

# Project Name: Traffic Accident Analysis: Identifying Patterns and Insights to Enhance Road Safety

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## Task-05



**Analyze traffic accident data to identify patterns related to road conditions, weather, and time of day. Visualize accident hotspots and contributing factors.**

**Dataset :-**

**<https://www.kaggle.com/code/harshalbhamare/us-accident-eda>**

PRODIGY INFOTECH

## Project Introduction

- Traffic accidents are a critical public safety concern worldwide, leading to loss of life, property damage, and economic burden.
- With the increasing availability of data, analyzing accident patterns can provide actionable insights to improve road safety.
- This project explores a comprehensive dataset of traffic accidents to identify key trends and factors contributing to accidents, including weather conditions, time of day, location, and accident severity.
- By leveraging data visualization and analysis techniques, we aim to extract meaningful patterns to aid decision-making and preventive measures.

## Project Summary

This project involves an extensive analysis of traffic accident data. Key tasks include:

1. Cleaning and preprocessing the dataset to handle missing and inconsistent values.
2. Performing exploratory data analysis (EDA) to identify significant patterns related to accident severity, time of occurrence, and geographic distribution.
3. Visualizing insights using charts like pie charts, bar plots, histograms, and line plots to effectively communicate findings.
4. Highlighting trends in accidents by state, time of day, and weather conditions.
5. Providing actionable recommendations to stakeholders for enhancing road safety and reducing accidents.

## Business Objective

The primary business objective is to provide insights into traffic accident patterns to help policymakers, urban planners, and traffic authorities:

1. Identify high-risk areas (accident hotspots) for targeted interventions.
2. Understand the impact of weather and time of day on accidents to optimize traffic management strategies.
3. Enhance public awareness campaigns by focusing on key contributing factors like speeding, low visibility, or road infrastructure.
4. Reduce accidents and improve safety outcomes, leading to lower economic losses and better public well-being.

## Importing Libraries

```
In [66]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

## Loading the Dataset

```
In [67]: df= pd.read_csv('US_Accidents_Dec21_updated.csv')
```

In [68]: df

Out[68]:

	ID	Severity	Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat	End
0	A-1	3	2016-02-08 00:37:08	2016-02-08 06:37:08	40.108910	-83.092860	40.112060	-83.03
1	A-2	2	2016-02-08 05:56:20	2016-02-08 11:56:20	39.865420	-84.062800	39.865010	-84.04
2	A-3	2	2016-02-08 06:15:39	2016-02-08 12:15:39	39.102660	-84.524680	39.102090	-84.52
3	A-4	2	2016-02-08 06:51:45	2016-02-08 12:51:45	41.062130	-81.537840	41.062170	-81.53
4	A-5	3	2016-02-08 07:53:43	2016-02-08 13:53:43	39.172393	-84.492792	39.170476	-84.50
...	...	...	...	...	...	...	...	...
2845337	A-2845338	2	2019-08-23 18:03:25	2019-08-23 18:32:01	34.002480	-117.379360	33.998880	-117.37
2845338	A-2845339	2	2019-08-23 19:11:30	2019-08-23 19:38:23	32.766960	-117.148060	32.765550	-117.15
2845339	A-2845340	2	2019-08-23 19:00:21	2019-08-23 19:28:49	33.775450	-117.847790	33.777400	-117.85
2845340	A-2845341	2	2019-08-23 19:00:21	2019-08-23 19:29:42	33.992460	-118.403020	33.983110	-118.39
2845341	A-2845342	2	2019-08-23 18:52:06	2019-08-23 19:21:31	34.133930	-117.230920	34.137360	-117.23

2845342 rows × 47 columns



# Understanding the Data

```
In [69]: df.head(10)
```

Out[69]:

	ID	Severity	Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat	End_Lng	Distance
0	A-1	3	2016-02-08 00:37:08	2016-02-08 06:37:08	40.108910	-83.092860	40.112060	-83.031870	3.14
1	A-2	2	2016-02-08 05:56:20	2016-02-08 11:56:20	39.865420	-84.062800	39.865010	-84.048730	0.42
2	A-3	2	2016-02-08 06:15:39	2016-02-08 12:15:39	39.102660	-84.524680	39.102090	-84.523960	0.62
3	A-4	2	2016-02-08 06:51:45	2016-02-08 12:51:45	41.062130	-81.537840	41.062170	-81.535470	0.42
4	A-5	3	2016-02-08 07:53:43	2016-02-08 13:53:43	39.172393	-84.492792	39.170476	-84.501798	0.19
5	A-6	2	2016-02-08 08:16:57	2016-02-08 14:16:57	39.063240	-84.032430	39.067310	-84.058510	0.42
6	A-7	2	2016-02-08 08:15:41	2016-02-08 14:15:41	39.775650	-84.186030	39.772750	-84.188050	0.31
7	A-8	2	2016-02-08 11:51:46	2016-02-08 17:51:46	41.375310	-81.820170	41.367860	-81.821740	0.84
8	A-9	2	2016-02-08 14:19:57	2016-02-08 20:19:57	40.702247	-84.075887	40.699110	-84.084293	0.31
9	A-10	2	2016-02-08 15:16:43	2016-02-08 21:16:43	40.109310	-82.968490	40.110780	-82.984000	0.15

10 rows × 47 columns



```
In [70]: df.tail()
```

Out[70]:

	ID	Severity	Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat	End_Lng
2845337	A-2845338	2	2019-08-23 18:03:25	2019-08-23 18:32:01	34.00248	-117.37936	33.99888	-117.37094
2845338	A-2845339	2	2019-08-23 19:11:30	2019-08-23 19:38:23	32.76696	-117.14806	32.76555	-117.15361
2845339	A-2845340	2	2019-08-23 19:00:21	2019-08-23 19:28:49	33.77545	-117.84779	33.77740	-117.85721
2845340	A-2845341	2	2019-08-23 19:00:21	2019-08-23 19:29:42	33.99246	-118.40302	33.98311	-118.39561
2845341	A-2845342	2	2019-08-23 18:52:06	2019-08-23 19:21:31	34.13393	-117.23092	34.13736	-117.23934

5 rows × 47 columns



## checking columns in data

```
In [71]: df.columns
```

Out[71]: Index(['ID', 'Severity', 'Start\_Time', 'End\_Time', 'Start\_Lat', 'Start\_Lng', 'End\_Lat', 'End\_Lng', 'Distance(mi)', 'Description', 'Number', 'Street', 'Side', 'City', 'County', 'State', 'Zipcode', 'Country', 'Timezone', 'Airport\_Code', 'Weather\_Timestamp', 'Temperature(F)', 'Wind\_Chill(F)', 'Humidity(%)', 'Pressure(in)', 'Visibility(mi)', 'Wind\_Direction', 'Wind\_Speed(mph)', 'Precipitation(in)', 'Weather\_Condition', 'Amenity', 'Bump', 'Crossing', 'Give\_Way', 'Junction', 'No\_Exit', 'Railway', 'Roundabout', 'Station', 'Stop', 'Traffic\_Calming', 'Traffic\_Signal', 'Turning\_Loop', 'Sunrise\_Sunset', 'Civil\_Twilight', 'Nautical\_Twilight', 'Astronomical\_Twilight'], dtype='object')

## Shape of the dataframe

In [72]: `df.shape`

Out[72]: (2845342, 47)

## Info of the dataframe

In [73]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2845342 entries, 0 to 2845341
Data columns (total 47 columns):
#   Column                                Dtype
---  -
0   ID                                    object
1   Severity                             int64
2   Start_Time                           object
3   End_Time                             object
4   Start_Lat                            float64
5   Start_Lng                            float64
6   End_Lat                              float64
7   End_Lng                              float64
8   Distance(mi)                         float64
9   Description                           object
10  Number                               float64
11  Street                               object
12  Side                                 object
13  City                                 object
14  County                               object
15  State                                object
16  Zipcode                             object
17  Country                             object
18  Timezone                             object
19  Airport_Code                         object
20  Weather_Timestamp                    object
21  Temperature(F)                       float64
22  Wind_Chill(F)                        float64
23  Humidity(%)                          float64
24  Pressure(in)                         float64
25  Visibility(mi)                       float64
26  Wind_Direction                       object
27  Wind_Speed(mph)                      float64
28  Precipitation(in)                    float64
29  Weather_Condition                    object
30  Amenity                              bool
31  Bump                                  bool
32  Crossing                              bool
33  Give_Way                             bool
34  Junction                              bool
35  No_Exit                              bool
36  Railway                              bool
37  Roundabout                           bool
38  Station                              bool
39  Stop                                  bool
40  Traffic_Calming                       bool
41  Traffic_Signal                       bool
42  Turning_Loop                          bool
43  Sunrise_Sunset                       object
44  Civil_Twilight                       object
45  Nautical_Twilight                    object
46  Astronomical_Twilight                 object
dtypes: bool(13), float64(13), int64(1), object(20)
memory usage: 773.4+ MB
```


```
In [74]: df.dtypes.value_counts()
```

```
Out[74]: object      20  
float64    13  
bool       13  
int64       1  
dtype: int64
```

```
In [75]: df.describe()
```

```
Out[75]:
```

	Severity	Start_Lat	Start_Lng	End_Lat	End_Lng	Distance(mi)
count	2.845342e+06	2.845342e+06	2.845342e+06	2.845342e+06	2.845342e+06	2.845342e+06
mean	2.137572e+00	3.624520e+01	-9.711463e+01	3.624532e+01	-9.711439e+01	7.026779e-01
std	4.787216e-01	5.363797e+00	1.831782e+01	5.363873e+00	1.831763e+01	1.560361e+00
min	1.000000e+00	2.456603e+01	-1.245481e+02	2.456601e+01	-1.245457e+02	0.000000e+00
25%	2.000000e+00	3.344517e+01	-1.180331e+02	3.344628e+01	-1.180333e+02	5.200000e-02
50%	2.000000e+00	3.609861e+01	-9.241808e+01	3.609799e+01	-9.241772e+01	2.440000e-01
75%	2.000000e+00	4.016024e+01	-8.037243e+01	4.016105e+01	-8.037338e+01	7.640000e-01
max	4.000000e+00	4.900058e+01	-6.711317e+01	4.907500e+01	-6.710924e+01	1.551860e+02



```
In [76]: df.State.unique
```

```
Out[76]: <bound method Series.unique of 0          OH  
1          OH  
2          OH  
3          OH  
4          OH  
..  
2845337    CA  
2845338    CA  
2845339    CA  
2845340    CA  
2845341    CA  
Name: State, Length: 2845342, dtype: object>
```

```
In [82]: df_new=df[df['State']=='CA']
```

```
In [78]: df_new['IDD'] = df_new['ID'].astype('str').str.extractall('(\d+)').unstack()
```



In [79]: df\_new

Out[79]:

	ID	Severity	Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat	End
988	A-989	3	2016-03-22 18:53:11	2016-03-23 00:53:11	38.825840	-120.029214	38.827194	-120.00
989	A-990	2	2016-03-22 19:00:49	2016-03-23 01:00:49	37.358209	-121.840017	37.361596	-121.84
990	A-991	3	2016-03-22 20:07:32	2016-03-23 02:07:32	37.881943	-122.307987	37.885882	-122.30
991	A-992	2	2016-03-22 21:40:18	2016-03-23 03:40:18	37.881038	-122.307788	37.883458	-122.30
992	A-993	2	2016-03-22 21:36:42	2016-03-23 03:36:42	38.518811	-121.101664	38.518811	-121.10
...	...	...	...	...	...	...	...	...
2845337	A-2845338	2	2019-08-23 18:03:25	2019-08-23 18:32:01	34.002480	-117.379360	33.998880	-117.37
2845338	A-2845339	2	2019-08-23 19:11:30	2019-08-23 19:38:23	32.766960	-117.148060	32.765550	-117.14
2845339	A-2845340	2	2019-08-23 19:00:21	2019-08-23 19:28:49	33.775450	-117.847790	33.777400	-117.84
2845340	A-2845341	2	2019-08-23 19:00:21	2019-08-23 19:29:42	33.992460	-118.403020	33.983110	-118.39
2845341	A-2845342	2	2019-08-23 18:52:06	2019-08-23 19:21:31	34.133930	-117.230920	34.137360	-117.23

795868 rows × 48 columns



```
In [80]: df_new.head(10)
```

Out[80]:

	ID	Severity	Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat	End_Lng	Di
988	A-989	3	2016-03-22 18:53:11	2016-03-23 00:53:11	38.825840	-120.029214	38.827194	-120.030632	
989	A-990	2	2016-03-22 19:00:49	2016-03-23 01:00:49	37.358209	-121.840017	37.361596	-121.842044	
990	A-991	3	2016-03-22 20:07:32	2016-03-23 02:07:32	37.881943	-122.307987	37.885882	-122.308878	
991	A-992	2	2016-03-22 21:40:18	2016-03-23 03:40:18	37.881038	-122.307788	37.883458	-122.308366	
992	A-993	2	2016-03-22 21:36:42	2016-03-23 03:36:42	38.518811	-121.101664	38.518811	-121.101664	
993	A-994	2	2016-03-22 21:36:42	2016-03-23 03:36:42	38.518811	-121.101664	38.518811	-121.101664	
994	A-995	2	2016-03-23 03:48:55	2016-03-23 09:48:55	36.990300	-119.711460	36.990460	-119.711380	
995	A-996	2	2016-03-23 05:55:55	2016-03-23 11:55:55	37.425920	-122.098790	37.430420	-122.103520	
996	A-997	2	2016-03-23 06:39:54	2016-03-23 12:39:54	37.757450	-122.211310	37.750850	-122.205490	
997	A-998	2	2016-03-23 06:45:09	2016-03-23 12:45:09	37.316480	-121.967460	37.318100	-121.978100	

10 rows × 48 columns



```
In [81]: df_new.shape
```

```
Out[81]: (795868, 48)
```

```
In [83]: df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 795868 entries, 988 to 2845341
Data columns (total 47 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   ID                                    795868 non-null  object
1   Severity                             795868 non-null  int64
2   Start_Time                           795868 non-null  object
3   End_Time                             795868 non-null  object
4   Start_Lat                            795868 non-null  float64
5   Start_Lng                            795868 non-null  float64
6   End_Lat                              795868 non-null  float64
7   End_Lng                              795868 non-null  float64
8   Distance(mi)                         795868 non-null  float64
9   Description                           795868 non-null  object
10  Number                               256963 non-null  float64
11  Street                               795867 non-null  object
12  Side                                 795868 non-null  object
13  City                                 795861 non-null  object
14  County                              795868 non-null  object
15  State                               795868 non-null  object
16  Zipcode                             795469 non-null  object
17  Country                             795868 non-null  object
18  Timezone                            795469 non-null  object
19  Airport_Code                         794898 non-null  object
20  Weather_Timestamp                   780498 non-null  object
21  Temperature(F)                      773334 non-null  float64
22  Wind_Chill(F)                       664721 non-null  float64
23  Humidity(%)                         772282 non-null  float64
24  Pressure(in)                        778334 non-null  float64
25  Visibility(mi)                      777381 non-null  float64
26  Wind_Direction                      773393 non-null  object
27  Wind_Speed(mph)                     750221 non-null  float64
28  Precipitation(in)                   625445 non-null  float64
29  Weather_Condition                   776759 non-null  object
30  Amenity                             795868 non-null  bool
31  Bump                                795868 non-null  bool
32  Crossing                            795868 non-null  bool
33  Give_Way                            795868 non-null  bool
34  Junction                            795868 non-null  bool
35  No_Exit                             795868 non-null  bool
36  Railway                             795868 non-null  bool
37  Roundabout                          795868 non-null  bool
38  Station                             795868 non-null  bool
39  Stop                                795868 non-null  bool
40  Traffic_Calming                     795868 non-null  bool
41  Traffic_Signal                      795868 non-null  bool
42  Turning_Loop                        795868 non-null  bool
43  Sunrise_Sunset                      795761 non-null  object
44  Civil_Twilight                      795761 non-null  object
45  Nautical_Twilight                   795761 non-null  object
46  Astronomical_Twilight               795761 non-null  object
dtypes: bool(13), float64(13), int64(1), object(20)
memory usage: 222.4+ MB
```

```
In [84]: df_new.columns
```

```
Out[84]: Index(['ID', 'Severity', 'Start_Time', 'End_Time', 'Start_Lat', 'Start_Lng',  
              'End_Lat', 'End_Lng', 'Distance(mi)', 'Description', 'Number', 'Street',  
              'Side', 'City', 'County', 'State', 'Zipcode', 'Country', 'Timezone',  
              'Airport_Code', 'Weather_Timestamp', 'Temperature(F)', 'Wind_Chill(F)',  
              'Humidity(%)', 'Pressure(in)', 'Visibility(mi)', 'Wind_Direction',  
              'Wind_Speed(mph)', 'Precipitation(in)', 'Weather_Condition', 'Amenity',  
              'Bump', 'Crossing', 'Give_Way', 'Junction', 'No_Exit', 'Railway',  
              'Roundabout', 'Station', 'Stop', 'Traffic_Calming', 'Traffic_Signals',  
              'Turning_Loop', 'Sunrise_Sunset', 'Civil_Twilight', 'Nautical_Twilight',  
              'Astronomical_Twilight'],  
              dtype='object')
```

## Number of duplicated rows

```
In [85]: df_new.duplicated().sum()
```

```
Out[85]: 0
```

## find the Number of missing values in each column

```
In [86]: df_new.isnull().sum()
```

```
Out[86]: ID                                0
Severity                                0
Start_Time                             0
End_Time                               0
Start_Lat                              0
Start_Lng                              0
End_Lat                                0
End_Lng                                0
Distance(mi)                           0
Description                             0
Number                                538905
Street                                  1
Side                                    0
City                                    7
County                                 0
State                                  0
Zipcode                               399
Country                                0
Timezone                              399
Airport_Code                           970
Weather_Timestamp                       15370
Temperature(F)                          22534
Wind_Chill(F)                           131147
Humidity(%)                             23586
Pressure(in)                            17534
Visibility(mi)                           18487
Wind_Direction                          22475
Wind_Speed(mph)                         45647
Precipitation(in)                       170423
Weather_Condition                       19109
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                          107
Civil_Twilight                          107
Nautical_Twilight                       107
Astronomical_Twilight                   107
dtype: int64
```

## Check the percentage of missing values for each column

```
In [87]: missing_percentage = (df_new.isnull().sum() / len(df_new)) * 100
print(missing_percentage)
```

ID	0.000000
Severity	0.000000
Start_Time	0.000000
End_Time	0.000000
Start_Lat	0.000000
Start_Lng	0.000000
End_Lat	0.000000
End_Lng	0.000000
Distance(mi)	0.000000
Description	0.000000
Number	67.712862
Street	0.000126
Side	0.000000
City	0.000880
County	0.000000
State	0.000000
Zipcode	0.050134
Country	0.000000
Timezone	0.050134
Airport_Code	0.121880
Weather_Timestamp	1.931225
Temperature(F)	2.831374
Wind_Chill(F)	16.478486
Humidity(%)	2.963557
Pressure(in)	2.203129
Visibility(mi)	2.322873
Wind_Direction	2.823961
Wind_Speed(mph)	5.735499
Precipitation(in)	21.413476
Weather_Condition	2.401026
Amenity	0.000000
Bump	0.000000
Crossing	0.000000
Give_Way	0.000000
Junction	0.000000
No_Exit	0.000000
Railway	0.000000
Roundabout	0.000000
Station	0.000000
Stop	0.000000
Traffic_Calming	0.000000
Traffic_Signal	0.000000
Turning_Loop	0.000000
Sunrise_Sunset	0.013444
Civil_Twilight	0.013444
Nautical_Twilight	0.013444
Astronomical_Twilight	0.013444

dtype: float64

## Drop Columns

```
In [88]: df_new.drop(columns=['Precipitation(in)', 'Wind_Chill(F)'], inplace=True)
```

```
In [89]: df_new.drop(columns=['Number'], inplace=True)
```

**Street: 1 missing value**

```
In [90]: df_new['Street'].fillna(df_new['Street'].mode()[0], inplace=True)
```

**City: 7 missing values**

```
In [91]: df_new['City'].fillna(df_new['City'].mode()[0], inplace=True)
```

**Sunrise\_Sunset, Civil\_Twilight, Nautical\_Twilight, Astronomical\_Twilight: 107 missing values each**

```
In [92]: twilight_cols = ['Sunrise_Sunset', 'Civil_Twilight', 'Nautical_Twilight', 'Astronomical_Twilight']
for col in twilight_cols:
    df_new[col].fillna(df_new[col].mode()[0], inplace=True)
```

**Zipcode: 399 missing values, Timezone: 399 missing values, Airport\_Code: 970 missing values**

```
In [93]: code_cols = ['Zipcode', 'Timezone', 'Airport_Code']
for col in code_cols:
    df_new[col].fillna(df_new[col].mode()[0], inplace=True)
```

```
In [94]: # List of numerical columns
numerical_cols = ['Temperature(F)', 'Humidity(%)', 'Pressure(in)', 'Visibility(mi)']

# Impute with median
for col in numerical_cols:
    df_new[col].fillna(df_new[col].median(), inplace=True)
```

```
In [95]: # List of categorical columns
categorical_cols = ['Wind_Direction', 'Weather_Condition']

# Impute with mode
for col in categorical_cols:
    df_new[col].fillna(df_new[col].mode()[0], inplace=True)
```



```
In [96]: # Drop Wind_Speed(mph) if not relevant
df_new.drop(columns=['Wind_Speed(mph)'], inplace=True)
```

```
In [97]: # Convert 'Weather_Timestamp' to datetime format
df_new['Weather_Timestamp'] = pd.to_datetime(df_new['Weather_Timestamp'])
```

```
In [98]: # Use forward fill (fills missing values with the last valid timestamp)
df_new['Weather_Timestamp'].fillna(method='ffill', inplace=True)
```

## Again check the Number of missing values in each column

```
In [99]: df_new.isnull().sum()
```

```
Out[99]: ID                                0
Severity                                  0
Start_Time                              0
End_Time                                0
Start_Lat                               0
Start_Lng                               0
End_Lat                                 0
End_Lng                                 0
Distance(mi)                            0
Description                             0
Street                                  0
Side                                    0
City                                    0
County                                  0
State                                   0
Zipcode                                 0
Country                                 0
Timezone                                0
Airport_Code                            0
Weather_Timestamp                       0
Temperature(F)                          0
Humidity(%)                             0
Pressure(in)                            0
Visibility(mi)                          0
Wind_Direction                          0
Weather_Condition                       0
Amenity                                 0
Bump                                    0
Crossing                                0
Give_Way                                0
Junction                                0
No_Exit                                 0
Railway                                 0
Roundabout                              0
Station                                 0
Stop                                    0
Traffic_Calming                         0
Traffic_Signal                          0
Turning_Loop                             0
Sunrise_Sunset                          0
Civil_Twilight                          0
Nautical_Twilight                       0
Astronomical_Twilight                   0
dtype: int64
```

```
In [100]: df_new['Weather_Condition'].value_counts()
```

```
Out[100]: Fair                420881
Cloudy                78168
Mostly Cloudy        64487
Clear                55664
Partly Cloudy        53889
...
Thunder and Hail         1
Thunder / Windy         1
Dust Whirls             1
Light Snow Showers      1
Light Freezing Fog      1
Name: Weather_Condition, Length: 75, dtype: int64
```

```
In [101]: df_new.Side.unique()
```

```
Out[101]: array(['L', 'R', 'N'], dtype=object)
```

```
In [102]: # Identify categorical and numerical columns
categorical_cols = df_new.select_dtypes(include=['object', 'category']).columns
numerical_cols = df_new.select_dtypes(exclude=['object', 'category']).columns

# Get the number of unique values for each categorical column
categorical_unique = df_new[categorical_cols].nunique()

# Get the number of unique values for each numerical column
numerical_unique = df_new[numerical_cols].nunique()

# Create separate dataframes for categorical and numerical columns
categorical_df = pd.DataFrame({'Column': categorical_unique.index, 'Unique_Value': categorical_unique.values})
numerical_df = pd.DataFrame({'Column': numerical_unique.index, 'Unique_Value': numerical_unique.values})
```

```
In [103]: print("Categorical Columns Unique Values:")
categorical_df
```

Categorical Columns Unique Values:

Out[103]:

	Column	Unique_Values
0	ID	795868
1	Start_Time	548609
2	End_Time	671908
3	Description	290526
4	Street	38047
5	Side	3
6	City	1194
7	County	58
8	State	1
9	Zipcode	73981
10	Country	1
11	Timezone	2
12	Airport_Code	141
13	Wind_Direction	24
14	Weather_Condition	75
15	Sunrise_Sunset	2
16	Civil_Twilight	2
17	Nautical_Twilight	2
18	Astronomical_Twilight	2

```
In [104]: print("\nNumerical Columns Unique Values:")
          numerical_df
```

Numerical Columns Unique Values:

Out[104]:

	Column	Unique_Values
0	Severity	4
1	Start_Lat	258409
2	Start_Lng	263363
3	End_Lat	257584
4	End_Lng	262861
5	Distance(mi)	8234
6	Weather_Timestamp	204758
7	Temperature(F)	484
8	Humidity(%)	100
9	Pressure(in)	809
10	Visibility(mi)	53
11	Amenity	2
12	Bump	2
13	Crossing	2
14	Give_Way	2
15	Junction	2
16	No_Exit	2
17	Railway	2
18	Roundabout	2
19	Station	2
20	Stop	2
21	Traffic_Calming	2
22	Traffic_Signal	2
23	Turning_Loop	1

## Length of Unique Cities

```
In [117]: # Number of unique cities
          unique_cities = df_new['City'].nunique()
          print(f"Number of unique cities: {unique_cities}")
```

Number of unique cities: 1194

## Accident Count by Cities

```
In [118]: # Count of accidents by city
accidents_by_cities = df_new['City'].value_counts()
accidents_by_cities
```

```
Out[118]: Los Angeles      68963
Sacramento      32559
San Diego       26627
San Jose        13376
Riverside       12861
...
Sultana          1
Westmorland      1
West Sierra      1
Dillon Beach     1
Canyon Lake      1
Name: City, Length: 1194, dtype: int64
```

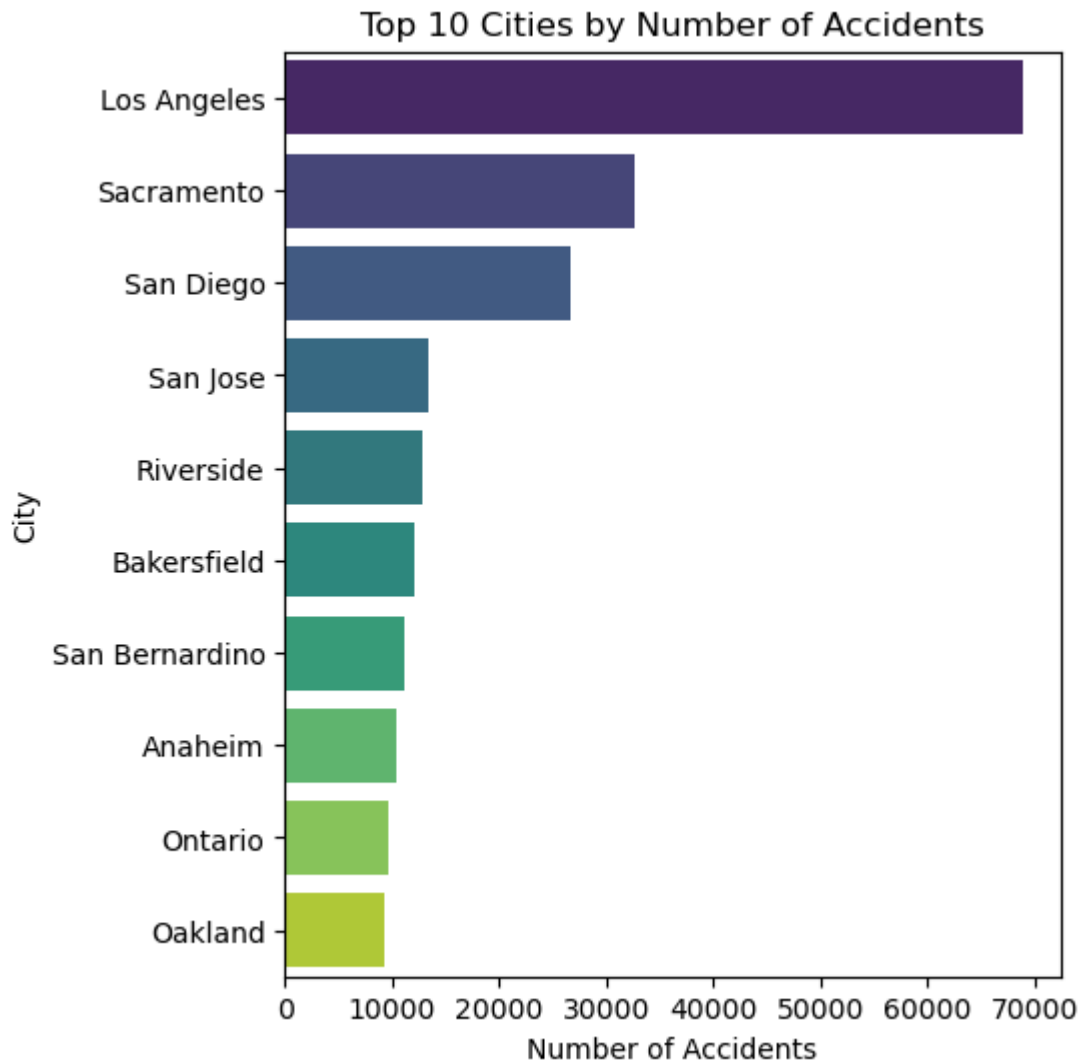
## Top 10 Cities by Number of Accidents

```
In [120]: # Top 10 cities with the most accidents
top_10_cities = accidents_by_cities.head(10)
print("Top 10 cities by number of accidents:")
print(top_10_cities)
```

```
Top 10 cities by number of accidents:
Los Angeles      68963
Sacramento      32559
San Diego       26627
San Jose        13376
Riverside       12861
Bakersfield     12044
San Bernardino  11249
Anaheim         10502
Ontario          9719
Oakland          9255
Name: City, dtype: int64
```

## Bar Chart of Top 10 Cities

```
In [121]: # Bar chart for top 10 cities
plt.figure(figsize=(5, 6))
sns.barplot(x=top_10_cities.values, y=top_10_cities.index, palette='viridis')
plt.title('Top 10 Cities by Number of Accidents')
plt.xlabel('Number of Accidents')
plt.ylabel('City')
plt.show()
```



## Group By Severity and City

```
In [122]: # Group by city and severity
severity_by_city = df_new.groupby(['City', 'Severity']).size().unstack(fill=0)

print("Accidents grouped by city and severity:")
print(severity_by_city.head())
```

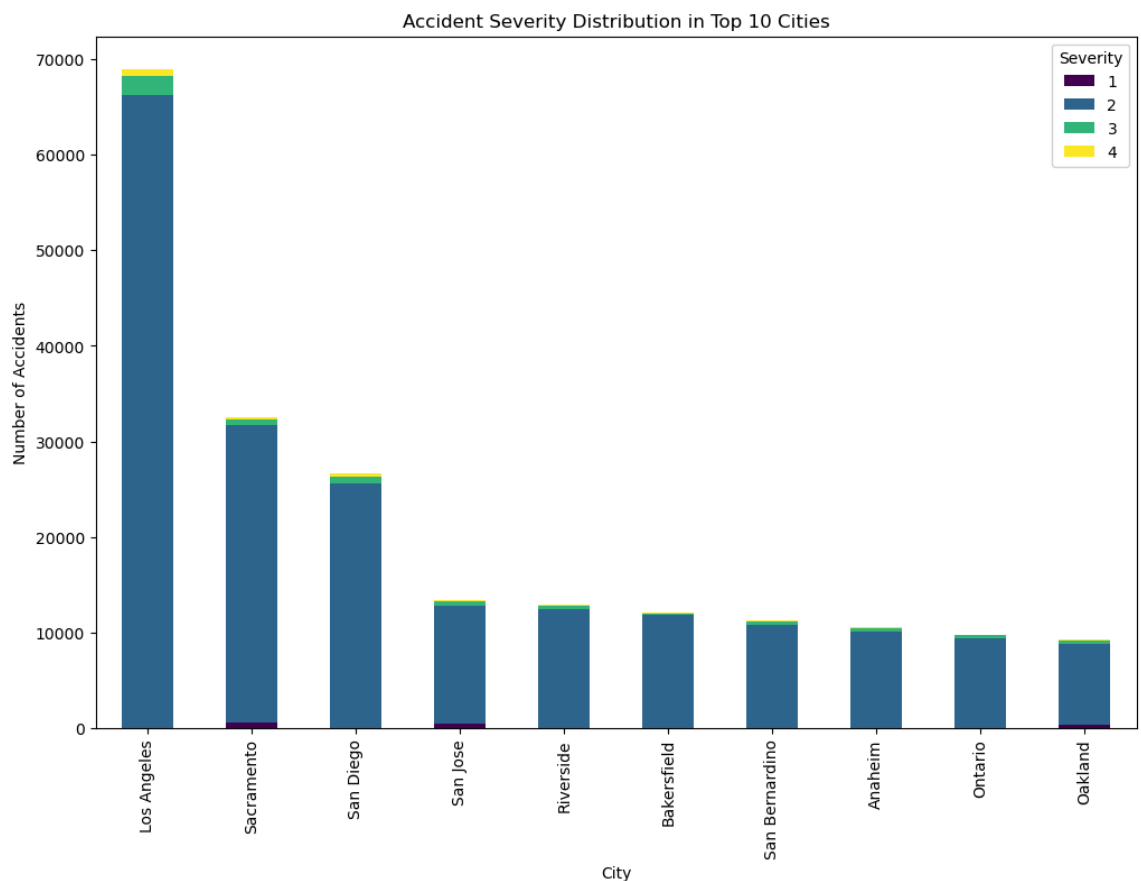
Accidents grouped by city and severity:

Severity	1	2	3	4
City				
Acampo	11	487	6	2
Acton	0	1231	57	21
Adelanto	0	188	2	5
Adin	0	11	0	0
Agoura Hills	0	656	38	14

## Stacked Bar Chart for Severity by City

```
In [123]: # Stacked bar chart for top 10 cities by severity
top_10_cities_severity = severity_by_city.loc[top_10_cities.index]

top_10_cities_severity.plot(kind='bar', stacked=True, figsize=(12, 8), color=['#1f77b4', '#2ca02c', '#d62728', '#ff7f0e'])
plt.title('Accident Severity Distribution in Top 10 Cities')
plt.xlabel('City')
plt.ylabel('Number of Accidents')
plt.legend(title='Severity')
plt.show()
```





## Group By Severity and ID

```
In [150]: # Group by severity and count unique IDs
severity_count = df_new.groupby('Severity')['ID'].nunique()
print("Number of unique accidents by severity:")
print(severity_count)

# Pie chart for severity distribution

severity_count.plot(kind='pie', autopct='%1.1f%', figsize=(8, 9), wedgeprops=dict(colors=['#ff9999', '#66b3ff', '#99ff99', '#ffcc99']))
plt.title('Distribution of Accidents by Severity')
plt.ylabel('') # Remove default ylabel
plt.show()
```

Number of unique accidents by severity:

Severity

1 5058

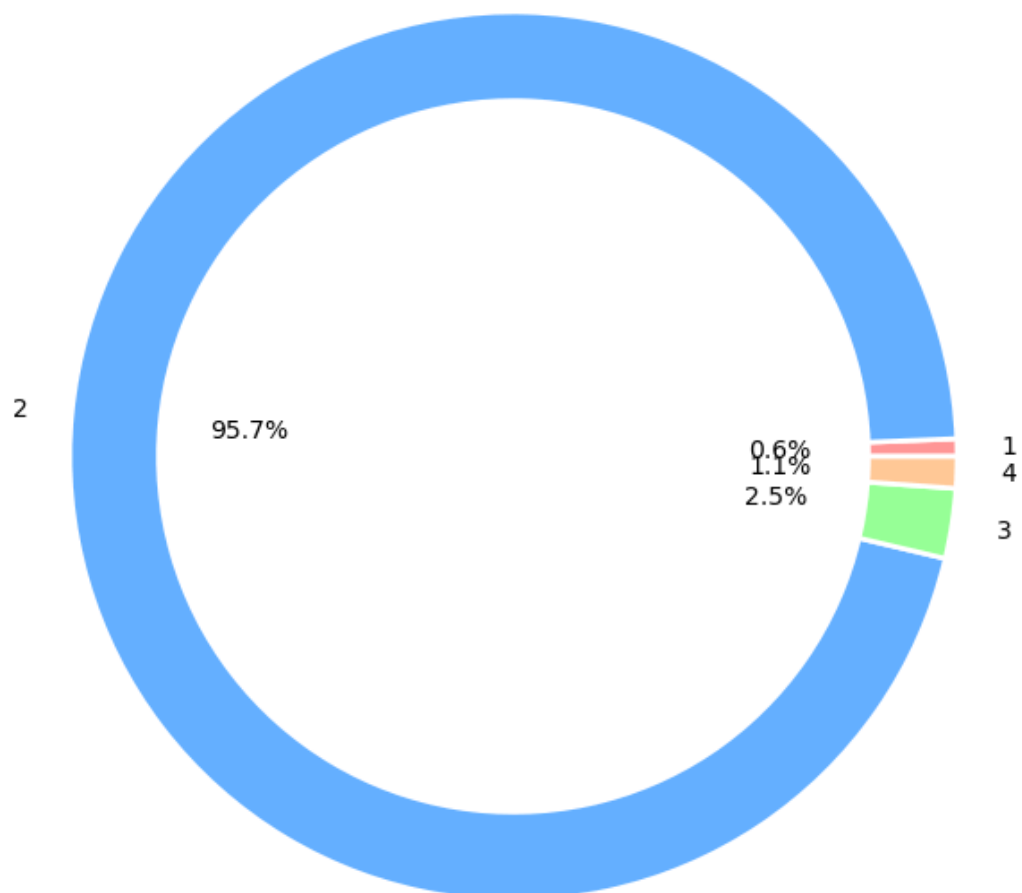
2 761462

3 20213

4 9135

Name: ID, dtype: int64

Distribution of Accidents by Severity



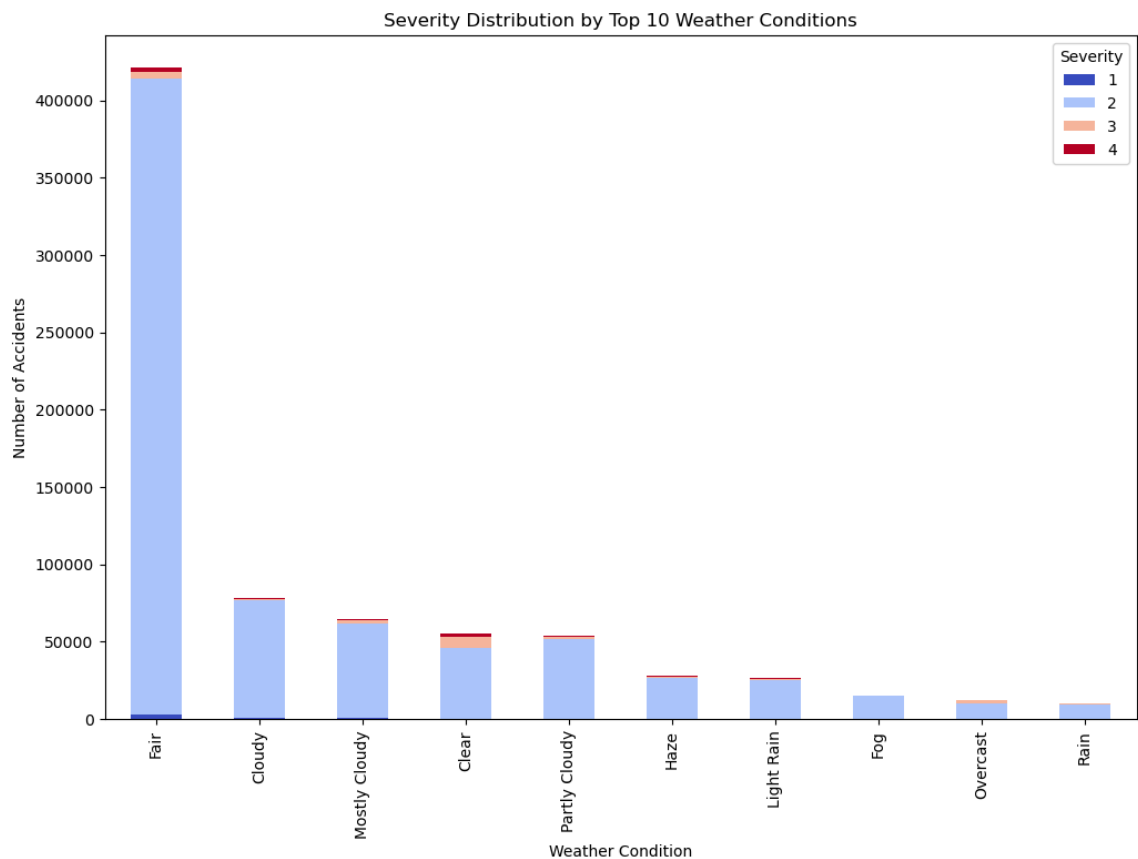
## Severity Distribution by Weather Condition

```
In [138]: # Group by weather condition and severity
weather_severity = df_new.groupby(['Weather_Condition', 'Severity']).size()

# Top 10 weather conditions by total accidents
top_weather_conditions = weather_severity.sum(axis=1).sort_values(ascending=False)

# Filter data for these conditions
top_weather_severity = weather_severity.loc[top_weather_conditions.index]

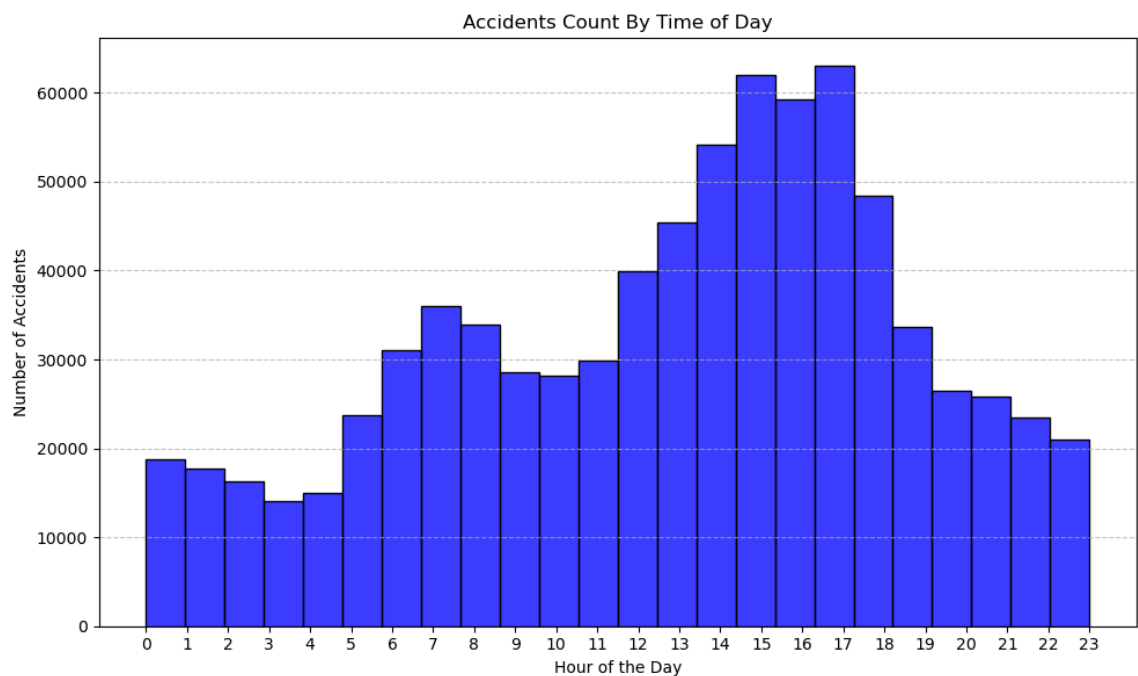
# Stacked bar chart
top_weather_severity.plot(kind='bar', stacked=True, figsize=(12, 8), colormap='magma')
plt.title('Severity Distribution by Top 10 Weather Conditions')
plt.xlabel('Weather Condition')
plt.ylabel('Number of Accidents')
plt.legend(title='Severity')
plt.show()
```



## Accidents count by the time of day

```
In [155]: # Extract hour from 'Start_Time'
df_new['Hour'] = df_new['Start_Time'].dt.hour

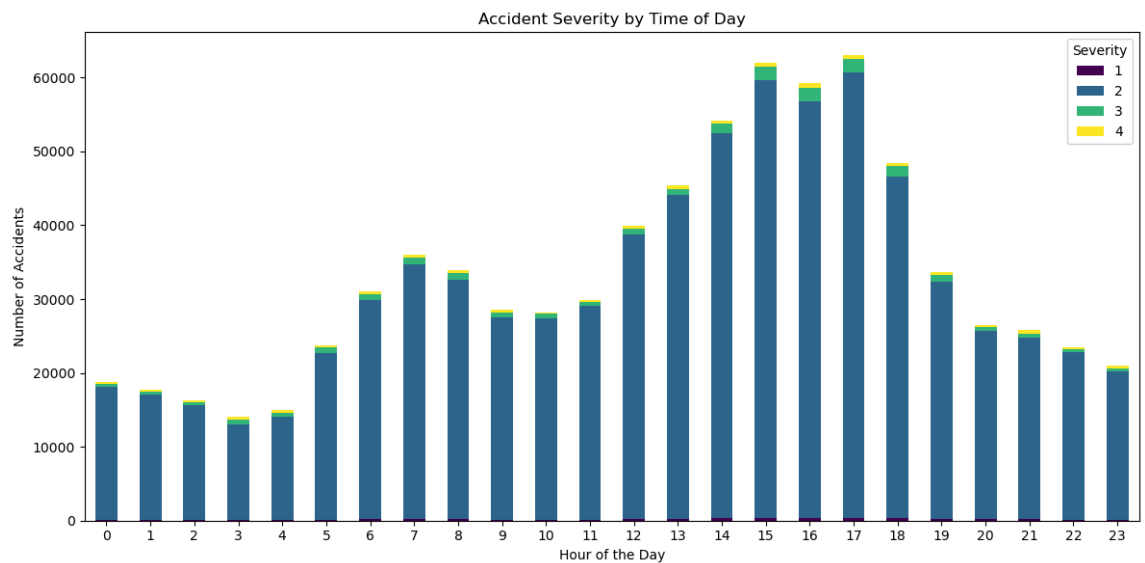
# Plot histogram for accidents count by time of day
plt.figure(figsize=(10, 6))
sns.histplot(df_new['Hour'], bins=24, kde=False, color='blue', edgecolor='b')
plt.title('Accidents Count By Time of Day')
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Accidents')
plt.xticks(range(0, 24)) # Set x-axis ticks from 0 to 23
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout() # Adjust layout for better fit
plt.show()
```



## Accident Severity by Time of Day

```
In [157]: # Group by hour and severity count
severity_by_hour = df_new.groupby(['Hour', 'Severity']).size().unstack()

# Plot severity by time of day
severity_by_hour.plot(kind='bar', stacked=True, figsize=(12, 6), colormap='
plt.title('Accident Severity by Time of Day')
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=0)
plt.legend(title='Severity')
plt.tight_layout()
plt.show()
```

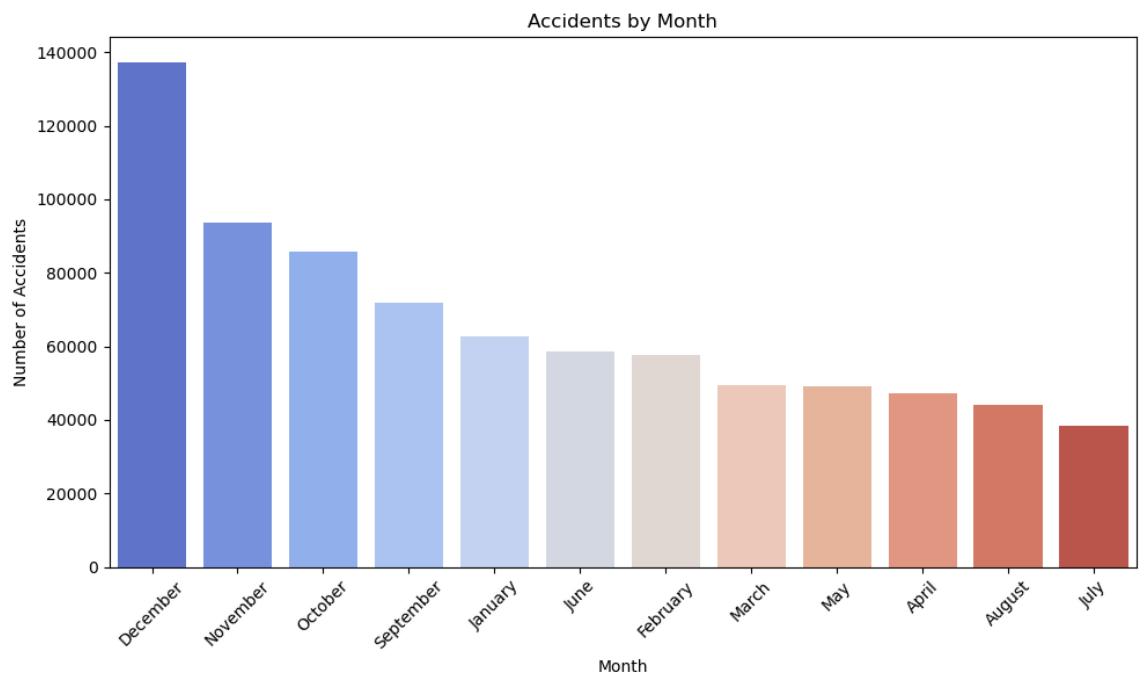


## Accidents by Month

```
In [162]: # Extract month from Start_Time
df_new['Month'] = df_new['Start_Time'].dt.month_name()

# Count accidents by month
monthly_accidents = df_new['Month'].value_counts()

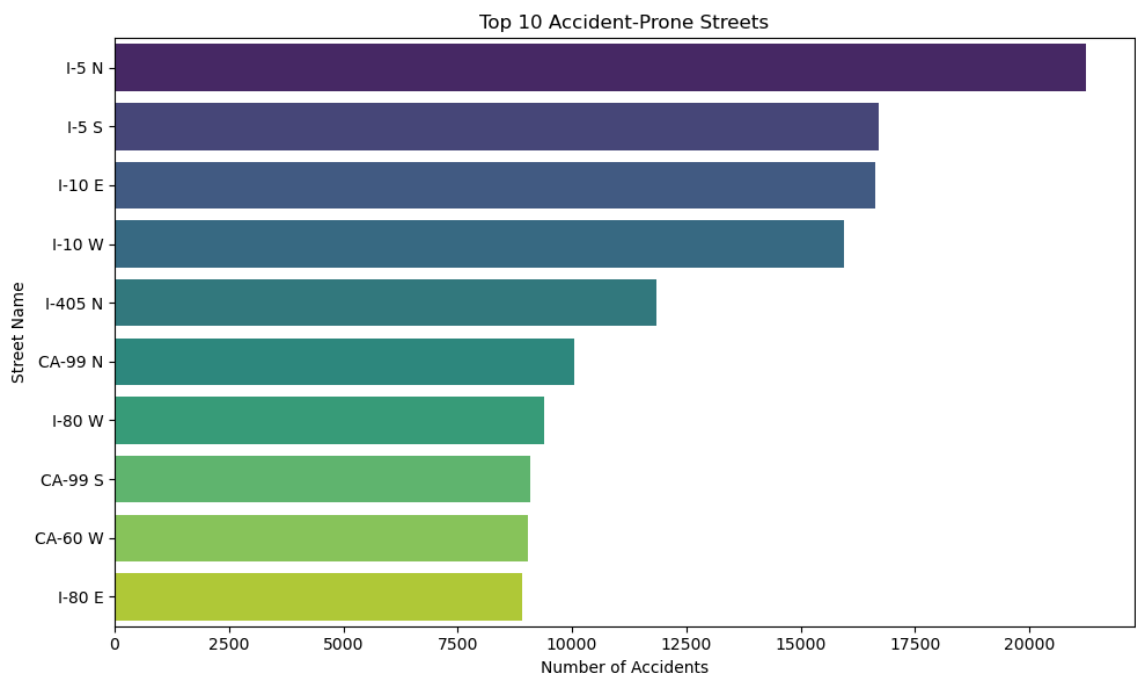
# Plot bar chart
plt.figure(figsize=(10, 6))
sns.barplot(x=monthly_accidents.index, y=monthly_accidents.values, palette=
plt.title('Accidents by Month')
plt.xlabel('Month')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



## # Count accidents by street

```
In [163]: # Count accidents by street
top_streets = df_new['Street'].value_counts().head(10)

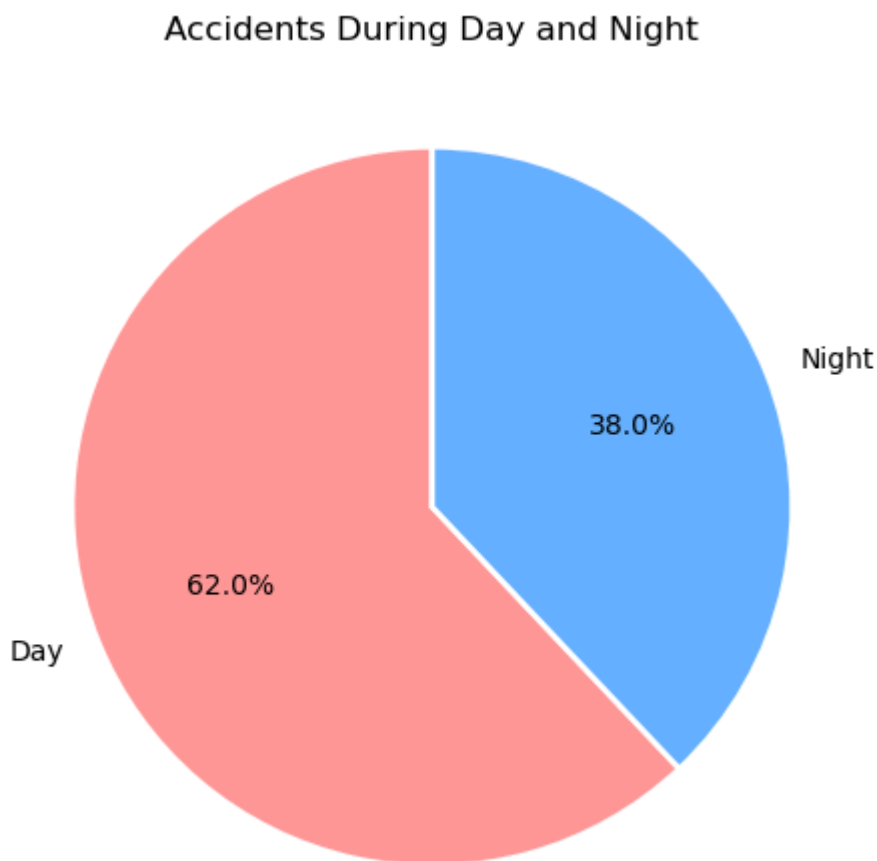
# Plot bar chart
plt.figure(figsize=(10, 6))
sns.barplot(x=top_streets.values, y=top_streets.index, palette='viridis')
plt.title('Top 10 Accident-Prone Streets')
plt.xlabel('Number of Accidents')
plt.ylabel('Street Name')
plt.tight_layout()
plt.show()
```



## Accidents During Day/Night

```
In [167]: # Count accidents by day and night
day_night_accidents = df_new['Sunrise_Sunset'].value_counts()

# Plot pie chart for accidents during day and night
day_night_accidents.plot(kind='pie', autopct='%1.1f%%', figsize=(6, 5),
                          colors=['#ff9999', '#66b3ff'], startangle=90,
                          wedgeprops={'edgecolor': 'w', 'linewidth': 2})
plt.title('Accidents During Day and Night')
plt.ylabel('') # Remove default ylabel
plt.tight_layout()
plt.show()
```



## Conclusion

- This project successfully identified key patterns in traffic accidents, such as the distribution of accidents by severity, time of day, weather conditions, and location.
- The analysis highlighted significant trends, including high accident occurrences during adverse weather and specific times of the day.
- By presenting these findings through intuitive visualizations, the project provides actionable insights for traffic authorities and policymakers.
- Implementing the recommendations derived from this analysis can contribute to improved road safety, reduced accidents, and enhanced public safety measures.

