Decision table for classifying point sources based on FIRST and 2MASS databases

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Abstract

With the availability of multiwavelength, multiscale and multiepoch astronomical catalogues, the number of features to describe astronomical objects has increased. The better features we select to classify objects, the higher the classification accuracy is. In this paper, we have used data sets of stars and quasars from near infrared band and radio band. Then best-first search method was applied to select features. For the data with selected features, the algorithm of decision table was implemented. The classification accuracy is more than 95.9%. As a result, the feature selection method improves the effectiveness and efficiency of the classification method. Moreover the result shows that decision table is robust and effective for discrimination of celestial objects and used for preselecting quasar candidates for large survey projects.

Key words: techniques: miscellaneous; methods: statistical; methods: data analysis; astronomical data bases: miscellaneous; catalogs; feature selection

1 Introduction

With the development of various multiwavelength projects, such as SDSS, GALEX, 2MASS, GSC-2, POSS2, RASS, FIRST and DENIS, astronomy is about to undergo a major paradigm shift. Data volumes are doubling every 20 months. Data sets are becoming larger, and more homogeneous. It is a challenge to deal with multi-terabyte databases efficiently and effectively for astronomers. Under this situation, astronomers will have to be just as familiar with mining data as with observing on telescopes. Classification, as one of data mining tasks, is a key issue in astronomy. Celestial objects are divided into different kinds of objects (e.g. stars, galaxies and quasars) by spectra, photometry or image, moreover each kind may be further subdivided.
In the last years there were many data mining algorithms successfully applied in astronomy. For instance, neural network methods were used for spectra classification; support vector machines (SVM) were employed in classification of multiwavelength data (Zhang & Zhao 2004); decision trees were used to automatically classify objects (Jarrett et al. 2000; Ball et al. 2006). In this paper we discuss an example in which we classify objects as quasars or stars using the cross-match results between a radio survey (the Faint Images of the Radio Sky at Twenty centimeters, FIRST) and a near infrared survey (the Two Micron All Sky Survey, 2MASS) by decision tables. Based on FIRST and 2MASS databases, the source candidates selected by decision tables are radio loud objects which is bright enough in near infrared band to be detected in 2MASS. According to special issues, astronomers may choose data from different bands. For example, in order to obtain X-ray strong objects, the data from RASS may be employed; for the study of properties of various objects in five optical bandpasses, SDSS is a good choice. Decision tables, like decision trees or neural networks, are classification models used for prediction. They are induced by machine learning algorithms. The classifier trained by the method helps guide the choice of which objects to follow up with spectroscopic measurements. Therefore the efficiency of telescopes will be improved and human efforts will be reduced.

This paper is organized as follows: Section 2 describes the sample and chosen attributes. Section 3 introduces the principle of decision tables. Section 4 lists the experiment result and discussion. Section 5 summarized this work.

2 Data Sample and Chosen Attributes

We describe here near infrared, radio and optical catalogs as follows:

The Two Micron All Sky Survey (2MASS) project (Cutri et al. 2003) is designed to close the gap between our current technical capability and our knowledge of the near-infrared sky. 2MASS uses two new, highly-automated 1.3-m telescopes, one at Mt. Hopkins, AZ, and one at CTIO, Chile. Each telescope is equipped with a three-channel camera, each channel consisting of a 256x256 array of HgCdTe detectors, capable of observing the sky simultaneously at j (1.25 µm), h (1.65 µm), and k (2.17 µm), to a 3σ limiting sensitivity of 17.1, 16.4 and 15.3 mag in the three bands. The number of 2MASS point sources adds up to 470,992,970.

The Faint Images of the Radio Sky at Twenty centimeters (FIRST) began in 1993. It uses the VLA (Very Large Array, a facility of the National Radio Astronomical Observatory (NRAO)) at a frequency of 1.4GHz, and it is slated to 10,000 square degree of the North and South Galactic Caps, to a sensitivity
of about 1 mJy with an angular resolution of about 5 arcsec. The images produced by an automated mapping pipeline have pixels of 1.8 arc sec, a typical rms of 0.15 mJy, and a resolution of 5 arcsec; the images are available on the Internet (see the FIRST home page at http://sundog.stsci.edu/ for details). The source catalogue is derived from the images. A new catalog (Becker et al. 2003) of the FIRST Survey has been released that includes all data taken from 1993 through September 2002, and contains about 811,000 sources covering 8,422 square degrees in the North Galactic cap and 611 square degrees in the South Galactic cap. The new catalog and images are accessible via the FIRST Search Engine and the FIRST Cutout Server.

The 12th edition catalogue of quasars and active nuclei (Cat. VII/248, Véron-Cetty & Véron 2006) is an update of the previous versions, which now contains 85221 quasars, 1122 BL Lac objects and 21737 active galaxies (including 9628 Seyfert 1s), almost doubling the number listed in the 11th edition. Just like the previous editions, no information about absorption lines of X-ray properties are given, but absolute magnitudes are given, assuming $H_0 = 50 \text{ km s}^{-1}\text{Mpc}^{-1}$ and $q_0 = 0$. In this edition the 20 cm radio flux is listed when available, in place of the 11 cm flux.

The Tycho-2 Catalogue (Cat. I/259, Hog et al. 2000) is an astrometric reference catalogue containing positions and proper motions as well as two-color photometric data for the 2.5 million brightest stars in the sky. The Tycho-2 positions and magnitudes are based on precisely the same observations as the original Tycho Catalogue (hereafter Tycho-1; see Cat. I/239) collected by the star mapper of the ESA Hipparcos satellite, but Tycho-2 is much bigger and slightly more precise, owing to a more advanced reduction technique. Components of double stars with separations down to 0.8 arcsec are included. Proper motions precise to about 2.5 mas yr$^{-1}$ are given.

We obtained 153135 entries with one to one matching between the FIRST and 2MASS catalogues within 5 arcsec radius. The entries were then cross-identified with the Véron-Cetty & Véron 2006 catalog and the Tycho-2 catalog within 5 arcsec radius, respectively. Similarly, we obtained 2389 quasars and 1353 stars from the 2MASS and FIRST catalogues. The chosen attributes from different bands are $\log F_{\text{peak}}$ ($F_{\text{peak}}$: peak flux density at 1.4 GHz), $\log F_{\text{int}}$ ($F_{\text{int}}$: integrated flux density at 1.4 GHz), $f_{\text{maj}}$ (fitted major axis before deconvolution), $f_{\text{min}}$ (fitted minor axis before deconvolution), $f_{\text{pa}}$ (fitted position angle before deconvolution), $j - h$ (near infrared index), $h - k$ (near infrared index), $k + 2.5 \log F_{\text{int}}$, $k + 2.5 \log F_{\text{peak}}$, $j + 2.5 \log F_{\text{peak}}$, $j + 2.5 \log F_{\text{int}}$, $b - v$ (optical index). $b - v$ is from the two catalogues: the quasar catalogue of Véron 2006 and the Tycho-2 Catalogue. Since the quasar catalogue of Véron 2006 is an inhomogeneous compilation, and the photometry from the Tycho-2 Catalogue was made in a specific system whose conversion to johnson $b - v$ relies on physical assumptions, the classification regarding $b - v$ is only used
as a rough reference.

Zhang & Zhao (2007) showed that $\log F_{\text{peak}}$, $\log F_{\text{int}}$, $k + 2.5\log F_{\text{int}}$, $k + 2.5\log F_{\text{peak}}$, $j + 2.5\log F_{\text{peak}}$, $j + 2.5\log F_{\text{int}}$ are useful to classify quasars from stars, and $f_{\text{maj}}$, $f_{\text{min}}$ and $f_{\text{pa}}$ are unimportant. To further see the statistical distribution of this sample and compare the distribution of this sample with all the sources from the cross-identification of 2MASS and FIRST catalogues, the scatter plots of some parameters are shown in Fig. 1. The scatter plots also indicate that the conclusion is reasonable, moreover, $b - v$ is helpful to nearly completely discriminate quasars from stars.

3 Decision Tables

A decision table consists of a hierarchical table in which each entry in a higher level table gets broken down by the values of a pair of additional attributes to form another table. The structure is similar to dimensional stacking. For the detailed principle of decision table, readers can refer to Kohavi (1995).

Given a training sample containing labelled instances, an induction algorithm builds a hypothesis in some representation. The representation we investigate here is a decision table with a default rule mapping to the majority class, which we abbreviate as DTM. A DTM consists of two components:

1. A schema, which is a set of features.

2. A body, which is a multiset of labelled instances. Each instance is made up of a value for each of the features in the schema and a value for the label.

Given an unlabelled instance $I$, the label assigned to the instance by a DTM classifier is computed as follows. Let $\ell$ be the set of labelled instances in the DTM exactly matching the giving instance $I$, where only the features in the schema are required to match and all other features are ignored. If $\ell = \emptyset$, return the majority class in the DTM; otherwise, return the majority class in $\ell$. Unknown values are treated as distinct values in the matching process.

Let $\text{err}(h, f)$ denote the error of a hypothesis $h$ for a given target function $f$. Since $f$ is never known for real-world problems, we estimate the error using an independent test set $\tau$ as

$$\hat{\text{err}}(h, \tau) = \frac{1}{|\tau|} \sum_{(x_i, y_i) \in \tau} L(h(x_i), y_i)$$

where $L$ is a loss function. In the rest of the paper we assume a zero-one loss function, i.e., zero if $h(x) = y$ and one otherwise. The approximate accuracy
Fig. 1. The scatter plots (filled circles represent stars; open ones represent quasars; triangles represent all sources from the cross-identification of 2MASS and FIRST catalogues.)
is defined as $1 - \hat{err}(h, \tau)$.

An optimal feature subset, $A^*$, for a given hypothesis space $H$ and a target function $f$ is a subset of the features $A^*$ such that there exists a hypothesis $h$ in $H$ using only features in $A^*$ and having the lowest possible error with respect to the target function $f$. (Note that the subset need not be unique.) As the following example shows, relevant features are not necessarily included in the optimal subset.

An induction algorithm using DTMs as the underlying hypothesis space must decide which instances to store in the table and which features to include in the schema. The algorithm is assumed to include the projections of all instances defined by the schema in the DTM, but we do not restrict the subset of features to use in the schema in any way. Let $A^* = \{X_1, ..., X_n\}$ be a set of features and let $S$ be a sample of $m$ instances over the features in $A$. Given a subset of features $A' \subseteq A$, $\text{DTM}(A', S)$ is the DTM with schema $A'$ and a body consisting of all instances in $S$ projected on $A'$. The goal of the induction algorithm is to choose a schema $A^*$ such that

$$A^* = \arg \min_{A' \subseteq A} \text{err}(\text{DTM}(A', S), f).$$

The schema $A^*$ consists of an optimal feature subset for a DTM under the assumption that all instances from the training set are stored in the body of the decision table.

4 Best-first Search for Feature Selection

Both filter and wrapper approaches can be applied for feature subset selection. Filter approaches use only the training data in the process of evaluation but wrapper approaches incorporated the induction algorithm as part of the evaluation in the search of the best possible feature subset. In this paper we apply best-first search as wrapping around decision table method to obtain optimal feature subsets. In order to search the space of feature subsets effectively, we transform the problem into a state space search and use best-first search to heuristically search the space. A forward selection procedure using best-first search is adopted (Ginsberg 1993). Forward selection implies an operation of addition for each expansion. The search states are nodes representing subsets of features. The idea of best-first search is to jump to the most promising node generated so far that has not been expanded. The search is stopped when an improved node has not been found in the previous $k$ expansions. An improved node is defined as a node that has an accuracy of not less than $x$ percent higher than the best node found so far.
To estimate future prediction accuracy, cross-validation, a standard accuracy estimation technique (Weiss & Kulikowski 1991; Breiman et al. 1984; Stone 1974), is adopted. Given an induction algorithm and a dataset, k-fold cross-validation divides the data into k approximately equally sized subsets, or folds. The induction algorithm is executed k times; each time it is trained on k − 1 folds and the generated hypothesis is tested on the rest fold, which serves as a test set. The estimated accuracy is computed as the average over the k test sets. If k equals the sample size, this is called “leave-one-out” cross-validation. “Leave-v-out” is a more elaborate and expensive version of cross-validation that involves leaving out all possible subsets of v cases.

5 Experiment and Discussion

Our experiments were done with the WEKA machine learning package (Witten & Frank 2005), which is a collection of machine learning algorithms for data mining tasks. Now we applied decision table method on all the datasets including 2389 quasars and 1353 stars. Best-first search for feature selection was executed and terminated by leave-one-out cross-validation after 5 non-improving subsets. We considered two situations: the sample with b − v and the sample without b − v. For the sample with b − v, the optimal feature subset was b − v from the 12 features (\( \log F_{\text{peak}}, \log F_{\text{int}}, j - h, h - k, k + 2.5 \log F_{\text{int}}, k + 2.5 \log F_{\text{peak}}, j + 2.5 \log F_{\text{peak}}, f_{\text{maj}}, f_{\text{min}}, f_{\text{pa}}, b - v \)). Then b − v was used to create a classifier by means of decision table algorithm. The estimated accuracy for each node was computed using 10-fold cross-validation. We got 2 classification rules. The time taken to build the classifier was 0.69 seconds (the configuration of the personal computer used to carry out this analysis is Microsoft Windows XP, Pentium (R) 4, 3.2 GHz CPU, 1.00 GB memory). The whole accuracy added up to 100%.

Then given the sample without b − v, we obtained the optimal feature subsets \( \log F_{\text{int}}, j + 2.5 \log F_{\text{peak}} \) and \( k + 2.5 \log F_{\text{int}} \) from the 11 features. The number of classification rules is 51. The time taken to the built model spent 0.66 seconds. Correctly classified instances were 3558, which occupied 95.1% of the whole sample; incorrectly classified instances were 184, occupying 4.9%. The accuracy of stars and quasars was 88.0% and 99.0%, respectively.

For the two samples, the classification results were shown in Table 1, the whole accuracy added up to 100.0% and 95.1%, separately.

In our case, when regarding the dataset from three bands, b − v is taken as the optimal feature by best-first search, which is consistent with the information from the scatter plot. While considering the dataset from radio and near-infrared bands, \( \log F_{\text{int}}, j + 2.5 \log F_{\text{peak}} \) and \( k + 2.5 \log F_{\text{int}} \) are selected as the
optimal feature subsets. This shows that the best-first search is a more effective feature selection technique than histogram of Zhang & Zhao (2007). The accuracy (95.1%) is satisfying, which is comparable to the accuracy (94.36%, 95.80% and 95.19%) by BBN, MLP and ADTree, respectively. This result indicates that decision table method is an efficient and effective algorithm to classify quasars from stars with the multiwavelength data. The accuracy (99.0%) of quasars is higher than that (88.0%) of stars, which possibly results from the fact that the number of quasars is larger than that of stars. Usually, the imbalanced sample is a factor that influences the performance of a classifier. Classifiers are easy to remember the rule of the majority of sample. Miss-classified instances also result from the attribute errors of stars and quasars. The existence of errors lead to overlap of stars and quasars in the classification space. Based on FIRST and 2MASS databases to preselect quasar candidates, the classification rules are extracted from radio and infrared bands, thus the selected candidates own characteristics of the two bands. As a result, the quasar candidates by the classifier are generally radio-loud and red quasars. If we want to obtain a complete sample, we need to consider other selection criteria, for example, consider more bands, or change bands.

6 Conclusion

The construction of a complete sample of quasars is helpful for studying the large-scale structure of the universe and the formation and evolution of galaxies. To reach this aim, we need efficient separation of quasars from other astronomical sources, of which it is an important issue to separate quasars from stars because they are both point sources from their images. In this work, we focus on this issue. With the development of detectors and the construction of observational stations, the observational attributes of celestial objects increase to hundreds or even thousands. Thus how to reduce the dimension of data seems more important for data analysts, astronomers or for the requirement of some algorithms. We applied a best-first search method to select out
the optimal feature subsets. Then the decision table algorithm was executed on the sample with $b - v$ and the sample without $b - v$. The classified accuracy is more than 95.0%, and the speed to build the model is very high. Therefore, from the point of view from accuracy and speed, this classification algorithm is satisfactory, especially faced with huge volumes and complexity of data. Since the selection criteria seriously depend on algorithms and data used, the classifiers obtained in some situation are inclined to select some kind of quasars. In our case, the classification rules obtained by decision tables is reasonable and applicable. As shown in Fig. 1, the rules may be used to preselect radio loud and red quasar candidates from the whole FIRST and 2MASS intersection. On account of this, we need to consider more criteria and other data to preselect quasar candidates. Decision table can be used to construct classifiers with other datasets and then preselect quasar candidates. Certainly, according to the interests and issues of astronomers, other kinds of data may be collected and used as training set, for example, spectra, images, photometry and so on. For the study of stars, various star samples are needed. For the study of galaxy, different galaxy samples are required. The training sample is as complete as possible and thus the obtained classifier can have a better prediction ability. Owing to the complex characteristics of astronomical data, for different problems, we need to develop appropriate and effective algorithms to solve them.

Acknowledgments We are very grateful to anonymous referees for their helpful comments and suggestions. This paper is funded by National Natural Science Foundation of China under grant No.10473013 and No.90412016.

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