In [ ]:
```
import seaborn as sns # importing the seaborn library
import matplotlib.pyplot as plt # importing the matplotlib.pyplot library
```

In [ ]:
```
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']
```

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

Out[ ]:

	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
5	13.6	5.032	3.808	10.744	12.920	835.50	139.91	CO
6	10.8	4.968	3.888	9.396	8.856	1068.73	167.02	CT
7	16.2	6.156	4.860	14.094	16.038	1137.87	151.48	DE
8	5.9	2.006	1.593	5.900	5.900	1273.89	136.05	DC
9	17.9	3.759	5.191	16.468	16.826	1160.13	144.18	FL
10	15.6	2.964	3.900	14.820	14.508	913.15	142.80	GA
11	17.5	9.450	7.175	14.350	15.225	861.18	120.92	HI
12	15.3	5.508	4.437	13.005	14.994	641.96	82.75	ID
13	12.8	4.608	4.352	12.032	12.288	803.11	139.15	IL
14	14.5	3.625	4.205	13.775	13.775	710.46	108.92	IN
15	15.7	2.669	3.925	15.229	13.659	649.06	114.47	IA
16	17.8	4.806	4.272	13.706	15.130	780.45	133.80	KS
17	21.4	4.066	4.922	16.692	16.264	872.51	137.13	KY
18	20.5	7.175	6.765	14.965	20.090	1281.55	194.78	LA
19	15.1	5.738	4.530	13.137	12.684	661.88	96.57	ME
20	12.5	4.250	4.000	8.875	12.375	1048.78	192.70	MD
21	8.2	1.886	2.870	7.134	6.560	1011.14	135.63	MA
22	14.1	3.384	3.948	13.395	10.857	1110.61	152.26	MI
23	9.6	2.208	2.784	8.448	8.448	777.18	133.35	MN
24	17.6	2.640	5.456	1.760	17.600	896.07	155.77	MS
25	16.1	6.923	5.474	14.812	13.524	790.32	144.45	MO
26	21.4	8.346	9.416	17.976	18.190	816.21	85.15	MT
27	14.9	1.937	5.215	13.857	13.410	732.28	114.82	NE
28	14.7	5.439	4.704	13.965	14.553	1029.87	138.71	NV
29	11.6	4.060	3.480	10.092	9.628	746.54	120.21	NH
30	11.2	1.792	3.136	9.632	8.736	1301.52	159.85	NJ
31	18.4	3.496	4.968	12.328	18.032	869.85	120.75	NM
32	12.3	3.936	3.567	10.824	9.840	1234.31	150.01	NY
33	16.8	6.552	5.208	15.792	13.608	708.24	127.82	NC
34	23.9	5.497	10.038	23.661	20.554	688.75	109.72	ND
35	14.1	3.948	4.794	13.959	11.562	697.73	133.52	OH

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
36	19.9	6.368	5.771	18.308	18.706	881.51	178.86	OK
37	12.8	4.224	3.328	8.576	11.520	804.71	104.61	OR
38	18.2	9.100	5.642	17.472	16.016	905.99	153.86	PA
39	11.1	3.774	4.218	10.212	8.769	1148.99	148.58	RI
40	23.9	9.082	9.799	22.944	19.359	858.97	116.29	SC
41	19.4	6.014	6.402	19.012	16.684	669.31	96.87	SD
42	19.5	4.095	5.655	15.990	15.795	767.91	155.57	TN
43	19.4	7.760	7.372	17.654	16.878	1004.75	156.83	TX
44	11.3	4.859	1.808	9.944	10.848	809.38	109.48	UT
45	13.6	4.080	4.080	13.056	12.920	716.20	109.61	VT
46	12.7	2.413	3.429	11.049	11.176	768.95	153.72	VA
47	10.6	4.452	3.498	8.692	9.116	890.03	111.62	WA
48	23.8	8.092	6.664	23.086	20.706	992.61	152.56	WV
49	13.8	4.968	4.554	5.382	11.592	670.31	106.62	WI
50	17.4	7.308	5.568	14.094	15.660	791.14	122.04	WY

Handling Null Values

In [ ]:

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

Out[ ]:

```
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

In [ ]:

```
df.describe() # describing about the df, i.e; metadat of columns with count, mean,
```

Out[ ]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses
count	51.000000	51.000000	51.000000	51.000000	51.000000	51.000000	51.000000
mean	15.790196	4.998196	4.886784	13.573176	14.004882	886.957647	134.493137
std	4.122002	2.017747	1.729133	4.508977	3.764672	178.296285	24.835922
min	5.900000	1.792000	1.593000	1.760000	5.900000	641.960000	82.750000
25%	12.750000	3.766500	3.894000	10.478000	11.348000	768.430000	114.645000
50%	15.600000	4.608000	4.554000	13.857000	13.775000	858.970000	136.050000
75%	18.500000	6.439000	5.604000	16.140000	16.755000	1007.945000	151.870000
max	23.900000	9.450000	10.038000	23.661000	21.280000	1301.520000	194.780000

Univariate

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

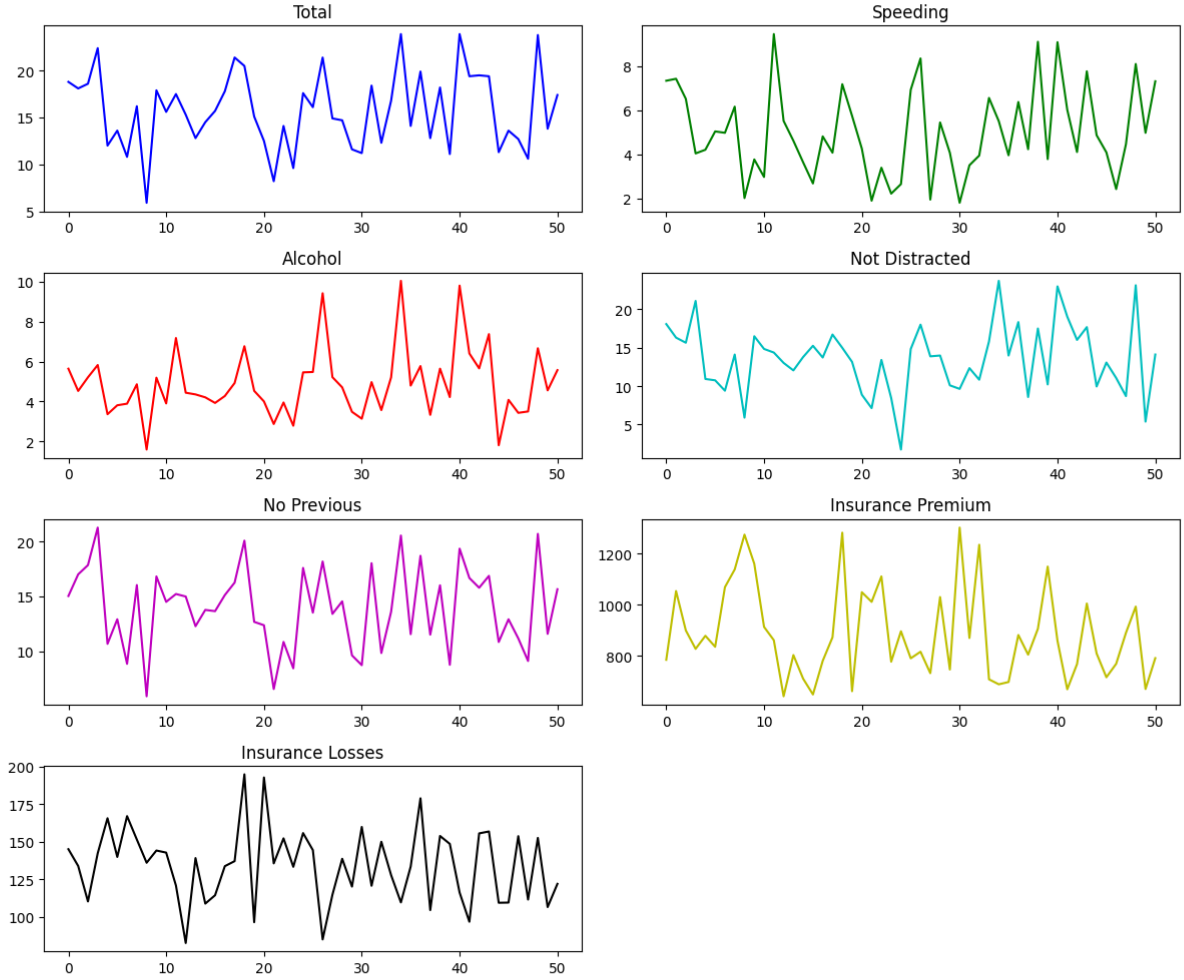
Objective: The primary goal is to describe and summarize the data, understand its central tendency, and identify patterns, outliers, and potential trends within that single variable.

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

In [ ]:

```
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
"""



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 fluctuati
"""


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 t
```

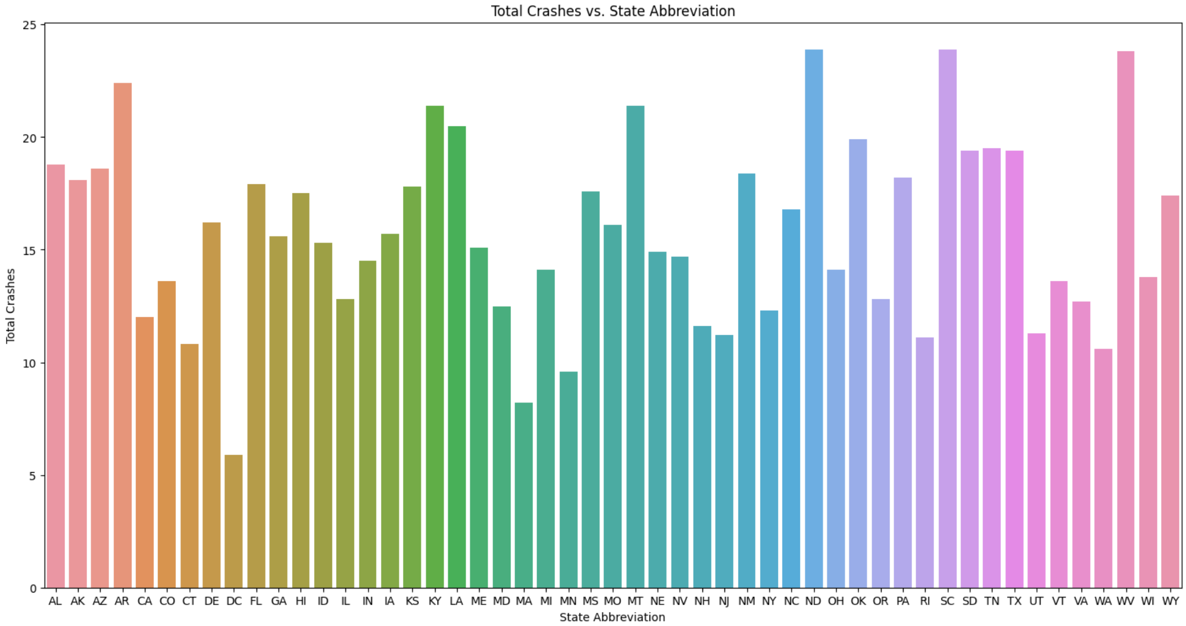
```
"""

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,
"""

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 fl
"""

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 pre
"""

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
"""

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



Barplot

In [ ]:
```
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-
The plot provides a clear comparison of car crash counts between states.
For example, states with abbreviations like "DC," "RI," and "NH" have relatively lo
This plot is useful for identifying states with higher or lower crash rates, which
"""
```

Out[ ]:
```
'\nInference:\nState abbreviations are on the x-axis, and the total number of cras
hes is on the y-axis.\nThe plot provides a clear comparison of car crash counts be
tween states.\nFor example, states with abbreviations like "DC," "RI," and "NH" ha
ve relatively lower total crash counts, while "TX," "CA," and "FL" have higher cra
sh 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'
```

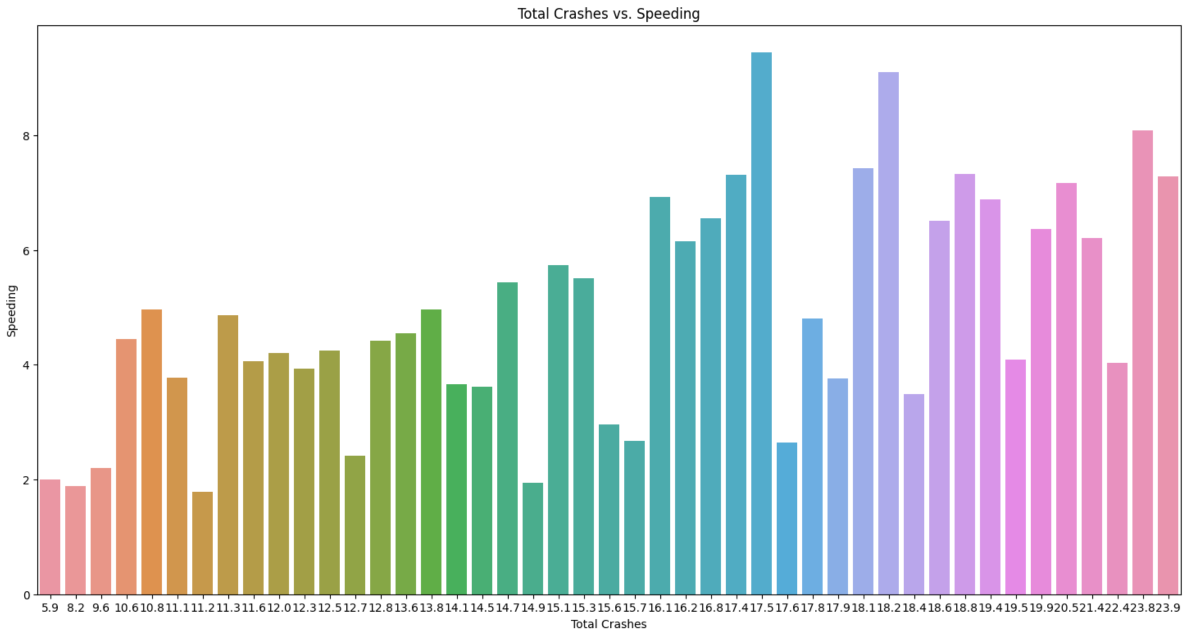


In [ ]:

```
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 crash
The plot allows us to examine how speeding contributes to the overall number of car
As the total number of crashes increases, there is a general trend of an increase i
This suggests that as the total number of car crashes goes up, the proportion of cr
Analyzing this relationship can help in understanding the impact of speeding on ove
"""
```

Out[ ]:

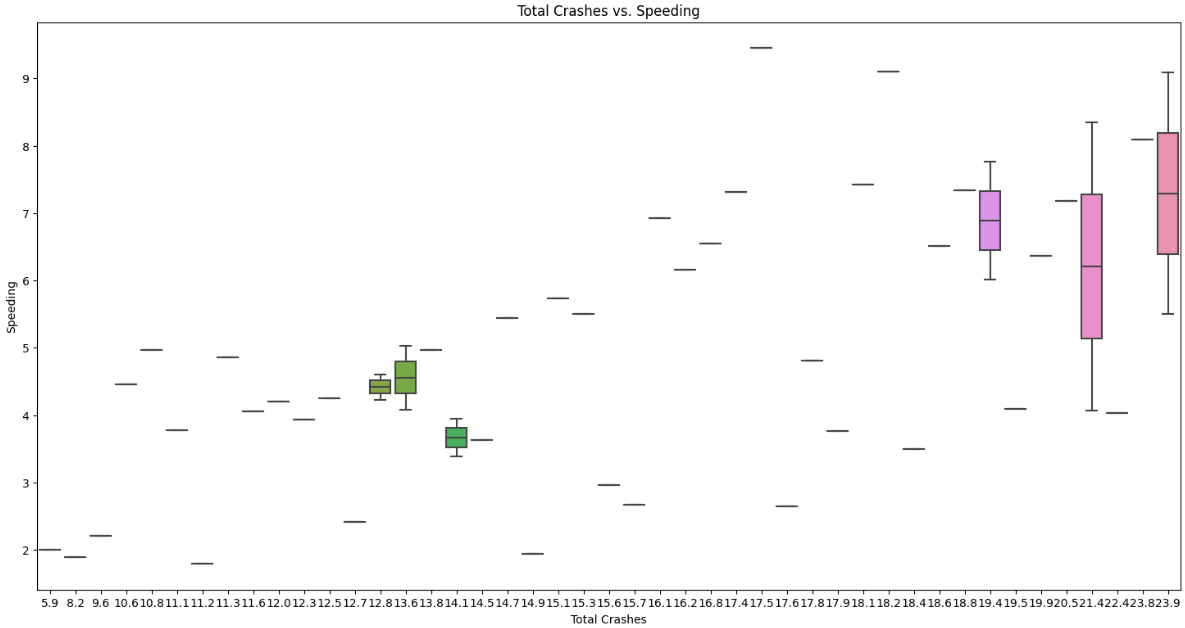
```
'\nInference:\nThe total number of crashes is represented on the x-axis, while the
number of crashes involving speeding is on the y-axis.\nThe plot allows us to exam
ine how speeding contributes to the overall number of car crashes.\nAs the total n
umber of crashes increases, there is a general trend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



Boxplot

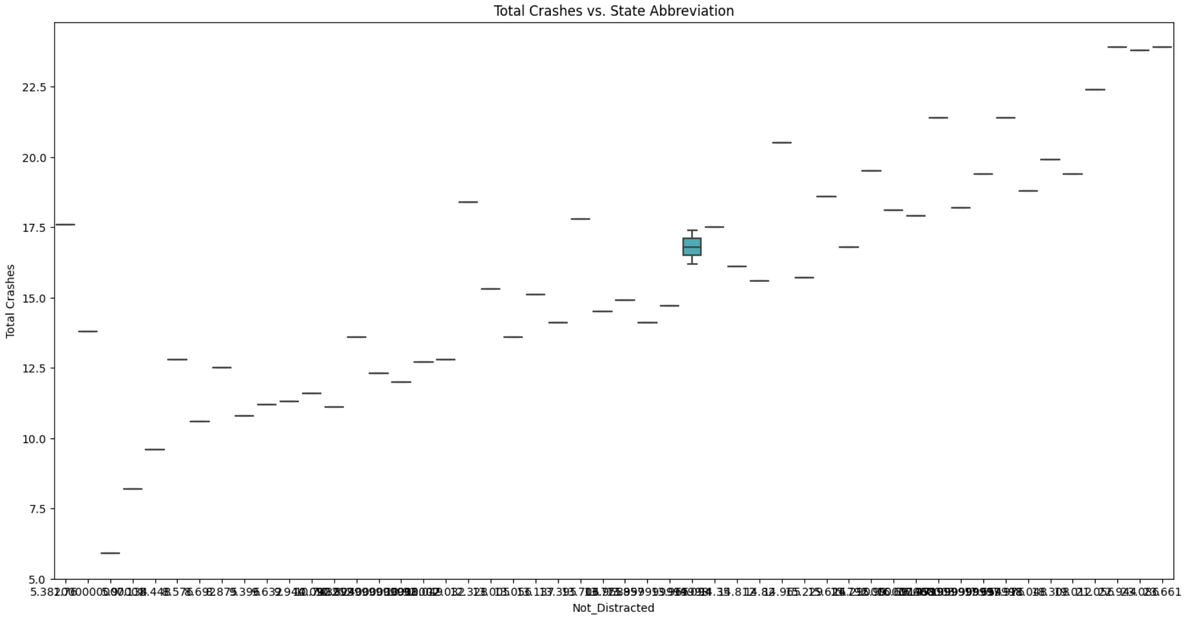
In [ ]:
```
plt.figure(figsize=(18,9))
sns.boxplot(x="total",y="speeding",data=df)
plt.ylabel('Speeding')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Speeding')

"""
Inference :
The box plot shows the distribution of speeding-related crashes within different to
As the total number of crashes increases, there is increasing variability in the nu
This highlights the relationship between total crashes and speeding incidents, indi
"""
```

Out[ ]:
```
'\nInference :\nThe box plot shows the distribution of speeding-related crashes wi
thin 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, indicati
ng the need for targeted interventions in states or situations with higher variabi
lity.\n'
```



In [ ]:
```
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 distract:
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 pot
This suggests that non-distracted drivers may be involved in more crashes, emphasiz
"""
```

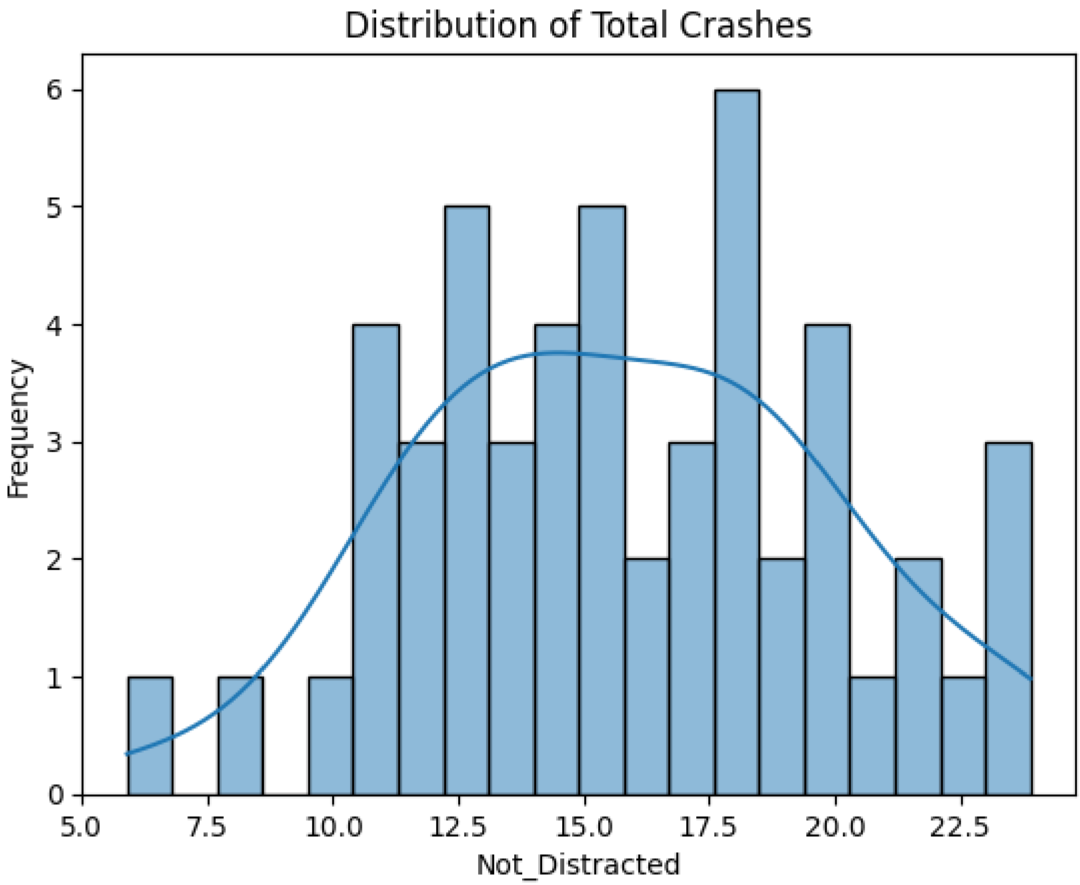
Out[ ]:
```
'\nInference :\nThe box plot illustrates the distribution of total crashes concern
ing the distraction status of drivers (Not Distracted).\nIt provides insights into
how distraction affects the total number of car crashes.\nThe plot shows varying t
otal crash counts based on the distraction 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 distrac
tion and driving behavior to improve road safety.\n'
```



Histogram

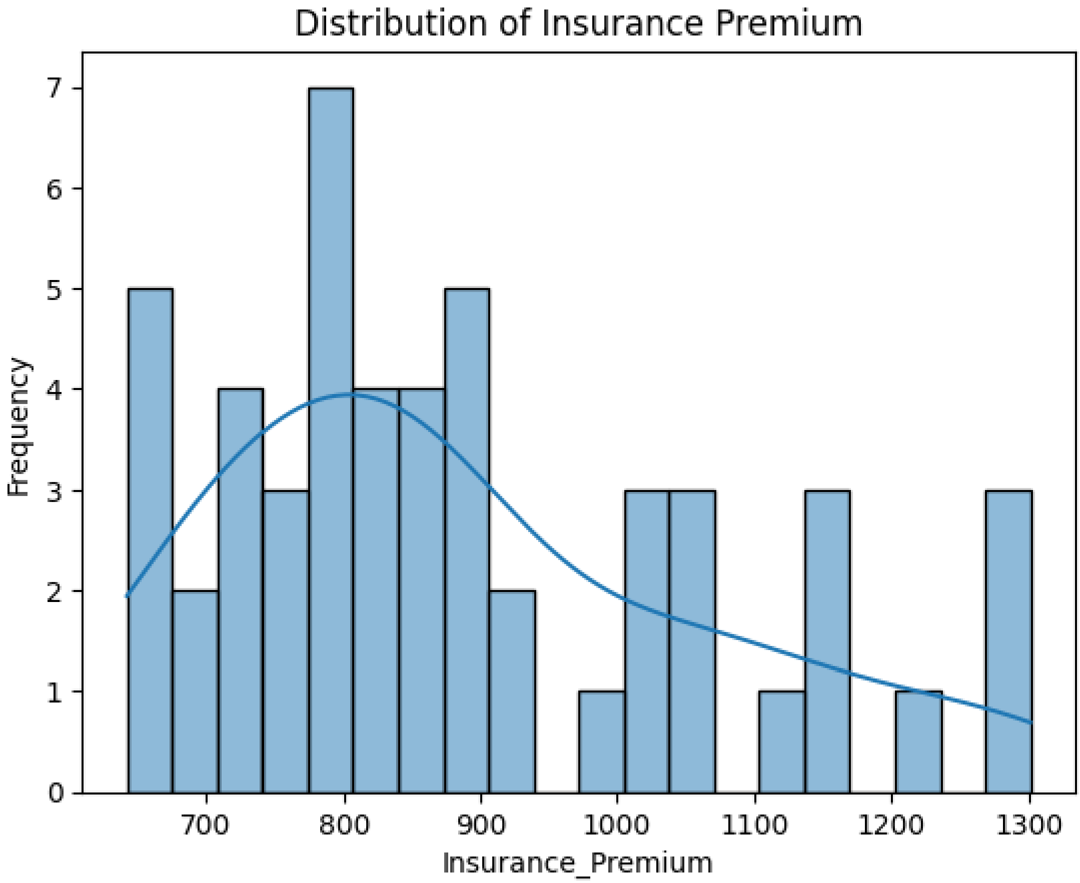
In [ ]:
```
sns.histplot(data=df, x='total', bins=20, kde=True)
plt.xlabel('Not_Distracted')
plt.ylabel('Frequency')
plt.title('Distribution of Total Crashes')

"""
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
There is a right-skewed distribution, indicating that a few instances have signific
This visualization helps understand the distribution of total crashes, which can be
"""
```

Out[ ]:
```
'\nInference :\nThe histogram displays the distribution of total car crashes.n.\nT
he 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 visu
alization helps understand the distribution of total crashes, which can be useful
for identifying common crash count ranges and outliers in the dataset.\n'
```



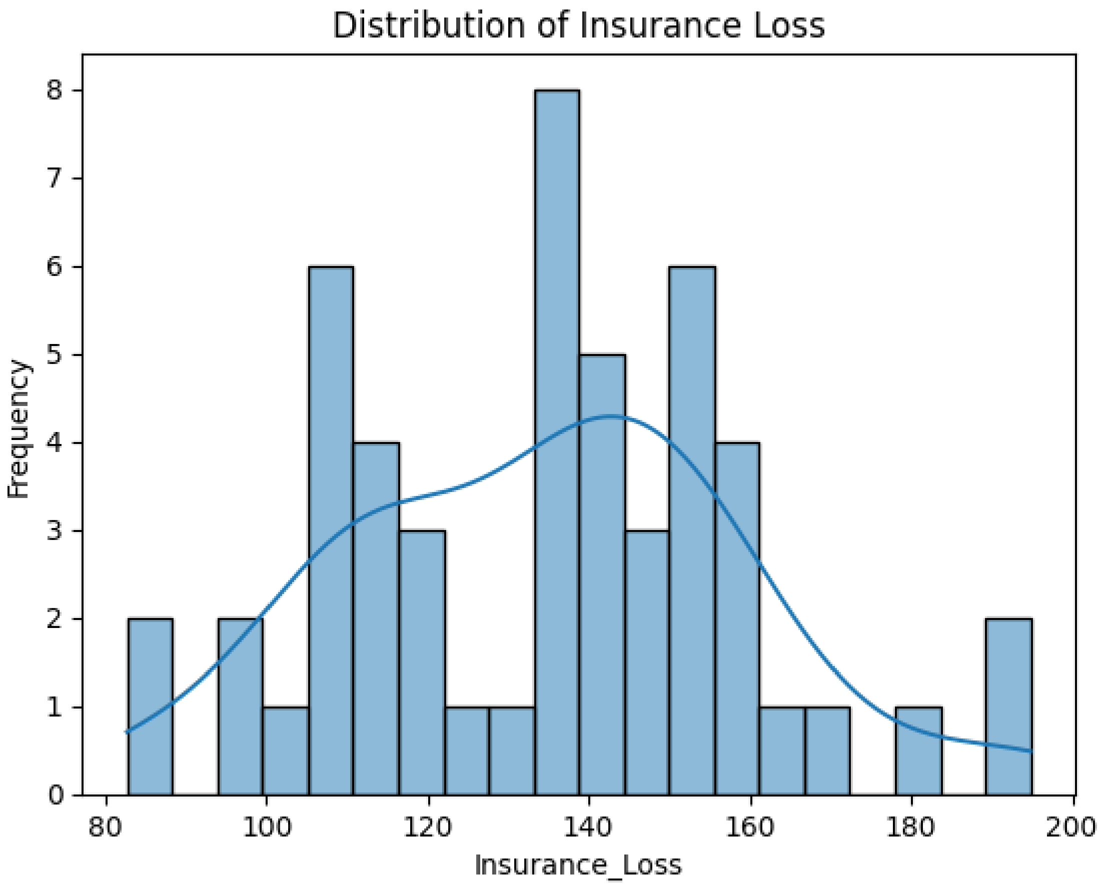
In [ ]:
```
sns.histplot(data=df, x='ins_premium', bins=20, kde=True)
plt.xlabel('Insurance_Premium')
plt.ylabel('Frequency')
plt.title('Distribution of Insurance Premium')

"""
Inference :
The histogram depicts the distribution of insurance premiums.
The plot shows that the most common insurance premium ranges have higher frequencie
The distribution appears to be right-skewed, suggesting that a few observations hav
This visualization aids in understanding the distribution of insurance premiums wit
"""
```

Out[ ]:
```
'\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, s
uggesting that a few observations have exceptionally high insurance premiums.\nThi
s visualization aids in understanding the distribution of insurance premiums withi
n the dataset, providing insights into common premium ranges and potential outlier
s.\n'
```



In [ ]:
```
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 range
The distribution appears right-skewed, indicating that a few instances have conside
This visualization helps in understanding the distribution of insurance losses with
"""
```

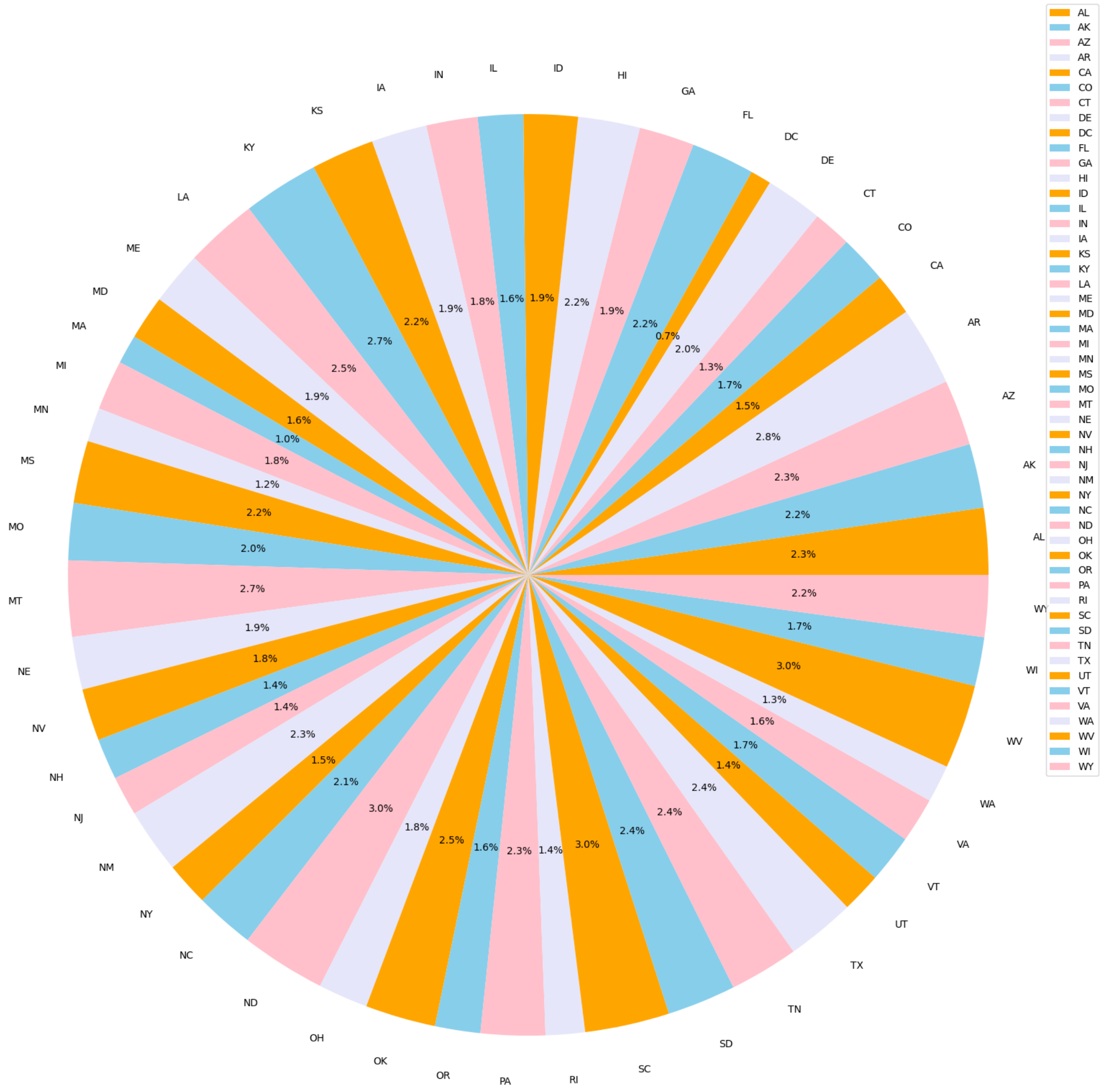
Out[ ]:
```
'\nInference :\nThe histogram represents the distribution of insurance losses.\nTh
e plot indicates that the majority of insurance losses fall within specific range
s, with peaks in frequency.\nThe distribution appears right-skewed, indicating tha
t a few instances have considerably higher insurance losses.\nThis visualization h
elps in understanding the distribution of insurance losses within the dataset, hig
hlighting common loss ranges and potential outliers.\n'
```



Piechart

In [ ]:
```
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','skyl
axes1.legend()

"""
Inference :
The pie chart visualizes the distribution of total car crashes across different sta
Each slice of the pie represents a state, and the size of the slice corresponds to 
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 t
"""
```

Out[ ]:
```
'\nInference :\nThe pie chart visualizes the distribution of total car crashes acr
oss different states, represented by their abbreviations.\nEach slice of the pie r
epresents a state, and the size of the slice corresponds to the percentage of tota
l crashes in that state.\nThe labels on the chart indicate the state abbreviation
s.\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 t
otal 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.

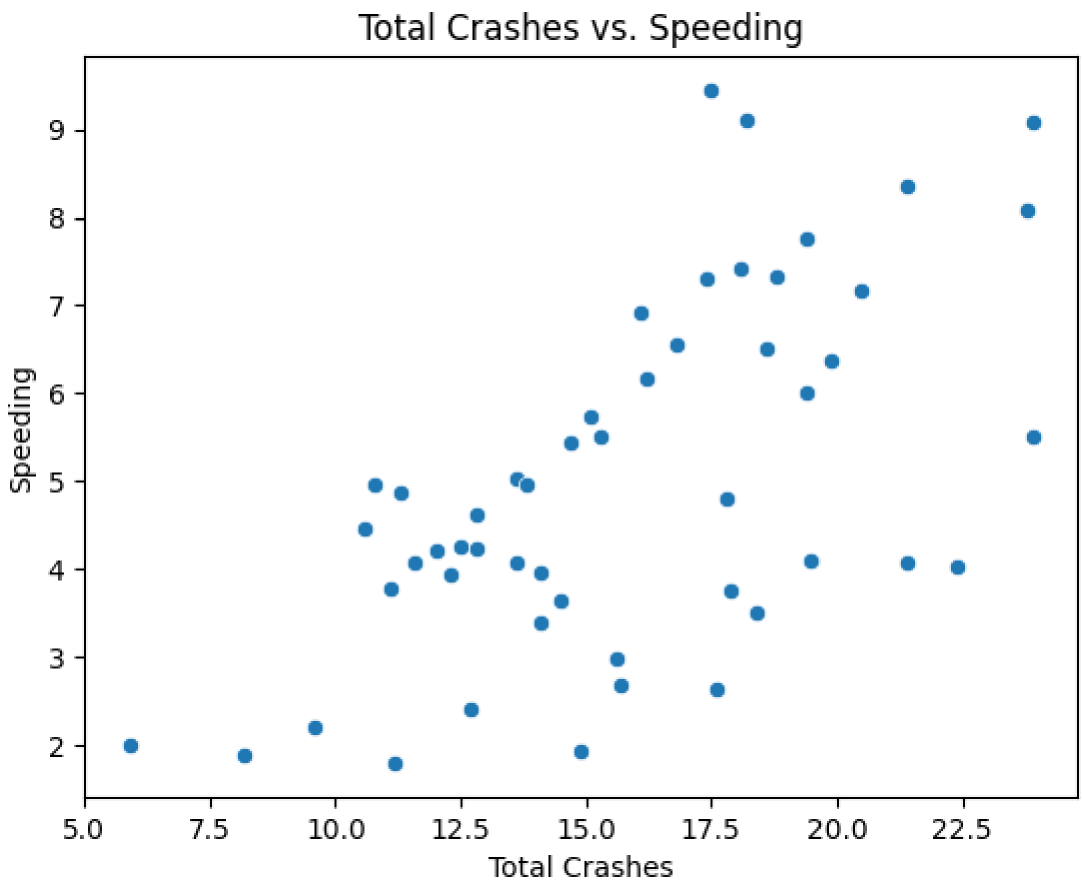
Scatterplot

In [ ]:
```
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 crashe
There doesn't appear to be a strong linear relationship between total crashes and s
```

```
The points are scattered across the plot without a clear trend, suggesting that tot
Further statistical analysis may be needed to quantify the relationship between the
"""
```

Out[ ]:

```
"\nInference :\nThe scatter plot visualizes the relationship between the total num
ber of car crashes and the number of crashes involving speeding.\nThere doesn't ap
pear to be a strong linear relationship between total crashes and speeding inciden
ts 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 correl
ated.\nFurther statistical analysis may be needed to quantify the relationship bet
ween these variables accurately.\n"
```

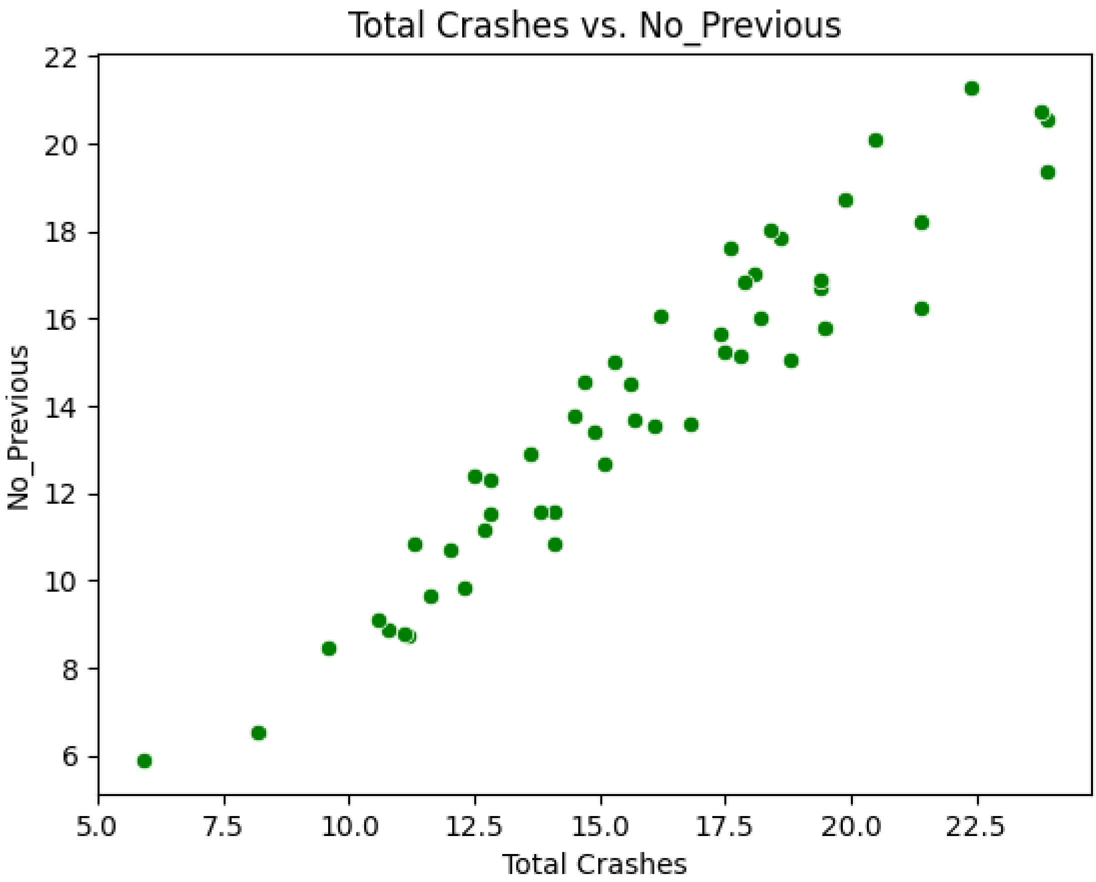


In [ ]:

```
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 crash
Similar to previous scatter plots, there isn't a distinct linear relationship betwe
The points are scattered without a clear trend, suggesting that total crashes may n
"""
```

Out[ ]:

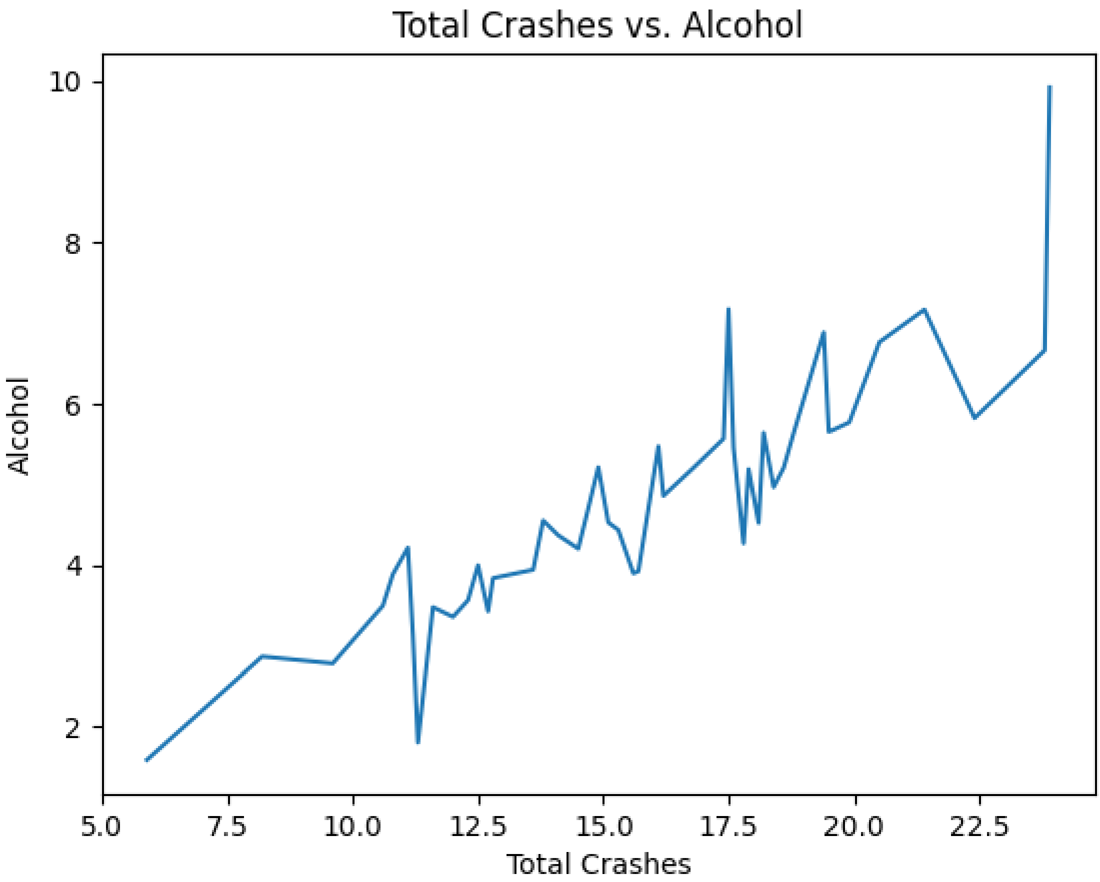
```
"\nInference :\nThe scatter plot illustrates the relationship between the total nu
mber of car crashes and crashes involving drivers with no previous incidents.\nSim
ilar to previous scatter plots, there isn't a distinct linear relationship between
total crashes and crashes involving drivers with no previous incidents.\nThe point
s are scattered without a clear trend, suggesting that total crashes may not direc
tly correlate with the absence of previous incidents in drivers. Further analysis
may be needed.\n"
```



Lineplot

In [ ]:
```
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
It visualizes how alcohol-related crashes fluctuate concerning the total number of
There isn't a clear linear relationship; the points on the line are scattered witho
This suggests that the total number of crashes may not have a straightforward corre
"""
```

Out[ ]:
```
"\nInference :\nThe line plot shows the association between total car crashes and
crashes involving alcohol.\nIt visualizes how alcohol-related crashes fluctuate co
ncerning the total number of crashes.\nThere isn't a clear linear relationship; th
e 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 alcoho
l-related incidents, warranting further analysis.\n"
```

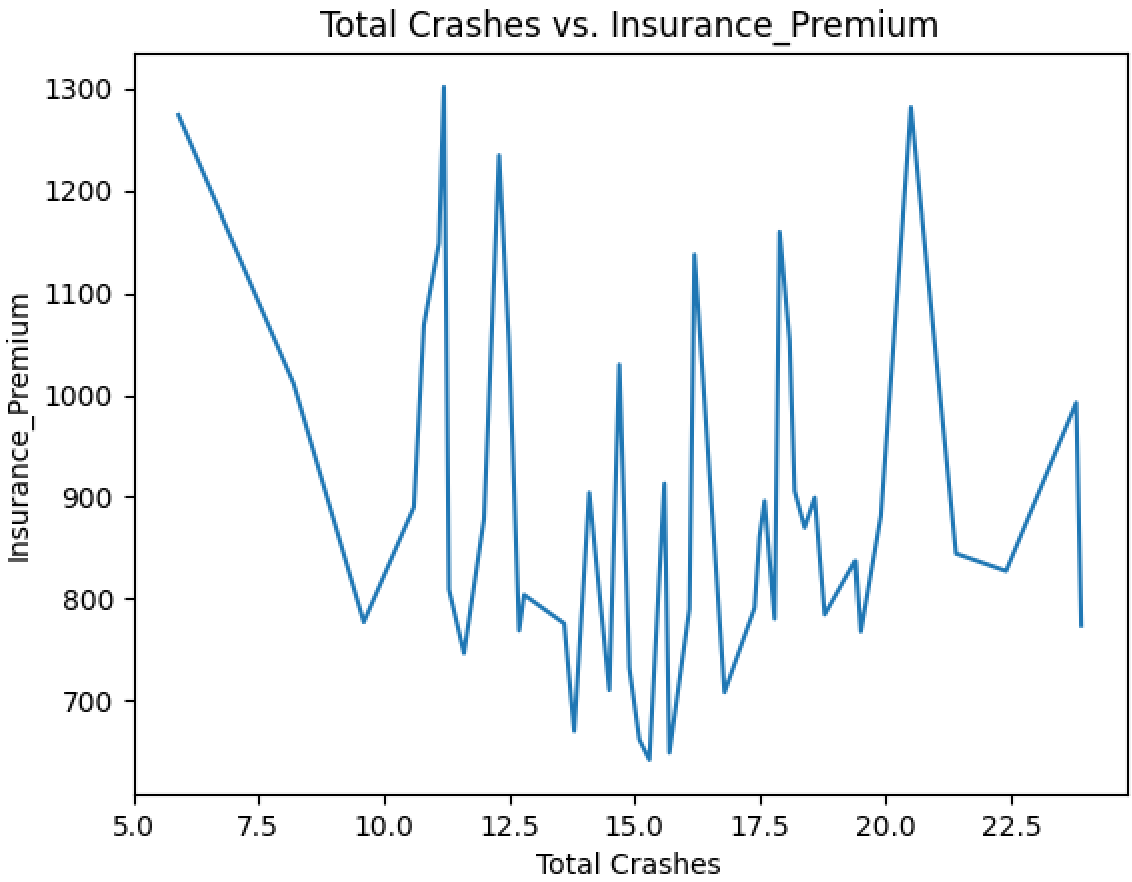


In [ ]:

```
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 p
It visualizes how insurance premiums vary in relation to the total number of crashe
The plot does not show a clear linear trend; points on the line are scattered witho
This suggests that the total number of crashes may not have a straightforward corre
"""
```

Out[ ]:

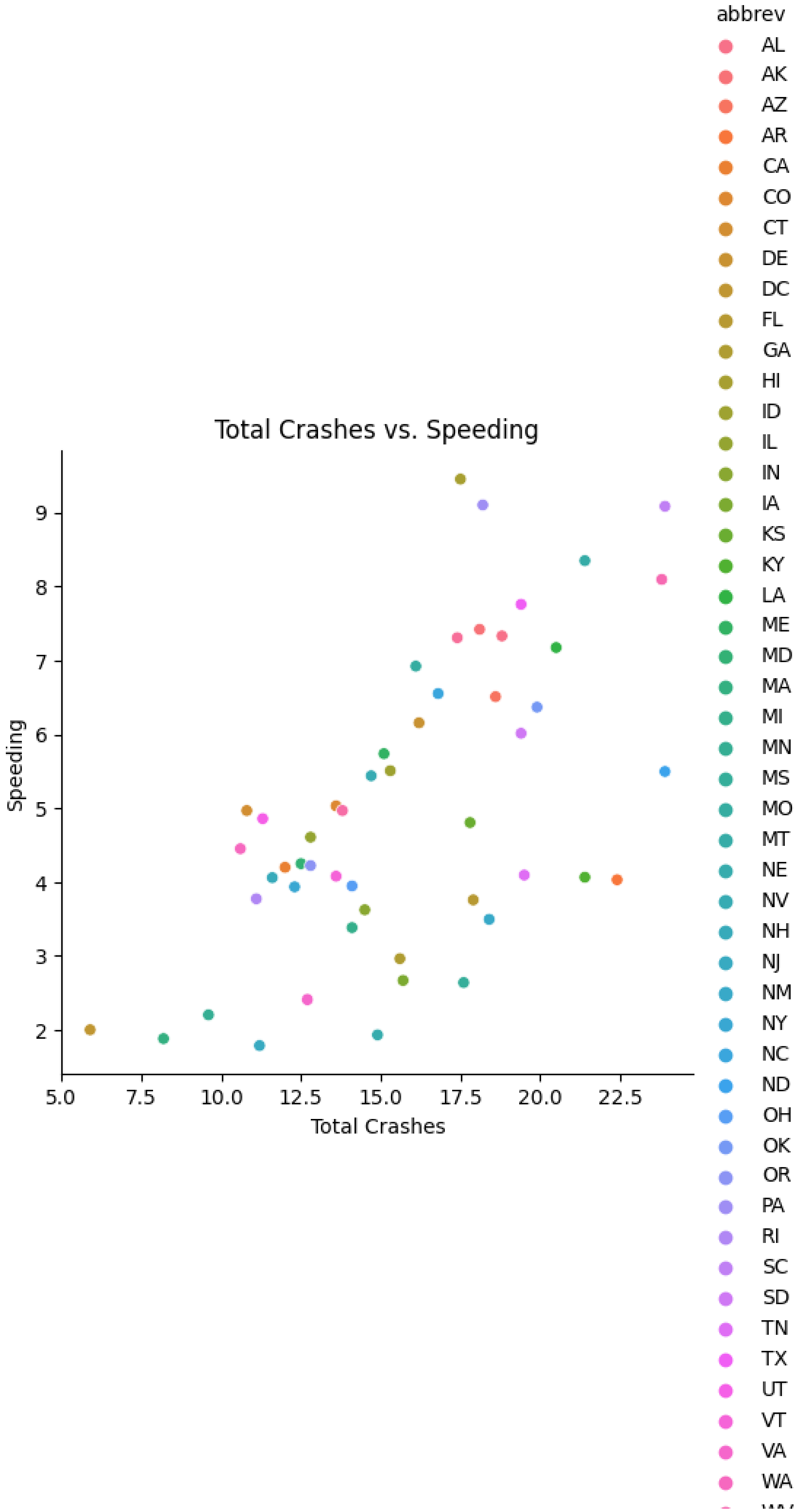
```
'\nInference :\nThe line plot represents the relationship between total car crashe
s and insurance premiums.\nIt visualizes how insurance premiums vary in relation t
o the total number of crashes.\nThe plot does not show a clear linear trend; point
s on the line are scattered without a clear pattern.\nThis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

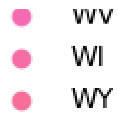


Replot

In [ ]:
```
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
Each point represents a data point in the dataset, with different states distinguis
The plot allows for a quick visual assessment of how speeding-related crashes vary
There is no clear linear trend; points are scattered without a distinct pattern, in
"""
```

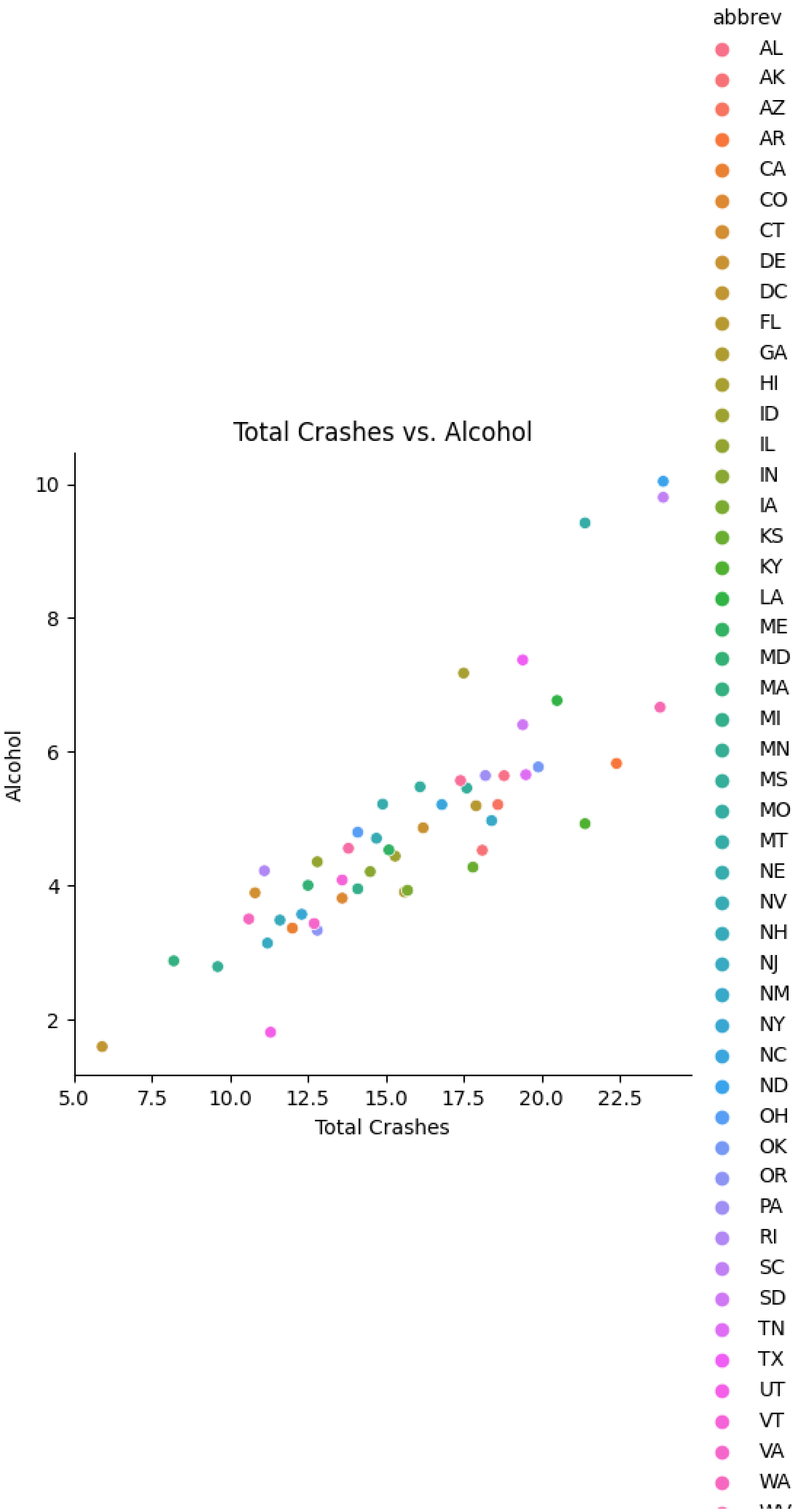
Out[ ]:
```
'\nInference :\nThe relational plot ("relplot") displays the relationship between
total car crashes and crashes involving speeding.\nEach point represents a data po
int in the dataset, with different states distinguished by colors (hue).\nThe plot
allows for a quick visual assessment of how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

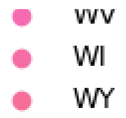

Total Crashes vs. Speeding
Speeding
Total Crashes
9
8
7
6
5
4
3
2
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
abbrev
AL
AK
AZ
AR
CA
CO
CT
DE
DC
FL
GA
HI
ID
IL
IN
IA
KS
KY
LA
ME
MD
MA
MI
MN
MS
MO
MT
NE
NV
NH
NJ
NM
NY
NC
ND
OH
OK
OR
PA
RI
SC
SD
TN
TX
UT
VT
VA
WA



In [ ]:
```
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 cras
Each point on the plot represents a data point in the dataset, and different states
The plot provides a visual comparison of how alcohol-related crashes vary with the
There isn't a clear linear trend in the relationship; points are scattered without
"""
```

Out[ ]:
```
'\nInference :\nThe relational plot ("relplot") illustrates the relationship betwe
en total car crashes and crashes involving alcohol.\nEach point on the plot repres
ents a data point in the dataset, and different states are color-coded for compari
son (hue).\nThe plot provides a visual comparison of how alcohol-related crashes v
ary with the total number of crashes in different states.\nThere isn\'t a clear li
near trend in the relationship; points are scattered without a distinct pattern, s
uggesting 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
10
8
6
4
2
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
Total Crashes
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



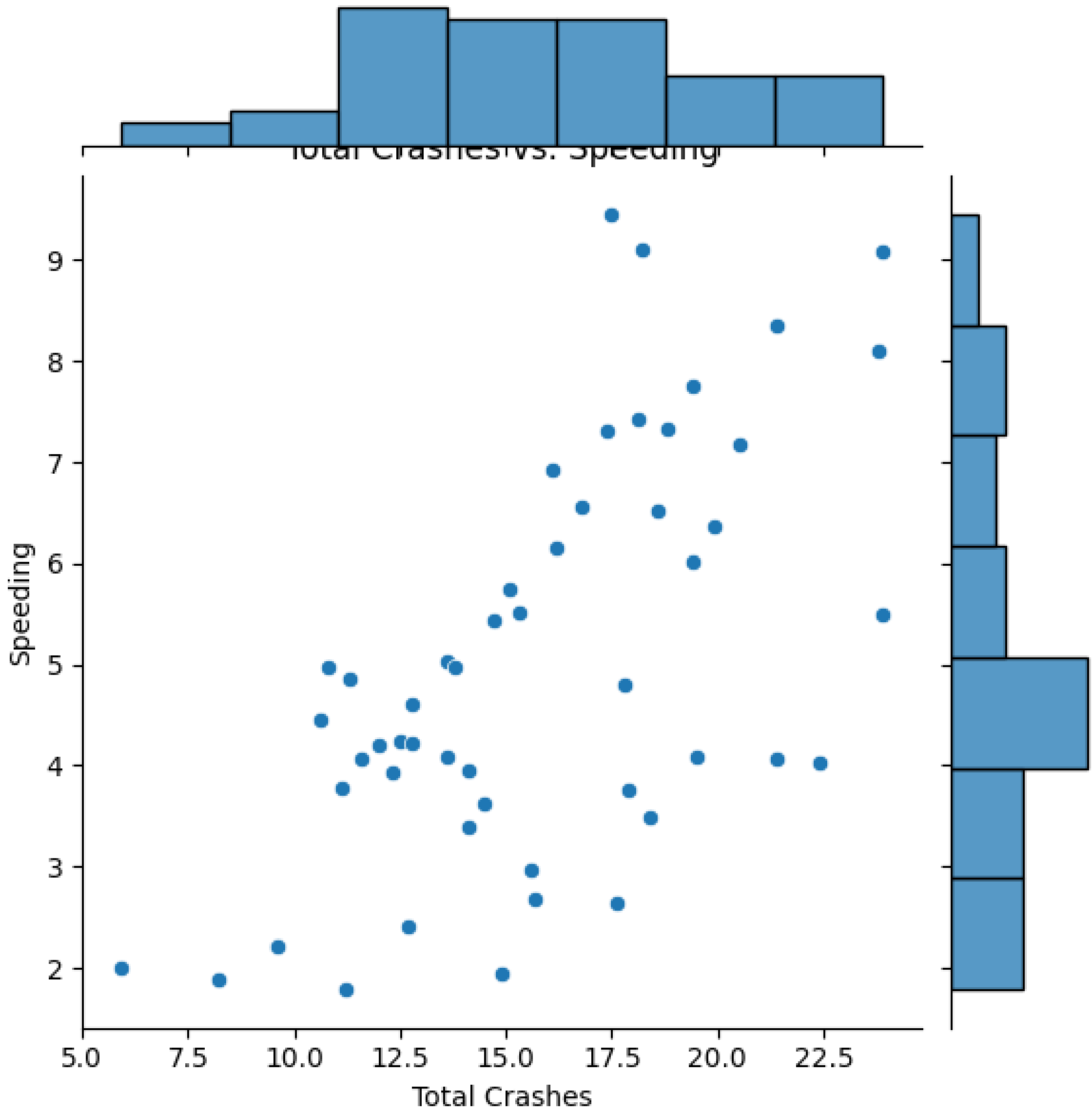
Jointplot

In [ ]:

```
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 invo
It combines a scatter plot and histograms to visualize the distribution and correla
The scatter plot shows that there isn't a strong linear relationship between total
The histograms on the top and right sides provide additional information about the
"""
```

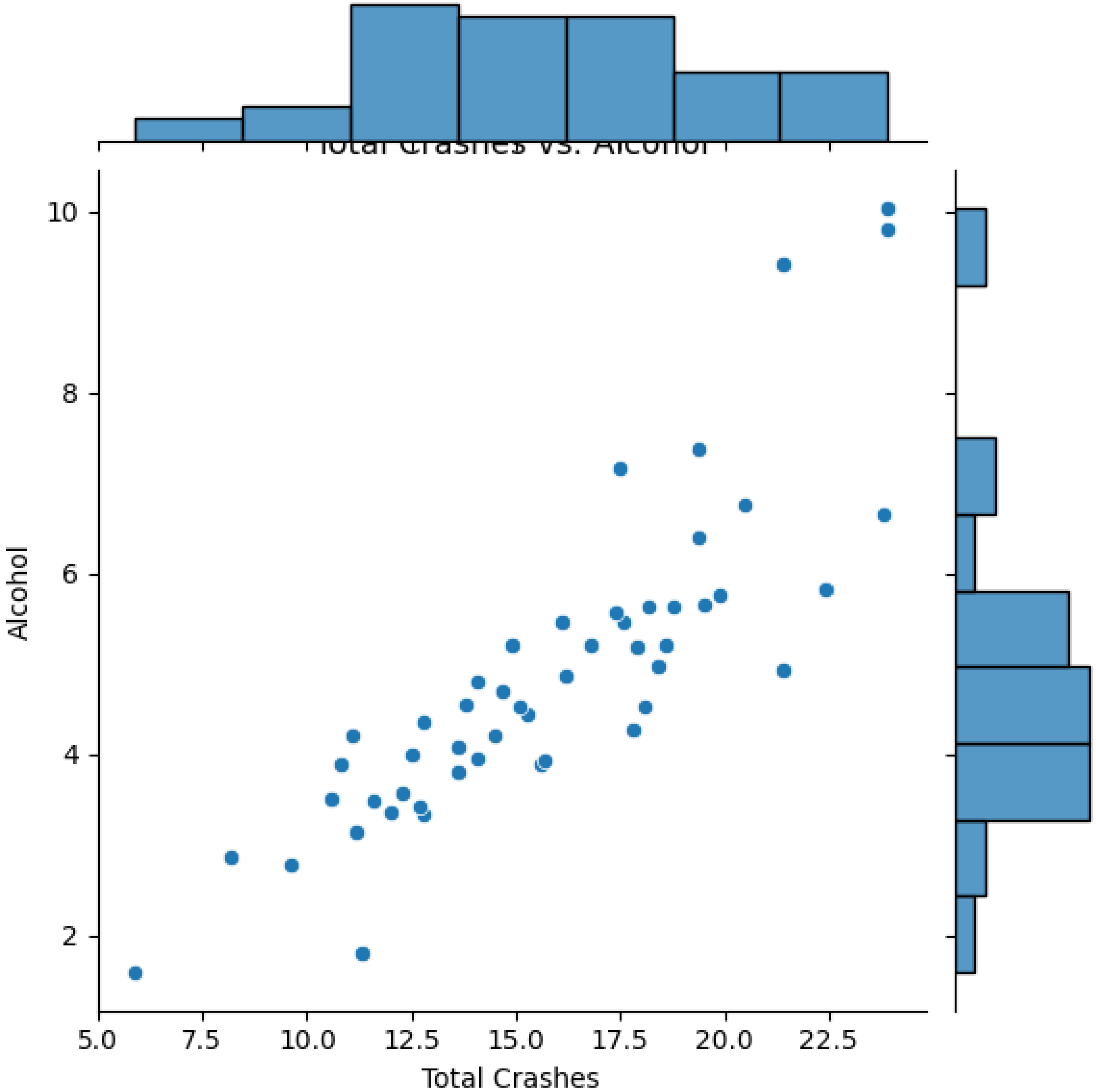
Out[ ]:

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



In [ ]:
```
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 in
It combines a scatter plot and histograms to provide insights into the distribution
The scatter plot shows that there isn't a strong linear relationship between total
The histograms on the top and right sides offer additional information about the di
"""
```

Out[ ]:
```
"\nInference :\nThe joint plot visualizes the relationship between total car crash
es and crashes involving alcohol.\nIt combines a scatter plot and histograms to pr
ovide insights into the distribution and correlation between the two variables.\nT
he 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.

In [ ]:

```
corr=df.corr() # Finding the co relation between all the fields in the dataset and
corr
```

```
<ipython-input-24-27e25d4587de>:1: FutureWarning: The default value of numeric_onl
y 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 war
ning.
  corr=df.corr() # Finding the co relation between all the fields in the dataset a
nd storing it in the variable 'corr'.
```

Out[ ]:

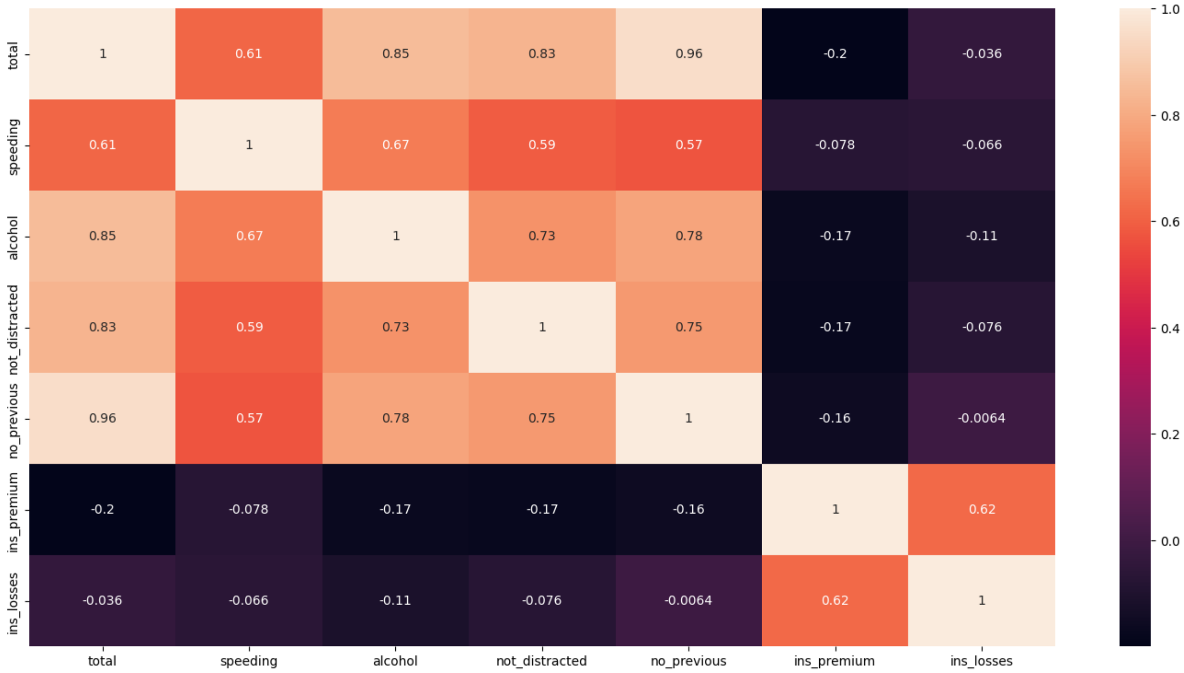
	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losse
total	1.000000	0.611548	0.852613	0.827560	0.956179	-0.199702	-0.03601
speeding	0.611548	1.000000	0.669719	0.588010	0.571976	-0.077675	-0.06592
alcohol	0.852613	0.669719	1.000000	0.732816	0.783520	-0.170612	-0.11254
not_distracted	0.827560	0.588010	0.732816	1.000000	0.747307	-0.174856	-0.07597
no_previous	0.956179	0.571976	0.783520	0.747307	1.000000	-0.156895	-0.00635
ins_premium	-0.199702	-0.077675	-0.170612	-0.174856	-0.156895	1.000000	0.62311
ins_losses	-0.036011	-0.065928	-0.112547	-0.075970	-0.006359	0.623116	1.00000

In [ ]:

```
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 represe
The heatmap allows for a quick assessment of which variables are strongly correlate
For example, if two variables have a dark-colored cell, it indicates a strong posit
This visualization is valuable for identifying potential relationships and depender
"""
```

Out[ ]:

```
'\nInference :\nThe heatmap visualizes the correlation between different variables
in the dataset.\nDarker colors indicate stronger positive correlations, while ligh
ter colors represent weaker or negative correlations.\nThe heatmap allows for a qu
ick 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 potentia
l relationships and dependencies within the dataset.\n'
```


total
speeding
alcohol
not_distracted
no_previous
ins_premium
ins_losses
1 0.61 0.85 0.83 0.96 -0.2 -0.036
0.61 1 0.67 0.59 0.57 -0.078 -0.066
0.85 0.67 1 0.73 0.78 -0.17 -0.11
0.83 0.59 0.73 1 0.75 -0.17 -0.076
0.96 0.57 0.78 0.75 1 -0.16 -0.0064
-0.2 -0.078 -0.17 -0.17 -0.16 1 0.62
-0.036 -0.066 -0.11 -0.076 -0.0064 0.62 1
1.0
0.8
0.6
0.4
0.2
0.0