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I'd: 9134

```
In [53]:
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
         import numpy as np
In [54]: #Reading csv_file
         df = pd.read_csv("carprices.csv")
In [16]: df.head()
Out[16]:
            Car Model Mileage Sell Price($) Age(yrs)
             BMW X5
          0
                      69000
                                 18000
                                            6
             BMW X5
          1
                      35000
                                 34000
                                            3
                                            5
          2
             BMW X5
                      57000
                                 26100
          3
             BMW X5
                      22500
                                 40000
                                            2
             BMW X5
                      46000
                                 31500
                                            4
         #converting string data to numeric using one hot Encoding
In [17]:
         carmodel = pd.get_dummies(df[['Car Model']], drop_first= True)
         carmodel.head()
Out[17]:
            0
                          1
                                                    0
                                                    0
                          1
          1
                                                    0
                                                    0
          3
```

0

1

```
In [18]: #Now merging
data = pd.concat([df, carmodel ], axis = 1)
data.head()
```

Out[18]:

	Car Model	Mileage	Sell Price(\$)	Age(yrs)	Car Model_BMW X5	Car Model_Mercedez Benz C class
0	BMW X5	69000	18000	6	1	0
1	BMW X5	35000	34000	3	1	0
2	BMW X5	57000	26100	5	1	0
3	BMW X5	22500	40000	2	1	0
4	BMW X5	46000	31500	4	1	0

```
In [19]: categorical_features = ['Car Model']
```

```
In [20]: data = data.drop(columns=categorical_features, axis=1)
    data.head()
```

Out[20]:

	Mileage	Sell Price(\$)	Age(yrs)	Car Model_BMW X5	Car Model_Mercedez Benz C class
0	69000	18000	6	1	0
1	35000	34000	3	1	0
2	57000	26100	5	1	0
3	22500	40000	2	1	0
4	46000	31500	4	1	0

```
In [23]: Y = data['Sell Price($)']
X = data.drop('Sell Price($)', axis=1)
```

```
In [25]: #LinearRegression
    from sklearn.linear_model import LinearRegression
    lm = LinearRegression()
    lm.fit(trainX, trainY)
```

```
HAMMAD IDS ASSIGNMENT 2
In [26]:
         Lm predict = lm.predict(testX)
         print("Prediction Using Linear Regression for test set: {}".format(Lm predict))
         Prediction Using Linear Regression for test set: [19630.09708738 26418.44660194
         28458.25242718 11600.
         data diff = pd.DataFrame({'Actual value': testY, 'Predicted value': Lm predict})
In [27]:
          data diff.head()
Out[27]:
              Actual value Predicted value
          10
                   20000
                          19630.097087
           5
                   29400
                          26418.446602
           9
                   22000
                          28458.252427
           8
                   12000
                          11600.000000
         #Performance Measurement of Linear Regression
In [28]:
         from sklearn import metrics
         meanAbErr = metrics.mean absolute error(testY, Lm predict)
         meanSqErr = metrics.mean_squared_error(testY, Lm_predict)
         rootMeanSqErr = np.sqrt(metrics.mean squared error(testY, Lm predict))
          print('R squared: {:.2f}'.format(lm.score(X,Y)*100))
         print('Mean Absolute Error:', meanAbErr)
          print('Mean Square Error:', meanSqErr)
          print('Root Mean Square Error:', rootMeanSqErr)
         R squared: 91.64
         Mean Absolute Error: 2552.4271844660216
         Mean Square Error: 12723878.310868148
         Root Mean Square Error: 3567.0545707723827
In [29]: #Implementing Decision Tree
          from sklearn.tree import DecisionTreeClassifier
         decision = DecisionTreeClassifier(random_state=1)
          decision.fit(trainX, trainY)
```

```
Out[29]: DecisionTreeClassifier(class weight=None, criterion='gini', max depth=None,
                     max features=None, max leaf nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min samples leaf=1, min samples split=2,
                     min weight fraction leaf=0.0, presort=False, random state=1,
                     splitter='best')
```

```
In [30]:
         descision predict = decision.predict(testX)
         print("Prediction Using Decision for test set: {}".format(descision_predict))
```

Prediction Using Decision for test set: [21000 26100 33000 19300]

```
In [31]: data_diff = pd.DataFrame({'Actual value': testY, 'Predicted value':descision_pred
data_diff.head()
```

Out[31]:

	Actual value	Predicted value
10	20000	21000
5	29400	26100
9	22000	33000
8	12000	19300

```
In [32]: #Performance Measurement of Decision
    from sklearn import metrics
    meanAbErr = metrics.mean_absolute_error(testY,descision_predict)
    meanSqErr = metrics.mean_squared_error(testY, descision_predict)
    rootMeanSqErr = np.sqrt(metrics.mean_squared_error(testY, descision_predict))
    print('R squared: {:.2f}'.format(decision.score(X,Y)*100))
    print('Mean Absolute Error:', meanAbErr)
    print('Mean Square Error:', meanSqErr)
    print('Root Mean Square Error:', rootMeanSqErr)
```

R squared: 69.23

Mean Absolute Error: 5650.0 Mean Square Error: 46545000.0

Root Mean Square Error: 6822.389610686273

```
In [33]: # Implementing KNN
from sklearn.neighbors import KNeighborsClassifier
```

kc = KNeighborsClassifier()
kc.fit(trainX, trainY)

```
In [34]: KN_predict = kc.predict(testX)
    print("Prediction Using KNN for test set: {}".format(KN_predict))
```

Prediction Using KNN for test set: [18000 18000 18000 18000]

```
In [35]: data_diff = pd.DataFrame({'Actual value': testY, 'Predicted value':KN_predict})
data_diff.head()
```

Out[35]:

	Actual value	Predicted value
10	20000	18000
5	29400	18000
9	22000	18000
8	12000	18000

```
In [36]: #Performance Measurement of KNN
    from sklearn import metrics
    meanAbErr = metrics.mean_absolute_error(testY,KN_predict)
    meanSqErr = metrics.mean_squared_error(testY, KN_predict)
    rootMeanSqErr = np.sqrt(metrics.mean_squared_error(testY, KN_predict))
    print('R squared: {:.2f}'.format(kc.score(X,Y)*100))
    print('Mean Absolute Error:', meanAbErr)
    print('Mean Square Error:', meanSqErr)
    print('Root Mean Square Error:', rootMeanSqErr)
```

R squared: 7.69

Mean Absolute Error: 5850.0 Mean Square Error: 46490000.0

Root Mean Square Error: 6818.357573492314

```
In [37]: #now calculating the accuracy
print(f'Linear Model Test Accuracy: {lm.score(trainX, trainY)}')
print(f'Decision Model Test Accuracy: {decision.score(trainX, trainY)}')
print(f'KNN Model Test Accuracy: {kc.score(trainX, trainY)}')
```

Linear Model Test Accuracy: 0.9709843743171688

Decision Model Test Accuracy: 1.0

KNN Model Test Accuracy: 0.1111111111111111

```
In [38]: print(f'Linear Model Accuracy: {lm.score(testX,Lm_predict)*100}%')
    print(f'Decision Tree Model Accuracy: {decision.score(testX, descision_predict)*:
    print(f'KNN Model Accuracy: {kc.score(testX,KN_predict)*100}%')
```

Linear Model Accuracy: 100.0%

Decision Tree Model Accuracy: 100.0%

KNN Model Accuracy: 100.0%

ANSWER NO "3D Objects"

#as above data shows that:

#linear model:best fit we can accept this

#Decision model:best fit we can accept this

#KNN model:overifit

Question No 2

```
In [44]: import pandas as pd
          import matplotlib.pyplot as plt
          import seaborn as sns
          import numpy as np
In [45]: df = pd.read csv("Q2data.csv")
         df
Out[45]:
             x1 x2
                      x3 x4
          0 6.5 8.6 NaN
          1 1.2 5.0
                     5.2
                          9
          2 4.0 2.0
                     8.7
                          5
          3 3.2 3.6
                     7.3
                          1
            5.2 7.1 NaN
                          3
          5 7.3 2.0
                     6.4
          6 5.5 4.1 NaN
                          5
In [46]: print("Correlation of X1 and X3:",df.x1.corr(df.x3))
         print("Correlation of X2 and X3:",df.x2.corr(df.x3))
         print("Correlation of X4 and X3:",df.x4.corr(df.x3))
         Correlation of X1 and X3: 0.24802925080387372
         Correlation of X2 and X3: -0.6964857161414854
         Correlation of X4 and X3: -0.6218855518005906
In [47]: df1 = df
         df1 = df1.dropna()
          df1
Out[47]:
             x1 x2 x3 x4
          1 1.2 5.0 5.2
          2 4.0 2.0 8.7
          3 3.2 3.6 7.3
                        1
          5 7.3 2.0 6.4
In [48]: train_X = np.array([1.2,4.0,3.2,7.3])
         train Y = np.array([5.2, 8.7, 7.3, 6.4])
```

```
HAMMAD IDS ASSIGNMENT 2
In [49]:
         from sklearn.linear model import LinearRegression
          regression = LinearRegression()
         regression.fit(train_X.reshape(-1,1),train_Y)
Out[49]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                   normalize=False)
In [50]: test_X = np.array([6.5,5.2,5.5])
In [51]:
         test Y = regression.predict(test X.reshape(-1,1))
         print(test_Y)
         df
         [7.27132704 7.08386096 7.12712237]
Out[51]:
             x1 x2
                      x3 x4
          0 6.5 8.6
                     NaN
          1 1.2 5.0
                     5.2
                          9
          2 4.0 2.0
                      8.7
                          5
          3 3.2 3.6
                     7.3
                          1
          4 5.2 7.1 NaN
                          3
          5 7.3 2.0
                          8
                      6.4
          6 5.5 4.1 NaN
                          5
In [52]: result = pd.DataFrame({'x1':[6.5,1.2,4.0,3.2,5.2,7.3,5.5],
                                  'x2':[8.6,5.0,2.0,3.6,7.1,2.0,4.1],
                                  'x3':[7.2,5.2,8.7,7.3,7.0,6.4,7.1],
                                  'x4':[4,9,5,1,3,8,5]})
         result
Out[52]:
             x1 x2 x3 x4
          0 6.5 8.6 7.2
          1 1.2 5.0 5.2
                         9
          2 4.0 2.0 8.7
          3 3.2 3.6 7.3
                        1
```

4 5.2 7.1 7.0 **5** 7.3 2.0 6.4 **6** 5.5 4.1 7.1