CONTINUOUS ASSESSMENT -1

Course Name: Machine Learning
Course Code: CSM354
Topic: Start-Up Profit Prediction

Student Details:

Name: SHAIK JULFEEN AHMADH
Section: K21UN
Roll Number: RK21UNA18
Reg. Number: 12110554

Startup Profit Prediction

Importing the libraries

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import statsmodels.api as sm

from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor as RF
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler
from statsmodels.stats.outliers_influence import variance_inflation_factor

%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Reading and undersatnding the data

Importing the dataset

```
df = pd.read_csv('50_Startups.csv')

df.head()
```

	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

```
df.shape

(50, 5)

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
```

NO null values found!

```
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
```

```
df['State'].value_counts()
```

```
New York      17
California    17
Florida       16
Name: State, dtype: int64
```

From the above Observation I conclude that it is balanced set

Data Visualization

Exploratory Data Analysis

- Exploring various feautures present in the dataset for better understanding

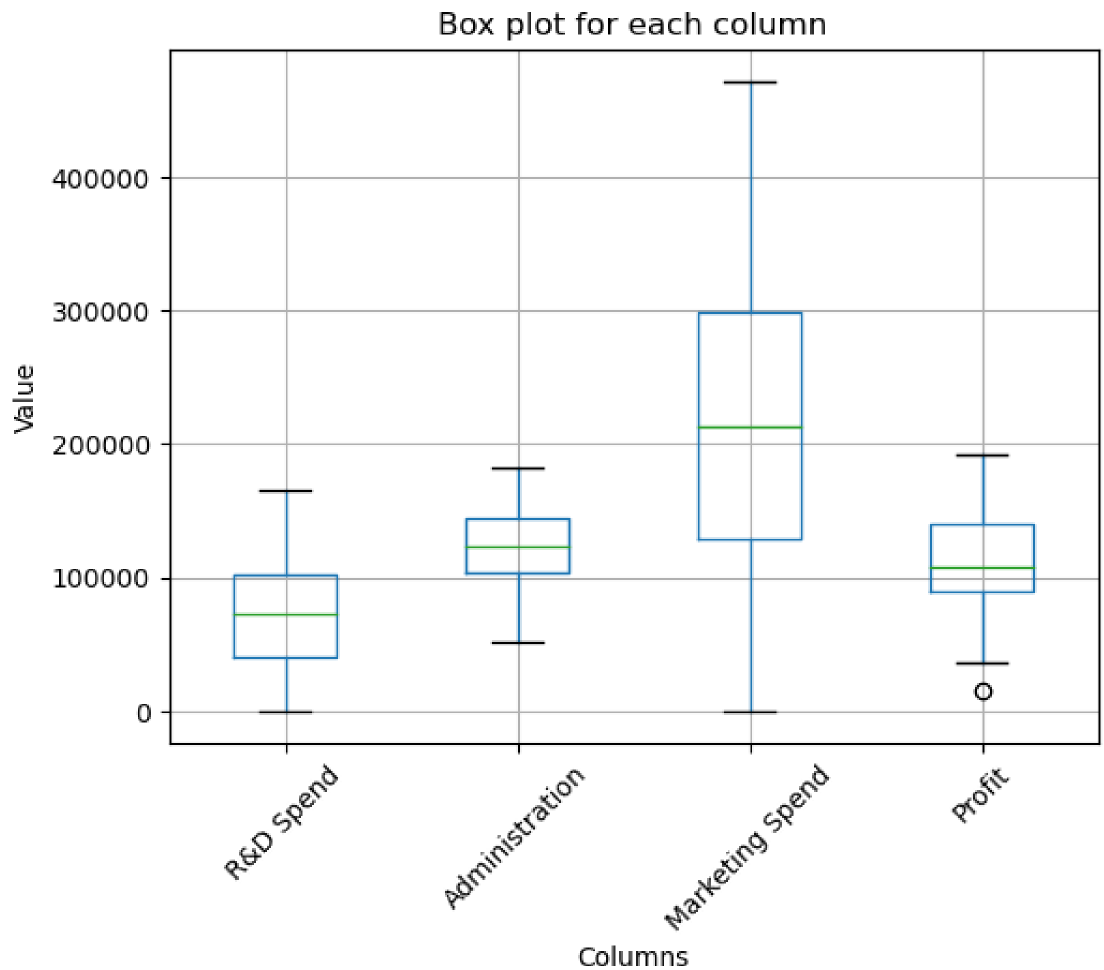
```
# Checking the null values
df.isnull().sum()
```

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

- The dataset is cleaned and has no null values

```
# Checking for outliers
df_numeric = df.drop(columns=["State"])
```

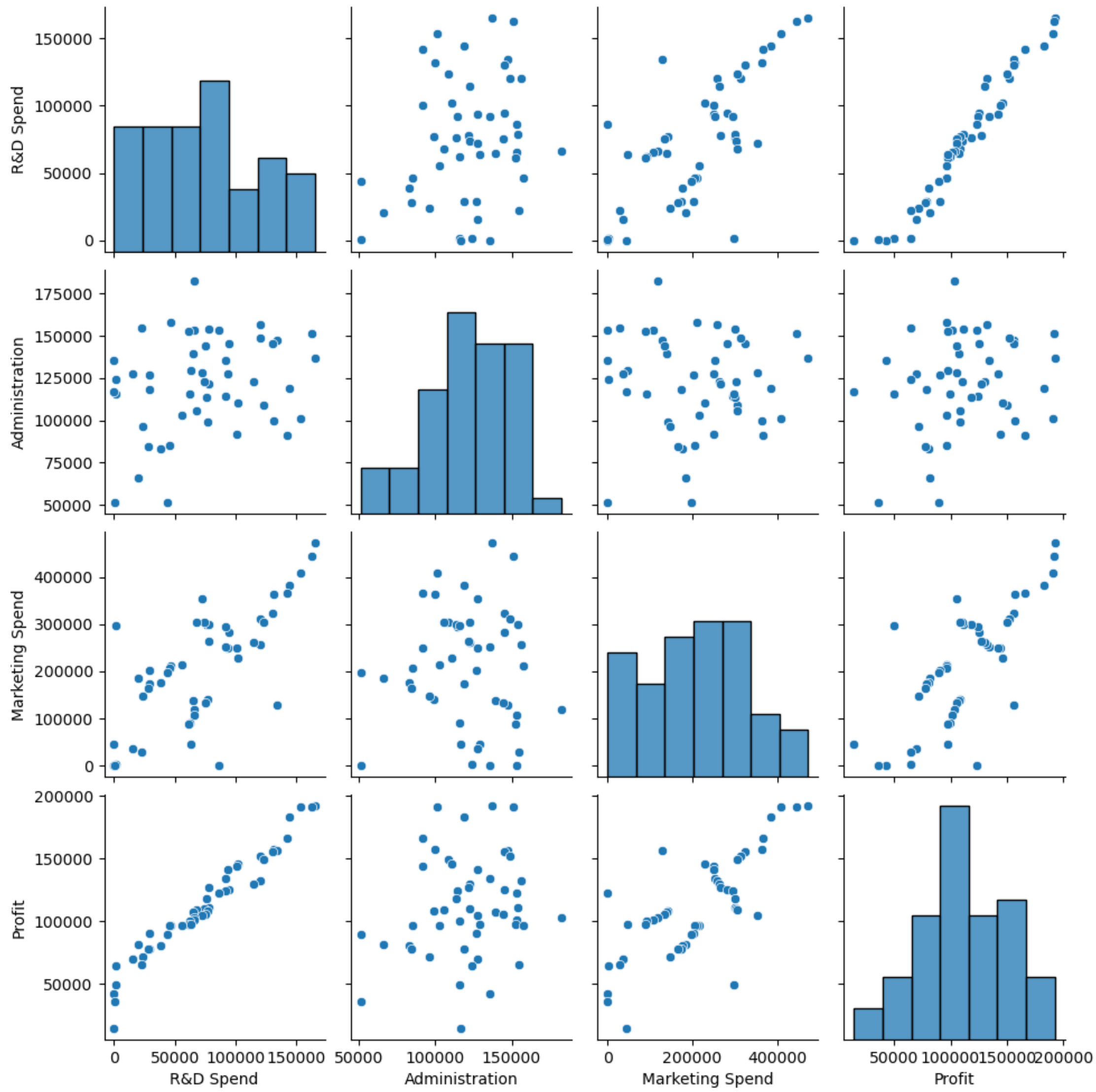
```
df_numeric.boxplot()
plt.title('Box plot for each column')
plt.ylabel('Value')
plt.xlabel('Columns')
plt.xticks(rotation=45)
plt.show()
```



- The dataset has no outliers present

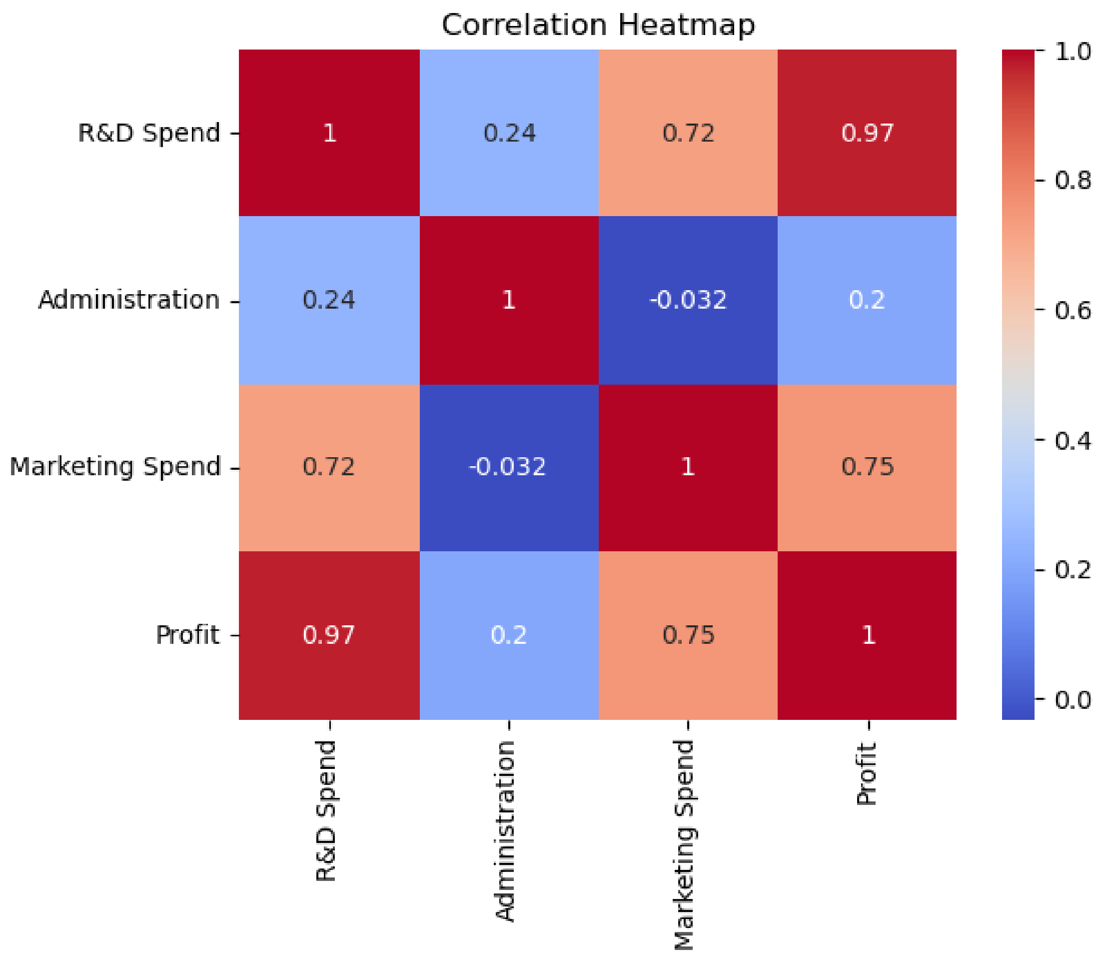
```
# Pairwise plot among all numerical columns
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x2762db9d9d0>
```



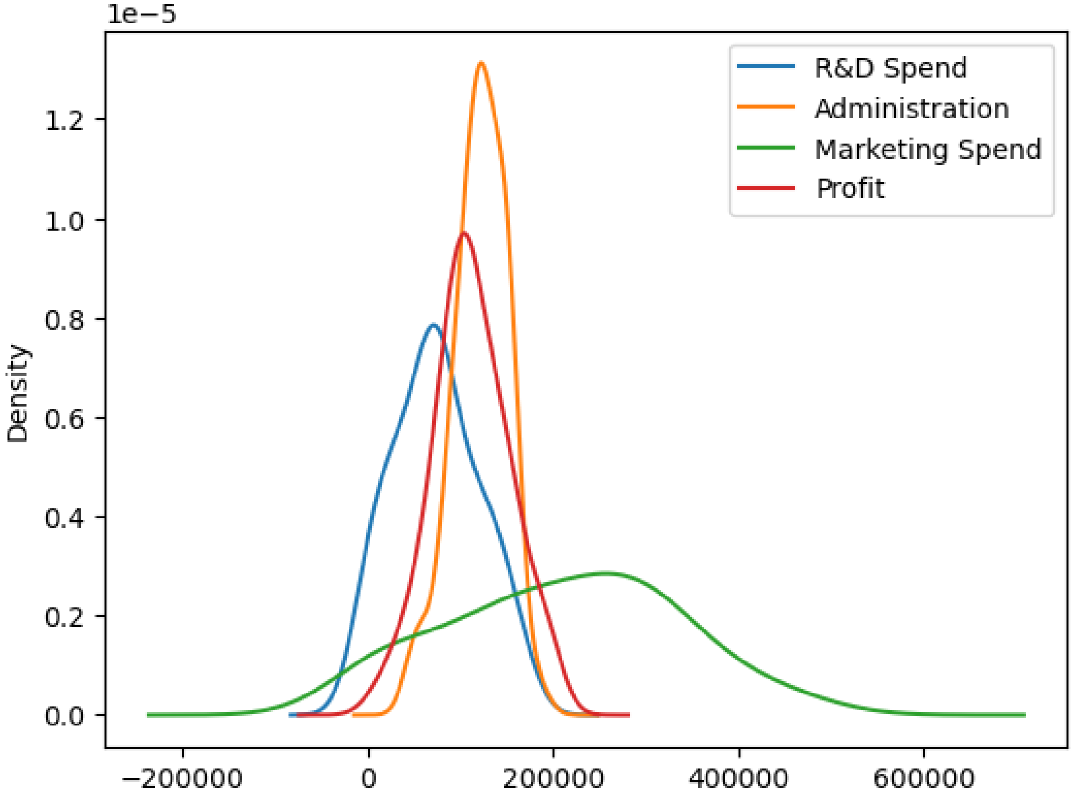
Based on this plot R&D spend is mostly correlated with the Profit. We can check the same using HeatMap

```
# HeatMAp used to find intercollinearity among numerical rows present in the dataset
corr = df.corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```




```
# Kernel Density Estimation : KDE is a non-parametric method for estimating
the probability density function of a random variable
df.plot.kde()
```

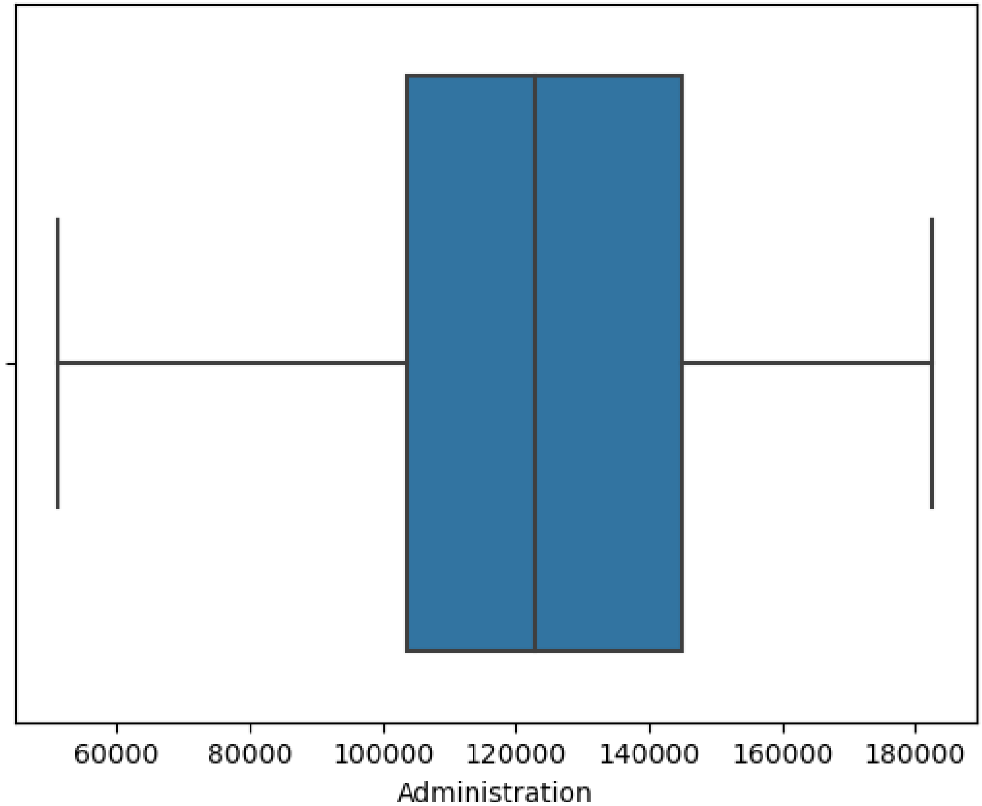
```
<AxesSubplot:ylabel='Density'>
```



- From the above plot its clear that all numerical features are normally distributed
- Detailed analysis of outliers

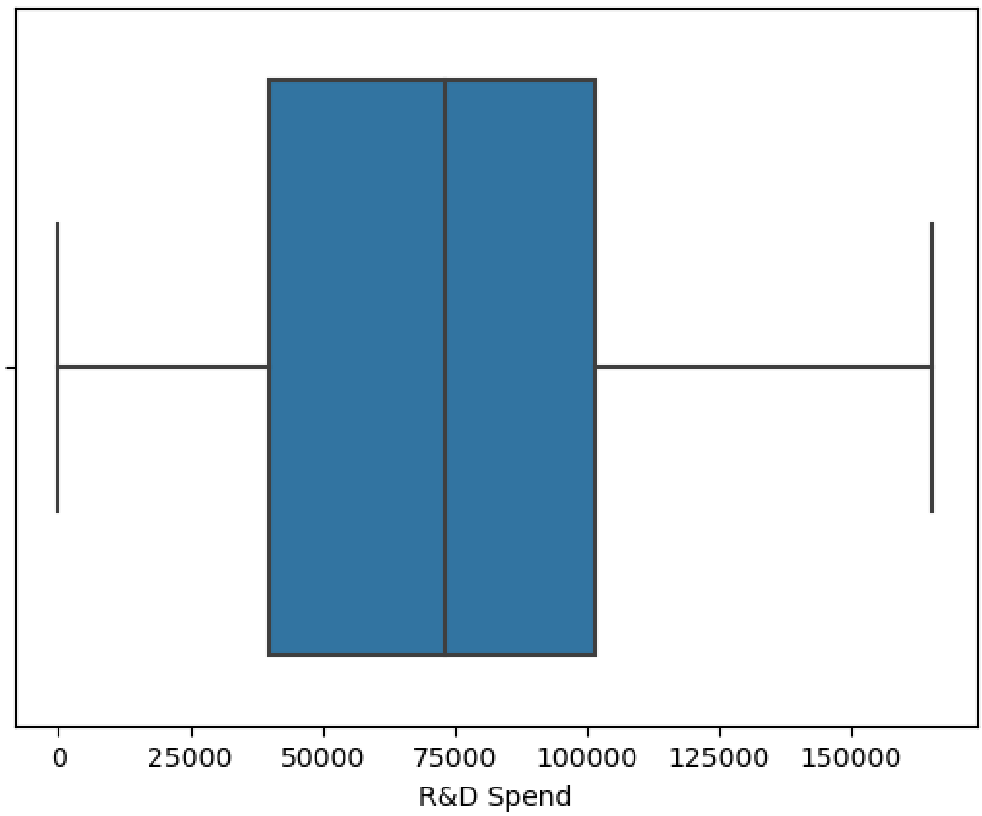
```
sns.boxplot(x=df['Administration'])
```

```
<AxesSubplot:xlabel='Administration'>
```



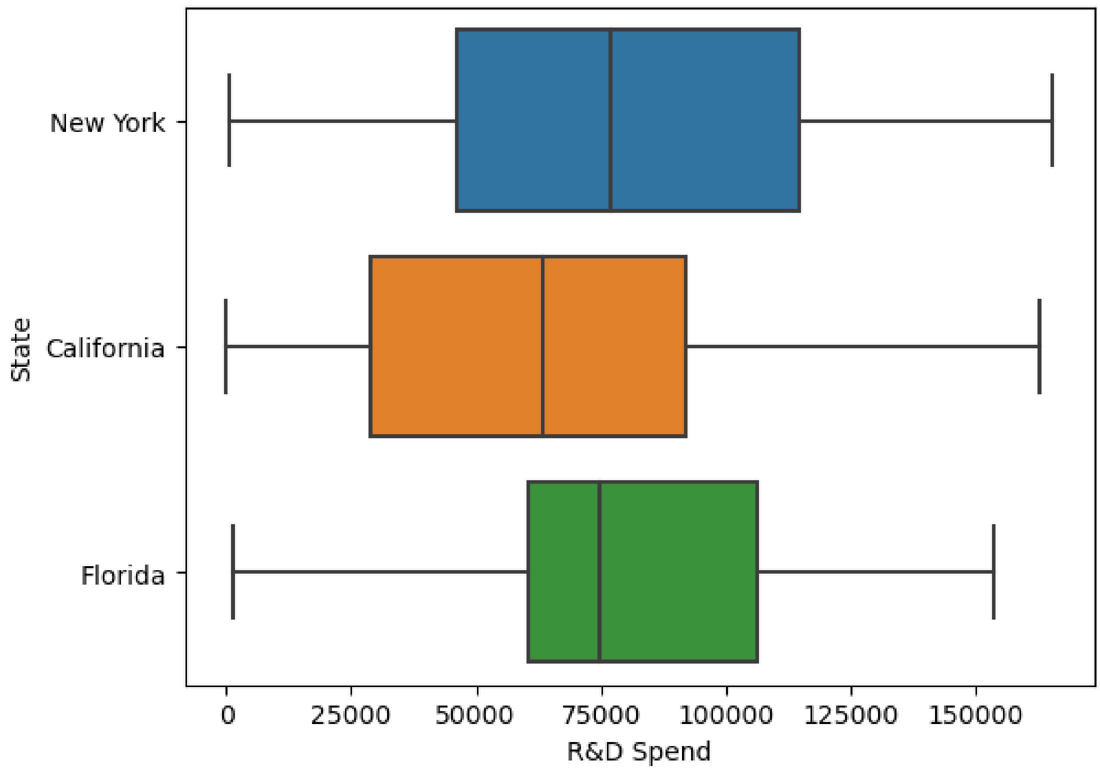

```
sns.boxplot(x=df['R&D Spend'])
```

<AxesSubplot:xlabel='R&D Spend'>




```
sns.boxplot(x=df['R&D Spend'],y=df['State'])
```

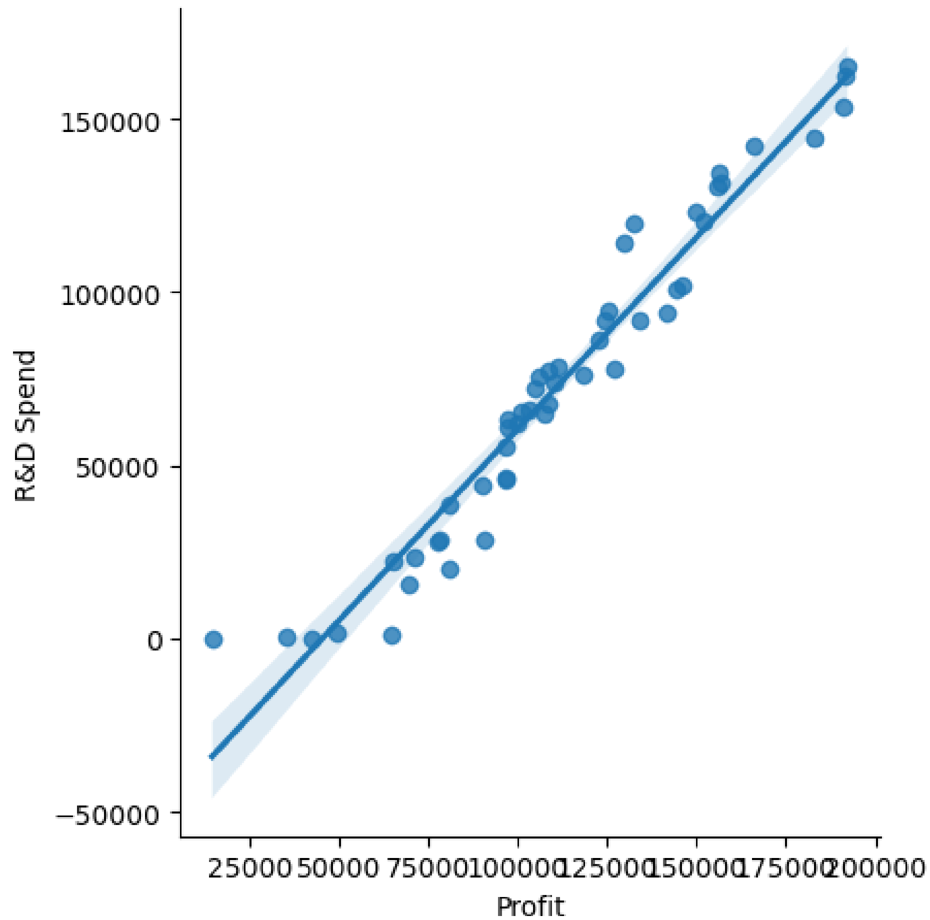
```
<AxesSubplot:xlabel='R&D Spend', ylabel='State'>
```



There are no outliers in the data

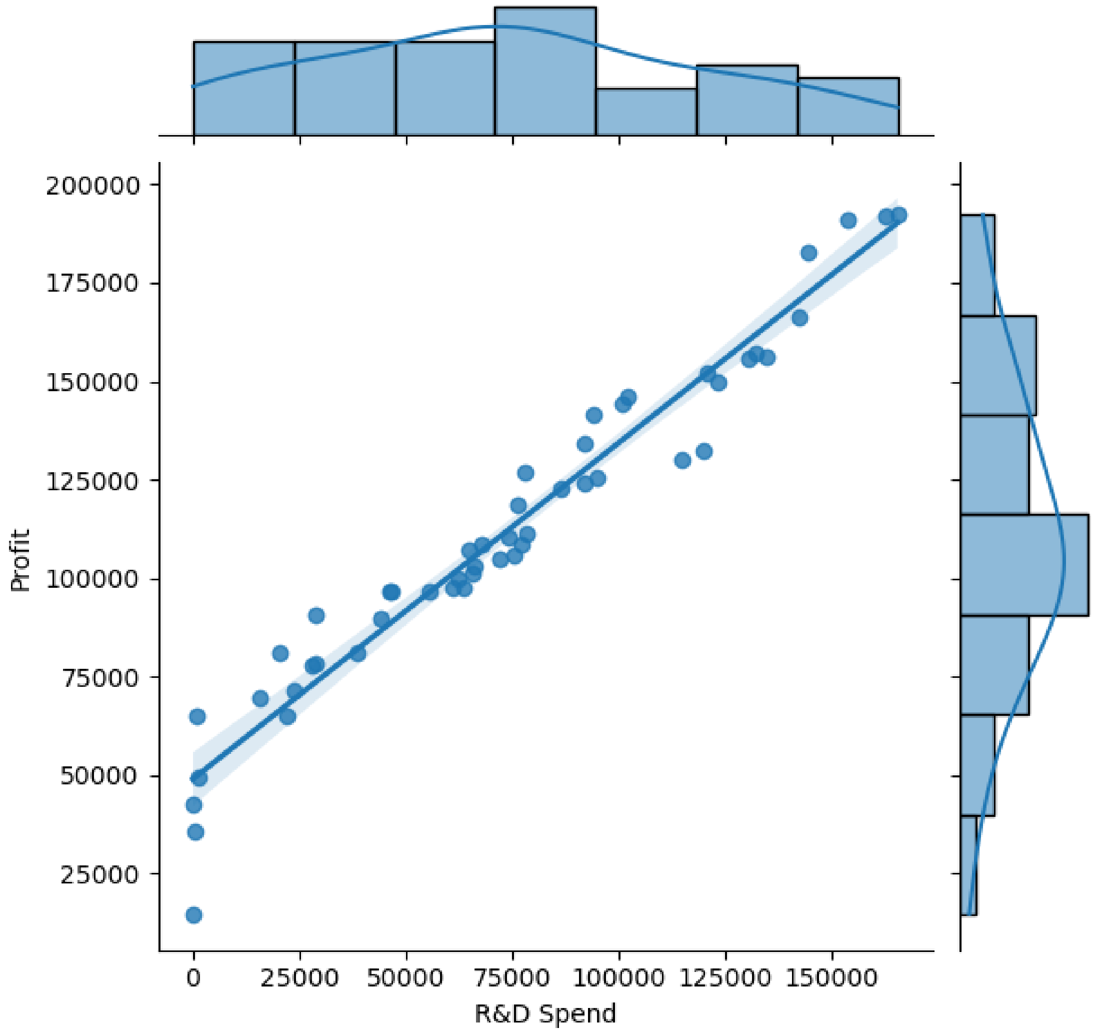
```
#lmplot used to create scatter plots with linear regression fits.

sns.lmplot(x='Profit',y='R&D Spend',data=df)
```

```
<seaborn.axisgrid.FacetGrid at 0x27630e1faf0>
```



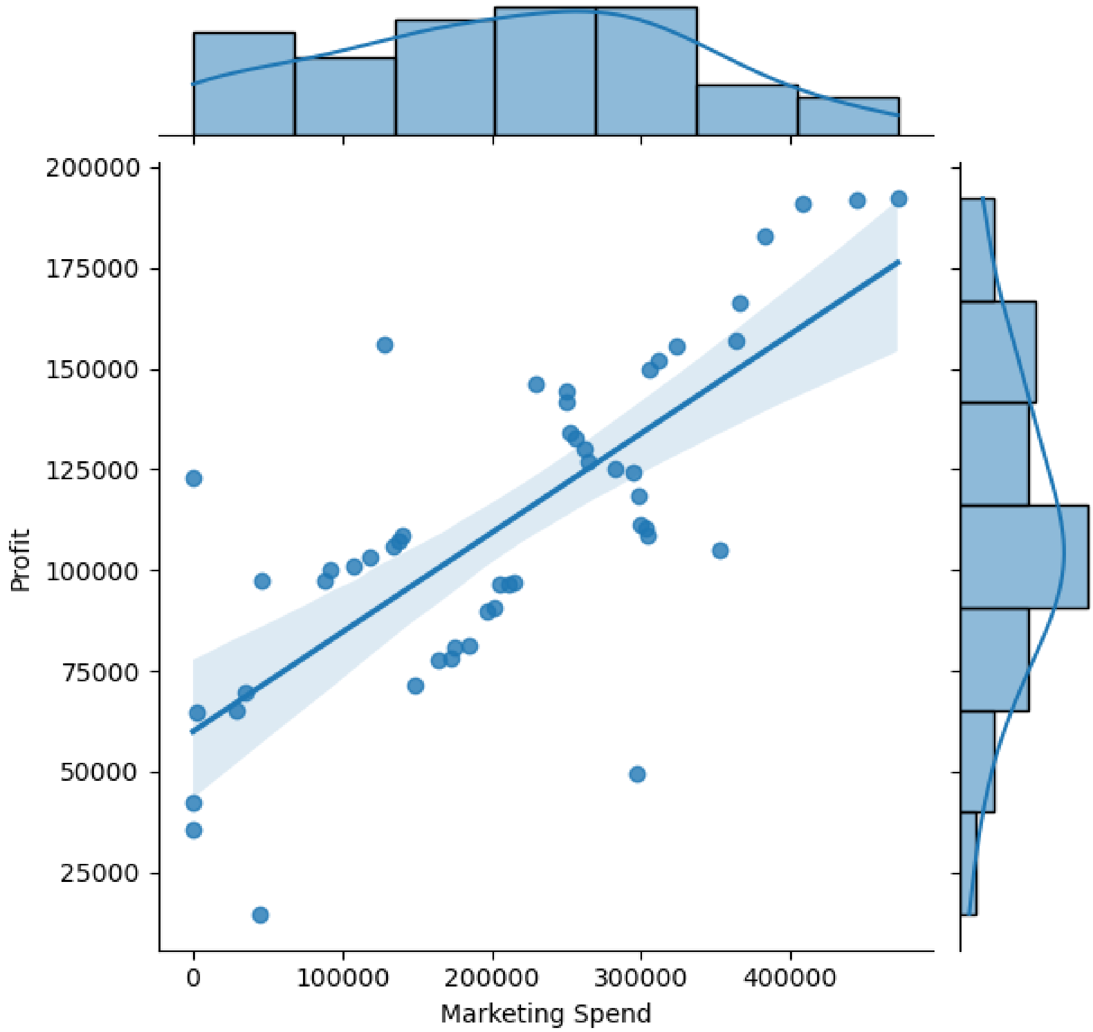

```python
# Understanding detailed relationship b/w 'R&D Spend' column and 'Profit' column
sns.jointplot(data=df, x="R&D Spend", y="Profit",kind="reg")
```

```
<seaborn.axisgrid.JointGrid at 0x27630f0e7c0>
```



- The terms are normllay distribution
- The best fit line clearly lies covering most of the points

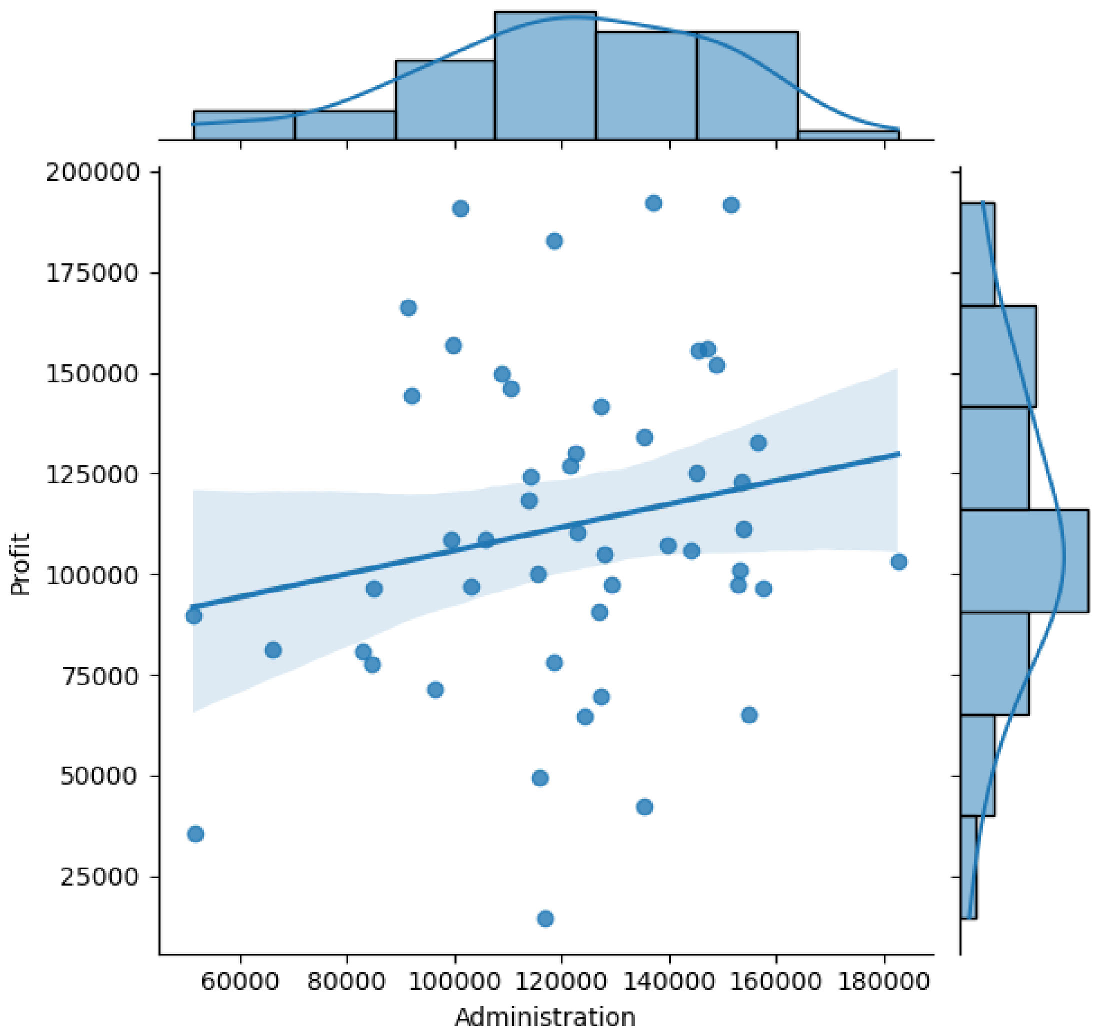
```
# Understanding relationship b/w 'Marketing Spend' Column and 'Profit' Column

sns.jointplot(data=df, x="Marketing Spend", y="Profit",kind='reg')

<seaborn.axisgrid.JointGrid at 0x2763101e0a0>
```



- The terms are normllay distribution
- The best fit line is trying to cover some data points

```
# Understanding relationship b/w 'Administration' Column and 'Profit' Column
sns.jointplot(data=df, x="Administration", y="Profit",kind='reg')
```

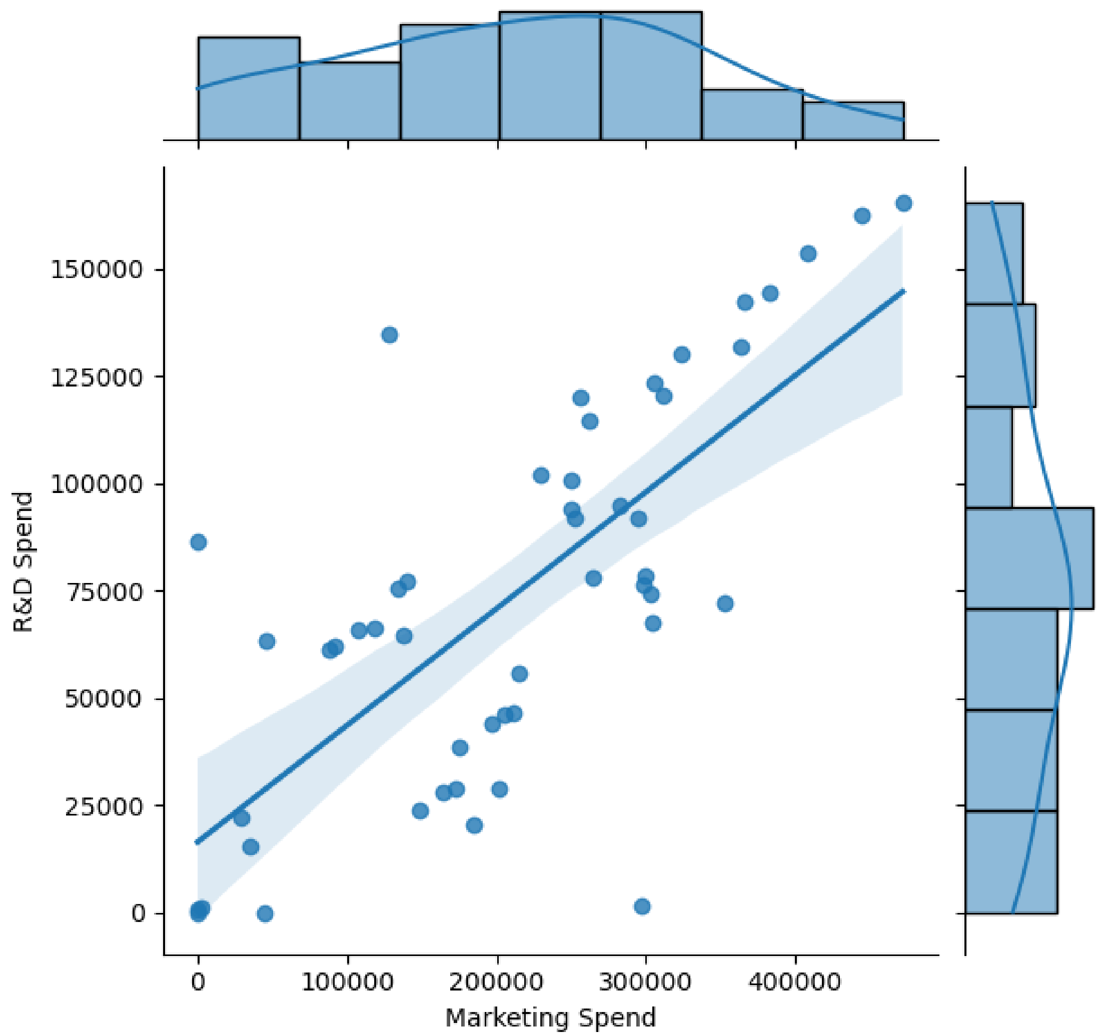
```
<seaborn.axisgrid.JointGrid at 0x276312b01f0>
```



- Althrough the terms are normally distributed , it doesnt explain Profir clearly

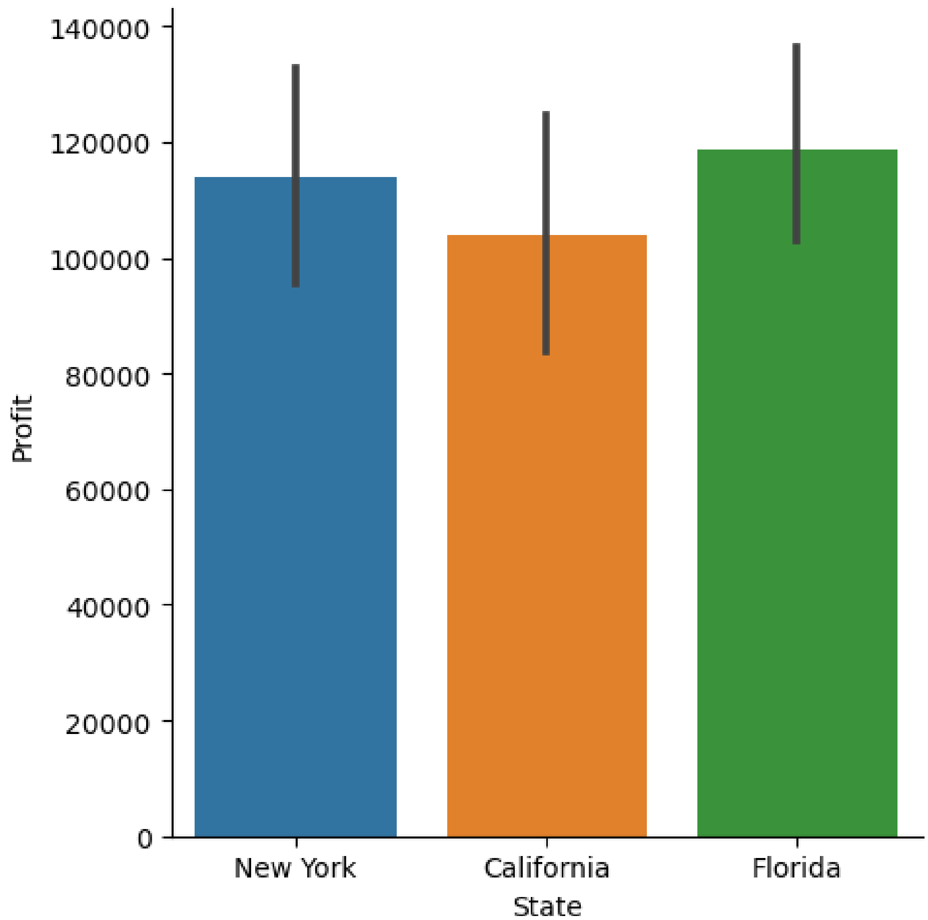
```
sns.jointplot(data=df, x="Marketing Spend", y="R&D Spend", kind="reg")
```

```
<seaborn.axisgrid.JointGrid at 0x27632928430>
```




```
# Understandeing relationship b/w catergorical varibale 'State' and target variable 'Profit'
sns.catplot(x="State", y="Profit", kind="bar", data=df)
```

```
<seaborn.axisgrid.FacetGrid at 0x27632d566d0>
```



Data Preparation

Splitting the dataset into the Training set and Test set

```
df_train, df_test = train_test_split(df, test_size = 0.2, random_state = 0)
```

```
df_train.head()
```

	R&D Spend	Administration	Marketing Spend	State	Profit
33	55493.95	103057.49	214634.81	Florida	96778.92
35	46014.02	85047.44	205517.64	New York	96479.51
26	75328.87	144135.98	134050.07	Florida	105733.54
34	46426.07	157693.92	210797.67	California	96712.80
18	91749.16	114175.79	294919.57	Florida	124266.90

Encoding

- The categorical column -'State' is encoded to numerical using OnehatEncoder and the reamining numerical are scaled using MinMaxScaler

```
numerical_columns = ['R&D Spend', 'Marketing
Spend','Administration','Profit']
categorical_columns = ['State']
```

```python
ct = ColumnTransformer(transformers=[
    ('num', MinMaxScaler(), numerical_columns),  # Apply MinMaxScaler to
numerical columns
    ('cat', OneHotEncoder(), categorical_columns)  # Apply OneHotEncoder to
categorical columns
], remainder='passthrough') # Keep remaining columns unchanged

df_train_transformed =ct.fit_transform(df_train)
df_test_transformed = ct.transform(df_test)

print(type(df_train_transformed))
print(type(df_test_transformed))
```

```
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
```

```python
# Convert the transformed arrays back to DataFrames
df_train = pd.DataFrame(df_train_transformed, columns=numerical_columns +
['encoded_' + col for col in
ct.named_transformers_['cat'].get_feature_names_out()])
df_test = pd.DataFrame(df_test_transformed, columns=numerical_columns +
['encoded_' + col for col in
ct.named_transformers_['cat'].get_feature_names_out()])

print(type(df_train))
print(type(df_test))
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.frame.DataFrame'>
```

```python
df_train.describe()
```

```
       R&D Spend  Marketing Spend  Administration     Profit  \
count  40.000000        40.000000       40.000000  40.000000
mean    0.433406         0.428461        0.677641   0.533646
std     0.282906         0.265022        0.246379   0.230775
min     0.000000         0.000000        0.000000   0.000000
25%     0.218371         0.259806        0.575948   0.411261
50%     0.431999         0.441214        0.698439   0.525378
75%     0.602505         0.630589        0.882500   0.666444
max     1.000000         1.000000        1.000000   1.000000

       encoded_State_California  encoded_State_Florida  encoded_State_New
York
count                 40.000000              40.000000
40.000000
mean                   0.400000               0.250000
0.350000
std                    0.496139               0.438529
0.483046
min                    0.000000               0.000000
```

```
0.000000
25%                    0.000000                 0.000000
0.000000
50%                    0.000000                 0.000000
0.000000
75%                    1.000000                 0.250000
1.000000
max                    1.000000                 1.000000
1.000000
```

Multiple Linear Regression

Multiple Linear Regression (MLR) is a statistical method used to model the relationship between multiple independent variables and a single dependent variable. It extends the simple linear regression model to handle situations where more than one predictor variable influences the target variable.

- MLR is supervised Regression model used for dealing with linear entities (the variables that exhibit a linear realtionship)

Initializing x_train , y_train

```
y_train = df_train['Profit']
X_train = df_train.drop(['Profit'],axis=1)
```

```
print(X_train.shape)
print(y_train.shape)
```

```
(40, 6)
(40,)
```

```
X_train.head()
```

```
   R&D Spend  Marketing Spend  Administration  encoded_State_California  \
0   0.335617         0.454943        0.486552                       0.0
1   0.278284         0.435618        0.317301                       0.0
2   0.455574         0.284134        0.872589                       0.0
3   0.280776         0.446810        1.000000                       1.0
4   0.554881         0.625116        0.591036                       0.0

   encoded_State_Florida  encoded_State_New York
0                    1.0                     0.0
1                    0.0                     1.0
2                    1.0                     0.0
3                    0.0                     0.0
4                    1.0                     0.0
```

```
y_train.head()
```

```
0    0.462312
1    0.460626
```

```
2    0.512737
3    0.461939
4    0.617103
Name: Profit, dtype: float64
```

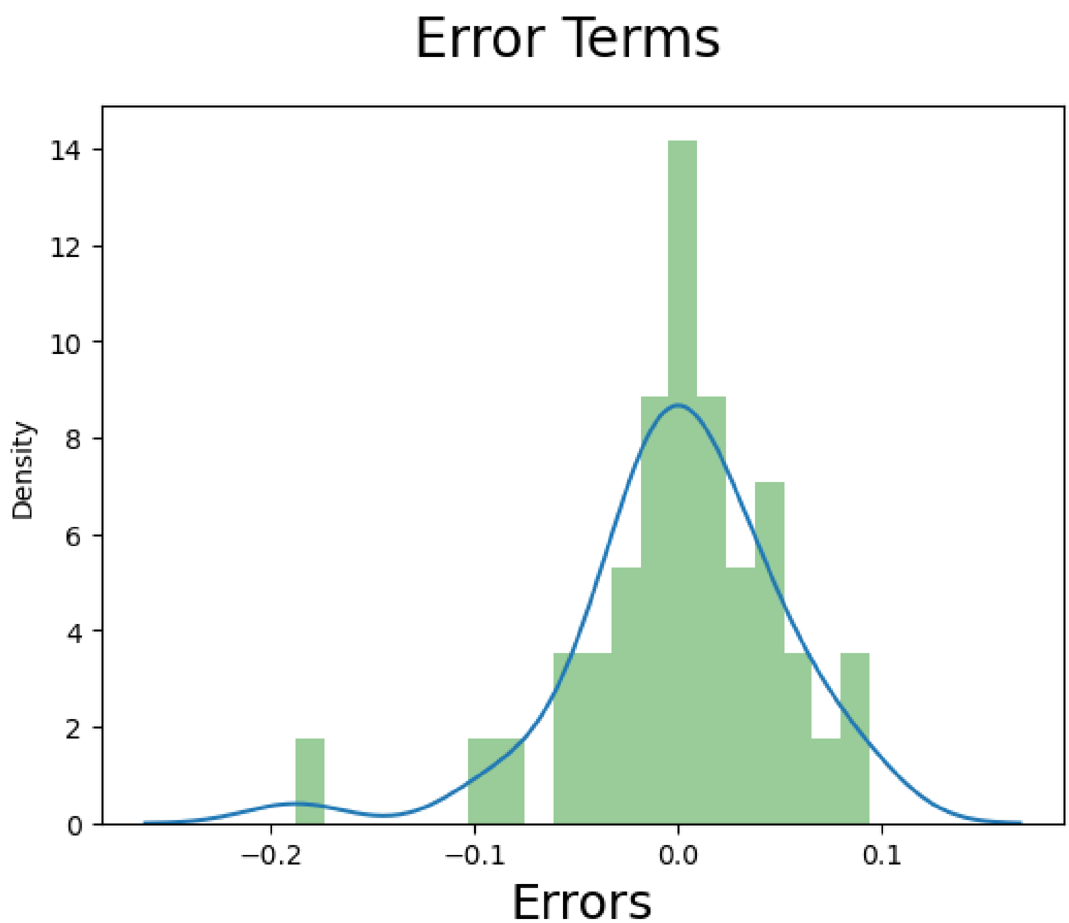
Training the Multiple Linear Regression model on the Training set

```
# Initialise teh Linear Regressor
linear_regressor = LinearRegression()

# Train the train data set
linear_regressor.fit(X_train, y_train)

# Predict the y_train using X_train
y_train_pred = linear_regressor.predict(X_train)

# Calculate Residuals
res = (y_train - y_train_pred)
```

Residual Analysis

```
# Residual analysis - checking weather the error terms are normally
distributed or not
fig = plt.figure()
sns.distplot(res, bins = 20,hist_kws={'color': 'green'})
fig.suptitle('Error Terms', fontsize = 20)
plt.xlabel('Errors', fontsize = 18)
```

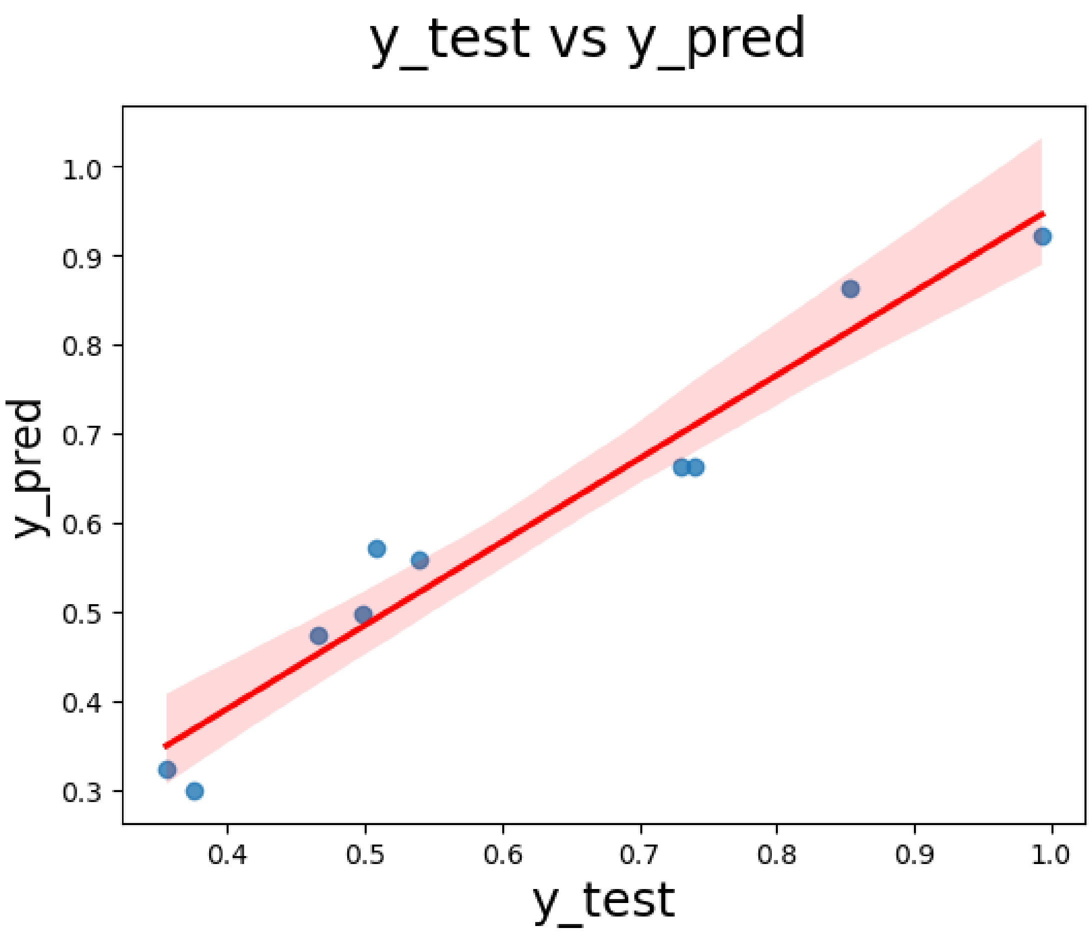
```
Text(0.5, 0, 'Errors')
```



- The error terms are normally distributed

Predicting the Test set results

```
# Initialize the X-test and y_test

y_test = df_test['Profit']
X_test = df_test.drop(['Profit'],axis=1)

# predict y_test using x_test
y_test_pred = linear_regressor.predict(X_test)

# Plot a scatter plot with predicted y value and test y value

fig = plt.figure()
sns.regplot(x=y_test,y= y_test_pred,data=df,line_kws={'color': 'red'})
fig.suptitle('y_test vs y_pred', fontsize = 20)
plt.xlabel('y_test', fontsize = 18)
plt.ylabel('y_pred', fontsize = 16)

Text(0, 0.5, 'y_pred')
```



Evaluating the Model

Let's evaluate our model performance by calculating the residual sum of squares and the explained variance score (R^2).

```
# Calculate the evaluation metrics

# The Coefficient of variables
print('Coefficient: ',linear_regressor.coef_)

# The intercept made by regression line
print('Intercept: ' ,  linear_regressor.intercept_)

# Absolute Mean Error = |yobs-ypred|
print('Absolute MEan Error: ', metrics.mean_absolute_error(y_test,
y_test_pred))

# Mean Square Error = |yobs - ypred|^2
print("Mean Square Error(MSE): ",metrics.mean_squared_error(y_test,
y_test_pred, squared=False))
```

```
# RMSE = rt(MSE)
print("Root MeanSquare Error(RMSE):
",np.sqrt(metrics.mean_squared_error(y_test,y_test_pred)))

print()

# R2_score = 1- (RSS/TSS)
print("R2 Score: ",metrics.r2_score(y_test,y_test_pred))
```

```
Coefficient:  [ 7.20192994e-01  9.72631281e-02  1.97053001e-02  4.87882416e-
04
 -4.91408761e-03  4.42620519e-03]
Intercept:  0.16596735725805262
Absolute MEan Error:  0.04231487478457284
Mean Square Error(MSE):  0.051458317522910246
Root MeanSquare Error(RMSE):  0.051458317522910246

R2 Score:  0.9347068473282426
```

Building the model using StatsModel for summary

```
import statsmodels.api as sm


# Add a constant
X_train_lm = sm.add_constant(X_train)

# Create a first fitted model
linear_model = sm.OLS(y_train, X_train_lm).fit()

# Check the parameters obtained

linear_model.params
```

```
const                          0.124476
R&D Spend                      0.720193
Marketing Spend                0.097263
Administration                 0.019705
encoded_State_California       0.041980
encoded_State_Florida          0.036578
encoded_State_New York         0.045918
dtype: float64
```

```
print(linear_model.summary())
```

```
                            OLS Regression Results
=============================================================================
=
Dep. Variable:                  Profit   R-squared:
0.950
Model:                             OLS   Adj. R-squared:
```

```
0.943
Method:                 Least Squares   F-statistic:
129.7
Date:                Tue, 02 Apr 2024   Prob (F-statistic):           3.91e-
21
Time:                        22:32:48   Log-Likelihood:
62.390
No. Observations:                  40   AIC:                             -
112.8
Df Residuals:                      34   BIC:                             -
102.6
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
===============
                               coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
---------------
const                        0.1245      0.022      5.588      0.000
0.079       0.170
R&D Spend                    0.7202      0.051     14.025      0.000
0.616       0.825
Marketing Spend              0.0973      0.052      1.884      0.068      -
0.008       0.202
Administration               0.0197      0.040      0.495      0.624      -
0.061       0.101
encoded_State_California     0.0420      0.013      3.143      0.003
0.015       0.069
encoded_State_Florida        0.0366      0.017      2.153      0.038
0.002       0.071
encoded_State_New York       0.0459      0.014      3.249      0.003
0.017       0.075
==============================================================================
=
Omnibus:                       15.823   Durbin-Watson:
2.468
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
23.231
Skew:                          -1.094   Prob(JB):                     9.03e-
06
Kurtosis:                       6.025   Cond. No.
1.17e+16
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

```
[2] The smallest eigenvalue is 6.43e-31. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

- The p-value of `Administration` is high(.0.05) so it should be removed for better results

Looking at the p-values, it looks like some of the variables aren't really significant (in the presence of other variables).

We could simply drop the variable with the highest, non-significant p value. A better way would be to supplement this with the VIF information.

Checking VIF

Variance Inflation Factor or VIF, gives a basic quantitative idea about how much the feature variables are correlated with each other. It is an extremely important parameter to test our linear model. The formula for calculating `VIF` is:

$ VIF_i = \frac{1}{1 - {R_i}^2} $

```
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Create a dataframe that will contain the names of all the feature variables
and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in
range(X_train.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif

                  Features   VIF
3  encoded_State_California  4.91
5    encoded_State_New York  4.49
4     encoded_State_Florida  4.07
0                 R&D Spend  2.70
1           Marketing Spend  2.40
2            Administration  1.23
```

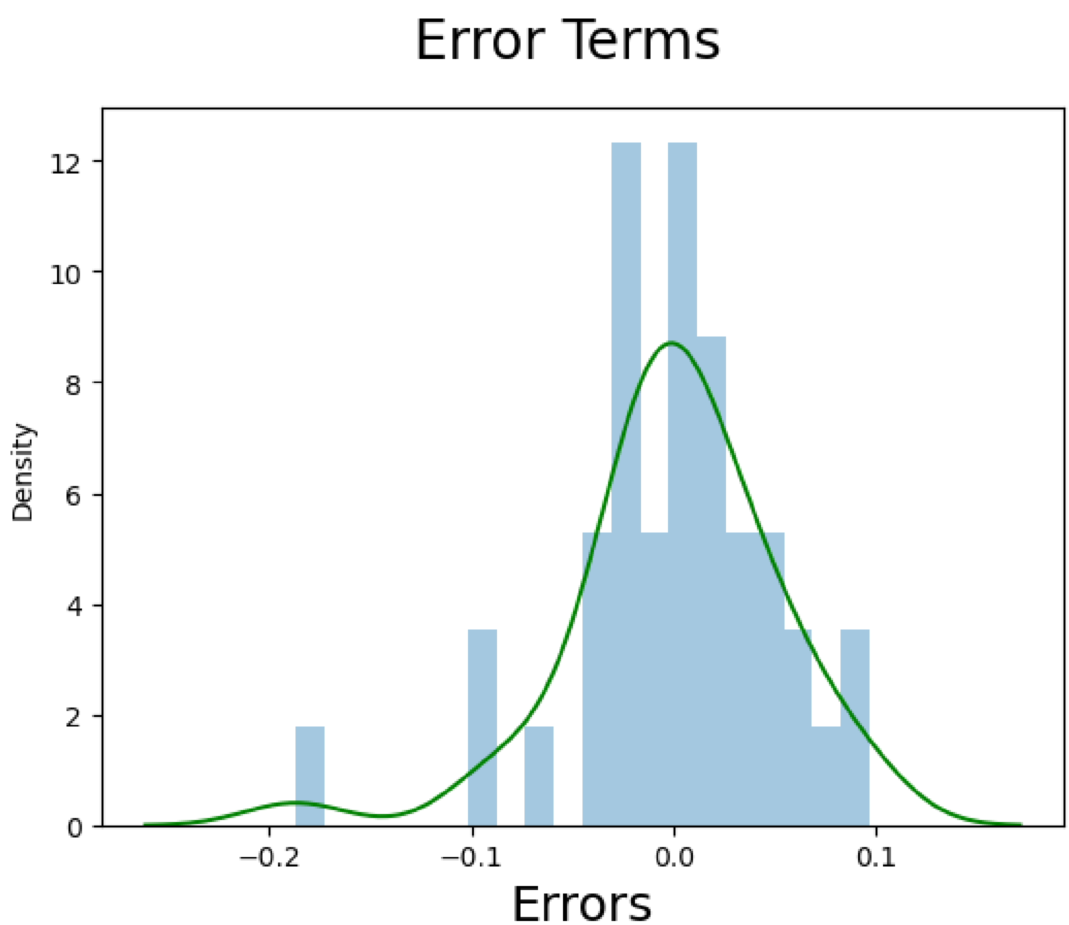
- The intercorelation /multicolinearity is less so the columns can be left alone

Removing the 'Administration' variable and rebuilding the model

```
# Remove the "Administration" column from X_train and X_test
X_train_updated = X_train.drop(['Administration'],axis=1)
X_test_updated = X_test.drop(['Administration'],axis=1)

#  Retrain the Linear Regression model
linear_regressor_updated = LinearRegression()
linear_regressor_updated.fit(X_train_updated, y_train)
```

```python
# Predict the y_train using X_test
y_train_pred_new = linear_regressor_updated.predict(X_train_updated)

# Calculate Residuals
res = (y_train - y_train_pred_new) # Residuals

# Residual analysis - checking weather the error terms are normally
distributed or not
fig = plt.figure()
sns.distplot(res, bins = 20,kde_kws={'color': 'green'})
fig.suptitle('Error Terms', fontsize = 20)
plt.xlabel('Errors', fontsize = 18)
```

```
Text(0.5, 0, 'Errors')
```



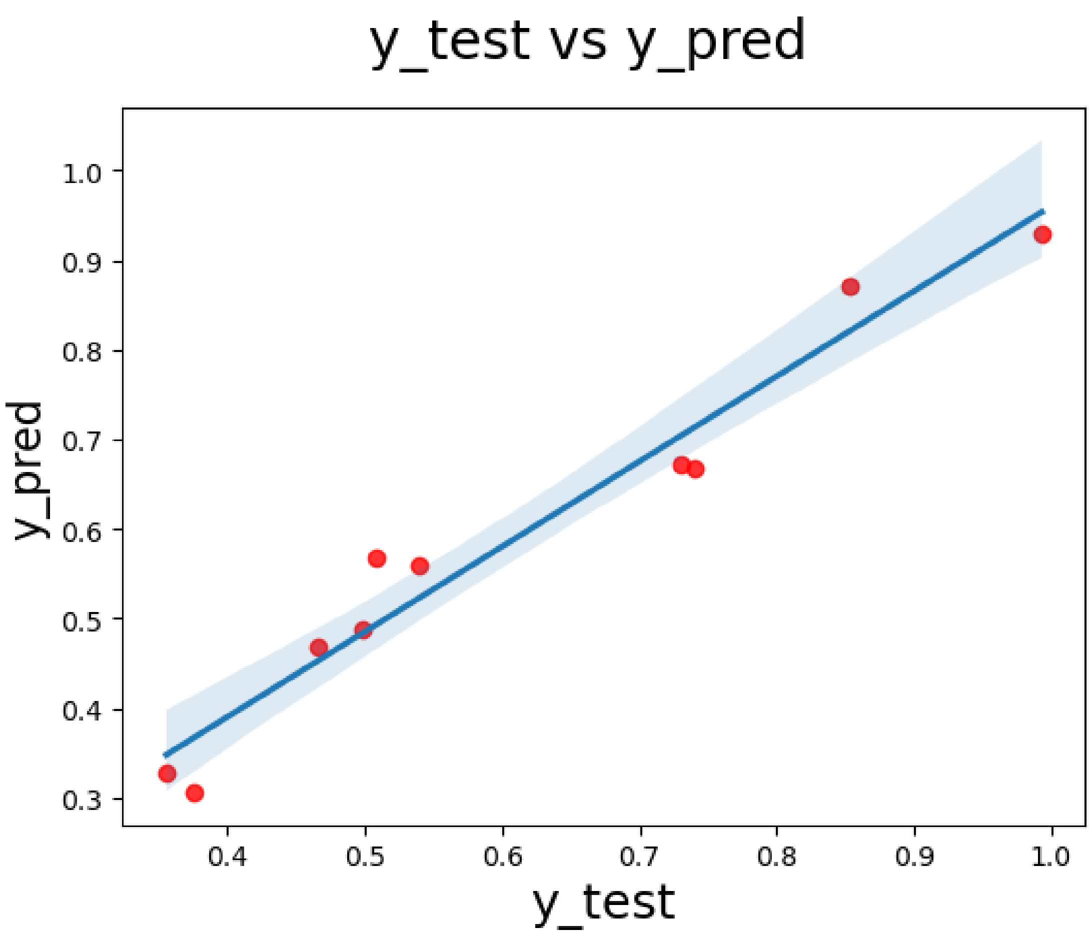
- the error terms/ residuals are normally distributed

Evaluate the performance of updated model on test data

```python
#  Evaluate the performance of the updated model
y_test_pred_new = linear_regressor_updated.predict(X_test_updated)
```

```python
# Plot a scatter plot with predicted y value and test y value

fig = plt.figure()
sns.regplot(x=y_test,y= y_test_pred_new,data=df,scatter_kws={'color': 'red'})
# used for specifying the color of scatter plot
fig.suptitle('y_test vs y_pred', fontsize = 20)
plt.xlabel('y_test', fontsize = 18)
plt.ylabel('y_pred', fontsize = 16)
```

```
Text(0, 0.5, 'y_pred')
```




```python
# Calculate the evaluation metrics

# The Coefficient of variables
print('Coefficient: ',linear_regressor_updated.coef_)

# The intercept made by regression line
print('Intercept: ' ,  linear_regressor_updated.intercept_)

# Absolute Mean Error = |yobs-ypred|
print('Absolute MEan Error: ', metrics.mean_absolute_error(y_test,
y_test_pred_new))
```

```
# Mean Square Error = |yobs - ypred|^2
print("Mean Square Error(MSE): ",metrics.mean_squared_error(y_test,
y_test_pred_new, squared=False))

# RMSE = rt(MSE)
print("Root MeanSquare Error(RMSE):
",np.sqrt(metrics.mean_squared_error(y_test,y_test_pred_new)))

print()

# R2_score = 1- (RSS/TSS)
print("R2 Score: ",metrics.r2_score(y_test,y_test_pred_new))
```

```
Coefficient:  [ 7.31063411e-01  9.02131542e-02  5.10211675e-04 -4.14383809e-
03
  3.63362642e-03]
Intercept:  0.17770571098352195
Absolute MEan Error:  0.0400334766484711
Mean Square Error(MSE):  0.04735835313888054
Root MeanSquare Error(RMSE):  0.04735835313888054

R2 Score:  0.9446968769427516
```

- Check for any redundant columns present/not

```
vif = pd.DataFrame()
vif['Features'] = X_train_updated.columns
vif['VIF'] = [variance_inflation_factor(X_train_updated.values, i) for i in
range(X_train_updated.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
4	encoded_State_New York	2.23
1	Marketing Spend	2.22
0	R&D Spend	2.21
3	encoded_State_Florida	1.97
2	encoded_State_California	1.94

- No redundant columns are present

Validating model using Statsmodel for evaluation metrics

```
import statsmodels.api as sm


# Add a constant
X_train_lm2 = sm.add_constant(X_train_updated)

# Create a first fitted model
```

```
linear_model_2 = sm.OLS(y_train, X_train_lm2).fit()

# Check the parameters obtained

linear_model_2.params
```

```
const                         0.133279
R&D Spend                     0.731063
Marketing Spend               0.090213
encoded_State_California      0.044937
encoded_State_Florida         0.040283
encoded_State_New York        0.048060
dtype: float64
```

```
print(linear_model_2.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                 Profit   R-squared:
0.950
Model:                            OLS   Adj. R-squared:
0.944
Method:                 Least Squares   F-statistic:
165.6
Date:                Tue, 02 Apr 2024   Prob (F-statistic):           3.19e-
22
Time:                        22:32:49   Log-Likelihood:
62.246
No. Observations:                  40   AIC:                             -
114.5
Df Residuals:                      35   BIC:                             -
106.0
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
===============
                               coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
---------------
const                        0.1333      0.013     10.055      0.000
0.106       0.160
R&D Spend                    0.7311      0.046     15.924      0.000
0.638       0.824
Marketing Spend              0.0902      0.049      1.838      0.074      -
0.009       0.190
encoded_State_California     0.0449      0.012      3.803      0.001
0.021       0.069
encoded_State_Florida        0.0403      0.015      2.671      0.011
```

```
0.010       0.071
encoded_State_New York       0.0481      0.013      3.611      0.001
0.021       0.075
==============================================================================
=
Omnibus:                      14.873   Durbin-Watson:
2.511
Prob(Omnibus):                 0.001   Jarque-Bera (JB):
21.150
Skew:                         -1.038   Prob(JB):                      2.56e-
05
Kurtosis:                      5.895   Cond. No.
2.46e+16
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 1.16e-31. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Insights from MLR Model

MLR can be implemented either by using Sckit Learn / Stats Model

- Using Sckit learn we got r2_score around 0.94
- Using Stats Model we got r2_score around 0.95
- This cost_function(r2_score) determines the quality of our multiple Linear Regression Model

Random Forest Regression

Random Forest Regression is a popular ensemble learning method used for both classification and regression tasks. It operates by constructing a multitude of decision trees during training and outputting the average prediction of the individual trees for regression tasks.

- Random Forest is a supervised learning algorithm that utilizes the ensemble of decision trees to improve predictive performance and reduce overfitting.

Data Preparation

Splitting the dataset into the Training set and Test set

```
df_train, df_test = train_test_split(df, test_size = 0.2, random_state = 0)

df_train.head()
```

```
    R&D Spend  Administration  Marketing Spend       State     Profit
33   55493.95       103057.49        214634.81     Florida   96778.92
35   46014.02        85047.44        205517.64    New York   96479.51
26   75328.87       144135.98        134050.07     Florida  105733.54
34   46426.07       157693.92        210797.67  California   96712.80
18   91749.16       114175.79        294919.57     Florida  124266.90
```

Encoding

```
numerical_columns = ['R&D Spend', 'Marketing
Spend','Administration','Profit']
categorical_columns = ['State']

from sklearn.preprocessing import MinMaxScaler

ct = ColumnTransformer(transformers=[
    ('num', MinMaxScaler(), numerical_columns),  # Apply MinMaxScaler to
numerical columns
    ('cat', OneHotEncoder(), categorical_columns)  # Apply OneHotEncoder to
categorical columns
], remainder='passthrough') # Keep remaining columns unchanged

df_train_transformed =ct.fit_transform(df_train)
df_test_transformed = ct.transform(df_test)

print(type(df_train_transformed))
print(type(df_test_transformed))

<class 'numpy.ndarray'>
<class 'numpy.ndarray'>

# Convert the transformed arrays back to DataFrames
df_train = pd.DataFrame(df_train_transformed, columns=numerical_columns +
['encoded_' + col for col in
ct.named_transformers_['cat'].get_feature_names_out()])
df_test = pd.DataFrame(df_test_transformed, columns=numerical_columns +
['encoded_' + col for col in
ct.named_transformers_['cat'].get_feature_names_out()])

print(type(df_train))
print(type(df_test))

<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.frame.DataFrame'>

df_train.describe()

       R&D Spend  Marketing Spend  Administration     Profit  \
count  40.000000        40.000000       40.000000  40.000000
mean    0.433406         0.428461        0.677641   0.533646
std     0.282906         0.265022        0.246379   0.230775
min     0.000000         0.000000        0.000000   0.000000
25%     0.218371         0.259806        0.575948   0.411261
```

```
50%      0.431999          0.441214         0.698439   0.525378
75%      0.602505          0.630589         0.882500   0.666444
max      1.000000          1.000000         1.000000   1.000000

       encoded_State_California  encoded_State_Florida  encoded_State_New
York
count                 40.000000              40.000000
40.000000
mean                   0.400000               0.250000
0.350000
std                    0.496139               0.438529
0.483046
min                    0.000000               0.000000
0.000000
25%                    0.000000               0.000000
0.000000
50%                    0.000000               0.000000
0.000000
75%                    1.000000               0.250000
1.000000
max                    1.000000               1.000000
1.000000
```

Initialising the target and predictor variable for train data set

```
y_train = df_train['Profit']
X_train = df_train.drop(['Profit'],axis=1)

print(X_train.shape)
print(y_train.shape)

(40, 6)
(40,)

X_train.head()

   R&D Spend  Marketing Spend  Administration  encoded_State_California  \
0   0.335617         0.454943        0.486552                       0.0
1   0.278284         0.435618        0.317301                       0.0
2   0.455574         0.284134        0.872589                       0.0
3   0.280776         0.446810        1.000000                       1.0
4   0.554881         0.625116        0.591036                       0.0

   encoded_State_Florida  encoded_State_New York
0                    1.0                     0.0
1                    0.0                     1.0
2                    1.0                     0.0
3                    0.0                     0.0
4                    1.0                     0.0

y_train.head()
```

```
0    0.462312
1    0.460626
2    0.512737
3    0.461939
4    0.617103
Name: Profit, dtype: float64
```

- All the above pre processing steps are same for both MLR and Random Forest

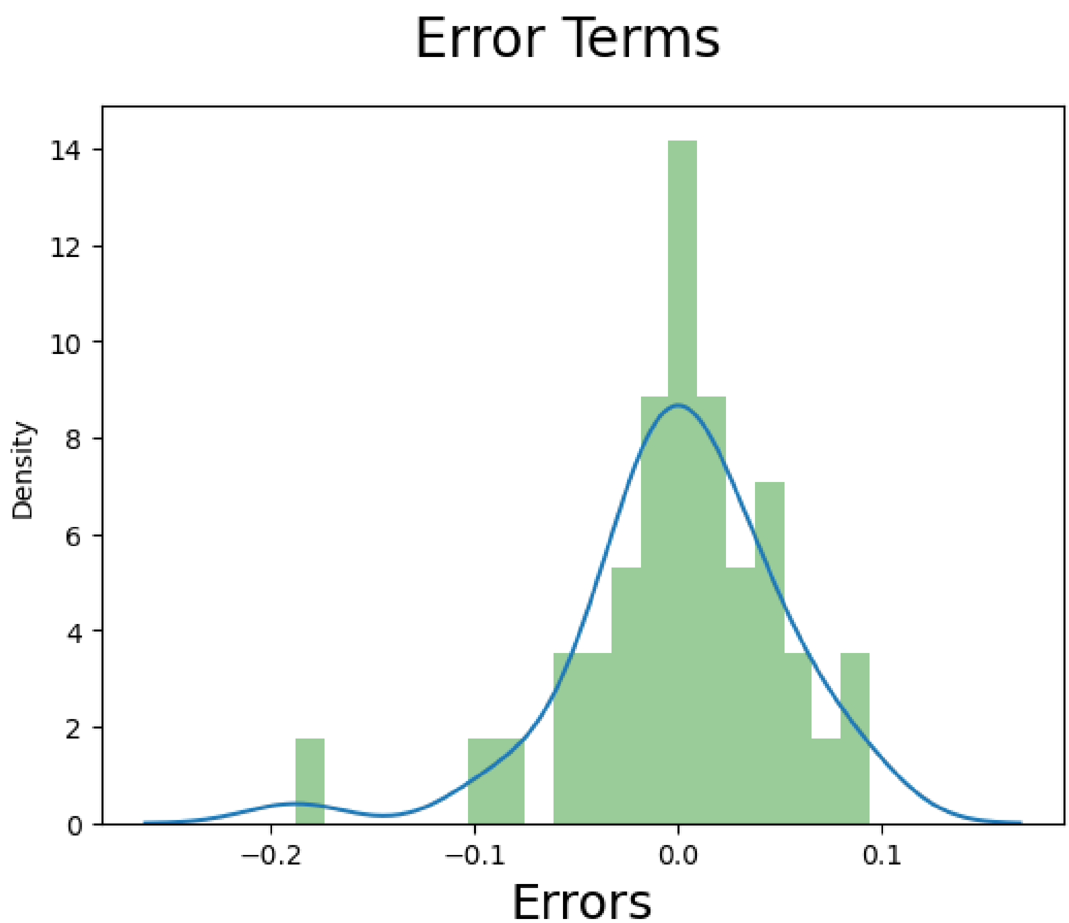
Training the Random forest model on training set

```
from sklearn.ensemble import RandomForestRegressor as RF
# Initialize the RandomForestRegressor
rf_regressor = RF(n_estimators=500)

# Train teh data set
rf_regressor.fit(X_train, y_train)

# Predict the y_train using X_train
y_train_pred = linear_regressor.predict(X_train)

# # Calculate Residuals (ycal - ypred)
res = (y_train - y_train_pred)
```

- the parameter n_estimators specifies the number of decision trees that will be used in the ensemble. Each decision tree in the Random Forest is referred to as an estimator.
- Therefore, n_estimators controls the size of the forest, or the number of trees in the ensemble.

Residual Analysis

```
# Residual analysis - checking weather the error terms are normally
distributed or not
fig = plt.figure()
sns.distplot(res, bins = 20,hist_kws={'color': 'green'})
fig.suptitle('Error Terms', fontsize = 20)
plt.xlabel('Errors', fontsize = 18)

Text(0.5, 0, 'Errors')
```

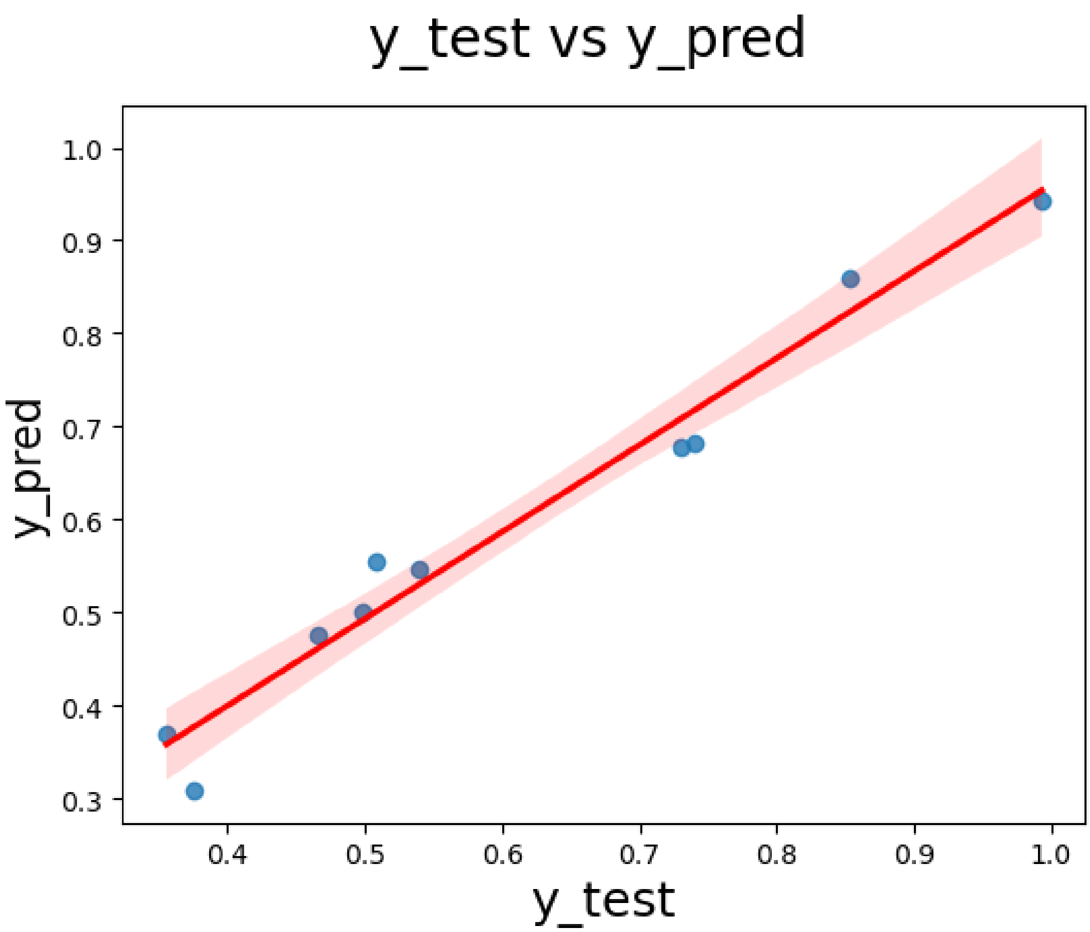


- The error terms are normally distributed

Predicting the Test set results

```
# Initialize the X-test and y_test

y_test = df_test['Profit']
X_test = df_test.drop(['Profit'],axis=1)

# predict y_test using x_test
y_test_pred = rf_regressor.predict(X_test)

# Plot a scatter plot with predicted y value and test y value

fig = plt.figure()
sns.regplot(x=y_test, y=y_test_pred,data=df, line_kws={'color': 'red'}) #
used for specfying  the color of regressionline
fig.suptitle('y_test vs y_pred', fontsize = 20)
plt.xlabel('y_test', fontsize = 18)
plt.ylabel('y_pred', fontsize = 16)
```

```
Text(0, 0.5, 'y_pred')
```



Evaluating the Model

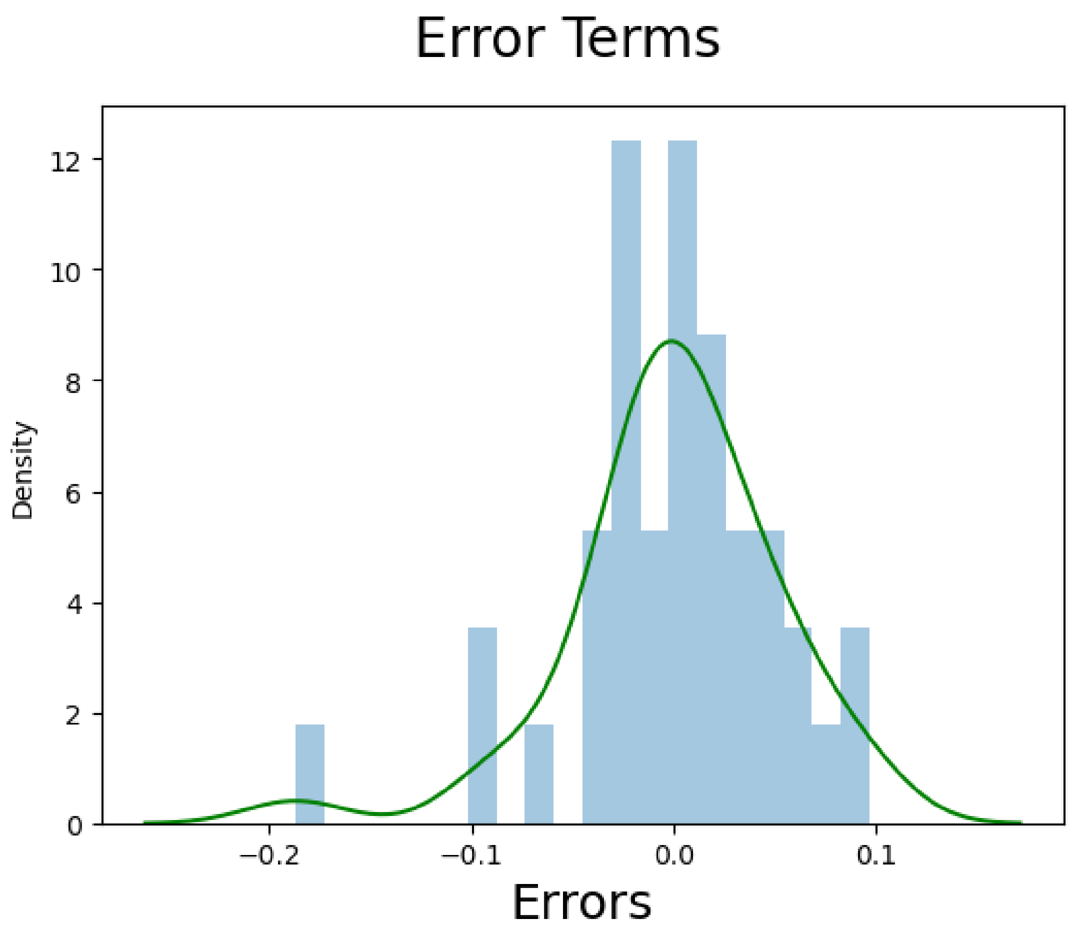
```
# Calculate the evaluation metrics

# Absolute Mean Error = |yobs-ypred|
print('Absolute Mean Error: ', metrics.mean_absolute_error(y_test,
y_test_pred))

# Mean Square Error = |yobs - ypred|^2
print("Mean Square Error(MSE): ",metrics.mean_squared_error(y_test,
y_test_pred, squared=False))

# RMSE = rt(MSE)
print("Root MeanSquare Error(RMSE):
",np.sqrt(metrics.mean_squared_error(y_test,y_test_pred)))

print()

# R2_score = 1- (RSS/TSS)
print("R2 Score: ",metrics.r2_score(y_test,y_test_pred))
```

```
Absolute Mean Error:  0.031335704593124 83
Mean Square Error(MSE):  0.039409202283800834
Root MeanSquare Error(RMSE):  0.039409202283800834

R2 Score:  0.9617041457050264
```

- The r2_score of `0.96` is really good which is significat measure the accuracy and correctness of our model
- Compared to MLR , with Random Forest the improved from 0.95 to `0.96`
- In the above case using MLR we found that 'Administration' variable has high p - value . so following which we will be removing it and rebuildig the model

```
# Remove the "Administration" column from X_train and X_test
X_train_updated = X_train.drop(['Administration'],axis=1)
X_test_updated = X_test.drop(['Administration'],axis=1)

#  Retrain the Linear Regression model
rf_regressor_updated = RF(n_estimators=500)
rf_regressor_updated.fit(X_train_updated, y_train)


# Predict the y_train using X_test
y_train_pred_new = linear_regressor_updated.predict(X_train_updated)

# Calculate Residuals
res = (y_train - y_train_pred_new)

# Residual analysis - checking weather the error terms are normally
distributed or not
fig = plt.figure()
sns.distplot(res, bins = 20,kde_kws={'color': 'green'})
fig.suptitle('Error Terms', fontsize = 20)
plt.xlabel('Errors', fontsize = 18)
```

```
Text(0.5, 0, 'Errors')
```



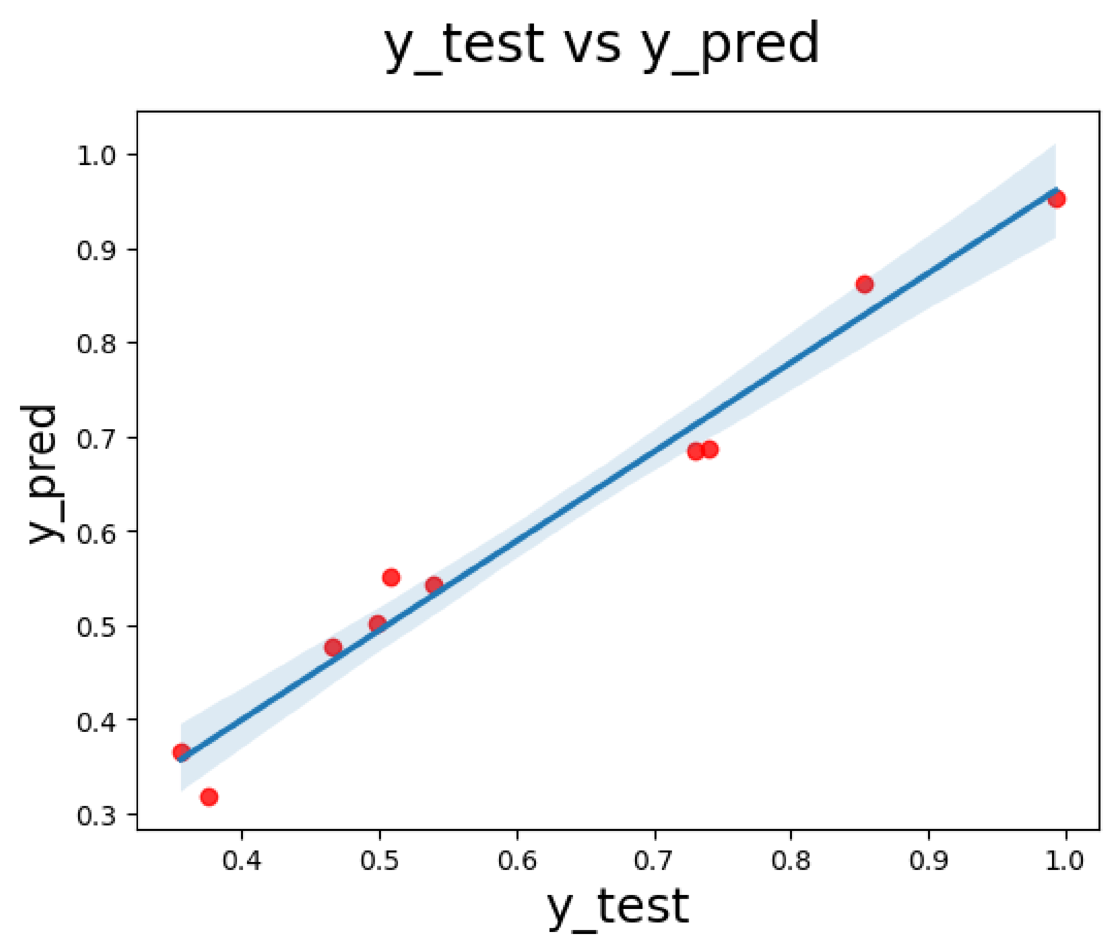
- The error terms are normally distributed

Evaluate the performance of updated model on test data

```
#  Evaluate the performance of the updated model
y_test_pred_new = rf_regressor_updated.predict(X_test_updated)
```

```
# Plot a scatter plot with predicted y value and test y value


fig = plt.figure()
sns.regplot(x=y_test, y= y_test_pred_new,data=df,scatter_kws={'color':
'red'})
fig.suptitle('y_test vs y_pred', fontsize = 20)
plt.xlabel('y_test', fontsize = 18)
plt.ylabel('y_pred', fontsize = 16)
```

```
Text(0, 0.5, 'y_pred')
```



Evaluating the Model

```
# Calculate the evaluation metrics

# Absolute Mean Error = |yobs-ypred|
print('Absolute Mean Error: ', metrics.mean_absolute_error(y_test,
y_test_pred_new))

# Mean Square Error = |yobs - ypred|^2
print("Mean Square Error(MSE): ",metrics.mean_squared_error(y_test,
y_test_pred_new, squared=False))

# RMSE = rt(MSE)
print("Root MeanSquare Error(RMSE):
",np.sqrt(metrics.mean_squared_error(y_test,y_test_pred_new)))

print()

# R2_score = 1- (RSS/TSS)
print("R2 Score: ",metrics.r2_score(y_test,y_test_pred_new))
```

```
Absolute Mean Error:  0.027130412985260234
Mean Square Error(MSE):  0.03424444902903638
Root MeanSquare Error(RMSE):  0.03424444902903638

R2 Score:  0.9710840916050402
```

- The r2_score slightly increased from 0.966 to 0.969 after removing the variable 'Administration'

Insights of RF Model

- The RF is implemented using sckit learn library
- The R2 score had a slight increase slight ater removing the redundant variables
- The accuracy of prediction using RF is more when compared to MLR

Save the models for Inference

```python
import joblib

#joblib.dump(scaler,"minmax_scaler.joblib")
#joblib.dump(ct, "col_transformer.joblib")
#joblib.dump(rf_regressor, "rf_regressor.joblib")
#joblib.dump(linear_regressor, "linear_regressor.joblib")
```

- These models will be further used while creating a interface using gradio for predicting the target variable

User Interface using Gradio

```python
import gradio as gr
import joblib
import warnings
warnings.filterwarnings('ignore')

# load models and transformer
ct = joblib.load("col_transformer.joblib")
linear_regressor = joblib.load("linear_regressor.joblib")
rf_regressor = joblib.load("rf_regressor.joblib")

def predict(R_and_D_Spending, Administration,   Marketing_spending,
      State, model = "Randomforest Regressor"):
    rdspending = int(R_and_D_Spending)
    admin = int(Administration)
    mspending = int(Marketing_spending)
    s = State

    inputs = ct.transform([[rdspending, admin, mspending, s]])
    print(inputs)
```

```python
    if model == "Randomforest Regressor":
        print("Using Randomforest Regression")
        model = rf_regressor
    else:
        print("Using Linear Regression")
        model = linear_regressor
    output = model.predict(inputs)

    return output

demo = gr.Interface(
    title="Profit Prediction",
    fn=predict,
    inputs=[gr.Text(label='R_and_D_Spending'),
            gr.Text(label='Administration'),
            gr.Text(label='Marketing_spending'),
            gr.Dropdown(['New York', 'California', 'Florida']),
            gr.Dropdown(["Randomforest Regressor", "LInear Regrssor"])],
    outputs="number")



if __name__ == "__main__":
    demo.launch(share=True)
```

```
Running on local URL:  http://127.0.0.1:7862
Running on public URL: https://064f9c92acabd2c941.gradio.live

This share link expires in 72 hours. For free permanent hosting and GPU
upgrades, run `gradio deploy` from Terminal to deploy to Spaces
(https://huggingface.co/spaces)

<IPython.core.display.HTML object>
```

Conclusions

1. Project Outcomes

- The main `aim` of the project is to `predict 'Profit'` obtained when a startup is placed in a particular 'State' with various factors effecting such as 'R&D Spend', 'MArketing Spend', 'Administration'

- The data set primarily has 5 variables - 'R&D Spend', 'MArketing Spend', 'Administration' , 'State' and 'Profit'

- The 'Profit' variable is taken as target variables -> predicted using other predictor variables

- In the process 2 Models are used

  - Multiple linear Regression
  - Random Forest Regression
- The quality of the model is checked using a mtreic(cost function) `R2_score`

- The MLR is implimented using 2 different

  - Using Sckit Learn We got a R-score around `0.94`
  - Using Stats Model We got around `0.95`
- With this we can conclude that MLR model gives good accuracy in predicting the target Variable

- The RF is implement using Sckit Learn library

  - Usinh which we got a final accuracy around `0.969`
- This score explains how good is our model in predicting the target variable

- Overall when compared to MLR , RF is used for providng better and more accurate resullts for predicting 'Profit'

2. Learning Outcomes

- Through this prject , I learnt in detail about machine learning algorithms such as `Multiple Linear Regression`, `Random Forest Regression`

1.Multiple Linear Regression (MLR):

- Understanding how to implement MLR using both scikit-learn and StatsModels libraries.
- Comparing the performance of MLR models using the R-squared metric.
- Appreciating the differences between scikit-learn and StatsModels in terms of implementation & performance evaluation.

2. Random Forest Regression (RF):

- Implementing Random Forest Regression using scikit-learn.
- Evaluating the performance of the RF model using the R-squared metric.
- Understanding how ensemble methods like Random Forest can improve predictive accuracy compared to simple linear regression models.

3. Evaluation Metrics:

- Understanding the importance of evaluation metrics like R-squared, RSS, MSE,RMSE in assessing model performance.
- Interpreting R-squared scores to gauge the goodness-of-fit of regression models.

4. ColumnTransformer:

- Learning how to preprocess data using ColumnTransformer to handle categorical and numerical variables simultaneously.
- Understanding the purpose and usage of ColumnTransformer in machine learning pipelines.
- Function of 'OneHotEncoder' used during conversion of categorical variables to numerical Variables

5. Gradio Library:

- Introduction to Gradio library for building interactive web interfaces for machine learning models.
- Understanding how to use Gradio to create user-friendly interfaces for model predictions.
- Exploring different input and output components provided by Gradio for model interaction.

Google Drive Link:

https://drive.google.com/drive/folders/1bMstkETpiripKbZIY5lkD8ftVnZXDjFy?usp=sharing