assignment-2-21bds0269

September 14, 2023

0.0.1 Assignment - 2 - Ajay Ganesh [21BDS0269]

- car_crashes data set imported from seaborn
- Done Visualization for the data set and writtern inference for each graph that has been observed.

[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
```

[ ]:
```
warnings.filterwarnings('ignore', category=FutureWarning)
# To Ignore Future Warnings

warnings.filterwarnings('ignore', category=UserWarning)
# To ignore user warnings
```

[ ]:
```
df = sns.load_dataset('car_crashes')
```

[ ]:
```
df
```

[ ]:

	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	
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	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	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
- 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
- ins_loss : Insurence company loss
- abbrev : Abbrevations of States of US (NH : New Hampshire , MD : Maryland)

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

[ ]:
```
total             0
speeding          0
alcohol           0
not_distracted    0
no_previous       0
ins_premium       0
ins_losses        0
abbrev            0
dtype: int64
```

[ ]:
```
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   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
```

[ ]:
```
df.describe()
```

[ ]:
```
           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
```

```
       ins_premium  ins_losses
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
```

[ ]:
```
df.head()
```

[ ]:
```
   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     AK
2      110.35     AZ
3      142.39     AR
4      165.63     CA
```

[ ]:
```
df.tail()
```

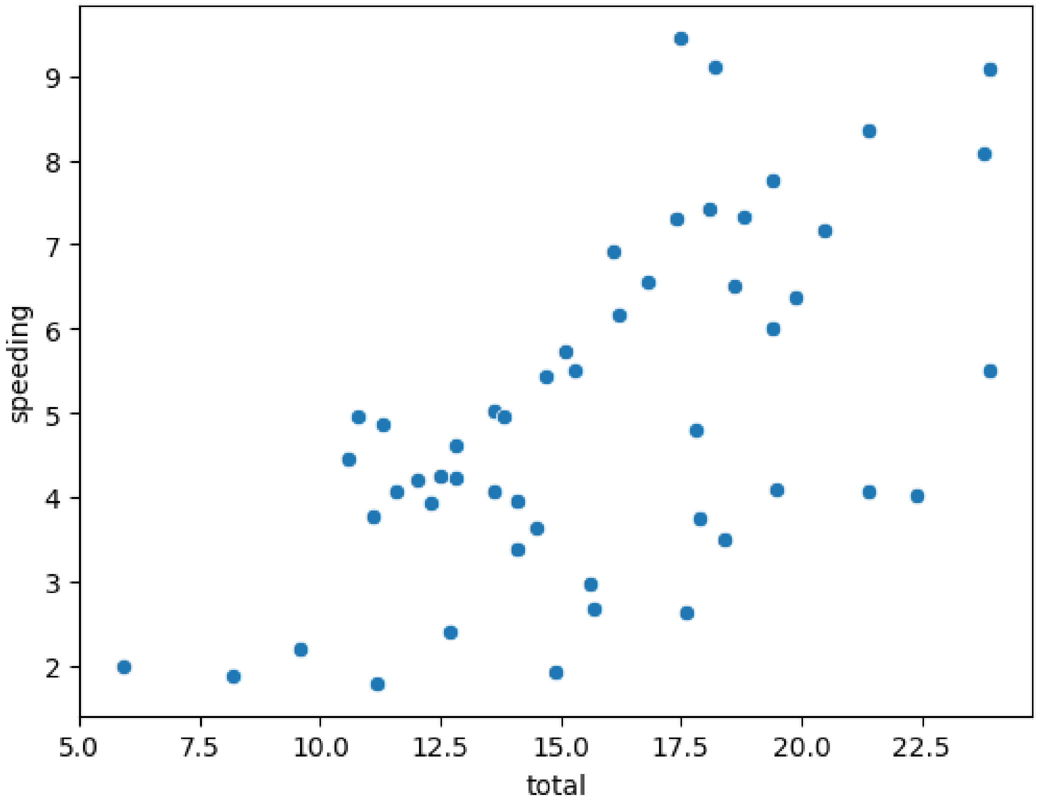
[ ]:
```
    total  speeding  alcohol  not_distracted  no_previous  ins_premium  \
46   12.7     2.413    3.429          11.049       11.176       768.95
47   10.6     4.452    3.498           8.692        9.116       890.03
48   23.8     8.092    6.664          23.086       20.706       992.61
49   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
```

[ ]:
```
df.shape
```

[ ]: (51, 8)

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

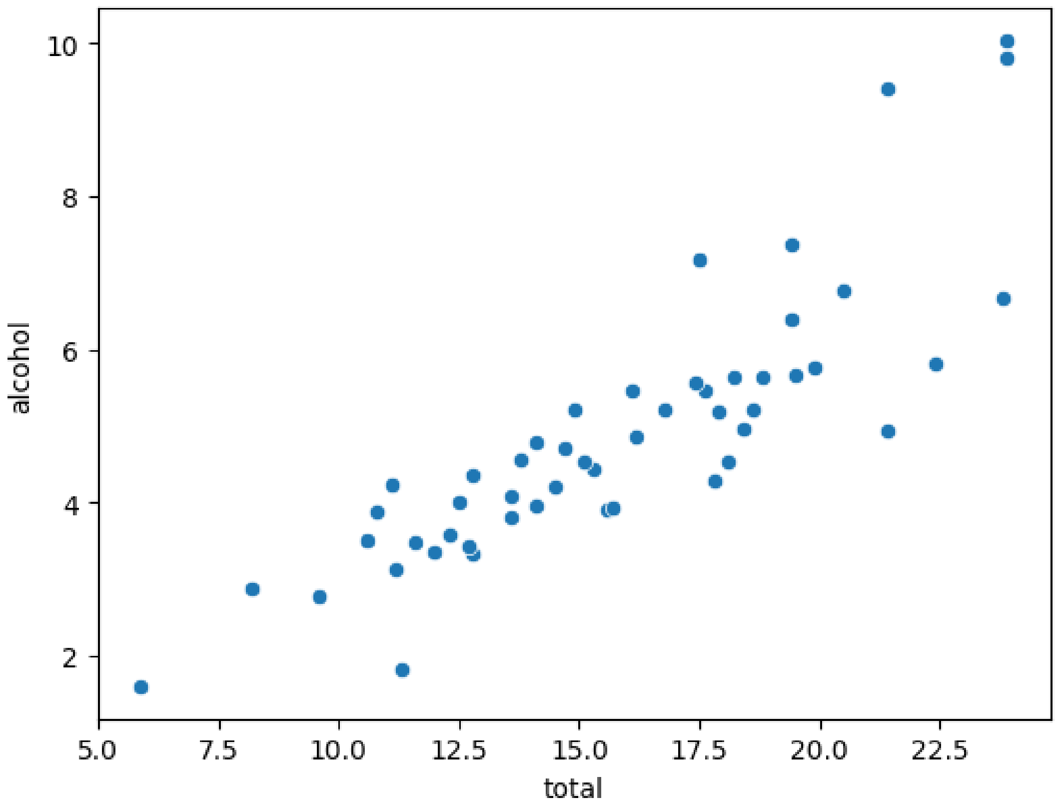
[ ]: <Axes: xlabel='total', ylabel='speeding'>



- Inference : Total drivers are increasing and car crashes due to speeding also increase , its like proportional but not totally proportional

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

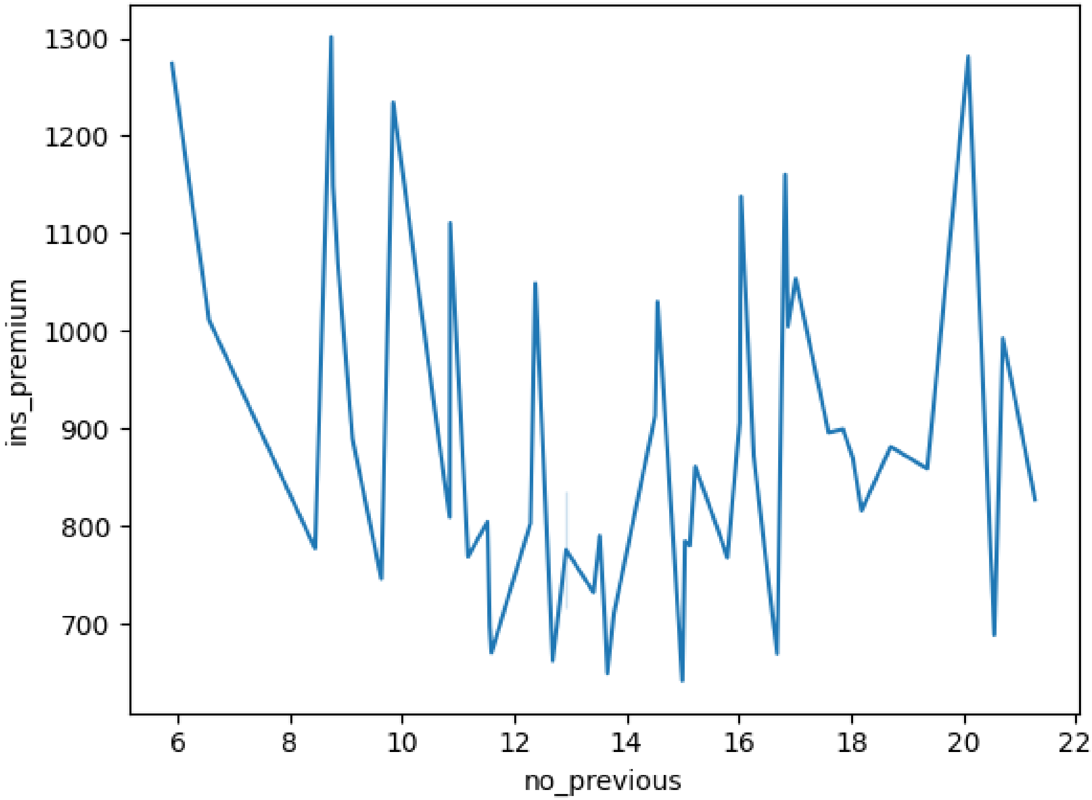
[ ]: <Axes: xlabel='total', ylabel='alcohol'>



- Inference : (Directly proportional) As total drivers are increasing , car crashes due to alcohol are also increasing

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

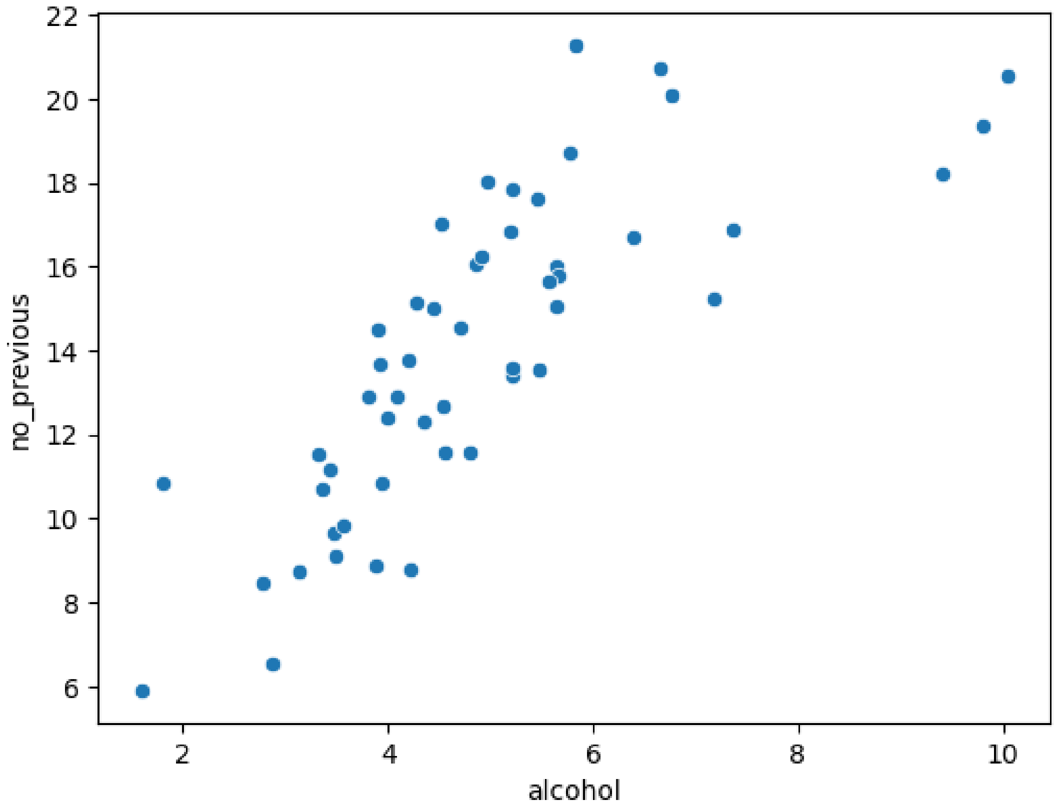
[ ]: <Axes: xlabel='no_previous', ylabel='ins_premium'>



- Inference : It was increasing and decreasing and the lowerst point is occured at 15 (no_previous) and highest at 9 (no_previous) [Approx]

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

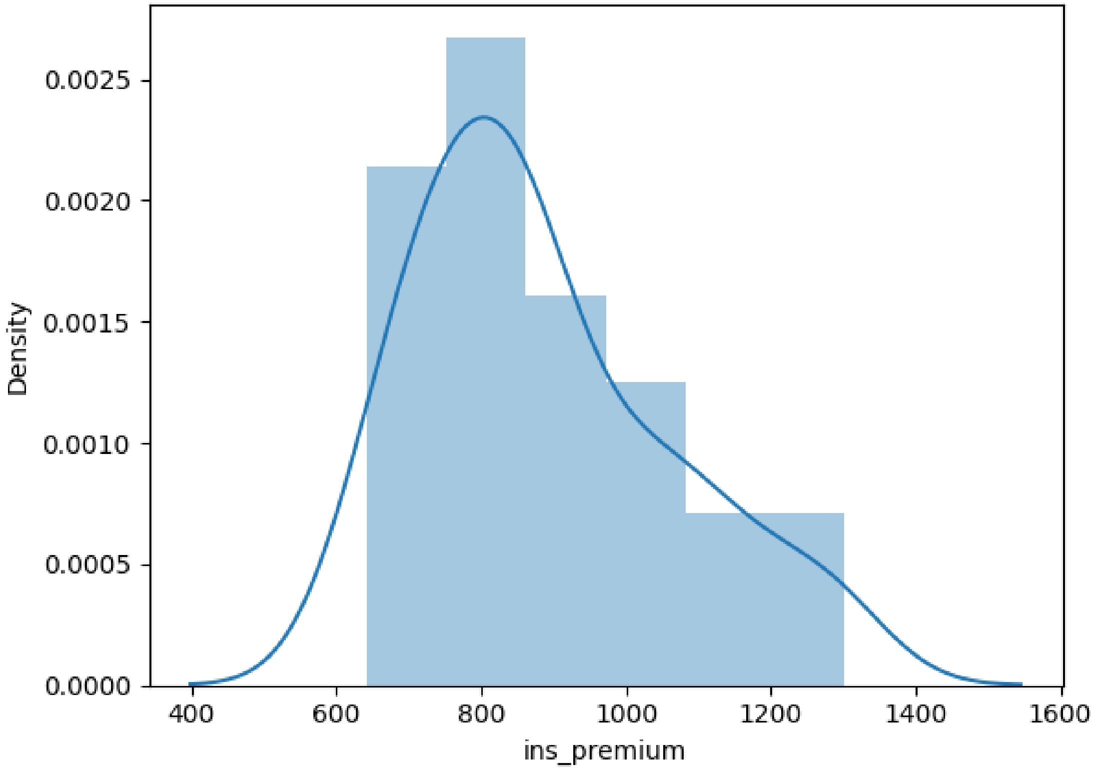
[ ]: <Axes: xlabel='alcohol', ylabel='no_previous'>



- Inference : Directly proportional (Alcohol and no_previous)

[ ]:
```
sns.distplot(df["ins_premium"])
```

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

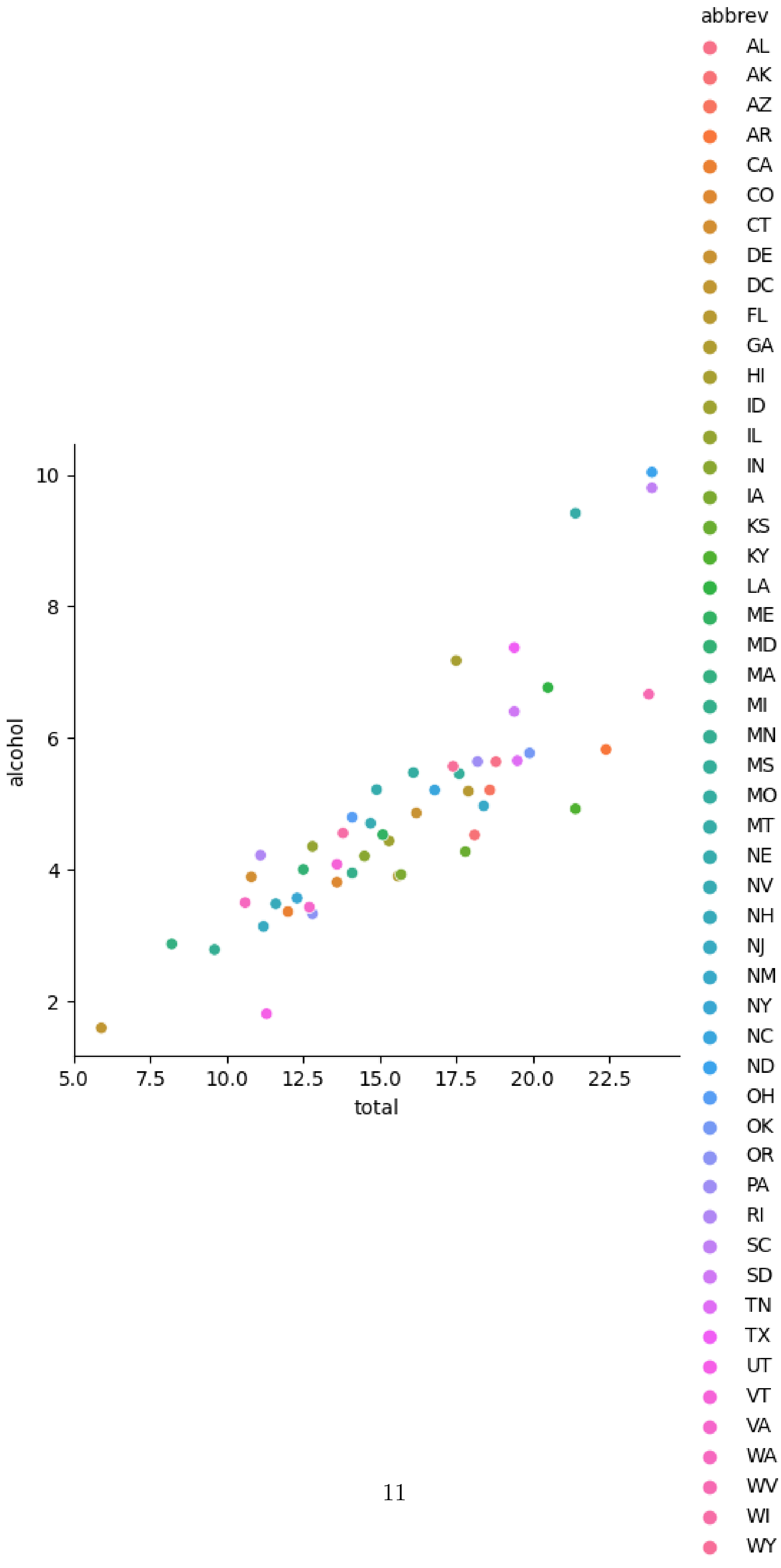


- Inference : Cars whose insurence premium is around 800 are going to crash more

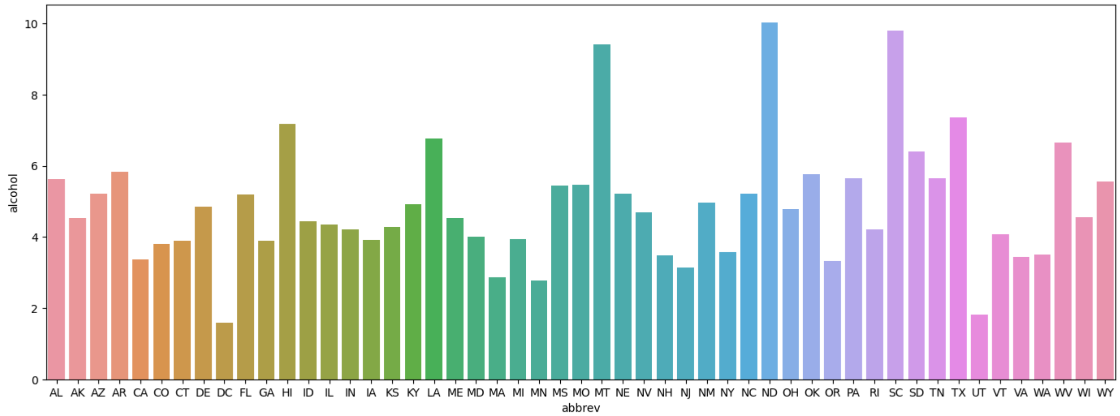
[ ]:
```
df["abbrev"].value_counts()
```

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

[ ]: <seaborn.axisgrid.FacetGrid at 0x7f20e7063af0>

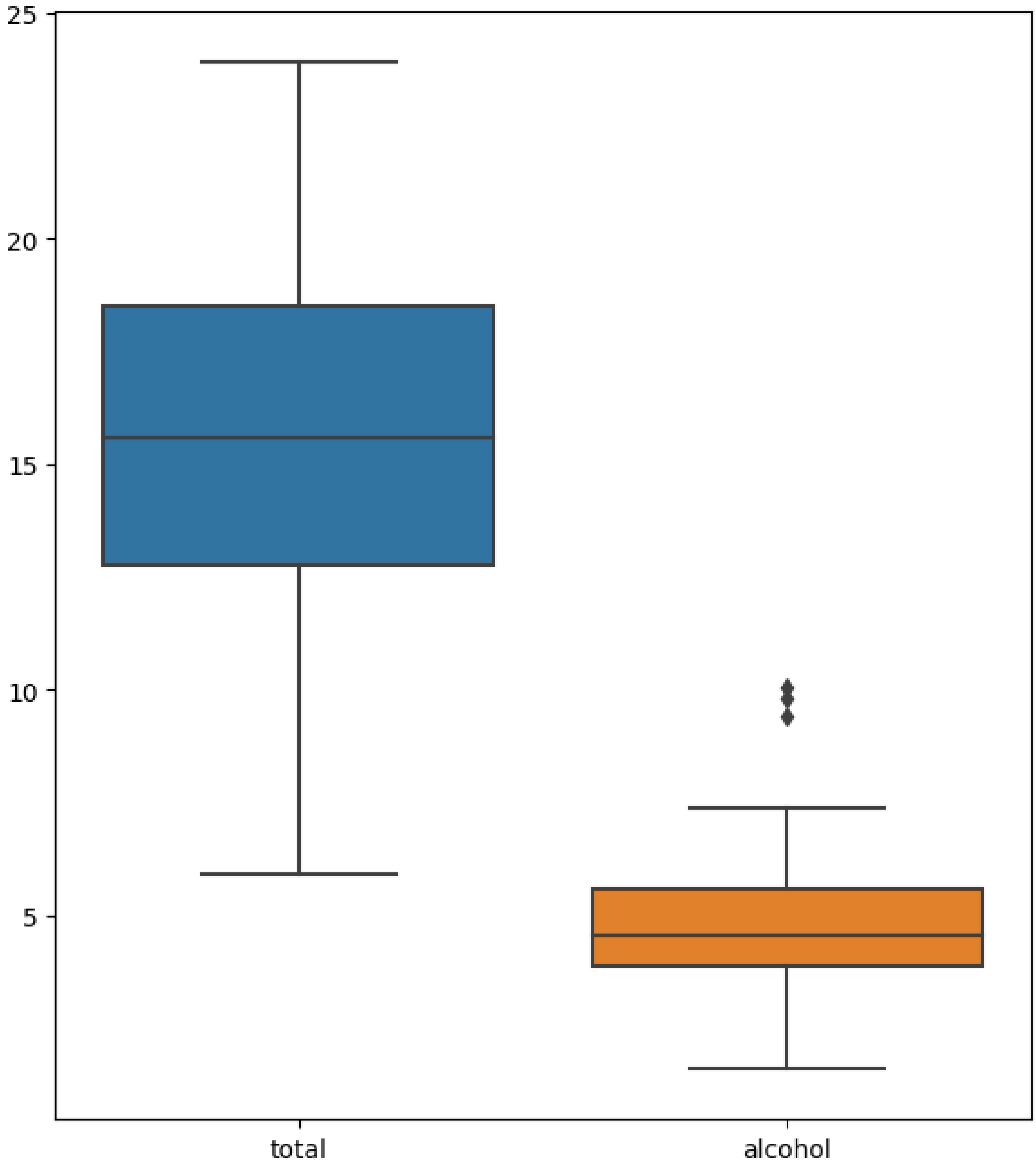

abbrev
AL
AK
AZ
AR
CA
CO
CT
DE
DC
FL
GA
HI
ID
IL
IN
IA
KS
KY
LA
ME
MD
MA
MI
MN
MS
MO
MT
NE
NV
NH
NJ
NM
NY
NC
ND
OH
OK
OR
PA
RI
SC
SD
TN
TX
UT
VT
VA
WA
WV
WI
WY
alcohol
total
10
8
6
4
2
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5

```
[ ]: plt.figure(figsize=(17, 6))
     sns.barplot(x="abbrev",y="alcohol",data=df)
     plt.show()
```



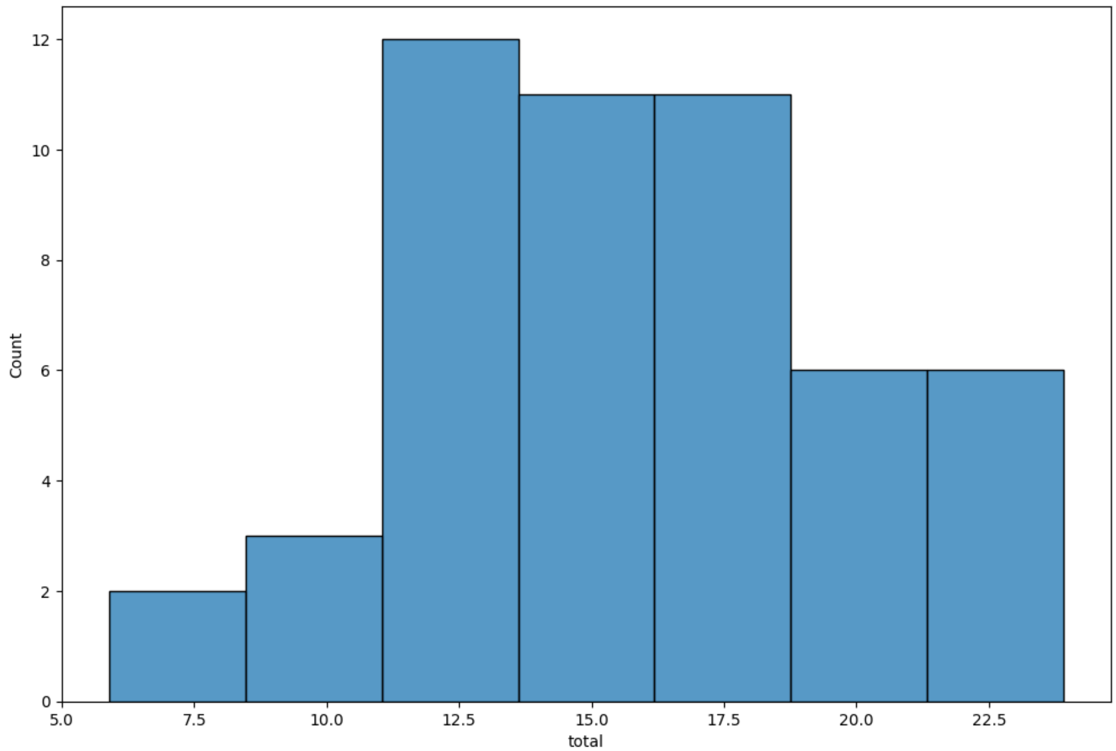
- Inference : In the ND (North Dakota, State in US) there are more % of alcoholic drivers and they are crashing the car

```
[ ]: 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)

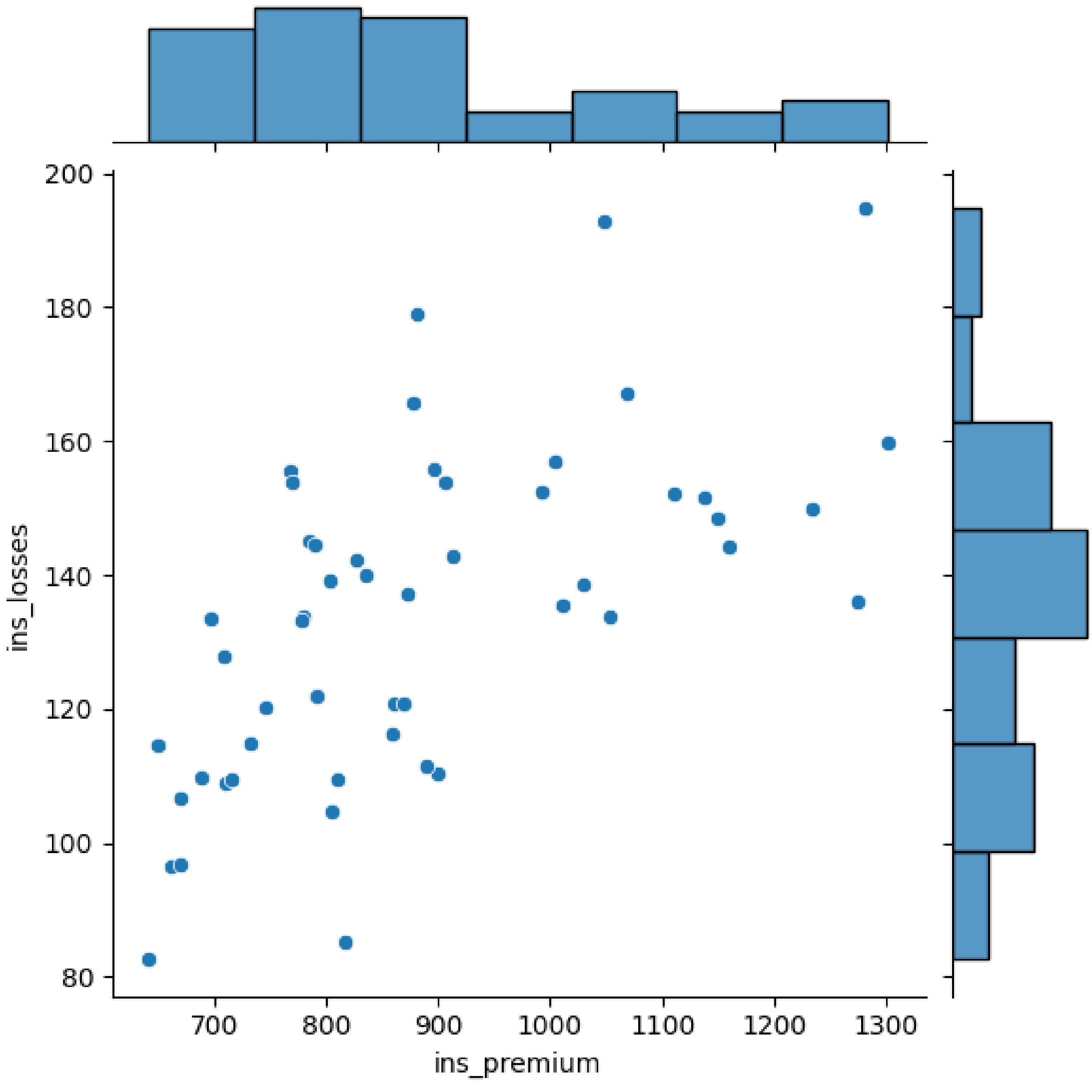
[ ]:
```
plt.figure(figsize=(12, 8))
sns.histplot(x="total",data=df)
plt.show()
```



- Inference: At 12.5 the count reached highest than others in data set

[ ]:
```
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

Correlation:

- ">0.5" - Highly correlated
- "<0.5" - less correlated
- "=0.5" - neutral

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

[ ]:
```
                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       -0.156895   -0.006359
ins_premium        1.000000    0.623116
ins_losses         0.623116    1.000000
```

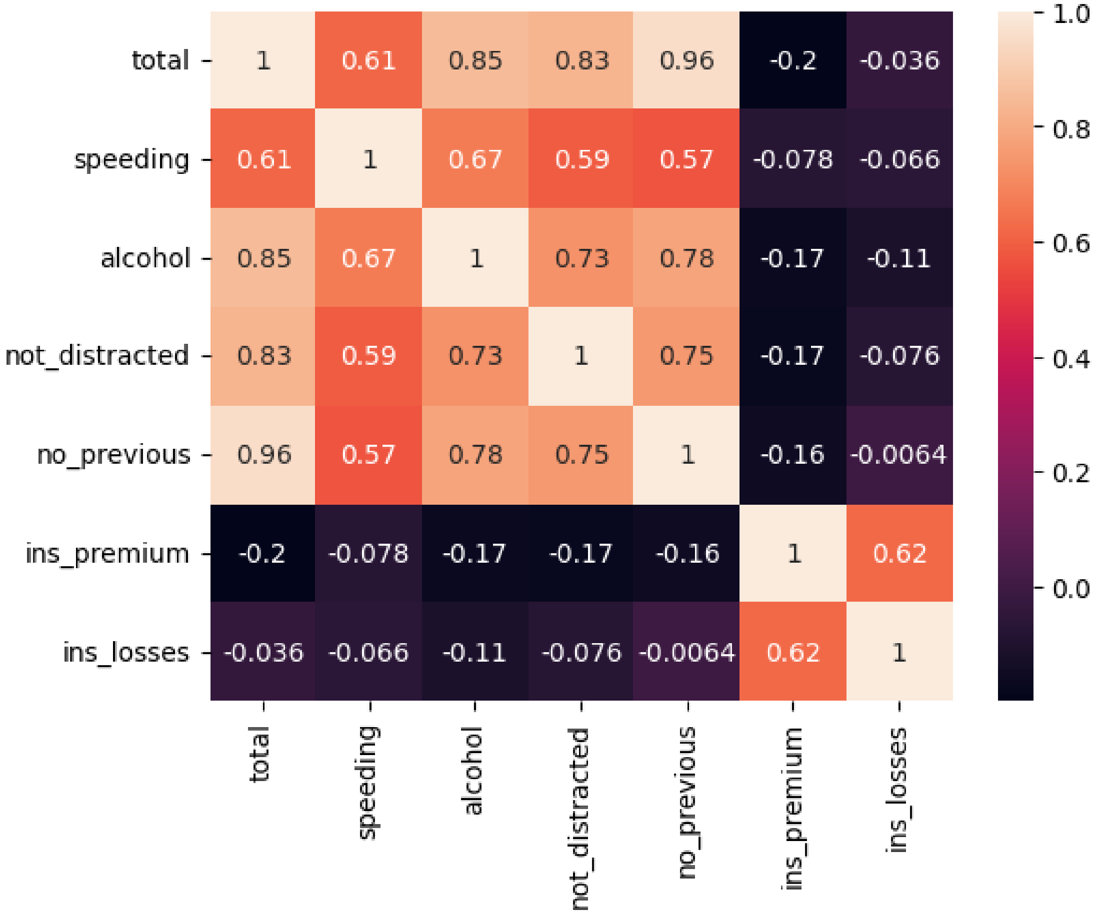
- Inference : From the corr() we can find all corellations values for each with other parameter how it was related

[ ]:
```
df[['total','alcohol']].corr()
```

[ ]:
```
            total   alcohol
total    1.000000  0.852613
alcohol  0.852613  1.000000
```

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

[ ]:
```
<Axes: >
```



Inference : * Highly correlated : Total and no_previous * Neutrally correlated : None * Less correlated : Total and ins_premium