ABHINAV KALLURI MORNING SESSION ASSIGNMENT-2

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [49]:
```
# For Data Preprocessing---
"""
#Steps:
#1. Import the necessary libraries
#2. Import the dataset
#3. handling null values
#4. dependent and independent variable seperation
#5. Encoding
#6. Split the data into training and testing sets
#7. Feature scaling
"""
```

Out[49]:
```
'\n#Steps:\n#1. Import the necessary libraries\n#2. Import the dataset\n#3. handling null values\n#4. dependent and independent variable seperation\n#5. Encoding\n#6. Split the data into training and testing sets\n#7. Feature scaling\n'
```

In [4]:
```
ak = sns.load_dataset('car_crashes')
```

In [5]:
```
ak
```

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

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
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
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]:

```
ak.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 [ ]:

```
total - Number of drivers involved in fatal collisions per billion miles
speeding - Number of drivers Involved In Fatal Collisions Who Were Speeding
alchol - Number of Drivers Involved In Fatal Collisions Who Were Alcohol-Impaired
not_distracted - Number of Drivers Involved In Fatal Collisions Who Were Not Distracte
no_previous - Number Of Drivers Involved In Fatal Collisions Who Had Not Been Involvec
ins_premium - Car Insurance Premiums($)

ins_loses - Losses incurred by insurance companies for collisions per insured driver (
```

```
abbrev - represents the states
```

In [7]:
```
ak.head()
```

Out[7]:

	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 [8]:
```
ak.head(2)
```

Out[8]:

	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

In [9]:
```
ak.tail(8)
```

Out[9]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
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 [10]:
```
ak.tail()
```

Out[10]:

	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 [11]:
```
ak.shape
```

Out[11]: (51, 8)

In [12]:
```
ak.describe()
```

Out[12]:

	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

In [13]:
```
corr = ak.corr()
corr
```

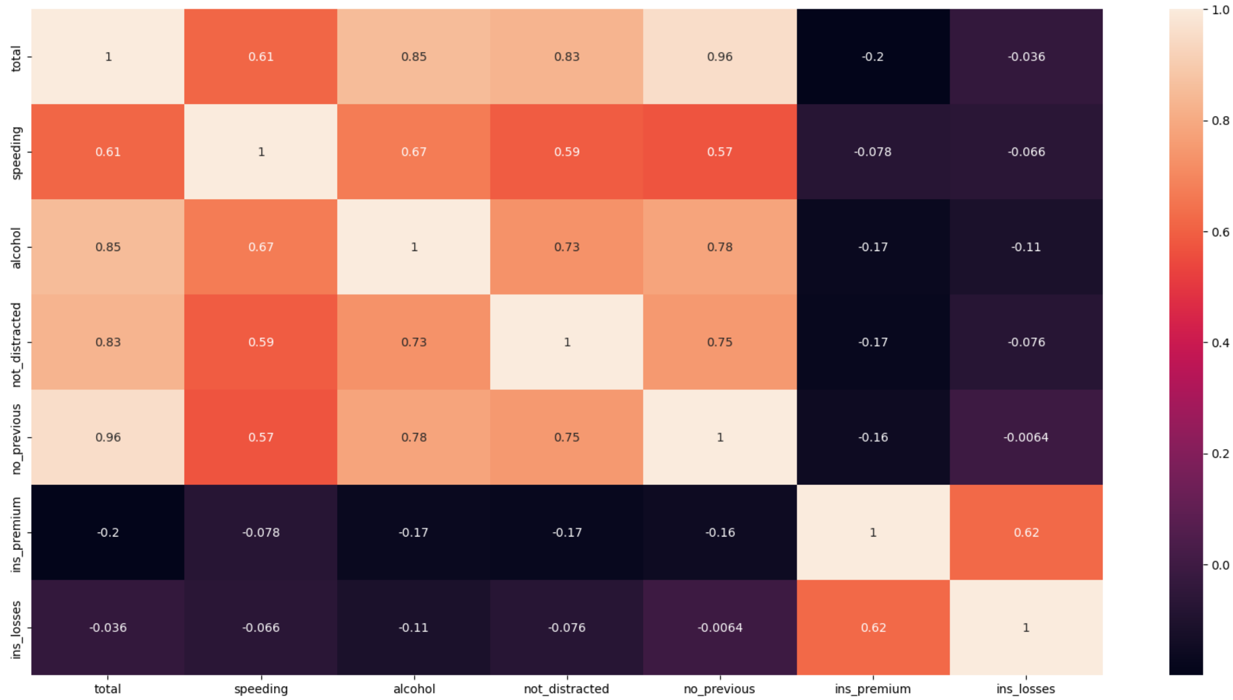
```
C:\Users\nagka\AppData\Local\Temp\ipykernel_14956\3288373526.py:1: FutureWarning: The
default value of numeric_only in DataFrame.corr is deprecated. In a future version, i
t will default to False. Select only valid columns or specify the value of numeric_on
ly to silence this warning.
  corr = ak.corr()
```

Out[13]:

	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

In [14]:
```
plt.subplots(figsize = (20,10))
sns.heatmap(corr,annot=True)
```

Out[14]: <Axes: >



In [15]:
```
ak["total"].value_counts()
```

Out[15]:
```
14.1    2
12.8    2
13.6    2
21.4    2
19.4    2
23.9    2
14.9    1
14.7    1
11.6    1
11.2    1
18.4    1
12.3    1
16.8    1
19.9    1
17.6    1
18.2    1
11.1    1
19.5    1
11.3    1
12.7    1
10.6    1
23.8    1
13.8    1
16.1    1
18.8    1
9.6     1
18.1    1
18.6    1
22.4    1
12.0    1
10.8    1
16.2    1
5.9     1
17.9    1
15.6    1
17.5    1
15.3    1
14.5    1
15.7    1
17.8    1
20.5    1
15.1    1
12.5    1
8.2     1
17.4    1
Name: total, dtype: int64
```

In [16]:
```
ak.alcohol.value_counts()
```

Out[16]:

```
5.208     2
5.640     1
4.218     1
4.704     1
3.480     1
3.136     1
4.968     1
3.567     1
10.038    1
4.794     1
5.771     1
3.328     1
5.642     1
9.799     1
9.416     1
6.402     1
5.655     1
7.372     1
1.808     1
4.080     1
3.429     1
3.498     1
6.664     1
4.554     1
5.215     1
5.474     1
4.525     1
5.456     1
5.824     1
3.360     1
3.808     1
3.888     1
4.860     1
1.593     1
5.191     1
3.900     1
7.175     1
4.437     1
4.352     1
4.205     1
3.925     1
4.272     1
4.922     1
6.765     1
4.530     1
4.000     1
2.870     1
3.948     1
2.784     1
5.568     1
Name: alcohol, dtype: int64
```

In [17]:

```
ak.isnull().any()
```

Out[17]:
```
total              False
speeding           False
alcohol            False
not_distracted     False
no_previous        False
ins_premium        False
ins_losses         False
abbrev             False
dtype: bool
```

In [18]:
```
ak.isnull().sum()
```

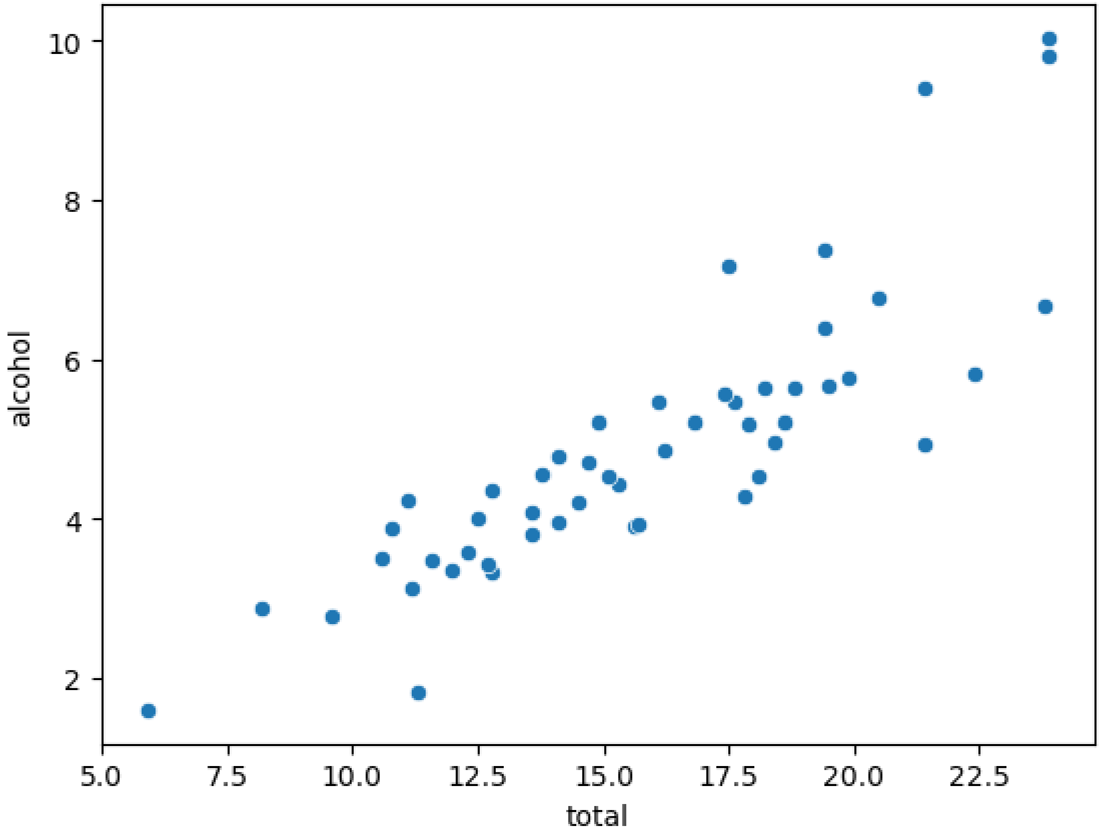
Out[18]:
```
total              0
speeding           0
alcohol            0
not_distracted     0
no_previous        0
ins_premium        0
ins_losses         0
abbrev             0
dtype: int64
```

DATA VISUALIZATION

In [ ]:
```
total - Number of drivers involved in fatal collisions per billion miles
speeding - Number of drivers Involved In Fatal Collisions Who Were Speeding
alchol - Number of Drivers Involved In Fatal Collisions Who Were Alcohol-Impaired
not_distracted - Number of Drivers Involved In Fatal Collisions Who Were Not Distracte
no_previous - Number Of Drivers Involved In Fatal Collisions Who Had Not Been Involvec
ins_premium - Car Insurance Premiums($)

ins_loses - Losses incurred by insurance companies for collisions per insured driver (

abbrev - represents the states
```

In [19]:
```
sns.scatterplot(x="total",y="alcohol", data=ak)
```

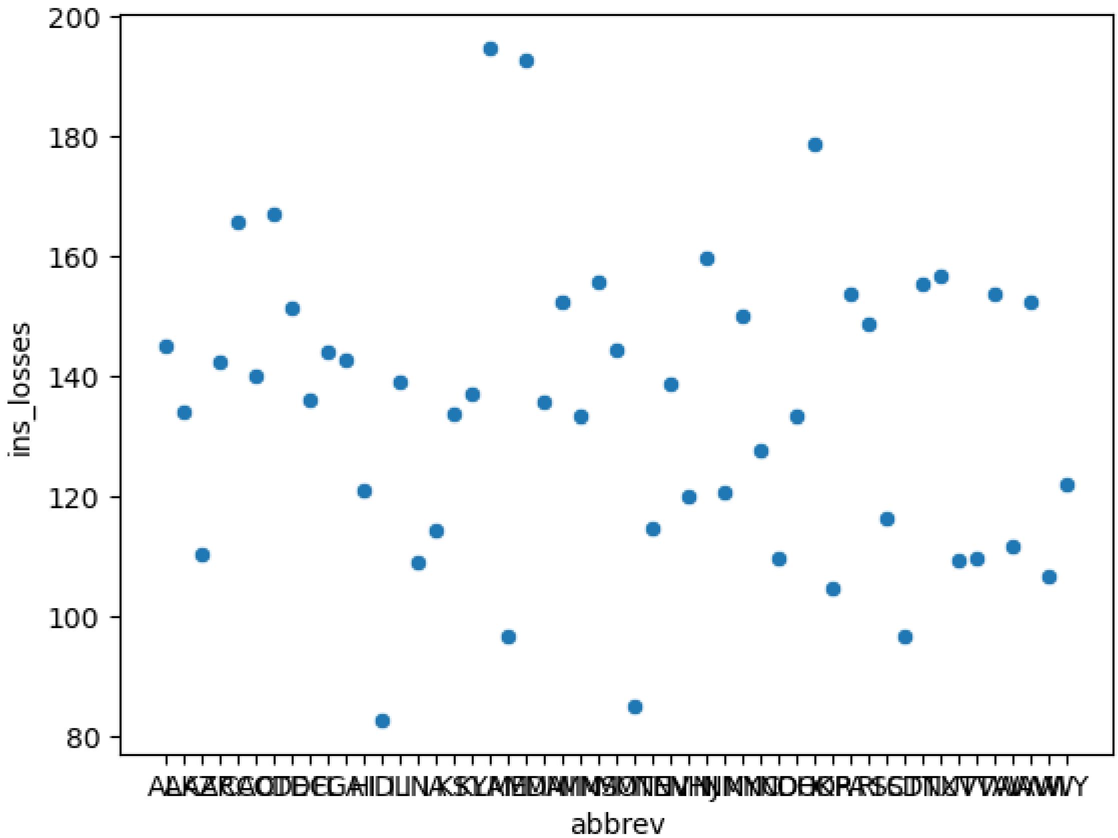
Out[19]:
```
<Axes: xlabel='total', ylabel='alcohol'>
```



In [ ]:
```
We can clearly see that Number of drivers involved in fatal collisions per billion mil
Number of Drivers Involved In Fatal Collisions Who Were Alcohol-Impaired. By this we c
drinking and driving are more prone to getting an accident. That is why it is recommen
If people drive without impairing with alcohol, the numbers of accidents would have be
```

In [20]:
```
sns.scatterplot(x="abbrev",y="ins_losses",data=ak)
```

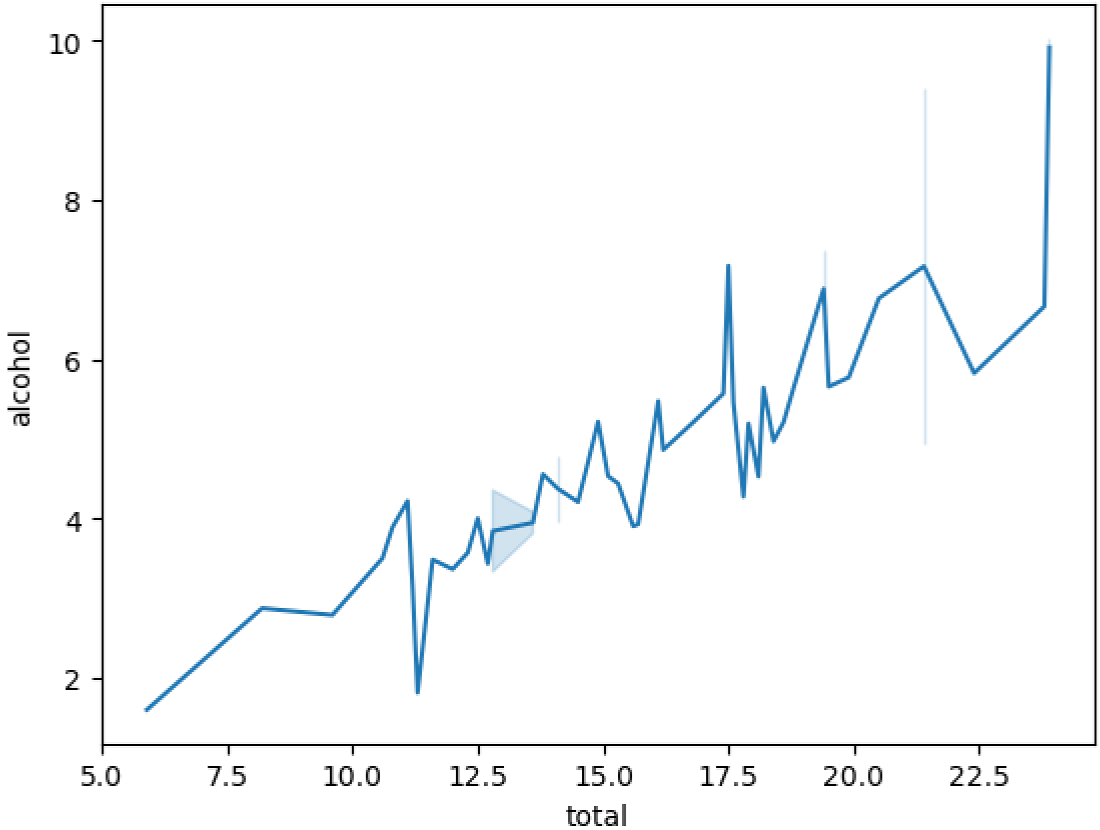
Out[20]:
```
<Axes: xlabel='abbrev', ylabel='ins_losses'>
```



In [ ]:
```
This graph shous the Losses incurred by insurance companies for collisions per insured
For example, In Arizona State, the insurance companies loss is around 110.35 dollars t
From the graph, we can see that Idaho state as the lowest insurance losses for the cor
insurance losses for the company.
```

In [21]:
```
#Lineplot
sns.lineplot(y="alcohol",x="total",data=ak)
```

Out[21]:
```
<Axes: xlabel='total', ylabel='alcohol'>
```



In [ ]:

```
We already discussed that the people who are drinking and driving are more prone to ac
conclusion justified. But for the same number of total people who faced an accident, t
accident was drinking alcohol was not exactly the same. Some states were affected by t
severely than the others.
```

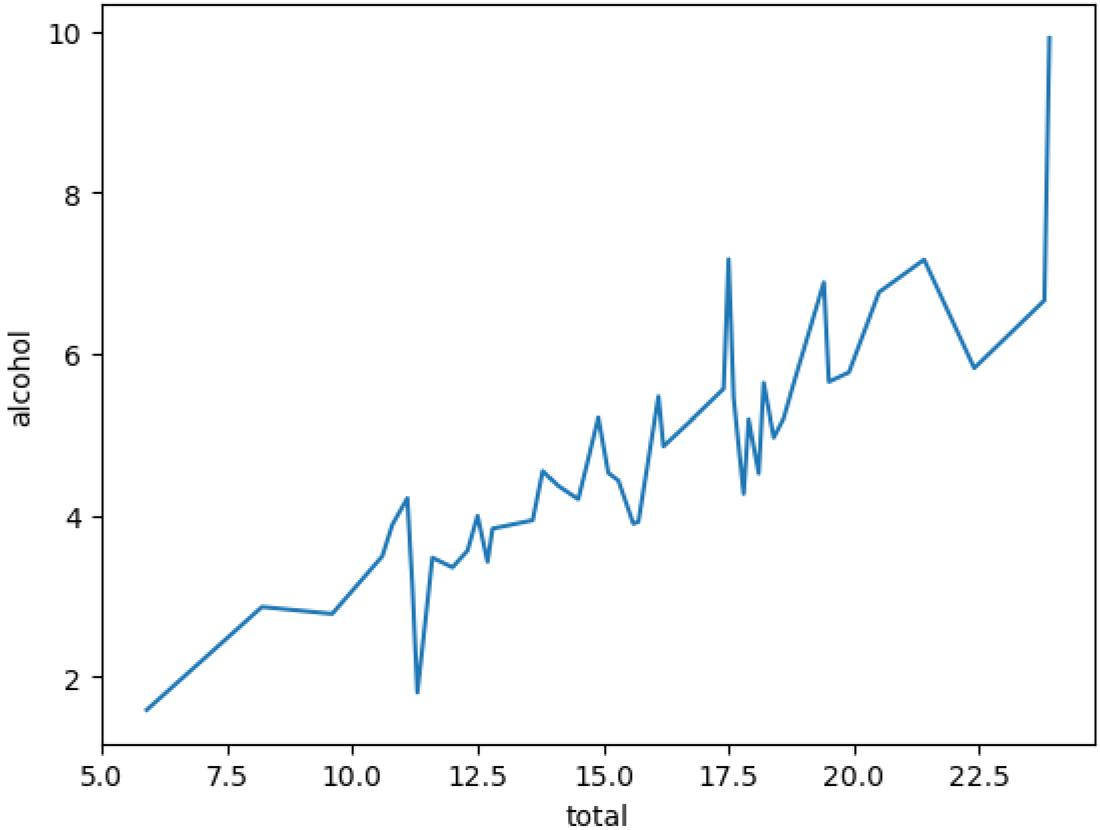
In [22]:

```
#Lineplot
sns.lineplot(y="alcohol",x="total",data=ak,ci=None)
```

```
C:\Users\nagka\AppData\Local\Temp\ipykernel_14956\2654429431.py:2: FutureWarning:

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

  sns.lineplot(y="alcohol",x="total",data=ak,ci=None)
```

Out[22]:

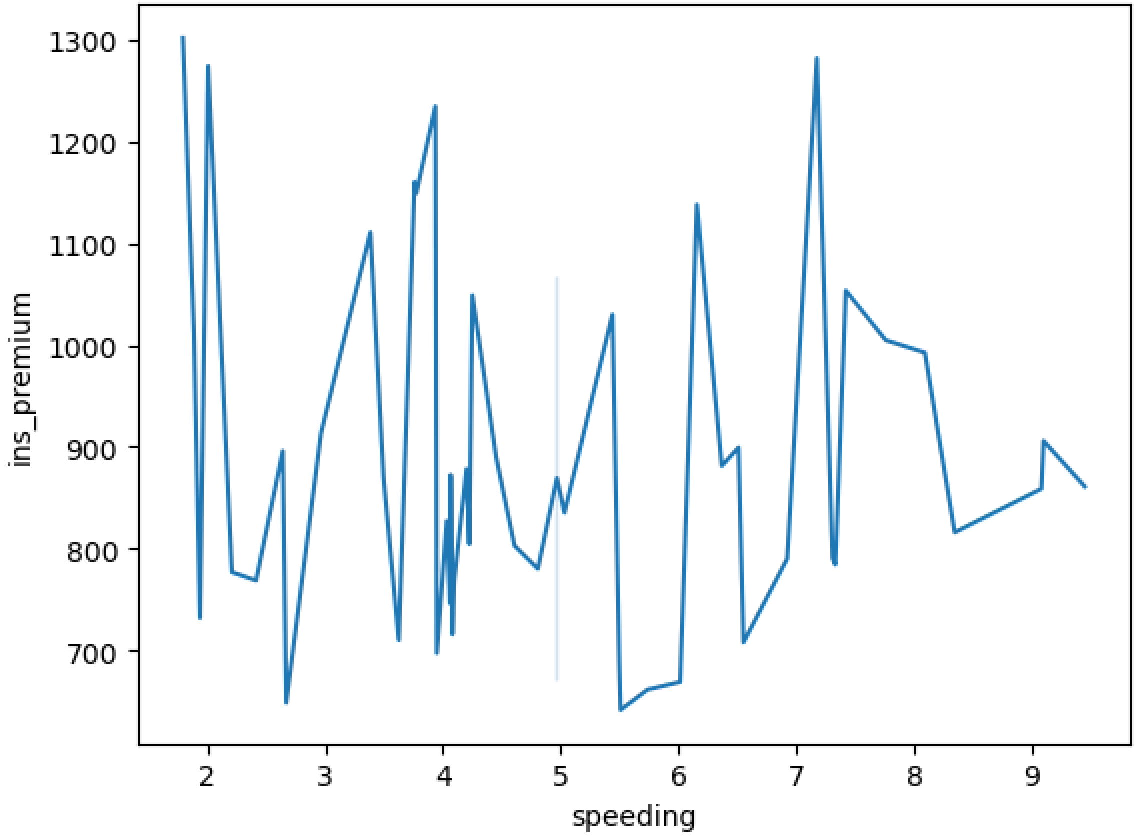
```
<Axes: xlabel='total', ylabel='alcohol'>
```



In [ ]:
```
We already discussed that the people who are drinking and driving are more prone to ac
conclusion justified. But for the same number of total people who faced an accident, t
accident was drinking alcohol was not exactly the same. Some states were affected by t
severely than the others.
```

In [50]:
```
sns.lineplot(y="ins_premium",x="speeding",data=ak)
```

Out[50]:
```
<Axes: xlabel='speeding', ylabel='ins_premium'>
```

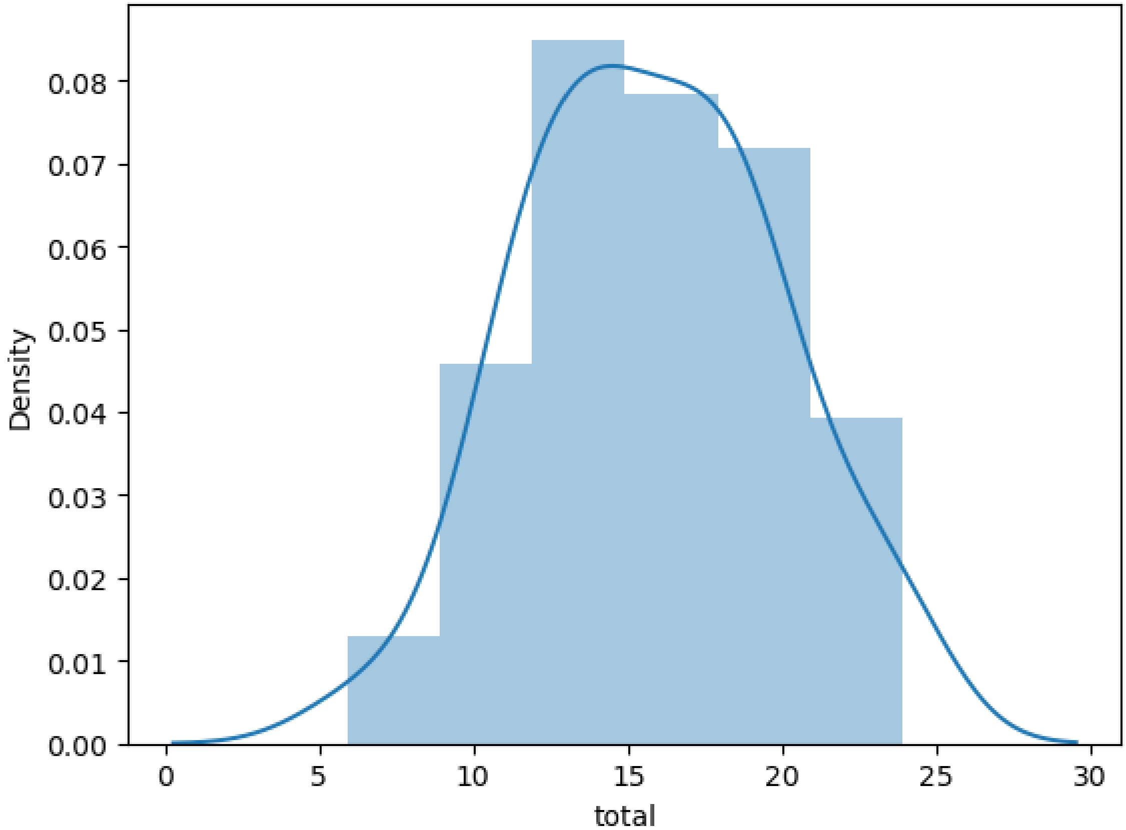


In [ ]:
```
The relation between people who faced the car crash majorly because of speeding and th
in their state are not exactly correlated in any way. The states where the Insurance p
New York, New Jersey and District of Columbia.
```

In [24]:
```
#Displot
sns.distplot(ak["total"])
```

```
C:\Users\nagka\AppData\Local\Temp\ipykernel_14956\2663308116.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(ak["total"])
```

Out[24]:
```
<Axes: xlabel='total', ylabel='Density'>
```

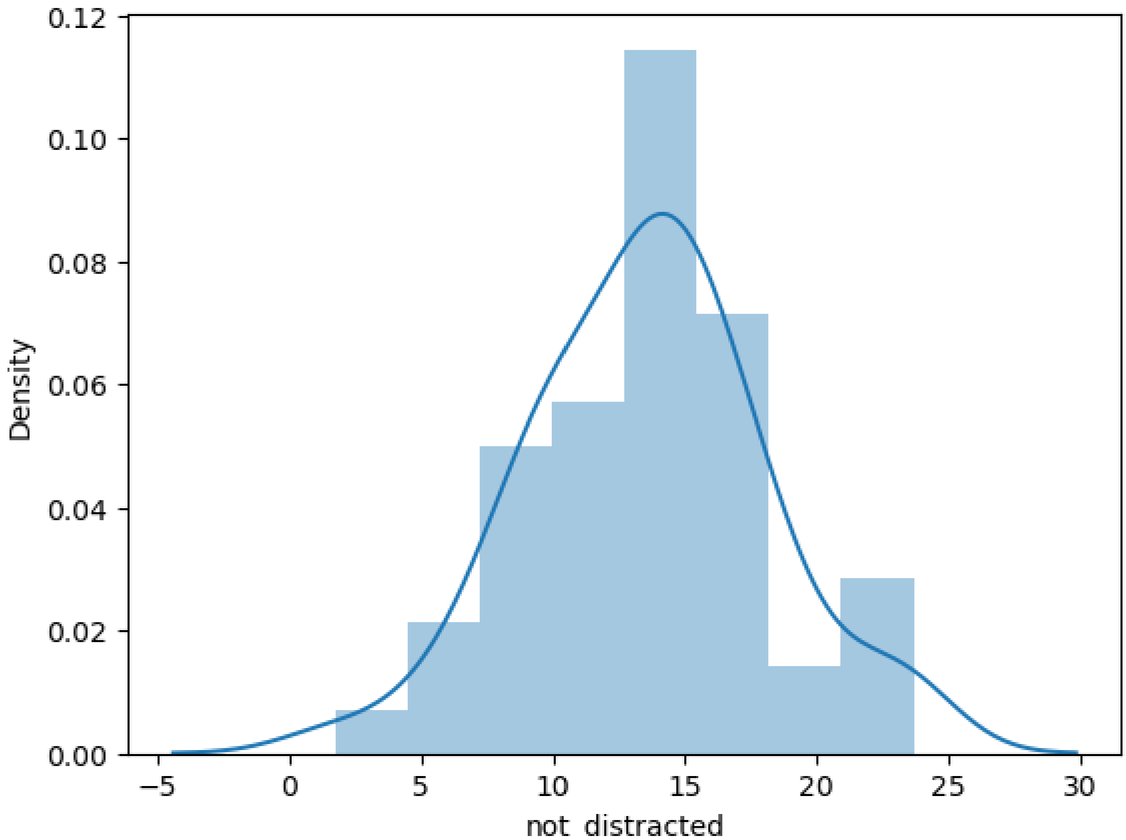


In [ ]:
```
This above distribution plot shows that the distribution is unimodal. And there are no
very less outliers in our data. We can observe the data is in a normal curve distribut
can see that the shape of the distribution graph is quite symmetric. The states where
than comapred to other states are Kentucky, Arkansas and Louisinia.
```

In [25]:
```
sns.distplot(ak["not_distracted"])
```

```
C:\Users\nagka\AppData\Local\Temp\ipykernel_14956\3265424172.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(ak["not_distracted"])
```

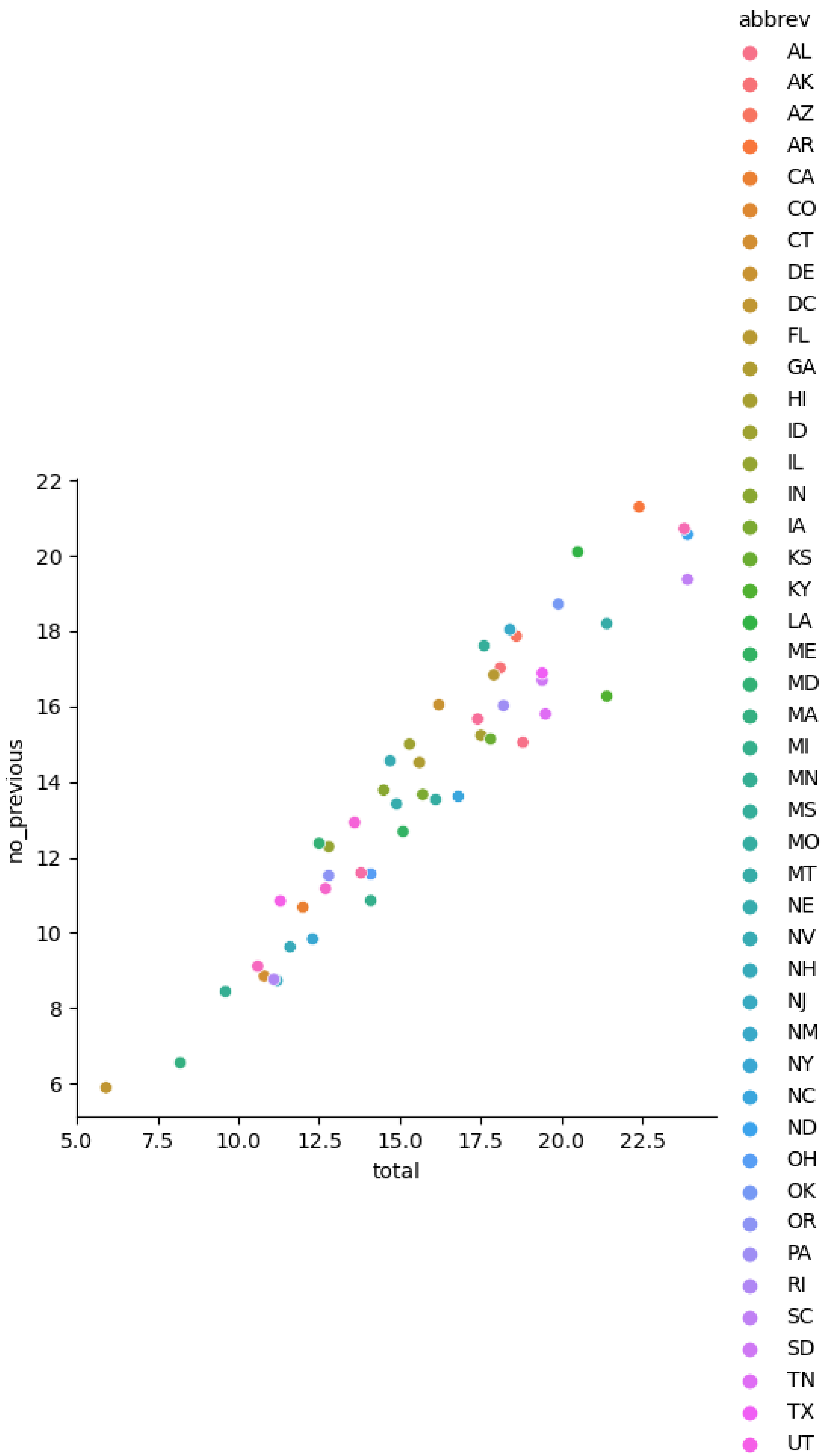
Out[25]:
```
<Axes: xlabel='not_distracted', ylabel='Density'>
```



In [ ]:
```
This above distribution plot shows that the distribution is unimodal. We can see that
Negatively Skewed as the Q2 is close to Q3. And there are not many infactvery less out
data is in a normal curve distribution shape. The states which involved people sufferi
distracted from driving were
```

In [52]:
```
#Relationplot
sns.relplot(x="total",y="no_previous",data=ak,hue="abbrev")
```

Out[52]:
```
<seaborn.axisgrid.FacetGrid at 0x1e4f9abb910>
```


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
22
20
18
16
14
12
10
8
6
no_previous
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
total

In [ ]:

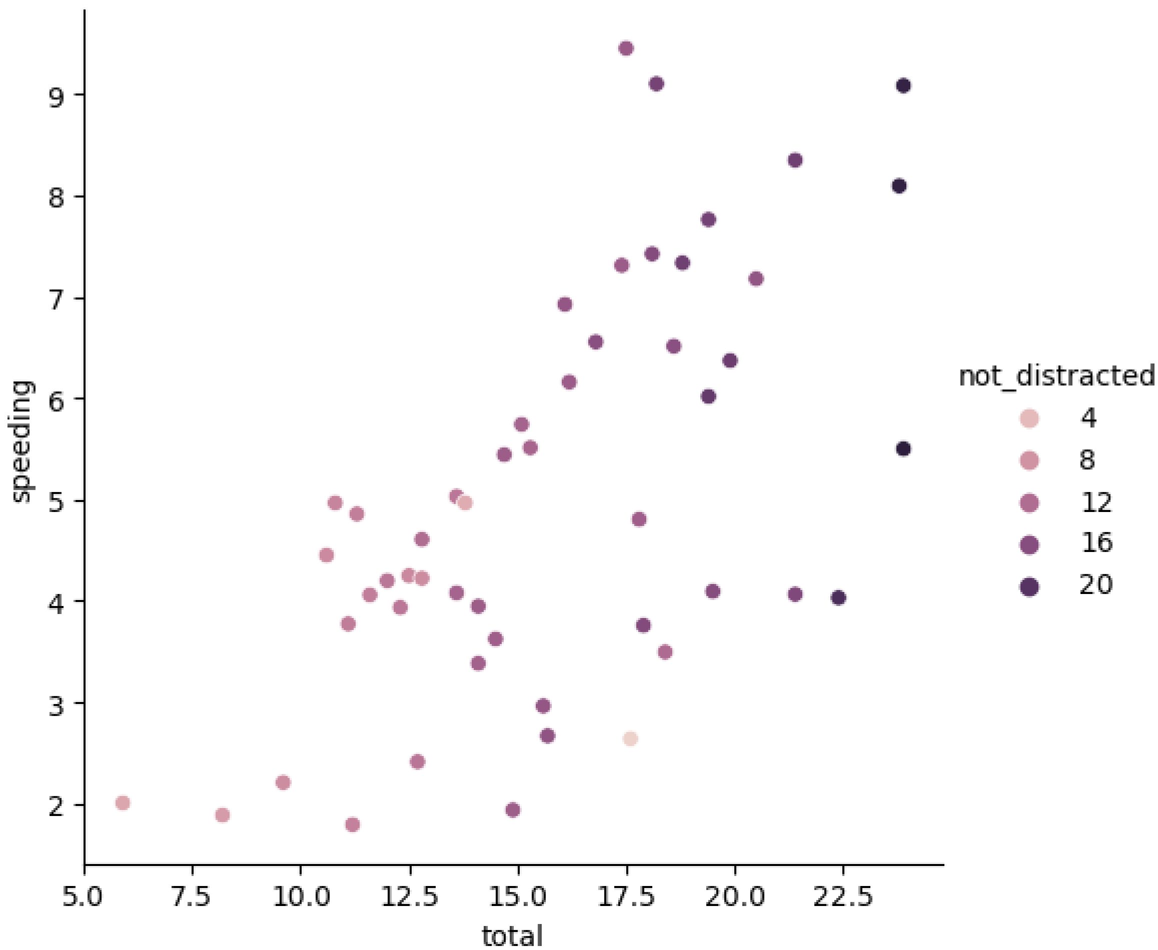
```
We can see that the total number of people who faced the accident had no previous most
related or positively corelated data. This graph clearly shows as the more number of p
found out to be having no previous record of any fatal accidents as such. 50 states ar
no_previous count of data in their respective states.
```

In [51]:

```
#Relationplot
sns.relplot(x="total",y="speeding",data=ak,hue="not_distracted")
```

Out[51]:

```
<seaborn.axisgrid.FacetGrid at 0x1e4f887d090>
```



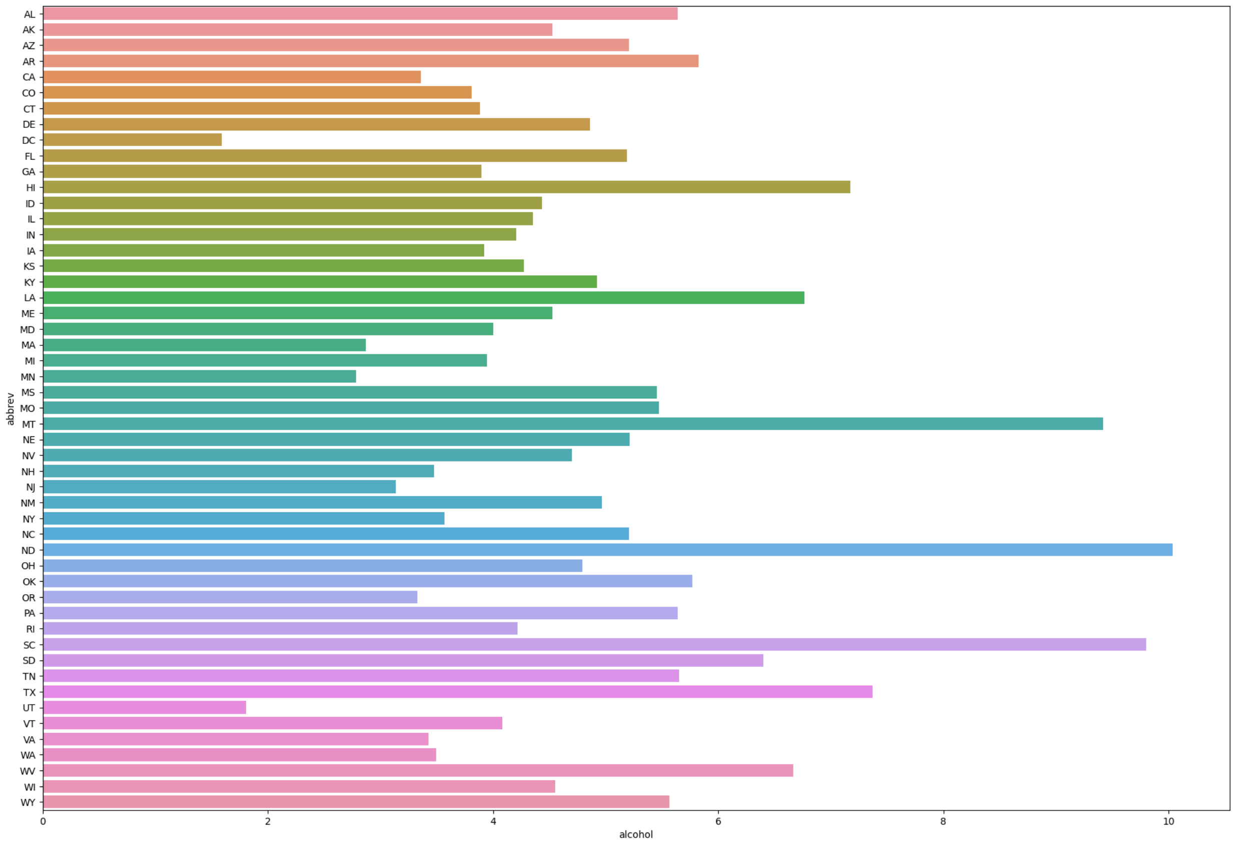
In [ ]:

```
This graph is almost scattered widely that is they are not very much related. But yes
who faced the fatal car crash were speeding but most of them are not speeding. So we c
who faced the accident were not at all distracted from driving but due to speeding the
were not speeding can be clearly seen as not being focussed that is being more distrac
```

In [53]:

```
#barplot
plt.subplots(figsize=(22,15))
sns.barplot(x="alcohol",y="abbrev",data=ak)
```

Out[53]: <Axes: xlabel='alcohol', ylabel='abbrev'>



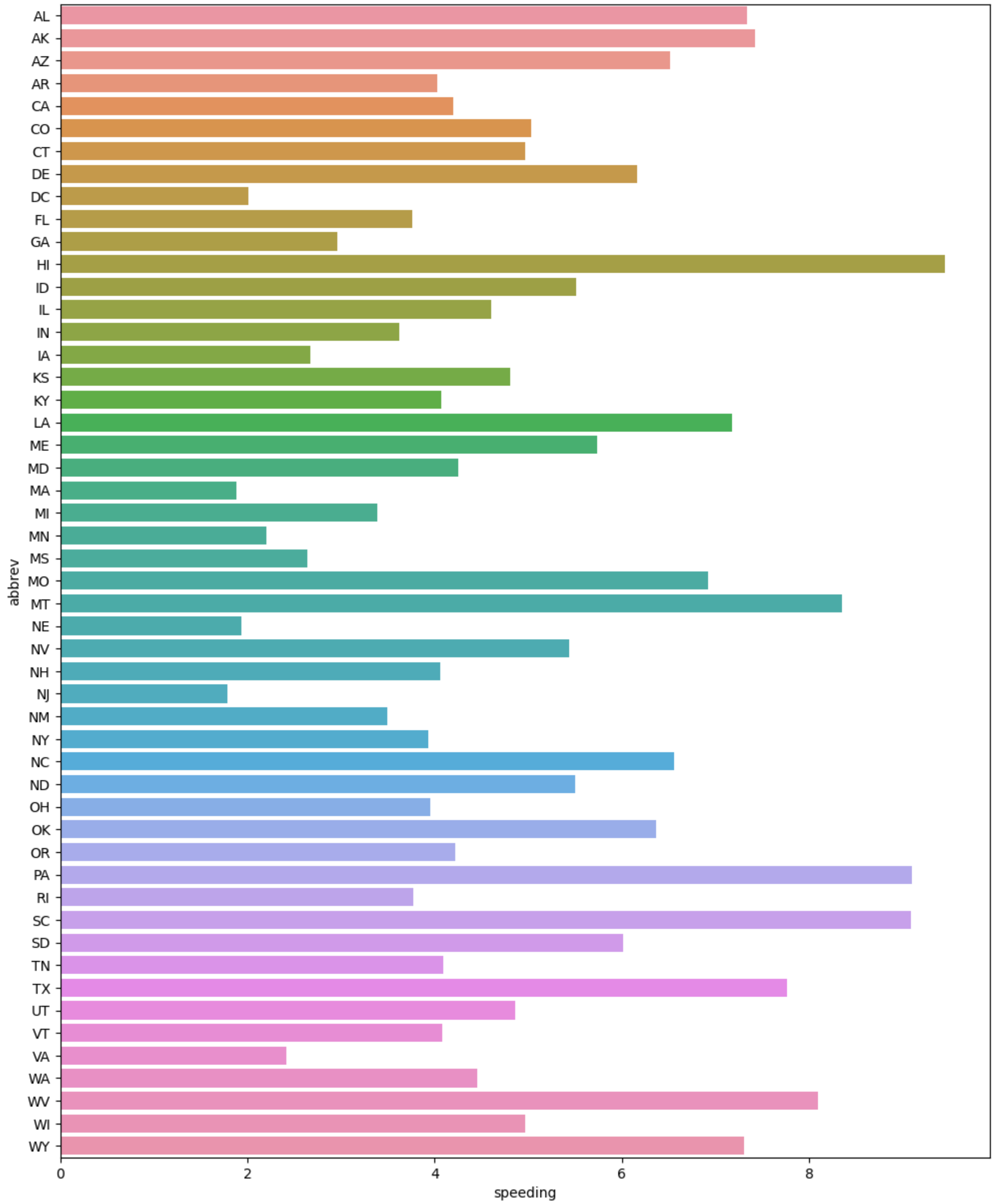
In [ ]:

```
This shows that how much that particular state was affected majorly becuase of consumi
took place because the driver was alcohol impaired. The top states that faced Alcohol
South Carolina.
```

In [54]:

```python
#barplot
plt.subplots(figsize=(12,15))
sns.barplot(x="speeding",y="abbrev",data=ak)
```

Out[54]: <Axes: xlabel='speeding', ylabel='abbrev'>



In [ ]:

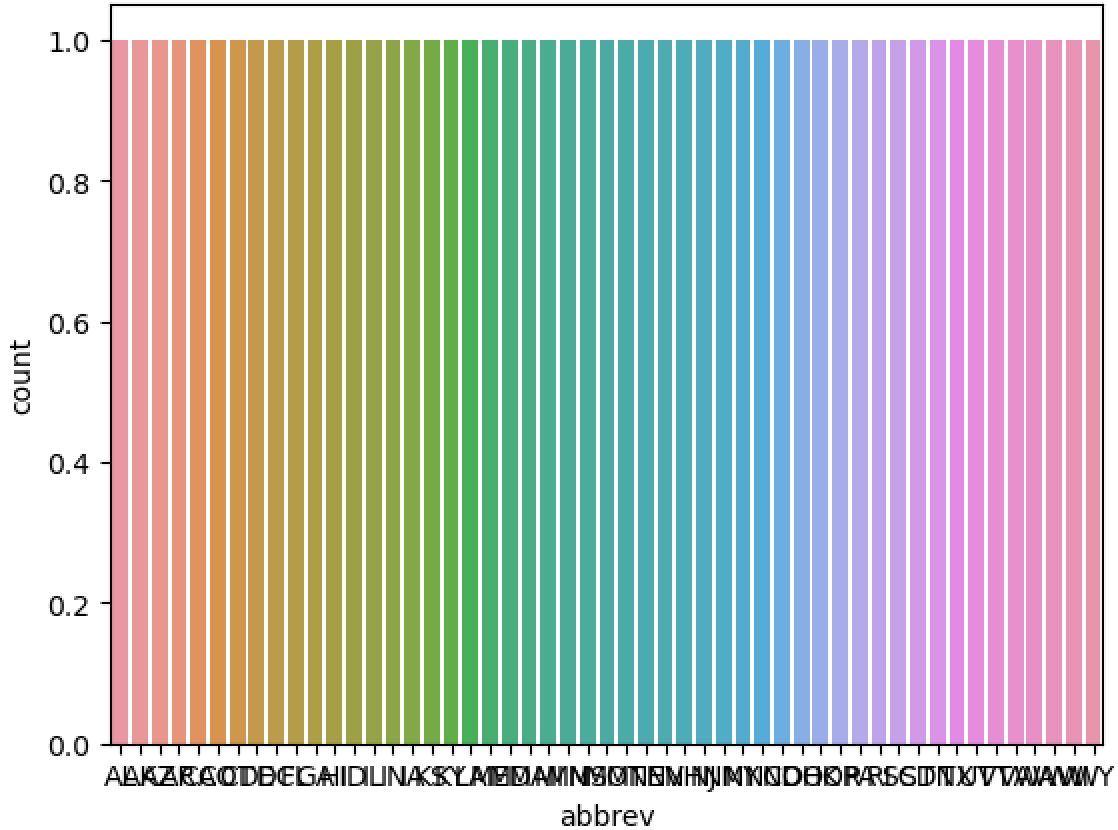
```
This shows that how much that particular state was affected majorly becuase of speedir
. That is how many car crashes took place because the driver was speeding. The top sta
issues were Hawaii, Pennsylvania and South Carolina.
```

In [30]:

```python
#countplot
sns.countplot(x="abbrev",data=ak)
```

Out[30]:

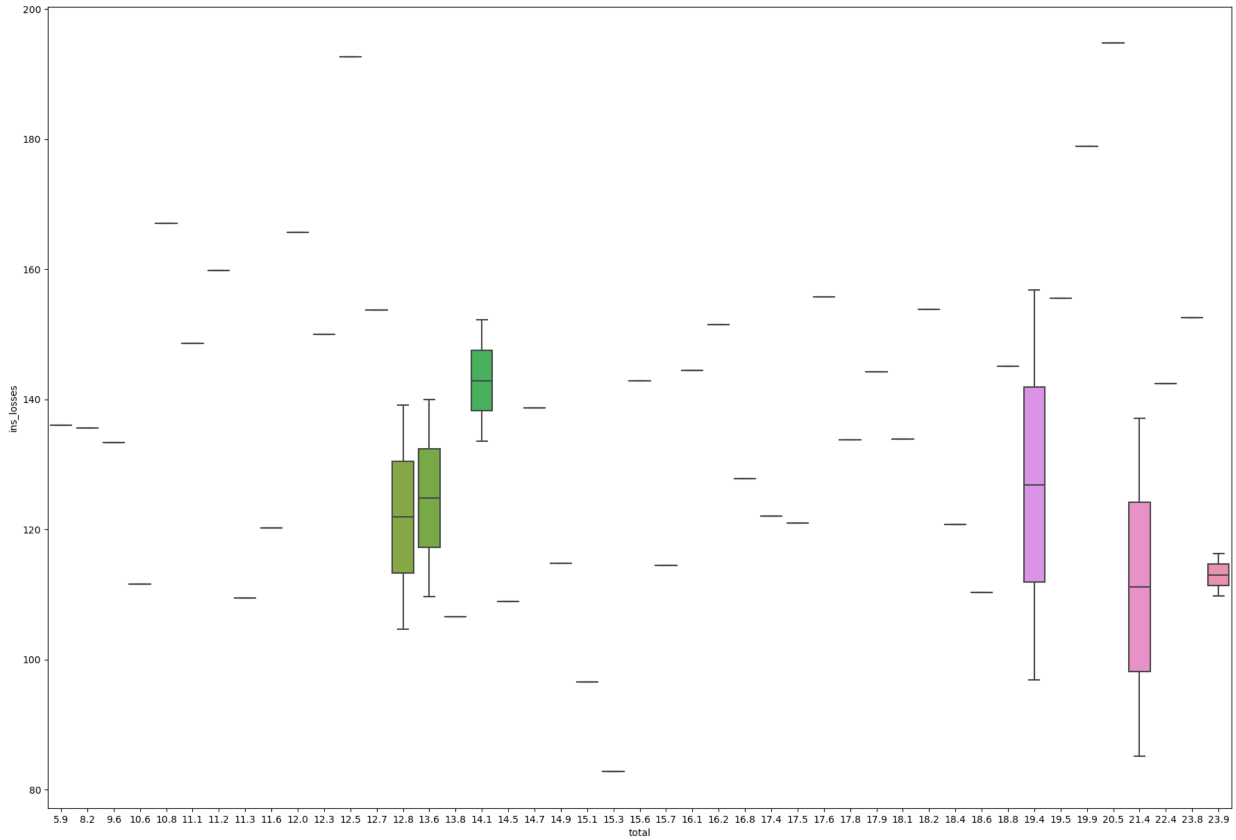
```
<Axes: xlabel='abbrev', ylabel='count'>
```



In [ ]:
```
This is a basic graph where we can see how many times a state has been repeated in the
we can every state frequency is exactly 1.
```

In [31]:
```
#boxplot
plt.subplots(figsize=(22,15))
sns.boxplot(x="total",y="ins_losses",data=ak)
```

Out[31]:
```
<Axes: xlabel='total', ylabel='ins_losses'>
```



In [ ]:

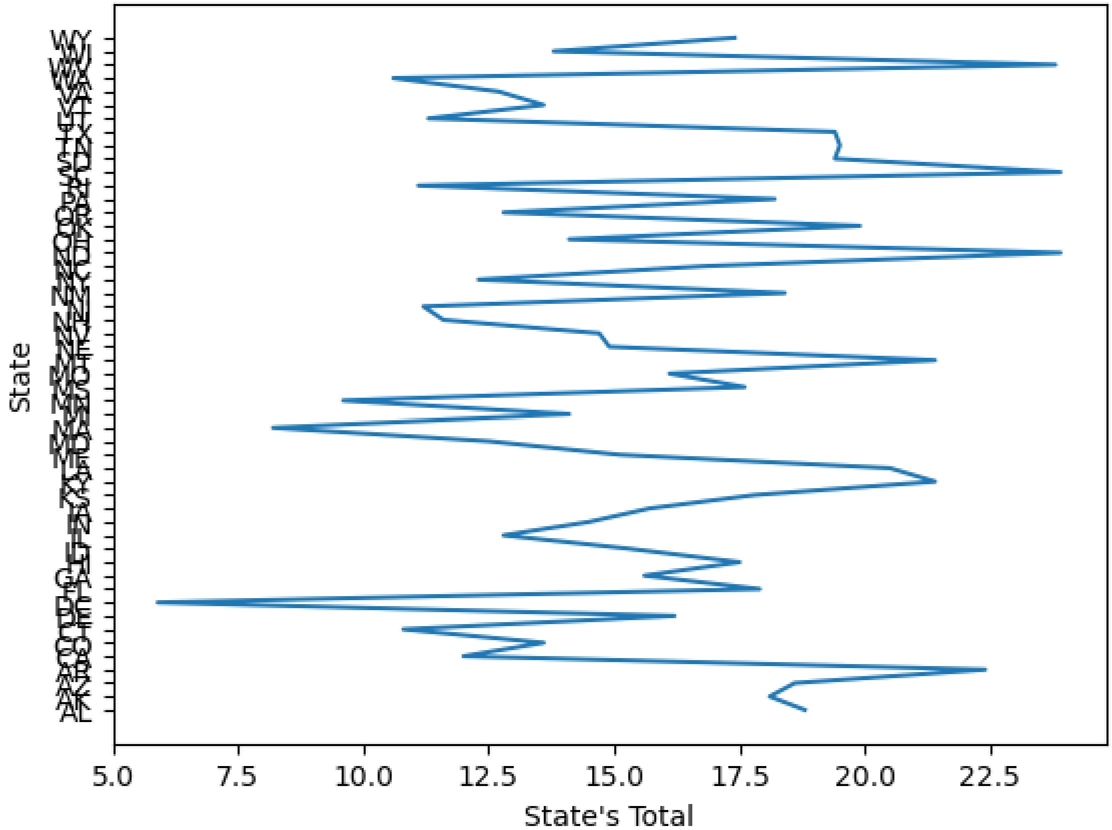
```
We can clearly see the data is not skewed positively nor negatively, i.e the data is r
equal distance to Q1 and Q3. We can also see that there no outliers in the data of the
```

In [55]:

```
x=ak["total"]
y=ak["abbrev"]
plt.plot(x,y)
plt.ylabel("State")
plt.xlabel("State's Total")
```

Out[55]:

```
Text(0.5, 0, "State's Total")
```



In [ ]:

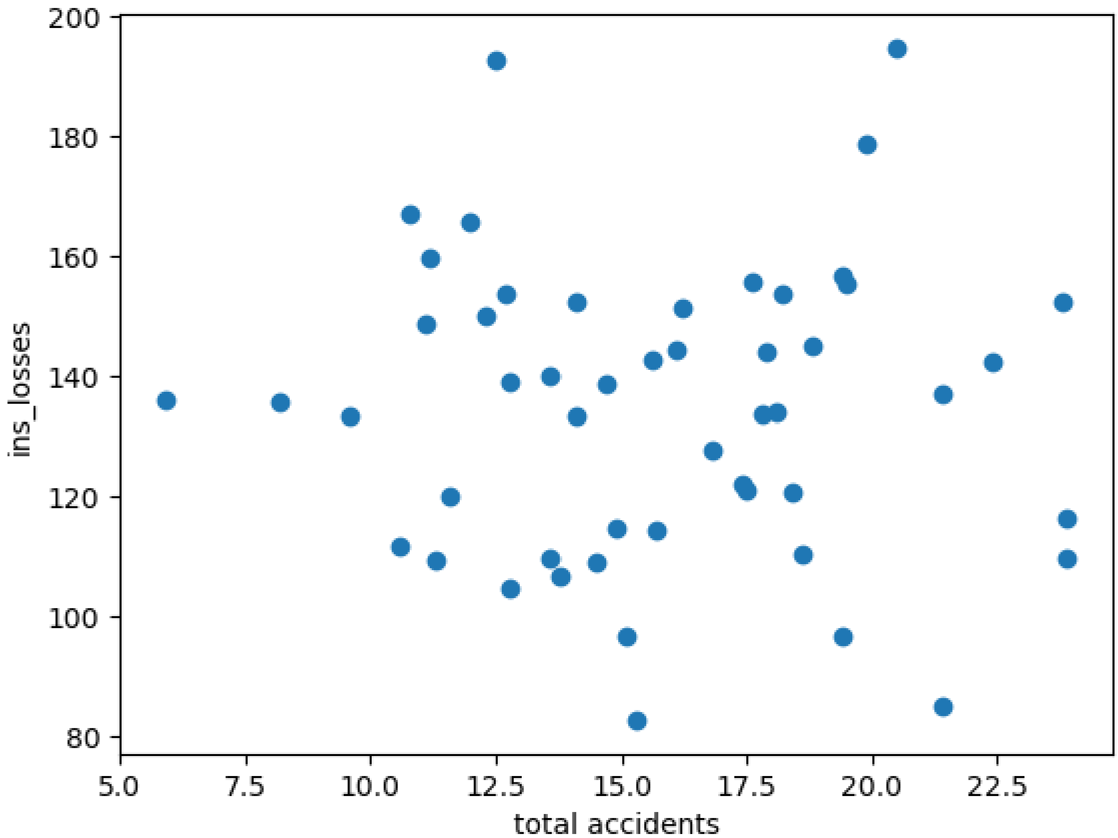
```
This line graph shows that in that particualr state how mnay fatal car crashes have ta
```

In [56]:

```
c=ak["total"]
d=ak["ins_losses"]
plt.scatter(c,d)
plt.xlabel("total accidents")
plt.ylabel("ins_losses")
```

Out[56]:

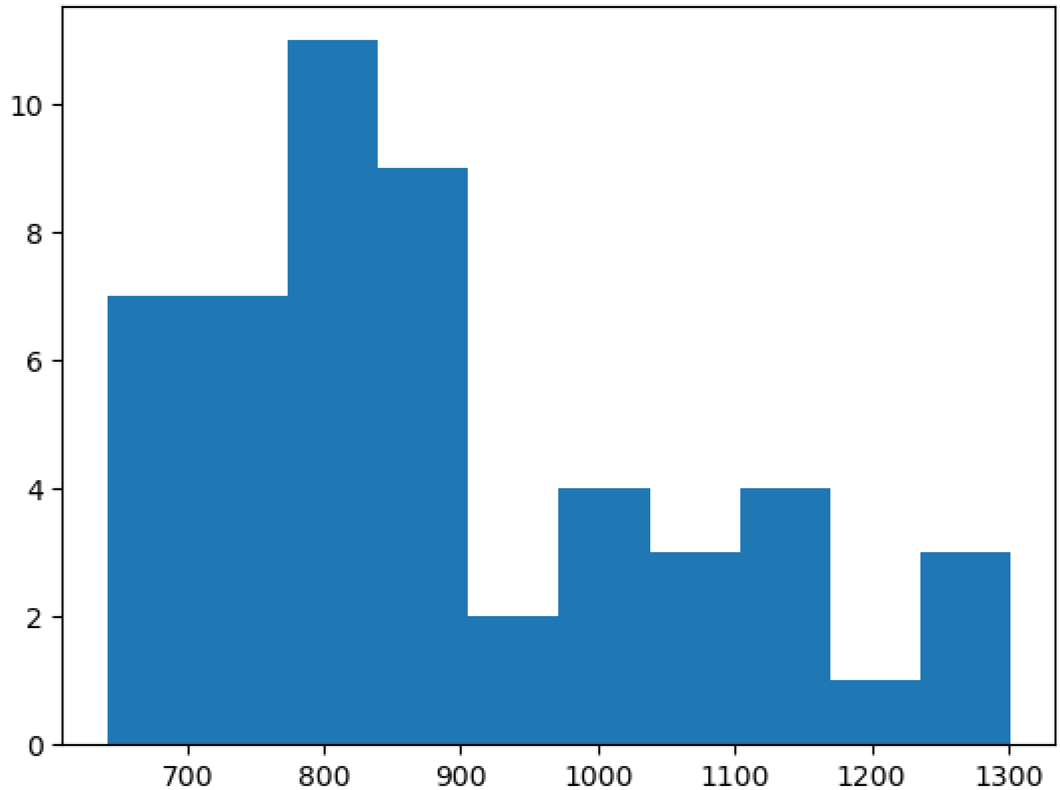
```
Text(0, 0.5, 'ins_losses')
```



In [ ]:
```
This graph is widely scattered as the insurance losses that the companies are facing t
varying from one state to another.
```

In [48]:
```
r = ak["ins_premium"]
plt.hist(r)
```

Out[48]:
```
(array([ 7.,  7., 11.,  9.,  2.,  4.,  3.,  4.,  1.,  3.]),
 array([ 641.96 ,  707.916,  773.872,  839.828,  905.784,  971.74 ,
        1037.696, 1103.652, 1169.608, 1235.564, 1301.52 ]),
 <BarContainer object of 10 artists>)
```



In [ ]:
```
This is a histogram depicting the Insurance Premium that the company is offering. This
```