In [1]:

```
print("NAME   : PAMPANI SONU DURGA AVINASH")
print("REG NO : 21BCE9333")
```

```
NAME   : PAMPANI SONU DURGA AVINASH
REG NO : 21BCE9333
```

In [2]:

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

In [4]:

```
print(sns.get_dataset_names())
```

```
['anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes', 'd
iamonds', 'dots', 'dowjones', 'exercise', 'flights', 'fmri', 'geyser', 'g
lue', 'healthexp', 'iris', 'mpg', 'penguins', 'planets', 'seaice', 'taxi
s', 'tips', 'titanic']
```

In [5]:

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

Out[5]:

	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
23	9.6	2.208	2.784	8.448	8.448	777.18	133.35	MN
24	17.6	2.640	5.456	1.760	17.600	896.07	155.77	MS
25	16.1	6.923	5.474	14.812	13.524	790.32	144.45	MO
26	21.4	8.346	9.416	17.976	18.190	816.21	85.15	MT
27	14.9	1.937	5.215	13.857	13.410	732.28	114.82	NE
28	14.7	5.439	4.704	13.965	14.553	1029.87	138.71	NV
29	11.6	4.060	3.480	10.092	9.628	746.54	120.21	NH
30	11.2	1.792	3.136	9.632	8.736	1301.52	159.85	NJ
31	18.4	3.496	4.968	12.328	18.032	869.85	120.75	NM
32	12.3	3.936	3.567	10.824	9.840	1234.31	150.01	NY
33	16.8	6.552	5.208	15.792	13.608	708.24	127.82	NC
34	23.9	5.497	10.038	23.661	20.554	688.75	109.72	ND

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
35	14.1	3.948	4.794	13.959	11.562	697.73	133.52	OH
36	19.9	6.368	5.771	18.308	18.706	881.51	178.86	OK
37	12.8	4.224	3.328	8.576	11.520	804.71	104.61	OR
38	18.2	9.100	5.642	17.472	16.016	905.99	153.86	PA
39	11.1	3.774	4.218	10.212	8.769	1148.99	148.58	RI
40	23.9	9.082	9.799	22.944	19.359	858.97	116.29	SC
41	19.4	6.014	6.402	19.012	16.684	669.31	96.87	SD
42	19.5	4.095	5.655	15.990	15.795	767.91	155.57	TN
43	19.4	7.760	7.372	17.654	16.878	1004.75	156.83	TX
44	11.3	4.859	1.808	9.944	10.848	809.38	109.48	UT
45	13.6	4.080	4.080	13.056	12.920	716.20	109.61	VT
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

In [6]:

```
df.info
```

Out[6]:
```
<bound method DataFrame.info of     total  speeding  alcohol  not_distrac
ted  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  >
```

In [7]:

```
df.describe()
```

Out[7]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_loss
count	51.000000	51.000000	51.000000	51.000000	51.000000	51.000000	51.0000
mean	15.790196	4.998196	4.886784	13.573176	14.004882	886.957647	134.4931
std	4.122002	2.017747	1.729133	4.508977	3.764672	178.296285	24.8359
min	5.900000	1.792000	1.593000	1.760000	5.900000	641.960000	82.7500
25%	12.750000	3.766500	3.894000	10.478000	11.348000	768.430000	114.6450
50%	15.600000	4.608000	4.554000	13.857000	13.775000	858.970000	136.0500
75%	18.500000	6.439000	5.604000	16.140000	16.755000	1007.945000	151.8700
max	23.900000	9.450000	10.038000	23.661000	21.280000	1301.520000	194.7800

In [8]:

```
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
```

In [ ]:

```
#to get first five records of dataset
```

In [10]:

```
df.head()
```

Out[10]:

	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

In [ ]:
```
#to get last five records of dataset
```

In [11]:
```
df.tail()
```

Out[11]:

	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

In [ ]:
```
#to get first six records we use df.head(6)
```

In [12]:
```
df.head(6)
```

Out[12]:

	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

In [13]:
```
df.isnull().sum()
```

Out[13]:
```
total             0
speeding          0
alcohol           0
not_distracted    0
no_previous       0
ins_premium       0
ins_losses        0
abbrev            0
dtype: int64
```

In [15]:
```
df.isnull().any()
```

Out[15]:
```
total             False
speeding          False
alcohol           False
not_distracted    False
no_previous       False
ins_premium       False
ins_losses        False
abbrev            False
dtype: bool
```

In [16]:
```
#to get the correlation
```

In [20]:
```
cor = df.corr()
cor
```

Out[20]:

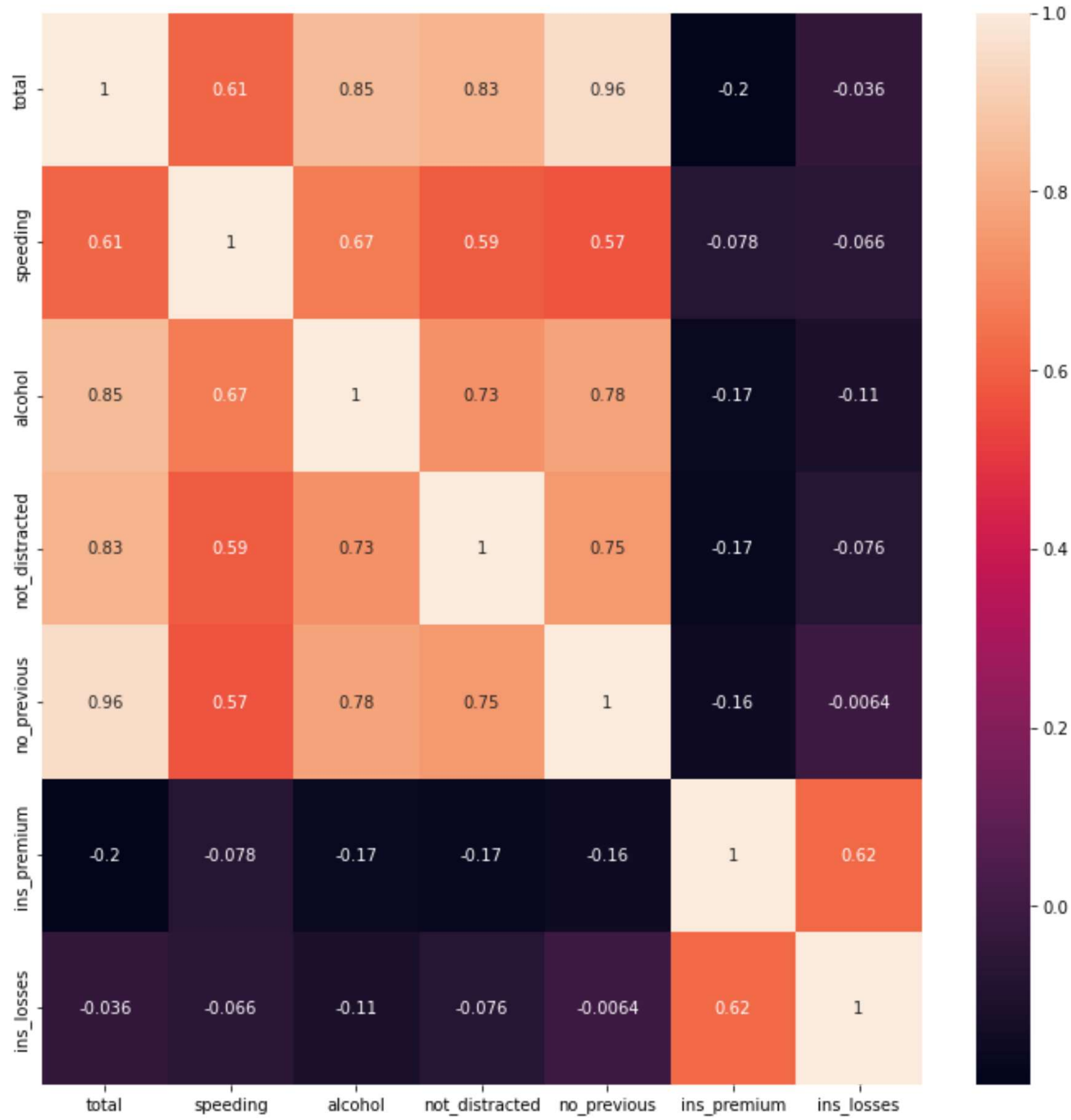
	total	speeding	alcohol	not_distracted	no_previous	ins_premium	i
total	1.000000	0.611548	0.852613	0.827560	0.956179	-0.199702	
speeding	0.611548	1.000000	0.669719	0.588010	0.571976	-0.077675	
alcohol	0.852613	0.669719	1.000000	0.732816	0.783520	-0.170612	
not_distracted	0.827560	0.588010	0.732816	1.000000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

heat map plot

In [21]:

```
plt.figure(figsize=(12,12))
sns.heatmap(cor,annot=True)
```

Out[21]: <AxesSubplot:>




```
Inference : from the above graph some are highly correlated (value >0.5) and
some are less correlated (less than <0.5) ex : here both the features total and speeding are highly
correlated because the value is greater than 0.61 which is greater than 0.5. if we take the features
total and ins_losses they are negativley correlated or we can say they are less correlated because
the value is -0.036 which is less than 0.5

```

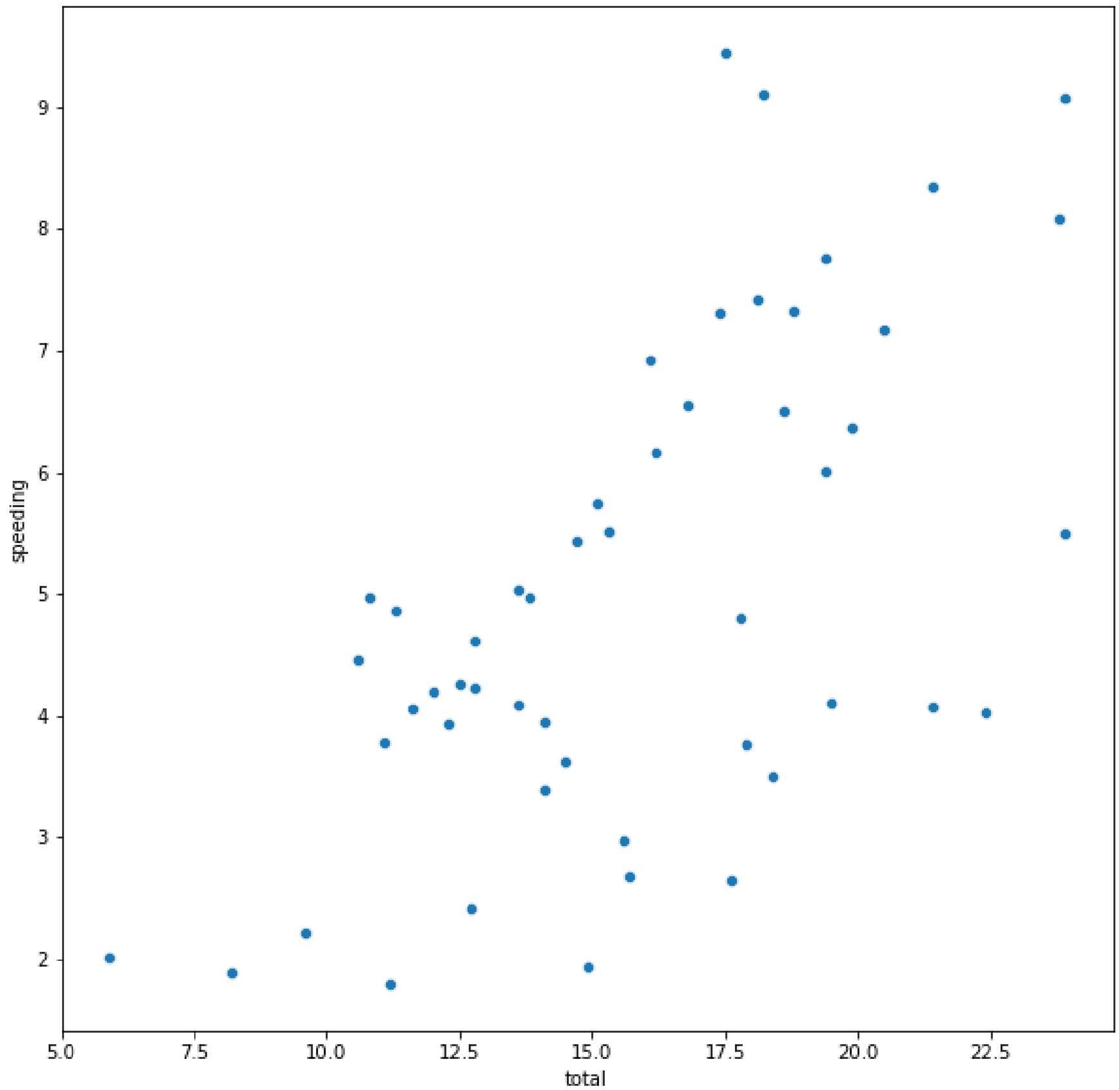
Scatter plot

In [22]:

```
plt.figure(figsize=(10,10))
sns.scatterplot(x="total",y="speeding",data=df)
```

Out[22]:

```
<AxesSubplot:xlabel='total', ylabel='speeding'>
```



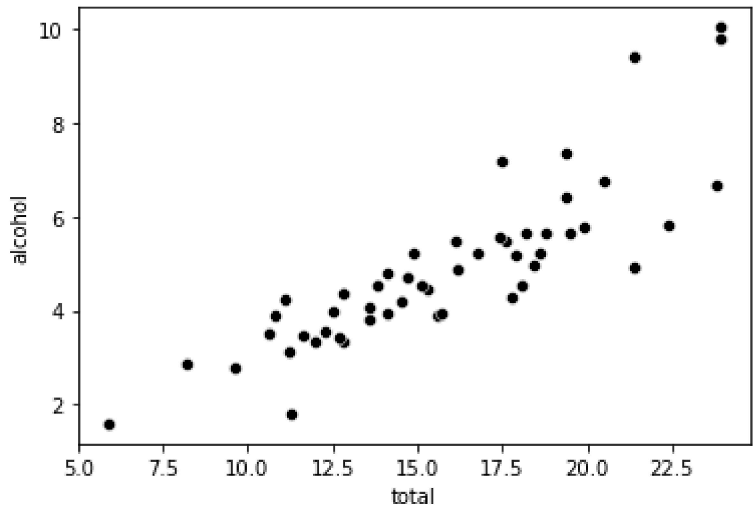

```
Inference : from the above graph we can we can say that the total number of
drivers in fatal collisions is linearly propotional percentage of drivers involved in fatal collisons who
were speeding
```

In [25]:

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

Out[25]:

```
<AxesSubplot:xlabel='total', ylabel='alcohol'>
```



Inference : From the above graph we can say that the total number of drivers involved in fatal collisions is linearly propotional percentage drivers involved in fatal collisions who were distracted

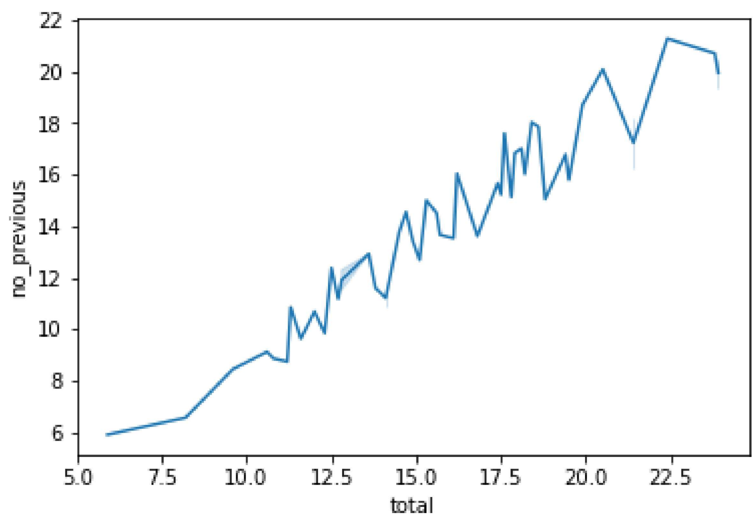
Lineplot

In [26]:

```python
sns.lineplot(x="total",y="no_previous",data=df)
```

Out[26]:

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

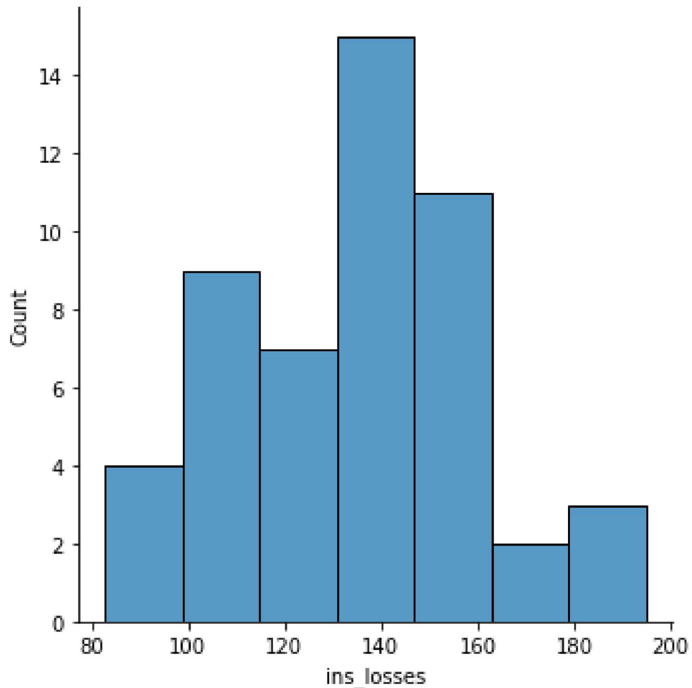


Inferecne : from the above graph we can say that the total number of drivers involved in fatal collisons is linerly propotional to percentage of drivers involved in fatal collisons who do not have previous

Displot

In [27]:
```
sns.displot(df["ins_losses"])
```

Out[27]: <seaborn.axisgrid.FacetGrid at 0x1e8705cec40>

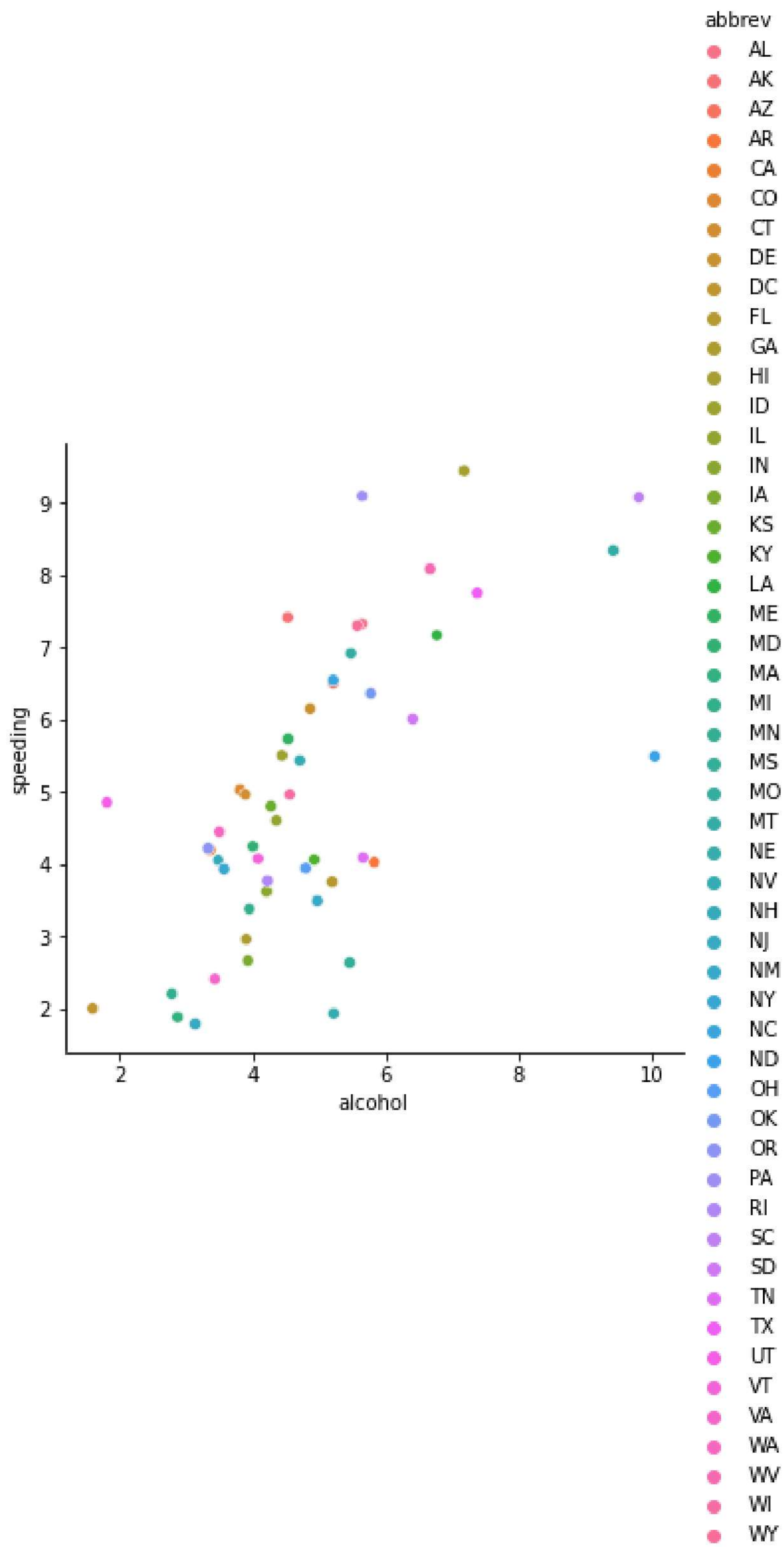


Inference : from the above graph we can say that ins_losses mostly lies b/w
100 and 160 and highest at 140

Relplot

In [28]:
```
sns.relplot(x="alcohol",y="speeding",data=df,hue="abbrev")
```

Out[28]: <seaborn.axisgrid.FacetGrid at 0x1e870782640>



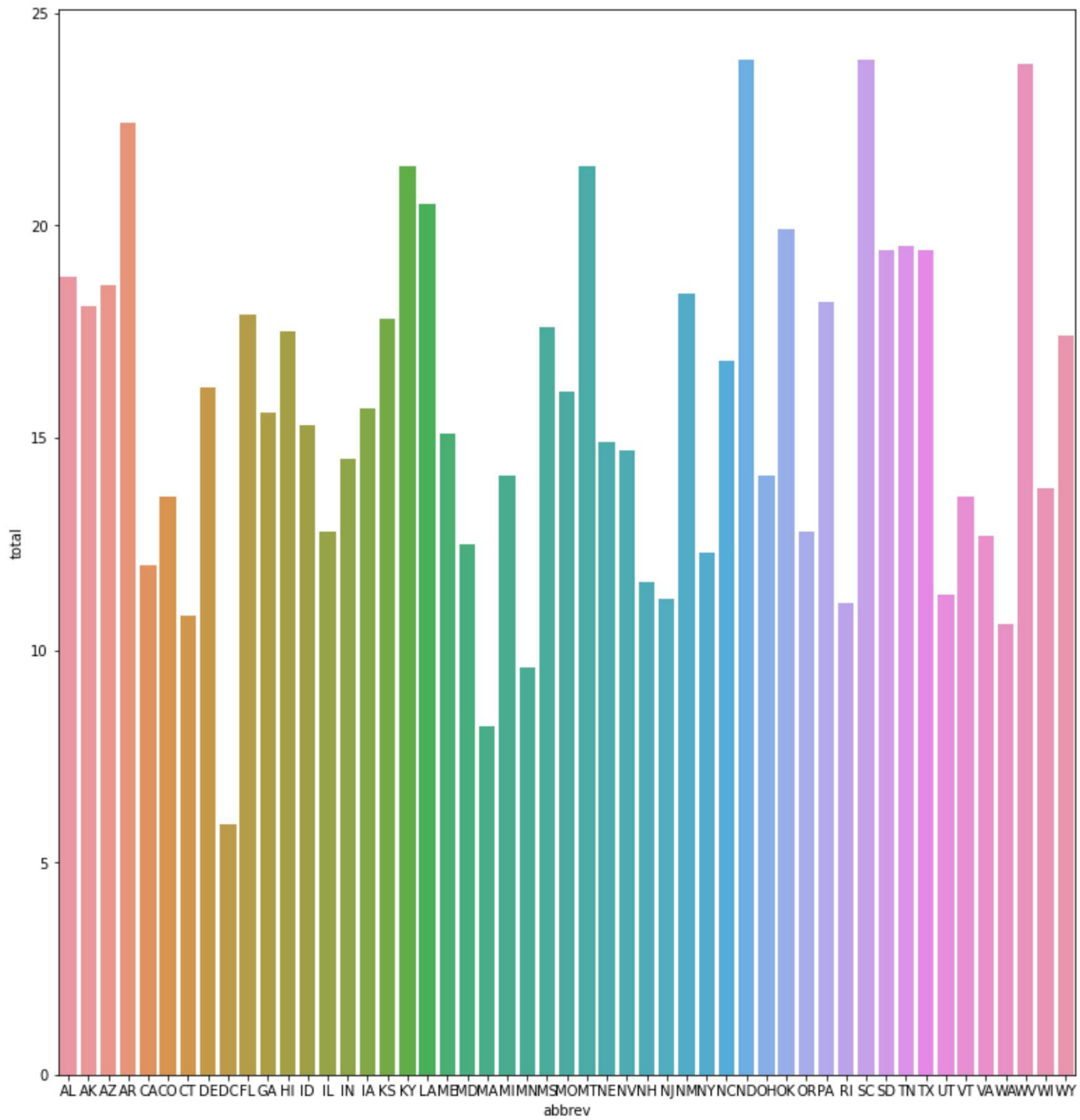

```
Inference : from the above graph we can say that when alocohol
```

consumption is increasing speeding also increases

Barplot

In [29]:

```
plt.figure(figsize=(13,14))
sns.barplot(x="abbrev",y="total",data=df)
plt.show()
```

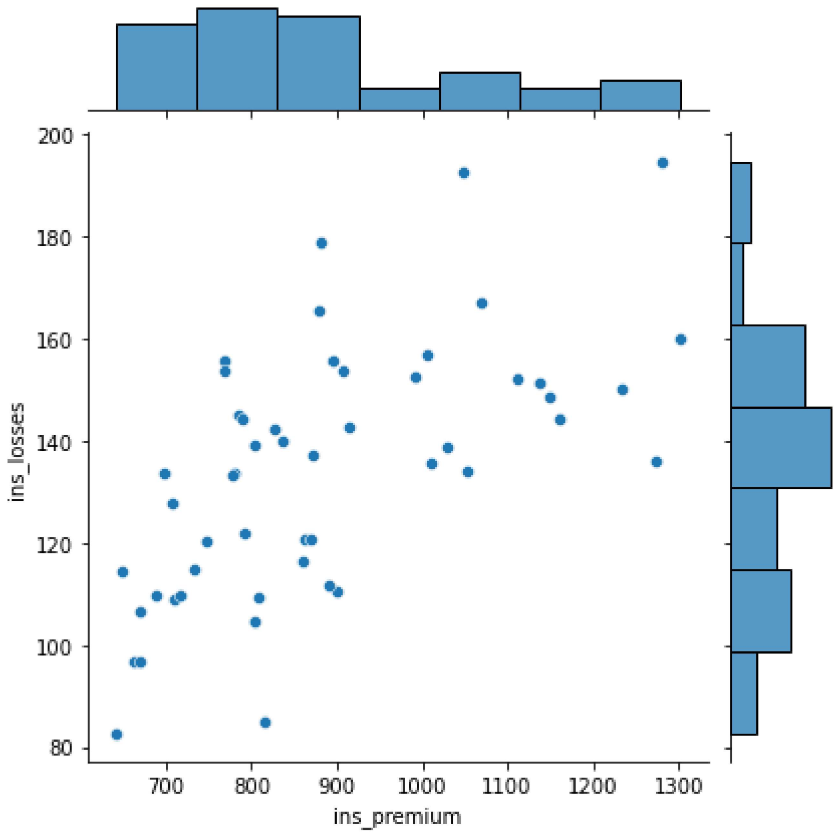


Inference : among all state ND has total no.of highest collisions

Joinplot

In [30]:
```
sns.jointplot(x="ins_premium",y="ins_losses",data=df)
```

Out[30]: <seaborn.axisgrid.JointGrid at 0x1e8710f9d60>



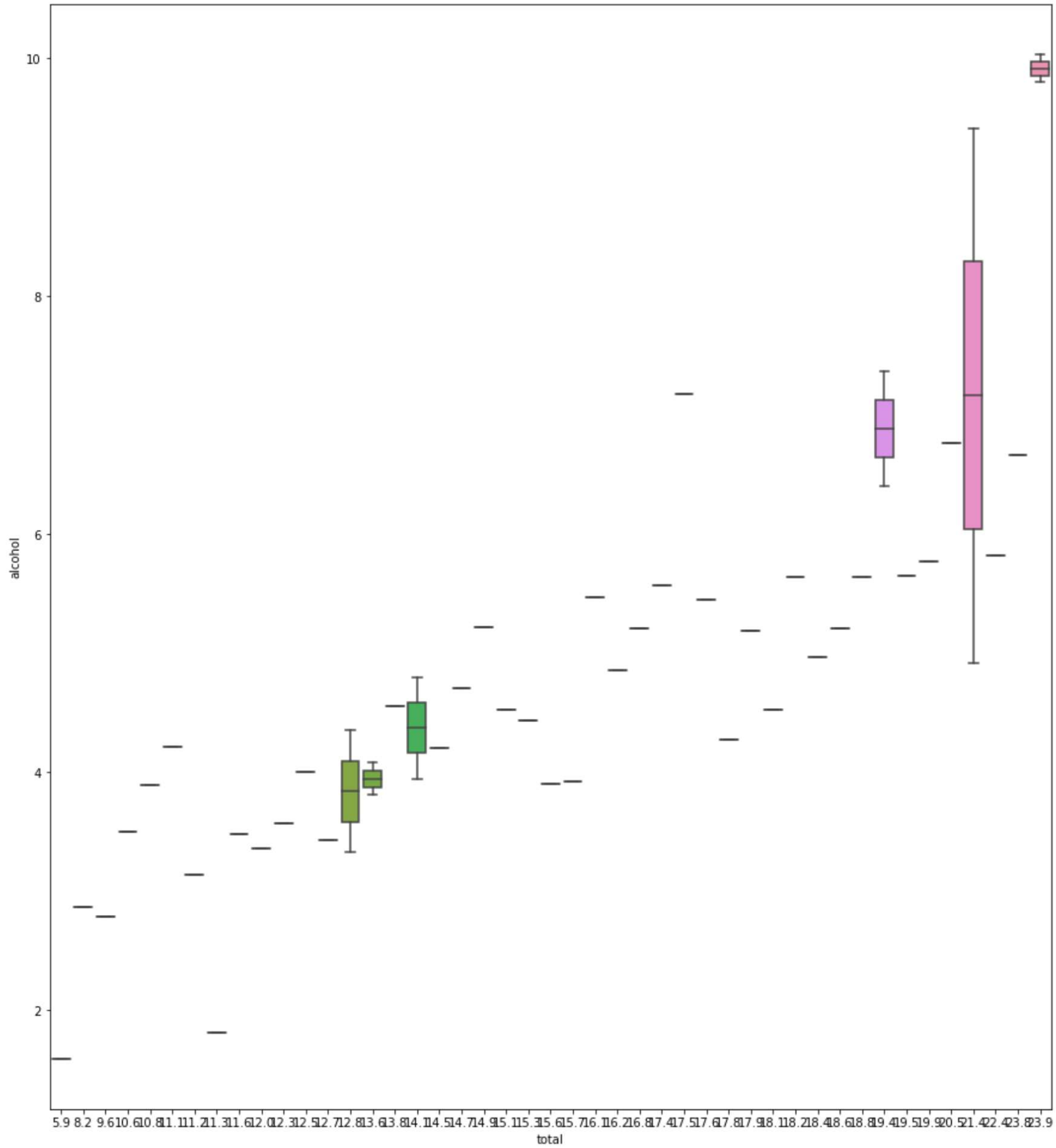
Inference : ins_premium and ins_looses are directly propotional to each other

Boxplot

In [31]:

```
plt.figure(figsize=(15,17))
sns.boxplot(x=df["total"],y=df["alcohol"],data=df)
```

Out[31]: <AxesSubplot:xlabel='total', ylabel='alcohol'>




```
Inferecnce: from the above graph we can say that there are no outliers
```