```
# !pip install openai
# !pip install tweepy
```

```
import tweepy
import pandas as pd
import openai
import time
import os
from datetime import datetime
```

Due to Pivoting datasets, we're able to avoid using the Twitter API key since the data was shared with us by Professor. When data was initially shared we had less than half of the original data which was in the millions in terms of the amount of information. Before loading the data in we wanted to label some of the data so we can be able to perform some EDA tasks on weather the tweet is positive or not based on true or false statements of the tweets After loading the data we were met with limiting the tweets so OpenAi can label them. Later we will train the 3000 tweets and test them against 300k tweets and see what insights we can drive from there.

Api Secret key

```
with open("api_keys.txt", 'r', encoding='utf-8') as api_file:
    api_keys = api_file.readlines()

for key in api_keys:
    if "bearer_token" in key:
        twitter_api_key = key.split('"')[1]
    elif "openai_token" in key:
        openai_api_key = key.split('"')[1]
```

Scrapping tweet data

```
def get_tweets_by_handle(handle, api_key, start_time, end_time, tweets):
    client = tweepy.Client(bearer_token=twitter_api_key, wait_on_rate_limit=True)
    user_id = client.get_user(username=handle).data.id
    tweets_data = client.get_users_tweets(id=user_id, max_results=100, start_time=start_time, end_time=end_time,
                                          tweet_fields=['id', 'text', 'created_at', 'context_annotations']).data


    for tweet in tweets_data:
        tweets['handle'].append(handle)
        tweets['tweet'].append(tweet.text)
        tweets['id'].append(tweet.id)
```

Label tweet with OpenAI

```
def check_sentiment_from_tweet(tweet: str, api_key: str) -> bool:
    openai.api_key = api_key
    prompt_text = tweet + ' is positive. True or False?'
    response = openai.Completion.create(model="text-ada-001",
                                        prompt=prompt_text,
                                        temperature=0, n=1,
                                        max_tokens=256).choices[0].text
    time.sleep(7)
    if 'true' in response.lower() or 'positive' in response.lower():
        return True
    else:
        return False
```

```
# tweets = pd.read_csv('data_tweet.csv')
# tweets = pd.DataFrame(tweets['text'])
```

```
# length_tweets = 3000
```

```
# tweets = tweets[:length_tweets]
```

```
# tweets['sentiment'] = tweets['text'].apply(lambda x: check_sentiment_from_tweet(x, openai_api_key))
```

export tweet data to csv

```
# tweets.to_csv('tweet_data.csv', index=False)
```

Before doing EDA we added in some preprocessing steps to remove stop words and unneeded grammars in the data tweets.

Preprocessing

```
import numpy as np
import re
import nltk
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
```

```
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('omw-1.4')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Kuro\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\Kuro\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to
[nltk_data]     C:\Users\Kuro\AppData\Roaming\nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
True
```

```
def process_data(data):
    documents = []
    stemmer = WordNetLemmatizer()

    for sen in range(0, len(data)):
        # Remove all the special characters
        document = re.sub(r'\W', ' ', str(data[sen]))
        # remove all single characters
        document = re.sub(r'\s+[a-zA-Z]\s+', ' ', document)
        # Remove single characters from the start
        document = re.sub(r'\^[a-zA-Z]\s+', ' ', document)
        # Substituting multiple spaces with single space
        document = re.sub(r'\s+', ' ', document, flags=re.I)
        # Removing prefixed 'b'
        document = re.sub(r'^b\s+', '', document)
        # Converting to Lowercase
        document = document.lower()
        # Lemmatization
        document = document.split()
        document = [stemmer.lemmatize(word) for word in document]
        document = ' '.join(document)
        documents.append(document)
    return documents
```

```
df = pd.read_csv('tweet_data.csv')
df.head()
```

	text	sentiment
0	in other news..... whats the 3-day sales analy...	True
1	At this point, I don't know where the Blu eCig...	False
2	Frustrating! Everyone should support the switc...	True
3	Alternative Medicine: Blu eCig promotes 'freed...	False

Splitting the data with y = sentiment and x = text tweet.

```
y = df['sentiment']
X = df['text']
```

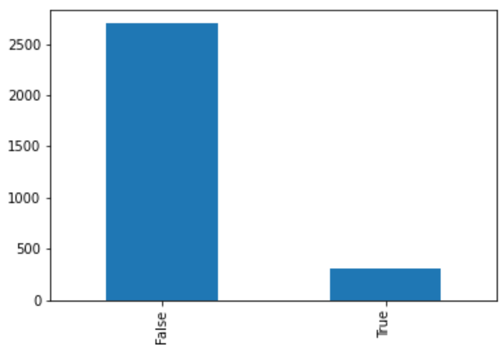
```
text_arr = process_data(X)
```

```
tfidfconverter = TfidfVectorizer(max_features=1500, stop_words=stopwords.words('english'))
X = tfidfconverter.fit_transform(text_arr).toarray()
```

EDA

```
df['sentiment'].value_counts().plot(kind='bar')
```

```
<AxesSubplot:>
```




```
print("There are %i corpus" %(len(text_arr)))
print("Percentage of positive corpus:", (len(df[df['sentiment']==True])))
print("Percentage of negative corpus", (len(df[df['sentiment']==False])))
```

```
There are 3000 corpus
Percentage of positive corpus: 303
Percentage of negative corpus 2697
```

Based on the plot bar chart we can see there are more negative tweets about vaping than there are positive tweets. We can visualize 2,697 negative tweets compared to 303 positive tweets.

```
from wordcloud import WordCloud, STOPWORDS

stopwords = set(STOPWORDS)
wordcloud = WordCloud(width = 800, height = 400,
            background_color ='white',
            stopwords = stopwords,
            min_font_size = 10).generate(' '.join(text_arr))

plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)
plt.show()
```

Our word cloud shows the popular words that pop up when vaping is discussed via on tweeter. Some of the popular word clouds are: ban vaping, lobbying, and smoking.

Machine learning

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15, random_state=20)
```

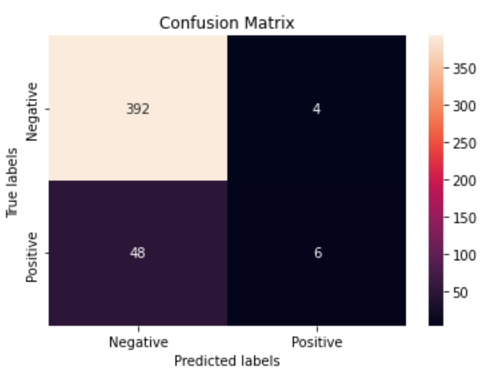
```
classifier = RandomForestClassifier(n_estimators=1000, random_state=0)
classifier.fit(X_train, y_train)
```

```
RandomForestClassifier(n_estimators=1000, random_state=0)
```

Confusion matrix

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
```

```
ax= plt.subplot()
sns.heatmap(cm, annot=True, fmt='g', ax=ax);
# labels, title and ticks
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.xaxis.set_ticklabels(['Negative','Positive']); ax.yaxis.set_ticklabels(['Negative','Positive']);
ax.set_title('Confusion Matrix');
```



Calculate precision, recall and f1-score

```
print("Report model\n")
print(classification_report(y_pred, y_test))
```

```
Report model

              precision    recall  f1-score   support

       False       0.99      0.89      0.94       440
        True       0.11      0.60      0.19        10

    accuracy                           0.88       450
   macro avg       0.55      0.75      0.56       450
weighted avg       0.97      0.88      0.92       450
```

Based on the f1 score the Radom Forest model does a good job of classifying our tweets. We know this based on the f1 score which is .94 %. However, the percentage for true statements is very low at .19 % something to think about later when comparing models.