**Practical No. 4**

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| Roll No.: K041 | Name: Anish Sudhan Nair |
| Class: B.Tech Cybersecurity | Batch: K2 |
| Date of Practical: 12/02/2022 | Date of Submission: 19/02/2022 |
| Grade: |  |

**Aim**: To implement ID3 algorithm

**Prerequisite:**

* Working of ID3 classification algorithm
* Understanding of fundamental programming constructs in C/C++/Java
* Basic features of WEKA tool

**Outcome:** After successful completion of this experiment students will be able to

* Implement the process of selecting the split attribute and analyze its importance in the working of ID3 Algorithm.
* Use Classifier tab in WEKA and create a Tree based classifier model for the data set given and analyze the model created.

**Theory:**

The ID3 algorithm begins with the original set S as the root node. On each iteration of the algorithm, it iterates through every unused attribute of the set S and calculates the [entropy](https://en.wikipedia.org/wiki/Entropy_(information_theory)) H(S) (or [information gain](https://en.wikipedia.org/wiki/Information_gain_in_decision_trees) IG(A)) of that attribute. It then selects the attribute which has the smallest entropy (or largest information gain) value. The set S is then split by the selected attribute (e.g. age is less than 50, age is between 50 and 100, age is greater than 100) to produce subsets of the data. The algorithm continues to recur on each subset, considering only attributes never selected before.  
Recursion on a subset may stop in one of these cases:

* Every element in the subset belongs to the same class (+ or -), then the node is turned into a leaf and labelled with the class of the examples
* There are no more attributes to be selected, but the examples still do not belong to the same class (some are + and some are -), then the node is turned into a leaf and labelled with the most common class of the examples in the subset
* There are no examples in the subset, this happens when no example in the parent set was found to be matching a specific value of the selected attribute, for example if there was no example with age >= 100. Then a leaf is created, and labelled with the most common class of the examples in the parent set.

Throughout the algorithm, the decision tree is constructed with each non-terminal node representing the selected attribute on which the data was split, and terminal nodes representing the class label of the final subset of this branch.

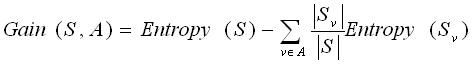
A measure used from Information Theory in the ID3 algorithm and many others used in decision tree construction is that of Entropy. Informally, the entropy of a dataset can be considered to be how disordered it is. It has been shown that entropy is related to information, in the sense that the higher the entropy, or uncertainty, of some data, then the more information is required in order to completely describe that data. In building a decision tree, we aim to decrease the entropy of the dataset until we reach leaf nodes at which point the subset that we are left with is pure, or has zero entropy and represents instances all of one class (all instances have the same value for the target attribute).

We measure the entropy of a dataset,S, with respect to one attribute, in this case the target attribute, with the following calculation:

Entropy Calculation  
where Pi is the proportion of instances in the dataset that take the ith value of the target attribute, which has C different values.

This probability measures give us an indication of how uncertain we are about the data. And we use a log2 measure as this represents how many bits we would need to use in order to specify what the class (value of the target attribute) is of a random instance.

We can use a measure called Information Gain, which calculates the reduction in entropy (Gain in information) that would result on splitting the data on an attribute, A.

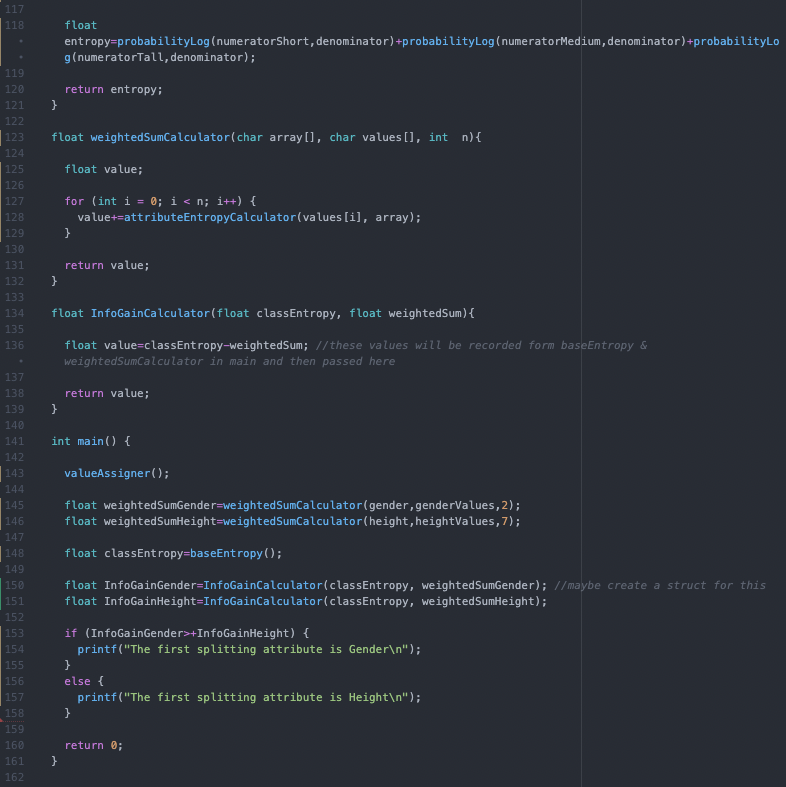
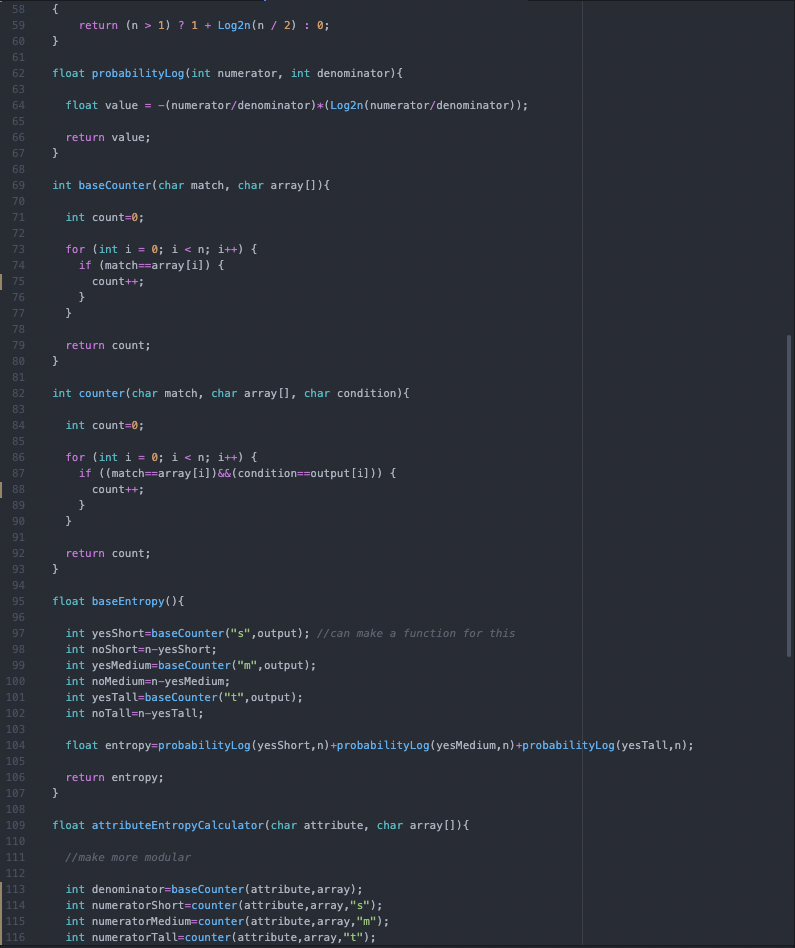
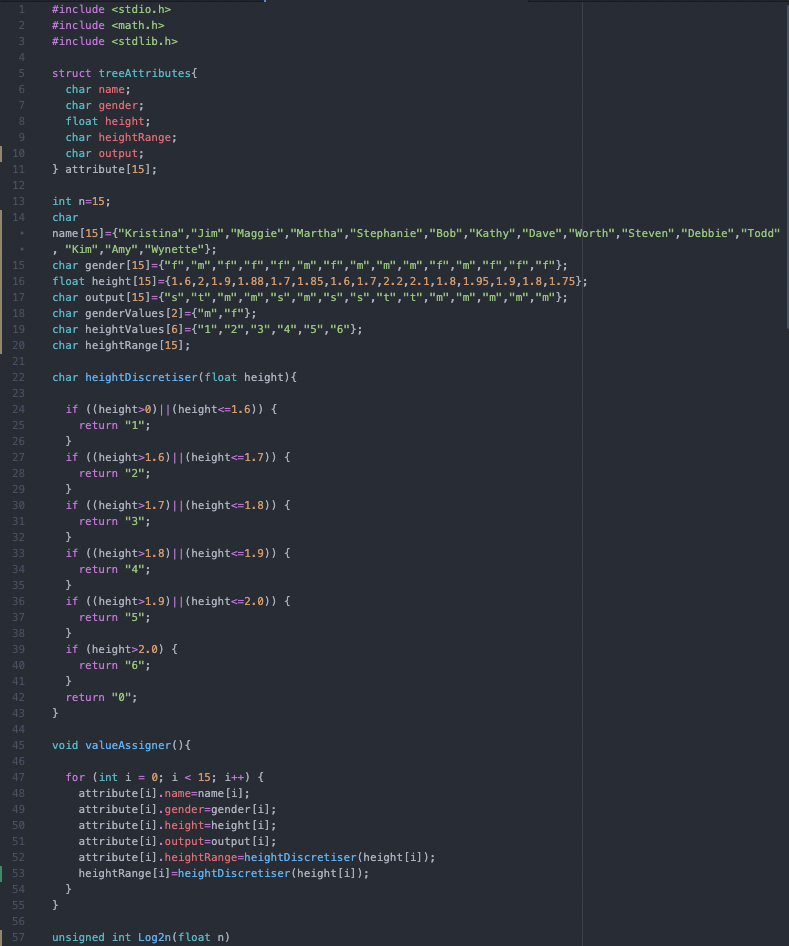
  
where v is a value of A , |Sv| is the subset of instances of S where A takes the value v,   
and |S| is the number of instances

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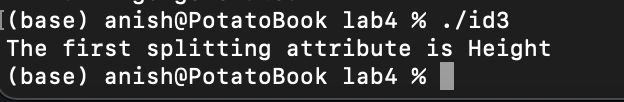
(TO BE COMPLETED BY STUDENTS)

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1. Implement an ID3 algorithm for selecting the first splitting attribute in the Height data set given below.

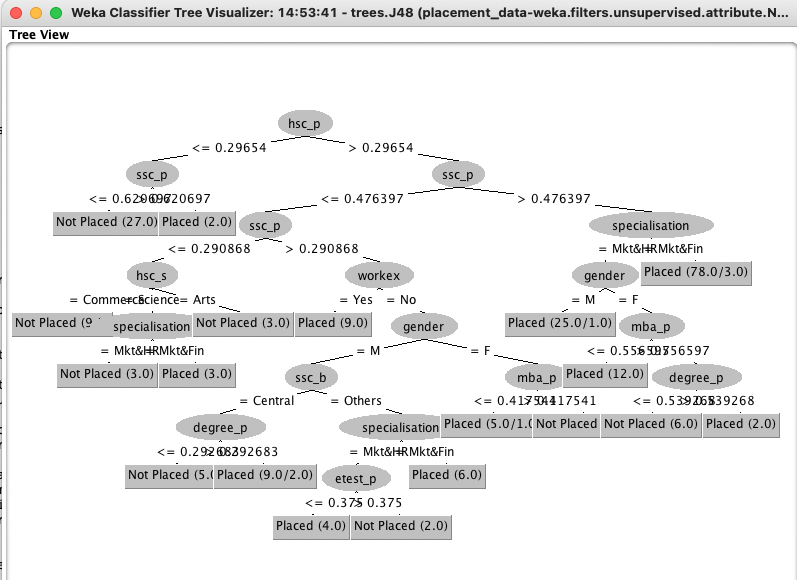
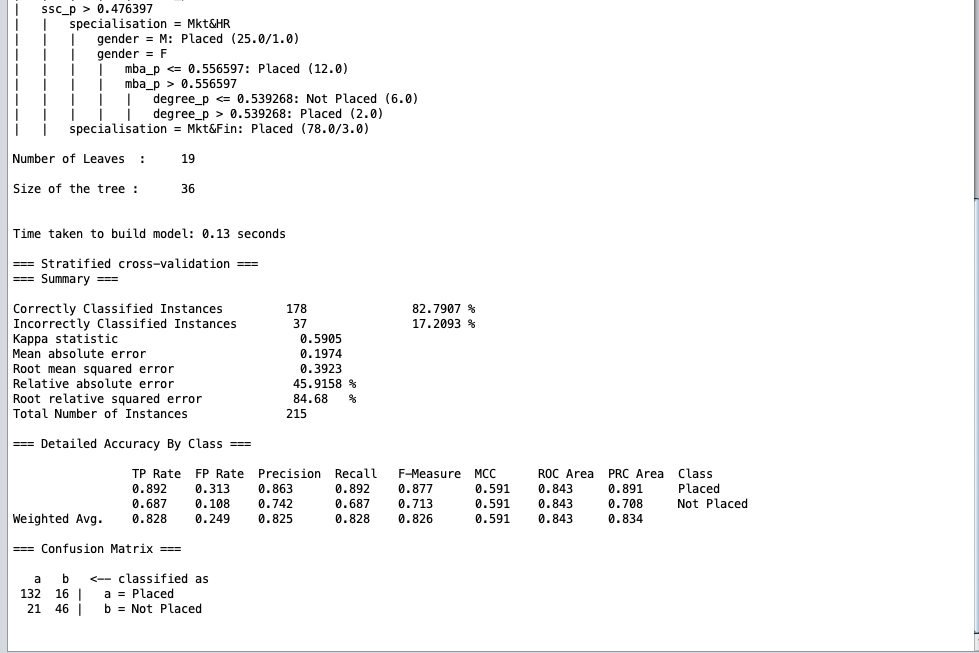
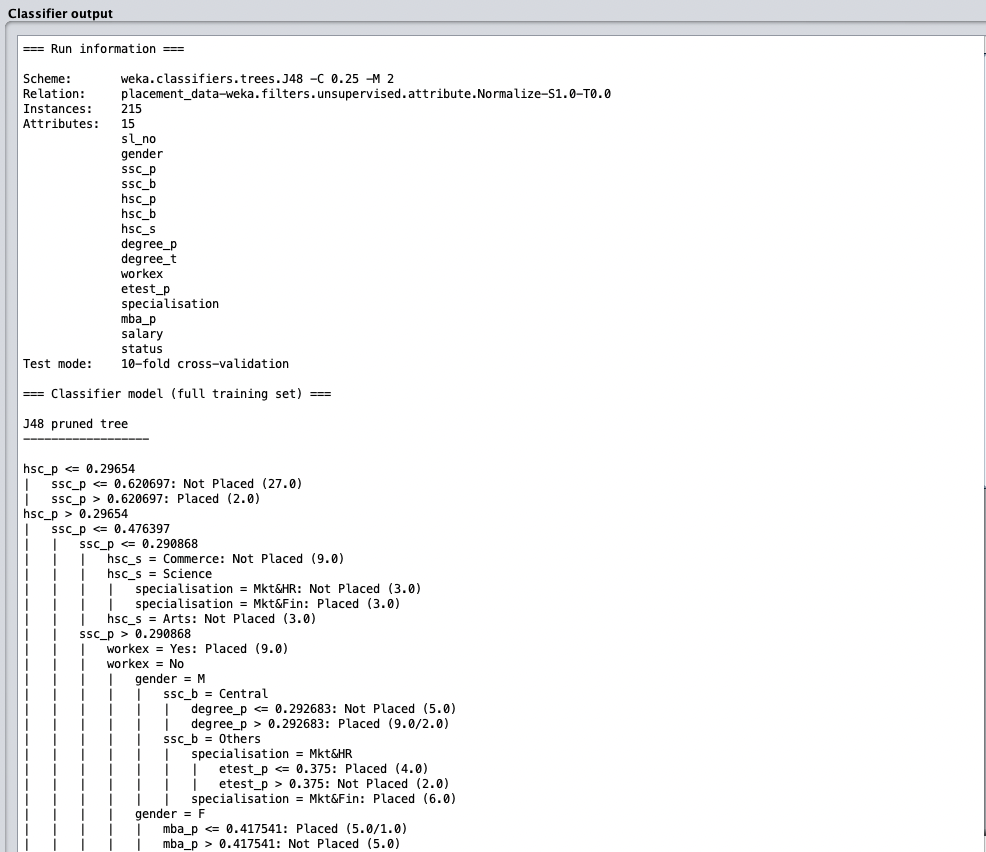
Code:

Output:



1. Using WEKA tool: For the placement data set given (Placement\_Data.csv), construct a decision tree using J48 and classify the tuple,

<F,0.950526,Others,0.461285,Others,Science,0.756098,Comm&Mgmt,Yes,0.791667,Mkt&Fin,0.808471,0.081081,Placed>



Therefore, on travelling the branches of the decision tree for the given tuple, we eventually reach specialization for which the tuple has Mkt&Fin and so is classified as Placed.

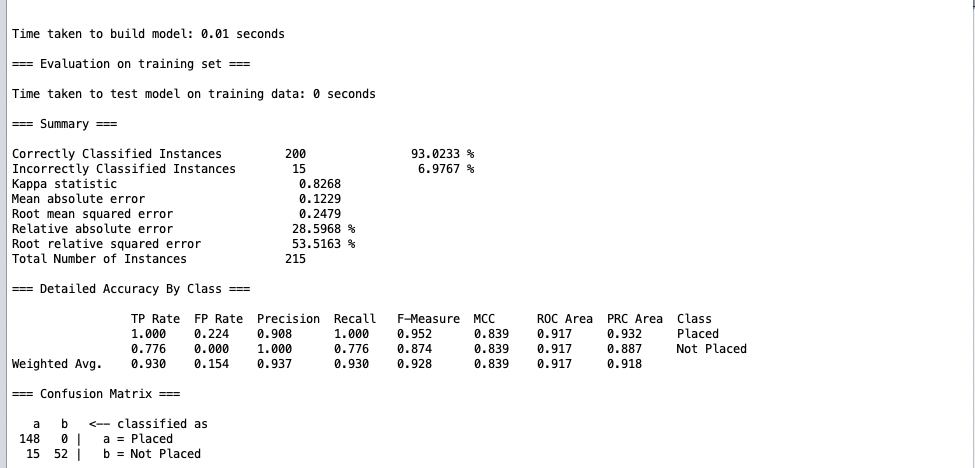
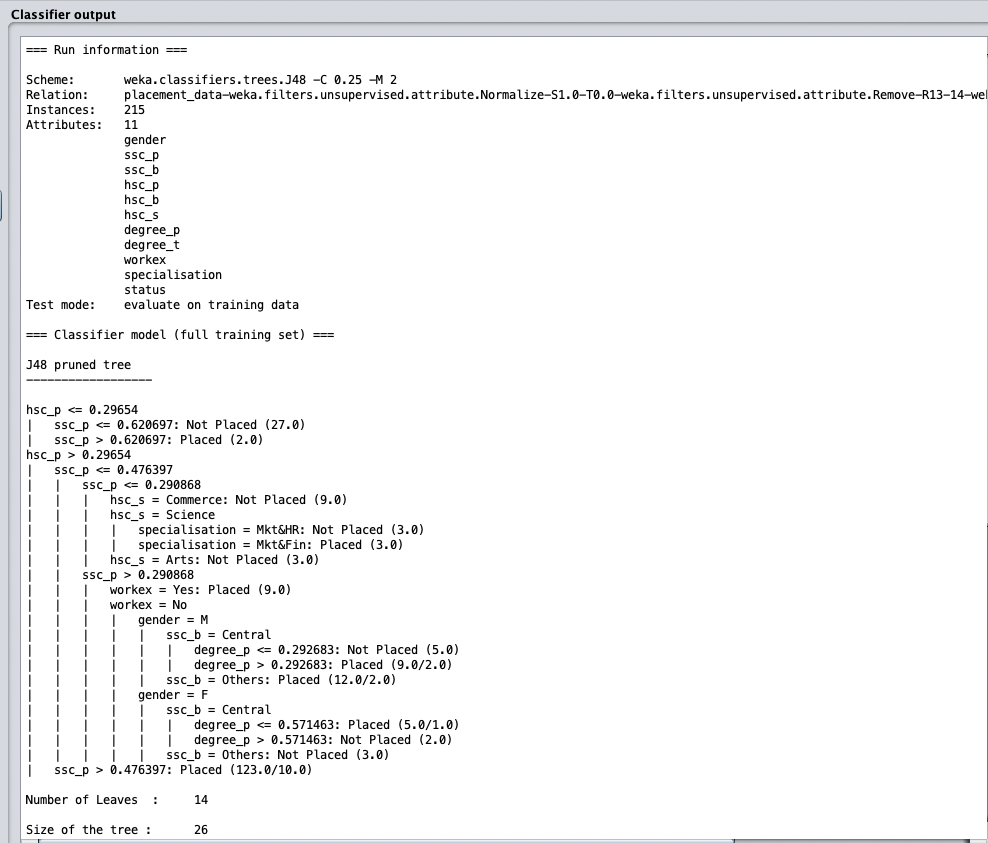
**Questions to be answered:**

1. What attributes do you think might be crucial in the decision making process of classification?

* The decision to choose a splitting attribute depends entirely on the information gain which is again dependent on the entropy. Thus, the attributes with least entropy ot most information gain would be most influential in charting a decision tree.

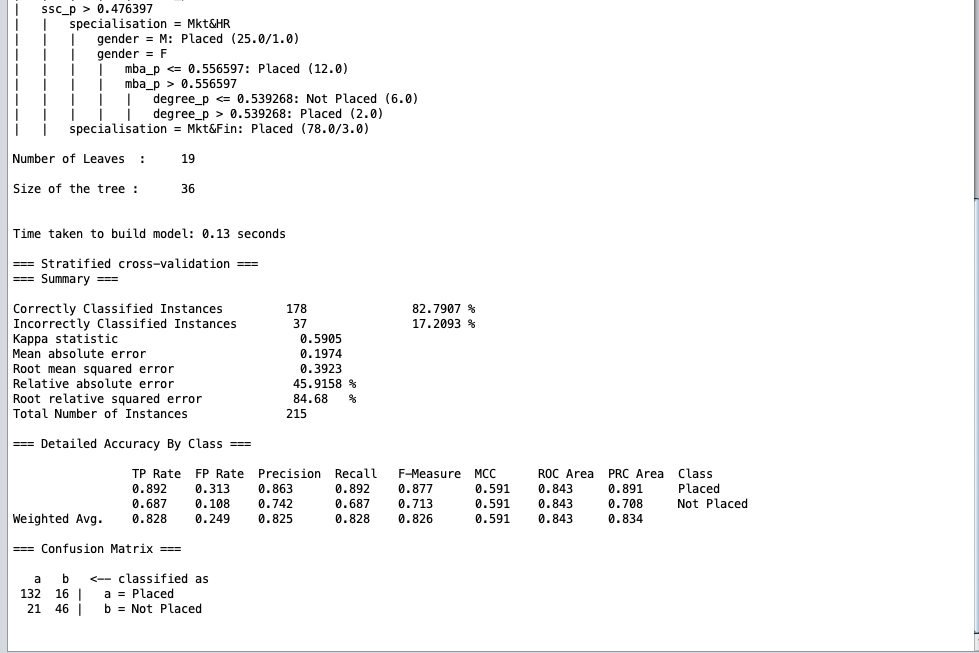
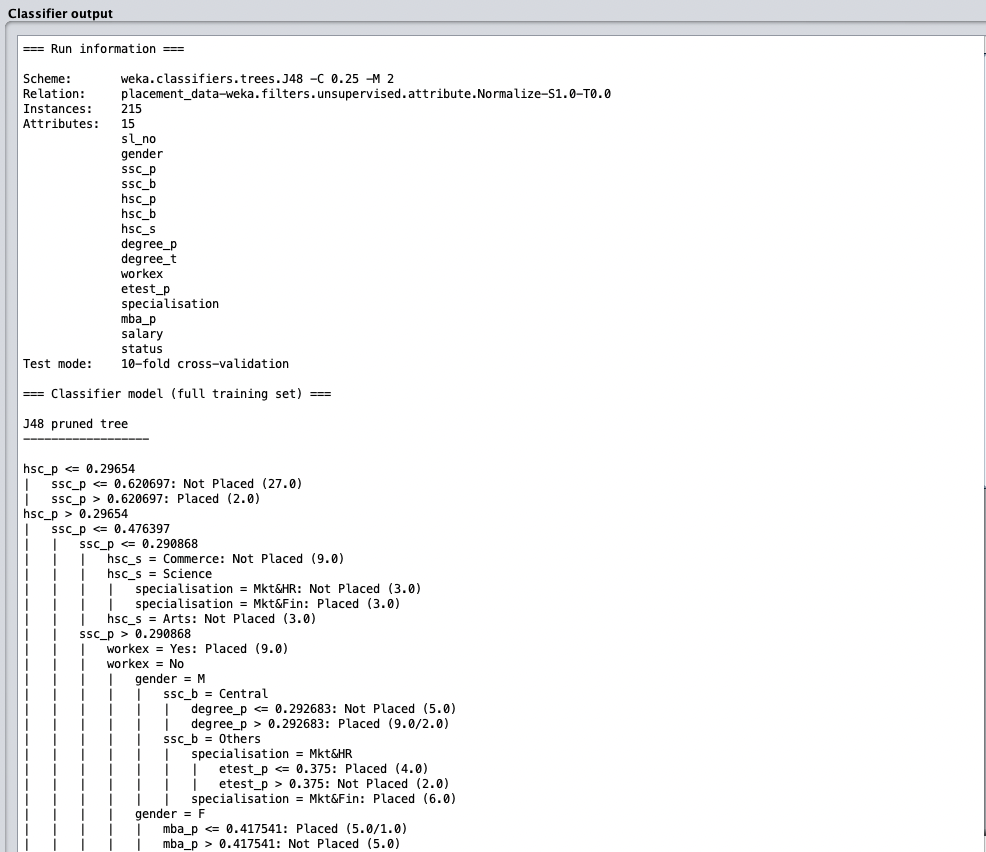
1. Does training a decision tree using cross validation have any improvement on the classification accuracy? Comment.

* Yes, cross validation (k fold) works by training the model on subsets of the entire dataset to ensure that all underlying trends are discovered, has a good ration of testing points (k folds -> k subsets -> k points) and iterates on the same data multiple times. Thus, by virtue of its very mechanism, cross validation yields higher levels of accuracy.
* Results from weka post cross validation training



1. How can you convert the above generated Decision tree into a series of *if - then – rules*

* Taking help of Weka:



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