Regno:21bce9587

33

36

19.9

6.368

20. 554 688.75 35 14.1 3 . 948 4.794 13.959 11.562 697.73

18.308

18.706

881.51

5.771

Assignment-02(08-09-23).ipynb

```
import numpy as np import pandas
  as pd import matplotlib. pyplot as
  plt import seaborn as sns
  print (sns .;et_dataset_names ( ) )
['anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes', 'diam
                                                                             car crashes', 'diamonds', 'dots', 'dowjones', 'exercise', 'flights', 'fmri', '
  df = sns.load dataset'car crashes
  print(df)
            total speeding alcohol not distracted no previous ins premium \
       e
             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
              10.8
                           4.968
                                     3.888
                                              9.396
                                                        8.856
                                                                  1068.73
       6
       7
              16.2
                           6.156
                                     4.860
                                              14.094
                                                        16.038
                                                                  1137.87
              5.9 2.006
                           1.593
                                     5.900
                                              5 .900
                                                        1273.89
       8
       9
              17.9
                           3.759
                                     5.191
                                              16 .468
                                                        16.826
                                                                 1160.13
              15.6
                           2.964
                                              14.820
                                                        14.508913.15
       10
                                     3. gee
              17.5
                           9.450
                                     7.175
                                              14.350
                                                        15.225 861.18
       11
             15.3 5.508 4.437 13 . 005 14.994 641.96 13 12.8 4.608 4.352 12.032
       12
              12.288 803.11
            14.5 3.625
       14
                           4.205
                                     13.775
                                              13.775 710.46
            15.72.669
                           3.925
                                     15 .229
                                              13.659
        15
                                                        649.06
            17.8 4.806
                           4.272
                                     13.706
                                              15.130 780.45
       16
            21.4 4.066
                                     16 .692 16 .264 872.51
                           4.922
       17
                                     14.965
            20.5 7.175
                           6.765
                                              20.0901281.55
       18
            15.1 5.738
                           4.530
                                     13.137
                                              12 .684 661.88
       20
            12.5 4.250 4. eee 8.875 12.375 1048.78 21 8.2 1.886 2.870 7.134 6.
             560 1011. 14
             14.1
                                    3 .948
                           3.384
                                              13.395
                                                        10.857 1110.61
       22
                           2.784
                                     8 .448
                                              8 .448
                                                        777.18
             9.6 2.208
       2417.6 2 . 640 5.456 1.760 17.6ee 896.07 25 16.1 6.923 5.474 14.812 13 .
       524 790.32
            21.4\ 8.\ 346
       26
                           9.416
                                     17.976 18.190816.21
            14.9 1.937
                           5.215
                                     13.857
                                              13.410
                                                        732.28
            14.75.439
                           4.704
                                     13.965
                                              14.553
                                                        1029.87
       28
       29
            11.6 4.060
                           3.
                                     10.092
                                              9.628
                                                        746.54
            11.2 1.792
                                     9.632
                                              8.736
                                                        1301.52
       30
                           3.136
            18.4 3.496
                           4.968
                                     12.328
                                              18.032
                                                        869.85
       31
            12.3 3.936
                           3.567
                                     10.824
                                              9.840
                                                        1234.31
       32
             16.8 6.552 5.208 15.792 13 . 608 708. 24 34 23.9 5.497 10.038 23 .661
```

3712.8	4. 2	24 3.32	8	8.576	11. 5	20	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	1148.9	99
40	23.9	9.082	9.799	22 .944	19.359	858.97	7
41	19.4	6.014	6.402	19 .012	16 .684	669.3	31 42
19.5	4.095	5.655	15.99015	. 795	767.91 4	3	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 4	6	12.7	
2.413	3.429	11.049	11.176	768.95 4	7	10.6	
4.452	3.498	8.692	9.116	890.03 4	8	23.8	8.
092	6.664	23.086	20.706	992.61 4	9	13.8	
4.968	4.554	5.382	11.592	670.31 5	0	17.4	7.
308	5.568	14.094	15 . 660	791. 14			
in a 1		la mary					

ins losses abbrev

 $\begin{array}{cccc} & 145.08 & \text{A} \\ 1 & 133.93 & \text{AK} \\ 2 & 110.35 & \text{AZ} \\ 3 & 142.39 & \text{AR} \end{array}$

sns. version

ⁱ e. 12.2 ⁱ

df. info()

https://c01ab.research.google.com/drive/1XDqMpQeOUkRRh4GZNV7GDWvOfhJFGCf8#scr011To=Abe18ivA_nPH&printMode--true 1/7 (class 'pandas. core. frame. DataFrame ' > RangeIndex: 51 entries, 0 to 50 Data columns (total 8 columns):

Column Non-Null Count Dryge

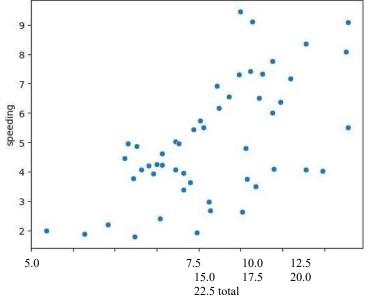
#	Column	Non -Null Count Dtype			
9	total	51 non-null	float64		
1	speeding	51 non-null	float64		
2	alcohol	51 non-null	float64		
3	not distracted	51 non-null	float64		
4	no_prevlous	51 non-null	float64		
5	Ins_premium	51 non-null	float64		
6	ins losses	51 non-null	float64		
7	abbrev	51 non-null	object		
14	0 +(1(7)	.1.1471)			

dtypes: float64(7), object(l) memory usage: 3.3+ KB

sns.scatterplot(x="total",y="speeding", data=df)

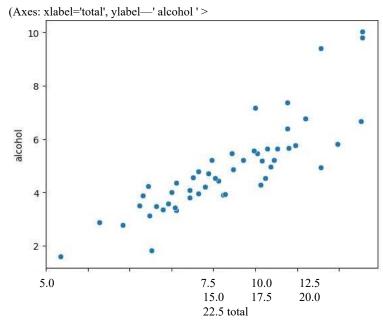
(Axes: xlabel='total', ylabel=' speeding' >

13/09/2023, 20:13 - Colaboratory



Inference: Here we can clearly observe that increase in speed has caused many car crashes. Which shows the direct proportionality in between total and speeding of car crashes.

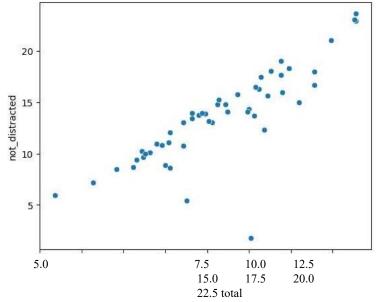
sns.catterplot(x="total",y="alcohol", data-df)



Inference: In the above graph, it is obvious that excessive alcohol consumption has contributed to numerous auto accidents. which demonstrates the direct correlation between the overall number Of crashes and alcohol use.

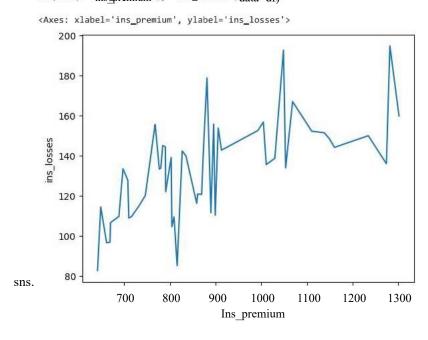
 $1\ XDqMpQeO\ kRRh4GZNV7G\ ^{)}WvOfhJFGCf8\#scrollTo=Abe18ivA_nPH\&pri_ntM0de=true\\ Assignment-02(08-09-23).\ ipynb$

 $sns. \ \ catterplot(x="total",y="not_distracted",data=df) \\ (Axes: xlabel='total',ylabel='not_distracted'>$

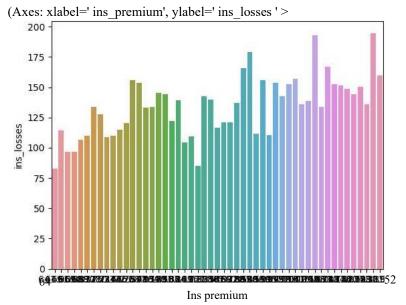


Inference: Here we can clearly observe that not_distracted has caused many car crashes. Which shows the direct proportionality in between total and not_distracted of car crashes.

ineplot(x="ins_premium",y="ins_losses",data=df)



sns. barplot(data=df x: " ins_premi um" "ins_ losses ")

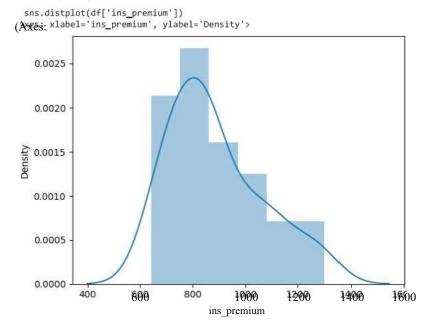


Inference: There is an irregular plotting of lineplot of ins_premium and ins_losses. which defines that insurance losses is directly proportional to insurance premium. where increse in insurance premium also tends to increase in insurance loss.

```
sns.distplot(df[ ' ins_premium' l)
     <ipython- input-4-2616b6ce983b> : 1: UserWarning:
```

"distplot• is a deprecated function and will be removed in seaborn vø.14.e.

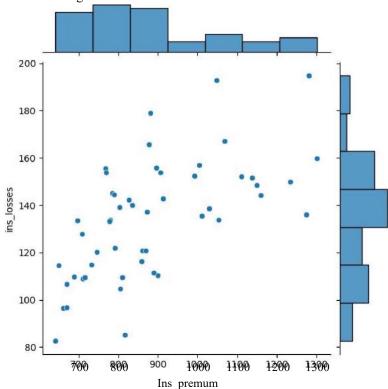
Please adapt your code to use either displot• (a figure-level function with similar flexibility) or •histplot• (an axes-level function for histograms) . For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751



Inference: The above graph is about the density Of the insurance premium where there is a huge increase in the density Of insurance premium at a point Of 800.

 $\label{lem:https://colab.research.google.com/drive/1XDqMpQe0UkRRh4GZNV7GDWvOfhJFGCf8\#scrollTo=Abe18ivA_nPH\&printMode=true \\ sns.jointplot(data=df, x="ins_premium", "ins_losses")$

< seaborn.axisgrid. JointGrid at Ox7d1d5bfbbe50>



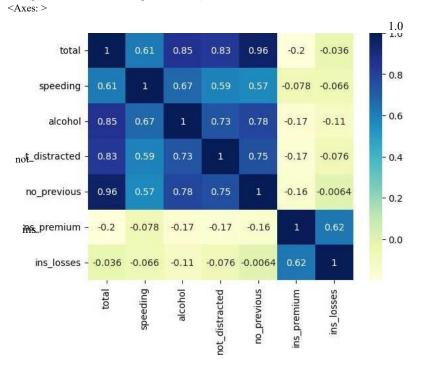
Inference: The above graph is about jointplot of ins_premium and ins_losses where the plotting of graph is randomly distributed through out the graph. We can observe the density of ins_premium and ins_losses where they show in great increase and decrease.

corr=df. corr()

<ipython-input-22-7d5195e2bf4d> : 1: FutureWarning: The default value of numeric_only in DataFrame. corr is deprecated. In a future versior corr=df. corr() total speeding alcohol not_distracted no_previous ins_premium ins_losses

1.000000	0.611548	0.852613	0.827560	0.956179	-o. 199702	0.036011
0.611548	1 .000000	0.669719	0.588010	0.571976	-0.077675	-0.065928
0.852613	0.669719	1 .000000	0.732816	o. 783520	-0.170612	-о. 112547
0.827560	0.588010	0.732816	1.000000	0.747307	-o. 174856	-0.075970
0.956179	0.571976	0.783520	0.747307	1.000000	-o. 156895	-0.006359
-0.199702	-0.077675	-0.170612	-о. 174856	-o. 156895	1 .000000	0.623116
-0.036011	-0.065928	-o. 112547	-0.075970	-0.006359	0.623116	1.000000
	0.611548 0.852613 0.827560 0.956179 -0.199702	0.611548 1.000000 0.852613 0.669719 0.827560 0.588010 0.956179 0.571976 -0.199702 -0.077675	0.611548 1.000000 0.669719 0.852613 0.669719 1.000000 0.827560 0.588010 0.732816 0.956179 0.571976 0.783520 -0.199702 -0.077675 -0.170612 -0.036011 -0.065928	0.611548 1.000000 0.669719 0.588010 0.852613 0.669719 1.000000 0.732816 0.827560 0.588010 0.732816 1.000000 0.956179 0.571976 0.783520 0.747307 -0.199702 -0.077675 -0.170612 -0.174856 -0.036011 -0.065928 -0.075970	0.611548 1.000000 0.669719 0.588010 0.571976 0.852613 0.669719 1.000000 0.732816 0.783520 0.827560 0.588010 0.732816 1.000000 0.747307 0.956179 0.571976 0.783520 0.747307 1.000000 -0.199702 -0.077675 -0.170612 -0.174856 -0.156895 -0.036011 -0.065928 -0.075970 -0.006359	0.611548 1.000000 0.669719 0.588010 0.571976 -0.077675 0.852613 0.669719 1.000000 0.732816 0.783520 -0.170612 0.827560 0.588010 0.732816 1.000000 0.747307 -0.174856 0.956179 0.571976 0.783520 0.747307 1.000000 -0.156895 -0.199702 -0.077675 -0.170612 -0.174856 -0.156895 1.000000 -0.036011 -0.065928 -0.075970 -0.006359 0.623116

 $https://c01 ab.research.googIe.com/drive/1XDqMpQeOUkRRh4GZNV7GDWvOfhJFGCf8\#scr011To=Abe18 iv A_nPH\&printMode=truesns. heatmap(corr, annot=True, cmap--"YIGnBu")$



Inferance: The above data is the correlation of the car crashs data. Where we can observe the clear correlation between each and every info of the car crashs data.

X

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