Haberman Cancer Survival DataSet

Toy Dataset: Haberman Dataset:(https://www.kaggle.com/gilsousa/habermans-survival-data-set (https://www.kaggle.com/gilsousa/habermans-survival-data-set)) Attribute Information: Age of patient at time of operation (numerical) Patient's year of operation (numerical) Number of positive axillary nodes detected (numerical) Survival status (class attribute): 1 = the patient survived 5 years or longer 2 = the patient died within 5 year OBJECTIVE: Given a new patient's (age, year-of-operation, count-of-positive-nodes-detected) we want to build a model which predicts if the patient will survive for more than 5 years after the operation or not. The following is the Exploratory Data Analysis for the same.

In [24]:

```
#Importing all Modules
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import warnings
warnings.filterwarnings('ignore')
sns.set()
%matplotlib inline
```

In [5]:

```
#Load Habermans Survival Dataset
#reading the data to pandas DataFrame
haberman=pd.read_csv('/Users/gopivudanrao/Data_Analysis_in_Python/habe
rman.csv')
```

In [6]:

```
#checking few records from dataset
haberman.head(5)
```

Out[6]:

	AgeAtOperation	YearOfOperation	NrPosAxillaryNodes	Survival
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

In [48]:
```
# (Q) how many data-points and features?
haberman.shape
```

Out[48]:
```
(306, 4)
```

In [49]:
```
#(Q) What are the column names in our dataset?
haberman.columns
```

Out[49]:
```
Index(['AgeAtOperation', 'YearOfOperation', 'NrPosAxillaryNodes', 'S
urvival'], dtype='object')
```

In [66]:
```
print('Total number of Points')
print(haberman.shape[0])

print('Total number of Features in Dataset')
print(haberman.shape[1])
#value_counts() is used to count distinct values
print('Distinct records for class variable Survival')
print(haberman['Survival'].value_counts())

#225 patients survived more than 5 years after Surgery thats about 73.
52% is Survival rate .
```

```
Total number of Points
306
Total number of Features in Dataset
4
Distinct records for class variable Survival
1    225
2     81
Name: Survival, dtype: int64
```

In [50]:
```
#(Q) How many data points for each class are present?

haberman["Survival"].value_counts()
```

Out[50]:
```
1    225
2     81
Name: Survival, dtype: int64
```

Survival status (class attribute) have two distinct values 1 = the patient survived 5 years or longer 2 = the patient died within 5 year

balanced-dataset vs imbalanced datasets

225 patients survived 5 years or longer and 81 patients died within 5 years

haberman Dataset is Imbalanced dataset as the number of data points for every class is different

73.52% Survived more than 5 years after Surgery 24.5% died within 5 years of Surgery

In [11]:
```
def show_missing():
    missing = haberman.columns[haberman.isnull().any()].tolist()
    return missing
```

In [15]:
```
#Checking if any data is missing/null in Dataset
print('Missing Data Count')
print(haberman[show_missing()].isnull().sum().sort_values(ascending =
False))

#Columns have no Missing values ,All features are populated with value
s
```

```
Missing Data Count
Series([], dtype: float64)
```

In [20]:
```
haberman.columns
```

Out[20]:
```
Index(['AgeAtOperation', 'YearOfOperation', 'NrPosAxillaryNodes', 'S
urvival'], dtype='object')
```

In [61]:
```
# more information about features and their datatypes
haberman.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306 entries, 0 to 305
Data columns (total 4 columns):
AgeAtOperation         306 non-null int64
YearOfOperation        306 non-null int64
NrPosAxillaryNodes     306 non-null int64
Survival               306 non-null int64
dtypes: int64(4)
memory usage: 9.6 KB
```

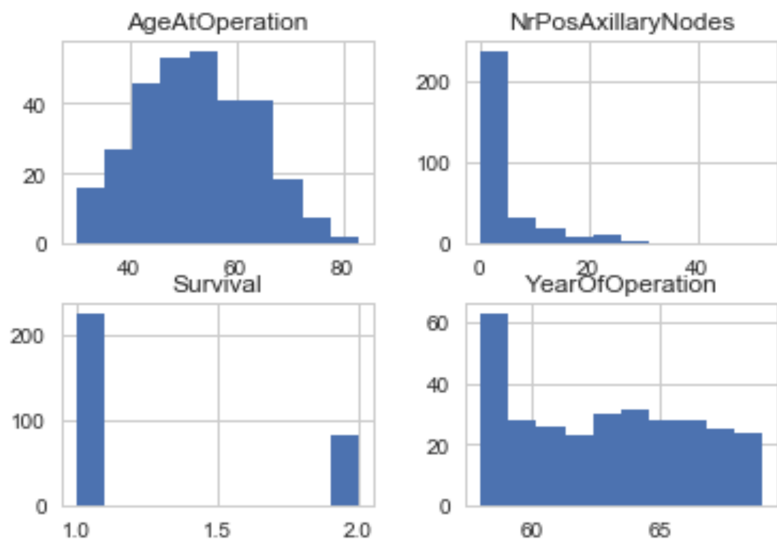
In [63]:
```
haberman.describe()
```

Out[63]:

	AgeAtOperation	YearOfOperation	NrPosAxillaryNodes	Survival
count	306.000000	306.000000	306.000000	306.000000
mean	52.457516	62.852941	4.026144	1.264706
std	10.803452	3.249405	7.189654	0.441899
min	30.000000	58.000000	0.000000	1.000000
25%	44.000000	60.000000	0.000000	1.000000
50%	52.000000	63.000000	1.000000	1.000000
75%	60.750000	65.750000	4.000000	2.000000
max	83.000000	69.000000	52.000000	2.000000

In [37]:
```
#Feature level Histogram
haberman.hist()
```

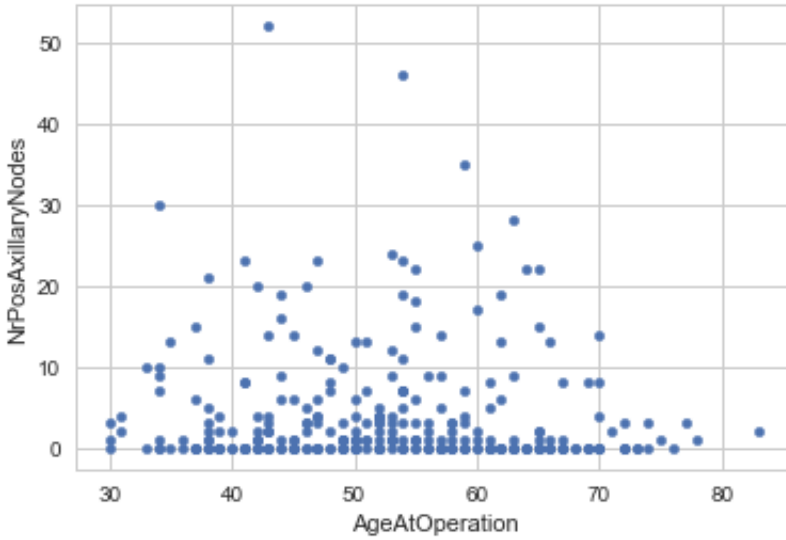
Out[37]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x118246438
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1183baf98
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1183cdcc0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x11813da58
>]], dtype=object)
```



2DScatter Plot

In [125]:
```
haberman.plot(kind='scatter',x='AgeAtOperation',y='NrPosAxillaryNodes'
)
```

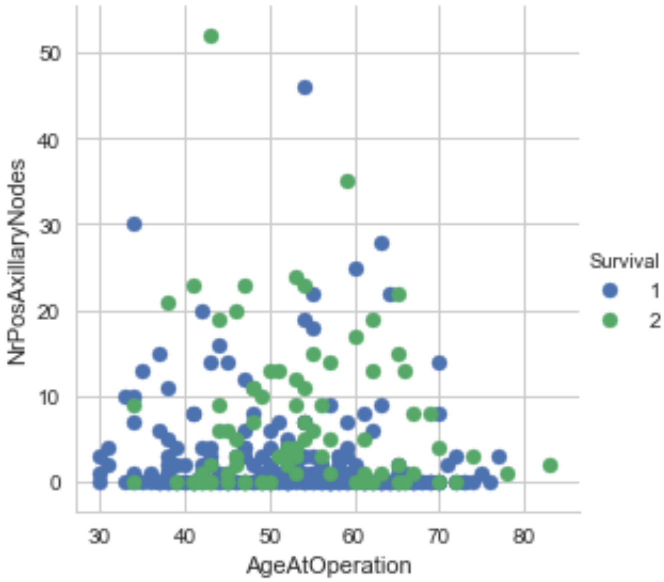
Out[125]: <matplotlib.axes._subplots.AxesSubplot at 0x1194e3eb8>



Observation : 1.Most of data points have 0 "NrPosAxillaryNodes" but Cannot Distinuish much of data points based on class label with scatter plot. 2.cannot make much sense out of it.

What if we color the points by thier class-label?

In [127]:
```
#Using Seaborn utilities  to distinguish the points by class Label
sns.set_style("whitegrid");
sns.FacetGrid(haberman, hue="Survival", size=4) \
   .map(plt.scatter, "AgeAtOperation", "NrPosAxillaryNodes") \
   .add_legend();
plt.show();
```

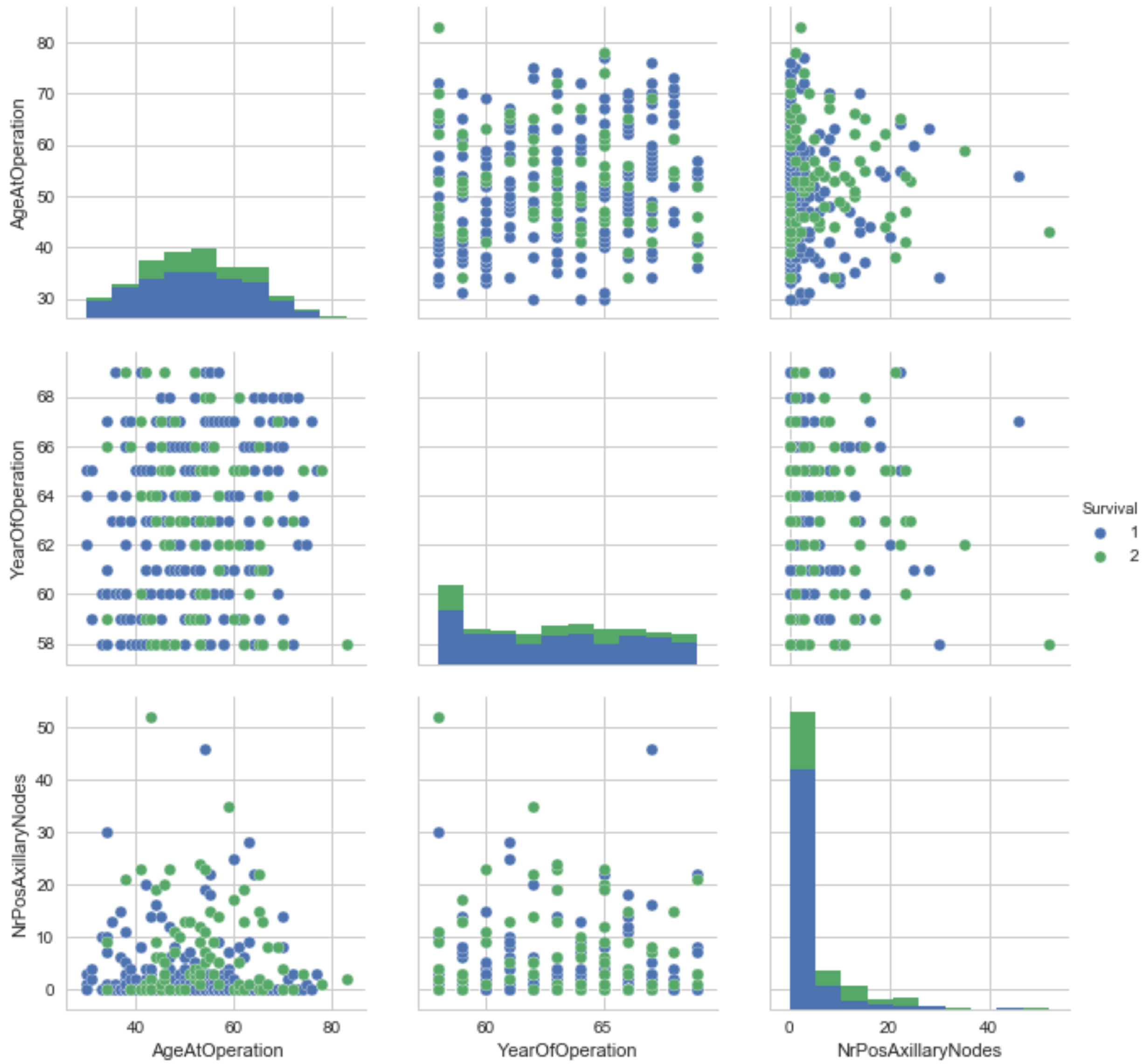


Obervation :

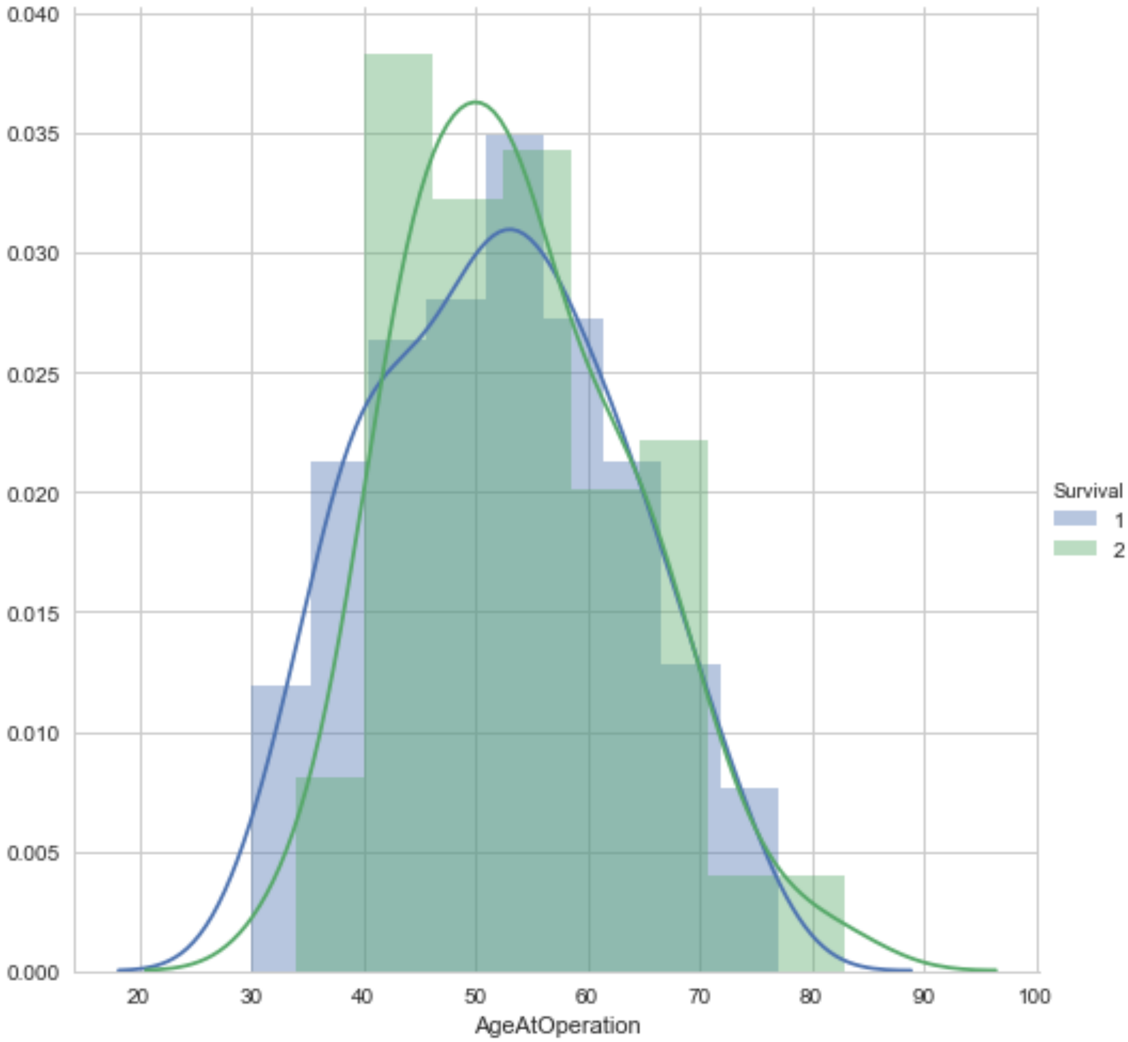
1. The plot distinuishes data points Separates Survival data points with color blue and green
2. AgeatOperation and NrPosAxillaryNodes features are useful for determining Survival class label
3. Many Survived have 0 NrPosAxillaryNodes
4. Patients died within 5 years have more than 1 NrPosAxillaryNodes and ageatoperation greater than 50

Pair Plot to visualize all features to determine which is best for predicting class label

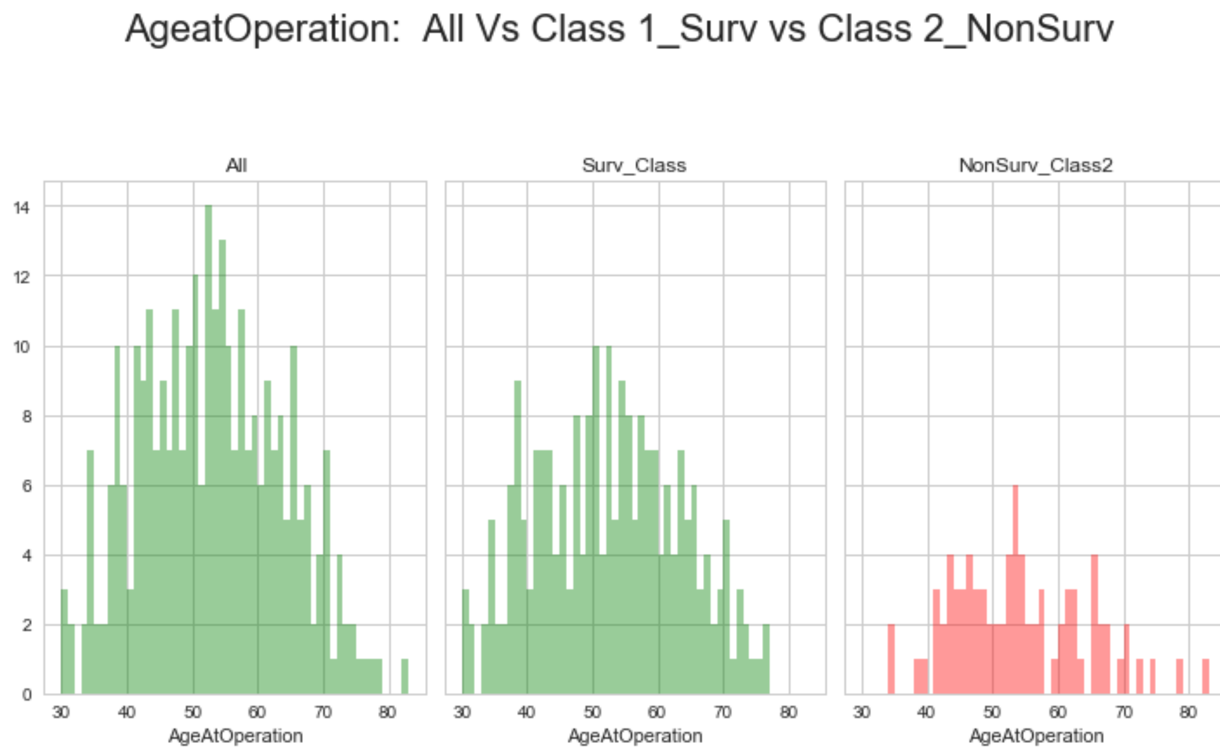
In [72]:
```
sns.set_style("whitegrid");
sns.pairplot(haberman, hue="Survival",
             vars=['AgeAtOperation', 'YearOfOperation', 'NrPosAxillary
Nodes'], size=3)
plt.show()
```



In [36]:
```
sns.set_style('whitegrid')
sns.FacetGrid(haberman,hue='Survival',size=7).map(sns.distplot,'AgeAtO
peration').add_legend()
plt.show()
```

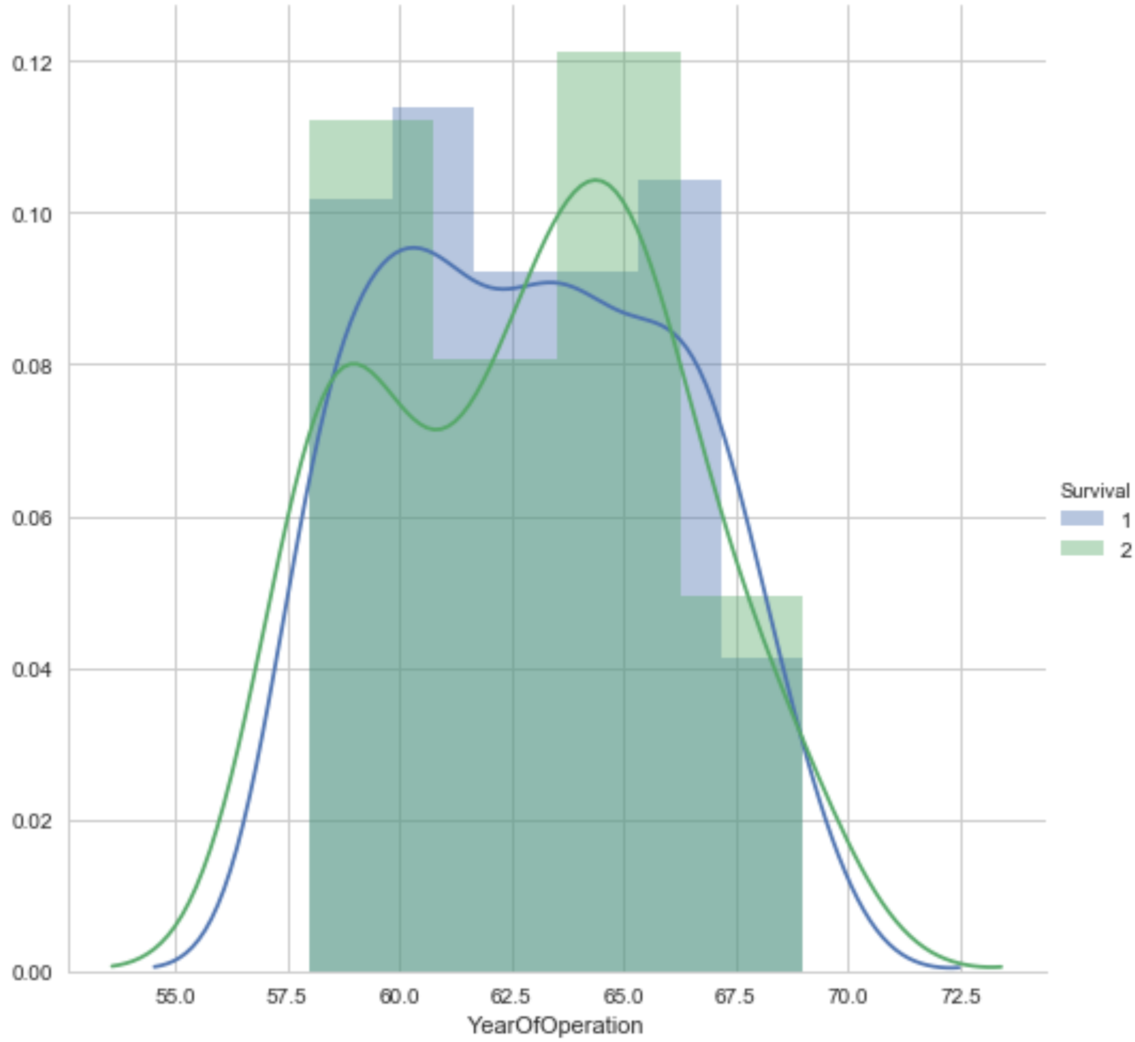


In [154]:
```
# 1. Studying 'ageatOperation' feature

fig, axs = plt.subplots(1, 3, sharex=True, sharey=True)

plt.suptitle("AgeatOperation:  All Vs Class 1_Surv vs Class 2_NonSurv"
, y=1.2, fontsize=22)
fig.set_figheight(5)
fig.set_figwidth(10)

axs[0].set_title('All')
sns.distplot(haberman['AgeAtOperation'],
             bins=range(min(haberman['AgeAtOperation']), max(haberman[
'AgeAtOperation']) + 1),
             color='g', kde=False, ax=axs[0])
axs[1].set_title('Surv_Class')
sns.distplot(Surv['AgeAtOperation'],
             bins=range(min(Surv['AgeAtOperation']), max(Surv['AgeAtOp
eration']) + 1),
             color='g', kde=False, ax=axs[1])


axs[2].set_title('NonSurv_Class2')
sns.distplot(NonSurv['AgeAtOperation'],
             bins=range(min(NonSurv['AgeAtOperation']), max(NonSurv['A
geAtOperation']) + 1),
             color='r', kde=False, ax=axs[2])

plt.tight_layout()
plt.show()
```

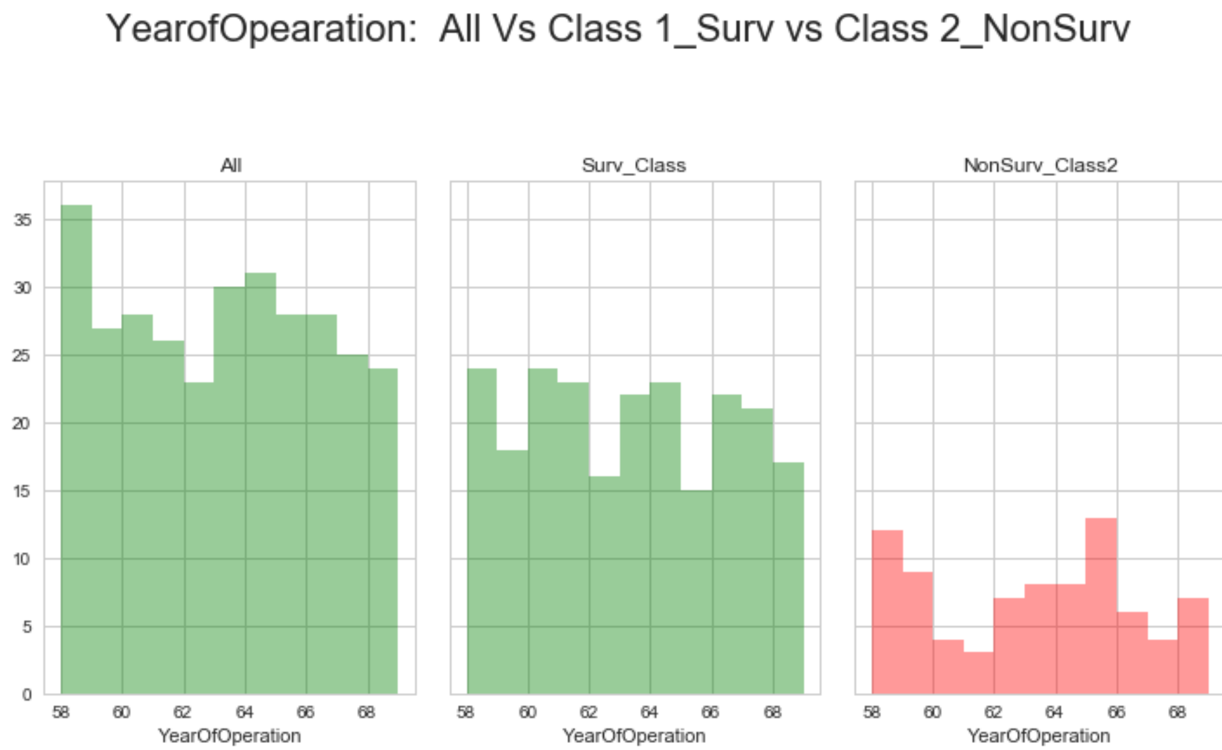


Observation: The AgeatOperation attribute feature have significance with regard to Survival rate. The patients survived after surgery for more than 5 years have less than 40 years

In [38]:
```
sns.set_style('whitegrid')
sns.FacetGrid(haberman,hue='Survival',size=7).map(sns.distplot,'YearOf
Operation').add_legend()
plt.show()
```


0.12
0.10
0.08
0.06
0.04
0.02
0.00
55.0
57.5
60.0
62.5
65.0
67.5
70.0
72.5
YearOfOperation
Survival
1
2

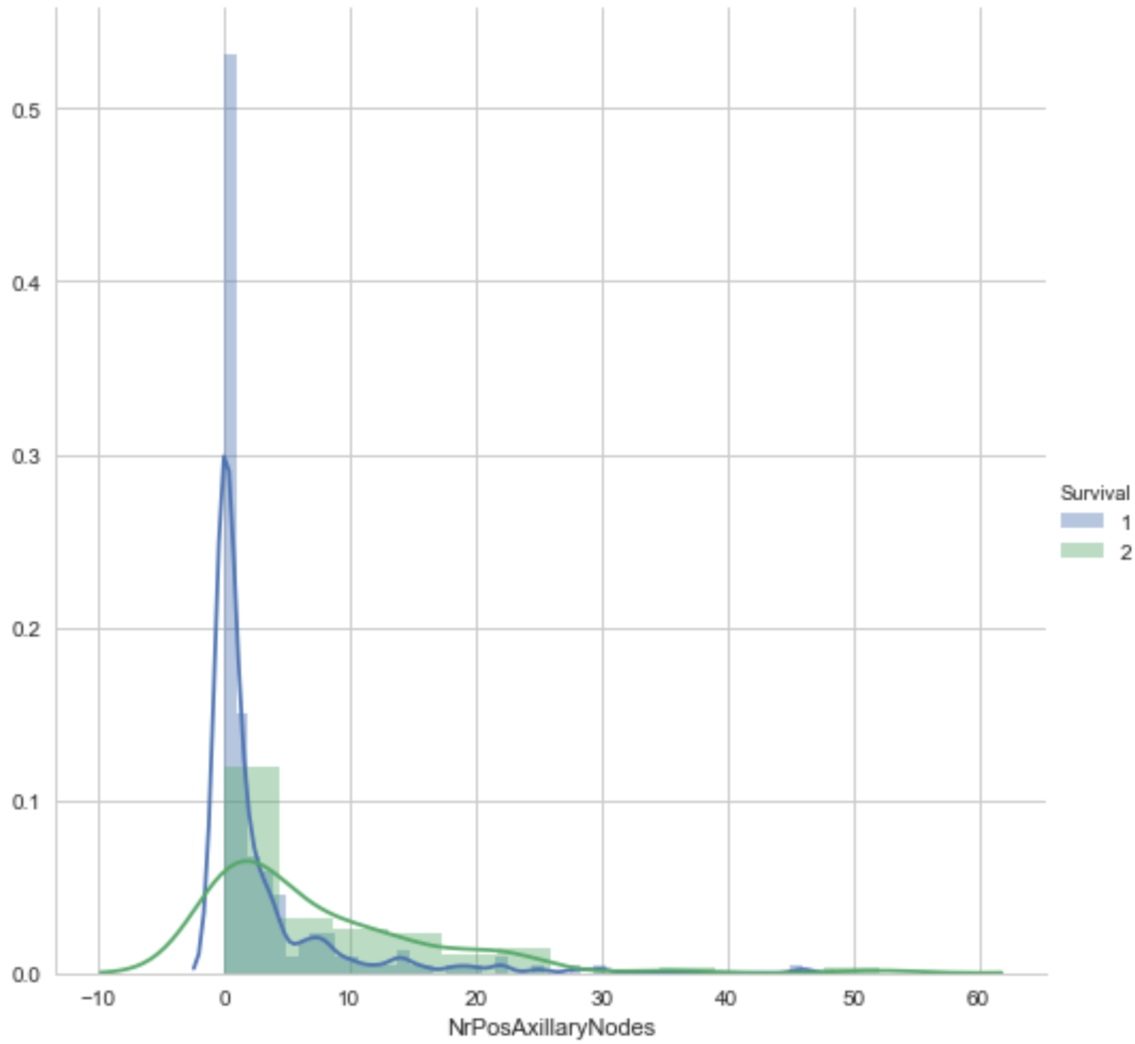
In [121]:
```
# 2. Studying 'YearofOperation' feature

fig, axs = plt.subplots(1, 3, sharex=True, sharey=True)

plt.suptitle("YearofOpearation:  All Vs Class 1_Surv vs Class 2_NonSur
v", y=1.2, fontsize=22)
fig.set_figheight(5)
fig.set_figwidth(10)

axs[0].set_title('All')
sns.distplot(haberman['YearOfOperation'],
             bins=range(min(haberman['YearOfOperation']), max(haberman
['YearOfOperation']) + 1),
             color='g', kde=False, ax=axs[0])
axs[1].set_title('Surv_Class')
sns.distplot(Surv['YearOfOperation'],
             bins=range(min(Surv['YearOfOperation']), max(Surv['YearOf
Operation']) + 1),
             color='g', kde=False, ax=axs[1])


axs[2].set_title('NonSurv_Class2')
sns.distplot(NonSurv['YearOfOperation'],
             bins=range(min(NonSurv['YearOfOperation']), max(NonSurv['
YearOfOperation']) + 1),
             color='r', kde=False, ax=axs[2])

plt.tight_layout()
plt.show()
```



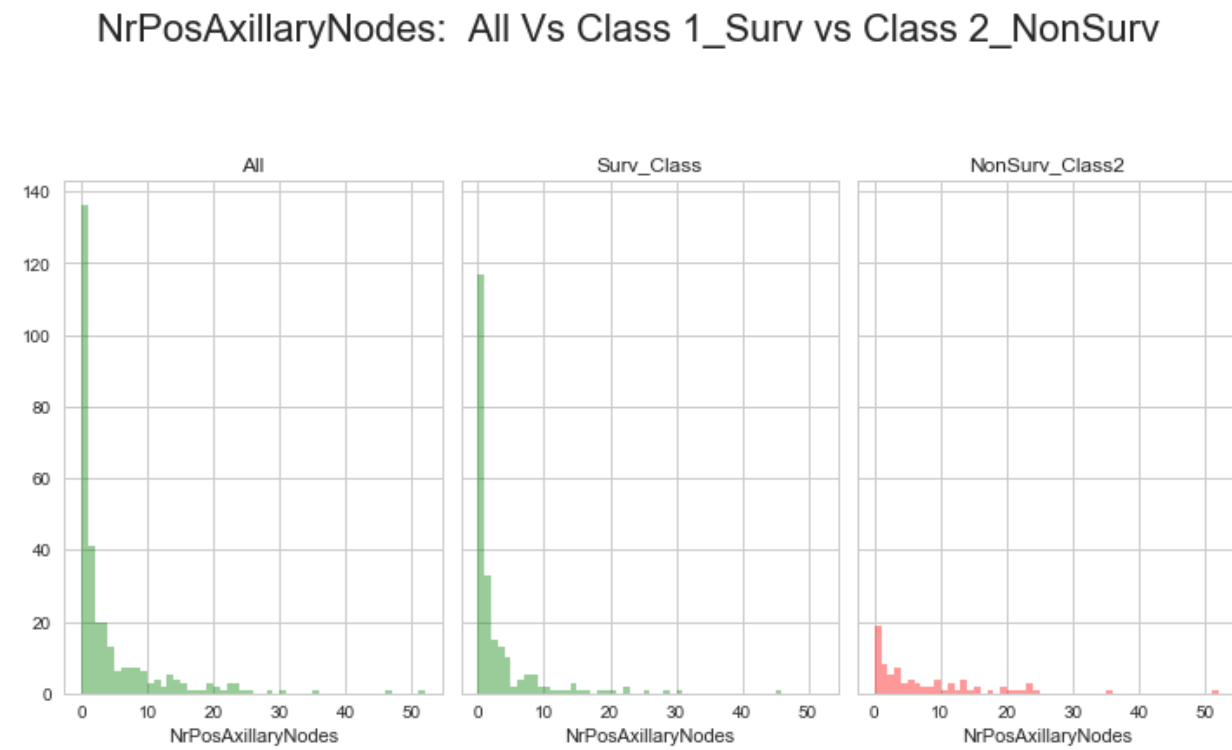
Observation : 1.There is not much we can infer from feature YearofOperation as the distribution look similar for both Survided and dead 2.From the year distribution, we can observe that people who didnt survive suddenly fall and rise in between 1958 and 1961.

```
There is too much overlap of data points  for both classes survived and de
ad
for feature Year of Operation. It does not seem to have any prominent effe
ct on patient's survival status.
```

In [39]:
```
#NrPosAxillaryNodes
sns.set_style('whitegrid')
sns.FacetGrid(haberman,hue='Survival',size=7).map(sns.distplot,'NrPosA
xillaryNodes').add_legend()
plt.show()
```



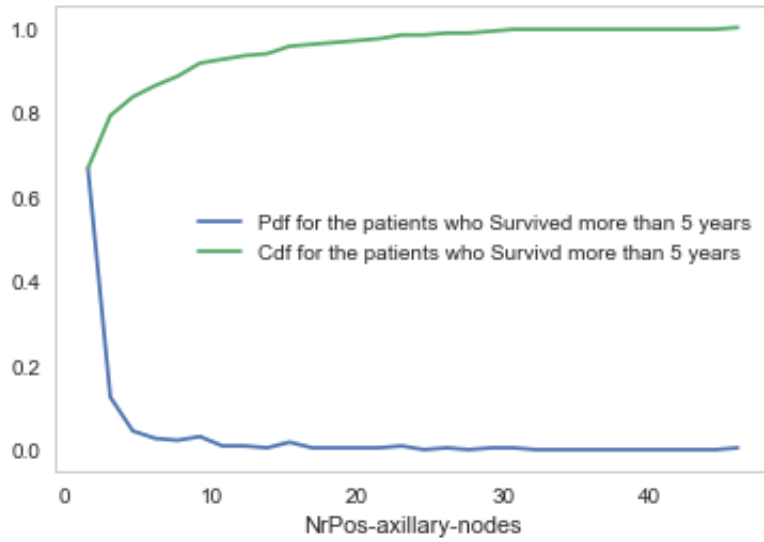
In [132]:
```
# 2. Studying 'Yearofoperation' feature

fig, axs = plt.subplots(1, 3, sharex=True, sharey=True)

plt.suptitle("NrPosAxillaryNodes:  All Vs Class 1_Surv vs Class 2_NonS
urv", y=1.2, fontsize=22)
fig.set_figheight(5)
fig.set_figwidth(10)

axs[0].set_title('All')
sns.distplot(haberman['NrPosAxillaryNodes'],
             bins=range(min(haberman['NrPosAxillaryNodes']), max(haber
man['NrPosAxillaryNodes']) + 1),
             color='g', kde=False, ax=axs[0])
axs[1].set_title('Surv_Class')
sns.distplot(Surv['NrPosAxillaryNodes'],
             bins=range(min(Surv['NrPosAxillaryNodes']), max(Surv['NrP
osAxillaryNodes']) + 1),
             color='g', kde=False, ax=axs[1])


axs[2].set_title('NonSurv_Class2')
sns.distplot(NonSurv['NrPosAxillaryNodes'],
             bins=range(min(NonSurv['NrPosAxillaryNodes']), max(NonSur
v['NrPosAxillaryNodes']) + 1),
             color='r', kde=False, ax=axs[2])

plt.tight_layout()
plt.show()
```



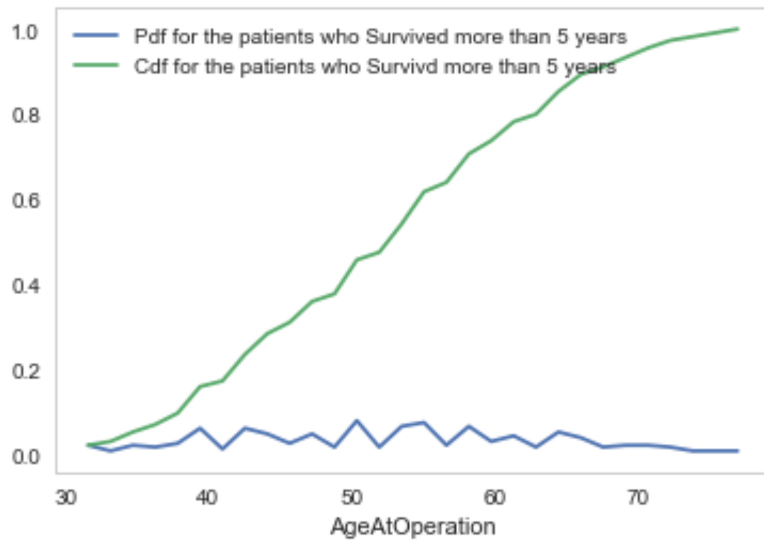
Observation: NRPosAxillaryNodes feature have significance with Survival Rate. Most survival patients have less than 5 PosAxillary nodes . This is very useful feature

PDF and CDF for class label

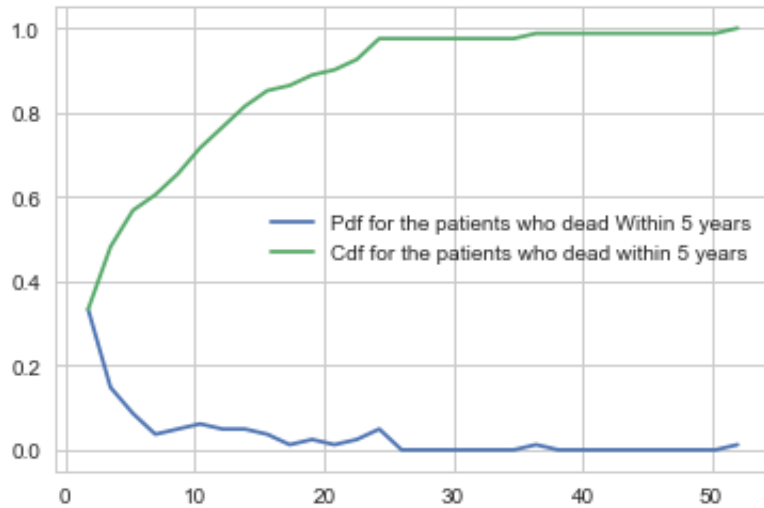
In [97]:
```
Surv = haberman.loc[haberman["Survival"]==1];
NonSurv = haberman.loc[haberman["Survival"] == 2];
counts,bin_edges=np.histogram(Surv['NrPosAxillaryNodes'], bins=30,
                                 density = True)
pdf = counts/(sum(counts))
#print(pdf);
#print(bin_edges);
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf);
plt.plot(bin_edges[1:], cdf)
plt.legend(['Pdf for the patients who Survived more than 5 years',
            'Cdf for the patients who Survivd more than 5 years'])
plt.xlabel('NrPos-axillary-nodes')
plt.grid()
```



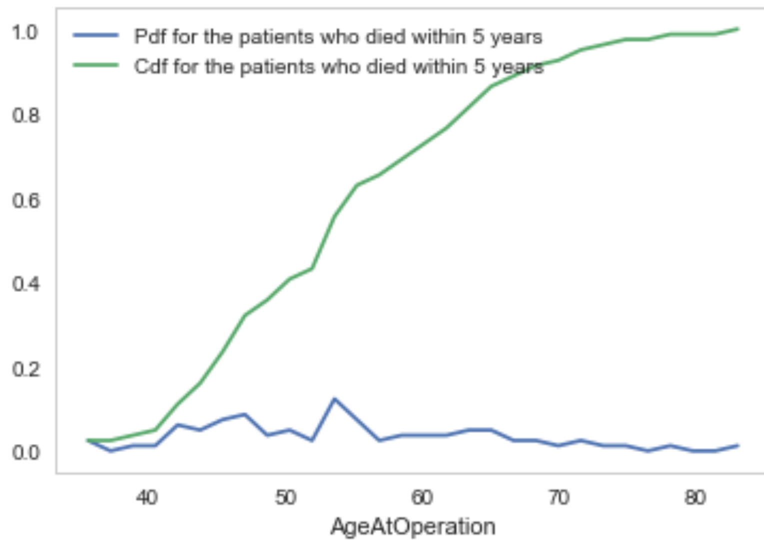
In [147]:
```
counts,bin_edges=np.histogram(Surv['AgeAtOperation'], bins=30,
                                  density = True)
pdf = counts/(sum(counts))
#print(pdf);
#print(bin_edges);
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf);
plt.plot(bin_edges[1:], cdf)
plt.legend(['Pdf for the patients who Survived more than 5 years',
            'Cdf for the patients who Survivd more than 5 years'])
plt.xlabel('AgeAtOperation')
plt.grid()
```



In [92]:
```
counts,bin_edges=np.histogram(NonSurv['NrPosAxillaryNodes'], bins=30,
                                 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.legend(['Pdf for the patients who dead Within 5 years',
            'Cdf for the patients who dead within 5 years'])
plt.show()
```



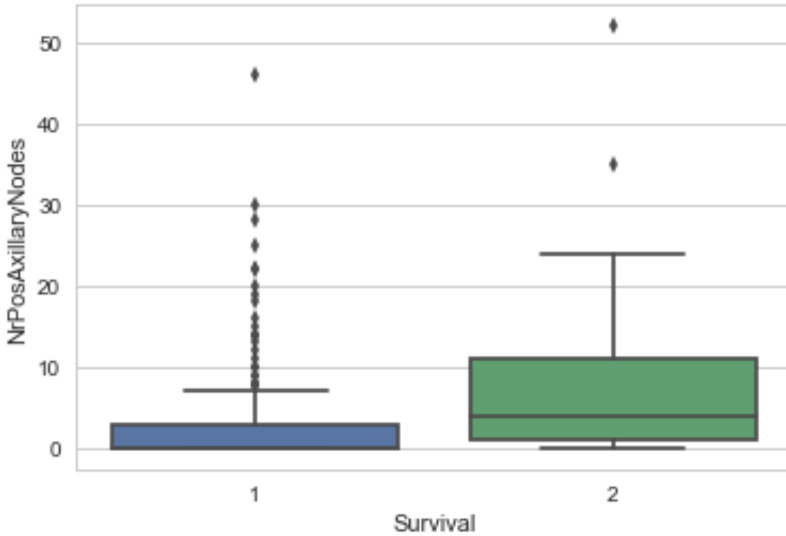
In [149]:
```
counts,bin_edges=np.histogram(NonSurv['AgeAtOperation'], bins=30,
                                          density = True)
pdf = counts/(sum(counts))
#print(pdf);
#print(bin_edges);
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf);
plt.plot(bin_edges[1:], cdf)
plt.legend(['Pdf for the patients who died within 5 years',
            'Cdf for the patients who died within 5 years'])
plt.xlabel('AgeAtOperation')
plt.grid()
```



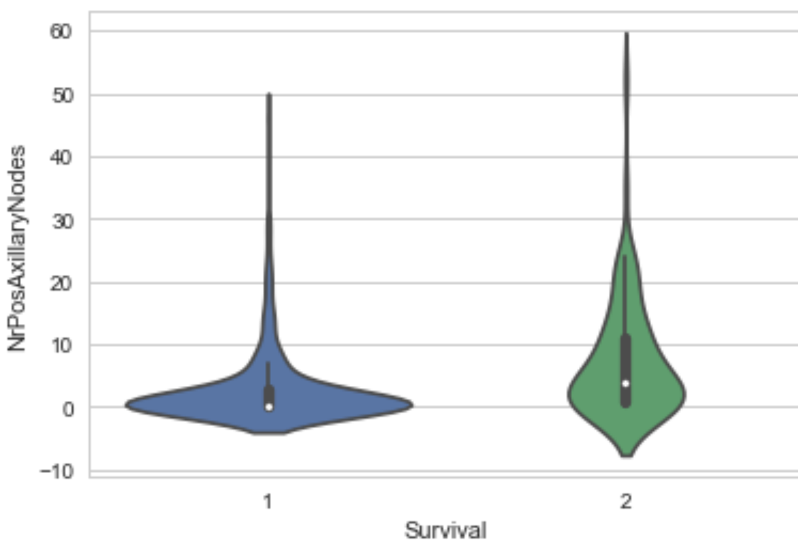
Observation 1.Looking at pdf,cdf plots the Ageatoperation of patients Survived having less than 40 years is about 20% while Ageatoperation for patients dead having less than 40 years is less than 5% .

1. Looking at pdf,cdf plots for NrPosAxillaryNodes,the patients survived more than 5 years with less than 5 PosAxillary Nodes at time of surgery is about 75%.
2. NrPosAxillaryNodes for patients dead having less than 5 NrPosAxillary nodes at time of surgery is 25%. 75% of patients having more than 5 NrPosAxillary nodes died within 5 years

In [137]:
```
sns.boxplot(x='Survival',y='NrPosAxillaryNodes',data=haberman)
plt.show()
```



In [135]:
```
sns.violinplot(x='Survival',y='NrPosAxillaryNodes',data=haberman,size=
8)
plt.show()
```



Mean and Std Deviation,IQR,Min and Max for class Label

In [130]:

```
Surv.describe()
```

Out[130]:

	AgeAtOperation	YearOfOperation	NrPosAxillaryNodes	Survival
count	225.000000	225.000000	225.000000	225.0
mean	52.017778	62.862222	2.791111	1.0
std	11.012154	3.222915	5.870318	0.0
min	30.000000	58.000000	0.000000	1.0
25%	43.000000	60.000000	0.000000	1.0
50%	52.000000	63.000000	0.000000	1.0
75%	60.000000	66.000000	3.000000	1.0
max	77.000000	69.000000	46.000000	1.0

In [131]:

```
#Mean and Std Deviation,IQR,Min and Max for Survival class
NonSurv.describe()
```

Out[131]:

	AgeAtOperation	YearOfOperation	NrPosAxillaryNodes	Survival
count	81.000000	81.000000	81.000000	81.0
mean	53.679012	62.827160	7.456790	2.0
std	10.167137	3.342118	9.185654	0.0
min	34.000000	58.000000	0.000000	2.0
25%	46.000000	59.000000	1.000000	2.0
50%	53.000000	63.000000	4.000000	2.0
75%	61.000000	65.000000	11.000000	2.0
max	83.000000	69.000000	52.000000	2.0

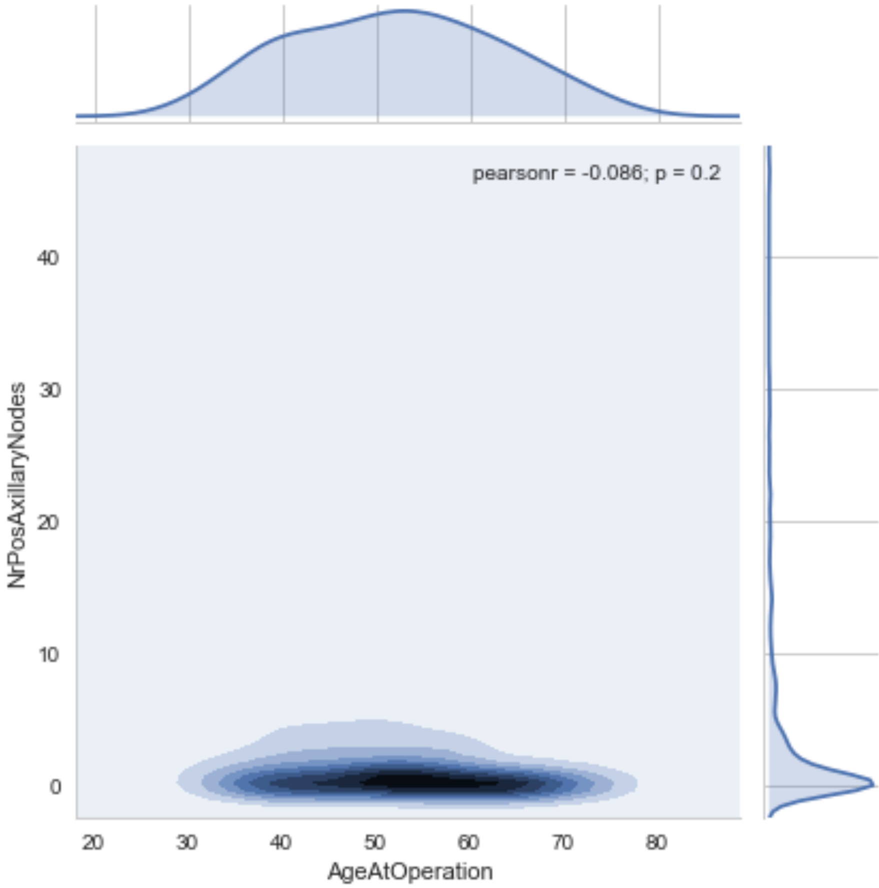
In [146]:
```
print("Total: Number of Patient whose age <40 = {}"
      .format(len(haberman[haberman['AgeAtOperation']<=40])))
print("Class 1: Number of Patient whose age <40 = {}"
      .format(len(Surv[Surv['AgeAtOperation']<=40])))
print("Class 2: Number of Patient whose age <40 = {}"
      .format(len(NonSurv[NonSurv['AgeAtOperation']<=40])))
```

```
Total: Number of Patient whose age <40 = 43
Class 1: Number of Patient whose age <40 = 39
Class 2: Number of Patient whose age <40 = 4
```

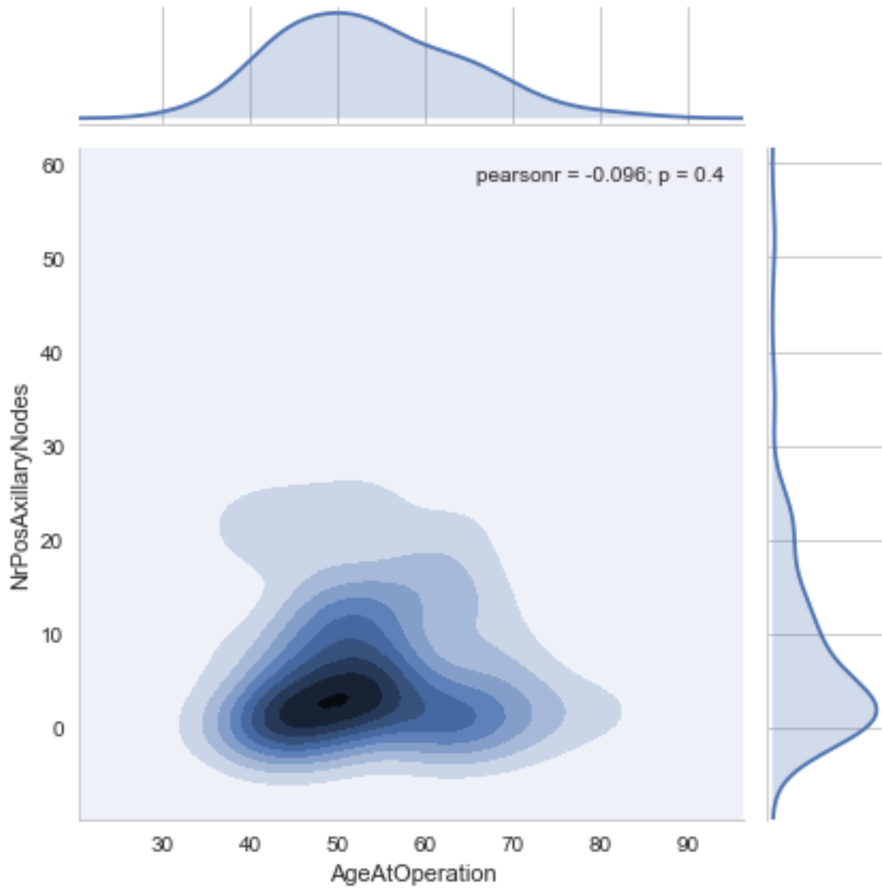
In [152]:
```
print("Total: Number of Patient whose PosAxillary Nodes  <3 = {}"
      .format(len(haberman[haberman['NrPosAxillaryNodes']<3])))
print("Class 1: Number of Patient whose PosAxillary Nodes <3 = {}"
      .format(len(Surv[Surv['NrPosAxillaryNodes']<=3])))
print("Class 2: Number of Patient whose PosAxillary Nodes <3 = {}"
      .format(len(NonSurv[NonSurv['NrPosAxillaryNodes']<=3])))
```

```
Total: Number of Patient whose PosAxillary Nodes  <3 = 197
Class 1: Number of Patient whose PosAxillary Nodes <3 = 178
Class 2: Number of Patient whose PosAxillary Nodes <3 = 39
```

In [142]:
```
sns.jointplot(x="AgeAtOperation", y="NrPosAxillaryNodes", data=Surv, k
ind="kde");
plt.show();
```


pearsonr = -0.086; p = 0.2
40
30
20
10
0
NrPosAxillaryNodes
20
30
40
50
60
70
80
AgeAtOperation

In [143]:
```
sns.jointplot(x="AgeAtOperation", y="NrPosAxillaryNodes", data=NonSurv
, kind="kde");
plt.show();
```



Conclusion

1. All patients < 34 years of AgeAtOperation survived for more than 5 years
2. No patient > 77 years of AgeAtOperation survived for more than 5 years
3. If patient's AgeAtOperation is <= 40 at the time of operation, chances of survival for more than 5 years is significantly higher at 90%(39/43)
4. Year of Operation doesn't seem to have any prominent effect on patient's survival status.
5. 44% of patients are detected with 0 NrPosAxillaryNodes
6. Also found that the maximum number of nodes detected for any patient is 52, 86% of patients are detected with < 10 NrPosAxillaryNodes
7. 75% of patients who survived for more than 5 years after the operation had NrPosAxillaryNodes <=3
8. 50% of patients who died within 5 years after the Surgery had NrPosAxillaryNodes >4