assignment-2

September 13, 2023

```
[1]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
[2]: print(sns.get_dataset_names())
     ['anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes',
     'diamonds', 'dots', 'dowjones', 'exercise', 'flights', 'fmri', 'geyser', 'glue',
     'healthexp', 'iris', 'mpg', 'penguins', 'planets', 'seaice', 'taxis', 'tips',
     'titanic']
[3]: df=sns.load_dataset('car_crashes')
[4]: df
[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
                                                            17.856
                                                                          899.47
                                              15.624
     3
          22.4
                    4.032
                             5.824
                                              21.056
                                                            21.280
                                                                          827.34
     4
          12.0
                    4.200
                             3.360
                                                                          878.41
                                              10.920
                                                            10.680
     5
                    5.032
          13.6
                             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
                             4.205
                    3.625
                                              13.775
                                                            13.775
                                                                          710.46
     15
          15.7
                             3.925
                    2.669
                                              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
                                                                          872.51
                                              16.692
                                                            16.264
          20.5
     18
                    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
                     ΙA
16
         133.80
                     KS
17
         137.13
                     ΚY
18
        194.78
                     LA
19
         96.57
                     ME
20
         192.70
                     MD
21
        135.63
                     MA
22
                     ΜI
        152.26
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
                     OK
36
        178.86
37
         104.61
                     OR
38
         153.86
                     PA
39
         148.58
                     RΙ
                     SC
40
         116.29
41
                     SD
         96.87
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
```

```
[5]: sns.__version__
```

[5]: '0.12.2'

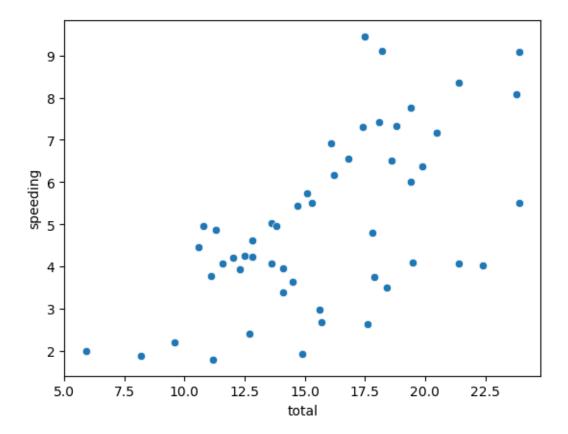
[6]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 8 columns):
```

Column Non-Null Count Dtype

```
total
                           51 non-null
                                            float64
      0
          speeding
                           51 non-null
                                            float64
      1
      2
          alcohol
                           51 non-null
                                            float64
      3
          not_distracted 51 non-null
                                            float64
          no_previous
                           51 non-null
                                            float64
      5
          ins_premium
                           51 non-null
                                            float64
          ins_losses
                           51 non-null
                                            float64
      6
      7
          abbrev
                           51 non-null
                                            object
     dtypes: float64(7), object(1)
     memory usage: 3.3+ KB
 [7]: df.head(5)
 [7]:
         total
                speeding alcohol not_distracted no_previous
                                                                  ins_premium \
                   7.332
                             5.640
      0
          18.8
                                            18.048
                                                          15.040
                                                                       784.55
                                                          17.014
      1
          18.1
                   7.421
                             4.525
                                            16.290
                                                                      1053.48
          18.6
                   6.510
                             5.208
                                            15.624
                                                          17.856
                                                                       899.47
          22.4
                   4.032
                             5.824
                                            21.056
                                                                       827.34
      3
                                                          21.280
          12.0
                   4.200
                            3.360
                                            10.920
                                                          10.680
                                                                       878.41
         ins_losses abbrev
      0
             145.08
                        ΑL
      1
             133.93
                        AK
      2
             110.35
                        AZ
      3
             142.39
                        AR
      4
             165.63
                        CA
[10]: sns.scatterplot(x="total",y="speeding",data=df)
```

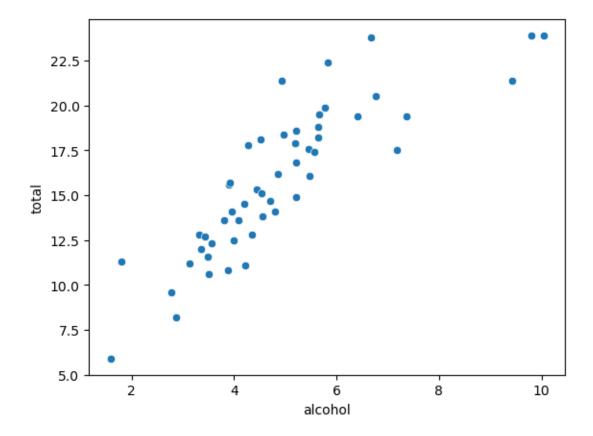
[10]: <Axes: xlabel='total', ylabel='speeding'>



Inference:from the plot we can say that as speeding-realted cases increases total car crashes is also increasing.

```
[11]: sns.scatterplot(x="alcohol",y="total",data=df)
```

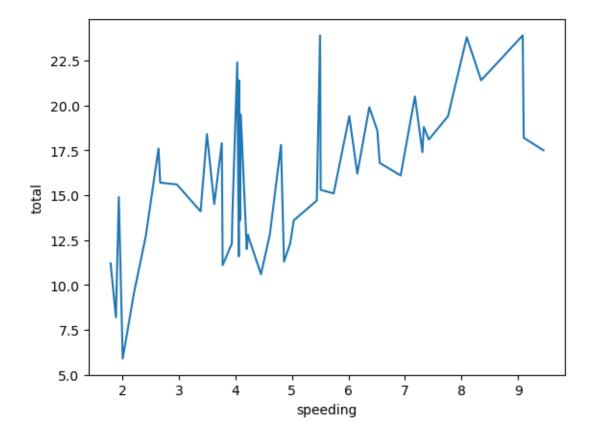
[11]: <Axes: xlabel='alcohol', ylabel='total'>



Inference:from the plot we can say that as alcohol-realted cases increases total car crashes is also increasing.

```
[20]: sns.lineplot(x="speeding",y="total",data=df,errorbar=None)
```

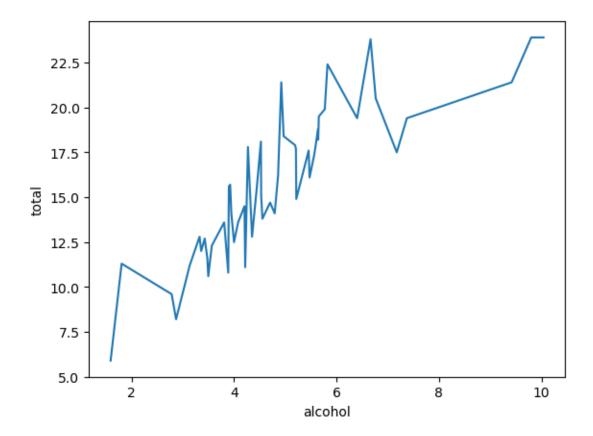
[20]: <Axes: xlabel='speeding', ylabel='total'>



Inference:it appears that as the frequency of speeding incidents increases, there is a corresponding increase in the total number of car crashes.

```
[16]: sns.lineplot(x="alcohol",y="total",data=df,errorbar=None)
```

[16]: <Axes: xlabel='alcohol', ylabel='total'>



Inference: it appears that as the frequency of alcohol incidents increases, there is a corresponding increase in the total number of car crashes.

[22]: sns.distplot(df['not_distracted'])

C:\Users\Vishal Gupta\AppData\Local\Temp\ipykernel_4508\1313687340.py:1:
UserWarning:

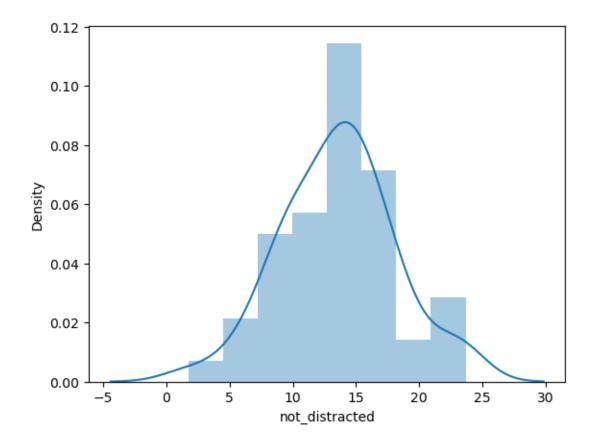
'distplot' is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(df['not_distracted'])

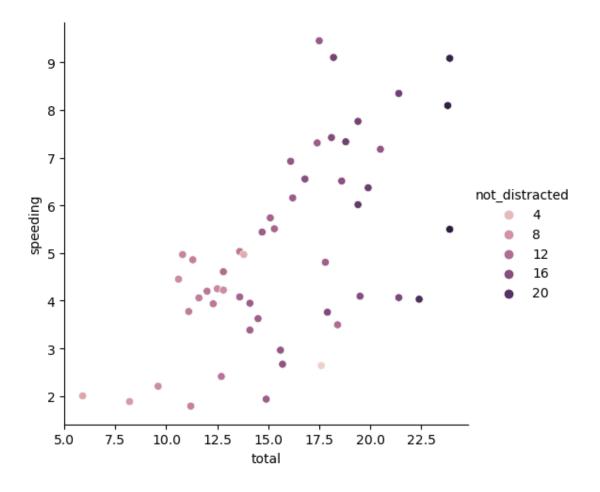
[22]: <Axes: xlabel='not_distracted', ylabel='Density'>



Inference:It is evident that the majority of observations cluster around a central value, forming a unimodal distribution.

```
[24]: sns.relplot(x="total",y="speeding",data=df,hue="not_distracted")
```

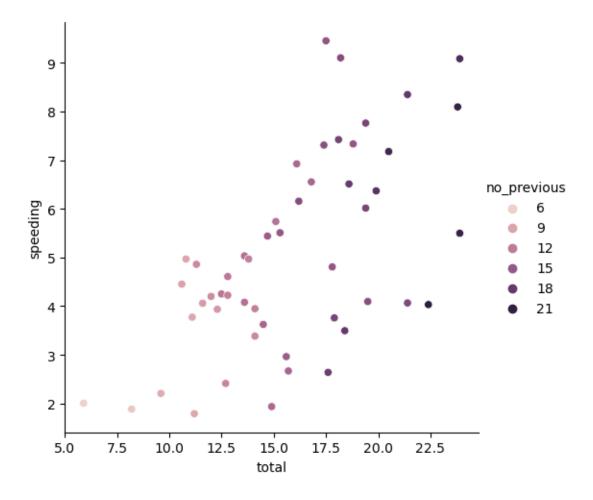
[24]: <seaborn.axisgrid.FacetGrid at 0x14b697ead10>



Inference: The x-axis represents the total number of car crashes, and the y-axis represents the number of speeding-related car crashes while being not distracted.

```
[26]: sns.relplot(x="total",y="speeding",data=df,hue="no_previous")
```

[26]: <seaborn.axisgrid.FacetGrid at 0x14b6a9fac50>

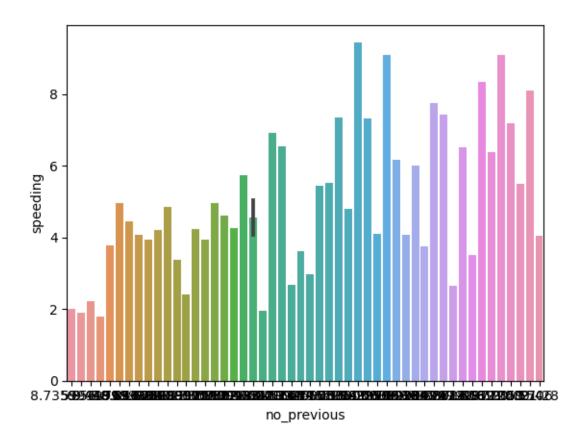


Inference: The x-axis represents the total number of car crashes, and the y-axis represents the number of speeding-related car crashes while having no records of previous crashes.

```
[28]: df["no_previous"].value_counts()
[28]: 12.920
                 2
      15.040
                 1
      16.016
                 1
      14.553
                 1
      9.628
      8.736
                 1
      18.032
                 1
      9.840
                 1
      13.608
                 1
      20.554
                 1
      11.562
                 1
      18.706
                 1
                 1
      11.520
```

```
8.769
                 1
      18.190
                 1
      19.359
                 1
      16.684
                 1
      15.795
                 1
      16.878
                 1
      10.848
                 1
      11.176
                 1
      9.116
                 1
      20.706
                 1
      11.592
                 1
      13.410
                 1
      13.524
                 1
      17.014
                 1
      17.600
                 1
      17.856
                 1
      21.280
                 1
      10.680
                 1
      8.856
                 1
      16.038
                 1
      5.900
                 1
      16.826
                 1
      14.508
                 1
      15.225
                 1
      14.994
                 1
      12.288
                 1
      13.775
                 1
      13.659
                 1
      15.130
                 1
      16.264
                 1
      20.090
                 1
      12.684
                 1
      12.375
                 1
      6.560
                 1
      10.857
                 1
      8.448
                 1
      15.660
                 1
      Name: no_previous, dtype: int64
[31]: sns.barplot(data=df,x="no_previous",y="speeding")
```

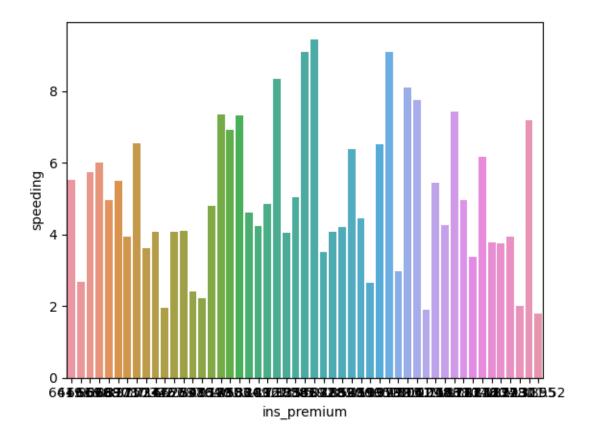
[31]: <Axes: xlabel='no_previous', ylabel='speeding'>



Inference: It's evident that the number of speeding-related car crashes tends to be higher for cases with 'no_previous' car crashes

```
[33]: sns.barplot(data=df,x="ins_premium",y="speeding")
```

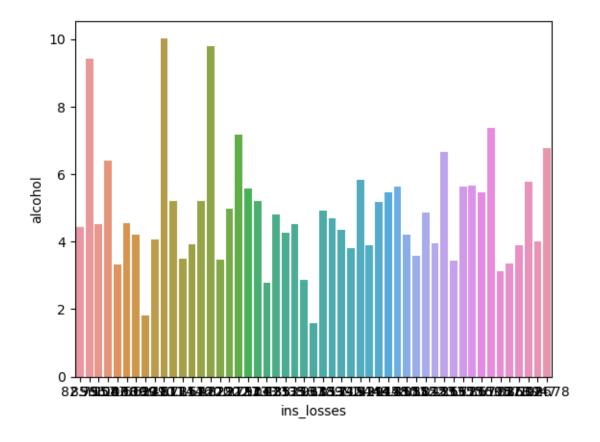
[33]: <Axes: xlabel='ins_premium', ylabel='speeding'>



Inference: The plot compares the number of car crashes involving speeding ('speeding') across different levels of insurance premiums ('ins_premium'). Some premium levels have higher numbers of such crashes, while others have lower numbers.

```
[34]: sns.barplot(data=df,x="ins_losses",y="alcohol")
```

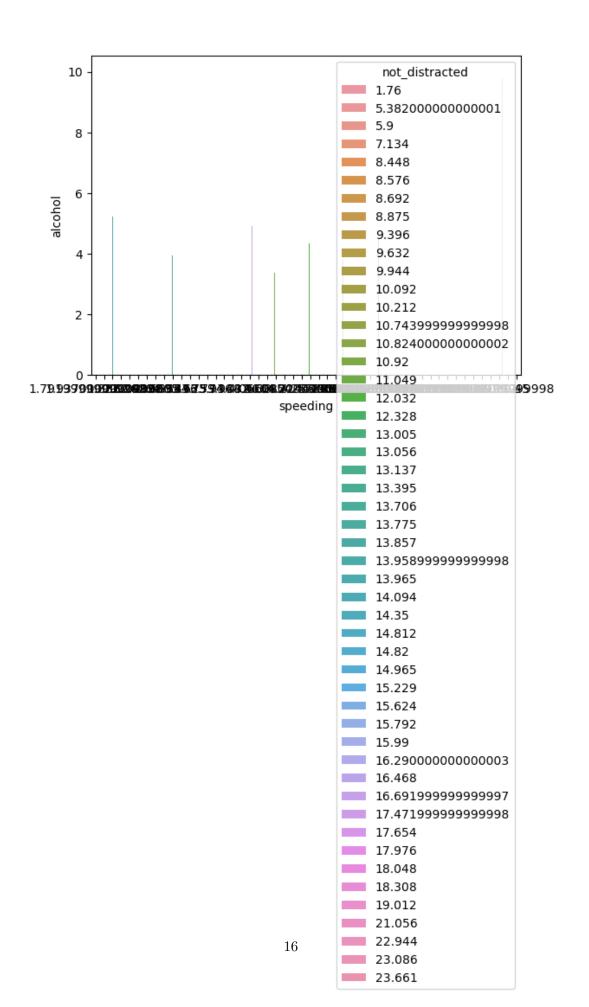
[34]: <Axes: xlabel='ins_losses', ylabel='alcohol'>



Inference: Some insurance loss levels have higher percentages of alcohol-impaired drivers, while others have lower percentages.

```
[35]: sns.barplot(data=df,x="speeding",y="alcohol",hue="not_distracted")
```

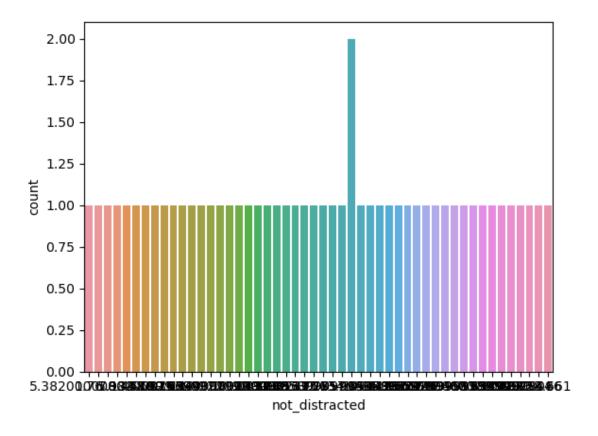
[35]: <Axes: xlabel='speeding', ylabel='alcohol'>



Inference: These variations suggest that driver distraction and impairment by alcohol may play roles in different levels of road safety incidents.

```
[41]: sns.countplot(x="not_distracted",data=df)
```

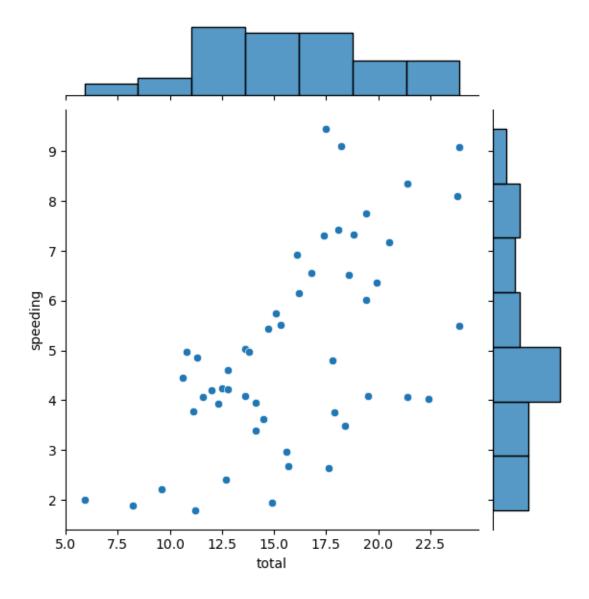
[41]: <Axes: xlabel='not_distracted', ylabel='count'>



Inference: In the dataset under consideration, a significant portion of drivers were reported as being non-distracted during the recorded incidents.

```
[44]: sns.jointplot(x="total",y="speeding",data=df)
```

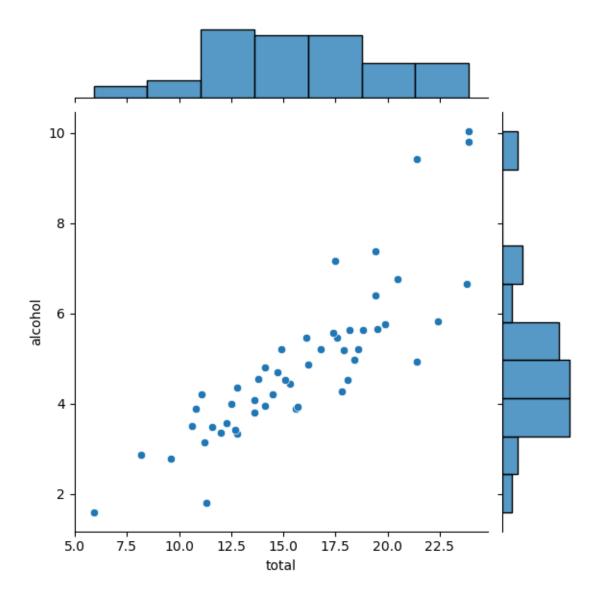
[44]: <seaborn.axisgrid.JointGrid at 0x14b71c3af50>



Inference:As the total number of car crashes increases, there tends to be an increase in the number of speeding-related car crashes.

```
[45]: sns.jointplot(x="total",y="alcohol",data=df)
```

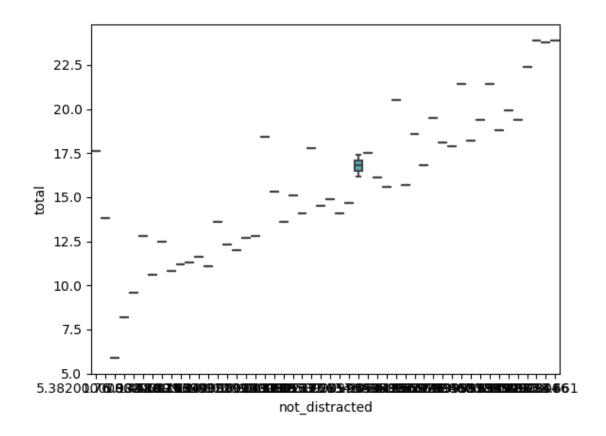
[45]: <seaborn.axisgrid.JointGrid at 0x14b71d8e1d0>



Inference: As the total number of car crashes increases, there tends to be an increase in the number of alcohol-related car crashes.

```
[46]: sns.boxplot(x="not_distracted",y="total",data=df)
```

[46]: <Axes: xlabel='not_distracted', ylabel='total'>



Inference: The plot compares the distribution of the total number of car crashes ('total') across 'not_distracted' drivers.

[47]: corr = df.corr()

C:\Users\Vishal Gupta\AppData\Local\Temp\ipykernel_4508\658818363.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()

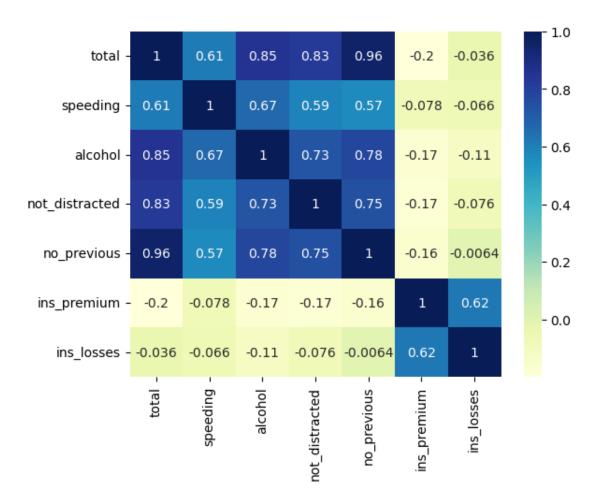
[48]: corr

[48]: total speeding alcohol not_distracted no_previous total 1.000000 0.611548 0.852613 0.827560 0.956179 speeding 0.571976 0.611548 1.000000 0.669719 0.588010 alcohol 0.852613 0.669719 1.000000 0.732816 0.783520 not_distracted 0.747307 0.827560 0.588010 0.732816 1.000000 0.956179 no_previous 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
                   -0.199702
                               -0.036011
total
speeding
                   -0.077675
                               -0.065928
alcohol
                               -0.112547
                   -0.170612
not_distracted
                   -0.174856
                               -0.075970
                               -0.006359
no_previous
                   -0.156895
ins_premium
                    1.000000
                                0.623116
ins_losses
                                1.000000
                    0.623116
```

[49]: sns.heatmap(corr,annot=True,cmap="YlGnBu")

[49]: <Axes: >



Inference: Warmer colors (shades of blue in this case) indicate positive correlations, while cooler colors (shades of green in this case) indicate negative correlations.

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