

```
In [9]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [12]: df=pd.read_csv('C:/Users/Vaibhav Shrivastava/Desktop/ai ml/car_crashes.csv')
```

```
In [3]: df.describe

<bound method NDFrame.describe of
0    18.8    7.332    5.640    18.048    15.040    784.55
1    18.1    7.421    4.525    16.290    17.014    1053.48
2    18.6    6.510    5.208    15.624    17.856    899.47
3    22.4    4.032    5.824    21.056    21.280    827.34
4    12.0    4.200    3.360    10.920    10.680    878.41
5    13.6    5.632    3.808    16.744    12.920    835.59
6    10.8    4.968    3.808    9.396    9.856    1068.73
7    16.2    6.156    4.860    14.094    16.038    1137.87
8     5.9    2.006    1.593     5.900     5.900    1273.89
9    17.9    3.759    5.191    16.468    16.826    1160.13
10    15.6    2.964    3.900    14.820    14.508    913.15
11    17.5    9.450    7.175    13.350    15.225    861.18
12    15.3    5.508    4.437    13.005    14.994    641.96
13    12.8    4.608    4.352    12.032    12.288    803.11
14    14.5    3.625    4.205    13.775    13.775    710.46
15    15.7    2.669    3.925    15.229    13.659    649.06
16    17.8    4.806    4.272    13.706    15.130    799.45
17    21.4    4.066    4.922    16.692    16.264    872.51
18    20.5    7.175    6.765    14.965    20.090    1281.55
19    15.1    5.738    4.530    13.137    12.684    661.88
20    12.5    4.250    4.090     8.875    12.375    1048.78
21     8.2    1.886    2.870     7.134     6.560    1011.14
22    14.1    3.384    3.948    13.395    10.857    1110.61
23     9.6    2.208    2.784     8.448     8.448     777.18
24    17.6    2.640    5.456     1.760    17.600     896.07
25    16.1    6.923    5.474    14.812    13.524    790.32
26    21.4    8.346    9.416    17.976    18.190    816.21
27    14.9    1.937    5.215    13.857    13.410    732.28
28    14.7    5.439    4.704    13.965    14.553    1029.87
29    11.6    4.060    3.489    10.692     9.628    746.54
30    11.2    1.792    3.136     9.632     8.736    1301.52
31    18.4    3.496    4.968    12.328    18.032    869.85
32    12.3    3.936    3.567    10.824     9.840    1234.31
33    16.8    6.552    5.208    15.792    13.608    708.24
34    23.9    5.497    10.038    23.661    20.554    688.75
35    14.1    3.948    4.794    13.959    11.562    697.73
36    19.9    6.368    5.771    18.308    18.706    881.51
37    12.8    4.224    3.328     8.576    11.520    804.71
38    18.2    9.100    5.642    17.472    16.016    905.99
39    11.1    3.774    4.218    10.212     8.769    1148.99
40    23.9    9.082    9.799    22.944    19.359    858.97
41    19.4    6.014    6.402    19.012    16.684    669.31
42    19.5    4.095    5.655    15.990    15.795    767.91
43    19.4    7.760    7.372    17.654    16.878    1004.75
44    11.3    4.859    1.808     9.944    10.848    809.38
45    13.6    4.080    4.080    13.056    12.920    716.20
46    12.7    2.413    3.429    11.049    11.176    768.95
47    10.6    4.452    3.498     8.692     9.116    890.03
48    23.8    8.092    6.664    23.086    20.706    992.61
49    13.8    4.968    4.554     5.382    11.592    670.31
50    17.4    7.308    5.568    14.094    15.660    791.14
```

```
ins_losses abbrev
0    145.08    AL
1    133.93    AK
2    110.35    AZ
3    142.39    AR
4    165.63    CA
5    139.91    CO
6    167.02    CT
7    151.48    DE
8    136.05    DC
9    144.18    FL
10   142.80    GA
11   120.92    HI
12    82.75    ID
13   139.15    IL
14   108.92    IN
15   114.47    IA
16   133.00    KS
17   137.13    KY
18   194.78    LA
19    96.57    ME
20   192.70    MD
21   135.63    MA
22   152.26    MI
23   133.35    MN
24   155.77    MS
25   144.45    MO
26    85.15    MT
27   114.82    NE
28   138.71    NV
29   120.21    NH
30   159.85    NJ
31   120.75    NM
32   150.01    NY
33   127.82    NC
34   109.72    ND
35   133.52    OH
36   178.86    OK
37   104.61    OR
38   153.86    PA
39   148.58    RI
40   116.29    SC
41    96.87    SD
42   155.57    TN
43   156.83    TX
44   109.48    UT
45   109.61    VT
46   153.72    VA
47   111.62    WA
48   152.56    WV
49   106.62    WI
50   122.04    WY  >
```

```
In [4]: df.info()

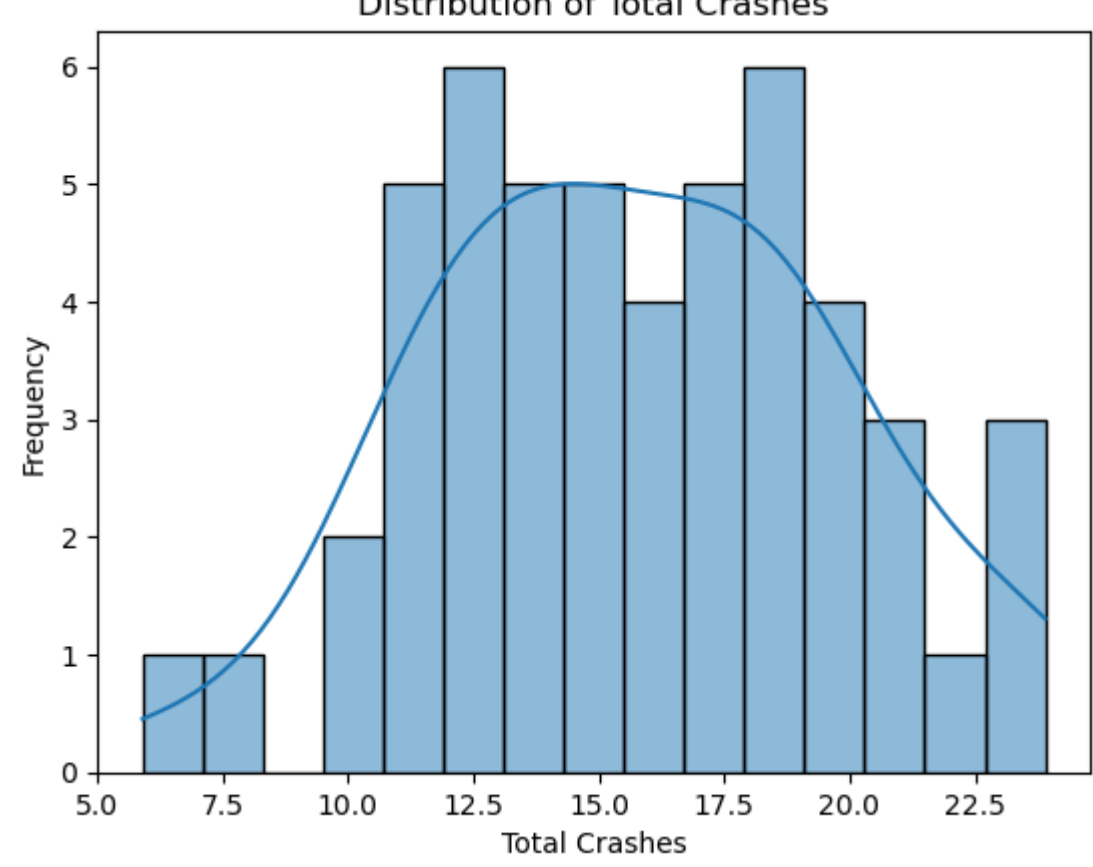
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 8 columns):
#   Column      Non-Null Count  Dtype
---  --
0   total        51 non-null    float64
1   speeding     51 non-null    float64
2   alcohol      51 non-null    float64
3   not_distracted  51 non-null    float64
4   no_previous  51 non-null    float64
5   ins_premium  51 non-null    float64
6   ins_losses   51 non-null    float64
7   abbrev       51 non-null    object
dtypes: float64(7), object(1)
memory usage: 3.3+ KB
```

```
In [5]: df.head()

total speeding alcohol not_distracted no_previous ins_premium ins_losses abbrev
0  18.8    7.332    5.640    18.048    15.040    784.55    145.08    AL
1  18.1    7.421    4.525    16.290    17.014    1053.48    133.93    AK
2  18.6    6.510    5.208    15.624    17.856    899.47    110.35    AZ
3  22.4    4.032    5.824    21.056    21.280    827.34    142.39    AR
4  12.0    4.200    3.360    10.920    10.680    878.41    165.63    CA
```

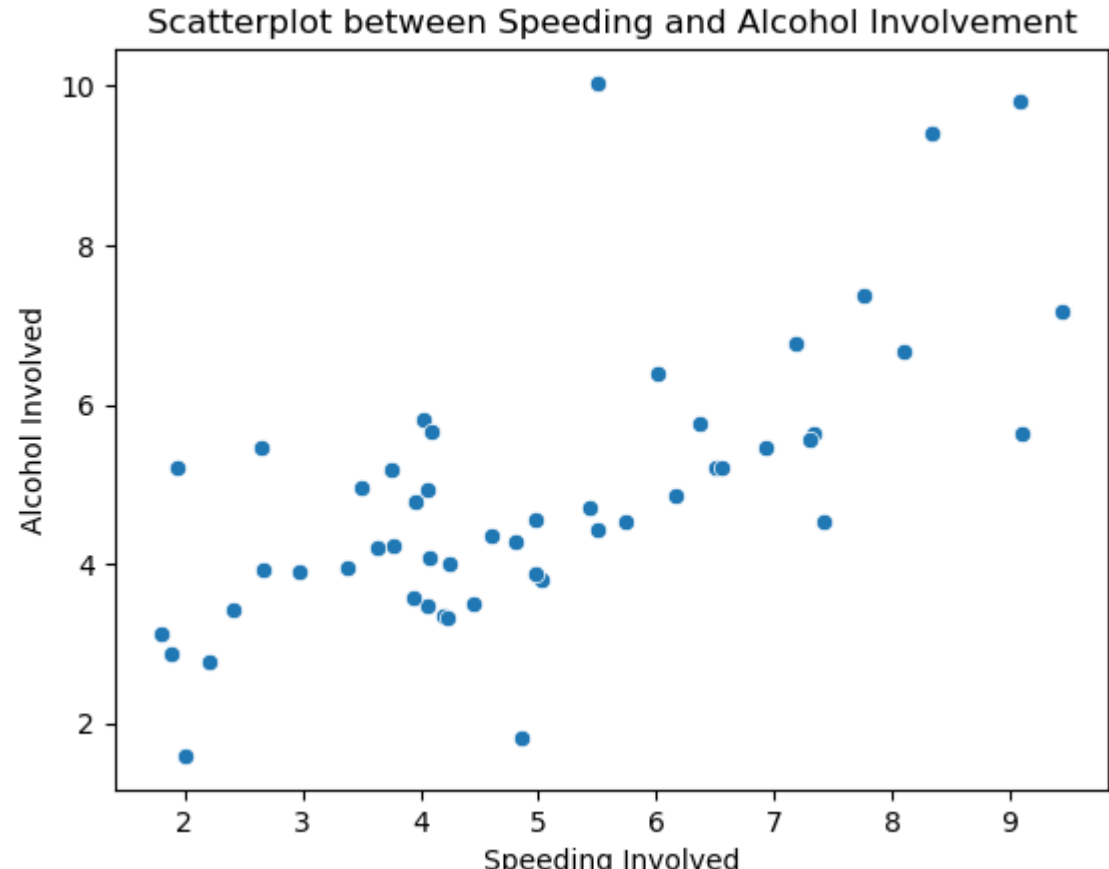
```
In [10]: # Histogram of 'total' crashes
sns.histplot(df[['total']], bins=15, kde=True)
plt.xlabel('Total Crashes')
plt.ylabel('Frequency')
plt.title('Distribution of Total Crashes')
plt.show()

# Inference: The histogram displays the distribution of total crashes. It appears to be right-skewed,
# indicating that most cities have a relatively low number of total crashes.
```



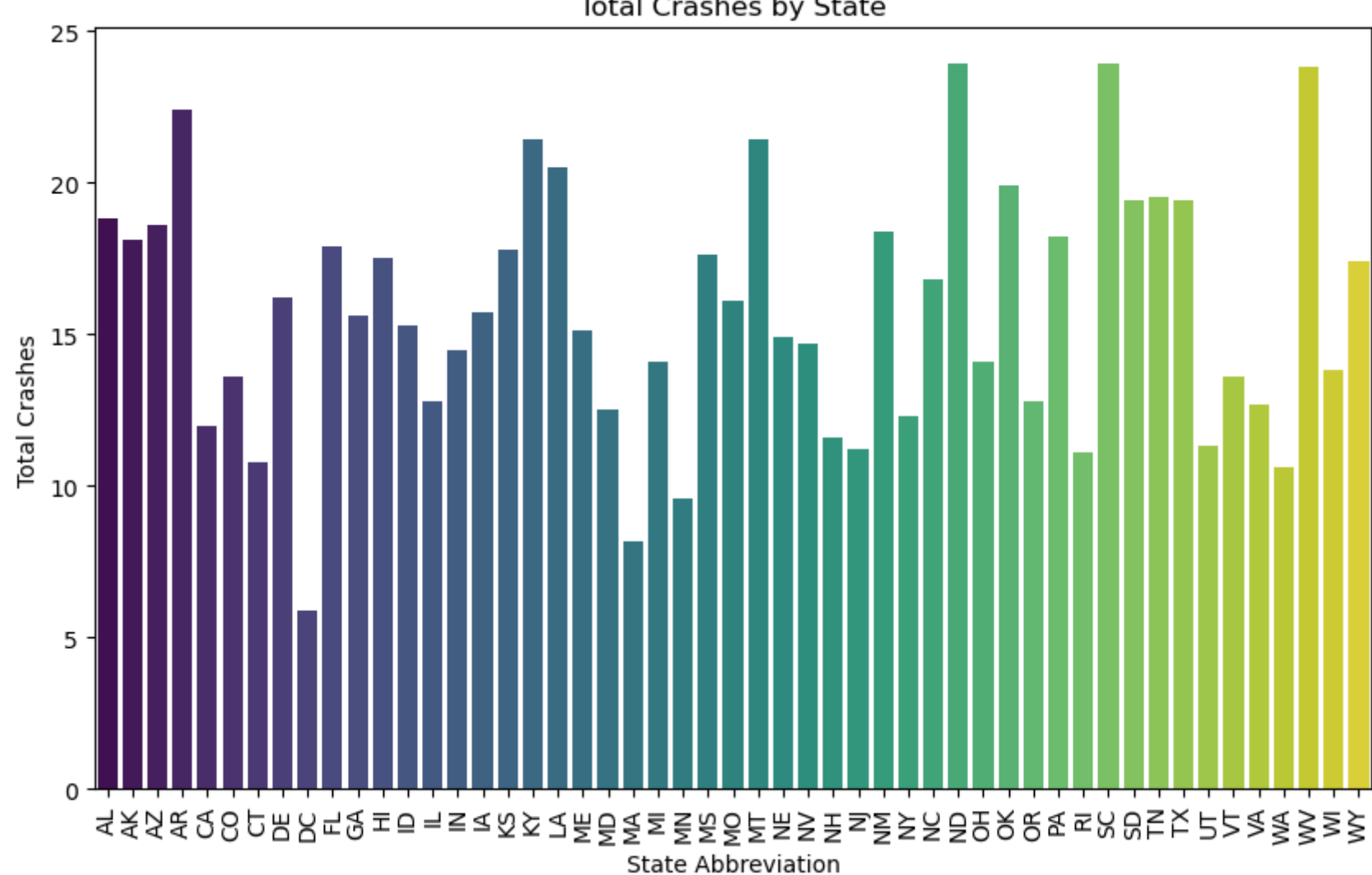
```
In [11]: # Scatterplot between 'speeding' and 'alcohol' involvement
sns.scatterplot(x='speeding', y='alcohol', data=df)
plt.xlabel('Speeding Involved')
plt.ylabel('Alcohol Involved')
plt.title('Scatterplot between Speeding and Alcohol Involvement')
plt.show()

# Inference: The scatterplot illustrates the relationship between speeding and alcohol involvement.
# It seems that there is no strong linear relationship between these two variables.
```



```
In [12]: # Bar chart of 'abbrev' vs. 'total' crashes
plt.figure(figsize=(10, 6))
sns.barplot(x='abbrev', y='total', data=df, palette='viridis')
plt.xlabel('State Abbreviation')
plt.ylabel('Total Crashes')
plt.title('Total Crashes by State')
plt.xticks(rotation=90)
plt.show()

# Inference: The bar chart displays the total crashes by state. For example, "SC" (South Carolina)
# appears to have a relatively high number of total crashes compared to other states.
```



```
In [13]: # Countplot of 'ins_premium' bins
plt.figure(figsize=(10, 6))
sns.countplot(x='ins_premium', data=df, palette='Set2')
plt.xlabel('Insurance Premium Level')
plt.ylabel('Count')
plt.title('Distribution of Insurance Premium Levels')
plt.xticks(rotation=90)
plt.show()

# Inference: The countplot visualizes the distribution of insurance premium levels.
# It helps to see how many cities fall into each premium level category.
```



```
In [14]: # Calculate the Frequency of alcohol involvement and no alcohol involvement
alcohol_counts = df['alcohol'].value_counts()

# Create a pie chart
plt.pie(alcohol_counts, labels=alcohol_counts.index, autopct='%1.1f%%', colors=['lightcoral', 'skyblue'])
plt.title('Percentage of Alcohol Involvement in Crashes')
plt.axis('equal') # Equal aspect ratio ensures that the pie is drawn as a circle.
plt.show()

# Inference: This pie chart represents the percentage of crashes involving alcohol ('Alcohol Involved' vs. 'No Alcohol').
# It provides insight into the proportion of crashes where alcohol was involved.
```

