Models

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In [1]:
```
%matplotlib inline
import numpy as np
import numpy.random as nd
import pandas as pd
import math
import matplotlib.pyplot as plt
import json
import matplotlib
import gzip
import os
import seaborn as sns

from sklearn.linear_model import LogisticRegressionCV
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import Imputer
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from IPython.display import display
from pandas.plotting import scatter_matrix

from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.ensemble import RandomForestClassifier
from sklearn.utils import resample
from sklearn.tree import DecisionTreeClassifier

from scipy.stats import ks_2samp

import statsmodels.api as sm
from statsmodels.api import OLS
```

Set botometer score cutoff for non-bot and bot

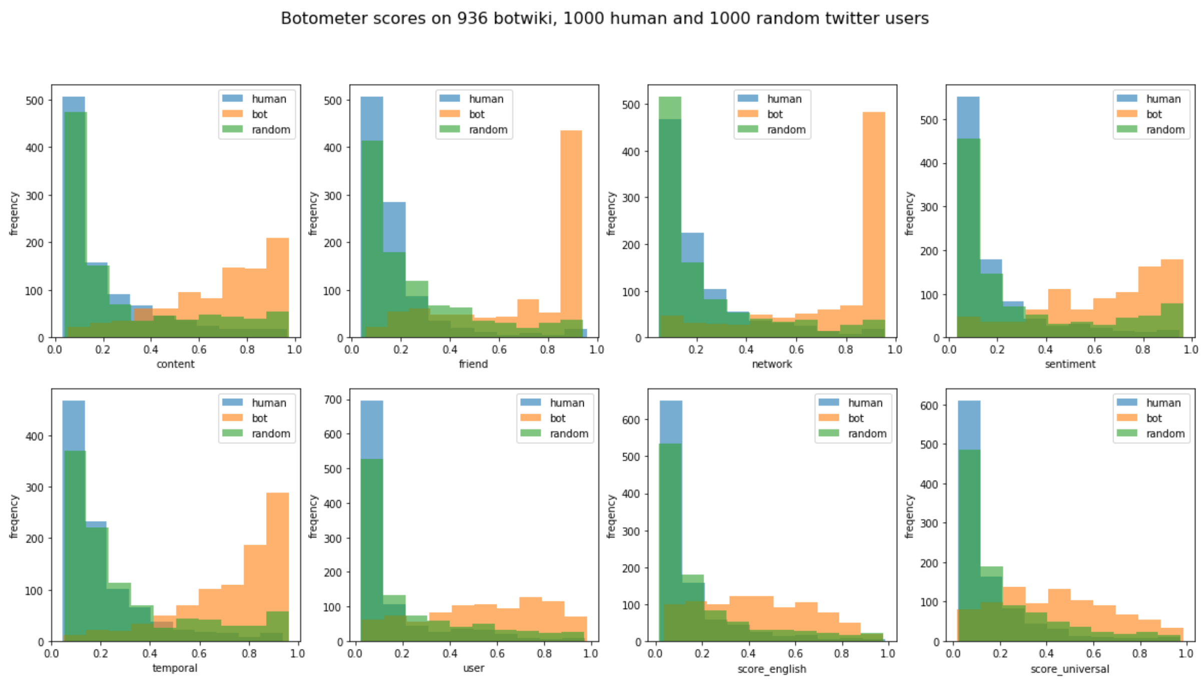
load botometer scores from file

In [2]:
```
def arrange_botometer_score(data_botometer,is_bot):
    account_score = []
    for i in (range(len(data_botometer))):
        for key,val in data_botometer[i].items():
            temp = key
        if temp != 'error':
            parameters = []
            parameters.append(is_bot)
            for key,val in data_botometer[i]['user'].items():
                parameters.append(val)
            for key,val in data_botometer[i]['categories'].items():
                parameters.append(val)
            for key,val in data_botometer[i]['scores'].items():
                parameters.append(val)
            account_score.append(parameters)

    account_score = pd.DataFrame(account_score)
    account_score.columns = columns = ['is_bot','id','screen_name',
                                       'content','friend','network',
                                       'sentiment','temporal','user',
                                       'score_english','score_universal'
                                      ]
    return account_score
```

In [3]:
```
with open('data/botometer_result_1000random.json') as handle:
    random_botometer = json.loads(handle.read())
with open('data/botometer_result_936bot.json') as handle:
    bot_botometer = json.loads(handle.read())
with open('data/botometer_result_1000_verified.json') as handle:
    human_botometer = json.loads(handle.read())
```

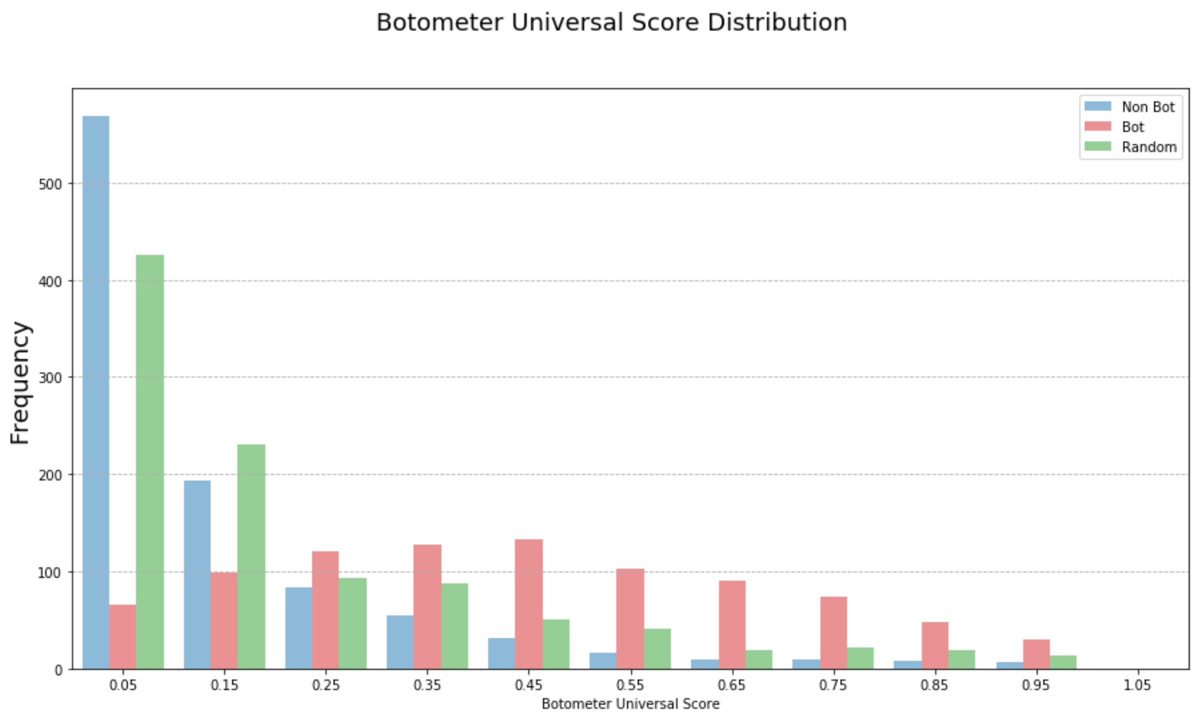
In [4]:
```
human_score = arrange_botometer_score(human_botometer,is_bot='False')
bot_score = arrange_botometer_score(bot_botometer,is_bot='Ture')
random_score = arrange_botometer_score(random_botometer,is_bot='unknow')
```

```
In [5]: fig, axs = plt.subplots(2, 4, figsize=(20, 10))
        col = 3
        for j in range(2):
            for i in range(4):
                axs[j,i].hist(human_score.iloc[:,col].tolist(), alpha=0.6,
                              label='human')
                axs[j,i].hist(bot_score.iloc[:,col].tolist(), alpha=0.6,
                              label='bot')
                axs[j,i].hist(random_score.iloc[:,col].tolist(), alpha=0.6,
                              label='random')
                axs[j,i].set_ylabel('freqency')
                axs[j,i].set_xlabel(human_score.columns[col])
                axs[j,i].legend()
                col=col+1

        fig.suptitle("Botometer scores on 936 botwiki, 1000 human "\
                     +"and 1000 random twitter users", fontsize=16)

        fig.savefig('fig/Botometer scores distribution.png', format = 'png')
```



Find the ratio of non-bot and bot in random set

In [6]:
```python
bins = np.arange(0,1.2,0.1)
plt.figure(figsize=(15, 8))
plt.hist([human_score.iloc[:,10].tolist(),
          bot_score.iloc[:,10].tolist(),
          random_score.iloc[:,10].tolist()],
         alpha=0.5, bins=bins, color=['C0', 'C3', 'C2'],
         label = ['Non Bot', 'Bot', 'Random'])
#plt.hist(, alpha=0.5, bins=bins, color='C3', label = 'Bot')
#plt.hist(, alpha=0.5, bins=bins, color='C2', label = 'Random')
plt.ylabel('Frequency', fontsize = 18)
plt.xlabel('Botometer Universal Score')
plt.xticks(np.arange(-0.05, 1.1, 0.1))
plt.xlim([0,1.1])
plt.grid(axis='y', linestyle='--')
plt.legend()

plt.suptitle("Botometer Universal Score Distribution", fontsize = 18)
plt.savefig('fig/score_universal_distribution.png', format = 'png')
plt.savefig('../docs/assets/images/score_universal_distribution.png',
            format = 'png')
```



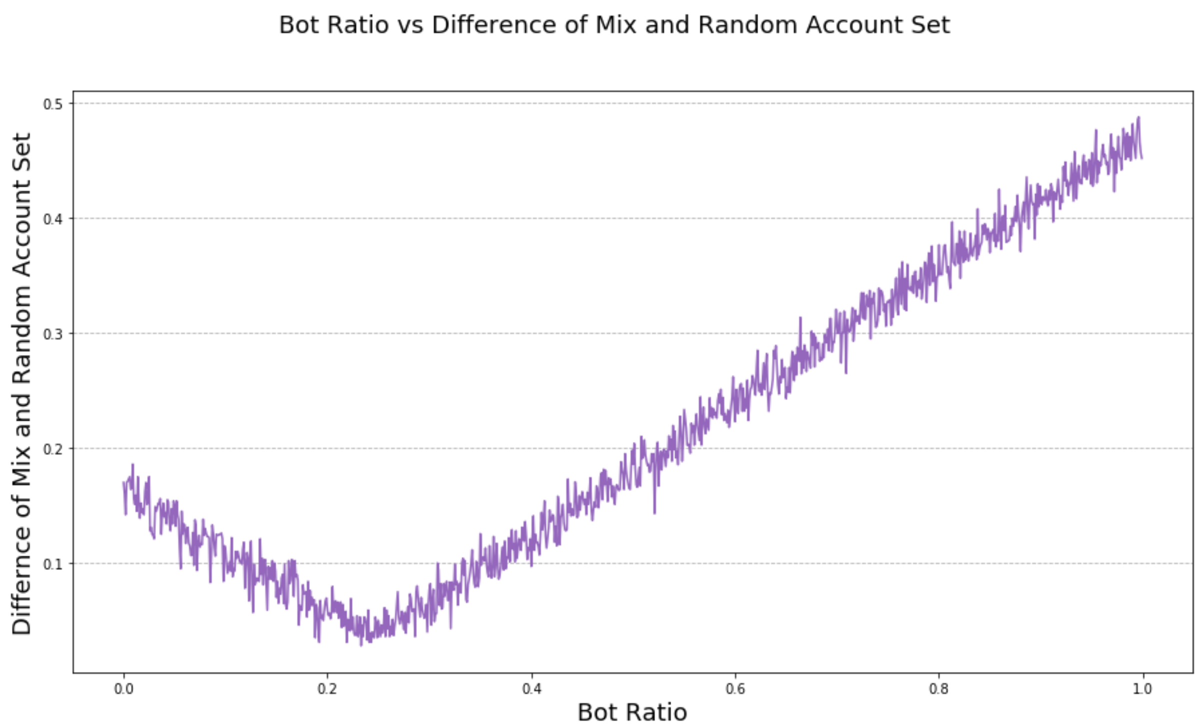
In [7]:
```
np.random.seed(123456)
x = random_score['score_universal']
y = human_score['score_universal']
z = bot_score['score_universal']


print('difference between random and human')
print(ks_2samp(x, y))
print('difference between random and bot')
print(ks_2samp(x, z))
```

```
difference between random and human
Ks_2sampResult(statistic=0.1559714867617108, pvalue=5.175986131548254e-
11)
difference between random and bot
Ks_2sampResult(statistic=0.47200000000000003, pvalue=1.3333627704181822
e-92)
```

In [8]:
```
np.random.seed(123)

def loss_function_bot_ratio(bot_ratio):
    human_number =  int(len (x) * (1-bot_ratio))
    bot_number = int (len (x) * bot_ratio)
    mix = np.random.choice(y,human_number).tolist() \
            + np.random.choice(z,bot_number).tolist()
    return ks_2samp(x, mix)[0]
```

In [9]:
```
p_random_mix = []
for bot_ratio in np.arange(0, 1, 0.001):
    p = loss_function_bot_ratio(bot_ratio)
    p_random_mix.append(p)
```

In [10]:
```
plt.figure(figsize=(15, 8))
plt.plot(np.arange(0, 1, 0.001),p_random_mix, color='C4')
plt.xlabel("Bot Ratio", fontsize = 18)
plt.ylabel("Differnce of Mix and Random Account Set", fontsize = 18)
plt.grid(axis='y', linestyle='--')

plt.suptitle("Bot Ratio vs Difference of Mix and Random Account Set",
             fontsize = 18)
plt.savefig('fig/bot_ratio.png', format = 'png')
plt.savefig('../docs/assets/images/bot_ratio.png', format = 'png')
```



In [11]:
```
best_bot_ratio = np.arange(0, 1, 0.001)\
                            [p_random_mix.index(min(p_random_mix))]
print("ratio of bot in random account set: ", best_bot_ratio)
```

```
ratio of bot in random account set:  0.233
```

Determin botmeter score cutoff : logistic regression

In [12]:
```
len(human_score.sample(int (len (x) * best_bot_ratio)))
```

Out[12]:
```
233
```

```
In [13]: best_human_number = int(len(x)*(1-best_bot_ratio))
         best_bot_number = int(len(x)*best_bot_ratio)

         human_bot_score_df =  human_score.sample(best_human_number)\
                                .append(bot_score.sample(best_bot_number))
         len (human_bot_score_df)
         print("training data including mixing of:")
         print("verified human: ",best_human_number,
               " bot:",best_bot_number,
               " total: ",len(human_bot_score_df))
```

```
training data including mixing of:
verified human:  767  bot: 233  total:  1000
```

```
In [14]: X_data = human_bot_score_df.iloc[:,10:11]
         y_data = pd.get_dummies(human_bot_score_df['is_bot'],
                                drop_first=True)['Ture']

         X_train, X_test = train_test_split(X_data, test_size = 0.2,
                                            random_state=90)
         y_train, y_test = train_test_split(y_data, test_size = 0.2,
                                            random_state=90)
```

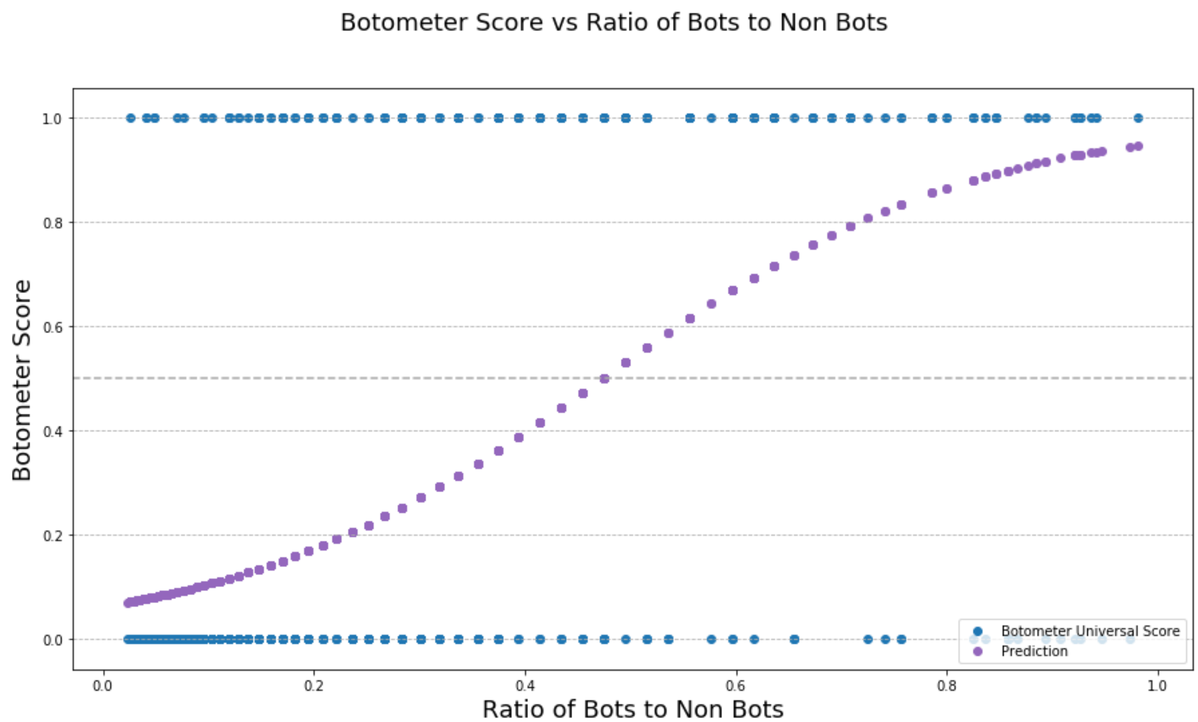
```
In [15]: def perfromance(model,X_train,X_test):
             y_pred_train = model.predict(X_train)
             y_pred_test = model.predict(X_test)

             #Perfromance Evaluation
             train_score = accuracy_score(y_train, y_pred_train)*100
             test_score = accuracy_score(y_test, y_pred_test)*100

             print("logistic regression model")
             print("Training Set Accuracy:",str(train_score)+'%')
             print("Testing Set Accuracy:",str(test_score)+'%')

             print()
             print("Rows: True Lables (0,1), \nColummns: Predicted Lables (0,1)")
             print("human","bot")

             print("train:")
             print(confusion_matrix(y_train, y_pred_train))
             print("test:")
             print(confusion_matrix(y_test, y_pred_test))
```

In [16]:
```
botometer_train_model = LogisticRegressionCV(Cs=10, cv=5)\
                                             .fit(X_train, y_train)
perfromance(botometer_train_model,X_train,X_test)
```

```
logistic regression model
Training Set Accuracy: 83.375%
Testing Set Accuracy: 79.0%

Rows: True Lables (0,1),
Colummns: Predicted Lables (0,1)
human bot
train:
[[582  35]
 [ 98  85]]
test:
[[141   9]
 [ 33  17]]
```

In [17]:
```
botometer_train_model = LogisticRegressionCV(Cs=10, cv=5)\
                                             .fit(X_data, y_data)
```

In [18]:
```
plt.figure(figsize=(15, 8))
plt.scatter(X_train, y_train, label = "Botometer Universal Score",
            color='C0')
plt.scatter(X_train, botometer_train_model.predict_proba(X_train)[:,1],
            label = "Prediction", color='C4')
plt.axhline(y=0.5, color='darkgray', linestyle='--')
plt.xlabel("Ratio of Bots to Non Bots", fontsize = 18)
plt.ylabel("Botometer Score", fontsize = 18)
plt.legend(loc='lower right')
plt.grid(axis='y', linestyle='--')

plt.suptitle("Botometer Score vs Ratio of Bots to Non Bots",
             fontsize = 18)
plt.savefig('fig/bot_cutoff.png', format = 'png')
plt.savefig('../docs/assets/images/bot_cutoff.png', format = 'png')
```



In [19]:
```
diff = (abs(botometer_train_model.predict_proba(X_train)[:,1]-0.5))\
                                                            .tolist()
cut_off = X_train["score_universal"].tolist()[diff.index(min(diff))]
```

In [20]:
```
print ("best cut off of score_universal_botometer is", round(cut_off,2))
```

```
best cut off of score_universal_botometer is 0.47
```

Read and clear data (1000 random accounts)

In [21]:
```
BOTOMETER_SCORE_THRESHOLD = 0.43

users_summary_df_gz_file = os.path.join('data',
                                        'users_final_agg_df.pkl.gz')
pd.set_option('display.max_colwidth', -1)

users_summary_df = pd.read_pickle(users_summary_df_gz_file,
                                  compression = 'gzip')
```

In [22]:
```
pd.set_option('display.max_rows', 350)
pd.set_option('display.max_colwidth', -1)

print(users_summary_df.shape)
display(users_summary_df.describe())
display(users_summary_df.dtypes)
```

```
(1000, 95)
```

	favourites_count	followers_count	friends_count	listed_count	statuses_count	scores.unive
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	997.00
mean	21331.004000	1867.186000	1139.991000	25.115000	31638.967000	0.21
std	39114.780324	7344.047951	4073.343137	92.364381	59896.719907	0.21
min	0.000000	0.000000	0.000000	0.000000	1.000000	0.02
25%	1550.250000	108.750000	167.000000	0.000000	2309.750000	0.06
50%	7982.500000	363.000000	397.500000	2.000000	9648.500000	0.11
75%	23129.750000	1094.500000	908.250000	11.000000	32057.500000	0.30
max	383288.000000	100730.000000	85123.000000	1550.000000	624250.000000	0.97

8 rows × 56 columns

contributors_enabled	bool
created_at	object
default_profile	bool
default_profile_image	bool
description	object
entities.description.urls	object
entities.url.urls	object
favourites_count	int64
follow_request_sent	bool
followers_count	int64
following	bool
friends_count	int64
geo_enabled	bool
has_extended_profile	bool
id_str	object
is_translation_enabled	bool
is_translator	bool
lang	object
listed_count	int64
location	object
name	object
notifications	bool
profile_background_color	object
profile_background_image_url	object
profile_background_image_url_https	object
profile_background_tile	bool
profile_banner_url	object
profile_image_url	object
profile_image_url_https	object
profile_link_color	object
profile_sidebar_border_color	object
profile_sidebar_fill_color	object
profile_text_color	object
profile_use_background_image	bool
protected	bool
screen_name	object
statuses_count	int64
time_zone	object
translator_type	object
url	object
utc_offset	object
verified	bool
user.id_str	object
scores.universal	float64
tweets_per_hour_00	float64
tweets_per_hour_01	float64
tweets_per_hour_02	float64
tweets_per_hour_03	float64
tweets_per_hour_04	float64
tweets_per_hour_05	float64
tweets_per_hour_06	float64
tweets_per_hour_07	float64
tweets_per_hour_08	float64
tweets_per_hour_09	float64
tweets_per_hour_10	float64
tweets_per_hour_11	float64
tweets_per_hour_12	float64

```
tweets_per_hour_13                      float64
tweets_per_hour_14                      float64
tweets_per_hour_15                      float64
tweets_per_hour_16                      float64
tweets_per_hour_17                      float64
tweets_per_hour_18                      float64
tweets_per_hour_19                      float64
tweets_per_hour_20                      float64
tweets_per_hour_21                      float64
tweets_per_hour_22                      float64
tweets_per_hour_23                      float64
tweets_per_hour                          object
mean_links_per_tweet                    float64
mean_words_per_tweet                    float64
mean_hashtags_per_tweet                 float64
mean_user_mentions_per_tweet            float64
mean_favourites_per_tweet               float64
mean_media_per_tweet                    float64
mean_user_symbols_per_tweet             float64
mean_retweets_per_tweet                 float64
mean_truncations_per_tweet              float64
mean_links_to_twitter                   float64
mean_links_to_top_social_media          float64
mean_links_to_top_digital_media         float64
mean_links_to_top_news                  float64
mean_links_to_top_products_services     float64
mean_links_to_top_celebrities           float64
mean_links_to_top_organizations         float64
mean_links_to_top_sports                float64
mean_links_to_top_adult                 float64
retweet_ratio                           float64
mean_ref_to_person                      float64
mean_ref_to_norp                        float64
mean_ref_to_org                         float64
mean_ref_to_gpe                         float64
mean_ref_to_product                     float64
mean_ref_to_law                         float64
mean_ref_to_money                       float64
dtype: object
```

In [23]:

```
users = users_summary_df.copy()
```

In [24]:
```
type_bool = []
type_int = []
type_float = []
type_other = []
for i in range(len(users.dtypes)):
    if users.dtypes[i] == 'bool':
        type_bool.append(i)
    if users.dtypes[i] == 'int64':
        type_int.append(i)
    if users.dtypes[i] == 'float64':
        type_float.append(i)
    if users.dtypes[i]!= 'bool' \
                            and users.dtypes[i]!= 'int64' \
                            and users.dtypes[i]!= 'float64':
        type_other.append(i)
print (len(type_bool),len(type_int),len(type_float),len(type_other))
```

```
14 5 51 25
```

In [25]:
```
users_clear = users.iloc[:,([43,14,20,7, 9, 11, 18, 36] \
                            + type_float[1:]+[2,3,12,13,15,25,33,41])]
users_clear.index = range(1000)
print(users_clear.shape)
print(users_clear.columns)
```

```
(1000, 66)
Index(['scores.universal', 'id_str', 'name', 'favourites_count',
       'followers_count', 'friends_count', 'listed_count', 'statuses_co
unt',
       'tweets_per_hour_00', 'tweets_per_hour_01', 'tweets_per_hour_0
2',
       'tweets_per_hour_03', 'tweets_per_hour_04', 'tweets_per_hour_0
5',
       'tweets_per_hour_06', 'tweets_per_hour_07', 'tweets_per_hour_0
8',
       'tweets_per_hour_09', 'tweets_per_hour_10', 'tweets_per_hour_1
1',
       'tweets_per_hour_12', 'tweets_per_hour_13', 'tweets_per_hour_1
4',
       'tweets_per_hour_15', 'tweets_per_hour_16', 'tweets_per_hour_1
7',
       'tweets_per_hour_18', 'tweets_per_hour_19', 'tweets_per_hour_2
0',
       'tweets_per_hour_21', 'tweets_per_hour_22', 'tweets_per_hour_2
3',
       'mean_links_per_tweet', 'mean_words_per_tweet',
       'mean_hashtags_per_tweet', 'mean_user_mentions_per_tweet',
       'mean_favourites_per_tweet', 'mean_media_per_tweet',
       'mean_user_symbols_per_tweet', 'mean_retweets_per_tweet',
       'mean_truncations_per_tweet', 'mean_links_to_twitter',
       'mean_links_to_top_social_media', 'mean_links_to_top_digital_med
ia',
       'mean_links_to_top_news', 'mean_links_to_top_products_services',
       'mean_links_to_top_celebrities', 'mean_links_to_top_organization
s',
       'mean_links_to_top_sports', 'mean_links_to_top_adult', 'retweet_
ratio',
       'mean_ref_to_person', 'mean_ref_to_norp', 'mean_ref_to_org',
       'mean_ref_to_gpe', 'mean_ref_to_product', 'mean_ref_to_law',
       'mean_ref_to_money', 'default_profile', 'default_profile_image',
       'geo_enabled', 'has_extended_profile', 'is_translation_enabled',
       'profile_background_tile', 'profile_use_background_image', 'veri
fied'],
      dtype='object')
```

In [26]:
```
X_data = users_clear.iloc[:,3:]
y_data = []
bot_number = 0
for i in range(len(users_clear)):
    if users_clear['scores.universal'][i] >= BOTOMETER_SCORE_THRESHOLD:
            y_data = y_data + [1]
            bot_number =bot_number +1
    else: y_data = y_data + [0]
print(X_data.shape, len(y_data))
print("bot number:" ,bot_number)
```

```
(1000, 63) 1000
bot number: 149
```

In [27]:
```
X_train, X_test = train_test_split(X_data,
                                   test_size = 0.2,
                                   random_state=90)
y_train, y_test = train_test_split(y_data,
                                   test_size = 0.2,
                                   random_state=90)
```

Logistic Regresion

In [28]:
```
def perfromance(model,X_train,X_test):
    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)

    #Perfromance Evaluation
    train_score = accuracy_score(y_train, y_pred_train)*100
    train_matrix = confusion_matrix(y_train, y_pred_train)
    test_score = accuracy_score(y_test, y_pred_test)*100
    test_matrix = confusion_matrix(y_test, y_pred_test)

    train_ture_negative = train_matrix[0][0]\
                        /(train_matrix[0][0]+train_matrix[0][1])*100
    train_ture_positive = train_matrix[1][1]\
                        /(train_matrix[1][0]+train_matrix[1][1])*100

    test_ture_negative = test_matrix[0][0]\
                        /(test_matrix[0][0]+test_matrix[0][1])*100
    test_ture_positive = test_matrix[1][1]\
                        /(test_matrix[1][0]+test_matrix[1][1])*100

    print()
    print("Rows: True Lables (0,1), \nColummns: Predicted Lables (0,1)")
    print("human","bot")

    print("train:")
    print(train_matrix)
    print("test:")
    print(test_matrix)

    print("Training Set total accuracy:",str(train_score)+'%')
    print("Training Set non-bot accuracy:",str(train_ture_negative)+'%')

    print("Training Set bot accuracy:",str(train_ture_positive)+'%')

    print("Test Set accuracy:",str(test_score)+'%')
    print("Test Set non-bot accuracy:",str(test_ture_negative)+'%')
    print("Test Set bot accuracy:",str(test_ture_positive)+'%')
```

In [29]:
```
def tuning_bot_weight(bot_weight):
    model = LogisticRegressionCV(Cs=10, cv=5,max_iter=1000,
                                 class_weight = {0:1,1:bot_weight})\
                                                   .fit(X_train,
                                                        y_train)


    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)

    train_score = accuracy_score(y_train, y_pred_train)*100
    train_matrix = confusion_matrix(y_train, y_pred_train)
    test_score = accuracy_score(y_test, y_pred_test)*100
    test_matrix = confusion_matrix(y_test, y_pred_test)

    train_ture_negative = train_matrix[0][0]\
                         /(train_matrix[0][0]+train_matrix[0][1])*100
    train_ture_positive = train_matrix[1][1]\
                         /(train_matrix[1][0]+train_matrix[1][1])*100

    test_ture_negative = test_matrix[0][0]\
                         /(test_matrix[0][0]+test_matrix[0][1])*100
    test_ture_positive = test_matrix[1][1]\
                         /(test_matrix[1][0]+test_matrix[1][1])*100

    accuracy = [bot_weight, train_score, train_ture_negative,
                train_ture_positive, test_score, test_ture_negative,
                test_ture_positive]
    return accuracy
```

In [30]:
```
bot_weight_accuracy = []
for bot_weight in range(5,11):
    bot_weight_accuracy.append(tuning_bot_weight(bot_weight))
bot_weight_accuracy = pd.DataFrame(bot_weight_accuracy,
                                   columns =['bot_weight',
                                             'train_score',
                                             'train_ture_negative',
                                             'train_ture_positive',
                                             'test_score',
                                             'test_ture_negative',
                                             'test_ture_positive'] )
```

```
/Users/blair/.pyenv/versions/3.6.7/lib/python3.6/site-packages/sklearn/
linear_model/logistic.py:757: ConvergenceWarning: lbfgs failed to conve
rge. Increase the number of iterations.
  "of iterations.", ConvergenceWarning)
```

In [31]:

```python
fig, axs = plt.subplots(1, 2, figsize=(15, 5))


axs[0].plot(bot_weight_accuracy.iloc[:,0],bot_weight_accuracy.iloc[:,1],
            label='Train Score', color='C2')
axs[0].plot(bot_weight_accuracy.iloc[:,0],bot_weight_accuracy.iloc[:,2],
            label='Train Non Bot', color='C0', alpha=0.5)
axs[0].plot(bot_weight_accuracy.iloc[:,0],bot_weight_accuracy.iloc[:,3],
            label='Train Bot', color='C3', alpha=0.5)
axs[0].set_xlabel('Bot / Non-bot Weight', fontsize = 18)
axs[0].set_ylabel('Accuracy (%)', fontsize = 18)
axs[0].legend()
axs[0].grid(axis='y', linestyle='--')


axs[1].plot(bot_weight_accuracy.iloc[:,0],bot_weight_accuracy.iloc[:,4],
            label='Test Score', color='C2')
axs[1].plot(bot_weight_accuracy.iloc[:,0],bot_weight_accuracy.iloc[:,5],
            label='Test Non Bot', color='C0', alpha=0.5)
axs[1].plot(bot_weight_accuracy.iloc[:,0],bot_weight_accuracy.iloc[:,6],
            label='Test Bot', color='C3', alpha=0.5)
axs[1].set_xlabel('Bot / Non-bot Weight', fontsize = 18)
axs[1].set_ylabel('Accuracy (%)', fontsize = 18)
axs[1].legend()
axs[1].grid(axis='y', linestyle='--')


fig.suptitle("Logistic Regression Model - Accuracy vs Weights",
             fontsize=18)
plt.savefig('../docs/assets/images/log_regression_model.png',
            format = 'png')
fig.savefig('fig/log_regression_model.png', format = 'png')
```

In [32]:
```
LR_model = LogisticRegressionCV(Cs=10, cv=5,max_iter=1000,
                                class_weight = {0:1,1:7}).fit(X_train,
                                                              y_train)
perfromance(LR_model,X_train,X_test)
```

```
Rows: True Lables (0,1),
Colummns: Predicted Lables (0,1)
human bot
train:
[[469 213]
 [ 36  82]]
test:
[[105  64]
 [ 12  19]]
Training Set total accuracy: 68.875%
Training Set non-bot accuracy: 68.76832844574781%
Training Set bot accuracy: 69.49152542372882%
Test Set accuracy: 62.0%
Test Set non-bot accuracy: 62.1301775147929%
Test Set bot accuracy: 61.29032258064516%
```

Random Forest

In [33]:
```
n_trees = 50
tree_depth = 5
RF_model = RandomForestClassifier(n_estimators=n_trees,
                                  max_depth=tree_depth,
                                  class_weight = {0:1,1:20}).fit(X_train,
                                                                 y_train)
```

In [34]:
```
perfromance(RF_model,X_train,X_test)
```

```
Rows: True Lables (0,1),
Colummns: Predicted Lables (0,1)
human bot
train:
[[589  93]
 [  2 116]]
test:
[[136  33]
 [  4  27]]
Training Set total accuracy: 88.125%
Training Set non-bot accuracy: 86.36363636363636%
Training Set bot accuracy: 98.30508474576271%
Test Set accuracy: 81.5%
Test Set non-bot accuracy: 80.4733727810651%
Test Set bot accuracy: 87.09677419354838%
```

In [35]:
```python
def tuning_tree_depth(tree_depth):
    model = RandomForestClassifier(n_estimators=n_trees,
                                   max_depth=tree_depth,
                                   class_weight = {0:1,1:20}).fit(X_train,
                                                                   y_train)

    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)

    train_score = accuracy_score(y_train, y_pred_train)*100
    train_matrix = confusion_matrix(y_train, y_pred_train)
    test_score = accuracy_score(y_test, y_pred_test)*100
    test_matrix = confusion_matrix(y_test, y_pred_test)

    train_ture_negative = train_matrix[0][0]\
                        /(train_matrix[0][0]+train_matrix[0][1])*100
    train_ture_positive = train_matrix[1][1]\
                        /(train_matrix[1][0]+train_matrix[1][1])*100

    test_ture_negative = test_matrix[0][0]\
                        /(test_matrix[0][0]+test_matrix[0][1])*100
    test_ture_positive = test_matrix[1][1]\
                        /(test_matrix[1][0]+test_matrix[1][1])*100

    accuracy = [tree_depth, train_score, train_ture_negative,
                train_ture_positive, test_score, test_ture_negative,
                test_ture_positive]
    return accuracy
```

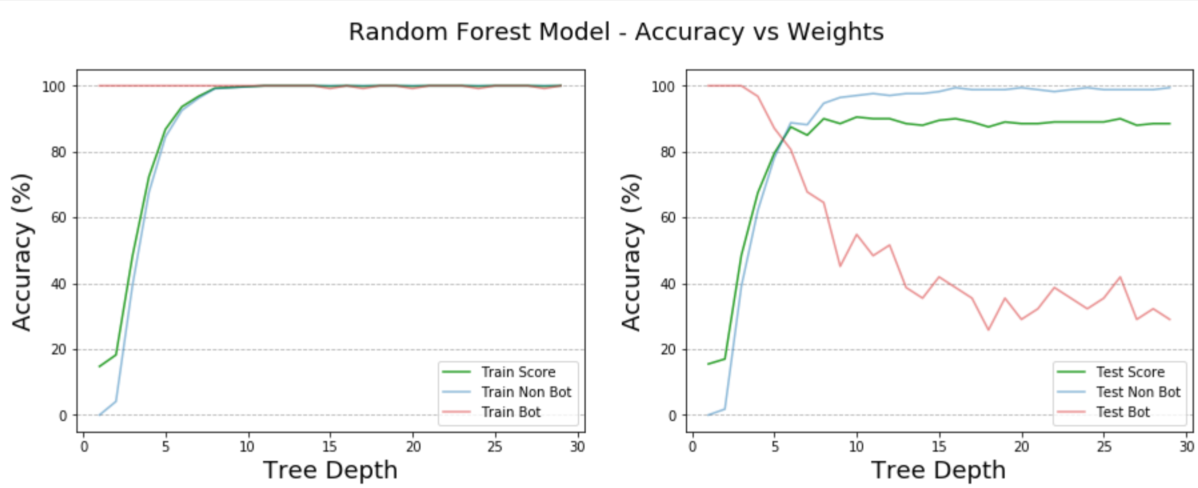
In [36]:
```python
tree_depth_accuracy = []
for tree_depth in range(1,30):
    tree_depth_accuracy.append(tuning_tree_depth(tree_depth))
tree_depth_accuracy = pd.DataFrame(tree_depth_accuracy,
                                   columns =['tree_depth',
                                             'train_score',
                                             'train_ture_negative',
                                             'train_ture_positive',
                                             'test_score',
                                             'test_ture_negative',
                                             'test_ture_positive'] )
```

In [37]:
```python
tree_depth_accuracy.head()
```

Out[37]:

	tree_depth	train_score	train_ture_negative	train_ture_positive	test_score	test_ture_negative
0	1	14.750	0.000000	100.0	15.5	0.000000
1	2	18.250	4.105572	100.0	17.0	1.775148
2	3	48.250	39.296188	100.0	48.5	39.053254
3	4	72.375	67.595308	100.0	67.5	62.130178
4	5	86.750	84.457478	100.0	79.5	78.106509

In [38]:
```
fig, axs = plt.subplots(1, 2, figsize=(15, 5))

axs[0].plot(tree_depth_accuracy.iloc[:,0],tree_depth_accuracy.iloc[:,1],

            label='Train Score', color='C2')
axs[0].plot(tree_depth_accuracy.iloc[:,0],tree_depth_accuracy.iloc[:,2],

            label='Train Non Bot', color='C0', alpha=0.5)
axs[0].plot(tree_depth_accuracy.iloc[:,0],tree_depth_accuracy.iloc[:,3],

            label='Train Bot', color='C3', alpha=0.5)
axs[0].set_xlabel('Tree Depth', fontsize=18)
axs[0].set_ylabel('Accuracy (%)', fontsize=18)
axs[0].legend()
axs[0].grid(axis='y', linestyle='--')

axs[1].plot(tree_depth_accuracy.iloc[:,0],tree_depth_accuracy.iloc[:,4],

            label='Test Score', color='C2')
axs[1].plot(tree_depth_accuracy.iloc[:,0],tree_depth_accuracy.iloc[:,5],

            label='Test Non Bot', color='C0', alpha=0.5)
axs[1].plot(tree_depth_accuracy.iloc[:,0],tree_depth_accuracy.iloc[:,6],

            label='Test Bot', color='C3', alpha=0.5)
axs[1].set_xlabel('Tree Depth', fontsize=18)
axs[1].set_ylabel('Accuracy (%)', fontsize=18)
axs[1].legend()
axs[1].grid(axis='y', linestyle='--')


fig.suptitle("Random Forest Model - Accuracy vs Weights", fontsize=18)
fig.savefig('fig/rf_model.png', format = 'png')
plt.savefig('../docs/assets/images/rf_model.png', format = 'png')
```



The best tree_depth is 5.

In [39]:
```
tree_depth = 5
n_trees = 50
RF_model = RandomForestClassifier(n_estimators=n_trees,
                                  max_depth=tree_depth,
                                  class_weight = {0:1,1:20}).fit(X_train,
                                                                   y_train)
perfromance(RF_model,X_train,X_test)
```

```
Rows: True Lables (0,1),
Colummns: Predicted Lables (0,1)
human bot
train:
[[575 107]
 [  0 118]]
test:
[[134  35]
 [  2  29]]
Training Set total accuracy: 86.625%
Training Set non-bot accuracy: 84.3108504398827%
Training Set bot accuracy: 100.0%
Test Set accuracy: 81.5%
Test Set non-bot accuracy: 79.28994082840237%
Test Set bot accuracy: 93.54838709677419%
```

bagging decision tree

In [40]:
```
def perfromance_bagging():
    train_score = accuracy_score(y_train, y_pred_train)*100
    train_matrix = confusion_matrix(y_train, y_pred_train)
    test_score = accuracy_score(y_test, y_pred_test)*100
    test_matrix = confusion_matrix(y_test, y_pred_test)

    train_ture_negative = train_matrix[0][0]\
                        /(train_matrix[0][0]+train_matrix[0][1])*100
    train_ture_positive = train_matrix[1][1]\
                        /(train_matrix[1][0]+train_matrix[1][1])*100

    test_ture_negative = test_matrix[0][0]\
                        /(test_matrix[0][0]+test_matrix[0][1])*100
    test_ture_positive = test_matrix[1][1]\
                        /(test_matrix[1][0]+test_matrix[1][1])*100

    print()
    print("Rows: True Lables (0,1), \nColummns: Predicted Lables (0,1)")
    print("human","bot")

    print("train:")
    print(train_matrix)
    print("test:")
    print(test_matrix)

    print("Training Set total accuracy:",str(train_score)+'%')
    print("Training Set non-bot accuracy:",str(train_ture_negative)+'%')

    print("Training Set bot accuracy:",str(train_ture_positive)+'%')

    print("Test Set accuracy:",str(test_score)+'%')
    print("Test Set non-bot accuracy:",str(test_ture_negative)+'%')
    print("Test Set bot accuracy:",str(test_ture_positive)+'%')
```

In [41]:
```
#Select overfit tree depth
tree_depth = 10
#Set number of trees
n_trees = 11

#Conduct bootstrapping and fit models to the date
np.random.seed(0)
bagging_train = np.zeros((X_train.shape[0], n_trees))
bagging_test = np.zeros((X_test.shape[0], n_trees))
bagging_models = []
for i in range(n_trees):
    bootstrapped_X, bootstrapped_y = resample(X_train, y_train)
    fitted_model = DecisionTreeClassifier(max_depth=tree_depth,
                                          class_weight = {0:1,1:1})\
                                                .fit(bootstrapped_X,
                                                     bootstrapped_y)
    bagging_models.append(fitted_model)
    bagging_train[:,i] = fitted_model.predict(X_train)
    bagging_test[:,i] = fitted_model.predict(X_test)

#Get Predictions across all models
y_pred_train = np.mean(bagging_train, axis=1) > .5
y_pred_test = np.mean(bagging_test, axis=1) > .5
```

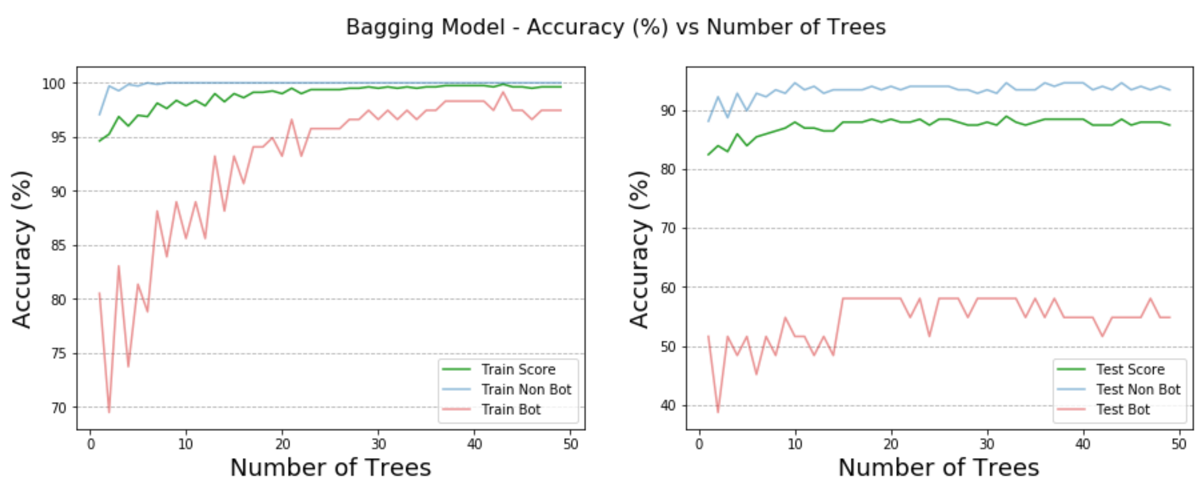
In [42]:
```
perfromance_bagging()
```

```
Rows: True Lables (0,1),
Colummns: Predicted Lables (0,1)
human bot
train:
[[682   0]
 [ 21  97]]
test:
[[158  11]
 [ 12  19]]
Training Set total accuracy: 97.375%
Training Set non-bot accuracy: 100.0%
Training Set bot accuracy: 82.20338983050848%
Test Set accuracy: 88.5%
Test Set non-bot accuracy: 93.49112426035504%
Test Set bot accuracy: 61.29032258064516%
```

In [43]:
```
def tuning_n_trees(n_trees):
   #Conduct bootstrapping and fit models to the date
    np.random.seed(0)
    bagging_train = np.zeros((X_train.shape[0], n_trees))
    bagging_test = np.zeros((X_test.shape[0], n_trees))
    bagging_models = []
    for i in range(n_trees):
        bootstrapped_X, bootstrapped_y = resample(X_train, y_train)
        fitted_model = DecisionTreeClassifier(max_depth=tree_depth,
                                             class_weight = {0:1,1:2})\
                                                   .fit(bootstrapped_X,

                                                        bootstrapped_y)
        bagging_models.append(fitted_model)
        bagging_train[:,i] = fitted_model.predict(X_train)
        bagging_test[:,i] = fitted_model.predict(X_test)

    #Get Predictions across all models
    y_pred_train = np.mean(bagging_train, axis=1) > .5
    y_pred_test = np.mean(bagging_test, axis=1) > .5

    train_score = accuracy_score(y_train, y_pred_train)*100
    train_matrix = confusion_matrix(y_train, y_pred_train)
    test_score = accuracy_score(y_test, y_pred_test)*100
    test_matrix = confusion_matrix(y_test, y_pred_test)

    train_ture_negative = train_matrix[0][0]\
                        /(train_matrix[0][0]+train_matrix[0][1])*100
    train_ture_positive = train_matrix[1][1]\
                        /(train_matrix[1][0]+train_matrix[1][1])*100

    test_ture_negative = test_matrix[0][0]\
                        /(test_matrix[0][0]+test_matrix[0][1])*100
    test_ture_positive = test_matrix[1][1]\
                        /(test_matrix[1][0]+test_matrix[1][1])*100

    accuracy = [n_trees, train_score, train_ture_negative,
                train_ture_positive, test_score, test_ture_negative,
                test_ture_positive]
    return accuracy
```

In [44]:
```
bagging_n_tree_accuracy = []
for n_trees in range(1,50):
    bagging_n_tree_accuracy.append(tuning_n_trees(n_trees))
bagging_n_tree_accuracy = pd.DataFrame(bagging_n_tree_accuracy,
                                       columns =['tree_depth',
                                                 'train_score',
                                                 'train_ture_negative',
                                                 'train_ture_positive',
                                                 'test_score',
                                                 'test_ture_negative',
                                                 'test_ture_positive'] )
```

In [45]:
```
fig, axs = plt.subplots(1, 2, figsize=(15, 5))

axs[0].plot(bagging_n_tree_accuracy.iloc[:,0],
            bagging_n_tree_accuracy.iloc[:,1],
            label='Train Score', color='C2')
axs[0].plot(bagging_n_tree_accuracy.iloc[:,0],
            bagging_n_tree_accuracy.iloc[:,2],
            label='Train Non Bot', color='C0', alpha=0.5)
axs[0].plot(bagging_n_tree_accuracy.iloc[:,0],
            bagging_n_tree_accuracy.iloc[:,3],
            label='Train Bot', color='C3', alpha=0.5)
axs[0].set_xlabel('Number of Trees', fontsize=18)
axs[0].set_ylabel('Accuracy (%)', fontsize=18)
axs[0].legend()
axs[0].grid(axis='y', linestyle='--')

axs[1].plot(bagging_n_tree_accuracy.iloc[:,0],
            bagging_n_tree_accuracy.iloc[:,4],
            label='Test Score', color='C2')
axs[1].plot(bagging_n_tree_accuracy.iloc[:,0],
            bagging_n_tree_accuracy.iloc[:,5],
            label='Test Non Bot', color='C0', alpha=0.5)
axs[1].plot(bagging_n_tree_accuracy.iloc[:,0],
            bagging_n_tree_accuracy.iloc[:,6],
            label='Test Bot', color='C3', alpha=0.5)
axs[1].set_xlabel('Number of Trees', fontsize=18)
axs[1].set_ylabel('Accuracy (%)', fontsize=18)
axs[1].legend()
axs[1].grid(axis='y', linestyle='--')


fig.suptitle("Bagging Model - Accuracy (%) vs Number of Trees",
             fontsize=16)
fig.savefig('../docs/assets/images/bagging_model.png', format = 'png')
fig.savefig('fig/bagging_model.png', format = 'png')
```

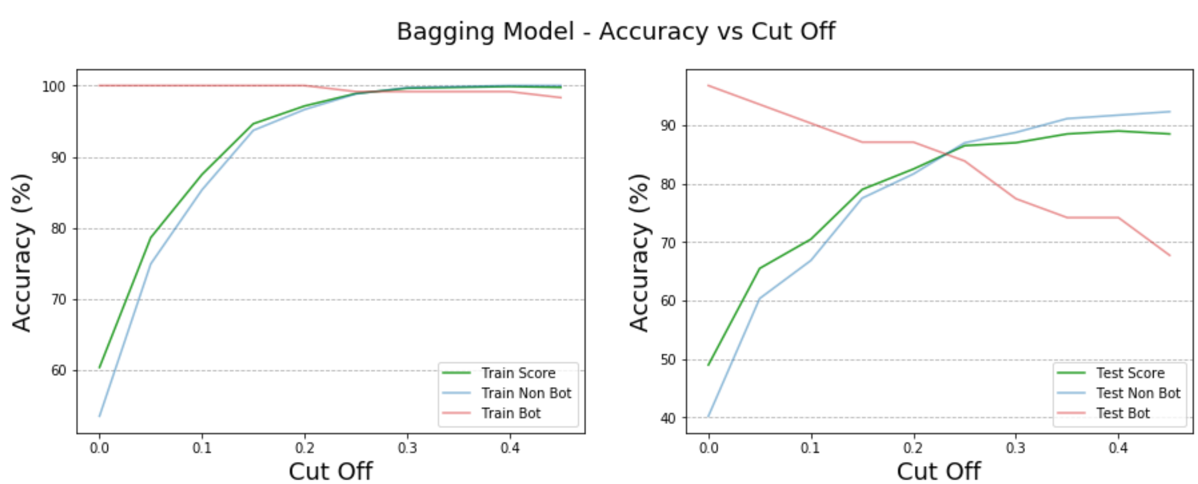


In [46]:
```
def bagging_tuning_cut_off(cut_off):
   #Conduct bootstrapping and fit models to the date
    np.random.seed(0)
    bagging_train = np.zeros((X_train.shape[0], n_trees))
    bagging_test = np.zeros((X_test.shape[0], n_trees))
    bagging_models = []
    for i in range(n_trees):
        bootstrapped_X, bootstrapped_y = resample(X_train, y_train)
        fitted_model = DecisionTreeClassifier(max_depth=tree_depth,
                                              class_weight = {0:1,1:2})\
                                                    .fit(bootstrapped_X,

                                                         bootstrapped_y)
        bagging_models.append(fitted_model)
        bagging_train[:,i] = fitted_model.predict(X_train)
        bagging_test[:,i] = fitted_model.predict(X_test)

    #Get Predictions across all models
    y_pred_train = np.mean(bagging_train, axis=1) > cut_off
    y_pred_test = np.mean(bagging_test, axis=1) > cut_off

    train_score = accuracy_score(y_train, y_pred_train)*100
    train_matrix = confusion_matrix(y_train, y_pred_train)
    test_score = accuracy_score(y_test, y_pred_test)*100
    test_matrix = confusion_matrix(y_test, y_pred_test)

    train_ture_negative = train_matrix[0][0]\
                          /(train_matrix[0][0]+train_matrix[0][1])*100
    train_ture_positive = train_matrix[1][1]\
                          /(train_matrix[1][0]+train_matrix[1][1])*100

    test_ture_negative = test_matrix[0][0]\
                          /(test_matrix[0][0]+test_matrix[0][1])*100
    test_ture_positive = test_matrix[1][1]\
                          /(test_matrix[1][0]+test_matrix[1][1])*100

    accuracy = [cut_off, train_score, train_ture_negative,
                train_ture_positive, test_score, test_ture_negative,
                test_ture_positive]
    return accuracy
```

In [47]:
```
bagging_cut_off_accuracy = []
n_tree = 51
for cut_off in np.arange(0,0.5,0.05):
    bagging_cut_off_accuracy.append(bagging_tuning_cut_off(cut_off))
bagging_cut_off_accuracy = pd.DataFrame(bagging_cut_off_accuracy,
                                        columns =['tree_depth',
                                                  'train_score',
                                                  'train_ture_negative',

                                                  'train_ture_positive',

                                                  'test_score',
                                                  'test_ture_negative',
                                                  'test_ture_positive'])
```

In [48]:

```
fig, axs = plt.subplots(1, 2, figsize=(15, 5))

axs[0].plot(bagging_cut_off_accuracy.iloc[:,0],
            bagging_cut_off_accuracy.iloc[:,1],
            label='Train Score', color='C2')
axs[0].plot(bagging_cut_off_accuracy.iloc[:,0],
            bagging_cut_off_accuracy.iloc[:,2],
            label='Train Non Bot', color='C0', alpha=0.5)
axs[0].plot(bagging_cut_off_accuracy.iloc[:,0],
            bagging_cut_off_accuracy.iloc[:,3],
            label='Train Bot', color='C3', alpha=0.5)
axs[0].set_xlabel('Cut Off', fontsize=18)
axs[0].set_ylabel('Accuracy (%)', fontsize=18)
axs[0].legend()
axs[0].grid(axis='y', linestyle='--')

axs[1].plot(bagging_cut_off_accuracy.iloc[:,0],
            bagging_cut_off_accuracy.iloc[:,4],
            label='Test Score', color='C2')
axs[1].plot(bagging_cut_off_accuracy.iloc[:,0],
            bagging_cut_off_accuracy.iloc[:,5],
            label='Test Non Bot', color='C0', alpha=0.5)
axs[1].plot(bagging_cut_off_accuracy.iloc[:,0],
            bagging_cut_off_accuracy.iloc[:,6],
            label='Test Bot', color='C3', alpha=0.5)
axs[1].set_xlabel('Cut Off', fontsize=18)
axs[1].set_ylabel('Accuracy (%)', fontsize=18)
axs[1].legend()
axs[1].grid(axis='y', linestyle='--')

fig.suptitle("Bagging Model - Accuracy vs Cut Off", fontsize=18)
fig.savefig('../docs/assets/images/bagging_model_cut_off.png',
            format = 'png')
fig.savefig('fig/bagging_model_cut_off.png', format = 'png')
```



In [49]:
```
#Select overfit tree depth
tree_depth = 10
#Set number of trees
n_trees = 51

#Conduct bootstrapping and fit models to the date
np.random.seed(0)
bagging_train = np.zeros((X_train.shape[0], n_trees))
bagging_test = np.zeros((X_test.shape[0], n_trees))
bagging_models = []
for i in range(n_trees):
    bootstrapped_X, bootstrapped_y = resample(X_train, y_train)
    fitted_model = DecisionTreeClassifier(max_depth=tree_depth,
                                          class_weight = {0:1,1:1})\
                                                .fit(bootstrapped_X,
                                                     bootstrapped_y)
    bagging_models.append(fitted_model)
    bagging_train[:,i] = fitted_model.predict(X_train)
    bagging_test[:,i] = fitted_model.predict(X_test)

#Get Predictions across all models
y_pred_train = np.mean(bagging_train, axis=1) > .2
y_pred_test = np.mean(bagging_test, axis=1) > .2
```

In [50]:
```
perfromance_bagging()
```

```
Rows: True Lables (0,1),
Colummns: Predicted Lables (0,1)
human bot
train:
[[663  19]
 [  1 117]]
test:
[[145  24]
 [  5  26]]
Training Set total accuracy: 97.5%
Training Set non-bot accuracy: 97.21407624633432%
Training Set bot accuracy: 99.15254237288136%
Test Set accuracy: 85.5%
Test Set non-bot accuracy: 85.79881656804734%
Test Set bot accuracy: 83.87096774193549%
```

website frequency

In [51]:
```
predictions=pd.DataFrame(columns=['user_id',
                                  'user_name',
                                  'scores_universal',
                                  'is_bot_by_botometer',
                                  'mean_links_to_twitter',
                                  'mean_links_to_top_social_media',
                                  'mean_links_to_top_digital_media',
                                  'mean_links_to_top_news',
                                  'mean_links_to_top_products_services',
                                  'mean_links_to_top_celebrities',
                                  'mean_links_to_top_organizations',
                                  'mean_links_to_top_sports',
                                  'mean_links_to_top_adult',
                                  'prediction_lg',
                                  'prediction_RF',
                                  'prediction_bagging_tree'])

is_bot_by_botometer=y_data
```

In [52]:
```
predictions['user_id'] = users_summary_df['user.id_str']
predictions['user_name'] = users_summary_df['name']
predictions['scores_universal'] = users_summary_df['scores.universal']
predictions['is_bot_by_botometer'] = is_bot_by_botometer

for i in ['mean_links_to_twitter',
          'mean_links_to_top_social_media',
          'mean_links_to_top_digital_media',
          'mean_links_to_top_news',
          'mean_links_to_top_products_services',
          'mean_links_to_top_celebrities',
          'mean_links_to_top_organizations',
          'mean_links_to_top_sports',
          'mean_links_to_top_adult']:
    predictions[i] = users_summary_df[i]
predictions.index = range(1000)
```

In [53]:
```
train_index = X_train.index.tolist()
test_index = X_test.index.tolist()
index = train_index + test_index
y_pred_bag = pd.DataFrame(y_pred_train.tolist() + y_pred_test.tolist())
y_pred_bag.columns = ['pred_bag']
y_pred_bag.index = index
y_pred_bag = y_pred_bag.sort_index()
y_pred_bag = pd.get_dummies(y_pred_bag['pred_bag'], drop_first=True)
y_pred_bag.columns = ['pred_bag']
```

In [54]:
```
predictions['prediction_lg'] = LR_model.predict(X_data)
predictions['prediction_RF'] = RF_model.predict(X_data)
predictions['prediction_bagging_tree'] = y_pred_bag['pred_bag']
```

In [55]:

```
vote = []
for i in range(len(predictions)):
    if np.mean(predictions.iloc[i,-4:-1]) > 0.5:
        vote = vote + [1]
    else: vote = vote + [0]
```

In [56]:

```
vote = []
for i in range(len(predictions)):
    if np.mean(predictions.iloc[i,-4:-1]) > 0.5:
        vote = vote + [1]
    else: vote = vote + [0]
```

In [57]:

```
predict_bot_index=predictions.index[predictions['prediction_RF']==1]
predict_non_bot_index=predictions.index[predictions['prediction_RF']==0]
```

In [58]:

```
total_website_sum = []
bot_website_sum = []
ratio = []

for i in ['mean_links_to_twitter',
          'mean_links_to_top_social_media',
          'mean_links_to_top_digital_media',
          'mean_links_to_top_news',
          'mean_links_to_top_products_services',
          'mean_links_to_top_celebrities',
          'mean_links_to_top_organizations',
          'mean_links_to_top_sports',
          'mean_links_to_top_adult']:
    total_website_sum = total_website_sum + [sum(predictions[i])]
    bot_website_sum = bot_website_sum \
                        + [sum(predictions[i][predict_bot_index])]
    ratio = ratio + [sum(predictions[i][predict_bot_index])\
                        /sum(predictions[i])]

total_website_sum = total_website_sum + [sum(total_website_sum)]
bot_website_sum = bot_website_sum + [sum(bot_website_sum)]
ratio = ratio + [sum(bot_website_sum)/sum(total_website_sum)]
```

In [59]:

```
bot_website_ratio = pd.DataFrame(ratio)
bot_website_ratio.index = ['mean_links_to_twitter',
                           'mean_links_to_top_social_media',
                           'mean_links_to_top_digital_media',
                           'mean_links_to_top_news',
                           'mean_links_to_top_products_services',
                           'mean_links_to_top_celebrities',
                           'mean_links_to_top_organizations',
                           'mean_links_to_top_sports',
                           'mean_links_to_top_adult',
                           'Total']
```

In [60]:
```
bot_website_ratio.iloc[0:9].sort_values(by=[0])
```

Out[60]:

	0
mean_links_to_top_sports	0.090909
mean_links_to_twitter	0.208805
mean_links_to_top_celebrities	0.393511
mean_links_to_top_digital_media	0.454819
mean_links_to_top_social_media	0.555639
mean_links_to_top_news	0.593913
mean_links_to_top_products_services	0.621033
mean_links_to_top_organizations	0.967320
mean_links_to_top_adult	1.000000

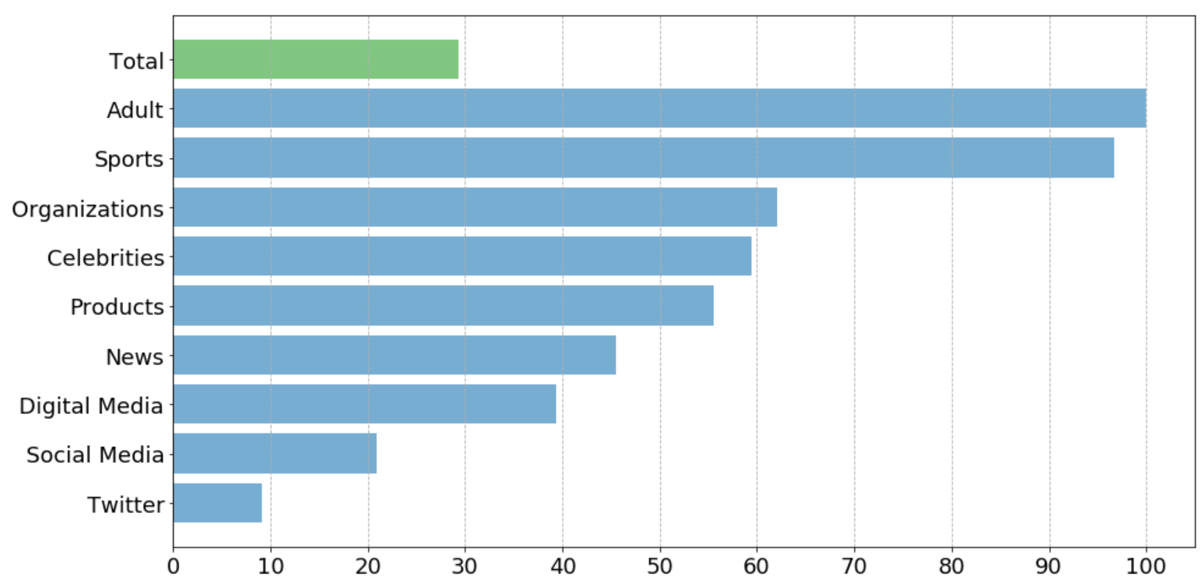
In [61]:
```
bot_website_ratio_each = bot_website_ratio.iloc[0:9].sort_values(by=[0])
bot_website_ratio_total= bot_website_ratio.iloc[9:10]
bot_website_ratio_total[0]
```

Out[61]:
```
Total    0.293066
Name: 0, dtype: float64
```

In [62]:

```
plt.figure(figsize=(15, 8))
plt.barh(range(9),bot_website_ratio_each[0] * 100, alpha = 0.6,
         color = 'C0')
plt.barh(9,bot_website_ratio_total[0] * 100, alpha = 0.6,
         color = 'C2')
plt.yticks(range(10), ['Twitter',
       'Social Media', 'Digital Media',
       'News', 'Products',
       'Celebrities', 'Organizations',
       'Sports', 'Adult','Total'], fontsize = 18)
plt.xticks(range(0,110,10),fontsize=18)
plt.grid(axis='x', linestyle='--')

plt.suptitle("Percentage of Most Popular Websites Tweeted By Bots",
             fontsize=18)
plt.savefig('fig/websites.png', format = 'png')
plt.savefig('../docs/assets/images/websites.png',
            format = 'png')
plt.show()
```

Percentage of Most Popular Websites Tweeted By Bots



In [ ]: