Profit_Prediction_for_Startups

June 7, 2024

#Table of Contents

1. IMPORTING REQUIRED LIBRARIES
2. IMPORTING DATA (CSV)
3. DATA CLEANING
   - CHECKING FOR NULL VALUES
4. EXPLORATORY DATA ANALYSIS
   - Heatmap using seaborn library
   - Outliers detection in the target variable
   - Histogram on Profit
   - Pair Plot
5. MODEL DEVELOPMENT
   - Splitting the data into training and testing data
   - Construct different regression algorithms
     - A. Linear Regression
     - B. Decision Tree Regression
     - C. Random Forest Regression
   - Calculate different regression metrics
     - A. Mean Absolute Error (MAE)
     - B. Mean Squared Error (MSE)
     - C. R-squared (R^2)
   - Visualize the model performance
     - Comparing the predicted values and actual values
     - To Choose the best model

PREDICTING COMPANY PROFIT USING MACHINE LEARNING REGRESSION MODELS

IMPORTING REQUIRED LIBRARIES

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```python
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

IMPORTING DATA (CSV)

[ ]:
```python
df = pd.read_csv('/content/50_Startups.csv')
df.head()
```

[ ]:

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

[ ]:
```python
df.tail()
```

[ ]:

	R&D Spend	Administration	Marketing Spend	Profit
45	1000.23	124153.04	1903.93	64926.08
46	1315.46	115816.21	297114.46	49490.75
47	0.00	135426.92	0.00	42559.73
48	542.05	51743.15	0.00	35673.41
49	0.00	116983.80	45173.06	14681.40

[ ]:
```python
df.describe()
```

[ ]:

	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

[ ]:
```python
print('There are ',df.shape[0],'rows and ', df.shape[1],'columns in the dataset.
↪')
```

```
There are  50 rows and  4 columns in the dataset.
```

[ ]:
```python
print('There are ',df.duplicated().sum(),'duplicate values in the dataset.')
#using duplicated() pre-defined function
```

```
There are  0 duplicate values in the dataset.
```

DATA CLEANING

CHECKING FOR NULL VALUES

[ ]:
```
# Check for missing values
print(df.isnull().sum())
```

```
R&D Spend          0
Administration     0
Marketing Spend    0
Profit             0
dtype: int64
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 4 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   Profit           50 non-null     float64
dtypes: float64(4)
memory usage: 1.7 KB
```

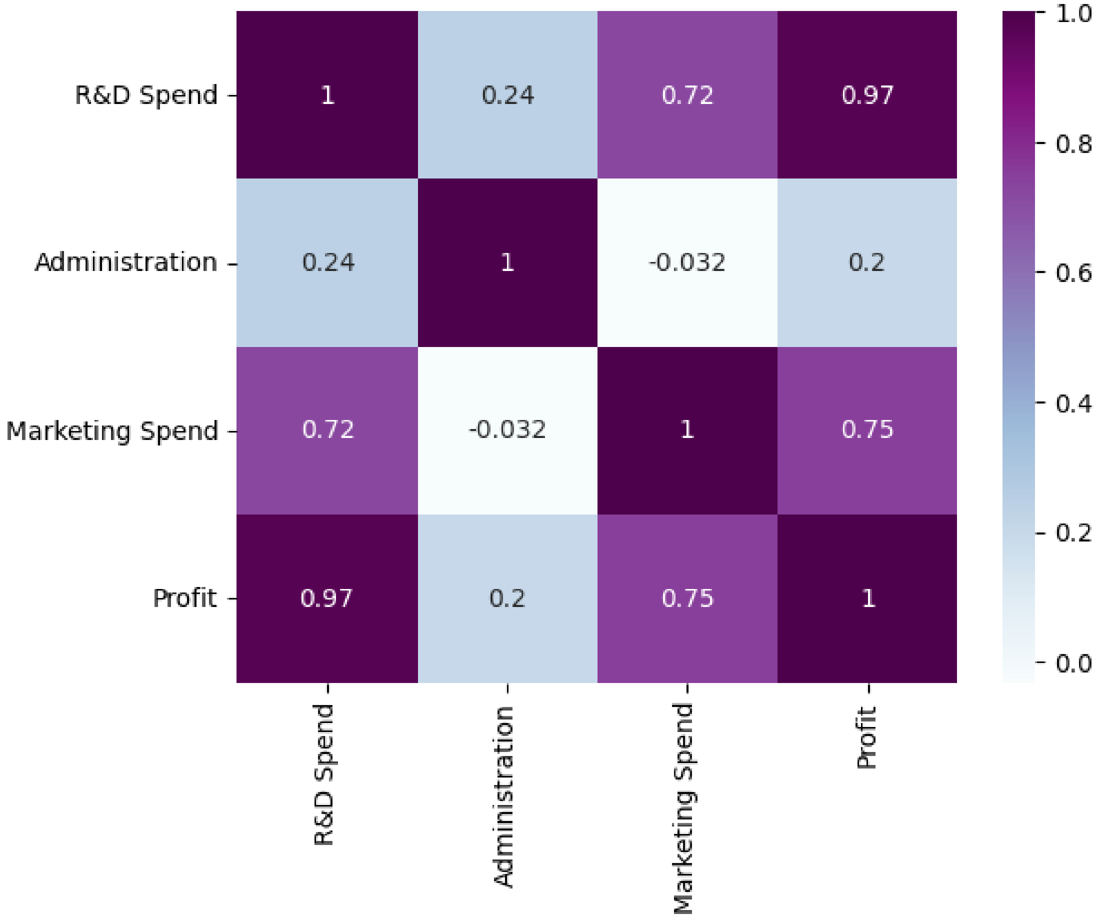
[ ]:
```
cor = df.corr()
cor
```

[ ]:

	R&D Spend	Administration	Marketing Spend	Profit
R&D Spend	1.000000	0.241955	0.724248	0.972900
Administration	0.241955	1.000000	-0.032154	0.200717
Marketing Spend	0.724248	-0.032154	1.000000	0.747766
Profit	0.972900	0.200717	0.747766	1.000000

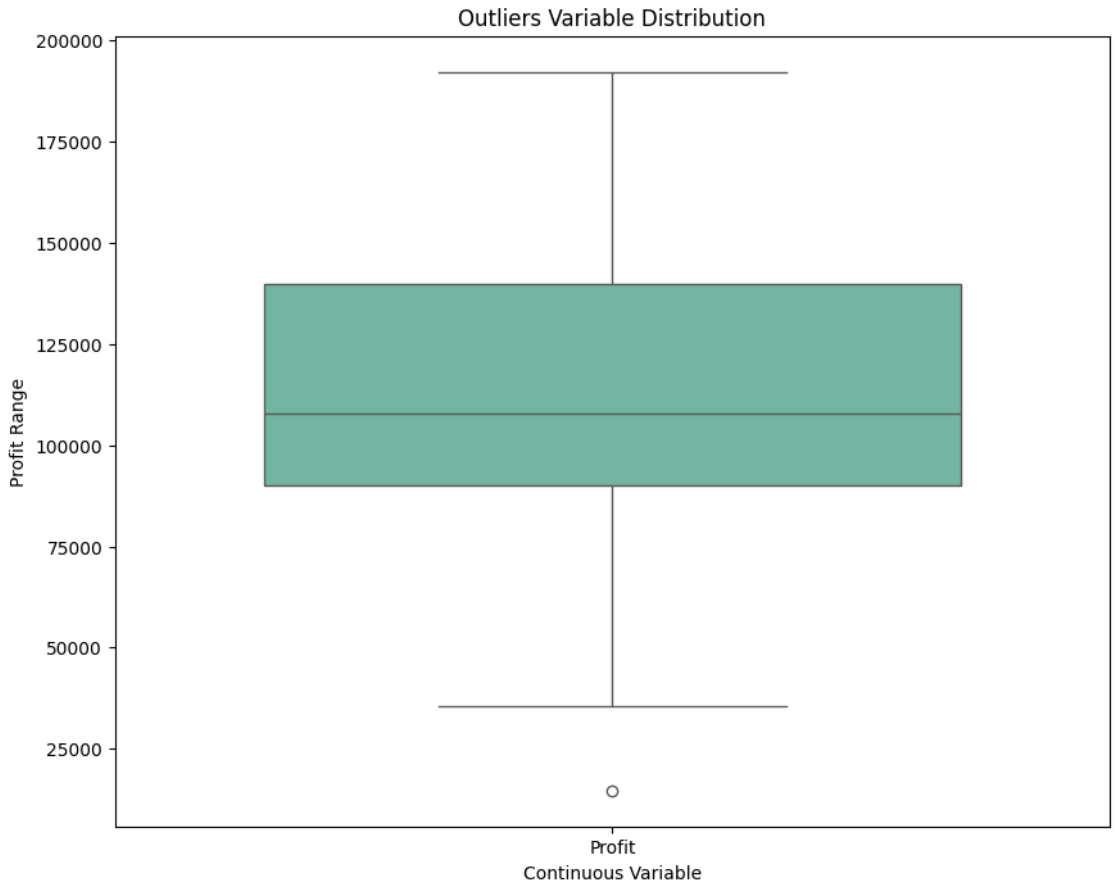
Heatmap using seaborn library

[ ]:
```
sns.heatmap(cor,annot=True,cmap='BuPu')
plt.show()
```



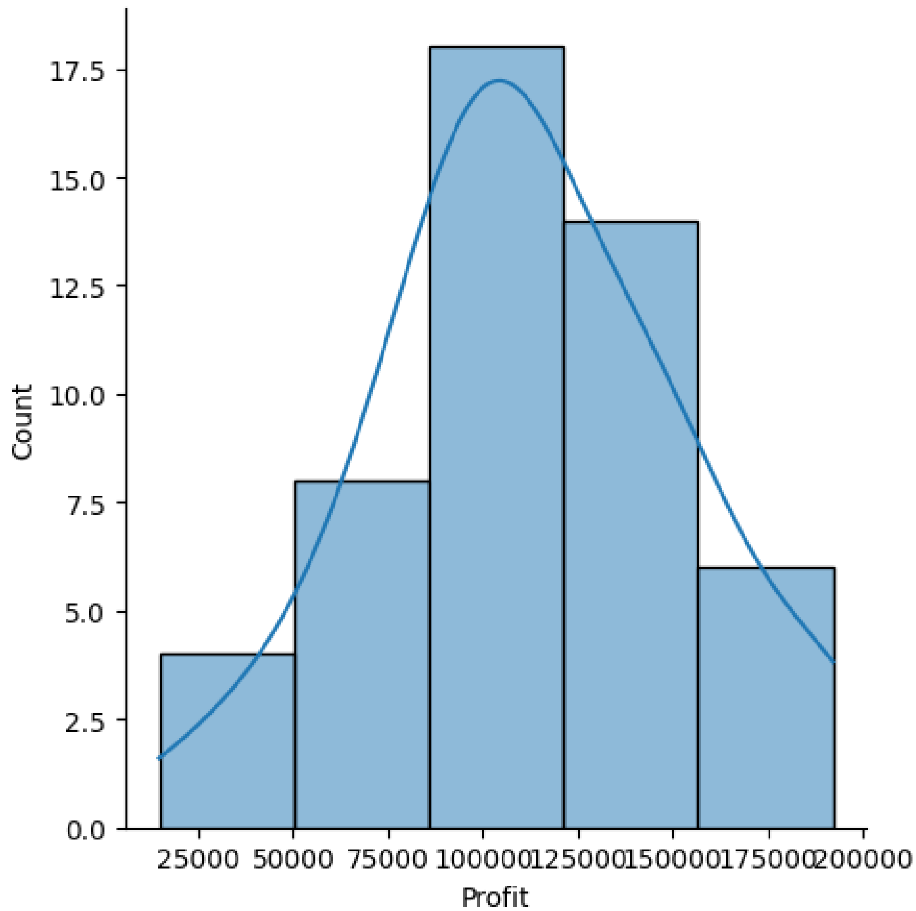
Outliers detection in the target variable

[ ]:
```
outliers = ['Profit']
plt.rcParams['figure.figsize'] = [10,8]
sns.boxplot(data=df[outliers], orient="v", palette="Set2", width=0.7)
#orient = "v" : vertical boxplot ,
#orient = "h" : horizontal boxplot

plt.title('Outliers Variable Distribution')
plt.ylabel('Profit Range')
plt.xlabel('Continuous Variable')

plt.show()
```



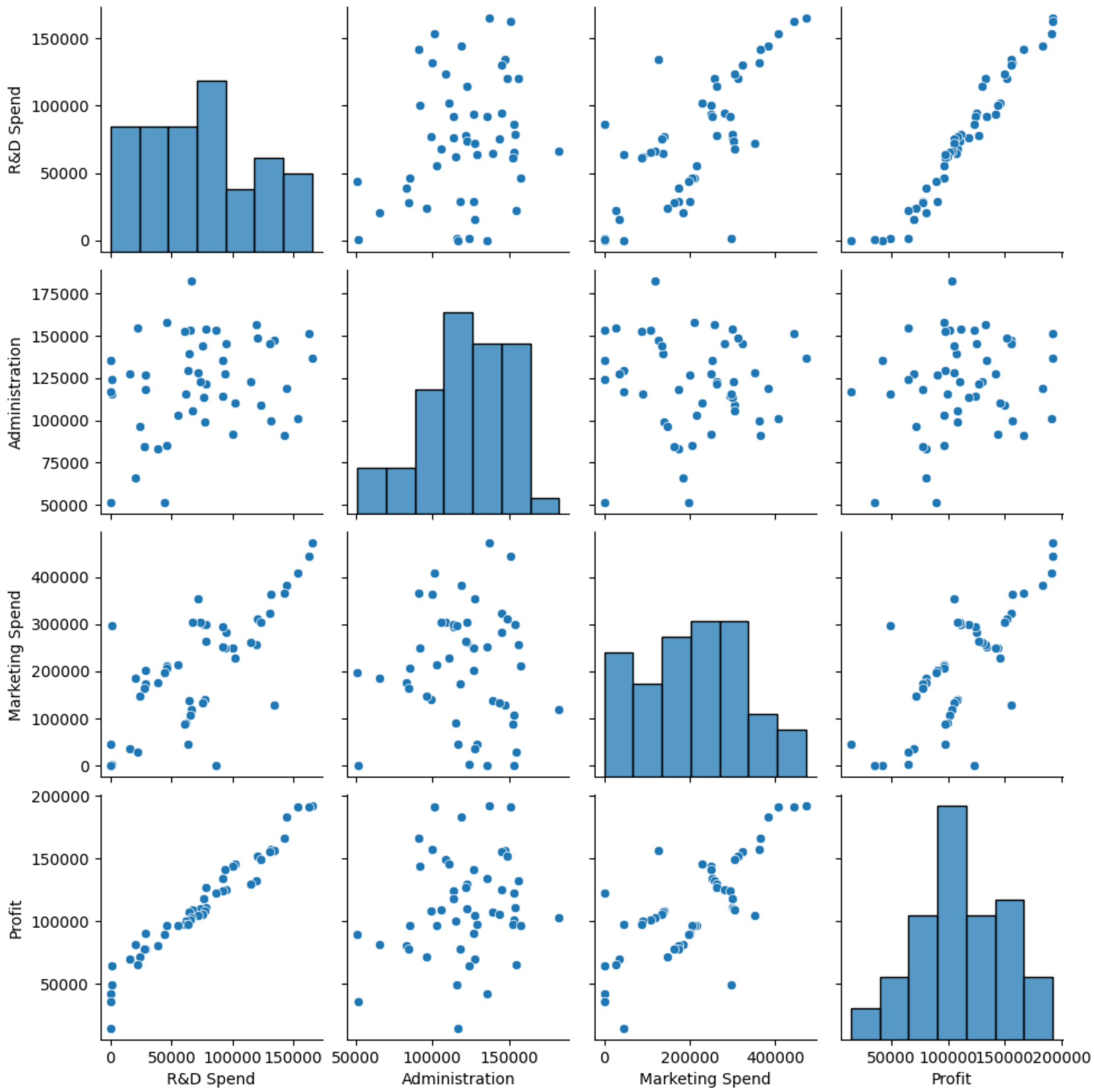
Histogram on Profit

[ ]:
```
sns.displot(df['Profit'], bins=5,kde=True)
plt.show()
```



Pair Plot

[ ]:
```
sns.pairplot(df)
plt.show()
```



MODEL DEVELOPMENT

[ ]:
```
X = df.iloc[:, :-1].values  # Features
y = df.iloc[:, -1].values   # Target variable (Profit)
```

[ ]:
```
# Import the necessary class
from sklearn.preprocessing import LabelEncoder

labelencoder = LabelEncoder()
X[:, 2] = labelencoder.fit_transform(X[:, 2])
X1 = pd.DataFrame(X)
X1.head()
```

```
[ ]:            0          1     2
     0  165349.20  136897.80  47.0
     1  162597.70  151377.59  46.0
     2  153441.51  101145.55  45.0
     3  144372.41  118671.85  44.0
     4  142107.34   91391.77  43.0
```

Splitting the data into training and testing data

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.6,␣
      ↪random_state=0)
     X_train
```

```
[ ]: array([[1.3187690e+05, 9.9814710e+04, 4.2000000e+01],
            [9.4657160e+04, 1.4507758e+05, 3.1000000e+01],
            [2.8754330e+04, 1.1854605e+05, 1.6000000e+01],
            [0.0000000e+00, 1.1698380e+05, 4.0000000e+00],
            [1.6259770e+05, 1.5137759e+05, 4.6000000e+01],
            [9.3863750e+04, 1.2732038e+05, 2.6000000e+01],
            [4.4069950e+04, 5.1283140e+04, 1.9000000e+01],
            [7.7044010e+04, 9.9281340e+04, 1.3000000e+01],
            [1.3461546e+05, 1.4719887e+05, 1.0000000e+01],
            [6.7532530e+04, 1.0575103e+05, 3.7000000e+01],
            [2.8663760e+04, 1.2705621e+05, 2.0000000e+01],
            [7.8389470e+04, 1.5377343e+05, 3.5000000e+01],
            [8.6419700e+04, 1.5351411e+05, 0.0000000e+00],
            [1.2333488e+05, 1.0867917e+05, 3.8000000e+01],
            [3.8558510e+04, 8.2982090e+04, 1.7000000e+01],
            [1.3154600e+03, 1.1581621e+05, 3.3000000e+01],
            [1.4437241e+05, 1.1867185e+05, 4.4000000e+01],
            [1.6534920e+05, 1.3689780e+05, 4.7000000e+01],
            [0.0000000e+00, 1.3542692e+05, 0.0000000e+00],
            [2.2177740e+04, 1.5480614e+05, 2.0000000e+00]])
```

Construct different regression algorithms

A. Linear Regression

```
[ ]: lin_reg = LinearRegression()
     lin_reg.fit(X_train, y_train)
     y_pred_lin = lin_reg.predict(X_test)
     y_pred_lin
```

```
[ ]: array([100927.31704798, 134226.52141799, 135058.69402383,  69607.61477333,
            183942.70747771, 113327.9049821 ,  63720.74696839,  96051.59874357,
            113823.43806907, 173783.01633461,  95053.72943631,  86486.18581817,
            109341.72356373,  87037.70399387, 128144.13269174, 162968.34274829,
            151393.39267092,  43399.42550607,  42808.28639507, 100331.07365795,
```

```
146985.55677234,  97025.15517852,  97783.01056754, 115919.71310582,
 65734.63342857, 115313.5740501 ,  56279.43382001, 154381.54979557,
127221.35809696, 100428.48692064])
```

B. Decision Tree Regression

```
[ ]: tree_reg = DecisionTreeRegressor(random_state=0)
     tree_reg.fit(X_train, y_train)
     y_pred_tree = tree_reg.predict(X_test)
     y_pred_tree
```

```
[ ]: array([111313.02, 141585.52, 141585.52,  78239.91, 182901.99, 108733.99,
             65200.33, 111313.02, 108552.04, 182901.99,  90708.19,  90708.19,
            111313.02,  90708.19, 141585.52, 156991.12, 149759.96,  49490.75,
             14681.4 , 111313.02, 149759.96, 108733.99, 108733.99, 108552.04,
             65200.33, 108552.04,  65200.33, 149759.96, 141585.52, 111313.02])
```

C. Random Forest Regression

```
[ ]: rf_reg = RandomForestRegressor(n_estimators=10, random_state=0)
     rf_reg.fit(X_train, y_train)
     y_pred_rf = rf_reg.predict(X_test)
     y_pred_rf
```

```
[ ]: array([110143.495, 119437.487, 129557.556,  79346.25 , 179591.784,
            137559.067,  77232.637, 104690.648, 112534.949, 164677.52 ,
             97912.308,  87217.256, 110401.398,  88585.77 , 119730.847,
            163293.459, 142500.883,  41414.513,  37153.393, 110143.495,
            136705.598, 107058.823, 108452.38 , 113050.755,  76461.749,
            109231.601,  76077.347, 149960.496, 125502.837, 110143.495])
```

Calculate different regression metric

A. Mean Absolute Error (MAE)

```
[ ]: mae_lin = mean_absolute_error(y_test, y_pred_lin)
     mae_tree = mean_absolute_error(y_test, y_pred_tree)
     mae_rf = mean_absolute_error(y_test, y_pred_rf)

     print(f"The Mean Absolute Error (MAE) for the Linear Regression model is:␣
      ↪{mae_lin}")
     print(f"The Mean Absolute Error (MAE) for the Decision Tree Regression is:␣
      ↪{mae_tree}")
     print(f"The Mean Absolute Error (MAE) for the Random Forest Regression is:␣
      ↪{mae_rf}")
```

```
The Mean Absolute Error (MAE) for the Linear Regression model is:
7711.388704173033
The Mean Absolute Error (MAE) for the Decision Tree Regression is:
```

```
9153.623000000001
The Mean Absolute Error (MAE) for the Random Forest Regression is:
8706.413933333337
```

B. Mean Squared Error (MSE)

[ ]:
```python
mse_lin = mean_squared_error(y_test, y_pred_lin)
mse_tree = mean_squared_error(y_test, y_pred_tree)
mse_rf = mean_squared_error(y_test, y_pred_rf)

print(f"The Mean Squared Error (MSE) for the Linear Regression model is:␣
↪{mse_lin}")
print(f"The Mean Squared Error (MSE) for the Decision Tree Regression is:␣
↪{mse_tree}")
print(f"The Mean Squared Error (MSE) for the Random Forest Regression is: ␣
↪{mse_rf}")
```

```
The Mean Squared Error (MSE) for the Linear Regression model is:
89640824.38194643
The Mean Squared Error (MSE) for the Decision Tree Regression is:
119800025.97291668
The Mean Squared Error (MSE) for the Random Forest Regression is:
128246868.31487516
```

C. R-squared (R^2)

[ ]:
```python
r2_lin = r2_score(y_test, y_pred_lin)
r2_tree = r2_score(y_test, y_pred_tree)
r2_rf = r2_score(y_test, y_pred_rf)

print(f"The R-squared (R²) for the Linear Regression model is: {r2_lin}")
print(f"The R-squared (R²) for the Decision Tree Regression is: {r2_tree}")
print(f"The R-squared (R²) for the Random Forest Regression is:  {r2_rf}")
```

```
The R-squared (R²) for the Linear Regression model is: 0.9152626678220548
The R-squared (R²) for the Decision Tree Regression is: 0.8867532213610698
The R-squared (R²) for the Random Forest Regression is:  0.8787684344035614
```

Visualize the model performance

Comparing the predicted values and actual values

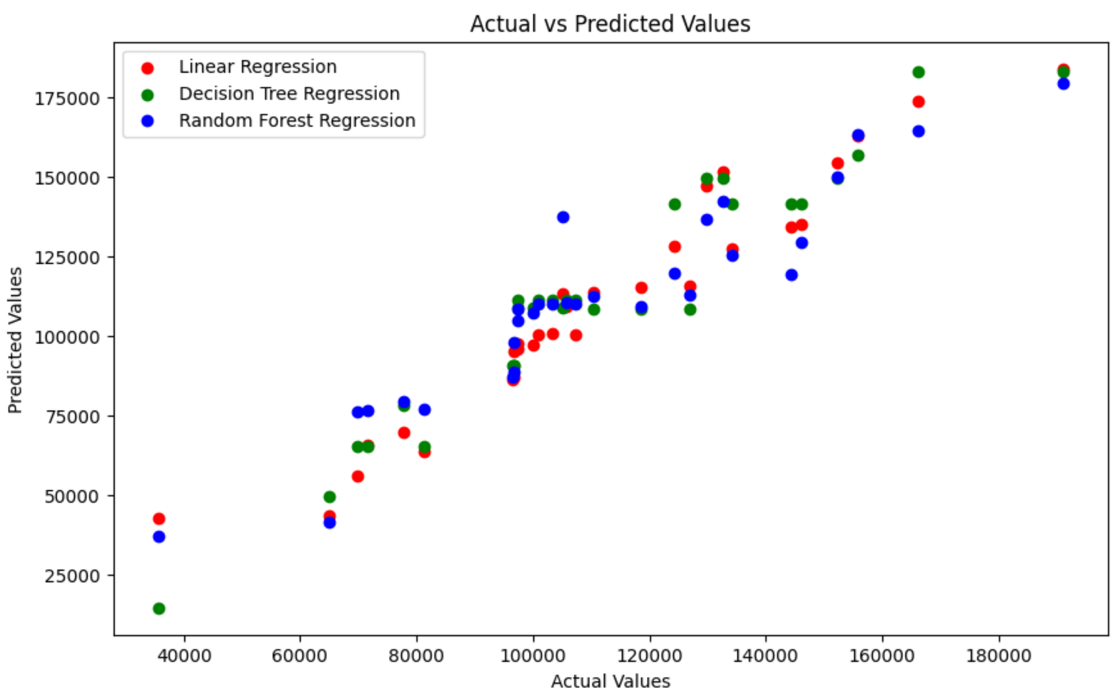
[ ]:
```python
df = pd.DataFrame(data={'Predicted value': y_pred_lin, 'Actual value': y_test})
df.head(10)
```

[ ]:

	Predicted value	Actual value
0	100927.317048	103282.38
1	134226.521418	144259.40
2	135058.694024	146121.95
3	69607.614773	77798.83

```
4     183942.707478     191050.39
5     113327.904982     105008.31
6      63720.746968      81229.06
7      96051.598744      97483.56
8     113823.438069     110352.25
9     173783.016335     166187.94
```

[ ]:
```python
# Plot the actual vs predicted values
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_lin, c='r', label='Linear Regression')
plt.scatter(y_test, y_pred_tree, c='g', label='Decision Tree Regression')
plt.scatter(y_test, y_pred_rf, c='b', label='Random Forest Regression')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs Predicted Values')
plt.legend()
plt.show()
```



To Choose the best model:

[ ]:
```python
# Create a dictionary of the models and their scores
model_scores = {
    'Linear Regression': (mae_lin, mse_lin, r2_lin),
    'Decision Tree Regression': (mae_tree, mse_tree, r2_tree),
    'Random Forest Regression': (mae_rf, mse_rf, r2_rf)
```

```python
}

# Print out the scores for comparison
for model_name, scores in model_scores.items():
    print(f"{model_name} - MAE: {scores[0]}, MSE: {scores[1]}, R²: {scores[2]}")

# Choose the best model based on R² score
best_model = max(model_scores, key=lambda k: model_scores[k][2])
print(f"The best model is: {best_model}")
```

```
Linear Regression - MAE: 7711.388704173033, MSE: 89640824.38194643, R²:
0.9152626678220548
Decision Tree Regression - MAE: 9153.623000000001, MSE: 119800025.97291668, R²:
0.8867532213610698
Random Forest Regression - MAE: 8706.413933333337, MSE: 128246868.31487516, R²:
0.8787684344035614
The best model is: Linear Regression
```