<u>HOMEWORK 8</u>

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COURSE: DATA MINING

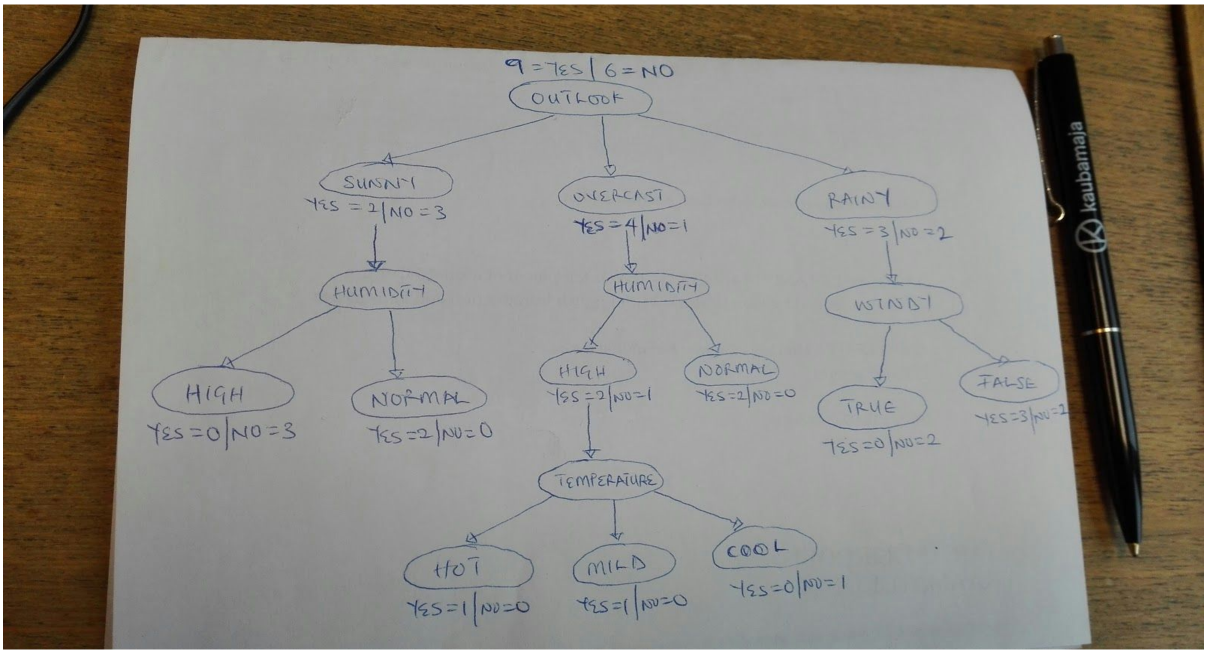
1. Read - http://www.r2d3.us/visual-intro-to-machine-learning-part-1/ What is the quality of the classifier? Can you understand when it works well and when not?

The quality of any classifier depends on several factors including but not limited to complexity, classification speed etc. In the above article, using the classifier the decision trees classifier can be argued to be about 80% okay because the data included categorical variables and this is what decision trees work better as (i.e. Decision trees cannot predict numerical variables). Also Decision trees are a good way of explaining how the classifier works to the targeted audience and this is due to the fact that they can be easily explained to most people (Bayesian also works well in this case too anyways).

In conclusion I can categorically state that decision tree is a good fit because we are predicting a category from data that is labelled however in the case wherever the data isn’t labelled then it will make more sense to perform clustering instead of classification

2. Use this small data example and build a decision tree (manually, explaining all steps/choices).

I made use of the ID3 algorithm for drawing this decision tree and below this image I have listed down both the data used and each step/choices made in the tree.



Given the data below

ord.	Outlook	Temp	Humidity	Windy	Play
1	Sunny	Hot	High	FALSE	No
2	Sunny	Hot	High	TRUE	No
3	Overcast	Hot	High	FALSE	Yes
4	Rainy	Mild	High	FALSE	Yes
5	Rainy	Cool	Normal	FALSE	Yes
6	Rainy	Cool	Normal	TRUE	No
7	Overcast	Cool	Normal	TRUE	Yes
8	Sunny	Mild	High	FALSE	No
9	Sunny	Cool	Normal	FALSE	Yes
10	Rainy	Mild	Normal	FALSE	Yes
11	Sunny	Mild	Normal	TRUE	Yes
12	Overcast	Mild	High	TRUE	Yes
13	Overcast	Hot	Normal	FALSE	Yes
14	Rainy	Mild	High	TRUE	No
15	Overcast	Cool	High	FALSE	No

And given the follow up question "providing that there is mild, overcast, high humidity and high wind weather - should one play tennis or not?", I proceeded by first identifying the best attribute for splitting the the training set of YES = 9 and NO = 6 and selected the outlook for this purpose because the after subsetting for YES and NO I discovered that overcast only has one "NO" response. Splitting the outlook into the three classifications the following results were obtained.

SUNNY (YES =2 & NO = 3)

ord.	Outlook	Temp	Humidity	Windy	Play
9	Sunny	Cool	Normal	FALSE	Yes
11	Sunny	Mild	Normal	TRUE	Yes
1	Sunny	Hot	High	FALSE	No
2	Sunny	Hot	High	TRUE	No
8	Sunny	Mild	High	FALSE	No

OVERCAST (YES = 4 & NO = 1)

ord.	Outlook	Temp	Humidity	Windy	Play
3	Overcast	Hot	High	FALSE	Yes
7	Overcast	Cool	Normal	TRUE	Yes
12	Overcast	Mild	High	TRUE	Yes
13	Overcast	Hot	Normal	FALSE	Yes
15	Overcast	Cool	High	FALSE	No

RAINY (YES = 3 & NO = 2)

ord.	Outlook	Temp	Humidity	Windy	Play
4	Rainy	Mild	High	FALSE	Yes
5	Rainy	Cool	Normal	FALSE	Yes

10	Rainy	Mild	Normal	FALSE	Yes
6	Rainy	Cool	Normal	TRUE	No
14	Rainy	Mild	High	TRUE	No

Since there were no pure sets yet I decided to further split into child nodes for all outcast values. Looking through the Sunny outlook I discovered that I could get two pure subsets by further splitting by Humidity

SUNNY AND HIGH HUMIDITY

ord.	Outlook	Temp	Humidity	Windy	Play
1	Sunny	Hot	High	FALSE	No
2	Sunny	Hot	High	TRUE	No
8	Sunny	Mild	High	FALSE	No

SUNNY AND NORMAL HUMIDITY

ord.	Outlook	Temp	Humidity	Windy	Play
9	Sunny	Cool	Normal	FALSE	Yes
11	Sunny	Mild	Normal	TRUE	Yes

At the node for the Overcast humidity I discovered the possibility to get one pure subset by splitting to a child node via humidity which I did

OVERCAST AND HIGH HUMIDITY

ord.	Outlook	Temp	Humidity	Windy	Play
3	Overcast	Hot	High	FALSE	Yes
12	Overcast	Mild	High	TRUE	Yes
15	Overcast	Cool	High	FALSE	No

OVERCAST AND NORMAL HUMIDITY

ord.	Outlook	Temp	Humidity	Windy	Play
7	Overcast	Cool	Normal	TRUE	Yes
13	Overcast	Hot	Normal	FALSE	Yes

After going through the data of the impure subset I figured out that it will be possible to split to three pure subsets using the temperature. Alas I got three pure subsets as can be seen below

OVERCAST WITH HIGH HUMIDITY AND HOT TEMPERATURE

ord.	Outlook	Temp	Humidity	Windy	Play
3	Overcast	Hot	High	FALSE	Yes

OVERCAST WITH HIGH HUMIDITY AND MILD TEMPERATURE

ord.	Outlook	Temp	Humidity	Windy	Play
12	Overcast	Mild	High	TRUE	Yes

OVERCAST WITH HIGH HUMIDITY AND COOL TEMPERATURE

ord.	Outlook	Temp	Humidity	Windy	Play
15	Overcast	Cool	High	FALSE	No

After getting the pure subsets for overcast, I proceeded to windy and after careful examination I discovered that I could get out two pure subsets using the Windy classification and alas I finally did.

RAIN AND WINDY TRUE

ord.	Outlook	Temp	Humidity	Windy	Play
6	Rainy	Cool	Normal	TRUE	No
14	Rainy	Mild	High	TRUE	No

RAIN AND WINDY FALSE

ord.	Outlook	Temp	Humidity	Windy	Play
4	Rainy	Mild	High	FALSE	Yes
5	Rainy	Cool	Normal	FALSE	Yes
10	Rainy	Mild	Normal	FALSE	Yes

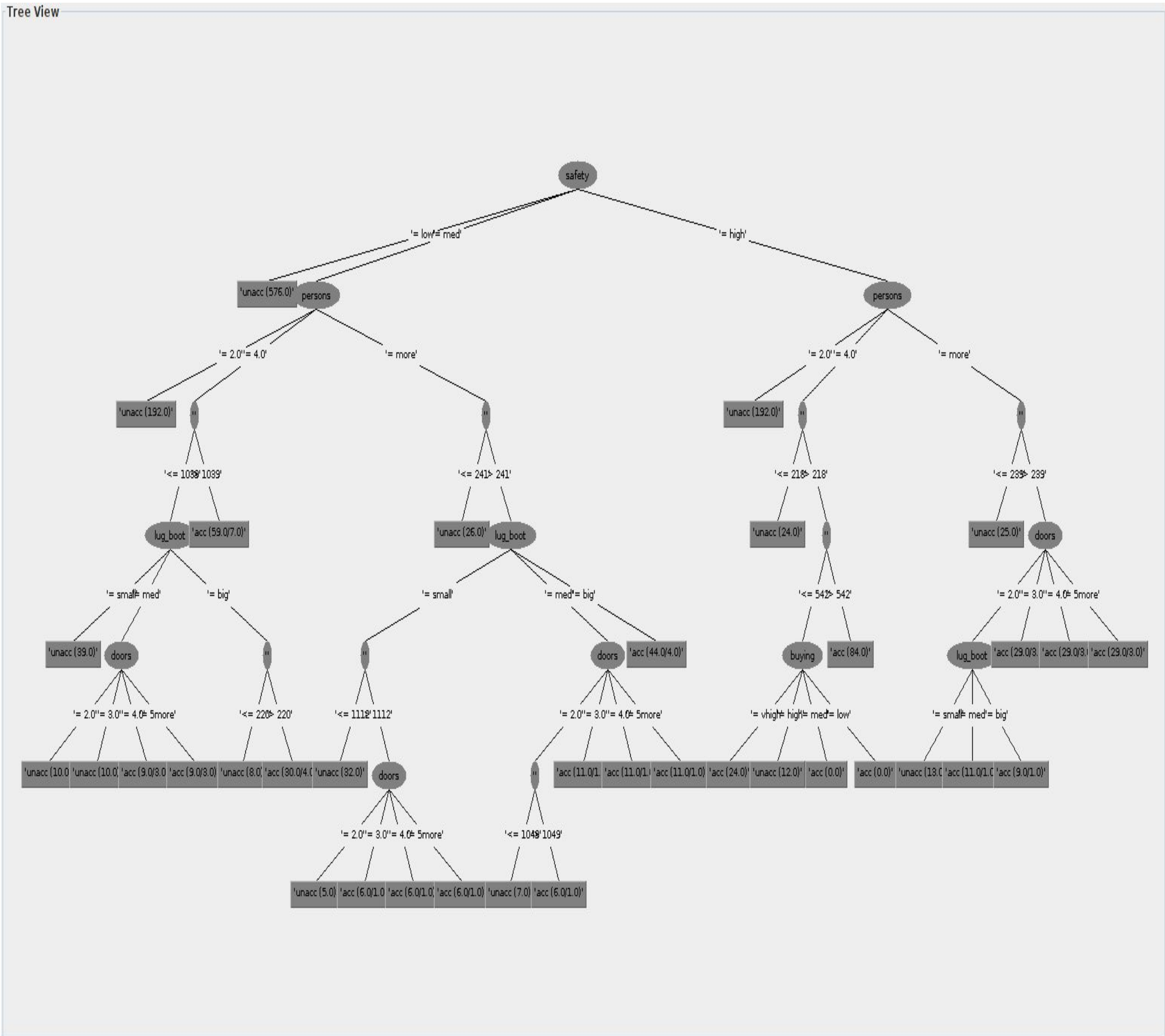
In conclusion from the decision tree above we can now give an answer to the question "providing that there is mild, overcast, high humidity and high wind weather - should one play tennis or not?" Which is that "Yes one should play Tennis"

3. Use the Cars data set and apply decision trees for classification. Describe the tree. (you can use R, or Weka (install Weka from here), or python...). Compare the decision tree approach to the association rules derived from the same data.

- To make your life easier, we recommend you remove observations with two infrequent classes - *good* and *v-good*. You can get the resulting dataset here
- in R, you can use library *rpart* to build the trees and *rpart.plot* to visualize them

In order to do this task I first converted the data into a .csv file by reading the .txt file into R, formatting it properly and writing it out to a .csv file using the following commands.

After this I proceeded to read the data into Weka and then proceeded to click on the classify tab and selected the J48 classifier to build the tree. I used the default parameters however I opted to build this tree with a training set. The resulting tree is as seen below



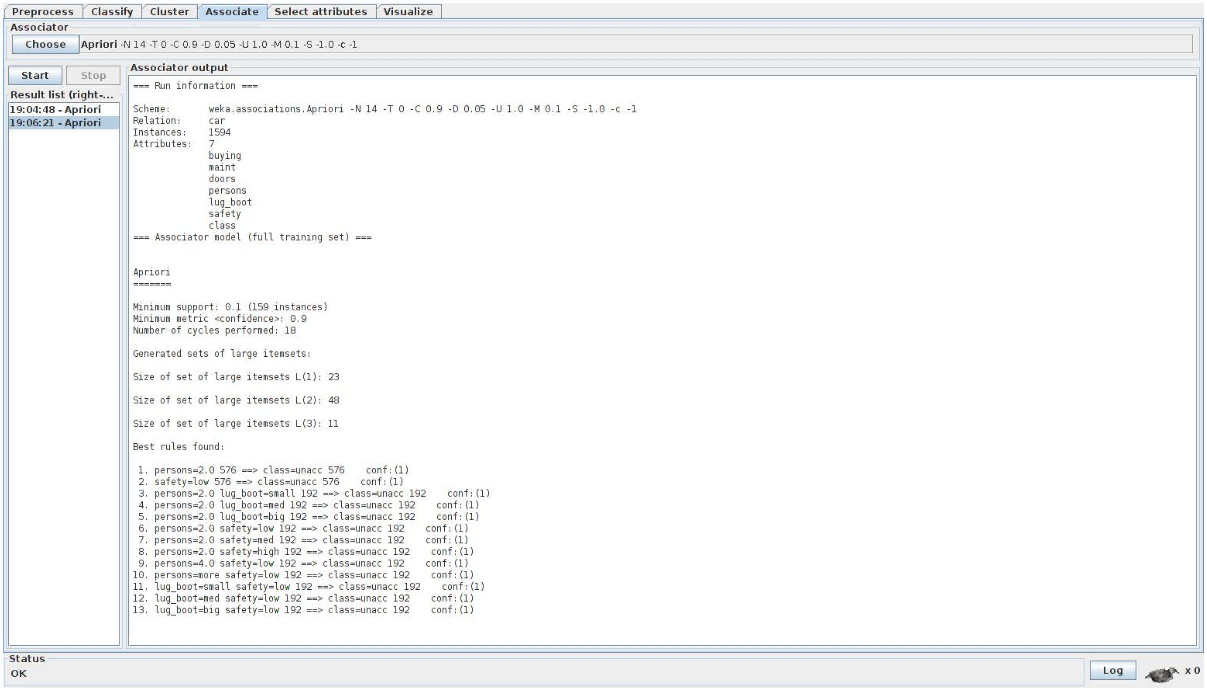
In the appendix section of this Homework you will find the complete breakdown of the entire tree that was visualized above.

Using the training set as my test option resulted in giving me 97.5533% classification accuracy which is quite high as can be seen in the summary below.

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

Correctly Classified Instances	1555	97.5533 %
Incorrectly Classified Instances	39	2.4467 %
Kappa statistic	0.9353	
Mean absolute error	0.0417	
Root mean squared error	0.1443	
Relative absolute error	11.3844 %	
Root relative squared error	33.7486 %	
Total Number of Instances	1594	

I also used the apriori algorithm in Weka to mine the rules and the following output was gotten after setting the number of rules to be generated to be 14



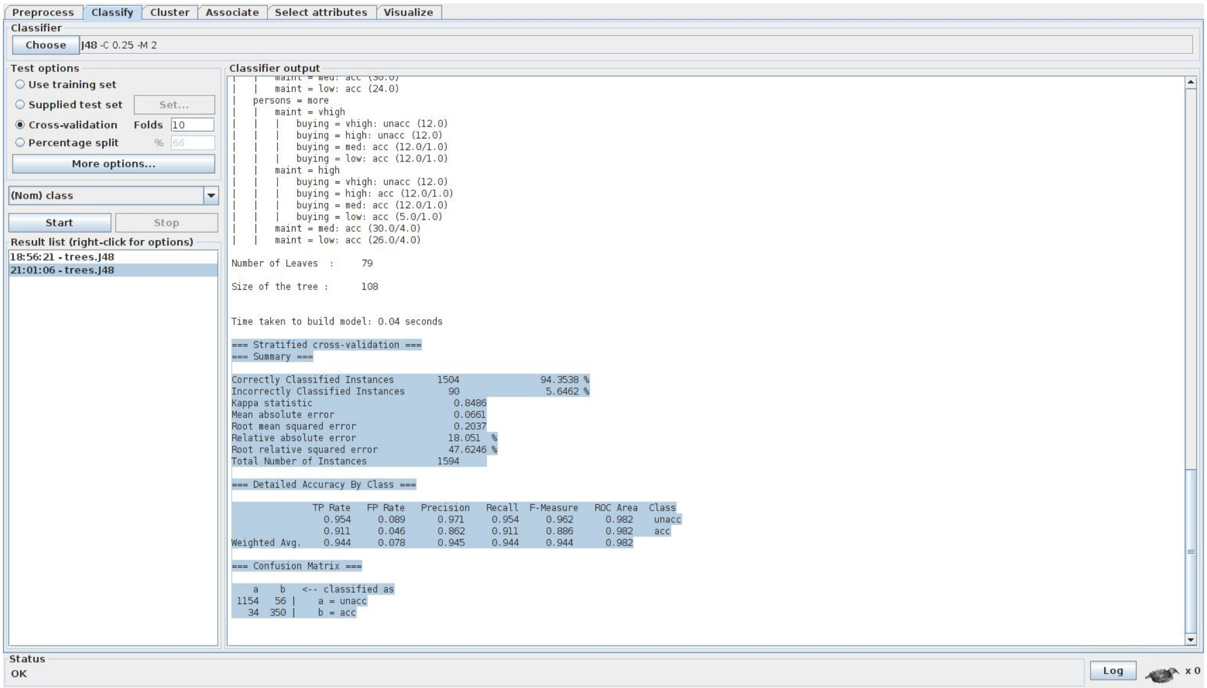
Best rules found:

1. persons=2.0 576 ==> class=unacc 576 conf:(1)
2. safety=low 576 ==> class=unacc 576 conf:(1)
3. persons=2.0 lug_boot=small 192 ==> class=unacc 192 conf:(1)
4. persons=2.0 lug_boot=med 192 ==> class=unacc 192 conf:(1)
5. persons=2.0 lug_boot=big 192 ==> class=unacc 192 conf:(1)
6. persons=2.0 safety=low 192 ==> class=unacc 192 conf:(1)
7. persons=2.0 safety=med 192 ==> class=unacc 192 conf:(1)
8. persons=2.0 safety=high 192 ==> class=unacc 192 conf:(1)
9. persons=4.0 safety=low 192 ==> class=unacc 192 conf:(1)
10. persons=more safety=low 192 ==> class=unacc 192 conf:(1)
11. lug_boot=small safety=low 192 ==> class=unacc 192 conf:(1)
12. lug_boot=med safety=low 192 ==> class=unacc 192 conf:(1)
13. lug_boot=big safety=low 192 ==> class=unacc 192 conf:(1)

In regards to comparison I can say that from my understanding, the basic difference between association rules and decision trees is simply that association rules basically focus on detecting relationships between categorical variables in the data set whereas the decision trees basically is purely a classification technique used predict a target (i.e. they map the set of record features into the class attribute which is the object of classification and target variable.

4. Use the same cars data set. Apply decision trees and Naive Bayes classifiers on the same data. Can you confirm that one method is better than the other in some way? Perform 10-fold cross-validation. Provide final results as 2x2 tables of TP. FP, FN, TN and some measures - accuracy, precision, recall.

a) Decision Tree



Applying cross validation for the Decision Tree classifier (using J48) the following values are obtainable for 2x2 tables of TP. FP, FN, TN

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

Correctly Classified Instances	1504	94.3538 %
Incorrectly Classified Instances	90	5.6462 %
Kappa statistic	0.8486	
Mean absolute error	0.0661	
Root mean squared error	0.2037	
Relative absolute error	18.051 %	
Root relative squared error	47.6246 %	
Total Number of Instances	1594	

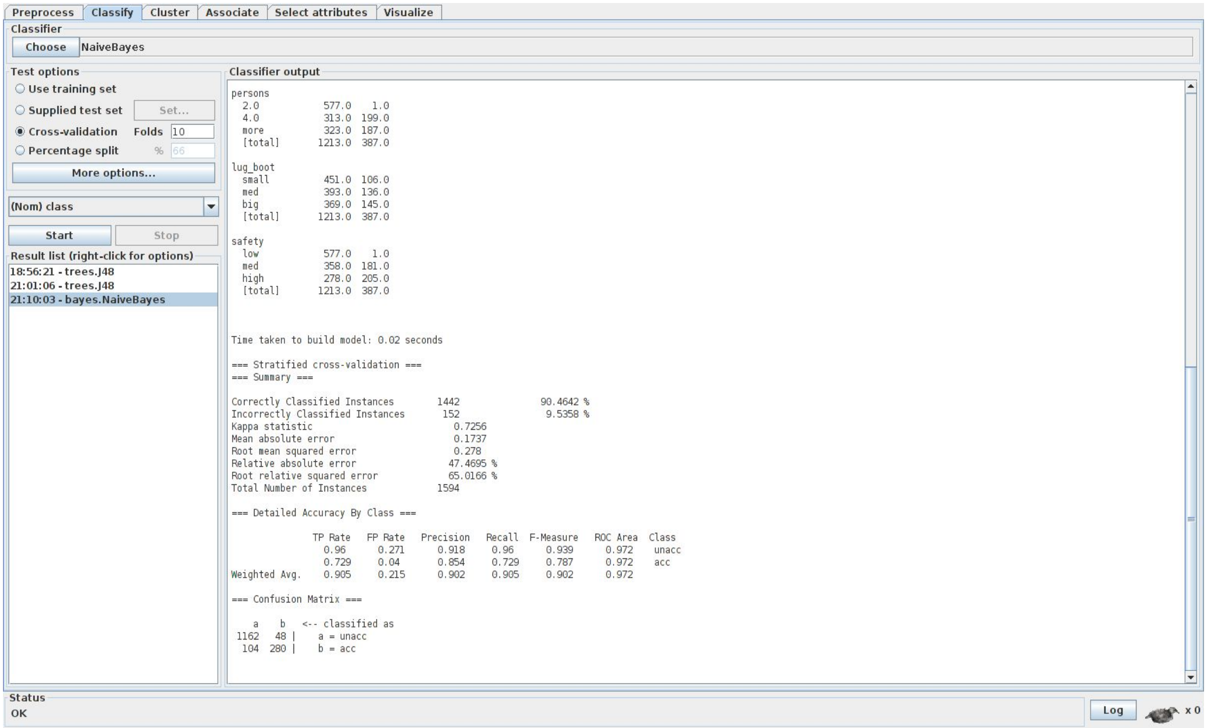
=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.954	0.089	0.971	0.954	0.962	0.982	unacc
	0.911	0.046	0.862	0.911	0.886	0.982	acc
Weighted Avg.	0.944	0.078	0.945	0.944	0.944	0.982	

=== Confusion Matrix ===

a	b	<-- classified as
1154	56 |	a = unacc
34	350 |	b = acc

b) NaiveBayes



Applying Naive bayes for the decision Tree classifier the following values are obtainable for 2x2 tables of TP. FP, FN, TN

=== Stratified cross-validation ===

=== Summary ===

Correctly Classified Instances	1442	90.4642 %
Incorrectly Classified Instances	152	9.5358 %
Kappa statistic	0.7256	
Mean absolute error	0.1737	
Root mean squared error	0.278	
Relative absolute error	47.4695 %	
Root relative squared error	65.0166 %	
Total Number of Instances	1594	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.96	0.271	0.918	0.96	0.939	0.972	unacc
	0.729	0.04	0.854	0.729	0.787	0.972	acc
Weighted Avg.	0.905	0.215	0.902	0.905	0.902	0.972	

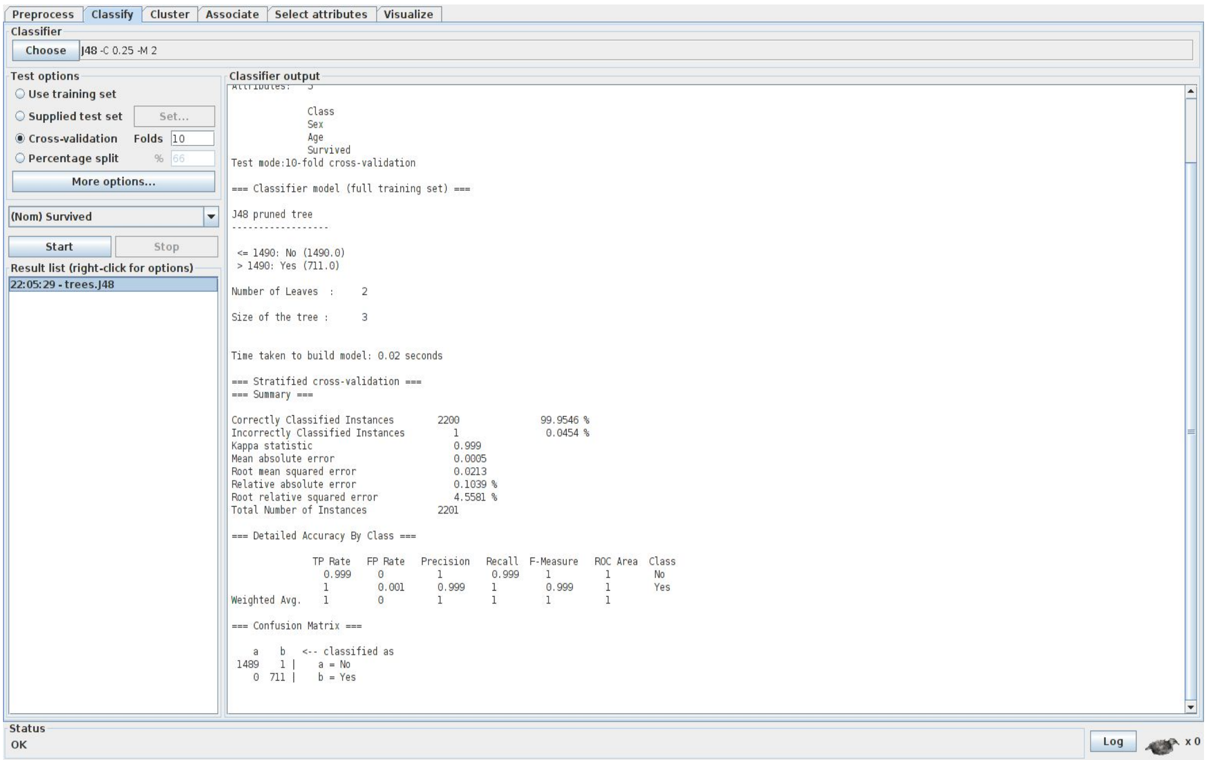
=== Confusion Matrix ===

a	b	<-- classified as
1162	48	a = unacc
104	280	b = acc

From the above output I can say that the Decision Tree classifier (J48) is better than the Naive Bayes classifier for this data because of the difference in accuracy. While the J48 classifier gave an accuracy (correctly classified instances) of 94.3538 % the Naive Bayes classifier gave an accuracy (correctly classified instances) of 90.4642 % however the time taken to generate the models differ as it took 0.04 seconds for the Decision tree as opposed to 0.02 seconds for the Naive Bayes.

5. Use the Titanic data set - compare your classifiers learned from Titanic data - decision trees, Bayes rules, association rules - and try to characterise the rules observed in data using these approaches. How can they be interpreted against each other?

a)Decision Trees (J48)

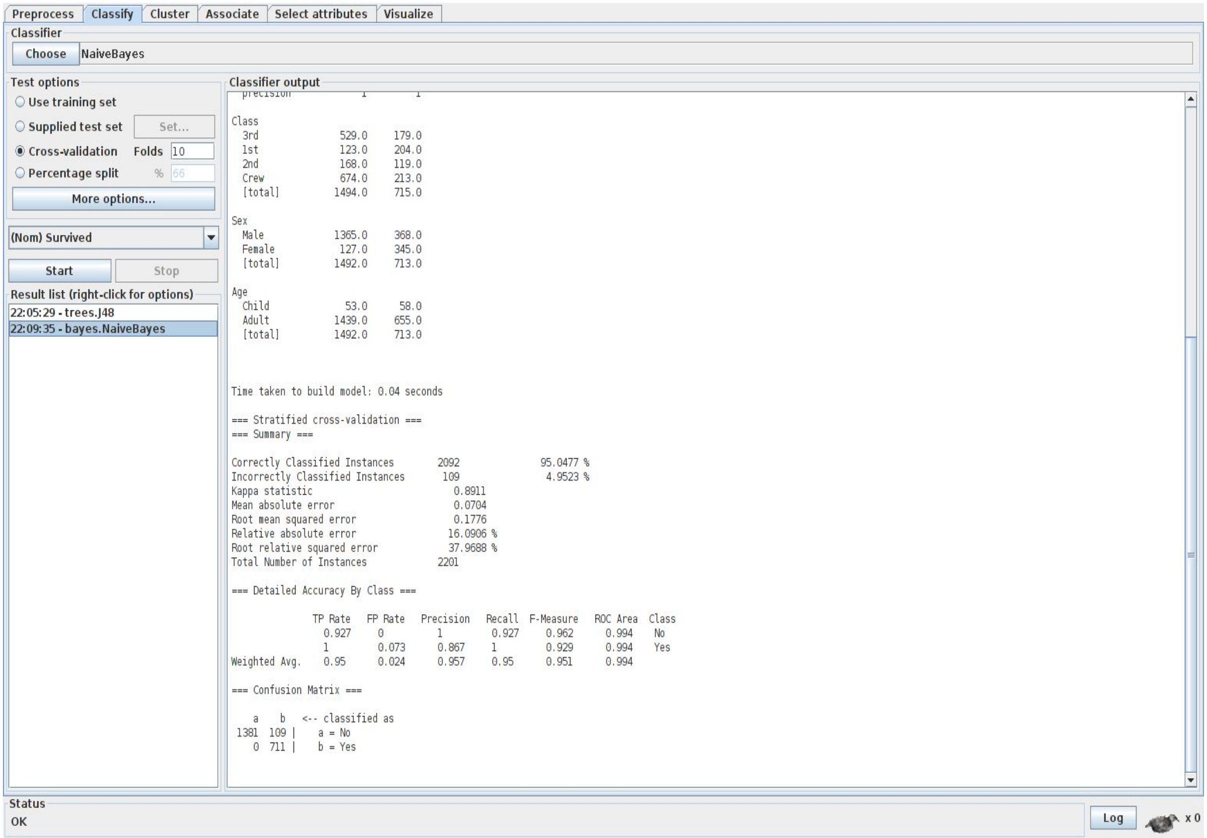


```
=== Run information ===

Scheme:weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     titanic
Instances:    2201
Attributes:   5

              Class
              Sex
              Age
              Survived
Test mode:10-fold cross-validation

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

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

 <= 1490: No (1490.0)
 > 1490: Yes (711.0)

Number of Leaves  :   2

Size of the tree :        3


Time taken to build model: 0.02 seconds

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

Correctly Classified Instances        2200               99.9546 %
Incorrectly Classified Instances         1                0.0454 %
Kappa statistic                          0.999
Mean absolute error                      0.0005
Root mean squared error                  0.0213
Relative absolute error                  0.1039 %
Root relative squared error              4.5581 %
Total Number of Instances             2201


=== Detailed Accuracy By Class ===
               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0.999     0          1         0.999     1          1        No
                 1         0.001      0.999     1         0.999      1        Yes
Weighted Avg.    1         0          1         1         1          1
```

=== Confusion Matrix ===

```
   a    b   <-- classified as
 1489    1 |    a = No
   0  711 |    b = Yes
```

2)Bayes Rule (NaiveBayes)



=== Run information ===

Scheme:weka.classifiers.bayes.NaiveBayes
Relation: titanic
Instances: 2201
Attributes: 5

Class
Sex
Age
Survived

Test mode:10-fold cross-validation

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

Naive Bayes Classifier

                 Class
Attribute           No      Yes
                (0.68)   (0.32)
===================================

  mean           745.5     1846
  std. dev.   430.1259  205.2478
  weight sum      1490      711
  precision          1        1

Class
  3rd            529.0    179.0
  1st            123.0    204.0
  2nd            168.0    119.0
  Crew           674.0    213.0
  [total]       1494.0    715.0

Sex
  Male          1365.0    368.0
  Female         127.0    345.0
  [total]       1492.0    713.0

Age
  Child           53.0     58.0
  Adult         1439.0    655.0
  [total]       1492.0    713.0


Time taken to build model: 0.04 seconds

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

Correctly Classified Instances        2092               95.0477 %
Incorrectly Classified Instances       109                4.9523 %
Kappa statistic                          0.8911
Mean absolute error                      0.0704
Root mean squared error                  0.1776
Relative absolute error                 16.0906 %
Root relative squared error             37.9688 %
Total Number of Instances             2201
```

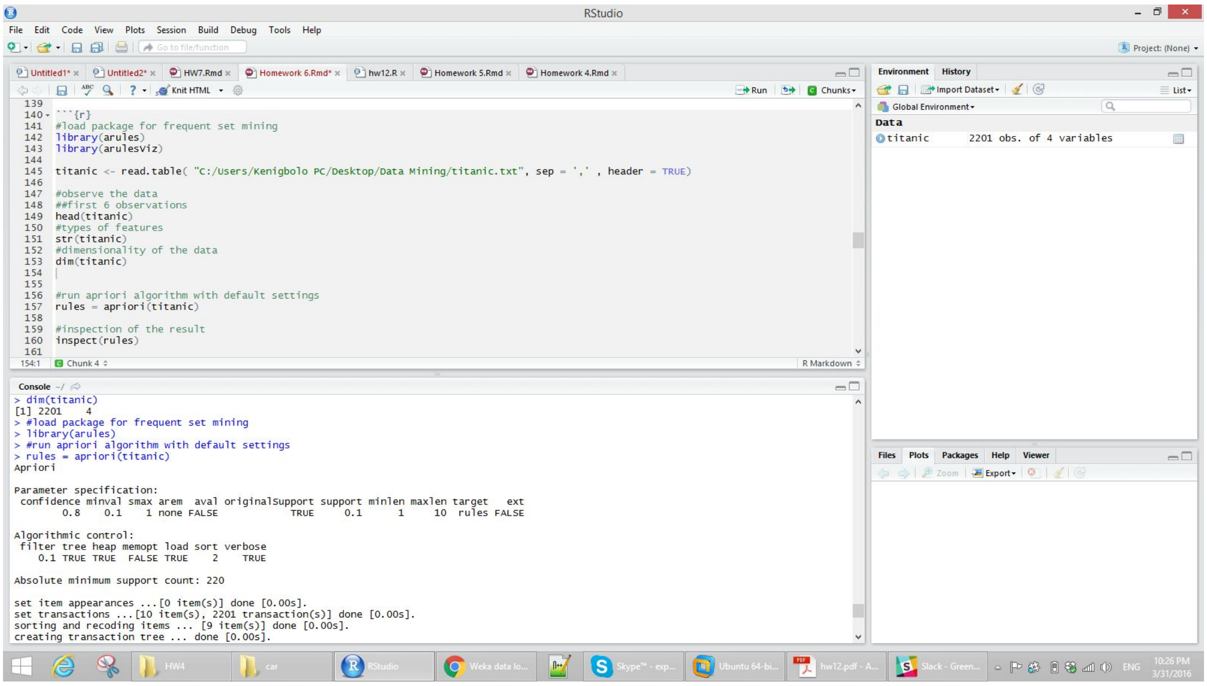
=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.927	0	1	0.927	0.962	0.994	No
	1	0.073	0.867	1	0.929	0.994	Yes
Weighted Avg.	0.95	0.024	0.957	0.95	0.951	0.994	

=== Confusion Matrix ===

```
   a    b   <-- classified as
 1381  109 |    a = No
    0  711 |    b = Yes
```

3)Association Rule(Apriori) -> Performed this with R




```
Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport support minlen maxlen target   ext
        0.8    0.1    1 none FALSE            TRUE     0.1      1     10  rules FALSE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 220
```

```
set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[10 item(s), 2201 transaction(s)] done [0.00s].
sorting and recoding items ... [9 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 3 4 done [0.00s].
writing ... [27 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].

   lhs                                rhs            support   confidence lift
1  {}                              => {Age=Adult}   0.9504771 0.9504771  1.0000000
2  {Class=2nd}                     => {Age=Adult}   0.1185825 0.9157895  0.9635051
3  {Class=1st}                     => {Age=Adult}   0.1449341 0.9815385  1.0326798
4  {Sex=Female}                    => {Age=Adult}   0.1930940 0.9042553  0.9513700
5  {Class=3rd}                     => {Age=Adult}   0.2848705 0.8881020  0.9343750
6  {Survived=Yes}                  => {Age=Adult}   0.2971377 0.9198312  0.9677574
7  {Class=Crew}                    => {Sex=Male}    0.3916402 0.9740113  1.2384742
8  {Class=Crew}                    => {Age=Adult}   0.4020900 1.0000000  1.0521033
9  {Survived=No}                   => {Sex=Male}    0.6197183 0.9154362  1.1639949
10 {Survived=No}                   => {Age=Adult}   0.6533394 0.9651007  1.0153856
11 {Sex=Male}                      => {Age=Adult}   0.7573830 0.9630272  1.0132040
12 {Sex=Female,Survived=Yes}       => {Age=Adult}   0.1435711 0.9186047  0.9664669
13 {Class=3rd,Sex=Male}            => {Survived=No} 0.1917310 0.8274510  1.2222950
14 {Class=3rd,Survived=No}         => {Age=Adult}   0.2162653 0.9015152  0.9484870
15 {Class=3rd,Sex=Male}            => {Age=Adult}   0.2099046 0.9058824  0.9530818
16 {Sex=Male,Survived=Yes}         => {Age=Adult}   0.1535666 0.9209809  0.9689670
17 {Class=Crew,Survived=No}        => {Sex=Male}    0.3044071 0.9955423  1.2658514
18 {Class=Crew,Survived=No}        => {Age=Adult}   0.3057701 1.0000000  1.0521033
19 {Class=Crew,Sex=Male}           => {Age=Adult}   0.3916402 1.0000000  1.0521033
20 {Class=Crew,Age=Adult}          => {Sex=Male}    0.3916402 0.9740113  1.2384742
21 {Sex=Male,Survived=No}          => {Age=Adult}   0.6038164 0.9743402  1.0251065
22 {Age=Adult,Survived=No}         => {Sex=Male}    0.6038164 0.9242003  1.1751385
23 {Class=3rd,Sex=Male,Survived=No}   => {Age=Adult}   0.1758292 0.9170616  0.9648435
24 {Class=3rd,Age=Adult,Survived=No}  => {Sex=Male}    0.1758292 0.8130252  1.0337773
25 {Class=3rd,Sex=Male,Age=Adult}     => {Survived=No} 0.1758292 0.8376623  1.2373791
26 {Class=Crew,Sex=Male,Survived=No}  => {Age=Adult}   0.3044071 1.0000000
1.0521033
27 {Class=Crew,Age=Adult,Survived=No} => {Sex=Male}    0.3044071 0.9955423
1.2658514
```

From analyzing the decision trees, Bayes rules, association rules it is obvious that sex clearly had the most significant relationship demonstrated within the dataset in terms of the rate of survival. It is also worth noting that the J48 classifier, using the test data set resulted in ~100% (99.9546 %) correctly classified instances as opposed to ~94% (95.0477 %) when using the NaiveBayes classifier.

6. (Bonus 1p) How to detect and avoid overfitting? What is the good (optimal?) size of the decision tree classifiers? Use the above Cars data, and for comparison use one of the two data sets - the Mushroom (LINK) or the Connect 4 (LINK).

APPENDIX
DECISION TREE FOR TASK 3

Test mode:evaluate on training data

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

J48 pruned tree

```
safety = low: unacc (576.0)
safety = med
|   persons = 2.0: unacc (192.0)
|   persons = 4.0
|   |   buying = vhigh
|   |   |   maint = vhigh: unacc (12.0)
|   |   |   maint = high: unacc (12.0)
|   |   |   maint = med
|   |   |   |   lug_boot = small: unacc (4.0)
|   |   |   |   lug_boot = med: unacc (4.0/2.0)
|   |   |   |   lug_boot = big: acc (4.0)
|   |   |   maint = low
|   |   |   |   lug_boot = small: unacc (4.0)
|   |   |   |   lug_boot = med: unacc (4.0/2.0)
|   |   |   |   lug_boot = big: acc (4.0)
|   |   buying = high
|   |   |   lug_boot = small: unacc (16.0)
|   |   |   lug_boot = med
|   |   |   |   doors = 2.0: unacc (4.0)
|   |   |   |   doors = 3.0: unacc (4.0)
|   |   |   |   doors = 4.0: acc (4.0/1.0)
|   |   |   |   doors = 5more: acc (4.0/1.0)
|   |   |   lug_boot = big
|   |   |   |   maint = vhigh: unacc (4.0)
|   |   |   |   maint = high: acc (4.0)
|   |   |   |   maint = med: acc (4.0)
|   |   |   |   maint = low: acc (4.0)
|   |   buying = med
|   |   |   maint = vhigh
|   |   |   |   lug_boot = small: unacc (4.0)
|   |   |   |   lug_boot = med: unacc (4.0/2.0)
|   |   |   |   lug_boot = big: acc (4.0)
|   |   |   maint = high
|   |   |   |   lug_boot = small: unacc (4.0)
|   |   |   |   lug_boot = med: unacc (4.0/2.0)
|   |   |   |   lug_boot = big: acc (4.0)
|   |   |   maint = med: acc (12.0)
```

```
|   |   |   maint = low: acc (6.0)
|   |   buying = low: acc (36.0/6.0)
|   persons = more
|   |   lug_boot = small
|   |   |   buying = vhigh: unacc (16.0)
|   |   |   buying = high: unacc (16.0)
|   |   |   buying = med
|   |   |   |   maint = vhigh: unacc (4.0)
|   |   |   |   maint = high: unacc (4.0)
|   |   |   |   maint = med: acc (4.0/1.0)
|   |   |   |   maint = low: acc (4.0/1.0)
|   |   |   buying = low
|   |   |   |   maint = vhigh: unacc (4.0)
|   |   |   |   maint = high: acc (4.0/1.0)
|   |   |   |   maint = med: acc (4.0/1.0)
|   |   |   |   maint = low: acc (4.0/1.0)
|   |   lug_boot = med
|   |   |   buying = vhigh
|   |   |   |   maint = vhigh: unacc (4.0)
|   |   |   |   maint = high: unacc (4.0)
|   |   |   |   maint = med: acc (4.0/1.0)
|   |   |   |   maint = low: acc (4.0/1.0)
|   |   |   buying = high
|   |   |   |   maint = vhigh: unacc (4.0)
|   |   |   |   maint = high: acc (4.0/1.0)
|   |   |   |   maint = med: acc (4.0/1.0)
|   |   |   |   maint = low: acc (4.0/1.0)
|   |   |   buying = med: acc (13.0/2.0)
|   |   |   buying = low: acc (10.0/1.0)
|   |   lug_boot = big
|   |   |   buying = vhigh
|   |   |   |   maint = vhigh: unacc (4.0)
|   |   |   |   maint = high: unacc (4.0)
|   |   |   |   maint = med: acc (4.0)
|   |   |   |   maint = low: acc (4.0)
|   |   |   buying = high
|   |   |   |   maint = vhigh: unacc (4.0)
|   |   |   |   maint = high: acc (4.0)
|   |   |   |   maint = med: acc (4.0)
|   |   |   |   maint = low: acc (4.0)
|   |   |   buying = med: acc (12.0)
|   |   |   buying = low: acc (8.0)
safety = high
|   persons = 2.0: unacc (192.0)
|   persons = 4.0
|   |   maint = vhigh
```

```
|   |   |   buying = vhigh: unacc (12.0)
|   |   |   buying = high: unacc (12.0)
|   |   |   buying = med: acc (12.0)
|   |   |   buying = low: acc (12.0)
|   |   maint = high
|   |   |   buying = vhigh: unacc (12.0)
|   |   |   buying = high: acc (12.0)
|   |   |   buying = med: acc (12.0)
|   |   |   buying = low: acc (6.0)
|   |   maint = med: acc (30.0)
|   |   maint = low: acc (24.0)
|   persons = more
|   |   maint = vhigh
|   |   |   buying = vhigh: unacc (12.0)
|   |   |   buying = high: unacc (12.0)
|   |   |   buying = med: acc (12.0/1.0)
|   |   |   buying = low: acc (12.0/1.0)
|   |   maint = high
|   |   |   buying = vhigh: unacc (12.0)
|   |   |   buying = high: acc (12.0/1.0)
|   |   |   buying = med: acc (12.0/1.0)
|   |   |   buying = low: acc (5.0/1.0)
|   |   maint = med: acc (30.0/4.0)
|   |   maint = low: acc (26.0/4.0)

Number of Leaves  :   79

Size of the tree :    108
```