_train_pred[:100],"r-*",label="Price_predicted")
plt.grid(b=None)
plt.xlabel("Record 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.

[67]:
```python
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)

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

[68]:
```
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) : 1385346045.2
```

2. Mean Squared Error (MSE)

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

[69]:
```
Train_MSE = np.round(Train_SSE/n,2)
print("Mean Squared Error (MSE) :",Train_MSE)
```

```
Mean Squared Error (MSE) : 138534604.52
```

3. Root Mean Squared Error (RMSE)

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

[70]:
```
Train_RMSE = np.round(np.sqrt(Train_MSE),2)
print("Root Mean Squared Error (RMSE) :",Train_RMSE)
```

```
Root Mean Squared Error (RMSE) : 11770.07
```

4. Mean Absolute Error (MAE)

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

[71]:
```
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) : 9833.33
```

5. Mean Absolute Percentage Error (MAPE)

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

[72]:
```
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) : 1.62
```

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

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

[73]:
```
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 %
```

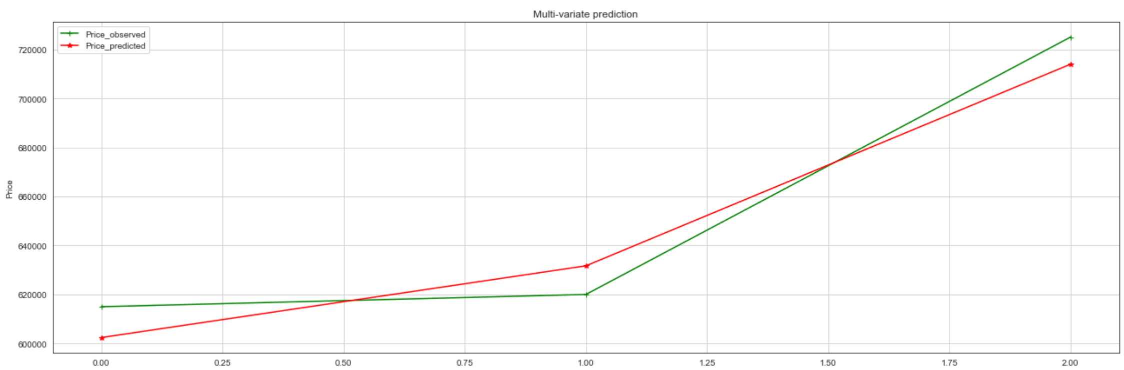
0.0.8 Step 6: Testing phase

[74]:
```
# 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

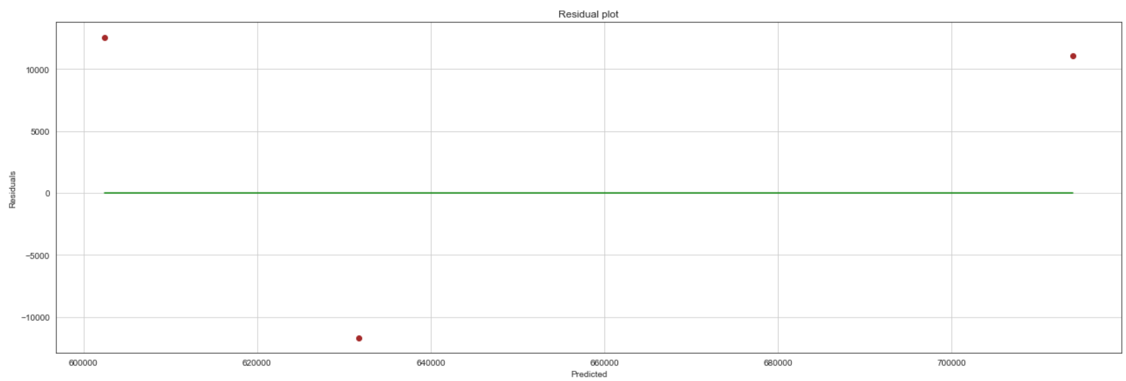
Plotting observed sale (x) and predicted sale (y) for test set

[75]:
```
# 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.

[76]:
```
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)

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

[77]:
```
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) : 416947606.45
```

2. Mean Squared Error (MSE)

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

[78]:
```
Test_MSE = np.round(Train_SSE/n,2)
print("Mean Squared Error (MSE) :",Test_MSE)
```

```
Mean Squared Error (MSE) : 461782015.07
```

3. Root Mean Squared Error (RMSE)

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

[79]:
```
Test_RMSE = np.round(np.sqrt(Test_MSE),2)
print("Root Mean Squared Error (RMSE) :",Test_RMSE)
```

```
Root Mean Squared Error (RMSE) : 21489.11
```

4. Mean Absolute Error (MAE)

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

[80]:
```
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) : 11772.6
```

5. Mean Absolute Percentage Error (MAPE)

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

[81]:
```
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) : 1.82
```

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

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

[82]:
```
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 : 95.0 %
```

0.0.11 Step 7. Underfitting and overfitting observation

[83]:
```
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              1385346045.2           416947606.45
MSE              138534604.52           461782015.07
RMSE             11770.07               21489.11
MAE              9833.33                11772.6
RS               95.0                   95.0
```

0.0.12 Step 8. Let us predict for future inputs

How much is the house price for 3200 square feet in monroe township? pass input as 3200,0,0 (third feature (monroe township) we dropped is taken as 1, in this case).

[84]:
```
model.predict([[3200,0,0]])
```

[84]:
```
array([613771.18644068])
```

How much is the house price for 2800 square feet in robinsvill? pass input as 2800,1,0 (third feature (monroe township) is taken as 0).

```
[85]: model.predict([[2800,1,0]])
```

```
[85]: array([594117.23163842])
```

How much is the house price for 3400 square feet in west windsor? pass input as 3400,0,1 (third feature (monroe township) we dropped is taken as 0).

```
[86]: model.predict([[3400,0,1]])
```

```
[86]: array([677549.43502825])
```