RevMexAA (Serie de Conferencias), **11**, 85–86 (2001)

ARTIFICIAL NEURAL NETWORKS IN STELLAR ASTRONOMY

R. K. Gulati[1] and L. Altamirano

Instituto Nacional de Astrofísica, Óptica y Electrónica, Tonantzintla, México

RESUMEN

La siguiente generación de levantamientos espectroscópicos ópticos, tal como el Sloan Digital Sky Survey y el levantamiento de campo de 2 grados, proporcionarán grandes bases de datos estelares. Nuevas herramientas serán necesarias para extraer información útil de estas bases de datos. En este árticulo demostramos las aplicaciones de las redes neuronales artificiales a las bases de datos estelares. En otra aplicación de éste método, predecimos clases espectrales y de luminosidad a partir del catálogo de índices espectrales. Se prevée la importancia de tales métodos para el estudio de poblaciones estelares.

ABSTRACT

Next generation of optical spectroscopic surveys, such as the Sloan Digital Sky Survey and the 2 degree field survey, will provide large stellar databases. New tools will be required to extract useful information from these. We show the applications of artificial neural networks to stellar databases. In another application of this method, we predict spectral and luminosity classes from the catalog of spectral indices. We assess the importance of such methods for stellar populations studies.

Key Words: **GALAXIES: STELLAR CONTENT — METHODS: STATISTICAL, DATA ANALYSIS, NUMERICAL — STARS: STELLAR CLASSIFICATION**

1. INTRODUCTION

Artificial neural networks (ANNs) have been used in diverse fields of astronomy, from detection of instrument defects to morphological classification of galaxies (for review see Storrie-Lombardi & Lahav 1994; and Miller 1993). In stellar astronomy, it has been employed for classification of stellar spectra (von Hippel et al. 1994; Weaver & Torres-Dodgen 1997) and parametrizing observed stellar spectra using a library of synthetic spectra (Bailer-Jones et al. 1998). One of us, with his co-workers, has also identified three areas in stellar astronomy where ANNs hold promise. First, they have applied it to classify digitized optical and ultraviolet stellar spectra (Gulati et al. 1994a; Gulati et al. 1994b; Singh et al. 1998). Second, they have used it to compare a set of observed spectra of F and G dwarfs with a library of synthetic spectra (Gulati et al., 1997a). Third, they have employed it to determine reddening properties from the low-dispersion ultraviolet spectra (Gulati et al. 1997b). The above applications were limited to a smaller databases available at that time. The advent of CCD devices, combined with multi-fiber spectrographs, have made possible to use efficiently small telescopes for large spectroscopic survey purposes. For example, Jones (1996) has built a homogeneous library of 684 stellar spectra using a 0.9 m coude feed instrument at the KPNO and has published a catalog of spectral indices in the wavelength regions 3820 − 4500 Å and 4780 − 5460 Å. In our recent work (Gulati et al. 1999), we have applied ANNs to this catalog to predict spectral classes from the spectral indices. In our continuing efforts to refine the methods and to explore its further potential, we demonstrate in this paper the capability of ANNs for predicting not only spectral types but luminosity classes too.

[1]gulati@inaoep.mx

2. ANNS METHOD AND ITS APPLICATIONS

Artificial neural networks are computer algorithms inspired from simple models of the biological brain. The use of ANNs is increasing in various fields, like astronomy, since Rumerhalt et al. (1986) proposed multi back propagation neural network (MBPN) algorithm. The basic idea behind this method is discussed at length in Gulati et al. (1994a). The working of MBPN requires a minimum of three layers; the first layer helps in bringing the input data which is processed at the second layer with a non-linear function, while the third layer provides the network classification. In a supervised neural network, the MBPN looks for an optimal solution by comparing network classes with those assigned from the training set. Once the network has converged to the threshold, the networks weights are applied to the test patterns to classify them in terms of trained classes.

We implemented this method to the Jones catalog of spectral indices in the wavelength range 4780−5460 Å. This region involves the Lick spectral indices as defined in Worthey et al. (1994). Even though the catalog was developed for stellar population studies, however it contains the necessary ingredients to be used for the classification problem. Before feeding input information into the network, we divided the catalog into two groups. The first group, the so called training set, was selected to cover all possible spectral and luminosity classes existing in the catalog. The second group contains stars with known spectral classes and hereafter referred to as a the test set. The networks were thus trained on 60% of the total sample. Since the number hidden layers depends upon the complexity in relationship between input patterns and output classes, different network configurations with a variety of hidden nodes were tried and the one giving the minimum formal root mean square error on correlation plots between the catalog and network classes were considered for classification of the test set. The output nodes in the spectral classification were used in continuous mode because the spectral classes can be represented as a continuous function. For luminosity classes, they are set to discrete modes, considering discreteness in groups of luminosity classes. In principle, the networks can be trained to replicate desired classes but such networks fails to generalize those patterns not present in the training set. So some tolerance on the threshold has be set.

The performance of the networks were judged by comparing the catalog spectral classes against network classes. The success rate for luminosity classes were gauged by making a confusion matrix, indicating how many dwarfs can be classified as a giants or dwarfs. Due to paucity of space we do not show any plot or table, but highlight the main results from this investigation and details will be described in Gulati & Altamirano (2000). The histogram of residuals (difference between ANNs and catalog class) suggests that 80% of the test sample are classified to an accuracy of 2-subclasses. There are a few cases where ANNs miss-classify the test stars with respect to the catalog classes. The confusion matrix for luminosity classes suggests that the success rate for accurate classification of dwarfs and giants is 97% and 91%, respectively.

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