Haberman Cancer Survival Data Set Exploratory Data Analysis

The Haberman's survival data set contains cases from a study that was conducted between 1958 and 1970 at the University of Chicago's Billings Hospital on the survival of patients who had undergone surgery for breast cancer.

Attribute Information:

Age of patient at time of operation (numerical) Patient's year of operation (year—1900, numerical) Number of positive auxillary nodes detected (numerical) Survival status (class attribute) 1 = the patient survived 5 years or longer 2 = the patient died within 5 years Setting the objective is the key in EDA which will structure your thoughts in the entire analysis. Here the objective is to predict whether the patient will survive after 5 years or not based upon the patient's age, year of treatment and the number of positive lymph nodes.

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

#load the haberman dataset by csv format

habersman=pd.read_csv("C:/Users/Excel/Desktop/CSV Files/haberman.csv")
habersman
```

Out[1]:

	age	op year	auxillary node	survival
0	30	64	1	1
1	30	62	3	1

	age	op year	auxillary node	survival
2	30	65	0	1
3	31	59	2	1
4	31	65	4	1
5	33	58	10	1
6	33	60	0	1
7	34	59	0	2
8	34	66	9	2
9	34	58	30	1
10	34	60	1	1
11	34	61	10	1
12	34	67	7	1
13	34	60	0	1
14	35	64	13	1
15	35	63	0	1
16	36	60	1	1
17	36	69	0	1
18	37	60	0	1
19	37	63	0	1
20	37	58	0	1
21	37	59	6	1
22	37	60	15	1
23	37	63	0	1

	age	op year	auxillary node	survival
24	38	69	21	2
25	38	59	2	1
26	38	60	0	1
27	38	60	0	1
28	38	62	3	1
29	38	64	1	1
...	...	...	...	...
276	67	66	0	1
277	67	61	0	1
278	67	65	0	1
279	68	67	0	1
280	68	68	0	1
281	69	67	8	2
282	69	60	0	1
283	69	65	0	1
284	69	66	0	1
285	70	58	0	2
286	70	58	4	2
287	70	66	14	1
288	70	67	0	1
289	70	68	0	1
290	70	59	8	1

	age	op year	auxillary node	survival
291	70	63	0	1
292	71	68	2	1
293	72	63	0	2
294	72	58	0	1
295	72	64	0	1
296	72	67	3	1
297	73	62	0	1
298	73	68	0	1
299	74	65	3	2
300	74	63	0	1
301	75	62	1	1
302	76	67	0	1
303	77	65	3	1
304	78	65	1	2
305	83	58	2	2

306 rows × 4 columns

In [2]:
```
print(habersman.shape)
print(habersman.columns)
```

```
(306, 4)
Index(['age', 'op year', 'auxillary node', 'survival'], dtype='object')
```

habersman dataset has 306 datapoints and 4 class variables

In [3]:
```python
habersman['survival'].value_counts()          #imbalanced  dataset
```

Out[3]:
```
1    225
2     81
Name: survival, dtype: int64
```

Habersman dataset is imbalanced dataset

In [4]:
```python
# convert classlabel numerical to categorical for better understanding
 .
habersman['survival']=habersman['survival'].map({1:'yes',2:'no'})
habersman['survival']=habersman['survival'].astype("category")
print(habersman.head())
```

```
   age  op year  auxillary node survival
0   30       64               1      yes
1   30       62               3      yes
2   30       65               0      yes
3   31       59               2      yes
4   31       65               4      yes
```

In [5]:
```python
#descriptive statistics
habersman.describe()
```

Out[5]:

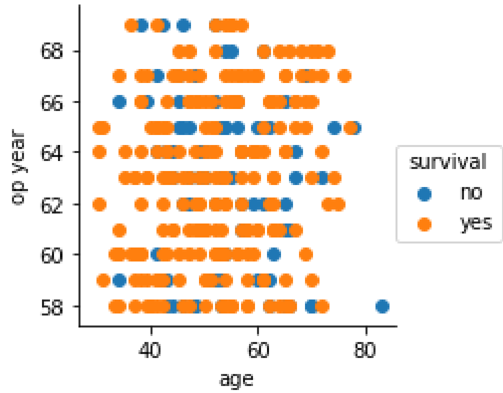
	age	op year	auxillary node
count	306.000000	306.000000	306.000000
mean	52.457516	62.852941	4.026144
std	10.803452	3.249405	7.189654
min	30.000000	58.000000	0.000000
25%	44.000000	60.000000	0.000000
50%	52.000000	63.000000	1.000000
75%	60.750000	65.750000	4.000000

	age	op year	auxillary node
max	83.000000	69.000000	52.000000

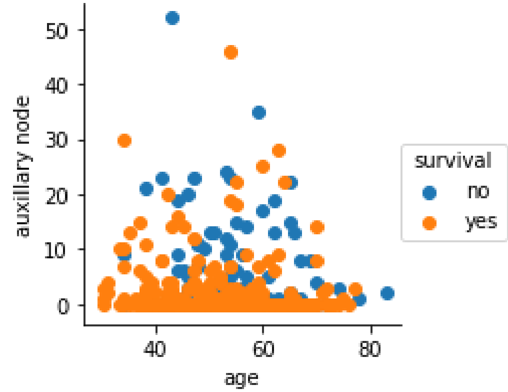
CONVERT NUMERICAL VALUE TO CATEGORICAL VALUE

BIVARIATE ANALYSIS

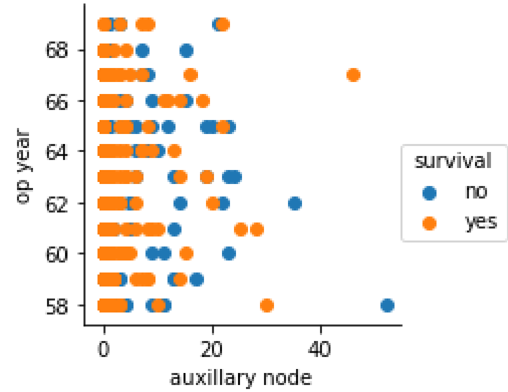
In [6]:
```
# Bivariate doesnot make any sense without color class label .we will d
o the simple hack with seaborn
sns.FacetGrid(habersman,hue="survival",size=3)\
   .map(plt.scatter,'age','op year')\
   .add_legend();
plt.show();
```



In [7]:
```
sns.FacetGrid(habersman,hue="survival",size=3)\
   .map(plt.scatter,'age','auxillary node')\
   .add_legend();
plt.show();
```



In [8]:
```
sns.FacetGrid(habersman,hue="survival",size=3)\
   .map(plt.scatter,'auxillary node','op year')\
   .add_legend();
plt.show();
```

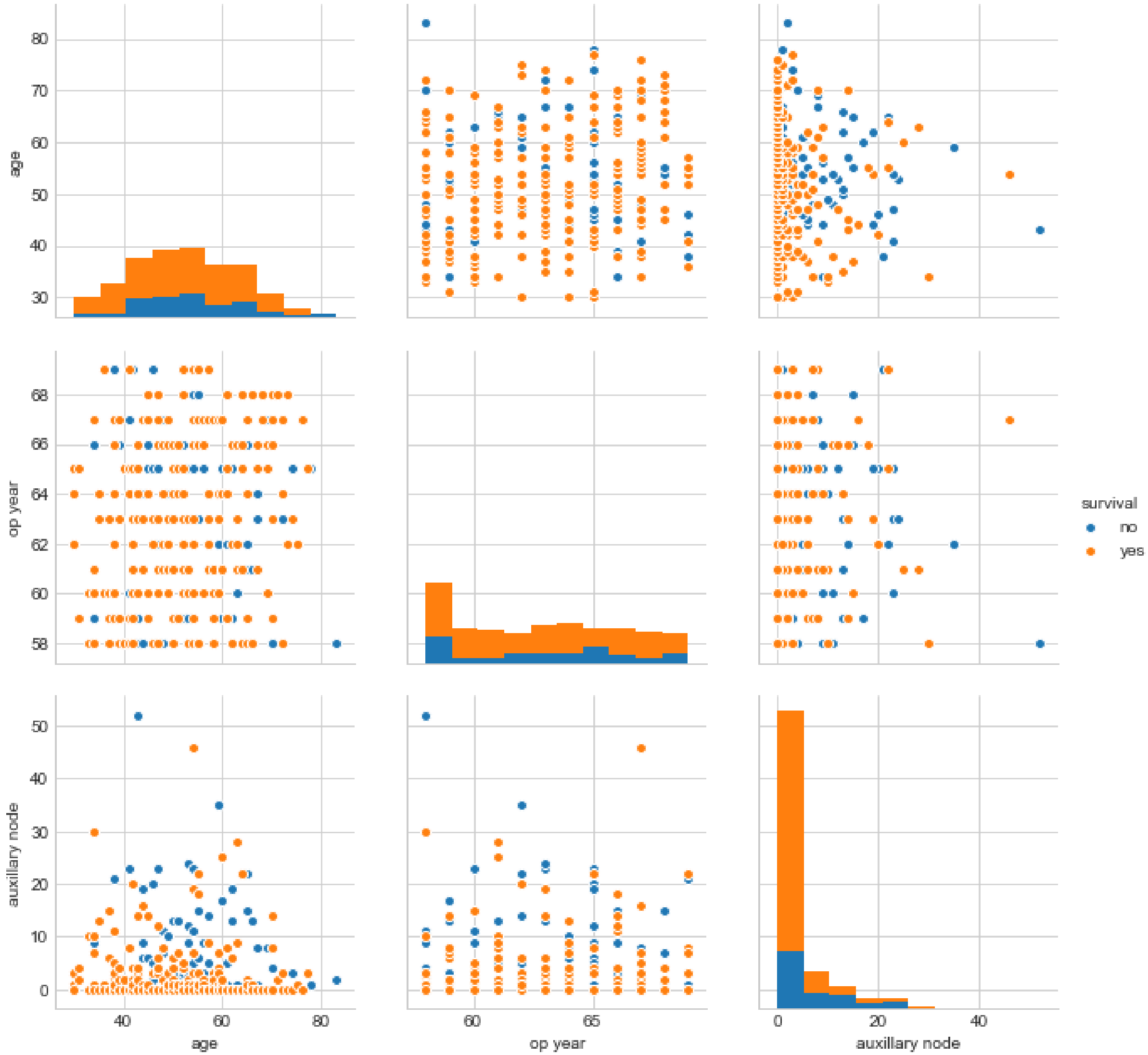


OBSERVATION: Its to difficult to classify the variables due to overlapping .but we can say most of the patient are survived at auxillary node zero.

In [9]:
```
# pairwise plot is used .when the numbers of features are in high dimen
sional.
# only we can visualize in 2d ,3d. but not in 4d .simple hack is used f
or 4d  like using pairplot
```

```
plt.close()
sns.set_style("whitegrid")
sns.pairplot(habersman, hue="survival", size=3)
plt.show
```

Out[9]: <function matplotlib.pyplot.show(*args, **kw)>



Observation: unable to classify due to overlapping

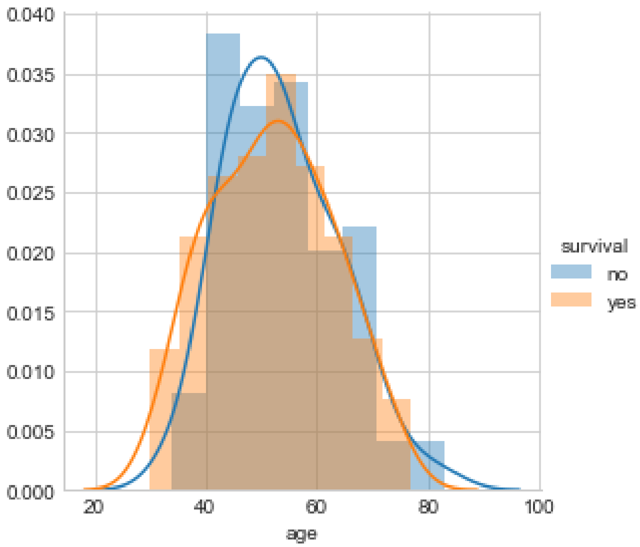
histogram and probability density

function(pdf)

In [10]:
```
# histogram

sns.FacetGrid(habersman,hue='survival',size=4)\
   .map(sns.distplot, 'age')\
   .add_legend();
plt.show();
```

```
C:\Users\Excel\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:646
2: UserWarning: The 'normed' kwarg is deprecated, and has been replaced
by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
C:\Users\Excel\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:646
2: UserWarning: The 'normed' kwarg is deprecated, and has been replaced
by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [11]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

```
sns.FacetGrid(habersman,hue='survival',size=4)\
   .map(sns.distplot, 'auxillary node')\
   .add_legend();
plt.show();
```

```
C:\Users\Excel\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:646
2: UserWarning: The 'normed' kwarg is deprecated, and has been replaced
by the 'density' kwarg.
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by the 'density' kwarg.
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```
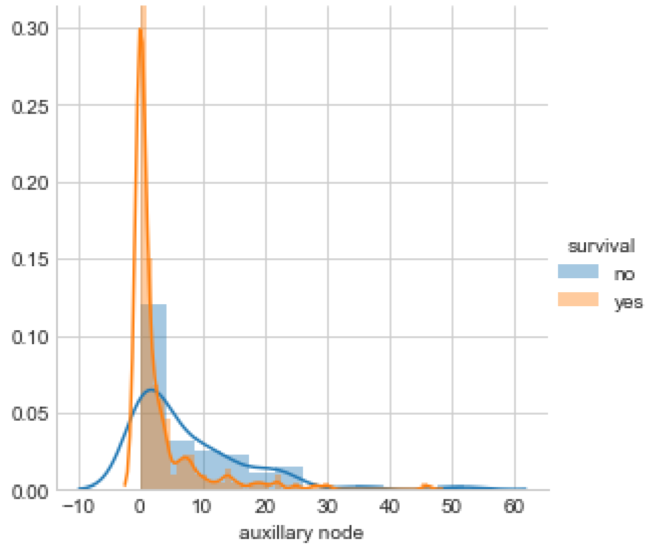
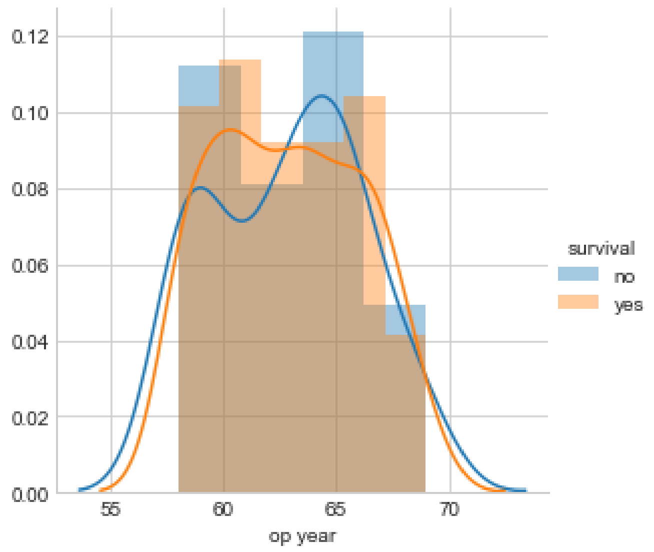



In [12]:
```
sns.FacetGrid(habersman,hue='survival',size=4)\
   .map(sns.distplot, 'op year')\
   .add_legend();
plt.show();
```

```
C:\Users\Excel\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:646
2: UserWarning: The 'normed' kwarg is deprecated, and has been replaced
by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

```
C:\Users\Excel\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:646
2: UserWarning: The 'normed' kwarg is deprecated, and has been replaced
by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



Observation:

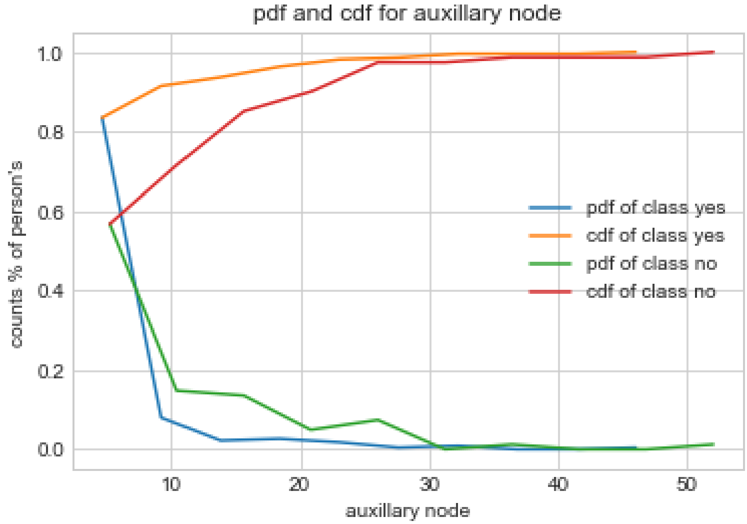
1. 30 to 35 percent patients are survived whose auxillary nodes between 0 to 5.
2. Most of the unsucessful operation are between op_year between 64 to 67.

cummulative density function (cdf)

In [13]:

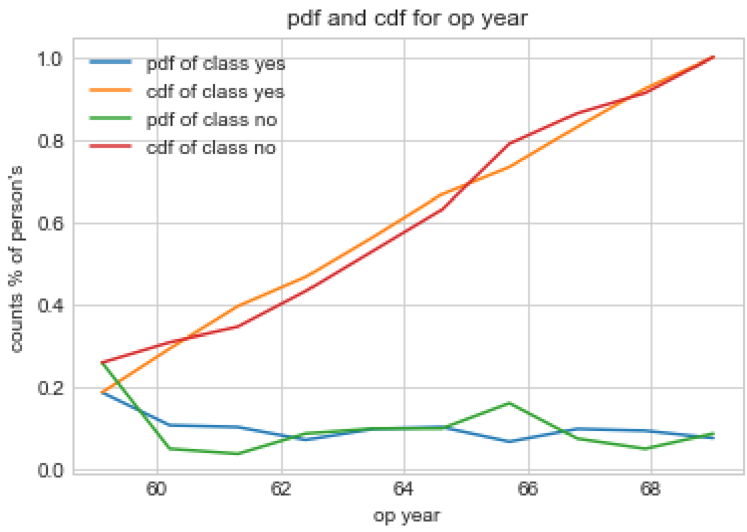
```
#https://www.kaggle.com/premvardhan/exploratory-data-analysis-haberman-
s-survival
yes = habersman.loc[habersman["survival"] == "yes"]
no = habersman.loc[habersman["survival"] =="no"]
label=[ "pdf of class yes","cdf of class yes","pdf of class no", "cdf o
f class no" ]
```

```
counts,bin_edges=np.histogram(yes['auxillary node'],bins=10,density=Tru
e)
pdf = counts/(sum(counts))
cdf = np.cumsum(pdf)
plt.title("pdf and cdf for auxillary node")
plt.xlabel("auxillary node")
plt.ylabel("counts % of person's")
plt.plot(bin_edges[1:], pdf)
plt.plot(bin_edges[1:], cdf)

counts, bin_edges = np.histogram(no["auxillary node"], bins=10, density
 = True)
pdf = counts/(sum(counts))
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:], pdf)
plt.plot(bin_edges[1:], cdf)
plt.legend(label)

plt.show()
```



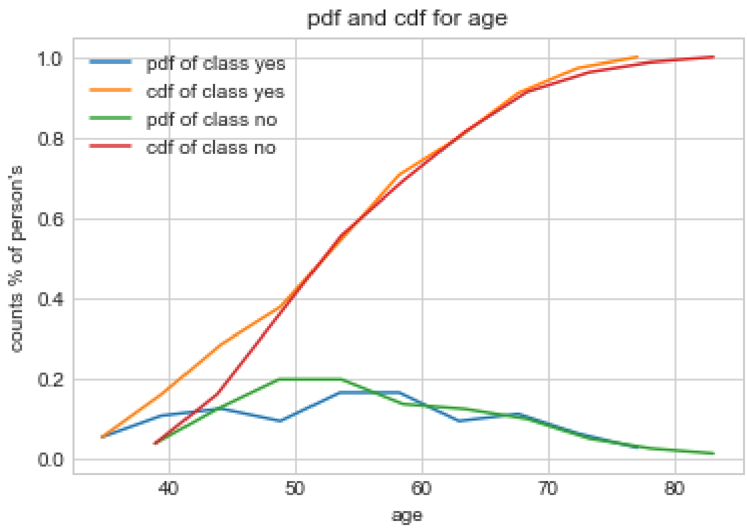
observation : patient have more than 46 auxillary node will not survive

```
In [14]: counts,bin_edges=np.histogram(yes['op year'],bins=10,density=True)
pdf = counts/(sum(counts))
cdf = np.cumsum(pdf)
plt.title("pdf and cdf for op year")
plt.xlabel("op year")
plt.ylabel("counts % of person's")
plt.plot(bin_edges[1:], pdf)
plt.plot(bin_edges[1:], cdf)

counts, bin_edges = np.histogram(no["op year"], bins=10, density = True
)
pdf = counts/(sum(counts))
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:], pdf)
plt.plot(bin_edges[1:], cdf)
plt.legend(label)

plt.show()
```




```
In [15]: counts,bin_edges=np.histogram(yes['age'],bins=10,density=True)
pdf = counts/(sum(counts))
cdf = np.cumsum(pdf)
```

```
plt.title("pdf and cdf for age")
plt.xlabel("age")
plt.ylabel("counts % of person's")
plt.plot(bin_edges[1:], pdf)
plt.plot(bin_edges[1:], cdf)

counts, bin_edges = np.histogram(no["age"], bins=10, density = True)
pdf = counts/(sum(counts))
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:], pdf)
plt.plot(bin_edges[1:], cdf)
plt.legend(label)

plt.show()
```

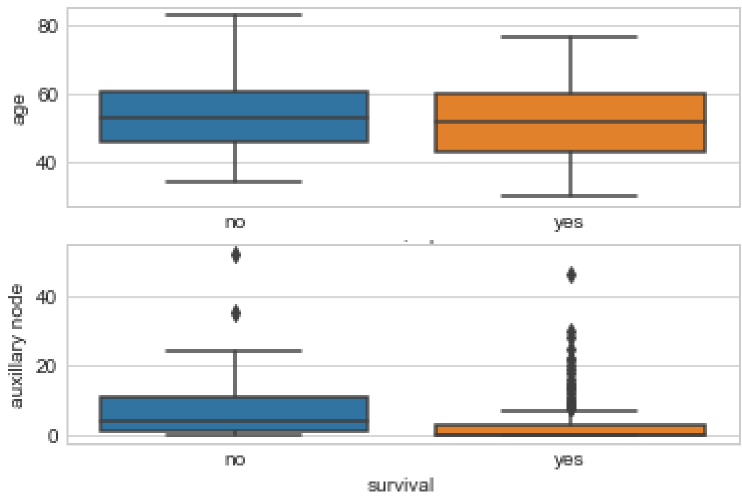


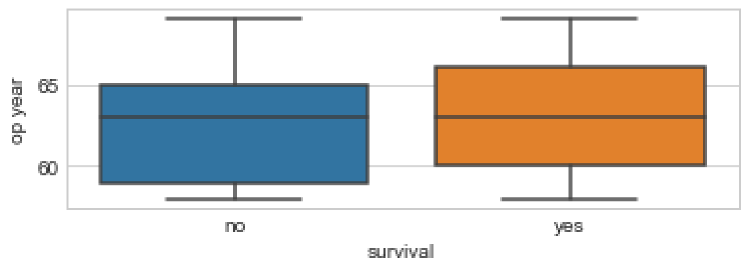
Box plot

In [16]:
```
#extension like quantiles
plt.close()
plt.figure(1)
plt.subplot(211)
```

```
sns.boxplot(x = 'survival', y = 'age', data = habersman)

plt.subplot(212)
sns.boxplot(x = 'survival', y = 'auxillary node', data = habersman)

plt.figure(2)
plt.subplot(211)
sns.boxplot(x = 'survival', y = 'op year', data = habersman)
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```





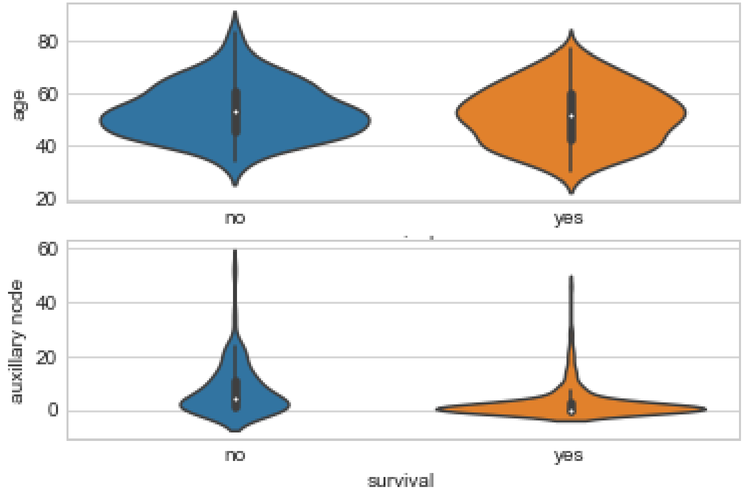
observation : most are the patients are survived at auxillary node between "0-5"

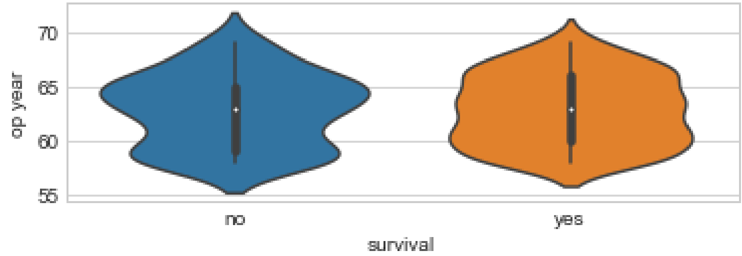
Violin plot

In [17]:

```
#its same like box plot
plt.close()
plt.figure(1)
plt.subplot(211)
sns.violinplot(x = 'survival', y = 'age', data = habersman)

plt.subplot(212)
sns.violinplot(x = 'survival', y = 'auxillary node', data = habersman)

plt.figure(2)
plt.subplot(211)
sns.violinplot(x = 'survival', y = 'op year', data = habersman)
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```





observation : most are the patients are survived at auxillary node between "0-5"

In [22]:
```
print("means:")
print(np.mean(yes['auxillary node']))
print(np.mean(no['auxillary node']))
# mean for op year
print(np.mean(yes['op year']))
print(np.mean(no['op year']))
#mean for age
print(np.mean(yes['age']))
print(np.mean(no['age']))
```

```
means:
2.7911111111111113
7.45679012345679
62.86222222222222
62.82716049382716
52.017777777777778
53.67901234567901
```

In [24]:
```
print("standard deviation:")
# std for auxillary node
print(np.std(yes['auxillary node']))
print(np.std(no['auxillary node']))
# std for op year
print(np.std(yes['op year']))
print(np.std(no['op year']))
#std for age
```

```
print(np.std(yes['age']))
print(np.std(no['age']))
```

```
standard deviation:
5.857258449412131
9.128776076761632
3.2157452144021956
3.3214236255207883
10.98765547510051
10.10418219303131
```

In [36]:

```
print('quantiles for auxillary node :')
print('quantile for auxillary node for sur_yes =',np.percentile(yes['auxillary node'],np.arange(0,100,25)))
print('quantile for auxillary node for sur_no =',np.percentile(no['auxillary node'],np.arange(0,100,25)))
print('90th percentiles for auxillary node :')
print('90th percentiles for auxillary node for sur_yes =',np.percentile(yes['auxillary node'],90))
print('90th percentiles for auxillary node for sur_no =',np.percentile(no['auxillary node'],90))

print('quantiles for age:')
print('quantile for age for sur_yes =',np.percentile(yes['age'],np.arange(0,100,25)))
print('quantile for age for sur_no =',np.percentile(no['age'],np.arange(0,100,25)))
print('90th percentiles for age :')
print('90th percentiles for age for sur_yes =',np.percentile(yes['age'],90))
print('90th percentiles for age for sur_no =',np.percentile(no['age'],90))
```

```
quantiles for auxillary node :
quantile for auxillary node for sur_yes = [0. 0. 0. 3.]
quantile for auxillary node for sur_no = [ 0.  1.  4. 11.]
90th percentiles for auxillary node :
90th percentiles for auxillary node for sur_yes = 8.0
90th percentiles for auxillary node for sur_no = 20.0

quantiles for age:
```

```
quantiles for age:
quantile for age for sur_yes = [30. 43. 52. 60.]
quantile for age for sur_no = [34. 46. 53. 61.]
90th percentiles for age :
90th percentiles for age for sur_yes = 67.0
90th percentiles for age for sur_no = 67.0
```

observation :

```
survival_yes for auxillary node :
```

1. 75% of the patients survived after 5 year with auxillary node at 3.
2. 90% of the patients survived after 5 years with auxillary node at 8. survival_no for auxillary node :
3. 75% of the patients died within 5 years with auxillary node at 11.
4. 50% of the patients died within 5 years with auxillary node at 4.
5. 90% of the patients died within 5 years with auxillary node at 20. survival_yes for the age:
6. 75% of the patients survied after 5 years at the age of 60.
7. 50% of the patients survied after 5 years at the age of 52.
8. 90% of the patients survived after 5 years at the age of 67. survival_no for age:
9. 75% of the patients survied after 5 years at the age of 61.
10. 50% of the patients survied after 5 years at the age of 53.
11. 90% of the patients survived after 5 years at the age of 67.

conclusion

1. The given dataset is imabalance datset.
2. Its more difficult to classify data due to overlapping.
3. Important feature in dataset is Auxillary node .
4. most main reason of patient survival is auxillary node range between ' 0-5 '.
5. Descriptive Statistics:

6. Average age of patients is 52 with standard deviation 10.8 and range is in between 30 and 83.
7. Average axillary nodes are 4 with standard deviation 3.2 and range is in between 0 and 52.
8. 75% of the patients have less than 5 auxillary nodes.
9. 25% of the patients have auxillary nodes.