911 Calls Exploring Data and Analysis

For this Exploring Data Analysis project, we will be analyzing some 911 call data from Kaggle. 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)

Exploring Data Analysis report contents:

- Data overview
- Data cleaning and Feature Engineering: Categorical Data
- Data cleaning and Feature Engineering: Numerical Data
- Hypothesis Testing (3 of them)
- Conducting a formal significance test for one of the hypotheses and discuss the results
- Suggestions for next steps in analyzing this data
- Summary of the quality of this data set and a request for additional data if needed

Exploring Data Analysis Initial Plans:

- Read data as dataset
- present the summary of characteristics of dataset and find out the data types of features of our dataset.
- Check Nan values, null values, outlier and perform data cleaning
- EDA -> Check makes statistical analysis like determining mean, median, correlation, standard deviation and do visualization while identifying features to use to predict.
- Feature engineering and Hypothesis analysis

EMS: Emergency Medical Services

Read Data as dataset
reading data and view what kind of data it is and look for columns and rows we have.

	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 17:40:00	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 17:40:00	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 17:40:00	NORRISTOWN	HAWS AVE	1
3	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401.0	EMS: CARDIAC EMERGENCY	2015-12-10 17:40:01	NORRISTOWN	AIRY ST & SWEDE ST	1
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	NaN	EMS: DIZZINESS	2015-12-10 17:40:01	LOWER POTTSGROVE	CHERRYWOOD CT & DEAD END	1

We need to check characteristics of our dataset and find the summary of each features data types we have

```
<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
```

```
lat              0
lng              0
desc             0
title            0
timeStamp        0
e                0
twp             43
addr           519
zip          12855
dtype: int64
```

Through dataset, our data shows that we have the following characteristics:

- Number of rows (entries): 99492
- Number of columns: 9
- Dataset features contains different data types like (floats, objects)
- Dataset features shows missing data:
    - there are 12855 missing data from zip (zip code) column
    - there are 43 missing data from twp (township) column
    - there are 519 missing data addr (address) column
- Most of our data is type of Object (String).

1. We need to find out most consecutive emergency that most frequently use 911 call.
2. find out the place where there are many emergencies between 2015-2016.
3. We will use hypothesis testing to find out time of day that has effect on volume of 911 calls.

The results of above steps will help us to find which models that can be used to track down the uses of volume of 911 calls and days of most emergency.

After adding other features of hour, month, and days of weeks of emergency calls, the results is the following

	lat	lng	desc	zip	title	timeStamp	twp	addr	e	Hour	Month	Day of Week
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	REINDEER CT & DEAD END	1	17	12	Thu
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	2015-12-10 17:40:00	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1	17	12	Thu
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	HAWS AVE	1	17	12	Thu
3	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401.0	EMS: CARDIAC EMERGENCY	2015-12-10 17:40:01	NORRISTOWN	AIRY ST & SWEDE ST	1	17	12	Thu
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	NaN	EMS: DIZZINESS	2015-12-10 17:40:01	LOWER POTTSGROVE	CHERRYWOOD CT & DEAD END	1	17	12	Thu

Data Cleaning and Feature Engineering

1. We will start with Data cleaning

we found that we have the following data that we need to be careful working with them:

- there are 12855 missing data from zip (zip code) column
- there are 43 missing data from twp (township) column
- there are 519 missing data addr (address) column

Thus:

- we will replace missing values of zip code into 0
- we will replace missing input data of township into noTown Provided
- we will replace missing values of address to its township

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99492 entries, 0 to 99491
Data columns (total 12 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           99492 non-null  float64
 4   title         99492 non-null  object
 5   timeStamp     99492 non-null  datetime64[ns]
 6   twp           99492 non-null  object
 7   addr          98973 non-null  object
 8   e             99492 non-null  int64
 9   Hour          99492 non-null  int64
 10  Month         99492 non-null  int64
 11  Day of Week   99492 non-null  object
dtypes: datetime64[ns](1), float64(3), int64(3), object(5)
memory usage: 9.1+ MB
```

Now we can see that data cleaning have taken place.

To proceed with our goal of finding out the reason of most consecutive emergencies that most frequently use 911 call. we need, here we are go:

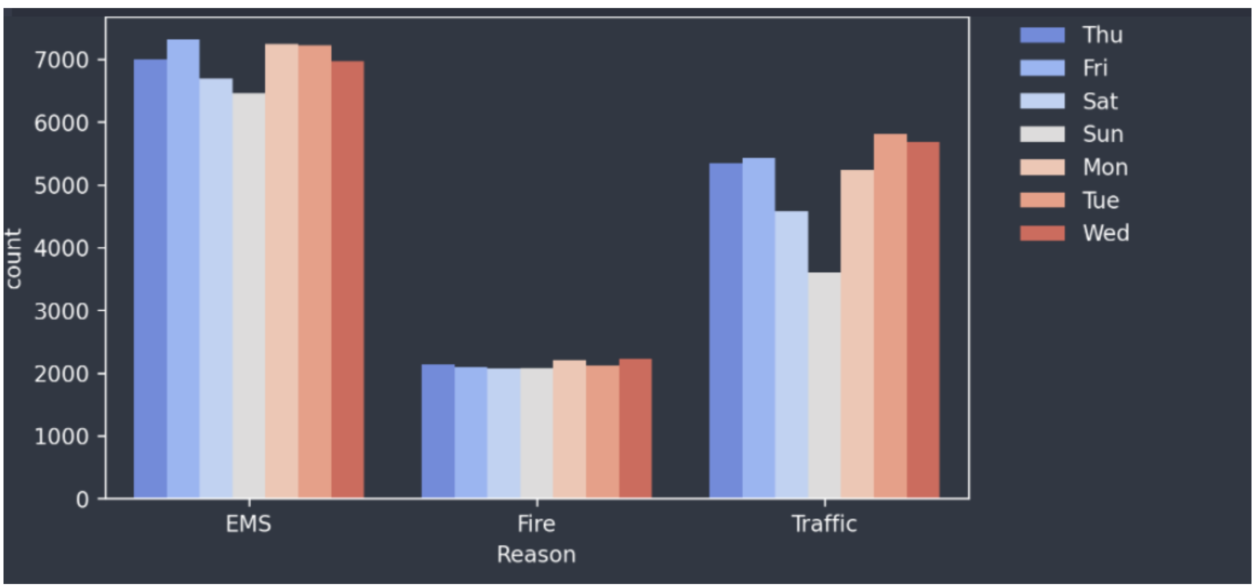
	lat	lng	desc	zip	title	timeStamp	twp	addr	e	Hour	Month	Day of Week	Reason
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0	EMS: BACK PAINS/INJURY	2015-12-10 17:40:00	NEW HANOVER	REINDEER CT & DEAD END	1	17	12	Thu	EMS
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	2015-12-10 17:40:00	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1	17	12	Thu	EMS
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	HAWS AVE	1	17	12	Thu	Fire
3	40.116153	-75.343513	AIRY ST & SWEDE ST; NORRISTOWN; Station 308A;...	19401.0	EMS: CARDIAC EMERGENCY	2015-12-10 17:40:01	NORRISTOWN	AIRY ST & SWEDE ST	1	17	12	Thu	EMS
4	40.251492	-75.603350	CHERRYWOOD CT & DEAD END; LOWER POTTSGROVE; S...	0.0	EMS: DIZZINESS	2015-12-10 17:40:01	LOWER POTTSGROVE	CHERRYWOOD CT & DEAD END	1	17	12	Thu	EMS

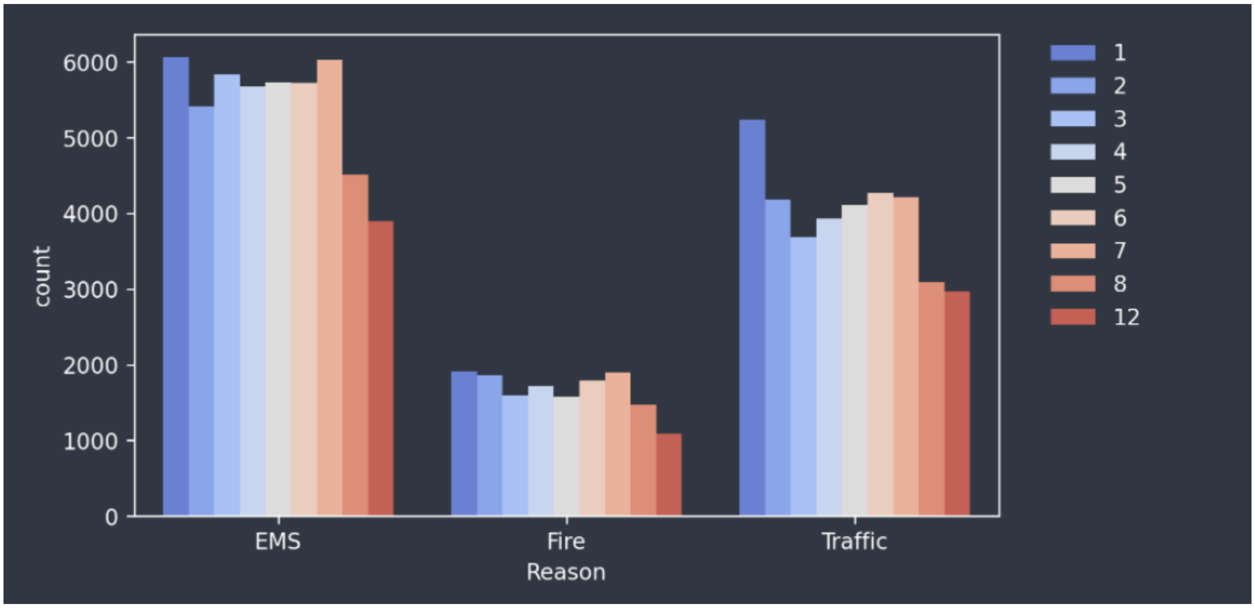
Key Findings and Insights, which synthesizes the results of Exploratory Data Analysis in an insightful and actionable manner

1. We need to see general statistical values of results from cleaning and feature engineering to describe our dataset

	lat	lng	zip	e	Hour	Month
count	99492.000000	99492.000000	99492.000000	99492.0	99492.000000	99492.000000
mean	40.159526	-75.317464	16752.030334	1.0	13.117085	4.983195
std	0.094446	0.174826	6460.927718	0.0	5.671564	3.012176
min	30.333596	-95.595595	0.000000	1.0	0.000000	1.000000
25%	40.100423	-75.392104	19006.000000	1.0	9.000000	3.000000
50%	40.145223	-75.304667	19131.000000	1.0	14.000000	5.000000
75%	40.229008	-75.212513	19440.000000	1.0	17.000000	7.000000
max	41.167156	-74.995041	77316.000000	1.0	23.000000	12.000000

The above results shows that there are no outliers in our data. Then, and the table provide mean, standard deviation, min max, median, quartiles for better visualization





From the above charts of reasons of call due to Days of week and month, the visualization shows that there is imbalanced data provided which might cause an issue while model classification

2. Then, we can start to find mean, median, correlation, standard deviation for each group to see the possibilities of model selection.

Reason	lat	lng	zip	e	Hour	Month
EMS	40.167055	-75.327201	17456.570207	1.0	12.771569	5.015406
Fire	40.155476	-75.319704	16766.697788	1.0	13.456166	4.970845
Traffic	40.150910	-75.303194	15781.176327	1.0	13.448466	4.944250

Reason	lat	lng	zip	e	Hour	Month
EMS	0.096620	0.180239	5605.714066	0.0	5.962304	2.987176
Fire	0.089404	0.185086	6426.186220	0.0	5.717137	2.971436
Traffic	0.092632	0.161416	7378.435335	0.0	5.196015	3.062346

- We can observe from the above results that emergency of Fire has much effect in volume of 911 calls as the hour it takes has greater mean and low standard deviation.
- EMS has least effect in volume of 911 calls as the hour it takes has low mean compared to other reasons.

we can observe that, we need to continue with applying transformation to our data to improve them for next step of model fit.

	Skew
Month	0.690686
Hour	-0.339847
zip	-2.192439
lat	-16.639012
lng	-21.550039

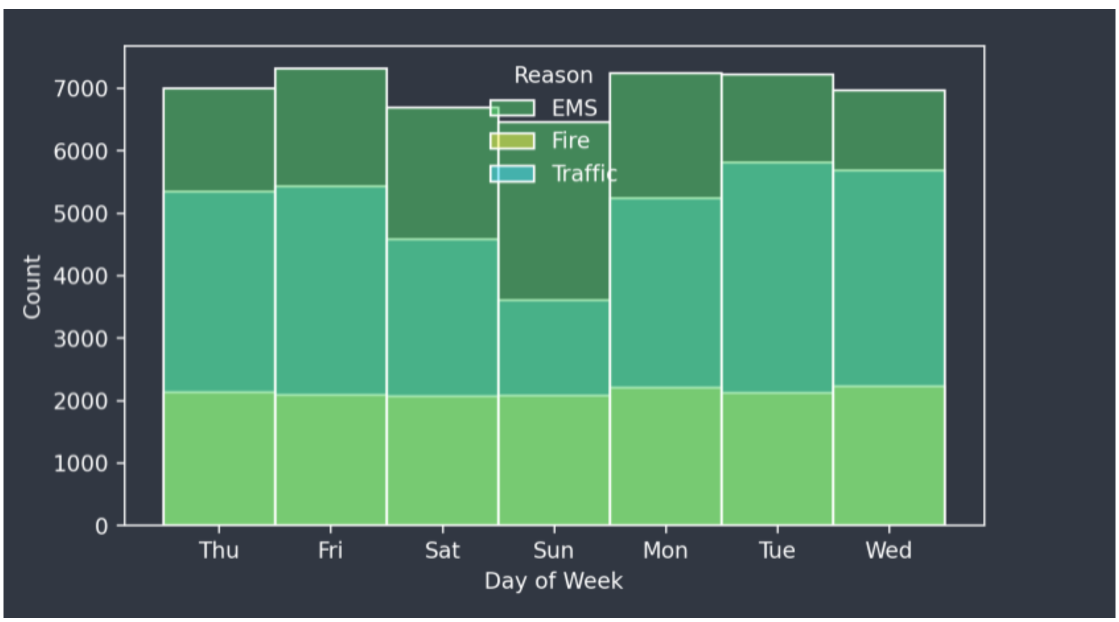
applying log transformation to skewed features from dataset

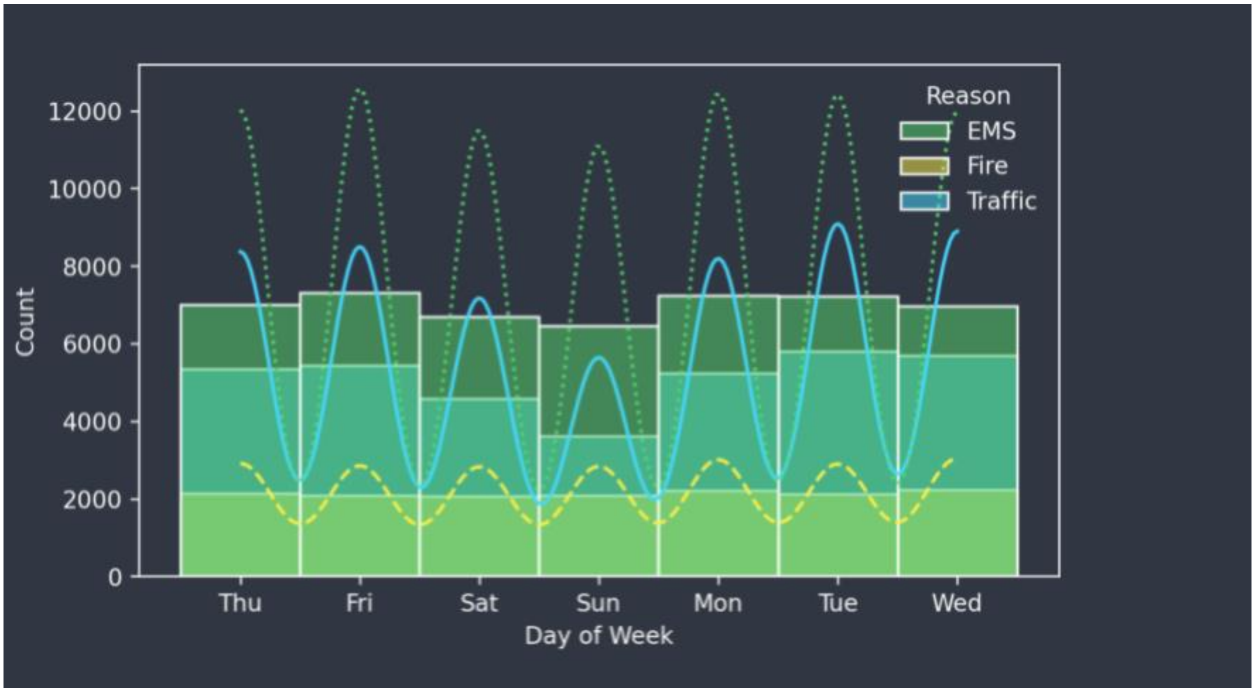
	Skew
log_Hour	-2.080357
log_zip	-2.210814
log_lat	-22.580780

	lat	lng	zip	e	Hour	Month	log_Month	log_Hour	log_zip	log_lat	log_lng
count	99492.000000	99492.000000	99492.000000	99492.0	99492.000000	99492.000000	99492.000000	99492.000000	99492.000000	99492.000000	0.0
mean	40.159526	-75.317464	16752.030334	1.0	13.117085	4.983195	1.652344	2.514484	8.589987	3.717453	NaN
std	0.094446	0.174826	6460.927718	0.0	5.671564	3.012176	0.542269	0.616399	3.308896	0.002349	NaN
min	30.333596	-95.595595	0.000000	1.0	0.000000	1.000000	0.693147	0.000000	0.000000	3.444691	NaN
25%	40.100423	-75.392104	19006.000000	1.0	9.000000	3.000000	1.386294	2.302585	9.852563	3.716018	NaN
50%	40.145223	-75.304667	19131.000000	1.0	14.000000	5.000000	1.791759	2.708050	9.859118	3.717108	NaN
75%	40.229008	-75.212513	19440.000000	1.0	17.000000	7.000000	2.079442	2.890372	9.875140	3.719142	NaN
max	41.167156	-74.995041	77316.000000	1.0	23.000000	12.000000	2.564949	3.178054	11.255669	3.741642	NaN

Hypothesis Testing of our dataset

We will use hypothesis testing to find out time of day that has effect on volume of 911 calls.





From the above histogram, we can formulate our hypothesis in this way:

1. time of day has some effect on volume of 911 calls
2. month has some effect on volume of 911 calls
3. EMS has great effect on volume of 911 calls

1. Time of day has some effect on volume of 911 calls

- our null hypothesis will be "time of day has no effect on volume of 911 calls"
- our alternative hypothesis will be "time of day has some effect on volume of 911 calls"

We need to find p-value. as p-value for a statistical model is the probability that when the null hypothesis is true, the statistical summary is equal to or greater than the actual observed results.

```
The probability of getting massive call on Monday is 1.0
The p-value for Monday is: 4.1630465706831465
The probability of getting massive call on Tuesday is 1.0
The p-value for Tuesday is: 3.911964866746967
The probability of getting massive call on Wednesday is 1.0
The p-value for Wednesday is: 3.3659707066538544
The probability of getting massive call on Thursday is 1.0
The p-value for Thursday is: 2.722665382792572
The probability of getting massive call on Friday is 1.0
The p-value for Friday is: 4.101235297308582
The probability of getting massive call on Saturday is 1.0
The p-value for Saturday is: 4.047523777904953
The probability of getting massive call on Sunday is 1.0
The p-value for Sunday is: 4.045005226649829
```

The above results shows that probability of getting massive 911 calls of emergency is 1 which is strange but somehow seems to be true. It means that our p-value is not explaining the observation fairly. but as the p-value is to low compared to significance level, we reject our null hypothesis and we can conclude that most time of day has some effect on volume of 911 calls.

```
Month
1     12.980159
2     13.110927
3     13.057472
4     12.936076
5     13.098310
6     13.252927
7     13.284996
8     12.961005
12    13.441210
Name: Hour, dtype: float64
```

2. month has some effect on volume of 911 calls

from the above data observations, there are missing data of September, October, and November. for simply, we can conclude that those months has no effect on volume of 911 calls which doesn't make sense since there is problem of missing data.

3. EMS has great effect on volume of 911 calls.

```
The probability of getting massive call for EMS  is 1.0
The p-value for EMS is: 1.55770530280906
The probability of getting massive call for Fire  is 1.0
The p-value for Fire is: 2.7034110671855007
The probability of getting massive call for Traffic  is 1.0
The p-value for Traffic is: 3.67583473273708
```

The above results shows that probability of getting massive 911 calls for different reasons of emergency provided is 1 which is strange but somehow seems to be true. It means that our p-values are not explaining the observation fairly except for p-value for traffic which is slightly greater than our significance level. but as the p-value is to low compared to significance level, we reject our null hypothesis for EMS and Fire, but we accept our null hypothesis for Traffic.

Next steps

The following steps need to considered:

- Missing data of months needs to be taken care of as it tends to reduce the confidences of model selection.
- It is highly recommended to request addition information to this data as its quality is not quite good. increase of features of data will be great.
- Dealing with known reasons we have, and the outcome is categorial data. this means that classification method is quite useful.
- I will suggest k-nearest neighbors to be used as classification method.

Summary of quality of data.

- The quality of data provides features that are quite useful but addition of other features is highly needed to make predictions and other analysis.

- We have seen that some provided data provided probability of 1, which is not quite true but its accurate is not bad.

- The selection process of model to be used so that the prediction is quite useful with our 911 calls dataset requires more observations which doesn't have missing data as we have seen.

The notebook can be accessed here: https://github.com/Emmanuel262/EDA_with_IBM