Morphological Classification of Galaxies by Human Eyes and by Artificial Neural Networks

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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 Network. We also show results from a comparative study we carried out using a new sample of over 800 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.

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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. Sandage 1961, de Vaucouleurs 1959, Morgan 1958, 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 an objective scheme 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 clearly of fundamental importance. But quantifying these properties requires reliable classification schemes. 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 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. Hence, the galaxy classification problem calls for new approaches (e.g. Spiekermann 1992; Storrie-Lombardi et al. 1992; Doi et al. 1992; Abraham et al. 1994).

2 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 (ANN), 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). For other astronomical applications see e.g. Odewahn et al. (1991) and Serra-Ricart et al. (1994). One ANN configuration consists of nodes arranged in a series of layers and utilizes the Backpropagation minimization algorithm (Rumelhart et al. 1986). In one configuration the galaxy parameters are fed into the input layer, and the T-type classification appears as a single continuous output. The 'hidden layer' allows non-linear boundaries in a complicated parameter space. In the 'training' phase the free parameters of the network ('weights') are determined by least-square minimization of the difference between the desired and true (i.e the expert's classification) type. Other network configurations are possible, including multiple output nodes which can provide Bayesian a posteriori probabilities for each class.

In pilot studies (Storrie-Lombardi et al. 1992, Lahav et al. 1994a) we have analysed the ESO-LV (Lauberts & Valentijn 1989) sample of about 5200 galaxies, using 13 machine parameters. We have utilized the Revised Hubble T-type (numerical stage) system (see de Vaucouleurs etal. 1991 for details). Although the T-type is only a one-dimensional scheme (extending from $T = -6$ to $T = +11$), it is commonly used and is convenient for computer algorithms compared with other, more descriptive schemes. We find that the rms dispersion between the ANN and the expert (LV) is about 2.1 T-units. (typical 'internal' scatter when nets with different initial random weights are used is about 0.6 units).

3 Human Classification of a New APM Galaxy Sample

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 a 'training set' for the Artificial Neural Networks and other automatic classifiers.

We have defined a sample from the APM Equatorial Catalogue of galaxies (Raychaudhury et al., in preparation) 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. P. 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).

Statistically, all 6 authors 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.

To better quantify the degree of agreement between observers we calculated for each pair of observers the variance (cf. Buta et al. 1994) taking into account only those galaxies for which both observers gave a classification. The dispersion between RC3 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' better agree 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. We also notice a weak trend for better agreement in classification for large galaxies which are face-on. Detailed analysis of this comparison will appear elsewhere (Naim et al. 1994, Lahav et al. 1994b). We also intend to evaluate the 'internal scatter' (i.e. reproducibility) of each observer, when classifying again the same data set or a set with lower resolution.

It is encouraging that the dispersion we found between the ANN and an expert is only slightly higher than the dispersion between two human experts. We note that for the ANN experiment we have used a different sample and that the 13 parameters are not optimal. We are currently in the process of extracting features from the APM images and training the ANNs according to the classification by the 6 observers (Naim et al., in preparation).

4 Discussion

Our preliminary results indicate that the ANNs can replicate the classification almost as well as human experts. We have presented a systematic comparison of galaxy classification by 6 observers for a new large data set of galaxy images. The comparison indicates that while the T-system is convenient, the scatter between observers in non-negligible. Future work will focus on ANNs which produce multi-dimensional classification, and 'unsupervised' algorithms (e.g. by generalizing Principal Component Analysis to non-linear mapping) which define a 'new Hubble sequence' without any prior human classification.

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