1.Import neccessary libaries nedded

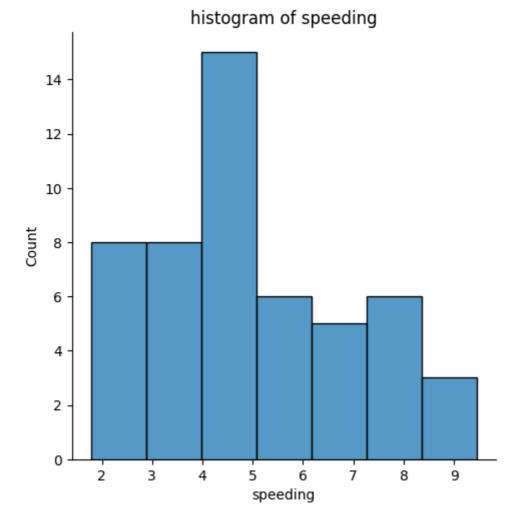
```
import numpy as np
In [ ]:
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
In [ ]:
        print(sns.get_dataset_names())
         ['anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes', 'diamonds',
         'dots', 'dowjones', 'exercise', 'flights', 'fmri', 'geyser', 'glue', 'healthexp',
         'iris', 'mpg', 'penguins', 'planets', 'seaice', 'taxis', 'tips', 'titanic']
        2.Loading Dataset
In [ ]: df=sns.load_dataset('car_crashes')
In [ ]: 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
                             51 non-null
                                             float64
         6 ins_losses
             abbrev
                             51 non-null
                                             object
        dtypes: float64(7), object(1)
        memory usage: 3.3+ KB
       df.shape
In [ ]:
        (51, 8)
Out[]:
        df.head(5)
In [ ]:
                         alcohol not_distracted no_previous ins_premium ins_losses abbrev
Out[ ]:
           total speeding
        0 18.8
                    7.332
                           5.640
                                        18.048
                                                   15.040
                                                               784.55
                                                                        145.08
                                                                                  AL
        1 18.1
                                                   17.014
                    7.421
                           4.525
                                        16.290
                                                              1053.48
                                                                        133.93
                                                                                  ΑK
        2 18.6
                    6.510
                           5.208
                                        15.624
                                                   17.856
                                                               899.47
                                                                        110.35
                                                                                  ΑZ
        3
           22.4
                    4.032
                           5.824
                                        21.056
                                                   21.280
                                                               827.34
                                                                        142.39
                                                                                  AR
           12.0
                    4.200
                                        10.920
                                                               878.41
                                                                                  CA
                           3.360
                                                   10.680
                                                                        165.63
```

plotting univariate distribution

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

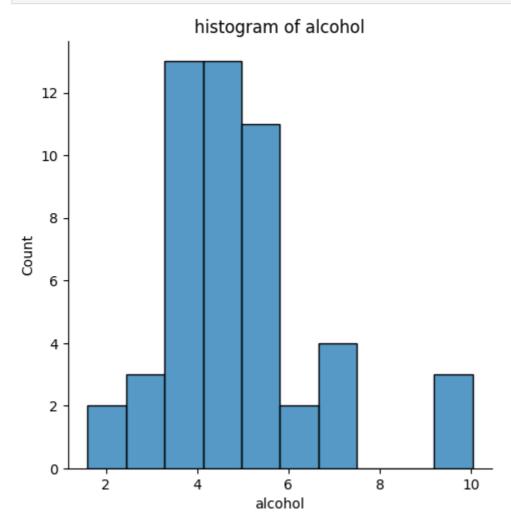
Inference: it shows how many accidents took per quantile and also shows standard deviation,mean,max

```
In []: #histogram
    sns.displot(df['speeding'])
    plt.title("histogram of speeding")
    plt.show()
```



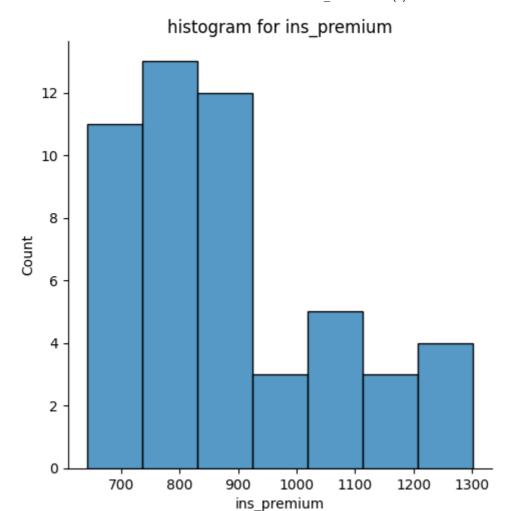
Inference: speeding ranges 4 to 5 has more count

```
In [ ]: sns.displot(df['alcohol'])
   plt.title("histogram of alcohol")
   plt.show()
```

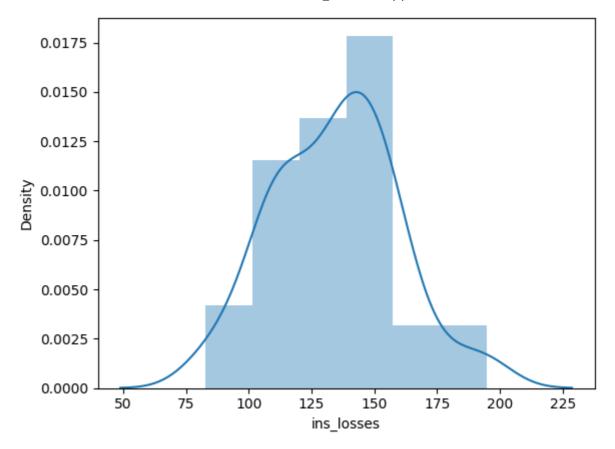


Inference:alcohol range from 4 to 5 hs highest count

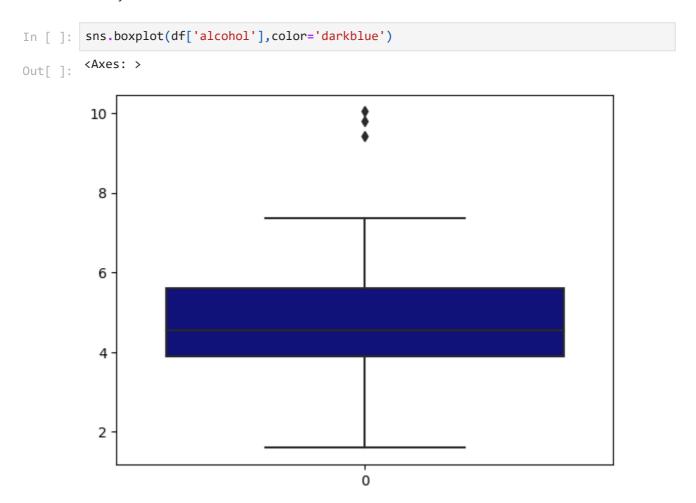
```
In [ ]: sns.displot(df['ins_premium'])
   plt.title("histogram for ins_premium")
   plt.show()
```



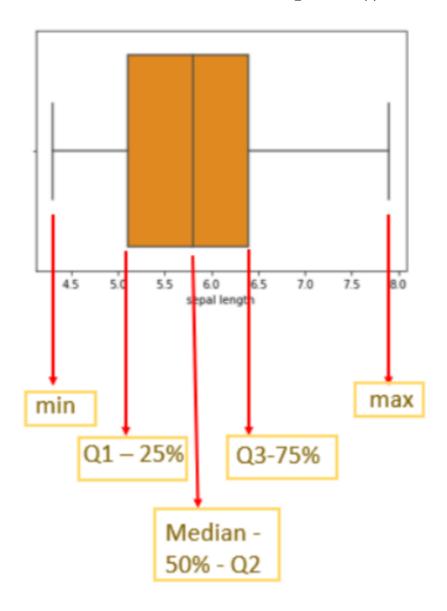
Inference:car ins_premium has highest count at 800

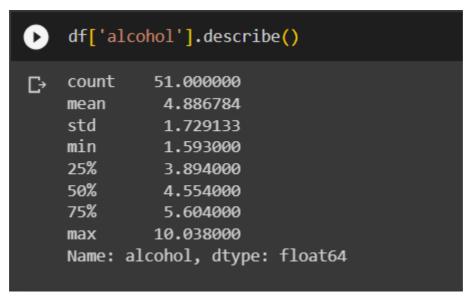


Inference: Losses incurred by insurance companies for collisions per insured driver occurs mostly at 150



Inference: it shows the descriptive statistics in order to detect the outliers which is used further for data preprocessing .This represent the 5 point statistics in a graphical manner

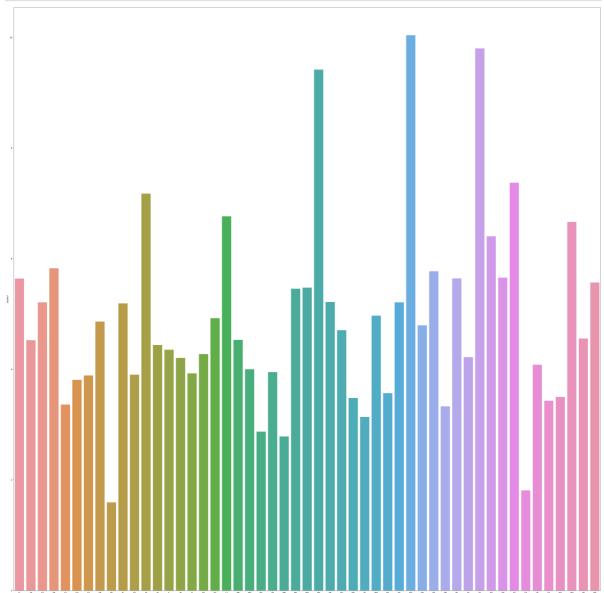




Bivariate distribution

Bar Plot

```
In [ ]: fig, ax1 = plt.subplots(figsize=(50, 50))
    sns.barplot(x="abbrev",y="alcohol",data=df, ax=ax1)
    plt.show()
```

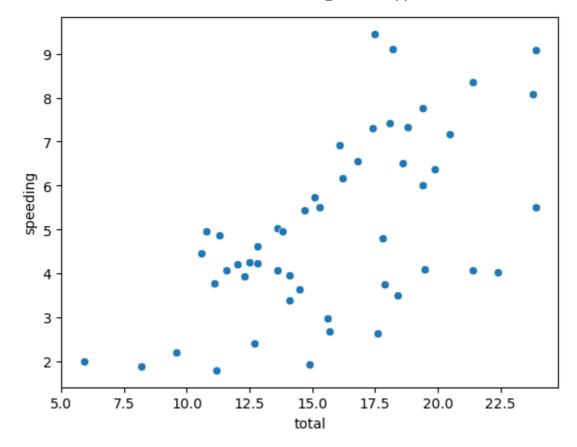


Inference:number of crashes that happened due to Alcohol intake is the highest in the country ND (North Dakota)

Scatter plot

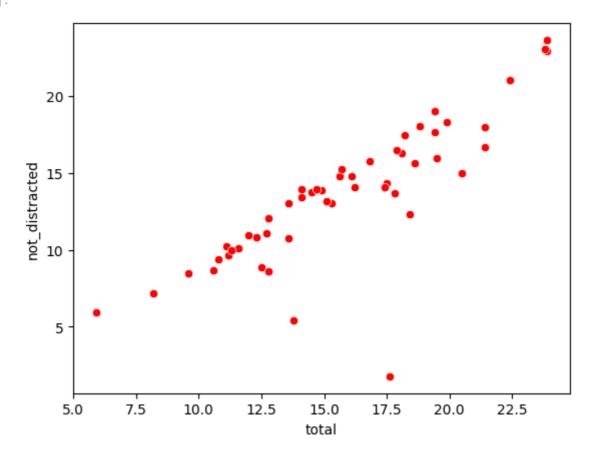
numerical vs numerical

```
In [ ]: sns.scatterplot(x="total",y="speeding",data=df)
Out[ ]: <Axes: xlabel='total', ylabel='speeding'>
```



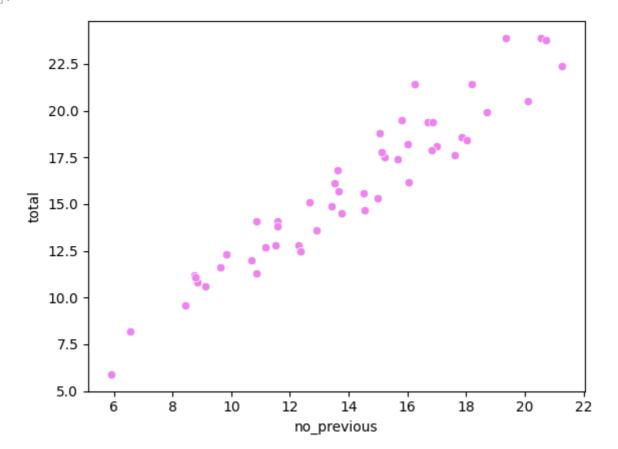
Inference:from the plot we can say that as speeding increases total car_crashes accident increases and on an avergae accidents were occurring at positionn between 4 to 7

```
In [ ]: sns.scatterplot(x="total",y="not_distracted",data=df,color="red")
Out[ ]: <Axes: xlabel='total', ylabel='not_distracted'>
```



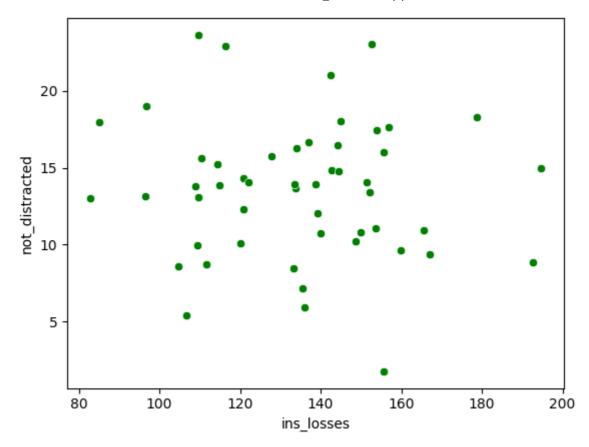
Inference: its shows a postive correlation whic represents the relation bw variables are proportionally incresing and aslo gives a best fit line

```
In [ ]: sns.scatterplot(x="no_previous",y="total",data=df,color="violet")
Out[ ]: <Axes: xlabel='no_previous', ylabel='total'>
```



Inference: we can conclude that as total accidents and no_previous increases proportionally which shows positive relationship. it is possible to find a line of best fit

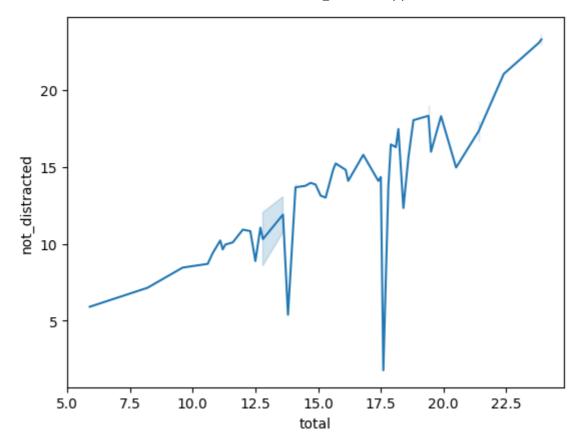
```
In [ ]: sns.scatterplot(x="ins_losses",y="not_distracted",data=df,color="green")
Out[ ]: <Axes: xlabel='ins_losses', ylabel='not_distracted'>
```



Inference: as ins_losses for company increases the not_distracted decreases which shows negative relationship.its a negative correlation

Line plot

```
In [ ]: sns.lineplot(x="total",y="not_distracted",data=df)
Out[ ]: <Axes: xlabel='total', ylabel='not_distracted'>
```

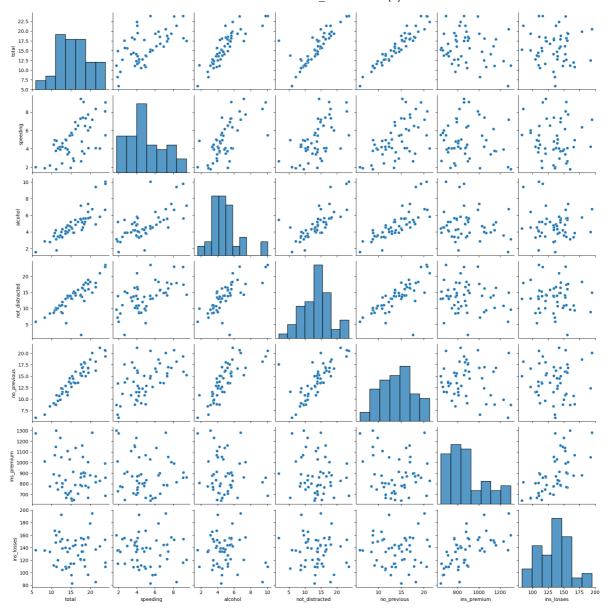


Inference: it can be inferenced that even though it has ups and downs, total number of crashes happened vs crashes happened even with drivers no distracted graph is increasing graph.

Pair Plot

```
In [ ]: sns.pairplot(df)
```

Out[]: <seaborn.axisgrid.PairGrid at 0x7e73f78a3fa0>



Inference: This Pair plot is used to understand the relations between two variables in whole datset, it is a matrix kind of plotting with x axis and y axis taking feature columns and also we can find the best set of features

- 1. The bars represent the distribution of the data for each variable
- 2. The dots representing the plotting of respective x axis and y axis:

In []:

Finding correlation for all features

```
In [ ]: p=df.corr()
p
```

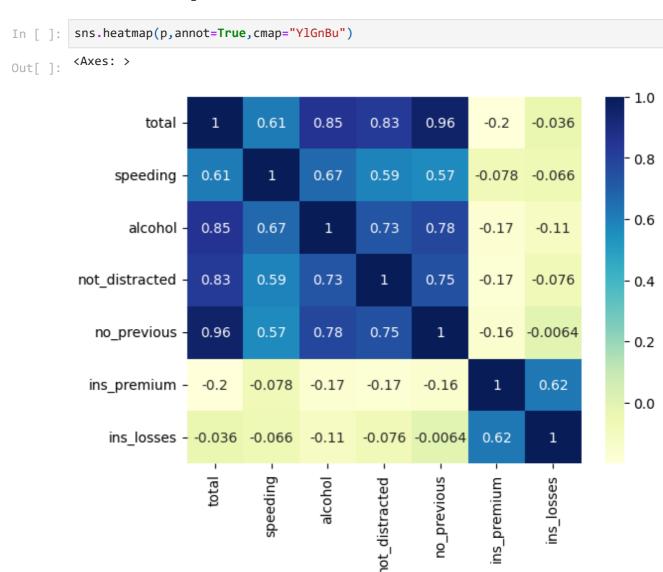
<ipython-input-30-3a7aec4522bf>:1: FutureWarning: The default value of numeric_onl
y in DataFrame.corr is deprecated. In a future version, it will default to False.
Select only valid columns or specify the value of numeric_only to silence this war
ning.

p=df.corr()

Out[]:		total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losse
	total	1.000000	0.611548	0.852613	0.827560	0.956179	-0.199702	-0.03601
	speeding	0.611548	1.000000	0.669719	0.588010	0.571976	-0.077675	-0.06592
	alcohol	0.852613	0.669719	1.000000	0.732816	0.783520	-0.170612	-0.11254
	not_distracted	0.827560	0.588010	0.732816	1.000000	0.747307	-0.174856	-0.07597
	no_previous	0.956179	0.571976	0.783520	0.747307	1.000000	-0.156895	-0.00635
	ins_premium	-0.199702	-0.077675	-0.170612	-0.174856	-0.156895	1.000000	0.62311
	ins_losses	-0.036011	-0.065928	-0.112547	-0.075970	-0.006359	0.623116	1.00000

Inference: It gives data from the region of -1 to 1 where greater than 0 can be considered as positively correlated and less than 0 are considered as neagtively corelated. From above premium insurance and intial loses are independent variables so they were negatively correlated. Speeding and alcohol are high positively correlated and not_distracted attribute is positively correlated

Heat Map



Inference: In the correlation heatmap,we can identify strong positive or negative correlations between variables. This represent the strongest positive correlation is found between the features "total" and "no_previous".

The negative correlation is found between no_previous histrory of accidents and insurance loss of company. That is, no previous accident histroy does not affect the losses of the insurance companies.

We can get carcrashes more precisely like higher the speeding there is a chance of more likely to have accident. In this extreme values can be seen in dark blue and minimal values are seen in light green