Information about the dataset: 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. Number of Instances: 306 Number of Attributes: 4 (including the class attribute) Attribute Information:
 Age = Age of patient at time of operation (numerical) Year = Patient's year of operation (year - 1900, numerical) Nodes = Number of positive axillary nodes detected (numerical) Status = Survival status (class attribute) 1 = the patient survived 5 years or longer 2 = the patient died within 5 year In [83]: # Importing the Libraries
<pre>import pandas as pd import seaborn as sns import matplotlib.pyplot as plt import numpy as np import warnings warnings.filterwarnings('ignore')</pre> File Location:
In [111 FILE_PATH = "https://raw.githubusercontent.com/Rahul-Kumaran/Exploratory_Data_Analysis_Haberman/master/Input/haberman.csv" Importing the dataset " Haberman.csv " In [112 # Using the pandas library the csv file is imported to analyse the data haberman = pd.read_csv(FILE_PATH)
In [113 # This command shows the first five rows and information in the dataset haberman.head() Out[113 age year nodes 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 In [87]: # Finding the shape of the dataset print(haberman.shape)
<pre>In [88]: # Finding the name of the columns in the dataset print(haberman.columns) Index(['age', 'year', 'nodes', 'status'], dtype='object') In [89]: # Finding the data type for the respective columns in the dataset haberman.info()</pre>
<pre><class 'pandas.core.frame.dataframe'=""> RangeIndex: 306 entries, 0 to 305 Data columns (total 4 columns): # Column Non-Null Count Dtype </class></pre>
<pre>dtypes: int64(4) memory usage: 9.7 KB In [90]: # Finding the dataset whether it is Balanced or Unbalanced.</pre>
Name: status, dtype: int64 1. This dataset is Unbalanced dataset because the status of survival is not balanced to analyse the data 2. This dataset shows that the 225 patients from 306 where survived more that 5 years and 81 patients where survived less that 5 years. In [91]: # Plotting the 2D Scatter plot
haberman.plot(kind='scatter', x='age', y='status') haberman.plot(kind='scatter', x='year', y='status') haberman.plot(kind='scatter', x='nodes', y='status') plt.show()
1.6 1.4 1.2
1.0 30 40 50 60 70 80 age 1.8
1.6 1.4 1.2
1.0 58 60 62 64 66 68 year 2.0 1.8
1.6 1.4 1.2 1.0
In [92]: # 2D Scatter plot with color coding sns.set_style("whitegrid"); sns.FacetGrid(haberman, hue="status", size=4) \ .map(plt.scatter, "age", "nodes") \ .add_legend();
plt.show(); 50 40 30
status 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Observations: 1. Due to Unbalanced data it is difficult to predict or sepearte the data. 2. More number of data has been overlapped to predict or analyse
<pre>In [93]: # pair plot plt.close(); sns.set_style("whitegrid"); sns.pairplot(haberman, hue="status", size=3); plt.show()</pre>
70 60 50 40
30 68 66 66 64 66 62 65 65 65 65 65 65 65 65 65 65 65 65 65
60 58 50 40
20 20 40 60 80 55 60 65 70 0 20 40 60
20 40 60 80 55 60 65 70 0 20 40 60 Observations: 1. Age and Nodes can be a useful feature to analyse the data. 2. By using the Nodes we can easily identified and seperate the data. PLOT 2 and PLOT 4:
We could actually see that the Age and the Year data is overlapping each other so it is difficult to separate or to analyse the data. So we will be rejecting these plot for analysis PLOT 3 and PLOT 7: In these plots there are some nodes which we can separate the data for analysis or it can be easy to analyse the data for survival. PLOT 6 AND PLOT 8:
These plots looks similar to the plot 2 and plot 4 due to more overlapping of data so we will be rejecting the data for analysis. In [94]: # Histogram sns.histplot(data=haberman, x="nodes", hue="status", multiple="stack") Out[94]: <axessubplot:xlabel='nodes', ylabel="Count"></axessubplot:xlabel='nodes',>
175 150 125 160 775
50 25 0 10 20 30 40 50 nodes In [95]: sns.FacetGrid(haberman, hue="status", size=7) \
<pre>.map(sns.distplot, "nodes") \ .add_legend(); plt.show();</pre>
0.4
0.2 status 1 2
0.1 0.0
Observations: It is noted that the people who have less nodes the survival rate is more. In [96]: sns.FacetGrid(haberman, hue="status", size=7) \ .map(sns.distplot, "age") \ .add_legend(); plt.show();
0.035
0.020 status 1 2
0.010
Observations: We could see that the patients whose age is in between 30 and 75 are having more number of chance for survival and also for death. These data cannot be analysed.
<pre>In [97]: sns.FacetGrid(haberman, hue="status", size=7) \ .map(sns.distplot, "year") \ .add_legend(); plt.show();</pre>
0.10
0.06 status 1 2
0.02 0.00 55.0 57.5 60.0 62.5 65.0 67.5 70.0 72.5 year
Observations: These looks similar to the histogram of Age where the survuval rate and death is equally same for analysing the data. These data cannot be analysed. In [98]: # CDF plot sns.ecdfplot(data=haberman, x="nodes", bue="status", stat="count")
<pre>sns.ecdfplot(data=haberman, x="nodes", hue="status", stat="count") Out[98]: <axessubplot:xlabel='nodes', ylabel="Count"> 225 200 175 150</axessubplot:xlabel='nodes',></pre>
125 8 100 75 50 25 0 10 20 30 40 50
In [99]: #Plot CDF of haberman long survival haberman_long = haberman.loc[haberman["status"] == 1] haberman_short = haberman.loc[haberman["status"] == 2]
<pre>counts, bin_edges = np.histogram(haberman_long['nodes'], bins=10,</pre>
<pre>plt.plot(bin_edges[1:], cdf) #Plot CDF of haberman short survival counts, bin_edges = np.histogram(haberman_short['nodes'], bins=10,</pre>
<pre>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)</pre>
plt.show(); [0.83555556 0.08
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.] 1.0 0.8 0.6
0.4 0.2 0.0 10 20 30 40 50 Observations:
Observations: 1. For long survival it shows that the node which is less than 5 will have 85% of chance of long survival. If the nodes is increasing the survival rate will be less. 2. For short survival it shows that the node which is less than 5 will have 56% of chance of survival. If the nodes increases the survival rate will be more less. In [100 # Finding the Mean, Standard Deviation and other Statistical data. haberman.describe()
Out[100 age year nodes status 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
25% 44.00000 60.00000 0.00000 1.000000 50% 52.00000 63.00000 1.000000 75% 60.750000 65.750000 4.000000 2.000000 max 83.000000 69.000000 52.000000 In [101 # Box Plot
<pre>sns.boxplot(x='status',y='nodes', data=haberman) plt.show()</pre> 50 40
Observations: 1. The threshold value for the long survival is 0 - 7. 2. The threshold value for the short survival is 0 - 25. 3. 25th and 50th percentile for the long survival is same.
3. 25th and 50th percentile for the long survival is same. 4. 50 % of short survival also lies in this threshold so there is 50% of chance for the short survival to survive. In [102 # Violin Plot sns.violinplot(x="status", y="nodes", data=haberman, size=8) plt.show() 00
50 40 80 20
Observations:
1. From violin 1, it shows that the nodes from 0 to 7 the density is more and the survival rate is also more. 2. From violin 2, it shows that the nodes from 0 to 25 the density is more and there is more chance for short survival. In [103 haberman_long.describe() Out[103 age
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 30.00000 58.00000 0.00000 1.0 25% 43.000000 60.00000 0.000000 1.0 50% 52.000000 63.000000 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 [104 haberman_short.describe() Out[104 age year nodes status
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