In [370]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import time
from scipy.stats import pearsonr
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.tree import plot_tree
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import roc_curve
from sklearn.metrics import accuracy_score
from sklearn.ensemble import BaggingClassifier
from imblearn.over_sampling import RandomOverSampler
pd.set_option('display.max_columns', None)
```

In [257]:
```
#Load All Scraped Data
user_stats = pd.read_csv("userStats.csv")
trending = pd.read_csv("trendingStats.csv", index_col=[0])
trending1718 = pd.read_csv("trendingStats-1718.csv", index_col=[0])
users_updated = pd.read_csv("users_updated.csv", index_col=[0])

users_4th = pd.read_csv('userStats5_4.csv')
trending_4th = pd.read_csv('trendingStats5_4.csv')
trending_4th.head()
```

Out[257]:

	Unnamed: 0	date_run	songTitle	authorName	private	duration	album	scheduleSe
0	6926430057246280453	05/04/21	Моя голова винтом	✨ Марго✌🏼	False	9	NaN	
1	6956939305335933701	05/04/21	suono originale	Khabane lame	False	23	NaN	
2	6945541245435381761	05/04/21	deja vu	Olivia Rodrigo	False	45	deja vu	
3	6840149587802475270	05/04/21	sonido original	George-G	False	8	NaN	
4	6757872491160406017	05/04/21	Teach Me How To Dougie	Classics Reborn	False	30	Teach Me How To Dougie	

In [258]:
```
#Reformat Indices and Column Names for Consistency
users_updated.rename(columns = {'Unnamed: 0.1': 'userID'}, inplace = Tru
e)
users_updated.reset_index(drop=True, inplace=True)
trending1718.reset_index(drop=True, inplace=True)
trending.reset_index(drop=True, inplace=True)
user_stats.rename(columns = {'Unnamed: 0': 'userID'}, inplace = True)
users_4th.rename(columns = {'Unnamed: 0': 'userID'}, inplace = True)
trending_4th.rename(columns = {'Unnamed: 0': 'soundID'}, inplace = True)

users_updated.head()
```

Out[258]:

	userID	soundID	date_run	followingCount	followerCount	heartCo
0	6953076077749161222	6947333417029733126	04/29/21	163	607200	10600(
1	6952496938612755717	6947333417029733126	04/29/21	117	1100000	26500(
2	6956386359766420742	6947333417029733126	04/29/21	13	45300000	1000000(
3	6951737718888025346	6947333417029733126	04/29/21	2	418800	4700(
4	6953055168808226054	6947333417029733126	04/29/21	455	2900000	119100(

In [259]:
```
#Concatenate our two user tables
users = pd.concat([user_stats, users_updated]).drop_duplicates()
users_29 = users[users['date_run'] == '04/29/21']
users_30 = users[users['date_run'] == '04/30/21']
users_29.head()
```

Out[259]:

	userID	soundID	date_run	followingCount	followerCount	heartCo
0	6953076077749161222	6947333417029733126	04/29/21	163	607200	10600(
1	6952496938612755717	6947333417029733126	04/29/21	117	1100000	26500(
2	6956386359766420742	6947333417029733126	04/29/21	13	45300000	1000000(
3	6951737718888025346	6947333417029733126	04/29/21	2	418800	4700(
4	6953055168808226054	6947333417029733126	04/29/21	455	2900000	119100(

In [260]:
```
#Get mean song data by user statistic
song_data_agg_29 = users_29.groupby(by=["soundID"]).mean()
song_data_agg_30 = users_30.groupby(by=["soundID"]).mean()
song_data_agg_4 = users_4th.groupby(by=["soundID"]).mean()

song_data_agg_29.head()
```

Out[260]:

	userID	followingCount	followerCount	heartCount	videoCount	dig
soundID						
37696	6.837558e+18	980.090	359312.595	9.207480e+06	422.975	17
118053679	6.846653e+18	511.705	1636966.990	5.334481e+07	387.040	10
158840031	6.826014e+18	474.555	252015.535	6.184097e+06	443.345	12
153013783613878272	6.864727e+18	1787.285	11544.580	1.825210e+05	202.750	12
222450775220682752	6.840913e+18	504.020	363976.810	8.794654e+06	445.860	23

In [261]:
```
def data_reformatter(df, columns_list):
    def binary_converter(col):
        convert = []
        for x in np.arange(len(col)):
            if col[x] == True:
                convert.append(1)
            else:
                convert.append(0)
        return convert
    for x in columns_list:
        df[x] = binary_converter(list(df[x]))
    return df

trending1718f = data_reformatter(trending1718, ['private', 'verified',
'openFavorite', 'privateAccount']).drop(columns = ['songTitle', 'uniqueI
d', 'nickname','authorName', 'album', 'secUid'])
trending_4ths = data_reformatter(trending_4th, ['private', 'verified',
'openFavorite', 'privateAccount']).drop(columns = ['songTitle', 'uniqueI
d', 'nickname','authorName', 'album', 'secUid'])


trending1718f['privateAccount'].unique()
```

Out[261]:
```
array([0, 1])
```

In [262]:

```
artist_avg = pd.DataFrame(trending1718f.groupby(by = ['artist_id']).mean
()['numTimesUsed'])
artist_avg_4th = pd.DataFrame(trending_4ths.groupby(by = ['artist_id']).
mean()['numTimesUsed'])

artist_avg = artist_avg.rename(columns = {'numTimesUsed': 'artistAvgPlay
s'})
artist_avg_4th = artist_avg_4th.rename(columns = {'numTimesUsed': 'artis
tAvgPlays'})

trending1718a = pd.merge(trending1718f, artist_avg, left_on = 'artist_i
d', right_on = 'artist_id', how = 'left').drop(columns = ['artist_id'])
trending_4thf = pd.merge(trending_4ths, artist_avg_4th, left_on = 'artis
t_id', right_on = 'artist_id', how = 'left').drop(columns = ['artist_id'
, 'date_run'])


trending1718a.head()
```

Out[262]:

	soundID	date_run	private	duration	scheduleSearchTime	numTimesUsed	crea
0	6947333417029733126	04/29/21	0	18	0	1700000	1.470
1	6853737142045231878	04/29/21	0	9	0	79900	1.571
2	6947428005501668101	04/29/21	0	8	0	627200	
3	6418356150286158594	04/29/21	0	39	0	202100	1.584
4	6956564930254457606	04/29/21	0	16	0	418	1.470

In [263]:
```
trending_29 = trending1718a[trending1718a['date_run'] == '04/29/21'].dro
p(columns = ['date_run'])
trending_30 = trending1718a[trending1718a['date_run'] == '04/30/21'].dro
p(columns = ['date_run'])


train_29th = pd.merge(song_data_agg_29, trending_29, left_on = 'soundID'
, right_on = 'soundID', how='left').drop_duplicates(subset = 'soundID').
drop(columns = 'userID')
test_30th = pd.merge(song_data_agg_30, trending_30, left_on = 'soundID',
right_on = 'soundID', how='left').drop_duplicates(subset = 'soundID').dr
op(columns = 'userID').replace([np.inf, -np.inf], np.nan).dropna(axis=0)
fourth = pd.merge(song_data_agg_4, trending_4thf, left_on = 'soundID', r
ight_on = 'soundID', how='left').drop_duplicates(subset = 'soundID').dro
p(columns = 'userID').replace([np.inf, -np.inf], np.nan).dropna(axis=0)
train_29th.head()
```

Out[263]:

	soundID	followingCount	followerCount	heartCount	videoCount	diggCount	
0	37696	980.090	359312.595	9.207480e+06	422.975	17265.790	9.2
1	118053679	511.705	1636966.990	5.334481e+07	387.040	10901.685	5.3
2	158840031	474.555	252015.535	6.184097e+06	443.345	12472.935	6.1
3	153013783613878272	1787.285	11544.580	1.825210e+05	202.750	12240.250	1.8
4	222450775220682752	504.020	363976.810	8.794654e+06	445.860	23047.290	8.7

In [264]:
```
top25_29 = train_29th.sort_values(by = 'numTimesUsed', ascending = False
).reset_index().loc[:,["soundID", "numTimesUsed"]][0:25]
top25_30 = test_30th.sort_values(by = 'numTimesUsed', ascending = False)
.reset_index().loc[:,["soundID", "numTimesUsed"]][0:25]
top_25_4 = fourth.sort_values(by = 'numTimesUsed', ascending = False).re
set_index().loc[:,["soundID", "numTimesUsed"]][0:25]
top25_29.head()
```

Out[264]:

	soundID	numTimesUsed
0	6800996740322297858	24000000
1	6857275312967796738	14700000
2	6586947002464996102	14600000
3	6791619226181306369	13500000
4	6842582526297393154	11400000

In [265]:
```
#Verify that the top 25 for the 29th and 30th are quite distinct from on
e another
similar = []
for x in list(top25_29):
    if x in list(top25_30):
        similar.append(1)
    else:
        similar.append(0)


#Since there are only two songs that overlap in these days out of the to
p 25, it's okay to use the 29th as train and
#30th as test
sum(similar)
```

Out[265]: 2

In [266]:
```
top_25_29th = []
for x in list(train_29th['soundID']):
    if x in list(top25_29['soundID']):
        top_25_29th.append(1)
    else:
        top_25_29th.append(0)

top_25_30th = []
for x in list(test_30th['soundID']):
    if x in list(top25_30['soundID']):
        top_25_30th.append(1)
    else:
        top_25_30th.append(0)

top_25_4th = []
for x in list(fourth['soundID']):
    if x in list(top_25_4['soundID']):
        top_25_4th.append(1)
    else:
        top_25_4th.append(0)

sum(top_25_30th)
```

Out[266]: 25

In [267]:
```
train_29th['top25'] = top_25_29th
test_30th['top25'] = top_25_30th
fourth['top25'] = top_25_4th

train_29th = train_29th.drop(columns = ['numTimesUsed'])
test_30th = test_30th.drop(columns = ['numTimesUsed'])
fourth = fourth.drop(columns = ['numTimesUsed'])

train_29th.head()
```

Out[267]:

	soundID	followingCount	followerCount	heartCount	videoCount	diggCount	
0	37696	980.090	359312.595	9.207480e+06	422.975	17265.790	9.2
1	118053679	511.705	1636966.990	5.334481e+07	387.040	10901.685	5.3
2	158840031	474.555	252015.535	6.184097e+06	443.345	12472.935	6.1
3	153013783613878272	1787.285	11544.580	1.825210e+05	202.750	12240.250	1.8
4	222450775220682752	504.020	363976.810	8.794654e+06	445.860	23047.290	8.7

In [268]:
```
#See if there's any deviance in average stats between top songs and not
 top songs in training set
train_29th_top_25 = train_29th[train_29th['top25'] == 1]
train_29th_not_25 = train_29th[train_29th['top25'] == 0]

train_29th_top_25.describe().apply(lambda s: s.apply(lambda x: format(x,
'f'))).drop(columns = ['soundID', 'top25'])
```

Out[268]:

	followingCount	followerCount	heartCount	videoCount	diggCount	
count	25.000000	25.000000	25.000000	25.000000	25.000000	25.(
mean	481.871600	5019598.257400	133299180.520000	524.735400	13281.972400	170124100.:
std	171.301201	2620586.597350	59949940.153053	112.619519	7280.686805	144594687.(
min	170.835000	1301581.020000	33230104.000000	342.295000	3810.610000	33230104.(
25%	383.390000	3365115.995000	85846500.000000	433.325000	9971.985000	108846500.(
50%	475.820000	4986643.900000	130368516.000000	531.115000	11548.950000	141368516.(
75%	554.445000	5699672.500000	158095000.000000	579.930000	14477.485000	168209180.(
max	975.470000	15035555.755000	289498725.500000	754.695000	42405.880000	784208725.:

In [269]:
```
train_29th_not_25.describe().apply(lambda s: s.apply(lambda x: format(x, 'f'))).drop(columns = ['soundID', 'top25'])
```

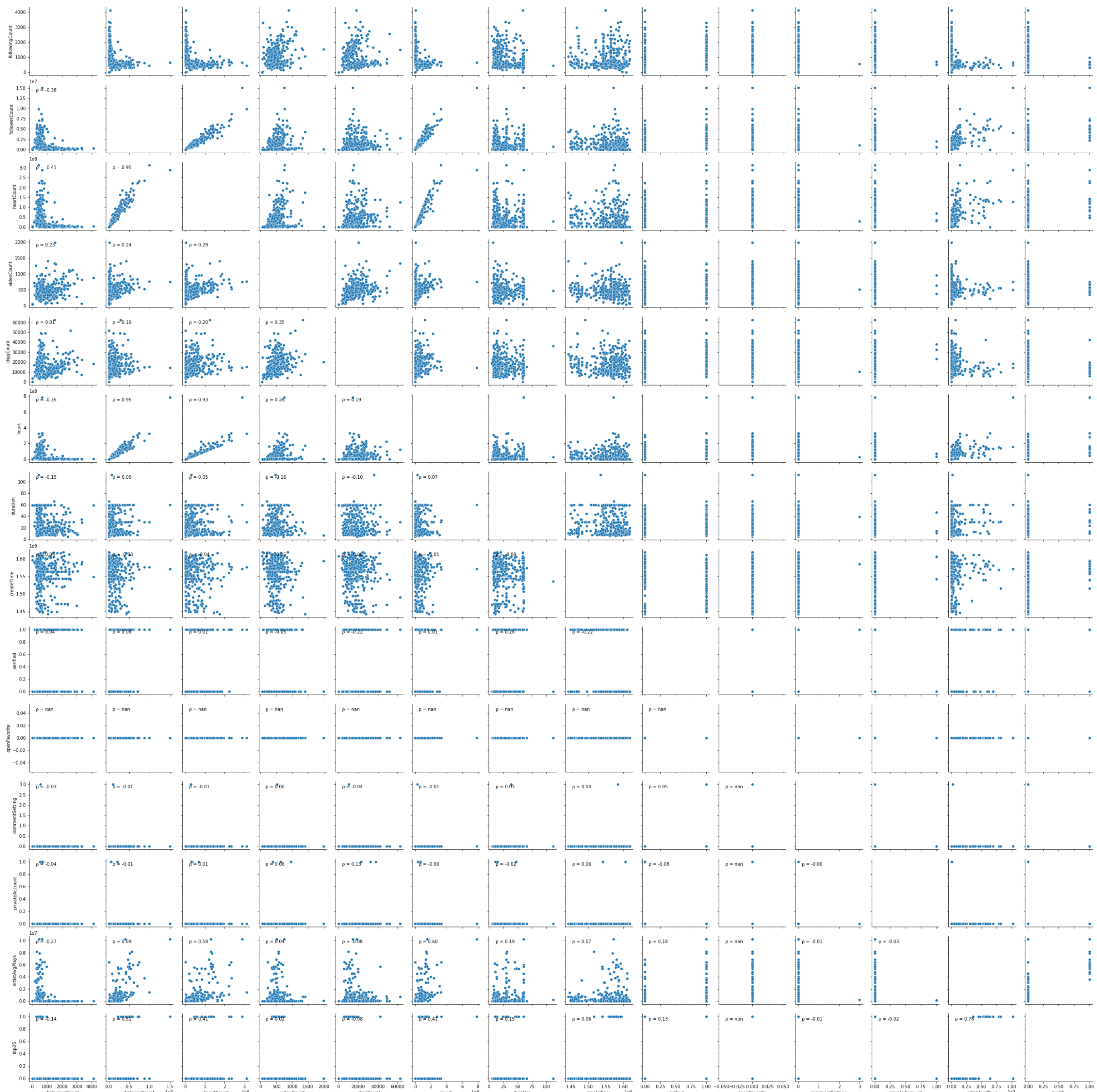
Out[269]:

	followingCount	followerCount	heartCount	videoCount	diggCount	
count	614.000000	614.000000	614.000000	614.000000	614.000000	614.(
mean	864.638853	1137462.854232	35645926.486519	498.892005	16330.551606	40276399.6
std	607.567530	1357039.254676	45005660.255641	266.657496	8922.155117	54223856.7
min	13.000000	574.000000	3224.181818	49.000000	63.000000	3224.1
25%	451.093750	206119.110000	4043681.437500	355.438750	10027.031250	4043681.4
50%	621.377500	660109.861285	17737955.500000	464.298485	14484.656543	18577936.2
75%	1110.042500	1630977.286250	53294209.875000	596.407500	20777.965000	57307454.3
max	4121.666667	9877157.465000	316556770.500000	4429.245000	81069.100000	420333599.5

In [225]:
```
#Visualize our training set with pairplots and correlations between feat
ures
def pairplotter_with_corr(dataset):
    def correlation_plot(x, y, ax=None, **kws):
        r, _ = pearsonr(x, y)
        ax = ax or plt.gca()
        ax.annotate(f'ρ = {r:.2f}', xy=(.1, .9), xycoords=ax.transAxes)
    pairplot = sns.pairplot(dataset, diag_kind = 'scatter')
    pairplot.map_lower(correlation_plot)
    plt.show()

#Drop irrelevant columns from above analysis
irr_cols = ['private', 'scheduleSearchTime', 'relation', 'stitchSetting'
, 'duetSetting', 'soundID']
train_visualizer = train_29th.copy().drop(columns = irr_cols)
train_vis = train_visualizer.replace([np.inf, -np.inf], np.nan).dropna(a
xis=0)
pairplotter_with_corr(train_vis)
```

```
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-pa
ckages/scipy/stats/stats.py:3845: PearsonRConstantInputWarning: An inpu
t array is constant; the correlation coefficent is not defined.
  warnings.warn(PearsonRConstantInputWarning())
```



In [336]:
```
#Drop all irrelevant columns
#This includes both the columns we deemed irrelevant before and features with lower than 0.03 correlation with top25
irrelevant = ['private', 'scheduleSearchTime', 'relation', 'stitchSetting', 'duetSetting', 'followingCount', 'videoCount', 'diggCount', 'openFavorite', 'commentSetting', 'privateAccount']
train_final = train_29th.drop(columns = irrelevant).replace([np.inf, -np.inf], np.nan).dropna(axis=0)
test_final = test_30th.drop(columns = irrelevant).replace([np.inf, -np.inf], np.nan).dropna(axis=0)
fourth_final = fourth.drop(columns = irrelevant).replace([np.inf, -np.inf], np.nan).dropna(axis=0)

train_y = train_final['top25']
train_x = train_final.drop(columns = ['top25'])

test_y = test_final['top25']
test_x = test_final.drop(columns = ['top25'])

fourth_y = fourth_final['top25']
fourth_x = fourth_final.drop(columns = ['top25'])

sum(train_y)
```

Out[336]: 18

In [337]:
```
#Since our data is way too unbalanced, we must sample bootstrap from the training set in order to more accurately train

#Use imblearn to resample our data
ros = RandomOverSampler(random_state=42)

train_x1, train_y1 = ros.fit_resample(train_x, train_y)
```

In [ ]:
```
#Cross validation for our ccp_alpha parameter
grid_values = {'ccp_alpha': np.linspace(0, 0.01, 61),
               'min_samples_leaf': [10],
               'min_samples_split': [20],
               'max_depth': [100],
               'random_state': [2]}
dtr = RandomForestClassifier()
best_ccps = []

#Bootstrap the optimal parameter value from different random states
for x in np.arange(300, 310):
    cv = KFold(n_splits = 5, random_state = x, shuffle = True)
    dtr_cv = GridSearchCV(dtr, param_grid = grid_values, scoring = 'accuracy', cv=cv, verbose=1)
    dtr_cv.fit(train_x, train_y)
    best_ccps.append(dtr_cv.best_params_['ccp_alpha'])
acc = dtr_cv.cv_results_['mean_test_score']
ccp = dtr_cv.cv_results_['param_ccp_alpha'].data
```

In [343]:
```
model = RandomForestClassifier(ccp_alpha = 0.05, min_samples_leaf = 10,
min_samples_split = 20, max_depth = 100)
model.fit(train_x1, train_y1)
predictions = model.predict(test_x)
predictions
```

Out[343]:
```
array([0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
0,
       0, 1, 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, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [344]:
```
#Show confusion matrix results
confusion = confusion_matrix(test_y, predictions)
print ("Confusion Matrix: \n", confusion)
```

```
Confusion Matrix:
 [[72  0]
 [14 11]]
```

In [375]:
```
#Calculate Precision
precision = precision_score(test_y, predictions)
precision
```

Out[375]:
```
1.0
```

In [373]:
```
#Calculate Recall
recall = recall_score(test_y, predictions)
recall
```

Out[373]:
```
0.44
```

In [374]:
```
#Calculate Accuracy Score
acc = accuracy_score(test_y, predictions)
acc
```

Out[374]:
```
0.8556701030927835
```

In [357]:
```
#Calculate FPR
tnr = recall_score(test_y, predictions, pos_label = 0)
fpr = 1 - tnr
fpr
```

Out[357]:
```
0.0
```

In [371]:

```
#Bootstrap Validation
def bootstrap_validation(test_data, test_label, model, metrics_list, sam
ple=500, random_state=66):
    tic = time.time()
    n_sample = sample
    n_metrics = len(metrics_list)
    output_array=np.zeros([n_sample, n_metrics])
    output_array[:]=np.nan
    print(output_array.shape)
    for bs_iter in range(n_sample):
        bs_index = np.random.choice(test_data.index, len(test_data.index
), replace=True)
        bs_data = test_data.loc[bs_index]
        bs_label = test_label.loc[bs_index]
        bs_predicted = model.predict(bs_data)
        for metrics_iter in range(n_metrics):
            metrics = metrics_list[metrics_iter]
            output_array[bs_iter, metrics_iter]=metrics(bs_label,bs_pred
icted)
#         if bs_iter % 100 == 0:
#             print(bs_iter, time.time()-tic)
    output_df = pd.DataFrame(output_array)
    return output_df
bootstrap = bootstrap_validation(test_x, test_y, model, metrics_list = [
accuracy_score, precision_score, recall_score], sample = 500)
bootstrap
```

```
(500, 3)
```

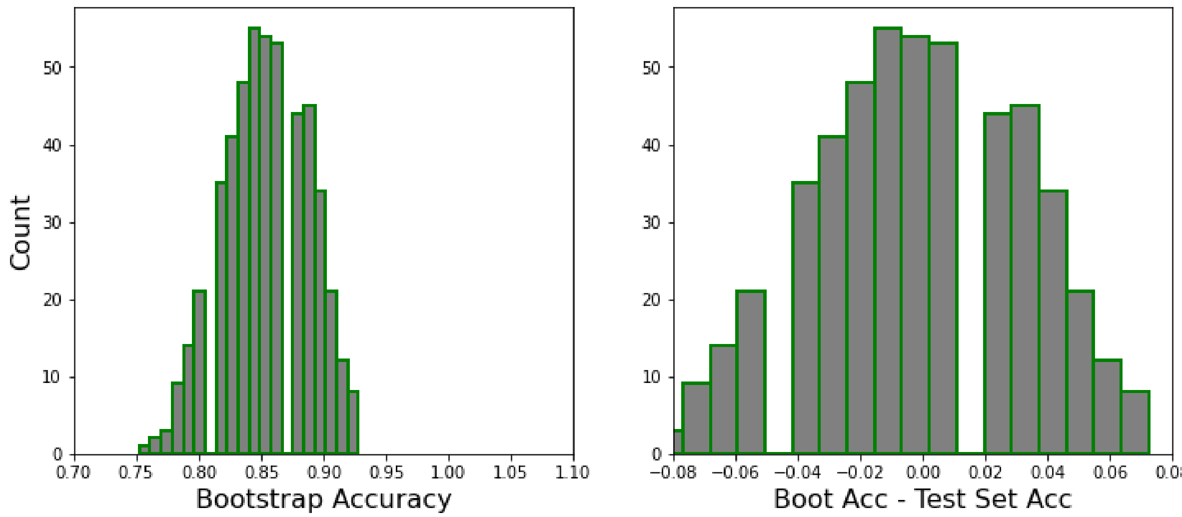
Out[371]:

	0	1	2
0	0.876289	1.0	0.538462
1	0.824742	1.0	0.346154
2	0.845361	1.0	0.347826
3	0.886598	1.0	0.450000
4	0.886598	1.0	0.560000
...	...	...	...
495	0.814433	1.0	0.437500
496	0.865979	1.0	0.458333
497	0.865979	1.0	0.409091
498	0.896907	1.0	0.545455
499	0.865979	1.0	0.500000

500 rows × 3 columns

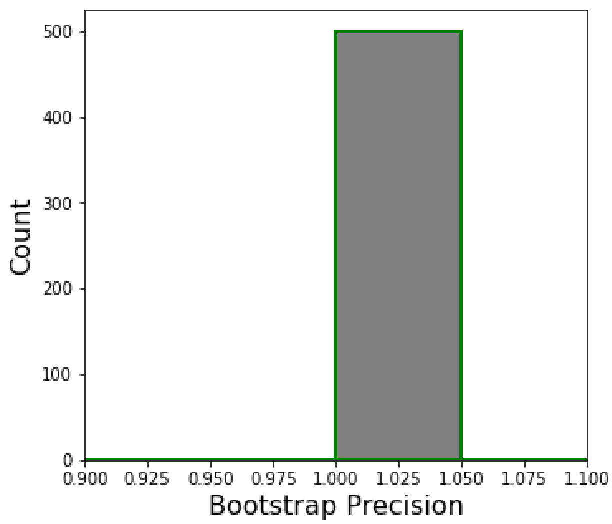
In [388]:
```
#Visualize our Bootstrap - Accuracy
fig, axs = plt.subplots(ncols=2, figsize=(12,5))
axs[0].set_xlabel('Bootstrap Accuracy', fontsize=16)
axs[1].set_xlabel('Boot Acc - Test Set Acc', fontsize=16)
axs[0].set_ylabel('Count', fontsize=16)
axs[0].hist(bootstrap.iloc[:,0], bins=20,edgecolor='green', linewidth=2,
color = "grey")
axs[0].set_xlim([0.7,1.1])
axs[1].hist(bootstrap.iloc[:,0]-acc, bins=20,edgecolor='green', linewidt
h=2,color = "grey")
axs[1].set_xlim([-0.08,0.08])
```

Out[388]: (-0.08, 0.08)



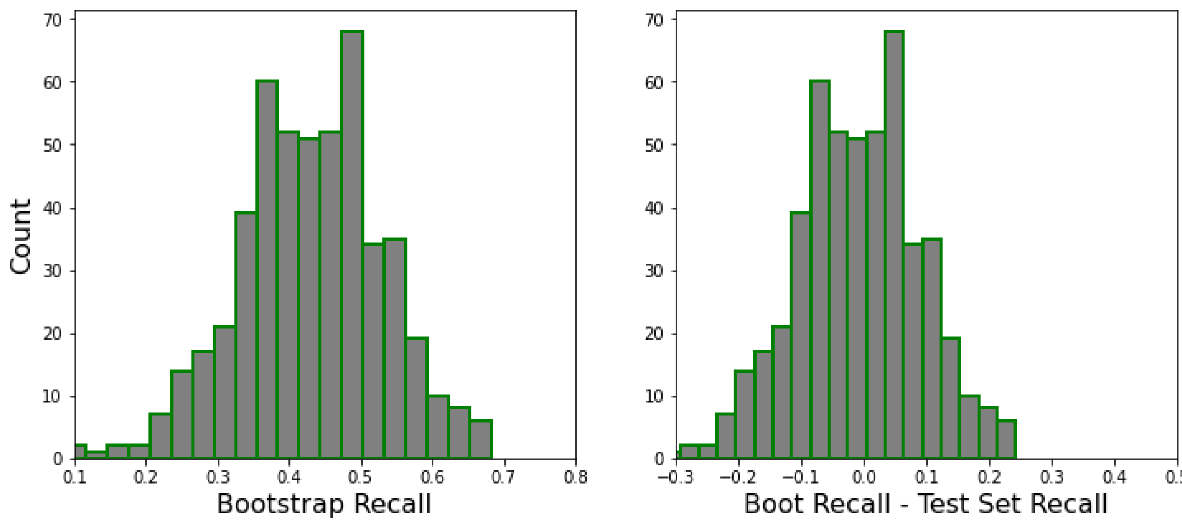
In [385]:
```
#Visualize our Bootstrap - Precision
fig, axs = plt.subplots(ncols=2, figsize=(12,5))
axs[0].set_xlabel('Bootstrap Precision', fontsize=16)
axs[1].set_xlabel('Boot Prec - Test Set Prec', fontsize=16)
axs[0].set_ylabel('Count', fontsize=16)
axs[0].hist(bootstrap.iloc[:,1], bins=20,edgecolor='green', linewidth=2,
color = "grey")
axs[0].set_xlim([0.9,1.1])
axs[1].hist(bootstrap.iloc[:,1]-precision, bins=20,edgecolor='green', li
newidth=2,color = "grey")
axs[1].set_xlim([-0.03,0.07])
```

Out[385]: (-0.03, 0.07)



In [381]:
```
#Visualize our Bootstrap - Precision
fig, axs = plt.subplots(ncols=2, figsize=(12,5))
axs[0].set_xlabel('Bootstrap Recall', fontsize=16)
axs[1].set_xlabel('Boot Recall - Test Set Recall', fontsize=16)
axs[0].set_ylabel('Count', fontsize=16)
axs[0].hist(bootstrap.iloc[:,2], bins=20,edgecolor='green', linewidth=2,
color = "grey")
axs[0].set_xlim([0.1,0.8])
axs[1].hist(bootstrap.iloc[:,2]-recall, bins=20,edgecolor='green', linew
idth=2,color = "grey")
axs[1].set_xlim([-0.3,0.5])
```

Out[381]: (-0.3, 0.5)



In [ ]: