EDA : 911 Calls

Exploratory Data Analysis(EDA) performed on Dataset obtained from [Kaggle (https://www.kaggle.com/mchirico/montcoalert)](https://www.kaggle.com/mchirico/montcoalert). 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)

note: this is a notebook to practice my data analysis , visualization and pandas skills . This was also a part of a capstone project of [this (https://www.udemy.com/course/python-for-data-science-and-machine-learning-bootcamp/)](https://www.udemy.com/course/python-for-data-science-and-machine-learning-bootcamp/) course.

Data and Setup

** Import numpy and pandas **

In [1]:

```
import numpy as np
import pandas as pd
```

** Import visualization libraries and set %matplotlib inline. **

In [2]:

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

** Read in the csv file as a dataframe called df **

In [3]:

```
df = pd.read_csv('911.csv')
```

** Check the info() of the df **

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99492 entries, 0 to 99491
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  object 
 6   twp        99449 non-null  object 
 7   addr       98973 non-null  object 
 8   e          99492 non-null  int64  
dtypes: float64(3), int64(1), object(5)
memory usage: 6.8+ MB
```

** Check the head of df **

In [5]:

```
df.head()
```

Out[5]:

	lat	lng	desc	zip	title	timeStamp	twp	
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0	EMS: BACK PAINS/INJURY	2015-12-10 17:40:00	NEW HANOVER	
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	2015-12-10 17:40:00	HATFIELD TOWNSHIP	
2	40.121182	-75.351975	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401.0	Fire: GAS-ODOR/LEAK	2015-12-10 17:40:00	NORRISTOWN	
3	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401.0	EMS: CARDIAC EMERGENCY	2015-12-10 17:40:01	NORRISTOWN	
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	NaN	EMS: DIZZINESS	2015-12-10 17:40:01	LOWER POTTSGROVE	C

Basic Questions

What are the top 5 zipcodes for 911 calls?

In [6]:

```
df['zip'].value_counts().head()
```

Out[6]:

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

What are the top 5 townships (twp) for 911 calls?

In [7]:

```
df['twp'].value_counts().head()
```

Out[7]:

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

Creating new features

In the titles column there are "Reasons/Departments" specified before the title code. These are EMS, Fire, and Traffic. Using .apply() with a custom lambda expression to create a new column called "Reason" that contains this string value.

For example, if the title column value is EMS: BACK PAINS/INJURY , the Reason column value would be EMS.

In [9]:

```
df["Reason"] = df['title'].apply(lambda x:x.split(':')[0])
```

What is the most common Reason for a 911 call based off of this new column?

In [10]:

```
df['Reason'].value_counts().head()
```

Out[10]:

```
EMS        48877
Traffic    35695
Fire       14920
Name: Reason, dtype: int64
```

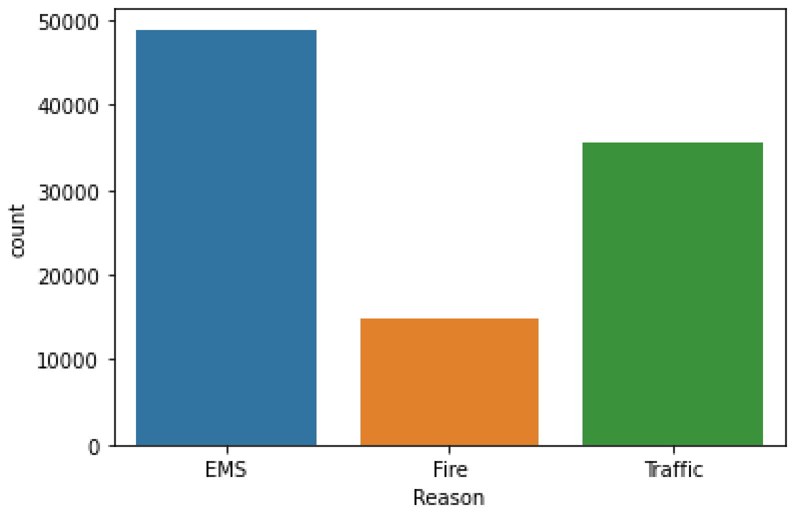
Now using seaborn to create a countplot of 911 calls by Reason.

In [11]:

```
sns.countplot(x=df['Reason'],data = df)
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x28b4b1f7508>
```



Here we can see that EMS clearly has a higher 911-call rate followed by Traffic and Fire.

In [12]:

```
type(df['timeStamp'].iloc[0])
```

Out[12]:

```
str
```

using pd.to_datetime to convert the column from strings to DateTime objects.

In [13]:

```
df['timeStamp'] = pd.to_datetime(df['timeStamp'] )
df['timeStamp']
```

Out[13]:

```
0        2015-12-10 17:40:00
1        2015-12-10 17:40:00
2        2015-12-10 17:40:00
3        2015-12-10 17:40:01
4        2015-12-10 17:40:01
                ...
99487    2016-08-24 11:06:00
99488    2016-08-24 11:07:02
99489    2016-08-24 11:12:00
99490    2016-08-24 11:17:01
99491    2016-08-24 11:17:02
Name: timeStamp, Length: 99492, dtype: datetime64[ns]
```

Using .apply() to create 3 new columns called Hour, Month, and Day of Week . Creating these columns based off of the timeStamp column

In [14]:

```
df['hour'] = df['timeStamp'].apply(lambda time:time.hour)
df['month'] = df['timeStamp'].apply(lambda time:time.month)
df['dow'] = df['timeStamp'].apply(lambda time:time.dayofweek)
df.head()
```

Out[14]:

	lat	lng	desc	zip	title	timeStamp	twp
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0	EMS: BACK PAINS/INJURY	2015-12-10 17:40:00	NEW HANOVER
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	2015-12-10 17:40:00	HATFIELD TOWNSHIP
2	40.121182	-75.351975	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401.0	Fire: GAS-ODOR/LEAK	2015-12-10 17:40:00	NORRISTOWN
3	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401.0	EMS: CARDIAC EMERGENCY	2015-12-10 17:40:01	NORRISTOWN
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	NaN	EMS: DIZZINESS	2015-12-10 17:40:01	LOWER POTTSGROVE

Notice how the Day of Week is an integer 0-6. Using the .map() with a dictionary to map the actual string

names to the day of the week:

In [15]:

```
dmap = {0:'Mon',1:'Tue',2:
       'Wed',3:'Thu',4:'Fir',5:'Sat',6:'Sun'}
```

In [16]:

```
df['dow'] = df['dow'].map(dmap)
```

In [17]:

```
df['dow']
```

Out[17]:

```
0        Thu
1        Thu
2        Thu
3        Thu
4        Thu
        ...
99487    Wed
99488    Wed
99489    Wed
99490    Wed
99491    Wed
Name: dow, Length: 99492, dtype: object
```

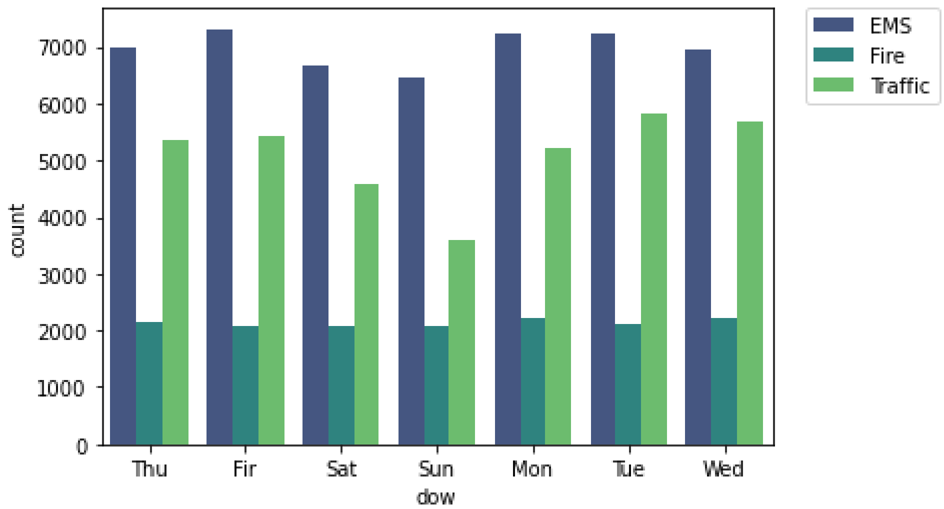
Using seaborn to create a countplot of the Day of Week column with the hue based off of the Reason column.

In [18]:

```
sns.countplot(x=df['dow'],hue = df['Reason'],palette = 'viridis')
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

Out[18]:

```
<matplotlib.legend.Legend at 0x28b4bab6608>
```



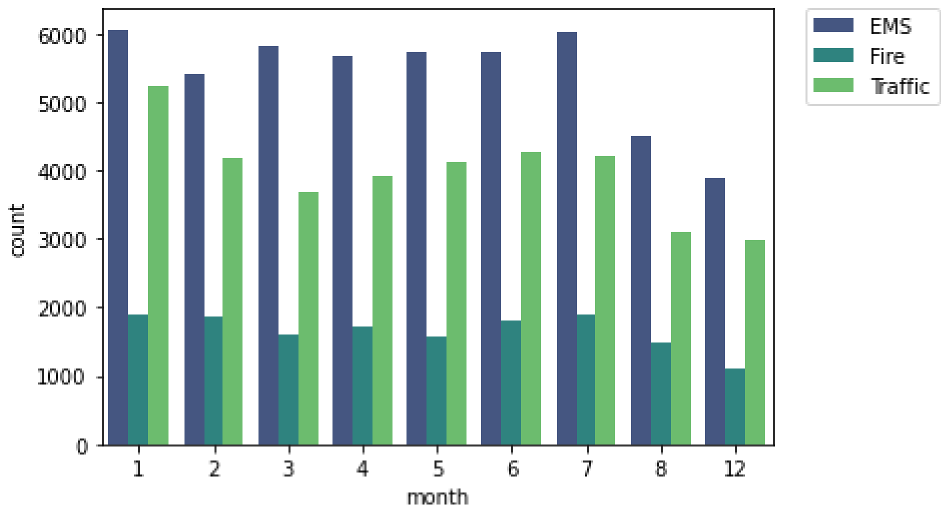
same for Month:

In [19]:

```
sns.countplot(x='month',data = df,hue='Reason',palette = 'viridis')
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

Out[19]:

```
<matplotlib.legend.Legend at 0x28b4bf20f08>
```



Months 9-11 are missing from this plot. Using groupby method to fix this issue

In [20]:

```
byMonth = df.groupby('month').count()
```

In [21]:

```
byMonth.head()
```

Out[21]:

month	lat	lng	desc	zip	title	timeStamp	twp	addr	e	Reason	hour
1	13205	13205	13205	11527	13205	13205	13203	13096	13205	13205	13205
2	11467	11467	11467	9930	11467	11467	11465	11396	11467	11467	11467
3	11101	11101	11101	9755	11101	11101	11092	11059	11101	11101	11101
4	11326	11326	11326	9895	11326	11326	11323	11283	11326	11326	11326
5	11423	11423	11423	9946	11423	11423	11420	11378	11423	11423	11423

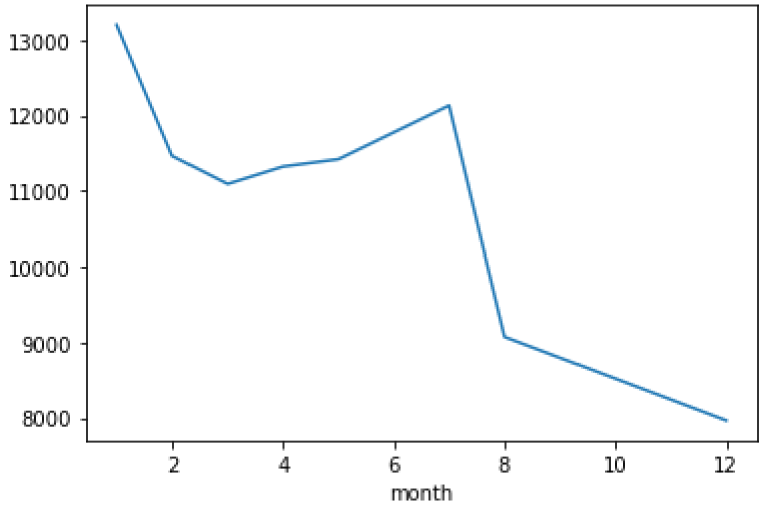
simple plot off of the dataframe indicating the count of calls per month:

In [22]:

```
byMonth['twp'].plot()
```

Out[22]:

<matplotlib.axes._subplots.AxesSubplot at 0x28b4c039a08>



Here we see that there is a clear dip in 911-calls during months 7-12

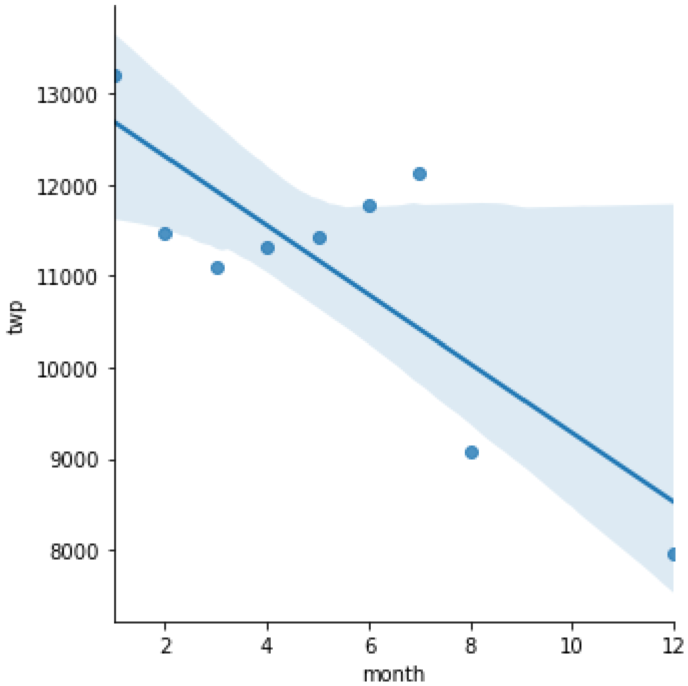
Using seaborn's lmplot() to create a linear fit on the number of calls per month

In [23]:

```
sns.lmplot(x='month',y='twp',data=byMonth.reset_index())
```

Out[23]:

```
<seaborn.axisgrid.FacetGrid at 0x28b4bbc24c8>
```



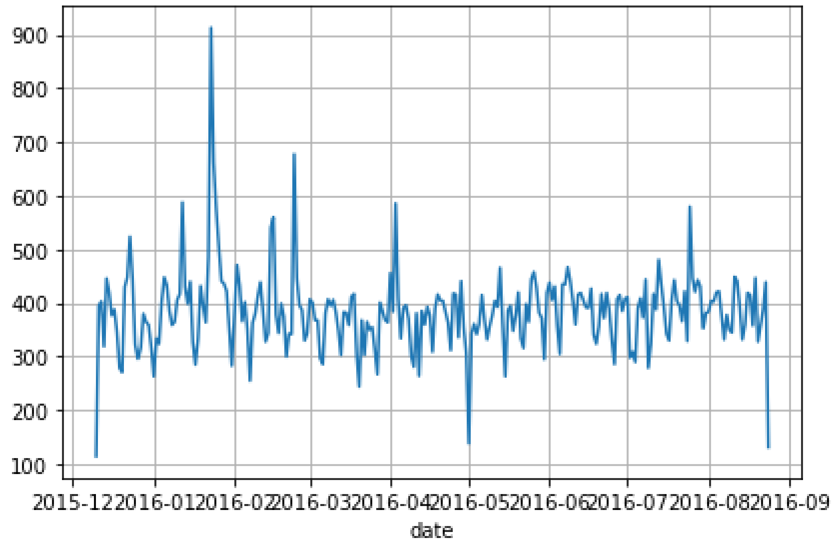
In [24]:

```
df['date'] = df['timeStamp'].apply(lambda x:x.date())
```

groupby this Date column with the count() aggregate and creating a plot of counts of 911 calls.

In [25]:

```
df.groupby('date').count()['twp'].plot()
plt.grid()
plt.tight_layout()
```



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

In [46]:

```
df[df['Reason']=='Traffic'].groupby('date').count().sort_values(by='twp',ascending=False).h
```

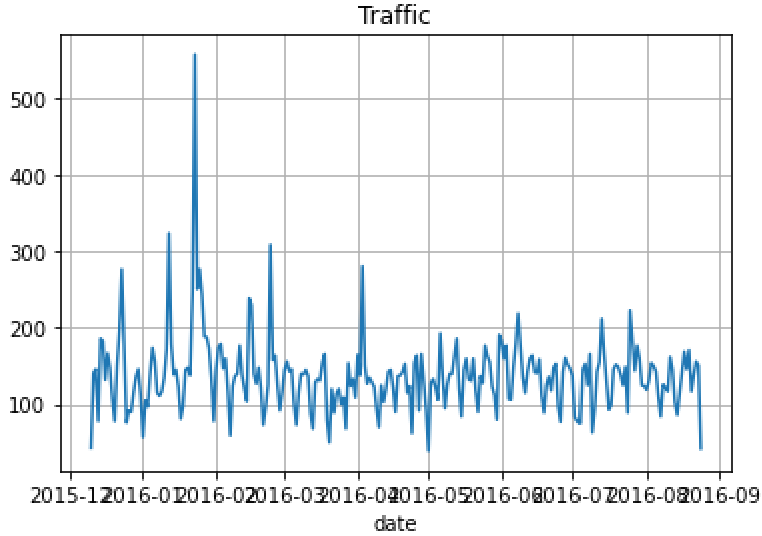
Out[46]:

	lat	lng	desc	zip	title	timeStamp	twp	addr	e	Reason	hour	month	dow
date													
2016-01-23	557	557	557	464	557	557	557	531	557	557	557	557	557
2016-01-12	324	324	324	286	324	324	324	319	324	324	324	324	324
2016-02-24	309	309	309	266	309	309	309	300	309	309	309	309	309
2016-04-03	281	281	281	246	281	281	281	281	281	281	281	281	281
2015-12-23	277	277	277	218	277	277	277	272	277	277	277	277	277

Here we observe that the date '2016-01-23' has the highest count of 911-calls , aslo confirmed by the following plot

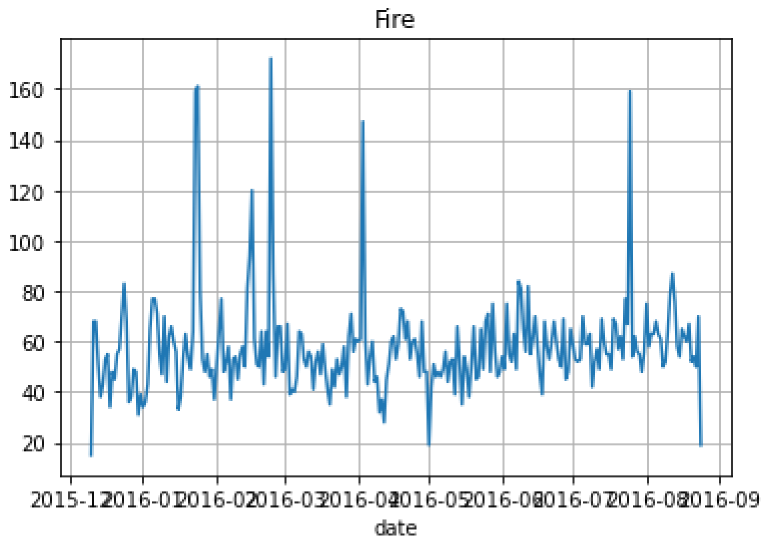
In [26]:

```
df[df['Reason']=='Traffic'].groupby('date').count()['twp'].plot()
plt.title('Traffic')
plt.grid()
```



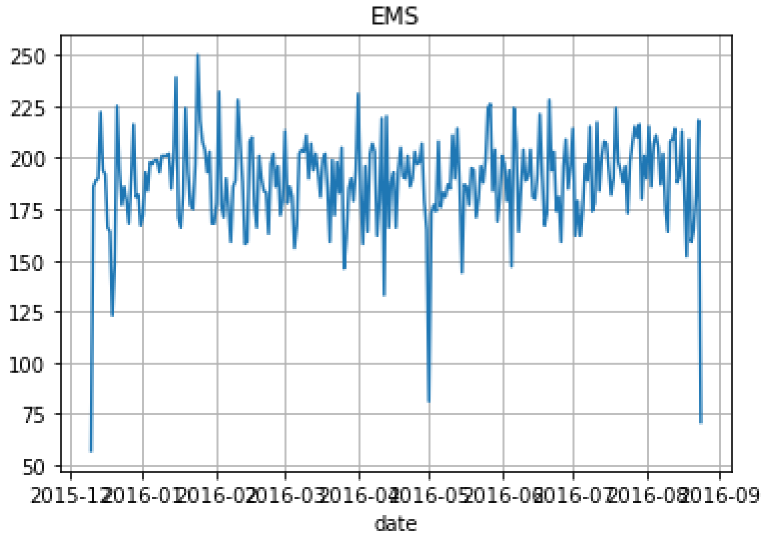
In [27]:

```
df[df['Reason']=='Fire'].groupby('date').count()['twp'].plot()
plt.title('Fire')
plt.grid()
```



In [28]:

```
df[df['Reason']=='EMS'].groupby('date').count()['twp'].plot()
plt.title('EMS')
plt.grid()
```



Creating heatmaps : using unstack() method to create a matrix which acts as an input to the heatmap.

In [29]:

```
dayhour = df.groupby(by=['dow','hour']).count()['Reason'].unstack()
dayhour
```

Out[29]:

hour	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	19
dow																	
Fir	275	235	191	175	201	194	372	598	742	752	...	932	980	1039	980	820	696
Mon	282	221	201	194	204	267	397	653	819	786	...	869	913	989	997	885	746
Sat	375	301	263	260	224	231	257	391	459	640	...	789	796	848	757	778	696
Sun	383	306	286	268	242	240	300	402	483	620	...	684	691	663	714	670	655
Thu	278	202	233	159	182	203	362	570	777	828	...	876	969	935	1013	810	698
Tue	269	240	186	170	209	239	415	655	889	880	...	943	938	1026	1019	905	731
Wed	250	216	189	209	156	255	410	701	875	808	...	904	867	990	1037	894	686

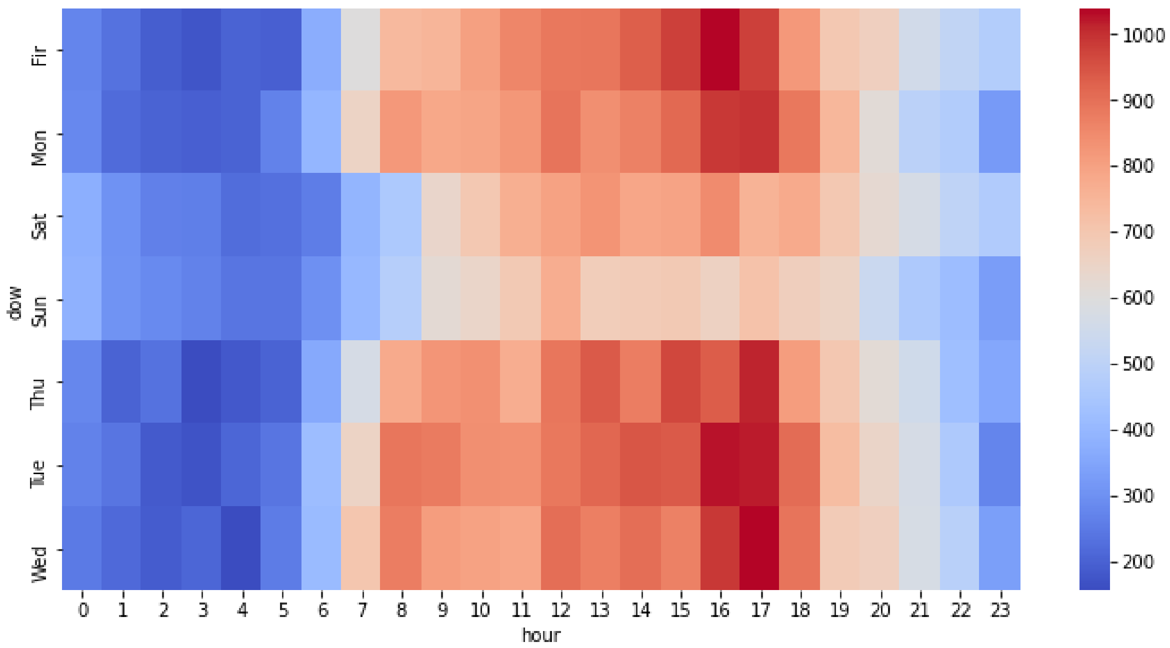
7 rows × 24 columns

In [37]:

```
plt.figure(figsize=(12,6))
sns.heatmap(dayhour,cmap='coolwarm')
```

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x28b4d0dc848>
```



Here we obeserve that most 911-calls are during 8am-6pm , with sundays having the least amount of activity

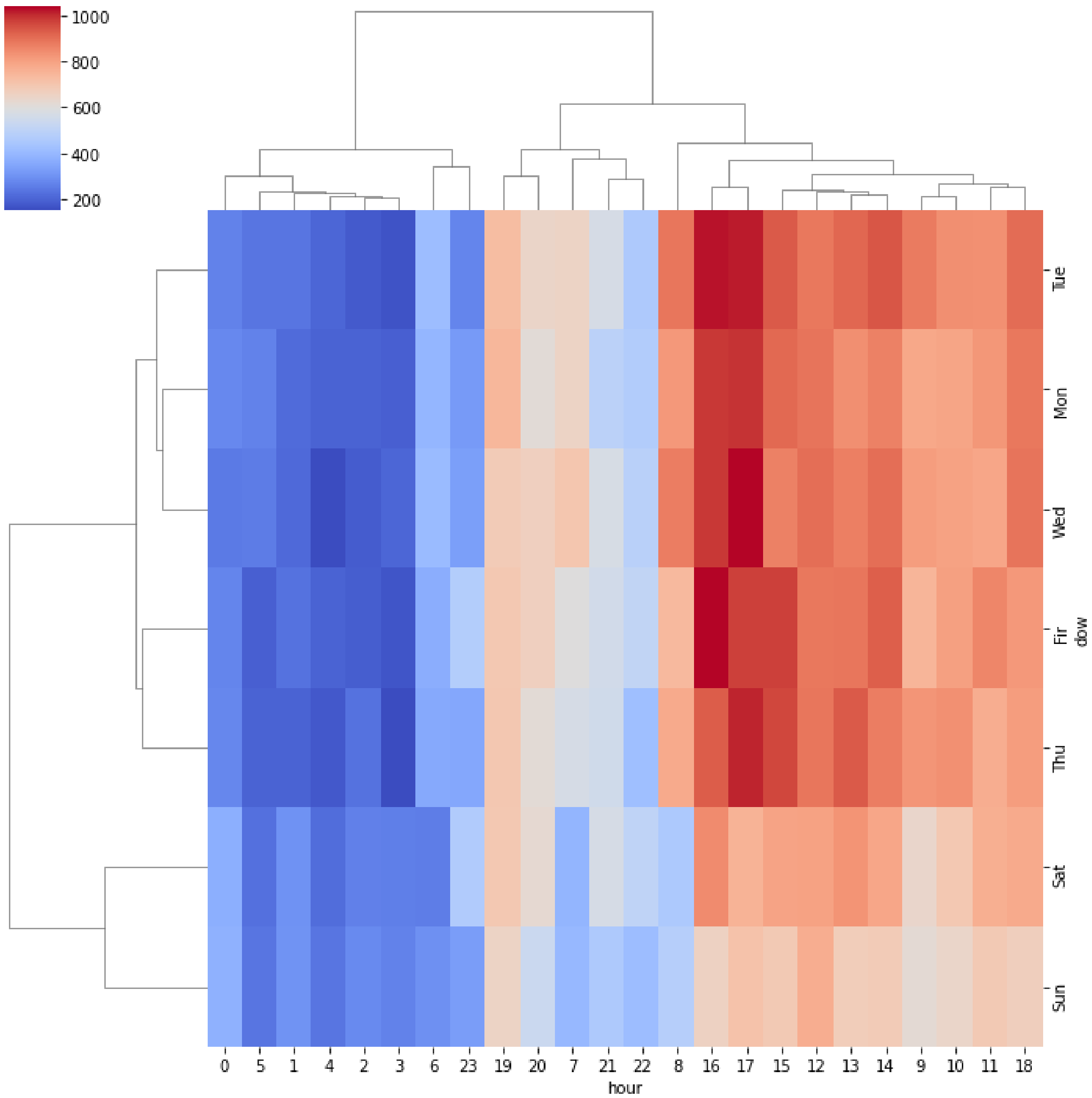
clustermap using this DataFrame.

In [35]:

```
sns.clustermap(dayhour,cmap='coolwarm')
```

Out[35]:

```
<seaborn.matrix.ClusterGrid at 0x28b4d0c3f88>
```



Observation:

- high amount of calls: Monday - Friday between 12pm-4pm
- lowest amount of calls: Saturday - Sunday

Using Month as the column.

In [32]:

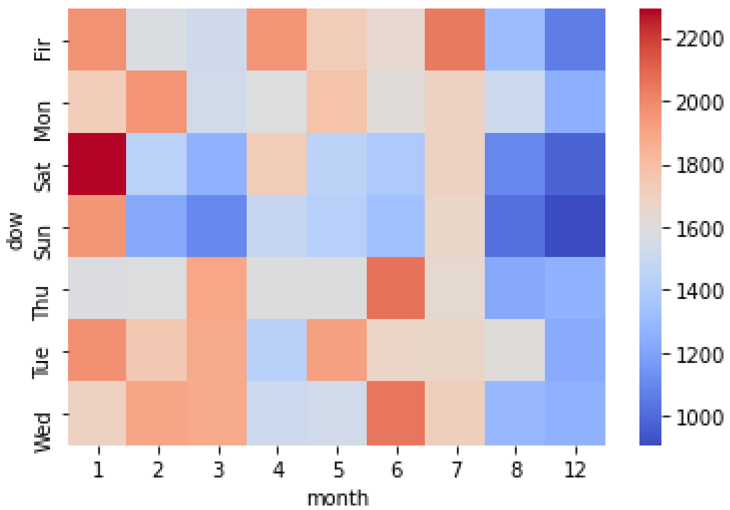
```
daymonth = df.groupby(by = ['dow','month']).count()['Reason'].unstack()
```

In [38]:

```
sns.heatmap(daymonth,cmap='coolwarm')
```

Out[38]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x28b4d6cad48>
```

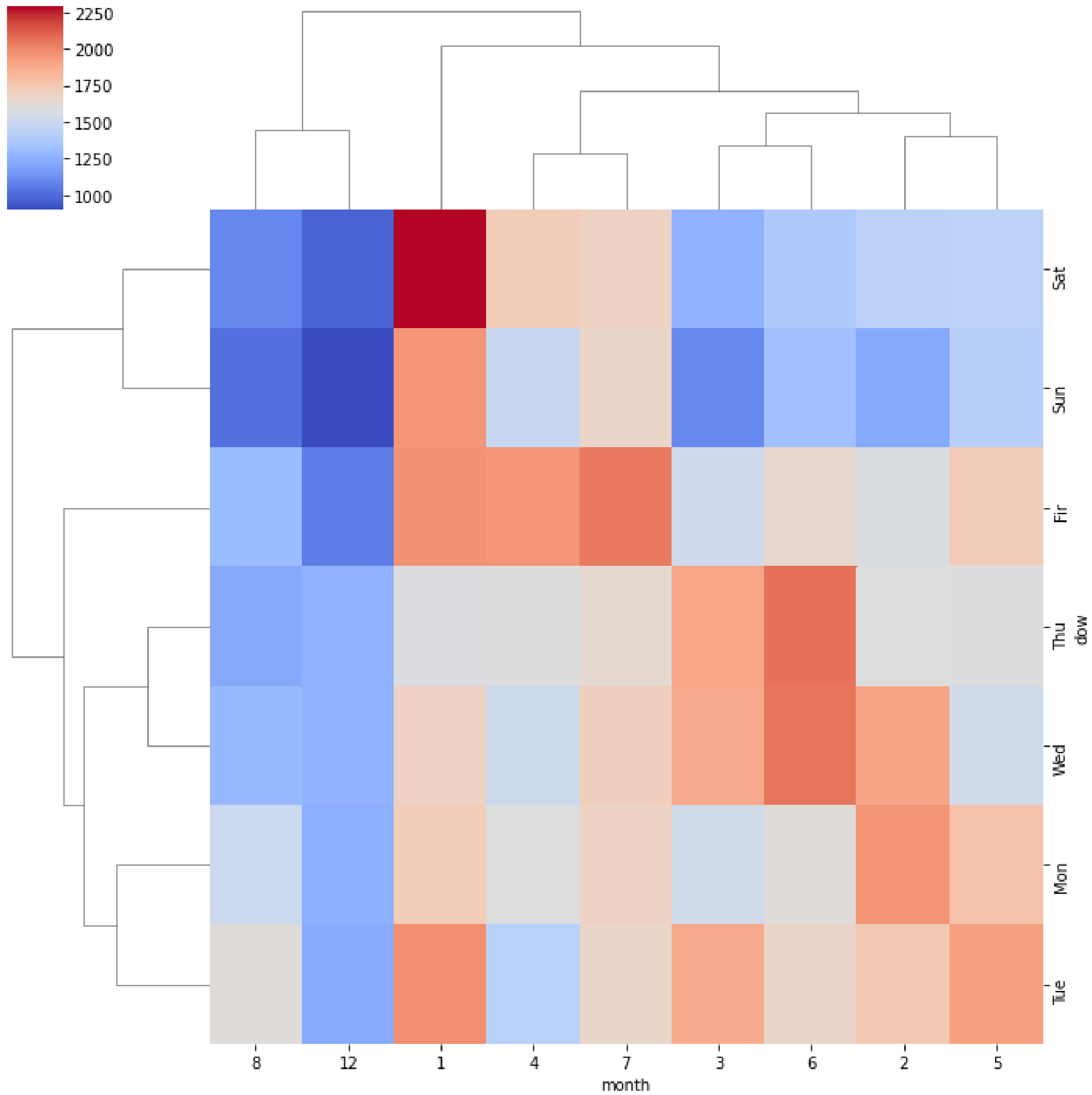


In [36]:

```
sns.clustermap(daymonth,cmap='coolwarm')
```

Out[36]:

<seaborn.matrix.ClusterGrid at 0x28b4d680848>



This is the end of the initial Exploratory Data Analysis(EDA) on 911-calls dataset. Will continue to update this notebook as my study in Data Science progresses.