## **Haberman's Survival 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.

### **Haberman's Survival Dataset**

Dataset: Haberman's Survival Data Set (https://www.kaggle.com/gilsousa/habermans-survival-data-set) Sources:(a) Donor: Tjen-Sien Lim (limt@stat.wisc.edu (mailto:limt@stat.wisc.edu)) (b) Date: March 4, 1999

• The Data Set contains 306 instances of patients who had undergone surgery for breast cancer. • Number of Attributes/Features: 4 (including the class attribute)

### 1. Age (numerical)

**Attributes** 

- 2. Operation year (year 1900, numerical) 3. Number of positive axillary nodes (numerical)
- 4. Survival status (class attribute)

## 1 = the patient survived 5 years or longer; 2 = the patient died within 5 year

**Attribute Information** 

• Survival status:

Represents the age at which patient underwent surgery (30-83).

• Operation year:

Represents the year in which the patient underwent surgery (1958-1969).

• Number of positive axillary lymph nodes:

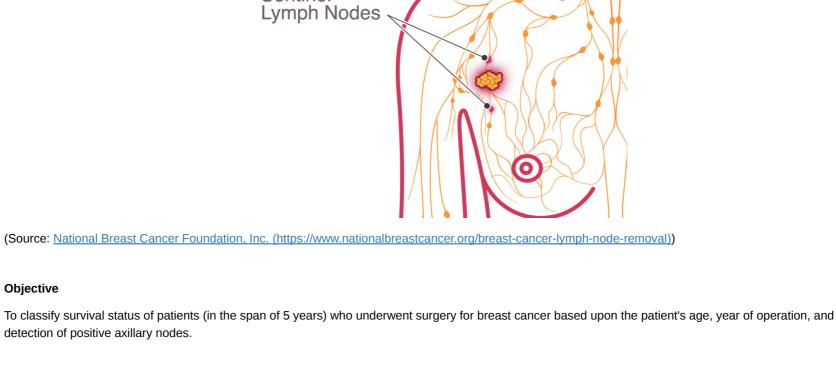
Lymph nodes are small, bean-shaped organs that act as filters along the lymph fluid channels. As lymph fluid leaves the breast and eventually goes back into the bloodstream, the lymph nodes try to catch and trap cancer cells before they reach other parts of the body. Having cancer cells in lymph nodes

under the arm suggests an increased risk of the cancer spreading. When lymph nodes are free, or clear, of cancer, the test results are negative. If lymph nodes have some cancer cells in them, they are called positive.

SENTINEL LYMPH NODES the lymph nodes closest to the tumor

Sentinel

Haberman's survival dataset contains this information as positive axillary nodes (0-52).



**Exploratory Data Analysis of Haberman's Survival Dataset** 

Objective

detection of positive axillary nodes.

2. Data Preparation and Data Loading In [3]: df.head(10) Out[3]: 0 1 2 3

#### **7** 34 59 0 2 **8** 34 66 9 2

Sample data at the top. First 10 data-points.

**297** 73 62 0 1

In [4]: df.tail(10)

Out[4]:

Out[8]:

4 31

operation\_year axil\_nodes

survival\_status

**9** 34 58 30 1

0 1 2 3

**296** 72 67 3 1

**304** 78 65 1 2 **305** 83 58 2 2 In [5]: df.shape Out[5]: (306, 4) Rows represent number of data-points and columns represent number of attributes/features. Dataset contains 306 data-points and 4 features. In [6]: df.columns = ['age'. 'operation vear'. 'axil nodes'. 'survival status'] df.columns

In [9]: df.info() <class 'pandas.core.frame.DataFrame'>

Mapping target values to 'yes' (patient survived after 5 years) and 'no' (patient died within 5 years) for meaningful classification.

df['survival\_status'] = df['survival\_status'].map({1: 'yes', 2: 'no'})

yes

yes

yes

yes

yes

yes

1

306 non-null int64 306 non-null int64

306 non-null int64

306 non-null int64

dtypes: int64(4) memory usage: 9.6 KB There are no missing values. In [10]: # unique values of target variable

In [11]: # map values of target values to 'yes' and 'no'

age operation\_year axil\_nodes survival\_status

65

RangeIndex: 306 entries, 0 to 305 Data columns (total 4 columns):

30 30 65 0 **3** 31 59 2

65

58

60

<class 'pandas.core.frame.DataFrame'> RangeIndex: 306 entries, 0 to 305 Data columns (total 4 columns):

df.head(10)

31

33

33

age

operation\_year axil\_nodes

survival\_status

In [13]: print(df.describe())

**Observations** 

dtypes: int64(3), object(1)

memory usage: 9.6+ KB

Out[11]:

0 34 59 no 66 9 34 no 58 30 ves

4

10

0

306 non-null int64

306 non-null int64

306 non-null int64

306 non-null object

operation\_year axil\_nodes count 306.000000 306.000000 306.000000 52.457516 62.852941 4.026144 mean std 10.803452 3.249405 58.000000 30.000000 min 44.000000 60.000000 25% 50% 52.000000 63.000000 65.750000 60.750000 75% 83.000000 69.000000 max In [14]: print(df.iloc[:.-11.value counts(0)) yes 225 81 no Name: survival\_status, dtype: int64 print(df.iloc[:.-1].value counts(1)\*100)

Name: survival\_status, dtype: float64

• Target variable is imbalanced with 74% 'yes' and 26% 'no' for survival among 306 patients.

• Although the maximum number of positive lymph nodes observed is 52, the average positive lymph nodes observed is about 4.

Univariate analysis is the simplest form of data analysis where the data being analyzed contains only one variable. Since it's a single variable, it doesn't deal

Probability density function (PDF) is a statistical expression that defines a probability distribution for a continuous random variable as opposed to a discrete random variable. When the PDF is graphically portrayed, the area under the curve will indicate the interval in which the variable will fall. The total area in this

• 25% of patients diagnosed with nill positive lymph nodes and 50% of patients diagnosed with a single lymph node.

with causes or relationships. The main purpose of univariate analysis is to describe the data and find patterns that exist within it.

Histograms are plotted to obtain the probability density of respective features. In [16]: | # the area under smoothened histogram is probability density

0.040

0.035

0.030

0.025

0.020

0.015

0.0

3. Univariate Analysis

3.1 Probability Density Function (PDF)

0.010 0.005

0.000 age PDF for feature label operation\_year 0.12 0.10

0.02 0.00 55.0 57.5 60.0 62.5 65.0 67.5 70.0 72.5 operation\_year PDF for feature label axil\_nodes 0.5 0.4 0.3 yes no 0.2 0.1

-100 30 50 axil nodes

3.2 Cumulative Distribution Function (CDF) Cumulative Distribution Function (CDF) is the result of cumulative sum of distributions in PDF.

**Sections** • 1. Import Libraries and Load Data • 2. Data Preparation and Data Loading • 3. Univariate Analysis • <u>4. Bivariate Analysis</u> • <u>5. Conclusions</u> 1. Import Libraries and Load Data In [1]: # import necesarry libraries import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns sns.set() In [2]: # load haberman.csv into a pandas DataFrame df = pd.read csv('haberman.csv', header = None) **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

 73 68 0 1 74 65 3 2 74 63 0 1 75 62 1 1 76 67 0 1 77 65 3 1 Sample data at the bottom. Last 10 data-points.

In [7]: print('Column names in the dataset are: ') Column names in the dataset are: Out[7]: Index(['age', 'operation year', 'axil nodes', 'survival status'], dtype='object') In [8]: df.head() age operation\_year axil\_nodes survival\_status 0 30 30 1 1 30 31 59 1

• The values of target variable 'survival\_status' are of integer datatype. print(list(df['survival status'].unique())) [1, 2] Value 1 represents survival of patient after 5 years of operation. • Value 2 represents nonsurvival of patient after 5 years of operation.

In [12]: df.info()

7.189654 0.000000 0.000000 1.000000 4.000000 52.000000 In [15]: print('\nPercentage target variable distribution\n') Percentage target variable distribution 73.529412 yes 26.470588

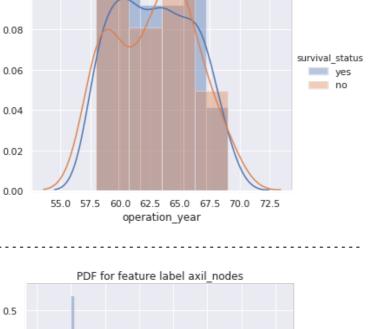
for i, label in enumerate(df.columns[:-1]): sns.FacetGrid(df, hue = 'survival\_status', height = 5).map(sns.distplot, label).add\_legend() plt.title('PDF for feature label + label) plt.show() print('-'\*50) /home/harishrb/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Using a non-tuple sequ ence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this wil l be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result. return np.add.reduce(sorted[indexer] \* weights, axis=axis) / sumval

PDF for feature label age

interval of the graph equals the probability of a continuous random variable occurring.

survival\_status

yes no



survival\_status

Massive overlap in the distribution of target classes is observed for all the features considered individually. Cumulative distribution function is helpful in obtaining more meaningful insights.

```
In [17]: # variables of target classes
          survived = df.loc[df['survival_status'] == 'yes']
          not survived = df.loc[df['survival status'] == 'no']
In [18]: for i, label in enumerate(df.columns[:-1]):
               # CDF for survived class
               counts, bin_edges = np.histogram(survived[label], bins=10, density = True)
              pdf = counts/(sum(counts))
              cdf = np.cumsum(pdf) * 100
              plt.plot(bin_edges[1:], cdf)
               # CDF for not survived class
              counts, bin_edges = np.histogram(not_survived[label], bins=10, density = True)
              pdf = counts/(sum(counts))
              cdf = np.cumsum(pdf) * 100
              plt.plot(bin_edges[1:], cdf)
              plt.xlabel(label)
              plt.ylabel('% of patients')
              plt.legend(('CDF of survived class','CDF of not_survived class'))
              plt.title('CDF for feature label ' + label)
              plt.show()
              print('-'*50)
                             CDF for feature label age
             100
                     - CDF of survived class
                      CDF of not_survived class
              80
           % of patients
              60
              40
              20
               0
                       40
                                       60
                                                70
                                                        80
                                      age
                         CDF for feature label operation_year
             100

    CDF of survived class

                      CDF of not_survived class
              90
              80
           % of patients
              70
```

100 90 of patients 80 % 70 CDF of survived class 60 CDF of not\_survived class 50 20 30 10 axil nodes Observations • 60% of non-surviving patients were above the age of 50.

3.3 Box Plot

60

The box plot (a.k.a. box and whisker diagram) is a standardized way of displaying the distribution of data based on the five number summary: minimum, first quartile, median, third quartile, and maximum. In the simplest box plot the central rectangle spans the first quartile to the third quartile (the interquartile range or

Quartile 2 --> 50th percentile or median

Quartile 3 --> 75th percentile

plt.show() print('-'\*50)

IQR). A segment inside the rectangle shows the median and "whiskers" above and below the box show the locations of the minimum and maximum. Quartile 1 --> 25th percentile

sns.boxplot(x = label,y = 'survival\_status', hue = 'survival\_status', data = df)
plt.title('Box plot for feature label ' + label)

survival\_status

50

distribution. This can be an effective and attractive way to show multiple distributions of data at once.

survival\_status yes yes no no

• Survival rate is slightly higher for the patients that underwent surgery after 1961. • About 82% of surviving patients had 5 or fewer positive axillary lympy nodes.

66

operation\_year

CDF for feature label axil nodes

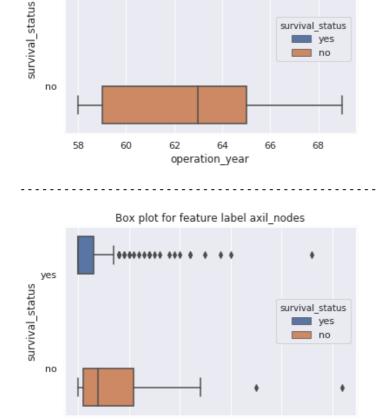
#### Inter Quartile Range (IQR) = Quartile 3 - Quartile 1 Upper whisker --> Quartile 1 - 1.5 \* IQR

Lower whisker --> Quartile 3 + 1.5 \* IQR Points outside the box are the outliers in data. In [19]: for i, label in enumerate(df.columns[:-1]):

yes survival\_status survival\_status yes yes no 30 80 40 50 60 70 age

Box plot for feature label operation year

Box plot for feature label age



20

30

plt.title('Violin plot for feature label ' + label)

Violin plot for feature label age

Violin plot for feature label operation\_year

axil\_nodes

# survival\_status

yes

no

-10

Observations

68

66

30

50

40

operation\_year 64 10

30 axil\_nodes

• The median age observed in surviving patients is around 52 and 75th percentile is around 60.

plt.show() print('-'\*50)

0

3.4 Violin Plot

10

In [20]: for i, label in enumerate(df.columns[:-1]):

20 30 40 50 60 70 80 90 age

Violin plot shows the distribution of quantitative data across several levels of one (or more) categorical variables such that those distributions can be compared. Unlike a box plot, in which all of the plot components correspond to actual datapoints, the violin plot features a kernel density estimation of the underlying

sns.violinplot(x = label, y = 'survival\_status', hue = 'survival\_status', data = df, palette = "Set2")

survival\_status survival\_status yes yes no no 55.0 62.5 65.0 70.0 operation\_year Violin plot for feature label axil\_nodes survival\_status yes yes no no survival\_status

## • The median positive axillary lymph nodes observed in surviving patients is 0 and 75th percentile is less than 5. • The median positive axillary lymph nodes observed in non-surviving patients is around 4 and 75th percentile is around 11. 4. Bivariate Analysis Bivariate analysis is the simultaneous analysis of two variables (attributes). It explores the concept of relationship between two variables, whether there exists an association and the strength of this association, or whether there are differences between two variables and the significance of these differences. **4.1 Scatter Plot** A scatter plot is a two-dimensional data visualization that uses dots to represent the values obtained for two different variables - one plotted along the x-axis and the other plotted along the y-axis. Scatter plots are sometimes called correlation plots because they show how two variables are correlated. In [21]: # 2-D Scatter plot with color-coding for each class of target variable. for i, label in enumerate(df.columns[1:-1]): sns.FacetGrid(df, hue = 'survival\_status', height = 5).map(plt.scatter, 'age', label).add\_legend() plt.title('Scatter plot for age and ' + label)

Scatter plot for age and operation\_year

50

60

Scatter plot for age and axil\_nodes

70

80

60 58

survival\_status yes no

survival\_status yes no

axil\_nodes 10 30 60 70 4.2 Pair Plot Pair plot is used to understand the best set of features to explain a relationship between two variables or to form the most separated clusters. In [22]: sns.pairplot(df, hue = 'survival\_status', height = 4) plt.show() 80 70 60 50 40 30 68 66 operation year 64

survival\_status 62 60 58 50 40 axil\_nodes 10 20 60 100 55 65 70 20 operation\_year axil\_nodes age • Target classes massively overlap in the presence of feature label age. • In comparison, the scatter plot of axillary lymph nodes vs. operation year seems to separate target classes better.

## Observations

5. Conclusions

1. Dataset is significantly small with only 306 instances. Deriving intuitions from fewer data-points to classify survival or non-survival is inefficient. 2. Dataset is imbalanced with 74% of instances belonging to one of the two target classes. 3. Target classes massively overlap and are not linearly separable. Simple linear separation models are not useful in the classification of survival status. 4. The feature 'axil\_nodes' is the most informative among other features.

5. It has been observed that patients with fewer positive axillary nodes have higher chances of survival and vice versa.

References:

#### [1] https://www.nationalbreastcancer.org/ (https://www.nationalbreastcancer.org/) [2] https://www.breastcancer.org/symptoms/diagnosis/lymph\_nodes (https://www.breastcancer.org/symptoms/diagnosis/lymph\_nodes)

[3] https://www.kaggle.com/gilsousa/habermans-survival-data-set (https://www.kaggle.com/gilsousa/habermans-survival-data-set)

[4] https://www.kaggle.com/vj1998/haberman-s-survival-exploratory-data-analysis (https://www.kaggle.com/vj1998/haberman-s-survival-exploratory-data-analysis (https://www.kaggle.com/vj1998/haberman-s

analysis) [5] https://www.kaggle.com/gokulkarthik/haberman-s-survival-exploratory-data-analysis (https://www.kaggle.com/gokulkarthik/haberman-s-survival-exploratorydata-analysis)

[6] https://towardsdatascience.com/will-habermans-survival-data-set-make-you-diagnose-cancer-8f40b3449673 (https://towardsdatascience.com/willhabermans-survival-data-set-make-you-diagnose-cancer-8f40b3449673)

 $\label{thm:com/questions/19125722/adding-a-legend-to-pyplot-in-matplotlib-in-the-most-simple-manner-possible (https://stackoverflow.com/questions/19125722/adding-a-legend-to-pyplot-in-matplotlib-in-the-most-simple-manner-possible (https://stackoverflow.com/questions/19125722/adding-a-legend-to-pyplot-in-matplotlib-in-matplot$  $\underline{/questions/19125722/adding-a-legend-to-pyplot-in-matplotlib-in-the-most-simple-manner-possible)}$ 

[8] http://www.physics.csbsju.edu/stats/box2.html (http://www.physics.csbsju.edu/stats/box2.html)

 $\begin{tabular}{ll} \begin{tabular}{ll} \be$ [10] https://www.saedsayad.com/bivariate\_analysis.htm (https://www.saedsayad.com/bivariate\_analysis.htm)

[12] https://www.quora.com/What-are-pair-plots (https://www.quora.com/What-are-pair-plots)

[11] https://chartio.com/learn/dashboards-and-charts/what-is-a-scatter-plot/ (https://chartio.com/learn/dashboards-and-charts/what-is-a-scatter-plot/)

 $\textbf{[13]} \ \underline{\text{https://stackoverflow.com/questions/35465557/how-to-apply-color-in-markdown (https://stackoverflow.com/questions/35465557/how-to-apply-color-in-markdown (https://stackoverflow.com/qu$ markdown)