assignment-2-8-sep

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```
[]: # Step 1: Import necessary libraries
     import seaborn as sns
     import matplotlib.pyplot as plt
[]: 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'l
[]: # Step 2: Load the car crashes dataset
     df=sns.load_dataset('car_crashes')
     df
[]:
         total
                speeding
                           alcohol
                                    not_distracted no_previous
                                                                   ins_premium \
          18.8
                    7.332
                             5.640
                                             18.048
                                                                         784.55
                                                           15.040
          18.1
                    7.421
                             4.525
                                             16.290
     1
                                                           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
                                                                         878.41
                                             10.920
                                                           10.680
     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
                                                                        1160.13
                                             16.468
                                                           16.826
          15.6
     10
                    2.964
                             3.900
                                             14.820
                                                           14.508
                                                                         913.15
     11
          17.5
                             7.175
                   9.450
                                             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
                                                           12.684
                                                                         661.88
                                             13.137
```

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

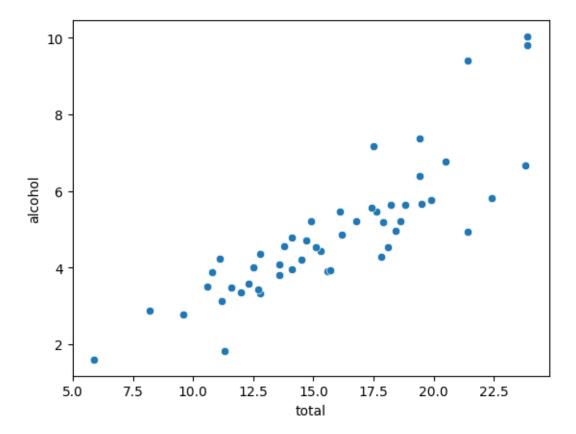
```
14
         108.92
                     IN
15
         114.47
                     ΙA
16
         133.80
                     KS
17
         137.13
                     ΚY
18
         194.78
                     LA
19
          96.57
                     ME
20
         192.70
                     MD
21
         135.63
                     MA
22
         152.26
                     ΜI
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
                     NC
         127.82
34
         109.72
                     \mathtt{ND}
35
         133.52
                     OH
36
         178.86
                     OK
37
                     OR
         104.61
38
         153.86
                     PA
39
         148.58
                     RΙ
40
         116.29
                     SC
41
         96.87
                     SD
42
         155.57
                     TN
43
                     \mathsf{TX}
         156.83
44
         109.48
                     UT
45
                     VT
         109.61
46
         153.72
                     VA
47
         111.62
                     WA
48
         152.56
                     WV
49
         106.62
                     WI
50
         122.04
                     WY
```

[]: df.head(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
                       ΑK
     2
            110.35
                       AZ
     3
            142.39
                       AR
     4
            165.63
                       CA
[]: 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
     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
         ins losses
                         51 non-null
                                         float64
         abbrev
                                         object
     7
                         51 non-null
    dtypes: float64(7), object(1)
    memory usage: 3.3+ KB
[]: # 1. scatterplot
     sns.scatterplot(x="total", y="alcohol", data=df)
```

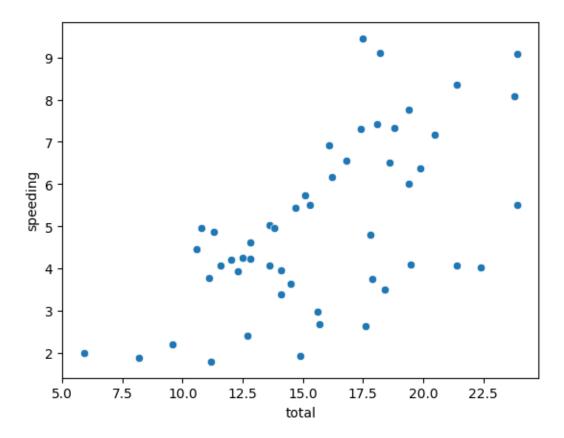
```
[]: <Axes: xlabel='total', ylabel='alcohol'>
```



Inference : It indicating that as the total number of car crashes increases, alcohol consumption tends to be higher in those areas.

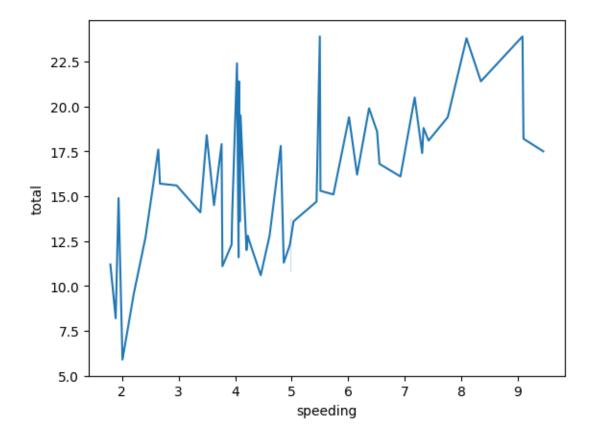
```
[]: # 1. scatterplot
sns.scatterplot(x="total", y="speeding", data=df)
```

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



```
[]: # 2.Lineplot of total vs. speeding sns.lineplot(x="speeding", y="total", data=df)
```

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



The total number of crashes increases with speeding, but the relationship is not linear.

```
[]: # 3.Distplot
sns.distplot(df["not_distracted"])
```

<ipython-input-10-0f037b766c6e>:2: UserWarning:

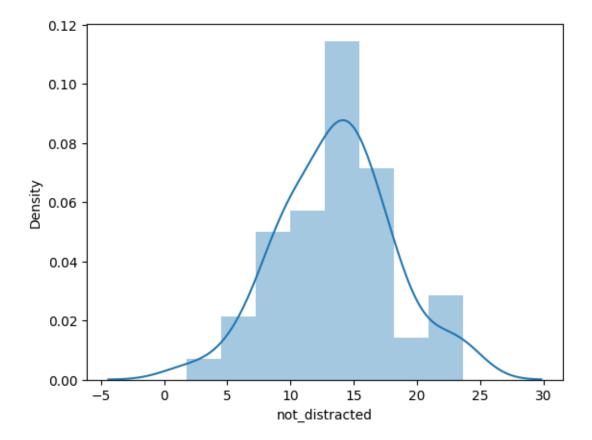
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

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 $\verb|https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751|$

sns.distplot(df["not_distracted"])

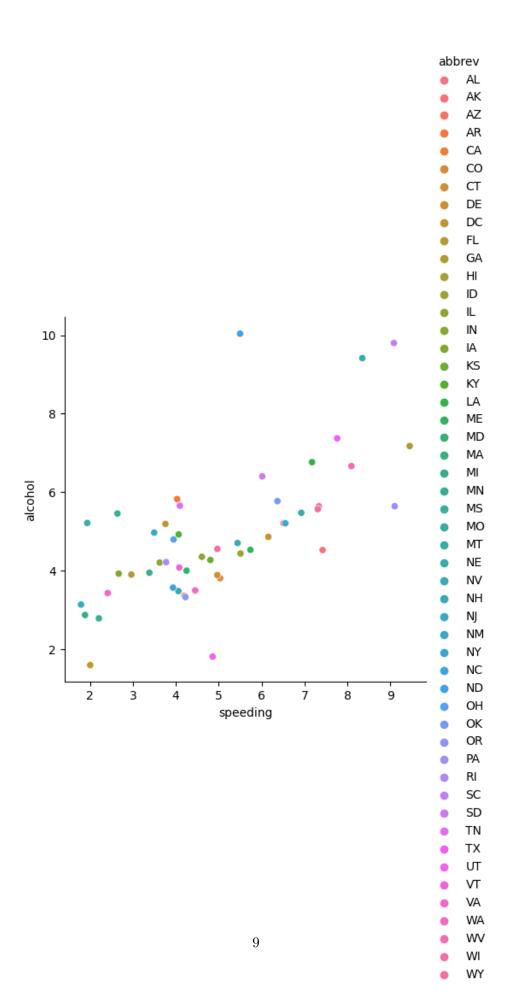
[]: <Axes: xlabel='not_distracted', ylabel='Density'>



The distribution of not_distracted is bimodal, meaning that there are two distinct peaks $\frac{1}{2}$

```
[]: # 4.Relplot
sns.relplot(x="speeding", y="alcohol", hue="abbrev", data=df)
```

[]: <seaborn.axisgrid.FacetGrid at 0x7be17fbb7820>



Here is a positive correlation between speeding and alcohol, but the relationship varies by state abbreviation.

[]: df["abbrev"].value_counts() []: AL 1 PA1 NV1 NH1 NJ1 NM 1 NY1 NC1 ND 1 OH 1 OK 1 OR 1 RI 1 MT1 SC1 SD1 TN1 ΤX 1 UT 1 VT 1 VA 1 WA1 WV1 WI 1 NE1 MO 1 ΑK 1 ID 1 ΑZ 1 AR 1 CA 1 CO 1 CT 1 DE 1 DC 1 FL1 GA 1 ΗI 1 IL 1 MS1

IN 1 ΙA KS ΚY LA 1 ME1 MD 1 MA1 ΜI 1 MN1 WY Name: abbrev, dtype: int64

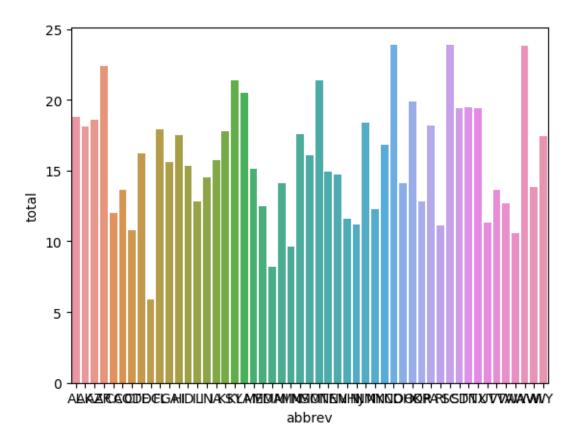
[]: # 5.Barplot sns.barplot(data=df,x="abbrev",y="total",ci=None)

<ipython-input-13-15f1a0469e23>:2: FutureWarning:

The 'ci' parameter is deprecated. Use 'errorbar=None' for the same effect.

sns.barplot(data=df,x="abbrev",y="total",ci=None)

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

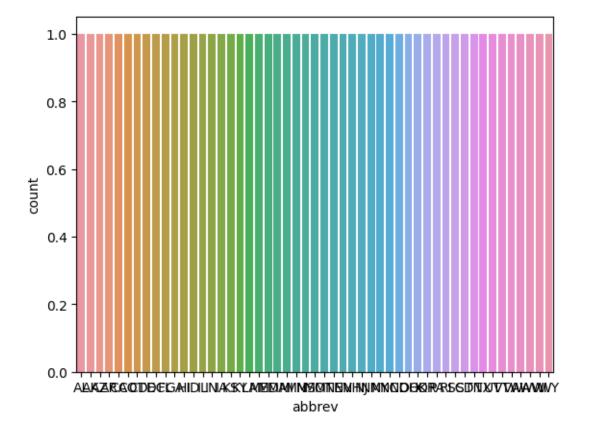


Inference

- The state with the most total crashes is CA, followed by TX and FL.
- The state with the fewest total crashes is WY, followed by ND and SD.

```
[]: #6.countplot sns.countplot(x='abbrev', data=df)
```

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



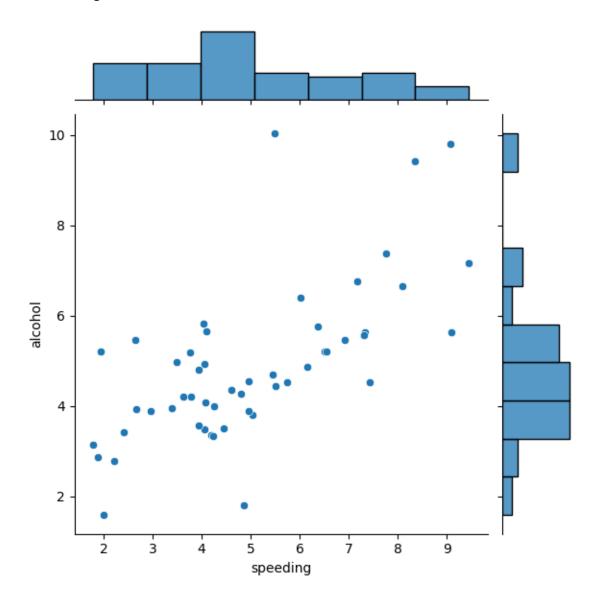
```
[]: len(df['abbrev'].unique())
```

[]: 51

Inference: There are 51 states in this dataset.

```
[]: # 7. Jointplot of speeding and alcohol sns.jointplot(x="speeding", y="alcohol", data=df)
```

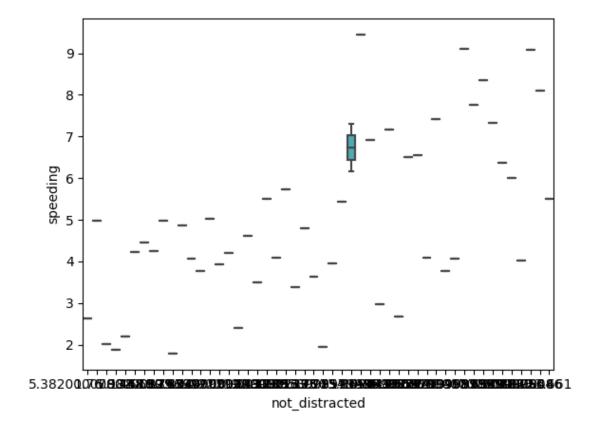
[]: <seaborn.axisgrid.JointGrid at 0x7be17fbb75b0>



Inference: There is a positive correlation between speeding and alcohol involvement in car crashes.

```
[]: #8.Boxplot of speeding of each not_distracted category sns.boxplot(x="not_distracted", y="speeding", data=df)
```

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



Inference: The median percentage of drivers involved in fatal collisions who were speeding is higher for the lower categories of not_distracted than for the higher categories. This means that states with lower percentages of drivers involved in fatal collisions who were not distracted tend to have higher percentages of drivers involved in fatal collisions who were speeding.

```
[]: corr=df.corr() corr
```

<ipython-input-23-7d5195e2bf4d>: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.

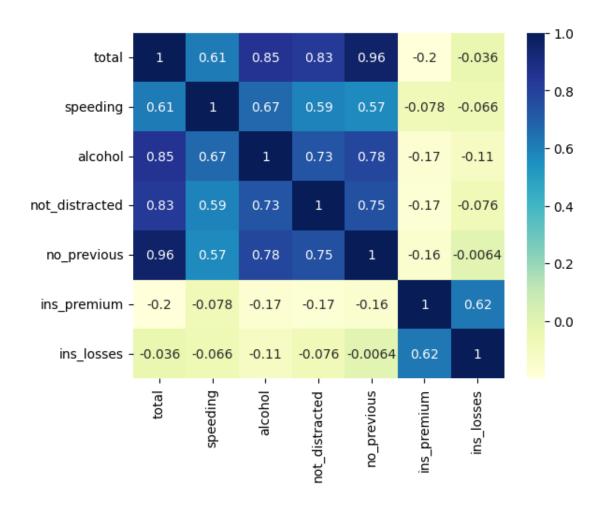
corr=df.corr()

```
[]:
                        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
     {\tt not\_distracted}
                        -0.174856
                                     -0.075970
     no_previous
                        -0.156895
                                     -0.006359
     ins_premium
                         1.000000
                                      0.623116
     ins_losses
                         0.623116
                                      1.000000
[]: #9.Heatmap
```

sns.heatmap(corr,annot=True,cmap="YlGnBu")

[]: <Axes: >

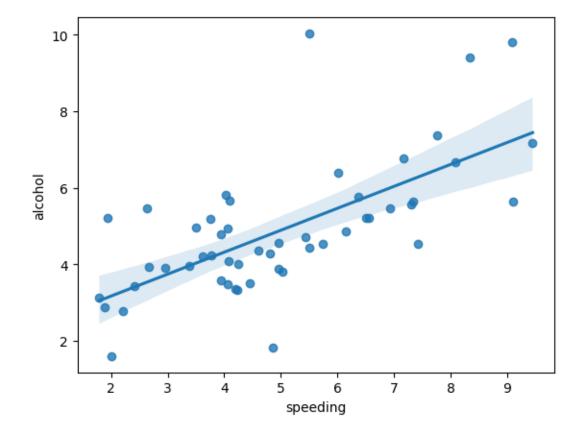


Inference: The heatmap shows that some variables have strong positive correlations, such as total and alcohol, speeding and alcohol, and ins_premium and ins_losses.

This means that these variables tend to increase or decrease together. Some variables have weak or negative correlations, such as no_previous and not_distracted, speeding and no_previous, and total and not_distracted. This means that these variables tend to have no or inverse relationship.

```
[]: #10. Regression plots
sns.regplot(x='speeding', y='alcohol', data=df)
```

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



Inference: There is a positive linear relationship between speeding and alcohol involvement in car crashes. The regplot also shows the 95% confidence interval for the regression line.