9-1999

A Review of Automated Stellar Spectral Classification and Surveys

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September 1999

Contribution to the report of IAU Commission 45 (Stellar Classification)
to appear in the IAU triennial reports on astronomy.

Modern spectroscopic surveys and automated classifiers are becoming so inextricably linked that it is difficult even to summarize one without discussing the other. Some of the automated classifiers are being built because of current analysis needs, though with a clear anticipation of future, larger surveys. Other automated classifiers are being designed specifically for future surveys. Automated classifiers may be applied to databases already in hand, to real-time analysis at the telescope, or one day to on-board satellite analysis where the raw data are too bulky to save and transmit. In addition, many current spectroscopic surveys target galaxies. These surveys may contain stars either by accident or by a purposeful, but minority, assignment of input slits or fibers to stars. Nontheless, these surveys still represent vast sources of stellar spectral data. Our review embarks by discussing current work, both on automated stellar classification and surveys, and then finishes with plans and portents for the future.

Automated spectral classification

A large part of the effort in automating stellar spectral classification has focused on automating the MK system, and most of this effort has concentrated on the application of supervised feed-forward neural networks. The earliest refereed work can be found in papers by Gulati et al. (1994, ApJ, 426, 340), von Hippel et al. (1994, MNRAS, 269, 97), Weaver & Torres-Dodgen (1995, ApJ, 446, 300), and Vieira & Ponz (1995, A&AS, 111, 393). These authors focused primarily on spectral type classification of intermediate to low resolution spectra (1–15 Å) in the optical and UV. They all used similar methods (namely training and testing on two separate pre-classified sets of spectra), although specific network architectures, optimization, and regularization techniques differed.

In the past few years, these groups have developed their work further. Weaver & Torres-Dodgen (1997, ApJ, 487, 847) used a set of $\sim$250 low resolution (15 Å) O–M, I–V spectra (5800–8900 Å) to produce median classification precisions of 0.5 spectral subtypes and 0.2 luminosity classes. Bailer-Jones et al. (1998, MNRAS, 298, 361) used a database of over 5000 optical (3800–5200 Å) spectra at intermediate resolution ($\simeq$3 Å) and achieved a spectral type classification error of $\sigma = 0.8$ subtypes across the full range of spectral types present (B2–M7). They used a probabilistic network for luminosity class determination, and achieved correct high confidence dwarf/giant discrimination across this range for over 95% of cases. Their work also shows how Principal Components Analysis can be used to identify unusual spectra and compress the data by a factor of 30 without any loss of classification accuracy. Singh et al. (1998, MNRAS, 295, 312) trained their networks on 55 spectra (3500–8900 Å, $\Delta\lambda = 11$ Å) in the range O–M and report a global classification error of $\sigma = 2.2$ subtypes, also using PCA-compressed spectra. In the UV, Vieira & Ponz (1998, ASP Conf. Ser. 145, 508) used 229 IUE low dispersion spectra (1150–3200 Å, $\Delta\lambda = 2$ Å) of O3 to K0 stars in both a feed-forward neural network (achieving $\sigma = 1.10$ spectral subtypes) and an unsupervised Self-Organizing Map ($\sigma = 1.62$). Results in the UV were also reported by Mukherjee et al. (1996, Ap&SS, 239, 361).

Spectral classification is a means to an end, namely the determination of physical stellar parameters. Two groups have focused on automated methods of determining physical parameters directly. Katz et al. (1998, A&A, 338, 151; also see Soubiran et al. 1998, A&AS 133, 221) have developed a minimum distance method (a generalization of χ^2 minimization, e.g. Takeda 1995, PASJ, 47, 287) to parametrize spectra in terms of $T_{\rm eff}$, [M/H], and log(g) by finding the most closely matching template spectrum. The template grid consisted of 211 spectra (3900–6800 Å, $\Delta\lambda \simeq 0.1$ Å) with $4000\,\mathrm{K} \leq \mathrm{T_{eff}} \leq 6300\,\mathrm{K}$, $-0.29 \leq$ [M/H] $\leq +0.35$, and log(g) for main sequence and evolved stars. At SNR=100, the *internal accuracy* of the method (obtained by parametrizing each template spectrum by removing it from the grid) is 86 K, 0.16 dex, and 0.28 dex for $\mathrm{T_{eff}}$, [M/H], and log(g), respectively. Bailer-Jones et al. (1997, MNRAS, 292, 157) used a neural network trained on synthetic spectra to determine $\mathrm{T_{eff}}$ for real spectra of different luminosity classes. This also gave rise to a $\mathrm{T_{eff}}$–SpT calibration across the range B2–M7 accurate to 3–6% and showed evidence for metallicity sensitivity. Gulati et al. (1997, A&A, 322, 933) used this approach and a χ^2 minimization method to obtain a $\mathrm{T_{eff}}$–SpT calibration for G and K dwarfs to within ± 250 K.

In the context of optimizing the photometric/spectroscopic system for the GAIA mission (see below), Bailer-Jones (2000, in preparation) has assessed the accuracy with which $\mathrm{T_{eff}}$, [M/H], and log(g) can be obtained from spectra at a range of SNRs (1000, 50, 20, 10, 5) and (two pixel) resolutions ($\Delta\lambda = 25, 50, 100, 200, 400$). He generated a set of 3500 synthetic spectra over a large wavelength coverage (3000-10000 Å) with $\mathrm{T_{eff}}$, [M/H], and log(g) in the ranges 4000 to 30000, -3.0 to $+1.0$, and 2.0 to 5.0, respectively. Using feed-forward neural networks, the $\Delta\lambda = 100$ Å spectra at a SNR of 10 permitted $\mathrm{T_{eff}}$ determination to better than 2%, and average errors for [M/H] and log(g) of 0.24 and 0.37 dex, respectively. As these values are similar to the finest sampling of the parameters in the training data grid, the performance is almost certainly data (rather than model) limited. He has also assessed the relative performance of several newly proposed multi-band filter systems for determining physical parameters.

Readers will note that over the past few years there has been considerable progress in automated classification and physical parametrization. It is clear that good quality two or even three dimensional parametrization/classification is now possible. However, some general points about the recent research should be highlighted. In all of the work discussed above, the quoted accuracies are averaged across a large range of physical parameters: The quality of performance typically varies markedly, with some regions of parameter space being considerably better or worse than others. Moreover, the above studies have usually only looked at 'normal' stars, and then only at the well defined parameters of $\mathrm{T_{eff}}$, [M/H], and log(g) (or SpT and LC on the MK system). The true value of automated methods will be in their application to large surveys, such as SDSS and GAIA. Thus the method must be able to cope with the additional complications of unselected targets, such as binarity, extinction, and variable abundance ratios. In practice, therefore, survey classification methods will have to be somewhat more sophisticated and robust than those currently available. Some work has been done on extinction (e.g. Gulati et al. 1997, PASP, 109, 843) and binarity (Weaver 1999, in preparation). Equally important is the fact that many future surveys will probe populations very different from those on which the MK system was developed. It is therefore vitally important that classification/parametrization systems are adopted which maximize the scientific return from the survey. The determination of physical parameters directly from spectra is clearly desirable. A past criticism of this approach has been that reparameterization will be required as new models are developed. However, since modeling astrophysical phenomena is the goal of our profession, and since the current generation of high speed computers and storage media make this reparameterization relatively easy, we should proceed with physical parameterization undaunted.

Surveys

In the category of ongoing surveys, Balayan, Abrahamyan, Gigoyan, and their colleagues have published a number of papers (see 1997, Ap, 40, 413 and references therein) on the stars and their classifications from the Second Byurakan Sky Survey. Their survey contains more than 1700 starlike objects with photographic magnitudes brighter than 19.5.

A survey of similar size, the Hamburg/ESO Objective-Prism survey (Wisotzki et al., 1996, A&AS, 115, 227) was primarily organized to find QSOs in the range $12.5 \leq \mathrm{B} \leq 17.5$, but there are also a significant number of stars in this survey. Christlieb et al. (1999, Galactic Halo Conf, 259) are developing an automated search for metal-poor halo stars from this database. Their catalog should reach ~ 1 magnitude deeper and cover 4.5 times the volume as the very successful HK Survey of Beers and collaborators.

The survey of Beers and collaborates (1992, AJ, 103, 1987) is currently being actively followed up (e.g. 1999, Galactic Halo Conf., 202), rather than enlarged. Work is underway to automate the parameter determination and analysis of these data (Rhee, Beers & Irwin, 1999, BAAS, 194, 8411).

An innovate survey using a transit telescope with a liquid mirror primary and 33 intermediate (200 to 400 Å) band filters has already reported (Hickson & Mulrooney, 1998, astro-ph/9710044) initial results. While not strictly a spectroscopic survey, the large number of passbands allow the survey team to convert the multi-band imaging into low resolution spectroscopy for QSOs, galaxies, and a few hundred thousand Galactic stars.

Surveys of a few thousand stars may benefit from automated classification techniques. Automated techniques will be essential, however, for the largest surveys. Perhaps the largest survey undertaken to date, the Sloan Digital Sky Survey (SDSS, http://www.sdss.org/), will obtain spectra for over one million objects to R $\sim$ 18 with a spectral range of 3900–9100 Å, R=2000, and SNR $\geq$ 13 per Å for the faintest objects. Although this survey targets galaxies, it will aid work on automated stellar classification both by the large number of stars accidentally observed and by the development of automated galaxy classification techniques.

Looking towards the future there are many more surveys in the development stages. While most are targeted towards galaxies, ESA's GAIA, for example, will be a very impressive example of bringing multiple, extremely high precision instruments and automated techniques together to determine the type, distance, and radial velocity for $\sim$1 billion Galactic stars. Automated techniques are here so essential that the satellite is being built around expert systems and much of the data processing may be done on-board, with results transmitted to Earth. Automated techniques are expected to show their greatest strength when tuned to a particular survey, and GAIA should be an outstanding example of this approach.