Comparison of decision tree methods for finding active objects

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Abstract

The automated classification of objects from large catalogues or survey projects is an important task in many astronomical surveys. Faced with various classification algorithms, astronomers should select the method according to their requirements. Here we describe several kinds of decision trees for finding active objects by multi-wavelength data, such as REPTree, Random Tree, Decision Stump, Random Forest, J48, NBTree, AdTree. All decision tree approaches investigated are in the WEKA package. The classification performance of the methods is presented. In the process of classification by decision tree methods, the classification rules are easily obtained, moreover these rules are clear and easy to understand for astronomers. As a result, astronomers are inclined to prefer and apply them, thus know which attributes are important to discriminate celestial objects. The experimental results show that when various decision trees are applied in discriminating active objects (quasars, BL Lac objects and active galaxies) from non-active objects (stars and galaxies), ADTree is the best only in terms of accuracy, Decision Stump is the best only considering speed, J48 is the optimal choice considering both accuracy and speed.

Key words: techniques: miscellaneous; methods: statistical; methods: data analysis; astronomical data bases: miscellaneous; catalogs; decision trees

1 Introduction

With the development and deployment of a variety of large surveys, including 2MASS (the Two Micron All Sky Survey), SDSS (the Sloan Digital Sky Survey), DENIS (the Deep Near Infrared Survey), DIVA, GAIA, etc., astronomical data are measured by Terabytes, even Petabytes. How to automatedly collect, save, process, analyze the huge amount of database is an important task for astronomers. To meet the need, different methods are developed. For example, Neural networks (NN) has been employed for spectral classification
of stars (Storrie-Lombardi et al. 1994; Gulati et al. 1994), for physical measurement of star spectra (Bailer-Jones et al. 1997), for spectral classification of galaxies (Sodrê & Cuevas 1994), for morphological classification of galaxies (Storrie-Lombardi et al. 1992; Adams & Woolley 1994) and for discriminating stars and galaxies in digitized photographic plates (Odewahn & Nielsen 1994), for fast cosmological parameter estimation (Auld et al. 2007) and for separating quasars from stars (Zhang & Zhao 2007). Support vector machines (SVMs) have also been successfully applied to automatic classification (Zhang & Zhao 2003, 2004), object detection (Qu et al. 2003), identification of red variables (Williams et al. 2004) and redshift estimation (Wadadekar 2005). Decision trees were applied for building an online system for automated classification of X-ray sources (McGlynn et al. 2004), for star-galaxy classification problems (Djorgovski et al. 1994; Fayyad et al. 1993) and for star-galaxy Classification (Ball et al. 2006).

Each technique has its pros and cons. The largest merit of NN methods is that they are general: they can deal with problems with high dimensions and even with complex distributions of objects in the $n$-dimensional parameter space. NN is becoming popular in astronomy due to its associated memory characteristic and generalization capability. However, the relative importance of potential input variables, long training process, and interpretative difficulties have often been criticized. Although SVM has high performance in classification problems (Zhang & Zhao, 2003), the rules obtained by SVM algorithm are hard to understand directly. Moreover, one possible drawback of SVM is its computational cost.

Owing to the above-mentioned drawbacks of NN and SVM, the purpose of this study is to explore the performance of classification using various decision tree approaches. Decision tree methods exhibit the capability of modeling complex relationship between variables without strong model assumptions. Besides, unlike NN, they are able to identify “important” independent variables through the built tree and basis functions when many potential variables are considered. Thirdly, decision trees do not need a long training process and hence can save lots of modeling time when the data set is huge. Finally, one strong advantage of decision trees over other classification techniques is that the resulting classification model can be easily interpreted. They not only point out which variables are important in classifying objects/observations, but also indicate that a particular object/observation belongs to a specific class when the built rules are satisfied. The final fact has important implications and can help astronomers make better decisions. To be more clear, the advantages of decision tree methods are listed as follows:

(1) Decision trees are easy to understand;

(2) Decision trees are easily converted to a set of production rules;
(3) Decision trees can classify both categorical and numerical data, but the output attribute must be categorical;

(4) There are no a priori assumptions about the nature of the data.

Certainly, decision tree algorithms also have their disadvantages. For instance, multiple output attributes are not allowed. They are unstable. Slight variations in the training data can cause different attribute selections at each choice point within the tree. The effect can be significant since attribute choices affect all descendant subtrees. Trees created from numeric data sets can be quite complex since attribute splits for numeric data are binary. It is the rules for splitting that population at the nodes that are simple, but that there can be large numbers of nodes if the tree is not pruned. However, when researchers want to obtain clear rules or distinguish which parameters influence the classification results, they are inclined to choose decision trees.

Since decision trees have the described advantages, they have proven to be effective tools in handling forecasting and classification problems (McGlynn, et al. 2004; Zhang & Zhao, 2007). In this paper we describe and apply some decision tree methods for separating active objects from multiband data. Section 2 introduces decision tree methods. The sample is indicated in Section 3. The experiment and discussion are given in Section 4. Finally Section 5 summarizes the results.

2 Methods

Decision trees represent a supervised approach to classification. A decision tree is a simple structure where non-terminal nodes represent tests on one or more attributes and terminal nodes reflect decision outcomes. The ordinary tree consists of one root, branches, nodes (places where branches are divided) and leaves. In the same way the decision tree consists of nodes which stand for circles, the branches stand for segments connecting the nodes. A decision tree is usually drawn from left to right or beginning from the root downwards, so it is easier to draw it. The first node is a root. The end of the chain “root - branch - node-....- node” is called “leaf”. From each internal node (i.e. not a leaf) may grow out two or more branches. Each node corresponds with a certain characteristic and the branches correspond with a range of values. These ranges of values must give a partition of the set of values of the given characteristic.

Decision trees we study are from WEKA (The Waikato Environment for Knowledge Analysis). WEKA is a tool for data analysis and includes implementations of data pre-processing, classification, regression, clustering, asso-
association rules, and visualization by different algorithms. A book describing the software was published in 2005 by Ian H. Witten and Eibe Frank (Witten and Frank, 2005). WEKA’s binaries and sources are freely available. Implemented methods include instance-based learning algorithms, statistical learning like Bayes methods and tree-like algorithms like ID3 and J4.8 (slightly modified C4.5). Including combinations of classifiers, e.g. bagging and boosting schemes, there are over sixty methods available in WEKA.

The following gives the short introduction of various decision tree algorithms.

2.1 REPTree

REPTree is a fast decision tree learner which builds a decision/regression tree using information gain as the splitting criterion, and prunes it using reduced-error pruning. It only sorts values for numeric attributes once. Missing values are dealt with using C4.5’s method of using fractional instances.

2.2 RandomTree

With \( k \) random features at each node., a random tree is a tree drawn at random from a set of possible trees. In this context “at random” means that each tree in the set of trees has an equal chance of being sampled. Another way of saying this is that the distribution of trees is “uniform”. Random trees can be generated efficiently and the combination of large sets of random trees generally leads to accurate models. Random tree models have been extensively developed in the field of Machine Learning in the recent years.

2.3 J48

J48 is slightly modified C4.5 in WEKA. The C4.5 algorithm generates a classification-decision tree for the given data-set by recursive partitioning of data. The decision is grown using Depth-first strategy. The algorithm considers all the possible tests that can split the data set and selects a test that gives the best information gain. For each discrete attribute, one test with outcomes as many as the number of distinct values of the attribute is considered. For each continuous attribute, binary tests involving every distinct values of the attribute are considered. In order to gather the entropy gain of all these binary tests efficiently, the training data set belonging to the node in consideration is sorted for the values of the continuous attribute and the entropy gains of the binary cut based on each distinct values are calculated in one scan of
the sorted data. This process is repeated for each continuous attributes. For a deeper introduction of this method, readers can refer to (Mitchell 1997; Quinlan 1986).

2.4 DecisionStump

A decision stump is basically a one-level decision tree where the split at the root level is based on a specific attribute/value pair.

2.5 Random Forest

Random forest (Breiman, 2001) is an ensemble of unpruned classification or regression trees, induced from bootstrap samples of the training data, using random feature selection in the tree induction process. Prediction is made by aggregating (majority vote for classification or averaging for regression) the predictions of the ensemble. Random forest generally exhibits a substantial performance improvement over the single tree classifier such as CART and C4.5. It yields generalization error rate that compares favorably to Adaboost, yet is more robust to noise.

2.6 NBTree

The naive Bayesian tree learner, NBTree (Kohavi 1996), combined naive Bayesian classification and decision tree learning. In an NBTree, a local naive Bayes is deployed on each leaf of a traditional decision tree, and an instance is classified using the local naive Bayes on the leaf into which it falls. The algorithm for learning an NBTree is similar to C4.5. After a tree is grown, a naive Bayes is constructed for each leaf using the data associated with that leaf. An NBTree classifies an example by sorting it to a leaf and applying the naive Bayes in that leaf to assign a class label to it. NBTree frequently achieves higher accuracy than either a naive Bayesian classifier or a decision tree learner.

2.7 ADTree

The alternating decision tree (ADTree) is a generalization of decision trees, voted decision trees and voted decision stumps. A general alternating tree defines a classification rule as follows. An instance defines a set of paths in the alternating tree. As in standard decision trees, when a path reaches a
decision node it continues with the child which corresponds to the outcome of the decision associated with the node. However, when reaching a prediction node, the path continues with all of the children of the node. More precisely, the path splits into a set of paths, each of which corresponds to one of the children of the prediction node. We call the union of all the paths reached in this way for a given instance the “multi-path” associated with that instance. The sign of the sum of all the prediction nodes that included in a multi-path is the classification which the tree associates with the instance. The basic algorithm can refer to Freund & Mason (1999).

3 Sample

We adopted the same sample as that in Zhang & Zhao (2004). The sample include the multiwavelength data of 3,718 stars, 173 normal galaxies, 909 quasars, 135 BL Lacs and 612 active galaxies from optical (USNO A-2.0), X-ray (The ROSAT Bright Source and Faint Source) and infrared bands (2MASS). The chosen attributes from different bands are $B - R$ (optical color), $B + 2.5 \log (CR)$, $\log CR$ (source count-rate in the broad energy band), $HR1$ (hardness ratio 1), $HR2$ (hardness ratio 2), $ext$ (source extent), $extl$ (likelihood of source extent), $J - H$ (infrared color), $H - K_s$ (infrared color), $J + 2.5 \log (CR)$. In the following sections, AGNs represent quasars, BL Lacs and active galaxies, non-AGNs for stars and normal galaxies.

4 Experiment and Discussion

We conduct experiments to compare various decision tree algorithms which are implemented within the WEKA framework (Witten and Frank, 2005). We use the implementation of REPTree, Random Tree, Decision Stump, Random Forest, J48, NBTree and AdTree in WEKA with default parameters. In our experiment, the accuracy on the sample has been obtained using 10-fold cross validation, which is helpful to prevent overfitting. In the following, accuracy is an average of any $9/10$ sample as training set and the rest as testing set for 10 times. Missing values are also processed using the mechanism in WEKA.

For REPTree, the number of trees to create a classifier is 4,305. In the case of RandomTree, the number adds up to 90,699. DecisionStump chooses $H - K_s$ as the standard attribute for classification. When $H - K_s \leq 0.3285$ and $H - K_s$ is missing, objects are identified as non-AGNs, while $H - K_s > 0.3285$, objects are classified as AGNs. For J48, we used pruning and a confidence factor of 0.25. In the case of RandomForest, 10 trees were used for creating the forest for the experiments, each constructed while considering 4 random
features. Out of bag error (Breiman, 2001) is 0.086. For ADTree, tree size (total number of nodes) is 31, leaves (number of predictor nodes) is 21. All the experiment results are shown in Table 1 and Table 2. Table 1 shows the number of correct instances and incorrect instances, the accuracy of AGNs and Non-AGNs. Table 2 gives the number of trees to build models, the accuracy and the time to build each model by 10-fold cross validation for the individual classifiers, respectively.

Table 1
The classification results for various decision trees

| Methods    | No. of correct instances | No. of incorrect instances | Accuracy of AGNs | Accuracy of Non-AGNs |
|------------|--------------------------|---------------------------|------------------|----------------------|
| REPTree    | 4410                     | 1137                      | 33.15%           | 99.23%               |
| RandomTree | 4850                     | 697                       | 64.07%           | 97.38%               |
| DecisionStump | 5282                   | 265                       | 93.36%           | 96.02%               |
| RandomForest | 5375                    | 172                       | 93.06%           | 98.54%               |
| J48        | 5383                     | 164                       | 93.60%           | 98.51%               |
| NBTree     | 5392                     | 155                       | 95.17%           | 98.07%               |
| ADTree     | 5397                     | 150                       | 95.29%           | 98.15%               |

Table 2
The performance for various decision Trees

| Methods    | No. of Trees | Accuracy | Time to build models (seconds) |
|------------|--------------|----------|-------------------------------|
| REPTree    | 4305         | 79.50%   | 6.70                          |
| RandomTree | 90699        | 87.43%   | 5.33                          |
| DecisionStump | 1            | 95.22%   | 0.09                          |
| RandomForest | 10           | 96.90%   | 70.72                         |
| J48        | 41           | 97.04%   | 0.53                          |
| NBTree     | 37           | 97.21%   | 60.42                         |
| ADTree     | 31           | 97.30%   | 1.53                          |

From Table 1, REPTree and RandomTree show better performance to classify Non-AGNs, but poor performance in separating AGNs. For the number of Non-AGNs is more than two times as that of AGNs, REPTree and RandomTree are easy to obtain rules from large datasets, so both the two methods are not fit to deal with imbalanced samples. As shown by Table 2, the rank of
accuracy for these decision trees is ADTree (97.30%), NBTree (97.21%), J48 (97.04%), RandomForest (96.90%), DecisionStump (95.22%), RandomTree (87.43%), REPTree (79.50%). The performance of ADTree, NBTree, J48 and RandomForest is comparable. REPTree is the most inferior. Of all the decision tree methods, DecisionStump has highest speed in building the model and takes 0.09 s while RandomForest is the slowest model requiring 70.72 s for the same. Considering both accuracy and speed, ADTree and J48 are the best choices.

The accuracy obtained by decision tree method as presented here is somewhat inferior to the earlier reported accuracy (Zhang & Zhao 2004) of 97.80% by Learning Vector Quantisation (LVQ), 98.05% by Single Layer Perceptron (SLP), and 98.31% by Support Vector Machines (SVMs). But the rules obtained by decision tree algorithms are clear and easy to understand, so astronomers are inclined to employ them and know which attributes are important, thus may choose good features to describe the physics of celestial objects.

5 Conclusion

We briefly reviewed and implemented decision tree methods (i.e. REPTree, Random Tree, Decision Stump, Random Forest, J48, NBTree and AdTree) in the WEKA framework, focusing on the problem of differentiating AGN candidates from non-AGN. Decision Stump, Random Forest, J48, NBTree and AdTree show better performance for our problem (more than 95.00%), but REPTree and Random Tree are also useful and may be better fit to deal with other problems. In our case, ADTree shows the best performance only in terms of accuracy, Decision Stump is the best only considering speed, J48 is the optimal choice considering both accuracy and speed. In the process of knowledge discovery, choice of parameters and the construction of high quality training/test data sets are important steps. The large survey projects are in urgent need of automated classification systems. Apparently several methods can not meet the requirements of astronomical research due to the quantities, quality and complexity of astronomical data. Therefore various techniques are required to test and employ in order to get reliable classifications. Not only supervised methods should be tried, but also unsupervised methods and other methods especially for outlier detection should be experimented. In addition, the ensembles of some methods are needed. For example, when facing difficulty in applying neural network algorithms in high dimensional spaces, some data preprocessing may be considered. On these occasions, feature selection/extraction methods may be used for reducing dimensions or noise. Future work includes testing these methods for other types of astronomical objects, such as nebulas and clusters, or for other types of data, for instance, images.
and spectra. These methods can be used for redshift measurement, physical parameter measurement of celestial objects, or morphology classification of galaxies, and also for feature selection.

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