

# Assignment1-EDA

September 28, 2018

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

```
In [2]: df=pd.read_csv('./haberman.csv',names=['Age','Op_Year','axil_nodes_det','Surv_status'])
```

```
In [3]: df.head()
```

```
Out[3]:
```

	Age	Op_Year	axil_nodes_det	Surv_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

#We have data of patient who has undergone surgery for breast cancer . #After surgery did the patient survived for 5 years or not?? #with given data we have to explore that which feature has impact on survival of patient and how much.

## Basic Data Intuition

```
In [4]: df.shape
# Shows 306 data point and 4 feature
```

```
Out[4]: (306, 4)
```

```
In [5]: df.info()
```

```
# No Null data enteries in any data points
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 306 entries, 0 to 305
```

```
Data columns (total 4 columns):
```

```
Age                306 non-null int64
```

```
Op_Year            306 non-null int64
```

```
axil_nodes_det     306 non-null int64
```

```
Surv_status        306 non-null int64
```

```
dtypes: int64(4)
```

```
memory usage: 9.6 KB
```

```

In [6]: df.columns

Out[6]: Index(['Age', 'Op_Year', 'axil_nodes_det', 'Surv_status'], dtype='object')

In [11]: df.Surv_status.value_counts()

Out[11]: 1    225
         2     81
         Name: Surv_status, dtype: int64

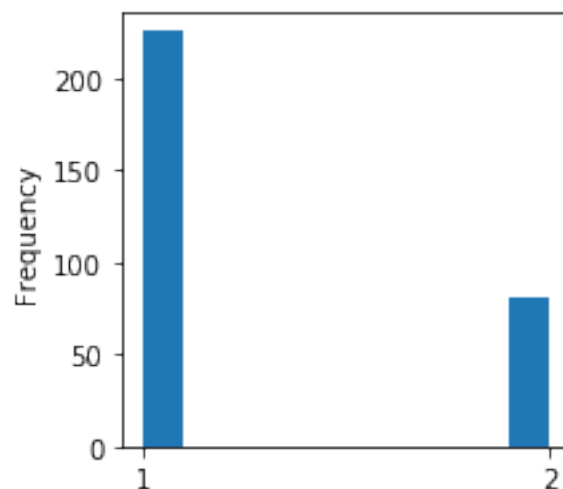
In [7]: df.Surv_status.value_counts()/df.shape[0]

         # No of "Not Survived" is almost 1/4 of total data points.

Out[7]: 1    0.735294
         2    0.264706
         Name: Surv_status, dtype: float64

In [14]: plt.figure()
         plt.subplot()
         df.Surv_status.plot(kind='hist',xticks=[1,2],figsize=(3,3),)
         plt.show()

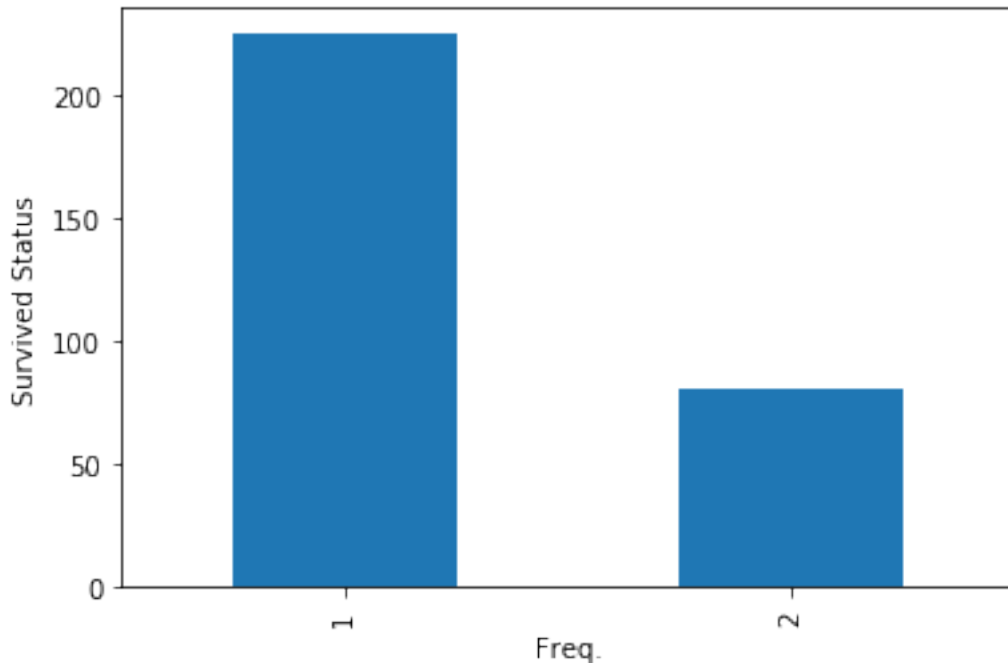
```



```

In [22]: df.Surv_status.value_counts().sort_index().plot('bar')
         plt.xlabel("Freq.")
         plt.ylabel("Survived Status")
         plt.show()

```



Bar and Hist plot to see the proportion of data points available to each class

### 0.0.1 Univariate analysis(PDF, CDF, Dist-plot)

```
In [7]: df_Survived=df.loc[df.Surv_status==1]
        df_Notsurvived=df.loc[df.Surv_status==2]
```

```
In [9]: def plot_pdf_cdf(pdf,cdf,bins_points,title,cdf_title):
        plt.plot(bins_points[1:],pdf,label=title)
        plt.plot(bins_points[1:],cdf,label=cdf_title)
        plt.legend()
```

```
# plt.grid()
# plt.show()
```

*# bins\_point[1:] is used because there are total 11 points which is 1 more than pdf s*

```
In [11]: plt.figure(3)
```

```
age,bins_points_age=np.histogram(a=df_Notsurvived.Age,bins=10)
pdf_age=age/sum(age)
print(pdf_age)
print(bins_points_age)
cdf_age=np.cumsum(pdf_age)
plot_pdf_cdf(pdf_age,cdf_age,bins_points_age,"NotSurvivedAge_PDF","NotSurvivedAge_CDF")
```

```

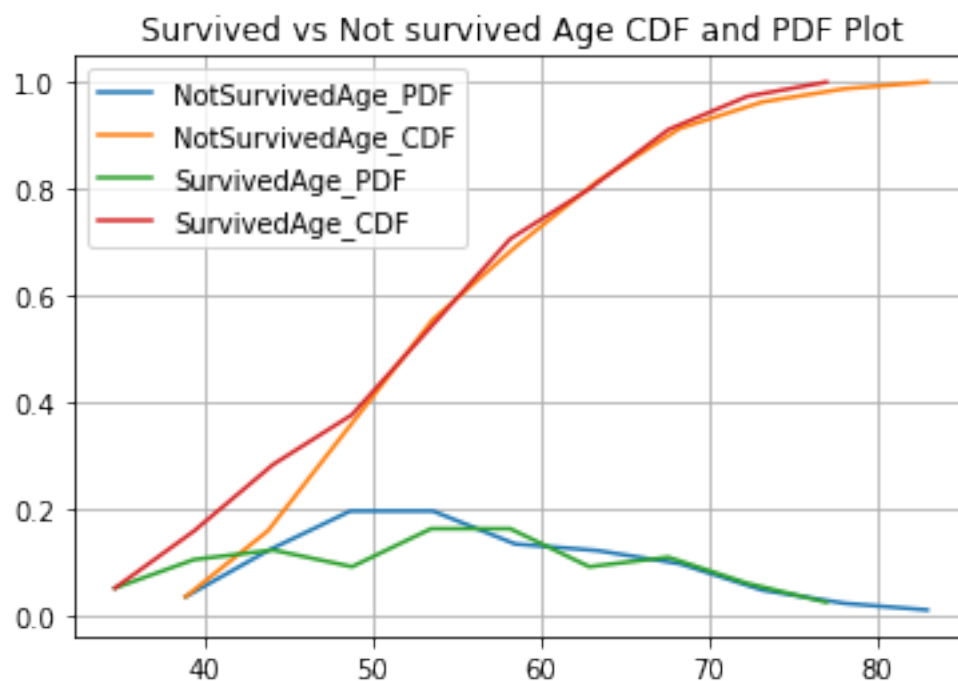
age,bins_points_age=np.histogram(a=df_Survived.Age,bins=10)
pdf_age=age/sum(age)
print(pdf_age)
print(bins_points_age)
cdf_age=np.cumsum(pdf_age)
plot_pdf_cdf(pdf_age,cdf_age,bins_points_age,"SurvivedAge_PDF","SurvivedAge_CDF")
plt.legend()
plt.title("Survived vs Not survived Age CDF and PDF Plot")
plt.grid()
plt.show();

```

```

[ 0.03703704  0.12345679  0.19753086  0.19753086  0.13580247  0.12345679
 0.09876543  0.04938272  0.02469136  0.01234568]
[ 34.  38.9  43.8  48.7  53.6  58.5  63.4  68.3  73.2  78.1  83. ]
[ 0.05333333  0.10666667  0.12444444  0.09333333  0.16444444  0.16444444
 0.09333333  0.11111111  0.06222222  0.02666667]
[ 30.  34.7  39.4  44.1  48.8  53.5  58.2  62.9  67.6  72.3  77. ]

```



Multiple crossover doesnt give clear insight about age effect but cahnces of “not surviving” has more chances compare to “surviving”

```

In [12]: plt.figure(2)
         plt.subplot()

```

```

node,bins_points_node=np.histogram(df_Notsurvived.axil_nodes_det,bins=10)
pdf_node=node/sum(node)
print(pdf_node)
print(bins_points_node)
cdf_node=np.cumsum(pdf_node)
plot_pdf_cdf(pdf_node,cdf_node,bins_points_node,"NotSurvivedNode_PDF","NotSurvivedNode

```

```

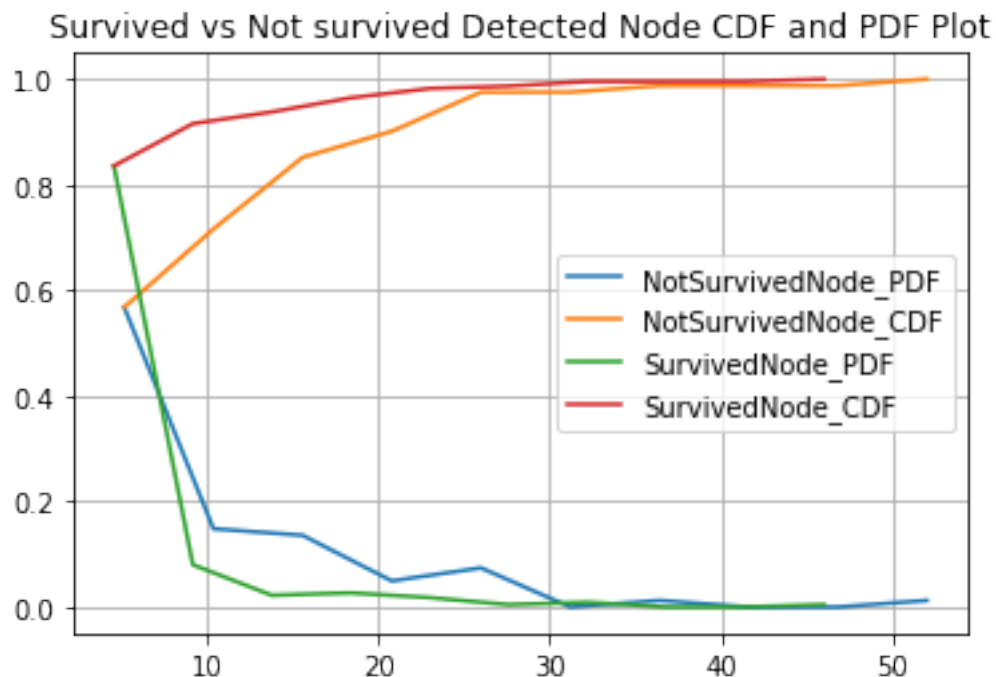
node,bins_points_node=np.histogram(df_Survived.axil_nodes_det,bins=10)
pdf_node=node/sum(node)
print(pdf_node)
print(bins_points_node)
cdf_node=np.cumsum(pdf_node)
plot_pdf_cdf(pdf_node,cdf_node,bins_points_node,"SurvivedNode_PDF","SurvivedNode_CDF")
plt.legend()
plt.title("Survived vs Not survived Detected Node CDF and PDF Plot")
plt.grid()
plt.show();

```

```

[ 0.56790123  0.14814815  0.13580247  0.04938272  0.07407407  0.
  0.01234568  0.          0.          0.01234568]
[ 0.   5.2  10.4  15.6  20.8  26.   31.2  36.4  41.6  46.8  52. ]
[ 0.83555556  0.08          0.02222222  0.02666667  0.01777778  0.00444444
  0.00888889  0.          0.          0.00444444]
[ 0.   4.6   9.2  13.8  18.4  23.   27.6  32.2  36.8  41.4  46. ]

```



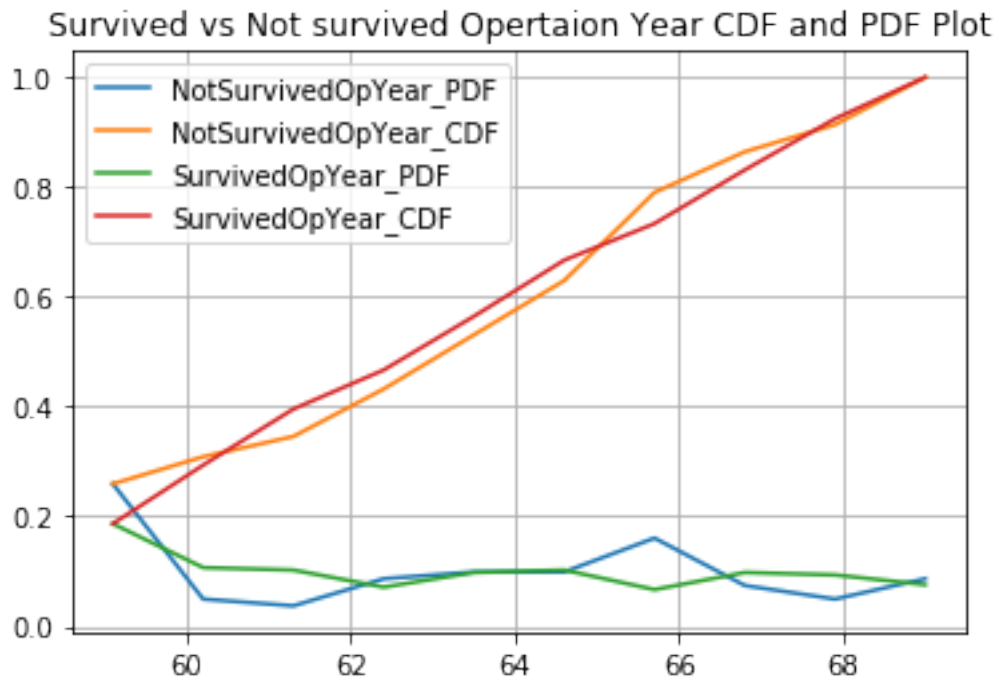
If the “No. of nodes detected” is < 10 then chances of “Surviving” is more than “Not surviving”

```
In [13]: plt.figure(1)
```

```
yr,bins_points_yr=np.histogram(a=df_Notsurvived.Op_Year,bins=10)
pdf_yr=yr/sum(yr)
print(pdf_yr)
print(bins_points_yr)
cdf_yr=np.cumsum(pdf_yr)
plot_pdf_cdf(pdf_yr,cdf_yr,bins_points_yr,"NotSurvivedOpYear_PDF","NotSurvivedOpYear_CDF")
```

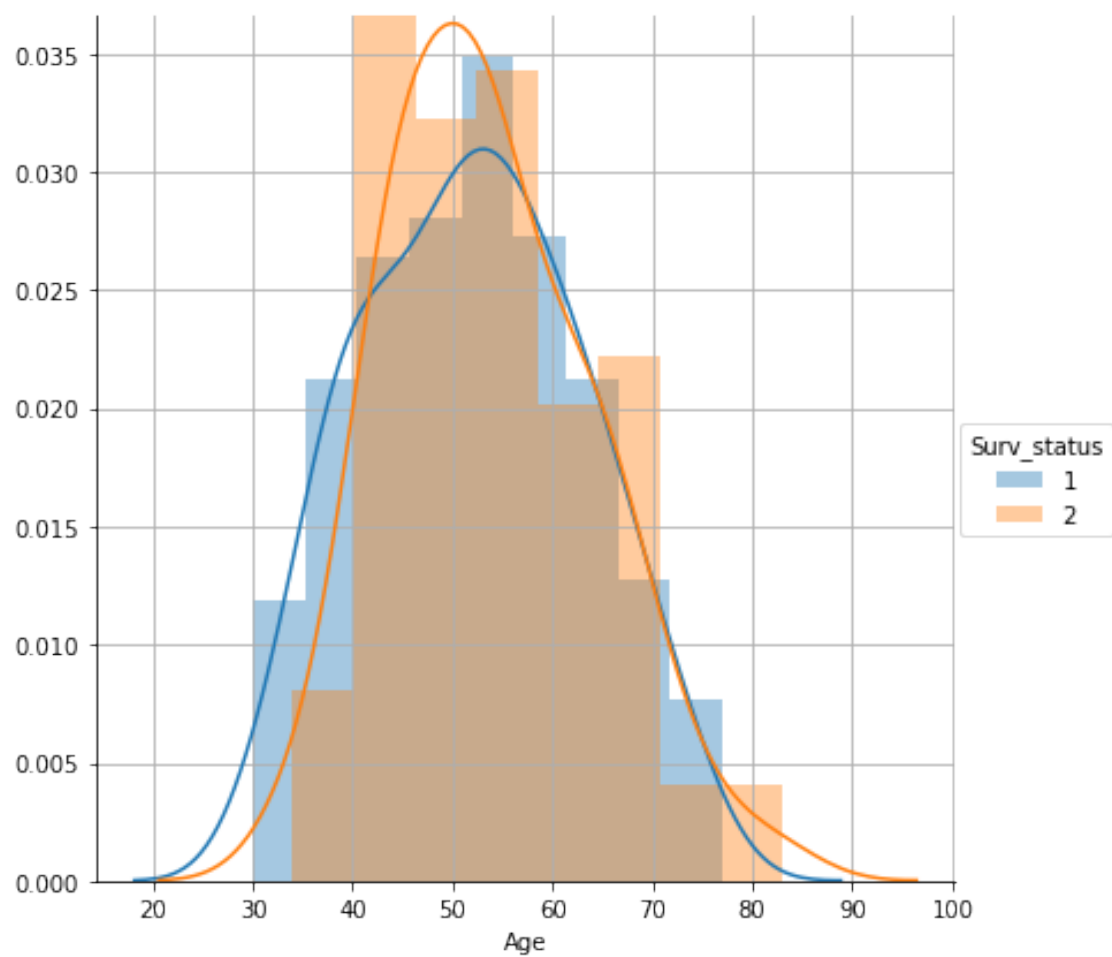
```
yr,bins_points_yr=np.histogram(a=df_Survived.Op_Year,bins=10)
pdf_yr=yr/sum(yr)
print(pdf_yr)
print(bins_points_yr)
cdf_yr=np.cumsum(pdf_yr)
plot_pdf_cdf(pdf_yr,cdf_yr,bins_points_yr,"SurvivedOpYear_PDF","SurvivedOpYear_CDF")
plt.legend()
plt.title("Survived vs Not survived Opertaion Year CDF and PDF Plot")
plt.grid()
plt.show();
```

```
[ 0.25925926  0.04938272  0.03703704  0.08641975  0.09876543  0.09876543
 0.16049383  0.07407407  0.04938272  0.08641975]
[ 58.  59.1  60.2  61.3  62.4  63.5  64.6  65.7  66.8  67.9  69. ]
[ 0.18666667  0.10666667  0.10222222  0.07111111  0.09777778  0.10222222
 0.06666667  0.09777778  0.09333333  0.07555556]
[ 58.  59.1  60.2  61.3  62.4  63.5  64.6  65.7  66.8  67.9  69. ]
```



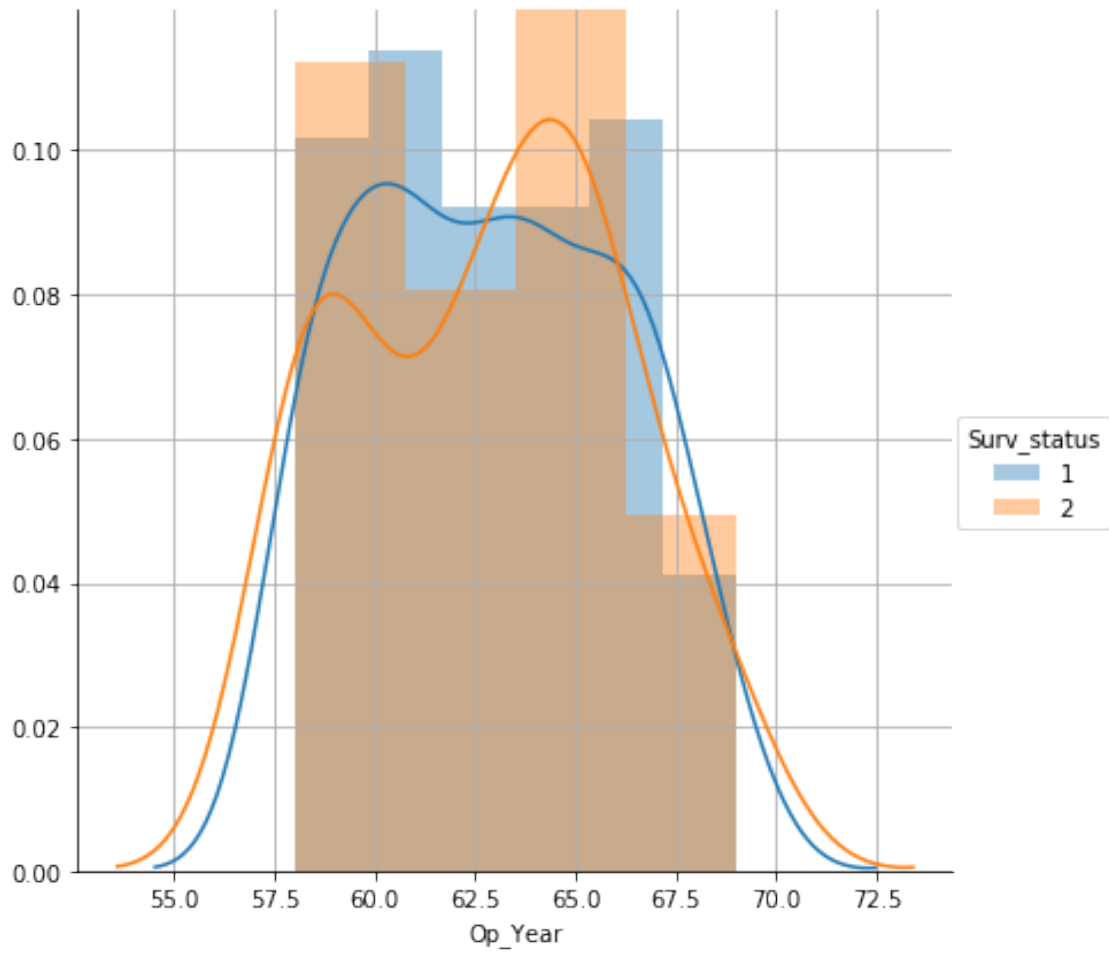
cdf indicates that except some year (65 to 67 and <61) the chance of “surviving” is more

```
In [23]: sns.FacetGrid(data=df,hue='Surv_status',size=6).map(sns.distplot,"Age").add_legend();
plt.grid()
plt.show();
```

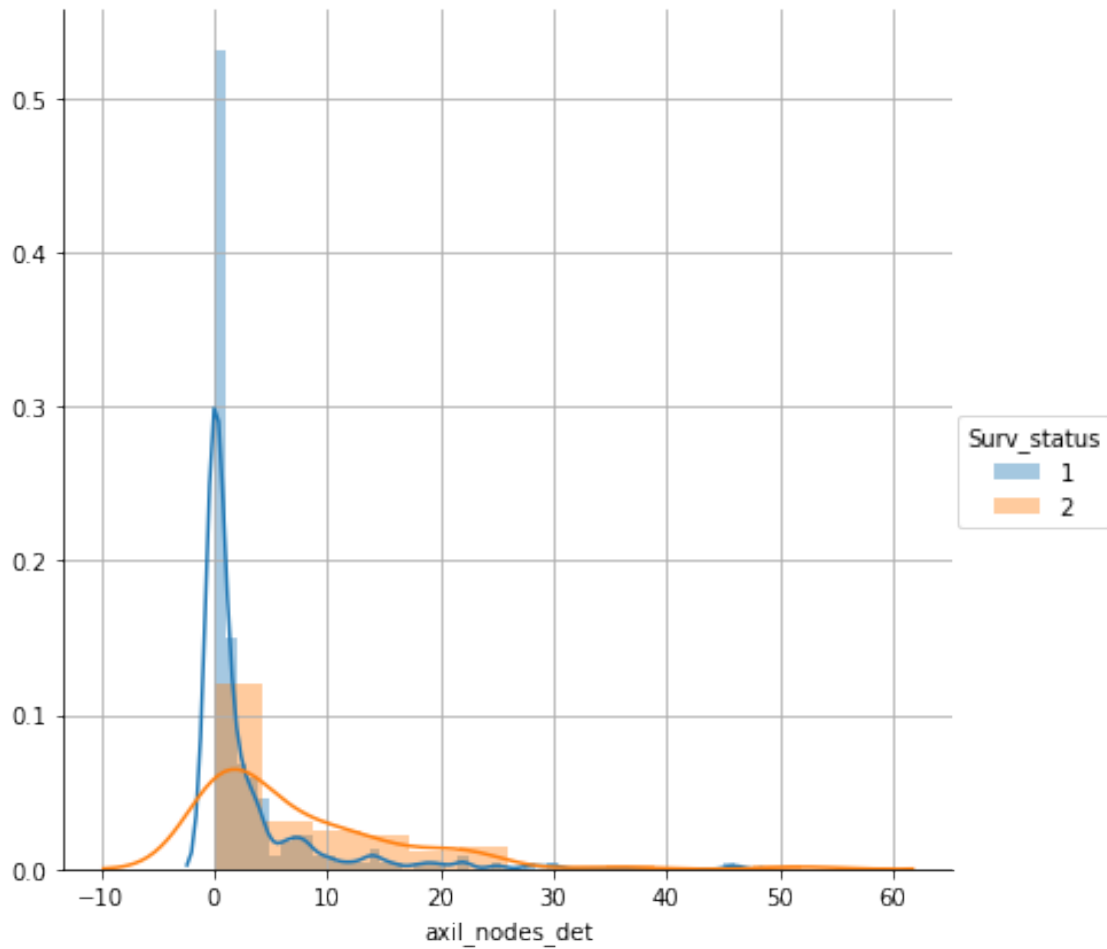


```
In [33]: sns.FacetGrid(data=df,hue="Surv_status",size=6).map(sns.distplot,"Op_Year").add_legend()  
plt.grid()  
plt.show()
```





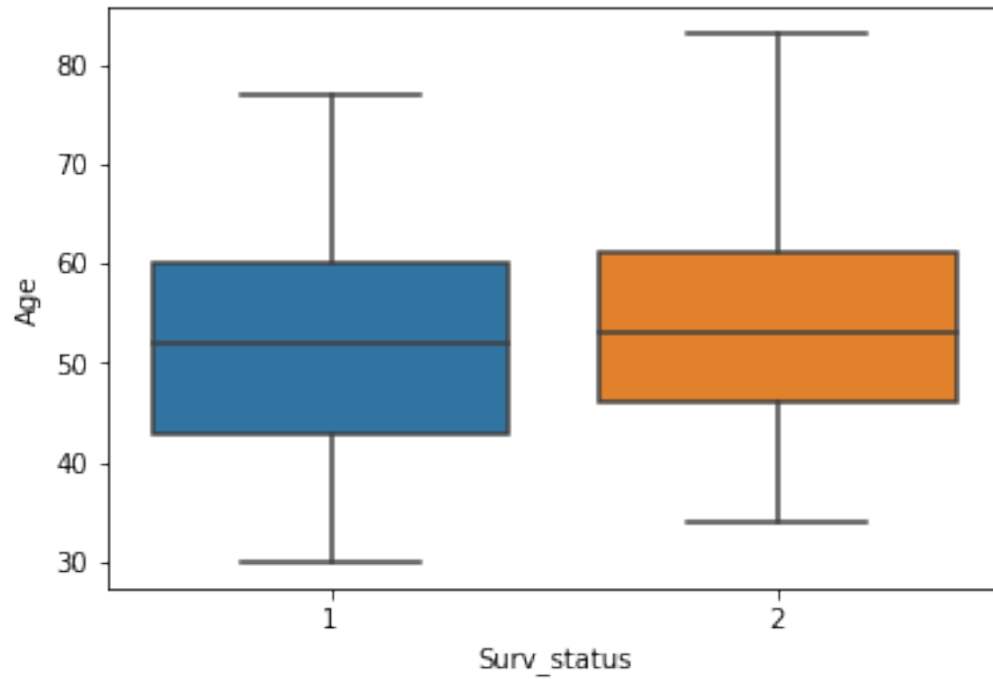
```
In [30]: sns.FacetGrid(data=df,hue="Surv_status",size=6).map(sns.distplot,"axil_nodes_det").add_subplot(1,1,1)
plt.grid()
plt.show()
```



Except the distplot of “axil nodes detected” the other distplots are jumbled and doesnot give clear picture where as “axil\_nodes\_det”<10 gives more surviving hope.

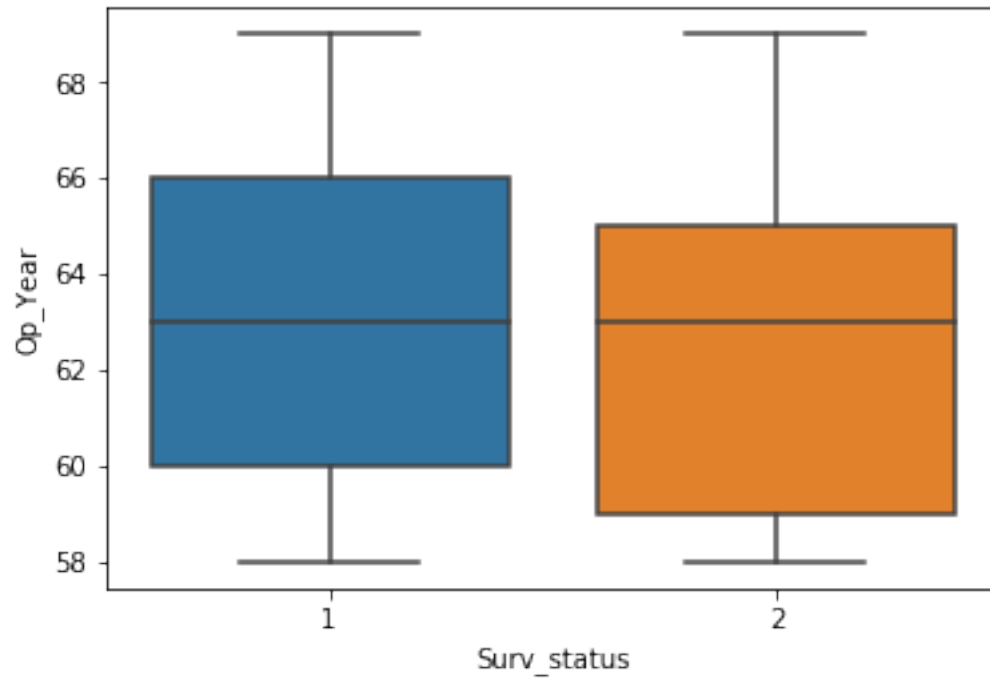
### 0.0.2 Box Plot and Voilin plot

```
In [26]: sns.boxplot(data=df,x='Surv_status',y='Age')  
plt.show()
```



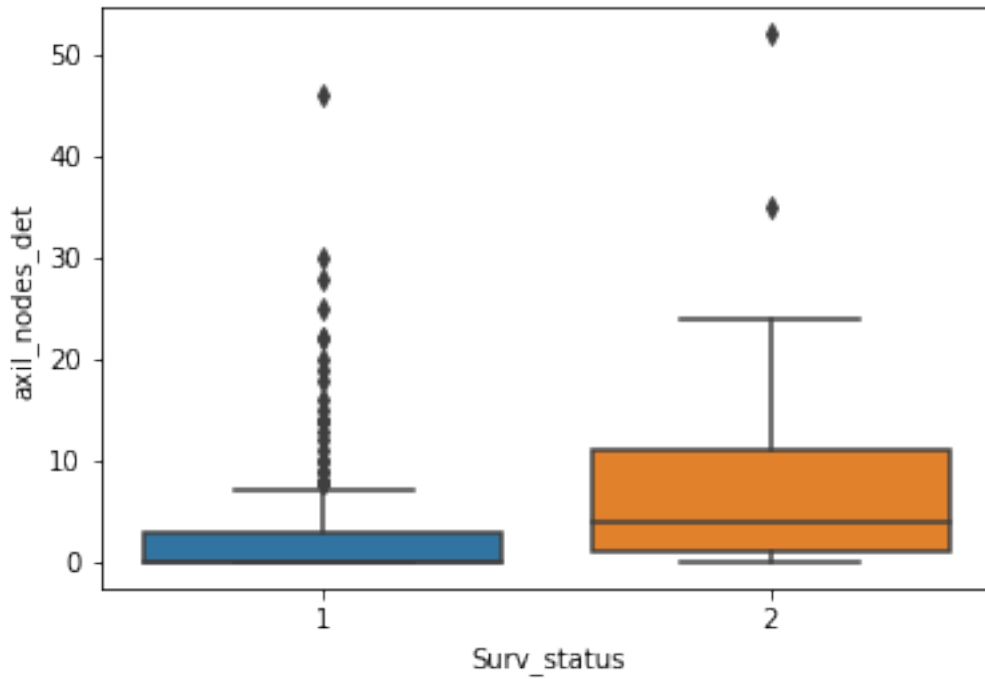
Both looks same but early Age guys have more survival chances while whisker of “not survived” shows late age might lead to fail operation.

```
In [28]: sns.boxplot(data=df,x='Surv_status',y='Op_Year')  
         plt.show()
```



Here early opertaions (Intial years of operations) were more failure while later year has more sucess chances

```
In [29]: sns.boxplot(data=df,x='Surv_status',y='axil_nodes_det')  
plt.show()
```

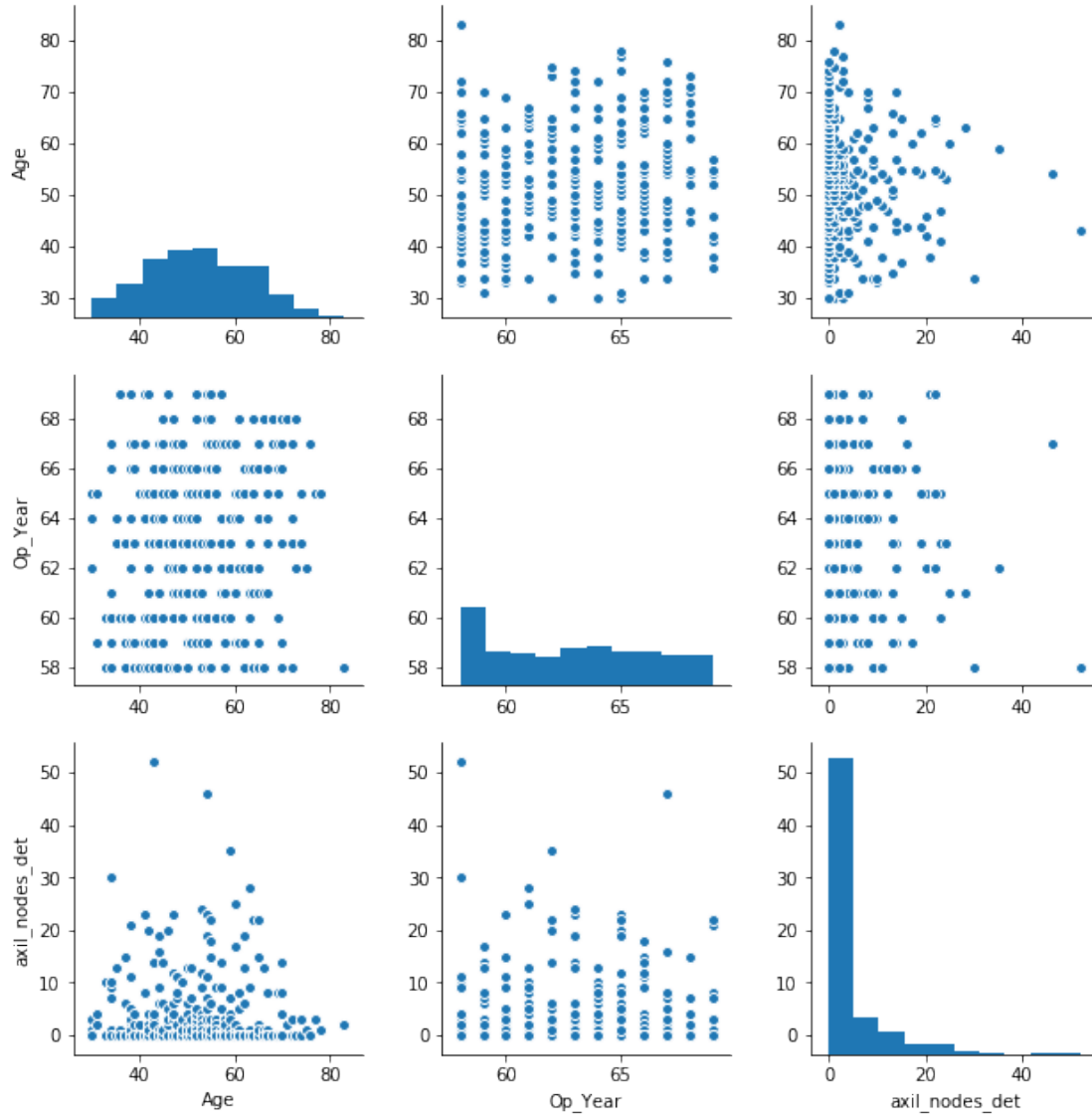


The median of both box's are low this might be outlier issue but more axil nodes detected has more not surviving chances.

Data seems nicely distributed for "Age" and "Op\_Year" but "axil\_nodes\_det" has outliers which is impacting the the pattern

### 0.1 Bi Variate Analysis (Pair Plot)

```
In [23]: sns.pairplot(data=df.iloc[:,0:-1],size=3)
plt.show()
```



## 0.2 Conclusion : PDF and CDFs has given below insights :

- 1) "detected nodes" has more impact on "survival" as lower the nodes , surviving chances are more.
- 2) as age increases the chance of "not surviving" is more
- 3) From Box plot there is slight indication of outliers as very few data points belongs to 30+ range..
- 4) Pair plots indicates relation between axil\_nodes\_det and age.
- 5) Based on feature importance above visualization shows importance in following order:  
"axil\_nodes\_det"> "Age">"Op\_Year"