Aim

1. This notebook is aimed to get data ready for EDA
2. Cleaning data handling Nans based on basic analysis

EDA

In [1]:
```
import os

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
```

In [2]:
```
DATA_ROOT = "../data/"
```

metadata

Sr. No.	Attribute	Description
1	ID	This is a unique identifier of the accident record.
2	Source	Indicates source of the accident report (i.e. the API which reported the accident.).
3	TMC	A traffic accident may have a Traffic Message Channel (TMC) code which provides more detailed description of the event.
4	Severity	Shows the severity of the accident, a number between 1 and 4, where 1 indicates the least impact on traffic (i.e., short delay as a result of the accident) and 4 indicates a significant impact on traffic (i.e., long delay).
5	Start_Time	Shows start time of the accident in local time zone.
6	End_Time	Shows end time of the accident in local time zone. End time here refers to when the impact of accident on traffic flow was dismissed.
7	Start_Lat	Shows latitude in GPS coordinate of the start point.
8	Start_Lng	Shows longitude in GPS coordinate of the start point.
9	End_Lat	Shows latitude in GPS coordinate of the end point.
10	End_Lng	Shows longitude in GPS coordinate of the end point.
11	Distance(mi)	The length of the road extent affected by the accident.
12	Description	Shows natural language description of the accident.
13	Number	Shows the street number in address field.
14	Street	Shows the street name in address field.
15	Side	Shows the relative side of the street (Right/Left) in address field.
16	City	Shows the city in address field.
17	County	Shows the county in address field.

Sr. No.	Attribute	Description
18	State	Shows the state in address field.
19	Zipcode	Shows the zipcode in address field.
20	Country	Shows the country in address field.
21	Timezone	Shows timezone based on the location of the accident (eastern, central, etc.).
22	Airport_Code	Denotes an airport-based weather station which is the closest one to location of the accident.
23	Weather_Timestamp	Shows the time-stamp of weather observation record (in local time).
24	Temperature(F)	Shows the temperature (in Fahrenheit).
25	Wind_Chill(F)	Shows the wind chill (in Fahrenheit).
26	Humidity(%)	Shows the humidity (in percentage).
27	Pressure(in)	Shows the air pressure (in inches).
28	Visibility(mi)	Shows visibility (in miles).
29	Wind_Direction	Shows wind direction.
30	Wind_Speed(mph)	Shows wind speed (in miles per hour).
31	Precipitation(in)	Shows precipitation amount in inches, if there is any.
32	Weather_Condition	Shows the weather condition (rain, snow, thunderstorm, fog, etc.)
33	Amenity	A POI annotation which indicates presence of amenity in a nearby location.
34	Bump	A POI annotation which indicates presence of speed bump or hump in a nearby location.
35	Crossing	A POI annotation which indicates presence of crossing in a nearby location.
36	Give_Way	A POI annotation which indicates presence of give_way in a nearby location.
37	Junction	A POI annotation which indicates presence of junction in a nearby location.
38	No_Exit	A POI annotation which indicates presence of no_exit in a nearby location.
39	Railway	A POI annotation which indicates presence of railway in a nearby location.
40	Roundabout	A POI annotation which indicates presence of roundabout in a nearby location.
41	Station	A POI annotation which indicates presence of station in a nearby location.
42	Stop	A POI annotation which indicates presence of stop in a nearby location.
43	Traffic_Calming	A POI annotation which indicates presence of traffic_calming in a nearby location.
44	Traffic_Signal	A POI annotation which indicates presence of traffic_signal in a nearby location.
45	Turning_Loop	A POI annotation which indicates presence of turning_loop in a nearby location.

Sr. No.	Attribute	Description
46	Sunrise_Sunset	Shows the period of day (i.e. day or night) based on sunrise/sunset.
47	Civil_Twilight	Shows the period of day (i.e. day or night) based on civil twilight.
48	Nautical_Twilight	Shows the period of day (i.e. day or night) based on nautical twilight.
49	Astronomical_Twilight	Shows the period of day (i.e. day or night) based on astronomical twilight.

In [3]:
```
df = pd.read_csv(f"{DATA_ROOT}/raw/accidents.csv")
```

In [4]:
```
df.head()
```

Out[4]:

	ID	Source	TMC	Severity	Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat
0	A-1	MapQuest	201.0	3	2016-02-08 05:46:00	2016-02-08 11:00:00	39.865147	-84.058723	NaN
1	A-2	MapQuest	201.0	2	2016-02-08 06:07:59	2016-02-08 06:37:59	39.928059	-82.831184	NaN
2	A-3	MapQuest	201.0	2	2016-02-08 06:49:27	2016-02-08 07:19:27	39.063148	-84.032608	NaN
3	A-4	MapQuest	201.0	3	2016-02-08 07:23:34	2016-02-08 07:53:34	39.747753	-84.205582	NaN
4	A-5	MapQuest	201.0	2	2016-02-08 07:39:07	2016-02-08 08:09:07	39.627781	-84.188354	NaN

5 rows × 49 columns

In [5]:
```
df.columns
```

Out[5]:
```
Index(['ID', 'Source', 'TMC', 'Severity', 'Start_Time', 'End_Time',
       'Start_Lat', 'Start_Lng', 'End_Lat', 'End_Lng', 'Distance(mi)',
       'Description', 'Number', 'Street', 'Side', 'City', 'County', 'State',
       'Zipcode', 'Country', 'Timezone', 'Airport_Code', 'Weather_Timestam
p',
       'Temperature(F)', 'Wind_Chill(F)', 'Humidity(%)', 'Pressure(in)',
       'Visibility(mi)', 'Wind_Direction', 'Wind_Speed(mph)',
       'Precipitation(in)', 'Weather_Condition', 'Amenity', 'Bump', 'Crossin
g',
       'Give_Way', 'Junction', 'No_Exit', 'Railway', 'Roundabout', 'Statio
n',
       'Stop', 'Traffic_Calming', 'Traffic_Signal', 'Turning_Loop',
       'Sunrise_Sunset', 'Civil_Twilight', 'Nautical_Twilight',
       'Astronomical_Twilight'],
      dtype='object')
```

Check Nans

check which columns have nans

In [6]:
```
nan_cols_series = df.isna().any()
nan_cols_series
```

Out[6]:
```
ID                       False
Source                   False
TMC                       True
Severity                 False
Start_Time               False
End_Time                 False
Start_Lat                False
Start_Lng                False
End_Lat                   True
End_Lng                   True
Distance(mi)             False
Description               True
Number                    True
Street                   False
Side                     False
City                      True
County                   False
State                    False
Zipcode                   True
Country                  False
Timezone                  True
Airport_Code              True
Weather_Timestamp         True
Temperature(F)            True
Wind_Chill(F)             True
Humidity(%)               True
Pressure(in)              True
Visibility(mi)            True
Wind_Direction            True
Wind_Speed(mph)           True
Precipitation(in)         True
Weather_Condition         True
Amenity                  False
Bump                     False
Crossing                 False
Give_Way                 False
Junction                 False
No_Exit                  False
Railway                  False
Roundabout               False
Station                  False
Stop                     False
Traffic_Calming          False
Traffic_Signal           False
Turning_Loop             False
Sunrise_Sunset            True
Civil_Twilight            True
Nautical_Twilight         True
Astronomical_Twilight     True
dtype: bool
```

In [7]:
```
nan_cols_series[nan_cols_series]
```

Out[7]:
```
TMC                     True
End_Lat                 True
End_Lng                 True
Description             True
Number                  True
City                    True
Zipcode                 True
Timezone                True
Airport_Code            True
Weather_Timestamp       True
Temperature(F)          True
Wind_Chill(F)           True
Humidity(%)             True
Pressure(in)            True
Visibility(mi)          True
Wind_Direction          True
Wind_Speed(mph)         True
Precipitation(in)       True
Weather_Condition       True
Sunrise_Sunset          True
Civil_Twilight          True
Nautical_Twilight       True
Astronomical_Twilight   True
dtype: bool
```

Handling missing values

Handling missing numerical values

1. Mean Imputation
2. Median Imputation
3. Mode Imputation
4. Remove NaNs
5. model based imputation

Handling missing categorical values

1. Mode imputation
   A. replace with most occuring category
   B. `note` data set should not be highly skewed
   C. this type of strategy will make data highly imbalanced if nan count is very high
2. Median imputation
3. Threshold based imputation
   A. distribute categories based on distribution of categories across the data
   B. so that distribution of categories is not changed
   C. i.e weighted sampling from categories
4. Model based imputation
   A. training a classifier by dropping rows of column which has missing values
      a. and predicting on the rows that are dropped

`NOTE` :

As this is a time bound task will take some tradeoffs with best possible method to handle nans

In [8]:
```
nan_cols = nan_cols_series[nan_cols_series].index.values.tolist()
```

In [9]:
```
# get nan percentage

percent_missing = df[nan_cols].isnull().sum() * 100 / len(df)
```

In [10]:
```
percent_missing.sort_values(ascending=False)
```

Out[10]:
```
End_Lat                  70.548896
End_Lng                  70.548896
Number                   64.402694
Precipitation(in)        57.657793
Wind_Chill(F)            53.171675
TMC                      29.451104
Wind_Speed(mph)          12.938490
Weather_Condition         2.166941
Visibility(mi)            2.158915
Humidity(%)               1.983341
Temperature(F)            1.870779
Wind_Direction            1.675595
Pressure(in)              1.590441
Weather_Timestamp         1.233003
Airport_Code              0.192337
Timezone                  0.110428
Zipcode                   0.030424
Nautical_Twilight         0.003273
Sunrise_Sunset            0.003273
Civil_Twilight            0.003273
Astronomical_Twilight     0.003273
City                      0.003188
Description               0.000028
dtype: float64
```

initial thoughts on missing data

1. ```plain_text
   End_Lat                  70.548896
   End_Lng                  70.548896
   ```
   - almost 70% of the data is missing
   - imputing/ handling this column will not add any value
   - skipping these columns from further analysis/ modelling
2. ```plain_text
   Number                   64.402694
   ```
   - Number (i.e street number) alone does not convey any meaning
   - Occurence of street number with another descriptor variables like street name, city etc will add more value
   - skipping number from further analysis
   - filling with `-1` for identifying missing street number
3. ```plain_text
   Precipitation(in)        57.657793
   Wind_Chill(F)            53.171675
   ```
   - imputing weather data would include interfacing open source apis
   - this would be an extensive task
   - for each city/ state these variables would have different distribution
     - need to check distribution by grouping these variables
   ```

- then impute

4. plain_text

   ```
   TMC                      29.451104
   ```
   - we can treat nans as a different category here and make the analysis
   - fillna with `0.0` will work here as missing percentage is not very high
5. plain_text

   ```
   Wind_Speed(mph)          12.938490
   ```
   - we can impute values here using methods mentioned in above section for numerical values
   - we need to check distribution of data here before we impute
6. plain_text

   ```
   Weather_Condition         2.166941
   Visibility(mi)            2.158915
   Humidity(%)               1.983341
   Temperature(F)            1.870779
   Wind_Direction            1.675595
   Pressure(in)              1.590441
   Weather_Timestamp         1.233003
   Airport_Code              0.192337
   Timezone                  0.110428
   Zipcode                   0.030424
   Nautical_Twilight         0.003273
   Sunrise_Sunset            0.003273
   Civil_Twilight            0.003273
   Astronomical_Twilight     0.003273
   City                      0.003188
   Description               0.000028
   ```
   - rest of the values are too small for given scale
   - and can be easily imputed using simple methods like mean fill / median fill
   - this will vary from numerical and categorical variables accordingly

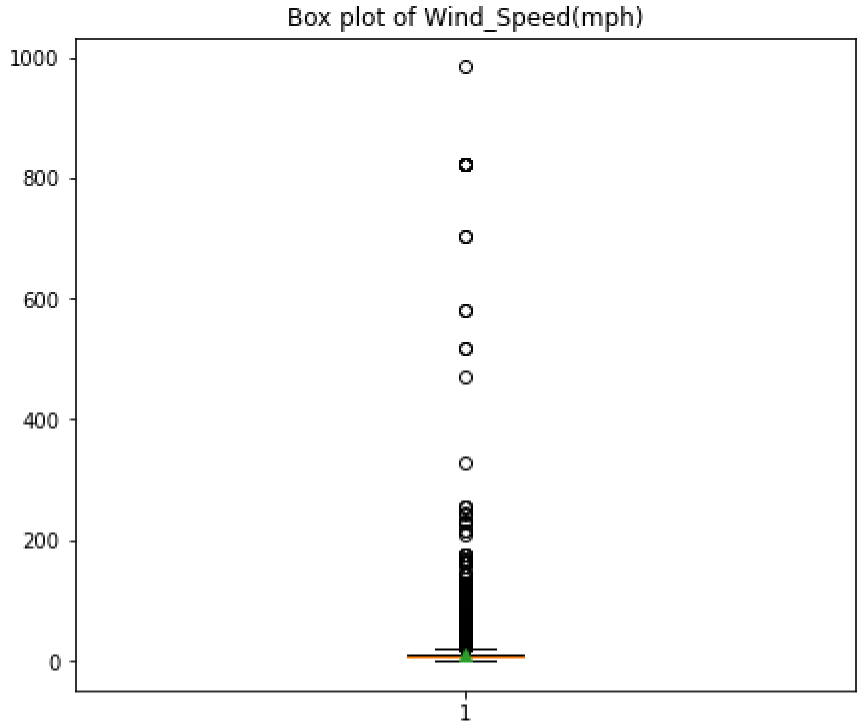
`Number`, `TMC`

In [11]:
```
df["Number"] = df["Number"].fillna(-1)
df["TMC"] = df["TMC"].fillna(0.0)
```

1. As Number has significant % of nans in order to make data consistent adding `-1` as street number
2. As TMC has significant % of nans filling nans with a category `0.0`

`Wind_Speed(mph)`

In [12]:
```
plt.figure(figsize=[7, 6])
plt.title("Box plot of Wind_Speed(mph)")
plt.boxplot(
    df["Wind_Speed(mph)"].dropna().values, showmeans=True,
)
plt.show()
```



1. Wind_Speed(mph) is skewed data, imputing with median
2. as Wind_Speed(mph) nan % is around 13% imputing with mode would have added to the skew

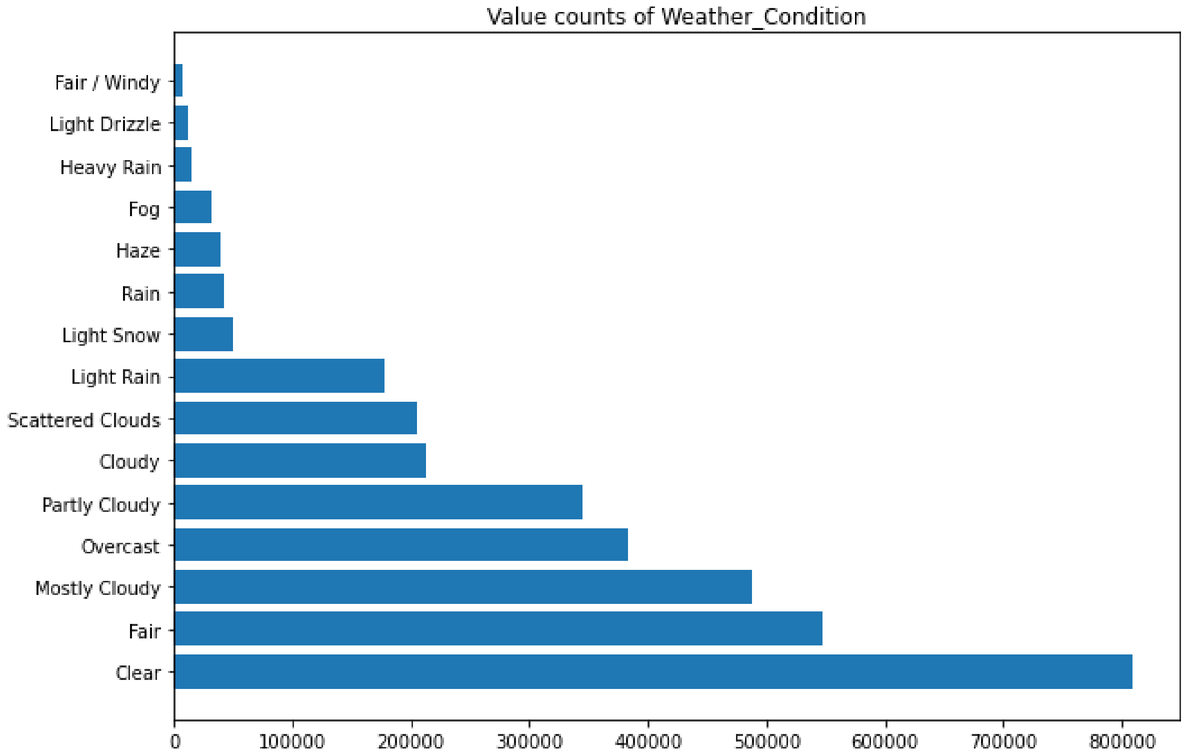
In [13]:
```
df["Wind_Speed(mph)"].median()
```

Out[13]:
```
7.0
```

In [14]:
```
df["Wind_Speed(mph)"] = df["Wind_Speed(mph)"].fillna(df["Wind_Speed(mph)"].m
```

Weather_Condition

In [15]:
```
plt.figure(figsize=[10, 7])
plt.title("Value counts of Weather_Condition")
weather_cond_counts = (
    df["Weather_Condition"].value_counts().head(15).reset_index().values
)
plt.barh(
    weather_cond_counts[:, 0], weather_cond_counts[:, 1],
)
plt.show()
```



1. there is high skew in categorical data
2. but Weather_Condition nans are around 2%
3. we can randomly sample from top 10-15 values and impute

In [16]:
```
weather_cond_counts[:10]
```

Out[16]:
```
array([['Clear', 808202],
       ['Fair', 547721],
       ['Mostly Cloudy', 488094],
       ['Overcast', 382485],
       ['Partly Cloudy', 344815],
       ['Cloudy', 212878],
       ['Scattered Clouds', 204660],
       ['Light Rain', 176942],
       ['Light Snow', 50435],
       ['Rain', 42016]], dtype=object)
```

In [17]:
```
import random

list_of_candidates = weather_cond_counts[:10, 0]
number_of_items_to_pick = df["Weather_Condition"].isna().sum()
probability_distribution = (
    weather_cond_counts[:10, 1] / weather_cond_counts[:10, 1].sum()
)
draw = random.choices(
    list_of_candidates, k=number_of_items_to_pick, weights=probability_distr
)
```

In [18]:
```
# fill nan values with random sample with weighted probabilities
df.loc[df["Weather_Condition"].isnull(), "Weather_Condition"] = draw
```

`Visibility(mi)`, `Humidity(%)`, `Temperature(F)`, `Pressure(in)`

In [19]:
```
df["Visibility(mi)"].fillna(df["Visibility(mi)"].mean(), inplace=True)
df["Humidity(%)"].fillna(df["Humidity(%)"].mean(), inplace=True)
df["Temperature(F)"].fillna(df["Temperature(F)"].mean(), inplace=True)
df["Visibility(mi)"].fillna(df["Visibility(mi)"].mean(), inplace=True)
df["Pressure(in)"].fillna(df["Pressure(in)"].mean(), inplace=True)
```

1. each of above columns have very less nan % ≈ 1.5% imputing with mean

`Wind_Direction`

In [20]:
```
df["Wind_Direction"] = df["Wind_Direction"].fillna("none")
```

1. very less nan % ≈ around 1.5%
2. treating nan as `none` category

`Weather_Timestamp`

In [21]:
```
# number of days' gap between Start_Time and Weather_Timestamp
(
    pd.to_datetime(df["Start_Time"]) - pd.to_datetime(df["Weather_Timestamp"
).dt.days.describe().astype(int)
```

Out[21]:
```
count    3470294
mean           0
std            0
min           -1
25%           -1
50%            0
75%            0
max            0
dtype: int64
```

In [22]:
```
# number of hours' gap between Start_Time and Weather_Timestamp
t = (
    pd.to_datetime(df["Start_Time"]) - pd.to_datetime(df["Weather_Timestamp"
).dt.total_seconds()
```

In [23]:
```
(t / 60).describe()
```

Out[23]:
```
count    3.470294e+06
mean    -5.289606e-01
std      3.434439e+01
min     -1.430283e+03
25%     -1.131667e+01
50%      6.666667e-02
75%      1.138333e+01
max      1.381000e+03
dtype: float64
```

1. making assumption that all variables will be available during inference time
2. Closest estimate of Weather_Timestamp would be Start_Time based on the data above
   A. as more than data 50% of data has 0 days difference
   B. more than 50% of data has Weather_Timestamp 6 hours(or less) earlier to Start_Time

In [24]:
```
df["Weather_Timestamp"] = df["Weather_Timestamp"].fillna(df["Start_Time"])
```

`Others`

In [25]:
```
df["Airport_Code"] = df["Airport_Code"].fillna(df["Airport_Code"].mode().val
df["Timezone"] = df["Timezone"].fillna(df["Timezone"].mode().values[0])
df["Nautical_Twilight"] = df["Nautical_Twilight"].fillna(
    df["Nautical_Twilight"].mode().values[0]
)
df["Sunrise_Sunset"] = df["Sunrise_Sunset"].fillna(
    df["Sunrise_Sunset"].mode().values[0]
)
df["Civil_Twilight"] = df["Civil_Twilight"].fillna(
    df["Civil_Twilight"].mode().values[0]
)
df["Astronomical_Twilight"] = df["Astronomical_Twilight"].fillna(
    df["Astronomical_Twilight"].mode().values[0]
)
df["City"] = df["City"].fillna(df["City"].mode().values[0])
df["Description"] = df["Description"].fillna("empty")

df["Zipcode"] = df["Zipcode"].fillna(df["Zipcode"].mode().values[0])
```

Recheck missing values

In [28]:
```
recheck_nans_series = df.isna().any()
recheck_nans_series[recheck_nans_series]
```

Out[28]:
```
End_Lat              True
End_Lng              True
Wind_Chill(F)        True
Precipitation(in)    True
dtype: bool
```

In [36]:
```
rm_cols = recheck_nans_series[recheck_nans_series].index.tolist()
rm_cols
```

Out[36]:
```
['End_Lat', 'End_Lng', 'Wind_Chill(F)', 'Precipitation(in)']
```

- ignoring the above columns as nan % is very high
- time required to impute these values would be high

Save cleaned data to csv

In [33]:
```
dir_path = f"{DATA_ROOT}/eda/"
os.makedirs(dir_path, exist_ok=True)
```

In [39]:
```
cols = df.columns.tolist()
for i in rm_cols:
    cols.remove(i)
```

In [41]:
```
file_path = f"{dir_path}/clean-data.csv"
df.to_csv(file_path, index=False, columns=cols)
```