severity_analysis_0_1

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- Development Env : Jupyter Lab
- Module : Severity Analysis and Forecasting
- Summary : This module will perform Severity Analysis using EDA .

[1463]:
```
import os
import warnings
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from pylab import rcParams
import statsmodels.api as sm
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX

from mpl_toolkits.mplot3d import Axes3D
from pandas.plotting import scatter_matrix
from IPython.display import Image
import pydotplus
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import preprocessing
from sklearn import svm
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix, mean_squared_error
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics
from sklearn import preprocessing
from sklearn.tree import export_graphviz
from sklearn.cluster import DBSCAN
from sklearn import metrics
from sklearn.datasets import make_blobs
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.ensemble import RandomForestRegressor
from sklearn.neural_network import MLPRegressor
```

```
from sklearn.datasets import make_regression
from fbprophet import Prophet
print("Loaded Successfully -- -- -- -- -- -- -- -- -- -- -- -- --")
```

```
Loaded Successfully -- -- -- -- -- -- -- -- -- -- -- -- --
```

Defining input/output directory

[1464]:
```
input_path = "../../data/raw/"
output_path = "../../data/pre_processing/"
image_path = "../../figures/"
```

Load dataset as Dataframe

[1465]:
```
df = pd.read_csv(input_path+"US_Accidents_June20.csv",␣
↪parse_dates=['Start_Time','End_Time'])
df.head()
df.tail()
```

[1465]:

	ID	Source	TMC	Severity	Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat	End_Lng	…
3513612	A-3513776	Bing	NaN	2	2019-08-23 18:03:25	2019-08-23 18:32:01	34.00248	-117.37936	33.99888	-117.37094	…
3513613	A-3513777	Bing	NaN	2	2019-08-23 19:11:30	2019-08-23 19:38:23	32.76696	-117.14806	32.76555	-117.15363	…
3513614	A-3513778	Bing	NaN	2	2019-08-23 19:00:21	2019-08-23 19:28:49	33.77545	-117.84779	33.77740	-117.85727	…
3513615	A-3513779	Bing	NaN	2	2019-08-23 19:00:21	2019-08-23 19:29:42	33.99246	-118.40302	33.98311	-118.39565	…
3513616	A-3513780	Bing	NaN	2	2019-08-23 18:52:06	2019-08-23 19:21:31	34.13393	-117.23092	34.13736	-117.23934	…

	Roundabout	Station	Stop	Traffic_Calming	Traffic_Signal	Turning_Loop	Sunrise_Sunset	Civil_Twilight	Nautical_Twilight	Astronomical_Twilight
3513612	False	False	False	False	False	False	Day	Day	Day	Day
3513613	False	False	False	False	False	False	Day	Day	Day	Day
3513614	False	False	False	False	False	False	Day	Day	Day	Day
3513615	False	False	False	False	False	False	Day	Day	Day	Day
3513616	False	False	False	False	False	False	Day	Day	Day	Day

```
3513612                  Day
3513613                  Day
3513614                  Day
3513615                  Day
3513616                  Day

[5 rows x 49 columns]
```

0.0.1 Check basic statistics

[1466]:
```
df.describe()
```

[1466]:
```
                TMC      Severity     Start_Lat     Start_Lng       End_Lat  \
count  2.478818e+06  3.513617e+06  3.513617e+06  3.513617e+06  1.034799e+06
mean   2.080226e+02  2.339929e+00  3.654195e+01 -9.579151e+01  3.755758e+01
std    2.076627e+01  5.521935e-01  4.883520e+00  1.736877e+01  4.861215e+00
min    2.000000e+02  1.000000e+00  2.455527e+01 -1.246238e+02  2.457011e+01
25%    2.010000e+02  2.000000e+00  3.363784e+01 -1.174418e+02  3.399477e+01
50%    2.010000e+02  2.000000e+00  3.591687e+01 -9.102601e+01  3.779736e+01
75%    2.010000e+02  3.000000e+00  4.032217e+01 -8.093299e+01  4.105139e+01
max    4.060000e+02  4.000000e+00  4.900220e+01 -6.711317e+01  4.907500e+01

            End_Lng  Distance(mi)        Number  Temperature(F)  \
count  1.034799e+06  3.513617e+06  1.250753e+06    3.447885e+06
mean  -1.004560e+02  2.816167e-01  5.975383e+03    6.193512e+01
std    1.852879e+01  1.550134e+00  1.496624e+04    1.862106e+01
min   -1.244978e+02  0.000000e+00  0.000000e+00   -8.900000e+01
25%   -1.183440e+02  0.000000e+00  8.640000e+02    5.000000e+01
50%   -9.703438e+01  0.000000e+00  2.798000e+03    6.400000e+01
75%   -8.210168e+01  1.000000e-02  7.098000e+03    7.590000e+01
max   -6.710924e+01  3.336300e+02  9.999997e+06    1.706000e+02

       Wind_Chill(F)   Humidity(%)  Pressure(in)  Visibility(mi)  \
count   1.645368e+06  3.443930e+06  3.457735e+06    3.437761e+06
mean    5.355730e+01  6.511427e+01  2.974463e+01    9.122644e+00
std     2.377334e+01  2.275558e+01  8.319758e-01    2.885879e+00
min    -8.900000e+01  1.000000e+00  0.000000e+00    0.000000e+00
25%     3.570000e+01  4.800000e+01  2.973000e+01    1.000000e+01
50%     5.700000e+01  6.700000e+01  2.995000e+01    1.000000e+01
75%     7.200000e+01  8.400000e+01  3.009000e+01    1.000000e+01
max     1.150000e+02  1.000000e+02  5.774000e+01    1.400000e+02

       Wind_Speed(mph)  Precipitation(in)
count     3.059008e+06       1.487743e+06
mean      8.219025e+00       1.598256e-02
std       5.262847e+00       1.928262e-01
min       0.000000e+00       0.000000e+00
```

```
25%       5.000000e+00       0.000000e+00
50%       7.000000e+00       0.000000e+00
75%       1.150000e+01       0.000000e+00
max       9.840000e+02       2.500000e+01
```

0.0.2 Check Datatype of the columns.

[1467]:
```
df.dtypes
```

[1467]:
```
ID                          object
Source                      object
TMC                        float64
Severity                     int64
Start_Time          datetime64[ns]
End_Time            datetime64[ns]
Start_Lat                  float64
Start_Lng                  float64
End_Lat                    float64
End_Lng                    float64
Distance(mi)               float64
Description                 object
Number                     float64
Street                      object
Side                        object
City                        object
County                      object
State                       object
Zipcode                     object
Country                     object
Timezone                    object
Airport_Code                object
Weather_Timestamp           object
Temperature(F)             float64
Wind_Chill(F)              float64
Humidity(%)                float64
Pressure(in)               float64
Visibility(mi)             float64
Wind_Direction              object
Wind_Speed(mph)            float64
Precipitation(in)          float64
Weather_Condition           object
Amenity                       bool
Bump                          bool
Crossing                      bool
Give_Way                      bool
Junction                      bool
No_Exit                       bool
```

```
Railway                    bool
Roundabout                 bool
Station                    bool
Stop                       bool
Traffic_Calming            bool
Traffic_Signal             bool
Turning_Loop               bool
Sunrise_Sunset           object
Civil_Twilight           object
Nautical_Twilight        object
Astronomical_Twilight    object
dtype: object
```

0.0.3 Check NaN values

[1468]:
```
df.isna().sum()
```

[1468]:
```
ID                         0
Source                     0
TMC                  1034799
Severity                   0
Start_Time                 0
End_Time                   0
Start_Lat                  0
Start_Lng                  0
End_Lat                2478818
End_Lng                2478818
Distance(mi)               0
Description                1
Number                 2262864
Street                     0
Side                       0
City                     112
County                     0
State                      0
Zipcode                 1069
Country                    0
Timezone                3880
Airport_Code            6758
Weather_Timestamp      43323
Temperature(F)         65732
Wind_Chill(F)        1868249
Humidity(%)            69687
Pressure(in)           55882
Visibility(mi)         75856
Wind_Direction         58874
Wind_Speed(mph)       454609
```

```
Precipitation(in)        2025874
Weather_Condition          76138
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               115
Civil_Twilight               115
Nautical_Twilight            115
Astronomical_Twilight        115
dtype: int64
```

- The severity of the accident, a number between 1 and 4, where 1 indicates the least impact on traffic (i.e., short delay as a result of the accident) and 4 indicates a significant impact on traffic (i.e., long delay).

[1469]:
```
columns = ['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']
```

[1470]:
```
def bar_plot (xs, ys, df, fx, fy, title=''):
    fig, ax = plt.subplots(figsize = (fx, fy))
    sns.set_context("paper")
    bar = sns.barplot(x = xs, y = ys, data = df)
    bar.set_title(title)
    plt.savefig(f'../../figures/{title}.jpeg')
    plt.show()
```

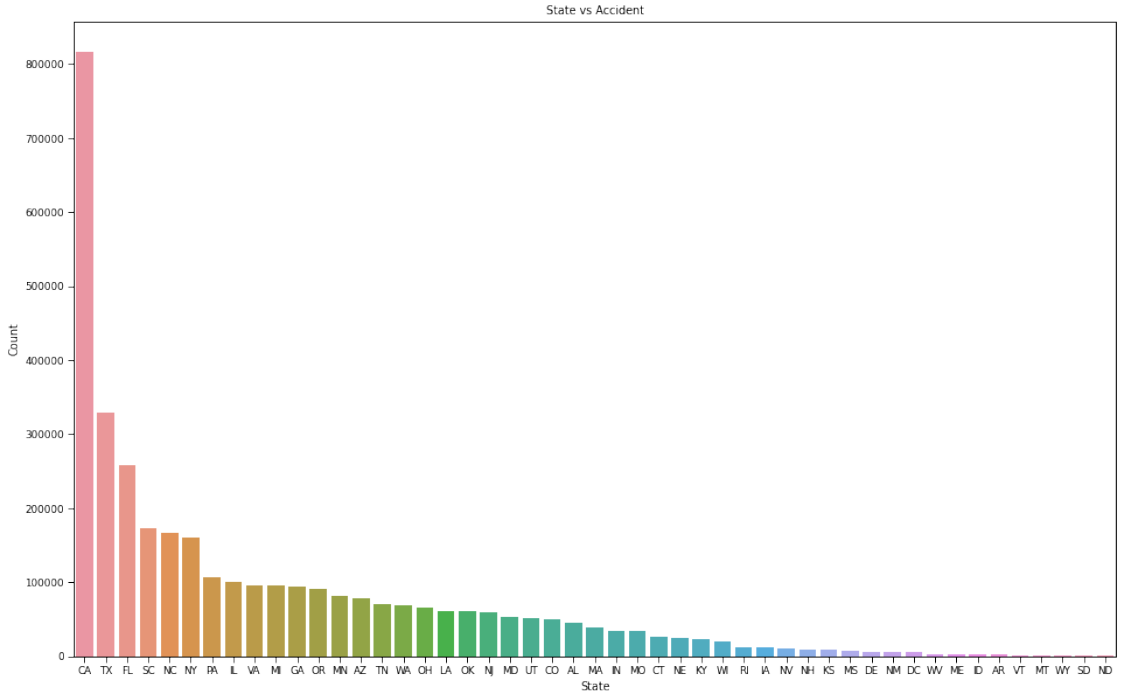
0.1 Visualization

We will visualize the plots based on different features of the dataset. Later, we will analyze the severity and severity rate for different features.

State vs Accident

[1471]:
```
df_state = df.groupby('State')['ID'].agg(len).sort_values(ascending = False).
↪to_frame().reset_index().rename(columns = {'ID': 'Count'})
```

[1472]:
```
bar_plot('State', 'Count', df_state, 16, 10, 'State vs Accident')
```

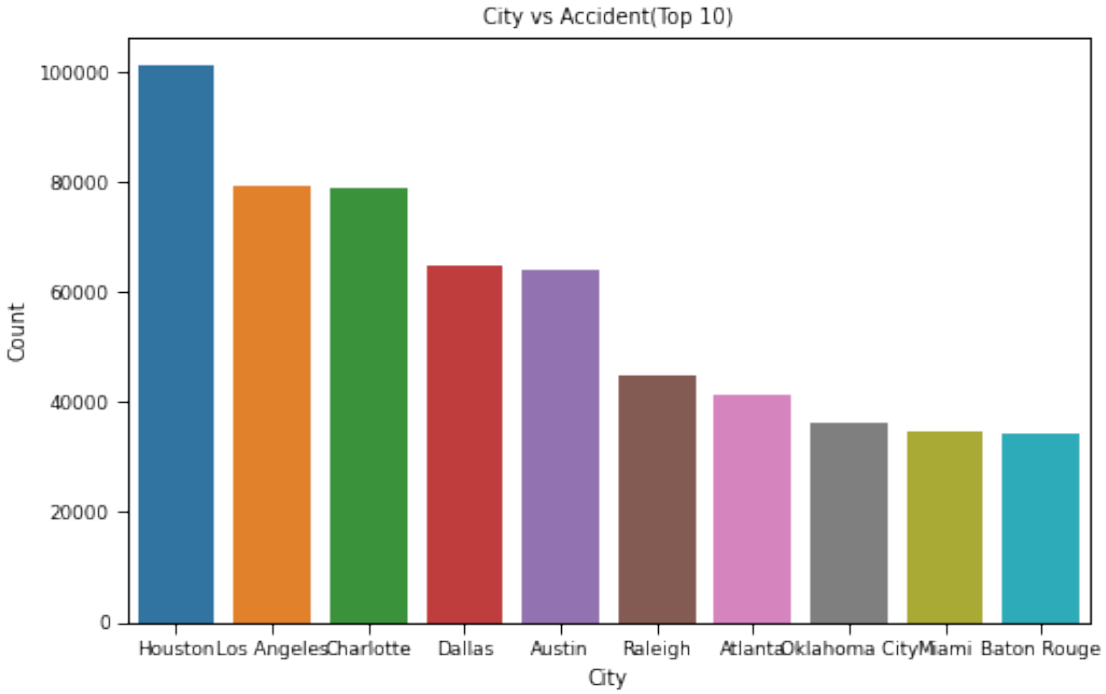


- The accident is higher in CA while it's lower in ND.

City vs Accident

[1473]:
```
df_city = df.groupby('City')['ID'].agg(len).sort_values(ascending = False).
↪to_frame().reset_index().rename(columns = {'ID': 'Count'})
```

[1474]:
```
bar_plot('City', 'Count', df_city[:10], 8, 5, 'City vs Accident(Top 10)')
```

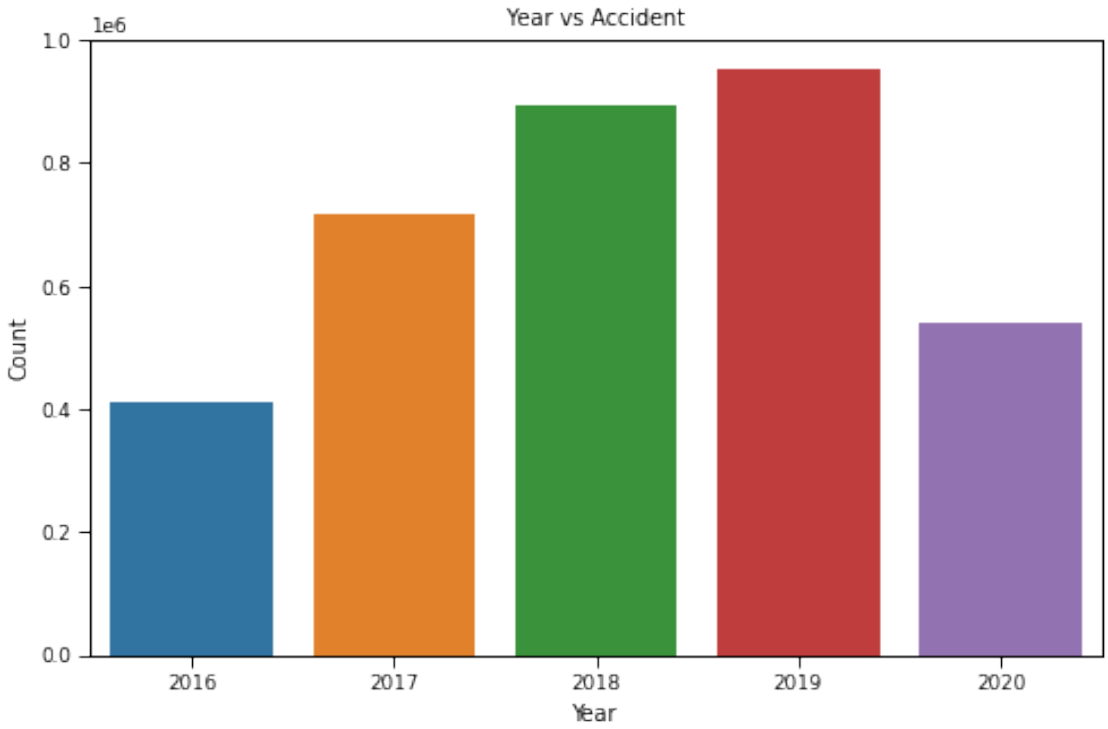


- Houston has more accident.
- The accident is higher in bigger cities.

0.1.1 Year vs Accident

[1475]:
```
df['Year'] = df.Start_Time.dt.year
df_year = df.groupby('Year')['ID'].agg(len).sort_values(ascending = False).
 ↪to_frame().reset_index().rename(columns = {'ID': 'Count'})
```

[1476]:
```
bar_plot('Year', 'Count', df_year, 8, 5, 'Year vs Accident')
```

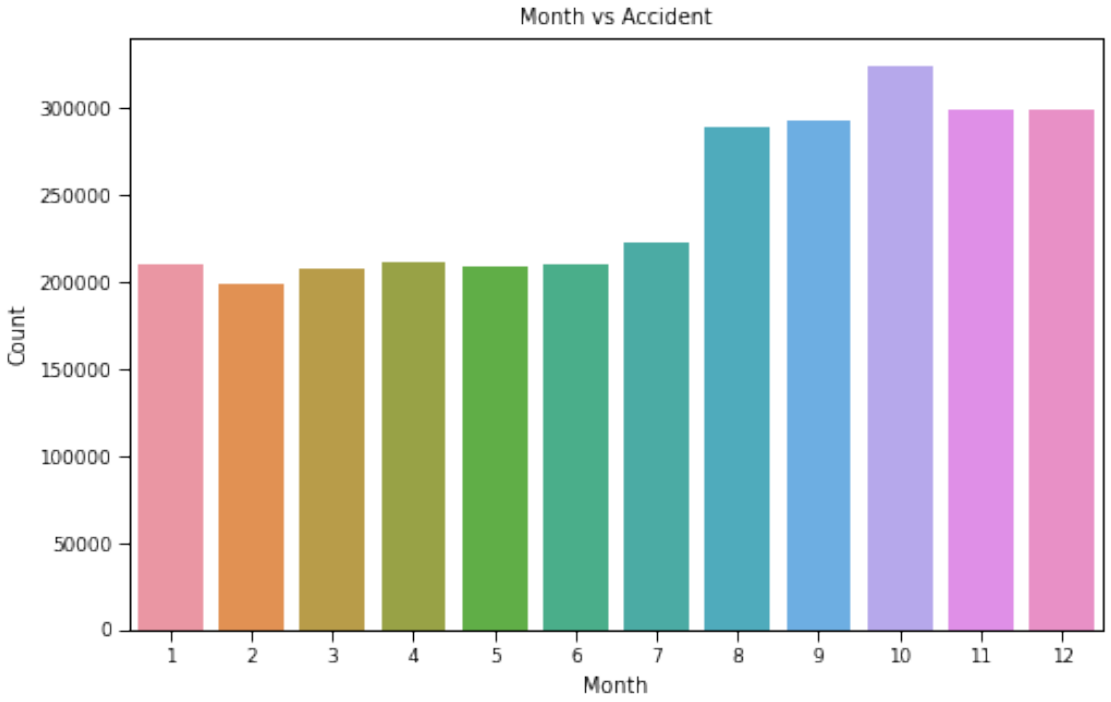


- The accident number increased upto 2019.
- The reason for less number of accident is because of the data which is limited to June, 2020.

0.1.2 Month vs Accident

[1477]:
```
df_lt_2020 = df[df['Year'] < 2020]
df_lt_2020['Month'] = df_lt_2020.Start_Time.dt.month
df_month = df_lt_2020.groupby('Month')['ID'].agg(len).sort_values(ascending =␣
↪False).to_frame().reset_index().rename(columns = {'ID': 'Count'})
```

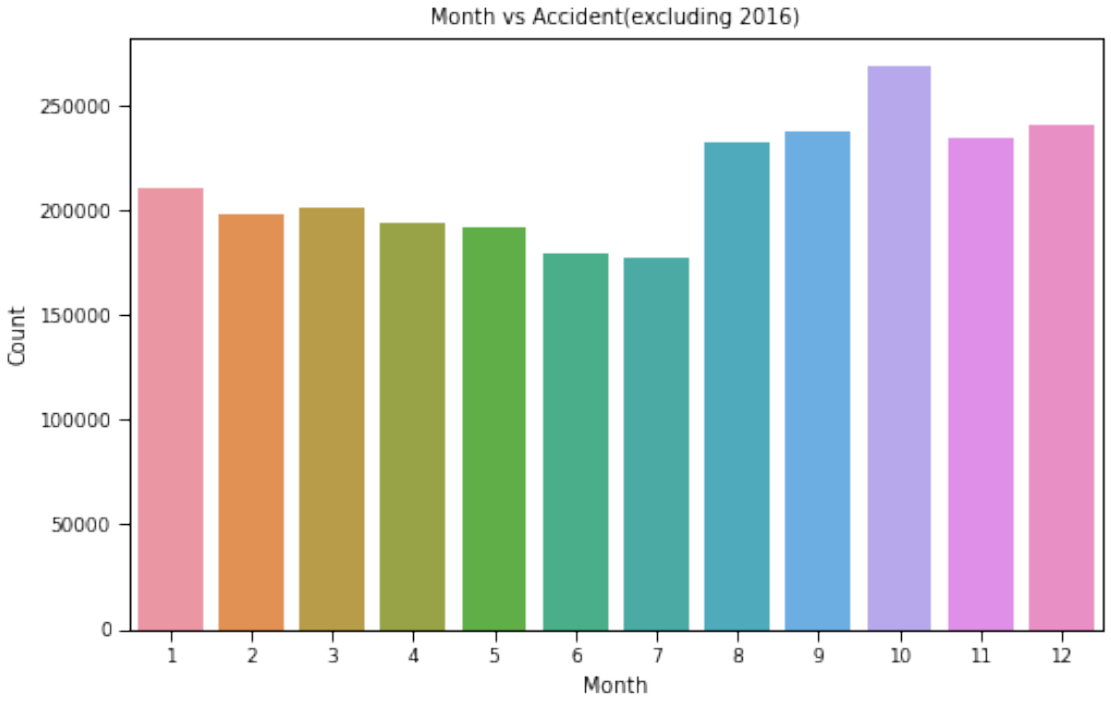
[1478]:
```
bar_plot('Month', 'Count', df_month, 8, 5, 'Month vs Accident')
```



- The number of accident are higher from August to December.
- Let's see by excluding data from 2016 as the numbers are very low for first six month.

[1479]:
```
df_16_19 = df[df['Year'] < 2020]
df_16_19 = df_16_19[df_16_19['Year'] > 2016]
df_16_19['Month'] = df_16_19.Start_Time.dt.month
df_month_1619 = df_16_19.groupby('Month')['ID'].agg(len).sort_values(ascending␣
↪= False).to_frame().reset_index().rename(columns = {'ID': 'Count'})
```

[1480]:
```
bar_plot('Month', 'Count', df_month_1619, 8, 5, 'Month vs Accident(excluding␣
↪2016)')
```

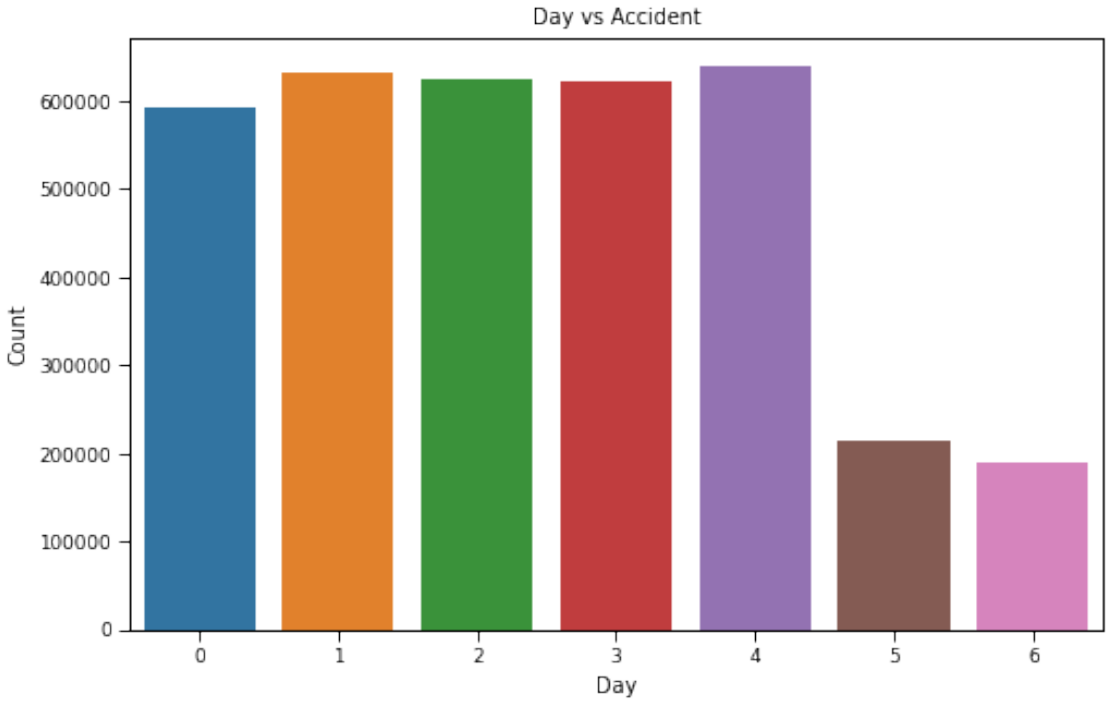


- It had slight effect for first five month.

0.1.3 Day vs Accident

[1481]:
```
df['Day'] = df.Start_Time.dt.weekday
df_day = df.groupby('Day')['ID'].agg(len).sort_values(ascending = False).
↪to_frame().reset_index().rename(columns = {'ID': 'Count'})
```

[1482]:
```
bar_plot('Day', 'Count', df_day, 8, 5, 'Day vs Accident')
```

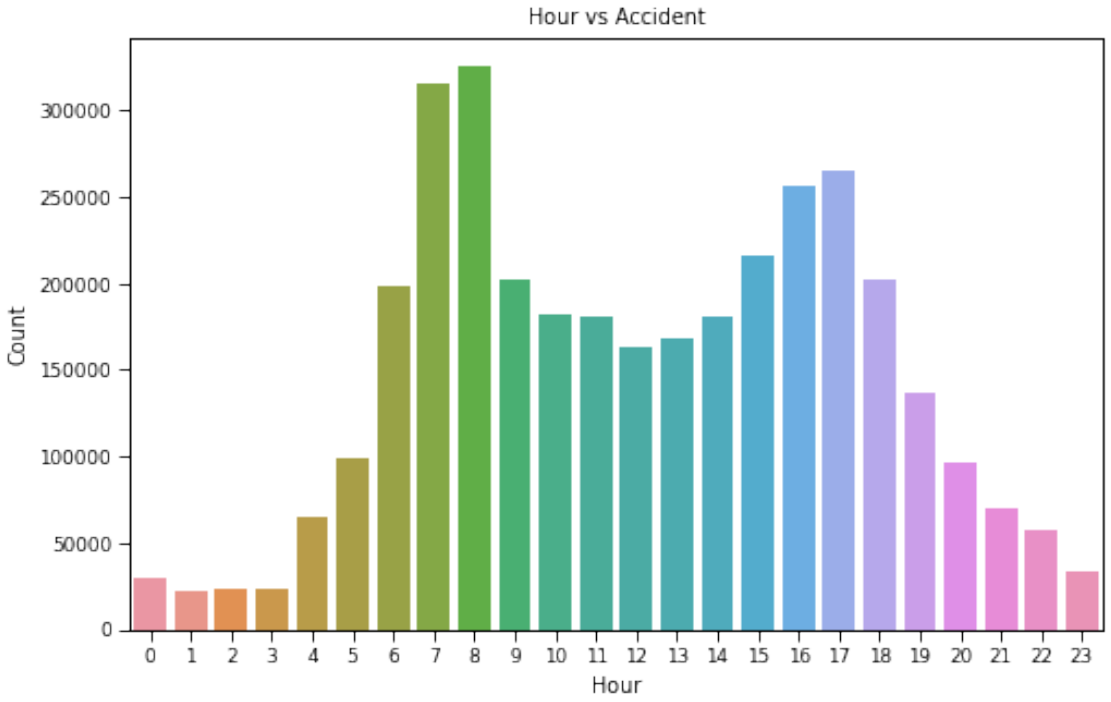


- The accident occurs mostly in weekdays and is highest on Friday.

0.2 Hour vs Accident

[1483]:
```
df['Hour'] = df.Start_Time.dt.hour
df_hour = df.groupby('Hour')['ID'].agg(len).to_frame().reset_index().
↪rename(columns = {'ID': 'Count'})
```

[1484]:
```
bar_plot('Hour', 'Count', df_hour, 8, 5, 'Hour vs Accident')
```



- The number of accident reported were higher at 6:00 am and 7:00 am and 4:00pm and 5:00 pm .
- It started decreasing after 5 and was low from 1:00 am to 3:00 am.

0.3 Length of Accident

[1485]:
```
df['Length'] = (df.End_Time - df.Start_Time)
data = [df["State"], df["Length"]]
headers = ["State", "Length"]
df_length = pd.concat(data, axis=1, keys=headers)
```

[1486]:
```
print('minimum length\n', df_length.min())
print('maximum length\n', df_length.max())
```

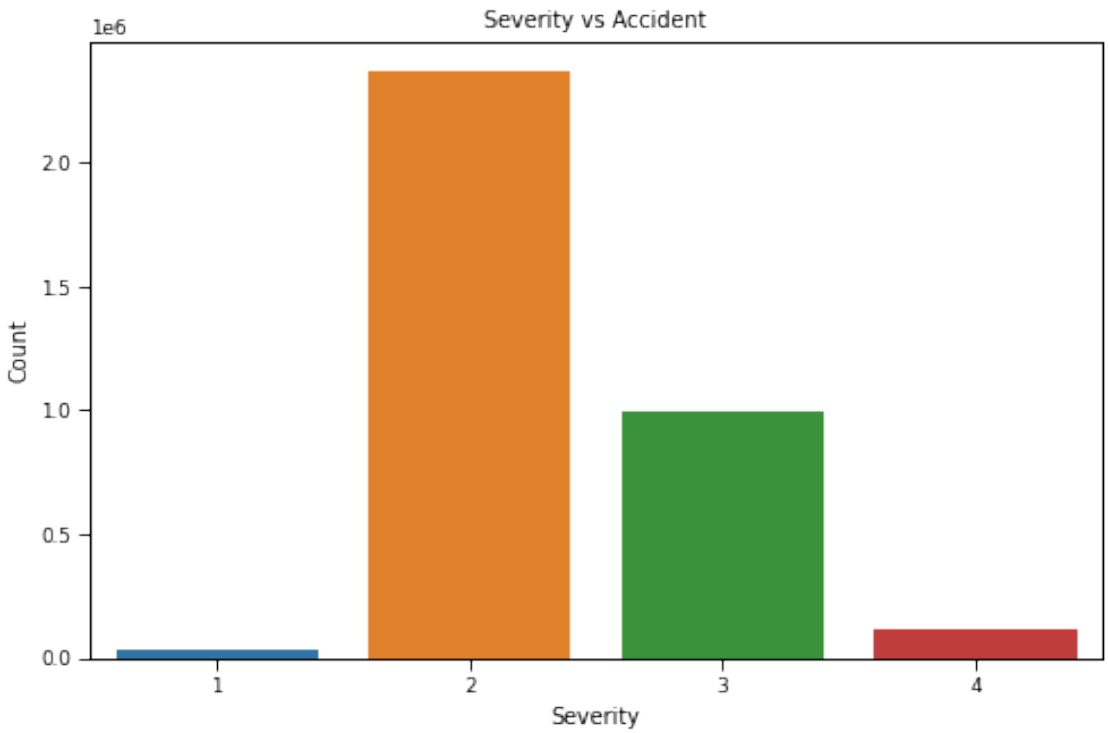
```
minimum length
 State                    AL
Length    -1 days +23:25:55
dtype: object
maximum length
 State                    WY
Length    987 days 11:15:29
dtype: object
```

- The minimimum time affected by the accident is negative while the maximum time is 987 days. The data should be anamolous.

0.4 Severity of Accident

[1487]:
```
df_severity = df.groupby('Severity')['ID'].agg(len).to_frame().reset_index().
↪rename(columns = {'ID': 'Count'})
```

[1488]:
```
bar_plot('Severity', 'Count', df_severity, 8, 5, 'Severity vs Accident')
```

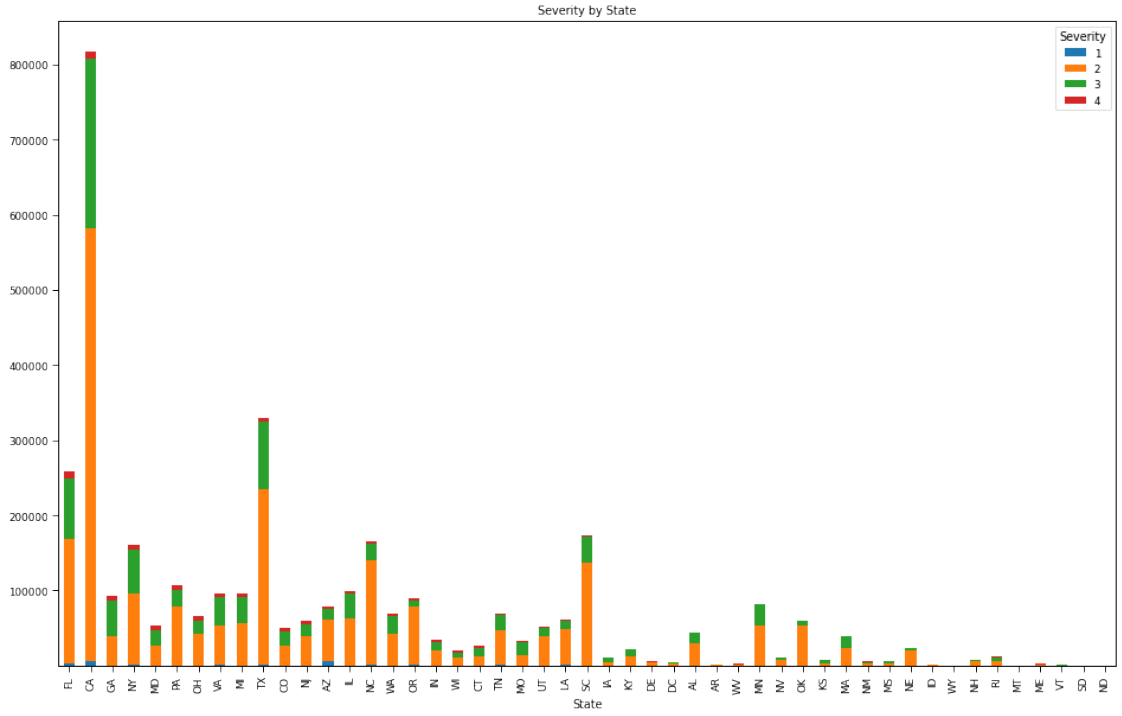


- Most of the accident reported were neither highly severe nor less.

[1489]:
```
def rate_df (df_st):
    df_rate = df_st.reset_index()
    index_name = df_st.index.name
    df_rate = df_rate.set_index(index_name)
    df_rate = df_rate.div(df_rate.sum(axis=1), axis=0)
    return df_rate
```

0.4.1 Severity By State

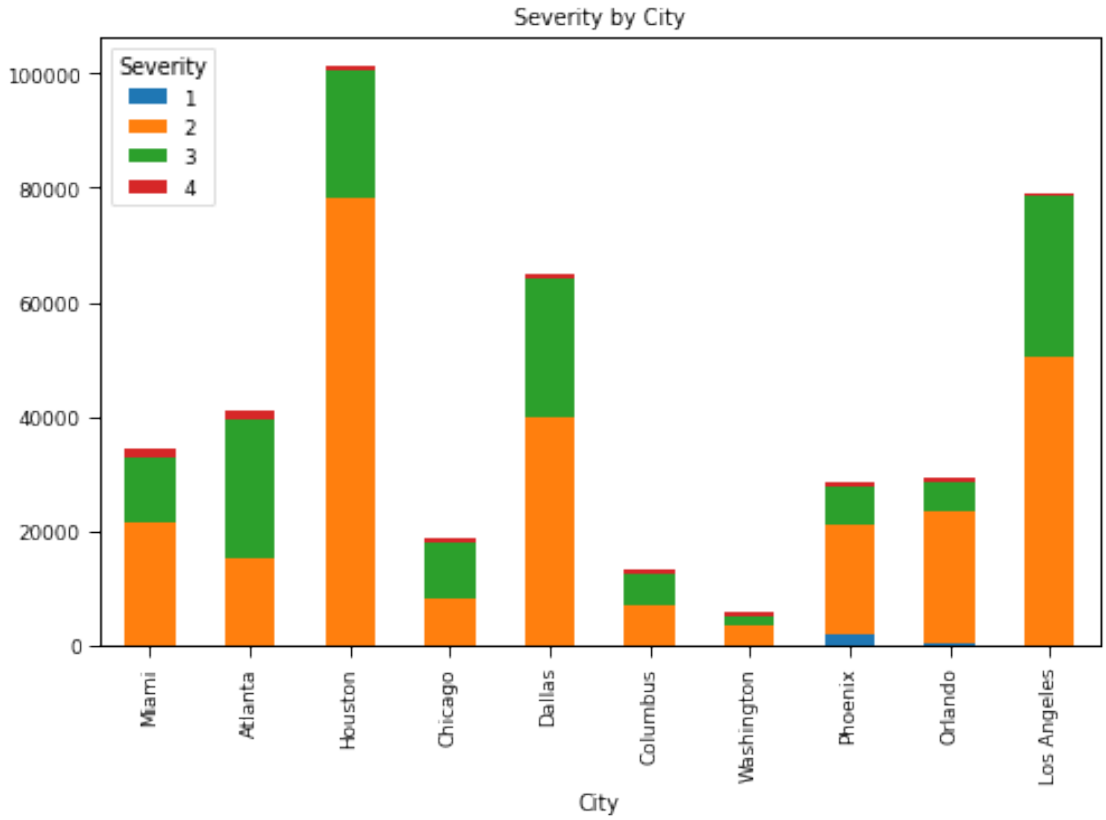
[1490]:
```
df_severe_state = df.groupby(['Severity','State']).size().reset_index().pivot(\
    columns='Severity', index='State', values=0)
df_severe_state = df_severe_state.sort_values(by=[4], ascending = False)
df_severe_state.plot(kind='bar', stacked=True, title='Severity by State',␣
↪figsize=(16,10)).get_figure().savefig(f'{image_path}Severity by State.jpeg')
```



- Highly severe accident were reported in Florida.
- AZ, CA, FL are the states with less severe accident.
- Most of the accident are of level 2.

0.4.2 Severity vs City (Top 10)

[1491]:
```
df_severe_city = df.groupby(['Severity','City']).size().reset_index().pivot(\
    columns='Severity', index='City', values=0)
df_severe_city = df_severe_city.sort_values(by=[4], ascending = False)
df_severe_city[:10].plot(kind='bar', stacked=True, title='Severity by City',␣
 ↪figsize=(8,5)).get_figure().savefig(f'{image_path}Severity by City.jpeg')
```



- The highest number of highly severe accident occurred in Maimi. Among these Washington has lowest number of accident and stays on 6th position for highly severe accident.

0.4.3 Severity vs Wind Direction

First, I will change the column values that are equivalent.

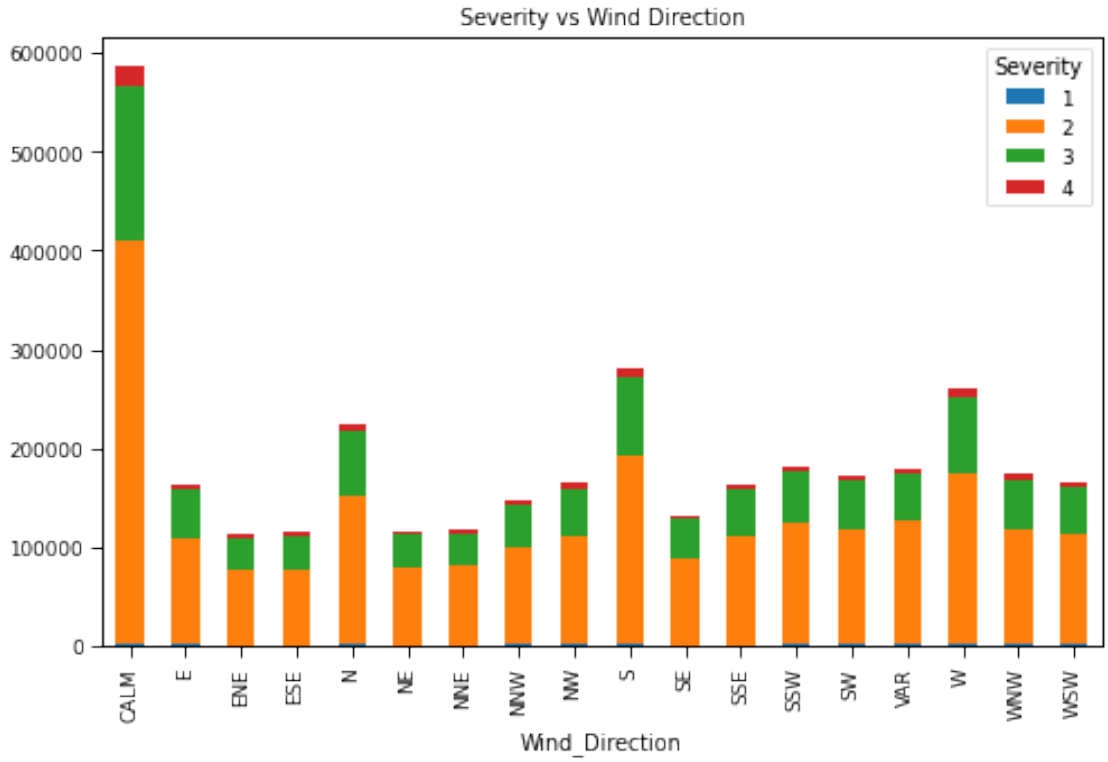
[1492]:
```
print(df.Wind_Direction.unique())
df.loc[(df.Wind_Direction == 'Calm'),'Wind_Direction']='CALM'
df.loc[(df.Wind_Direction == 'East'),'Wind_Direction']='E'
df.loc[(df.Wind_Direction == 'West'),'Wind_Direction']='W'
df.loc[(df.Wind_Direction == 'North'),'Wind_Direction']='N'
df.loc[(df.Wind_Direction == 'South'),'Wind_Direction']='S'
df.loc[(df.Wind_Direction == 'Variable'),'Wind_Direction']='VAR'
df.Wind_Direction.unique()
```

```
['Calm' 'SW' 'SSW' 'WSW' 'WNW' 'NW' 'West' 'NNW' 'NNE' 'South' 'North'
 'Variable' 'SE' 'SSE' 'ESE' 'East' 'NE' 'ENE' 'E' 'W' nan 'S' 'VAR'
 'CALM' 'N']
```

[1492]:
```
array(['CALM', 'SW', 'SSW', 'WSW', 'WNW', 'NW', 'W', 'NNW', 'NNE', 'S',
       'N', 'VAR', 'SE', 'SSE', 'ESE', 'E', 'NE', 'ENE', nan],
```

```
      dtype=object)
```

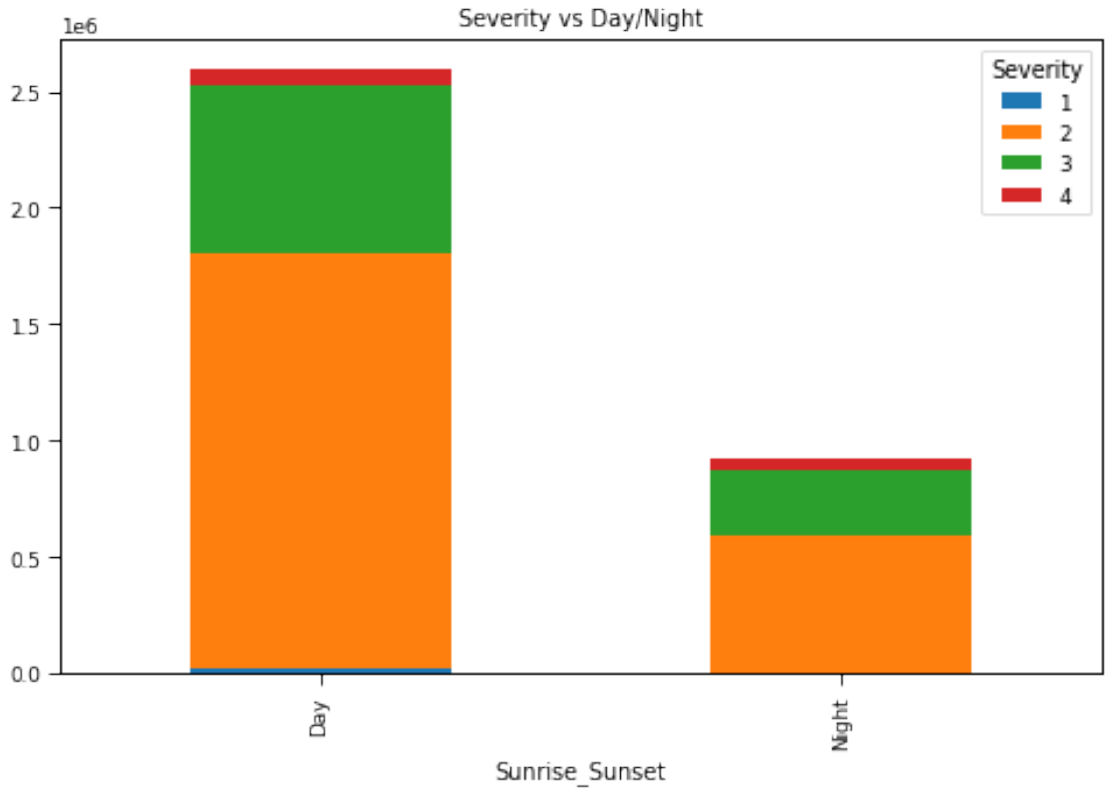
[1493]:
```
df_severe_wind = df.groupby(['Severity','Wind_Direction']).size().reset_index().
↪pivot(\
    columns='Severity', index='Wind_Direction', values=0)
df_severe_wind.plot(kind='bar', stacked=True, title='Severity vs Wind␣
↪Direction', figsize=(8,5)).get_figure().savefig(f'{image_path}Severity vs␣
↪Wind Direction.jpeg')
```



- Severity is high when the wind condition is calm and so is the number of accident.

0.4.4 Severity vs Day/Night

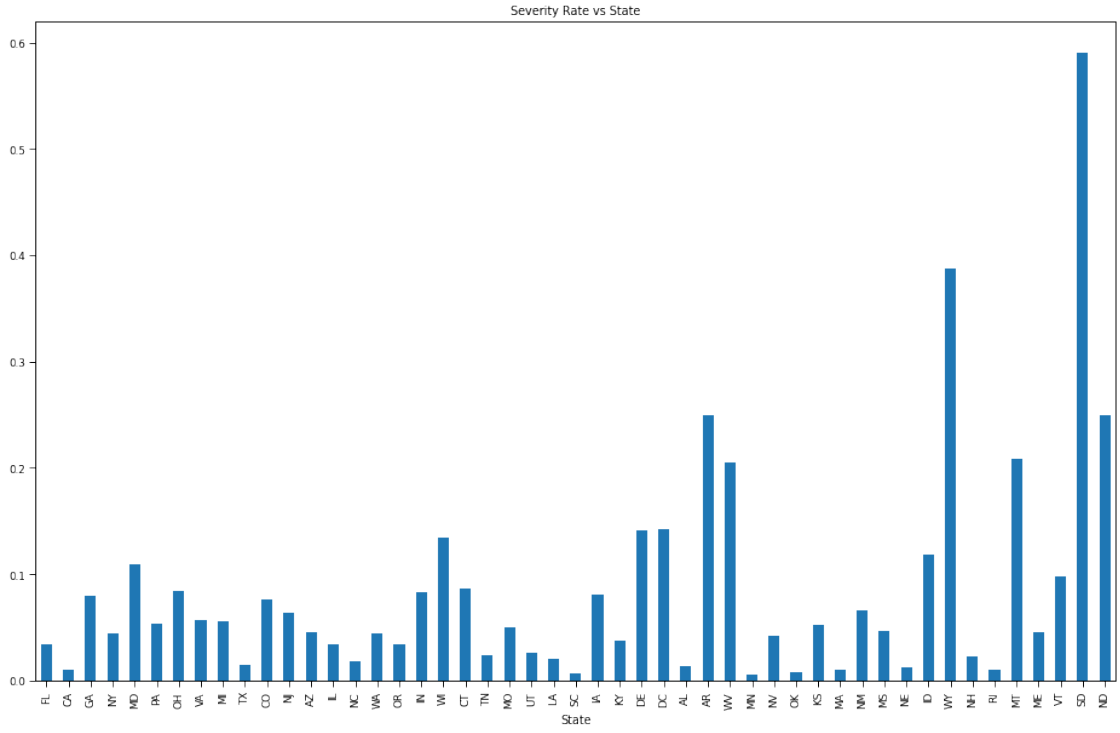
[1494]:
```
df_severe_day = df.groupby(['Severity','Sunrise_Sunset']).size().reset_index().
↪pivot(\
    columns='Severity', index='Sunrise_Sunset', values=0)
df_severe_day.plot(kind='bar', stacked=True, title='Severity vs Day/Night',␣
↪figsize=(8,5)).get_figure().savefig(f'{image_path}Severity vs Day_Night.
↪jpeg')
```



- Slightly more severe accident occuring in day.
- The number of highly severe accident is mostly proportion to the number of accident. So, it will be better to compare the severity rate instead of just count of severity.

0.4.5 Severity Rate By State

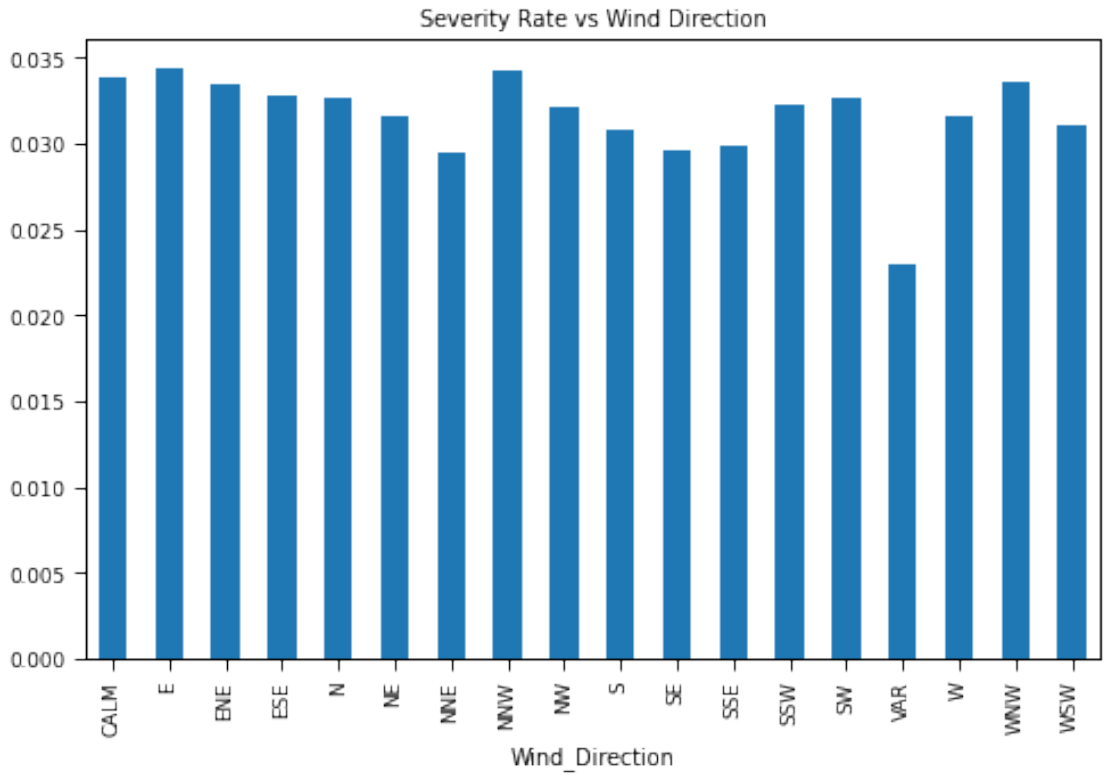
[1495]:
```
df_severity_state_rate = rate_df(df_severe_state)
df_severity_state_rate[4].plot(kind='bar', title='Severity Rate vs State',␣
↪figsize=(16,10)).get_figure().savefig(f'{image_path}Severity Rate vs State.
↪jpeg')
```



- The accident occured with highest severity rate in South Dakota.
- Lowest rate was in Minnesota

0.4.6 Severity Rate vs Wind Direction

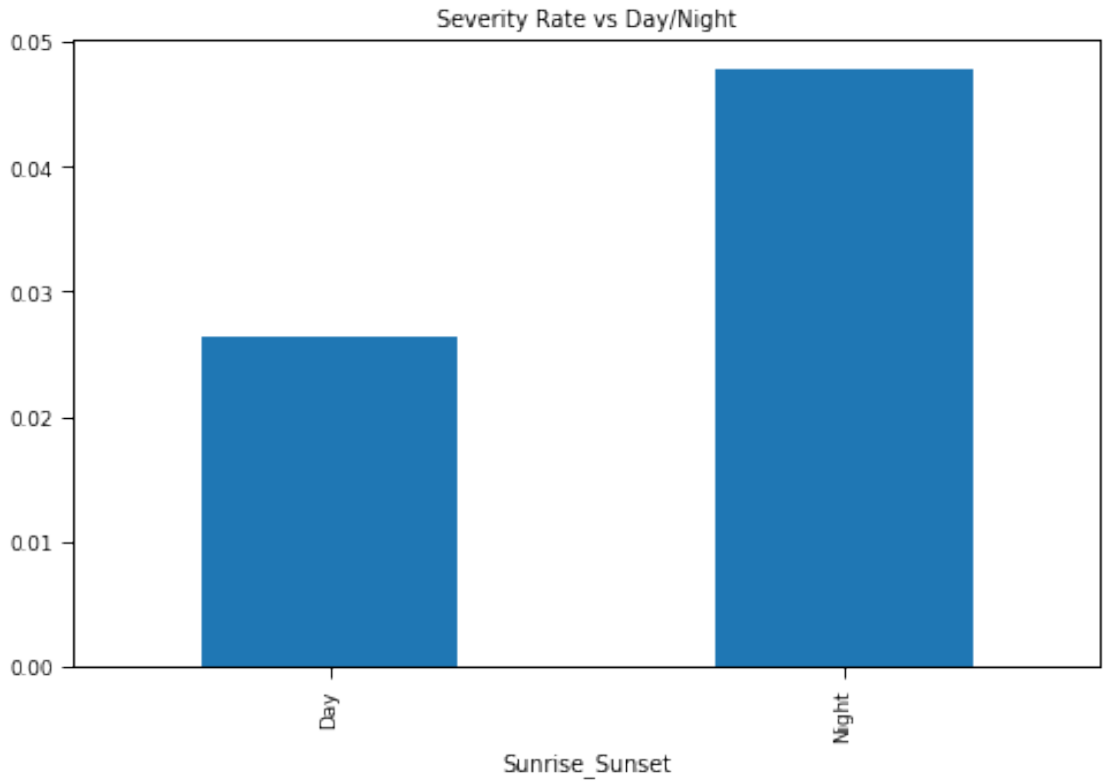
[1496]:
```
df_severity_wind_rate = rate_df(df_severe_wind)
df_severity_wind_rate[4].plot(kind='bar', title='Severity Rate vs Wind␣
↪Direction', figsize=(8,5)).get_figure().savefig(f'{image_path}Severity Rate␣
↪vs Wind Direction.jpeg')
```



- The rate is almost greater than 3% for each wind direction except for variable.

0.4.7 Severity Rate vs Day/Night

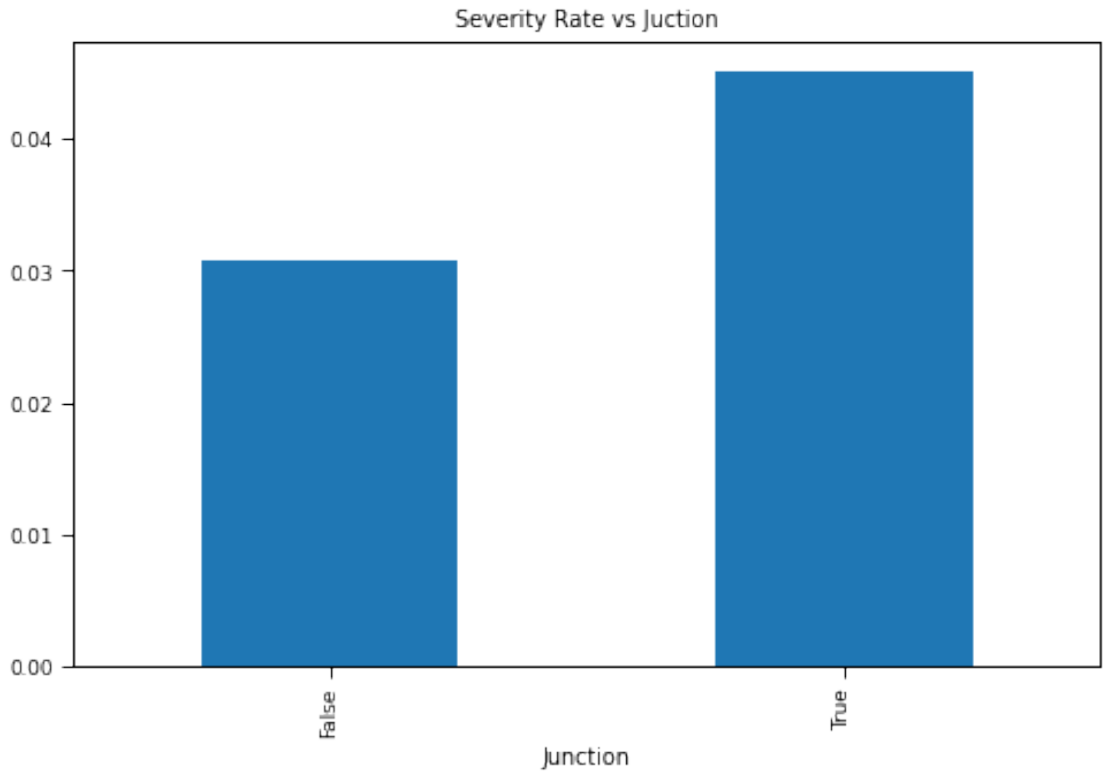
[1497]:
```
df_severity_day_rate = rate_df(df_severe_day)
df_severity_day_rate[4].plot(kind='bar', title='Severity Rate vs Day/Night',␣
↪figsize=(8,5)).get_figure().savefig(f'{image_path}Severity Rate vs Day_Night.
↪jpeg')
```



- We can see that the rate of severity is high during night.

0.4.8 Severity Rate vs Juction

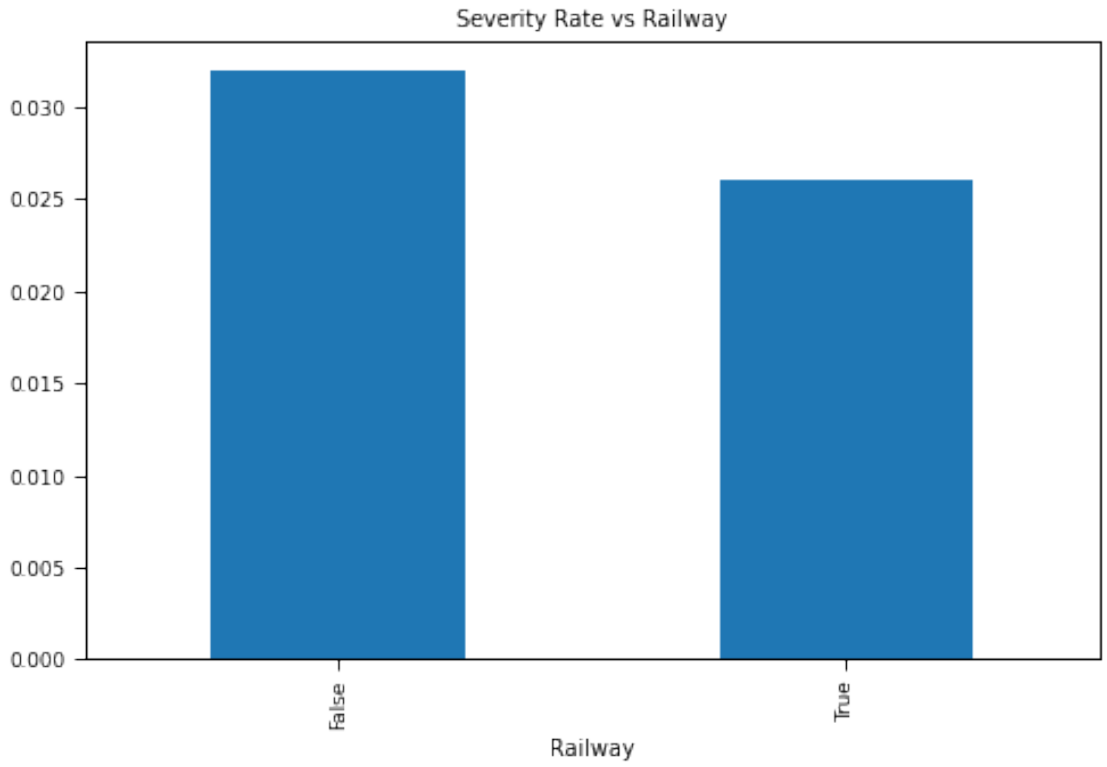
[1498]:
```
df_severe_juction = df.groupby(['Severity','Junction']).size().reset_index().
↪pivot(\
    columns='Severity', index='Junction', values=0)
df_severe_juction_rate = rate_df(df_severe_juction)
df_severe_juction_rate[4].plot(kind='bar', title='Severity Rate vs Juction',␣
↪figsize=(8,5)).get_figure().savefig(f'{image_path}Severity Rate vs Juction.
↪jpeg')
```



- As expected, it is high in Jucntion.

Severity Rate vs Railway

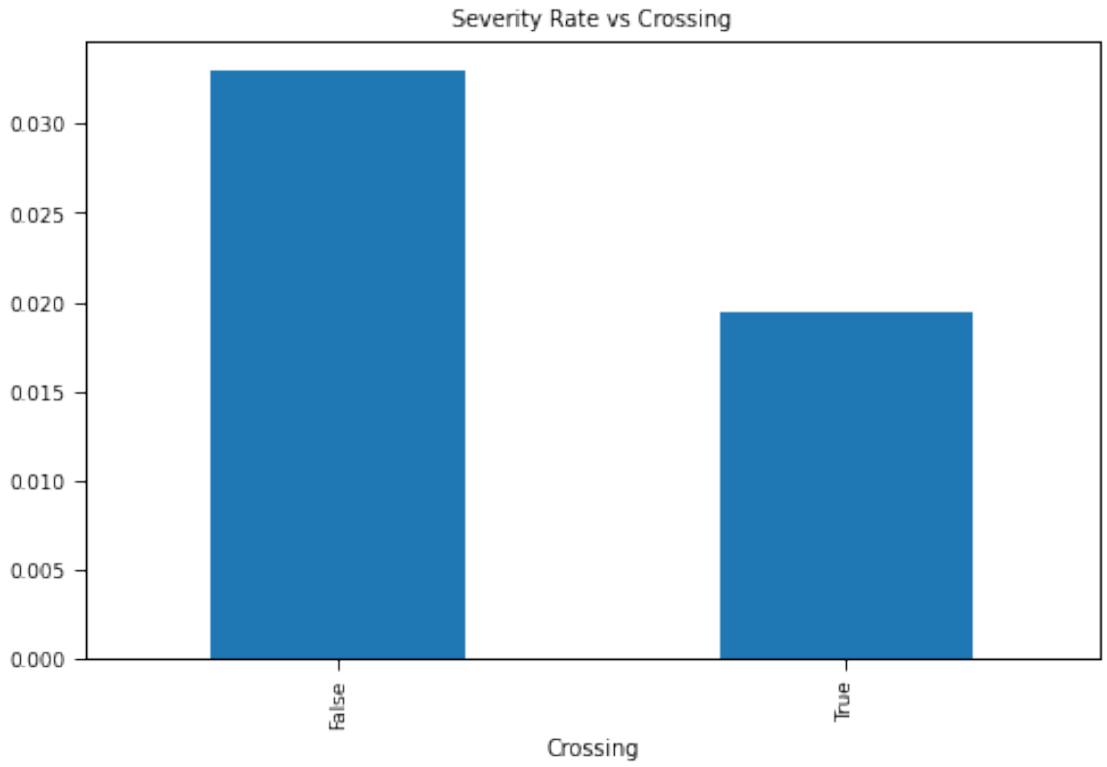
[1499]:
```
df_severe_railroad = df.groupby(['Severity','Railway']).size().reset_index().
↪pivot(\
    columns='Severity', index='Railway', values=0)
df_severe_railroad_rate = rate_df(df_severe_railroad)
df_severe_railroad_rate[4].plot(kind='bar', title='Severity Rate vs Railway',␣
↪figsize=(8,5)).get_figure().savefig(f'{image_path}Severity Rate vs Railway.
↪jpeg')
```



- The severetiy rate is low in railway.

Severity Rate vs Crossing

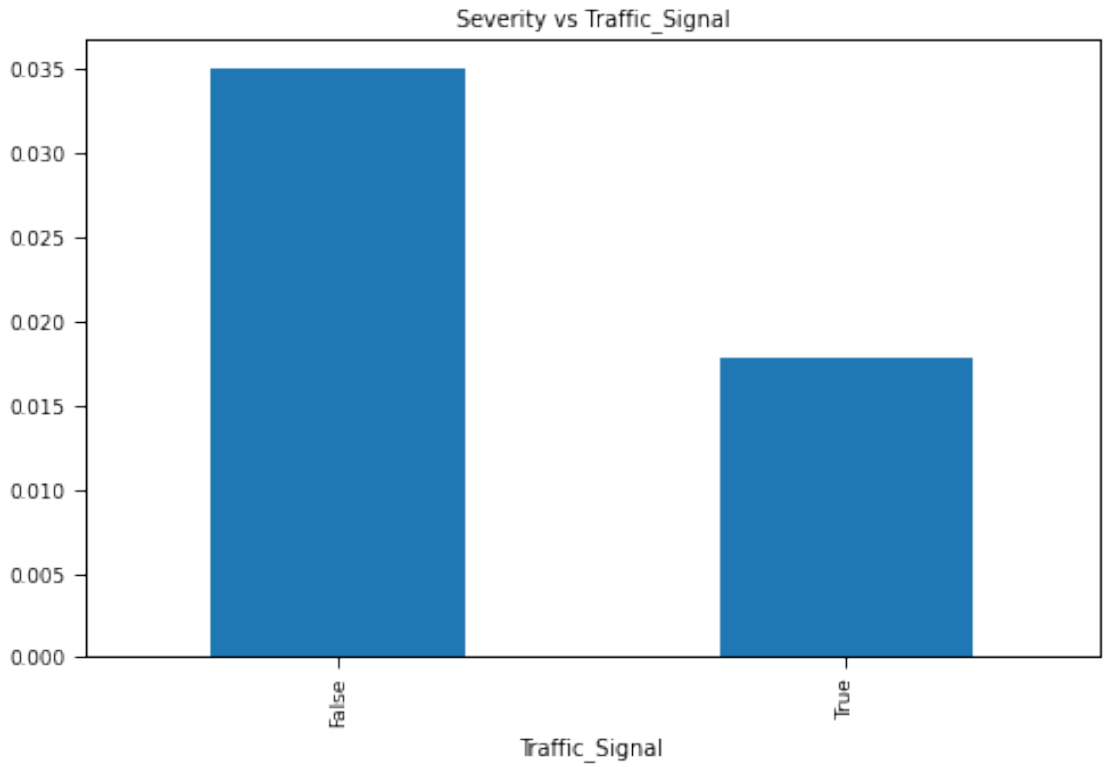
[1500]:
```
df_severe_crossing = df.groupby(['Severity','Crossing']).size().reset_index().
↪pivot(\
    columns='Severity', index='Crossing', values=0)
df_severe_crossing_rate = rate_df(df_severe_crossing)
df_severe_crossing_rate[4].plot(kind='bar', title='Severity Rate vs Crossing',␣
↪figsize=(8,5)).get_figure().savefig(f'{image_path}Severity Rate vs Crossing.
↪jpeg')
```



- Rate is low when compared to crossings.

0.4.9 Severity Rate vs Traffic Signals

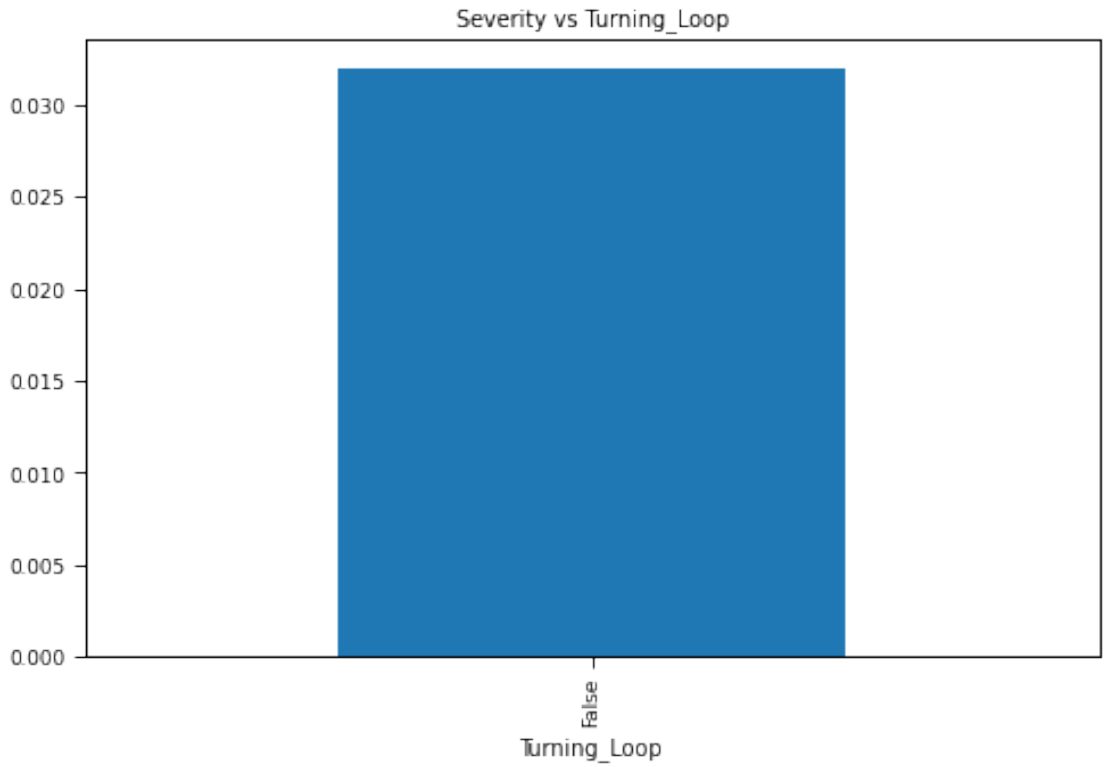
[1501]:
```
df_severe_Traffic_Signal = df.groupby(['Severity','Traffic_Signal']).size().
↪reset_index().pivot(\
    columns='Severity', index='Traffic_Signal', values=0)
df_severe_Traffic_Signal_rate = rate_df(df_severe_Traffic_Signal)
df_severe_Traffic_Signal_rate[4].plot(kind='bar', title='Severity vs␣
↪Traffic_Signal', figsize=(8,5)).get_figure().savefig(f'{image_path}Severity␣
↪by Traffic Signal.jpeg')
```



- The severity rate is low in the area corresponding to traffic signal.

0.4.10 Severity Rate vs Turning_Loop

[1502]:
```
df_severe_Turning_Loop = df.groupby(['Severity','Turning_Loop']).size().
↪reset_index().pivot(\
    columns='Severity', index='Turning_Loop', values=0)
df_severe_Turning_Loop_rate = rate_df(df_severe_Turning_Loop)
df_severe_Turning_Loop_rate[4].plot(kind='bar', title='Severity vs␣
↪Turning_Loop', figsize=(8,5)).get_figure().savefig(f'{image_path}Severity vs␣
↪Turning_Loop.jpeg')
```



- No severe accident occured at Turning Loop.

0.5 Conclusion

- State with severe climate condition like South Dakota, North Dakota has highest severity rate.
- Biggest states like California, Florida, etc., has lowest severity rate.
- It seems most of the people are cautious in areas with crossing, traffic signal, turning loops, etc.
- No severe accident were reported in turning loops.
- Severity rate is high for accident reported at Night.
- Almost every wind direction has similar severity rate.

[ ]: