911 call Analysis

Description of the problem
911.csv contains the call details to 911 from different locations. Provide as many insights as possible which will assist first responders for prioritizing their focus. First responders would like to know which area had maximum calls and see whether there is any modeling possible

Description of the data and how it will be used to solve the problem.
911.csv, Dataset source - www.Kaggle.com

lat : String variable, Latitude
lng: String variable, Longitude
desc: String variable, Description of the Emergency Call
zip: String variable, Zipcode
title: String variable, Title
timeStamp: String variable, YYYY-MM-DD HH:MM:SS
twp: String variable, Township
addr: String variable, Address
**e: String variable, Dummy variable (always 1)
**

Below are the different steps that will be showcased in this project

1. **Exploratory analysis of the data**
2. **Visualization of data using sea born**
3. **Identification of a major spike and visualizations**
4. **Data Summarization and visualization using Seaborn and WordCloud**
5. **Visualization of the Townships from where calls originated using Folium**
6. **Identification of the different neighborhoods using Foursquare API**
7. **Logistic regression on the data and analysis**
8. **Clustering of the data**
9. **Conclusion**

In [1]:
```
# Import the required libraries
import pandas as pd
import numpy as np
from bs4 import BeautifulSoup
import requests
```

In [2]:
```
# Import KMeans and graphic libraries
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:
```
import folium
```

In [4]:
```
CLIENT_ID='ZOO51K0TRLO3V1BXETAEBMWHHIO2C0DXTW05UWSNGTBS5G0E'
CLIENT_SECRET='ODKWIW1VFAKDYQ1PQNNJQU1RQDCA2QMV0UNTHXJHPBCR422B'
VERSION='20181511'
LIMIT=30
```

911.csv, Dataset source - Kaggle

lat : String variable, Latitude</i>
lng: String variable, Longitude
desc: String variable, Description of the Emergency Call
zip: String variable, Zipcode
title: String variable, Title
timeStamp: String variable, YYYY-MM-DD HH:MM:SS
twp: String variable, Township
addr: String variable, Address
e: String variable, Dummy variable (always 1)

In [5]:

In [6]:

Out[6]:
```
Index(['lat', 'lng', 'desc', 'zip', 'title', 'timeStamp', 'twp', 'addr', 'e'], dty
pe='object')
```

In [7]:
```
# find out the size of the dataset
```

Out[7]:
```
(423909, 9)
```

In [8]:

Out[8]:

	lat	lng	desc	zip	title	timeStamp	twp	addr	e
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0	EMS: BACK PAINS/INJURY	2015-12-10 17:10:52	NEW HANOVER	REINDEER CT & DEAD END	1
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	2015-12-10 17:29:21	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1
2	40.121182	-75.351975	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401.0	Fire: GAS-ODOR/LEAK	2015-12-10 14:39:21	NORRISTOWN	HAWS AVE	1
3	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401.0	EMS: CARDIAC EMERGENCY	2015-12-10 16:47:36	NORRISTOWN	AIRY ST & SWEDE ST	1
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	NaN	EMS: DIZZINESS	2015-12-10 16:56:52	LOWER POTTSGROVE	CHERRYWOOD CT & DEAD END	1

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 423909 entries, 0 to 423908
Data columns (total 9 columns):
lat           423909 non-null float64
lng           423909 non-null float64
desc          423909 non-null object
zip           371780 non-null float64
title         423909 non-null object
timeStamp     423909 non-null object
twp           423750 non-null object
addr          423909 non-null object
e             423909 non-null int64
dtypes: float64(3), int64(1), object(5)
memory usage: 21.0+ MB
```

In [10]:
```
# Column title is in the format <short code> : <description>. Creating a new column sc
```

In [11]:

Out[11]:

	lat	lng	desc	zip	title	timeStamp	twp	addr	e
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0	EMS: BACK PAINS/INJURY	2015-12-10 17:10:52	NEW HANOVER	REINDEER CT & DEAD END	1
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	2015-12-10 17:29:21	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1
2	40.121182	-75.351975	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401.0	Fire: GAS-ODOR/LEAK	2015-12-10 14:39:21	NORRISTOWN	HAWS AVE	1
3	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401.0	EMS: CARDIAC EMERGENCY	2015-12-10 16:47:36	NORRISTOWN	AIRY ST & SWEDE ST	1
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	NaN	EMS: DIZZINESS	2015-12-10 16:56:52	LOWER POTTSGROVE	CHERRYWOOD CT & DEAD END	1

In [12]:
```
# twp apparently is Township. Just renaming the column to give it better sense
```

In [13]:
```
#Convering the zip to String removing and removing the decimal value
# Change nan to Not available to make it move readable
df['zip'] = df['zip'].astype(str)
df['zip'] = df['zip'].apply(lambda x : str(x).split('.')[0])
```

In [14]:

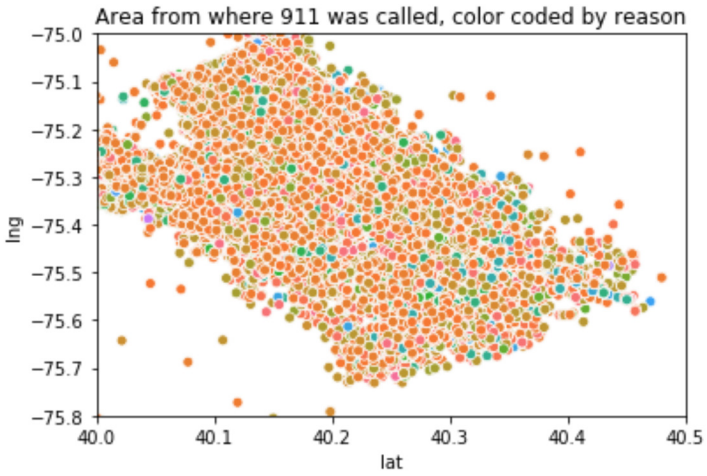
Out[14]:

	lat	lng	desc	zip	title	timeStamp	Township	addr	e
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525	EMS: BACK PAINS/INJURY	2015-12-10 17:10:52	NEW HANOVER	REINDEER CT & DEAD END	1
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446	EMS: DIABETIC EMERGENCY	2015-12-10 17:29:21	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1
2	40.121182	-75.351975	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401	Fire: GAS-ODOR/LEAK	2015-12-10 14:39:21	NORRISTOWN	HAWS AVE	1
3	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401	EMS: CARDIAC EMERGENCY	2015-12-10 16:47:36	NORRISTOWN	AIRY ST & SWEDE ST	1
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	Not Available	EMS: DIZZINESS	2015-12-10 16:56:52	LOWER POTTSGROVE	CHERRYWOOD CT & DEAD END	1

Lets start analyzing the data. Lets have a high level view on how the 911 calls are scattered, is it focused on a particular area or just scattered through out. Just to make it interesting , lets color code it based on the different title

In [15]:
```
sns.scatterplot(x='lat',y='lng',hue='title',data=df,legend=False)
plt.ylim(-75.8, -75)
plt.xlim(40, 40.5)
```

Out[15]: Text(0.5,1,'Area from where 911 was called, color coded by reason')



Looks like this does not help. Though it gives a general idea on the spread, it does not help in making any decisions. This is a crowded graph and is causing over plotting. Note that the legend is purposefully removed to make the graph visible

Lets get in to the dataset and find out moe about the data. Below table indicates that the maximum calls came from LOWER MERION. Below table shows the top 5 and bottom 5 Townships from where the calls originated

In [16]:
```
print('911 calls - Top 5 Townships')
print(df['Township'].value_counts().head(5))
print(' ')
print('911 calls - Bottom 5 Townships')
```

```
911 calls - Top 5 Townships
LOWER MERION    36441
ABINGTON        25835
NORRISTOWN      23883
UPPER MERION    22694
CHELTENHAM      19629
Name: Township, dtype: int64

911 calls - Bottom 5 Townships
HATFIELD BORO    865
BRYN ATHYN       835
GREEN LANE       259
PHILA COUNTY     172
LEHIGH COUNTY     95
Name: Township, dtype: int64
```

Lets start exploring the data. As one can see the 911 calls happen majorly for Vehicle accidents. As you can see top 2 reasons are related to Vehicles

In [183]:
```
df['title'] = df['title'].astype(str)
print("Top 5 ")
print(df['title'].value_counts().head(5))
print("Bottom 5 ")
```

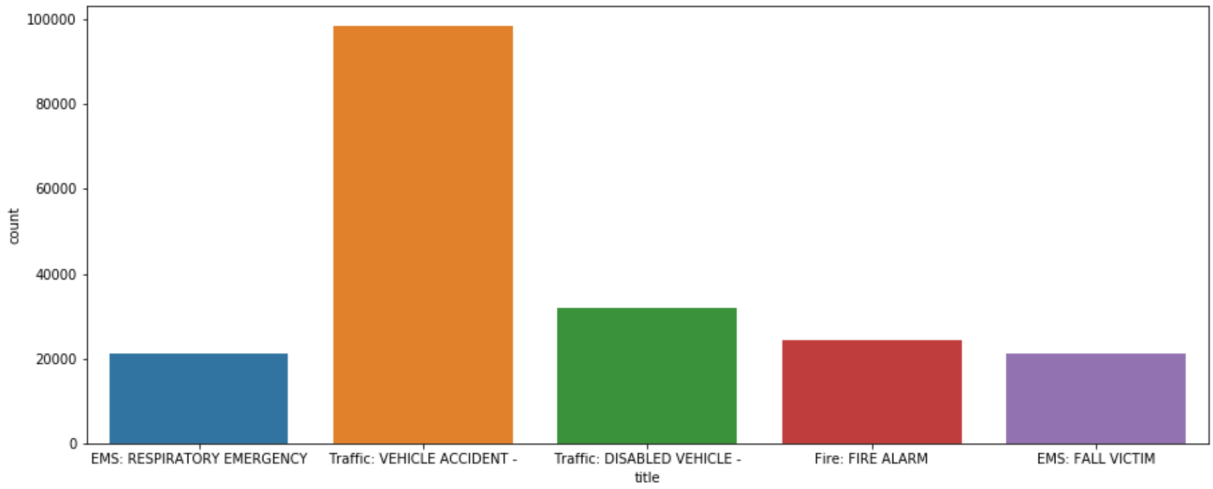
```
Top 5
Traffic: VEHICLE ACCIDENT -    98401
Traffic: DISABLED VEHICLE -    31871
Fire: FIRE ALARM               24380
EMS: FALL VICTIM               21253
EMS: RESPIRATORY EMERGENCY     21158
Name: title, dtype: int64
Bottom 5
EMS: HIT + RUN                 1
Fire: POISONING                1
Fire: UNRESPONSIVE SUBJECT     1
EMS: PUBLIC SERVICE            1
Fire: PRISONER IN CUSTODY      1
Name: title, dtype: int64
```

In [18]:
```
top5titles = ['Traffic: VEHICLE ACCIDENT -','Traffic: DISABLED VEHICLE -','Fire: FIRE
df_top5titles = df[df['title'].isin(top5titles)]
df_top5titles.head()
```

Out[18]:

	lat	lng	desc	zip	title	timeStamp	Township	addr
7	40.217286	-75.405182	COLLEGEVILLE RD & LYWISKI RD; SKIPPACK; Stati...	19426	EMS: RESPIRATORY EMERGENCY	2015-12-10 16:17:05	SKIPPACK	COLLEGEVILLE RD & LYWISKI RD
9	40.102398	-75.291458	BLUEROUTE & RAMP I476 NB TO CHEMICAL RD; PLYM...	19462	Traffic: VEHICLE ACCIDENT -	2015-12-10 17:35:41	PLYMOUTH	BLUEROUTE & RAMP I476 NB TO CHEMICAL RD
10	40.231990	-75.251891	RT202 PKWY & KNAPP RD; MONTGOMERY; 2015-12-10 ...	Not Available	Traffic: VEHICLE ACCIDENT -	2015-12-10 17:33:50	MONTGOMERY	RT202 PKWY & KNAPP RD
11	40.084161	-75.308386	BROOK RD & COLWELL LN; PLYMOUTH; 2015-12-10 @ ...	19428	Traffic: VEHICLE ACCIDENT -	2015-12-10 16:32:10	PLYMOUTH	BROOK RD & COLWELL LN
12	40.174131	-75.098491	BYBERRY AVE & S WARMINSTER RD; UPPER MORELAND;...	19040	Traffic: VEHICLE ACCIDENT -	2015-12-10 17:15:49	UPPER MORELAND	BYBERRY AVE & S WARMINSTER RD

In [19]:
```
# Visualize the 911 calls for the top 5 titles
plt.figure(figsize=(15,6))
sns.countplot(x='title',data=df_top5titles)
```



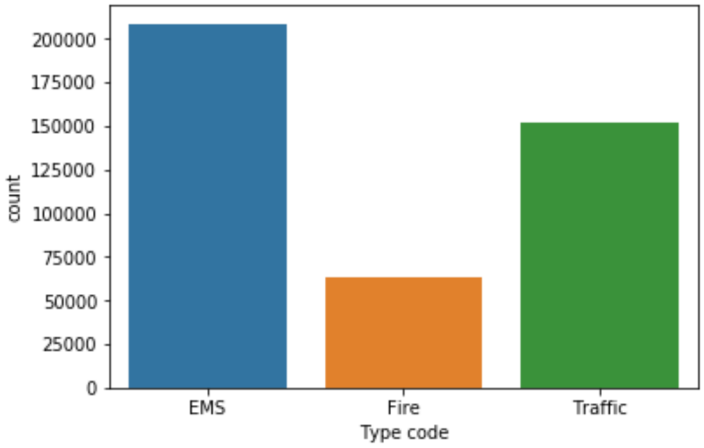
Looks like there are three different type codes available for the title..

1. **EMS**
2. **Fire**
3. **Traffic**

Below is the viualization of the 911 calls against these three categories

In [20]:

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0xfcd0d90>



Lets explore the calls based on different time parameters.. Note that the type needs to be changed before moving ahead

In [21]:

In [22]:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 423909 entries, 0 to 423908
Data columns (total 10 columns):
lat           423909 non-null float64
lng           423909 non-null float64
desc          423909 non-null object
zip           423909 non-null object
title         423909 non-null object
timeStamp     423909 non-null datetime64[ns]
Township      423750 non-null object
addr          423909 non-null object
e             423909 non-null int64
Type code     423909 non-null object
dtypes: datetime64[ns](1), float64(2), int64(1), object(6)
memory usage: 22.6+ MB
```

In [23]:

```
#Create three different columns to capture Hour, month and Week day seperately
df['Hour'] = df['timeStamp'].apply(lambda x: x.hour)
df['Month'] = df['timeStamp'].apply(lambda x: x.month).map({1:'Jan',2:'Feb',3:'Mar',4:
                                                            7:'Jul',8:'Aug',9:'Se
df['Week Day'] = df['timeStamp'].apply(lambda x: x.dayofweek).map({0:'Mon',1:'Tue',2:'
```

In [24]:

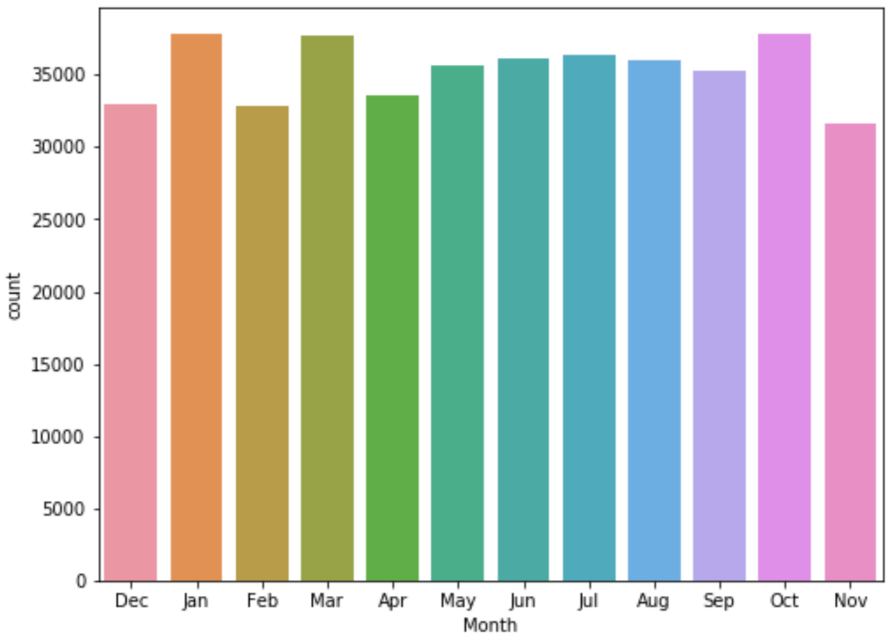
Out[24]:

	lat	lng	desc	zip	title	timeStamp	Township	addr	e	Type code
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525	EMS: BACK PAINS/INJURY	2015-12-10 17:10:52	NEW HANOVER	REINDEER CT & DEAD END	1	EMS
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446	EMS: DIABETIC EMERGENCY	2015-12-10 17:29:21	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1	EMS

Visualize the count of calls originated based on Month, week day and hour

In [25]:
```
plt.figure(figsize=(8,6))
```

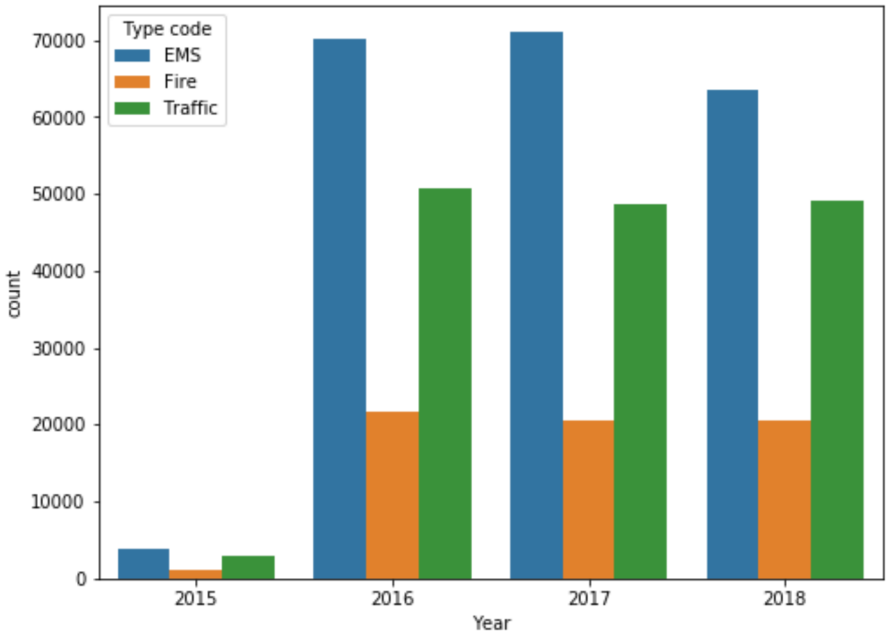
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x4b12610>



No definite pattern seen. Jan, Mar and Oct seems to be the highest hitters.. Other than that, no obvious pattern is seen. Lets move forward

In [26]:
```
plt.figure(figsize=(8,6))
```

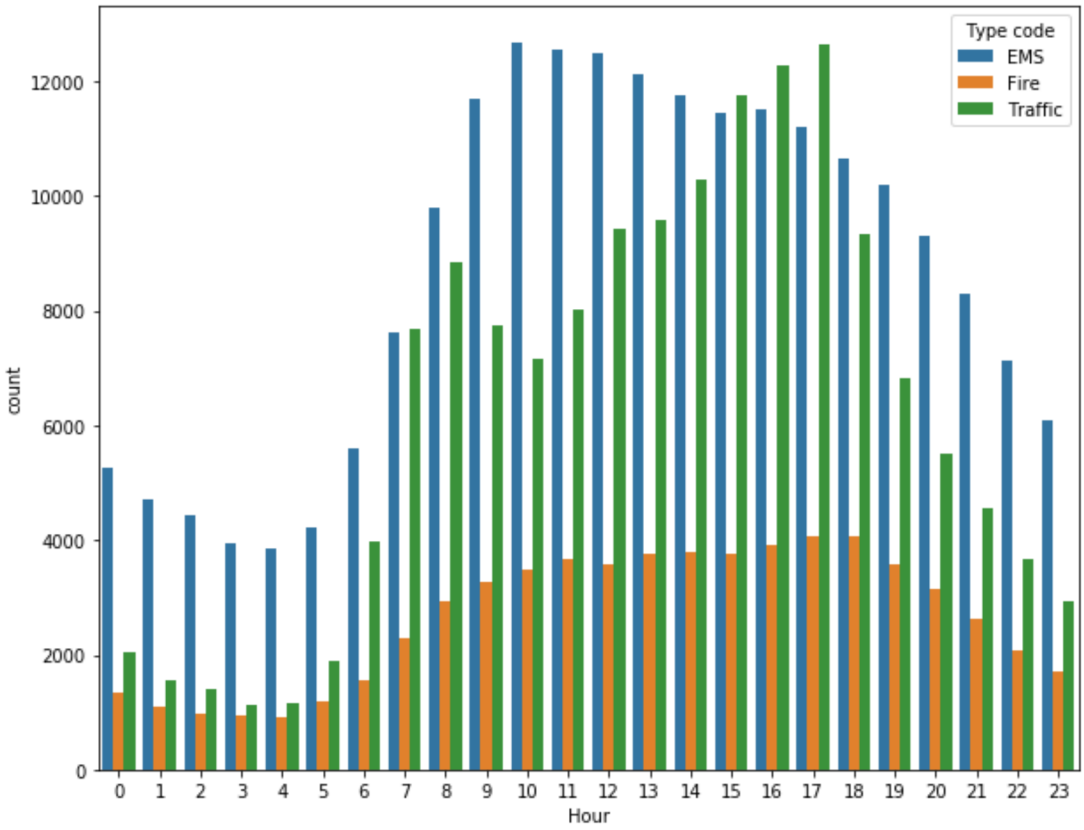
Out[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xffc18d0>
```



There seems to be a substantial jump in the number of call from 2015 to 2016.. This might be an anomaly. For all the years, the pattern seems to be the same for all three type codes, EMS type code is at the top , followed by Traffic and Fire

In [27]:
```
plt.figure(figsize=(10,8))
```

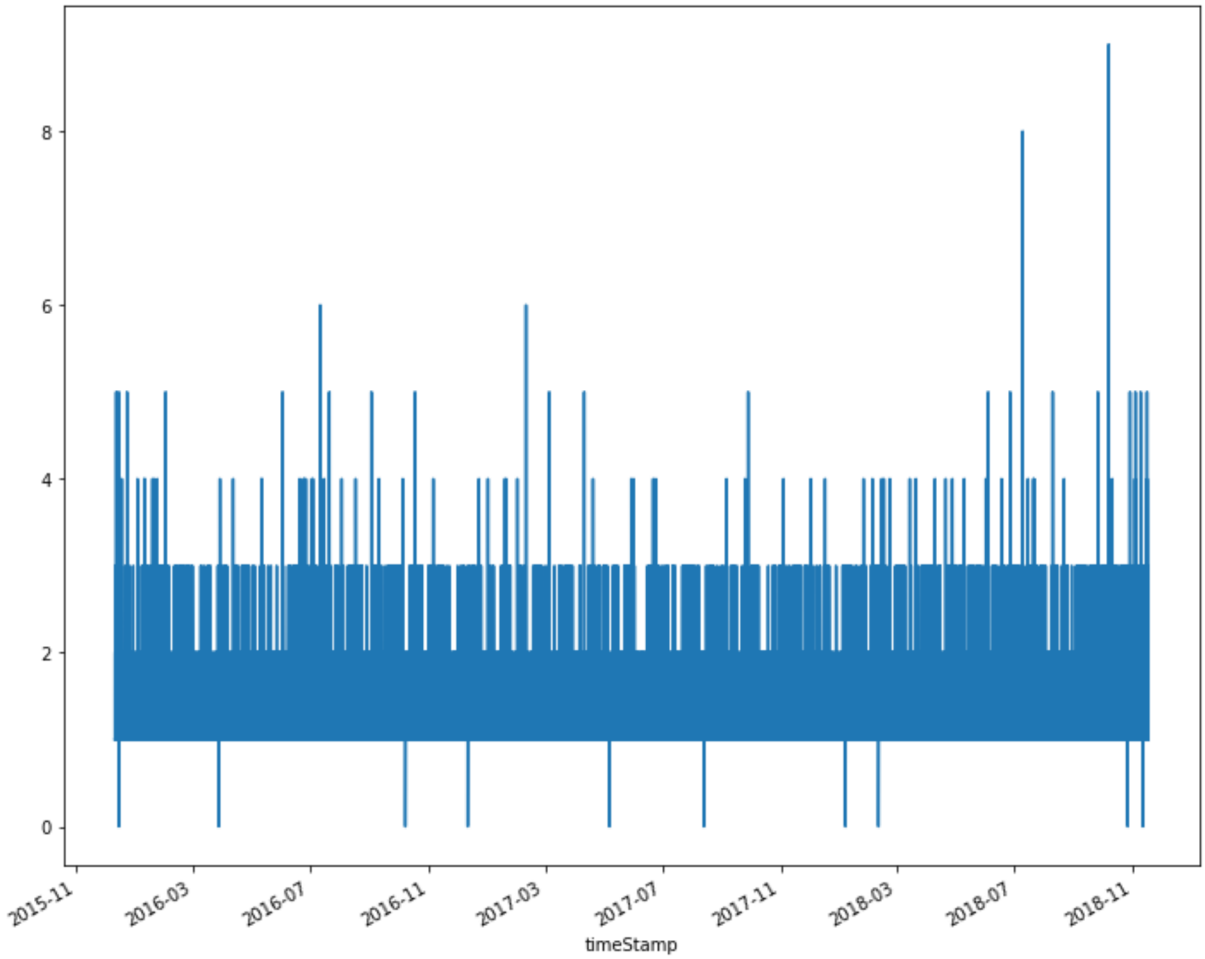
Out[27]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xfcbcd70>
```



1. Its interesting to note that, maximum calls happened between 4 PM and 6 PM for Traffic. May be because, that is the time when folks were rushing home
2. EMS related calls peaked at 09:00 AM and 10:00 AM and reducing as day progr eses
3. Fire related calls happened primariy during the business hours, reducing sh arply after 06:00 PM

Now lets try to plot the call on a time scale

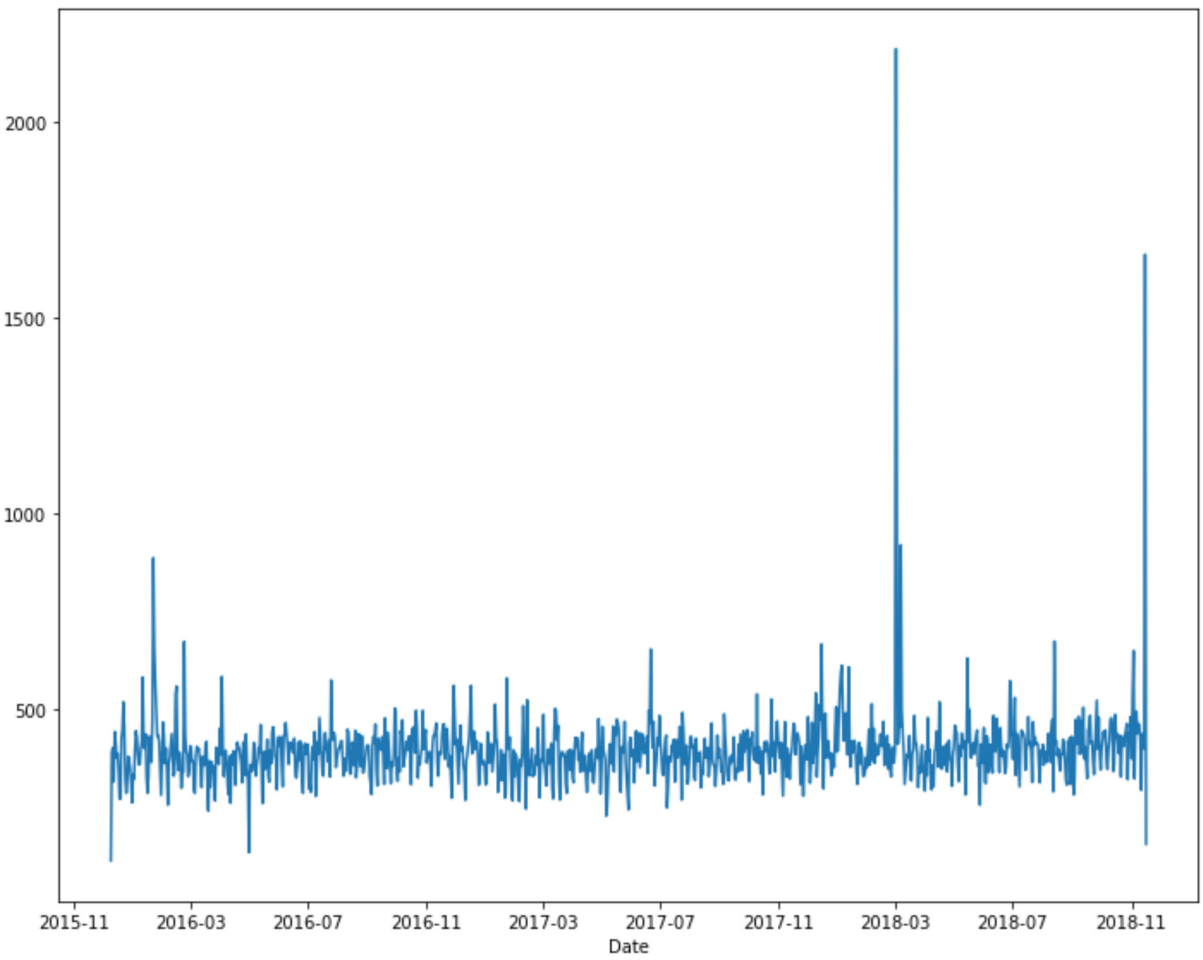
In [28]:
```
plt.figure(figsize=(10,8))
df.groupby('timeStamp').count()['Township'].plot()
```



The graph seems to be over crowded. Lets convert the timestamp to date and see whether the problem is getting sorted out

In [29]:

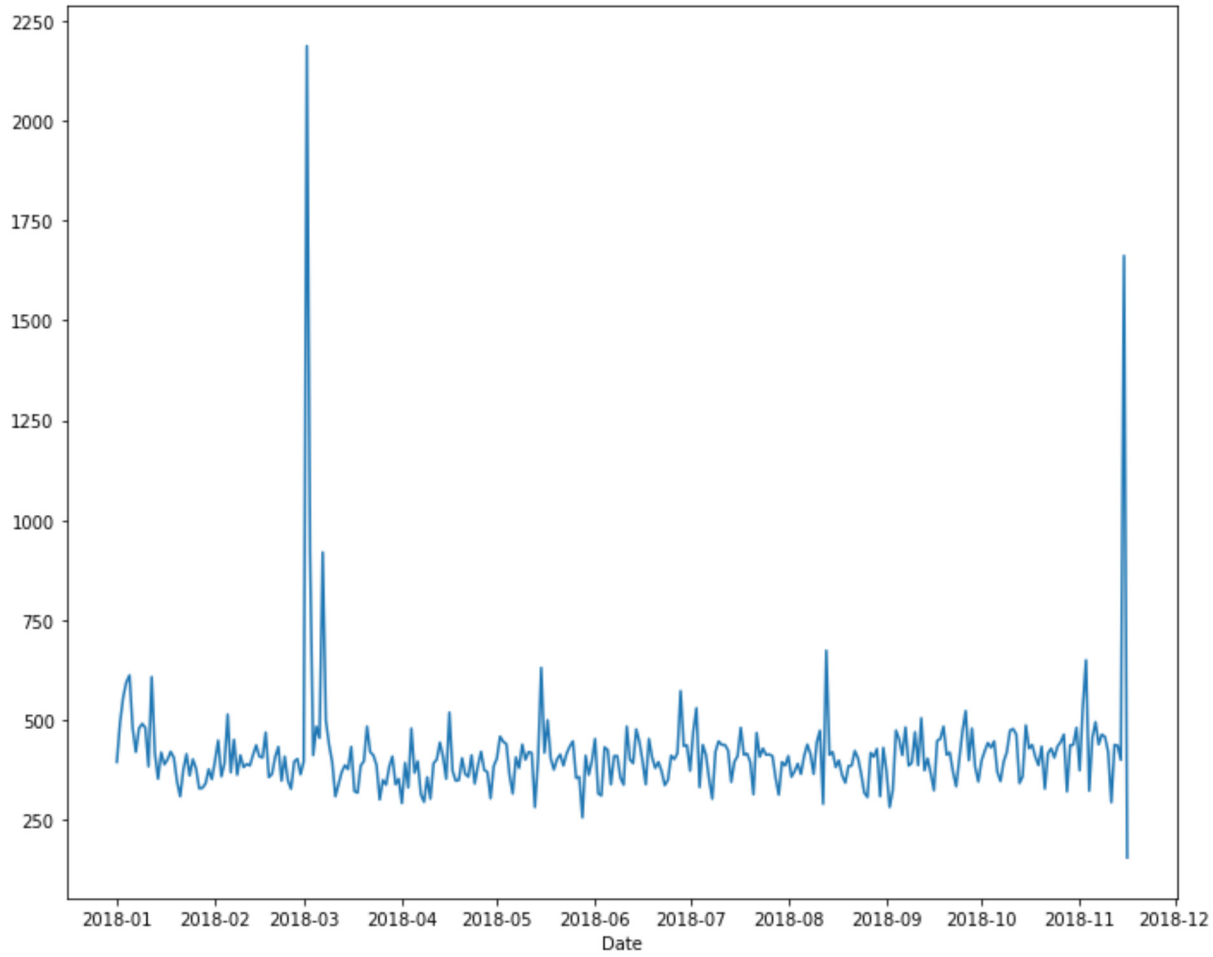
In [30]:
```
plt.figure(figsize=(10,8))
df.groupby('Date').count()['Township'].plot()
```



What happened during the 2018 time frame why this spike.. Lets try to drill down a bit more and try to figure out

In [31]:

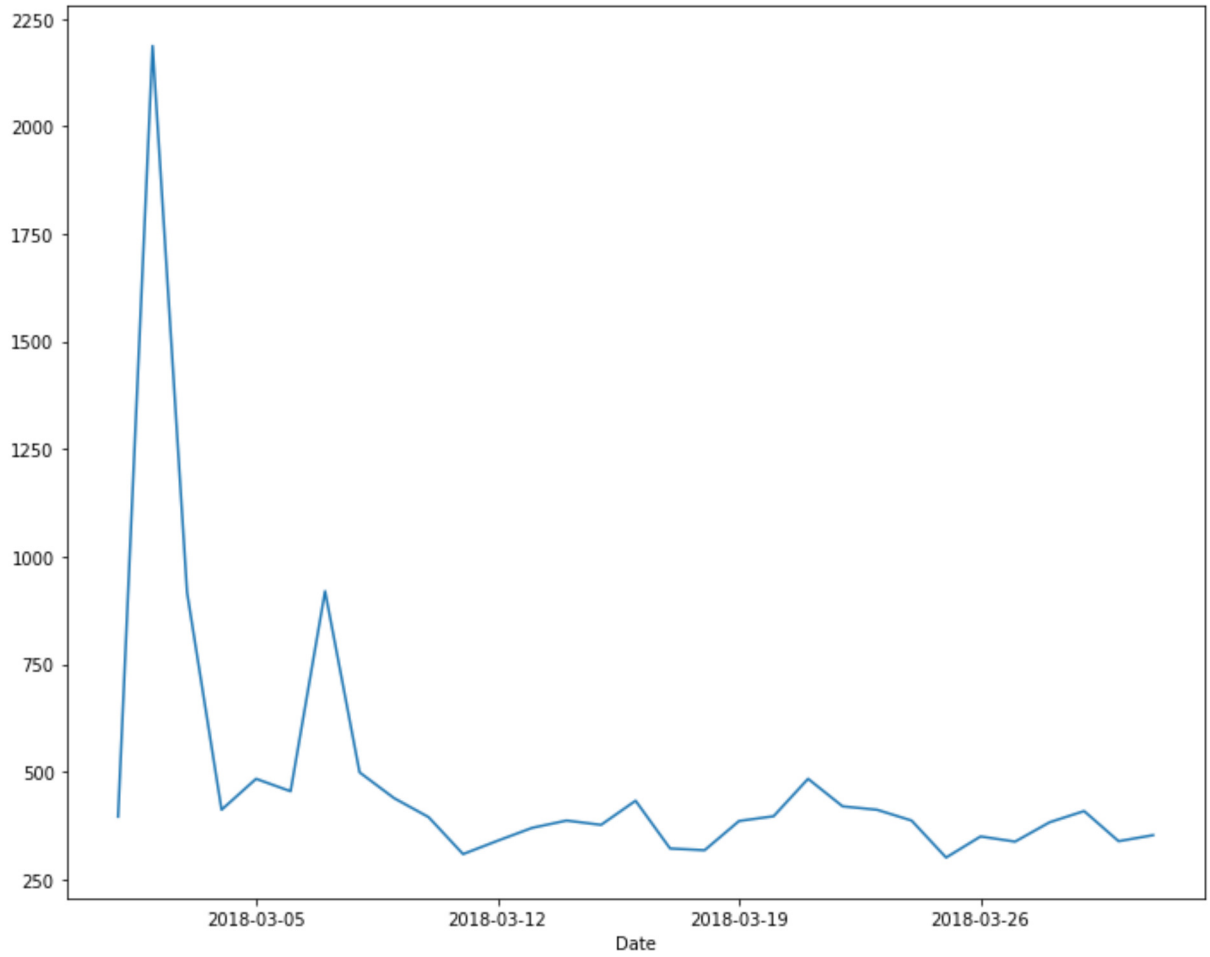
In [32]:
```
plt.figure(figsize=(10,8))
df_year2018.groupby('Date').count()['Township'].plot()
```



During the period of March, calls seems to have spiked.. Interesting. Lets drill down a bit more , this time with a hue on Type code

In [33]:

In [34]:
```
plt.figure(figsize=(10,8))
df_year2018_march.groupby('Date').count()['Township'].plot()
```



In [35]:
```
df_year2018_march['Dayno'] = df_year2018_march['Date'].apply(lambda x : x.day )
```

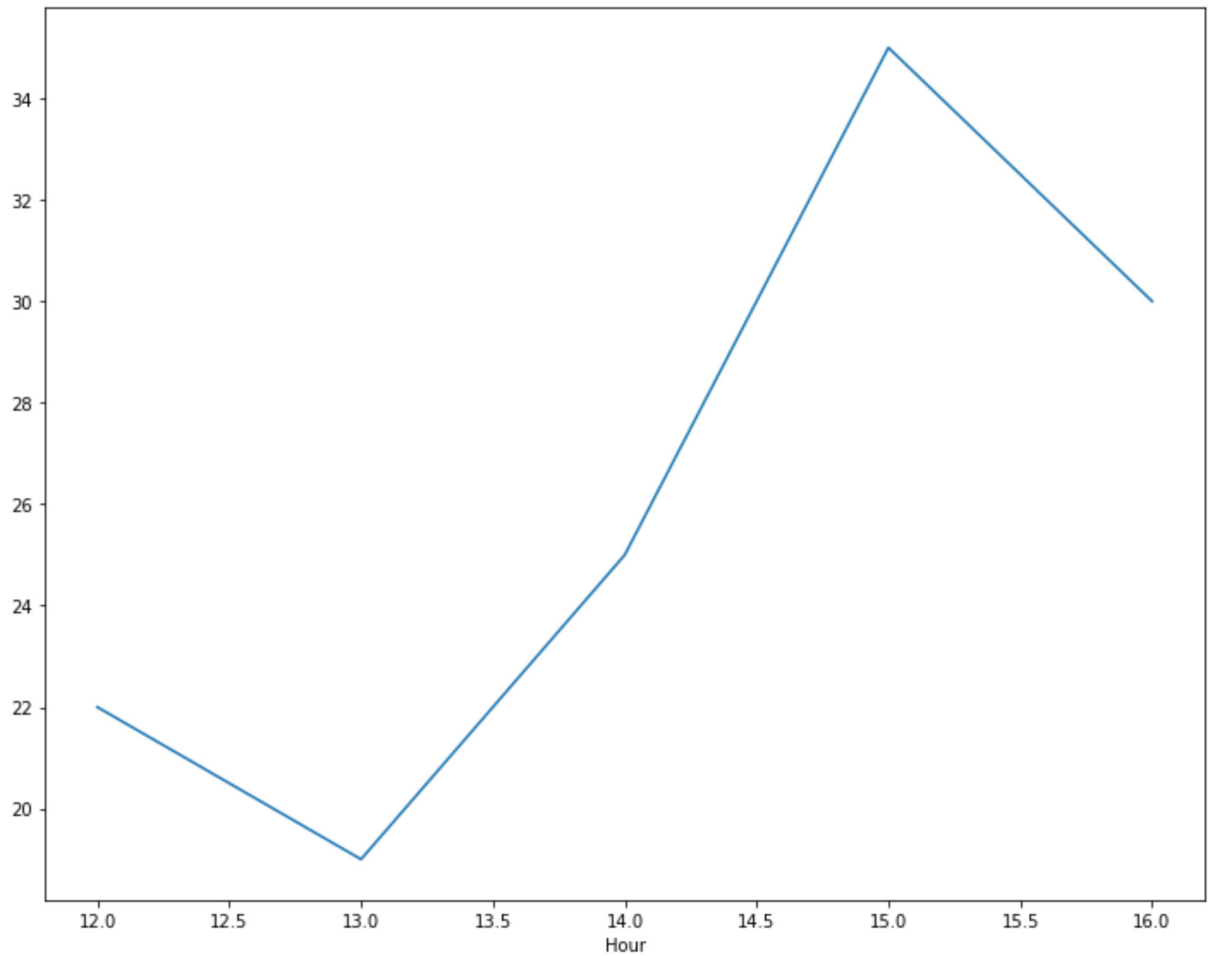
```
c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\ipy
kernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/
indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pandas-docs/stab
le/indexing.html#indexing-view-versus-copy)
  """Entry point for launching an IPython kernel.
```

In [36]:
```
plt.figure(figsize=(8,8))
df_year2018_march_df.groupby('Hour').count()['Township'].plot()
```

In [37]:

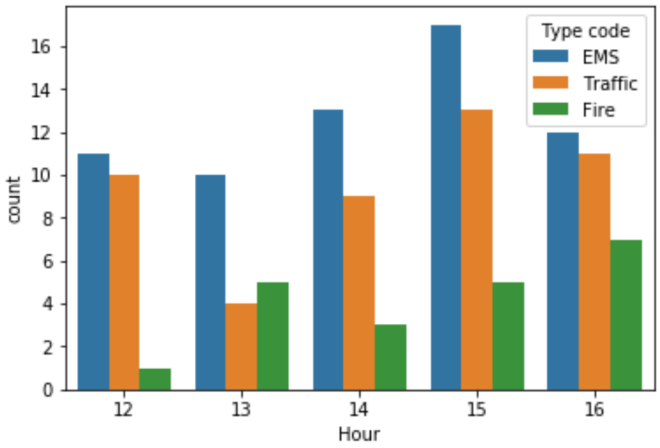
In [38]:
```
plt.figure(figsize=(10,8))
df_year2018_march_df_spiked.groupby('Hour').count()['Township'].plot()
```



Call spiked at 1:15:31

In [39]:

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x1c9893f0>



Above are the different calls that happened during the piked period

In [40]:

Out[40]:

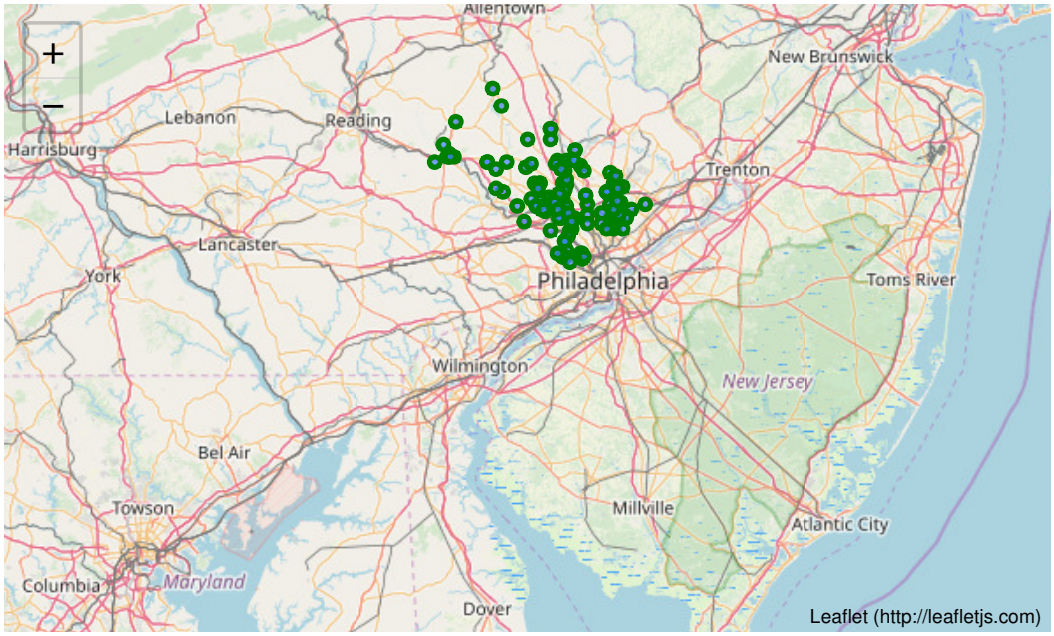
	lat	lng	desc	zip	title	timeStamp	Township	addr	e	T c
315040	40.236172	-75.278918	PENN ST & PARK DR; LANSDALE; Station 345; 201...	19446	EMS: ALLERGIC REACTION	2018-03-01 12:00:10	LANSDALE	PENN ST & PARK DR	1	E
315043	40.148557	-75.332151	W GERMANTOWN PIKE & SCENIC RD; EAST NORRITON; ...	19403	Traffic: VEHICLE ACCIDENT -	2018-03-01 12:01:49	EAST NORRITON	W GERMANTOWN PIKE & SCENIC RD	1	Tra

In [41]:
```
address = 'Philadelphia,USA'
geolocator = Nominatim()
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print(latitude,longitude)

mymap = folium.Map(location = [latitude, longitude],zoom_start=10)
for lat,long,name in zip(df_year2018_march_df_spiked['lat'],df_year2018_march_df_spike
    label = '{}'.format(name)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
          [lat, long],
          radius=3,
          popup=label,
          color='green',
          fill=True,
          fill_color='#4186FF',
          fill_opacity=0.7).add_to(mymap)
mymap
```

```
39.9524152 -75.1635755
```

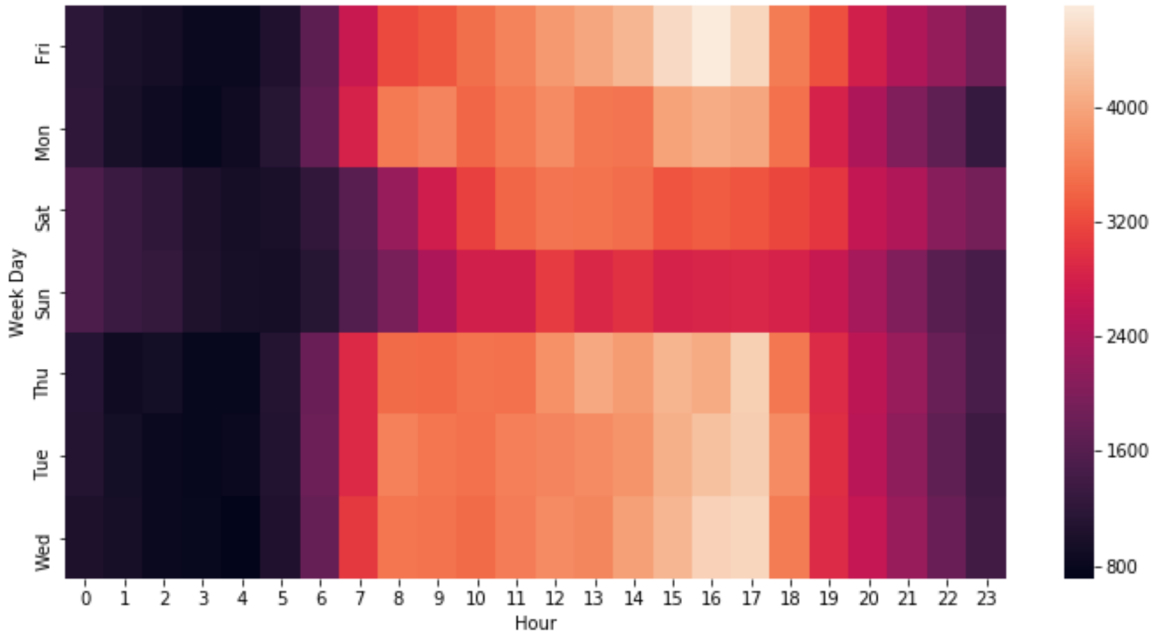
Out[41]:



Above are the coordinates in the map from where the calls happened

In [42]:
```
plt.figure(figsize=(12,6))
```

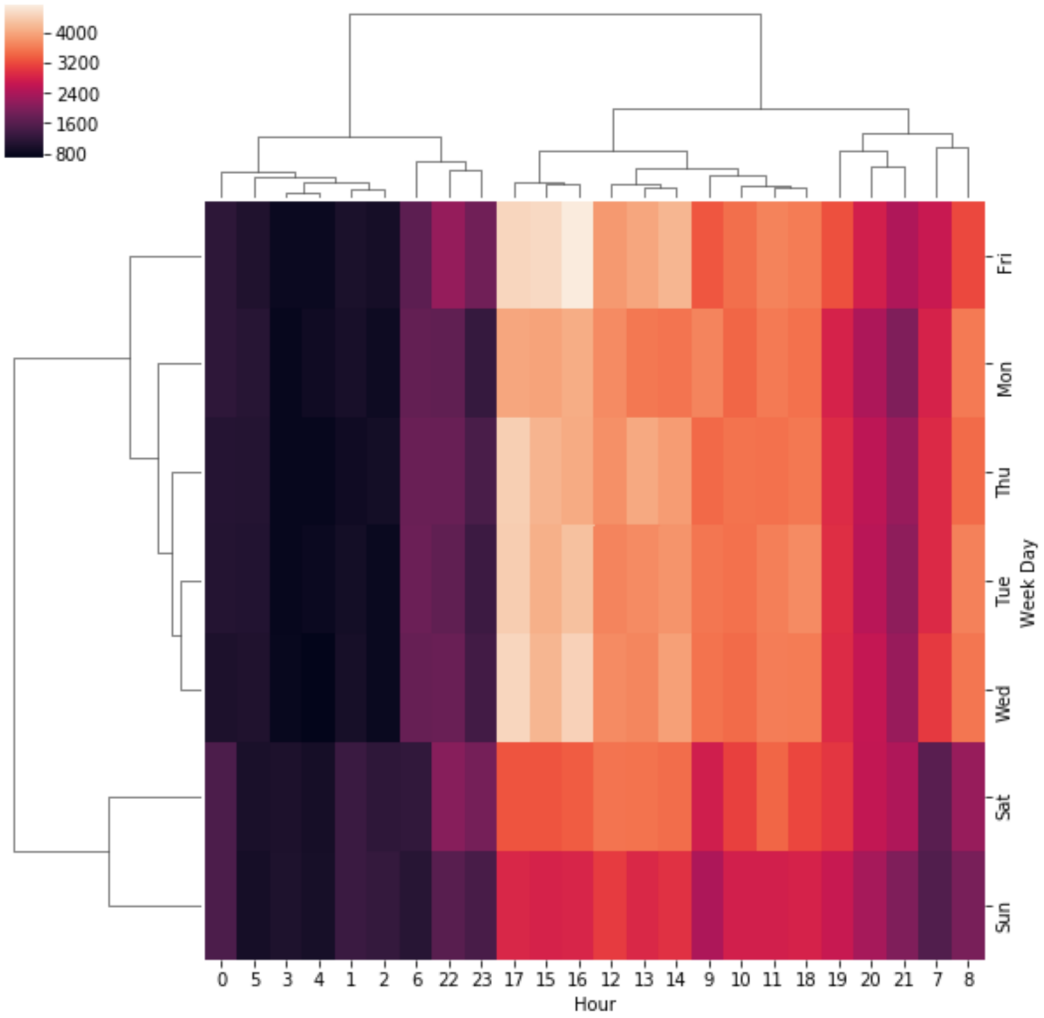
Out[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c352930>
```



Heat map on the 911 calls.. 17:00 during week days seems to be the time when most of the calls happen

In [43]:

Out[43]: <seaborn.matrix.ClusterGrid at 0xfc967b0>



Lets Generate a work cloud on the titles to see what pops up on the entire Dataset

In [44]:
```
df['title'][4:].to_csv('title.csv')
```

In [45]:
```
from wordcloud import WordCloud, STOPWORDS
```

In [46]:
```
cat_wc = WordCloud(
    background_color='white',
    max_words=2000,
    stopwords=stopwords
```

In [47]:

Out[47]: <wordcloud.wordcloud.WordCloud at 0x1af3e0b0>

In [48]:
```
fig = plt.figure()
fig.set_figwidth(14) # set width
fig.set_figheight(18) # set height

# display the cloud
plt.imshow(cat_wc, interpolation='bilinear')
plt.axis('off')
```

As expected , Vehicle accident and Traffic seems to be the one that is prominent

Now lets explore the venues around the areas when the spike happened. Above 2018 dataset is going to be the source

In [54]:
```
df_2018 = pd.read_csv('Data/Montgomery_2018.csv')
df_2018.head()
```

Out[54]:

	lat	lng	desc	zip	title	timeStamp	Township	
315040	40.236172	-75.278918	PENN ST & PARK DR; LANSDALE; Station 345; 201...	19446	EMS: ALLERGIC REACTION	2018-03-01 12:00:10	LANSDALE	PENN S
315043	40.148557	-75.332151	W GERMANTOWN PIKE & SCENIC RD; EAST NORRITON; ...	19403	Traffic: VEHICLE ACCIDENT -	2018-03-01 12:01:49	EAST NORRITON	W GERM PIKE &
315044	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401	EMS: CARDIAC EMERGENCY	2018-03-01 12:05:52	NORRISTOWN	A S\
315045	40.118073	-75.355405	LAFAYETTE ST & JAMISON ALY; NORRISTOWN; Stati...	19401	EMS: DIABETIC EMERGENCY	2018-03-01 12:03:36	NORRISTOWN	LAFAYE JAMI

In [72]:
```
df_venue_all = pd.DataFrame()
venues = None
for lat,long,name  in zip(df_year2018_march_df_spiked['lat'],df_year2018_march_df_spik
    url = 'https://api.foursquare.com/v2/venues/search?client_id={}&client_secret={}&l
    results = requests.get(url).json()
    try:
        venues = results['response']['venues']
        df_venues = json_normalize(venues)
        #print(df_venues.shape)
        df_venues['Township'] = name
        df_venues['Latitude'] = lat
        df_venues['Longitude'] = long
        df_venue_all = df_venue_all.append(df_venues)
    except:
        pass
```

In [73]:

Out[73]:
```
Index(['Latitude', 'Longitude', 'Township', 'categories', 'delivery.id',
       'delivery.provider.icon.name', 'delivery.provider.icon.prefix',
       'delivery.provider.icon.sizes', 'delivery.provider.name',
       'delivery.url', 'events.count', 'events.summary', 'hasPerk', 'id',
       'location.address', 'location.cc', 'location.city', 'location.country',
       'location.crossStreet', 'location.distance',
       'location.formattedAddress', 'location.labeledLatLngs', 'location.lat',
       'location.lng', 'location.neighborhood', 'location.postalCode',
       'location.state', 'name', 'referralId', 'venuePage.id'],
      dtype='object')
```

In [74]:
```
df_venue_all.drop(['delivery.id',
       'delivery.provider.icon.name', 'delivery.provider.icon.prefix',
       'delivery.provider.icon.sizes', 'delivery.provider.name',
       'delivery.url', 'events.count', 'events.summary', 'hasPerk', 'id','location.cc'
        'location.formattedAddress', 'location.labeledLatLngs','location.state', 'refe
```

In [75]:

Out[75]:

	Latitude	Longitude	Township	categories	location.address	location.crossStreet	location.
0	40.236172	-75.278918	LANSDALE	[{'id': '4f4533814b9074f6e4fb0106', 'name': 'M...	400 Penn St	NaN	
1	40.236172	-75.278918	LANSDALE	[{'id': '4bf58dd8d48988d1e8941735', 'name': 'B...	NaN	NaN	
2	40.236172	-75.278918	LANSDALE	[{'id': '4bf58dd8d48988d163941735', 'name': 'P...	300 E. Main St.	NaN	
3	40.236172	-75.278918	LANSDALE	[]	Broad street	NaN	
4	40.236172	-75.278918	LANSDALE	[{'id': '4bf58dd8d48988d1fb941735', 'name': 'H...	NaN	Line St. & Penn St.	

In [76]:
```
def get_category(row):
    category_list =  row['categories']
    if len(category_list)==0:
        return None
    else:
```

In [77]:
```
df_venue_all['categories'] = df_venue_all.apply(get_category,axis=1)
```

Out[77]:

	Latitude	Longitude	Township	categories	location.address	location.crossStreet	location.distance	location
0	40.236172	-75.278918	LANSDALE	Middle School	400 Penn St	NaN	46	40.235
1	40.236172	-75.278918	LANSDALE	Baseball Field	NaN	NaN	35	40.236
2	40.236172	-75.278918	LANSDALE	Park	300 E. Main St.	NaN	43	40.236
3	40.236172	-75.278918	LANSDALE	None	Broad street	NaN	598	40.241
4	40.236172	-75.278918	LANSDALE	Hobby Shop	NaN	Line St. & Penn St.	204	40.237

In [78]:

Out[78]:
```
Township
LOWER MERION          450
NORRISTOWN            270
HORSHAM               270
ABINGTON              240
POTTSTOWN             180
UPPER GWYNEDD         180
WHITEMARSH            180
PLYMOUTH              180
CHELTENHAM            150
UPPER MORELAND        150
EAST NORRITON         150
MONTGOMERY            150
WHITPAIN              150
WEST NORRITON         120
WORCESTER             120
LIMERICK               90
AMBLER                 60
SOUDERTON              60
SPRINGFIELD            60
UPPER PROVIDENCE       60
LOWER PROVIDENCE       60
LOWER MORELAND         60
CHESTER COUNTY         60
UPPER DUBLIN           60
HATBORO                60
RED HILL               30
UPPER MERION           30
DOUGLASS               30
EAST GREENVILLE        30
JENKINTOWN             30
FRANCONIA              30
SKIPPACK               30
LANSDALE               30
WEST POTTSGROVE        30
WEST CONSHOHOCKEN      30
PERKIOMEN              30
LOWER SALFORD          30
Name: Latitude, dtype: int64
```

In [184]:

Out[184]:

categories	
Office	137
Building	108
Doctor's Office	84
Automotive Shop	66
Gas Station	59
Church	58
Bank	51
Pizza Place	46
City	46
Medical Center	43
Bus Line	41
Gym	41
Dentist's Office	41
Intersection	41
Residential Building (Apartment / Condo)	41
Neighborhood	40
Salon / Barbershop	40
Other Great Outdoors	39
Park	38
Gym / Fitness Center	36
Miscellaneous Shop	32
Hotel	29
Mexican Restaurant	28
Nail Salon	28
Convenience Store	28
Café	27
Coffee Shop	24
Bar	23
American Restaurant	22
Fire Station	22
...	...
Fraternity House	1
Fountain	1
Market	1
Convention Center	1
Performing Arts Venue	1
Mattress Store	1
Outlet Mall	1
Other Repair Shop	1
Food Truck	1
Nursery School	1
Nightlife Spot	1
College Auditorium	1
Nature Preserve	1
Mountain	1
Motorcycle Shop	1
Motel	1
Mosque	1
College Quad	1
College Rec Center	1
Monument / Landmark	1
College Science Building	1
College Technology Building	1
Men's Store	1
Comic Shop	1
Community Center	1
Memorial Site	1
Meeting Room	1
Mediterranean Restaurant	1
Medical Supply Store	1
Yoga Studio	1

Most of the calls originated from LOWER MERION

In [81]:

Out[81]:
```
Index(['lat', 'lng', 'desc', 'zip', 'title', 'timeStamp', 'Township', 'addr',
       'e', 'Type code', 'Hour', 'Month', 'Week Day', 'Year', 'Date', 'Y'],
      dtype='object')
```

In [80]:

In [98]:
```
X = df[['lat', 'lng','Hour', 'Month', 'Week Day', 'Year']]
Y = df['Y']
X['Month'] = X['Month'].map({'Jan':1,'Feb':2,'Mar':3,'Apr':4,'May':5,'Jun':6,
                             'Jul':7,'Aug':8,'Sep':9,'Oct':10,'Nov':11,'Dec':12})
```

```
c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\ipy
kernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/
indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pandas-docs/stab
le/indexing.html#indexing-view-versus-copy)
  after removing the cwd from sys.path.
c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\ipy
kernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/
indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pandas-docs/stab
le/indexing.html#indexing-view-versus-copy)
  """
```

In [99]:

In [100]:

In [101]:
```
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
```

```
c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\skl
earn\linear_model\logistic.py:432: FutureWarning: Default solver will be changed t
o 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[101]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [102]:

In [103]:

In [104]:

```
              precision    recall  f1-score   support

           0       0.55      0.63      0.59     71013
           1       0.55      0.46      0.50     68877

   micro avg       0.55      0.55      0.55    139890
   macro avg       0.55      0.55      0.54    139890
weighted avg       0.55      0.55      0.55    139890
```

In [117]:

Out[117]:

```
0          NEW HANOVER
1    HATFIELD TOWNSHIP
2           NORRISTOWN
3           NORRISTOWN
4     LOWER POTTSGROVE
Name: Township, dtype: object
```

In [132]:

```
n = df['Township'].nunique()
t = df['Township'].unique()
tdict = {}
for i,tname in zip(range(n+1),t):
    tdict[tname] = i
tdict
```

In [143]:
```
df['Y'] = df['Type code'].apply(lambda x : 1 if x=='EMS' else 0)
X = df[['lat', 'lng','Hour', 'Month', 'Week Day', 'Year','nTownship']]
Y = df['Y']
X['Month'] = X['Month'].map({'Jan':1,'Feb':2,'Mar':3,'Apr':4,'May':5,'Jun':6,
                             'Jul':7,'Aug':8,'Sep':9,'Oct':10,'Nov':11,'Dec':12})
X['Week Day'] = X['Week Day'].map({'Mon':1,'Tue':2,'Wed':3,'Thu':4,'Fri':5,'Sat':6,'S
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
predictions = logmodel.predict(X_test)
from sklearn.metrics import classification_report
```

```
c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\ipy
kernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/
indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pandas-docs/stab
le/indexing.html#indexing-view-versus-copy)
  """
c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\ipy
kernel_launcher.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/
indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pandas-docs/stab
le/indexing.html#indexing-view-versus-copy)

c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\skl
earn\linear_model\logistic.py:432: FutureWarning: Default solver will be changed t
o 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

	precision	recall	f1-score	support
0	0.55	0.63	0.59	71013
1	0.55	0.46	0.50	68877
micro avg	0.55	0.55	0.55	139890
macro avg	0.55	0.55	0.54	139890
weighted avg	0.55	0.55	0.55	139890

In [136]:
```
n = df['title'].nunique()
t = df['title'].unique()
tdict = {}
for i,tname in zip(range(n+1),t):
    tdict[tname] = i
tdict
```

In [138]:
```
df['Y'] = df['Type code'].apply(lambda x : 1 if x=='EMS' else 0)

X = df[['lat', 'lng','Hour', 'Month', 'Week Day', 'Year','nTownship','ntitle']]
Y = df['Y']
X['Month'] = X['Month'].map({'Jan':1,'Feb':2,'Mar':3,'Apr':4,'May':5,'Jun':6,
                             'Jul':7,'Aug':8,'Sep':9,'Oct':10,'Nov':11,'Dec':12})
X['Week Day'] = X['Week Day'].map({'Mon':1,'Tue':2,'Wed':3,'Thu':4,'Fri':5,'Sat':6,'S
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
predictions = logmodel.predict(X_test)
from sklearn.metrics import classification_report,confusion_matrix
print(classification_report(y_test,predictions))
```

```
c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\ipy
kernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/
indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pandas-docs/stab
le/indexing.html#indexing-view-versus-copy)
  """
c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\ipy
kernel_launcher.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/
indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pandas-docs/stab
le/indexing.html#indexing-view-versus-copy)

c:\users\ibm_admin\appdata\local\programs\python\python36-32\lib\site-packages\skl
earn\linear_model\logistic.py:432: FutureWarning: Default solver will be changed t
o 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
              precision    recall  f1-score   support

           0       0.55      0.63      0.59     71013
           1       0.55      0.46      0.50     68877

   micro avg       0.55      0.55      0.55    139890
   macro avg       0.55      0.55      0.54    139890
weighted avg       0.55      0.55      0.55    139890

[[44976 26037]
 [37057 31820]]
```

In [145]:
```
```

Out[145]:
```
Index(['lat', 'lng', 'desc', 'zip', 'title', 'timeStamp', 'Township', 'addr',
       'e', 'Type code', 'Hour', 'Month', 'Week Day', 'Year', 'Date', 'Y',
       'nTownship', 'ntitle'],
      dtype='object')
```

In [150]:
```
n = df['desc'].nunique()
t = df['desc'].unique()
tdict = {}
for i,tname in zip(range(n+1),t):
    tdict[tname] = i
tdict
```

In [151]:
```
n = df['title'].nunique()
t = df['title'].unique()
tdict = {}
for i,tname in zip(range(n+1),t):
    tdict[tname] = i
tdict
```

In [160]:

In [161]:

Out[161]:
```
Index(['lat', 'lng', 'desc', 'zip', 'title', 'timeStamp', 'Township', 'addr',
       'e', 'Type code', 'Hour', 'Month', 'Week Day', 'Year', 'Date', 'Y',
       'nTownship', 'ntitle', 'ndesc'],
      dtype='object')
```

In [162]:

In [163]:
```
df_kmean['Month'] = df_kmean['Month'].map({'Jan':1,'Feb':2,'Mar':3,'Apr':4,'May':5,'J
                                'Jul':7,'Aug':8,'Sep':9,'Oct':10,'Nov':11,'Dec':12})
```

In [164]:

Out[164]:

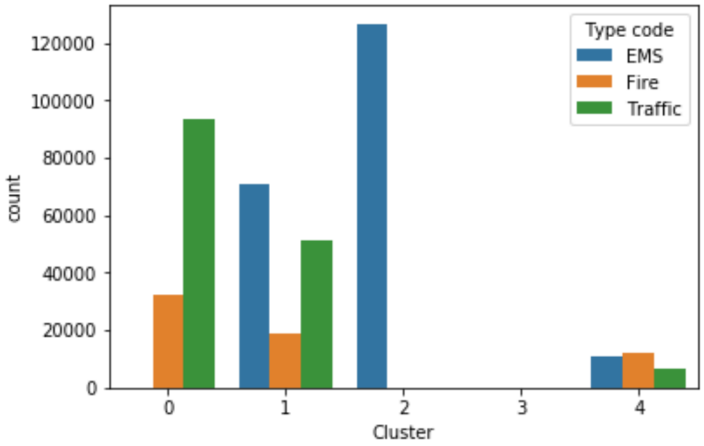
	lat	lng	Hour	Month	Week Day	Year	Y	nTownship	ntitle	ndesc
0	40.297876	-75.581294	17	12	4	2015	1	0	0	0
1	40.258061	-75.264680	17	12	4	2015	1	1	1	1
2	40.121182	-75.351975	14	12	4	2015	0	2	2	2
3	40.116153	-75.343513	16	12	4	2015	1	2	3	3
4	40.251492	-75.603350	16	12	4	2015	1	3	4	4

In [175]:
```
from sklearn.preprocessing import StandardScaler
df_kmean = StandardScaler().fit_transform(df_kmean)
c = 5

k_means = KMeans(init = "k-means++", n_clusters = c, n_init = 12)
k_means.fit(df_kmean)
```

In [181]:

Out[181]: <matplotlib.axes._subplots.AxesSubplot at 0x1af17d30>



In [178]:

Out[178]: 5

In [177]:

Out[177]:

	lat	lng	desc	zip	title	timeStamp	Township	addr	e	Type code	...
357795	22.986757	87.854975	RT202 SB & RAMP RT202 SB TO I76 WB; UPPER MERI...	Not Available	Traffic: VEHICLE ACCIDENT -	2018-06-11 16:59:29	UPPER MERION	RT202 SB & RAMP RT202 SB TO I76 WB	1	Traffic	...
369428	26.820553	30.802498	RAMP EGYPT RD TO RT422 EB & EGYPT RD; UPPER PR...	Not Available	Traffic: VEHICLE ACCIDENT -	2018-07-10 08:10:38	UPPER PROVIDENCE	RAMP EGYPT RD TO RT422 EB & EGYPT RD	1	Traffic	...
398440	0.000000	0.000000	RAMP EGYPT RD TO RT422 & EGYPT RD; UPPER PRO...	Not Available	EMS: UNKNOWN MEDICAL EMERGENCY	2018-09-20 07:07:49	UPPER PROVIDENCE	RAMP EGYPT RD TO RT422 & EGYPT RD	1	EMS	...
398739	22.986757	87.854975	RAMP RT202 SB TO I76 WB & RAMP N GULPH RD TO I...	Not Available	Traffic: DISABLED VEHICLE -	2018-09-20 20:01:42	UPPER MERION	RAMP RT202 SB TO I76 WB & RAMP N GULPH RD TO I...	1	Traffic	...
398740	22.986757	87.854975	RAMP RT202 SB TO I76 WB & RAMP N GULPH RD TO I...	Not Available	Traffic: DISABLED VEHICLE -	2018-09-20 20:02:29	UPPER MERION	RAMP RT202 SB TO I76 WB & RAMP N GULPH RD TO I...	1	Traffic	...

5 rows × 21 columns

In [179]:

Out[179]:

	lat	lng	desc	zip	title	timeStamp	Township	addr	e
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	Not Available	EMS: DIZZINESS	2015-12-10 16:56:52	LOWER POTTSGROVE	CHERRYWOOD CT & DEAD END	1
10	40.231990	-75.251891	RT202 PKWY & KNAPP RD; MONTGOMERY; 2015-12-10 ...	Not Available	Traffic: VEHICLE ACCIDENT -	2015-12-10 17:33:50	MONTGOMERY	RT202 PKWY & KNAPP RD	1
14	40.097222	-75.376195	SCHUYLKILL EXPY & CROTON RD UNDERPASS; UPPER M...	Not Available	Traffic: VEHICLE ACCIDENT -	2015-12-10 17:09:49	UPPER MERION	SCHUYLKILL EXPY & CROTON RD UNDERPASS	1
23	40.143326	-75.422819	RT422 & PAWLINGS RD OVERPASS; LOWER PROVIDENC...	Not Available	Traffic: DISABLED VEHICLE -	2015-12-10 18:00:38	LOWER PROVIDENCE	RT422 & PAWLINGS RD OVERPASS	1
24	40.153268	-75.189558	SUMMIT AVE & RT309 UNDERPASS; UPPER DUBLIN; 20...	Not Available	Traffic: VEHICLE ACCIDENT -	2015-12-10 17:58:22	UPPER DUBLIN	SUMMIT AVE & RT309 UNDERPASS	1

5 rows × 21 columns

Conclusion

1. **Data set has 423909 rows and 9 columns**
2. **maximum calls came from LOWER MERION, Least being LEHIGH COUNTY**
3. **Maximum calls happen due to Vehicle accidents**
4. **Calls belong to the below three categories**
   a. **EMS**
   b. **Fire**
   c. **Traffic**
5. **Calls under EMS category is the highest reason , followed by Fire and Traffic**
6. **Jan, Mar and Oct seems to be the highest hitters for the entire dataset**
7. **2015 data in the dataset seems to be having only a subset of the actual data. There seems to be a substantial jump in the number of call from 2015 to 2016.For all the years, the pattern seems to be the same for all three type codes, EMS type code is at the top , followed by Traffic and Fire**
8. **Maximum calls happened between 4 PM and 6 PM for Traffic**
9. **During March 2018 timeframe there has been a spike in the calls . Looking at the summary , looks like it is from LOWER MERION township that maximum calls originated Based on the different venues, looks like the calls originated which are near to Office building**
10. **Looking at the heat map, 17:00 during week days seems to be the time when most of the calls happen**
11. **Word cloud has Traffic accidents clearly standing out**
12. **Logitic regression does not yield good results, Probably the dataset does not have enough for logitic regression to work. Maximum accuracy that was achieved was just 55 %**
13. **Clustering algorithm, segrated all the records where the zip codes are not available.**
    a. **Cluster 0 - Maximum Traffic related calls**
    b. **Cluster 1 - Maximum EMS related calls**
    c. **Cluster 2 - Zip code is missing**
    d. **Cluster 3 - where the calls were at the minimum**

In [ ]: