ASSIGNMENT_2_DATA_VISUALIZATION_21BCE8974

September 14, 2023

1 Assignment-2

[ ]:
```
# E.Naga Sai Tarun Ganesh
# 21BCE8974
# VITAP MORNING SLOT
# Data Visualization  On car_crashes dataset.
```

[ ]:
```
# Importing the Data Visualization libraries
import seaborn as sns # importing the seaborn library
import matplotlib.pyplot as plt # importing the matplotlib.pyplot library
```

[ ]:
```
print(sns.get_dataset_names()) # Finding the inbuilt datasets in seaborn library
```

```
['anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes',
'diamonds', 'dots', 'dowjones', 'exercise', 'flights', 'fmri', 'geyser', 'glue',
'healthexp', 'iris', 'mpg', 'penguins', 'planets', 'seaice', 'taxis', 'tips',
'titanic']
```

[ ]:
```
df = sns.load_dataset('car_crashes') # Loading the dataset into variable 'df'
```

[ ]:
```
df # Printing the dataset
```

[ ]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	\
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	5.032	3.808	10.744	12.920	835.50	
6	10.8	4.968	3.888	9.396	8.856	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	14.350	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	780.45
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	4.000	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	3.480	10.092	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      133.80   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
```

Handling Null Values

[ ]:
```
df.isnull().any() # No null values, hence no need of data manipulation
```

```
[ ]: total              False
     speeding           False
     alcohol            False
     not_distracted     False
     no_previous        False
     ins_premium        False
     ins_losses         False
     abbrev             False
     dtype: bool
```

Dataset Demographics/Statistics

```
[ ]: df.describe() # describing about the df, i.e; metadat of columns with count,␣
      ↪mean, std, min etc
```

```
[ ]:            total   speeding    alcohol  not_distracted  no_previous  \
     count  51.000000  51.000000  51.000000       51.000000    51.000000
     mean   15.790196   4.998196   4.886784       13.573176    14.004882
     std     4.122002   2.017747   1.729133        4.508977     3.764672
     min     5.900000   1.792000   1.593000        1.760000     5.900000
     25%    12.750000   3.766500   3.894000       10.478000    11.348000
     50%    15.600000   4.608000   4.554000       13.857000    13.775000
     75%    18.500000   6.439000   5.604000       16.140000    16.755000
     max    23.900000   9.450000  10.038000       23.661000    21.280000

            ins_premium  ins_losses
     count    51.000000   51.000000
     mean    886.957647  134.493137
     std     178.296285   24.835922
     min     641.960000   82.750000
     25%     768.430000  114.645000
     50%     858.970000  136.050000
     75%    1007.945000  151.870000
     max    1301.520000  194.780000
```

Univariate

Definition: Univariate data analysis focuses on a single variable or dataset, examining its characteristics and distribution.

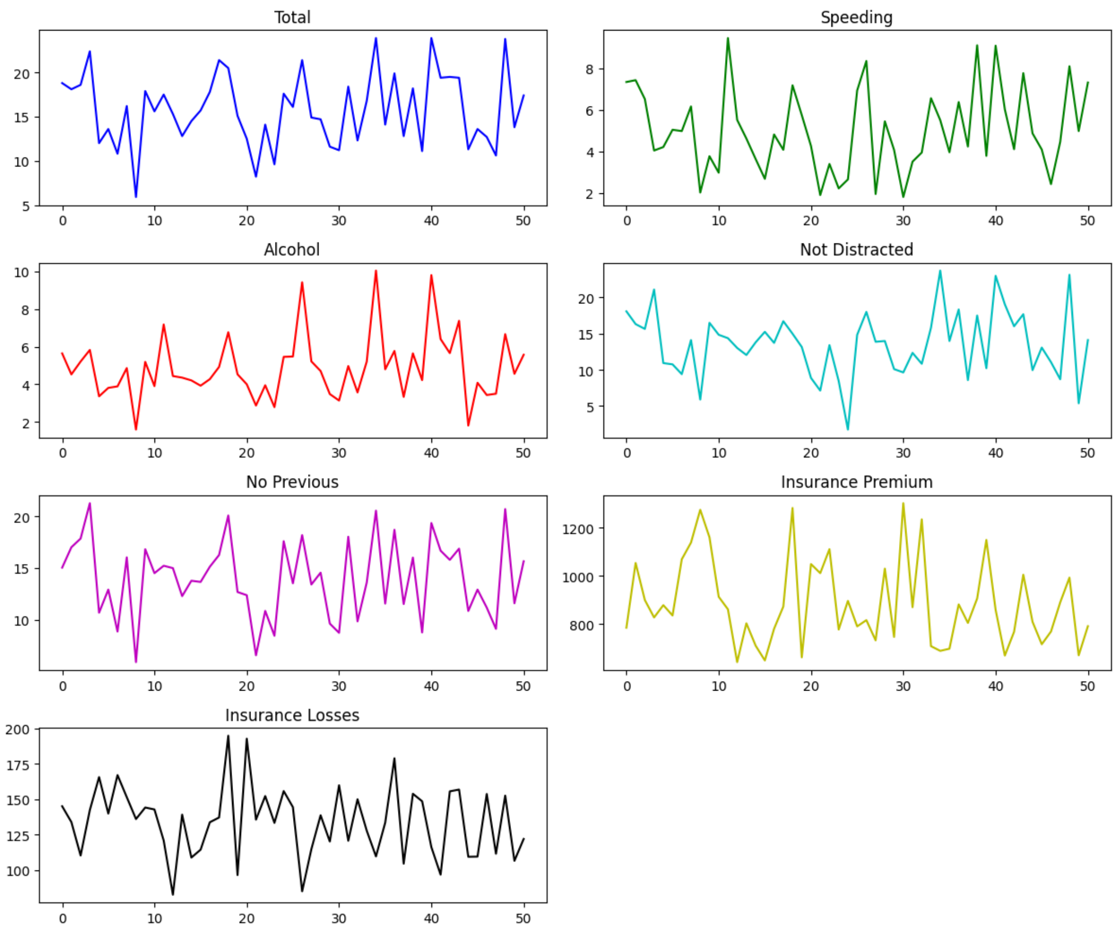
Objective: The primary goal is to describe and summarize the data, understand its central tendency, and identify patterns, outliers, and potential trends within that single variable.

Methods: Common methods include histograms, bar charts, box plots, summary statistics (mean, median, mode), and measures of dispersion (variance, standard deviation)

```
[ ]: plt.figure(figsize=(12, 10))

     plt.subplot(4, 2, 1)
     plt.plot(df['total'], 'b')
```

```
plt.title('Total')

"""
Total (Blue Line):
The graph shows the trend in total car crashes over the dataset.
Inference: There is a noticeable variation in the total number of car crashes␣
↪over time, but no specific pattern emerges.
"""


plt.subplot(4, 2, 2)
plt.plot(df['speeding'], 'g')
plt.title('Speeding')

"""
Speeding (Green Line):
This graph represents the trend in car crashes caused by speeding.
Inference: The number of car crashes due to speeding appears to have some␣
↪fluctuations but doesn't show a consistent upward or downward trend.
"""

plt.subplot(4, 2, 3)
plt.plot(df['alcohol'], 'r')
plt.title('Alcohol')

"""
Alcohol (Red Line):
The graph displays the trend in car crashes related to alcohol consumption.
Inference: There is some variation in car crashes involving alcohol, but no␣
↪clear trend is evident from the graph.
"""

plt.subplot(4, 2, 4)
plt.plot(df['not_distracted'], 'c')
plt.title('Not Distracted')

"""
Not Distracted (Cyan Line):
This graph illustrates the trend in car crashes where drivers were not␣
↪distracted.
Inference: The number of car crashes by non-distracted drivers shows␣
↪fluctuations, but no significant trend is apparent.
"""

plt.subplot(4, 2, 5)
plt.plot(df['no_previous'], 'm')
plt.title('No Previous')
```

```
"""
No Previous (Magenta Line):
The graph shows the trend in car crashes by drivers with no previous incidents.
Inference: Car crashes by drivers with no previous incidents appear to have␣
↪some fluctuations but no discernible trend.
"""

plt.subplot(4, 2, 6)
plt.plot(df['ins_premium'], 'y')
plt.title('Insurance Premium')

"""
Insurance Premium (Yellow Line):
This graph represents the trend in insurance premiums.
Inference: The graph doesn't provide clear insights into the trend in insurance␣
↪premiums over time, as it seems to fluctuate without a distinct pattern.
"""

plt.subplot(4, 2, 7)
plt.plot(df['ins_losses'], 'k')
plt.title('Insurance Losses')

"""
Insurance Losses (Black Line):
The graph displays the trend in insurance losses.
Inference: Similar to insurance premiums, insurance losses also appear to␣
↪fluctuate without a clear trend.
"""

plt.tight_layout() # Used to allocate gaps between the labels and plots
```

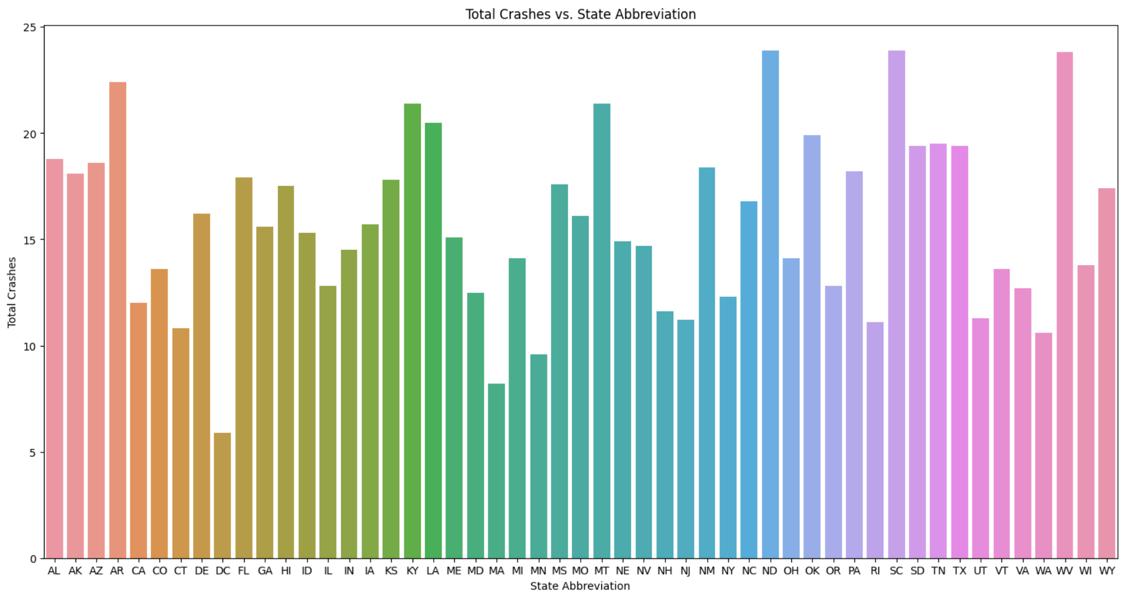


Barplot

```
[ ]: plt.figure(figsize=(18, 9))
sns.barplot(data=df,x='abbrev', y='total',errorbar=None)
plt.xlabel('State Abbreviation')
plt.ylabel('Total Crashes')
plt.title('Total Crashes vs. State Abbreviation')

"""
Inference:
State abbreviations are on the x-axis, and the total number of crashes is on the y-axis.
The plot provides a clear comparison of car crash counts between states.
For example, states with abbreviations like "DC," "RI," and "NH" have relatively lower total crash counts, while "TX," "CA," and "FL" have higher crash counts.
This plot is useful for identifying states with higher or lower crash rates, which can be valuable for further analysis or policy considerations.
```

```
"""
```

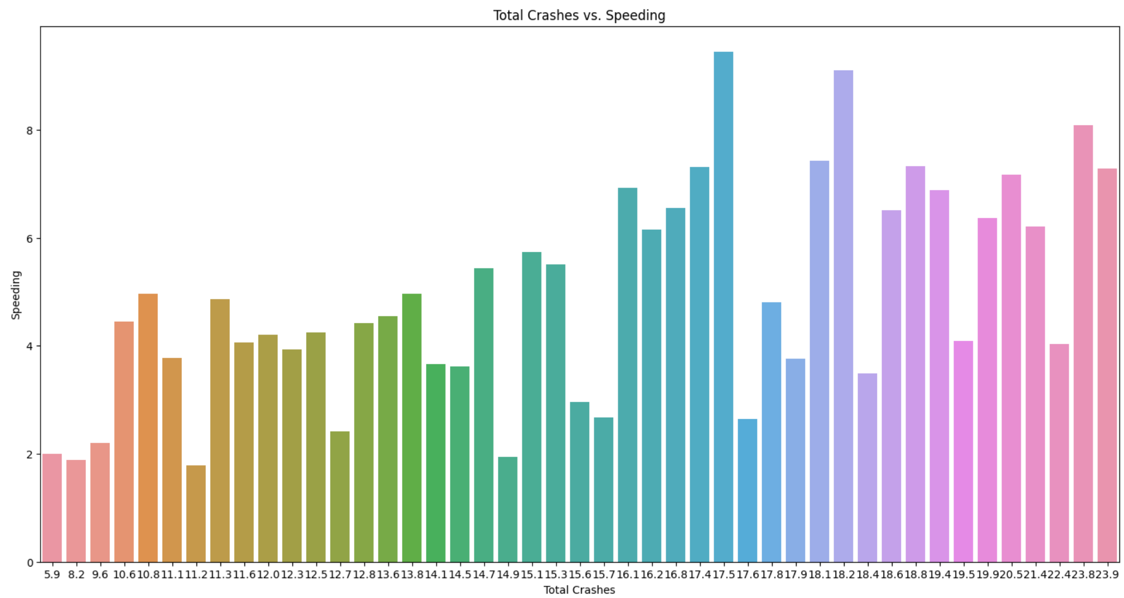
[ ]: '\nInference:\nState abbreviations are on the x-axis, and the total number of crashes is on the y-axis.\nThe plot provides a clear comparison of car crash counts between states.\nFor example, states with abbreviations like "DC," "RI," and "NH" have relatively lower total crash counts, while "TX," "CA," and "FL" have higher crash counts.\nThis plot is useful for identifying states with higher or lower crash rates, which can be valuable for further analysis or policy considerations.\n'



[ ]:
```
plt.figure(figsize=(18, 9))
sns.barplot(data=df,x='total', y='speeding',errorbar=None)
plt.ylabel('Speeding')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Speeding')

"""
Inference:
The total number of crashes is represented on the x-axis, while the number of␣
↪crashes involving speeding is on the y-axis.
The plot allows us to examine how speeding contributes to the overall number of␣
↪car crashes.
As the total number of crashes increases, there is a general trend of an␣
↪increase in the number of crashes involving speeding.
This suggests that as the total number of car crashes goes up, the proportion␣
↪of crashes involving speeding also tends to increase.
```

```
Analyzing this relationship can help in understanding the impact of speeding on␣
↪overall road safety and may inform targeted interventions to reduce␣
↪speeding-related accidents.
"""
```

[ ]: '\nInference:\nThe total number of crashes is represented on the x-axis, while the number of crashes involving speeding is on the y-axis.\nThe plot allows us to examine how speeding contributes to the overall number of car crashes.\nAs the total number of crashes increases, there is a general trend of an increase in the number of crashes involving speeding.\nThis suggests that as the total number of car crashes goes up, the proportion of crashes involving speeding also tends to increase.\nAnalyzing this relationship can help in understanding the impact of speeding on overall road safety and may inform targeted interventions to reduce speeding-related accidents.\n'

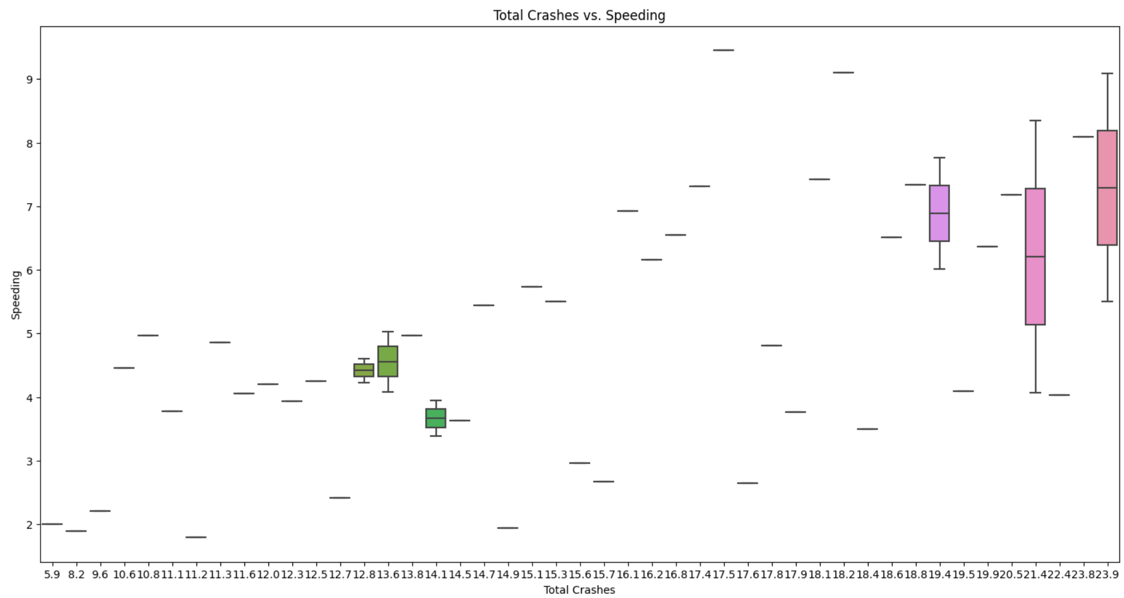


Boxplot

[ ]:
```
plt.figure(figsize=(18,9))
sns.boxplot(x="total",y="speeding",data=df)
plt.ylabel('Speeding')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Speeding')

"""
Inference :
The box plot shows the distribution of speeding-related crashes within␣
↪different total crash categories.
```

```
As the total number of crashes increases, there is increasing variability in␣
↪the number of crashes involving speeding.
This highlights the relationship between total crashes and speeding incidents,␣
↪indicating the need for targeted interventions in states or situations with␣
↪higher variability.
"""
```

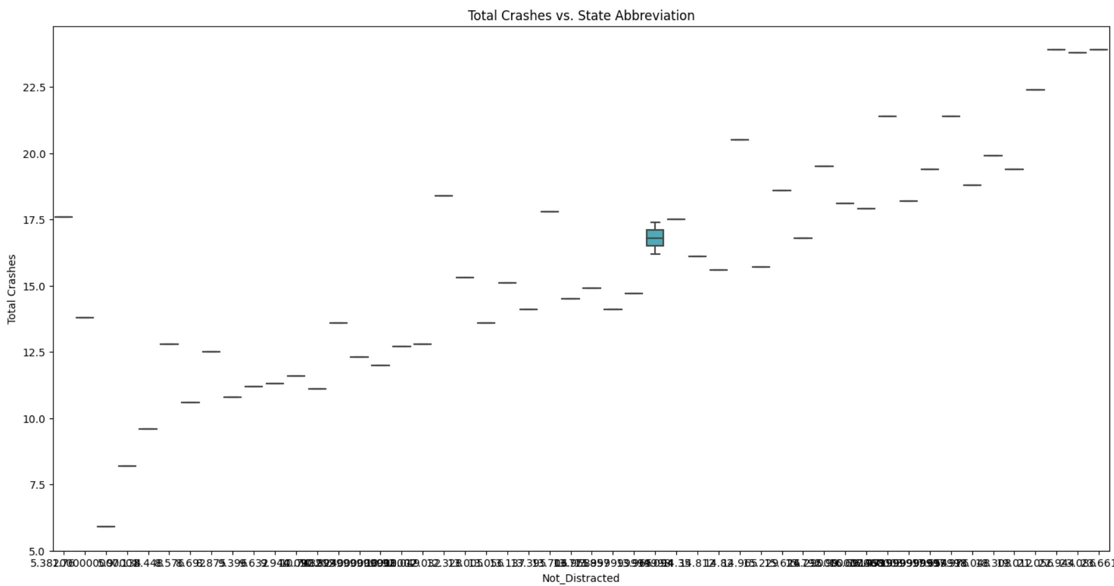
[ ]: '\nInference :\nThe box plot shows the distribution of speeding-related crashes within different total crash categories.\nAs the total number of crashes increases, there is increasing variability in the number of crashes involving speeding.\nThis highlights the relationship between total crashes and speeding incidents, indicating the need for targeted interventions in states or situations with higher variability.\n'



[ ]:
```
plt.figure(figsize=(18,9))
sns.boxplot(x="not_distracted",y="total",data=df)
plt.xlabel('Not_Distracted')
plt.ylabel('Total Crashes')
plt.title('Total Crashes vs. State Abbreviation')

"""
Inference :
The box plot illustrates the distribution of total crashes concerning the␣
↪distraction status of drivers (Not Distracted).
It provides insights into how distraction affects the total number of car␣
↪crashes.
```

```
The plot shows varying total crash counts based on the distraction status, with␣
  ↪potentially higher crashes when drivers are not distracted.
This suggests that non-distracted drivers may be involved in more crashes,␣
  ↪emphasizing the need for examining the causes of distraction and driving␣
  ↪behavior to improve road safety.
"""
```

[ ]:
```
'\nInference :\nThe box plot illustrates the distribution of total crashes
concerning the distraction status of drivers (Not Distracted).\nIt provides
insights into how distraction affects the total number of car crashes.\nThe plot
shows varying total crash counts based on the distraction status, with
potentially higher crashes when drivers are not distracted.\nThis suggests that
non-distracted drivers may be involved in more crashes, emphasizing the need for
examining the causes of distraction and driving behavior to improve road
safety.\n'
```

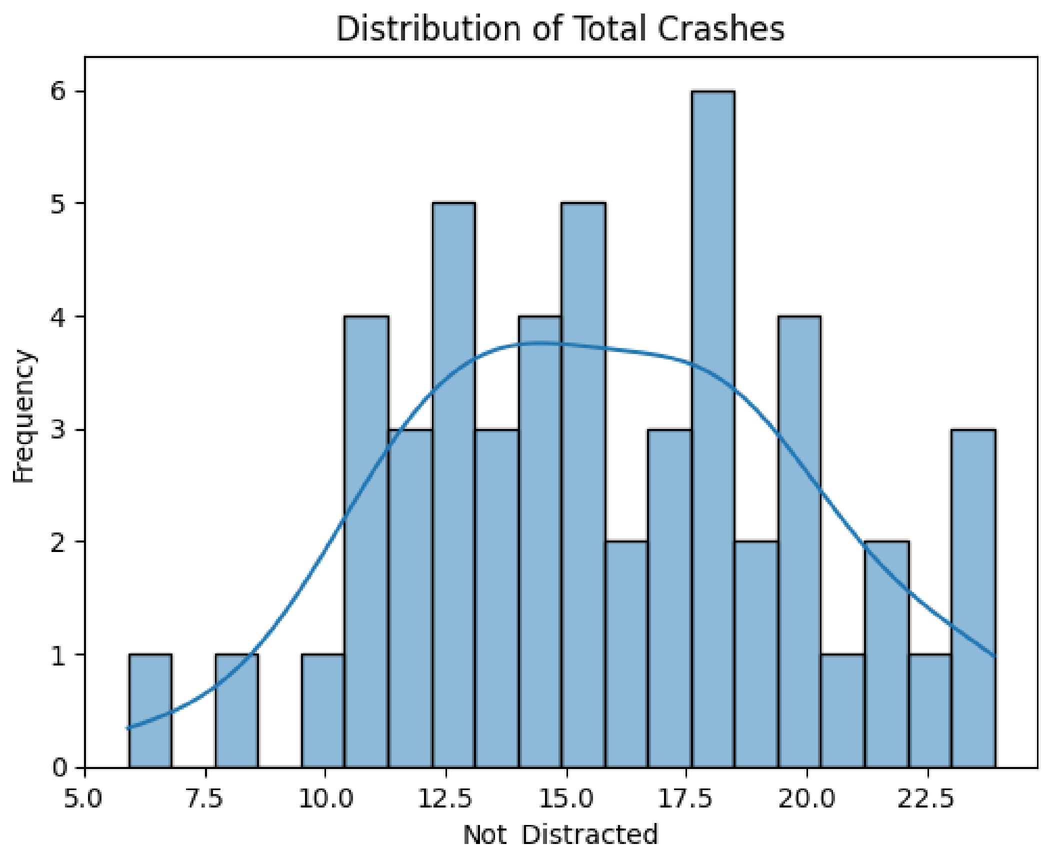


Histogram

[ ]:
```
sns.histplot(data=df, x='total', bins=20, kde=True)
plt.xlabel('Not_Distracted')
plt.ylabel('Frequency')
plt.title('Distribution of Total Crashes')

"""
Inference :
The histogram displays the distribution of total car crashes.n.
The plot shows that the majority of observations fall within a relatively low␣
  ↪range of total crashes, with a peak in frequency.
```

```
There is a right-skewed distribution, indicating that a few instances have␣
  ↪significantly higher crash counts.
This visualization helps understand the distribution of total crashes, which␣
  ↪can be useful for identifying common crash count ranges and outliers in the␣
  ↪dataset.
"""
```

[ ]: '\nInference :\nThe histogram displays the distribution of total car crashes.n.\nThe plot shows that the majority of observations fall within a relatively low range of total crashes, with a peak in frequency.\nThere is a right-skewed distribution, indicating that a few instances have significantly higher crash counts.\nThis visualization helps understand the distribution of total crashes, which can be useful for identifying common crash count ranges and outliers in the dataset.\n'

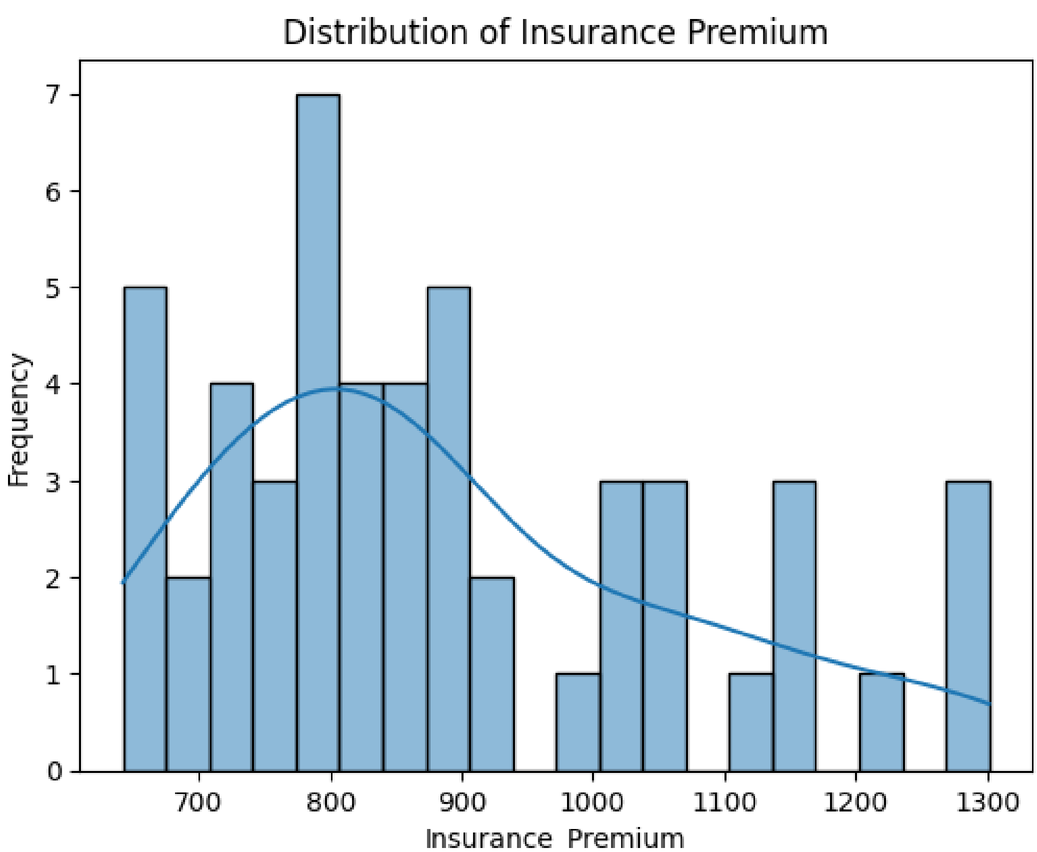


[ ]:
```
sns.histplot(data=df, x='ins_premium', bins=20, kde=True)
plt.xlabel('Insurance_Premium')
plt.ylabel('Frequency')
plt.title('Distribution of Insurance Premium')
```

```
"""
Inference :
The histogram depicts the distribution of insurance premiums.
The plot shows that the most common insurance premium ranges have higher␣
↪frequencies, forming peaks in the distribution.
The distribution appears to be right-skewed, suggesting that a few observations␣
↪have exceptionally high insurance premiums.
This visualization aids in understanding the distribution of insurance premiums␣
↪within the dataset, providing insights into common premium ranges and␣
↪potential outliers.
"""
```

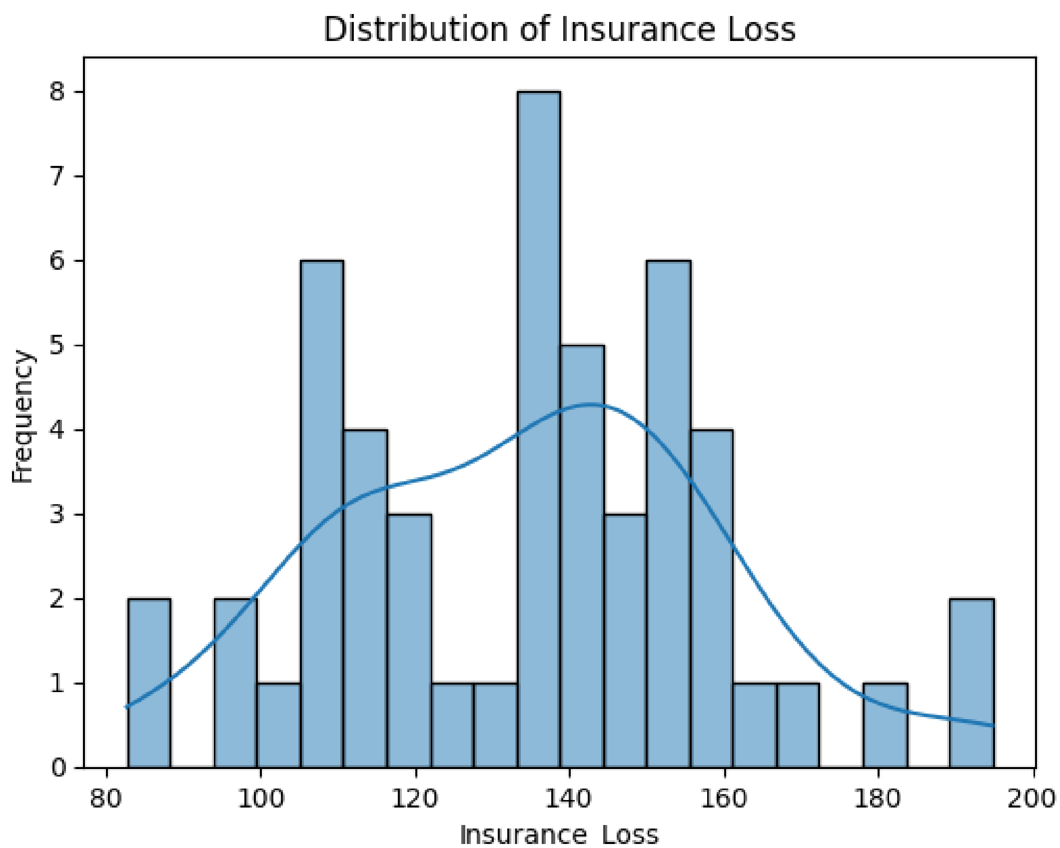
[ ]:

```
'\nInference :\nThe histogram depicts the distribution of insurance
premiums.\nThe plot shows that the most common insurance premium ranges have
higher frequencies, forming peaks in the distribution.\nThe distribution appears
to be right-skewed, suggesting that a few observations have exceptionally high
insurance premiums.\nThis visualization aids in understanding the distribution
of insurance premiums within the dataset, providing insights into common premium
ranges and potential outliers.\n'
```



[ ]:
```
sns.histplot(data=df, x='ins_losses', bins=20, kde=True)
plt.xlabel('Insurance_Loss')
plt.ylabel('Frequency')
plt.title('Distribution of Insurance Loss')

"""
Inference :
The histogram represents the distribution of insurance losses.
The plot indicates that the majority of insurance losses fall within specific␣
↪ranges, with peaks in frequency.
The distribution appears right-skewed, indicating that a few instances have␣
↪considerably higher insurance losses.
This visualization helps in understanding the distribution of insurance losses␣
↪within the dataset, highlighting common loss ranges and potential outliers.
"""
```

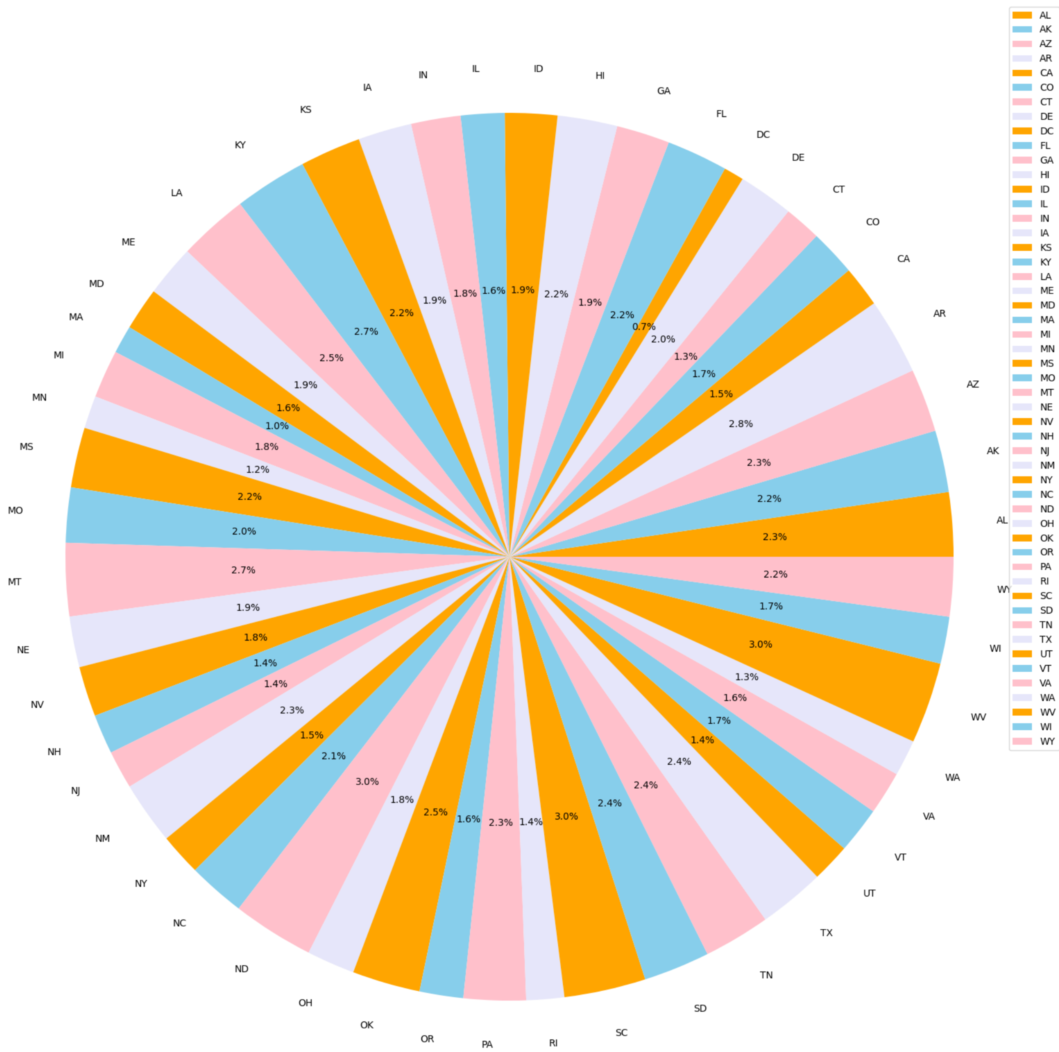
[ ]:
```
'\nInference :\nThe histogram represents the distribution of insurance
losses.\nThe plot indicates that the majority of insurance losses fall within
specific ranges, with peaks in frequency.\nThe distribution appears right-
skewed, indicating that a few instances have considerably higher insurance
losses.\nThis visualization helps in understanding the distribution of insurance
losses within the dataset, highlighting common loss ranges and potential
outliers.\n'
```



Piechart

```
[ ]: fig = plt.figure(figsize=(20,20))
axes1 = fig.add_axes([0.1,0.1,0.8,0.8])  # (left,bottom,width,height)
axes1.pie(df['total'],labels=df['abbrev'],autopct='%0.1f%%',colors
 ↪=['orange','skyblue','pink','lavender']) # %0.1f%% specifies percentage upto
 ↪1 decimal
axes1.legend()

"""
Inference :
The pie chart visualizes the distribution of total car crashes across different
 ↪states, represented by their abbreviations.
Each slice of the pie represents a state, and the size of the slice corresponds
 ↪to the percentage of total crashes in that state.
The labels on the chart indicate the state abbreviations.
The legend provides a key to identify which state each slice represents.
This pie chart allows for a quick comparison of the contribution of each state
 ↪to the total number of car crashes in the datase
"""
```

```
[ ]: '\nInference :\nThe pie chart visualizes the distribution of total car crashes across different states, represented by their abbreviations.\nEach slice of the pie represents a state, and the size of the slice corresponds to the percentage of total crashes in that state.\nThe labels on the chart indicate the state abbreviations.\nThe legend provides a key to identify which state each slice represents.\nThis pie chart allows for a quick comparison of the contribution of each state to the total number of car crashes in the datase\n'
```



Bivariate

Definition: Bivariate data analysis involves the analysis of two variables to explore their relationship and interactions.

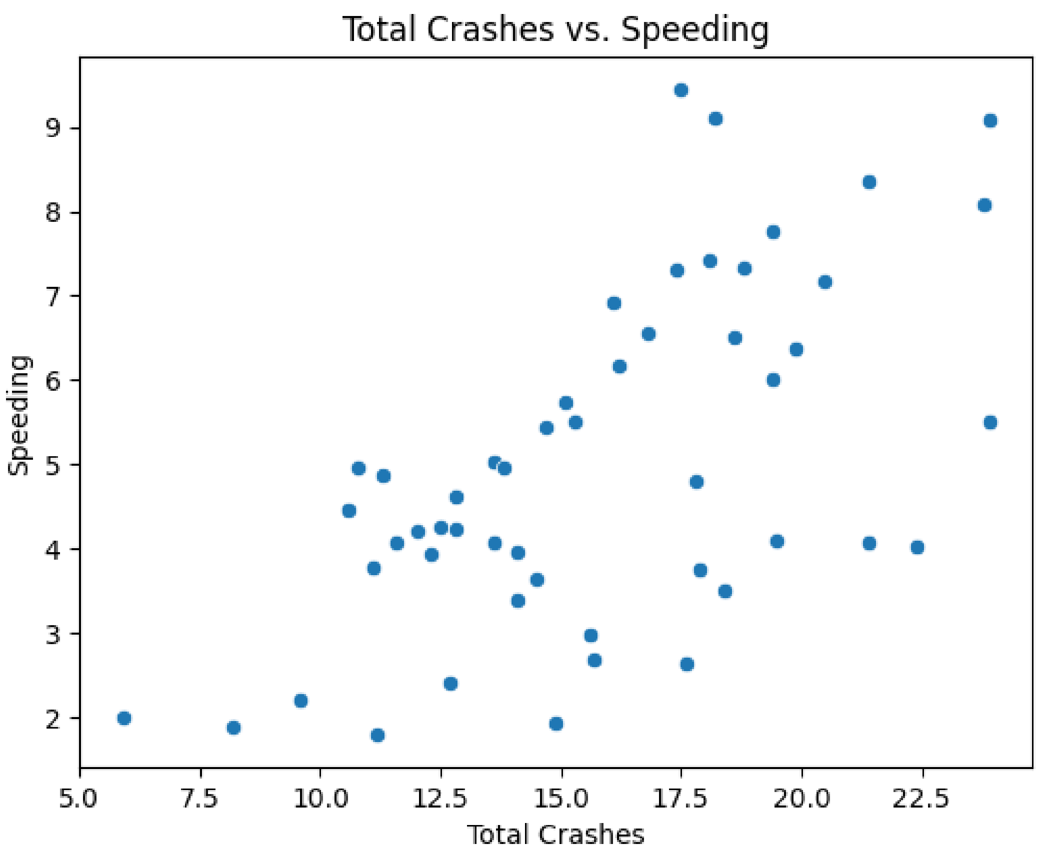
Objective: The primary goal is to understand how two variables are related, whether they exhibit correlation or causation, and to identify patterns or associations between them.

Methods: Common methods include scatter plots, line graphs, correlation coefficients (e.g., Pearson correlation), and hypothesis tests (e.g., t-tests) to determine if relationships are statistically significant.

Scatterplot

[ ]:
```
sns.scatterplot(x="total",y='speeding',data=df)
plt.ylabel('Speeding')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Speeding')

"""
Inference :
The scatter plot visualizes the relationship between the total number of car␣
↪crashes and the number of crashes involving speeding.
There doesn't appear to be a strong linear relationship between total crashes␣
↪and speeding incidents based on this scatter plot.
The points are scattered across the plot without a clear trend, suggesting that␣
↪total crashes and speeding may not be strongly correlated.
Further statistical analysis may be needed to quantify the relationship between␣
↪these variables accurately.
"""
```

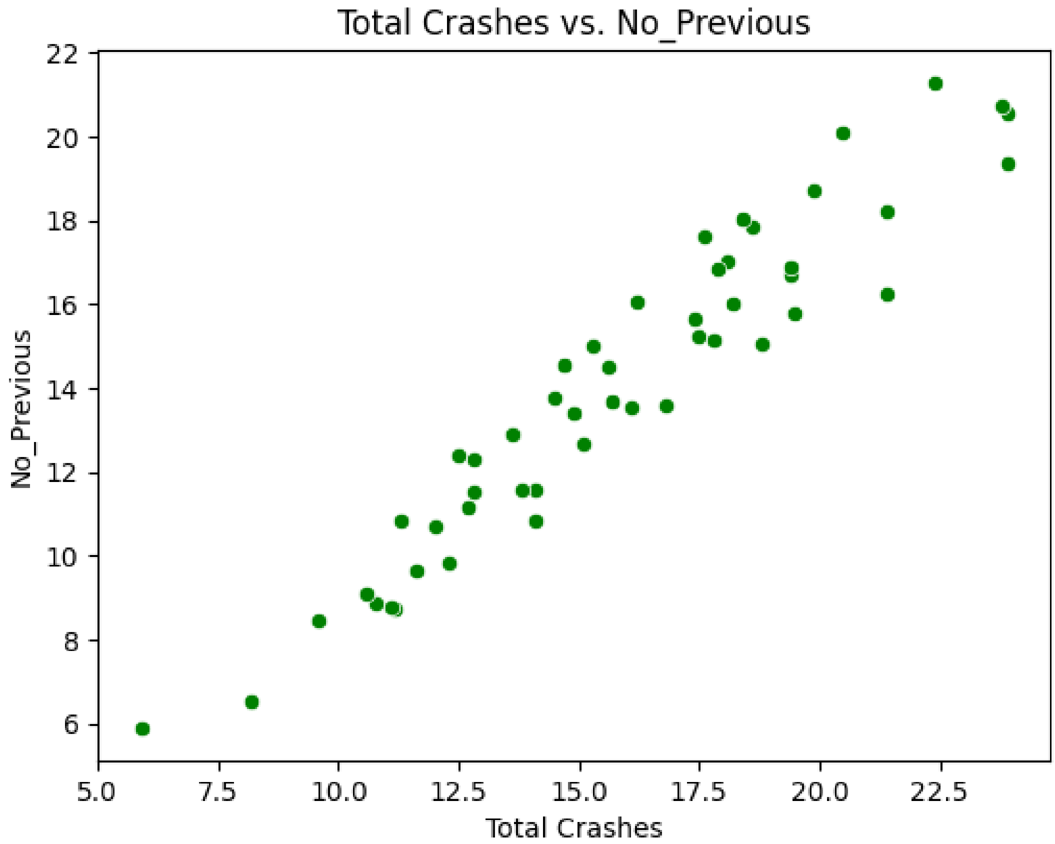
[ ]:
```
"\nInference :\nThe scatter plot visualizes the relationship between the total
number of car crashes and the number of crashes involving speeding.\nThere
doesn't appear to be a strong linear relationship between total crashes and
speeding incidents based on this scatter plot.\nThe points are scattered across
the plot without a clear trend, suggesting that total crashes and speeding may
not be strongly correlated.\nFurther statistical analysis may be needed to
quantify the relationship between these variables accurately.\n"
```



[ ]:
```
sns.scatterplot(x="total",y='no_previous',data=df,c='g')
plt.ylabel('No_Previous')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. No_Previous')

"""
Inference :
The scatter plot illustrates the relationship between the total number of car␣
↪crashes and crashes involving drivers with no previous incidents.
Similar to previous scatter plots, there isn't a distinct linear relationship␣
↪between total crashes and crashes involving drivers with no previous␣
↪incidents.
The points are scattered without a clear trend, suggesting that total crashes␣
↪may not directly correlate with the absence of previous incidents in drivers.
↪ Further analysis may be needed.
"""
```

[ ]:
```
"\nInference :\nThe scatter plot illustrates the relationship between the total
number of car crashes and crashes involving drivers with no previous
```

```
incidents.\nSimilar to previous scatter plots, there isn't a distinct linear
relationship between total crashes and crashes involving drivers with no
previous incidents.\nThe points are scattered without a clear trend, suggesting
that total crashes may not directly correlate with the absence of previous
incidents in drivers. Further analysis may be needed.\n"
```

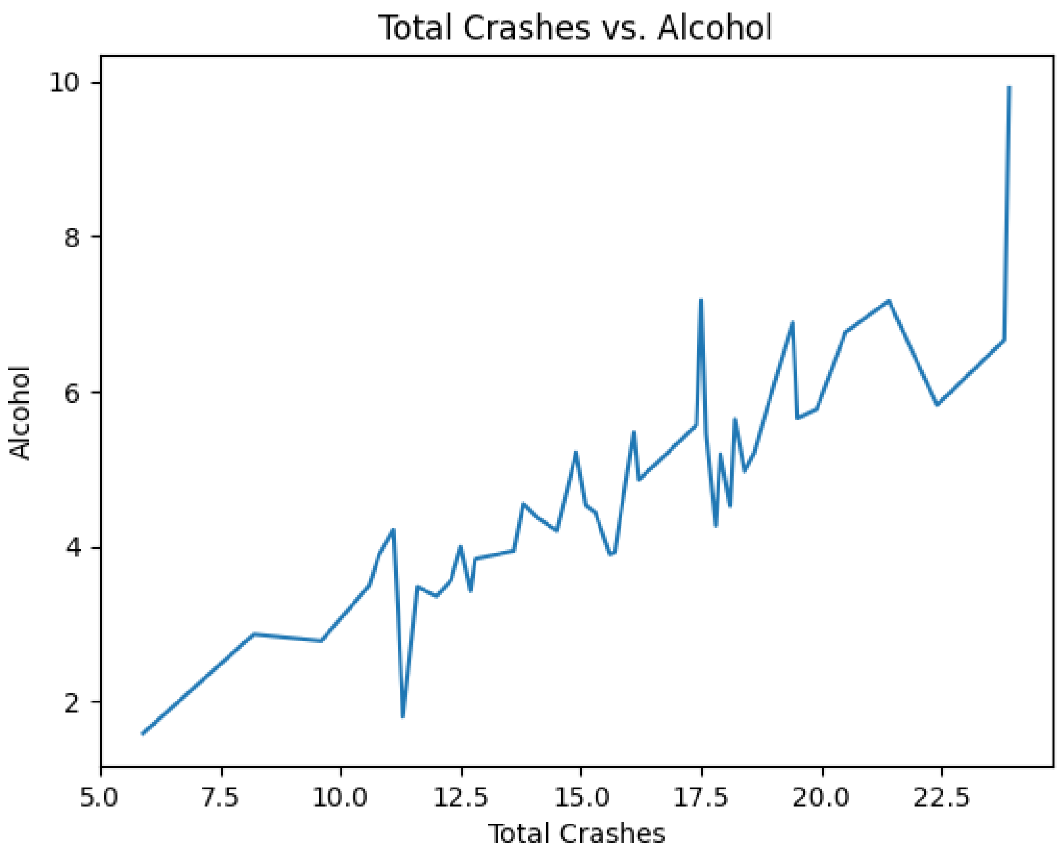


Lineplot

```
[ ]: sns.lineplot(x="total",y="alcohol",data=df,errorbar=None)
plt.ylabel('Alcohol')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Alcohol')
"""
Inference :
The line plot shows the association between total car crashes and crashes␣
 ↪involving alcohol.
It visualizes how alcohol-related crashes fluctuate concerning the total number␣
 ↪of crashes.
There isn't a clear linear relationship; the points on the line are scattered␣
 ↪without a distinct pattern.
```

```
This suggests that the total number of crashes may not have a straightforward␣
↪correlation with alcohol-related incidents, warranting further analysis.
"""
```

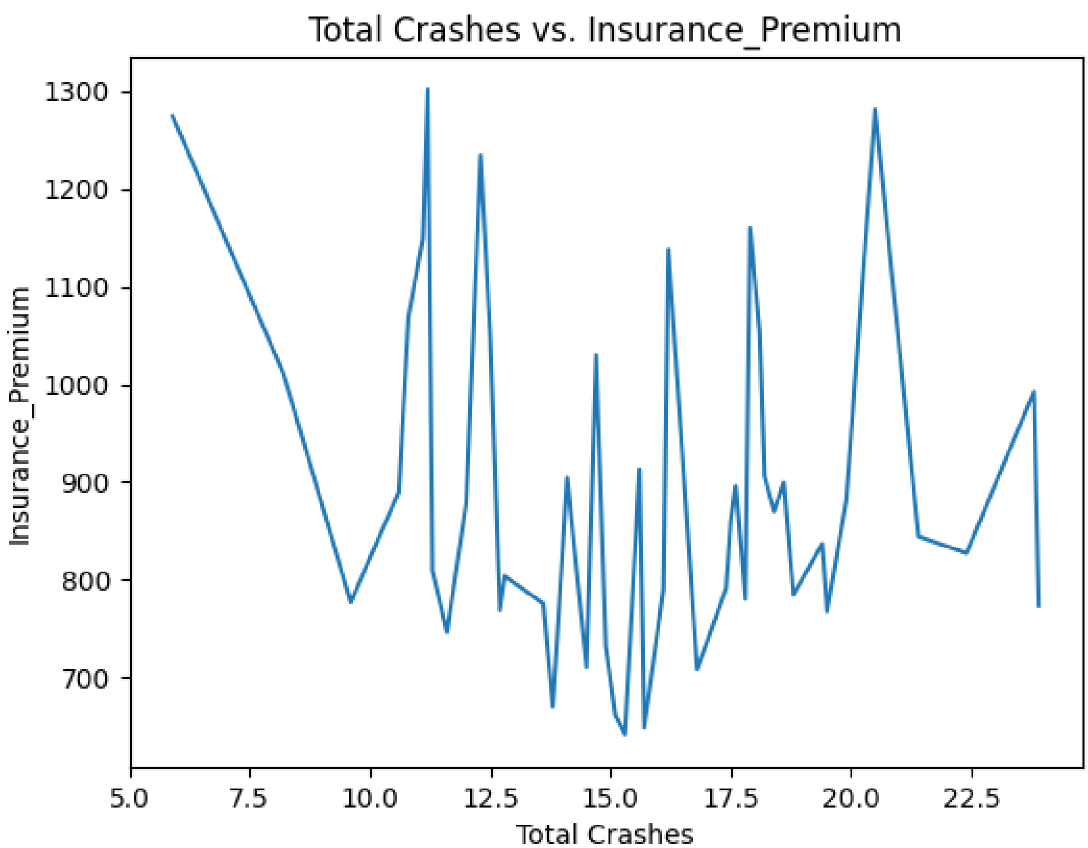
[ ]: "\nInference :\nThe line plot shows the association between total car crashes and crashes involving alcohol.\nIt visualizes how alcohol-related crashes fluctuate concerning the total number of crashes.\nThere isn't a clear linear relationship; the points on the line are scattered without a distinct pattern.\nThis suggests that the total number of crashes may not have a straightforward correlation with alcohol-related incidents, warranting further analysis.\n"



[ ]:
```
sns.lineplot(x="total",y="ins_premium",data=df,errorbar=None)
plt.ylabel('Insurance_Premium')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Insurance_Premium')

"""
Inference :
```

```
The line plot represents the relationship between total car crashes and␣
↪insurance premiums.
It visualizes how insurance premiums vary in relation to the total number of␣
↪crashes.
The plot does not show a clear linear trend; points on the line are scattered␣
↪without a clear pattern.
This suggests that the total number of crashes may not have a straightforward␣
↪correlation with insurance premiums, necessitating further investigation.
"""
```

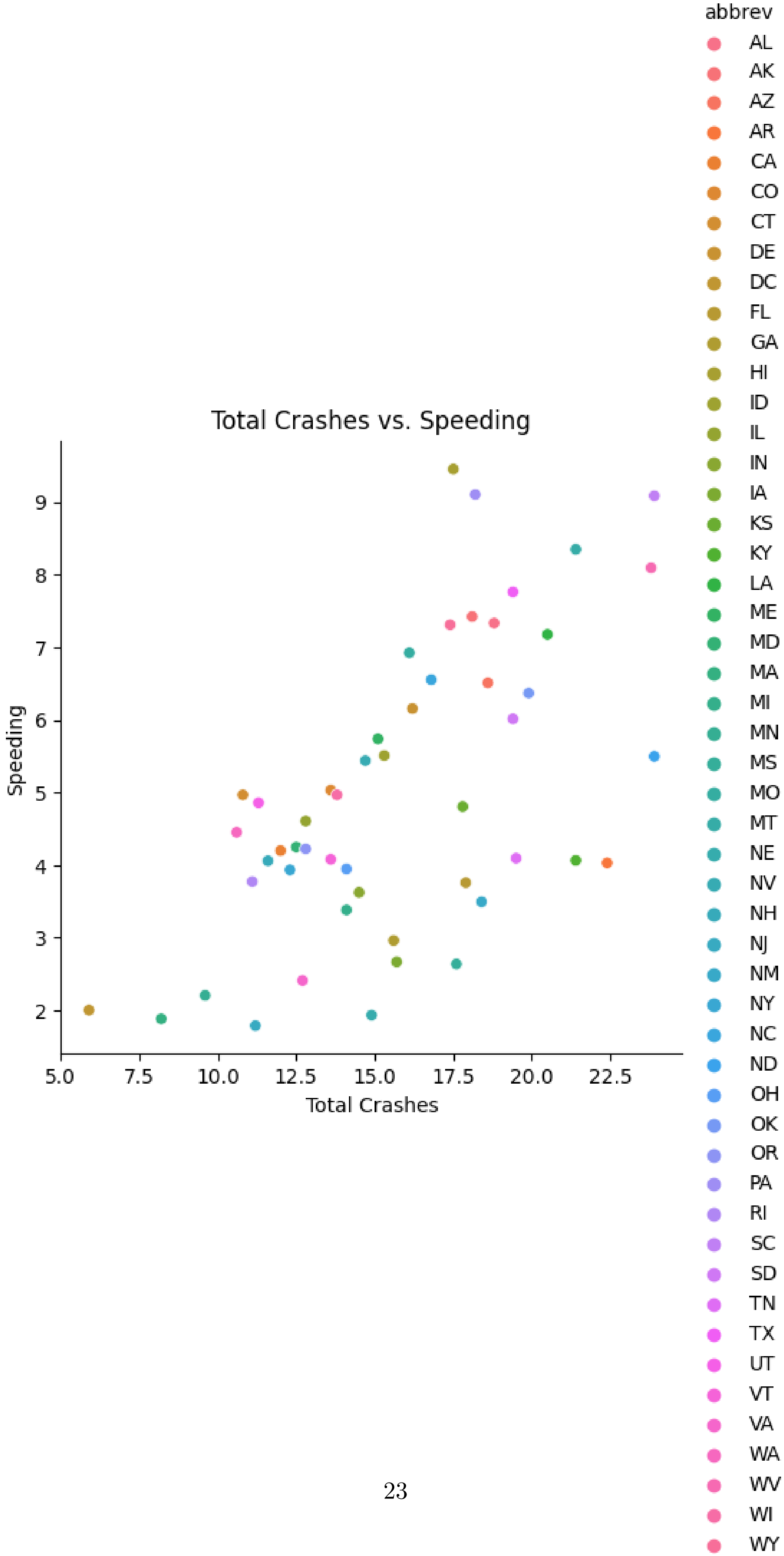
[ ]: '\nInference :\nThe line plot represents the relationship between total car crashes and insurance premiums.\nIt visualizes how insurance premiums vary in relation to the total number of crashes.\nThe plot does not show a clear linear trend; points on the line are scattered without a clear pattern.\nThis suggests that the total number of crashes may not have a straightforward correlation with insurance premiums, necessitating further investigation.\n'



Replot

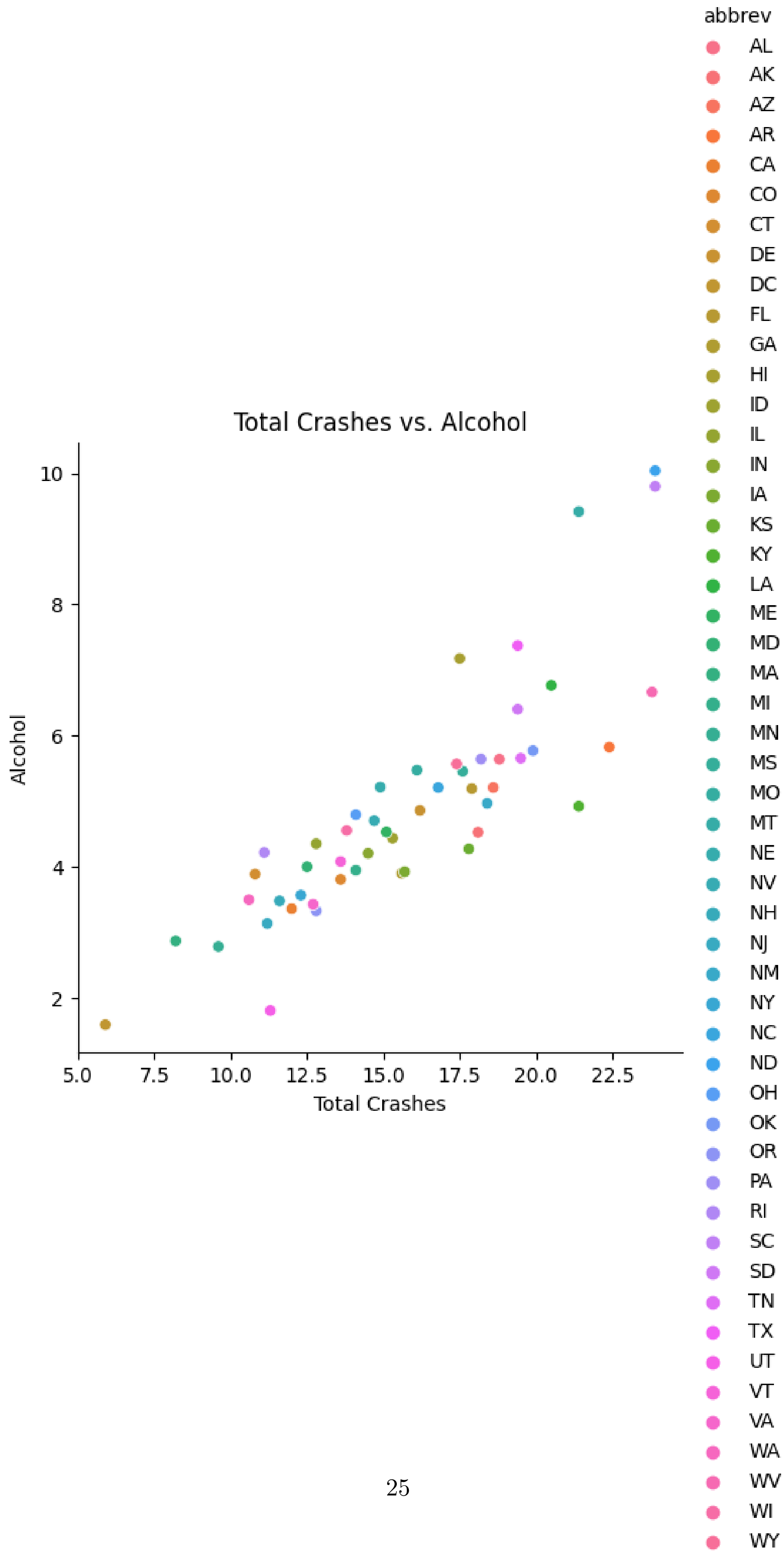
[ ]:
```python
sns.relplot(x="total",y="speeding",data=df,hue="abbrev")
plt.ylabel('Speeding')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Speeding')

"""
Inference :
The relational plot ("relplot") displays the relationship between total car␣
↪crashes and crashes involving speeding.
Each point represents a data point in the dataset, with different states␣
↪distinguished by colors (hue).
The plot allows for a quick visual assessment of how speeding-related crashes␣
↪vary concerning the total number of crashes in different states.
There is no clear linear trend; points are scattered without a distinct␣
↪pattern, indicating that the relationship between total crashes and speeding␣
↪incidents may not be straightforward and may vary by state. Further analysis␣
↪may be required to explore state-specific trends.
"""
```

[ ]:
```
'\nInference :\nThe relational plot ("relplot") displays the relationship
between total car crashes and crashes involving speeding.\nEach point represents
a data point in the dataset, with different states distinguished by colors
(hue).\nThe plot allows for a quick visual assessment of how speeding-related
crashes vary concerning the total number of crashes in different states.\nThere
is no clear linear trend; points are scattered without a distinct pattern,
indicating that the relationship between total crashes and speeding incidents
may not be straightforward and may vary by state. Further analysis may be
required to explore state-specific trends.\n'
```


Total Crashes vs. Speeding
Speeding
Total Crashes
2
3
4
5
6
7
8
9
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
abbrev
AL
AK
AZ
AR
CA
CO
CT
DE
DC
FL
GA
HI
ID
IL
IN
IA
KS
KY
LA
ME
MD
MA
MI
MN
MS
MO
MT
NE
NV
NH
NJ
NM
NY
NC
ND
OH
OK
OR
PA
RI
SC
SD
TN
TX
UT
VT
VA
WA
WV
WI
WY

[ ]:
```python
sns.relplot(x="total",y="alcohol",data=df,hue="abbrev")
plt.ylabel('Alcohol')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Alcohol')

"""
Inference :
The relational plot ("relplot") illustrates the relationship between total car␣
 ↪crashes and crashes involving alcohol.
Each point on the plot represents a data point in the dataset, and different␣
 ↪states are color-coded for comparison (hue).
The plot provides a visual comparison of how alcohol-related crashes vary with␣
 ↪the total number of crashes in different states.
There isn't a clear linear trend in the relationship; points are scattered␣
 ↪without a distinct pattern, suggesting that the association between total␣
 ↪crashes and alcohol-related incidents may differ by state. Further␣
 ↪state-specific analysis may be needed to explore this further.
"""
```

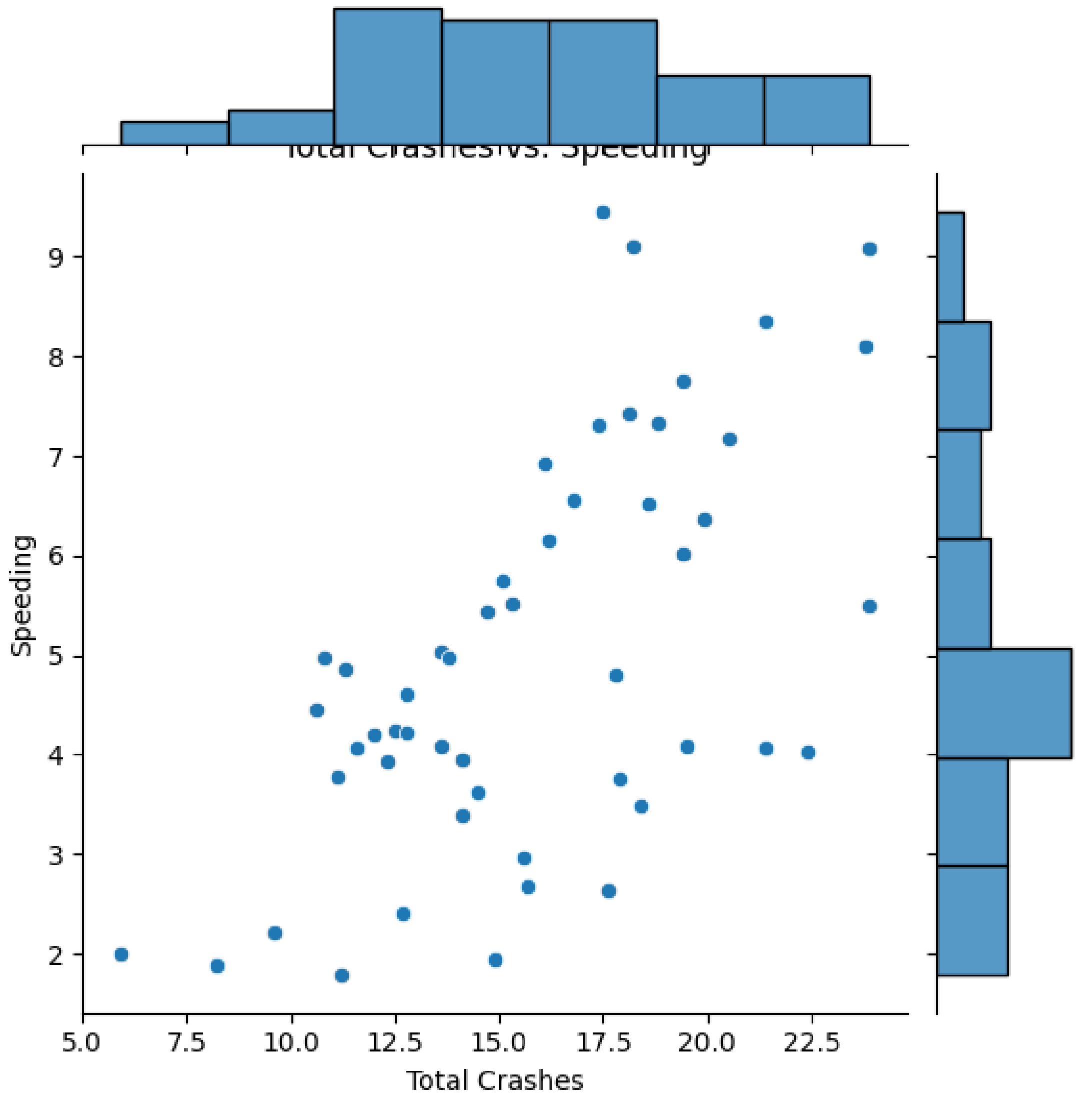
[ ]:
```
'\nInference :\nThe relational plot ("relplot") illustrates the relationship
between total car crashes and crashes involving alcohol.\nEach point on the plot
represents a data point in the dataset, and different states are color-coded for
comparison (hue).\nThe plot provides a visual comparison of how alcohol-related
crashes vary with the total number of crashes in different states.\nThere isn\'t
a clear linear trend in the relationship; points are scattered without a
distinct pattern, suggesting that the association between total crashes and
alcohol-related incidents may differ by state. Further state-specific analysis
may be needed to explore this further.\n'
```


Total Crashes vs. Alcohol
Alcohol
Total Crashes
10
8
6
4
2
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
abbrev
AL
AK
AZ
AR
CA
CO
CT
DE
DC
FL
GA
HI
ID
IL
IN
IA
KS
KY
LA
ME
MD
MA
MI
MN
MS
MO
MT
NE
NV
NH
NJ
NM
NY
NC
ND
OH
OK
OR
PA
RI
SC
SD
TN
TX
UT
VT
VA
WA
WV
WI
WY

Jointplot

[ ]:
```
sns.jointplot(x="total",y="speeding",data=df)
plt.ylabel('Speeding')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Speeding')

"""
Inference :
The joint plot displays the relationship between total car crashes and crashes␣
 ↪involving speeding.
It combines a scatter plot and histograms to visualize the distribution and␣
 ↪correlation between the two variables.
The scatter plot shows that there isn't a strong linear relationship between␣
 ↪total crashes and speeding incidents.
The histograms on the top and right sides provide additional information about␣
 ↪the distributions of both variables.
"""
```

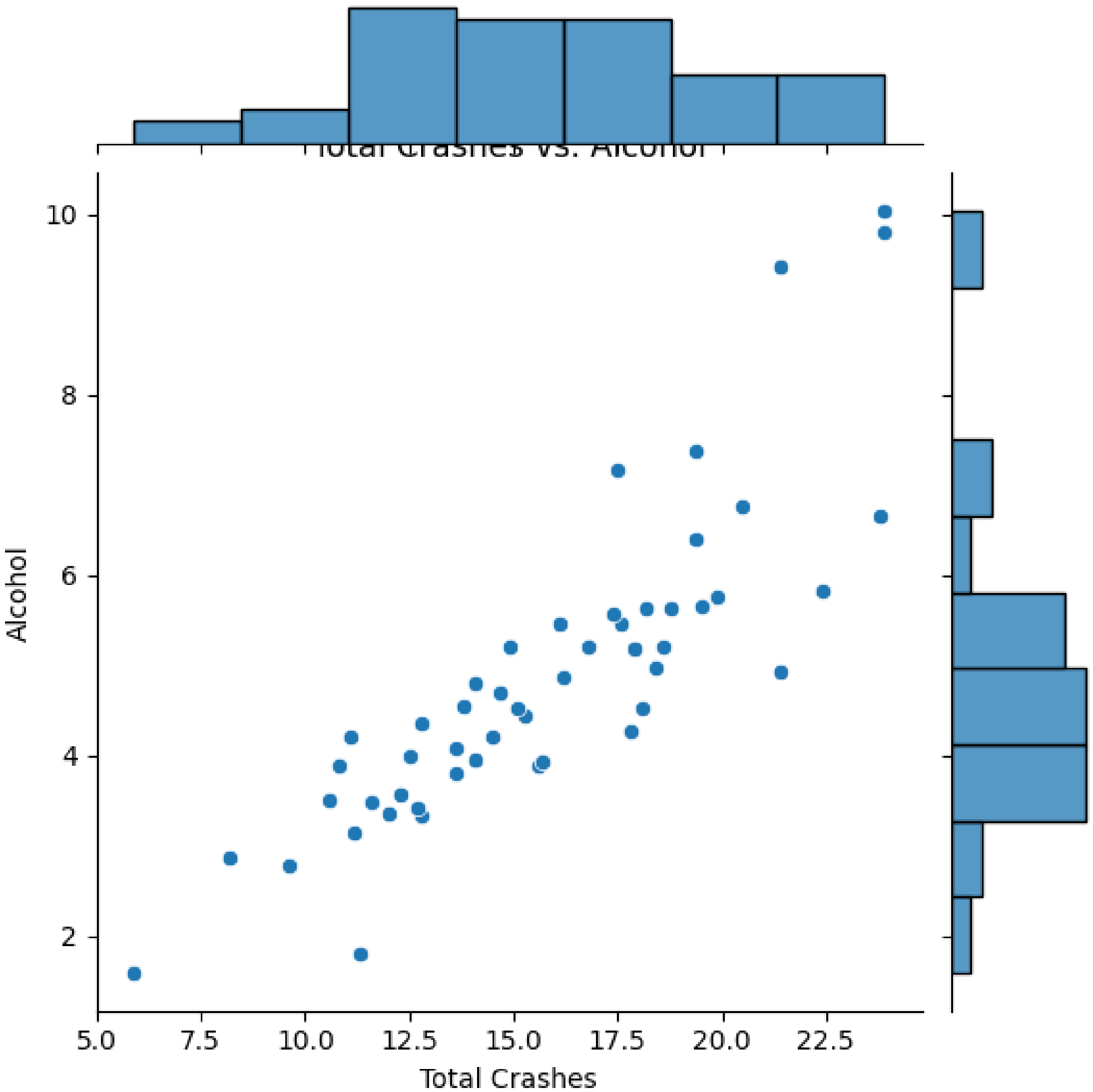
[ ]:
```
"\nInference :\nThe joint plot displays the relationship between total car
crashes and crashes involving speeding.\nIt combines a scatter plot and
histograms to visualize the distribution and correlation between the two
variables.\nThe scatter plot shows that there isn't a strong linear relationship
between total crashes and speeding incidents.\nThe histograms on the top and
right sides provide additional information about the distributions of both
variables.\n"
```



[ ]:
```python
sns.jointplot(x="total",y="alcohol",data=df)
plt.ylabel('Alcohol')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Alcohol')

"""
Inference :
The joint plot visualizes the relationship between total car crashes and␣
↪crashes involving alcohol.
It combines a scatter plot and histograms to provide insights into the␣
↪distribution and correlation between the two variables.
```

```
The scatter plot shows that there isn't a strong linear relationship between␣
    ↪total crashes and alcohol-related incidents.
The histograms on the top and right sides offer additional information about␣
    ↪the distributions of both variables.
"""
```

[ ]:
```
"\nInference :\nThe joint plot visualizes the relationship between total car
crashes and crashes involving alcohol.\nIt combines a scatter plot and
histograms to provide insights into the distribution and correlation between the
two variables.\nThe scatter plot shows that there isn't a strong linear
relationship between total crashes and alcohol-related incidents.\nThe
histograms on the top and right sides offer additional information about the
distributions of both variables.\n"
```



Multivariate

Definition: Multivariate data analysis deals with the examination of three or more variables simultaneously, often in complex datasets.

Objective: The primary goal is to uncover intricate relationships, dependencies, and patterns involving multiple variables. It aims to explore how these variables collectively impact the outcome or phenomenon under study.

Methods: Common methods include multiple regression analysis, principal component analysis (PCA), factor analysis, cluster analysis, and machine learning techniques like decision trees, random forests, and neural networks. These methods enable the exploration of complex interactions and dependencies among multiple variables.

[ ]:
```
corr=df.corr() # Finding the co relation between all the fields in the dataset␣
↪and storing it in the variable 'corr'.
```

```
<ipython-input-25-f8732931ad62>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  corr=df.corr() # Finding the co relation between all the fields in the dataset
and storing it in the variable 'corr'.
```

[ ]:
```
corr # Displaying the data
```

[ ]:
```
                   total  speeding   alcohol  not_distracted  no_previous  \
total           1.000000  0.611548  0.852613        0.827560     0.956179
speeding        0.611548  1.000000  0.669719        0.588010     0.571976
alcohol         0.852613  0.669719  1.000000        0.732816     0.783520
not_distracted  0.827560  0.588010  0.732816        1.000000     0.747307
no_previous     0.956179  0.571976  0.783520        0.747307     1.000000
ins_premium    -0.199702 -0.077675 -0.170612       -0.174856    -0.156895
ins_losses     -0.036011 -0.065928 -0.112547       -0.075970    -0.006359

                ins_premium  ins_losses
total             -0.199702   -0.036011
speeding          -0.077675   -0.065928
alcohol           -0.170612   -0.112547
not_distracted    -0.174856   -0.075970
no_previous       -0.156895   -0.006359
ins_premium        1.000000    0.623116
ins_losses         0.623116    1.000000
```

[ ]:
```
plt.subplots(figsize=(18,9))
sns.heatmap(corr,annot=True)

"""
```

```
Inference :
The heatmap visualizes the correlation between different variables in the␣
↪dataset.
Darker colors indicate stronger positive correlations, while lighter colors␣
↪represent weaker or negative correlations.
The heatmap allows for a quick assessment of which variables are strongly␣
↪correlated and which are not.
For example, if two variables have a dark-colored cell, it indicates a strong␣
↪positive correlation between them.
This visualization is valuable for identifying potential relationships and␣
↪dependencies within the dataset.
"""
```

[ ]: '\nInference :\nThe heatmap visualizes the correlation between different variables in the dataset.\nDarker colors indicate stronger positive correlations, while lighter colors represent weaker or negative correlations.\nThe heatmap allows for a quick assessment of which variables are strongly correlated and which are not.\nFor example, if two variables have a dark-colored cell, it indicates a strong positive correlation between them.\nThis visualization is valuable for identifying potential relationships and dependencies within the dataset.\n'