WORK TO BE DONE-

-Models to be evaluated(IMPLEMENTED BEFORE BALANCING)

KNearestNeighbors

LogisticRegression

NaiveBayes (Gaussian, Bernoulli, Multinomial)

DecicionTree

RandomForest

XGBoost

-THE OUTPUT AFTER IMPLEMENTING THE MODELS SHOULD BE ACCURACY, PRECISION, F1 SCORE, RECALL

- PLOT ROC AND PRECISION- RECALL CURVES FOR THE 2 BEST PERFORMING MODELS
- AFTER THE BALANCING , PLOT THE DIFFERENCE FOR THE 2 BEST PERFORMING MODELS(I.E DIFFERENCE BEFORE AND AFTER BALANCING IN THE CURVES)

-PLOT THE CONFUSION MATRICES OF THE 2 BEST PERFORMING MODELS

-PLOT THE FEATURE IMPOTANCE CHART FOR BOTH THE BEST PERFORMING MODELS

-DO MODEL EMSEMBLING FOR THE 2 BEST MODELS

-FIND THE BEST PERFORMING MODEL BY USING PARAMETER TUNING

In [1]:

```
import os
import sys
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')


# Basics
import pandas as pd
import psycopg2 as pg
import numpy as np
import pickle

# Visuals
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn import *

# Models
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression  # Replace with your own model
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb

from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier

# Model support
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (accuracy_score, classification_report, confusion_matrix, f1_score, au
                             precision_score, recall_score, roc_auc_score, roc_curve,
                             precision_recall_curve)
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import precision_recall_curve, average_precision_score
```

In [2]:
```
df = pd.read_csv(r'C:\Users\Tanmayee\OneDrive\Documents\Personal\Inifinte Solutions\Twitter Bot De
df
```

Out[2]:

	Unnamed: 0	created_at	default_profile	default_profile_image	description	favourites_count	followers_count
0	0	2009-07-04 22:41:51	False	False	NaN	5007	102
1	1	2010-01-17 22:54:19	False	False	Television producer. Emmy Award winner. Disney...	1038	60
2	2	2012-03-01 06:05:32	False	False	NaN	2257	599
3	3	2009-09-01 04:52:30	False	False	NaN	6407	116
4	4	2010-01-27 17:17:23	False	False	Productor de Televisión - Embajador de @Tienda...	20866	74448
...	...	...	...	...	...	...	...
37433	37433	2010-12-07 08:11:16	False	False	Self Made Plus Model, #BeautyIsNotASize, CEO @...	59660	257294
37434	37434	2010-12-04 13:17:22	False	False	Gazeteci/Journalist ...	0	74666
37435	37435	2009-10-06 23:53:30	False	False	Modelo y Actriz Venezolana/ Venezuelan Model &...	28	255941
37436	37436	2013-03-24 21:04:16	True	False	Indian!...Actor!...Need no more!	621	2678042
37437	37437	2011-01-10 04:01:02	False	False	📖 Poeta, Autor, Escritor, dois Livros Publicado...	4526	471451

37438 rows × 23 columns

In [3]:
```
df.head()
```

Out[3]:

	Unnamed: 0	created_at	default_profile	default_profile_image	description	favourites_count	followers_count	friends_cou
0	0	2009-07-04 22:41:51	False	False	NaN	5007	102	1
1	1	2010-01-17 22:54:19	False	False	Television producer. Emmy Award winner. Disney...	1038	60	1
2	2	2012-03-01 06:05:32	False	False	NaN	2257	599	4
3	3	2009-09-01 04:52:30	False	False	NaN	6407	116	3
4	4	2010-01-27 17:17:23	False	False	Productor de Televisión - Embajador de @Tienda...	20866	74448	

5 rows × 23 columns

In [4]:
```
df['bot'] = df['account_type'].apply(lambda x: 1 if x == 'bot' else 0)
df['default_profile'] = df['default_profile'].astype(int)
df['default_profile'] = df['default_profile'].astype(int)
df['default_profile_image'] = df['default_profile_image'].astype(int)
df['geo_enabled'] = df['geo_enabled'].astype(int)
df['verified'] = df['verified'].astype(int)

# datetime conversion
df['created_at'] = pd.to_datetime(df['created_at'])
# hour created
df['hour_created'] = pd.to_datetime(df['created_at']).dt.hour
```

In [5]:
```
dfr = df[['bot', 'screen_name', 'created_at', 'hour_created', 'verified', 'location', 'geo_enablec
          'default_profile', 'default_profile_image', 'favourites_count', 'followers_count', 'f
          'statuses_count', 'average_tweets_per_day', 'account_age_days']]
```

In [6]:
```
del df
```

In [7]:
```
dfr.head()
```

Out[7]:

	bot	screen_name	created_at	hour_created	verified	location	geo_enabled	lang	default_profile	default_profile_i
0	1	paty_castroo	2009-07-04 22:41:51	22	0	Maringá, Brasil	0	NaN	0	
1	0	CBirckner	2010-01-17 22:54:19	22	0	Atlanta	0	en	0	
2	0	amf_jay	2012-03-01 06:05:32	6	0	unknown	1	NaN	0	
3	0	SaraCavolo	2009-09-01 04:52:30	4	0	Brooklyn, NY	1	NaN	0	
4	0	DavidHenaoModel	2010-01-27 17:17:23	17	1	Miami, FL	1	es	0	

In [8]:
```
dfr.describe()
```

Out[8]:

	bot	hour_created	verified	geo_enabled	default_profile	default_profile_image	favourites_count	f
count	37438.000000	37438.000000	37438.000000	37438.000000	37438.000000	37438.000000	37438.000000	
mean	0.331882	12.371040	0.201693	0.456141	0.419894	0.014905	12302.062183	
std	0.470895	7.325433	0.401270	0.498079	0.493548	0.121173	33923.650237	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	5.000000	0.000000	0.000000	0.000000	0.000000	362.000000	
50%	0.000000	14.000000	0.000000	0.000000	0.000000	0.000000	2066.000000	
75%	1.000000	19.000000	0.000000	1.000000	1.000000	0.000000	8879.000000	
max	1.000000	23.000000	1.000000	1.000000	1.000000	1.000000	885123.000000	

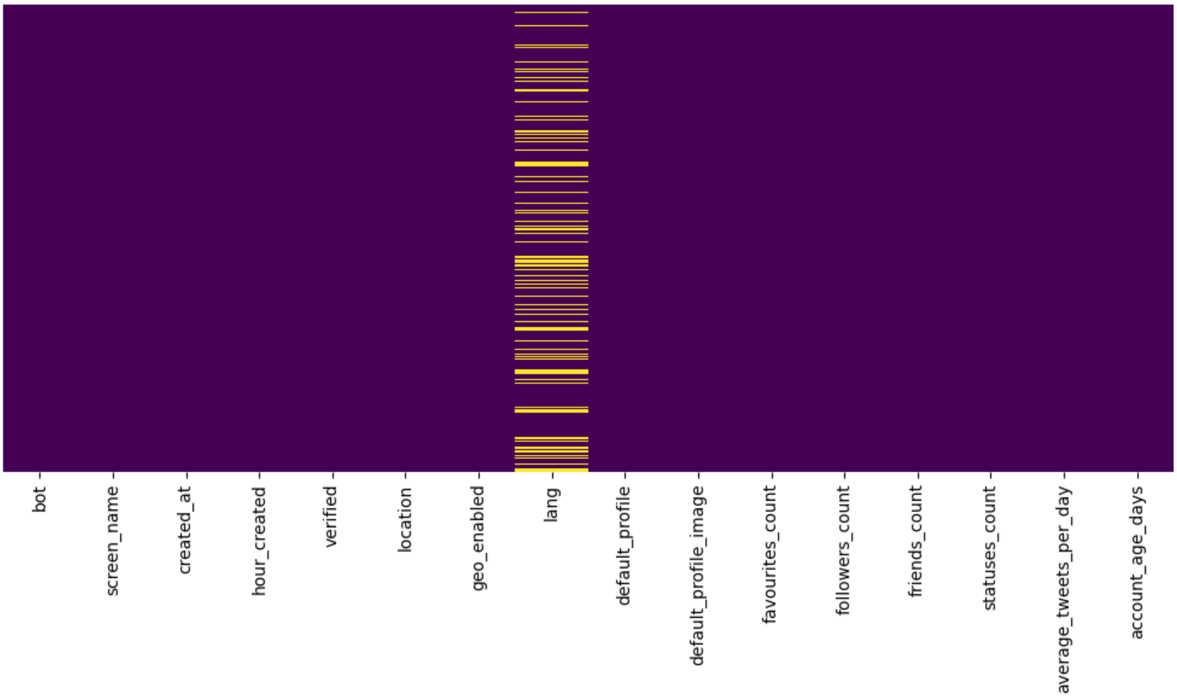
In [9]:
```
dfr.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 37438 entries, 0 to 37437
Data columns (total 16 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   bot                    37438 non-null  int64
 1   screen_name            37438 non-null  object
 2   created_at             37438 non-null  datetime64[ns]
 3   hour_created           37438 non-null  int64
 4   verified               37438 non-null  int32
 5   location               37435 non-null  object
 6   geo_enabled            37438 non-null  int32
 7   lang                   29481 non-null  object
 8   default_profile        37438 non-null  int32
 9   default_profile_image  37438 non-null  int32
 10  favourites_count       37438 non-null  int64
 11  followers_count        37438 non-null  int64
 12  friends_count          37438 non-null  int64
 13  statuses_count         37438 non-null  int64
 14  average_tweets_per_day 37438 non-null  float64
 15  account_age_days       37438 non-null  int64
dtypes: datetime64[ns](1), float64(1), int32(4), int64(7), object(3)
memory usage: 4.0+ MB
```

In [10]:
```
dfr.isnull().sum()
```

Out[10]:
```
bot                          0
screen_name                  0
created_at                   0
hour_created                 0
verified                     0
location                     3
geo_enabled                  0
lang                      7957
default_profile              0
default_profile_image        0
favourites_count             0
followers_count              0
friends_count                0
statuses_count               0
average_tweets_per_day       0
account_age_days             0
dtype: int64
```

In [11]:
```python
def get_heatmap(df):
    #This function gives heatmap of all NaN values
    plt.figure(figsize=(10,6))
    sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap='viridis')
    plt.tight_layout()
    return plt.show()

get_heatmap(dfr)
```

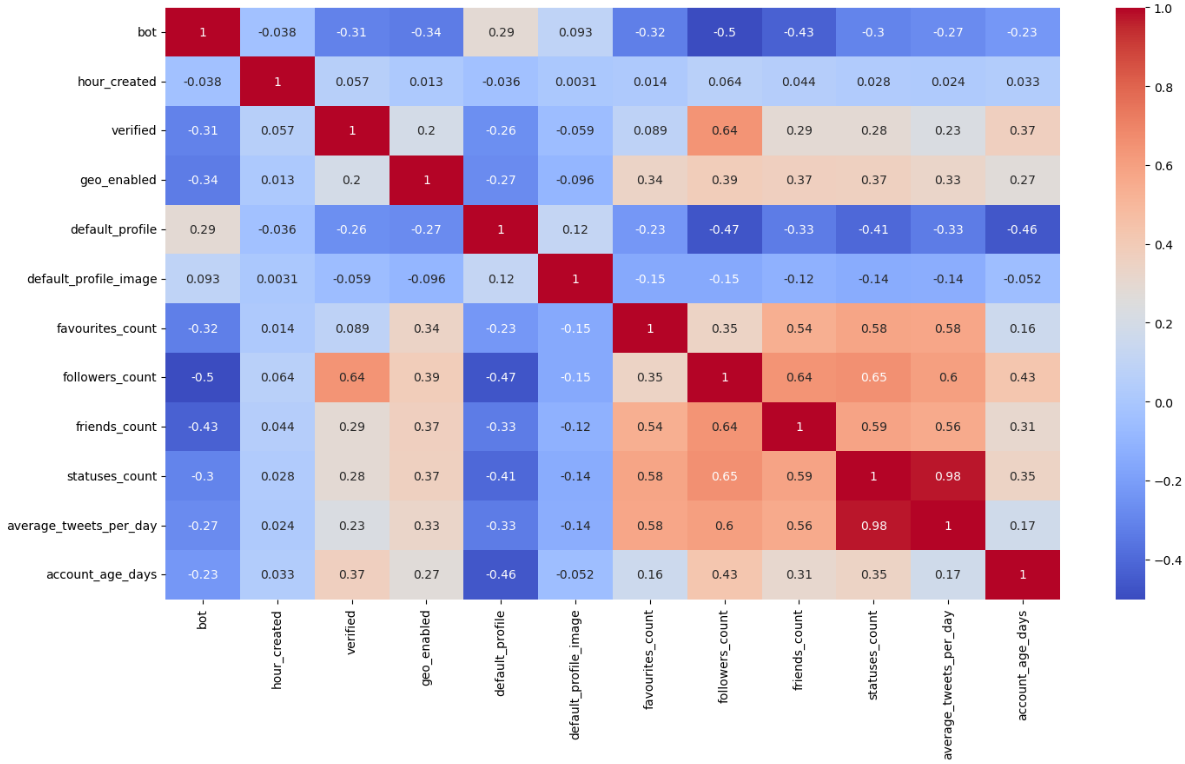


In [12]:
```python
dfr.corr(method='spearman')
```

Out[12]:

	bot	hour_created	verified	geo_enabled	default_profile	default_profile_image	favourites
bot	1.000000	-0.038169	-0.309593	-0.336145	0.290070	0.092601	-0.
hour_created	-0.038169	1.000000	0.056505	0.013082	-0.035677	0.003095	0.
verified	-0.309593	0.056505	1.000000	0.196153	-0.264979	-0.058531	0.
geo_enabled	-0.336145	0.013082	0.196153	1.000000	-0.273882	-0.095831	0.
default_profile	0.290070	-0.035677	-0.264979	-0.273882	1.000000	0.115994	-0
default_profile_image	0.092601	0.003095	-0.058531	-0.095831	0.115994	1.000000	-0
favourites_count	-0.322031	0.014405	0.089247	0.340518	-0.231188	-0.151153	1.
followers_count	-0.501959	0.063930	0.644321	0.385186	-0.467994	-0.151764	0.
friends_count	-0.426074	0.044371	0.289737	0.366762	-0.333771	-0.116620	0.
statuses_count	-0.304257	0.028382	0.284226	0.365665	-0.405820	-0.138945	0.
average_tweets_per_day	-0.273598	0.023798	0.229656	0.326320	-0.334909	-0.135270	0.
account_age_days	-0.230037	0.032696	0.369423	0.266917	-0.462041	-0.051714	0.

In [13]:
```
plt.figure(figsize=(15,9))
sns.heatmap(dfr.corr(method='spearman'), cmap='coolwarm', annot=True)
plt.tight_layout()
plt.show()
```

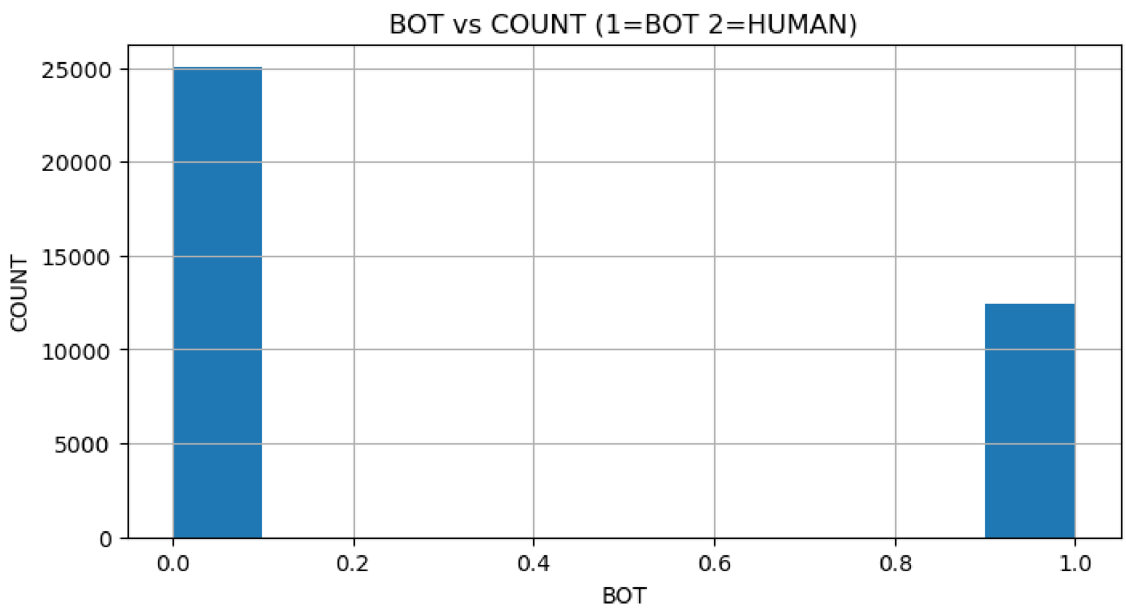


In [14]:
```
dfr['bot'].value_counts(dropna=False)
```

Out[14]:
```
0    25013
1    12425
Name: bot, dtype: int64
```

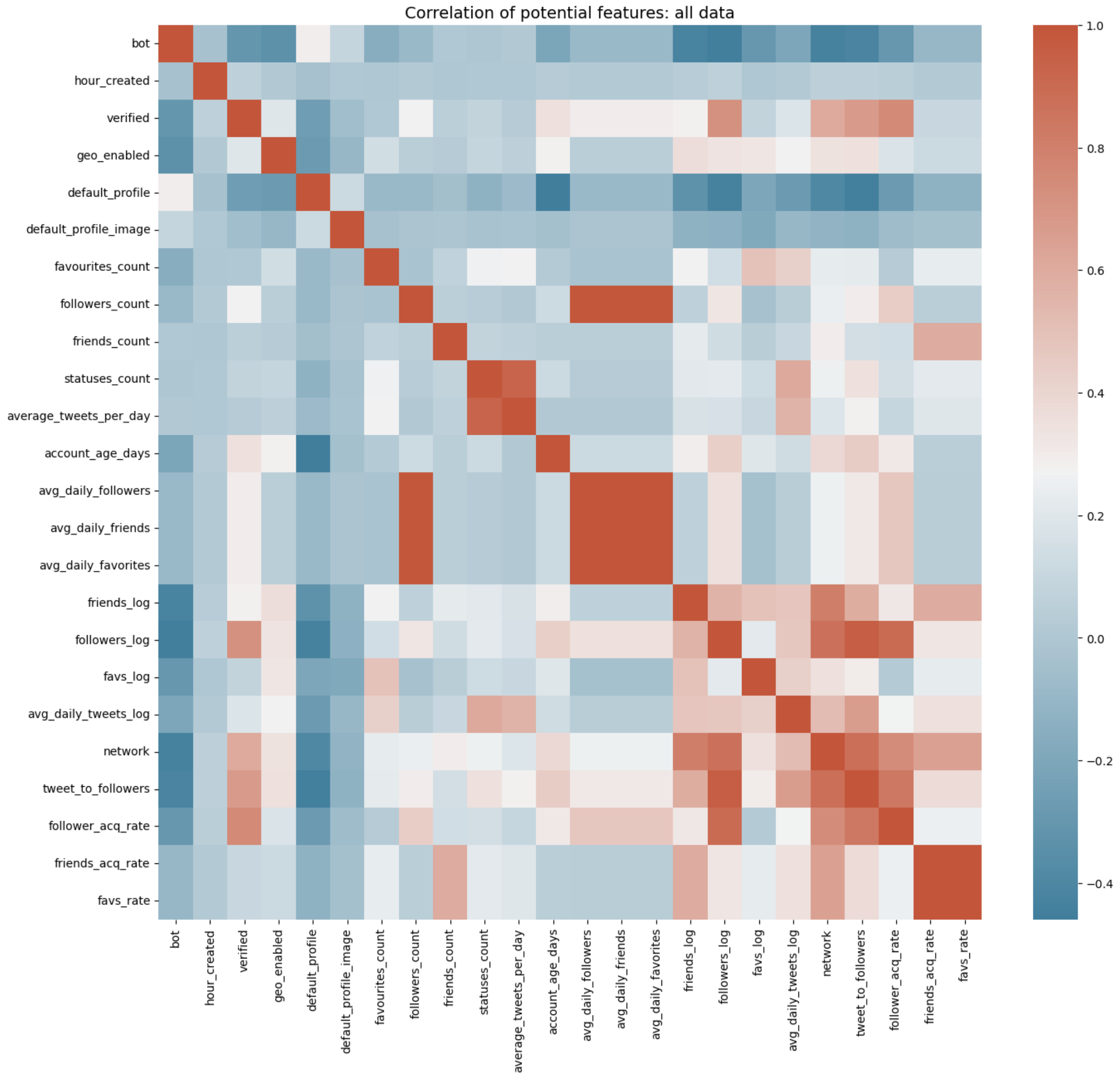
In [15]:
```
plt.figure(figsize=(8,4))
dfr['bot'].hist()
plt.xlabel('BOT')
plt.ylabel('COUNT')
plt.title('BOT vs COUNT (1=BOT 2=HUMAN)')
```

Out[15]:
```
Text(0.5, 1.0, 'BOT vs COUNT (1=BOT 2=HUMAN)')
```



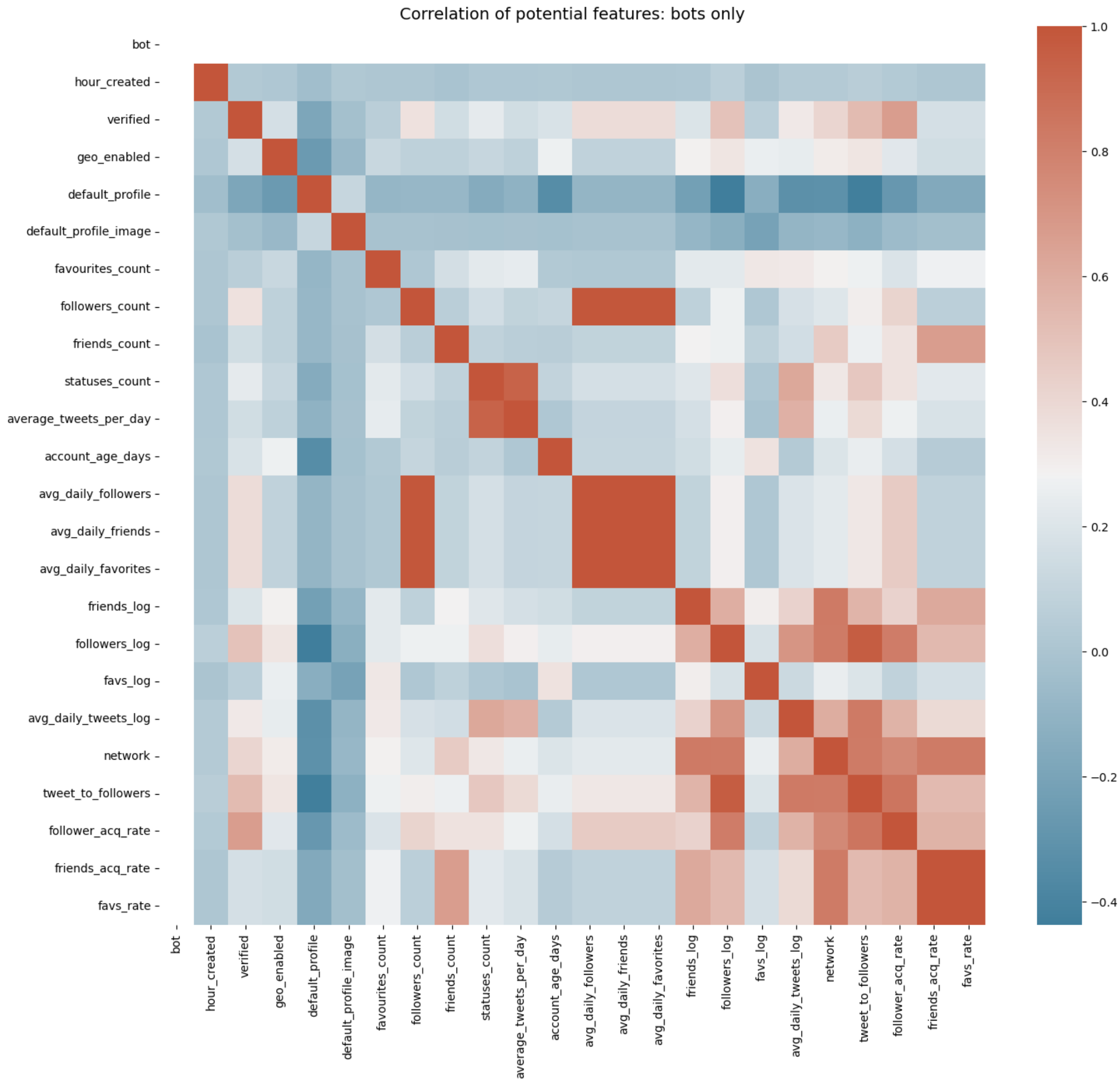
In [16]:
```python
# Interesting features to look at:
dfr['avg_daily_followers'] = np.round(dfr['followers_count'] / dfr['account_age_days'])
dfr['avg_daily_friends'] = np.round(dfr['followers_count'] / dfr['account_age_days'])
dfr['avg_daily_favorites'] = np.round(dfr['followers_count'] / dfr['account_age_days'])

# Log transformations for highly skewed data
dfr['friends_log'] = np.round(np.log(1 + dfr['friends_count']), 3)
dfr['followers_log'] = np.round(np.log(1 + dfr['followers_count']), 3)
dfr['favs_log'] = np.round(np.log(1 + dfr['favourites_count']), 3)
dfr['avg_daily_tweets_log'] = np.round(np.log(1+ dfr['average_tweets_per_day']), 3)

# Possible interaction features
dfr['network'] = np.round(dfr['friends_log'] * dfr['followers_log'], 3)
dfr['tweet_to_followers'] = np.round(np.log( 1+ dfr['statuses_count']) * np.log(1+ dfr['followers_

# Log-transformed daily acquisition metrics for dist. plots
dfr['follower_acq_rate'] = np.round(np.log(1 + (dfr['followers_count'] / dfr['account_age_days']))
dfr['friends_acq_rate'] = np.round(np.log(1 + (dfr['friends_count'] / dfr['account_age_days'])), 3
dfr['favs_rate'] = np.round(np.log(1 + (dfr['friends_count'] / dfr['account_age_days'])), 3)
```

In [17]:
```python
plt.figure(figsize=(16,14), dpi=100)
cmap = sns.diverging_palette(230, 20, as_cmap=True)

sns.heatmap(dfr.corr(), cmap=cmap, annot=False)
plt.title('Correlation of potential features: all data', fontsize=14);
```

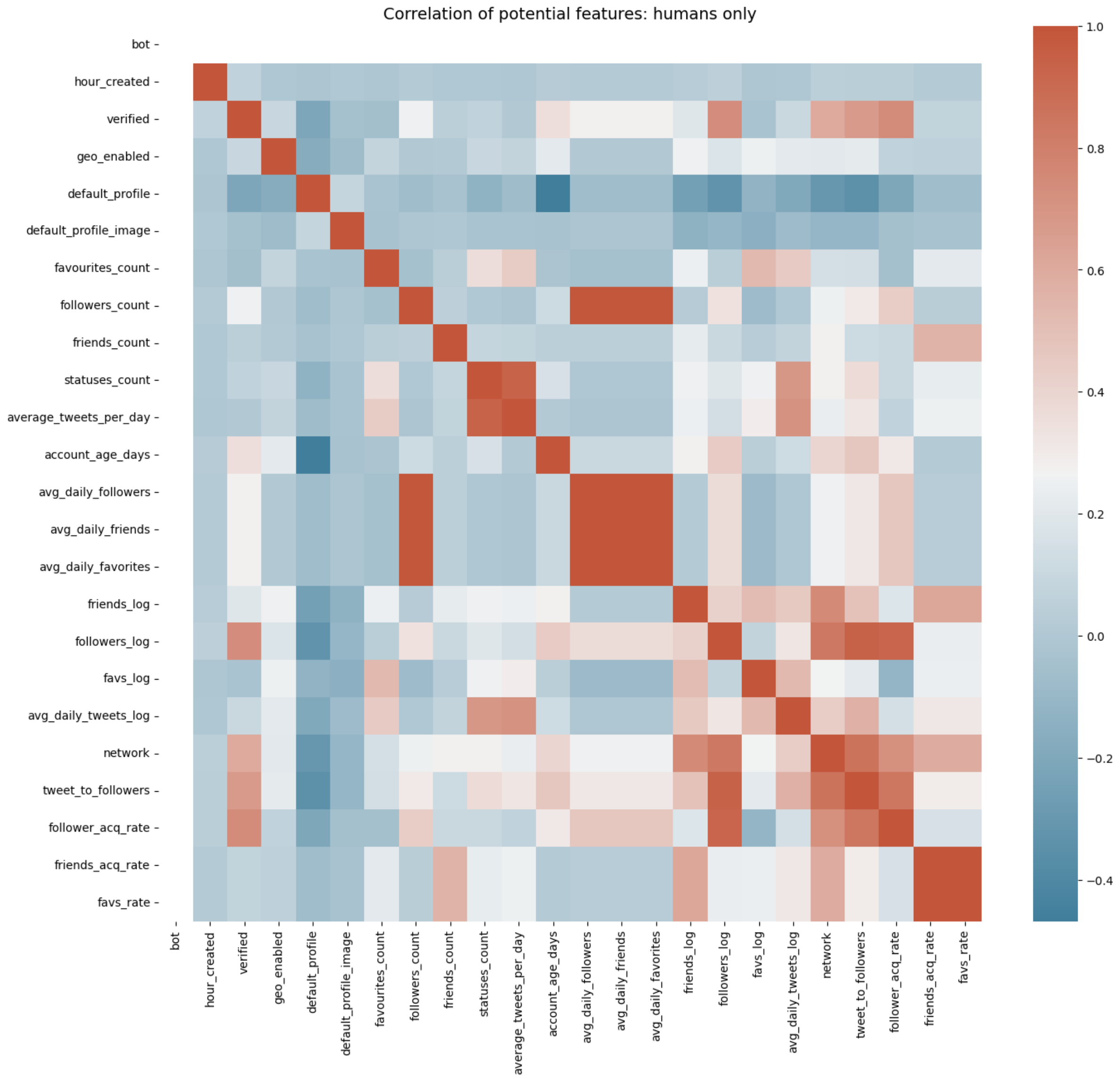


In [18]:
```python
bots = dfr[dfr['bot'] == 1]
humans = dfr[dfr['bot'] == 0]
```

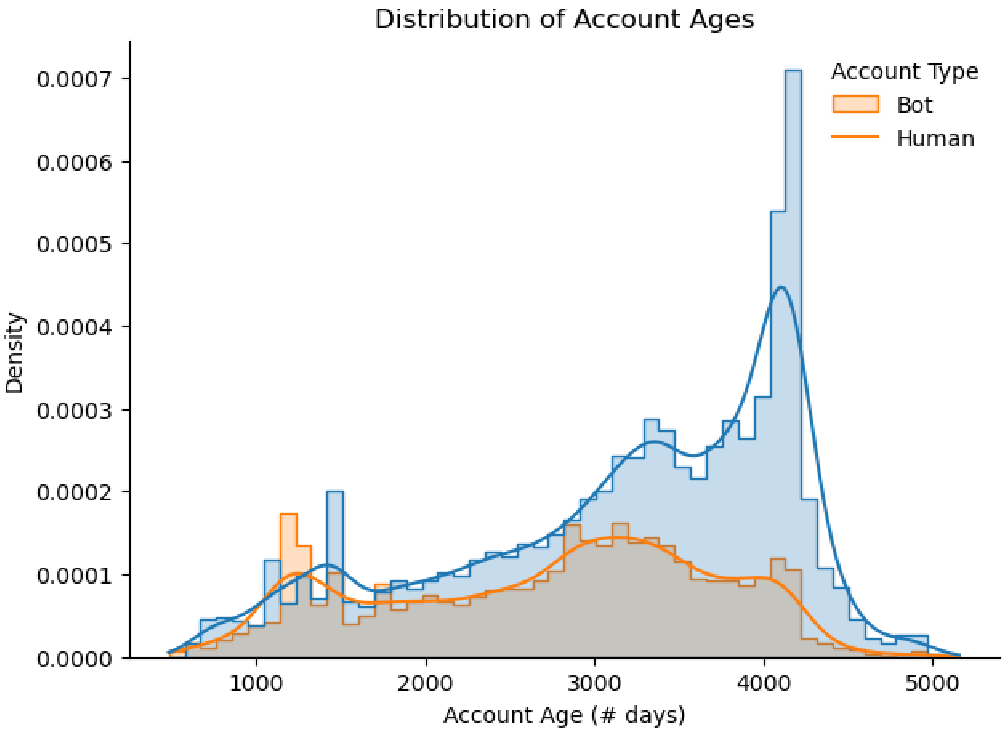
In [19]:
```
plt.figure(figsize=(16,14), dpi=100)
cmap = sns.diverging_palette(230, 20, as_cmap=True)

sns.heatmap(bots.corr(), cmap=cmap, annot=False)
plt.title('Correlation of potential features: bots only', fontsize=14);
```



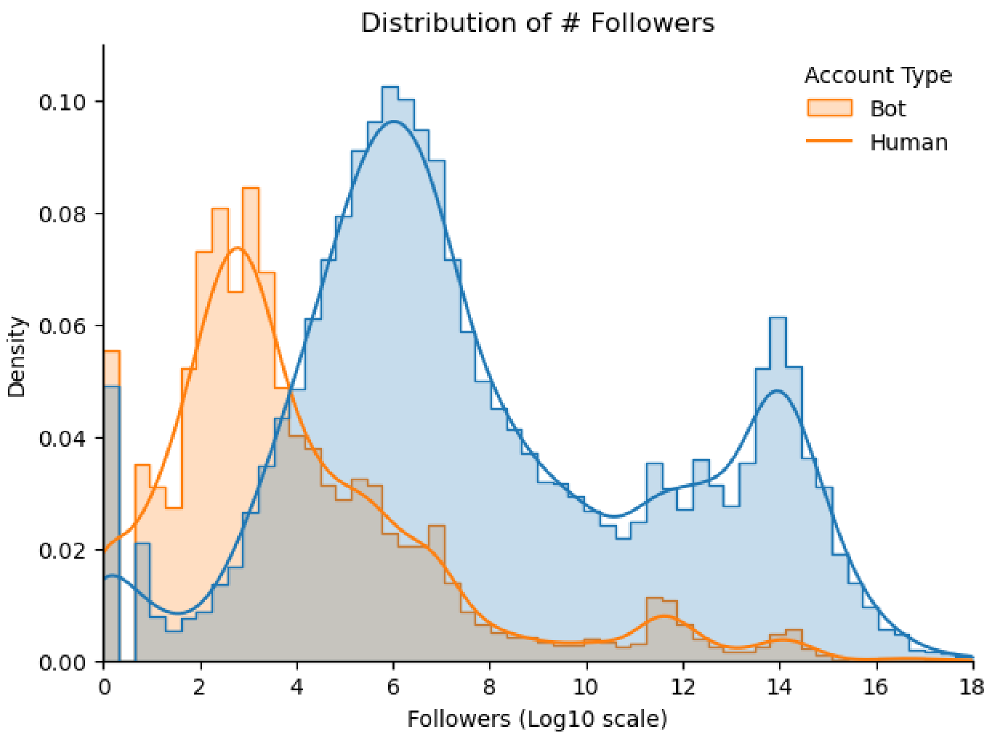
In [20]:
```
plt.figure(figsize=(16,14), dpi=100)
cmap = sns.diverging_palette(230, 20, as_cmap=True)

sns.heatmap(humans.corr(), cmap=cmap, annot=False)
plt.title('Correlation of potential features: humans only', fontsize=14);
```



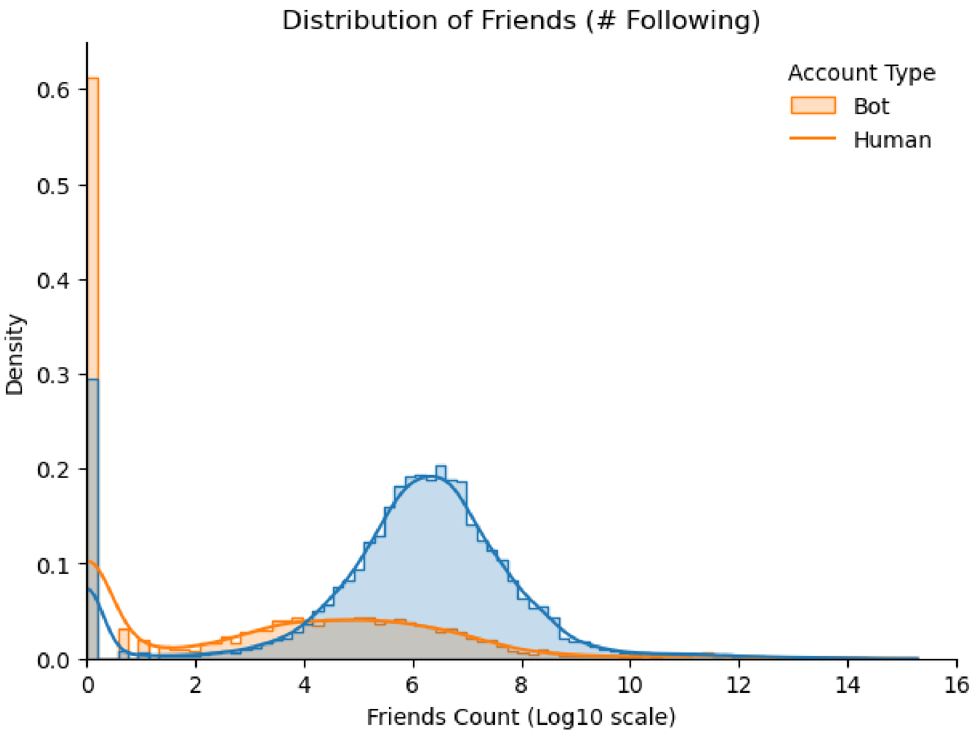
In [21]:
```
plt.figure(figsize=(7,5), dpi=100)
sns.histplot(x='account_age_days', data=dfr, hue='bot', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)

plt.legend(title='Account Type', loc='upper right', labels=['Bot', 'Human'], frameon=False)
plt.title('Distribution of Account Ages', fontsize=12)
plt.xlabel('Account Age (# days)', fontsize=10)
plt.ylabel('Density', fontsize=10)
sns.despine();
```



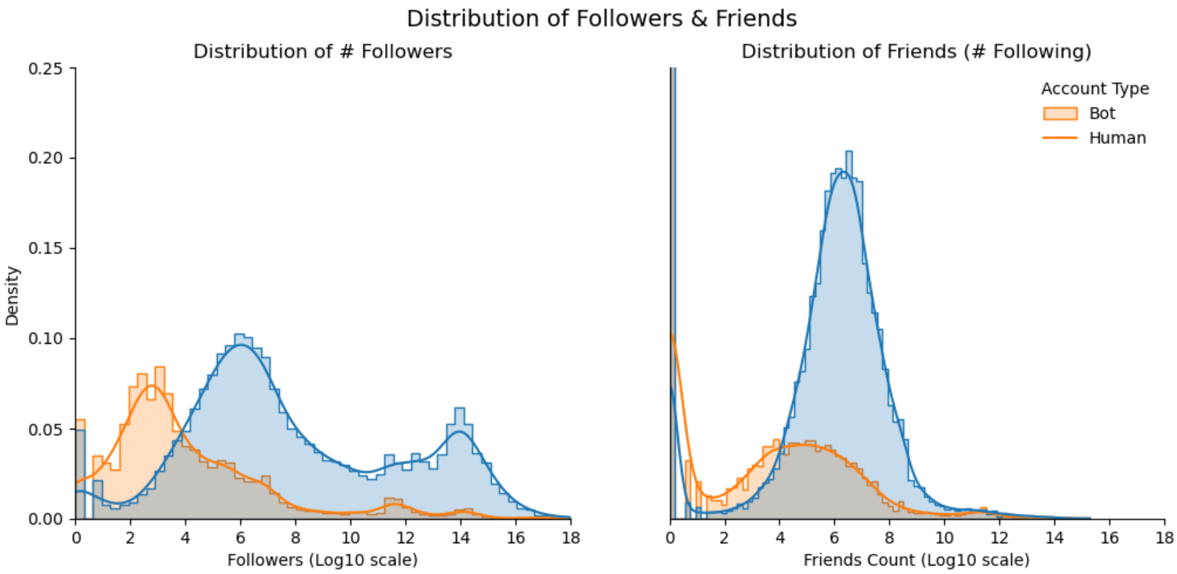
In [22]:
```python
plt.figure(figsize=(7,5), dpi=100)
sns.histplot(x='followers_log', data=dfr, hue='bot', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)

plt.legend(title='Account Type', loc='upper right', labels=['Bot', 'Human'], frameon=False)
plt.title('Distribution of # Followers', fontsize=12)
plt.xlabel('Followers (Log10 scale)', fontsize=10)
plt.ylabel('Density', fontsize=10)
plt.xlim(0, 18)
plt.ylim(0, 0.11)
sns.despine();
#plt.savefig('imgs/dist_followers.png');
```



In [23]:
```
plt.figure(figsize=(7,5), dpi=100)
sns.histplot(x='friends_log', data=dfr, hue='bot', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)

plt.legend(title='Account Type', loc='upper right', labels=['Bot', 'Human'], frameon=False)
plt.title('Distribution of Friends (# Following)', fontsize=12)
plt.xlabel('Friends Count (Log10 scale)', fontsize=10)
plt.ylabel('Density', fontsize=10)
plt.xlim(0, 16)
plt.ylim(0, 0.65)
sns.despine();
```

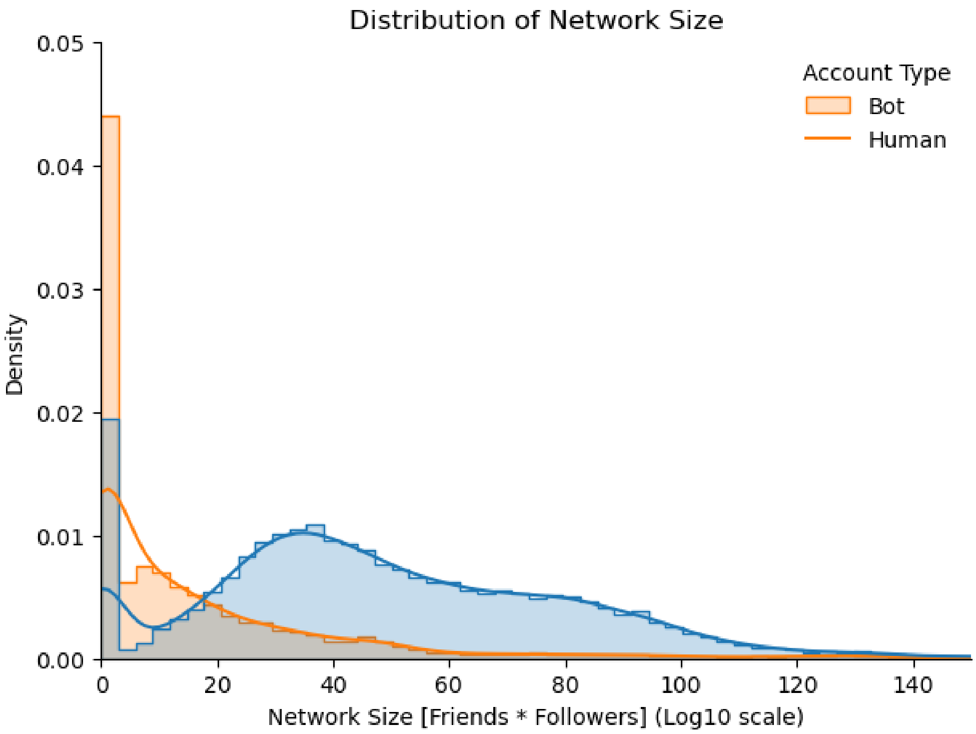


In [24]:
```
plt.figure(figsize=(12,5), dpi=100)
plt.suptitle('Distribution of Followers & Friends', fontsize=14)

plt.subplot(1, 2, 1)
sns.histplot(x='followers_log', data=dfr, hue='bot', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=False)
plt.title('Distribution of # Followers', fontsize=12)
plt.xlabel('Followers (Log10 scale)', fontsize=10)
plt.ylabel('Density', fontsize=10)
plt.xlim(0, 18)
plt.ylim(0, 0.25)
sns.despine()

plt.subplot(1, 2, 2)
sns.histplot(x='friends_log', data=dfr, hue='bot', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)

plt.legend(title='Account Type', loc='upper right', labels=['Bot', 'Human'], frameon=False)
plt.title('Distribution of Friends (# Following)', fontsize=12)
plt.xlabel('Friends Count (Log10 scale)', fontsize=10)
plt.ylabel("")
plt.yticks([])
plt.xlim(0, 18)
plt.ylim(0, 0.25)
sns.despine();
#plt.savefig('imgs/dist_followers_friends.png');
```

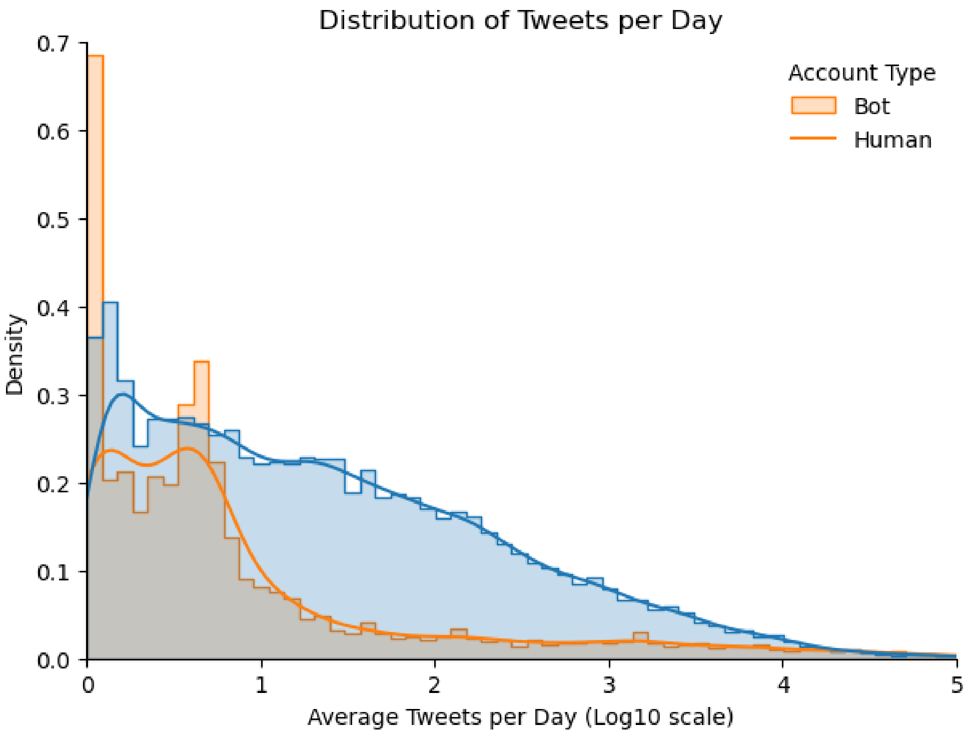


In [25]:

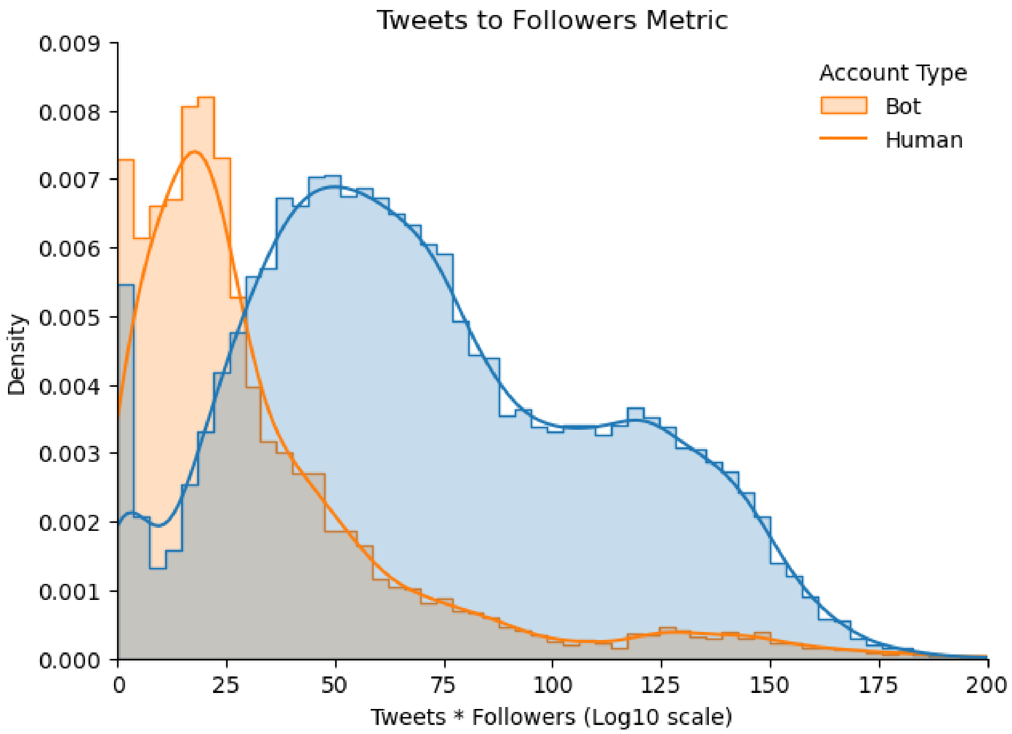
```
plt.figure(figsize=(7,5), dpi=100)
sns.histplot(x='network', data=dfr, hue='bot', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)

plt.legend(title='Account Type', loc='upper right', labels=['Bot', 'Human'], frameon=False)
plt.title('Distribution of Network Size', fontsize=12)
plt.xlabel('Network Size [Friends * Followers] (Log10 scale)', fontsize=10)
plt.ylabel('Density', fontsize=10)
plt.xlim(0, 150)
plt.ylim(0, 0.05)
sns.despine();
#plt.savefig('imgs/network_size.png');
```



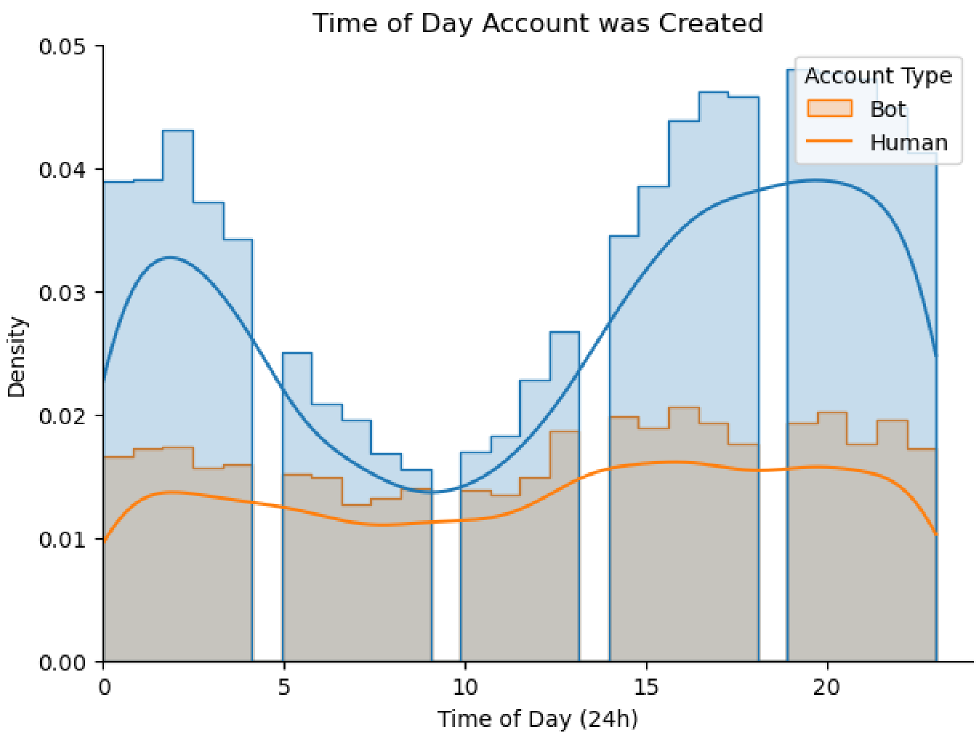
In [26]:
```python
plt.figure(figsize=(7,5), dpi=100)
sns.histplot(x='avg_daily_tweets_log', data=dfr, hue='bot', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)

plt.legend(title='Account Type', loc='upper right', labels=['Bot', 'Human'], frameon=False)
plt.title("Distribution of Tweets per Day", fontsize=12)
plt.xlabel('Average Tweets per Day (Log10 scale)', fontsize=10)
plt.ylabel('Density', fontsize=10)
plt.xlim(0, 5)
plt.ylim(0, 0.7)
sns.despine();
#plt.savefig('imgs/tweets_per_day.png');
```



In [27]:
```
plt.figure(figsize=(7,5), dpi=100)
sns.histplot(x='tweet_to_followers', data=dfr, hue='bot', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)

plt.legend(title='Account Type', loc='upper right', labels=['Bot', 'Human'], frameon=False)
plt.title("Tweets to Followers Metric", fontsize=12)
plt.xlabel('Tweets * Followers (Log10 scale)', fontsize=10)
plt.ylabel('Density', fontsize=10)
plt.xlim(0, 200)
plt.ylim(0, 0.009)
sns.despine();
#plt.savefig('imgs/tweets_to_followers.png');
```

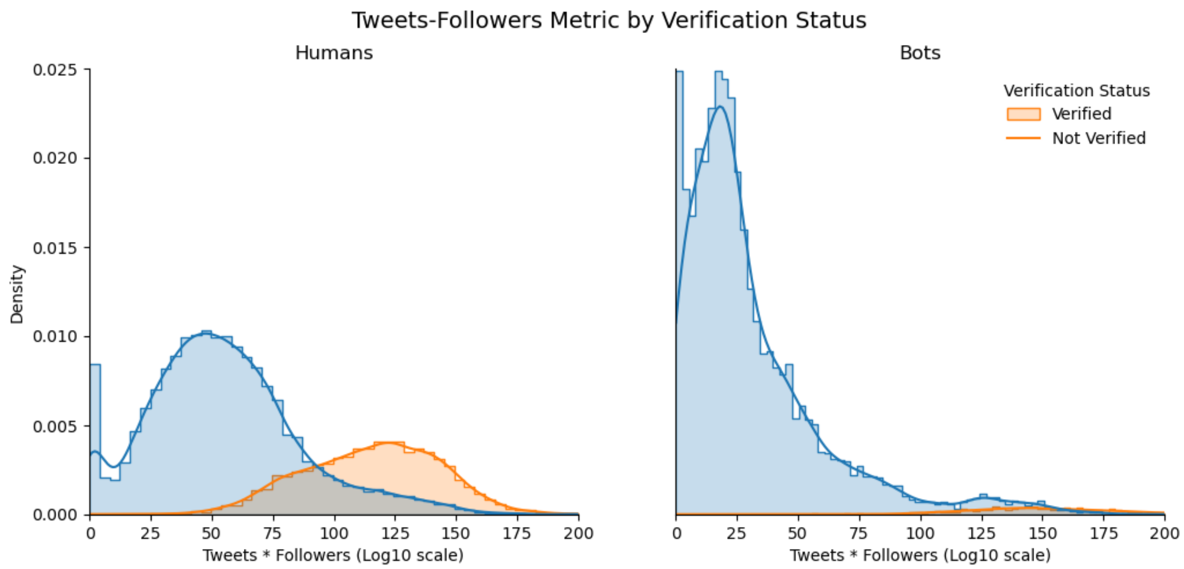


In [28]:
```
plt.figure(figsize=(7,5), dpi=100)
sns.histplot(x='hour_created', data=dfr, hue='bot', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)

plt.legend(title='Account Type', loc='best', labels=['Bot', 'Human'])
plt.title("Time of Day Account was Created", fontsize=12)
plt.xlabel('Time of Day (24h)', fontsize=10)
plt.ylabel('Density', fontsize=10)
plt.xlim(0, 24)
plt.ylim(0, 0.05)
sns.despine();
#plt.savefig('imgs/hour_created.png');
```

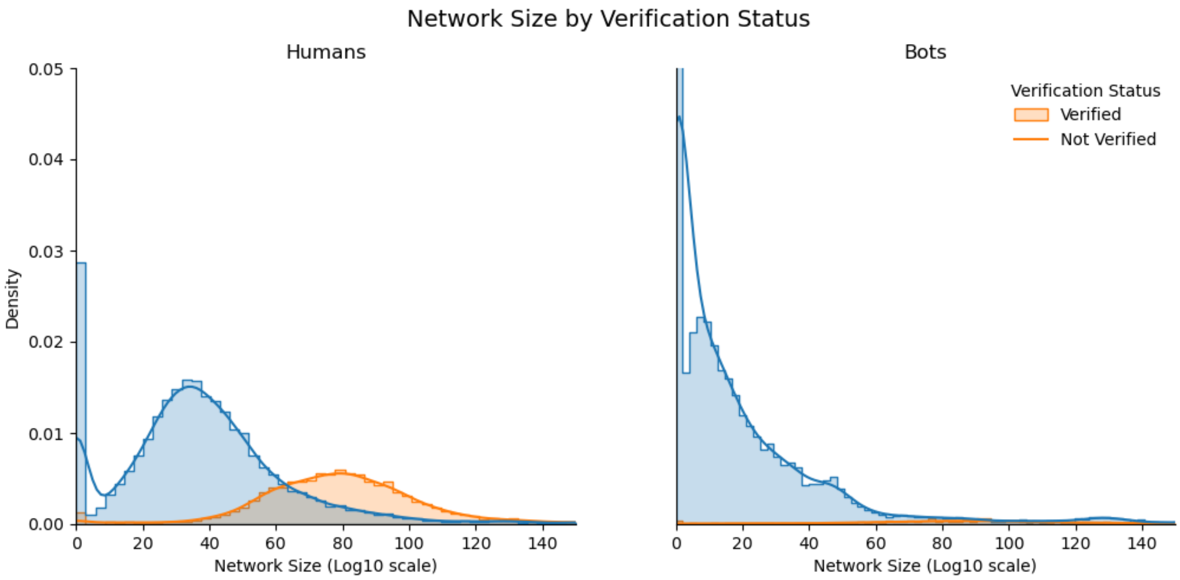


In [29]:

```
plt.figure(figsize=(12,5), dpi=100)
plt.suptitle('Tweets-Followers Metric by Verification Status', fontsize=14)

plt.subplot(1, 2, 1)
sns.histplot(x='tweet_to_followers', data=humans, hue='verified', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=False)

plt.title("Humans", fontsize=12)
plt.xlabel('Tweets * Followers (Log10 scale)', fontsize=10)
plt.ylabel('Density', fontsize=10)
sns.despine(bottom = True, left = True)
plt.xlim(0, 200)
plt.ylim(0, 0.025)

plt.subplot(1, 2, 2)
sns.histplot(x='tweet_to_followers', data=bots, hue='verified', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)

plt.legend(title='Verification Status', loc='upper right', labels=['Verified', 'Not Verified'], fr
plt.title("Bots", fontsize=12)
plt.xlabel('Tweets * Followers (Log10 scale)', fontsize=10)
plt.ylabel("")
plt.yticks([])
sns.despine()
plt.xlim(0, 200)
plt.ylim(0, 0.025);
#plt.savefig('imgs/tweets_to_follows_by_verification_status.png');
```



In [30]:
```
plt.figure(figsize=(12,5), dpi=100)
plt.suptitle('Network Size by Verification Status', fontsize=14)

plt.subplot(1, 2, 1)
sns.histplot(x='network', data=humans, hue='verified', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=False)
plt.xlabel('Network Size (Friends * Followers)')
plt.title("Humans", fontsize=12)
plt.xlabel('Network Size (Log10 scale)', fontsize=10)
plt.ylabel('Density', fontsize=10)
sns.despine(bottom = True, left = True)
plt.xlim(0, 150)
plt.ylim(0, 0.05)

plt.subplot(1, 2, 2)
sns.histplot(x='network', data=bots, hue='verified', alpha=.25,
             kde=True, stat='density', common_bins=True, element='step', legend=True)
plt.xlabel('Network Size (Friends * Followers)')
plt.legend(title='Verification Status', loc='upper right', labels=['Verified', 'Not Verified'], fr
plt.title("Bots", fontsize=12)
plt.xlabel('Network Size (Log10 scale)', fontsize=10)
plt.ylabel("")
plt.yticks([])
sns.despine()
plt.xlim(0, 150)
plt.ylim(0, 0.05);
#plt.savefig('imgs/network_size_by_verification_status.png');
```



In [31]:
```
features = ['verified',
            #'created_at',
            #'hour_created',
            #'lang',
            #'acct_location',
            'geo_enabled',
            'default_profile',
            'default_profile_image',
            'favourites_count',
            'followers_count',
            'friends_count',
            'statuses_count',
            'average_tweets_per_day',
            #'avg_daily_followers',
            #'avg_daily_friends',
            #'avg_daily_favorites',
            'network',
            'tweet_to_followers',
            'follower_acq_rate',
            'friends_acq_rate',
            'favs_rate'
           ]

X = dfr[features]
y = dfr['bot']
```

In [32]:
```
!pip install psycopg2
```

```
Requirement already satisfied: psycopg2 in c:\users\tanmayee\anaconda3\lib\site-packages (2.9.7)

WARNING: Ignoring invalid distribution -rotobuf (c:\users\tanmayee\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\tanmayee\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\tanmayee\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\tanmayee\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\tanmayee\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (c:\users\tanmayee\anaconda3\lib\site-packages)
```

In [33]:
```
X, X_test, y, y_test = train_test_split(X, y, test_size=.3, random_state=1234)
```

Decision Tree Classifier

In [34]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, roc_curve, auc
from sklearn.model_selection import train_test_split


dt = DecisionTreeClassifier(criterion='entropy', min_samples_leaf=50, min_samples_split=10)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)

dt = dt.fit(X_train, y_train)
y_pred_train = dt.predict(X_train)
y_pred_test = dt.predict(X_test)

print("Training Accuracy: %.5f" %accuracy_score(y_train, y_pred_train))
print("Test Accuracy: %.5f" %accuracy_score(y_test, y_pred_test))
```

```
Training Accuracy: 0.86644
Test Accuracy: 0.84673
```

In [35]:
```python
# Print the classification report for the test set
report = classification_report(y_test, y_pred_test)
print("Classification Report (Test Set):\n", report)
```

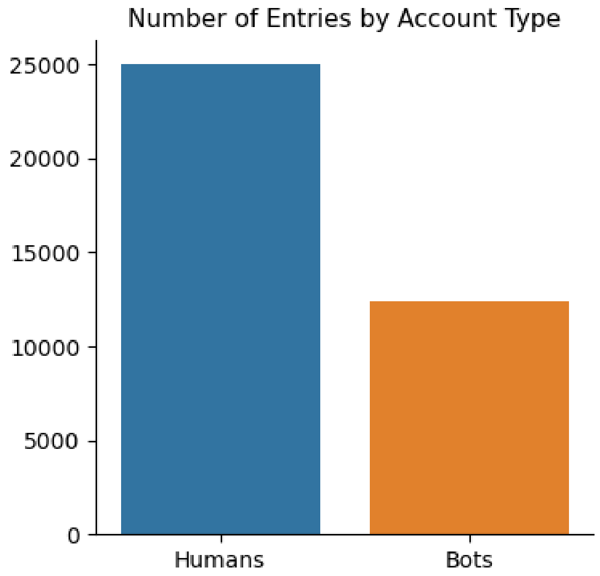
```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.85      0.93      0.89      5260
           1       0.83      0.68      0.75      2602

    accuracy                           0.85      7862
   macro avg       0.84      0.80      0.82      7862
weighted avg       0.85      0.85      0.84      7862
```

BALANCING DATASET

In [36]:
```python
num_bots = len(dfr[dfr['bot'] == 1])
num_humans = len(dfr[dfr['bot'] == 0])

print("Number of bots: ", num_bots)
print("Number of humans: ", num_humans)
print(f'Bots / Total %: {(num_bots / len(dfr))*100:.2f}')
```

```
Number of bots:  12425
Number of humans:  25013
Bots / Total %: 33.19
```

In [37]:
```python
types = ['Humans', 'Bots']
counts = [num_humans, num_bots]

plt.figure(figsize=(4, 4))
sns.barplot(x = types, y = counts)
plt.title("Number of Entries by Account Type", fontsize=11)
sns.despine();
```



Random Forest

In [38]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1234)

# Create and train a Random Forest classifier
model = RandomForestClassifier(random_state=1234)  # You can adjust hyperparameters here
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_rf = model.predict(X_test)

# Evaluate the model's performance (e.g., accuracy)
training_accuracy = accuracy_score(y_train, model.predict(X_train))
test_accuracy = accuracy_score(y_test, y_pred_rf)

print(f"Training Accuracy: {training_accuracy:.5f}")
print(f"Test Accuracy: {test_accuracy:.5f}")
```

```
Training Accuracy: 1.00000
Test Accuracy: 0.87281
```

In [39]:
```
# Print the classification report for the test set
report = classification_report(y_test, y_pred_rf)
print("Classification Report (Test Set):\n", report)
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.88      0.94      0.91      5188
           1       0.86      0.75      0.80      2674

    accuracy                           0.87      7862
   macro avg       0.87      0.84      0.85      7862
weighted avg       0.87      0.87      0.87      7862
```

KNN

In [40]:
```
# Create and train a KNN classifier (you can specify the number of neighbors with n_neighbors)
knn_model = KNeighborsClassifier(n_neighbors=5)  # Example: 5 neighbors
knn_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_knn = knn_model.predict(X_test)

# Evaluate the model's performance (e.g., accuracy)
training_accuracy = accuracy_score(y_train, model.predict(X_train))
test_accuracy = accuracy_score(y_test, y_pred_knn)

print(f"Training Accuracy: {training_accuracy:.5f}")
print(f"Test Accuracy: {test_accuracy:.5f}")
```

```
Training Accuracy: 1.00000
Test Accuracy: 0.84355
```

In [41]:
```
# Print the classification report for the test set
report = classification_report(y_test, y_pred_knn)
print("Classification Report (Test Set):\n", report)
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.86      0.91      0.88      5188
           1       0.80      0.72      0.76      2674

    accuracy                           0.84      7862
   macro avg       0.83      0.81      0.82      7862
weighted avg       0.84      0.84      0.84      7862
```

Logistic Regression

In [42]:
```
# Create and train a logistic regression model
logistic_regression_model = LogisticRegression(random_state=1234)
logistic_regression_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_lr = logistic_regression_model.predict(X_test)

# Evaluate the model's performance (e.g., accuracy)
training_accuracy = accuracy_score(y_train, logistic_regression_model.predict(X_train))
test_accuracy = accuracy_score(y_test, y_pred_lr)

print(f"Training Accuracy: {training_accuracy:.5f}")
print(f"Test Accuracy: {test_accuracy:.5f}")
```

```
Training Accuracy: 0.67215
Test Accuracy: 0.65861
```

In [43]:
```
# Print the classification report for the test set
report = classification_report(y_test, y_pred_lr)
print("Classification Report (Test Set):\n", report)
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.67      0.97      0.79      5188
           1       0.48      0.05      0.10      2674

    accuracy                           0.66      7862
   macro avg       0.57      0.51      0.44      7862
weighted avg       0.60      0.66      0.55      7862
```

GaussianNB

In [44]:
```
# Create and train a Gaussian Naive Bayes classifier
gnb = GaussianNB()
gnb.fit(X_train, y_train)

# Make predictions on the test set
y_pred_gnb = gnb.predict(X_test)

# Evaluate the Gaussian Naive Bayes model's performance (e.g., accuracy)
training_accuracy_gnb = accuracy_score(y_train, gnb.predict(X_train))
test_accuracy_gnb = accuracy_score(y_test, y_pred_gnb)

print("Gaussian Naive Bayes:")
print(f"Training Accuracy: {training_accuracy_gnb:.5f}")
print(f"Test Accuracy: {test_accuracy_gnb:.5f}")
```

```
Gaussian Naive Bayes:
Training Accuracy: 0.71849
Test Accuracy: 0.72043
```

In [45]:
```
# Print the classification report for the test set
report = classification_report(y_test, y_pred_gnb)
print("Classification Report (Test Set):\n", report)
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.92      0.63      0.75      5188
           1       0.56      0.89      0.69      2674

    accuracy                           0.72      7862
   macro avg       0.74      0.76      0.72      7862
weighted avg       0.80      0.72      0.73      7862
```

Bernoulli Naive Bayes classifier

In [46]:
```
# Create and train a Bernoulli Naive Bayes classifier
bnb = BernoulliNB()
bnb.fit(X_train, y_train)

# Make predictions on the test set
y_pred_bnb = bnb.predict(X_test)

# Evaluate the Bernoulli Naive Bayes model's performance (e.g., accuracy)
training_accuracy_bnb = accuracy_score(y_train, bnb.predict(X_train))
test_accuracy_bnb = accuracy_score(y_test, y_pred_bnb)

print("Bernoulli Naive Bayes classifier:")
print(f"Training Accuracy: {training_accuracy_gnb:.5f}")
print(f"Test Accuracy: {test_accuracy_gnb:.5f}")
```

```
Bernoulli Naive Bayes classifier:
Training Accuracy: 0.71849
Test Accuracy: 0.72043
```

In [47]:
```
# Print the classification report for the test set
report = classification_report(y_test, y_pred_bnb)
print("Classification Report (Test Set):\n", report)
```

```
Classification Report (Test Set):
              precision    recall  f1-score   support

           0       0.75      0.91      0.82      5188
           1       0.70      0.41      0.52      2674

    accuracy                           0.74      7862
   macro avg       0.73      0.66      0.67      7862
weighted avg       0.73      0.74      0.72      7862
```

Multinomial Naive Bayes classifier

In [48]:
```
# Create and train a Multinomial Naive Bayes classifier
mnb = MultinomialNB()
mnb.fit(X_train, y_train)

# Make predictions on the test set
y_pred_mnb = mnb.predict(X_test)

# Evaluate the Multinomial Naive Bayes model's performance (e.g., accuracy)
training_accuracy_mnb = accuracy_score(y_train, mnb.predict(X_train))
test_accuracy_mnb = accuracy_score(y_test, y_pred_mnb)

print("\nMultinomial Naive Bayes:")
print(f"Training Accuracy: {training_accuracy_mnb:.5f}")
print(f"Test Accuracy: {test_accuracy_mnb:.5f}")
```

```

Multinomial Naive Bayes:
Training Accuracy: 0.46718
Test Accuracy: 0.47393
```

In [49]:
```
# Print the classification report for the test set
report = classification_report(y_test, y_pred_mnb)
print("Classification Report (Test Set):\n", report)
```

```
Classification Report (Test Set):
              precision    recall  f1-score   support

           0       0.95      0.21      0.35      5188
           1       0.39      0.98      0.56      2674

    accuracy                           0.47      7862
   macro avg       0.67      0.60      0.45      7862
weighted avg       0.76      0.47      0.42      7862
```

XGBoost

In [50]:
```
# Create and train an XGBoost classifier
xgb_model = xgb.XGBClassifier(random_state=1234)
xgb_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_xgb = xgb_model.predict(X_test)

# Evaluate the XGBoost model's performance (e.g., accuracy)
training_accuracy_xgb = accuracy_score(y_train, xgb_model.predict(X_train))
test_accuracy_xgb = accuracy_score(y_test, y_pred_xgb)

print("XGBoost Classifier:")
print(f"Training Accuracy: {training_accuracy_xgb:.5f}")
print(f"Test Accuracy: {test_accuracy_xgb:.5f}")
```

```
XGBoost Classifier:
Training Accuracy: 0.94129
Test Accuracy: 0.87344
```

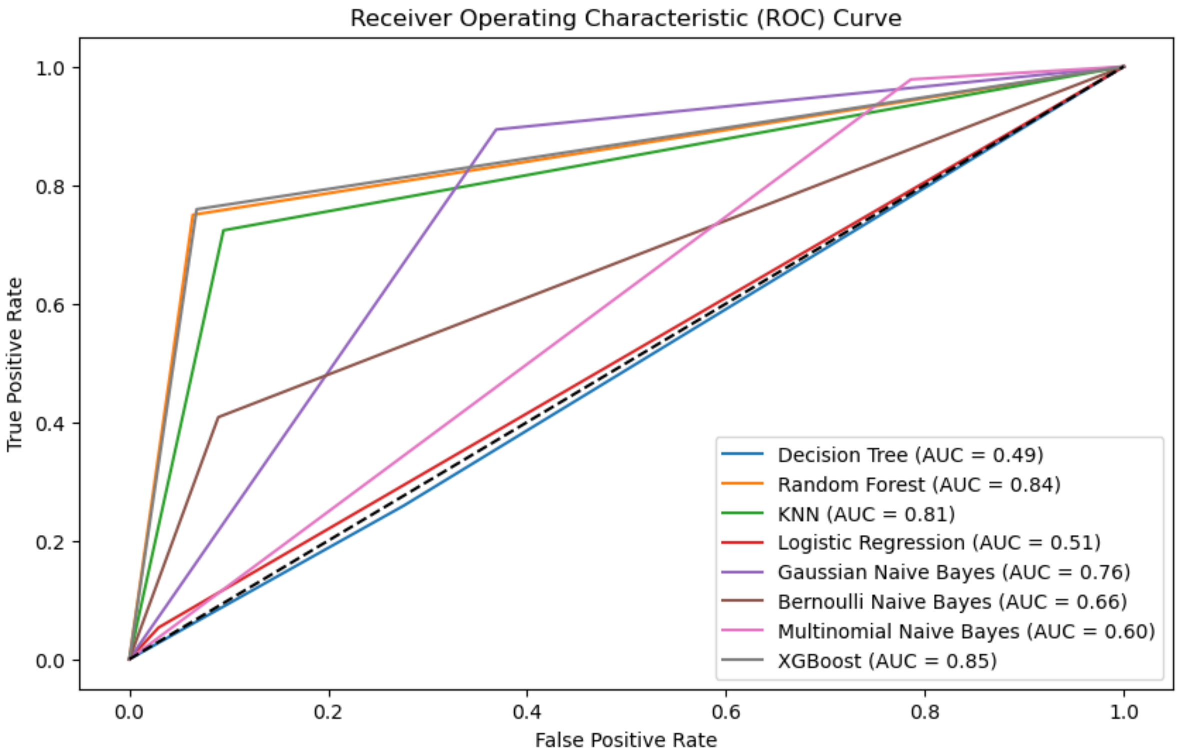
In [51]:
```
# Print the classification report for the test set
report = classification_report(y_test, y_pred_xgb)
print("Classification Report (Test Set):\n", report)
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.88      0.93      0.91      5188
           1       0.85      0.76      0.80      2674

    accuracy                           0.87      7862
   macro avg       0.87      0.85      0.85      7862
weighted avg       0.87      0.87      0.87      7862
```

ROC

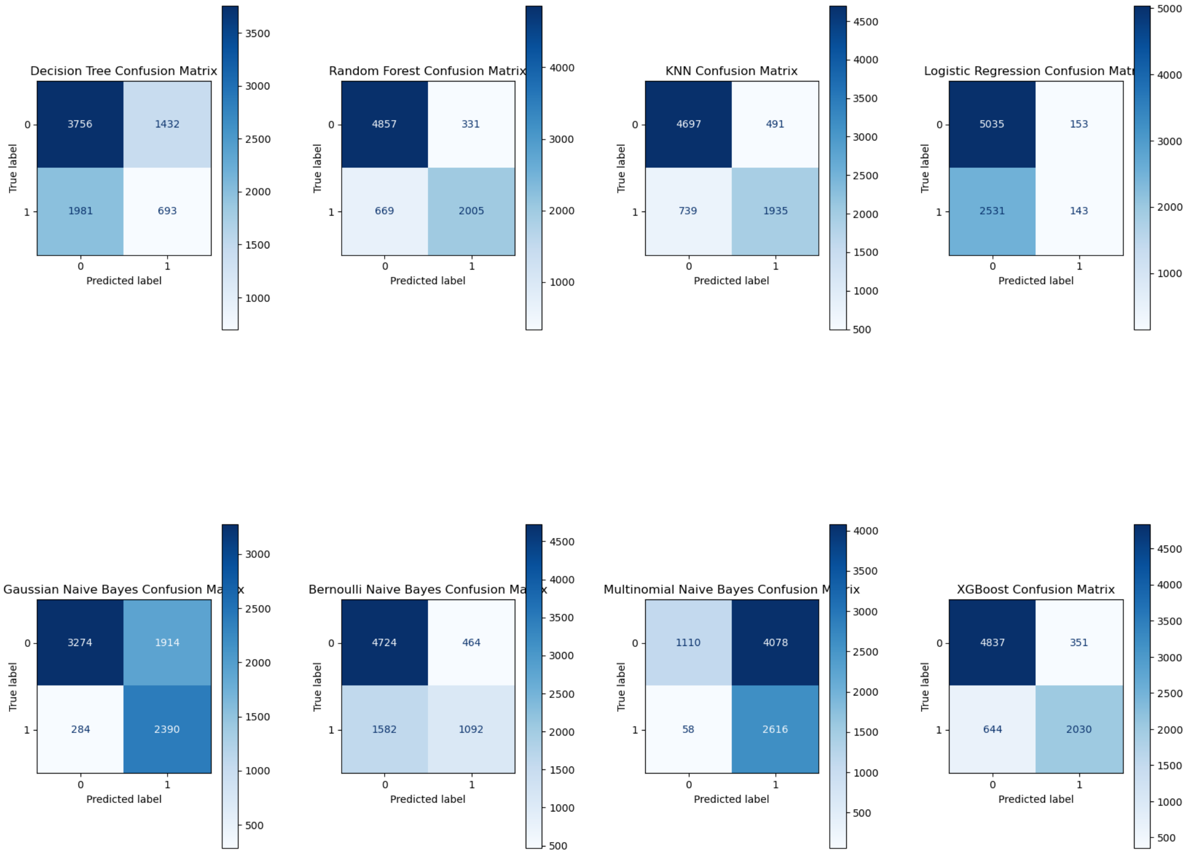
In [52]:
```
# Define the classifiers and their names
classifiers = [
    ('Decision Tree', DecisionTreeClassifier(criterion='entropy', min_samples_leaf=50, min_samples
    ('Random Forest', RandomForestClassifier(random_state=1234)),
    ('KNN', KNeighborsClassifier(n_neighbors=5)),
    ('Logistic Regression', LogisticRegression(random_state=1234)),
    ('Gaussian Naive Bayes', GaussianNB()),
    ('Bernoulli Naive Bayes', BernoulliNB()),
    ('Multinomial Naive Bayes', MultinomialNB()),
    ('XGBoost', xgb.XGBClassifier(random_state=1234))
]
```

In [53]:
```
# Create a figure and axis for the ROC curve plot
plt.figure(figsize=(10, 6))

# Plot ROC curves for each classifier
for clf_name, y_pred in zip(classifiers, [y_pred_test, y_pred_rf, y_pred_knn, y_pred_lr, y_pred_gr
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'{clf_name[0]} (AUC = {roc_auc:.2f})')

# Plot the diagonal line (random classifier)
plt.plot([0, 1], [0, 1], 'k--')

# Set labels and legend
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')

# Show the ROC curve plot
plt.show()
```



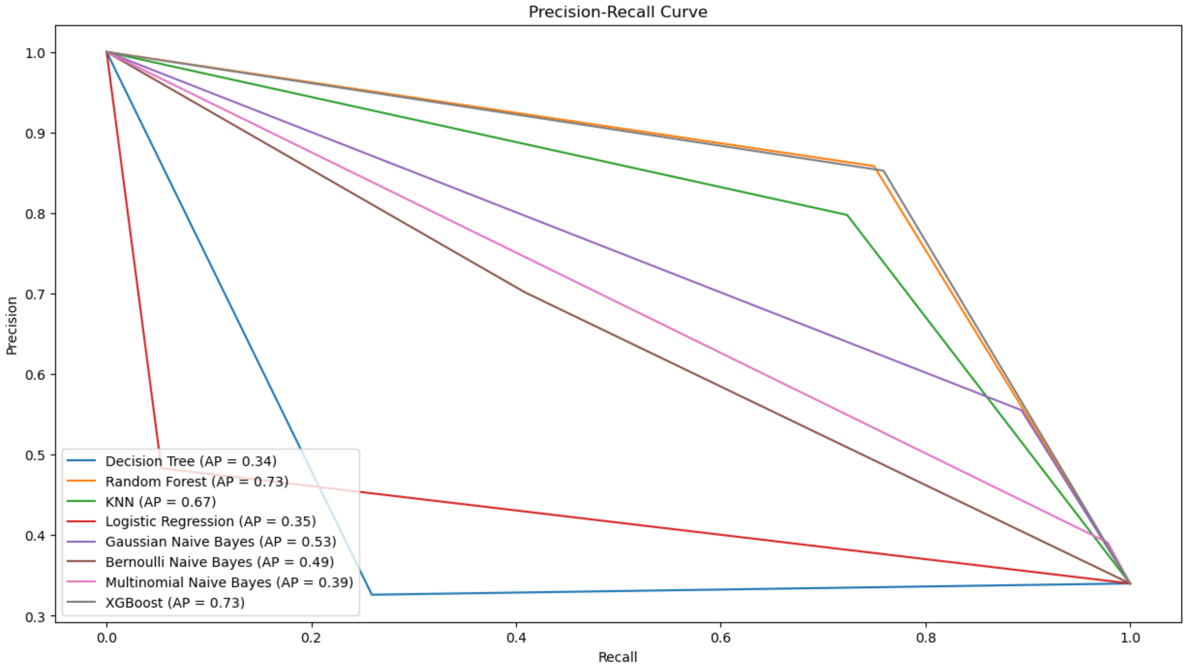
Confusion Matrix

In [54]:
```
# Create a figure and axis for the confusion matrix plot
fig, axes = plt.subplots(2, 4, figsize=(20, 15))
plt.subplots_adjust(wspace=0.4, hspace=0.6)

# Plot confusion matrices for each classifier
for i, (clf_name, y_pred) in enumerate(zip(classifiers, [y_pred_test, y_pred_rf, y_pred_knn, y_pre
    ax = axes[i // 4, i % 4]
    cm = confusion_matrix(y_test, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[0, 1])
    disp.plot(cmap=plt.cm.Blues, ax=ax)
    ax.set_title(f'{clf_name[0]} Confusion Matrix')

# Show the confusion matrix plot
plt.show()
```



Precision and Recall Curve

In [55]:
```
# Create a figure and axis for the Precision-Recall curve plot
plt.figure(figsize=(15, 8))

# Plot Precision-Recall curves for each classifier
for clf_name, y_pred in zip(classifiers, [y_pred_test, y_pred_rf, y_pred_knn, y_pred_lr, y_pred_gr
    precision, recall, _ = precision_recall_curve(y_test, y_pred)
    average_precision = average_precision_score(y_test, y_pred)
    plt.plot(recall, precision, label=f'{clf_name[0]} (AP = {average_precision:.2f})')

# Set labels and legend
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc='lower left')

# Show the Precision-Recall curve plot
plt.show()
```



Comparison of Models

In [56]:
```
# Define the models and their predictions
models = [
    ("Decision Tree", y_pred_test),
    ("Random Forest", y_pred_rf),
    ("KNN", y_pred_knn),
    ("Logistic Regression", y_pred_lr),
    ("Gaussian Naive Bayes", y_pred_gnb),
    ("XGBoost", y_pred_xgb)
]

# Create an empty DataFrame to store the classification reports
report_df = pd.DataFrame(columns=["Model", "Accuracy", "Precision", "Recall", "F1-Score", "Support

# Iterate through the models and calculate classification reports
for model_name, y_pred in models:
    report = classification_report(y_test, y_pred, output_dict=True)
    accuracy = accuracy_score(y_test, y_pred)
    report_dict = {
        "Model": model_name,
        "Accuracy": accuracy,
        "Precision": report["weighted avg"]["precision"],
        "Recall": report["weighted avg"]["recall"],
        "F1-Score": report["weighted avg"]["f1-score"],
        "Support": report["weighted avg"]["support"]
    }
    report_df = report_df.append(report_dict, ignore_index=True)

# Print the comparison table
print(report_df)
```

```
                  Model  Accuracy  Precision    Recall  F1-Score Support
0         Decision Tree  0.565887   0.542942  0.565887  0.551963    7862
1         Random Forest  0.872806   0.871919  0.872806  0.870522    7862
2                   KNN  0.843551   0.841455  0.843551  0.841573    7862
3   Logistic Regression  0.658611   0.603450  0.658611  0.553767    7862
4  Gaussian Naive Bayes  0.720427   0.796077  0.720427  0.727028    7862
5               XGBoost  0.873442   0.872327  0.873442  0.871512    7862
```

Hyper Parameter Tunning

Decision Tree Classifier

In [57]:
```python
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)

# Define the DecisionTreeClassifier
dt = DecisionTreeClassifier(random_state=101)

# Define the hyperparameters and their possible values for tuning
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 10, 20, 30, 40, 50],
    'min_samples_split': [2, 5, 10, 20],
    'min_samples_leaf': [1, 2, 4, 8]
}

# Create a GridSearchCV object with cross-validation (e.g., 5-fold cross-validation)
grid_search = GridSearchCV(estimator=dt, param_grid=param_grid, cv=5, scoring='accuracy', verbose=

# Perform the grid search on the training data
grid_search.fit(X_train, y_train)

# Get the best hyperparameters and the corresponding model
best_params = grid_search.best_params_
best_dt_model = grid_search.best_estimator_

# Train the best model on the entire training dataset
best_dt_model.fit(X_train, y_train)

# Make predictions on the test set using the best model
y_pred_test = best_dt_model.predict(X_test)

# Evaluate the best model's performance
test_accuracy = accuracy_score(y_test, y_pred_test)

# Print the best hyperparameters and test accuracy
print("Best Hyperparameters:", best_params)
print("Test Accuracy with Best Model: {:.5f}".format(test_accuracy))
```

```
Fitting 5 folds for each of 192 candidates, totalling 960 fits
Best Hyperparameters: {'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf': 1, 'min_samp
les_split': 20}
Test Accuracy with Best Model: 0.85487
```

In [58]:
```python
# Make predictions on the test set using the best model
y_pred_test_dt = best_dt_model.predict(X_test)

# Generate the classification report
report = classification_report(y_test, y_pred_test_dt)

# Print the classification report
print("Classification Report (Test Set):\n", report)
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.86      0.93      0.90      5260
           1       0.84      0.70      0.76      2602

    accuracy                           0.85      7862
   macro avg       0.85      0.82      0.83      7862
weighted avg       0.85      0.85      0.85      7862
```

Random Forest

In [59]:
```python
# Define the RandomForestClassifier with a smaller set of hyperparameters
model = RandomForestClassifier(n_estimators=100, max_depth=10, random_state=1234)

# Train the model on the training dataset
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_rf = model.predict(X_test)

# Evaluate the model's performance
training_accuracy = accuracy_score(y_train, model.predict(X_train))
test_accuracy = accuracy_score(y_test, y_pred_rf)

# Print the classification report
report = classification_report(y_test, y_pred_rf)
print("Classification Report (Test Set):\n", report)

# Print training and test accuracy
print(f"Training Accuracy: {training_accuracy:.5f}")
print(f"Test Accuracy: {test_accuracy:.5f}")
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.86      0.93      0.90      5260
           1       0.84      0.70      0.76      2602

    accuracy                           0.86      7862
   macro avg       0.85      0.82      0.83      7862
weighted avg       0.85      0.86      0.85      7862

Training Accuracy: 0.90373
Test Accuracy: 0.85589
```

KNN

In [60]:
```python
# Define the KNeighborsClassifier with a smaller set of hyperparameters
knn_model = KNeighborsClassifier(n_neighbors=5, weights='uniform', p=2)

# Train the model on the training dataset
knn_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_knn = knn_model.predict(X_test)

# Evaluate the model's performance
training_accuracy = accuracy_score(y_train, knn_model.predict(X_train))
test_accuracy = accuracy_score(y_test, y_pred_knn)

# Print the classification report
report = classification_report(y_test, y_pred_knn)
print("Classification Report (Test Set):\n", report)

# Print training and test accuracy
print(f"Training Accuracy: {training_accuracy:.5f}")
print(f"Test Accuracy: {test_accuracy:.5f}")
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.87      0.91      0.89      5260
           1       0.79      0.72      0.75      2602

    accuracy                           0.84      7862
   macro avg       0.83      0.81      0.82      7862
weighted avg       0.84      0.84      0.84      7862

Training Accuracy: 0.88465
Test Accuracy: 0.84355
```

Logistic Regression

In [61]:
```python
# Define the LogisticRegression model with default hyperparameters
logistic_regression_model = LogisticRegression(random_state=1234)

# Train the model on the training dataset
logistic_regression_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_lr = logistic_regression_model.predict(X_test)

# Evaluate the model's performance
training_accuracy = accuracy_score(y_train, logistic_regression_model.predict(X_train))
test_accuracy = accuracy_score(y_test, y_pred_lr)

# Print the classification report
report = classification_report(y_test, y_pred_lr)
print("Classification Report (Test Set):\n", report)

# Print training and test accuracy
print(f"Training Accuracy: {training_accuracy:.5f}")
print(f"Test Accuracy: {test_accuracy:.5f}")
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.67      0.97      0.80      5260
           1       0.47      0.05      0.09      2602

    accuracy                           0.67      7862
   macro avg       0.57      0.51      0.44      7862
weighted avg       0.61      0.67      0.56      7862

Training Accuracy: 0.66861
Test Accuracy: 0.66726
```

Gaussian Naive Bayes

In [62]:
```python
# Create and train a Gaussian Naive Bayes classifier
gnb = GaussianNB()
gnb.fit(X_train, y_train)

# Make predictions on the test set
y_pred_gnb = gnb.predict(X_test)

# Evaluate the Gaussian Naive Bayes model's performance
training_accuracy_gnb = accuracy_score(y_train, gnb.predict(X_train))
test_accuracy_gnb = accuracy_score(y_test, y_pred_gnb)

# Print the classification report
report = classification_report(y_test, y_pred_gnb)
print("Classification Report (Test Set):\n", report)

# Print training and test accuracy
print("Gaussian Naive Bayes:")
print(f"Training Accuracy: {training_accuracy_gnb:.5f}")
print(f"Test Accuracy: {test_accuracy_gnb:.5f}")
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.93      0.60      0.73      5260
           1       0.53      0.90      0.67      2602

    accuracy                           0.70      7862
   macro avg       0.73      0.75      0.70      7862
weighted avg       0.79      0.70      0.71      7862

Gaussian Naive Bayes:
Training Accuracy: 0.69925
Test Accuracy: 0.69957
```

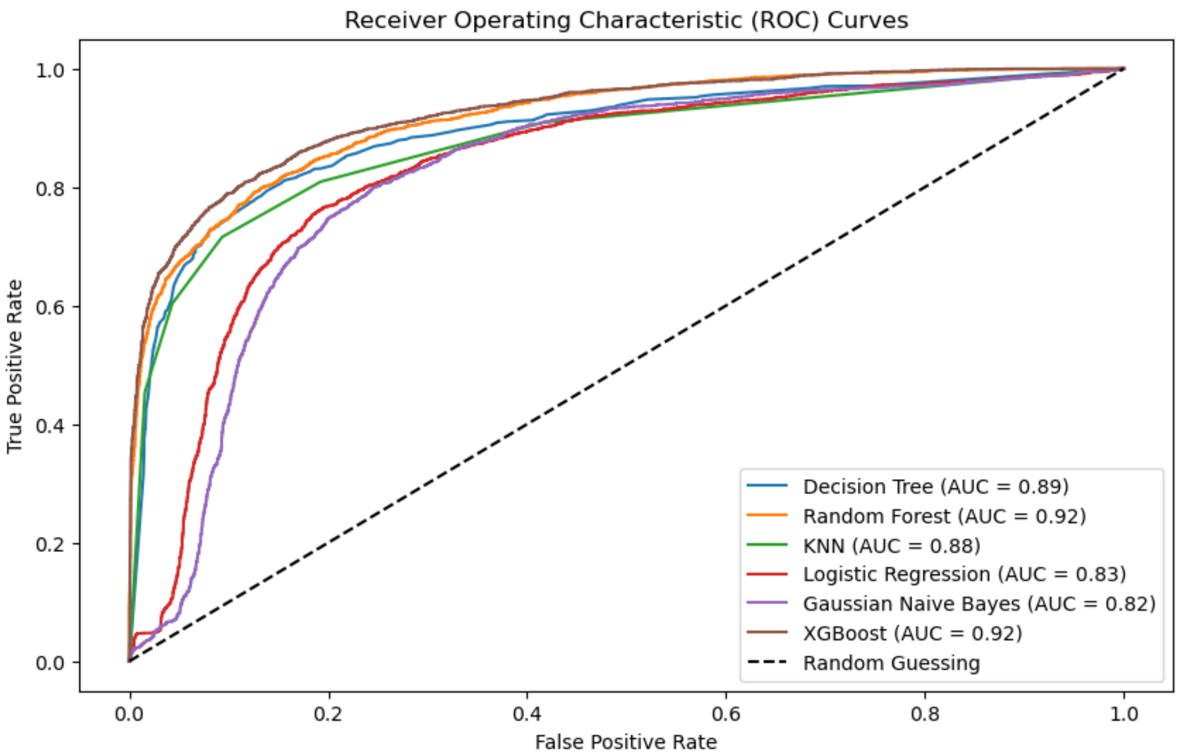
XG Boost

In [63]:
```python
# Create and train an XGBoost classifier with default hyperparameters
xgb_model = xgb.XGBClassifier(random_state=1234)
xgb_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_xgb = xgb_model.predict(X_test)

# Evaluate the XGBoost model's performance
training_accuracy_xgb = accuracy_score(y_train, xgb_model.predict(X_train))
test_accuracy_xgb = accuracy_score(y_test, y_pred_xgb)

# Print the classification report
report = classification_report(y_test, y_pred_xgb)
print("Classification Report (Test Set):\n", report)

# Print training and test accuracy
print("XGBoost Classifier:")
print(f"Training Accuracy: {training_accuracy_xgb:.5f}")
print(f"Test Accuracy: {test_accuracy_xgb:.5f}")
```

```
Classification Report (Test Set):
               precision    recall  f1-score   support

           0       0.88      0.93      0.91      5260
           1       0.85      0.74      0.79      2602

    accuracy                           0.87      7862
   macro avg       0.86      0.84      0.85      7862
weighted avg       0.87      0.87      0.87      7862

XGBoost Classifier:
Training Accuracy: 0.94271
Test Accuracy: 0.86912
```

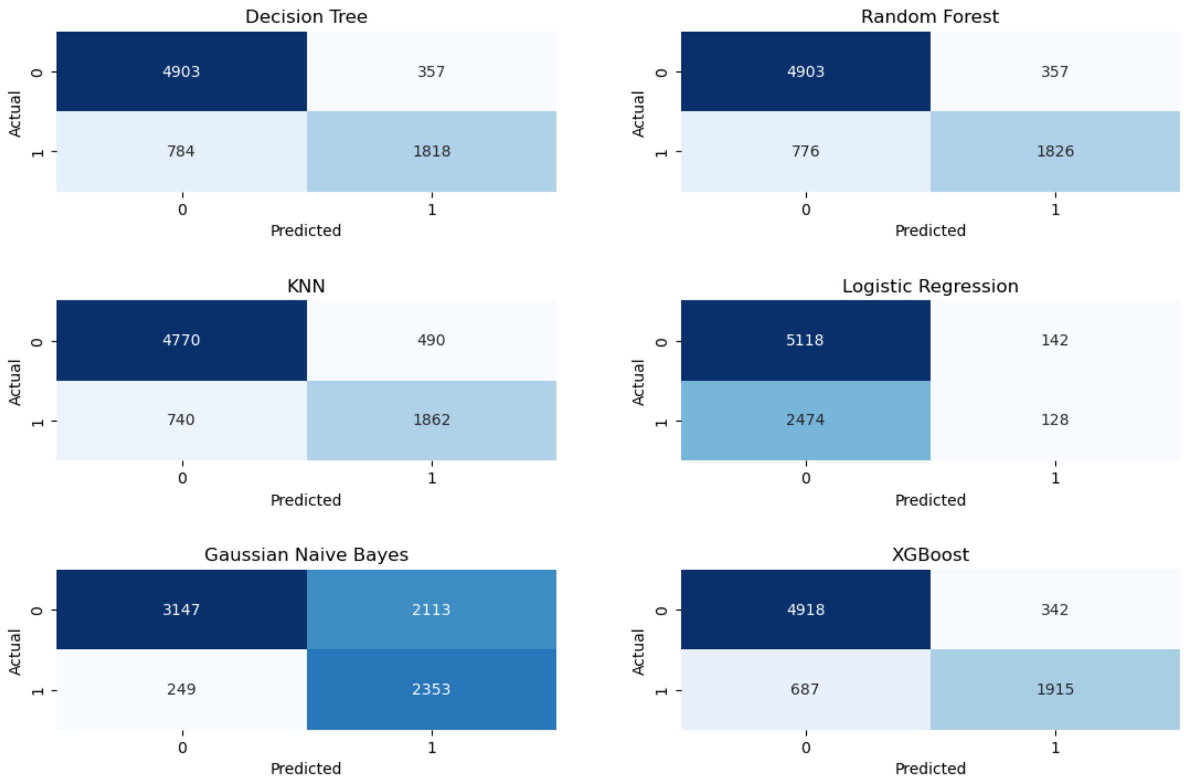
ROC

In [64]:
```python
# Define the models and their names
models = [
    (best_dt_model, "Decision Tree"),
    (model, "Random Forest"),
    (knn_model, "KNN"),
    (logistic_regression_model, "Logistic Regression"),
    (gnb, "Gaussian Naive Bayes"),
    (xgb_model, "XGBoost")
]

# Set up the plot
plt.figure(figsize=(10, 6))

# Iterate through the models
for model, model_name in models:
    # Get the predicted probabilities for class 1 (positive class)
    if hasattr(model, "predict_proba"):
        y_score = model.predict_proba(X_test)[:, 1]
    else:
        y_score = model.decision_function(X_test)

    # Compute ROC curve and ROC area
    fpr, tpr, _ = roc_curve(y_test, y_score)
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve for each model
    plt.plot(fpr, tpr, label=f'{model_name} (AUC = {roc_auc:.2f})')

# Plot ROC curve for random guessing
plt.plot([0, 1], [0, 1], 'k--', label='Random Guessing')

# Set plot labels and legend
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curves')
plt.legend(loc='lower right')

# Show the plot
plt.show()
```



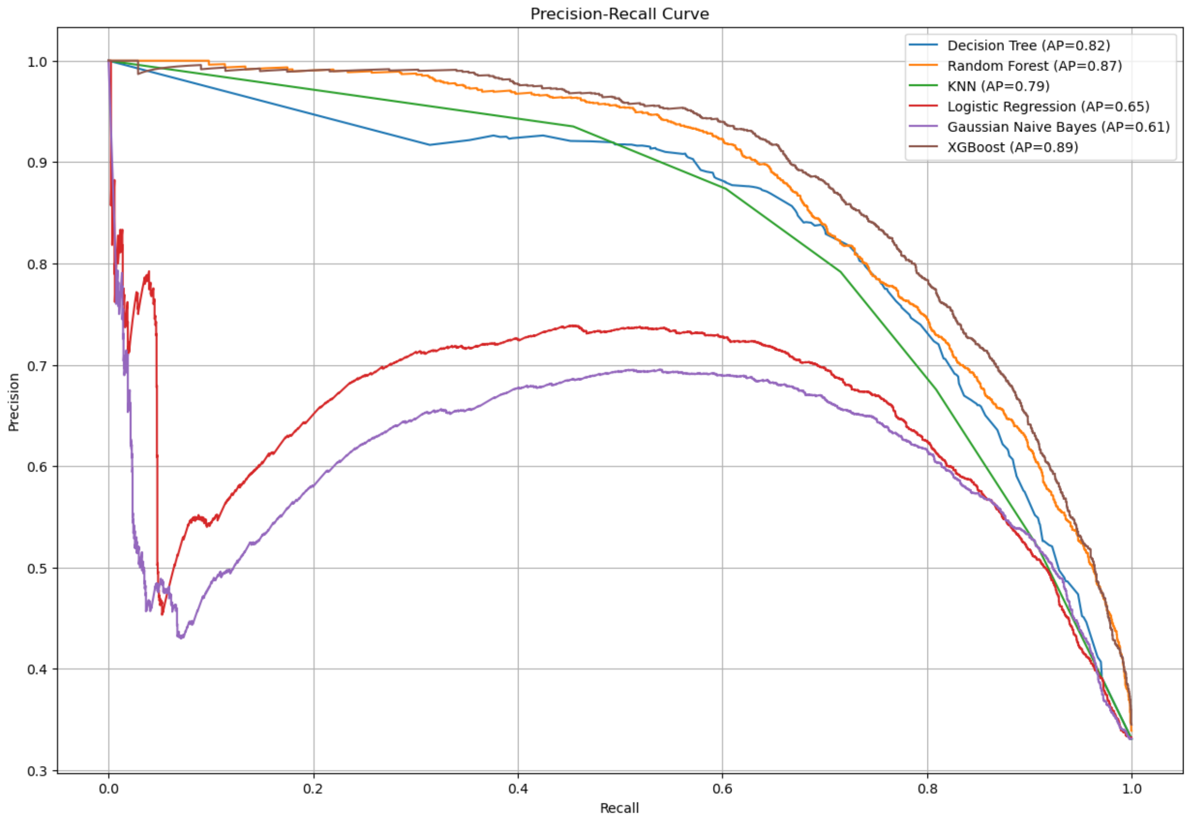
Confusion Matrix

In [65]:
```python
# Set up the plot grid
num_models = len(models)
cols = 2  # Number of columns in the plot grid
rows = (num_models + 1) // cols  # Calculate the number of rows

# Set up the overall figure
fig, axes = plt.subplots(rows, cols, figsize=(12, 8))
fig.tight_layout(pad=5.0)  # Adjust the spacing between subplots

# Iterate through the models
for i, (model, model_name) in enumerate(models):
    # Calculate the position of the current subplot in the grid
    ax = axes[i // cols, i % cols]

    # Get predicted labels
    y_pred = model.predict(X_test)

    # Calculate the confusion matrix
    cm = confusion_matrix(y_test, y_pred)

    # Plot the confusion matrix as a heatmap
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False, ax=ax)
    ax.set_title(f'{model_name}')
    ax.set_xlabel('Predicted')
    ax.set_ylabel('Actual')

# Adjust layout for the last subplot if the number of models is odd
if num_models % 2 != 0:
    fig.delaxes(axes[rows - 1, cols - 1])

# Show the plot
plt.show()
```



Precision and Recall

In [66]:
```python
# Set up the plot
plt.figure(figsize=(15, 10))

# Iterate through the models
for model, model_name in models:
    # Get predicted probabilities for the positive class
    if hasattr(model, "predict_proba"):
        y_probs = model.predict_proba(X_test)[:, 1]
    else:
        y_probs = model.decision_function(X_test)

    # Calculate precision-recall curve values
    precision, recall, _ = precision_recall_curve(y_test, y_probs)

    # Calculate the average precision score
    average_precision = average_precision_score(y_test, y_probs)

    # Plot the precision-recall curve
    plt.plot(recall, precision, label=f'{model_name} (AP={average_precision:.2f})')

# Set plot labels and legend
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc='best')

# Show the plot
plt.grid()
plt.show()
```



In [67]:

```
# Define the models and their predictions
models = [
    ("Decision Tree", y_pred_test_dt),
    ("Random Forest", y_pred_rf),
    ("KNN", y_pred_knn),
    ("Logistic Regression", y_pred_lr),
    ("Gaussian Naive Bayes", y_pred_gnb),
    ("XGBoost", y_pred_xgb)
]

# Create an empty DataFrame to store the results
report_df = pd.DataFrame(columns=["Model", "Precision", "Recall", "F1-Score", "Support", "Accuracy

# Iterate through the models and calculate classification reports
for model_name, y_pred in models:
    report = classification_report(y_test, y_pred, output_dict=True)
    accuracy = accuracy_score(y_test, y_pred)
    report_dict = {
        "Model": model_name,
        "Precision": report["weighted avg"]["precision"],
        "Recall": report["weighted avg"]["recall"],
        "F1-Score": report["weighted avg"]["f1-score"],
        "Support": report["weighted avg"]["support"],
        "Accuracy": accuracy
    }
    report_df = report_df.append(report_dict, ignore_index=True)

# Print the comparison table
print(report_df)
```

```
                  Model  Precision    Recall  F1-Score Support  Accuracy
0         Decision Tree   0.853444  0.854872  0.851216    7862  0.854872
1         Random Forest   0.854456  0.855889  0.852339    7862  0.855889
2                   KNN   0.841197  0.843551  0.841420    7862  0.843551
3   Logistic Regression   0.607920  0.667260  0.562359    7862  0.667260
4  Gaussian Naive Bayes   0.794358  0.699568  0.706835    7862  0.699568
5               XGBoost   0.867846  0.869117  0.866549    7862  0.869117
```

Comparison with and without Hyper Parameter Tunning

In [68]:
```
# Print the table after hyperparameter tuning
print("Table after Hyperparameter Tuning:")
print(report_df)

# Define the models and their predictions (before tuning)
models_before_tuning = [
    ("Decision Tree", y_pred_test),
    ("Random Forest", y_pred_rf),
    ("KNN", y_pred_knn),
    ("Logistic Regression", y_pred_lr),
    ("Gaussian Naive Bayes", y_pred_gnb),
    ("XGBoost", y_pred_xgb)
]

# Create an empty DataFrame to store the classification reports (before tuning)
report_df_before_tuning = pd.DataFrame(columns=["Model", "Accuracy", "Precision", "Recall", "F1-Sc

# Iterate through the models and calculate classification reports (before tuning)
for model_name, y_pred in models_before_tuning:
    report = classification_report(y_test, y_pred, output_dict=True)
    accuracy = accuracy_score(y_test, y_pred)
    report_dict = {
        "Model": model_name,
        "Accuracy": accuracy,
        "Precision": report["weighted avg"]["precision"],
        "Recall": report["weighted avg"]["recall"],
        "F1-Score": report["weighted avg"]["f1-score"],
        "Support": report["weighted avg"]["support"]
    }
    report_df_before_tuning = report_df_before_tuning.append(report_dict, ignore_index=True)

# Print the table before hyperparameter tuning
print("\nTable before Hyperparameter Tuning:")
print(report_df_before_tuning)
```

```
Table after Hyperparameter Tuning:
                  Model  Precision    Recall  F1-Score Support  Accuracy
0         Decision Tree   0.853444  0.854872  0.851216    7862  0.854872
1         Random Forest   0.854456  0.855889  0.852339    7862  0.855889
2                   KNN   0.841197  0.843551  0.841420    7862  0.843551
3   Logistic Regression   0.607920  0.667260  0.562359    7862  0.667260
4  Gaussian Naive Bayes   0.794358  0.699568  0.706835    7862  0.699568
5               XGBoost   0.867846  0.869117  0.866549    7862  0.869117

Table before Hyperparameter Tuning:
                  Model  Accuracy  Precision    Recall  F1-Score Support
0         Decision Tree  0.854872   0.853444  0.854872  0.851216    7862
1         Random Forest  0.855889   0.854456  0.855889  0.852339    7862
2                   KNN  0.843551   0.841197  0.843551  0.841420    7862
3   Logistic Regression  0.667260   0.607920  0.667260  0.562359    7862
4  Gaussian Naive Bayes  0.699568   0.794358  0.699568  0.706835    7862
5               XGBoost  0.869117   0.867846  0.869117  0.866549    7862
```

1) XGBoost has the highest values for Precision, Recall, F1-Score, and Accuracy among all the models. It appears to be the top-performing model after hyperparameter tuning.

2) Random Forest also has high values for Precision, Recall, F1-Score, and Accuracy, making it one of the top-performing models.

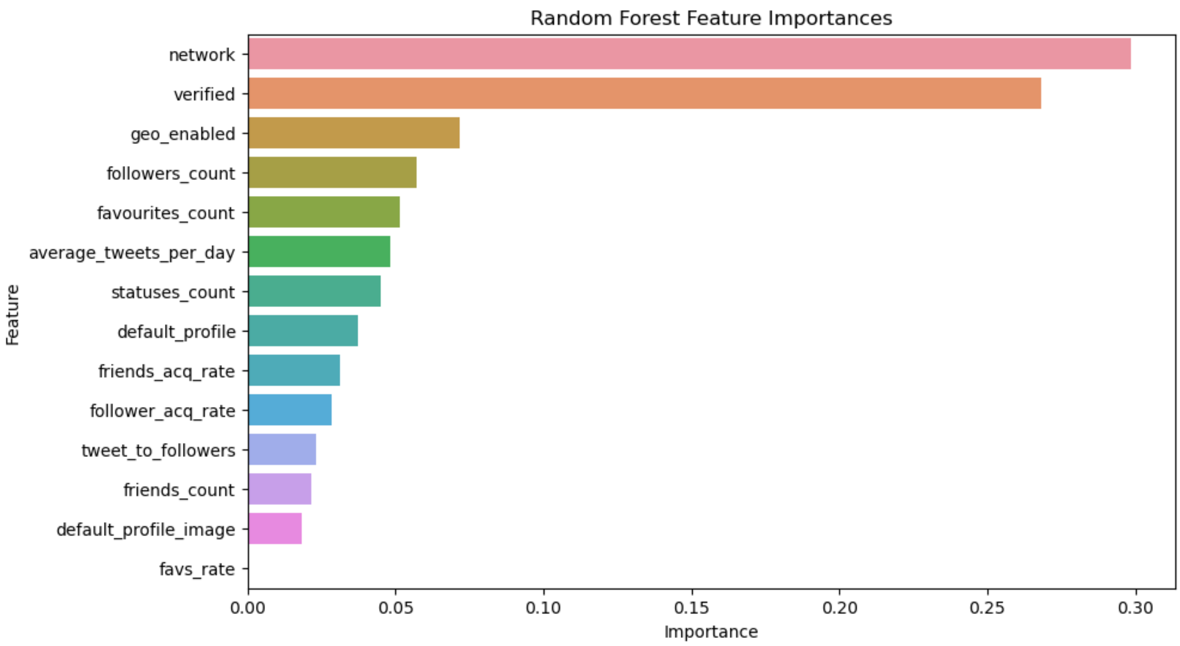
Ensemble Learning

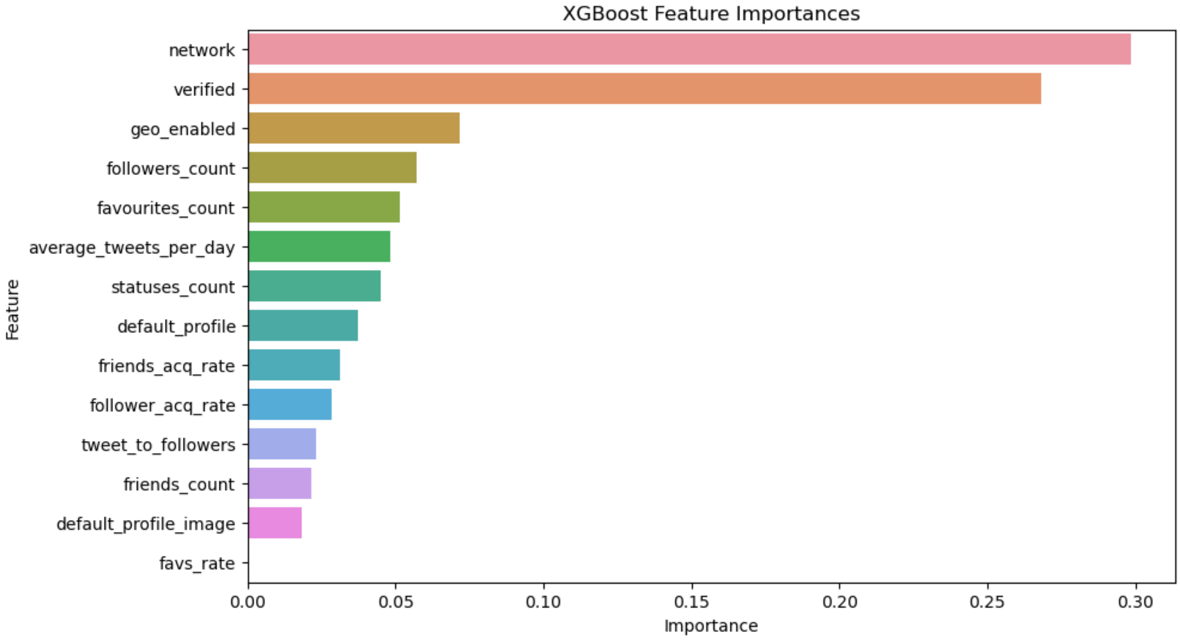
In [69]:
```
from sklearn.ensemble import VotingClassifier

# Create individual models
model_rf = RandomForestClassifier(n_estimators=100, max_depth=10, random_state=1234)
model_xgb = xgb.XGBClassifier(random_state=1234)

# Create a VotingClassifier
ensemble_model = VotingClassifier(estimators=[
    ('Random Forest', model_rf),
    ('XGBoost', model_xgb)
], voting='soft')  # 'soft' for weighted average, 'hard' for majority vote

# Train the ensemble model on the training dataset
ensemble_model.fit(X_train, y_train)

# Make predictions on the test set using the ensemble model
y_pred_ensemble = ensemble_model.predict(X_test)

# Evaluate the ensemble model's performance
training_accuracy_ensemble = accuracy_score(y_train, ensemble_model.predict(X_train))
test_accuracy_ensemble = accuracy_score(y_test, y_pred_ensemble)

# Print the classification report for the ensemble model
report_ensemble = classification_report(y_test, y_pred_ensemble)
print("Classification Report (Test Set) - Ensemble:\n", report_ensemble)

# Print training and test accuracy for the ensemble model
print("Ensemble Model:")
print(f"Training Accuracy: {training_accuracy_ensemble:.5f}")
print(f"Test Accuracy: {test_accuracy_ensemble:.5f}")
```

```
Classification Report (Test Set) - Ensemble:
               precision    recall  f1-score   support

           0       0.87      0.94      0.91      5260
           1       0.86      0.72      0.78      2602

    accuracy                           0.87      7862
   macro avg       0.87      0.83      0.84      7862
weighted avg       0.87      0.87      0.87      7862

Ensemble Model:
Training Accuracy: 0.92826
Test Accuracy: 0.86848
```

Feature Importance Chart

In [70]:
```python
# Feature importances for RandomForestClassifier
rf_feature_importances = model.feature_importances_

# Get the column names (feature names)
feature_names = X.columns

# Create a DataFrame to store feature names and their importances
rf_feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': rf_feature_import

# Sort the DataFrame by importance in descending order
rf_feature_importance_df = rf_feature_importance_df.sort_values(by='Importance', ascending=False)

# Plot the feature importances for RandomForestClassifier
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=rf_feature_importance_df)
plt.title('Random Forest Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()

# Feature importances for XGBoostClassifier
xgb_feature_importances = xgb_model.feature_importances_

# Create a DataFrame to store feature names and their importances for XGBoost
xgb_feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': xgb_feature_impo

# Sort the DataFrame by importance in descending order
xgb_feature_importance_df = xgb_feature_importance_df.sort_values(by='Importance', ascending=False

# Plot the feature importances for XGBoostClassifier
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=xgb_feature_importance_df)
plt.title('XGBoost Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```




XGBoost Feature Importances
network
verified
geo_enabled
followers_count
favourites_count
average_tweets_per_day
statuses_count
default_profile
friends_acq_rate
follower_acq_rate
tweet_to_followers
friends_count
default_profile_image
favs_rate
Feature
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Importance

```
In [ ]:
```