



ACCIDENT SEVERITY PREDICTION

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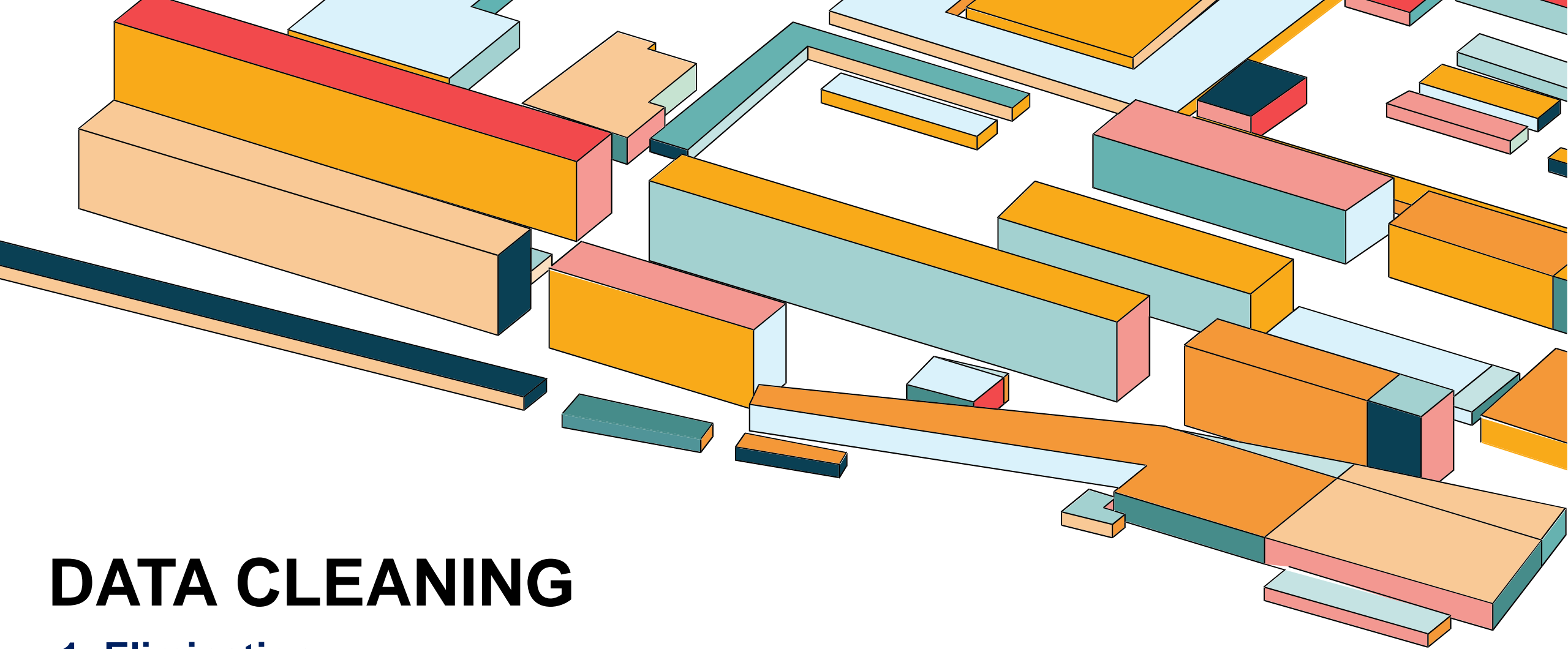
INTRODUCTION

2319 Accidents
every day

US Accidents (2016 - 2021)

- This is a dataset on nationwide traffic accidents including data from 49 states in the US.
- It originally included 4.2 million accident records and 47 columns which we have reduced to 30 after data cleaning and preprocessing.
- The dataset includes information on factors like location, time, weather conditions and severity of an accident.
- We will be using these attributes to analyze the circumstances of the accidents, draw insights from it and create a ML model to predict the severity of an accident based on certain assumed attributes.

California



DATA CLEANING

1. Elimination
2. Simplification
3. Transformation

ELIMINATION

Handling columns with large number of empty values :

```
In [5]: df.isna().sum()
```

```
Out[5]: ID          0          Country          0          Junction          0
Severity          0          Timezone          3659          No_Exit          0
Start_Time        0          Airport_Code        9549          Railway          0
End_Time          0          Weather_Timestamp    50736          Roundabout        0
Start_Lat         0          Temperature(F)    69274          Station          0
Start_Lng         0          Wind_Chill(F)     469643          Stop              0
End_Lat           0          Humidity(%)       73092          Traffic_Calming    0
End_Lng           0          Pressure(in)      59200          Traffic_Signal     0
Distance(mi)      0          Visibility(mi)    70546          Turning_Loop       0
Description       0          Wind_Direction    73775          Sunrise_Sunset     2867
Number           1743911          Wind_Speed(mph)   157944          Civil_Twilight     2867
Street            2          Precipitation(in) 549458          Nautical_Twilight  2867
Side              0          Weather_Condition 70636          Astronomical_Twilight 2867
City              137          Amenity           0          dtype: int64
County            0          Bump              0
State             0          Crossing           0
Zipcode           1319          Give_Way          0
```

ELIMINATION

Dropping columns which have only one class :

```
In [9]: ▶ cat_names = ['Country', 'Timezone', 'Bump', 'Crossing',  
                        'Junction', 'No_Exit', 'Railway', 'Roundabout', 'Station',  
                        'Stop', 'Traffic_Signal', 'Turning_Loop', 'Sunrise_Sunset']  
print("Unique count of categorical features:")  
for i in cat_names:  
    print(i, df[i].unique().size)
```

Unique count of categorical features:

Country 1

Timezone 5

Bump 2

Crossing 2

Junction 2

No_Exit 2

Railway 2

Roundabout 2

Station 2

Stop 2

Traffic_Signal 2

Turning_Loop 1

Sunrise_Sunset 3

SIMPLIFICATION

Wind Direction :

```
In [11]: ▶ print("Wind Direction: ", df['Wind_Direction'].unique())
```

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



```
In [12]: ▶ df.loc[df['Wind_Direction']=='Calm', 'Wind_Direction'] = 'CALM'
df.loc[(df['Wind_Direction']=='West')|(df['Wind_Direction']=='WSW')|(df['Wind_Direction']=='WNW'), 'Wind_Direction'] = 'W'
df.loc[(df['Wind_Direction']=='South')|(df['Wind_Direction']=='SSW')|(df['Wind_Direction']=='SSE'), 'Wind_Direction'] = 'S'
df.loc[(df['Wind_Direction']=='North')|(df['Wind_Direction']=='NNW')|(df['Wind_Direction']=='NNE'), 'Wind_Direction'] = 'N'
df.loc[(df['Wind_Direction']=='East')|(df['Wind_Direction']=='ESE')|(df['Wind_Direction']=='ENE'), 'Wind_Direction'] = 'E'
df.loc[df['Wind_Direction']=='Variable', 'Wind_Direction'] = 'VAR'
print("Wind Direction after simplification: ", df['Wind_Direction'].unique())
```

```
Wind Direction after simplification: ['SW' 'CALM' 'W' 'N' 'S' 'NW' 'E' 'SE' nan 'VAR' 'NE']
```

SIMPLIFICATION

Weather Condition :

Weather Conditions: ['', 'Clear', 'Cloudy', 'Drifting Snow', 'Drizzle', 'Dust', 'Dust Whirls', 'Dust Whirls Nearby', 'Dust Whirlwinds', 'Duststorm', 'Fair', 'Fog', 'Funnel Cloud', 'Hail', 'Haze', 'Heavy ', 'Heavy Drizzle', 'Heavy Ice Pellets', 'Heavy Rain', 'Heavy Rain Shower', 'Heavy Rain Showers', 'Heavy Sleet', 'Heavy Snow', 'Heavy T-Storm', 'Heavy Thunderstorms', 'Ice Pellets', 'Light ', 'Light Drizzle', 'Light Fog', 'Light Haze', 'Light Ice Pellets', 'Light Rain', 'Light Rain Shower', 'Light Rain Showers', 'Light Sleet', 'Light Snow', 'Light Snow Shower', 'Light Snow Showers', 'Light Thunderstorms', 'Low Drifting Snow', 'Mist', 'N/A Precipitation', 'Overcast', 'Partial Fog', 'Patches of Fog', 'Rain', 'Rain Shower', 'Rain Showers', 'Sand', 'Scattered Clouds', 'Shallow Fog', 'Showers in the Vicinity', 'Sleet', 'Small Hail', 'Smoke', 'Snow', 'Snow Grains', 'Snow Nearby', 'Squalls', 'T-Storm', 'Thunder', 'Thunder in the Vicinity', 'Thunderstorm', 'Thunderstorms', 'Tornado', 'Volcanic Ash', 'Widespread Dust', 'Windy', 'Wintry Mix']



	Weather_Condition	Clear	Cloud	Rain	Heavy_Rain	Snow	Heavy_Snow	Fog
0	Light Rain	False	False	True	False	False	False	False
1	Light Rain	False	False	True	False	False	False	False
2	Overcast	False	True	False	False	False	False	False
3	Mostly Cloudy	False	True	False	False	False	False	False
4	Mostly Cloudy	False	True	False	False	False	False	False
...
4232536	Fair	False	False	False	False	False	False	False
4232537	Fair	False	False	False	False	False	False	False
4232538	Partly Cloudy	False	True	False	False	False	False	False
4232539	Fair	False	False	False	False	False	False	False
4232540	Fair	False	False	False	False	False	False	False

SIMPLIFICATION

Converting Boolean columns to 0 's and 1's :

Amenity	bool	Clear	bool
Bump	bool	Cloud	bool
Crossing	bool	Rain	bool
Give_Way	bool	Heavy_Rain	bool
Junction	bool	Snow	bool
No_Exit	bool	Heavy_Snow	bool
Railway	bool	Fog	bool
Roundabout	bool		
Station	bool		
Stop	bool		
Traffic_Calming	bool		
Traffic_Signal	bool		

Junction	No_Exit	Railway	Roundabout	Station	Stop	Traffic_Calming
False	False	False	False	False	False	False
False	False	False	False	False	False	False
True	False	False	False	False	False	False



Junction	No_Exit	Railway	Roundabout	Station	Stop	Traffic_Calming
0	1	1	0	0	1	1
0	0	1	0	0	1	0
0	0	1	0	0	1	0

TRANSFORMATION

Mapping 'Start_Time' to 'Year', 'Month', 'Weekday', 'Day' (in a year), 'Hour', and 'Minute' (in a day) :

	Start_Time
0	2016-02-08 00:37:08
1	2016-02-08 05:56:20
2	2016-02-08 06:15:39
3	2016-02-08 06:51:45
4	2016-02-08 07:53:43



Year	Month	Weekday	Day	Hour	Minute
2016	2	0	39	0	37.0
2016	2	0	39	5	356.0
2016	2	0	39	6	375.0
2016	2	0	39	6	411.0
2016	2	0	39	7	473.0

TRANSFORMATION

Replacing missing values with median for Precipitation :

```
df['Precipitation(in)'] = df['Precipitation(in)'].fillna(df['Precipitation(in)'].median())
```

```
df['Precipitation(in)'].head(5)
```

```
0    0.00  
1    0.02  
2    0.02  
3     NaN  
4    0.01
```

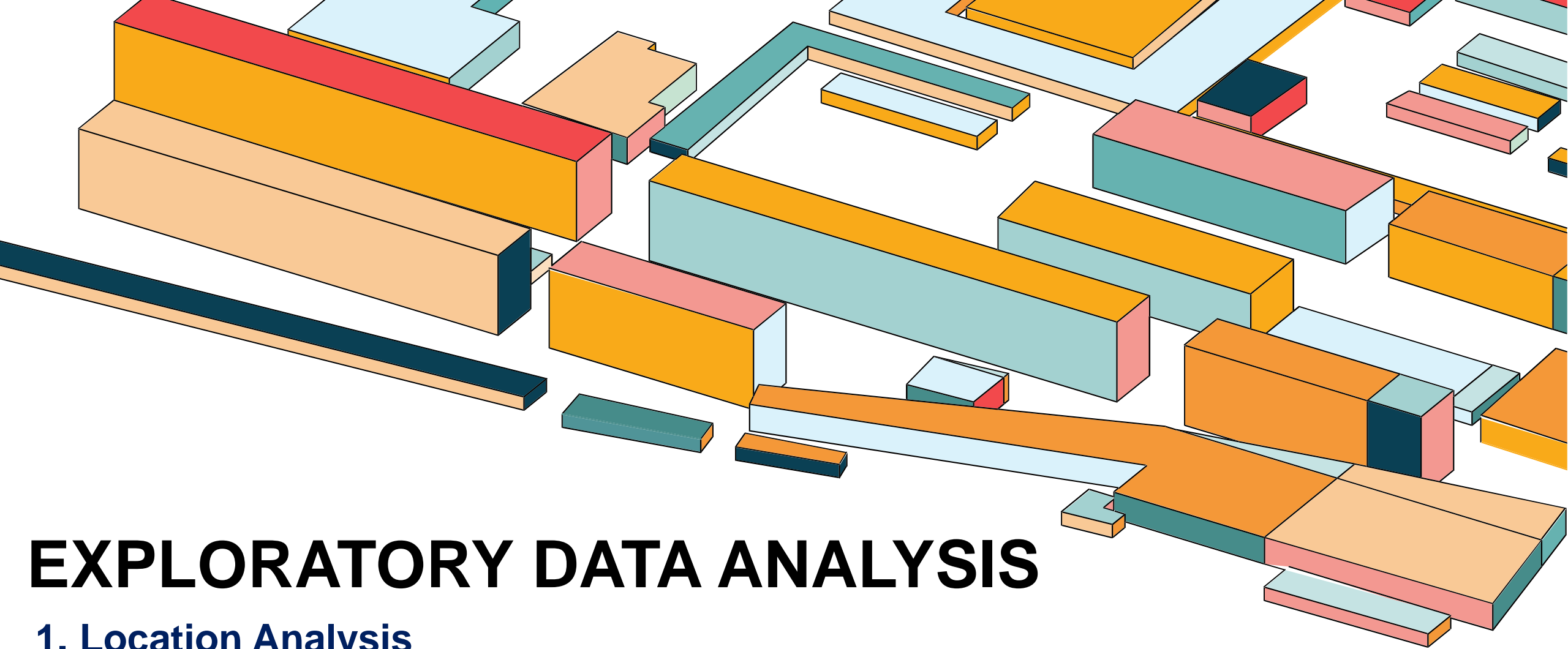
Name: Precipitation(in), dtype: float64



```
df['Precipitation(in)'].head(5)
```

```
0    0.00  
1    0.02  
2    0.02  
3    0.00  
4    0.01
```

Name: Precipitation(in), dtype: float64

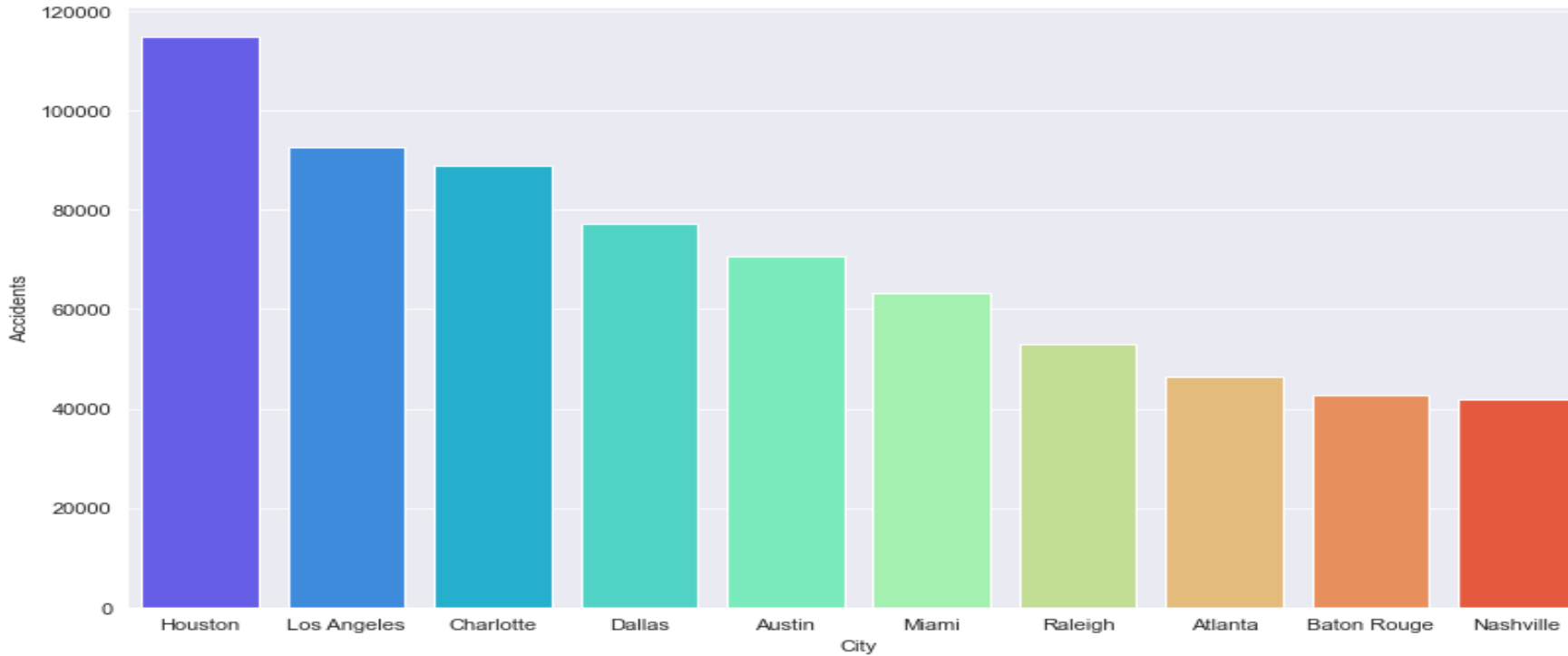


EXPLORATORY DATA ANALYSIS

1. Location Analysis
2. Time Analysis
3. Weather Conditions Analysis

LOCATION ANALYSIS

City Analysis



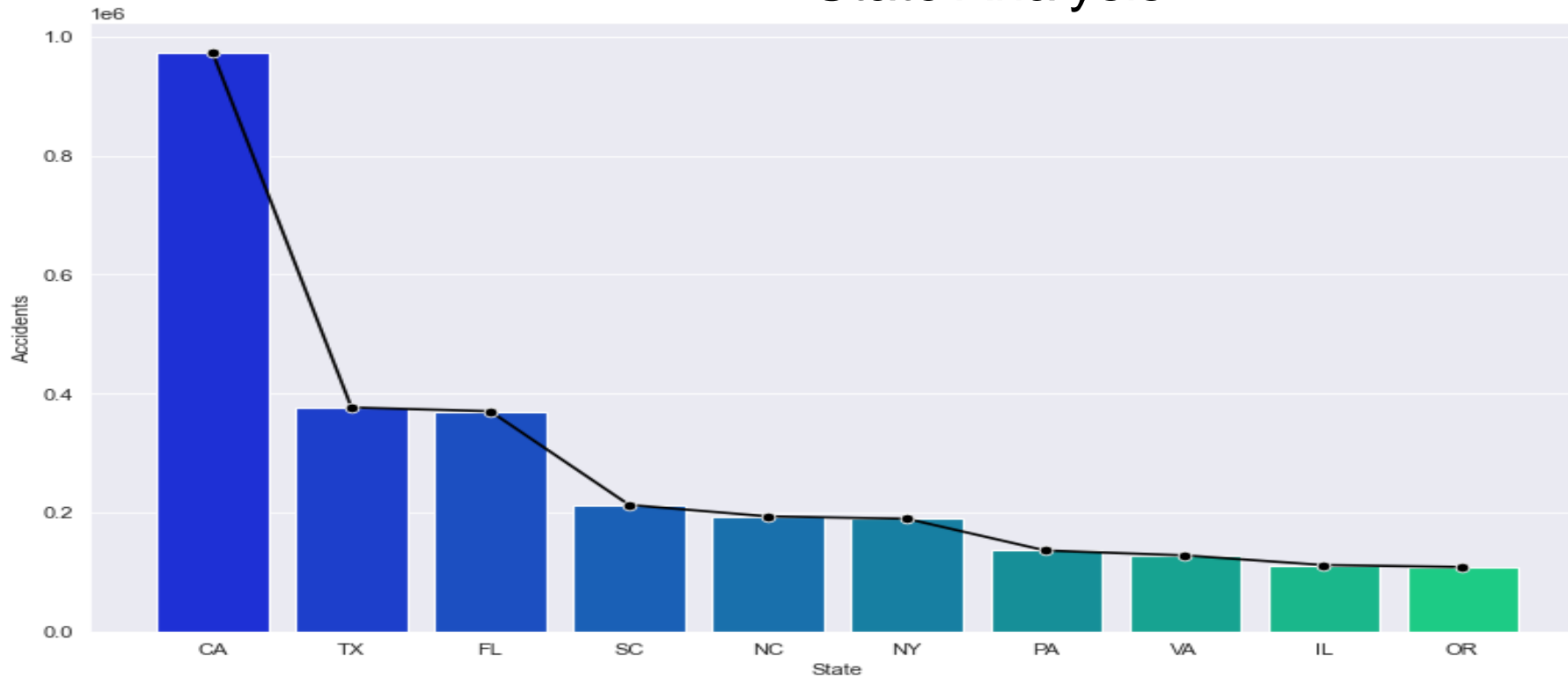
	City	Accidents
0	Houston	114905
1	Los Angeles	92701
2	Charlotte	88887
3	Dallas	77303
4	Austin	70538
5	Miami	63162
6	Raleigh	52876
7	Atlanta	46328
8	Baton Rouge	42814
9	Nashville	41850

Insights :

1. Houston is the city recording the largest number of accidents in the past 5 years in the USA, followed closely by Los Angeles and Charlotte.
2. Out of all accidents occurring in 12249 cities of the USA, 16% of them are hosted in these 10 cities.
3. 3 of the top 10 cities with most accidents are from the state of Texas.

LOCATION ANALYSIS

State Analysis



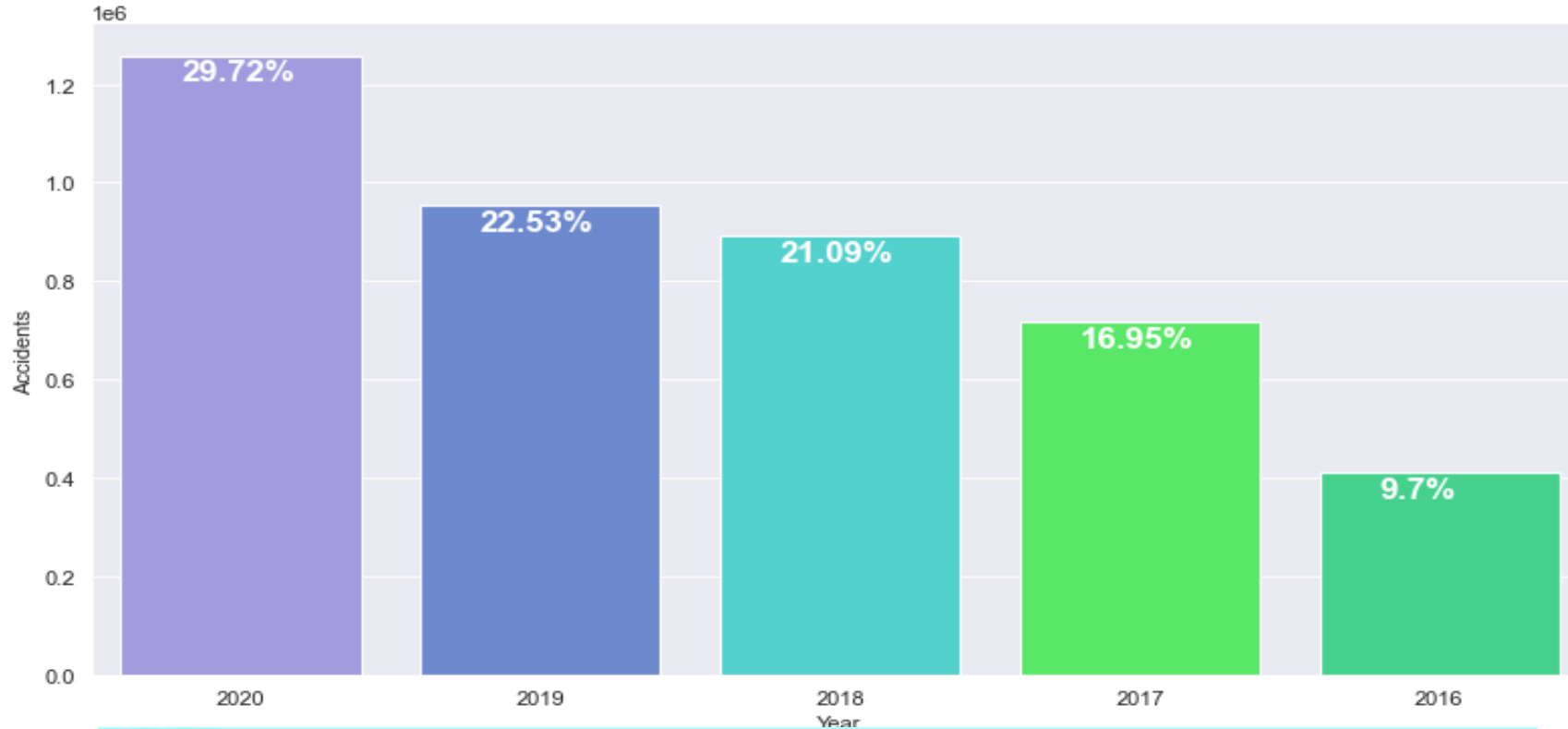
Insights

1. California is the state recording most accidents, followed by Texas and Florida.
2. Out of 50 states in the USA, these 10 states make up for 66% of all recorded accidents, with the top 3 states hosting a shocking 41% of those accidents.
3. South Dakota reported the lowest number of accidents for the period 2016-2020, averaging at 44 a year.

	State	Accidents
0	CA	972577
1	TX	376445
2	FL	370102
3	SC	212712
4	NC	193453
5	NY	189486
6	PA	136049
7	VA	127949
8	IL	111711
9	OR	108350
48	SD	220

TIME ANALYSIS

Yearly Analysis



	Year	Accidents
0	2020	1258101
1	2019	953690
2	2018	892591
3	2017	717459
4	2016	410559

Insights

The number of accidents keep on increasing steadily every year to the extent where 2020 contributes to nearly 30% of all accidents recorded.

TIME ANALYSIS

Monthly Analysis



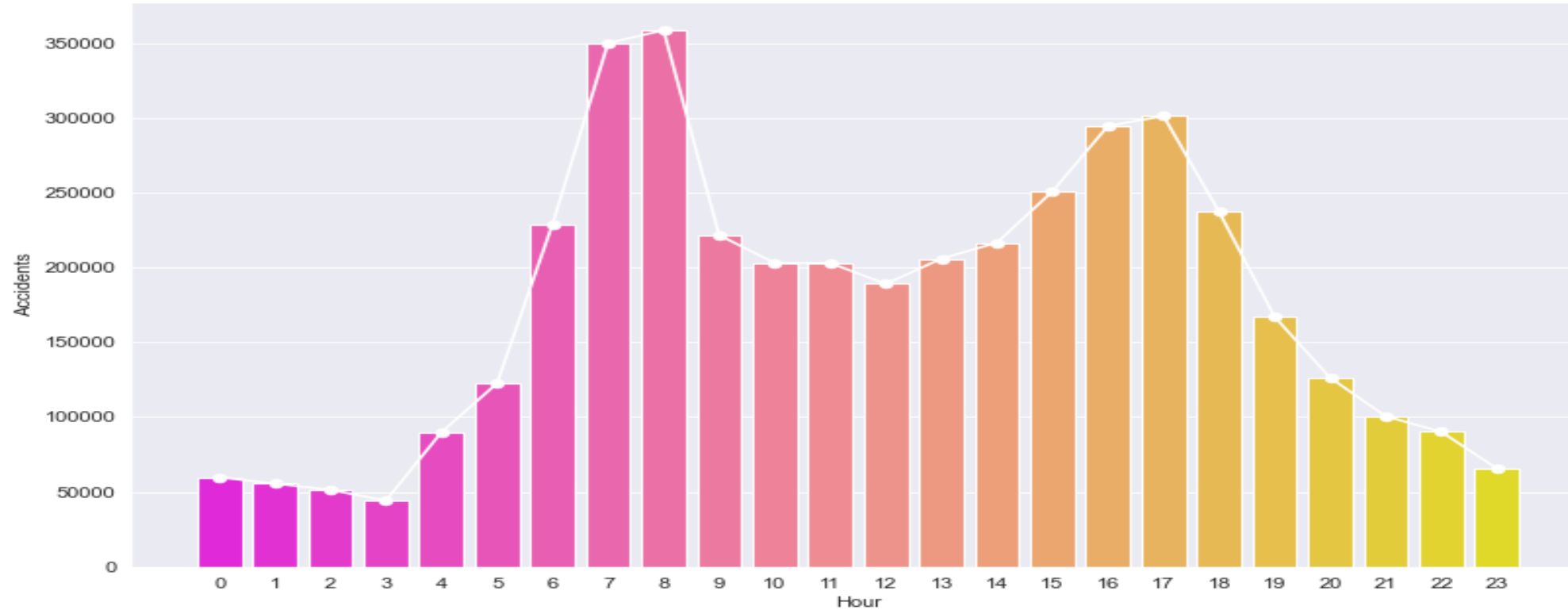
Insights

For the last five years, accidents have shown a pattern of increasing towards the end of the year, where the final 3 months account for 35% of annually recorded accidents.

	Month	Accidents
0	Dec	521994
1	Nov	493835
2	Oct	464868
3	Sep	381189
4	Aug	326226
5	Jun	310348
6	Jan	301921
7	Apr	299477
8	May	296597
9	Mar	293371
10	Feb	284389
11	Jul	258185

TIME ANALYSIS

Hourly Analysis

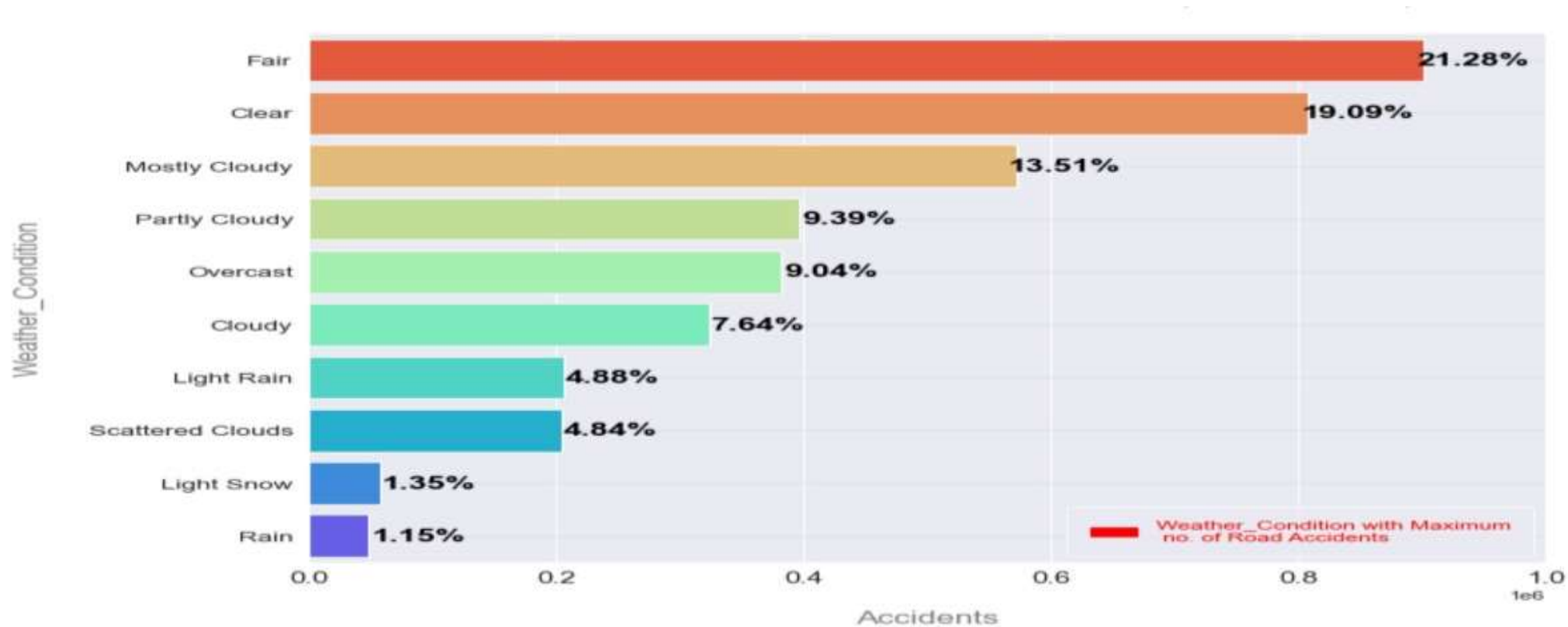


Insights

The morning times of 7-8am and evening times of 4-5pm have been the most accident prone hours, suggesting office timings might have a role to play in these accidents.

	Hour	Accidents
0	8	358419
1	7	349933
2	17	301109
3	16	294585
4	15	250797
5	18	237043
6	6	228870
7	9	221536
8	14	216502
9	13	205845
10	10	202991
11	11	202902
12	12	188986
13	19	166955
14	20	126253
15	5	122517
16	21	100517
17	22	90149
18	4	89815
19	23	65697
20	0	59772
21	1	55597
22	2	51363
23	3	44247

WEATHER CONDITIONS ANALYSIS

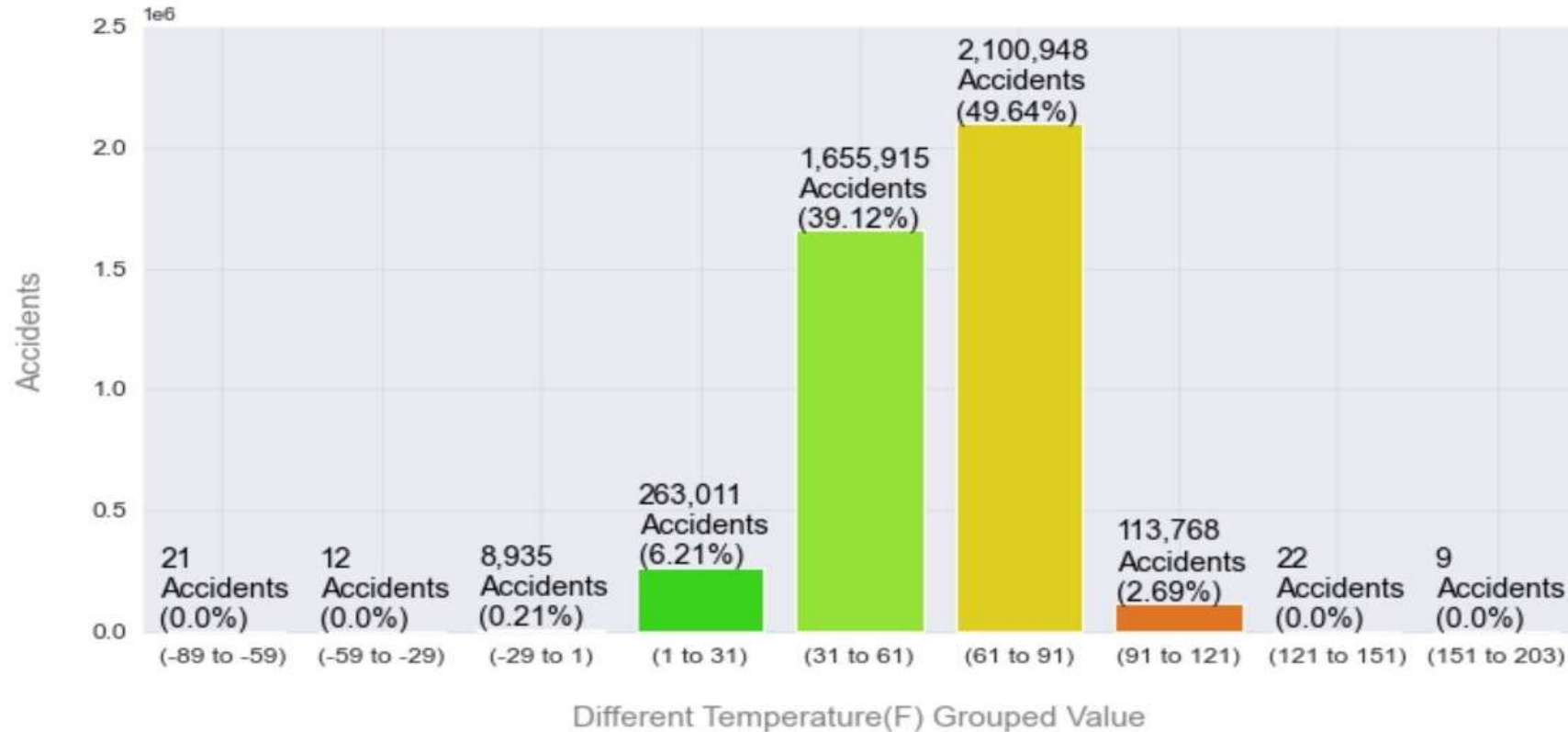


Insights

Ironically, statistics show that 40% of accidents have occurred when the weather conditions are fair and clear.

WEATHER CONDITIONS ANALYSIS

Temperature Analysis



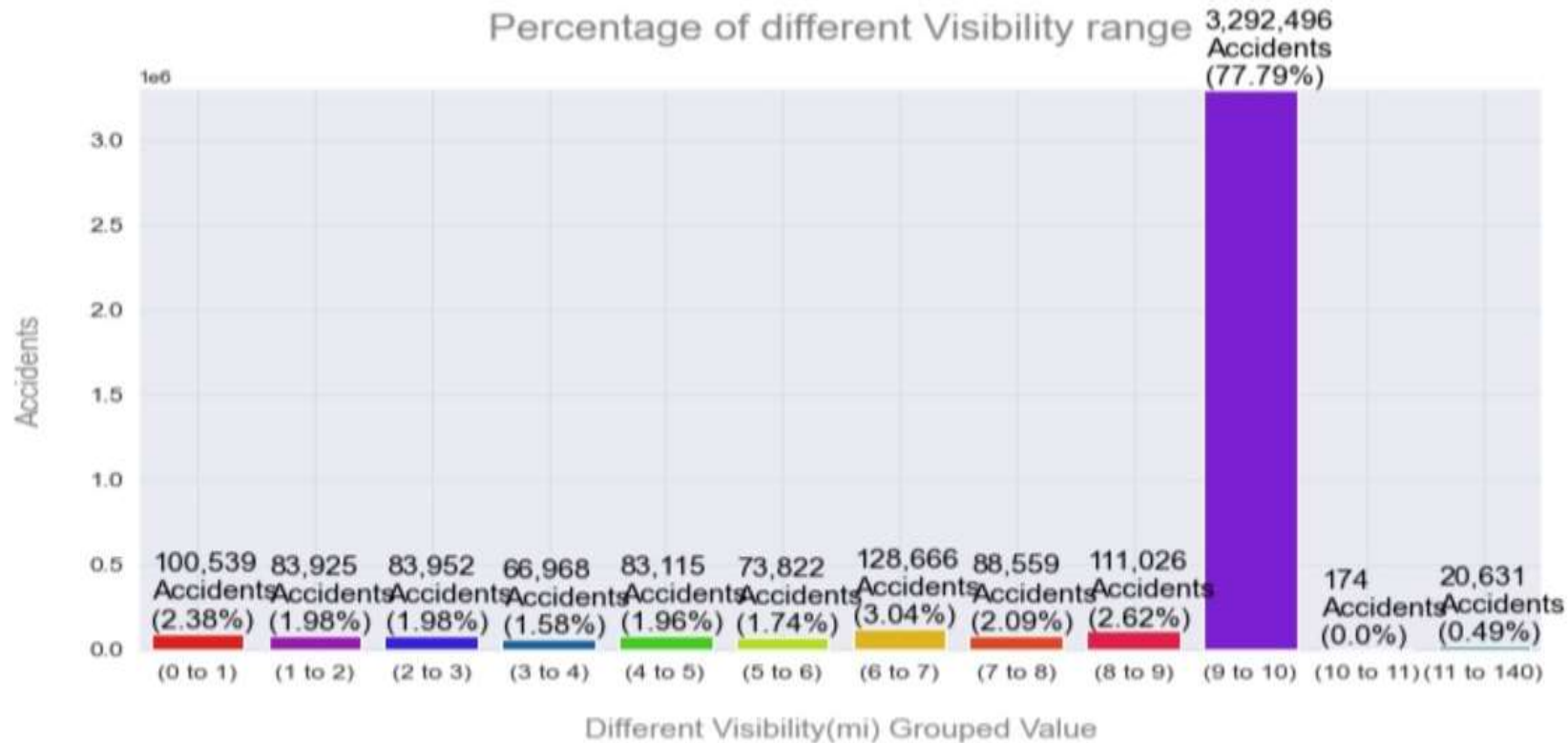
	Temperature(F)	Accidents
0	68.0	91544
1	77.0	90039
2	59.0	86344
3	73.0	84210
4	63.0	80070
...
835	111.4	1
836	119.0	1
837	113.9	1
838	113.4	1
839	-32.8	1

Insights

The temperature range of 61(F)-91(F) accounts for nearly 50% of all accidents recorded.

WEATHER CONDITIONS ANALYSIS

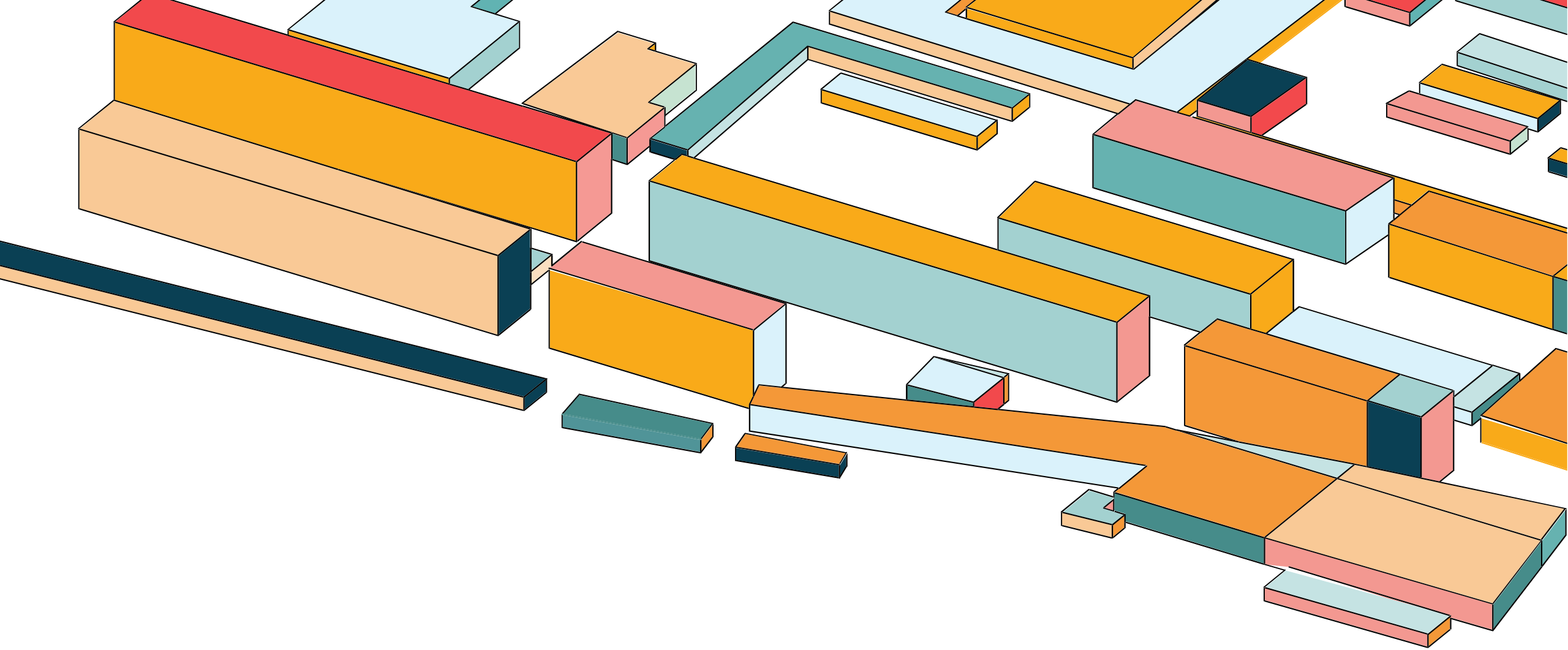
Visibility Analysis



	Visibility(mi)	Accidents
0	10.00	3292390
1	7.00	128662
2	9.00	111023
3	8.00	88557
4	5.00	83097
...
82	101.00	1
83	16.00	1
84	0.31	1
85	3.20	1
86	43.00	1

Insights

77% of accidents occurred when drivers had visibility between 9-10 miles.



MACHINE LEARNING

CLASS IMBALANCE

We have a class imbalance issue because there are 2440379 instances of accidents with severity 1 but not as many instances with severity 0, 2 & 3.

```
In [36]: y = df['Severity'].copy()  
X = df.drop('Severity', axis=1).copy()
```

```
In [37]: y.unique()
```

```
Out[37]: array([3, 2, 4, 1], dtype=int64)
```

```
In [38]: y = y-1
```

```
In [39]: pd.DataFrame(y).value_counts()
```

```
Out[39]: Severity  
0      25536  
1    2440379  
2     149543  
3     125058  
Name: Severity, dtype: int64
```

UNDER-SAMPLING

We use under-sampling to reduce the number of instances of accidents with severity 1 from 2440379 down to 200000.

UnderSampling

```
In [40]: from imblearn.under_sampling import NearMiss

sampling_strategy = {1: 200000}
nr = NearMiss(sampling_strategy=sampling_strategy)

X, y = nr.fit_resample(X, y.ravel())
```

```
In [41]: pd.DataFrame(y).value_counts()
```

```
Out[41]: 1    200000
         2    149543
         3    125058
         0     25536
         dtype: int64
```

OVERSAMPLING

We use oversampling to increase the number of instances of accidents with severity 0, 2 & 3 to 200000.

OverSampling

```
In [42]: from imblearn.over_sampling import RandomOverSampler

sampling_strategy1 = {0: 200000, 2: 200000, 3: 200000}
oversample = RandomOverSampler(sampling_strategy=sampling_strategy1)

X_miss, y_miss = oversample.fit_resample(X, y)
```

```
In [43]: pd.DataFrame(y_miss).value_counts()
```

```
Out[43]: 0    200000
         1     20000
         2    200000
         3    200000
         dtype: int64
```

TRAIN TEST SPLIT

We have 640000 examples in our training dataset and 160000 examples in our testing dataset.

Train Test Split

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_miss, y_miss, train_size=0.8, random_state=100)

print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)

(640000, 100) (640000,) (160000, 100) (160000,)
```


STANDARDIZATION

Our dataset contains variables that are different in scale – **Temperature** can have values on a scale of **32-212** and **Precipitation** can have values on scale of **0-2(inches)**.

As these two columns are different in scale, they are Standardized to have common scale while building machine learning model.

Standardization

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

XGBOOST

Xgboost

```
model = xgb.XGBClassifier()  
model.fit(X_train, y_train)
```

▸ XGBClassifier

```
predicted_y = model.predict(X_test)
```

```
from sklearn import metrics  
print(metrics.classification_report(y_test, predicted_y))
```

	precision	recall	f1-score	support
0	0.84	0.96	0.90	40040
1	0.85	0.81	0.83	39971
2	0.74	0.75	0.74	39796
3	0.82	0.74	0.78	40193
accuracy			0.82	160000
macro avg	0.81	0.82	0.81	160000
weighted avg	0.81	0.82	0.81	160000

DECISION TREE

Decision Tree

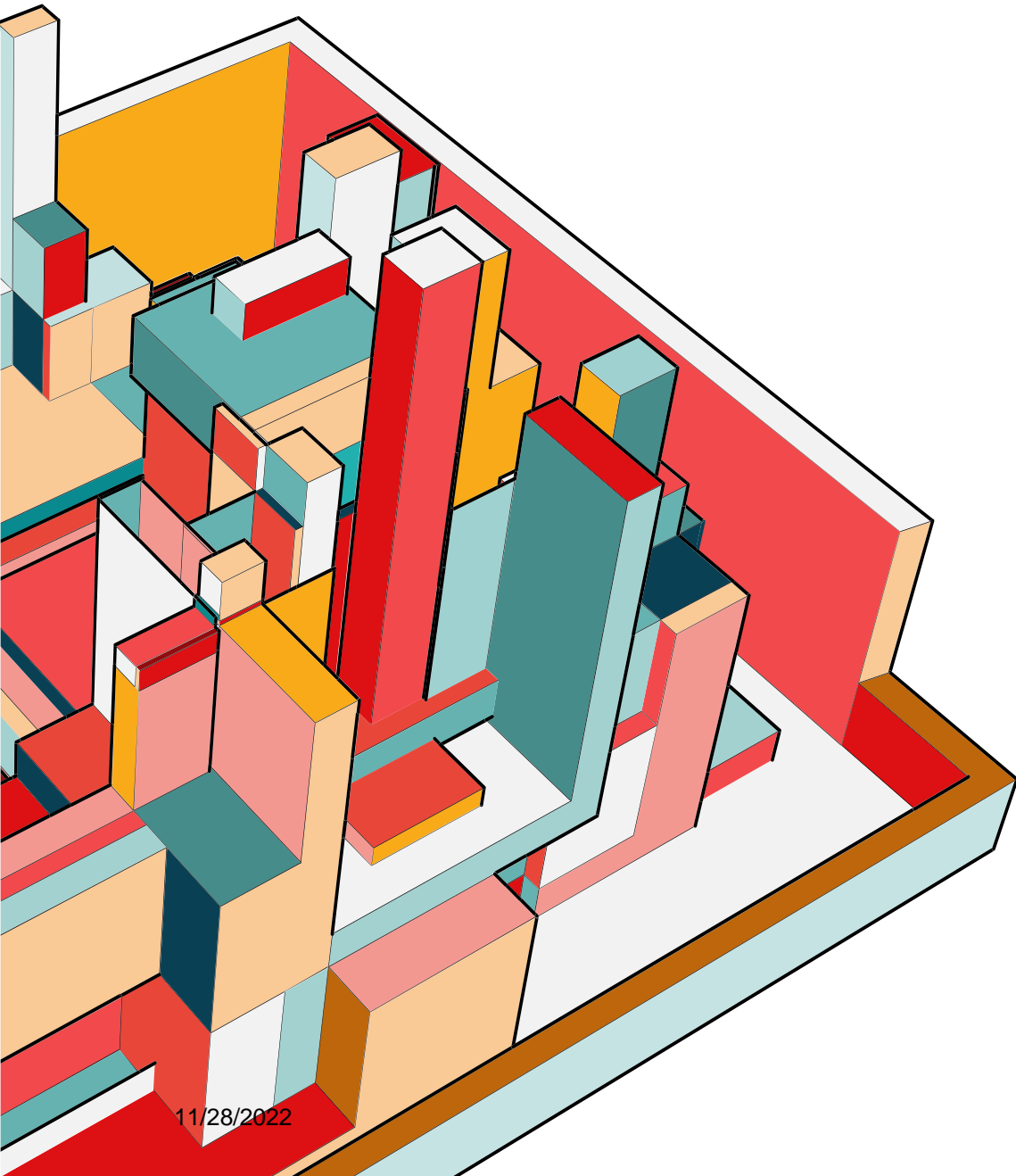
```
from sklearn.tree import DecisionTreeClassifier
```

```
clf = DecisionTreeClassifier()  
clf = clf.fit(X_train,y_train)
```

```
y_pred = clf.predict(X_test)
```

```
print(metrics.classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.96	1.00	0.98	40040
1	0.92	0.85	0.88	39971
2	0.84	0.83	0.83	39796
3	0.85	0.88	0.87	40193
accuracy			0.89	160000
macro avg	0.89	0.89	0.89	160000
weighted avg	0.89	0.89	0.89	160000



FLASK APP

Please go the following link to predict the severity
of an accident on a scale of 4 –

<https://accident-severity.herokuapp.com/>

THANK YOU