

Data mining Term project (option 1)

Comparison of Decision trees and Support Vector Machine

Johanna Del Pino (jmd53), Kijit Desai (kd227)



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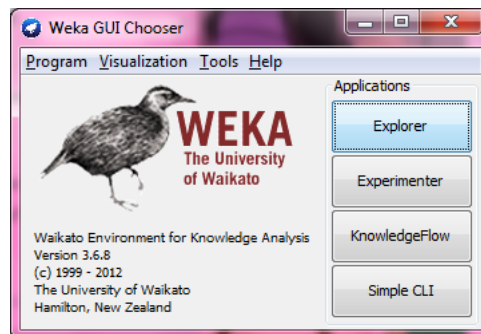
Figure 1 - CSV file of Training dataset

Decision Tree (C4.5)

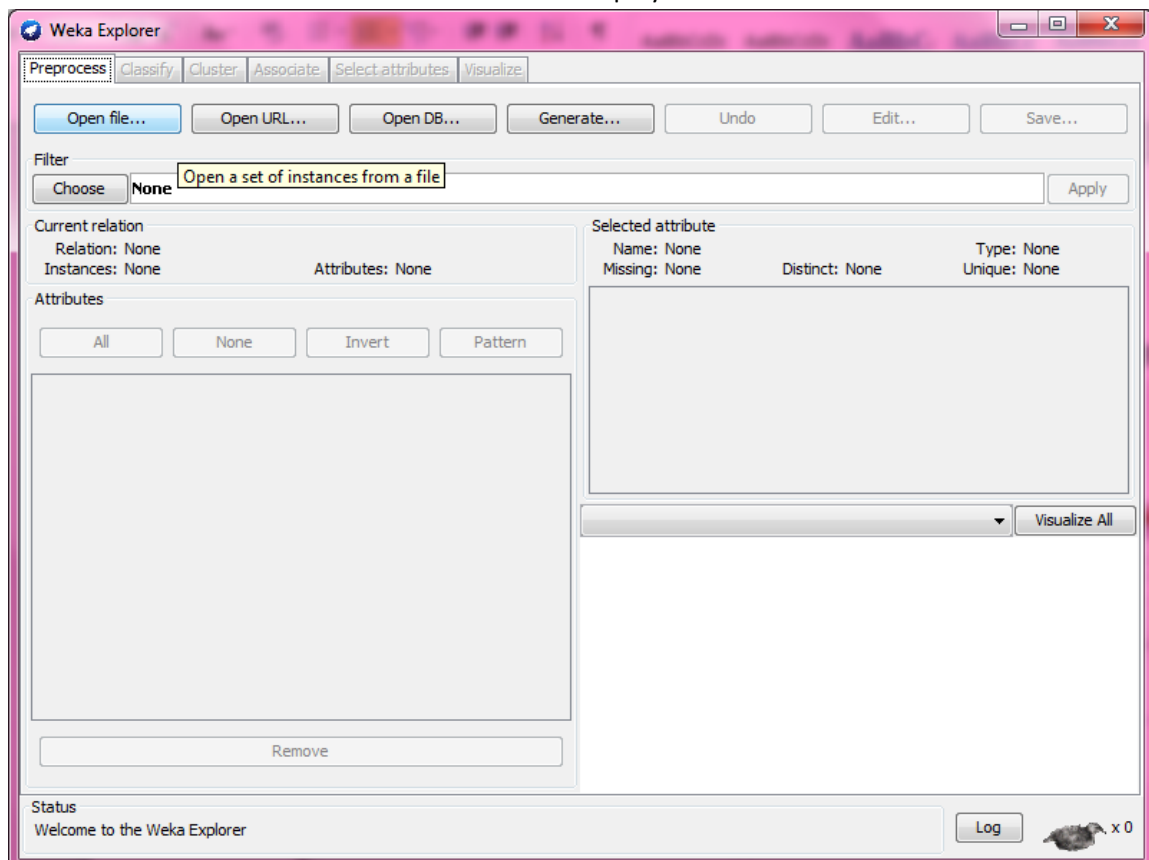
The ID3 algorithm classifies data with discrete values; in order for WEKA to recognize the dataset values as discrete a preprocessing phase must be done in the data before running the algorithm. In this phase the Discretization of the dataset is done, along with the filtering of the “Sample code number” attribute that is not needed for the classification.

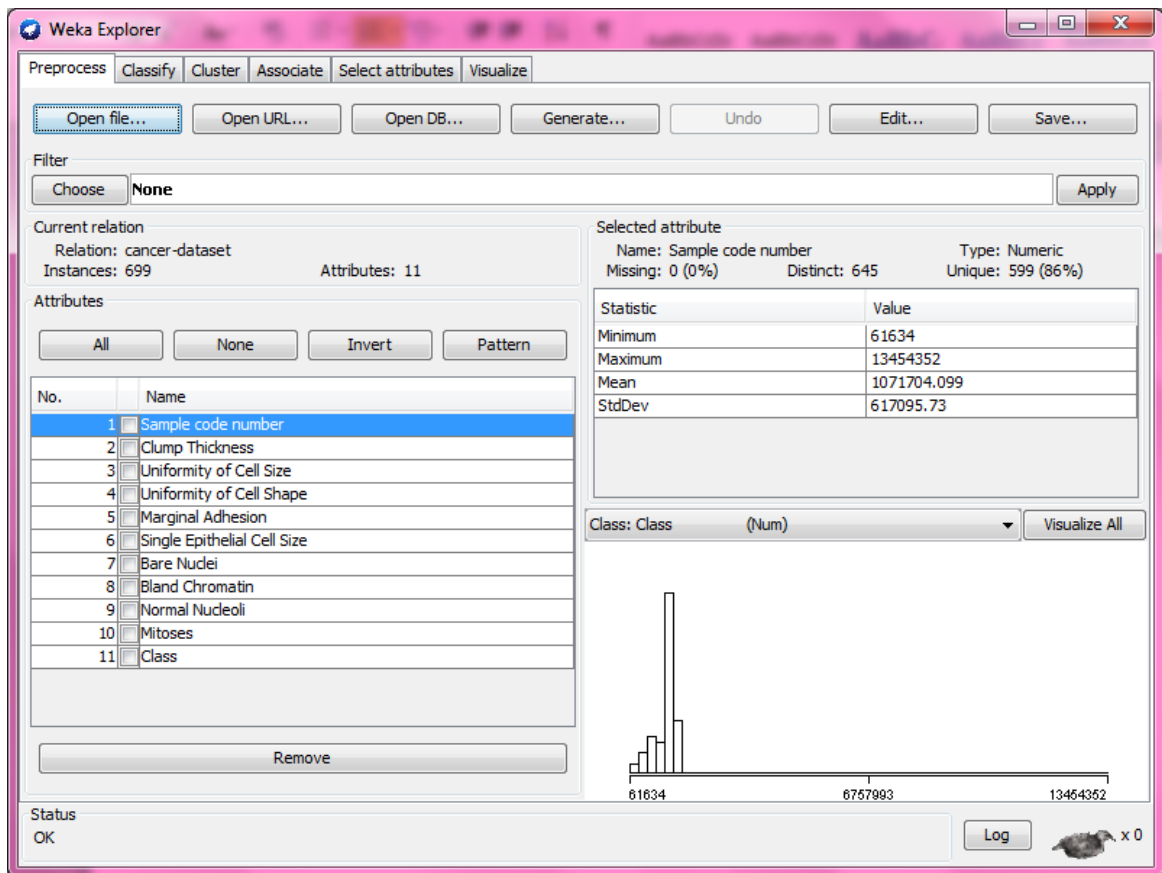
Data Preprocessing

1. **Opening WEKA:** We open the WEKA tool and click in the “Explorer” button

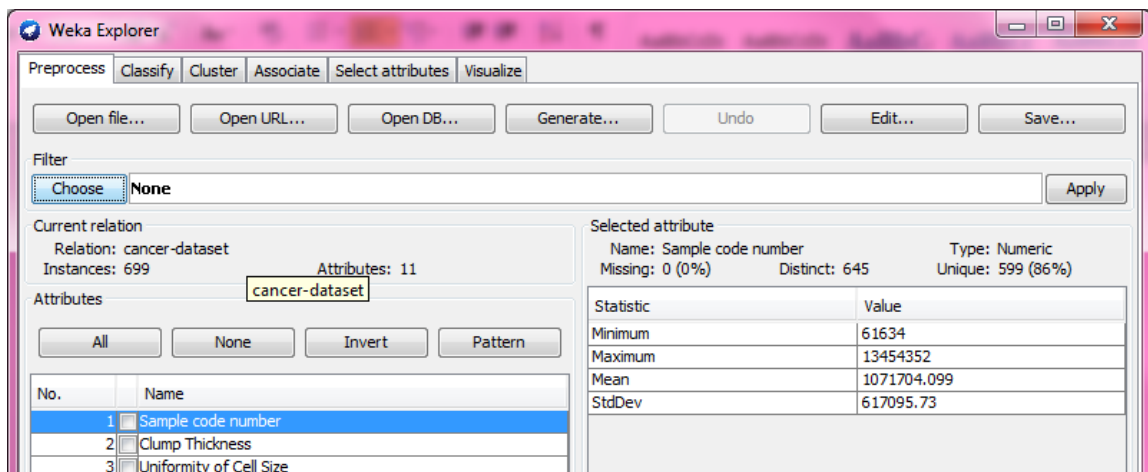


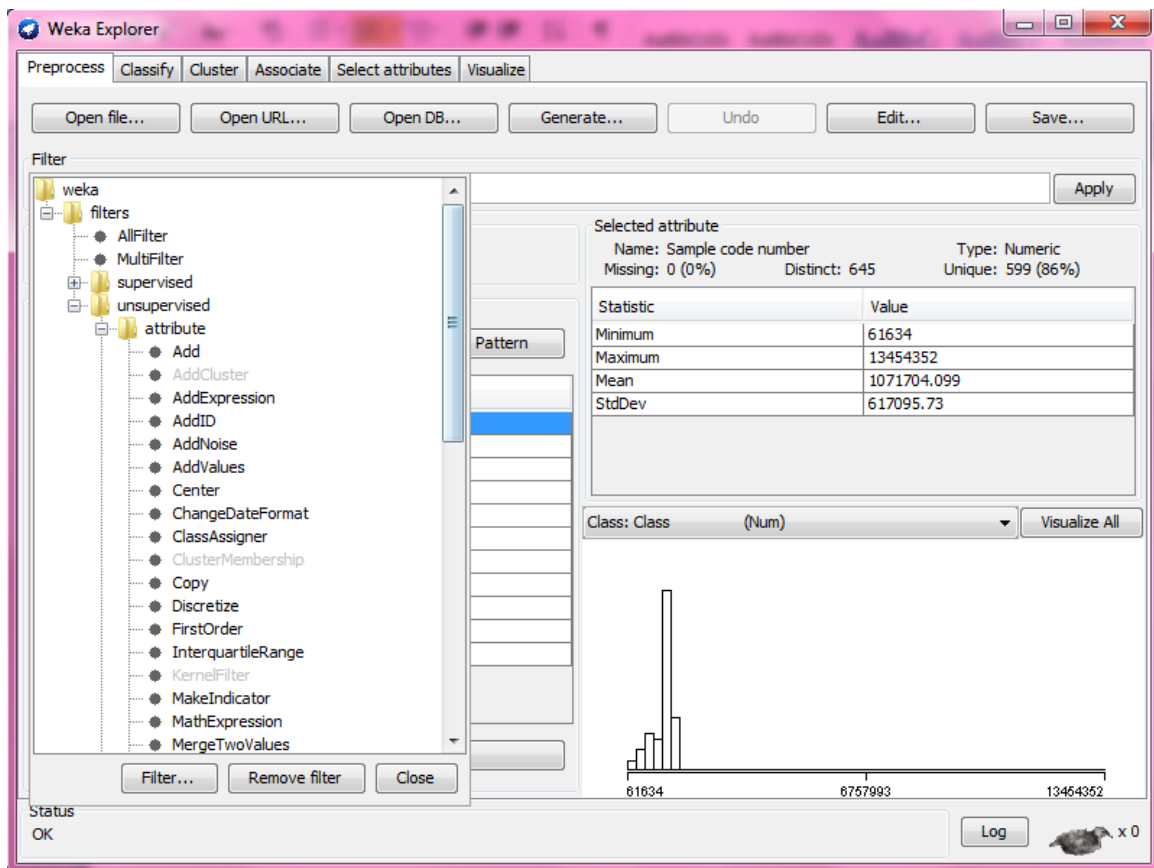
2. **Loading the dataset:** In the new window we choose the “Open file” option to upload the CSV file. Then we choose the CSV file and WEKA will display the data and its attributes.



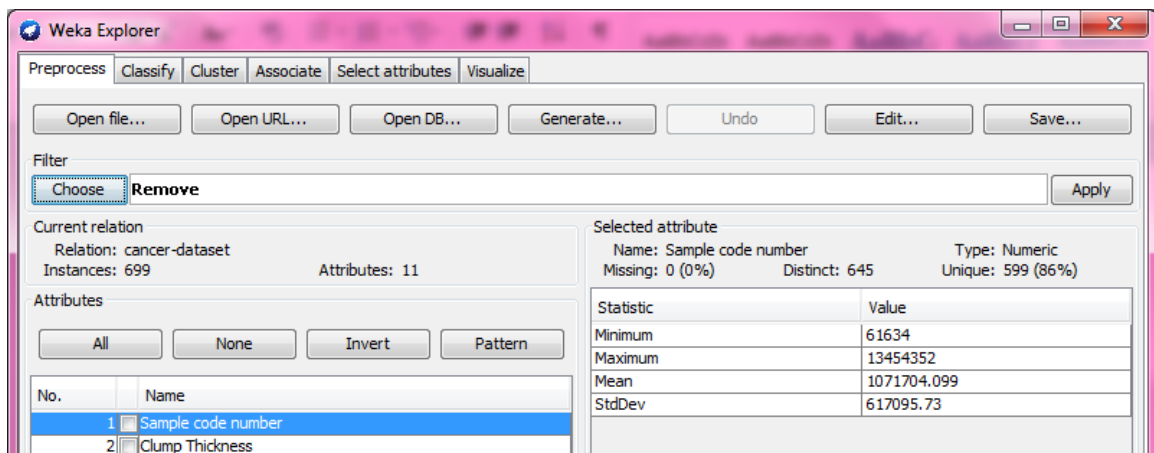


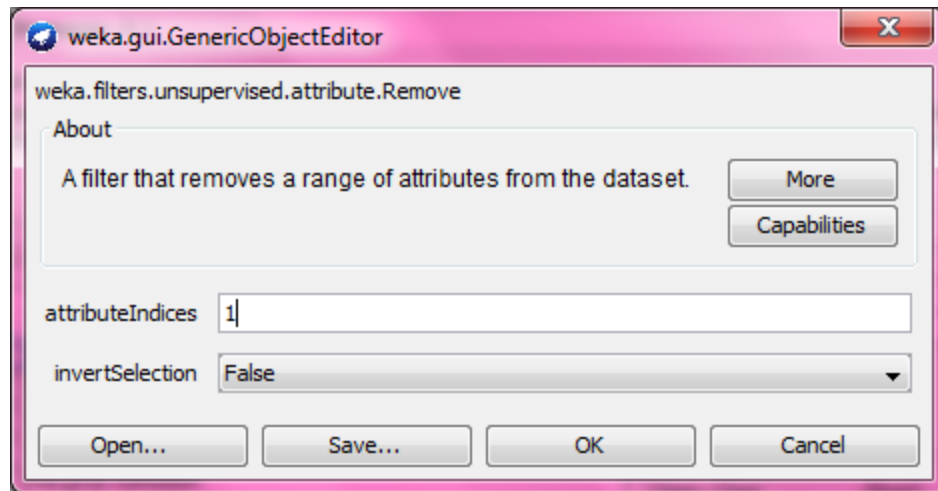
- Removing the first attribute:** We proceed to create a filter to remove the "Sample code number" attribute by clicking in the *Choose* button located under the word *Filter*, and then we choose the option filters -> unsupervised -> attribute -> remove.



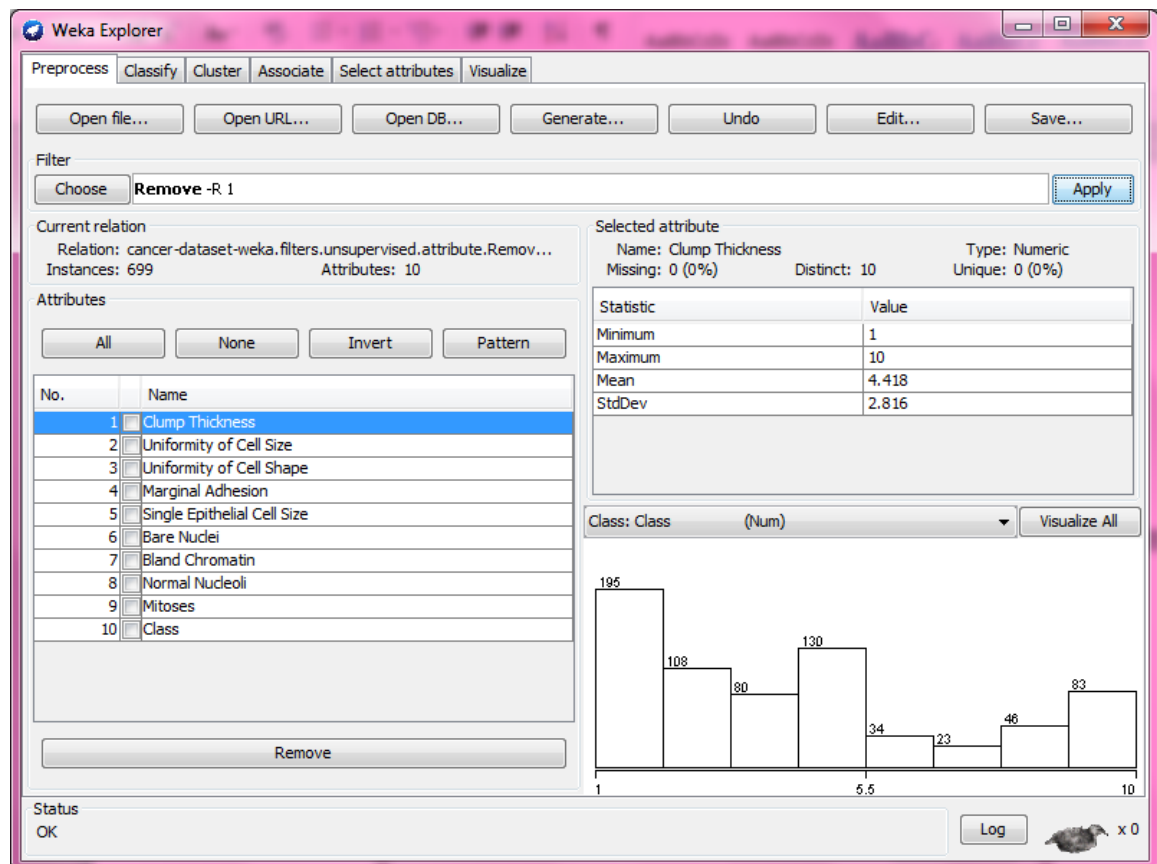


We double click in the text field with the word "Remove" in it. A small window will appeared in which we must specify the number of the attribute we want to remove, and then press the OK button. Note that the *invertSelection* option must be set as false.





Then we click on the *Apply* button next to the text field and the first attribute will be removed. After this we save this dataset as an “arff” file by clicking the *Save* button on the upper left corner of the window.

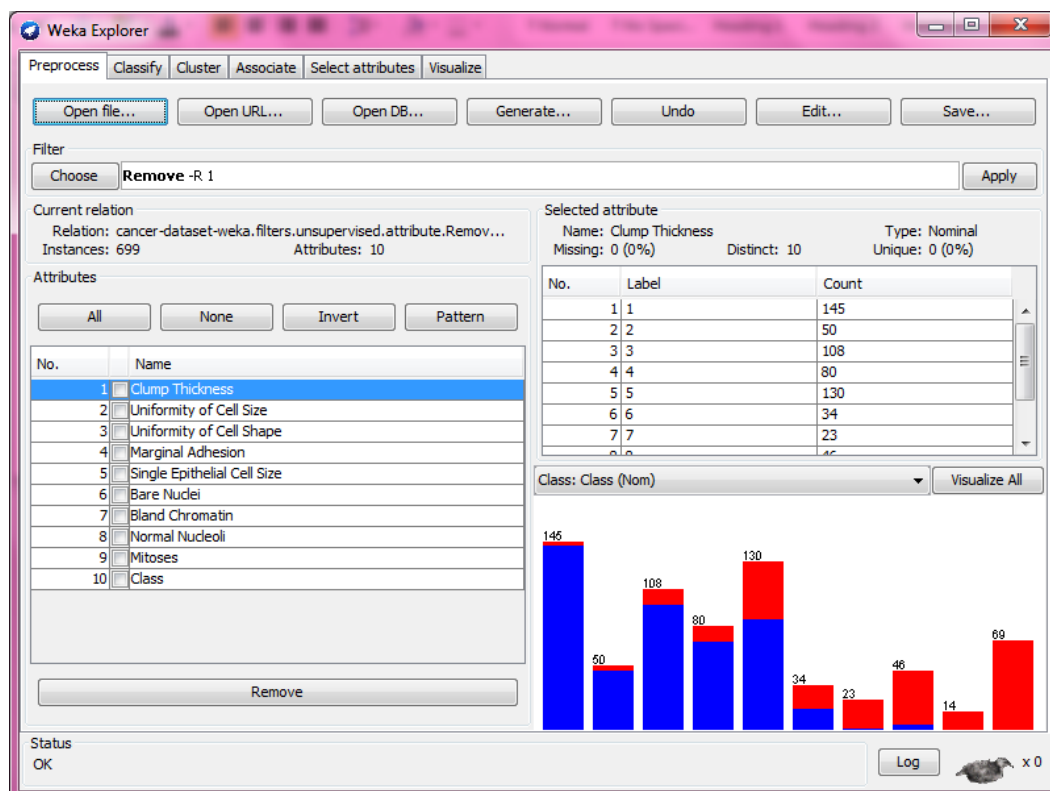
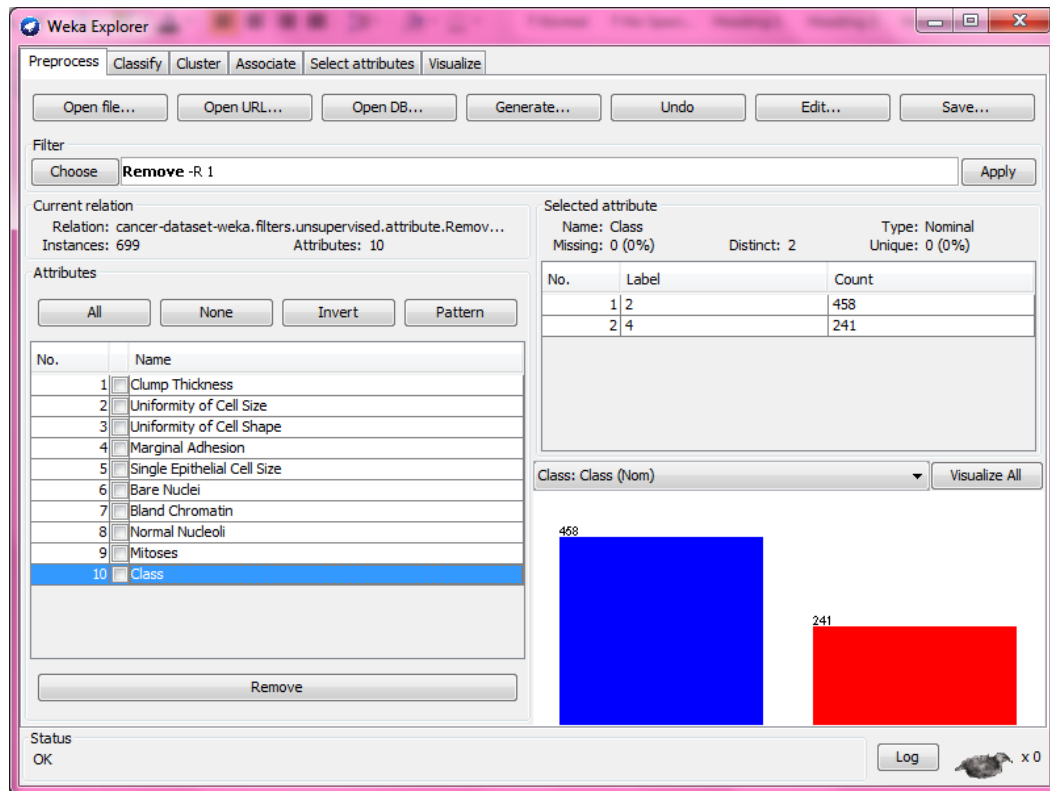


4. **Discretizing the dataset:** For this we need to go to the *arrf* file and open it as text. The *numeric* type must be replaced by the group of discrete numbers that the attribute can have. In our dataset case, all the attributes can have a value between 1-10, so the *numeric* word will be replaced by {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}. The Class attribute can only have 2 and 4 as values so its discrete numbers will be {2, 4}

```
1 @relation cancer-dataset-weka.filters.unsupervised.attribute.Remove-R1
2
3 @attribute 'Clump Thickness' numeric
4 @attribute 'Uniformity of Cell Size' numeric
5 @attribute 'Uniformity of Cell Shape' numeric
6 @attribute 'Marginal Adhesion' numeric
7 @attribute 'Single Epithelial Cell Size' numeric
8 @attribute 'Bare Nuclei' numeric
9 @attribute 'Bland Chromatin' numeric
10 @attribute 'Normal Nucleoli' numeric
11 @attribute Mitoses numeric
12 @attribute 'Class' numeric
13
14 @data
15 5,1,1,1,2,1,3,1,1,2
16 5,4,4,5,7,10,3,2,1,2
```

```
1 @relation cancer-dataset-weka.filters.unsupervised.attribute.Remove-R1
2
3 @attribute 'Clump Thickness' {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
4 @attribute 'Uniformity of Cell Size' {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
5 @attribute 'Uniformity of Cell Shape' {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
6 @attribute 'Marginal Adhesion' {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
7 @attribute 'Single Epithelial Cell Size' {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
8 @attribute 'Bare Nuclei' {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
9 @attribute 'Bland Chromatin' {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
10 @attribute 'Normal Nucleoli' {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
11 @attribute Mitoses {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
12 @attribute 'Class' {2, 4}
13
14 @data
15 5,1,1,1,2,1,3,1,1,2
16 5,4,4,5,7,10,3,2,1,2
```

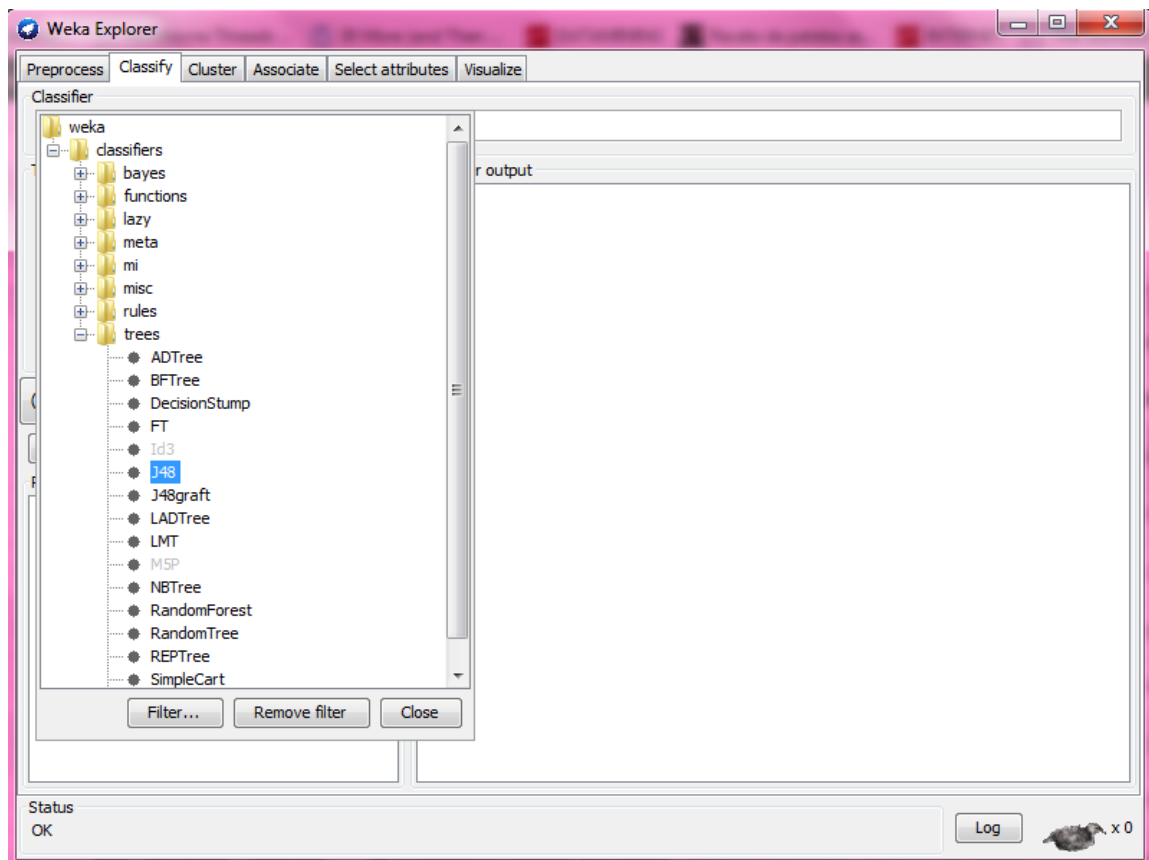
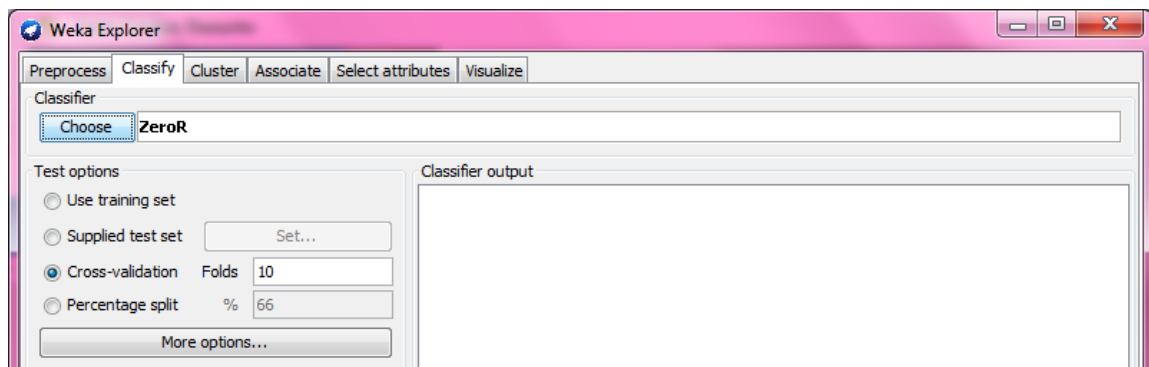

After this step we reload our *arff* file, and now the data will be displayed with different colors depending on the class which the case belongs. *Blue* for benign cases and *Red* for malign cases.



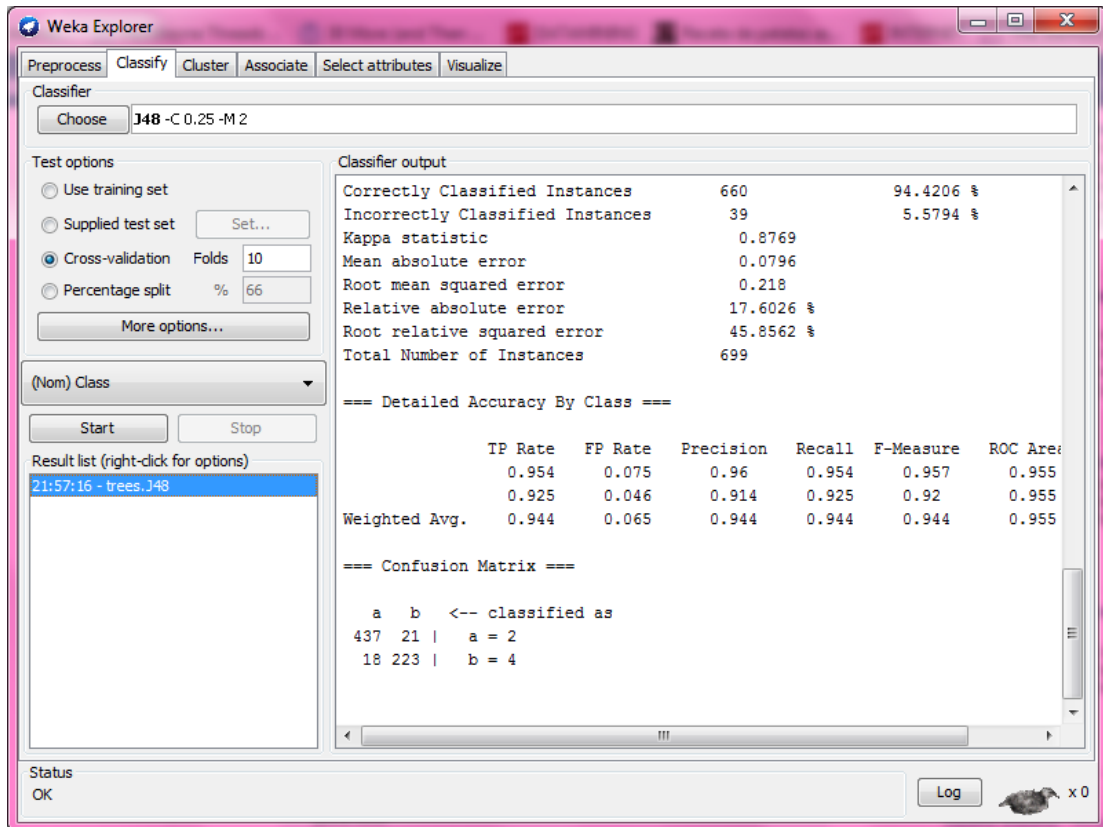
Running the algorithm

Note: in WEKA the ID3 algorithm only operates on nominal attributes; and because the attributes of our dataset are numeric the J48 algorithm will be used instead. It must be clear that the ID3 algorithm is the precursor of the J48 algorithm so won't be any alteration in the results because of this change.

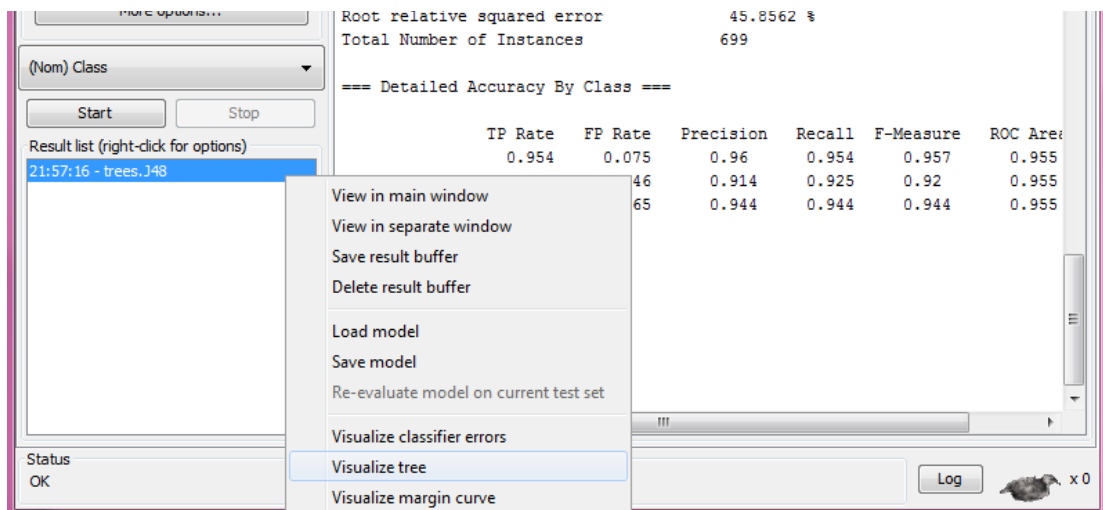
1. **Setting the Algorithm:** Select the *Classify* tab. Then click on the *Choose* button below the text "Classifier" and next to the text field. Then, in the list of algorithm displayed we proceed to choose the option classifiers-> trees -> J48.

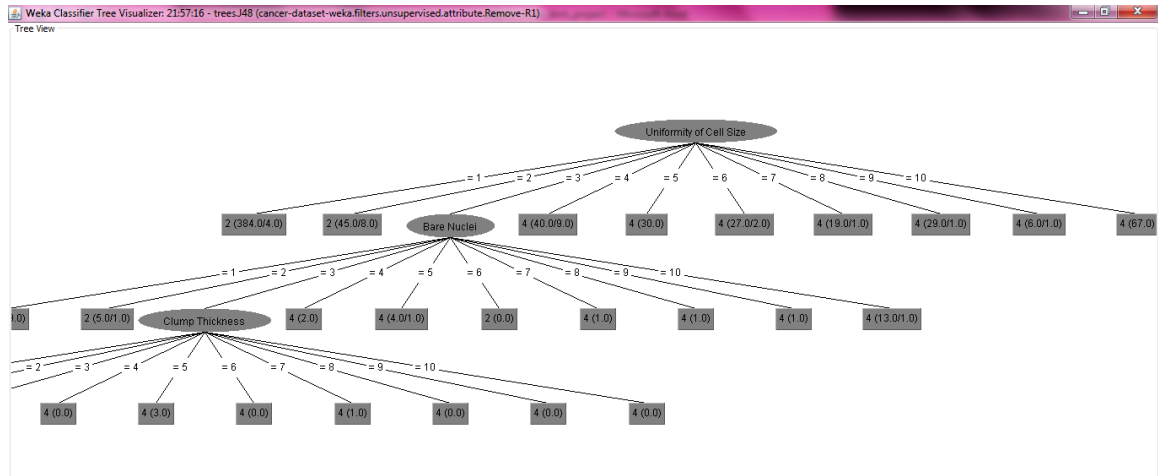


To do the evaluation using the 10-Fold Cross Validation, we need to set this method in the *Test options* area by choosing the *Cross-validation* option. Also we need to set the number of folds as ten. To run the algorithm we click on the *Start* button and WEKA will proceed to make the evaluations in the dataset and present the results in the *Classifier output* area.



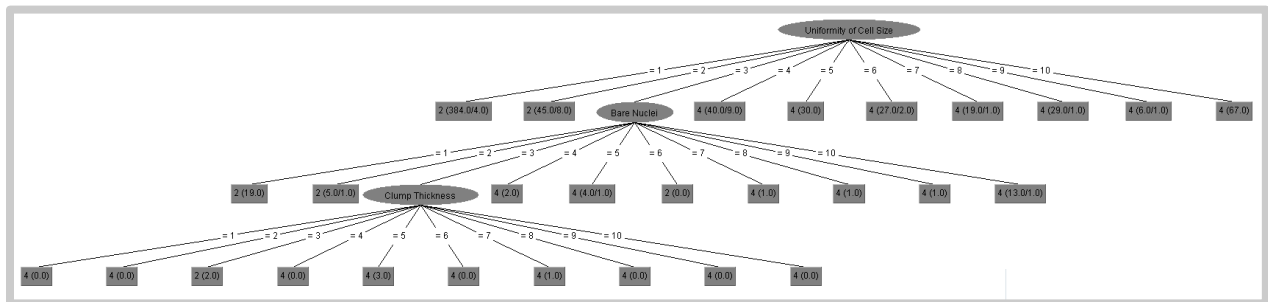
To view the decision tree of the dataset make a right click on the result description displayed in the *Result list* area. Then select the option *Visualize tree*, a new window will appear with the decision tree display on it.





Decision Tree

- Number of Leaves : 28
- Size of the tree: 31



Classifier Output

=== Run information ===

Scheme:weka.classifiers.trees.J48 -C 0.25 -M 2

Relation: cancer-dataset-weka.filters.unsupervised.attribute.Remove-R1

Instances: 699

Attributes: 10

- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape
- Marginal Adhesion
- Single Epithelial Cell Size
- Bare Nuclei
- Bland Chromatin
- Normal Nucleoli
- Mitoses
- Class

Test mode:10-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree

Uniformity of Cell Size = 1: 2 (384.0/4.0)

Uniformity of Cell Size = 2: 2 (45.0/8.0)

Uniformity of Cell Size = 3

| Bare Nuclei = 1: 2 (19.0)

| Bare Nuclei = 2: 2 (5.0/1.0)

| Bare Nuclei = 3

| | Clump Thickness = 1: 4 (0.0)

| | Clump Thickness = 2: 4 (0.0)

| | Clump Thickness = 3: 2 (2.0)

| | Clump Thickness = 4: 4 (0.0)

| | Clump Thickness = 5: 4 (3.0)

| | Clump Thickness = 6: 4 (0.0)

| | Clump Thickness = 7: 4 (1.0)

| | Clump Thickness = 8: 4 (0.0)

| | Clump Thickness = 9: 4 (0.0)

| | Clump Thickness = 10: 4 (0.0)

| Bare Nuclei = 4: 4 (2.0)

| Bare Nuclei = 5: 4 (4.0/1.0)

| Bare Nuclei = 6: 2 (0.0)

| Bare Nuclei = 7: 4 (1.0)

| Bare Nuclei = 8: 4 (1.0)

| Bare Nuclei = 9: 4 (1.0)

| Bare Nuclei = 10: 4 (13.0/1.0)

Uniformity of Cell Size = 4: 4 (40.0/9.0)
Uniformity of Cell Size = 5: 4 (30.0)
Uniformity of Cell Size = 6: 4 (27.0/2.0)
Uniformity of Cell Size = 7: 4 (19.0/1.0)
Uniformity of Cell Size = 8: 4 (29.0/1.0)
Uniformity of Cell Size = 9: 4 (6.0/1.0)
Uniformity of Cell Size = 10: 4 (67.0)

Number of Leaves : 28

Size of the tree : 31

Time taken to build model: 0.06 seconds

=== Stratified cross-validation ===

=== Summary ===

Correctly Classified Instances	660	94.4206 %
Incorrectly Classified Instances	39	5.5794 %
Kappa statistic	0.8769	
Mean absolute error	0.0796	
Root mean squared error	0.218	
Relative absolute error	17.6026 %	
Root relative squared error	45.8562 %	
Total Number of Instances	699	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.954	0.075	0.96	0.954	0.957	0.955	2
	0.925	0.046	0.914	0.925	0.92	0.955	4
Weighted Avg.	0.944	0.065	0.944	0.944	0.944	0.955	

=== Confusion Matrix ===

```
a  b  <-- classified as
437 21 | a = 2
18 223 | b = 4
```

Results

- True Benign: 437
- False Benign: 21
- True Malign: 223
- False Malign: 18

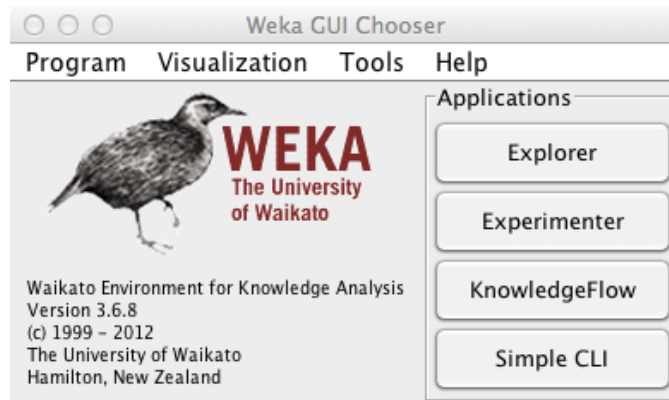
Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
2	0.954	0.075	0.96	0.954	0.957	0.955
4	0.925	0.046	0.914	0.925	0.92	0.955
Weighted Avg.	0.944	0.065	0.94	0.944	0.944	0.955

Support Vector Machines

Support Vector Machines are supervised models in data mining that analyze data, recognize patterns and classify the data into classes. In the dataset we will be using for this tool, we have to apply pre-processing to obtain discrete data before running the algorithm.

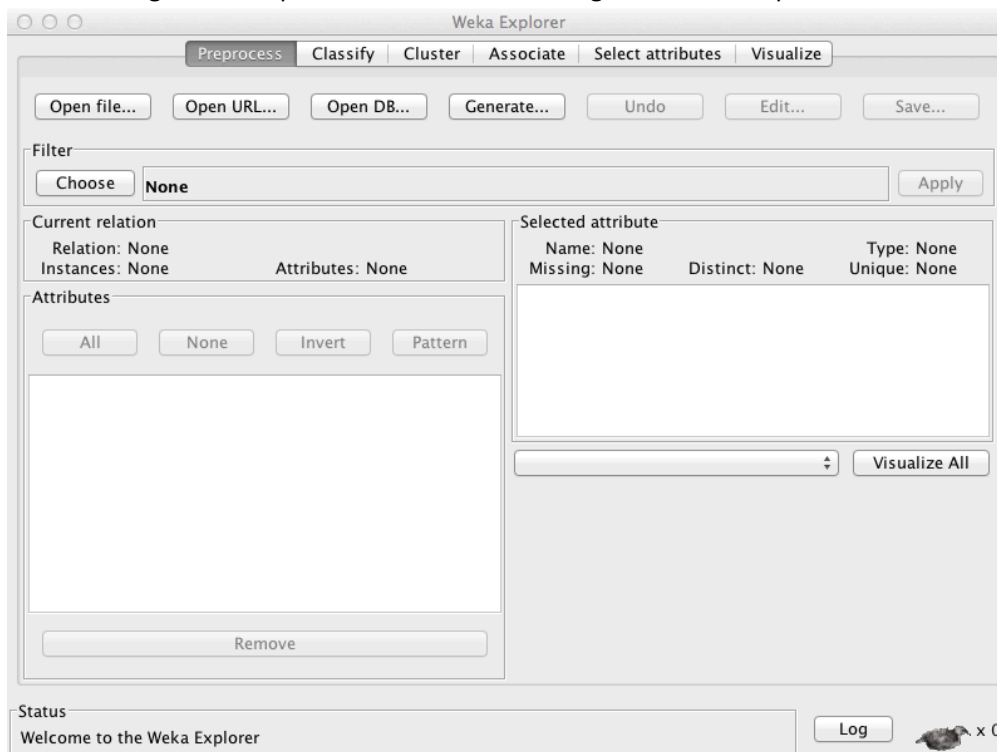
1. Starting Weka tool

Open the Weka toolkit and click on the Explorer button.



2. Loading Dataset

After clicking on the Explorer button the following window will open.



Now, Click on the “Open file...” button and select you dataset(it can be a .csv or .arff file). If it is a .csv file, you will have to discretize the dataset following steps for data-preprocessing as elaborated in the Decision Tree(C4.5) tutorial. After than you can continue with the remaining steps of this tutorial.

Once your .arff file has been loaded, Weka will display different colors depending on the class which the case belongs. *Blue* for benign cases and *Red* for malign cases.

The screenshot shows the Weka Explorer application window. The 'Preprocess' tab is active. The 'Open file...' button is highlighted. The 'Filter' section shows 'None' selected. The 'Current relation' section displays 'Relation: cancer-dataset-weka.filters.unsupervised.a...' with 699 instances and 10 attributes. The 'Attributes' section shows a list of attributes, with 'Class' selected. The 'Selected attribute' section shows 'Name: Class', 'Missing: 0 (0%)', 'Distinct: 2', and 'Type: Nominal'. A table below shows the distribution of the 'Class' attribute:

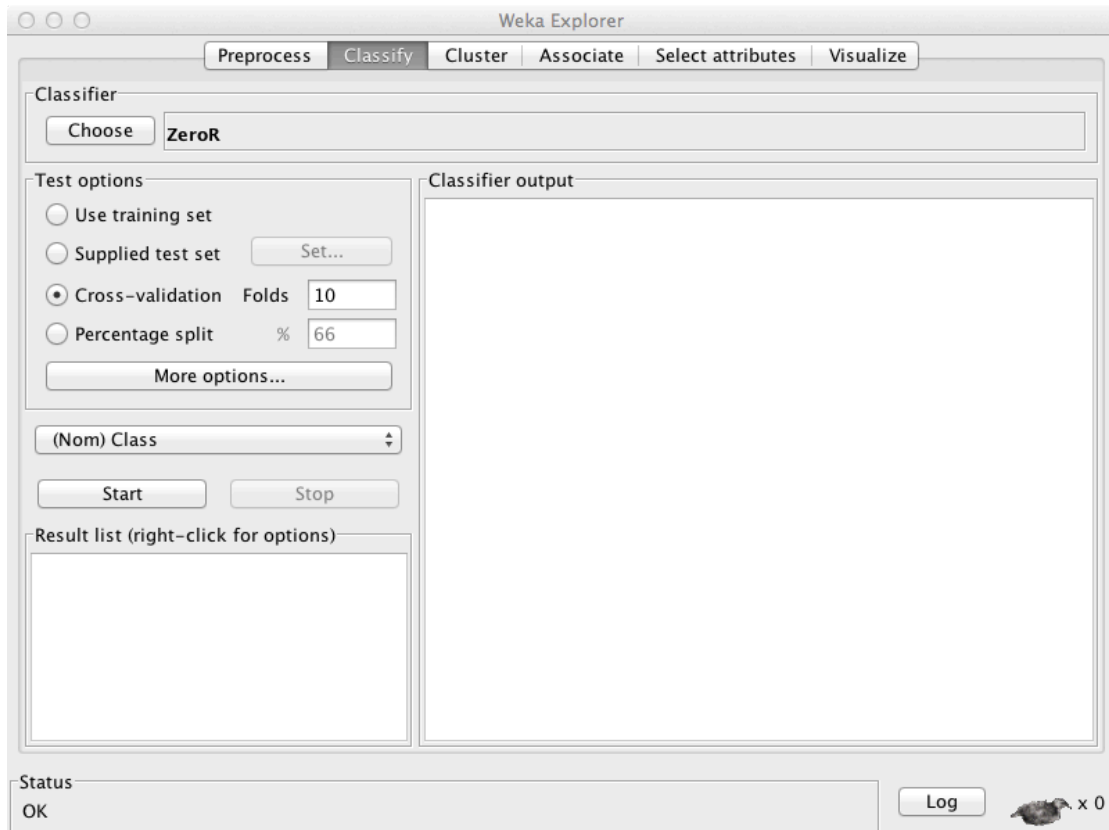
No.	Label	Count
1	2	458
2	4	241

The 'Class: Class (Nom)' dropdown is set to 'Class (Nom)'. A bar chart visualization shows two bars: a blue bar for class 2 (458) and a red bar for class 4 (241). The status bar at the bottom shows 'OK' and a 'Log' button.

Running the Algorithm

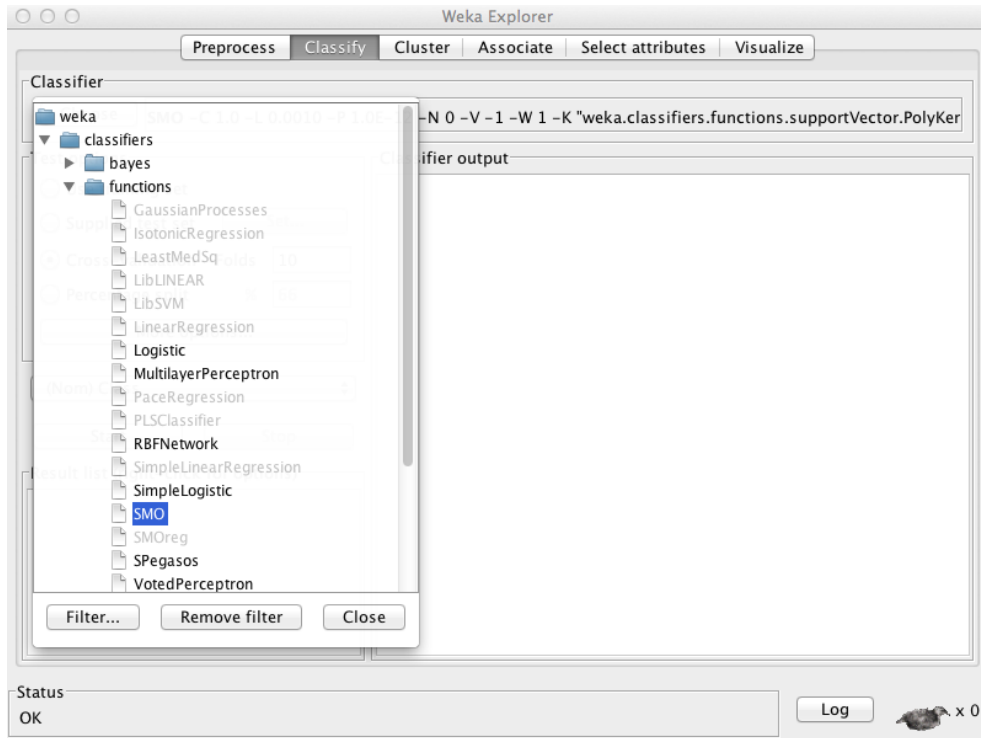
3. Classifying

Now, Click on the “Classify” tab at the top of the window and the window should look like this,



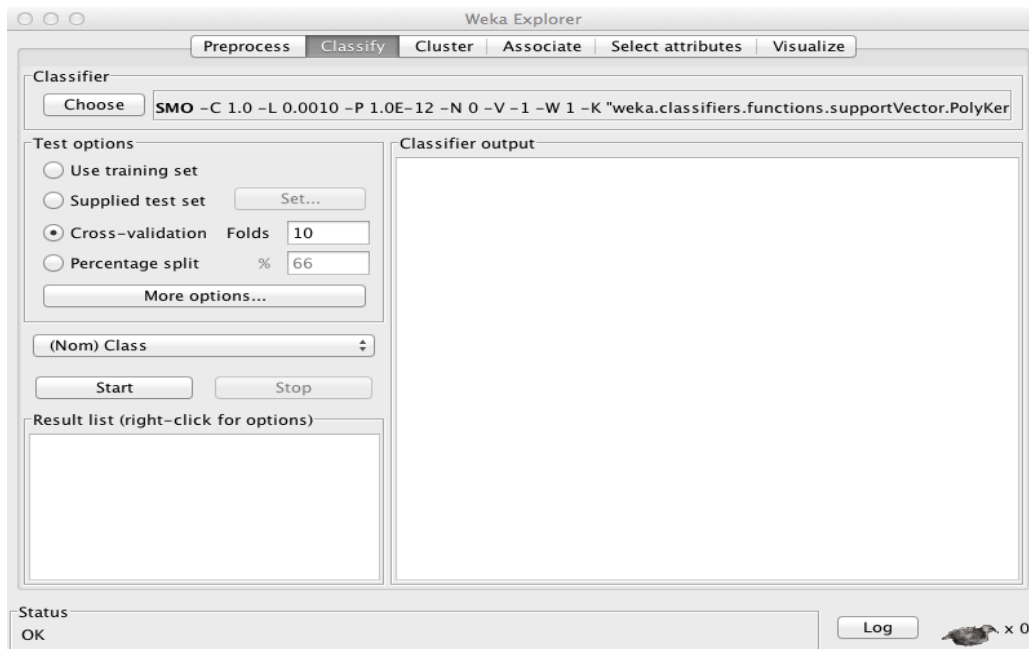
4. Selecting Classifier Filter

Now, We select the Classifier, click on the “Choose” button below Classifier and select the “SMO” filter from the given option . SMO is a SVM filter.

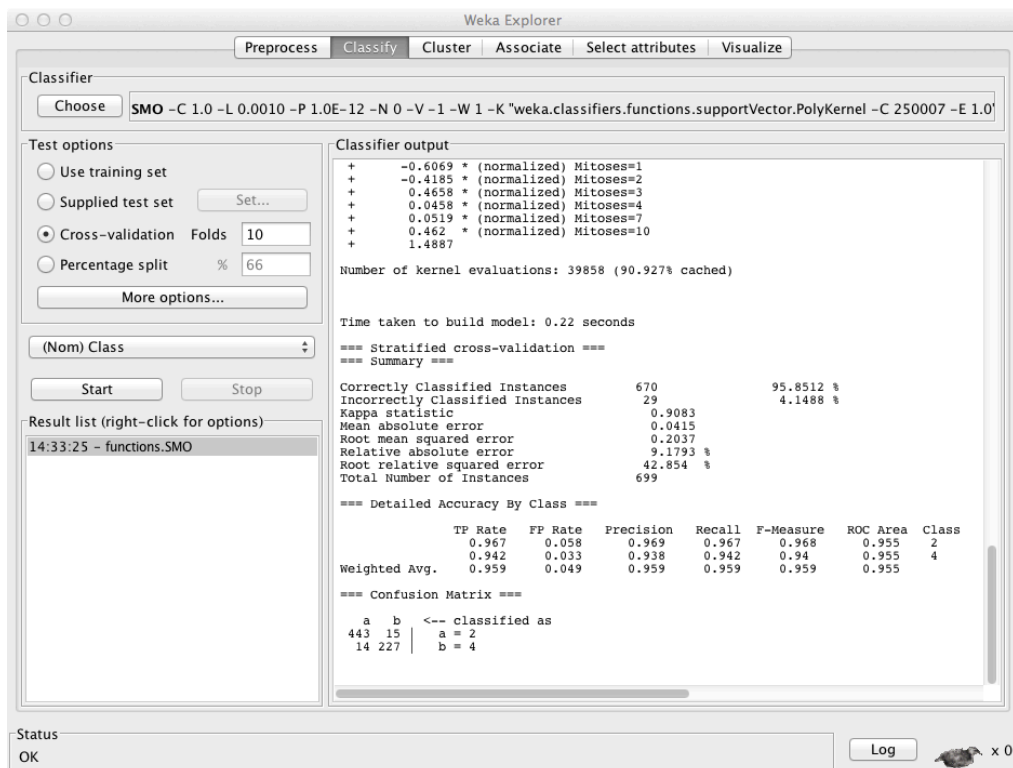


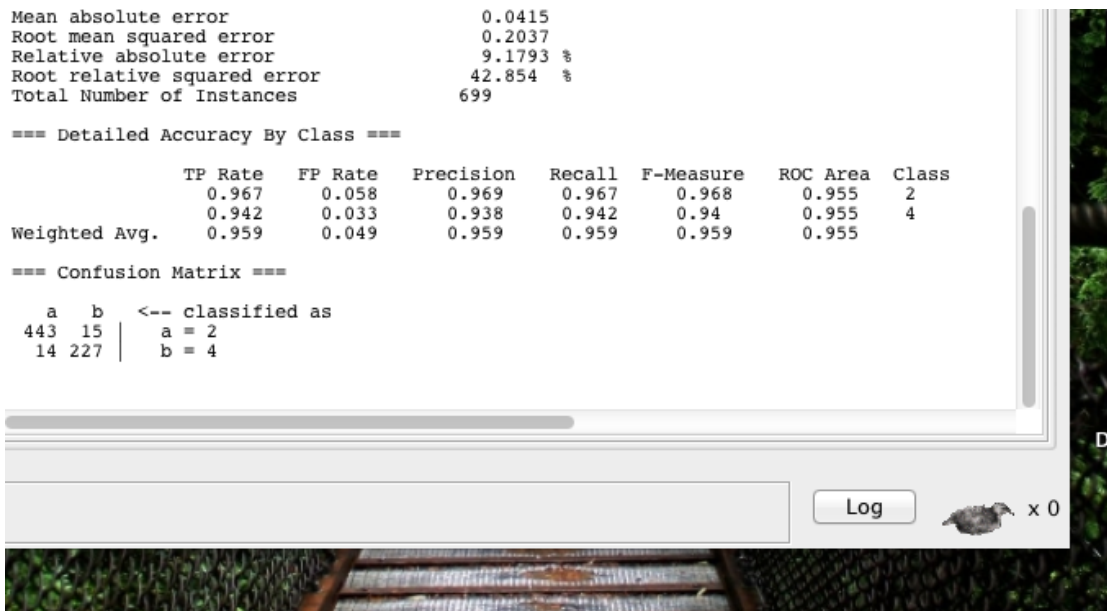
5. Running the SVM classifier

Now, under Test options, select “Cross-Validation” with 10 folds(you can specify a different number of folds as per your requirement).



After selecting the Test option, Click start and Weka will run the SVM and the result will be displayed as per the next window.





The output obtained gives us the true positive, false positive , precision , recall ROC for the test sample. This allows us to grade the accuracy for the classifier.

Classifier Output

=== Run information ===

Scheme:weka.classifiers.functions.SMO -C 1.0 -L 0.0010 -P 1.0E-12 -N 0 -V -1 -W 1 -K
"weka.classifiers.functions.supportVector.PolyKernel -C 250007 -E 1.0"

Relation: cancer-dataset-weka.filters.unsupervised.attribute.Remove-R1-
weka.filters.unsupervised.attribute.Discretize-B10-M-1.0-R1,2,3,4,5,6,7,8,9

Instances: 699

Attributes: 10

Clump Thickness

Uniformity of Cell Size

Uniformity of Cell Shape

Marginal Adhesion

Single Epithelial Cell Size

Bare Nuclei

Bland Chromatin

Normal Nucleoli

Mitoses

Class

Test mode:10-fold cross-validation

=== Classifier model (full training set) ===

SMO

Kernel used:

Linear Kernel: $K(x,y) = \langle x,y \rangle$

Classifier for classes: 2, 4

BinarySMO

Machine linear: showing attribute weights, not support vectors.

-0.7999 * (normalized) Clump Thickness=1
+ 0.1609 * (normalized) Clump Thickness=2
+ -0.0973 * (normalized) Clump Thickness=3

- + -0.4661 * (normalized) Clump Thickness=4
- + -0.4235 * (normalized) Clump Thickness=5
- + -0.757 * (normalized) Clump Thickness=6
- + 0.7853 * (normalized) Clump Thickness=7
- + 0.0781 * (normalized) Clump Thickness=8
- + 0.377 * (normalized) Clump Thickness=9
- + 1.1424 * (normalized) Clump Thickness=10
- + -0.5701 * (normalized) Uniformity of Cell Size=1
- + 0.0147 * (normalized) Uniformity of Cell Size=2
- + -0.054 * (normalized) Uniformity of Cell Size=3
- + -0.3618 * (normalized) Uniformity of Cell Size=4
- + 0.1242 * (normalized) Uniformity of Cell Size=5
- + 0.1607 * (normalized) Uniformity of Cell Size=6
- + -0.2776 * (normalized) Uniformity of Cell Size=7
- + 0.0331 * (normalized) Uniformity of Cell Size=8
- + 0.0828 * (normalized) Uniformity of Cell Size=9
- + 0.848 * (normalized) Uniformity of Cell Size=10
- + -0.6141 * (normalized) Uniformity of Cell Shape=1
- + -0.8623 * (normalized) Uniformity of Cell Shape=2
- + 0.3367 * (normalized) Uniformity of Cell Shape=3
- + 0.0722 * (normalized) Uniformity of Cell Shape=4
- + 0.5204 * (normalized) Uniformity of Cell Shape=5
- + -0.023 * (normalized) Uniformity of Cell Shape=6
- + -0.3138 * (normalized) Uniformity of Cell Shape=7
- + 0.2503 * (normalized) Uniformity of Cell Shape=8

- + 0.4934 * (normalized) Uniformity of Cell Shape=9
- + 0.14 * (normalized) Uniformity of Cell Shape=10
- + -0.2767 * (normalized) Marginal Adhesion=1
- + -0.2161 * (normalized) Marginal Adhesion=2
- + -0.4446 * (normalized) Marginal Adhesion=3
- + 0.5876 * (normalized) Marginal Adhesion=4
- + -0.215 * (normalized) Marginal Adhesion=5
- + 0.0432 * (normalized) Marginal Adhesion=6
- + 0 * (normalized) Marginal Adhesion=7
- + 0.1526 * (normalized) Marginal Adhesion=8
- + -0.0749 * (normalized) Marginal Adhesion=9
- + 0.444 * (normalized) Marginal Adhesion=10
- + 0.0491 * (normalized) Single Epithelial Cell Size=1
- + -0.093 * (normalized) Single Epithelial Cell Size=2
- + -0.1685 * (normalized) Single Epithelial Cell Size=3
- + 0.1564 * (normalized) Single Epithelial Cell Size=4
- + 0.3348 * (normalized) Single Epithelial Cell Size=5
- + 0.2325 * (normalized) Single Epithelial Cell Size=6
- + -1.2362 * (normalized) Single Epithelial Cell Size=7
- + -0.2752 * (normalized) Single Epithelial Cell Size=8
- + 1 * (normalized) Single Epithelial Cell Size=10
- + -1.0405 * (normalized) Bare Nuclei=1
- + -0.5017 * (normalized) Bare Nuclei=2
- + -0.3412 * (normalized) Bare Nuclei=3
- + -0.2828 * (normalized) Bare Nuclei=4

+ -0.15 * (normalized) Bare Nuclei=5
+ 0.8277 * (normalized) Bare Nuclei=6
+ -0.2789 * (normalized) Bare Nuclei=7
+ 0.2527 * (normalized) Bare Nuclei=8
+ 0.7264 * (normalized) Bare Nuclei=9
+ 0.7882 * (normalized) Bare Nuclei=10
+ -0.6998 * (normalized) Bland Chromatin=1
+ -0.3522 * (normalized) Bland Chromatin=2
+ -0.1926 * (normalized) Bland Chromatin=3
+ -0.0886 * (normalized) Bland Chromatin=4
+ 0.0426 * (normalized) Bland Chromatin=5
+ -0.1697 * (normalized) Bland Chromatin=6
+ 0.1967 * (normalized) Bland Chromatin=7
+ 0.3212 * (normalized) Bland Chromatin=8
+ 0.2344 * (normalized) Bland Chromatin=9
+ 0.708 * (normalized) Bland Chromatin=10
+ -0.1236 * (normalized) Normal Nucleoli=1
+ -1.1778 * (normalized) Normal Nucleoli=2
+ 0.1662 * (normalized) Normal Nucleoli=3
+ 0.2401 * (normalized) Normal Nucleoli=4
+ -0.2096 * (normalized) Normal Nucleoli=5
+ 0.1674 * (normalized) Normal Nucleoli=6
+ -0.1995 * (normalized) Normal Nucleoli=7
+ -0.5755 * (normalized) Normal Nucleoli=8
+ 0.3762 * (normalized) Normal Nucleoli=9

+ 1.3362 * (normalized) Normal Nucleoli=10
 + -0.6069 * (normalized) Mitoses=1
 + -0.4185 * (normalized) Mitoses=2
 + 0.4658 * (normalized) Mitoses=3
 + 0.0458 * (normalized) Mitoses=4
 + 0.0519 * (normalized) Mitoses=7
 + 0.462 * (normalized) Mitoses=10
 + 1.4887

Number of kernel evaluations: 39858 (90.927% cached)

Time taken to build model: 0.24 seconds

=== Stratified cross-validation ===

=== Summary ===

Correctly Classified Instances	670	95.8512 %
Incorrectly Classified Instances	29	4.1488 %
Kappa statistic	0.9083	
Mean absolute error	0.0415	
Root mean squared error	0.2037	
Relative absolute error	9.1793 %	
Root relative squared error	42.854 %	

Total Number of Instances 699

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.967	0.058	0.969	0.967	0.968	0.955	2
	0.942	0.033	0.938	0.942	0.94	0.955	4
Weighted Avg.	0.959	0.049	0.959	0.959	0.959	0.955	

=== Confusion Matrix ===

a b <-- classified as

443 15 | a = 2

14 227 | b = 4

Results

- True Benign: 443
- False Benign: 15
- True Malign: 227
- False Malign: 14

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
2	0.967	0.058	0.969	0.967	0.968	0.955
4	0.942	0.033	0.938	0.942	0.94	0.955
Weighted Avg.	0.959	0.049	0.959	0.959	0.959	0.955

Cross Validation Results and Comparisons

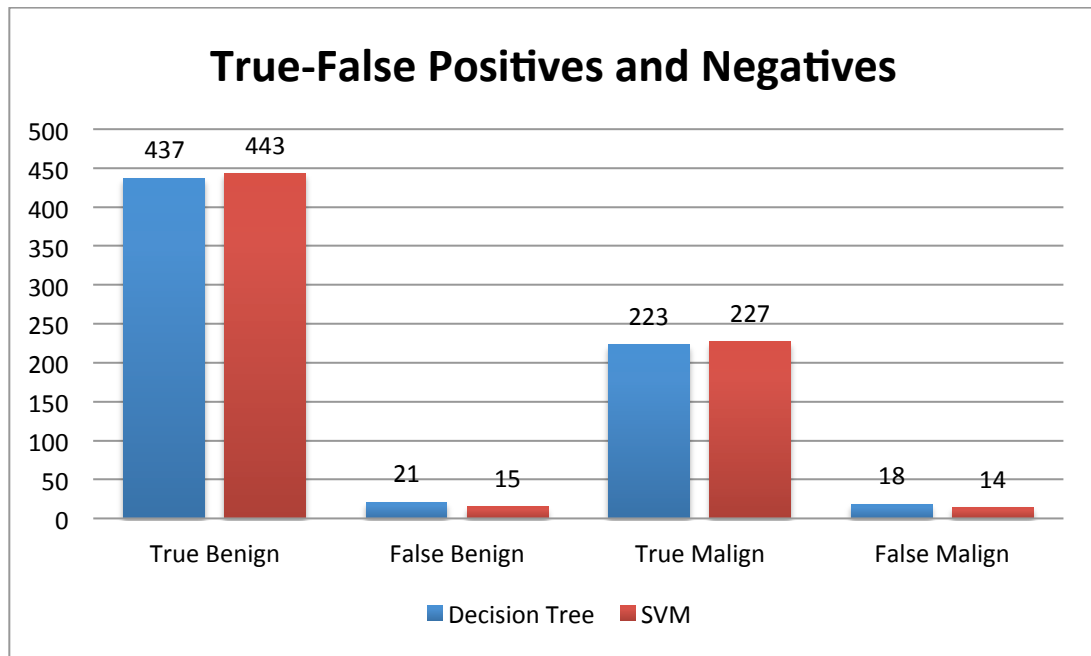


Figure 2 - True - False Positives and Negatives chart

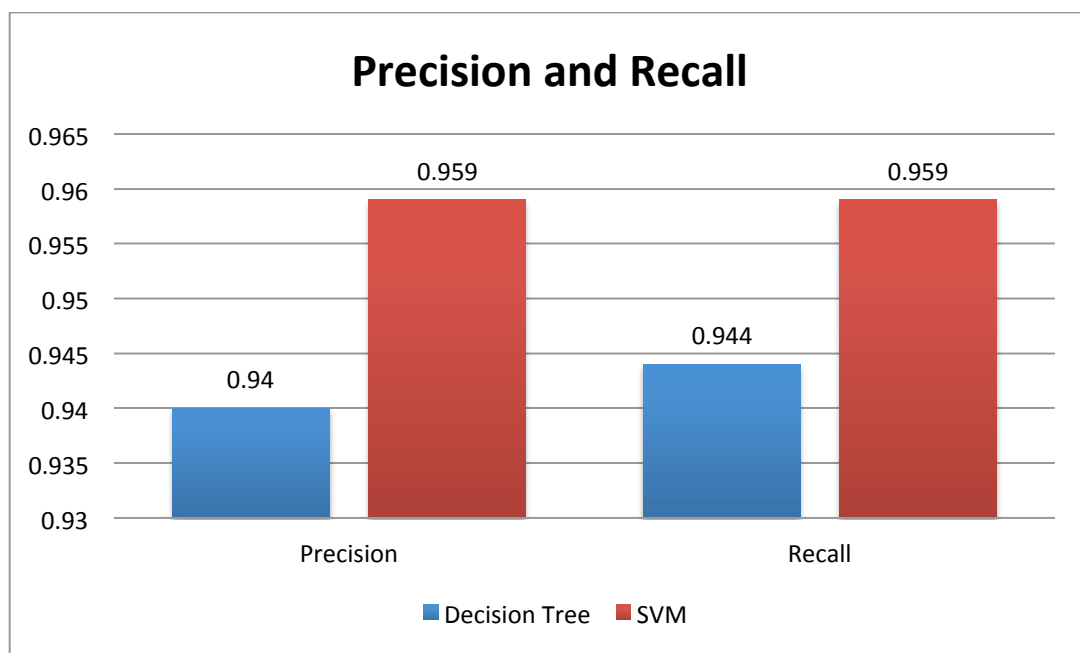


Figure 3 - Precision and Recall

With Respect to the charts above, we can infer from the results that the SVM algorithm had better performance compared to the Decision tree algorithm. As we can observe from Figure 2, that both algorithms gave us close results. However the SVM algorithm predicted more cases correctly than Decision tree algorithm as well as the number of cases predicted wrong were less compared to decision tree. Figure 3 shows that SVM classifies the cases more accurately and the results are more relevant. So, we can conclude that SVM is the more optimal algorithm that can be used for this dataset.