AhmedHesham_Task2

July 9, 2023

0.1 Importing Libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
```

0.2 Reading Data:

[2]:
```
df_train = pd.read_csv("US_Accidents_March23.csv")

pd.options.display.float_format = '{:.4f}'.format
```

0.3 Data Exploration:

0.3.1 Exploring data shape

[3]:
```
pd.set_option('display.max_columns', None)
df_train
```

[3]:
```
                    ID   Source  Severity           Start_Time  \
0                  A-1  Source2         3  2016-02-08 05:46:00
1                  A-2  Source2         2  2016-02-08 06:07:59
2                  A-3  Source2         2  2016-02-08 06:49:27
3                  A-4  Source2         3  2016-02-08 07:23:34
4                  A-5  Source2         2  2016-02-08 07:39:07
```

```
…             …        …       …                  …
7728389  A-7777757  Source1        2  2019-08-23 18:03:25
7728390  A-7777758  Source1        2  2019-08-23 19:11:30
7728391  A-7777759  Source1        2  2019-08-23 19:00:21
7728392  A-7777760  Source1        2  2019-08-23 19:00:21
7728393  A-7777761  Source1        2  2019-08-23 18:52:06

                    End_Time  Start_Lat  Start_Lng  End_Lat   End_Lng  \
0        2016-02-08 11:00:00    39.8651   -84.0587      NaN       NaN
1        2016-02-08 06:37:59    39.9281   -82.8312      NaN       NaN
2        2016-02-08 07:19:27    39.0631   -84.0326      NaN       NaN
3        2016-02-08 07:53:34    39.7478   -84.2056      NaN       NaN
4        2016-02-08 08:09:07    39.6278   -84.1884      NaN       NaN
…                          …          …         …       …        …
7728389  2019-08-23 18:32:01    34.0025  -117.3794  33.9989 -117.3709
7728390  2019-08-23 19:38:23    32.7670  -117.1481  32.7655 -117.1536
7728391  2019-08-23 19:28:49    33.7754  -117.8478  33.7774 -117.8573
7728392  2019-08-23 19:29:42    33.9925  -118.4030  33.9831 -118.3957
7728393  2019-08-23 19:21:31    34.1339  -117.2309  34.1374 -117.2393

         Distance(mi)                                        Description  \
0              0.0100  Right lane blocked due to accident on I-70 Eas…
1              0.0100  Accident on Brice Rd at Tussing Rd. Expect del…
2              0.0100  Accident on OH-32 State Route 32 Westbound at …
3              0.0100  Accident on I-75 Southbound at Exits 52 52B US…
4              0.0100  Accident on McEwen Rd at OH-725 Miamisburg Cen…
…                   …                                                …
7728389        0.5430                          At Market St - Accident.
7728390        0.3380    At Camino Del Rio/Mission Center Rd - Accident.
7728391        0.5610  At Glassell St/Grand Ave - Accident. in the ri…
7728392        0.7720     At CA-90/Marina Fwy/Jefferson Blvd - Accident.
7728393        0.5370               At Highland Ave/Arden Ave - Accident.

                            Street         City         County State  \
0                           I-70 E       Dayton     Montgomery    OH
1                         Brice Rd  Reynoldsburg      Franklin    OH
2                  State Route 32  Williamsburg      Clermont    OH
3                           I-75 S       Dayton     Montgomery    OH
4        Miamisburg Centerville Rd       Dayton     Montgomery    OH
…                                …            …              …   …
7728389                Pomona Fwy E    Riverside      Riverside    CA
7728390                      I-8 W    San Diego      San Diego    CA
7728391             Garden Grove Fwy       Orange         Orange    CA
7728392              San Diego Fwy S  Culver City    Los Angeles    CA
7728393                     CA-210 W     Highland  San Bernardino    CA

            Zipcode Country    Timezone Airport_Code    Weather_Timestamp  \
```

```
0              45424     US  US/Eastern        KFFO  2016-02-08 05:58:00
1         43068-3402     US  US/Eastern        KCMH  2016-02-08 05:51:00
2              45176     US  US/Eastern        KI69  2016-02-08 06:56:00
3              45417     US  US/Eastern        KDAY  2016-02-08 07:38:00
4              45459     US  US/Eastern        KMGY  2016-02-08 07:53:00
…                  …    …           …            …                  …
7728389        92501     US  US/Pacific        KRAL  2019-08-23 17:53:00
7728390        92108     US  US/Pacific        KMYF  2019-08-23 18:53:00
7728391        92866     US  US/Pacific        KSNA  2019-08-23 18:53:00
7728392        90230     US  US/Pacific        KSMO  2019-08-23 18:51:00
7728393        92346     US  US/Pacific        KSBD  2019-08-23 20:50:00

         Temperature(F)  Wind_Chill(F)  Humidity(%)  Pressure(in)  \
0               36.9000            NaN      91.0000       29.6800
1               37.9000            NaN     100.0000       29.6500
2               36.0000        33.3000     100.0000       29.6700
3               35.1000        31.0000      96.0000       29.6400
4               36.0000        33.3000      89.0000       29.6500
…                     …              …            …             …
7728389         86.0000        86.0000      40.0000       28.9200
7728390         70.0000        70.0000      73.0000       29.3900
7728391         73.0000        73.0000      64.0000       29.7400
7728392         71.0000        71.0000      81.0000       29.6200
7728393         79.0000        79.0000      47.0000       28.6300

         Visibility(mi) Wind_Direction  Wind_Speed(mph)  Precipitation(in)  \
0               10.0000           Calm              NaN             0.0200
1               10.0000           Calm              NaN             0.0000
2               10.0000             SW           3.5000                NaN
3                9.0000             SW           4.6000                NaN
4                6.0000             SW           3.5000                NaN
…                     …              …                …                  …
7728389         10.0000              W          13.0000             0.0000
7728390         10.0000             SW           6.0000             0.0000
7728391         10.0000            SSW          10.0000             0.0000
7728392         10.0000             SW           8.0000             0.0000
7728393          7.0000             SW           7.0000             0.0000

        Weather_Condition  Amenity   Bump  Crossing  Give_Way  Junction  \
0              Light Rain    False  False     False     False     False
1              Light Rain    False  False     False     False     False
2                Overcast    False  False     False     False     False
3           Mostly Cloudy    False  False     False     False     False
4           Mostly Cloudy    False  False     False     False     False
…                       …        …      …         …         …         …
7728389              Fair    False  False     False     False     False
7728390              Fair    False  False     False     False     False
```

```
7728391     Partly Cloudy    False  False     False     False      True
7728392              Fair    False  False     False     False     False
7728393              Fair    False  False     False     False     False

         No_Exit  Railway  Roundabout  Station   Stop  Traffic_Calming  \
0          False    False       False    False  False            False
1          False    False       False    False  False            False
2          False    False       False    False  False            False
3          False    False       False    False  False            False
4          False    False       False    False  False            False
…            …        …           …        …      …              …
7728389    False    False       False    False  False            False
7728390    False    False       False    False  False            False
7728391    False    False       False    False  False            False
7728392    False    False       False    False  False            False
7728393    False    False       False    False  False            False

         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
…                   …             …              …              …
7728389           False         False            Day            Day
7728390           False         False            Day            Day
7728391           False         False            Day            Day
7728392           False         False            Day            Day
7728393           False         False            Day            Day

        Nautical_Twilight Astronomical_Twilight
0                   Night                 Night
1                   Night                   Day
2                     Day                   Day
3                     Day                   Day
4                     Day                   Day
…                    …                    …
7728389               Day                   Day
7728390               Day                   Day
7728391               Day                   Day
7728392               Day                   Day
7728393               Day                   Day

[7728394 rows x 46 columns]
```

[4]:
```
df_train.columns
```

```
[4]: Index(['ID', 'Source', 'Severity', 'Start_Time', 'End_Time', 'Start_Lat',
       'Start_Lng', 'End_Lat', 'End_Lng', 'Distance(mi)', 'Description',
       'Street', 'City', 'County', 'State', 'Zipcode', 'Country', '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'],
      dtype='object')
```

```
[5]: print("train data info")
df_train.info()
```

```
train data info
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7728394 entries, 0 to 7728393
Data columns (total 46 columns):
 #   Column                 Dtype
---  ------                 -----
 0   ID                     object
 1   Source                 object
 2   Severity               int64
 3   Start_Time             object
 4   End_Time               object
 5   Start_Lat              float64
 6   Start_Lng              float64
 7   End_Lat                float64
 8   End_Lng                float64
 9   Distance(mi)           float64
 10  Description            object
 11  Street                 object
 12  City                   object
 13  County                 object
 14  State                  object
 15  Zipcode                object
 16  Country                object
 17  Timezone               object
 18  Airport_Code           object
 19  Weather_Timestamp      object
 20  Temperature(F)         float64
 21  Wind_Chill(F)          float64
 22  Humidity(%)            float64
 23  Pressure(in)           float64
 24  Visibility(mi)         float64
 25  Wind_Direction         object
```

```
26  Wind_Speed(mph)        float64
27  Precipitation(in)      float64
28  Weather_Condition      object
29  Amenity                bool
30  Bump                   bool
31  Crossing               bool
32  Give_Way               bool
33  Junction               bool
34  No_Exit                bool
35  Railway                bool
36  Roundabout             bool
37  Station                bool
38  Stop                   bool
39  Traffic_Calming        bool
40  Traffic_Signal         bool
41  Turning_Loop           bool
42  Sunrise_Sunset         object
43  Civil_Twilight         object
44  Nautical_Twilight      object
45  Astronomical_Twilight  object
dtypes: bool(13), float64(12), int64(1), object(20)
memory usage: 2.0+ GB
```

0.3.2 Statistics Summary

[6]:
```
df_train.describe()
```

[6]:
```
          Severity     Start_Lat     Start_Lng       End_Lat       End_Lng  \
count 7728394.0000 7728394.0000 7728394.0000 4325632.0000 4325632.0000
mean        2.2124       36.2012      -94.7025       36.2618      -95.7256
std         0.4875        5.0761       17.3918        5.2729       18.1079
min         1.0000       24.5548     -124.6238       24.5660     -124.5457
25%         2.0000       33.3996     -117.2194       33.4621     -117.7543
50%         2.0000       35.8240      -87.7666       36.1835      -88.0279
75%         2.0000       40.0850      -80.3537       40.1789      -80.2471
max         4.0000       49.0022      -67.1132       49.0750      -67.1092

       Distance(mi)  Temperature(F)  Wind_Chill(F)  Humidity(%)  Pressure(in)  \
count  7728394.0000    7564541.0000   5729375.0000 7554250.0000  7587715.0000
mean         0.5618         61.6633        58.2510      64.8310       29.5390
std          1.7768         19.0137        22.3898      22.8210        1.0062
min          0.0000        -89.0000       -89.0000       1.0000        0.0000
25%          0.0000         49.0000        43.0000      48.0000       29.3700
50%          0.0300         64.0000        62.0000      67.0000       29.8600
75%          0.4640         76.0000        75.0000      84.0000       30.0300
max        441.7500        207.0000       207.0000     100.0000       58.6300
```

```
       Visibility(mi)  Wind_Speed(mph)  Precipitation(in)
count     7551296.0000     7157161.0000       5524808.0000
mean            9.0904           7.6855             0.0084
std             2.6883           5.4250             0.1102
min             0.0000           0.0000             0.0000
25%            10.0000           4.6000             0.0000
50%            10.0000           7.0000             0.0000
75%            10.0000          10.4000             0.0000
max           140.0000        1087.0000            36.4700
```

0.3.3 Checking null values

[7]:
```python
print("train data null cells")
print(df_train.isnull().sum())
```

```
train data null cells
ID                             0
Source                         0
Severity                       0
Start_Time                     0
End_Time                       0
Start_Lat                      0
Start_Lng                      0
End_Lat                  3402762
End_Lng                  3402762
Distance(mi)                   0
Description                    5
Street                     10869
City                         253
County                         0
State                          0
Zipcode                     1915
Country                        0
Timezone                    7808
Airport_Code               22635
Weather_Timestamp         120228
Temperature(F)            163853
Wind_Chill(F)            1999019
Humidity(%)               174144
Pressure(in)              140679
Visibility(mi)            177098
Wind_Direction            175206
Wind_Speed(mph)           571233
Precipitation(in)        2203586
Weather_Condition         173459
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              23246
Civil_Twilight              23246
Nautical_Twilight           23246
Astronomical_Twilight       23246
dtype: int64
```

[8]:
```python
df_train.isnull().sum().sort_values(ascending=False)/len(df_train)
```

[8]:
```
End_Lat                  0.4403
End_Lng                  0.4403
Precipitation(in)        0.2851
Wind_Chill(F)            0.2587
Wind_Speed(mph)          0.0739
Visibility(mi)           0.0229
Wind_Direction           0.0227
Humidity(%)              0.0225
Weather_Condition        0.0224
Temperature(F)           0.0212
Pressure(in)             0.0182
Weather_Timestamp        0.0156
Nautical_Twilight        0.0030
Civil_Twilight           0.0030
Sunrise_Sunset           0.0030
Astronomical_Twilight    0.0030
Airport_Code             0.0029
Street                   0.0014
Timezone                 0.0010
Zipcode                  0.0002
City                     0.0000
Description              0.0000
Traffic_Signal           0.0000
Roundabout               0.0000
Station                  0.0000
Stop                     0.0000
Traffic_Calming          0.0000
Country                  0.0000
```

```
Turning_Loop             0.0000
No_Exit                  0.0000
End_Time                 0.0000
Start_Time               0.0000
Severity                 0.0000
Railway                  0.0000
Crossing                 0.0000
Junction                 0.0000
Give_Way                 0.0000
Bump                     0.0000
Amenity                  0.0000
Start_Lat                0.0000
Start_Lng                0.0000
Distance(mi)             0.0000
Source                   0.0000
County                   0.0000
State                    0.0000
ID                       0.0000
dtype: float64
```

0.4 Data Preprocessing: In this section we handle all null values with converting some features either from categorical to numerical or binary and from continyous to discerete form (bin groups)

0.4.1 Dropping unneccesary columns ["End_Lat", "End_Lang", "Perceptation", "Wind_Chill"]

from data exploration section, we can see that there are null values in many columns. So this will be a bit challenging cleaning most of those columns. For "End_Lat" and "End_Lang" columns we will just drop them, as they are not that effective features we may need same as "Perceptation" and "Wind_Chill". Also "Turning_Loop" column will be dropped as its value is constant and doesn't change.

[9]:
```
df_train.columns
```

[9]:
```
Index(['ID', 'Source', 'Severity', 'Start_Time', 'End_Time', 'Start_Lat',
       'Start_Lng', 'End_Lat', 'End_Lng', 'Distance(mi)', 'Description',
       'Street', 'City', 'County', 'State', 'Zipcode', 'Country', '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'],
      dtype='object')
```

[10]:
```
df_train.drop(["End_Lat", "End_Lng", "Precipitation(in)","Wind_Chill(F)",␣
↪"Turning_Loop"], axis=1, inplace=True)
```

0.4.2 Changing Boolean Columns to numerical 0/1 [Night/False –> 0 , Day/True –> 1]

[11]:
```
cols_to_convert = ['Sunrise_Sunset', 'Civil_Twilight', 'Nautical_Twilight',␣
↪'Astronomical_Twilight']


for col in cols_to_convert:
    df_train[col] = df_train[col].map({"Night":0, "Day":1})
```

[12]:
```
cols_to_convert = ['Amenity', 'Bump', 'Crossing', 'Give_Way', 'Junction',␣
↪'No_Exit',
                   'Railway', 'Roundabout', 'Station', 'Stop',␣
↪'Traffic_Calming',
                   'Traffic_Signal']

for col in cols_to_convert:
    df_train[col] = df_train[col].map({True:1, False:0})
```

[13]:
```
df_train
```

[13]:
```
                ID   Source  Severity           Start_Time  \
0              A-1  Source2         3  2016-02-08 05:46:00
1              A-2  Source2         2  2016-02-08 06:07:59
2              A-3  Source2         2  2016-02-08 06:49:27
3              A-4  Source2         3  2016-02-08 07:23:34
4              A-5  Source2         2  2016-02-08 07:39:07
…                …        …       …                    …
7728389  A-7777757  Source1         2  2019-08-23 18:03:25
7728390  A-7777758  Source1         2  2019-08-23 19:11:30
7728391  A-7777759  Source1         2  2019-08-23 19:00:21
7728392  A-7777760  Source1         2  2019-08-23 19:00:21
7728393  A-7777761  Source1         2  2019-08-23 18:52:06

                    End_Time  Start_Lat  Start_Lng  Distance(mi)  \
0        2016-02-08 11:00:00    39.8651   -84.0587        0.0100
1        2016-02-08 06:37:59    39.9281   -82.8312        0.0100
2        2016-02-08 07:19:27    39.0631   -84.0326        0.0100
3        2016-02-08 07:53:34    39.7478   -84.2056        0.0100
4        2016-02-08 08:09:07    39.6278   -84.1884        0.0100
…                        …        …        …          …
7728389  2019-08-23 18:32:01    34.0025  -117.3794        0.5430
7728390  2019-08-23 19:38:23    32.7670  -117.1481        0.3380
```

```
7728391  2019-08-23 19:28:49    33.7754  -117.8478        0.5610
7728392  2019-08-23 19:29:42    33.9925  -118.4030        0.7720
7728393  2019-08-23 19:21:31    34.1339  -117.2309        0.5370

                                              Description  \
0        Right lane blocked due to accident on I-70 Eas…
1        Accident on Brice Rd at Tussing Rd. Expect del…
2        Accident on OH-32 State Route 32 Westbound at …
3        Accident on I-75 Southbound at Exits 52 52B US…
4        Accident on McEwen Rd at OH-725 Miamisburg Cen…
…                                                     …
7728389                           At Market St - Accident.
7728390   At Camino Del Rio/Mission Center Rd - Accident.
7728391  At Glassell St/Grand Ave - Accident. in the ri…
7728392     At CA-90/Marina Fwy/Jefferson Blvd - Accident.
7728393               At Highland Ave/Arden Ave - Accident.

                           Street          City          County State  \
0                        I-70 E        Dayton      Montgomery    OH
1                      Brice Rd  Reynoldsburg        Franklin    OH
2                State Route 32  Williamsburg        Clermont    OH
3                        I-75 S        Dayton      Montgomery    OH
4        Miamisburg Centerville Rd        Dayton      Montgomery    OH
…                             …           …               …   …
7728389                Pomona Fwy E     Riverside       Riverside    CA
7728390                      I-8 W     San Diego       San Diego    CA
7728391            Garden Grove Fwy        Orange          Orange    CA
7728392             San Diego Fwy S   Culver City     Los Angeles    CA
7728393                    CA-210 W      Highland  San Bernardino    CA

            Zipcode Country    Timezone Airport_Code    Weather_Timestamp  \
0             45424      US  US/Eastern         KFFO  2016-02-08 05:58:00
1        43068-3402      US  US/Eastern         KCMH  2016-02-08 05:51:00
2             45176      US  US/Eastern         KI69  2016-02-08 06:56:00
3             45417      US  US/Eastern         KDAY  2016-02-08 07:38:00
4             45459      US  US/Eastern         KMGY  2016-02-08 07:53:00
…                 …     …           …            …                  …
7728389       92501      US  US/Pacific         KRAL  2019-08-23 17:53:00
7728390       92108      US  US/Pacific         KMYF  2019-08-23 18:53:00
7728391       92866      US  US/Pacific         KSNA  2019-08-23 18:53:00
7728392       90230      US  US/Pacific         KSMO  2019-08-23 18:51:00
7728393       92346      US  US/Pacific         KSBD  2019-08-23 20:50:00

         Temperature(F)  Humidity(%)  Pressure(in)  Visibility(mi)  \
0               36.9000      91.0000       29.6800         10.0000
1               37.9000     100.0000       29.6500         10.0000
2               36.0000     100.0000       29.6700         10.0000
```

3	35.1000	96.0000	29.6400	9.0000
4	36.0000	89.0000	29.6500	6.0000
…	…	…	…	…
7728389	86.0000	40.0000	28.9200	10.0000
7728390	70.0000	73.0000	29.3900	10.0000
7728391	73.0000	64.0000	29.7400	10.0000
7728392	71.0000	81.0000	29.6200	10.0000
7728393	79.0000	47.0000	28.6300	7.0000

	Wind_Direction	Wind_Speed(mph)	Weather_Condition	Amenity	Bump	\
0	Calm	NaN	Light Rain	0	0	
1	Calm	NaN	Light Rain	0	0	
2	SW	3.5000	Overcast	0	0	
3	SW	4.6000	Mostly Cloudy	0	0	
4	SW	3.5000	Mostly Cloudy	0	0	
…	…	…	…	…	…	
7728389	W	13.0000	Fair	0	0	
7728390	SW	6.0000	Fair	0	0	
7728391	SSW	10.0000	Partly Cloudy	0	0	
7728392	SW	8.0000	Fair	0	0	
7728393	SW	7.0000	Fair	0	0	

	Crossing	Give_Way	Junction	No_Exit	Railway	Roundabout	Station	\
0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	
…	…	…	…	…	…	…	…	
7728389	0	0	0	0	0	0	0	
7728390	0	0	0	0	0	0	0	
7728391	0	0	1	0	0	0	0	
7728392	0	0	0	0	0	0	0	
7728393	0	0	0	0	0	0	0	

	Stop	Traffic_Calming	Traffic_Signal	Sunrise_Sunset	\
0	0	0	0	0.0000	
1	0	0	0	0.0000	
2	0	0	1	0.0000	
3	0	0	0	0.0000	
4	0	0	1	1.0000	
…	…	…	…	…	
7728389	0	0	0	1.0000	
7728390	0	0	0	1.0000	
7728391	0	0	0	1.0000	
7728392	0	0	0	1.0000	
7728393	0	0	0	1.0000	

```
         Civil_Twilight  Nautical_Twilight  Astronomical_Twilight
0                0.0000             0.0000                 0.0000
1                0.0000             0.0000                 1.0000
2                0.0000             1.0000                 1.0000
3                1.0000             1.0000                 1.0000
4                1.0000             1.0000                 1.0000
…                  …                 …                     …
7728389          1.0000             1.0000                 1.0000
7728390          1.0000             1.0000                 1.0000
7728391          1.0000             1.0000                 1.0000
7728392          1.0000             1.0000                 1.0000
7728393          1.0000             1.0000                 1.0000

[7728394 rows x 41 columns]
```

[14]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7728394 entries, 0 to 7728393
Data columns (total 41 columns):
 #   Column                 Dtype
---  ------                 -----
 0   ID                     object
 1   Source                 object
 2   Severity               int64
 3   Start_Time             object
 4   End_Time               object
 5   Start_Lat              float64
 6   Start_Lng              float64
 7   Distance(mi)           float64
 8   Description            object
 9   Street                 object
 10  City                   object
 11  County                 object
 12  State                  object
 13  Zipcode                object
 14  Country                object
 15  Timezone               object
 16  Airport_Code           object
 17  Weather_Timestamp      object
 18  Temperature(F)         float64
 19  Humidity(%)            float64
 20  Pressure(in)           float64
 21  Visibility(mi)         float64
 22  Wind_Direction         object
 23  Wind_Speed(mph)        float64
```

```
 24  Weather_Condition      object
 25  Amenity                int64
 26  Bump                   int64
 27  Crossing               int64
 28  Give_Way               int64
 29  Junction               int64
 30  No_Exit                int64
 31  Railway                int64
 32  Roundabout             int64
 33  Station                int64
 34  Stop                   int64
 35  Traffic_Calming        int64
 36  Traffic_Signal         int64
 37  Sunrise_Sunset         float64
 38  Civil_Twilight         float64
 39  Nautical_Twilight      float64
 40  Astronomical_Twilight  float64
dtypes: float64(12), int64(13), object(16)
memory usage: 2.4+ GB
```

0.4.3 Changing Source Column to Numerical

[15]:
```
df_train["Source"] = df_train["Source"].replace({"Source1":1, "Source2":2,␣
↪"Source3":3})
```

0.4.4 Create bin groups of Temperature, Humidity and Pressure columns

[16]:
```
df_train['Temperature_binned'] = pd.cut(df_train['Temperature(F)'], bins=4)
df_train['Humidity_binned'] = pd.cut(df_train['Humidity(%)'], bins=4)
df_train['Pressure_binned'] = pd.cut(df_train['Pressure(in)'], bins=4)
```

0.4.5 Handling Null Values

For the remaining columns we can either drop the null values as the portion is not that big, or we try to get the correlation between columns and try to fill the null values with suitable values.

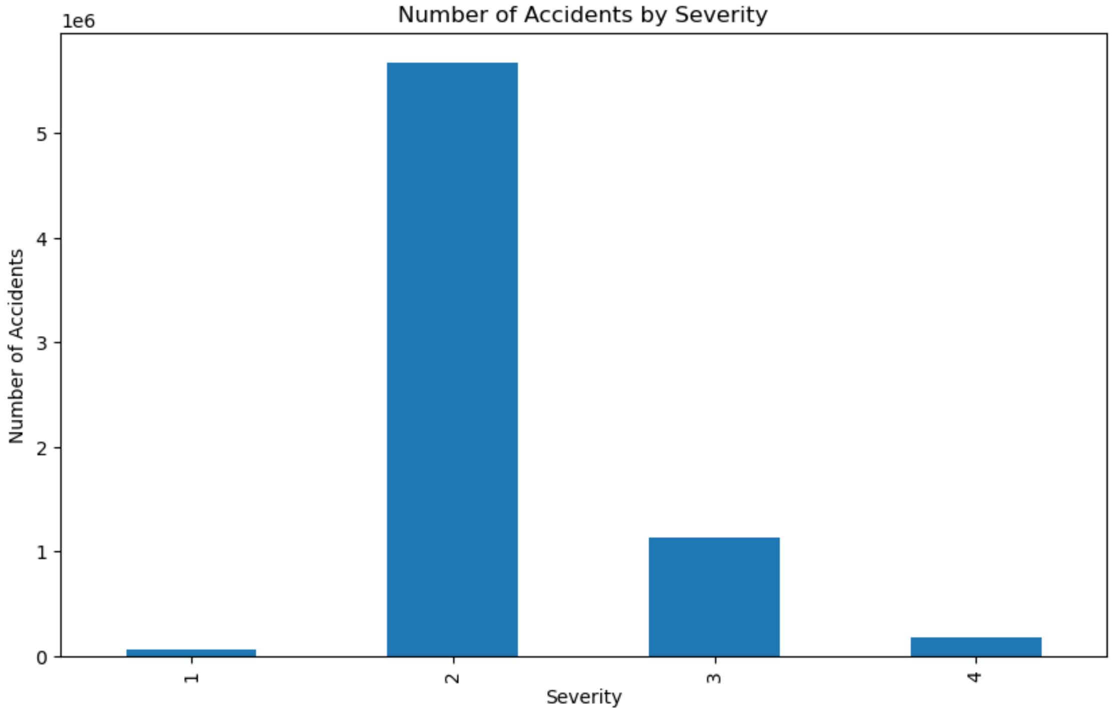
[17]:
```
print(len(df_train))
df_train = df_train.dropna()
df_train = df_train.reset_index()
print(len(df_train))
```

```
7728394
7051556
```

As we can see removing the null values didn't affect the data that much and we still have large amount of data to do our analysis, so we will go along with this approach

0.5 Descriptive Analysis:

[38]:
```
plt.figure(figsize=(10,6))
df_train['Severity'].value_counts().sort_index().plot(kind='bar')
plt.title('Number of Accidents by Severity')
plt.xlabel('Severity')
plt.ylabel('Number of Accidents')
plt.show()
```

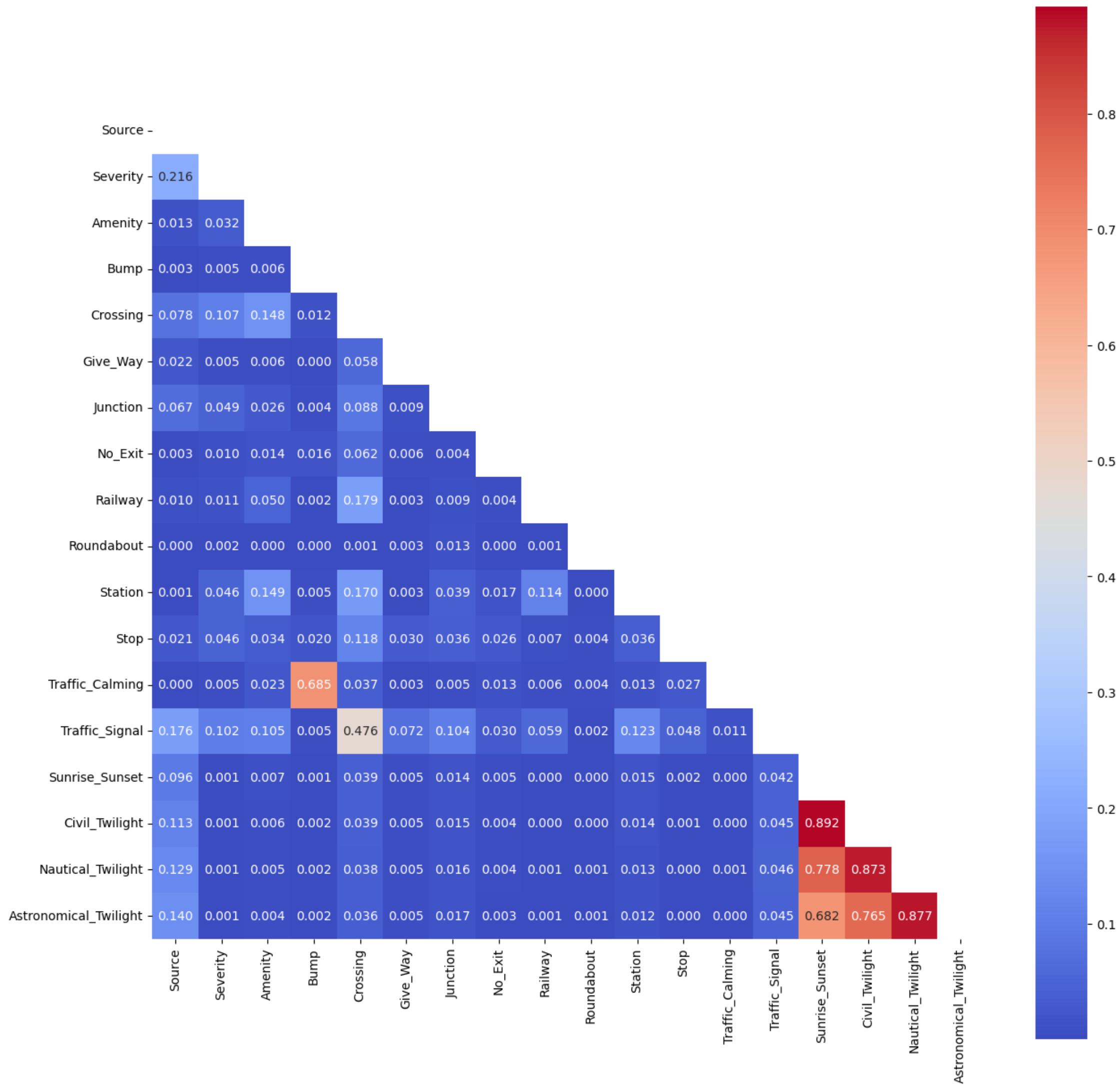


A first insight to see how biased our data is, adn from the above figure we can observe that the data is very biased toward severity 2 accidents. To be noted from this observation, that due to this bias only trends can be investigated, but no specific relationships between severity type and any factor can be analysed, as in any case we will find that any analysis we do will be in the favour of severity 2. If we want to avoid this bias, we should balance the data by either gathering more data or removing random portions of the data till all the severities are equal in ratios. Another approach is to make this task a binary task where to convert the severities to "severity2" or "not severity2" by compining all the other severities on one category then balancing both categories by removing the excess data.

Investigating cocorrelations between severity and different factors

[39]:
```
selected_columns = ["Source", "Severity", 'Amenity', 'Bump', 'Crossing',␣
 ↪'Give_Way',
                    'Junction', 'No_Exit', 'Railway', 'Roundabout', 'Station',␣
 ↪'Stop',
```

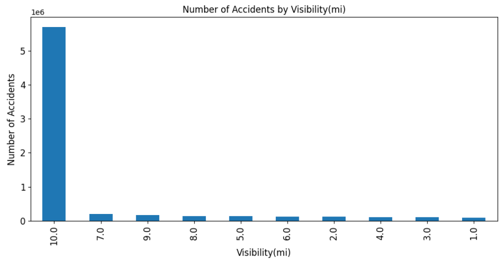
```
                    'Traffic_Calming', 'Traffic_Signal', 'Sunrise_Sunset',
                    'Civil_Twilight', 'Nautical_Twilight',␣
 ↪'Astronomical_Twilight']

correlation_matrix = df_train[selected_columns].corr().abs()

mask = np.triu(np.ones_like(correlation_matrix, dtype=bool))

plt.figure(figsize=(15,15))
sns.heatmap(correlation_matrix, annot=True, fmt=".3f", mask=mask, square=True,␣
 ↪cmap='coolwarm')
plt.show()
```

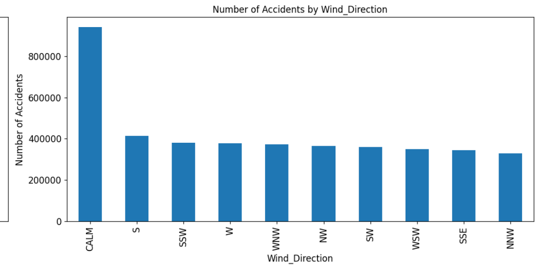


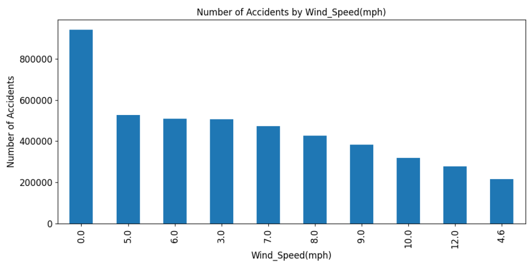
Findings: as expected it is hard to find any specific relations between severity and any of the factors due to the bias in the data.

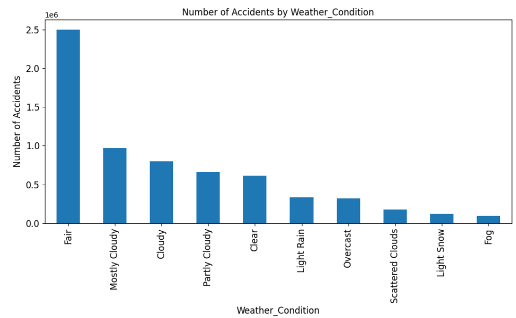
Investigating Weather Impact on accidents

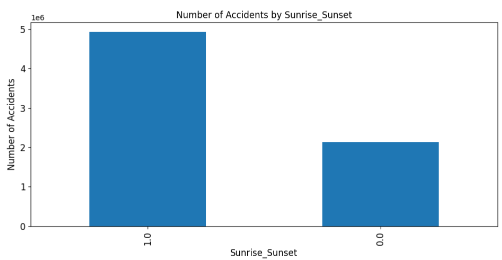
[22]:
```
features = ['Visibility(mi)', 'Wind_Direction', 'Wind_Speed(mph)',␣
↪'Weather_Condition',
            'Sunrise_Sunset', 'Civil_Twilight', 'Nautical_Twilight',␣
↪'Astronomical_Twilight',
            'Temperature_binned', 'Humidity_binned', 'Pressure_binned']

n_cols = 2
n_rows = int(np.ceil(len(features) / n_cols))

fig, axs = plt.subplots(n_rows, n_cols, figsize=(10*n_cols, 6*n_rows))

for i, feature in enumerate(features):
    row = i // n_cols
    col = i % n_cols
    df_train[feature].value_counts().sort_values(ascending=False).head(10).
↪plot(kind='bar', ax=axs[row, col])
    axs[row, col].set_title(f'Number of Accidents by {feature}',fontsize=12)
    axs[row, col].set_xlabel(feature,fontsize=12)
    axs[row, col].set_ylabel('Number of Accidents',fontsize=12)
    axs[row, col].tick_params(axis='x', labelsize=12)
    axs[row, col].tick_params(axis='y', labelsize=12)

if len(features) % n_cols != 0:
    for col in range(len(features) % n_cols, n_cols):
        fig.delaxes(axs[n_rows - 1, col])

plt.tight_layout()
plt.show()
```

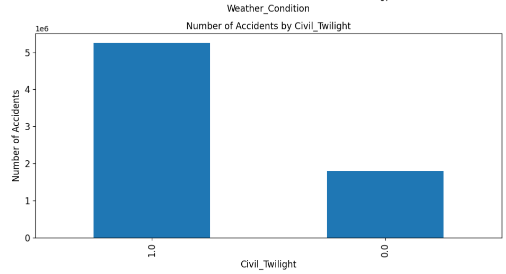

Number of Accidents by Visibility(mi)
1e6
Number of Accidents
Visibility(mi)
10.0
7.0
9.0
8.0
5.0
6.0
2.0
4.0
3.0
1.0

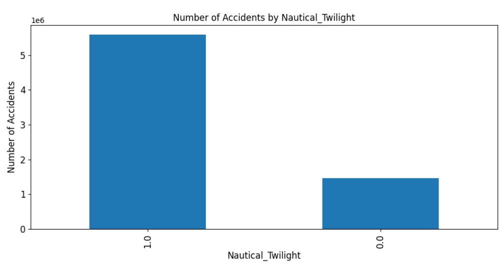

Number of Accidents by Wind_Direction
Number of Accidents
Wind_Direction
CALM
S
SSW
W
WNW
NW
SW
WSW
SSE
NNW

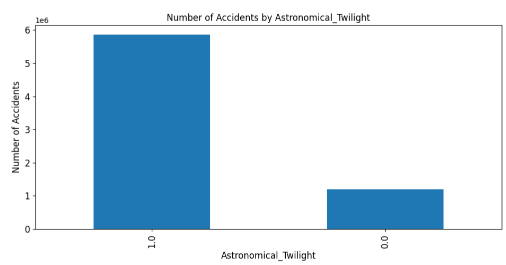

Number of Accidents by Wind_Speed(mph)
Number of Accidents
Wind_Speed(mph)
0.0
5.0
6.0
3.0
7.0
8.0
9.0
10.0
12.0
4.6

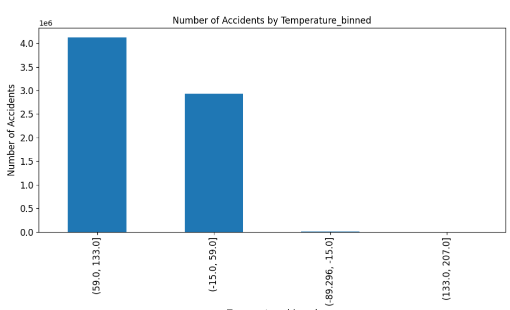

Number of Accidents by Weather_Condition
1e6
Number of Accidents
Weather_Condition
Fair
Mostly Cloudy
Cloudy
Partly Cloudy
Clear
Light Rain
Overcast
Scattered Clouds
Light Snow
Fog

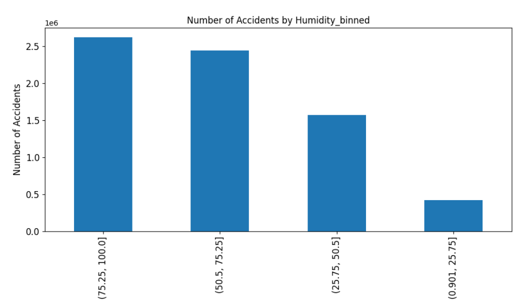

Number of Accidents by Sunrise_Sunset
1e6
Number of Accidents
Sunrise_Sunset
1.0
0.0

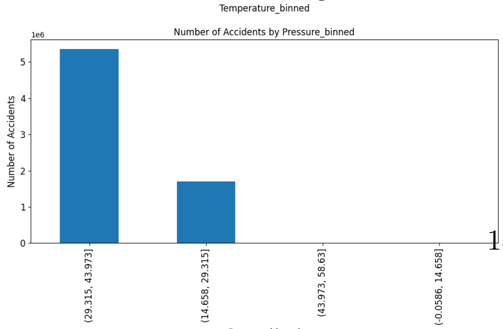

Number of Accidents by Civil_Twilight
1e6
Number of Accidents
Civil_Twilight
1.0
0.0


Number of Accidents by Nautical_Twilight
1e6
Number of Accidents
Nautical_Twilight
1.0
0.0


Number of Accidents by Astronomical_Twilight
1e6
Number of Accidents
Astronomical_Twilight
1.0
0.0


Number of Accidents by Temperature_binned
1e6
Number of Accidents
Temperature_binned
(59.0, 133.0]
(-15.0, 59.0]
(-89.296, -15.0]
(133.0, 207.0]


Number of Accidents by Humidity_binned
1e6
Number of Accidents
Humidity_binned
(75.25, 100.0]
(50.5, 75.25]
(25.75, 50.5]
(0.901, 25.75]

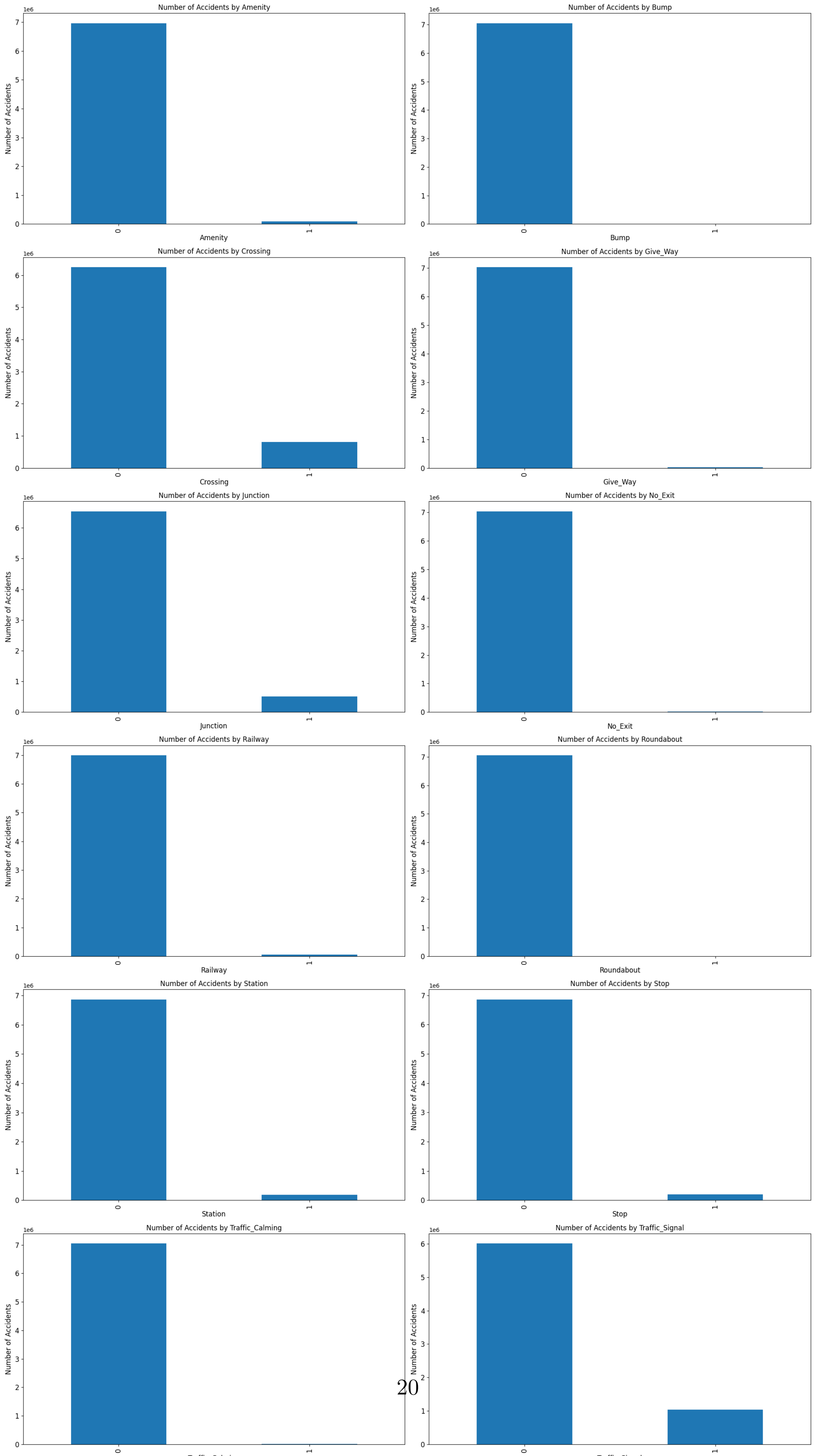

Number of Accidents by Pressure_binned
1e6
Number of Accidents
Pressure_binned
(29.315, 43.973]
(14.658, 29.315]
(43.973, 58.63]
(-0.0586, 14.658]

Findings: From the above figures we can find that:

- According to Night/Day time: Most of the accidents occured at day, as the portion of cars and vehicles on the road during the day is much much higher than that during the night because of the school time, work time, most of the people are awake at day, …,etc.
- According to cabin Weather Conditions: As expected most of the accidents occured on good(Fair) weather conditions which includes good temperature, normal pressure, good visibility,…,etc. And again this is because of the high portion of vehicles on the road during these conditions, as while under any other condition that can be categorized as bad conditions; roads are closed, people are afraid to drive and most activities are paused.

0.5.1 Investigating Surrounding Road Services Impact on Accidents

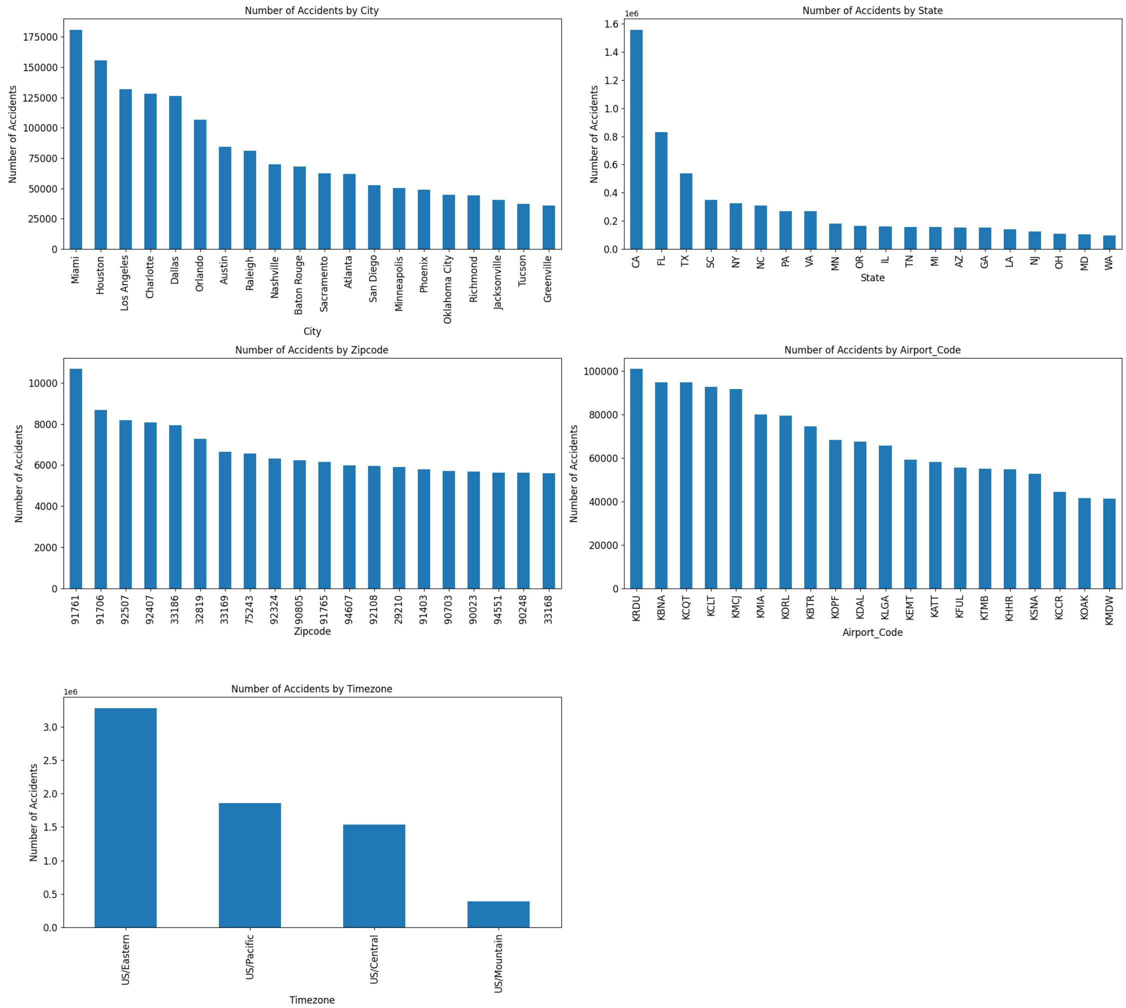
[24]:
```
features = ['Amenity', 'Bump', 'Crossing', 'Give_Way', 'Junction', 'No_Exit',
            'Railway', 'Roundabout', 'Station', 'Stop', 'Traffic_Calming',
            'Traffic_Signal']

n_cols = 2
n_rows = int(np.ceil(len(features) / n_cols))

fig, axs = plt.subplots(n_rows, n_cols, figsize=(10*n_cols, 6*n_rows))

for i, feature in enumerate(features):
    row = i // n_cols
    col = i % n_cols
    df_train[feature].value_counts().sort_values(ascending=False).head(10).
 ↪plot(kind='bar', ax=axs[row, col])
    axs[row, col].set_title(f'Number of Accidents by {feature}',fontsize=12)
    axs[row, col].set_xlabel(feature,fontsize=12)
    axs[row, col].set_ylabel('Number of Accidents',fontsize=12)
    axs[row, col].tick_params(axis='x', labelsize=12)
    axs[row, col].tick_params(axis='y', labelsize=12)

if len(features) % n_cols != 0:
    for col in range(len(features) % n_cols, n_cols):
        fig.delaxes(axs[n_rows - 1, col])

plt.tight_layout()
plt.show()
```


Number of Accidents by Amenity
Amenity
Number of Accidents by Bump
Bump
Number of Accidents by Crossing
Crossing
Number of Accidents by Give_Way
Give_Way
Number of Accidents by Junction
Junction
Number of Accidents by No_Exit
No_Exit
Number of Accidents by Railway
Railway
Number of Accidents by Roundabout
Roundabout
Number of Accidents by Station
Station
Number of Accidents by Stop
Stop
Number of Accidents by Traffic_Calming
Traffic_Calming
Number of Accidents by Traffic_Signal
Traffic_Signal
Number of Accidents
1e6

Findings: No insight can be observed or concluded from these figures and it needs more investigations.

0.5.2 Investigating Trends based on location

[25]:
```
features = ["City","State", "Zipcode", "Airport_Code", "Timezone"]

n_cols = 2
n_rows = int(np.ceil(len(features) / n_cols))

fig, axs = plt.subplots(n_rows, n_cols, figsize=(10*n_cols, 6*n_rows))

for i, feature in enumerate(features):
    row = i // n_cols
    col = i % n_cols
    df_train[feature].value_counts().sort_values(ascending=False).head(20).
 ↪plot(kind='bar', ax=axs[row, col])
    axs[row, col].set_title(f'Number of Accidents by {feature}',fontsize=12)
    axs[row, col].set_xlabel(feature,fontsize=12)
    axs[row, col].set_ylabel('Number of Accidents',fontsize=12)
    axs[row, col].tick_params(axis='x', labelsize=12)
    axs[row, col].tick_params(axis='y', labelsize=12)

if len(features) % n_cols != 0:
    for col in range(len(features) % n_cols, n_cols):
        fig.delaxes(axs[n_rows - 1, col])

plt.tight_layout()
plt.show()
```



Findings: From the above figures we can find that:

- According to location: Most of the accidents happened in CA state as observed and the number of accidents is very high compared to the state following CA. And this need more investigating to search for the real causes of this number of accidents, and may be some more restict road rules can be applied.

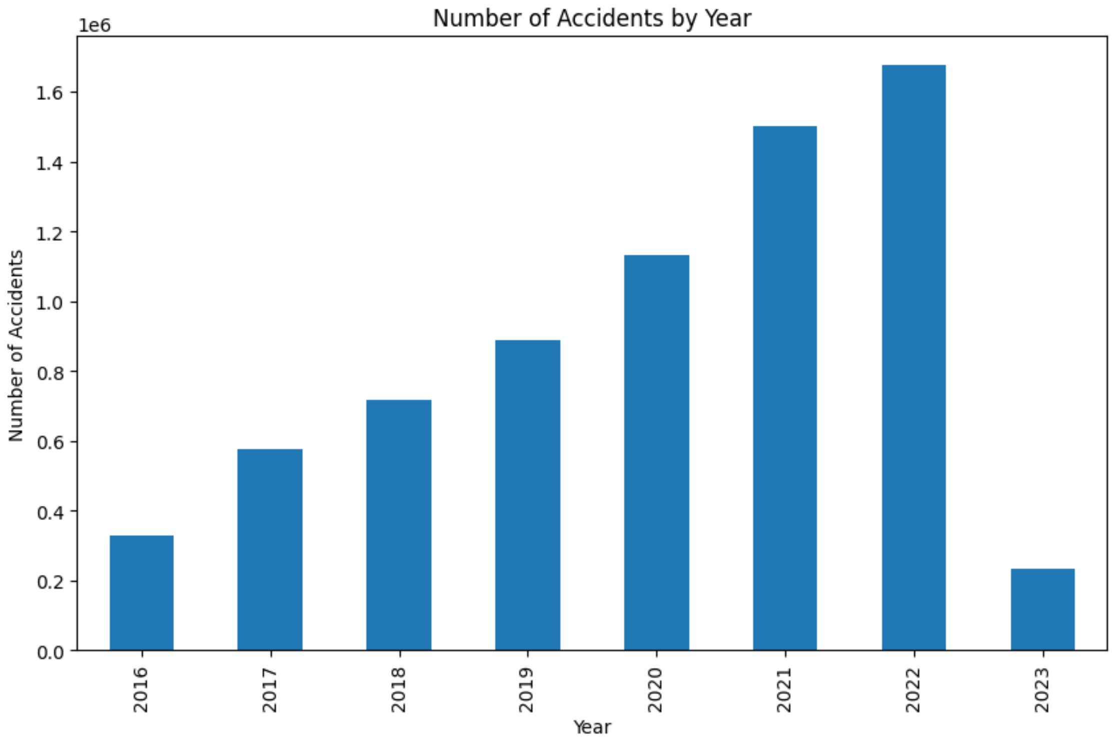
0.5.3 Investigating Trends based on year/month/week/day/time

[75]:

```
df_train.Start_Time = pd.to_datetime(df_train.Start_Time, format="mixed")
df_train['Month']   = df_train['Start_Time'].dt.month
df_train['Year']    = df_train['Start_Time'].dt.year
df_train['Week']    = df_train['Start_Time'].dt.isocalendar().week
df_train['Weekday'] = df_train['Start_Time'].dt.weekday
df_train['Hour']    = df_train['Start_Time'].dt.hour
```

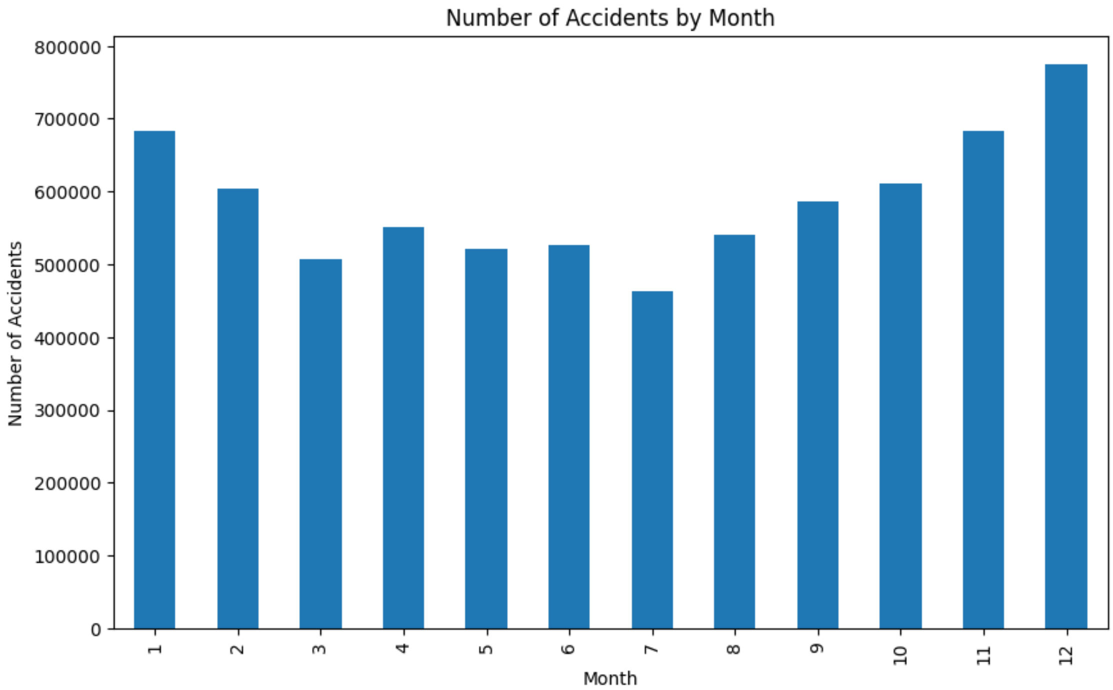
Year Analysis

[71]:
```
plt.figure(figsize=(10,6))
df_train['Year'].value_counts().sort_index().plot(kind='bar')
plt.title('Number of Accidents by Year')
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.show()
```



Month Analysis

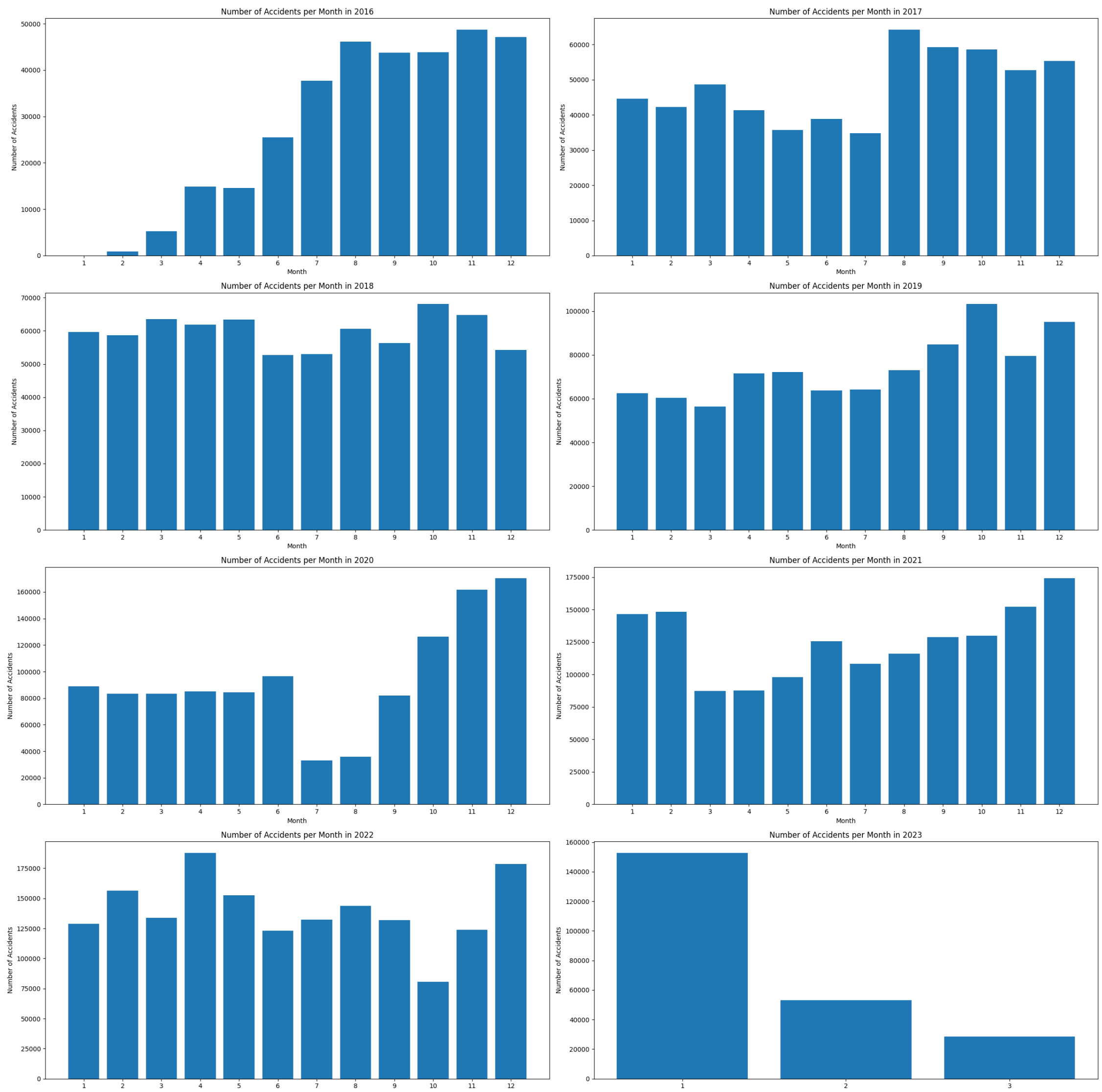
[72]:
```
plt.figure(figsize=(10,6))
df_train['Month'].value_counts().sort_index().plot(kind='bar')
plt.title('Number of Accidents by Month')
plt.xlabel('Month')
plt.ylabel('Number of Accidents')
plt.show()
```



Months per year analysis

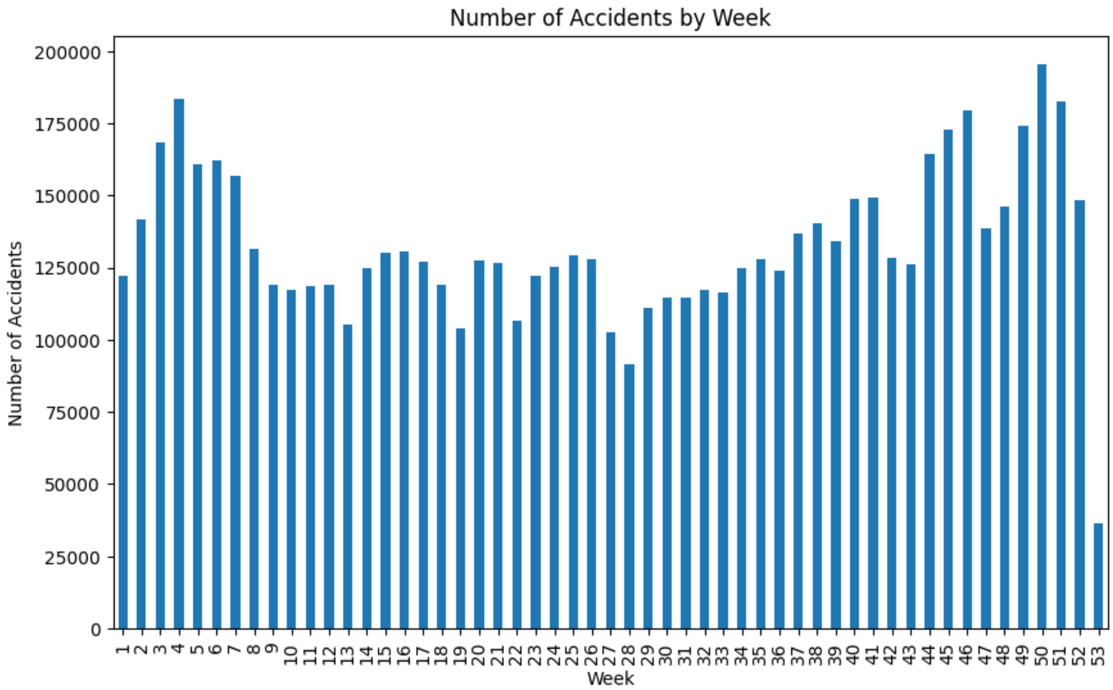
[73]:
```
grouped = df_train.groupby(['Year', 'Month']).size().
    ↪reset_index(name='Accident_Count')

n_cols = 2
n_years = len(grouped['Year'].unique())
n_rows = int(np.ceil(n_years / n_cols))

fig, axs = plt.subplots(n_rows, n_cols, figsize=(12*n_cols, 6*n_rows))

for i, year in enumerate(grouped['Year'].unique()):
    row = i // n_cols
    col = i % n_cols
    monthly_data = grouped[grouped['Year'] == year]
    axs[row, col].bar(monthly_data['Month'], monthly_data['Accident_Count'],␣
    ↪tick_label=monthly_data['Month'])
    axs[row, col].set_title(f'Number of Accidents per Month in {year}')
    axs[row, col].set_xlabel('Month')
    axs[row, col].set_ylabel('Number of Accidents')

if n_years % n_cols != 0:
    for col in range(n_years % n_cols, n_cols):
        fig.delaxes(axs[n_rows - 1, col])
```

```
plt.tight_layout()
plt.show()
```



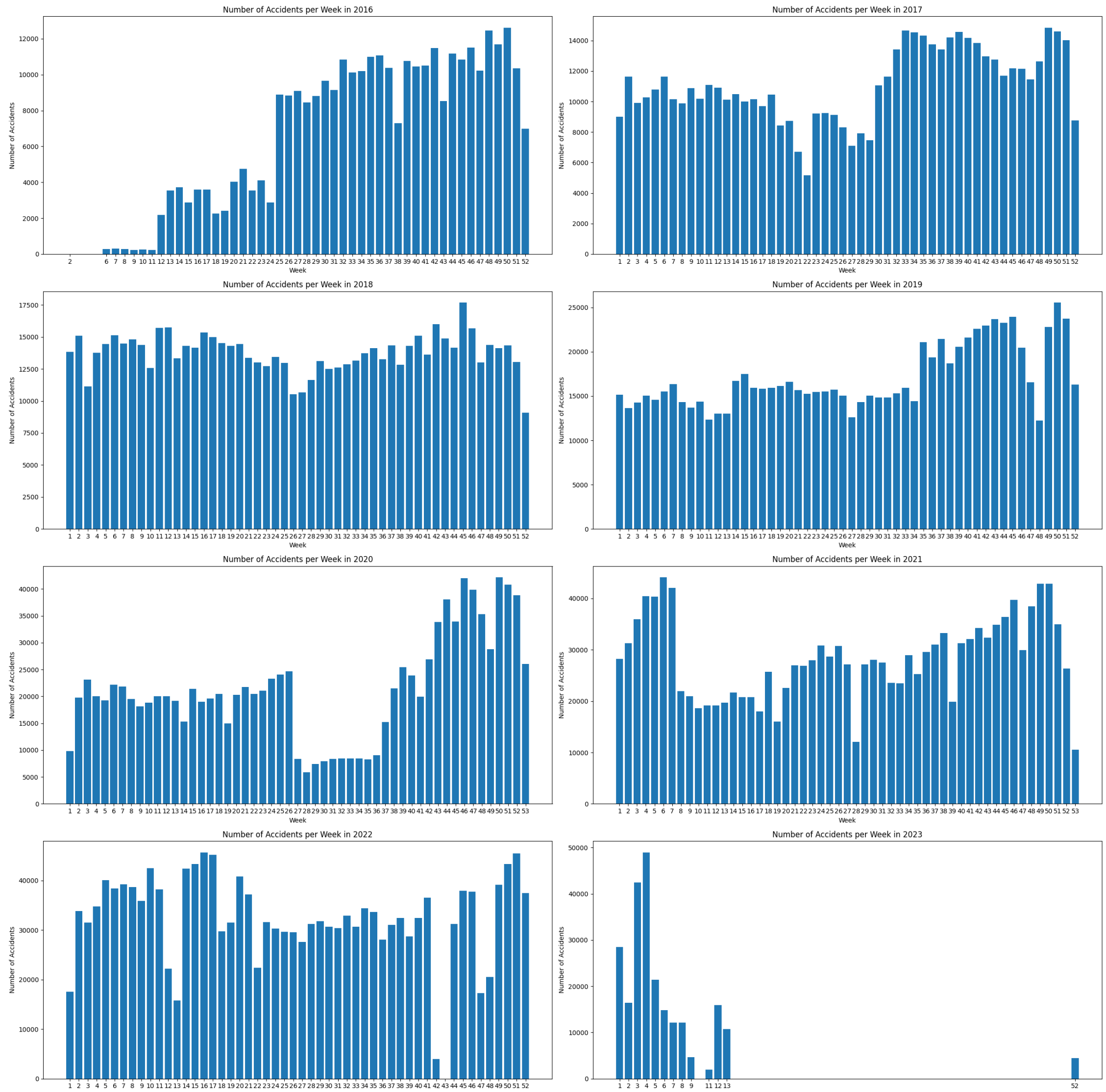
Week Analysis

[76]:
```
plt.figure(figsize=(10,6))
df_train['Week'].value_counts().sort_index().plot(kind='bar')
plt.title('Number of Accidents by Week')
plt.xlabel('Week')
plt.ylabel('Number of Accidents')
plt.show()
```



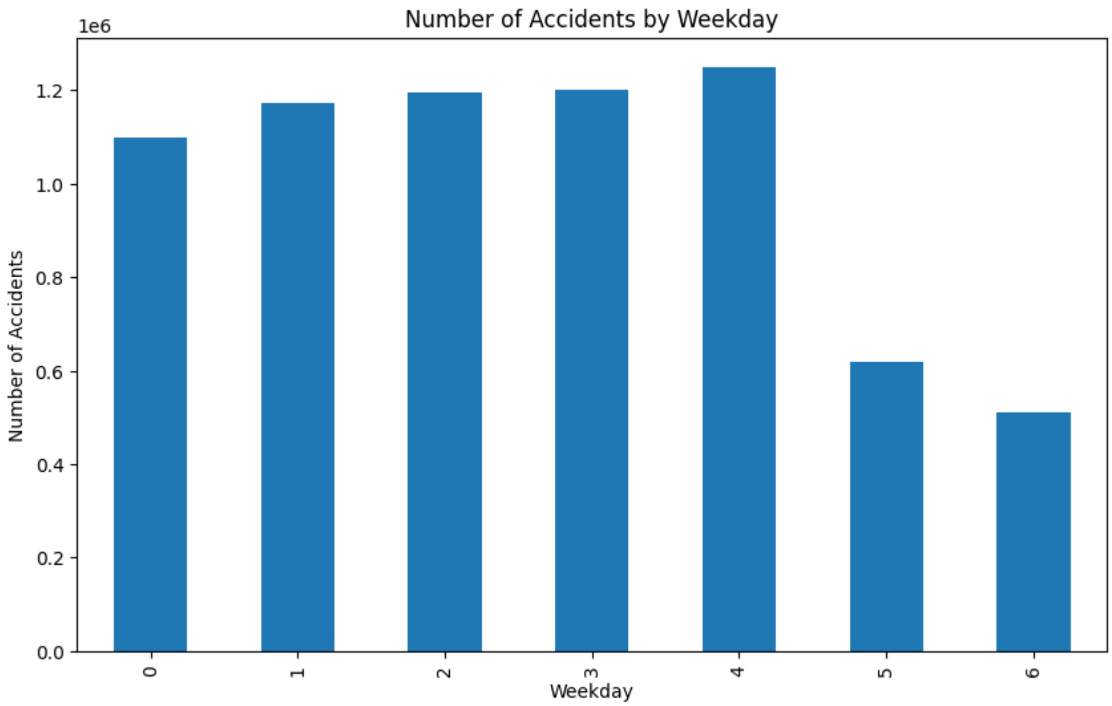
[78]:
```
df_train['Week'] = df_train['Week'].fillna(-1).astype(int)
grouped = df_train.groupby(['Year', 'Week']).size().
↪reset_index(name='Accident_Count')

n_cols = 2
n_years = len(grouped['Year'].unique())
n_rows = int(np.ceil(n_years / n_cols))

fig, axs = plt.subplots(n_rows, n_cols, figsize=(12*n_cols, 6*n_rows))

for i, year in enumerate(grouped['Year'].unique()):
    row = i // n_cols
    col = i % n_cols
    weekly_data = grouped[grouped['Year'] == year]
    axs[row, col].bar(weekly_data['Week'], weekly_data['Accident_Count'],␣
↪tick_label=weekly_data['Week'])
    axs[row, col].set_title(f'Number of Accidents per Week in {year}')
    axs[row, col].set_xlabel('Week')
    axs[row, col].set_ylabel('Number of Accidents')

if n_years % n_cols != 0:
    for col in range(n_years % n_cols, n_cols):
        fig.delaxes(axs[n_rows - 1, col])
```

```
plt.tight_layout()
plt.show()
```



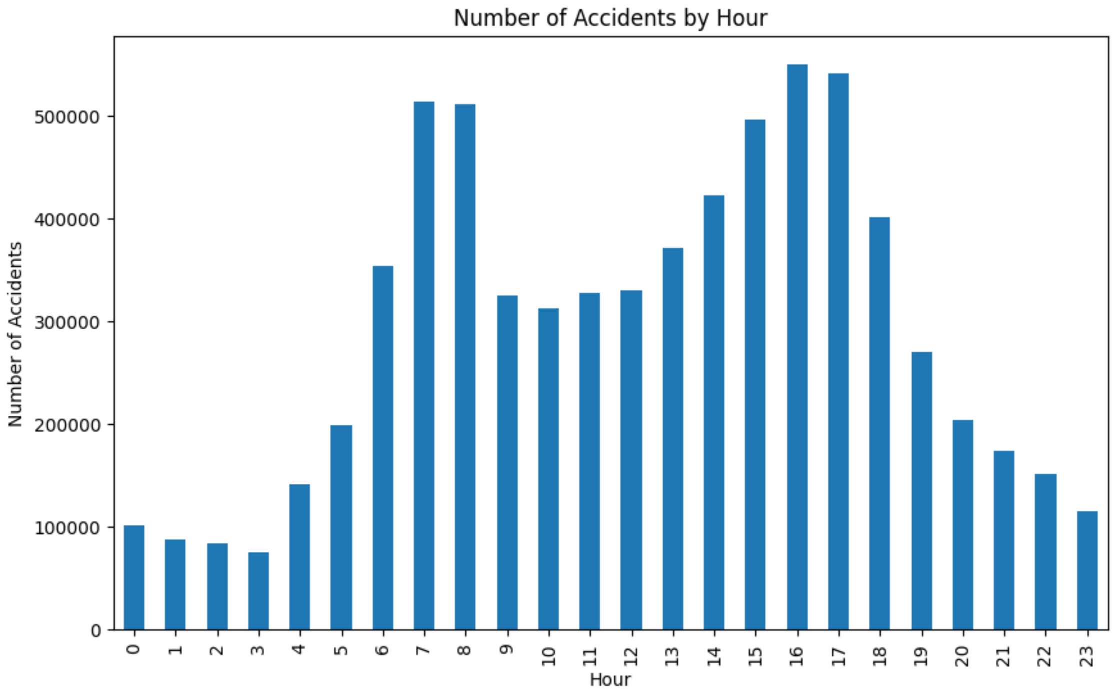
Weekday Analysis

[79]:
```
plt.figure(figsize=(10,6))
df_train['Weekday'].value_counts().sort_index().plot(kind='bar')
plt.title('Number of Accidents by Weekday')
plt.xlabel('Weekday')
plt.ylabel('Number of Accidents')
plt.show()
```



Hour Analysis

[80]:
```
plt.figure(figsize=(10,6))
df_train['Hour'].value_counts().sort_index().plot(kind='bar')
plt.title('Number of Accidents by Hour')
plt.xlabel('Hour')
plt.ylabel('Number of Accidents')
plt.show()
```



Findings: From the above figures we can find that:

- According to Year Analysis: It can be observed that the number of accidents has increased over years. Many factors can affect this increase like increasing population, new cars are made while old cars get cheaper and people started following travel trends and bough more cars
- According to Month Analysis: We can see that there is some increase in the accidents in last months and first month of the year, and this may be due to summer break and the new school term break. Though, it is not a general case where we need more investigations to confirsm this conclusion. Also, during 2020 we can see a noticable in the accidents number due to covid-19 panademic.
- According to Week Analysis: it is following the month analysis trend in the rate oof accidents.
- According to Weekday Analysis: we can see equal rates of accidents across all the workdays in the week while less accidents on weekends. That points us to conclude that during weekends many activities take a break and that leads to less portion of vehicles on the roads, thus fewer accidents.
- According to cabin Hour Analysis: There are two time periods with heightened activity: one occurs in the morning between 6 am and 9 am, while the other takes place between 3 pm and 6 pm. These observations support the notion that increased traffic during morning and evening rush hours may contribute to a higher incidence of accidents.

0.6 Machine Learning Models

0.6.1 converting categorical values to numerical values

[18]:
```
df_train = df_train.drop(["Street", 'Description',␣
↪'Civil_Twilight','Nautical_Twilight', 'Astronomical_Twilight','County',␣
↪'Country', 'index', 'ID','Start_Time', 'End_Time', 'Start_Lat', 'Start_Lng',␣
↪"Weather_Timestamp",'Temperature_binned', 'Humidity_binned',␣
↪'Pressure_binned'] ,axis=1)
label_encoder = LabelEncoder()

df_train['Source'] = label_encoder.fit_transform(df_train['Source'])


df_train['City'] = label_encoder.fit_transform(df_train['City'])


df_train['State'] = label_encoder.fit_transform(df_train['State'])


df_train['Airport_Code'] = label_encoder.fit_transform(df_train['Airport_Code'])

df_train['Zipcode'] = label_encoder.fit_transform(df_train['Zipcode'])

df_train['Timezone'] = label_encoder.fit_transform(df_train['Timezone'])

df_train['Weather_Condition'] = label_encoder.
↪fit_transform(df_train['Weather_Condition'])

df_train['Wind_Direction'] = label_encoder.
↪fit_transform(df_train['Wind_Direction'])
```

As noticed before the data is unblalanced and is so biased towards class severity 2. A suggested approach to solve this is to heirarichal classification and create multi classifiers than combine them together. * Binary Classifier 1: Class 2 vs [Class 1,3,4] * Binary Classifier 1: Class 3 vs [Class 1,4] * Binary Classifier 1: Class 1 vs [Class 4]

This approach is some how similar to the one vs all approach, but due to the data impalance we can't do classification between severity 1 for rxample vs all, ratios between the two groups will be 1:100. So, what came to my mind is to mix between the one vs all algorithm and the heirarichal algorithm.

[19]:
```
X = df_train.drop('Severity', axis=1)
y = df_train['Severity']

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

```
print("step 0 \n")
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

step 0

[20]:
```
print("step 1 \n")
y_first = (y == 2).astype(int)
classifier_first = RandomForestClassifier(n_jobs=2)
classifier_first.fit(X_scaled, y_first)

print("step 2 \n")
X_second = X_scaled[y != 2]
y_second = (y[y != 2] == 3).astype(int)
classifier_second = RandomForestClassifier(n_jobs=2)
classifier_second.fit(X_second, y_second)

print("step 3 \n")
X_third = X_scaled[(y != 2) & (y != 3)]
y_third = (y[(y != 2) & (y != 3)] == 1).astype(int)
classifier_third = RandomForestClassifier(n_jobs=2)
classifier_third.fit(X_third, y_third)


def predict_hierarchical_model(X_test):
    X_test_scaled = scaler.transform(X_test)
    final_predictions = {}

    predictions_first = classifier_first.predict(X_test_scaled)

    class_2_indices = [i for i, x in enumerate(predictions_first) if x == 1]
    final_predictions.update({i: 2 for i in class_2_indices})
    X_test_rest_indices = [i for i, x in enumerate(predictions_first) if x == 0]
    X_test_rest = X_test_scaled[X_test_rest_indices]

    predictions_second = classifier_second.predict(X_test_rest)

    class_3_indices = [X_test_rest_indices[i] for i, x in␣
 ↪enumerate(predictions_second) if x == 1]
    final_predictions.update({i: 3 for i in class_3_indices})
    X_test_rest_indices = [X_test_rest_indices[i] for i, x in␣
 ↪enumerate(predictions_second) if x == 0]
    X_test_rest = X_test_scaled[X_test_rest_indices]

    predictions_third = classifier_third.predict(X_test_rest)
```

```
    class_1_indices = [X_test_rest_indices[i] for i, x in␣
↪enumerate(predictions_third) if x == 1]
    class_4_indices = [X_test_rest_indices[i] for i, x in␣
↪enumerate(predictions_third) if x == 0]
    final_predictions.update({i: 1 for i in class_1_indices})
    final_predictions.update({i: 4 for i in class_4_indices})

    final_predictions_sorted = [final_predictions[i] for i in␣
↪sorted(final_predictions)]

    return final_predictions_sorted


print("Predicting \n")
y_pred = predict_hierarchical_model(X_test)

print("Results \n")
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: ", accuracy)
print(classification_report(y_test, y_pred))
```

```
step 1

step 2

step 3

Predicting

Results

Accuracy:  0.9916238392639359
              precision    recall  f1-score   support

           1       0.99      0.99      0.99     13074
           2       0.99      1.00      0.99   1133919
           3       1.00      1.00      1.00    227753
           4       0.94      0.77      0.85     35566

    accuracy                           0.99   1410312
   macro avg       0.98      0.94      0.96   1410312
weighted avg       0.99      0.99      0.99   1410312
```

[20]:
```
params = {'C': [0.1, 1, 1000], 'solver': ['lbfgs', 'liblinear'], "max_iter" :␣
↪[100, 1000, 10000]}
```

```
classifier = LogisticRegression()

print("step 1")
y_first = (y == 2).astype(int)
# classifier_first = LogisticRegression()
classifier_first = GridSearchCV(classifier, params, cv=5)
classifier_first.fit(X_scaled, y_first)
print("best params: ", classifier_first.best_params_, "\n")
print("best score: ", classifier_first.best_score_, "\n")

print("step 2 \n")
X_second = X_scaled[y != 2]
y_second = (y[y != 2] == 3).astype(int)
# classifier_second = LogisticRegression()
classifier_second = GridSearchCV(classifier, params, cv=5)
classifier_second.fit(X_second, y_second)
print("best params: ", classifier_second.best_params_, "\n")
print("best score: ", classifier_second.best_score_, "\n")

print("step 3 \n")
X_third = X_scaled[(y != 2) & (y != 3)]
y_third = (y[(y != 2) & (y != 3)] == 1).astype(int)
# classifier_third = LogisticRegression()
classifier_third = GridSearchCV(classifier, params, cv=5)
classifier_third.fit(X_third, y_third)
print("best params: ", classifier_third.best_params_, "\n")
print("best score: ", classifier_third.best_score_, "\n")



def predict_hierarchical_model(X_test):
    X_test_scaled = scaler.transform(X_test)
    final_predictions = {}

    predictions_first = classifier_first.predict(X_test_scaled)

    class_2_indices = [i for i, x in enumerate(predictions_first) if x == 1]
    final_predictions.update({i: 2 for i in class_2_indices})
    X_test_rest_indices = [i for i, x in enumerate(predictions_first) if x == 0]
    X_test_rest = X_test_scaled[X_test_rest_indices]

    predictions_second = classifier_second.predict(X_test_rest)

    class_3_indices = [X_test_rest_indices[i] for i, x in 
 ↪enumerate(predictions_second) if x == 1]
    final_predictions.update({i: 3 for i in class_3_indices})
```

```
    X_test_rest_indices = [X_test_rest_indices[i] for i, x in␣
↪enumerate(predictions_second) if x == 0]
    X_test_rest = X_test_scaled[X_test_rest_indices]

    predictions_third = classifier_third.predict(X_test_rest)

    class_1_indices = [X_test_rest_indices[i] for i, x in␣
↪enumerate(predictions_third) if x == 1]
    class_4_indices = [X_test_rest_indices[i] for i, x in␣
↪enumerate(predictions_third) if x == 0]
    final_predictions.update({i: 1 for i in class_1_indices})
    final_predictions.update({i: 4 for i in class_4_indices})

    final_predictions_sorted = [final_predictions[i] for i in␣
↪sorted(final_predictions)]

    return final_predictions_sorted


print("Predicting \n")
y_pred = predict_hierarchical_model(X_test)

print("Results \n")
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: ", accuracy)
print(classification_report(y_test, y_pred))
```

```
step 1
best params:  {'C': 0.1, 'max_iter': 100, 'solver': 'lbfgs'}

best score:  0.7349434942576842

step 2

best params:  {'C': 1, 'max_iter': 100, 'solver': 'liblinear'}

best score:  0.820304615803052

step 3

best params:  {'C': 0.1, 'max_iter': 100, 'solver': 'liblinear'}

best score:  0.8556376610693569

Predicting

Results
```

```
Accuracy:  0.8059181230819847

C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support

           1       0.00      0.00      0.00     13074
           2       0.81      0.98      0.89   1133919
           3       0.52      0.09      0.16    227753
           4       0.12      0.00      0.00     35566

    accuracy                           0.81   1410312
   macro avg       0.36      0.27      0.26   1410312
weighted avg       0.74      0.81      0.74   1410312


C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[45]:

```python
print("step 1 \n")
y_first = (y == 2).astype(int)
classifier_first = DecisionTreeClassifier()
classifier_first.fit(X_scaled, y_first)

print("step 2 \n")
X_second = X_scaled[y != 2]
y_second = (y[y != 2] == 3).astype(int)
classifier_second = DecisionTreeClassifier()
classifier_second.fit(X_second, y_second)

print("step 3 \n")
X_third = X_scaled[(y != 2) & (y != 3)]
y_third = (y[(y != 2) & (y != 3)] == 1).astype(int)
classifier_third = DecisionTreeClassifier()
classifier_third.fit(X_third, y_third)
```

```python
def predict_hierarchical_model(X_test):
    X_test_scaled = scaler.transform(X_test)
    final_predictions = {}

    predictions_first = classifier_first.predict(X_test_scaled)

    class_2_indices = [i for i, x in enumerate(predictions_first) if x == 1]
    final_predictions.update({i: 2 for i in class_2_indices})
    X_test_rest_indices = [i for i, x in enumerate(predictions_first) if x == 0]
    X_test_rest = X_test_scaled[X_test_rest_indices]

    predictions_second = classifier_second.predict(X_test_rest)

    class_3_indices = [X_test_rest_indices[i] for i, x in␣
 ↪enumerate(predictions_second) if x == 1]
    final_predictions.update({i: 3 for i in class_3_indices})
    X_test_rest_indices = [X_test_rest_indices[i] for i, x in␣
 ↪enumerate(predictions_second) if x == 0]
    X_test_rest = X_test_scaled[X_test_rest_indices]

    predictions_third = classifier_third.predict(X_test_rest)

    class_1_indices = [X_test_rest_indices[i] for i, x in␣
 ↪enumerate(predictions_third) if x == 1]
    class_4_indices = [X_test_rest_indices[i] for i, x in␣
 ↪enumerate(predictions_third) if x == 0]
    final_predictions.update({i: 1 for i in class_1_indices})
    final_predictions.update({i: 4 for i in class_4_indices})

    final_predictions_sorted = [final_predictions[i] for i in␣
 ↪sorted(final_predictions)]

    return final_predictions_sorted

print("Predicting \n")
y_pred = predict_hierarchical_model(X_test)

print("Results \n")
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: ", accuracy)
print(classification_report(y_test, y_pred))
```

step 1

step 2

```
step 3

Accuracy:  0.9916351842712818
              precision    recall  f1-score   support

           1       0.98      1.00      0.99     13074
           2       1.00      0.99      0.99   1133919
           3       0.99      1.00      1.00    227753
           4       0.82      0.94      0.87     35566

    accuracy                           0.99   1410312
   macro avg       0.95      0.98      0.96   1410312
weighted avg       0.99      0.99      0.99   1410312
```

NOTE: * Many other experiments on different classifiers were done, but unfortunately their cells ouput was omitted while doing other experiments, and some of them can take many hours to run so I will just right the results without showing the output.

- Another point to mention is that I didn't use grid search for decision tree or random forest classifiers as they already gave perfect scores. Also, I wanted to use deep learning techniques like NN but as I mentioned earlier, other classifiers did the job effeciently.
- Also to note that on a side notebook, I manually inspected that the classifiers are working correctly by picking random samples from the df_train and classify it, then check the prediction.

Results:

- In general, tree based classifiers like decision trees and random forest showed superity in performance over other classifiers as any ther calssifier only predicts one class when given any other class.
- The main reason for this outweight in the performance of the tree based classifiers is their feature interactions. Tree-based models can naturally capture interactions between different features specially that can be represented in the form of if else statements.
- There are also other reasons like:
  - Ability of tree based Classifiers to handle imbalanced datasets reasonably well. They build the model based on the structure of the data and can make decisions based on conditions that might only apply to a small subset of the data
  - Surpass od tree based classifiers to model complex non-linear decision boundaries.