Necessary imports In [72]: import pandas as pd import numpy as np import seaborn as sns import matplotlib.pyplot as plt **Understanding data** In [73]: data = pd.read_csv('haberman.csv') print(data.head()) age year nodes status 0 30 64 1 1 1 30 62 3 2 30 65 0 1 3 31 59 2 1 4 31 65 4 1 In [74]: data.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 306 entries, 0 to 305 Data columns (total 4 columns): age 306 non-null int64 year 306 non-null int64 nodes 306 non-null int64 status 306 non-null int64 dtypes: int64(4) memory usage: 9.6 KB In [75]: data.columns Out[75]: Index(['age', 'year', 'nodes', 'status'], dtype='object') In [76]: print (data.head()) age year nodes status 0 30 64 1 1 1 30 62 3 2 30 65 0 3 31 59 2 1 4 31 65 4 In [77]: """A manual inspection of data seems to give only two class labels. Either 1 or 2 but we would confirm""" print(data['status'].unique()) [1 2] In [78]: data.describe() Out[78]: status age year nodes **count** 306.000000 306.000000 306.000000 306.000000 1.264706 **mean** 52.457516 62.852941 4.026144 **std** 10.803452 3.249405 7.189654 0.441899 min 30.000000 58.000000 0.000000 1.000000 60.000000 **25**% 44.000000 0.000000 1.000000 1.000000 **50**% 52.000000 63.000000 1.000000 **75**% 60.750000 65.750000 4.000000 2.000000 **max** 83.000000 69.000000 52.000000 2.000000 Before plotting, we also can find how many of the people treated survived and how many didn't In [71]: print ('count of people who survived and who didn\'t') print (data['status'].value counts()) print ('ratio of people who survived and who didn\'t') print (data['status'].value_counts(normalize = True)) count of people who survived and who didn't 1 225 2 81 Name: status, dtype: int64 ratio of people who survived and who didn't 1 0.735294 2 0.264706 Name: status, dtype: float64 **OBSERVATIONS** • The dataset is complete with no null values • The mean age is approx 52 • The nodes has most of the data in 75th percentile with an absurdly huge outlier of 52 nodes • approximately 73% people survived after the treatment Plotting data and inferencing from it In [97]: # 1 d scatter plot index = 1 print (list(data.columns)) for feature in list(data.columns[:-1]): plt.figure(index) data status1 = data.loc[data['status'] == 1] data_status2 = data.loc[data['status'] == 2] plt.plot(data_status1[feature], np.zeros_like(data_status1[feature]), 'o', label = 'survived') plt.plot(data_status2[feature], np.zeros_like(data_status2[feature]), 'o', label = 'died') plt.xlabel(feature) plt.legend() index += 1 ['age', 'year', 'nodes', 'status'] survived died 0.04 0.02 0.00 -0.02 -0.04 50 60 survived died 0.02 -0.02 -0.04 62 64 66 68 survived died 0.04 0.02 0.00 -0.02 -0.04 30 Observations Nothing useful can be observed/inferenced from the data In [126]: # 2d scatter plot data.plot(kind = 'scatter', x = 'age', y = 'nodes') plt.show() 40 60 Observations: Nothing can be deduced from the above graph (we need to color the nodes) In [128]: # using seaborn for plotting plt.close() plt.figure(1) sns.set_style('whitegrid'); sns.FacetGrid(data, hue='status', height = 5) \ .map(plt.scatter, 'age', 'nodes') \ .add_legend(); plt.figure(2) sns.set_style('whitegrid'); sns.FacetGrid(data, hue='status', height = 5) \ .map(plt.scatter,'year','nodes') \ .add_legend(); plt.figure(3) sns.set_style('whitegrid'); sns.FacetGrid(data, hue='status', height = 5) \ .map(plt.scatter, 'age', 'year') \ .add_legend(); plt.show() <Figure size 432x288 with 0 Axes> 64 Observations: • No correlation between age, year and number of nodes can be observed Trying univariate analysis In [101]: for feature in list(data.columns[:-1]): fig = sns.FacetGrid(data,hue='status',height = 5) fig.map(sns.distplot, feature).add_legend() plt.show() 0.040 0.035 0.030 0.025 0.020 1 2 0.015 0.010 0.005 0.000 50 60 70 80 30 40 0.12 0.10 0.08 status 0.06 1 0.04 0.02 0.00 55.0 57.5 60.0 62.5 65.0 67.5 70.0 72.5 0.4 0.3 1 2 0.2 -10 0 10 20 30 40 50 60 nodes In [108]: plt.figure(figsize=(20,4)) for idx, feature in enumerate(list(data.columns[:-1])): plt.subplot(1, 3, idx+1) print("{} \n\n", format(feature)) counts, bin_edges = np.histogram(data[feature], bins=10, density=True) print("Bin Edges: {}".format(bin_edges)) pdf = counts/sum(counts) print("PDF: {}".format(pdf)) cdf = np.cumsum(pdf) print("CDF: {}".format(cdf)) plt.plot(bin_edges[1:], pdf, bin_edges[1:], cdf) plt.legend(['pdf_survived','cdf_survived']) plt.xlabel(feature) { } Bin Edges: [30. 35.3 40.6 45.9 51.2 56.5 61.8 67.1 72.4 77.7 83.] PDF: [0.05228758 0.08823529 0.1503268 0.17320261 0.17973856 0.13398693 0.13398693 0.05882353 0.02287582 0.00653595] CDF: [0.05228758 0.14052288 0.29084967 0.46405229 0.64379085 0.77777778 0.91176471 0.97058824 0.99346405 1. { } year Bin Edges: [58. 59.1 60.2 61.3 62.4 63.5 64.6 65.7 66.8 67.9 69.] PDF: [0.20588235 0.09150327 0.08496732 0.0751634 0.09803922 0.10130719 0.09150327 0.09150327 0.08169935 0.07843137] CDF: [0.20588235 0.29738562 0.38235294 0.45751634 0.55555556 0.65686275 0.74836601 0.83986928 0.92156863 1. { } nodes Bin Edges: [0. 5.2 10.4 15.6 20.8 26. 31.2 36.4 41.6 46.8 52.] PDF: [0.77124183 0.09803922 0.05882353 0.02614379 0.02941176 0.00653595 0.00326797 0. 0.00326797 0.00326797] CDF: [0.77124183 0.86928105 0.92810458 0.95424837 0.98366013 0.99019608 0.99346405 0.99346405 0.99673203 1. 1.0 pdf_survived 1.0 pdf_survived cdf_survived cdf_survived 0.8 0.8 0.6 0.6 0.6 pdf_survived cdf_survived 0.4 0.4 0.4 0.2 0.2 0.2 0.0 0.0 In [129]: # The node count is a feature that has reasonably visible affects hence plotting the node count values # and it's affect on survial status plt.figure(figsize = (10,8)) data_died = data.loc[data['status'] == 2] data_sur = data.loc[data['status'] == 1] counts, bin_edges = np.histogram(data_died['nodes'],bins = 10, density = True) pdf = counts / sum(counts) cdf = np.cumsum(pdf) plt.plot(bin_edges[1:],pdf) plt.plot(bin_edges[1:],cdf) counts, bin edges = np.histogram(data sur['nodes'], bins=10, density=True) pdf = counts/sum(counts) cdf = np.cumsum(pdf) plt.plot(bin_edges[1:], pdf) plt.plot(bin_edges[1:], cdf) plt.legend(['dead_pdf','dead_cdf','survived_pdf','survived_cdf']) plt.xlabel('nodes') plt.show() 1.0 0.8 0.6 dead_pdf dead_cdf survived_pdf survived_cdf 0.4 0.2 0.0 50 10 20 30 40 Observation • for now it can be observed that the number of nodes is a key factor in determining whether a patient lives or not. • the probability that the patient with less than equal to 4 nodes survives is very high. making box plots and violin plots for better visualization In [119]: plt.figure(figsize = (10,10)) sns.boxplot(x = 'status', y = 'nodes', data = data) plt.show() Observations • The boxplot of status = 1 has 75th percentile value approx 2 and having the 25th and 50th percentile oveerlaped • for boxplot of 2, the 25th percentile is at 2, 50th at 3 and 75th at 11.4 • The whiskers for boxplot 2 is also very large because higher Inter quartile range. In [123]: plt.figure(figsize = (10,10)) sns.violinplot(x = 'status',y = 'nodes',data = data) plt.show() Observations • This is a better version of the box plot with the same observations as that of before. • 75th percentile of patients who died have node count < 11 • 50 percentile of the same below 3 and 25 percentile below 2 • The violin plot for status = 1 shows dense nature of values corresponding to the number of nodes which can be observed from the distplot and the mean In [125]: # I will plot the contour plot of the same to better observe the density! plt.figure(figsize = (10,10)) sns.jointplot(x = 'status', y = 'nodes', data = data, kind = 'kde') plt.show() <Figure size 720x720 with 0 Axes>

0.50 0.75 1.00 1.25 1.50 1.75 2.00 2.25 2.50

surface cannot be visualised from the plots.

• This contour plot confirms the greater density of the boxplot for status 1 corresponding to the number of nodes

• Number of nodes is an important feature and if number of nodes are less, the patient is likely to survive.

• We need to add additional features to better fit the data, features incorporating nodes and age can work(polynomial features)

• To make a model out of the given data just by observing the closeness of the data is not possible because a visible boundary/plane/any n-dimensional

Observations:

CONCLUSIONS