# MUKESH PATEL SCHOOL OF TECHNOLOGY MANAGEMENT AND ENGINEERING

(Affiliated to NMIMS Deemed to be University, Mumbai)



## **Data Extraction and Processing**

Project Report

on

"Analysis of the 911 Emergency Calls from Montgomery County"

#### Submitted by:

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### **About the Dataset**

**Dataset Title:** Emergency – 911 Calls, Montgomery Country

URL for Dataset Download:

https://www.kaggle.com/datasets/mchirico/montcoalert

The 911 emergency call dataset contains collection of information related to the emergency calls made on 911 Montgomery County, PA, due to various reasons as this serves as a crucial lifeline for residents and visitors in times of distress. This dataset contains details about the exact location of the emergency stations that are contacted, description of emergency, detail about the emergency, timestamp, etc. which are used to perform various analysis and visualization.

Description about the attributes in the dataset:

Attribute Name	Description
Lat	Latitude of the station
Lng	Longitude of the station
Desc	Description of the Emergency Call
Zip	Zipcode
title	Emergency Reason
Timestamp	Timestamp of Call (YYYY-MM-DD HH:MM:SS)
Twp	Township
Addr	Address
e	Dummy Variable (always 1)

#### **DATA EXPLORATION**

• Importing pandas, numpy, seaborn, matplotlib.pyplot, geopandas and plotly.express libraries

```
[ ] import pandas as pd
import numpy as np

[ ] import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

[ ] import geopandas as gpd
import plotly.express as px
```

• Reading the dataset and displaying the first 5 values



• Printing all the columns of the dataframe

```
[ ] print(dataframe.columns)

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

• .shape -> shows the total number of rows and columns in the dataset

```
[ ] print(dataframe.shape)
(663522, 9)
```

There are 663522 rows and 9 columns

• .dtypes-> gives the data type of the attributes used in the dataset

```
[ ] print(dataframe.dtypes)
    lat
                float64
                float64
    lng
    desc
                object
                float64
    zip
    title
               object
    timeStamp
                object
    addr
                object
                  int64
    dtype: object
```

• .isnull.sum() -> checks the null values and returns the total null values present for all attributes.

```
[ ] dataframe.isnull().sum()
                     0
    lng
                     0
    desc
                     0
                 80199
    zip
    title
                     0
    timeStamp
                     0
    twp
                   293
                     0
    addr
                     0
    dtype: int64
```

Zip and twp comprises of null values

• .describe() -> generates descriptive statistics summarizing the distribution of numerical data.

```
[ ] print(dataframe.describe())

        lat
        lng
        zip
        e

        count
        663522.000000
        663522.000000
        583323.000000
        663522.0

        mean
        40.158162
        -75.300105
        19236.055791
        1.0

        std
        0.220641
        1.672884
        298.222637
        0.0

                                                    -119.698206
                                                          -75.392735 19038.000000
-75.305143 19401
                                                                                      1104.000000
         min
                               0.000000
                                                                                                                           1.0
         25%
                              40.100344
                                                                                                                           1.0
         58%
                              40.143927
                                                                                                                           1.0
                                                           -75.211865 19446.000000
         75%
                              40.229008
                                                                                                                           1.0
         max
                              51.335390
                                                           87.854975 77316.000000
                                                                                                                           1.0
```

• Converts the 'timeStamp' column to a datetime format, sorts the DataFrame based on the 'timeStamp' column, and prints the 'timeStamp' column without any further modifications

```
[ ] #sorting of timeStamp in ascending order
    #dataframe['timeStamp'] = dataframe['timeStamp']

dataframe['timeStamp'] = pd.to_datetime(dataframe['timeStamp'], format='%Y-%m-%d
%H:%M')

sorted_dataframe = dataframe.sort_values(by='timeStamp', ascending=False)

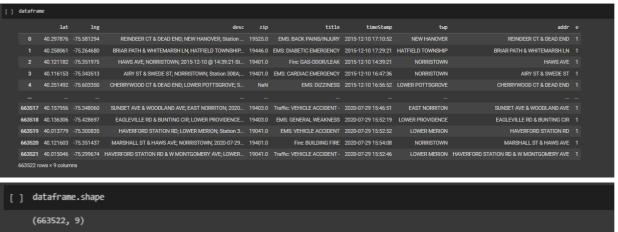
print(dataframe['timeStamp'])

0     2015-12-10 17:10:52
1     2015-12-10 17:29:21
2     2015-12-10 16:47:36
4     2015-12-10 16:56:52
...
663517     2020-07-29 15:46:51
663518     2020-07-29 15:52:19
663519     2020-07-29 15:52:52
663520     2020-07-29 15:52:52
663521     2020-07-29 15:52:46
Name: timeStamp, Length: 663522, dtype: datetime64[ns]
```

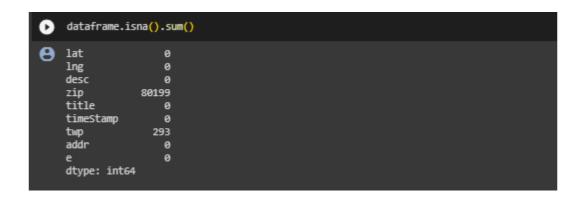
• Sorting the titles in ascending alphabetical order

```
[ ] # Sort the incident titles in ascending alphabetical order
    sorted_dataframe = dataframe.sort_values(by='title', ascending=True)
    dataframe['title'].head(25)
               EMS: BACK PAINS/INJURY
              EMS: DIABETIC EMERGENCY
                  Fire: GAS-ODOR/LEAK
               EMS: CARDIAC EMERGENCY
                       EMS: DIZZINESS
                     EMS: HEAD INJURY
                 EMS: NAUSEA/VOMITING
         EMS: RESPIRATORY EMERGENCY
                EMS: SYNCOPAL EPISODE
    8
         Traffic: VEHICLE ACCIDENT -
         Traffic: VEHICLE ACCIDENT -
    10
         Traffic: VEHICLE ACCIDENT -
    11
        Traffic: VEHICLE ACCIDENT -
    13
         Traffic: VEHICLE ACCIDENT -
          Traffic: VEHICLE ACCIDENT
    14
          Traffic: VEHICLE ACCIDENT -
    15
         EMS: RESPIRATORY EMERGENCY
                      EMS: DIZZINESS
                EMS: VEHICLE ACCIDENT
        Traffic: DISABLED VEHICLE -
    19
    20
        Traffic: VEHICLE ACCIDENT -
         Traffic: DISABLED VEHICLE -
                 Fire: APPLIANCE FIRE
          Traffic: DISABLED VEHICLE -
    23
          Traffic: VEHICLE ACCIDENT -
    Name: title, dtype: object
```

• Printing the dataframe



#### **DATA PREPROCESSING**



Dropping all the null values

```
[ ] df=dataframe.dropna()
```

• converts the 'timeStamp' column to a string type and then splits it into separate 'Date' and 'Time' columns based on the space character



• dropping the entire column 'e' which has dummy values

```
(20) df = df.drop(['e'],axis=1)
```

```
[21] df.isna().sum()
     lat
     lng
                  0
     desc
     zip
                  0
     title
                  0
     timeStamp
                  0
     twp
                  0
     addr
                  0
     Date
                  а
     Time
     dtype: int64
```

Shows that the dataset has no null values and the column 'e' has been dropped out.

• Dropping the missing values from the DataFrame 'df' and subsequently counts the non-null values for each column.

```
[22] df.dropna(inplace=True)
     df.count()
     lat
                  29714
     lng
                  29714
     desc
                  29714
     zip
                  29714
     title
                  29714
     timeStamp
                  29714
     twp
                  29714
     addr
                  29714
     Date
                  29714
     Time
                  29714
     dtype: int64
```

• the 'desc' column in the DataFrame 'df' is split on the string 'Station', and the resulting second part is further split on ';' to extract the first part.

```
[23] df['desc'].str.split('Station', expand=True)[1].str.split(';', expand=True)[0]

0 332
1 345
2 :STA27
3 308A
5 345
...
33968 369
33969 None
33970 None
33971 None
33972 EMS
Name: 0, Length: 29714, dtype: object
```

• Extracting the substring after the second occurrence of ';' in the 'desc' column, then extracts the text after 'Station' and assigns it to the 'Station\_num' column in the DataFrame 'df'

```
[24] #station from description
    df_station = pd.DataFrame()
    df_station = df['desc'].str.split(';', expand=False)
    df_station

    df_station = df_station.str[2]
    df_station = df_station.str.extract(rf'Station\s+(.+)')
    df_station

    df['Station_num'] = df_station
```

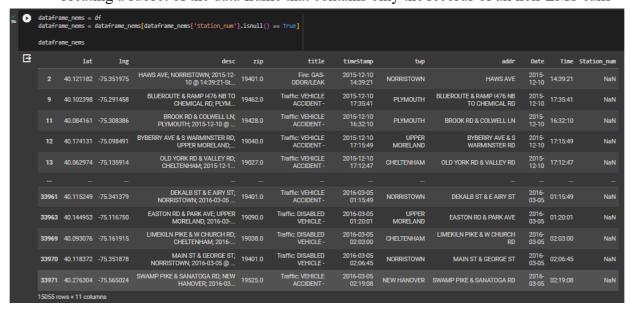
• Checking for null values in the dataframe



• Creating a subset of the data frame that contains only the records of all EMS calls



• Creating a subset of the data frame that contains only the records of all non-EMS calls



- Converting given field to pandas timestamp format.
- Selecting hours using dt.hour from the timeStamp data field.
- Storing all the hours in a number format in a new column called 'Timing'

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

• Creating a data map, containing string values corresponding to the time of call to categorize the data.

```
[ ] df['timeStamp']= pd.to_datetime(df['timeStamp'])
    time = df['timeStamp'].iloc[0]
    time.hour
    df['Timing'] = df['timeStamp'].apply(lambda time: time.hour)
```

• Maping and replacing the values in the 'Timings' column.

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

• Storing data about hour, day and month when the call took place, by extracting the corresponding values using dt.hour,dt.month, dt.weekday.

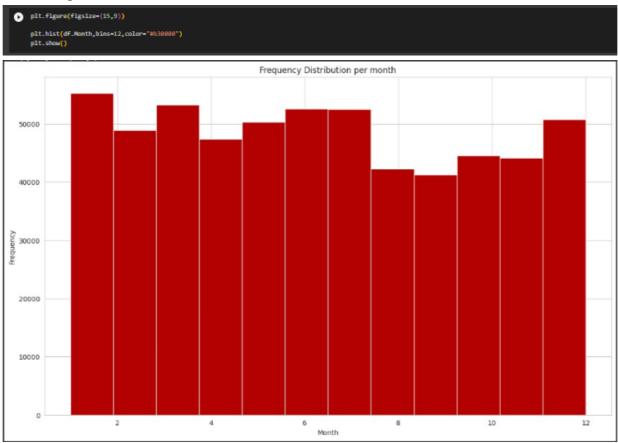
```
[32] df['Hour'] = df.timeStamp.dt.hour
df['Month'] = df.timeStamp.dt.month
df['DayOfWeek'] = df.timeStamp.dt.weekday
```

- Here, the records stored in the title column are used to extract the category of call (EMS, Fire, Traffic) into a separate field labelled Call\_Category.
- The extended reason such as head injury, gas leak or accident is separately stored in another field labelled Call Reason.

```
[ ] df['Call_Category'] = df.title.str.split(':', expand=True)[0]
    df['Call_Reason'] = df.title.str.split(':', expand=True)[1].str.replace(' -', '')
```

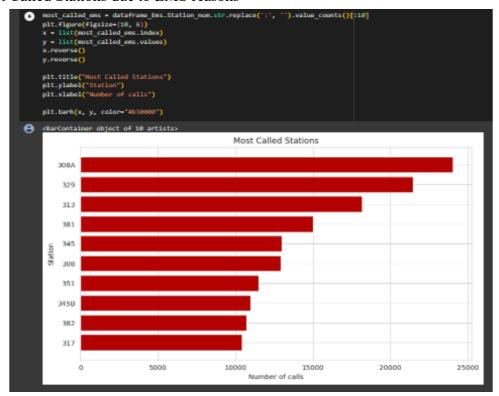
# **DATA VISUALIZATION**

• Histogram to indicate the number of calls made each month



The maximum number of calls were made in January followed by March and then June & July

• Most Called Stations due to EMS reasons

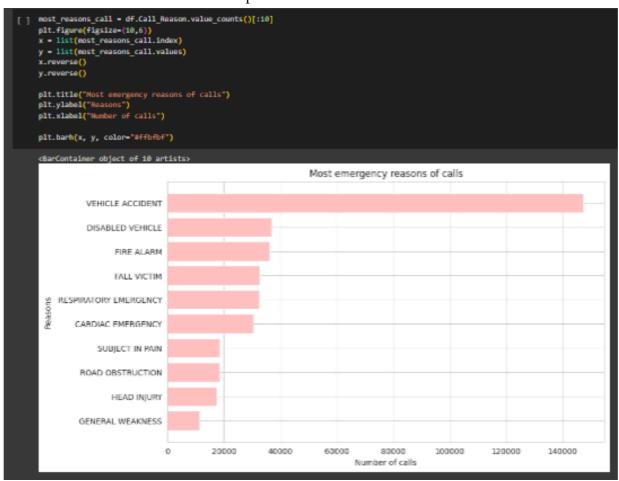


The most called station number is 308A.

• Top 10 Townships who have called 911

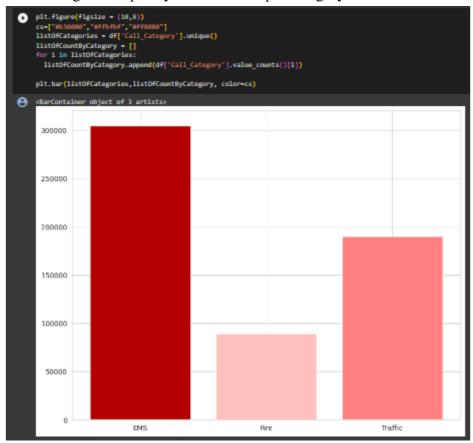
```
LOWER MERION 55498
ABINGTON 39947
NORRISTOWN 37633
UPPER MERION 36018
CHELTENHAM 36574
POTTSTOWN 27387
UPPER MORELAND 22932
LOWER PROVIDENCE 22476
PLYNOUTH 20116
UPPER DUBLIN 18862
Name: twp, dtype: int64
```

• Most number calls made with respect to reasons



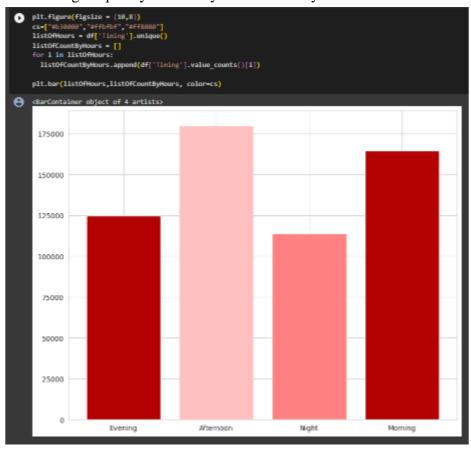
The most number of emergency calls are made because of Vehicle Accidents

• Bar Plot indicating the frequency of calls made per category



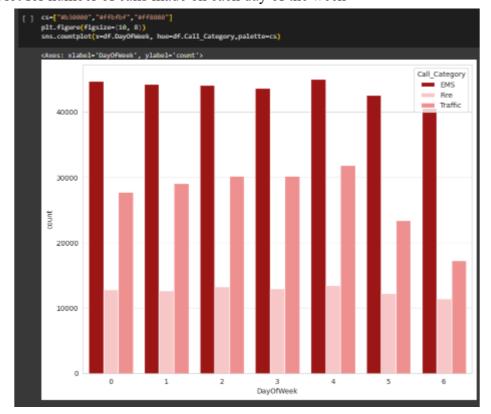
The most number of 911 calls are made because of EMS followed by traffic and Fire reasons.

• Bar Plot indicating frequency of calls by time of the day

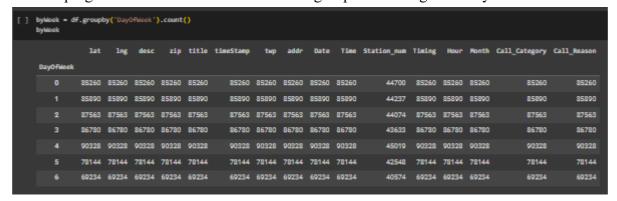


The most number of calls were made in the Afternoon

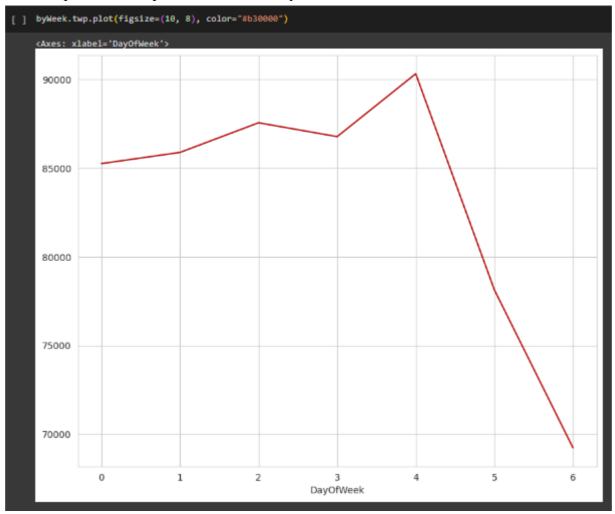
• Bar Plot for number of calls made on each day of the week



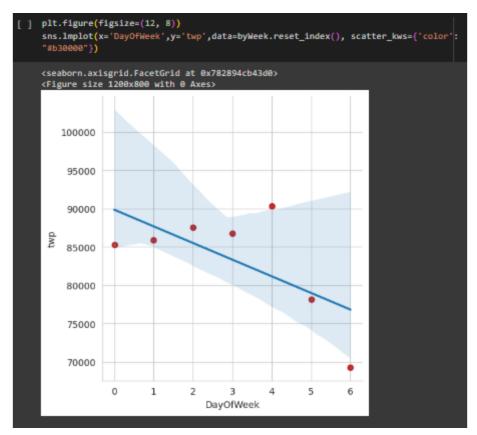
• Grouping the count of occurrences for each group and storing in the 'byWeek' DataFrame



• Line plot of the 'twp' column from the 'byWeek' DataFrame

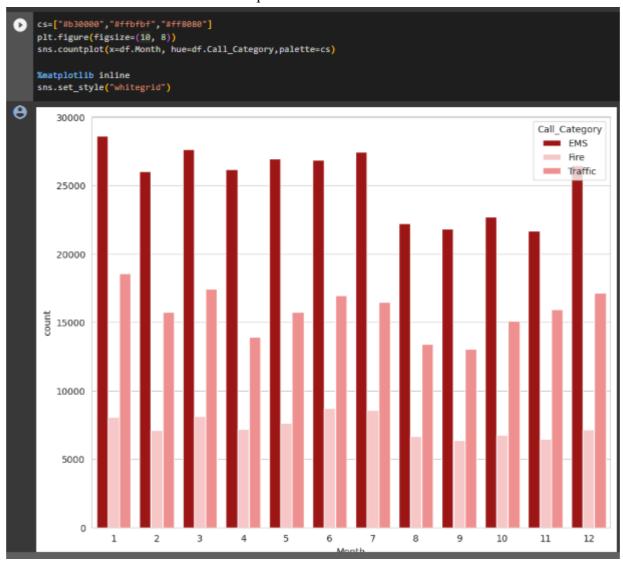


Maximum calls are made on the 5<sup>th</sup> Day of the Week

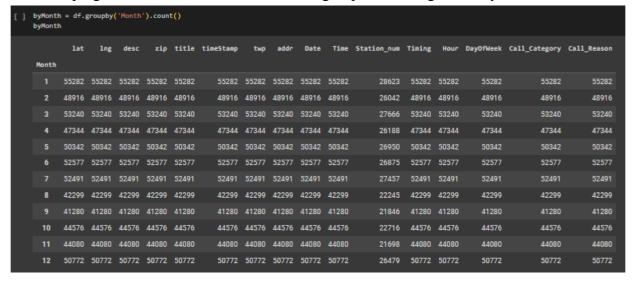


The provided code generates a scatter plot with a linear regression model (lmplot) using Seaborn. The plot visualizes the relationship between the 'DayOfWeek' and 'twp' columns from the 'byWeek' DataFrame. There is negative co-relation.

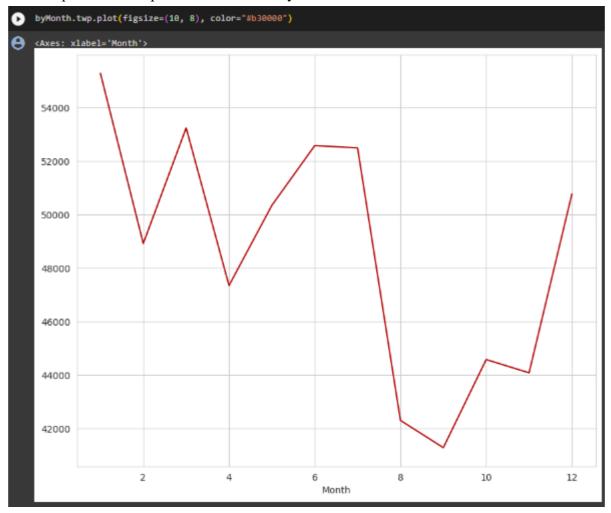
• Bar Plot for number of calls made per Month



• Grouping the count of occurrences for each group and storing in the 'byMonth' DataFrame

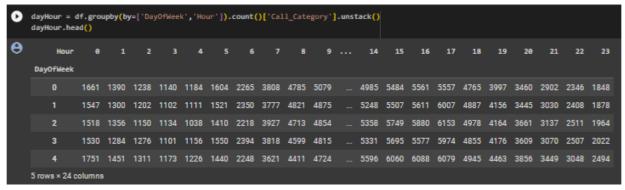


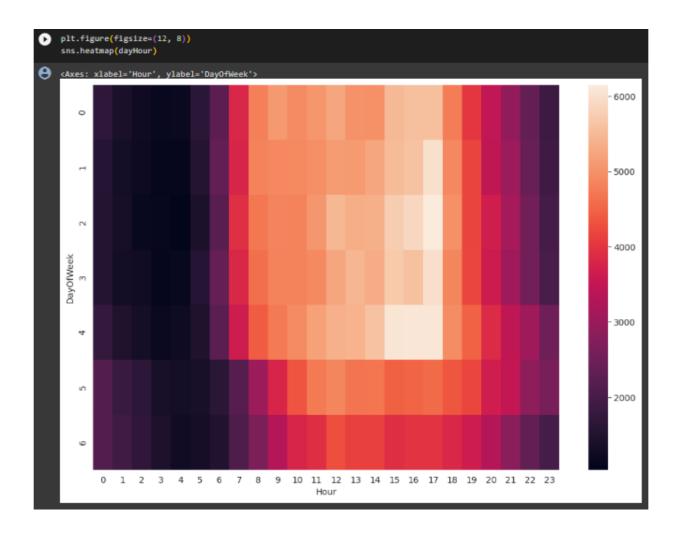
• Line plot of the 'twp' column from the 'byMonth' DataFrame



There is a sudden drop in the number of emergency calls made in the month of September, a steady number of calls were made from June to July and the most of calls were made in January.

• The code groups the DataFrame 'df' by both the 'DayOfWeek' and 'Hour' columns, counts the occurrences of 'Call\_Category' for each group, and aggregates the counts and .unstack() reshapes the grouped data, pivoting the inner level of the hierarchical index (Hour) to the columns and the outer level index, creating a new DataFrame 'dayHour' where the rows represent 'DayOfWeek' and the columns represent 'Hour'.





From this heatmap, we can conclude that the maximum number of calls were made in the middle of the week from 15:00hrs – 17:00hrs. The least amount of calls are made at the start of almost all days of the week. Also, as observed in the previous bar plots, our inference about the maximum calls being made during the afternoon can be verified.

#### **CONCLUSION**

In this project, we analysed the data collected in the Montgomery County, PA that contains records of emergency calls made to Montgomery County in Pennsylvania. We aimed to understand and analyse any trends present across emergency calls made in the county & aimed to visualize the data that spanned across multiple years.

We also wanted to understand what the majority of emergency calls were, pertaining to the type of emergency that are broadly classified in three categories: EMS, Fire & Traffic.

While performing, we started with an original dataset from Kaggle (sourced from www.montgomerycountypa.gov), containing 663522 records, each containing 9 attributes.

Throughout the project we carried out the following tasks:

- understanding the shape of the dataset
- understanding the nature of the attributes stored in the dataset
- indetifying any anamolies/inconcistencies in the dataset
- data cleaning such as removal of null values from the dataset
- extracting critical information about the emergency call into seperate attributes
- visualizing the a-forementioned data accurately, such that it can be used for inference and analysis

In conclusion, after performing data extraction & processing on the given dataset, we were able to gain a comprehensive understanding of the nature of the emergency calls made.

#### PYTHON CODE LINK

https://colab.research.google.com/drive/10G9i33NFULJnEiKyez69jsfJX-aOHpgy?usp=sharing