# Lab3_Group2_Final

November 6, 2020

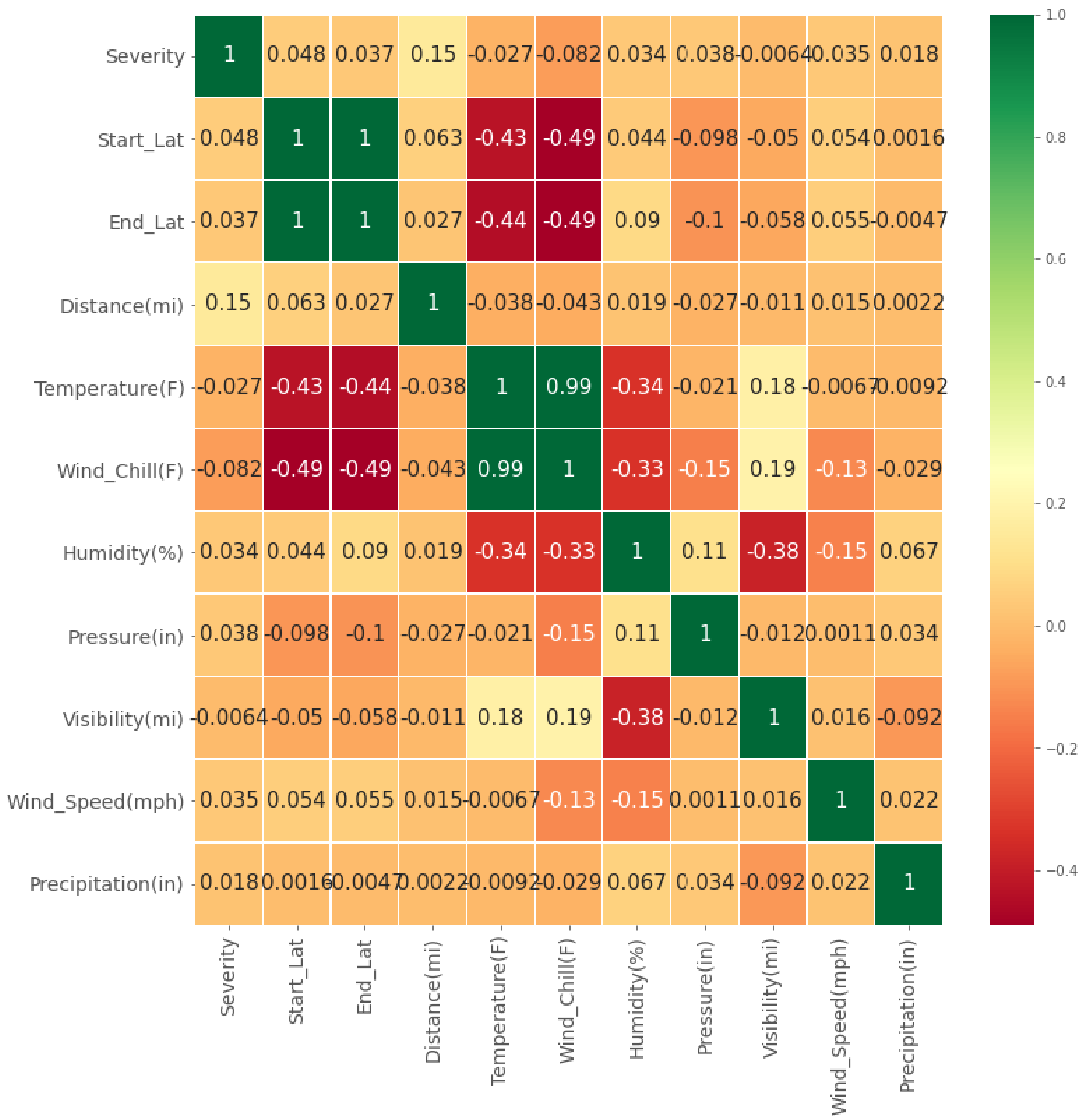
[1]:
```python
# Import related libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
plt.style.use('ggplot')
pd.set_option('display.max_rows', 100)
pd.set_option('display.max_columns', 50)
import warnings
warnings.filterwarnings("ignore")
```

## 0.1 Data Review

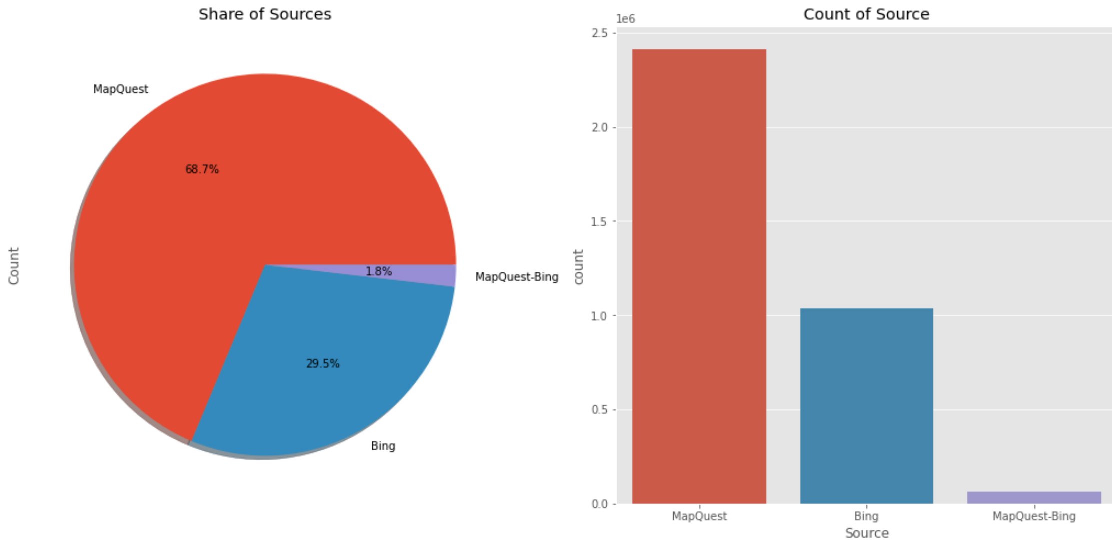
[436]:
```python
# Import the dataset
df = pd.read_csv('C:/Users/AS/Downloads/data/US_Accidents_June20.csv')
```

## 0.2 Data Visualization

[437]:
```python
# Correlation
fig = sns.heatmap(
    df[['Severity', 'Start_Lat', 'End_Lat', 'Distance(mi)',
        'Temperature(F)', 'Wind_Chill(F)','Humidity(%)', 'Pressure(in)',
        'Visibility(mi)', 'Wind_Speed(mph)', 'Precipitation(in)']].corr(),
    annot = True, cmap = 'RdYlGn', linewidths = 0.2, annot_kws = {'size':15})
fig = plt.gcf()
fig.set_size_inches(12,12)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.show()
```

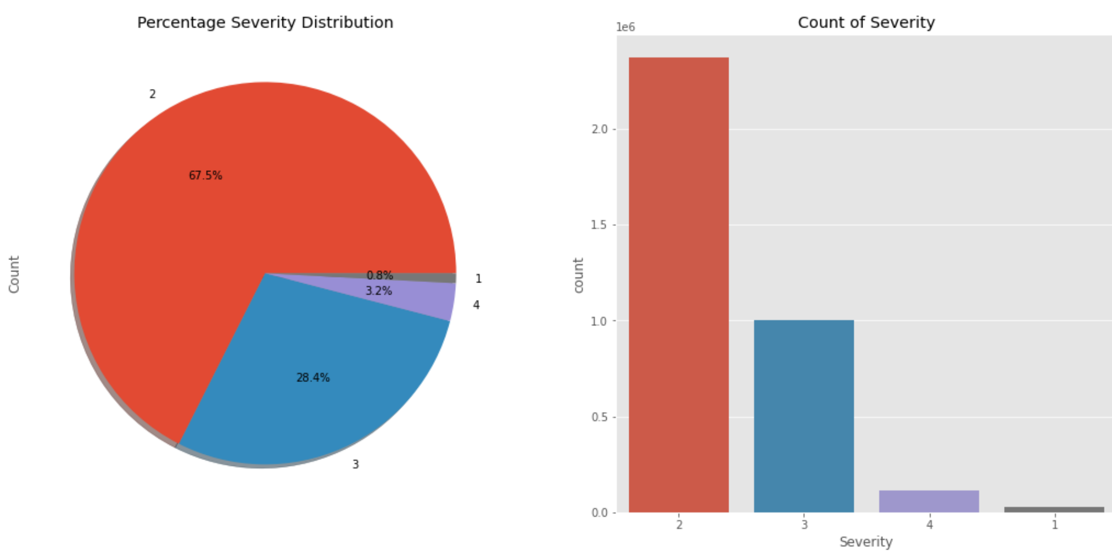



[441]:
```
# Source of Data
f, ax = plt.subplots(1, 2, figsize=(18,8))
df['Source'].value_counts().plot.pie(autopct = '%1.1f%%', ax = ax[0], shadow =␣
 ↪True)
ax[0].set_title('Share of Sources')
ax[0].set_ylabel('Count')
sns.countplot('Source', data = df, ax = ax[1], order = df['Source'].
 ↪value_counts().index)
ax[1].set_title('Count of Source')
plt.show()
```



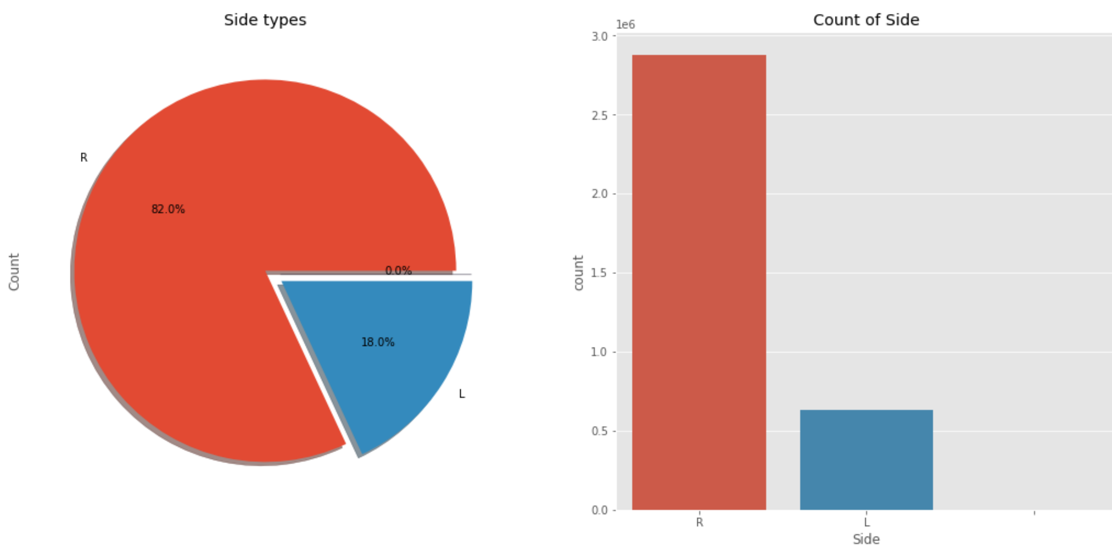

[8]:

```
# Severity
f, ax = plt.subplots(1, 2, figsize=(18,8))
df['Severity'].value_counts().plot.pie(autopct = '%1.1f%%', ax = ax[0], shadow = True)
ax[0].set_title('Percentage Severity Distribution')
ax[0].set_ylabel('Count')
sns.countplot('Severity', data = df, ax = ax[1], order = df['Severity'].value_counts().index)
ax[1].set_title('Count of Severity')
plt.show()
```



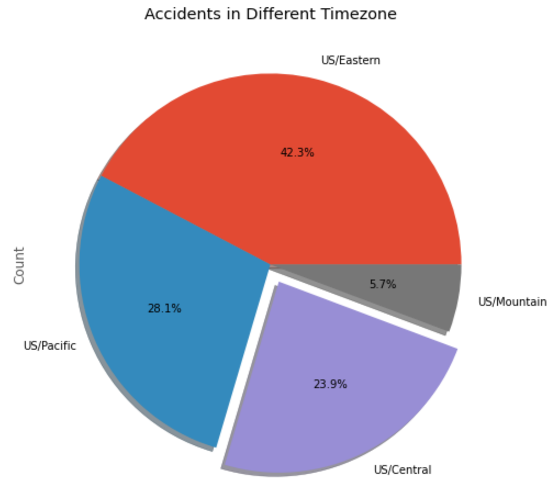
[9]:

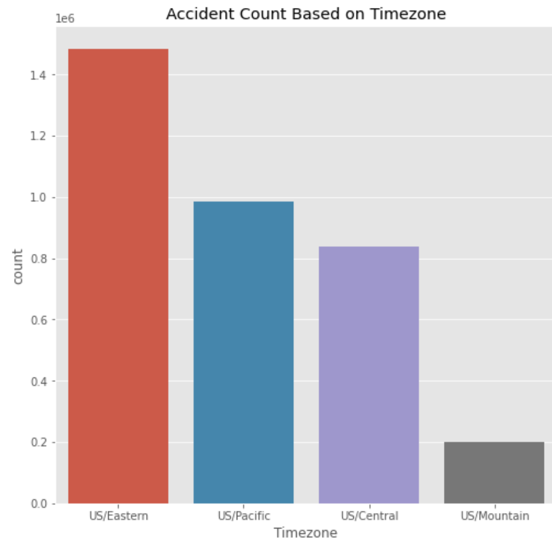
```
# Side: There are three things mentioned in side (Right Left and third one is a␣
↪blank space)
f, ax = plt.subplots(1, 2, figsize=(18,8))
df['Side'].value_counts().plot.pie(explode=[0, 0.1, 0.1], autopct = '%1.1f%%',␣
↪ax = ax[0], shadow = True)
ax[0].set_title('Side types')
ax[0].set_ylabel('Count')
sns.countplot('Side', data = df, ax = ax[1], order = df['Side'].value_counts().
↪index)
ax[1].set_title('Count of Side')
plt.show()
```




[10]:

```
# USA has four time zones Pacific, Mountain, Central and Eastern as we move␣
↪from West to the east of the country
f,ax=plt.subplots(1,2,figsize=(18,8))
df['Timezone'].value_counts().plot.pie(explode=[0,0,0.1,0],autopct='%1.
↪1f%%',ax=ax[0],shadow=True)
ax[0].set_title('Accidents in Different Timezone')
ax[0].set_ylabel('Count')
sns.countplot('Timezone',data=df,ax=ax[1],order=df['Timezone'].value_counts().
↪index)
ax[1].set_title('Accident Count Based on Timezone')
plt.show()
```

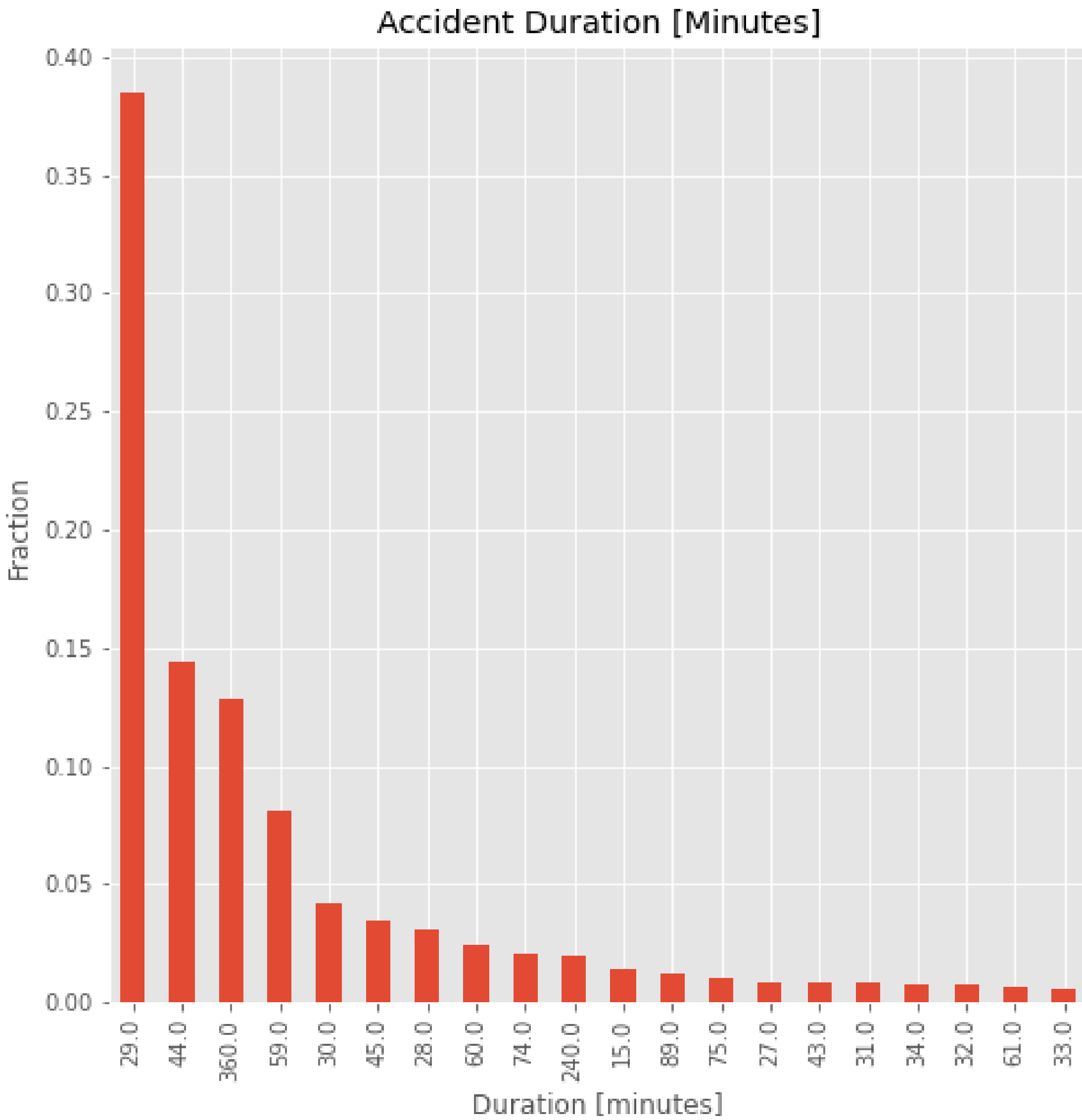



[264]:
```
# Time taken to clear the traffice
df['Start_Time'] = pd.to_datetime(df.Start_Time, format='%Y-%m-%d %H:%M:%S')
df['End_Time'] = pd.to_datetime(df.End_Time, format='%Y-%m-%d %H:%M:%S')
df['diff'] = (df['End_Time']-df['Start_Time'])
```

[12]:
```
top20 = df['diff'].astype('timedelta64[m]').value_counts().nlargest(20)
print('top 20 accident durations correspond to {:.1f}% of the data'.
 ↪format(top20.sum()*100/len(df['diff'])))
(top20/top20.sum()).plot.bar(figsize=(8,8))
plt.title('Accident Duration [Minutes]')
plt.xlabel('Duration [minutes]')
plt.ylabel('Fraction');
```

```
top 20 accident durations correspond to 81.8% of the data
```



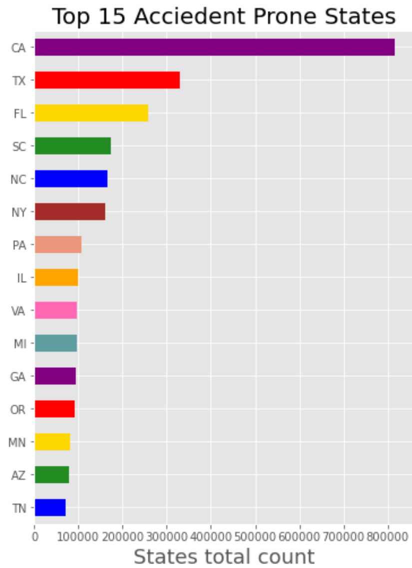

From the above curve we can see that most of the accidents take less than an hours time to get resolved. But more than 12% of the accidents are taking 360 minutes to resolve.

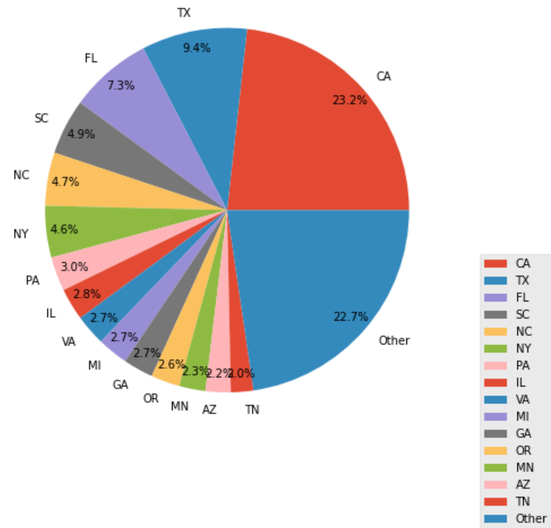
[13]:
```
# create df for state accidents
import plotly.graph_objects as go
state_count_acc = pd.value_counts(df['State'])

fig = go.Figure(data = go.Choropleth(
    locations = state_count_acc.index,
    z = state_count_acc.values.astype(float),
    locationmode = 'USA-states',
    colorscale = 'Reds',
```

```
    colorbar_title = "Count Accidents",
))

fig.update_layout(
    title_text = '2016 - 2020 US Traffic Accident Dataset by State',
    geo_scope='usa',
)
fig.show()
```

[14]:
```
# Acceident in different states
fig,ax = plt.subplots(1, 2, figsize = (15, 8))
clr = ("blue", "forestgreen", "gold", "red",␣
 ↪"purple",'cadetblue','hotpink','orange','darksalmon','brown')
df.State.value_counts().sort_values(ascending = False)[:15].sort_values().
 ↪plot(kind = 'barh', ax = ax[0], color = clr)
ax[0].set_title("Top 15 Acciedent Prone States", size = 20)
ax[0].set_xlabel('States total count', size = 18)

count = df['State'].value_counts()
groups = list(df['State'].value_counts().index)[:15]
counts = list(count[:15])
counts.append(count.agg(sum) - count[:15].agg(sum))
groups.append('Other')
type_dict = pd.DataFrame({"group": groups, "counts": counts})
qx = type_dict.plot(kind = 'pie', y = 'counts', labels = groups, autopct = '%1.
 ↪1f%%',
                    pctdistance = 0.9, radius = 1.2, ax = ax[1])
plt.legend(loc = 0, bbox_to_anchor = (1.15, 0.4))
plt.subplots_adjust(wspace = 0.5, hspace = 0)
plt.ioff()
plt.ylabel('')
```

[14]: Text(0, 0.5, '')



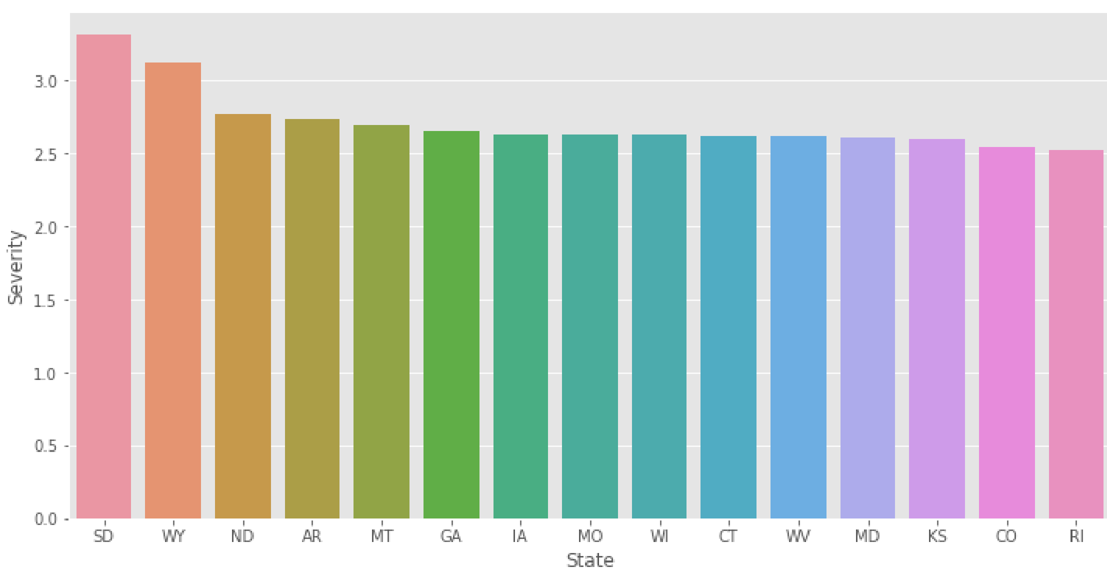




We can see that more accidents are happening in state of California(CA), Texas(TX) and Florida(FL)

[15]:
```
# Severity accidents
df_sever = df.sample(n=10000)

fig = go.Figure(
    data = go.Scattergeo(
        locationmode = 'USA-states',
        lon = df_sever['Start_Lng'],
        lat = df_sever['Start_Lat'],
        text = df_sever['City'],
        mode = 'markers',
        marker = dict(
            size = 8,
            opacity = 0.5,
            reversescale = False,
            autocolorscale = False,
            symbol = 'circle',
            line = dict(
                width = 1,
                color = 'rgba(102, 102, 102)'),
            colorscale = 'Reds',
            color = df_sever['Severity'],
            colorbar_title = "Severity"
        )
    )
```

```
)

fig.update_layout(
        title = 'Severity of accidents',
        geo = dict(
            scope='usa',
            projection_type='albers usa',
            showland = True,
            landcolor = "rgb(250, 250, 250)",
            subunitcolor = "rgb(217, 217, 217)",
            countrycolor = "rgb(217, 217, 217)",
            countrywidth = 0.7,
            subunitwidth = 0.7
        ),
    )
fig.show()
```

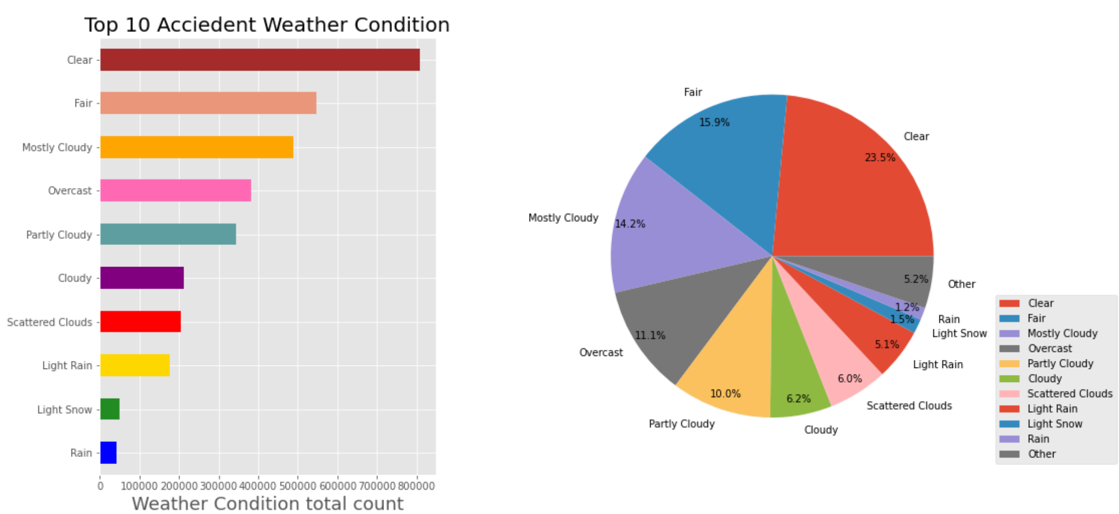
[16]:
```
# Severity in different states
df_top_Severity_State=df.groupby('State').agg({'Severity':'mean'}).
 ↪sort_values('Severity',ascending=False).reset_index()

plt.figure(figsize=(12,6))
sns.barplot(y = "Severity", x = "State", data = df_top_Severity_State.head(15))
plt.ioff()
```




[17]:
```
# Weather confition for the accidents
fig,ax = plt.subplots(1, 2, figsize = (15, 8))
```

```
clr = ("blue", "forestgreen", "gold", "red",␣
↪"purple",'cadetblue','hotpink','orange','darksalmon','brown')
df.Weather_Condition.value_counts().sort_values(ascending = False)[:10].
↪sort_values().plot(
    kind = 'barh', ax = ax[0], color = clr)
ax[0].set_title("Top 10 Acciedent Weather Condition", size = 20)
ax[0].set_xlabel('Weather Condition total count', size = 18)

count = df['Weather_Condition'].value_counts()
groups = list(df['Weather_Condition'].value_counts().index)[:10]
counts = list(count[:10])
counts.append(count.agg(sum) - count[:10].agg(sum))
groups.append('Other')
type_dict = pd.DataFrame({"group": groups, "counts": counts})
qx = type_dict.plot(kind = 'pie', y = 'counts', labels = groups, autopct = '%1.
↪1f%%',
                        pctdistance = 0.9, radius = 1.2, ax = ax[1])
plt.legend(loc = 0, bbox_to_anchor = (1.15, 0.4))
plt.subplots_adjust(wspace = 0.5, hspace = 0)
plt.ioff()
plt.ylabel('')
```

[17]: Text(0, 0.5, '')




Most accidents occure when the weather is clear. Maybe people drive faster and inattention when the weather is clear, and more carefully when the weather is bad.

[18]:
```
# Where are Accidents occuring
bool_cols = [col for col in df.columns if df[col].dtype == np.dtype('bool')] #␣
↪find the bool type columns
```

```
booldf = df[bool_cols]
more_than_one = booldf[booldf.sum(axis = 1) > 1] # find combination with more␣
 ↪than 1 fact
print('There are {} more than one fact metadata rows, which are {:.1f}% of the␣
 ↪data'.format(
    len(more_than_one), 100*len(more_than_one)/len(df)
))
```

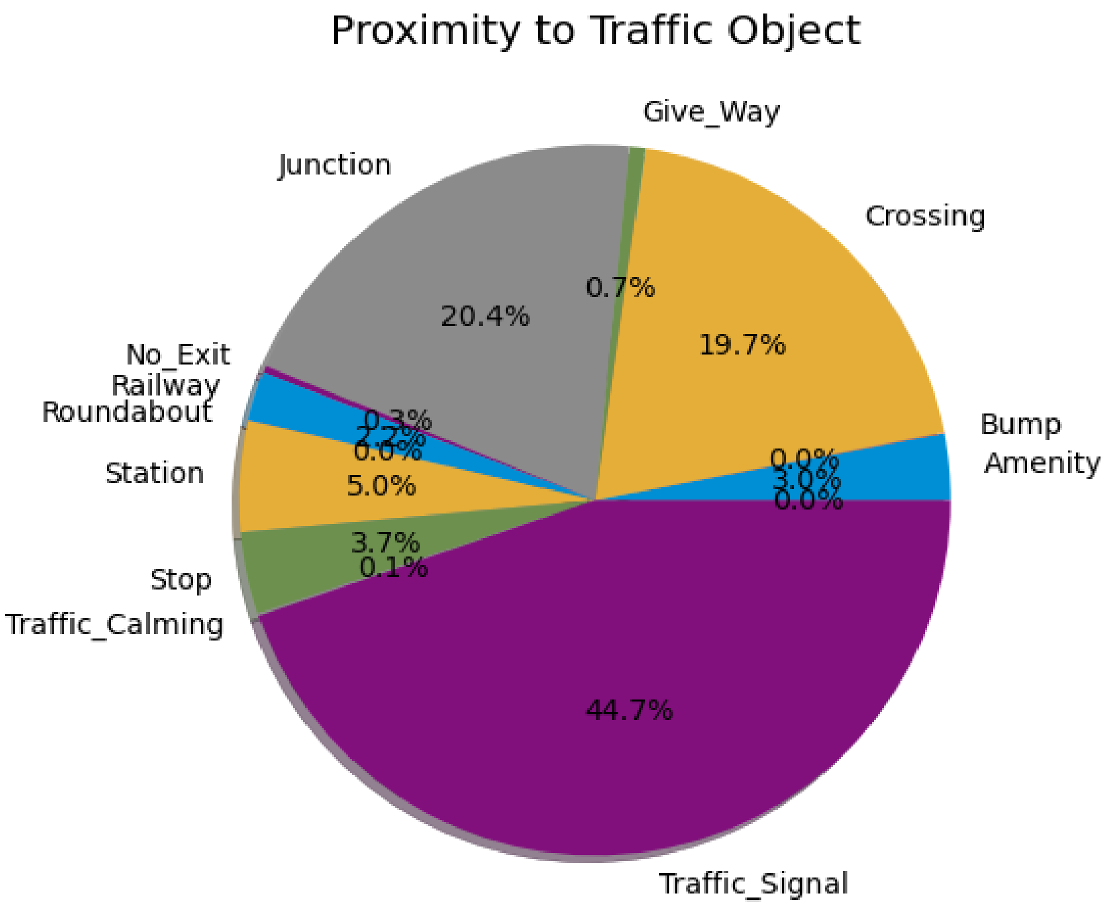
```
There are 284711 more than one fact metadata rows, which are 8.1% of the data
```

[19]:
```
bools = booldf.sum(axis = 0)
bools
```

[19]:
```
Amenity             42082
Bump                  606
Crossing           274526
Give_Way             9564
Junction           284449
No_Exit              4384
Railway             31175
Roundabout            184
Station             70321
Stop                51976
Traffic_Calming      1401
Traffic_Signal     623623
Turning_Loop            0
dtype: int64
```

[20]:
```
plt.figure(figsize=(9,8))
plt.style.use('fivethirtyeight')
bools.plot.pie(autopct='%1.1f%%', shadow = True)
plt.ylabel('')
plt.title('Proximity to Traffic Object')
```

[20]:
```
Text(0.5, 1.0, 'Proximity to Traffic Object')
```

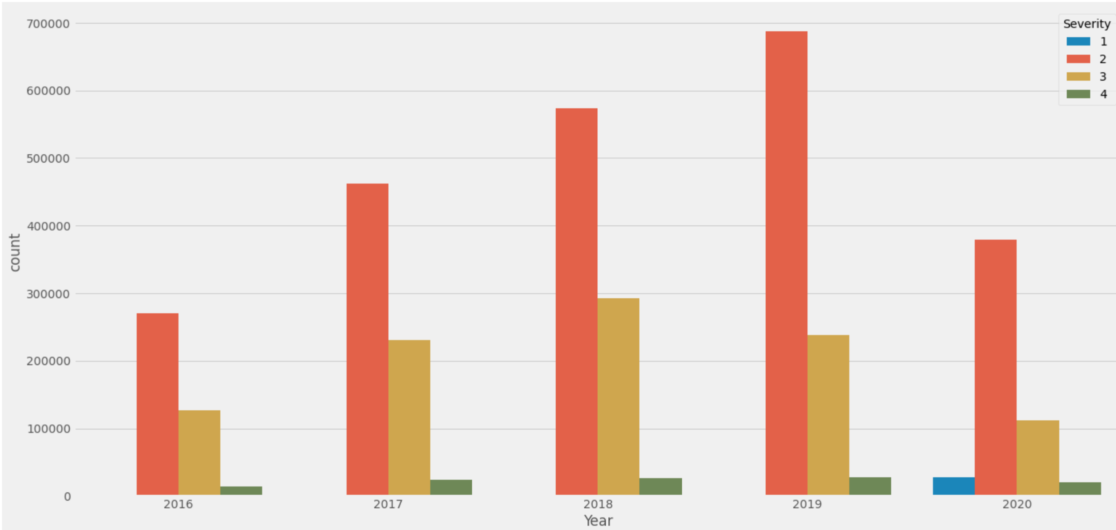



We can see that more accidents are happening near traffic signal,junction, and crossings

[21]:
```
# Extract year, month, day, hour and weekday
df['Year'] = df['Start_Time'].dt.year
df['Month'] = df['Start_Time'].dt.month
df['Day'] = df['Start_Time'].dt.day
df['Hour'] = df['Start_Time'].dt.hour
df['Weekday'] = df['Start_Time'].dt.strftime('%a')
```

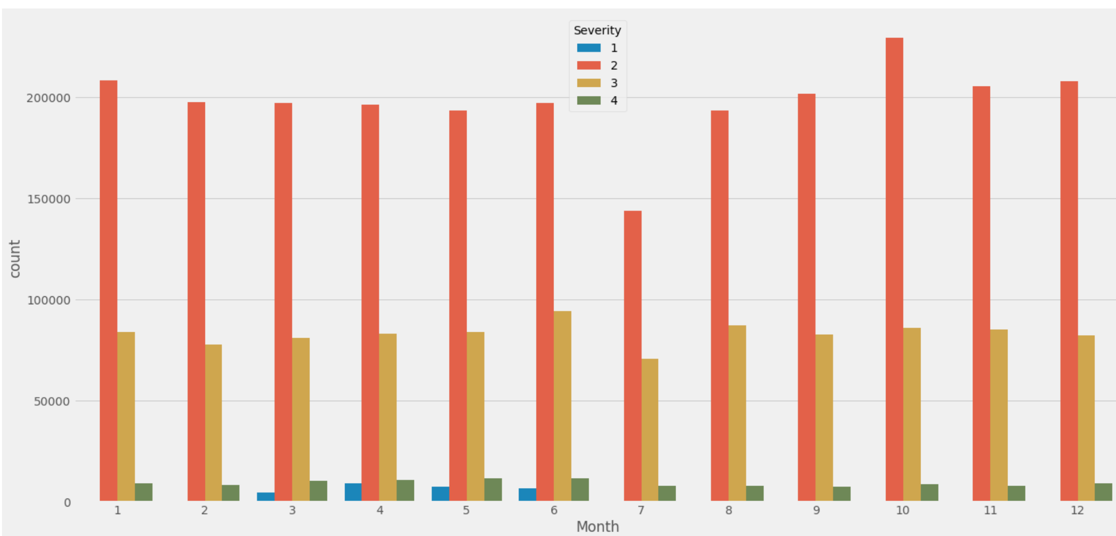
[22]:
```
plt.figure(figsize = (20, 10))
sns.countplot(x = "Year", hue = "Severity", data = df)
```

[22]: <AxesSubplot:xlabel='Year', ylabel='count'>



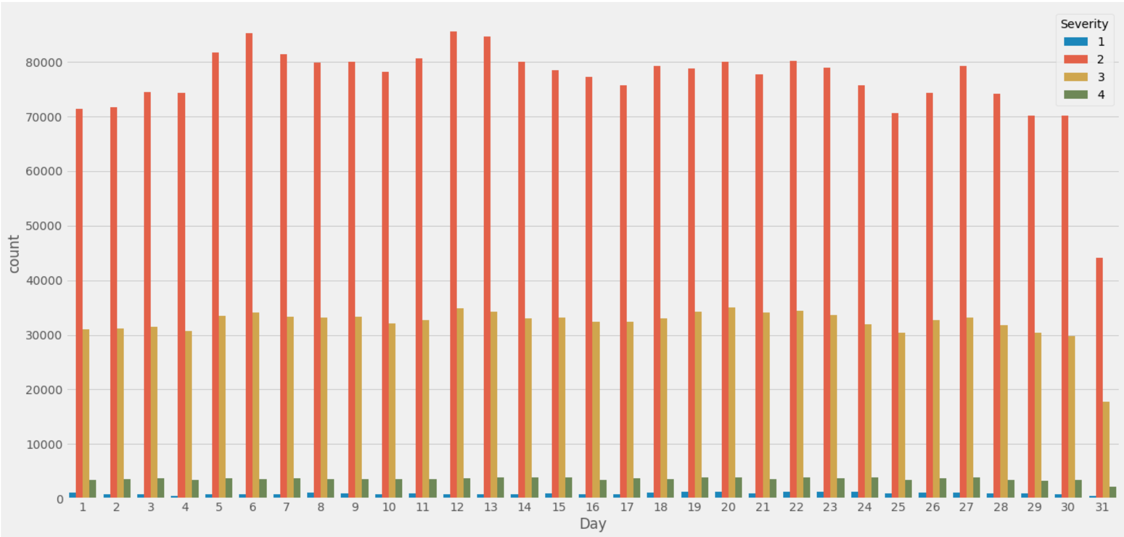

[23]:
```
plt.figure(figsize = (20, 10))
sns.countplot(x = "Month", hue = "Severity", data = df)
```

[23]: <AxesSubplot:xlabel='Month', ylabel='count'>



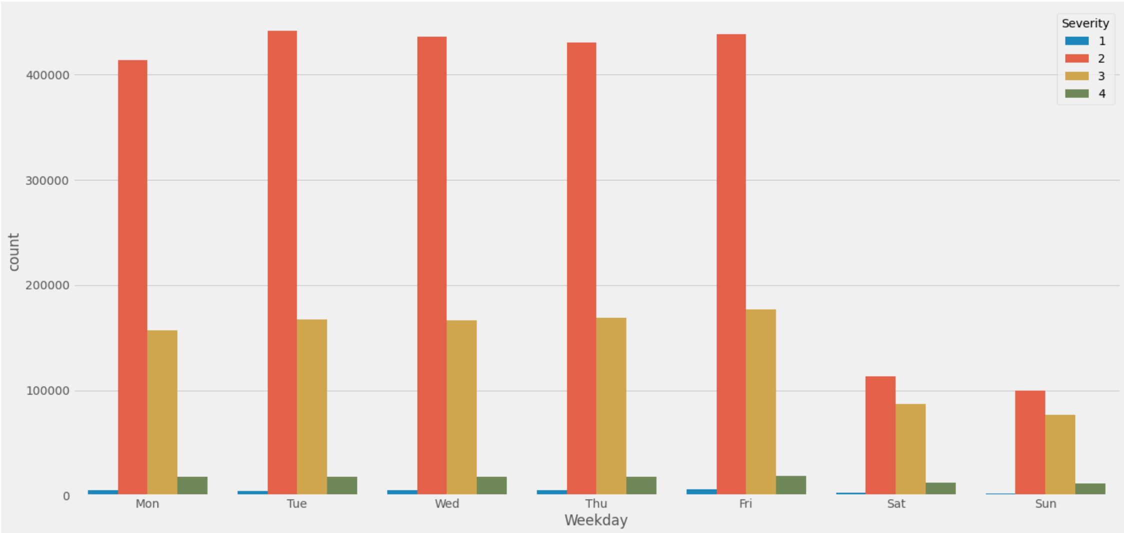

[24]:
```
plt.figure(figsize=(20, 10))
sns.countplot(x = "Day", hue = "Severity", data = df)
```

[24]: <AxesSubplot:xlabel='Day', ylabel='count'>



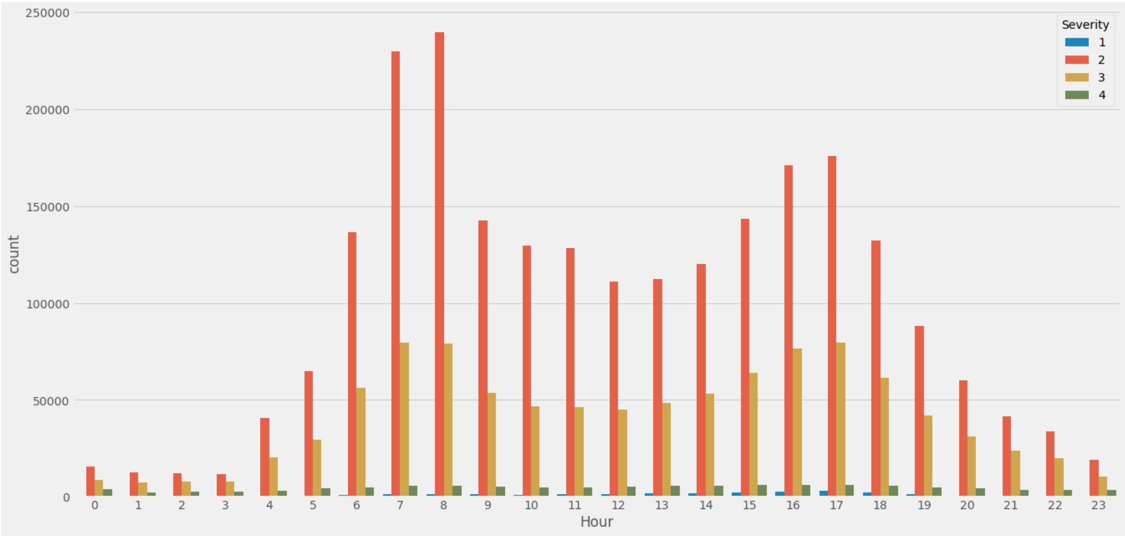

[25]:
```
plt.figure(figsize=(20, 10))
sns.countplot(x = "Weekday", hue = "Severity", data = df)
```

[25]: <AxesSubplot:xlabel='Weekday', ylabel='count'>



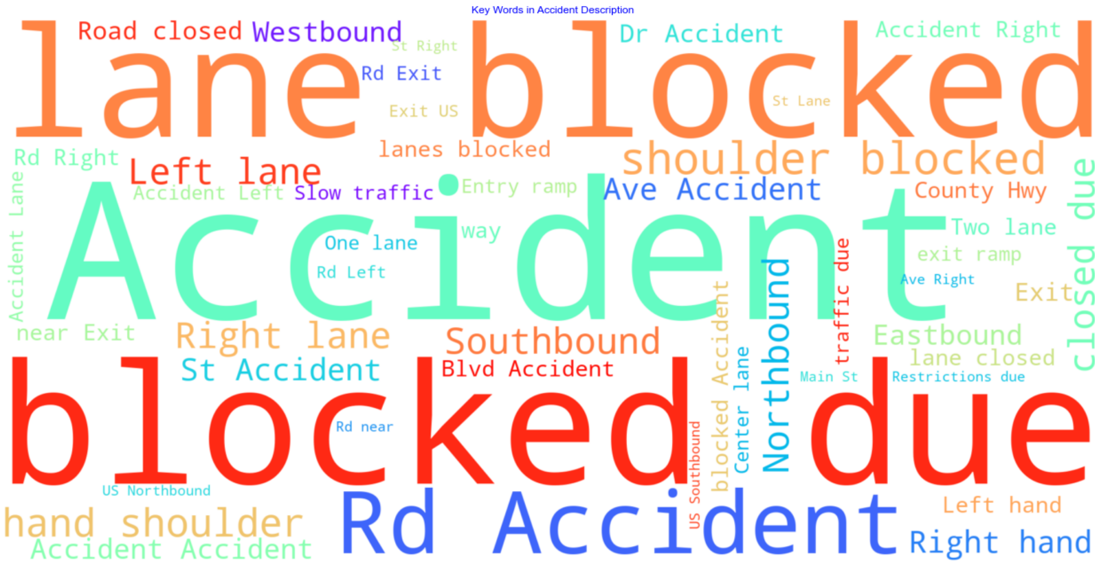

[26]:
```
plt.figure(figsize=(20, 10))
sns.countplot(x = "Hour", hue = "Severity", data = df)
```

[26]: <AxesSubplot:xlabel='Hour', ylabel='count'>




[27]:

```
# Key Words in Description
from wordcloud import WordCloud
plt.style.use('seaborn')
wrds1 = df["Description"].str.split("(").str[0].value_counts().keys()

wc1 = WordCloud(scale = 5, max_words = 50, colormap = "rainbow",
                mode = "RGBA", background_color = "white").generate(" ".
 ↪join(wrds1))
plt.figure(figsize = (20, 15))
plt.imshow(wc1,interpolation = "bilinear")
plt.axis("off")
plt.title("Key Words in Accident Description", color = 'b')
plt.show()
```




## 0.3 Data Clearning

[28]:
```python
# copy the dataframe before start cleaning the data
df_tmp = df.copy()
```

**Clean the outliers of the time_duration**

[29]:
```python
# Check if there is any negative time_duration values
df_tmp.loc[df_tmp['diff']/np.timedelta64(1, 'm') <= 0]

# Drop the rows with above
df_tmp['diff'] = df_tmp['diff']/np.timedelta64(1, 'm')
df_tmp = df_tmp[df_tmp['diff'] > 0]
```

[29]:

| | ID | Source | TMC | Severity | Start_Time | \ |
|---|---|---|---|---|---|---|
| 69719 | A-69721 | MapQuest | 201.0 | 3 | 2016-11-06 01:38:13 | |
| 69720 | A-69722 | MapQuest | 241.0 | 2 | 2016-11-06 01:38:45 | |
| 69721 | A-69723 | MapQuest | 201.0 | 3 | 2016-11-06 01:35:47 | |
| 69722 | A-69724 | MapQuest | 201.0 | 2 | 2016-11-06 01:32:24 | |
| 69723 | A-69725 | MapQuest | 201.0 | 2 | 2016-11-06 01:33:05 | |
| 309387 | A-309390 | MapQuest | 201.0 | 2 | 2016-11-06 01:51:04 | |
| 309388 | A-309391 | MapQuest | 201.0 | 2 | 2016-11-06 01:51:49 | |
| 860988 | A-861014 | MapQuest | 201.0 | 2 | 2019-11-03 01:25:16 | |
| 861024 | A-861050 | MapQuest | 201.0 | 2 | 2019-11-03 01:47:49 | |
| 861041 | A-861067 | MapQuest | 201.0 | 2 | 2019-11-03 01:34:54 | |
| 861475 | A-861501 | MapQuest | 201.0 | 3 | 2019-11-03 01:20:44 | |
| 861494 | A-861520 | MapQuest | 201.0 | 3 | 2019-11-03 01:44:47 | |
| 861495 | A-861521 | MapQuest | 201.0 | 2 | 2019-11-03 01:43:50 | |

| | | | | | |
|---|---|---|---|---|---|
| 1497823 | A-1497855 | MapQuest | 201.0 | 3 | 2018-11-04 01:30:41 |
| 1497824 | A-1497856 | MapQuest | 201.0 | 3 | 2018-11-04 01:40:28 |
| 2234574 | A-2234614 | MapQuest | 201.0 | 2 | 2017-11-05 01:56:55 |
| 2234659 | A-2234699 | MapQuest | 241.0 | 3 | 2017-11-05 01:32:24 |
| 2234660 | A-2234700 | MapQuest | 201.0 | 2 | 2017-11-05 01:55:55 |
| 3104499 | A-3104659 | Bing | NaN | 2 | 2019-11-03 01:57:00 |
| 3104975 | A-3105135 | Bing | NaN | 2 | 2019-11-03 01:13:00 |
| 3104978 | A-3105138 | Bing | NaN | 2 | 2019-11-03 01:22:00 |
| 3232740 | A-3232900 | Bing | NaN | 2 | 2018-11-04 01:51:53 |

| | End_Time | Start_Lat | Start_Lng | End_Lat | End_Lng | \ |
|---|---|---|---|---|---|---|
| 69719 | 2016-11-06 01:37:57 | 34.032963 | -118.435738 | NaN | NaN | |
| 69720 | 2016-11-06 01:38:23 | 34.053040 | -118.228264 | NaN | NaN | |
| 69721 | 2016-11-06 01:35:31 | 33.804443 | -118.207527 | NaN | NaN | |
| 69722 | 2016-11-06 01:31:50 | 34.134960 | -117.597748 | NaN | NaN | |
| 69723 | 2016-11-06 01:32:33 | 34.070320 | -117.208679 | NaN | NaN | |
| 309387 | 2016-11-06 01:20:49 | 47.608002 | -122.296280 | NaN | NaN | |
| 309388 | 2016-11-06 01:21:35 | 47.530354 | -122.270004 | NaN | NaN | |
| 860988 | 2019-11-03 01:12:56 | 42.793083 | -78.818367 | NaN | NaN | |
| 861024 | 2019-11-03 01:17:08 | 43.091412 | -75.747284 | NaN | NaN | |
| 861041 | 2019-11-03 01:34:31 | 41.043110 | -73.835861 | NaN | NaN | |
| 861475 | 2019-11-03 01:06:33 | 45.635433 | -122.663467 | NaN | NaN | |
| 861494 | 2019-11-03 01:44:26 | 37.561687 | -122.036362 | NaN | NaN | |
| 861495 | 2019-11-03 01:13:31 | 37.730671 | -121.747063 | NaN | NaN | |
| 1497823 | 2018-11-04 01:00:17 | 34.172119 | -118.467529 | NaN | NaN | |
| 1497824 | 2018-11-04 01:09:39 | 34.067585 | -117.201378 | NaN | NaN | |
| 2234574 | 2017-11-05 01:26:32 | 47.121880 | -122.434883 | NaN | NaN | |
| 2234659 | 2017-11-05 01:02:02 | 34.045719 | -117.310364 | NaN | NaN | |
| 2234660 | 2017-11-05 01:25:05 | 33.923199 | -117.857597 | NaN | NaN | |
| 3104499 | 2019-11-03 01:22:55 | 43.024010 | -71.195290 | 43.024880 | -71.190330 | |
| 3104975 | 2019-11-03 01:05:47 | 34.041208 | -118.064316 | 34.041208 | -118.064316 | |
| 3104978 | 2019-11-03 01:14:47 | 36.326633 | -119.279029 | 36.326633 | -119.279029 | |
| 3232740 | 2018-11-04 01:21:22 | 40.705504 | -111.888270 | 40.703211 | -111.888260 | |

| | Distance(mi) | Description | \ |
|---|---|---|---|
| 69719 | 0.010 | Accident on I-10 Eastbound at Exits 3A 3B I-405. | |
| 69720 | 0.010 | Lane blocked due to accident on US-101 Northbo… | |
| 69721 | 0.010 | Accident on I-710 Northbound at Exits 3A 3B Wi… | |
| 69722 | 1.230 | Hov lane blocked due to accident on CA-210 Eas… | |
| 69723 | 0.010 | Accident on Lugonia Ave at Alabama St. | |
| 309387 | 0.010 | Accident on Martin Luther King Jr Way at Cherr… | |
| 309388 | 0.010 | Accident on Rainier Ave at Elmgrove St. | |
| 860988 | 6.210 | Accident on I-90 Eastbound from Exit 57 NY-75 … | |
| 861024 | 0.000 | Accident on I-90 Eastbound at Exit 34 NY-13 Pe… | |
| 861041 | 0.000 | Accident on I-87 Northbound at Exit 7A Saw Mil… | |
| 861475 | 0.000 | Center lane closed due to accident on I-5 Nort… | |
| 861494 | 0.000 | Accident on I-880 Northbound at Decoto Rd. | |

| | | |
|---|---|---|
| 861495 | 0.000 | Accident on Raymond Rd at Dagnino Rd. |
| 1497823 | 0.000 | #4 lane blocked due to accident on I-405 North… |
| 1497824 | 0.000 | #1 lane blocked due to accident on I-210 Eastb… |
| 2234574 | 0.000 | Right lane blocked due to accident on WA-7 Pac… |
| 2234659 | 0.000 | One lane blocked due to accident on I-215 Sout… |
| 2234660 | 0.000 | Accident on Lambert Rd at Sunflower St. |
| 3104499 | 0.258 | At Old Manchester Rd/Exit 4 - Accident. |
| 3104975 | 0.000 | At CA-19/Rosemead Blvd - Accident. |
| 3104978 | 0.000 | At Ben Maddox Way - Accident. |
| 3232740 | 0.158 | At Bank Ave - Accident. Two lanes blocked. |

| | Number | Street | Side | City | County \ |
|---|---|---|---|---|---|
| 69719 | NaN | San Diego Fwy S | R | Los Angeles | Los Angeles |
| 69720 | NaN | US-101 N | R | Los Angeles | Los Angeles |
| 69721 | NaN | W Willow St | R | Long Beach | Los Angeles |
| 69722 | NaN | CA-210 E | R | Rancho Cucamonga | San Bernardino |
| 69723 | 1298.0 | Alabama St | L | Redlands | San Bernardino |
| 309387 | 2733.0 | E Cherry St | R | Seattle | King |
| 309388 | 8099.0 | Rainier Ave S | R | Seattle | King |
| 860988 | NaN | I-90 W | R | Buffalo | Erie |
| 861024 | NaN | I-90 E | R | Canastota | Madison |
| 861041 | NaN | I-87 N | R | Irvington | Westchester |
| 861475 | 1814.0 | W Reserve St | L | Vancouver | Clark |
| 861494 | NaN | I-880 N | R | Newark | Alameda |
| 861495 | 4357.0 | Raymond Rd | R | Livermore | Alameda |
| 1497823 | NaN | Burbank Blvd | R | Van Nuys | Los Angeles |
| 1497824 | 987.0 | Tennessee St | R | Redlands | San Bernardino |
| 2234574 | 100.0 | 149th St S | L | Tacoma | Pierce |
| 2234659 | NaN | I-215 S | R | Colton | San Bernardino |
| 2234660 | 292.0 | Sunflower St | R | Brea | Orange |
| 3104499 | NaN | Old Manchester Rd | R | Raymond | Rockingham |
| 3104975 | NaN | Rosemead Blvd | R | South El Monte | Los Angeles |
| 3104978 | NaN | CA-198 E | R | Visalia | Tulare |
| 3232740 | NaN | S State St | R | Salt Lake City | Salt Lake |

| | State | Zipcode | Country | Timezone | Airport_Code \ |
|---|---|---|---|---|---|
| 69719 | CA | 90064 | US | US/Pacific | KSMO |
| 69720 | CA | 90033 | US | US/Pacific | KCQT |
| 69721 | CA | 90810 | US | US/Pacific | KLGB |
| 69722 | CA | 91737 | US | US/Pacific | KONT |
| 69723 | CA | 92374-2814 | US | US/Pacific | KSBD |
| 309387 | WA | 98122-4935 | US | US/Pacific | KBFI |
| 309388 | WA | 98118-4444 | US | US/Pacific | KBFI |
| 860988 | NY | 14219 | US | US/Eastern | KBUF |
| 861024 | NY | 13032 | US | US/Eastern | KSYR |
| 861041 | NY | 10533 | US | US/Eastern | KHPN |
| 861475 | WA | 98663-3362 | US | US/Pacific | KVUO |

```
861494     CA       94560      US   US/Pacific         KPAO
861495     CA  94551-9776      US   US/Pacific         KLVK
1497823    CA       91411      US   US/Pacific         KVNY
1497824    CA       92374      US   US/Pacific         KSBD
2234574    WA       98444      US   US/Pacific         KTCM
2234659    CA       92324      US   US/Pacific         KSBD
2234660    CA  92821-4725      US   US/Pacific         KFUL
3104499    NH       03077      US   US/Eastern         KMHT
3104975    CA       91733      US   US/Pacific         KEMT
3104978    CA       93292      US   US/Pacific         KVIS
3232740    UT       84115      US  US/Mountain         KSLC

           Weather_Timestamp  Temperature(F)  Wind_Chill(F)  …  \
69719    2016-11-06 01:51:00            57.0            NaN  …
69720    2016-11-06 01:47:00            59.0            NaN  …
69721    2016-11-06 01:34:00            59.0            NaN  …
69722    2016-11-06 01:53:00            55.9            NaN  …
69723    2016-11-06 01:38:00            57.2            NaN  …
309387   2016-11-06 01:53:00            50.0            NaN  …
309388   2016-11-06 01:53:00            50.0            NaN  …
860988   2019-11-03 01:54:00            34.0           27.0  …
861024   2019-11-03 01:54:00            39.0           34.0  …
861041   2019-11-03 01:56:00            40.0           37.0  …
861475   2019-11-03 00:53:00            42.0           42.0  …
861494   2019-11-03 06:47:00            39.0           39.0  …
861495   2019-11-03 01:53:00            41.0           41.0  …
1497823  2018-11-04 01:51:00            63.0            NaN  …
1497824  2018-11-04 01:42:00            59.5            NaN  …
2234574  2017-11-05 01:58:00            39.9            NaN  …
2234659  2017-11-05 01:39:00            59.7            NaN  …
2234660  2017-11-05 01:53:00            62.1            NaN  …
3104499  2019-11-03 01:53:00            32.0           32.0  …
3104975  2019-11-03 00:53:00            55.0           55.0  …
3104978  2019-11-03 00:56:00            45.0           45.0  …
3232740  2018-11-04 01:54:00            39.0           32.3  …

         Precipitation(in)  Weather_Condition  Amenity   Bump  Crossing  \
69719                  NaN              Clear    False  False     False
69720                  NaN              Clear    False  False     False
69721                  NaN      Mostly Cloudy    False  False     False
69722                  NaN              Clear    False  False     False
69723                  NaN              Clear    False  False     False
309387                0.09         Light Rain     True  False      True
309388                0.09         Light Rain     True  False      True
860988                0.00      Mostly Cloudy    False  False     False
861024                0.00      Partly Cloudy    False  False     False
861041                0.00               Fair    False  False     False
```

```
861475                  0.00                 Fair    False  False     False
861494                   NaN                 Fair    False  False     False
861495                  0.00                 Fair    False  False     False
1497823                  NaN                Clear    False  False     False
1497824                  NaN                Clear    False  False     False
2234574                 0.00             Overcast    False  False     False
2234659                  NaN             Overcast    False  False     False
2234660                  NaN             Overcast    False  False     False
3104499                 0.00                 Fair    False  False     False
3104975                 0.00                 Fair    False  False     False
3104978                 0.00                 Fair    False  False     False
3232740                  NaN     Scattered Clouds    False  False      True

         Give_Way Junction  No_Exit  Railway  Roundabout  Station   Stop  \
69719       False    False    False    False       False    False  False
69720       False    False    False    False       False    False  False
69721       False     True    False    False       False    False  False
69722       False    False    False    False       False    False  False
69723       False    False    False    False       False    False  False
309387      False    False    False    False       False     True  False
309388      False    False    False    False       False    False  False
860988      False    False    False    False       False    False  False
861024      False    False    False    False       False    False  False
861041      False    False    False    False       False    False  False
861475      False    False    False    False       False    False  False
861494      False    False    False    False       False    False  False
861495      False    False    False    False       False    False  False
1497823     False    False    False    False       False    False  False
1497824     False    False    False    False       False    False  False
2234574     False    False    False    False       False    False  False
2234659     False    False    False    False       False    False  False
2234660     False    False    False    False       False    False  False
3104499     False    False    False    False       False    False  False
3104975     False    False    False    False       False    False  False
3104978     False     True    False    False       False    False  False
3232740     False    False    False    False       False    False   True

         Traffic_Calming  Traffic_Signal  Turning_Loop  Sunrise_Sunset  \
69719              False           False         False           Night
69720              False           False         False           Night
69721              False           False         False           Night
69722              False           False         False           Night
69723              False            True         False           Night
309387             False            True         False           Night
309388             False           False         False           Night
860988             False           False         False           Night
861024             False           False         False           Night
```

```
861041          False          False          False          Night
861475          False          False          False          Night
861494          False          False          False          Night
861495          False          False          False          Night
1497823         False           True          False          Night
1497824         False          False          False          Night
2234574         False          False          False          Night
2234659         False          False          False          Night
2234660         False           True          False          Night
3104499         False          False          False          Night
3104975         False          False          False          Night
3104978         False          False          False          Night
3232740         False          False          False          Night

        Civil_Twilight  Nautical_Twilight  Astronomical_Twilight  \
69719            Night              Night                  Night
69720            Night              Night                  Night
69721            Night              Night                  Night
69722            Night              Night                  Night
69723            Night              Night                  Night
309387           Night              Night                  Night
309388           Night              Night                  Night
860988           Night              Night                  Night
861024           Night              Night                  Night
861041           Night              Night                  Night
861475           Night              Night                  Night
861494           Night              Night                  Night
861495           Night              Night                  Night
1497823          Night              Night                  Night
1497824          Night              Night                  Night
2234574          Night              Night                  Night
2234659          Night              Night                  Night
2234660          Night              Night                  Night
3104499          Night              Night                  Night
3104975          Night              Night                  Night
3104978          Night              Night                  Night
3232740          Night              Night                  Night

                     diff  Year Month Day Hour Weekday
69719   -1 days +23:59:44  2016    11   6    1     Sun
69720   -1 days +23:59:38  2016    11   6    1     Sun
69721   -1 days +23:59:44  2016    11   6    1     Sun
69722   -1 days +23:59:26  2016    11   6    1     Sun
69723   -1 days +23:59:28  2016    11   6    1     Sun
309387  -1 days +23:29:45  2016    11   6    1     Sun
309388  -1 days +23:29:46  2016    11   6    1     Sun
860988  -1 days +23:47:40  2019    11   3    1     Sun
```

```
861024  -1 days +23:29:19  2019     11    3     1      Sun
861041  -1 days +23:59:37  2019     11    3     1      Sun
861475  -1 days +23:45:49  2019     11    3     1      Sun
861494  -1 days +23:59:39  2019     11    3     1      Sun
861495  -1 days +23:29:41  2019     11    3     1      Sun
1497823 -1 days +23:29:36  2018     11    4     1      Sun
1497824 -1 days +23:29:11  2018     11    4     1      Sun
2234574 -1 days +23:29:37  2017     11    5     1      Sun
2234659 -1 days +23:29:38  2017     11    5     1      Sun
2234660 -1 days +23:29:10  2017     11    5     1      Sun
3104499 -1 days +23:25:55  2019     11    3     1      Sun
3104975 -1 days +23:52:47  2019     11    3     1      Sun
3104978 -1 days +23:52:47  2019     11    3     1      Sun
3232740 -1 days +23:29:29  2018     11    4     1      Sun

[22 rows x 55 columns]
```

[31]:

```
# review the status of missing values for each column
num = df_tmp.isna().sum()
num
```

[31]:

```
ID                          0
Source                      0
TMC                   1034795
Severity                    0
Start_Time                  0
End_Time                    0
Start_Lat                   0
Start_Lng                   0
End_Lat               2478800
End_Lng               2478800
Distance(mi)                0
Description                 1
Number                2262850
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)         1868237
Humidity(%)             69687
```

```
Pressure(in)                 55882
Visibility(mi)               75856
Wind_Direction               58874
Wind_Speed(mph)             454602
Precipitation(in)          2025863
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
diff                             0
Year                             0
Month                            0
Day                              0
Hour                             0
Weekday                          0
dtype: int64
```

[32]:
```
# replace na in Precipitation(in) with 0
df_tmp['Precipitation(in)'] = df_tmp['Precipitation(in)'].fillna(0)
```

**Clean the outliers in 'Distance(mi)', 'Temperature(F)', 'Pressure(in)', 'Visibility(mi)', and 'Wind_Speed(mph)'**

[33]:
```
# check how much outliers these columns has by 3 sigma rules
outlier_list = ['Distance(mi)', 'Temperature(F)', 'Pressure(in)',
                'Visibility(mi)', 'Wind_Speed(mph)',
                'Precipitation(in)']

for item in outlier_list:

    df_tmp[item + '_zscore'] = (df_tmp[item] - df_tmp[item].mean())/
 ↪df_tmp[item].std()
    z_abnormal = abs(df_tmp[item + '_zscore']) > 3
    print(item + ' has ' + str(z_abnormal.sum()) + ' outliers')
```

```
Distance(mi) has 37756 outliers
Temperature(F) has 13420 outliers
Pressure(in) has 84587 outliers
Visibility(mi) has 32400 outliers
Wind_Speed(mph) has 21468 outliers
Precipitation(in) has 7417 outliers
```

[34]:
```
# drop the outliers
for item in outlier_list:

    median = df_tmp[item].median()
    std = df_tmp[item].std()
    df_tmp = df_tmp[(df_tmp[item] - median).abs() <= std * 3]
```

**Deal with missing values**

[36]:
```
# Set the list of features to include in Machine Learning
feature_lst=['Severity','Start_Time','Start_Lng','Start_Lat','Distance(mi)',
             'Side','City','County','State','Timezone','Temperature(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','Hour','Weekday']
```

[37]:
```
# Select the dataset to include only the selected features
df_sel = df_tmp[feature_lst].copy()
```

[38]:
```
# drop the rows with missing values
df_sel.dropna(subset = df_sel.columns[df_sel.isnull().mean()!=0], how = 'any',␣
 ↪axis = 0, inplace = True)
```

[39]:
```
# convert all bool columns to int type data (0,1)
df_sel[bool_cols] = df_sel[bool_cols].astype(int)
```

## 0.4 Select the sample data for analysing (state of interest, and the City of interest)

Due to the limitation of personal laptop, the whole US dataset is too big to handle

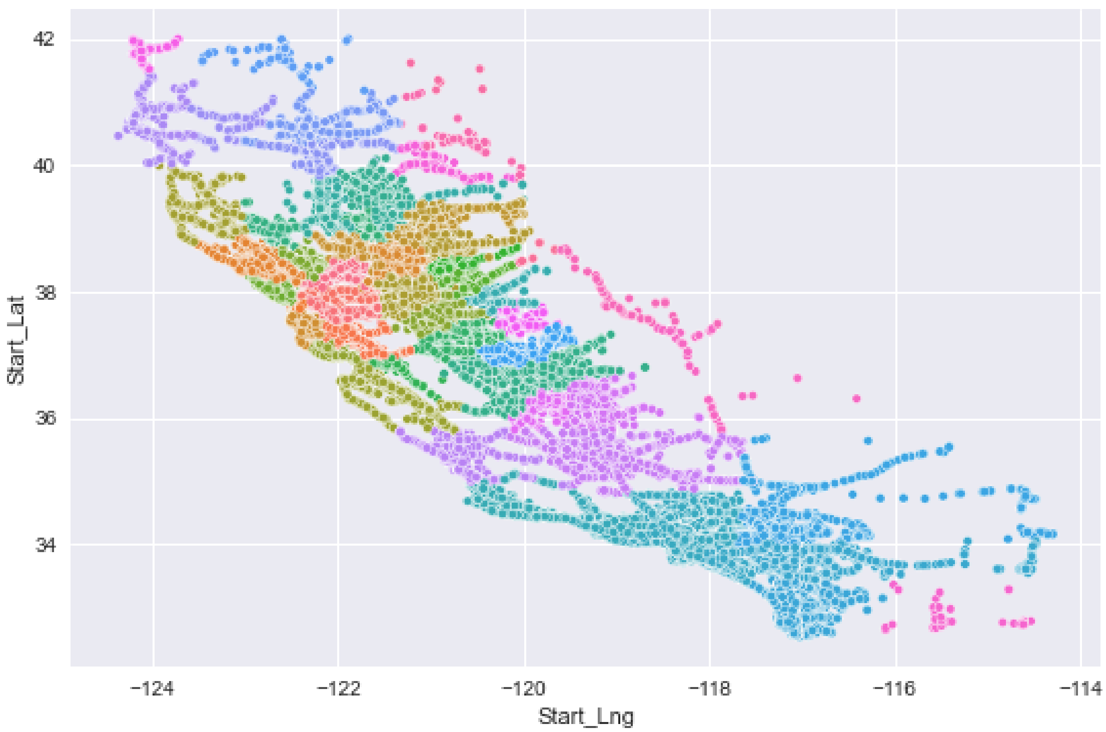
[201]:
```
# Select the state of South Carolina, which has the most accident records
df_state = df_sel.loc[df_sel.State == 'CA'].copy()
df_state.drop('State', axis = 1, inplace = True)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 650415 entries, 728 to 3513616
Data columns (total 33 columns):
Severity              650415 non-null int64
Start_Time            650415 non-null datetime64[ns]
```

```
 Start_Lng              650415 non-null float64
 Start_Lat              650415 non-null float64
 Distance(mi)           650415 non-null float64
 Side                   650415 non-null object
 City                   650415 non-null object
 County                 650415 non-null object
 Timezone               650415 non-null object
 Temperature(F)         650415 non-null float64
 Humidity(%)            650415 non-null float64
 Pressure(in)           650415 non-null float64
 Visibility(mi)         650415 non-null float64
 Wind_Direction         650415 non-null object
 Wind_Speed(mph)        650415 non-null float64
 Precipitation(in)      650415 non-null float64
 Weather_Condition      650415 non-null object
 Amenity                650415 non-null int32
 Bump                   650415 non-null int32
 Crossing               650415 non-null int32
 Give_Way               650415 non-null int32
 Junction               650415 non-null int32
 No_Exit                650415 non-null int32
 Railway                650415 non-null int32
 Roundabout             650415 non-null int32
 Station                650415 non-null int32
 Stop                   650415 non-null int32
 Traffic_Calming        650415 non-null int32
 Traffic_Signal         650415 non-null int32
 Turning_Loop           650415 non-null int32
 Sunrise_Sunset         650415 non-null object
 Hour                   650415 non-null int64
 Weekday                650415 non-null object
dtypes: datetime64[ns](1), float64(9), int32(13), int64(2), object(8)
memory usage: 136.5+ MB
```

[42]:

```
# Map of accidents, color code by county
sns.scatterplot(x = 'Start_Lng', y = 'Start_Lat', data = df_state, hue =␣
 ↪'County', legend = False, s = 20)
plt.show()
```




[202]:
```
# find the city with most accident cases
city = df_state.City.value_counts().sort_values(ascending = False)[:10]
city
```

[202]:
```
Los Angeles       56120
Sacramento        28805
San Diego         22663
San Jose          17454
Oakland           12811
Riverside         10925
Long Beach         9953
San Francisco      8810
Anaheim            8496
San Bernardino     7701
Name: City, dtype: int64
```

[44]:
```
# Select the city with most cases for modeling
df_city = df_state.loc[df_state.City == 'Los Angeles'].copy()
df_city.drop('City', axis = 1, inplace = True)
```

[45]:
```
df_city['Severity'].value_counts(normalize = True) * 100
```

[45]:
```
2    66.760513
3    32.435852
4     0.789380
1     0.014255
Name: Severity, dtype: float64
```

Which means our prediction accuracy should at least above the percentage of the highest counted one. Because if a model predicts all the case's to that severity, it will get the accuracy same as that percentage.

**Deal with categorical data: pd.get_dummies()**

[46]:
```python
# Generate dummies for categorical data
df_city.drop('Start_Time', axis = 1, inplace = True)
df_city_dummy = pd.get_dummies(df_city, drop_first = True)
```

## 0.5 Predict the accident severity with various supervised machine learning algorithms

**Import the machine learning libraries**

[18]:
```python
# Import LogisticRegression
from sklearn.linear_model import LogisticRegression

# Import KNeighborsClassifier from sklearn.neighbors
from sklearn.neighbors import KNeighborsClassifier

# Import DecisionTreeClassifier from sklearn.tree
from sklearn.tree import DecisionTreeClassifier

# Import RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve, auc
```

**Data preparation: train_test_split**

[48]:
```python
# Set the target for the prediction
target='Severity'

# set X and y
y = df_city_dummy[target]
X = df_city_dummy.drop(target, axis = 1)
```

```
# Split the data set into training and testing data sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,␣
↪random_state = 21, stratify = y)
```

[49]:
```
# List of classification algorithms
algo_lst = ['Logistic Regression', 'K-Nearest Neighbors', 'Decision Trees',␣
↪'Random Forest']

# Initialize an empty list for the accuracy for each algorithm
accuracy_lst = []
```

**Algorithm A. Logistic regression**

[50]:
```
# Logistic regression
lr = LogisticRegression(random_state = 0)
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)

# Get the accuracy score
acc = accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)

print("[Logistic regression algorithm] accuracy_score: {:.3f}.".format(acc))
```

```
[Logistic regression algorithm] accuracy_score: 0.704.
```

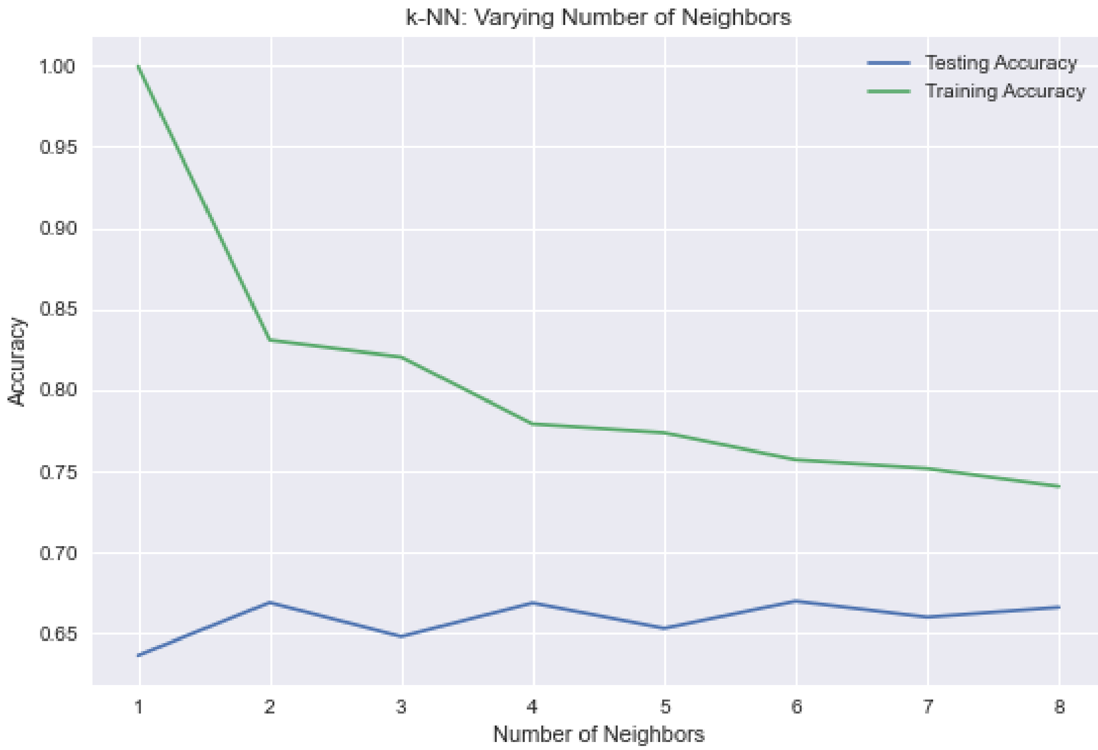
**Algorithm B. The K-Nearest Neighbors (KNN) algorithm**

[51]:
```
# Create a k-NN classifier with 6 neighbors
knn = KNeighborsClassifier(n_neighbors = 4)

# Fit the classifier to the data
knn.fit(X_train, y_train)

# Predict the labels for the training data X
y_pred = knn.predict(X_test)

# Get the accuracy score
acc = accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)

print('[K-Nearest Neighbors (KNN)] knn.score: {:.3f}.'.format(knn.score(X_test,␣
↪y_test)))
print('[K-Nearest Neighbors (KNN)] accuracy_score: {:.3f}.'.format(acc))
```

```
[K-Nearest Neighbors (KNN)] knn.score: 0.669.
[K-Nearest Neighbors (KNN)] accuracy_score: 0.669.
```

Optmize the number of neighors: plot the accuracy versus number of neighbors

[52]:
```python
# Setup arrays to store train and test accuracies
neighbors = np.arange(1, 9)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

# Loop over different values of k
for i, n_neighbor in enumerate(neighbors):

    # Setup a k-NN Classifier with n_neighbor
    knn = KNeighborsClassifier(n_neighbors = n_neighbor)

    # Fit the classifier to the training data
    knn.fit(X_train, y_train)

    #Compute accuracy on the training set
    train_accuracy[i] = knn.score(X_train, y_train)

    #Compute accuracy on the testing set
    test_accuracy[i] = knn.score(X_test, y_test)

# Generate plot
plt.title('k-NN: Varying Number of Neighbors')
plt.plot(neighbors, test_accuracy, label = 'Testing Accuracy')
plt.plot(neighbors, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.show()
```




**Algorithm C. Decision Tree**

[53]:
```
# Instantiate dt_entropy, set 'entropy' as the information criterion
dt_entropy = DecisionTreeClassifier(max_depth = 10, criterion = 'entropy',␣
↪random_state = 1)

# Fit dt_entropy to the training set
dt_entropy.fit(X_train, y_train)

# Use dt_entropy to predict test set labels
y_pred = dt_entropy.predict(X_test)

# Evaluate accuracy_entropy
accuracy_entropy = accuracy_score(y_test, y_pred)

# Print accuracy_entropy
print('[Decision Tree -- entropy] accuracy_score: {:.3f}.'.
↪format(accuracy_entropy))

# Instantiate dt_gini, set 'gini' as the information criterion
dt_gini = DecisionTreeClassifier(max_depth = 10, criterion = 'gini',␣
↪random_state = 1)
```

```
# Fit dt_entropy to the training set
dt_gini.fit(X_train, y_train)

# Use dt_entropy to predict test set labels
y_pred= dt_gini.predict(X_test)

# Evaluate accuracy_entropy
accuracy_gini = accuracy_score(y_test, y_pred)

# Append to the accuracy list
acc = accuracy_gini
accuracy_lst.append(acc)

# Print accuracy_gini
print('[Decision Tree -- gini] accuracy_score: {:.3f}.'.format(accuracy_gini))
```

```
[Decision Tree -- entropy] accuracy_score: 0.818.
[Decision Tree -- gini] accuracy_score: 0.809.
```

**Algorithm D. Random Forest**

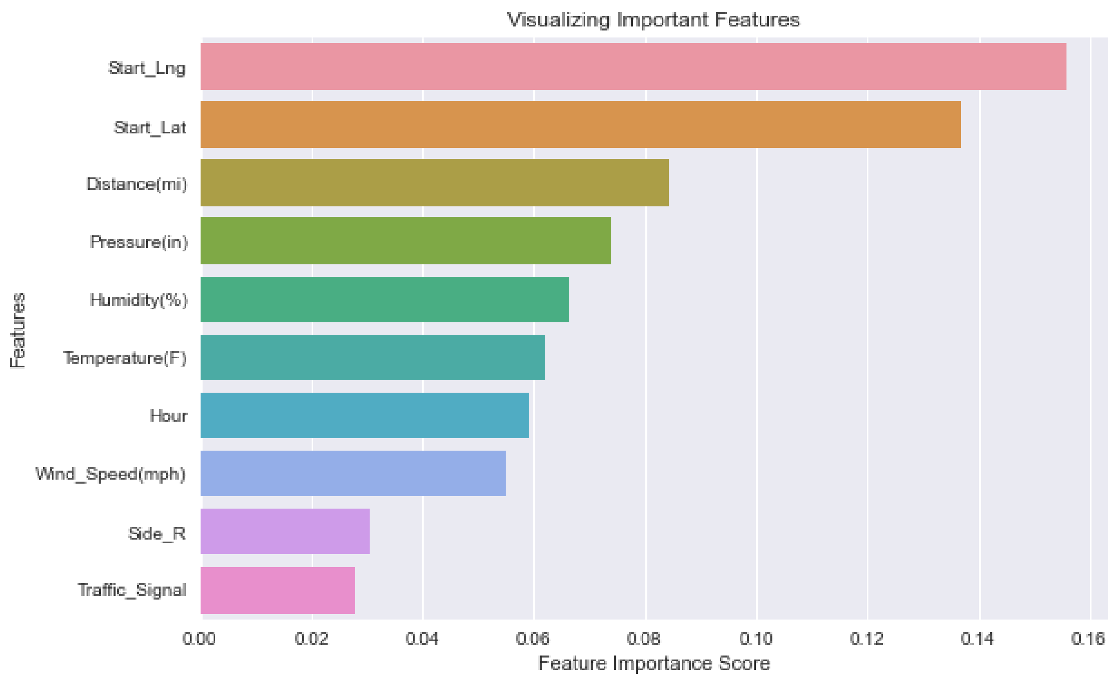
[54]:
```
#Create a Gaussian Classifier
clf = RandomForestClassifier(n_estimators = 100)

#Train the model
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

# Model Accuracy, how often is the classifier correct?
print("[Randon forest algorithm] accuracy_score: {:.3f}.".format(acc))
```

```
[Randon forest algorithm] accuracy_score: 0.809.
```

Find the most important features

[55]:
```
feature_imp = pd.Series(clf.feature_importances_, index = X.columns).
↪sort_values(ascending = False)

# Creating a bar plot, displaying only the top k features
k = 10
sns.barplot(x = feature_imp[:10], y = feature_imp.index[:k])

# Add labels to your graph
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```




[56]:
```python
# List top k important features
k = 20
feature_imp.sort_values(ascending = False)[:k]
```

[56]:
```
Start_Lng                  0.155800
Start_Lat                  0.136912
Distance(mi)               0.084278
Pressure(in)               0.073940
Humidity(%)                0.066338
Temperature(F)             0.061989
Hour                       0.059239
Wind_Speed(mph)            0.055023
Side_R                     0.030569
Traffic_Signal             0.027936
Weather_Condition_Fair     0.022207
Visibility(mi)             0.017734
Weather_Condition_Clear    0.016928
Junction                   0.012951
Sunrise_Sunset_Night       0.011065
Weekday_Sat                0.009557
Weekday_Wed                0.008803
Weekday_Sun                0.008688
Weekday_Tue                0.008631
Weekday_Thu                0.008388
dtype: float64
```

[57]:
```
# Create a selector object that will use the random forest classifier to␣
↪identify features which importance > 0.04
sfm = SelectFromModel(clf, threshold = 0.04)

# Train the selector
sfm.fit(X_train, y_train)

feat_labels = X.columns

# Print the names of the most important features
for feature_list_index in sfm.get_support(indices = True):
    print(feat_labels[feature_list_index])
```

```
Start_Lng
Start_Lat
Distance(mi)
Temperature(F)
Humidity(%)
Pressure(in)
Wind_Speed(mph)
Hour
```

[58]:
```
# Transform the data to create a new dataset containing only the most important␣
↪features
X_important_train = sfm.transform(X_train)
X_important_test = sfm.transform(X_test)

# Create a new random forest classifier for the most important features
clf_important = RandomForestClassifier(n_estimators = 500, random_state = 0,␣
↪n_jobs = -1)

# Train the new classifier on the new dataset containing the most important␣
↪features
clf_important.fit(X_important_train, y_train)
```

[58]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=-1, oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

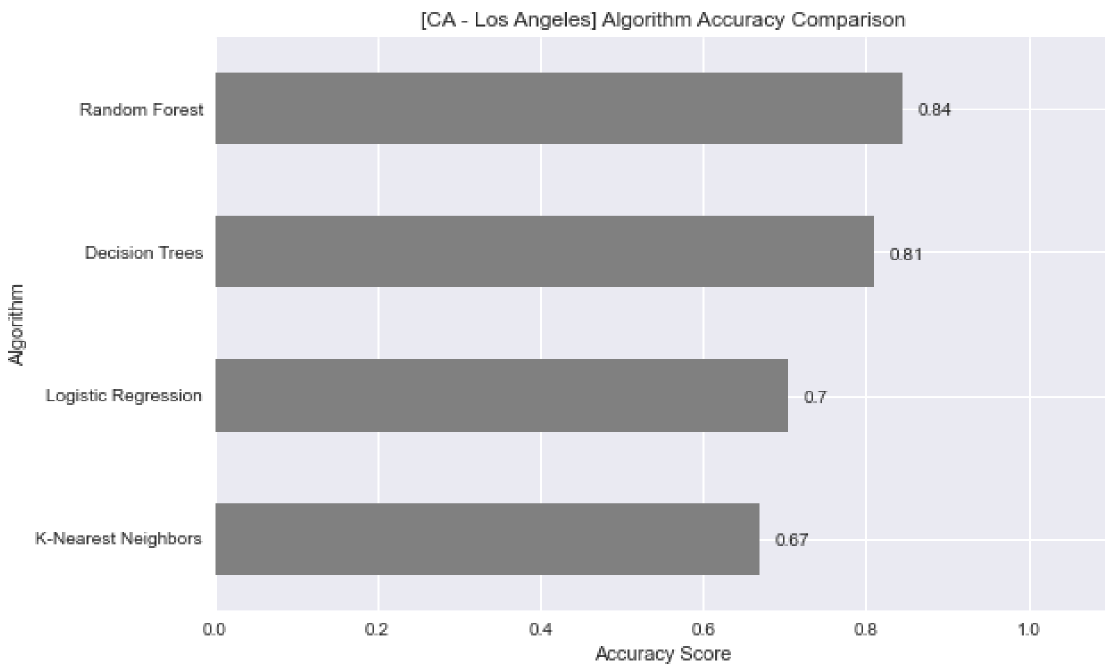
[59]:
```
# Apply The Full Featured Classifier To The Test Data
y_pred = clf.predict(X_test)
```

```python
# View The Accuracy Of Our Full Feature Model
print('[Randon forest algorithm -- Full feature] accuracy_score: {:.3f}.'.
 ↪format(accuracy_score(y_test, y_pred)))

# Apply The Full Featured Classifier To The Test Data
y_important_pred = clf_important.predict(X_important_test)

# View The Accuracy Of Our Limited Feature Model
print('[Randon forest algorithm -- Limited feature] accuracy_score: {:.3f}.'.
 ↪format(accuracy_score(y_test, y_important_pred)))

# Get the accuracy score
acc = accuracy_score(y_test, y_important_pred)

# Append to the accuracy list
accuracy_lst.append(acc)
```

```
[Randon forest algorithm -- Full feature] accuracy_score: 0.832.
[Randon forest algorithm -- Limited feature] accuracy_score: 0.844.
```

**Accuracy Score VS. Algorithm**

[60]:
```python
# Generate a list of ticks for y-axis
y_ticks = np.arange(len(algo_lst))

# Combine the list of algorithms and list of accuracy scores into a dataframe,␣
 ↪sort the value based on accuracy score
df_acc = pd.DataFrame(list(zip(algo_lst, accuracy_lst)), columns =␣
 ↪['Algorithm', 'Accuracy_Score']).sort_values(by = ['Accuracy_Score'],␣
 ↪ascending = True)

# Make a plot
ax = df_acc.plot.barh('Algorithm', 'Accuracy_Score', align = 'center', legend =␣
 ↪False, color = '0.5')

# Add the data label on to the plot
for i in ax.patches:
    # get_width pulls left or right; get_y pushes up or down
    ax.text(i.get_width() + 0.02, i.get_y() + 0.2, str(round(i.get_width(),␣
 ↪2)), fontsize = 10)

# Set the limit, lables, ticks and title
plt.xlim(0, 1.1)
plt.xlabel('Accuracy Score')
plt.yticks(y_ticks, df_acc['Algorithm'], rotation = 0)
plt.title('[CA - Los Angeles] Algorithm Accuracy Comparison')
plt.show()
```




## 0.6 Time Series Forecasting For Road Accidents in one specific State

**Auto Regressive Integrated Moving Average (ARIMA) model**

[ ]:
```
# save the cleaned dataframe to a csv file
# df_sel.to_csv('C:/Users/AS/Downloads/data/US_Accidents_forecast.csv', index =␣
↪False, index_label = None)
```

[2]:
```
import datetime
from pylab import rcParams
import statsmodels.api as sm
warnings.filterwarnings("ignore")
```

[3]:
```
# Import the cleaned dataset
df_forecast = pd.read_csv('C:/Users/AS/Downloads/data/US_Accidents_forecast.
↪csv')
```

[4]:
```
# Set the list of features to include in Machine Learning
feature_lst_2=['Start_Time','Severity','Start_Lng','Start_Lat','Distance(mi)',
               'Side','State','Temperature(F)','Humidity(%)','Pressure(in)',
               'Visibility(mi)','Wind_Speed(mph)','Weather_Condition',
               'Traffic_Signal','Hour','Weekday']
```

[65]:
```
# Select the dataset to include only the selected features
df_forecast = df_forecast[feature_lst_2].copy()
df_forecast['Count'] = 1
```

[66]:
```
df_forecast.Timestamp = pd.to_datetime(df_forecast.Start_Time, format='%Y-%m-%d␣
↪%H:%M:%S')
```

[67]:
```
df_forecast['Start_Time_date'] = pd.DatetimeIndex(df_forecast.Timestamp).date
```

[424]:
```
# Check out the Data for a specific State
df_fc_spe = df_forecast.loc[df_forecast.State == 'CA'].copy()
df_fc_spe.head()
```

[424]:
```
                  Start_Time  Severity   Start_Lng  Start_Lat  Distance(mi)  \
24179    2016-03-22 17:44:13         2 -121.364571  38.713371         0.010
24187    2016-03-22 23:57:48         3 -122.065567  37.980061         0.010
1963359  2016-03-22 20:07:32         3 -122.307987  37.881943         0.276
24177    2016-03-22 21:44:11         2 -121.415352  38.608391         0.010
24180    2016-03-22 21:05:57         3 -121.273888  38.739998         0.010

        Side State  Temperature(F)  Humidity(%)  Pressure(in)  Visibility(mi)  \
24179      L    CA            60.8         42.0         30.21             9.0
24187      R    CA            52.0         71.0         30.23            10.0
1963359    R    CA            57.0         64.0         30.24            10.0
24177      L    CA            51.8         67.0         30.26            10.0
24180      R    CA            53.6         58.0         30.25            10.0

         Wind_Speed(mph) Weather_Condition  Traffic_Signal  Hour Weekday  \
24179                6.9             Clear               1    17     Tue
24187                4.6             Clear               0    23     Tue
1963359              8.1     Partly Cloudy               0    20     Tue
24177                3.5             Clear               0    21     Tue
24180                4.6             Clear               0    21     Tue

         Count Start_Time_date
24179        1      2016-03-22
24187        1      2016-03-22
1963359      1      2016-03-22
24177        1      2016-03-22
24180        1      2016-03-22
```

[425]:
```
# Set the Date for index
df_fc_spe['Start_Time_date'] = pd.to_datetime(df_fc_spe.Start_Time_date,␣
↪format='%Y-%m-%d')
acc_spec = df_fc_spe.set_index('Start_Time_date')
acc_spec.index
```

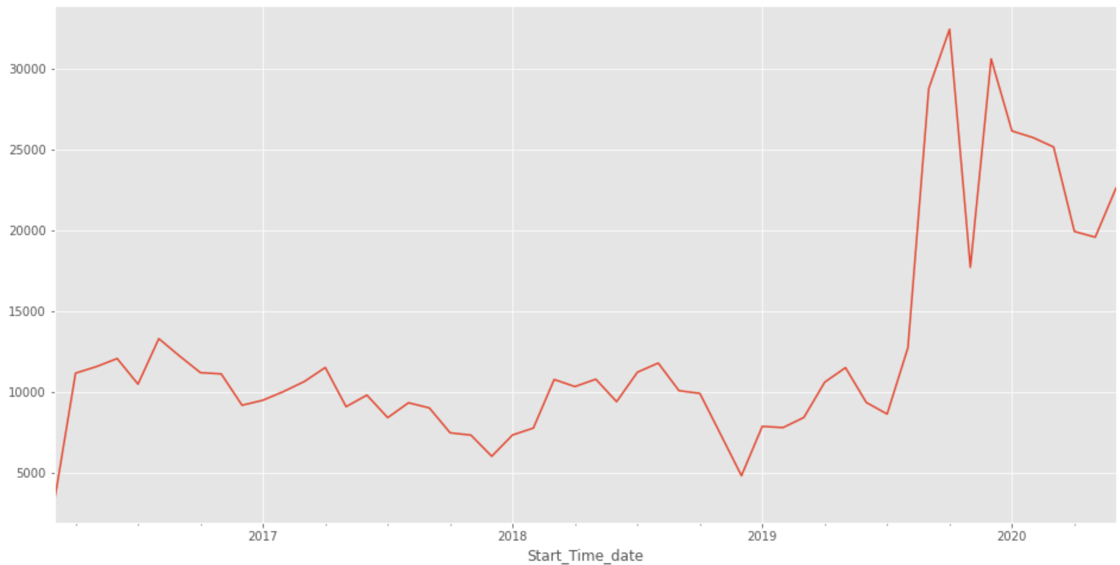
[425]:
```
DatetimeIndex(['2016-03-22', '2016-03-22', '2016-03-22', '2016-03-22',
               '2016-03-22', '2016-03-22', '2016-03-22', '2016-03-22',
               '2016-03-22', '2016-03-22',
               …
```

```
                  '2020-06-30', '2020-06-30', '2020-06-30', '2020-06-30',
                  '2020-06-30', '2020-06-30', '2020-06-30', '2020-06-30',
                  '2020-06-30', '2020-06-30'],
                 dtype='datetime64[ns]', name='Start_Time_date', length=650415,
freq=None)
```

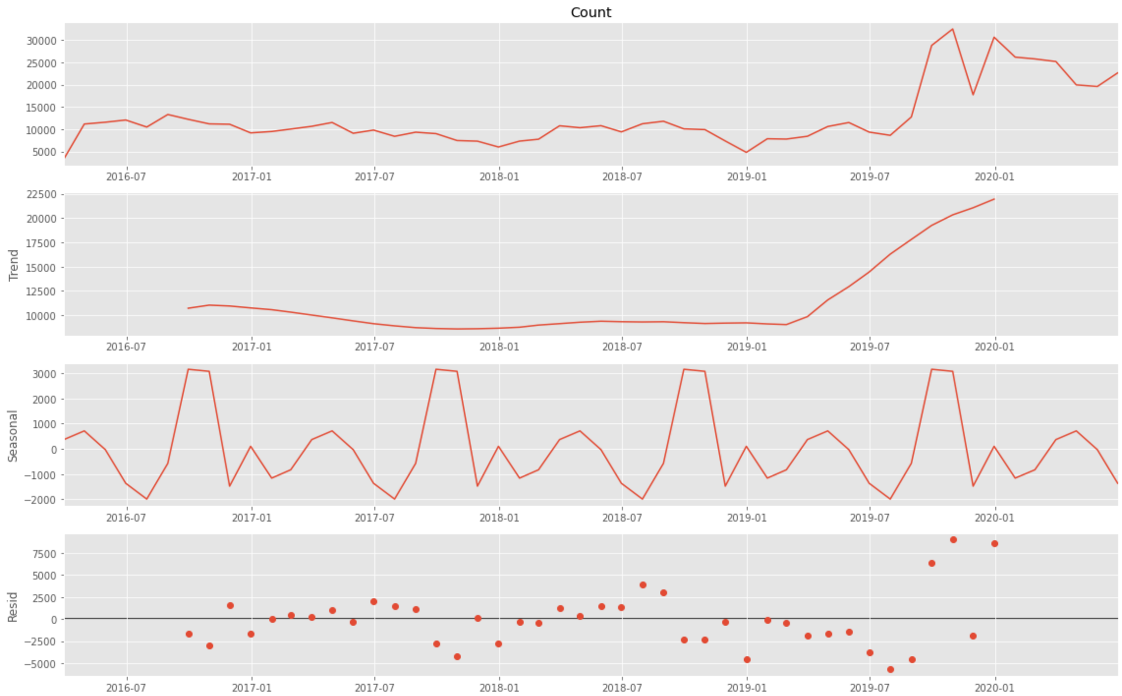
[426]:
```
y_spec = acc_spec['Count'].resample('M').sum()
```

[429]:
```
rn_spec = np.where(y_spec.index == '2019-12-31')
n = int(rn_spec[0]) + 1
```

[428]:
```
y_spec.plot(figsize=(16, 8))
plt.show()
```




[430]:
```
# visualise the data using time-series decomposition which decompose time␣
 ↪series into three distinct components:
# trend, seasonality, and noise.
rcParams['figure.figsize'] = 16, 10
decomposition = sm.tsa.seasonal_decompose(y_spec, model='additive')
fig = decomposition.plot()
plt.show()
```




[431]:
```python
# Parameter combinations for seasonal ARIMA
p = d = q = range(0, 2)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]
```

[377]:
```python
# use a "grid search" to find the optimal set of parameters that yields the best performance for ARIMA model
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(y_spec[:n],
                                            order = param,
                                            seasonal_order = param_seasonal,
                                            enforce_stationarity = False,
                                            enforce_invertibility = False)
            results = mod.fit()
            print('ARIMA{}x{}12 - AIC:{}'.format(param, param_seasonal, results.aic))

        except:
            continue
```

```
ARIMA(0, 0, 0)x(0, 0, 0, 12)12 - AIC:979.4273732610349
ARIMA(0, 0, 0)x(0, 0, 1, 12)12 - AIC:1365.5727695260152
```

```
ARIMA(0, 0, 0)x(0, 1, 0, 12)12 - AIC:682.9871031272089
ARIMA(0, 0, 0)x(0, 1, 1, 12)12 - AIC:444.90524281681127
ARIMA(0, 0, 0)x(1, 0, 0, 12)12 - AIC:704.7926489651738
ARIMA(0, 0, 0)x(1, 0, 1, 12)12 - AIC:1367.6904076447106
ARIMA(0, 0, 0)x(1, 1, 0, 12)12 - AIC:465.68332435176467
ARIMA(0, 0, 0)x(1, 1, 1, 12)12 - AIC:441.4333327812981
ARIMA(0, 0, 1)x(0, 0, 0, 12)12 - AIC:932.3783544649402
ARIMA(0, 0, 1)x(0, 0, 1, 12)12 - AIC:3827.6458355236273
ARIMA(0, 0, 1)x(0, 1, 0, 12)12 - AIC:652.407333493177
ARIMA(0, 0, 1)x(0, 1, 1, 12)12 - AIC:417.5398967809095
ARIMA(0, 0, 1)x(1, 0, 0, 12)12 - AIC:689.5481512815007
ARIMA(0, 0, 1)x(1, 0, 1, 12)12 - AIC:3539.145187675308
ARIMA(0, 0, 1)x(1, 1, 0, 12)12 - AIC:457.1584276451849
ARIMA(0, 0, 1)x(1, 1, 1, 12)12 - AIC:419.5377203858947
ARIMA(0, 1, 0)x(0, 0, 0, 12)12 - AIC:860.0212165535962
ARIMA(0, 1, 0)x(0, 0, 1, 12)12 - AIC:1270.5687945583882
ARIMA(0, 1, 0)x(0, 1, 0, 12)12 - AIC:638.343520325064
ARIMA(0, 1, 0)x(0, 1, 1, 12)12 - AIC:407.5406891181471
ARIMA(0, 1, 0)x(1, 0, 0, 12)12 - AIC:656.210477028506
ARIMA(0, 1, 0)x(1, 0, 1, 12)12 - AIC:2592.591597535879
ARIMA(0, 1, 0)x(1, 1, 0, 12)12 - AIC:429.77661205234267
ARIMA(0, 1, 0)x(1, 1, 1, 12)12 - AIC:409.5387164511369
ARIMA(0, 1, 1)x(0, 0, 0, 12)12 - AIC:840.4172836581823
ARIMA(0, 1, 1)x(0, 0, 1, 12)12 - AIC:1917.5529223847786
ARIMA(0, 1, 1)x(0, 1, 0, 12)12 - AIC:619.2495225942914
ARIMA(0, 1, 1)x(0, 1, 1, 12)12 - AIC:389.0842501019831
ARIMA(0, 1, 1)x(1, 0, 0, 12)12 - AIC:655.7845552605228
ARIMA(0, 1, 1)x(1, 0, 1, 12)12 - AIC:2229.715907705357
ARIMA(0, 1, 1)x(1, 1, 0, 12)12 - AIC:430.83264782526476
ARIMA(0, 1, 1)x(1, 1, 1, 12)12 - AIC:391.049872313511
ARIMA(1, 0, 0)x(0, 0, 0, 12)12 - AIC:883.9365734612862
ARIMA(1, 0, 0)x(0, 0, 1, 12)12 - AIC:1350.5858050295553
ARIMA(1, 0, 0)x(0, 1, 0, 12)12 - AIC:660.6059843033833
ARIMA(1, 0, 0)x(0, 1, 1, 12)12 - AIC:430.2954819256927
ARIMA(1, 0, 0)x(1, 0, 0, 12)12 - AIC:658.9721670266343
ARIMA(1, 0, 0)x(1, 0, 1, 12)12 - AIC:1272.9991202806227
ARIMA(1, 0, 0)x(1, 1, 0, 12)12 - AIC:431.65554610591494
ARIMA(1, 0, 0)x(1, 1, 1, 12)12 - AIC:432.26992262252986
ARIMA(1, 0, 1)x(0, 0, 0, 12)12 - AIC:860.428458650118
ARIMA(1, 0, 1)x(0, 0, 1, 12)12 - AIC:2527.3390123920244
ARIMA(1, 0, 1)x(0, 1, 0, 12)12 - AIC:640.7844354895325
ARIMA(1, 0, 1)x(0, 1, 1, 12)12 - AIC:410.3836700770396
ARIMA(1, 0, 1)x(1, 0, 0, 12)12 - AIC:657.391037822451
ARIMA(1, 0, 1)x(1, 0, 1, 12)12 - AIC:2174.5041500376456
ARIMA(1, 0, 1)x(1, 1, 0, 12)12 - AIC:432.1122224108316
ARIMA(1, 0, 1)x(1, 1, 1, 12)12 - AIC:412.35436834060863
ARIMA(1, 1, 0)x(0, 0, 0, 12)12 - AIC:860.3735153475362
ARIMA(1, 1, 0)x(0, 0, 1, 12)12 - AIC:1223.4131490049356
```

```
ARIMA(1, 1, 0)x(0, 1, 0, 12)12 - AIC:639.3328810285408
ARIMA(1, 1, 0)x(0, 1, 1, 12)12 - AIC:409.07014219093503
ARIMA(1, 1, 0)x(1, 0, 0, 12)12 - AIC:638.0779716301504
ARIMA(1, 1, 0)x(1, 0, 1, 12)12 - AIC:1397.672987947693
ARIMA(1, 1, 0)x(1, 1, 0, 12)12 - AIC:410.9547653529601
ARIMA(1, 1, 0)x(1, 1, 1, 12)12 - AIC:411.0406967981893
ARIMA(1, 1, 1)x(0, 0, 0, 12)12 - AIC:842.2046376842674
ARIMA(1, 1, 1)x(0, 0, 1, 12)12 - AIC:2330.4988152647543
ARIMA(1, 1, 1)x(0, 1, 0, 12)12 - AIC:621.1713196424049
ARIMA(1, 1, 1)x(0, 1, 1, 12)12 - AIC:390.7933422057563
ARIMA(1, 1, 1)x(1, 0, 0, 12)12 - AIC:639.3544155894712
ARIMA(1, 1, 1)x(1, 0, 1, 12)12 - AIC:619.3140263891471
ARIMA(1, 1, 1)x(1, 1, 0, 12)12 - AIC:412.5141735822761
ARIMA(1, 1, 1)x(1, 1, 1, 12)12 - AIC:392.79681257126515
```

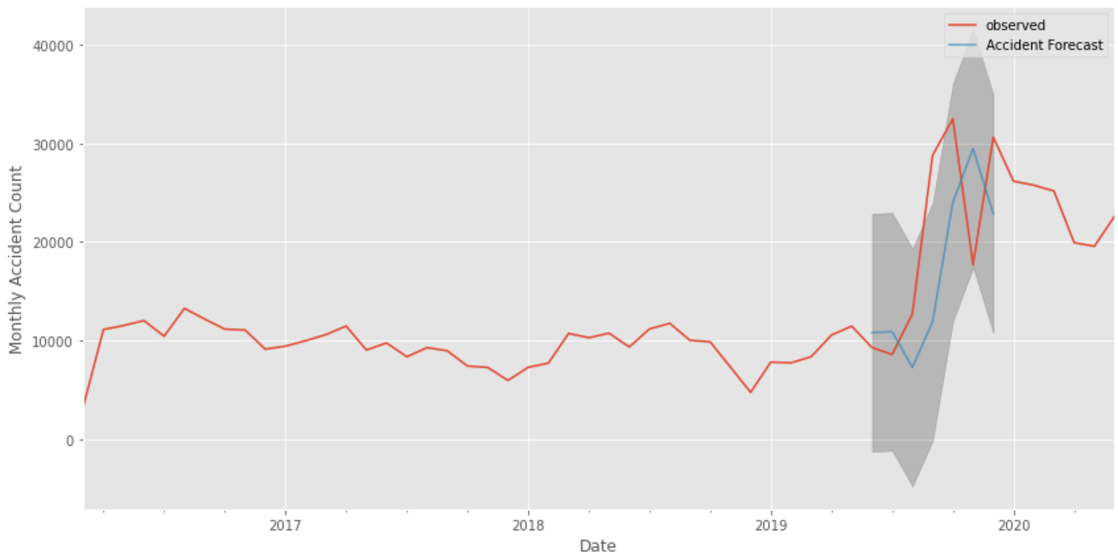
CA: ARIMA(0, 1, 1)x(0, 1, 1, 12) yields the lowest AIC 389.08.

[432]:
```python
# Fitting the ARIMA Model
mod = sm.tsa.statespace.SARIMAX(y_spec[:n],
                                order = (0,1,1),
                                seasonal_order = (0,1,1,12),
                                enforce_stationarity = False,
                                enforce_invertibility = False)
results_spec = mod.fit()
print(results.summary().tables[1])
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.8750      0.101      8.662      0.000       0.677       1.073
ma.L1         -1.0000    887.138     -0.001      0.999   -1739.759    1737.759
ar.S.L12      -0.5273      0.229     -2.304      0.021      -0.976      -0.079
ma.S.L12       0.9993    887.211      0.001      0.999   -1737.901    1739.900
sigma2      1265.4366      0.385   3282.995      0.000    1264.681    1266.192
==============================================================================
```

[434]:
```python
pred_spec = results_spec.get_prediction(start = pd.to_datetime('2019-06-30'),␣
 ↪dynamic = False)
pred_ci_spec = pred_spec.conf_int()
ax = y_spec['2016':].plot(label = 'observed')
pred_spec.predicted_mean.plot(ax = ax,
                              label = 'Accident Forecast',
                              alpha = .7,
                              figsize = (14, 7))
ax.fill_between(pred_ci_spec.index,
                pred_ci_spec.iloc[:, 0],
                pred_ci_spec.iloc[:, 1], color = 'k', alpha = .2)
ax.set_xlabel('Date')
```

```
ax.set_ylabel('Monthly Accident Count')
plt.legend()
plt.show()
```

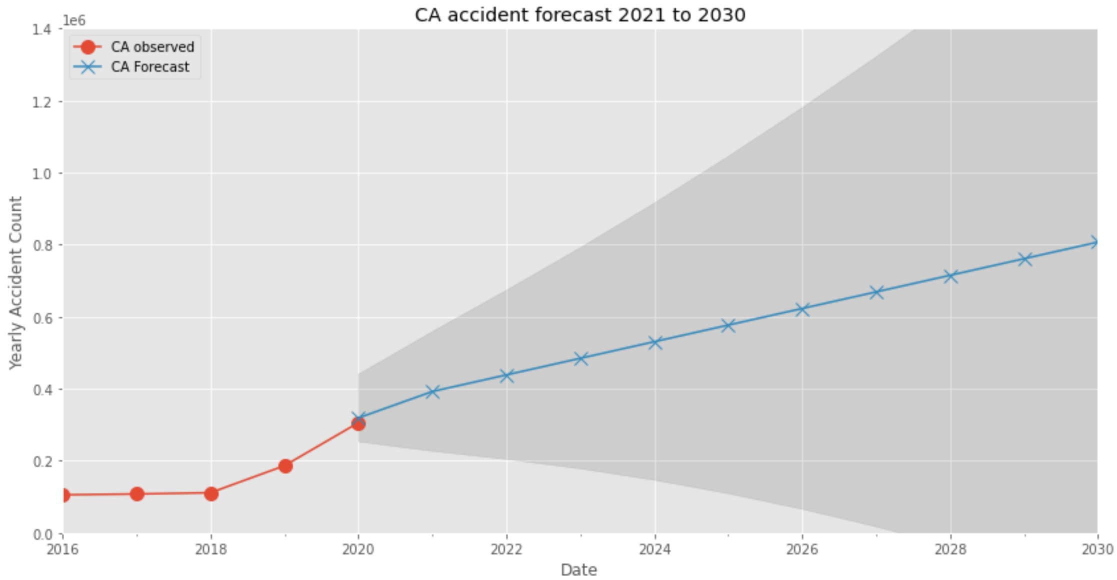



[380]:
```
# Use mean squared error (MSE) to check the accuracy of this model
y_forecasted = pred.predicted_mean
y_truth = y_spec['2020-01-01':]
mse = ((y_forecasted - y_truth) ** 2).mean()
print('The Mean Squared Error of the forecasts is {}'.format(round(mse, 2)))
```

```
The Mean Squared Error of the forecasts is 636637.42
```

[389]:
```
# Visualising the number of road accident in USA in next years
pred_uc = results.get_forecast(steps = 132)
pred_ci = pred_uc.conf_int(alpha = 0.5).resample('Y').sum()
pred_y_s = pd.concat([y_spec[-6:], pred_uc.predicted_mean[6:]]).round()
obse_y_s = pd.concat([y_spec, pred_uc.predicted_mean[:6]]).round()
ax = obse_y_s.resample('Y').sum().plot(label = 'CA observed', figsize = (14,␣
 ↪7), marker='o', markersize = 10)
pred_y_s.resample('Y').sum().plot(ax = ax, label = 'CA Forecast', marker='x',␣
 ↪markersize = 10)
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.10)
ax.set_xlabel('Date')
ax.set_ylabel('Yearly Accident Count')
plt.title('CA accident forecast 2021 to 2030')
plt.legend(loc = 2)
```

```
plt.ylim(ymin = 0, ymax = 1400000)
plt.show()
```



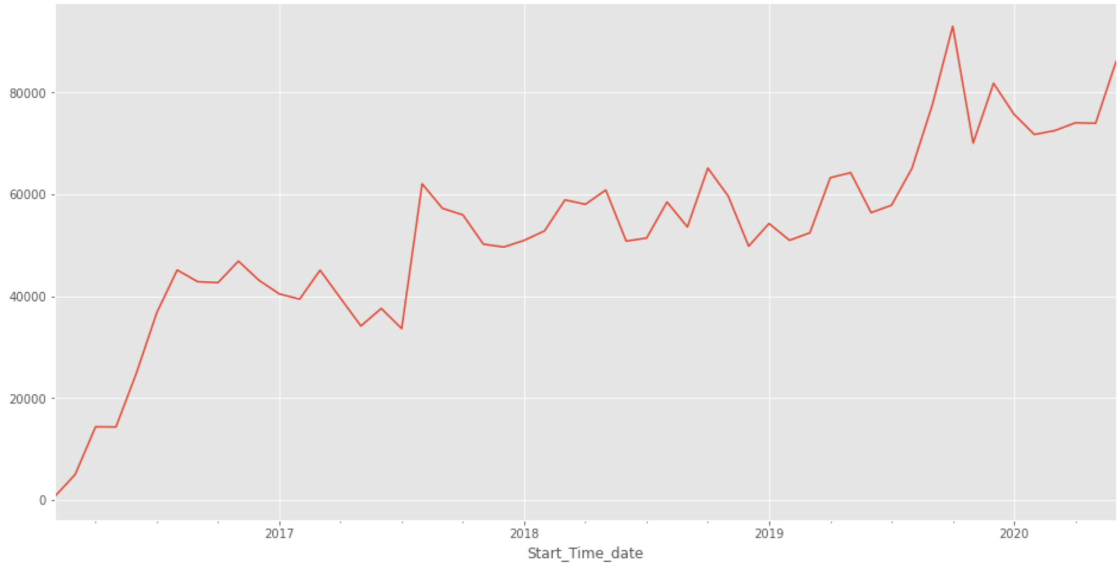

### 0.7 Time Series Forecasting For Road Accidents in US and each state

[403]:
```
# forecasting for the US
df_forecast['Count']=1
df_forecast['Start_Time_date'] = pd.to_datetime(df_forecast.Start_Time_date,␣
↪format='%Y-%m-%d')
```

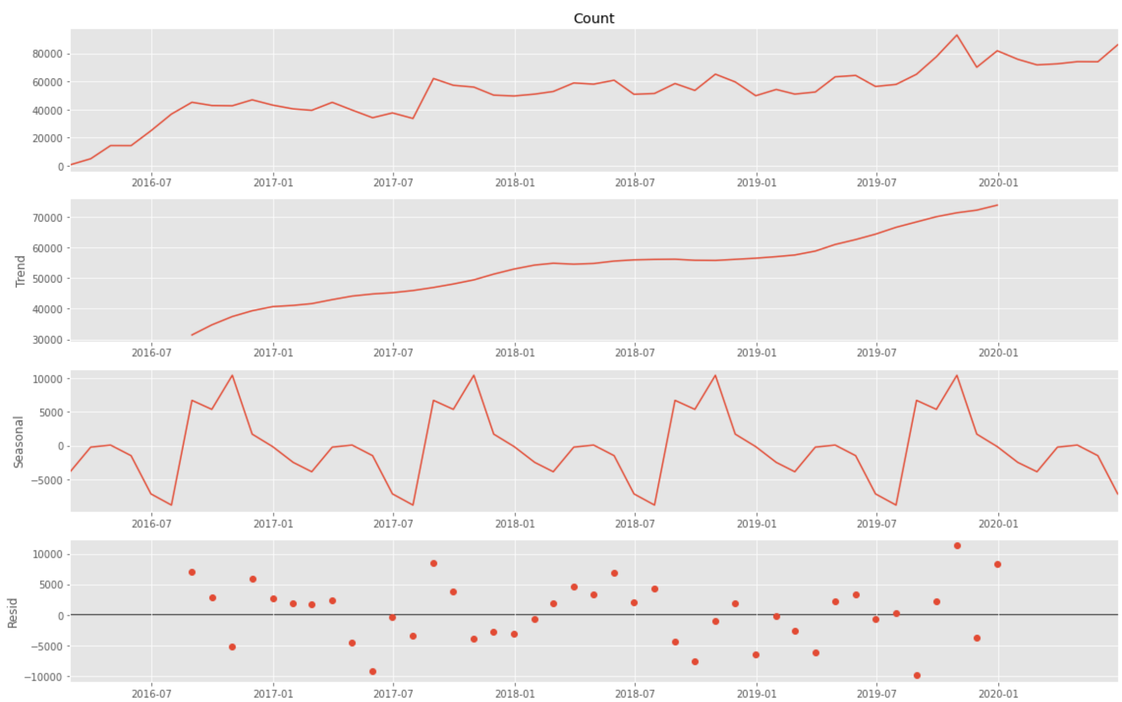
[404]:
```
# Set the Date for index
df_forecast.sort_values('Start_Time_date', inplace = True)
accident_US = df_forecast.set_index('Start_Time_date')
```

[405]:
```
y_us = accident_US['Count'].resample('M').sum()
```

[406]:
```
y_us.plot(figsize=(16, 8))
plt.show()
```

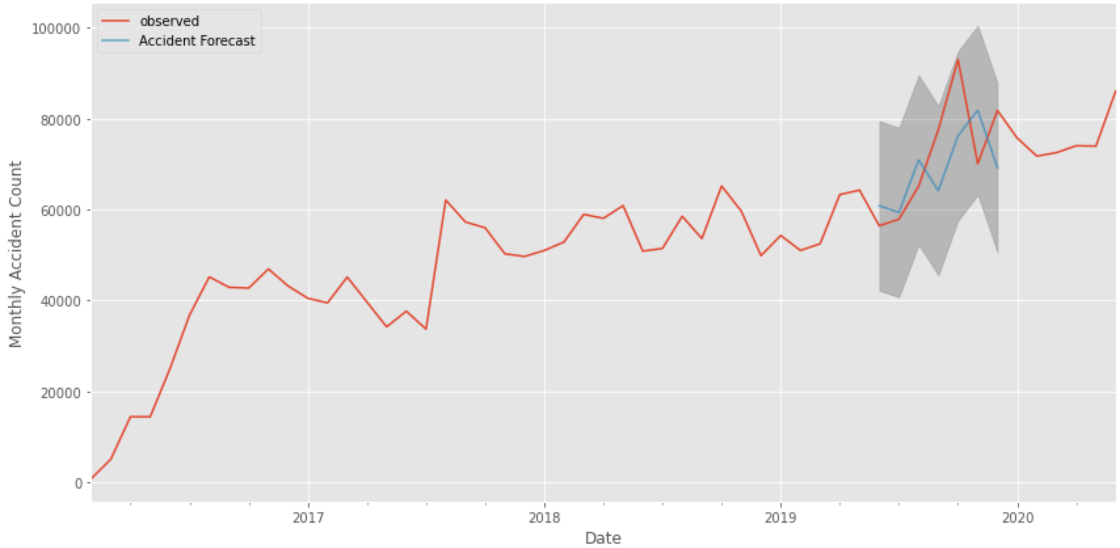



[407]:
```
rcParams['figure.figsize'] = 16, 10
decomposition = sm.tsa.seasonal_decompose(y_us, model='additive')
fig = decomposition.plot()
plt.show()
```

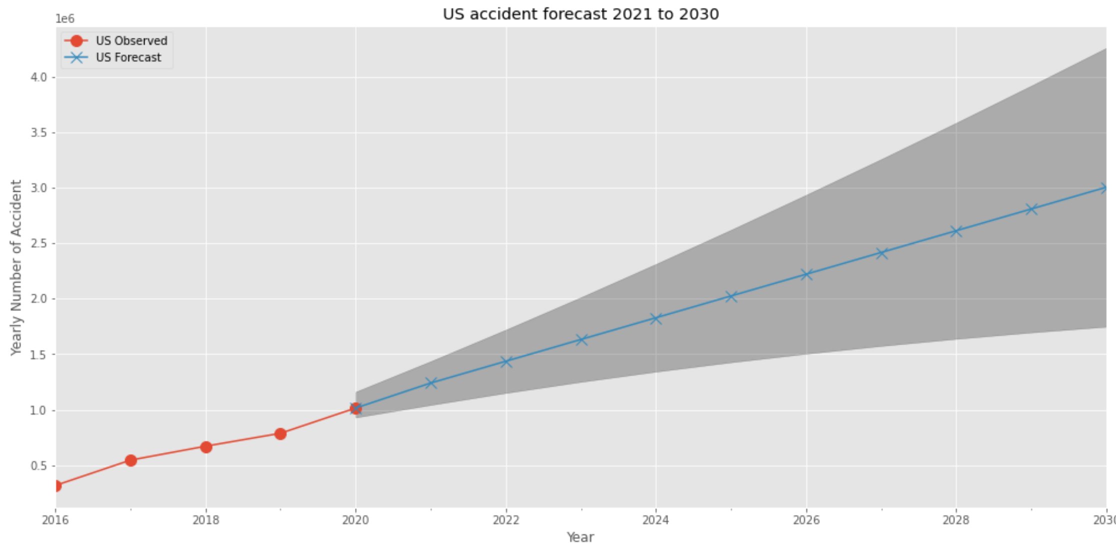


[409]:
```python
# use a "grid search" to find the optimal set of parameters that yields the␣
↪best performance for ARIMA model
results_us = []
p = d = q = range(0, 2)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d,␣
↪q))]

for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(y_us[:47],
                                            order = param,
                                            seasonal_order = param_seasonal,
                                            enforce_stationarity = True,
                                            enforce_invertibility = True)
            results_ite = mod.fit()
        except:
            continue
        res_aic = results_ite.aic
        if results_ite.aic <= res_aic:
            res_aic = results_ite.aic
            results_us=([param, param_seasonal, results_ite.aic])

mod = sm.tsa.statespace.SARIMAX(y_us[:47],
                                order = results_aic[0],
                                seasonal_order = results_aic[1],
                                enforce_stationarity = True,
                                enforce_invertibility = True)
results_us = mod.fit()
print(results_us.summary().tables[1])
```

[416]:
```python
pred_us = results_us.get_prediction(start = pd.to_datetime('2019-06-30'),␣
↪dynamic = False)
pred_ci_us = pred_us.conf_int()
ax = y_us['2016':].plot(label = 'observed')
pred_us.predicted_mean.plot(ax = ax,
                            label = 'Accident Forecast',
                            alpha = .7,
                            figsize = (14, 7))
ax.fill_between(pred_ci_us.index,
                pred_ci_us.iloc[:, 0],
                pred_ci_us.iloc[:, 1], color = 'k', alpha = .2)
ax.set_xlabel('Date')
ax.set_ylabel('Monthly Accident Count')
plt.legend(loc = 2)
plt.show()
```




[417]:
```
# Visualising the number of road accident in USA in next years
pred_uc = results_us.get_forecast(steps = 132)
pred_ci_us = pred_uc.conf_int(alpha = 0.5).resample('Y').sum()
pred_y = pd.concat([y_us[-6:], pred_uc.predicted_mean[6:]]).round() # add␣
↪observed 2020 6 month to the beginning of prediction for yearly count
obse_y = pd.concat([y_us, pred_uc.predicted_mean[6:12]]).round() # add␣
↪predicted 2020 6 month to the end of observed for yearly count
ax = obse_y.resample('Y').sum().plot(label = 'US Observed', figsize = (17, 8),␣
↪marker='o', markersize = 10)
pred_y.resample('Y').sum().plot(ax = ax, label = 'US Forecast', marker='x',␣
↪markersize = 10)
ax.fill_between(pred_ci_us.index,
                pred_ci_us.iloc[:, 0],
                pred_ci_us.iloc[:, 1], color='k', alpha=.25)
ax.set_xlabel('Year')
ax.set_ylabel('Yearly Number of Accident')
plt.title('US accident forecast 2021 to 2030')
plt.legend(loc = 2)
plt.show()
```




**Forecast for all states**

[256]:
```
state_info = df_forecast.State.unique()
print(sorted(state_info))
```

```
['AL', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL', 'GA', 'IA', 'ID', 'IL',
'IN', 'KS', 'KY', 'LA', 'MA', 'MD', 'ME', 'MI', 'MN', 'MO', 'MS', 'MT', 'NC',
'ND', 'NE', 'NH', 'NJ', 'NM', 'NV', 'NY', 'OH', 'OK', 'OR', 'PA', 'RI', 'SC',
'SD', 'TN', 'TX', 'UT', 'VA', 'VT', 'WA', 'WI', 'WV', 'WY']
```

[185]:
```
state_list = ['AL', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL', 'GA', 'IA',
              'ID', 'IL', 'IN', 'KS', 'KY', 'LA', 'MA', 'MD', 'ME', 'MI', 'MN',
              'MO', 'MS', 'MT', 'NC', 'ND', 'NE', 'NH', 'NJ', 'NM', 'NV', 'NY',
              'OH', 'OK', 'OR', 'PA', 'RI', 'SC', 'SD', 'TN', 'TX', 'UT', 'VA',
              'VT', 'WA', 'WI', 'WV', 'WY']

for item in state_list:

    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2020-06-30')[0].tolist()
    print('%s: '%item + '%s'%row_number)
```

```
AL: [48]
AR: [48]
AZ: [48]
CA: [51]
CO: []
CT: [51]
DC: [48]
DE: [51]
```

```
FL: [48]
GA: [48]
IA: [51]
ID: [48]
IL: [50]
IN: [52]
KS: [48]
KY: [52]
LA: [48]
MA: [51]
MD: [51]
ME: [50]
MI: [52]
MN: [51]
MO: [51]
MS: [48]
MT: []
NC: [48]
ND: []
NE: [51]
NH: [51]
NJ: [51]
NM: []
NV: [50]
NY: [51]
OH: [52]
OK: [48]
OR: [48]
PA: [52]
RI: [51]
SC: [48]
SD: []
TN: [48]
TX: [48]
UT: []
VA: [48]
VT: [45]
WA: [48]
WI: [50]
WV: [52]
WY: []
```

[316]:
```
accident_US.State.value_counts().sort_values(ascending = False)
```

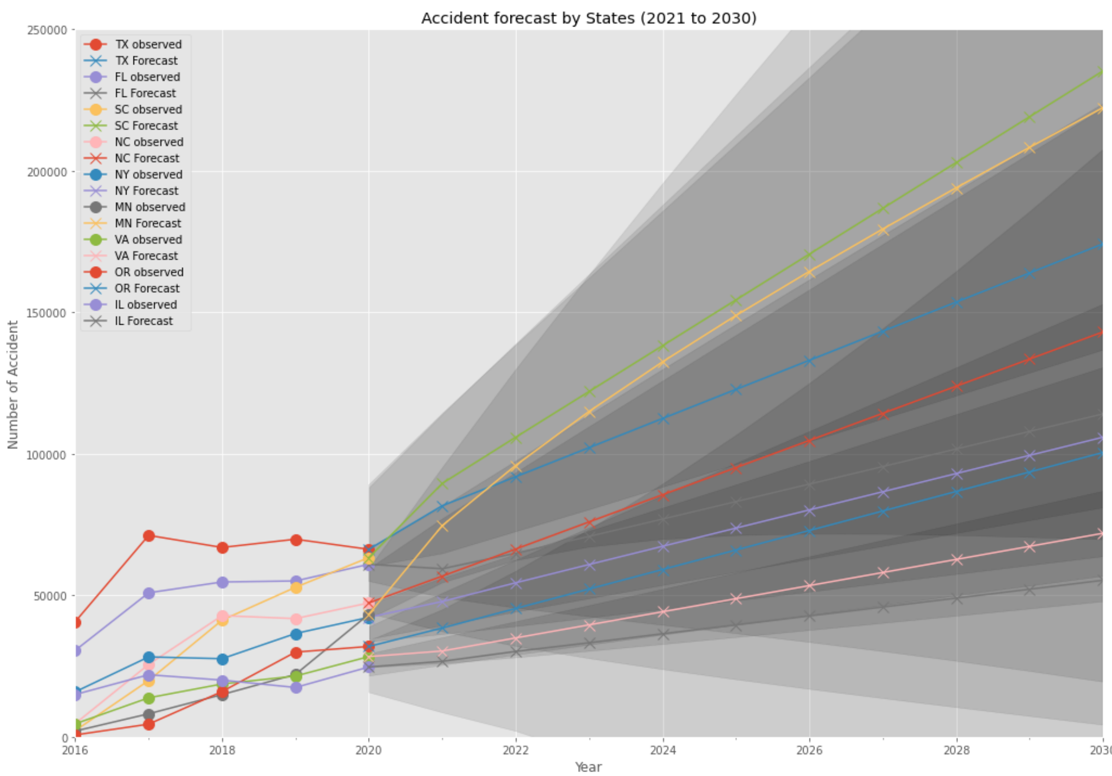
[316]:
```
CA    650415
TX    275742
FL    222472
```

```
SC    140687
NC    137023
NY    128063
IL     86061
MI     81875
PA     80408
GA     75293
VA     72860
OR     65230
MN     61626
TN     59079
WA     56593
AZ     55411
OH     54988
LA     53369
OK     52930
NJ     45580
AL     38029
MD     31470
MA     30390
MO     28955
IN     26909
CT     21350
NE     19825
KY     19418
WI     15953
CO     15823
UT     14480
RI      9748
IA      7682
NH      5874
MS      5353
DE      5059
NV      4925
KS      4718
DC      3673
NM      2969
ME      1704
WV      1596
AR      1578
ID       933
VT       438
WY       169
MT       161
SD        30
ND        25
Name: State, dtype: int64
```

from above, we see certain states: = ['CO', 'MT', 'ND', 'NM', 'SD', 'UT', 'WY'] are lack of data for analysis. We will leave these states at this moment.

[350]:
```python
state_list_1 = ['TX', 'FL', 'SC', 'NC', 'NY', 'MN', 'VA', 'OR', 'IL']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = 0, ymax = 250000)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')

# for item in df_forecast_1.State.unique():
for item in state_list_1:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p,␣
 ↪d, q))]

    for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = True,
                                                enforce_invertibility = True)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = True,
                                    enforce_invertibility = True)
    results = mod.fit()
```

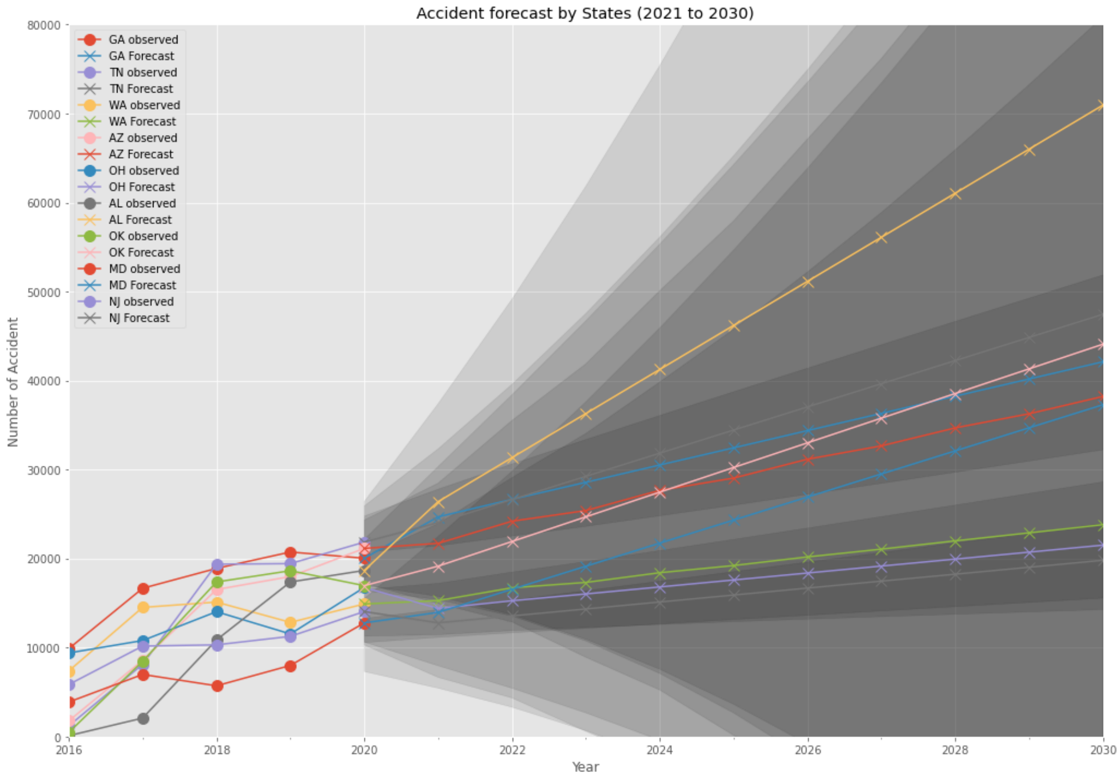
```
    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).
↪round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).
↪round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪Forecast', marker='x', markersize = 10)
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
    plt.legend(loc = 2)
```




[351]:
```
state_list_2 = ['GA', 'TN', 'WA', 'AZ', 'OH', 'AL', 'OK', 'MD', 'NJ']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = 0, ymax = 80000)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')
```

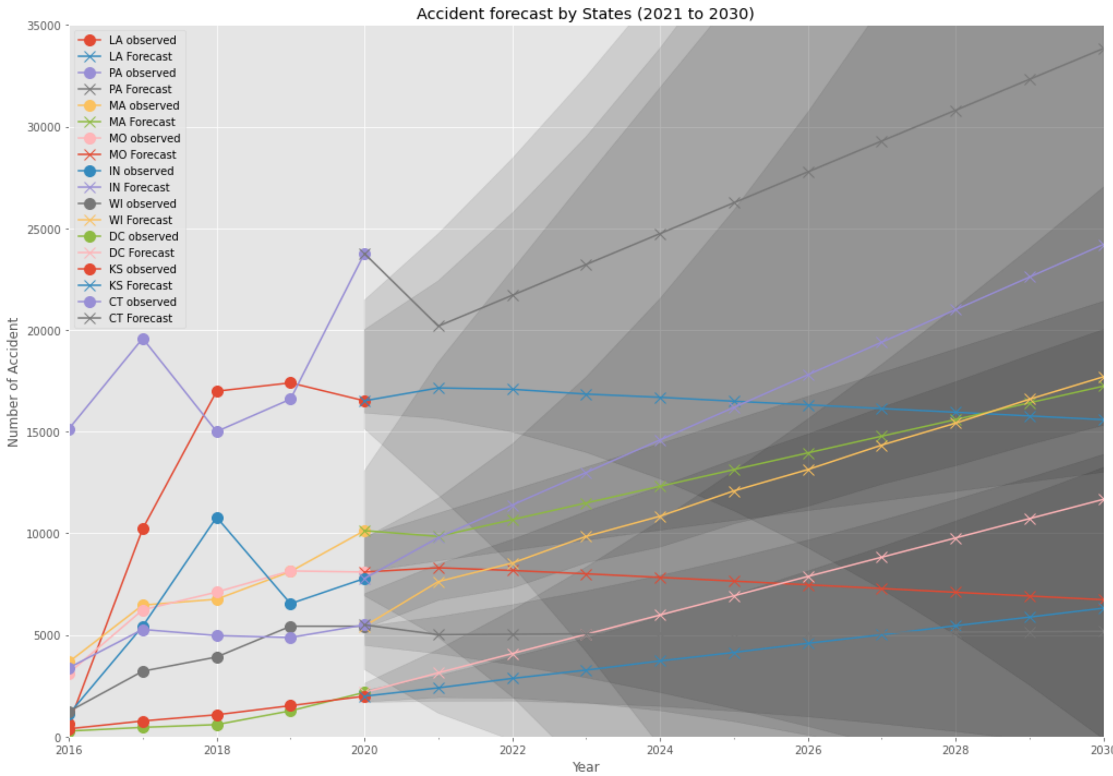
```
# for item in df_forecast_1.State.unique():
for item in state_list_2:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p,␣
↪d, q))]

    for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = False,
                                                enforce_invertibility = False)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = False,
                                    enforce_invertibility = False)
    results = mod.fit()

    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).
↪round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).
↪round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪Forecast', marker='x', markersize = 10)
```

```
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
    plt.legend(loc = 2)
```




[355]:
```
state_list_3 = ['LA', 'PA', 'MA', 'MO', 'IN', 'WI', 'DC', 'KS', 'CT']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = 0, ymax = 35000)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')

# for item in df_forecast_1.State.unique():
for item in state_list_3:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
```

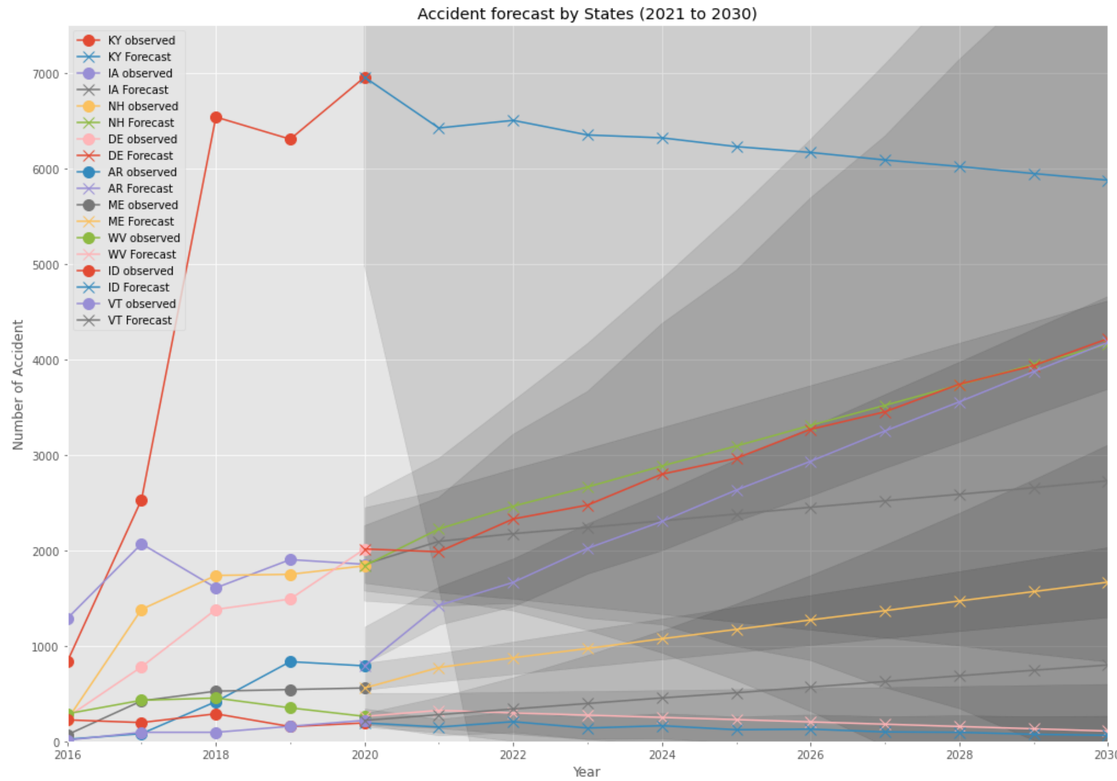
```
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p,␣
↪d, q))]

    for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = False,
                                                enforce_invertibility = False)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = False,
                                    enforce_invertibility = False)
    results = mod.fit()

    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).
↪round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).
↪round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪Forecast', marker='x', markersize = 10)
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
    plt.legend(loc = 2)
```




[363]:

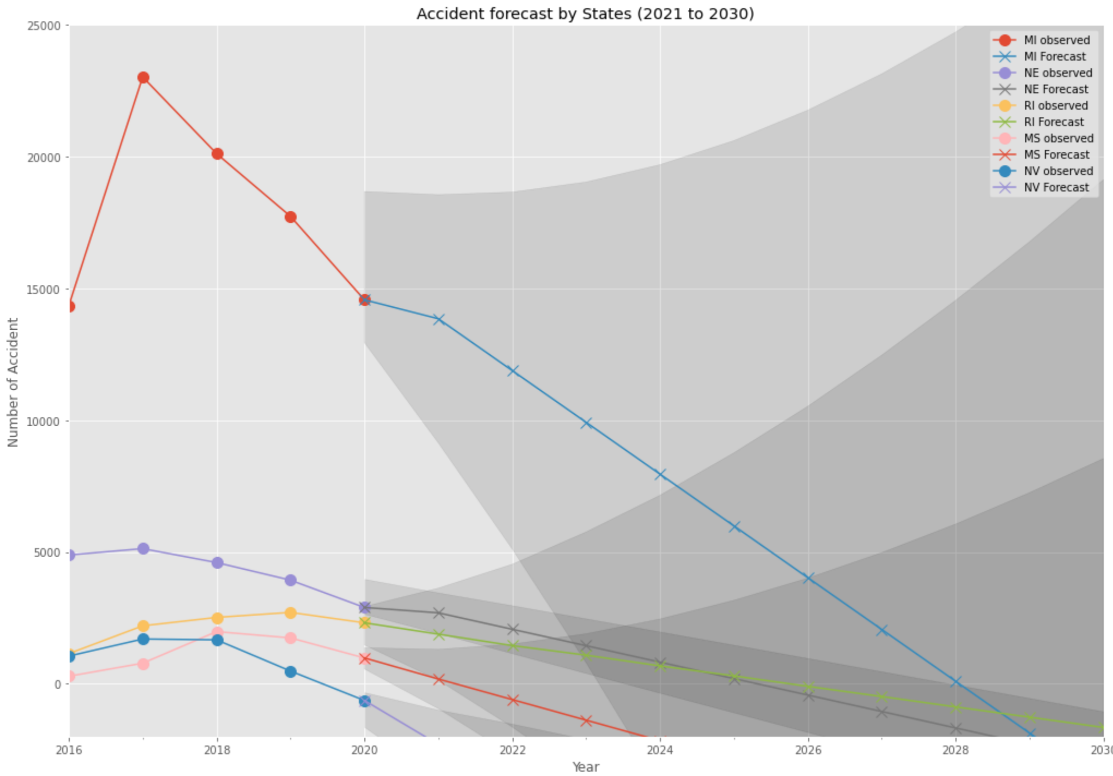
```
state_list_4 = ['KY', 'IA', 'NH', 'DE', 'AR', 'ME', 'WV', 'ID', 'VT']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = 0, ymax = 7500)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')

# for item in df_forecast_1.State.unique():
for item in state_list_4:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p,␣
↪d, q))]

    for param in pdq:
```

```
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = False,
                                                enforce_invertibility = False)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = False,
                                    enforce_invertibility = False)
    results = mod.fit()

    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).
↪round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).
↪round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪Forecast', marker='x', markersize = 10)
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
    plt.legend(loc = 2)
```




[422]:
```
state_list_5 = ['MI', 'NE', 'RI', 'MS', 'NV']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = -2000, ymax = 25000)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')

# for item in df_forecast_1.State.unique():
for item in state_list_5:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p,␣
↪d, q))]

    for param in pdq:
```

```
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = False,
                                                enforce_invertibility = False)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = False,
                                    enforce_invertibility = False)
    results = mod.fit()

    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).
↪round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).
↪round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+'␣
↪Forecast', marker='x', markersize = 10)
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
    plt.legend(loc = 1)
```


Accident forecast by States (2021 to 2030)
Number of Accident
Year
25000
20000
15000
10000
5000
0
2016
2018
2020
2022
2024
2026
2028
2030
MI observed
MI Forecast
NE observed
NE Forecast
RI observed
RI Forecast
MS observed
MS Forecast
NV observed
NV Forecast

```
[ ]:
```