Importing Libraries:

In [4]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from yellowbrick.regressor import ResidualsPlot
```

In [5]:
```
#!pip install yellowbrick
```

Loading Dataframe:

In [6]:
```
dataframe = pd.read_csv(r"C:\Users\Dev Patel\Desktop\Materials\Linear Regression\1000_C
dataframe
```

Out[6]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.800	471784.1000	New York	192261.83000
1	162597.70	151377.590	443898.5300	California	191792.06000
2	153441.51	101145.550	407934.5400	Florida	191050.39000
3	144372.41	118671.850	383199.6200	New York	182901.99000
4	142107.34	91391.770	366168.4200	Florida	166187.94000
...	...	...	...	...	...
995	54135.00	118451.999	173232.6695	California	95279.96251
996	134970.00	130390.080	329204.0228	California	164336.60550
997	100275.47	241926.310	227142.8200	California	413956.48000
998	128456.23	321652.140	281692.3200	California	333962.19000
999	161181.72	270939.860	295442.1700	New York	476485.43000

1000 rows × 5 columns

Preprocessing Data:

In [7]:
```
dataframe.index
```

Out[7]:
```
RangeIndex(start=0, stop=1000, step=1)
```

In [8]:
```
len(dataframe)
```

Out[8]:
```
1000
```

In [9]:
```
dataframe.describe()
```

Out[9]:

	R&D Spend	Administration	Marketing Spend	Profit
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	81668.927200	122963.897612	226205.058419	119546.164656
std	46537.567891	12613.927535	91578.393542	42888.633848
min	0.000000	51283.140000	0.000000	14681.400000
25%	43084.500000	116640.684850	150969.584600	85943.198543
50%	79936.000000	122421.612150	224517.887350	117641.466300
75%	124565.500000	129139.118000	308189.808525	155577.107425
max	165349.200000	321652.140000	471784.100000	476485.430000

Looking at the table above, we can say that there are no outliers in any column as the mean and median for every column is almost the same.

Checking the datatypes of each column:

In [10]:
```
dataframe.dtypes
```

Out[10]:
```
R&D Spend          float64
Administration     float64
Marketing Spend    float64
State               object
Profit             float64
dtype: object
```

Checking if there are any null values:

In [11]:
```
dataframe.isna().sum()
```

Out[11]:
```
R&D Spend          0
Administration     0
Marketing Spend    0
State              0
Profit             0
dtype: int64
```

There are no null values.

Looking at the columns, state column appears to have only 3 values in repetition. To confirm this:

In [12]:
```
dataframe.columns
```

Out[12]:
```
Index(['R&D Spend', 'Administration', 'Marketing Spend', 'State', 'Profit'], dtype='obje
ct')
```

In [13]:
```
dataframe.State.unique()
```

Out[13]:
```
array(['New York', 'California', 'Florida'], dtype=object)
```

Confirm that there are only 3 values in repetition in State Column.

Encoding to State Column to Numbers:

In [14]:
```
dataframe.State = dataframe.State.astype('category')
```

In [15]:
```
dataframe.dtypes
```

Out[15]:
```
R&D Spend           float64
Administration      float64
Marketing Spend     float64
State              category
Profit              float64
dtype: object
```

In [16]:
```
dataframe.State = dataframe.State.cat.codes
```

In [17]:
```
dataframe.head(10)
```

Out[17]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	2	192261.83
1	162597.70	151377.59	443898.53	0	191792.06
2	153441.51	101145.55	407934.54	1	191050.39
3	144372.41	118671.85	383199.62	2	182901.99
4	142107.34	91391.77	366168.42	1	166187.94
5	131876.90	99814.71	362861.36	2	156991.12
6	134615.46	147198.87	127716.82	0	156122.51
7	130298.13	145530.06	323876.68	1	155752.60
8	120542.52	148718.95	311613.29	2	152211.77
9	123334.88	108679.17	304981.62	0	149759.96

Extracting Features and Target Variable:

In [18]:
```
X = dataframe.iloc[:,:-1]
y = dataframe.iloc[:,-1]
```

In [19]:
```
X.head(10)
```

Out[19]:

	R&D Spend	Administration	Marketing Spend	State
0	165349.20	136897.80	471784.10	2
1	162597.70	151377.59	443898.53	0
2	153441.51	101145.55	407934.54	1
3	144372.41	118671.85	383199.62	2
4	142107.34	91391.77	366168.42	1
5	131876.90	99814.71	362861.36	2
6	134615.46	147198.87	127716.82	0
7	130298.13	145530.06	323876.68	1
8	120542.52	148718.95	311613.29	2
9	123334.88	108679.17	304981.62	0

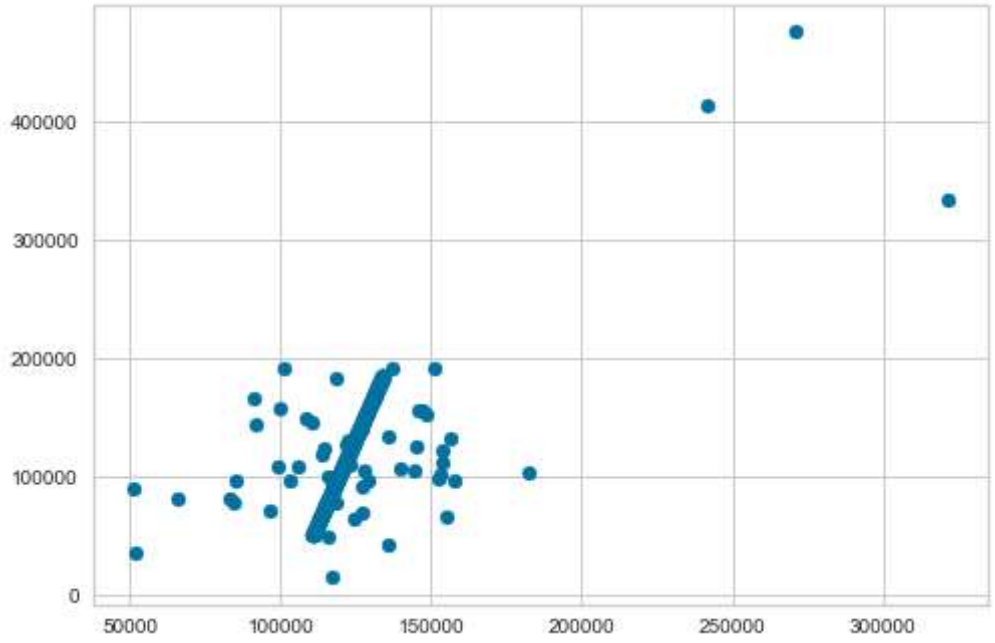
In [20]:
```
y.head(10)
```

Out[20]:
```
0    192261.83
1    191792.06
2    191050.39
3    182901.99
4    166187.94
5    156991.12
6    156122.51
7    155752.60
8    152211.77
9    149759.96
Name: Profit, dtype: float64
```

Checking Linear Relationship:

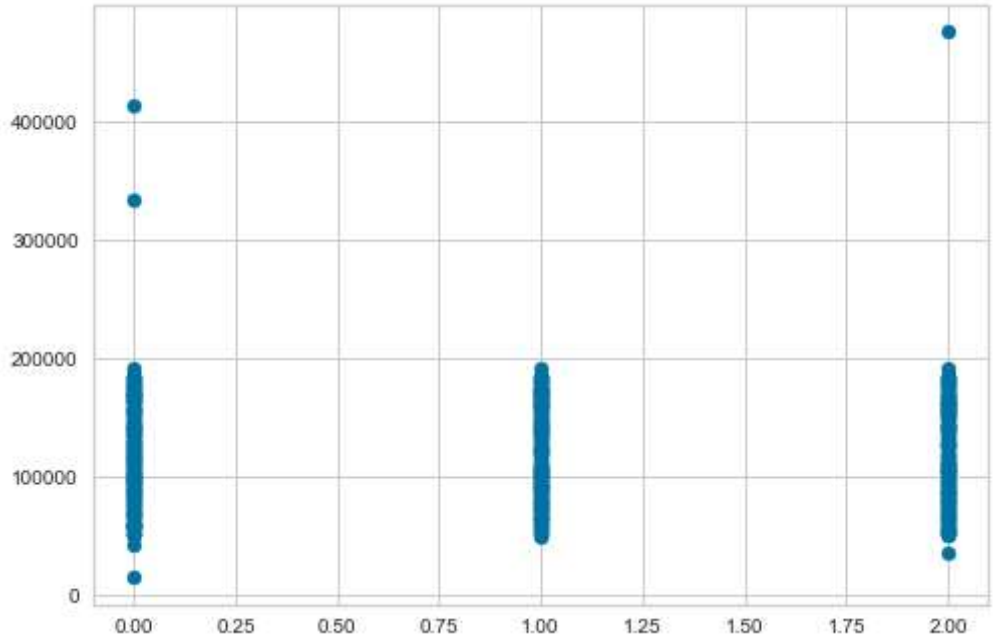
In [21]:
```
plt.scatter(dataframe.Administration, y)
```

Out[21]:
```
<matplotlib.collections.PathCollection at 0x22ee73276a0>
```



In [22]:
```
plt.scatter(dataframe.State, y)
```

Out[22]:
```
<matplotlib.collections.PathCollection at 0x22ee729b1c0>
```

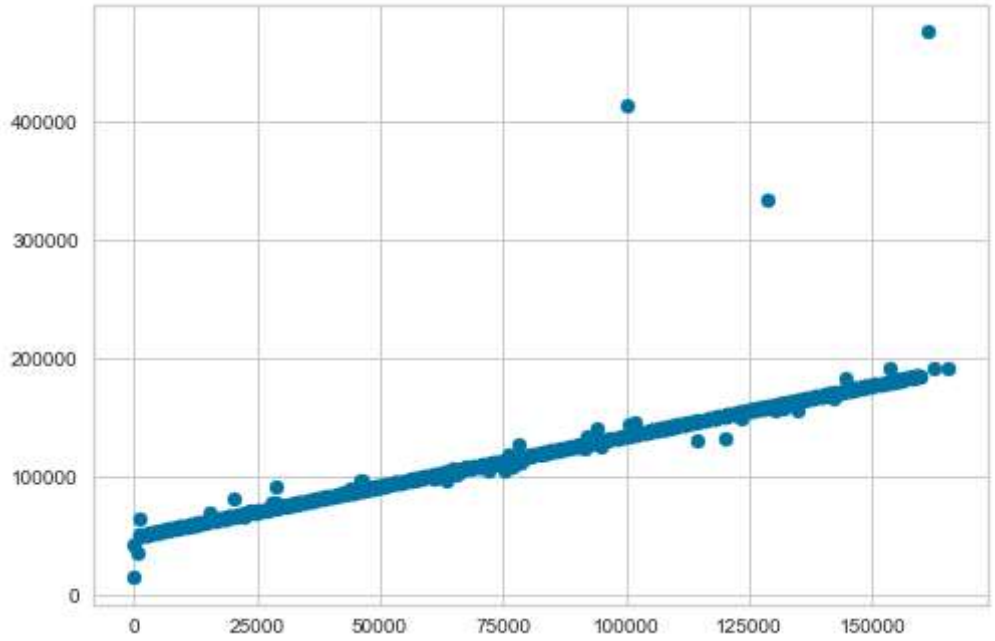


In [23]:
```
dataframe.columns
```

Out[23]:
```
Index(['R&D Spend', 'Administration', 'Marketing Spend', 'State', 'Profit'], dtype='obje
ct')
```

In [24]:
```
plt.scatter(dataframe['R&D Spend'], y)
```

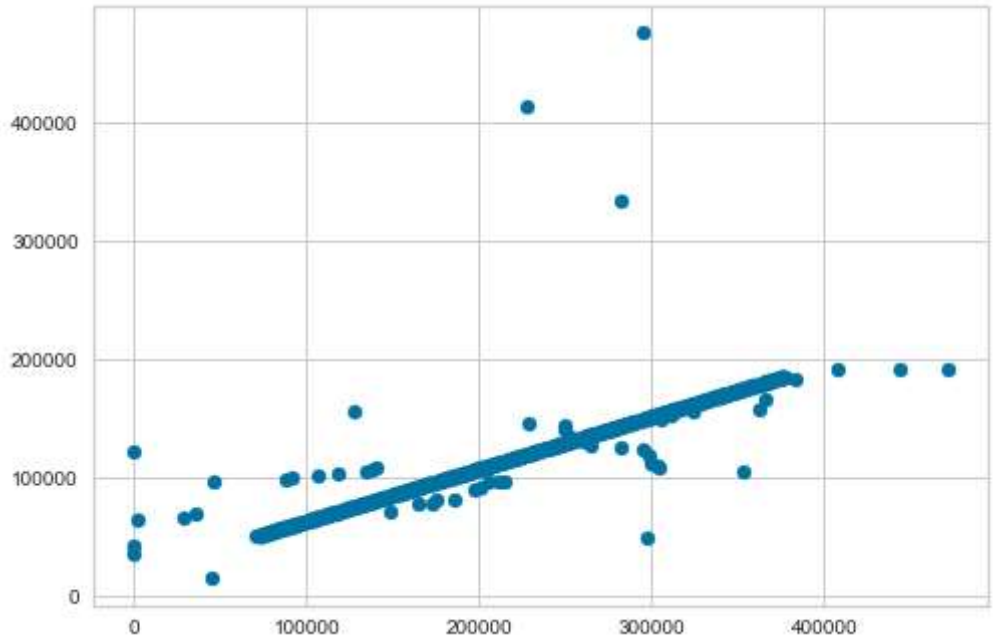
Out[24]:
```
<matplotlib.collections.PathCollection at 0x22ee73f6370>
```



Little Colinearity between R&D Spend and Profit.

In [25]:
```
plt.scatter(dataframe['Marketing Spend'], y)
```

Out[25]:
```
<matplotlib.collections.PathCollection at 0x22ee72bac40>
```



Little Colinearity between Marketing Spend and Profit.

Checking the Correlation between Features and Target:

In [26]:
```
dataframe.corr()
```

Out[26]:

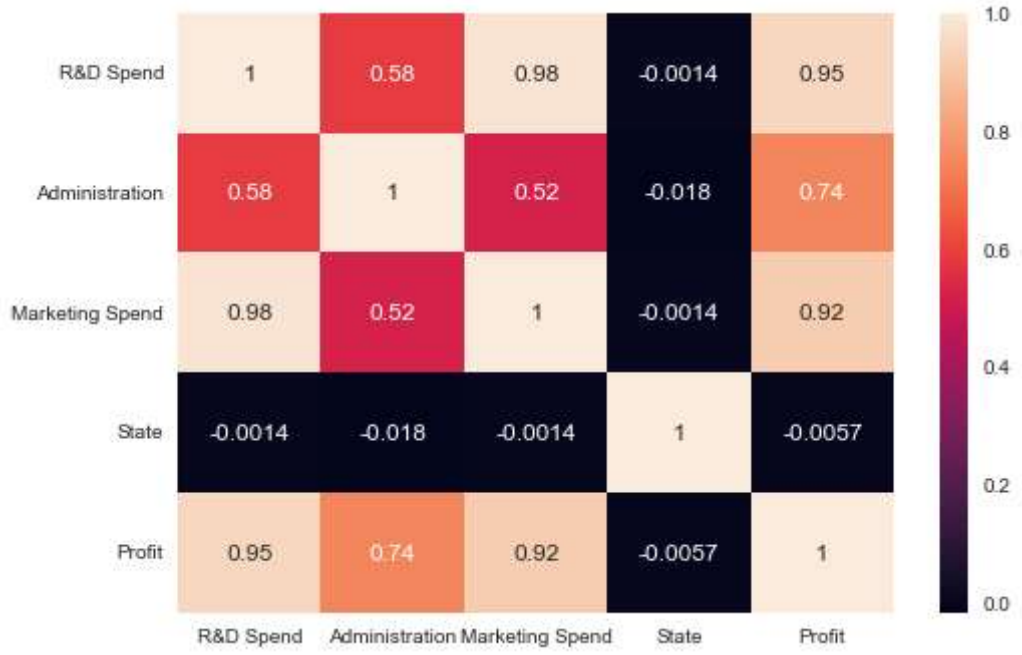
	R&D Spend	Administration	Marketing Spend	State	Profit
R&D Spend	1.000000	0.582434	0.978407	-0.001360	0.945245
Administration	0.582434	1.000000	0.520465	-0.018386	0.741560
Marketing Spend	0.978407	0.520465	1.000000	-0.001420	0.917270
State	-0.001360	-0.018386	-0.001420	1.000000	-0.005718
Profit	0.945245	0.741560	0.917270	-0.005718	1.000000

In [27]:

```
sns.heatmap(dataframe.corr(), annot=True)
```

Out[27]:

```
<AxesSubplot:>
```



Homoscedasticity Assumption:

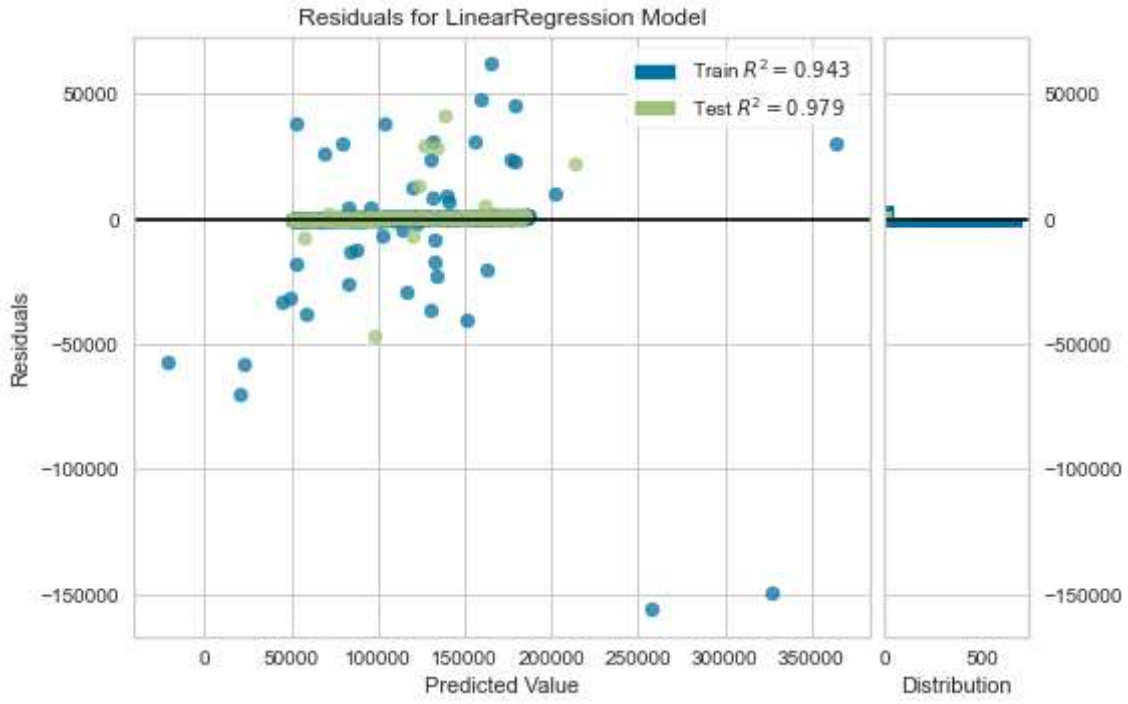
In [28]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state =
```

In [29]:

```
model = LinearRegression()
visualizer = ResidualsPlot(model)

visualizer.fit(X_train, y_train)
visualizer.score(X_test, y_test)
visualizer.poof()
```



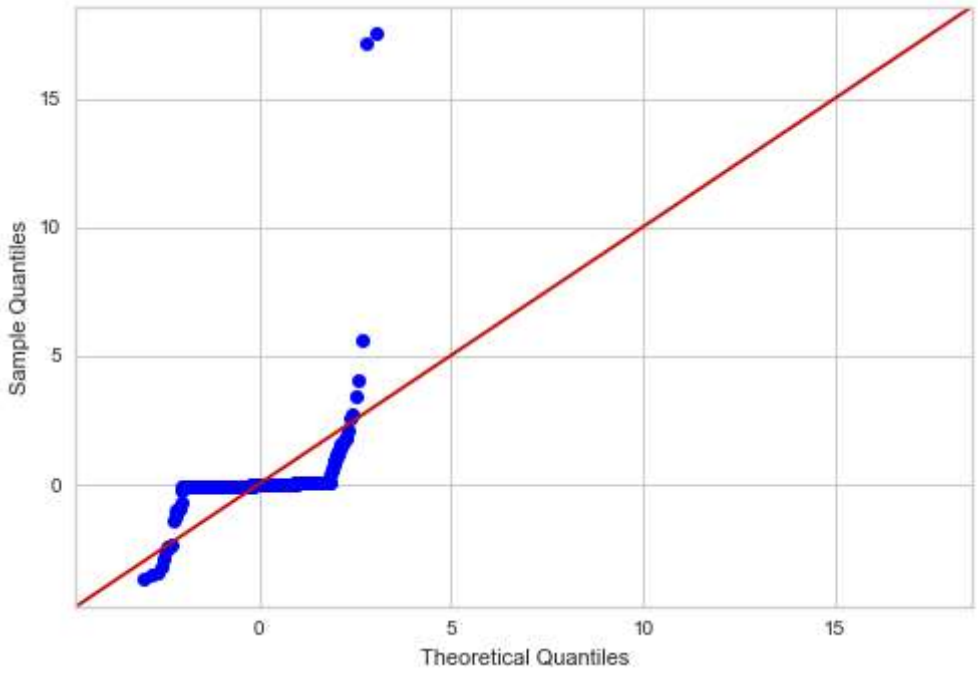
Out[29]:
```
<AxesSubplot:title={'center':'Residuals for LinearRegression Model'}, xlabel='Predicted
Value', ylabel='Residuals'>
```

In the above visualisation, the train and test data are randomly distributed => which means it is good to go ahead.

Normal distribution of error terms

In [30]:
```
lin_reg = sm.OLS(y_train,X_train).fit()
res = lin_reg.resid
sm.qqplot(res, fit = True, line = '45')
plt.show()
```

```
C:\Users\Dev Patel\anaconda3\lib\site-packages\statsmodels\graphics\gofplots.py:993: Use
rWarning: marker is redundantly defined by the 'marker' keyword argument and the fmt str
ing "bo" (-> marker='o'). The keyword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)
```



In [31]:
```
lin_reg.summary()
```

Out[31]:

OLS Regression Results

Dep. Variable:	Profit	**R-squared (uncentered):**	0.991
Model:	OLS	**Adj. R-squared (uncentered):**	0.991
Method:	Least Squares	**F-statistic:**	2.144e+04
Date:	Sun, 13 Feb 2022	**Prob (F-statistic):**	0.00
Time:	12:12:25	**Log-Likelihood:**	-8656.2
No. Observations:	800	**AIC:**	1.732e+04
Df Residuals:	796	**BIC:**	1.734e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
R&D Spend	0.9867	0.039	25.081	0.000	0.909	1.064
Administration	0.5337	0.014	36.870	0.000	0.505	0.562
Marketing Spend	-0.1117	0.020	-5.522	0.000	-0.151	-0.072
State	-762.6233	514.819	-1.481	0.139	-1773.187	247.941

Omnibus:	1508.998	**Durbin-Watson:**	1.998
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1734702.454
Skew:	13.180	**Prob(JB):**	0.00
Kurtosis:	229.597	**Cond. No.**	3.40e+05

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 3.4e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Training the Model:

In [32]:
```
len(X_train),len(X_test),len(y_train),len(y_test)
```

Out[32]:
```
(800, 200, 800, 200)
```

Fitting the model:

In [33]:
```
linearmodel = LinearRegression()
linearmodel.fit(X_train,y_train)
```

Out[33]:
```
LinearRegression()
```

Predicting the values for Features test values:

In [1]:
```
y_pred = linearmodel.predict(X_test)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
C:\Users\DEVPAT~1\AppData\Local\Temp/ipykernel_13644/1832318632.py in <module>
----> 1 y_pred = linearmodel.predict(X_test)

NameError: name 'linearmodel' is not defined
```

Evaluating the Model:

In [35]:
```
from sklearn.metrics import r2_score
```

In [36]:
```
r2_score(y_test,y_pred)
```

Out[36]:
```
0.9792310863532366
```

finding coefficients and intercepts

In [37]:
```
# coefficient
print(linearmodel.coef_)
```

```
[4.97816006e-01 1.08546691e+00 1.05643653e-01 1.59613600e+02]
```

In [38]:
```
# intercepts
print(linearmodel.intercept_)
```

```
-78458.73743377237
```

Final Prediction:

In [39]:
```
lin_reg.predict([[150000,100000,250000,2],[30000,45000,233333,2]])
```

Out[39]:
```
array([171922.51147406,  26029.5945345 ])
```

Training the Model without R&D Spend:

In [40]:
```
X1 = dataframe.iloc[:,1:-1]
X1.head(10)
```

Out[40]:

	Administration	Marketing Spend	State
0	136897.80	471784.10	2
1	151377.59	443898.53	0
2	101145.55	407934.54	1
3	118671.85	383199.62	2
4	91391.77	366168.42	1
5	99814.71	362861.36	2
6	147198.87	127716.82	0
7	145530.06	323876.68	1
8	148718.95	311613.29	2
9	108679.17	304981.62	0

In [41]:
```
X1_train, X1_test, y1_train, y1_test = train_test_split(X1,y, test_size=0.2)
```

In [42]:
```
model = LinearRegression()

model.fit(X1_train,y1_train)
```

Out[42]:
```
LinearRegression()
```

In [43]:
```
y1_pred = model.predict(X1_test)
```

In [44]:
```
r2_score(y1_test,y1_pred)
```

Out[44]:
```
0.9211781183122325
```

Training the Model without Marketing Spend:

In [45]:
```
X2 = X.drop('Marketing Spend', axis=1)
```

In [46]:
```
X2.head(10)
```

Out[46]:

	R&D Spend	Administration	State
0	165349.20	136897.80	2
1	162597.70	151377.59	0
2	153441.51	101145.55	1
3	144372.41	118671.85	2
4	142107.34	91391.77	1
5	131876.90	99814.71	2
6	134615.46	147198.87	0
7	130298.13	145530.06	1
8	120542.52	148718.95	2
9	123334.88	108679.17	0

In [47]:
```
X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y, test_size=0.2)
```

In [48]:
```
model2 = LinearRegression()

model2.fit(X2_train, y2_train)
```

Out[48]:
```
LinearRegression()
```

In [49]:
```
y2_pred = model2.predict(X2_test)
```

In [50]:
```
r2_score(y2_test, y2_pred)
```

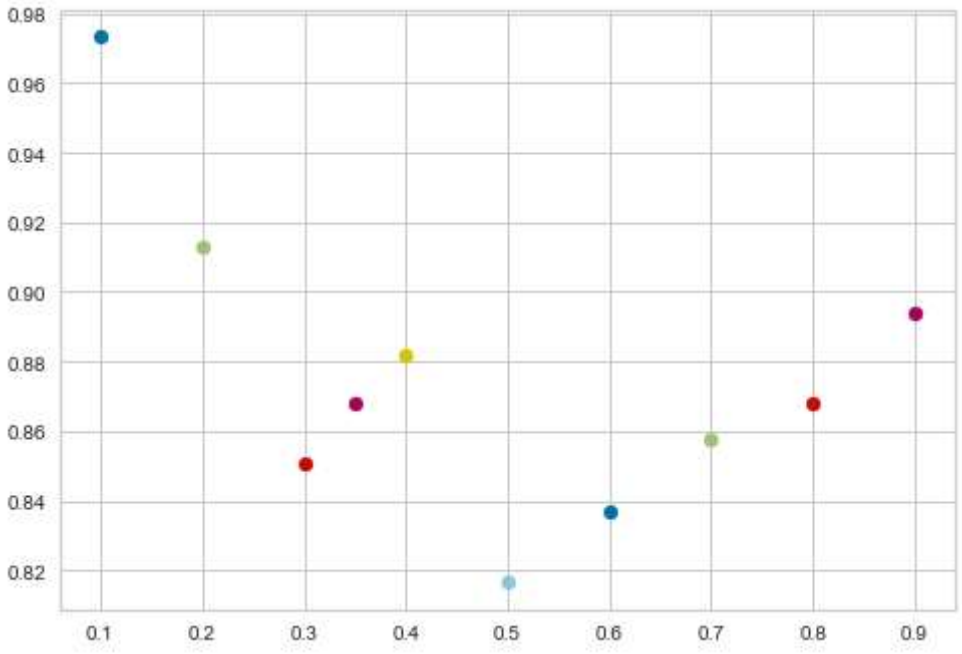
Out[50]:
```
0.988851143760152
```

In [51]:
```
def LinearRegressor(test_size):
    X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y, test_size=test_size,

    model2 = LinearRegression()
    model2.fit(X2_train, y2_train)
    y2_pred = model2.predict(X2_test)
    return r2_score(y2_test, y2_pred)
```

In [52]:
```
list_ = [0.1,0.2,0.3,0.35,0.4,0.5,0.6,0.7,0.8,0.9]
```

```
for i in list_:
    plt.scatter(i,LinearRegressor(i))
```



In [53]:
```
r2_score(y, lin_reg.predict(X))
```

Out[53]:
```
0.9339935246599163
```

Decision Tree Regressor:

In [54]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [55]:
```
tree = DecisionTreeRegressor()
tree.fit(X_train, y_train)
r2_score(y_test, tree.predict(X_test))
```

Out[55]:
```
0.9862867264984755
```

In [56]:
```
#plt.plot(X, tree.predict(X), color='blue')
#plt.scatter(X, y, color='red')
#plt.title('Decision Tree Regressor')
#plt.ylabel('Profit ->')
#plt.xlabel('Target Variables ->')
#plt.show()
```

In [57]:
```
r2_score(y, tree.predict(X))
```

Out[57]:
```
0.9976690643272643
```

Random Forest Regressor:

In [58]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [59]:
```
forest = RandomForestRegressor()
forest.fit(X_train, y_train)
r2_score(y_test, forest.predict(X_test))
```

Out[59]:
```
0.9955505845654864
```

In [60]:
```
r2_score(y, forest.predict(X))
```

Out[60]:
```
0.995488027301464
```

Polynomial Regressor:

In [61]:
```
from sklearn.preprocessing import PolynomialFeatures
```

In [62]:
```
poly = PolynomialFeatures(degree=2)
X_poly = poly.fit_transform(X_train)
```

In [63]:
```
poly_model = LinearRegression()
poly_model.fit(X_poly, y_train)
r2_score(y_test, poly_model.predict(poly.fit_transform(X_test)))
```

Out[63]:
```
0.9905687672513792
```

In [64]:
```
r2_score(y, poly_model.predict(poly.fit_transform(X)))
```

Out[64]:
```
0.9722350096001151
```

Ridge Regression:

In [65]:
```
from sklearn.linear_model import Ridge
```

In [66]:
```
ridge = Ridge()
ridge.fit(X_train, y_train)
y_pred = ridge.predict(X_test)
r2_score(y_test, y_pred)
```

Out[66]:
```
0.9792312362782487
```

In [67]:

```
r2_score(y,ridge.predict(X))
```

Out[67]:
```
0.9496128845755906
```

Lasso Regression:

In [68]:
```
from sklearn.linear_model import Lasso
```

In [69]:
```
lasso = Lasso()
lasso.fit(X_train, y_train)
r2_score(y_test, lasso.predict(X_test))
```

Out[69]:
```
0.9792318392627924
```

In [70]:
```
r2_score(y,lasso.predict(X))
```

Out[70]:
```
0.9496129864576205
```