Abstract – The rapid increase in data on galaxy images at low and high redshift calls for re-examination of the classification schemes and for new automatic objective methods. Here we present a classification method by Artificial Neural Networks. We also show results from a comparative study we carried out using a new sample of 830 APM digitised galaxy images. These galaxy images were classified by 6 experts independently. It is shown that the 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 $T$-type units. Similar methods can be applied to automatic classification of galaxy spectra. We illustrate it by Principal Component Analysis of galaxy spectra, and discuss future large surveys.

key-words – methods: data analysis - 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, 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.
Quantifying galaxy morphology is important for various reasons. First, it provides important clues to the origin of galaxies and their formation processes. For example, understanding the origin of the type frequency and the density-morphology relation is of fundamental importance. Second, galaxies can also be used as standard candles. As such they can be used to measure redshift-independent distances by methods such as the luminosity-rotation velocity (Tully-Fisher) relation for spirals and the diameter-velocity dispersion for ellipticals. Clearly any observational programme requires an a priori target list of objects for photometric or spectrographic measurements.

Therefore 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 ($z \sim 0.4$).

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 and the Sloan digital sky surveys yield millions of galaxies. Classifying very large data sets is obviously beyond the capability of a single person. Clearly, classification problems in Astronomy call for new approaches (e.g. Thonnat 1988; 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).

Artificial Neural Networks (ANNs) have recently been utilised in Astronomy for a wide range of problems, e.g. from adaptive optics to galaxy classification (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 morphological classification of galaxies, using the ESO-LV (Lauberts & Valentijn 1989) sample with 13 parameters and $\sim 5200$ galaxies, as analysed by ANNs in Storrie-Lombardi et al. (1992) and Lahav et al. (1995), and for a new sample of $\sim 830$ APM galaxies (Naim et al. 1994, 1995).

The outline of this review 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. (ii) To use the human classification as ‘training sets’ for the Artificial Neural Networks and other automatic classifiers.

We have defined a sample from the APM Equatorial Catalogue of galaxies (Raychaudhury et al. 1995) 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, (hereafter RB, HC, GV, AD, JH and vdB, respectively) kindly classified the same images on the $T$ system (a conversion to this system was done in the case of vdB).

Four examples of the human classification are given in Figure 1. 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 % are obtained only to within 2 types. GV and vdB, who classified galaxies over many more years than the others, were rather conservative and did not classify about a third of the galaxy images which are saturated or of low quality. The other observers were more liberal and classified almost all the galaxies.

For each pair of observers $a$ and $b$ the variance was calculated (cf. Buta et al. 1994):

$$\sigma_{ab}^2 = \frac{1}{N_{ab}} \sum_i [T_{a,i} - T_{b,i}]^2,$$

where the sum is over the $N_{ab}$ galaxies for which both observers gave a classification. The rms dispersion between RC3 (de Vaucouleurs et al. 1991) and any of the observers (2.2 $T$-units on average) is larger than between 2 observers who looked at the same APM images (between 1.3 to 2.3 $T$-units, 1.8 on average). This reflects the fact that any classification depends on the colour, size and quality of the images used, i.e. there is no ‘universal’ classification. Another interesting result is that observers who belong to the same ‘school’ agree better with each other than with others. For example, the dispersion between deV and HC is only 1.5 and between HC and RB only 1.3 units. This
indicates that systematic ‘training’ can reduce the scatter between two human experts. Detailed analysis and interpretation of this comparison will appear elsewhere (Naim et al. 1994, Lahav et al. 1994).

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. AUTOMATIC 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 for a summary).

3.1 ANNs as non-linear minimization algorithms

It is very 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

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

where the sum is over the galaxies, is minimized. The function $f(w, x)$ is the ‘network’. 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 in terms of

\[
z = \sum_k w_k x_k,
\]

(3)

where the sum here is over the input parameters 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 \( f(z) = \tanh(z) \). Another element of non-linearity is provided by the ‘hidden-layers’. The ‘hidden layers’ allow curved boundaries around clouds of data points in the parameter space. 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). The Backpropagation algorithm (Rumelhart, Hinton & Williams 1986) is one of the most popular ANN minimization algorithms. However, there are other more efficient methods such as 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:

\[
P(T_j|x) = \frac{P(x|T_j) \ P(T_j)}{\sum_k P(x|T_k) \ P(T_k)}
\]

(4)

i.e. the a posteriori probability for a class \( T_j \) given the parameters vector \( x \) 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 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).
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-Loéve or Hotelling transform, and is closely related to the technique of Singular Value Decomposition. By identifying the 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). A simple net configuration \(M : M' : M\) (known as encoder) with linear transfer functions allows finding \(M'\) linear combinations of the original \(M\) parameters. The idea is to force the output layer to reproduce the input layer, by least-squares minimization. If the number of ‘neck units’ \(M'\) equals \(M\) then the output will exactly reproduce the input. However, if \(M' < M\), the net will find, after minimization, the optimal linear combination. By changing the transfer function from linear to non-linear (e.g. a sigmoid) one can allow ‘non-linear PCA’. Serra-Ricart et al. (1993) have compared standard PCA to non-linear encoder, illustrating how the latter successfully identifies classes in the data.

**3.4 Recent results for galaxy morphological classification by ANNs**

Storrie-Lombardi et al. (1992) and Lahav et al. (1995) have analysed with ANNs the ESO-LV (Lauberts & Valentijn 1989) sample of about 5200 galaxies, using 13 machine parameters. 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 get dispersion \(\Delta T_{\text{rms}} \sim 2.1\) 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%.
More recently, we have applied (Naim et al. 1995) 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 is 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, is achieved when the ANN is trained and tested on the mean type as deduced from all available expert classifications. For more details and the scatter diagram $T(\text{experts})$ vs. $T(\text{ANN})$ see A. Naim in this volume. 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.

Similar successful results are reported by S. Odewhan using the Minnesota galaxy sample in this volume, and other interesting computational approaches to classification are presented by M. Thonnat.

4. SPECTRAL CLASSIFICATION OF GALAXIES

Galaxy spectra provide another probe of the intrinsic galaxy properties. The integrated spectrum of a faint galaxy is an important measure of its stellar composition as well as its dynamical properties. Moreover, spectral properties correlate fairly closely with morphology. Indeed, as the spectra are more directly related to the underlying astrophysics, they are a more robust classifier for evolutionary and environmental probes. Spectra can be obtained to larger redshifts than ground-based morphologies and, as 1-D datasets, are easier to analyse. 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 out carried 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 Sodré & Cuevas (1994), Heyl (1994), and Connolly et al.(1994).

Spectral classification is important for several practical and fundamental reasons. In order to derive luminosities corrected for the effects of redshift the $k$-correction (Pence 1976) must be estimated for each galaxy. The rest-frame spectral energy distribution is needed, which can be obtained by matching the observed spectrum against templates of local galaxies.

The proportion of sources in each class as a function of luminosity and redshift is of major interest. Apart from its relevance for environmental and evolutionary studies, new classes of objects may be discovered as outliers in spectral parameter space. Furthermore, by incorporating spectral features
Figure 2: Principal Component Analysis applied to 55 galaxy spectra galaxy spectra (of Kennicutt 1992), evaluated over the range 3712-4110 Å. The mean spectra and the first 3 eigen-vectors (together account for 94 % of the variance) are shown vs. the wavelength. The PCA was computed after removing the mean spectra. The 1st and 3rd components are shifted by (+0.3) and (-0.4) to clarify the presentation. The plot indicated that the Principal Components identify objectively well known lines, e.g. the 1st PC finds the [OII] 3727 line.

Figure 3: Projection of the galaxy spectra on the First Principal Component axis (as derived in Figure 2) vs. the morphological T-type. This analysis illustrates that spectral parameters, objectively extracted, can be used to classify galaxies.

with other parameters (e.g. colour and velocity dispersion) an ‘H-R diagram for galaxies’ can be examined with possible important implications for theories of galaxy formation.

To illustrate some of these ideas, we have performed a PCA analysis of Kennicutt’s sample of 55 galaxy spectra over the rest-frame interval 3712-4110 Å including important features such as [OII] 3727 and the 4000 Å break. While the input contains 200 channels, the First Principal Component accounts for 75% of the total variance. Figure 2 shows the mean spectra, and the first 3 eigen-vectors as a function of wavelength. We see that the First PC identifies objectively e.g. the [OII]3727 line. For each of the galaxies, the projection of the 200 channels on the First PC axis versus the morphological T-type is shown in Figure 3. The correlation confirms that spectral features, when efficiently extracted, can be used to classify galaxies. For similar analyses see Sodré & Cuevas (1994) and Connolly et al. (1994). 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 (or k-correction) from the spectra, similar to the ANN classification of galaxy images.

These approaches will no doubt be applied to new large surveys such as the Sloan Digital Sky survey and the 2-degree-field (2dF) 400-fibre facility at the Anglo-Australian Telescope. In particular, we intend to carry out automatic classification for 250,000 galaxy spectra, proposed to be measured with the 2dF by a UK-Australian collaboration.
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 $2 \tau$-units.

The challenge for the future is to develop efficient methods for feature extraction and a ‘unsupervised’ algorithms, combining multi-wavelength information to define a ‘new Hubble sequence’ without any prior human classification.

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