vit-si-assignment-2

September 14, 2023

0.0.1 SmartBridge Assessment -2 RISHIKA SAHOO 21BCB0184

• car_crashes data set imported from seaborn

17

21.4

4.066

4.922

• Done Visualization for the data set and writtern inference for each graph that has been observed.

```
[2]: import seaborn as sns
     import matplotlib.pyplot as plt
     import warnings
[3]: warnings.filterwarnings('ignore', category=FutureWarning)
     # To Ignore Future Warnings
     warnings.filterwarnings('ignore', category=UserWarning)
     # To ignore user warnings
[4]: df = sns.load_dataset('car_crashes')
[5]: df
[5]:
         total
                 speeding
                           alcohol
                                     not_distracted
                                                      no_previous
                                                                    ins_premium
          18.8
                    7.332
     0
                             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
                                              14.094
                                                                         1137.87
                             4.860
                                                            16.038
     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
          17.5
     11
                    9.450
                             7.175
                                              14.350
                                                            15.225
                                                                          861.18
     12
          15.3
                    5.508
                             4.437
                                              13.005
                                                            14.994
                                                                          641.96
          12.8
     13
                    4.608
                             4.352
                                              12.032
                                                            12.288
                                                                          803.11
                                                                          710.46
     14
          14.5
                    3.625
                             4.205
                                              13.775
                                                            13.775
     15
          15.7
                    2.669
                             3.925
                                              15.229
                                                            13.659
                                                                          649.06
     16
          17.8
                    4.806
                             4.272
                                              13.706
                                                                          780.45
                                                            15.130
```

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

0.1 About Data set:

- total : No of Drivers involved per billion miles
- $\bullet\,$ speeding : % of drivers involed in car crashes by speeding
- alcohol : % of drivers involved in car cashes by alcohol
- not_distracted : % of drivers involved without distraction

- no_previous : % of drivers involved without previous crashes records
- ins_premium : Car insurence premium range
- \bullet ins_loss : Insurence company loss
- abbrev: Abbrevations of States of US (NH: New Hampshire, MD: Maryland)

[6]: df.isnull().sum()

[6]: total 0 speeding 0 alcohol 0 ${\tt not_distracted}$ 0 no_previous 0 0 ins_premium ins_losses 0 0 abbrev dtype: int64

[7]: 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	${\tt not_distracted}$	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

[8]: df.describe()

[8]:		total	speeding	alcohol	not_distracted	no_previous	\
	count	51.000000	51.000000	51.000000	51.000000	51.000000	
	mean	15.790196	4.998196	4.886784	13.573176	14.004882	
	std	4.122002	2.017747	1.729133	4.508977	3.764672	
	min	5.900000	1.792000	1.593000	1.760000	5.900000	
	25%	12.750000	3.766500	3.894000	10.478000	11.348000	
	50%	15.600000	4.608000	4.554000	13.857000	13.775000	
	75%	18.500000	6.439000	5.604000	16.140000	16.755000	
	max	23.900000	9.450000	10.038000	23.661000	21.280000	

```
count
                51.000000
                            51.000000
      mean
              886.957647
                           134.493137
      std
               178.296285
                            24.835922
      min
              641.960000
                            82.750000
      25%
              768.430000
                           114.645000
      50%
              858.970000
                           136.050000
      75%
              1007.945000
                           151.870000
      max
              1301.520000
                           194.780000
 [9]:
     df.head()
 [9]:
         total
                 speeding
                           alcohol not_distracted no_previous
                                                                    ins_premium \
      0
          18.8
                    7.332
                              5.640
                                              18.048
                                                            15.040
                                                                          784.55
          18.1
                    7.421
      1
                              4.525
                                              16.290
                                                            17.014
                                                                         1053.48
      2
          18.6
                    6.510
                              5.208
                                              15.624
                                                            17.856
                                                                          899.47
          22.4
      3
                    4.032
                              5.824
                                              21.056
                                                            21.280
                                                                          827.34
          12.0
                    4.200
                                                                          878.41
      4
                              3.360
                                              10.920
                                                            10.680
         ins_losses abbrev
      0
              145.08
                         AL
      1
              133.93
                         ΑK
      2
              110.35
                         AZ
      3
                         AR
              142.39
      4
              165.63
                         CA
     df.tail()
[10]:
[10]:
          total
                  speeding
                            alcohol
                                      not_distracted no_previous
                                                                     ins_premium \
      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
                                                5.382
      49
           13.8
                     4.968
                               4.554
                                                             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
                          WΙ
      50
               122.04
                          WY
[11]: df.shape
```

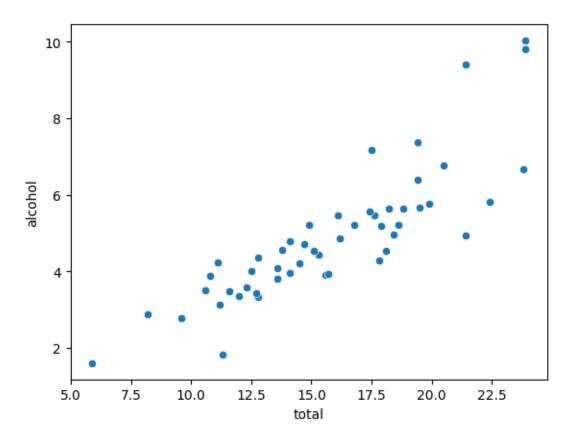
ins_losses

ins_premium

[11]: (51, 8)

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

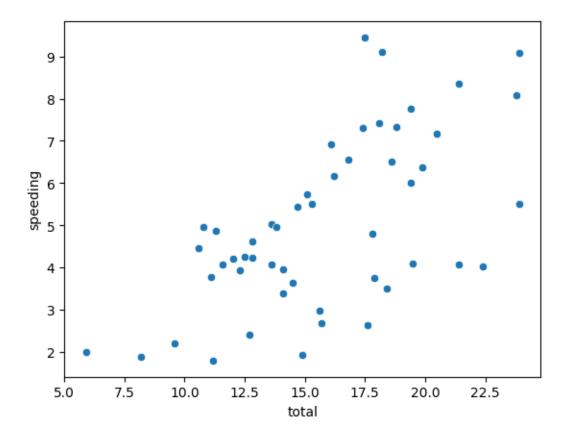
[12]: <Axes: xlabel='total', ylabel='alcohol'>



• Inference : As total drivers are increasing , car crashes due to alcohol are also increasing so directly proportional.

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

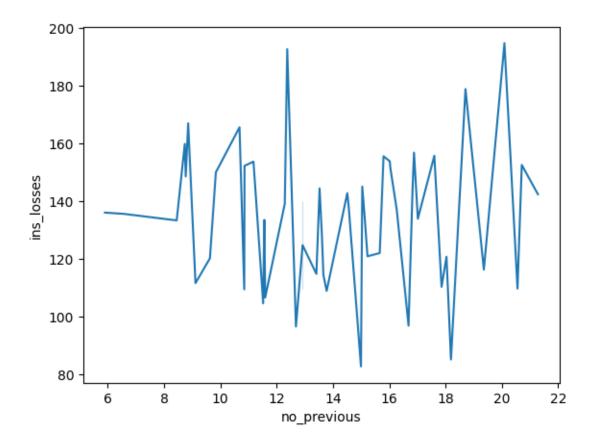
[13]: <Axes: xlabel='total', ylabel='speeding'>



• Inference : As total drivers increasing car crashes due to speeding also increases but not directly proportional

```
[14]: sns.lineplot(x="no_previous",y="ins_losses",data=df)
```

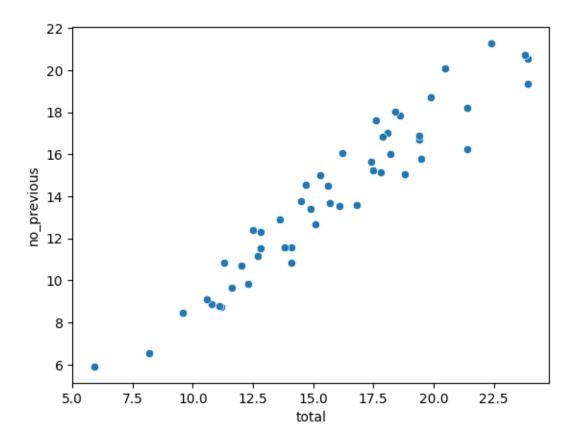
[14]: <Axes: xlabel='no_previous', ylabel='ins_losses'>



• Inference : It was increasing and decreasing and the lowerst point is occured at 15 (no_previous) and highest at 190 (no_previous) [Approx]

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

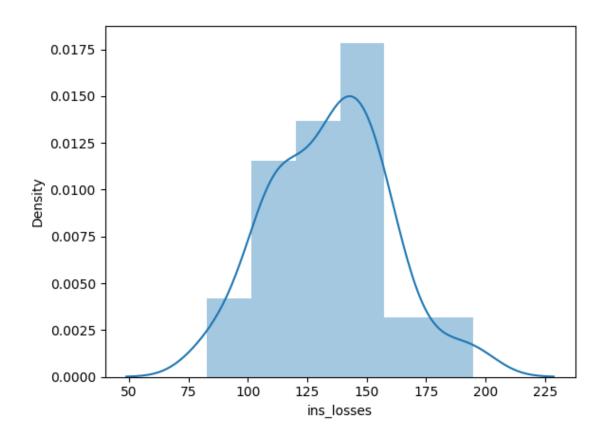
[15]: <Axes: xlabel='total', ylabel='no_previous'>



• Inference : Alcohol and no_previous are directly proportional

```
[17]: sns.distplot(df["ins_losses"])
```

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



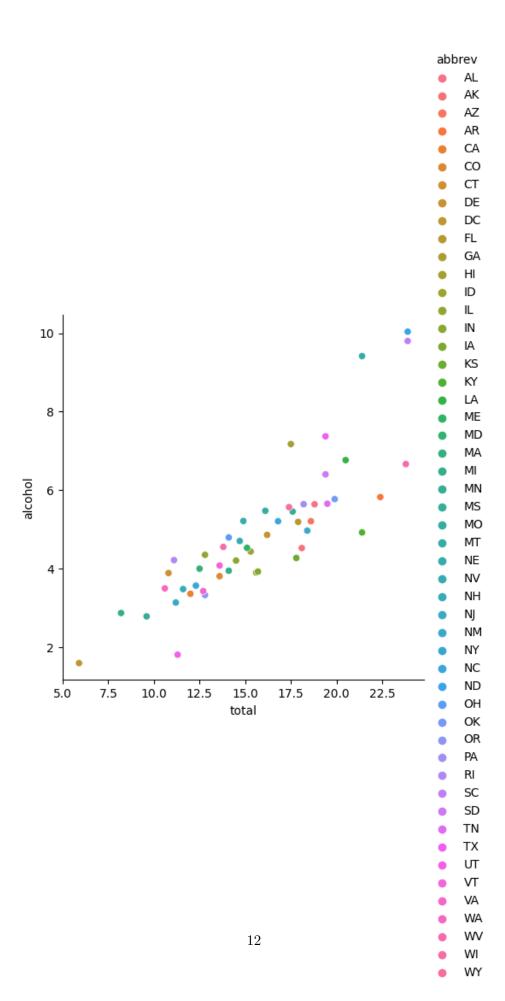
• Inference : Cars whose insurance losses is around 150 are going to crash more(approx)

```
[22]: df["abbrev"].value_counts()
```

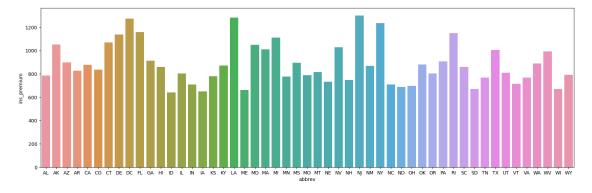
```
[22]: AL
                  1
         PA
                  1
         NV
                  1
         NH
         NJ
                  1
         NM
                  1
         NY
                  1
         NC
                  1
         ND
                  1
         ОН
                  1
                  1
         OK
         \mathtt{OR}
                  1
         RI
                  1
         MT
                  1
         SC
                  1
         SD
                  1
         \mathtt{TN}
                  1
         \mathsf{TX}
                  1
```

```
UT
            1
      VT
            1
            1
      VA
      WA
            1
      WV
            1
      WI
            1
      NE
            1
      MO
            1
      AK
             1
      ID
            1
      ΑZ
            1
      AR
            1
      CA
            1
      CO
            1
      CT
            1
      DE
            1
      DC
            1
      FL
            1
      GA
            1
      ΗI
            1
      ΙL
            1
      MS
            1
      IN
             1
      ΙA
            1
      KS
             1
      ΚY
            1
      LA
             1
      ME
            1
      MD
            1
      MA
            1
            1
      ΜI
      MN
             1
      WY
             1
      Name: abbrev, dtype: int64
[23]: sns.relplot(x="total",y="alcohol",data=df,hue="abbrev")
```

[23]: <seaborn.axisgrid.FacetGrid at 0x7c31a54c94e0>

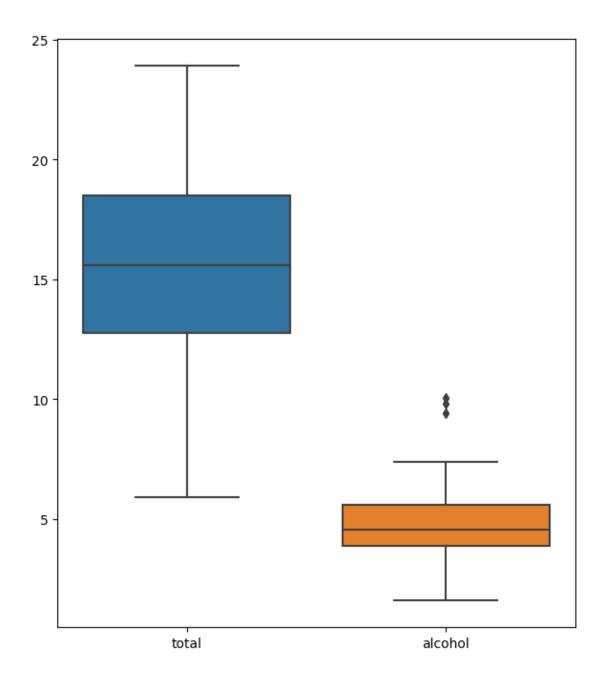


```
[19]: plt.figure(figsize=(20, 6))
sns.barplot(x="abbrev",y="ins_premium",data=df)
plt.show()
```



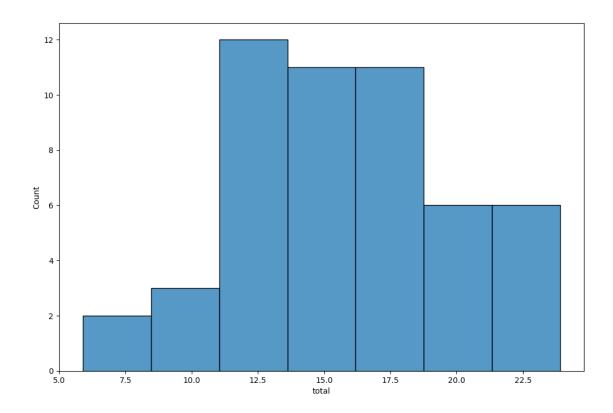
 $\bullet\,$ Inference : In the LA and NJ there are more % of insurance premium

```
[21]: boxplot_for = df[['total', 'alcohol']]
  plt.figure(figsize=(7, 8))
  sns.boxplot(data=boxplot_for)
  plt.show()
```



• Inference : From the above boxplot , we can see a outliner between 9 and 11 (approximately)

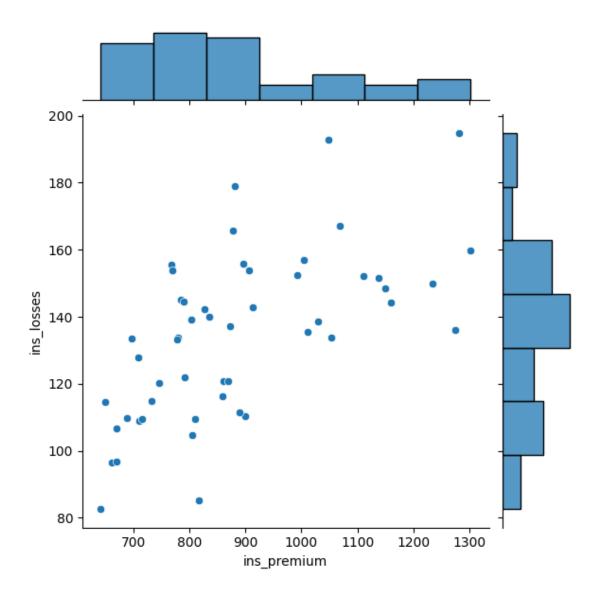
```
[24]: plt.figure(figsize=(12, 8))
sns.histplot(x="total",data=df)
plt.show()
```



 $\bullet\,$ Inference: At 12.5 the count reached highest than others in data set

```
[25]: plt.figure(figsize=(17, 12))
sns.jointplot(x="ins_premium",y="ins_losses",data=df)
plt.show()
```

<Figure size 1700x1200 with 0 Axes>



• Inference: As the ins_premiums increases the ins_losses are also increasing (Nearly Directly proportional). This is a graph of combination of bivariate and univariate

```
[26]: correlation_value = df.corr(numeric_only=True) correlation_value
```

[26]:		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
                                -0.006359
                   -0.156895
ins_premium
                    1.000000
                                 0.623116
ins_losses
                    0.623116
                                 1.000000
  • Inference : From the corr() we can find all corellations values for each with other parameter
```

how it was related

```
[27]: df[['total', 'alcohol']].corr()
[27]:
                  total
                          alcohol
      total
               1.000000
                         0.852613
                         1.000000
      alcohol
               0.852613
[28]: sns.heatmap(correlation_value,annot=True)
```

[28]: <Axes: >

