```
import warnings
warnings.filterwarnings("ignore")
import numpy as np
import pandas as pd
data=pd.read_csv("/content/drive/My Drive/applied ai/assignments/habermann/haberman.csv")
```

data.head()

C→		age	year	nodes	status
	0	30	64	1	1
	1	30	62	3	1
	2	30	65	0	1
	3	31	59	2	1
	4	31	65	4	1

data.info()

Observation:

- 1) There are 4 attributes in which 3 are the features and 1 class attribute.
- 2) year between 1958-1969.
- 3)If patient is survived more than 5 years after the surgery then it is represented as 1 and if the pat represented as 2.
- 4) There are 306 patients.
- 5) Among the 4 features one is target/class attribute then remaining

there are 3 features age, year and nodes

Understanding

1) It is a 3 dimension dataset so we can analyse the datase with pairplots

- 2)there is no missing values in the dataset
- 3)It is a binary classification model

```
data['status'].value_counts()

    1    225
         2    81
         Name: status, dtype: int64
```

Here we can observe that the data is imbalanced which means class of status is not similar

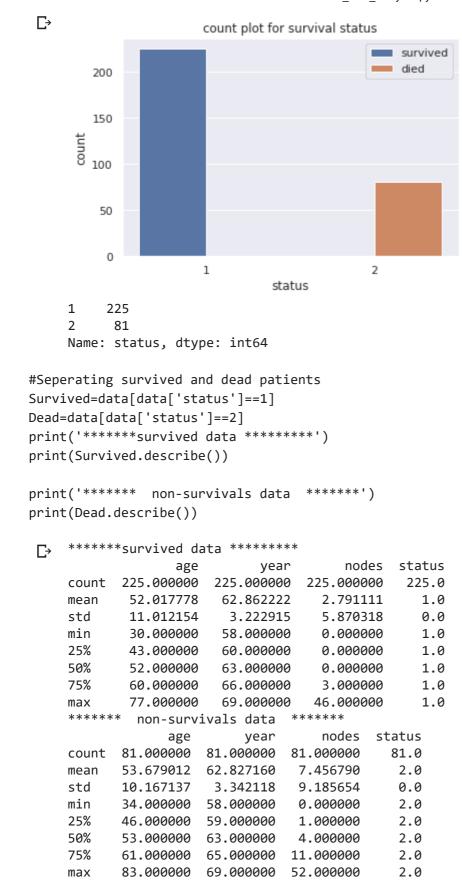
data.isnull()

г.									
L→	age		year	nodes	status				
	0	False	False	False	False				
	1	False	False	False	False				
	2	False	False	False	False				
	3	False	False	False	False				
	4	False	False	False	False				
	301	False	False	False	False				
	302	False	False	False	False				
	303	False	False	False	False				
	304	False	False	False	False				
	305	False	False	False	False				
	306 rows × 4 columns								

There are no null points

```
#plotting number of patients survival status
import seaborn as sns
import matplotlib.pyplot as plt

sns.set(style="darkgrid")
sns.countplot(x="status",hue='status',data=data)
plt.legend(['survived','died'])
plt.title('count plot for survival status')
plt.show()
data['status'].value_counts()
```



Observation:

- 1)No.of patients who are survied: 225 and dead: 81
- 2) The average age of patients who are survived: 52 and dead:53
- 3)On an average every survived patient contain 2 to 3 nodes and dead patients contain 7 to 8

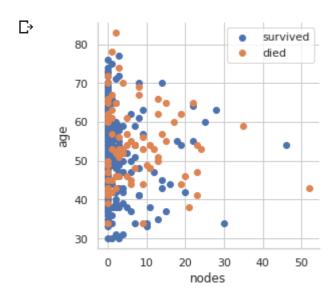
4) Standard deviation of age is 11 (that is the spread of age from the mean is 11 years)

Understanding

From the above information 50% patients survived with zero nodes. By observing mean of nodes c number of nodes when compared to dead patients.

Percentiles are little confusing. But one thing is comformed that people with no nodes are survived

```
sns.set_style('whitegrid')
sns.FacetGrid(data, hue='status', height=4) \
   .map(plt.scatter, 'nodes', 'age')
plt.legend(['survived','died'])
plt.show();
```

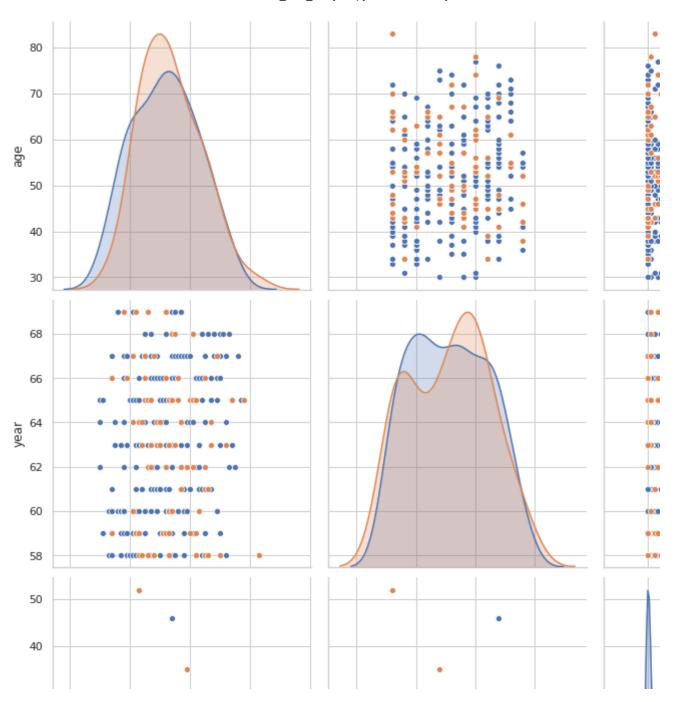


In this plot on x-axis no.of nodes and on y-axis patients agewise. There is a confusion that it diffict age with no.of nodes

so, plotting pair plots for better understanding

```
sns.set_style("whitegrid");
sns.pairplot(data, hue="status", height=4);
plt.title('pairplot')
plt.legend(['survived','died'])
plt.show()
```

 \Box

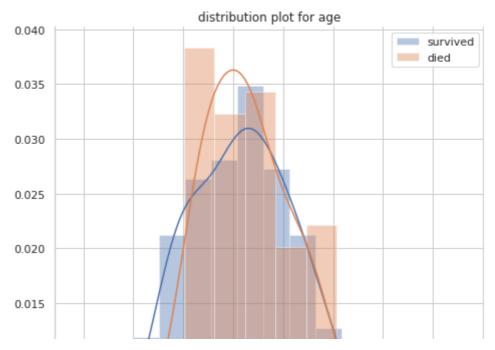


plots 1,5 and 9 it shows the density of data with respective features. Remaining all plots are overla

```
sns.FacetGrid(data, hue="status", height=7) \
    .map(sns.distplot, "age")
plt.title('distribution plot for age')
plt.legend(['survived','died'])
plt.show();
```

0 0 0 0

C→

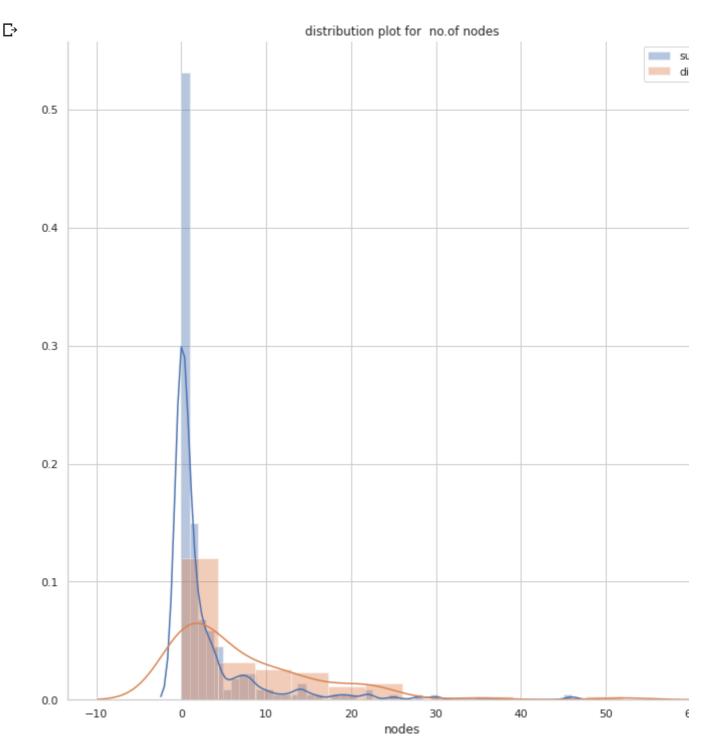


from above plot we can observe that the age from around 30 to 34 thereis no deaths and from age this is not enough to predict

```
sns.FacetGrid(data, hue="status", height=7) \
    .map(sns.distplot, "year")
plt.legend(['survived','died'])
plt.title('distribution plot for year of surgery')
plt.show();
```



```
sns.FacetGrid(data, hue="status", size=10) \
    .map(sns.distplot, "nodes")
plt.legend(['survived','died'])
plt.title('distribution plot for no.of nodes')
plt.show();
```



from this plot we can say that,

1)if nodes <= 0 then there are no deaths

2)else if nodes between 0 to 4(approx) then there will be more no.of chances of survive since this is not enough to predict

```
counts, bin_edges = np.histogram(data['nodes'], bins=10,
 density = True)
pdf = counts/(sum(counts))
print(pdf);
print(bin_edges);
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf);
plt.plot(bin_edges[1:], cdf)
plt.title('pdf and cdf for nodes')
plt.legend(['pdf','cdf'])
     [0.77124183 0.09803922 0.05882353 0.02614379 0.02941176 0.00653595
      0.00326797 0.
                             0.00326797 0.00326797]
            5.2 10.4 15.6 20.8 26. 31.2 36.4 41.6 46.8 52.
     <matplotlib.legend.Legend at 0x7f22a10c16d8>
                       pdf and cdf for nodes
      1.0
      0.8
      0.6
                                                   pdf
                                                   cdf
      0.4
      0.2
```

This plot says every thing that

10

0.0

L→

1)If nodes are incresing then the survival chances of survival are decreasing gradually 2)there are 60-80% of survival chances if noeds are <5(approx)

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```
sns.boxplot(x='status',y='nodes', data=data)
plt.title('box-plots for status and nodes')
plt.legend(['Survived','Dead'])
plt.show()
```

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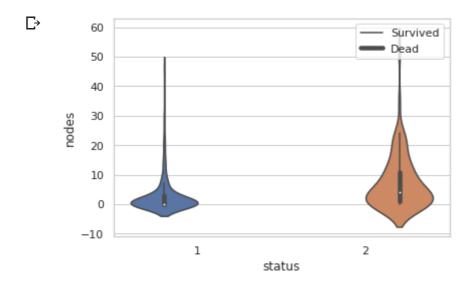
30

https://colab.research.google.com/drive/1iyEXiDQEp2m-PpnESo lKt1yOS9pps j#scrollTo=LJqNt 8jlxod&printMode=true



From the above box plot after 5 nodes(approx) the deaths increasing drastically i.e,from the mean of dead plot

sns.violinplot(x='status', y='nodes',data=data,hue='status')
plt.legend(['Survived','Dead'])
plt.show()



From this plot it is clear that in the survival violin the density is high from 0-1 nodes When nodes are incresing no.of deaths also increasing

Conclusion

from all features nodes gave significant result

Patients who had less than a single node are survived.

Patients from 1to3 nodes survival chances are high.