911 Calls Capstone Project - Solutions

For this project, I analyzed some 911 call data from Kaggle. Being an exploratory analysis to better understand how emergency calls behave, where we can also answer where we should place facilities to better respond to these emergency calls.

The data contains the following fields:

```
→ 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)
```

However, I made some changes to the dataset to try to fix it with python, so I put some letters at the end of the values in the lat and lng columns, added some empty rows and columns.

Setup

Importing libraries that will be used

In [1]:
```
import pandas as pd
import numpy as np
```

Importing visualization libraries

In [2]:
```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid') # change the general style of the plots (just because I like
import io
from PIL import Image
from IPython import display
import cufflinks as cf
cf.go_offline()

# Displays output inline
%matplotlib inline
```

Loading the data

Loading the csv file as a dataframe called df

In [3]:
```
df = pd.read_csv('911_edit.csv', sep=';') # This file is too big to put on Github, so if
```

```
df.head(3)
```

Out[3]:

	lat	lng	desc	zip	title	timeStamp	twp	addr	
0	40,2978759	-75,5812935nn	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0	EMS: BACK PAINS/INJURY	10/12/2015 17:40	NEW HANOVER	REINDEER CT & DEAD END	1
1	40,2580614nn	-75,2646799	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	10/12/2015 17:40	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1
2	40,1211818	-75,3519752	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401.0	Fire: GAS-ODOR/LEAK	10/12/2015 17:40	NORRISTOWN	HAWS AVE	1

There are some letter at the end of values columns in the lat and lng that need to be removed. Also there are three empty columns which aren't nedded

---

Pre-processing

In [4]:
```
# removing null collumns
df.dropna(axis=1, how="all",inplace=True) # parameter HOW because we want to remove colu
print(df.columns)
```

```
Index(['lat', 'lng', 'desc', 'zip', 'title', 'timeStamp', 'twp', 'addr', 'e'], dtype='ob
ject')
```

In [5]:
```
# seeing if there are empty rows
df['lat'].isnull().value_counts()
```

Out[5]:
```
False    99492
True        17
Name: lat, dtype: int64
```

In [6]:
```
# removing null rows
df.dropna(axis=0, how='all', inplace=True)
df['lat'].isnull().value_counts()
```

Out[6]:
```
False    99492
Name: lat, dtype: int64
```

Function

In [7]:
```
# fix the letters in the lat and lng columns
def remove_nn(value):

    if type(value) is str:
        return value.replace('n','')
    else:
        return value

# test
remove_nn("406030nn")
```

Out[7]:
```
'406030'
```

In [8]:
```python
# apply in the collumns
df['lat'] = df['lat'].apply(remove_nn)
df['lng'] = df['lng'].apply(remove_nn)
df.head(5)
```

Out[8]:

	lat	lng	desc	zip	title	timeStamp	twp	addr	e
0	40,2978759	-75,5812935	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0	EMS: BACK PAINS/INJURY	10/12/2015 17:40	NEW HANOVER	REINDEER CT & DEAD END	1.0
1	40,2580614	-75,2646799	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	10/12/2015 17:40	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1.0
2	40,1211818	-75,3519752	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401.0	Fire: GAS-ODOR/LEAK	10/12/2015 17:40	NORRISTOWN	HAWS AVE	1.0
3	40,116153	-75,343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401.0	EMS: CARDIAC EMERGENCY	10/12/2015 17:40	NORRISTOWN	AIRY ST & SWEDE ST	1.0
4	40,251492	-75,6033497	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	NaN	EMS: DIZZINESS	10/12/2015 17:40	LOWER POTTSGROVE	CHERRYWOOD CT & DEAD END	1.0

In [9]:
```python
# The changes that I made broke the timeStamp column, so I will replace the column of th
df_or = pd.read_csv("911.csv")
df_or.head()
```

Out[9]:

	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 [10]:
```
df['timeStamp'] = df_or['timeStamp']
df.head()
```

Out[10]:

	lat	lng	desc	zip	title	timeStamp	twp	addr	e
0	40,2978759	-75,5812935	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	1.0
1	40,2580614	-75,2646799	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	2015-12-10 17:29:21	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1.0
2	40,1211818	-75,3519752	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	1.0
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	1.0
4	40,251492	-75,6033497	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	NaN	EMS: DIZZINESS	2015-12-10 16:56:52	LOWER POTTSGROVE	CHERRYWOOD CT & DEAD END	1.0

Check the info() of the df

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 99492 entries, 0 to 99508
Data columns (total 9 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   lat        99492 non-null  object 
 1   lng        99492 non-null  object 
 2   desc       99492 non-null  object 
 3   zip        86637 non-null  float64
 4   title      99492 non-null  object 
 5   timeStamp  99492 non-null  object 
 6   twp        99449 non-null  object 
 7   addr       98973 non-null  object 
 8   e          99492 non-null  float64
dtypes: float64(2), object(7)
memory usage: 7.6+ MB
```

In [12]:
```
# Converting the lat and lng to float
""" obs: My excel is in Portuguese so when I changed the values in the first two columns
the decimal separator changed. So I needed to switch to """

df['lat'] = df['lat'].str.replace(',','.').astype(float)
df['lng'] = df['lng'].str.replace(',','.').astype(float)

# Converting "e" column to int64 (just to be the same as the original dataset)
df['e'] = df['e'].astype('int64')
```

In [13]:
```
# See the type of "timeStamp" column
type(df['timeStamp'].iloc[0])
```

Out[13]: str

In [14]:
```
# We can't work with data in str type, so it's necessary to convert the timeStamp colum
df['timeStamp'] = pd.to_datetime(df['timeStamp'])
```

In [15]:
```
type(df['timeStamp'].iloc[0]) # now we can manipulate dates and times

# Work with timeStamp becomes possible grab specific attributes from a Datetime object b
```

Out[15]:
```
pandas._libs.tslibs.timestamps.Timestamp
```

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 99492 entries, 0 to 99508
Data columns (total 9 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   lat        99492 non-null  float64
 1   lng        99492 non-null  float64
 2   desc       99492 non-null  object
 3   zip        86637 non-null  float64
 4   title      99492 non-null  object
 5   timeStamp  99492 non-null  datetime64[ns]
 6   twp        99449 non-null  object
 7   addr       98973 non-null  object
 8   e          99492 non-null  int64
dtypes: datetime64[ns](1), float64(3), int64(1), object(4)
memory usage: 7.6+ MB
```

In [17]:
```
# Removing outliers
# We have 3 latitudes that are very different from the other values, indicating that the
df.lat.sort_values()
```

Out[17]:
```
67120    30.333596
25726    32.387090
57273    39.745533
88516    39.745533
75249    39.956497
           ...
13604    40.584929
57577    40.584929
71621    40.584929
7761     40.584929
8378     41.167156
Name: lat, Length: 99492, dtype: float64
```

In [18]:
```
df.lng.sort_values()
```

Out[18]:
```
67120   -95.595595
25726   -86.276106
57273   -84.395256
88516   -84.395256
63388   -77.686813
           ...
48628   -75.012379
11295   -75.008877
52019   -75.008041
1528    -75.000755
52063   -74.995041
Name: lng, Length: 99492, dtype: float64
```

In [19]:
```
df.drop([67120,25726,8378], inplace=True) # Removing by index that we can see above
```

Thus, the pre-processing step ends here

Analytics

Find the top 5 zipcodes for 911 calls

In [20]:
```
df['zip'].value_counts().head(5)
```

Out[20]:
```
19401.0    6979
19464.0    6643
19403.0    4854
19446.0    4748
19406.0    3174
Name: zip, dtype: int64
```

Top 5 townships (twp) for 911 calls

In Brazil, we doesn't have this kind of division so it was a little strange for me. I assumed it's like cities (many quotes hahah)

In [21]:
```
df['twp'].value_counts().head(5)
```

Out[21]:
```
LOWER MERION    8443
ABINGTON        5977
NORRISTOWN      5890
UPPER MERION    5227
CHELTENHAM      4575
Name: twp, dtype: int64
```

Unique title codes

To see how many kinds of emergency kinds are in the dataset

In [22]:
```
df['title'].nunique()
```

Out[22]:
```
110
```

Creating new features

In the titles column there are "Reasons/Departments" specified before the title code

In [23]:
```
# Create a new column called "Reason" that contains only the title code **
df['Reason'] = df['title'].apply(lambda title: title.split(':')[0])
```

In [24]:
```
reason_count = df['Reason'].value_counts()
reason_count_p = df['Reason'].value_counts(normalize=True)
pd.concat([reason_count, round(reason_count_p,2)], axis=1, keys=['count', 'percentage'])
```

Out[24]:

	count	percentage
EMS	48875	0.49
Traffic	35694	0.36
Fire	14920	0.15

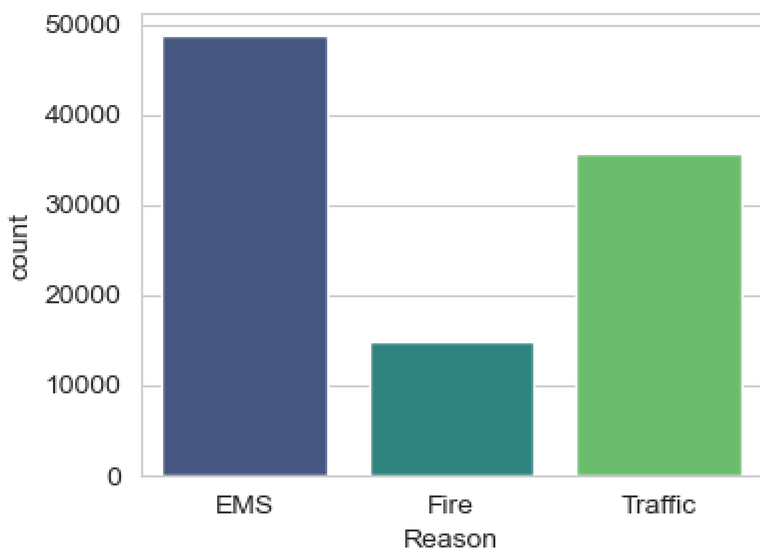
We can see that the dataset has three categories EMS, Fire, and Traffic.

Also, the most common emergency is EMS (almost 50% of the cases) which is a emergency services that provide urgent pre-hospital treatment and stabilisation for serious illness and injuries and transport to definitive care. It is important to note that this classification can be confused with "Traffic" and vice versa.

Using seaborn to create a countplot of 911 calls by Reason.

In [25]:
```
plt.figure(figsize=(4,3))
sns.countplot(x='Reason',data=df,palette='viridis')
```

Out[25]: <AxesSubplot:xlabel='Reason', ylabel='count'>



To focues in time information, I created 3 new columns called Hour, Month, and Day of Week to understand the distribution and whether there are any patterns

In [26]:
```
# using the lambda function as it is a simple and punctual function

df['Hour'] = df['timeStamp'].apply(lambda time: time.hour)
df['Month'] = df['timeStamp'].apply(lambda time: time.month)
df['Year']= df['timeStamp'].apply(lambda time: time.year)
df['Day of Week'] = df['timeStamp'].apply(lambda time: time.dayofweek)
df.head(2)
```

Out[26]:

	lat	lng	desc	zip	title	timeStamp	twp	addr	e	Reason
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	EMS
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	EMS

The Day of Week is an integer 0-6. So using the .map() with a dictionary to map the actual string names to the day of the week:

In [27]:
```
dmap = {0:'Mon',1:'Tue',2:'Wed',3:'Thu',4:'Fri',5:'Sat',6:'Sun'}
```

In [28]:
```
df['Day of Week'] = df['Day of Week'].map(dmap)
df.head(2)
```

Out[28]:

	lat	lng	desc	zip	title	timeStamp	twp	addr	e	Reason
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	EMS
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	EMS

In [29]:
```
print(f"Min. Date: {df['timeStamp'].min()}")
print(f"Max. Date: {df['timeStamp'].max()}")
```

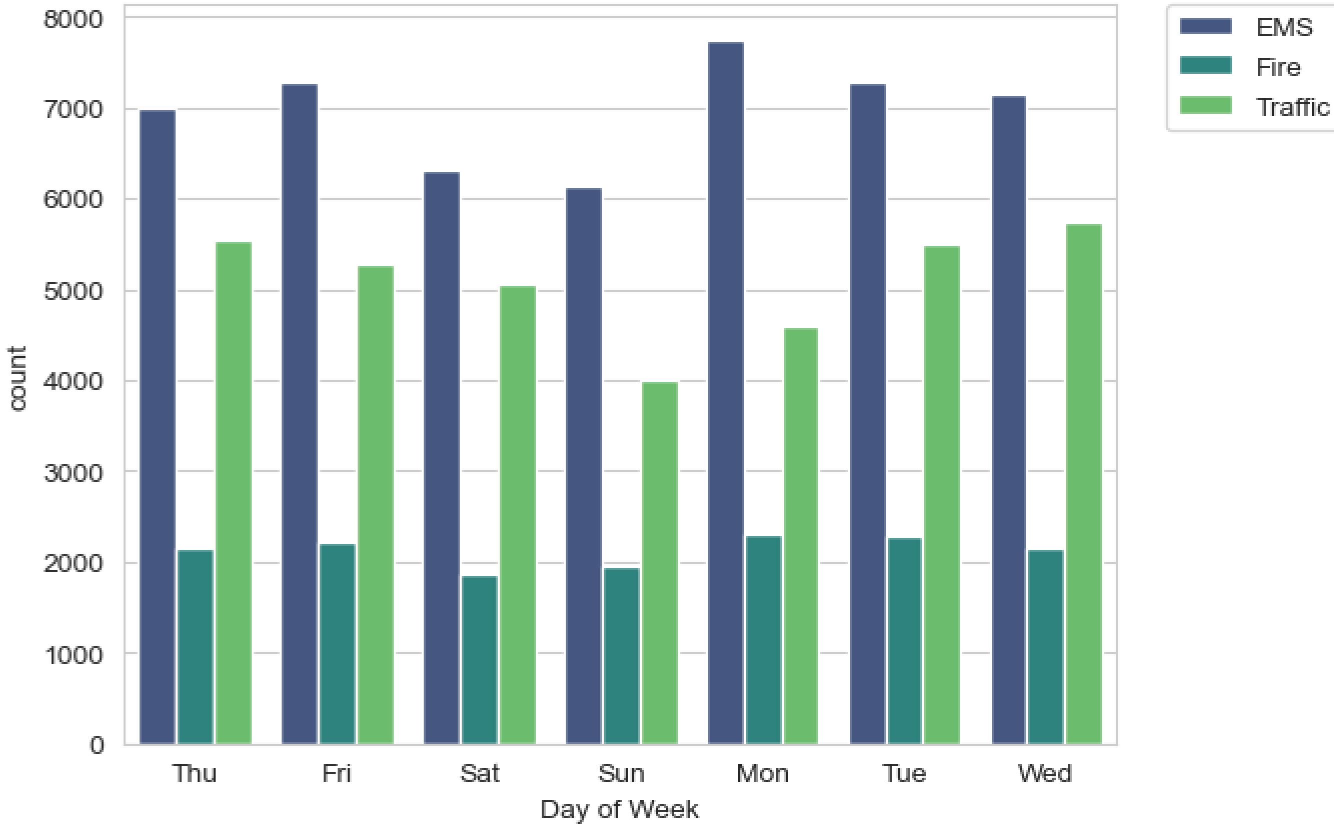
```
Min. Date: 2015-12-10 14:39:21
Max. Date: 2016-08-25 19:10:15
```

Using seaborn to create a countplot of the Day of Week column with the hue based off of the Reason column.

In [30]:
```
sns.countplot(x='Day of Week',data=df,hue='Reason',palette='viridis', )
print(df.groupby('Day of Week')['Reason'].count().sort_values(ascending=False))

# To relocate the legend
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

```
Day of Week
Tue    15057
Wed    15043
Fri    14763
Thu    14679
Mon    14625
Sat    13236
Sun    12086
Name: Reason, dtype: int64
```

Out[30]:
```
<matplotlib.legend.Legend at 0x1da43bf39d0>
```

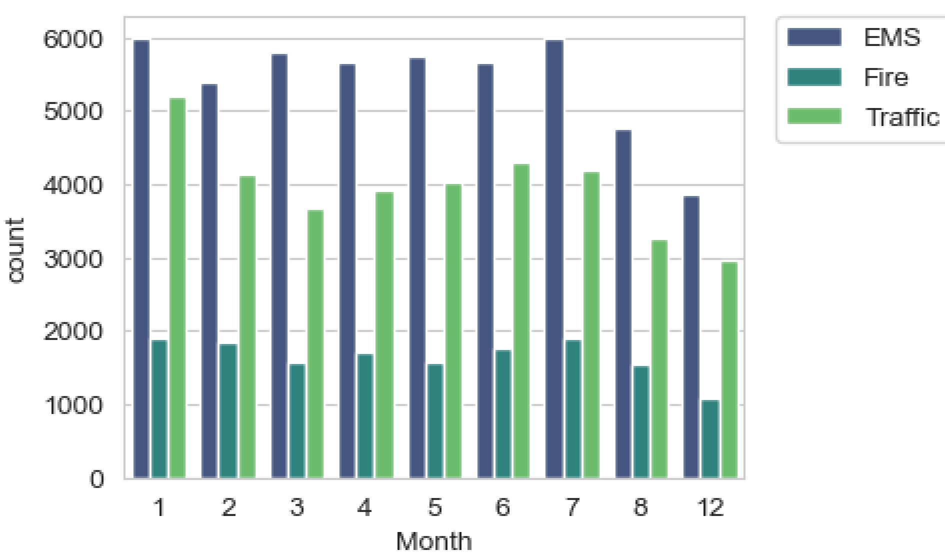


So Tuesday was the Day of Week which had more Emergency Calls, followed by Wednesday. Other point is that Fire was almost constant. When we look to Traffic, we can see an interessant patern, where Sunday had the smaller frequency which could be explain by the caracteristic about the day, because people don't go out a lot in Sunday.

Now do the same for Month:

In [31]:
```
plt.figure(figsize=(4,3))
sns.countplot(x='Month',data=df,hue='Reason',palette='viridis')

# To relocate the legend
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

Out[31]:
```
<matplotlib.legend.Legend at 0x1da5a7ba100>
```



January was the month with the most emergency calls, followed by July and June.

For some reason, it is missing some months -> 9,10, and 11 are not there

We can fill in this information by plotting the information in another way, possibly a simple line plot that fills in the missing months

In [32]:
```
byMonth = df.groupby('Month').count()
byMonth.head()
```

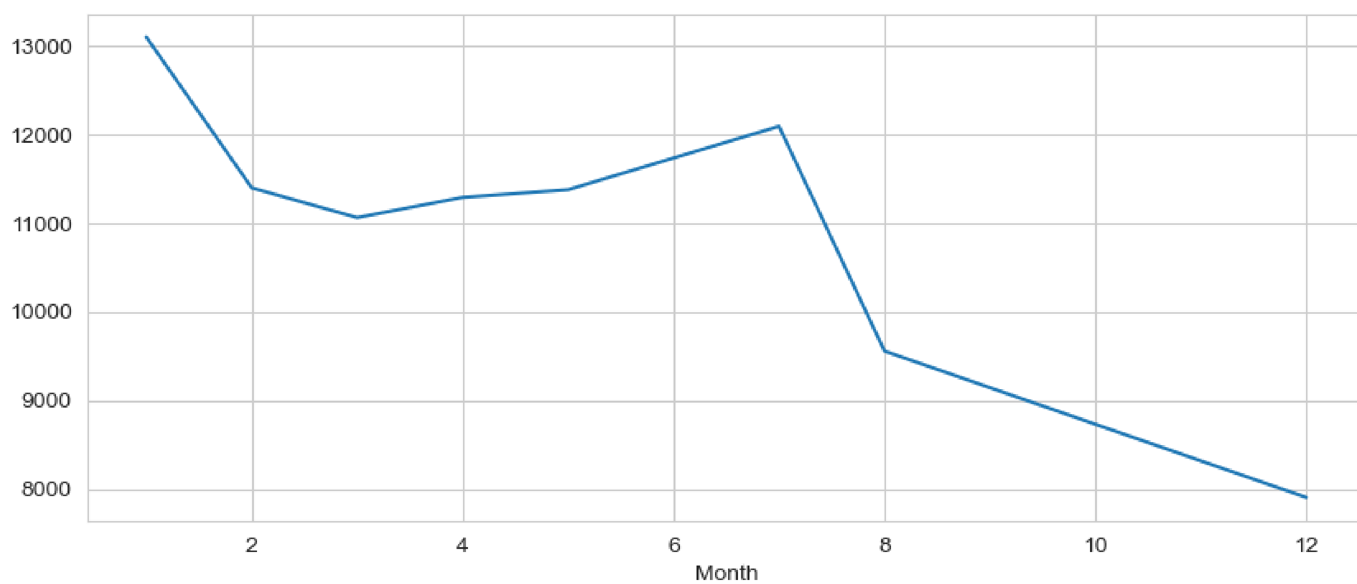
Out[32]:

Month	lat	lng	desc	zip	title	timeStamp	twp	addr	e	Reason	Hour	Year	Day of Week
1	13095	13095	13095	11421	13095	13095	13094	12986	13095	13095	13095	13095	13095
2	11395	11395	11395	9861	11395	11395	11393	11324	11395	11395	11395	11395	11395
3	11059	11059	11059	9737	11059	11059	11050	11018	11059	11059	11059	11059	11059
4	11287	11287	11287	9856	11287	11287	11284	11244	11287	11287	11287	11287	11287
5	11374	11374	11374	9914	11374	11374	11371	11330	11374	11374	11374	11374	11374

Now we can create a simple plot off of the dataframe indicating the count of calls per month.

In [33]:
```
plt.figure(figsize=(10,4))
byMonth['Reason'].plot()
```

Out[33]:
```
<AxesSubplot:xlabel='Month'>
```

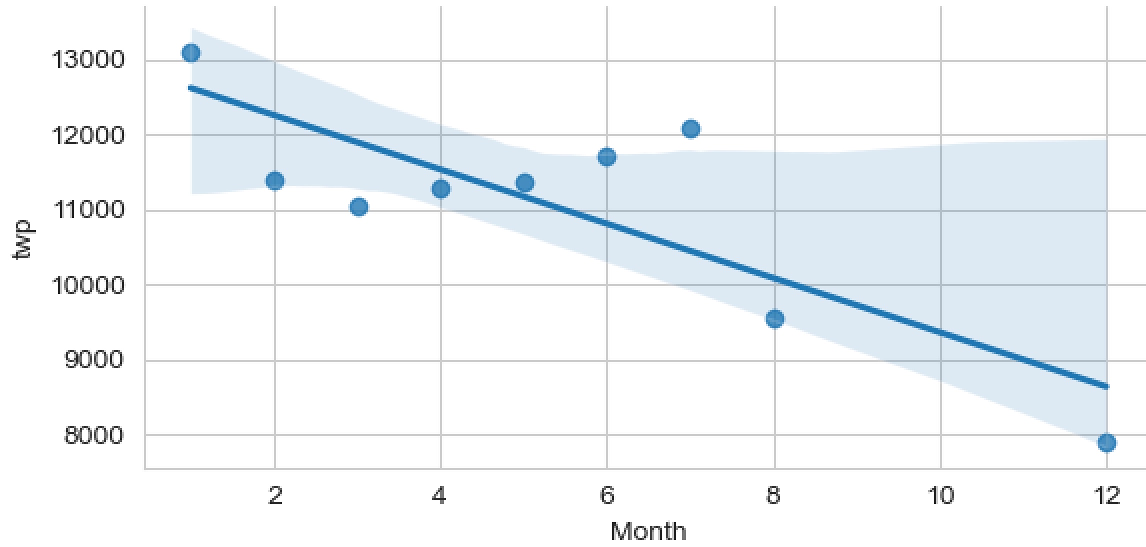


Although we do not have data for months 9, 10 and 11, it is likely that it followed the trend shown in the graph above.

Using seaborn lmplot() to create a linear fit on the number of calls per month, i.e., see the regression line

In [34]:
```
sns.lmplot(x='Month',y='twp',data=byMonth.reset_index(),height=3, aspect=2)
# ps: We can use any column to do the plot, because is a counting in y axis and the valu
```

Out[34]:
```
<seaborn.axisgrid.FacetGrid at 0x1da5791ad00>
```



So, as I said before and looking at the regression line above, we were able to at least get an idea of how the data could be in the months that had no data

Creating a new column called 'Date' that contains the date from the timeStamp column for to see the distribution per date

In [35]:
```
df['Date'] = df['timeStamp'].apply(lambda t: t.date())
df['Date'].head(1)
```

Out[35]:
```
0    2015-12-10
Name: Date, dtype: object
```

In [36]:
```
# mean of calls per date
print(f"Mean: {df.groupby('Date')['Reason'].count().mean()}")

# median of calls per date
print(f"Median: {df.groupby('Date')['Reason'].count().median()}")
```

```
Mean: 382.65
Median: 381.5
```

Both calculations were made to understand the data, as we have that the mean is more susceptible to extreme values, so it is normally used when the data are arranged homogeneously. The median is less influenced by very high or very low values. Despite the two values being close, I adopted the median as the standard for the other calculations in order to avoid problems with days that may have connection peaks.

In [37]:
```
# median of calls per reason
ems_median = df[df['Reason'] == 'EMS'].groupby('Date')['Reason'].count().median()
traffic_median = df[df['Reason'] == 'Traffic'].groupby('Date')['Reason'].count().median(
fire_median = df[df['Reason'] == 'Fire'].groupby('Date')['Reason'].count().median()




print('Median by Date:\n')
print(f"EMS: {ems_median}")
print(f"Traffic: {traffic_median}")
print(f"Fire: {fire_median}")
```

```
Median by Date:

EMS: 189.0
Traffic: 134.0
Fire: 56.0
```

In [38]:
```python
# Top 3 dates with the most numbers of calls
df.groupby('Date')['Reason'].count().sort_values(ascending=False).head(3)
```

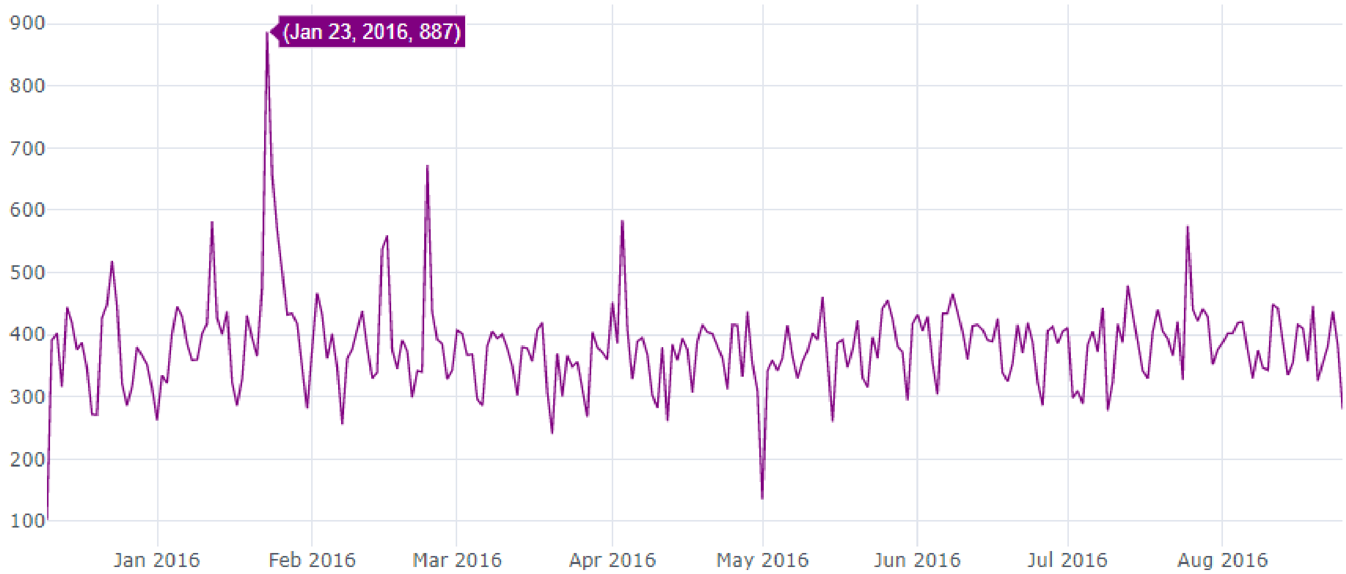
Out[38]:
```
Date
2016-01-23    887
2016-02-24    673
2016-01-24    657
Name: Reason, dtype: int64
```

Groupby this Date column with the count() aggregate and create a plot of counts of 911 calls

I used cufflinks because it's more interactive and helps a lot with graph analysis. However, to be able to see it here on GitHub, I took a print of the graph generated by the commented code, that's why it has Image(filename)

In [39]:
```python
#df.groupby('Date')['Reason'].count().iplot(theme="white", color="purple")
display.Image('all.png')
```

Out[39]:



In [40]:
```python
print(f"\033[1mSo Jan 23, 2016 was {round(((931-384)/384)*100)}% above the median for em
```

```
So Jan 23, 2016 was 142% above the median for emergency calls
```

We can see that on Jan 23, 2016 there was a spike in emergency calls (931 calls). Researching I found that on the 22nd to the 24th there was an intense blizzard in the northeastern of the USA. (https://www.weather.gov/media/lwx/Bliz2016.pdf)

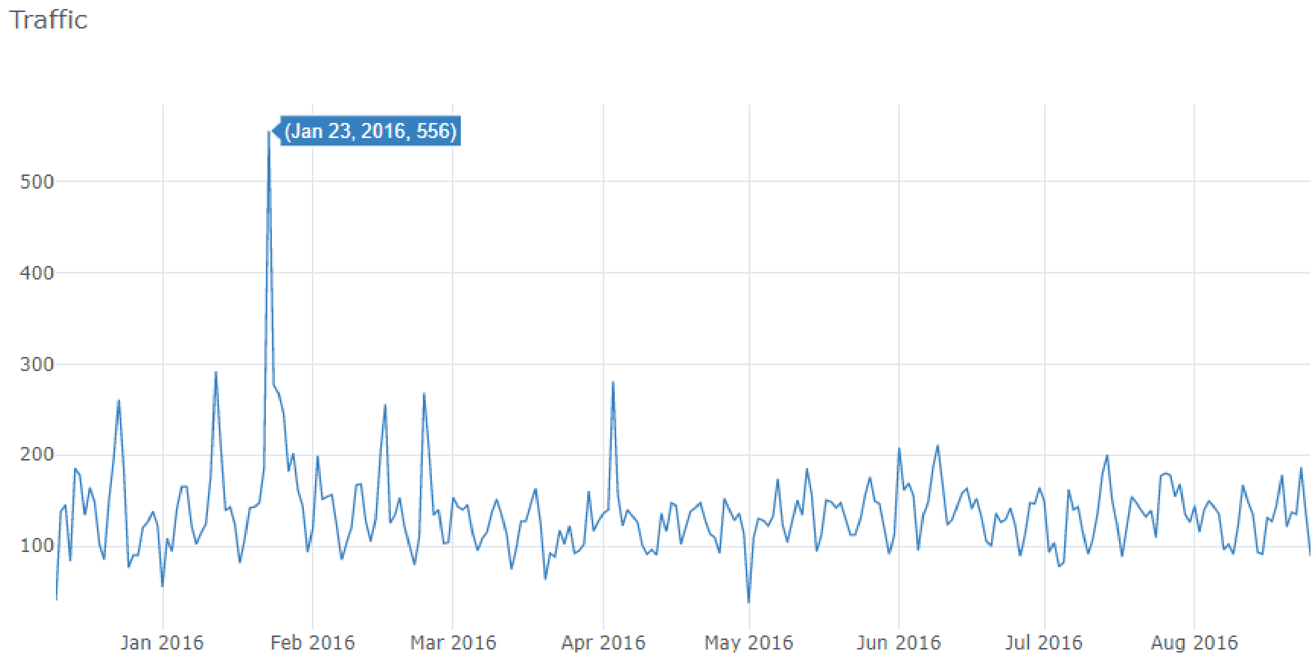
Now recreating this plot but create 3 separate plots with each plot representing a Reason for the 911 call

If exists some correlation with the spike in the Jan 23,2016 with the blizzard probably emergency calls by "Traffic" will be bigger than other Reason, because in blizzards the streets/roads are more dangerous to drive.

Blizzards combine the limited visibility of fog with the slippery roads you can expect from ice and snow. Driving in a blizzard makes it incredibly difficult to see what is going on around you, be seen by other road users and maintain control of your vehicle. (https://www.epermittest.com/drivers-education/driving-blizzard)

In [41]:
```python
#df[df['Reason']=='Traffic'].groupby('Date').count()['twp'].iplot(title="Traffic",colors
display.Image('traffic_date.png')
```

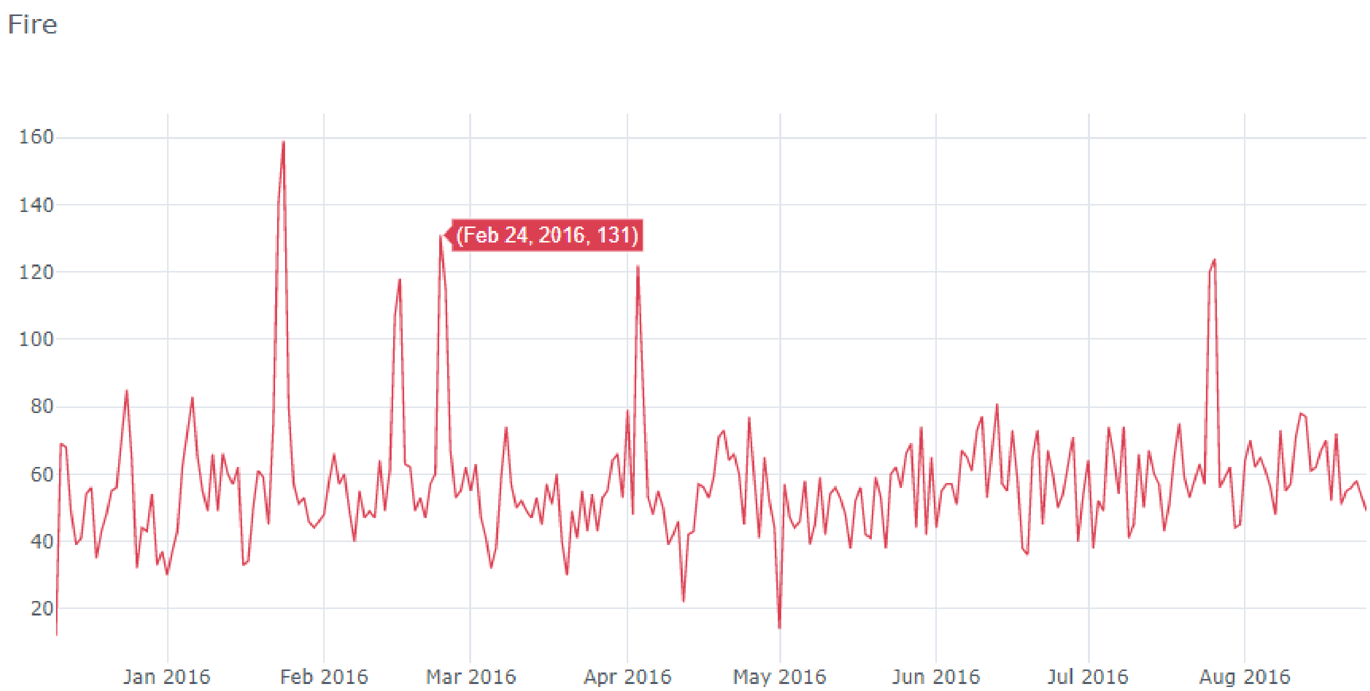
Out[41]:



In [42]:

```
#df[df['Reason']=='Fire'].groupby('Date').count()['twp'].iplot(title="Fire",colors="red"
display.Image('fire_date.png')
```

Out[42]:

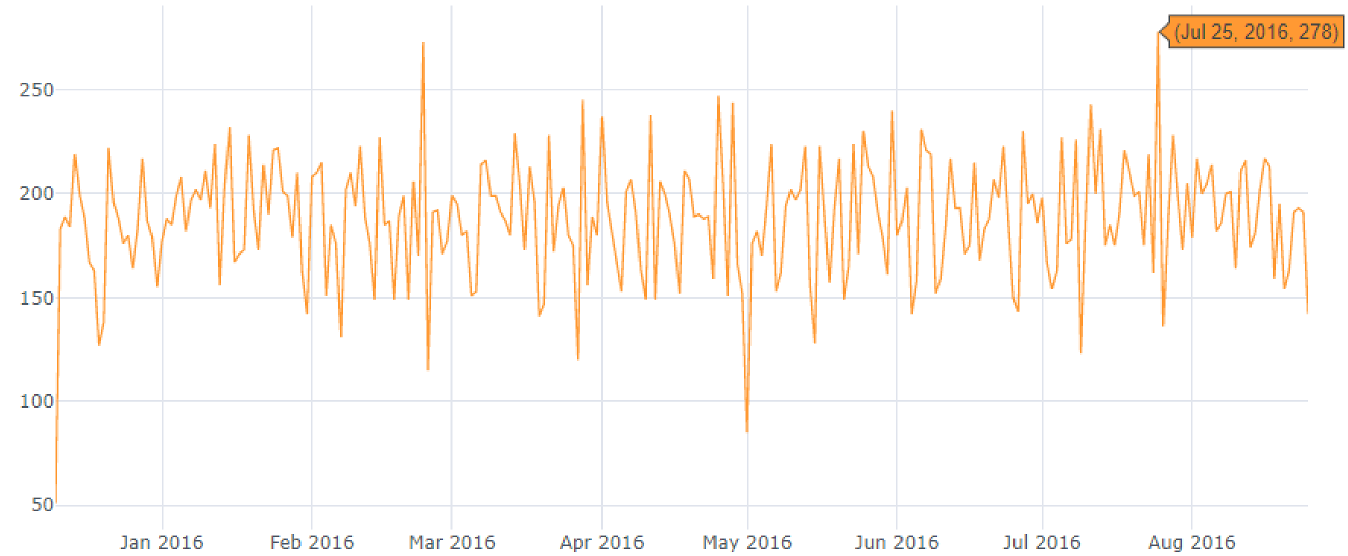


In [43]:

```
#df[df['Reason']=='EMS'].groupby('Date').count()['twp'].iplot(title="EMS",theme='white')
display.Image('ems_date.png')
```

Out[43]:

EMS



Trying show all 3 graph in just 1

I spent a long time thinking about how to do it and I don't know if the way I did it was the best hahah. So if you know a simple way or another way to do this let me know.

In [44]:
```
multi_index_df = df.groupby(by=['Date','Reason']).count()['twp']
multi_index_df
```

Out[44]:
```
Date        Reason
2015-12-10  EMS         51
            Fire        12
            Traffic     40
2015-12-11  EMS        183
            Fire        69
                      ...
2016-08-24  Fire        53
            Traffic    136
2016-08-25  EMS        142
            Fire        49
            Traffic     89
Name: twp, Length: 780, dtype: int64
```

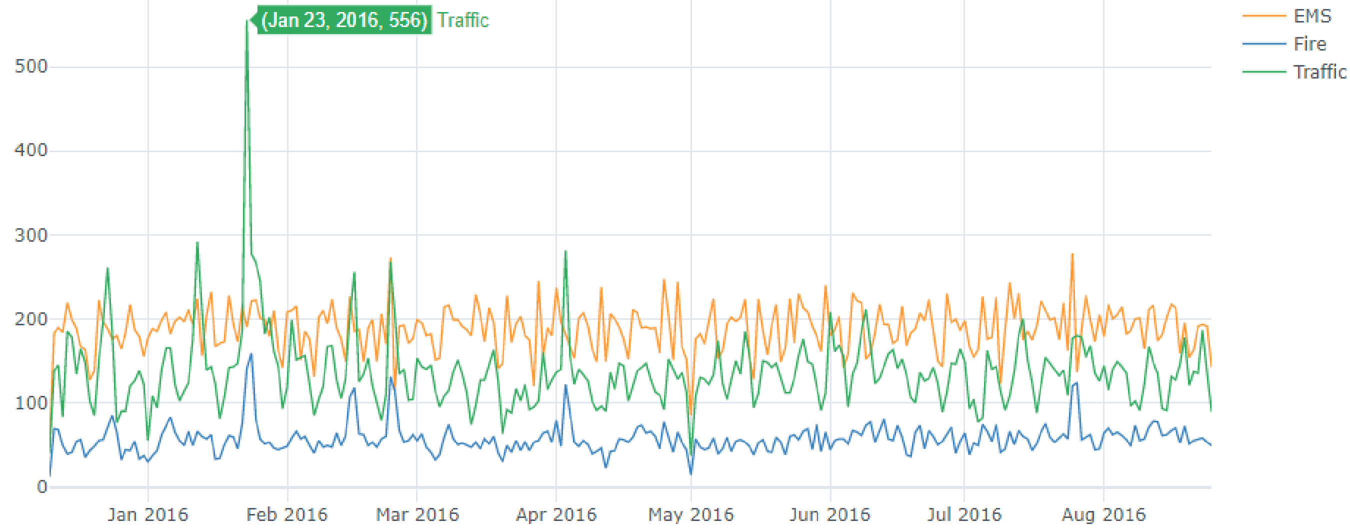
In [45]:
```
df_graphics = multi_index_df.unstack()
df_graphics.head(3)
```

Out[45]:

Reason Date	EMS	Fire	Traffic
2015-12-10	51	12	40
2015-12-11	183	69	138
2015-12-12	189	68	145

In [46]:
```
#df_graphics.iplot(theme='white')
display.Image('allinone.png')
```

Out[46]:



In [47]:
```
# % of Traffic in all emergency calls in 23 Jan,2016
print(f"{(559/913):.0%}")

# Traffic above median per date
print(f"{((559-traffic_median)/traffic_median):.0%}")

# Fire above median
print(f"{((158-fire_median)/fire_median):.0%}")
```

```
61%
317%
182%
```

As we can see, the most common type of emergency call on Jan 23, 2016 was "Traffic" (61% of all calls) and that day it was above the daily median in 308%. Another point is that we have a peak in calls of the "Fire" type, going from a daily median of 55 to 158 (an increase of 187%)

"Traffic" has more spikes and more fluctuations compared to others.

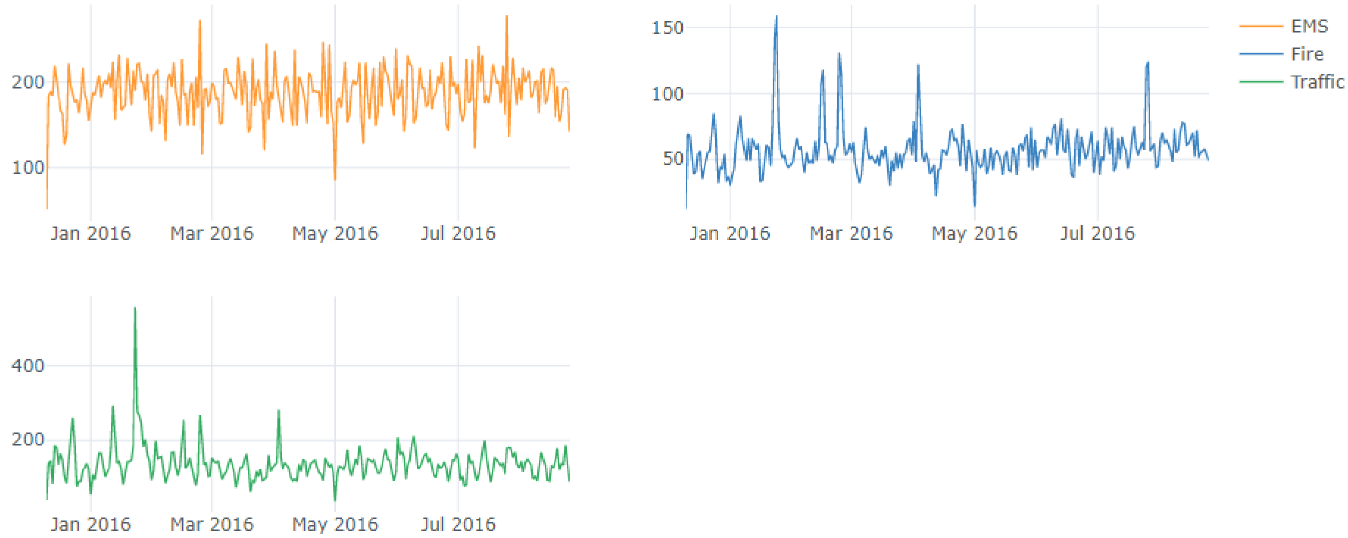
Finally, we can see that at the beginning of April we have a "stabilization" of the values, that is, they are closer to the medians of each type of emergency call and maintain a more constant behavior

---

Plotly and Cufflinks are great for data visualization. It's possible to separate the graph as a "subplot" in matplot just by adding the parameter (subplots=True), in addition, we can customize it in several ways due to the various parameters that Iplot has

In [48]:
```
#df_graphics.iplot(subplots=True, theme='white')
display.Image('threegraphs.png')
```

Out[48]:



Heatmaps

Day of Week vs Month

Now creating heatmaps with seaborn and our data. First is needed to restructure the dataframe

A heatmap is a graphical representation of data where each value of a matrix is represented as a color, this makes it easier to understand the information understanding of the information

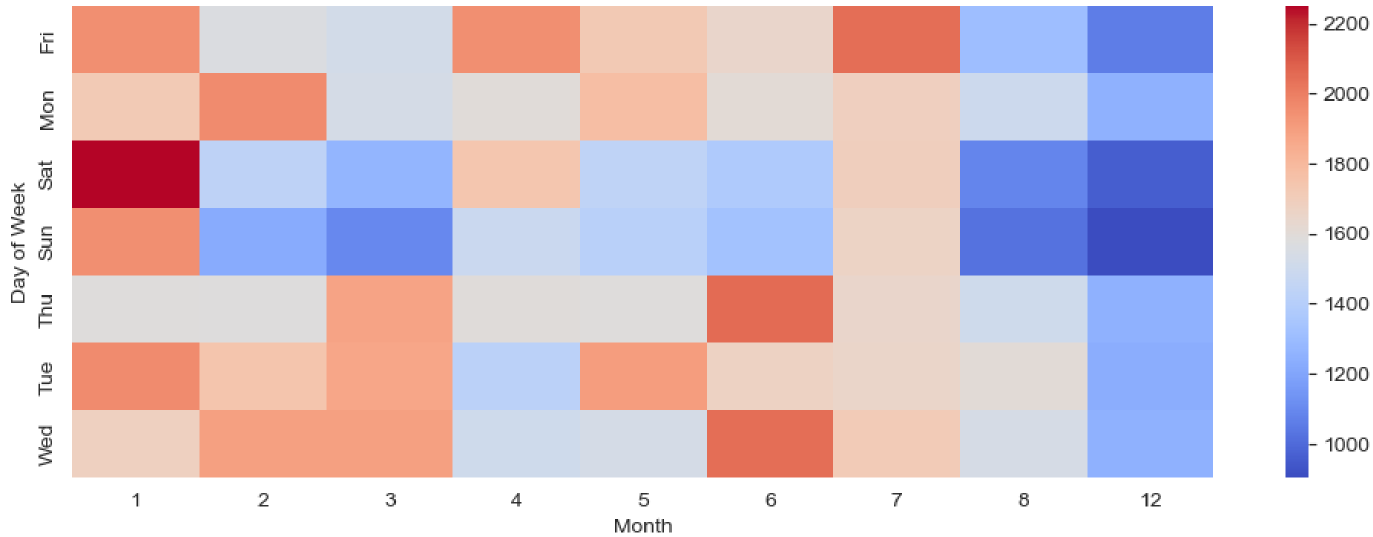
In [49]:
```
dayMonth = df.groupby(by=['Day of Week','Month']).count()['Reason'].unstack()
dayMonth
```

Out[49]:

Month Day of Week	1	2	3	4	5	6	7	8	12
Fri	1950	1564	1521	1949	1725	1646	2042	1308	1058
Mon	1718	1959	1534	1594	1776	1609	1685	1499	1251
Sat	2252	1434	1264	1736	1438	1376	1691	1085	960
Sun	1947	1223	1097	1486	1413	1329	1667	1020	904
Thu	1584	1582	1883	1592	1585	2055	1642	1505	1251
Tue	1961	1743	1871	1421	1904	1671	1650	1602	1234
Wed	1683	1890	1889	1509	1533	2045	1711	1536	1247

In [50]:
```
plt.figure(figsize=(12,4))
sns.heatmap(dayMonth,cmap='coolwarm')
```

Out[50]: <AxesSubplot:xlabel='Month', ylabel='Day of Week'>



When we look at the day of the week by month, Saturdays in January stand out with a high concentration of the number of cases

Day of Week vs Hour

Now repeating these same plots and operations, for a DataFrame that shows the Day of Week vs Hour

In [51]:
```
dayHour = df.groupby(by=['Day of Week','Hour']).count()['Reason'].unstack()
dayHour
```

Out[51]:

Hour	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	19	20	21	22
Day of Week																				
Fri	271	227	187	184	201	209	368	635	723	749	...	927	971	1036	972	793	720	636	561	518
Mon	280	213	213	182	213	267	404	679	828	795	...	860	939	964	994	878	732	611	471	463
Sat	369	293	257	254	224	243	262	396	479	630	...	771	800	813	765	767	703	609	561	498
Sun	362	316	280	266	233	246	301	408	496	620	...	692	671	668	717	673	648	519	464	388
Thu	283	204	237	163	179	223	386	607	789	848	...	901	989	935	1034	815	685	610	538	409
Tue	267	237	184	167	216	252	421	674	884	851	...	948	941	1014	1019	867	722	642	560	434
Wed	241	221	179	215	154	253	433	728	858	807	...	927	901	1010	1062	882	686	675	564	494

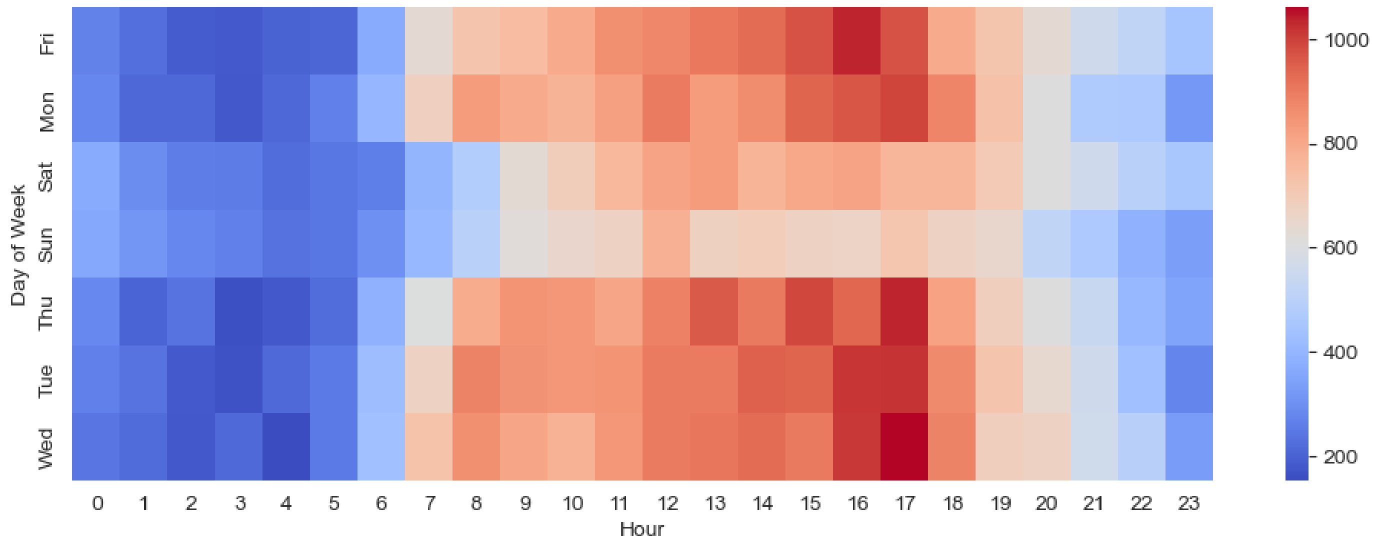
7 rows × 24 columns

In [52]:
```
# top 4 highest occurrences by day and hour
dayHour.unstack().nlargest(4)
```

Out[52]:
```
Hour  Day of Week
17    Wed            1062
16    Fri            1036
17    Thu            1034
      Tue            1019
dtype: int64
```

In [53]:
```
plt.figure(figsize=(12,4))
sns.heatmap(dayHour,cmap='coolwarm')
```

Out[53]: <AxesSubplot:xlabel='Hour', ylabel='Day of Week'>



Here we can see some interesting things.

- From 8am to 6pm are the times that have the most call records, this can be explained by the fact that it is business hours, that is, it is precisely when there are more people awake and also doing things, so the probability of an emergency happening increases due to of the amount of people.
- We can highlight that the times with the highest number of occurrences are at 4 pm and 5 pm. On the other hand, the times with the lowest number of occurrences are in the early morning between 2 am and 3 am.

Reason vs Hour

Now repeating these same plots and operations, for a DataFrame that shows the Reason vs Hour

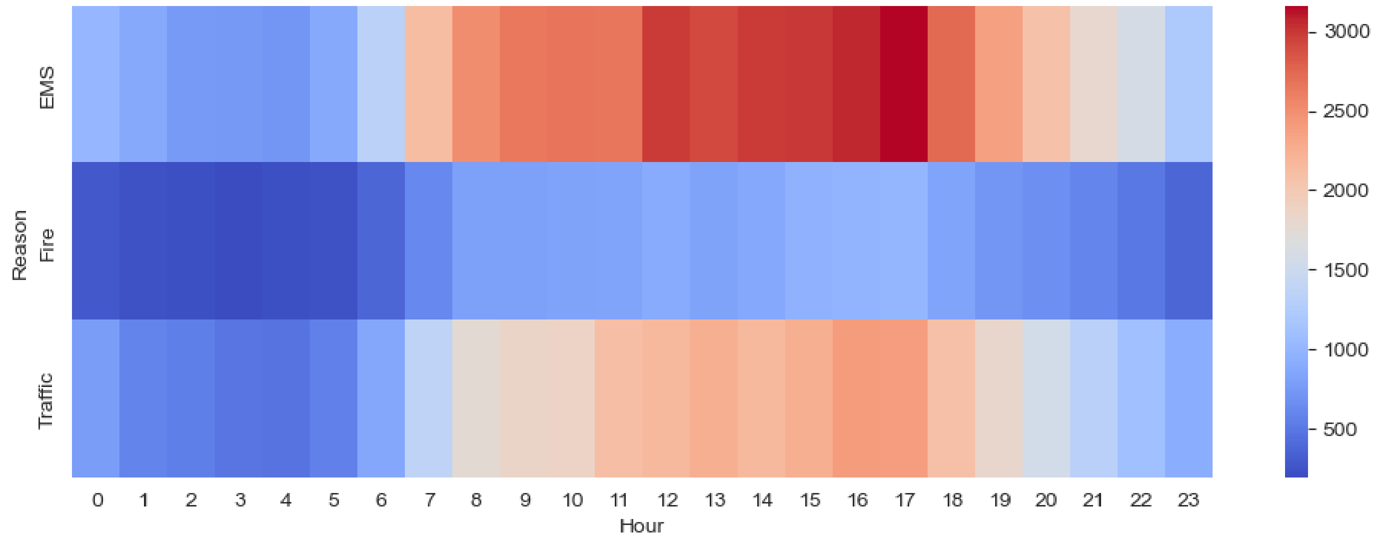
In [54]:
```
hourReason = df.groupby(by=['Reason','Hour']).count()['Date'].unstack()
```

In [55]:
```
hourReason.unstack().nlargest(7)
```

Out[55]:
```
Hour  Reason
17    EMS       3163
16    EMS       3061
15    EMS       3000
14    EMS       2988
12    EMS       2978
13    EMS       2914
18    EMS       2739
dtype: int64
```

In [56]:
```
plt.figure(figsize=(12,4))
sns.heatmap(hourReason,cmap='coolwarm')
```

Out[56]: <AxesSubplot:xlabel='Hour', ylabel='Reason'>



Here we can see how occurrences are distributed by time and type. Thus, it is concluded that the values highlighted above (4 pm and 5 pm) come from an emergency call of the 'Traffic' type, which makes sense, since it is the rush hour when there are more people in traffic and who are more tired because of the work routine, so there is a greater probability of accidents of this type.

On the other hand, we can observe that the EMS are more constant occurrences during the day, mainly in the middle of the morning and beginning of the afternoon (I didn't think of any hypothesis for this). EMS as said has a median occurrence higher than the others, so although "Traffic" has much higher peaks, it does not have a median value greater than "EMS"

Finally, we have that occurrences of the "Fire" type are more punctual, so we don't have such outliers, but like the others, they occur more during business hours.

Abstract: The more people doing day-to-day activities, the greater the chances of having an accident. Be careful :)

Maps

I thought it was cool to show a real map of the city to see where the calls come from

If you want to learn more about this kind of plot: https://www.kaggle.com/code/alexisbcook/interactive-maps#The-data

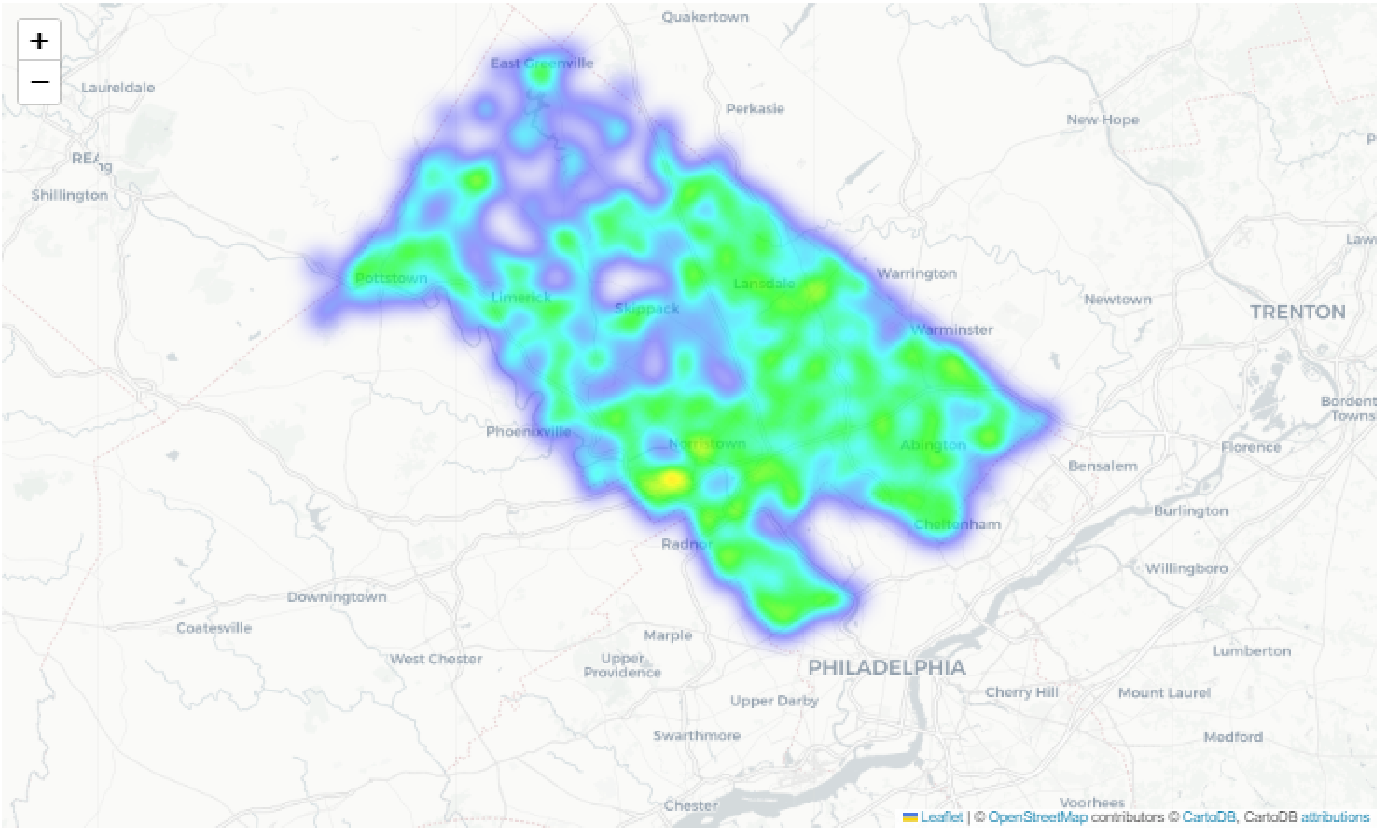
In [57]:
```
# Importing libraries
import folium
import math
from folium import Choropleth, Circle, Marker
from folium.plugins import HeatMap, MarkerCluster
```

In [58]:
```
# Separating by reason. I wanted to see the case highlighted, that is, 4 p.m. to 5 p.m.
map_traffic = df[(df['Reason'] == 'Traffic') & (df['Hour'].isin(range(16,18)))]
```

In [59]:
```
m = folium.Map(location=[40.243821, -75.649367], tiles='cartodbpositron', zoom_start=8)

# Add points to the map
"""mc = MarkerCluster()
for idx, row in map_traffic.iterrows():
    if not math.isnan(row['lng']) and not math.isnan(row['lat']):
```

```
        mc.add_child(Marker([row['lat'], row['lng']]))
m.add_child(mc)"""

# Add a heatmap to the base map
HeatMap(data=map_traffic[['lat', 'lng']], radius=10).add_to(m)

#Display the map
display.Image(filename='heatmap_traffic.png')   #m
```

Out[59]:



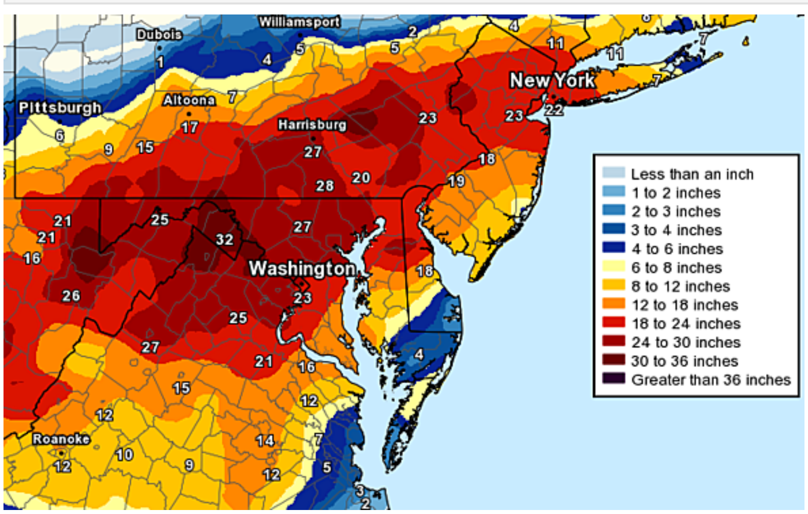
Traffic accidents, as expected, occur more in centers and on major highways, mainly at intersections.

Blizzard (22-24 Jan, 2016)

"The Blizzard of 2016 flooded coastal communities and piled up over 40 inches of snow, with incredible drifts. It set new snowstorm records at New York City and Baltimore."

In [60]:
```
from IPython import display
display.Image("https://cms.accuweather.com/wp-content/uploads/2016/01/590x366_01252031_s
```

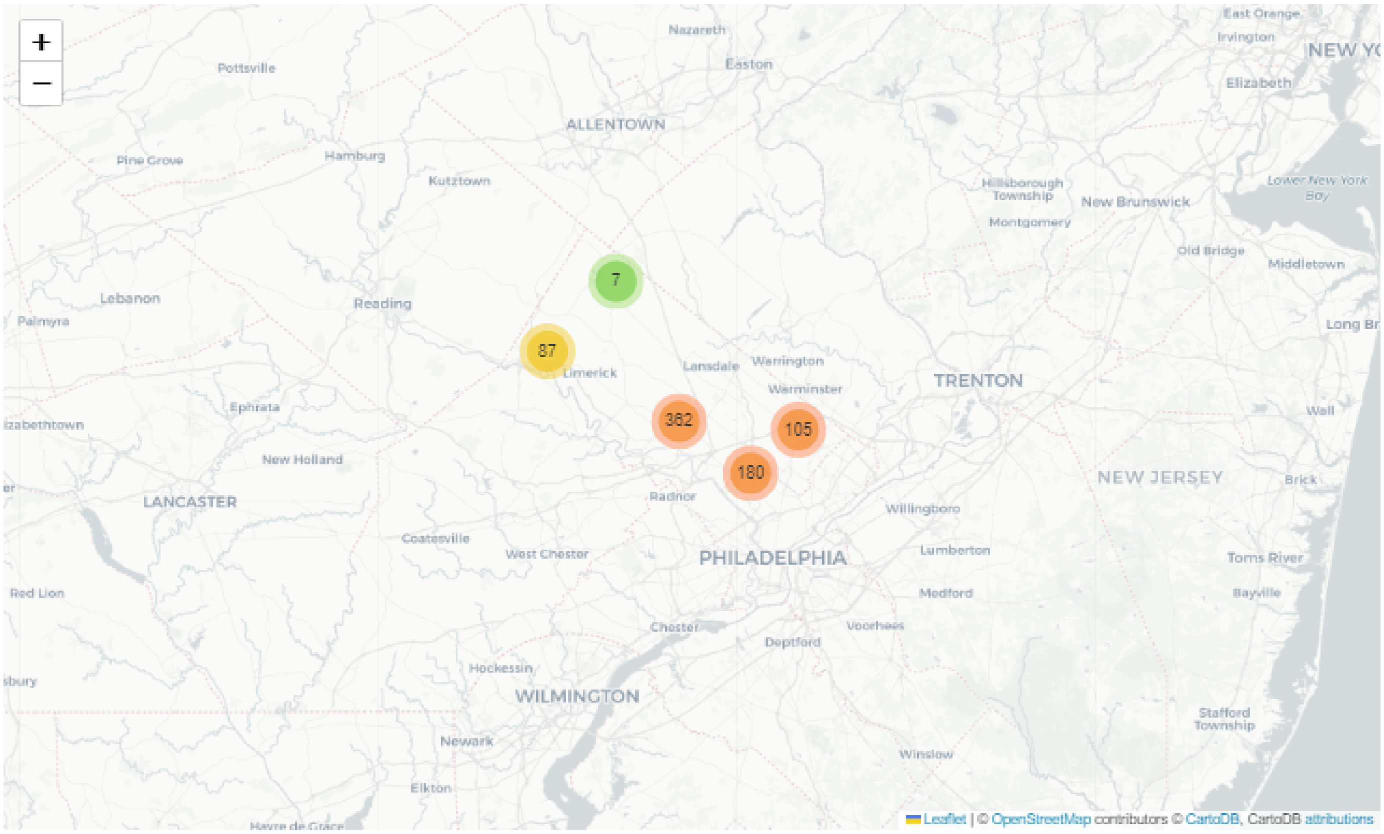
Out[60]:



In [61]:
```
blizzard_traffic = df[(df['Reason'] == 'Traffic') & (df['timeStamp'] >= '2016-01-22') &
```

In [62]:
```
# Create a base map
m_2 = folium.Map(location=[40.243821, -75.649367], tiles='cartodbpositron', zoom_start=8

# Add points to the map
mcd = MarkerCluster()
for idx, row in blizzard_traffic.iterrows():
    if not math.isnan(row['lng']) and not math.isnan(row['lat']):
        mcd.add_child(Marker([row['lat'], row['lng']]))
m_2.add_child(mcd)

# Display the map
display.Image('blizzard_traffic.png') #m_2
```

Out[62]:

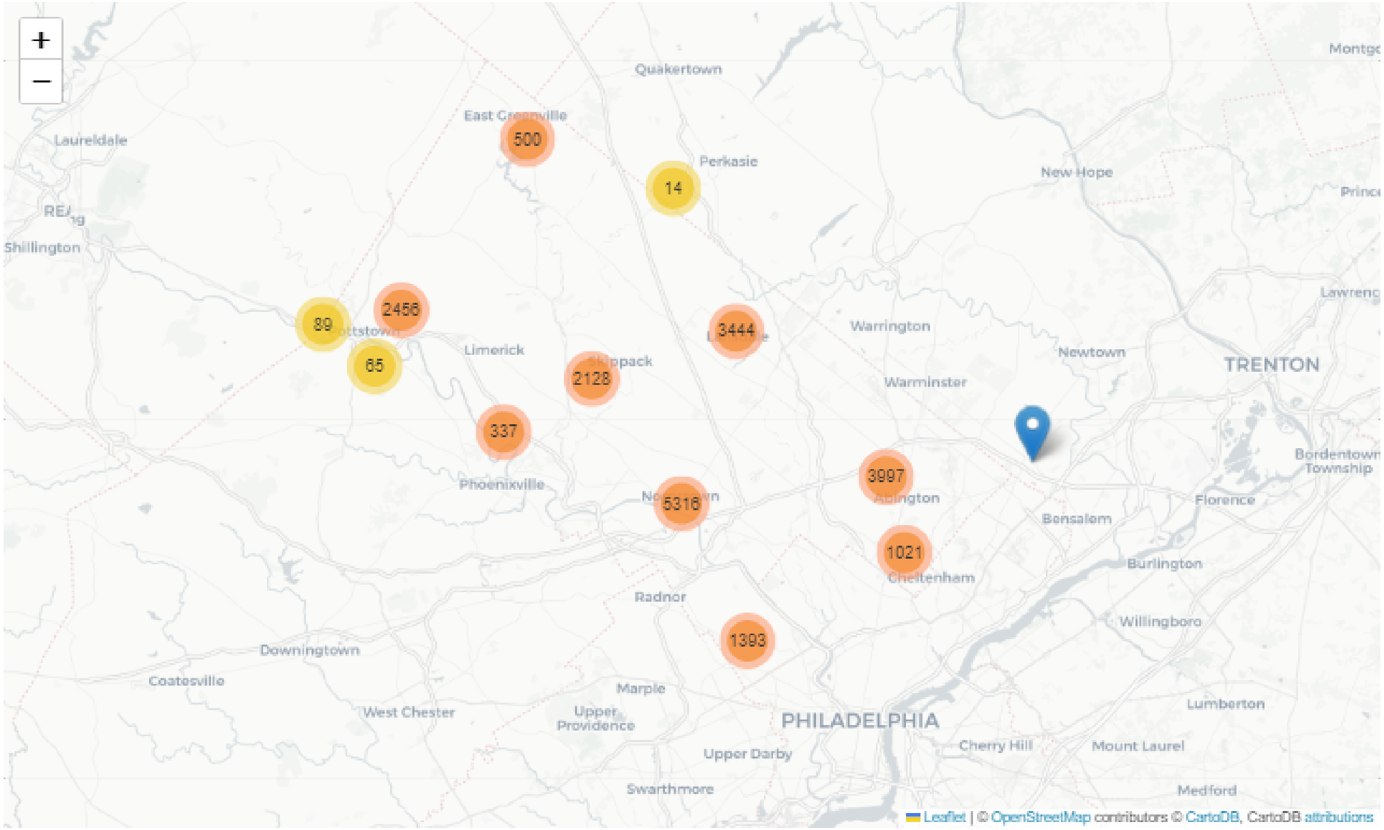


Finally, I found interesting to see the EMS, since it is the type of emergency that has the highest frequency, so I limited it to the times with the highest concentration of cases, as seen earlier. The goal was to see if it had any correlation with the location.

In [63]:
```
EMS = df[(df['Reason'] == 'EMS') & (df['Hour'].isin(range(11,18)))]
```

In [64]:
```
# Create a base map
m_3 = folium.Map(location=[40.243821, -75.649367], tiles='cartodbpositron', zoom_start=8

# Add points to the map
mcd2 = MarkerCluster()
for idx, row in EMS.iterrows():
    if not math.isnan(row['lng']) and not math.isnan(row['lat']):
        mcd2.add_child(Marker([row['lat'], row['lng']]))
m_3.add_child(mcd2)

# Display the map
display.Image('EMS.png') #m_3
```

Out[64]:



Knowing that there are some concentrations in certain areas we could see several other indicators to understand how the place is or something like that.

Using the website for example: https://www.city-data.com/county/Philadelphia_County-PA.html

---

Machine Learning Model

I focused on applying the K-Means method using only to the EMS data, since they represent almost 50% of the cases in the entire database.

In [65]:
```
# Importing
from sklearn.cluster import KMeans
```

In [66]:
```
# separating the data from EMS
df_EMS = df[df['Reason'] == 'EMS']
X = df_EMS[['lat','lng']]
X.head()
```

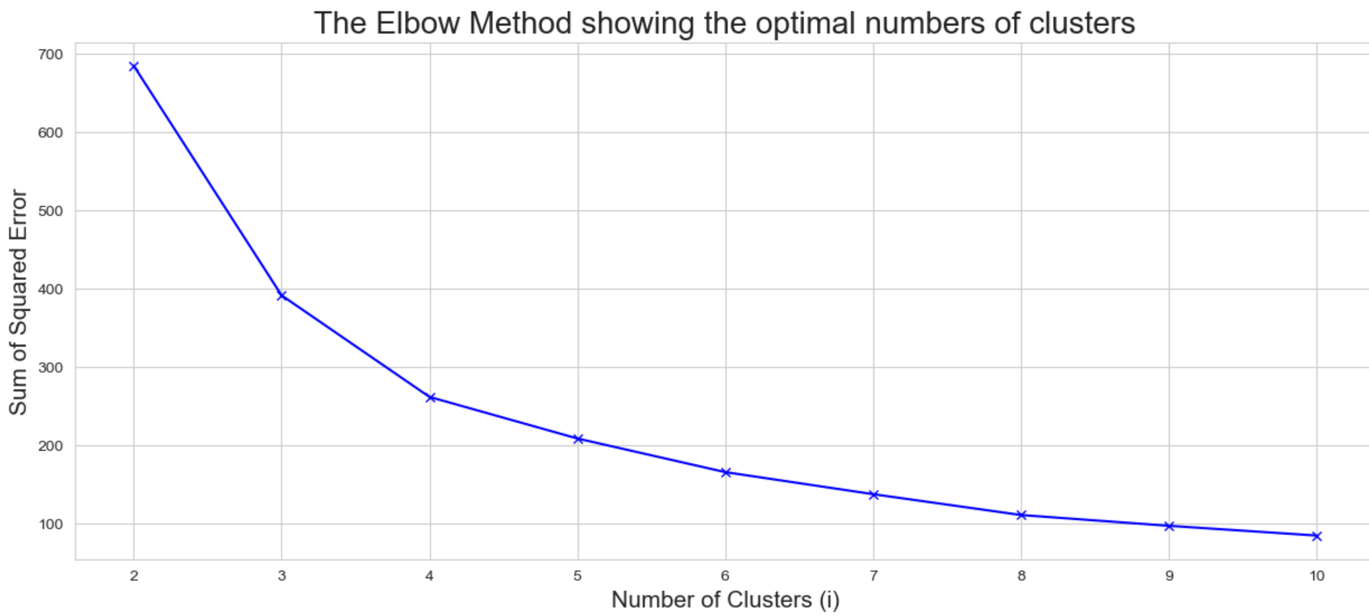
Out[66]:

	lat	lng
0	40.297876	-75.581294
1	40.258061	-75.264680
3	40.116153	-75.343513
4	40.251492	-75.603350
5	40.253473	-75.283245

In [67]:
```
# using elbow method to find the optimum cluster numbers in K-means
```

```
sse = []

K = range(2,11)
for i in K:
    kmeans = KMeans(n_clusters=i)
    kmeans.fit(X)
    sse.append(kmeans.inertia_)
```

In [68]:
```
plt.figure(figsize=(15,6))
plt.plot(K, sse, 'bx-')
plt.xlabel('Number of Clusters (i)', fontsize = 15)
plt.ylabel('Sum of Squared Error', fontsize = 15)
plt.title('The Elbow Method showing the optimal numbers of clusters', fontsize = 20)
plt.show()
```



It was not very clear to identify the right 'K' using the elbow method. So, I used also the Silhouette score

In [69]:
```
from sklearn.metrics import silhouette_score

X = df_EMS[['lat','lng']]
print("Clusters\tSilhoutte Score\n")
for n_cluster in range(2, 11):
    kmeans = KMeans(n_clusters=n_cluster).fit(X)
    label = kmeans.labels_
    sil_coeff = silhouette_score(X, label, metric='euclidean')
    print("k = {} \t--> \t{}".format(n_cluster, sil_coeff))
```

```
Clusters        Silhoutte Score

k = 2   -->     0.4943289513959l215
k = 3   -->     0.4596900986644844
k = 4   -->     0.505550619809182
k = 5   -->     0.4800250732790006
k = 6   -->     0.4816194321919607
k = 7   -->     0.4984803500411124
k = 8   -->     0.5016000961943013
k = 9   -->     0.49510648074738955
k = 10  -->     0.46136006706515775
```

In the Elbow chart we can see that values above 3 would be a good fit, so in the Silhouette score we had that k = 4 gives the highest Silhouette Score

In [70]:
```
kmeans = KMeans(n_clusters=4)
kmeans.fit(X)
```

```
sse.append(kmeans.inertia_)
```

In [71]:
```
X['cluster_label'] = kmeans.fit_predict(X)
```

In [72]:
```
X.head(3)
```

Out[72]:

	lat	lng	cluster_label
0	40.297876	-75.581294	2
1	40.258061	-75.264680	1
3	40.116153	-75.343513	0

In [75]:
```
centers = pd.DataFrame(kmeans.cluster_centers_, columns=[['lat','lng']])
centers
```

Out[75]:

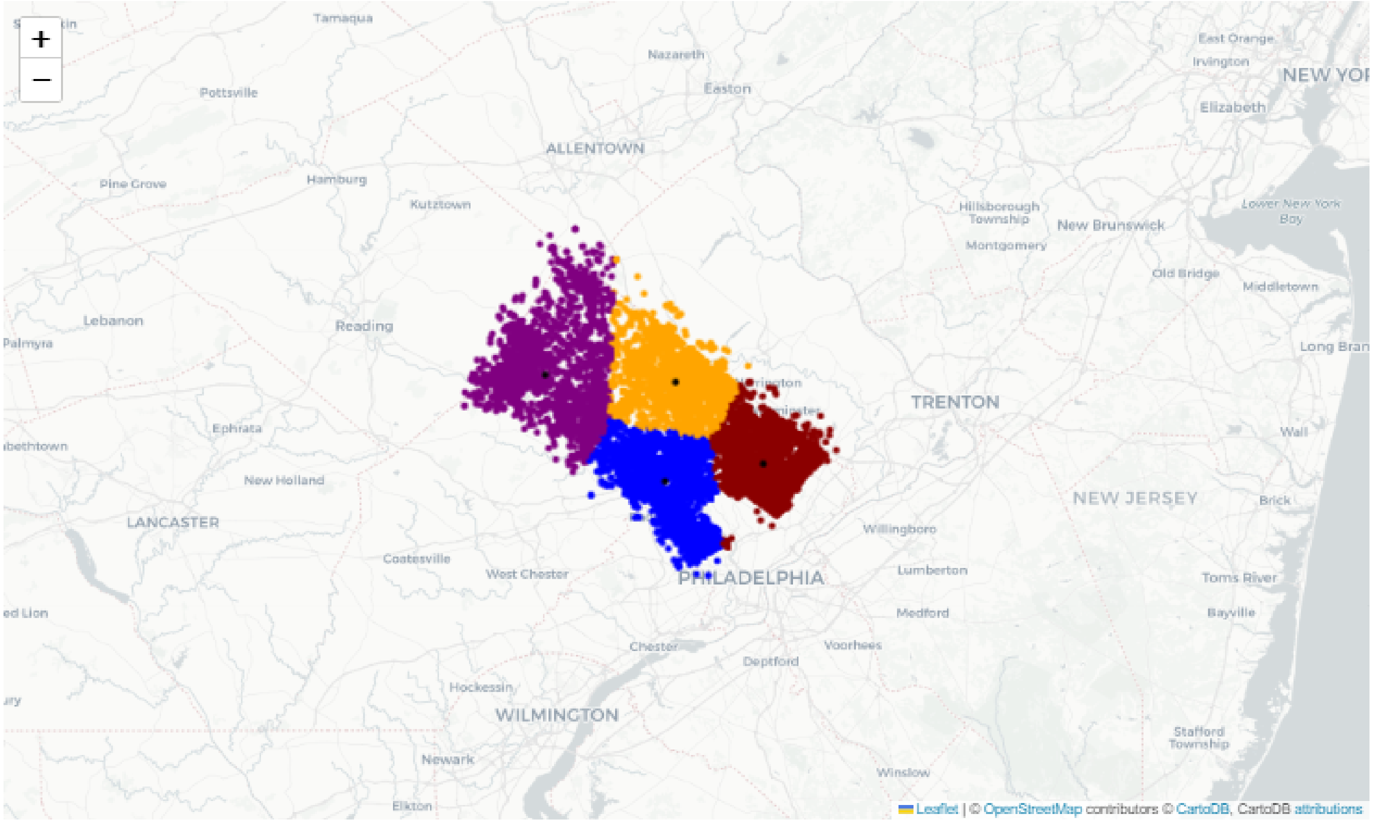
	lat	lng
0	40.098978	-75.333746
1	40.249289	-75.312572
2	40.260185	-75.570181
3	40.125895	-75.139225

In [76]:
```
X['cluster_label'].value_counts()
```

Out[76]:
```
0    17080
3    12556
2     9753
1     9486
Name: cluster_label, dtype: int64
```

In [80]:
```
# Create a base map
m_4 = folium.Map(location=[40.243821, -75.649367], tiles='cartodbpositron', zoom_start=8


def color_producer(val):
    if val == 0:
        return 'blue'
    elif val == 1:
        return 'orange'
    elif val == 2:
        return 'purple'
    else:
        return 'darkred'

# Add a bubble map to the base map
for i in range(0,len(X)):
    Circle(
        location=[X.iloc[i]['lat'], X.iloc[i]['lng']],
        radius=20,
        color=color_producer(X.iloc[i]['cluster_label'])).add_to(m_4)

for a in range(0,len(centers)):
    Circle(
        location=[centers.iloc[a]['lat'],centers.iloc[a]['lng']],
        radius=30,
        color='black').add_to(m_4)

# Display the map
display.Image('ems_kmeans.png') #m_4
```

Out[80]:



Here we can see how the model clustered the data. The black dots are the centroids, i.e. data points that represent the center of each cluster (the mean) and may not necessarily be a member of the data set.

Therefore, considering only EMS, we must place the facilities to attend these cases close to the centroids to better respond to emergency calls, if there is only a budget for one point, it would be interesting that it was close to the centroid of Cluster 0 (blue), where we have a greater concentration of EMS cases.

Thanks!

If you've found some english error or something that you want to share, please tell me