Problem Fromation

1. **In this example, we want to investigate "what factors/variables affect the performance of revenue"**
2. **Our aim is to go back to the business and make suggestions about how to generate more revenue**
3. **Make Revenue predictions given specific variable values Hence our Dependent variable (y) is Revenue**

Installing Packages

In [1]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, explained_variance_score, mean_absolute_error, r
from math import sqrt
```

Converting .txt to .csv

In [2]:
```
read_file = pd.read_csv (r'C:\Users\96653\Desktop\python project\Liner Regression Ana
read_file.to_csv (r'C:\Users\96653\Desktop\python project\Liner Regression Analysis\Ne
```

Loading data

In [3]:
```
raw_data=pd.read_csv(r'C:\Users\96653\Desktop\python project\Liner Regression Analysis
```

Shape of Data

In [4]:
```
print(raw_data.shape)
```
```
(185, 11)
```

In [5]:
```
raw_data
```
Out[5]:

	Date	Week	Week_ID	Month	Month_ID	Year	Day_Name	Visitors	Revenue	Marketing Spend	Pr
0	09/11/2020	46.0	34.0	11.0	11.0	2020.0	Monday	707.0	465.0	651.375	No Pr
1	10/11/2020	46.0	34.0	11.0	11.0	2020.0	Tuesday	1455.0	10386.0	1298.250	Promo
2	11/11/2020	46.0	34.0	11.0	11.0	2020.0	Wednesday	1520.0	12475.0	1559.375	Promo
3	12/11/2020	46.0	34.0	11.0	11.0	2020.0	Thursday	1726.0	11712.0	1801.750	No Pr
4	13/11/2020	46.0	34.0	11.0	11.0	2020.0	Friday	2134.0	10000.0	2614.500	No Pr
...	...	...	...	...	...	...	...	...	...	...	
180	08/05/2021	19.0	60.0	5.0	17.0	2021.0	Saturday	1483.0	5927.0	1121.875	No Pr
181	09/05/2021	20.0	61.0	5.0	17.0	2021.0	Sunday	1303.0	3861.0	871.000	No Pr
182	10/05/2021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
183	11/05/2021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
184	12/05/2021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

185 rows × 11 columns

In [6]:
```
#Running 5 rows
raw_data.head()
```
Out[6]:

	Date	Week	Week_ID	Month	Month_ID	Year	Day_Name	Visitors	Revenue	Marketing Spend	Prom
0	09/11/2020	46.0	34.0	11.0	11.0	2020.0	Monday	707.0	465.0	651.375	No Prom
1	10/11/2020	46.0	34.0	11.0	11.0	2020.0	Tuesday	1455.0	10386.0	1298.250	Promotic Re
2	11/11/2020	46.0	34.0	11.0	11.0	2020.0	Wednesday	1520.0	12475.0	1559.375	Promotic Blu
3	12/11/2020	46.0	34.0	11.0	11.0	2020.0	Thursday	1726.0	11712.0	1801.750	No Prom
4	13/11/2020	46.0	34.0	11.0	11.0	2020.0	Friday	2134.0	10000.0	2614.500	No Prom

Data Preprocessing

Explotary Data Analysis*

In [7]:
```
#Checking for null values
raw_data.isnull().sum()
#Summarizing---How many null/missing values by coloumn
```
Out[7]:
```
Date              0
Week              3
Week_ID           3
Month             3
Month_ID          3
Year              3
Day_Name          3
Visitors          3
Revenue           3
Marketing Spend   3
Promo             3
dtype: int64
```

Visualizing Missing Values

In [8]:
```
raw_data[raw_data['Week'].isnull()]
```
Out[8]:

	Date	Week	Week_ID	Month	Month_ID	Year	Day_Name	Visitors	Revenue	Marketing Spend	Promo
182	10/05/2021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
183	11/05/2021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
184	12/05/2021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Ways of dealling with Missing Data

1. **Delete the whole observation if all the coloumns are null e.g(here)**
2. **Replace the NULL value with another value (mean, rolling mean, last day value, closest day value, mode, median, zero, etc) if only one or two coloumns are missing**

In [9]:
```
#Deleting null values

raw_data.dropna()

#it drops all observation that has any values are null.
```
Out[9]:

	Date	Week	Week_ID	Month	Month_ID	Year	Day_Name	Visitors	Revenue	Marketing Spend	P
0	09/11/2020	46.0	34.0	11.0	11.0	2020.0	Monday	707.0	465.0	651.375000	No P
1	10/11/2020	46.0	34.0	11.0	11.0	2020.0	Tuesday	1455.0	10386.0	1298.250000	Prom
2	11/11/2020	46.0	34.0	11.0	11.0	2020.0	Wednesday	1520.0	12475.0	1559.375000	Prom
3	12/11/2020	46.0	34.0	11.0	11.0	2020.0	Thursday	1726.0	11712.0	1801.750000	No P
4	13/11/2020	46.0	34.0	11.0	11.0	2020.0	Friday	2134.0	10000.0	2614.500000	No P
...	...	...	...	...	...	...	...	...	...	...	
177	05/05/2021	19.0	60.0	5.0	17.0	2021.0	Wednesday	1400.0	7284.0	1119.600000	No P
178	06/05/2021	19.0	60.0	5.0	17.0	2021.0	Thursday	2244.0	13021.0	2067.888889	Prom
179	07/05/2021	19.0	60.0	5.0	17.0	2021.0	Friday	2023.0	4587.0	1450.200000	No P
180	08/05/2021	19.0	60.0	5.0	17.0	2021.0	Saturday	1483.0	5927.0	1121.875000	No P
181	09/05/2021	20.0	61.0	5.0	17.0	2021.0	Sunday	1303.0	3861.0	871.000000	No P

182 rows × 11 columns

In [10]:
```
# For deleting specific column null values

raw_data = raw_data.dropna(subset = ['Week'])

# printing the shape

raw_data
```
Out[10]:

	Date	Week	Week_ID	Month	Month_ID	Year	Day_Name	Visitors	Revenue	Marketing Spend	P
0	09/11/2020	46.0	34.0	11.0	11.0	2020.0	Monday	707.0	465.0	651.375000	No P
1	10/11/2020	46.0	34.0	11.0	11.0	2020.0	Tuesday	1455.0	10386.0	1298.250000	Prom
2	11/11/2020	46.0	34.0	11.0	11.0	2020.0	Wednesday	1520.0	12475.0	1559.375000	Prom
3	12/11/2020	46.0	34.0	11.0	11.0	2020.0	Thursday	1726.0	11712.0	1801.750000	No P
4	13/11/2020	46.0	34.0	11.0	11.0	2020.0	Friday	2134.0	10000.0	2614.500000	No P
...	...	...	...	...	...	...	...	...	...	...	
177	05/05/2021	19.0	60.0	5.0	17.0	2021.0	Wednesday	1400.0	7284.0	1119.600000	No P
178	06/05/2021	19.0	60.0	5.0	17.0	2021.0	Thursday	2244.0	13021.0	2067.888889	Prom
179	07/05/2021	19.0	60.0	5.0	17.0	2021.0	Friday	2023.0	4587.0	1450.200000	No P
180	08/05/2021	19.0	60.0	5.0	17.0	2021.0	Saturday	1483.0	5927.0	1121.875000	No P
181	09/05/2021	20.0	61.0	5.0	17.0	2021.0	Sunday	1303.0	3861.0	871.000000	No P

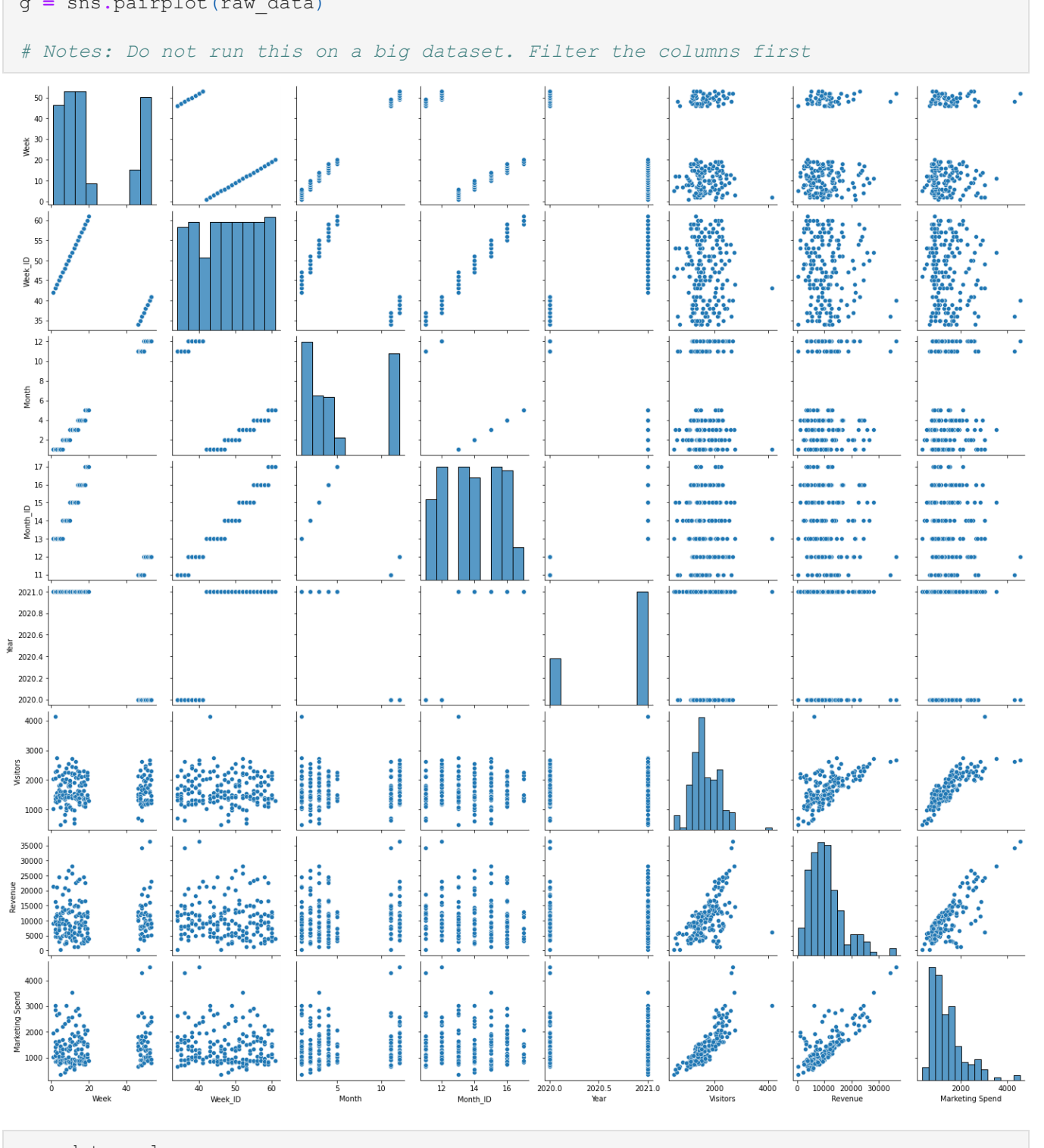
182 rows × 11 columns

In [11]:
```
# Visualizing null observation after dropping
raw_data.isnull().sum()
```
Out[11]:
```
Date              0
Week              0
Week_ID           0
Month             0
Month_ID          0
Year              0
Day_Name          0
Visitors          0
Revenue           0
Marketing Spend   0
Promo             0
dtype: int64
```

Investigate all the elements whithin each Feature

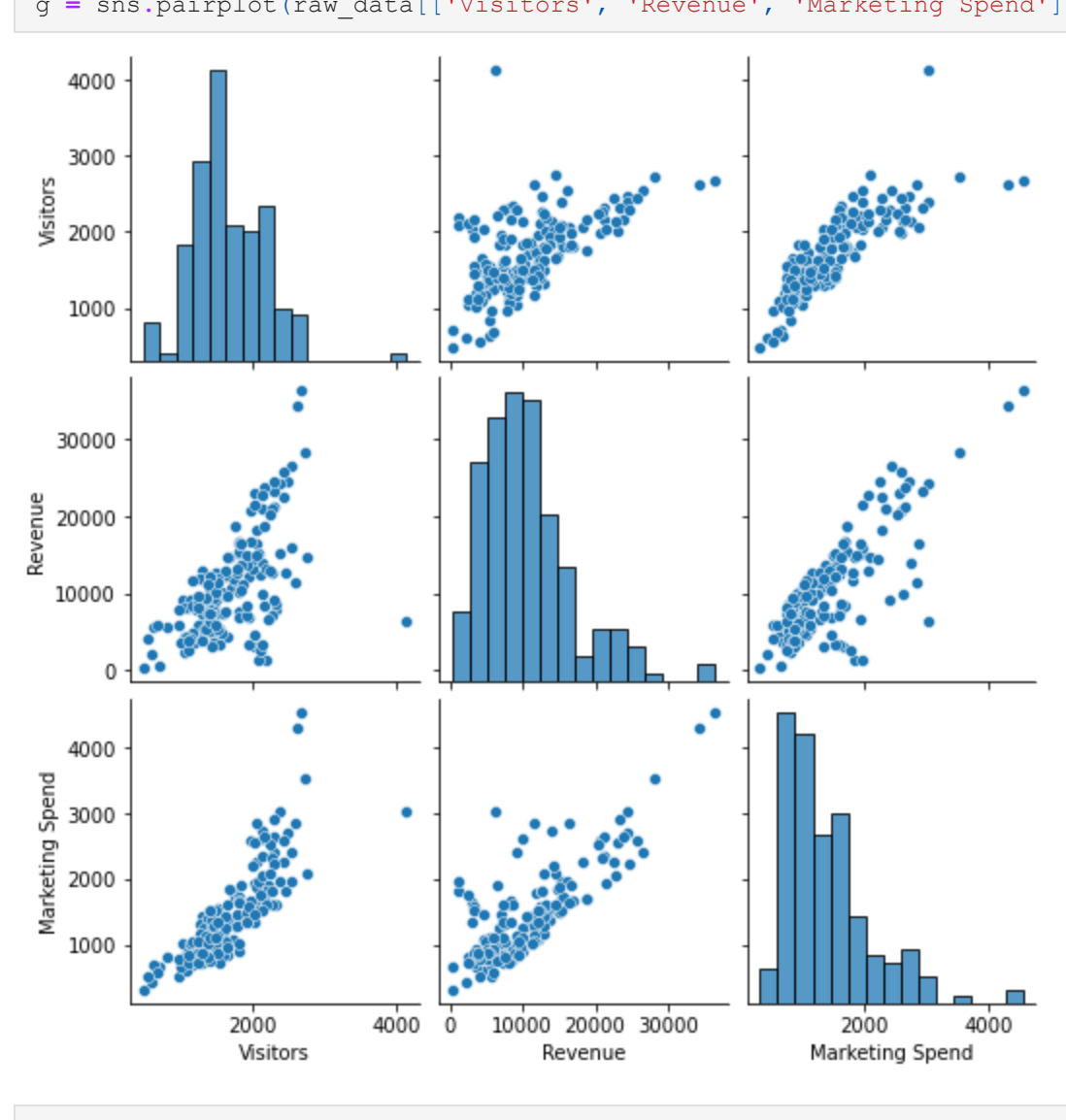
In [12]:
```
#np.unique find unique values from each coloumn

for column in raw_data:
    unique_vals = np.unique(raw_data[column])
    nr_values = len(unique_vals)
    if nr_values < 10:
        print('The number of values for feature {} :{} -- {}'.format(column, nr_value
    else:
        print('The number of values for feature {} :{}'.format(column, nr_values))
```
```
The number of values for feature Date :182
The number of values for feature Week :28
The number of values for feature Week_ID :28
The number of values for feature Month :7 -- [ 1.  2.  3.  4.  5. 11. 12.]
The number of values for feature Month_ID :7 -- [11. 12. 13. 14. 15. 16. 17.]
The number of values for feature Year :2 -- [2020. 2021.]
The number of values for feature Day_Name :7 -- ['Friday' 'Monday' 'Saturday' 'Sunday'
'Thursday' 'Tuesday' 'Wednesday']
The number of values for feature Visitors :175
The number of values for feature Revenue :181
The number of values for feature Marketing Spend :182
The number of values for feature Promo :3 -- ['No Promo' 'Promotion Blue' 'Promotion R
ed']
```

In [13]:
```
# Visualize the data using seaborn Pairplots

g = sns.pairplot(raw_data)

# Notes: Do not run this on a big dataset. Filter the columns first
```

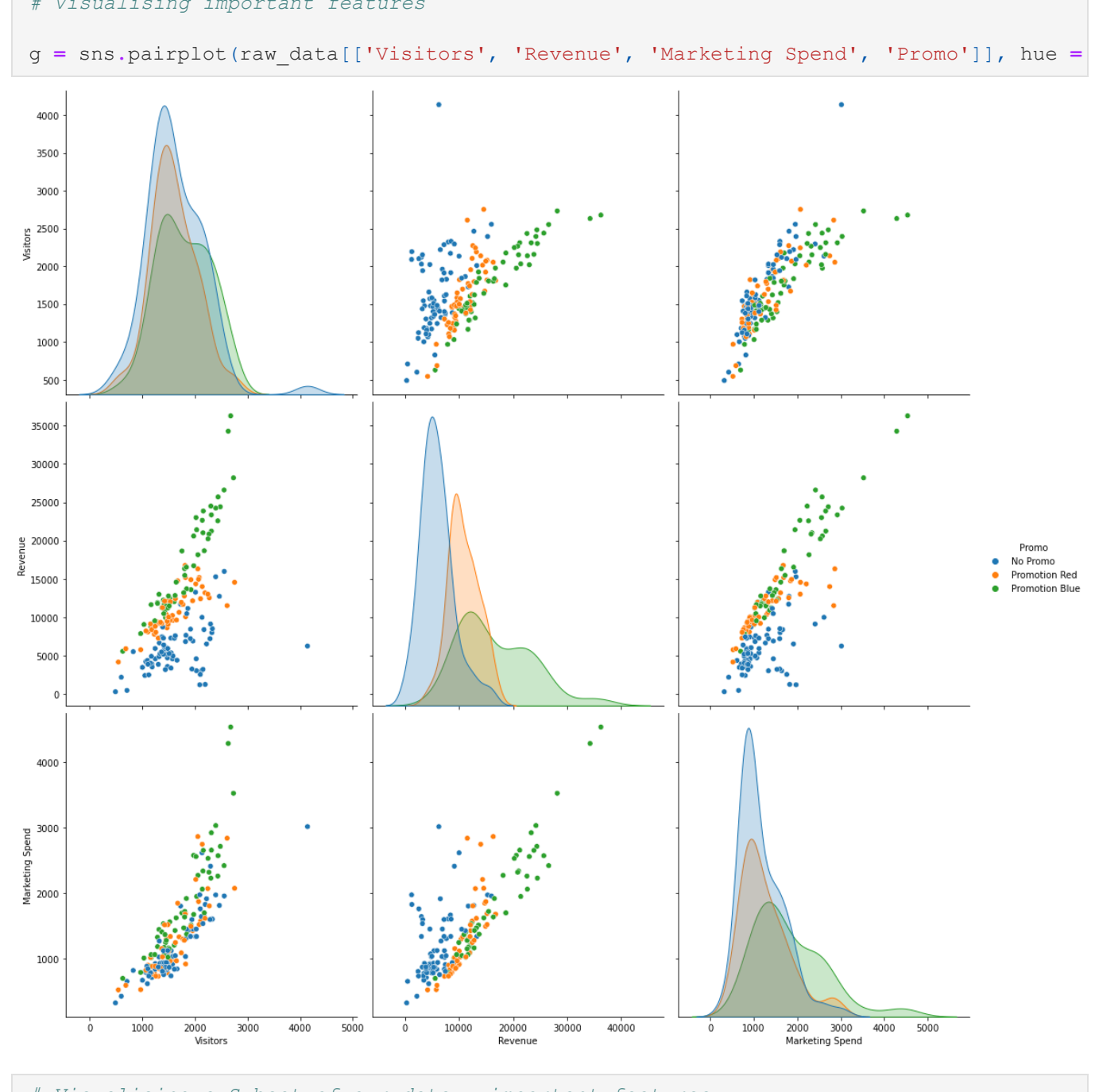


In [14]:
```
raw_data.columns
```
Out[14]:
```
Index(['Date', 'Week', 'Week_ID', 'Month', 'Month_ID', 'Year', 'Day_Name',
       'Visitors', 'Revenue', 'Marketing Spend', 'Promo'],
      dtype='object')
```

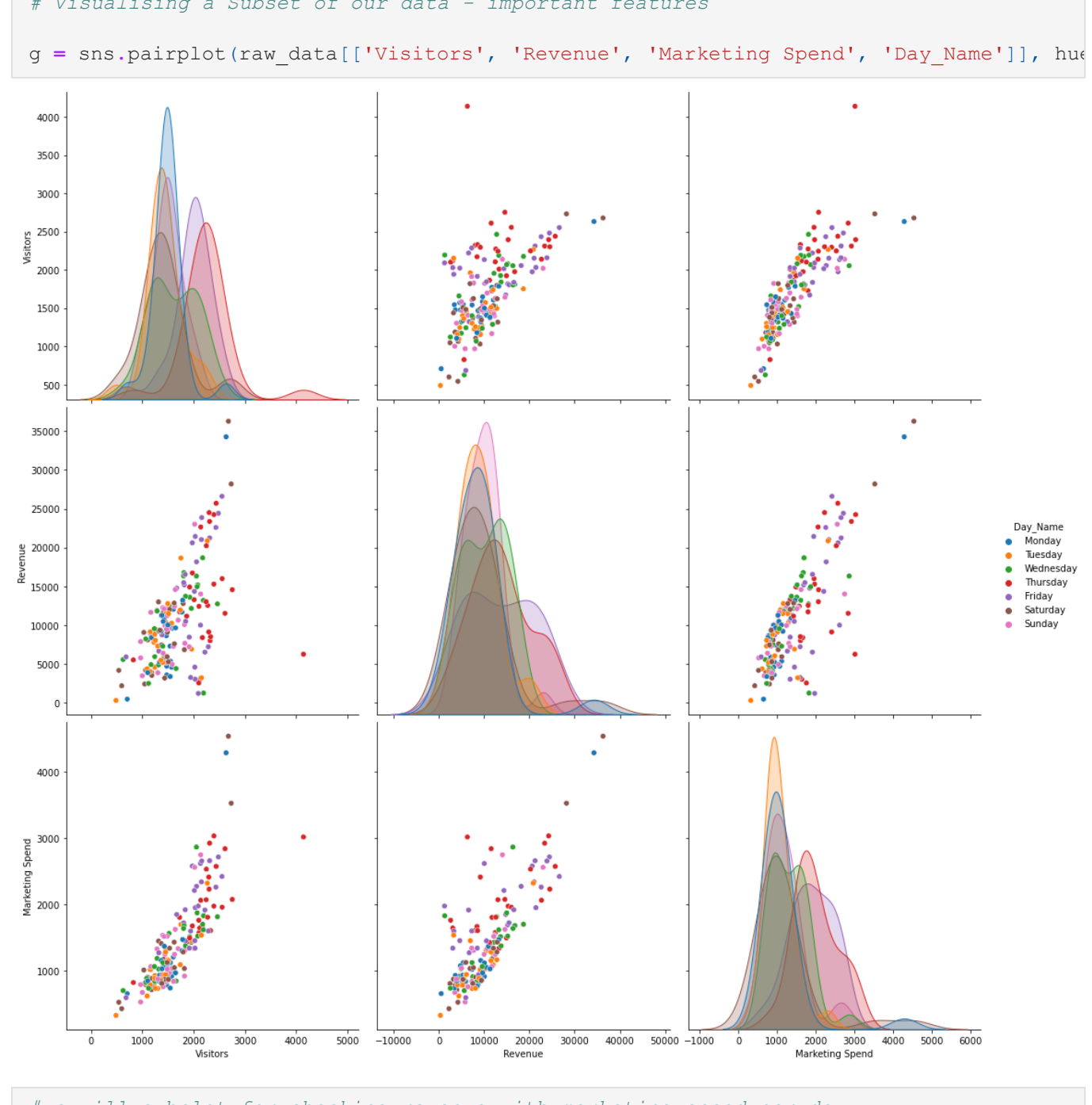
In [15]:
```
# Visualising a Subset of our data

g = sns.pairplot(raw_data[['Visitors', 'Revenue', 'Marketing Spend']])
```



In [16]:
```
# Visualising important features

g = sns.pairplot(raw_data[['Visitors', 'Revenue', 'Marketing Spend', 'Promo']], hue =
```



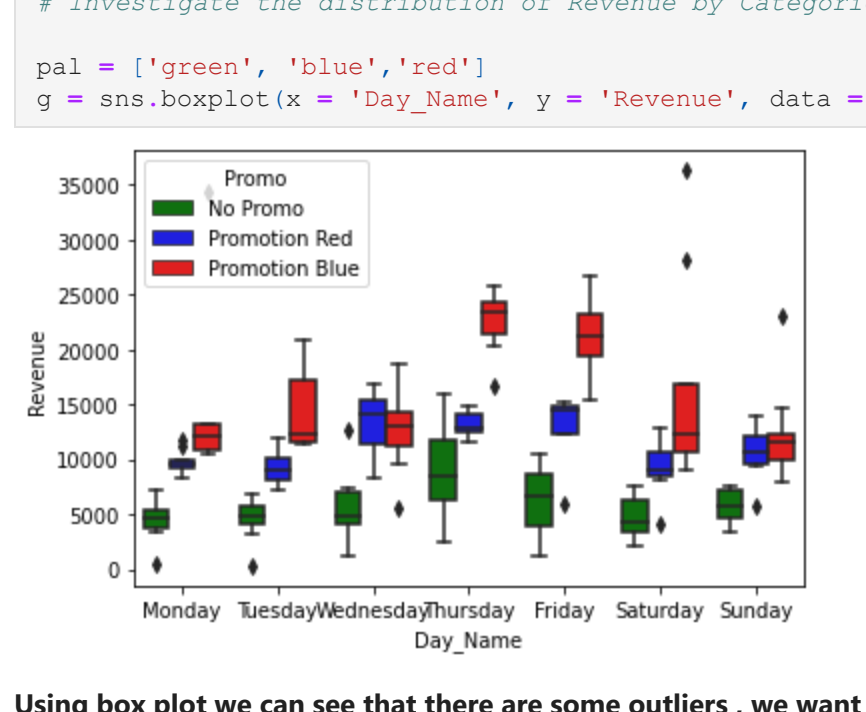
In [17]:
```
# Visualising a Subset of our data - important features

g = sns.pairplot(raw_data[['Visitors', 'Revenue', 'Marketing Spend', 'Day_Name']], hue
```



In [18]:
```
#we will subplot for checking revenue with marketing speed per day
g = sns.lmplot(x = 'Marketing Spend', y = 'Revenue', data = raw_data, col = 'Day_Name
               scatter_kws = {'color':'green'}, ci = False)
```

Every single day it is showing reletionship between marketing spend with revenue, so have to keep date in data, so we have to convert it into numeric representation 0/1

In [19]:
```
# Investigate the distribution of Revenue by Categorical Variables

pal = ['green', 'blue','red']
g = sns.boxplot(x = 'Day_Name', y = 'Revenue', data = raw_data, hue = 'Promo',palette
```



Using box plot we can see that there are some outliers , we want to remove that outliers

Data Cleaning

In [20]:
```
raw_data[raw_data['Revenue'] > 27000]
```
Out[20]:

	Date	Week	Week_ID	Month	Month_ID	Year	Day_Name	Visitors	Revenue	Marketing Spend	Pr
14	23/11/2020	48.0	36.0	11.0	11.0	2020.0	Monday	2632.0	34278.0	4284.750	Promo
47	26/12/2020	52.0	40.0	12.0	12.0	2020.0	Saturday	2678.0	36283.0	4535.375	Promo
124	13/03/2021	11.0	52.0	3.0	15.0	2021.0	Saturday	2732.0	28196.0	3524.500	Promo

Deleting outliers

In [21]:
```
# we will take all the data excepting above

raw_data = raw_data[raw_data['Revenue'] < 27000]

raw_data.shape
```
Out[21]:
```
(179, 11)
```

In [22]:
```
# Column names
raw_data.columns
```
Out[22]:
```
Index(['Date', 'Week', 'Week_ID', 'Month', 'Month_ID', 'Year', 'Day_Name',
       'Visitors', 'Revenue', 'Marketing Spend', 'Promo'],
      dtype='object')
```

Selecting Columns

In [23]:
```
# we will Select usefull only columns
raw_data = raw_data[['Day_Name','Visitors', 'Revenue', 'Marketing Spend', 'Promo']]

#visualize the raw data
raw_data.head(10)
```
Out[23]:

	Day_Name	Visitors	Revenue	Marketing Spend	Promo
0	Monday	707.0	465.0	651.375000	No Promo
1	Tuesday	1455.0	10386.0	1298.250000	Promotion Red
2	Wednesday	1520.0	12475.0	1559.375000	Promotion Blue
3	Thursday	1726.0	11712.0	1801.750000	No Promo
4	Friday	2134.0	10000.0	2614.500000	No Promo
5	Saturday	1316.0	12996.0	1444.000000	Promotion Blue
6	Sunday	1287.0	11929.0	1325.444444	Promotion Blue
7	Monday	1548.0	5359.0	1119.111111	No Promo
8	Tuesday	1448.0	12016.0	1092.363636	Promotion Blue
9	Wednesday	1362.0	7441.0	906.700000	No Promo

Converting Categorical data into Numerical Value

In [24]:
```
# Making categorical variables into numeric representation

new_raw_data = pd.get_dummies(raw_data, columns = ['Promo', 'Day_Name'])

# Visualizing the data
new_raw_data.head()
```
Out[24]:

	Visitors	Revenue	Marketing Spend	Promo_No Promo	Promo_Promotion Blue	Promo_Promotion Red	Day_Name_Friday	Day_Nam
0	707.0	465.0	651.375	1	0	0	0	
1	1455.0	10386.0	1298.250	0	0	1	0	
2	1520.0	12475.0	1559.375	0	1	0	0	
3	1726.0	11712.0	1801.750	1	0	0	0	
4	2134.0	10000.0	2614.500	1	0	0	1	

Feature Selection

In this example, we do not have many variables so we should use all of the data but in some cases, you have thousands of variables and you will need to filter them in order to save computational time.

Two ways to help us select the important features are:

1. Correlation
2. Feature Importance

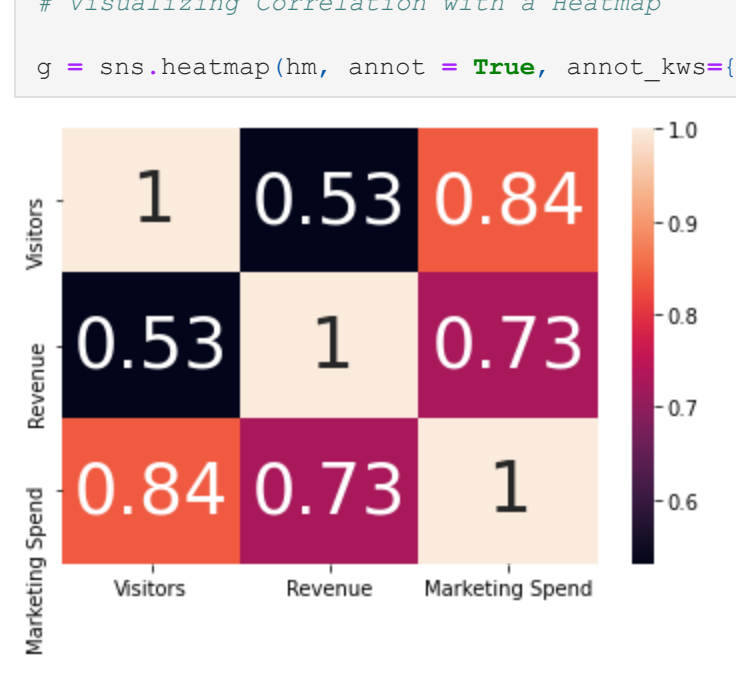
In [25]:
```
# Running Correlation

hm = new_raw_data[['Visitors','Revenue','Marketing Spend']].corr()
hm
```
Out[25]:

	Visitors	Revenue	Marketing Spend
Visitors	1.000000	0.531602	0.837313
Revenue	0.531602	1.000000	0.725675
Marketing Spend	0.837313	0.725675	1.000000

Notes

1. corr() is used to find the pairwise correlation of all columns in the dataframe. Any null values are automatically excluded
2. The closer to 1 or -1 the better. As one variable increases, the other variable tends to also increase / decrease
3. 0.8 +- is Strong Correlation, 0.6 to 0.8 +- is moderate Correlation & the other values, there is no correlation

In [26]:
```
# Visualizing Correlation with a Heatmap

g = sns.heatmap(hm, annot = True, annot_kws={'size':35})
```



Steps of Running Feature Importance

1. Split the data into X & y
2. Run a Tree-based estimators (i.e. decision trees & random forests)
3. Run Feature Importance

In [27]:
```
# X will be Independent variable everything except Revenue
# Y is Dependent Variable, Revenue

X2 = new_raw_data.drop('Revenue', axis = 1)

# if we want to pass data in algorithm we have to turn x into values

X = new_raw_data.drop('Revenue', axis = 1).values

y = new_raw_data['Revenue']

print(X.shape)
print(y.shape)
```
```
(179, 12)
(179,)
```

In [28]:
```
X2
```
Out[28]:

	Visitors	Marketing Spend	Promo_No Promo	Promo_Promotion Blue	Promo_Promotion Red	Day_Name_Friday	Day_Name_Mo
0	707.0	651.375000	1	0	0	0	
1	1455.0	1298.250000	0	0	1	0	
2	1520.0	1559.375000	0	1	0	0	
3	1726.0	1801.750000	1	0	0	0	
4	2134.0	2614.500000	1	0	0	1	
...	...	...	...	...	...	...	
177	1400.0	1119.600000	1	0	0	0	
178	2244.0	2067.888889	0	0	1	0	
179	2023.0	1450.200000	1	0	0	1	
180	1483.0	1121.875000	1	0	0	0	
181	1303.0	871.000000	1	0	0	0	

179 rows × 12 columns

In [29]:
```
y
```
Out[29]:
```
0        465.0
1      10386.0
2      12475.0
3      11712.0
4      10000.0
        ...
177     7284.0
178    13021.0
179     4587.0
180     5927.0
181     3861.0
Name: Revenue, Length: 179, dtype: float64
```

In [30]:
```
X
```
Out[30]:
```
array([[7.070000e+02, 6.513750e+02, 1.000000e+00, ..., 0.000000e+00,
        0.000000e+00, 0.000000e+00],
       [1.455000e+03, 1.298250e+03, 0.000000e+00, ..., 0.000000e+00,
        1.000000e+00, 0.000000e+00],
       [1.520000e+03, 1.559375e+03, 0.000000e+00, ..., 0.000000e+00,
        0.000000e+00, 1.000000e+00],
       ...,
       [2.023000e+03, 1.450200e+03, 1.000000e+00, ..., 0.000000e+00,
        0.000000e+00, 0.000000e+00],
       [1.483000e+03, 1.121875e+03, 1.000000e+00, ..., 0.000000e+00,
        0.000000e+00, 0.000000e+00],
       [1.303000e+03, 8.710000e+02, 1.000000e+00, ..., 0.000000e+00,
        0.000000e+00, 0.000000e+00]])
```

In [31]:
```
# Run a Tree-based estimators (i.e. decision trees & random forests)

dt = DecisionTreeClassifier(random_state=15, criterion  = 'entropy', max_depth = 10)
dt.fit(X,y)
```
Out[31]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=10, random_state=15)
```

Notes:

The importance of a feature is calculated as the (normalized) total reduction of entropy (other criterions too) brought by that feature or the higher information gain.

In [32]:
```
# Running Feature Importance

for i, column in enumerate(new_raw_data.drop('Revenue', axis = 1)):
    print('The feature importance for {} is: {:.3f}'.format(column, dt.feature_importa
```
```
The feature importance for Visitors is: 0.332
The feature importance for Marketing Spend is: 0.438
The feature importance for Promo_No Promo is: 0.032
The feature importance for Promo_Promotion Blue is: 0.047
The feature importance for Promo_Promotion Red is: 0.045
The feature importance for Day_Name_Friday is: 0.013
The feature importance for Day_Name_Monday is: 0.014
The feature importance for Day_Name_Saturday is: 0.013
The feature importance for Day_Name_Sunday is: 0.016
The feature importance for Day_Name_Thursday is: 0.020
The feature importance for Day_Name_Tuesday is: 0.017
The feature importance for Day_Name_Wednesday is: 0.013
```

Most important feature here is Marketing Spend -> Visitors-> Promo Blue-> Thursday

Notes:

Our data is fine so ..

1. we have not normalised / scale our data
2. we have not done any feature engineering - created new features
3. we have not joined multiple datasets together
4. we have not aggregated any of our data

Splitting the Raw Data - Hold-out validation

In [33]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.80, test_size =

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)

# Official Doc: https://scikit-learn.org/stable/modules/generated/sklearn.model_selec
```
```
(143, 12)
(36, 12)
(143,)
(36,)
```

> ### What is Linear Regression Analysis

- Linear regression is a widely used machine learning model that predicts continues numbers as outputs; not classes
- It models the relationship of 2 plus variables by fitting a linear equation to observed data
- In linear regression you have 1 dependent variable (y) and 1 plus independent variables (X)
- Before you attempt to model the data, you should check if there is a relationship between the variables first; a good way is to use a scatterplot to visualise the data

Running Linear Regression

In [35]:
```
# Training the Regression

lm = LinearRegression(fit_intercept = True)
lm.fit(X_train, y_train)

y_pred = lm.predict(X_train)

# SK-Learn official doc: https://scikit-learn.org/stable/modules/generated/sklearn.li
```

In [36]:
```
# Actiaal Values
y_train
```
Out[36]:
```
73      3021.0
32      6654.0
141     5478.0
154    10027.0
122    25704.0
        ...
159     5274.0
131     4169.0
121    13201.0
136    11524.0
143    23368.0
Name: Revenue, Length: 143, dtype: float64
```

In [39]:
```
# Predicted values
y_pred
```
Out[39]:
```
array([ 8705.50803238,  6472.17869274,  4440.32746821,  9854.13421815,
       20470.49081201, 13259.20147968, 13412.43936843, 19071.25323458,
        1011.80212161, 20962.47300197,  4753.61288693, 13648.41721974,
       13374.77268825, 20422.87899345,  8853.79300499,  8916.13289802,
       13498.94148289,  6205.52346237,  8286.46917634, 16700.31444964,
       19236.89110222,  2507.01947954,  9022.95702143, 20585.16837547,
       10157.53082079,  3629.09878399, 15744.20305379,  4665.32195611,
       15487.29412778,  9371.6680232 , 10657.85245056, 17391.63379279,
        7356.21819439,  3764.06039853,  4311.99089777, 13112.10851617,
        3605.07141122, 13380.08175878, 11521.68147579,  7416.01143452,
        7660.84372446, 10797.8869771 ,  8353.41108964, 15286.88903789,
       20134.1178417 ,  2802.64541887,  9446.08236768, 12611.79941142,
        9506.08359716, 14949.57797928, 12301.04535283,  4146.95924223,
       11605.50687406, 12673.508552  , 15904.41280179,  2849.35768349,
       18911.6336204 , 19043.35234105, 12677.01444098,  4970.92663645,
        4438.02704902, 15782.03265996,  4803.08002424,  8740.67974156,
        3894.32137802, 10488.94870908, 15883.44048808,  7180.38550272,
        9826.10896404,  4196.47978254, 11753.06586213, 15270.32573523,
        3782.40950251, 13303.25187386,  3255.00684752, 18703.97459452,
        8126.19913661,  8537.34381714,  3496.5952153 ,  5314.97689254,
       18290.9185137 ,  8706.13970677, 17697.85165818,  4972.24951743,
       10095.35604912, 13735.50194354, 10202.90413128,  9093.96529945,
       14733.3930298 , 12012.98604928,  9863.56915438, 12825.93082981,
       14594.48836447,  4262.69584459,  1579.26516425,  8560.87312054,
       14322.95099685,  7828.85797663,  8247.44879732, 13684.43101025,
       19251.28483456, 19962.82214625,  3470.61768712, 12581.24603729,
        5053.18608338, 12239.57300659, 22129.4535853 ,  9121.47686996,
        9654.85323749, 11507.66191395, 13442.14435515, 13628.68585085,
       11717.15473786, 13870.05764026,  9410.39817874,  9075.56411507,
       10994.25898762, 16633.07755414, 16916.3118079 , 10677.31642927,
        4096.23693459,  7643.42438254, 14648.90987724, 10289.38612756,
       11045.11300565,  8763.78006368,  8139.58898973, 14352.62389938,
        3764.11720897,  8769.14106879,  9411.37891827,  3269.47524393,
        8841.15541323,  3934.92498491, 13812.74568881,  4155.75140547,
        7470.9963159 ,  7307.8718898 ,  3527.92184465,  6183.35973133,
       12432.4426435 , 18471.75989409, 21641.73571728])
```

In [40]:
```
y_pred.shape
```
Out[40]:
```
(143,)
```

We want prediced y_train of X_train so that we can evaluate our model.

Evaluating the Model

In [46]:
```
# Model Accuracy on training dataset

print('The Accuracy  on the training dataset is: ', lm.score(X_train, y_train) )
print("")
print('The Accuracy R^2  on the training dataset is: ',r2_score(y_train,y_pred) )
print("")
```
```
The Accuracy  on the training dataset is:  0.791949990505602

The Accuracy R^2  on the training dataset is:  0.791949990505602
```

In [47]:
```
# Model Accuracy on testing dataset
print('The Accuracy  on the testing dataset is: ', lm.score(X_test, y_test) )

print("")
```
```
The Accuracy  on the testing dataset is:  0.751190386538668
```

Notes:

- The accuracy score represents the coefficient of determination ($R2$). This is at max 1, but can be negative. It will be 0 if you predict the mean of y for all observations.
- The R Square is measure of how close the data are to the fitted regression line.
- In this case we can say that our model explains 79% of the training data & 75% of the testing data
- The RMSE is the standard deviation of the residuals. Residuals is the difference between the predicted value and the regression line. Hence RMSE is a measure of how spread your residuals are.
- The mean absolute error (MAE) is the average of all the absolute errors. The absolute error is the difference between the true value (y_train) and the predicted value (y_pred).
- Coeff are the weights
- The intercept is the expected mean value of Y when all X=0

In [48]:
```
# The Root Mean Squared Error (RMSE)
print('The RMSE  on the training dataset is: ',sqrt(mean_squared_error(y_train,y_pred)
print("")
print('The RMSE  on the testing dataset is: ',sqrt(mean_squared_error(y_test,lm.predic

print("")
```

```
The RMSE  on the training dataset is:  2618.561282656437

The RMSE  on the testing dataset is:  2340.4200873490113
```

Links
R2 Link: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.r2_score.html
RMSE Link: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.mean_squared_error.html
MAE Link: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.mean_absolute_error.html

---

In [49]:
```
# The Mean Absolute Error (MAE)
print('The MAE  on the training dataset is: ',mean_absolute_error(y_train,y_pred))
print("")
print('The MAE  on the testing dataset is: ',mean_absolute_error(y_test,lm.predict(X_t


print("")
```

```
The MAE  on the training dataset is:  1928.0670665528867

The MAE  on the testing dataset is:  1692.3835577162286
```

Error is dropped for unseen data

In [50]:
```
# Coefficients
print('Coefficients: ', lm.coef_ )
```

```
Coefficients:  [ 9.72168996e-01  3.69561477e+00 -4.29587654e+03  3.72469059e+03
  5.71185949e+02  7.38005738e+02 -3.52308895e+02 -9.02241594e+02
 -1.55867567e+02  8.14821481e+02  1.50084913e+02 -2.92494076e+02]
```

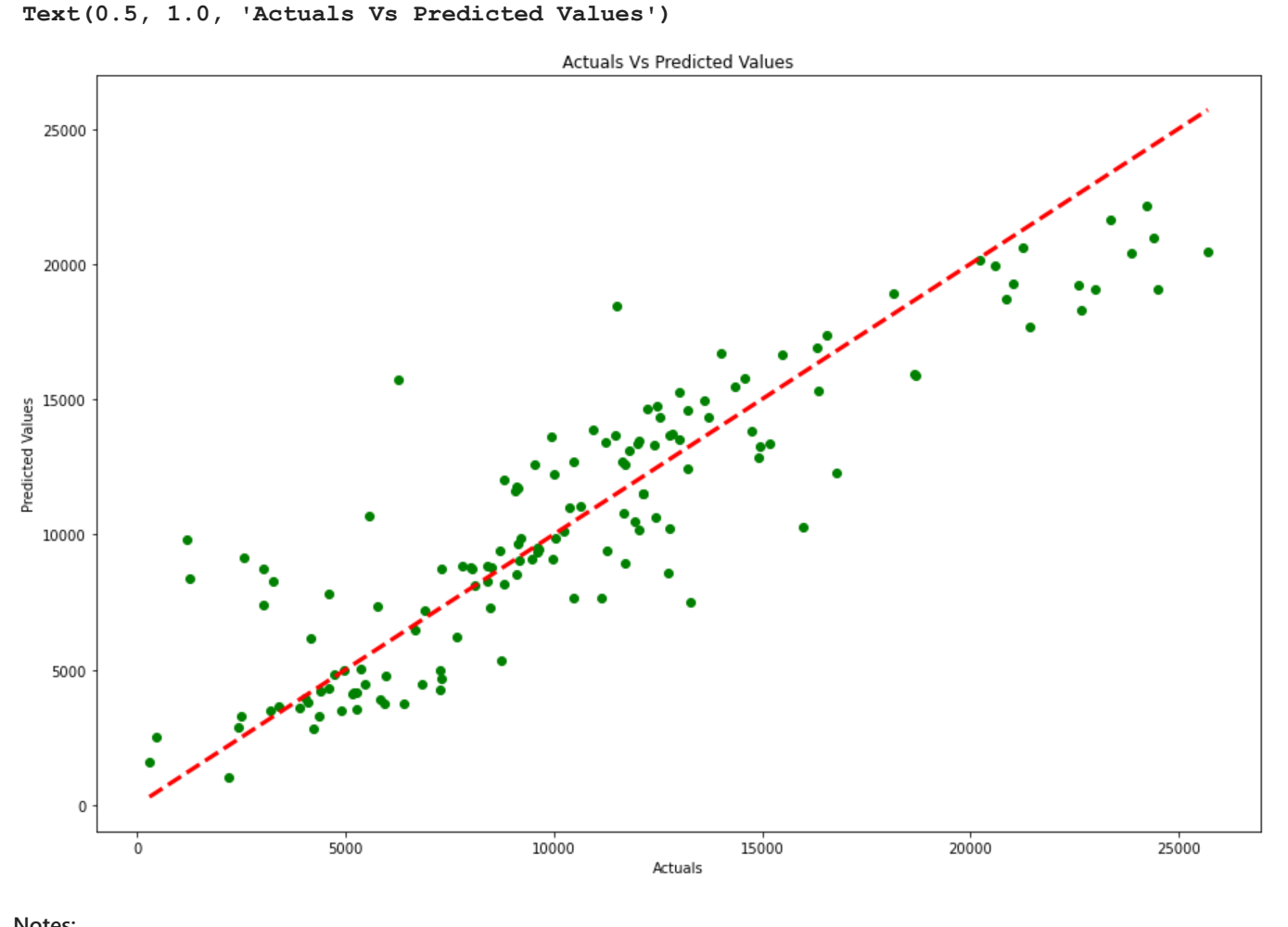
Each of these no are corresponding to our X variable. We have 12 independent variable

In [51]:
```
# The Intercept
print('Intercept: ', lm.intercept_)
```

```
Intercept:  4060.650366499697
```

In [52]:
```
# Plotting Actuals Vs Predicted

plt.figure(figsize=(15,10))

plt.scatter(y_train, y_pred, c='green')
plt.plot([y_train.min(), y_train.max()], [y_train.min(), y_train.max()], 'k--', c='rec
plt.xlabel('Actuals')
plt.ylabel('Predicted Values')
plt.title('Actuals Vs Predicted Values')
# increase size
```

Out[52]:
```
Text(0.5, 1.0, 'Actuals Vs Predicted Values')
```

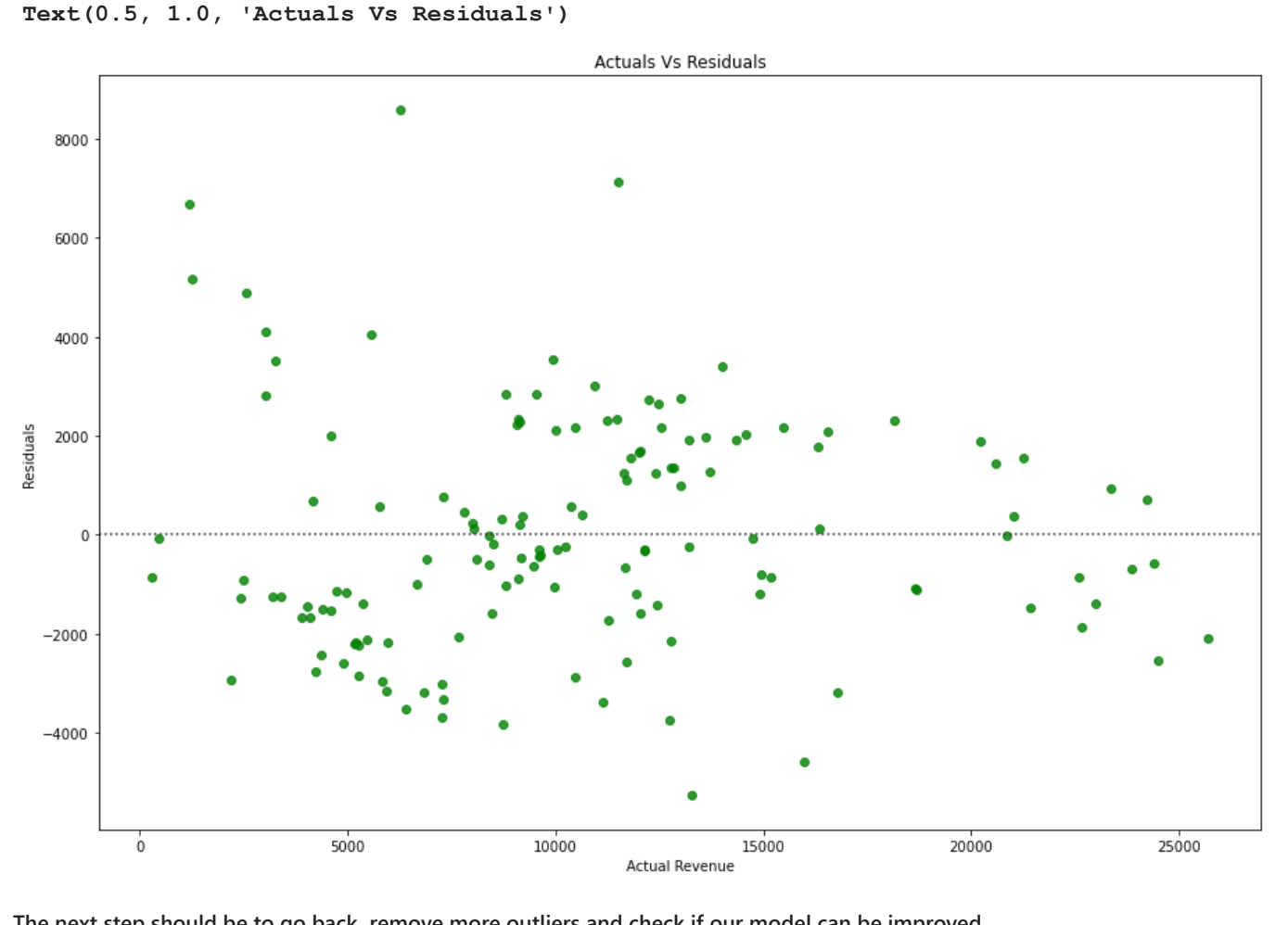


Notes:

- **This is not a regression line**
- **The closer data points are to the red line, better the model is.**
- **The further away the data points is the worst our prediction is**

In [54]:
```
# Ploting Residuals

plt.figure(figsize=(15,10))

sns.residplot(y_train, y_pred, color='green')
plt.xlabel('Actual Revenue')
plt.ylabel('Residuals')
plt.title('Actuals Vs Residuals')
```

Out[54]:
```
Text(0.5, 1.0, 'Actuals Vs Residuals')
```



The next step should be to go back, remove more outliers and check if our model can be improved

How to use our L. Regression model to Make Predictions

In [55]:
```
# Passing Coeff into a table

Coeff = lm.coef_
Coeff.shape
```

Out[55]:
```
(12,)
```

In [57]:
```
# We want to make it column
# Reshaping
Coeff = Coeff.reshape(-1,12)
Coeff
```

Out[57]:
```
array([[ 9.72168996e-01,  3.69561477e+00, -4.29587654e+03,
         3.72469059e+03,  5.71185949e+02,  7.38005738e+02,
        -3.52308895e+02, -9.02241594e+02, -1.55867567e+02,
         8.14821481e+02,  1.50084913e+02, -2.92494076e+02]])
```

In [59]:
```
X2
```

Out[59]:

	Visitors	Marketing Spend	Promo_No Promo	Promo_Promotion Blue	Promo_Promotion Red	Day_Name_Friday	Day_Name_Mo
0	707.0	651.375000	1	0	0	0	
1	1455.0	1298.250000	0	0	1	0	
2	1520.0	1559.375000	0	1	0	0	
3	1726.0	1801.750000	1	0	0	0	
4	2134.0	2614.500000	1	0	0	1	
...	...	...	...	...	...	...	
177	1400.0	1119.600000	1	0	0	0	
178	2244.0	2067.888889	0	0	1	0	
179	2023.0	1450.200000	1	0	0	1	
180	1483.0	1121.875000	1	0	0	0	
181	1303.0	871.000000	1	0	0	0	

179 rows × 12 columns

In [58]:
```
# Creating a Dataframe
Coeff_df = pd.DataFrame(Coeff, columns = [X2.columns])

# Displaying
Coeff_df
```

Out[58]:

	Visitors	Marketing Spend	Promo_No Promo	Promo_Promotion Blue	Promo_Promotion Red	Day_Name_Friday	Day_Name_Mon
0	0.972169	3.695615	-4295.87654	3724.69059	571.185949	738.005738	-352.308

In [78]:
```
# Making Predictions

# Variables
Day = 'Day_Name_Friday'
Visitors = 8000
Marketing_Spend = 5000
Promo = 'Promo_Promotion Red'

# Regression Formula for pred
# y = a + bx + ..   # Where y = price, a = intercept,  b = no. of Visitors and x = coe

# Prediction Calculator

pred1 = (lm.intercept_) + (Coeff_df[[Day]].values[0] * 1) + Coeff_df[['Visitors']].val

#pred1 = (lm.intercept_) + (Coeff_df[Day].values[0] * 1) + (Coeff_df['Visitors'].value



print('The predicted Revenue is: ', pred1)
```

```
The predicted Revenue is:  [31625.26784989]
```

In [ ]: