Haberman

June 5, 2018

1 Title: Haberman's Survival Data

The dataset 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.

1.1 Attribute Information:

a)Age of patient at time of operation (numerical) b)Patient's year of operation (year - 1900, numerical) c)Number of positive axillary nodes detected (numerical) d)Survival status (class attribute) 1 = the patient survived 5 years or longer 2 = the patient died within 5 year

1.2 Objective:

if any new candidates details such as age, operated year, number of positive nodes are provided then we need to predict if that person will survive for more than 5 years or not post operation, by doing analysys on the dataset provided.

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

```
In [2]: # Load data from CSV into Dataframe by adding the column headings
        data = pd.read_csv('haberman.csv', names =['age', 'op_year','pos_nodes', 'survival'])
        # print shape, columns, first 5 rows
        print(data.shape)
        print(data.columns)
        print(data.head())
```

```
(306, 4)
Index(['age', 'op_year', 'pos_nodes', 'survival'], dtype='object')
   age  op_year  pos_nodes  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 [3]: print(data) # print whole data set
```

```
     age  op_year  pos_nodes  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
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
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
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 x 4 columns]
```

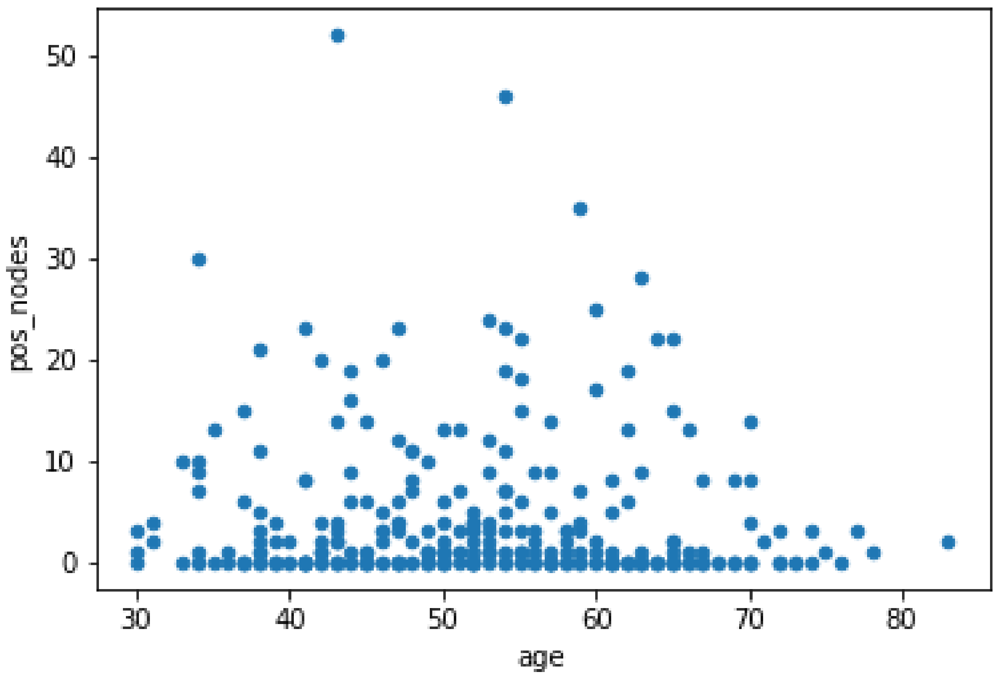
```
In [4]: # Check the count of survivals to the ones died with in 5 years after surgery
        print(data['survival'].value_counts())
```

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

This concludes that it is an imbalance dataset with (225:81)

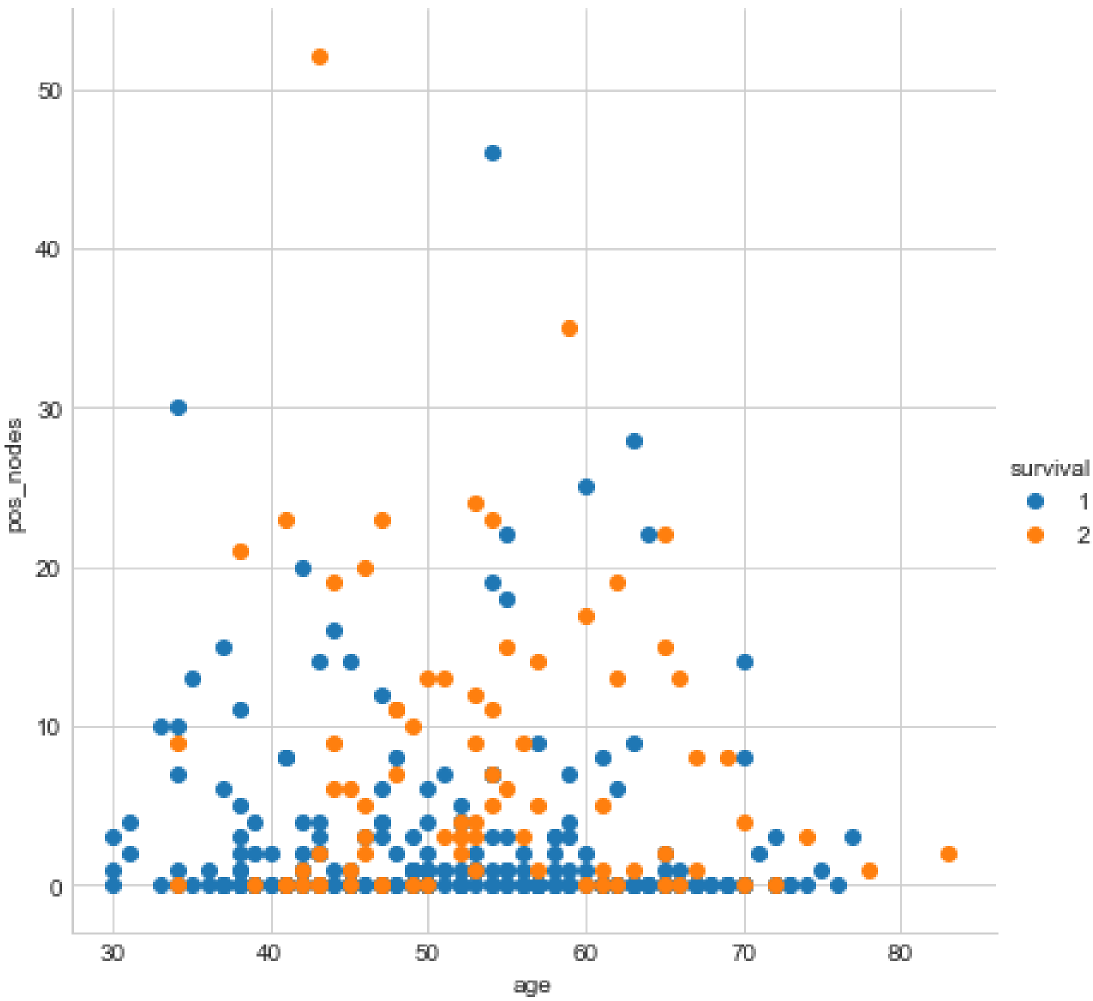
2 Lets start plotting 2D scatter plot:

```
In [5]: data.plot(kind= 'scatter',x='age', y = 'pos_nodes' )
        plt.show()
```

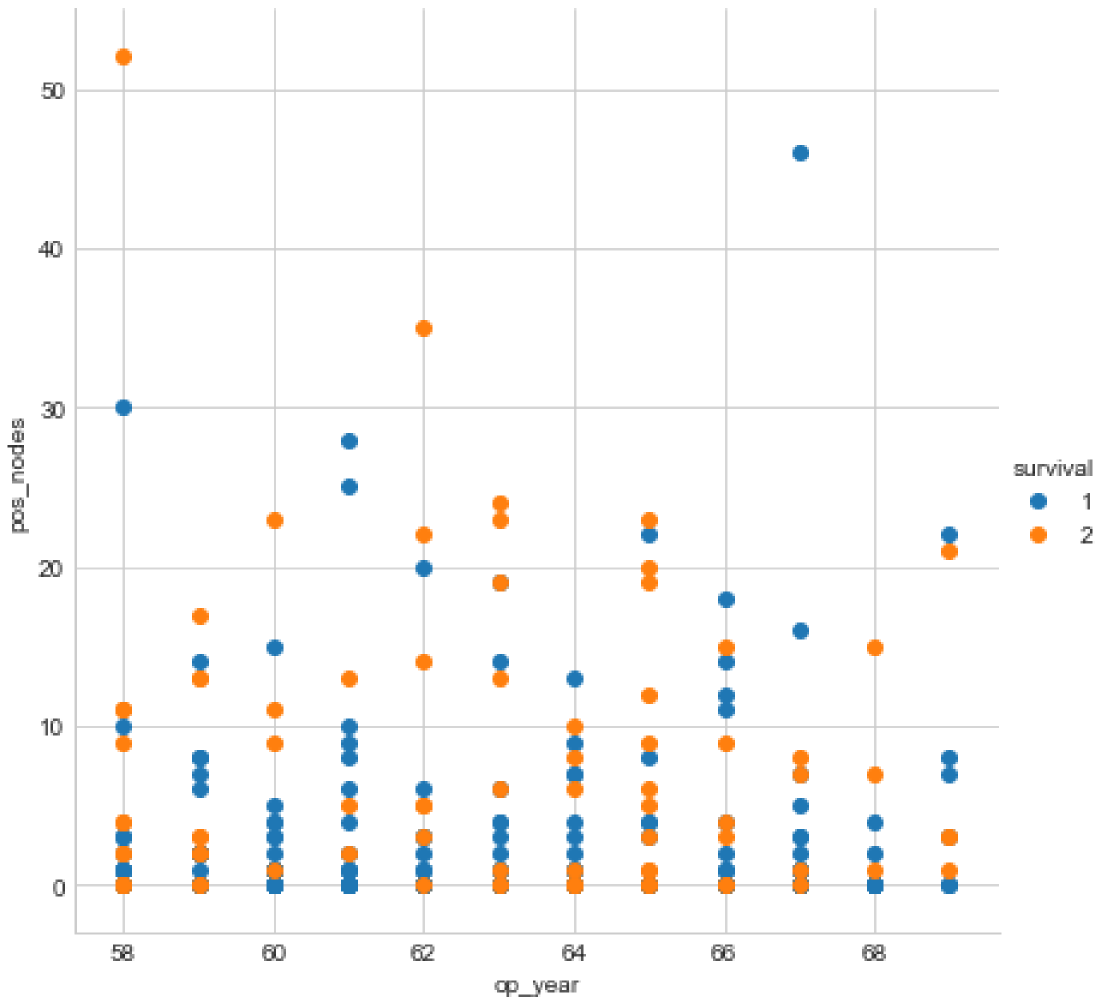


With the above plot we didnt get any insights. So we will move forward and plot with both survival class

In [7]:
```
# 2-D Scatter plot with color-coding for surviver and non-survivers class on age and po
sns.set_style('whitegrid')
sns.FacetGrid(data,hue='survival',size=6).map(plt.scatter,'age','pos_nodes') \
.add_legend()
plt.show()
```

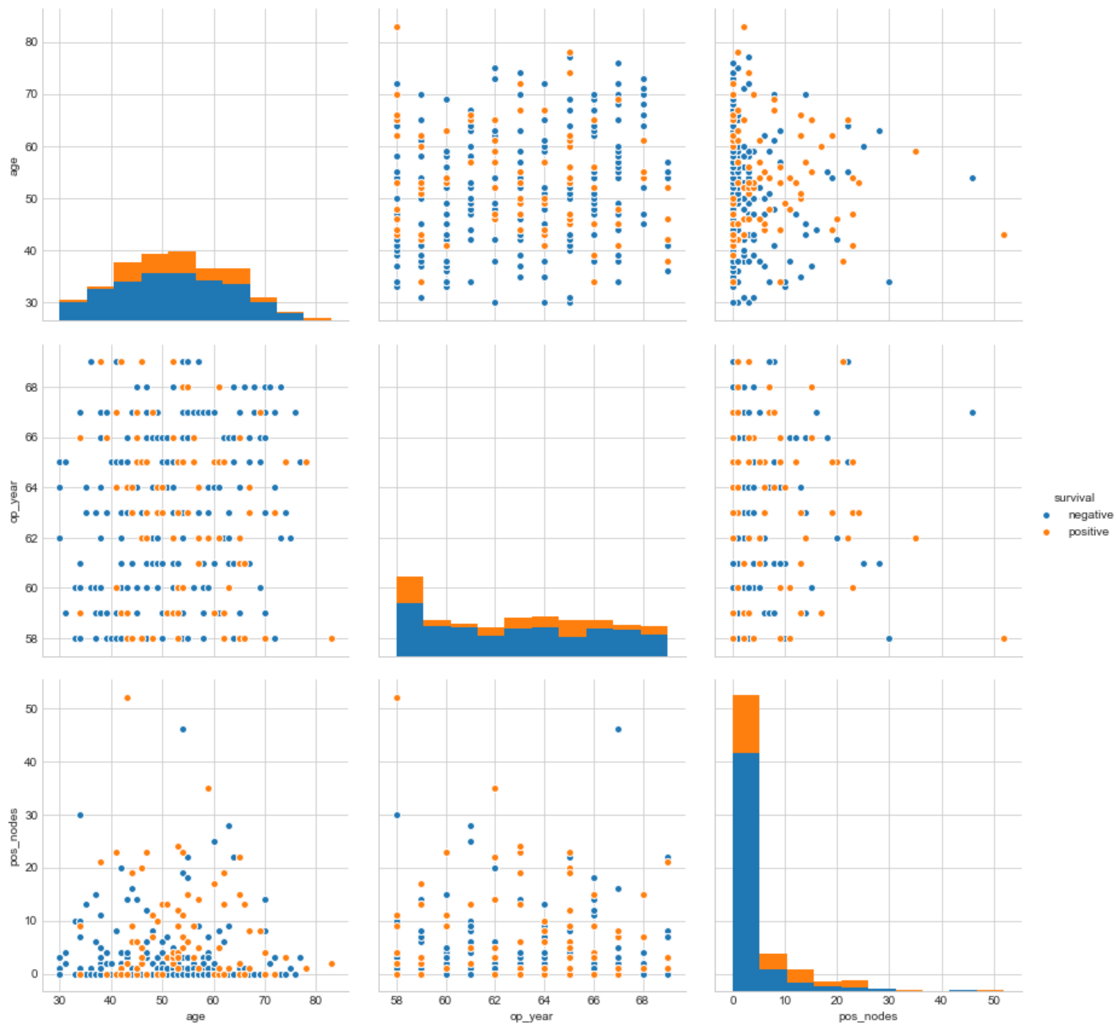



```
In [10]: # 2-D Scatter plot with color-coding for surviver and non-survivers class on operatio
         sns.set_style('whitegrid')
         sns.FacetGrid(data, hue ='survival', size = 6).map(plt.scatter,'op_year','pos_nodes')
         .add_legend()
         plt.show()
```



Both the plots doesnt give much information as it is hard to seperate the data points
Now let us try if we can get something from pairplots:

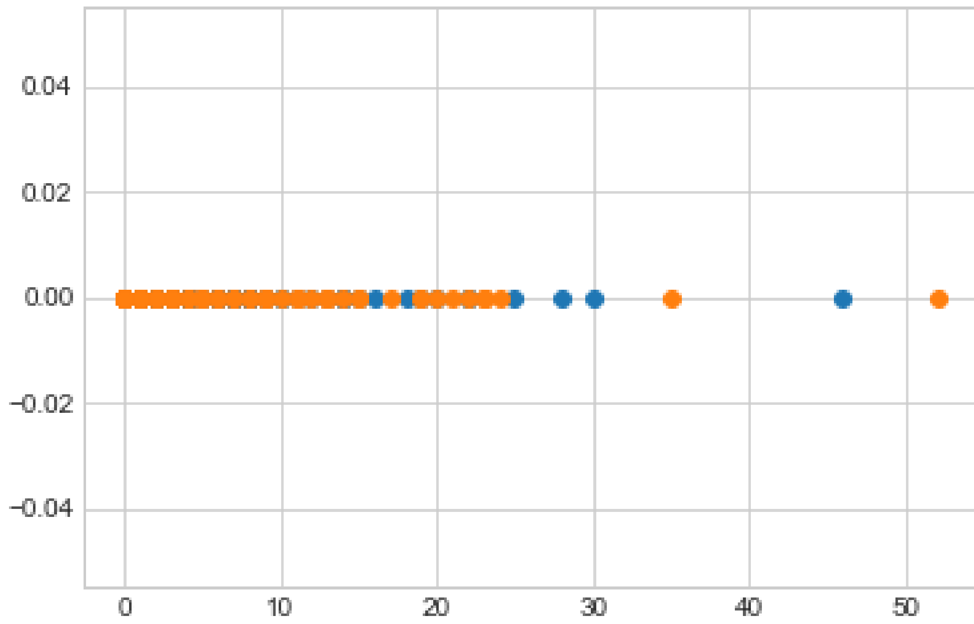
```
In [11]: data['survival'] = data['survival'].apply(lambda x: 'negative' if x == 1 else 'positi
         #['age', 'op_year','pos_nodes', 'survival']
         plt.close()
         sns.set_style('whitegrid')
         sns.pairplot(data, hue = 'survival', size = 4)
         plt.show()
```



Even here we are not able to make or seperate the data poits.
Lets try doing univariate analysys:

3 Univariate analysys

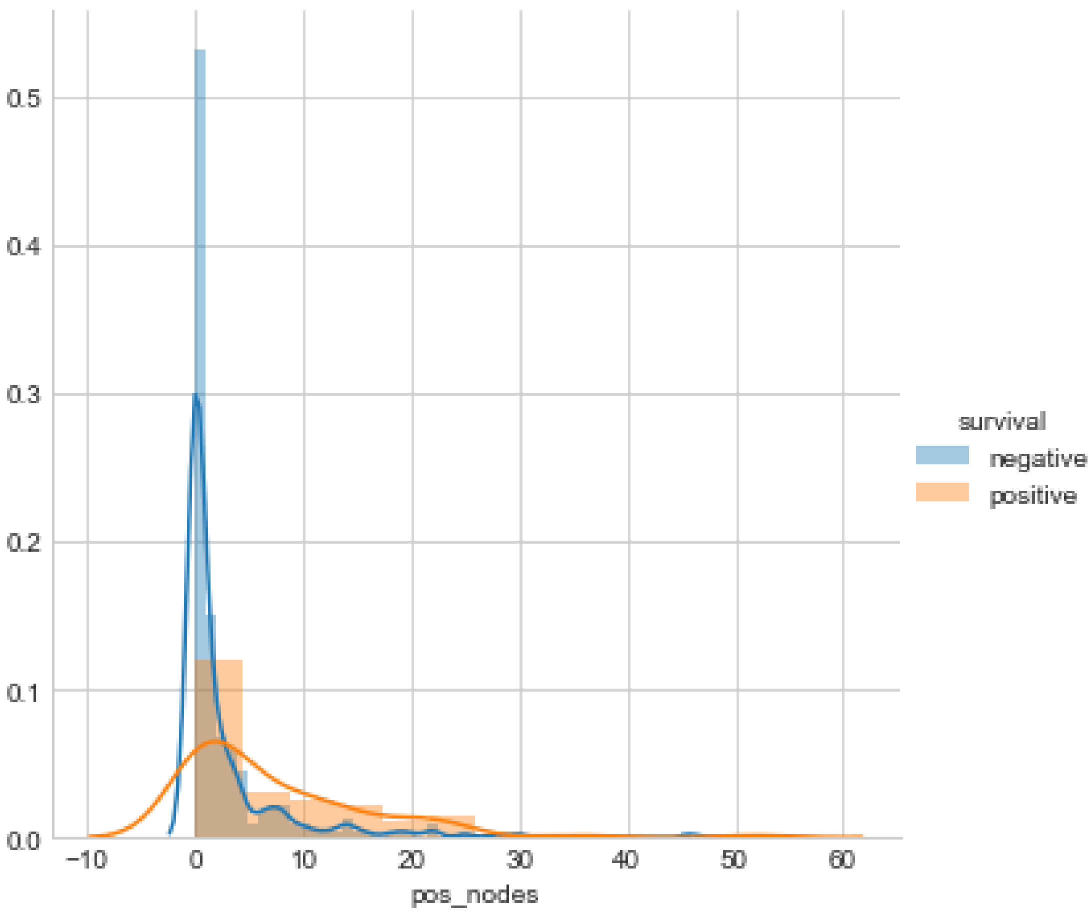
In [33]:
```
#separating survived and others dataset for better understanding and ease of working

data_neg = data.loc[data['survival'] == 'negative']
data_pos = data.loc[data['survival'] == 'positive']
#['age', 'op_year','pos_nodes', 'survival']
plt.plot(data_neg['pos_nodes'],np.zeros_like(data_neg['pos_nodes']), 'o')
plt.plot(data_pos['pos_nodes'],np.zeros_like(data_pos['pos_nodes']), 'o')
plt.show()
```



Even this doesn't give much details

Lets plot histogram on positive nodes detected and check the details

```
In [34]: sns.FacetGrid(data, hue = 'survival', size =5).map(sns.distplot, 'pos_nodes') \
         .add_legend()
         plt.show()
```



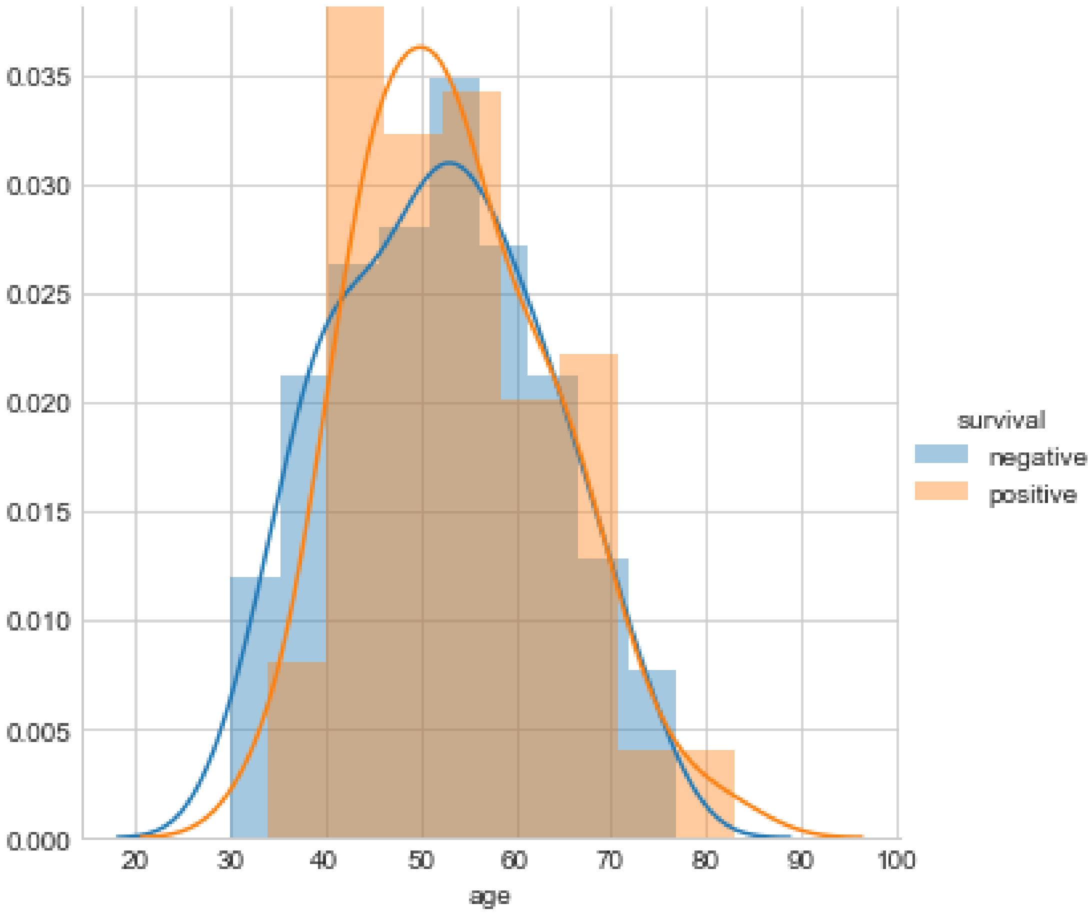

```
In [39]: print('Number of Patient for whom positive nodes detected is less than 2 = {}'
               .format(len(data[data['pos_nodes']<=2])))
         print('Number of survived Patients for whom positive nodes detected is less than 2 =
               .format(len(data_neg[data_neg['pos_nodes']<=2])))
         print('Number of other Patients for whom positive nodes detected is less than 2 = {}'
               .format(len(data_pos[data_pos['pos_nodes']<=2])))
```

```
Number of Patient for whom positive nodes detected is less than 2 = 197
Number of survived Patients for whom positive nodes detected is less than 2 = 165
Number of other Patients for whom positive nodes detected is less than 2 = 32
```

```
In [42]: #conclusion with detected positive nodes
         pct_survived = 165/197*100
         print(pct_survived,'% patients survived who were detected with less than or equal to
```

```
83.75634517766497 % patients survived who were detected with less than or equal to 2 nodes
```

In [43]: # Lets check the same on Age
```
sns.FacetGrid(data, hue = 'survival', size =5).map(sns.distplot, 'age') \
.add_legend()
plt.show()
```



In [46]:
```
print(data_neg['age'].describe())
```

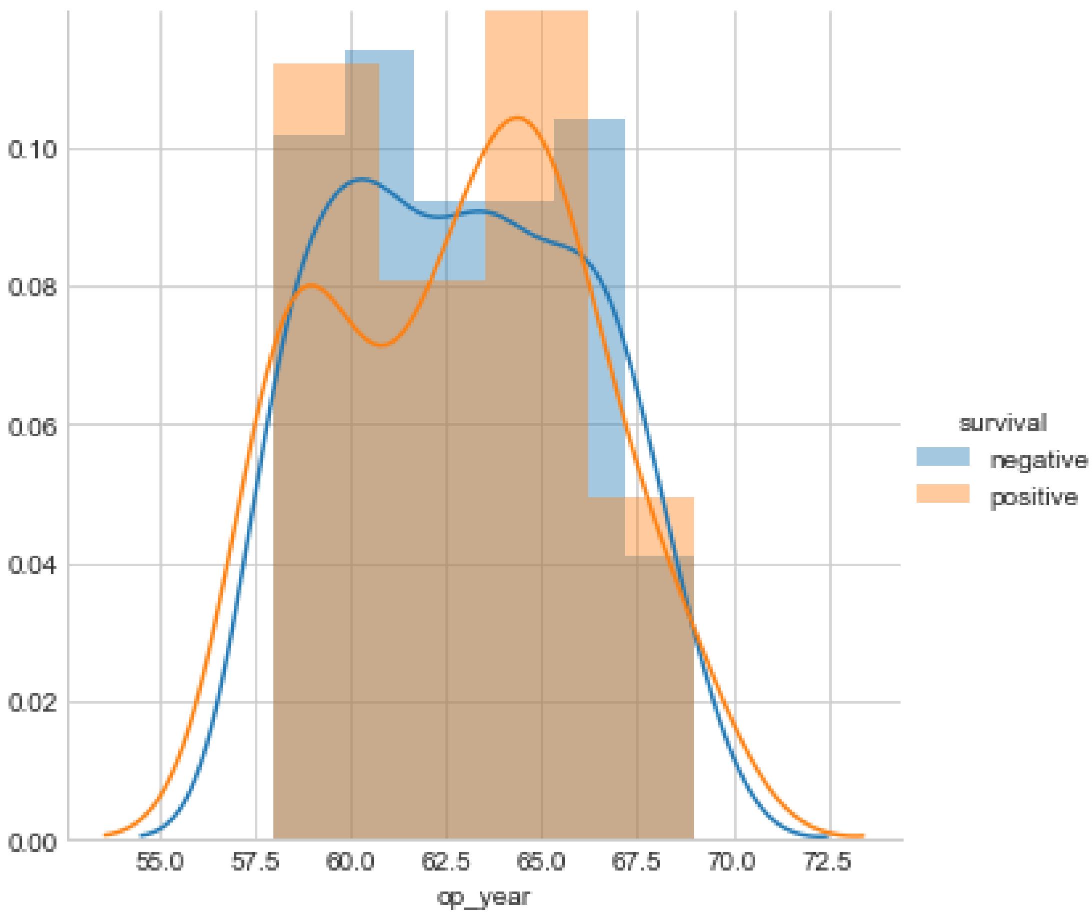
```
count    225.000000
mean      52.017778
std       11.012154
min       30.000000
25%       43.000000
50%       52.000000
75%       60.000000
max       77.000000
Name: age, dtype: float64
```

In [48]:
```
print(data_pos['age'].describe())
```

```
count    81.000000
mean     53.679012
std      10.167137
min      34.000000
25%      46.000000
50%      53.000000
75%      61.000000
max      83.000000
Name: age, dtype: float64
```

All the Patients whose age is less than 34 survived for more than 5 years and none of them survived for 5 years if their age is more then 77

```
In [49]: # Now let us check on operation year
         sns.FacetGrid(data, hue = 'survival', size =5).map(sns.distplot, 'op_year') \
         .add_legend()
         plt.show()
```



Cant draw much insights from the above plot

4 Mean Variance and Standard deviation

In [50]:
```
import math
#for negative result
print('Avg age is:',np.mean(data_neg['age']))
print('Avg age with outlier is:',np.mean(np.append(data_neg['age'],2000)))
print('Avg no of positive nodes is:',np.mean(data_neg['pos_nodes']))
#for positive result
print('Avg age is:',np.mean(data_pos['age']))
print('Avg age with outlier is:',np.mean(np.append(data_pos['age'],2000)))
print('Avg no of positive nodes is:',np.mean(data_pos['pos_nodes']))


print('Std-dev:')
print('STD of age is:',np.std(data_neg['age']))
print('STD of age is:',np.std(data_pos['age']))
print('Std of positive nodes is:',np.std(data_neg['pos_nodes']))
print('STD of Positive nodes:',np.std(data_pos['pos_nodes']))
#Calculating Std with Variance
var = np.var(data_neg['age'])
std = math.sqrt(var)
print('var and STD of age are:', var, std)
```

```
Avg age is: 52.017777777777778
Avg age with outlier is: 60.63716814159292
Avg no of positive nodes is: 2.7911111111111113
Avg age is: 53.67901234567901
Avg age with outlier is: 77.41463414634147
Avg no of positive nodes is: 7.45679012345679
Std-dev:
STD of age is: 10.98765547510051
STD of age is: 10.10418219303131
Std of positive nodes is: 5.857258449412131
STD of Positive nodes: 9.128776076761632
var and STD of age are: 120.72857283950623 10.98765547510051
```

5 Median, Quantiles, Percentiles and Median average deviation

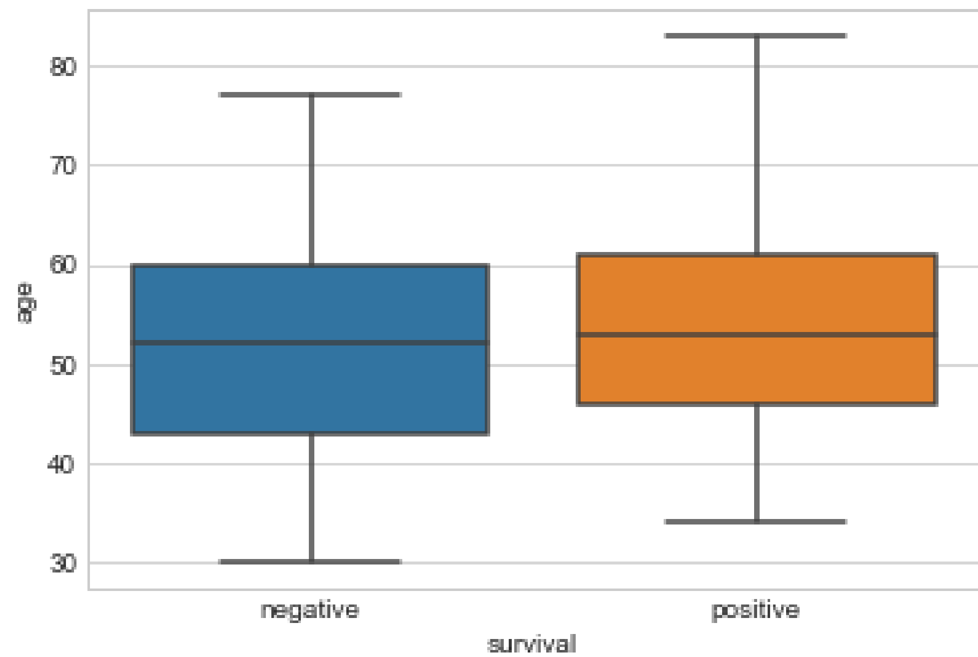
In [51]:
```
#Median, Quantiles, Percentiles and MAD
#for negative result
print('Avg age is:',np.median(data_neg['age']))
print('Avg age with outlier is:',np.median(np.append(data_neg['age'],2000)))
print('Avg no of positive nodes is:',np.median(data_neg['pos_nodes']))
#for positive result
print('Avg age is:',np.median(data_pos['age']))
print('Avg age with outlier is:',np.median(np.append(data_pos['age'],2000)))
print('Avg no of positive nodes is:',np.median(data_pos['pos_nodes']))
```

```
print('Quantiles')
print(np.percentile(data_neg['age'],np.arange(0, 100, 25)))
print(np.percentile(data_pos['age'],np.arange(0, 100, 25)))
print(np.percentile(data_neg['pos_nodes'], np.arange(0, 100, 25)))
print(np.percentile(data_pos['pos_nodes'], np.arange(0, 100, 25)))


from statsmodels import robust
print ('Median Absolute Deviation')
print(robust.mad(data_neg['age']))
print(robust.mad(data_pos['age']))
print(robust.mad(data_neg['pos_nodes']))
print(robust.mad(data_pos['pos_nodes']))
```

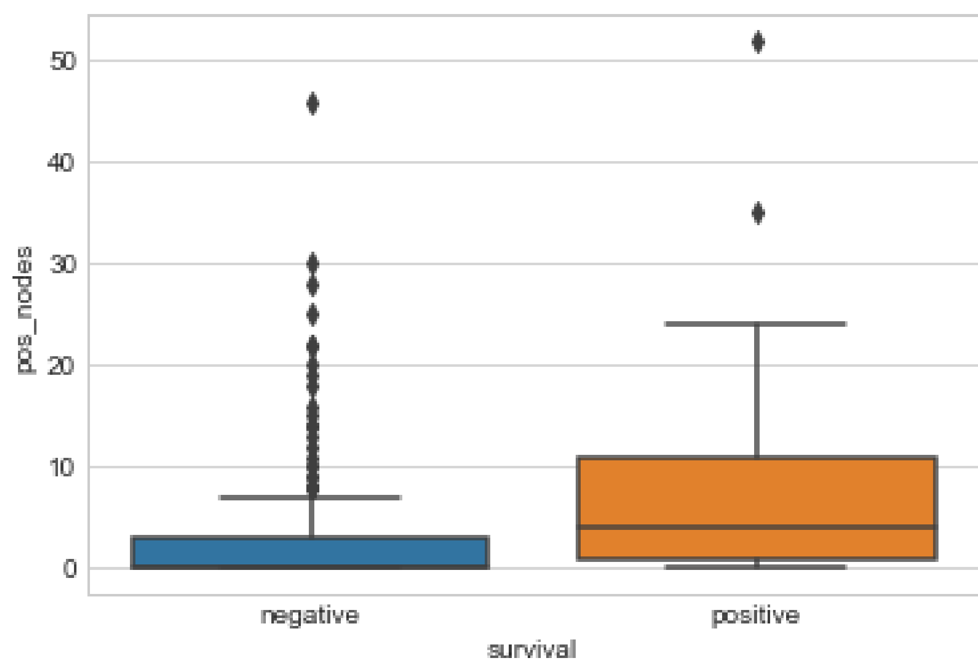
```
Avg age is: 52.0
Avg age with outlier is: 52.0
Avg no of positive nodes is: 0.0
Avg age is: 53.0
Avg age with outlier is: 53.0
Avg no of positive nodes is: 4.0
Quantiles
[30. 43. 52. 60.]
[34. 46. 53. 61.]
[0. 0. 0. 3.]
[ 0.  1.  4. 11.]
Median Absolute Deviation
13.343419966550417
11.860817748044816
0.0
5.930408874022408
```

6 Box plots

```
In [52]: sns.boxplot(x='survival',y='age', data=data)
         plt.show()
```

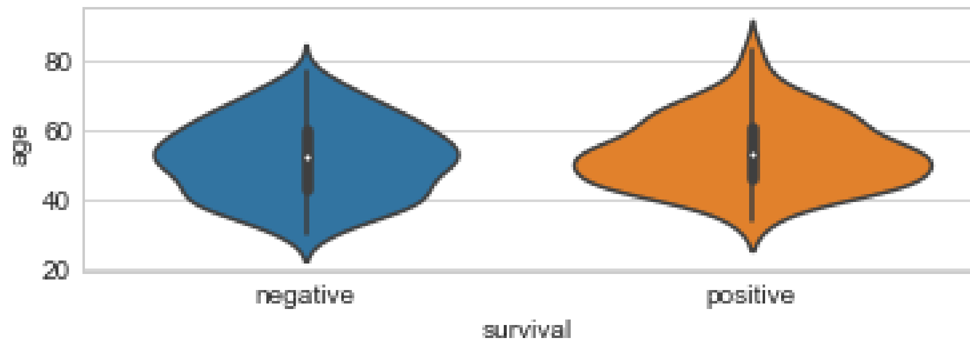


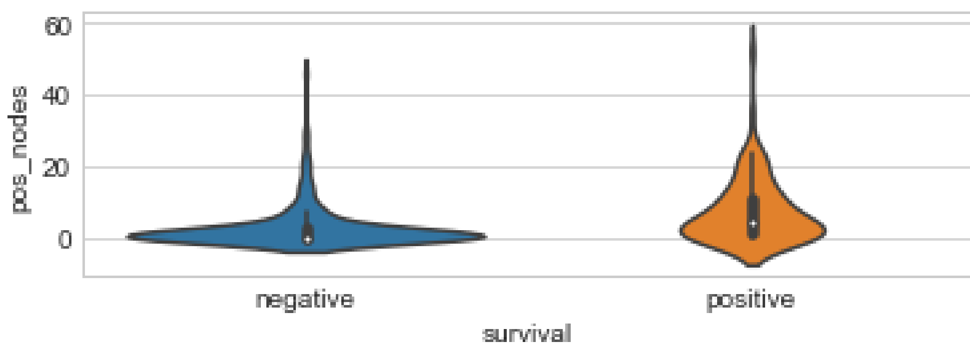

```
In [53]: sns.boxplot(x='survival',y='pos_nodes', data=data)
         plt.show()
```



7 Violin plots

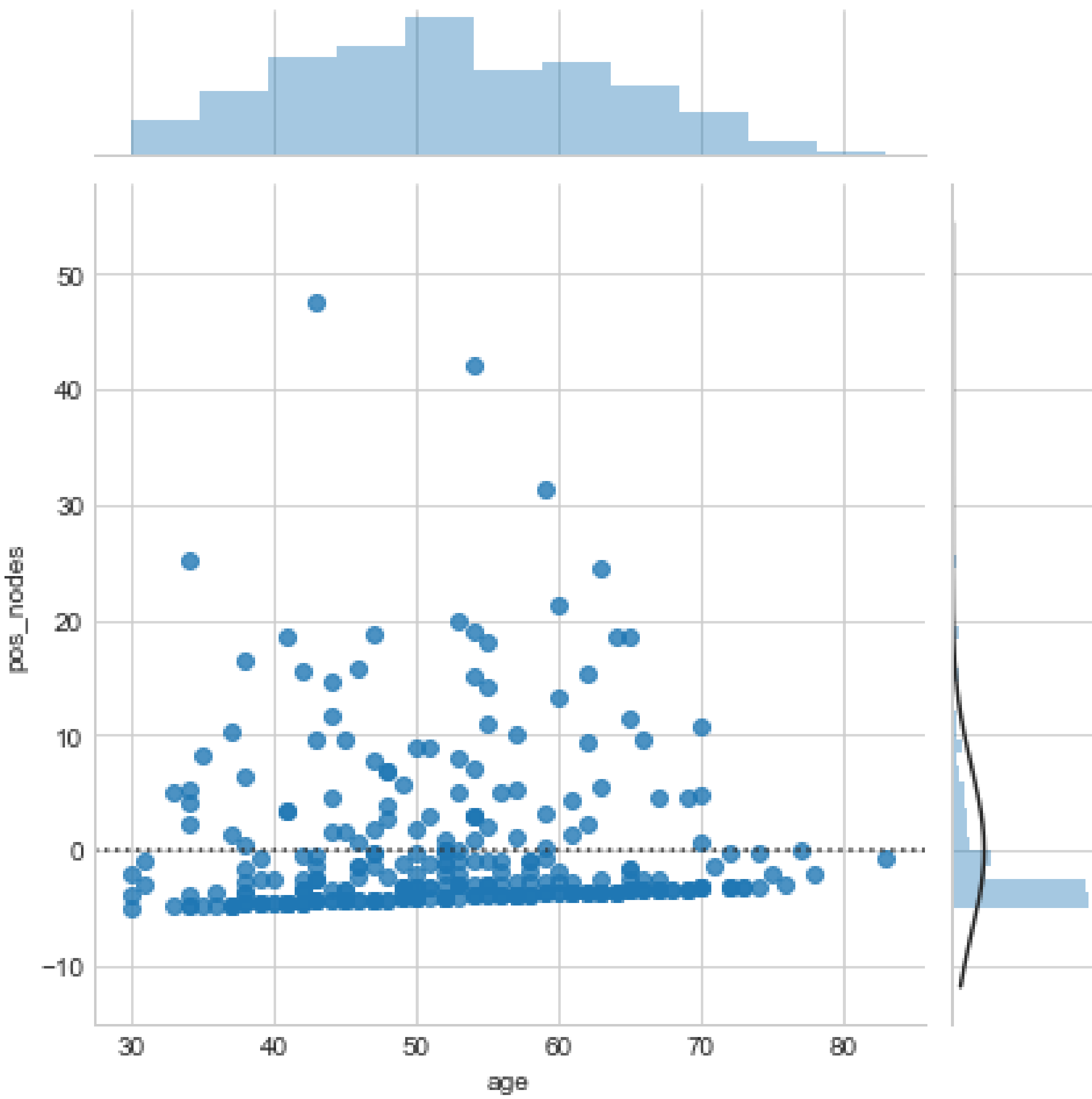
```
In [54]: plt.figure(1)
         plt.subplot(211)
         sns.violinplot(x='survival',y='age', data=data)
         plt.show()
         plt.subplot(212)
         sns.violinplot(x='survival',y='pos_nodes', data=data)
         plt.show()
```

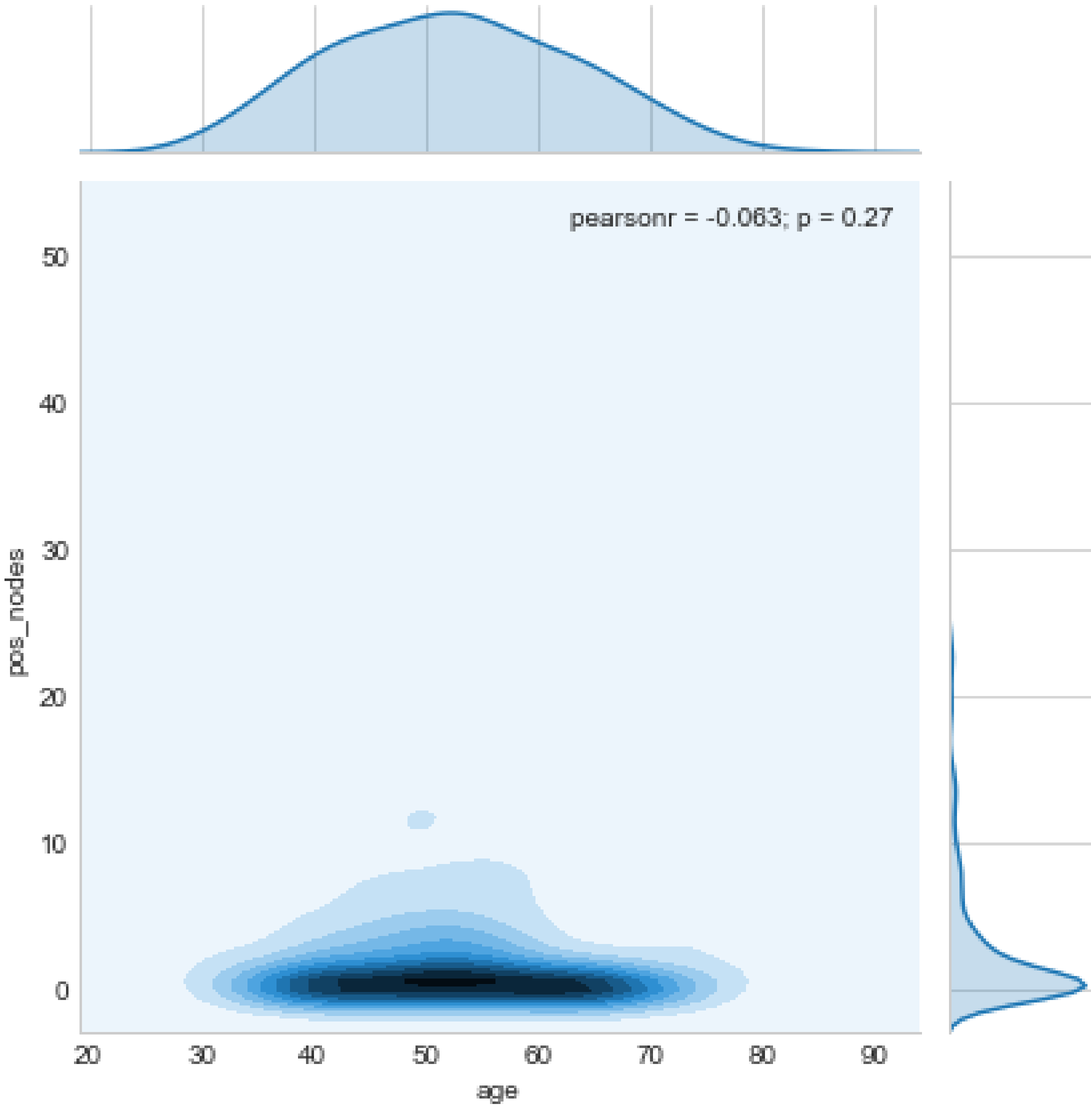




8 contour plot

```
In [55]: sns.jointplot(y='pos_nodes',x='age', data=data, kind = 'resid')
         plt.show()

         sns.jointplot(y='pos_nodes',x='age', data=data, kind = 'kde')
         plt.show()
```


pos_nodes
age
50
40
30
20
10
0
−10
30
40
50
60
70
80



9 Conclusion

All the Patients whose age is less than 34 survived for more than 5 years and none of them survived for 5 years if their age is more then 77

Almost 84% patients survived who were detected with less than or equal to 2 nodes

It is difficult to predict exactly if a person will survive for more than 5 years post operation, with the details provided using the visual method. So Machine learning algorithms would be handy and can predict more accurately than visual methods.