Using Scikit-Learn and NLTK to build a Naive Bayes Classifier that identifies subtweets

In all tables, assume:

- "➊" represents a single hashtag
- "➋" represents a single URL
- "➌" represents a single mention of username (e.g. "@noah")

Import libraries

```
%matplotlib inline
```

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction import text
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import KFold
from sklearn.pipeline import Pipeline
from sklearn.externals import joblib
from os.path import basename, splitext
from random import choice, sample
from nltk.corpus import stopwords
from string import punctuation
from pprint import pprint
from glob import glob

import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

import scipy.stats
import itertools
import enchant
import nltk
import json
import re
```

Set up some regex patterns

```
hashtags_pattern = re.compile(r'(\#[a-zA-Z0-9]+)')
```

```
urls_pattern = re.compile(r'(?i)\b((?:https?://|www\d{0,3}[.]|[a-z0-9.\-]+[.][a-z]{2,4}/)(?:[^\s()<>]|\(([^\s()<>]+|(
```

```
at_mentions_pattern = re.compile(r'(?<=^|(?<=[^a-zA-Z0-9-\.]))@([A-Za-z0-9_]+)')
```

Prepare English dictionary for language detection

```
english_dict = enchant.Dict("en_US")
```

Use NLTK's tokenizer instead of Scikit's

```
tokenizer = nltk.casual.TweetTokenizer(preserve_case=False, reduce_len=True)
```

Prepare for viewing long text in CSVs and ones with really big and small numbers

```
pd.set_option("max_colwidth", 1000)
```

```
pd.options.display.float_format = "{:.4f}".format
```

Load the two data files

Only use tweets with at least 50% English words

Also, make the mentions of usernames, URLs, and hashtags generic

```
def load_data(filename, threshold=0.5):
    data = [(hashtags_pattern.sub("➊",
             urls_pattern.sub("➋",
             at_mentions_pattern.sub("➌",
             t["tweet_data"]["full_text"])))
             .replace("\u2018", "'")
             .replace("\u2019", "'")
             .replace("\u201c", "\"")
             .replace("\u201d", "\"")
             .replace("&quot;", "\"")
             .replace("&amp;", "&")
             .replace("&gt;", ">")
             .replace("&lt;", "<"))
            for t in json.load(open(filename))
            if t["tweet_data"]["user"]["lang"] == "en"
            and t["reply"]["user"]["lang"] == "en"]
    new_data = []
    for tweet in data:
        tokens = tokenizer.tokenize(tweet)
        english_tokens = [english_dict.check(token) for token in tokens]
        percent_english_words = sum(english_tokens)/len(english_tokens)
        if percent_english_words >= threshold:
            new_data.append(tweet)
    return new_data
```

```
subtweets_data = load_data("../data/other_data/subtweets.json")
```

```
non_subtweets_data = load_data("../data/other_data/non_subtweets.json")
```

Show examples

```
print("Subtweets dataset example:")
print(choice(subtweets_data))
```

```
Subtweets dataset example:
This little girls to weird for me pure retard
```

```python
print("Non-subtweets dataset example:")
print(choice(non_subtweets_data))
```

```
Non-subtweets dataset example:
TESTED: "The Golf Infomercial" Wedge Test

Do golf infomercial wedges really work?

VIEW RESULTS: ❷ ❷
```

Find the length of the smaller dataset

```python
smallest_length = len(min([subtweets_data, non_subtweets_data], key=len))
```

Cut both down to be the same length

```python
subtweets_data = subtweets_data[:smallest_length]
```

```python
non_subtweets_data = non_subtweets_data[:smallest_length]
```

```python
print("Smallest dataset length: {}".format(len(subtweets_data)))
```

```
Smallest dataset length: 7837
```

Prepare data for training

```python
subtweets_data = [(tweet, "subtweet") for tweet in subtweets_data]
```

```python
non_subtweets_data = [(tweet, "non-subtweet") for tweet in non_subtweets_data]
```

Combine them

```python
training_data = subtweets_data + non_subtweets_data
```

Create custom stop words to include generic usernames, URLs, and hashtags, as well as common English first names

```python
names_lower = set([name.lower() for name in open("../data/other_data/first_names.txt").read().split("\n")])
```

```python
generic_tokens = {"❶", "❷", "❸"}
```

```python
stop_words = text.ENGLISH_STOP_WORDS | names_lower | generic_tokens
```

Build the pipeline

```
sentiment_pipeline = Pipeline([
    ("vectorizer", TfidfVectorizer(tokenizer=tokenizer.tokenize,
                                   ngram_range=(1, 3),
                                   stop_words=stop_words)),
    ("classifier", MultinomialNB())
])
```

K-Folds splits up and separates out 10 training and test sets from the data, from which the classifier is trained and the confusion matrix and classification reports are updated

```
def confusion_matrices(training_data, num_folds=10):
    text_training_data = np.array([row[0] for row in training_data])
    class_training_data = np.array([row[1] for row in training_data])
    kf = KFold(n_splits=num_folds, random_state=42, shuffle=True)

    cnf_matrix_test = np.zeros((2, 2), dtype=int)
    cnf_matrix_train = np.zeros((2, 2), dtype=int)

    test_reports = []
    train_reports = []
    for i, (train_index, test_index) in enumerate(kf.split(text_training_data)):

        text_train, text_test = text_training_data[train_index], text_training_data[test_index]
        class_train, class_test = class_training_data[train_index], class_training_data[test_index]

        sentiment_pipeline.fit(text_train, class_train)

        predictions_test = sentiment_pipeline.predict(text_test)
        predictions_train = sentiment_pipeline.predict(text_train)

        cnf_matrix_test += confusion_matrix(class_test, predictions_test)
        cnf_matrix_train += confusion_matrix(class_train, predictions_train)

        print("Test Data Iteration {}:".format(i+1))

        test_report = classification_report(class_test, predictions_test, digits=4)
        test_reports.append(test_report)
        print(test_report)

        print(("Test Data Null Accuracy: {:.4f}\n"
               .format(max(pd.value_counts(pd.Series(class_test)))/float(len(class_test)))))
        print(("Test Data Accuracy: {:.4f}\n"
               .format(accuracy_score(class_test, predictions_test))))
        print("="*53)

        print("Train Data Iteration {}:".format(i+1))

        train_report = classification_report(class_train, predictions_train, digits=4)
        train_reports.append(train_report)
        print(train_report)

        print(("Train Data Null Accuracy: {:.4f}\n"
               .format(max(pd.value_counts(pd.Series(class_train)))/float(len(class_train)))))
        print(("Train Data Accuracy: {:.4f}\n"
               .format(accuracy_score(class_train, predictions_train))))
        print("="*53)

    def reports_mean(reports):
        reports_lists_of_strings = [report.split("\n") for report in reports]
        reports = [[[float(e) for e in report_string[2][16:].split()],
                    [float(e) for e in report_string[3][16:].split()],
                    [float(e) for e in report_string[5][16:].split()]]
                   for report_string in reports_lists_of_strings]
        mean_list = np.mean(np.array(reports), axis=0).tolist()
        print("              precision    recall  f1-score   support")
        print()
        print("non-subtweet     {0:.4f}     {1:.4f}     {2:.4f}      {3:d}".format(mean_list[0][0],
                                                                                mean_list[0][1],
```

```
                                                                 mean_list[0][2],
                                                                 int(mean_list[0][3])))
        print("    subtweet     {0:.4f}     {1:.4f}     {2:.4f}      {3:d}".format(mean_list[1][0],
                                                                 mean_list[1][1],
                                                                 mean_list[1][2],
                                                                 int(mean_list[1][3])))

        print()
        print(" avg / total     {0:.4f}     {1:.4f}     {2:.4f}      {3:d}".format(mean_list[2][0],
                                                                 mean_list[2][1],
                                                                 mean_list[2][2],
                                                                 int(mean_list[2][3])))

        print()
        print("="*53)

    print("Test Data Averages Across All Folds:")
    reports_mean(test_reports)
    print("Train Data Averages Across All Folds:")
    reports_mean(train_reports)
    return {"Test": cnf_matrix_test, "Train": cnf_matrix_train}
```

```
%%time
cnf_matrices = confusion_matrices(training_data)
cnf_matrix_test = cnf_matrices["Test"]
cnf_matrix_train = cnf_matrices["Train"]
```

```
Test Data Iteration 1:
              precision    recall  f1-score   support

non-subtweet     0.7338    0.6431    0.6855       793
    subtweet     0.6758    0.7613    0.7160       775

 avg / total     0.7052    0.7015    0.7006      1568

Test Data Null Accuracy: 0.5057

Test Data Accuracy: 0.7015

=====================================================
Train Data Iteration 1:
              precision    recall  f1-score   support

non-subtweet     0.9907    0.9806    0.9856      7044
    subtweet     0.9808    0.9908    0.9858      7062

 avg / total     0.9857    0.9857    0.9857     14106

Train Data Null Accuracy: 0.5006

Train Data Accuracy: 0.9857

=====================================================
Test Data Iteration 2:
              precision    recall  f1-score   support

non-subtweet     0.6940    0.6324    0.6618       789
    subtweet     0.6584    0.7176    0.6867       779

 avg / total     0.6763    0.6747    0.6742      1568

Test Data Null Accuracy: 0.5032

Test Data Accuracy: 0.6747

=====================================================
Train Data Iteration 2:
              precision    recall  f1-score   support

non-subtweet     0.9908    0.9786    0.9847      7048
```

```
    subtweet     0.9789    0.9909    0.9849      7058

 avg / total     0.9848    0.9848    0.9848     14106

Train Data Null Accuracy: 0.5004

Train Data Accuracy: 0.9848

=====================================================
Test Data Iteration 3:
              precision    recall  f1-score   support

non-subtweet     0.7021    0.6866    0.6943       769
    subtweet     0.7047    0.7196    0.7121       799

 avg / total     0.7034    0.7034    0.7033      1568

Test Data Null Accuracy: 0.5096

Test Data Accuracy: 0.7034

=====================================================
Train Data Iteration 3:
              precision    recall  f1-score   support

non-subtweet     0.9869    0.9829    0.9849      7068
    subtweet     0.9829    0.9869    0.9849      7038

 avg / total     0.9849    0.9849    0.9849     14106

Train Data Null Accuracy: 0.5011

Train Data Accuracy: 0.9849

=====================================================
Test Data Iteration 4:
              precision    recall  f1-score   support

non-subtweet     0.7313    0.6355    0.6800       801
    subtweet     0.6651    0.7562    0.7077       767

 avg / total     0.6989    0.6945    0.6936      1568

Test Data Null Accuracy: 0.5108

Test Data Accuracy: 0.6945

=====================================================
Train Data Iteration 4:
              precision    recall  f1-score   support

non-subtweet     0.9907    0.9802    0.9854      7036
    subtweet     0.9805    0.9908    0.9856      7070

 avg / total     0.9856    0.9855    0.9855     14106

Train Data Null Accuracy: 0.5012

Train Data Accuracy: 0.9855

=====================================================
Test Data Iteration 5:
              precision    recall  f1-score   support

non-subtweet     0.7078    0.6560    0.6809       779
    subtweet     0.6828    0.7322    0.7067       788

 avg / total     0.6952    0.6943    0.6939      1567

Test Data Null Accuracy: 0.5029
```

```
Test Data Accuracy: 0.6943

====================================================
Train Data Iteration 5:
              precision    recall  f1-score   support

non-subtweet     0.9871    0.9829    0.9849      7058
    subtweet     0.9829    0.9871    0.9850      7049

 avg / total     0.9850    0.9850    0.9850     14107

Train Data Null Accuracy: 0.5003

Train Data Accuracy: 0.9850

====================================================
Test Data Iteration 6:
              precision    recall  f1-score   support

non-subtweet     0.6836    0.6583    0.6707       758
    subtweet     0.6906    0.7145    0.7023       809

 avg / total     0.6872    0.6873    0.6870      1567

Test Data Null Accuracy: 0.5163

Test Data Accuracy: 0.6873

====================================================
Train Data Iteration 6:
              precision    recall  f1-score   support

non-subtweet     0.9874    0.9846    0.9860      7079
    subtweet     0.9845    0.9873    0.9859      7028

 avg / total     0.9860    0.9860    0.9860     14107

Train Data Null Accuracy: 0.5018

Train Data Accuracy: 0.9860

====================================================
Test Data Iteration 7:
              precision    recall  f1-score   support

non-subtweet     0.7003    0.6285    0.6625       751
    subtweet     0.6876    0.7525    0.7185       816

 avg / total     0.6937    0.6930    0.6917      1567

Test Data Null Accuracy: 0.5207

Test Data Accuracy: 0.6930

====================================================
Train Data Iteration 7:
              precision    recall  f1-score   support

non-subtweet     0.9860    0.9852    0.9856      7086
    subtweet     0.9851    0.9859    0.9855      7021

 avg / total     0.9855    0.9855    0.9855     14107

Train Data Null Accuracy: 0.5023

Train Data Accuracy: 0.9855

====================================================
Test Data Iteration 8:
              precision    recall  f1-score   support
```

```
non-subtweet     0.7342    0.6429    0.6855       812
    subtweet     0.6612    0.7497    0.7027       755

 avg / total     0.6990    0.6943    0.6938      1567

Test Data Null Accuracy: 0.5182

Test Data Accuracy: 0.6943

=====================================================
Train Data Iteration 8:
             precision    recall  f1-score   support

non-subtweet     0.9906    0.9795    0.9850      7025
    subtweet     0.9799    0.9908    0.9853      7082

 avg / total     0.9852    0.9852    0.9852     14107

Train Data Null Accuracy: 0.5020

Train Data Accuracy: 0.9852

=====================================================
Test Data Iteration 9:
             precision    recall  f1-score   support

non-subtweet     0.7321    0.6429    0.6846       829
    subtweet     0.6472    0.7358    0.6886       738

 avg / total     0.6921    0.6867    0.6865      1567

Test Data Null Accuracy: 0.5290

Test Data Accuracy: 0.6867

=====================================================
Train Data Iteration 9:
             precision    recall  f1-score   support

non-subtweet     0.9919    0.9796    0.9857      7008
    subtweet     0.9801    0.9921    0.9861      7099

 avg / total     0.9860    0.9859    0.9859     14107

Train Data Null Accuracy: 0.5032

Train Data Accuracy: 0.9859

=====================================================
Test Data Iteration 10:
             precision    recall  f1-score   support

non-subtweet     0.7060    0.6799    0.6927       756
    subtweet     0.7116    0.7361    0.7236       811

 avg / total     0.7089    0.7090    0.7087      1567

Test Data Null Accuracy: 0.5175

Test Data Accuracy: 0.7090

=====================================================
Train Data Iteration 10:
             precision    recall  f1-score   support

non-subtweet     0.9870    0.9849    0.9859      7081
    subtweet     0.9848    0.9869    0.9859      7026

 avg / total     0.9859    0.9859    0.9859     14107

Train Data Null Accuracy: 0.5019
```

```
Train Data Accuracy: 0.9859

====================================================
Test Data Averages Across All Folds:
              precision    recall  f1-score   support

non-subtweet     0.7125    0.6506    0.6798       783
    subtweet     0.6785    0.7376    0.7065       783

 avg / total     0.6960    0.6939    0.6933      1567

====================================================
Train Data Averages Across All Folds:
              precision    recall  f1-score   support

non-subtweet     0.9889    0.9819    0.9854      7053
    subtweet     0.9820    0.9890    0.9855      7053

 avg / total     0.9855    0.9854    0.9854     14106

====================================================
CPU times: user 1min 8s, sys: 1.76 s, total: 1min 10s
Wall time: 1min 12s
```

See the most informative features

How does "MultinomialNB.coef_" work?

```
def most_informative_features(pipeline, n=10000):
    vectorizer = pipeline.named_steps["vectorizer"]
    classifier = pipeline.named_steps["classifier"]

    class_labels = classifier.classes_

    feature_names = vectorizer.get_feature_names()

    top_n_class_1 = sorted(zip(classifier.coef_[0], feature_names))[:n]
    top_n_class_2 = sorted(zip(classifier.coef_[0], feature_names))[-n:]

    return {class_labels[0]: pd.DataFrame({"Log Probability": [tup[0] for tup in top_n_class_1],
                                           "Feature": [tup[1] for tup in top_n_class_1]}),
            class_labels[1]: pd.DataFrame({"Log Probability": [tup[0] for tup in reversed(top_n_class_2)],
                                           "Feature": [tup[1] for tup in reversed(top_n_class_2)]})}
```

```
%%time
most_informative_features_all = most_informative_features(sentiment_pipeline)
```

```
CPU times: user 1.34 s, sys: 39.3 ms, total: 1.38 s
Wall time: 1.38 s
```

```
most_informative_features_non_subtweet = most_informative_features_all["non-subtweet"]
```

```
most_informative_features_subtweet = most_informative_features_all["subtweet"]
```

```
final_features = most_informative_features_non_subtweet.join(most_informative_features_subtweet,
                                                             lsuffix=" (Non-subtweet)",
                                                             rsuffix=" (Subtweet)")
final_features.to_csv("../data/other_data/most_informative_features.csv")
final_features.head(25)
```

	Feature (Non-subtweet)	Log Probability (Non-subtweet)	Feature (Subtweet)	Log Probability (Subtweet)
0	! ! &	-12.6618	.	-7.5300
1	! ! (	-12.6618	,	-7.9193
2	! !)	-12.6618	"	-8.0928
3	! ! .	-12.6618	people	-8.3903
4	! ! 100	-12.6618	?	-8.4594
5	! ! 15	-12.6618	don't	-8.5588
6	! ! 3	-12.6618	like	-8.5889
7	! ! 5	-12.6618	just	-8.6754
8	! ! 8am	-12.6618	i'm	-8.6969
9	! ! :)	-12.6618	!	-8.9031
10	! ! ;)	-12.6618	it's	-8.9727
11	! ! absolutely	-12.6618	...	-9.0431
12	! ! amazing	-12.6618	you're	-9.0488
13	! ! ask	-12.6618	:	-9.0704
14	! ! awesome	-12.6618	know	-9.0928
15	! ! big	-12.6618	twitter	-9.1443
16	! ! bite	-12.6618	friends	-9.1650
17	! ! close	-12.6618	time	-9.2879
18	! ! collection	-12.6618	want	-9.2923
19	! ! come	-12.6618	u	-9.3004
20	! ! don't	-12.6618	really	-9.3518
21	! ! enter	-12.6618	shit	-9.3699
22	! ! epic	-12.6618	good	-9.4017
23	! ! extremely	-12.6618	think	-9.4155
24	! ! family	-12.6618	make	-9.4225

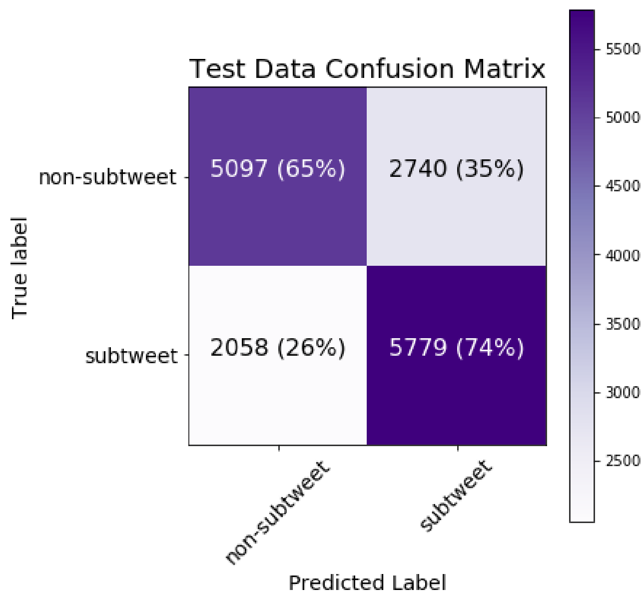
Define function for visualizing confusion matrices

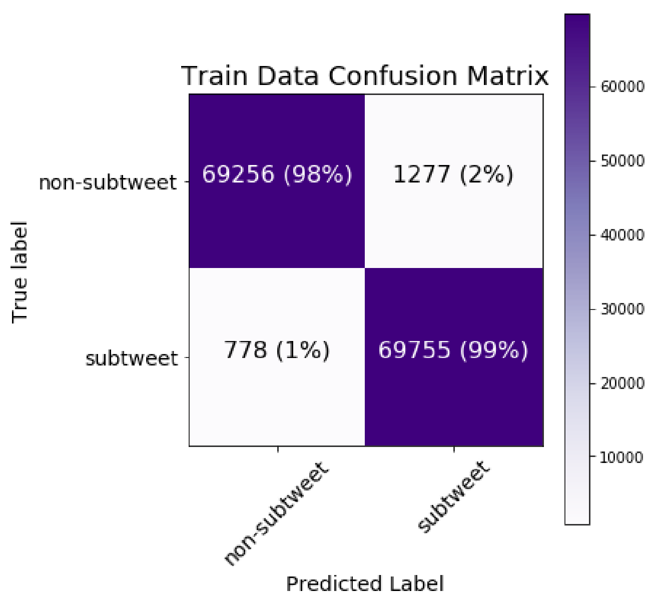
```
def plot_confusion_matrix(cm, classes=["non-subtweet", "subtweet"],
                          title="Confusion Matrix", cmap=plt.cm.Purples):

    cm_normalized = cm.astype("float") / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation="nearest", cmap=cmap)
    plt.colorbar()

    plt.title(title, size=18)

    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45, fontsize=14)
    plt.yticks(tick_marks, classes, fontsize=14)

    thresh = cm.max() / 2.
```

```
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, "{} ({:.0%})".format(cm[i, j], cm_normalized[i, j]),
                 horizontalalignment="center", size=16,
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()

    plt.ylabel("True label", fontsize=14)
    plt.xlabel("Predicted Label", fontsize=14)
```

Show the matrices

```
np.set_printoptions(precision=2)

plt.figure(figsize=(6, 6))
plot_confusion_matrix(cnf_matrix_test, title="Test Data Confusion Matrix")

plt.figure(figsize=(6, 6))
plot_confusion_matrix(cnf_matrix_train, title="Train Data Confusion Matrix")

plt.show()
```





Update matplotlib style

```
plt.style.use("fivethirtyeight")
```

Save the classifier for another time

```
joblib.dump(sentiment_pipeline, "../data/other_data/subtweets_classifier.pkl");
```

Print tests for the classifier

```
def process_tweets_for_testing(filenames):
    dataframes = {}
    for filename in filenames:
        username = splitext(basename(filename))[0][:-7]
        dataframes[username] = {}

        user_df = pd.read_csv(filename).dropna()
        user_df["Text"] = user_df["Text"].str.replace(hashtags_pattern, "➊")
        user_df["Text"] = user_df["Text"].str.replace(urls_pattern, "➋")
        user_df["Text"] = user_df["Text"].str.replace(at_mentions_pattern, "➌")
        user_df["Text"] = user_df["Text"].str.replace("\u2018", "'")
        user_df["Text"] = user_df["Text"].str.replace("\u2019", "'")
        user_df["Text"] = user_df["Text"].str.replace("\u201c", "\"")
        user_df["Text"] = user_df["Text"].str.replace("\u201d", "\"")
        user_df["Text"] = user_df["Text"].str.replace("&quot;", "\"")
        user_df["Text"] = user_df["Text"].str.replace("&amp;", "&")
        user_df["Text"] = user_df["Text"].str.replace("&gt;", ">")
        user_df["Text"] = user_df["Text"].str.replace("&lt;", "<")

        predictions = sentiment_pipeline.predict_proba(user_df["Text"])[:, 1].tolist()
        user_df["SubtweetProbability"] = predictions

        dataframes[username]["all"] = user_df

        scores = user_df[["SubtweetProbability"]].rename(columns={"SubtweetProbability": username})

        dataframes[username]["scores"] = scores
        dataframes[username]["stats"] = scores.describe()

    return dataframes
```

Load the CSV files

```
filenames = glob("../data/data_for_testing/friends_data/*.csv")
```

```
%%time
dataframes = process_tweets_for_testing(filenames)
```

```
CPU times: user 9.09 s, sys: 153 ms, total: 9.24 s
Wall time: 9.52 s
```

Show a random table

```
chosen_username = choice(list(dataframes.keys()))
dataframes[chosen_username]["all"].sort_values(by="SubtweetProbability", ascending=False).head(5)
```

	Text	Date	Favorites	Retweets	Tweet ID	SubtweetProbability

	Text	Date	Favorites	Retweets	Tweet ID	SubtweetProbability
2092	I hate when people overuse emojis	2015-06-26 13:01:35	0	0	614478624197091328	0.8579
2137	Also you don't need to resort to social media 24/7 to complain about your very privileged life ¯_(ツ)_/¯	2015-06-15 17:24:46	1	0	610558590278070272	0.8443
2151	When I try to be supportive and caring I get ignored and then I'm told I'm not being supportive or caring ¯_(ツ)_/¯	2015-06-13 08:44:07	0	0	609702789896372224	0.8366
2134	What he doesn't know (unless he stalks my twitter which I know he does) is that I have fake accounts following all his social media	2015-06-15 17:26:41	0	0	610559074820861953	0.8177
1510	If you don't have tweet notifications turned on for me are we really friends	2016-07-14 14:21:21	1	0	753655639465922560	0.8076

Prepare statistics on tweets

```
tests_df = pd.concat([df_dict["scores"] for df_dict in dataframes.values()], ignore_index=True)
```

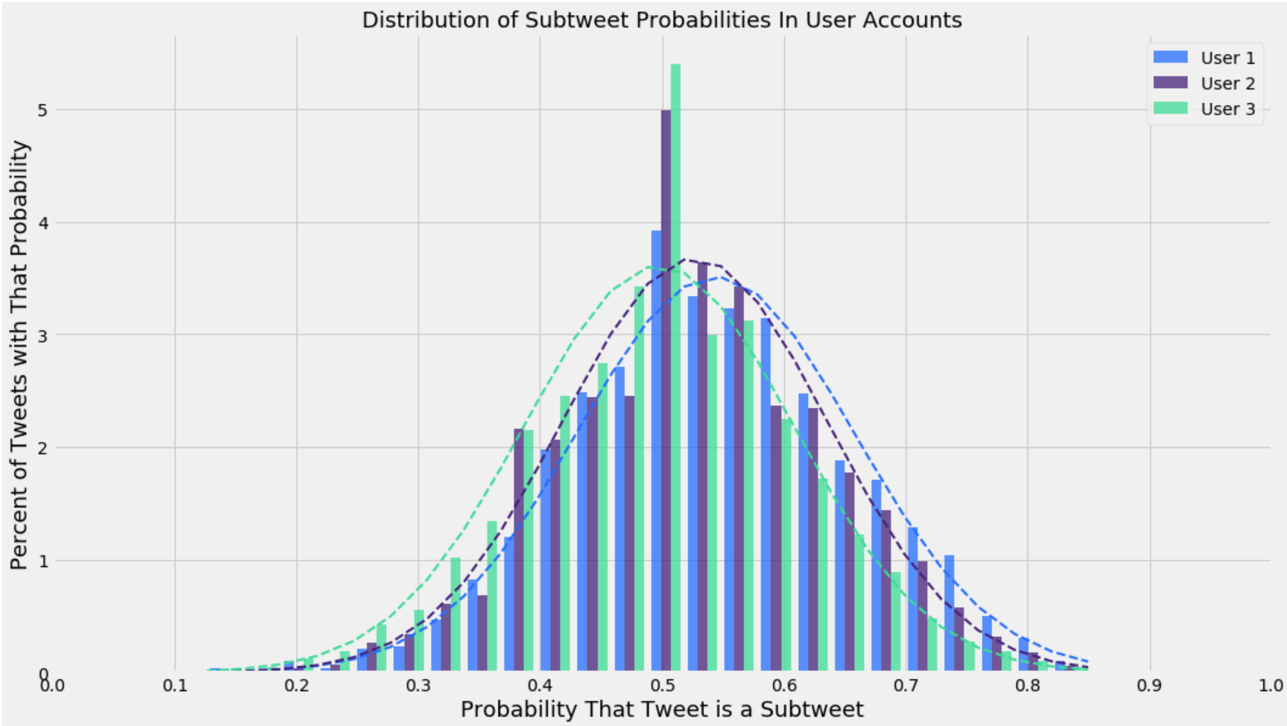
```
tests_df.describe()
```

	adhaardesai	akrapf96	generatedtext	gothodile	juliaeberry	kayleesue	keithohara
count	621.0000	2640.0000	2066.0000	3488.0000	4356.0000	1939.0000	1169.0000
mean	0.4996	0.5086	0.5438	0.5270	0.5187	0.4976	0.4388

	adhaardesai	akrapf96	generatedtext	gothodile	juliaeberry	kayleesue	keithohara
std	0.1059	0.1150	0.1136	0.1086	0.1023	0.1106	0.0981
min	0.1981	0.0953	0.1266	0.1626	0.1522	0.0566	0.1497
25%	0.4291	0.4304	0.4669	0.4538	0.4492	0.4260	0.3733
50%	0.4971	0.5037	0.5417	0.5217	0.5180	0.4981	0.4379
75%	0.5670	0.5847	0.6213	0.5982	0.5843	0.5669	0.5016
max	0.8457	0.8579	0.8497	0.8749	0.8674	0.8766	0.8157

Plot a histogram with three random users

```
random_choices = sample(list(dataframes.values()), 3)
scores = [df_dict["scores"][df_dict["scores"].columns[0]].tolist()
          for df_dict in random_choices]

fig = plt.figure(figsize=(16, 9))
ax = fig.add_subplot(111)

n, bins, patches = ax.hist(scores,
                           bins="scott",
                           color=["#256EFF", "#46237A", "#3DDC97"],
                           density=True,
                           label=["User 1", "User 2", "User 3"],
                           alpha=0.75)

stats = [df_dict["stats"][df_dict["stats"].columns[0]].tolist()
         for df_dict in random_choices]

line_1 = scipy.stats.norm.pdf(bins, stats[0][1], stats[0][2])
ax.plot(bins, line_1, "--", color="#256EFF", linewidth=2)

line_2 = scipy.stats.norm.pdf(bins, stats[1][1], stats[1][2])
ax.plot(bins, line_2, "--", color="#46237A", linewidth=2)

line_3 = scipy.stats.norm.pdf(bins, stats[2][1], stats[2][2])
ax.plot(bins, line_3, "--", color="#3DDC97", linewidth=2)

ax.set_xticks([float(x/10) for x in range(11)], minor=False)
ax.set_title("Distribution of Subtweet Probabilities In User Accounts", fontsize=18)
ax.set_xlabel("Probability That Tweet is a Subtweet", fontsize=18)
ax.set_ylabel("Percent of Tweets with That Probability", fontsize=18)

ax.legend()

plt.show()
```



Plot a histogram with all of them

First, get some statistics

```
new_tests_df = pd.concat([df_dict["scores"].rename(columns={df_dict["scores"].columns[0]:"SubtweetProbability"})
                          for df_dict in dataframes.values()], ignore_index=True)

new_tests_df_stats = new_tests_df.describe()
```

Then view them

```
new_tests_df_stats
```

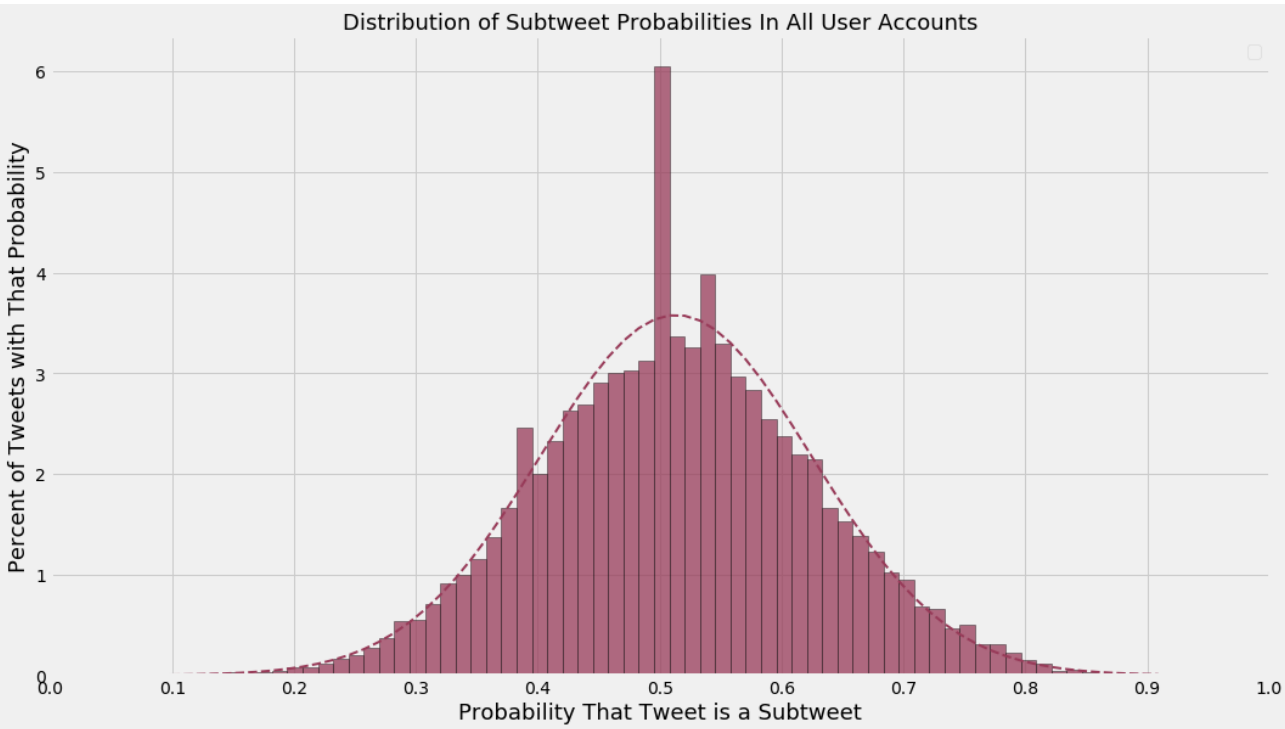
	SubtweetProbability
count	28632.0000
mean	0.5133
std	0.1115
min	0.0566
25%	0.4385
50%	0.5093
75%	0.5860
max	0.9091

Now plot

```
fig = plt.figure(figsize=(16, 9))
ax = fig.add_subplot(111)

n, bins, patches = ax.hist(new_tests_df["SubtweetProbability"].tolist(),
```

```
                              bins="scott",
                              color="#983B59",
                              edgecolor="black",
                              density=True,
                              alpha=0.75)

line = scipy.stats.norm.pdf(bins, new_tests_df_stats["SubtweetProbability"][1],
                              new_tests_df_stats["SubtweetProbability"][2])

ax.plot(bins, line, "--", color="#983B59", linewidth=2)


ax.set_xticks([float(x/10) for x in range(11)], minor=False)
ax.set_title("Distribution of Subtweet Probabilities In All User Accounts", fontsize=18)
ax.set_xlabel("Probability That Tweet is a Subtweet", fontsize=18)
ax.set_ylabel("Percent of Tweets with That Probability", fontsize=18)

ax.legend()

plt.show()
```

```
No handles with labels found to put in legend.
```



Statisitics on training data

Remove mentions of usernames for these statistics

```
training_data = [(tweet[0]
                  .replace("➊", "")
                  .replace("➋", "")
                  .replace("➌", "")) for tweet in training_data]
```

Lengths

```
length_data = [len(tweet) for tweet in training_data]
```

```
length_data_for_stats = pd.DataFrame({"Length": length_data, "Tweet": training_data})
```

```
# length_data_for_stats = length_data_for_stats[length_data_for_stats["Length"] <= 280]
```

```
# length_data_for_stats = length_data_for_stats[length_data_for_stats["Length"] >= 5]
```

```
length_data = length_data_for_stats.Length.tolist()
```

Top 5 longest tweets

```
length_data_for_stats.sort_values(by="Length", ascending=False).head()
```

	Length	Tweet
8887	281	This Tweet does not endorse the use of Nazi Symbols in any form! I think the image which has been published on social media and MSM is a day or two old. It conjures up strong emotions for many people, My question is simple what meaning do you think is being conveyed by the image?
2198	281	I need to learn how to do this. I ask "how can I help" a lot because I genuinely want to make things better for friends , but this *can* put a burden back upon those who are suffering. Sometimes it may be best to just have exuberant and fearless compassion the same way a pet does
1531	281	hi! I'm not normally v personal like this and I probably won't be at least for a v long time but I thought I'd share this \nwhile I was scrolling on Twitter today I had like a sudden impulse to just dump all my thoughts about what id been reading and seeing and so far it actually-
10533	281	Some people are undecided about testing on animals. Understandable. There's so much propaganda and secrecy about it. Here's a quick test though, & you're answer should tell you. What would you do if some man came to your house & squirted disinfectant in your beautiful dog's eyes?
10521	281	Enthralled by Raja Shiv Chhatrapati, a well mounted magnum opus on life of the Maratha warrior at Red Fort. Vividly brought out his philosophies, struggles, inspiration from mother Jijayee & penchant for gender equality through well conceived music, dance & dialogues. A must see!

Top 5 shortest tweets

```
length_data_for_stats.sort_values(by="Length", ascending=True).head()
```

	Length	Tweet
7699	1	A
3473	2	no
5896	2	uh
6676	2	i-
2038	2	Ha

Tweet length statistics

```
length_data_for_stats.describe()
```

	Length
count	15674.0000
mean	106.8089
std	73.8680
min	1.0000
25%	48.0000
50%	87.0000
75%	150.0000
max	281.0000

Punctuation

```
punctuation_data = [len(set(punctuation).intersection(set(tweet))) for tweet in training_data]
```

```
punctuation_data_for_stats = pd.DataFrame({"Punctuation": punctuation_data, "Tweet": training_data})
```

Top 5 most punctuated tweets

```
punctuation_data_for_stats.sort_values(by="Punctuation", ascending=False).head()
```

	Punctuation	Tweet
8957	11	Going to go ahead and crown myself the absolute emperor of finding things on menus that sound interesting, deciding I would like to try them, then being told "I'm sorry sir, that's actually not available..."\n\n[then why the @#$% is it ON YOUR MENUUUUUUUU--]
6725	9	4-yo: DADDEEEEEE!? LET'S PLAY!\nMe: Ok, baby. \n4yo: you play w/ her. put a dress on her DADDEEEEEE. \nMe: Ok. *puts doll in dollhouse*\n4yo: SHE DOESN'T GO THERE!!
11718	9	Self-employed people: have you ever turned to social media to call out a client who is many weeks/months delinquent on a payment? \n(Obviously, you're probably burning a bridge with that move, but if they don't pay...)
13365	9	Billboard Hot 100: (-3) Tell Me You Love Me, [19 weeks]. *peak: *
11845	9	Tucker Carlson Tonight & TFW you're asking about America\nbut you're scolded it's really about Israel ...\n \nTucker: "What is the American national security interest ... in Syria?"\n\nSen. Wicker(R): "Well, if you care about Israel ..." \n\nThat was the exact question & answer\nShocking

Tweets punctuation statistics

```
punctuation_data_for_stats.describe()
```

	Punctuation
count	15674.0000
mean	1.9168

	Punctuation
std	1.5787
min	0.0000
25%	1.0000
50%	2.0000
75%	3.0000
max	11.0000

Stop words

```
stop_words_data = [len(set(stopwords.words("english")).intersection(set(tweet.lower())))
                   for tweet in training_data]
```

```
stop_words_data_for_stats = pd.DataFrame({"Stop words": stop_words_data, "Tweet": training_data})
```

Top 5 tweets with most stop words

```
stop_words_data_for_stats.sort_values(by="Stop words", ascending=False).head()
```

	Stop words	Tweet
0	8	I don't yet have adequate words to do so, but someday I wanna write about the beautiful dance which happens in Google docs between a writer & a good editor working simultaneously towards a deadline. When it's working, it's a beautiful dance—though no one really sees it.
9063	8	Honestly yea i fucked up but all of you are trash asf and your opinions mean nothing to me because mother fucker i can fix shit but yall are to close minded to see.
9035	8	The role of DAG Rod Rosenstein will be an Oscar winner in the future film about the Trump presidency. I'd like the story of the first few months to be told through the eyes of the bewildered Sean Spicer.
9038	8	Done watching 'Hacksaw Ridge'. If there's one thing I learned from that movie, it is simply, Have Faith in God.
9039	8	I feel people who can't celebrate or at the very least respect Cardi B's success have never watched the grind from the ground up. They can't understand that her work ethic has gotten her where she is now. You don't have to stand for what's she's about but she's worked for it

Top 5 tweets with fewest stop words

```
stop_words_data_for_stats.sort_values(by="Stop words", ascending=True).head()
```

	Stop words	Tweet
3632	0	...
8290	0	24
11925	0	FUCK
10940	0	78 ... !

	Stop words	Tweet
1796	0	fuck u

Tweets stop words statistics

```
stop_words_data_for_stats.describe()
```

	Stop words
count	15674.0000
mean	7.1515
std	1.3116
min	0.0000
25%	7.0000
50%	8.0000
75%	8.0000
max	8.0000

Unique words

```
unique_words_data = [len(set(tokenizer.tokenize(tweet))) for tweet in training_data]
```

```
unique_words_data_for_stats = pd.DataFrame({"Unique words": unique_words_data, "Tweet": training_data})
```

```
# unique_words_data_for_stats = unique_words_data_for_stats[unique_words_data_for_stats["Unique words"] >= 2]
```

```
unique_words_data = unique_words_data_for_stats["Unique words"].tolist()
```

Top 5 tweets with most unique words

```
unique_words_data_for_stats.sort_values(by="Unique words", ascending=False).head()
```

	Tweet	Unique words
13936	GIVE AWAY!\n\nThe rules are really easy, all you have to do is :\n1. Must be following me (i check) \n2. RT and fav this tweet\n3. tag your mutuals/anyone\n4. only 1 winner! \n5. i ship worldwide;) \n\nit ends in 8th May 2018 or when this tweet hit 2k RT and like!\n\nGood luck! ❤️	59
4881	got into a tepid back nd forth w/ a uknowwhoAJ+columnist bc i said they steal their "hot takes" from blk twitter & alike. wallahi my bdeshi ass did not sign up 4 this app to be called asinine by a 30yrold pakistani whos whole politics is Post Colonial Memes for Oriental Minded T-	57
7013	Crazy how wrong u can be about someone. A girl I graduated w/ was always doing drugs& got pregnant at 16. I assumed she'd end up being a loser but it turn out she now has 4 beautiful kids& is making over $4,500/month just off of child support payments from the 3 different dads	57

	Tweet	Unique words
4992	Got into an argument w/ someone I went to HS w/ & I would js like to repeat again tht I cannot wait to stunt on all the ppl who were bitches to me in HS @ our reunion. Catch me rollin up w/ my sexy ass gf, a nice car, a bomb body & the career of my dreams as a big fuck u to them	55
11542	Thought I'd bring this back... and no, I'm not talking about myself here. I wish just once I'd be so bored with my life that I'd find the time to bash people/celebs I don't like.. I mean if I despise someone THAT much, why still watch his/her every move? 🤦‍♀️	55

Top 5 tweets with fewest unique words

```
unique_words_data_for_stats.sort_values(by="Unique words", ascending=True).head()
```

	Tweet	Unique words
6106	Annoying	1
2525	Bitch	1
12087	Chandler	1
14559	Yes yes yes yes yes yes	1
14442	Hello\n	1

Tweets unique words statistics

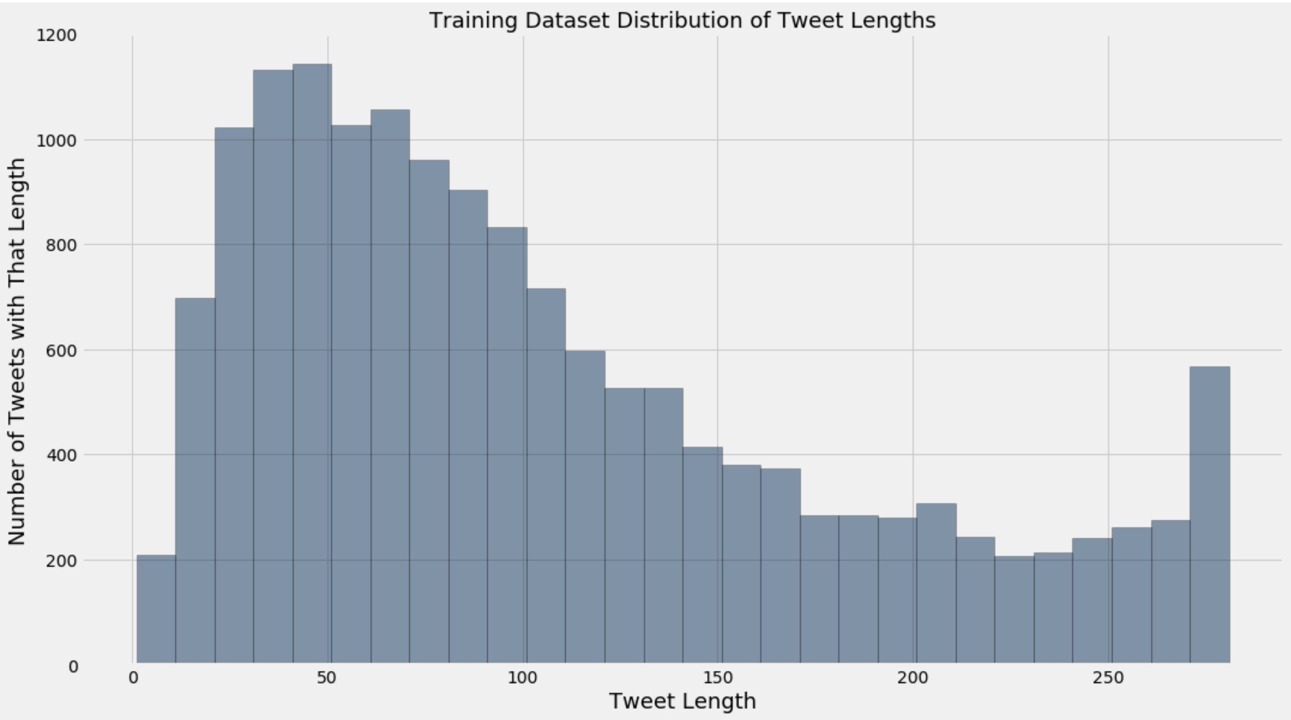
```
unique_words_data_for_stats.describe()
```

	Unique words
count	15674.0000
mean	19.2412
std	11.9298
min	1.0000
25%	10.0000
50%	17.0000
75%	27.0000
max	59.0000

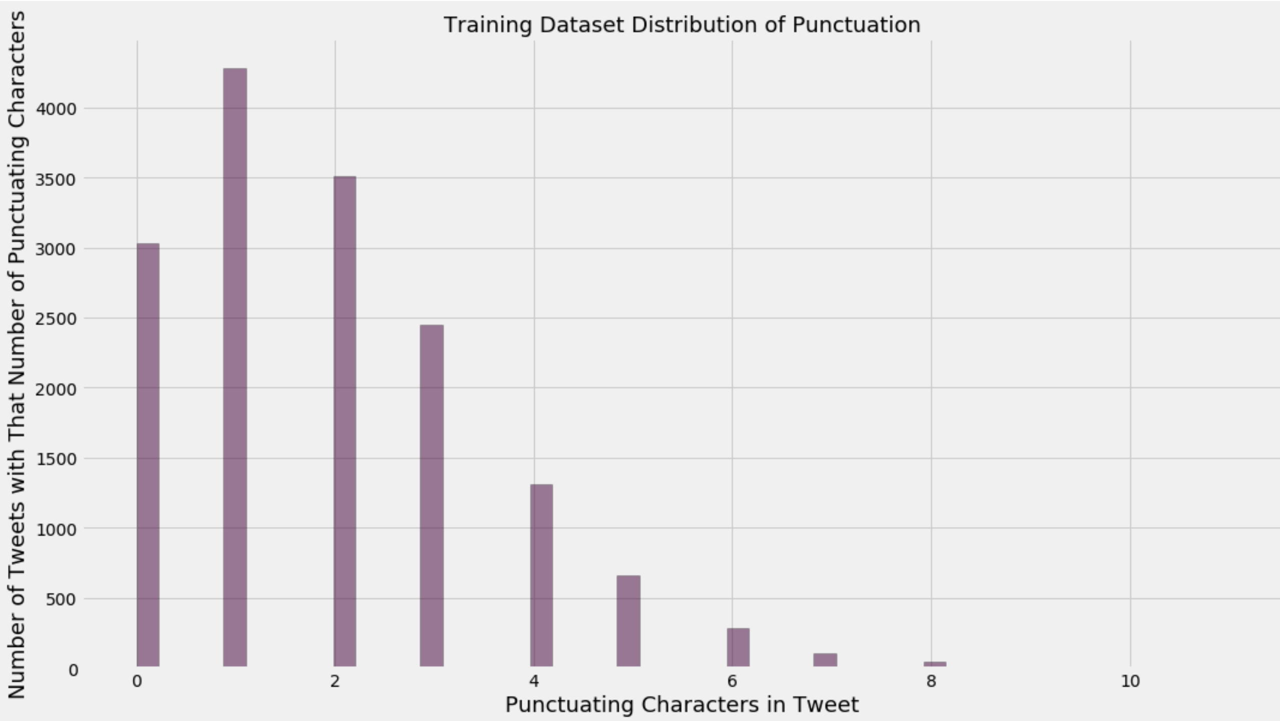
Plot them

```
length_mean = length_data_for_stats.describe().Length[1]
length_std = length_data_for_stats.describe().Length[2]

fig = plt.figure(figsize=(16, 9))
ax = fig.add_subplot(111)

n, bins, patches = ax.hist(length_data,
                           bins="scott",
                           edgecolor="black",
                           # density=True,
                           color="#12355b",
```

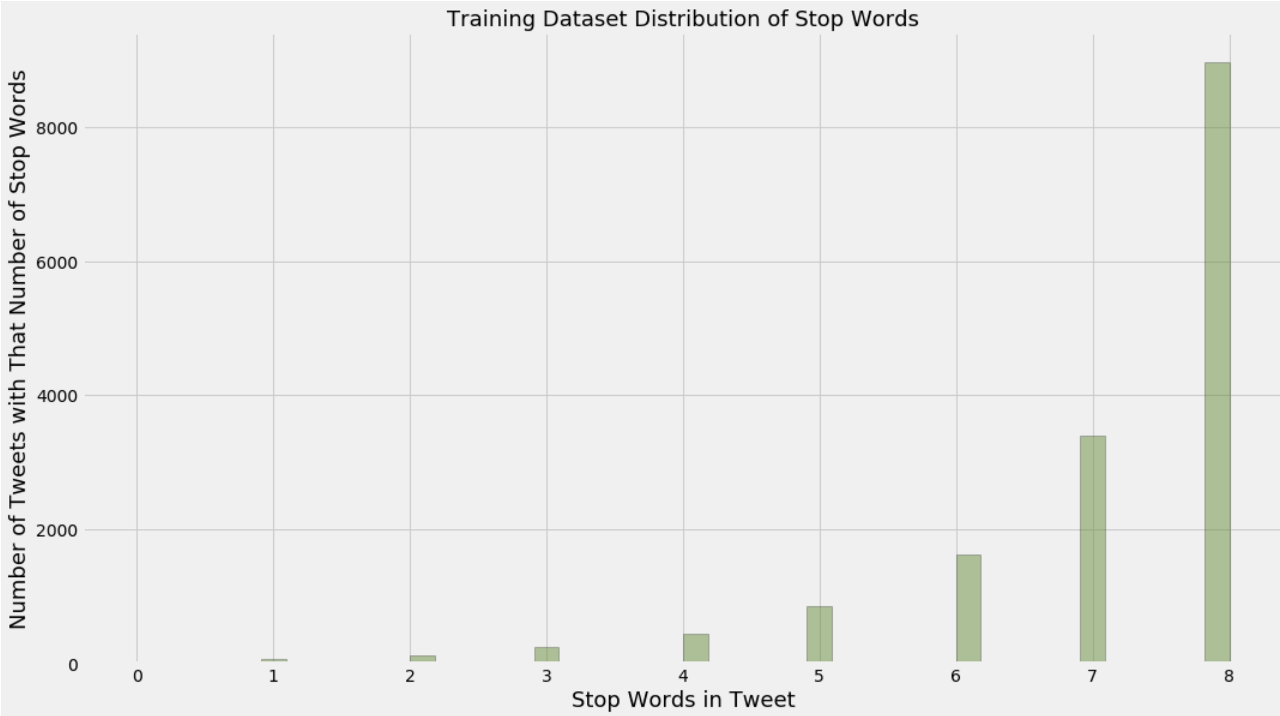
```
                           alpha=0.5)

# length_line = scipy.stats.norm.pdf(bins, length_mean, length_std)
# ax.plot(bins, length_line, "--", linewidth=3, color="#415d7b")

ax.set_title("Training Dataset Distribution of Tweet Lengths", fontsize=18)
ax.set_xlabel("Tweet Length", fontsize=18);
ax.set_ylabel("Number of Tweets with That Length", fontsize=18);

plt.show()
```



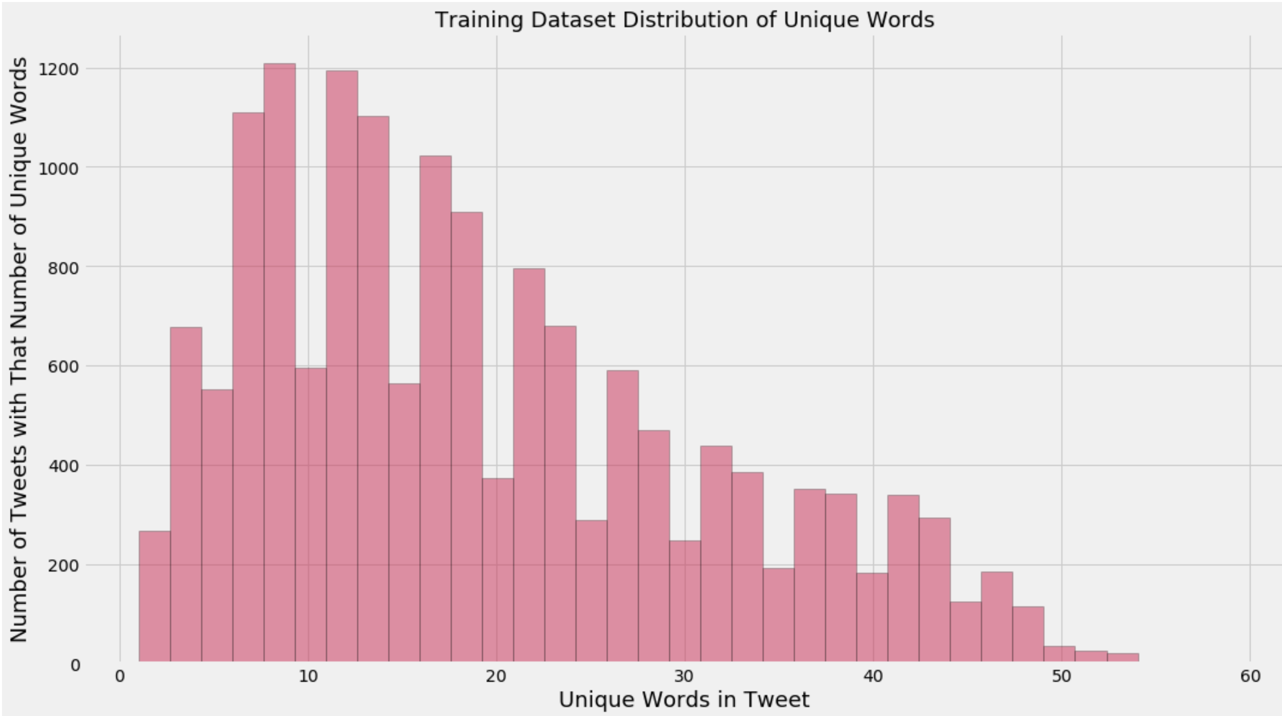

```
punctuation_mean = punctuation_data_for_stats.describe().Punctuation[1]
punctuation_std = punctuation_data_for_stats.describe().Punctuation[2]

fig = plt.figure(figsize=(16, 9))
ax = fig.add_subplot(111)

n, bins, patches = ax.hist(punctuation_data,
                           bins="scott",
                           edgecolor="black",
                           # density=True,
                           color="#420039",
                           alpha=0.5)

# punctution_line = scipy.stats.norm.pdf(bins, punctuation_mean, punctuation_std)
# ax.plot(bins, punctution_line, "--", linewidth=3, color="#673260")

ax.set_title("Training Dataset Distribution of Punctuation", fontsize=18)
ax.set_xlabel("Punctuating Characters in Tweet", fontsize=18)
ax.set_ylabel("Number of Tweets with That Number of Punctuating Characters", fontsize=18)

plt.show()
```




```
stop_words_mean = stop_words_data_for_stats.describe()["Stop words"][1]
stop_words_std = stop_words_data_for_stats.describe()["Stop words"][2]

fig = plt.figure(figsize=(16, 9))
ax = fig.add_subplot(111)

n, bins, patches = ax.hist(stop_words_data,
                           bins="scott",
                           edgecolor="black",
                           # density=True,
                           color="#698f3f",
                           alpha=0.5)

# stop_words_line = scipy.stats.norm.pdf(bins, stop_words_mean, stop_words_std)
# ax.plot(bins, stop_words_line, "--", linewidth=3, color="#87a565")

ax.set_title("Training Dataset Distribution of Stop Words", fontsize=18)
ax.set_xlabel("Stop Words in Tweet", fontsize=18)
ax.set_ylabel("Number of Tweets with That Number of Stop Words", fontsize=18)

plt.show()
```




```
unique_words_mean = unique_words_data_for_stats.describe()["Unique words"][1]
unique_words_std = unique_words_data_for_stats.describe()["Unique words"][2]

fig = plt.figure(figsize=(16, 9))
ax = fig.add_subplot(111)

n, bins, patches = ax.hist(unique_words_data,
                           bins="scott",
                           edgecolor="black",
                           # density=True,
                           color="#ca2e55",
                           alpha=0.5)

# unique_words_line = scipy.stats.norm.pdf(bins, unique_words_mean, unique_words_std)
# ax.plot(bins, unique_words_line, "--", linewidth=3, color="#d45776")

ax.set_title("Training Dataset Distribution of Unique Words", fontsize=18)
ax.set_xlabel("Unique Words in Tweet", fontsize=18)
ax.set_ylabel("Number of Tweets with That Number of Unique Words", fontsize=18)

plt.show()
```



Training Dataset Distribution of Unique Words
Number of Tweets with That Number of Unique Words
Unique Words in Tweet
0
200
400
600
800
1000
1200
0
10
20
30
40
50
60