Haberman's Survival

July 14, 2018

1 Haverman's Survival DataSet

1.1 Brief Description :

The Haberman's survival 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.

1.2 Attributes :

- Age of patient at time of operation (numerical)
- Patient's year of operation (year - 1900, 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

1.3 Objective :

To predict whether the breast cancer patient will survive after 5 years based upon features like patient's age, year of treatment and the number of positive axillary lymph nodes.

```
In [1]: # importing packages for later use
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sb
```

1.4 1. Data fetching

```
In [2]: # Here I'm fetching data from 'haberman.csv' file
        suv_data = pd.read_csv('haberman.csv', names=['age', 'operation_year', 'axillary_nodes
        print(suv_data.head())
```

```
   age  operation_year  axillary_nodes  survived_5_years
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
```

1.5 2. Data Preparation

```
In [3]: suv_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306 entries, 0 to 305
Data columns (total 4 columns):
age                 306 non-null int64
operation_year      306 non-null int64
axillary_nodes      306 non-null int64
survived_5_years    306 non-null int64
dtypes: int64(4)
memory usage: 9.6 KB
```

```
In [4]: """
        1. As here the column 'survived_5_years' have data in integer format that will create 
           classes.
        2. So, I'm conerting data to string and the data type as categoty.
        """
        # Assigning 'yes' to 1 and 'no' to 0 in column 'survived_5_years'.
        suv_data['survived_5_years'] = suv_data['survived_5_years'].apply(lambda x: 'yes' if x 
        # Converting data type to category
        suv_data['survived_5_years'] = suv_data['survived_5_years'].astype('category')
        # Reading top 5 recors of dataset
        print(suv_data.head())
```

```
   age  operation_year  axillary_nodes survived_5_years
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]: suv_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306 entries, 0 to 305
Data columns (total 4 columns):
age                 306 non-null int64
operation_year      306 non-null int64
axillary_nodes      306 non-null int64
survived_5_years    306 non-null category
dtypes: category(1), int64(3)
memory usage: 7.6 KB
```

1.5.1 Observation :

- There are four colums in this dataset three of them are integer and one is category type.
- The column 'survived_5_years' have 2 classes they are : 'yes' and 'no'. These two signifies that the patient is alive or not after five years.

1.6 3. High level statistics

In [6]:
```
print("No. of points : ",suv_data.shape[0])
print("No. of features : ",suv_data.shape[1])
print("No. of classes : ", suv_data['survived_5_years'].describe().unique()[1])
```

```
No. of points :  306
No. of features :  4
No. of classes :  2
```

In [7]:
```
print("Data points per class : ")
print(suv_data['survived_5_years'].value_counts())
print("\nData point distribution percentage per class:")
print(suv_data['survived_5_years'].value_counts(normalize=True))
```

```
Data points per class :
yes    225
no      81
Name: survived_5_years, dtype: int64

Data point distribution percentage per class:
yes    0.735294
no     0.264706
Name: survived_5_years, dtype: float64
```

In [8]:
```
suv_data.describe()
```

Out[8]:

	age	operation_year	axillary_nodes
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
max	83.000000	69.000000	52.000000

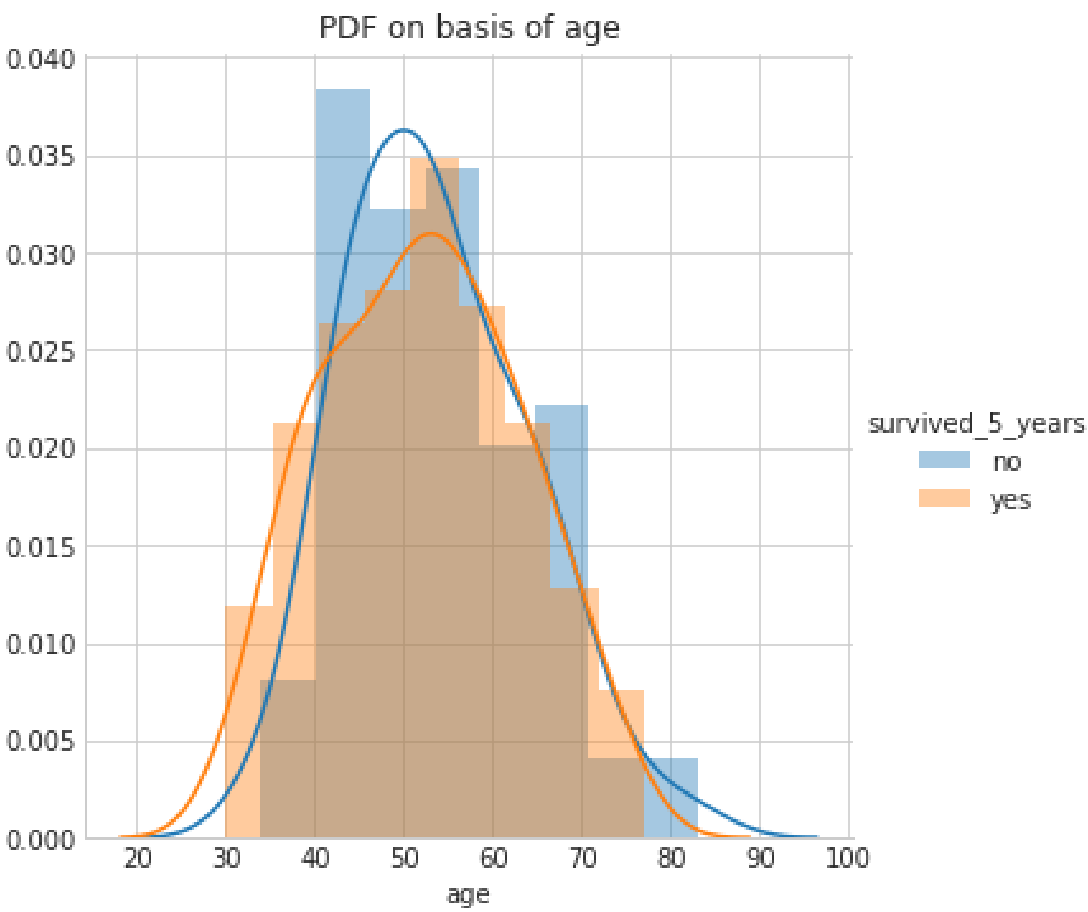
1.6.1 Observarion :

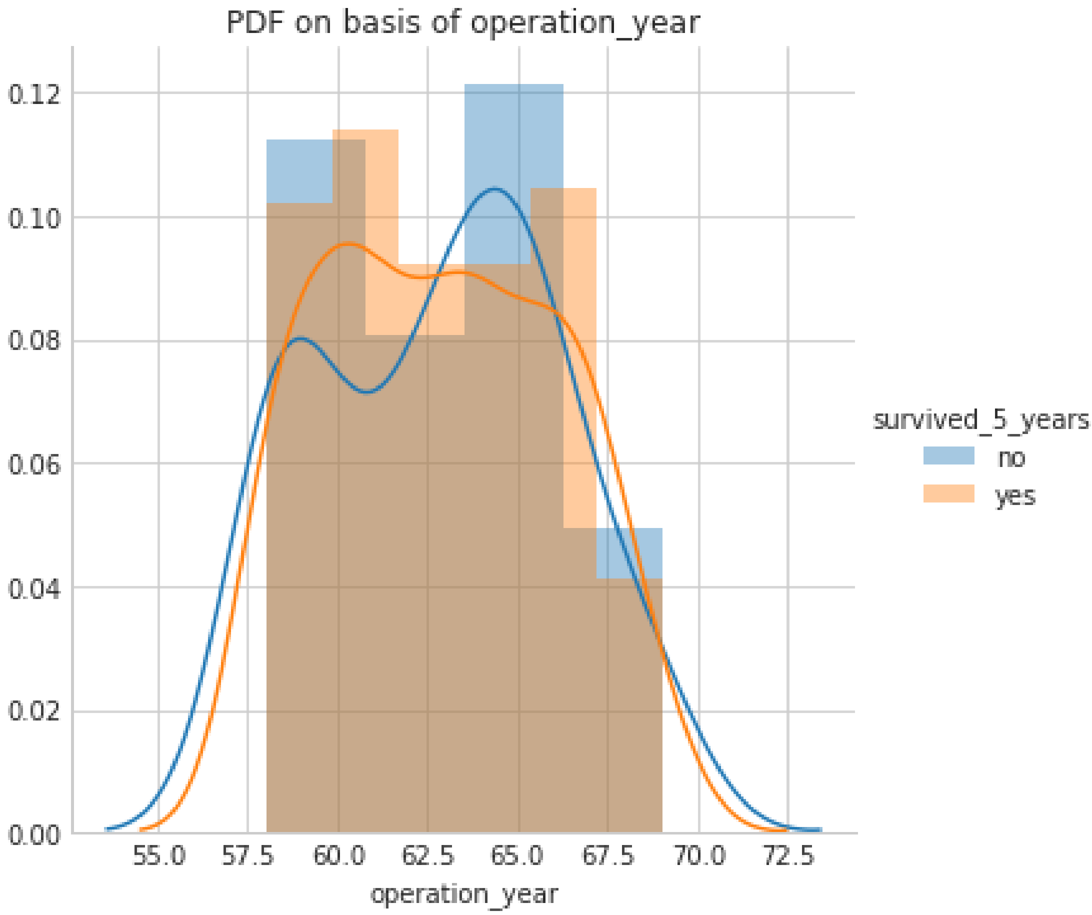
- This dataset contains medical record of 306 patients.
- These patients age vary from 30 to 83.

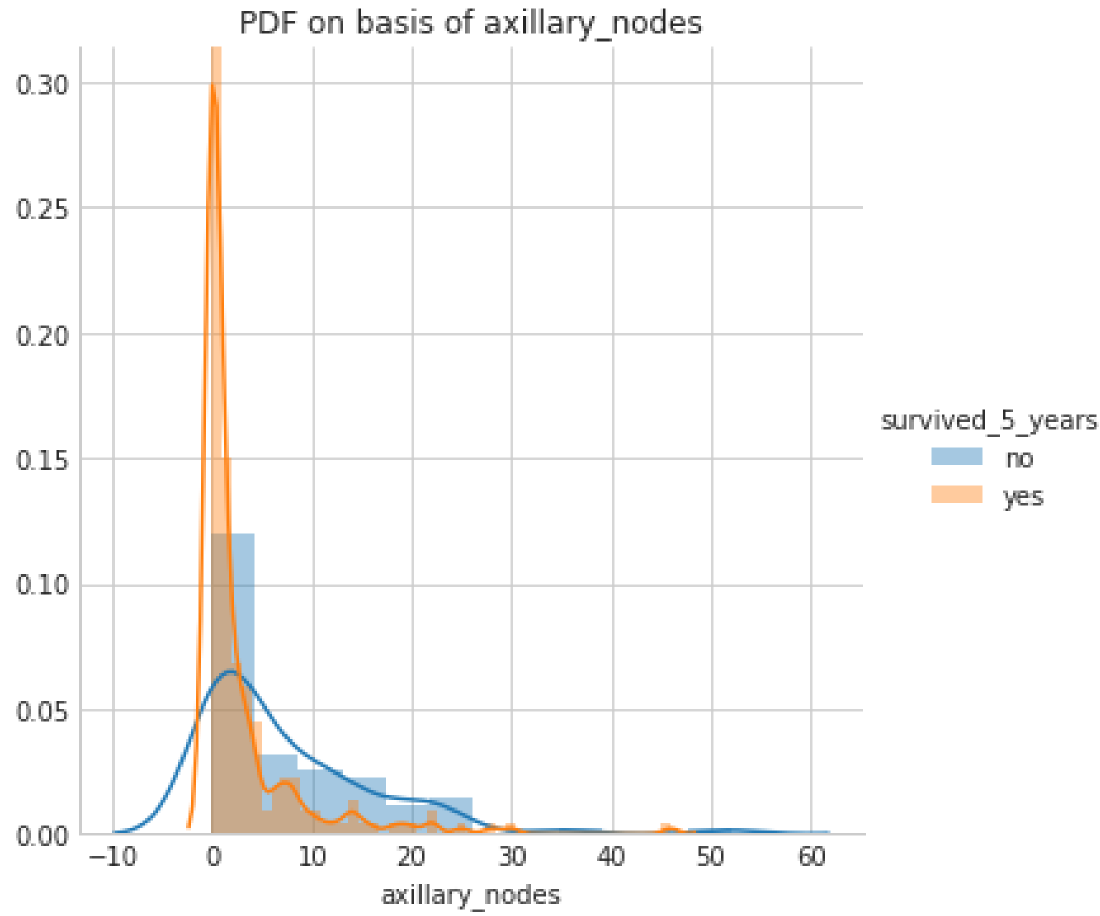
- There are higher chances of breast cancer to women in their 50's (i.e. more precisely in age of 52).
- Approximately 75% of patients have less than 5 positive lymph nodes and nearly 25% of the patients have no positive lymph nodes.
- After the 5 years of the operation 225 people are alive and 81 people have died.
- This dataset is a imbalanced dataset because 73% people belongs to the surviver class.

1.7 4. Univariate Analysis

In [14]:
```
# Histogram/Density Plot and PDF
"""
Through histogram we can get density of data through height in a certain data point.
PDF is the smooth histogram.
Below the bars are histogram and the lines are PDF.
"""
for feature in list(suv_data.columns[:-1]):
    sb.FacetGrid(suv_data, hue='survived_5_years', size=5)\
    .map(sb.distplot, feature)\
    .add_legend()
    plt.title('PDF on basis of '+feature)
    plt.show()
```




PDF on basis of operation_year
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
operation_year
survived_5_years
no
yes




```
In [15]: plt.close()# This line of code releses the memory that have been occupied by previous

         # CDF plot
         """
         CDF is the integration of PDF
         """
         # This list stores the data of patients who are alive.
         surv_yes = suv_data.loc[suv_data["survived_5_years"] == "yes"];
         # This list stores the data of patients who are dead.
         surv_no = suv_data.loc[suv_data["survived_5_years"] == "no"];

         # CDF plot for all features from list of alive patients.
         plt.figure(figsize=(20,5))
         for index, feature in enumerate(list(suv_data.columns[:-1])):
             plt.subplot(1, 3, index+1)
             counts, bin_edges = np.histogram(surv_yes[feature],\
                                              bins=10, density = True)
             pdf = counts/(sum(counts))
```

```
            print("\n",feature,":\n")
            print("BIN Width : ",bin_edges);
            print("PDF : ",pdf);
            cdf = np.cumsum(pdf)
            print("CDF : ",cdf);
            pdf, = plt.plot(bin_edges[1:],pdf,label='PDF')
            cdf, = plt.plot(bin_edges[1:], cdf,label='CDF')
            plt.xlabel(feature)
            plt.legend([pdf, cdf])
            plt.title('CDF of survived patient by '+feature)
        print("\n","*"*45,"CDF of survived patient.","*"*45)
        plt.show()

        # CDF plot for all features from list of dead patients.
        plt.figure(figsize=(20,5))
        for index, feature in enumerate(list(suv_data.columns[:-1])):
            plt.subplot(1, 3, index+1)
            counts, bin_edges = np.histogram(surv_no[feature],\
                                             bins=10, density = True)
            pdf = counts/(sum(counts))
            print("\n",feature,":\n")
            print("BIN Width : ",bin_edges);
            print("PDF : ",pdf);
            cdf = np.cumsum(pdf)
            print("CDF : ",cdf);
            pdf, = plt.plot(bin_edges[1:],pdf,label='PDF')
            cdf, = plt.plot(bin_edges[1:], cdf,label='CDF')
            plt.xlabel(feature)
            plt.legend([pdf, cdf])
            plt.title('CDF of not survived patient by '+feature)
        print("\n","*"*45,"CDF of not survived patient.","*"*45)
        plt.show()
```

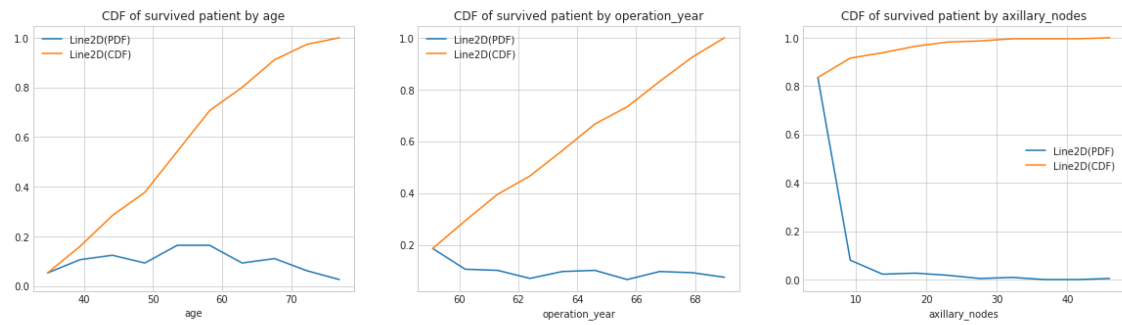
```
 age :

BIN Width :  [30.  34.7 39.4 44.1 48.8 53.5 58.2 62.9 67.6 72.3 77. ]
PDF :  [0.05333333 0.10666667 0.12444444 0.09333333 0.16444444 0.16444444
 0.09333333 0.11111111 0.06222222 0.02666667]
CDF :  [0.05333333 0.16       0.28444444 0.37777778 0.54222222 0.70666667
 0.8        0.91111111 0.97333333 1.        ]

 operation_year :

BIN Width :  [58.  59.1 60.2 61.3 62.4 63.5 64.6 65.7 66.8 67.9 69. ]
PDF :  [0.18666667 0.10666667 0.10222222 0.07111111 0.09777778 0.10222222
 0.06666667 0.09777778 0.09333333 0.07555556]
CDF :  [0.18666667 0.29333333 0.39555556 0.46666667 0.56444444 0.66666667
```

0.73333333 0.83111111 0.92444444 1.   ]

axillary_nodes :

BIN Width : [0.   4.6 9.2 13.8 18.4 23. 27.6 32.2 36.8 41.4 46.]
PDF : [0.83555556 0.08   0.02222222 0.02666667 0.01777778 0.00444444
 0.00888889 0.   0.   0.00444444]
CDF : [0.83555556 0.91555556 0.93777778 0.96444444 0.98222222 0.98666667
 0.99555556 0.99555556 0.99555556 1.   ]

*** CDF of survived patient. **********************



age :

BIN Width : [34. 38.9 43.8 48.7 53.6 58.5 63.4 68.3 73.2 78.1 83.]
PDF : [0.03703704 0.12345679 0.19753086 0.19753086 0.13580247 0.12345679
 0.09876543 0.04938272 0.02469136 0.01234568]
CDF : [0.03703704 0.16049383 0.35802469 0.55555556 0.69135802 0.81481481
 0.91358025 0.96296296 0.98765432 1.   ]

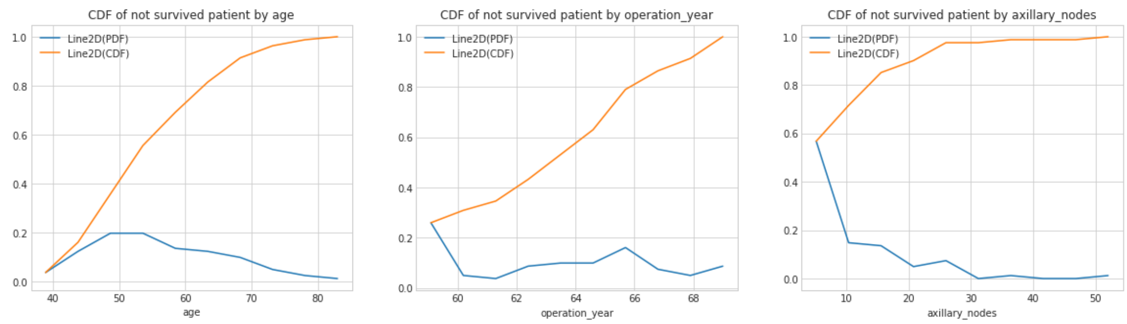
operation_year :

BIN Width : [58. 59.1 60.2 61.3 62.4 63.5 64.6 65.7 66.8 67.9 69.]
PDF : [0.25925926 0.04938272 0.03703704 0.08641975 0.09876543 0.09876543
 0.16049383 0.07407407 0.04938272 0.08641975]
CDF : [0.25925926 0.30864198 0.34567901 0.43209877 0.5308642 0.62962963
 0.79012346 0.86419753 0.91358025 1.   ]

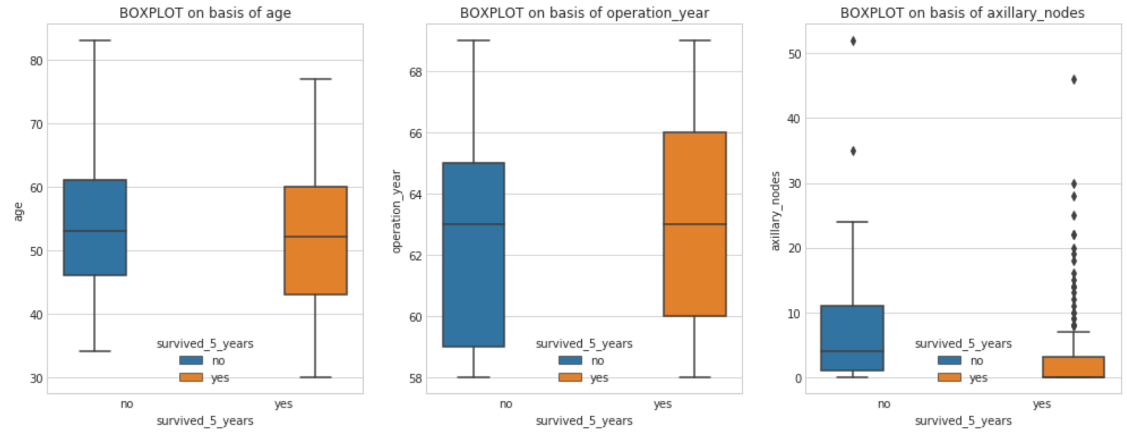
axillary_nodes :

BIN Width : [0.   5.2 10.4 15.6 20.8 26. 31.2 36.4 41.6 46.8 52.]
PDF : [0.56790123 0.14814815 0.13580247 0.04938272 0.07407407 0.
 0.01234568 0.   0.   0.01234568]

```
CDF :  [0.56790123 0.71604938 0.85185185 0.90123457 0.97530864 0.97530864
 0.98765432 0.98765432 0.98765432 1.        ]

 ********************************************* CDF of not survived patient. *******************
```




```
In [16]: plt.close()

         # BOX PLOT
         fig, axes = plt.subplots(1, 3, figsize=(17,6))
         for index, feature in enumerate(list(suv_data.columns[:-1])):
             sb.boxplot( x='survived_5_years', y=feature, data=suv_data, ax=axes[index], hue='s
             .set_title('BOXPLOT on basis of '+feature)
         plt.show()
```



1.7.1 Observation :

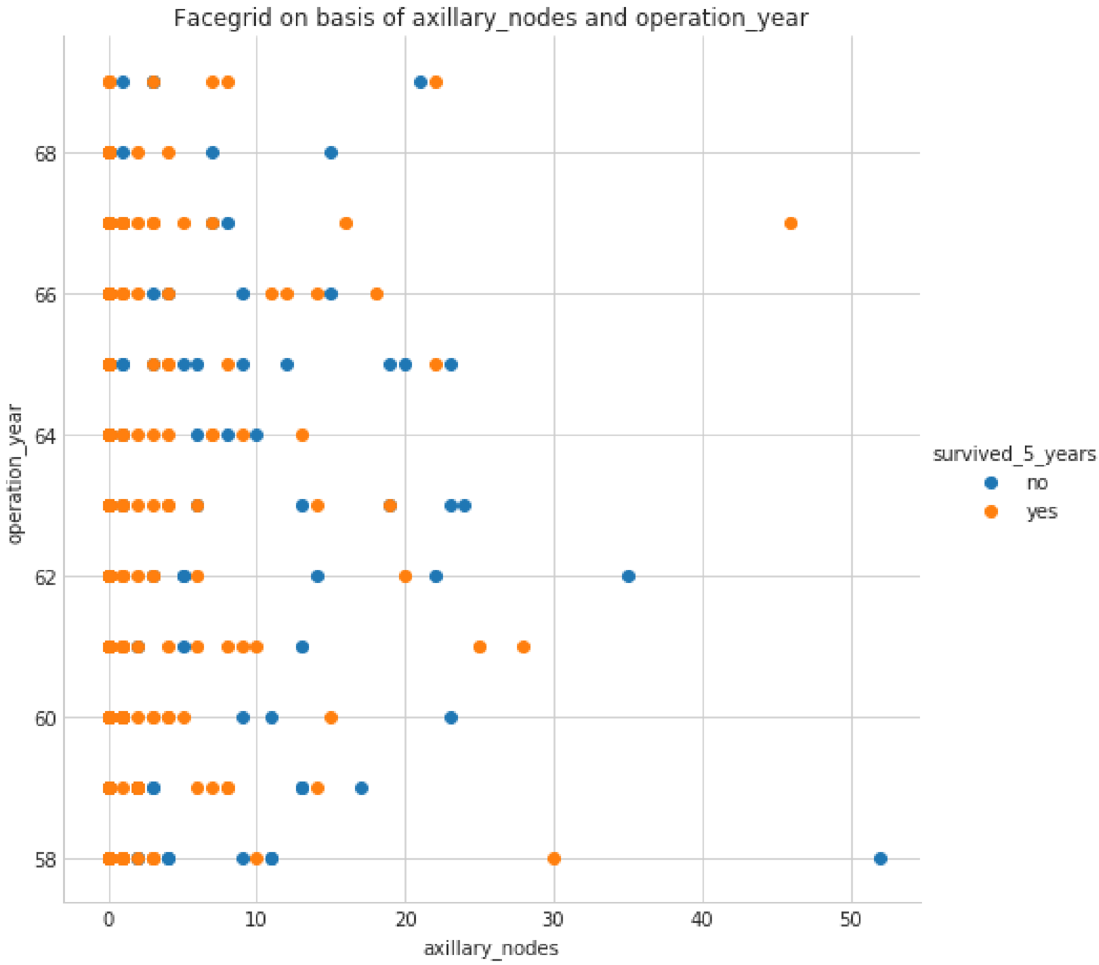
- Almost 85% of the patients have less than or equal to 5(i.e. 0-5) positive axillary lymph node.
- There is a higher chance of survival if the operation have done in the age 30 to early 40's.
- Survival rate slightly increases after year of 1995 compared to before.

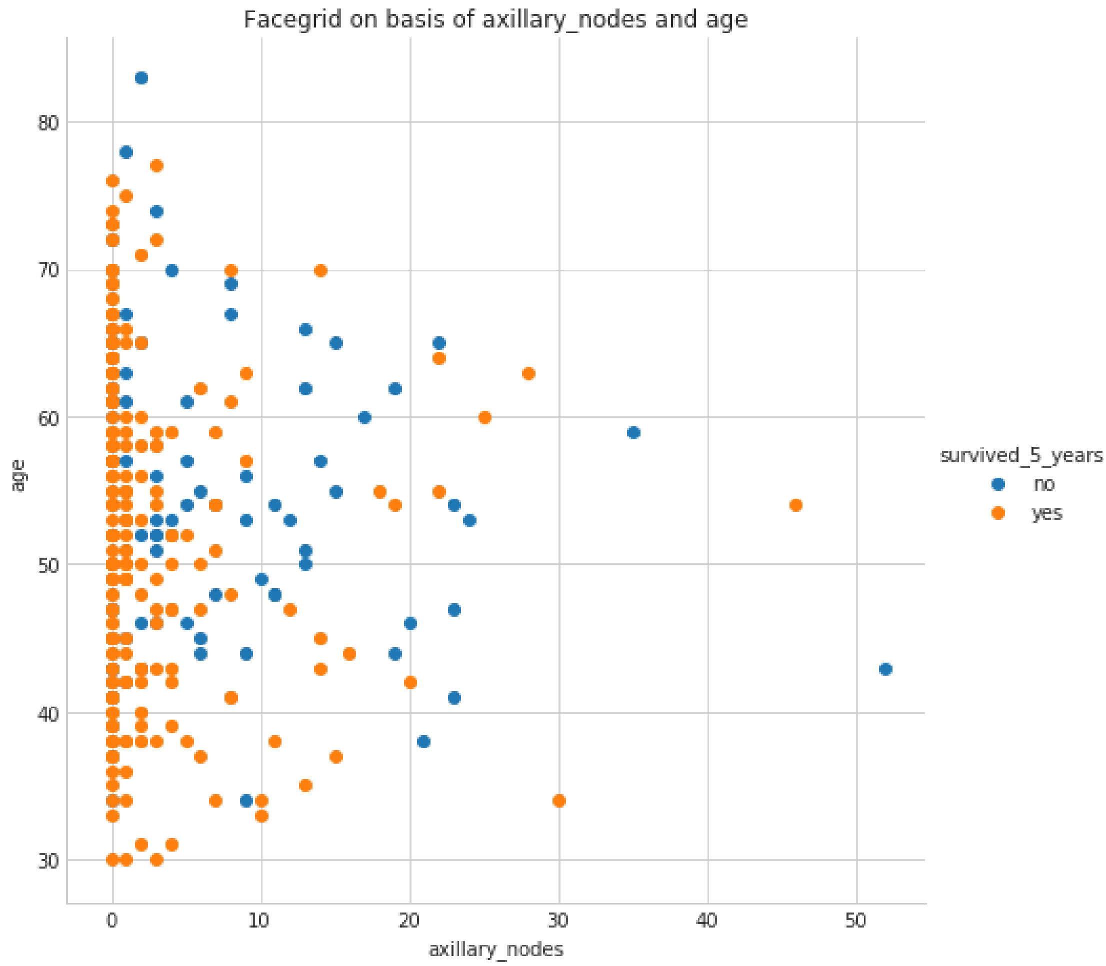
1.8 5. Bivariate analysis

In [18]:
```
# Pair plots
sb.pairplot(suv_data, hue = 'survived_5_years', size=4)
plt.show()
```

In [23]:
```
# SCATTERPLOT for features for better classification

sb.set_style("whitegrid")
sb.FacetGrid(suv_data, hue="survived_5_years", size=7) \
   .map(plt.scatter, "axillary_nodes", "operation_year") \
   .add_legend()
plt.title('Facegrid on basis of axillary_nodes and operation_year')

sb.FacetGrid(suv_data, hue="survived_5_years", size=7) \
   .map(plt.scatter, "axillary_nodes", "age") \
   .add_legend()
```

```python
plt.title('Facegrid on basis of axillary_nodes and age')
plt.show()
```





1.9 Conclusion :

By scattering the data points between {operation_year, axillary_nodes} and {age, axillary_nodes}, we can see the better classification between the two clases than other scatter plots.

`<> @devbox <>`