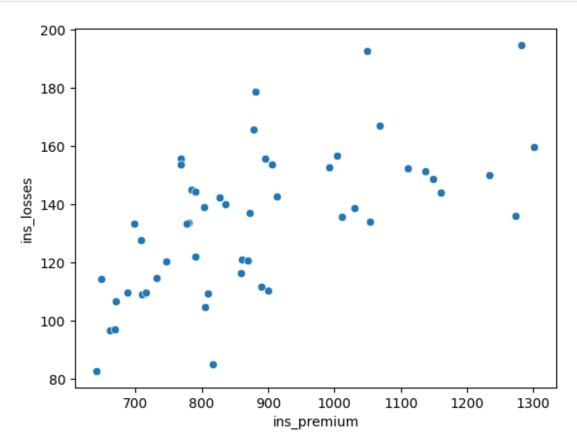
```
#21bce8954
#Aditya Bajaj
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
print(sns.get dataset names())
['anagrams', 'anscombe', 'attention', 'brain networks', 'car crashes',
'diamonds', 'dots', 'dowjones', 'exercise', 'flights', 'fmri', 'geyser', 'glue', 'healthexp', 'iris', 'mpg', 'penguins', 'planets', 'seaice', 'taxis', 'tips', 'titanic']
df=sns.load dataset('car crashes')
df
    total speeding alcohol not distracted no previous
                                                                   ins premium
                          5.640
0
     18.8
                7.332
                                           18.048
                                                          15.040
                                                                         784.55
                                                                        1053.48
     18.1
                7.421
                                           16.290
                                                          17.014
                          4.525
     18.6
                6.510
                          5.208
                                           15.624
                                                                         899.47
                                                          17.856
     22.4
                4.032
3
                          5.824
                                           21.056
                                                          21.280
                                                                         827.34
     12.0
                4.200
                                           10.920
                                                          10.680
                                                                         878.41
4
                          3.360
                                           10.744
     13.6
                5.032
                          3.808
                                                          12.920
                                                                         835.50
     10.8
                4.968
                          3.888
                                            9.396
                                                           8.856
                                                                        1068.73
     16.2
7
                6.156
                          4.860
                                           14.094
                                                          16.038
                                                                        1137.87
      5.9
                2.006
                          1.593
                                            5.900
                                                           5.900
                                                                        1273.89
     17.9
                                                          16.826
                                                                        1160.13
                3.759
                          5.191
                                           16.468
10
     15.6
                2.964
                                           14.820
                                                          14.508
                                                                         913.15
                          3.900
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
                                           12.032
13
     12.8
                4.608
                          4.352
                                                          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
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 29 29 29 29 29 29 29 29 29 29 29 29	ins_losse 145.0 133.9 110.3 142.3 165.6 139.9 167.0 151.4 136.0 144.1 142.8 120.9 82.7 139.1 108.9 114.4 133.8 137.1 194.7 96.5 192.7 135.6 152.2 133.3 155.7 144.4 85.1 114.8 138.7 120.2	88 AL 83 AK 85 AZ 89 AR 63 CA 61 CO 62 CT 68 DE 65 DC 68 FL 60 GA 61 ID 67 IA 60 KS 63 KY 68 MA 66 MI 65 MN 67 MS 65 MN 67 MS 65 MT 65 NE 61 NV				

```
30
        159.85
                    NJ
31
        120.75
                    NM
32
        150.01
                    NY
33
        127.82
                    NC
        109.72
34
                    ND
35
        133.52
                    0H
36
                    0K
        178.86
37
        104.61
                    0R
38
        153.86
                    PA
39
        148.58
                    RI
40
        116.29
                    SC
         96.87
                    SD
41
42
        155.57
                    TN
43
        156.83
                    TX
44
        109.48
                    UT
45
        109.61
                    ۷T
46
                    VA
        153.72
47
        111.62
                    WA
48
                    WV
        152.56
49
        106.62
                    WI
50
        122.04
                    WY
df.shape
(51, 8)
df.head()
          speeding alcohol not_distracted no_previous
                                                              ins_premium
   total
              7.332
    18.8
                        5.640
                                        18.048
                                                      15.040
                                                                    784.55
                                        16.290
    18.1
              7.421
                       4.525
                                                      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
    12.0
                                        10.920
                                                                    878.41
              4.200
                       3.360
                                                      10.680
   ins_losses
0
       145.08
1
       133.93
2
       110.35
3
       142.39
       165.63
df.columns
```

```
Index(['total', 'speeding', 'alcohol', 'not_distracted',
'no_previous',
       'ins_premium', 'ins_losses'],
      dtype='object')
df.isnull().sum()
total
                   0
speeding
                   0
alcohol
                   0
                   0
not distracted
                   0
no_previous
                   0
ins premium
ins losses
                   0
abbrev
                   0
dtype: int64
df=df.drop(columns='abbrev')
sns.scatterplot(x="ins premium",y="ins losses",data=df)
<AxesSubplot: xlabel='ins_premium', ylabel='ins_losses'>
```



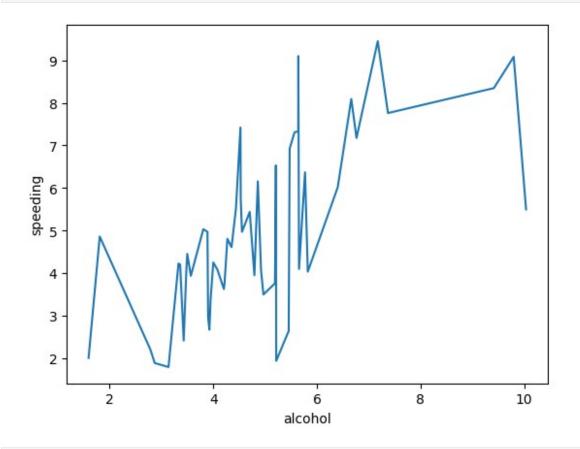
sns.lineplot(x="alcohol",y="speeding",data=df,ci=None)

C:\Users\adiforwhat\AppData\Local\Temp\ipykernel\_3776\2741251668.py:1:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

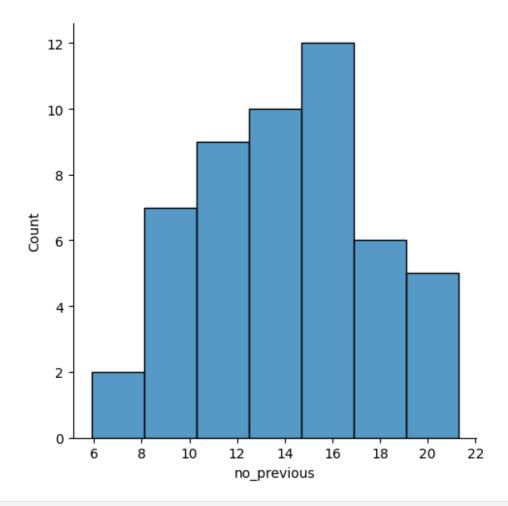
sns.lineplot(x="alcohol",y="speeding",data=df,ci=None)

<AxesSubplot: xlabel='alcohol', ylabel='speeding'>

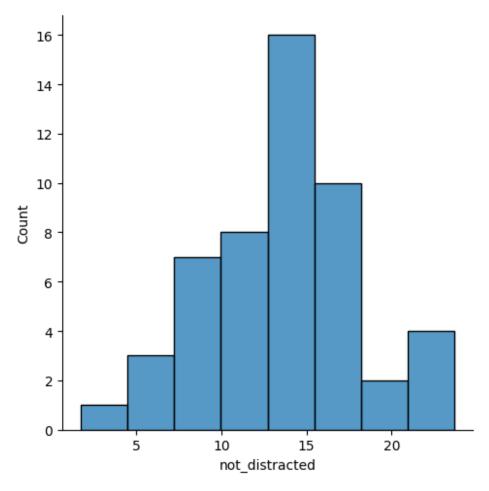


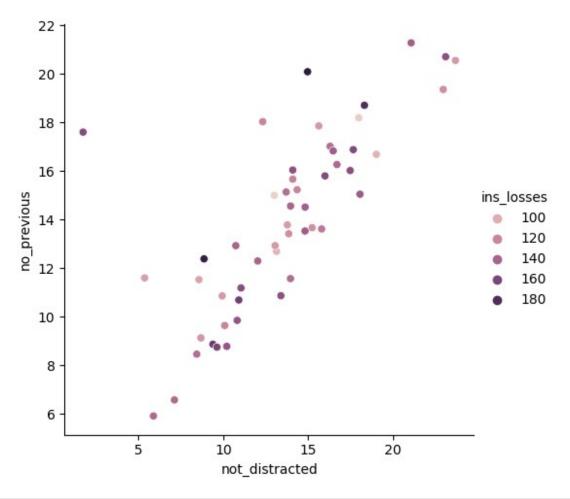
sns.displot(df['no\_previous'])

<seaborn.axisgrid.FacetGrid at 0x1d9cf1c17b0>

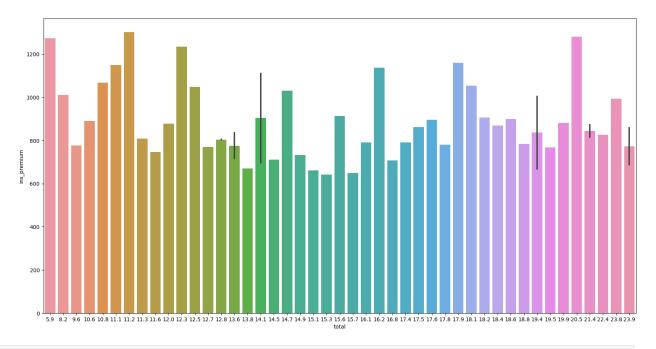


sns.displot(df['not\_distracted'])
<seaborn.axisgrid.FacetGrid at 0x1d9cf1c1390>





```
plt.figure(figsize=(20,10))
sns.barplot(x="total",y="ins_premium",data=df)
<AxesSubplot: xlabel='total', ylabel='ins_premium'>
```



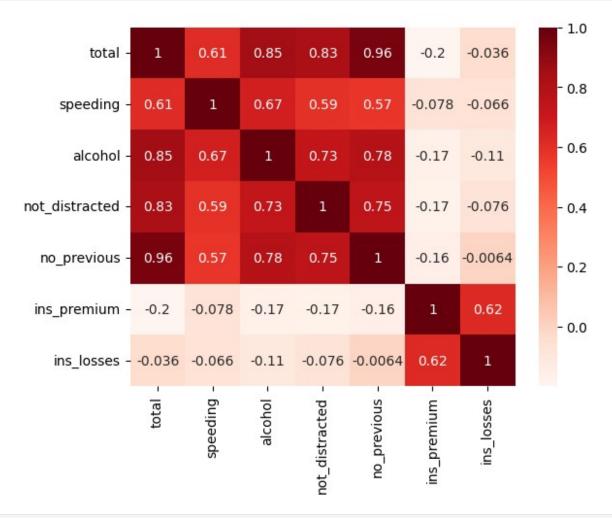
df						
	total	speeding	alcohol	not_distracted	no_previous	ins_premium
0	18.8	7.332	5.640	18.048	15.040	784.55
1	18.1	7.421	4.525	16.290	17.014	1053.48
2	18.6	6.510	5.208	15.624	17.856	899.47
3	22.4	4.032	5.824	21.056	21.280	827.34
4	12.0	4.200	3.360	10.920	10.680	878.41
5	13.6	5.032	3.808	10.744	12.920	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
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24	139 108 114 133 137 194	.08 .93 .35 .39 .63 .91 .02 .48 .05 .18 .80 .92 .75 .15 .92 .47 .80 .13 .78 .57				

```
25
        144.45
26
         85.15
27
        114.82
28
        138.71
        120.21
29
30
        159.85
31
        120.75
32
        150.01
        127.82
33
34
        109.72
        133.52
35
36
        178.86
37
        104.61
38
        153.86
39
        148.58
40
        116.29
41
         96.87
42
        155.57
43
        156.83
44
        109.48
45
        109.61
        153.72
46
47
        111.62
48
        152.56
49
        106.62
50
        122.04
corr=df.corr()
corr
                    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
                 0.852613
                                                        0.732816
alcohol
                            0.669719
                                       1.000000
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
                   -\overline{0}.199702
                                -0.036011
total
```

```
speeding
                  -0.077675
                               -0.065928
alcohol
                               -0.112547
                  -0.170612
not distracted
                  -0.174856
                               -0.075970
                               -0.006359
no previous
                  -0.156895
ins premium
                   1.000000
                                0.623116
ins_losses
                   0.623116
                                1.000000
sns.heatmap(corr,annot=True,cmap="Reds")
<AxesSubplot: >
```

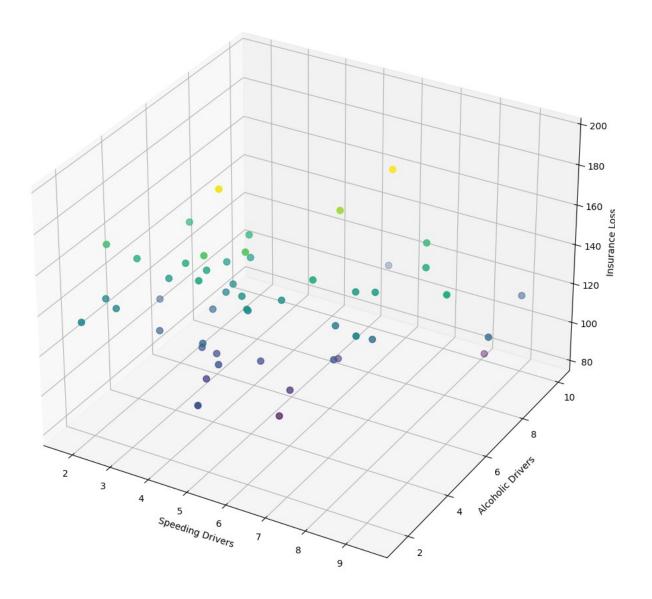


```
fig = plt.figure(figsize=(12, 12))
ax = fig.add_subplot(111, projection='3d')

# Extracting data
x = df['speeding']
y = df['alcohol']
z = df['ins_losses']

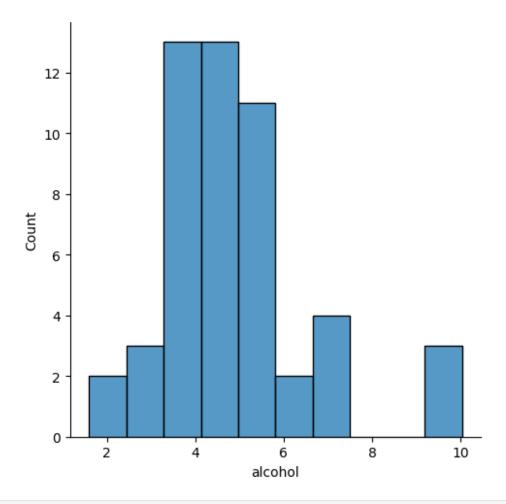
# Creating the scatter plot
ax.scatter(x, y, z, c=z, cmap='viridis', s=50)

# Adding labels
ax.set_xlabel('Speeding Drivers')
ax.set_ylabel('Alcoholic Drivers')
ax.set_zlabel('Insurance Loss')
plt.show()
```



sns.displot(df["alcohol"])

<seaborn.axisgrid.FacetGrid at 0x1d9d911bdf0>

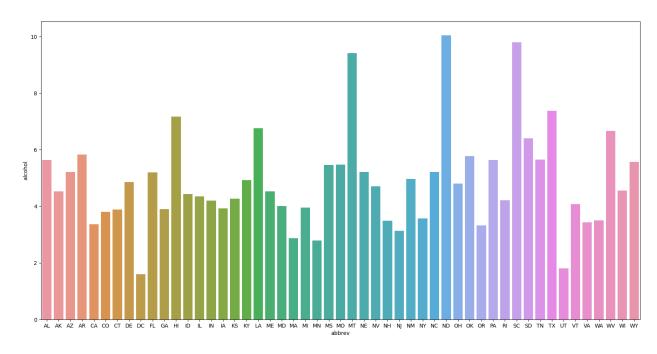


df						
	total	speeding	alcohol	not_distracted	no_previous	ins_premium
0	18.8	7.332	5.640	18.048	15.040	784.55
1	18.1	7.421	4.525	16.290	17.014	1053.48
2	18.6	6.510	5.208	15.624	17.856	899.47
3	22.4	4.032	5.824	21.056	21.280	827.34
4	12.0	4.200	3.360	10.920	10.680	878.41
5	13.6	5.032	3.808	10.744	12.920	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

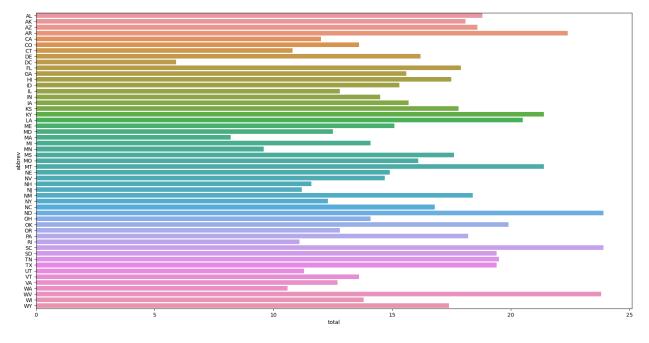
35 36 37 38 39	14.1 19.9 12.8 18.2	3.948 6.368 4.224	4.794 5.771 3.328	13.959 18.308	11.562 18.706	697.73 881.51
37 38	12.8 18.2	4.224		18.308	18.706	881.51
38	18.2		3.328			
		0 100		8.576	11.520	804.71
39		9.100	5.642	17.472	16.016	905.99
	11.1	3.774	4.218	10.212	8.769	1148.99
40	23.9	9.082	9.799	22.944	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
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16	ins_losse 145.0 133.9 110.3 142.3 165.6 139.9 167.0 151.4 136.0 144.1 142.8 120.9 82.7 139.1 108.9 114.4 133.8	8 AL 3 AK 5 AZ 9 AR 3 CA 1 CO 2 CT 8 DE 5 DC 8 FL 0 GA 2 HI 5 ID 5 IL 7 IA				

```
17
        137.13
                     KY
        194.78
18
                     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
                     0H
36
        178.86
                     0K
        104.61
37
                     0R
38
        153.86
                     PA
39
                     RI
        148.58
40
        116.29
                     SC
41
         96.87
                     SD
42
        155.57
                     TN
43
        156.83
                     TX
44
                     UT
        109.48
45
        109.61
                     VT
46
        153.72
                     VA
47
        111.62
                     WA
48
        152.56
                     WV
49
        106.62
                    WI
50
        122.04
                    WY
plt.figure(figsize=(20,10))
sns.barplot(data=df,x="abbrev",y="alcohol")
<AxesSubplot: xlabel='abbrev', ylabel='alcohol'>
```



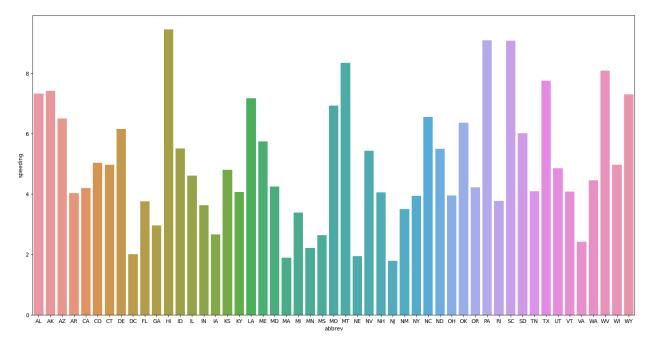
Can see that ND state has the most car crashes caused due to alcoholism!

```
plt.figure(figsize=(20,10))
sns.barplot(data=df,x="total",y="abbrev")
<AxesSubplot: xlabel='total', ylabel='abbrev'>
```



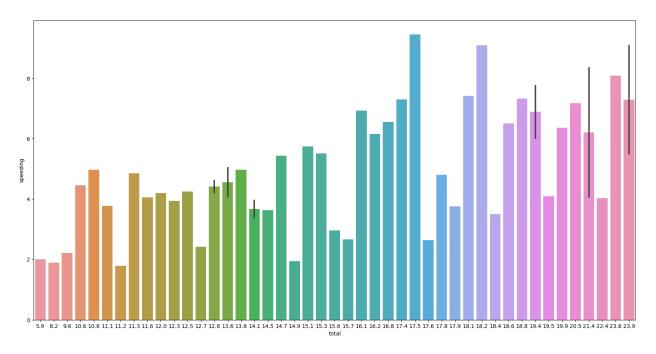
can infer that ND state has the most car crashes as well!

```
plt.figure(figsize=(20,10))
sns.barplot(data=df,x="abbrev",y="speeding")
<AxesSubplot: xlabel='abbrev', ylabel='speeding'>
```



While hl state has the most car crashes caused due to speeding

```
plt.figure(figsize=(20,10))
sns.barplot(x="total",y="speeding",data=df)
<AxesSubplot: xlabel='total', ylabel='speeding'>
```



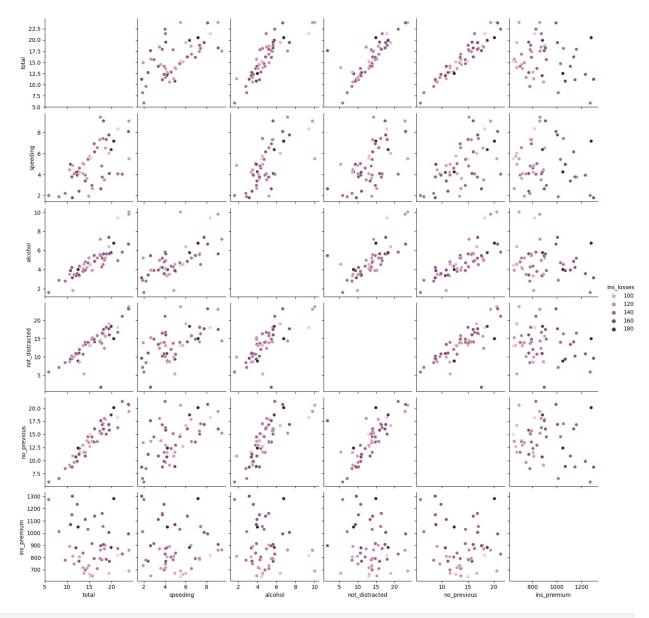
we can notice from the plot that the car crashes will increase always when there is an increment in any of the four factors (alcohol, speeding, no distract, and no previous)

there is no relationship between the changing of alcoholic people and any other category, it seems like the more we have alcoholic, the more we have crashes despite any other factor

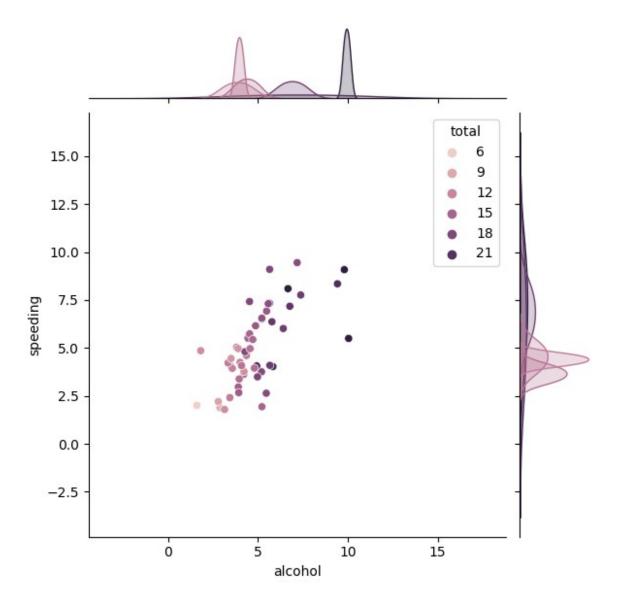
from the plot, it is safe to say that focused people (not distracted) have a normal number of crashes even if they were speeding! .. but whenever they drink, crashes happend

we have a strong lead that says doesn't affect crashes that mush, it is mostly on alcohol

```
sns.pairplot(data=df,hue="ins_losses")
<seaborn.axisgrid.PairGrid at 0x1d9df20ba60>
```



sns.jointplot(data= df, y='speeding' , x='alcohol', hue='total')
<seaborn.axisgrid.JointGrid at 0x1d9e4743460>



proof that speeding and alcohol definitely raises the number of crashes!