Exploratory Data Analysis (EDA) and Data Visualization

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In this Exploratory Data Analysis and Visualization notebook, we want to explore the 911 call data from Kaggle.com

The Dataset

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
df = pd.read_csv('911.csv')
```

Discriptive Statistics

We first check the data information to see the number of observations, datatype, memory usages etc.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 105957 entries, 0 to 105956
Data columns (total 9 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   lat        105957 non-null  float64
 1   lng        105957 non-null  float64
 2   desc       105957 non-null  object
 3   zip        92735 non-null   float64
 4   title      105957 non-null  object
 5   timeStamp  105957 non-null  object
 6   twp        105924 non-null  object
 7   addr       105957 non-null  object
 8   e          105957 non-null  int64
dtypes: float64(3), int64(1), object(5)
memory usage: 7.3+ MB
```

A first look of the data

```
df.head()
```

	lat	lng	desc	zip
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0
2	40.121182	-75.351975	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401.0
3	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401.0
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	NaN

Some data related questions. For example,

- What are the top 10 zipcodes for 911 calls?

  ```
  df.zip.value_counts().head(10)
  ```

  ```
  zip
  19401.0    7445
  19464.0    7122
  19403.0    5189
  19446.0    5060
  19406.0    3404
  19002.0    3238
  ```

```
19468.0    3202
19454.0    2984
19090.0    2832
19046.0    2779
Name: count, dtype: int64
```

- What are the top 10 twonships for the 911 calls?

```
df.twp.value_counts().head(10)
```

```
twp
LOWER MERION         9069
ABINGTON             6403
NORRISTOWN           6265
UPPER MERION         5551
CHELTENHAM           4882
POTTSTOWN            4448
UPPER MORELAND       3658
LOWER PROVIDENCE     3435
PLYMOUTH             3371
HORSHAM              3142
Name: count, dtype: int64
```

Feature Engineering

Sometimes creating new features from the existing features helps understand the data better. For example, for this dataset, we can create a new column called `Reason` for emergency 911 call.

```
df['reason'] = df.title.apply(lambda title: title.split(':')[0])
df.head(3)
```

	lat	lng	desc	zip	tit
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0	EM
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EM
2	40.121182	-75.351975	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401.0	Fi

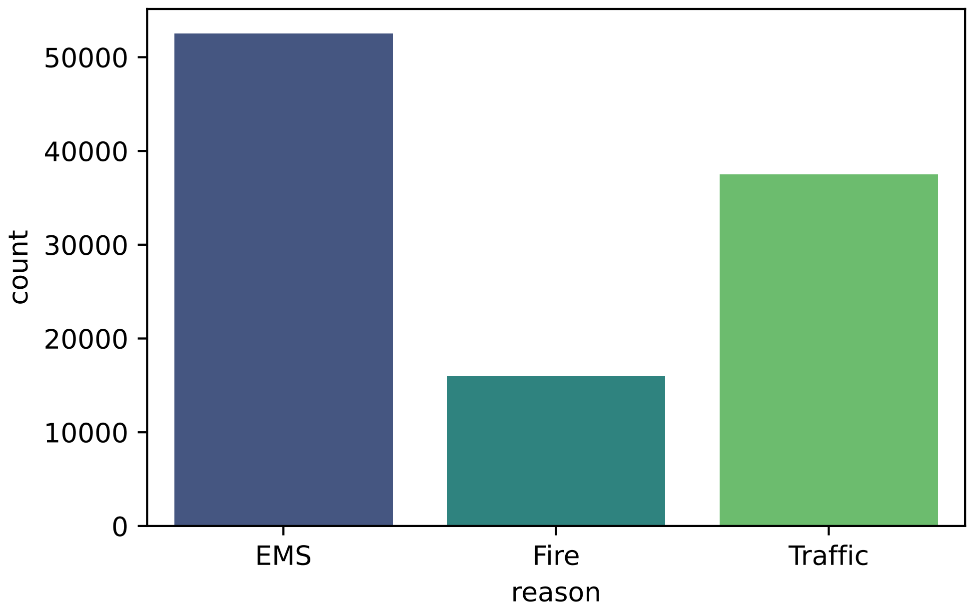
what are top reasons for the emergency calls?

```
df.reason.value_counts()
```

```
reason
EMS        52515
Traffic    37505
Fire       15937
Name: count, dtype: int64
```

visualization of the reason column

```
sns.countplot(x=df.reason, hue=df.reason, palette='viridis')
```



The `timeStamp` column contains time information year-month-day hour:minute:second format but in string value/object. So we can convert this column to obtain new features.

```
df['timeStamp'] = pd.to_datetime(df.timeStamp)
time = df.timeStamp.iloc[0]
```

```
/tmp/ipykernel_7913/1994586768.py:1: UserWarning:

Could not infer format, so each element will be parsed individually, falling back to `dateuti
```

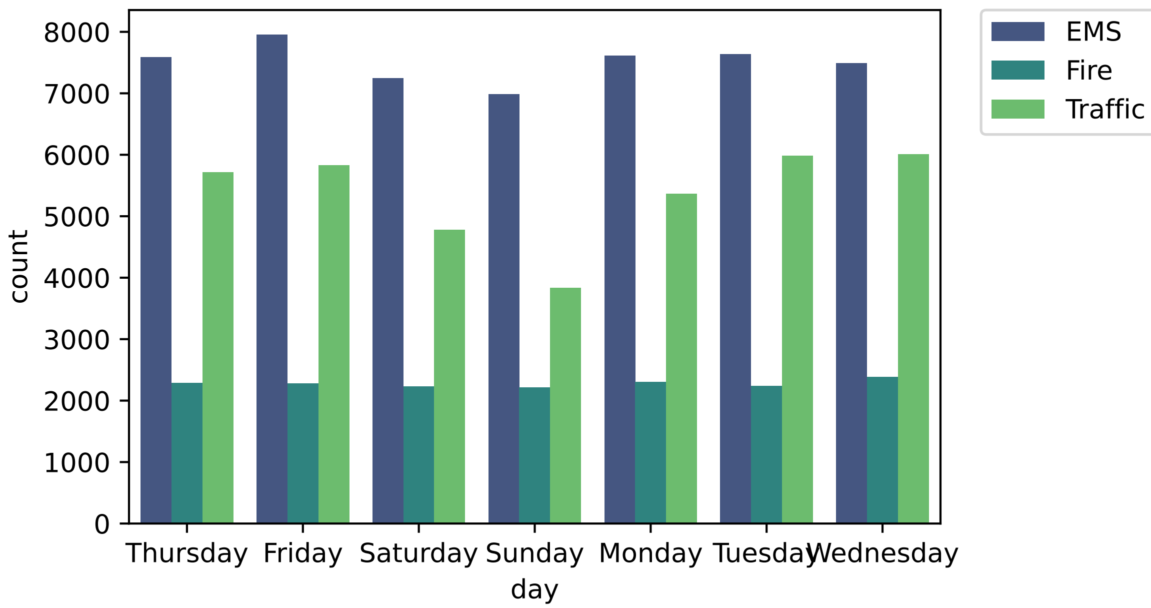
Let's create new features called `hour`, `month`, and `day` of the calls.

```
df['hour'] = df.timeStamp.apply(lambda time: time.hour)
df['month'] = df.timeStamp.apply(lambda time: time.month)
df['day'] = df.timeStamp.apply(lambda time: time.dayofweek)
days = {
    0:'Monday', 1:'Tuesday', 2:'Wednesday',
    3:'Thursday', 4:'Friday', 5:'Saturday',
    6:'Sunday'
    }
df.day = df.day.map(days)
df = df[
    ['lat','lng','zip','twp','e','reason',
    'month','day','hour','title','timeStamp',
    'desc','addr']
    ]
df.head(3)
```

	lat	lng	zip	twp	e	reason	month	day	hour	titl
0	40.297876	-75.581294	19525.0	NEW HANOVER	1	EMS	12	Thursday	17	EM
1	40.258061	-75.264680	19446.0	HATFIELD TOWNSHIP	1	EMS	12	Thursday	17	EM
2	40.121182	-75.351975	19401.0	NORRISTOWN	1	Fire	12	Thursday	14	Fir

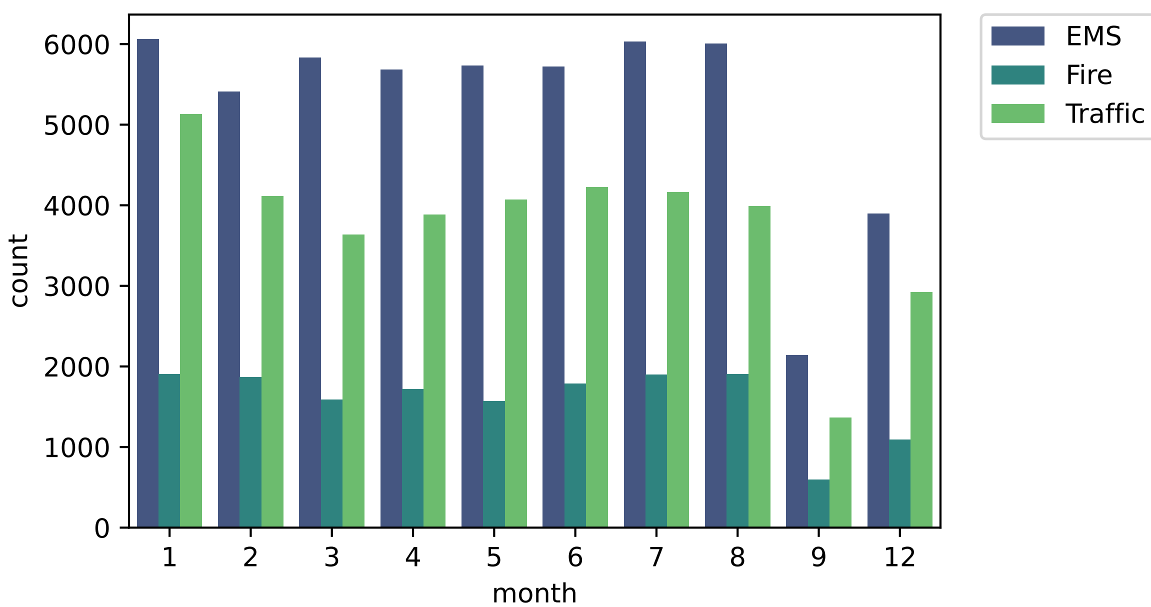
Now that we have almost a clean dataset, we can analyze the reason column based on the days of the week or months of a year.

```
sns.countplot(x='day', data= df, hue='reason', palette='viridis')
plt.legend(bbox_to_anchor=(1.05,1), loc=2, borderaxespad=0.0)
```



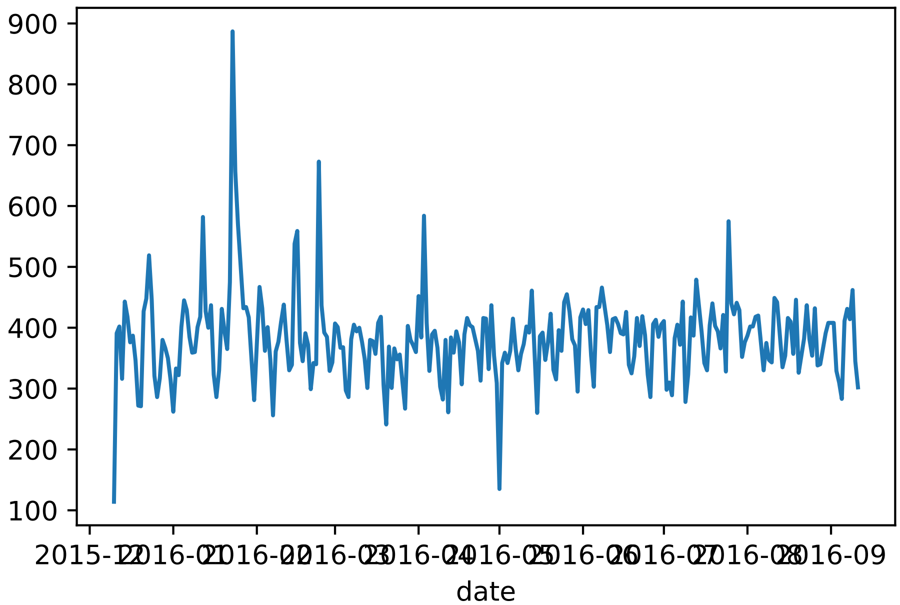
For the month column

```
sns.countplot(x='month', data= df, hue='reason', palette='viridis')
plt.legend(bbox_to_anchor=(1.05,1), loc=2, borderaxespad=0.0)
```



To create a time series data

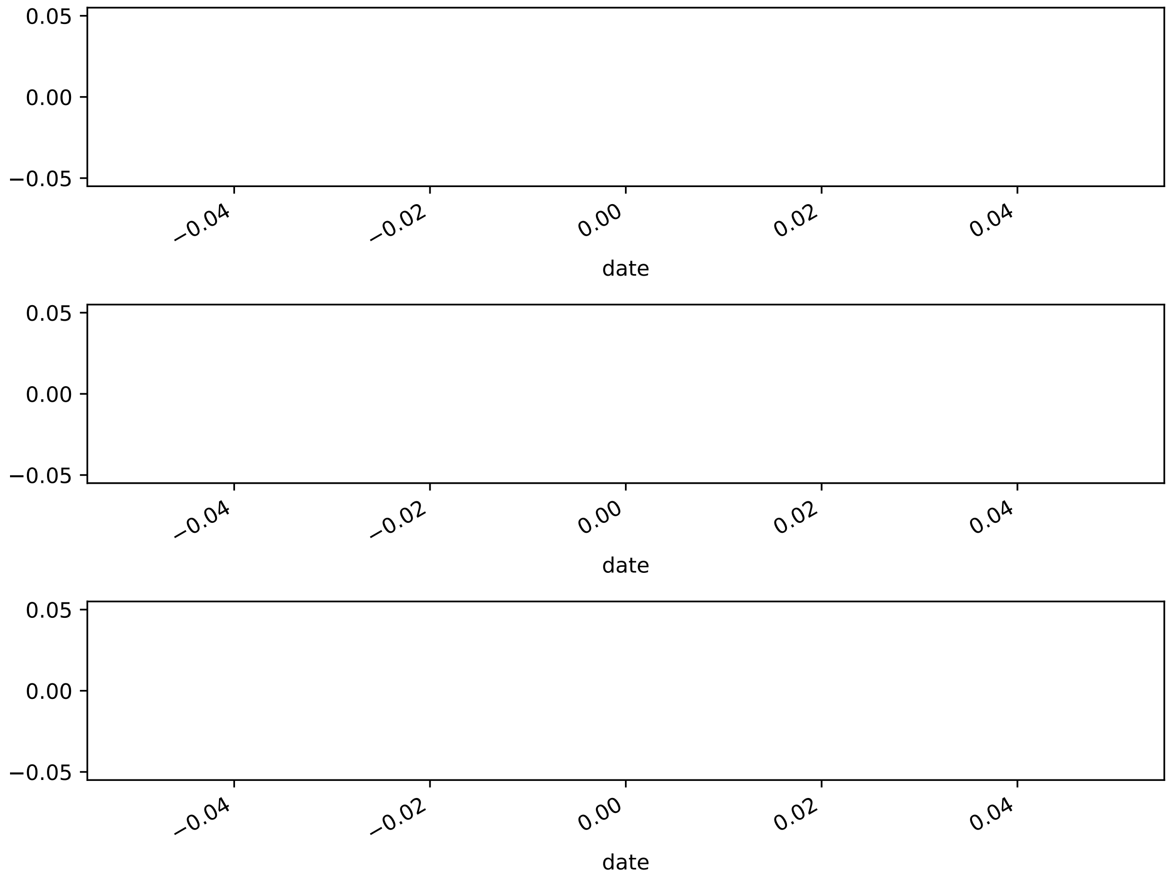
```
df['date'] = df['timeStamp'].apply(lambda time: time.date())
df.groupby('date').count()['twp'].plot()
```



Now to see for each reason

```
start_date = pd.to_datetime('2019-01-01')


df['date'] = pd.to_datetime(df['date'])


fig = plt.figure(figsize=(7.9,6))

ax1 = fig.add_subplot(311)
df[(df['reason'] == 'Traffic') & (df['date'] >= start_date)].groupby('date').count()['twp'].p

ax2 = fig.add_subplot(312)
df[(df['reason'] == 'Fire') & (df['date'] >= start_date)].groupby('date').count()['twp'].plo

ax3 = fig.add_subplot(313)
df[(df['reason'] == 'EMS') & (df['date'] >= start_date)].groupby('date').count()['twp'].plot

plt.tight_layout()
```

```
plt.show()
```



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