Roadmap to
M5P Classifier Output

Blackwell Data Set Example

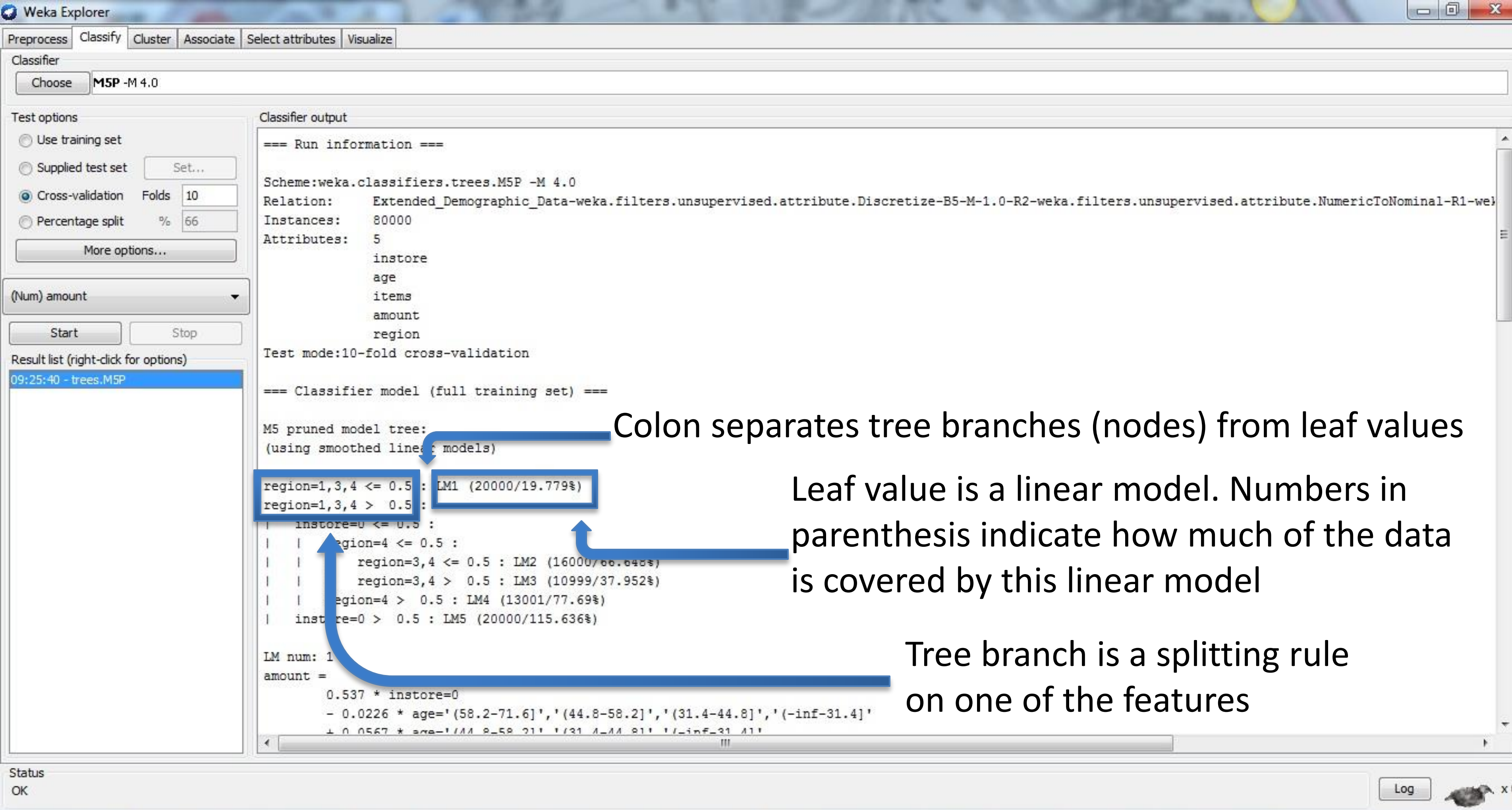
(in_store attribute)

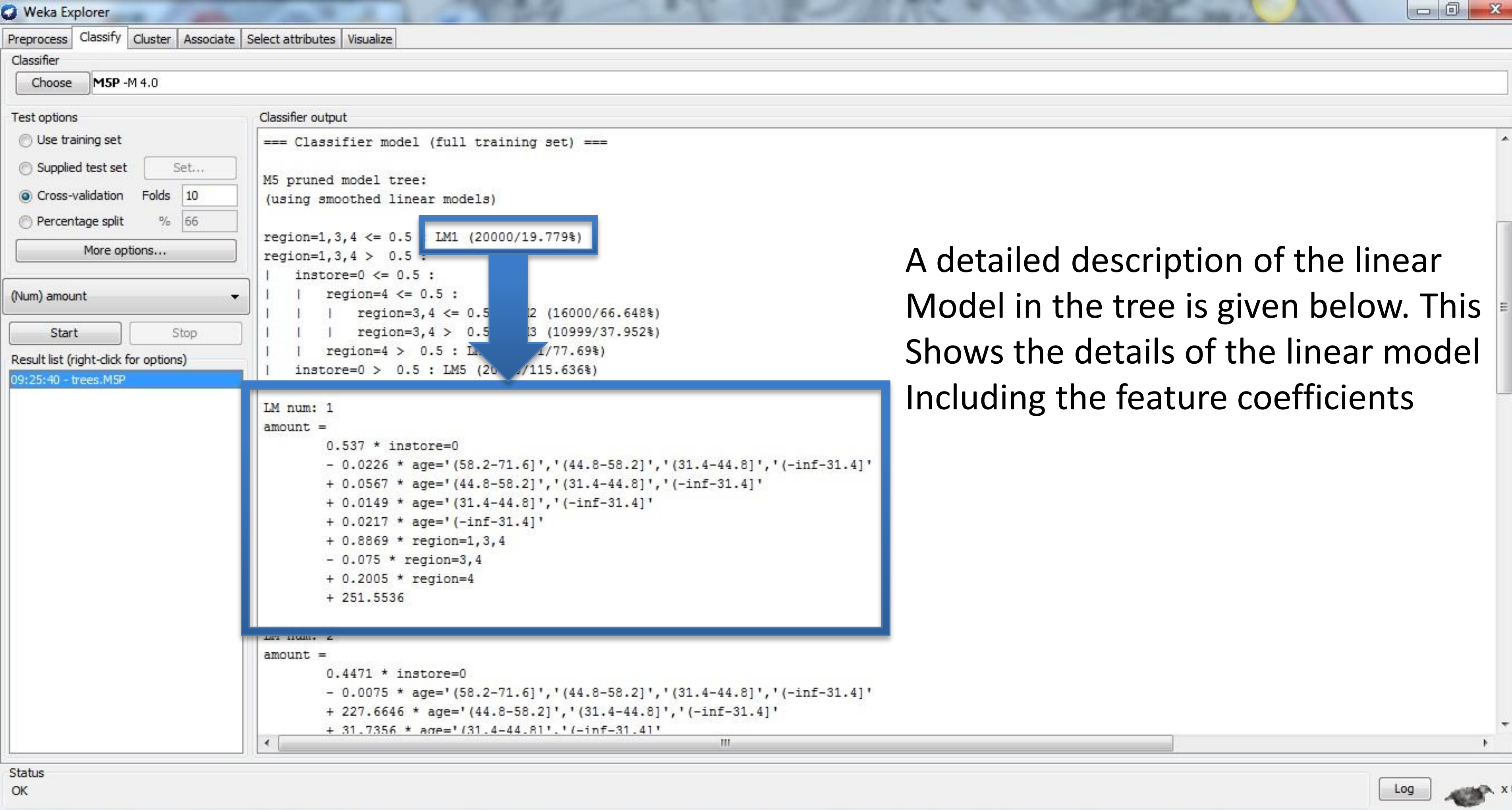
M5P (P stands for prime) generates M5 model trees using the M5’ (read M5 prime) algorithm, introduced in 1997 by Wang & Witten. This was an enhancement of the M5 algorithm introduced in 1992 by Quinlan.

In Weka, M5P decision trees and M5 Rule-based classifiers both use M5Base as the base class (algorithmic foundation).

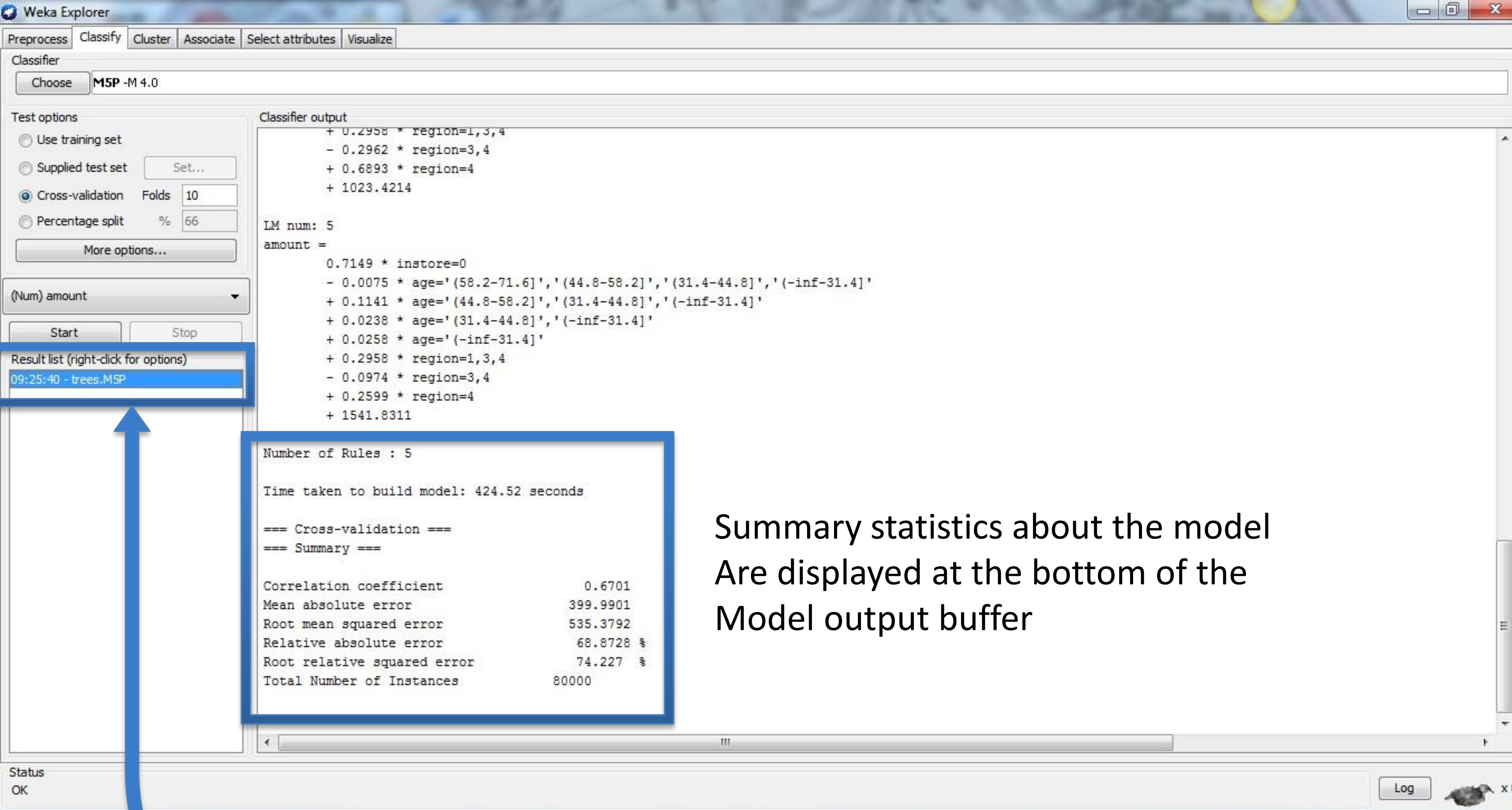
The M5P decision tree is also known as a "model" tree. Model trees are decision trees with linear regression functions at the leaves. They can be used to make predictions for a numeric target (class) attribute.

Intuitively this can be visualized as making a tree of linear models, where the tree structure allows linear models at the leaves to take on distinct parameter values to fit the data more closely.


Weka Explorer
Preprocess
Classify
Cluster
Associate
Select attributes
Visualize
Classifier
Choose
M5P -M 4.0
Test options
Use training set
Supplied test set
Set...
Cross-validation
Folds
10
Percentage split
%
66
More options...
(Num) amount
Start
Stop
Result list (right-click for options)
09:25:40 - trees.M5P
Classifier output
=== Run information ===
Scheme:weka.classifiers.trees.M5P -M 4.0
Relation: Extended_Demographic_Data-weka.filters.unsupervised.attribute.Discretize-B5-M-1.0-R2-weka.filters.unsupervised.attribute.NumericToNominal-R1-wek
Instances: 80000
Attributes: 5
instore
age
items
amount
region
Test mode:10-fold cross-validation
=== Classifier model (full training set) ===
M5 pruned model tree:
(using smoothed linear models)
region=1,3,4 <= 0.5 : LM1 (20000/19.779%)
region=1,3,4 > 0.5 :
region=3,4 <= 0.5 : LM2
region=3,4 > 0.5 : LM3 (10999/37.952%)
LM4 (13001/77.69%)
0.5 : LM5 (20000/115.636%)
LM num: 1
amount =
0.537 * instore=0
- 0.0226 * age='(58.2-71.6]','(44.8-58.2]','(31.4-44.8]','(-inf-31.4]'
Status
OK
Log
x 0
Colon separates tree branches (nodes) from leaf values
Leaf value is a linear model. Numbers in parenthesis indicate how much of the data is covered by this linear model
Tree branch is a splitting rule on one of the features

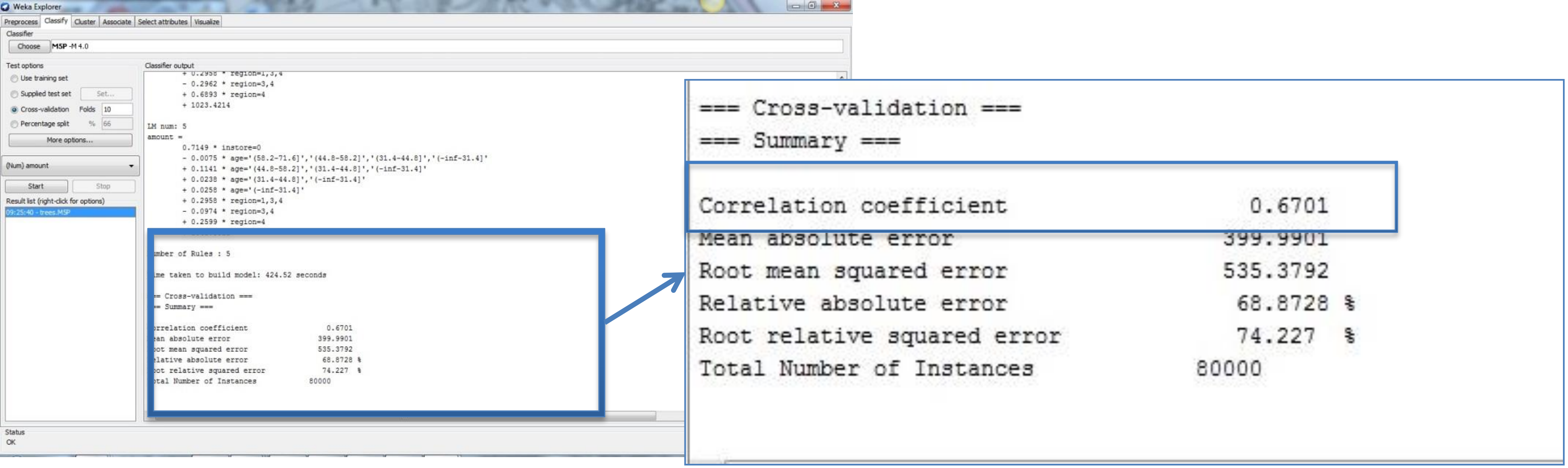


A detailed description of the linear Model in the tree is given below. This Shows the details of the linear model Including the feature coefficients



Summary statistics about the model
Are displayed at the bottom of the
Model output buffer

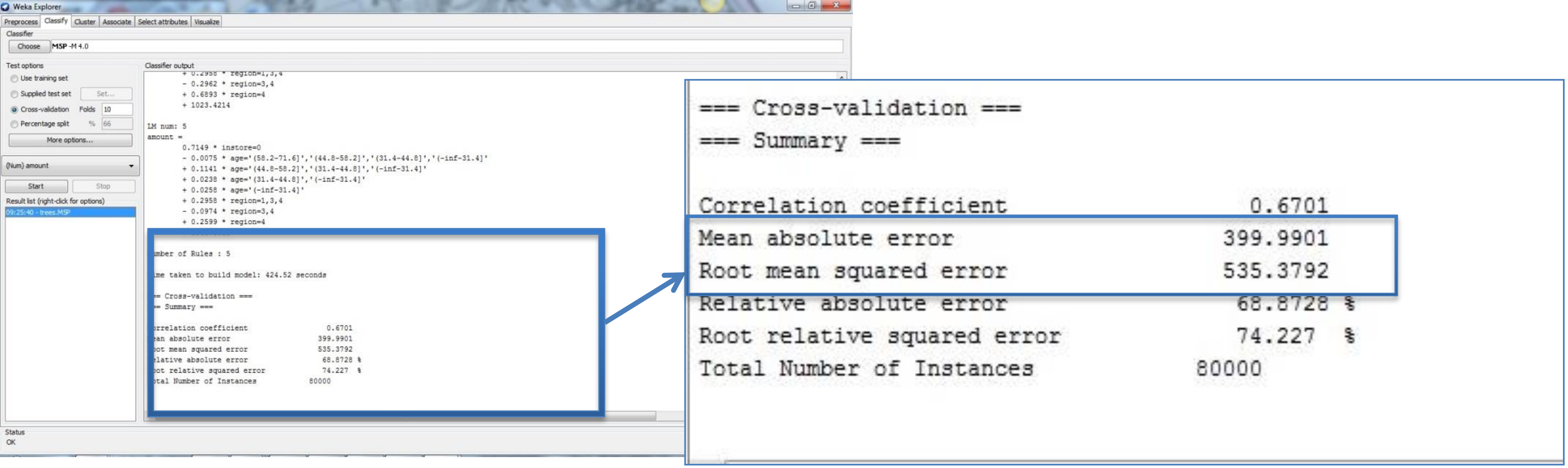
Explore the learned tree further:
right-click > Visualize tree
View a classifier error plot:
right-click > Visualize classifier errors



Summary Statistics
These statistics can be used to evaluate the model's success in predicting the numeric outcome.

Correlation Coefficient
In WEKA, the correlation coefficient (R, or multiple correlation coefficient) expresses the correlation between the predicted and actual class values. It is a measure of how well the predicted values from a forecast model "fit" new instances. In this example, cross validation was used.

A simple way to think about the correlation coefficient is as a score of how well the classifier's predicted labels correlate with the true labels. A score close to one indicates that the classifier predictions correlate very highly with the true labels. A score near zero means that the classifier's predictions have very little correlation with the true labels (in other words they carry no predictive value). And a score close to negative one means the classifier's predictions are consistently the opposite of the true labels. This last case still has predictive value, because if you know that the classifier consistently chooses the opposite of the true label, you can invert the classifier prediction and still get good performance.



Summary Statistics (Continued)

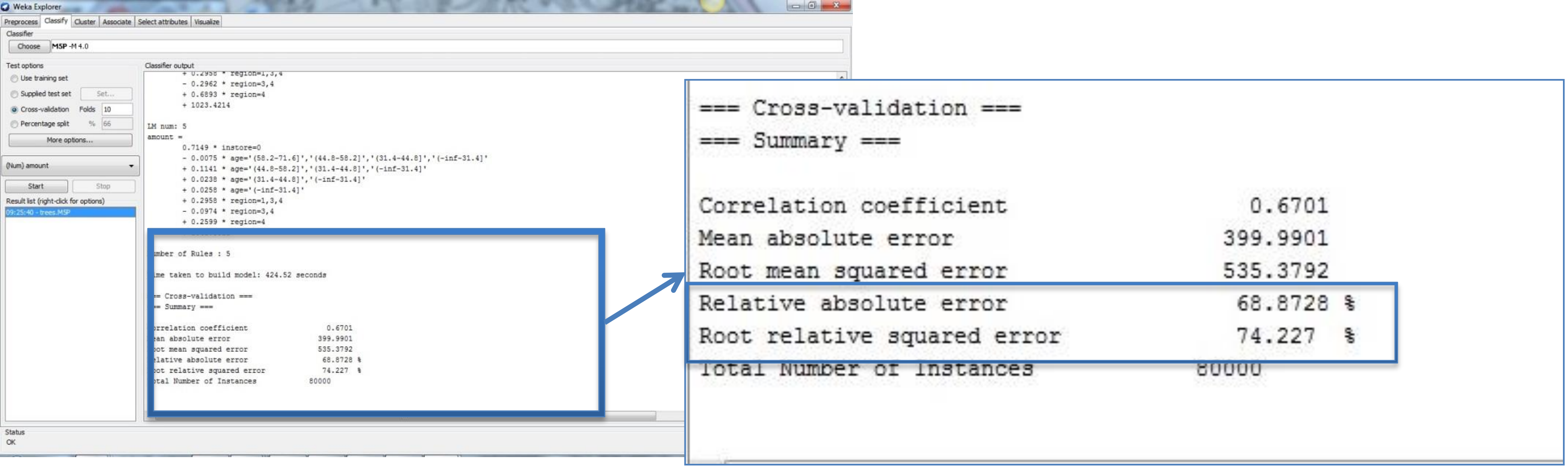
The following statistics are different measures of error. It is useful to try to gain some insight as to what acceptable ranges of error are for the problem being addressed - particularly in the engineering domain. If that is not known, you simply want to achieve the lowest error possible and record that information for comparison with future efforts to improve it.

Mean absolute error (MAE)

The mean absolute error measures the average magnitude of errors in the set of predictions, without considering their direction. As the name suggests, MAE is the average over the all the verified predictions of the absolute values of the differences between the predicted and verified observations. All the individual differences are weighted equally in the average.
Rule of Thumb: Since this statistic measures the magnitude of error, lower values are better than a higher values. The threshold of acceptable MAE is a function of the classification task and data set being analyzed.

Root Mean-Squared Error (RMSE)

RMSE is an alternative to MAE. It also measures the average magnitude of errors in a set of predictions. Expressing this formula in words, the difference between forecast and corresponding observed values are each squared and then averaged over the sample. Finally, the square root of the average is taken. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors. This means the RMSE is most useful when large errors are particularly undesirable. Conversely, mean-squared error tends to exaggerate the effect of outliers.
Rule of Thumb: Since this statistic measures the magnitude of error, lower values are better than higher values.



Summary Statistics (Continued)

Root Relative Squared Error

The error is made relative to what it would have been if a simple predictor would have been used. The simple predictor is just the average of the actual values for the attribute being predicted. It is calculated by taking the total of the squared error (discussed on the previous slide) and dividing it by the total squared error of the simple (default) predictor.
Rule of Thumb: Since this statistic measures the magnitude of error, lower values are better than a higher values.

Relative Absolute Error

This is statistic is similar to the Root Relative Squared Error. The absolute error is made relative to the simple predictor as with the Root Relative Squared Error. The Relative Absolute Error is calculated by taking the Mean Absolute Error (discussed in the previous slide) and dividing it by the mean absolute error of the default predictor (the average of the actual values being predicted.)
Rule of Thumb*:* Since this statistic measures the magnitude of error, lower values are better than a higher values.

M5P Resources:
http://www.opentox.org/dev/documentation/components/m5p
http://weka.sourceforge.net/doc.dev/weka/classifiers/trees/M5P.html

Original academic papers:
http://sci2s.ugr.es/keel/pdf/algorithm/congreso/1992-Quinlan-AI.pdf
http://www.cs.waikato.ac.nz/pubs/wp/1996/uow-cs-wp-1996-31.pdf

http://homepages.inf.ed.ac.uk/jcavazos/SMART07/paper_9_9.pdf
Read section: 3.4

Advanced reference:
http://link.springer.com/article/10.1023%2FA%3A1007421302149