TWEET SENTIMENT ANALYSIS

Importing Libraries

In [96]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings("ignore")
```

Reading csv

In [97]:
```
Final_df=pd.read_csv("tweets-engagement-metrics.csv")
```

In [98]:
```
Final_df.head()
```

Out[98]:

	Unnamed: 0	UserID	Gender	LocationID	City	State	StateCode	Country	
0	0	tw-1267804344	Unknown	1	Elbasan	Elbasan	AL	Albania	6981552
1	1	tw-4762500137	Female	10	Luanda	Luanda	AO	Angola	6905067
2	2	tw-4762500137	Female	10	Luanda	Luanda	AO	Angola	6983158
3	3	tw-928769635	Female	13	NaN	NaN	NaN	Argentina	6856630
4	4	tw-457193677	Unknown	13	NaN	NaN	NaN	Argentina	7032934

In [99]:
```
Final_df=Final_df.drop('Unnamed: 0',axis=1)
Final_df
```

Out[99]:

	UserID	Gender	LocationID	City	State	StateCode	Country	
0	tw-1267804344	Unknown	1	Elbasan	Elbasan	AL	Albania	698155297
1	tw-4762500137	Female	10	Luanda	Luanda	AO	Angola	690506796
2	tw-4762500137	Female	10	Luanda	Luanda	AO	Angola	698315842
3	tw-928769635	Female	13	NaN	NaN	NaN	Argentina	685663098
4	tw-457193677	Unknown	13	NaN	NaN	NaN	Argentina	703293482
...	...	...	...	...	...	...	...	
102057	tw-75190953	Male	6279	Ho Chi Minh City	Ho Chi Minh City	VN	Vietnam	697563129
102058	tw-594926522	Male	6283	Lusaka	Lusaka	ZM	Zambia	684750918
102059	tw-594926522	Male	6283	Lusaka	Lusaka	ZM	Zambia	689738393
102060	tw-95376359	Unisex	6287	Ndola	Copperbelt	ZM	Zambia	702581824
102061	tw-448919812	Unisex	6288	Harare	Harare Province	ZW	Zimbabwe	705055534

102062 rows × 19 columns

Understanding the structure of the Data

In [100]:
```
Final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 102062 entries, 0 to 102061
Data columns (total 19 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   UserID        102062 non-null  object 
 1   Gender        102062 non-null  object 
 2   LocationID    102062 non-null  int64  
 3   City          99783 non-null   object 
 4   State         100165 non-null  object 
 5   StateCode     100336 non-null  object 
 6   Country       102062 non-null  object 
 7   TweetID       102062 non-null  object 
 8   Hour          102062 non-null  int64  
 9   Day           102062 non-null  int64  
 10  Weekday       102062 non-null  object 
 11  IsReshare     102062 non-null  bool   
 12  Reach         102062 non-null  int64  
 13  RetweetCount  102062 non-null  int64  
 14  Likes         102062 non-null  int64  
 15  Klout         102062 non-null  int64  
 16  Sentiment     102062 non-null  float64
 17  Lang          102062 non-null  object 
 18  text          102062 non-null  object 
dtypes: bool(1), float64(1), int64(7), object(10)
memory usage: 14.1+ MB
```

In [101]:
```
Final_df.describe()
```

Out[101]:

	LocationID	Hour	Day	Reach	RetweetCount	Like
count	102062.000000	102062.000000	102062.000000	1.020620e+05	102062.000000	102062.00000
mean	2836.207687	11.416149	15.898709	8.426389e+03	7.986449	0.14968
std	1330.294460	6.062294	8.401409	8.777762e+04	96.914644	2.55749
min	1.000000	0.000000	1.000000	0.000000e+00	0.000000	0.00000
25%	1601.000000	7.000000	9.000000	1.520000e+02	0.000000	0.00000
50%	3738.000000	11.000000	16.000000	4.540000e+02	0.000000	0.00000
75%	3774.000000	16.000000	23.000000	1.519000e+03	3.000000	0.00000
max	6289.000000	23.000000	31.000000	1.034245e+07	26127.000000	133.00000

In [102]:
```
Final_df.shape
```

Out[102]: (102062, 19)

In [103]:
```
Final_df.columns
```

Out[103]:
```
Index(['UserID', 'Gender', 'LocationID', 'City', 'State', 'StateCode',
       'Country', 'TweetID', 'Hour', 'Day', 'Weekday', 'IsReshare', 'Reach',
       'RetweetCount', 'Likes', 'Klout', 'Sentiment', 'Lang', 'text'],
      dtype='object')
```

Handling the missing values

In [104]:
```
missing_values = Final_df.isnull().sum()
missing_values
```

Out[104]:
```
UserID             0
Gender             0
LocationID         0
City            2279
State           1897
StateCode       1726
Country            0
TweetID            0
Hour               0
Day                0
Weekday            0
IsReshare          0
Reach              0
RetweetCount       0
Likes              0
Klout              0
Sentiment          0
Lang               0
text               0
dtype: int64
```

In [105]:
```
Final_df.dropna(inplace=True)
Final_df
```

Out[105]:

	UserID	Gender	LocationID	City	State	StateCode	Country	
0	tw-1267804344	Unknown	1	Elbasan	Elbasan	AL	Albania	698155297
1	tw-4762500137	Female	10	Luanda	Luanda	AO	Angola	690506796
2	tw-4762500137	Female	10	Luanda	Luanda	AO	Angola	698315842
11	tw-3339262295	Unisex	14	Buenos Aires	Buenos Aires F.D.	AR	Argentina	685668386
12	tw-40031027	Unknown	14	Buenos Aires	Buenos Aires F.D.	AR	Argentina	688021501
...	...	...	...	...	...	...	...	
102057	tw-75190953	Male	6279	Ho Chi Minh City	Ho Chi Minh City	VN	Vietnam	697563129
102058	tw-594926522	Male	6283	Lusaka	Lusaka	ZM	Zambia	684750918
102059	tw-594926522	Male	6283	Lusaka	Lusaka	ZM	Zambia	689738393
102060	tw-95376359	Unisex	6287	Ndola	Copperbelt	ZM	Zambia	702581824
102061	tw-448919812	Unisex	6288	Harare	Harare Province	ZW	Zimbabwe	705055534

99768 rows × 19 columns

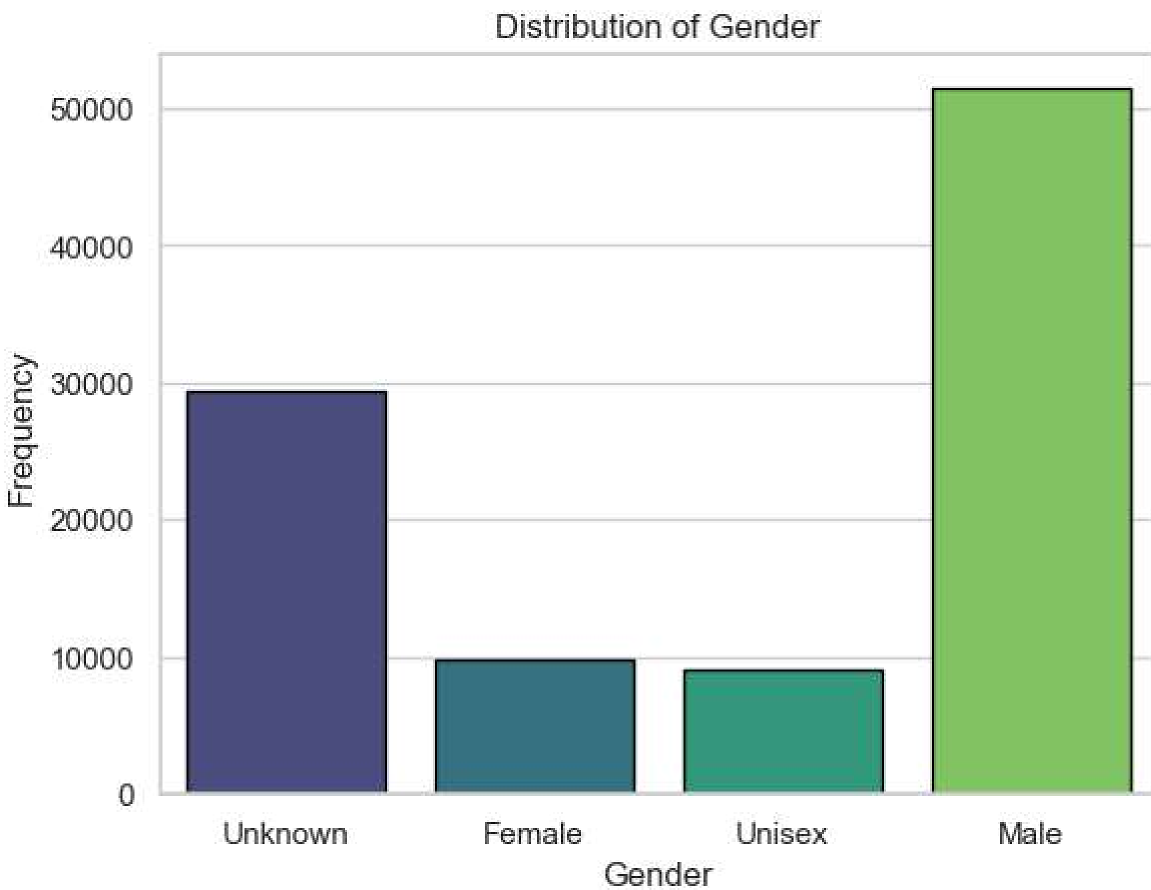
In [106]:
```
Final_df.shape
```

Out[106]: (99768, 19)

Visualisation

Gender

In [107]:
```
gender_distribution = Final_df['Gender']

sns.countplot(x=gender_distribution,edgecolor='black',palette='viridis')
plt.title('Distribution of Gender')
plt.xlabel('Gender')
plt.ylabel('Frequency')
plt.show()
```

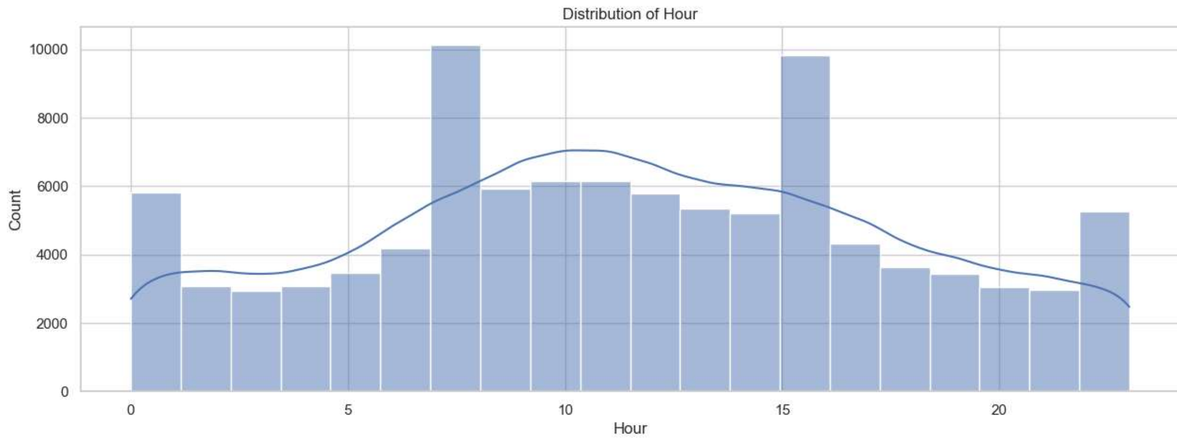


Inference:

Data shows significant male skewness & 'Unknown' presence, but engagement within identified genders appears balanced.

Hour

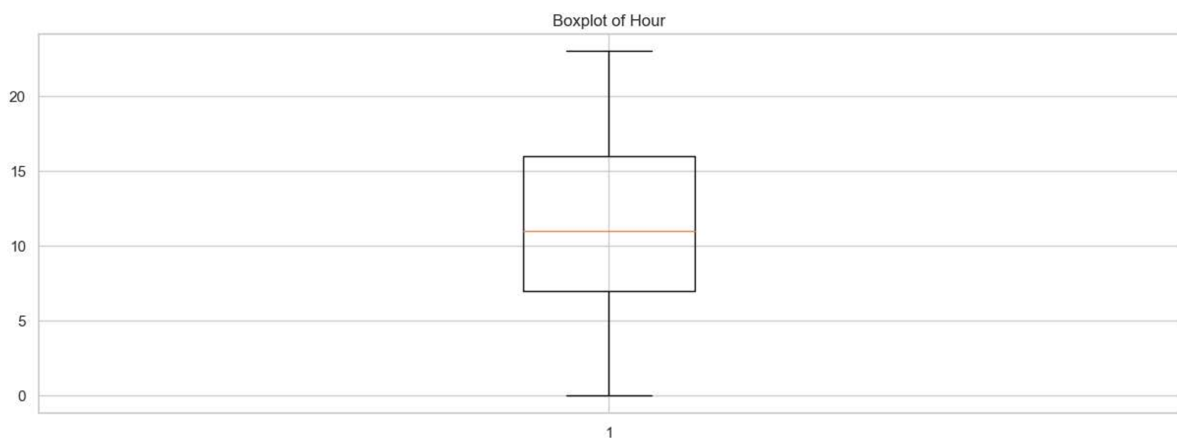
In [108]:
```
plt.figure(figsize=(15, 5))
sns.histplot(Final_df['Hour'], bins=20, kde=True)
plt.title(f'Distribution of Hour')

plt.show()
```



Inferences:

The distribution of Hour shows that there is a peak in the afternoon. There is also a smaller peak in the evening.

In [109]:
```
plt.figure(figsize=(15, 5))
plt.boxplot(Final_df['Hour'])
plt.title('Boxplot of Hour')

plt.show()
```

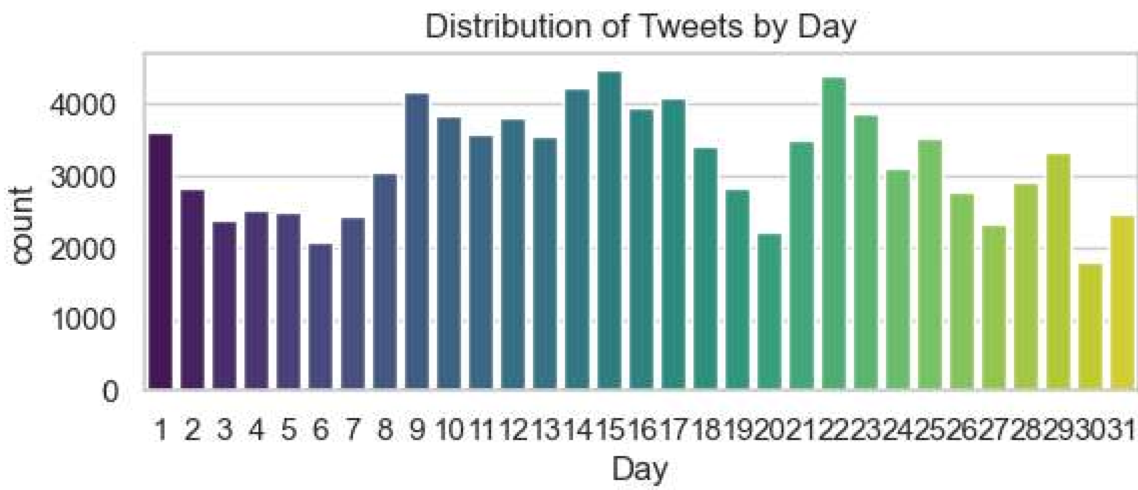


Inferences:

The boxplot suggests two peaks: a larger one in the afternoon and a smaller one in the evening. The distribution is bimodal, symmetric, and includes a few outliers.

Day

In [110]:
```
# Distribution of Tweets by Day
plt.subplot(2, 1, 1)
sns.countplot(x='Day', data=Final_df, palette='viridis')
plt.title('Distribution of Tweets by Day')
plt.show()
```

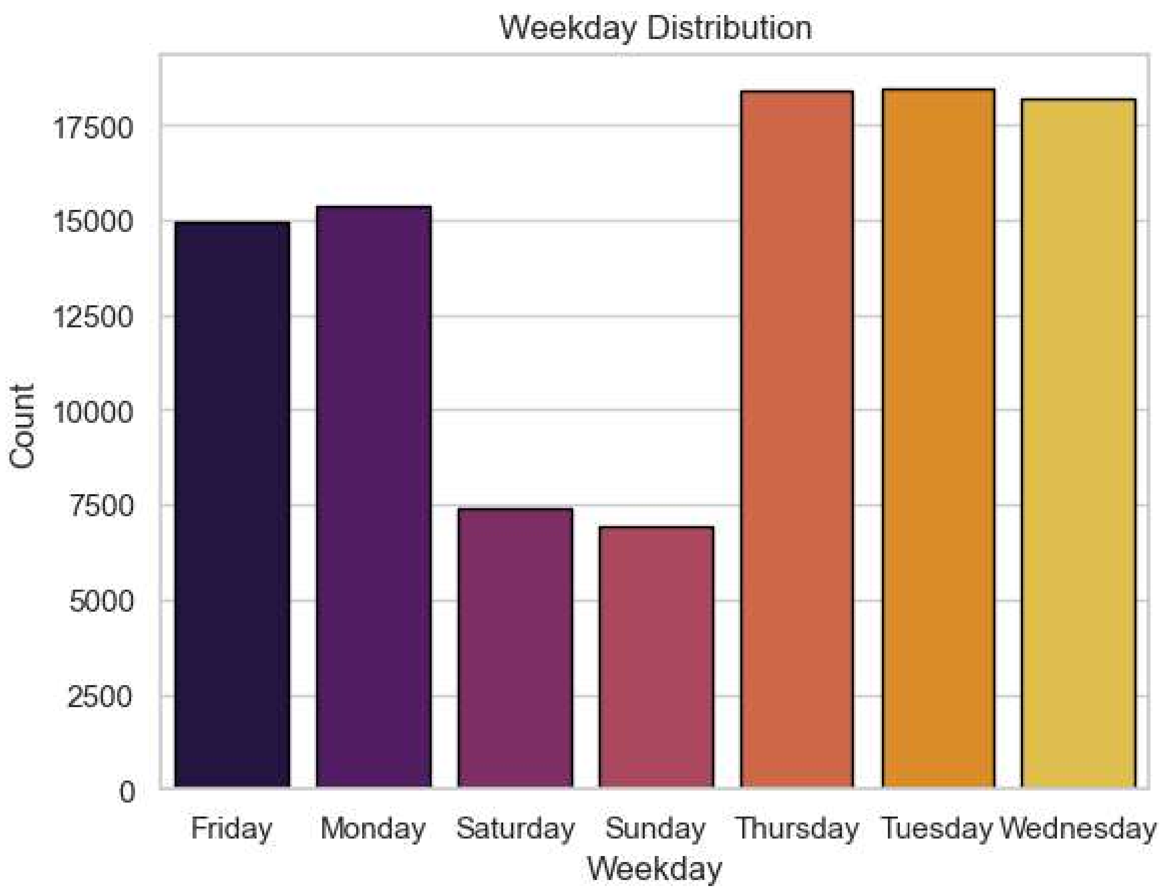


Inference:

Tweets peak on Sun-mornings & evenings, hinting at weekend joy & workday neutrality, with potential Sunday language shift.

Weekday

In [111]:
```
weekday_distribution = Final_df['Weekday']

sns.countplot(x=weekday_distribution, edgecolor='black',palette='inferno')
plt.title('Weekday Distribution')
plt.xlabel('Weekday')
plt.ylabel('Count')
plt.show()
```

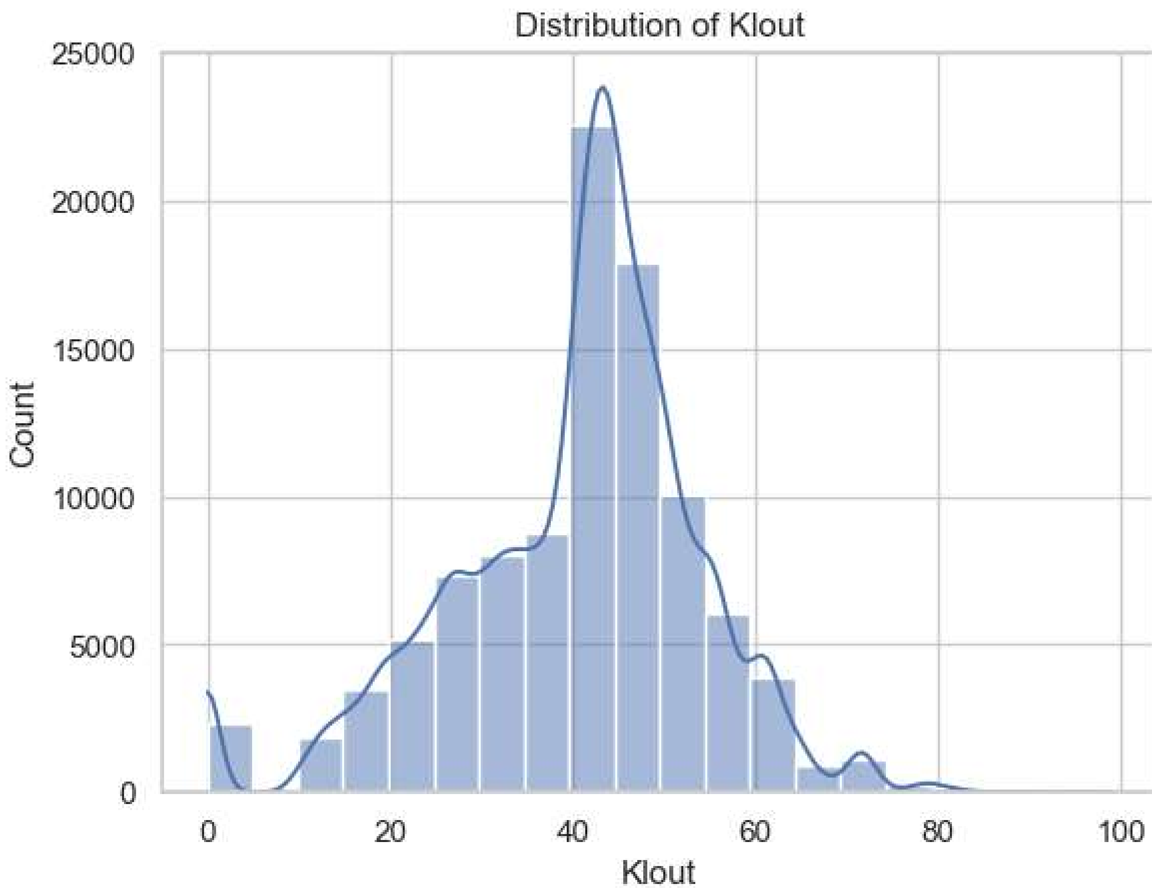


Inference:

The distribution of Day shows that there is a slight peak in the number of users on Saturdays and Sundays. This is likely because these are the weekends. There is also a small peak in the number of users on Fridays.

Klout

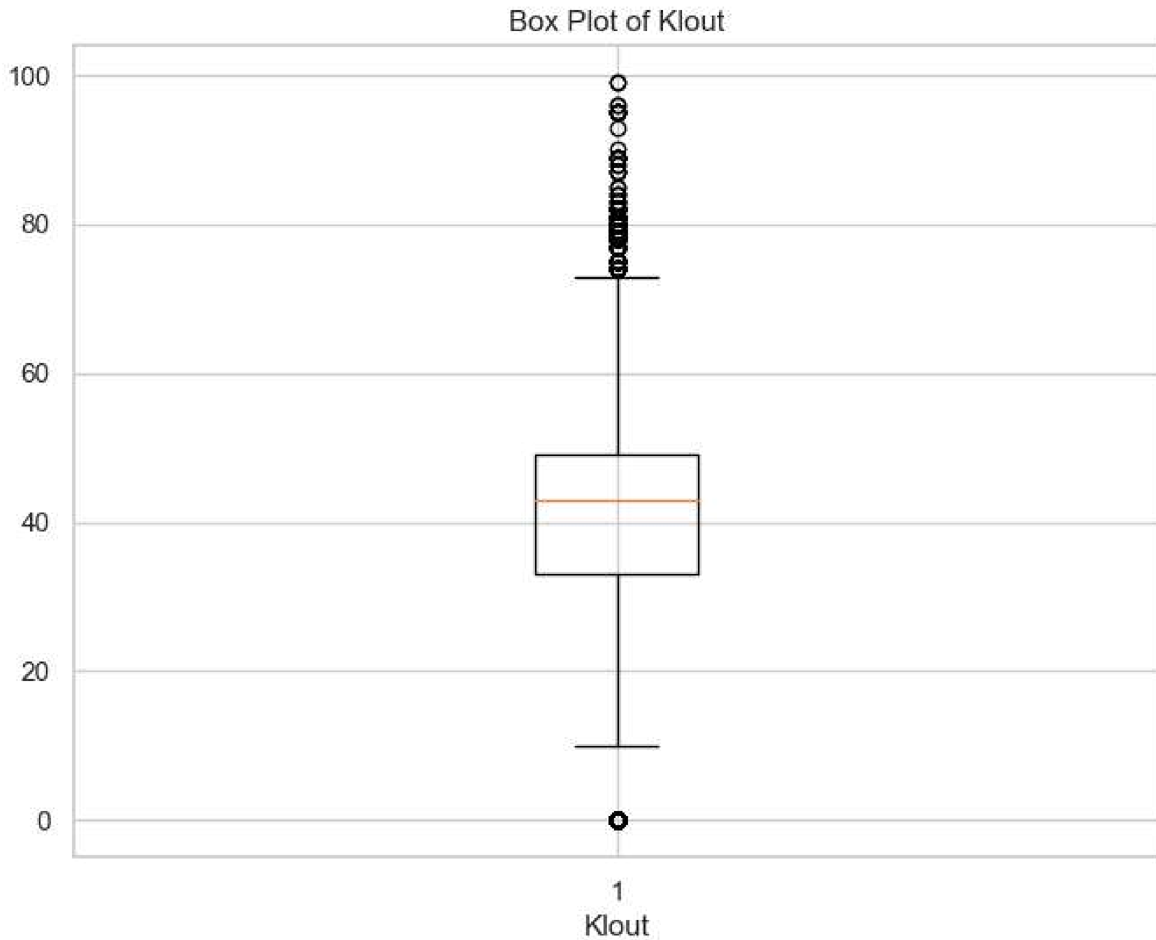
In [112]:
```
sns.histplot(Final_df['Klout'], bins=20, kde=True)
plt.title('Distribution of Klout')
plt.show()
```



Inferences:

Klout scores are calculated is biased towards people who have a lot of followers and who are very active on social media.

In [113]:
```
plt.figure(figsize=(8, 6))
plt.boxplot(Final_df['Klout'])
plt.title('Box Plot of Klout')
plt.xlabel('Klout')
plt.show()
```



Inferences:

Most people have a relatively low Klout score, but there are a few people with very high Klout scores.

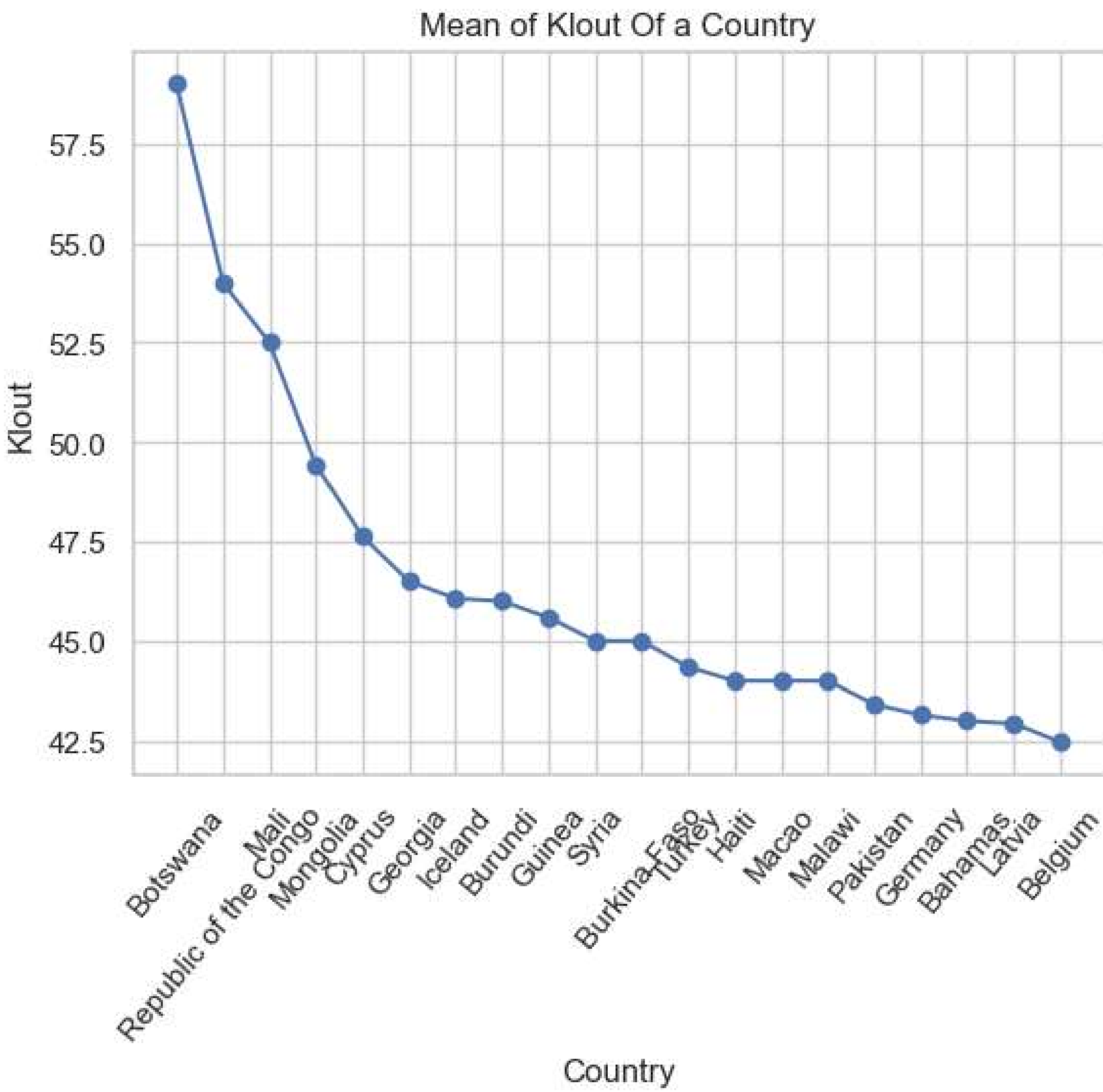
Klout Per Country

In [114]:
```
kpc = Final_df.groupby('Country')['Klout'].mean().reset_index()
kpc=kpc.sort_values(by='Klout', ascending=False)
kpc=kpc.iloc[:20,:]
kpc
```

Out[114]:

	Country	Klout
14	Botswana	59.000000
98	Republic of the Congo	54.000000
72	Mali	52.500000
76	Mongolia	49.428571
28	Cyprus	47.625000
39	Georgia	46.500000
50	Iceland	46.071429
18	Burundi	46.000000
45	Guinea	45.590909
115	Syria	45.000000
17	Burkina Faso	45.000000
121	Turkey	44.348303
47	Haiti	44.000000
68	Macao	44.000000
70	Malawi	44.000000
87	Pakistan	43.414062
40	Germany	43.146810
7	Bahamas	43.000000
64	Latvia	42.932203
10	Belgium	42.465649

In [115]:
```
plt.plot(kpc['Country'], kpc['Klout'], marker='o')
plt.title('Mean of Klout Of a Country')
plt.xlabel('Country')
plt.ylabel('Klout')
plt.xticks(rotation=50)
plt.grid(True)
plt.show()
```

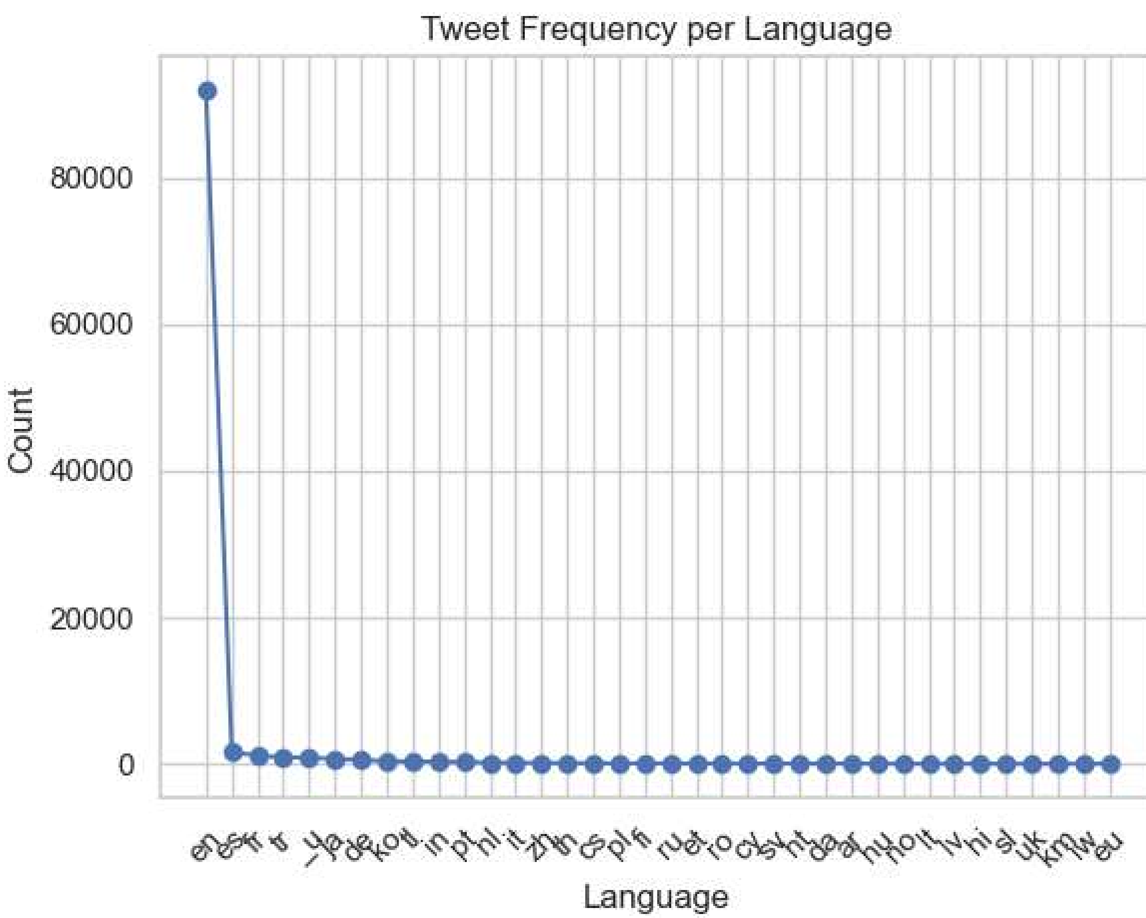


Inferences:

A significant portion of highly engaged tweets on Twitter, as measured by Klout scores, originate from African countries,with the notable exception of US.

Language

In [116]:
```
lang_counts = Final_df['Lang'].value_counts().reset_index()
lang_counts.columns = ['Language', 'Count']

plt.plot(lang_counts['Language'], lang_counts['Count'], marker='o')
plt.title('Tweet Frequency per Language')
plt.xlabel('Language')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



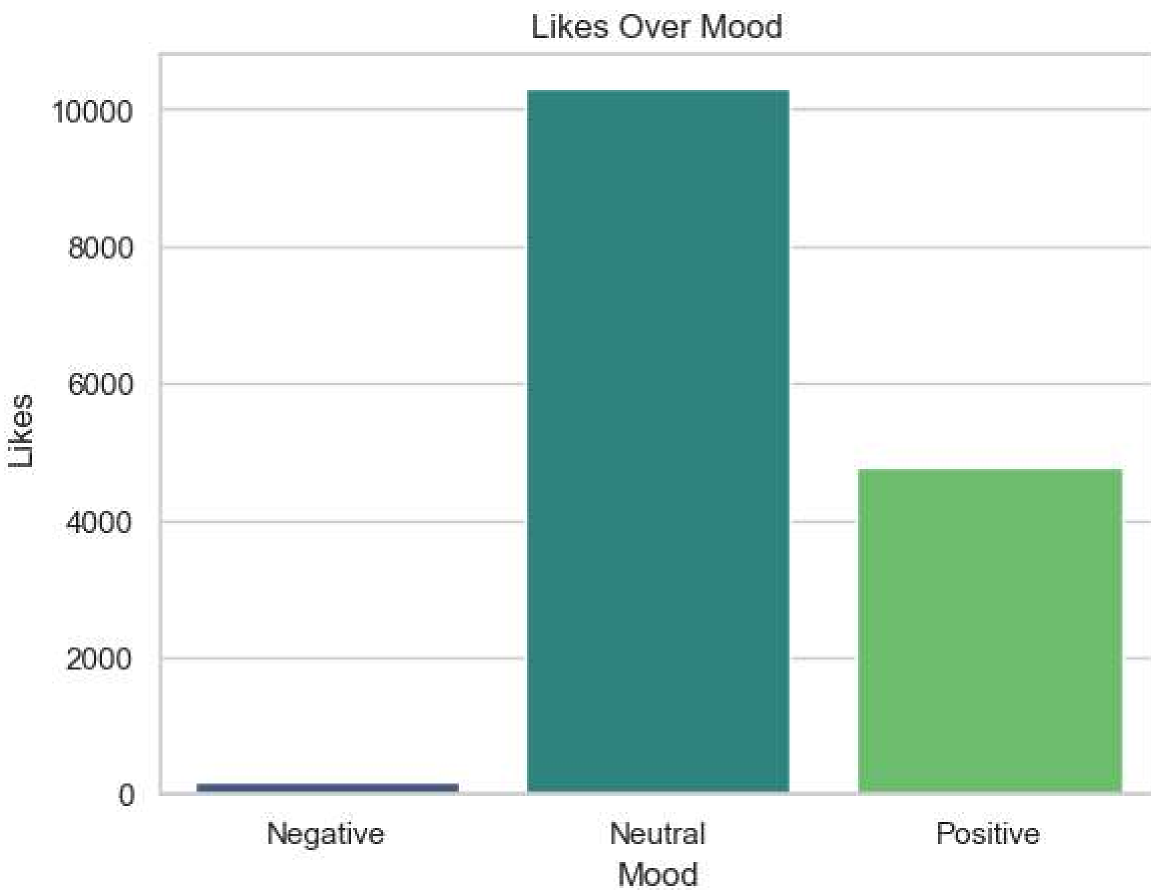
Inference:

English reigns, yet a vibrant multilingual mix beckons: consider diverse engagement and non-English outreach.

Coorelation Analysis

In [117]:
```
sns.set(style="whitegrid")

numerical_features = ['Hour', 'Day', 'Reach', 'RetweetCount', 'Likes', 'Klout'

correlation_matrix = Final_df[numerical_features].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewi
plt.title('Correlation Matrix for Numerical Features')
plt.show()
```

In [118]:
```
Final_df['Mood'] = Final_df['Sentiment'].apply(lambda x: 'Positive' if x > 0 e

like_per_mood = Final_df.groupby('Mood')['Likes'].sum().reset_index()

sns.barplot(x='Mood', y='Likes', data=like_per_mood, palette='viridis')
plt.title('Likes Over Mood')
plt.xlabel('Mood')
plt.ylabel('Likes')
plt.show()
```



Inference:

```
Tweets with a neutral mood received more likes than negative tweets b
ut less than positive tweets. This suggests that people are somewhat
interested in neutral content, but it doesn't evoke the same strong e
motions as positive or negative content.
```

Model Building:

Filter out non-English languages from the dataset.

In [119]:
```
Final_df = Final_df[Final_df['Lang']=='en']
```

Text processing

In [120]:
```
Final_df['text']=Final_df['text'].astype(str)
Final_df['text']=Final_df['text'].apply(lambda x:x.lower())
```

Removing the stop words [LIMIT-5000Characters]

In [121]:
```
from sklearn.feature_extraction.text import CountVectorizer

cv=CountVectorizer(max_features=5000,stop_words='english')
```

In [122]:
```
vectors= cv.fit_transform(Final_df['text']).toarray()
```

In [123]:
```
vectors
```

Out[123]:
```
array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]], dtype=int64)
```

In [124]:
```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder
from sklearn.pipeline import Pipeline
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
```

Substituting stem

In [125]:
```
import nltk
from nltk.stem.porter import *
ps=PorterStemmer()
```

In [126]:
```
def stem(text):
  y=[]
  for i in text.split():
    y.append(ps.stem(i))
  return " ".join(y)
```

In [127]:
```
Final_df['text']= Final_df['text'].apply(stem)
```

In [128]:
```
Final_df
```

Out[128]:

	UserID	Gender	LocationID	City	State	StateCode	Country	
0	tw-1267804344	Unknown	1	Elbasan	Elbasan	AL	Albania	698155297
1	tw-4762500137	Female	10	Luanda	Luanda	AO	Angola	690506796
2	tw-4762500137	Female	10	Luanda	Luanda	AO	Angola	698315842
12	tw-40031027	Unknown	14	Buenos Aires	Buenos Aires F.D.	AR	Argentina	688021501
13	tw-40031027	Unknown	14	Buenos Aires	Buenos Aires F.D.	AR	Argentina	703289433
...	...	...	...	...	...	...	...	
102057	tw-75190953	Male	6279	Ho Chi Minh City	Ho Chi Minh City	VN	Vietnam	697563129
102058	tw-594926522	Male	6283	Lusaka	Lusaka	ZM	Zambia	684750918
102059	tw-594926522	Male	6283	Lusaka	Lusaka	ZM	Zambia	689738393
102060	tw-95376359	Unisex	6287	Ndola	Copperbelt	ZM	Zambia	702581824
102061	tw-448919812	Unisex	6288	Harare	Harare Province	ZW	Zimbabwe	705055534

91887 rows × 20 columns

In [129]:
```
from sklearn.preprocessing import LabelEncoder
le_model = LabelEncoder()
Final_df['Label'] = le_model.fit_transform(Final_df['Mood'])
```

Training model:

Splitting the dataset into testing and training sets:

In [130]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(Final_df['text'], Final_df
                                                    test_size=0.2, random_stat
```

In [131]:
```
print("Shape of X_train: ", X_train.shape)
print("Shape of X_test: ", X_test.shape)
```

```
Shape of X_train:  (73509,)
Shape of X_test:  (18378,)
```

Model Training

In [132]:
```
clf = Pipeline([
    ('vectorizer_tri_grams', TfidfVectorizer()),
    ('random_forest', (RandomForestClassifier()))
])
```

In [133]:
```

clf.fit(X_train, y_train)
```

Out[133]:
```
Pipeline
  TfidfVectorizer
RandomForestClassifier
```

The prevalence of neutral sentiment tweets far surpasses the relatively low count of negative tweets, making a meaningful comparison between the two challenging.

Evaluation of the Model

In [134]:
```

from sklearn.metrics import accuracy_score, classification_report
```

In [135]:
```
# Get the predictions for X_test and store it in y_pred
y_pred = clf.predict(X_test)
```

In [136]:
```
print(accuracy_score(y_test, y_pred))
```

```
0.9123408423114594
```

In [137]:
```
# Print classification report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.52      0.68      1014
           1       0.89      0.99      0.94     12286
           2       0.96      0.80      0.87      5078

    accuracy                           0.91     18378
   macro avg       0.94      0.77      0.83     18378
weighted avg       0.92      0.91      0.91     18378
```

Testing our model:

In [138]:
```
test_df=Final_df.iloc[:50000, :]
```

In [139]:
```
test=Final_df['text'][1000]
```

In [140]:
```
test_text = test_df['text'][1000]
print(f"{test} ===> {test_df['Label'][1000]}")
```

```
rt @awscloud: new the aw #bigdata blog: turn emr into a massiv s3 process eng
in with campanil https://blogs.aws.amazon.com/bigdata/post/tx1xu0oqazer3mi/tu
rning-amazon-emr-into-a-massive-amazon-s3-processing-engine-with-campanile?ad
bsc=social_blogs_20160129_57773736&adbid=693195696921403394&adbpl=tw&adbpr=66
780587 (https://blogs.aws.amazon.com/bigdata/post/tx1xu0oqazer3mi/turning-ama
zon-emr-into-a-massive-amazon-s3-processing-engine-with-campanile?adbsc=socia
l_blogs_20160129_57773736&adbid=693195696921403394&adbpl=tw&adbpr=66780587) h
ttps:// (https://) ===> 1
```

In [141]:
```
test = clf.predict([test_text])
```

In [142]:
```
classes = ['Negative', 'Neutral', 'Positive']

print(f"True Label: {test_df['Mood'][1000]}")
print(f'Predict Label: {classes[test[0]]}')
```

```
True Label: Neutral
Predict Label: Neutral
```

Conclusion:

```
We have analysed the sentiment of the tweet with the accuracy :
91% .
```