Startup Profit Prediction

April 8, 2025

1 Linear Regression model for Prediction of Startup price

[63]:
```python
# import the important libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

[65]:
```python
# load dataset
df = pd.read_csv('50_Startups.csv')
```

[67]:
```python
df.head()
```

[67]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94

[69]:
```python
# information of the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   R&D Spend        50 non-null     float64
 1   Administration   50 non-null     float64
 2   Marketing Spend  50 non-null     float64
 3   State            50 non-null     object
 4   Profit           50 non-null     float64
dtypes: float64(4), object(1)
memory usage: 2.1+ KB
```

[70]:
```python
# summary statistics
df.describe()
```

[70]:

	R&D Spend	Administration	Marketing Spend	Profit
count	50.000000	50.000000	50.000000	50.000000
mean	73721.615600	121344.639600	211025.097800	112012.639200
std	45902.256482	28017.802755	122290.310726	40306.180338
min	0.000000	51283.140000	0.000000	14681.400000
25%	39936.370000	103730.875000	129300.132500	90138.902500
50%	73051.080000	122699.795000	212716.240000	107978.190000
75%	101602.800000	144842.180000	299469.085000	139765.977500
max	165349.200000	182645.560000	471784.100000	192261.830000

Data Description The independent variables(x) used in this dataset are R&D spending, Administration and Marketing Spending. The dependent variable(y) is Profit.

```
No missing values.

All numerical features are floats.

State is a categorical variable → needs encoding.

R&D Spend shows a strong spread and likely has a direct influence on Profit
```

[74]:
```
# checking the missing values
df.isnull().sum()
```

[74]:
```
R&D Spend          0
Administration     0
Marketing Spend    0
State              0
Profit             0
dtype: int64
```

1.1 Encoding Categorical Variable and Split the Data

```
Encode State using one-hot encoding (because it's categorical).
Separate features (x) and target (y).
Split the data into training and testing sets.
```

[118]:
```
# One-hot encode the 'State' column
data_encoded = pd.get_dummies(df, columns=['State'], drop_first=True)

# Features and Target
x = data_encoded.drop('Profit', axis=1)   # independent feature
y = data_encoded['Profit']                # Dependent feature (target variable)
```

[120]:
```
# tarin-test split
from sklearn.model_selection import train_test_split
```

[126]:
```
# Train-Test Split (80% train, 20% test)
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2,␣
↪random_state=42)
```

[128]:
```
x_test
```

[128]:

	R&D Spend	Administration	Marketing Spend	State_Florida	State_New York
13	91992.39	135495.07	252664.93	False	False
39	38558.51	82982.09	174999.30	False	False
30	61994.48	115641.28	91131.24	True	False
45	1000.23	124153.04	1903.93	False	True
17	94657.16	145077.58	282574.31	False	True
48	542.05	51743.15	0.00	False	True
26	75328.87	144135.98	134050.07	True	False
25	64664.71	139553.16	137962.62	False	False
32	63408.86	129219.61	46085.25	False	False
19	86419.70	153514.11	0.00	False	True

[130]:
```
y_test
```

[130]:
```
13    134307.35
39     81005.76
30     99937.59
45     64926.08
17    125370.37
48     35673.41
26    105733.54
25    107404.34
32     97427.84
19    122776.86
Name: Profit, dtype: float64
```

1.2 Train the Model

[132]:
```
# Initializing the model

from sklearn.linear_model import LinearRegression
```

[135]:
```
# initializing the model
model = LinearRegression()

# Fit the model on training data
model.fit(x_train,y_train)
```

[135]:
```
LinearRegression()
```

[138]:
```
# Make Predictions on Test Data
y_pred = model.predict(x_test)
```

[140]:
```
y_pred
```

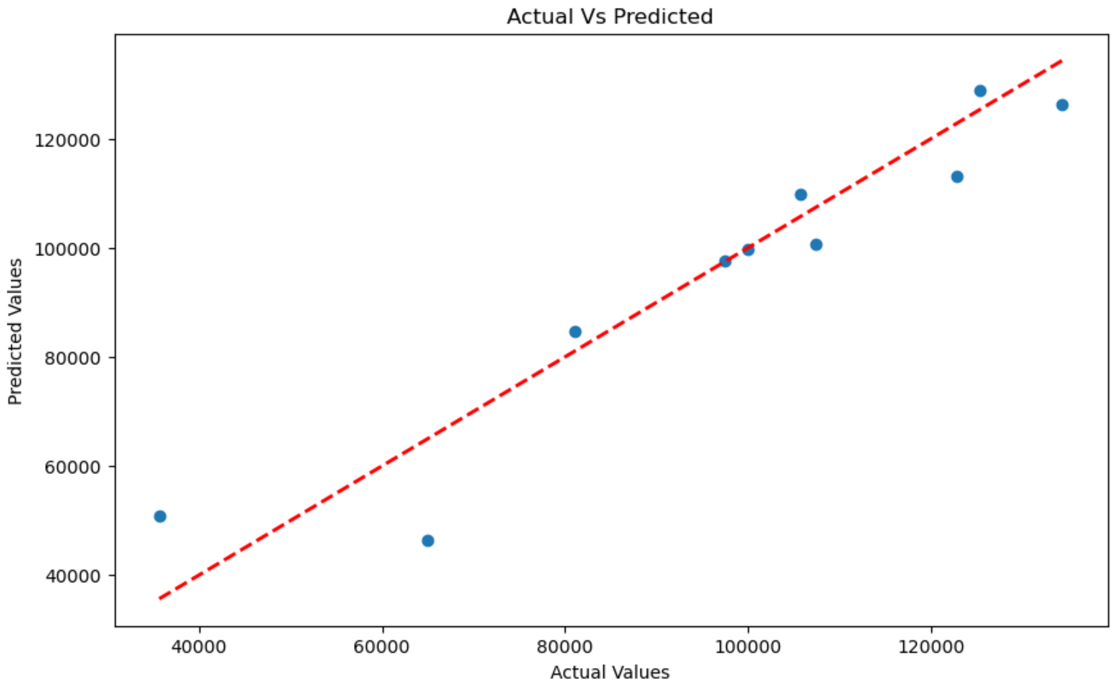
[140]:
```
array([126362.87908255,  84608.45383634,  99677.49425147,  46357.46068582,
       128750.48288504,  50912.4174188 , 109741.35032702, 100643.24281647,
        97599.27574594, 113097.42524432])
```

1.3 Visualization of Predictions vs Actual

[174]:
```
# Compare Actual vs Predicted values

comparison_df = pd.DataFrame({
    'Actual Profit': y_test.values,
    'Predicted Profit': y_pred.round(2),
    'Differcence in Actual and pred': np.subtract(y_test.values, y_pred.
 ↪round(2))
})

print(comparison_df)
```

```
   Actual Profit  Predicted Profit  Differcence in Actual and pred
0      134307.35         126362.88                         7944.47
1       81005.76          84608.45                        -3602.69
2       99937.59          99677.49                          260.10
3       64926.08          46357.46                        18568.62
4      125370.37         128750.48                        -3380.11
5       35673.41          50912.42                       -15239.01
6      105733.54         109741.35                        -4007.81
7      107404.34         100643.24                         6761.10
8       97427.84          97599.28                         -171.44
9      122776.86         113097.43                         9679.43
```

[151]:
```
# plot the scatter plot to find the relation between actual values and␣
 ↪predicted values

plt.figure(figsize = (10, 6))
plt.scatter(y_test, y_pred)
# Plot the perfect prediction line
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',␣
 ↪lw=2)
plt.title("Actual Vs Predicted")
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.show()
```



1.4 Evaluation parameters

[156]:
```
# Evaluation parameters
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

[164]:
```
mse = mean_squared_error(y_test, y_pred)
mse
```

[164]: 82010363.04430102

[166]:
```
rmse = np.sqrt(mse)
rmse
```

[166]: 9055.957323458466

[170]:
```
mae = mean_absolute_error(y_test, y_pred)
mae
```

[170]: 6961.477813252382

[176]:
```
r2 = r2_score(y_test, y_pred)
print(r2)
```

0.8987266414328637

An R^2 score(Coefficient of Determination) of 0.8987 means the model explains approximately 90% of the variation in Profit. Our model captures almost all the important patterns in the data.

[189]:
```
data_encoded.columns
```

[189]:
```
Index(['R&D Spend', 'Administration', 'Marketing Spend', 'Profit',
       'State_Florida', 'State_New York'],
      dtype='object')
```

[179]:
```
print(model.coef_)
```

```
[ 8.05630064e-01 -6.87878823e-02  2.98554429e-02  9.38793006e+02
  6.98775997e+00]
```

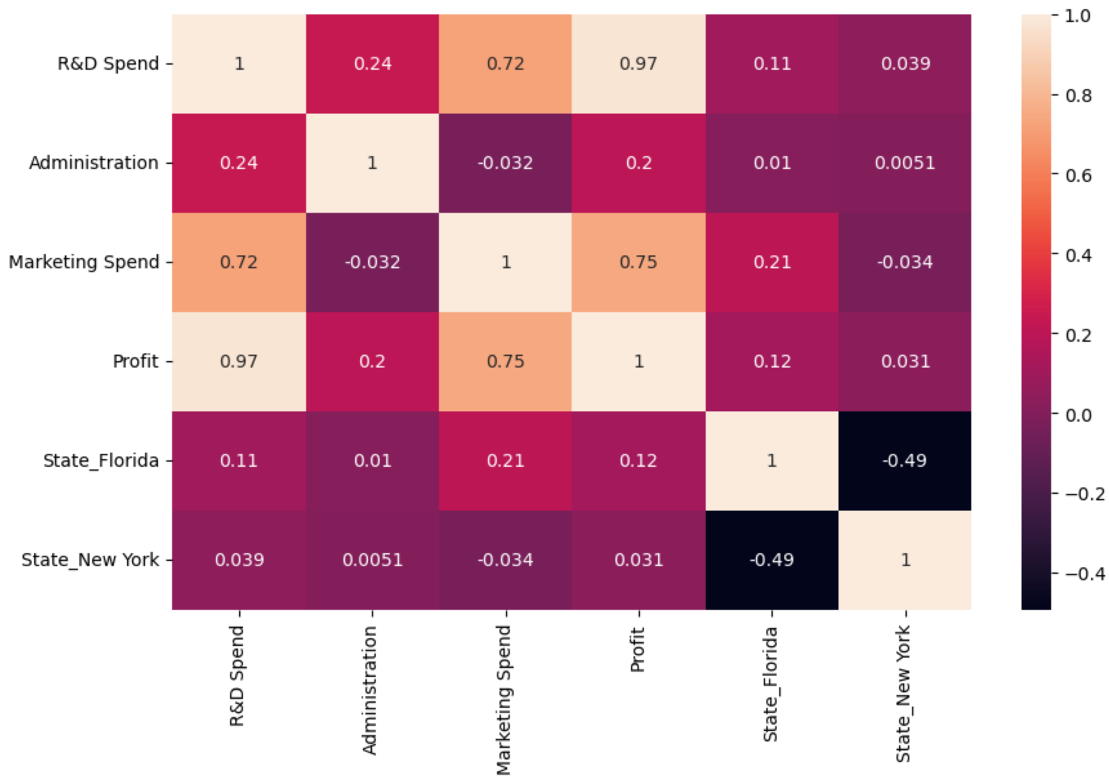
[211]:
```
coefficients = pd.DataFrame({'Features': x.columns, 'Coefficients': model.
 ↪coef_}).sort_values(by = 'Coefficients', ascending = False)
```

[213]:
```
print(coefficients)
```

```
          Features  Coefficients
3    State_Florida    938.793006
4   State_New York      6.987760
0        R&D Spend      0.805630
2  Marketing Spend      0.029855
1   Administration     -0.068788
```

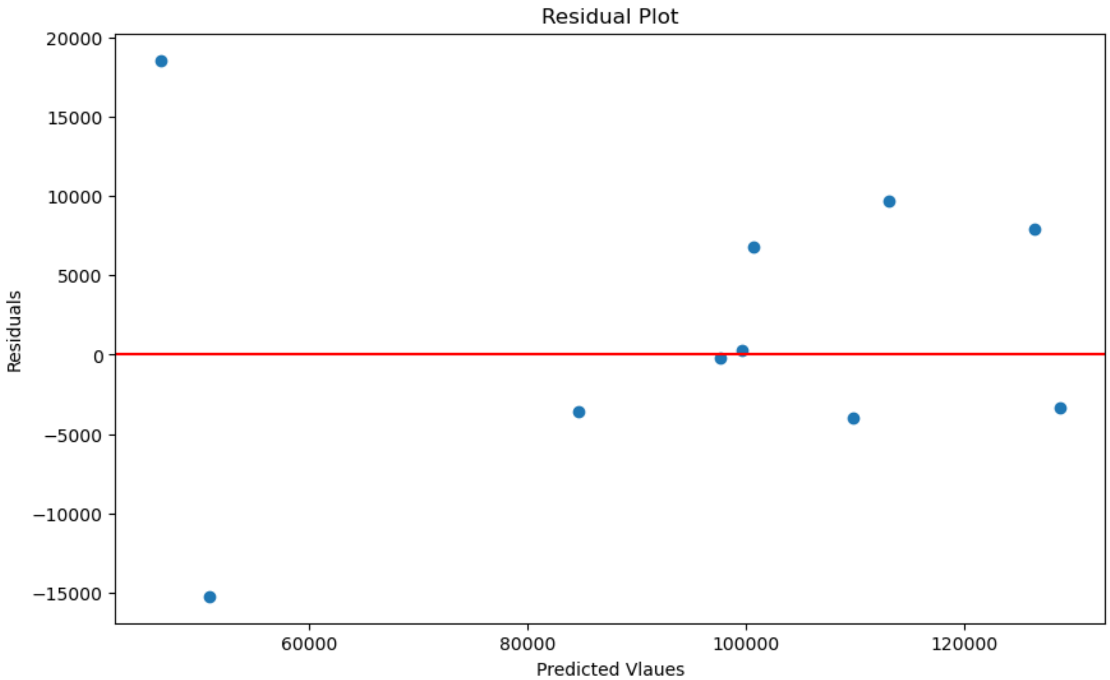
For every 1 unit increase in R&D, profit increases by ~0.81 units (keeping others constant).

[199]:
```
# Checking for correlation
plt.figure(figsize=(10, 6))
sns.heatmap(data_encoded.corr(), annot=True)
plt.show()
```



[217]:

```
# calculate the residuals(errors)

residuals = y_test - y_pred

# plot the residuals
plt.figure(figsize=(10,6))
plt.scatter(y_pred,residuals)
plt.axhline(y= 0,color ='r',linestyle = '-')
plt.xlabel('Predicted Vlaues')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()
```




```
Residuals are randomly scattered around the zero line → Suggests that the model captures the li
Confirms that Linear Regression is appropriate for this dataset.
```

1.4.1 Model Performance Review (Linear Regression)

- **R² Score**: `0.8987` → Model explains ~90% of variance in Profiits).
- **Top Influencer**: R&D Spend → Strongest positive correlation with Profit.
- **Location Impact**: Minimal → Business success more dependent on R&D than State.
- **Model Fit**: Good generalization on unseen data (20% test set).

Conclusion: Strong baseline model with high explanatory power. Clean, interpretable, and practical for business insights.

[ ]: