Introduction to Data Science 5

Overview

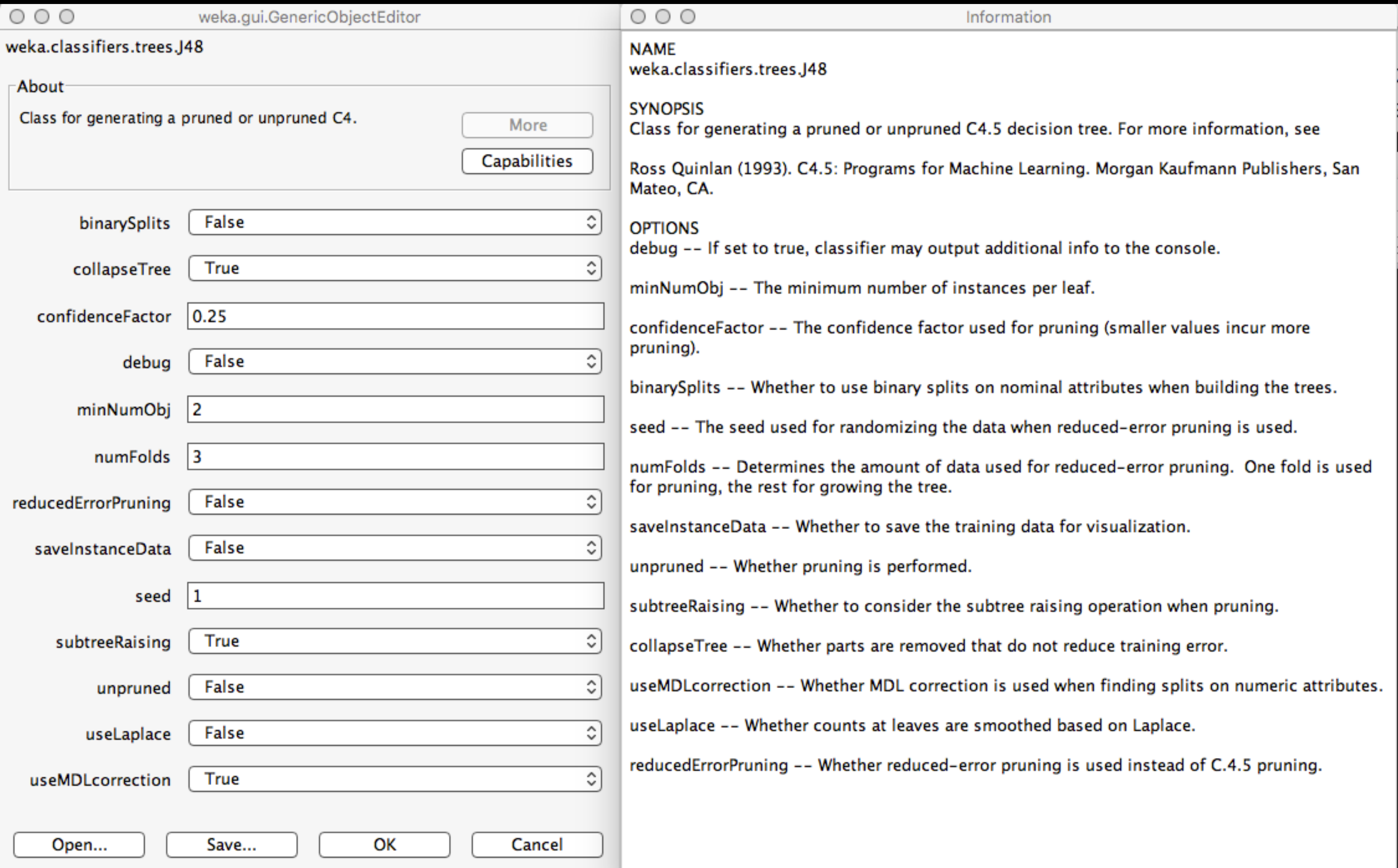
Optimisation of parameters in J48

Comparing (variants) of classifiers

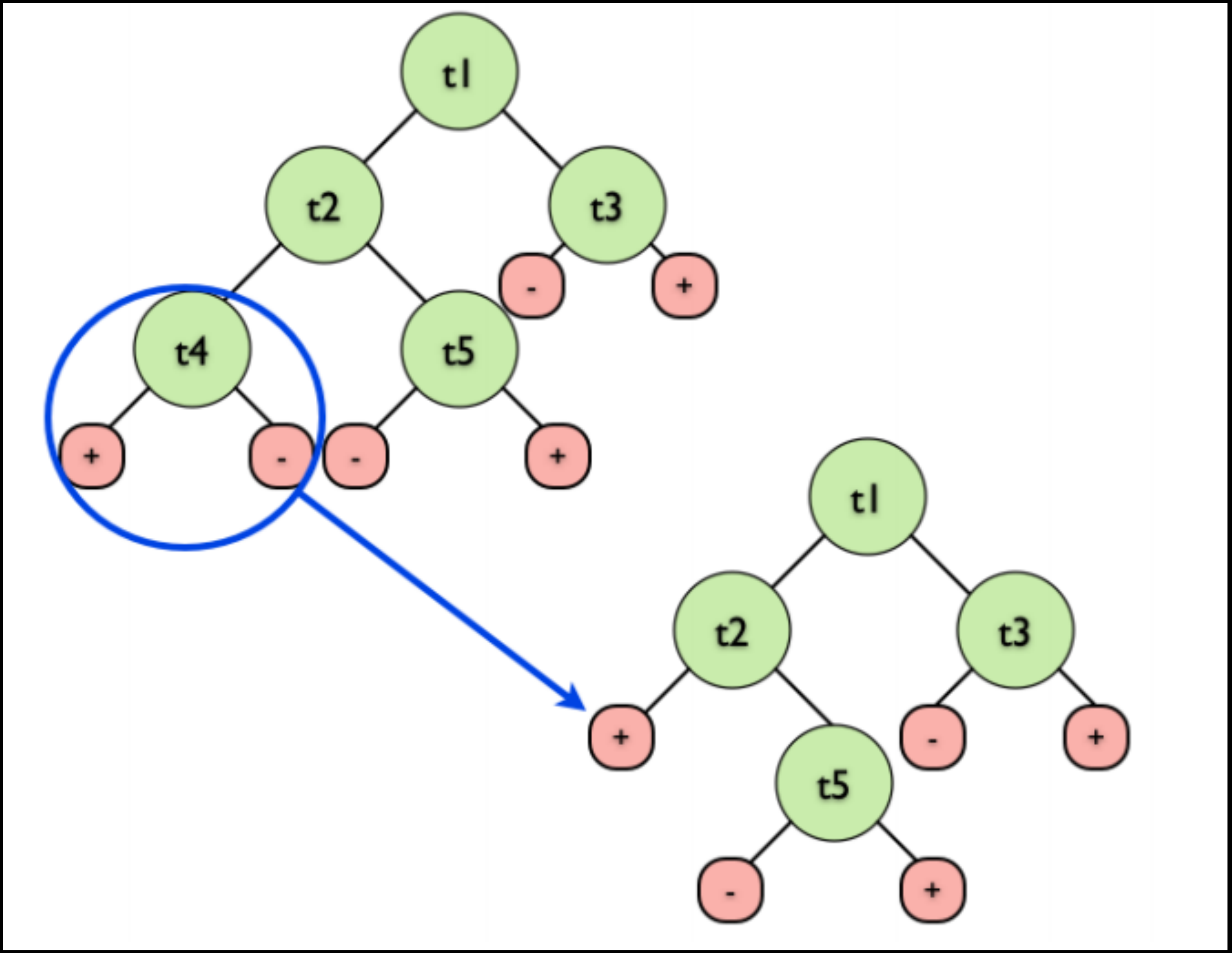
Evaluation with the t-test

WEKA's Experimenter

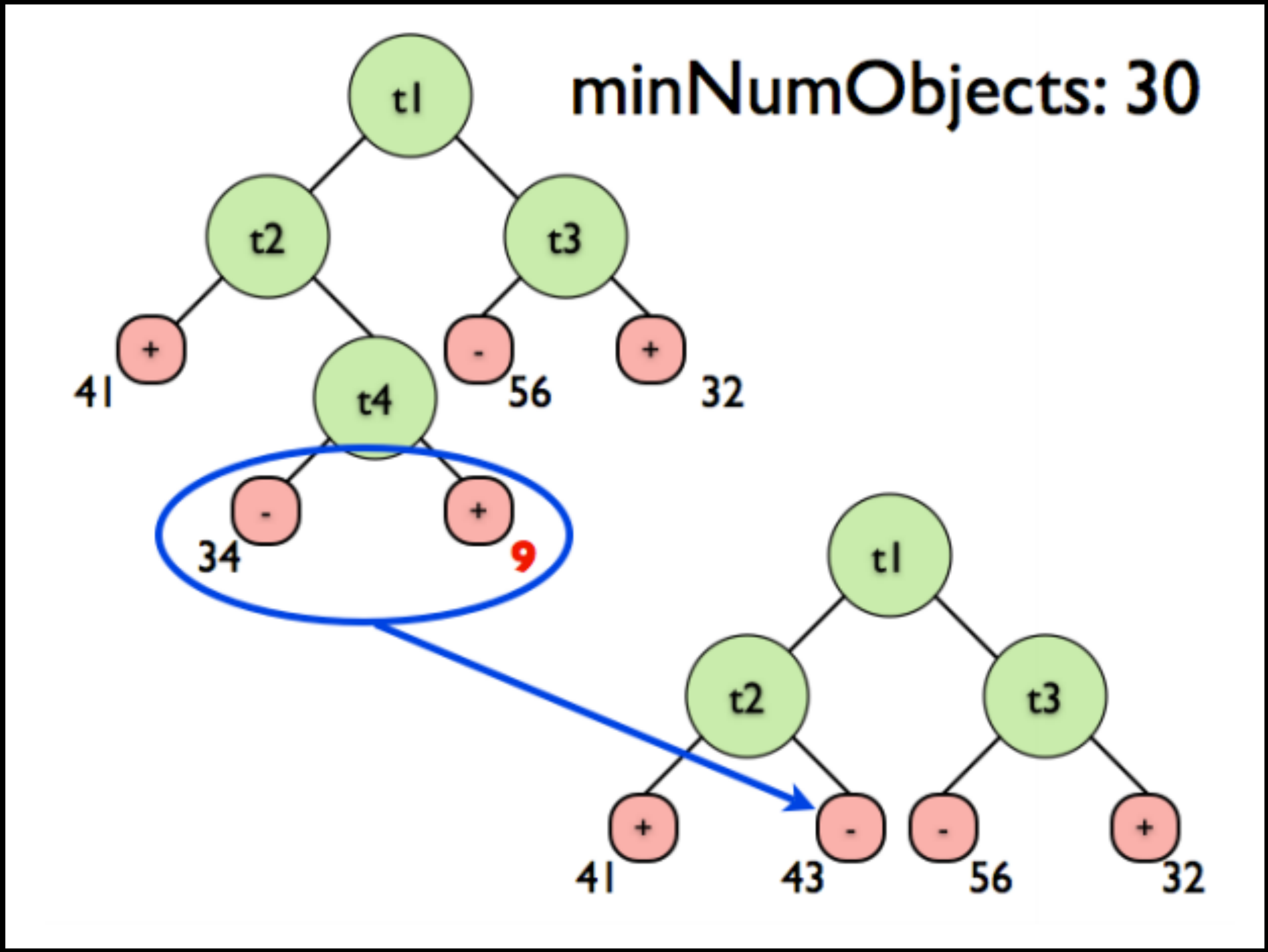
J48


weka.gui.GenericObjectEditor
weka.classifiers.trees.J48
About
Class for generating a pruned or unpruned C4.
More
Capabilities
binarySplits False
collapseTree True
confidenceFactor 0.25
debug False
minNumObj 2
numFolds 3
reducedErrorPruning False
saveInstanceData False
seed 1
subtreeRaising True
unpruned False
useLaplace False
useMDLcorrection True
Open...
Save...
OK
Cancel
Information
NAME
weka.classifiers.trees.J48
SYNOPSIS
Class for generating a pruned or unpruned C4.5 decision tree. For more information, see
Ross Quinlan (1993). C4.5: Programs for Machine Learning. Morgan Kaufmann Publishers, San Mateo, CA.
OPTIONS
debug -- If set to true, classifier may output additional info to the console.
minNumObj -- The minimum number of instances per leaf.
confidenceFactor -- The confidence factor used for pruning (smaller values incur more pruning).
binarySplits -- Whether to use binary splits on nominal attributes when building the trees.
seed -- The seed used for randomizing the data when reduced-error pruning is used.
numFolds -- Determines the amount of data used for reduced-error pruning. One fold is used for pruning, the rest for growing the tree.
saveInstanceData -- Whether to save the training data for visualization.
unpruned -- Whether pruning is performed.
subtreeRaising -- Whether to consider the subtree raising operation when pruning.
collapseTree -- Whether parts are removed that do not reduce training error.
useMDLcorrection -- Whether MDL correction is used when finding splits on numeric attributes.
useLaplace -- Whether counts at leaves are smoothed based on Laplace.
reducedErrorPruning -- Whether reduced-error pruning is used instead of C.4.5 pruning.

Pruning

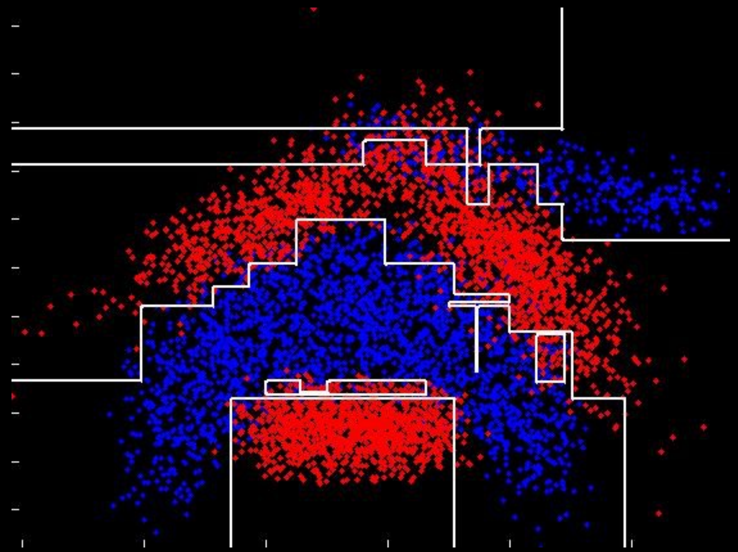


Pruning

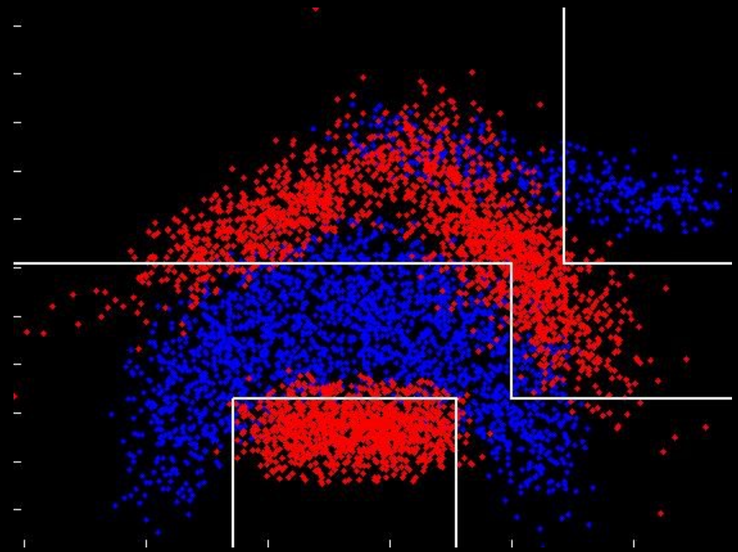


Pruning reduces the complexity of the decision tree

complex tree (unpruned)



Less complex tree (pruned)



Model complexity

A pruned decision tree is less complex, than an unpruned one

Less complex models tend to generalise better (= perform better on unseen data), provided that they are sufficiently complex to capture the structure of the data

kNN versus decision tree

In the kNN classifier, the k parameter tunes the complexity

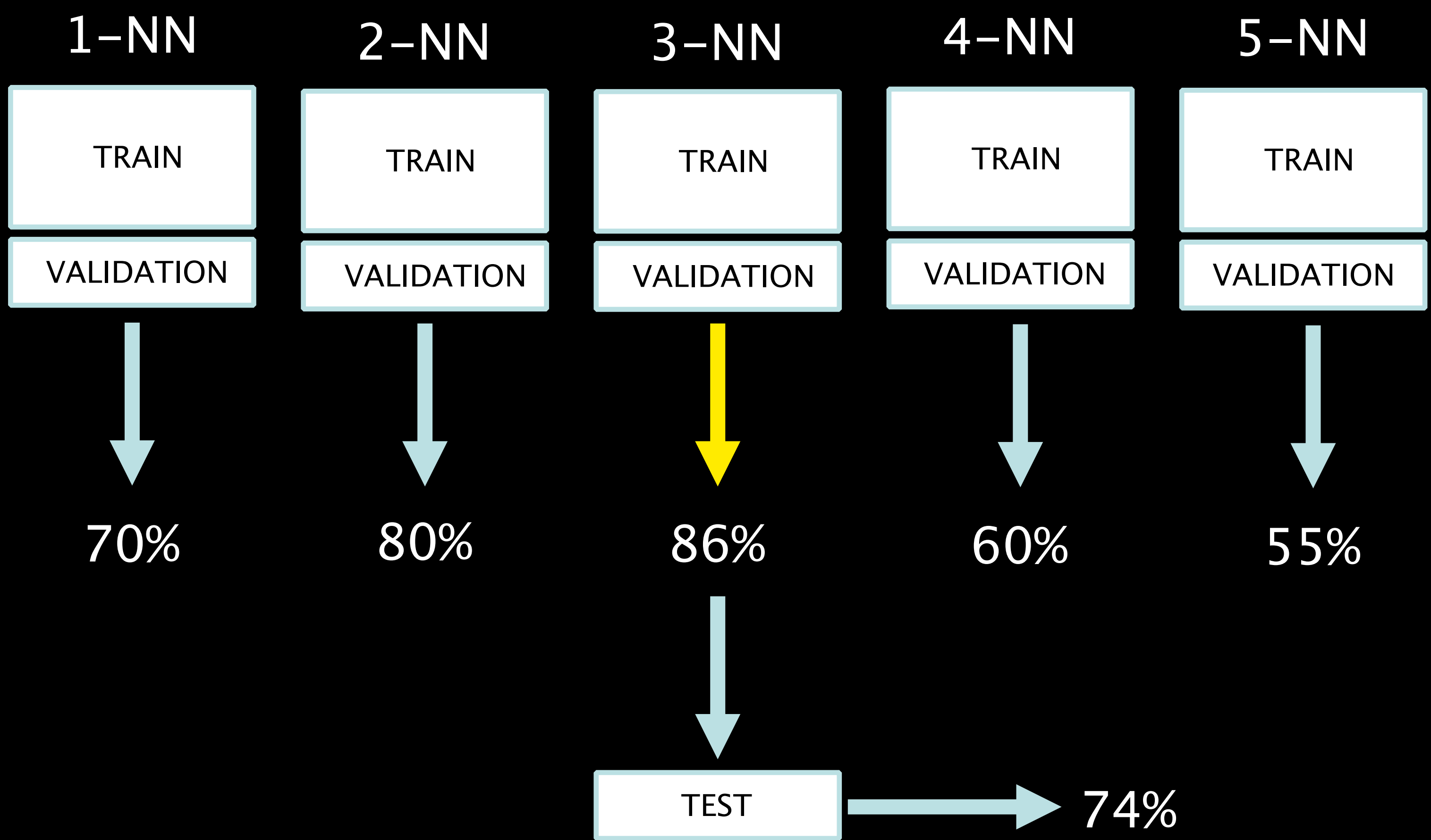
In the decision tree classifier, pruning tunes the complexity

Increasing k or pruning: less complexity

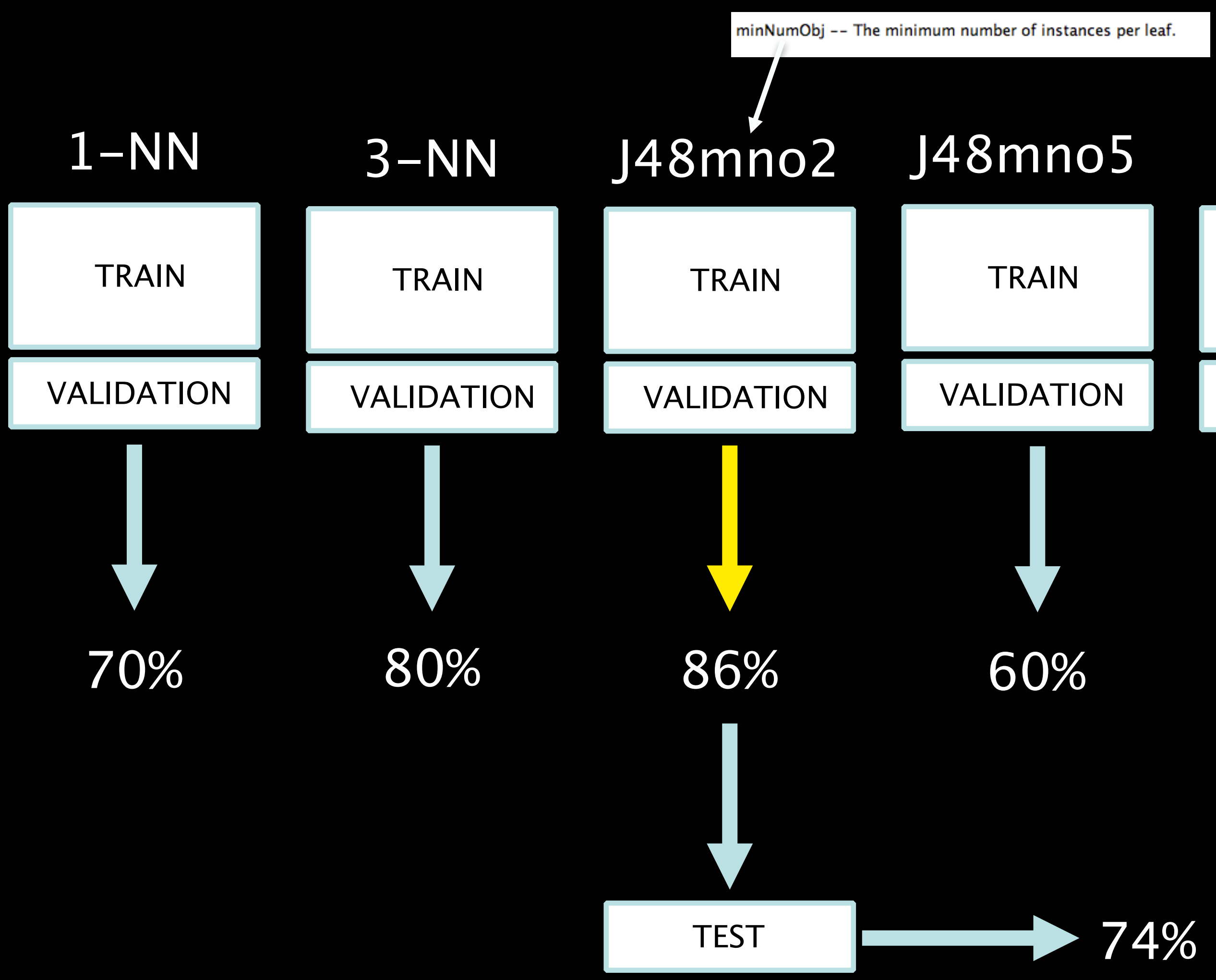
Decreasing k or pruning: more complexity

Comparing (variants) of classifiers

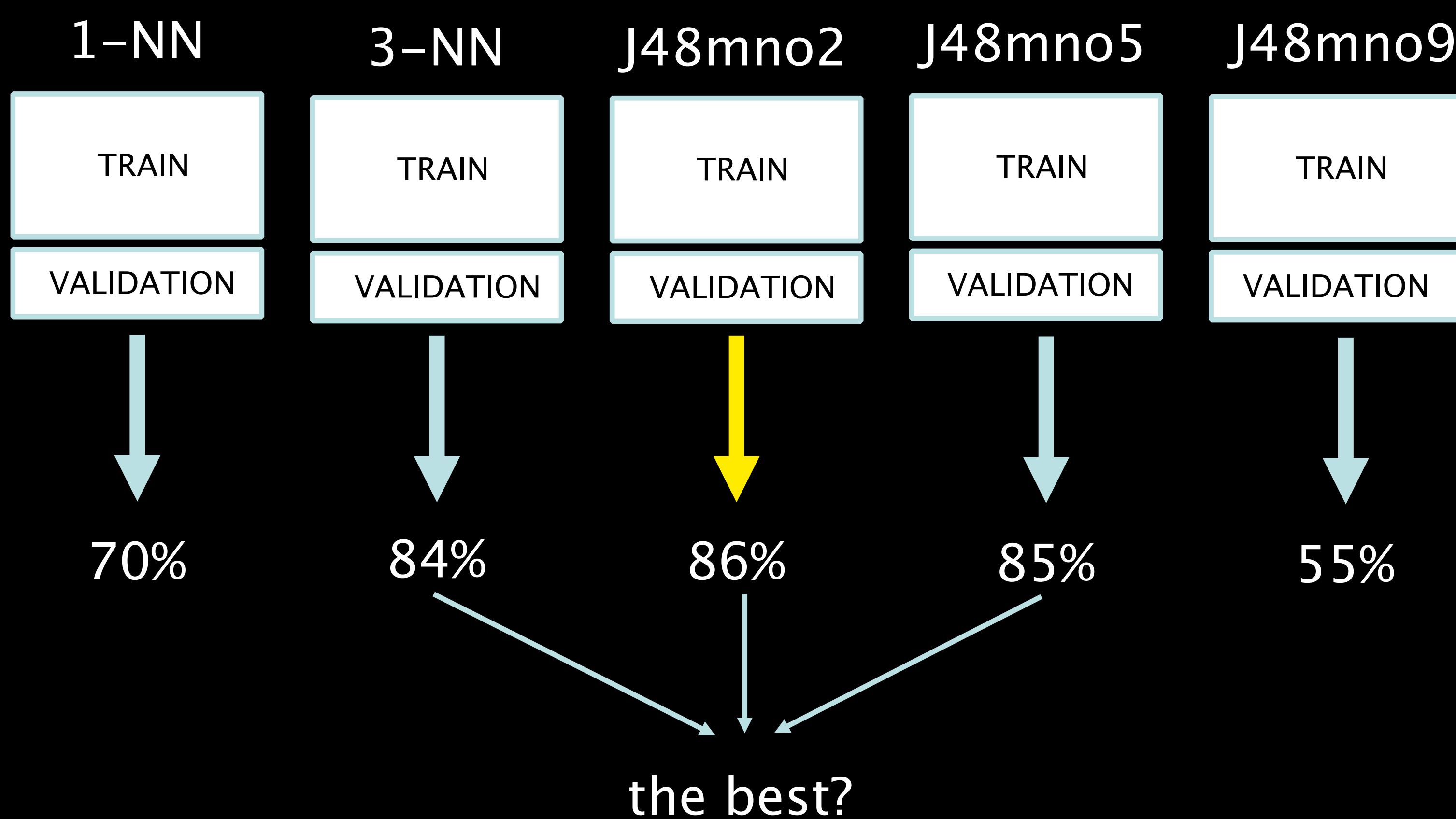
Parameter optimisation (example, see also p.149 WEKA book)



Model selection / parameter optimisation



Significant differences?



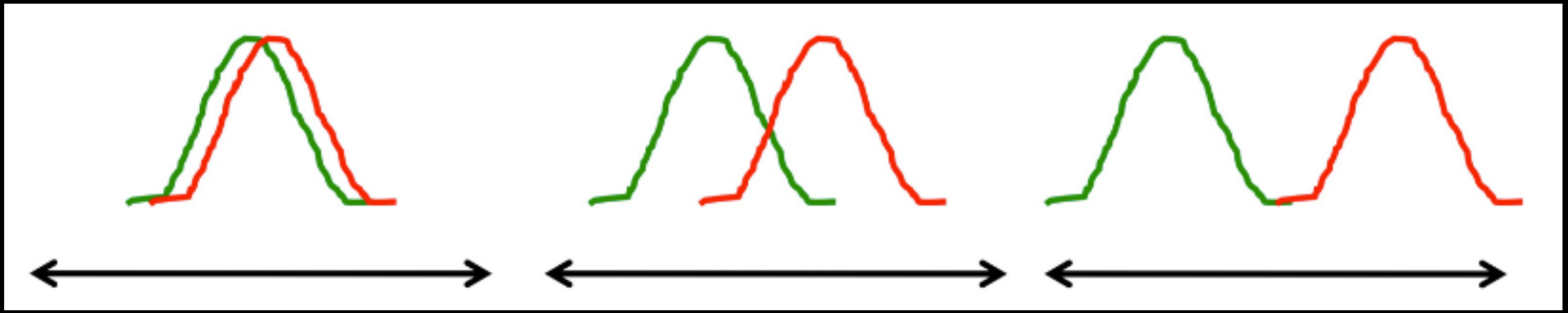
Validation performance is an average score

In case of 10-fold cross validation, it is an average of the scores over 10 folds

So, each validation performance has a standard deviation associated with it

To decide if two scores (averages) differ, you need to perform a statistical test

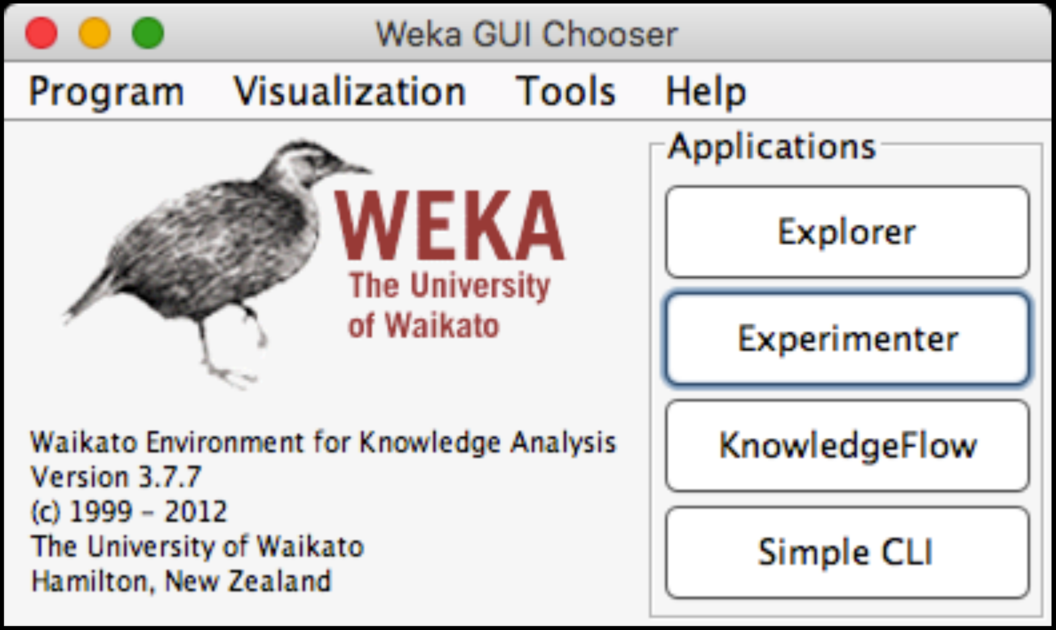
t-test and p-value

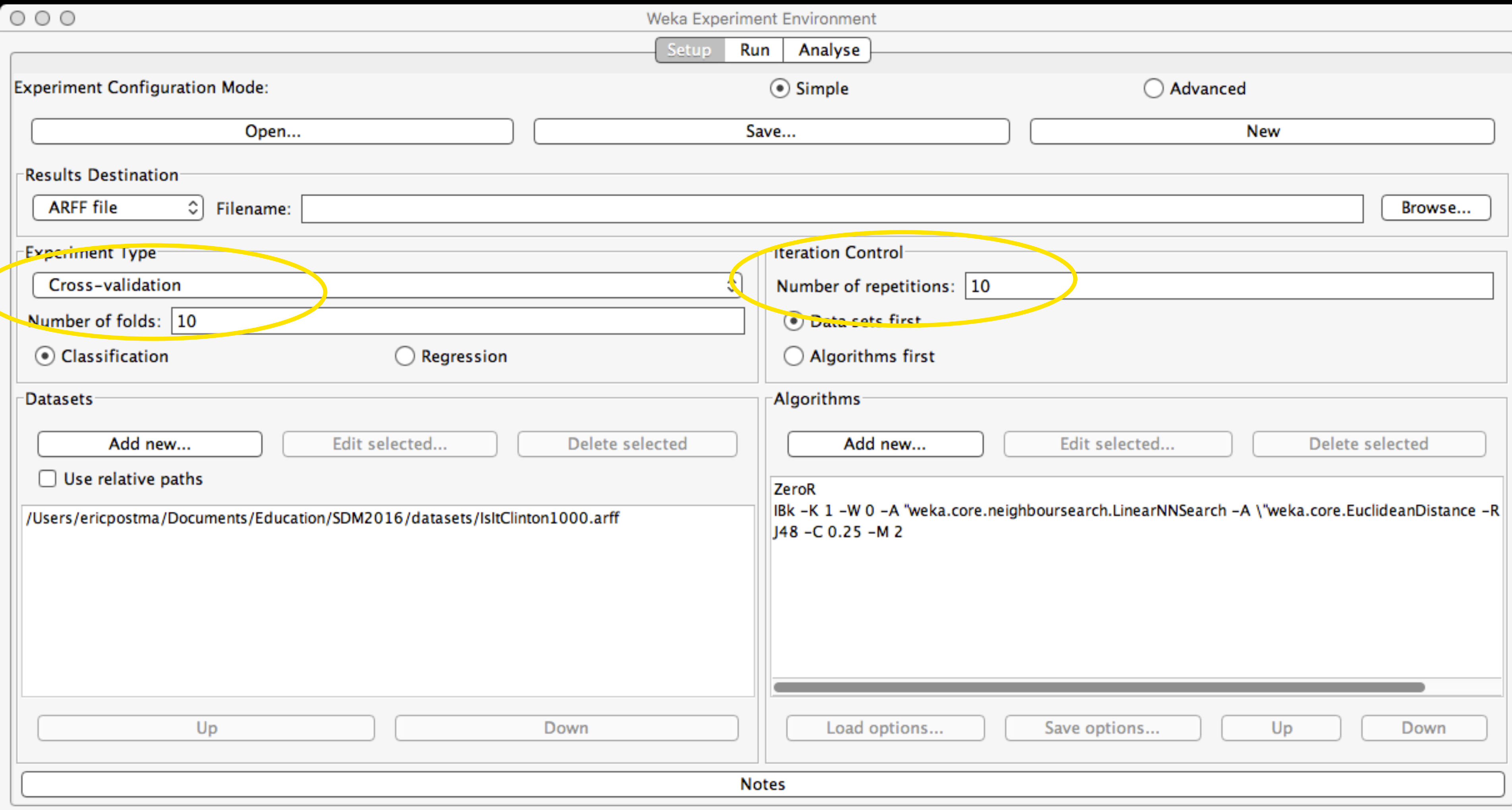


p=0.05 means: in 1 of 20 experiments you wrongly declare a difference to be significant

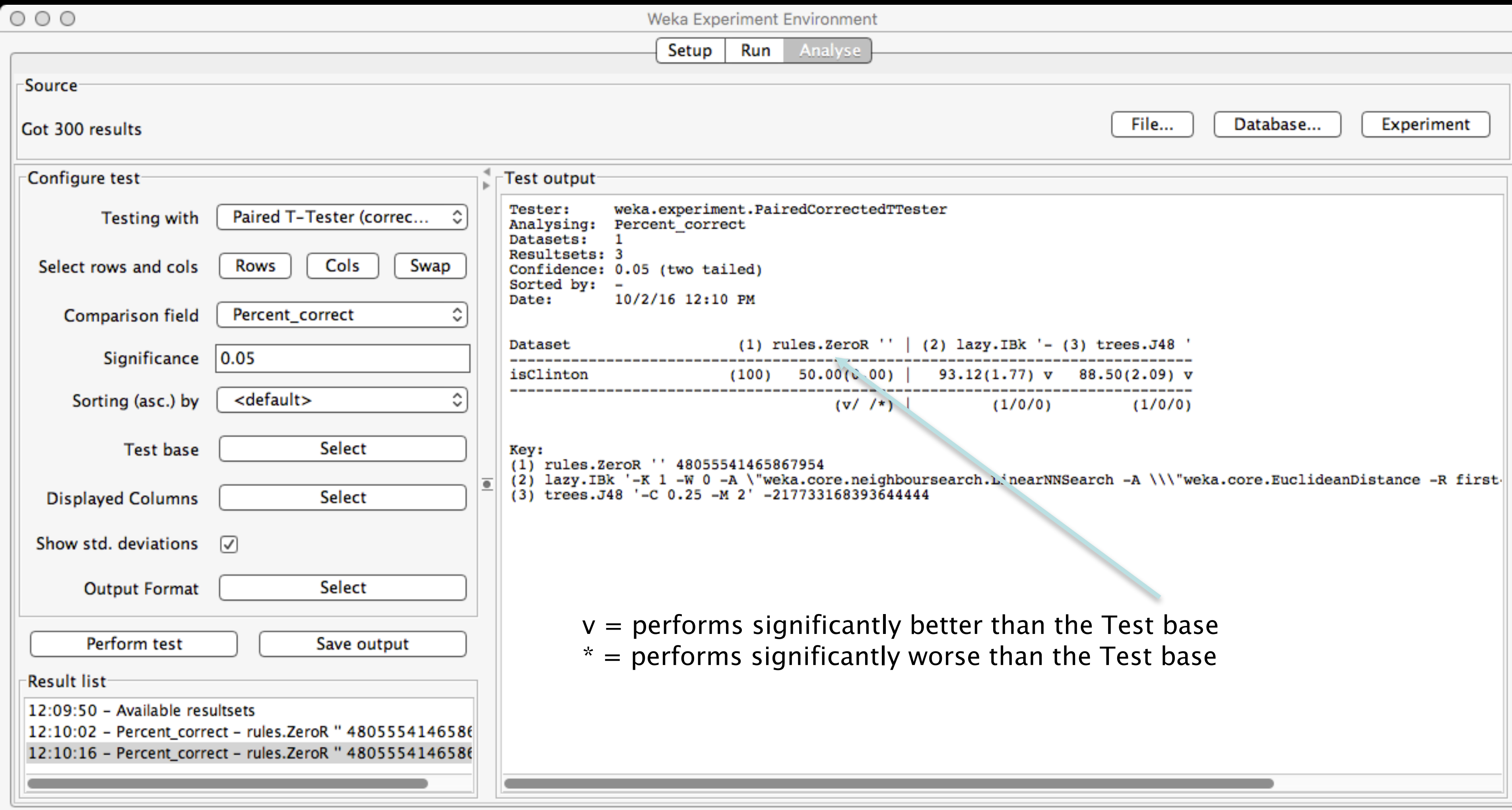
p=pvalue means: in 1 of 1/pvalue experiments you wrongly declare a difference to be significant

WEKA Experimenter





In total 100 runs (10 x 10cv experiments) will be performed



v = performs significantly better than the Test base

* = performs significantly worse than the Test base

Required Reading

Bouckaert, R.R. & Frank, E. (2004). Evaluating the Replicability of Significance Tests for Comparing Learning Algorithms.
In H. Dai, R. Srikant, & C. Zhang (Eds.), Advances in Knowledge Discovery and Data Mining, Volume 3056 of the series Lecture Notes in Computer Science pp 3-12. Springer.

http://www.cs.waikato.ac.nz/~eibe/pubs/bouckaert_and_frank.pdf