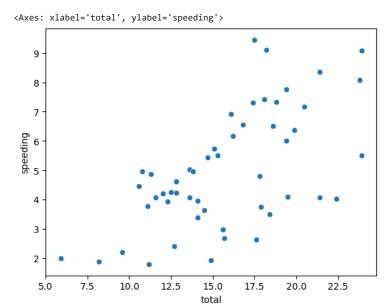
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
print(sns.get_dataset_names())
     ['anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes', 'diamonds', 'dots', 'dowjones', 'exercise', 'flights', 'fmri', '§
df = sns.load_dataset('car_crashes')
print(df)
          12.7
                   2.413
                             3.429
                                            11.049
                                                         11.176
                                                                       768.95
С→
     47
                                             8.692
                                                                       890.03
          10.6
                   4.452
                            3.498
                                                           9.116
     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
         17.4
                   7.308
                            5.568
                                            14.094
                                                         15.660
                                                                       791.14
         ins_losses abbrev
     0
             145.08
     1
             133.93
                        ΑK
     2
             110.35
                        ΑZ
     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
                        GΑ
     11
             120.92
     12
              82.75
                        ID
             139.15
     13
                        ΙL
     14
             108.92
                         IN
     15
             114.47
                        IA
             133.80
     16
                        KS
     17
             137.13
                         ΚY
     18
             194.78
                         LA
     19
              96.57
                        ME
     20
             192.70
                        MD
     21
             135.63
                        MA
     22
             152.26
                        ΜI
     23
                        MN
             133.35
     24
             155.77
                        MS
     25
             144.45
     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
                        ОН
     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
                         \mathsf{TN}
     43
                        TX
             156.83
     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
sns.__version__
     '0.12.2'
df.info()
```

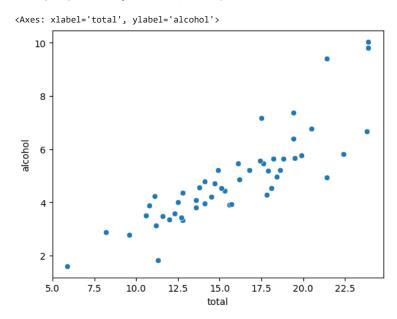
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 8 columns):
    Column
                     Non-Null Count Dtype
0
    total
                     51 non-null
                                     float64
1
     speeding
                     51 non-null
                                     float64
                                     float64
     alcohol
                     51 non-null
    not_distracted
                     51 non-null
                                     float64
                                     float64
    no_previous
                     51 non-null
     ins_premium
                     51 non-null
                                     float64
     ins_losses
                                     float64
                     51 non-null
     abbrev
                     51 non-null
                                     object
dtypes: float64(7), object(1)
memory usage: 3.3+ KB
```

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



Inference: In the above graph we can observe that plotting of the points with total in x-axis and speeding in y-axis. Here we can clearly observe that increase in speed has caused many car crashes. Which shows the direct proportionality in between total and speeding of car crashes.

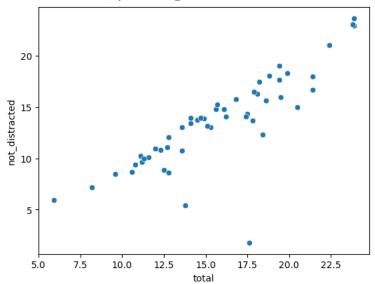
sns.scatterplot(x="total",y="alcohol",data=df)



Inference: In the above graph we can observe that plotting of the points with total in x-axis and alcohol in y-axis. Here we can clearly observe that more drinking of alcohol has caused many car crashes. Which shows the direct proportionality in between total and alcohol of car crashes.

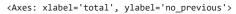
sns.scatterplot(x="total",y="not_distracted",data=df)

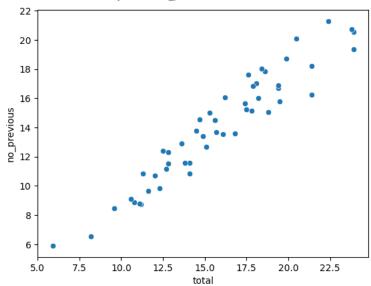
<Axes: xlabel='total', ylabel='not_distracted'>



Inference: In the above graph we can observe that plotting of the points with total in x-axis and not_distracted in y-axis. Here we can clearly observe that not_distracted has caused many car crashes. Which shows the direct proportionality in between total and not_distracted of car crashes.

sns.scatterplot(x="total",y="no_previous",data=df)





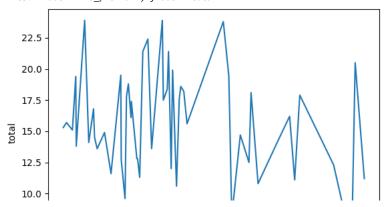
Inference: In the above graph we can observe that plotting of the points with total in x-axis and no_previous in y-axis. Here we can clearly observe that no_previous has caused many car crashes. Which shows the direct proportionality in between total and no_previous of car crashes.

sns.lineplot(x="ins_premium",y="total",data=df,ci=None)

<ipython-input-18-eca919d1edb3>:1: FutureWarning:

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

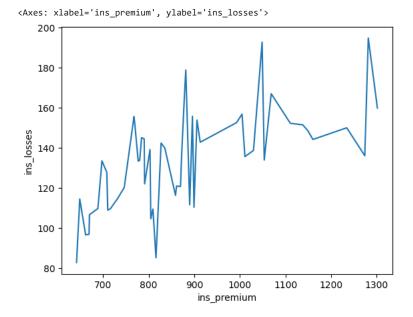
sns.lineplot(x="ins_premium",y="total",data=df,ci=None)
<Axes: xlabel='ins_premium', ylabel='total'>



Inference: In the above lineplot graph the relation between ins_premium in x=asix and total in y-asix. There is an irregular plotting of lineplot of ins_premium and total. which defines that very large number of car crash has been done their insurance premium.

E A |

sns.lineplot(x="ins_premium",y="ins_losses",data=df)



sns.barplot(data=df,x="ins_premium",y="ins_losses")

```
<Axes: xlabel='ins_premium', ylabel='ins_losses'>
200 -
```

Inference: In the above two graph the relation between ins_premium in x=asix and ins_losses in y-asix. There is an irregular plotting of lineplot of ins_premium and ins_losses, which defines that insurance losses is directly proportional to insurance premium, where increse in insurance premium also tends to increase in insurance loss.

For a guide to updating your code to use the new functions, please see $\frac{\text{https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751}}{\text{https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751}}$

800

1000

ins premium

Inference: The above graph is about the density of the insurance premium where there is a huge increase in the density of insurance premium at a point of 800.

1400

1600

1200

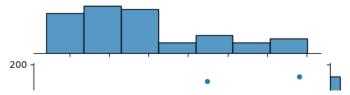
sns.jointplot(data=df,x="ins_premium",y="ins_losses")

600

0.0000

400

<seaborn.axisgrid.JointGrid at 0x7d1d5bfbbe50>



Inference: The above graph is about jointplot of ins_premium and ins_losses where the plotting of graph is randomly distributed through out the graph. We can observe the density of ins_premium and ins_losses where they show in great increase and decrease.

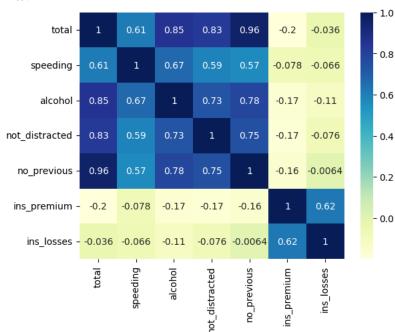
corr=df.corr()

<ipython-input-22-7d5195e2bf4d>:1: FutureWarning: The default value of numeric_only in C
 corr=df.corr()

	total	speeding	alcohol	${\sf not_distracted}$	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	
1							•

sns.heatmap(corr,annot=True,cmap="YlGnBu")

<Axes: >



Inferance: The above data is the correlation of the car crashs data. Where we can observe the clear correaltion between each and every info of the car crashs data.

√ 1s completed at 9:59 AM