cs109a_group25_tweet_bots

December 12, 2018

```
In [1]: # RUN THIS CELL FOR FORMAT
        import requests
        from IPython.core.display import HTML
        styles = requests.get("https://raw.githubusercontent.com/Harvard-IACS/2018-CS109A/maste
        HTML(styles)

Out[1]: <IPython.core.display.HTML object>
```

1 CS109A Introduction to Data Science

Harvard University Fall 2018 Instructors: Pavlos Protopapas, Kevin Rader

2 Final Project: Group 25 - Twitter Bot Detection

Project Team: Yankai Su, Susheel Chandar Elango, Mohan Indugula **Project Guide**: Brandon Lee

2.1 Motivation

In today's world where there is thousands of tweets produced every second, the impact of tweets influencing about various widespread events ranging from day to day activities, stories, reviews or ratings on a product/company/individual, perceptions on a public body like a political party/movement, etc. is very high. The role and usage of automated accounts known as the social-media bots plays a widespread role in creating an influence or spreading a message/perception through content generated with no direct human involvement. Hence, the importance to identify such **social-media bots** and tweets generated by them is important to avoid being influenced by agendas or perceptions created by such automated accounts.

2.2 Problem Statement

This project aims at detecting the Twitter bots i.e. these automated twitter accounts by using the tweets data generated by these accounts. The project will use the live twitter data made available through the Twitter developer API to analyze tweeting patterns of an user and classify them as a human user or a Twitter bot. The project will take a **supervised approach** to perform classification by utilizing a set of pre-labelled data that already has identified users who are human users and Twitter bots. This pre-labelled data along with the features that is extracted from the raw tweets of these users will be used to train **classification models** to classify twitter bot users. The features extracted will also apply **Natural Language Processing** techniques to perform **sentiment analysis and Topic based Modeling** on the tweet data

2.3 Implementation Structure of the Notebook

The implementation in the notebook has been organized into different sections as per the Data Science lifecycle process that was followed during the execution of this project
1) Interfacing with Twitter Developer API
2) Data Preparation - Includes Raw Data Collection, Data Preprocessing, Data Cleansing and Standardization, Feature Extraction
3) Exploratory Data Analysis
4) Model Training and Validation - Includes training and validation of all the classification models, stacking metalearner and the Topic based classification model training
5) Train and Validation Results and Statistics
6) Test Data Preparation and Models Validation using test data set

In [154]:
```
%matplotlib inline
from IPython.display import Markdown, display

import sys
import math
import os
import random
random.seed(112358)
import base64
import string
import re
from collections import Counter

import csv
import jsonpickle
import json

from time import sleep
from datetime import datetime

import pandas as pd
import numpy as np
import numpy.random as nd
from scipy.stats import expon

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.base import TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
```

```python
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegressionCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.svm import SVC
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import GradientBoostingClassifier

import keras
from keras import models
from keras.models import Sequential
from keras.layers import Dense, Flatten, Dropout
from keras.constraints import MaxNorm
from keras import regularizers

import tweepy # Library to access Twitter Developer API

# Natural Language Processing related Libraries used for Sentiment Analysis and Topi
from textblob import TextBlob #For Sentiment Analysis

import nltk # Natural Language Toolkit for Topic Modeling
nltk.download('stopwords')

import spacy # NLP Library
nlp = spacy.load('en_core_web_sm')

from nltk.corpus import stopwords

from spacy.lang.en import English
parser = English()

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.stop_words import ENGLISH_STOP_WORDS
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\tv775c\AppData\Roaming\nltk_data...
```

```
[nltk_data]   Package stopwords is already up-to-date!
```

```
In [79]: def printmd(string):
             display(Markdown(string))

         #Seaborn settings
         sns.set(style="darkgrid")
         flatui = ["#34495e", "#1abc9c", "#e74c3c", "#2ecc71", "#9b59b6", "#3498db", "#95a5a6"]
         sns.set_palette(flatui)

         #Pandas Settings
         pd.set_option('display.width', 1500)
         pd.set_option('display.max_columns', 100)

         # Global Constants
         TWEET_EXTRACT_LOCATION_TRAIN = 'tweet_extract_data/' # Location of extracted Tweet fi
         TWEET_EXTRACT_LOCATION_TEST = 'tweet_test_extract_data/' # Location of extracted Twee
         DATA_FILE_SUFFIX = '.dat' # Extension used for the JSON data files
         SUCCESS_USER_STATS = 'success_user_stats.csv' # Data file containing list of users fo
         RESTRICTED_USER_STATS = 'restricted_user_stats.csv' # Data file containing list of re
         CONSOLIDATED_FEATURES = 'consolidated_features.csv' # Data file containing list of co
```

```
In [80]: import warnings
         warnings.filterwarnings("ignore", category=UserWarning, module="sklearn")
```

3 Instantiate Connection with Twitter Developer API

Use the API Key and Secret code provided by twitter for the app subscription and initiate a connection using tweepy

```
In [81]: # Replace the API_KEY and API_SECRET with your application's key and secret.
         API_KEY = "<USE_SUBSCRIPTION_APP_API_KEY>"
         API_SECRET = "<USE_SUBSCRIPTION_APP_API_SECRET>"

         # Authenticate user API Key and Secret code
         auth = tweepy.AppAuthHandler(API_KEY, API_SECRET)
         api = tweepy.API(auth, wait_on_rate_limit=True, wait_on_rate_limit_notify=True)

         if (not api):
             print ("Can't Authenticate")
             sys.exit(-1)
```

```
In [82]: # Method Implementation to Fetch tweets posted by a specified user
         # NOTE: Twitter only allows access to a users most recent 3200 tweets with this metho
         def get_all_tweets_json(user_id, no_of_tweets=200, tweet_max_id = None):
             '''Fetch the most recent tweets as per no_of_tweets mentioned for the given user_
```

```
        Args:
            user_id: Twitter User ID of an user as recognized by Twitter developer API
            no_of_tweets: No of recent tweets to fetch for the user. Default set to 20
            tweet_max_id: The Max ID of the twitter status that should be fetched

        Returns:
            new_tweets: Array of tweets containing individual tweets in JSON format
    '''

    # Array initiated to hold the JSON formatted tweets extracted for the user
    new_tweets = []
    try:
        # Make initial request for most recent tweets (200 is the maximum allowed cou
        if tweet_max_id == None:
            new_tweets = api.user_timeline(user_id = user_id ,count = no_of_tweets)
        else:
            new_tweets = api.user_timeline(user_id = user_id ,count = no_of_tweets, ma
    except tweepy.TweepError as e:
        raise
    except tweepy.RateLimitError as rate_err:
        raise

    return new_tweets
```

4 Data Preparation

Raw Data Collection

Read Pre-labelled twitter user set obtained from botometer (varo-2017)

In [83]:
```
# Read the Pre-classified data set containing twitter user labeled as either Bots (1)
labelled_df=pd.read_csv('varol-2017.dat', delimiter='\t' ,header=None)

# Filter the Data frame and limit to the User ID and Bot Flag columns
labelled_df.columns = ['user_id', 'bot_flg']

# Determine no of users in the labelled data classified as Bots(1) and who are determ
labelled_df.groupby(['bot_flg']).count()
```

Out[83]:

bot_flg	user_id
0	1747
1	826

Extract Tweet data from Twitter developer API for twitter users in the pre-labelled data set

In [84]:
```
# Method Implementation to extract tweets for a set of users
def extract_tweets_for_users(labelled_users, target_location):
    '''Extract upto 3200 tweets for the given set of labelled users
```

```
        and store the tweets for each individual user in <user_id>.data file in the t
        stats of success_users for whom data was retreived successfully and restricte
        whom data retreival was not successful are also written out to the target loc

    Args:
        labelled_users: Datframe containing set of labelled users with twitter_use
        target_location: Location where the data files with extracted tweets shoul

    Returns:
        success_users: Dataframe containining list of successful users for whom da
        restricted_users: Dataframe containining list of restricted users
'''

# Instantiate a Dataframe to store the restricted users whose information cannot
restricted_users = pd.DataFrame(columns=['user_id', 'bot_flg', 'reason'])
success_users = pd.DataFrame(columns=['user_id', 'bot_flg'])

# Loop through each user in labelled_users and write the json extracts into '<use
max_tweet_cnt = 3000
stop_process = False
for index, row in labelled_users.iterrows():
    user_id = row['user_id']
    curr_id = None # Latest tweet ID retreived for the current user

    # Check if rate limit has reached by checking stop_process flag before procee
    if stop_process == True:
        break

    # Open Write handle for '<user_id>.dat' file to write the extracted json feed
    with open(target_location + str(user_id) + DATA_FILE_SUFFIX, 'w') as f:

        try:
            # Initiate remaining count to max count
            remaining_cnt = max_tweet_cnt

            # Check if still max count has not reached by checking remaining coun
            while remaining_cnt > 0:

                tweet_cnt = 0
                tweet_extracts = None
                # Check if tweets have been retreived for user in this session
                # by checking the id of the last tweet retreived
                if curr_id == None:
                    tweet_extracts = get_all_tweets_json(user_id, 200)
                else:
                    tweet_extracts = get_all_tweets_json(user_id, 200, curr_id)

                # Encode each json tweet retreived and write to the user dat file
```

```
                for tweet in tweet_extracts:
                    curr_id = tweet._json.get('id') - 1
                    f.write(jsonpickle.encode(tweet._json, unpicklable=False) +'\r
                    tweet_cnt = tweet_cnt + 1

                # Update remaining count to reach max limit
                remaining_cnt = max_tweet_cnt - tweet_cnt

                # If no tweets was available to retreive then move to next user
                if tweet_cnt == 0:
                    break;

            # Append stats of current users to success users dataframe
            success_users = success_users.append({'user_id': user_id, 'bot_flg': :
                                                  , ignore_index=True)
        except tweepy.TweepError as e:
            # Handle TweepError encountered during extraction and update restricte
            restricted_users = restricted_users.append({'user_id': user_id, 'bot_:
                                                        , 'reason': e.reason}, ig
        except tweepy.RateLimitError as rate_err:
            # Handle limit reached error and mark to stop retreival process
            print('Tweet Data Extraction terminated due to RATE LIMIT ERROR')
            print('Current User ID - ' + user_id)
            stop_process = True

    # Close user data file handle
    f.close()

# Write Success User and Restricted user stats to CSV file
success_users.to_csv(target_location + SUCCESS_USER_STATS, index=False)
restricted_users.to_csv(target_location + RESTRICTED_USER_STATS, index=False)

return success_users, restricted_users
```

In [85]:
```
# MARKED FOR EXECUTION AS NEEDED - NOTE - EXTRACTION TAKES A LONG TIME
# Download the latest 3000 tweets as json for each user in varol-2017.dat (labelled_d

# success_users, restricted_users = extract_tweets_for_users(labelled_df, TWEET_EXTRA
```

Data Preprocessing

Utility methods to help in Data Processing

In [127]:
```
# Lambda function to check if an Object is NULL and return 0 if yes and 1 if not nul
check_if_null = lambda obj: 0 if obj == None else 1

# Lambda function to Binary code a boolean value - True to 1 and False to 0
binary_code_boolean = lambda boolean: 1 if boolean == True else 0
```

```
# Lambda function to get count of a list
get_count = lambda array: 0 if (array == None or (type(array) is not list)) else len

# Utility function to separate hashtag topics from the given string phrase
def extract_hash_tags(s):
    return set(part[1:] for part in s.split() if part.startswith('#'))

# Utility method to Clean the provided text content
def cleanTagText(text):
    text = str(text.encode(encoding='ascii',errors='replace'))
    text = text.strip().replace("\n", " ").replace("\r", " ").replace("\\n", " ").rep
    text = text.replace("?", "").replace("\'","").replace("_","").replace("~","").rep
    text = text.lower()
    return text
```

Parse the JSON feeds of the tweets received and create a flattened data frame with extracted and preprocessed attributes

Cleanse, modify and update attributes extracted from the tweet feeds

Data Cleansing and Standardisation

Parse the JSON feeds of the tweets received and create a flattened data frame with extracted and preprocessed attributes

Cleanse, modify and update attributes extracted from the tweet feeds

In [128]:
```
# Method Implementation to parse and extract features from tweets posted by a specif
# Approx 14 User level features and 17 Tweet level features are extracted from the T

def parse_and_extract_tweets_for_user(user_id, source_location):
    '''Parse the JSON tweets for the given user id and extract the features.
       Features extracted will be user level features and tweet level features

      Args:
          user_id: Twitter User ID of an user as recognized by Twitter developer AP
          source_location: Location of the dat files from which tweets are to be ex
      Returns:
          user_features_df: Dataframe containining user level features for the give
          tweet_features_df: Dataframe of tweets containing features extracted from

    '''
    user_features_df = None
    tweets_list = []
    has_user_data = False

    # Parse the JSON Feed file with tweets obtained from Twitter for the given User
    with open(source_location + str(user_id) + DATA_FILE_SUFFIX) as fjson:
        tweet_jsons = fjson.readlines()
    fjson.close()

    # Loop through all tweets and extract tweet level features for each tweet
```

```
# Extract User level features from the tweet object just for the first tweet
for current_tweet in tweet_jsons:

    # Load the tweet object into a dictionary by decoding the JSON string
    tweet_dict = json.loads(current_tweet)

    # Extract User level features just from the first tweet
    # All Boolean attributes are binary encoded to 1 (True) or 0 (False)
    if has_user_data == False:
        usr_features = {}

        # Get the user object as dictionary from the tweet
        user_dict = tweet_dict.get('user', {})

        # Get ID of the user (Number)
        usr_features['user_id'] = user_dict.get('id')

        # Boolean attribute - True indicates user has not altered default profil
        usr_features['default_profile'] = binary_code_boolean(user_dict.get('defa
        # Boolean attribute - True indicates user has not altered default profil
        usr_features['default_profile_image'] = binary_code_boolean(user_dict.ge

        # Int attribute - Number of tweets user has liked in lifetime of account
        usr_features['favourites_count'] = user_dict.get('favourites_count')
        # Int attribute - Number of current followers for this account
        usr_features['followers_count'] = user_dict.get('followers_count')
        # Int attribute - Number of users being followed by this account
        usr_features['friends_count'] = user_dict.get('friends_count')
        # Int attribute - Number of public lists that this user is a member of
        usr_features['listed_count'] = user_dict.get('listed_count')
        # Int attribute - Number of tweets (including retweets) issued by this u
        usr_features['statuses_count'] = user_dict.get('statuses_count')

        # Boolean attribute - True - Indicates user has enabled geo tagging of t
        usr_features['geo_enabled'] = binary_code_boolean(user_dict.get('geo_enal
        # Boolean attribute - True - Indicates user has chosen to protect their
        usr_features['protected'] = binary_code_boolean(user_dict.get('protected
        # Boolean attribute - True - Indicates user has a verified account
        usr_features['verified'] = binary_code_boolean(user_dict.get('verified')

        # Twitter Internal attributes
        # Boolean attribute - True - Indicates user has an extended profile
        usr_features['has_extended_profile'] = binary_code_boolean(user_dict.get
        # Boolean attribute - True - Indicates if the user is a participant of T
        usr_features['is_translator'] = binary_code_boolean(user_dict.get('is_tra

        # String attribute - Denotes the code of the language set for the user a
        usr_features['user_lang'] = user_dict.get('lang')
```

```
    # Create a dataframe for the user features
    user_features_df = pd.DataFrame(data=usr_features, index=[0])
    has_user_data = True

# Extract Tweet Level Features to be consolidated and grouped to user level
tweet_features ={}
tweet_features['user_id'] = user_id

# Get ID of the Tweet (Number)
tweet_features['tweet_id'] = tweet_dict.get('id')

# Perform SENTIMENT ANALYSIS on the text content of the tweet
sentiment_score = TextBlob(tweet_dict.get('text')).sentiment
# Calculate Polarity (Level of emotion) score (Range 0-1) from sentiment ana
tweet_features['senti_polarity'] = sentiment_score.polarity
# Calculate Subjectivity score (Range 0-1) from sentiment analysis
# 0 is very Objective and 1 is very subjective
tweet_features['senti_subjectivity'] = sentiment_score.subjectivity

# String attribute - Indicates date and timestamp when the tweet was created
# Convert to Date/Time object
tweet_features['created_at'] = pd.to_datetime(tweet_dict.get('created_at'))

# Int attribute - Indicates number of times this tweet has been liked by use
tweet_features['favorite_count'] = tweet_dict.get('favorite_count')
# Int attribute - Indicates number of times this tweet has been retweeted by
tweet_features['retweet_count'] = tweet_dict.get('retweet_count')

# Boolean attribute - True Indicates that tweet is associated with a place
tweet_features['place_reference'] = check_if_null(tweet_dict.get('place')) #
# Boolean attribute - True Indicates that tweet contains possibly sensitive
tweet_features['possibly_sensitive'] = binary_code_boolean(tweet_dict.get('p
# Boolean attribute - True Indicates that tweet is a reply to an existing tw
tweet_features['is_a_reply'] = check_if_null(tweet_dict.get('in_reply_to_sta
# Boolean attribute - True Indicates that this tweet is a Quoted tweet
tweet_features['is_quote_status'] = binary_code_boolean(tweet_dict.get('is_q
# Boolean attribute - True Indicates that this tweet is a retweet of an exis
tweet_features['is_a_retweet'] = check_if_null(tweet_dict.get('retweeted_sta

# Extract Info on Media and external entitities associated with the tweet
entities_dict = tweet_dict.get('entities', {}) #**
# Int attribute - Indicates number of Hash tags referred to in the tweet
tweet_features['hash_tags_cnt'] = get_count(entities_dict.get('hashtags'))
# Int attribute - Indicates number of media content attached with the tweet
tweet_features['media_cnt'] = get_count(entities_dict.get('media'))
# Int attribute - Indicates number of URLs and links embedded in the tweet
tweet_features['url_ref_cnt'] = get_count(entities_dict.get('urls'))
```

```
            # Int attribute - Indicates number of symbols embedded in the tweet
            tweet_features['symbols_cnt'] = get_count(entities_dict.get('symbols'))
            # Int attribute - Indicates number of User references in the tweet
            tweet_features['user_ref_cnt'] = get_count(entities_dict.get('user_mentions'

            # Extract Hash tags from the tweet text to perform topic modeling
            hash_tags = ''
            if get_count(entities_dict.get('hashtags')) > 0:
                hash_tags = ' '.join(list(filter(None,extract_hash_tags(cleanTagText(twe
            tweet_features['hash_tags'] = hash_tags

            # Add the tweet to the list of user tweets parsed
            tweets_list.append(tweet_features)

        # Create a dataframe for the tweet features
        tweet_features_df = pd.DataFrame(data=tweets_list)

        return user_features_df, tweet_features_df
```

Feature Extraction

Extract, Derive and Create new features from the attributes extracted from the tweet feeds

```
In [88]: # Method implementation to consolidate, merge tweet level stats gathered to user leve
         # Stats are merged based on the number of tweets collected for the user. Usually ~300

         def Merge_tweet_stats_to_user_level(user_id, tweet_cnt, tweet_features_df):
             '''Parse the JSON tweets for the given user id and extract the features.
                Features extracted will be user level features and tweet level features

               Args:
                   user_id: Twitter User ID of an user as recognized by Twitter developer API
                   tweet_cnt: Count of tweets extracted for the user
                   tweet_features_df: Dataframe of tweets containing features extracted from
               Returns:
                   tweet_merged_df: Dataframe for tweet level features consolidated to user l
             '''
             merged_stats = {}

             # Calculate Mean of Sentiment analysis scores across all messages created by user
             # Value range is between 0 and 1
             merged_stats['senti_polarity'] = round(tweet_features_df['senti_polarity'].mean()
             merged_stats['senti_subjectivity'] = round(tweet_features_df['senti_subjectivity'

             # Calculate Mean stats of all binary value (0 or 1) features
             merged_stats['place_reference'] = round(tweet_features_df['place_reference'].mean
             merged_stats['possibly_sensitive'] = round(tweet_features_df['possibly_sensitive'
             merged_stats['is_a_reply'] = round(tweet_features_df['is_a_reply'].mean(),3)
             merged_stats['is_quote_status'] = round(tweet_features_df['is_quote_status'].mean
```

```
        merged_stats['is_a_retweet'] = round(tweet_features_df['is_a_retweet'].mean(),3)

        # Calculate Mean stats of all integer value features
        merged_stats['favorite_count'] = round(tweet_features_df['favorite_count'].mean()
        merged_stats['retweet_count'] = round(tweet_features_df['retweet_count'].mean(),3
        merged_stats['hash_tags_cnt'] = round(tweet_features_df['hash_tags_cnt'].mean(),3
        merged_stats['media_cnt'] = round(tweet_features_df['media_cnt'].mean(),3)
        merged_stats['url_ref_cnt'] = round(tweet_features_df['url_ref_cnt'].mean(),3)
        merged_stats['symbols_cnt'] = round(tweet_features_df['symbols_cnt'].mean(),3)
        merged_stats['user_ref_cnt'] = round(tweet_features_df['user_ref_cnt'].mean(),3)

        # Calculate the Tweeting frequency in Hours based on Creation Time Interval and t
        creation_intrval = tweet_features_df['created_at'].max() - tweet_features_df['crea
        merged_stats['tweet_freq_hrs'] = round((creation_intrval.days*24 +
                                        creation_intrval.seconds//3600) / int(twee

        # Consolidate all hash tags from all user messages into 1 string
        hash_tags = tweet_features_df['hash_tags'].str.cat(sep=' ').strip()
        #str(tweet_features_df['hash_tags'].apply(' '.join)).strip()
        if hash_tags == '':
            hash_tags = 'none'
        merged_stats['hash_tags'] = ' '.join(set(hash_tags.split()))

        # Create a Dataframe with the Merged stats
        tweet_merged_df = pd.DataFrame(data=merged_stats, index=[0])

        return tweet_merged_df
```

```
In [89]: def consolidate_features_at_user_level(source_location):
        '''Extract, parse and Consolidate all Features for each user in the extracted dat

           Args:
               source_location: Location of the dat files from which tweets are to be ext
           Returns:
               consolidated_ftrs_df: Dataframe with consolidated features for all users
        '''
        # Create a Dataframe with users for whom data was extracted successfully
        success_users_df = pd.read_csv(source_location + SUCCESS_USER_STATS)

        # For each user.. Parse, extract features on user and tweet level.. then merge tw
        consolidated_ftrs_df = pd.DataFrame()
        for index, row in success_users_df.iterrows():
            # Parse, extract features on user and tweet level
            user_features_df, tweet_features_df = parse_and_extract_tweets_for_user(row['
            tweet_count = len(tweet_features_df.index)

            if tweet_count > 0:
                # Merge tweet level features to user level based on aggregation
```

```
                tweet_merged_df = Merge_tweet_stats_to_user_level(row['user_id'], tweet_co

                # Merge the user and aggregated tweet features and Concat to a consolidat
                consolidated_ftrs_df = consolidated_ftrs_df.append(pd.concat([user_feature
                                                                              , axis=1), ig

        # Merge the consolidated features with the pre classification labels
        consolidated_ftrs_df = consolidated_ftrs_df.join(success_users_df.set_index('user_

        # Just In Case - Drop NaN and Null rows
        consolidated_ftrs_df = consolidated_ftrs_df.dropna()

        # Write the Consolidated features to the source location for later retreival
        consolidated_ftrs_df.to_csv(source_location + CONSOLIDATED_FEATURES, index=False)

        return consolidated_ftrs_df
```

In [90]:

```
consolidated_ftrs_df = pd.read_csv(TWEET_EXTRACT_LOCATION_TRAIN + CONSOLIDATED_FEATURE

# MARKED FOR EXECUTION AS NEEDED - NOTE - PARSING and CONSOLIDATES TAKES A LONG TIME
# Extract and consolidate all features for every user
# consolidated_ftrs_df = consolidate_features_at_user_level(TWEET_EXTRACT_LOCATION_TRA

consolidated_ftrs_df.describe()
```

Out[90]:

	user_id	default_profile	default_profile_image	favourites_count	followe
count	2.139000e+03	2139.000000	2139.000000	2139.000000	213
mean	1.364801e+09	0.421225	0.039271	6027.263675	167
std	1.303371e+09	0.493871	0.194284	14488.054908	819
min	1.325300e+04	0.000000	0.000000	0.000000	
25%	2.365333e+08	0.000000	0.000000	94.000000	12
50%	7.511447e+08	0.000000	0.000000	1325.000000	34
75%	2.582829e+09	1.000000	0.000000	5977.500000	84
max	4.627817e+09	1.000000	1.000000	289192.000000	24792

In [91]:

```
# Preview the consolidated features
consolidated_ftrs_df.head()
```

Out[91]:

	user_id	default_profile	default_profile_image	favourites_count	followers_cou
0	44324787	1	0	15011	
1	3098421349	1	0	88	2
2	554067867	1	0	2707	
3	256597786	1	0	10	1
4	103351486	0	0	55	1

In [92]:

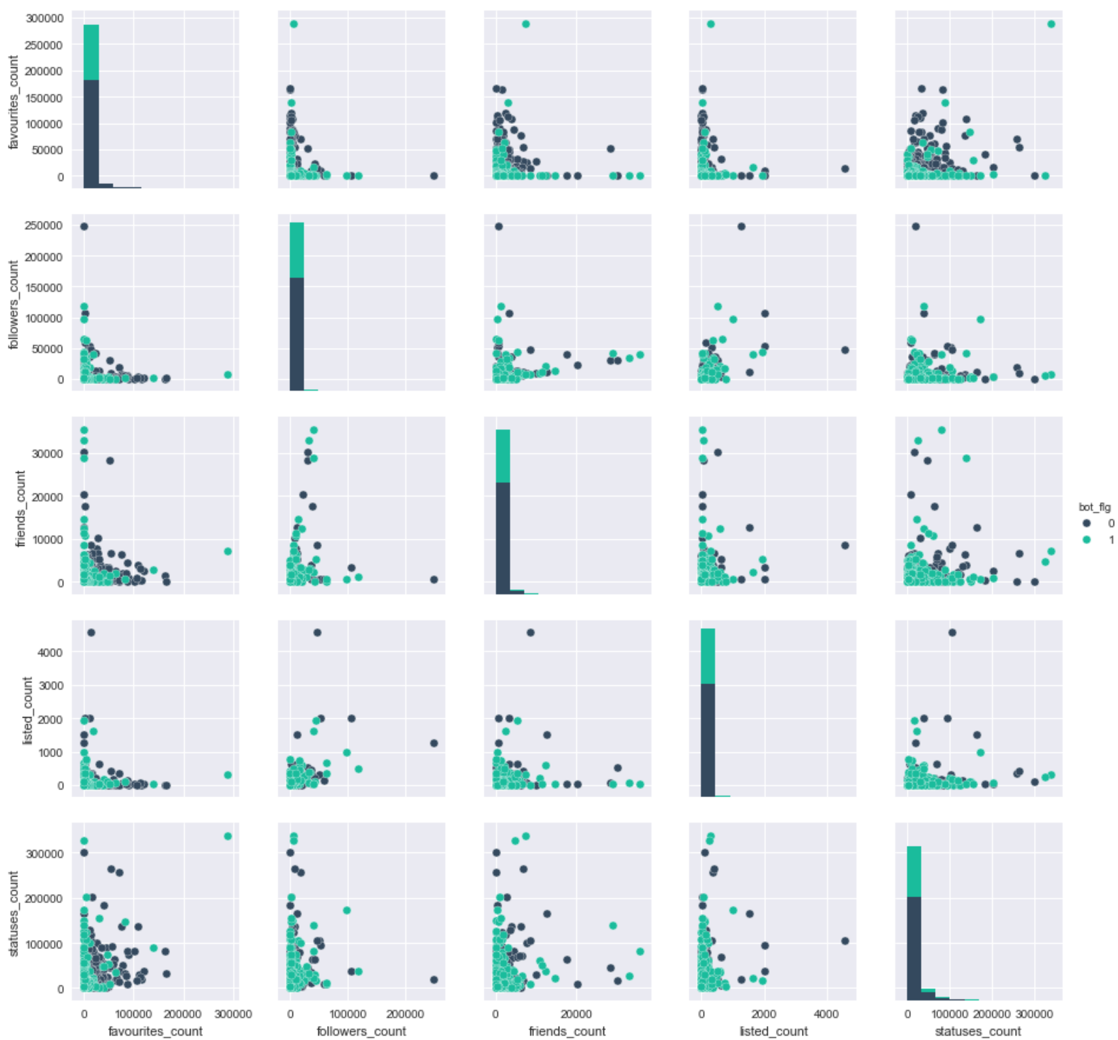
```
# Drop user_id from the dataframe as that is not needed for classification
consolidated_ftrs_df = consolidated_ftrs_df.drop(["user_id"], axis=1)
```

5 Exploratory Data Analysis on the extracted features and attributes

Matrix plot of User Level count features across Bot and Human classes

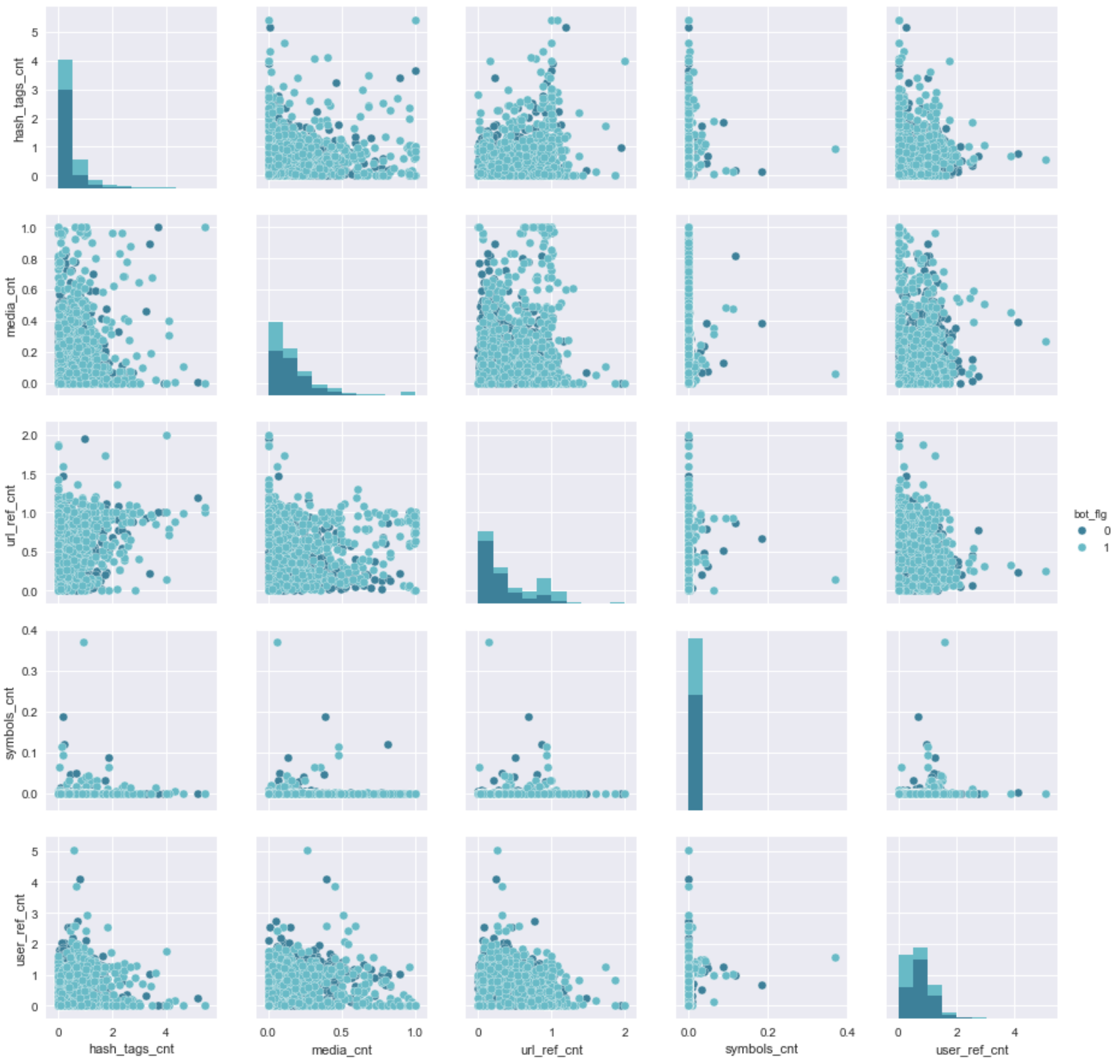
In [93]:
```
# Separate Bot and Human data into separate frames for analysis
df_bot = consolidated_ftrs_df[consolidated_ftrs_df.bot_flg==1]
df_human = consolidated_ftrs_df[consolidated_ftrs_df.bot_flg==0]
```

In [94]:
```
# Create a Matrix plot across Bot and Human classes
ax = sns.pairplot(consolidated_ftrs_df, hue="bot_flg"
                          , vars=['favourites_count', 'followers_count', 'friends_count', 'li
                            'statuses_count'])
```



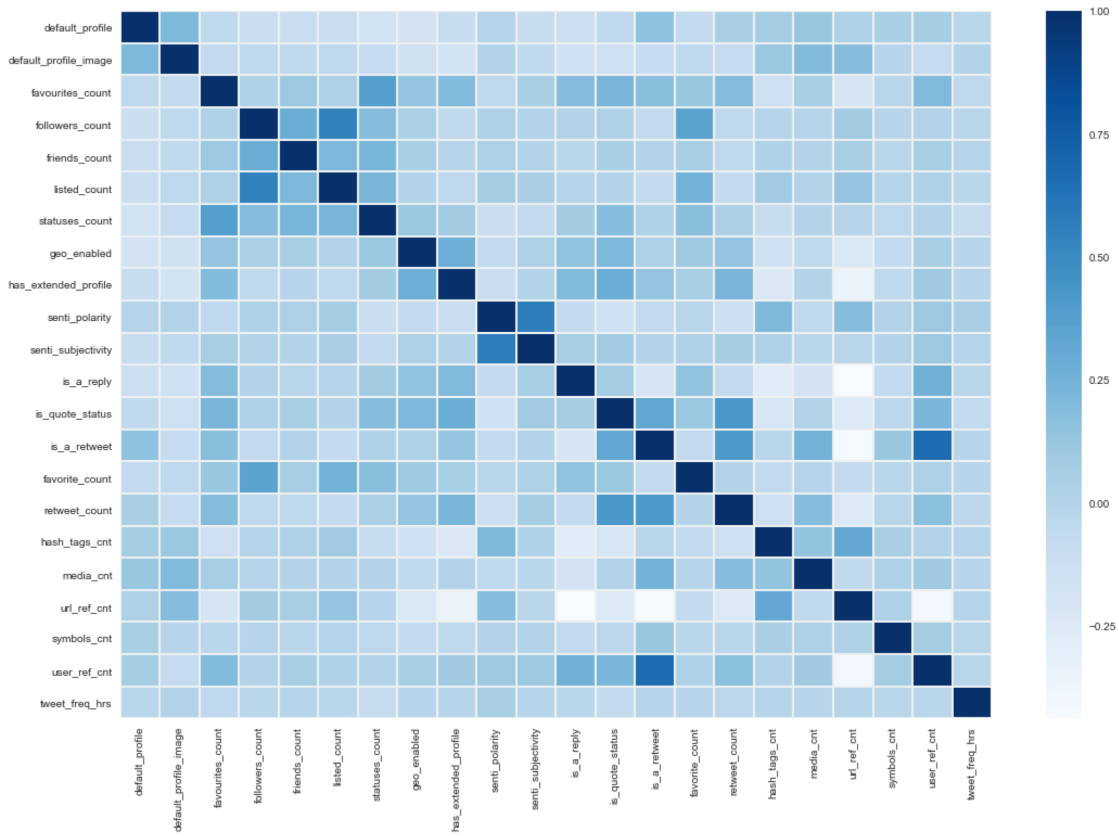
Matrix plot of Tweet Level Entity features across Bot and Human classes

In [95]:
```
# Create a Matrix plot across Bot and Human classes
ax = sns.pairplot(consolidated_ftrs_df, hue="bot_flg", palette="GnBu_d"
                          , vars=['hash_tags_cnt', 'media_cnt', 'url_ref_cnt', 'symbols_cnt'
```



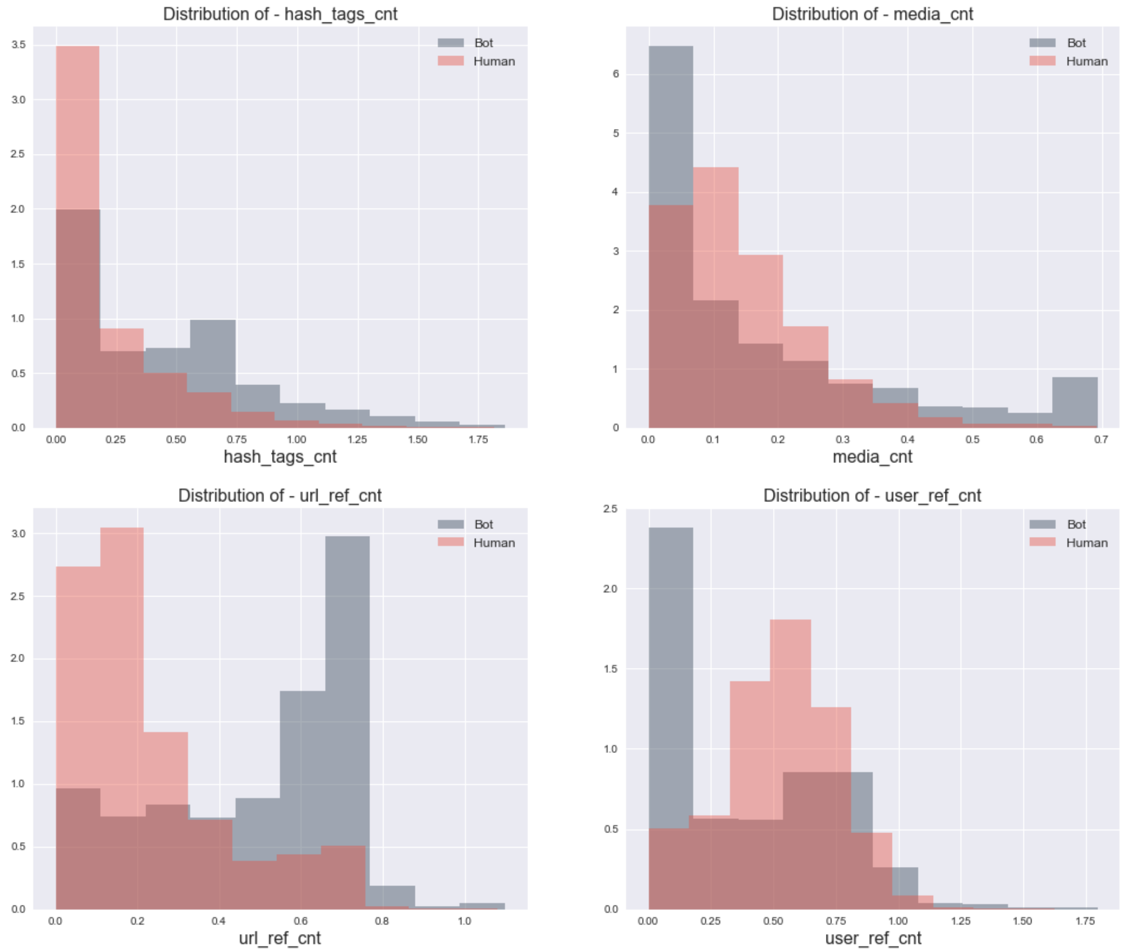
Heat map of the correlation matrix for the numeric features

In [96]:
```
# Initialize the Figure
fig, ax = plt.subplots(1, 1, figsize=(18, 12))

# Calculate the correlation between the numeric features
corr = consolidated_ftrs_df.drop(['bot_flg', "user_lang", 'protected', 'verified', 'i
                                  , 'possibly_sensitive', 'place_reference','hash_tag
                                 , axis=1, errors='ignore').corr()

# Generate a heatmap on the correlation matrix
ax = sns.heatmap(corr,cmap='Blues', linewidth=1, linecolor='#ecf0f1', ax=ax)
```



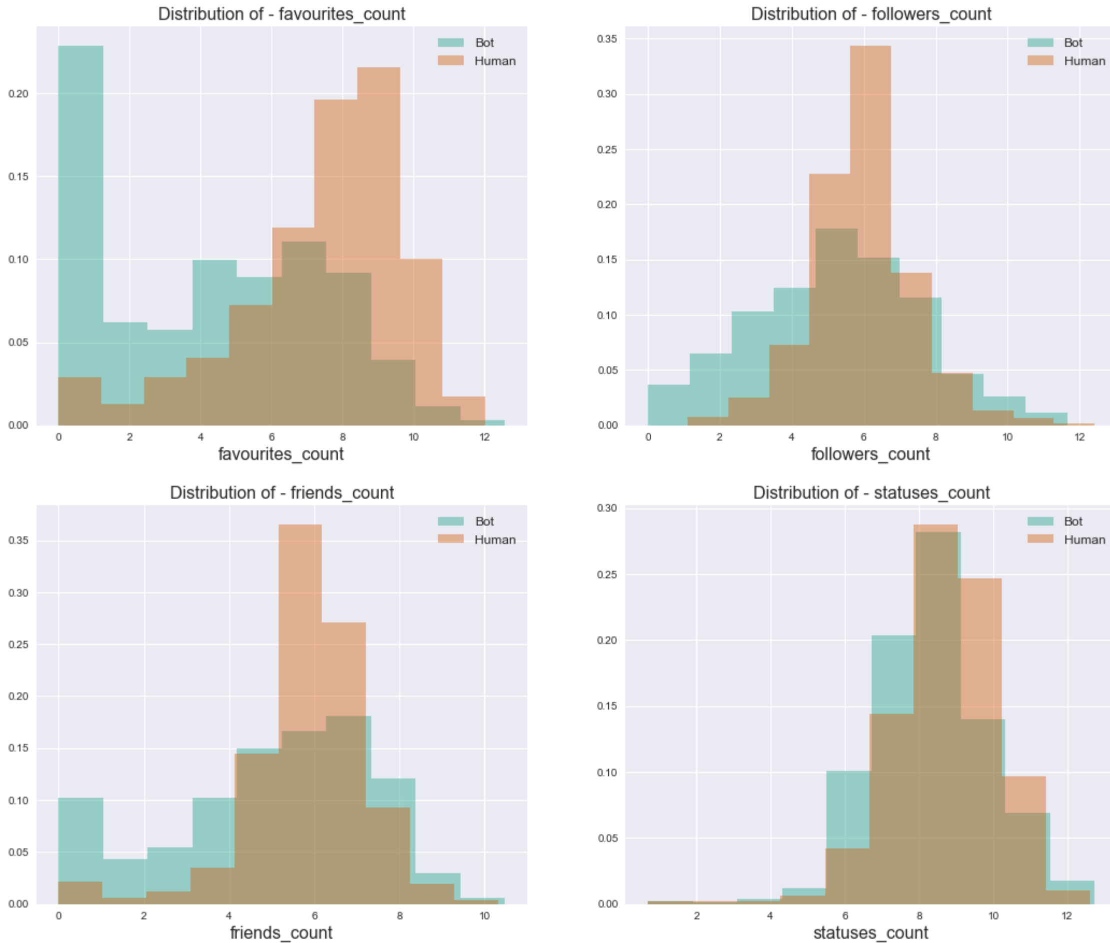
Distribution plot of Tweet Level Entities across Bot and Human classes

```
In [97]: # Initialize the Figure with 2X2 subplots
         fig, ax = plt.subplots(2, 2, figsize=(18, 15))
         idx = 1

         # for all entity counts, plot a overlaying histogram subplot of Bot and Human classes
         for cnt in ['hash_tags_cnt', 'media_cnt', 'url_ref_cnt', 'user_ref_cnt']:
             plt.subplot(2, 2, idx)
             plt.hist(np.log(df_bot[cnt]+1), alpha=0.4, color='#2c3e50', label="Bot", density=
             plt.hist(np.log(df_human[cnt]+1), alpha=0.4, color='#e74c3c', label="Human", dens
             plt.xlabel(cnt, fontsize = 16)
             plt.title('Distribution of - ' + cnt, fontsize = 16)
             plt.legend(fontsize = 12)
             idx += 1

         plt.show()
```



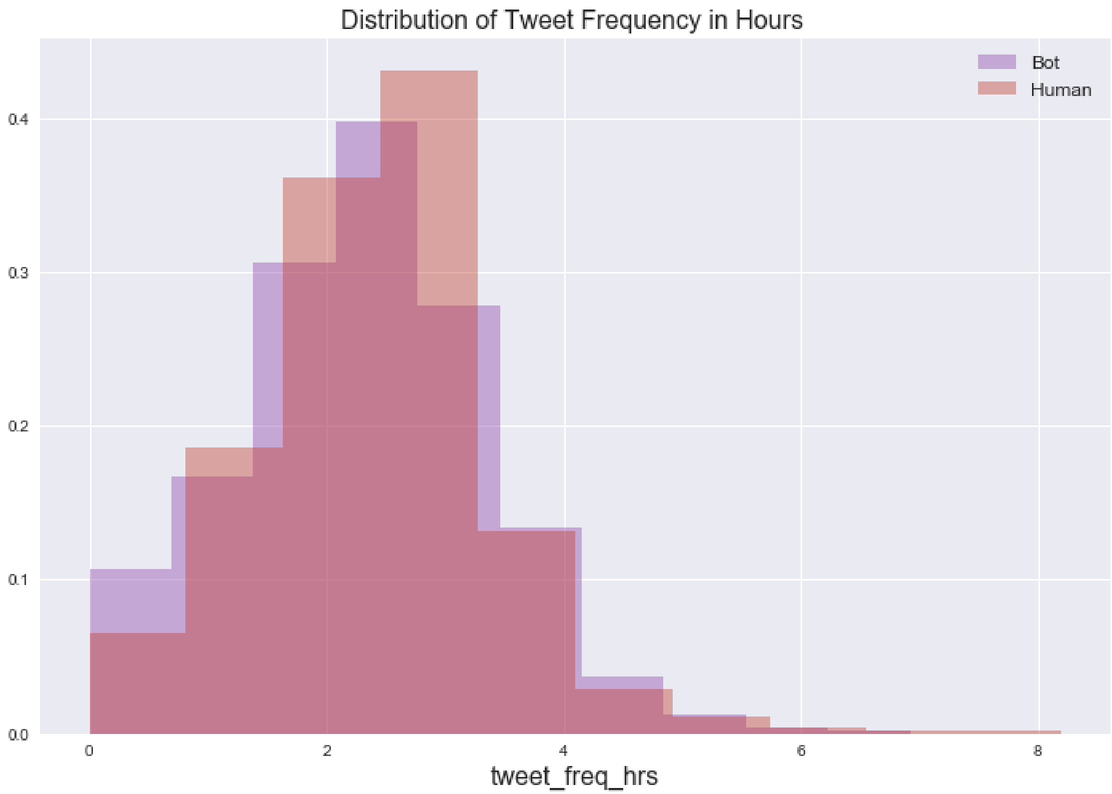
Distribution plot of User Level Count features across Bot and Human classes

```
In [98]: # Initialize the Figure with 2X2 subplots
         fig, ax = plt.subplots(2, 2, figsize=(18, 15))
         idx = 1

         # for all user level counts, plot a overlaying histogram subplot of Bot and Human cla
         for cnt in ['favourites_count', 'followers_count', 'friends_count', 'statuses_count']
             plt.subplot(2, 2, idx)
             plt.hist(np.log(df_bot[cnt]+1), alpha=0.4, color='#16a085', label="Bot", density=
             plt.hist(np.log(df_human[cnt]+1), alpha=0.4, color='#d35400', label="Human", dens
             plt.xlabel(cnt, fontsize = 16)
             plt.title('Distribution of - ' + cnt, fontsize = 16)
             plt.legend(fontsize = 12)
             idx += 1

         plt.show()
```



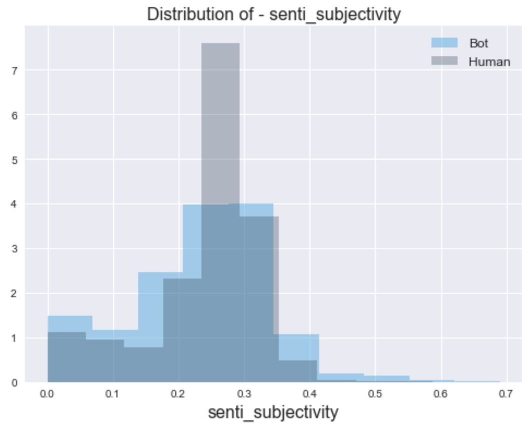
Distribution plot of Tweet Frequency in Hours across Bot and Human classes

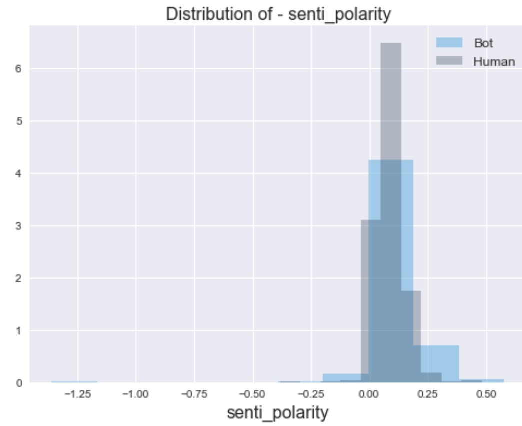
```
In [99]: # Initialize the Figure with 2X2 subplots
         fig, ax = plt.subplots(1, 1, figsize=(12, 8))
         idx = 1

         # for tweeting frequency, plot a overlaying histogram subplot of Bot and Human classe
         for cnt in ['tweet_freq_hrs']:
             plt.subplot(1, 1, idx)
             plt.hist(np.log(df_bot[cnt]+1), alpha=0.4, color='#8e44ad', label="Bot", density='
             plt.hist(np.log(df_human[cnt]+1), alpha=0.4, color='#c0392b', label="Human", dens
             plt.xlabel(cnt, fontsize = 16)
             plt.title('Distribution of Tweet Frequency in Hours ', fontsize = 16)
             plt.legend(fontsize = 12)
             idx += 1

         plt.show()
```



Distribution plot of Sentiment analysis scores of Tweets across Bot and Human classes

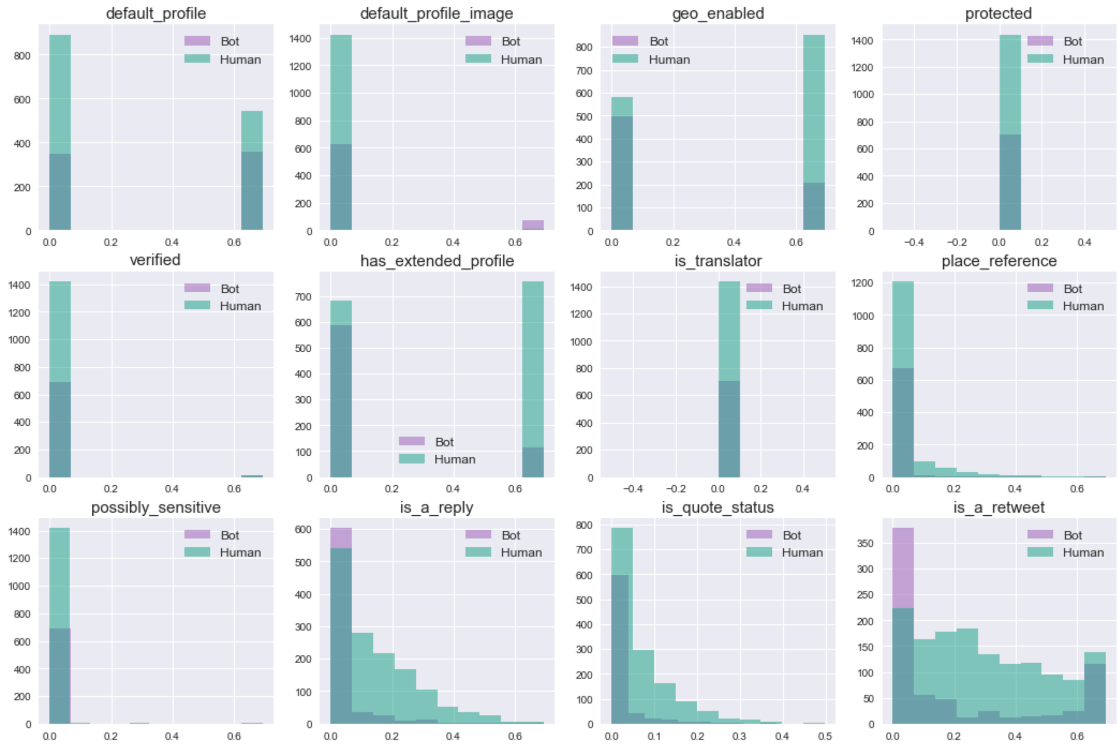
In [100]:
```
# Initialize the Figure with 2X2 subplots
fig, ax = plt.subplots(1, 2, figsize=(18, 6))
idx = 1

# for sentiment analysis scores, plot a overlaying histogram subplot of Bot and Huma
for cnt in ['senti_subjectivity', 'senti_polarity']:
    plt.subplot(1, 2, idx)
    plt.hist(np.log(df_bot[cnt]+1), alpha=0.4, color='#3498db', label="Bot", density=
    plt.hist(np.log(df_human[cnt]+1), alpha=0.3, color='#2c3e50', label="Human", dens
    plt.xlabel(cnt, fontsize = 16)
    plt.title('Distribution of - ' + cnt, fontsize = 16)
    plt.legend(fontsize = 12)
    idx += 1

plt.show()
```





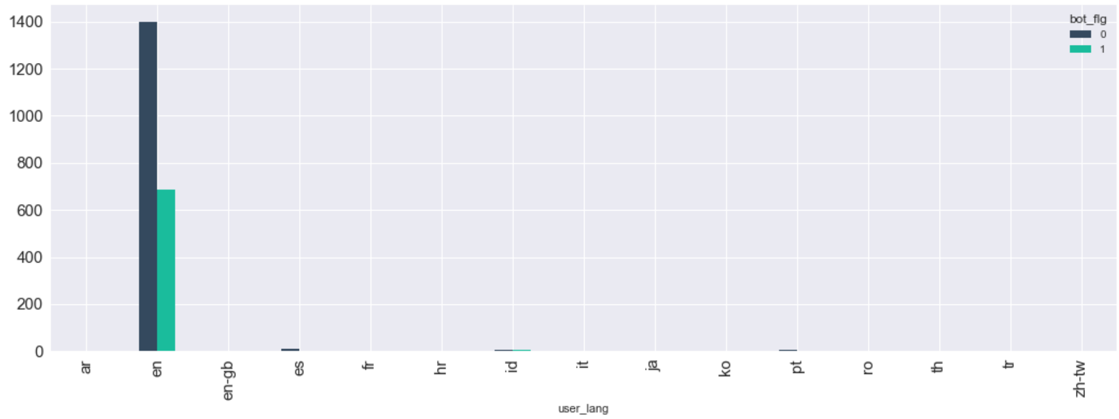
Distribution plot of Categorical features

In [101]:
```python
# Initialize the Figure with 2X2 subplots
fig, ax = plt.subplots(3, 4, figsize=(18, 12))
idx = 1

# for all categorical, plot a overlaying histogram subplot of Bot and Human classes
for cnt in ['default_profile', 'default_profile_image', 'geo_enabled', 'protected'
            , 'verified', 'has_extended_profile', 'is_translator','place_reference'
            ,'possibly_sensitive','is_a_reply', 'is_quote_status', 'is_a_retweet']:
    plt.subplot(3, 4, idx)
    plt.hist(np.log(df_bot[cnt]+1), alpha=0.5, color='#9b59b6', label="Bot")
    plt.hist(np.log(df_human[cnt]+1), alpha=0.5, color='#16a085', label="Human")
    plt.title(cnt, fontsize = 15)
    plt.legend(fontsize = 12)
    idx += 1

plt.show()
```



Distribution of User Languages across User classes

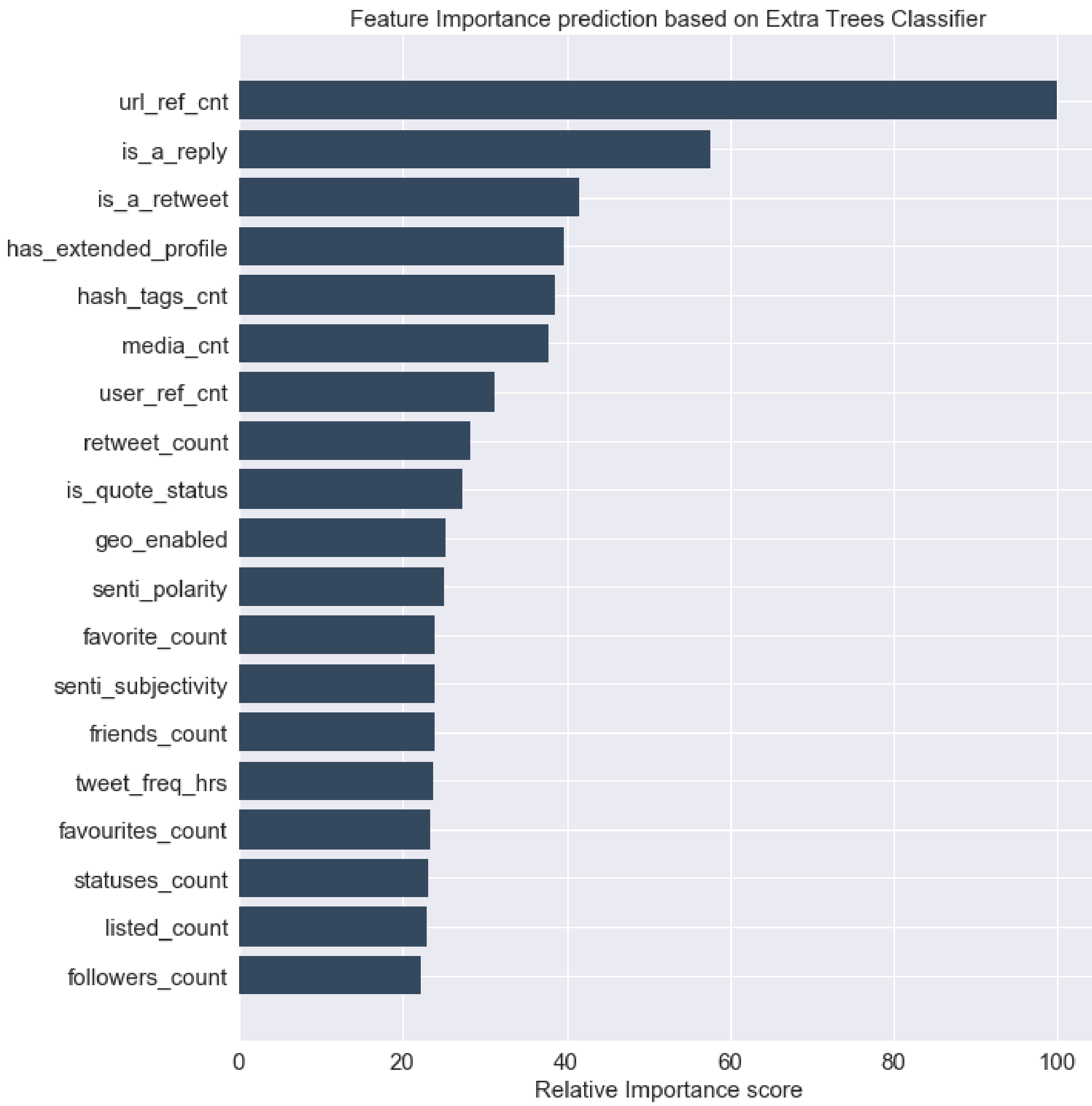
```
In [102]: # Initialize the Figure
          fig, ax = plt.subplots(1, 1, figsize=(18, 6))
          plt.xticks(fontsize = 15)
          plt.yticks(fontsize = 15)

          # for Both human and bot classes, plot a bar plot subplot of different languages use
          ax = pd.crosstab(consolidated_ftrs_df.user_lang, consolidated_ftrs_df.bot_flg).plot.b
```



Feature Importance

Drop features that does not seem to differing distribution patterns between the human and bot classes in the EDA Process and thene evaluate the importance of the remaining features using Extra Trees Classifier

In [103]:
```
# Drop the categorical values that does not seem to be providing value based on EDA
processed_data_df = consolidated_ftrs_df.drop(['protected',  'verified', 'is_transla
                                                , 'possibly_sensitive', 'place_refe
                                              , 'default_profile', 'symbols_cnt', 'I
                                            ], axis=1, errors='ignore')


# Instantiate an ExtraTreeClassifier model with 100 estimators and fit with the pred
ext_tree_clf = ExtraTreesClassifier(n_estimators = 100)
ext_tree_clf.fit(processed_data_df.drop(["bot_flg"], axis=1), processed_data_df["bot_

# Evaluate the feature importance from the fit model
feature_importance = ext_tree_clf.feature_importances_

# Calculate relative importance score of the features and plot them in descending or
feature_importance = 100.0 * (feature_importance / np.abs(feature_importance).max())
sorted_idx = np.argsort(np.abs(feature_importance))
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(10,12))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, processed_data_df.drop(["bot_flg"], axis=1).columns[sorted_idx], font
plt.xlabel('Relative Importance score', fontsize=15)
plt.title('Feature Importance prediction based on Extra Trees Classifier', fontsize=
plt.tick_params(labelsize=15)

plt.show()
```

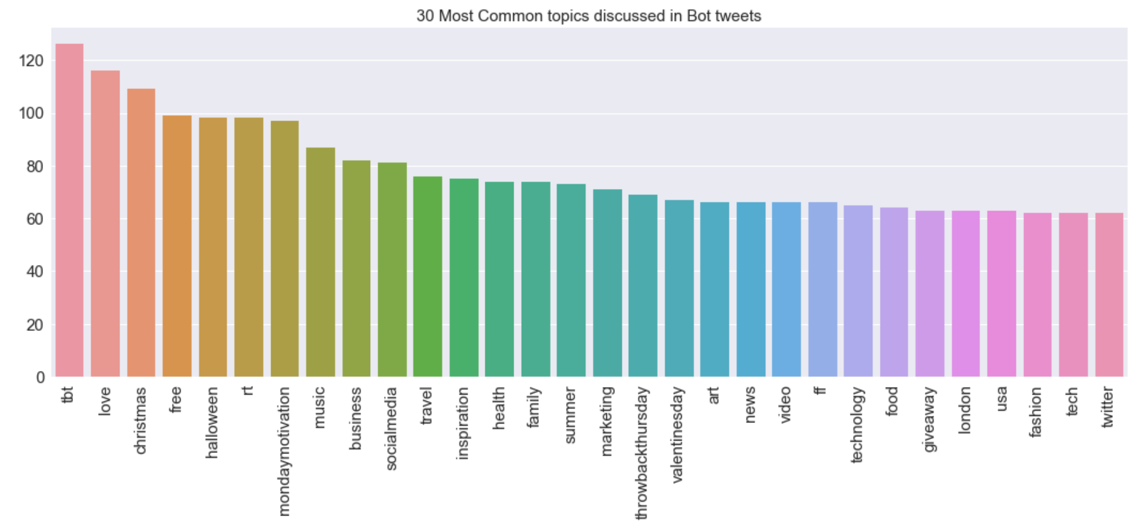


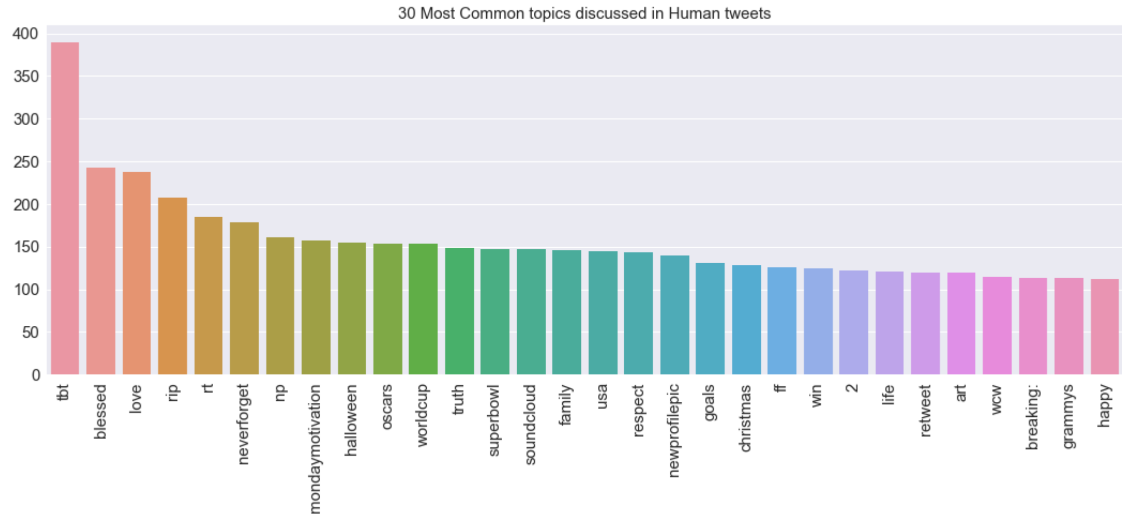
Topic Based Modeling - Distribution of Hash tag topics used

In [104]:
```
# Plot the most used topics from the given set of topics
def plot_most_used_topics(topics, class_type, top_n=20):
    '''Calculate the Most used topics from the given set of topic and
       plot the top_n topics and the number of times they have been used

      Args:
          topics: Dataseries containing all the topics to assess.
          class_type: Type of the user class being assessed
          top_n: count of top n features to plot. Default is 20
    '''

    # Extract the consolidated topics in a list as a separte topic items
```

```
    text_clean = ' '.join([text for text in topics]).split()
    text_clean = [ x for x in text_clean if x is not '1']

    # Use counter to count the number of times each topic is used and extract the to
    counts = Counter(text_clean)
    common_words = [word[0] for word in counts.most_common(top_n)]
    common_counts = [word[1] for word in counts.most_common(top_n)]

    # Plot a Bar plot for the top n topics
    fig = plt.figure(figsize=(18,6))
    sns.barplot(x=common_words, y=common_counts)
    plt.title(str(top_n) + ' Most Common topics discussed in '+ class_type + ' tweets
    plt.xticks(rotation=90)
    plt.tick_params(labelsize=15)
    plt.show()
```

In [105]:
```
# Plot the top 30 Topics discussed by Bot class users from our training data set
plot_most_used_topics(df_bot['hash_tags'], 'Bot', 30)

# Plot the top 30 Topics discussed by Human class users from our training data set
plot_most_used_topics(df_human['hash_tags'], 'Human', 30)
```



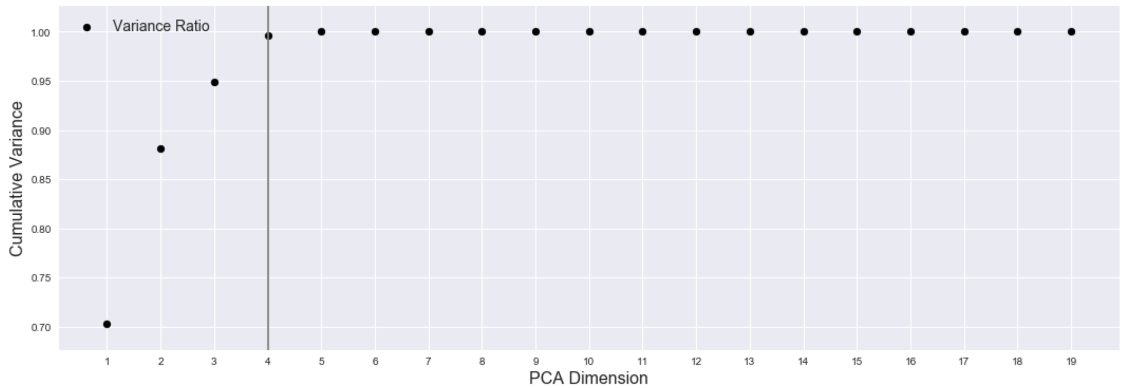


Cummulative plot of PCA variance ratio of principal features

In [106]:
```
# Initialize PCA for 19 components and fit on the normalized training data
pca = PCA(n_components=19)
pca.fit(processed_data_df.drop(["bot_flg"], axis=1))

# Initialize a figure for the Variance plot
fig, ax = plt.subplots(figsize=(18, 6))

# Draw a scatter plot on the cumulative sum on the explained variance percentage for
ax.scatter(range(1,len(pca.explained_variance_ratio_)+1), np.cumsum(pca.explained_va
           ,color='black', label='Variance Ratio')

# Define Plot Labels and legends
plt.xlabel("PCA Dimension", fontsize = 16)
plt.ylabel("Cumulative Variance", fontsize = 16)
plt.xticks(np.arange(1,len(pca.explained_variance_ratio_)+1, step=1))
plt.legend(fontsize = 14);

# Determine the number of principal components at which 95% variance is explained
comp_count = 0
cum_sum = 0
for ratio in pca.explained_variance_ratio_:
    comp_count += 1
    cum_sum += ratio
    if cum_sum >= 0.95 :
        break

# Draw a vertical axis line to indicate the optimal number of principal components
plt.axvline(comp_count, color='.5')
print('Number of principal components explaining atleast 95% variance - ', comp_coun
```

```
    plt.show()
```

```
Number of principal components explaining atleast 95% variance -  4
```



Dataset splitting, One-hot encoding of categorical features, Scaling and Normalization

Scale and Normalize data attributes to follow an uniform scaling for proper weightage of features by the model

Perform One-hot encoding for category based features

```
In [107]: # Perform One Hot Encoding to add dummy columns for categorical values of User Langu
          # processed_data_df=pd.get_dummies(processed_data_df, columns=['user_lang'], drop_fi

In [108]: # Method Implementation to Separate the X (Predictor) and y (Response) variables in
          def separate_X_and_y(data, outcome_col_name='bot_flg'):
              '''Separate the predictor variables and outcome variable to separate dataframes

                 Args:
                     data: Dataframe containing predictor and Response variables.
                     outcome_col_name: Name of the response column to extract
                 Returns:
                     X_df: Normalized predictor features of Training data set.
                     y_df: Outcome variable list of Training data set.
              '''
              # Separate Predictor and Response variables in dataset
              X_df = data.drop([outcome_col_name], axis=1)
              y_df = data[outcome_col_name]

              # Reset Index of data set for consistency
              X_df = X_df.reset_index(drop=True)
              y_df = y_df.reset_index(drop=True)

              return X_df, y_df
```

```
# Method Implementation to split data to train and test data set and scale predictor
def split_train_and_test(data, outcome_col_name='bot_flg', scale_type='MinMax', split
    '''Split the data into train and test data set and scale them

       Args:
           data: Dataframe containing predictor and Response variables.
           outcome_col_name: Name of the response column to extract
           Scale_type: Type of scaling to perform 'MinMax' or 'Standard'
           split_ratio: Ratio of data to split in training and test data set
       Returns:
           X_train_scale: Scaled predictor features of Training data set.
           y_train: Outcome variable list of Training data set.
           X_val_scale: Scaled predictor features of Test data set.
           y_val: Outcome variable list of Test data set.
    '''

    # Make a 80-20 Split of the data to get training and test data
    data_train, data_test = train_test_split(data, random_state=90, test_size=split_r
                                             , stratify=data[outcome_col_name])

    # Separate Predictor and Response variables in Training and Test dataset
    X_train, y_train = separate_X_and_y(data_train, outcome_col_name)
    X_val, y_val = separate_X_and_y(data_test, outcome_col_name)

    # Check scale_type and use appropriate scaler
    if scale_type == 'MinMax':
        # Initialize a Min Max scaler to normalize all predcitor variables between 0
        scaler = MinMaxScaler()
    else:
        # Initialize a Standard scaler to scale all predcitor variables based on mea
        scaler = StandardScaler()

    # Fit scaler based on Training data
    scaler.fit(X_train.values)

    # Transform to Normalize Training data set
    X_train_scaled = scaler.transform(X_train.values)
    X_train_scale = pd.DataFrame(X_train_scaled)
    X_train_scale.columns = list(X_train)

    # Transform to Normalize Test data set
    X_val_scaled = scaler.transform(X_val.values)
    X_val_scale = pd.DataFrame(X_val_scaled)
    X_val_scale.columns = list(X_val)

    return X_train_scale, y_train, X_val_scale, y_val
```

In [109]:
```
X_train_scale, y_train, X_val_scale, y_val = split_train_and_test(processed_data_df)
```

6 Model Training and Validation

Creation, Training and Validation of classification models

In [110]:
```
# Dictionary of Models to compare
models_to_compare = {}
acc_stats_table_data = {}

TRAIN = 'Train'
VALIDATION = 'Validation'
TEST = 'Test'
```

Utility Method for gathering model accuracy and model comparisons

In [184]:
```
# Method implementation to calculate classifier prediction accuracy and CV scores
def get_classifier_accuracy(model, X_data, y_data, model_title, data_type=TRAIN, cv_
    ''' Calculate the Accuracy and Mean Cross validation score of the model
        Add the model to the comparison Dictionary

       Args:
           model The classifier model used to fit and predict the classifiers
           X_data: Dataframe containing the predictor variables.
           y_data: Dataframe containing the outcome variable.
           model_title: Title of the model to use for reporting
           data_type: Type of data being plotted (Train/Validation/Test). Default va
           cv_fold: Cross Validation Fold used. Default value is 5
           print_stats: Flag to indicate if accuracy stats must be printed. Default
        Return:
           accuracy: Prediction accuracy Score of the model
           cv_scores: Cross validation scores of the model
    '''

    # Add to the model list to compare
    models_to_compare[model_title] = model

    # Generate predictions for the given data set
    predictions = np.round(model.predict(X_data))

    accuracy = accuracy_score(y_data, predictions)
    # Report stats only when print flag is set to True
    if print_stats == True:
        print("%s Model - (%s) Prediction Accuracy: %0.2f" % (model_title, data_type

    cv_mean = 0
    cv_std = 0
    cv_scores = None
    # Check if the model has a score method before CV validation
    if hasattr(model, 'score') and data_type==TRAIN:
        # Calculate Cross validation accuracy score of the model using x fold cross
```

```
        cv_scores = cross_val_score(model, X_data, y_data, cv=cv_fold)
        cv_mean = cv_scores.mean()
        cv_std = cv_scores.std()

        if print_stats == True:
            print("%s (%s) Cross Validation accuracy and 95 percent CI: %0.2f (+/- %
                      % (model_title, data_type, cv_mean, cv_std * 2))

        # Plot the prediction accuracy and cross validation scores for cv_fold itera
        fig = plt.figure(figsize=(12,4))
        plt.plot(range(1,cv_fold+1), cv_scores, marker= 'o', c = '#c0392b', label='C
        plt.fill_between(range(1,cv_fold+1), [cv_mean + (2* cv_std)] * cv_fold ,[cv_
                         , color = '#1abc9c', alpha=0.2, label='+/- 2 SDev of CV mea
        plt.axhline(accuracy, c = '#2c3e50', label='Accuracy Score', linewidth=2)

        # Set title, axis values and legends for the plot
        bot = 0.7
        if cv_scores.min() < 0.75:
            bot = cv_scores.min()-0.05
        plt.title(model_title +' - Prediction accuracy and CV scores for each fold -
        plt.xlabel('CV fold iterations', fontsize = 15)
        plt.ylabel('Score', fontsize = 15)
        plt.ylim(bottom=bot, top=1)

        plt.xlim(left=1, right=cv_fold)
        plt.legend(fontsize = 15)
        plt.show()
    else:
        cv_mean = accuracy


    # Add accuracy stats to the stats table
    type_stats = acc_stats_table_data.get(data_type, {});
    if model_title != 'Topic Model':
        if data_type==TRAIN:
            type_stats[model_title] = [model_title, round(accuracy,3), round(cv_mean
                                       , round(cv_std*2,2), confusion_matrix(y_data,
        else:
            type_stats[model_title] = [model_title, round(accuracy,3), confusion_mat

        acc_stats_table_data[data_type] = type_stats;

    return accuracy, cv_scores

# Render the Accuracy stats of Model in tabular format
def renderAccuracyStatsIable(stats_table_data, data_type, plot_type='CV Accuracy'):
    ''' Method to Render the Accuracy stats of Model in tabular format
```

```
    Args:
        stats_table_data: List of Lists containing model accuracy stats in a tabu
        data_type: Type of the data for which the status has been gathered for (T
        plot_type: Type of score to be used to render the bar plots. Default is '
'''
type_stats = stats_table_data.get(data_type, {});

# Title of Column Labels to report Accuracy
if data_type==TRAIN:
    colLabels = ['Model Title', 'Prediction Accuracy', 'CV Accuracy', '95% CI (+/
else:
    colLabels = ['Model Title', 'Prediction Accuracy', 'TN, FP, FN, TP']
    plot_type='Prediction Accuracy'

print('** %s ** Comparison Table of Accuracy stats for different classifiation mo
# Render the Stats of different models in a table for better comparability
fig = plt.figure(figsize=(18,5))
ax = plt.subplot(111, frame_on=False)

# Do some data prep for table
models = []
cv_scrs = []
acc_scrs = []
table_data = []
for key, val in type_stats.items():
    models.append(val[0])
    acc_scrs.append(val[1])
    cv_scrs.append(val[2])
    table_data.append(val)

tbl = plt.table(cellText=table_data, colLabels=colLabels,loc='top')
tbl.set_fontsize(16)
tbl.scale(1, 4)

# Set colors for the bar plots
bar_color = '#16a085'
high_color = '#e67e22'
if data_type == TEST:
    bar_color = '#2980b9'
    high_color = '#34495e'

ylabel = 'Cross Validation Score'
bar_scrs = cv_scrs
if plot_type != 'CV Accuracy':
    ylabel = 'Prediction Accuracy Score'
    bar_scrs = acc_scrs

# Render a bar chart of the model accuracy scores
```

```
    ax.set_ylim(bottom=min(bar_scrs)-0.05, top= max(max(bar_scrs),1))
    y_pos = np.arange(len(models))
    barlist = plt.bar(y_pos, bar_scrs, align='center', color=bar_color)
    barlist[bar_scrs.index(max(bar_scrs))].set_color(high_color)
    plt.xticks(y_pos, models)
    plt.ylabel(ylabel)
    plt.title('Classification Model')

    plt.show()
```

Trivial Classification - Baseline Model

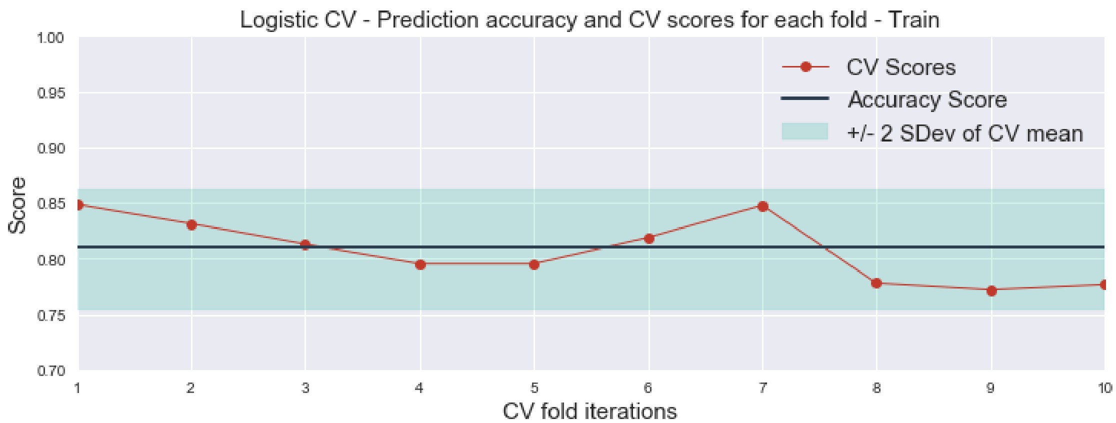
```
In [112]: # Implement a trivial model that predicts Human class (0) for any input
          def predict_trivial(X):
              return np.zeros(len(X))

          # Make trivial predictions on the train data set and calculate scores
          trivial_predictions = predict_trivial(X_train_scale)
          baseline_accuracy = accuracy_score(y_train, trivial_predictions)
          print("Baseline Accuracy from Trivial Model:" + str(round(baseline_accuracy, 2)))
```

```
Baseline Accuracy from Trivial Model:0.67
```

Logistic Regression CV

```
In [113]: LOGISTIC_CLF = 'Logistic CV' # Model Title constant for Logistic Classifier

          # Initialize a Logistic CV Regression model with L2 regualarization
          lcv_clf = LogisticRegressionCV(cv=5, penalty='l2', max_iter=1000, multi_class = 'ovr

          # Fit the model with the training set data
          lcv_clf.fit(X_train_scale, y_train)

          # Report Prediction accuracy on Train and Validation Data sets
          lcv_train_acc, lcv_train_cv = get_classifier_accuracy(lcv_clf, X_train_scale, y_trai
          lcv_val_acc, lcv_val_cv = get_classifier_accuracy(lcv_clf, X_val_scale, y_val, LOGIS
```

```
Logistic CV Model - (Train) Prediction Accuracy: 0.81
Logistic CV (Train) Cross Validation accuracy and 95 percent CI: 0.81 (+/- 0.05)
```

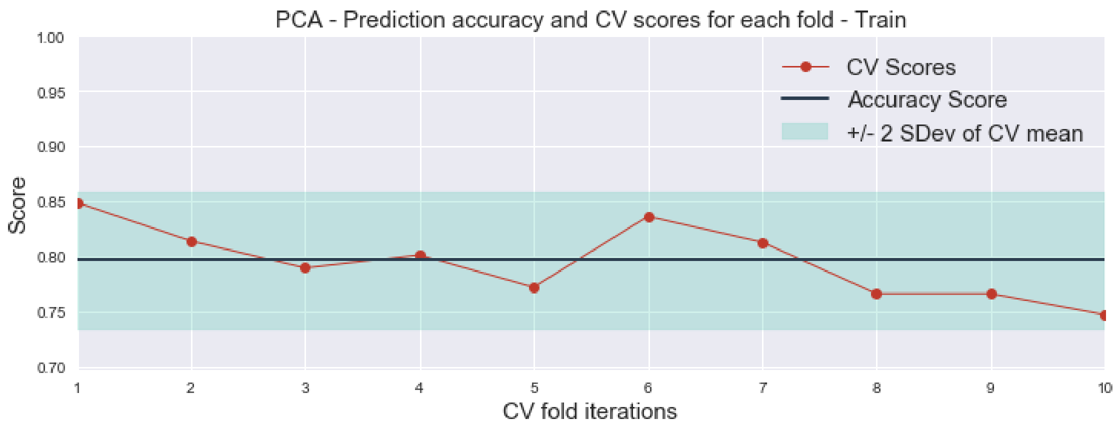



```
Logistic CV Model - (Validation) Prediction Accuracy: 0.83
```

Principal Component Analysis (PCA) Classifier

```
In [114]: PCA_CLF = 'PCA' # Model Title constant for PCA Classifier

          # Initialize a PCA instnace for 4 principal components and fit using the scaled trai
          pca = PCA(n_components=comp_count)
          pca.fit(X_train_scale)

          # Transform the scaled training and test data set using the fitted PCA model
          X_train_pca_4 = pca.transform(X_train_scale)
          X_val_pca_4 = pca.transform(X_val_scale)

          # Instantiate a Logisitic classification model for the data set transformed with 3 p
          #pca_3_clf = LogisticRegressionCV(cv=5, penalty='l2', max_iter=1000, multi_class = '
          pca_4_clf = LogisticRegression(C=1000000, solver='newton-cg', max_iter=250)

          # Fit the model with the training set data
          pca_4_clf.fit(X_train_pca_4, y_train)

          # Report Prediction accuracy on Train and Validation Data sets
          pca_4_train_acc, pca_4_train_cv = get_classifier_accuracy(pca_4_clf, X_train_pca_4, y
          pca_4_val_acc, pca_4_val_cv = get_classifier_accuracy(pca_4_clf, X_val_pca_4, y_val,
```

```
PCA Model - (Train) Prediction Accuracy: 0.80
PCA (Train) Cross Validation accuracy and 95 percent CI: 0.80 (+/- 0.06)
```

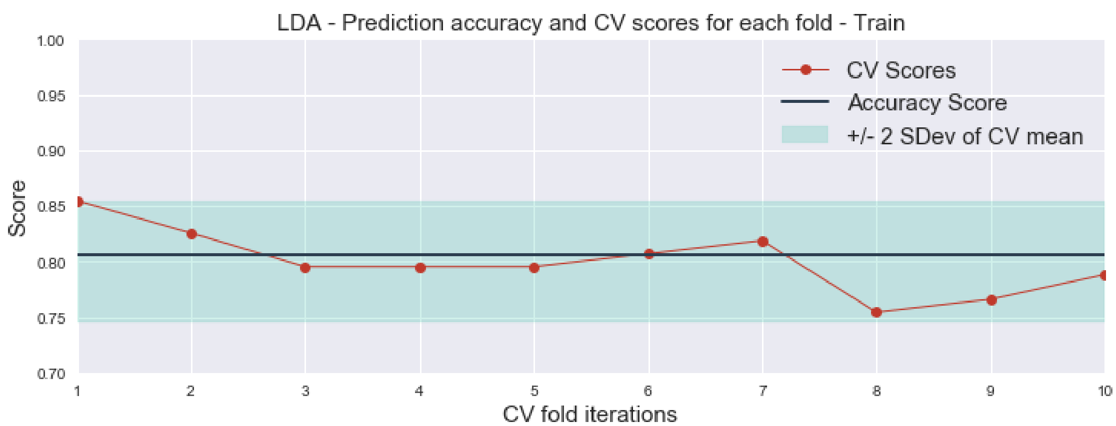



```
PCA Model - (Validation) Prediction Accuracy: 0.82
```

Linear Discriminant Analysis (LDA) Classifier

```
In [115]: LDA_CLF = 'LDA' # Model Title constant for LDA Classifier

          # Initialize a LDA Model
          lda = LinearDiscriminantAnalysis()

          # Fit the model with the training set data
          lda.fit(X_train_scale, y_train)

          # Report Prediction accuracy on Train and Validation Data sets
          lda_train_acc, lda_train_cv = get_classifier_accuracy(lda, X_train_scale, y_train, LI
          lda_val_acc, lda_val_cv = get_classifier_accuracy(lda, X_val_scale, y_val, LDA_CLF, V
```

```
LDA Model - (Train) Prediction Accuracy: 0.81
LDA (Train) Cross Validation accuracy and 95 percent CI: 0.80 (+/- 0.05)
```

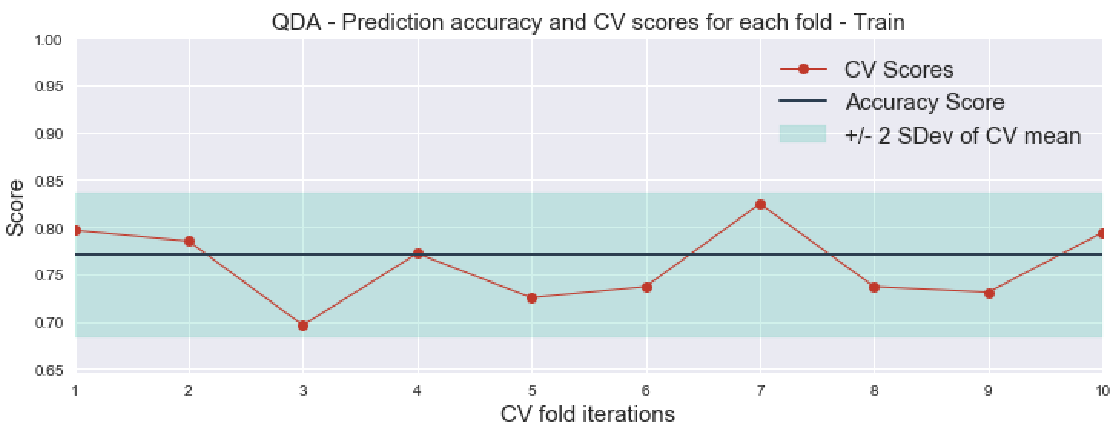


```
LDA Model - (Validation) Prediction Accuracy: 0.82
```

Quadratic Discriminant Analysis (QDA) Classifier

```
In [116]: QDA_CLF = 'QDA' # Model Title constant for QDA Classifier

          # Initialize a LDA Model
          qda = QuadraticDiscriminantAnalysis()

          # Fit the model with the training set data
          qda.fit(X_train_scale, y_train)

          # Report Prediction accuracy on Train and Validation Data sets
          qda_train_acc, qda_train_cv = get_classifier_accuracy(qda, X_train_scale, y_train, QI
          qda_val_acc, qda_val_cv = get_classifier_accuracy(qda, X_val_scale, y_val, QDA_CLF, V
```

```
QDA Model - (Train) Prediction Accuracy: 0.77
QDA (Train) Cross Validation accuracy and 95 percent CI: 0.76 (+/- 0.08)
```

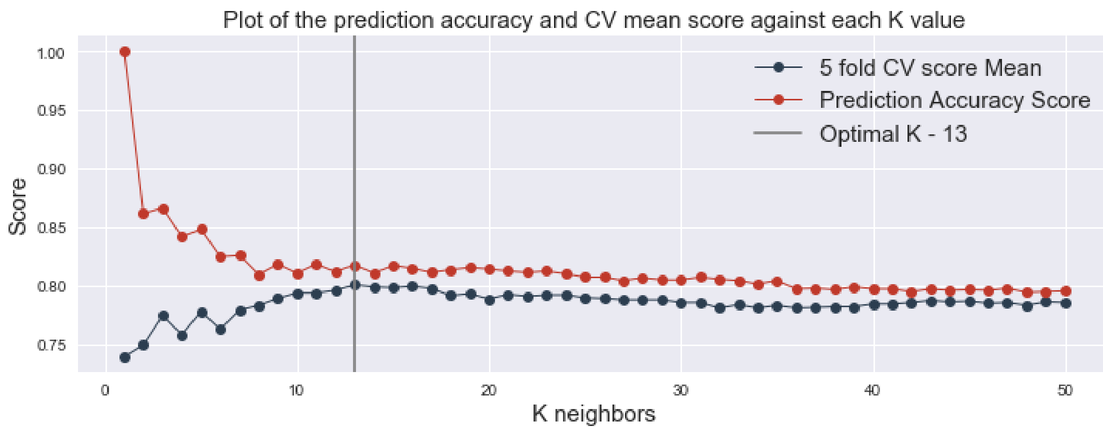



```
QDA Model - (Validation) Prediction Accuracy: 0.80
```

k-Nearest-Neighbors Classifier

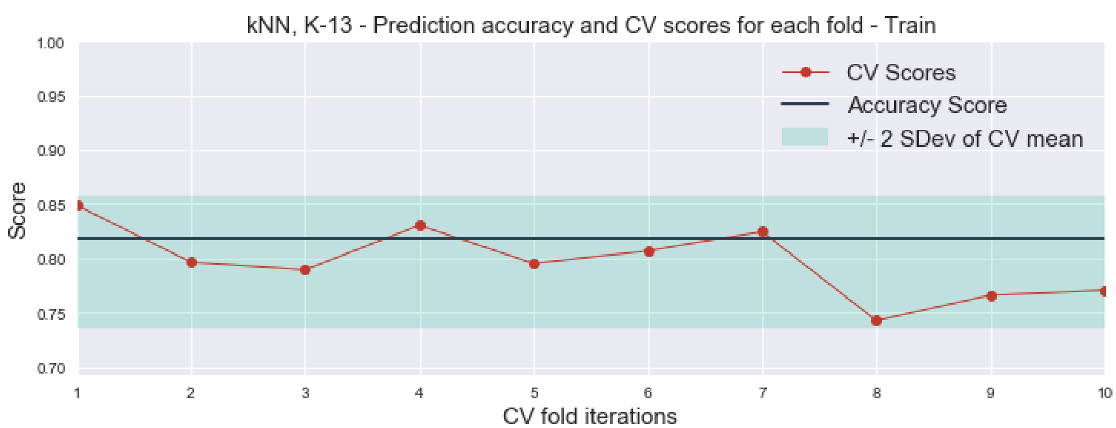
```
In [117]: # Instantiate lists to hold accuracy and fitted model per k-value
          knn_accuracy = []
          knn_cv_means = []
          knn_models = {}
```

```
max_cv_mean = 0
optimal_k = 0
max_k = 51
# Loop from k neighbors from 1 to max K
for k in range(1,max_k):
    #Instantiate a kNN classifier for k neighbors
    knn_clf = KNeighborsClassifier(n_neighbors=k)

    # Fit for the training data
    knn_clf.fit(X_train_scale, y_train)

    # Check accuracy using prediction on the training data
    predictions = knn_clf.predict(X_train_scale)
    acc_score = accuracy_score(y_train, predictions)
    knn_accuracy.append(acc_score)

    # Check accuracy for 5-fold cross validation test and take the mean
    cv_mean = cross_val_score(knn_clf, X_train_scale, y_train, cv=5).mean()
    knn_cv_means.append(cv_mean)
    knn_models[k] = knn_clf

    # update K with max CV Mean score
    if cv_mean > max_cv_mean:
        max_cv_mean = cv_mean
        optimal_k = k

# Plot the prediction accuracy andf 5 fold cross validation mean for each tree depth
fig = plt.figure(figsize=(12,4))
plt.plot(range(1,max_k), knn_cv_means,marker= 'o', c = '#2c3e50', label='5 fold CV sc
plt.plot(range(1,max_k), knn_accuracy,marker= 'o', c = '#c0392b', label='Prediction A
plt.axvline(optimal_k, color='.5', label='Optimal K - ' + str(optimal_k))

# Set title, axis values and legends for the plot
plt.title('Plot of the prediction accuracy and CV mean score against each K value', f
plt.xlabel('K neighbors', fontsize = 15)
plt.ylabel('Score', fontsize = 15)
plt.legend(fontsize = 15)
plt.show()
```




```
In [118]: KNN_CLF = 'kNN, K-'+str(optimal_k) # Model Title constant for kNN Classifier

          # Report Prediction accuracy on Train and Validation Data sets
          knn_train_acc, knn_train_cv = get_classifier_accuracy(knn_models[optimal_k], X_train_
          knn_val_acc, knn_val_cv = get_classifier_accuracy(knn_models[optimal_k], X_val_scale
```

```
kNN, K-13 Model - (Train) Prediction Accuracy: 0.82
kNN, K-13 (Train) Cross Validation accuracy and 95 percent CI: 0.80 (+/- 0.06)
```

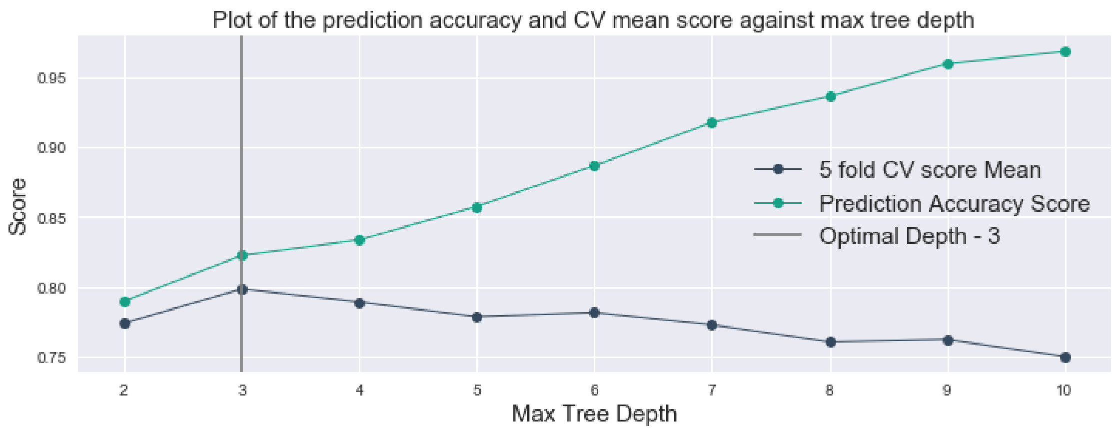



```
kNN, K-13 Model - (Validation) Prediction Accuracy: 0.82
```

Decision Tree Classifier

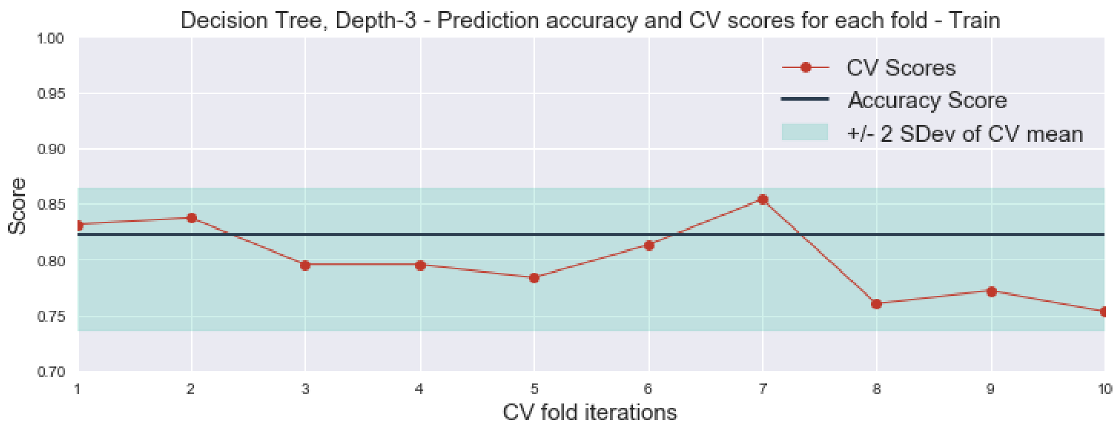
```
In [119]: # Instantiate lists to hold tree depths, accuracy and fitted model per depth
          tree_depths=[]
```

```
accuracy = []
cv_means = []
tree_models = {}

optimal_depth = 0
max_cv_mean = 0
# Loop from tree depth 2 to 10
for depth in range(2,11):
    #Instantiate a Decision Tree classifier for the current depth using gini index a
    dt_clf = DecisionTreeClassifier(criterion='gini',max_depth=depth)

    # Fit for the training data
    dt_clf.fit(X_train_scale, y_train)

    # Check accuracy using prediction on the training data
    predictions = dt_clf.predict(X_train_scale)
    acc_score = accuracy_score(y_train, predictions)
    accuracy.append(acc_score)

    # Check accuracy for 5-fold cross validation test and take the mean
    cv_mean = cross_val_score(dt_clf, X_train_scale, y_train, cv=5).mean()
    cv_means.append(cv_mean)
    tree_depths.append(depth)
    tree_models[depth] = dt_clf

    # update K with max CV Mean score
    if cv_mean > max_cv_mean:
        max_cv_mean = cv_mean
        optimal_depth = depth

# Plot the prediction accuracy andf 5 fold cross validation mean for each tree depth
fig = plt.figure(figsize=(12,4))
plt.plot(tree_depths, cv_means,marker= 'o', c = '#34495e', label='5 fold CV score Mea
plt.plot(tree_depths, accuracy,marker= 'o', c = '#16a085', label='Prediction Accurac
plt.axvline(optimal_depth, color='.5', label='Optimal Depth - ' + str(optimal_depth)

# Set title, axis values and legends for the plot
plt.title('Plot of the prediction accuracy and CV mean score against max tree depth'
plt.xlabel('Max Tree Depth', fontsize = 15)
plt.ylabel('Score', fontsize = 15)
plt.legend(fontsize = 15)
plt.show()
```




```
In [121]: DT_CLF = 'Decision Tree, Depth-'+str(optimal_depth) # Model Title constant for Decis

          # Report Prediction accuracy on Train and Validation Data sets
          dt_train_acc, dt_train_cv = get_classifier_accuracy(tree_models[optimal_depth], X_tra
          dt_val_acc, dt_val_cv = get_classifier_accuracy(tree_models[optimal_depth], X_val_sca
```

```
Decision Tree, Depth-3 Model - (Train) Prediction Accuracy: 0.82
Decision Tree, Depth-3 (Train) Cross Validation accuracy and 95 percent CI: 0.80 (+/- 0.06)
```

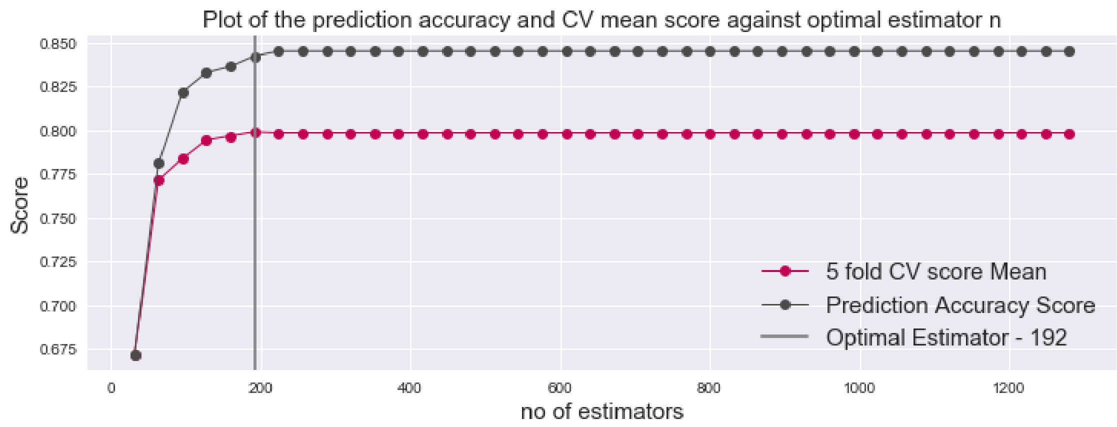



```
Decision Tree, Depth-3 Model - (Validation) Prediction Accuracy: 0.79
```

Gradient Boost Classifier

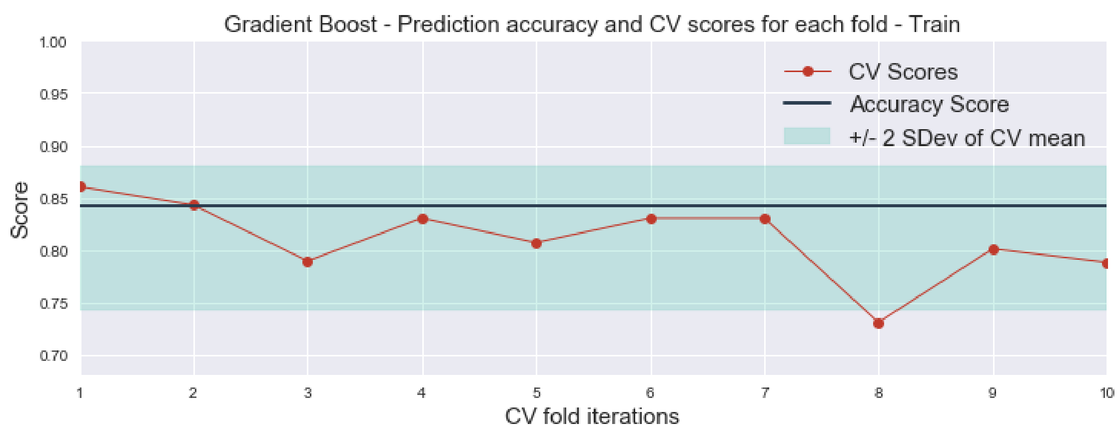
```
In [122]: # Instantiate lists to hold estimator counts, accuracy and fitted model per estimato
          gb_estimators=[]
```

```
accuracy = []
cv_means = []
gb_models = {}

optimal_gb_estimator = 0
max_cv_mean = 0

# Loop from estimator 1*32 to 40*32
for idx in range(1,41):
    est = 32*idx

    # Instantiate a Gradient Boosting classifier for the optimal depth using tol of 
    gb_clf = GradientBoostingClassifier(n_estimators= est, validation_fraction=0.2, 
                                        , n_iter_no_change=5, tol=0.001,random_state

    # Fit for the training data
    gb_clf.fit(X_train_scale, y_train)

    # Check accuracy using prediction on the training data
    predictions = gb_clf.predict(X_train_scale)
    acc_score = accuracy_score(y_train, predictions)
    accuracy.append(acc_score)

    # Check accuracy for 5-fold cross validation test and take the mean
    cv_mean = cross_val_score(gb_clf, X_train_scale, y_train, cv=5).mean()
    cv_means.append(cv_mean)
    gb_estimators.append(est)
    gb_models[est] = gb_clf

    # update estimator with max CV Mean score if current score is atleast 0.001 grea
    if cv_mean > max_cv_mean +0.001:
        max_cv_mean = cv_mean
        optimal_gb_estimator = est

# Plot the prediction accuracy andf 5 fold cross validation mean for each tree depth
fig = plt.figure(figsize=(12,4))
plt.plot(gb_estimators, cv_means,marker= 'o', c = '#C30052', label='5 fold CV score 
plt.plot(gb_estimators, accuracy,marker= 'o', c = '#4C4A48', label='Prediction Accura
plt.axvline(optimal_gb_estimator, color='.5', label='Optimal Estimator - ' + str(opti

# Set title, axis values and legends for the plot
plt.title('Plot of the prediction accuracy and CV mean score against optimal estimato
plt.xlabel('no of estimators', fontsize = 15)
plt.ylabel('Score', fontsize = 15)
plt.legend(fontsize = 15)
plt.show()
```




```
In [123]: GRAD_BOOST_CLF = 'Gradient Boost' # Model Title constant for Gradient Boost Classifi

          # Report Prediction accuracy on Train and Validation Data sets
          gb_train_acc, gb_train_cv = get_classifier_accuracy(gb_models[optimal_gb_estimator]
                                                              , X_train_scale, y_train, GRAD_B
          gb_val_acc, gb_val_cv = get_classifier_accuracy(gb_models[optimal_gb_estimator]
                                                          , X_val_scale, y_val, GRAD_BOOST_CLF
```

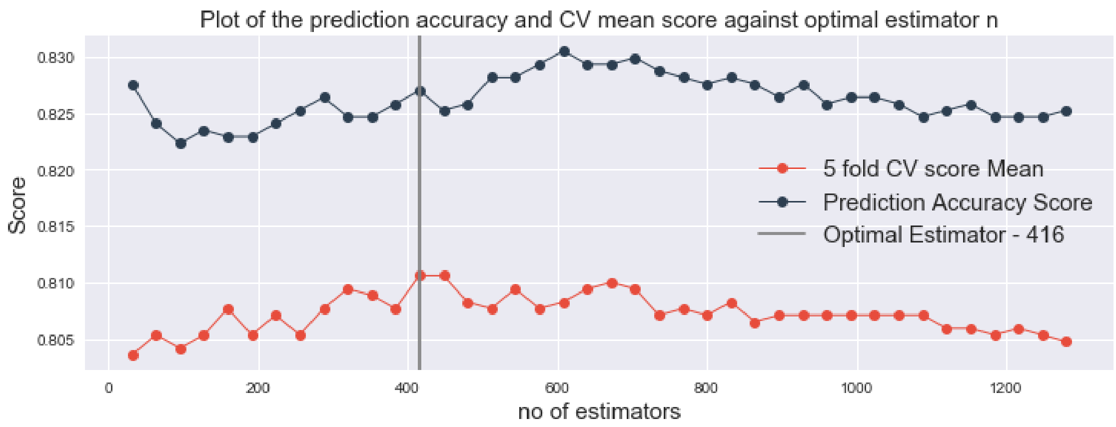
```
Gradient Boost Model - (Train) Prediction Accuracy: 0.84
Gradient Boost (Train) Cross Validation accuracy and 95 percent CI: 0.81 (+/- 0.07)
```




```
Gradient Boost Model - (Validation) Prediction Accuracy: 0.80
```

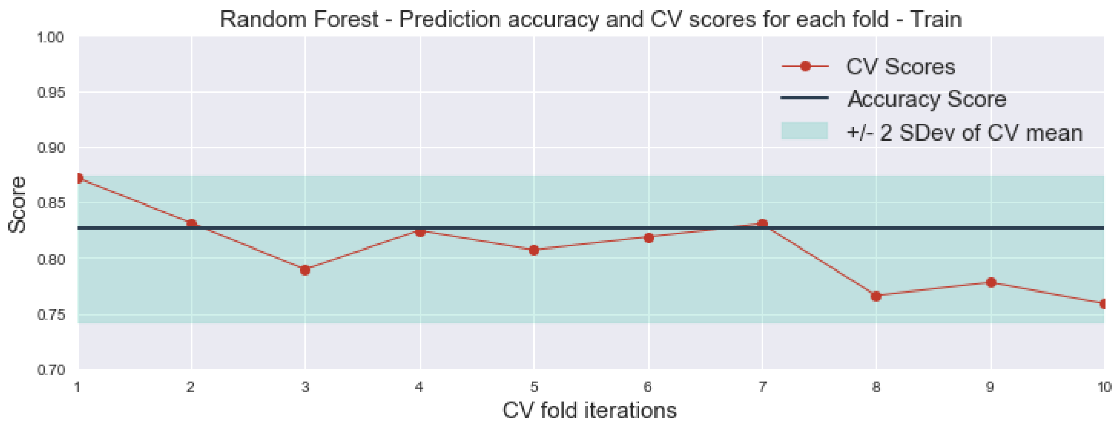
Random Forest Classifier

In [124]:
```
# Instantiate lists to hold estimator counts, accuracy and fitted model per estimato
rf_estimators=[]
accuracy = []
cv_means = []
rf_models = {}

optimal_rf_estimator = 0
max_cv_mean = 0

# Loop from estimator 1*32 to 40*32
for idx in range(1,41):
    est = 32*idx
    #est = 2**idx
    #Instantiate a Decision Tree classifier for the optimal depth using gini index a
    rf_clf = RandomForestClassifier(n_estimators= est, max_depth=optimal_depth, crite

    # Fit for the training data
    rf_clf.fit(X_train_scale, y_train)

    # Check accuracy using prediction on the training data
    predictions = rf_clf.predict(X_train_scale)
    acc_score = accuracy_score(y_train, predictions)
    accuracy.append(acc_score)

    # Check accuracy for 5-fold cross validation test and take the mean
    cv_mean = cross_val_score(rf_clf, X_train_scale, y_train, cv=5).mean()
    cv_means.append(cv_mean)
    rf_estimators.append(est)
    rf_models[est] = rf_clf

    # update estimator with max CV Mean score if current score is atleast 0.001 grea
    if cv_mean > max_cv_mean +0.001:
        max_cv_mean = cv_mean
        optimal_rf_estimator = est

# Plot the prediction accuracy andf 5 fold cross validation mean for each tree depth
fig = plt.figure(figsize=(12,4))
plt.plot(rf_estimators, cv_means,marker= 'o', c = '#e74c3c', label='5 fold CV score 
plt.plot(rf_estimators, accuracy,marker= 'o', c = '#2c3e50', label='Prediction Accura
plt.axvline(optimal_rf_estimator, color='.5', label='Optimal Estimator - ' + str(opti

# Set title, axis values and legends for the plot
plt.title('Plot of the prediction accuracy and CV mean score against optimal estimato
plt.xlabel('no of estimators', fontsize = 15)
plt.ylabel('Score', fontsize = 15)
plt.legend(fontsize = 15)
plt.show()
```




```
In [125]: RAND_FOREST_CLF = 'Random Forest' # Model Title constant for Random Forest Classifie

          # Report Prediction accuracy on Train and Validation Data sets
          rf_train_acc, rf_train_cv = get_classifier_accuracy(rf_models[optimal_rf_estimator]
                                                              , X_train_scale, y_train, RAND_F
          rf_val_acc, rf_val_cv = get_classifier_accuracy(rf_models[optimal_rf_estimator]
                                                          , X_val_scale, y_val, RAND_FOREST_CL
```

```
Random Forest Model - (Train) Prediction Accuracy: 0.83
Random Forest (Train) Cross Validation accuracy and 95 percent CI: 0.81 (+/- 0.07)
```

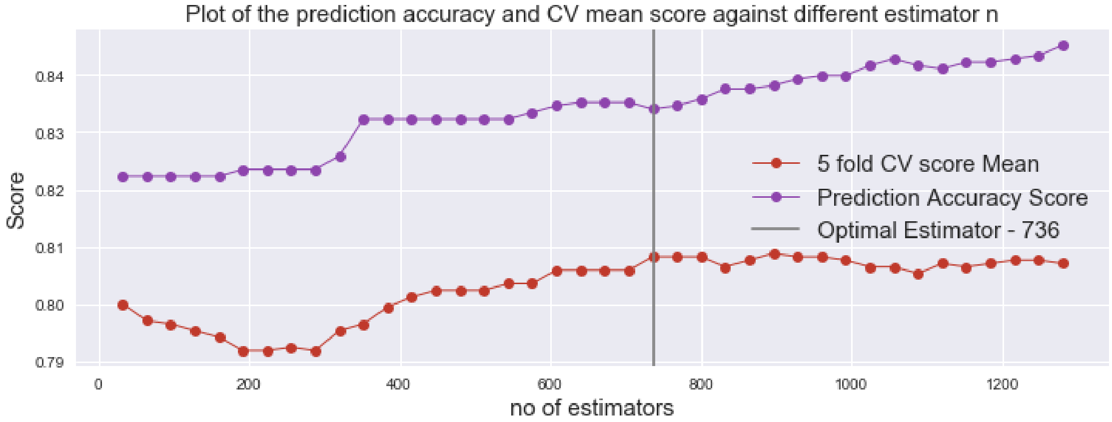



```
Random Forest Model - (Validation) Prediction Accuracy: 0.81
```

Boosting Adaboost Classifier

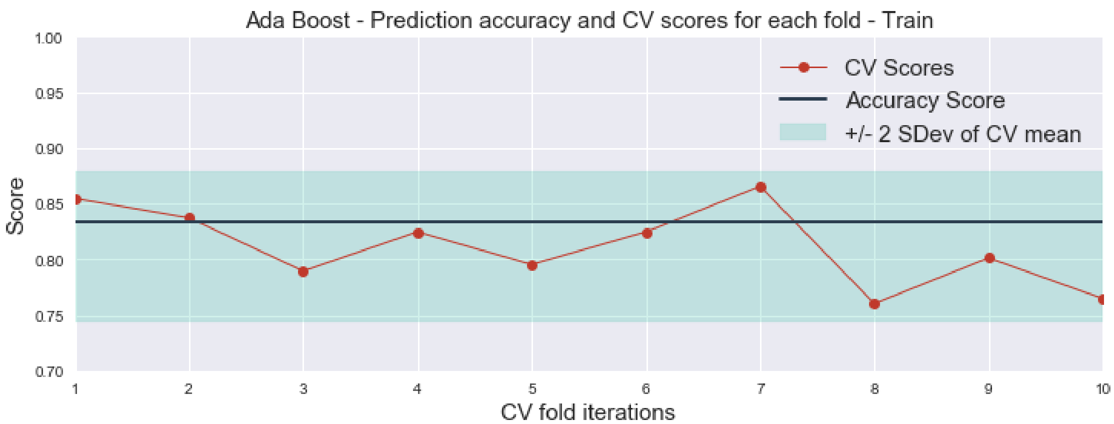
```
In [126]: # Instantiate lists to hold estimator counts, accuracy and fitted model per estimato
          boost_estimators=[]
          accuracy = []
          cv_means = []
          boost_models = {}

          optimal_boost_estimator = 0
          max_cv_mean = 0
          # Loop from estimator 1*32 to 40*32
          for idx in range(1,41):
              est = 32*idx

              # Initialize a base learner decision tree with provided optimal depth
              base_clf = DecisionTreeClassifier(max_depth=optimal_depth)

              # Initialize a ADA boost classifier using the base DT and provided hyper params
              ada_boost_clf = AdaBoostClassifier(base_estimator=base_clf,n_estimators=est, lea

              # Train the classifier using the train data set
              ada_boost_clf.fit(X_train_scale, y_train)

              # Check accuracy using prediction on the training data
              predictions = ada_boost_clf.predict(X_train_scale)
              acc_score = accuracy_score(y_train, predictions)
              accuracy.append(acc_score)

              # Check accuracy for 5-fold cross validation test and take the mean
              cv_mean = cross_val_score(ada_boost_clf, X_train_scale, y_train, cv=5).mean()
              cv_means.append(cv_mean)
              boost_estimators.append(est)
              boost_models[est] = ada_boost_clf

              # update estimator with max CV Mean score if current score is atleast 0.001 grea
              if cv_mean > max_cv_mean +0.001:
                  max_cv_mean = cv_mean
                  optimal_boost_estimator = est

          # Plot the prediction accuracy andf 5 fold cross validation mean for each tree depth
          fig = plt.figure(figsize=(12,4))
          plt.plot(boost_estimators, cv_means,marker= 'o', c = '#c0392b', label='5 fold CV sco
          plt.plot(boost_estimators, accuracy,marker= 'o', c = '#8e44ad', label='Prediction Ac
          plt.axvline(optimal_boost_estimator, color='.5', label='Optimal Estimator - ' + str(

          # Set title, axis values and legends for the plot
          plt.title('Plot of the prediction accuracy and CV mean score against different estim
          plt.xlabel('no of estimators', fontsize = 15)
          plt.ylabel('Score', fontsize = 15)
          plt.legend(fontsize = 15)
```

```
plt.show()
```




```
In [143]: BOOSTING_CLF = 'Ada Boost' # Model Title constant for Boosting Classifier

          # Report Prediction accuracy on Train and Validation Data sets
          ada_boost_train_acc, ada_boost_train_cv = get_classifier_accuracy(boost_models[optima
                                                                              , X_train_scale, y_
          ada_boost_val_acc, ada_boost_val_cv = get_classifier_accuracy(boost_models[optimal_bo
                                                                          , X_val_scale, y_val, B
```

```
Ada Boost Model - (Train) Prediction Accuracy: 0.83
Ada Boost (Train) Cross Validation accuracy and 95 percent CI: 0.81 (+/- 0.07)
```



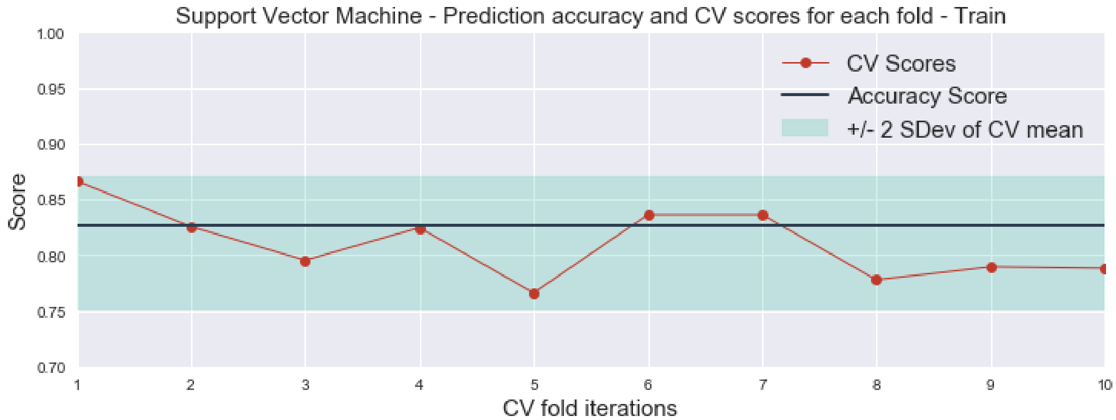

```
Ada Boost Model - (Validation) Prediction Accuracy: 0.80
```

Support Vector Machine (SVM) Classifier using SVC

```
In [144]: # Parameter grid to use during the Randomized Grid search CV
          parameters = {'kernel':['linear', 'rbf', 'sigmoid'], 'C': expon(scale=100), 'gamma':

          # svc base classifier to use
          svc = SVC(gamma="scale")

          # Instantiate a Randomized search CV instance and fit the training data to determine
          rand_cv_clf = RandomizedSearchCV(svc, parameters, cv=5)
          rand_cv_clf.fit(X_train_scale, y_train)
          svc_clf = rand_cv_clf.best_estimator_
```

```
In [185]: SVM_CLF = 'Support Vector Machine' # Model Title constant for SVM Classifier

          # Train the best svg classifier obtained from grid search with the train data set
          svc_clf.fit(X_train_scale, y_train)

          # Report Prediction accuracy on Train and Validation Data sets
          svc_train_acc, svc_train_cv = get_classifier_accuracy(svc_clf, X_train_scale, y_trai
          svc_val_acc, svc_val_cv = get_classifier_accuracy(svc_clf, X_val_scale, y_val, SVM_C
```

```
Support Vector Machine Model - (Train) Prediction Accuracy: 0.83
Support Vector Machine (Train) Cross Validation accuracy and 95 percent CI: 0.81 (+/- 0.06)
```




```
Support Vector Machine Model - (Validation) Prediction Accuracy: 0.82
```

Neural Network Classifier

```
In [146]: # Get the models training history
          def plot_nn_training_history(model_history):
```

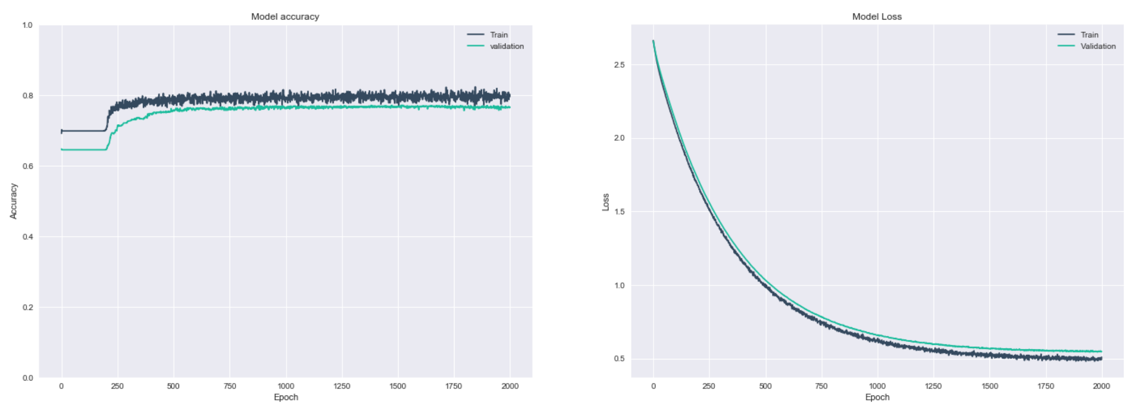
```
    ''' Method to plot the accuracy and loss statistics from the model's training hi

       Args:
           model_history: History object obtained from the trained model
    '''
    # Initiate a figure for the plot
    fig = plt.figure(figsize=(24,8))

    # Create a subplot for the Accuracy stats
    plt.subplot(1, 2, 1)
    plt.plot(model_history.history['acc'])
    plt.plot(model_history.history['val_acc'])
    plt.ylim(bottom=0, top=1)
    plt.title('Model accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'validation'])

    # Create a subplot for the Loss stats
    plt.subplot(1, 2, 2)
    plt.plot(model_history.history['loss'])
    plt.plot(model_history.history['val_loss'])
    plt.title('Model Loss')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Validation'])

    plt.show()
```

In [147]:
```
# Prepocess DF to NP arrays
X_train_nn = X_train_scale.values
y_train_nn = y_train.values

X_val_nn = X_val_scale.values
y_val_nn = y_val.values
```

In [148]:
```
# Instantiate a Sequential Model
ann_model = Sequential()

# Add a dropout regularization for input of the first hidden layer
ann_model.add(Dropout(0.25))

# Add the 1st hidden layer
# 100 Nodes, and relu activation
ann_model.add(Dense(100, input_dim=X_train_nn.shape[1], activation='relu'
                    , kernel_regularizer=keras.regularizers.l2(0.01)))

# Add the 2nd hidden layer
```

```
# 50 Nodes, and relu activation
ann_model.add(Dense(50, activation='relu', kernel_regularizer=keras.regularizers.l2(

# Add the 3rd hidden layer
# 50 Nodes, and relu activation
ann_model.add(Dense(50, activation='relu', kernel_regularizer=keras.regularizers.l2(

# Add the 4th hidden layer
# 50 Nodes, and relu activation
ann_model.add(Dense(50, activation='relu', kernel_regularizer=keras.regularizers.l2(

# Add the Output layer
# 1 Node for 2 output classes, and sigmoid activation
ann_model.add(Dense(1, activation='sigmoid'))

# Compile the model with a SGD optimizer and binary_crossentropy loss function
ann_model.compile(optimizer='sgd', loss='binary_crossentropy', metrics=['accuracy'])

# Fit the model with the training data with 2000 training epochs with a batch size o
mod = ann_model.fit(X_train_nn, y_train_nn, epochs=2000, batch_size=128, validation_
```

In [149]:
```
# Plot the accuracy and loss stats for the regulated model
plot_nn_training_history(ann_model.history)
```



In [150]:
```
# Evaluate the Regularized model accuracy on the training data
ann_model.evaluate(x=X_train_nn, y=y_train_nn, batch_size=64)
```

```
1711/1711 [==============================] - ETA:  - 0s 12us/step
```

Out[150]: [0.5087215290440237, 0.7849210992603536]

In [151]:
```
# Evaluate the Regularized model accuracy on the validation data
ann_model.evaluate(x=X_val_nn, y=y_val_nn, batch_size=64)
```

```
428/428 [==============================] - ETA:  - 0s 19us/step
```

```
Out[151]: [0.49052348482274566, 0.8130841093642689]
```

```
In [152]: NN_CLF = 'Neural Net' # Model Title constant for NN Classifier

          # Report Prediction accuracy on Train and Validation Data sets
          ann_train_acc, ann_train_cv = get_classifier_accuracy(ann_model, X_train_nn, y_train_
          ann_val_acc, ann_val_cv = get_classifier_accuracy(ann_model, X_val_nn, y_val_nn, NN_C
```

```
Neural Net Model - (Train) Prediction Accuracy: 0.78
Neural Net Model - (Validation) Prediction Accuracy: 0.81
```

Natural Language Processing (NLP)- Classification based on Topic Modeling

Topic modeling based on Hashtags used in the tweet text messages of the user

```
In [155]: # Constants with STOP LIST and noise symbols to extract and clean from the topics
          STOPLIST = set(stopwords.words('english') + list(ENGLISH_STOP_WORDS))
          SYMBOLS = " ".join(string.punctuation).split(" ") + ["-", "...", "", ""]
```

```
In [156]: # Class to implement Text transformation using TransformerMixin from sklearn
          class CleanTextTransformer(TransformerMixin):
             def transform(self, X, **transform_params):
                  return [cleanText(text) for text in X]
             def fit(self, X, y=None, **fit_params):
                  return self
             def get_params(self, deep=True):
                  return {}

          # utility method to clean text content
          def cleanText(text):
              text = text.strip().replace("\n", " ").replace("\r", " ")
              text = text.lower()
              return text

          # utility method to tokenize text content
          def tokenizeText(sample):
              tokens = parser(sample)
              lemmas = []
              for tok in tokens:
                  lemmas.append(tok.lemma_.lower().strip() if tok.lemma_ != "-PRON-" else tok.l
              tokens = lemmas
              tokens = [tok for tok in tokens if tok not in STOPLIST]
              tokens = [tok for tok in tokens if tok not in SYMBOLS]
              return tokens

          # Utility method to report the top N Most informative topics from the topic based mo
```

```
def printNMostInformative(vectorizer, clf, N):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    topClass1 = coefs_with_fns[:N]
    topClass2 = coefs_with_fns[:-(N + 1):-1]
    class1_lst = []
    for feat in topClass1:
        feat_dict = {}
        feat_dict['Coefficient'] = feat[0]
        feat_dict['Topic'] = feat[1]
        class1_lst.append(feat_dict)
    cls1_df = pd.DataFrame(data=class1_lst)

    class2_lst = []
    for feat in topClass2:
        feat_dict = {}
        feat_dict['Coefficient'] = feat[0]
        feat_dict['Topic'] = feat[1]
        class2_lst.append(feat_dict)
    cls2_df = pd.DataFrame(data=class2_lst)
    return cls1_df, cls2_df
```

Split Training and Validation data set from the consolidated data set

```
In [157]: # Extract the hash_tags feature containting the topic information and the response v
          topic_data_df = consolidated_ftrs_df[['hash_tags', 'bot_flg']]

          # Spli the data set into Traing and Validation sets
          topic_data_train, topic_data_val = train_test_split(topic_data_df, test_size = 0.2
                                                              , random_state=90, stratify=topic

          # Form the Predictor and Response data sets for train and validation
          X_topic_data_train = topic_data_train['hash_tags']
          y_topic_data_train = topic_data_train['bot_flg']
          X_topic_data_val = topic_data_val['hash_tags']
          y_topic_data_val = topic_data_val['bot_flg']
```

Fit the classification model to do Topic based classification

```
In [138]: # Instantiate a vectorizer to break down the multiple topics from the messages thru
          vectorizer = CountVectorizer(tokenizer=tokenizeText, ngram_range=(1,1))

          # Instantiate a LinearSVC classifier to use as part of the topic based classificatio
          linear_svc_clf = LinearSVC()

          # Define a pipeline that will clean the text content, vectorize it and fit the conte
          tpipe = Pipeline([('cleanText', CleanTextTransformer()), ('vectorizer', vectorizer),

          # Train the model based on the aggregated topics
```

```
tpipe.fit(X_topic_data_train, y_topic_data_train)

# Determine the top 10 topics used by the classifier during classification
cls1_df, cls2_df = printNMostInformative(vectorizer, linear_svc_clf, 10)
```

In [142]:
```
print("Top 10 topics used as features to predict: Class 1")
cls1_df.head(10)
```

```
Top 10 topics used as features to predict: Class 1
```

Out[142]:

	Coefficient	Topic
0	-0.910986	itrotter
1	-0.835408	lolsided
2	-0.835408	danielpadillaonggv
3	-0.831407	socialsecurity
4	-0.752205	dad
5	-0.560587	kita
6	-0.558833	akhir
7	-0.532553	ifwedate
8	-0.502815	worldafroday
9	-0.498887	tuesdaythought

In [140]:
```
print("Top 10 topics used as features to predict: Class 2")
cls2_df.head(10)
```

```
Top 10 topics used as features to predict: Class 2
```

Out[140]:

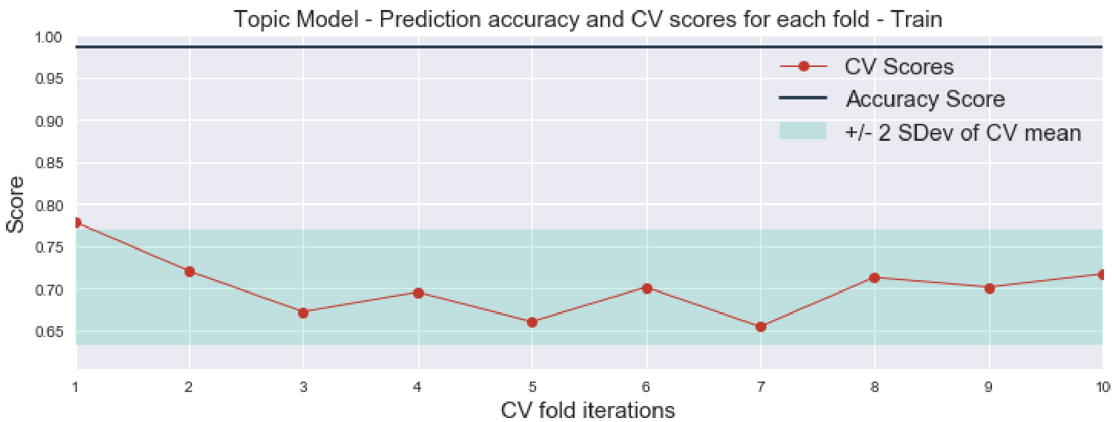
	Coefficient	Topic
0	0.889049	trecru
1	0.806954	2017
2	0.543762	floodaware
3	0.498687	kueez
4	0.497928	freenazanin
5	0.497926	realhuman
6	0.497926	cuntscorner
7	0.497926	snoopdog
8	0.497926	eurekamag
9	0.495390	jb17

In [158]:
```
# Make predictions using the topic modeling classifier on the Test data set and calc
tpreds_train = tpipe.predict(X_topic_data_train)
topic_train_acc = accuracy_score(y_topic_data_train, tpreds_train)

# Report the accuracy scores on Training data set
printmd_color("Topic Modeling Accuracy on %s data set - %0.2f" % (TRAIN, topic_train_
```

Topic Modeling Accuracy on Train data set - 0.99

In [186]:
```
TOPIC_CLF = 'Topic Model'
topic_train_acc, topic_train_cv = get_classifier_accuracy(tpipe, X_topic_data_train
                                                          , y_topic_data_train, TOPI
```

```
Topic Model Model - (Train) Prediction Accuracy: 0.99
Topic Model (Train) Cross Validation accuracy and 95 percent CI: 0.70 (+/- 0.07)
```



In [159]:
```
# Make predictions using the topic modeling classifier on the validation data set an
tpreds_val = tpipe.predict(X_topic_data_val)
topic_val_acc = accuracy_score(y_topic_data_val, tpreds_val)

# Report the accuracy scores on validation data set
printmd_color("Topic Modeling Accuracy on %s data set - %0.2f" % (VALIDATION, topic_
```

Topic Modeling Accuracy on Validation data set - 0.71

7 STACKING - Ensembling of multi Classifier output using a meta learner

In [160]:
```
# Calculate the Stacking metalearner predictions using provided classifiers for the
def calculate_metalearner_predictions(models_to_compare, X_data, y_data, data_type=T
    ''' Method to calculate metalearner predictions using stacked output of classifi
        Also calculate the prediction accuracy based on the true output

       Args:
           models_to_compare: Dictionary containing various fitted classifier models
           X_data: Input predictor data set for the classifier models
           y_data: True output data for the provided predictors
           data_type: Type of the data set that is passed. Default is TRAIN

       Returns:
```

```
        stacked_preds: array of predictions from the metalearner for the given da
    '''
    individual_preds = pd.DataFrame() # DF to store predictions from all the classif

    # Iterate through all classifier models and predict to combine meta learner outp
    for title, model in models_to_compare.items():
        # Exclude PCA model for stacking
        if title != PCA_CLF and title != QDA_CLF:
            # Concat predictions of the current model as a new column to the predict
            individual_preds = pd.concat([individual_preds, pd.DataFrame(np.round(mod
                                                                                , columns=[

    # Initialize a stacked predictions of all 0 output
    stacked_preds = np.zeros(individual_preds.shape[0])

    # Iterate through each classifier prediction and stack all true predictions
    for i in range(individual_preds.shape[0]):
        if individual_preds.values[i].mean() > 0.5:
            stacked_preds[i] = 1

    # Calculate accuracy based on stacked predictions
    acc_scr = accuracy_score(y_data, stacked_preds)

    # Report Accuracy
    h3_start = '<h3 style="padding-top:10px;padding-bottom:10px;padding-left:5px;bac
    h3_end = '</h3>'
    printmd(h3_start + 'Stacking Accuracy score on the %s data set - %0.2f' % (data_

    return stacked_preds

# Utility method for formatted print
def printmd_color(text, color='#1abc9c'):
    h3_start = '<h3 style="padding-top:10px;padding-bottom:10px;padding-left:5px;bac
    h3_end = '</h3>'
    printmd(h3_start + text + h3_end)
```

8 Train and Validation - Prediction Results and Stats

Comparison of prediction accuracies across classifiers - TRAIN dataset

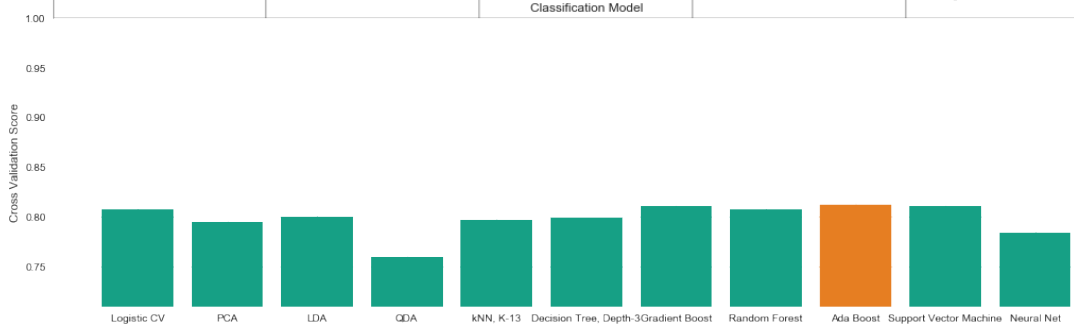
In [161]:
```
# Stacking Classification Accuracy score for Training Data
stacked_predictions_train = calculate_metalearner_predictions(models_to_compare, X_t
```

Stacking Accuracy score on the Train data set - 0.83

In [162]:
```
# Compare classifier accuracy stats for Training data
renderAccuracyStatsIable(acc_stats_table_data, TRAIN)
```

```
** Train ** Comparison Table of Accuracy stats for different classifiation models
```

Model Title	Prediction Accuracy	CV Accuracy	95% CI (+/-)	TN, FP, FN, TP
Logistic CV	0.811	0.808	0.05	[1008 141 183 379]
PCA	0.797	0.795	0.06	[1015 134 213 349]
LDA	0.806	0.8	0.05	[1005 144 188 374]
QDA	0.771	0.76	0.08	[840 309 82 480]
kNN, K-13	0.818	0.797	0.06	[1025 124 188 374]
Decision Tree, Depth-3	0.822	0.799	0.06	[992 157 147 415]
Gradient Boost	0.842	0.811	0.07	[1034 115 155 407]
Random Forest	0.827	0.808	0.07	[1020 129 167 395]
Ada Boost	0.834	0.812	0.07	[1001 148 136 426]
Support Vector Machine	0.827	0.811	0.06	[1002 147 149 413]
Neural Net	0.785	0.785	0	[1053 96 272 290]



Comparison of prediction accuracies across classifiers - VALIDATION Dataset

```
In [163]: # Stacking Classification Accuracy score for Validation Data
          stacked_predictions_val = calculate_metalearner_predictions(models_to_compare, X_val_
```

Stacking Accuracy score on the Validation data set - 0.82

```
In [164]: # Compare classifier accuracy stats for Validation data
          renderAccuracyStatsIable(acc_stats_table_data, VALIDATION)
```

```
** Validation ** Comparison Table of Accuracy stats for different classifiation models
```

Model Title	Prediction Accuracy	TN, FP, FN, TP
Logistic CV	0.829	[261 27 46 94]
PCA	0.815	[261 27 52 88]
LDA	0.822	[256 32 44 96]
QDA	0.799	[224 64 22 118]
kNN, K-13	0.822	[259 29 47 93]
Decision Tree, Depth-3	0.787	[247 41 50 90]
Gradient Boost	0.804	[258 30 54 86]
Random Forest	0.813	[258 30 50 90]
Ada Boost	0.804	[253 35 49 91]
Support Vector Machine	0.825	[253 35 40 100]
Neural Net	0.813	[269 19 61 79]

9 Test Data Preparation and Models validation

Data Preparation

In [165]:
```
# Read the Pre-classified data set containing twitter user labeled as either Bots (1
labelled_df_test = pd.read_csv('cresci_2017_test_prelabelled.csv')

# Determine no of users in the labelled data classified as Bots(1) and who are deter
labelled_df_test.groupby(['bot_flg']).count()
```

Out[165]:
```
         user_id
bot_flg
0            526
1            392
```

In [166]:
```
# MARKED FOR EXECUTION AS NEEDED - NOTE - EXTRACTION TAKES A LONG TIME
# Download the latest 3000 tweets as json for each user in cresci_2017_test_prelabel

# success_users_test, restricted_users_test = extract_tweets_for_users(labelled_df_t
```

In [167]:
```
consolidated_ftrs_df_test = pd.read_csv(TWEET_EXTRACT_LOCATION_TEST + CONSOLIDATED_FI

# MARKED FOR EXECUTION AS NEEDED - NOTE - PARSING and CONSOLIDATES TAKES A LONG TIME
# Extract and consolidate all features for every user
#consolidated_ftrs_df_test = consolidate_features_at_user_level(TWEET_EXTRACT_LOCATI

consolidated_ftrs_df_test = consolidated_ftrs_df_test.sample(frac=1)
consolidated_ftrs_df_test.describe()
```

Out[167]:

	user_id	default_profile	default_profile_image	favourites_count	follo
count	7.590000e+02	759.000000	759.000000	759.000000	7
mean	2.422529e+09	0.351779	0.005270	7017.304348	7
std	6.407658e+08	0.477840	0.072452	17609.872465	32
min	8.572704e+08	0.000000	0.000000	0.000000	
25%	2.241075e+09	0.000000	0.000000	1.000000	
50%	2.548562e+09	0.000000	0.000000	57.000000	1
75%	2.886263e+09	1.000000	0.000000	5345.000000	4
max	4.331280e+09	1.000000	1.000000	202812.000000	596

In [168]:
```
# Drop user_id from the dataframe as that is not needed for classification
consolidated_ftrs_df_test = consolidated_ftrs_df_test.drop(["user_id"], axis=1, erro

# Drop the categorical values that does not seem to be providing value based on EDA
cols_to_drop = ['protected',  'verified', 'is_translator', 'possibly_sensitive', 'pl
               , 'user_lang', 'default_profile_image', 'default_profile', 'symbols_c
processed_data_df_test = consolidated_ftrs_df_test.drop(cols_to_drop, axis=1, errors

# Split the test data after scaling through normalization
X_test_scale, y_test, dummyX, dummyY = split_train_and_test(processed_data_df_test, s
```

Prediction Results on Test Data

Ensembing based on Stacking

In [169]:
```
stacked_predictions_test = calculate_metalearner_predictions(models_to_compare, X_tes
```

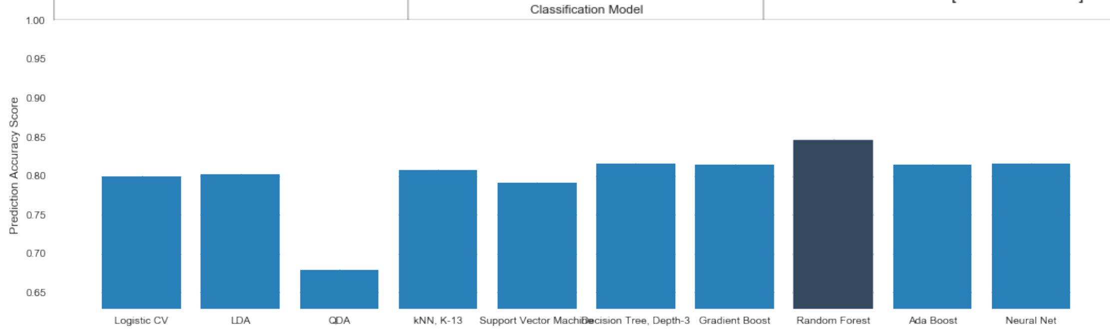
Stacking Accuracy score on the Test data set - 0.81

Comparison of prediction accuracies across classifiers - TEST Dataset

In [183]:
```
# Compare classifier accuracy stats for Test data
renderAccuracyStatsIable(acc_stats_table_data, TEST, 'Prediction Accuracy')
```

```
** Test ** Comparison Table of Accuracy stats for different classifiation models
```

Model Title	Prediction Accuracy	TN, FP, FN, TP
Logistic CV	0.799	[371 24 127 229]
LDA	0.802	[373 22 127 229]
QDA	0.679	[307 88 153 203]
kNN, K-13	0.808	[378 17 127 229]
Support Vector Machine	0.791	[365 30 127 229]
Decision Tree, Depth-3	0.816	[375 20 118 238]
Gradient Boost	0.814	[373 22 118 238]
Random Forest	0.846	[380 15 101 255]
Ada Boost	0.814	[373 22 118 238]
Neural Net	0.816	[384 11 127 229]



Classification based on Topic Modeling - TEST Dataset

```
In [171]: # Extract the Hast_tags feature containing the topics information and the response f
          topic_data_df_test = consolidated_ftrs_df_test[['hash_tags', 'bot_flg']]

          # Form the test predictor and response data set for topic modeling based classificat
          X_topic_data_test = topic_data_df_test['hash_tags']
          y_topic_data_test = topic_data_df_test['bot_flg']

          # Predict based on the test topics
          topic_test_preds = tpipe.predict(X_topic_data_test)

          # Report Accuracy score from the Test predictions
          topic_test_acc = accuracy_score(y_topic_data_test, topic_test_preds)
          printmd_color("Topic Modeling Accuracy on %s data set - %0.2f" % (TEST, topic_test_ac
```

Topic Modeling Accuracy on Test data set - 0.85
Prediction accuracies across base classifiers - TEST Dataset
Logistic Classifier CV

```
In [172]: lcv_test_acc, lcv_test_cv = get_classifier_accuracy(lcv_clf, X_test_scale, y_test, L
```

```
Logistic CV Model - (Test) Prediction Accuracy: 0.80
```

Linear Discriminant Analysis (LDA)

```
In [173]: lda_test_acc, lda_test_cv = get_classifier_accuracy(lda, X_test_scale, y_test, LDA_CI
```

```
LDA Model - (Test) Prediction Accuracy: 0.80
```

Quadratic Discriminant Analysis (QDA)

```
In [174]: qda_test_acc, qda_test_cv = get_classifier_accuracy(qda, X_test_scale, y_test, QDA_CI
```

```
QDA Model - (Test) Prediction Accuracy: 0.68
```

k Nearest Neigbors Classifier (kNN)

```
In [175]: knn_test_acc, knn_test_cv = get_classifier_accuracy(knn_models[optimal_k], X_test_sca
```

```
kNN, K-13 Model - (Test) Prediction Accuracy: 0.81
```

Support Vector Machine (SVM) using SVC

```
In [176]: svc_test_acc, svc_test_cv = get_classifier_accuracy(svc_clf, X_test_scale, y_test, SV
```

```
Support Vector Machine Model - (Test) Prediction Accuracy: 0.79
```

Decision Tree

```
In [177]: dt_test_acc, dt_test_cv = get_classifier_accuracy(tree_models[optimal_depth], X_test_
```

```
Decision Tree, Depth-3 Model - (Test) Prediction Accuracy: 0.82
```

Gradient Boost Ensembling

```
In [178]: gb_test_acc, gb_test_cv = get_classifier_accuracy(gb_models[optimal_gb_estimator]
                                                        , X_test_scale, y_test, GRAD_BOOST_
```

```
Gradient Boost Model - (Test) Prediction Accuracy: 0.81
```

Random Forest Ensembling

```
In [179]: rf_test_acc, rf_test_cv = get_classifier_accuracy(rf_models[optimal_rf_estimator]
                                                        , X_test_scale, y_test, RAND_FOREST
```

Random Forest Model - (Test) Prediction Accuracy: 0.85

Adaptive Boosting Ensembling

```
In [180]: boost_test_acc, boost_test_cv = get_classifier_accuracy(boost_models[optimal_boost_es
                                                                  , X_test_scale, y_test, BOOS
```

Ada Boost Model - (Test) Prediction Accuracy: 0.81

Neural Networks

```
In [181]: ann_test_acc, ann_test_cv = get_classifier_accuracy(ann_model, X_test_scale.values, y
```

Neural Net Model - (Test) Prediction Accuracy: 0.82

```
In [182]: stacked_predictions_test = calculate_metalearner_predictions(models_to_compare, X_tes
```

Stacking Accuracy score on the Test data set - 0.81