Exploratory Data Analysis of Haberman Cancer Survival Dataset

Dataset:https://www.kaggle.com/gilsousa/habermans-survival-data-set

Data Description:

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.

Attribute Information:

1. Age of patient at time of operation (numerical)
2. Patients year of operation (year - 1900, numerical)
3. Number of positive axillary nodes detected (numerical)
4. Survival status (class attribute) 1 = the patient survived 5 years or longer 2 = the patient died within 5 year

1. Objective:

Predict whether the patient will survive after 5 years or not based on parameters like patient's age, Patient's year of treatment, number of axillary nodes and Survival status.

Importing the required packages

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import os
```

In [2]:

```
# Changing the Directory
os.chdir("D:/Project Files")
```

In [3]:

```
# Loading the Haberman's Survival Data Set
data= pd.read_csv("haberman.csv", names=["age", "Patient's Year of Operation","number of axillary
nodes", "Survival Status"])
```

Observation:

We have Loaded dataset(haberman.csv) using Pandas and given Column names based on the attribute information.

2. High Level Statistics of the dataset

In [57]:

```
# How many data points and features in the dataset
data.shape
```

Out[57]:

(306, 4)

Observation:

There are 306 (total number of rows) data points and 4 (total number of columns) features.

In [5]:

```
# Column names in the dataset
data.columns
```

Out[5]:

```
Index(['age', 'Patient's Year of Operation', 'number of axillary nodes',
       'Survival Status'],
      dtype='object')
```

Observation:

There are 4 Columns based on the given data attribute.

In [6]:

```
data.head(5)
```

Out[6]:

	age	Patient's Year of Operation	number of axillary nodes	Survival 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

Observation:

Now, we have seen the skeleton of the dataset. Let's see by checking the first 5 data points.

In [7]:

```
data['Survival Status'].unique()
```

Out[7]:

```
array([1, 2], dtype=int64)
```

There are 2 classes in Target attribute(Survival Status) i.e. Class 1 and Class 2

In [8]:

```
# Number of Class in dataset
data['Survival Status'].value_counts()
```

Out[8]:

```
1    225
2     81
Name: Survival Status, dtype: int64
```

Observation:

Of the total 306 data points, Class 1's, 225 patients survived 5 years or longer and Class 2's, 81 patients died within 5 years based on the given attribute. It is imbalance data set because class 1 has 225 data points and class 2 has data points.

In [9]:

```
# Calculate the Percentage of each Class
data["Survival Status"].value_counts()*100/data.shape[0]          #data.shape[0] is for total n
umber of rows i.e.306
```

Out[9]:

```
1    73.529412
2    26.470588
Name: Survival Status, dtype: float64
```

Observation:

1. 73.52% of Class 1 patients survived 5 years or longer
2. 26.47% of Class 2 patients died within 5 years

In [10]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306 entries, 0 to 305
Data columns (total 4 columns):
age                           306 non-null int64
Patient's Year of Operation   306 non-null int64
number of axillary nodes      306 non-null int64
Survival Status               306 non-null int64
dtypes: int64(4)
memory usage: 9.6 KB
```

Observations:

1. There are no missing values in the dataset.
2. The attribute(Survival Status) has integer values but we need to convert it to categorical value for analysis. The values in attribute(Survival Status) are 1 for the patient survived 5 years or longer and 2 for the patient died within 5 years. Hence, We need to mapped to 'yes' for 1 (Patient Survived 5 years or longer) and 'no' for 2 (patient died within 5 years)
3. From the information, all elements are non-null and it has int values.

In [20]:

```
data["Survival Status"] = data["Survival Status"].map({1:"Patient_Survived", 2:"Pateint_died"})
```

Observation: Converting integer values(1 and 2) of attribute(Survival Status) into categorical values i.e. 1= Patient_Survived and 2= Patient _died

In [21]:

```
data.tail(5)
```

Out[21]:

	age	Patient's Year of Operation	number of axillary nodes	Survival Status
301	75	62	1	Patient_Survived
302	76	67	0	Patient_Survived
303	77	65	3	Patient_Survived
304	78	65	1	Pateint_died
305	83	58	2	Pateint_died

Patient's Year of number of axillary

Observation: checking the last 5 data points after converting integer values in categorical values and making the atrribute (Patient's Year of Operation) in YYYY Format.

In [22]:

```
data.describe()
```

Out[22]:

	age	Patient's Year of Operation	number of 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

Observation:

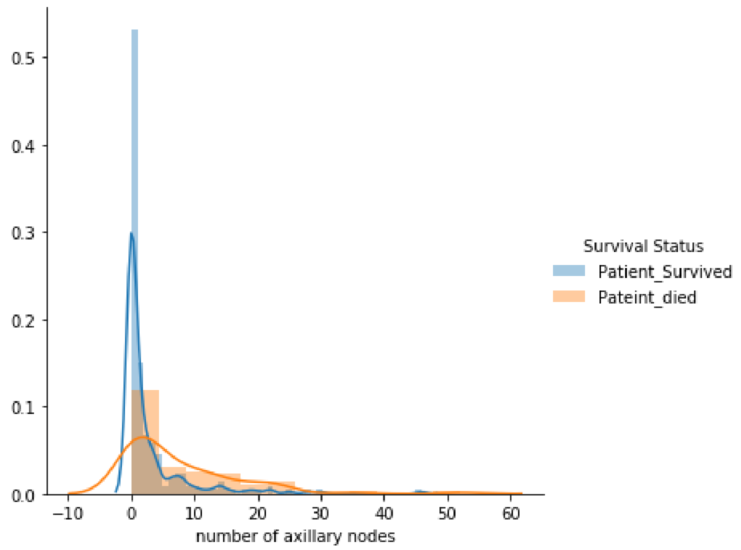
```
1. There are 306 instances that we have in the dataset.
2. The average of all the datapoints for a particular column(age) is ~52.
3. std tells how much dispersion is there in the dat points.
4. The minimum value of age is 30 and maximum value is 83.  Similarly, the minimum value of
number of axillary nodes is 0 and maximum value is 52
```

3. Univariate Analysis

PDF

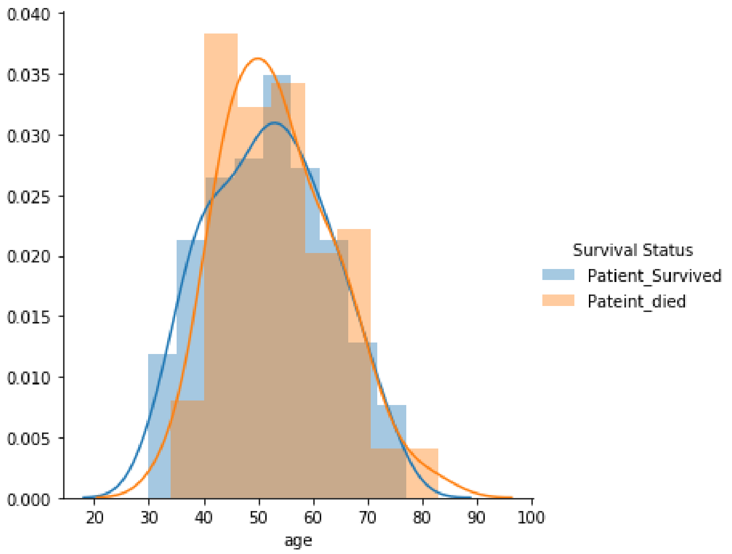
In [23]:

```
sns.FacetGrid(data, hue="Survival Status", size=5).map(sns.distplot, "number of axillary nodes").ad
d_legend()
plt.show()
import warnings                         # warnings
warnings.filterwarnings("ignore")
```



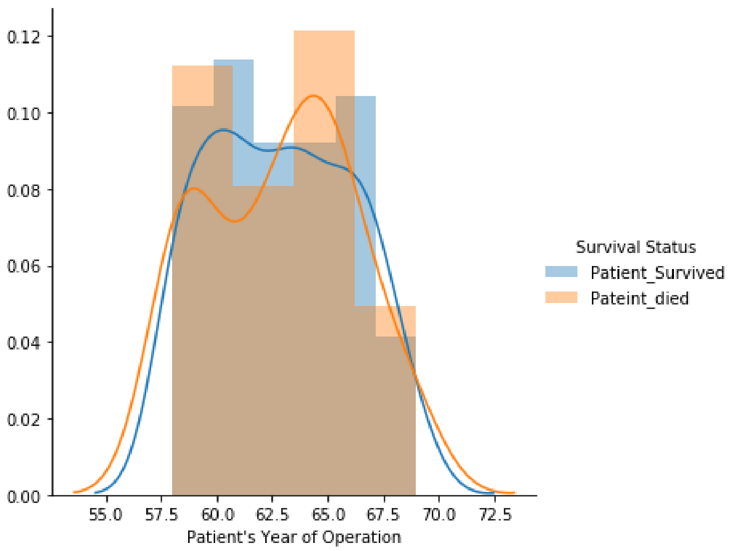
In [24]:

```
sns.FacetGrid(data, hue="Survival Status", size=5).map(sns.distplot, "age").add_legend()
plt.show()
```



In [25]:

```
sns.FacetGrid(data, hue="Survival Status", size=5).map(sns.distplot, "Patient's Year of Operation")
.add_legend()
plt.show()
```



Observation:

1. From the above PDFs(Univariate analysis) both age and Patient's Year of Operation are not good features for useful insights as the distribution is more similar for both people who survived and also dead.
2. number of axillary nodes is the only feature that is useful to know about the survival status of patients as there is difference between the distributions of both Classes. From this distribution, we can infer that most survival patients have fallen into zero (number of axillary nodes).
3. From the Patient's Year of Operation distribution, we can observe that people who didn't survive rise and fall between 1957 and 1960 and more number of people are not survived in the year 1965.

In [18]:

```
Patient_Survived = data.loc[data["Survival Status"] ==1]
Patient_died = data.loc[data["Survival Status"] ==2]
```

In [41]:

```
data.tail()
```

Out[41]:

	age	Patient's Year of Operation	number of axillary nodes	Survival Status
301	75	62	1	Patient_Survived
302	76	67	0	Patient_Survived
303	77	65	3	Patient_Survived
304	78	65	1	Pateint_died
305	83	58	2	Pateint_died

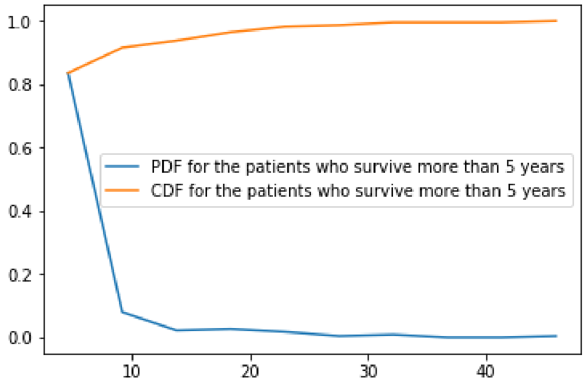
CDF

In [27]:

```
counts, bin_edges = np.histogram(Patient_Survived["number of axillary nodes"], bins=10, density = True)
pdf = counts/(sum(counts))
print(pdf)
print(bin_edges)

# Compute CDF
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:], pdf)
plt.plot(bin_edges[1:], cdf)
plt.legend(['PDF for the patients who survive more than 5 years', 'CDF for the patients who survive more than 5 years'])
plt.show()
```

```
[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. ]
```



Observation:

1. We observe that for all features the statistics are similar for number of axillary nodes .

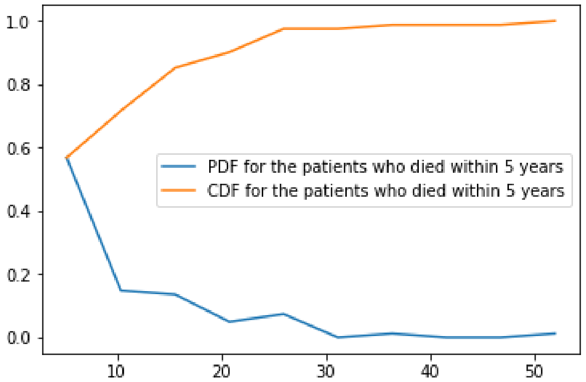
In [28]:

```
counts, bin_edges = np.histogram(Patient_died["number of axillary nodes"], bins=10, density = True)
pdf = counts/(sum(counts))
print(pdf)
print(bin_edges)

# Compute CDF
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.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. ]
```



Observations:

1. Patients above 46 axillary nodes is considered as died within 5 years.

Performing Summary Statistics to distinguish between the Survival and not survival

In [29]:

```
print("Summary Statistics of Patients who survive more than 5 years or longer:")
Patient_Survived.describe()
```

```
Summary Statistics of Patients who survive more than 5 years or longer:
```

Out[29]:

	age	Patient's Year of Operation	number of axillary nodes	Survival Status
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 [30]:

```
print("Summary Statistics of Patients who died within 5 years:")
Patient_died.describe()
```

```
Summary Statistics of Patients who died within 5 years:
```

Out[30]:

	age	Patient's Year of Operation	number of axillary nodes	Survival Status
count	81.000000	81.000000	81.000000	81.0

	age	Patient's Year of Operation	number of axillary nodes	Survival Status
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

Observation:

```
1. From both the tables, we observe that almost for all the features the statistics are sim
ilar except for number_axillary_nodes.
2. The mean of attribute(number of axillary nodes) os more for patients who died within 5 y
ears than patient who have survived for more than 5 years or longer.
3. From the observation of CDF's, we can conclude that patients above 46 axillary nodes con
sidered as Patient_died within 5 years.
```

Median, Percentile, Quantile, IOQ and MAD

In [31]:

```
print("\nMedians:")
print(np.median(Patient_Survived["number of axillary nodes"]))

# Median with an Outlier
print(np.median(np.append(Patient_Survived["number of axillary nodes"],50)))
print(np.median(Patient_died["number of axillary nodes"]))
```

```
Medians:
0.0
0.0
4.0
```

In [32]:

```
print("\n 90th Percentiles:")
print(np.percentile(Patient_Survived["number of axillary nodes"],90))
print(np.percentile(Patient_died["number of axillary nodes"], 90))



from statsmodels import robust
print("\n Median Absolute Deviation")
print(robust.mad(Patient_Survived["number of axillary nodes"]))
print(robust.mad(Patient_died["number of axillary nodes"]))
```

```
 90th Percentiles:
8.0
20.0

 Median Absolute Deviation
0.0
5.930408874022408
```

In [52]:

```
print("\nQuantiles:")
print(np.percentile(Patient_Survived["number of axillary nodes"], np.arange(0,100,25)))
print(np.percentile(Patient_died["number of axillary nodes"], np.arange(0,100,25)))
```

```
Quantiles:
[0. 0. 0. 3.]
[ 0.  1.  4. 11.]
```

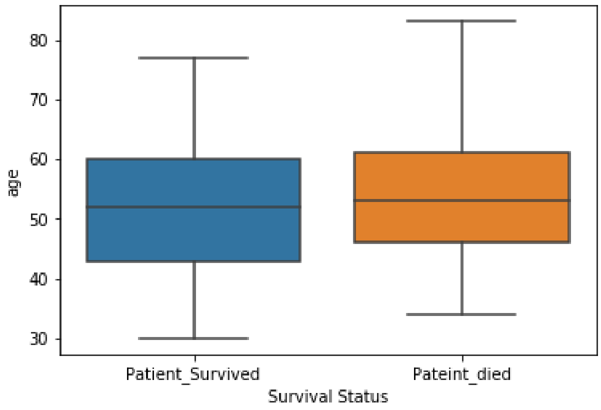
Box Plot and Whiskers

In [160]:

```
sns.boxplot(x="Survival Status", y ="age", data= data)
```

Out[160]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x8d520f0>
```



Observation:

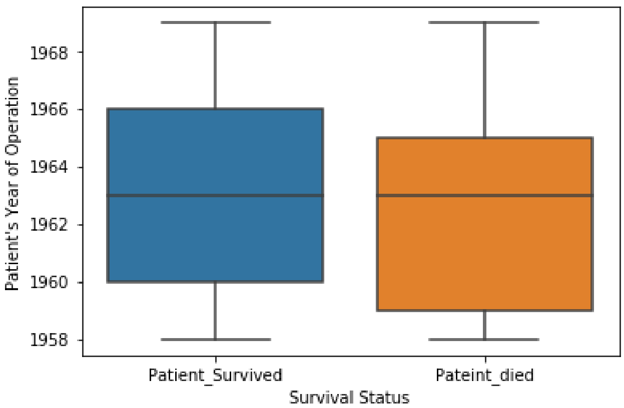
1. Patients who survived have age between 42 to 60 years.
2. Patients who died have age between 48 to 64 years.

In [161]:

```
sns.boxplot(x="Survival Status", y ="Patient's Year of Operation", data= data)
```

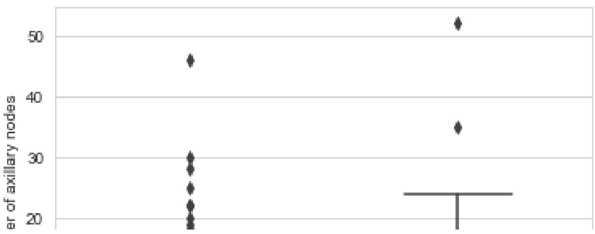
Out[161]:

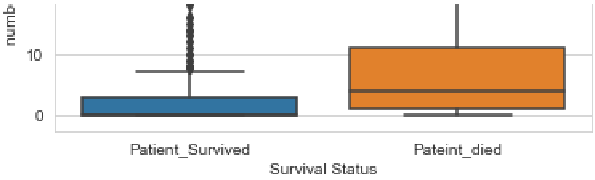
```
<matplotlib.axes._subplots.AxesSubplot at 0x4f71c50>
```



In [56]:

```
sns.boxplot(x="Survival Status", y="number of axillary nodes", data=data)
plt.show()
```

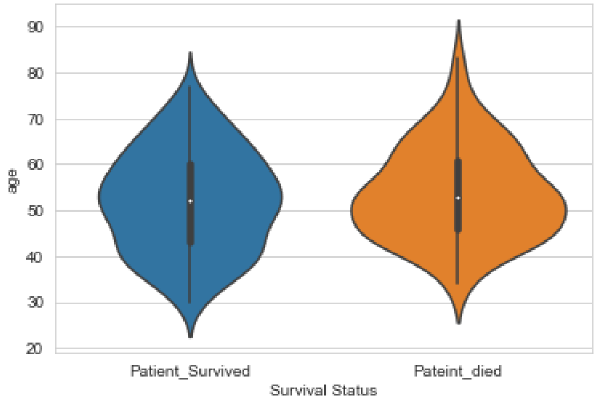




Violin Plots

In [53]:

```
sns.violinplot(x="Survival Status", y="age", data=data, size=7)
plt.show()
```

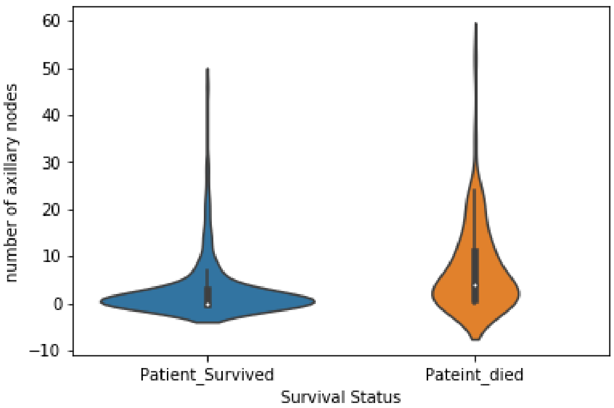


Observation:

```
1. More number of Patients who have Survived have age between 42 to 60 years.
2. More number of Patients who have died have age between 45 to 61 years.
```

In [36]:

```
sns.violinplot(x="Survival Status", y="number of axillary nodes", data=data, size=7)
plt.show()
```



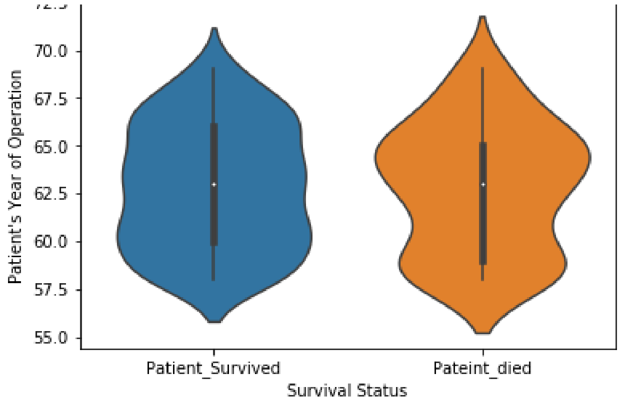
Observation:

```
1. The number of axillary nodes of the Patient_Survived is highly densed from 0 to ~4.
2. 80% of the patients have less than or equal to 4 number of axillary nodes (looking to Vi
olin plot of age and number of axillary nodes.
```

In [37]:

```
sns.violinplot(x="Survival Status", y="Patient's Year of Operation", data=data, size=7)
plt.show()
```

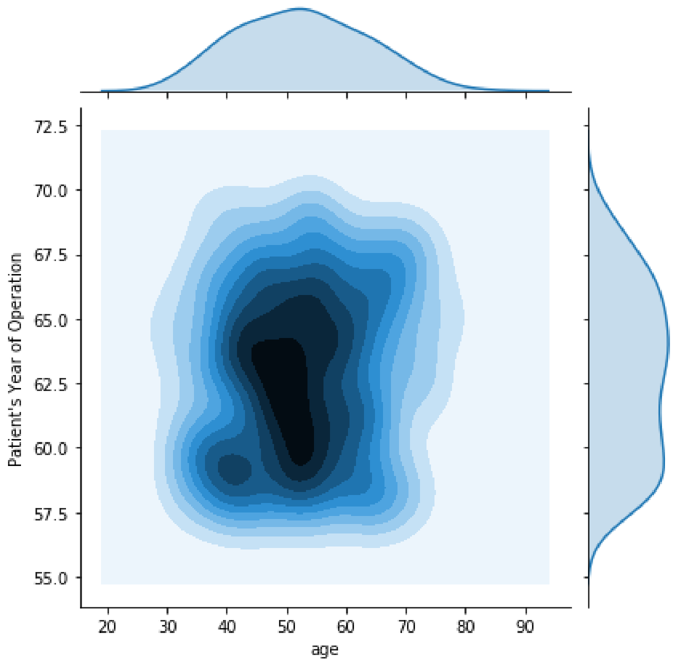
72.5



Contour Plot

In [40]:

```
# 2D Density plot, contors-plot
sns.jointplot(x="age", y="Patient's Year of Operation", data=data, kind="kde")
plt.show()
```



Observation: There are more patients who have undergone operation during the year 1958 to 1964 and patients age between 43 to 58.

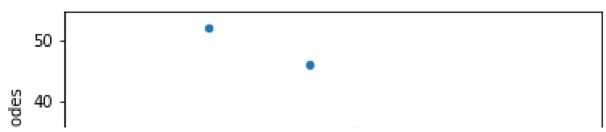
4. Bi-Variate Analysis

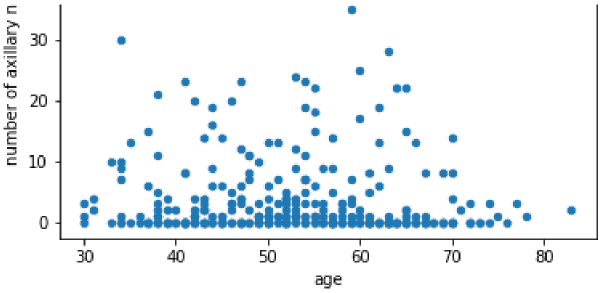
2-D Scatter Plots

Observation:

In [42]:

```
data.plot(kind="Scatter", x='age', y='number of axillary nodes')
plt.show()
```

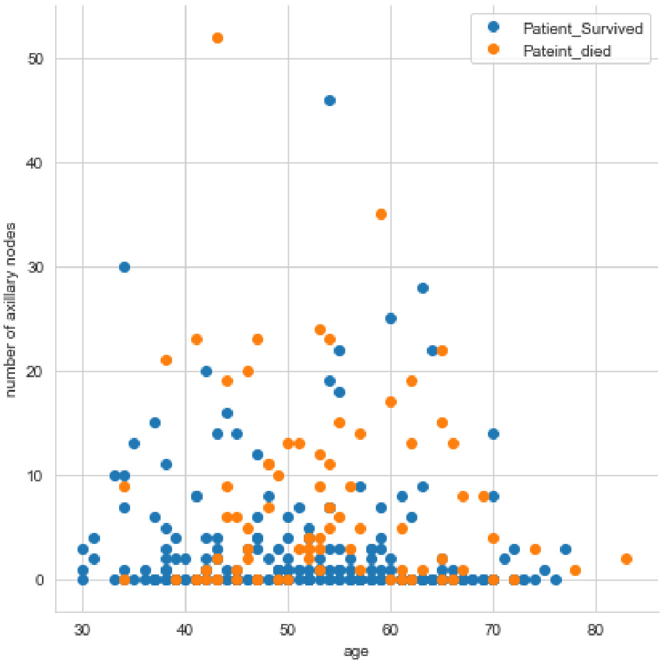




Observation: Most of the patients lie on the 0 number of axillary nodes.

In [43]:

```
# 2-D Scatter Plot with color-coding for each survival Status
# Here 'sns' corresponds to seaborn
sns.set_style("whitegrid")
sns.FacetGrid(data, hue="Survival Status" ,size=6)\
.map(plt.scatter, "age", "number of axillary nodes")
plt.legend()
plt.show()
```



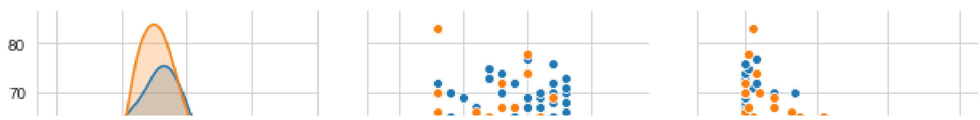
Observation:

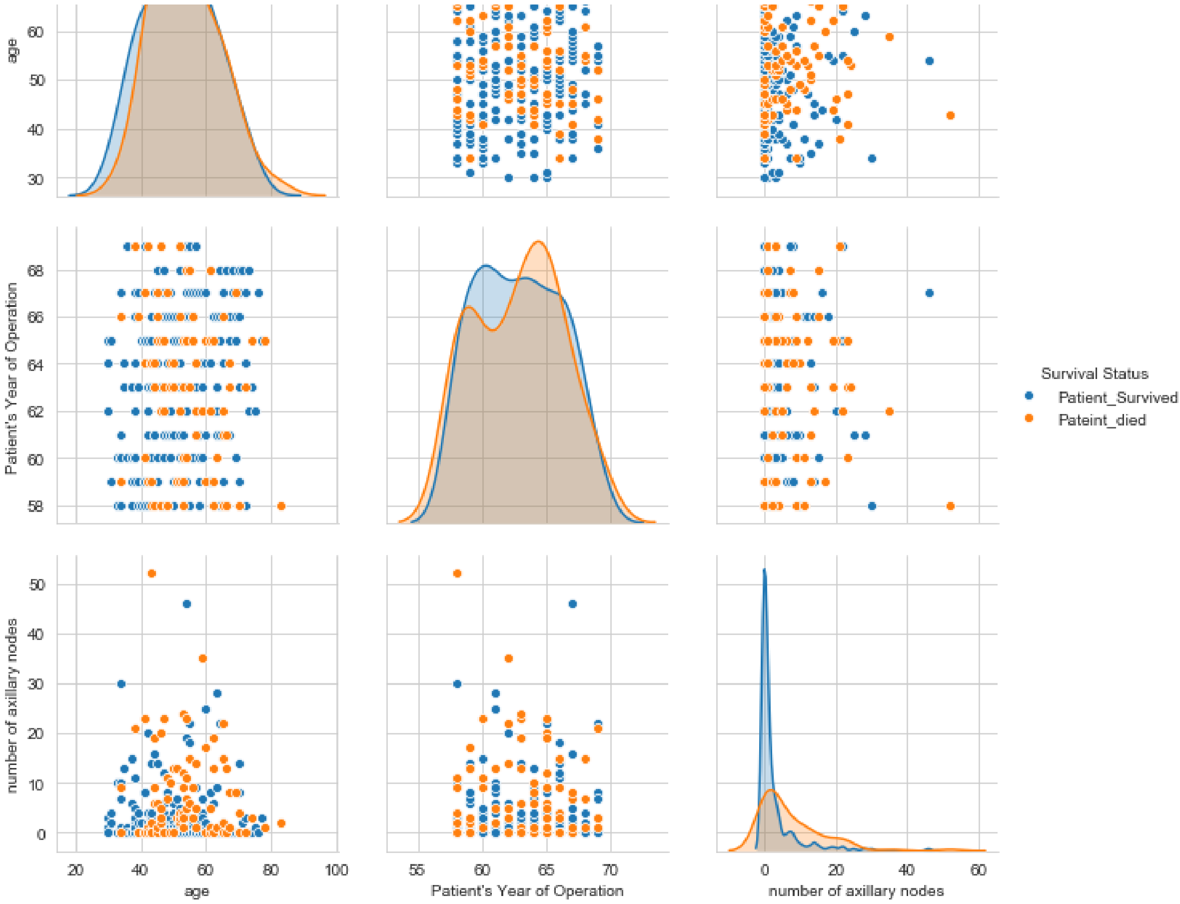
1. Most of the patients have zero number of axillary nodes
2. Blue Points(Patient_Survived) and Orange Points(Patient_died) are not easily separated. That's why we cannot make any decision regarding patient's survival.
3. The reason we plot 2-D Scatter plot of all pair of features to make good classification.

Pair-Plot

In [50]:

```
plt.close()
sns.set_style("whitegrid")
sns.pairplot(data, hue="Survival Status", size=3)
plt.show()
# The diagonal
```





Observation:

```
1. age versus number of axillary nodes is helpful to get the insight that most patients who
Survived have 0 number of        axillary nodes.
2. With Pair plot, we cannot distinguish the data easily because most of them are
overlapping.
```

Conclusion:

1. There are 306 observations with 4 features in the Haberman dataset.
2. The Haberman dataset is imbalanced dataset as we see in attribute(Survival Status): i. 2225 patients belongs to Survival Status 1 (patients who survived 5 years or longer) ii. 81 patients belongs to Survival Status 2 (patients who died within 5 years)
3. Uni-Variate analysis (PDF): i. Attributes age and Patient's Year of Operation are not useful features to get insights as the distribution is more similar for both patients who survived and dead. ii. number of axillary nodes is the only feature that is useful to know about the survival status of patients.From this, we can infer that most survival patients have fallen into zero (number of axillary nodes). iii. From the Patient's Year of Operation distribution, we observe that more number of people are not survived in the year of operation 1965.
4. Uni-Variate analysis (CDF): i. While plotting CDF, we observe that Patients above 46 axillary nodes is considered as died within 5 years.
5. Boxplot: With Plotting Box-Plot, we have conclude two observations: i. Survived Patients have age between 42 to 60 years. ii. Patients who died have age between 48 to 64 years.
6. Violin Plot: i. With plotting Violin plot, we see 80% of the patients have less than or equal to 4 number of axillary nodes (looking to Violin plot of age and number of axillary nodes.
7. Contour Plot: i. There seems to be more patients who have undergone operation during the year 1958 to 1964 and the patients age between 43 to 58.
8. Bi-Variate Analysis(Scatter Plot): i. Most of the patients have zero number of axillary nodes ii. We cannot distinguish between the patients who survived and patients who died.
9. Bi-Variate Analysis (Pair-Plot): i. age versus number of axillary nodes is helpful features to get the insight that most patients who Survived have 0 number of axillary nodes. ii. age and Patient's Year of Operation have overlapping Curves thats why it is difficult for classifying the Survival Status.
10. Mean age of patients who survived is 52 years and who died is 54 years (as we performed Summary Statistics)

References:

1. https://www.kaggle.com/gilsousa/habermans-survival-data-set
2. https://medium.com/@gokulkarthikk/habermans-cancer-survival-visual-exploratory-data-analysis-using-python-e7dcb7ac01ed
3. https://www.kaggle.com/premvardhan/exploratory-data-analysis-haberman-s-survival
4. https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/multivariate-probability-density-contour-plot-1/
5. https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/box-plot-with-whiskers-1/
6. https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/violin-plots-1/
7. https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/cdfcumulative-distribution-function-1/