```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
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']
```

```
df=sns.load_dataset('car_crashes')
```

```
df
```

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
0	18.8	7.332	5.640	18.048	15.040	784.55	145.08	AL
1	18.1	7.421	4.525	16.290	17.014	1053.48	133.93	AK
2	18.6	6.510	5.208	15.624	17.856	899.47	110.35	AZ
3	22.4	4.032	5.824	21.056	21.280	827.34	142.39	AR
4	12.0	4.200	3.360	10.920	10.680	878.41	165.63	CA
5	13.6	5.032	3.808	10.744	12.920	835.50	139.91	CO
6	10.8	4.968	3.888	9.396	8.856	1068.73	167.02	CT
7	16.2	6.156	4.860	14.094	16.038	1137.87	151.48	DE
8	5.9	2.006	1.593	5.900	5.900	1273.89	136.05	DC
9	17.9	3.759	5.191	16.468	16.826	1160.13	144.18	FL
10	15.6	2.964	3.900	14.820	14.508	913.15	142.80	GA
11	17.5	9.450	7.175	14.350	15.225	861.18	120.92	HI
12	15.3	5.508	4.437	13.005	14.994	641.96	82.75	ID
13	12.8	4.608	4.352	12.032	12.288	803.11	139.15	IL
14	14.5	3.625	4.205	13.775	13.775	710.46	108.92	IN
15	15.7	2.669	3.925	15.229	13.659	649.06	114.47	IA
16	17.8	4.806	4.272	13.706	15.130	780.45	133.80	KS
17	21.4	4.066	4.922	16.692	16.264	872.51	137.13	KY
18	20.5	7.175	6.765	14.965	20.090	1281.55	194.78	LA
19	15.1	5.738	4.530	13.137	12.684	661.88	96.57	ME
20	12.5	4.250	4.000	8.875	12.375	1048.78	192.70	MD
21	8.2	1.886	2.870	7.134	6.560	1011.14	135.63	MA
22	14.1	3.384	3.948	13.395	10.857	1110.61	152.26	MI

```
df.info
```

```
<bound method DataFrame.info of     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
```

```
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.head()
```

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
0	18.8	7.332	5.640	18.048	15.040	784.55	145.08	AL
1	18.1	7.421	4.525	16.290	17.014	1053.48	133.93	AK
2	18.6	6.510	5.208	15.624	17.856	899.47	110.35	AZ
3	22.4	4.032	5.824	21.056	21.280	827.34	142.39	AR
4	12.0	4.200	3.360	10.920	10.680	878.41	165.63	CA

```
df.describe()
```

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses
count	51.000000	51.000000	51.000000	51.000000	51.000000	51.000000	51.000000
mean	15.790196	4.998196	4.886784	13.573176	14.004882	886.957647	134.493137
std	4.122002	2.017747	1.729133	4.508977	3.764672	178.296285	24.835922
min	5.900000	1.792000	1.593000	1.760000	5.900000	641.960000	82.750000
25%	12.750000	3.766500	3.894000	10.478000	11.348000	768.430000	114.645000
50%	15.600000	4.608000	4.554000	13.857000	13.775000	858.970000	136.050000
75%	18.500000	6.439000	5.604000	16.140000	16.755000	1007.945000	151.870000
max	23.900000	9.450000	10.038000	23.661000	21.280000	1301.520000	194.780000

```
df.tail()
```

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
46	12.7	2.413	3.429	11.049	11.176	768.95	153.72	VA
47	10.6	4.452	3.498	8.692	9.116	890.03	111.62	WA
48	23.8	8.092	6.664	23.086	20.706	992.61	152.56	WV
49	13.8	4.968	4.554	5.382	11.592	670.31	106.62	WI
50	17.4	7.308	5.568	14.094	15.660	791.14	122.04	WY

```
df.isnull().any()
```

```
total             False
speeding          False
alcohol           False
```

```
not_distracted    False
no_previous       False
ins_premium       False
ins_losses        False
abbrev            False
dtype: bool
```

```
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.isna().sum()
```

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

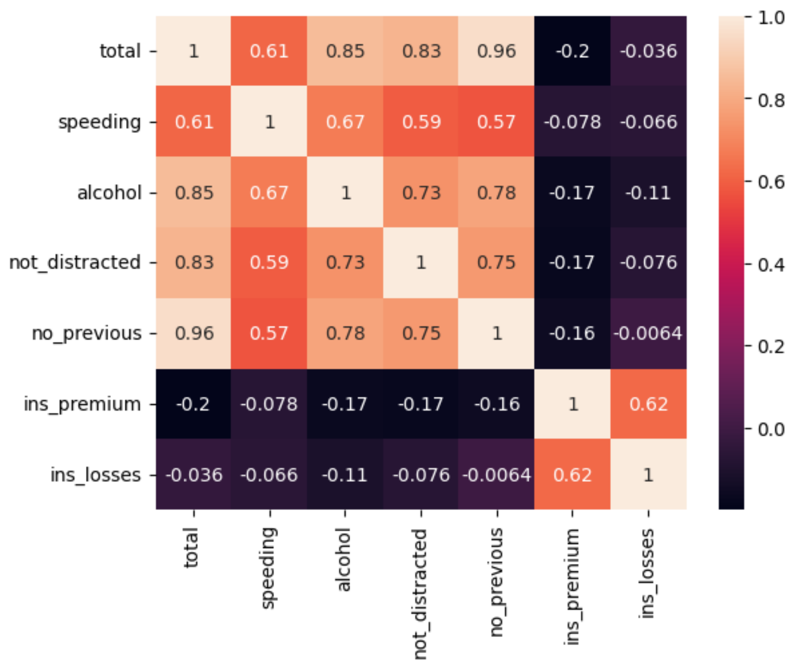
```
cor=df.corr()
cor
```

```
<ipython-input-13-7a446f931109>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a f
  cor=df.corr()
```

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses
total	1.000000	0.611548	0.852613	0.827560	0.956179	-0.199702	-0.036011
speeding	0.611548	1.000000	0.669719	0.588010	0.571976	-0.077675	-0.065928
alcohol	0.852613	0.669719	1.000000	0.732816	0.783520	-0.170612	-0.112547
not_distracted	0.827560	0.588010	0.732816	1.000000	0.747307	-0.174856	-0.075970
no_previous	0.956179	0.571976	0.783520	0.747307	1.000000	-0.156895	-0.006359
ins_premium	-0.199702	-0.077675	-0.170612	-0.174856	-0.156895	1.000000	0.623116
ins_losses	-0.036011	-0.065928	-0.112547	-0.075970	-0.006359	0.623116	1.000000

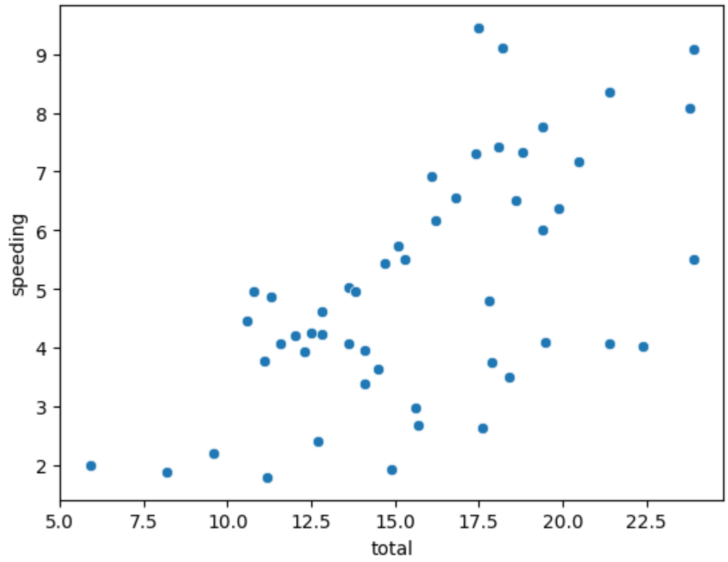
```
sns.heatmap(cor,annot=True)
```

```
<Axes: >
```



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

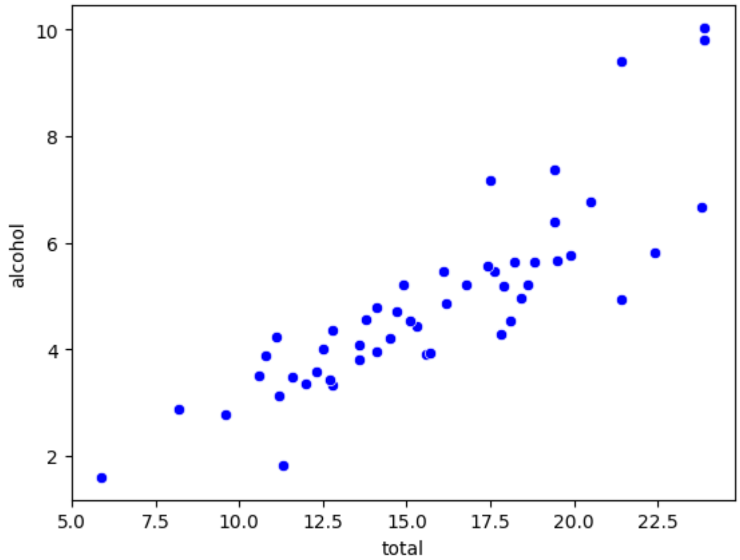
<Axes: xlabel='total', ylabel='speeding'>



inference: from the above graph,it is very evident that the total number of drivers in fatal collisions is directly or linearly proportional to the percentage of drivers involved in fatal collisions,who are speeding.

```
sns.scatterplot(x='total',y='alcohol',data=df,color="b")
```

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



inference:from the above graph it is very evident that the total number of drivers in fatal collisions is linerly proportinal to the percentage of drivers involved in fatal collisions,consuming alchohol.

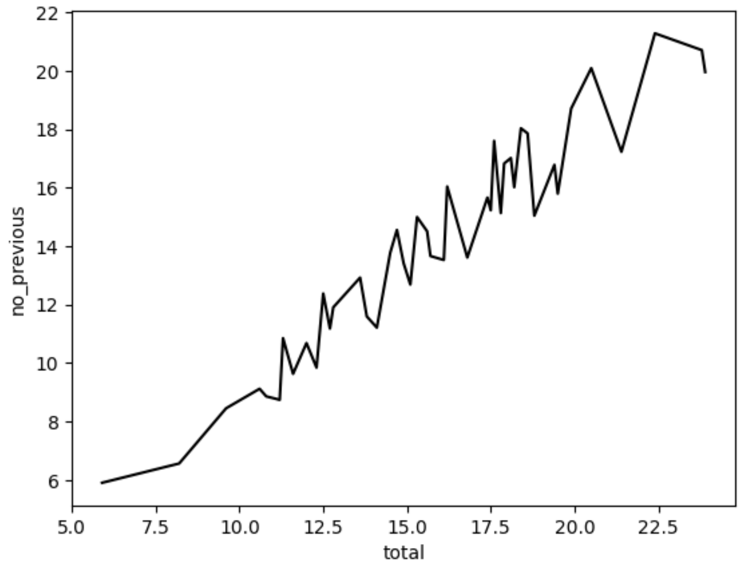
```
sns.scatterplot(x='total',y="not_distracted",data=df,color="g")
```

```
<Axes: xlabel='total', ylabel='not_distracted'>
```

inference:from the above graph it is very evident that the total number of drivers in fatal collisions is linerly proportinal to the percentage of drivers involved in fatal collisions,who are not getting distracted.

```
#lineplot
sns.lineplot(x='total',y='no_previous',data=df,errorbar=None,color="black")
```

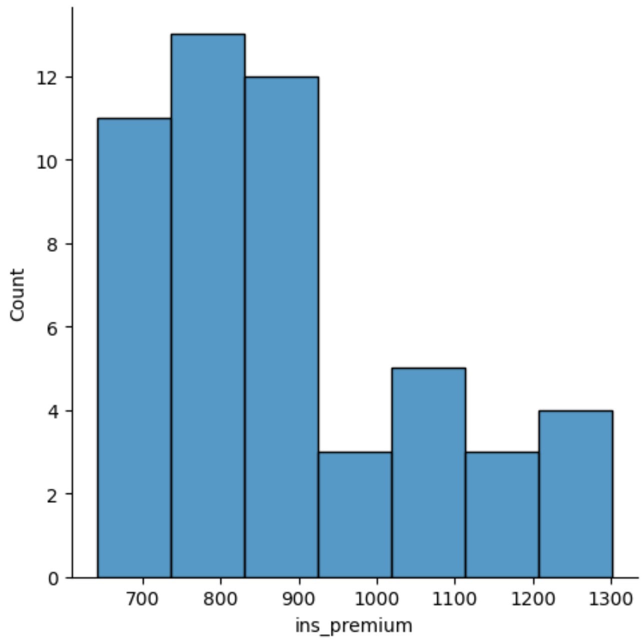
```
<Axes: xlabel='total', ylabel='no_previous'>
```



inference:from the above graph it is very evident that the total number of drivers in fatal collisions is linerly proportinal to the percentage of drivers involved in fatal collisions,who do not have previous accidents.

```
#distributionplot
sns.displot(df['ins_premium'])
```

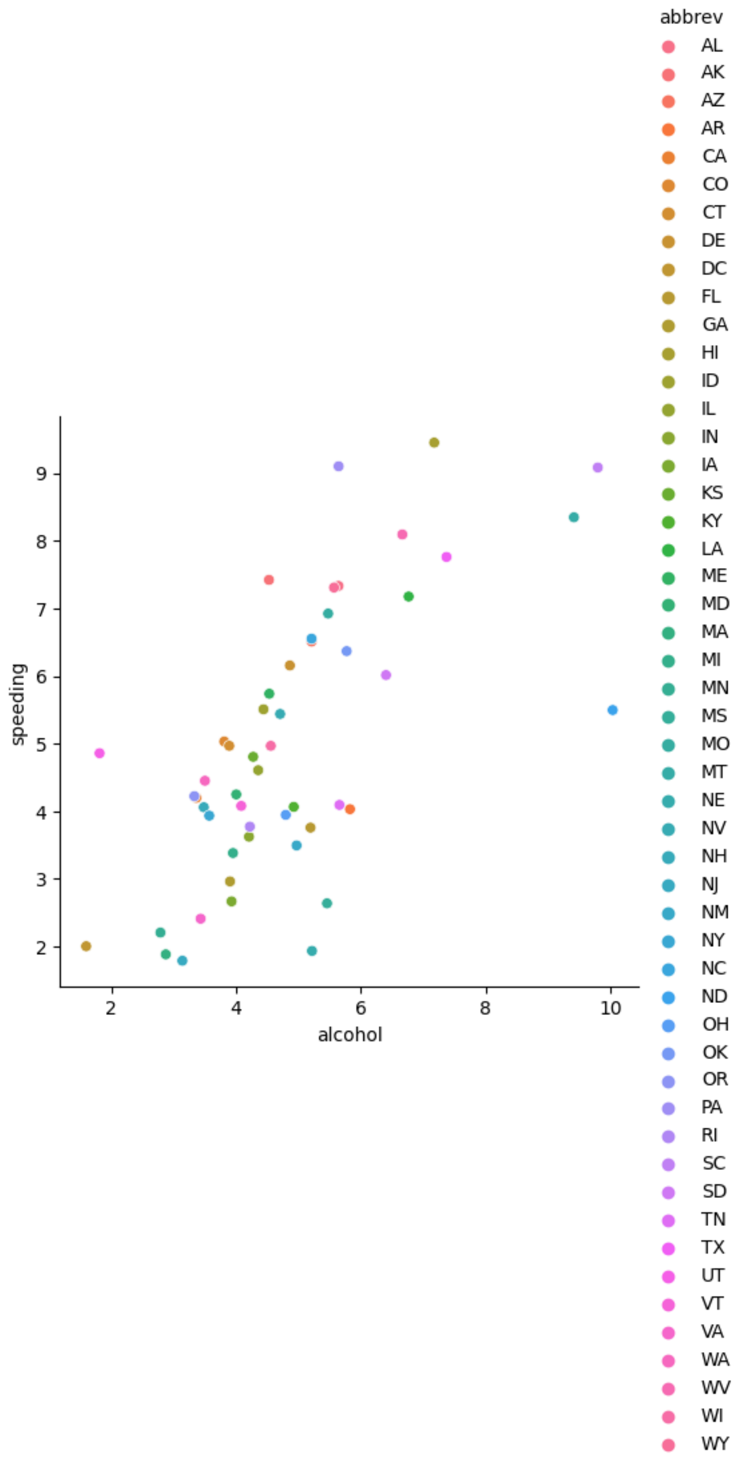
```
<seaborn.axisgrid.FacetGrid at 0x794871145300>
```



inference:ins_premium in average lies between 300 to 900

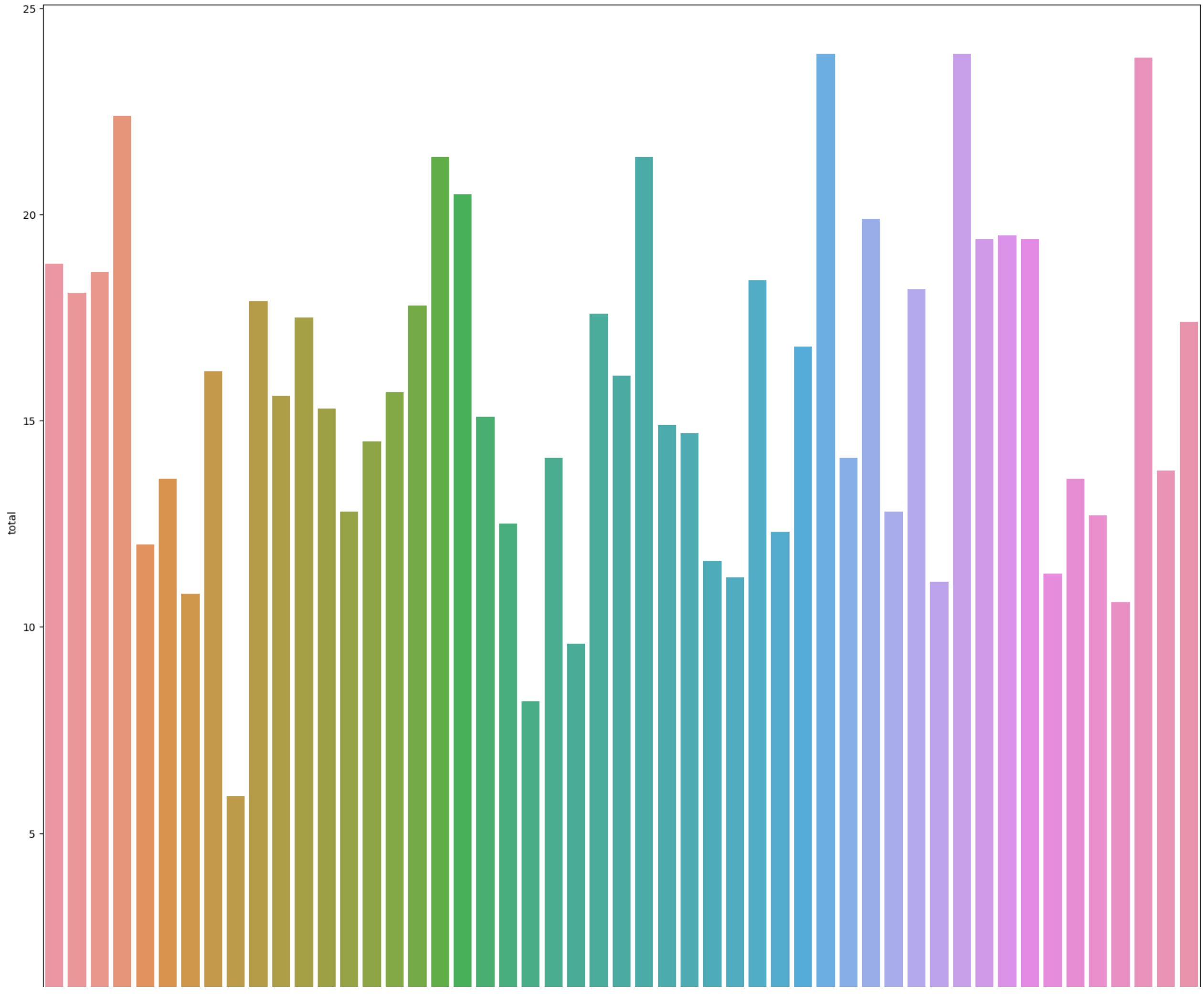
```
#RelPlot
sns.relplot(x='alcohol',y='speeding',data=df,hue="abbrev")
```

```
<seaborn.axisgrid.FacetGrid at 0x79487116ee00>
```



innference:with an increase in alcohol consumption,speeding also increases.

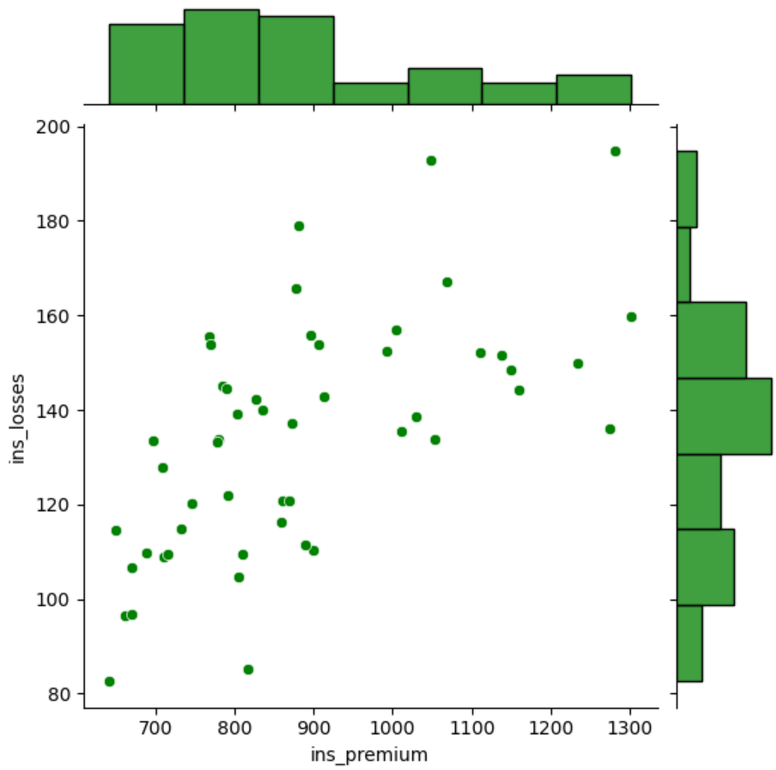
```
#barplot
plt.figure(figsize=(20,18))
sns.barplot(data=df,x="abbrev",y="total")
plt.show()
```



inference:state ND has the total no of highest collisions

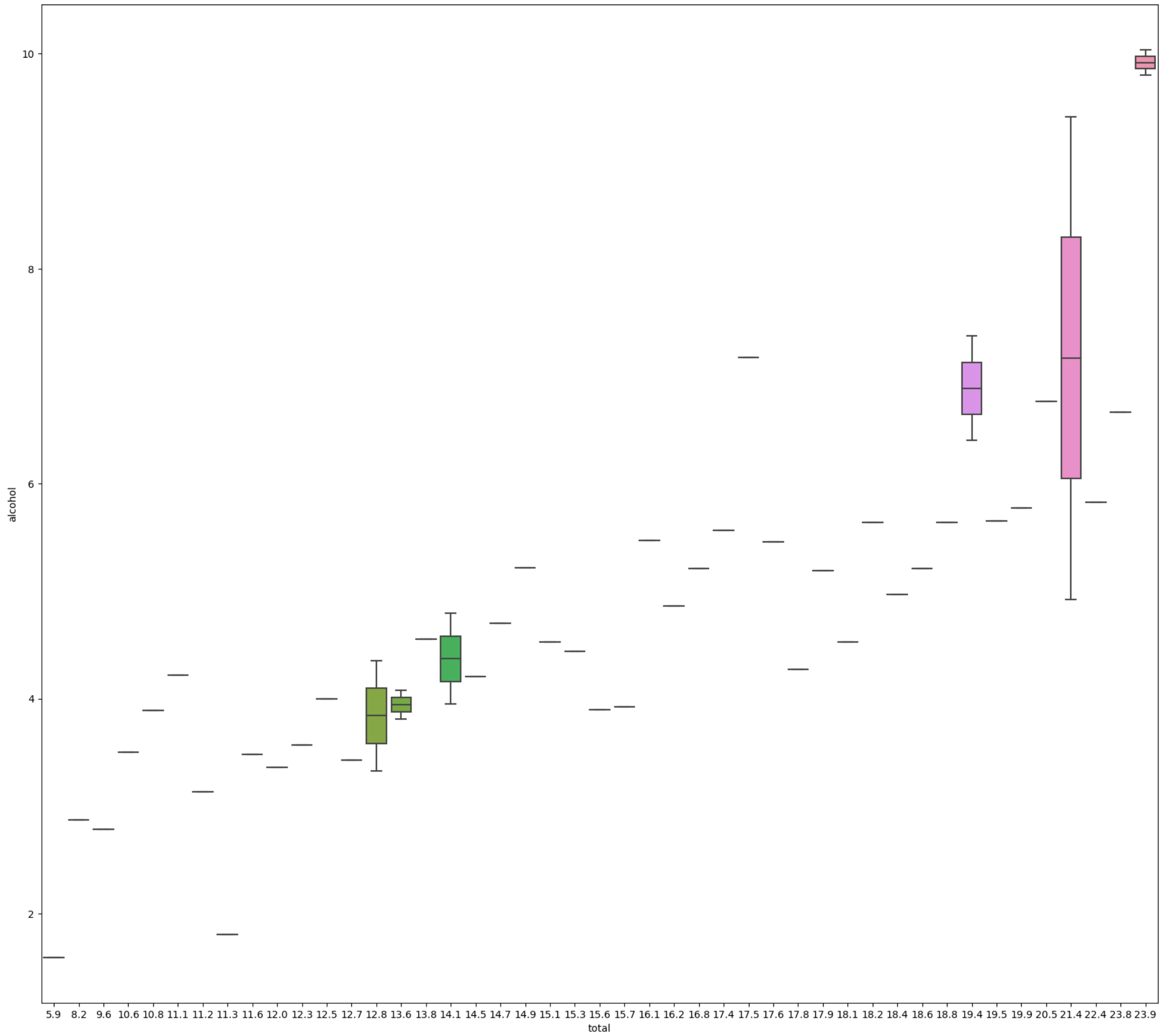
```
#jointplot
sns.jointplot(x="ins_premium",y="ins_losses",data=df,color="green")
```

```
<seaborn.axisgrid.JointGrid at 0x794870535d80>
```



inference:premium and losses are directly related

```
#boxplot
plt.figure(figsize=(20,18))
sns.boxplot(x=df["total"],y=df["alcohol"],data=df)
plt.show()
```




```
inference: no outliners
```

inference: no outliners

0s completed at 11:10 PM