accidents_models_bakyt

November 29, 2023

0.1 1 Data preparation & cleaning

0.1.1 Loading libraries and file

[ ]:
```
import datetime as dt
import pandas as pd
import numpy as np
import requests
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import h2o
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
from imblearn.under_sampling import RandomUnderSampler, TomekLinks
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.model_selection import train_test_split
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score
from math import radians, sin, cos, sqrt, atan2
from shapely.geometry import Polygon
from sklearn.preprocessing import LabelEncoder
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import AdaBoostClassifier
from statsmodels.tools.tools import add_constant

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from xgboost import XGBClassifier
```

```
from imblearn.ensemble import BalancedBaggingClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler
from sklearn.linear_model import LinearRegression
from h2o.automl import H2OAutoML
from tpot import TPOTClassifier
import torch
from torch import nn
from torch.utils.data import TensorDataset, DataLoader
from sklearn.metrics import r2_score
# from tensorflow.keras.models import Sequential
# from tensorflow.keras.layers import Dense
# from tensorflow.keras.optimizers import Adam
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
import xgboost
from sklearn.metrics import mean_squared_error, r2_score, roc_auc_score
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import KFold, cross_val_score
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error
from sklearn.svm import SVC
import sys
from sklearn.mixture import GaussianMixture
from sklearn import metrics
from matplotlib.ticker import FuncFormatter
import random
from nltk.corpus import stopwords
# from nltk.tokenize import word_tokenize
# from nltk.stem import WordNetLemmatizer
```

[ ]:
```
# read the file
accidents_sub = pd.read_csv('./dataset/US_Accidents_March23.csv')
accidents_sub.shape
```

[ ]:
```
(7728394, 46)
```

[ ]:
```
# check numeric features
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
numeric_df = accidents_sub.select_dtypes(include=numerics)
print("There are", len(numeric_df.columns), "numeric columns.")
```

There are 13 numeric columns.

0.2 2. Exploratory Data Analysis

0.2.1 Modify some information for the data and the columns

[ ]:
```
# change format of time from FLOAT to DATE
accidents_sub['Start_Time'] = pd.to_datetime(accidents_sub["Start_Time"],␣
 ↪errors="coerce")
accidents_sub['End_Time'] = pd.to_datetime(accidents_sub["End_Time"],␣
 ↪errors="coerce")
# Add new column YEAR, MONTH , DAY and Hour ... to create new features
accidents_sub["Start_Year"]=accidents_sub["Start_Time"].dt.year
accidents_sub["Start_Hour"]=accidents_sub["Start_Time"].dt.hour
accidents_sub["Start_Month"]=accidents_sub["Start_Time"].dt.month
accidents_sub["Start_Day"]=accidents_sub["Start_Time"].dt.day_name()
```

[ ]:
```
# Remove the following unneeded columns since they are not going to be used for␣
 ↪eda for sure
accidents_sub = accidents_sub.drop(['ID','Source', 'Street', 'Zipcode',␣
 ↪'County','Country'], axis =1 )
```

[ ]:
```
# # Add new column Delay in min which is duration between start and end time
# accidents_sub["Delay_min"]=accidents_sub["End_Time"] -␣
 ↪accidents_sub["Start_Time"]
# accidents_sub["Delay_min"]=accidents_sub["Delay_min"].apply(lambda x: x.
 ↪total_seconds() / 60)
# # accidents_sub["Delay"]

# # Add new column Weekend
# accidents_sub["Is_Weekend"] = accidents_sub["Start_Day"].isin(["Saturday",␣
 ↪"Sunday"])
```

[ ]:
```
# check modified data frame after removing and adding 6 features accordingly
accidents_sub.head()
```

[ ]:

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

	End_Lat	End_Lng	Distance(mi)	\
0	NaN	NaN	0.01	
1	NaN	NaN	0.01	
2	NaN	NaN	0.01	
3	NaN	NaN	0.01	

```
4      NaN      NaN          0.01

                                          Description          City  …  \
0  Right lane blocked due to accident on I-70 Eas…        Dayton  …
1  Accident on Brice Rd at Tussing Rd. Expect del…  Reynoldsburg  …
2  Accident on OH-32 State Route 32 Westbound at …  Williamsburg  …
3  Accident on I-75 Southbound at Exits 52 52B US…        Dayton  …
4  Accident on McEwen Rd at OH-725 Miamisburg Cen…        Dayton  …

  Traffic_Signal Turning_Loop Sunrise_Sunset Civil_Twilight  \
0          False        False          Night          Night
1          False        False          Night          Night
2           True        False          Night          Night
3          False        False          Night            Day
4           True        False            Day            Day

   Nautical_Twilight  Astronomical_Twilight  Start_Year  Start_Hour  \
0              Night                  Night        2016           5
1              Night                    Day        2016           6
2                Day                    Day        2016           6
3                Day                    Day        2016           7
4                Day                    Day        2016           7

   Start_Month Start_Day
0            2    Monday
1            2    Monday
2            2    Monday
3            2    Monday
4            2    Monday

[5 rows x 44 columns]
```

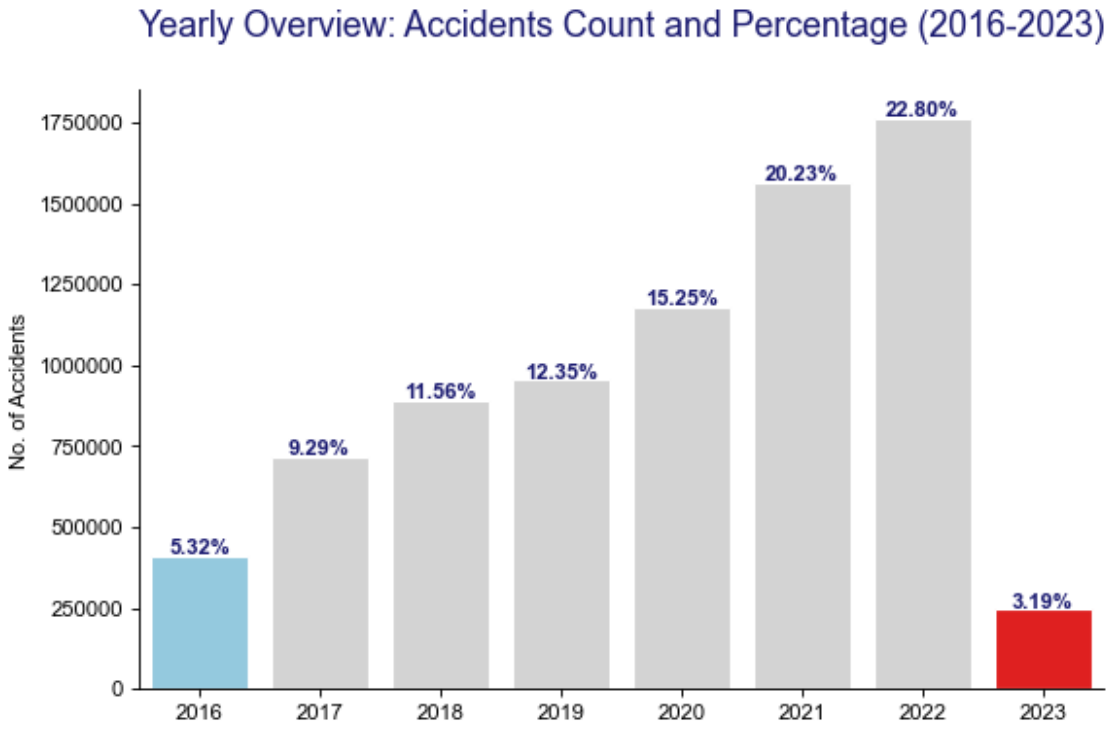
0.2.2 Yearly overview of accidents for given data

[ ]:
```
# prepare query to analyze number of accidents over the all years
year_df = pd.DataFrame(accidents_sub['Start_Year'].value_counts()).
 ↪reset_index().sort_values(by='Start_Year', ascending=True)
year = year_df.rename(columns={'index':'year','Start_Year':'cases'})
```

[ ]:
```
# distribution of road accidents are as follows
fig, ax = plt.subplots(figsize = (8,5), dpi = 80)
sns.set_style('ticks') # style must be one of white, dark, whitegrid, darkgrid,␣
 ↪ticks

# Determine the colors (as before)
colors = ['red' if val == max(year['cases']) else 'skyblue' if val ==␣
 ↪min(year['cases']) else 'lightgrey' for val in year['cases']]
```

```
sns.barplot(x=year.year, y=year.cases, palette=colors)
ax.spines[('top')].set_visible(False)
ax.spines[('right')].set_visible(False)
ax.set_xlabel(None)
ax.set_ylabel("No. of Accidents")
ax.set_title('Yearly Overview: Accidents Count and Percentage (2016-2023)\n',␣
 ↪fontdict = {'fontsize':16 , 'color':'MidnightBlue'})

# Customize Y-axis tick labels to show real numbers
def format_func(value, _):
    return f'{value:.0f}'  # Format as whole numbers
ax.yaxis.set_major_formatter(FuncFormatter(format_func))
total_accidents = accidents_sub.shape[0]
for p in ax.patches :
    height = p.get_height()
    ax.text(p.get_x() + p.get_width()/2,
            height + 5000,
            '{:.2f}%'.format(height/total_accidents*100),
            ha = "center",
            fontsize = 10, weight='bold', color='MidnightBlue')

for i in ['top','right']:
    side = ax.spines[i]
    side.set_visible(False)

plt.show()
```

```
C:\Users\st123\AppData\Local\Temp\ipykernel_15064\549144554.py:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=year.year, y=year.cases, palette=colors)
```



0.3 3. Data Engineering

Let us to select last 3 years in order to make data set smaller and testing with recent data (it covers more 60% of all data)

[ ]:
```
# accidents_sub = accidents_sub[accidents_sub["Start_Year"]>2020]
accidents_sub = accidents_sub[(accidents_sub["Start_Year"] >= 2020) &␣
 ↪(accidents_sub["Start_Year"] <= 2023)]
```

[ ]:
```
# check the size of the reduced data set
accidents_sub.shape
```

[ ]:
```
(4751751, 44)
```

[ ]:
```
unique_values_per_column = accidents_sub.nunique()
print(unique_values_per_column)
```

```
Severity                    4
Start_Time                3056401
End_Time                  3699935
Start_Lat                 1736522
Start_Lng                 1779752
End_Lat                   1335536
End_Lng                   1358950
```

```
Distance(mi)              20884
Description             2353754
City                      12450
State                        49
Timezone                      4
Airport_Code               1989
Weather_Timestamp        470499
Temperature(F)              177
Wind_Chill(F)               194
Humidity(%)                 100
Pressure(in)               1094
Visibility(mi)               51
Wind_Direction               18
Wind_Speed(mph)              93
Precipitation(in)           235
Weather_Condition           111
Amenity                       2
Bump                          2
Crossing                      2
Give_Way                      2
Junction                      2
No_Exit                       2
Railway                       2
Roundabout                    2
Station                       2
Stop                          2
Traffic_Calming               2
Traffic_Signal                2
Turning_Loop                  1
Sunrise_Sunset                2
Civil_Twilight                2
Nautical_Twilight             2
Astronomical_Twilight         2
Start_Year                    4
Start_Hour                   24
Start_Month                  12
Start_Day                     7
dtype: int64
```

[ ]:
```
# let's define unique values and nature of each feature
unique_values_in_dataset = accidents_sub.apply(lambda x: x.unique())
print(unique_values_in_dataset)
```

```
Severity                                                [1, 2, 3, 4]
Start_Time              [2022-09-08T05:49:30.000000000, 2022-09-08T02:…
End_Time                [2022-09-08T06:34:53.000000000, 2022-09-08T04:…
Start_Lat               [41.946796, 34.521172, 37.542839, 40.896629, 4…
Start_Lng               [-88.20809200000002, -117.958076, -77.44178000…
```

```
End_Lat                 [nan, 45.666976, 41.39837, 40.846945, 33.71453…
End_Lng                 [nan, -94.176184, -75.48420300000002, -73.9336…
Distance(mi)            [0.0, 1.9099999666213991, 1.5900000333786009, …
Description             [Crash on CR-11 Army Trail Rd at IL-59., Crash…
City                    [Bartlett, Littlerock, Richmond, Alliance, Ind…
State                   [IL, CA, VA, OH, PA, SC, NJ, NY, FL, NC, TX, A…
Timezone                [US/Central, US/Pacific, US/Eastern, US/Mounta…
Airport_Code            [KDPA, KPMD, KRIC, KCAK, KBKL, KTHV, KTZR, KCM…
Weather_Timestamp       [2022-09-08 05:52:00, 2022-09-08 01:53:00, 202…
Temperature(F)          [58.0, 86.0, 68.0, 62.0, 63.0, 65.0, 53.0, 70…
Wind_Chill(F)           [58.0, 86.0, 68.0, 62.0, 63.0, 65.0, 53.0, 70…
Humidity(%)             [90.0, 28.0, 96.0, 86.0, 87.0, 93.0, 99.0, 97…
Pressure(in)            [29.24, 27.35, 29.71, 28.71, 29.37, 29.45, 29…
Visibility(mi)          [10.0, 7.0, 9.0, nan, 8.0, 2.0, 4.0, 0.25, 5.0…
Wind_Direction          [CALM, W, N, NNE, SSE, WNW, nan, NE, E, SE, NW…
Wind_Speed(mph)         [0.0, 6.0, 8.0, 3.0, 5.0, 7.0, 9.0, nan, 10.0,…
Precipitation(in)       [0.0, nan, 0.17, 0.3, 0.02, 0.01, 0.24, 0.22, …
Weather_Condition       [Fair, Mostly Cloudy, Partly Cloudy, Cloudy, n…
Amenity                                                  [False, True]
Bump                                                     [False, True]
Crossing                                                 [False, True]
Give_Way                                                 [False, True]
Junction                                                 [False, True]
No_Exit                                                  [False, True]
Railway                                                  [False, True]
Roundabout                                               [False, True]
Station                                                  [False, True]
Stop                                                     [False, True]
Traffic_Calming                                          [False, True]
Traffic_Signal                                           [True, False]
Turning_Loop                                                   [False]
Sunrise_Sunset                                      [Night, Day, nan]
Civil_Twilight                                      [Night, Day, nan]
Nautical_Twilight                                   [Day, Night, nan]
Astronomical_Twilight                               [Day, Night, nan]
Start_Year                                 [2022, 2021, 2020, 2023]
Start_Hour              [5, 2, 6, 4, 0, 16, 21, 1, 3, 13, 10, 14, 15, …
Start_Month                       [9, 8, 7, 6, 5, 4, 3, 2, 1, 12, 11, 10]
Start_Day               [Thursday, Wednesday, Tuesday, Monday, Sunday,…
dtype: object
```

[ ]:
```
for column in accidents_sub.columns:
    print(accidents_sub[column].value_counts())
```

```
2    4161669
3     411394
4     112291
1      66397
```

```
Name: Severity, dtype: int64
2021-01-26 16:16:13    253
2021-01-26 16:17:33    170
2021-02-16 06:42:43    157
2021-11-21 18:37:51    125
2020-12-16 13:53:25     99
                      …
2020-06-16 19:32:28      1
2020-06-16 19:32:06      1
2020-06-16 19:30:28      1
2020-06-16 19:33:33      1
2020-01-01 00:31:17      1
Name: Start_Time, Length: 3056401, dtype: int64
2021-11-22 08:00:00    129
2020-02-14 00:00:00     46
2021-06-09 20:23:43     42
2020-02-12 00:00:00     42
2021-07-12 23:41:50     41
                      …
2022-10-07 16:54:56      1
2022-03-04 17:47:42      1
2022-06-19 04:26:31      1
2022-09-14 08:14:15      1
2020-01-01 00:59:51      1
Name: End_Time, Length: 3699935, dtype: int64
34.858849    544
25.964170    359
25.702455    358
28.451602    355
27.447751    350
             …
36.672119      1
36.639610      1
29.909071      1
35.945362      1
38.840700      1
Name: Start_Lat, Length: 1736522, dtype: int64
-82.260422     545
-80.165855     362
-80.332105     359
-81.477678     355
-73.942825     355
               …
-122.176242      1
-96.744919       1
-96.748212       1
-84.013504       1
-76.942320       1
```

```
Name: Start_Lng, Length: 1779752, dtype: int64
28.450015    1039
25.701774     860
25.684322     836
28.449928     794
25.686252     720
             …
35.235395       1
37.789134       1
42.337090       1
37.327668       1
38.840730       1
Name: End_Lat, Length: 1335536, dtype: int64
-81.471375     1037
-80.334179      860
-80.416621      836
-81.477219      794
-80.416521      721
               …
-120.964830       1
-122.361519       1
-120.601107       1
-121.423960       1
-76.942230        1
Name: End_Lng, Length: 1358950, dtype: int64
0.000     1305735
0.008       13168
0.009       12570
0.010       11811
0.007       11244
           …
12.328          1
13.918          1
35.819          1
35.656          1
22.942          1
Name: Distance(mi), Length: 20884, dtype: int64
A crash has occurred causing no to minimum delays. Use caution.
9593
Accident
6616
An unconfirmed report of a crash has been received. Use caution.
3799
A crash has occurred use caution.
2894
A crash has occurred with minimal delay to traffic. Prepare to slow or move over
for worker safety.                    2672
                                       …
```

```
Left hand shoulder blocked due to accident on I-64 Eastbound from Exit 205
Raphine Rd to Exits 213 213A 213B US-11.       1
Right hand shoulder blocked due to accident on I-279 Northbound at I-79.
1
Right hand shoulder blocked and right lane blocked due to accident on I-79
Northbound at Exit 73 PA-910.                  1
Left hand shoulder blocked due to accident on I-79 Southbound at Exit 73 PA-910.
1
Closed at St Barnabas Rd - Road closed due to accident.
1
Name: Description, Length: 2353754, dtype: int64
Miami             155730
Los Angeles        90590
Orlando            83571
Houston            76289
Dallas             72873
                   …
Mirror Lake            1
North Branford         1
Harrodsburg            1
North Weymouth         1
Greenbank              1
Name: City, Length: 12450, dtype: int64
CA    1077880
FL     656332
TX     284651
SC     235854
VA     223308
NY     209860
PA     206153
NC     195683
MN     129249
TN     109074
OR     108741
AZ     108275
LA      97209
MD      97053
NJ      90648
GA      85564
IL      82512
MI      73385
AL      64667
OH      62234
UT      55511
CO      50687
MO      48261
CT      48175
WA      46707
```

```
IN      37174
OK      32348
MA      28974
MT      27992
AR      21031
WI      17087
IA      15961
DC      14971
KS      14092
KY      13120
NV      12140
WV      11520
DE       9661
ID       9616
MS       9219
RI       6462
NE       6361
NM       5304
ND       3444
WY       3266
NH       3132
ME        633
VT        341
SD        229
Name: State, dtype: int64
US/Eastern     2301900
US/Pacific     1257278
US/Central      918053
US/Mountain     269810
Name: Timezone, dtype: int64
KCQT    69345
KMIA    66776
KBNA    61460
KORL    59291
KRDU    59210
        …
KRCA        1
KRAP        1
KIML        1
KCUT        1
KAXO        1
Name: Airport_Code, Length: 1989, dtype: int64
2022-03-13 01:53:00    1311
2021-01-26 15:53:00     651
2022-05-13 16:53:00     558
2022-03-13 01:55:00     545
2021-01-15 22:53:00     521
                       …
```

```
2022-12-30 03:34:00       1
2022-11-07 20:18:00       1
2022-08-07 11:40:00       1
2022-01-01 00:18:00       1
2020-01-06 19:50:00       1
Name: Weather_Timestamp, Length: 470499, dtype: int64
 73.0     114184
 72.0     107372
 75.0     105118
 77.0     104695
 70.0     103321
          …
-45.0         1
-40.0         1
 189.0        1
 203.0        1
-50.0         1
Name: Temperature(F), Length: 177, dtype: int64
 73.0     113138
 72.0     106535
 75.0     104068
 77.0     103748
 70.0     102362
          …
-51.0         1
-69.0         1
-49.0         1
 138.0        1
-80.0         1
Name: Wind_Chill(F), Length: 194, dtype: int64
93.0     179690
100.0    164745
87.0     103473
90.0     100545
89.0      88078
         …
5.0        2439
4.0        1090
3.0         420
2.0         115
1.0          36
Name: Humidity(%), Length: 100, dtype: int64
29.96    59259
29.97    59044
29.94    57901
29.95    57822
29.99    57523
         …
```

```
21.38        1
58.03        1
21.81        1
21.70        1
21.73        1
Name: Pressure(in), Length: 1094, dtype: int64
10.00     3748555
7.00       127211
9.00       109333
2.00        88195
8.00        87244
5.00        86278
1.00        81074
6.00        75694
4.00        73948
3.00        72659
0.25        24863
0.50        23541
0.75        19156
0.00         6879
13.00        5528
15.00        3747
20.00        1820
0.12         1525
40.00         544
25.00         366
0.38          306
0.06          283
30.00         274
80.00         249
50.00         217
0.63          215
0.88          149
75.00         118
100.00         47
70.00          42
12.00          40
0.19           36
60.00          34
35.00          32
45.00           9
90.00           8
23.00           7
0.99            7
120.00          5
22.00           4
0.31            4
65.00           4
```

```
47.00           2
19.00           2
42.00           2
16.00           2
14.00           2
78.00           1
140.00          1
98.00           1
34.00           1
Name: Visibility(mi), dtype: int64
CALM    824585
S       360180
W       331352
N       266138
E       243873
WNW     233301
SSW     232563
NW      231586
SW      220564
WSW     216166
NNW     211068
SSE     210206
VAR     209940
SE      183044
ESE     171578
ENE     161708
NE      158511
NNE     155178
Name: Wind_Direction, dtype: int64
0.0      824602
5.0      457517
6.0      443372
3.0      438484
7.0      412721
          …
121.0         1
107.0         1
188.0         1
100.0         1
68.0          1
Name: Wind_Speed(mph), Length: 93, dtype: int64
0.00    4214444
0.01      94769
0.02      45727
0.03      31064
0.04      23313
         …
1.76          1
```

```
1.88          1
1.81          1
2.36          1
1.96          1
Name: Precipitation(in), Length: 235, dtype: int64
Fair                         2225277
Cloudy                        701493
Mostly Cloudy                 603293
Partly Cloudy                 403265
Light Rain                    211746
                              …
Thunder and Hail / Windy           1
Heavy Rain Shower / Windy          1
Sand / Windy                       1
Heavy Sleet / Windy                1
Drifting Snow                      1
Name: Weather_Condition, Length: 111, dtype: int64
False    4697393
True       54358
Name: Amenity, dtype: int64
False    4749253
True        2498
Name: Bump, dtype: int64
False    4265759
True      485992
Name: Crossing, dtype: int64
False    4732620
True       19131
Name: Give_Way, dtype: int64
False    4429836
True      321915
Name: Junction, dtype: int64
False    4739836
True       11915
Name: No_Exit, dtype: int64
False    4713492
True       38259
Name: Railway, dtype: int64
False    4751606
True         145
Name: Roundabout, dtype: int64
False    4627357
True      124394
Name: Station, dtype: int64
False    4622421
True      129330
Name: Stop, dtype: int64
False    4746794
```

```
True        4957
Name: Traffic_Calming, dtype: int64
False    4197534
True      554217
Name: Traffic_Signal, dtype: int64
False    4751751
Name: Turning_Loop, dtype: int64
Day      3138760
Night    1589852
Name: Sunrise_Sunset, dtype: int64
Day      3351169
Night    1377443
Name: Civil_Twilight, dtype: int64
Day      3582086
Night    1146526
Name: Nautical_Twilight, dtype: int64
Day      3771465
Night     957147
Name: Astronomical_Twilight, dtype: int64
2022    1762452
2021    1563753
2020    1178913
2023     246633
Name: Start_Year, dtype: int64
16    369212
17    354168
15    348089
7     313691
14    298485
8     293046
18    264533
13    254328
6     236598
12    215741
11    199612
9     185379
10    184737
19    179635
5     144232
20    143449
21    133688
22    119299
4     106228
23     99793
0      89193
1      79087
2      74276
3      65252
```

```
Name: Start_Hour, dtype: int64
12    547439
1     541765
11    460922
2     460154
4     375420
6     361207
9     358728
10    350301
5     349003
3     347029
8     310549
7     289234
Name: Start_Month, dtype: int64
Friday       828309
Thursday     789654
Wednesday    774491
Tuesday      746691
Monday       703257
Saturday     498270
Sunday       411079
Name: Start_Day, dtype: int64
```

Initial ObServation shows some features are dominated by single value thus variety is presented by 1% or even less, for example:

Name: Roundabout, domination of one variable value: True is 0.003% - False 4751606 True 145

Name: Bump, domination of one variable value: True is 0.05% - False 4749253 True 2498

Name: Traffic_Calming, domination of one variable value: True is 0.1% - False 4746794 True 4957

Name: Weather_Condition - Heavy Sleet / Windy 1 Sand / Windy 1 Heavy Rain Shower / Windy 1 Blowing Snow Nearby 1 Drifting Snow 1

[ ]:
```
accidents_sub.head()
```

[ ]:
```
        Severity          Start_Time            End_Time  Start_Lat  \
512217         1 2022-09-08 05:49:30 2022-09-08 06:34:53  41.946796
512218         1 2022-09-08 02:02:05 2022-09-08 04:31:32  34.521172
512219         1 2022-09-08 05:14:12 2022-09-08 07:38:17  37.542839
512220         1 2022-09-08 06:22:57 2022-09-08 06:52:42  40.896629
512221         2 2022-09-08 06:36:20 2022-09-08 07:05:58  41.409359

         Start_Lng  End_Lat  End_Lng  Distance(mi)  \
512217  -88.208092      NaN      NaN          0.00
512218 -117.958076      NaN      NaN          0.00
512219  -77.441780      NaN      NaN          0.00
512220  -81.178452      NaN      NaN          0.00
512221  -81.644318      NaN      NaN          1.91
```

```
                                                Description          City  …  \
512217             Crash on CR-11 Army Trail Rd at IL-59.      Bartlett  …
512218        Crash on CA-138 Pearblossom Hwy at 96th St.    Littlerock  …
512219         Crash on 2nd St Northbound at Franklin St.      Richmond  …
512220  Crash on US-62 Atlantic Blvd Westbound after O…      Alliance  …
512221  Crash on entry ramp to I-77 Northbound at Exit…  Independence  …

       Traffic_Signal Turning_Loop Sunrise_Sunset Civil_Twilight  \
512217           True        False          Night          Night
512218          False        False          Night          Night
512219           True        False          Night          Night
512220          False        False          Night          Night
512221          False        False          Night            Day

        Nautical_Twilight  Astronomical_Twilight  Start_Year  Start_Hour  \
512217                Day                    Day        2022           5
512218              Night                  Night        2022           2
512219              Night                  Night        2022           5
512220                Day                    Day        2022           6
512221                Day                    Day        2022           6

        Start_Month Start_Day
512217            9  Thursday
512218            9  Thursday
512219            9  Thursday
512220            9  Thursday
512221            9  Thursday

[5 rows x 44 columns]
```

[ ]:
```
accidents_sub.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4751751 entries, 512217 to 7246341
Data columns (total 44 columns):
 #   Column                 Dtype
---  ------                 -----
 0   Severity               int64
 1   Start_Time             datetime64[ns]
 2   End_Time               datetime64[ns]
 3   Start_Lat              float64
 4   Start_Lng              float64
 5   End_Lat                float64
 6   End_Lng                float64
 7   Distance(mi)           float64
 8   Description            object
 9   City                   object
```

```
 10  State                   object
 11  Timezone                object
 12  Airport_Code            object
 13  Weather_Timestamp       object
 14  Temperature(F)          float64
 15  Wind_Chill(F)           float64
 16  Humidity(%)             float64
 17  Pressure(in)            float64
 18  Visibility(mi)          float64
 19  Wind_Direction          object
 20  Wind_Speed(mph)         float64
 21  Precipitation(in)       float64
 22  Weather_Condition       object
 23  Amenity                 bool
 24  Bump                    bool
 25  Crossing                bool
 26  Give_Way                bool
 27  Junction                bool
 28  No_Exit                 bool
 29  Railway                 bool
 30  Roundabout              bool
 31  Station                 bool
 32  Stop                    bool
 33  Traffic_Calming         bool
 34  Traffic_Signal          bool
 35  Turning_Loop            bool
 36  Sunrise_Sunset          object
 37  Civil_Twilight          object
 38  Nautical_Twilight       object
 39  Astronomical_Twilight   object
 40  Start_Year              int64
 41  Start_Hour              int64
 42  Start_Month             int64
 43  Start_Day               object
dtypes: bool(13), datetime64[ns](2), float64(12), int64(4), object(13)
memory usage: 1.2+ GB
```

Stats Distribution

[ ]:
```
accidents_sub.describe()
```

[ ]:
```
           Severity     Start_Lat     Start_Lng       End_Lat       End_Lng  \
count  4.751751e+06  4.751751e+06  4.751751e+06  3.595240e+06  3.595240e+06
mean   2.119867e+00  3.601684e+01 -9.424960e+01  3.599296e+01 -9.486553e+01
std    4.250981e-01  5.163296e+00  1.748346e+01  5.285267e+00  1.792230e+01
min    1.000000e+00  2.455480e+01 -1.245481e+02  2.456601e+01 -1.245457e+02
25%    2.000000e+00  3.312941e+01 -1.171799e+02  3.304288e+01 -1.174662e+02
50%    2.000000e+00  3.580159e+01 -8.673347e+01  3.590953e+01 -8.677518e+01
```

```
75%    2.000000e+00  3.997373e+01 -8.023257e+01  3.998256e+01 -8.018690e+01
max    4.000000e+00  4.900050e+01 -6.748413e+01  4.900222e+01 -6.748413e+01

       Distance(mi)  Temperature(F)  Wind_Chill(F)   Humidity(%)  \
count  4.751751e+06    4.643873e+06   4.606635e+06  4.636693e+06
mean   7.349116e-01    6.123374e+01   5.994121e+01  6.446963e+01
std    1.885829e+00    1.914043e+01   2.131319e+01  2.297849e+01
min    0.000000e+00   -8.900000e+01  -8.900000e+01  1.000000e+00
25%    0.000000e+00    4.800000e+01   4.700000e+01  4.800000e+01
50%    1.420000e-01    6.300000e+01   6.300000e+01  6.700000e+01
75%    7.640000e-01    7.600000e+01   7.600000e+01  8.400000e+01
max    4.417500e+02    2.070000e+02   2.070000e+02  1.000000e+02

       Pressure(in)  Visibility(mi)  Wind_Speed(mph)  Precipitation(in)  \
count  4.659125e+06    4.640264e+06     4.621585e+06       4.548062e+06
mean   2.935496e+01    9.052302e+00     7.349406e+00       5.803461e-03
std    1.110632e+00    2.550064e+00     5.547325e+00       5.200175e-02
min    0.000000e+00    0.000000e+00     0.000000e+00       0.000000e+00
25%    2.917000e+01    1.000000e+01     3.000000e+00       0.000000e+00
50%    2.969000e+01    1.000000e+01     7.000000e+00       0.000000e+00
75%    2.996000e+01    1.000000e+01     1.000000e+01       0.000000e+00
max    5.863000e+01    1.400000e+02     1.087000e+03       3.647000e+01

         Start_Year    Start_Hour   Start_Month
count  4.751751e+06  4.751751e+06  4.751751e+06
mean   2.021227e+03  1.246597e+01  6.481211e+00
std    8.804931e-01  5.679916e+00  3.737475e+00
min    2.020000e+03  0.000000e+00  1.000000e+00
25%    2.021000e+03  8.000000e+00  3.000000e+00
50%    2.021000e+03  1.300000e+01  6.000000e+00
75%    2.022000e+03  1.700000e+01  1.000000e+01
max    2.023000e+03  2.300000e+01  1.200000e+01
```

Stats Distribution and variability of the data

o Over 75% of accident visibility is 10 miles or less. (Even at 25%, it's still 10 Miles or less, showing the concentration of the distribution towards one point).

o The temperature has a mean of 61.2° F, with a range of [-89 , 207]. Beyond that, with a std of 19.1, we can assume a fairly wide temperature variability for the United States.

o More than 75% of wind speeds are at 10 mph or less, but there are instances of extreme wind 1087 mph, which can seriously affect accidents.

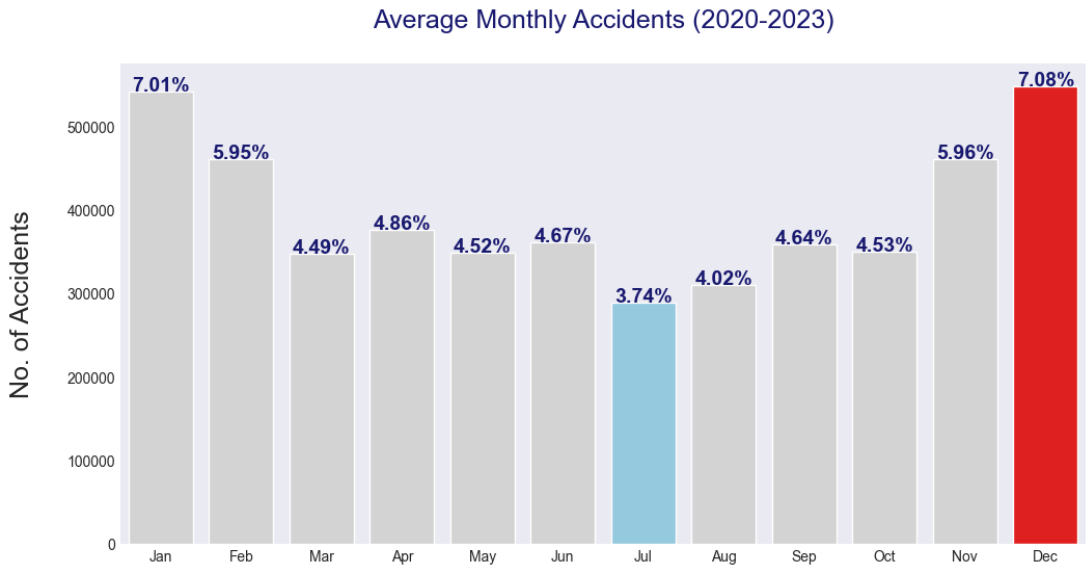
0.4 4. Data Design and Visualization

0.4.1 Average Monthly Accidents

[ ]:
```
month_df = pd.DataFrame(accidents_sub.Start_Time.dt.month.value_counts()).
 ↪reset_index()
month = month_df.rename(columns={'index':'Start_month#','Start_Time':'cases'}).
 ↪sort_values(by='Start_month#', ascending=True)

# adding month name as a column
month_map = {1:'Jan' , 2:'Feb' , 3:'Mar' , 4:'Apr' , 5:'May' , 6:'Jun', 7:'Jul'␣
 ↪, 8:'Aug', 9:'Sep',10:'Oct' , 11:'Nov' , 12:'Dec'}
month['month_name'] = month['Start_month#'].map(month_map)

# ============================================================
plt.style.use('seaborn-v0_8-dark')
fig, ax = plt.subplots(figsize = (12,6), dpi = 100)
sns.set_style('ticks')

# Determine the colors (as before)
colors = ['red' if val == max(month['cases']) else 'skyblue' if val ==␣
 ↪min(month['cases']) else 'lightgrey' for val in month['cases']]

sns.barplot(x=month.month_name, y=month.cases, palette=colors)

ax.set_title('Average Monthly Accidents (2020-2023)\n', fontdict = {'fontsize':
 ↪18 , 'color':'MidnightBlue'})
ax.set_ylabel("\nNo. of Accidents\n", fontsize = 18)
ax.set_xlabel(None)

# Customize Y-axis tick labels to show real numbers
def format_func(value, _):
    return f'{value:.0f}'  # Format as whole numbers
ax.yaxis.set_major_formatter(FuncFormatter(format_func))

for p in ax.patches :
    height = p.get_height()
    ax.text(p.get_x() + p.get_width()/2,
            height + 1000,
            '{:.2f}%'.format(height/total_accidents*100),
            ha = "center",
            fontsize = 14, weight='bold', color='MidnightBlue')
for i in ['top', 'right']:
    side = ax.spines[i]
    side.set_visible(False)
plt.show()
```

```
C:\Users\st123\AppData\Local\Temp\ipykernel_15064\3997322216.py:16:
```

```
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=month.month_name, y=month.cases, palette=colors)
```



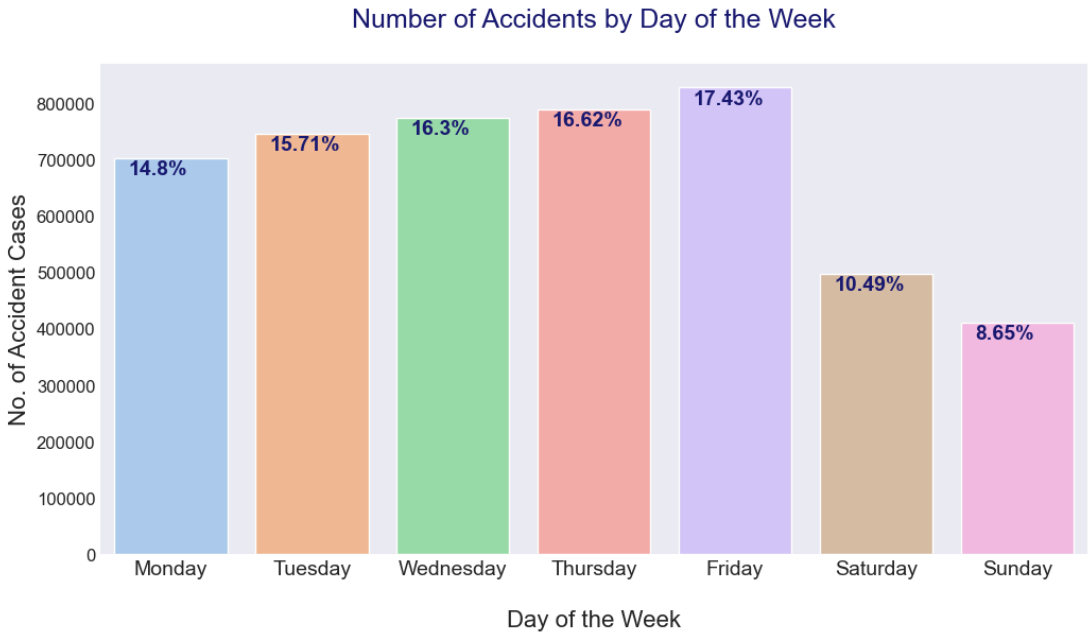
Observation - Surprisingly behaviour in July is low (it is explained by epidem period in COVID break)

0.4.2 Average per day of week Accidents

[ ]:
```
dow = pd.DataFrame(accidents_sub['Start_Time'].dt.dayofweek.value_counts()).
 ↪reset_index()
dow = dow.rename(columns={'index':'day_of_week', 'Start_Time':'cases'}).
 ↪sort_values(by='day_of_week')
day_map = {0:'Monday' , 1:'Tuesday' , 2:'Wednesday' , 3:"Thursday" , 4:'Friday'␣
 ↪, 5:"Saturday" , 6:'Sunday'}
dow['weekday'] = dow['day_of_week'].map(day_map)

# ============================================================
plt.style.use('seaborn-v0_8-dark')
fig, ax = plt.subplots(figsize = (12,6), dpi = 100)
sns.set_style('ticks')

ax=sns.barplot(y=dow.cases, x=dow.weekday, palette='pastel')
```

```
plt.title('Number of Accidents by Day of the Week\n', size=18,␣
 ↪color='MidnightBlue')
plt.ylabel('\nNo. of Accident Cases', fontsize=16)
plt.xlabel('\nDay of the Week', fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=12)

total = accidents_sub.shape[0]
for i in ax.patches:
    ax.text(i.get_x()+0.1, i.get_height()-20000,
    str(round((i.get_height()/total)*100, 2))+'%',
    va = "center", fontsize=14, weight='bold', color='MidnightBlue')

for i in ['top', 'right']:
    side = ax.spines[i]
    side.set_visible(False)

# Customize Y-axis tick labels to show real numbers
def format_func(value, _):
    return f'{value:.0f}'  # Format as whole numbers
ax.yaxis.set_major_formatter(FuncFormatter(format_func))

plt.show()
```

```
C:\Users\st123\AppData\Local\Temp\ipykernel_15064\2235287897.py:11:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax=sns.barplot(y=dow.cases, x=dow.weekday, palette='pastel')
```



Observation: Surprising behaviour on Sunday and Saturday (explained with obvious evidence less trafic in weekend)

0.4.3 Average per Hour of Day Accidents

[ ]:
```
hour_of_day = pd.DataFrame(accidents_sub['Start_Hour'].value_counts()).
  ↪reset_index().rename(columns={'index':'hour','Start_Hour':'cases'})
hour_of_day.sort_values(by='hour', inplace=True)
# hour_of_day
# ============================================================
plt.style.use('seaborn-v0_8-dark')
fig, ax = plt.subplots(figsize=(12, 6), dpi=100)
sns.set_style('ticks')
colors = []
for x in hour_of_day['cases']:
    if int(hour_of_day[hour_of_day['cases'] == x]['hour']) <=11:
        if x == max(list(hour_of_day['cases'])[:12]):
            colors.append('red')
        else:
            colors.append('skyblue')
    else:
        if x == max(list(hour_of_day['cases'])[12:]):
            colors.append('red')
        else:
            colors.append('lightgrey')
```

```
# Create a bar plot of 'hourly_accident_rate'
sns.barplot(x=hour_of_day.hour, y=hour_of_day.cases, palette=colors)

plt.title('Hourly Accident Rate\n', size=16, color='MidnightBlue')
plt.ylabel('\nAccident Cases', fontsize=12)
plt.xlabel('\nTime of Day', fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)

for i in ['top', 'right']:
    side = ax.spines[i]
    side.set_visible(False)

plt.show()
```

```
C:\Users\st123\AppData\Local\Temp\ipykernel_15064\2225894603.py:22:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=hour_of_day.hour, y=hour_of_day.cases, palette=colors)
```

Observation: the most frequent hours for accidents fall just before regular office hours start or end (before trafic jam)

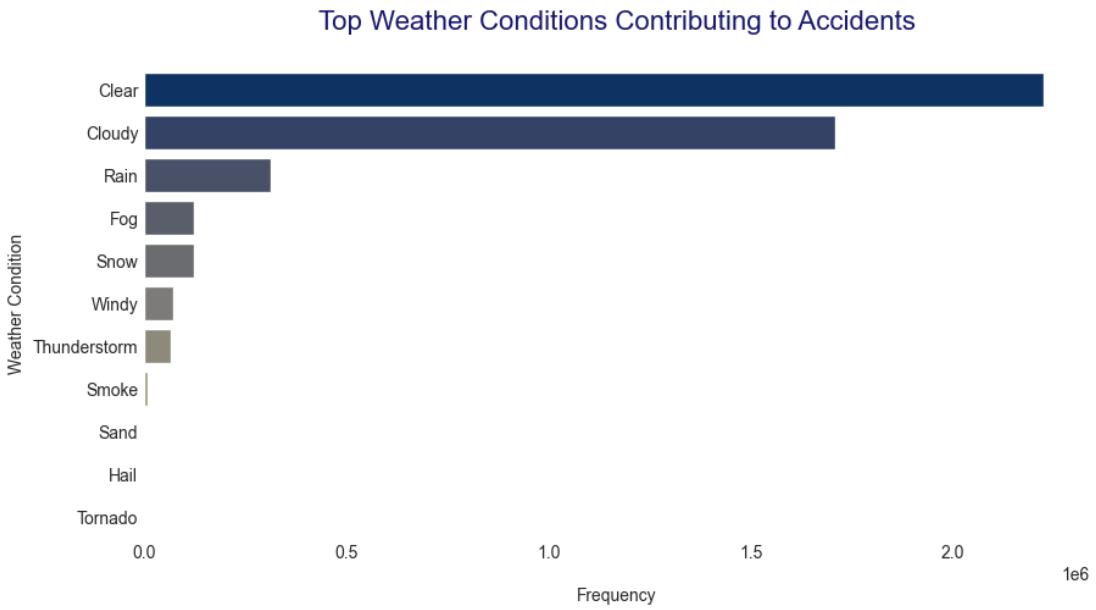
0.4.4 What is the most frequent weather conditions for accidents

[ ]:
```
# wc stands for weather condition, let's find key words for each condition
accidents_sub.loc[accidents_sub["Weather_Condition"].str.
 ↪contains("Thunder|T-Storm", na=False), "Weather_Condition"] = "Thunderstorm"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.
 ↪contains("Snow|Sleet|Wintry", na=False), "Weather_Condition"] = "Snow"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.
 ↪contains("Rain|Drizzle|Shower", na=False), "Weather_Condition"] = "Rain"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.
 ↪contains("Wind|Squalls", na=False), "Weather_Condition"] = "Windy"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.
 ↪contains("Hail|Pellets", na=False), "Weather_Condition"] = "Hail"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.contains("Fair",␣
 ↪na=False), "Weather_Condition"] = "Clear"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.
 ↪contains("Cloud|Overcast", na=False), "Weather_Condition"] = "Cloudy"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.
 ↪contains("Mist|Haze|Fog", na=False), "Weather_Condition"] = "Fog"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.contains("Sand|Dust",␣
 ↪na=False), "Weather_Condition"] = "Sand"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.
 ↪contains("Smoke|Volcanic Ash", na=False), "Weather_Condition"] = "Smoke"
accidents_sub.loc[accidents_sub["Weather_Condition"].str.contains("N/A␣
 ↪Precipitation", na=False), "Weather_Condition"] = np.nan
```

[ ]:
```
wc = pd.DataFrame(accidents_sub['Weather_Condition'].value_counts()).
 ↪reset_index().sort_values(by='Weather_Condition', ascending=False)
wc.rename(columns={'index':'weather_condition', 'Weather_Condition':
 ↪'frequency'}, inplace=True)

# data = accidents_sub['Weather_Condition'].sum().sort_values(ascending=False)
# ================================================================================
# Create a figure and axis
fig, ax = plt.subplots(figsize=(10, 5))
sns.set_style('ticks')
sns.barplot(x='frequency', y='weather_condition', data=wc, palette='cividis',␣
 ↪orient='h')
# sns.barplot(x=data.values, y=data.index, orient="h", hue=data.index,␣
 ↪palette='cividis', legend=False)

# Add labels and title
ax.set_xlabel('\nFrequency')
ax.set_ylabel('\nWeather Condition')
ax.set_title('\nTop Weather Conditions Contributing to Accidents\n',␣
 ↪fontsize=16, color='MidnightBlue')
```

```
plt.xticks(rotation=0)  # Adjust the rotation angle of x-axis labels

# Increase the font size of the axis tick labels
sns.set(rc={'xtick.labelsize': 10, 'ytick.labelsize': 10})

# Remove top and right spines
for i in ['top', 'right']:
    ax.spines[i].set_visible(False)

# Show the plot
plt.show()
```

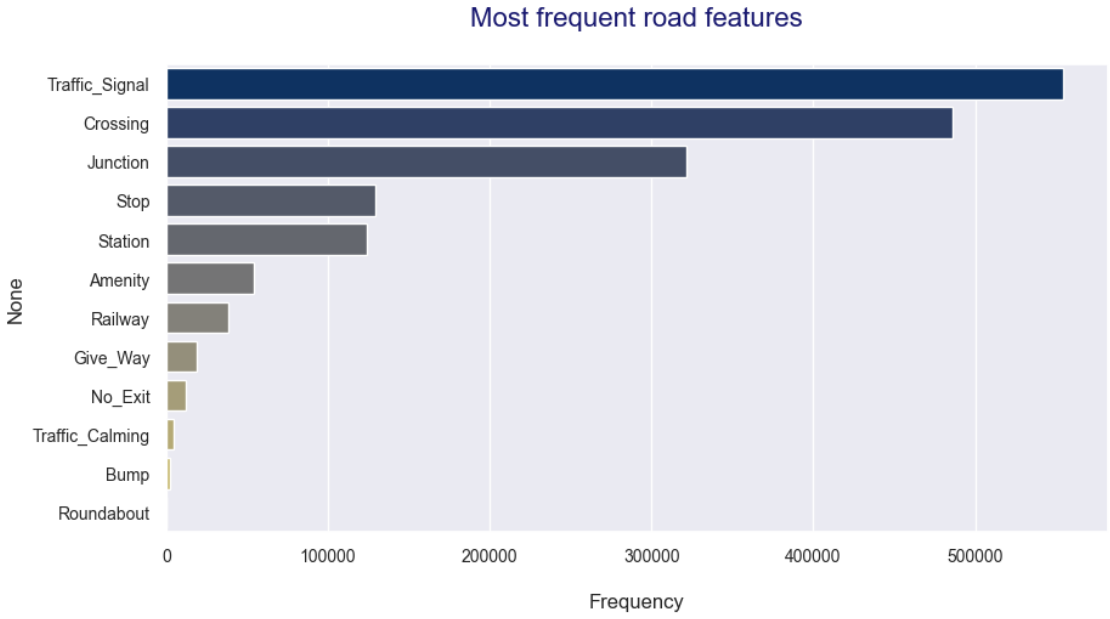
```
C:\Users\st123\AppData\Local\Temp\ipykernel_15064\2781335697.py:9:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='frequency', y='weather_condition', data=wc, palette='cividis',
orient='h')
```



Observation: Surprising fact most accidents happen at the sunny days and low correlation with bad weather curcumstances

0.4.5 What is the most frequent road conditions for accidents

```
[ ]: road_features = ["Amenity", "Bump", "Crossing", "Give_Way", "Junction",␣
      ↪"No_Exit", "Railway", "Roundabout", "Station", "Stop", "Traffic_Calming",␣
      ↪"Traffic_Signal"]

     data = accidents_sub[road_features].sum().sort_values(ascending=False)

     fig, ax = plt.subplots(figsize=(10,5))
     # sns.barplot(x=data.values, y=data.index, orient="h", palette='cividis')
     sns.barplot(x=data.values, y=data.index, orient="h", hue=data.index,␣
      ↪palette='cividis', legend=False)

     plt.title("Most frequent road features\n", fontsize=16, color='MidnightBlue')
     plt.xlabel("\nFrequency")

     plt.show()
```



Observation: Surprising fact most accidents happen at the sunny days and low correlation with bad weather curcumstances

0.4.6 What description says about accident?

```
[ ]: import nltk
     import random
     from nltk.corpus import stopwords
     stop = stopwords.words("english") + ["-"]
```

```
nltk.download("stopwords")
# stop_words=stopwords.words("english")
# new_stopping_words = stop_words[:len(stop_words)-36]
# new_stopping_words.remove("not")
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\st123\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[ ]:
```
True
```

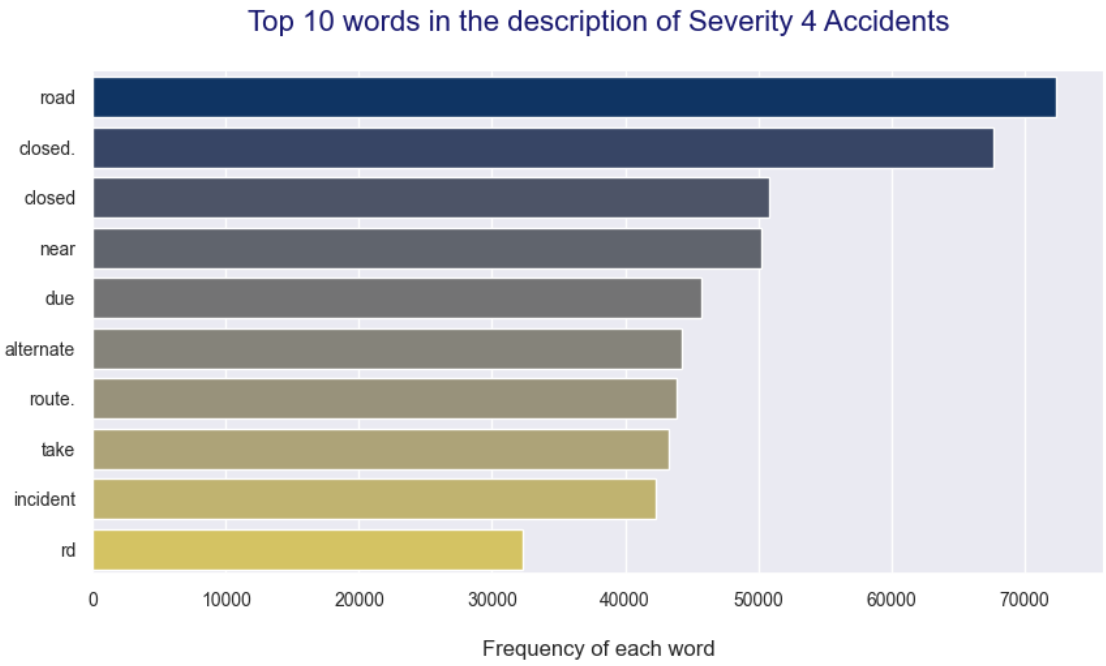
[ ]:
```
# let us find key words from description for accident with severity 4 (most␣
 ↪higher for importance)
description_s4 = accidents_sub[accidents_sub["Severity"] == 4]["Description"] #␣
 ↪filter the key data
# Split the description
df_words = description_s4.str.lower().str.split(expand=True).stack()
```

[ ]:
```
# If the word is not in the stopwords list
counts = df_words[~df_words.isin(stop)].value_counts()[:10]
print(counts)
```

```
road          72352
closed.       67679
closed        50874
near          50257
due           45768
alternate     44292
route.        43916
take          43274
incident      42285
rd            32325
dtype: int64
```

[ ]:
```
# visualize the frequencies of the top 10 words in the description
fig, ax = plt.subplots(figsize=(10,5), dpi=100)
sns.set_style('ticks')
sns.barplot(x=counts.values, y=counts.index, orient="h", palette = "cividis")
# sns.barplot(x=counts.values, y=counts.index, orient="h")

ax.set_title("Top 10 words in the description of Severity 4 Accidents\n",␣
 ↪fontsize=16, color='MidnightBlue')
ax.set_xlabel("\nFrequency of each word\n")
ax.set_ylabel(None)
for i in ['top', 'right']:
    side = ax.spines[i]
    side.set_visible(False)
plt.show()
```

```
C:\Users\st123\AppData\Local\Temp\ipykernel_15064\2058021307.py:4:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=counts.values, y=counts.index, orient="h", palette = "cividis")
```



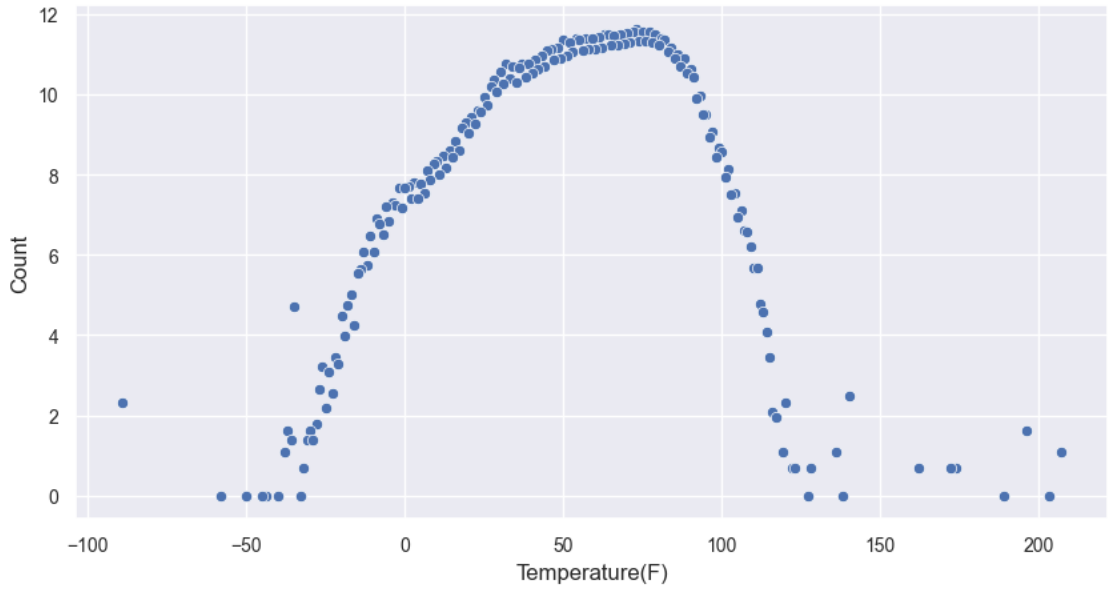
Observation:- Obviously most accidents assosiated with closing Roads due to some reasons

0.4.7 What temperature says about accident?

[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import math
warnings.filterwarnings("ignore")
sns.set_style("darkgrid")
import matplotlib.font_manager as font_manager
from matplotlib import ticker
import matplotlib.font_manager as font_manager
from matplotlib.ticker import FuncFormatter
import matplotlib.ticker as ticker
import matplotlib.patches as mpatches
```

```
import matplotlib.patheffects as PathEffects
```

[ ]:
```
temp_counts = accidents_sub["Temperature(F)"].value_counts().reset_index()
temp_counts.columns = ["Temperature(F)", "Count"]
# temp_counts
plt.figure(figsize=(10, 5))  # Adjust the figure size as needed
# plt.xticks(filtered_df["Hour"].unique())
sns.scatterplot(temp_counts,x="Temperature(F)",y=temp_counts["Count"].
  ↪apply(lambda x:math.log(x)))
plt.show()
```

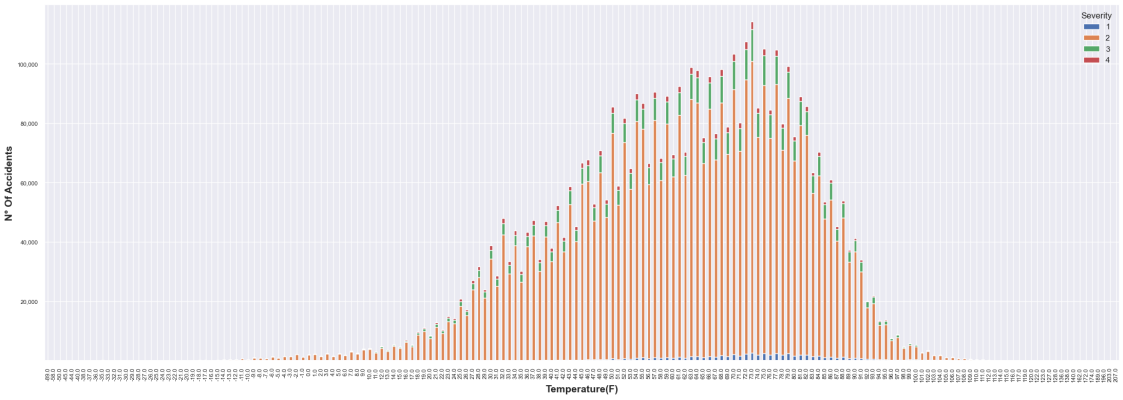


[ ]:
```
crosstab=pd.crosstab(accidents_sub["Temperature(F)"],accidents_sub["Severity"])
crosstab
```

[ ]:
```
Severity        1  2  3  4
Temperature(F)
-89.0           0  6  4  0
-58.0           0  1  0  0
-50.0           0  1  0  0
-45.0           0  1  0  0
-44.0           0  1  0  0
…              .. .. .. ..
 174.0          0  2  0  0
 189.0          0  1  0  0
 196.0          0  5  0  0
 203.0          0  0  1  0
 207.0          0  2  0  1
```

```
[177 rows x 4 columns]
```

[ ]:
```
# sns.set_palette("Set2")
# sns.set_style('ticks')

crosstab.plot(kind="bar",stacked=True,
              figsize=(27,9),
              rot=90,
              fontsize=8
              )
label_font_bold = font_manager.FontProperties(weight='bold')
plt.xlabel("Temperature(F)",fontsize=14,fontproperties=label_font_bold)
plt.ylabel("N° Of Accidents",fontsize=14,fontproperties=label_font_bold)

formatter = ticker.FuncFormatter(lambda x, pos: '{:,.0f}'.format(x))
plt.gca().yaxis.set_major_formatter(formatter)

plt.show()
```

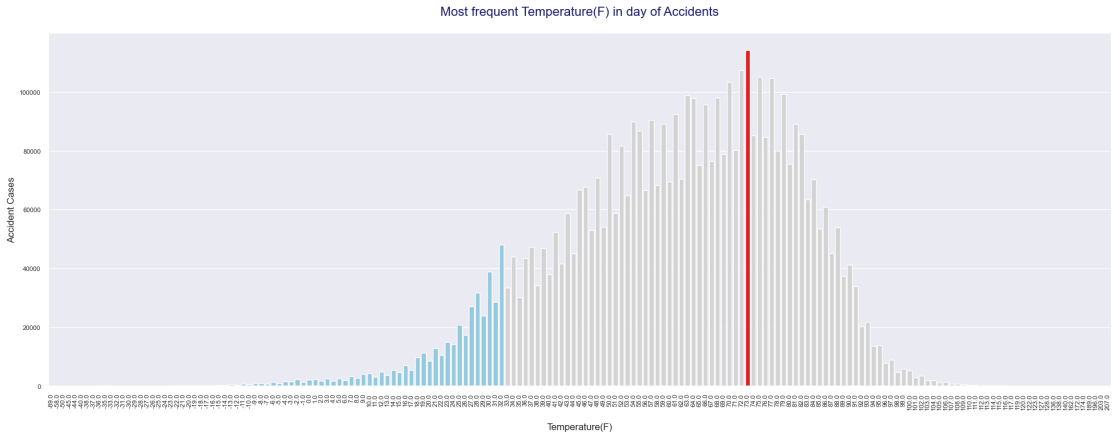


[ ]:
```
temp_of_day = pd.DataFrame(accidents_sub['Temperature(F)'].value_counts()).
 ↪reset_index().rename(columns={'index':'Temperature','Temperature(F)':
 ↪'cases'})
temp_of_day.sort_values(by='Temperature', inplace=True)
temp_of_day
```

[ ]:
```
     Temperature  cases
145        -89.0     10
167        -58.0      1
176        -50.0      1
172        -45.0      1
170        -44.0      1
..           …    …
```

```
160         174.0       2
174         189.0       1
150         196.0       5
175         203.0       1
156         207.0       3

[177 rows x 2 columns]
```

[ ]:
```
fig, ax = plt.subplots(figsize=(24,8), dpi=100)
sns.set_style('ticks')

colors = []
for x in temp_of_day['cases']:
    if int(temp_of_day[temp_of_day['cases'] == x]['Temperature'].iloc[0]) <=32:
        if x == max(list(temp_of_day['cases'])[:120]):
            colors.append('red')
        else:
            colors.append('skyblue')
    else:
        if x == max(list(temp_of_day['cases'])[100:]):
            colors.append('red')
        else:
            colors.append('lightgrey')

# Create a bar plot of 'hourly_accident_rate'
sns.barplot(x=temp_of_day.Temperature, y=temp_of_day.cases, palette=colors)

plt.title('Most frequent Temperature(F) in day of Accidents\n', size=16,␣
 ↪color='MidnightBlue')
plt.ylabel('\nAccident Cases', fontsize=12)
plt.xlabel('\nTemperature(F)', fontsize=12)
plt.xticks(rotation=90, fontsize=8)
plt.yticks(fontsize=8)

for i in ['top', 'right']:
    side = ax.spines[i]
    side.set_visible(False)

plt.show()
```



Observation: most accidents are happened at 73 Fahrenheit or 23 Celsius which is about almost room temperature

0.5 5. Data Preprocessing

Imputation and missing values

[ ]:
```
# next steps about data imputation
accidents_sub.isnull().sum()
```

[ ]:
```
Severity                    0
Start_Time                  0
End_Time                    0
Start_Lat                   0
Start_Lng                   0
End_Lat                1156511
End_Lng                1156511
Distance(mi)                0
Description                 4
City                      170
State                       0
Timezone                 4710
Airport_Code            17076
Weather_Timestamp       83638
Temperature(F)         107878
Wind_Chill(F)          145116
Humidity(%)            115058
Pressure(in)            92626
Visibility(mi)         111487
Wind_Direction         130210
Wind_Speed(mph)        130166
Precipitation(in)      203689
Weather_Condition      110655
```

```
Amenity                        0
Bump                           0
Crossing                       0
Give_Way                       0
Junction                       0
No_Exit                        0
Railway                        0
Roundabout                     0
Station                        0
Stop                           0
Traffic_Calming                0
Traffic_Signal                 0
Turning_Loop                   0
Sunrise_Sunset             23139
Civil_Twilight             23139
Nautical_Twilight          23139
Astronomical_Twilight      23139
Start_Year                     0
Start_Hour                     0
Start_Month                    0
Start_Day                      0
dtype: int64
```

[ ]:
```
#filling missing values with interpolate method
# limit is Maximum number of consecutive NaNs to fill. Must be greater than 0.
accidents_sub.fillna(method='ffill', limit=5, inplace=True)
accidents_sub.fillna(method='bfill', limit=5, inplace=True)
```

[ ]:
```
accidents_sub.isnull().sum()
```

[ ]:
```
Severity                       0
Start_Time                     0
End_Time                       0
Start_Lat                      0
Start_Lng                      0
End_Lat                  1156506
End_Lng                  1156506
Distance(mi)                   0
Description                    0
City                           0
State                          0
Timezone                       0
Airport_Code                   0
Weather_Timestamp            961
Temperature(F)               968
Wind_Chill(F)                971
Humidity(%)                  968
```

```
Pressure(in)                961
Visibility(mi)              961
Wind_Direction              964
Wind_Speed(mph)             964
Precipitation(in)          1361
Weather_Condition           961
Amenity                       0
Bump                          0
Crossing                      0
Give_Way                      0
Junction                      0
No_Exit                       0
Railway                       0
Roundabout                    0
Station                       0
Stop                          0
Traffic_Calming               0
Traffic_Signal                0
Turning_Loop                  0
Sunrise_Sunset                0
Civil_Twilight                0
Nautical_Twilight             0
Astronomical_Twilight         0
Start_Year                    0
Start_Hour                    0
Start_Month                   0
Start_Day                     0
dtype: int64
```

[ ]:
```
# remove rows with zero values
accidents_sub = accidents_sub.dropna()
missing_values = accidents_sub.isna()
missing_counts = accidents_sub.isna().sum()
total_missing = accidents_sub.isna().sum().sum()
```

[ ]:
```
accidents_sub.isnull().sum()
```

[ ]:
```
Severity              0
Start_Time            0
End_Time              0
Start_Lat             0
Start_Lng             0
End_Lat               0
End_Lng               0
Distance(mi)          0
Description           0
City                  0
```

```
State                    0
Timezone                 0
Airport_Code             0
Weather_Timestamp        0
Temperature(F)           0
Wind_Chill(F)            0
Humidity(%)              0
Pressure(in)             0
Visibility(mi)           0
Wind_Direction           0
Wind_Speed(mph)          0
Precipitation(in)        0
Weather_Condition        0
Amenity                  0
Bump                     0
Crossing                 0
Give_Way                 0
Junction                 0
No_Exit                  0
Railway                  0
Roundabout               0
Station                  0
Stop                     0
Traffic_Calming          0
Traffic_Signal           0
Turning_Loop             0
Sunrise_Sunset           0
Civil_Twilight           0
Nautical_Twilight        0
Astronomical_Twilight    0
Start_Year               0
Start_Hour               0
Start_Month              0
Start_Day                0
dtype: int64
```

Cleared data frame and statistics

[ ]:
```
accidents_sub.columns
```

[ ]:
```
Index(['Severity', 'Start_Time', 'End_Time', 'Start_Lat', 'Start_Lng',
       'End_Lat', 'End_Lng', 'Distance(mi)', 'Description', 'City', 'State',
       'Timezone', 'Airport_Code', 'Weather_Timestamp', 'Temperature(F)',
       'Wind_Chill(F)', 'Humidity(%)', 'Pressure(in)', 'Visibility(mi)',
       'Wind_Direction', 'Wind_Speed(mph)', 'Precipitation(in)',
       'Weather_Condition', 'Amenity', 'Bump', 'Crossing', 'Give_Way',
       'Junction', 'No_Exit', 'Railway', 'Roundabout', 'Station', 'Stop',
       'Traffic_Calming', 'Traffic_Signal', 'Turning_Loop', 'Sunrise_Sunset',
```

```
       'Civil_Twilight', 'Nautical_Twilight', 'Astronomical_Twilight',
       'Start_Year', 'Start_Hour', 'Start_Month', 'Start_Day'],
      dtype='object')
```

[ ]:
```
accidents_sub.describe()
```

[ ]:

	Severity	Start_Lat	Start_Lng	End_Lat	End_Lng
count	3.595200e+06	3.595200e+06	3.595200e+06	3.595200e+06	3.595200e+06
mean	2.062069e+00	3.599279e+01	-9.486576e+01	3.599302e+01	-9.486537e+01
std	3.619444e-01	5.285052e+00	1.792273e+01	5.285289e+00	1.792234e+01
min	1.000000e+00	2.456603e+01	-1.245481e+02	2.456601e+01	-1.245457e+02
25%	2.000000e+00	3.304191e+01	-1.174668e+02	3.304331e+01	-1.174662e+02
50%	2.000000e+00	3.590953e+01	-8.677509e+01	3.590968e+01	-8.677517e+01
75%	2.000000e+00	3.998321e+01	-8.018832e+01	3.998258e+01	-8.018690e+01
max	4.000000e+00	4.900050e+01	-6.748413e+01	4.900222e+01	-6.748413e+01

	Distance(mi)	Temperature(F)	Wind_Chill(F)	Humidity(%)
count	3.595200e+06	3.595200e+06	3.595200e+06	3.595200e+06
mean	8.828053e-01	6.108479e+01	5.976274e+01	6.372479e+01
std	1.857249e+00	1.939736e+01	2.163662e+01	2.297815e+01
min	0.000000e+00	-8.900000e+01	-8.900000e+01	1.000000e+00
25%	7.500000e-02	4.800000e+01	4.600000e+01	4.700000e+01
50%	2.830000e-01	6.300000e+01	6.300000e+01	6.600000e+01
75%	9.690000e-01	7.600000e+01	7.600000e+01	8.300000e+01
max	1.551860e+02	2.070000e+02	2.070000e+02	1.000000e+02

	Pressure(in)	Visibility(mi)	Wind_Speed(mph)	Precipitation(in)
count	3.595200e+06	3.595200e+06	3.595200e+06	3.595200e+06
mean	2.935432e+01	9.060771e+00	7.429183e+00	5.508962e-03
std	1.136505e+00	2.538379e+00	5.613030e+00	4.764102e-02
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	2.918000e+01	1.000000e+01	3.000000e+00	0.000000e+00
50%	2.972000e+01	1.000000e+01	7.000000e+00	0.000000e+00
75%	2.997000e+01	1.000000e+01	1.000000e+01	0.000000e+00
max	5.863000e+01	1.400000e+02	1.087000e+03	2.400000e+01

	Start_Year	Start_Hour	Start_Month
count	3.595200e+06	3.595200e+06	3.595200e+06
mean	2.021365e+03	1.284385e+01	6.609678e+00
std	8.735475e-01	5.805648e+00	3.815319e+00
min	2.020000e+03	0.000000e+00	1.000000e+00
25%	2.021000e+03	8.000000e+00	3.000000e+00
50%	2.021000e+03	1.400000e+01	6.000000e+00
75%	2.022000e+03	1.700000e+01	1.000000e+01
max	2.023000e+03	2.300000e+01	1.200000e+01

0.6 6. Feature Selection

chosing most salient features for selected label

```
[ ]: X = accidents_sub[['Start_Month', 'Start_Year', 'Start_Hour', 'Start_Lat',␣
      ↪'Temperature(F)', 'Wind_Speed(mph)', 'Distance(mi)']]
     y = accidents_sub['Severity']
     # df['column_name'] = pd.to_numeric(df['column_name'], errors='coerce')
```

splitting to train and test datasets

```
[ ]: from sklearn.model_selection import train_test_split

     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
      ↪random_state = 42)
```

0.7 7. Model Selection

0.7.1 Classification metrics

first of all we check classification accuraccy and confusion matrix for 3 models: Logistic Regression (LR), Random Forest (RF), Gradient boosting (GB)

```
[ ]: # Gradient boosting.....
     from sklearn.ensemble import GradientBoostingClassifier
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import accuracy_score, classification_report

     # Assuming you have your features in X and labels in y
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
      ↪random_state=42)

     # Create a GradientBoostingClassifier
     model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,␣
      ↪max_depth=3, random_state=42)

     # Train the classifier
     model.fit(X_train, y_train)

     # Make predictions on the test set
     y_pred = model.predict(X_test)

     # Evaluate the accuracy
     accuracy = accuracy_score(y_test, y_pred)
     print(f'Accuracy: {accuracy:.2f}')
     print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.95
              precision    recall  f1-score   support
```

```
           1       0.76      0.20      0.32      5604
           2       0.96      1.00      0.98    683609
           3       0.63      0.20      0.30      9227
           4       0.46      0.02      0.04     20600

    accuracy                           0.95    719040
   macro avg       0.70      0.36      0.41    719040
weighted avg       0.94      0.95      0.94    719040
```

[ ]:
```python
# Random Forest (the most appropriate to our problem and it will be seen from␣
 ↪the accuracy report)
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report

# Assuming X contains your features and y contains your target variable
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Create a random forest classifier
model = RandomForestClassifier(n_estimators=100, random_state=42)

# Train the model on the training set
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')

# You can also print a classification report for more detailed metrics
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.95
              precision    recall  f1-score   support

           1       0.71      0.57      0.63      5604
           2       0.97      0.98      0.98    683609
           3       0.70      0.54      0.61      9227
           4       0.29      0.17      0.21     20600

    accuracy                           0.95    719040
   macro avg       0.67      0.57      0.61    719040
weighted avg       0.94      0.95      0.95    719040
```

[ ]:
```
# Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report

# Create a logistic regression model
model = LogisticRegression(multi_class='auto', solver='lbfgs', max_iter=1000)

# Train the model on the training set
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')

# You can also print a classification report for more detailed metrics
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.95
              precision    recall  f1-score   support

           1       0.00      0.00      0.00      5604
           2       0.95      1.00      0.97    683609
           3       0.12      0.00      0.00      9227
           4       0.00      0.00      0.00     20600

    accuracy                           0.95    719040
   macro avg       0.27      0.25      0.24    719040
weighted avg       0.91      0.95      0.93    719040
```

Observation: preliminary validation using classification metrics shows better results for random forest algorythm

0.7.2 Cross validation

in order to that let us run cross validation of those 3 models and make sure that random forest is the most suitable model for our problem

[ ]:
```
# the list of algorithms for classification as Baselines are
from sklearn.linear_model import LogisticRegression  #drawing a line based on␣
 ↪linear regression but used for classification
from sklearn.ensemble import RandomForestClassifier  #using trees to classify
from sklearn.svm import SVC  #drawing a line based on maximum distance used as␣
 ↪support vector classification

# validate with random_state 42
```

```
lr = LogisticRegression(multi_class='auto', solver='lbfgs', max_iter=1000)
rf = RandomForestClassifier(n_estimators=100, random_state=42)
gbc = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,␣
 ↪max_depth=3)

models = [lr, rf, gbc]

# perform cross validation using KFold
from sklearn.model_selection import KFold, cross_val_score

kfold = KFold(n_splits = 5, shuffle = True, random_state=42)

for model in models:
    score = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')  #f1, recall, precision, accuracy
    print("Sklearn Model: ", model)
    print("Scores: ", score, "- Scores mean: ", score.mean(), "- Scores std: ",␣
 ↪score.std())  #out of 1 ; 1 means perfect accuracy
# #Classification report
# y_pred = model.predict(X_test)
# accuracy = accuracy_score(y_test, y_pred)
# print(f'Accuracy: {accuracy:.2f}')
# # also print a classification report for more detailed metrics
# print(classification_report(y_test, y_pred))
```

```
Sklearn Model:  LogisticRegression(max_iter=1000)
Scores:  [0.95094675 0.95079551 0.95081637 0.95077638 0.95081289] - Scores mean:
0.9508295783266577 - Scores std:  6.028715428619598e-05
Sklearn Model:  RandomForestClassifier(random_state=42)
Scores:  [0.95310588 0.95317541 0.95275645 0.95288684 0.9527947 ] - Scores mean:
0.9529438556964841 - Scores std:  0.00016762422618359535
Sklearn Model:  GradientBoostingClassifier()
Scores:  [0.9537856  0.95349181 0.95394728 0.95372128 0.95370216] - Scores mean:
0.9537296256119271 - Scores std:  0.00014689221138946033
```

Observation: cross validation has confirmed our selection of random forest model gains a higher accuracy scores

0.7.3 Gread Search for best model

find the best parameters for the the model

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import accuracy_score

# Assuming X contains your features and y contains your target variable
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Create a random forest classifier
rf_classifier = RandomForestClassifier()

# Define the hyperparameter grid to search
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Create the grid search with cross-validation
grid = GridSearchCV(estimator=rf_classifier, param_grid=param_grid, cv=3,␣
 ↪scoring='accuracy')

# Fit the grid search to the data
grid.fit(X_train, y_train)

# Print the best hyperparameters found
print("Best Hyperparameters:", grid.best_params_)

# Get the best model from the grid search
Best_model_rf = grid.best_estimator_

# Make predictions on the test set using the best model
y_pred = Best_model_rf.predict(X_test)

# Evaluate the performance of the best model
accuracy = accuracy_score(y_test, y_pred)

print(f'Accuracy of the Best Model: {accuracy:.2f}')
```

```
The Kernel crashed while executing code in the the current cell or a previous␣
 ↪cell. Please review the code in the cell(s) to identify a possible cause of␣
 ↪the failure. Click <a href='https://aka.ms/vscodeJupyterKernelCrash'>here</a>␣
 ↪for more info. View Jupyter <a href='command:jupyter.viewOutput'>log</a> for␣
 ↪further details.
```

save the best model

[ ]:
```
import pickle
# save the model
filename = r'./model/Best_model_accident.pkl'
pickle.dump(grid, open(filename,'wb'))
```

```
# # check the file created as per the path above
# loaded_grid = pickle.load(open(filename, 'rb'))

# accidents_sub['column_name'] = pd.to_numeric(accidents_sub['column_name'],␣
 ↪errors='coerce')
accidents_sub.head()
```