

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 POTTSRGROVE; 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 townships 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

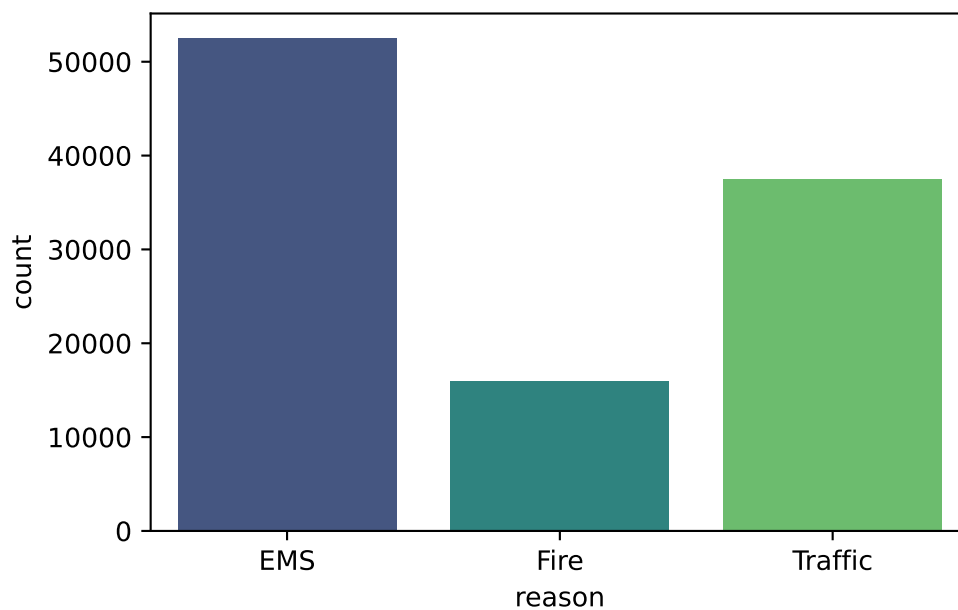
what are top reasons for the emergency calls?

```
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_7730/1994586768.py:1: UserWarning:

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

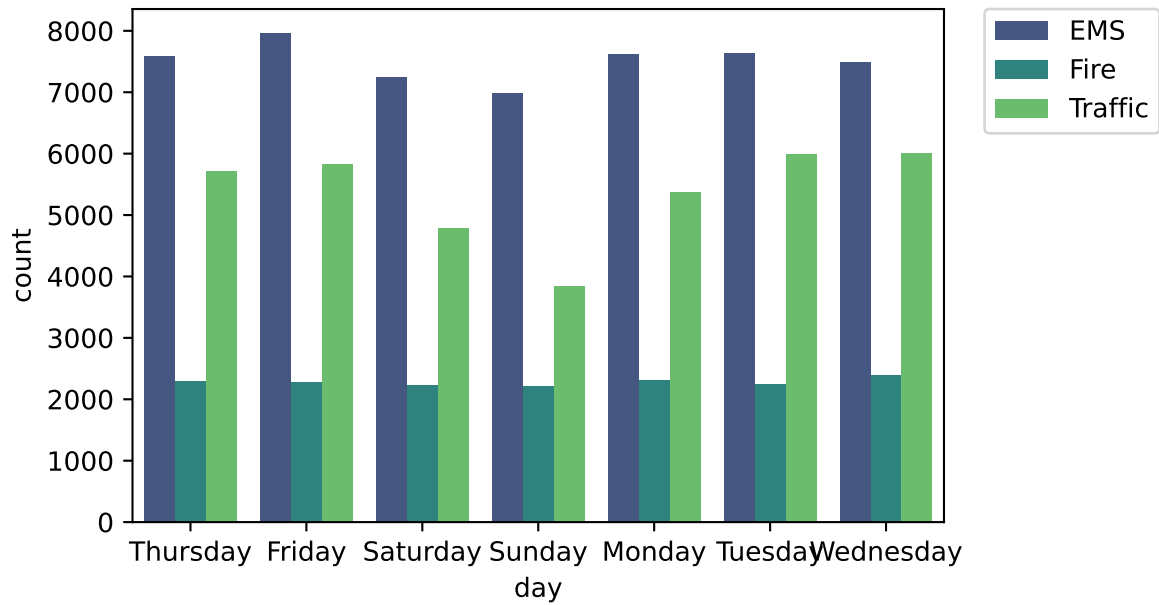
Let's create new features called `hour`, `month`, and `day` of the calls.

```
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	title
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

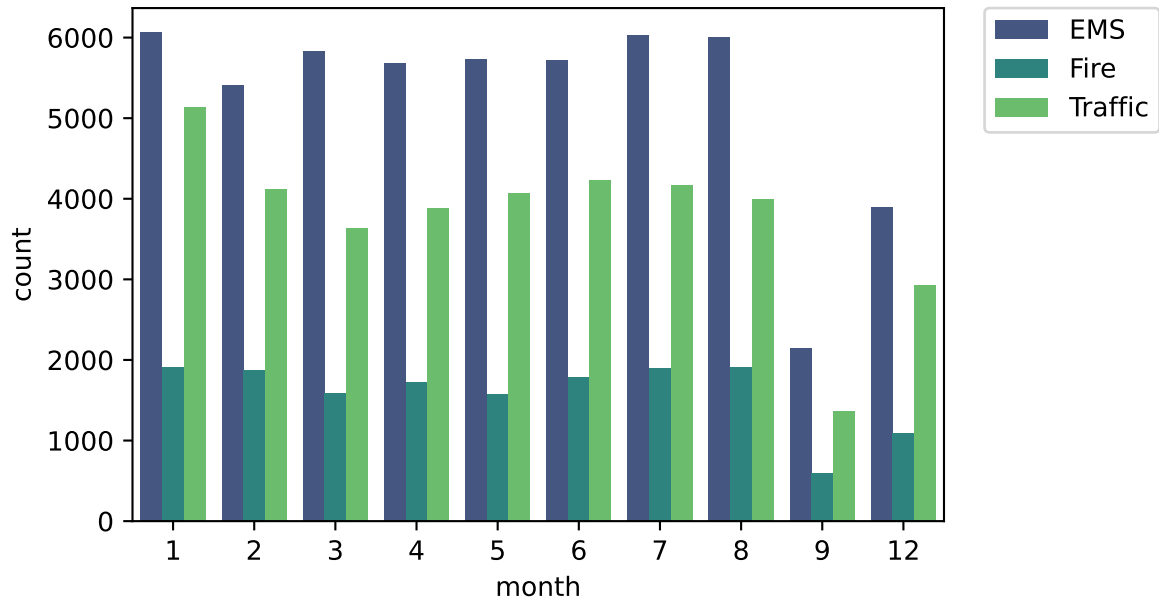
Now that we have almost a clean dataset, we can analyze the reason column based on the days of the week or months of a year.

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



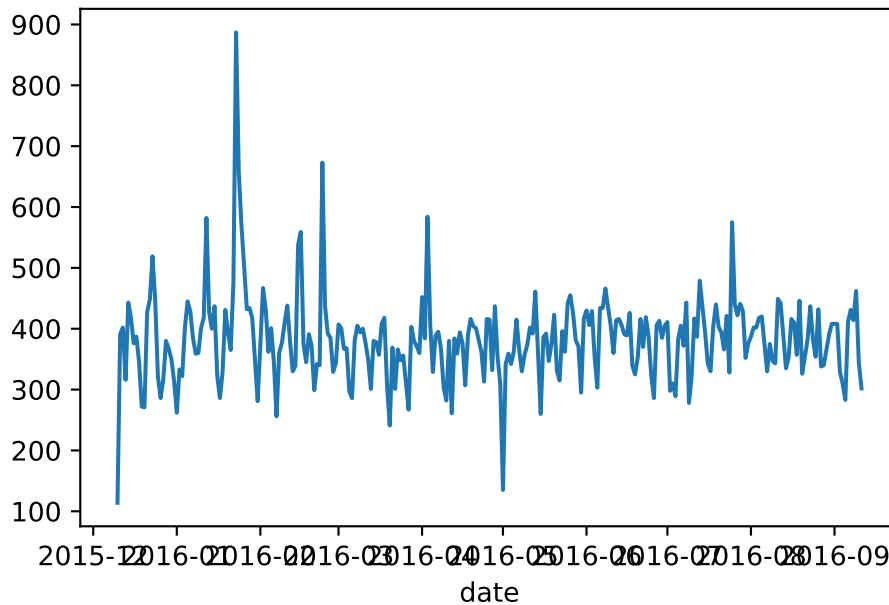
For the month column

```
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))

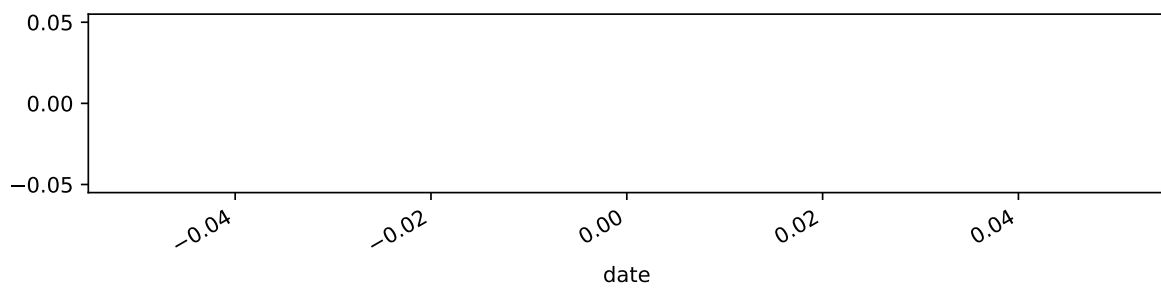
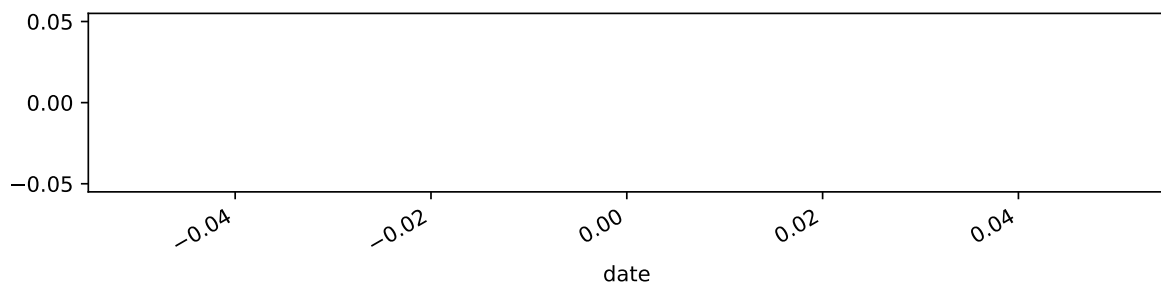
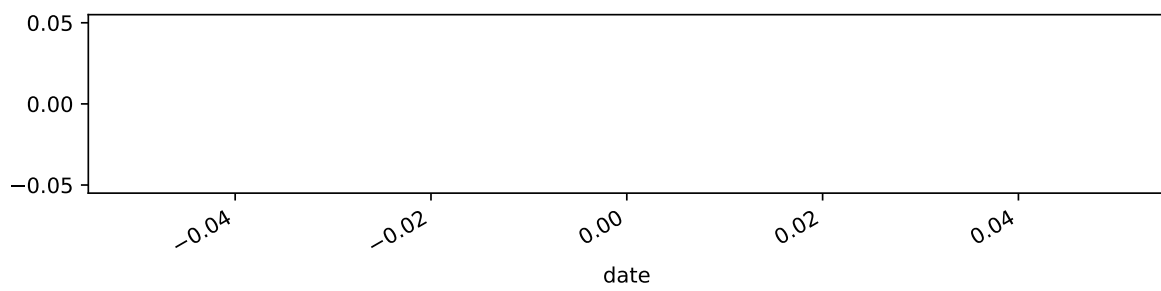
ax1 = fig.add_subplot(311)
df[(df['reason'] == 'Traffic') & (df['date'] >= start_date)].groupby('date').count()['twp'].plot()

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

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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