```
# G.Sai Spandana
# 21bce7149
# VITAP MORNING SLOT
```

```
# 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
```

```
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	ins_losses	a
0	18.8	7.332	5.640	18.048	15.040	784.55	145.08	
1	18.1	7.421	4.525	16.290	17.014	1053.48	133.93	
2	18.6	6.510	5.208	15.624	17.856	899.47	110.35	
3	22.4	4.032	5.824	21.056	21.280	827.34	142.39	
4	12.0	4.200	3.360	10.920	10.680	878.41	165.63	
5	13.6	5.032	3.808	10.744	12.920	835.50	139.91	
6	10.8	4.968	3.888	9.396	8.856	1068.73	167.02	
7	16.2	6.156	4.860	14.094	16.038	1137.87	151.48	
8	5.9	2.006	1.593	5.900	5.900	1273.89	136.05	
9	17.9	3.759	5.191	16.468	16.826	1160.13	144.18	
10	15.6	2.964	3.900	14.820	14.508	913.15	142.80	
11	17.5	9.450	7.175	14.350	15.225	861.18	120.92	
12	15.3	5.508	4.437	13.005	14.994	641.96	82.75	
13	12.8	4.608	4.352	12.032	12.288	803.11	139.15	

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
```

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

	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)

```
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 t
"""

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.
"""

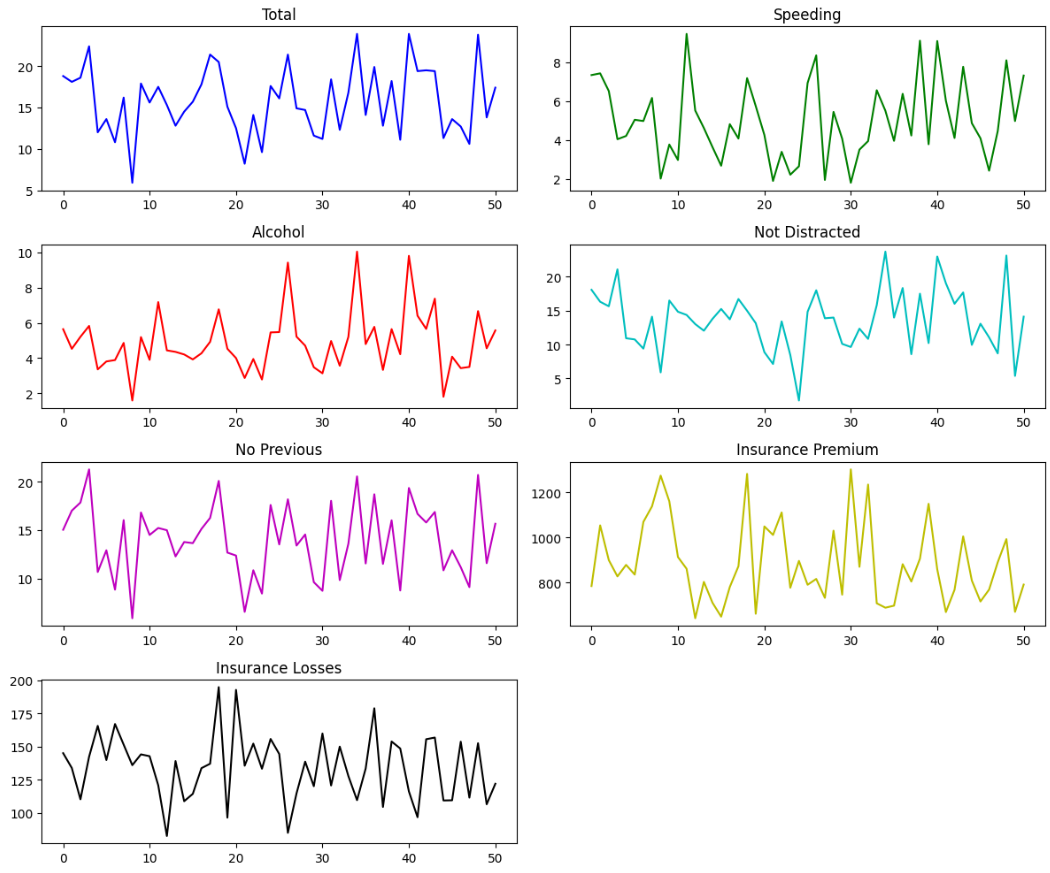
plt.subplot(4, 2, 6)
plt.plot(df['ins_premium'], 'y')
plt.title('Insurance Premium')

"""
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 di
"""

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.
"""

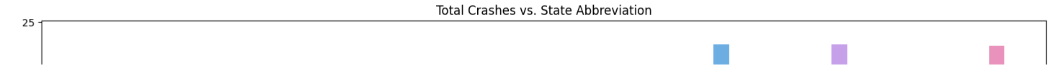
plt.tight_layout()
```



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')
```

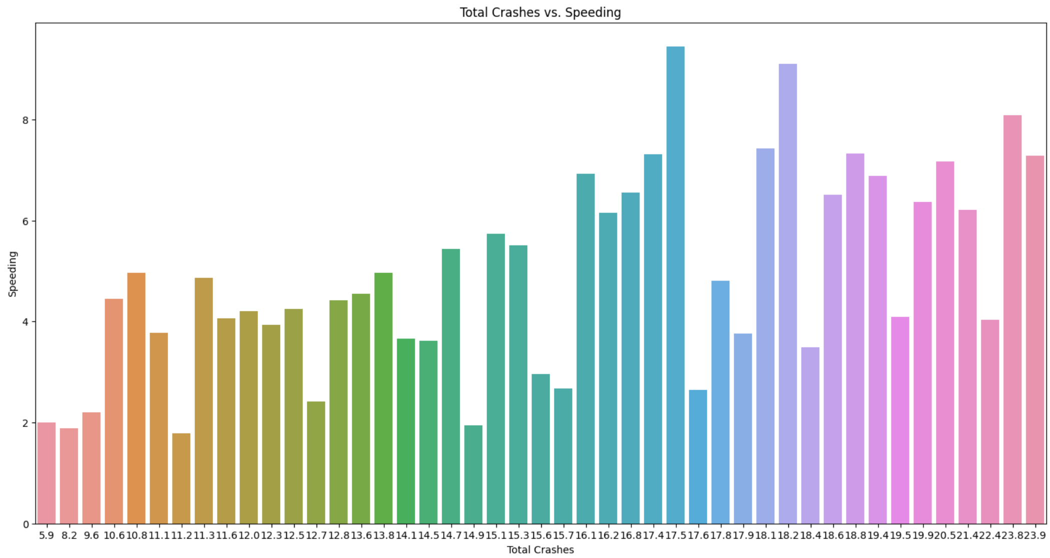
```
Text(0.5, 1.0, 'Total Crashes vs. State Abbreviation')
```




```
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
"""
```

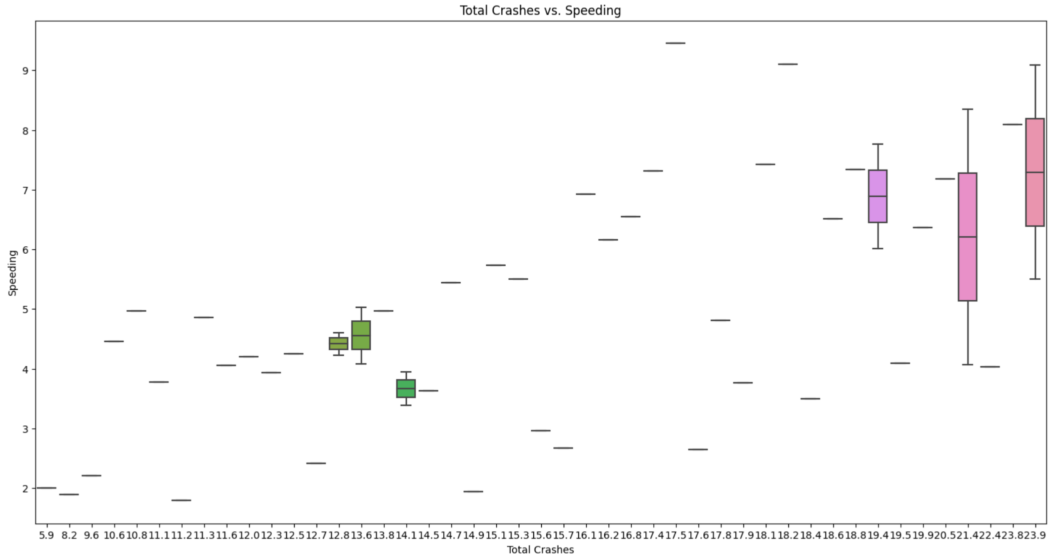
```
'\nInference:\nThe total number of crashes is represented on the x-axis, while the number of crashes i
nvolving speeding is on the y-axis.\nThe plot allows us to examine how speeding contributes to the ove
rall number of car crashes.\nAs the total number of crashes increases, there is a general trend of an
increase in the number of crashes involving speeding.\nThis suggests that as the total number of car c
rashes goes up, the proportion of crashes involving speeding also tends to increase.\nAnalyzing this r
elationship can help in understanding the impact of speeding on overall road safety and may inform tar
geted 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')
```

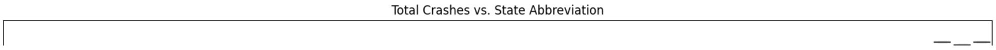
```
Text(0.5, 1.0, 'Total Crashes vs. Speeding')
```




```
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 distracte
This suggests that non-distracted drivers may be involved in more crashes, emphasizing the need for examining the causes of distraction a
"""
```

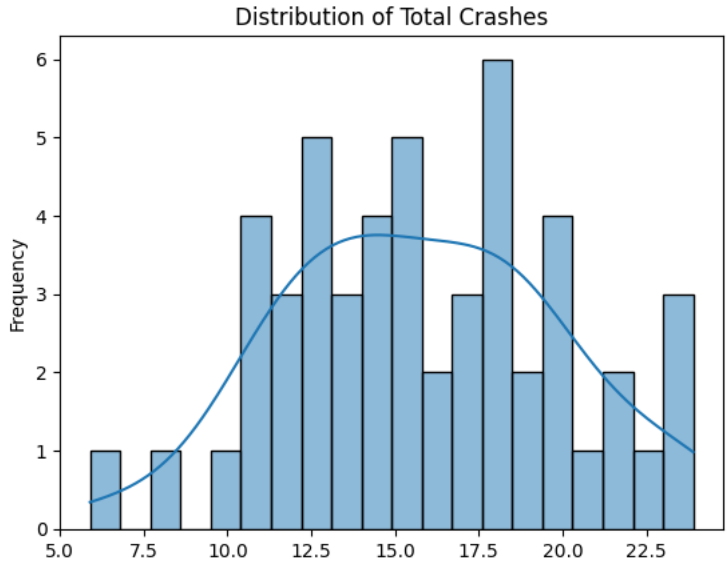
```
'\nInference :\nThe box plot illustrates the distribution of total crashes concerning the distraction
status of drivers (Not Distracted).\nIt provides insights into how distraction affects the total numbe
r of car crashes.\nThe plot shows varying total crash counts based on the distraction status,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




```
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
"""
```

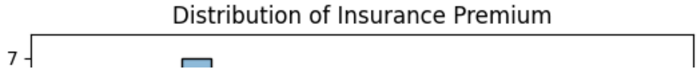
```
'\nInference :\nThe histogram displays the distribution of total car crashes.n.\nThe plot shows that t
he majority of observations fall within a relatively low range of total crashes, with a peak in freque
ncy.\nThere is a right-skewed distribution, indicating that a few instances have significantly higher
crash counts.\nThis visualization helps understand the distribution of total crashes, which can be use
ful 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 premiu
"""
```

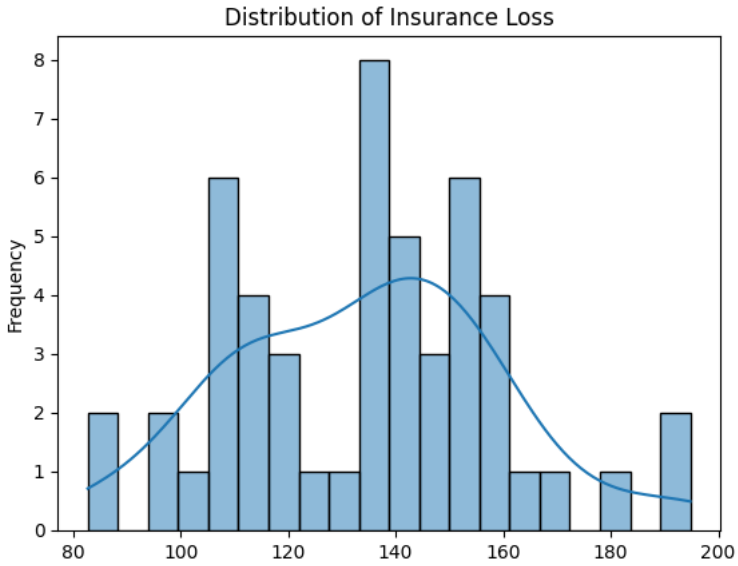
```
'\nInference :\nThe histogram depicts the distribution of insurance premiums.\nThe plot shows that the
most common insurance premium ranges have higher frequencies, forming peaks in the distribution.\nThe
distribution appears to be right-skewed, suggesting that a few observations have exceptionally high in
surance premiums.\nThis visualization aids in understanding the distribution of insurance premiums wit
hin 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 pc
"""
```

```
'\nInference :\nThe histogram represents the distribution of insurance losses.\nThe plot indicates tha
t the majority of insurance losses fall within specific ranges, with peaks in frequency.\nThe distribu
tion appears right-skewed, indicating that a few instances have considerably higher insurance losse
s.\nThis visualization helps in understanding the distribution of insurance losses within the dataset,
highlighting common loss ranges and potential outliers.\n'
```




```
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 percentag
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 state
s, represented by their abbreviations.\nEach slice of the pie represents a state, and the size of the
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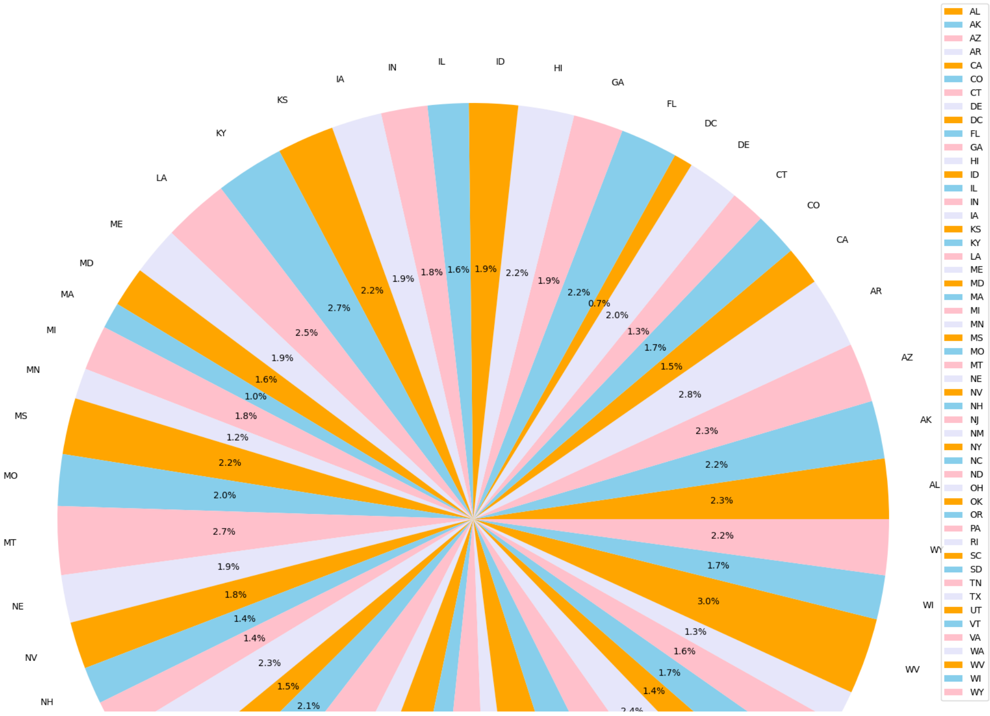
r crashes in the datase\n'
```



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')

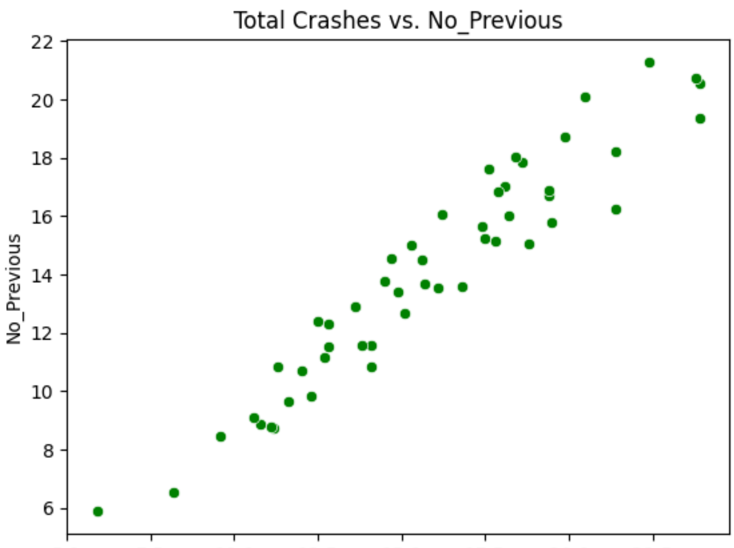
"""
Inference :
The scatter plot visualizes the relationship between the total number of car crashes and the number of crashes involving speeding.
There doesn't appear to be a strong linear relationship between total crashes and speeding incidents based on this scatter plot.
The points are scattered across the plot without a clear trend, suggesting that total crashes and speeding may not be strongly correlatec
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 a
nd 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 acr
oss the plot without a clear trend, suggesting that total crashes and speeding may not be strongly cor
related.\nFurther statistical analysis may be needed to quantify the relationship between these variab
les 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 inci
Similar to previous scatter plots, there isn't a distinct linear relationship between total crashes and crashes involving drivers with nc
The points are scattered without a clear trend, suggesting that total crashes may not directly correlate with the absence of previous inc
"""
```

```
'\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 is
n't a distinct linear relationship between total crashes and crashes involving drivers with no previou
s incidents.\nThe points are scattered without a clear trend, suggesting that total crashes may not di
rectly correlate with the absence of previous incidents in drivers. Further analysis may be needed.\n'
```



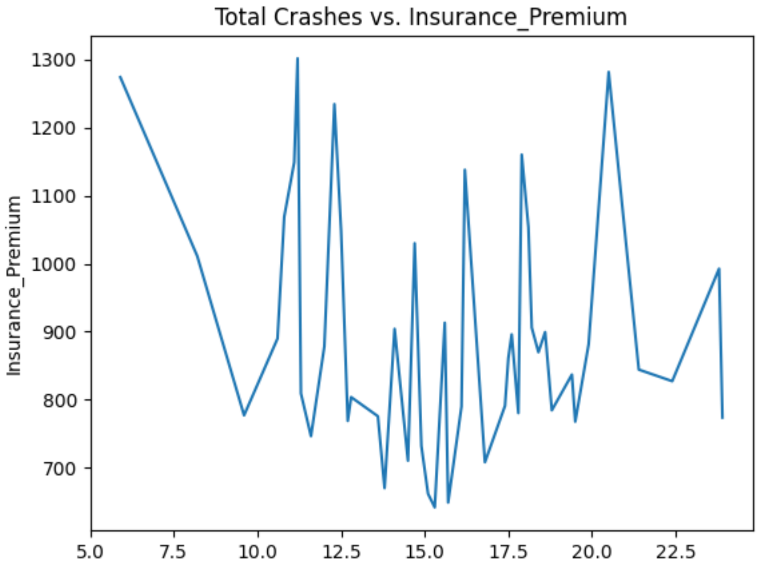

```
sns.lineplot(x="total",y="alcohol",data=df,errorbar=None)
plt.ylabel('Alcohol')
plt.xlabel('Total Crashes')
plt.title('Total Crashes vs. Alcohol')
"""
Inference :
The line plot shows the association between total car crashes and crashes involving alcohol.
It visualizes how alcohol-related crashes 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 furt
"""
```

```
'\nInference :\nThe line plot shows the association between total car crashes and crashes involving al
cohol.\nIt visualizes how alcohol-related crashes fluctuate concerning the total number of crashes.\nT
here isn't a clear linear relationship; the points on the line are scattered without a distinct patter
n.\nThis suggests that the total number of crashes may not have a straightforward correlation with alc
```

```
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
"""
```

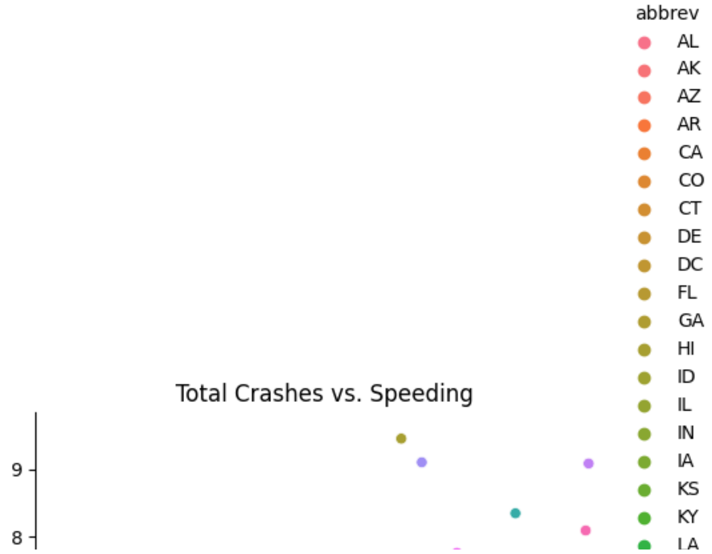
```
'\nInference :\nThe line plot represents the relationship between total car crashes and insurance prem
iums.\nIt visualizes how insurance premiums vary in relation to the total number of crashes.\nThe plot
does not show a clear linear trend; points on the line are scattered without a clear pattern.\nThis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




```
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 st
There is no clear linear trend; points are scattered without a distinct pattern, indicating that the relationship between total crashes a
"""
```

```
'\nInference :\nThe relational plot ("relplot") displays the relationship between total car crashes an
d crashes involving speeding.\nEach point represents a data point in the dataset, with different state
s distinguished by colors (hue).\nThe plot allows for a quick visual assessment of how speeding-relate
d crashes vary concerning the total number of crashes in different states.\nThere is no clear linear t
rend; 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'
```




```
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 be
"""
```

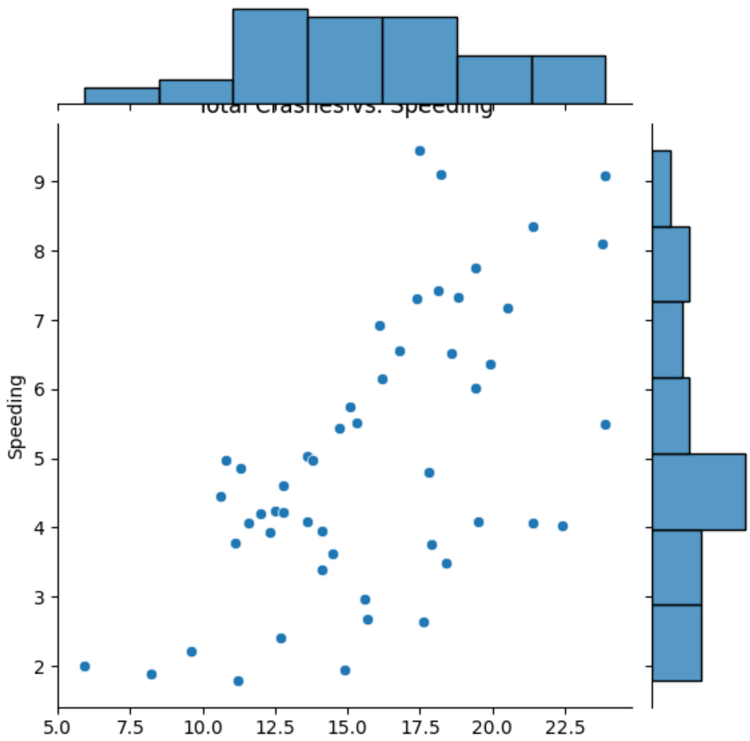
```
'\nInference :\nThe relational plot ("relplot") illustrates the relationship between total car crashes
and crashes involving alcohol.\nEach point on the plot represents a data point in the dataset, and dif
ferent states are color-coded for comparison (hue).\nThe plot provides a visual comparison of how alco
hol-related crashes vary with the total number of crashes in different states.\nThere isn\'t a clear l
inear 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-spe
cific analysis may be needed to explore this further.\n'
```

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.
"""
```

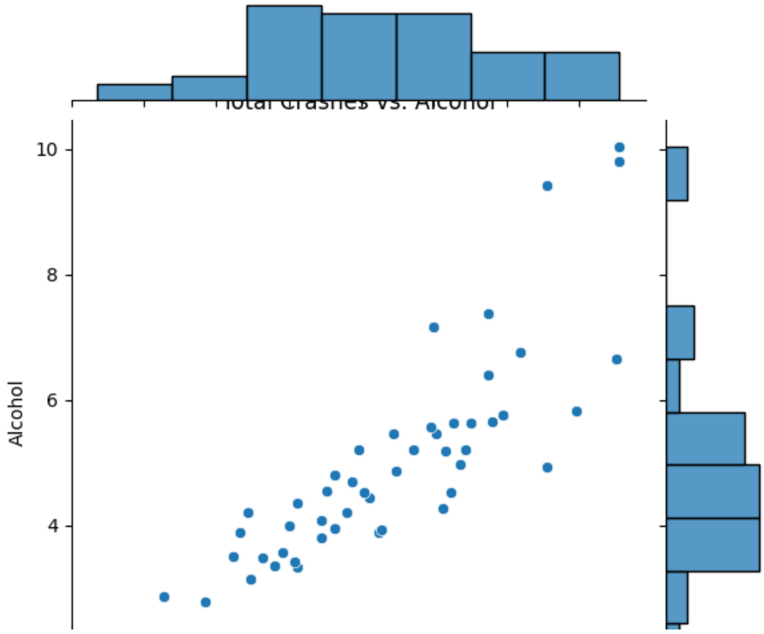
```
'\nInference :\nThe joint plot displays the relationship between total car crashes and crashes involvi
ng speeding.\nIt combines a scatter plot and histograms to visualize the distribution and correlation
between the two variables.\nThe scatter plot shows that there isn't a strong linear relationship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




```
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 invol
ving 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 relati
onship 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-24-f8732931ad62>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
  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	ins_premium	ins_losses
total	1.000000	0.611548	0.852613	0.827560	0.956179	-0.199702	-0.036011
speeding	0.611548	1.000000	0.669719	0.588010	0.571976	-0.077675	-0.065928
alcohol	0.852613	0.669719	1.000000	0.732816	0.783520	-0.170612	-0.112547
not_distracted	0.827560	0.588010	0.732816	1.000000	0.747307	-0.174856	-0.075970
no_previous	0.956179	0.571976	0.783520	0.747307	1.000000	-0.156895	-0.006359
ins_premium	-0.199702	-0.077675	-0.170612	-0.174856	-0.156895	1.000000	0.623116
ins_losses	-0.036011	-0.065928	-0.112547	-0.075970	-0.006359	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.
"""
```

```
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