PRML LAB-3

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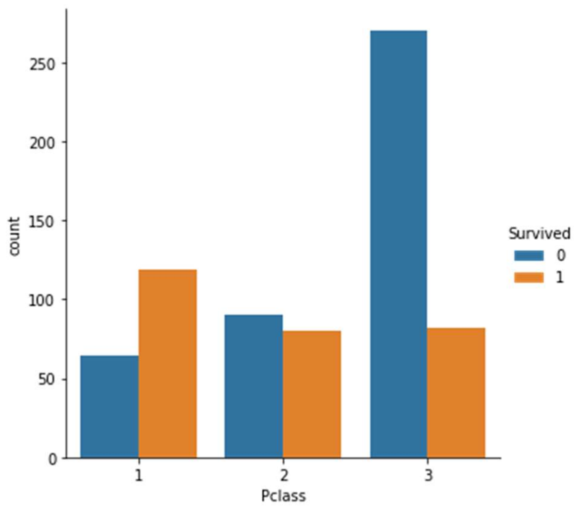
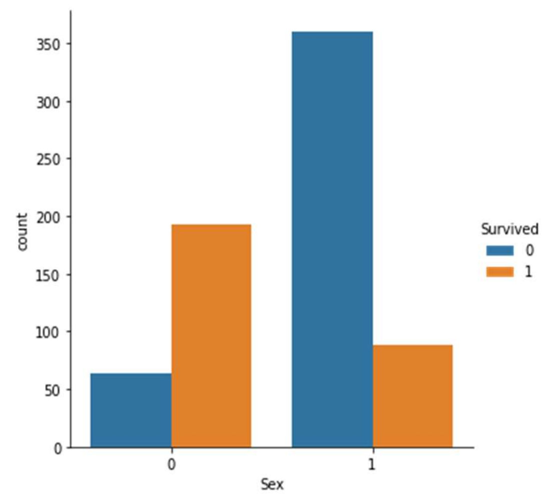
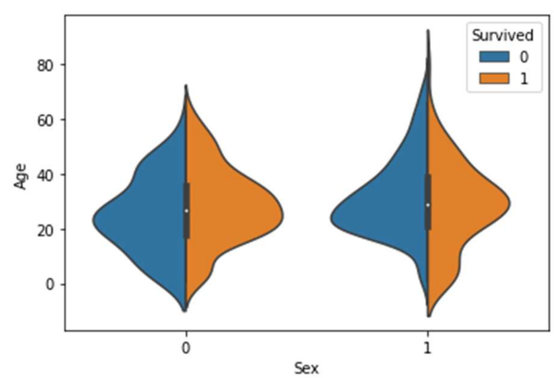
Q-1)

1.) DATA VISUALIZATION







We mainly visualize the plots of “Pclass” and its count, “Sex” and its count, Relation between “Sex” and “Age”. All plots have “Survived” as the key. For the same plots are: -

2.) Identifying the naïve bayes

For identifying the naïve bayes variant we can find all the scores of different variants as shown:

```
GaussianNB() --> 0.15602836879432624
CategoricalNB() --> 0.2198581560283688
ComplementNB() --> 0.375886524822695
MultinomialNB() --> 0.36879432624113473
BernoulliNB() --> 0.15602836879432624
mse on combining categorical and gaussian 0.3120567375886525
```

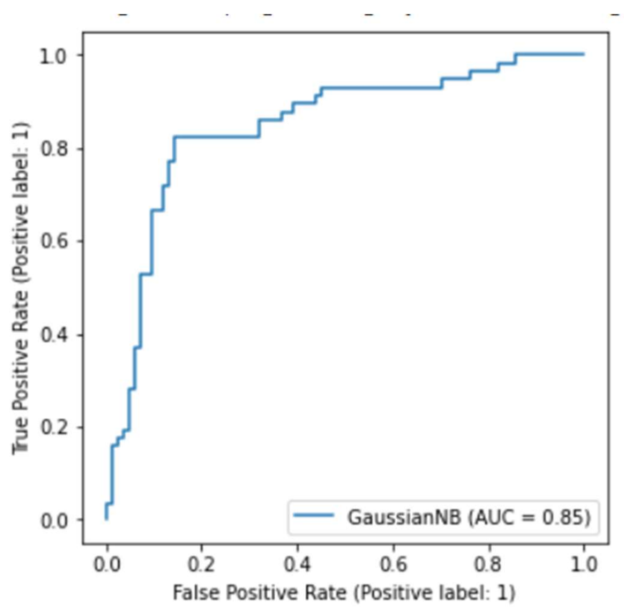
From the above observations of mean squared errors we can confirm that Gaussian naïve bayes variant should be used. We will also use the Heat map to rule out the highly correlated features.

3.) Performance based on metrics

Evaluation Metrics: -

```
0.8439716312056738
Confusion Matrix -->
[[72 12]
 [10 47]]
Precision Score --> 0.7966101694915254
Recall Score --> 0.8245614035087719
F1-Score --> 0.8103448275862069
```

Plotting of curve: -

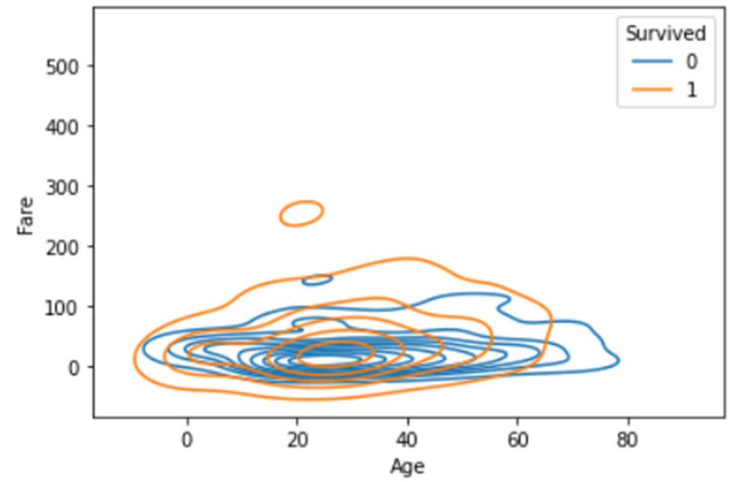


4.) 5-fold Cross Validation

On performing Cross Validation, we get 77% of score as mean score.

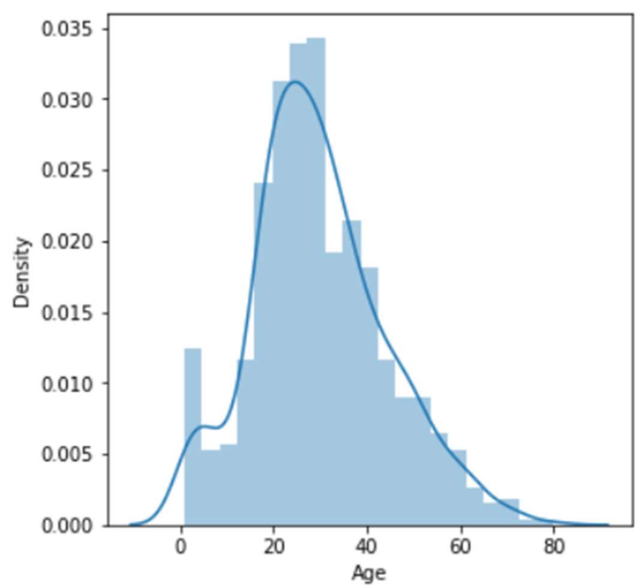
```
0.7773049645390071
```

5.) Plotting the Contour Plots between different Features



6.) Comparing With the Decision Tree Classifier

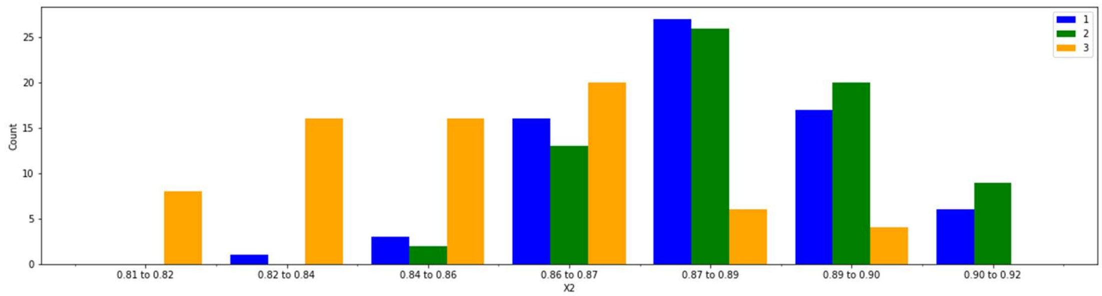
```
Model_DTC score --> 0.7276595744680852
Model_Gaussian score --> 0.7773049645390071
```

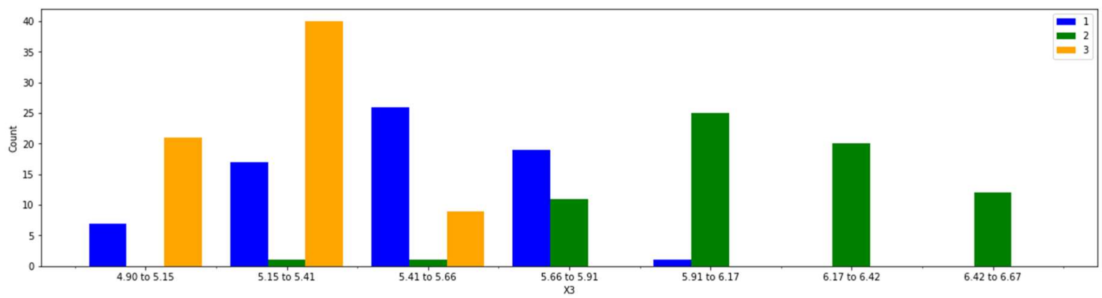


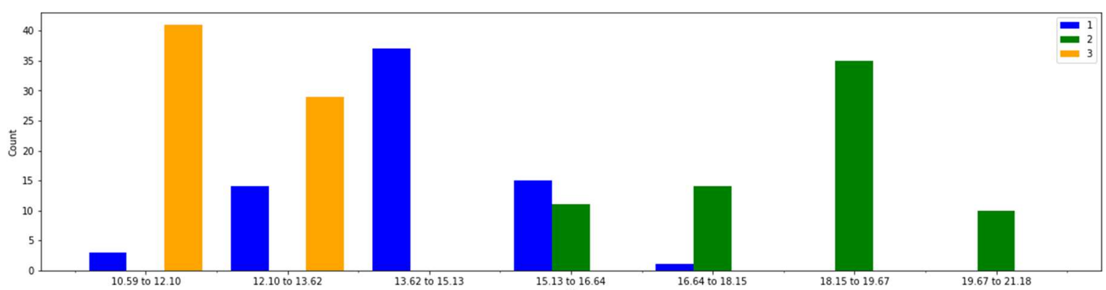
We can see that it is normal distribution hence Gaussian Variant of Naïve Bayes is better than Decision Tree Classifier. In Naive Bayes we assume that features are independent of each other. A major advantage of this variant is that it rarely produces a overfitted model.

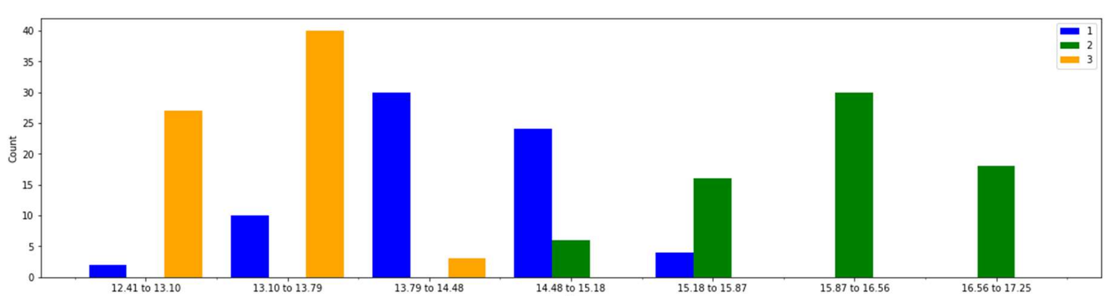
Q-2)

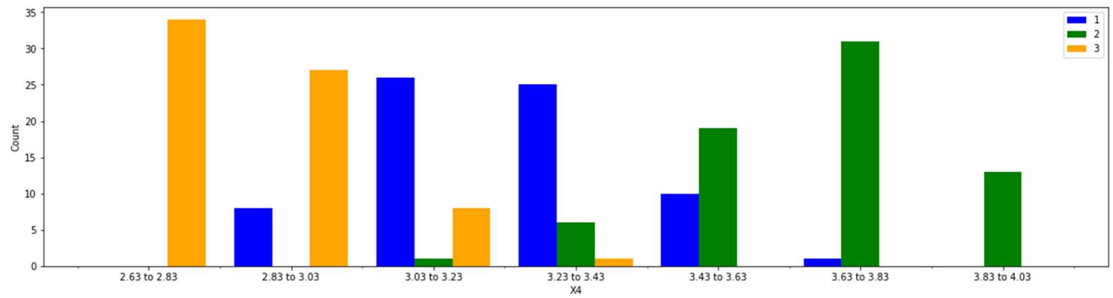
1.) Plotting Histogram

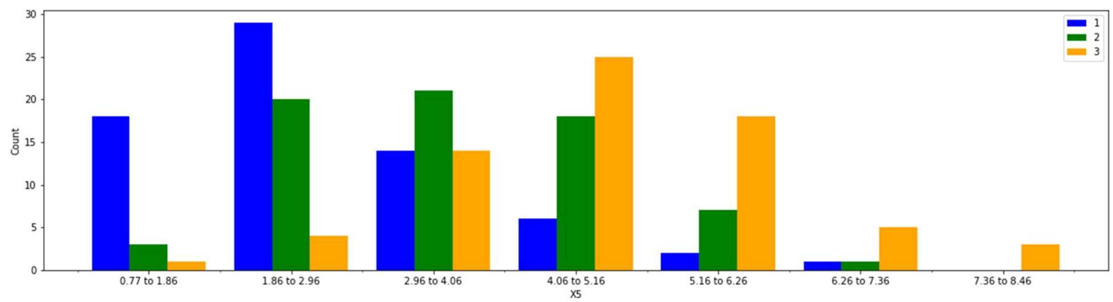


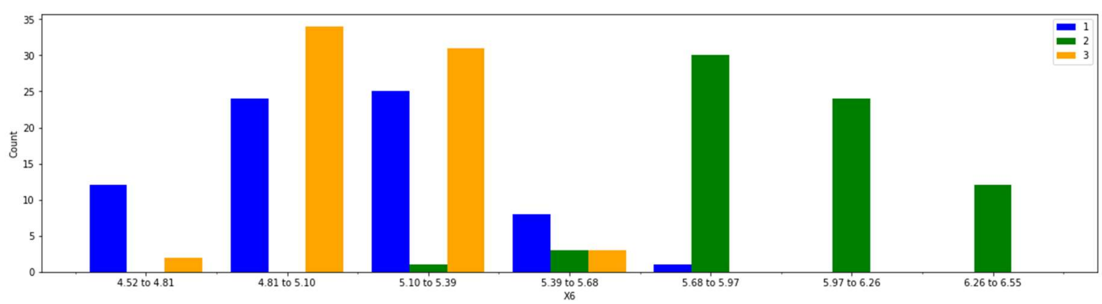












2.) Prior Probability of Classes

```
{1: 0.3333333333333333, 2: 0.3333333333333333, 3: 0.3333333333333333}
```

3.) Discretize the bins

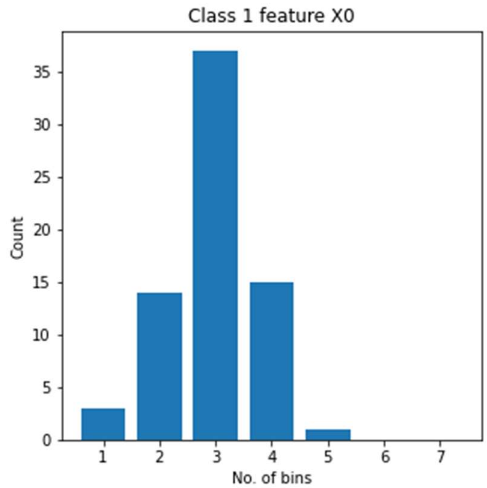
	X0	X1	X2	X3	X4	X5	X6	Y
0	4	4	4	4	4	2	3	1
1	3	4	5	3	4	1	2	1
2	3	3	7	2	4	2	2	1
3	3	3	6	2	4	2	1	1
4	4	4	7	3	5	1	3	1
...	...	...	...	...	...	...	...	...
205	2	2	5	1	2	3	2	3
206	1	1	3	1	1	4	2	3
207	2	2	6	2	4	7	2	3
208	1	2	3	2	2	3	2	3
209	2	2	4	2	2	5	2	3

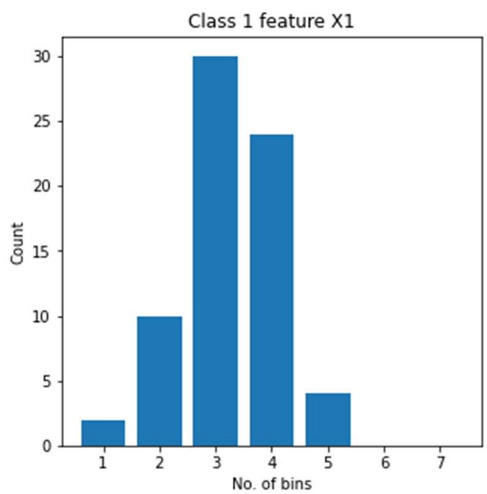
210 rows × 8 columns

4.) Likelihood/Class Conditional Probability

```
Class 1 X0
{1: 0.04285714285714286, 2: 0.2, 3: 0.5285714285714286, 4: 0.21428571428571427, 5: 0.014285714285714285, 6: 0.0, 7: 0.0}
Class 1 X1
{1: 0.02857142857142857, 2: 0.14285714285714285, 3: 0.42857142857142855, 4: 0.34285714285714286, 5: 0.05714285714285714, 6: 0.0, 7: 0.0}
Class 1 X2
{1: 0.0, 2: 0.014285714285714285, 3: 0.04285714285714286, 4: 0.22857142857142856, 5: 0.38571428571428573, 6: 0.24285714285714285, 7: 0.08571428571428572}
Class 1 X3
{1: 0.1, 2: 0.24285714285714285, 3: 0.37142857142857144, 4: 0.2714285714285714, 5: 0.014285714285714285, 6: 0.0, 7: 0.0}
Class 1 X4
{1: 0.0, 2: 0.11428571428571428, 3: 0.37142857142857144, 4: 0.35714285714285715, 5: 0.14285714285714285, 6: 0.014285714285714285, 7: 0.0}
Class 1 X5
{1: 0.2571428571428571, 2: 0.4142857142857143, 3: 0.2, 4: 0.08571428571428572, 5: 0.02857142857142857, 6: 0.014285714285714285, 7: 0.0}
Class 1 X6
{1: 0.17142857142857143, 2: 0.34285714285714286, 3: 0.35714285714285715, 4: 0.11428571428571428, 5: 0.014285714285714285, 6: 0.0, 7: 0.0}
Class 2 X0
{1: 0.0, 2: 0.0, 3: 0.0, 4: 0.15714285714285714, 5: 0.2, 6: 0.5, 7: 0.14285714285714285}
Class 2 X1
{1: 0.0, 2: 0.0, 3: 0.0, 4: 0.08571428571428572, 5: 0.22857142857142856, 6: 0.42857142857142855, 7: 0.2571428571428571}
Class 2 X2
{1: 0.0, 2: 0.0, 3: 0.02857142857142857, 4: 0.18571428571428572, 5: 0.37142857142857144, 6: 0.2857142857142857, 7: 0.12857142857142856}
Class 2 X3
{1: 0.0, 2: 0.014285714285714285, 3: 0.014285714285714285, 4: 0.15714285714285714, 5: 0.35714285714285715, 6: 0.2857142857142857, 7: 0.17142857142857143}
Class 2 X4
{1: 0.0, 2: 0.0, 3: 0.014285714285714285, 4: 0.08571428571428572, 5: 0.2714285714285714, 6: 0.44285714285714284, 7: 0.18571428571428572}
Class 2 X5
{1: 0.04285714285714286, 2: 0.2857142857142857, 3: 0.3, 4: 0.2571428571428571, 5: 0.1, 6: 0.014285714285714285, 7: 0.0}
Class 2 X6
{1: 0.0, 2: 0.0, 3: 0.014285714285714285, 4: 0.04285714285714286, 5: 0.42857142857142855, 6: 0.34285714285714286, 7: 0.17142857142857143}
Class 3 X0
{1: 0.5857142857142857, 2: 0.4142857142857143, 3: 0.0, 4: 0.0, 5: 0.0, 6: 0.0, 7: 0.0}
Class 3 X1
{1: 0.38571428571428573, 2: 0.5714285714285714, 3: 0.04285714285714286, 4: 0.0, 5: 0.0, 6: 0.0, 7: 0.0}
Class 3 X2
{1: 0.11428571428571428, 2: 0.22857142857142856, 3: 0.22857142857142856, 4: 0.2857142857142857, 5: 0.08571428571428572, 6: 0.05714285714285714, 7: 0.0}
Class 3 X3
{1: 0.3, 2: 0.5714285714285714, 3: 0.12857142857142856, 4: 0.0, 5: 0.0, 6: 0.0, 7: 0.0}
Class 3 X4
{1: 0.4857142857142857, 2: 0.38571428571428573, 3: 0.11428571428571428, 4: 0.014285714285714285, 5: 0.0, 6: 0.0, 7: 0.0}
Class 3 X5
{1: 0.014285714285714285, 2: 0.05714285714285714, 3: 0.2, 4: 0.35714285714285715, 5: 0.2571428571428571, 6: 0.07142857142857142, 7: 0.02857142857142857}
Class 3 X6
{1: 0.02857142857142857, 2: 0.4857142857142857, 3: 0.44285714285714284, 4: 0.04285714285714286, 5: 0.0, 6: 0.0, 7: 0.0}
```

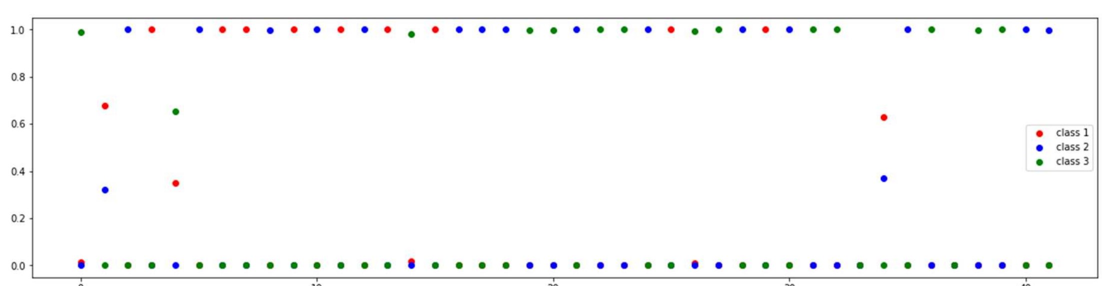
5.) Comparing the Plots





By comparing the plots, we can see that the histogram plotted for a particular feature and a particular class is similar to the count of unique elements after discretizing as bins.

6.) Posterior Probabilities



By analysing the plot we can find that posterior probabilities are nearly 1 or 0 for most of the cases.