21BCE7247_Indhu_Assignment-2_Data_Visualization

September 13, 2023

0.1 Importing Libraries

[1]:
```
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

0.2 Loading Dataset Car_Crashes

[2]:
```
df = pd.read_csv('car_crashes.csv')
```

[3]:
```
df
```

[3]:

	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

0.2.1 Description of Car_Crashes DataSet

Each row represents data for a specific entity or state.

Description of the columns in the dataset is as follows:

total: Total number or rate related to car crashes.

speeding: Data related to speeding and its impact on car crashes.

alcohol: Data related to alcohol consumption and its impact on car crashes.

not_distracted: Data related to being not distracted while driving and its impact on car crashes.

no_previous: Data related to having no previous incidents and its impact on car crashes.

ins_premium: Insurance premium data.

ins_losses: Insurance losses data.

abbrev: Abbreviation or code for the state or entity.

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

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

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

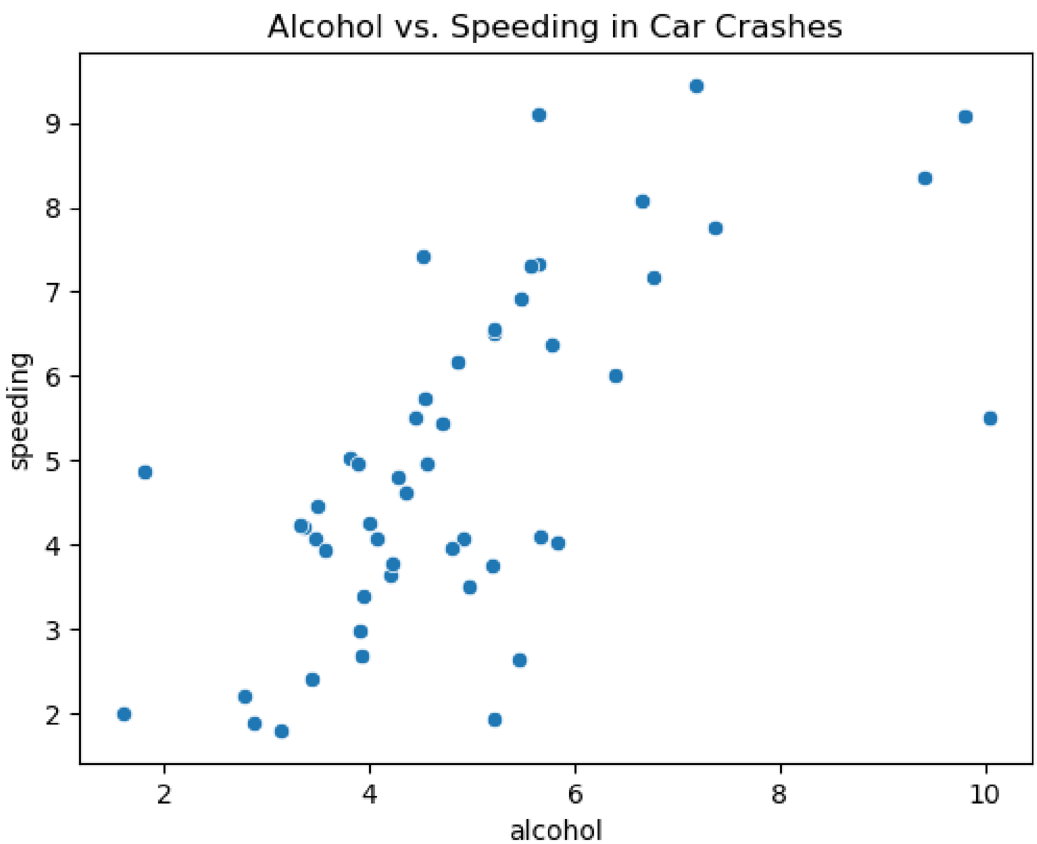
[5]:
```
   total  speeding  alcohol  not_distracted  no_previous  ins_premium  \
0   18.8     7.332    5.640          18.048       15.040       784.55
1   18.1     7.421    4.525          16.290       17.014      1053.48
2   18.6     6.510    5.208          15.624       17.856       899.47
3   22.4     4.032    5.824          21.056       21.280       827.34
4   12.0     4.200    3.360          10.920       10.680       878.41

   ins_losses abbrev
0      145.08     AL
1      133.93     AK
2      110.35     AZ
3      142.39     AR
4      165.63     CA
```

0.3 Data Visualization with Inference

- Scatter Plot

[6]:
```
sns.scatterplot(x="alcohol", y="speeding", data=df)
plt.title("Alcohol vs. Speeding in Car Crashes")
```

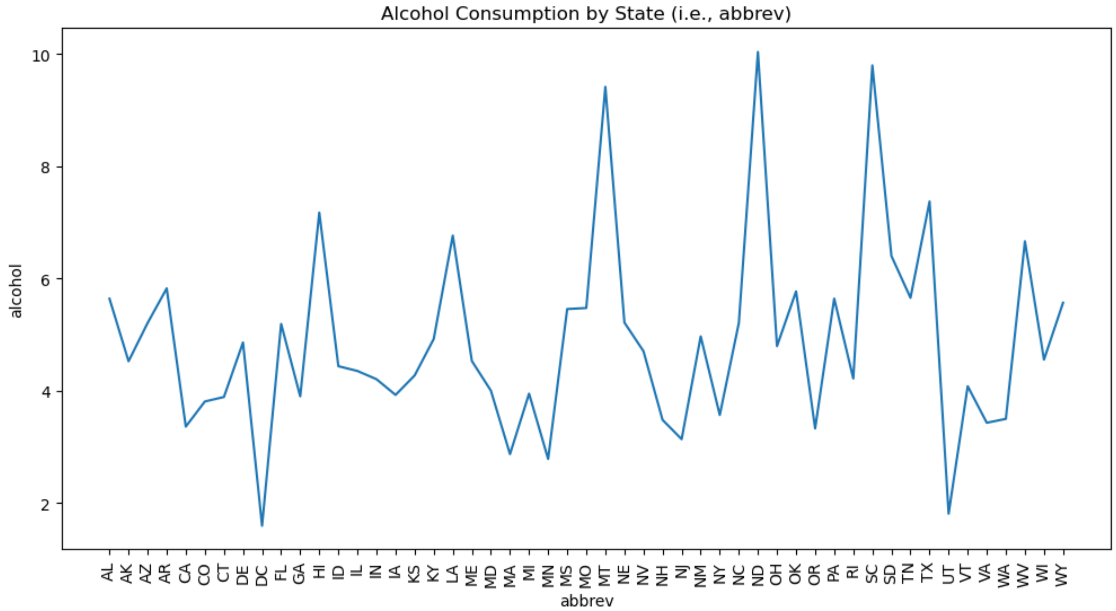
[6]:
```
Text(0.5, 1.0, 'Alcohol vs. Speeding in Car Crashes')
```



Inference: The scatter plot shows a positive correlation between alcohol consumption and speeding involvement in car crashes, stating that higher alcohol consumption tend to have higher speeding involvement.

- Line Plot

[7]:
```
plt.figure(figsize=(12, 6))
sns.lineplot(x='abbrev', y='alcohol', data=df)
plt.title('Alcohol Consumption by State (i.e., abbrev)')
plt.xticks(rotation=90)
plt.show()
```



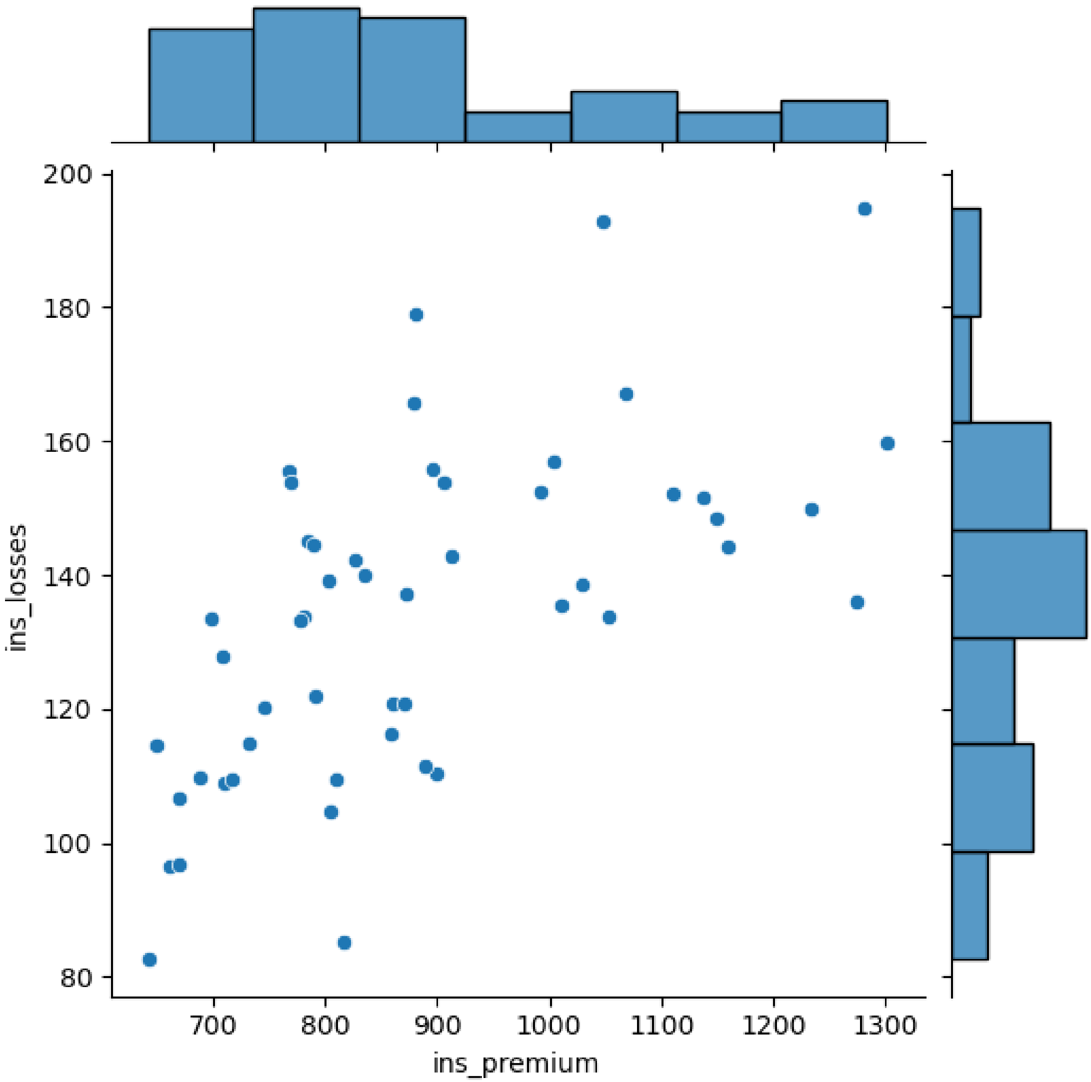
Inference: The line plot shows the alcohol consumption of each state (abbrev). It appears that state (abbrev) “ND” has the highest alcohol consumption among the observed states.

- Joint Plot

[8]:
```
plt.figure(figsize=(12, 8))
sns.jointplot(x='ins_premium', y='ins_losses', data=df)
```

[8]:
```
<seaborn.axisgrid.JointGrid at 0x19e3a160310>
```

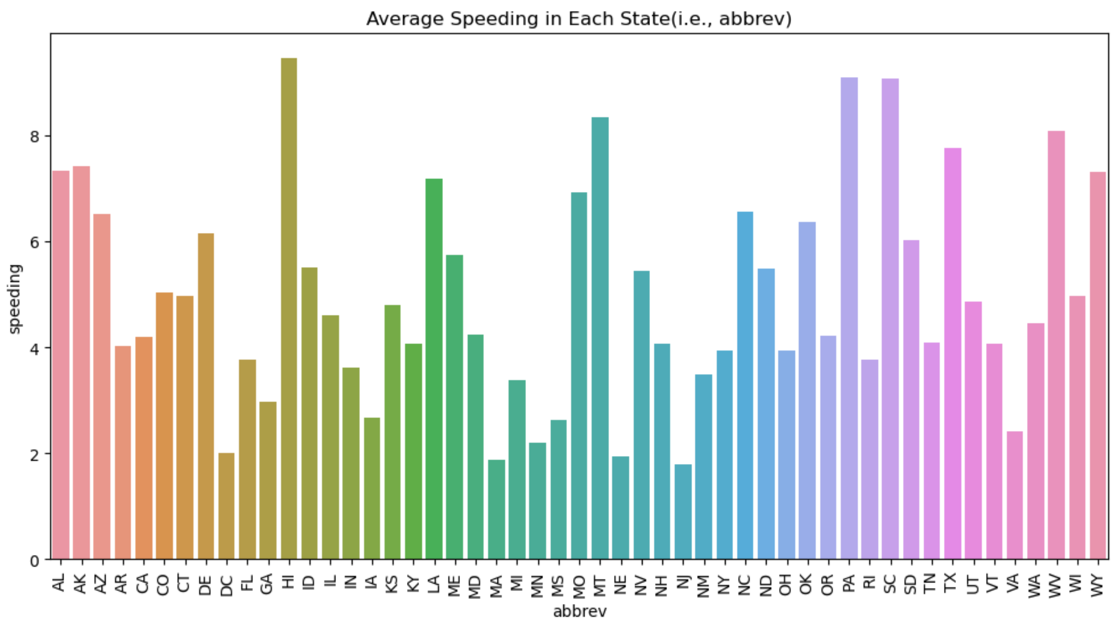
```
<Figure size 1200x800 with 0 Axes>
```



Inference: The joint plot displays the bivariate relationship between insurance premium and losses.The lower insurance premiums is associated with lower insurance losses.

- Bar Plot

[9]:
```
plt.figure(figsize=(12, 6))
sns.barplot(x='abbrev', y='speeding', data=df)
plt.title('Average Speeding in Each State(i.e., abbrev)')
plt.xticks(rotation=90)
plt.show()
```

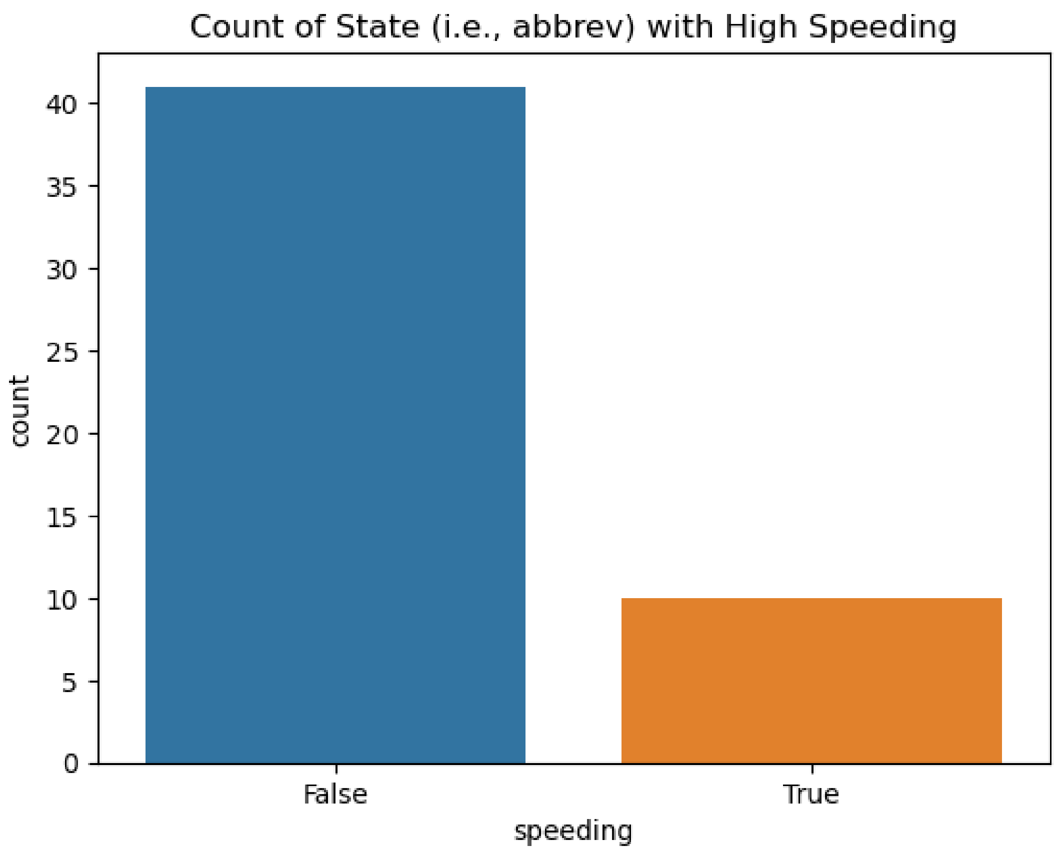


Inference: state (abbrev) "NJ" has the lowest speeding, while state "HI" has the highest average speeding among the state (abbrev).

- Count Plot

[10]:
```
sns.countplot(x=df['speeding'] > 7)
plt.title('Count of State (i.e., abbrev) with High Speeding')
```

[10]: `Text(0.5, 1.0, 'Count of State (i.e., abbrev) with High Speeding')`

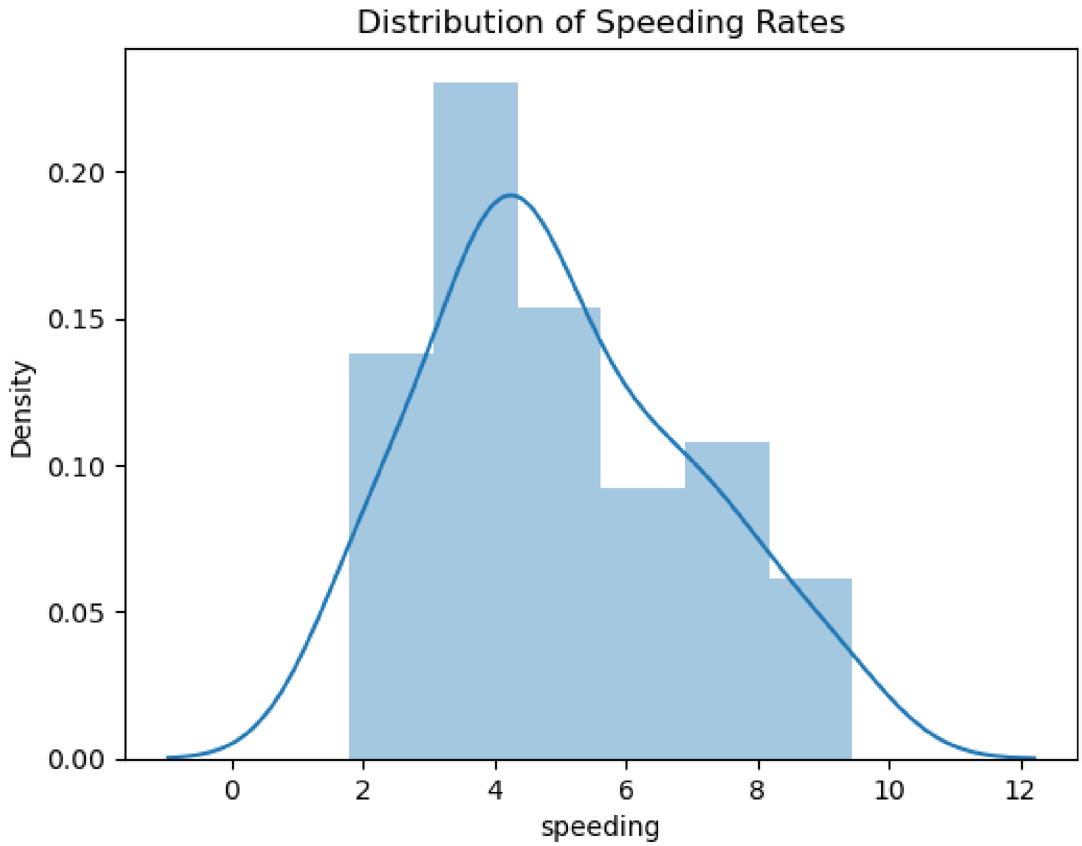


Inference: The count plot shows that a significant number of states (abbrev) have low speeding rates (speeding < 7). This states that a substantial portion of the states (abbrev) has below-average speeding behavior.

- Distribution Plot

[21]:
```
sns.distplot(df['speeding'])
plt.title('Distribution of Speeding Rates')
```

[21]: Text(0.5, 1.0, 'Distribution of Speeding Rates')

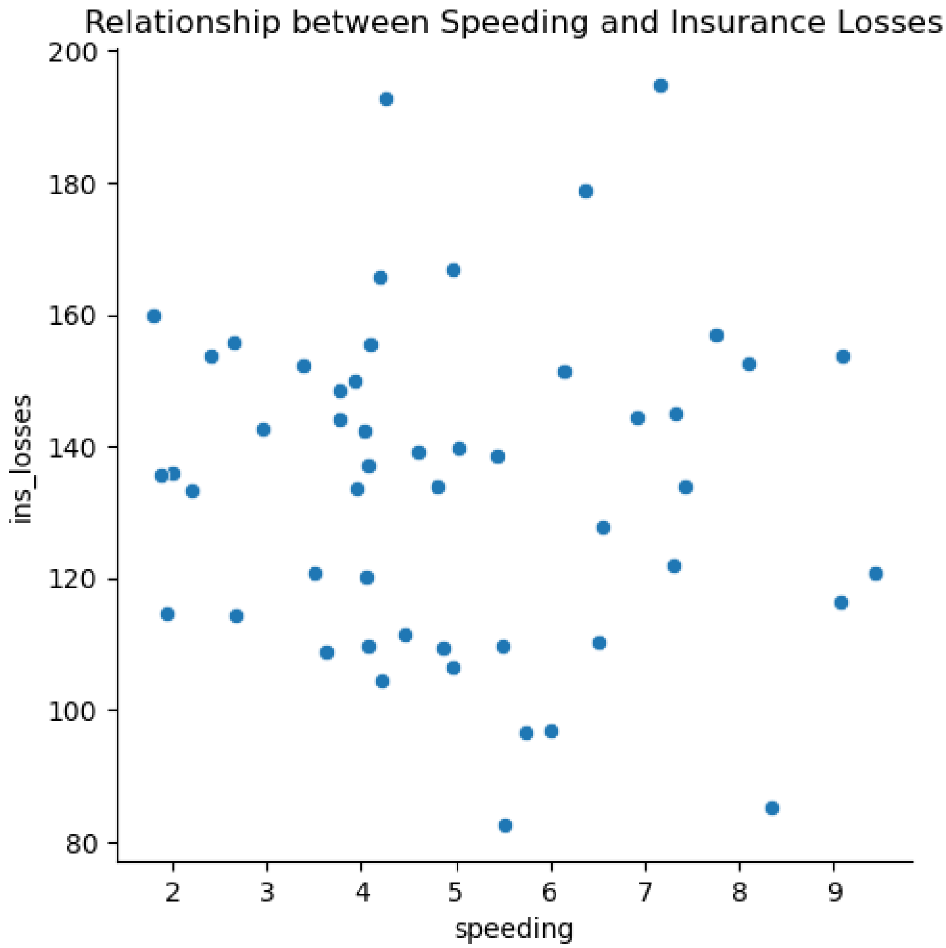


Inference: This displot provides a visual representation of the distribution of speeding rates across the dataset. It states that the distribution is right-skewed, indicating that a majority of the observed data points have lower speeding rates (speeding < 7) , while a smaller number of data points have higher speeding rates.

- Relationship Plot

[12]:
```
sns.relplot(x='speeding', y='ins_losses', data=df)
plt.title('Relationship between Speeding and Insurance Losses')
```

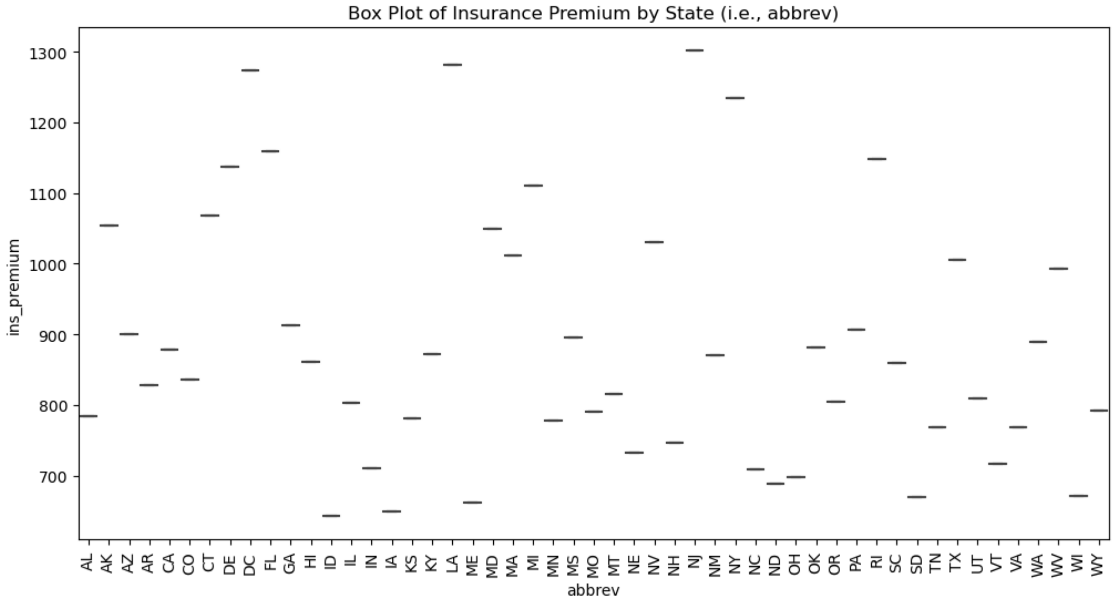
[12]:
```
Text(0.5, 1.0, 'Relationship between Speeding and Insurance Losses')
```



Inference :- There is a positive correlation between speeding and insurance losses. States (abbrev) with higher average speeding tend to have higher insurance losses.

- Box Plot

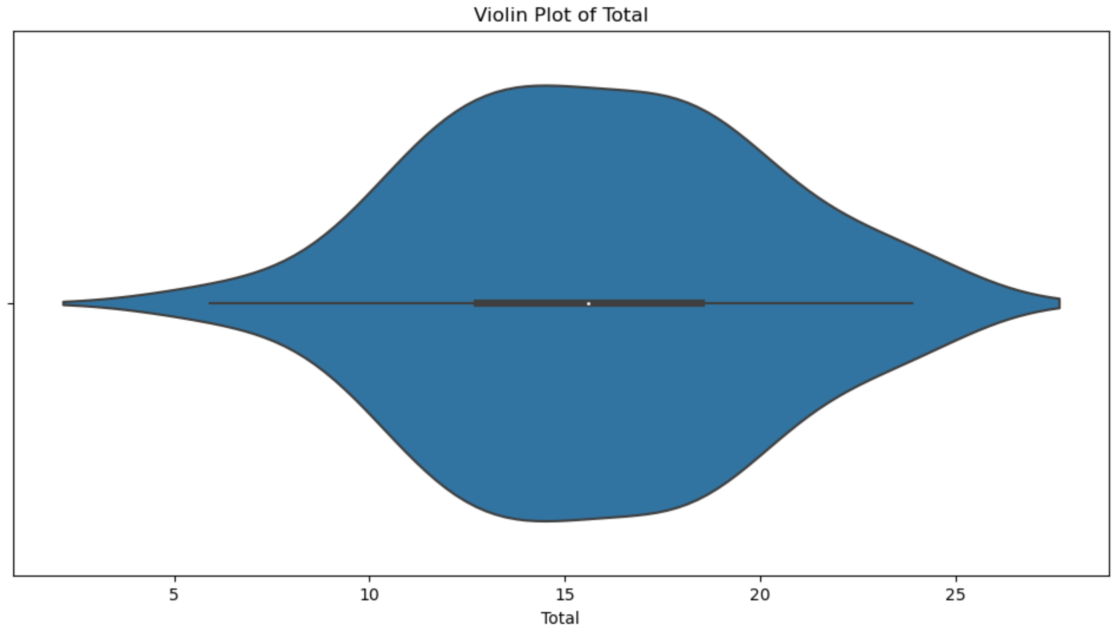
[13]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(x='abbrev', y='ins_premium', data=df)
plt.title('Box Plot of Insurance Premium by State (i.e., abbrev)')
plt.xticks(rotation=90)
plt.show()
```



Inference :- The box plot shows the distribution of insurance premiums by state. It highlights variations in ins_premium amounts across different states, with some states having higher ins_premiums.

- Violin Plot

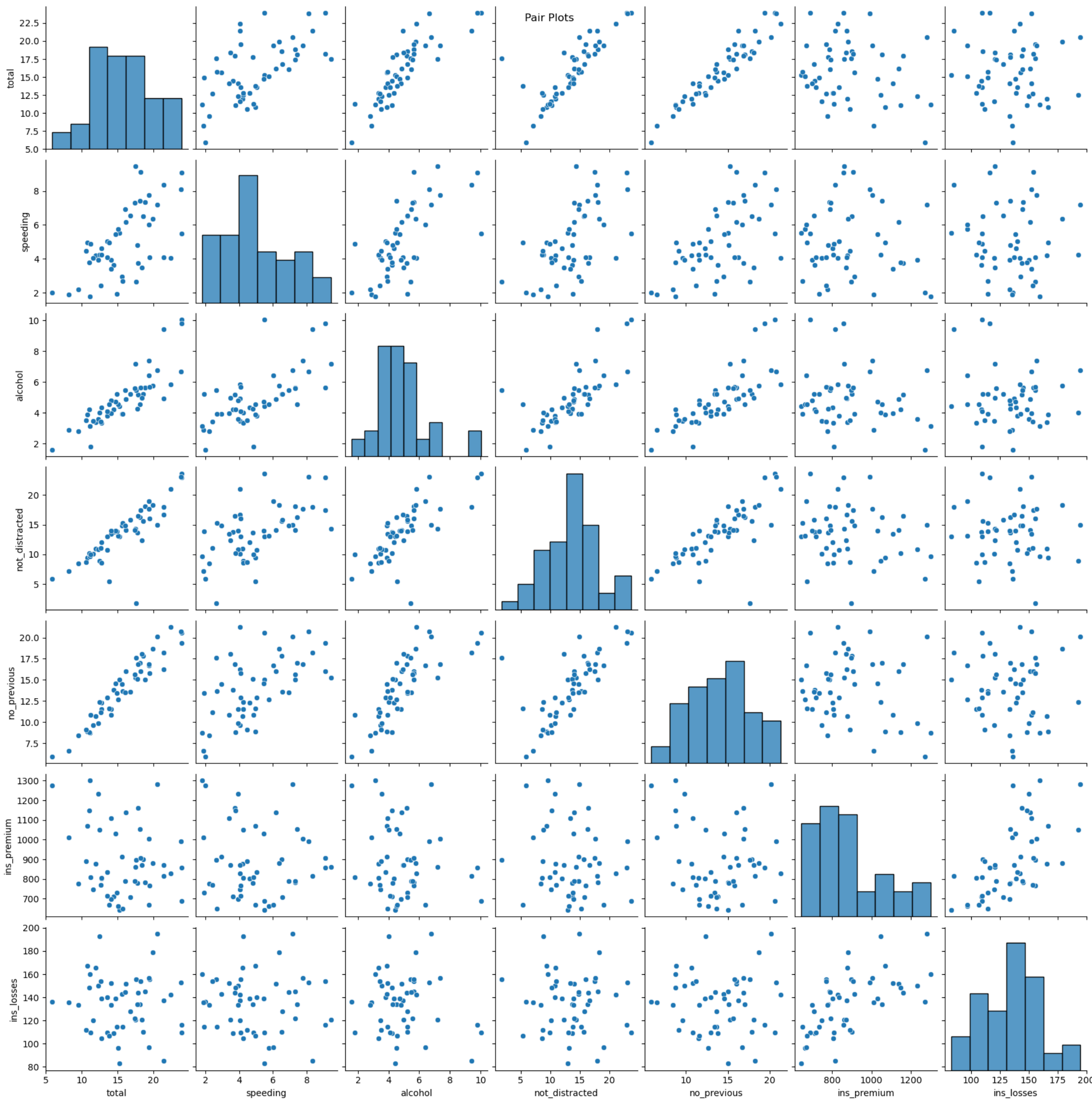
[14]:
```
plt.figure(figsize=(12, 6))
sns.violinplot(x=df["total"])
plt.title('Violin Plot of Total')
plt.xlabel('Total')
plt.show()
```



Inference :- The white dot in the center of the violin represents the median value i.e., 15.6.The violin appears to be roughly symmetrical, indicating that the data distribution is somewhat balanced.

- Pair Plot

[15]:
```
sns.pairplot(df[['total', 'speeding', 'alcohol', 'not_distracted',␣
↪'no_previous', 'ins_premium', 'ins_losses']])
plt.suptitle('Pair Plots')
plt.show()
```

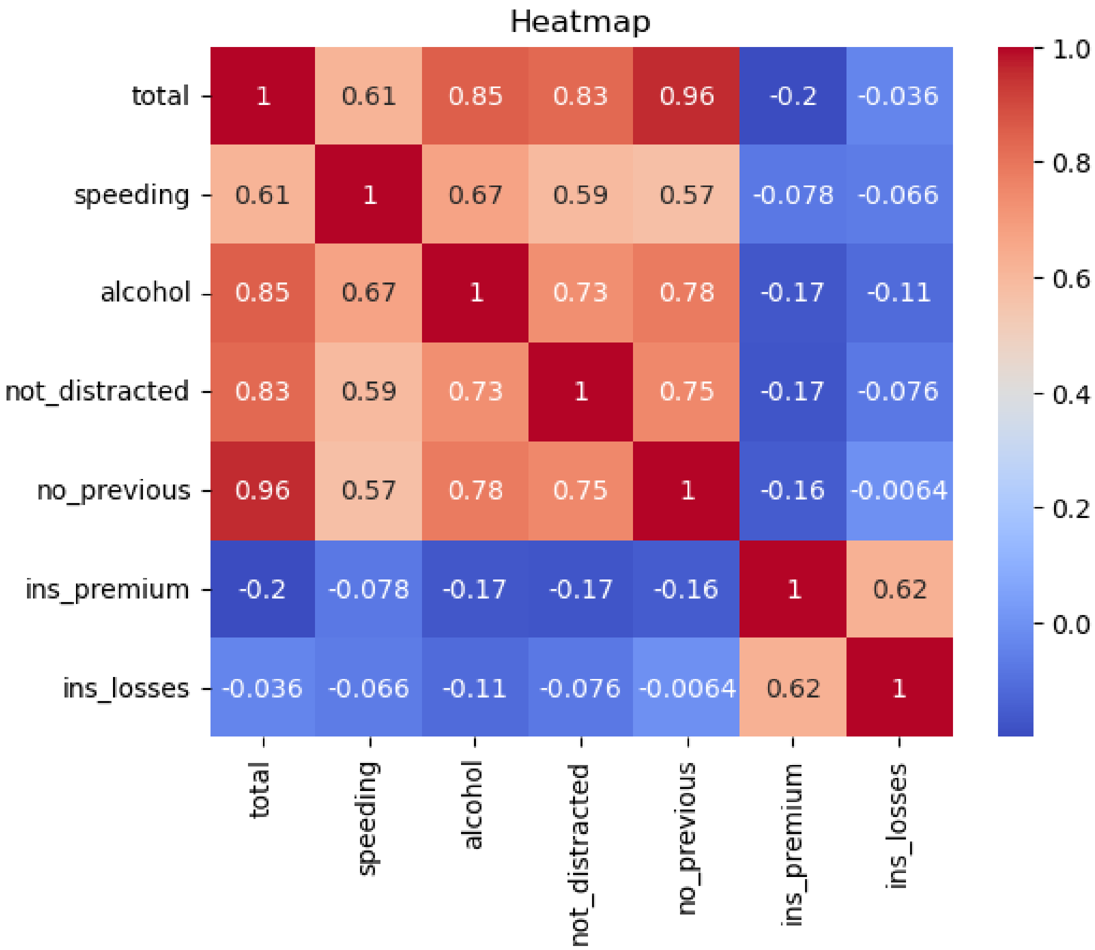


Inference :- This pair plot displays pairwise scatter plots for selected columns (total,speeding, alcohol, not_distracted,no_previous,ins_premium, ins_losses). It allows for the visualization of relationships between these variables.

- HeatMap

[20]:
```
corr=df.corr()
sns.heatmap(corr, annot=True, cmap="coolwarm")
plt.title("Heatmap")
```

[20]: Text(0.5, 1.0, 'Heatmap')



Inference:- From the heatmap,we can state that the alcohol consumption and speeding have a more significant influence on the total number of car crashes that occur.