Name: - L PRATHYUSHA

ABC Company

a. Basic description of the data

1. loading and inspecting the data
2. data cleaning

b. Handling missing values. 3. data analysis (analysis of every plot and graph is explained properly)

c. Data Visualization on various features. barplot, histogram, pairplot, displot, heatmap, boxplot, joint plot(hex,reg,kde), relplot, pointplot, countplot, stripplot

d. Splitting the data as test and train.

e. Model building. (Linear/Logistic Regression)

conclusion and learnings

In [2]:

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

from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.ar_model import AutoReg

from pmdarima import auto_arima
#ignore harmless warnings
import warnings
warnings.filterwarnings("ignore")
from textblob import TextBlob
```

a. Basic description of the data

Loading and inspecting the data

loading the csv data

A CSV file (Comma Separated Values file) is a type of plain text file that uses specific structuring to arrange tabular data.

pandas recognized that the first line of the CSV contained column names, and used them automatically. pandas is also using zero-based integer indices in the DataFrame. That’s because we didn’t tell it what our index should be.

In [4]:

```
data=pd.read_csv('C:/Users/Prathyu Lachireddy/Desktop/ESE_2.csv - ESE_2.csv.csv')
data
```

Out[4]:

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

1000 rows × 5 columns

In [5]:

```
# Loading the head and tail data

data.head()
```

Out[5]:

	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 [6]:

```
data.tail()
```

Out[6]:

	R&D Spend	Administration	Marketing Spend	State	Profit
995	54135.00	118451.999	173232.6695	California	95279.96251
996	134970.00	130390.080	329204.0228	California	164336.60550
997	100275.47	241926.310	227142.8200	California	413956.48000
998	128456.23	321652.140	281692.3200	California	333962.19000
999	161181.72	270939.860	295442.1700	New York	476485.43000

Data Cleaning

In [7]:

```
data.shape
```

Out[7]:

```
(1000, 5)
```

In [8]:

```
len(data)
```

Out[8]:

```
1000
```

In [9]:

```
data.dtypes
```

Out[9]:

```
R&D Spend          float64
Administration     float64
Marketing Spend    float64
State               object
Profit             float64
dtype: object
```

In [10]:

```
#This shows the all the titles of the data since this is a huge data to deal with,
#this code will be really helpful to analyze later.
data.columns
```

Out[10]:

```
Index(['R&D Spend', 'Administration', 'Marketing Spend', 'State', 'Profit'],
dtype='object')
```

In [ ]:

```

```

b. Handling missing values

In [61]:

```
#isnull() function detect missing values in the given series object.
#It return a boolean same-sized object indicating if the values are NA.
#Missing values gets mapped to True and non-missing value gets mapped to False .

import numpy as np
data.isnull().sum()

#There are no missing values or any Null values in this data
```

Out[61]:

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

In [12]:

```
#data.fillna(method='ffill')

null_values=data.fillna(np.mean(data))
null_values
```

Out[12]:

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

1000 rows × 5 columns

Basic analysis

In [14]:

```
#Smallest or minimum value of the column can be extracted though is code

data["Profit"].min()
```

Out[14]:

```
14681.4
```

In [15]:

```
data['Profit'].max()
```

Out[15]:

```
476485.43
```

In [16]:

```
# this shows the mean which is nothing but the average value of the data though out the who
# the result is saying that the average temperature in this area is 11 degrees.

mean1 = data['Profit'].mean()
mean1
```

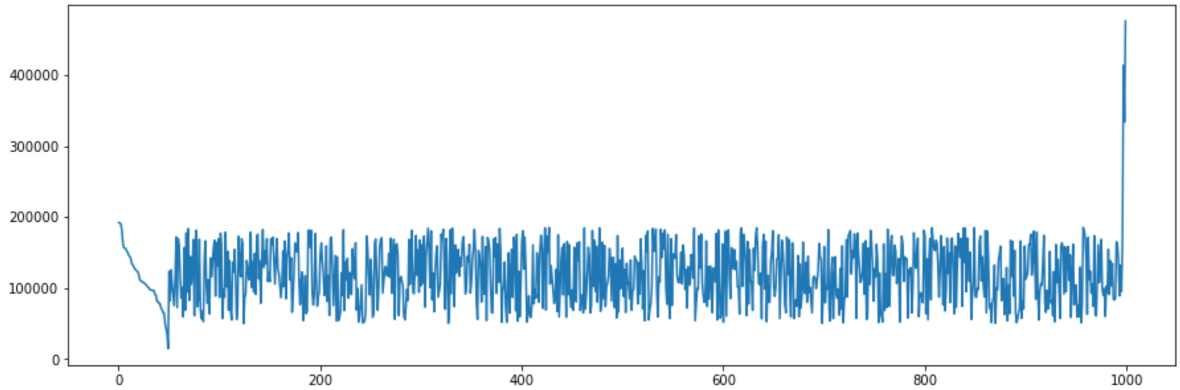
Out[16]:

```
119546.1646556102
```

In [17]:

```
#the graph shows that variations in the data in the due course of time.

import matplotlib.pyplot as plt
fig_dims = (15, 5)
fig, ax = plt.subplots(figsize=fig_dims)
data['Profit'].plot()
plt.show()
```



Unique values

In [22]:

```
data[2:3]
```

Out[22]:

	R&D Spend	Administration	Marketing Spend	State	Profit
2	153441.51	101145.55	407934.54	Florida	191050.39

In [18]:

```
#nunique() function return number of unique elements in the object.
#It returns a scalar value which is the count of all the unique values in the Index.
data.nunique()
```

Out[18]:

```
R&D Spend          997
Administration     998
Marketing Spend    996
State                3
Profit             998
dtype: int64
```

In [23]:

```
data['Profit'].nunique()
```

Out[23]:

```
998
```

Number of values in the data

In [25]:

```
# this shows the the number of numerical data is there under each of the categories in the

#value_counts()
data.State.value_counts()
```

Out[25]:

```
California    344
New York      334
Florida       322
Name: State, dtype: int64
```

In [27]:

```
#This code will display only the clear weather
#filtering
#data.head(2)
data[data.State == 'New York']

#or

#groupby()
#data.head(2)
data.groupby('State').get_group('New York')

#Here we are taking all the Clear weather data values from the summary in the weather data
# if there was clear weather for a person to go out.
```

Out[27]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.8000	471784.1000	New York	192261.83000
3	144372.41	118671.8500	383199.6200	New York	182901.99000
5	131876.90	99814.7100	362861.3600	New York	156991.12000
8	120542.52	148718.9500	311613.2900	New York	152211.77000
15	114523.61	122616.8400	261776.2300	New York	129917.04000
...	...	...	...	...	...
985	63615.00	119852.0486	191524.3554	New York	103378.64470
987	41289.00	116554.8432	148446.2774	New York	84305.73556
991	131106.00	129819.4269	321748.4242	New York	161035.62360
994	97209.00	124813.3635	256344.0701	New York	132077.70900
999	161181.72	270939.8600	295442.1700	New York	476485.43000

334 rows × 5 columns

In [32]:

```
# we need to observe that in order to snow the data that is recorded should be more or less
data[(data['State']=='New York') & (data['Profit'] > 150000)]
```

Out[32]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.8000	471784.1000	New York	192261.8300
3	144372.41	118671.8500	383199.6200	New York	182901.9900
5	131876.90	99814.7100	362861.3600	New York	156991.1200
8	120542.52	148718.9500	311613.2900	New York	152211.7700
65	126549.00	129146.4284	312955.6803	New York	157142.6178
...	...	...	...	...	...
947	131981.00	129948.6509	323436.7391	New York	161783.1286
957	159746.00	134049.1125	377009.3824	New York	185502.5285
959	144520.00	131800.4675	347630.7738	New York	172495.0881
991	131106.00	129819.4269	321748.4242	New York	161035.6236
999	161181.72	270939.8600	295442.1700	New York	476485.4300

98 rows × 5 columns

c. DATA VISUALISATION

In [37]:

```
D2=data[0:500]
D2
```

Out[37]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.8000	471784.1000	New York	192261.8300
1	162597.70	151377.5900	443898.5300	California	191792.0600
2	153441.51	101145.5500	407934.5400	Florida	191050.3900
3	144372.41	118671.8500	383199.6200	New York	182901.9900
4	142107.34	91391.7700	366168.4200	Florida	166187.9400
...	...	...	...	...	...
495	146341.00	132069.4011	351144.3983	New York	174050.7527
496	20181.00	113437.5176	107718.3338	California	66273.3533
497	105465.00	126032.6472	272274.0447	California	139130.7386
498	58528.00	119100.7772	181708.9750	Florida	99032.8645
499	107739.00	126368.4819	276661.7339	New York	141073.3972

500 rows × 5 columns

BAR GRAPH

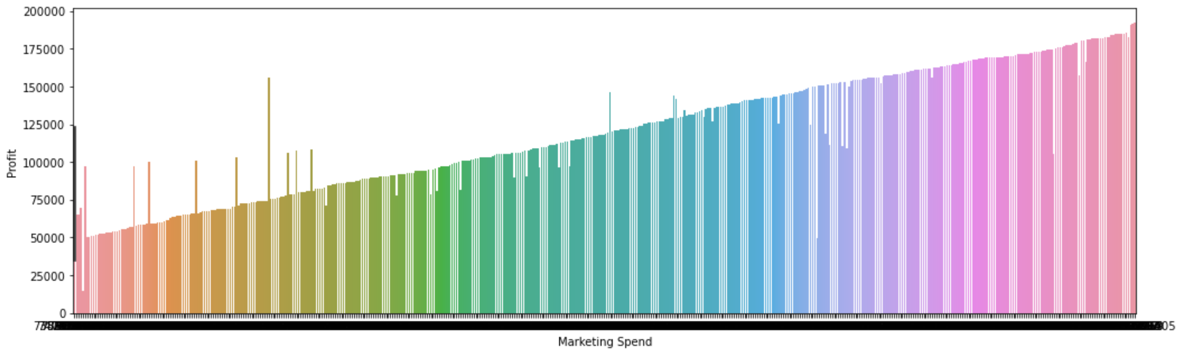
In [38]:

```
#the trend of the data shows that the data is increasing and the activities done by the ABC
#the realtion between the marketing spend and as well as the profit is very high as there h
#that are being caused by marketing like the highest is close to 200000 which is the maximu

fig_dims = (17, 5)
fig, ax = plt.subplots(figsize=fig_dims)
sns.barplot(D2['Marketing Spend'],D2['Profit'])
```

Out[38]:

```
<AxesSubplot:xlabel='Marketing Spend', ylabel='Profit'>
```



HISTOGRAM

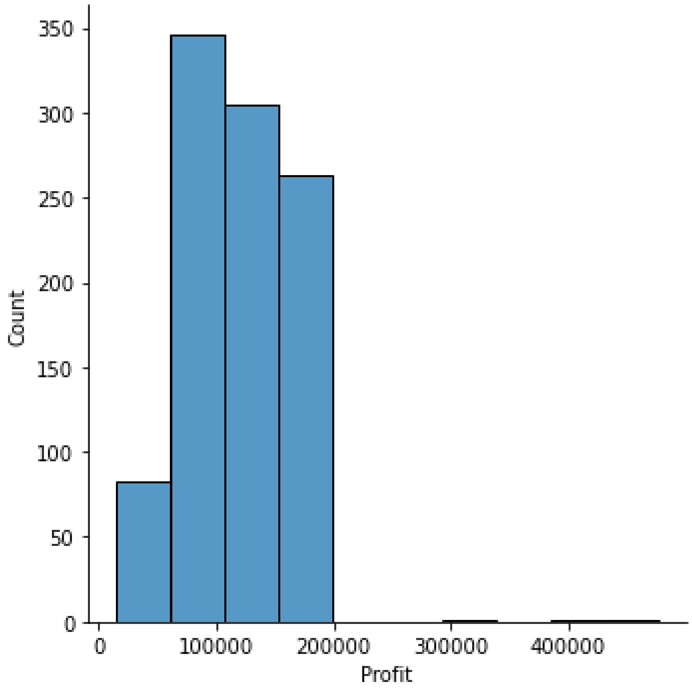
In [39]:

```
#distplot lets you show a histogram with a line on it. This can be shown in all kinds of va
#distplot() function is used to plot the distplot. The distplot represents the univariate d
#i.e. data distribution of a variable against the density distribution.
#The seaborn. distplot() function accepts the data variable as an argument and returns the
#the bin size shows the number of bars that are being ploted

sns.displot(data['Profit'],bins=10)
```

Out[39]:

```
<seaborn.axisgrid.FacetGrid at 0x1b92ee1f8b0>
```

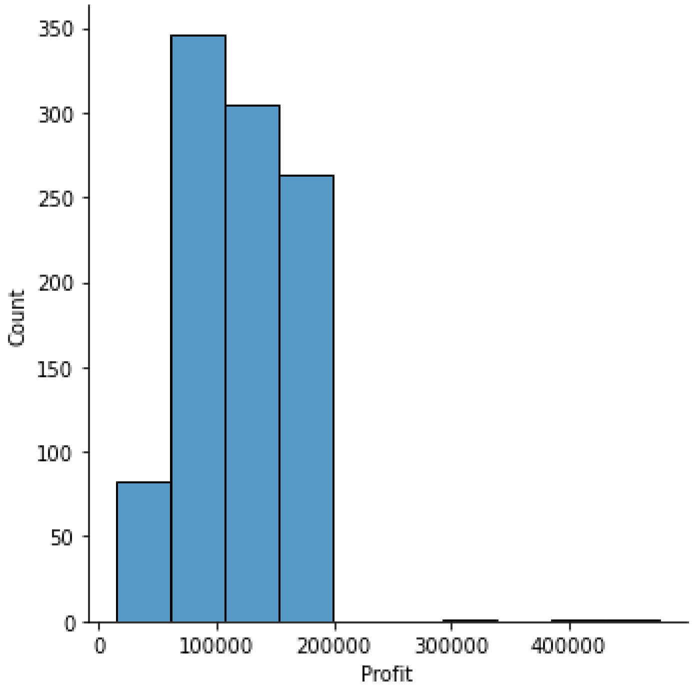


In [40]:

```
sns.displot(data['Profit'],bins=10)
```

Out[40]:

```
<seaborn.axisgrid.FacetGrid at 0x1b930003af0>
```



Heat map

In [41]:

```
correlation=data.corr()
correlation
```

Out[41]:

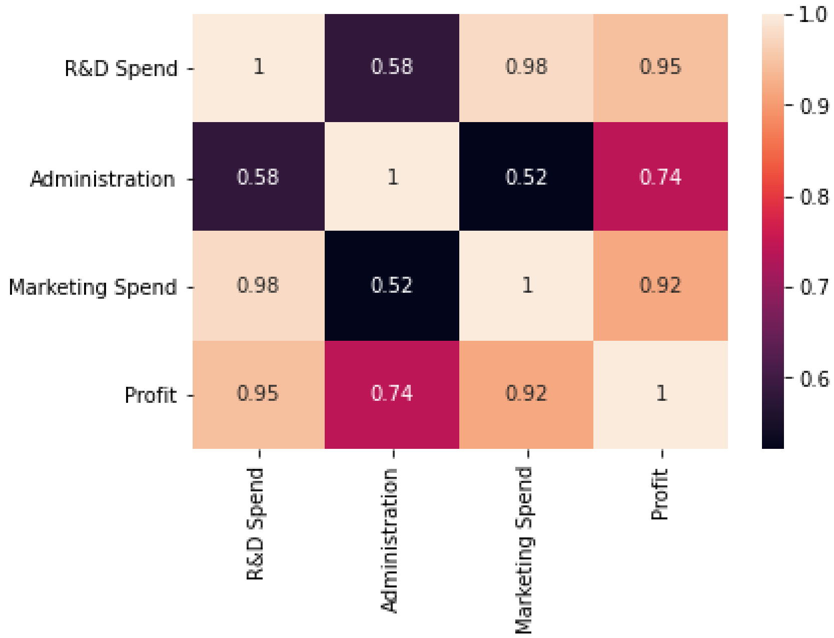
	R&D Spend	Administration	Marketing Spend	Profit
R&D Spend	1.000000	0.582434	0.978407	0.945245
Administration	0.582434	1.000000	0.520465	0.741560
Marketing Spend	0.978407	0.520465	1.000000	0.917270
Profit	0.945245	0.741560	0.917270	1.000000

In [42]:

```
sns.heatmap(correlation,xticklabels=correlation.columns,yticklabels=correlation.columns,ann
```

Out[42]:

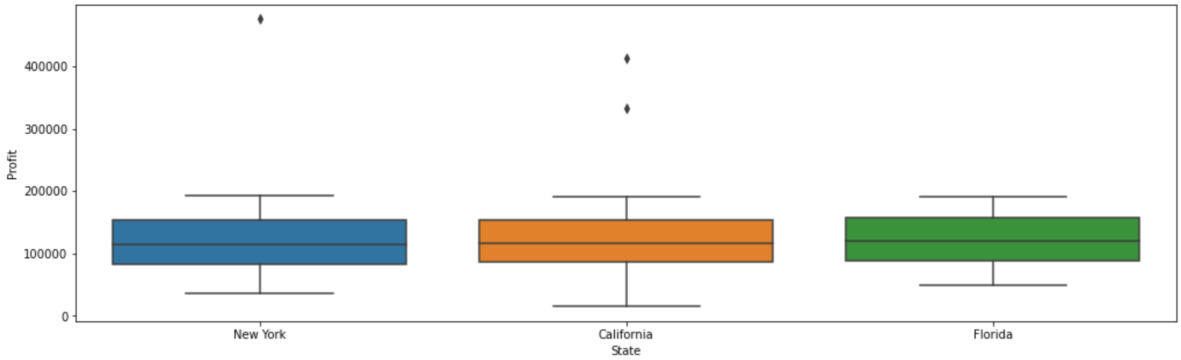
```
<AxesSubplot:>
```



SEABORN PLOT

In [45]:

```
P=data.head(1000)
fig_dims = (17, 5)
fig, ax = plt.subplots(figsize=fig_dims)
fig=sns.boxplot(data=P, x='State',y='Profit')
plt.show()
```

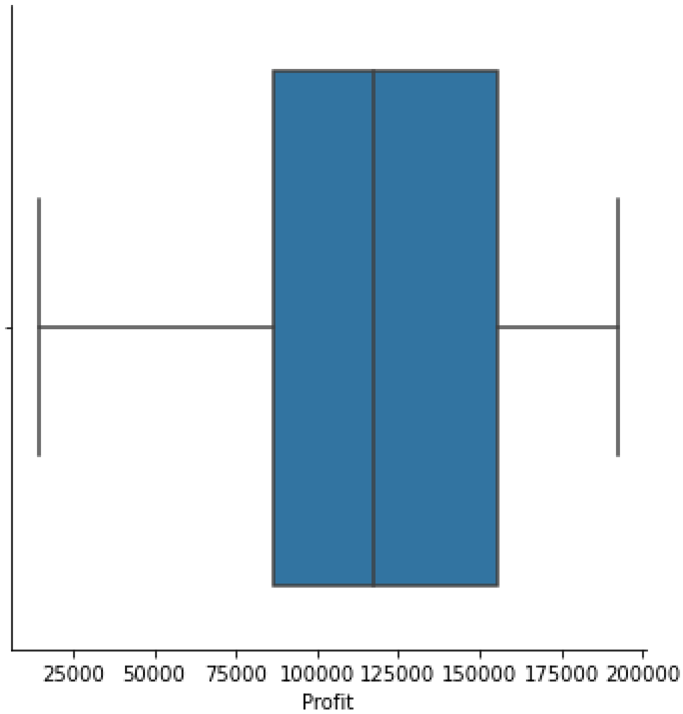


In [46]:

```
sns.catplot(x='Profit', kind='box',data=D2)
```

Out[46]:

```
<seaborn.axisgrid.FacetGrid at 0x1b92fdfb4f0>
```



ANALYSIS for boxplot: - A boxplot is a standardized way of displaying the distribution of data based on a five number summary (“minimum”, first quartile (Q1) divided 25%, median, third quartile (Q3) upper 25% , and “maximum”). the box plot which is shown above depicts the temperature in the weather data and it is observed that the left line(wisker) shows the lower point which is between 0-5 and the median here is 15 degrees in temperature. Boxplots do really help us to understand the quartiles part of the data. the right wisker shows the highest temperature recorded which is 30 degrees. but the points which are places ouside the line are known as the outliers of the data where in this case the rare recorded temperatures in a particular geographic area.

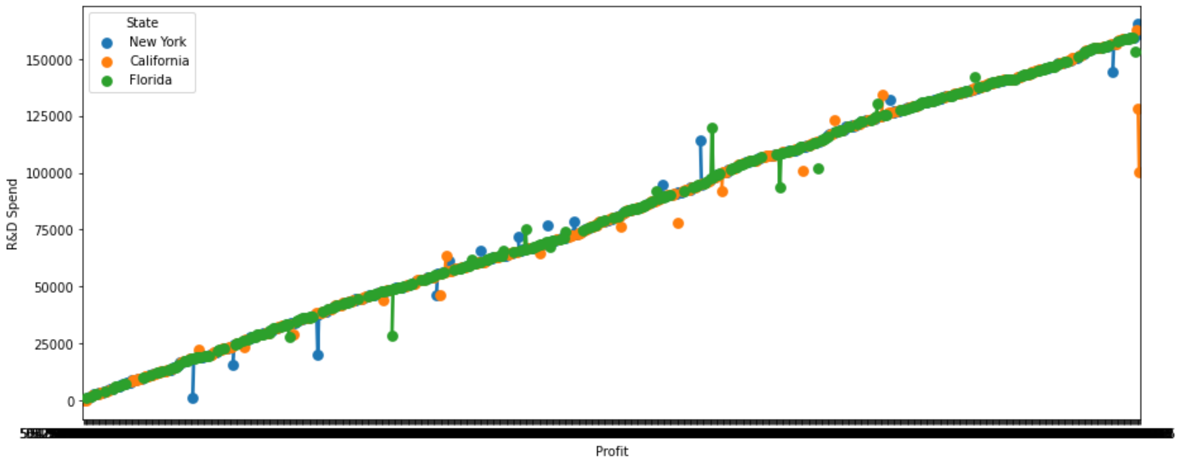
In [47]:

```
# ANALYSIS: - Variable 1: - humidity and variable 2: - temperature
# this graph shows the points of the two variables that are being chosen in different vario

fig_dims = (15, 6)
fig, ax = plt.subplots(figsize=fig_dims)
sns.pointplot(data['Profit'],data['R&D Spend'],hue=data['State'],ax=ax)
```

Out[47]:

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



ANALYSIS: -the graphs depicts the graphical representation between aparent and temperature. This is a figure-level function for visualizing statistical relationships using two common approaches. Scatter Plots- Each plot point is an independent observation, every colour depicts a differernt weather condition in the Summary data.

here it could be observed that the relation between the R&D and the profit is good in Florida and the strength of is good in this city as in terms of profits due to the crowding of the data points.

PAIR PLOT

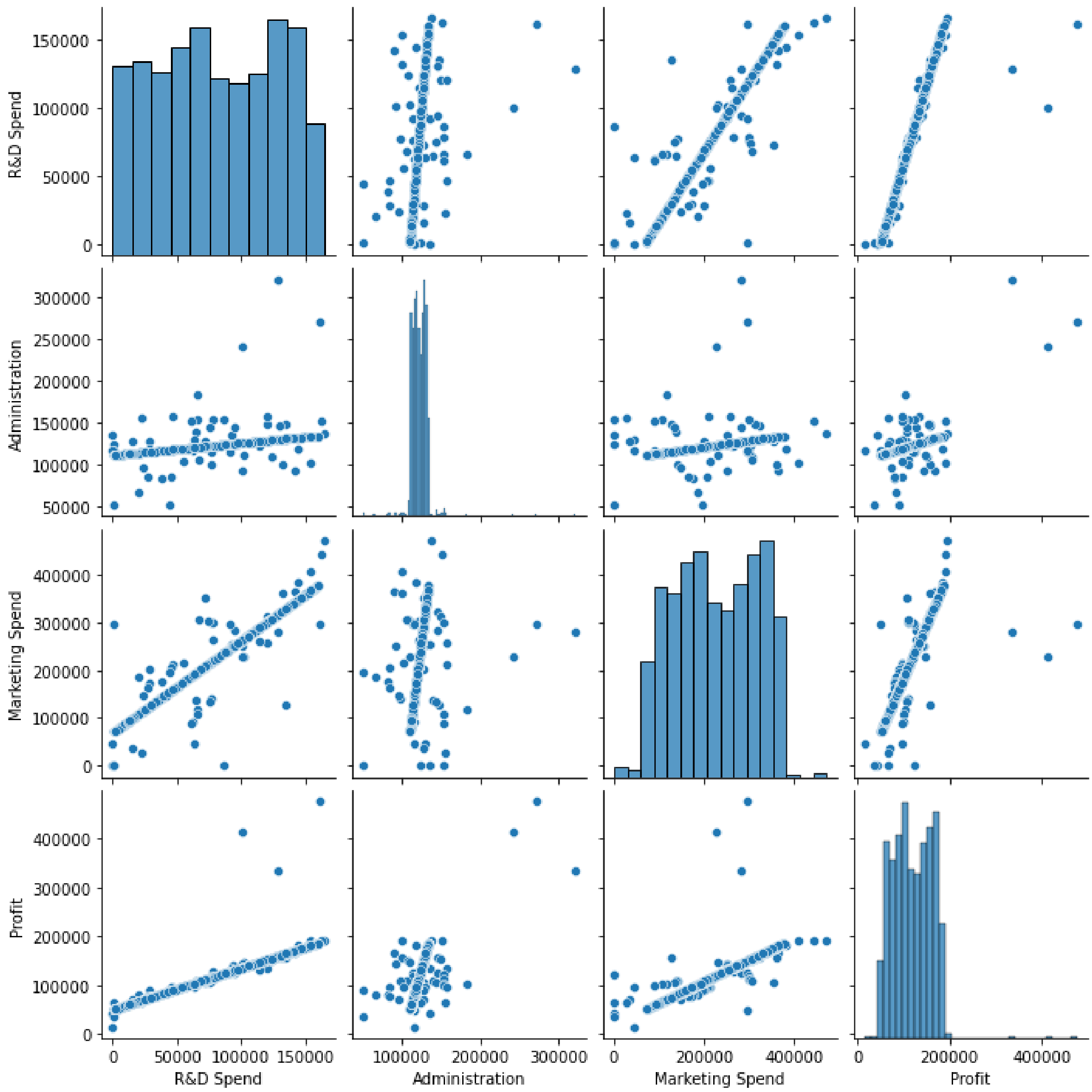
In [48]:

```
import seaborn as sns

sns.pairplot(data)
```

Out[48]:

```
<seaborn.axisgrid.PairGrid at 0x1b9347b2ca0>
```



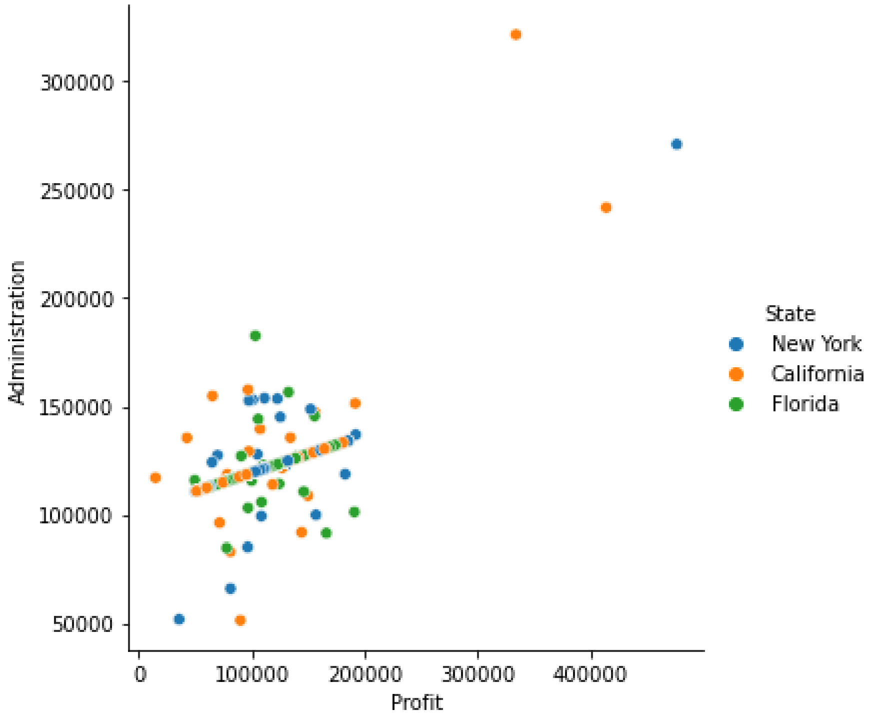
ANALYSIS: -

In [53]:

```
sns.relplot(x='Profit',y='Administration',hue='State',data=data)
```

Out[53]:

<seaborn.axisgrid.FacetGrid at 0x1b934d67eb0>



ANALYSIS: - the graphs depicts the graphical representation between aparent and temperature. This is a figure-level function for visualizing statistical relationships using two common approaches. Scatter Plots- Each plot point is an independent observation, every colour depicts a differernt weather condition in the Summary data

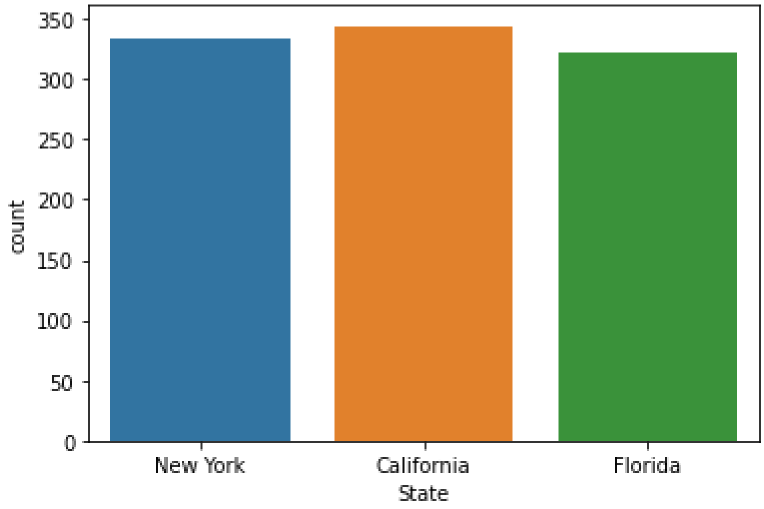
COUNT PLOT

In [54]:

```
sns.countplot(data['State'])
```

Out[54]:

```
<AxesSubplot:xlabel='State', ylabel='count'>
```



ANALYSIS: - it Shows the counts of observations in each categorical bin using bars. A count plot can be thought of as a histogram across a categorical, instead of quantitative, variable. here the values of each city in which the company is in is having it's profits coming from mostly from california as it is near to 350 and them followed by new york and florida

In [55]:

```
data[2:3]
```

Out[55]:

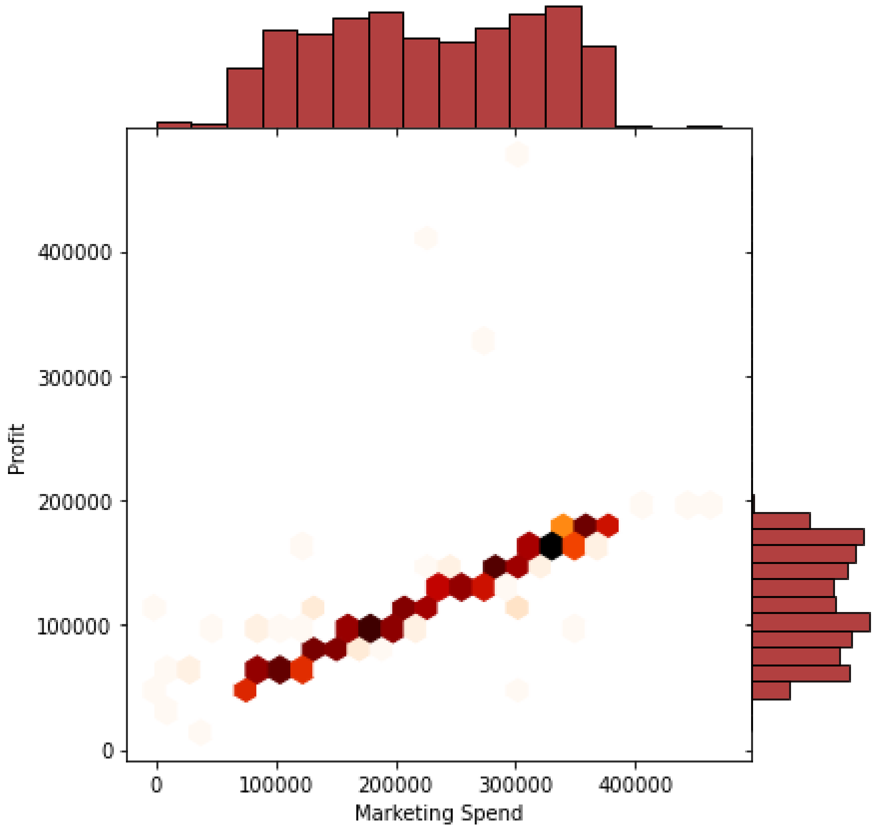
	R&D Spend	Administration	Marketing Spend	State	Profit
2	153441.51	101145.55	407934.54	Florida	191050.39

In [57]:

```
cmap=plt.cm.gist_heat_r
sns.jointplot(data['Marketing Spend'],data['Profit'],kind="hex",space=0, color=cmap(.6), cm
```

Out[57]:

```
<seaborn.axisgrid.JointGrid at 0x1b936aa7790>
```



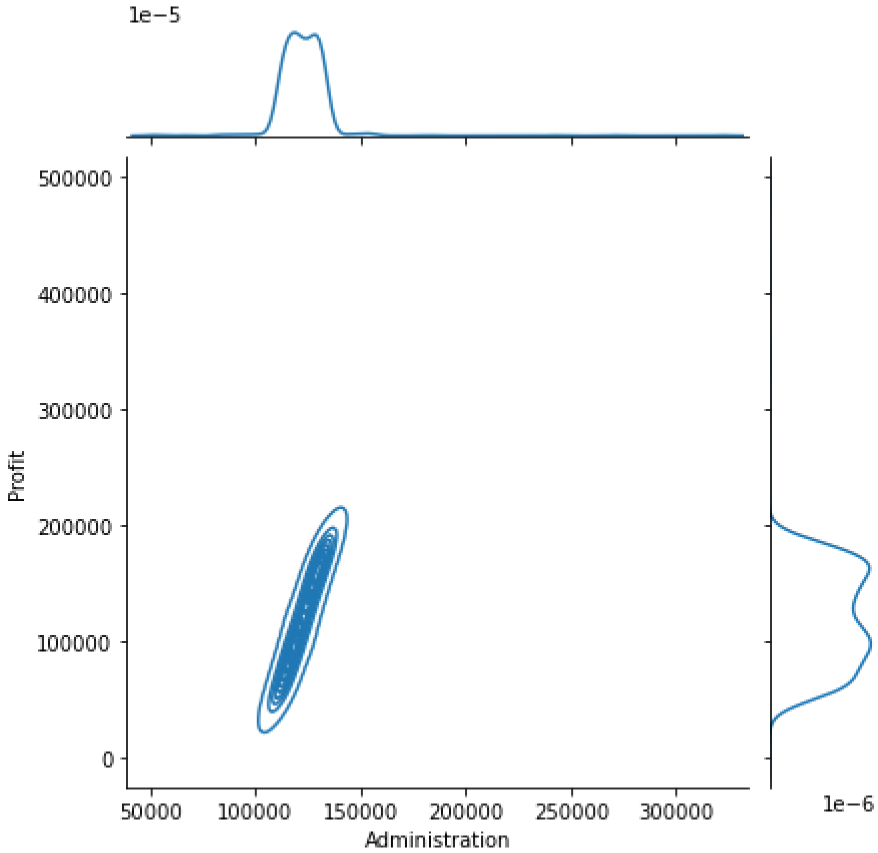
ANALYSIS: -

In [59]:

```
sns.jointplot(data['Administration'],data['Profit'],kind="kde")
```

Out[59]:

```
<seaborn.axisgrid.JointGrid at 0x1b936d08e50>
```



In [64]:

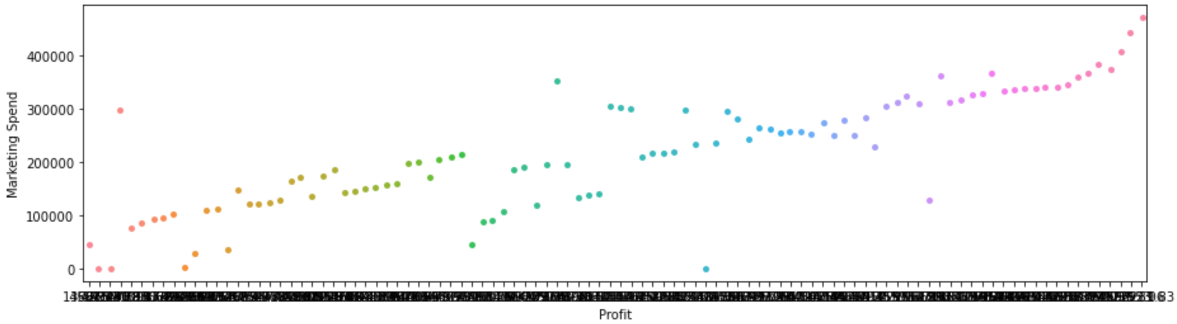
```
DATA2=data[0:500]
```

In [63]:

```
fig_dims = (15, 4)
fig, ax = plt.subplots(figsize=fig_dims)
sns.stripplot(DATA2['Profit'],DATA2['Marketing Spend'])
```

Out[63]:

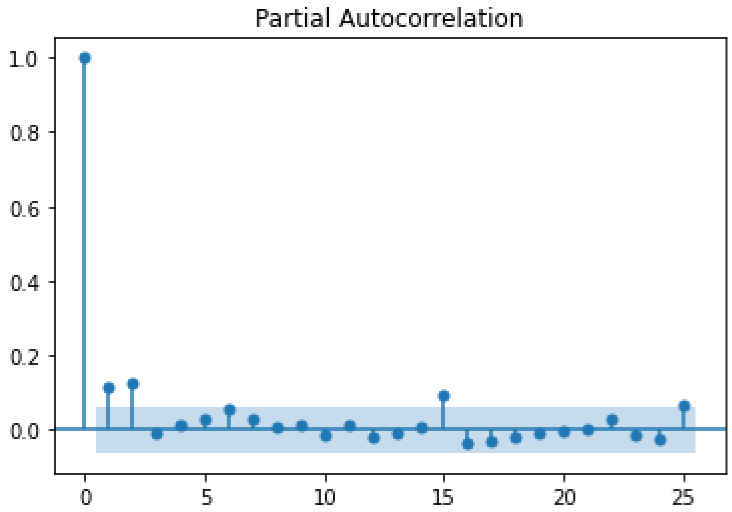
```
<AxesSubplot:xlabel='Profit', ylabel='Marketing Spend'>
```

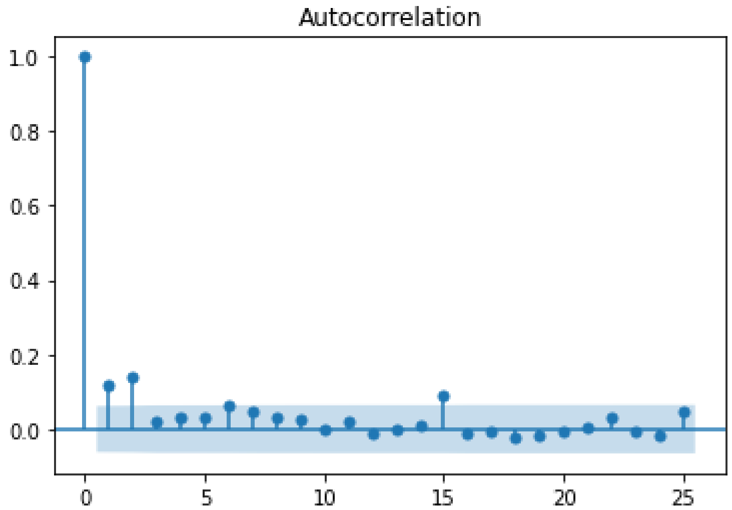


In [94]:

```
from statsmodels.graphics.tsaplots import plot_pacf,plot_acf
pacf=plot_pacf(data['Profit'],lags=25)
acf=plot_acf(data['Profit'],lags=25)

#x- axis= time
#y- axis= Correlation
#higher the value the more the correlation in the data and the time.
#partial sees on the direct effect(previous and current time lag) and autocorrelation will
```





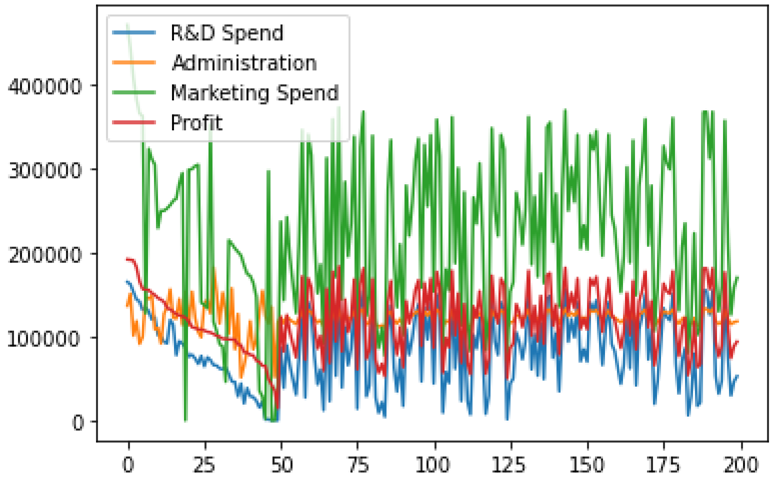
In [95]:

```
data[:200].plot()

#ANALYSIS: - it could be observed that the green lines on the graph is being concentrated b
#through this graph we can say that the most of the profits of the company are due to the e
#it is a healthy sign
```

Out[95]:

```
<AxesSubplot:>
```



d. Splitting the data as test and train.

In [65]:

```
print(data.shape)
train=data.loc[:-10]
test=data.loc[-20:]

print(train.shape,test.shape)
```

```
(1000, 5)
(0, 5) (1000, 5)
```

In [68]:

```
stepwise_fit= auto_arima(data['Profit'],trace=True,
                        suppress_warnings=True)

stepwise_fit
```

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=24147.684, Time=1.42 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=24173.601, Time=0.03 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=24161.242, Time=0.08 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=24164.549, Time=0.12 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=26343.754, Time=0.02 sec
 ARIMA(1,0,2)(0,0,0)[0] intercept   : AIC=24147.197, Time=0.27 sec
 ARIMA(0,0,2)(0,0,0)[0] intercept   : AIC=24146.597, Time=0.17 sec
 ARIMA(0,0,3)(0,0,0)[0] intercept   : AIC=24147.879, Time=0.21 sec
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=24159.283, Time=0.22 sec
 ARIMA(1,0,3)(0,0,0)[0] intercept   : AIC=24148.930, Time=0.32 sec
 ARIMA(0,0,2)(0,0,0)[0]             : AIC=25682.644, Time=0.13 sec

Best model:  ARIMA(0,0,2)(0,0,0)[0] intercept
Total fit time: 3.356 seconds
```

Out[68]:

```
ARIMA(order=(0, 0, 2), scoring_args={}, suppress_warnings=True)
```

Analysis of Auto Arima: - It takes into account the AIC and BIC values generated (as you can see in the code) to determine the best combination of parameters. AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values are estimators to compare models. The lower these values, the better is the model

In [76]:

```
data[0:1]
```

Out[76]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.2	136897.8	471784.1	New York	192261.83

In [77]:

```
X = data['R&D Spend']
y = data['Profit']
```

In [78]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, test_size = 0.3
```

In [79]:

```
# Let's now take a look at the train dataset

X_train.head()
```

Out[79]:

```
420    125425.0
278     14349.0
218      6166.0
363     49407.0
850     46307.0
Name: R&D Spend, dtype: float64
```

In [80]:

```
y_train.head()
```

Out[80]:

```
420    156182.39430
278     61291.12602
218     54300.45973
363     91240.87291
850     88592.56966
Name: Profit, dtype: float64
```

In [92]:

```
# Add a constant to X_test
X_test_sm = sm.add_constant(X_test)

# Predict the y values corresponding to X_test_sm
y_pred = lr.predict(X_test_sm)
```

In [93]:

```
y_pred.head()
```

Out[93]:

```
249     90437.164301
353    185419.793210
537    109402.979764
424     68618.798939
564     71662.630252
dtype: float64
```

e. Model building. (Linear/Logistic Regression)

In [81]:

```
import statsmodels.api as sm
```

In [82]:

```
# Add a constant to get an intercept
X_train_sm = sm.add_constant(X_train)

# Fit the resgression line using 'OLS'
lr = sm.OLS(y_train, X_train_sm).fit()
```

In [83]:

```
# Print the parameters, i.e. the intercept and the slope of the regression line fitted
lr.params
```

Out[83]:

```
const        48191.172300
R&D Spend        0.877438
dtype: float64
```

In [84]:

```
# Performing a summary operation lists out all the different parameters of the regression l
print(lr.summary())
```

```
                            OLS Regression Results                            
==============================================================================
==
Dep. Variable:                 Profit   R-squared:                       0.8
59
Model:                            OLS   Adj. R-squared:                  0.8
59
Method:                 Least Squares   F-statistic:                     425
6.
Date:                Fri, 18 Jun 2021   Prob (F-statistic):          2.95e-2
99
Time:                        10:55:51   Log-Likelihood:                -779
8.4
No. Observations:                 700   AIC:                         1.560e+
04
Df Residuals:                     698   BIC:                         1.561e+
04
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
==
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
--
const       4.819e+04   1266.169     38.061      0.000    4.57e+04    5.07e+
04
R&D Spend      0.8774      0.013     65.240      0.000       0.851       0.9
04
==============================================================================
==
Omnibus:                     1427.099   Durbin-Watson:                   2.0
11
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1832260.4
28
Skew:                          15.460   Prob(JB):                         0.
00
Kurtosis:                     251.725   Cond. No.                     1.89e+
05
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
[2] The condition number is large, 1.89e+05. This might indicate that there
are
strong multicollinearity or other numerical problems.
```

ANALYSIS: - The values we are concerned with are -

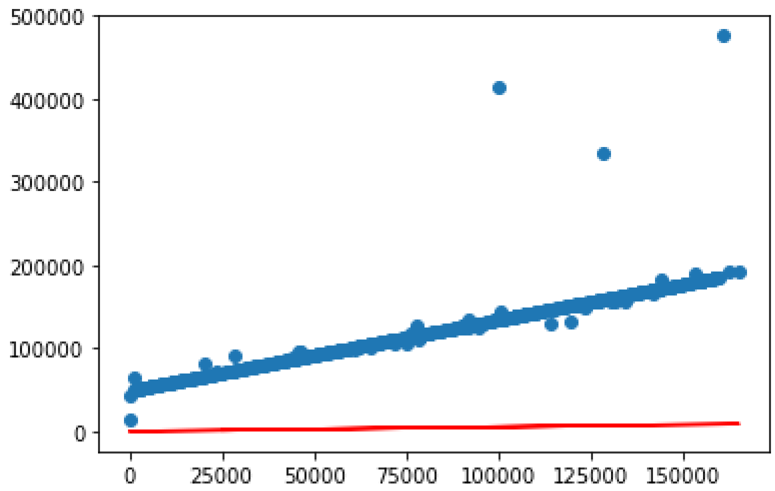
1. The coefficients and significance (p-values)
2. R-squared

the coefficient value of R and D is statistically significant as there is low p value, R-squared is basically the difference between the square of the actual values and the predicted values, here the r squared is 0.85 which is close to 1 which is a good and a healthy sign.

Equation: - SALES = 4.81 + 0.87 * R&D spend

In [88]:

```
plt.scatter(X_train, y_train)
plt.plot(X_train, 6.948 + 0.054*X_train, 'r')
plt.show()
```

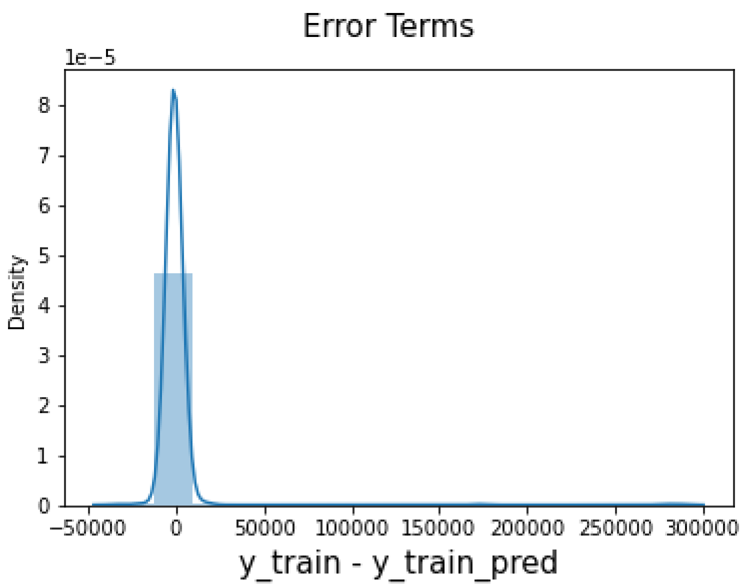


In [89]:

```
y_train_pred = lr.predict(X_train_sm)
res = (y_train - y_train_pred)
```

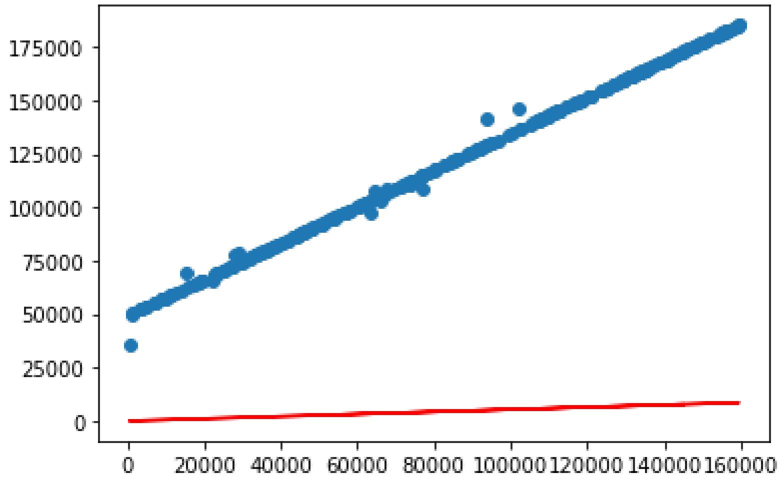
In [90]:

```
fig = plt.figure()
sns.distplot(res, bins = 15)
fig.suptitle('Error Terms', fontsize = 15)                  # Plot heading
plt.xlabel('y_train - y_train_pred', fontsize = 15)         # X-label
plt.show()
```



In [91]:

```
plt.scatter(X_test, y_test)
plt.plot(X_test, 6.948 + 0.054 * X_test, 'r')
plt.show()
```



In [102]:

```
sarimax_model= SARIMAX(data['Profit'],order=(1,1,1),seasonal_order=(1,1,1,4),exog=data['Mar
```

In [103]:

```
res=sarimax_model.fit(disp=False)
```

In [104]:

```
res.summary()
```

Out[104]:

SARIMAX Results

Dep. Variable:	Profit	**No. Observations:**	1000
Model:	SARIMAX(1, 1, 1)x(1, 1, 1, 4)	**Log Likelihood**	-10936.550
Date:	Fri, 18 Jun 2021	**AIC**	21885.100
Time:	11:26:40	**BIC**	21914.517
Sample:	0	**HQIC**	21896.283
	- 1000		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
Marketing Spend	0.4239	0.015	27.883	0.000	0.394	0.454
ar.L1	-0.4184	0.022	-18.695	0.000	-0.462	-0.375
ma.L1	-0.0564	0.025	-2.228	0.026	-0.106	-0.007
ar.S.L4	0.0247	0.030	0.833	0.405	-0.033	0.083
ma.S.L4	-0.9855	0.081	-12.187	0.000	-1.144	-0.827
sigma2	2.737e+08	9.9e-10	2.76e+17	0.000	2.74e+08	2.74e+08

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	2071184.51
Prob(Q):	0.98	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.07	**Skew:**	9.36
Prob(H) (two-sided):	0.56	**Kurtosis:**	225.73

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 7.25e+31. Standard errors may be unstable.

Conclusion and learnings

CONCLUSION: - In ABC Company, after few analysis and interpretations i could observe that the most of the profit made by the marketing activities of the company. There are spending their expenditure on the marketing activities and is helping them to do the promotional activities and leading them to generate profits.

Here, in this assignment i have included all the concepts of cleaning, panfas, using all the plots and with some research i have understood additional plots like jointplots and different categories among them. like: -

a. Give the basic description of the data.

b. Handling missing values.

c. Data Visualization on various features.

d. Splitting the data as test and train.

e. Model building. (Linear/Logistic Regression)

analyse and interpret the real time data set and i have learnt on how does a real data is interpreted. i would like to talk about the importance of analytics, Analytics allow you to quantify the effects of making a change to your marketing strategy, and that's invaluable to the process of improving and optimizing online marketing campaigns. The biggest benefit of utilizing proper analytics is being able to identify strengths and weaknesses. For example, let's say you run a blog for your car detailing business. You're just starting out, and aren't sure what kinds of posts will bring you the most traffic, or provide the most value to your readers. If you're using analytics, you'll be able to measure which blog posts attract the most traffic, which get the least traffic, which have a high bounce rate, a low bounce rate, and so on. It will be easy to tell which blog posts are performing better or worse than others. since i had to develop everything from the base data it was very insightful as it totally was interpretation based. this kind of interpretation would be used even in the real organisation the key idea is to collect data about the organization and use them to improve operations. Raw form of data is not of any use.If you are trying to bring any significant improvement in your business, then analytics is your best bet to bring about an informed transformation.

In [ ]:

```

```