Multiple Linear Regression

In [1]:
```
#Import libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
%matplotlib inline
```

In [2]:
```
# Import data file

dataset=pd.read_csv('insurance.csv')

dataset.head()
```

Out[2]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

Encoding categorical data

In [3]:
```
objList = dataset.select_dtypes(include = "object").columns
print (objList)
```

```
Index(['sex', 'smoker', 'region'], dtype='object')
```

In [4]:
```
#Label Encoding for object to numeric conversion
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

for feat in objList:
    dataset[feat] = le.fit_transform(dataset[feat].astype(str))

print (dataset.info())

dataset.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1338 non-null   int64  
 1   sex       1338 non-null   int64  
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64  
 4   smoker    1338 non-null   int64  
 5   region    1338 non-null   int64  
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(5)
memory usage: 73.3 KB
None
```

Out[4]:

	age	sex	bmi	children	smoker	region	charges
0	19	0	27.900	0	1	3	16884.92400
1	18	1	33.770	1	0	2	1725.55230
2	28	1	33.000	3	0	2	4449.46200
3	33	1	22.705	0	0	1	21984.47061
4	32	1	28.880	0	0	1	3866.85520

Create X and y arrays

In [5]:
```
# Create X set and y set. They are arrays and vectors
#X=dataset.iloc[:,0].values
X=dataset.iloc[:,:-1].values
print(X)
y=dataset.iloc[:,-1].values

print(y)
```

```
[[19.    0.   27.9   0.    1.    3.  ]
 [18.    1.   33.77  1.    0.    2.  ]
 [28.    1.   33.    3.    0.    2.  ]
 ...
 [18.    0.   36.85  0.    0.    2.  ]
 [21.    0.   25.8   0.    0.    3.  ]
 [61.    0.   29.07  0.    1.    1.  ]]
[16884.924   1725.5523  4449.462  ...  1629.8335  2007.945  29141.3603]
```

Creating Training and Test Data Sets

In [6]:
```
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=44)
```

Training Multiple Linear Regression on Training set

In [7]:
```
from sklearn.linear_model import LinearRegression #Calling LinearRegression Class
regressor=LinearRegression() #Creating an object of LinearRegression
regressor.fit(X_train, y_train) #Method of the linear regression class

#Note: LinearRegression Class takes care of Dummy Variable trap
```

Out[7]:
```
LinearRegression()
```

Note: Backward elimination is irrelevant because the Scikit-Learn library automatically takes care of selecting the statistically significant features when training the model to make accurate predictions.

Predicting Test set results

In [8]:
```
y_pred=regressor.predict(X_test) # Predicting values on test data
#print(y_pred)
```

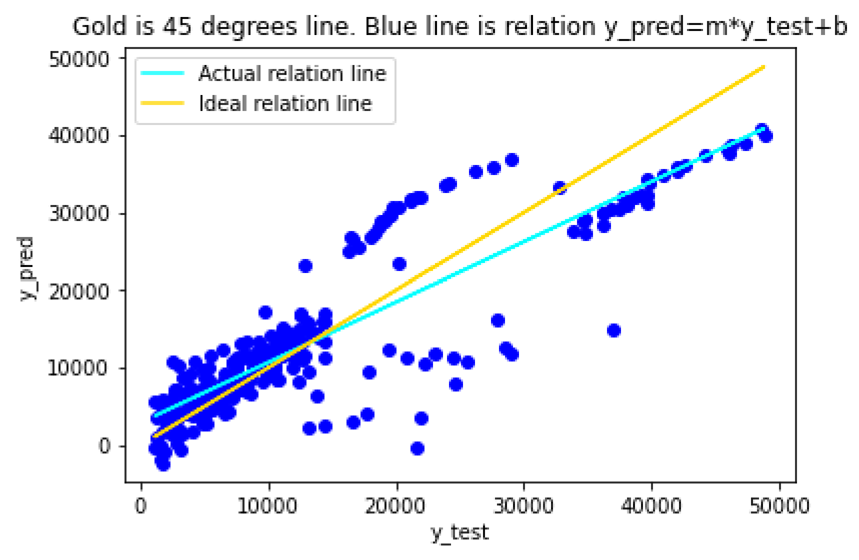
In [9]:
```
np.set_printoptions(precision=2)
#  To display with two decimal points all printed values
```

In [10]:
```
#print(np.concatenate((y_pred.reshape(len(y_pred),1),
#y_test.reshape(len(y_test), 1)),axis=1))
#Concatenate both y_pred and y_test as column vectors
```

Representation of Y_pred vs Y_test in simple scatter plot and line representation.

The gold line represents an ideal match between "measuring devices" The blue line represents the actual match between Y_pred and Y_test.

In [11]:
```
plt.scatter(y_test, y_pred,  color='blue')
m, b = np.polyfit(y_test, y_pred, 1) # 1 is the degree of the polynomial to fit.
plt.plot(y_test, m*y_test+b, color='cyan', label="Actual relation line")
plt.plot(y_test, y_test, color='gold', label="Ideal relation line")
plt.title("Gold is 45 degrees line. Blue line is relation y_pred=m*y_test+b")
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.legend()
plt.show()
print("Slope: m=","{:.2f}".format(m))
print("Intercept: b=","{:.2f}".format(b))
```




```
Slope: m= 0.78
Intercept: b= 2924.65
```

Calculating Regression model's precision (Aspect Ratio: AR)

In [12]:
```
#Estimating correlation coefficient and R^2 between Y_pred and Y_test

correlation_matrix = np.corrcoef(y_test, y_pred)
correlation_xy = correlation_matrix[0,1]
r_squared = correlation_xy**2
print("R-squared between y_pred and y_test: ", "{:.2f}".format(r_squared))
```

```
R-squared between y_pred and y_test:  0.75
```

In [13]:
```
# Aspect ratio calculation (precision)
AR=(1-correlation_xy)**(0.5-1)
print(" 'Aspect Ratio': ", "{:.2f}".format(AR))
```

```
 'Aspect Ratio':  2.76
```

A good correlation coefficient is >=0.98, yielding an aspect ratio of 7 to 1 (minimum suggested when comparing a measuring device (y_test or the regression model) against a master measuring device (y_test).

Obtaining model coefficients

In [14]:
```
# Obtaining the model equation
print(regressor.coef_)
print(regressor.intercept_)
```

```
[  254.21  -233.99   345.45   502.46 23966.6   -344.46]
-12095.637432727546
```

Explained variance score for Multiple Regression

The Explained Variance Score (EVS) best possible value is 1.0. Lower values are worse.

$$EVS = 1 - \frac{var(y_{test} - y_{pred})}{var(y_{test})}$$

In [15]:
```
from sklearn.metrics import explained_variance_score
EVS=explained_variance_score(y_test, y_pred, multioutput='uniform_average')
print("EVS: ","{:.2f}".format(EVS))
```

```
EVS:  0.75
```