DATA WAREHOUSING AND DATA MINING LAB

Credit Risk Assessment

Description: The business of banks is making loans. Assessing the credit worthiness of an applicant is of crucial importance. You have to develop a system to help a loan officer decide whether the credit of a customer is good, or bad. A bank‟s business rules regarding loans must consider two opposing factors. On the one hand, a bank wants to make as many loans as possible. Interest on these loans is the ban‟s profit source. On the other hand, a bank cannot afford to make too many bad loans. Too many bad loans could lead to the collapse of the bank. The bank‟s loan policy must involve a compromise not too strict, and not too lenient.

To do the assignment, you first and foremost need some knowledge about the world of credit . You can acquire such knowledge in a number of ways.

1. Knowledge Engineering. Find a loan officer who is willing to talk. Interview her and try to represent her knowledge in the form of production rules.
2. Books. Find some training manuals for loan officers or perhaps a suitable textbook on finance. Translate this knowledge from text form to production rule form.
3. Common sense. Imagine yourself as a loan officer and make up reasonable rules which can be used to judge the credit worthiness of a loan applicant.
4. Case histories. Find records of actual cases where competent loan officers correctly judged when not to, approve a loan application.

The German Credit Data :

Actual historical credit data is not always easy to come by because of confidentiality rules. Here is one such dataset (original) Excel spreadsheet version of the German credit data (download from web).

In spite of the fact that the data is German, you should probably make use of it for this assignment, (Unless you really can consult a real loan officer !)

A few notes on the German dataset :

- DM stands for Deutsche Mark, the unit of currency, worth about 90 cents Canadian (but looks and acts like a quarter).
- Owns_telephone. German phone rates are much higher than in Canada so fewer people own telephones.
- Foreign_worker. There are millions of these in Germany (many from Turkey). It is very hard to get German citizenship if you were not born of German parents.
- There are 20 attributes used in judging a loan applicant. The goal is the classify the applicant into one of two categories, good or bad.

Subtasks : (Turn in your answers to the following tasks)

EXPERIMENT-1

1.1 OBJECTIVE:

List all the categorical (or nominal) attributes and the real-valued attributes separately.

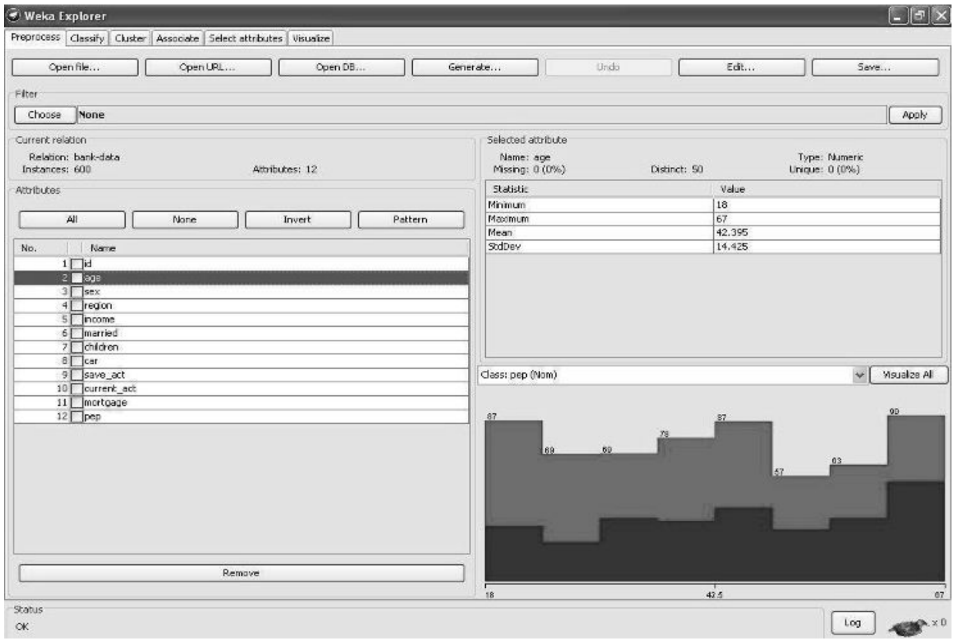
1.2 RESOURCES:

Weka mining tool

1.3 PROCEDURE:

1) Open the Weka GUI Chooser.
2) Select EXPLORER present in Applications.
3) Select Preprocess Tab.
4) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
5) Clicking on any attribute in the left panel will show the basic statistics on that selected attribute.

1.4 OUTPUT:



Filter: None

Current relation
Relation: bank-data
Instances: 600   Attributes: 12

Attributes

No.	Name
1	id
2	age
3	sex
4	region
5	income
6	married
7	children
8	car
9	save_act
10	current_act
11	mortgage
12	pep

Selected attribute
Name: age   Type: Numeric
Missing: 0 (0%)   Distinct: 50   Unique: 0 (0%)

Statistic	Value
Minimum	18
Maximum	67
Mean	42.395
StdDev	14.425

Class: pep (Nom)

87 69 69 78 87 57 63 90

18 42.5 67

Status
OK

EXPERIMENT-2

2.1 OBJECTIVE:

Which attributes do you think might be crucial in making the credit assessment? Come up with some simple rules in plain English using your selected attributes.

2.2 RESOURCES:

Weka mining tool

2.3 THEORY:

Association rule mining is defined as: Let be a set of *n* binary attributes called items. Let be a set of transactions called the database. Each transaction in *D* has a unique transaction ID and contains a subset of the items in *I*. A rule is defined as an implication of the form X=>Y where X,Y C I and X Π Y=Φ . The sets of items (for short itemsets) X and Y are called antecedent (left hand side or LHS) and consequen*t* (right hand side or RHS) of the rule respectively.

To illustrate the concepts, we use a small example from the supermarket domain.

The set of items is *I* = {milk,bread,butter,beer} and a small database containing the items (1 codes presence and 0 absence of an item in a transaction) is shown in the table to the right. An example rule for the supermarket could be meaning that if milk and bread is bought, customers also buy butter.

Note: this example is extremely small. In practical applications, a rule needs a support of several hundred transactions before it can be considered statistically significant, and datasets often contain thousands or millions of transactions.

To select interesting rules from the set of all possible rules, constraints on various measures of significance and interest can be used. The best known constraints are minimum thresholds on support and confidence. The support supp(*X*) of an itemset *X* is defined as the proportion of transactions in the data set which contain the itemset. In the example database, the itemset {milk, bread} has a support of 2 / 5 = 0.4 since it occurs in 40% of all transactions (2 out of 5 transactions).

The confidence of a rule is defined. For example, the rule has a confidence of 0.2 / 0.4 = 0.5 in the database, which means that for 50% of the transactions containing milk and bread the rule is correct. Confidence can be interpreted as an estimate of the probability *P*(*Y* | *X*), the probability of finding the RHS of the rule in transactions under the condition that these transactions also contain the LHS .

ALGORITHM:

Association rule mining is to find out association rules that satisfy the predefined minimum support and confidence from a given database. The problem is usually decomposed into two sub problems. One is to find those itemsets whose occurrences exceed a predefined threshold in the database; those itemsets are called frequent or large itemsets. The second problem is to generate association rules from those large itemsets with the constraints of minimal confidence.

Suppose one of the large itemsets is Lk, Lk = {I1, I2, … , Ik}, association rules with this itemsets are generated in the following way: the first rule is {I1, I2, … , Ik1} and {Ik}, by checking the confidence this rule can be determined as interesting or not. Then other rule are generated by deleting the last items in the antecedent and inserting it to the consequent, further the confidences of the new rules are checked to determine the interestingness of them. Those processes iterated until the antecedent becomes empty.

Since the second subproblem is quite straight forward, most of the researches focus on the first subproblem. The Apriori algorithm finds the frequent sets *L* In Database *D*.

· Find frequent set *Lk* - 1.

· Join Step.

o *Ck* is generated by joining *Lk* - 1with itself

· Prune Step.

o Any (*k* - 1) itemset that is not frequent cannot be a subset of a

frequent *k* itemset, hence should be removed.

Where · (*Ck*: Candidate itemset of size *k*)

· (*Lk*: frequent itemset of size

k) Apriori Pseudocode

```
Apriori (T,£)
L<{ Large 1itemsets that appear in more than transactions }
K<2
while L(k1)≠ Φ
C(k)<Generate( Lk - 1)
for transactions t € T
C(t)Subset(Ck,t)
for candidates c € C(t)
count[c]<count[ c]+1
L(k)<{ c € C(k)| count[c] ≥ £
K<K+ 1
return Ụ L(k) k
```

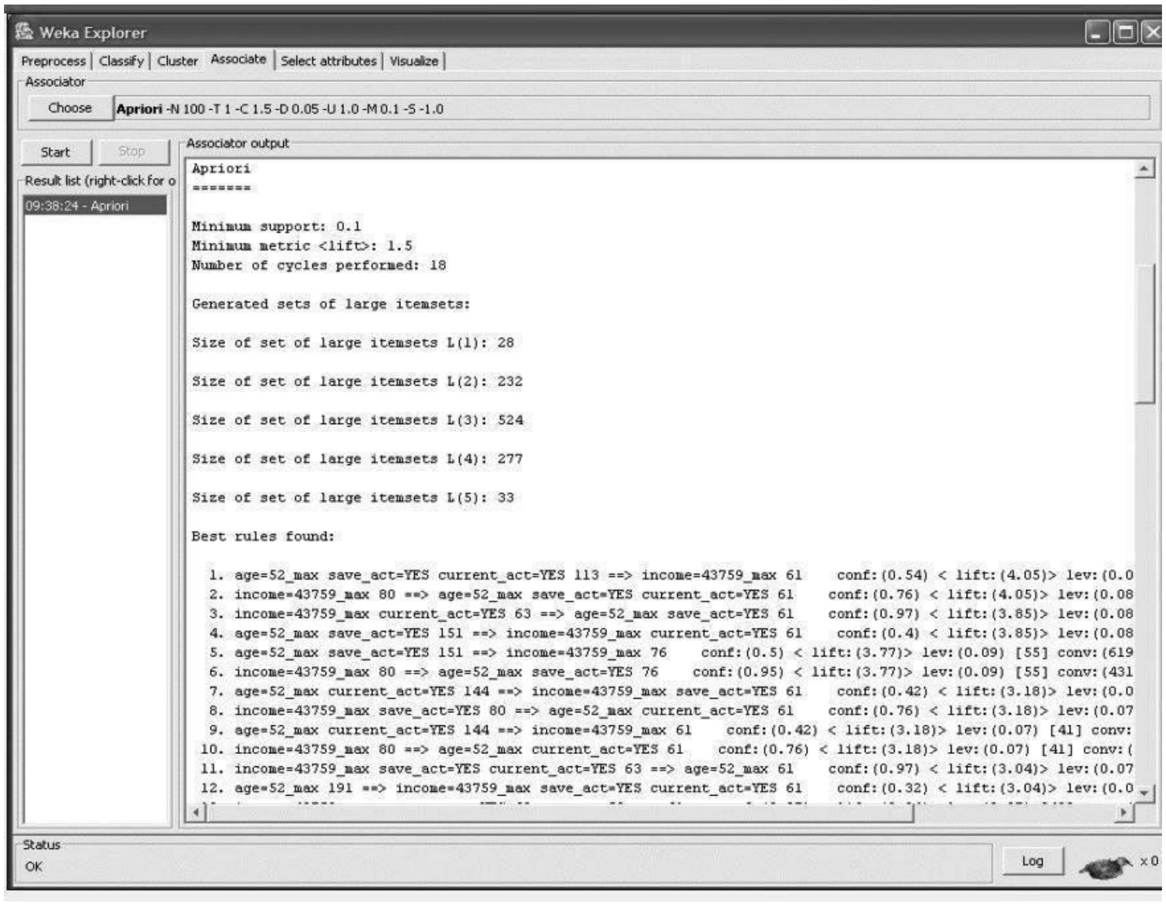
2.4 PROCEDURE:

1) Given the Bank database for mining.
2) Select EXPLORER in WEKA GUI Chooser.
3) Load "Bank.csv" in Weka by Open file in Preprocess tab.
4) Select only Nominal values.
5) Go to Associate Tab.
6) Select Apriori algorithm from "Choose " button present in Associator

```
weka.associations.Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1
```

7) Select Start button
8) Now we can see the sample rules.

2.5 OUTPUT:


Weka Explorer
Preprocess | Classify | Cluster | Associate | Select attributes | Visualize
Associator
Choose
Start
Stop
Result list (right-click for o
09:38:24 - Apriori
Associator output
Status
OK
Log
x 0

```
Apriori -N 100 -T 1 -C 1.5 -D 0.05 -U 1.0 -M 0.1 -S -1.0
```

```
Apriori
=======

Minimum support: 0.1
Minimum metric <lift>: 1.5
Number of cycles performed: 18

Generated sets of large itemsets:

Size of set of large itemsets L(1): 28

Size of set of large itemsets L(2): 232

Size of set of large itemsets L(3): 524

Size of set of large itemsets L(4): 277

Size of set of large itemsets L(5): 33

Best rules found:

  1. age=52_max save_act=YES current_act=YES 113 ==> income=43759_max 61    conf:(0.54) < lift:(4.05)> lev:(0.0
  2. income=43759_max 80 ==> age=52_max save_act=YES current_act=YES 61    conf:(0.76) < lift:(4.05)> lev:(0.08
  3. income=43759_max current_act=YES 63 ==> age=52_max save_act=YES 61    conf:(0.97) < lift:(3.85)> lev:(0.08
  4. age=52_max save_act=YES 151 ==> income=43759_max current_act=YES 61    conf:(0.4) < lift:(3.85)> lev:(0.08
  5. age=52_max save_act=YES 151 ==> income=43759_max 76    conf:(0.5) < lift:(3.77)> lev:(0.09) [55] conv:(619
  6. income=43759_max 80 ==> age=52_max save_act=YES 76    conf:(0.95) < lift:(3.77)> lev:(0.09) [55] conv:(431
  7. age=52_max current_act=YES 144 ==> income=43759_max save_act=YES 61    conf:(0.42) < lift:(3.18)> lev:(0.0
  8. income=43759_max save_act=YES 80 ==> age=52_max current_act=YES 61    conf:(0.76) < lift:(3.18)> lev:(0.07
  9. age=52_max current_act=YES 144 ==> income=43759_max 61    conf:(0.42) < lift:(3.18)> lev:(0.07) [41] conv:
 10. income=43759_max 80 ==> age=52_max current_act=YES 61    conf:(0.76) < lift:(3.18)> lev:(0.07) [41] conv:(
 11. income=43759_max save_act=YES current_act=YES 63 ==> age=52_max 61    conf:(0.97) < lift:(3.04)> lev:(0.07
 12. age=52_max 191 ==> income=43759_max save_act=YES current_act=YES 61    conf:(0.32) < lift:(3.04)> lev:(0.0
```

EXPERIMENT-3

3.1 OBJECTIVE:

*What attributes do you think might be crucial in making the bank assessment?

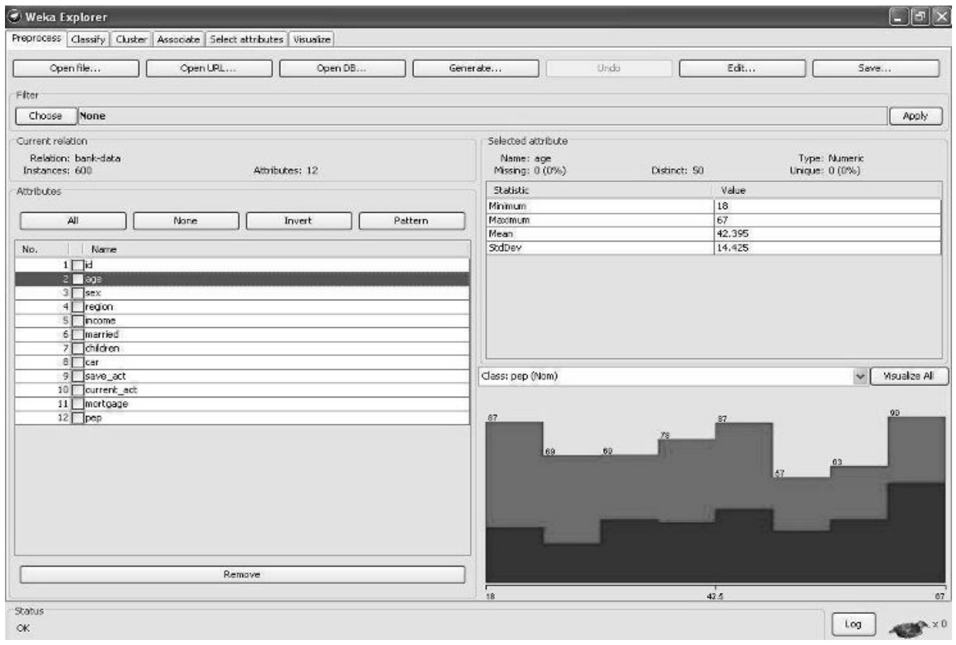
3.2 RESOURCES:

Weka mining tool

3.3 PROCEDURE:

1) Open the Weka GUI Chooser.
2) Select EXPLORER present in Applications.
3) Select Preprocess Tab.
4) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
5) Clicking on any attribute in the left panel will show the basic statistics on that selected attribute.

3.4 OUTPUT:



Current relation

Relation: bank-data
Instances: 600 Attributes: 12

Selected attribute

Name: age Type: Numeric
Missing: 0 (0%) Distinct: 50 Unique: 0 (0%)

Statistic	Value
Minimum	18
Maximum	67
Mean	42.395
StdDev	14.425

Attributes

No.	Name
1	id
2	age
3	sex
4	region
5	income
6	married
7	children
8	car
9	save_act
10	current_act
11	mortgage
12	pep

Class: pep (Nom)

EXPERIMENT-4

4.1 OBJECTIVE:

One type of model that you can create is a decision tree. Train a decision tree using the complete dataset as the training data. Report the model obtained after training.

4.2 RESOURCES:

Weka mining tool

4.3 THEORY:

Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data. For example, a classification model could be used to identify loan applicants as low, medium, or high credit risks. A classification task begins with a data set in which the class assignments are known. For example, a classification model that predicts credit risk could be developed based on observed data for many loan applicants over a period of time.

In addition to the historical credit rating, the data might track employment history, home ownership or rental, years of residence, number and type of investments, and so on. Credit rating would be the target, the other attributes would be the predictors, and the data for each customer would constitute a case.

Classifications are discrete and do not imply order. Continuous, floating point values would indicate a numerical, rather than a categorical, target. A predictive model with a numerical target uses a regression algorithm, not a classification algorithm. The simplest type of classification problem is binary classification. In binary classification, the target attribute has only two possible values: for example, high credit rating or low credit rating. Multiclass targets have more than two values: for example, low, medium, high, or unknown credit rating. In the model build (training) process, a classification algorithm finds relationships between the values of the predictors and the values of the target. Different classification algorithms use different techniques for finding relationships. These relationships are summarized in a model, which can then be applied to a different data set in which the class assignments are unknown.

Classification models are tested by comparing the predicted values to known target values in a set of test data. The historical data for a classification project is typically divided into two data sets: one for building the model; the other for testing the model. Scoring a classification model results in class assignments and probabilities for each case. For example, a model that classifies customers as low, medium, or high value would also predict the probability of each classification for each customer. Classification has many applications in customer segmentation, business modeling, marketing, credit analysis, and biomedical and drug response modeling.

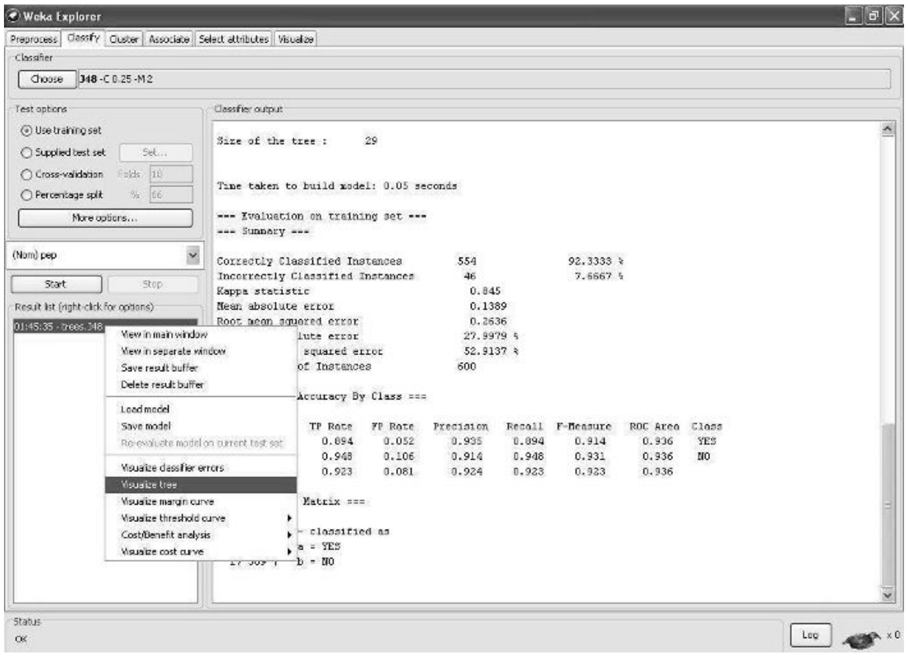
Different Classification Algorithms: Oracle Data Mining provides the following algorithms for classification:

- Decision Tree - Decision trees automatically generate rules, which are conditional statements that reveal the logic used to build the tree.
- Naive Bayes - Naive Bayes uses Bayes' Theorem, a formula that calculates a probability by counting the frequency of values and combinations of values in the historical data.

4.4 PROCEDURE:

1) Open Weka GUI Chooser.
2) Select EXPLORER present in Applications.
3) Select Preprocess Tab.
4) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
5) Go to Classify tab.
6) Here the c4.5 algorithm has been chosen which is entitled as j48 in Java and can be selected by clicking the button choose and select tree j48
7) Select Test options “Use training set”
8) if need select attribute.
9) Click Start.
10) Now we can see the output details in the Classifier output.
11) Right click on the result list and select “visualize tree”option .

4.5 OUTPUT:



Classifier: J48 -C 0.25 -M 2

Test options: [✓ Use training set] Supplied test set / Cross-validation Folds 10 / Percentage split % 66

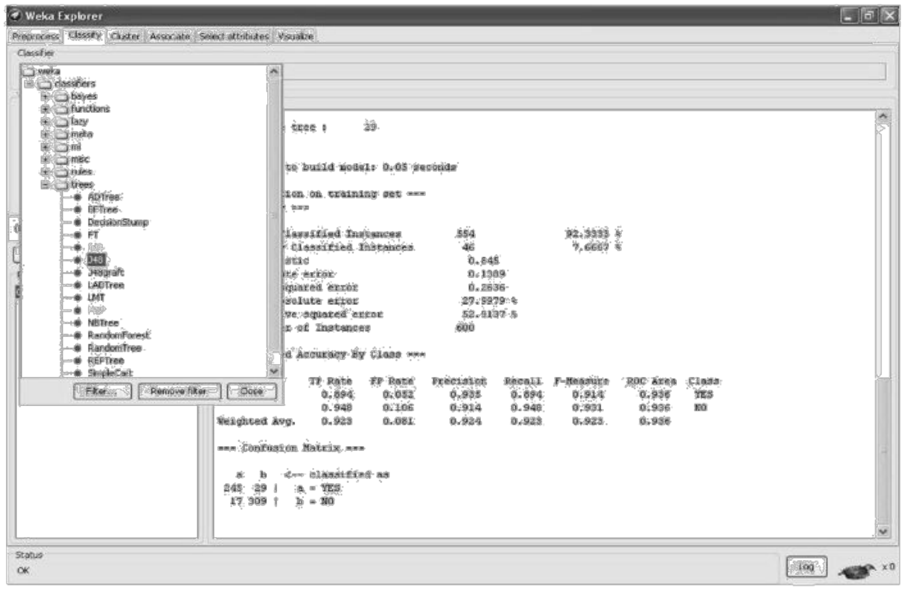
(Nom) pep

Result list (right-click for options): 01:45:35 - trees.J48

Classifier output

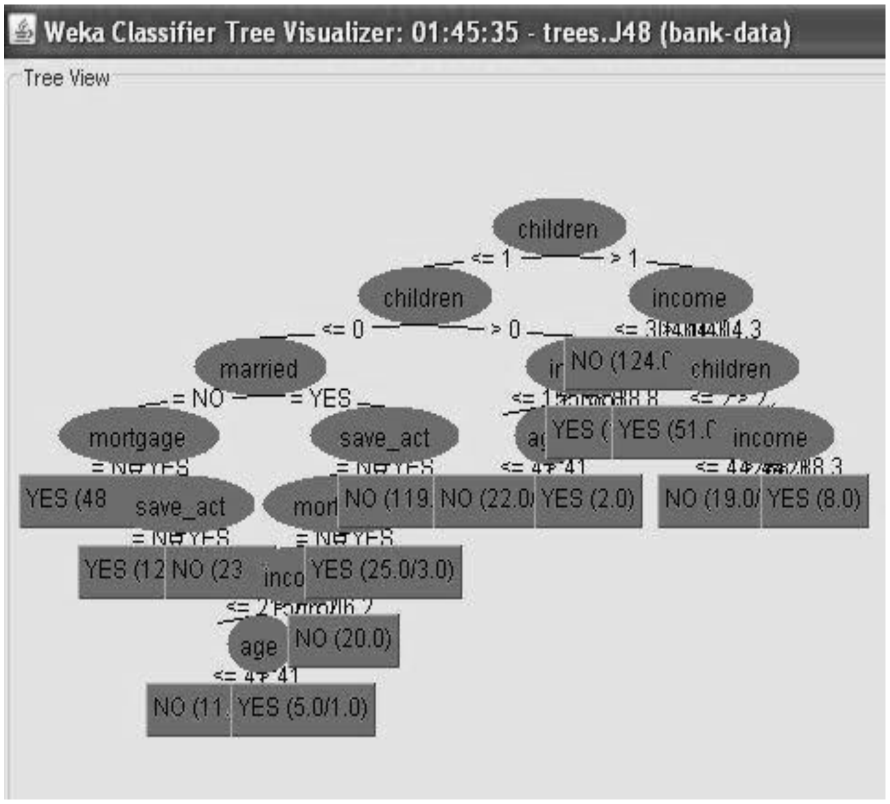
```
Size of the tree :      29


Time taken to build model: 0.05 seconds

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances         554               92.3333 %
Incorrectly Classified Instances        46                7.6667 %
Kappa statistic                          0.845
Mean absolute error                      0.1389
Root mean squared error                  0.2636
                  lute error            27.9979 %
                   squared error        52.9137 %
                  of Instances         600

                  Accuracy By Class ===

                    TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                      0.894     0.052     0.935      0.894     0.914      0.936    YES
                      0.948     0.106     0.914      0.948     0.931      0.936    NO
                      0.923     0.081     0.924      0.923     0.923      0.936

                   Matrix ===

                  - classified as
                  a = YES
                  b = NO
```

Status
OK



```
 tree :        29


 to build model: 0.05 seconds

 ion on training set ===
 ===

 lassified Instances         554               92.3333 %
 Classified Instances         46                7.6667 %
 stic                          0.845
 te error                      0.1309
 quared error                  0.2636
 solute error                 27.9979 %
 ve squared error             52.6137 %
 r of Instances              600

 d Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0.894     0.052     0.935      0.894     0.914      0.936    YES
                 0.948     0.106     0.914      0.948     0.931      0.936    NO
Weighted Avg.    0.923     0.081     0.924      0.923     0.923      0.936

=== Confusion Matrix ===

   a   b   <-- classified as
 248  29 |   a = YES
  17 309 |   b = NO
```

The decision tree constructed by using the implemented C4.5 algorithm



EXPERIMENT-5

5.1 OBJECTIVE:

Suppose you use your above model trained on the complete dataset, and classify credit good/bad for each of the examples in the dataset. What % of examples can you classify correctly? (This is also called testing on the training set) Why do you think you cannot get 100 % training accuracy?

5.2 RESOURCES:

Weka mining tool

5.3 THEORY:

Naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. For example, a fruit may be considered to be an apple if it is red, round, and about 4" in diameter. Even though these features depend on the existence of the other features, a naive Bayes classifier considers all of these properties to independently contribute to the probability that this fruit is an apple.

An advantage of the naive Bayes classifier is that it requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. Because independent variables are assumed, only the variances of the variables for each class need to be determined and not the entire covariance matrix The naive Bayes probabilistic model :

The probability model for a classifier is a conditional model

P(C|F1 ....Fn) over a dependent class variable *C* with a small number of outcomes or *classes*, conditional on several feature variables *F*1 through *Fn*. The problem is that if the number of features *n* is large or when a feature can take on a large number of values, then basing such a model on probability tables is infeasible. We therefore reformulate the model to make it more tractable.

Using Bayes" theorem, we write

P(C|F1...............Fn)=[{p(C)p(F1..................Fn|C)}/p(F1,........Fn)]

In plain English the above equation can be written as

Posterior= [(prior *likehood)/evidence]

In practice we are only interested in the numerator of that fraction, since the denominator does not depend on *C* and the values of the features *Fi* are given, so that the denominator is effectively constant. The numerator is equivalent to the joint probability model p(C,F1........Fn) which can be rewritten as follows, using repeated applications of the definition of conditional probability:

p(C,F1........Fn) =p(C) p(F1............Fn|C) =p(C)p(F1|C) p(F2.........Fn|C,F1,F2)

=p(C)p(F1|C) p(F2|C,F1)p(F3.........Fn|C,F1,F2)

= p(C)p(F1|C) p(F2|C,F1)p(F3.........Fn|C,F1,F2)......p(Fn|C,F1,F2,F3.........Fn1)

Now the "naive" conditional independence assumptions come into play: assume that each feature *Fi* is conditionally independent of every other feature *Fj* for j≠i .

This means that p(Fi|C,Fj)=p(Fi|C) and so the joint model can be expressed as p(C,F1,.......Fn)=p(C)p(F1|C)p(F2|C)...........= p(C)π p(Fi|C)

This means that under the above independence assumptions, the conditional distribution over the class variable *C* can be expressed like this:

p(C|F1..........Fn)= p(C) πp(Fi|C) Z

where *Z* is a scaling factor dependent only on F1.........Fn, i.e., a constant if the values of the feature variables are known.

Models of this form are much more manageable, since they factor into a so called *class prior p*(*C*) and independent probability distributions p(Fi|C). If there are *k* classes and if a model for each p(Fi|C=c) can be expressed in terms of *r* parameters, then the corresponding naive Bayes model has (k - 1) + $n\ r\ k$ parameters. In practice, often $k = 2$ (binary classification) and $r = 1$ (Bernoulli variables as features) are common, and so the total number of parameters of the naive Bayes model is $2n + 1$, where *n* is the number of binary features used for prediction

P(h/D)= P(D/h) P(h) P(D)

• P(h) : Prior probability of hypothesis h

• P(D) : Prior probability of training data D

• P(h/D) : Probability of h given D

• P(D/h) : Probability of D given h

Naïve Bayes Classifier : Derivation

• D : Set of tuples

– Each Tuple is an „n" dimensional attribute vector

– X : (x1,x2,x3,…. xn)

• Let there me „m" Classes : C1,C2,C3…Cm

• NB classifier predicts X belongs to Class Ci iff

– P (Ci/X) > P(Cj/X) for 1<= j <= m , j <> i

• Maximum Posteriori Hypothesis

– P(Ci/X) = P(X/Ci) P(Ci) / P(X)

– Maximize P(X/Ci) P(Ci) as P(X) is

constant Naïve Bayes Classifier : Derivation

• With many attributes, it is computationally expensive to evaluate P(X/Ci)

• Naïve Assumption of "class conditional independence"

• P(X/Ci) = n P(xk/ Ci)

k = 1

• P(X/Ci) = P(x1/Ci) * P(x2/Ci) *…* P(xn/ Ci)

5.4 PROCEDURE:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Go to Classify tab.
7) Choose Classifier “Tree”
8) Select “NBTree” i.e., Navie Baysiean tree.
9) Select Test options “Use training set”
10) if need select attribute.
11) Now start weka.
12) Now we can see the output details in the Classifier output.

5.5 OUTPUT:

```
=== Evaluation on training set ===
=== Summary ===
Correctly Classified Instances          554            92.3333 %

Incorrectly Classified Instances         46             7.6667 %

Kappa statistic                         0.845

Mean absolute error                    0.1389

Root mean squared error                 0.2636

Relative absolute error                27.9979 %

Root relative squared error             52.9137 %

Total Number of Instances                600

=== Detailed Accuracy By Class ===

    TP Rate     FP Rate     Precision     Recall     F-Measure     ROC Area     Class

     0.894       0.052        0.935        0.894       0.914         0.936       YES

     0.948       0.106        0.914        0.948       0.931         0.936       NO

                                    Weighted Avg.

     0.923       0.081        0.924        0.923       0.923         0.936
```

```
=== Confusion Matrix ===

    A      b

    24529

    17309

<-- classified as
a = YES   , b = NO
```

EXPERIMENT-6

6.1 OBJECTIVE:

*Find out the correctly classified instances, root mean squared error, kappa statistics, and mean absolute error for weather data set?

6.2 RESOURCES:

Weka mining tool

6.3 THEORY:

Naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. For example, a fruit may be considered to be an apple if it is red, round, and about 4" in diameter. Even though these features depend on the existence of the other features, a naive Bayes classifier considers all of these properties to independently contribute to the probability that this fruit is an apple.

An advantage of the naive Bayes classifier is that it requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. Because independent variables are assumed, only the variances of the variables for each class need to be determined and not the entire covariance matrix The naive Bayes probabilistic model :

The probability model for a classifier is a conditional model

P(C|F1 ....Fn) over a dependent class variable *C* with a small number of outcomes or *classes*, conditional on several feature variables *F*1 through *Fn*. The problem is that if the number of features *n* is large or when a feature can take on a large number of values, then basing such a model on probability tables is infeasible. We therefore reformulate the model to make it more tractable.

Using Bayes‟ theorem, we write

P(C|F1...............Fn)=[{p(C)p(F1..................Fn|C)}/p(F1,........Fn)]

In plain English the above equation can be written as

Posterior= [(prior *likehood)/evidence]

In practice we are only interested in the numerator of that fraction, since the denominator does not depend on *C* and the values of the features *Fi* are given, so that the denominator is effectively constant. The numerator is equivalent to the joint probability model p(C,F1........Fn) which can be rewritten as follows, using repeated applications of the definition of conditional probability:

p(C,F1........Fn) =p(C) p(F1...........Fn|C) =p(C)p(F1|C) p(F2.........Fn|C,F1,F2)

=p(C)p(F1|C) p(F2|C,F1)p(F3.........Fn|C,F1,F2)

= p(C)p(F1|C) p(F2|C,F1)p(F3.........Fn|C,F1,F2)......p(Fn|C,F1,F2,F3.........Fn1)

Now the "naive" conditional independence assumptions come into play: assume that each feature *Fi* is conditionally independent of every other feature *Fj* for j≠i .

This means that p(Fi|C,Fj)=p(Fi|C) and so the joint model can be expressed as p(C,F1,.......Fn)=p(C)p(F1|C)p(F2|C)..........= p(C)π p(Fi|C)

This means that under the above independence assumptions, the conditional distribution over the class variable *C* can be expressed like this:

p(C|F1..........Fn)= p(C) πp(Fi|C) Z

where *Z* is a scaling factor dependent only on F1.........Fn, i.e., a constant if the values of the feature variables are known.

Models of this form are much more manageable, since they factor into a so called *class prior p*(*C*) and independent probability distributions p(Fi|C). If there are *k* classes and if a model for each p(Fi|C=c) can be expressed in terms of *r* parameters, then the corresponding naive Bayes model has (*k* - 1) + *n r k* parameters. In practice, often *k* = 2 (binary classification) and *r* = 1 (Bernoulli variables as features) are common, and so the total number of parameters of the naive Bayes model is 2*n* + 1, where *n* is the number of binary features used for prediction

P(h/D)= P(D/h) P(h) P(D)

• P(h) : Prior probability of hypothesis h

• P(D) : Prior probability of training data D

• P(h/D) : Probability of h given D

• P(D/h) : Probability of D given h

Naïve Bayes Classifier : Derivation

• D : Set of tuples

– Each Tuple is an „n" dimensional attribute vector

– X : (x1,x2,x3,…. xn)

• Let there me „m" Classes : C1,C2,C3…Cm

• NB classifier predicts X belongs to Class Ci iff

– P (Ci/X) > P(Cj/X) for 1<= j <= m , j <> i

• Maximum Posteriori Hypothesis

– P(Ci/X) = P(X/Ci) P(Ci) / P(X)

– Maximize P(X/Ci) P(Ci) as P(X) is

constant Naïve Bayes Classifier : Derivation

• With many attributes, it is computationally expensive to evaluate P(X/Ci)

• Naïve Assumption of "class conditional independence"

• P(X/Ci) = n P(xk/ Ci)

k = 1

• P(X/Ci) = P(x1/Ci) * P(x2/Ci) *…* P(xn/ Ci)

6.4 PROCEDURE:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Go to Classify tab.
7) Choose Classifier “Tree”
8) Select “NBTree” i.e., Navie Baysiean tree.
9) Select Test options “Use training set”
10) if need select attribute.
11) Now start weka.
12) Now we can see the output details in the Classifier output.

6.5 OUTPUT:

```
=== Evaluation on training set ===
=== Summary ===
Correctly Classified Instances        554          92.3333 %

Incorrectly Classified Instances       46           7.6667 %

Kappa statistic                      0.845

Mean absolute error                  0.1389

Root mean squared error              0.2636

Relative absolute error              27.9979 %

Root relative squared error          52.9137 %

Total Number of Instances             600

=== Detailed Accuracy By Class ===

   TP Rate      FP Rate      Precision      Recall      F-Measure      ROC Area      Class

    0.894        0.052        0.935         0.894        0.914          0.936         YES

    0.948        0.106        0.914         0.948        0.931          0.936         NO

                                      Weighted Avg.

    0.923        0.081        0.924         0.923        0.923          0.936
```

```
=== Confusion Matrix ===

        A          b

        24529

        17309

<-- classified as
a = YES   , b = NO
```

EXPERIMENT-7

7.1 OBJECTIVE:

Is testing on the training set as you did above a good idea? Why or Why not?

7.2 RESOURCES:

Weka Mining tool

7.3 PROCEDURE:

1) In Test options, select the Supplied test set radio button
2) Click Set
3) Choose the file which contains records that were not in the training set we used to create the model.
4) Click Start(WEKA will run this test data set through the model we already created.)
5) Compare the output results with that of the 4th experiment

7.4 OUTPUT:

This can be experienced by the different problem solutions while doing practice.

The important numbers to focus on here are the numbers next to the "Correctly Classified Instances" (92.3 percent) and the "Incorrectly Classified Instances" (7.6 percent). Other important numbers are in the "ROC Area" column, in the first row (the 0.936); Finally, in the "Confusion Matrix," it shows the number of false positives and false negatives. The false positives are 29, and the false negatives are 17 in this matrix.

Based on our accuracy rate of 92.3 percent, we say that upon initial analysis, this is a good model.

One final step to validating our classification tree, which is to run our test set through the model and ensure that accuracy of the model

Comparing the "Correctly Classified Instances" from this test set with the "Correctly Classified Instances" from the training set, we see the accuracy of the model, which indicates that the model will not break down with unknown data, or when future data is applied to it.

EXPERIMENT-8

8.1 OBJECTIVE:

One approach for solving the problem encountered in the previous question is using cross-validation? Describe what is cross -validation briefly. Train a Decision Tree again using cross - validation and report your results. Does your accuracy increase/decrease? Why?

8.2 RESOURCES:

Weka mining tool

8.3 THEORY:

Decision tree learning, used in data mining and machine learning, uses a decision tree as a predictive model which maps observations about an item to conclusions about the item's target value In these tree structures, leaves represent classifications and branches represent conjunctions of features that lead to those classifications. In decision analysis, a decision tree can be used to visually and explicitly represent decisions and decision making. In data mining, a decision tree describes data but not decisions; rather the resulting classification tree can be an input for decision making. This page deals with decision trees in data mining.

Decision tree learning is a common method used in data mining. The goal is to create a model that predicts the value of a target variable based on several input variables. Each interior node corresponds to one of the input variables; there are edges to children for each of the possible values of that input variable. Each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf.

A tree can be "learned" by splitting the source set into subsets based on an attribute value test. This process is repeated on each derived subset in a recursive manner called recursive partitioning. The recursion is completed when the subset at a node all has the same value of the target variable, or when splitting no longer adds value to the predictions. In data mining, trees can be described also as the combination of mathematical and computational techniques to aid the description, categorization and generalization of a given set of data.

Data comes in records of the form:

(x, y) = (x1, x2, x3..., xk, y)

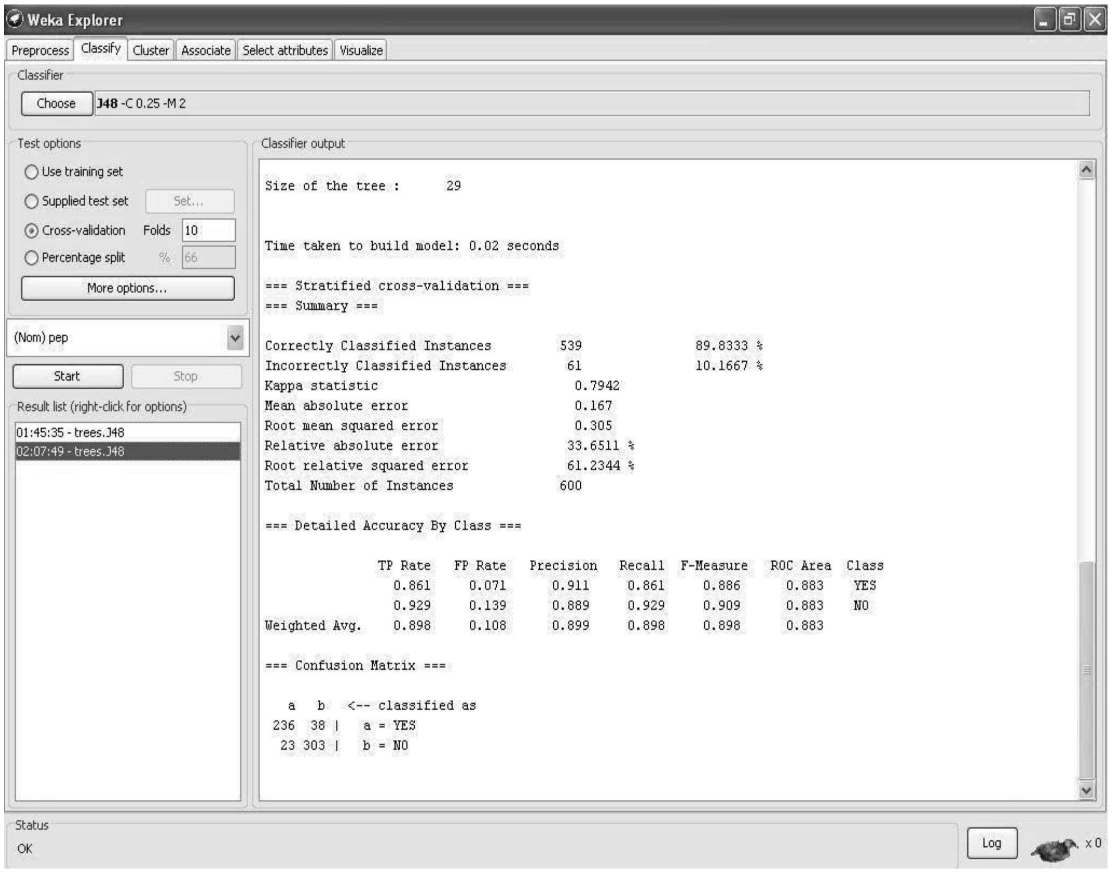
The dependent variable, Y, is the target variable that we are trying to understand, classify or generalize. The vector x is comprised of the input variables, x1, x2, x3 etc., that are used for that task.

8.4 PROCEDURE:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.

6) Go to Classify tab.
7) Choose Classifier “Tree”
8) Select J48
9) Select Test options “Cross-validation”.
10) Set “Folds” Ex:10
11) if need select attribute.
12) now Start weka.
13)now we can see the output details in the Classifier output.
14)Compare the output results with that of the 4th experiment
15) check whether the accuracy increased or decreased?

8.5 OUTPUT:



J48 -C 0.25 -M 2

Cross-validation Folds 10
Percentage split % 66

(Nom) pep

01:45:35 - trees.J48
02:07:49 - trees.J48

```
Size of the tree :      29


Time taken to build model: 0.02 seconds

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

Correctly Classified Instances         539               89.8333 %
Incorrectly Classified Instances        61               10.1667 %
Kappa statistic                          0.7942
Mean absolute error                      0.167
Root mean squared error                  0.305
Relative absolute error                 33.6511 %
Root relative squared error             61.2344 %
Total Number of Instances              600

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0.861     0.071      0.911     0.861     0.886      0.883    YES
                 0.929     0.139      0.889     0.929     0.909      0.883    NO
Weighted Avg.    0.898     0.108      0.899     0.898     0.898      0.883

=== Confusion Matrix ===

   a   b   <-- classified as
 236  38 |   a = YES
  23 303 |   b = NO
```

Status: OK

=== Stratified cross-validation ===

=== Summary ===

```
Correctly Classified Instances         539          89.8333 %
Incorrectly Classified Instances        61          10.1667 %
Kappa statistic                      0.7942
Mean absolute error                      0.167
Root mean squared error                      0.305
```

```
Relative absolute error            33.6511 %

Root relative squared error        61.2344 %

Total Number of Instances            600


=== Detailed Accuracy By Class ===


   TP Rate     FP Rate     Precision     Recall     F-Measure     ROC Area     Class

    0.861       0.071        0.911        0.861        0.886         0.883       YES

    0.929       0.139        0.889        0.929        0.909         0.883       NO

                                      Weighted Avg.

    0.898       0.108        0.899        0.898        0.898         0.883


=== Confusion Matrix ===

  a   b <-- classified as

 236 38 | a = YES 23

 303 | b = NO
```

EXPERIMENT-9

9.1 OBJECTIVE

Check to see if the data shows a bias against "foreign workers" (attribute 20), or "personal -status" (attribute 9). One way to do this (perhaps rather simple minded) is to remove these attributes from the dataset and see if the decision tree created in those cases is significantly different from the full dataset case which you have already done. To remove an attribute you can use the preprocess tab in Weka's GUI Explorer. Did removing these attributes have any significant effect? Discuss.

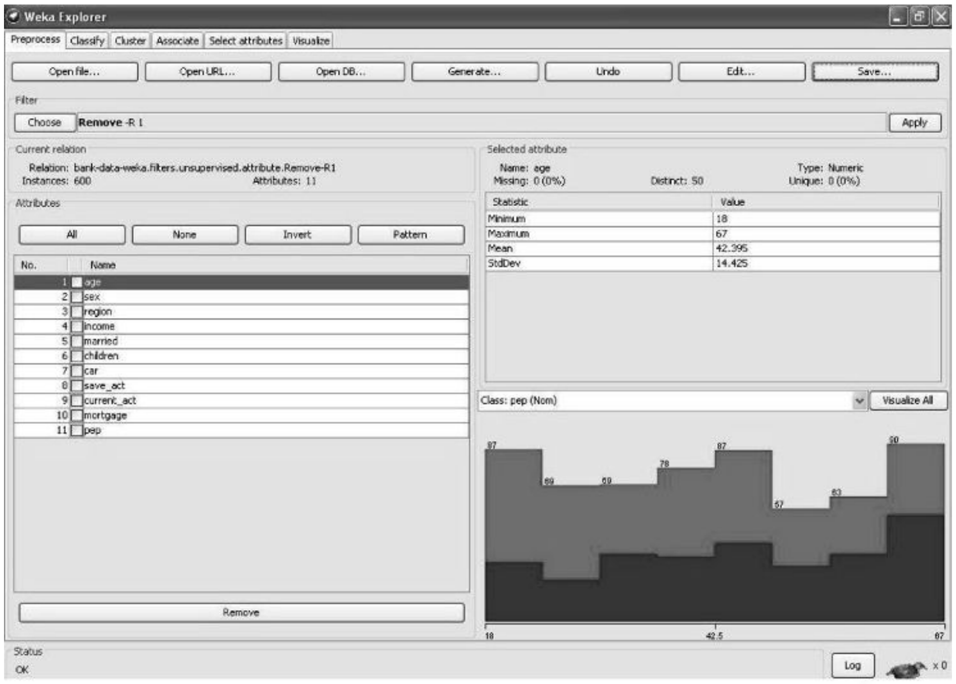
9.2 RESOURCES:

Weka mining tool

9.3 PROCEDURE:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) In the "Filter" panel, click on the "Choose" button. This will show a popup window with list available filters.
7) Select “weka.filters.unsupervised.attribute.Remove”
8) Next, click on text box immediately to the right of the "Choose" button
9) In the resulting dialog box enter the index of the attribute to be filtered out (Make sure that the "invert Selection" option is set to false)
10) Then click "OK" . Now, in the filter box you will see "Remove -R 1"
11) Click the "Apply" button to apply this filter to the data. This will remove the "id" attribute and create a new working relation
12) To save the new working relation as an ARFF file, click on save button in the top panel.
13) Go to OPEN file and browse the file that is newly saved (attribute deleted file)
14) Go to Classify tab.
15) Choose Classifier “Tree”
16) Select j48 tree
17) Select Test options “Use training set”
18) If need select attribute.
19) Now start weka.
20) Now we can see the output details in the Classifier output.
21) Right click on the result list and select ” visualize tree “option .
22) Compare the output results with that of the 4th experiment
23) Check whether the accuracy increased or decreased.
24) Check whether removing these attributes have any significant effect.

9.4 OUTPUT:



Weka Explorer

Filter: Remove -R 1

Current relation
Relation: bank-data-weka.filters.unsupervised.attribute.Remove-R1
Instances: 600 Attributes: 11

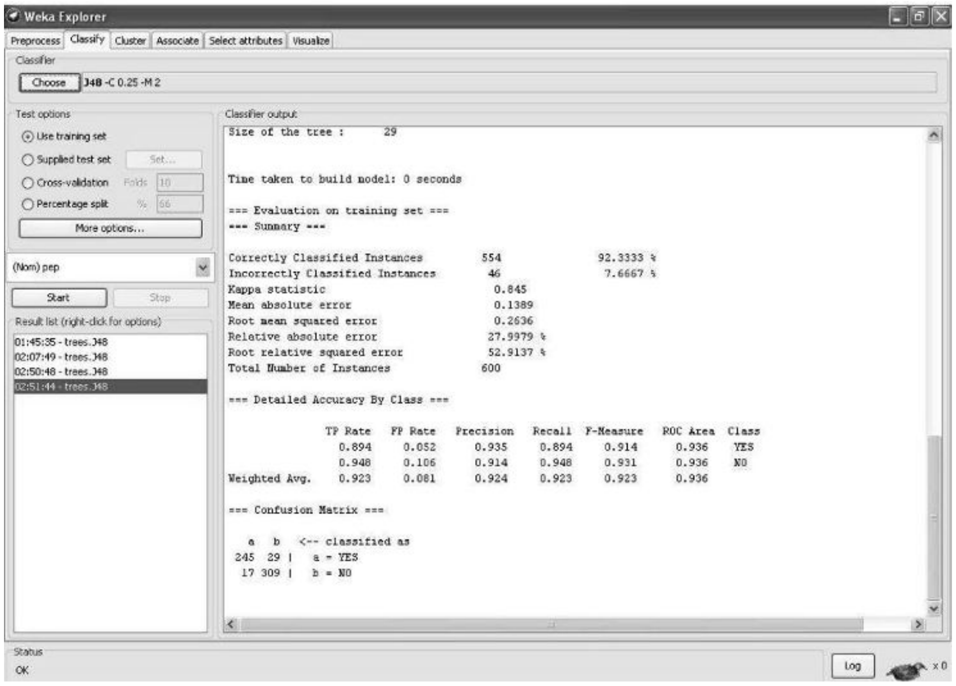
Selected attribute
Name: age Type: Numeric
Missing: 0 (0%) Distinct: 50 Unique: 0 (0%)

Statistic	Value
Minimum	18
Maximum	67
Mean	42.395
StdDev	14.425

No.	Name
1	age
2	sex
3	region
4	income
5	married
6	children
7	car
8	save_act
9	current_act
10	mortgage
11	pep

Class: pep (Nom)

Status
OK



Weka Explorer

Classifier: J48 -C 0.25 -M 2

Test options: [✓ Use training set] Supplied test set, Cross-validation Folds 10, Percentage split % 66

(Nom) pep

Result list (right-click for options)
01:45:35 - trees.J48
02:07:49 - trees.J48
02:50:48 - trees.J48
02:51:44 - trees.J48

Classifier output

```
Size of the tree :      29


Time taken to build model: 0 seconds

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances         554               92.3333 %
Incorrectly Classified Instances        46                7.6667 %
Kappa statistic                          0.845
Mean absolute error                      0.1389
Root mean squared error                  0.2636
Relative absolute error                 27.9979 %
Root relative squared error             52.9137 %
Total Number of Instances              600

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0.894     0.052     0.935      0.894     0.914      0.936    YES
                 0.948     0.106     0.914      0.948     0.931      0.936    NO
Weighted Avg.    0.923     0.081     0.924      0.923     0.923      0.936

=== Confusion Matrix ===

   a   b   <-- classified as
 245  29 |   a = YES
  17 309 |   b = NO
```

Status
OK

EXPERIMENT-10

10.1 OBJECTIVE:

*Load the „weather.arff‟ dataset in Weka and run the ID3 classification algorithm. What problem do you have and what is the solution?

10.2 RESOURCES:

Weka Mining tool

10.3 PROCEDURE:

1) In Test options, select the Supplied test set radio button
2) click Set
3) Choose the file which contains records that were not in the training set we used to create the model.
4) Click Start (WEKA will run this test data set through the model we already created.)
5) Compare the output results with that of the 4th experiment

10.4 OUTPUT:

This can be experienced by the different problem solutions while doing practice.

The important numbers to focus on here are the numbers next to the "Correctly Classified Instances" (92.3 percent) and the "Incorrectly Classified Instances" (7.6 percent). Other important numbers are in the "ROC Area" column, in the first row (the 0.936); finally, in the "Confusion Matrix," it shows the number of false positives and false negatives. The false positives are 29, and the false negatives are 17 in this matrix.

Based on our accuracy rate of 92.3 percent, we say that upon initial analysis, this is a good model.

One final step to validating our classification tree, which is to run our test set through the model and ensure that accuracy of the model

Comparing the "Correctly Classified Instances" from this test set with the "Correctly Classified Instances" from the training set, we see the accuracy of the model, which indicates that the model will not break down with unknown data, or when future data is applied to it.

EXPERIMENT-11

11.1 OBJECTIVE:

Another question might be, do you really need to input so many attributes to get good results? Maybe only a few would do. For example, you could try just having attributes 2, 3, 5, 7, 10, 17 (and 21, the class attribute (naturally)). Try out some combinations. (You had removed two attributes in problem 7. Remember to reload the arff data file to get all the attributes initially before you start selecting the ones you want).

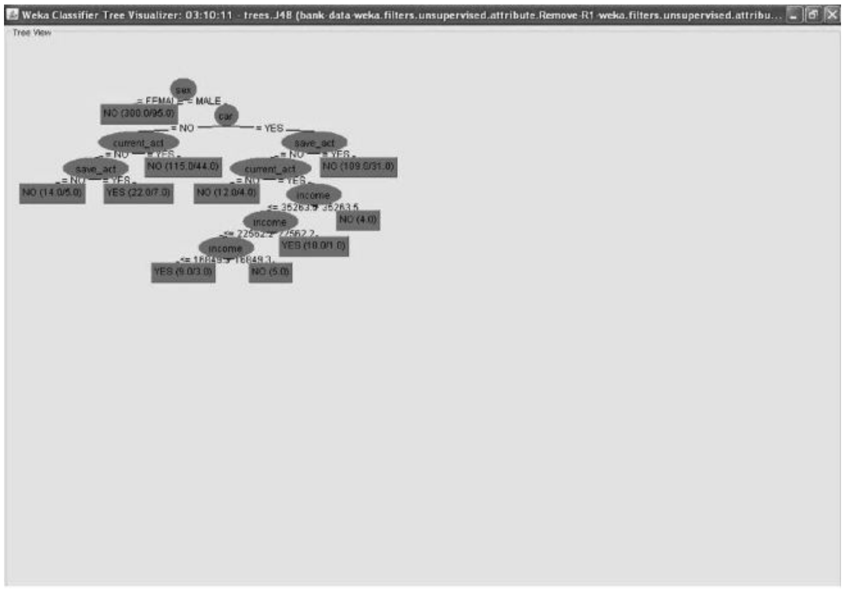
11.2 RESOURCES:

Weka mining tool.

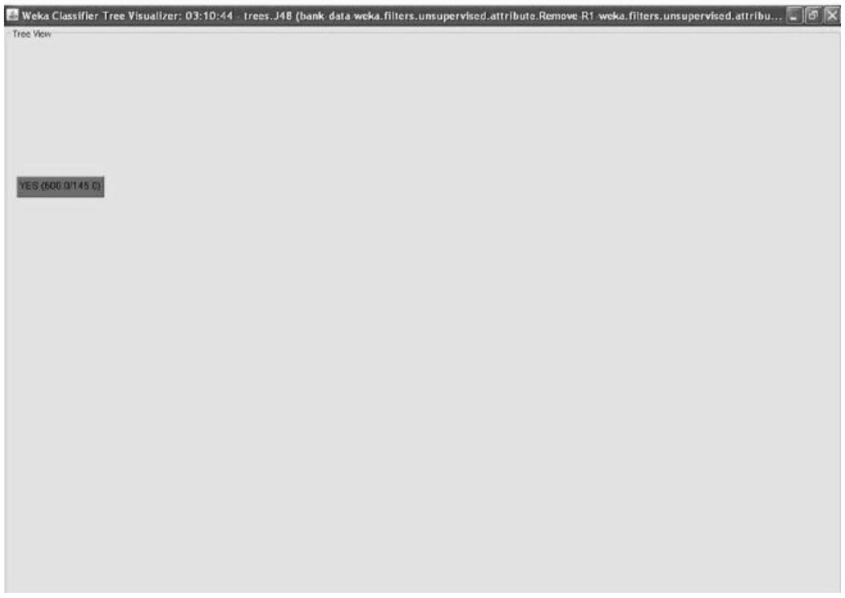
11.3 PROCEDURE:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Select some of the attributes from attributes list which are to be removed. With this step only the attributes necessary for classification are left in the attributes panel.
7) The go to Classify tab.
8) Choose Classifier “Tree”
9) Select j48
10) Select Test options “Use training set”
11) If need select attribute.
12) Now start Weka.
13) Now we can see the output details in the Classifier output.
14) Right click on the result list and select “visualize tree” option.
15) Compare the output results with that of the 4th experiment.
16) Check whether the accuracy increased or decreased?
17) Check whether removing these attributes have any significant effect.

11.4 OUTPUT:



Weka Classifier Tree Visualizer: 03:10:11 - trees.J48 (bank-data-weka.filters.unsupervised.attribute.Remove-R1-weka.filters.unsupervised.attribu...
Tree View
sex
= FEMALE
= MALE
NO (300.0/95.0)
car
= NO
= YES
current_act
save_act
= NO
= YES
NO (115.0/44.0)
NO (109.0/31.0)
save_act
current_act
= NO
= YES
NO (14.0/5.0)
YES (22.0/7.0)
NO (12.0/4.0)
income
<= 35263.5
> 35263.5
NO (4.0)
income
<= 22562.2
> 22562.2
YES (18.0/1.0)
income
<= 16849.3
> 16849.3
YES (9.0/3.0)
NO (5.0)



Weka Classifier Tree Visualizer: 03:10:44 - trees.J48 (bank-data-weka.filters.unsupervised.attribute.Remove-R1-weka.filters.unsupervised.attribu...
Tree View
YES (600.0/145.0)

EXPERIMENT-12

12.1 OBJECTIVE:

Sometimes, the cost of rejecting an applicant who actually has a good credit (case 1) might be higher than accepting an applicant who has bad credit (case 2). Instead of counting the misclassifications equally in both cases, give a higher cost to the first case (say cost 5) and lower cost to the second case. You can do this by using a cost matrix in Weka. Train your Decision Tree again and report the Decision Tree and cross -validation results. Are they significantly different from results obtained in problem 6 (using equal cost)?

12.2 RESOURCES:

Weka mining tool

12.3 PROCEDURE:

1) Given the Bank database for mining.

2) Use the Weka GUI Chooser.

3) Select EXPLORER present in Applications.

4) Select Preprocess Tab.

5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.

6) Go to Classify tab.

7) Choose Classifier “Tree”

8) Select j48

9) Select Test options “Training set”.

10) Click on “more options”.

11) Select cost sensitive evaluation and click on set button

12) Set the matrix values and click on resize. Then close the window.

13) Click Ok

14) Click start.

15) We can see the output details in the Classifier output

16) Select Test options “Cross-validation”.

17) Set “Folds” Ex: 10

18) if need select attribute.

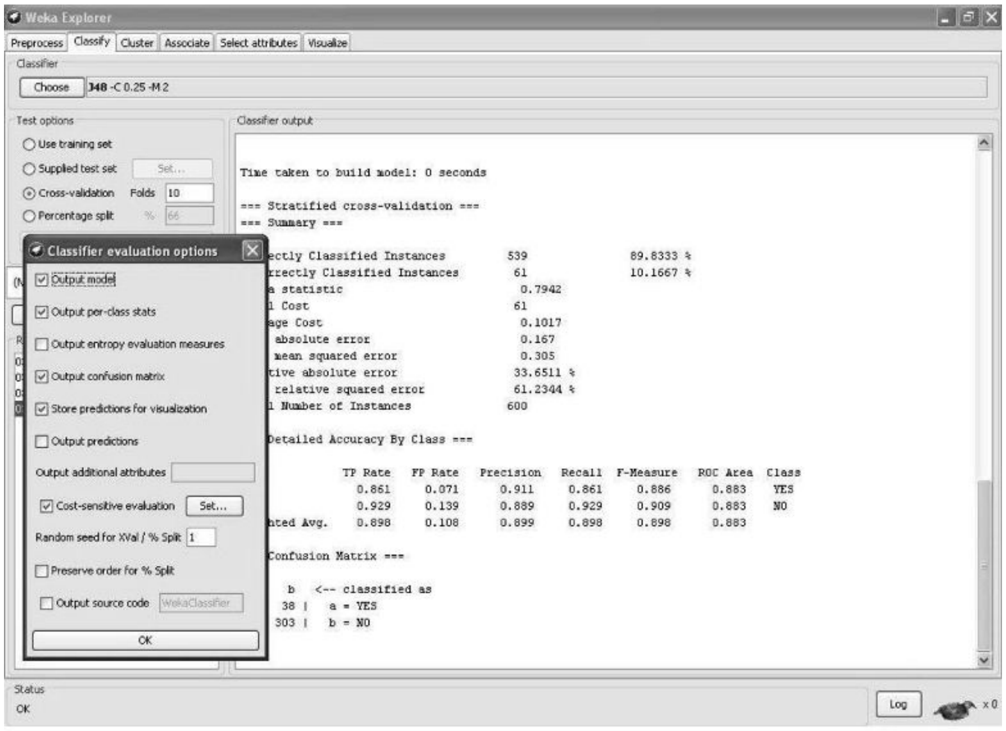
19) Now start weka.

20) Now we can see the output details in the Classifier output.

21) Compare results of 15th and 20th steps.

22) Compare the results with that of experiment 6.

12.4 OUTPUT:



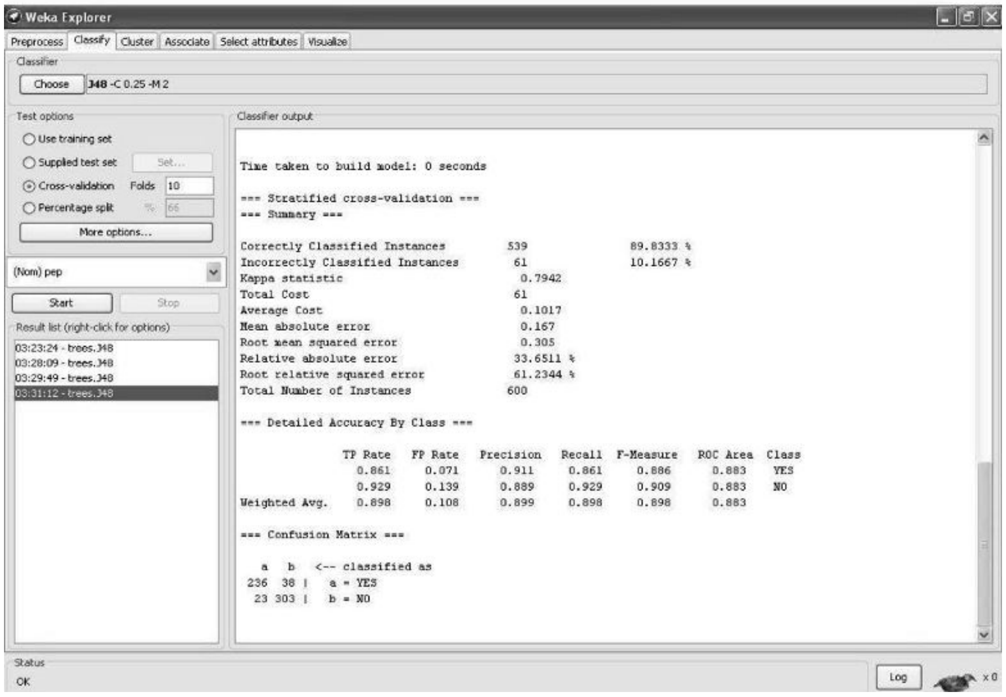
Classifier: J48 -C 0.25 -M 2

Test options:
- ◯ Use training set
- ◯ Supplied test set
- ◉ Cross-validation Folds 10
- ◯ Percentage split % 66

Classifier evaluation options:
- ☑ Output model
- ☑ Output per-class stats
- ☐ Output entropy evaluation measures
- ☑ Output confusion matrix
- ☑ Store predictions for visualization
- ☐ Output predictions
- Output additional attributes
- ☑ Cost-sensitive evaluation
- Random seed for XVal / % Split 1
- ☐ Preserve order for % Split
- ☐ Output source code WekaClassifier
- OK

Classifier output:

```
Time taken to build model: 0 seconds

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

ectly Classified Instances         539               89.8333 %
rrectly Classified Instances        61               10.1667 %
a statistic                          0.7942
l Cost                              61
age Cost                             0.1017
 absolute error                      0.167
 mean squared error                  0.305
tive absolute error                 33.6511 %
 relative squared error             61.2344 %
l Number of Instances              600

Detailed Accuracy By Class ===

           TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
             0.861     0.071     0.911      0.861     0.886      0.883    YES
             0.929     0.139     0.889      0.929     0.909      0.883    NO
hted Avg.    0.898     0.108     0.899      0.898     0.898      0.883

Confusion Matrix ===

   b   <-- classified as
  38 |   a = YES
 303 |   b = NO
```



Classifier: J48 -C 0.25 -M 2

Test options:
- ◯ Use training set
- ◯ Supplied test set
- ◉ Cross-validation Folds 10
- ◯ Percentage split % 66

(Nom) pep

Result list (right-click for options)
- 03:23:24 - trees.J48
- 03:28:09 - trees.J48
- 03:29:49 - trees.J48
- 03:31:12 - trees.J48

Classifier output:

```
Time taken to build model: 0 seconds

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

Correctly Classified Instances         539               89.8333 %
Incorrectly Classified Instances        61               10.1667 %
Kappa statistic                          0.7942
Total Cost                              61
Average Cost                             0.1017
Mean absolute error                      0.167
Root mean squared error                  0.305
Relative absolute error                 33.6511 %
Root relative squared error             61.2344 %
Total Number of Instances              600

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0.861     0.071     0.911      0.861     0.886      0.883    YES
                 0.929     0.139     0.889      0.929     0.909      0.883    NO
Weighted Avg.    0.898     0.108     0.899      0.898     0.898      0.883

=== Confusion Matrix ===

   a   b   <-- classified as
 236  38 |   a = YES
  23 303 |   b = NO
```

EXPERIMENT-13

13.1 OBJECTIVE:

Do you think it is a good idea to prefer simple decision trees instead of having long complex decision trees? How does the complexity of a Decision Tree relate to the bias of the model?

13.2 RESOURCES:

Weka mining tool

13.3 PROCEDURE:

This will be based on the attribute set, and the requirement of relationship among attribute we want to study. This can be viewed based on the database and user requirement.

EXPERIMENT-14

14.1 OBJECTIVE:

*Run the J48 and 1Bk classifiers using-the cross-validation strategy with various fold levels. Compare the accuracy results. Hold out strategy with three percentage levels. Compare the accuracy results.

14.2 RESOURCES:

Weka mining tool

14.3 THEORY:

Reduced-error pruning

- ➢ Each node of the (over-fit) tree is examined for pruning
- ➢ A node is pruned (removed) only if the resulting pruned tree performs no worse than the original over the validation set
- ➢ Pruning a node consists of
  - • Removing the sub-tree rooted at the pruned node
  - • Making the pruned node a leaf node
  - • Assigning the pruned node the most common classification of the training instances attached to that node
- ➢ Pruning nodes iteratively
  - • Always select a node whose removal most increases the DT accuracy over the validation set
  - • Stop when further pruning decreases the DT accuracy over the validation set

IF (Children=yes) Λ (income=>30000)

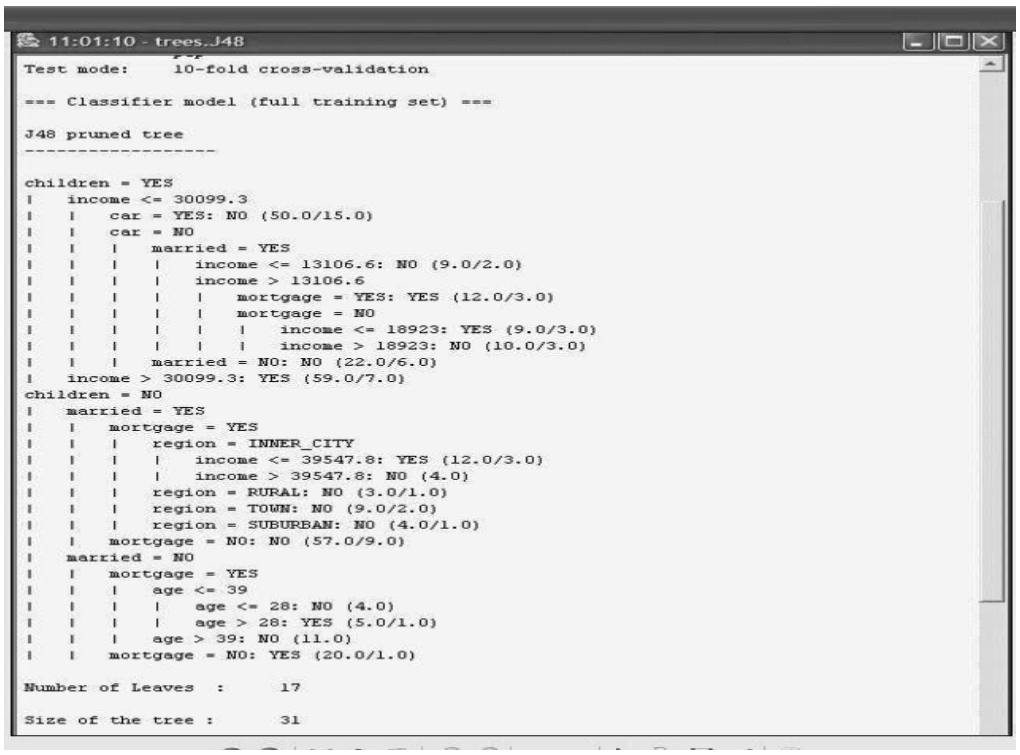
THEN (car=Yes)

14.4 PROCEDURE:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Select some of the attributes from attributes list
7) Go to Classify tab.
8) Choose Classifier “Tree”
9) Select “NBTree” i.e., Navie Bayesian tree.
10) Select Test options “Use training set”
11) Right click on the text box besides choose button, select show properties
12) Now change unprune mode “false” to “true”.
13) Change the reduced error pruning % as needed.
14) If need select attribute.
15) Now start Weka.
16) Now we can see the output details in the Classifier output.

17) Right click on the result list and select “visualize tree” option.

14.5 OUTPUT:



11:01:10 - trees.J48

```
Test mode:     10-fold cross-validation

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

J48 pruned tree
------------------

children = YES
|   income <= 30099.3
|   |   car = YES: NO (50.0/15.0)
|   |   car = NO
|   |   |   married = YES
|   |   |   |   income <= 13106.6: NO (9.0/2.0)
|   |   |   |   income > 13106.6
|   |   |   |   |   mortgage = YES: YES (12.0/3.0)
|   |   |   |   |   mortgage = NO
|   |   |   |   |   |   income <= 18923: YES (9.0/3.0)
|   |   |   |   |   |   income > 18923: NO (10.0/3.0)
|   |   |   married = NO: NO (22.0/6.0)
|   income > 30099.3: YES (59.0/7.0)
children = NO
|   married = YES
|   |   mortgage = YES
|   |   |   region = INNER_CITY
|   |   |   |   income <= 39547.8: YES (12.0/3.0)
|   |   |   |   income > 39547.8: NO (4.0)
|   |   |   region = RURAL: NO (3.0/1.0)
|   |   |   region = TOWN: NO (9.0/2.0)
|   |   |   region = SUBURBAN: NO (4.0/1.0)
|   |   mortgage = NO: NO (57.0/9.0)
|   married = NO
|   |   mortgage = YES
|   |   |   age <= 39
|   |   |   |   age <= 28: NO (4.0)
|   |   |   |   age > 28: YES (5.0/1.0)
|   |   |   age > 39: NO (11.0)
|   |   mortgage = NO: YES (20.0/1.0)

Number of Leaves  :     17

Size of the tree :      31
```

EXPERIMENT-15

15.1 OBJECTIVE:

You can make your Decision Trees simpler by pruning the nodes. one approach is to use Reduced Error Pruning -Explain this idea briefly. Try reduced error pruning for training your Decision Trees using cross -validation (you can do this in Weka) and report the Decision Tree you obtain? Also, report your accuracy using the pruned model. Does your accuracy increase?

15.2 RESOURCES:

Weka mining tool

15.3 THEORY:

Reduced-error pruning

❖ Each node of the (over-fit) tree is examined for pruning

❖ A node is pruned (removed) only if the resulting pruned tree performs no worse than the original over the validation set

➢ Pruning a node consists of

• Removing the sub-tree rooted at the pruned node

• Making the pruned node a leaf node

• Assigning the pruned node the most common classification of the training instances attached to that node

➢ Pruning nodes iteratively

• Always select a node whose removal most increases the DT accuracy over the validation set

• Stop when further pruning decreases the DT accuracy over the validation set

IF (Children=yes) Λ (income=>30000)

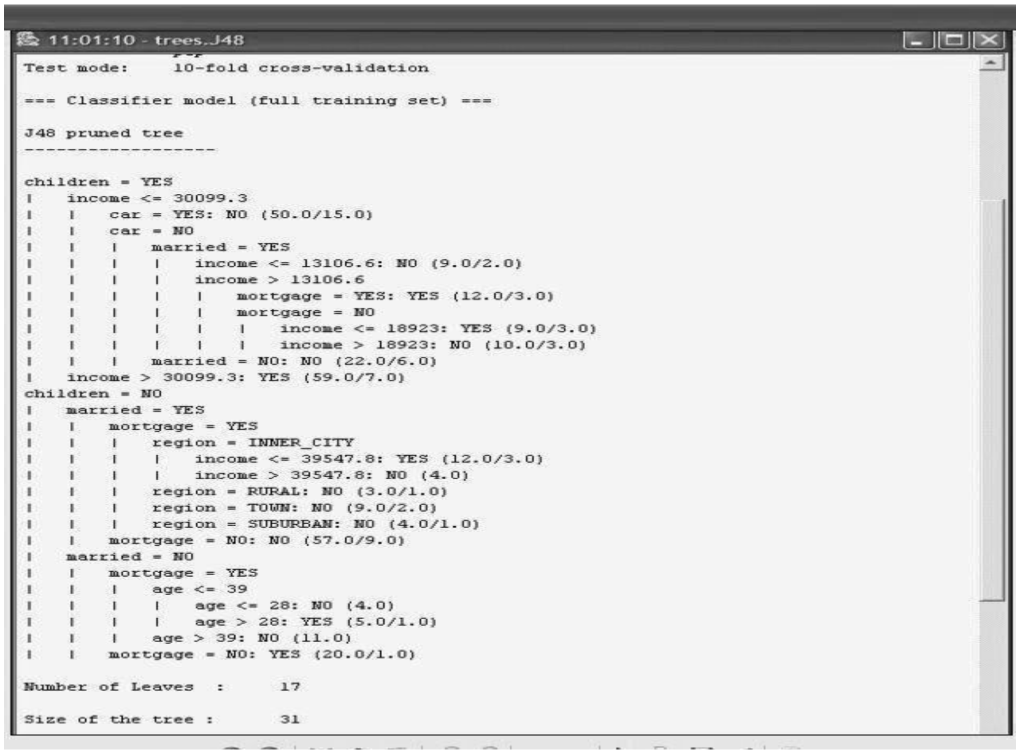
THEN (car=Yes)

15.4 PROCEDURE:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Select some of the attributes from attributes list
7) Go to Classify tab.
8) Choose Classifier “Tree”
9) Select “NBTree” i.e., Navie Bayesian tree.
10) Select Test options “Use training set”
11) Right click on the text box besides choose button, select show properties
12) Now change unprone mode “false” to “true”.
13) Change the reduced error pruning % as needed.

14) If need select attribute.
15) Now start weka.
16) Now we can see the output details in the Classifier output.
17) Right click on the result list and select ” visualize tree “option.

15.5 OUTPUT:



```
Test mode:     10-fold cross-validation

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

J48 pruned tree
------------------

children = YES
|   income <= 30099.3
|   |   car = YES: NO (50.0/15.0)
|   |   car = NO
|   |   |   married = YES
|   |   |   |   income <= 13106.6: NO (9.0/2.0)
|   |   |   |   income > 13106.6
|   |   |   |   |   mortgage = YES: YES (12.0/3.0)
|   |   |   |   |   mortgage = NO
|   |   |   |   |   |   income <= 18923: YES (9.0/3.0)
|   |   |   |   |   |   income > 18923: NO (10.0/3.0)
|   |   |   married = NO: NO (22.0/6.0)
|   income > 30099.3: YES (59.0/7.0)
children = NO
|   married = YES
|   |   mortgage = YES
|   |   |   region = INNER_CITY
|   |   |   |   income <= 39547.8: YES (12.0/3.0)
|   |   |   |   income > 39547.8: NO (4.0)
|   |   |   region = RURAL: NO (3.0/1.0)
|   |   |   region = TOWN: NO (9.0/2.0)
|   |   |   region = SUBURBAN: NO (4.0/1.0)
|   |   mortgage = NO: NO (57.0/9.0)
|   married = NO
|   |   mortgage = YES
|   |   |   age <= 39
|   |   |   |   age <= 28: NO (4.0)
|   |   |   |   age > 28: YES (5.0/1.0)
|   |   |   age > 39: NO (11.0)
|   |   mortgage = NO: YES (20.0/1.0)

Number of Leaves  :     17

Size of the tree :      31
```

EXPERIMENT-16

16.1 OBJECTIVE:

(Extra Credit): How can you convert a Decision Trees into "if –then -else rules". Make up your own small Decision Tree consisting of 2 - 3 levels and convert it into a set of rules. There also exist different classifiers that output the model in the form of rules -one such classifier in Weka is rules. PART, train this model and report the set of rules obtained. Sometimes just one attribute can be good enough in making the decision, yes, just one! Can you predict what attribute that might be in this dataset? OneR classifier uses a single attribute to make decisions (it chooses the attribute based on minimum error). Report the rule obtained by training a one R classifier. Rank the performance of j48, PART and OneR.

16.2 RESOURCES:

Weka mining tool.

16.3 PROCEDURE:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Select some of the attributes from attributes list
7) Go to Classify tab.
8) Choose Classifier “Trees Rules”
9) Select “J48”.
10) Select Test options “Use training set”
11) If need select attribute.
12) Now start weka.
13) Now we can see the output details in the Classifier output.
14) Right click on the result list and select ” visualize tree “option .
(or)

➢
```
java weka.classifiers.trees.J48 -t c:\temp\bank.arff
```

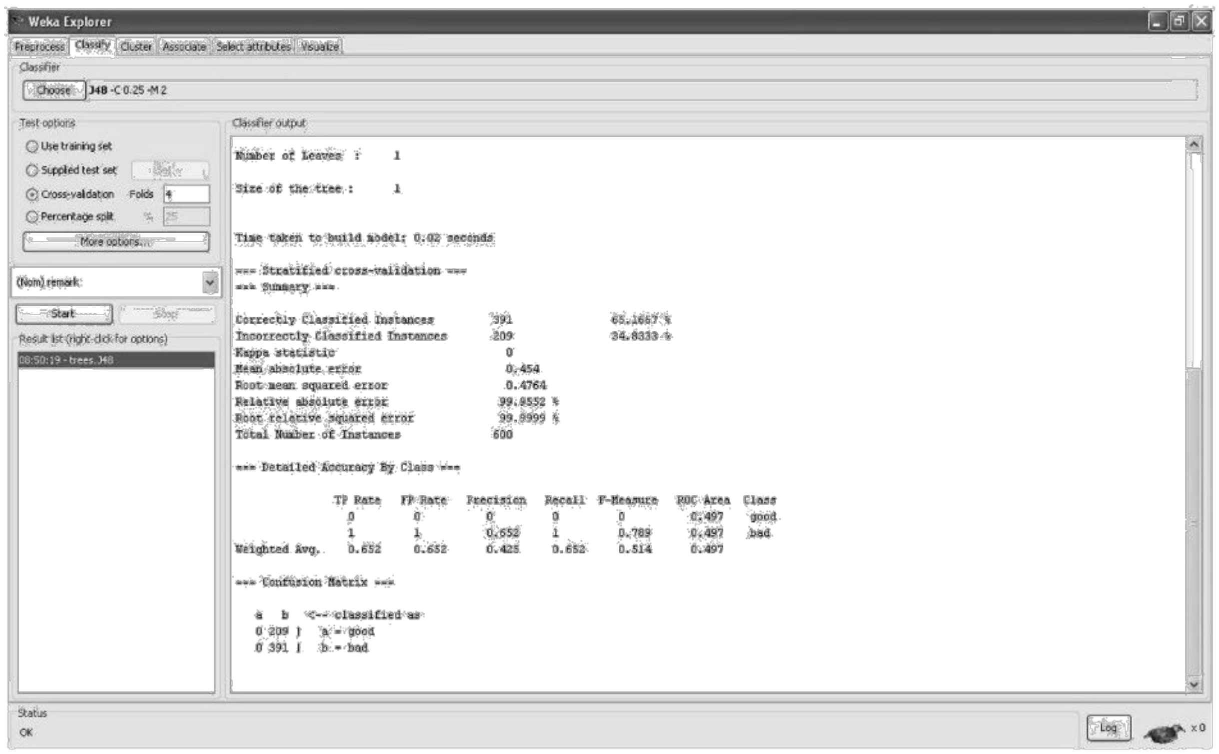
Procedure for “OneR”:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Select some of the attributes from attributes list
7) Go to Classify tab.
8) Choose Classifier “Rules”
9) Select “OneR”.
10) Select Test options “Use training set”

11) if need select attribute.
12) Now start weka.
13) Now we can see the output details in the Classifier output.

Procedure for “PART”:
1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Select some of the attributes from attributes list
7) Go to Classify tab.
8) Choose Classifier “Rules”.
9) Select “PART”.
10) Select Test options “Use training set”
11) if need select attribute.
12) Now start weka.
13) Now we can see the output details in the Classifier output.
Attribute relevance with respect to the class – relevant attribute (*science*)
IF accounting=1 THEN class=A (Error=0, Coverage = 7 instance)
IF accounting=0 THEN class=B (Error=4/13, Coverage = 13 instances)

12.4 OUTPUT:



J48 -C 0.25 -M 2

Cross-validation Folds 4

(Nom) remark

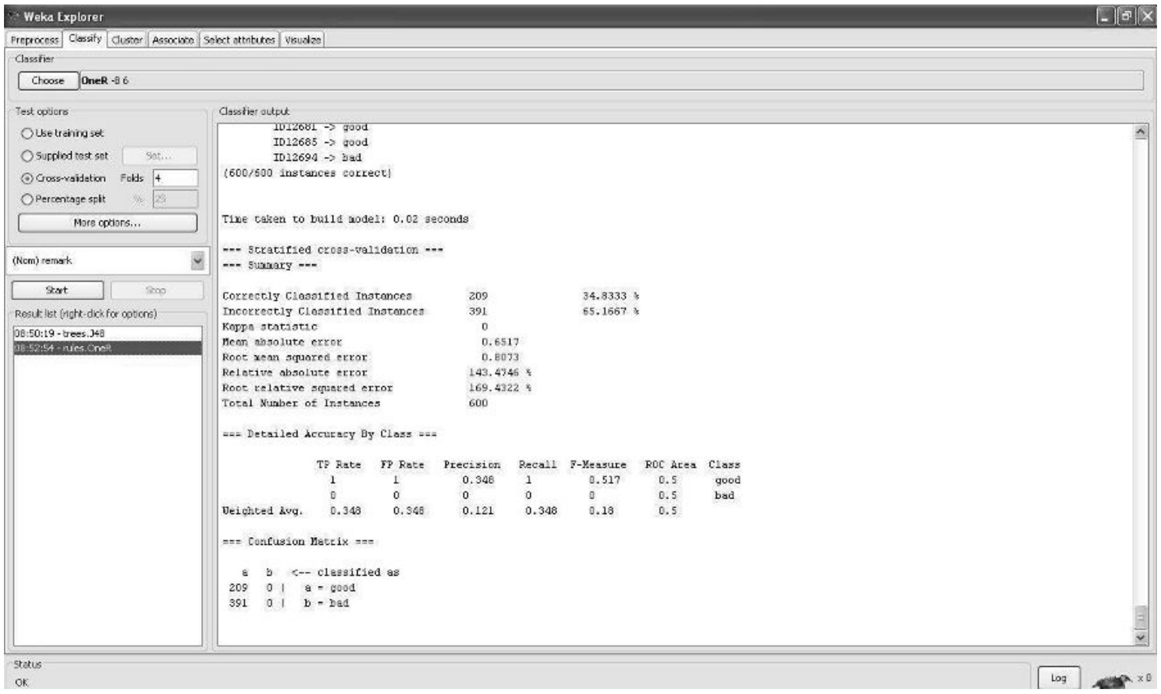
08:50:19 - trees.J48

```
Number of Leaves  :     1

Size of the tree :      1


Time taken to build model: 0.02 seconds

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

Correctly Classified Instances         391               65.1667 %
Incorrectly Classified Instances       209               34.8333 %
Kappa statistic                          0
Mean absolute error                      0.454
Root mean squared error                  0.4764
Relative absolute error                 99.9552 %
Root relative squared error             99.9999 %
Total Number of Instances              600

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0         0          0         0         0          0.497    good
                 1         1          0.652     1         0.789      0.497    bad
Weighted Avg.    0.652     0.652      0.425     0.652     0.514      0.497

=== Confusion Matrix ===

   a   b   <-- classified as
   0 209 |   a = good
   0 391 |   b = bad
```

OK

J48

One R



OneR -B 6

Cross-validation Folds 4

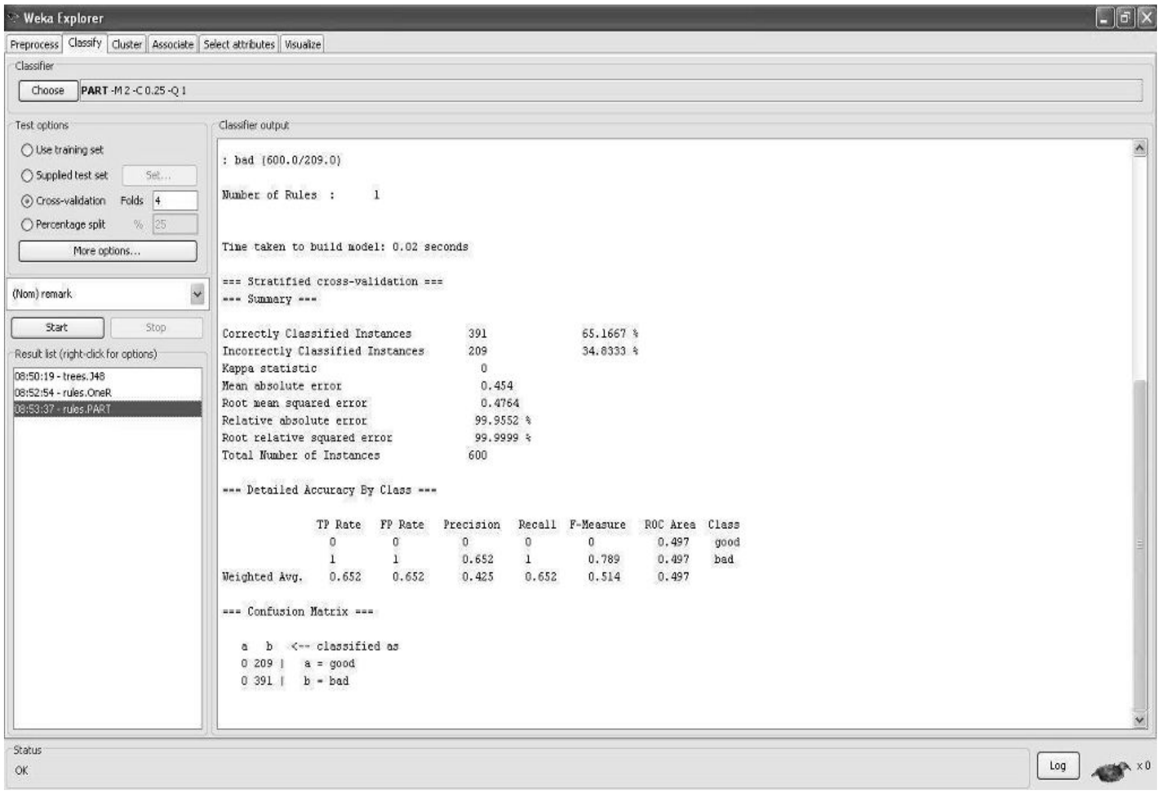
(Nom) remark

08:50:19 - trees.J48
08:52:54 - rules.OneR

```
        ID12681 -> good
        ID12685 -> good
        ID12694 -> bad
(600/600 instances correct)


Time taken to build model: 0.02 seconds

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

Correctly Classified Instances         209               34.8333 %
Incorrectly Classified Instances       391               65.1667 %
Kappa statistic                          0
Mean absolute error                      0.6517
Root mean squared error                  0.8073
Relative absolute error                143.4746 %
Root relative squared error            169.4322 %
Total Number of Instances              600

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 1         1          0.348     1         0.517      0.5      good
                 0         0          0         0         0          0.5      bad
Weighted Avg.    0.348     0.348      0.121     0.348     0.18       0.5

=== Confusion Matrix ===

   a   b   <-- classified as
 209   0 |   a = good
 391   0 |   b = bad
```

OK

PART



PART -M 2 -C 0.25 -Q 1

[✓ Cross-validation] Folds 4

% 25

(Nom) remark

08:50:19 - trees.J48
08:52:54 - rules.OneR
08:53:37 - rules.PART

```
: bad (600.0/209.0)

Number of Rules  :      1


Time taken to build model: 0.02 seconds

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

Correctly Classified Instances         391               65.1667 %
Incorrectly Classified Instances       209               34.8333 %
Kappa statistic                          0
Mean absolute error                      0.454
Root mean squared error                  0.4764
Relative absolute error                 99.9552 %
Root relative squared error             99.9999 %
Total Number of Instances              600

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0         0          0         0         0          0.497    good
                 1         1          0.652     1         0.789      0.497    bad
Weighted Avg.    0.652     0.652      0.425     0.652     0.514      0.497

=== Confusion Matrix ===

   a   b   <-- classified as
   0 209 |   a = good
   0 391 |   b = bad
```

EXPERIMENT-17

17.1 OBJECTIVE:

*Run J48 and Naïve Bayes classifiers on the following datasets and determine the accuracy:

1.vehicle.arff
2.kr-vs-kp.arff
3.glass.arff
4.wave-form-5000.arff

On which datasets does the Naïve Bayes perform better?

17.2 RESOURCES:

Weka mining tool.

17.3 PROCEDURE:

1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Select some of the attributes from attributes list
7) Go to Classify tab.
8) Choose Classifier “Trees Rules”
9) Select “J48”.
10) Select Test options “Use training set”
11) If need select attribute.
12) Now start weka.
13) Now we can see the output details in the Classifier output.
14) Right click on the result list and select ” visualize tree “option .

(or)

➢ java weka.classifiers.trees.J48 -t c:\temp\bank.arff

Procedure for “OneR”:

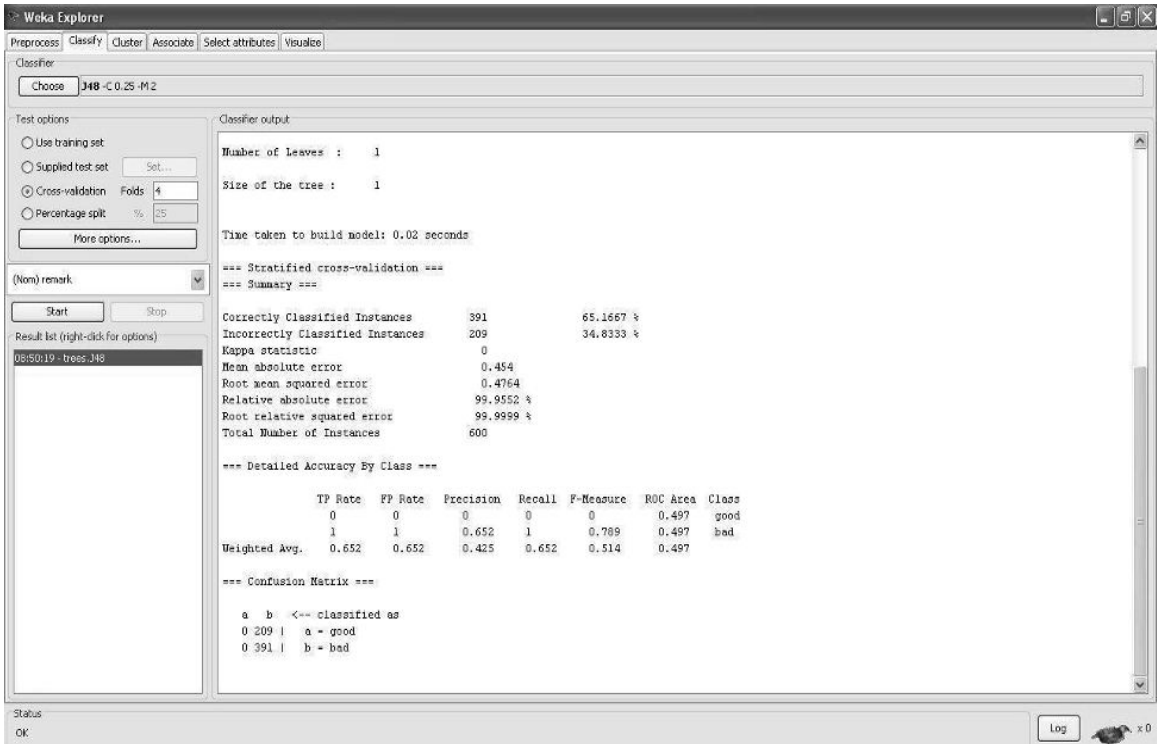
1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Select some of the attributes from attributes list
7) Go to Classify tab.
8) Choose Classifier “Rules”
9) Select “OneR”.
10) Select Test options “Use training set”
11) if need select attribute.

12) Now start weka.
13) Now we can see the output details in the Classifier output.

Procedure for “PART”:
1) Given the Bank database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.
6) Select some of the attributes from attributes list
7) Go to Classify tab.
8) Choose Classifier “Rules”.
9) Select “PART”.
10) Select Test options “Use training set”
11) if need select attribute.
12) Now start weka.
13) Now we can see the output details in the Classifier output.
Attribute relevance with respect to the class – relevant attribute (*science*)
IF accounting=1 THEN class=A (Error=0, Coverage = 7 instance)
IF accounting=0 THEN class=B (Error=4/13, Coverage = 13 instances)

17.4 OUTPUT:

J48



J48 -C 0.25 -M 2

Test options: [✓ Cross-validation] Folds 4; Percentage split % 25

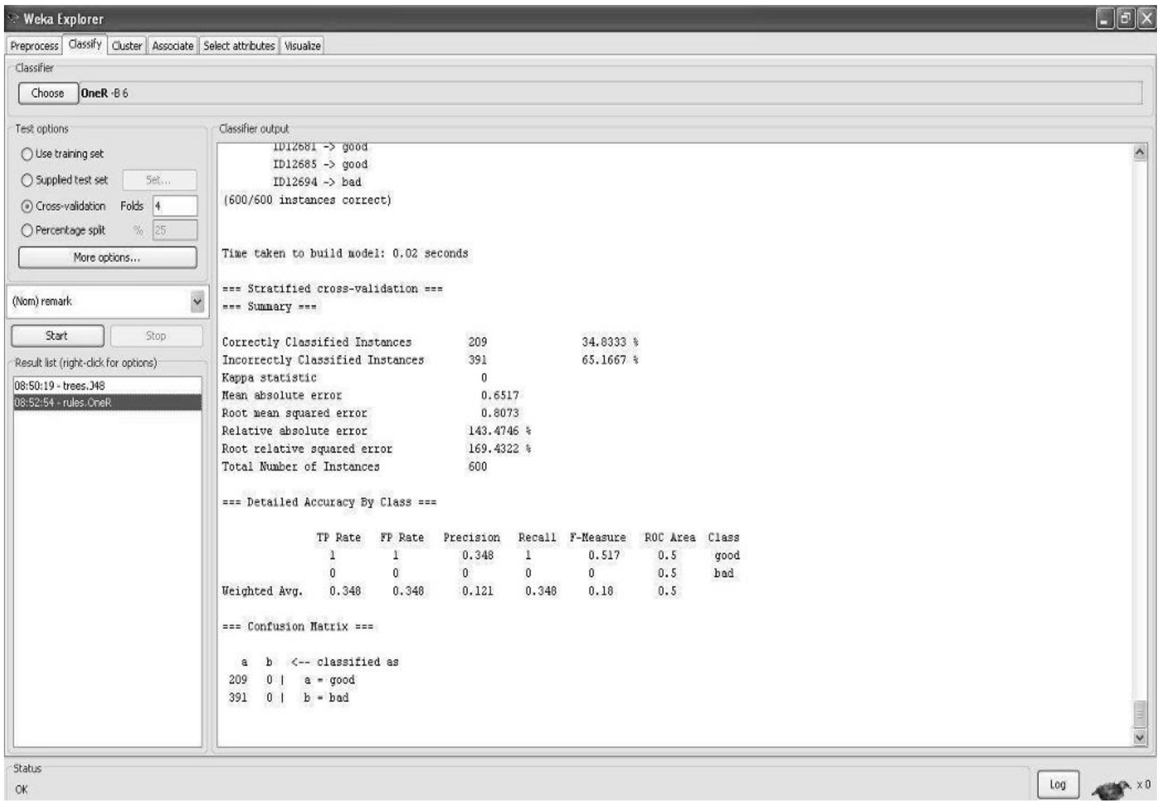
(Nom) remark

08:50:19 - trees.J48

```
Number of Leaves  :     1

Size of the tree :      1


Time taken to build model: 0.02 seconds

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

Correctly Classified Instances         391               65.1667 %
Incorrectly Classified Instances       209               34.8333 %
Kappa statistic                          0
Mean absolute error                      0.454
Root mean squared error                  0.4764
Relative absolute error                 99.9552 %
Root relative squared error             99.9999 %
Total Number of Instances              600

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0         0          0         0         0          0.497    good
                 1         1          0.652     1         0.789      0.497    bad
Weighted Avg.    0.652     0.652      0.425     0.652     0.514      0.497

=== Confusion Matrix ===

   a   b   <-- classified as
   0 209 |   a = good
   0 391 |   b = bad
```

Status
OK

One R



Classifier: OneR -B 6

Test options: ( ) Use training set, ( ) Supplied test set, [✓ Cross-validation] Folds 4, ( ) Percentage split % 25

(Nom) remark

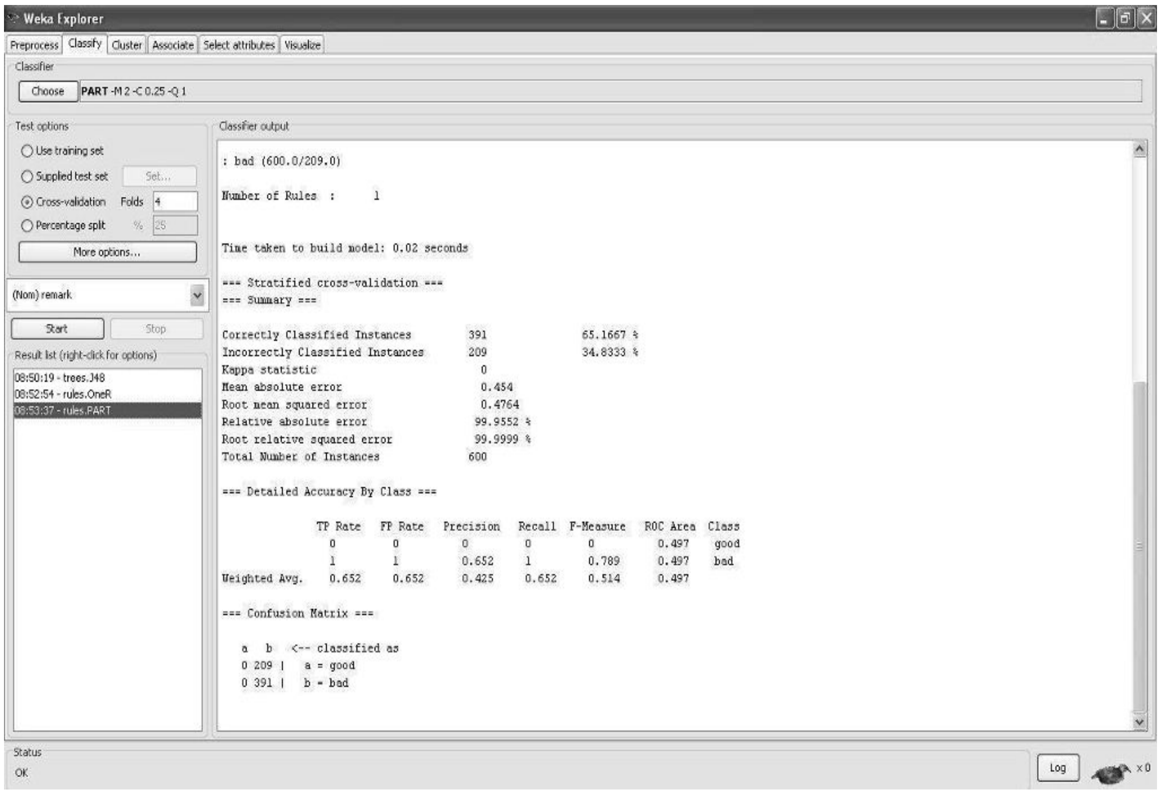
Result list (right-click for options):
08:50:19 - trees.J48
08:52:54 - rules.OneR

Classifier output

```
       ID12681 -> good
       ID12685 -> good
       ID12694 -> bad
(600/600 instances correct)


Time taken to build model: 0.02 seconds

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

Correctly Classified Instances         209               34.8333 %
Incorrectly Classified Instances       391               65.1667 %
Kappa statistic                          0
Mean absolute error                      0.6517
Root mean squared error                  0.8073
Relative absolute error                143.4746 %
Root relative squared error            169.4322 %
Total Number of Instances              600

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 1         1         0.348     1         0.517      0.5      good
                 0         0         0         0         0          0.5      bad
Weighted Avg.    0.348     0.348     0.121     0.348     0.18       0.5

=== Confusion Matrix ===

   a   b   <-- classified as
 209   0 |   a = good
 391   0 |   b = bad
```

Status: OK

PART



Classifier: PART -M 2 -C 0.25 -Q 1

Test options: ( ) Use training set, ( ) Supplied test set, [✓ Cross-validation] Folds 4, ( ) Percentage split % 25

(Nom) remark

Result list (right-click for options):
08:50:19 - trees.J48
08:52:54 - rules.OneR
08:53:37 - rules.PART

Classifier output

```
: bad (600.0/209.0)

Number of Rules  :      1


Time taken to build model: 0.02 seconds

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

Correctly Classified Instances         391               65.1667 %
Incorrectly Classified Instances       209               34.8333 %
Kappa statistic                          0
Mean absolute error                      0.454
Root mean squared error                  0.4764
Relative absolute error                 99.9552 %
Root relative squared error             99.9999 %
Total Number of Instances              600

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0         0         0         0         0          0.497    good
                 1         1         0.652     1         0.789      0.497    bad
Weighted Avg.    0.652     0.652     0.425     0.652     0.514      0.497

=== Confusion Matrix ===

   a   b   <-- classified as
   0 209 |   a = good
   0 391 |   b = bad
```

Status: OK