ARTIFICIAL NEURAL NETWORKS AS A TOOL FOR GALAXY CLASSIFICATION

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We describe an Artificial Neural Network (ANN) approach to classification of galaxy images and spectra. ANNs can replicate the classification of galaxy images by a human expert to the same degree of agreement as that between two human experts, to within $2\sigma$-type units. Similar methods are applied to classification of galaxy spectra. In particular, Principal Component Analysis of galaxy spectra can be used to compress the data, to suppress noise and to provide input to the ANNs. These and other classification methods will soon be applied to the Anglo-Australian 2-degree-Field (2dF) redshift survey of 250,000 galaxies.

1 Introduction

The morphological classification of bright galaxies is still mainly done visually by dedicated individuals, in the spirit of Hubble’s (1936) original scheme and its modifications (e.g. Morgan 1958, de Vaucouleurs 1959, 1991, Sandage 1961, van den Bergh 1976). It is remarkable that these somewhat subjective classification labels for galaxies correlate well with physical properties such as colour and dynamical properties. However, one would like eventually to devise schemes of classification which can be related to the physical processes of galaxy formation. While there have been in recent years significant advances in observational techniques (e.g. telescopes, detectors and reduction algorithms) as well as in theoretical modelling (e.g. N-body and hydrodynamics simulations), galaxy classification remains a subjective area. Galaxy classification is important for both practical reasons of producing large catalogues for statistical and observational programs, as well as for establishing some underlying physics (in analogy with the H-R diagram for stars). Moreover, understanding the morphology of galaxies at low redshift is crucial for any meaningful comparison with galaxy images obtained with the Hubble Space Telescope at higher redshift (e.g. the Hubble Deep Field).

Most of our current knowledge of galaxy morphology is based on the pioneering work of several dedicated observers who classified thousands of galaxies and catalogued them. However, projects such as the APM/2dF and the Sloan digital sky surveys will yield millions of galaxy images and spectra. Classifying
very large data sets is obviously beyond the capability of a single person and
classification problems in Astronomy call for new approaches (e.g. Odewhan
et al. 1991; Francis et al. 1992; Spiekermann 1992; Storrie-Lombardi et al.
1992; Doi et al. 1992; Serra-Ricart et al. 1993; Abraham et al. 1994, 1996).

Artificial Neural Networks (ANNs) have recently been utilised in Astron-
omy for a wide range of problems, e.g. from adaptive optics to galaxy classifi-
cation (for review see Miller 1993 and Storrie-Lombardi & Lahav 1994). The
ANNs approach should be viewed as a general statistical framework, rather
than as an esoteric approach. Some special cases of ANNs are statistics we are
all familiar with. However, the ANNs can do better, by allowing non-linearity.

Here we illustrate these points by examples from the problem of morpholog-
ical classification of galaxies, using the ESO-LV (Lauberts & Valentijn 1989)
sample with 13 parameters and \( \sim 5200 \) galaxies, as analysed by ANNs (Storrie-
Lombardi et al. 1992; Lahav et al. 1996), and for a sample of \( \sim 830 \) APM
galaxies (Naim et al. 1995a, 1995b). We also describe a pilot study of galaxy
spectral classification (Folkes, Lahav & Maddox 1996). The outline of this
article is as follows. In §2 we present a comparative study between experts, in
§3 we discuss ANNs and their application to the morphological classification
problem, and in §4 we consider spectral classification of galaxies.

2 Human Classification of APM Galaxies

The motivation for performing a comparison between different experts is two-
fold: (i) to study systematically the degree of agreement and reproducibility
between observers, and (ii) to use the human classification as ‘training sets’
for the Artificial Neural Networks and other automated classifiers.

We have defined a sample from the APM Equatorial Catalogue of galaxies (Raychaudhury et al. 1997) selected from IIIaJ (broad blue band) plates
taken with the UK Schmidt telescope at Siding Spring, Australia. We chose a
subsample of 831 galaxies with major diameter \( D \geq 1.2 \) arcmin. The galaxies
were scanned in raster mode at a resolution of 1 arcsec by the APM facility at
Cambridge.

R. Buta, H. Corwin, G. de Vaucouleurs, A. Dressler, J. Huchra and S. van
den Bergh, kindly classified the same images on the T system. Statistically,
all 6 experts agreed on the exact T-type for only 8 galaxies out of the 831
(i.e. less than 1 %). Agreement between pairs of observers in excess of 80 %
were obtained only to within 2 types. For each pair of observers \( a \) and \( b \) the
variance was calculated (cf. Buta et al. 1994):

\[
\sigma_{ab}^2 = \frac{1}{N_{ab}} \sum_i \left[ T_{a,i} - T_{b,i} \right]^2,
\]
where the sum is over the $N_{ab}$ galaxies for which both observers gave a classification. The rms dispersion between between two observers who looked at the same APM images is between 1.3 to 2.3 $T$-units, 1.8 on average. Detailed analysis and interpretation of this comparison appear elsewhere (Lahav et al. 1995, Naim et al. 1995a). As we show below, it is encouraging that the dispersion we found between the ANN and an expert is similar to the dispersion between two human experts.

3 Automated Classification by Artificial Neural Networks

The challenge is to design a computer algorithm which will reproduce classification to the same degree a student or a colleague of the human expert can do it. Such an automated procedure usually involves two steps: (i) feature extraction from the digitised image, e.g. the galaxy profile, the extent of spiral arms, the colour of the galaxy, or an efficient compression of the image pixels into a smaller number of coefficients (e.g. Fourier or Principal Component Analysis). (ii) A classification procedure, in which a computer ‘learns’ from a ‘training set’ for which a human expert provided his or her classification.

Artificial Neural Networks (ANNs), originally suggested as simplified models of the human brain, are computer algorithms which provide a convenient general-purpose framework for classification (Hertz et al. 1991). ANNs are related to other statistical methods common in Astronomy and other fields. In particular ANNs generalise Bayesian methods, multi-parameter fitting, Principal Component Analysis (PCA), Wiener filtering and regularisation methods (e.g. Lahav 1994, Lahav et al. 1996).

3.1 ANNs as non-linear minimization algorithms

It is common in Astronomy to fit a model with several (or many) free parameters to the observations. This regression is usually done by means of $\chi^2$ minimization. A simple example of a ‘model’ is a polynomial with the coefficients as the free parameters. Consider now the specific problem of morphological classification of galaxies. If the type is $T$ (e.g. on de Vaucouleurs’ numerical system [-6,11]) and we have a set of parameters $x$ (e.g. diameters and colours) then we would like to find free parameters $w$ (‘weights’) such that

$$\sigma^2 = \frac{1}{N_{gal}} \sum_i [T_i - f(w, x_i)]^2,$$

It remains to be tested to what extent an expert reproduces his/her own classification.
where the sum is over the galaxies, is minimized. The non-linear function $f(\mathbf{w}, \mathbf{x})$ represents the ‘network’, which consists of a set of input nodes, a set of output nodes and one or more layers of ‘hidden’ nodes between the input and output layers. The ‘hidden layers’ allow curved boundaries around clouds of data points in the parameter space. Note the similarity between eq. (2) and eq. (1). Rather than looking at the variance between two experts, we minimize here the variance between the expert and the network. Commonly $f$ is written as a function of:

$$z = \sum_k w_k x_k,$$

where the sum here is over the inputs to each node. A ‘linear network’ has $f(z) = z$, while a non-linear transfer function could be a sigmoid $f(z) = 1/[1 + \exp(-z)]$ or $f(z) = \tanh(z)$. While in most computational problems we only have 10-1000 nodes, in the brain there are $\sim 10^{10}$ neurons, each with $\sim 10^4$ connections.

For a given Network architecture the first step is the ‘training’ of the ANN. In this step the weights are determined by minimizing ‘least-squares’ (e.g. eq. 2). Efficient minimization algorithms include Backpropagation (Rumelhart, Hinton & Williams 1986) and Quasi-Newton (e.g. Hertz et al. 1991).

The interpretation of the output depends on the network configuration. For example, a single output node provides an ‘analog’ output (e.g. predicting the type or luminosity of a galaxy), while several output nodes can be used to assign Bayesian probabilities to different classes (e.g. 5 morphological types of galaxies).

### 3.2 The Bayesian connection

A classifier can be formulated from first principles according to Bayes theorem:

$$P(T_j | \mathbf{x}) = \frac{P(\mathbf{x} | T_j) P(T_j)}{\sum_k P(\mathbf{x} | T_k) P(T_k)}$$

i.e. the a posteriori probability for a class $T_j$ given the parameters vector $\mathbf{x}$ is proportional to the probability for data given a class (as can be derived from a training set) times the prior probability for a class (as can be evaluated from the frequency of classes in the training set). However, applying eq. (4) requires parameterization of the probabilities involved. It is common, although not always adequate, to use multivariate Gaussians.
It can be shown that the ANN behaves like a Bayesian classifier, i.e. the output nodes produce Bayesian \textit{a posteriori} probabilities (e.g. Gish 1990), although it does not implement Bayes theorem directly. It is reassuring (and should be used as a diagnostic) that the sum of the probabilities in an ‘ideal’ network add up approximately to unity. For more rigorous and general Bayesian approaches for modelling ANNs see MacKay (1992).

\subsection*{3.3 PCA, data compression and unsupervised algorithms}

Principal Component Analysis (PCA) allows reducing the dimensionality of the input parameter space. A pattern can be thought of as being characterized by a point in an $M$-dimensional parameter space. One may wish a more compact data description, where each pattern is described by $M'$ quantities, with $M' \ll M$. This can be accomplished by Principal Component Analysis (PCA), a well known statistical tool commonly used in Astronomy (e.g. Murtagh & Heck 1987 and references therein). The PCA method is also known in the literature as Karhunen-Loève or Hotelling transform, and is closely related to the technique of Singular Value Decomposition. By identifying the \textit{linear} combination of input parameters with maximum variance, PCA finds $M'$ variables (Principal Components) that can be most effectively used to characterize the inputs. PCA is in fact an example of ‘unsupervised learning’, in which an algorithm or a linear ‘network’ discovers for itself features and patterns (see e.g. Hertz et al. 1991 for review). ANNs can be used to generate ‘non-linear PCA’. Serra-Ricart et al. (1993) have compared standard PCA to ‘non-linear PCA’, illustrating how the latter successfully identifies classes in the data. Another unsupervised method is Kohonen’s Self Organized Map, recently used e.g. for star/galaxy separation (Mahonen & Hakala 1995) and galaxy morphological classification (Naim et al. 1996).

\subsection*{3.4 Results for galaxy morphological classification by ANNs}

Storrie-Lombardi et al. (1992) and Lahav et al. (1996) have analysed with ANNs the ESO-LV (Lauberts & Valentijn 1989) sample of about 5200 galaxies, using 13 machine parameters (all scaled to be distance independent). Using a network configuration 13:3:1 (with 46 weights, including ‘bias’) for the ESO-LV galaxy data, with both the input data and the output $T$-type scaled to the range $[0, 1]$ and with sigmoid transfer functions, we found dispersion $\Delta T_{\text{rms}} \sim 2$
between the ANN and the experts (LV) over the $T$-scale [-5, 11].

For a net configuration 13:13:5, where the output layer corresponds to probabilities for 5 broad classes (E, S0, Sa+Sb, Sc+Sd, Irr), we found a success rate for perfect match of 64%. Our experiments indicate that non-linear ANNs can achieve better classification than the naive Bayesian classifier with Gaussian probability functions, for which the success rate is only 56%.

Naim et al. (1995b) have applied the same techniques to the APM sample of 830 galaxies described above, by extracting features directly from the images, and training the net on the human classification from the 6 experts. When the network was trained and tested on individual expert, the rms dispersion varies between 1.9 to 2.3 $T$-units over the 6 experts. A better agreement, 1.8 $T$-units, was achieved when the ANN was trained and tested on the mean type as deduced from all available expert classifications. There is a remarkable similarity in the dispersion between two human experts and that between ANN and experts! In other words, our results indicate that the ANNs can replicate the expert’s classification of the APM sample as well as other colleagues or students of the expert can do.

4 Spectral Classification of Galaxies

Galaxy spectra provide another probe of the intrinsic galaxy properties. The integrated spectrum of a galaxy is an important measure of its stellar composition as well as its dynamical properties. Spectra can be obtained to larger redshifts than morphologies and, as 1-D datasets, are easier to analyse. Apart from its relevance for environmental and evolutionary studies, new classes of objects may be discovered as outliers in spectral parameter space.

Although the concept of spectral classification of galaxies dates from Humason (1936) and Morgan & Mayall (1957), few uniform data sets are available and most contain only a small number of galaxies (e.g. Kennicutt 1992). Recent spectral analyses for classification were carried out by Francis et al. (1992) for QSO spectra, von-Hippel et al. (1994) and Storrie-Lombardi et al. (1994) for stellar spectra, and in particular for galaxy spectra by Connolly et al. (1995) and Sodré & Cuevas (1996).

In a recent pilot-study Folkes, Lahav & Maddox (1996) analysed the spectra of Kennicutt (1992) and simulated the spectra expected to be observed with the 2-degree-field (2dF) 400-fibre facility at the Anglo-Australian Telescope. PCA was used to compress the spectra from ~ 800 wavelength bands to ~ 8 principal components. The first principal component shows correspondence to well-known lines (e.g. $H_\alpha$, $H_\beta$, and OII). The first few principal components provide a useful new compact space to describe a spectroscopic Hubble
sequence. Moreover, reconstruction by using only 8 components allows us to recover successfully the underlying signal from noisy spectra. It is also possible to use a sample for which both the $T$-type and the spectra are available and to train an ANN to predict $T$-type. In a sense, the ANN provides here mapping between galaxy spectrum and image. Reliable classification, with more than 90% of the normal galaxies correctly classified into 5 broad bins, can be expected to the magnitude limit of the 2dF survey ($b_J = 19.7$). The ANN classification is more successful than either a $\chi^2$ template matching approach or a classification based solely on the projection on the first principal component. We intend to carry out automated classification using the above and other methods for the 250,000 2dF galaxy spectra.

5 Discussion

It is encouraging that in the problem of morphological classification of galaxies, one of the last remaining subjective areas in Astronomy, ANNs can replicate the classification by a human expert almost to the same degree of agreement as that between two human experts, to within 2 $T$-units. A pilot study shows that spectral classification can be done, with future applications to the 2dF redshift survey. The challenge for the future is to develop efficient methods for feature extraction and ‘unsupervised’ algorithms, combining multi-wavelength information to define a ‘new Hubble sequence’ without any prior human classification.

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