assignment-2-thridiva

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ASSIGNMENT-2(MORNING SLOT)

```
[2]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
[4]: 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']
[5]: df=sns.load dataset("car crashes")
[5]:
         total
                speeding
                           alcohol
                                    not_distracted no_previous
                                                                   ins_premium \
                    7.332
     0
          18.8
                             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
                                                                         827.34
          22.4
                    4.032
                             5.824
                                             21.056
                                                           21.280
     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
          15.7
     15
                    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
                      ΙA
16
         133.80
                      KS
17
                      ΚY
         137.13
18
         194.78
                      LA
19
                      ME
          96.57
20
                      MD
         192.70
21
         135.63
                      MA
22
         152.26
                      ΜI
23
         133.35
                      MN
24
         155.77
                      MS
25
                      MO
         144.45
26
          85.15
                      MT
27
         114.82
                      NE
28
                      NV
         138.71
29
         120.21
                      NH
30
                      NJ
         159.85
31
         120.75
                      NM
32
         150.01
                      \mathtt{N}\mathtt{Y}
33
         127.82
                      NC
34
         109.72
                      ND
35
         133.52
                      OH
36
         178.86
                      OK
37
         104.61
                      OR
38
                      PA
         153.86
39
         148.58
                      RΙ
40
                      SC
         116.29
41
          96.87
                      SD
42
         155.57
                      TN
43
         156.83
                      TX
44
         109.48
                      UT
                      VT
45
         109.61
46
         153.72
                      VA
47
         111.62
                      WA
48
         152.56
                      WV
49
         106.62
                      WI
                      WY
50
         122.04
```

[6]: df.head()

[6]: speeding alcohol not_distracted no_previous ins_premium \ total 7.332 5.640 0 18.8 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 21.056 827.34 21.280

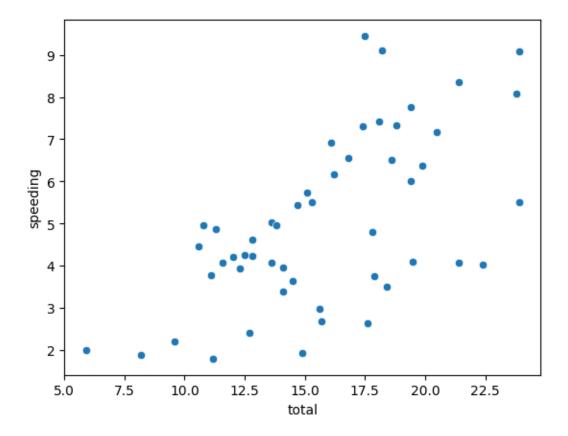
```
4
         12.0
                   4.200
                             3.360
                                             10.920
                                                           10.680
                                                                         878.41
        ins_losses abbrev
     0
             145.08
                        AL
     1
             133.93
                        AK
     2
             110.35
                        AZ
     3
             142.39
                        AR
     4
             165.63
                        CA
    INFERENCE: This is the head function which gives the top 5 data values
[7]: df.tail()
[7]:
         total
                 speeding
                            alcohol
                                     not_distracted
                                                      no_previous
                                                                     ins_premium
                    2.413
     46
          12.7
                              3.429
                                              11.049
                                                            11.176
                                                                          768.95
     47
          10.6
                    4.452
                              3.498
                                               8.692
                                                             9.116
                                                                          890.03
                    8.092
     48
          23.8
                              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
     46
             153.72
                          VA
     47
             111.62
                          WA
     48
             152.56
                          WV
     49
              106.62
                          WI
     50
              122.04
                          WY
    INFERENCE: This is the head function which gives the bottom 5 data values
[8]:
     sns.__version__
[8]: '0.12.2'
[9]:
    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
                           51 non-null
                                            float64
          speeding
     2
          alcohol
                           51 non-null
                                            float64
     3
         not_distracted 51 non-null
                                            float64
     4
                           51 non-null
                                            float64
         no_previous
     5
          ins_premium
                           51 non-null
                                            float64
     6
          ins_losses
                           51 non-null
                                            float64
     7
          abbrev
                           51 non-null
                                            object
```

 ${\tt dtypes: float64(7), object(1)}$

memory usage: 3.3+ KB

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

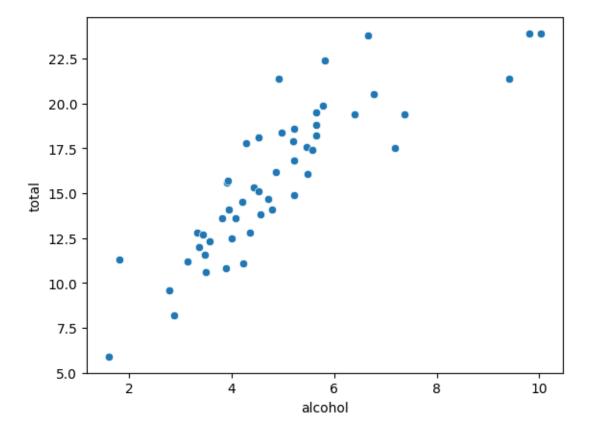
[10]: <Axes: xlabel='total', ylabel='speeding'>



INFERENCE:—> From the above Scatter plot we can say that when the speeding is increasing then total is also increasing !!

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

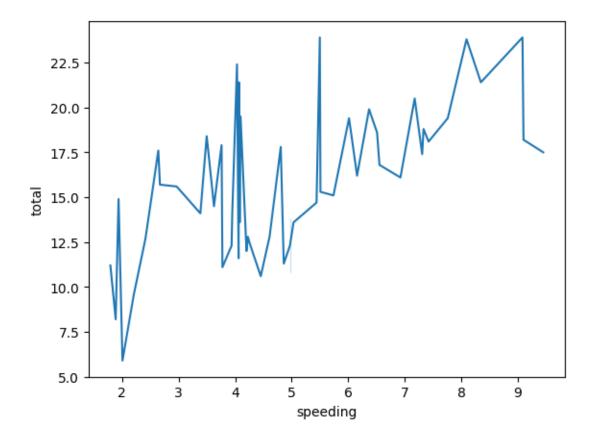
[11]: <Axes: xlabel='alcohol', ylabel='total'>



 $\label{eq:scatterplot} \mbox{INFERENCE:} \longrightarrow \mbox{By the above Scatterplot we can say that alcohol drinkers increasing, total is increasing}$

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

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



INFERENCE:—> From the above Scatter plot we can say that when the speeding is increasing then total is also increasing !!

[13]: sns.distplot(df["total"])

<ipython-input-13-0d5ead9bfd1a>:1: UserWarning:

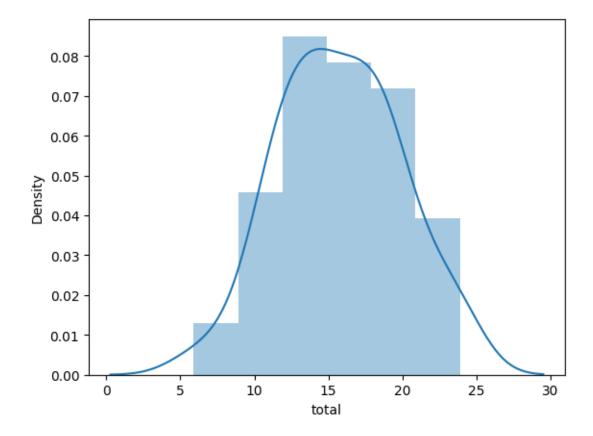
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

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["total"])

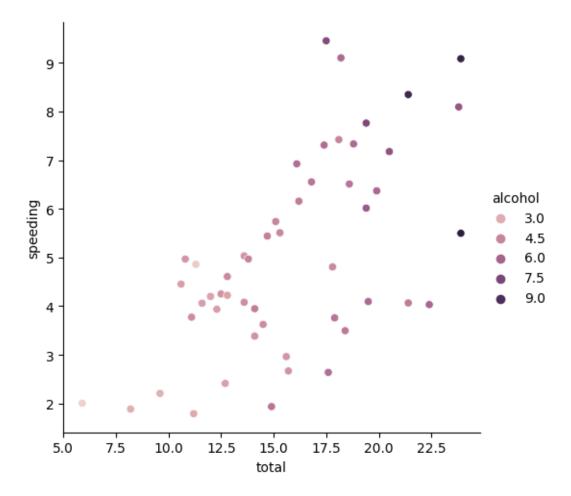
[13]: <Axes: xlabel='total', ylabel='Density'>



INFERENCE:—> By the above distplot it gives the histogram combined with kernel density function gives the distplot , By this we can say that the total is mostly ranging from approximately from 12 to 18.

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

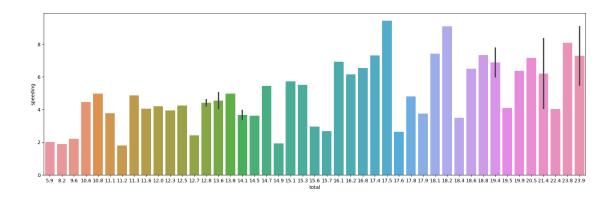
[14]: <seaborn.axisgrid.FacetGrid at 0x7ae557bac940>



INFERENCE: BY this relational plot we can say that it visualise how variables within a dataset relate to each other. here we can see the relation between the total and speeding going on increasing.

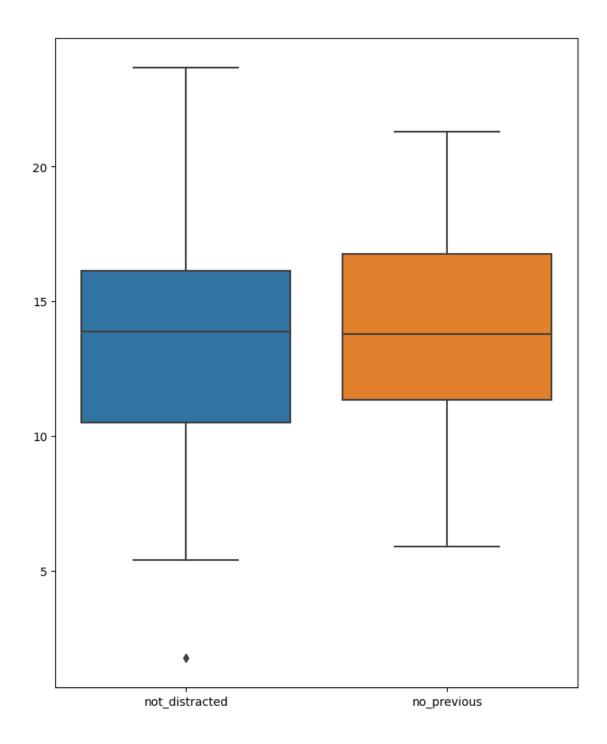
[15]: df["alcohol"].value_counts() [15]: 5.208 2 5.640 1 4.218 1 4.704 1 3.480 1 3.136 1 4.968 1 3.567 1 10.038 1 4.794 1 5.771 1 3.328 1 1 5.642

```
9.799
                 1
      9.416
                 1
      6.402
                 1
      5.655
                 1
      7.372
                 1
      1.808
                 1
      4.080
                 1
      3.429
                 1
      3.498
                 1
      6.664
                 1
      4.554
                 1
      5.215
                 1
      5.474
                 1
      4.525
                 1
      5.456
                 1
      5.824
                 1
      3.360
                 1
      3.808
                 1
      3.888
                 1
      4.860
                 1
      1.593
                 1
      5.191
                 1
      3.900
                 1
      7.175
                 1
      4.437
                 1
      4.352
                 1
      4.205
                 1
      3.925
                 1
      4.272
                 1
      4.922
                 1
      6.765
                 1
      4.530
                 1
      4.000
                 1
      2.870
                 1
      3.948
                 1
      2.784
                 1
      5.568
                 1
      Name: alcohol, dtype: int64
[16]: plt.figure(figsize=(20, 6))
      sns.barplot(data=df,x="total",y="speeding")
      plt.show()
```



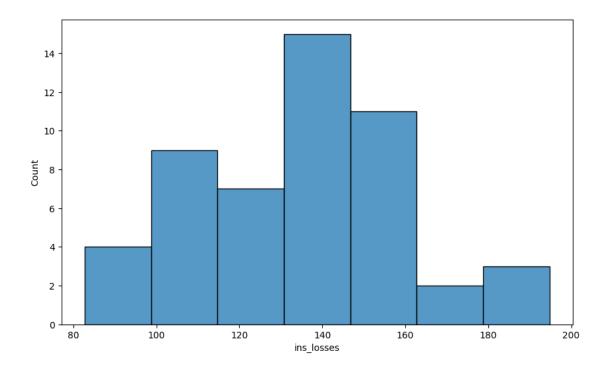
INFERENCE:—> By this barplot we can say that at 17.5(total) the speeding reaches the heightest.

```
[17]: plt.figure(figsize=(8,10))
sns.boxplot(df[["not_distracted","no_previous"]])
plt.show()
```

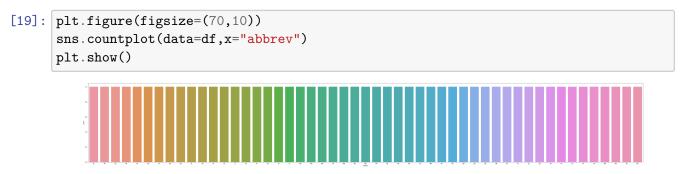


INFERENCE:—> By this boxplot in between not_distracted the we can see a outlayer point in between 1 and 2

```
[18]: plt.figure(figsize=(10,6))
sns.histplot(x="ins_losses",data=df)
plt.show()
```



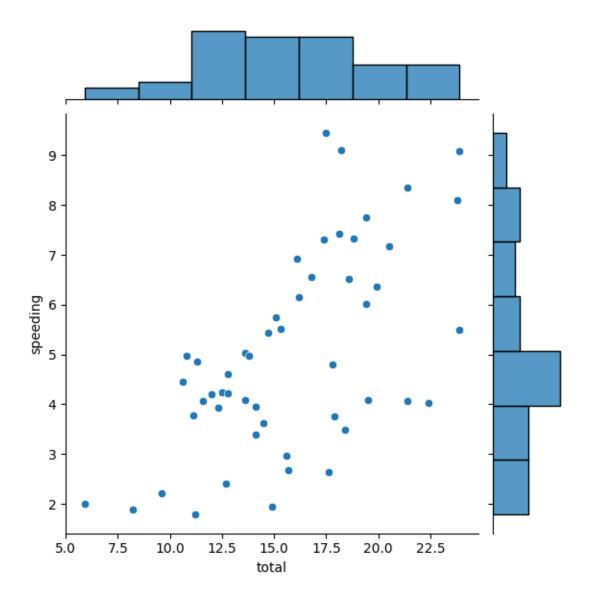
INFERENCE:—-> By this above histplot we can say that in between 130 and 150 (ins_losses) the count reaches heighest.



INFERENCE: By this count plot we can say that plot occur in categorical variable which we performed on the abbrev data.

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

[20]: <seaborn.axisgrid.JointGrid at 0x7ae5538daa70>



INFERENCE: By the jointplot we can say that it gives the relation between two variables with bivariate and univariate graphs. Here we can see that total and speeding is increasing.

<ipython-input-21-7d5195e2bf4d>: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.

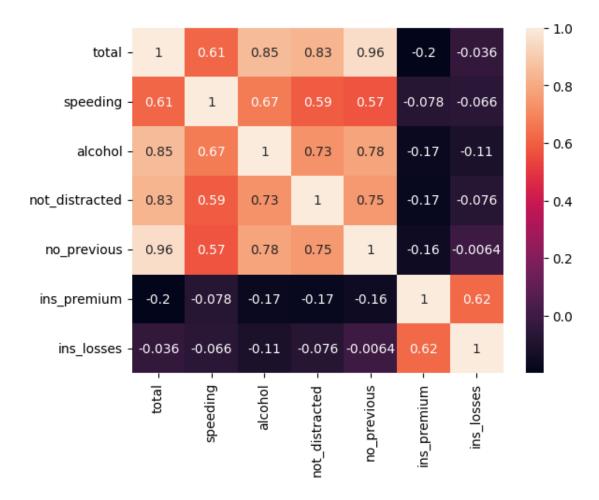
corr=df.corr()

```
[21]:
                                            alcohol
                                 speeding
                                                     not_distracted
                                                                      no_previous
                         total
                                 0.611548
      total
                      1.000000
                                           0.852613
                                                            0.827560
                                                                         0.956179
      speeding
                      0.611548 1.000000
                                           0.669719
                                                            0.588010
                                                                         0.571976
      alcohol
                                 0.669719
                                           1.000000
                                                            0.732816
                      0.852613
                                                                         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
```

INFERENCE: By this we came to know the corelation of the data >0.5 is highly correlated <0.5 is less correlated

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

[22]: <Axes: >



INFERENCE:—> By this heatmap we can say that the highest correlation is 0.96 this occur in between no_previous and total.

```
[34]: plt.figure(figsize=(60,6))
sns.stripplot(x="total",y="speeding",data=df)
plt.show()
```

INFERENCE:By this strip plot we can observe that at 17.5(total) it reaches to the highest point nearly 9 at speeding.

```
[35]: plt.figure(figsize=(100,6)) sns.swarmplot(x="not_distracted", y="no_previous", hue="alcohol", data=df)
```



INFERENCE: By this swarmplot we can say that it is increasing and at 21.056 (not_distracted) reaches the highest & reaching the (no_previous) side above 20.