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Homework 2

Scripting for Data Analysis

8/26/2018 For this assignment, I will be using jupyter notebooks to perform my analysis, as well as my writeup. I find the structure of having all written exploration and all code in one place helps to digest some material, as well as allowing for rapid prototyping and quick changes.

The goal of this assignment is to read in some form of JSON data, whether that be from an API like tweepy, or straight from a mongodb. I'd like to consolidate the two, just to get some more practice using a document store like pymongo as well as a social media API, which I have worked with in the past, but know have a bit more practice dissecting lists of dictionaries. I also might explore using a pretrained sentiment analysis model (NLTK) to show some notion of a distribution between positive and negative sentiment over time - I've found this to be a sometimes viable source for mass labeling datasets, although there is a bit of a negative bias when using NLTK (bias is unavoidable when dealing with human annotation tasks).

Setting up a mongodb connection

```
In [217]: from pymongo import MongoClient
          client = MongoClient('localhost', 27017)  #Set up client

          #b.create_collection('tweets')
          db.list_collection_names()
          client.list_database_names()
          client.drop_database('twitter_storage')
          client.list_database_names()

Out[217]: ['admin', 'config', 'local', 'usgs']

In [218]: from time import localtime, strftime
          import timeit
          import time
          import pymongo
          from pymongo import MongoClient
          import warnings

          client = MongoClient('localhost', 27017)  #Set up client
```

```
def create_db(database, collection_name):
    start = time.time()
    #wasn't sure if this just rewrote over it. I don't believe it does, but that's t
    #borrowed some of the below from the db_fn notebook. Seems like an easier way of
    dbname = name.lower()
    dbname = dbname.replace('#', '')
    dbname = dbname.replace(' ', '')
    dbCollection = collect.lower()
    dbCollection = dbCollection.replace('#', '')
    dbCollection = dbCollection.replace(' ', '')
    # use database named usgs or create it if not there already
    db = client[dbname]
    # create collection
    collection = db[dbCollection]
    end = time.time()
    #Logs
    print('DB: |{}| is ready @ {}'.format(
        dbname, strftime("%Y-%m-%d %H:%M:%S", localtime())))
    print('-------------------------')
    print('DBcollection: |{}| is ready @ {}'.format(
        dbCollection, strftime("%Y-%m-%d %H:%M:%S", localtime())))
    print('-------------------------')
    print('Time taken to execute: {} seconds'.format(end - start))


#instantiate
name = 'twitter_storage'
collect = 'tweets'

create_db(name, collect)

#Testing upload
#create_db(name, collect)
#collection.insert_one({'j': 1})
#client.list_database_names()
```

```
DB: |twitter_storage| is ready @ 2018-08-26 22:18:21
-------------------------
DBcollection: |tweets| is ready @ 2018-08-26 22:18:21
-------------------------
Time taken to execute: 0.0 seconds
```

Starting with twython The first step here will be to collect some data from tweepy. I had luckily set up a twitter dev account in a previous class, so I'm taking the keys from that notebook. I'm trying to do focus on functional programming over scripting, so I'm breaking this into some main functions that I want to call. This could then be easily transferred to a .py file and ran.

As far as the actual query, I settled on Donald Trump. I know this is a pretty common project since he's very active on twitter, but I have never explored things like mass-sentiment analysis of an individual based on tweets.

```
In [219]: import tweepy

          #Likely want to import this in from a separate .py file where possible. Didn't think
          consumer_key = 'K3qj35aGWoALJaBdqSUgszqoc'
          consumer_secret = 'hyBrGQXXbyTah2btx29di8w92SlgFN9fu48sOKjCJKJpiZI4Zx'
          access_token = '1019690305237311488-b04ol1OxAOznie1ir1wWlneoetChYx'
          access_token_secret = 'QPc4KDfNraTT5S63kcvu5t8GTL1H5y5MkyE9EZCupvUQD'

          q = 'Donald Trump'


          def fetch_tweets(query,
                           consumer_key=consumer_key,
                           consumer_secret=consumer_secret,
                           access_token=access_token,
                           access_token_secret=access_token_secret):
              '''
              query: string
              '''

              try:
                  auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
                  auth.set_access_token(access_token, access_token_secret)
                  api = tweepy.API(auth)
                  placeholder = []

                  #This is the cleanest way I could think of doing this.
                  #I'm basically trying to bypass the 100 tweet limit by continuing w/ a neste
                  for i in api.search(q=query, lang="en", count=100):
                      placeholder.append(
                          i._json
                      )  #transforming to json and storing in a list named placeholder
                      counter = len(placeholder)
                      if counter > 5000:
                          break
                      else:
                          for i in api.search(q=query, lang="en", count=100):
                              placeholder.append(
                                  i._json
                              )  #transforming to json and storing in a list named placeholder
                              continue

                  print('You have successfully scraped and pulled {} tweets'.format(
                      len(placeholder)))
                  return placeholder
              except:
                  print('Unable to scrape tweets')


          tweets = fetch_tweets(
              query='Donald Trump')  #Save an instance with the json data

          collection.insert_many(tweets)
```

```
You have successfully scraped and pulled 5051 tweets
```

```
Out[219]: <pymongo.results.InsertManyResult at 0x1f7c502abc8>
```

0.0.1 From here, I thought it might be interesting to look at the distribution of my 5000+ tweets by location.

This is a bit wonky, but it's definitely a learning experience. It's important to note that the 5k tweets that I pulled came in with a range of a matter of seconds, so showing any kind of time series distribution would be at the 'second' level. That's why I'm avoiding that here. Instead, looking at a distribution of tweet count by region, I can begin to see a sample of the total population. We also start to notice some of the flaws with manual entry form submission for application access - The variation in the manner of responses is inherently flawed. United States and USA are listed as two different Geos. 'God Bless Our Veterans' is listed as a geo in its own regard - That makes me think that people are becoming increasingly aware of the abilities for scrapers and humans alike to form a profile based on their web data.

```
In [224]: tweets[0]

          times = []
          geos = []
          text = []

          from collections import Counter
          #Store data in lists
          for i in tweets:
              times.append(i['created_at'])
              geos.append(i['user']['location'])
              text.append(i['text'])

          import pandas as pd
          #Convert lists to a pandas dataframe for grouping
          df = pd.DataFrame()
          df['geos'] = geos
          df['time'] = times
          df['text'] = text
```

```
        #Group by count of geos
        df_geos = df['geos'].groupby(by=geos).count()[1:]
        df_geos = pd.DataFrame(df_geos.sort_values(ascending=False)[:10])
        df_geos.reset_index(inplace=True)
        display(df_geos)
```

```
                   index  geos
0                    USA   172
1          United States   170
2           Florida, USA    90
3     North Carolina, USA    80
4          Nashville, TN    72
5        California, USA    71
6    European Union     63
7  Sydney, New South Wales    57
8           Tokyo, Japan    51
9      San Francisco, CA    51
```

Sentiment Analysis Next, I'd like to show something like the above but with the added twist of some kind of scoring mechanism to show sentiment of tweets by region of the fixed period of time. I don't necessarily want to build my own classifier here, so I'll use a neural net with pretrained weights based off of fitting on social media text.

- Admittedly, it would have been better for me to do some kind of string match against a list of viable geos across the world. As I moved through this assignment, it made it very difficult to actual do analysis because most users don't enter realistic locations into apps/websites when signing up for service.

```
In [221]: #!pip install vaderSentiment
          #http://t-redactyl.io/blog/2017/04/using-vader-to-handle-sentiment-analysis-with-soc
          from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

          #prime sentiment analyzer
          analyser = SentimentIntensityAnalyzer()


          #def print_sentiment_scores(sentence):
          #    snt = analyser.polarity_scores(sentence)
          #    print("{:-<40} {}".format(sentence, str(snt)))


          #Append dict scores to a list
          empty = []
          for i in text:
              empty.append(analyser.polarity_scores(i))

          #convert list of dicts to dataframe
          polarity = pd.DataFrame(empty)
```

```
In [222]: #Add the columns from the polarity df to the original df with the geo data
          df['negative_score'] = polarity['neg']
          df['neutral_score'] = polarity['neu']
          df['positive_score'] = polarity['pos']

          #Group by geos + score
          import numpy as np
          sent_geo = df.groupby(
              ['geos'])[['negative_score', 'neutral_score', 'positive_score']].sum()[1:]

          #Iterate through a list to display sorting by different scores
          score_types = ['negative_score', 'neutral_score', 'positive_score']
          for i in score_types:
              print('Displaying the top 5 geos, sorted by {} '.format(i))
              display(sent_geo.sort_values(by=i, ascending=False)[:5])

          #sent_geo.sort_values(by = 'negative_score', ascending= False)[:5]
```

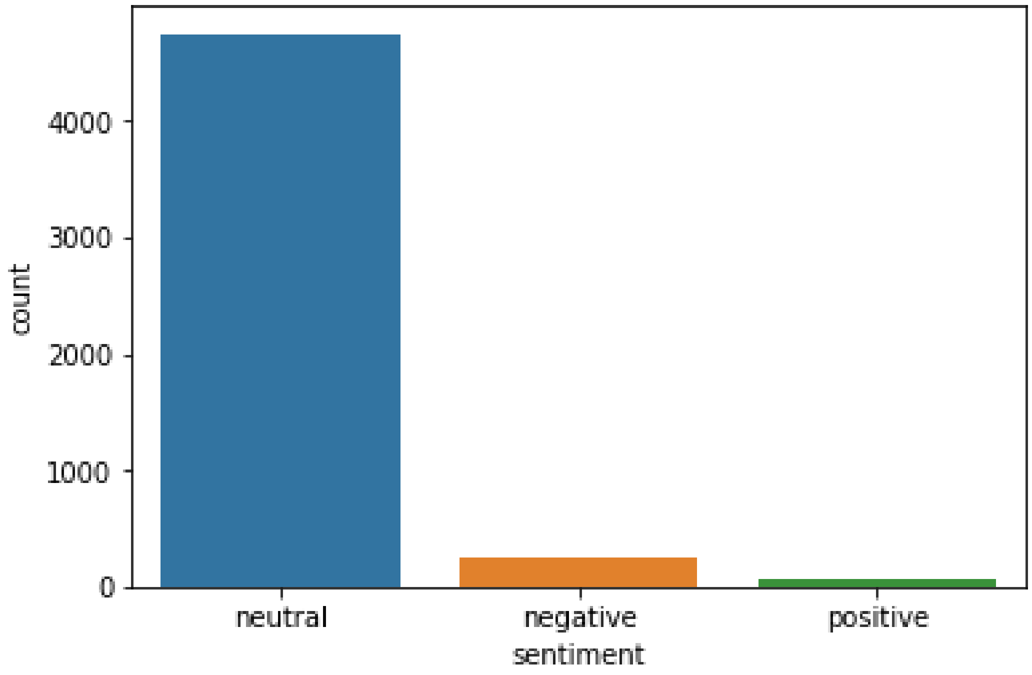
```
Displaying the top 5 geos, sorted by negative_score


                       negative_score  neutral_score  positive_score
geos
USA                            21.051        133.523          17.375
San Antonio TX                 20.727         18.963           9.310
Nashville, TN                  20.613         46.287           5.100
European Union           18.235         40.065           4.700
Germany                        17.748         29.070           4.182


Displaying the top 5 geos, sorted by neutral_score


                     negative_score  neutral_score  positive_score
geos
United States                12.079        145.783          12.150
USA                          21.051        133.523          17.375
Florida, USA                  8.774         81.226           0.000
North Carolina, USA           4.324         73.058           2.618
California, USA               5.180         65.820           0.000


Displaying the top 5 geos, sorted by positive_score


                             negative_score  neutral_score  positive_score
geos
USA                                  21.051        133.523          17.375
Tokyo, Japan                          5.610         30.141          15.249
```

```
United States                         12.079       145.783          12.150
Wherever Music Is Playing              8.040        20.360          11.600
Spokane Valley, WA (STATE)             0.000        39.474          11.526
```

```
In [223]: import matplotlib.pyplot as plt
          import seaborn as sns
          display(df.head(1))

          #Conditional Logic to create new var based on treshold
          df['sentiment'] = np.where(df['negative_score'] >= 0.33, 'negative',
                                     np.where(df['positive_score'] >= 0.33, 'positive',
                                             np.where(df['neutral_score'] >= 0.33, 'neutral', 0)

          display(df.head(5))

          #Plotting sentiment count by cat var
          sns.countplot(x = 'sentiment', data = df)
          plt.show()
          from collections import Counter
          Counter(df['sentiment'])
```

```
          geos                            time  \
0  Indiana, USA  Mon Aug 27 05:18:09 +0000 2018

                                                text  negative_score  \
0  @FaceLess1930 @DineshDSouza i present the man ...             0.0

   neutral_score  positive_score
0            1.0             0.0


            geos                            time  \
0   Indiana, USA  Mon Aug 27 05:18:09 +0000 2018
1                 Mon Aug 27 05:18:09 +0000 2018
2   Indiana, USA  Mon Aug 27 05:18:09 +0000 2018
3                 Mon Aug 27 05:18:08 +0000 2018
4  United States  Mon Aug 27 05:18:08 +0000 2018

                                                text  negative_score  \
0  @FaceLess1930 @DineshDSouza i present the man ...           0.000
1  Obama was the worst President in History!\nPre...           0.148
2  @FaceLess1930 @DineshDSouza i present the man ...           0.000
3  RT @DFBHarvard: You realize there is only ONE ...           0.214
4  Fox News Host Slams Dotard Don: What Good Is ...           0.099

   neutral_score  positive_score sentiment
0          1.000           0.000   neutral
```

```
1          0.652          0.200   neutral
2          1.000          0.000   neutral
3          0.786          0.000   neutral
4          0.776          0.125   neutral
```



```
Out[223]: Counter({'negative': 246, 'neutral': 4748, 'positive': 57})
```

In conclusion This was a very interesting, fun project. I spent the better part of two days researching and writing the code that led to this point. I also had some serious debugging issues that set me back, but ultimately helped me troubleshoot what was going on in my code. In terms of the actual results, they were very surprising, regarding the sentiment analysis portion of the task. I assumed that most of the tweets that were scraped would have a negative connotation, and it is possible that the Saber pretrained NN has some inherent bias towards neutral class mapping, but still, having over 90% of the tweets fall under that class is something. It should be noted that these tweets were pulled within about a one minute span of one another, so they aren't distributed over a number of days. To do that I imagine we could just run a daily job, similar to this, and store all of the documents in our mongodb (That's kind of why I included that part, as well as just refamiliarizing myself with the API).