Applied Analytics Project

Analyzing US Accident Data to Predict High-Risk Areas and Times in Massachusetts

Week 4 - Data processing and making data model ready

Major: Applied Analytics

Name: Gefan Wang, Chenhe Shi, Tianchen Liu

Date: 02.16.2025

1. Data Preprocessing Strategy:

To ensure an optimal dataset for model training and analysis, we applied several preprocessing steps to clean and transform the data. First, we removed non-essential features such as ID, Source, Country, State, End_Lat, and End_Lng to streamline the dataset. The Start_Time and End_Time columns were converted into datetime format for further analysis. Handling missing values was a critical step; for numerical columns like Wind_Chill(F), Precipitation(in), and Wind_Speed(mph), missing values were filled using the median as shown below.

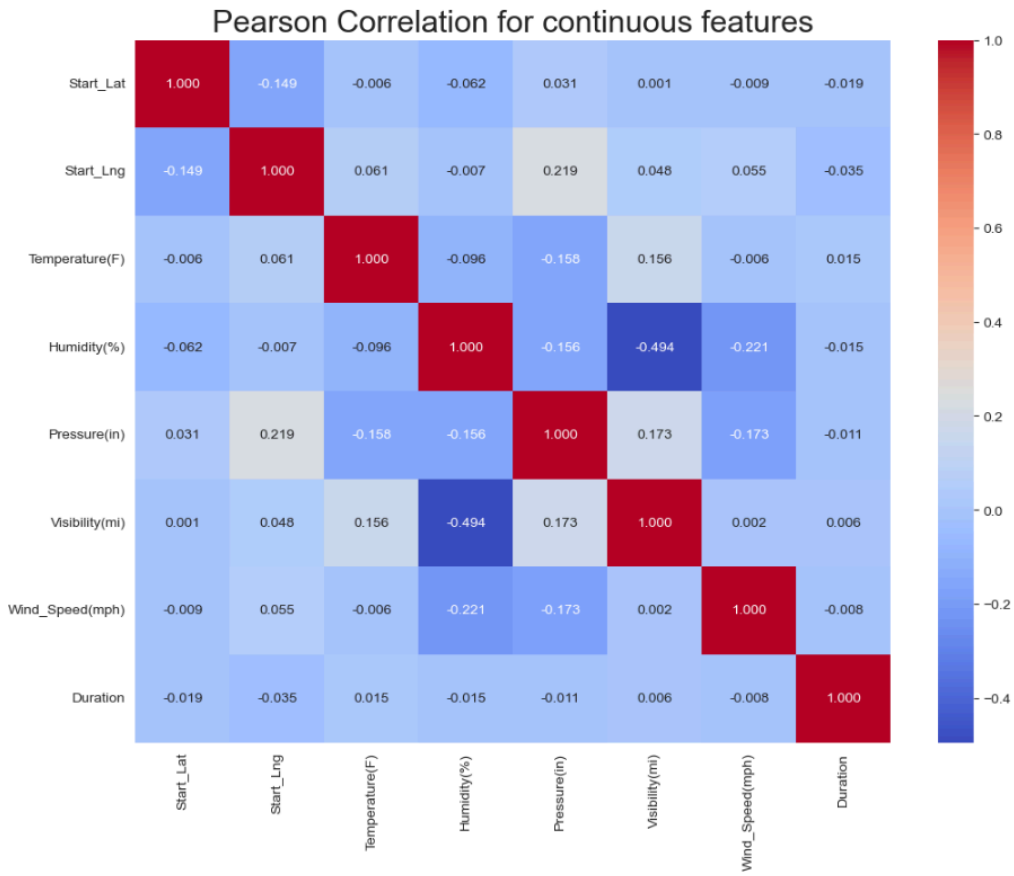
Median imputation

[234…

```
# Imputation by corresponding class Median value
data_preprocessed_median_df = data_preprocessed_df.copy()

# For numerical columns
for column_name in numerical_missing:
    data_preprocessed_median_df[column_name] = data_preprocessed_median_df.groupby('Severity')[column_name].transform(lambda

# # For categorical columns(Majority value imputation)
for column_name in categorical_missing:
    data_preprocessed_median_df[column_name] = data_preprocessed_median_df.groupby('Severity')[column_name].transform(lambda

# Drop NaN and reset index
data_preprocessed_median_df.dropna(inplace=True)
```

Meanwhile, for categorical columns such as Wind_Direction, Weather_Condition, and Sunrise_Sunset, missing values were imputed using the mode. Additionally, we extracted new time-based features from Start_Time and End_Time, such as the hour of the day and day of the week, to improve our analysis. On the other hand, duplicate rows were identified and removed to ensure data redundancy was minimized.

We also conducted a correlation analysis to examine relationships between accident severity and weather-related attributes. There are weak relationships between Pressure and Temperature, Pressure and Humidity, Wind_Speed and Humidity, Wind_Speed and Pressure, Visibility and Humidity.

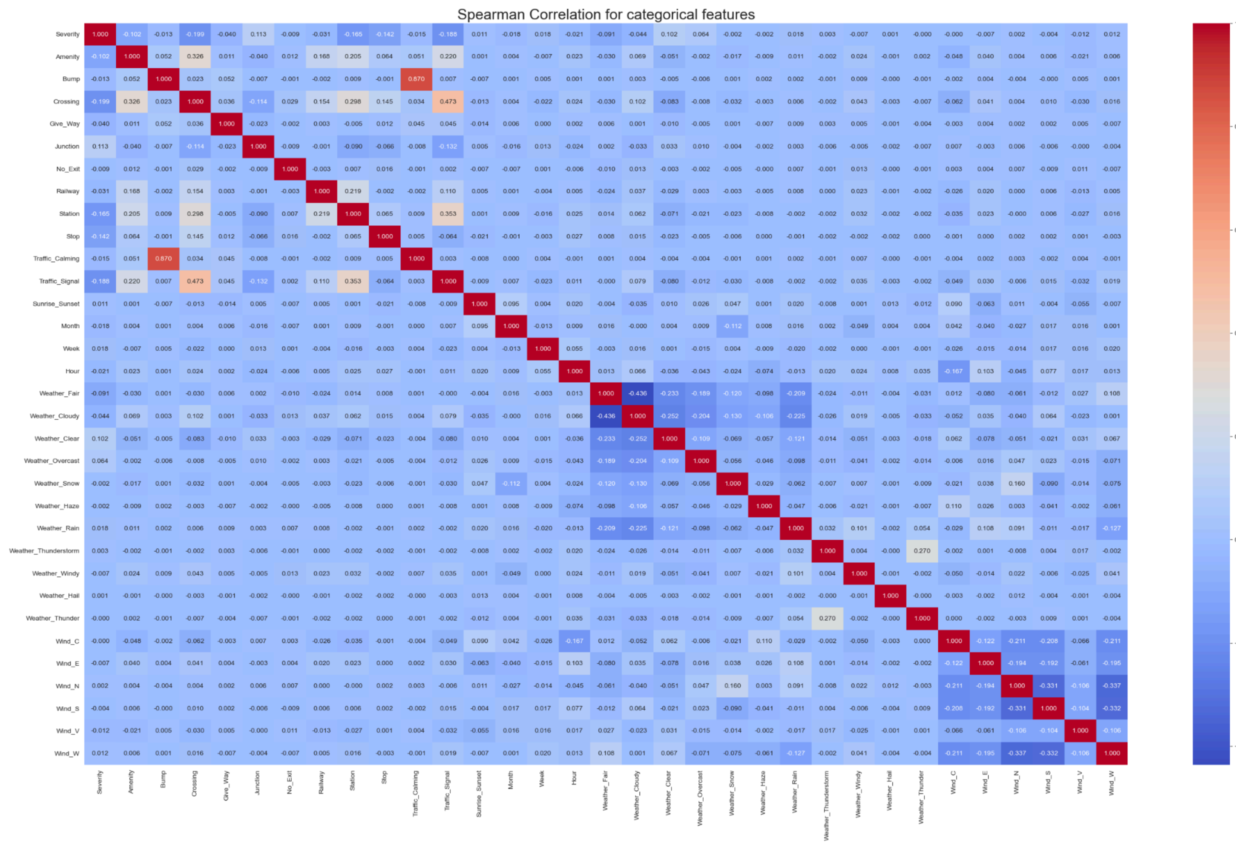


To address potential distortions, we treated outliers in key numerical features, including Distance(mi), Temperature(F), Humidity(%), Visibility(mi), and Pressure(in), by capping extreme values using the interquartile range (IQR) method. Further, numerical variables such as Distance(mi), Temperature(F), Humidity(%), and Wind_Speed(mph) were standardized to ensure consistent scaling across features. To make temperature data easier to analyze, we grouped it into different categories. For categorical variables, we converted Wind_Direction, Weather_Condition, and Timezone into separate binary columns using one-hot encoding. Meanwhile, features with a natural order, like Sunrise_Sunset and Civil_Twilight, were assigned numerical labels to preserve their ranking.

```
         Weather                                           Contain  \
0           Fair                                     'Fair / Windy'
1         Cloudy  'Mostly Cloudy', 'Partly Cloudy', 'Scattered C...
2          Clear                                            'Clear'
3       Overcast                                         'Overcast'
4           Snow  'Light Snow', 'Wintry Mix', 'Heavy Snow', 'Sno...
5           Haze  'Smoke', 'Fog', 'Mist', 'Shallow Fog', 'Haze /...
6           Rain  'Light Rain', 'Rain', 'Light Drizzle', 'Light ...
7   Thunderstorm  'Thunderstorms and Rain', 'Light Thunderstorms...
8          Windy  'Fair / Windy','Cloudy / Windy','Partly Cloudy...
9           Hail  'Small Hail', 'Light Ice Pellets', 'Ice Pellet...
10       Thunder  'Thunder in the Vicinity', 'Thunder', 'Thunder...
11          Dust  'Dust Whirls', 'Sand / Dust Whirlwinds', 'Sand...
12       Tornado                                          'Tornado'
13           N/A                                 'N/A Precipitation'

                     Key words
0                       'Fair'
1                      'Cloud'
2                      'Clear'
3                   'Overcast'
4       'Snow', 'Wintry', 'Sleet'
5  'Smoke', 'Fog', 'Mist', 'Haze'
6    'Rain', 'Drizzle', 'Showers'
7      'Thunderstorms', 'T-Storm'
8            'Windy', 'Squalls'
9          'Hail', 'Ice Pellets'
10                   'Thunder'
11                      'Dust'
12                   'Tornado'
13           'N/A Precipitation'
```

In [242…

```
# Transform the one-hot features, then delete them
onehot_df = pd.get_dummies(data_modelling_df['Wind_Direction'], prefix='Wind')
data_modelling_df = pd.concat([data_modelling_df, onehot_df], axis=1)
data_modelling_df.drop(one_hot_features, axis=1, inplace=True)
```



We identified key correlations among categorical features that highlight urban infrastructure patterns. Bump and Traffic_Calming showed a strong relationship, suggesting traffic calming measures frequently include speed bumps. Moderate correlations were observed between Crossing and Traffic_Signal, Crossing and Amenity, and Crossing and Station, indicating that pedestrian crossings are often placed near signals, public amenities, and transit stations for accessibility. Additionally, the link between Station and Traffic_Signal suggests traffic signals are common near transit hubs to manage pedestrian and vehicle flow efficiently. These insights provide a foundation for understanding how infrastructure elements interact and influence urban mobility.

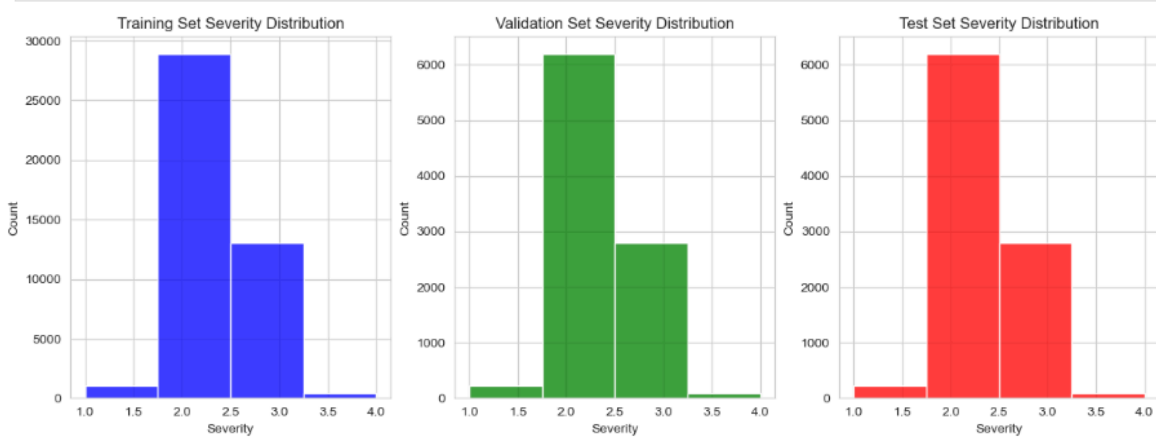
2. Redo the Dataset Split into Test, Train, Validation after Cleaning:

To ensure a robust and unbiased analysis, we split the dataset into three subsets: training (70%), validation (15%), and testing (15%). The training set was used for exploratory data analysis (EDA) and model training.

The severity distribution across training, validation, and test sets was analyzed to confirm the partitioning maintained the overall dataset characteristics. The distribution showed that severity level 2 had the highest proportion in all subsets, accounting for approximately 66.6% of the validation and test sets. Severity level 3 followed at around 30%, while severity levels 1 and 4 made up less than 1% each. The visual representation of severity distributions in the training, validation, and test sets demonstrated consistency, ensuring that our dataset split did not introduce bias in severity classification.

[251…

```
# Plot class distributions
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

sns.histplot(y_train, bins=4, ax=axes[0], kde=False, color="blue")
axes[0].set_title("Training Set Severity Distribution")

sns.histplot(y_val, bins=4, ax=axes[1], kde=False, color="green")
axes[1].set_title("Validation Set Severity Distribution")

sns.histplot(y_test, bins=4, ax=axes[2], kde=False, color="red")
axes[2].set_title("Test Set Severity Distribution")

plt.show()
```



3. Challenges & Solutions:

Several challenges emerged during data preprocessing. Missing data in key features, particularly weather-related attributes, required careful imputation strategies. Additionally, accident severity exhibited a class imbalance, which could negatively affect model performance, necessitating techniques such as oversampling and class weighting. Outlier influence was another concern, as extreme values in numerical data could distort model learning. Lastly, accident descriptions contained abbreviations and domain-specific terms, making text processing more complex.

To mitigate these issues, further refinement of the NLP model is required, including additional text preprocessing techniques. Feature engineering should be expanded to include more time-based or location-based insights to enhance predictive performance. Addressing class imbalance through oversampling techniques such as SMOTE or cost-sensitive learning will be critical for ensuring better model accuracy. Additionally, missing weather data may benefit from advanced imputation methods, such as regression-based techniques.

4. Next Week Schedule:

Our focus for next week is to build a NLP model by implementing and evaluating different text-processing techniques. Hyperparameter tuning will be conducted to optimize data transformations and encoding methods. Further feature selection will be carried out to determine the most impactful variables for the final predictive model. Finally, the models would help us to assess accident severity prediction and refine our approach based on performance evaluations.

Week4 Data processing and Feature engineering

February 16, 2025

1 Week 1.install and import necessary packages and import dataset

[ ]:
```
# install and import necessary packages

import sys
import subprocess

# List of required packages
packages = ['numpy', 'pandas', 'matplotlib', 'seaborn','scikit-learn','plotly']

# Install missing packages
for package in packages:
    try:
        __import__(package)
    except ImportError:
        subprocess.check_call([sys.executable, "-m", "pip", "install", package])

#import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import gc
from sklearn.model_selection import train_test_split
import plotly.express as px
from sklearn.preprocessing import LabelEncoder
```

```
Requirement already satisfied: scikit-learn in
/opt/anaconda3/lib/python3.12/site-packages (1.6.1)
Requirement already satisfied: numpy>=1.19.5 in
/opt/anaconda3/lib/python3.12/site-packages (from scikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in
/opt/anaconda3/lib/python3.12/site-packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in
/opt/anaconda3/lib/python3.12/site-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/opt/anaconda3/lib/python3.12/site-packages (from scikit-learn) (3.5.0)
```

[168]:
```python
#import data
accident_data = pd.read_csv("US_Accidents_MA.csv")
```

2 Week 2. Basic EDA

[169]:
```python
#look at datatype
accident_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 61996 entries, 0 to 61995
Data columns (total 46 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   ID                     61996 non-null  object
 1   Source                 61996 non-null  object
 2   Severity               61996 non-null  int64
 3   Start_Time             61996 non-null  object
 4   End_Time               61996 non-null  object
 5   Start_Lat              61996 non-null  float64
 6   Start_Lng              61996 non-null  float64
 7   End_Lat                7971 non-null   float64
 8   End_Lng                7971 non-null   float64
 9   Distance(mi)           61996 non-null  float64
 10  Description            61996 non-null  object
 11  Street                 61950 non-null  object
 12  City                   61996 non-null  object
 13  County                 61996 non-null  object
 14  State                  61996 non-null  object
 15  Zipcode                61996 non-null  object
 16  Country                61996 non-null  object
 17  Timezone               61996 non-null  object
 18  Airport_Code           61991 non-null  object
 19  Weather_Timestamp      61773 non-null  object
 20  Temperature(F)         61589 non-null  float64
 21  Wind_Chill(F)          45839 non-null  float64
 22  Humidity(%)            61491 non-null  float64
 23  Pressure(in)           61675 non-null  float64
 24  Visibility(mi)         59269 non-null  float64
 25  Wind_Direction         61673 non-null  object
 26  Wind_Speed(mph)        58632 non-null  float64
 27  Precipitation(in)      40353 non-null  float64
 28  Weather_Condition      59298 non-null  object
 29  Amenity                61996 non-null  bool
 30  Bump                   61996 non-null  bool
 31  Crossing               61996 non-null  bool
 32  Give_Way               61996 non-null  bool
 33  Junction               61996 non-null  bool
```

```
 34  No_Exit                61996 non-null  bool
 35  Railway                61996 non-null  bool
 36  Roundabout             61996 non-null  bool
 37  Station                61996 non-null  bool
 38  Stop                   61996 non-null  bool
 39  Traffic_Calming        61996 non-null  bool
 40  Traffic_Signal         61996 non-null  bool
 41  Turning_Loop           61996 non-null  bool
 42  Sunrise_Sunset         61992 non-null  object
 43  Civil_Twilight         61992 non-null  object
 44  Nautical_Twilight      61992 non-null  object
 45  Astronomical_Twilight  61992 non-null  object
dtypes: bool(13), float64(12), int64(1), object(20)
memory usage: 16.4+ MB
```

[170]:

```
#print number and percentage of null entries per variable
print('Null values per variable')
for column in accident_data.columns:
    print('{}: {} ({}%)'.format(column,pd.isnull(accident_data[column]).
 ↪sum(),(pd.isnull(accident_data[column]).sum()/len(accident_data))*100))
```

```
Null values per variable
ID: 0 (0.0%)
Source: 0 (0.0%)
Severity: 0 (0.0%)
Start_Time: 0 (0.0%)
End_Time: 0 (0.0%)
Start_Lat: 0 (0.0%)
Start_Lng: 0 (0.0%)
End_Lat: 54025 (87.14271888508937%)
End_Lng: 54025 (87.14271888508937%)
Distance(mi): 0 (0.0%)
Description: 0 (0.0%)
Street: 46 (0.07419833537647590%)
City: 0 (0.0%)
County: 0 (0.0%)
State: 0 (0.0%)
Zipcode: 0 (0.0%)
Country: 0 (0.0%)
Timezone: 0 (0.0%)
Airport_Code: 5 (0.008065036453964771%)
Weather_Timestamp: 223 (0.3597006258468288%)
Temperature(F): 407 (0.6564939673527325%)
Wind_Chill(F): 16157 (26.061358797341764%)
Humidity(%): 505 (0.814568681850442%)
Pressure(in): 321 (0.5177753403445383%)
Visibility(mi): 2727 (4.398670881992387%)
Wind_Direction: 323 (0.5210013549261243%)
```

```
Wind_Speed(mph): 3364 (5.426156526227499%)
Precipitation(in): 21643 (34.91031679463191%)
Weather_Condition: 2698 (4.351893670559391%)
Amenity: 0 (0.0%)
Bump: 0 (0.0%)
Crossing: 0 (0.0%)
Give_Way: 0 (0.0%)
Junction: 0 (0.0%)
No_Exit: 0 (0.0%)
Railway: 0 (0.0%)
Roundabout: 0 (0.0%)
Station: 0 (0.0%)
Stop: 0 (0.0%)
Traffic_Calming: 0 (0.0%)
Traffic_Signal: 0 (0.0%)
Turning_Loop: 0 (0.0%)
Sunrise_Sunset: 4 (0.006452029163171818%)
Civil_Twilight: 4 (0.006452029163171818%)
Nautical_Twilight: 4 (0.006452029163171818%)
Astronomical_Twilight: 4 (0.006452029163171818%)
```

[171]:

```
#look at distribution of data
accident_data.describe()
```

[171]:

	Severity	Start_Lat	Start_Lng	End_Lat	End_Lng	\
count	61996.000000	61996.000000	61996.000000	7971.000000	7971.000000	
mean	2.293842	42.336970	-71.204913	42.299983	-71.286296	
std	0.523010	0.227612	0.350009	0.244489	0.454490	
min	1.000000	41.274700	-73.476868	41.442540	-73.477854	
25%	2.000000	42.225157	-71.262665	42.178960	-71.344475	
50%	2.000000	42.347019	-71.120621	42.318780	-71.133590	
75%	3.000000	42.501911	-71.053139	42.467335	-71.052010	
max	4.000000	42.877491	-69.957573	42.876040	-69.984614	

	Distance(mi)	Temperature(F)	Wind_Chill(F)	Humidity(%)	\
count	61996.000000	61589.000000	45839.000000	61491.000000	
mean	0.244122	52.583681	45.853027	67.213950	
std	1.299053	19.167085	22.521689	20.612705	
min	0.000000	-13.000000	-26.300000	7.000000	
25%	0.000000	37.000000	28.500000	51.000000	
50%	0.000000	53.000000	43.000000	69.000000	
75%	0.000000	68.000000	65.000000	86.000000	
max	79.946000	98.100000	98.000000	100.000000	

	Pressure(in)	Visibility(mi)	Wind_Speed(mph)	Precipitation(in)
count	61675.000000	59269.000000	58632.000000	40353.000000
mean	29.930176	8.752235	9.175300	0.010531

```
std        0.316275      2.795481       5.474319          0.049839
min       27.790000      0.000000       0.000000          0.000000
25%       29.780000     10.000000       5.800000          0.000000
50%       29.950000     10.000000       8.100000          0.000000
75%       30.120000     10.000000      12.700000          0.000000
max       30.890000     10.500000     132.000000          2.820000
```

[172]:
```python
# Get the number of rows and columns
num_rows, num_columns = accident_data.shape

print(f"Number of rows: {num_rows}")
print(f"Number of columns: {num_columns}")
```

```
Number of rows: 61996
Number of columns: 46
```

[173]:
```python
#look at formatting of entries
accident_data.head()
```

[173]:
```
         ID   Source  Severity           Start_Time             End_Time  \
0  A-194264  Source2         2  2016-11-30 15:37:19  2016-11-30 17:08:21
1  A-194268  Source2         2  2016-11-30 16:14:24  2016-11-30 17:28:48
2  A-194269  Source2         3  2016-11-30 16:02:41  2016-11-30 17:25:00
3  A-194270  Source2         4  2016-11-30 14:12:49  2016-11-30 17:25:00
4  A-194271  Source2         3  2016-11-30 16:00:47  2016-11-30 17:15:31

   Start_Lat  Start_Lng  End_Lat  End_Lng  Distance(mi)  … Roundabout  \
0  42.144863 -72.599976      NaN      NaN          0.00  …      False
1  42.304436 -71.325317      NaN      NaN          0.00  …      False
2  42.428036 -71.258476      NaN      NaN          0.01  …      False
3  42.495930 -71.178238      NaN      NaN          0.01  …      False
4  42.525875 -70.972115      NaN      NaN          0.01  …      False

  Station   Stop Traffic_Calming Traffic_Signal Turning_Loop Sunrise_Sunset  \
0   False  False           False          False        False            Day
1   False  False           False           True        False          Night
2   False  False           False          False        False            Day
3   False  False           False          False        False            Day
4   False  False           False          False        False            Day

  Civil_Twilight Nautical_Twilight Astronomical_Twilight
0            Day               Day                   Day
1            Day               Day                   Day
2            Day               Day                   Day
3            Day               Day                   Day
4            Day               Day                   Day

[5 rows x 46 columns]
```

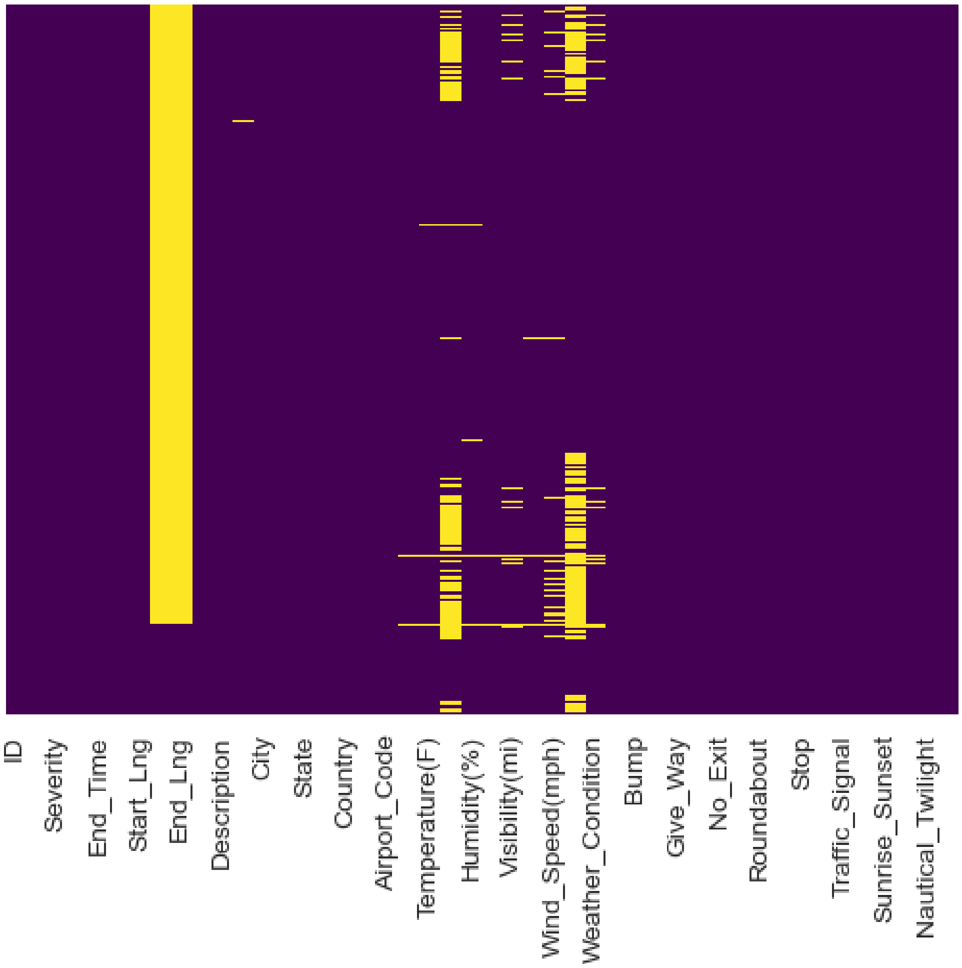
```
[174]: #looking to see ID format towards end
accident_data.tail()
```

```
[174]:              ID   Source  Severity           Start_Time             End_Time  \
61991  A-7776267  Source1         2  2019-08-21 18:01:55  2019-08-21 18:31:30
61992  A-7776802  Source1         2  2019-08-22 08:41:32  2019-08-22 09:11:10
61993  A-7777343  Source1         2  2019-08-23 21:40:04  2019-08-23 22:09:12
61994  A-7777349  Source1         2  2019-08-23 16:22:17  2019-08-23 16:52:10
61995  A-7777359  Source1         2  2019-08-23 19:12:21  2019-08-23 19:41:38

       Start_Lat  Start_Lng    End_Lat    End_Lng  Distance(mi)  …  \
61991  42.445630 -71.256440  42.439820 -71.258740         0.418  …
61992  42.383140 -71.076750  42.378460 -71.075840         0.327  …
61993  42.566199 -70.922008  42.567773 -70.919635         0.163  …
61994  42.097100 -71.058500  42.090840 -71.060250         0.442  …
61995  42.456159 -71.751316  42.460374 -71.742290         0.545  …

      Roundabout Station   Stop Traffic_Calming Traffic_Signal Turning_Loop  \
61991      False   False  False           False          False        False
61992      False   False  False           False          False        False
61993      False   False  False           False          False        False
61994      False   False  False           False          False        False
61995      False   False  False           False          False        False

      Sunrise_Sunset Civil_Twilight Nautical_Twilight Astronomical_Twilight
61991            Day            Day               Day                   Day
61992            Day            Day               Day                   Day
61993          Night          Night             Night                 Night
61994            Day            Day               Day                   Day
61995            Day            Day               Day                   Day

[5 rows x 46 columns]
```

3 Week 3 Advanced EDA and Data split

```
[175]: # Deal with all the missing values

sns.heatmap(accident_data.isnull(),yticklabels=False,cbar=False,cmap='viridis')
# plotting a heatmap of missing values in columns
```

```
[175]: <Axes: >
```



[176]:
```
# Filling in the missing values in three of the columns related to weather␣
↪condition

accident_data["Wind_Chill(F)"] = accident_data['Wind_Chill(F)'].
↪fillna(accident_data['Wind_Chill(F)'].mean())
accident_data["Precipitation(in)"] = accident_data['Precipitation(in)'].
↪fillna(accident_data['Precipitation(in)'].mean())
accident_data["Wind_Speed(mph)"] = accident_data['Wind_Speed(mph)'].
↪fillna(accident_data['Wind_Speed(mph)'].mean())
```

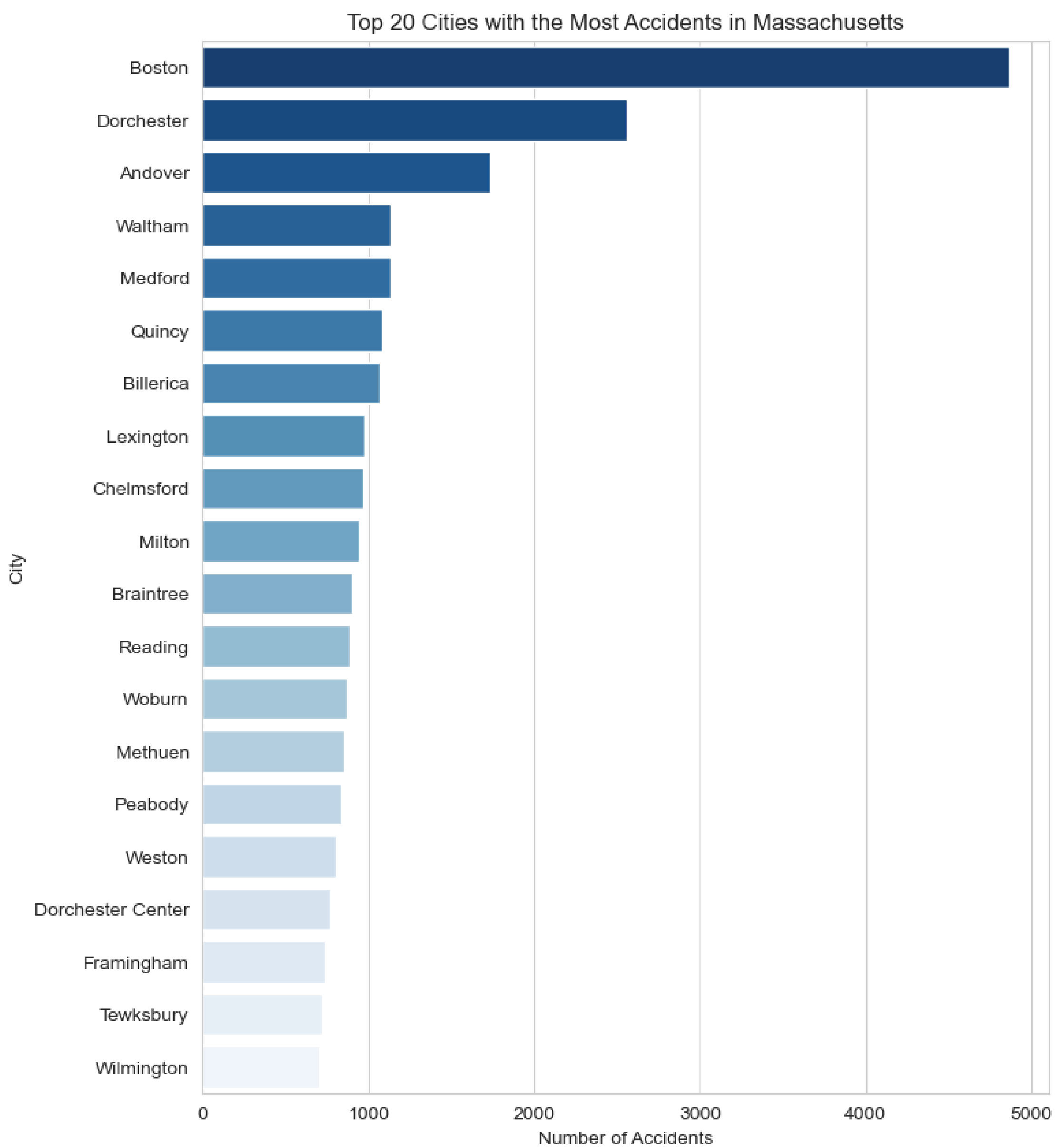
[177]:
```
# Which City has the maximum no: of accidents?

city_wise_counts = accident_data.groupby('City')['ID'].count().reset_index()
city_wise_counts = city_wise_counts.sort_values(by = "ID",ascending=False)

max_accident_city = city_wise_counts.iloc[0]  # Get the top city
```

```
print(f"The city with the highest number of accidents in Massachusetts is␣
↪{max_accident_city['City']} with {max_accident_city['ID']} accidents.")
```

```
The city with the highest number of accidents in Massachusetts is Boston with
4866 accidents.
```

[178]:
```
# Get top 20 cities
top_20_cities = city_wise_counts.head(20)

# Set Seaborn style
sns.set_style("whitegrid")

# Create the figure
f, ax = plt.subplots(figsize=(8, 10))

# Create the bar plot
sns.barplot(y="City", x="ID", data=top_20_cities, ax=ax, palette="Blues_r")

# Add title and labels
ax.set_title("Top 20 Cities with the Most Accidents in Massachusetts")
ax.set_xlabel("Number of Accidents")
ax.set_ylabel("City")

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

```
/var/folders/x6/yvl9g72j20q30dzkb5yqg1z80000gn/T/ipykernel_46096/2744639619.py:1
1: 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.
```

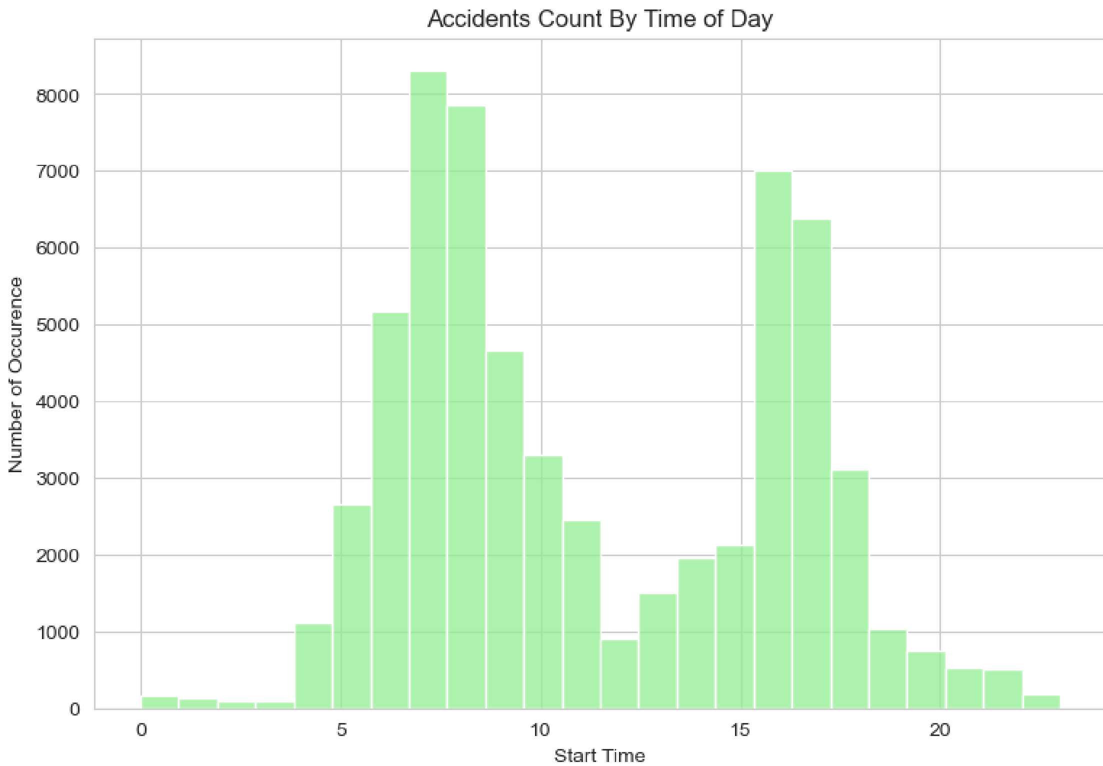


[179]:
```
# Group accident data by City and State, getting their latitude and longitude
city_wise_counts = accident_data.groupby(["City", "State"])[["Start_Lat",␣
↪"Start_Lng"]].first().reset_index()
city_wise_counts["Accident_Count"] = accident_data.groupby(["City",␣
↪"State"])["ID"].count().values

# Create a scatter geo plot for 50 city-wise accidents
top_cities = city_wise_counts.nlargest(50, "Accident_Count")  # Show only top␣
↪50 cities
fig = px.scatter_geo(
```

```python
    top_cities,
    lat="Start_Lat",
    lon="Start_Lng",
    size="Accident_Count",
    hover_name="City",
    hover_data={"State": True, "Accident_Count": True},
    color="Accident_Count",
    color_continuous_scale="spectral_r",
    title="Top 50 Cities with the Most Accidents in the Massachusetts",
    scope="usa"
)
fig.show()
```

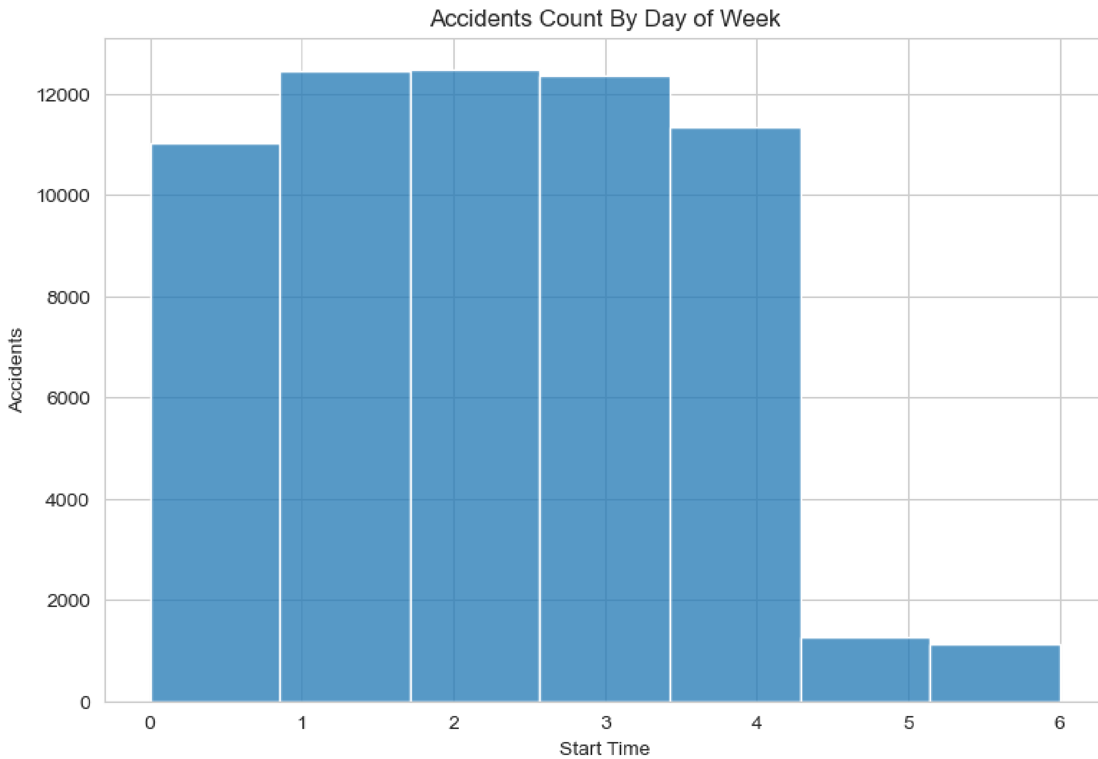
[180]:
```python
# Accidents based on Time

accident_data["Start_Time"] = pd.to_datetime(accident_data["Start_Time"],␣
 ↪format="mixed", errors="coerce")

# To find the accidents by time of day

fig, ax = plt.subplots(figsize=(9,6))
sns.histplot(accident_data.Start_Time.dt.
 ↪hour,bins=24,kde=False,color='lightgreen')

plt.xlabel("Start Time")
plt.ylabel("Number of Occurence")
plt.title('Accidents Count By Time of Day')
```

[180]:
```
Text(0.5, 1.0, 'Accidents Count By Time of Day')
```



[181]:
```python
# To find the accidents by Day of the week

fig, ax = plt.subplots(figsize=(9,6))
sns.histplot(accident_data.Start_Time.dt.dayofweek,bins=7,kde=False)

plt.xlabel("Start Time")
plt.ylabel("Accidents")
plt.title('Accidents Count By Day of Week')
```

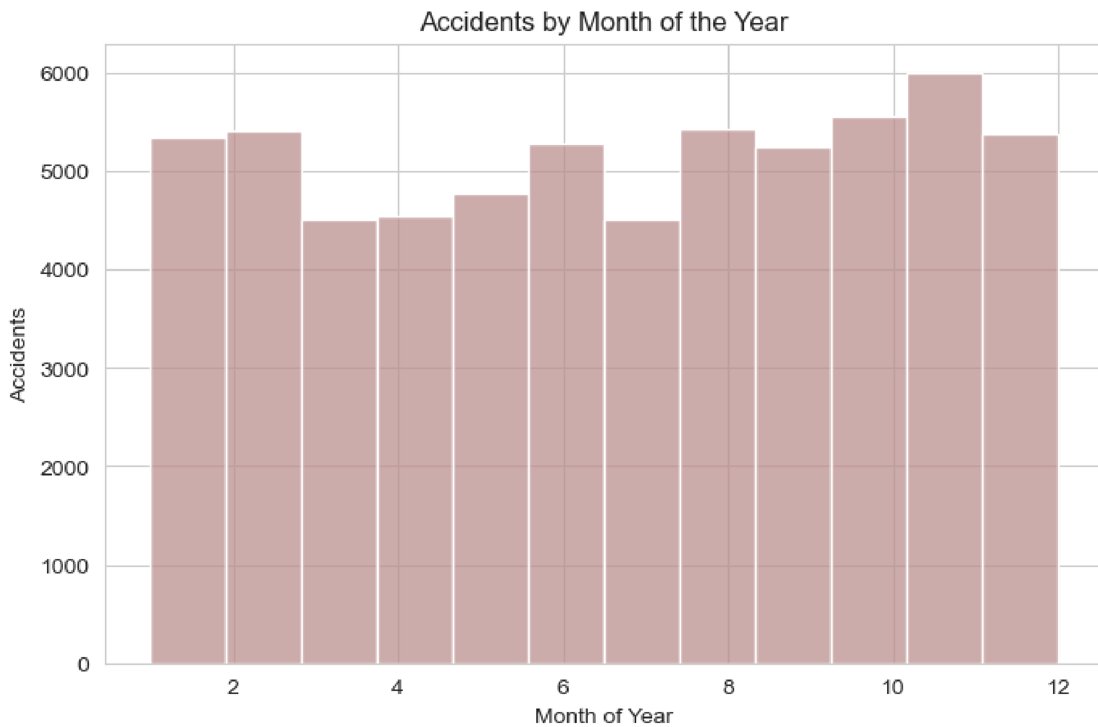
[181]: Text(0.5, 1.0, 'Accidents Count By Day of Week')



[182]:

```
# To find the accidents by the month of the year

fig, ax = plt.subplots(figsize=(8,5))
sns.histplot(accident_data['Start_Time'].dt.month, bins = 12,color='rosybrown')

plt.xlabel("Month of Year")
plt.ylabel("Accidents")
plt.title('Accidents by Month of the Year')
```

[182]: Text(0.5, 1.0, 'Accidents by Month of the Year')



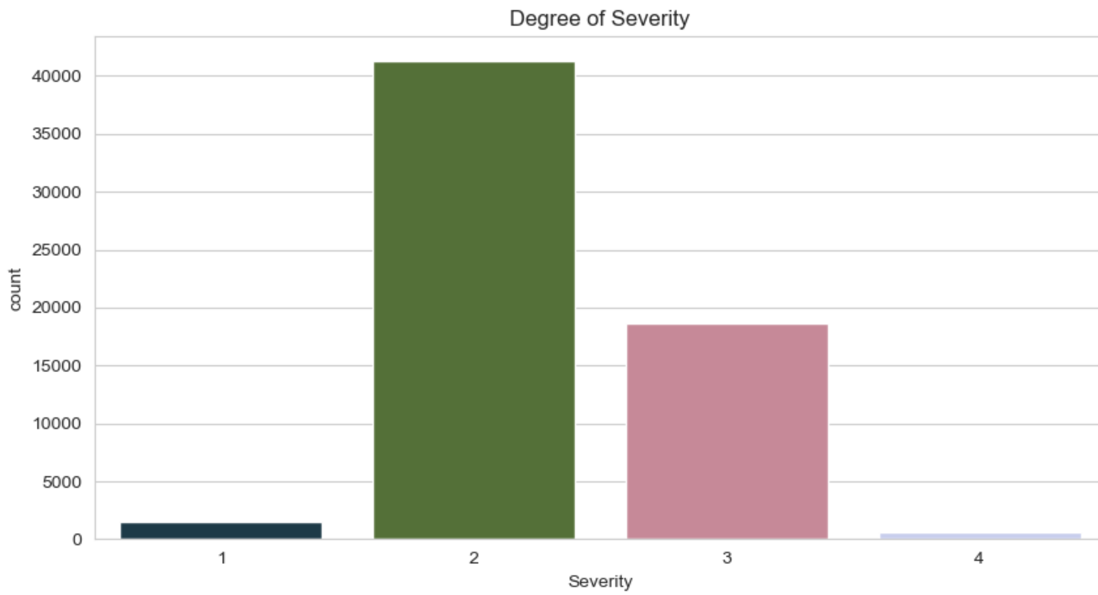
[183]:
```
# Accidents based on Severity and Weather Conditions

df_severity = accident_data.groupby('Severity')['ID'].count()
df_severity
```

[183]:
```
Severity
1     1500
2    41326
3    18623
4      547
Name: ID, dtype: int64
```

[184]:
```
fig, ax = plt.subplots(figsize = (10,5))
sev = sns.countplot(x="Severity", data=accident_data, palette = "cubehelix")
sev.set_title("Degree of Severity")
```

```
/var/folders/x6/yvl9g72j20q30dzkb5yqg1z80000gn/T/ipykernel_46096/2458966032.py:2
: 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.
```

[184]: Text(0.5, 1.0, 'Degree of Severity')



[185]:
```
weather = accident_data.iloc[:, 20:30]
weather['Severity'] = accident_data['Severity']
weather.head()
```

[185]:

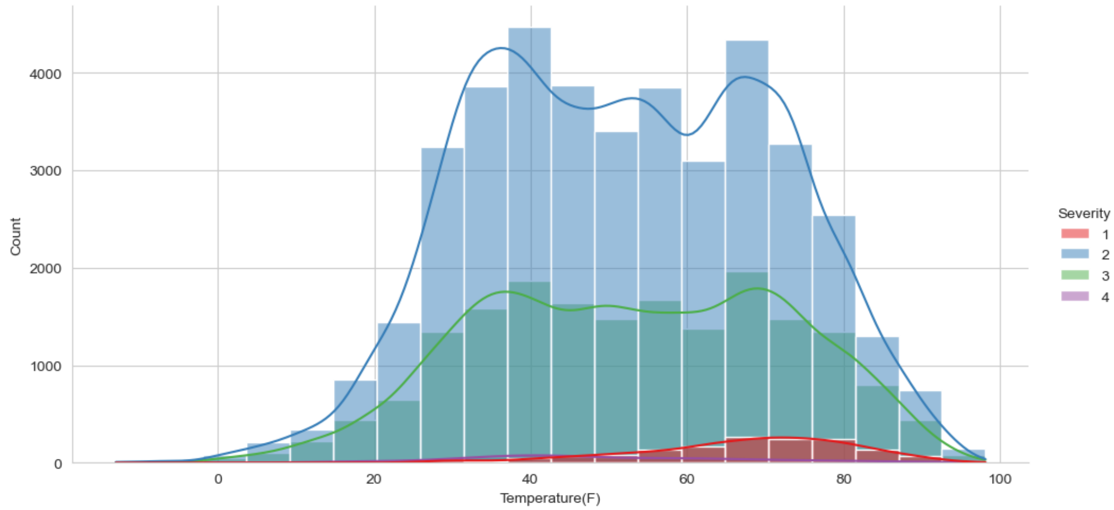
	Temperature(F)	Wind_Chill(F)	Humidity(%)	Pressure(in)	Visibility(mi)	\
0	48.2	45.853027	100.0	29.87	3.0	
1	48.0	45.853027	89.0	29.96	5.0	
2	46.9	45.853027	86.0	30.01	5.0	
3	46.0	41.900000	89.0	30.01	3.0	
4	46.0	41.900000	100.0	29.97	6.0	

	Wind_Direction	Wind_Speed(mph)	Precipitation(in)	Weather_Condition	\
0	Variable	3.5	0.010531	Light Rain	
1	ENE	5.8	0.050000	Rain	
2	ENE	6.9	0.080000	Rain	
3	East	8.1	0.010000	Light Rain	
4	NNE	8.1	0.070000	Light Rain	

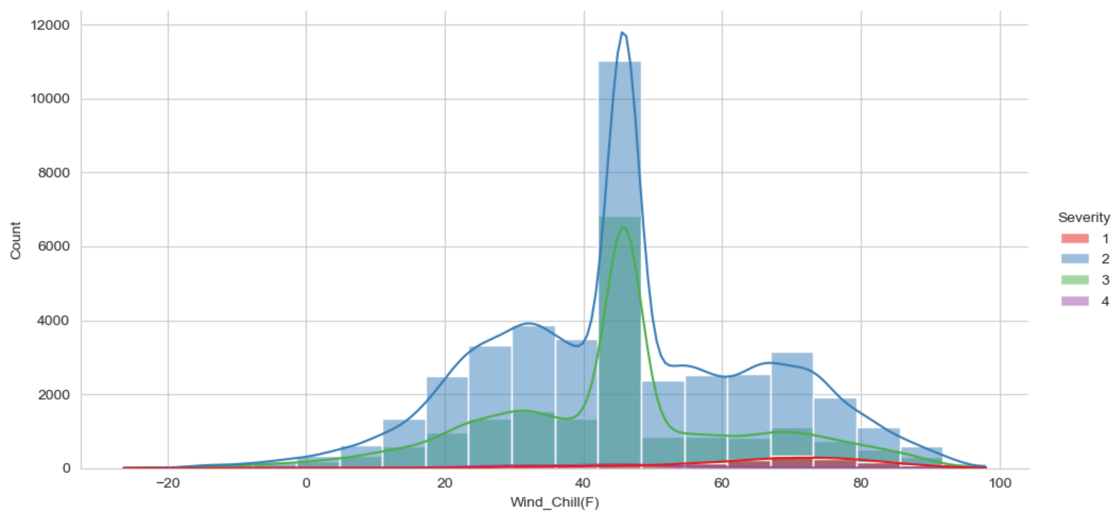
	Amenity	Severity
0	False	2
1	False	2
2	False	3

```
3     False          4
4     False          3
```

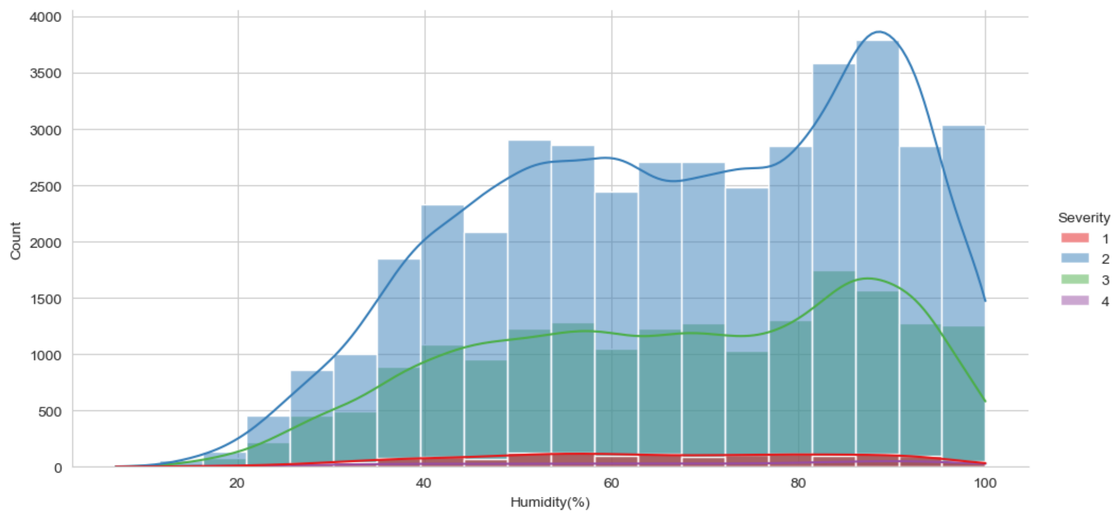
[186]:
```
sns.displot(weather, x="Temperature(F)", hue="Severity", palette="Set1",␣
 ↪height=5, aspect=2,bins=20,kde=True);
```



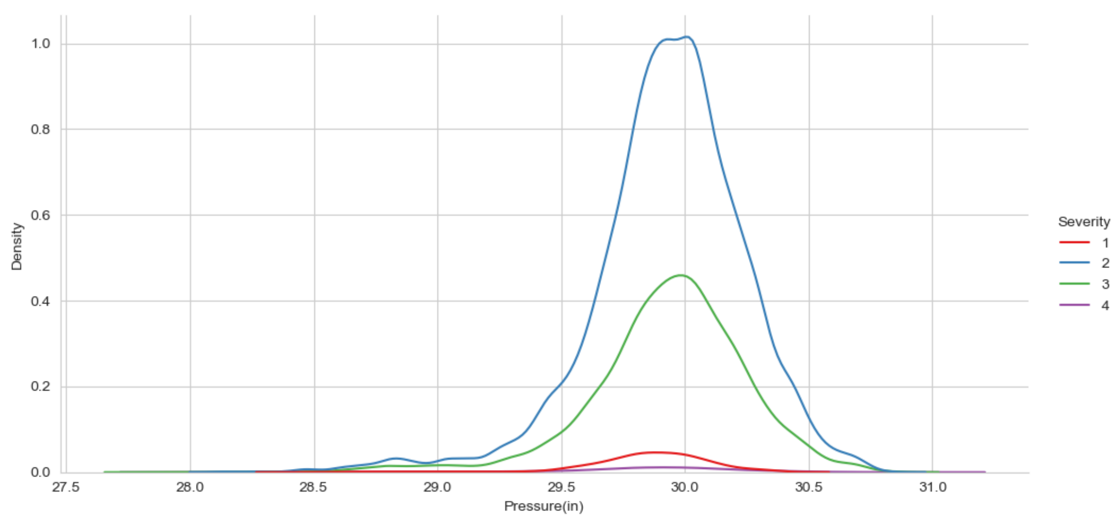
[187]:
```
sns.displot(weather, x="Wind_Chill(F)", hue="Severity",palette="Set1",␣
 ↪height=5, aspect=2,bins=20,kde=True);
```



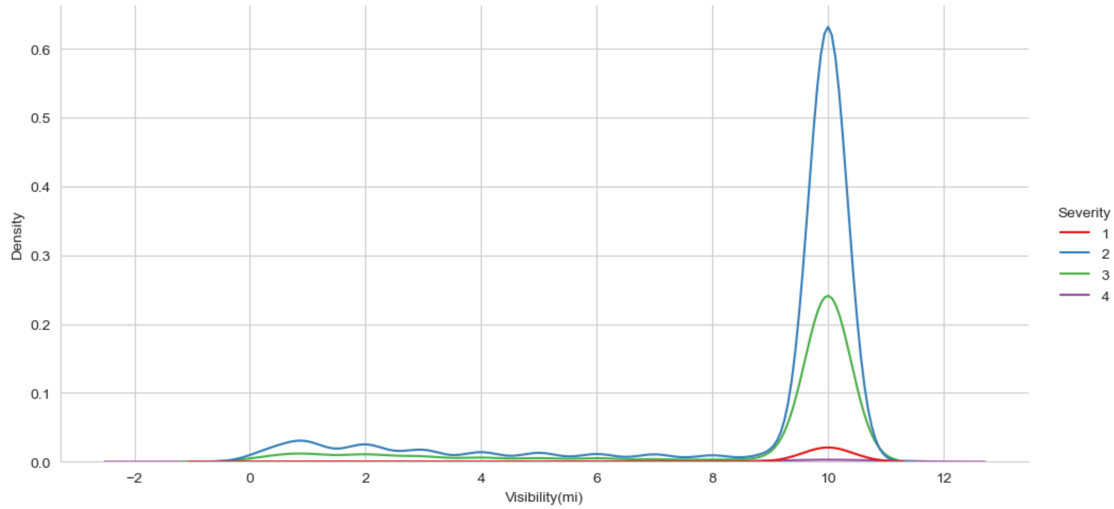
[188]:
```
sns.displot(weather, x="Humidity(%)", hue="Severity", palette="Set1", height=5,␣
 ↪aspect=2,bins=20,kde=True);
```



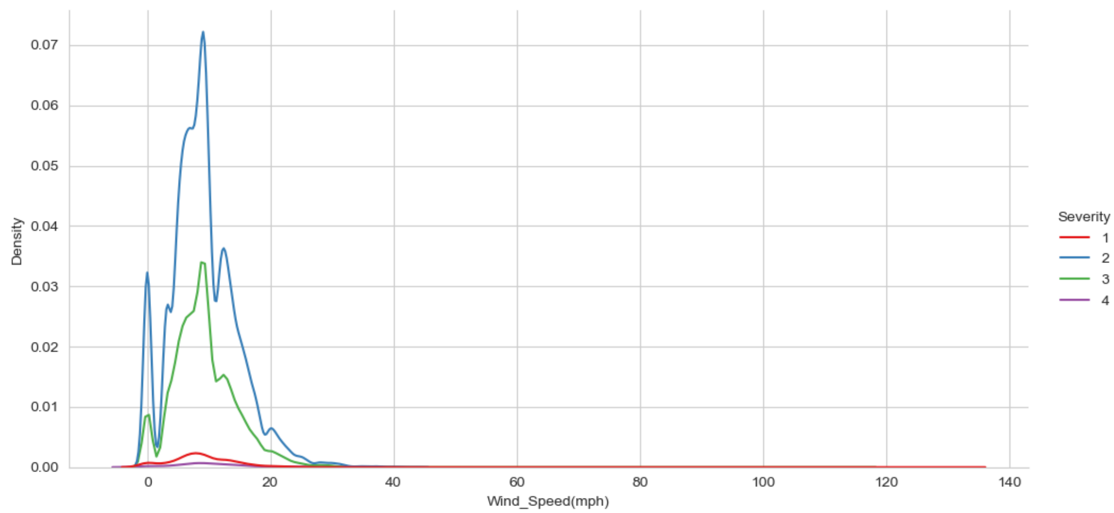
[189]:
```
sns.displot(weather, x="Pressure(in)", hue="Severity", palette="Set1",␣
↪height=5, aspect=2,kind='kde');
```



[190]:
```
sns.displot(weather, x="Visibility(mi)", hue="Severity", palette="Set1",␣
↪height=5, aspect=2,kind='kde');
```



[191]:
```
sns.displot(weather, x="Wind_Speed(mph)", hue="Severity", palette="Set1",␣
↪height=5, aspect=2,kind='kde');
```



4 Week 4: Data processing & Feature engineering

[ ]:
```
# Irrelevant columns
# ID is unique and meaningless for the dataset; Description: I don't do text␣
↪mining, and I will do text classification later, therefore It's useless;␣
↪Country: All the data is from MA ;Weather_Timestamp: The timestamp of␣
↪weather observation record. It's useless here.
irrelavant_columns = ['ID','Description','Country','Weather_Timestamp']
```

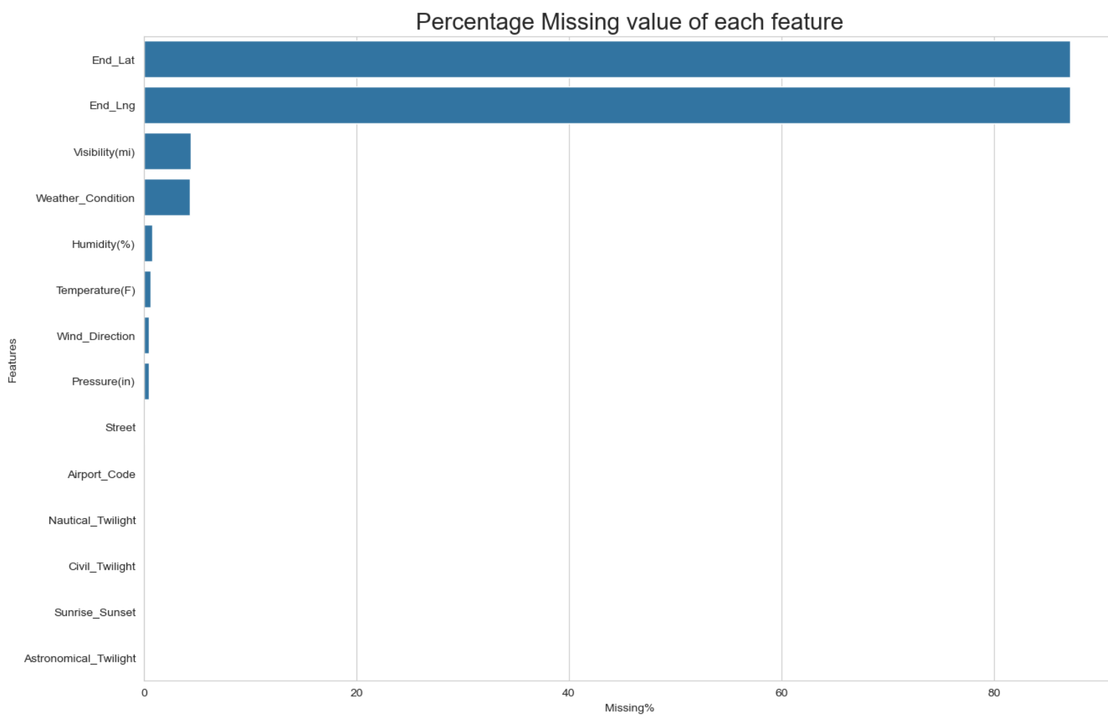
```
data_preprocessed_df = accident_data.drop(irrelavant_columns, axis=1)
```

Drop the column with Missing Value(>40%)

[228]:
```
# Replace the empty data with NaN
data_preprocessed_df.replace("", float("NaN"), inplace=True)
data_preprocessed_df.replace(" ", float("NaN"), inplace=True)

# Count missing value(NaN, na, null, None) of each columns, Then transform the␣
↪result to a pandas dataframe.
count_missing_value = data_preprocessed_df.isna().sum() / data_preprocessed_df.
↪shape[0] * 100
count_missing_value_df = pd.DataFrame(count_missing_value.
↪sort_values(ascending=False), columns=['Missing%'])
```

[229]:
```
# Visualize the percentage(>0) of Missing value in each column.
missing_value_df = count_missing_value_df[count_missing_value_df['Missing%'] >␣
↪0]

plt.figure(figsize=(15, 10)) # Set the figure size
missing_value_graph = sns.barplot(y = missing_value_df.index, x = "Missing%",␣
↪data=missing_value_df, orient="h")
missing_value_graph.set_title("Percentage Missing value of each feature",␣
↪fontsize = 20)
missing_value_graph.set_ylabel("Features")
```

[229]:
```
Text(0, 0.5, 'Features')
```



[230]:
```
## Drop the column with Missing value(>40%)
missing_value_40_df = count_missing_value_df[count_missing_value_df['Missing%']␣
↪> 40]
data_preprocessed_df.drop(missing_value_40_df.index, axis=1, inplace=True)
missing_value_40_df
```

[230]:
```
          Missing%
End_Lat  87.142719
End_Lng  87.142719
```

Data type correcting

[231]:
```
# Convert Time to datetime64[ns]
data_preprocessed_df['Start_Time'] = pd.
↪to_datetime(data_preprocessed_df['Start_Time'])
data_preprocessed_df['End_Time'] = pd.
↪to_datetime(data_preprocessed_df['End_Time'], errors='coerce')
```

[232]:
```
# Display all the missing value
missing_value_df
```

[232]:
```
                        Missing%
End_Lat                87.142719
End_Lng                87.142719
Visibility(mi)          4.398671
Weather_Condition       4.351894
Humidity(%)             0.814569
Temperature(F)          0.656494
Wind_Direction          0.521001
Pressure(in)            0.517775
Street                  0.074198
Airport_Code            0.008065
Nautical_Twilight       0.006452
Civil_Twilight          0.006452
Sunrise_Sunset          0.006452
Astronomical_Twilight   0.006452
```

[233]:
```
# Categorize the missing value to numerical and categorical for imputation␣
↪purpose
numerical_missing = ['Wind_Speed(mph)', 'Visibility(mi)','Humidity(%)',␣
↪'Temperature(F)', 'Pressure(in)']
categorical_missing = ['Weather_Condition','Wind_Direction', 'Sunrise_Sunset',␣
↪'Civil_Twilight', 'Nautical_Twilight', 'Astronomical_Twilight']
```

Median imputation

[234]:
```
# Imputation by corresponding class Median value
data_preprocessed_median_df = data_preprocessed_df.copy()

# For numerical columns
for column_name in numerical_missing:
    data_preprocessed_median_df[column_name] = data_preprocessed_median_df.
 ↪groupby('Severity')[column_name].transform(lambda x:x.fillna(x.median()))

# # For categorical columns(Majority value imputation)
for column_name in categorical_missing:
    data_preprocessed_median_df[column_name] = data_preprocessed_median_df.
 ↪groupby('Severity')[column_name].transform(lambda x:x.fillna(x.fillna(x.
 ↪mode().iloc[0])))

# Drop NaN and reset index
data_preprocessed_median_df.dropna(inplace=True)
```

Feature engineering

[254]:
```
# Choose relevant features

data_best_df = data_preprocessed_median_df
relevant_features = ['Severity', 'Start_Time', 'End_Time', 'Start_Lat',␣
 ↪'Start_Lng',
       'Temperature(F)', 'Humidity(%)', 'Pressure(in)', 'Visibility(mi)',
       'Wind_Direction', 'Wind_Speed(mph)', 'Weather_Condition', 'Amenity',
       'Bump', 'Crossing', 'Give_Way', 'Junction', 'No_Exit', 'Railway',
       'Roundabout', 'Station', 'Stop', 'Traffic_Calming', 'Traffic_Signal',
       'Turning_Loop', 'Sunrise_Sunset']
data_modelling_df = data_best_df[relevant_features].copy()

print(data_modelling_df.columns)
```

```
Index(['Severity', 'Start_Time', 'End_Time', 'Start_Lat', 'Start_Lng',
       'Temperature(F)', 'Humidity(%)', 'Pressure(in)', 'Visibility(mi)',
       'Wind_Direction', 'Wind_Speed(mph)', 'Weather_Condition', 'Amenity',
       'Bump', 'Crossing', 'Give_Way', 'Junction', 'No_Exit', 'Railway',
       'Roundabout', 'Station', 'Stop', 'Traffic_Calming', 'Traffic_Signal',
       'Turning_Loop', 'Sunrise_Sunset'],
      dtype='object')
```

[237]:
```
# Duration = End_Time - Start_Time; Create a new feature for modeling.
data_modelling_df['Duration'] = (data_modelling_df['End_Time'] -␣
 ↪data_modelling_df['Start_Time']).dt.total_seconds() / 3600
data_modelling_df.drop('End_Time', axis=1, inplace=True)
```

[238]:
```
# Transform Month/week/Hour to different features
data_modelling_df["Month"] = data_modelling_df["Start_Time"].dt.month
```

```
data_modelling_df["Week"] = data_modelling_df["Start_Time"].dt.dayofweek
data_modelling_df["Hour"] = data_modelling_df["Start_Time"].dt.hour
data_modelling_df.drop("Start_Time", axis=1, inplace=True)
```

One Hot Encoding

[ ]:
```
# Select features that are suitable for One Hot Encoding
one_hot_features = ['Wind_Direction', 'Weather_Condition']

# Wind_Direction Categorizing
data_modelling_df.loc[data_modelling_df['Wind_Direction'].str.startswith('C'),␣
↪'Wind_Direction'] = 'C' #Calm
data_modelling_df.loc[data_modelling_df['Wind_Direction'].str.startswith('E'),␣
↪'Wind_Direction'] = 'E' #East, ESE, ENE
data_modelling_df.loc[data_modelling_df['Wind_Direction'].str.startswith('W'),␣
↪'Wind_Direction'] = 'W' #West, WSW, WNW
data_modelling_df.loc[data_modelling_df['Wind_Direction'].str.startswith('S'),␣
↪'Wind_Direction'] = 'S' #South, SSW, SSE
data_modelling_df.loc[data_modelling_df['Wind_Direction'].str.startswith('N'),␣
↪'Wind_Direction'] = 'N' #North, NNW, NNE
data_modelling_df.loc[data_modelling_df['Wind_Direction'].str.startswith('V'),␣
↪'Wind_Direction'] = 'V' #Variable
```

[240]:
```
# Weather_Condition Categorizing
# Fair, Cloudy, Clear, Overcast, Snow, Haze, Rain, Thunderstorm, Windy, Hail,␣
↪Thunder, Dust, Tornado
data_modelling_df['Weather_Fair'] = np.
↪where(data_modelling_df['Weather_Condition'].str.contains('Fair',␣
↪case=False, na = False), 1, 0)
data_modelling_df['Weather_Cloudy'] = np.
↪where(data_modelling_df['Weather_Condition'].str.contains('Cloudy',␣
↪case=False, na = False), 1, 0)
data_modelling_df['Weather_Clear'] = np.
↪where(data_modelling_df['Weather_Condition'].str.contains('Clear',␣
↪case=False, na = False), 1, 0)
data_modelling_df['Weather_Overcast'] = np.
↪where(data_modelling_df['Weather_Condition'].str.contains('Overcast',␣
↪case=False, na = False), 1, 0)
data_modelling_df['Weather_Snow'] = np.
↪where(data_modelling_df['Weather_Condition'].str.
↪contains('Snow|Wintry|Sleet', case=False, na = False), 1, 0)
data_modelling_df['Weather_Haze'] = np.
↪where(data_modelling_df['Weather_Condition'].str.
↪contains('Smoke|Fog|Mist|Haze', case=False, na = False), 1, 0)
data_modelling_df['Weather_Rain'] = np.
↪where(data_modelling_df['Weather_Condition'].str.
↪contains('Rain|Drizzle|Showers', case=False, na = False), 1, 0)
```

```
data_modelling_df['Weather_Thunderstorm'] = np.
↪where(data_modelling_df['Weather_Condition'].str.
↪contains('Thunderstorms|T-Storm', case=False, na = False), 1, 0)
data_modelling_df['Weather_Windy'] = np.
↪where(data_modelling_df['Weather_Condition'].str.contains('Windy|Squalls',␣
↪case=False, na = False), 1, 0)
data_modelling_df['Weather_Hail'] = np.
↪where(data_modelling_df['Weather_Condition'].str.contains('Hail|Ice␣
↪Pellets', case=False, na = False), 1, 0)
data_modelling_df['Weather_Thunder'] = np.
↪where(data_modelling_df['Weather_Condition'].str.contains('Thunder',␣
↪case=False, na = False), 1, 0)
data_modelling_df['Weather_Dust'] = np.
↪where(data_modelling_df['Weather_Condition'].str.contains('Dust',␣
↪case=False, na = False), 1, 0)
data_modelling_df['Weather_Tornado'] = np.
↪where(data_modelling_df['Weather_Condition'].str.contains('Tornado',␣
↪case=False, na = False), 1, 0)
```

[241]:

```
# Define the weather categories and keywords
weather_data = {
    "Weather": [
        "Fair", "Cloudy", "Clear", "Overcast", "Snow", "Haze", "Rain",
        "Thunderstorm", "Windy", "Hail", "Thunder", "Dust", "Tornado", "N/A"
    ],
    "Contain": [
        "'Fair / Windy'",
        "'Mostly Cloudy', 'Partly Cloudy', 'Scattered Clouds', 'Cloudy /␣
↪Windy', 'Partly Cloudy / Windy', 'Mostly Cloudy / Windy', 'Funnel Cloud'",
        "'Clear'",
        "'Overcast'",
        "'Light Snow', 'Wintry Mix', 'Heavy Snow', 'Snow', 'Light Snow /␣
↪Windy', 'Blowing Snow', 'Snow / Windy', 'Snow and Sleet', 'Blowing Snow /␣
↪Windy', 'Sleet', 'Light Snow and Sleet', 'Light Snow with Thunder', 'Light␣
↪Snow Showers', 'Heavy Snow with Thunder','Heavy Snow / Windy', 'Light␣
↪Sleet', 'Heavy Sleet', 'Snow and Sleet / Windy', 'Thunderstorms and Snow',␣
↪'Light Thunderstorms and Snow', 'Heavy Blowing Snow','Light Sleet / Windy',␣
↪'Sleet / Windy', 'Snow Showers', 'Light Blowing Snow', 'Light Snow␣
↪Shower','Drifting Snow','Low Drifting Snow','Light Snow and Sleet / Windy',␣
↪'Snow Grains', 'Light Snow Grains', 'Rain and Sleet', 'Thunder / Wintry␣
↪Mix', 'Thunder / Wintry Mix / Windy', 'Wintry Mix / Windy'",
        "'Smoke', 'Fog', 'Mist', 'Shallow Fog', 'Haze / Windy', 'Patches of␣
↪Fog', 'Light Freezing Fog', 'Fog / Windy', 'Smoke / Windy', 'Partial Fog',␣
↪'Patches of Fog / Windy','Light Haze','Light Fog'",
```

```
        "'Light Rain', 'Rain', 'Light Drizzle', 'Light Rain Shower', 'Heavy␣
↪Rain', 'Light Freezing Rain', 'Drizzle', 'Rain / Windy', 'Drizzle and Fog',␣
↪'Light Rain with Thunder', 'Light Rain / Windy', 'Heavy Drizzle', 'Heavy␣
↪Rain / Windy', 'Showers in the Vicinity', 'Light Freezing Drizzle', 'Light␣
↪Drizzle / Windy', 'Heavy Rain Shower', 'Rain Showers', 'Light Rain Showers',␣
↪'Rain Shower', 'Freezing Rain','Light Freezing Rain / Windy', 'Drizzle /␣
↪Windy','Light Rain Shower / Windy', 'Freezing Drizzle', 'Heavy Freezing␣
↪Rain','Heavy Rain Showers','Heavy Freezing Drizzle', 'Rain and Sleet',␣
↪'Freezing Rain / Windy'",
        "'Thunderstorms and Rain', 'Light Thunderstorms and Rain', 'Heavy␣
↪Thunderstorms and Rain', 'T-Storm', 'Heavy T-Storm', 'Heavy T-Storm /␣
↪Windy', 'T-Storm / Windy', 'Heavy Thunderstorms and Snow', 'Thunderstorms␣
↪and Snow', 'Light Thunderstorms and Snow', 'Light Thunderstorm', 'Heavy␣
↪Thunderstorms with Small Hail'",
        "'Fair / Windy','Cloudy / Windy','Partly Cloudy / Windy', 'Mostly␣
↪Cloudy / Windy','Light Snow / Windy','Fog / Windy', 'Smoke / Windy','Rain /␣
↪Windy','Light Rain / Windy','Heavy Rain / Windy','Light Drizzle / Windy',␣
↪'Blowing Dust / Windy', 'Heavy T-Storm / Windy', 'T-Storm / Windy', 'Squalls␣
↪/ Windy', 'Thunder / Windy', 'Blowing Snow / Windy', 'Squalls', 'Heavy Snow /
↪ Windy', 'Snow and Sleet / Windy', 'Light Freezing Rain / Windy', 'Patches␣
↪of Fog / Windy', 'Light Rain Shower / Windy', 'Light Sleet / Windy', 'Sleet /
↪ Windy', 'Light Snow and Sleet / Windy', 'Widespread Dust / Windy', 'Thunder␣
↪/ Wintry Mix / Windy', 'Wintry Mix / Windy', 'Thunder and Hail / Windy',␣
↪'Freezing Rain / Windy'",
        "'Small Hail', 'Light Ice Pellets', 'Ice Pellets', 'Thunder and␣
↪Hail','Light Hail','Heavy Ice Pellets', 'Hail', 'Heavy Thunderstorms with␣
↪Small Hail', 'Thunder and Hail / Windy'",
        "'Thunder in the Vicinity', 'Thunder', 'Thunder / Windy', 'Light Snow␣
↪with Thunder', 'Heavy Snow with Thunder','Thunder and Hail', 'Thunder /␣
↪Wintry Mix', 'Thunder / Wintry Mix / Windy', 'Thunder and Hail / Windy'",
        "'Dust Whirls', 'Sand / Dust Whirlwinds', 'Sand / Dust Whirls Nearby',␣
↪'Blowing Sand', 'Blowing Dust / Windy', 'Widespread Dust', 'Blowing Dust',␣
↪'Widespread Dust / Windy'",
        "'Tornado'",
        "'N/A Precipitation'"
    ],
    "Key words": [
        "'Fair'", "'Cloud'", "'Clear'", "'Overcast'", "'Snow', 'Wintry',␣
↪'Sleet'", "'Smoke', 'Fog', 'Mist', 'Haze'", "'Rain', 'Drizzle', 'Showers'",␣
↪"'Thunderstorms', 'T-Storm'", "'Windy', 'Squalls'", "'Hail', 'Ice Pellets'",␣
↪"'Thunder'", "'Dust'", "'Tornado'", "'N/A Precipitation'"
    ]
}

# Create DataFrame
weather_df = pd.DataFrame(weather_data)
```

```
# Display table
print(weather_df)
```

```
         Weather                                            Contain  \
0           Fair                                      'Fair / Windy'
1         Cloudy  'Mostly Cloudy', 'Partly Cloudy', 'Scattered C…
2          Clear                                            'Clear'
3       Overcast                                         'Overcast'
4           Snow  'Light Snow', 'Wintry Mix', 'Heavy Snow', 'Sno…
5           Haze  'Smoke', 'Fog', 'Mist', 'Shallow Fog', 'Haze /…
6           Rain  'Light Rain', 'Rain', 'Light Drizzle', 'Light …
7   Thunderstorm  'Thunderstorms and Rain', 'Light Thunderstorms…
8          Windy  'Fair / Windy','Cloudy / Windy','Partly Cloudy…
9           Hail  'Small Hail', 'Light Ice Pellets', 'Ice Pellet…
10       Thunder  'Thunder in the Vicinity', 'Thunder', 'Thunder…
11          Dust  'Dust Whirls', 'Sand / Dust Whirlwinds', 'Sand…
12       Tornado                                          'Tornado'
13           N/A                               'N/A Precipitation'

                      Key words
0                        'Fair'
1                       'Cloud'
2                       'Clear'
3                    'Overcast'
4        'Snow', 'Wintry', 'Sleet'
5   'Smoke', 'Fog', 'Mist', 'Haze'
6     'Rain', 'Drizzle', 'Showers'
7       'Thunderstorms', 'T-Storm'
8              'Windy', 'Squalls'
9            'Hail', 'Ice Pellets'
10                    'Thunder'
11                       'Dust'
12                    'Tornado'
13          'N/A Precipitation'
```

[242]:
```
# Transform the one-hot features, then delete them
onehot_df = pd.get_dummies(data_modelling_df['Wind_Direction'], prefix='Wind')
data_modelling_df = pd.concat([data_modelling_df, onehot_df], axis=1)
data_modelling_df.drop(one_hot_features, axis=1, inplace=True)
```

Label Encoding

[ ]:
```
# Select features that are suitable for Label Encoding
label_encoding_features = ['Amenity','Bump', 'Crossing', 'Give_Way',␣
↪'Junction', 'No_Exit', 'Railway','Roundabout', 'Station', 'Stop',␣
↪'Traffic_Calming', 'Traffic_Signal','Turning_Loop', 'Sunrise_Sunset']
```

```
# Label Encoding
for feature in label_encoding_features:
    data_modelling_df[feature] = LabelEncoder().
 ↪fit_transform(data_modelling_df[feature])
```

[244]:
```
data_modelling_df
```

[244]:
```
       Severity  Start_Lat  Start_Lng  Temperature(F)  Humidity(%)  \
0             2  42.144863 -72.599976            48.2        100.0
1             2  42.304436 -71.325317            48.0         89.0
2             3  42.428036 -71.258476            46.9         86.0
3             4  42.495930 -71.178238            46.0         89.0
4             3  42.525875 -70.972115            46.0        100.0
…           …         …         …              …           …
61991         2  42.445630 -71.256440            80.0         81.0
61992         2  42.383140 -71.076750            76.0         85.0
61993         2  42.566199 -70.922008            63.0         70.0
61994         2  42.097100 -71.058500            79.0         42.0
61995         2  42.456159 -71.751316            70.0         63.0

       Pressure(in)  Visibility(mi)  Wind_Speed(mph)  Amenity  Bump  …  \
0             29.87             3.0              3.5        0     0  …
1             29.96             5.0              5.8        0     0  …
2             30.01             5.0              6.9        0     0  …
3             30.01             3.0              8.1        0     0  …
4             29.97             6.0              8.1        0     0  …
…               …              …                …      …    …   …
61991         29.67            10.0              7.0        0     0  …
61992         29.82             1.0              3.0        0     0  …
61993         29.89            10.0              6.0        0     0  …
61994         29.91            10.0              8.0        0     0  …
61995         29.62            10.0              5.0        0     0  …

       Weather_Hail  Weather_Thunder  Weather_Dust  Weather_Tornado  Wind_C  \
0                 0                0             0                0   False
1                 0                0             0                0   False
2                 0                0             0                0   False
3                 0                0             0                0   False
4                 0                0             0                0   False
…              …                …             …                …     …
61991             0                0             0                0   False
61992             0                0             0                0   False
61993             0                0             0                0   False
61994             0                0             0                0   False
61995             0                0             0                0   False

       Wind_E  Wind_N  Wind_S  Wind_V  Wind_W
```

```
0        False   False   False    True   False
1         True   False   False   False   False
2         True   False   False   False   False
3         True   False   False   False   False
4        False    True   False   False   False
…        …      …      …      …      …
61991    False   False    True   False   False
61992    False   False    True   False   False
61993    False    True   False   False   False
61994    False   False   False   False    True
61995    False    True   False   False   False

[61471 rows x 45 columns]
```

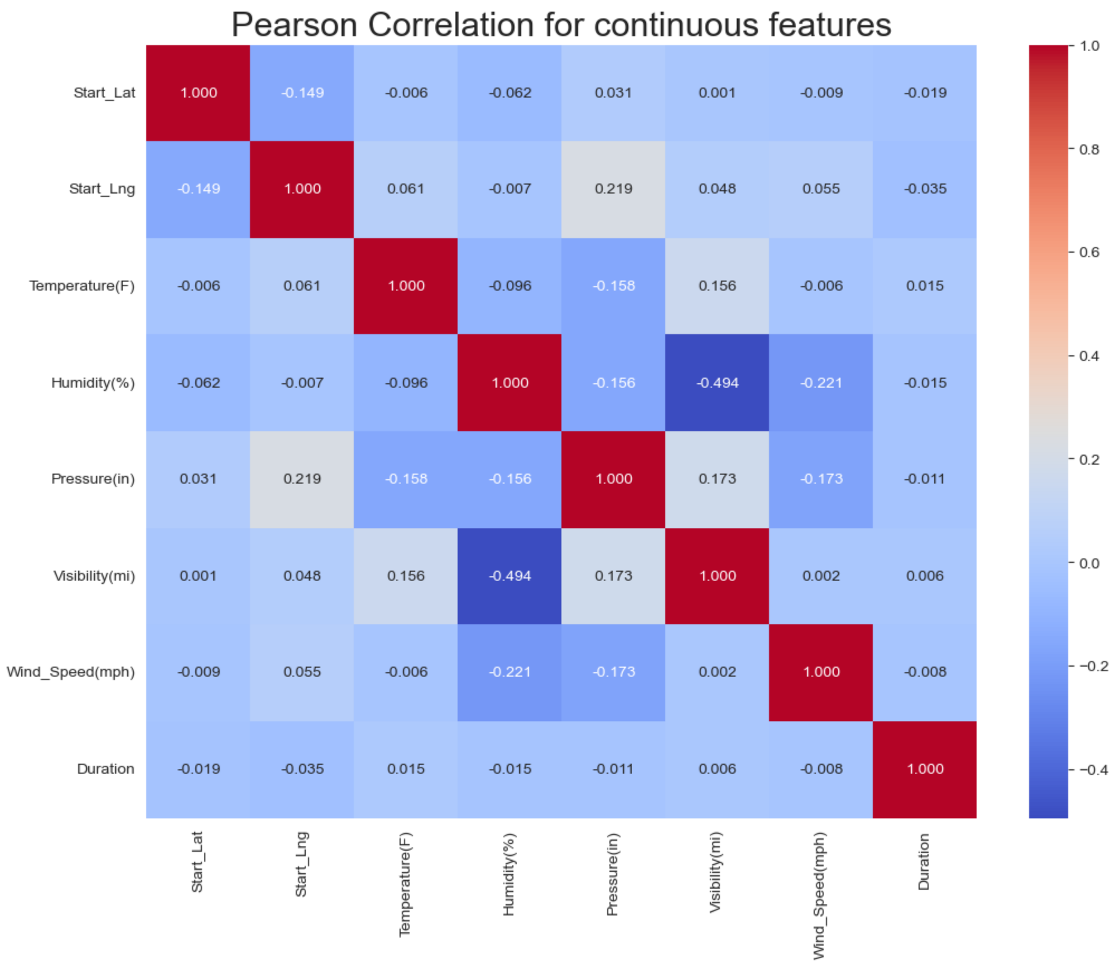
Correlation Analysis

[252]:
```python
def style_corr(v, props=''):
    return props if (v < -0.4 or v > 0.4) and v != 1 else None

continuous_feature = ['Start_Lat', 'Start_Lng', 'Temperature(F)','Humidity(%)',␣
↪'Pressure(in)', 'Visibility(mi)', 'Wind_Speed(mph)', 'Duration']
data_modelling_df[continuous_feature].corr().style.map(style_corr, props='color:
↪red;')
```

[252]:
```
<pandas.io.formats.style.Styler at 0x363eddd60>
```

[246]:
```python
# Show the heatmap
plt.figure(figsize=(12,9))
sns.heatmap(data_modelling_df[continuous_feature].corr(), cmap="coolwarm",␣
↪annot = True, fmt='.3f').set_title('Pearson Correlation for continuous␣
↪features', fontsize=22)
```

[246]:
```
Text(0.5, 1.0, 'Pearson Correlation for continuous features')
```



There are weak relationship between:

Pressure and Temperature

Pressure and Humidity;

Wind_Speed and Humidity;

Wind_Speed and Pressure;

Visibility and Humidity

[247]:
```
# Find the data with all the same value and drop
unique_counts = data_modelling_df.drop(continuous_feature, axis=1).
  ↪astype("object").describe().loc['unique']
feature_all_same = list(unique_counts[unique_counts == 1].index)
data_modelling_df.drop(feature_all_same, axis=1, inplace=True)
```

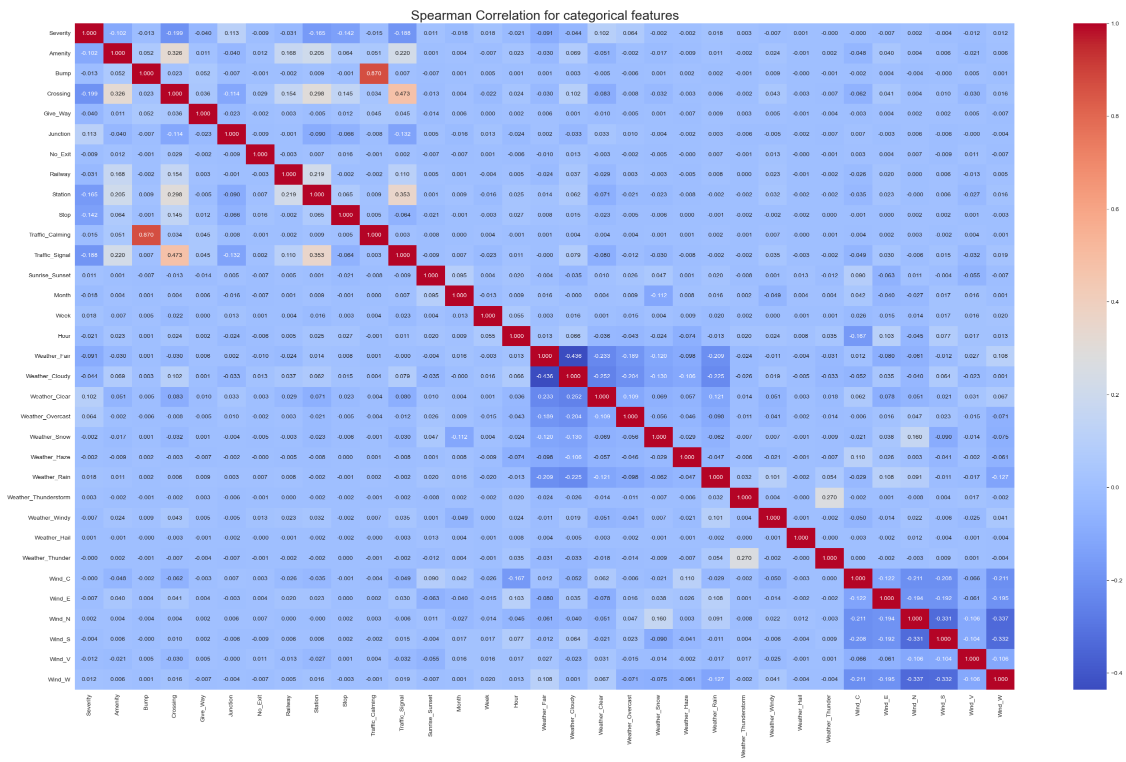
[253]:
```
# Display the correlation table for categorical features
```

```
data_modelling_df.drop(continuous_feature, axis=1).corr(method='spearman').
    ↪style.map(style_corr, props='color:red;')
```

[253]: <pandas.io.formats.style.Styler at 0x3150293a0>

[249]:
```
# Show the heatmap
plt.figure(figsize=(35,20))
sns.heatmap(data_modelling_df.drop(continuous_feature, axis=1).
    ↪corr(method='spearman'), cmap="coolwarm", annot = True, fmt='.3f').
    ↪set_title('Spearman Correlation for categorical features', fontsize=22)
```

[249]: Text(0.5, 1.0, 'Spearman Correlation for categorical features')



We can find Strong relationship:

Bump and Traffic_Calming

moderate relationship:

Crossing and Traffic_Signal;

Crossing and Amenity;

Crossing and station;

station and Traffic_Signal

Split Data

[255]:
```
# Define features (X) and target variable (y)
X = data_modelling_df.drop(columns=["Severity"])
y = data_modelling_df["Severity"]

# Split into training (70%) and temp (30%) using stratification
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

# Split temp set into validation (15%) and test (15%) using stratification
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=42, stratify=y_temp
)

# Print dataset distribution
print("Training set distribution:\n", y_train.value_counts(normalize=True))
print("\nValidation set distribution:\n", y_val.value_counts(normalize=True))
print("\nTest set distribution:\n", y_test.value_counts(normalize=True))
```

```
Training set distribution:
 Severity
2    0.664668
3    0.302726
1    0.024309
4    0.008297
Name: proportion, dtype: float64

Validation set distribution:
 Severity
2    0.664678
3    0.302679
1    0.024292
4    0.008351
Name: proportion, dtype: float64

Test set distribution:
 Severity
2    0.664678
3    0.302787
1    0.024292
4    0.008242
Name: proportion, dtype: float64
```

[251]:
```
# Plot class distributions
fig, axes = plt.subplots(1, 3, figsize=(15, 5))
```

```
sns.histplot(y_train, bins=4, ax=axes[0], kde=False, color="blue")
axes[0].set_title("Training Set Severity Distribution")

sns.histplot(y_val, bins=4, ax=axes[1], kde=False, color="green")
axes[1].set_title("Validation Set Severity Distribution")

sns.histplot(y_test, bins=4, ax=axes[2], kde=False, color="red")
axes[2].set_title("Test Set Severity Distribution")

plt.show()
```