21BCE8975 - Assignment-2

September 14, 2023

0.1 Assignment-2

Name: Chigulla Somu Vinay Raj

Registration number: 21BCE8975

Email: vinayraj.21bce8975@vitapstudent.ac.in

Mobile Number: 9491604860

0.1.1 import seaborn and matplotlib.pyplot

[1]:

```
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:

```
df=sns.load_dataset("car_crashes")
df
```

[2]:

```
    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
```

[3]:

```
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
```

[4]:

```
df.head()
```

[4]:

```
   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
```

0.1.2 Heat map

[5]:

```
corr=df.corr()
corr
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_11292\3182140910.py: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()
```

[5]:

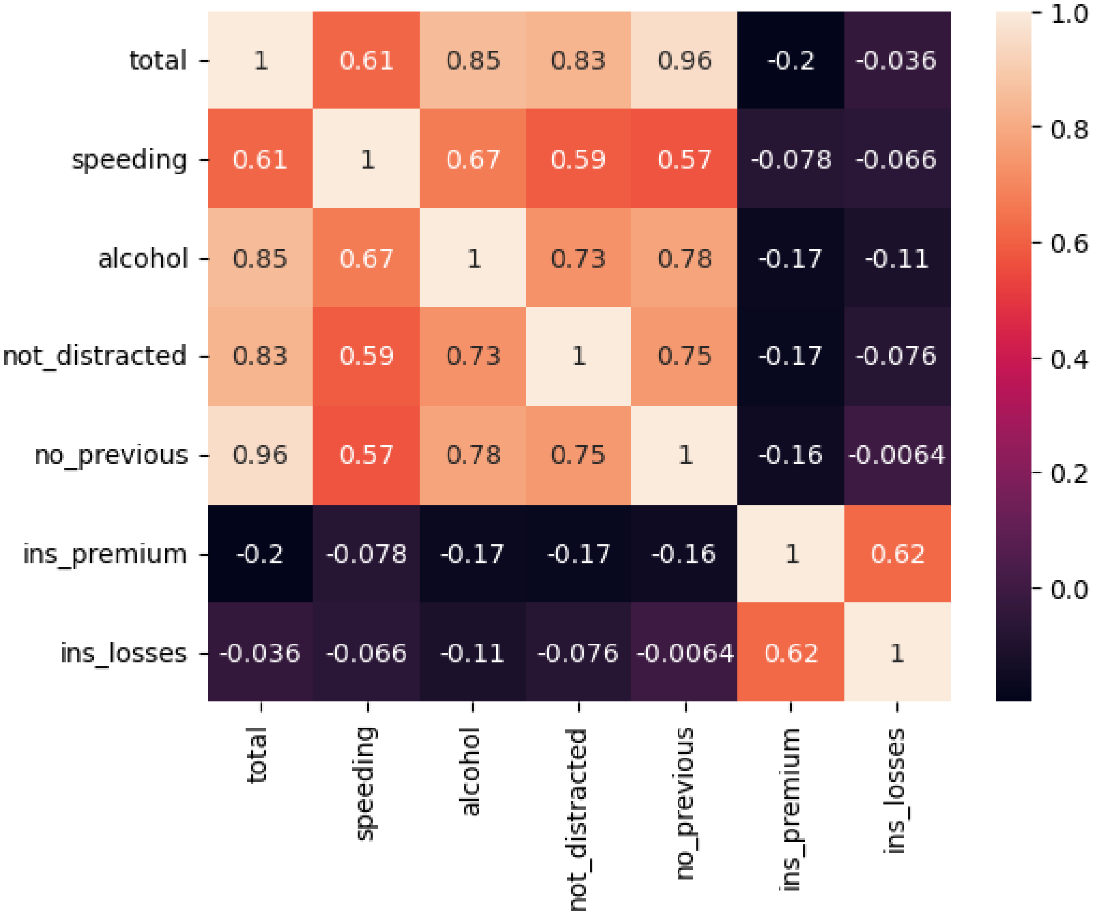
```
                   total  speeding   alcohol  not_distracted  no_previous  \
total           1.000000  0.611548  0.852613        0.827560     0.956179
speeding        0.611548  1.000000  0.669719        0.588010     0.571976
alcohol         0.852613  0.669719  1.000000        0.732816     0.783520
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
```

[6]:
```
sns.heatmap(corr,annot=True)
```

[6]:
```
<Axes: >
```



[7]:
```
df.isnull().any()
```

[7]:
```
total             False
speeding          False
alcohol           False
not_distracted    False
no_previous       False
ins_premium       False
ins_losses        False
abbrev            False
```

```
dtype: bool
```

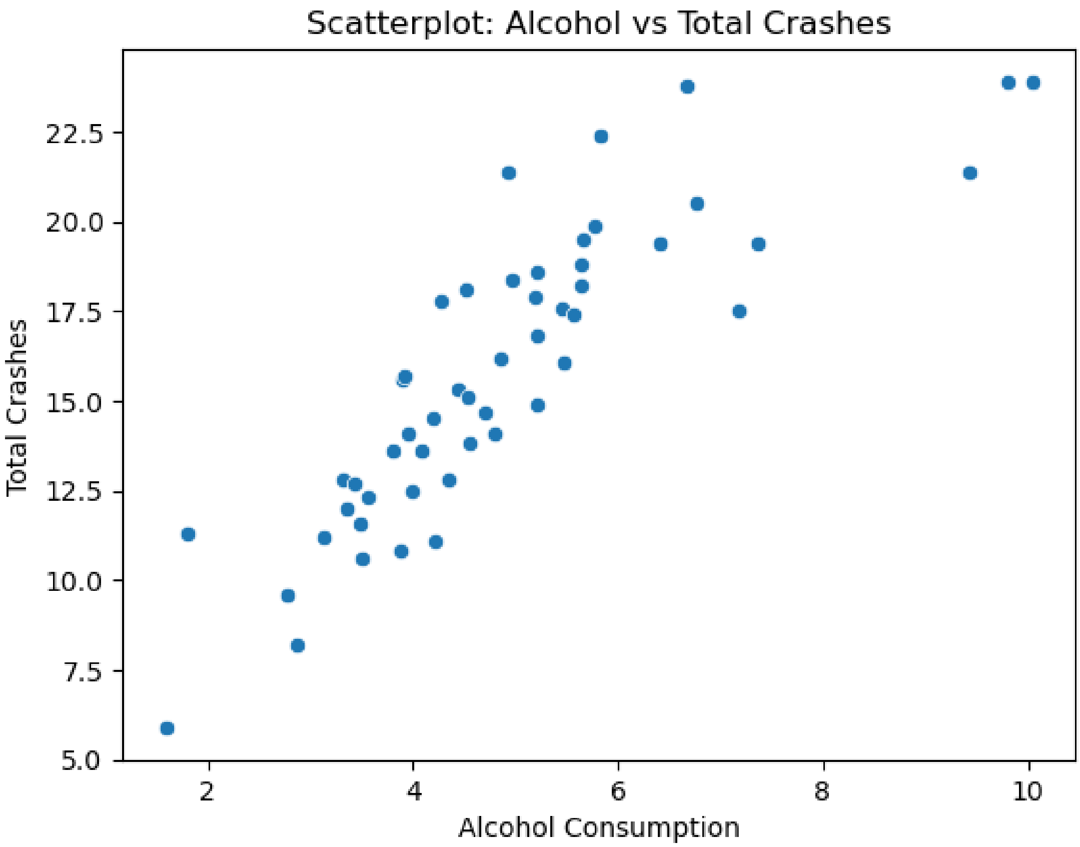
[8]:
```
df.isnull().sum()
```

[8]:
```
total             0
speeding          0
alcohol           0
not_distracted    0
no_previous       0
ins_premium       0
ins_losses        0
abbrev            0
dtype: int64
```

0.1.3 Scatter Plot

[9]:
```
sns.scatterplot(x="alcohol", y="total", data=df)
plt.title("Scatterplot: Alcohol vs Total Crashes")
plt.xlabel("Alcohol Consumption")
plt.ylabel("Total Crashes")
```

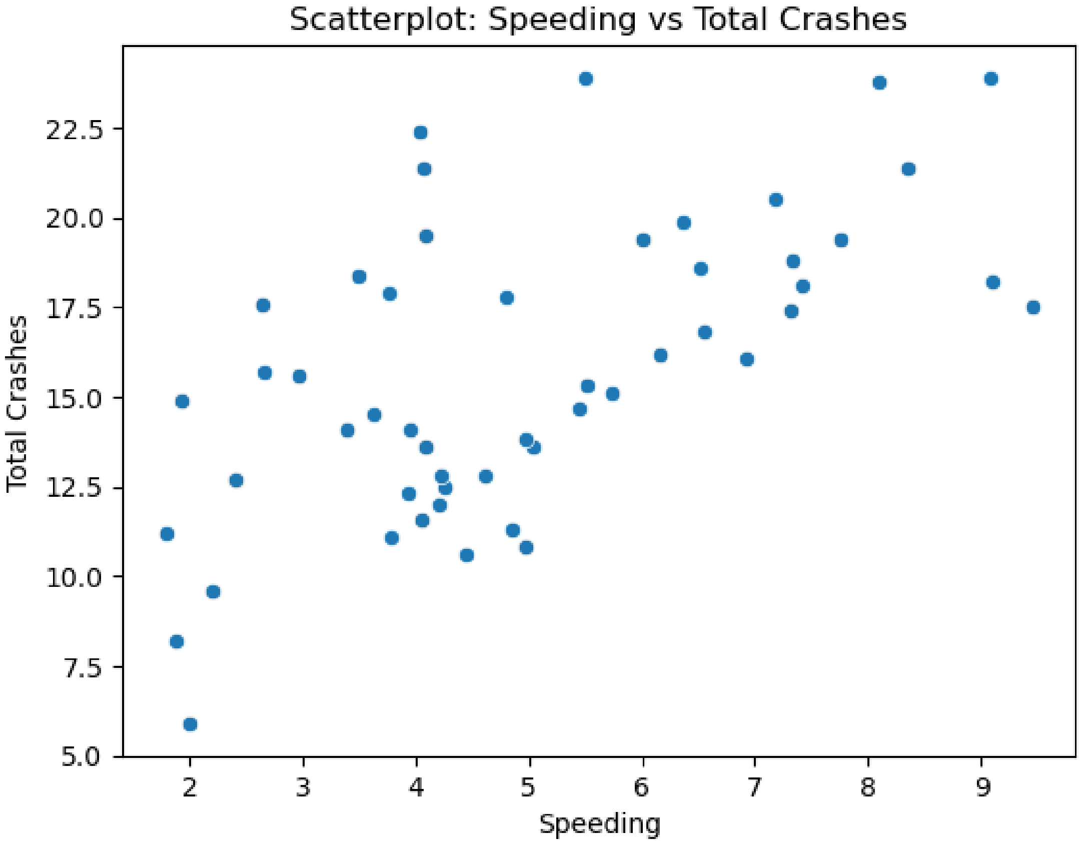
[9]:
```
Text(0, 0.5, 'Total Crashes')
```



Inference: Positive correlation between alcohol consumption and total crashes from the above plot, i.e as the alcohol consumption increases the total crashes increases.

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

```
[10]: Text(0, 0.5, 'Total Crashes')
```

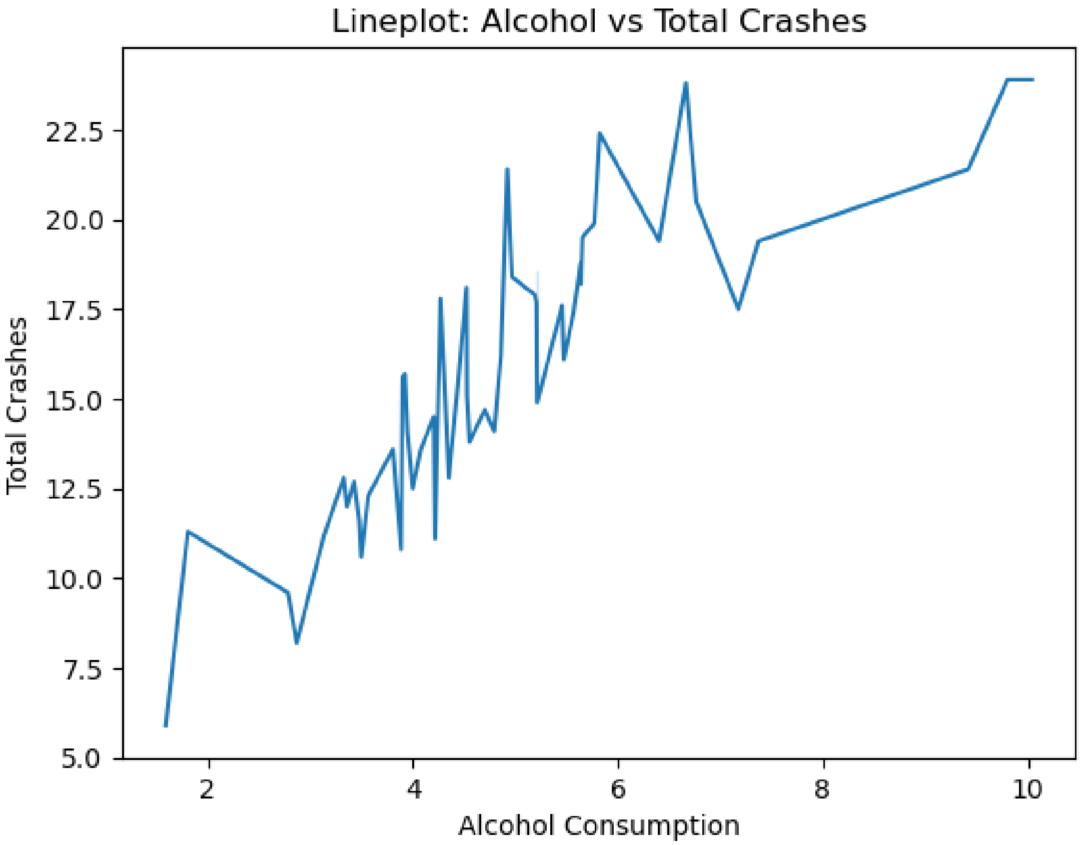


Inference: Speeding and total crashes doesn't have a proper linear trend.

0.1.4 Linear Plot

```
[11]: sns.lineplot(x="alcohol", y="total", data=df)
      plt.title("Lineplot: Alcohol vs Total Crashes")
      plt.xlabel("Alcohol Consumption")
      plt.ylabel("Total Crashes")
```

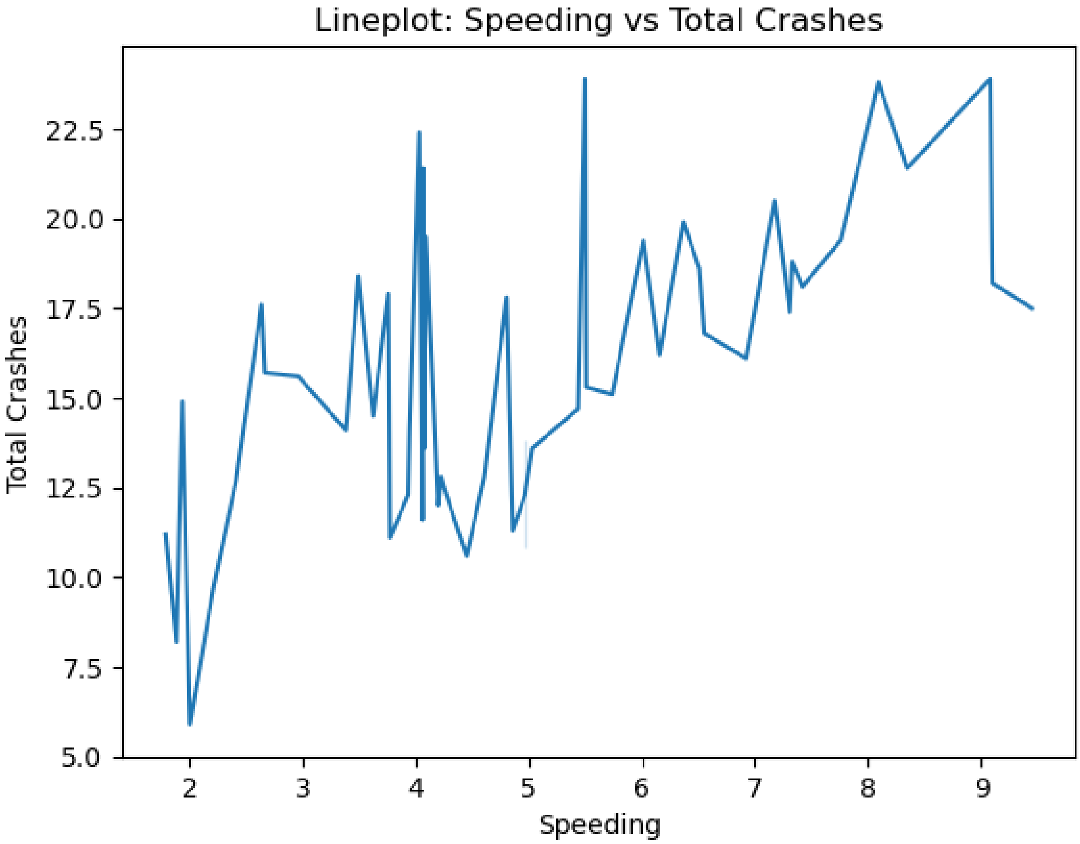
```
[11]: Text(0, 0.5, 'Total Crashes')
```



Inference: No obvious linear trend between alcohol consumption and total crashes.

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

```
[12]: Text(0, 0.5, 'Total Crashes')
```

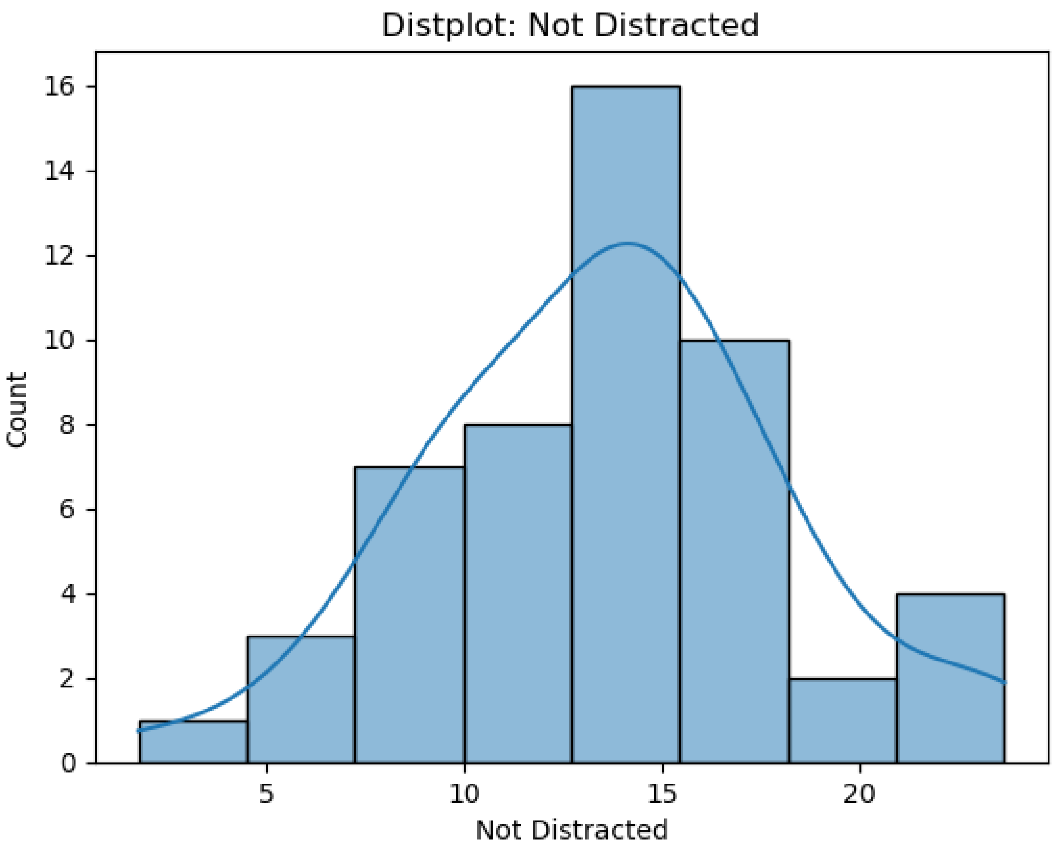


Inference: Speeding doesn't exhibit a consistent linear relationship with total crashes.

0.1.5 Distribution Plot

```
[13]: sns.histplot(df["not_distracted"], kde=True)
      plt.title("Distplot: Not Distracted")
      plt.xlabel("Not Distracted")
```

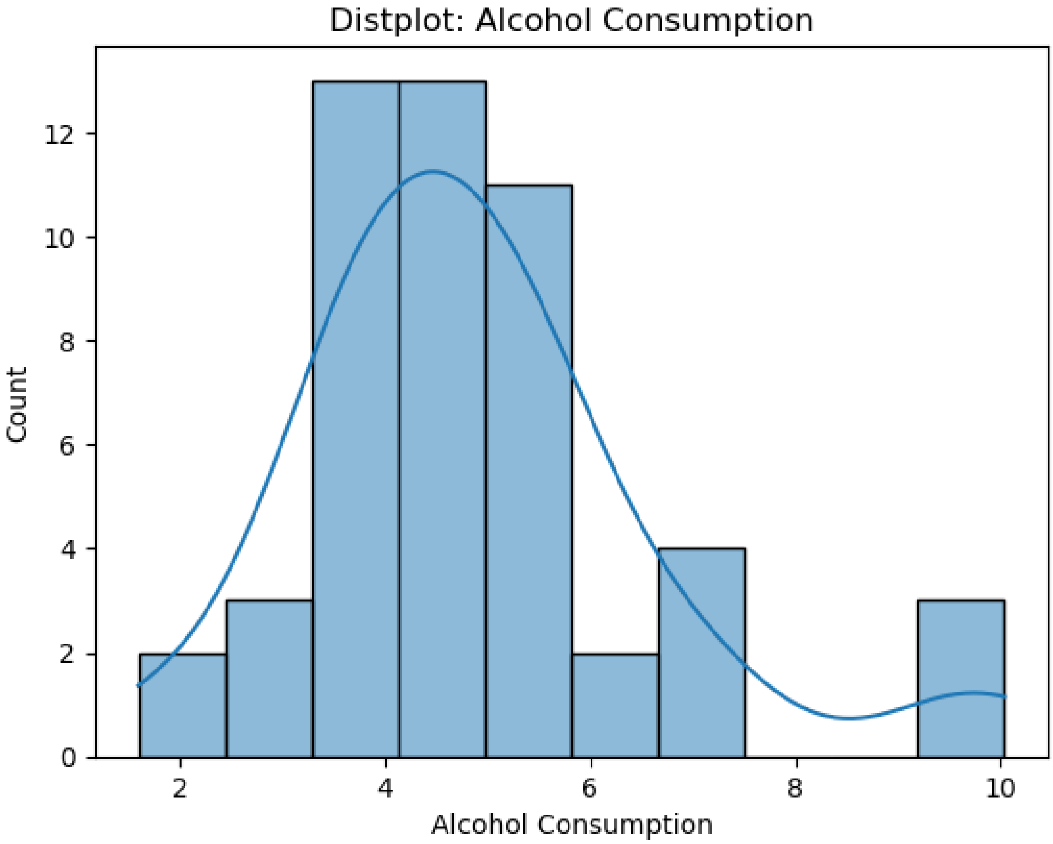
```
[13]: Text(0.5, 0, 'Not Distracted')
```



Inference: The distribution of “not_distracted” values is right-skewed

```
[14]: sns.histplot(df["alcohol"], kde=True)
      plt.title("Distplot: Alcohol Consumption")
      plt.xlabel("Alcohol Consumption")
```

```
[14]: Text(0.5, 0, 'Alcohol Consumption')
```

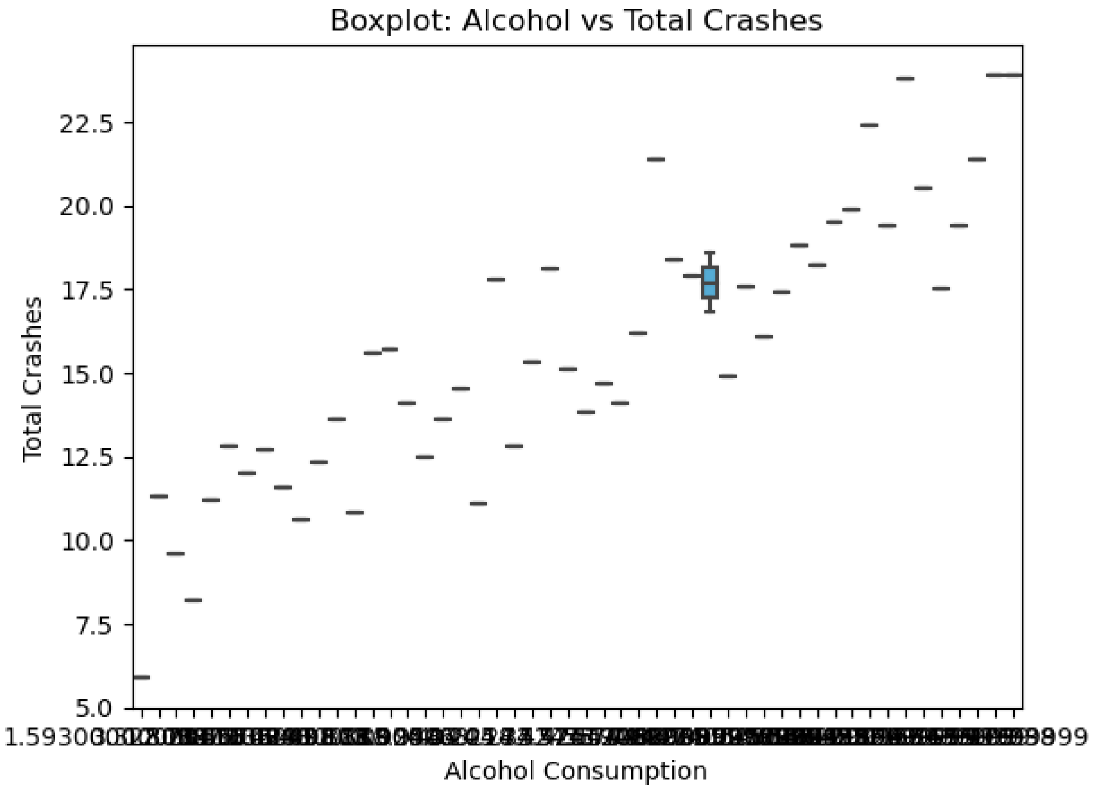


Inference: The distribution of alcohol consumption appears to be right-skewed as well

0.1.6 Box Plot

[15]:
```
sns.boxplot(x="alcohol", y="total", data=df)
plt.title("Boxplot: Alcohol vs Total Crashes")
plt.xlabel("Alcohol Consumption")
plt.ylabel("Total Crashes")
```

[15]:
```
Text(0, 0.5, 'Total Crashes')
```



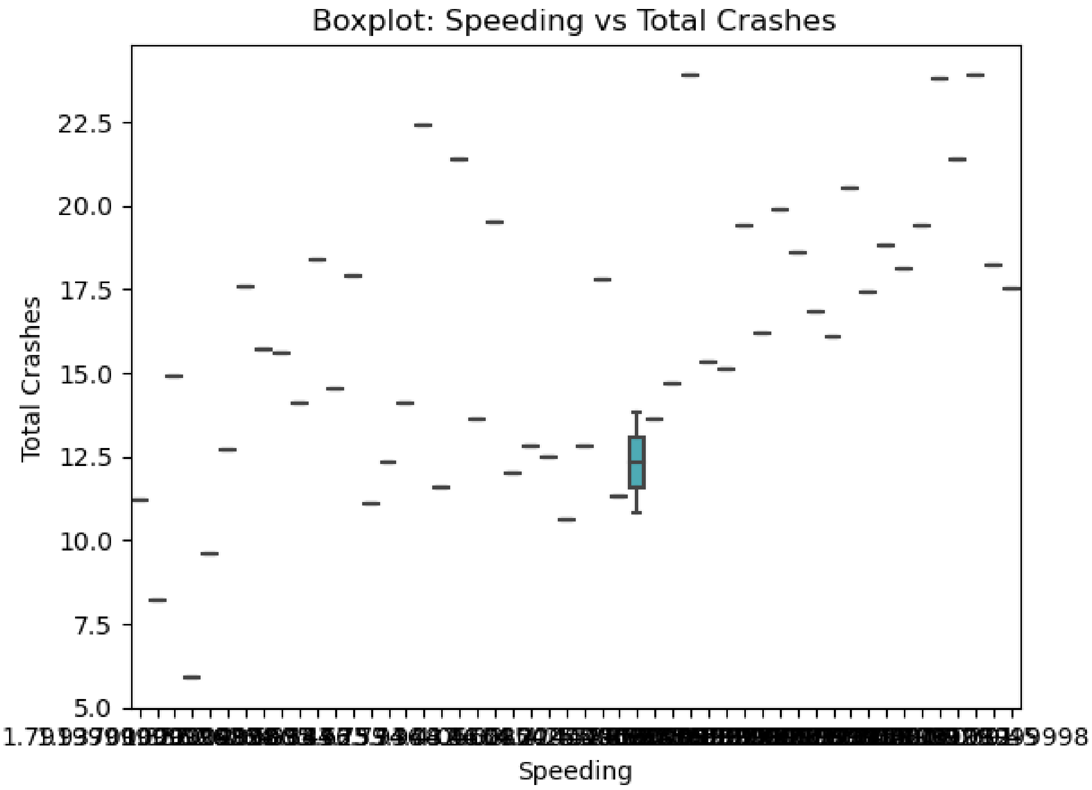
Inference: The boxplot shows the distribution of total crashes for different levels of alcohol consumption. The lines indicates the outliers

[16]:

```
sns.boxplot(x="speeding", y="total", data=df)
plt.title("Boxplot: Speeding vs Total Crashes")
plt.xlabel("Speeding")
plt.ylabel("Total Crashes")
```

[16]:

```
Text(0, 0.5, 'Total Crashes')
```

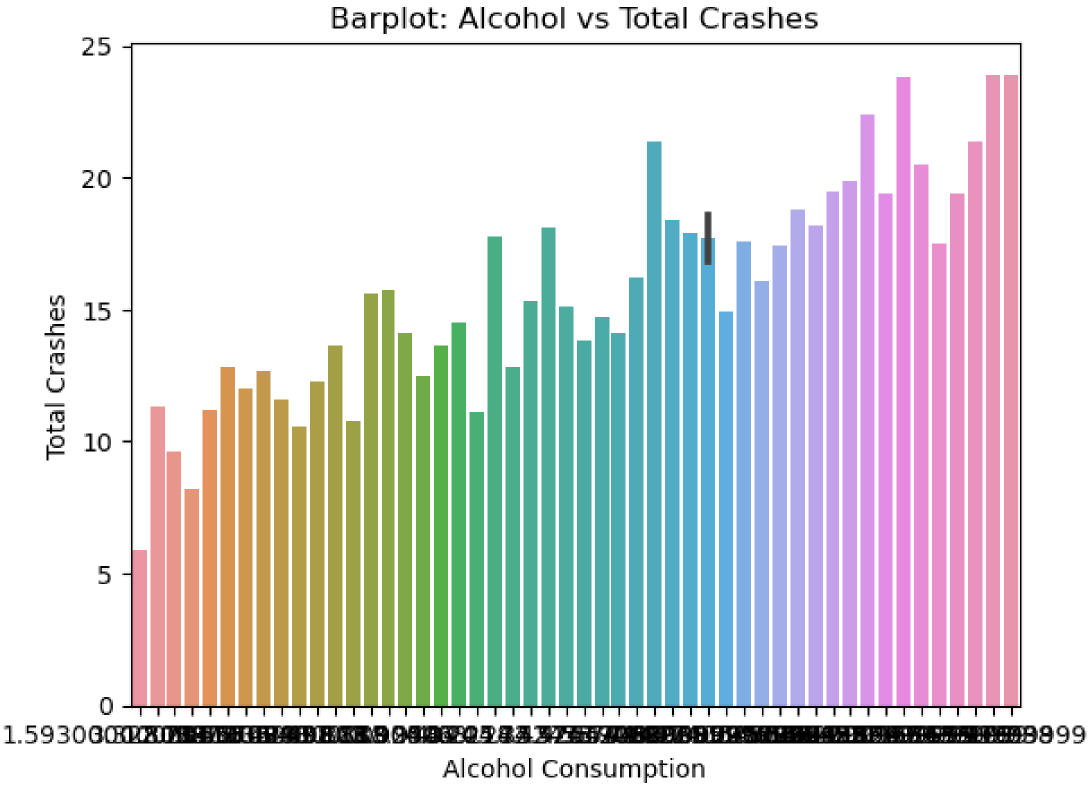


Inference: The boxplot illustrates the distribution of total crashes for different levels of speeding. The lines indicate the outliers.

0.1.7 Bar Plot

[17]:
```
sns.barplot(x="alcohol", y="total", data=df)
plt.title("Barplot: Alcohol vs Total Crashes")
plt.xlabel("Alcohol Consumption")
plt.ylabel("Total Crashes")
```

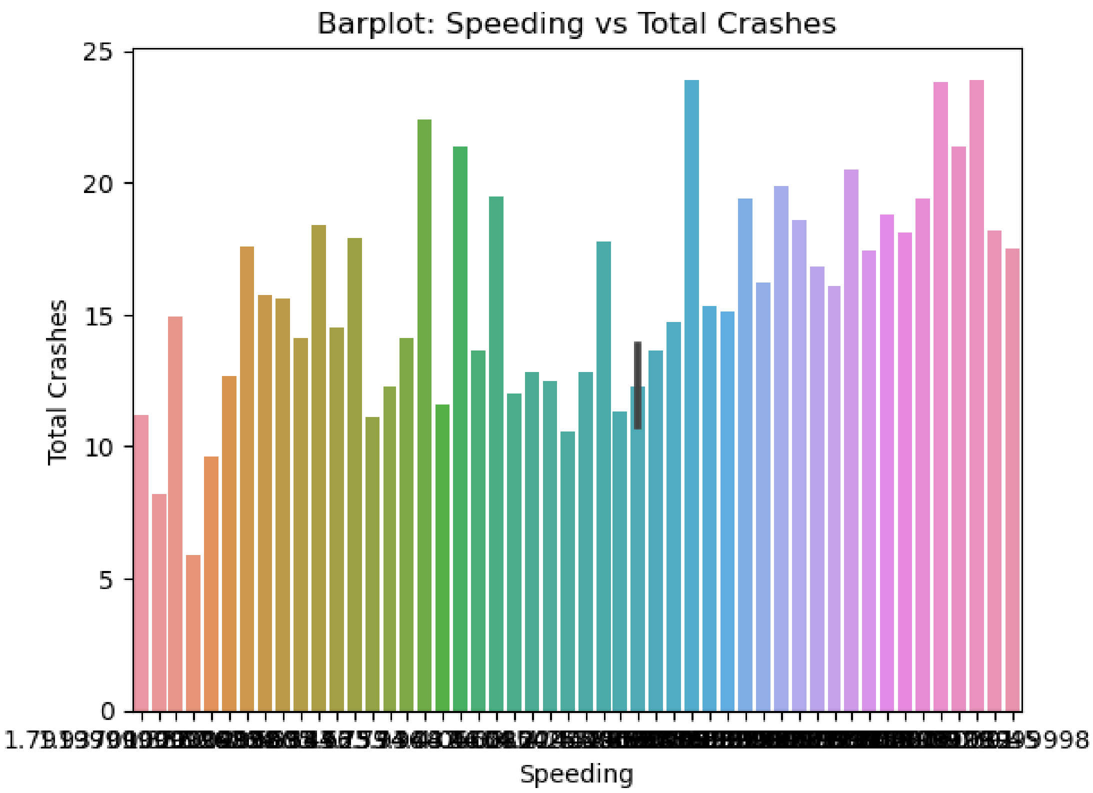
[17]:
```
Text(0, 0.5, 'Total Crashes')
```



Inference: The barplot displays the mean total crashes for different levels of alcohol consumption. So, if the alcohol consumption is high, then total crashes are also high.

[18]:
```
sns.barplot(x="speeding", y="total", data=df)
plt.title("Barplot: Speeding vs Total Crashes")
plt.xlabel("Speeding")
plt.ylabel("Total Crashes")
```

[18]:
```
Text(0, 0.5, 'Total Crashes')
```

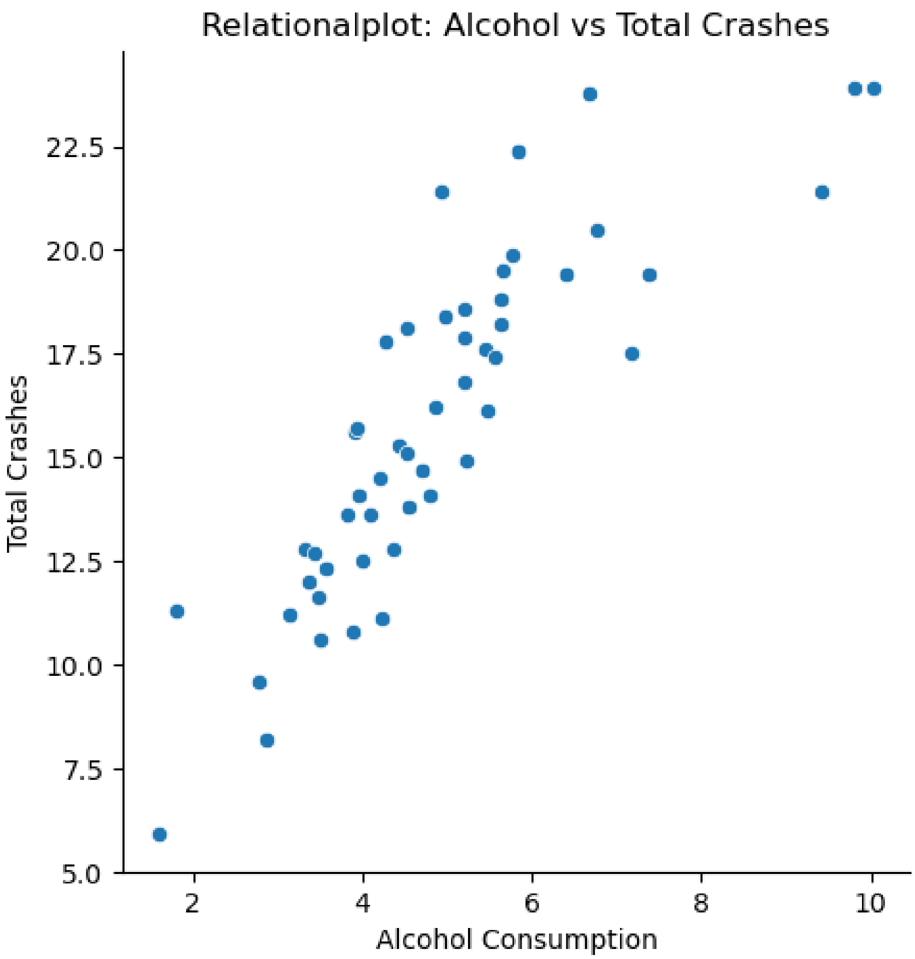


Inference: The barplot shows the mean total crashes for different levels of speeding. The crashes are high even at low speed levels also.

0.1.8 Relational Plot

[19]:
```
sns.relplot(x="alcohol", y="total", data=df, kind="scatter")
plt.title("Relationalplot: Alcohol vs Total Crashes")
plt.xlabel("Alcohol Consumption")
plt.ylabel("Total Crashes")
```

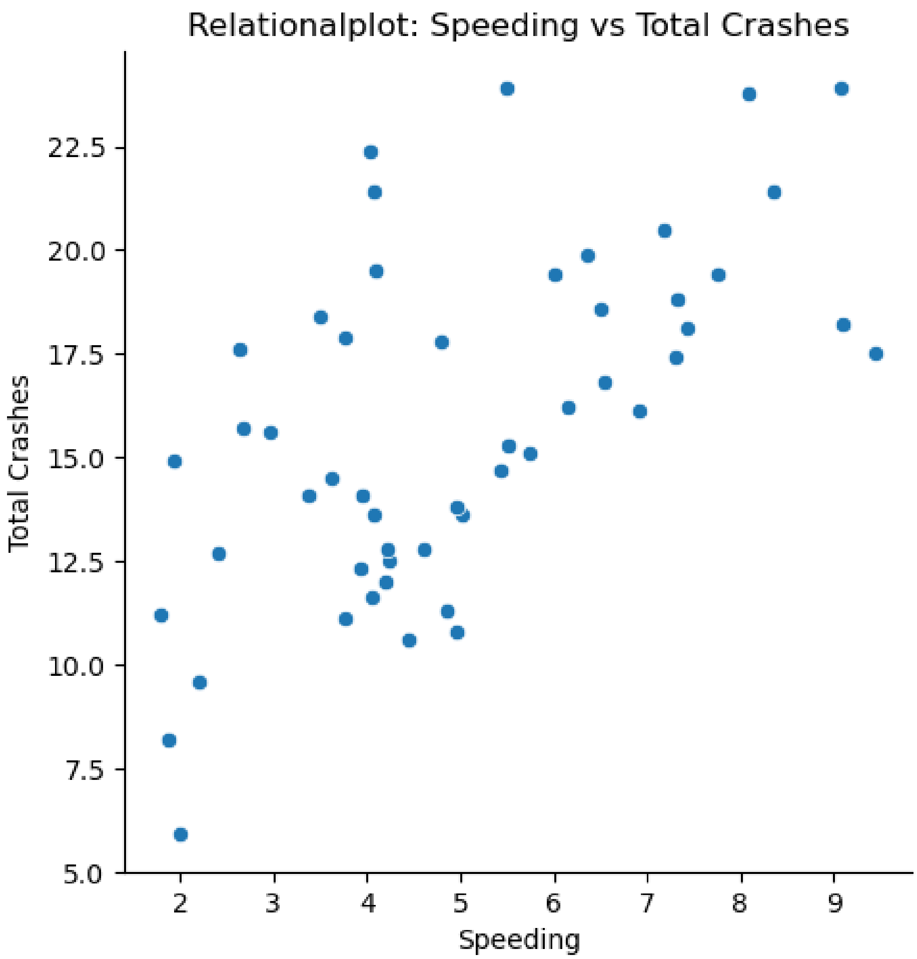
[19]:
```
Text(0.5694444444444446, 0.5, 'Total Crashes')
```



Inference: The plot in the relationalplot visualizes the relationship between alcohol consumption and total crashes and it is directly proportional.

```
[20]: sns.relplot(x="speeding", y="total", data=df, kind="scatter")
      plt.title("Relationalplot: Speeding vs Total Crashes")
      plt.xlabel("Speeding")
      plt.ylabel("Total Crashes")
```

```
[20]: Text(0.5694444444444446, 0.5, 'Total Crashes')
```

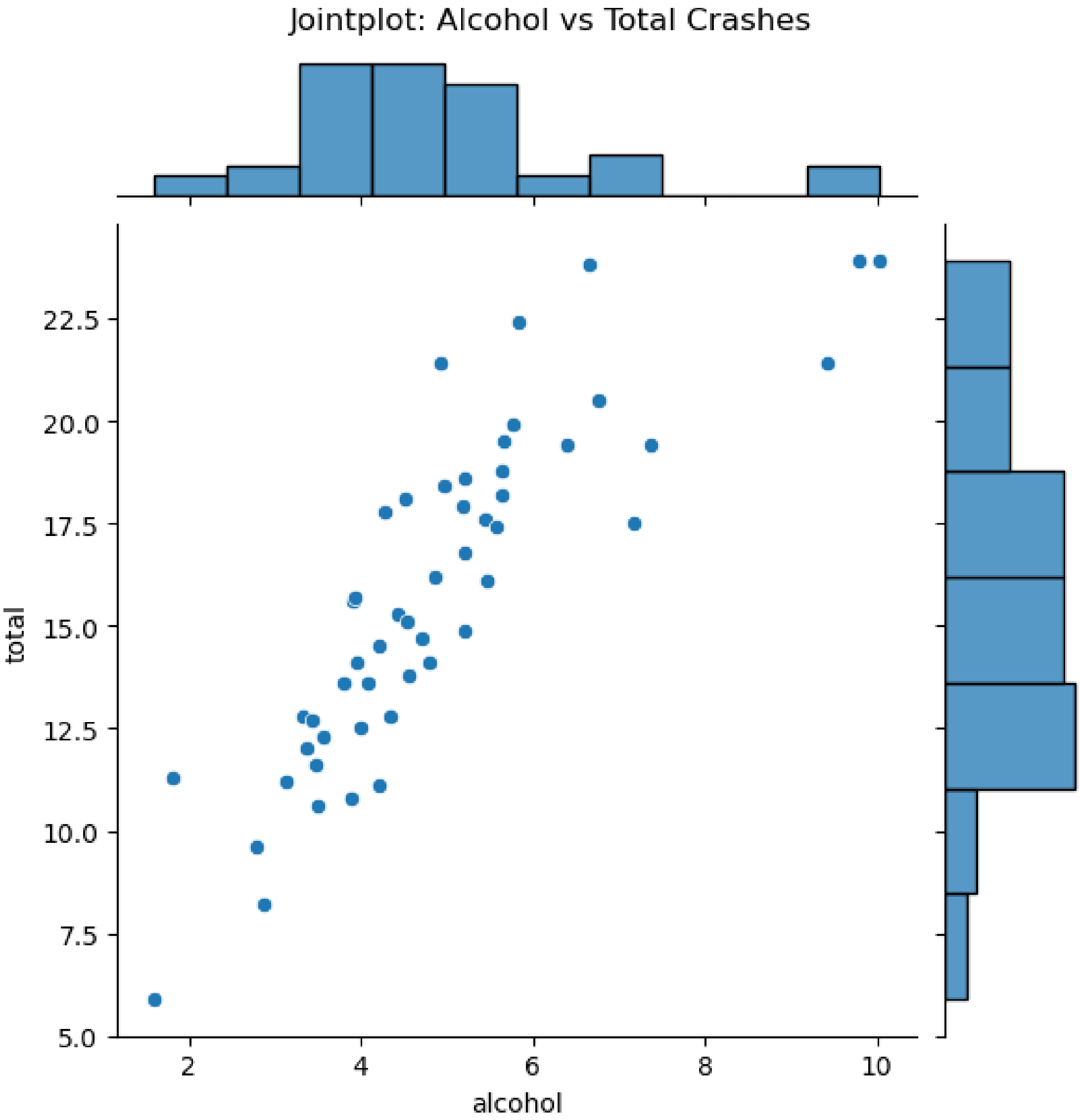


Inference: The scatter plot in the relationalplot illustrates the relationship between speeding and total crashes and it is not in a specific pattern.

0.1.9 Joint Plot

[21]:
```
sns.jointplot(x="alcohol", y="total", data=df, kind="scatter")
plt.suptitle("Jointplot: Alcohol vs Total Crashes", y=1.02)
```

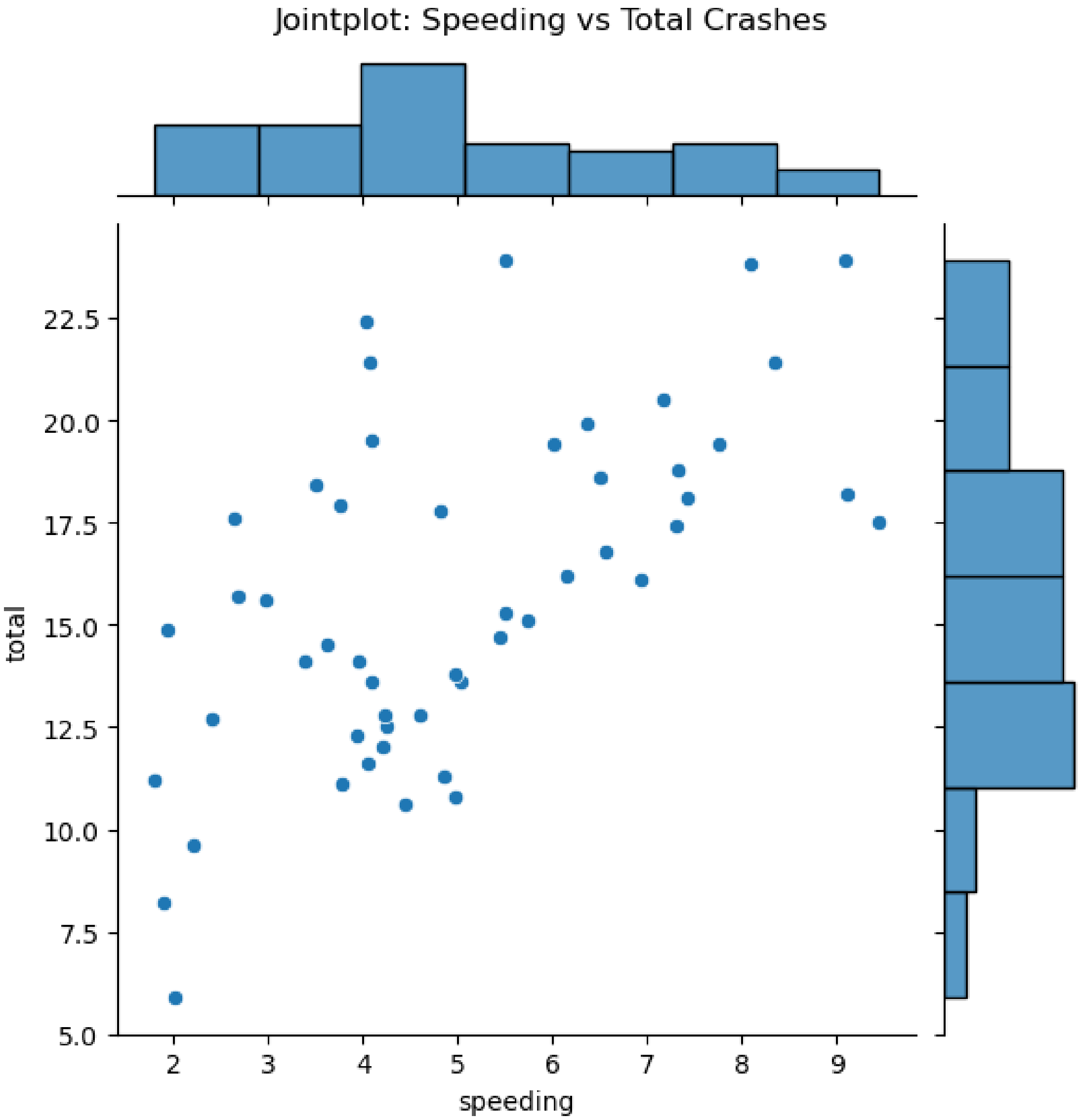
[21]:
```
Text(0.5, 1.02, 'Jointplot: Alcohol vs Total Crashes')
```



Inference: The plot in the jointplot reveals the relationship between alcohol consumption and total crashes. So, as the alcohol increases, the total crashes also increase.

[22]:
```
sns.jointplot(x="speeding", y="total", data=df, kind="scatter")
plt.suptitle("Jointplot: Speeding vs Total Crashes", y=1.02)
```

[22]:
```
Text(0.5, 1.02, 'Jointplot: Speeding vs Total Crashes')
```



Inference: The plot in the jointplot shows the relationship between speeding and total crashes. The plot is not in a specific pattern.

```
[ ]:
```

```
[ ]:
```