A.Y. 2021-2022

LAB EXPERIMENT NO. 01

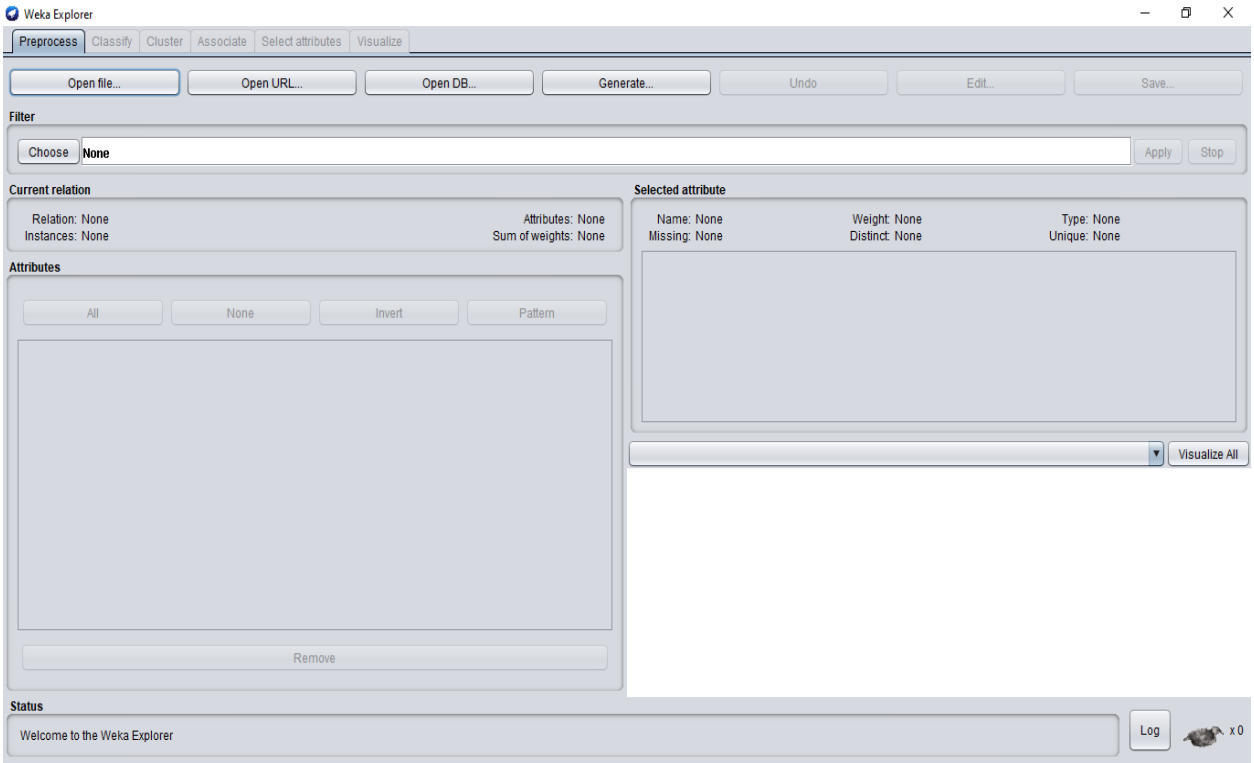
Aim: Perform data Pre-processing task using Weka data mining tool

Theory:

WEKA - an open source software provides tools for data preprocessing, implementation of several Machine Learning algorithms, and visualization tools so that you can develop machine learning techniques and apply them to real-world data mining problems

Tasks performed through Weka:

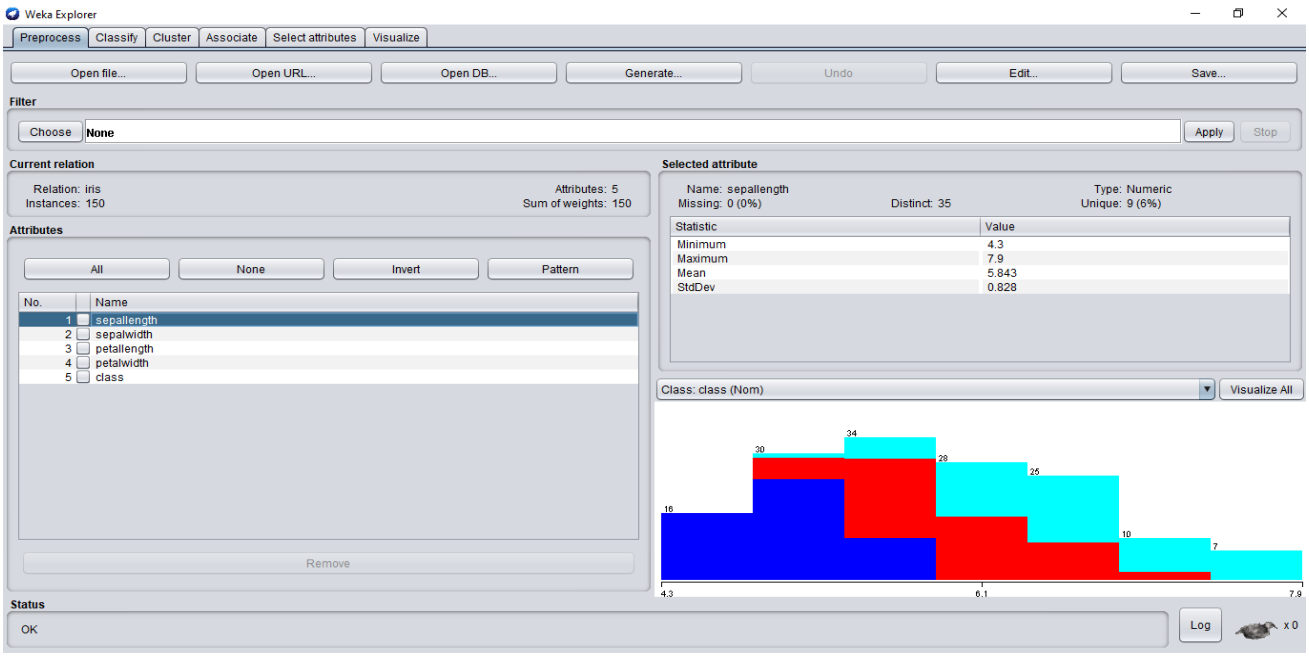
Preprocessing:
Classification:
Clustering:
Association Rule:
Select Attributes:
Visualization:



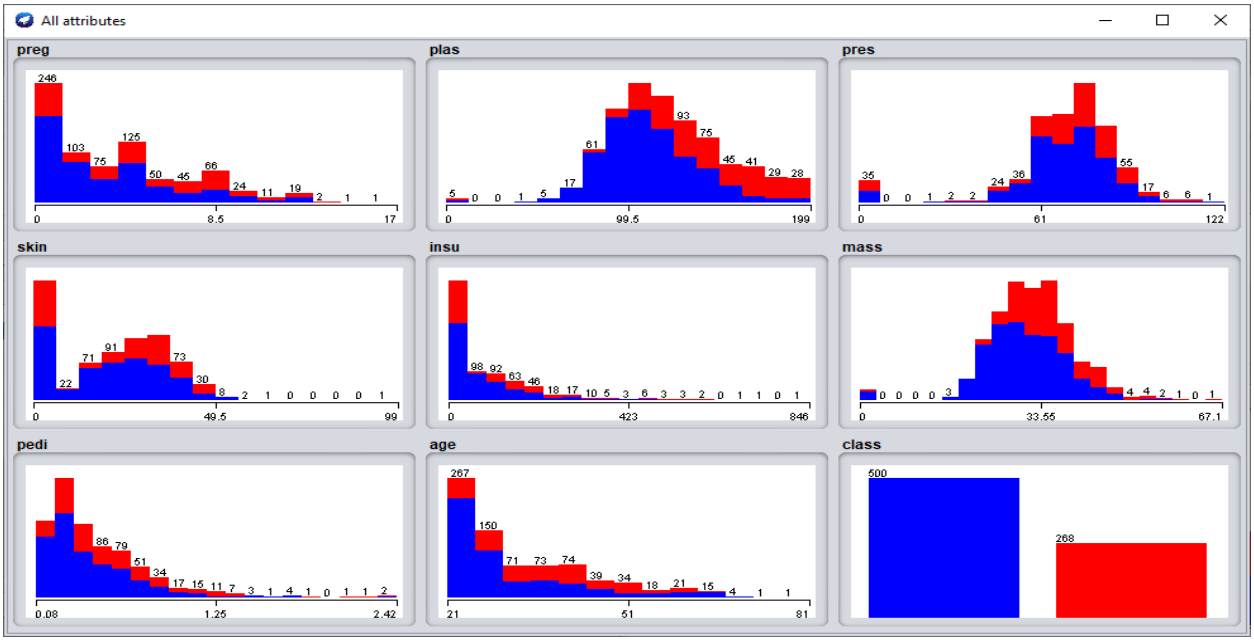
Weka GUI

Preprocessing activities to be observed in Weka:

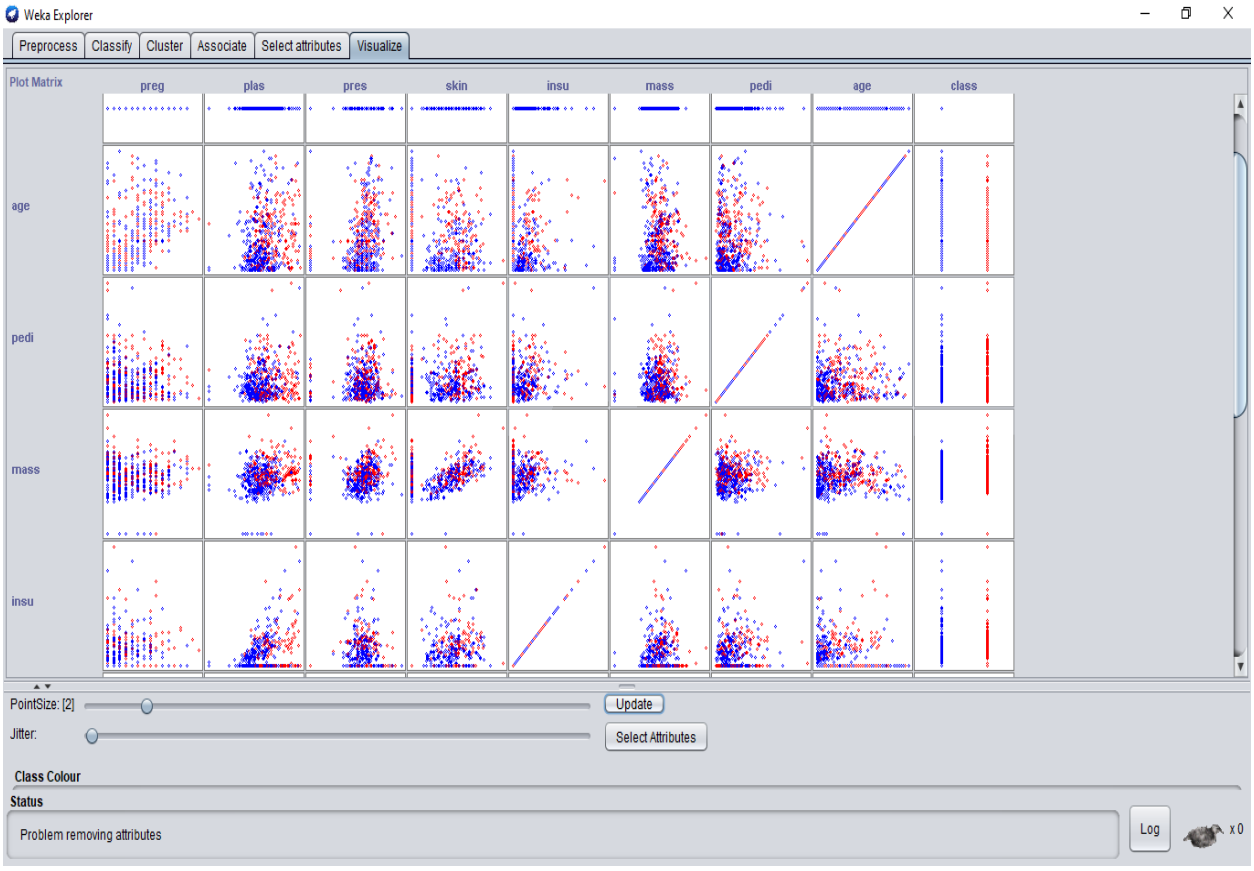
1. **Visualization:** Visualize scatter plot for all the attributes from dataset selected from Weka. Determine correlation if any using these plots for different datasets



Weka on loading **Prima Diabetes dataset**



Visualize all – Distribution Plot



Correlation between the features

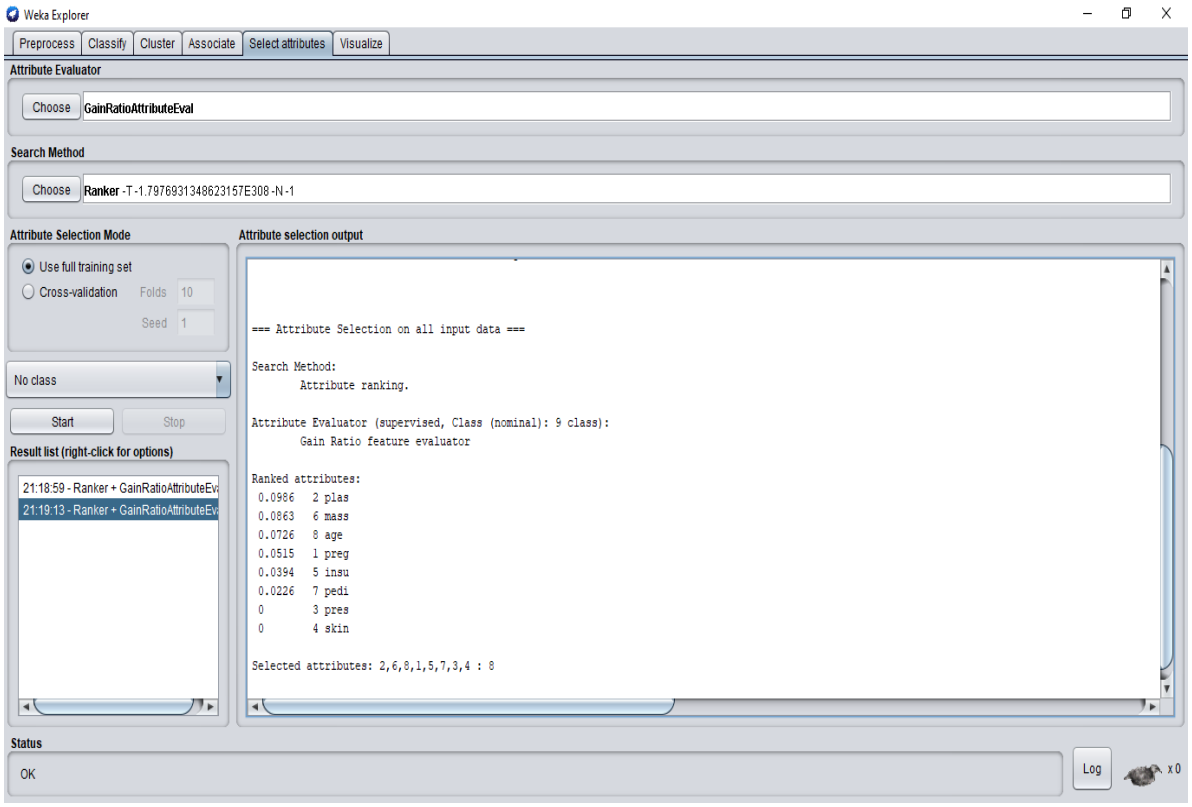
Thus, upon performing **data visualization** we observed :

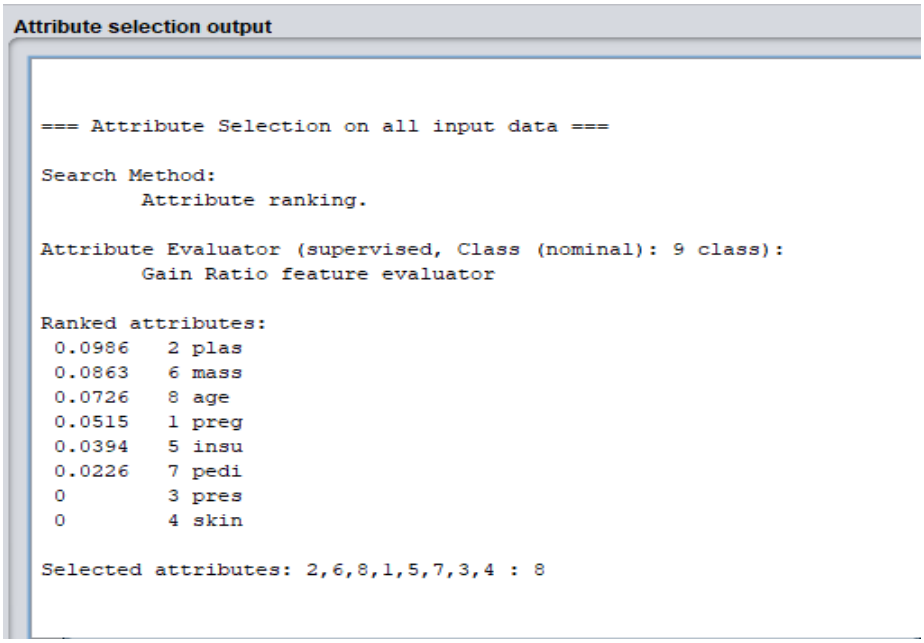
i) The data distribution with respect to each features and the skewness of the data with respect to that feature.

ii) **Scatter plot** between the features. For e.g in the Prima Diabetes dataset:

- Age vs Pregnancy have no co-relation.
- Plasma vs insurance were positively correlated
- Mass vs skin was positively correlated.

2. **Select Attributes:** Apply suitable feature selection filter like GainRatio etc to choose relevant attributes from the list of attributes. Observe the ranks / priority provided by the filter.

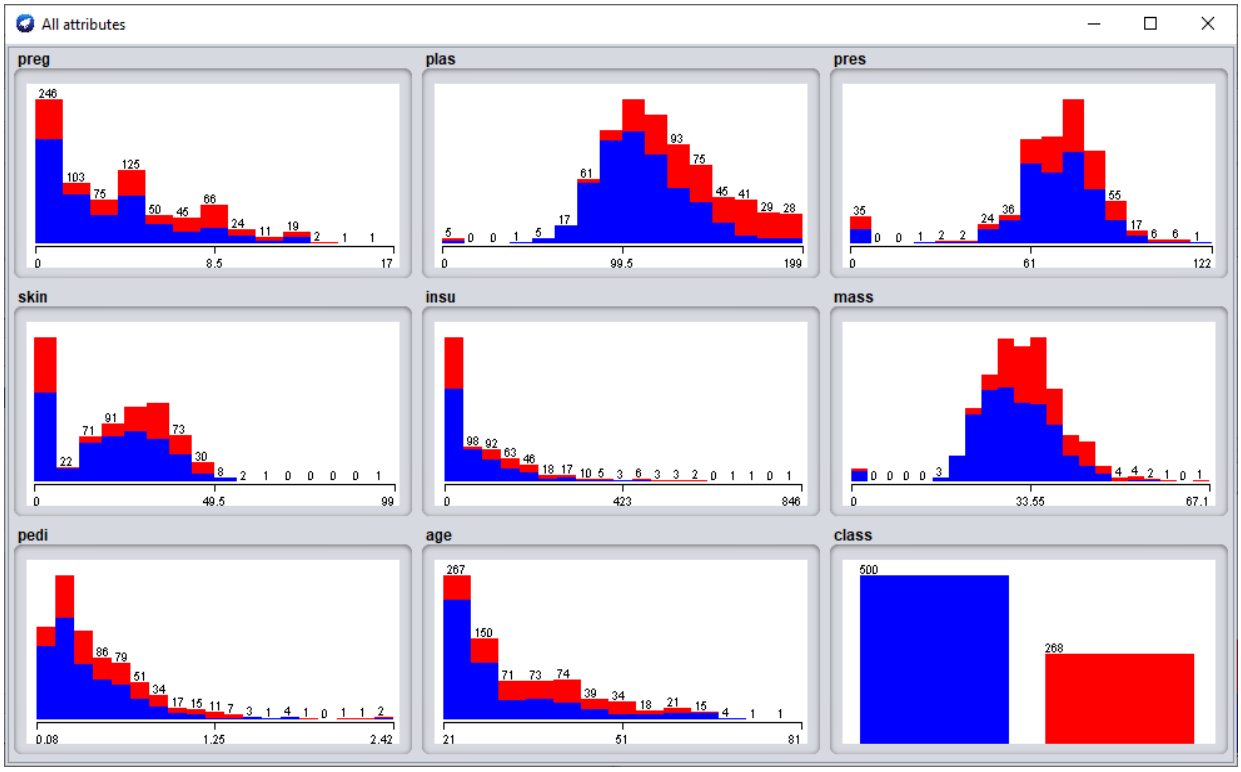




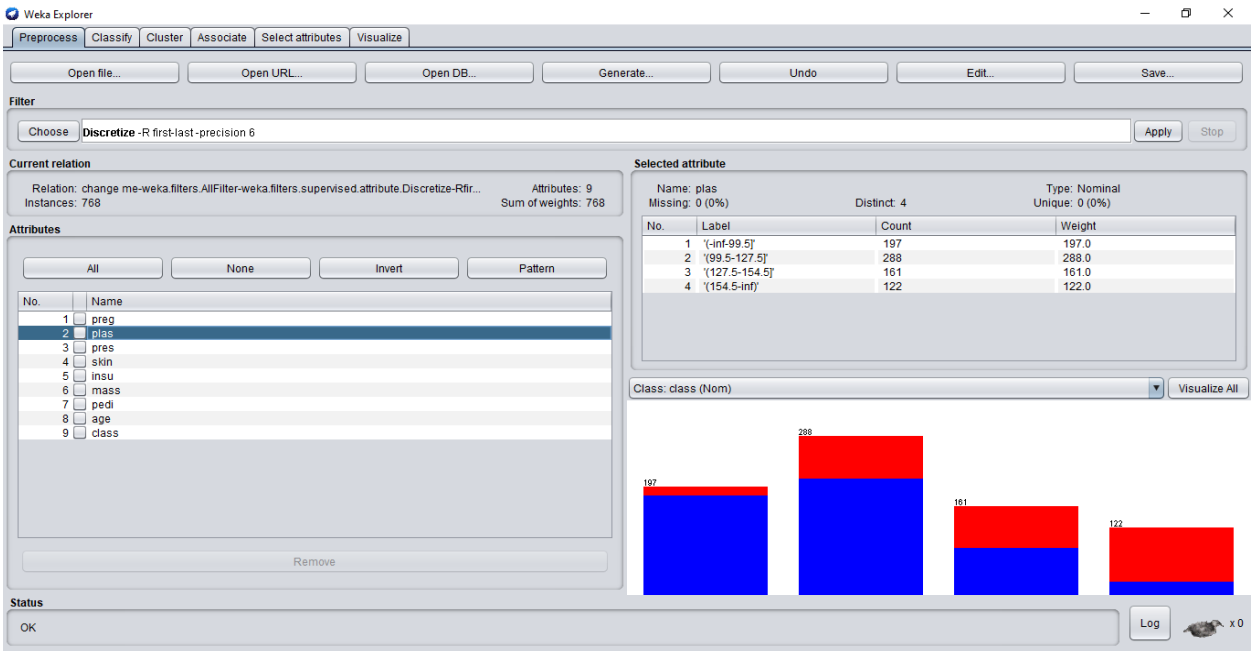
Using attribute evaluator as InfoGainAttributeEval on Ranker Search method in the Select Attribute tab we got the order and values of the most important attributes through entropy which further is used for clusters/classification. Thus, from this we know that attribute 'plas' , 'mass' then 'age' and so on hold importance while clustering the instances.

3. Preprocessing:

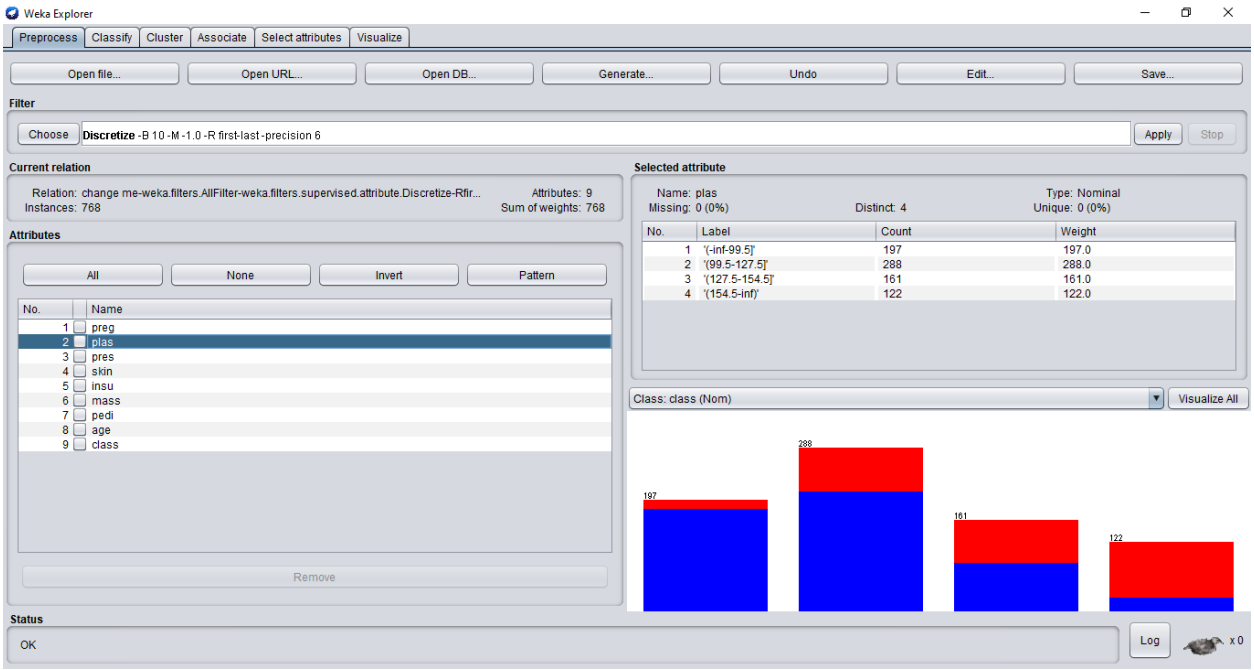
a. Visualize All: Select this button to visualize histograms of all attributes.



b. Filter: Choose Discretization under Unsupervised and Supervised methods. Observe the discretization and the outliers.

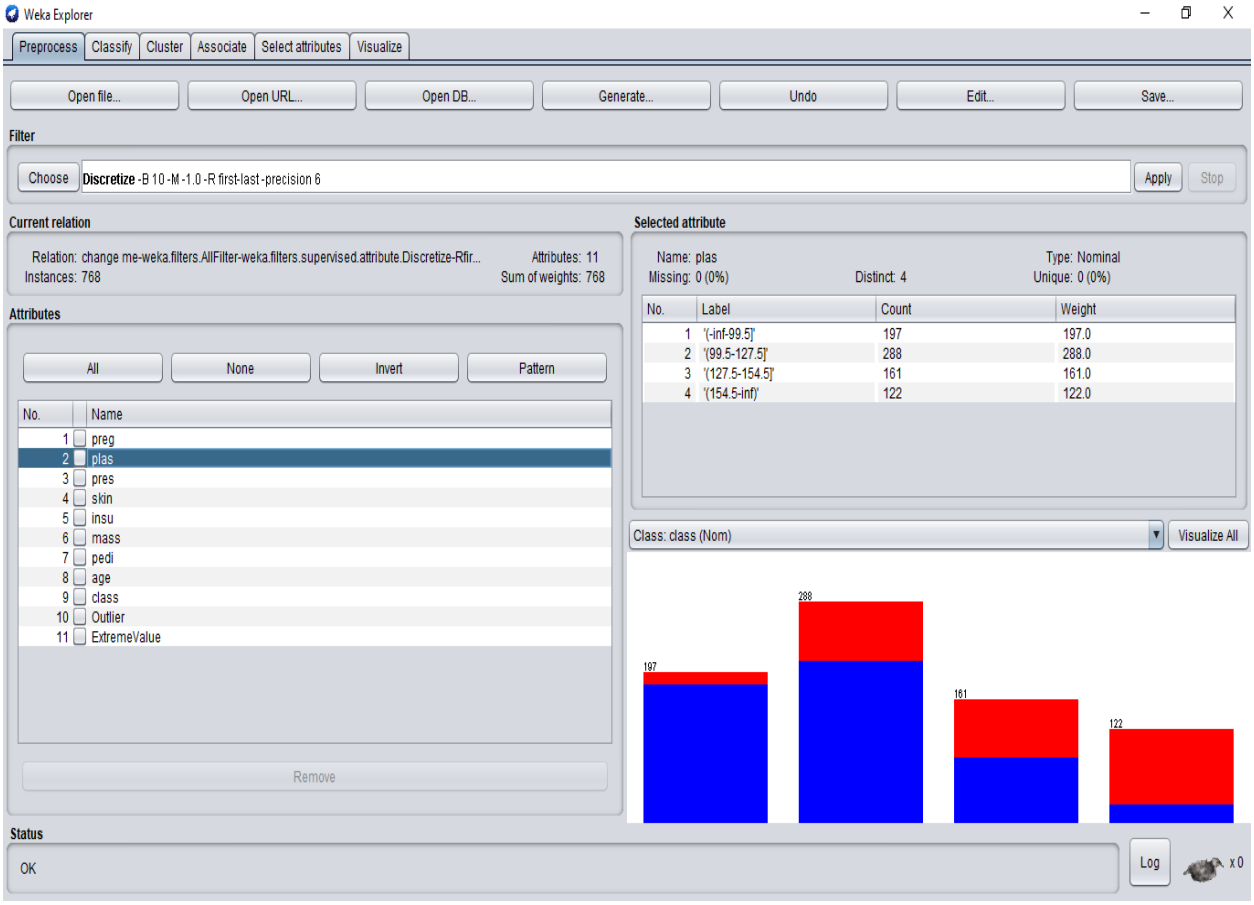


Filter – Supervised Discretize



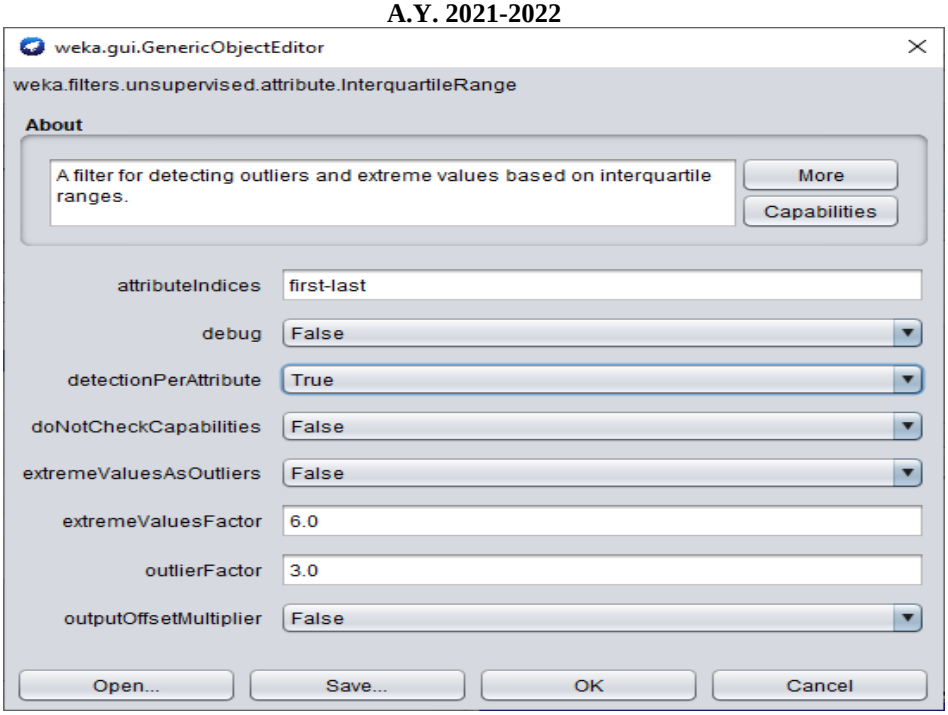
Filter – Unsupervised Discretize

c. **IQR:** Observe the IQR values for a selected attribute. Observe the outlier and extreme values

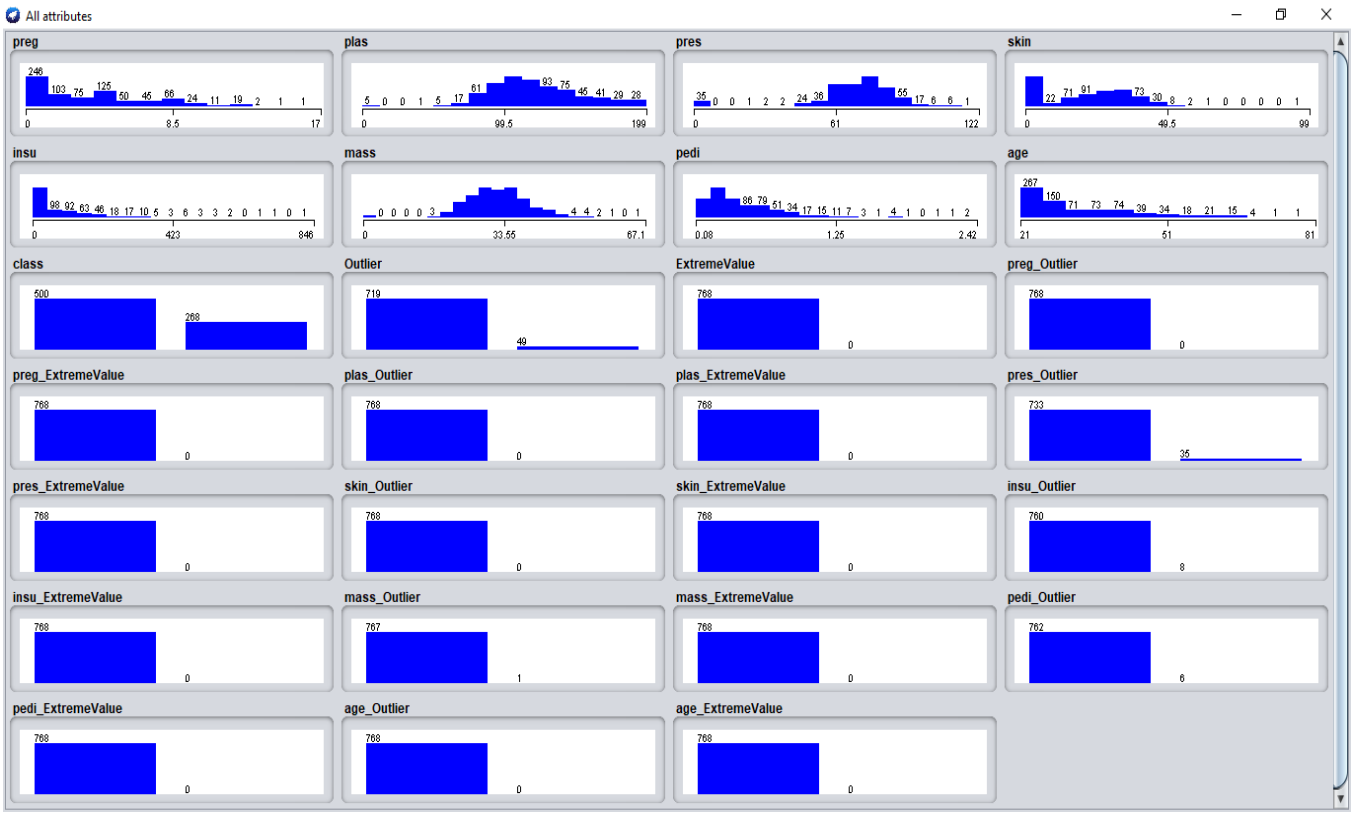


Filter – IOR

Thus, by using IOR filter we can look at the outliers i.e. those values which are outside the 1.5*IOR range. Data cleaning is necessary as these extreme outliers do affect the model accuracy.

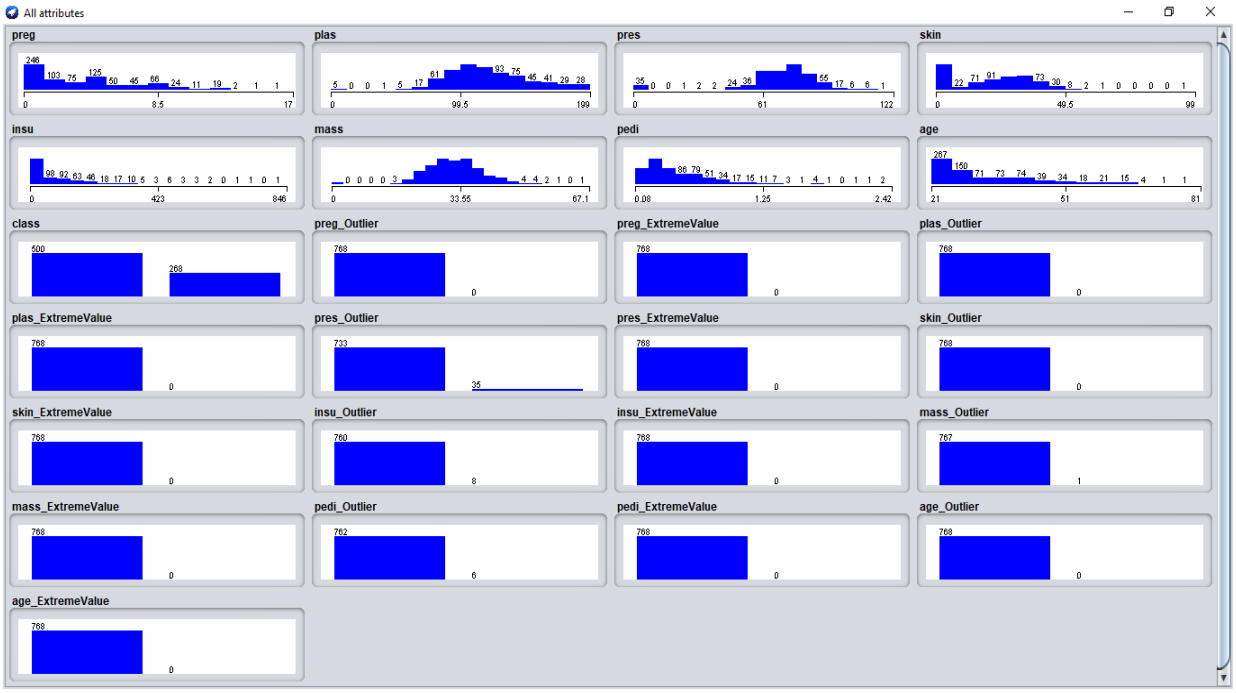


IOR → detectPerAttribute – True

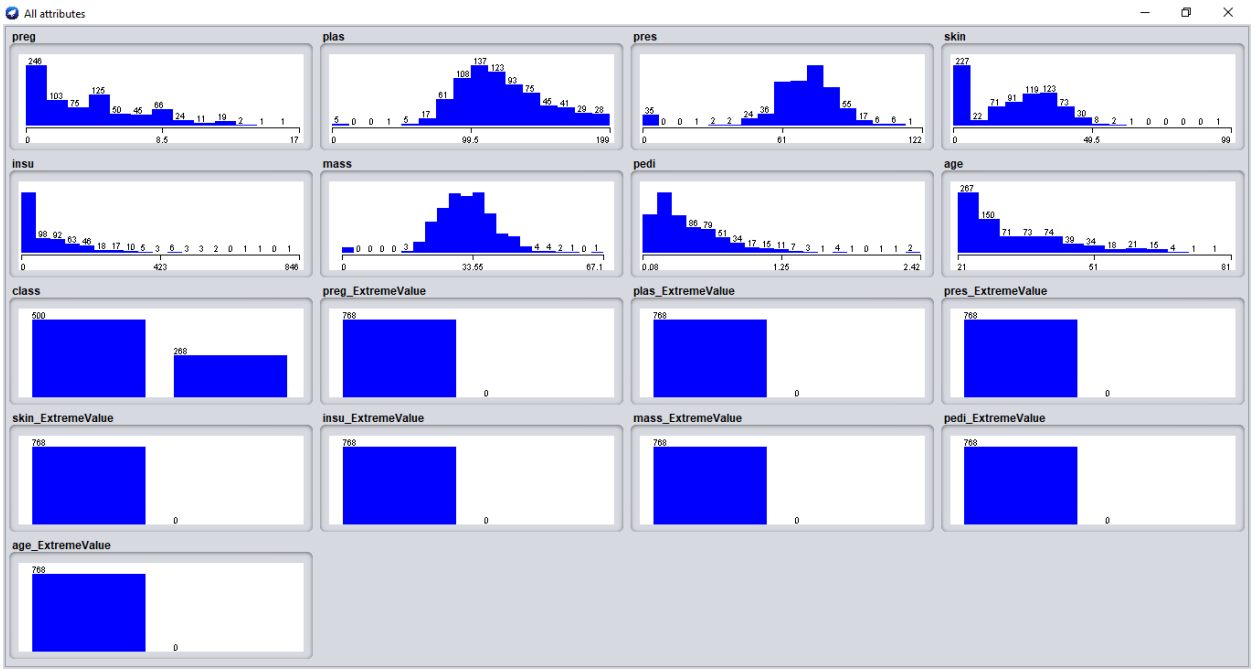


Visualize all – Outliers and Extreme Values

d. Removethevalue: Remove instances with outlier values and show the screenshots of dataset before and after the removal.

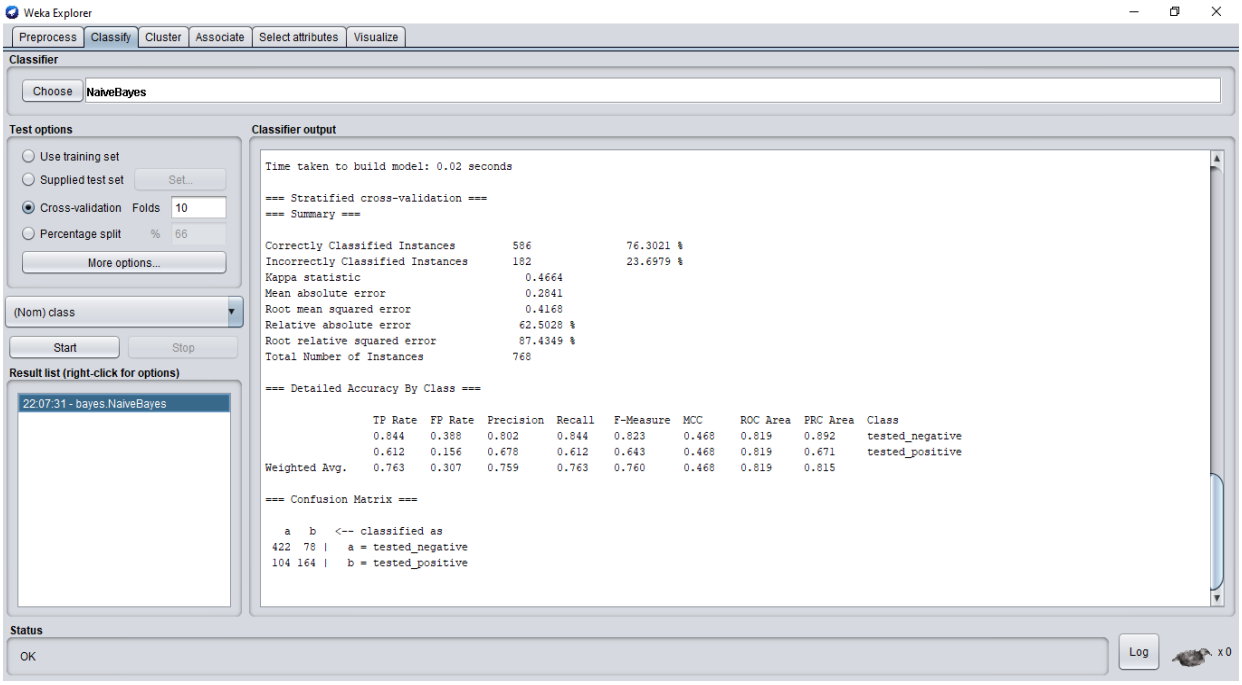


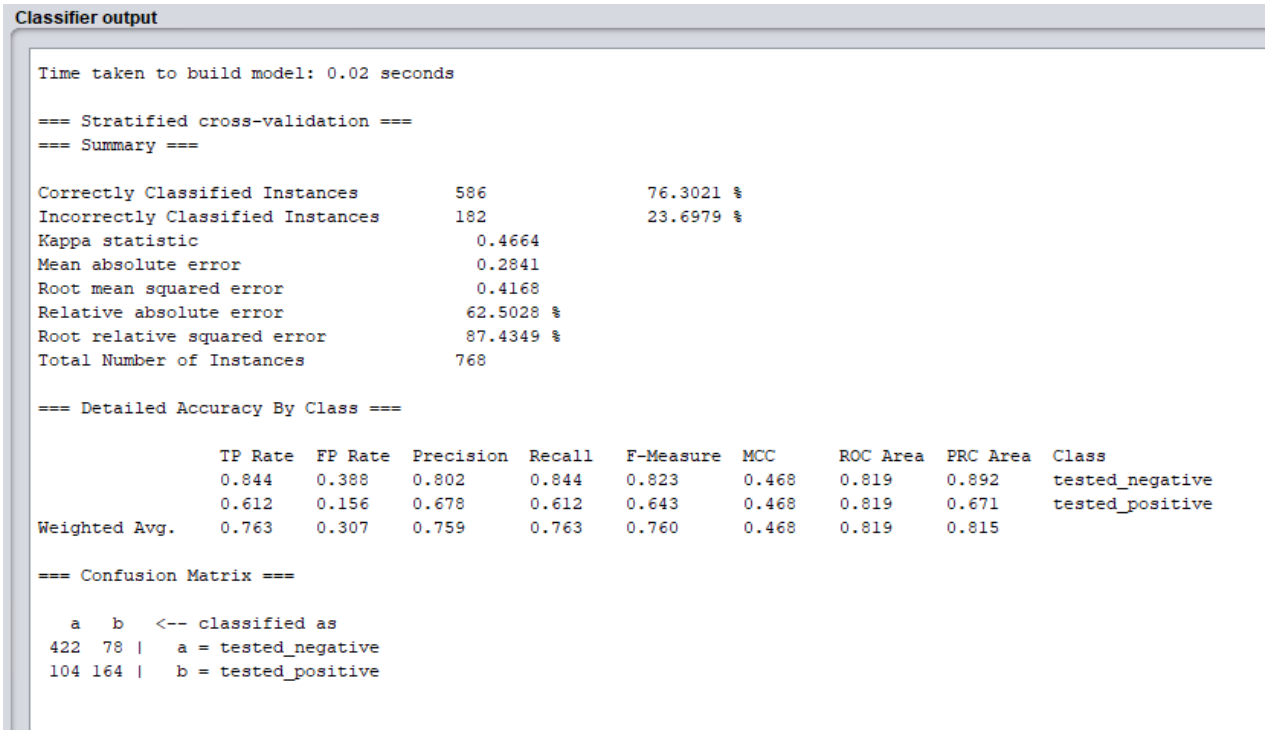
Before Removal of Outliers



After Removal of Outliers

4. **Classification:** Perform NB and Random Forest classification





Naïve Bayes on pima diabetes

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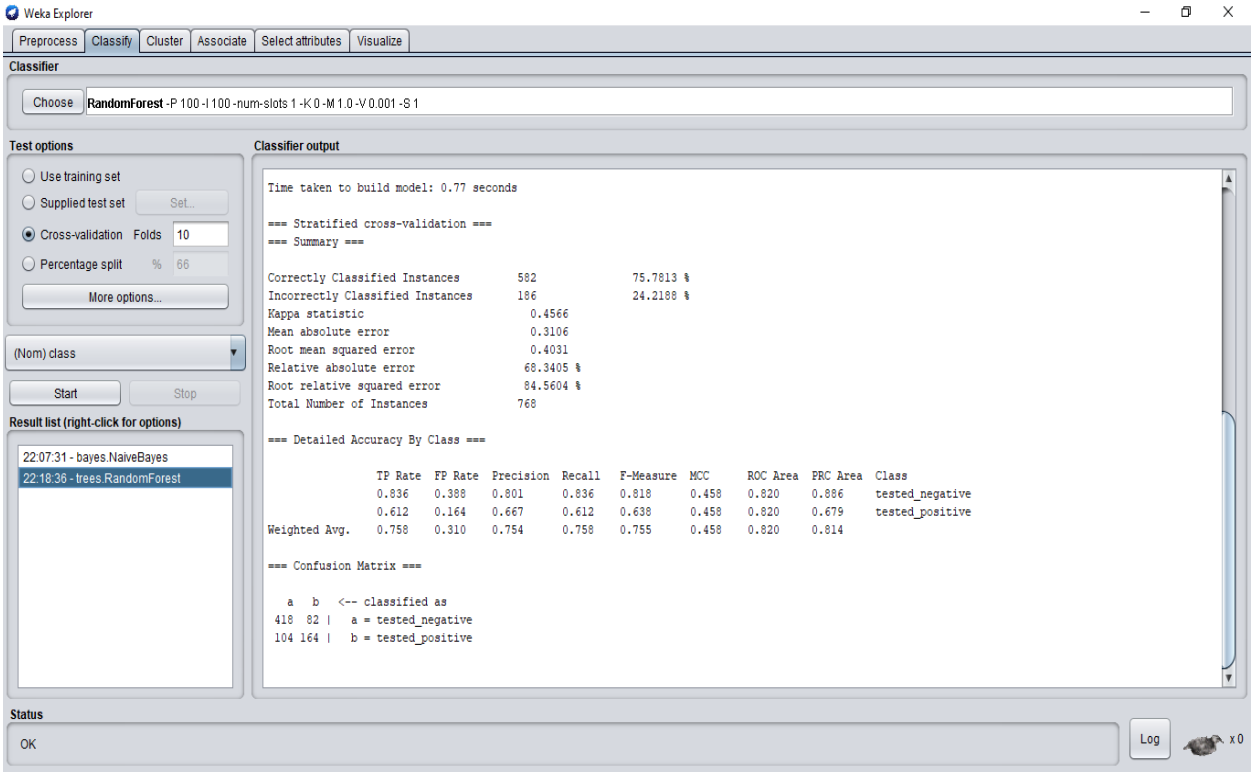
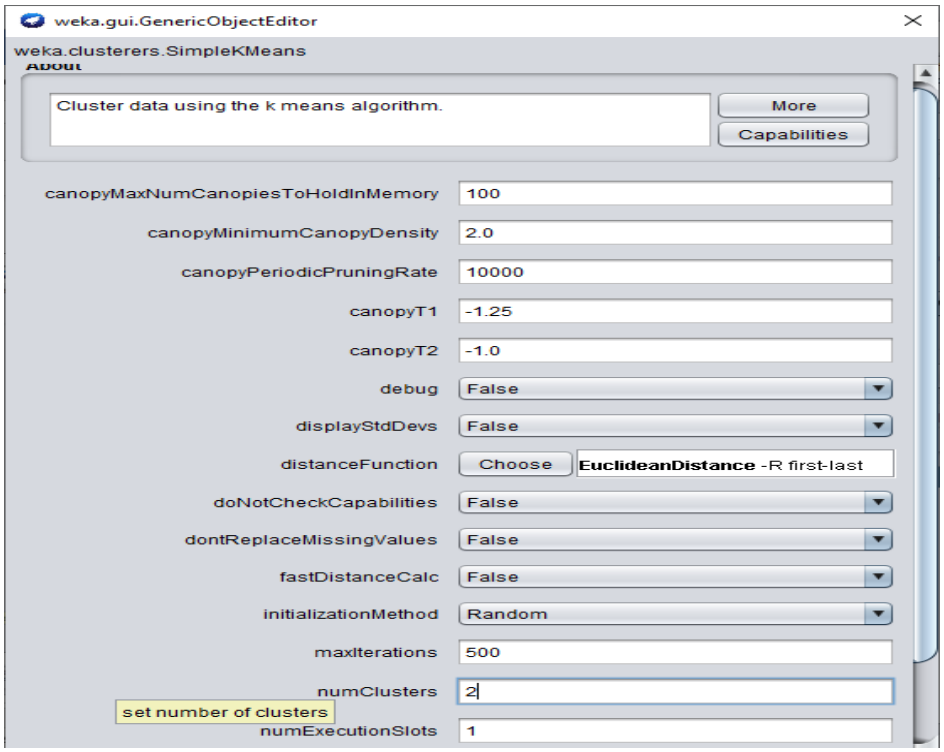


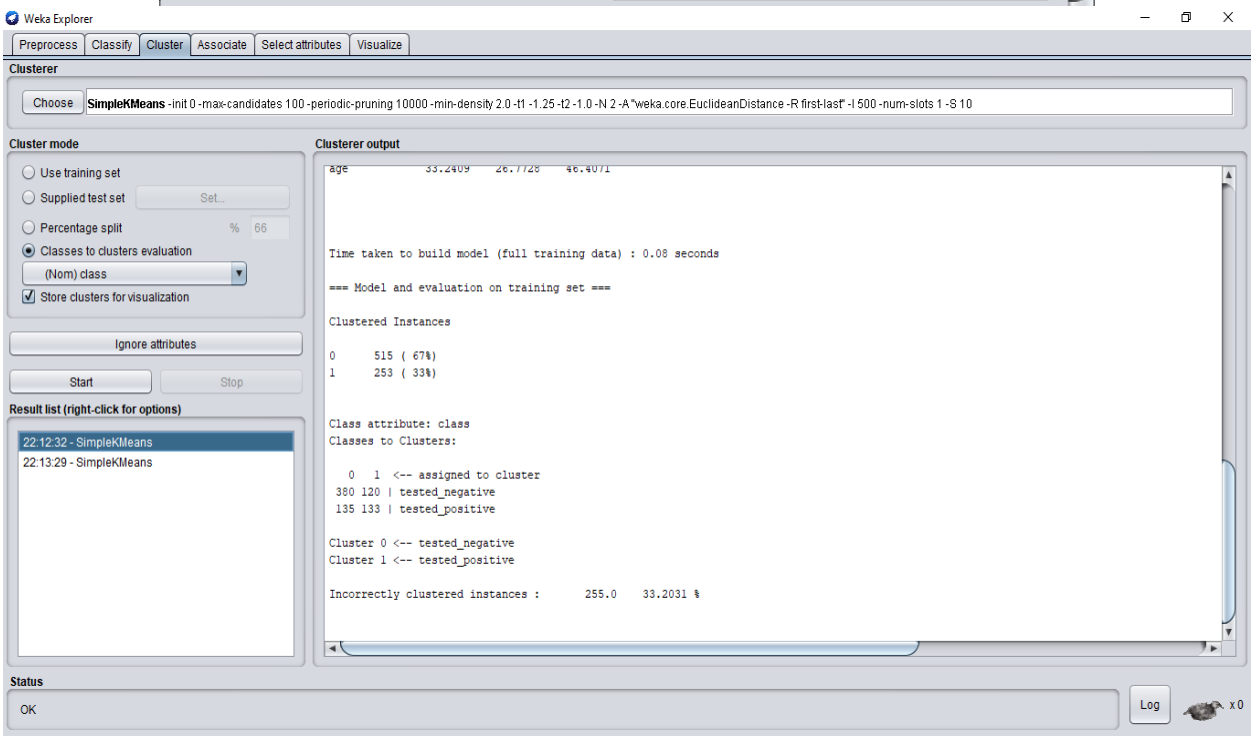
Classifier output

```
Time taken to build model: 0.77 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         582               75.7813 %
Incorrectly Classified Instances       186               24.2188 %
Kappa statistic                          0.4566
Mean absolute error                      0.3106
Root mean squared error                  0.4031
Relative absolute error                 68.3405 %
Root relative squared error             84.5604 %
Total Number of Instances              768

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.836    0.388    0.801      0.836    0.818      0.458    0.820     0.886     tested_negative
                 0.612    0.164    0.667      0.612    0.638      0.458    0.820     0.679     tested_positive
Weighted Avg.    0.758    0.310    0.754      0.758    0.755      0.458    0.820     0.814

=== Confusion Matrix ===

   a   b   <-- classified as
 418  82 |   a = tested_negative
 104 164 |   b = tested_positive
```

Random Forest Classifier

5. **Clustering:** Perform kmeans, hierarchical clustering and explain the output





SimpleKmeans

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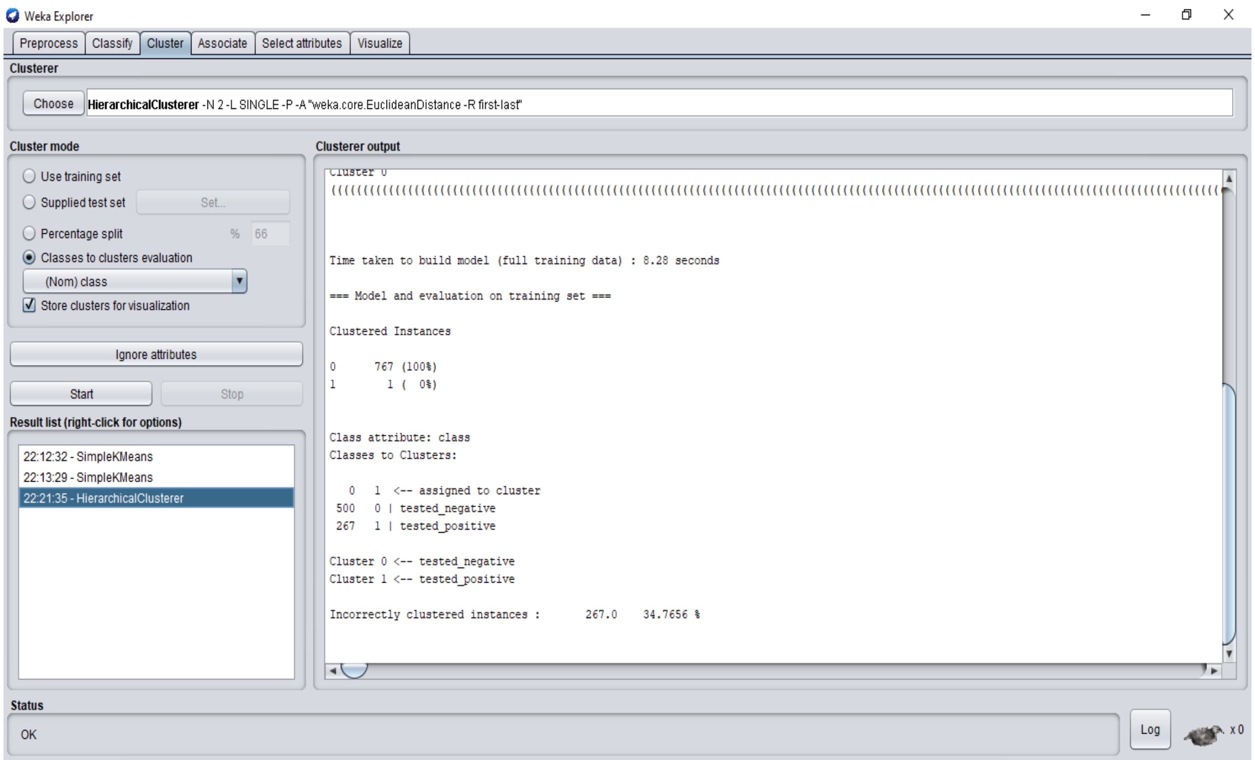
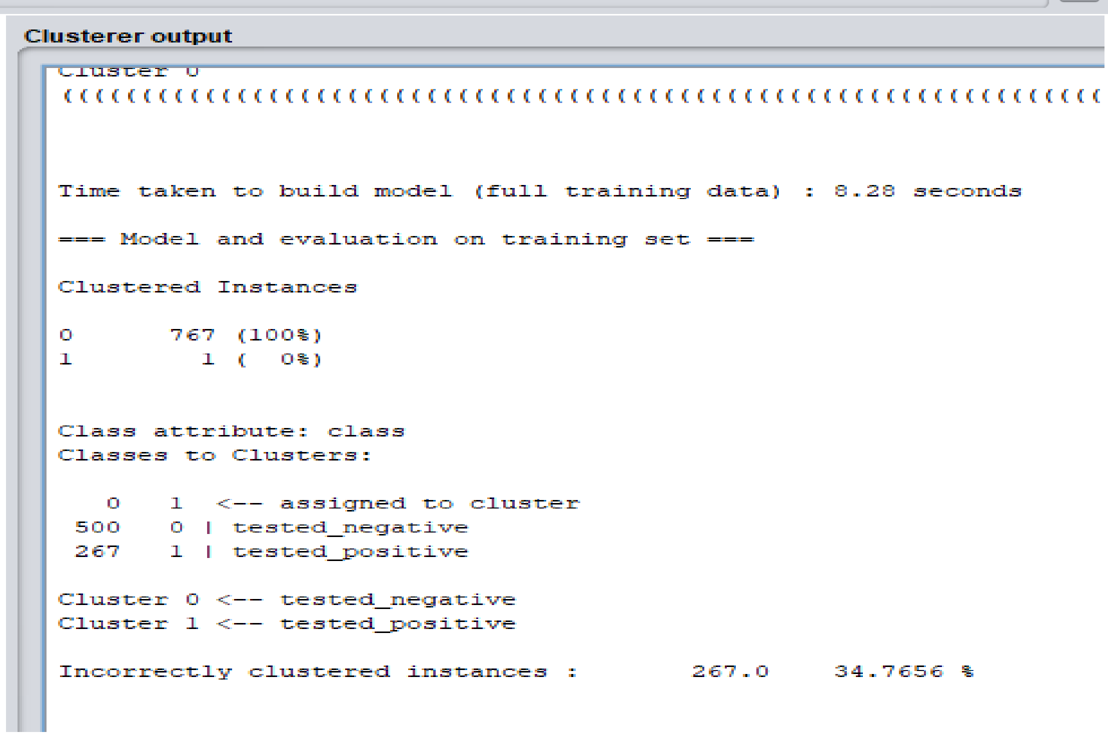




Hierarchical Clustering

In clustering the dataset by **KMeans Clustering**, we classified the dataset into 2 clusters:

Cluster 0 – tested_negative
Cluster 1 – tested_positive

Out of which a total of 515 instances we classified into Cluster0 and 253 instances were classified into Cluster 1. But out of 515 instances in the Cluster 0, 135 instances were wrongly classified as those were labelled tested_positive in the actual dataset. Similarly in the cluster1 120 instances were wrongly classified as those were labelled as tested_negative in the original dataset.

Thus, overall the incorrectly clustered instances were 255 misclassified instances which results to 33.203% error.

```
Class attribute: class
Classes to Clusters:

   0   1  <-- assigned to cluster
 380 120 | tested_negative
 135 133 | tested_positive

Cluster 0 <-- tested_negative
Cluster 1 <-- tested_positive

Incorrectly clustered instances :       255.0    33.2031 %
```

In clustering the dataset by **Hierarchical Clustering**, we classified the dataset into 2 clusters:

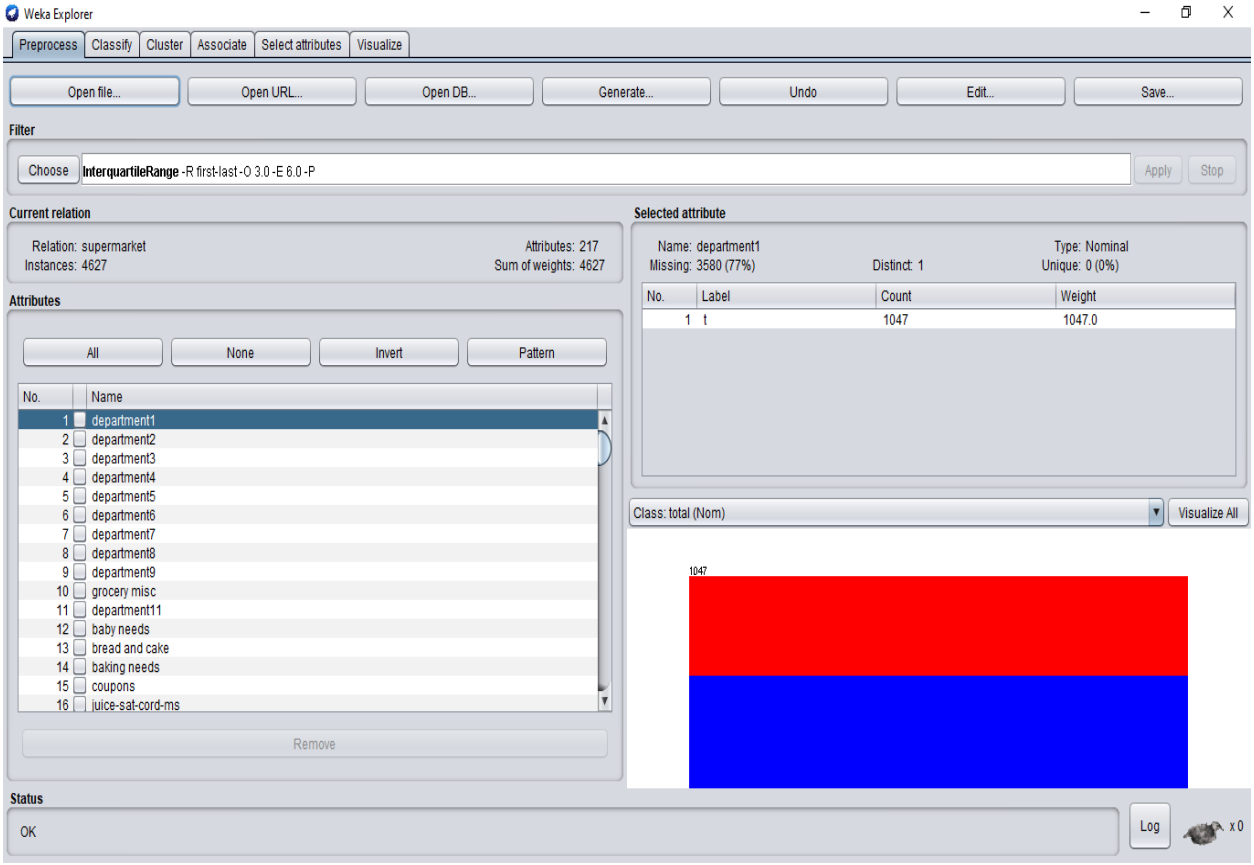
Cluster 0 – tested_negative
Cluster 1 – tested_positive

Out of which a total of 767 instances we classified into Cluster0 and 1 data instance was classified into Cluster 1. But out of 767 instances in the Cluster 0, 267 instances were wrongly classified as those were labelled tested_positive in the actual dataset. In the cluster1, 0 instances were wrongly classified.

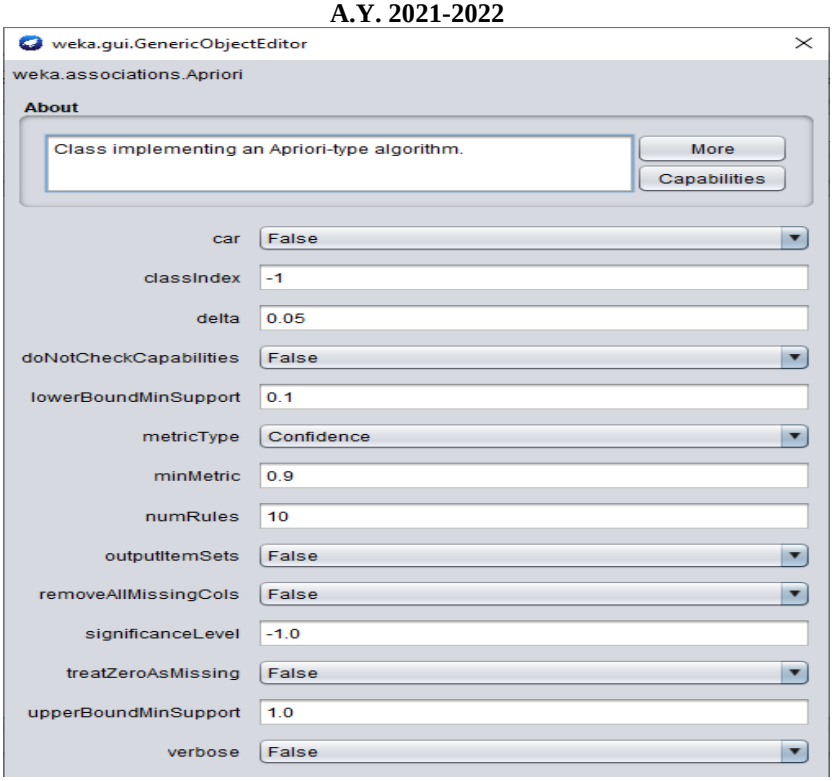
Thus, overall the incorrectly clustered instances were 255 misclassified instances which results to 34.7656% error.

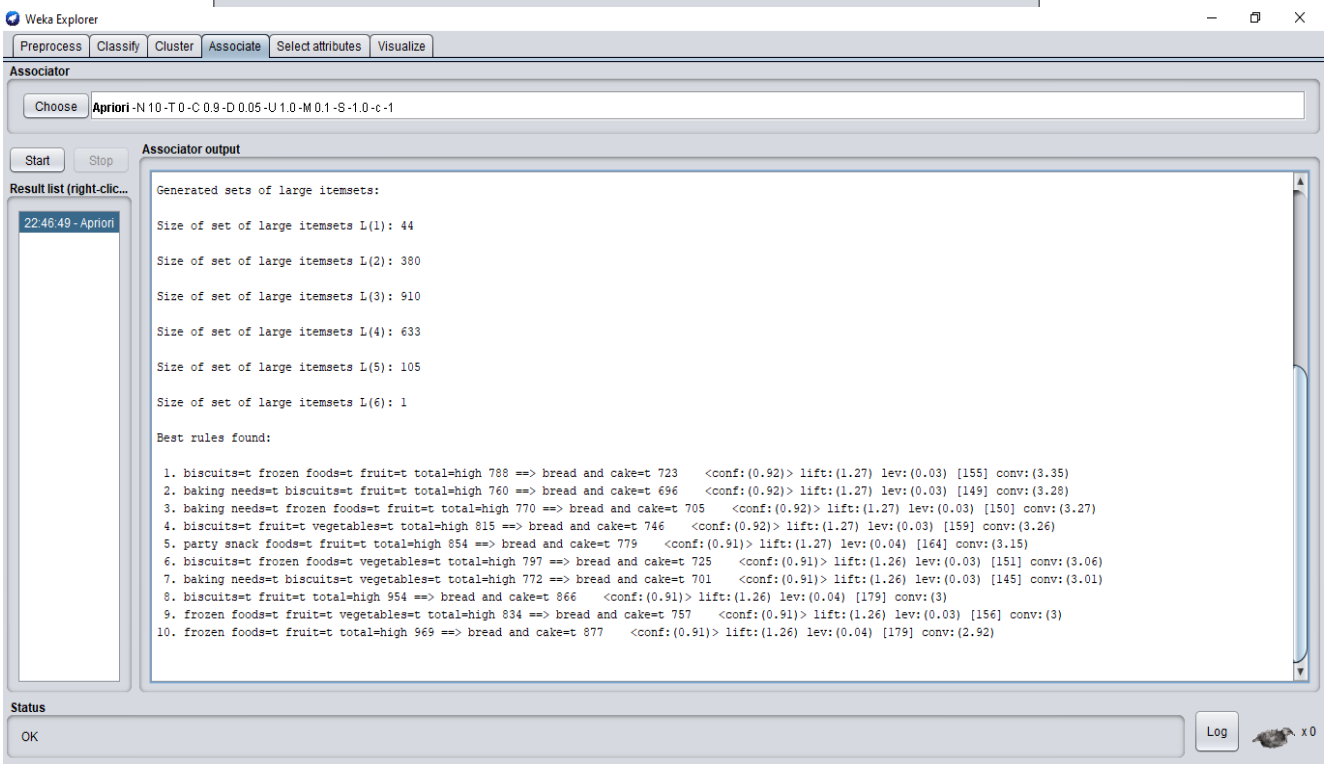
```
Class attribute: class
Classes to Clusters:

   0   1  <-- assigned to cluster
 500   0 | tested_negative
 267   1 | tested_positive

Cluster 0 <-- tested_negative
Cluster 1 <-- tested_positive

Incorrectly clustered instances :       267.0     34.7656 %
```

6. **Association rule mining:** Perform apriori algo and show the rules created



Supermarket dataset





Association Rules generated by Apriori Analysis

```
Best rules found:

 1. biscuits=t frozen foods=t fruit=t total=high 788 ==> bread and cake=t 723    <conf:(0.92)> lift:(1.27) lev:(0.03) [155] conv:(3.35)
 2. baking needs=t biscuits=t fruit=t total=high 760 ==> bread and cake=t 696    <conf:(0.92)> lift:(1.27) lev:(0.03) [149] conv:(3.28)
 3. baking needs=t frozen foods=t fruit=t total=high 770 ==> bread and cake=t 705    <conf:(0.92)> lift:(1.27) lev:(0.03) [150] conv:(3.27)
 4. biscuits=t fruit=t vegetables=t total=high 815 ==> bread and cake=t 746    <conf:(0.92)> lift:(1.27) lev:(0.03) [159] conv:(3.26)
 5. party snack foods=t fruit=t total=high 854 ==> bread and cake=t 779    <conf:(0.91)> lift:(1.27) lev:(0.04) [164] conv:(3.15)
 6. biscuits=t frozen foods=t vegetables=t total=high 797 ==> bread and cake=t 725    <conf:(0.91)> lift:(1.26) lev:(0.03) [151] conv:(3.06)
 7. baking needs=t biscuits=t vegetables=t total=high 772 ==> bread and cake=t 701    <conf:(0.91)> lift:(1.26) lev:(0.03) [145] conv:(3.01)
 8. biscuits=t fruit=t total=high 954 ==> bread and cake=t 866    <conf:(0.91)> lift:(1.26) lev:(0.04) [179] conv:(3)
 9. frozen foods=t fruit=t vegetables=t total=high 834 ==> bread and cake=t 757    <conf:(0.91)> lift:(1.26) lev:(0.03) [156] conv:(3)
10. frozen foods=t fruit=t total=high 969 ==> bread and cake=t 877    <conf:(0.91)> lift:(1.26) lev:(0.04) [179] conv:(2.92)
```

Conclusion:

In this experiment we learnt to about Weka tool used for data preprocessing, implementation of several Machine Learning algorithms, and visualization tools. Using data visualization we can see the correlation between the features and also the distribution of data for each feature thereby, performing necessary pre-processing needed, like transformation to normalize the skewness in the data. Other pre-processing being data cleaning like removing outliers (i.e those values outside the 1.5IQR range). Also, through Select Attribute we got the preference of each attribute with respect to InfoGain. Then I performed Naives Bayes and Random Forest Classification on the dataset using cross validation. I also performed Clustering Algorithms like Simple KMeans and Hierarchical Clustering and observed the numbers of data instances were correctly and wrongly classified into the new clusters. Finally, performed Association mining using Apriori Algorithm and displayed the association rules.