AKADEMIA WSB

DATA EXPLORATION METHODS

LAB.2

MULTIPLE LINEAR REGRESSION

Teacher:

Msc. Damian Skipiol

Student:

Alessandro Vavalà
48045

BUSINESS PROBLEM

- What has the greatest impact on the success of a Startup (Profit)?
- Which Sturtups are the most profitable?
- What is the impact of the Startup Profit in the state in which it is launched?•Which startups would you invest in?

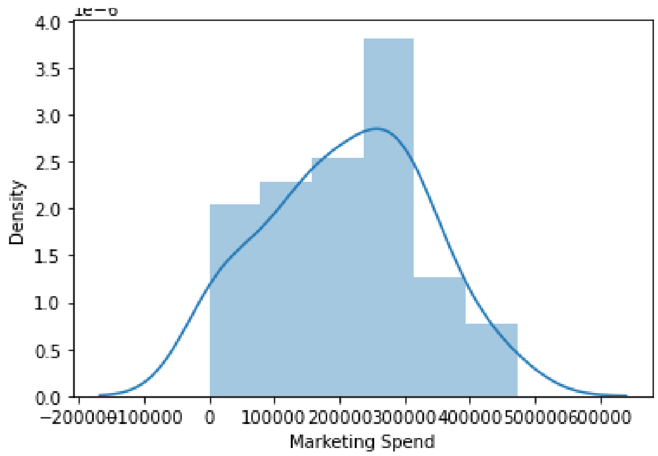
The dataset is composed of 50 Startups and for each of them it is specified R&D Spend; Administration; Marketing Spend; State; Profit

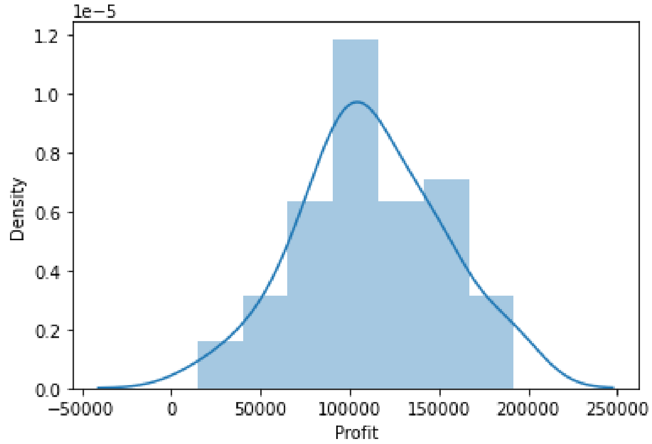
	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94

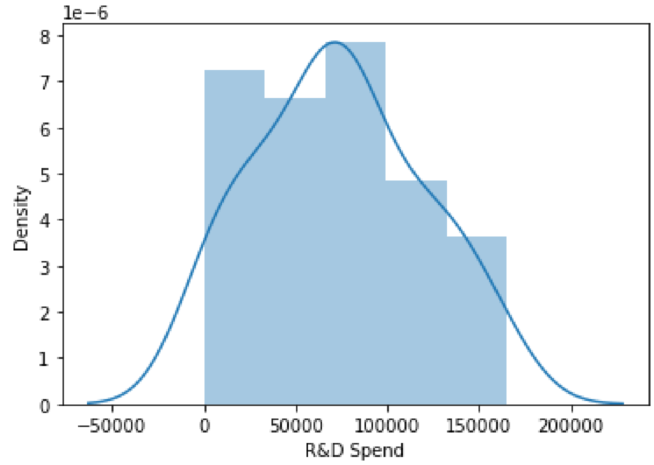
	count	mean	std	min	25%	50%	75%	max
R&D Spend	50.0	73721.6156	45902.256482	0.00	39936.3700	73051.080	101602.8000	165349.20
Administration	50.0	121344.6396	28017.802755	51283.14	103730.8750	122699.795	144842.1800	182645.56
Marketing Spend	50.0	211025.0978	122290.310726	0.00	129300.1325	212716.240	299469.0850	471784.10
Profit	50.0	112012.6392	40306.180338	14681.40	90138.9025	107978.190	139765.9775	192261.83

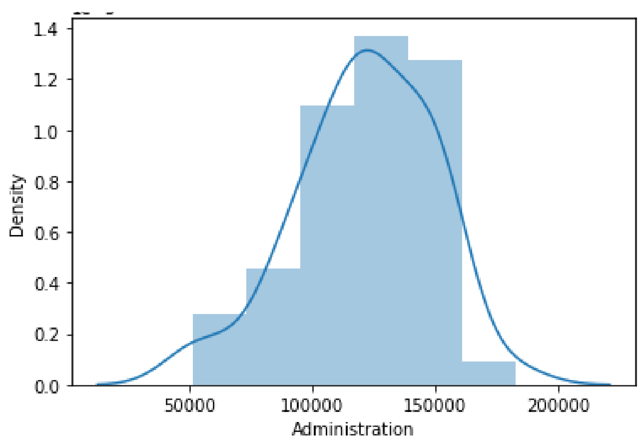
VARIABLES DISTRIBUTION

	count	mean	std	min	25%	50%	75%	max
R&D Spend	50.0	73721.6156	45902.256482	0.00	39936.3700	73051.080	101602.8000	165349.20
Administration	50.0	121344.6396	28017.802755	51283.14	103730.8750	122699.795	144842.1800	182645.56
Marketing Spend	50.0	211025.0978	122290.310726	0.00	129300.1325	212716.240	299469.0850	471784.10
Profit	50.0	112012.6392	40306.180338	14681.40	90138.9025	107978.190	139765.9775	192261.83



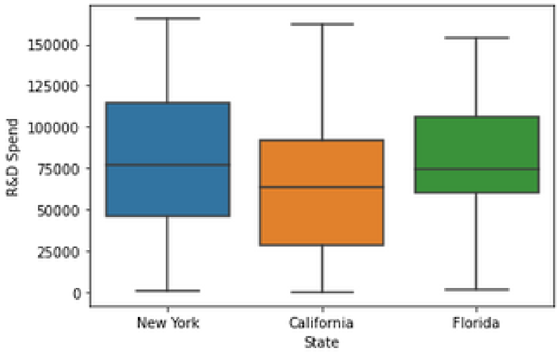


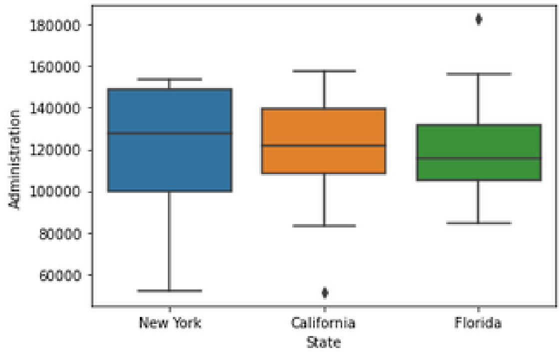


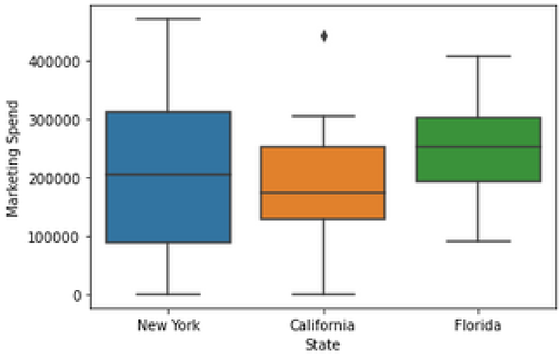


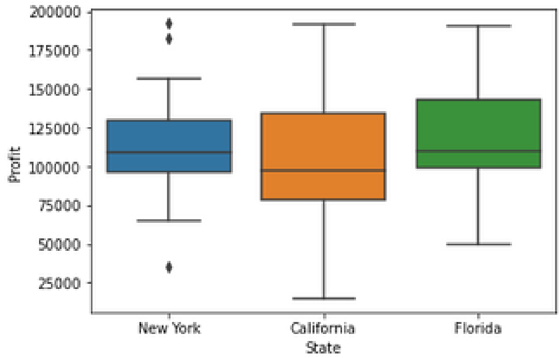
Looking at the Histograms, the variable R&D Spend is the most balanced among all the variables. But the variables have a high standard deviation which indicates a high spread of the data. R&D Spend and Marketing Spend are the two variables with the highest range.

BOXPLOTS







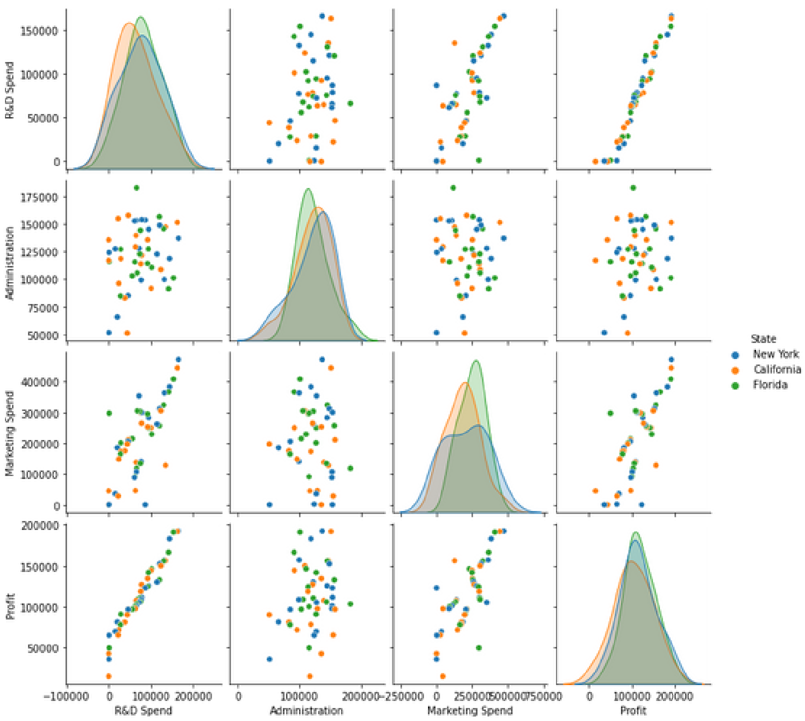


Startups in New York State for R&D Spend, Administration and Marketing Spend have the highest data range. But for Profit, the least. The data range for California and Florida are similar in all variables.

	State	California	Florida	New York
Profit	count	17.000000	16.000000	17.000000
	mean	103905.175294	118774.024375	113756.446471
	std	44446.359357	35605.470428	41140.258117
	min	14681.400000	49490.750000	35673.410000
	25%	78239.910000	99147.922500	96479.510000
	50%	97427.840000	109543.120000	108552.040000
	75%	134307.350000	142719.627500	129917.040000
	max	191792.060000	191050.390000	192261.830000

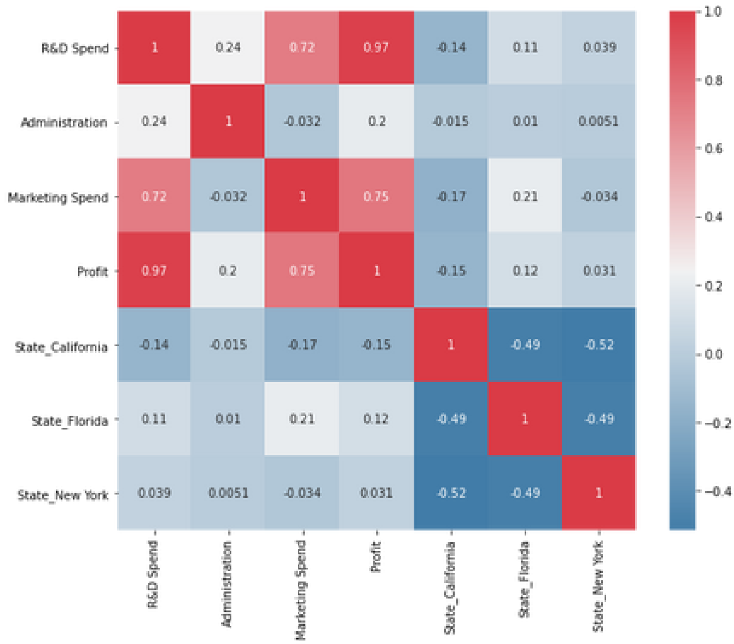
Startup in Florida record the average highest profit

CORRELATIONS



The variable Profit is strongly positively correlated with R&D Spend (97%). It is possible to see this corraltion in the matrix: when R&D Spend increases, Profit increses as well.

Another Variable highly correlated with Profit is Marketing Spend (75%).



Even though, Startups in Florida have the highest mean Profit the correlation between Florida (encoded) and Profit is low (12%). Florida is the highest correlated State with Profit, in fact California has a negative correlation (also the lowest mean profit for Startups), and New York State close to 0

MULTIPLE LINEAR REGRESSION MODEL

Profit is the dependent variable and R&D Spend; Administration; Marketing Spend; California_State; Florida_State and New York_State are the independent variable.
The dataset has been splitted in: 6/8 test set and 2/8 training set, random state = 120.

```
X_train Dataset Description and values:
DescribeResult(nobs=12, minmax=(array([-1.17717755, -1.99727037, -1.74312698, -0.71774056, -0.68599434,
       -0.71774056]), array([2.01641149, 1.20641936, 2.15394309, 1.39326109, 1.45773797,
       1.39326109])), mean=array([-0.09271446, -0.18355409, -0.20978689, -0.18999015,  0.0285831 ,
        0.16184346]), variance=array([0.72983213, 1.04907528, 1.18695436, 0.91152163, 1.114082  ,
       1.18160212]), skewness=array([ 1.07251991, -0.02661623,  0.60113141,  1.15470054,  0.70710678,
        0.3380617 ]), kurtosis=array([ 1.25506902, -0.89279112, -0.03488538, -0.66666667, -1.5       ,
       -1.88571429]))
X_train Array shape : (12, 6)

X_test Dataset Description and values:
DescribeResult(nobs=38, minmax=(array([-1.62236202, -2.52599402, -1.74312698, -0.71774056, -0.68599434,
       -0.71774056]), array([1.95586034, 2.2101405 , 1.9236004 , 1.39326109, 1.45773797,
       1.39326109])), mean=array([ 0.02927825,  0.05796445,  0.06624849,  0.05999689, -0.00902624,
       -0.05110846]), variance=array([1.13070597, 1.02508625, 0.97969186, 1.06495463, 1.01978914,
       0.98888644]), skewness=array([-0.011931  , -0.62240563, -0.26346215,  0.54554473,  0.79259392,
        0.79259392]), kurtosis=array([-1.06910775,  0.51401057, -0.78496263, -1.70238095, -1.37179487,
       -1.37179487]))
X_test Array shape: (38, 6)

y_train Dataset Description and values:
DescribeResult(nobs=12, minmax=(-1.1732089932266025, 2.0112033342229885), mean=-0.05345667459201751, variance=0.7091016764498884, skewness=1.17040
89277287444, kurtosis=1.1423428522763723)

y_test Dataset Description and values:
DescribeResult(nobs=38, minmax=(-2.4393132298487346, 1.9994299695211237), mean=0.01688105513432062, variance=1.1393178731215392, skewness=-0.16021
194627704477, kurtosis=-0.3894092119289203)

X_Train and y_train shape:
(12, 6)
(12,)
```

Here some statistics of the two sets are presented.

CHOOSING MODEL AND VARIBALES

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                 Profit   R-squared (uncentered):                   0.977
Model:                            OLS   Adj. R-squared (uncentered):              0.961
Method:                 Least Squares   F-statistic:                              60.24
Date:                Thu, 07 Jul 2022   Prob (F-statistic):                    1.33e-05
Time:                        10:17:57   Log-Likelihood:                          8.2401
No. Observations:                  12   AIC:                                     -6.480
Df Residuals:                       7   BIC:                                     -4.056
Df Model:                           5
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
R&D Spend            0.9386      0.113      8.302      0.000       0.671       1.206
Administration      -0.0550      0.067     -0.815      0.442      -0.215       0.105
Marketing Spend      0.0437      0.079      0.555      0.596      -0.142       0.230
State_California    -0.0211      0.039     -0.535      0.609      -0.114       0.072
State_Florida        0.0063      0.032      0.195      0.851      -0.070       0.082
State_New York       0.0149      0.034      0.445      0.670      -0.064       0.094
==============================================================================
Omnibus:                        0.011   Durbin-Watson:                   1.921
Prob(Omnibus):                  0.994   Jarque-Bera (JB):                0.161
Skew:                           0.042   Prob(JB):                        0.922
Kurtosis:                       2.438   Cond. No.                     3.93e+15
==============================================================================
```

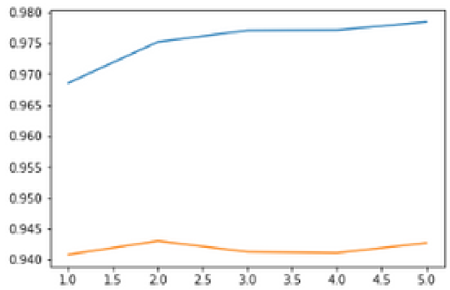
Here is the results of the regressor created based on the training set.
It's possible to state that:
- The model explains 97,7% of the change of Profit.
- Except for R&D all the variable have a high P-Value. It means that R&D Spend is a statistically significant variable
- The high positive coefficient of R&D Spend (0.9386) indicates the positive relationship between Profit and R&D Spend: the value of the independent variable increases and the mean of the dependent variable also tends to increase

```
Dropping State_Florida and running regression again because pvalue is: 0.8509642642298341
Dropping State_New York and running regression again because pvalue is: 0.8757574682889988
Dropping State_California and running regression again because pvalue is: 0.5888729810953166
Dropping Marketing Spend and running regression again because pvalue is: 0.7183204129431902
Dropping Administration and running regression again because pvalue is: 0.07841596657802424
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                 Profit   R-squared (uncentered):                  0.967
Model:                            OLS   Adj. R-squared (uncentered):             0.964
Method:                 Least Squares   F-statistic:                             319.2
Date:                Thu, 07 Jul 2022   Prob (F-statistic):                   1.79e-09
Time:                        11:53:50   Log-Likelihood:                         5.9420
No. Observations:                  12   AIC:                                    -9.884
Df Residuals:                      11   BIC:                                    -9.399
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
R&D Spend      0.9651      0.054     17.866      0.000       0.846       1.084
==============================================================================
Omnibus:                        4.060   Durbin-Watson:                   1.549
Prob(Omnibus):                  0.131   Jarque-Bera (JB):                1.936
Skew:                           0.979   Prob(JB):                        0.380
Kurtosis:                       3.187   Cond. No.                         1.00
==============================================================================
```

Also by using SelectKbest method, the best variable to predict 'Profit' is R&D Spend.

For a reliable Regressor model all the variables with a P-Value higher than 0.05. The only statistically significant variable is R&D Spend.




```python
### Best score k = 1
selector = SelectKBest(f_regression, k = 1)
X_train_transformed = selector.fit_transform(X_train, y_train)
X_test_transformed = selector.transform(X_test)
column_names[selector.get_support()]
```

```
Index(['R&D Spend'], dtype='object')
```

RESULTS

Coefficient: 0.97007809
the positive coefficient indicates the positive relationship between R&D Spend and Profit. As it was stated before.

Intercept: 0.03648358766432768

Mean Squared Error: 0.07
The MSE is the average squared distance between the actual and predicted values. Lower is better the model has predicted.

R squared: 94%
The independent variable (R&D Spend) can explain a portion of 94% of the variance in the dependent variable (Profit).

Laboratory 2 - Data Exploration

26th June 2022

Multiple Linear regression

Import Libs

In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

import seaborn as sns

from sklearn.ensemble import RandomForestRegressor
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.neural_network import MLPRegressor
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.preprocessing import PolynomialFeatures
from sklearn.svm import SVR

import statsmodels.api as sm

import warnings
warnings.filterwarnings('ignore')

pd.set_option('display.max.columns', None)
```

Data loading and overview

In [2]:

```
df = pd.read_csv("50_Startups.csv")
df.head()
```

Out[2]:

	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

In [3]:

```
# statistics of the dataset
df.describe().T
```

Out[3]:

	count	mean	std	min	25%	50%

	count	mean	std	min	25%	50%	
R&D Spend	50.0	73721.6156	45902.256482	0.00	39936.3700	73051.080	10160:
Administration	50.0	121344.6396	28017.802755	51283.14	103730.8750	122699.795	14484
Marketing Spend	50.0	211025.0978	122290.310726	0.00	129300.1325	212716.240	29946!
Profit	50.0	112012.6392	40306.180338	14681.40	90138.9025	107978.190	13976

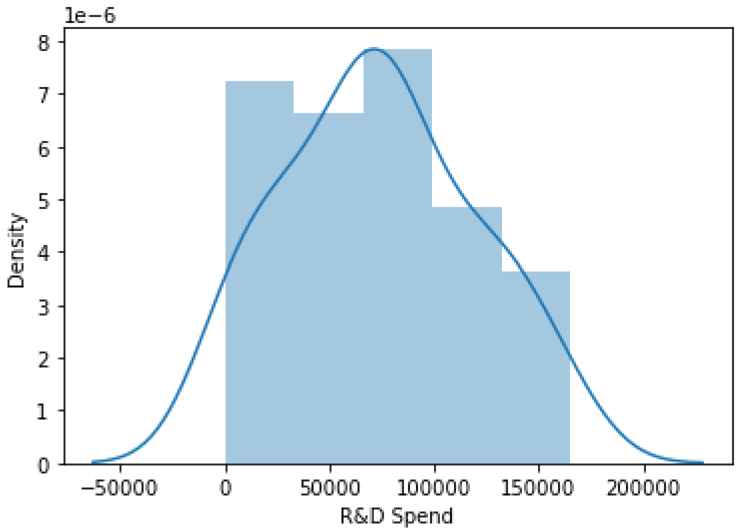
EDA

Distplot

We look at the distribution

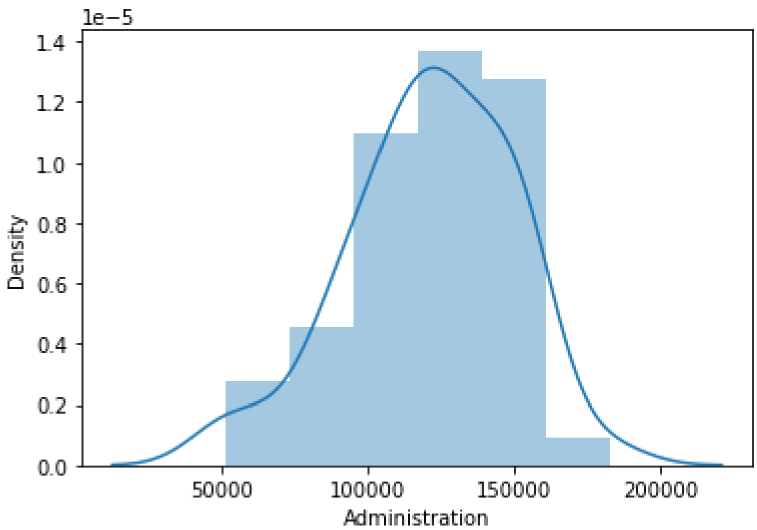
In [4]:
```
sns.distplot(df['R&D Spend'])
```

Out[4]: <AxesSubplot:xlabel='R&D Spend', ylabel='Density'>



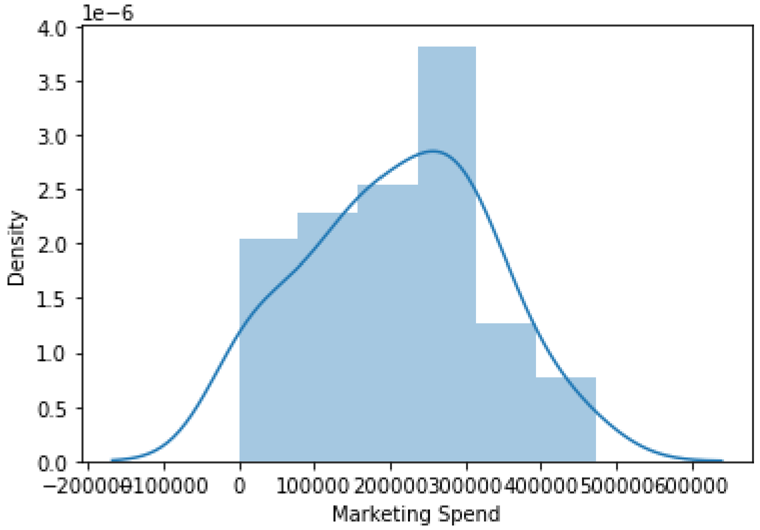
In [5]:
```
sns.distplot(df['Administration'])
```

Out[5]: <AxesSubplot:xlabel='Administration', ylabel='Density'>



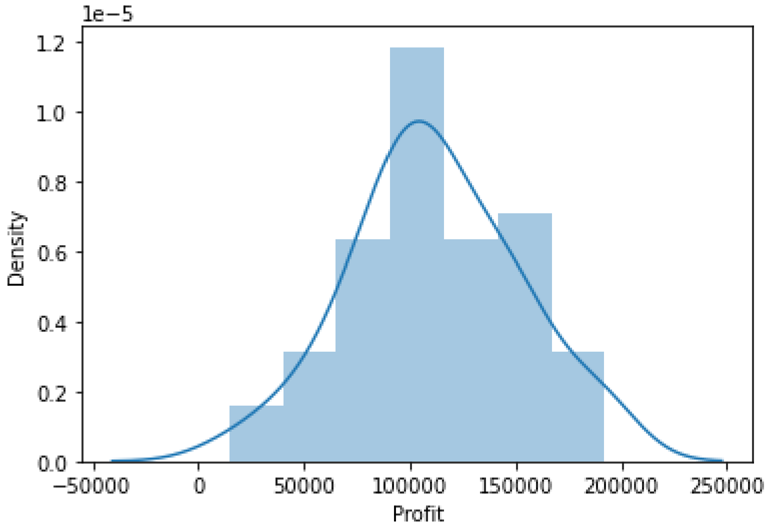
In [6]:
```python
sns.distplot(df['Marketing Spend'])
```

Out[6]: <AxesSubplot:xlabel='Marketing Spend', ylabel='Density'>



In [7]:
```python
sns.distplot(df['Profit'])
```

Out[7]: <AxesSubplot:xlabel='Profit', ylabel='Density'>

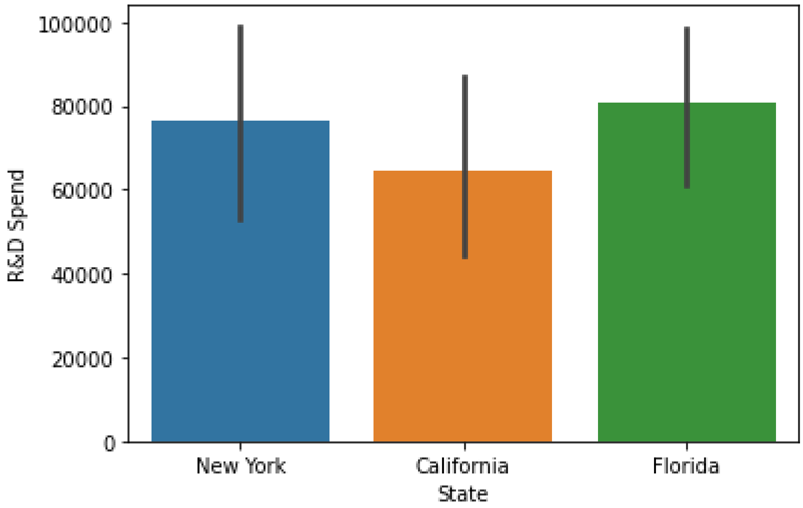


Feature distribution is not normal

Barplot

In [8]:
```python
sns.barplot(x = 'State', y = 'R&D Spend', data = df)
```

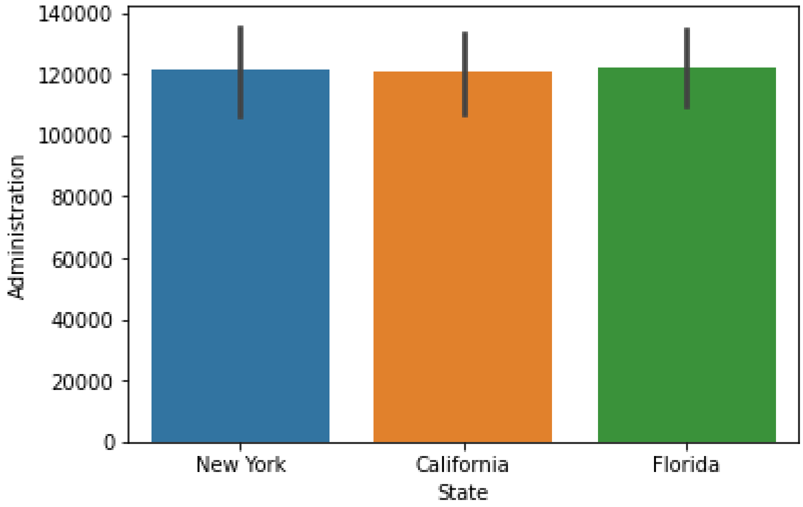
Out[8]: <AxesSubplot:xlabel='State', ylabel='R&D Spend'>



In [9]:

```
sns.barplot(x = 'State', y = 'Administration', data = df)
```

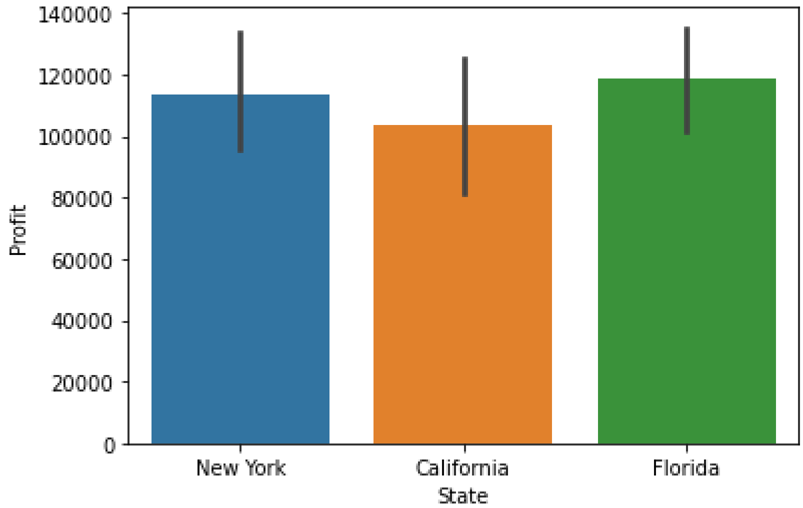
Out[9]: <AxesSubplot:xlabel='State', ylabel='Administration'>



In [10]:

```
sns.barplot(x = 'State', y = 'Profit', data = df)
```

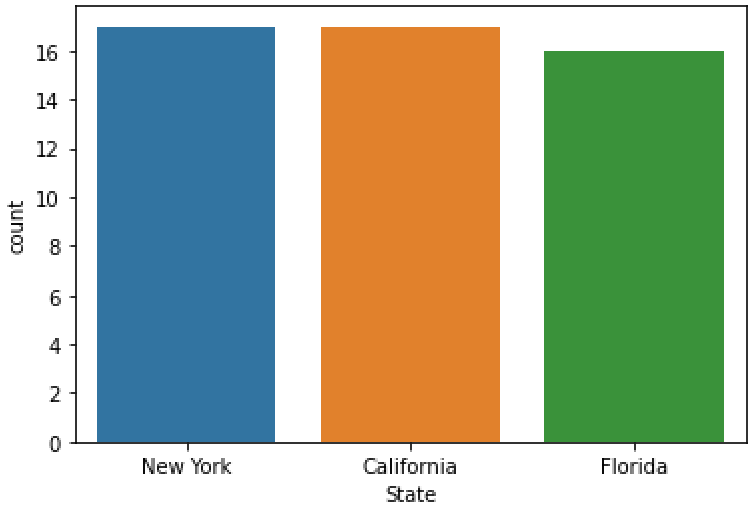
Out[10]: <AxesSubplot:xlabel='State', ylabel='Profit'>



Countplot

In [11]:
```
sns.countplot(x = 'State', data = df)
```

Out[11]: <AxesSubplot:xlabel='State', ylabel='count'>



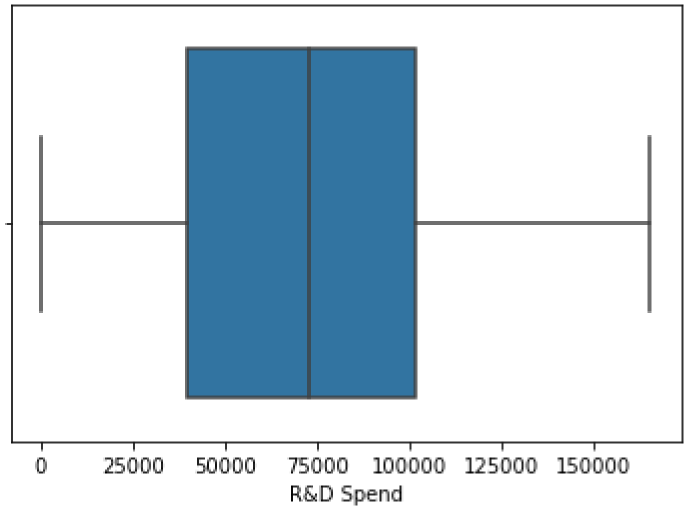
In [ ]:

Boxplot

We look at outliers

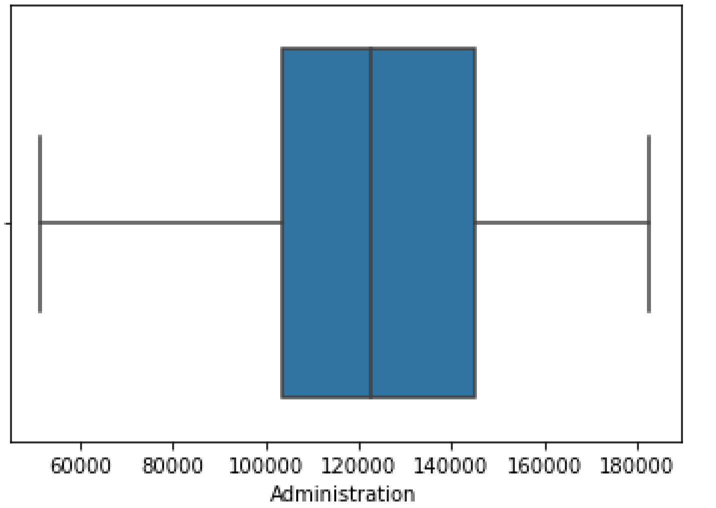
In [12]:
```
sns.boxplot(x = 'R&D Spend', data = df)
```

Out[12]: <AxesSubplot:xlabel='R&D Spend'>



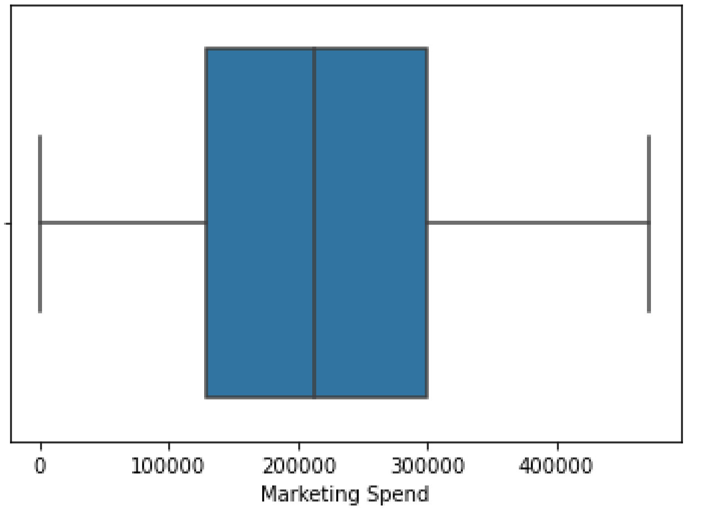
In [13]:
```
sns.boxplot(x = 'Administration', data = df)
```

Out[13]: <AxesSubplot:xlabel='Administration'>



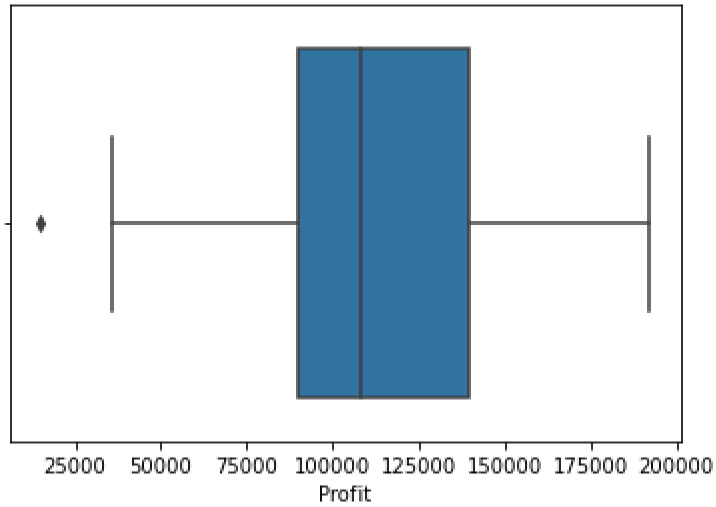
In [14]:
```
sns.boxplot(x = 'Marketing Spend', data = df)
```

Out[14]: <AxesSubplot:xlabel='Marketing Spend'>



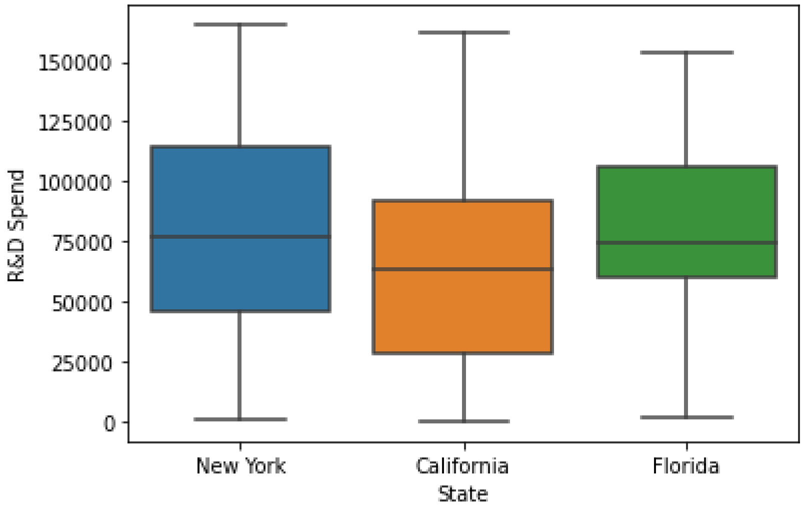
In [15]:
```
sns.boxplot(x = 'Profit', data = df)
```

Out[15]: <AxesSubplot:xlabel='Profit'>



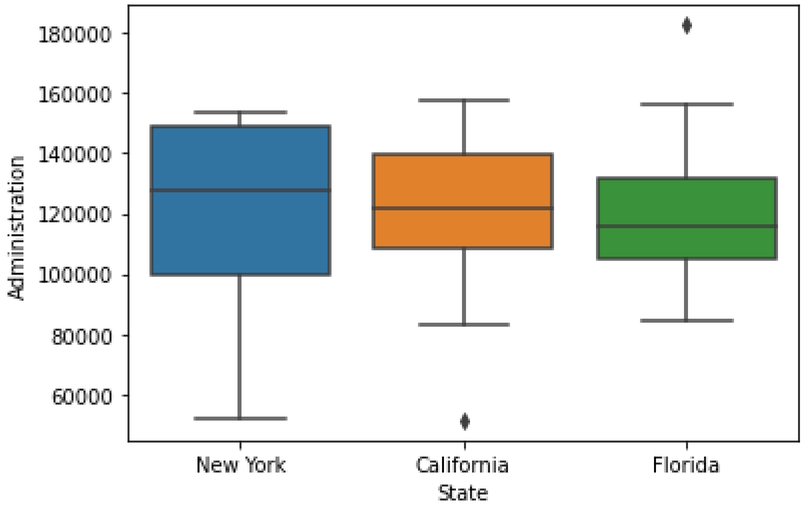
In [16]:
```
sns.boxplot(x = 'State', y = 'R&D Spend', data = df)
```

Out[16]: <AxesSubplot:xlabel='State', ylabel='R&D Spend'>



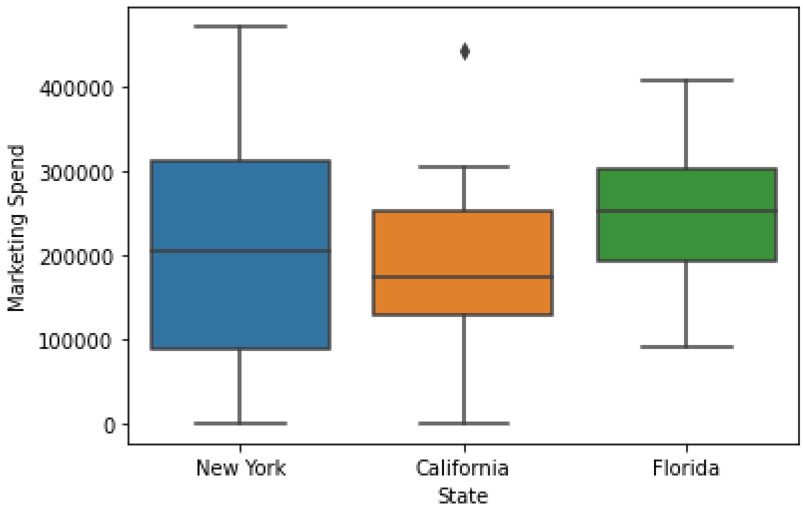
In [17]:
```
sns.boxplot(x = 'State', y = 'Administration', data = df)
```

Out[17]: <AxesSubplot:xlabel='State', ylabel='Administration'>



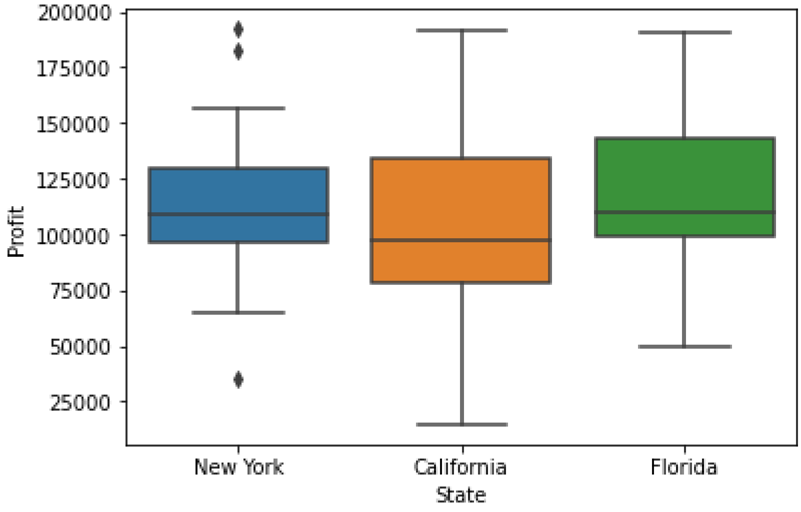
In [18]:
```
sns.boxplot(x = 'State', y = 'Marketing Spend', data = df)
```

Out[18]: <AxesSubplot:xlabel='State', ylabel='Marketing Spend'>



In [19]:
```
sns.boxplot(x = 'State', y = 'Profit', data = df)
```

Out[19]: <AxesSubplot:xlabel='State', ylabel='Profit'>



In [20]:
```
# profit statistics for each state
df[['Profit', 'State']].groupby('State').describe().T
```

Out[20]:

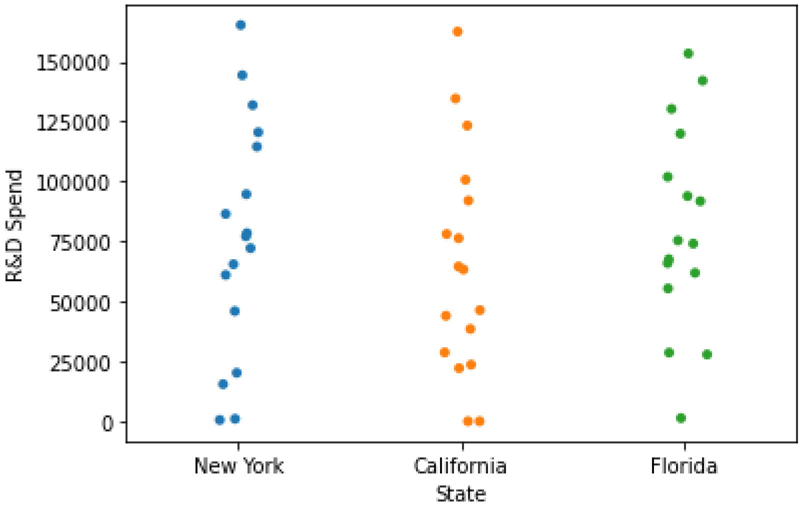
	State	California	Florida	New York
Profit	**count**	17.000000	16.000000	17.000000
	mean	103905.175294	118774.024375	113756.446471
	std	44446.359357	35605.470428	41140.258117
	min	14681.400000	49490.750000	35673.410000
	25%	78239.910000	99147.922500	96479.510000
	50%	97427.840000	109543.120000	108552.040000
	75%	134307.350000	142719.627500	129917.040000
	max	191792.060000	191050.390000	192261.830000

Striplot

Feature scattering

In [21]:
```
sns.stripplot(x ='State', y= 'R&D Spend', data = df)
```

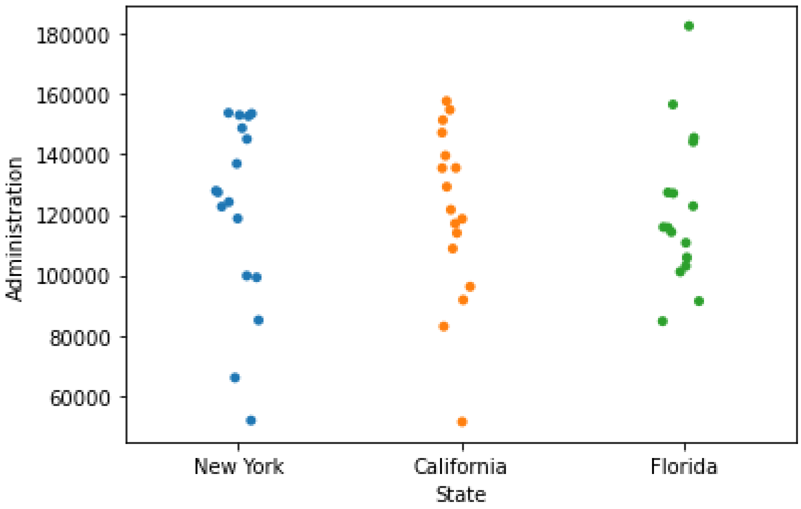
Out[21]: <AxesSubplot:xlabel='State', ylabel='R&D Spend'>



In [22]:

```
sns.stripplot(x ='State', y= 'Administration', data = df)
```

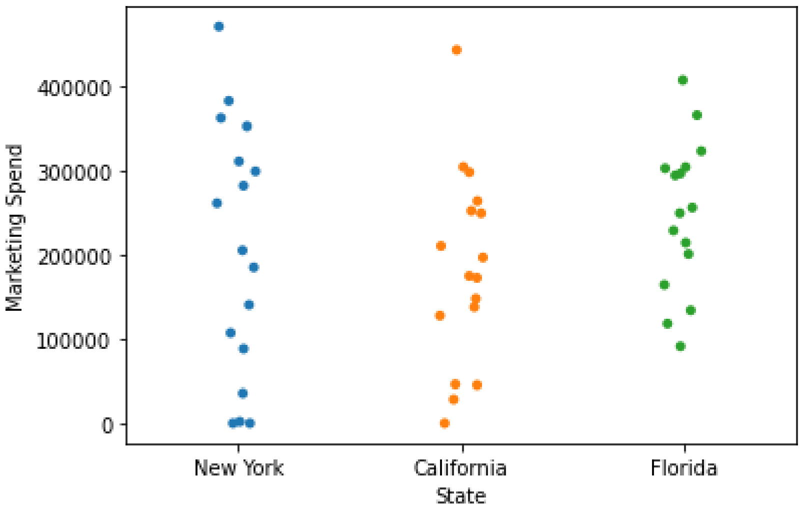
Out[22]: <AxesSubplot:xlabel='State', ylabel='Administration'>



In [23]:

```
sns.stripplot(x ='State', y= 'Marketing Spend', data = df)
```

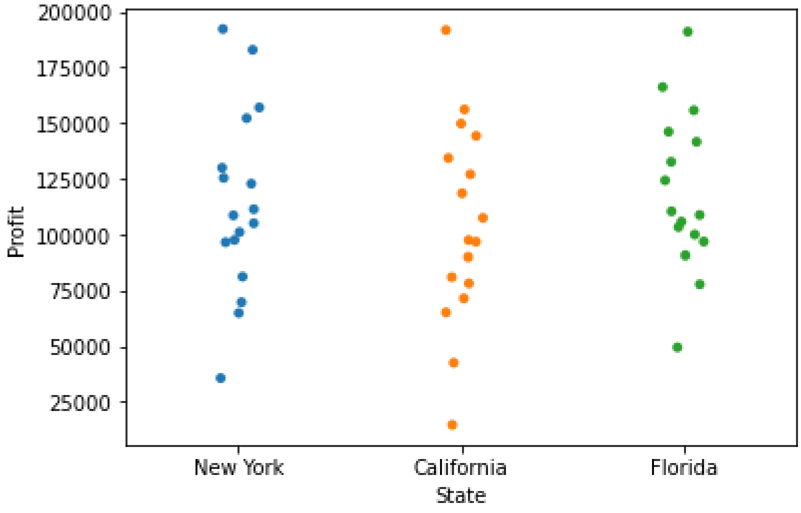
Out[23]: <AxesSubplot:xlabel='State', ylabel='Marketing Spend'>



In [24]:

```
sns.stripplot(x ='State', y= 'Profit', data = df)
```

Out[24]: <AxesSubplot:xlabel='State', ylabel='Profit'>

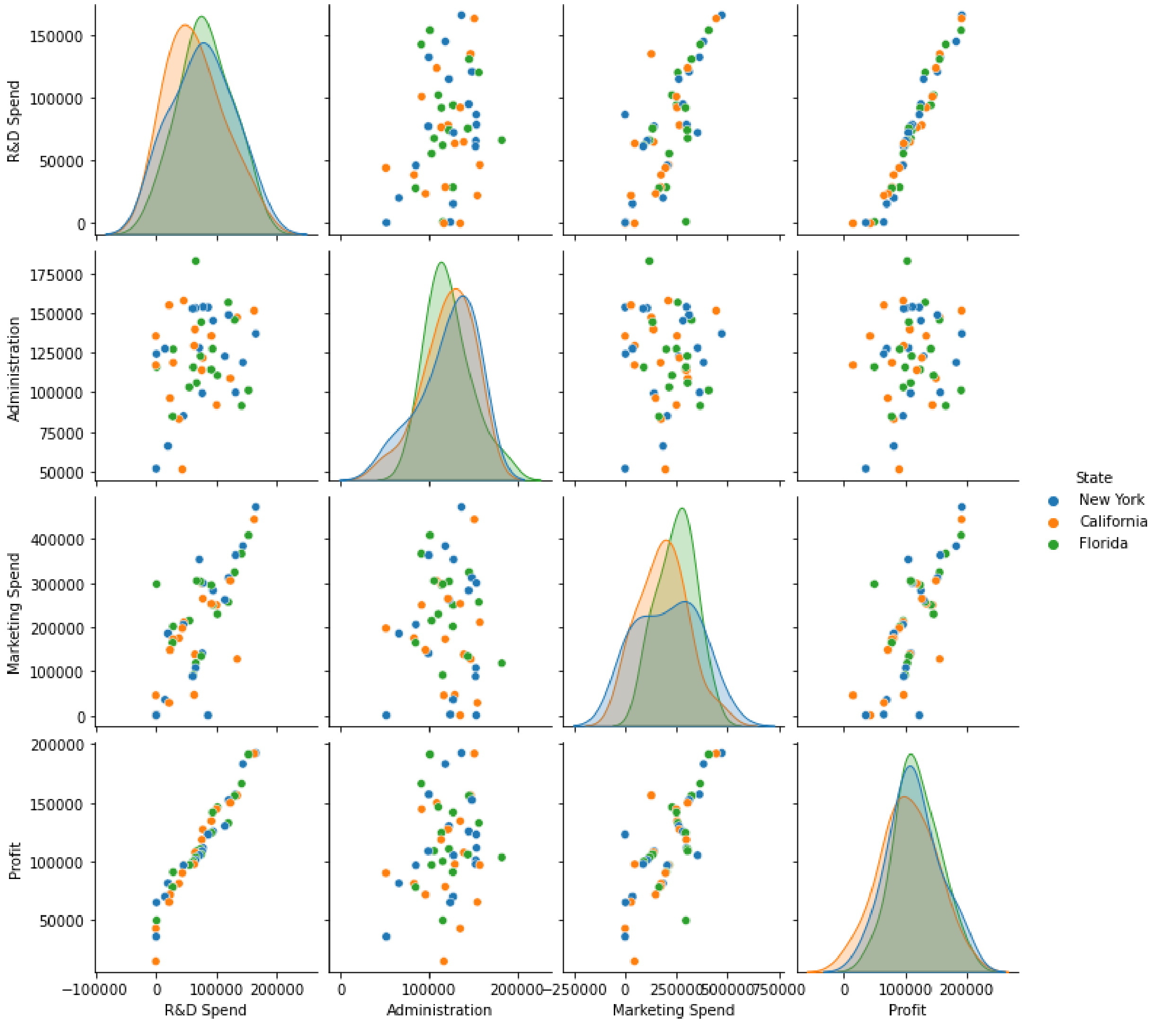


Matrix

In [25]:

```python
# matrix shows the correlation between variables and the density plot
sns.pairplot(df, hue = 'State')
```

Out[25]: <seaborn.axisgrid.PairGrid at 0x7fa69bd3d610>

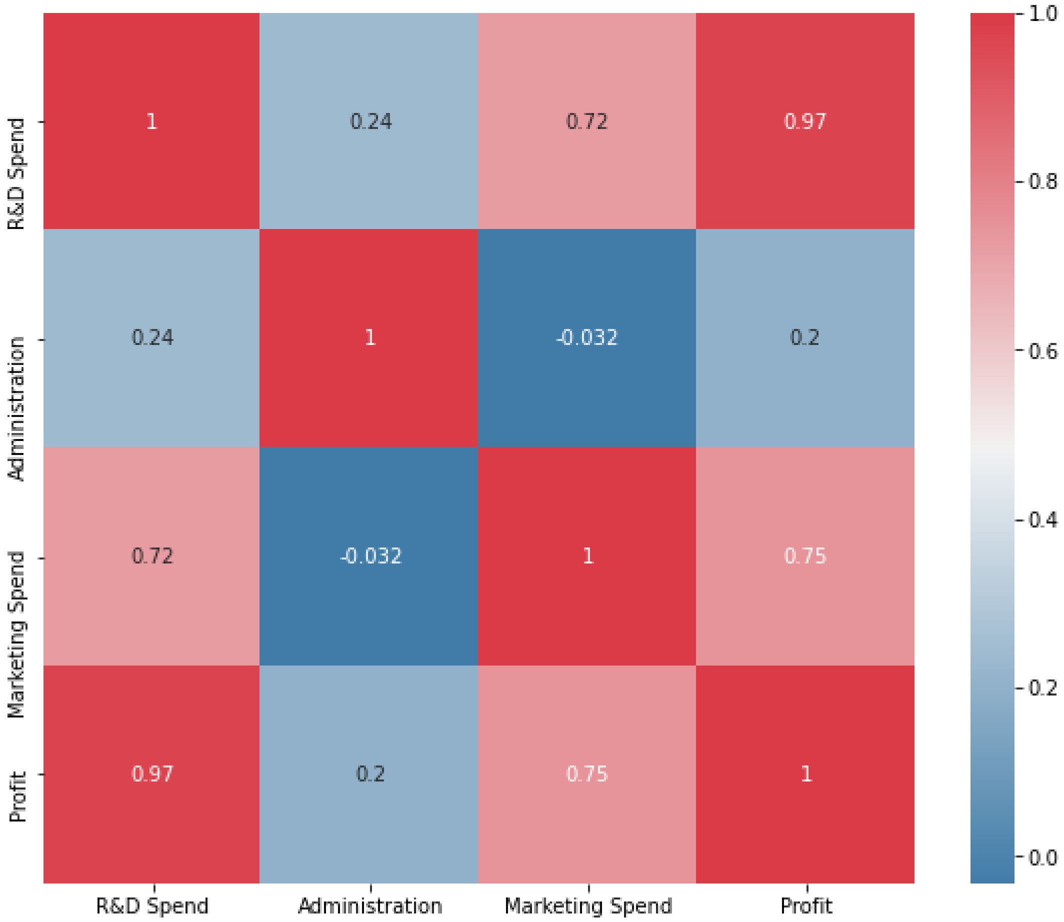


In [26]:

```python
f, ax = plt.subplots(figsize=(10,8))
```

```python
corr = df.corr()
sns.heatmap(corr, annot=True, mask=np.zeros_like(corr, dtype=np.bool),
            cmap = sns.diverging_palette(240, 10, as_cmap = True),
            square = True, ax = ax)
```

Out[26]: <AxesSubplot:>



Data preprocessing

In [27]:

```python
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
```

In [28]:

```python
df.isnull().sum()
```

Out[28]:

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

OneHotEncoder

In [29]:
```
df.State.describe()
```

Out[29]:
```
count           50
unique           3
top       New York
freq            17
Name: State, dtype: object
```

In [30]:
```
# encoding the categorical features
df = pd.get_dummies(df, columns=['State'])
df.head()
```

Out[30]:

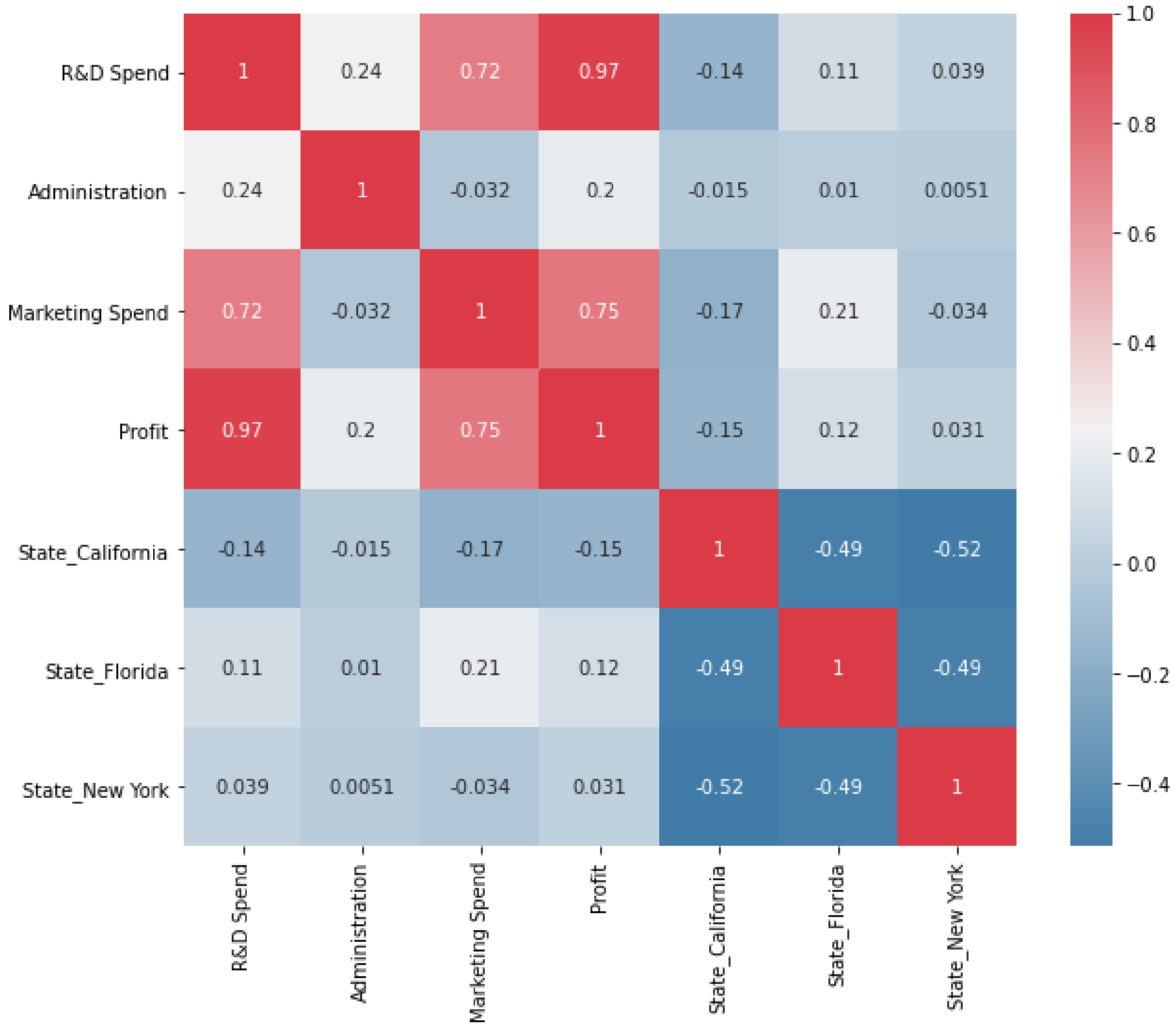
	R&D Spend	Administration	Marketing Spend	Profit	State_California	State_Florida	State_New York
0	165349.20	136897.80	471784.10	192261.83	0	0	1
1	162597.70	151377.59	443898.53	191792.06	1	0	0
2	153441.51	101145.55	407934.54	191050.39	0	1	0
3	144372.41	118671.85	383199.62	182901.99	0	0	1
4	142107.34	91391.77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

In [31]:
```
df.corr()['Profit'].sort_values()
```

Out[31]:
```
State_California   -0.145837
State_New York      0.031368
State_Florida       0.116244
Administration      0.200717
Marketing Spend     0.747766
R&D Spend           0.972900
Profit              1.000000
Name: Profit, dtype: float64
```

In [32]:
```
f, ax = plt.subplots(figsize=(10,8))
corr = df.corr()
sns.heatmap(corr, annot=True, mask=np.zeros_like(corr, dtype=np.bool),
            cmap = sns.diverging_palette(240, 10, as_cmap = True),
            square = True, ax = ax)
```

Out[32]:
```
<AxesSubplot:>
```



Modeling

We uses scalling

In [33]:

```
# Normalization of the dataset
std = StandardScaler()
df_std = std.fit_transform(df)
df_std = pd.DataFrame(df_std, columns = df.columns)
```

In [34]:

```
X = df_std.drop(['Profit'], axis = 1) # dataset of independent variables
y = df_std.Profit #dependent variable
```

Train split test

In [35]:

```
#splitting into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y
                                                    ,test_size = 6/8
                                                    ,random_state = 120)
```

In [36]:

```
from scipy import stats

# printing out the training sets and test sets, the size along with various s
print()
```

```python
print("X_train Dataset Description and values:")
print(stats.describe(X_train))
print("X_train Array shape : " + str(X_train.shape))
#print(X_train)
print()
print("X_test Dataset Description and values:")
print(stats.describe(X_test))
print("X_test Array shape: " + str(X_test.shape))
#print(X_test)
print()
print("y_train Dataset Description and values:")
print(stats.describe(y_train))
#print(y_train)
print()
print("y_test Dataset Description and values:")
print(stats.describe(y_test))
#print(y_test)
print()
print("X_Train and y_train shape:")
print(X_train.shape)
print(y_train.shape)
```

```
X_train Dataset Description and values:
DescribeResult(nobs=12, minmax=(array([-1.17717755, -1.99727037, -1.74312698,
-0.71774056, -0.68599434,
       -0.71774056]), array([2.01641149, 1.20641936, 2.15394309, 1.39326109,
1.45773797,
       1.39326109])), mean=array([-0.09271446, -0.18355409, -0.20978689, -0.18
999015,  0.0285831 ,
        0.16184346]), variance=array([0.72983213, 1.04907528, 1.18695436, 0.91
152163, 1.114082  ,
       1.18160212]), skewness=array([ 1.07251991, -0.02661623,  0.60113141,
1.15470054,  0.70710678,
        0.3380617 ]), kurtosis=array([ 1.25506902, -0.89279112, -0.03488538, -
0.66666667, -1.5        ,
       -1.88571429]))
X_train Array shape : (12, 6)

X_test Dataset Description and values:
DescribeResult(nobs=38, minmax=(array([-1.62236202, -2.52599402, -1.74312698,
-0.71774056, -0.68599434,
       -0.71774056]), array([1.95586034, 2.2101405 , 1.9236004 , 1.39326109,
1.45773797,
       1.39326109])), mean=array([ 0.02927825,  0.05796445,  0.06624849,  0.05
999689, -0.00902624,
       -0.05110846]), variance=array([1.13070597, 1.02508625, 0.97969186, 1.06
495463, 1.01978914,
       0.98888644]), skewness=array([-0.011931   , -0.62240563, -0.26346215,
0.54554473,  0.79259392,
        0.79259392]), kurtosis=array([-1.06910775,  0.51401057, -0.78496263, -
1.70238095, -1.37179487,
       -1.37179487]))
X_test Array shape: (38, 6)

y_train Dataset Description and values:
DescribeResult(nobs=12, minmax=(-1.1732089932266025, 2.0112033342229885), mean
=-0.05345667459201751, variance=0.7091016764498884, skewness=1.170408927728744
4, kurtosis=1.142342852276372З)

y_test Dataset Description and values:
DescribeResult(nobs=38, minmax=(-2.4393132298487346, 1.9994299695211237), mean
=0.01688105513432062, variance=1.1393178731215392, skewness=-0.160211946277044
77, kurtosis=-0.3894092119289203)

X_Train and y_train shape:
(12, 6)
(12,)
```

In [37]:
```
# regressor summary
regressor = sm.OLS(y_train, X_train).fit()
print(regressor.summary())

X_train_dropped = X_train.copy()
```

```
                                 OLS Regression Results
==============================================================================
=========
Dep. Variable:                 Profit   R-squared (uncentered):
0.977
Model:                            OLS   Adj. R-squared (uncentered):
0.961
Method:                 Least Squares   F-statistic:
60.24
Date:                Thu, 07 Jul 2022   Prob (F-statistic):
1.33e-05
Time:                        18:26:10   Log-Likelihood:
8.2401
No. Observations:                  12   AIC:
-6.480
Df Residuals:                       7   BIC:
-4.056
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
======
                       coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------
R&D Spend            0.9386      0.113      8.302      0.000       0.671
1.206
Administration      -0.0550      0.067     -0.815      0.442      -0.215
0.105
Marketing Spend      0.0437      0.079      0.555      0.596      -0.142
0.230
State_California    -0.0211      0.039     -0.535      0.609      -0.114
0.072
State_Florida        0.0063      0.032      0.195      0.851      -0.070
0.082
State_New York       0.0149      0.034      0.445      0.670      -0.064
0.094
==============================================================================
Omnibus:                        0.011   Durbin-Watson:                   1.921
Prob(Omnibus):                  0.994   Jarque-Bera (JB):                0.161
Skew:                           0.042   Prob(JB):                        0.922
Kurtosis:                       2.438   Cond. No.                     3.93e+15
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not con
tain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correct
ly specified.
[3] The smallest eigenvalue is 1.44e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

The function removes features with high p-value

In [38]:
```
while True:
    if max(regressor.pvalues) > 0.05:
        drop_variable = regressor.pvalues[regressor.pvalues == max(regressor.
        print("Dropping " + drop_variable.index[0] + " and running regression
        X_train_dropped = X_train_dropped.drop(columns = [drop_variable.index
        regressor = sm.OLS(y_train, X_train_dropped).fit()
    else:
```

```
        print("All p values less than 0.05")
        break
```

```
Dropping State_Florida and running regression again because pvalue is: 0.85096
42642298341
Dropping State_New York and running regression again because pvalue is: 0.8757
574682889988
Dropping State_California and running regression again because pvalue is: 0.58
88729810953166
Dropping Marketing Spend and running regression again because pvalue is: 0.718
3204129431902
Dropping Administration and running regression again because pvalue is: 0.0784
1596657802424
All p values less than 0.05
```

In [39]:

```
# printing regression summary after having drop all the variables with high p
print(regressor.summary())
```

```
                                 OLS Regression Results
==============================================================================
=========
Dep. Variable:                 Profit   R-squared (uncentered):
0.967
Model:                            OLS   Adj. R-squared (uncentered):
0.964
Method:                 Least Squares   F-statistic:
319.2
Date:                Thu, 07 Jul 2022   Prob (F-statistic):
1.79e-09
Time:                        18:26:11   Log-Likelihood:
5.9420
No. Observations:                  12   AIC:
-9.884
Df Residuals:                      11   BIC:
-9.399
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
R&D Spend      0.9651      0.054     17.866      0.000       0.846       1.084
==============================================================================
Omnibus:                        4.060   Durbin-Watson:                   1.549
Prob(Omnibus):                  0.131   Jarque-Bera (JB):                1.936
Skew:                           0.979   Prob(JB):                        0.380
Kurtosis:                       3.187   Cond. No.                         1.00
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not con
tain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correct
ly specified.
```

Uses SelectKBest

In [40]:

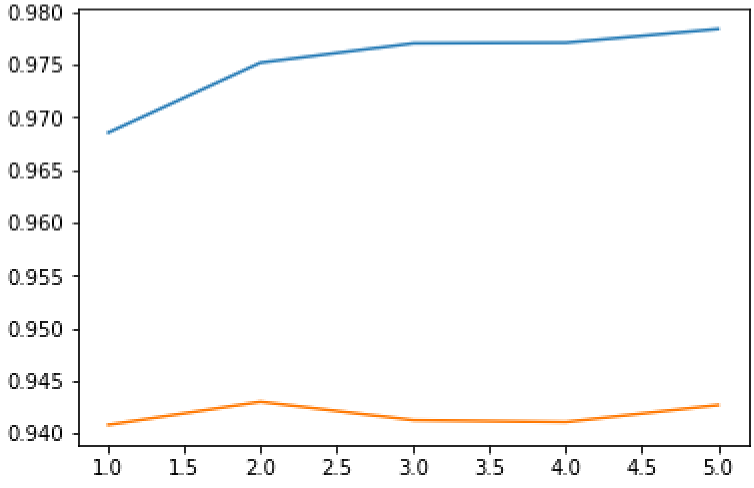
```
# SelectKBest shows what the best number of feature for the model according t
column_names = df.drop(columns = ['Profit']).columns
no_of_features = []
r_squared_train = []
r_squared_test = []


for k in range(1, 6):
    selector = SelectKBest(f_regression, k = k)
    X_train_transformed = selector.fit_transform(X_train, y_train)
```

```
    X_test_transformed = selector.transform(X_test)
    regressor = LinearRegression()
    regressor.fit(X_train_transformed, y_train)
    no_of_features.append(k)
    r_squared_train.append(regressor.score(X_train_transformed, y_train))
    r_squared_test.append(regressor.score(X_test_transformed, y_test))

sns.lineplot(x = no_of_features, y = r_squared_train, legend = 'full')
sns.lineplot(x = no_of_features, y = r_squared_test, legend = 'full')
```

Out[40]: <AxesSubplot:>



In [41]:

```
### Best score k = 1
selector = SelectKBest(f_regression, k = 1)
X_train_transformed = selector.fit_transform(X_train, y_train)
X_test_transformed = selector.transform(X_test)
column_names[selector.get_support()]
```

Out[41]: Index(['R&D Spend'], dtype='object')

In [42]:

```
def regression_model(model):
    """
    Will fit the regression model passed and will return the regressor object
    """
    regressor = model
    regressor.fit(X_train_transformed, y_train)
    score = regressor.score(X_test_transformed, y_test)
    return regressor, score
```

In [43]:

```
# checking which model perform better
model_performance = pd.DataFrame(columns = ["Features", "Model", "Score"])

models_to_evaluate = [LinearRegression(), Ridge(), Lasso(), SVR(), RandomFore:

for model in models_to_evaluate:
    regressor, score = regression_model(model)
    model_performance = model_performance.append({"Features": "Linear","Model

model_performance
```

Out[43]:

	Features	Model	Score
0	Linear	LinearRegression()	0.94

	Features	Model	Score
1	Linear	Ridge()	0.93
2	Linear	Lasso()	-0.00
3	Linear	SVR()	0.69
4	Linear	(DecisionTreeRegressor(max_features='auto', ra...	0.83
5	Linear	MLPRegressor()	0.91

In [44]:

```
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
# Create linear regression object
regr = LinearRegression()

# Train the model using the training sets
regr.fit(X_train_transformed, y_train)

# Make predictions using the testing set
y_pred = regr.predict(X_test_transformed)

# Eveluation metrics
print("__ \n")
print('Coefficients: \n', regr.coef_)
print("__ \n")
print('Intercept: \n', regr.intercept_)
print("__ \n")
# The mean squared error
print('Mean squared error: %.2f'
      % mean_squared_error(y_test, y_pred))
print("__ \n")

# The coefficient of determination: 1 is perfect prediction
print('R-Squared: %.2f'
      % r2_score(y_test, y_pred))
print("__ \n")

print("MAE: %.2f" % mean_absolute_error(y_test, y_pred))
print("__\n")
```

```
__

Coefficients: 
 [0.97007809]
__

Intercept: 
 0.03648358766432768
__

Mean squared error: 0.07
__

R-Squared: 0.94
__

MAE: 0.20
__
```

In [ ]: