Car Accident Severity vs Road Visibility

Group A6

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The problem We Are Seeking to Answer

Historically:

- There tends to be an increase in car accidents, when road visibility is poor
- Studies have explored the impact of weather on road safety

The problem at hand:

- We are investigating the potential correlation between the severity of car accidents and road visibility conditions in the United States

Data Driven approach

- Objective, quantitative evidence that can be used to inform decisions, policies, and interventions
- Uncover patterns, trends, and correlations that might not be visible through theoretical reasoning alone

Possible Outcomes and The Ideal Experiment

Possible outcomes:

- Outcome 1: Fail to reject the null hypothesis
- Outcome 2: reject the null hypothesis

The Ideal Experiment:

- Chi square test of independence

Hypothesis:

- H0: No relationship between the severity of accident and visibility
- Ha: Apparent relationship between the severity of accident and visibility

Data Collection:

- A dataset that collects data consistently over time to minimize seasonal or temporal effects

Confounding Variables:

- Zip code, time zone, humidity, wind speed, and etc.
- Address through regression or stratification

Steps To Perform The Test

Data Preparation:

- Discretize visibility (e.g., Low: 0-1 miles, Excellent: >10 miles).
- Contingency table creation.

Hypothesis Formulation:

- Null: No association.
- Alternative: Significant association.

Chi-Square Test:

- Chi-Square Statistic formula.
- Degrees of freedom: (r-1)(c-1).
- P-value criteria (e.g., $\alpha = 0.05$).

Interpretation:

- Significant (or not) association based on p-value.

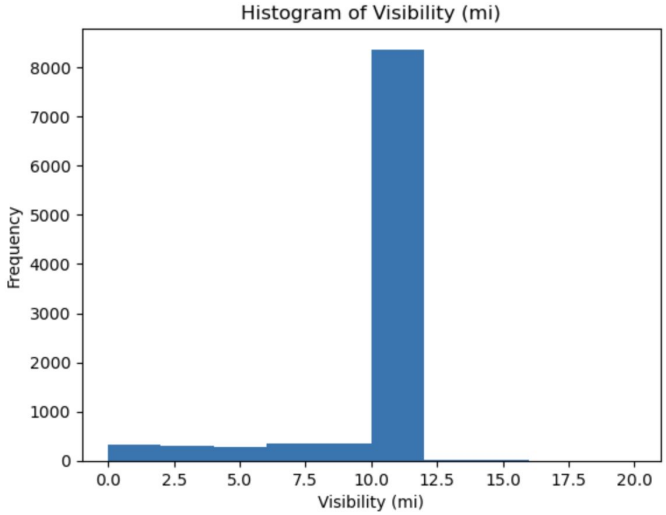
Reporting:

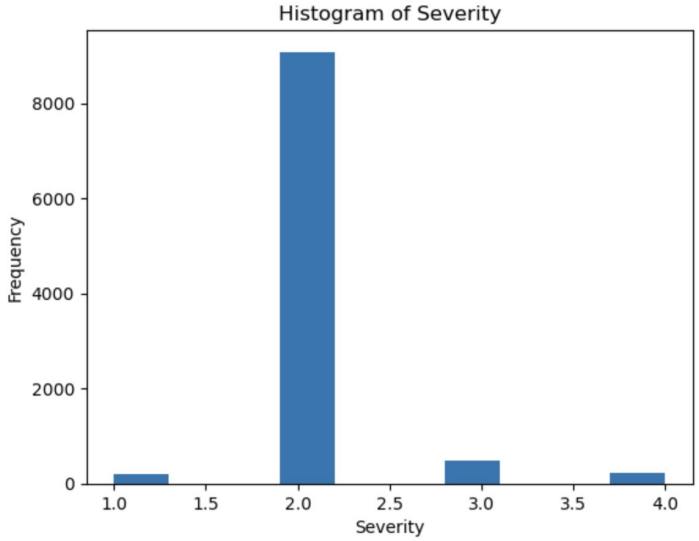
- Test statistic, p-value, conclusion, effect size

Descriptive Statistics and Visualization

```
sampled_df = df.sample(n=10000, random_state=42)
sampled_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 202953 to 144659
Data columns (total 44 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   ID                     10000 non-null  object
 1   Source                 10000 non-null  object
 2   Severity               10000 non-null  int64
 3   Start_Time             10000 non-null  object
 4   End_Time               10000 non-null  object
 5   Start_Lat              10000 non-null  float64
 6   Start_Lng              10000 non-null  float64
 7   Distance(mi)           10000 non-null  float64
 8   Description            10000 non-null  object
 9   Street                 9970 non-null   object
 10  City                   9999 non-null   object
 11  County                 10000 non-null  object
 12  State                  10000 non-null  object
 13  Zipcode                10000 non-null  object
 14  Country                10000 non-null  object
 15  Timezone               10000 non-null  object
 16  Airport_Code           10000 non-null  object
 17  Weather_Timestamp      10000 non-null  object
 18  Temperature(F)         9963 non-null   float64
 19  Wind_Chill(F)          9884 non-null   float64
 20  Humidity(%)            9946 non-null   float64
 21  Pressure(in)           9985 non-null   float64
 22  Visibility(mi)         10000 non-null  float64
 23  Wind_Direction         9918 non-null   object
 24  Wind_Speed(mph)        9918 non-null   float64
 25  Precipitation(in)      9803 non-null   float64
 26  Weather_Condition      9981 non-null   object
 27  Amenity                10000 non-null  bool
 28  Bump                   10000 non-null  bool
 29  Crossing               10000 non-null  bool
 30  Give_Way               10000 non-null  bool
 31  Junction               10000 non-null  bool
 32  No_Exit                10000 non-null  bool
 33  Railway                10000 non-null  bool
 34  Roundabout             10000 non-null  bool
 35  Station                10000 non-null  bool
 36  Stop                   10000 non-null  bool
 37  Traffic_Calming        10000 non-null  bool
 38  Traffic_Signal         10000 non-null  bool
 39  Turning_Loop           10000 non-null  bool
 40  Sunrise_Sunset         9909 non-null   object
 41  Civil_Twilight         9909 non-null   object
 42  Nautical_Twilight      9909 non-null   object
 43  Astronomical_Twilight  9909 non-null   object
dtypes: bool(13), float64(10), int64(1), object(20)
memory usage: 2.6+ MB
```





	Severity	Visibility(mi)
0	3	10.0
1	2	10.0
2	2	10.0
3	3	9.0
4	2	6.0
5	3	7.0
6	2	7.0
7	3	7.0
8	2	5.0
9	3	3.0

	Severity	Visibility(mi)
count	7.551296e+06	7.551296e+06
mean	2.211485e+00	9.090376e+00
std	4.864240e-01	2.688316e+00
min	1.000000e+00	0.000000e+00
25%	2.000000e+00	1.000000e+01
50%	2.000000e+00	1.000000e+01
75%	2.000000e+00	1.000000e+01
max	4.000000e+00	1.400000e+02

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7551296 entries, 0 to 7728393
Data columns (total 2 columns):
 #   Column          Dtype
---  ------          -----
 0   Severity        int64
 1   Visibility(mi)  float64
dtypes: float64(1), int64(1)
memory usage: 172.8 MB
```

Data Preparation

Discretize visibility i.e, Categorize ‘visibility’ into ‘visibility category’ based on the following rules:

Low Visibility: Less than 1 mile (0-1 miles)
Moderate Visibility: 1 to 3 miles (1-3 miles)
Good Visibility: 3 to 10 miles (3-10 miles)
Excellent Visibility: More than 10 miles (> 10 miles)

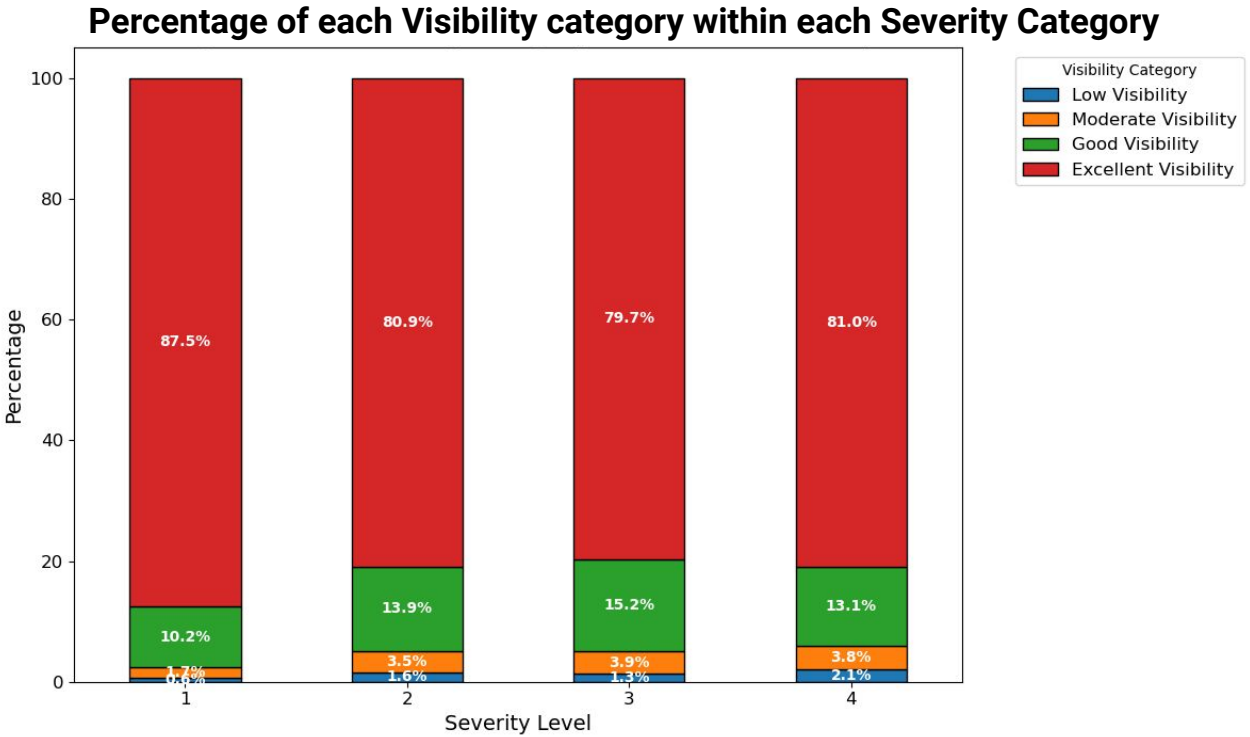
	Severity	Visibility(mi)	Visibility Category
0	3	10.0	Excellent Visibility
1	2	10.0	Excellent Visibility
2	2	10.0	Excellent Visibility
3	3	9.0	Good Visibility
4	2	6.0	Good Visibility

Contingency Table:

Severity	Excellent Visibility	Good Visibility	Moderate Visibility	Low Visibility	Total by Severity
1	58113	6755	1145	418	66431.0
2	4871883	838746	211998	96117	6018744.0
3	1011275	192280	48877	16394	1268826.0
4	159805	25821	7467	4202	197295.0
Total by Visibility	6101076	1063602	269487	117131	NaN

Null Hypothesis H0: No significant association between Road Visibility and Severity of an Accident
Alternative Hypothesis H1: Significant association between Road Visibility and Severity of an Accident

Visualizations:



Chi-Square Test:

```
from scipy.stats import chi2_contingency
# Perform the chi-square test of independence
chi2, p, dof, expected = chi2_contingency(contingency_table)

chi2, p, dof, expected
```

```
(4962.777704613812,
 0.0,
 9,
 array([[1.03043629e+03, 2.37075740e+03, 9.35682358e+03, 5.36729827e+04],
        [9.33590080e+04, 2.14794025e+05, 8.47741653e+05, 4.86284931e+06],
        [1.96812386e+04, 4.52812487e+04, 1.78714471e+05, 1.02514904e+06],
        [3.06031715e+03, 7.04096855e+03, 2.77890519e+04, 1.59404662e+05]]))
```

Chi-Square statistic: 4962.78; p-value = 0; degrees of freedom: 9

The very small p-value (0.0) suggests that there is a statistically significant association between the "Severity of Accident" and "Visibility of Road" categories.

This means that the distribution of accident severities is dependent of the visibility conditions

Limitations

- Variable is categorical - hard to measure
- Chi square tests association, excludes direction of association
- Further analysis - regression model
- Confounding variables
  - Road Conditions
  - Time of Day
  - Weather Conditions
  - Environmental Features
  - Driver Behavior

Future Expectations

- Logistic regression to address ordinal data and confounding variables
- Improved understanding for risk assessment
- May alter road signs or speed control if finding is significant
- Greater awareness about road conditions
- Reduction in accident severity


Thank You!