NewYork Twitter

August 8, 2019

[1]:
```
Name= 'Catherine Bui'
Organization= 'Center For Community Innovation'
Project= 'Twitter Displacement Study'
```

[1]:
```
%%time
import pandas as pd
import matplotlib.pyplot as plt
from scipy import stats
import subprocess
from pathlib import Path
import csv
import numpy as np
from io import StringIO
import dask.dataframe as das
import datetime
```

```
CPU times: user 9.43 s, sys: 812 ms, total: 10.2 s
Wall time: 21.1 s
```

1 ANALYZING TWITTER TWEETS IN NEW YORK

FIRST PART OF TASKS

1. Compare full set of tweets a census tract level to those with home location to see differences in spatial distribution
   a. Tracts with greater/lesser share of all tweets vs home location tweets
   b. by tract, % of tweets missing home_tract
2. Summarize distribution of tweets by user - # of users with more than 5 tweets in a tract – compare to overall distribution
3. Using tweets with home location, summary statistics of the share of tweets in a tract in the time period.

The census of tract is the unit of metric. Home location was determined by: A home location (tract) needs to: Receive at least 10 tweets, Sent from >7 different days, Sent from 8 or more different hours of the day.

If multiple locations satisfy, we take the location with the most tweets as the home location
The number of rows in the original data is 75368830.

1.0.1 READING THE CSV FILE WITH DASK

1. Clean and prepare the data. We need to rename the columns, drop any missing values, convert any values into its appropriate type to perform calculations, and to collect each calculations such as total tweets into multiple csv files for one final output compilation.

[2]:
```
%%time
#file is the original ny raw data, file2 is the power user ny data.
file = "/scratch/public/catherinebui/ny_twitter.csv"
file2 = '/scratch/public/kushk/ny_one_tweet_per_day.csv'
ds = das.read_csv(file)
ds = ds.rename(columns = {'ny_with_homeloc.csv': 'id'})
```

```
CPU times: user 241 ms, sys: 7.82 ms, total: 249 ms
Wall time: 350 ms
```

[5]:
```
#count of how many unique tracts in the raw data
len(ds['tract'].unique())
```

[5]:
```
3489
```

[9]:
```
ds['tract'] = ds['tract'].apply(lambda x: str(x)[0:6])
ds.groupby('tract').count().reset_index().to_csv('ny_tract_*.csv')
```

[9]:
```
['ny_tract_0.csv']
```

[14]:
```
pd.read_csv('ny_tract_0.csv')['tract'].unique()
```

[14]:
```
array([340030., 340130., 340139., 340170., 340179., 340230., 340258.,
       340259., 340270., 340311., 340312., 340350., 340390., 360050.,
       360470., 360471., 360593., 360594., 360595., 360599., 360610.,
       360810., 360811., 360850., 360870., 361190., 361199., 900101.,
       900102.,      nan, 360479., 360819.])
```

[ ]:
```
34003, 34013, 34017, 34023, 34025, 34027, 34031, 34035, 34039, 36005, 36047,
36059, 36061, 36081, 36085, 36087, 36119, 90010, 360479, 360819
```

2 Cleaning and Analyzing with Raw Data

2.0.1 GROUPING BY TRACT

First, we group the tweets by tract so we can find the % of missing tracts, count of tweets with specific filters, count of users in tract,etc.

[14]:
```
groupbytract= ds.groupby('tract')
```

[59]:
```
#SHOW THE COUNT OF TWEETS PER TRACT
groupbytract.count().head(819)
```

[59]:

	id	u_id	lat	lon	date	home_tract	diff_tract
tract							
9.001010e+09	2610	2610	2610	2610	2610	2610	2610

9.001010e+09	4746	4746	4746	4746	4746	4746	4746
9.001010e+09	2953	2953	2953	2953	2953	2953	2953
9.001010e+09	15253	15253	15253	15253	15253	15226	15226
9.001010e+09	11688	11688	11688	11688	11688	11688	11688
9.001010e+09	18220	18220	18220	18220	18220	18219	18219
9.001011e+09	18168	18168	18168	18168	18168	18155	18155
9.001011e+09	3687	3687	3687	3687	3687	3687	3687
9.001011e+09	6458	6458	6458	6458	6458	6458	6458
9.001011e+09	9573	9573	9573	9573	9573	9573	9573
9.001011e+09	9632	9632	9632	9632	9632	9632	9632
9.001011e+09	6674	6674	6674	6674	6674	6674	6674
9.001011e+09	7503	7503	7503	7503	7503	7495	7495
9.001011e+09	6130	6130	6130	6130	6130	6129	6129
9.001021e+09	47082	47082	47082	47082	47082	47081	47081
9.001022e+09	50910	50910	50910	50910	50910	50910	50910
9.001022e+09	33850	33850	33850	33850	33850	33835	33835
3.400300e+10	19180	19180	19180	19180	19180	19180	19180
3.400300e+10	6814	6814	6814	6814	6814	6813	6813
3.400300e+10	16803	16803	16803	16803	16803	16803	16803
3.400300e+10	8228	8228	8228	8228	8228	8228	8228
3.400300e+10	64651	64651	64651	64651	64651	64651	64651
3.400300e+10	62938	62938	62938	62938	62938	62938	62938
3.400300e+10	77091	77091	77091	77091	77091	77091	77091
3.400300e+10	13749	13749	13749	13749	13749	13749	13749
3.400300e+10	25234	25234	25234	25234	25234	25232	25232
3.400300e+10	23244	23244	23244	23244	23244	23244	23244
3.400300e+10	32461	32461	32461	32461	32461	32461	32461
3.400300e+10	67113	67113	67113	67113	67113	67113	67113
3.400300e+10	64391	64391	64391	64391	64391	64387	64387
...	...	...	...	...	...	...	...
3.403118e+10	25467	25467	25467	25467	25467	25467	25467
3.403118e+10	34341	34341	34341	34341	34341	34341	34341
3.403118e+10	18928	18928	18928	18928	18928	18927	18927
3.403118e+10	18067	18067	18067	18067	18067	18067	18067
3.403118e+10	93914	93914	93914	93914	93914	93914	93914
3.403118e+10	59380	59380	59380	59380	59380	59380	59380
3.403118e+10	73795	73795	73795	73795	73795	73794	73794
3.403118e+10	41675	41675	41675	41675	41675	41675	41675
3.403118e+10	71453	71453	71453	71453	71453	71453	71453
3.403118e+10	30636	30636	30636	30636	30636	30636	30636
3.403118e+10	34463	34463	34463	34463	34463	34463	34463
3.403118e+10	59989	59989	59989	59989	59989	59989	59989
3.403118e+10	33181	33181	33181	33181	33181	33181	33181
3.403118e+10	38728	38728	38728	38728	38728	38728	38728
3.403118e+10	74725	74725	74725	74725	74725	74725	74725
3.403120e+10	25983	25983	25983	25983	25983	25983	25983
3.403120e+10	36260	36260	36260	36260	36260	36260	36260

```
3.403120e+10   76580   76580   76580   76580   76580       76580       76580
3.403122e+10   17586   17586   17586   17586   17586       17586       17586
3.403122e+10   68856   68856   68856   68856   68856       68856       68856
3.403122e+10    1542    1542    1542    1542    1542        1542        1542
3.403124e+10   21975   21975   21975   21975   21975       21975       21975
3.403124e+10    9020    9020    9020    9020    9020        9020        9020
3.403125e+10  125073  125073  125073  125073  125073      125073      125073
3.403125e+10   14554   14554   14554   14554   14554       14554       14554
3.403125e+10   28656   28656   28656   28656   28656       28656       28656
3.403125e+10   50251   50251   50251   50251   50251       50251       50251
3.403125e+10    9906    9906    9906    9906    9906        9906        9906
3.403125e+10   38006   38006   38006   38006   38006       38006       38006
3.403125e+10   14895   14895   14895   14895   14895       14895       14895

[819 rows x 7 columns]
```

[5]:
```
#Count the total tweets in each tract
idpertract= groupbytract.count().drop(['u_id', 'lat', 'lon',
                                       'home_tract', 'date'], axis =1).
 ↪reset_index()
idpertract = idpertract[idpertract['tract'] != 0]
idpertract  = idpertract.rename(columns = {'id': 'total_tweets'})
```

[34]:
```
idpertract.head(10)
```

[34]:

	tract	id
1	9001010101	2610
2	9001010201	4746
3	9001010202	2953
4	9001010300	15253
5	9001010400	11688
6	9001010500	18220
7	9001010600	18168
8	9001010700	3687
9	9001010800	6458
10	9001010900	9573

[10]:
```
idpertract.to_csv('nytract_*.csv')
```

[10]:
```
['nytract_0.csv']
```

There are 3488 tracts in New York dataset.

2. Show the percentage of missing home tracts per tract (in decimals)

Looking for bias in home location since home location was generated, not given.

[15]:
```
#Count the number of tweets in a missing home tract in each tract
nullpertract = groupbytract.apply(lambda x: x.isnull().sum())
nullpertract = nullpertract.drop(['id', 'u_id', 'lat', 'lon', 'tract', 'date'],␣
 ↪axis = 1).rename(columns = {'home_tract': 'miss_home_tract'}).reset_index()
```

```
/usr/local/linux/anaconda3/lib/python3.5/site-packages/ipykernel_launcher.py:2:
UserWarning: `meta` is not specified, inferred from partial data. Please provide
`meta` if the result is unexpected.
  Before: .apply(func)
  After:  .apply(func, meta={'x': 'f8', 'y': 'f8'}) for dataframe result
  or:     .apply(func, meta=('x', 'f8'))            for series result
```

[ ]:
```
nullpertract.to_csv('missing_*.csv')
```

[17]:
```
missing = ['missing_000.csv','missing_001.csv','missing_002.csv','missing_003.
 ↪csv','missing_004.csv',
 'missing_005.csv','missing_006.csv','missing_007.csv','missing_008.
 ↪csv','missing_009.csv',
 'missing_010.csv','missing_011.csv','missing_012.csv','missing_013.
 ↪csv','missing_014.csv',
 'missing_015.csv','missing_016.csv','missing_017.csv','missing_018.csv',␣
 ↪'missing_019.csv',
 'missing_020.csv','missing_021.csv','missing_022.csv','missing_023.
 ↪csv','missing_024.csv',
 'missing_025.csv','missing_026.csv','missing_027.csv','missing_028.csv',
 'missing_029.csv','missing_030.csv','missing_031.csv','missing_032.
 ↪csv','missing_033.csv',
 'missing_034.csv','missing_035.csv','missing_036.csv','missing_037.
 ↪csv','missing_038.csv',
 'missing_039.csv','missing_040.csv','missing_041.csv','missing_042.
 ↪csv','missing_043.csv','missing_044.csv','missing_045.csv','missing_046.
 ↪csv','missing_047.csv','missing_048.csv', 'missing_049.csv',
 'missing_050.csv', 'missing_051.csv','missing_052.csv', 'missing_053.csv',␣
 ↪'missing_054.csv','missing_055.csv', 'missing_056.csv','missing_057.csv',
 'missing_058.csv','missing_059.csv','missing_060.csv', 'missing_061.csv',
 'missing_062.csv','missing_063.csv','missing_064.csv', 'missing_065.csv',␣
 ↪'missing_066.csv','missing_067.csv',
 'missing_068.csv', 'missing_069.csv', 'missing_070.csv', 'missing_071.
 ↪csv','missing_072.csv', 'missing_073.csv',
 'missing_074.csv', 'missing_075.csv', 'missing_076.csv', 'missing_077.
 ↪csv','missing_078.csv', 'missing_079.csv','missing_080.csv','missing_081.
 ↪csv','missing_082.csv','missing_083.csv',
 'missing_084.csv', 'missing_085.csv','missing_086.csv','missing_087.
 ↪csv','missing_088.csv',
 'missing_089.csv', 'missing_090.csv','missing_091.csv','missing_092.
 ↪csv','missing_093.csv','missing_094.csv','missing_095.csv','missing_096.csv',
 'missing_097.csv', 'missing_098.csv','missing_099.csv','missing_100.
 ↪csv','missing_101.csv',
 'missing_102.csv','missing_103.csv','missing_104.csv','missing_105.csv',
```

```
 'missing_106.csv','missing_107.csv','missing_108.csv','missing_109.
↪csv','missing_110.csv','missing_111.csv', 'missing_112.csv','missing_113.
↪csv','missing_114.csv','missing_115.csv',
 'missing_116.csv','missing_117.csv', 'missing_118.csv','missing_119.csv',
 'missing_120.csv', 'missing_121.csv','missing_122.csv','missing_123.
↪csv','missing_124.csv',
 'missing_125.csv','missing_126.csv', 'missing_127.csv', 'missing_128.
↪csv','missing_129.csv',
 'missing_130.csv','missing_131.csv','missing_132.csv']
pd.concat(pd.read_csv(f) for f in missing).to_csv('missing.csv')
```

2.1 GROUPING BY ID

1. Count the number of tweets per user. Create a summary statistics

[5]:
```
#Groupby user id function
groupbyuid = ds.groupby('u_id')
```

[9]:
```
#Show first 10 rows of tweets per user count
groupbyuid.count().drop(['lat', 'lon', 'home_tract',
                         'tract', 'diff_tract', 'date'], axis =1).head(10)
```

[9]:
```
                  id
u_id
1.668805e-308    104
1.668805e-308    953
1.668805e-308   1395
1.668805e-308    229
1.668805e-308   1286
1.668805e-308    264
1.668805e-308    760
1.668805e-308    419
1.668805e-308    494
1.668805e-308    106
```

2.2 Per tract, how many users have more than 5 tweets?

1. Group by tract and group by u_id.
2. Then, filter u_id with tweets more than 5.
3. Reset the index
4. Group by tract and get the count of users with more than 5 tweets

[56]:
```
#Groupby tract and user id and count id
uidt = ds.groupby(['tract', 'u_id']).count()
```

[ ]:
```
#Show the first 10 rows of the users with more than 5 tweets in each tract
uidt[uidt['id'] > 5].head(10)
```

[6]:
```
#Unique count in each tract specifically the unique users in each tract
totalusers = groupbytract.apply(lambda x: x.nunique())
totalusers = totalusers.drop(['tract', 'id', 'lat', 'lon', 'date',␣
↪'home_tract'], axis = 1).reset_index()
totalusers = totalusers.rename(columns = {'u_id': 'total_users'})
```

```
/usr/local/linux/anaconda3/lib/python3.5/site-packages/ipykernel_launcher.py:1:
UserWarning: `meta` is not specified, inferred from partial data. Please provide
`meta` if the result is unexpected.
  Before: .apply(func)
  After:  .apply(func, meta={'x': 'f8', 'y': 'f8'}) for dataframe result
  or:     .apply(func, meta=('x', 'f8'))            for series result
  """Entry point for launching an IPython kernel.
```

[ ]:
```
totalusers.to_csv('totalusers_*.csv')
```

[7]:
```
totalusers = ['totalusers_000.csv',
 'totalusers_001.csv', 'totalusers_002.csv','totalusers_003.csv',␣
↪'totalusers_004.csv','totalusers_005.csv','totalusers_006.csv',
 'totalusers_007.csv', 'totalusers_008.csv', 'totalusers_009.csv',␣
↪'totalusers_010.csv', 'totalusers_011.csv',
 'totalusers_012.csv', 'totalusers_013.csv','totalusers_014.csv','totalusers_015.
↪csv', 'totalusers_016.csv', 'totalusers_017.csv',
 'totalusers_018.csv','totalusers_019.csv', 'totalusers_020.csv','totalusers_021.
↪csv','totalusers_022.csv','totalusers_023.csv','totalusers_024.csv',
 'totalusers_025.csv', 'totalusers_026.csv','totalusers_027.csv','totalusers_028.
↪csv','totalusers_029.csv','totalusers_030.csv','totalusers_031.csv',␣
↪'totalusers_032.csv',
 'totalusers_033.csv', 'totalusers_034.csv','totalusers_035.csv',
 'totalusers_036.csv','totalusers_037.csv', 'totalusers_038.csv','totalusers_039.
↪csv', 'totalusers_040.csv', 'totalusers_041.csv', 'totalusers_042.csv',
 'totalusers_043.csv', 'totalusers_044.csv', 'totalusers_045.csv',
 'totalusers_046.csv','totalusers_047.csv','totalusers_048.csv','totalusers_049.
↪csv', 'totalusers_050.csv','totalusers_051.csv',
 'totalusers_052.csv', 'totalusers_053.csv', 'totalusers_054.csv',␣
↪'totalusers_055.csv',
 'totalusers_056.csv', 'totalusers_057.csv','totalusers_058.csv','totalusers_059.
↪csv', 'totalusers_060.csv','totalusers_061.csv',
 'totalusers_062.csv','totalusers_063.csv','totalusers_064.csv', 'totalusers_065.
↪csv','totalusers_066.csv','totalusers_067.csv','totalusers_068.
↪csv','totalusers_069.csv',
 'totalusers_070.csv','totalusers_071.csv','totalusers_072.csv', 'totalusers_073.
↪csv','totalusers_074.csv', 'totalusers_075.csv', 'totalusers_076.csv',
 'totalusers_077.csv', 'totalusers_078.csv', 'totalusers_079.csv',␣
↪'totalusers_080.csv',
```

```
 'totalusers_081.csv', 'totalusers_082.csv', 'totalusers_083.csv',␣
 ↪'totalusers_084.csv', 'totalusers_085.csv', 'totalusers_086.
 ↪csv','totalusers_087.csv', 'totalusers_088.csv',
 'totalusers_089.csv', 'totalusers_090.csv', 'totalusers_091.
 ↪csv','totalusers_092.csv', 'totalusers_093.csv','totalusers_094.csv',␣
 ↪'totalusers_095.csv',
 'totalusers_096.csv','totalusers_097.csv','totalusers_098.csv','totalusers_099.
 ↪csv', 'totalusers_100.csv','totalusers_101.csv','totalusers_102.
 ↪csv','totalusers_103.csv','totalusers_104.csv',
 'totalusers_105.csv','totalusers_106.csv','totalusers_107.csv','totalusers_108.
 ↪csv','totalusers_109.csv',
 'totalusers_110.csv','totalusers_111.csv','totalusers_112.csv', 'totalusers_113.
 ↪csv','totalusers_114.csv','totalusers_115.csv',
 'totalusers_116.csv','totalusers_117.csv','totalusers_118.csv','totalusers_119.
 ↪csv','totalusers_120.csv','totalusers_121.csv',
 'totalusers_122.csv','totalusers_123.csv', 'totalusers_124.csv',
 'totalusers_125.csv','totalusers_126.csv','totalusers_127.csv','totalusers_128.
 ↪csv', 'totalusers_129.csv', 'totalusers_130.csv','totalusers_131.csv',␣
 ↪'totalusers_132.csv']

pd.concat(pd.read_csv(f) for f in totalusers).to_csv('totalusers.csv')
```

[51]:

```
totalusers.head(10)
```

[51]:

	tract	total_users
0	3.400301e+10	869
1	3.401302e+10	798
2	3.402300e+10	3423
3	3.403903e+10	698
4	3.600501e+10	1474
5	3.600502e+10	289
6	3.600503e+10	434
7	3.606100e+10	2405
8	3.606102e+10	1195
9	3.608100e+10	289

[45]:

```
##We only want to look at u_id column. Ignore the other columns.
uidt[uidt['id'] > 5].reset_index().groupby(['tract']).count().head(819)
```

[45]:

tract	u_id	id	lat	lon	date	home_tract	diff_tract
9.001010e+09	43	43	43	43	43	43	43
9.001010e+09	68	68	68	68	68	68	68
9.001010e+09	54	54	54	54	54	54	54
9.001010e+09	162	162	162	162	162	162	162
9.001010e+09	126	126	126	126	126	126	126
9.001010e+09	225	225	225	225	225	225	225
9.001011e+09	328	328	328	328	328	328	328

9.001011e+09	82	82	82	82	82	82	82
9.001011e+09	116	116	116	116	116	116	116
9.001011e+09	128	128	128	128	128	128	128
9.001011e+09	201	201	201	201	201	201	201
9.001011e+09	98	98	98	98	98	98	98
9.001011e+09	160	160	160	160	160	160	160
9.001011e+09	117	117	117	117	117	117	117
9.001020e+09	7	7	7	7	7	7	7
9.001021e+09	208	208	208	208	208	208	208
9.001022e+09	189	189	189	189	189	189	189
9.001022e+09	283	283	283	283	283	283	283
3.400300e+10	258	258	258	258	258	258	258
3.400300e+10	179	179	179	179	179	179	179
3.400300e+10	263	263	263	263	263	263	263
3.400300e+10	167	167	167	167	167	167	167
3.400300e+10	231	231	231	231	231	231	231
3.400300e+10	563	563	563	563	563	563	563
3.400300e+10	387	387	387	387	387	387	387
3.400300e+10	116	116	116	116	116	116	116
3.400300e+10	201	201	201	201	201	201	201
3.400300e+10	201	201	201	201	201	201	201
3.400300e+10	237	237	237	237	237	237	237
3.400300e+10	282	282	282	282	282	282	282
...	...	...	...	...	...	...	...
3.403118e+10	429	429	429	429	429	429	429
3.403118e+10	341	341	341	341	341	341	341
3.403118e+10	210	210	210	210	210	210	210
3.403118e+10	242	242	242	242	242	242	242
3.403118e+10	211	211	211	211	211	211	211
3.403118e+10	147	147	147	147	147	147	147
3.403118e+10	467	467	467	467	467	467	467
3.403118e+10	367	367	367	367	367	367	367
3.403118e+10	507	507	507	507	507	507	507
3.403118e+10	469	469	469	469	469	469	469
3.403118e+10	380	380	380	380	380	380	380
3.403118e+10	365	365	365	365	365	365	365
3.403118e+10	287	287	287	287	287	287	287
3.403118e+10	365	365	365	365	365	365	365
3.403118e+10	212	212	212	212	212	212	212
3.403118e+10	298	298	298	298	298	298	298
3.403118e+10	965	965	965	965	965	965	965
3.403120e+10	145	145	145	145	145	145	145
3.403120e+10	376	376	376	376	376	376	376
3.403120e+10	342	342	342	342	342	342	342
3.403122e+10	232	232	232	232	232	232	232
3.403122e+10	1103	1103	1103	1103	1103	1103	1103
3.403122e+10	19	19	19	19	19	19	19

```
3.403124e+10   187   187   187   187   187          187          187
3.403124e+10    93    93    93    93    93           93           93
3.403125e+10  1184  1184  1184  1184  1184         1184         1184
3.403125e+10   115   115   115   115   115          115          115
3.403125e+10   456   456   456   456   456          456          456
3.403125e+10   757   757   757   757   757          757          757
3.403125e+10   164   164   164   164   164          164          164

[819 rows x 7 columns]
```

[8]:
```
uidt[uidt['id'] > 5].reset_index().groupby(['tract']).count()['u_id'].describe().
↪compute()
```

[8]:
```
count    3480.000000
mean      287.092816
std       508.430123
min         1.000000
25%        84.000000
50%       165.000000
75%       293.000000
max      7059.000000
dtype: float64
```

[61]:
```
#Count the users with at least 5 tweets in each tract and convert it to a csv
id5 = uidt[uidt['id'] >= 5].reset_index().groupby(['tract']).count().
↪reset_index()
id5 = id5.rename(columns = {'u_id': 'userwith5_count'})
id5 = id5.drop(['id', 'lat', 'lon', 'date', 'home_tract'], axis = 1)
```

[12]:
```
id5.head(10)
```

[12]:
```
          tract  u_id   id  lat  lon  date  home_tract
0  9.001010e+09    43   43   43   43    43          43
1  9.001010e+09    68   68   68   68    68          68
2  9.001010e+09    54   54   54   54    54          54
3  9.001010e+09   162  162  162  162   162         162
4  9.001010e+09   126  126  126  126   126         126
5  9.001010e+09   225  225  225  225   225         225
6  9.001011e+09   328  328  328  328   328         328
7  9.001011e+09    82   82   82   82    82          82
8  9.001011e+09   116  116  116  116   116         116
9  9.001011e+09   128  128  128  128   128         128
```

[62]:
```
id5.to_csv('id5_*.csv')
```

[62]:
```
['id5_0.csv']
```

[67]:
```
#count of tweets sent from home (local tweets) in each tract
hometweets = ds[ds['home_tract'] == ds['tract']].groupby('tract').count().
↪drop(['u_id', 'lat', 'lon',
```

```
                                            'home_tract', 'date'], axis =1).
 ↪reset_index()
hometweets = hometweets.rename(columns = {'id': 'tweets_sent_from_home'})
hometweets.to_csv('hometweets_*.csv')
```

[67]:
```
['hometweets_0.csv']
```

3 Adding Time as a Variable

SECOND ROUND OF ANALYSIS 1. Keeping tract in mind, what day and time are tweets sent often? 2. Comparing tract == home_tract, are there a correlation with day/time to home_tract? 3. Calculate the odds ratio

We didn't drop the home tract initially because we needed to calculate the % tweets with missing home location in each tract. However, in this round of analysis, we drop all null values in column 'home_tract' so that we can begin aggregating and counting real numbers.

[10]:
```
ds=ds.dropna(subset = ['home_tract'])
```

3.0.1 Hour Breakdown

[4]:
```
#The hour is given by the last two digits of the column 'date'
#We group by tract and hour and count the tweets sent in each hour in each tract
ds['hour'] = ds['date'].str[11:13]
hour_count = ds.groupby(['tract', 'hour']).aggregate({'id': 'count'})
hour_count.rename(columns = {'id': 'count'})
hour_helper = ds.groupby(['tract']).aggregate({'id': 'count'})
```

[22]:
```
#An example displayed of what to expect
hour_count.head(10)
```

[22]:
```
                    id
tract         hour
9.001010e+09  00   209
              01   237
              02   208
              03   144
              04   105
              05    53
              06    35
              07    23
              08    28
              09    24
```

[ ]:
```
#We categorize and pivot the table so that the hours will be column
#names and ready for our output file
hour_count = hour_count.reset_index()
hour_count=hour_count.categorize(columns = ['hour'])
hour_count = hour_count.pivot_table(values = 'id',
```

```
                                    columns = 'hour', index= 'tract' )
```

[14]:
```
hour_count.to_csv('hour_count_*.csv')
```

[14]:
```
['hour_count_0.csv']
```

3.0.2 Day Breakdown

Days (Mon-Sun) – seven time periods

The weekday method of the datetime object will return 0 if it's Monday and 6 if it's Sunday so on.

[5]:
```
#We create a datetime object for the date
ds['date_helper'] = ds['date'].str[0:10]
ds['weekday'] = ds.date_helper.map(lambda x: pd.to_datetime(x).weekday() if x !=␣
 ↪'foo' else np.nan)
```

[15]:
```
ds.head(10)
```

[15]:
```
             id            u_id        lat        lon                  date  \
0  2.117852e-293  1.668805e-308  40.636800 -73.659319  2012-07-26T00:49:21Z
1  2.117846e-293  1.668805e-308  40.778059 -73.954124  2012-07-26T00:49:15Z
2  2.117863e-293  1.668805e-308  40.918340 -73.804538  2012-07-26T00:49:30Z
3  2.117864e-293  1.668805e-308  40.923364 -74.146670  2012-07-26T00:49:31Z
4  2.117863e-293  1.668805e-308  40.694654 -73.733507  2012-07-26T00:49:31Z
5  2.117883e-293  1.668805e-308  40.755179 -73.976723  2012-07-26T00:49:47Z
6  2.117884e-293  1.668805e-308  40.771426 -73.973501  2012-07-26T00:49:48Z
7  2.117892e-293  1.668805e-308  40.650541 -73.931422  2012-07-26T00:49:55Z
8  2.117898e-293  1.668805e-308  40.622028 -74.332462  2012-07-26T00:50:00Z
9  2.117896e-293  1.668805e-308  40.777575 -74.353625  2012-07-26T00:49:58Z

          tract    home_tract date_helper  weekday
0  3.605941e+10  3.605941e+10  2012-07-26        3
1  3.606101e+10  3.608101e+10  2012-07-26        3
2  3.611901e+10  3.611901e+10  2012-07-26        3
3  3.403118e+10  3.403118e+10  2012-07-26        3
4  3.608106e+10  3.608106e+10  2012-07-26        3
5  3.606101e+10  3.606102e+10  2012-07-26        3
6  3.606101e+10  3.606102e+10  2012-07-26        3
7  3.604709e+10  3.604712e+10  2012-07-26        3
8  3.403904e+10  3.403904e+10  2012-07-26        3
9  3.401302e+10  3.401300e+10  2012-07-26        3
```

[6]:
```
#Count of tweets in each day from Monday to Sunday in each tract
weekday_count = ds.groupby(['tract', 'weekday']).aggregate({'id': 'count'})
weekday_count = weekday_count.reset_index()
```

[8]:
```
weekday_count.head(7)
```

[8]:
```
          tract  weekday   id
0  9.001010e+09        0  321
```

```
1  9.001010e+09        1  349
2  9.001010e+09        2  307
3  9.001010e+09        3  377
4  9.001010e+09        4  377
5  9.001010e+09        5  428
6  9.001010e+09        6  451
```

[7]:
```
weekday_count = weekday_count.categorize(columns = ['weekday'])
weekday_count = weekday_count.pivot_table(values = 'id',
                                          columns = 'weekday',
                                          index = 'tract')
```

[8]:
```
weekday_count.to_csv("weekday_count_*.csv")
```

[8]:
```
['weekday_count_0.csv']
```

3.0.3 Weekday and Weekend Breakdown

Disclaimer: the 'weekday' column above and weekday_count were to calculate the numbers in each day from Monday to Sunday, but the analysis below is specifically for weekday and weekend as defined here:

weekday (Mon-Fri (until 18:00)); weekend (starting 18:00 on Friday until 4:00 on Monday)

Thus, the next function will separate the day and hour into the correct categories.

[6]:
```
#Monday is 0 and Sunday is 6
valuesweekday= [1,2,3]
valuesweekend = [6, 5]
# time = ds[['weekday', 'hour']]

before_18 = ['00', '01', '02', '03', '04', '05', '06', '07', '08', '09',
             '10', '11', '12', '13', '14', '15', '16', '17', '18']

def weekday(row):
    if row['weekday'] in valuesweekday:
        return 1
    elif row['weekday']== 0 & (row['hour'] not in ['00', '01', '02', '03']):
        return 1
    elif row['weekday'] == 4 & (row['hour'] in before_18):
        return 1
    else:
        return 0
ds['WEEKDAY'] = ds.apply(lambda x: weekday(x), axis = 1, meta = 'float64')
```

[7]:
```
weekday_sum = ds.groupby(['tract', 'WEEKDAY']).aggregate({'id': 'count'})
weekday_sum = weekday_sum.reset_index()
```

[10]:
```
weekday_sum.head(3)
```

[10]:
```
          tract  WEEKDAY    id
0  9.001010e+09        0  1026
```

```
1  9.001010e+09        1  1584
2  9.001010e+09        0  1482
```

[8]:
```
%%time
weekday_sum = weekday_sum.categorize(columns  = ['WEEKDAY'])
weekday_sum = weekday_sum.pivot_table(values = 'id', columns = 'WEEKDAY', index␣
↪= 'tract')
```

```
CPU times: user 5h 37min 36s, sys: 20min 8s, total: 5h 57min 45s
Wall time: 5h 29min 13s
```

[9]:
```
%%time
weekday_sum.to_csv("weekday_sum_*.csv")
```

```
CPU times: user 6h 30min 1s, sys: 35min 4s, total: 7h 5min 5s
Wall time: 6h 20min 22s
```

[9]:
```
['weekday_sum_0.csv']
```

3.0.4 Daytime and Nighttime Breakdown

day and night are defined as: day (4:00 – 18:00), evening/night (18:00 to 04:00)

[4]:
```
dayvalues = ['04', '05', '06', '07', '08', '09', '10', '11', '12', '13','14',␣
↪'15', '16', '17', '18']
def day(row):
    if row['hour'] in dayvalues:
        return 1
    else:
        return 0
ds['daytime'] = ds.apply(lambda x: day(x), axis =1, meta = 'float64')
```

[25]:
```
daytime_count = ds.groupby(['tract', 'daytime']).aggregate({'id': 'count'})
daytime_count = daytime_count.reset_index()
daytime_count = daytime_count.categorize(columns = ['daytime'])
daytime_count = daytime_count.pivot_table(values = 'id', columns= 'daytime',␣
↪index = 'tract')
```

[ ]:
```
daytime_count.to_csv('daytime_count_*.csv')
```

3.1 GEOGRAPHICAL ANALYSIS

GEO TAG: local, neighbors, (non-local & non-neighbors)

- Number of Tweets by GEOGRAPHY
- Geog (3 categories) * Days (7 categories) = 21 combo-categories
- Geog (3 categories) * Time of Day (2 categories) = 6 combo-categories
- Geog (3 categories) * Weekday/Weekend (2 categories) = 6 combo-categories

– Geog (3 categories) * Time of Day (2 categories) * Weekday/Weekend (2 categories) = 12 combo-categories

Local is defined as tweets sent from home. Non-local is defined as tweets sent from other tracts, but not neighboring tracts. Non-neighbor is defined as tweets sent from neighboring tracts. The New York twitter raw data actually include tweets from New Jersey, Connecticut, and New York.

[12]:
```
#Include NY, NJ, and CT nearest neighbors of each tract
ny_nn= pd.read_csv('ny_nearestneighbor_output_meters.csv')
nj_nn = pd.read_csv('nj_nearestneighbor_output_meters.csv')
ct_nn = pd.read_csv('ct_nearestneighbor_output_meters.csv')
```

[13]:
```
nn = pd.concat([ny_nn, nj_nn, ct_nn])
##a function that takes in the SRC_GEOID and returns an array of NBR_GEOID
def neighbors(src):
    for i in nn['SRC_GEOID'].unique():
        if i == src:
            table=nn[nn['SRC_GEOID'] == i]
            return np.array(table['NBR_GEOID'])
    return []
neighbors(36081003900)
```

[13]:
```
array([36081003700, 36081004500, 36081008500])
```

[14]:
```
#We create a dictionary of tract number and a list of its neighboring tract
n_ = []
for i in nn['SRC_GEOID'].unique():
    n_.append(neighbors(i))
nn = pd.DataFrame(nn['SRC_GEOID'].unique())
nn['neighbors'] = n_
nn = nn.rename(columns = {0: 'SRC_GEOID'})
neighbormap = dict(zip(nn['SRC_GEOID'], nn['neighbors']))
```

3.1.1 NEIGHBORS

In the next lines of codes, we will be counting the number of neighboring tweets, neighboring tweets given hour, day, weekday, and daytime/nighttime.

It's important to clean up the data before starting. This time, we will be removing null values of 'tract' column. We had also removed the null values in 'home_tract' previously. If you're starting this portion without doing the Time analysis breakdown. The code is provided below. Just uncomment it. We also convert the float values of 'tract' and 'home_tract columns into int values to match with the neighbormap dictionary. We will use this cleanup for Local and Non-Neighbor Analysis as well.

[11]:
```
#ds = ds.dropna(subset = ['home_tract'])
ds = ds.dropna(subset= ['tract'])
ds['tract'] = ds['tract'].astype('int')
ds['home_tract'] = ds['home_tract'].astype('int')
```

The function below 'neighbor_check' uses the neighbormap where the keys are home_tract values. We then check if the tract matches the home_tract, if tract matches a neighboring tract of the home_tract, and if home_tract is in the neighbors. Thus, it also sets all the tweets from outside of the New York region as 0.

[23]:
```
def neighbor_check(x):
    if np.any(neighbormap.get(x['home_tract']) != None):
        if x['tract'] in neighbormap.get(x['home_tract']):
            return 1
        else:
            return 0
    else:
        return 0
```

[24]:
```
#apply neighbor_check to the dataset and create a new column 'neighbor'
ds['neighbor'] = ds.apply(lambda x: neighbor_check(x), axis = 1, meta =␣
 ↪'float64')
#eliminate all the tweets from outside of the New York region
ds= ds[(ds["tract"].isin(neighbormap.keys())) & (ds["home_tract"].
 ↪isin(neighbormap.keys()))]
```

[108]:
```
ds.head(3)
```

[108]:
```
              id          u_id        lat        lon                  date  \
0  2.117852e-293  1.668805e-308  40.636800 -73.659319  2012-07-26T00:49:21Z
1  2.117846e-293  1.668805e-308  40.778059 -73.954124  2012-07-26T00:49:15Z
2  2.117863e-293  1.668805e-308  40.918340 -73.804538  2012-07-26T00:49:30Z

         tract   home_tract  neighbor
0  36059413002  36059412200         1
1  36061014601  36081005100         0
2  36119005300  36119005300         0
```

[19]:
```
neighbor = ds[ds['neighbor'] == 1]
neighbor_count = neighbor.groupby(['tract']).aggregate({'id': 'count'})
neighbor_count = neighbor_count.reset_index()
neighbor_count = neighbor_count.rename(columns = {'id': 'neighbor_tweets'})
```

[107]:
```
%%time
neighbor_count.to_csv('neighbor_count_*.csv')
```

```
CPU times: user 22h 40min, sys: 1min 19s, total: 22h 41min 20s
Wall time: 22h 3min 46s
```

[107]:
```
['neighbor_count_0.csv']
```

[17]:
```
%%time
neighbor_count.to_csv('neighbor_count_*.csv')
```

```
CPU times: user 1d 8h 51min 36s, sys: 3h 5min 2s, total: 1d 11h 56min 39s
Wall time: 1d 1h 55min 28s
```

[17]:
```
['neighbor_count_0.csv']
```

[20]:
```
neighbor['hour'] = neighbor['date'].str[11:13]
neighbor['date_helper'] = neighbor['date'].str[0:10]
neighbor['day'] = neighbor.date_helper.map(
    lambda x: pd.to_datetime(x).weekday() if x != 'foo' else np.nan)
valuesweekday= [1,2,3]
valuesweekend = [6, 5]
# time = ds[['weekday', 'hour']]

before_18 = ['00', '01', '02', '03', '04', '05', '06', '07', '08', '09',
             '10', '11', '12', '13', '14', '15', '16', '17', '18']

def neighbor_week_day(row):
    if row['day'] in valuesweekday:
        return 1
    elif row['day']== 0 & (row['hour'] not in ['00', '01', '02', '03']):
        return 1
    elif row['day'] == 4 & (row['hour'] in before_18):
        return 1
    else:
        return 0
neighbor['WEEKDAY'] = neighbor.apply(lambda x: neighbor_week_day(x), axis = 1,␣
 ↪meta = 'float64')
```

[21]:
```
neighbor_weekday_sum = neighbor.groupby(['tract', 'WEEKDAY']).aggregate({'id':␣
 ↪'count'})
neighbor_weekday_sum = neighbor_weekday_sum.reset_index()
neighbor_weekday_sum  = neighbor_weekday_sum.categorize(columns = ['WEEKDAY'])
```

[22]:
```
%%time
neighbor_weekday_sum = neighbor_weekday_sum.pivot_table(
    values = 'id', columns = 'WEEKDAY', index = 'tract')
```

```
CPU times: user 28 ms, sys: 0 ns, total: 28 ms
Wall time: 22.8 ms
```

[23]:
```
%%time
neighbor_weekday_sum.to_csv("neighbor_weekday_sum_*.csv")
```

```
CPU times: user 8h 59min 54s, sys: 16min 48s, total: 9h 16min 42s
Wall time: 8h 48min 41s
```

[23]:
```
['neighbor_weekday_sum_0.csv']
```

[19]:
```
dayvalues = ['04', '05', '06', '07', '08', '09', '10', '11', '12', '13','14',␣
 ↪'15', '16', '17', '18']
def neighbor_day(row):
    if row['hour'] in dayvalues:
        return 1
```

```
    else:
        return 0
neighbor['daytime'] = neighbor.apply(lambda x: neighbor_day(x), axis =1, meta =␣
 ↪'float64')
```

[20]:
```
%%time
#GROUPING BY DAYTIME/NIGHTIME
neighbor_daytime_count = neighbor.groupby(['tract', 'daytime']).aggregate({'id':␣
 ↪'count'})
neighbor_daytime_count = neighbor_daytime_count.reset_index()
neighbor_daytime_count = neighbor_daytime_count.categorize(columns = ['daytime'])
neighbor_daytime_count = neighbor_daytime_count.pivot_table(
    values = 'id', columns= 'daytime', index = 'tract')
```

```
CPU times: user 3h 43min 27s, sys: 2min 58s, total: 3h 46min 25s
Wall time: 3h 37min 19s
```

[21]:
```
%%time
neighbor_daytime_count.to_csv('neighbor_daytime_count_*.csv')
```

```
CPU times: user 3h 43min 12s, sys: 2min 58s, total: 3h 46min 10s
Wall time: 3h 37min 10s
```

[21]:
```
['neighbor_daytime_count_0.csv']
```

3.1.2 LOCAL

[11]:
```
%%time
#counting the number of tweets in local home_tract
local = ds[ds['tract'] == ds['home_tract']]
local_count = local.groupby(['tract']).aggregate({'id': 'count'})
local_count = local_count.reset_index()
local_count = local_count.rename(columns = {'id': 'local_tweets'})
```

```
CPU times: user 32 ms, sys: 0 ns, total: 32 ms
Wall time: 25.2 ms
```

[ ]:
```
local_count.to_csv('local_count_*.csv')
```

[12]:
```
%%time
#GROUPING BY HOUR
local['hour'] = local['date'].str[11:13]
local_hour_count = local.groupby(['tract', 'hour']).aggregate({'id': 'count'})
local_hour_count = local_hour_count.reset_index()
```

```
CPU times: user 32 ms, sys: 0 ns, total: 32 ms
Wall time: 28.5 ms
```

[ ]:
```
local_hour_count = local_hour_count.categorize(columns = ['hour'])
local_hour_count = local_hour_count.pivot_table(values = 'id',
                                    columns = 'hour', index= 'tract')
```

[13]:
```
local_hour_count.to_csv('local_hour_count_*.csv')
```

[13]:
```
['local_hour_count_0.csv']
```

[13]:
```
local['date_helper'] = ds['date'].str[0:10]
local['day'] = local.date_helper.map(
    lambda x: pd.to_datetime(x).weekday() if x != 'foo' else np.nan)
```

[14]:
```
%%time
#GROUPING BY DAY
local_day_count = local.groupby(['tract', 'day']).aggregate({'id': 'count'})
local_day_count = local_day_count.reset_index()
local_day_count = local_day_count.categorize(columns = ['day'])
local_day_count = local_day_count.pivot_table(values = 'id',
                                         columns = 'day',
                                         index = 'tract')
```

```
CPU times: user 2h 59min 35s, sys: 17min 44s, total: 3h 17min 19s
Wall time: 2h 51min 5s
```

[15]:
```
local_day_count.to_csv('local_day_count_*.csv')
```

[15]:
```
['local_day_count_0.csv']
```

[14]:
```
valuesweekday= [1,2,3]
valuesweekend = [6, 5]
# time = ds[['weekday', 'hour']]

before_18 = ['00', '01', '02', '03', '04', '05', '06', '07', '08', '09',
             '10', '11', '12', '13', '14', '15', '16', '17', '18']

def week_day(row):
    if row['day'] in valuesweekday:
        return 1
    elif row['day']== 0 & (row['hour'] not in ['00', '01', '02', '03']):
        return 1
    elif row['day'] == 4 & (row['hour'] in before_18):
        return 1
    else:
        return 0
local['WEEKDAY'] = local.apply(lambda x: week_day(x), axis = 1, meta = 'float64')
```

[ ]:
```
%%time
#GROUPING BY WEEKDAY
# local['WEEKDAY'] = local.apply(lambda x: weekday(x), axis = 1, meta =␣
 ↪'float64')
```

```
local_weekday_sum = local.groupby(['tract', 'WEEKDAY']).aggregate({'id':␣
↪'count'})
local_weekday_sum = local_weekday_sum.reset_index()
local_weekday_sum = local_weekday_sum.categorize(columns = ['WEEKDAY'])
```

[ ]:
```
local_weekday_sum = local_weekday_sum.pivot_table(
    values = 'id', columns = 'WEEKDAY', index = 'tract')
local_weekday_sum = local_weekday_sum.rename(
    columns = {'0': 'local_weekend_oddratio', '1': 'local_weekday_oddratio'})
```

[ ]:
```
%%time
local_weekday_sum.to_csv("local_weekday_sum_*.csv")
```

[17]:
```
dayvalues = ['04', '05', '06', '07', '08', '09', '10', '11', '12', '13','14',␣
↪'15', '16', '17', '18']
def localday(row):
    if row['hour'] in dayvalues:
        return 1
    else:
        return 0
local['daytime'] = local.apply(lambda x: localday(x), axis =1, meta = 'float64')
```

[18]:
```
%%time
#GROUPING BY DAYTIME/NIGHTIME
# local['daytime'] = local.apply(lambda x: day(x), axis =1, meta = 'float64')
local_daytime_count = local.groupby(['tract', 'daytime']).aggregate({'id':␣
↪'count'})
local_daytime_count = local_daytime_count.reset_index()
local_daytime_count = local_daytime_count.categorize(columns = ['daytime'])
local_daytime_count = local_daytime_count.pivot_table(
    values = 'id', columns= 'daytime', index = 'tract')
```

```
CPU times: user 4h 12min 8s, sys: 14min 50s, total: 4h 26min 59s
Wall time: 4h 2min 22s
```

[19]:
```
%%time
local_daytime_count.to_csv('local_daytime_count_*.csv')
```

```
CPU times: user 4h 13min 33s, sys: 15min 21s, total: 4h 28min 55s
Wall time: 4h 3min 50s
```

[19]:
```
['local_daytime_count_0.csv']
```

3.1.3 NONLOCAL

[25]:
```
%%time
#counting the number of tweets
#where the home_tract isn't local or a neighboring tract
other = ds[(ds['neighbor'] == 0) & (ds['tract'] != ds['home_tract'])]
other_count = other.groupby(['tract']).aggregate({'id': 'count'})
other_count = other_count.reset_index()
other_count = other_count.rename(columns = {'id': 'other_tweets'})
```

```
CPU times: user 32 ms, sys: 4 ms, total: 36 ms
Wall time: 33.8 ms
```

[ ]:
```
%%time
other_count.to_csv('other_count_*.csv')
```

[ ]:
```
#GROUPING BY HOUR
%%time
other['hour'] = other['date'].str[11:13]
other_hour_count = other.groupby(['tract', 'hour']).aggregate({'id': 'count'})
other_hour_count = other_hour_count.reset_index()
```

[ ]:
```
%%time
other_hour_count = other_hour_count.categorize(columns = ['hour'])
other_hour_count = other_hour_count.pivot_table(values = 'id',
                                    columns = 'hour', index= 'tract')
```

[ ]:
```
%%time
other_hour_count.to_csv('other_hour_count_*.csv')
```

[ ]:
```
%%time
#GROUPING BY DAY
other['date_helper'] = other['date'].str[0:10]
other['day'] = local.date_helper.map(
    lambda x: pd.to_datetime(x).weekday() if x != 'foo' else np.nan)
other_day_count = other.groupby(['tract', 'day']).aggregate({'id': 'count'})
other_day_count = other_day_count.reset_index()
```

[ ]:
```
%%time
other_day_count = other_day_count.categorize(columns = ['day'])
other_day_count = other_day_count.pivot_table(values = 'id',
                                         columns = 'day',
                                         index = 'tract')
```

[ ]:
```
%%time
other_day_count.to_csv('other_day_count_*.csv')
```

[ ]:
```
valuesweekday= [1,2,3]
valuesweekend = [6, 5]
# time = ds[['weekday', 'hour']]
```

```
before_18 = ['00', '01', '02', '03', '04', '05', '06', '07', '08', '09',
             '10', '11', '12', '13', '14', '15', '16', '17', '18']

def other_weekday(row):
    if row['day'] in valuesweekday:
        return 1
    elif row['day']== 0 & (row['hour'] not in ['00', '01', '02', '03']):
        return 1
    elif row['day'] == 4 & (row['hour'] in before_18):
        return 1
    else:
        return 0
```

[ ]:
```
%%time
#GROUPING BY WEEKDAY
other['WEEKDAY'] = other.apply(lambda x: other_weekday(x), axis = 1, meta =␣
 ↪'float64')
other_weekday_sum = other.groupby(['tract', 'WEEKDAY']).aggregate({'id':␣
 ↪'count'})
other_weekday_sum = other_weekday_sum.reset_index()
other_weekday_sum = other_weekday_sum.categorize(columns  = ['WEEKDAY'])
other_weekday_sum = other_weekday_sum.pivot_table(
    values = 'id', columns = 'WEEKDAY', index = 'tract')
other_weekday_sum = other_weekday_sum.rename(
    columns = {'0': 'other_weekend_oddratio', '1': 'other_weekday_oddratio'})
```

[ ]:
```
other_weekday_sum.to_csv("other_weekday_sum_*.csv")
```

[ ]:
```
dayvalues = ['04', '05', '06', '07', '08', '09', '10', '11', '12', '13','14',␣
 ↪'15', '16', '17', '18']
def other_day(row):
    if row['hour'] in dayvalues:
        return 1
    else:
        return 0
```

[ ]:
```
#GROUPING BY DAYTIME/NIGHTIME
other['daytime'] = other.apply(lambda x: other_day(x), axis =1, meta = 'float64')
other_daytime_count = other.groupby(
    ['tract', 'daytime']).aggregate({'id': 'count'})
other_daytime_count = other_daytime_count.reset_index()
other_daytime_count = other_daytime_count.categorize(columns = ['daytime'])
other_daytime_count = other_daytime_count.pivot_table(
    values = 'id', columns= 'daytime', index = 'tract')
```

[ ]:
```
other_daytime_count.to_csv('other_daytime_count_*.csv')
```

4 ORGANIZING THE OUTPUT FILE

Include all the data from above and compiling it into one csv file

[18]:
```
output = pd.read_csv('nytract_0.csv')
missingcsv = pd.read_csv('missing.csv')
id5csv = pd.read_csv('id5_0.csv')
totaluserscsv = pd.read_csv('totalusers.csv')
hometract = pd.read_csv('tweetsh_0.csv')
hometweets = pd.read_csv('hometweets_0.csv')
hourcsv = pd.read_csv('hour_count_0.csv')
weekdaycsv = pd.read_csv('weekday_count_0.csv')
weekday_or_weekend = pd.read_csv('weekday_sum_0.csv')
daytime_or_night = pd.read_csv('daytime_count_0.csv')
localcsv= pd.read_csv('local_count_0.csv')
local_hour = pd.read_csv('local_hour_count_0.csv')
local_day = pd.read_csv('local_day_count_0.csv')
local_weekday = pd.read_csv('local_weekday_sum_0.csv')
local_daytime = pd.read_csv('local_daytime_count_0.csv')
neighborcsv = pd.read_csv('neighbor_count_0.csv')
neighbor_weekday= pd.read_csv('neighbor_weekday_sum_0.csv')
neighbor_daytime = pd.read_csv('neighbor_daytime_count_0.csv')
```

[19]:
```
hourcsv= hourcsv.rename(columns = {'00': '12AM', '01': '1AM', '02': '2AM', '03':␣
↪'3AM', '04': '4AM',
                                   '05': '5AM', '06': '6AM',
                         '07': '7AM', '08':'8AM', '09': '9AM', '10': '10AM',␣
↪'11': '11AM',
                                   '12': '12PM', '13': '1PM', '14': '2PM',
                         '15': '3PM', '16':'4PM', '17' : '5PM', '18': '6PM',␣
↪'19' : '7PM',
                                   '20': '8PM', '21': '9PM', '22': '10PM', '23':␣
↪'11PM'})
local_hour = local_hour.rename(columns = {'00': '12AM', '01': '1AM', '02':␣
↪'2AM', '03': '3AM', '04': '4AM',
                                   '05': '5AM', '06': '6AM',
                         '07': '7AM', '08':'8AM', '09': '9AM', '10': '10AM',␣
↪'11': '11AM',
                                   '12': '12PM', '13': '1PM', '14': '2PM',
                         '15': '3PM', '16':'4PM', '17' : '5PM', '18': '6PM',␣
↪'19' : '7PM',
                                   '20': '8PM', '21': '9PM', '22': '10PM', '23':␣
↪'11PM'})
hourcsv.columns = ['tract'] + ["oddratio_"+ str(col)
                              for col in hourcsv.columns if str(col) != 'tract']
local_hour.columns = ['tract'] + ["local_oddratio_"+ str(col)
                                 for col in local_hour.columns if str(col) !=␣
↪'tract']
```

```
weekdaycsv= weekdaycsv.rename(columns = {'0': 'Monday_oddratio', '1':␣
 ↪'Tuesday_oddratio',
                                         '2': 'Wednesday_oddratio', '3':␣
 ↪'Thursday_oddratio',
                            '4': 'Friday_oddratio', '5': 'Saturday_oddratio',
                                         '6': 'Sunday_oddratio'})
weekday_or_weekend = weekday_or_weekend.rename(columns = {'1':␣
 ↪'weekday_oddratio',
                                                          '0':␣
 ↪'weekend_oddratio'})
daytime_or_night = daytime_or_night.rename(columns = {'1': 'daytime_oddratio',
                                                      '0':'nighttime_oddratio'})
local_day = local_day.rename(columns = {'0': 'local_Monday_oddratio',
                                        '1': 'local_Tuesday_oddratio',
                                         '2': 'local_Wednesday_oddratio',
                                        '3': 'local_Thursday_oddratio',
                            '4': 'local_Friday_oddratio', '5':␣
 ↪'local_Saturday_oddratio',
                                         '6': 'local_Sunday_oddratio'})
local_weekday = local_weekday.rename(columns = {'1': 'local_weekday_oddratio',
                                                '0': 'local_weekend_oddratio'})
local_daytime = local_daytime.rename(columns = {'1': 'local_daytime_oddratio',
                                                '0':'local_nighttime_oddratio'})
neighbor_weekday = neighbor_weekday.rename(columns = {'1':␣
 ↪'neighbor_weekday_oddratio',
                                                      '0':␣
 ↪'neighbor_weekend_oddratio'})
neighbor_daytime = neighbor_daytime.rename(columns = {'1':␣
 ↪'neighbor_daytime_oddratio',
                                                      '0':
 ↪'neighbor_nighttime_oddratio'})
```

[20]:
```
output= output[['tract', 'id']]
missingcsv = missingcsv[['tract', 'miss_home_tract']]
localcsv= localcsv[['tract', 'local_tweets']]
id5csv = id5csv[['tract', 'userwith5_count']]
totaluserscsv = totaluserscsv[['tract', 'total_users']]
hometweets = hometweets[['tract', 'tweets_sent_from_home']]
tweetsh = hometract[['tract', 'tweets_hometract']]
neighborcsv = neighborcsv[['tract', 'neighbor_tweets']]
output = output.merge(
    missingcsv, on = 'tract', how = 'inner').merge(
    id5csv, on = 'tract', how = 'inner').merge(
    totaluserscsv, on = 'tract', how = 'inner').merge(
    tweetsh, on = 'tract', how = 'inner').merge(
    hometweets, on = 'tract', how = 'inner').merge(
    hourcsv, on = 'tract', how = 'inner').merge(
```

```
    weekdaycsv, on ='tract', how='inner').merge(
    weekday_or_weekend, on = 'tract', how ='inner').merge(
    daytime_or_night, on = 'tract', how = 'inner').merge(
    localcsv, on = 'tract', how = 'inner').merge(
    local_hour, on = 'tract', how = 'inner').merge(
    local_day, on = 'tract', how = 'inner').merge(
    local_weekday, on ='tract', how = 'inner').merge(
    local_daytime, on = 'tract', how = 'inner').merge(
    neighborcsv, on = 'tract', how = 'inner').merge(
    neighbor_weekday, on = 'tract', how = 'inner').merge(
    neighbor_daytime, on = 'tract', how = 'inner')
```

[21]:
```
output = output.rename(columns = {'id': 'total_tweets'})
output['count_miss_home_tract'] = output['miss_home_tract']
output['miss_home_tract'] = output['miss_home_tract']/output['total_tweets']
output['percent_of_tweets'] = output['total_tweets']/75368830
output['tweets_hometract'] = np.around(
    output['total_tweets'] - (output['total_tweets'] *␣
 ↪output['miss_home_tract'])).astype('int')
output['percent_of_tweets_ht'] = output['tweets_hometract']/75368830
output['percent_of_tweets_sent_from_home_alltwitter'] =␣
 ↪output['tweets_sent_from_home']/75368830
output['percent_of_tweets_sent_from_home_bytract'] =␣
 ↪output['tweets_sent_from_home']/output['total_tweets']
output['percent_of_users']= output['total_users']/163724
output['percent_of_users_5_tweet'] = output['userwith5_count']/
 ↪output['total_users']
output['other_weekday_oddratio'] = (output['total_tweets'] -␣
 ↪output['local_weekday_oddratio'] - output['neighbor_weekday_oddratio'])/
 ↪output['total_tweets']
output['other_weekend_oddratio'] = (output['total_tweets'] -␣
 ↪output['local_weekend_oddratio'] - output['neighbor_weekend_oddratio'])/
 ↪output['total_tweets']
output['other_daytime_oddratio'] = (output['total_tweets'] -␣
 ↪output['local_daytime_oddratio'] - output['neighbor_daytime_oddratio'])/
 ↪output['total_tweets']
output['other_nighttime_oddratio'] = (output['total_tweets'] -␣
 ↪output['local_nighttime_oddratio'] - output['neighbor_nighttime_oddratio'])/
 ↪output['total_tweets']
#producing the odd ratios for the hours, days, weekday, weekend, daytime,␣
 ↪nighttime
for i in hourcsv.columns:
    if i != 'tract':
        output[i] = output[i]/output['total_tweets']

for i in daytime_or_night.columns:
    if i != 'tract':
```

```
        output[i] = output[i]/output['total_tweets']

for i in weekdaycsv.columns:
    if i !='tract':
        output[i] = output[i]/output['total_tweets']

for i in weekday_or_weekend.columns:
    if i != 'tract':
        output[i] = output[i]/output['total_tweets']

for i in local_day.columns:
    if i != 'tract':
        output[i] = output[i]/output['total_tweets']
for i in local_hour.columns:
    if i != 'tract':
        output[i] = output[i]/output['total_tweets']
for i in local_weekday.columns:
    if i != 'tract':
        output[i] = output[i]/output['total_tweets']
for i in local_daytime.columns:
    if i != 'tract':
        output[i] = output[i]/output['total_tweets']
for i in neighbor_daytime.columns:
    if i != 'tract':
        output[i] = output[i]/output['total_tweets']
for i in neighbor_weekday.columns:
    if i != 'tract':
        output[i] = output[i]/output['total_tweets']

#geographical analysis
output['other_tweets'] = output['total_tweets'] - output['local_tweets'] -␣
 ↪output['neighbor_tweets']
output['percent_of_neighbor_tweets_pertract'] = output['neighbor_tweets']/␣
 ↪output['total_tweets']
output['percent_of_other_tweets_pertract'] = output['other_tweets']/
 ↪output['total_tweets']
```

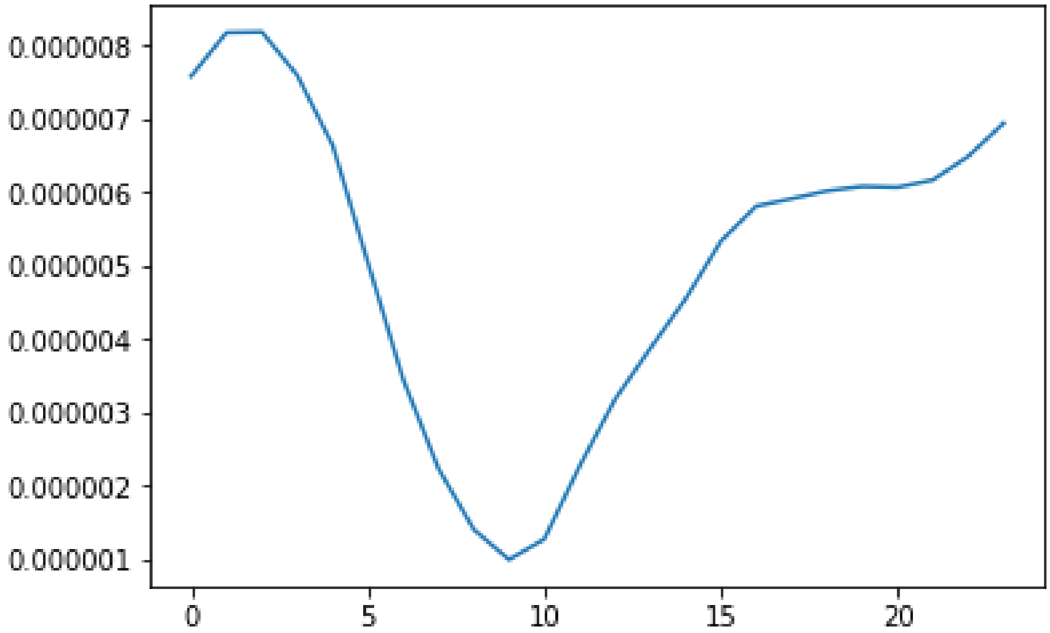
[22]:
```
output.to_csv('NYtwitter_output_12_17_2.csv', index = False)
```

4.1 VISUALIZATION

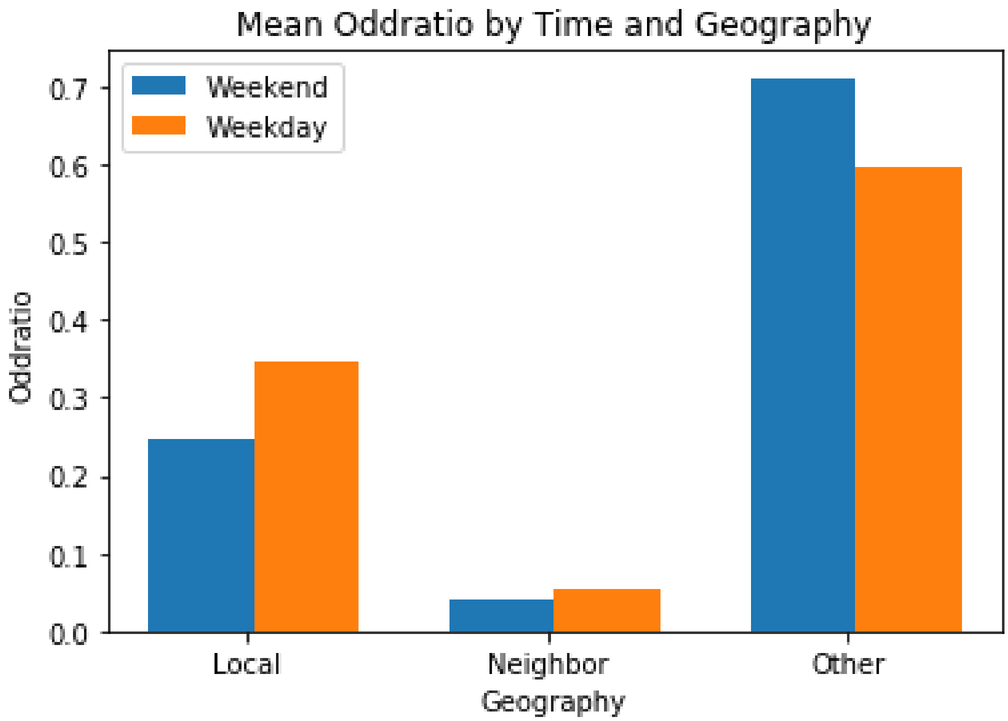
[12]:
```
meanhour=[]
for i in hourcsv.columns:
    if i != 'tract':
        meanhour.append(np.mean(output[i]/output['total_tweets']))
plt.plot(meanhour)
# 0 is 12AM - 23 is 11PM
```

```python
print('There are alot of tweets that occurred at night and after noon')
```

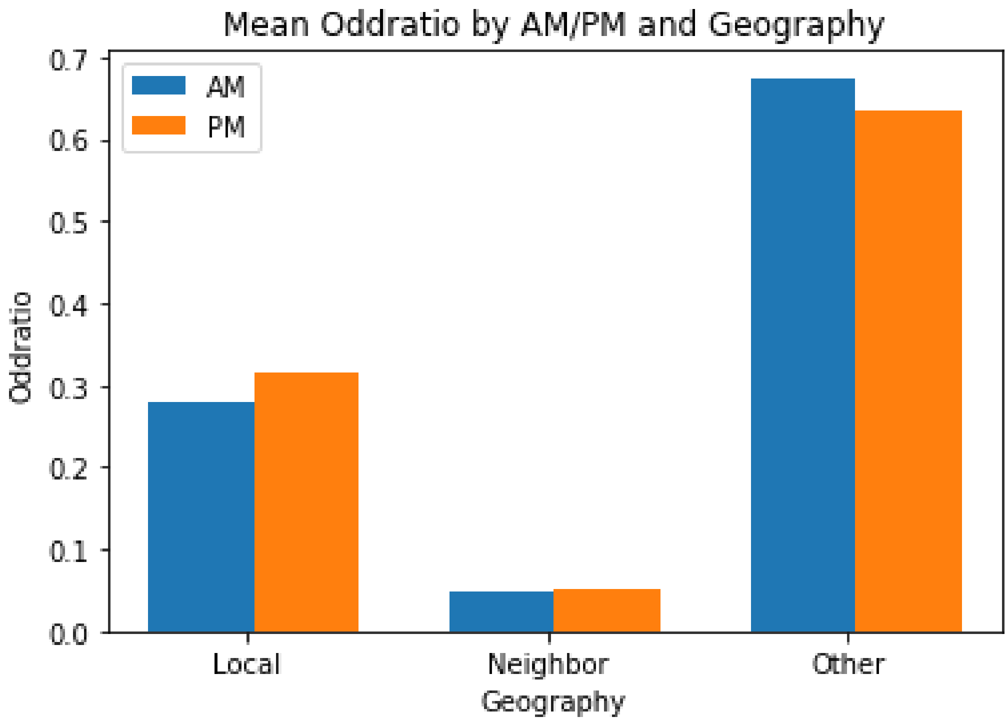
```
There are alot of tweets that occurred at night and after noon
```



[13]:
```python
n = np.arange(3)
bar_width = 0.35
plt.bar(n, [np.mean(output['local_weekend_oddratio']),
          np.mean(output['neighbor_weekend_oddratio']),
          np.mean(output['other_weekend_oddratio'])], bar_width,
            label = "Weekend" )
plt.bar(n + bar_width, [np.mean(output['local_weekday_oddratio']),
          np.mean(output['neighbor_weekday_oddratio']),
          np.mean(output['other_weekday_oddratio'])], bar_width,
       label = 'Weekday')
plt.xlabel("Geography")
plt.ylabel("Oddratio")
plt.xticks(n+ 0.15, ['Local', 'Neighbor', 'Other'])
plt.title("Mean Oddratio by Time and Geography")
plt.legend();
```



[14]:
```
n = np.arange(3)
bar_width = 0.35
plt.bar(n, [np.mean(output['local_daytime_oddratio']),
          np.mean(output['neighbor_daytime_oddratio']),
          np.mean(output['other_daytime_oddratio'])], bar_width,
            label = "AM" )
plt.bar(n + bar_width, [np.mean(output['local_nighttime_oddratio']),
          np.mean(output['neighbor_nighttime_oddratio']),
          np.mean(output['other_nighttime_oddratio'])], bar_width,
       label = 'PM')
plt.xlabel("Geography")
plt.ylabel("Oddratio")
plt.xticks(n+ 0.15, ['Local', 'Neighbor', 'Other'])
plt.title("Mean Oddratio by AM/PM and Geography")
plt.legend();
```



5 NON NEIGHBOR ANALYSIS on POWER USERS

We will be working with file2 on using only power users of the NY dataset. Below are the codes if you need to rerun them again if you started on this section without doing the sections above.

[ ]:
```
# ds = das.read_csv(file2)
#ds = ds.rename(columns = {'ny_with_homeloc.csv': 'id'})
# ds = ds.dropna(subset = ['home_tract'])
# ds = ds.dropna(subset= ['tract'])
# ds['tract'] = ds['tract'].astype('int')
# ds['home_tract'] = ds['home_tract'].astype('int')
```

This function create_csv will groupby tract and demographic variable such as nonwhite and income level. It will categorize and pivot table it so that the demographic variables will be column names. In each cell, there will be the number of tweets with the demographic variable condition for that tract. It will then convert the dataframe to a csv. We will use all the csvs and compile it to one csv output file later.

[11]:
```
def create_csv(demo_variable):
    g = other.groupby(['tract', demo_variable]).aggregate(
        {'u_id': 'count'}).reset_index()
    g = g.categorize(columns = demo_variable)
    g = g.pivot_table(values = 'u_id',
                      columns = demo_variable,
```

```
                         index = 'tract')
    g.to_csv('NY_' + demo_variable + '_*.csv')
```

[47]:
```
demo_var = pd.read_csv('NY_demo_variables_dummies.csv')
```

[13]:
```
demo_var = demo_var.rename(columns = {'GEOid2': 'home_tract'})
```

[14]:
```
#The values in the demo_var were True and False so we will convert it into␣
 ↪numbers
#so it will be easier to calculate.
demo_var['LI_under80'] = demo_var['LI_under80'].apply(lambda x: 1 if x == True␣
 ↪else 0)
demo_var['LI_above120'] =demo_var['LI_above120'].apply(lambda x: 1 if x == True␣
 ↪else 0)
demo_var['MI_80_120']= demo_var['MI_80_120'].apply(lambda x: 1 if x == True else␣
 ↪0)
demo_var['aboverm_per_col16']= demo_var['aboverm_per_col16'].apply(lambda x: 1␣
 ↪if x == True else 0)
demo_var['aboverm_per_nonwhite'] = demo_var['aboverm_per_nonwhite'].apply(lambda␣
 ↪x: 1 if x == True else 0)
```

Disclaimer: Some tracts do not have a Low, Middle, or High Income coding so it's all marked as 0. Thus, the total tweets will be counted beforehand.

[26]:
```
#Joining the non-neighbor table with the home tract variables csv (demo_var)
other = other.merge(demo_var, on = 'home_tract', how = 'inner')
```

[43]:
```
#Here we count the total tweets in each tract
other_count = other.groupby(['tract']).aggregate({'u_id': 'count'})
other_count = other_count.reset_index()
other_count = other_count.rename(columns = {'u_id': 'other_tweets'})
other_count.to_csv('ny_demo_one_user_countp2_*.csv')
```

[43]:
```
['ny_demo_one_user_countp2_0.csv']
```

[25]:
```
%%time
create_csv('LI_under80')
```

```
CPU times: user 3h 22min 7s, sys: 18min 49s, total: 3h 40min 56s
Wall time: 3h 7min 1s
```

[26]:
```
%%time
create_csv('LI_above120')
```

```
CPU times: user 2h 59min 1s, sys: 11min 46s, total: 3h 10min 48s
Wall time: 2h 52min 9s
```

[27]:
```
%%time
create_csv('MI_80_120')
```

```
CPU times: user 3h 11min 3s, sys: 16min 27s, total: 3h 27min 31s
Wall time: 2h 58min 20s
```

[30]:
```
%%time
create_csv('aboverm_per_col16')
```

```
CPU times: user 3h 19min 19s, sys: 18min 36s, total: 3h 37min 56s
Wall time: 3h 9min 56s
```

[29]:
```
%%time
create_csv('aboverm_per_nonwhite')
```

```
CPU times: user 3h 13min 7s, sys: 19min 17s, total: 3h 32min 24s
Wall time: 2h 57min 55s
```

[64]:
```
under80 = pd.read_csv('NY_LI_under80_0.csv') # 0 and 1
above120 = pd.read_csv('NY_LI_above120_0.csv') # 0 and 1
MI = pd.read_csv('NY_MI_80_120_0.csv') # 0 and 1
col15 = pd.read_csv('NY_aboverm_per_col16_0.csv') # 0 and 1
nonwhite = pd.read_csv('NY_aboverm_per_nonwhite_0.csv') # 0 and 1
```

[65]:
```
MI = MI[['tract', '1']].rename({'1': 'ct_othertweets_MI_80_120AMI'}, axis =1)
above120 = above120[['tract', '1']].rename({'1':␣
↪'ct_othertweets_HI_above_120AMI'}, axis =1)
under80 = under80[['tract', '1']].rename({'1': 'ct_othertweets_LI_under80AMI'},␣
↪axis =1)
nonwhite = nonwhite.rename({'1': 'ct_othertweets_aboverm_per_nonwhite',
                         '0': 'ct_othertweets_underm_per_nonwhite'}, axis = 1)
col15 = col15.rename({'1': 'ct_othertweets_aboverm_per_col',
                         '0': 'ct_othertweets_underm_per_col'}, axis =1)
```

[66]:
```
twitter_demo_ny = MI.merge(above120, on = 'tract', how = 'inner').merge(
under80, on = 'tract', how = 'inner').merge(
nonwhite, on = 'tract', how = 'inner').merge(
col15, on = 'tract', how = 'inner').merge(
pd.read_csv('ny_demo_one_user_count_0.csv'), on = 'tract', how = 'inner')
twitter_demo_ny= twitter_demo_ny.fillna(0)
# twitter_demo_ny['total_nonneighbortweets'] =␣
↪twitter_demo_ny['ct_othertweets_HI_above_120AMI'] +␣
↪twitter_demo_ny['ct_othertweets_LI_under80AMI'] +␣
↪twitter_demo_ny['ct_othertweets_MI_80_120AMI']
```

[67]:
```
for i in twitter_demo_ny.columns:
    if i not in ['Unnamed: 0', 'other_tweets', 'tract']:
        twitter_demo_ny['%_'+ i[2:len(i)]] = twitter_demo_ny[i]/
↪twitter_demo_ny['other_tweets']
```

[70]:
```
twitter_demo_ny.to_csv('Twitter_NN_NewYork_demog_11_20.csv')
```

[3]:
```
new = pd.read_csv('Twitter_NN_NewYork_demog_11_20.csv')
```

[ ]:
```
twitter_demo_ny
```

[12]:
```
#checking if the 31 counties are in the power user file
counties = ['36027', '36071', '36079', '36103', '36105', '36111',
            '34019', '34021', '34029', '34029', '34037', '34041']
```

[13]:
```
#counting the number of tweets in each counties.
ds['county'] = ds['tract'].apply(lambda x: str(x)[0:5] if str(x)[0] != '9' else␣
 ↪str(x)[0:4])
ds.groupby('county').aggregate({'id':'count'}).reset_index().
 ↪to_csv('test_countfull_*.csv')
```

```
/usr/local/linux/anaconda3/lib/python3.5/site-
packages/dask/dataframe/core.py:2184: UserWarning: `meta` is not specified,
inferred from partial data. Please provide `meta` if the result is unexpected.
  Before: .apply(func)
  After:  .apply(func, meta={'x': 'f8', 'y': 'f8'}) for dataframe result
  or:     .apply(func, meta=('x', 'f8'))            for series result
  warnings.warn(msg)
```

[13]: ['test_countfull_0.csv']

[ ]: