In [113]:

```
# Import Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import f1_score, mean_squared_error
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn import linear_model, metrics
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score
import xgboost as xgb
```

In [91]:

```
# Reading datasets and storing them in a dataframe
train_data = pd.read_csv('C:/Users/hp/Desktop/EAI 6000 Project/Features_Variant_1
```

In [93]:

```
# Defining the columns for the dataset attributes
train_data.columns = ['Comments','Checkins','TalkingAbout','Category','Derived5',
```

In [94]:

```
# Describing the dataset
train_data.describe()
```

Out[94]:

	Comments	Checkins	TalkingAbout	Category	Derived5	Derived6	
count	4.094800e+04	40948.000000	4.094800e+04	40948.000000	40948.000000	40948.000000	4094
mean	1.313830e+06	4676.247949	4.480133e+04	24.255348	1.586280	443.324998	5
std	6.785834e+06	20593.423357	1.109349e+05	19.950496	20.753426	496.698029	8
min	3.600000e+01	0.000000	0.000000e+00	1.000000	0.000000	0.000000	
25%	3.673400e+04	0.000000	6.980000e+02	9.000000	0.000000	45.000000	
50%	2.929110e+05	0.000000	7.141000e+03	18.000000	0.000000	241.000000	2
75%	1.204214e+06	99.000000	5.026400e+04	32.000000	0.000000	717.000000	7
max	4.869723e+08	186370.000000	6.089942e+06	106.000000	2341.000000	2341.000000	234

8 rows × 54 columns

In [95]:
```
# To get the info of the training dataset
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40948 entries, 0 to 40947
Data columns (total 54 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Comments                  40948 non-null  int64  
 1   Checkins                  40948 non-null  int64  
 2   TalkingAbout              40948 non-null  int64  
 3   Category                  40948 non-null  int64  
 4   Derived5                  40948 non-null  int64  
 5   Derived6                  40948 non-null  int64  
 6   Derived7                  40948 non-null  float64
 7   Derived8                  40948 non-null  float64
 8   Derived9                  40948 non-null  float64
 9   Derived10                 40948 non-null  int64  
 10  Derived11                 40948 non-null  int64  
 11  Derived12                 40948 non-null  float64
 12  Derived13                 40948 non-null  float64
 13  Derived14                 40948 non-null  float64
 14  Derived15                 40948 non-null  int64  
 15  Derived16                 40948 non-null  int64  
 16  Derived17                 40948 non-null  float64
 17  Derived18                 40948 non-null  float64
 18  Derived19                 40948 non-null  float64
 19  Derived20                 40948 non-null  int64  
 20  Derived21                 40948 non-null  int64  
 21  Derived22                 40948 non-null  float64
 22  Derived23                 40948 non-null  float64
 23  Derived24                 40948 non-null  float64
 24  Derived25                 40948 non-null  int64  
 25  Derived26                 40948 non-null  int64  
 26  Derived27                 40948 non-null  float64
 27  Derived28                 40948 non-null  float64
 28  Derived29                 40948 non-null  float64
 29  CC1                       40948 non-null  int64  
 30  CC2                       40948 non-null  int64  
 31  CC3                       40948 non-null  int64  
 32  CC4                       40948 non-null  int64  
 33  CC5                       40948 non-null  int64  
 34  BaseTime                  40948 non-null  int64  
 35  PostLength                40948 non-null  int64  
 36  PostShareCount            40948 non-null  int64  
 37  PostPromotionStatus       40948 non-null  int64  
 38  HLocal                    40948 non-null  int64  
 39  PostPublishedWeekday40    40948 non-null  int64  
 40  Post PublishedWeekday 41  40948 non-null  int64  
 41  Post published weekday42  40948 non-null  int64  
 42  Post published weekday43  40948 non-null  int64  
 43  Post published weekday44  40948 non-null  int64  
 44  Post published weekday45  40948 non-null  int64  
 45  Post published weekday46  40948 non-null  int64  
 46  Base DateTime weekday47   40948 non-null  int64  
 47  Base DateTime weekday48   40948 non-null  int64  
 48  Base DateTime weekday49   40948 non-null  int64  
 49  Base DateTime weekday50   40948 non-null  int64  
 50  Base DateTime weekday51   40948 non-null  int64  
 51  Base DateTime weekday52   40948 non-null  int64  
 52  Base DateTime weekday53   40948 non-null  int64  
 53  Targets                   40948 non-null  int64  
dtypes: float64(15), int64(39)
memory usage: 16.9 MB
```

In [56]:

```
# Testing for the null values in all the datasets
train_data.isnull().sum()
```

Out[56]:

```
Comments                    0
Checkins                    0
TalkingAbout                0
Category                    0
Derived5                    0
Derived6                    0
Derived7                    0
Derived8                    0
Derived9                    0
Derived10                   0
Derived11                   0
Derived12                   0
Derived13                   0
Derived14                   0
Derived15                   0
Derived16                   0
Derived17                   0
Derived18                   0
Derived19                   0
Derived20                   0
Derived21                   0
Derived22                   0
Derived23                   0
Derived24                   0
Derived25                   0
Derived26                   0
Derived27                   0
Derived28                   0
Derived29                   0
CC1                         0
CC2                         0
CC3                         0
CC4                         0
CC5                         0
BaseTime                    0
PostLength                  0
PostShareCount              0
PostPromotionStatus         0
HLocal                      0
PostPublishedWeekday40      0
Post PublishedWeekday 41    0
Post published weekday42    0
Post published weekday43    0
Post published weekday44    0
Post published weekday45    0
Post published weekday46    0
Base DateTime weekday47     0
Base DateTime weekday48     0
Base DateTime weekday49     0
Base DateTime weekday50     0
Base DateTime weekday51     0
Base DateTime weekday52     0
Base DateTime weekday53     0
```

```
Targets               0
dtype: int64
```

In [98]:
```
# Computing correlationamen between different columns in the same dataframe
train_data.corr().head()
```

Out[98]:

	Comments	Checkins	TalkingAbout	Category	Derived5	Derived6	Derived7	Deri
Comments	1.000000	0.044838	0.623436	-0.042171	0.059575	0.158716	0.166424	0.14
Checkins	0.044838	1.000000	0.166848	-0.060189	-0.002830	0.169241	0.154965	0.12
TalkingAbout	0.623436	0.166848	1.000000	-0.148700	0.181431	0.482027	0.518602	0.45
Category	-0.042171	-0.060189	-0.148700	1.000000	-0.041649	-0.313588	-0.229955	-0.18
Derived5	0.059575	-0.002830	0.181431	-0.041649	1.000000	0.127578	0.474401	0.55

5 rows × 54 columns

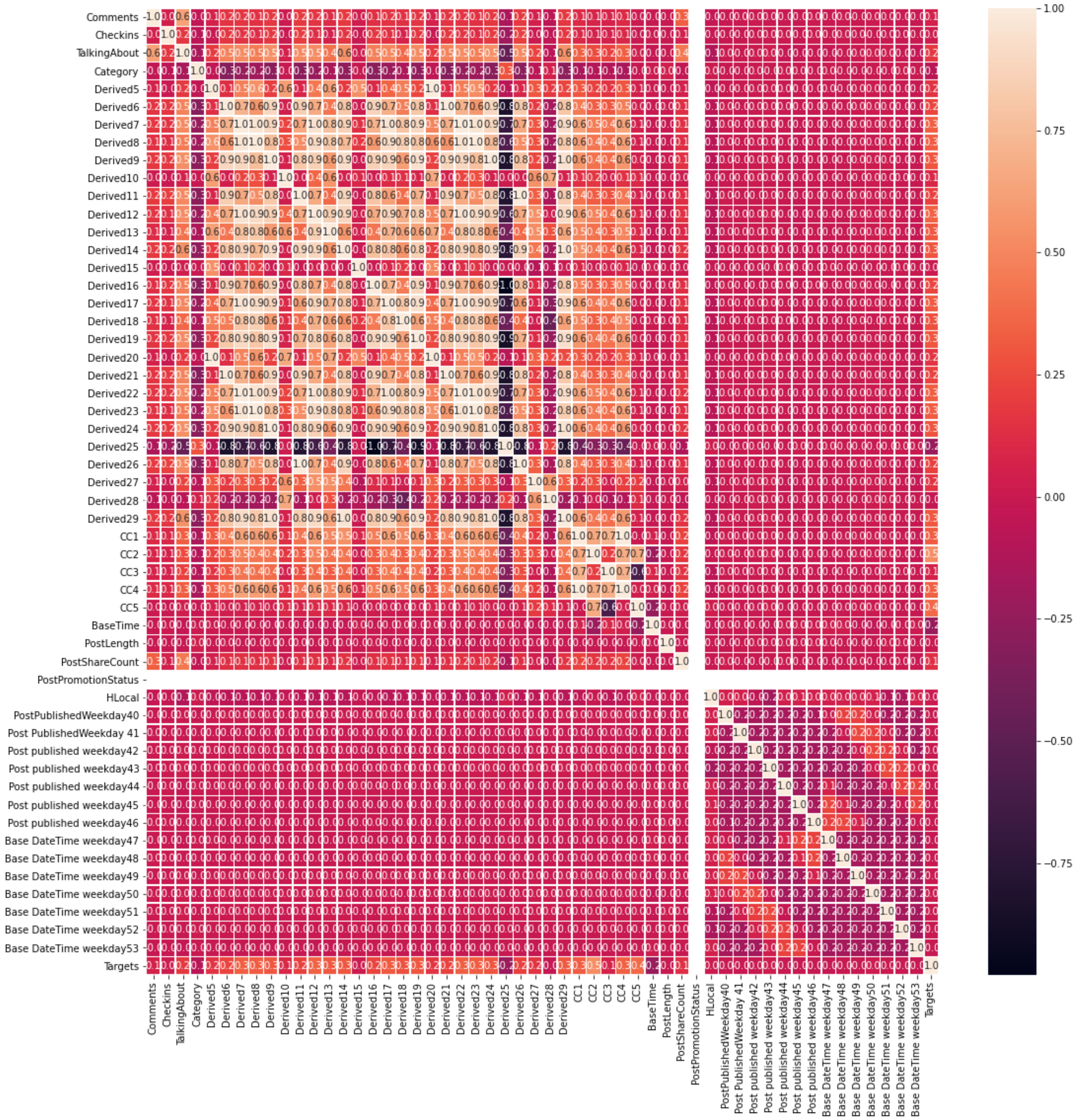
In [99]:
```
# Computing correlationamen between different columns in the same dataframe
train_data.corr().tail()
```

Out[99]:

	Comments	Checkins	TalkingAbout	Category	Derived5	Derived6	Derived7	Derive
Base DateTime weekday50	0.003839	-0.006828	0.020420	-0.003172	0.004395	0.010831	0.005507	0.0013
Base DateTime weekday51	0.006069	0.000311	0.024482	-0.002929	0.006180	0.005465	0.013241	0.0127
Base DateTime weekday52	-0.003046	0.000871	-0.011427	0.011919	-0.000474	-0.001986	-0.001629	-0.0012
Base DateTime weekday53	-0.008856	-0.004316	-0.022733	-0.001766	-0.009083	-0.006290	-0.011291	-0.0096
Targets	0.058918	0.022981	0.177329	-0.073680	0.156940	0.231437	0.334984	0.3253

5 rows × 54 columns

In [100]:
```
# Plotting a heatmap
f,ax = plt.subplots(figsize=(18, 18))
sns.heatmap(train_data.corr(), annot=True, linewidths=.5, fmt= '.1f',ax=ax)
# To Show the heatmap
plt.show()
```



In [101]:

```
# Defining the input and output variables
x = train_data[['Comments','Checkins','TalkingAbout','Category','Derived5','Deri
y = train_data['Targets']
```

In [104]:

```
# 3. Split the data into 90% training and 10% test sets.
# Splitting the dataset into train and test datsets into 90% an 10% respectively
x_train_data, x_test_data, y_train_data, y_test_data = train_test_split(x, y, tes
```

In [105]:

```
# Standardization of the input data
stdScalar = StandardScaler()
X_train_data_std = stdScalar.fit_transform(x_train_data)
X_test_data = stdScalar.transform(x_test_data)
```

In [109]:

```
# 4. Build a Linear Regressor and find the Mean Squared Error(MSE) and R2 for the
# Linear Regression Model
linModel = linear_model.LinearRegression()
linModel.fit(X_train_data_std, y_train_data)
```

Out[109]:

```
LinearRegression()
```

In [111]:

```
print(linModel.intercept_)
print(linModel.coef_)
```

```
7.392044549964865
[ 1.43330237e-01 -1.93791082e-01 -2.42341662e+00 -2.42116181e-01
 -1.83255240e+01  1.11778887e+01  9.67648046e+01  1.61059819e+01
 -2.42363073e+01 -2.29734638e+00 -2.22318148e+00 -4.12833461e+08
  2.97391219e+00 -2.21293786e+00  5.05524470e-01  5.05286277e+00
  3.50356788e+08  7.02593143e-01 -9.75333142e+00  1.54988674e+01
 -1.22523819e+01 -9.62719814e+01 -1.69214789e+01  2.85868513e+01
  2.51400373e-01  1.54406046e+00  1.93349264e+08  1.14033954e+00
  1.01610566e+00  7.88179866e+00 -3.03862219e+13  2.82968991e+13
 -1.08084370e+01  3.71333520e+13 -4.09838867e+00 -7.42187500e-02
  2.95166016e+00 -6.67167670e+12  8.09570312e-01 -3.00036610e+13
 -3.20788983e+13 -3.26184670e+13 -3.32997793e+13 -3.20537108e+13
 -3.22167363e+13 -3.14294352e+13  1.36492292e+13  1.32702676e+13
  1.34958287e+13  1.39577778e+13  1.39911098e+13  1.37090142e+13
  1.37843711e+13]
```

In [112]:

```
# Predicting the output
y_predcited = Linear_model.predict(X_test_data)
print(y_predcited)
```

```
[-14.43022108  11.12837267  17.60884142 ...   0.96040392  -4.45365858
  -3.18022108]
```

In [119]:

```
# Mean Square Error and Model Scores
print(metrics.mean_squared_error(y_test_data,y_predcited))
print(np.sqrt(metrics.mean_squared_error(y_test_data,y_predcited)))
print(r2_score(y_test_data,y_predcited ))
```

```
684.410967436207
26.161249347770205
0.3245565925529871
```

In [114]:

```
# 5. Build a Decision Tree Regressor and find the Mean Squared Error for the test
# Decision tree Regression
tree_reg = tree.DecisionTreeRegressor(max_depth=6)
tree_reg.fit(X_train_data_std, y_train_data)
```

Out[114]:

```
DecisionTreeRegressor(max_depth=6)
```

In [115]:

```
print(tree_reg.score(X_test_data,y_test_data))
y_pred = tree_reg.predict(X_test_data)
```

```
0.4664504352216271
```

In [116]:

```
print('Mean Squared Error:', metrics.mean_squared_error(y_test_data, y_pred))
```

```
Mean Squared Error: 540.6332636887569
```

In [117]:

```
importantFeatures = tree_reg.feature_importances_
print(importantFeatures)
```

```
[3.97192644e-03 1.77276266e-02 0.00000000e+00 1.35992570e-02
 5.65110851e-04 1.58726424e-03 1.48889506e-02 5.03765294e-03
 0.00000000e+00 1.06562896e-04 0.00000000e+00 3.44842224e-02
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 7.05741371e-03 0.00000000e+00
 2.21231290e-03 0.00000000e+00 0.00000000e+00 3.84810387e-02
 0.00000000e+00 0.00000000e+00 2.07156604e-03 0.00000000e+00
 0.00000000e+00 0.00000000e+00 3.50044665e-01 0.00000000e+00
 5.91085182e-02 2.76528428e-03 2.74154006e-01 0.00000000e+00
 1.65706025e-01 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 6.43059535e-03 0.00000000e+00 0.00000000e+00
 0.00000000e+00]
```

In [118]:

```
tree.plot_tree(tree_reg)
```

```
amples = 94\nvalue = 36.989'),
 Text(14.556521739130435, 15.531428571428563, 'mse = 1133.568\nsamples = 93\n
value = 33.957'),
 Text(20.37913043478261, 15.531428571428563, 'mse = 0.0\nsamples = 1\nvalue =
319.0'),
 Text(34.93565217391304, 77.65714285714284, 'X[30] <= 0.588\nmse = 3662.217\n
samples = 406\nvalue = 50.293'),
 Text(29.11304347826087, 46.59428571428572, 'X[34] <= -1.663\nmse = 2865.975
\nsamples = 359\nvalue = 42.616'),
 Text(26.20173913043478, 15.531428571428563, 'mse = 5888.113\nsamples = 109\n
value = 75.183'),
 Text(32.02434782608696, 15.531428571428563, 'mse = 884.243\nsamples = 250\nv
alue = 28.416'),
 Text(40.75826086956522, 46.59428571428572, 'X[33] <= 1.461\nmse = 5854.911\n
samples = 47\nvalue = 108.936'),
 Text(37.84695652173913, 15.531428571428563, 'mse = 5418.715\nsamples = 43\nv
alue = 100.512'),
 Text(43.6695652173913, 15.531428571428563, 'mse = 1579.25\nsamples = 4\nvalu
e = 199.5'),
 Text(65.50434782608696, 108.72, 'X[23] <= 2.521\nmse = 29909.968\nsamples =
```

In [86]:

```
# 6. Build a GBM OR XgBoost Regressor model and find the Mean Squared Error for th
# XG Boost Regressor Analysis
xgbRegressor = xgb.XGBRegressor(
    n_estimators=100,
    reg_lambda=1,
    gamma=0,
    max_depth=3
)
xgbRegressor.fit(X_train_data_std, y_train_data)
# Predicted the output
y_pred = xgbRegressor.predict(X_test_data)


#7. What model gives the best results in terms of the MSE?
mean_squared_error(y_test_data, y_pred)
```

Out[86]:

```
363.13131254355744
```

Linear Regression Model gives the best results in terms of the MSE