In [ ]:

```
# importing stuff
import tweepy
import numpy as np
import pandas as pd
import keys
import re
from nltk.stem import SnowballStemmer
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
import nltk
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
from sklearn.metrics import silhouette_score
from sklearn.manifold import MDS
from sklearn.decomposition import TruncatedSVD
import seaborn as sns
from sklearn.metrics.pairwise import euclidean_distances
```

Introduction

In this project, I used the contents of users' tweets to cluster the users by their similarities. Using the Twitter API, I got data about a user, including the content of their tweets. Then I used TF-IDF or term frequency-inverse document frequency to quantify how often users used various words. After quantifying their word choices and frequencies I could group various users by their similarities and differences using a clustering technique called K-means clustering.

In order to get data from the twitter API I had to create an app on the twitter development page, which gave me the credentials to make get requests to twitter. Below I'm authenticating to twitter and then creating an API object which I can use to make requests. (e.g user_time_line(), get_user(), etc.)

In [ ]:

```
consumerKey = keys.consumerKey
consumerKeySecret = keys.consumerKeySecret
AccessToken = keys.AccessToken
AccessTokenSecret = keys.AccessTokenSecret

#Authenticate to Twitter
auth = tweepy.OAuthHandler(consumerKey,consumerKeySecret)
auth.set_access_token(AccessToken, AccessTokenSecret)

# Create API object
api = tweepy.API(auth, wait_on_rate_limit=True)

# testing
try:
    api.verify_credentials()
    print("Authentication OK")
except:
    print("Error during authentication")
```

```
Authentication OK
```

This method takes in a parameter text and "cleans" it. Most tweets contain lots of noise such as emojis, hashtags, referencing other users, and more. For any text this method removes the username, hashtage, urls, punctuation, numbers, stopwords (the, at, in, etc.), and stems the text (words like going -> go). What's left is the key words in each text that actually give us insights about the user.

In [ ]:

```python
def clean_text(text):
    cleaned_text = text

    # lower case
    cleaned_text = " ".join([word.lower() for word in cleaned_text.split()])

    # remove username
    cleaned_text = re.sub("@[^w\s]+"," ",cleaned_text)

    # remove hashtags
    cleaned_text = re.sub("#[^w\s]+"," ",cleaned_text)

    # remove urls
    cleaned_text = re.sub(r'http\S+', '', cleaned_text)

    # remove rt (for retweet)
    cleaned_text = re.sub("rt"," ",cleaned_text)

    # remove punctuation
    cleaned_text = re.sub('[^\w]',' ',cleaned_text)

    # remove numbers
    cleaned_text = re.sub("[\d-]"," ",cleaned_text)

    # stem
    stemmer = SnowballStemmer("english")
    cleaned_text = stemmer.stem(cleaned_text)

    # remove stop words
    words = word_tokenize(cleaned_text)
    words = [word for word in words if not word in stopwords.words()]
    cleaned_text = " ".join(words)

    return cleaned_text

clean_text("@bengardiner rand0m text #DS121 https://google.com more random text") #  --
```

Out[ ]:

```
'rand text random text'
```

Data

The following code gets 30 twitter users than I am following, and it collects 100 of their most recent tweets. From these 100 tweets for all 30 users, I get the text from each tweet and "clean" it using the clean_text method. Leaving a large dataset where the columns represent the user and the rows represent the cleaned contents of one of their tweets.

In [ ]:
```
my_user_id = api.get_user(screen_name="bengardiner2021").id
following = api.get_friends(user_id=my_user_id,count=30)

data = []
names = []
for person in following:

    name = person.name
    id = person.id

    timeline = api.user_timeline(user_id=id, count = 100) # timeline of tweets
    tweet_texts = [clean_text(t.text) for t in timeline]

    names.append(name)
    print(name)
    data.append(tweet_texts)

data = np.array(data).T # rotating data so tweet t aligns with column user name
df = pd.DataFrame(data,columns=names)
df
```

```
Kevin Hart
NPR
Steve Harvey
Jim Cramer
Jimmy Kimmel Live
CNBC
Mike Pence
New York Post
The Guardian
BBC Breaking News
ABC News
HuffPost
Forbes
ashton kutcher
TIME
WIRED
SZA
Kim Kardashian
Rihanna
Marvel Studios
Boris Johnson
Hugh Jackman
Stephen Colbert
NAACP
Leader McConnell
The Tonight Show
International Space Station
Cristiano Ronaldo
Seth Rogen
Nancy Pelosi
```

Out[ ]:

Kevin Hart	NPR	Steve Harvey	Jim Cramer	Jimmy Kimmel Live	CNBC	Mike Pence	New York Post

	Kevin Hart	NPR	Steve Harvey	Jim Cramer	Jimmy Kimmel Live	CNBC	Mike Pence	New York Post
0	wooooow	russian energy giant decision cut gas expo pol...	mercy goes roast mode something might fun like...	trade	terrific ten	finally heading back office feel pressured rep...	supreme cou save religious libe football coach...	texas seeks block biden rule allowing border o...
1	laughs days	ramadan holiest month islamic calendar might k...	went sleeping car dollars longest running host...	put us	ohio senate race heating hypocrisy	house capitol riot probe seeks testimony key g...	freedom loving american follow join fight cons...	nursing home covid victim sues cuomo derosa wr...
2	time starring wahlberg amp hitting august th wait	fda proposing ban menthol flavored cigarettes ...	hate pharmacist yell prescription ready	ryan pick	mypillow mike lindell seems fixated jimmy	investing club qualcomm ceo says chipmaker aut...	new episode episode american freedom sits wtgi...	beat jennifer aniston liz hurley hottest woman...
3		disney says florida pledged protect reedy cree...	behind every moment adversity lesson blessing ...	stock draft time	tonight	listen big day tech earnings apple amazon inte...	special edition hear freedom loving leaders co	aidan hutchinson family lives vegas nfl draft
4	posted photo	icymi talks storytelling	already know crazy anthony anderson momma stev...	alphabet coming right back	make sure tune tonight see performance jimmy k...	investing club eli lilly strong qua promising ...	tomorrow wtgingrich walker miss	dow jumps points rebound tech stocks
...	...	...	...	...	...	...	...	...
95	live nation announced monday stage together ju...	russia reputation highly skilled secretive mil...	wilson always know exactly say	slob cramer stupid work	friday feeling	watch president biden delivers remarks suppo u...	wtgingrich released bold vision america built ...	intense video shows truck erupt massive fireba...
96	imagine chris rock kevin conversation looked s...	projects million people flee ukraine result ca...	wow know beautiful story	going back six tie nonsense	amp read sweet tweets	years big american banks warren buffett favori...	freedom agenda conservative path victory	new episode renaissance podcast listen full ep...
97	brought tickets kevin x chris rock barclays b ...	talking elon musk twitter twitter spaces witz	wesleyadi	cramer faber shut go cutty sark fooling around...	band night two late night tv performances two ...	denmark becomes first country halt covid vacci...	pence biden equity budget shows left believe a...	elon musk buys twitter billion via

	Kevin Hart	NPR	Steve Harvey	Jim Cramer	Jimmy Kimmel Live	CNBC	Mike Pence	New York Post
98	comedy	talking elon musk twitter witz	wesleyadi absolutely way steve harvey posted t...	stock futures move ticks every bps treasurys	new host	jpmorgan calls energy stocks highest convictio...	recent world crises proved joe biden failed po...	best chinos pants sho
99	excited chris rock kevin show	tuesday draws close kyiv moscow key developmen...		gap much inventory	let matt damon	turkey wants neutral ukraine treaty tightrope	freedom agenda call standing strong russian ag...	johnny depp amber heard trial via

100 rows × 30 columns

Methodology

From our dataset containing tweet texts, I decided to use the TF-IDF vectorizer to turn our lists of tweet contents into a matrix. For every word in the dataset we can see how often the user uses it with respect to the words overall popularity. For example, Kevin Hart's information is shown below; he seemed to use the words tickets, presale, posted, kevin, and photo a lot. Understanding that there was still a lot of noise in the data matrix I decided the use SVD and analyse the principal components of the matrix to see if I could reduce it. Using PCA, which centers the data and approximates it to a lower rank, we are given a smaller and slightly more managable matrix that still contained useful information.

In [ ]:

```
texts = []
for i in range(len(names)):
    name = names[i]
    tweets_text = data[:,i]
    text = " ".join(tweets_text)
    texts.append(text)

vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(texts).todense()

u,s,vh = np.linalg.svd(X)

# graphing principal components
plt.plot(s)
plt.plot([5,5],[0,s[5]], "--",c="orange")
plt.plot(5,s[5],"x",c="orange")
plt.ylim(bottom=0.75)
plt.ylabel("principal components")
```

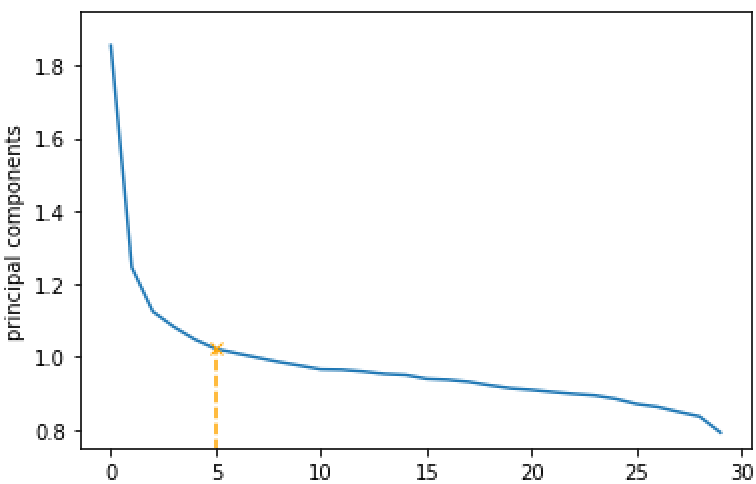
```
# svd = TruncatedSVD()
# red_X = svd.fit_transform(X)
pca = PCA(5)
red_X = pca.fit_transform(X)


X_df = pd.DataFrame(X,columns=vectorizer.get_feature_names_out(), index=names).T
X_df

print(X_df["Kevin Hart"].sort_values(ascending=False)) # shows the most used words for
print()
print("X shape:",X.shape)
print("reduced X shape:",red_X.shape)
```

```
tickets    0.309236
presale    0.298231
posted     0.290079
kevin      0.242971
photo      0.234422
             ...
found      0.000000
fought     0.000000
fou        0.000000
foster     0.000000
vibes      0.000000
Name: Kevin Hart, Length: 7355, dtype: float64

X shape: (30, 7355)
reduced X shape: (30, 5)
C:\Users\benga\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\utils\va
lidation.py:593: FutureWarning: np.matrix usage is deprecated in 1.0 and will raise a Ty
peError in 1.2. Please convert to a numpy array with np.asarray. For more information se
e: https://numpy.org/doc/stable/reference/generated/numpy.matrix.html
  warnings.warn(
```



Methodology (Continued)

For our clustering algorithm I decided to use KMeans because it is simple, and since we used it in class. In deciding how many clusters to use, I compared the silhouette score with the number of clusters. Looking at the graph, it's clear that 6 clusters has the highest score, so that is the number of clusters I decided to pick

In [ ]:

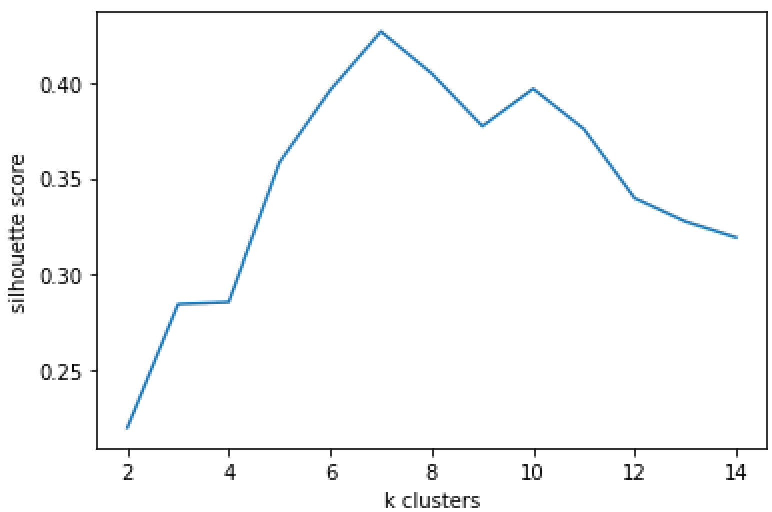
```
def kmeans(k):
    km = KMeans(k)
    km.fit(red_X)
    labels = km.predict(red_X)
    score = silhouette_score(red_X,labels)
    scores.append(score)

    return labels

scores = []
for i in np.arange(2,15):
    kmeans(i)

plt.plot(np.arange(2,15),scores)
plt.xlabel("k clusters")
plt.ylabel("silhouette score")

labels = kmeans(7)
clustered = pd.DataFrame(
    [names,labels]
).T
```



Analysis

Below I've printed the clusters using the hyperparameters selected above. Overall, it seems like the clusters are relatively accurate in clustering similar twitter users. One cluster contains many news sources (NPR, TIME, New York Post, etc.), another cluster contains comedians and entertainment users (Jimmy Kimmel, Stephen Colbert, the Tonight show, etc.), another contains politicians or political organizations (Nancy Pelosi, Mike Pence, Leader McConnell etc.), and another groups british users (Boris Johnson, BBC breaking news, the Guardian).

In [ ]:

```
# prints the user names in each label group
for label in np.unique(clustered.iloc[:,1]):
    df = clustered.where(clustered[1] == label).dropna()
    print(df)
    print()
```

```
                    0  1
6          Mike Pence  0
24  Leader McConnell  0
29      Nancy Pelosi  0

                     0  1
0           Kevin Hart  1
2         Steve Harvey  1
13      ashton kutcher  1
15               WIRED  1
16                 SZA  1
18             Rihanna  1
27  Cristiano Ronaldo  1
28          Seth Rogen  1

                 0  1
3      Jim Cramer  2
5            CNBC  2
7   New York Post  2
12         Forbes  2

                     0  1
8         The Guardian  3
9   BBC Breaking News  3
20       Boris Johnson  3

                     0  1
4   Jimmy Kimmel Live  4
17     Kim Kardashian  4
21       Hugh Jackman  4
22     Stephen Colbert  4
25    The Tonight Show  4

           0  1
1        NPR  5
10  ABC News  5
11  HuffPost  5
14      TIME  5
23     NAACP  5

                                 0  1
19               Marvel Studios  6
26  International Space Station  6
```

Conclusion

Overall, the clustering did a pretty good job at grouping together twitter users. While the score is still quite low, it still does a relatively good job of grouping together similar users. There are some issues however. Most real tweets on twitter are either advertisements from bots or simply random useless texts. If this project was used for many more random users, instead of a small sample of relatively similar and popular twitter accounts, it might struggle. Also, getting all the tweet information from the users takes a long time, so the data collection process isn't very effecient for getting lots of tweets from lots of users.

References

information regarding connecting to the twitter api from - https://realpython.com/twitter-bot-python-tweepy/

information regarding cleaning twitter tweets from - https://towardsdatascience.com/basic-tweet-preprocessing-in-python-efd8360d529e

information regarding PCA, TF-IDF vectorizer, kmeans, and more from - Mayank Varia's DS121 lecture slides