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AUTOMATED STELLAR SPECTRAL CLASSIFICATION AND PARAMETERIZATION FOR THE MASSES

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ABSTRACT: Stellar spectroscopic classification has been successfully automated by a number of groups. Automated classification and parameterization work best when applied to a homogeneous data set, and thus these techniques primarily have been developed for and applied to large surveys. While most ongoing large spectroscopic surveys target extragalactic objects, many stellar spectra have been and will be obtained. We briefly summarize past work on automated classification and parameterization, with emphasis on the work done in our group. Accurate automated classification in the spectral type domain and parameterization in the temperature domain have been relatively easy. Automated parameterization in the metallicity domain, formally outside the MK system, has also been effective. Due to the subtle effects on the spectrum, automated classification in the luminosity domain has been somewhat more difficult, but still successful. In order to extend the use of automated techniques beyond a few surveys, we present our current efforts at building a web-based automated stellar spectroscopic classification and parameterization machine. Our proposed machinery would provide users with MK classifications as well as the astrophysical parameters of effective temperature, surface gravity, mean abundance, abundance anomalies, and microturbulence.

1. A BRIEF HISTORY OF AUTOMATED CLASSIFICATION

Current or planned large-scale surveys, such as the Sloan Digital Sky Survey (York et al. 2000) or the GAIA mission (scheduled for launch around 2011), have led to increased interest in automated spectral classifiers (e.g., Bailer-Jones 2000). There are many other reasons to develop automated classifiers, not the least of which are the homogeneity of the results and the repeatability of the process. Automated spectral classification of stars goes back decades. For instance, in an early attempt Jones (1966) fit a few major stellar lines and correlated these indexes with MK type (Morgan, Keenan, & Kellman 1943). Malyuto & Shvelidze (1994) later developed this technique further. Unfortunately, the line fitting technique suffers from the disadvantage that one has first to know the approximate stellar type before determining which lines to fit, otherwise very different features will be found at the same wavelengths. Kurtz (1983; see also LaSala 1994) developed a minimum vector distance technique that matched spectra to a library of standards weighting the comparison to different spectral regions for different types of stars. The minimum vector distance technique has had some success – classifying stellar spectral types to within $\sigma=2.2$ spectral subtypes – but refining this technique is cumbersome since the weighting vectors need to be carefully established, yet they vary as a function of spectral type and luminosity class.

In the middle of the last decade four independent groups (Gulati et al. 1994; von Hippel et al. 1994; Vieira & Ponz 1995; Weaver & Torres-Dodgen 1995) began to successfully apply artificial neural networks (ANNs) to the spectral classification problem. Neural networks are trained to yield classifications that are identical to those previously assigned, and thus have the advantage that the ANN builder need not become a classification expert, but rather can rely on the true experts in the field, via their many previous classifications. For example, von Hippel et al. built an ANN using the objective prism spectra and classifications of Houk (1982, and references therein), who had at that time already classified more than 10^5 stars. This first generation of neural networks were applied to low resolution ultraviolet (Vieira & Ponz 1995) or optical (the other three studies) spectra and achieved $\sigma=0.6$ spectral subtypes and $\sigma=0.35$ luminosity classes for A stars and returned $E(B-V)$ (Weaver & Torres-Dodgen 1995), or $\sigma < 2$ subtypes over the broad range of O3 to M4 stars. These studies validated the ANN approach and indicated its tremendous potential.

The second generation of ANN spectral classification studies (Weaver & Torres-Dodgen 1997; Bailer-Jones, Irwin, & von Hippel 1998; Singh, Gulati, & Gupta 1998; Weaver 2000) focused on increasing sample size and moving on to two-dimensional classification. At this point spectral type classification became very good, with $\sigma=0.5-0.7$ subtypes. Luminosity classification quality varied from $\sigma \approx 0.3$ luminosity classes (Weaver & Torres-Dodgen 1997) to a statistically reliable luminosity classification for dwarfs and giants, though not sub-giants (Bailer-Jones et al. 1998). Interestingly, Weaver (2000) also showed that he could provide two dimensional classification for both components of artificial binaries!

A few ANN studies (Bailer-Jones et al. 1997; Snider et al. 2001) moved from MK stellar classification to parameterization of astrophysical parameters (T_{eff} , $\log(g)$, $[\text{Fe}/\text{H}]$). Although the philosophy of classification and parameterization are different, they strive to serve the same community. Classification seeks to place any program star within the framework defined by a series of standards. Since the MK classification system is so widely used and the connection to stellar parameters such as absolute magnitude, surface temperature, and mass, are in general well known, this has been a productive route for studying individual stars, local stellar populations, and Galactic structure. Stellar parameterization seeks to skip the initial step of MK classification and directly determine atmospheric parameters. The cost is that the results are model dependent, but in many parts of the HR diagram model spectra look very much, though not exactly, like real stellar spectra. In addition, model atmospheres can be easily constructed for subsolar metallicity, and therefore these can be applied to spectra which would not be possible to classify on the MK system. Bailer-Jones et al. (1997) passed their objective prism spectra through ANNs trained on stellar atmosphere models and derived a detailed mapping between MK classifications and the Kurucz (1979, 1992) model atmosphere set they used (as implemented with the program SPECTRUM by Gray & Corbally 1994). They also reported that the mean metallicity in the solar neighborhood, as represented by Houk's (1982) objective prism spectra, is slightly subsolar, at $[\text{Fe}/\text{H}] = -0.2$. Snider et al. (2001) turned the problem around and trained ANNs on real stellar spectra using atmospheric parameters previously derived from fine abundance analysis work in the literature, now in three-dimensional parameter space. They achieved $\sigma(T_{\text{eff}}) \approx 150$ K, $\sigma(\log(g)) \approx 0.33$ dex, and $\sigma(\text{Fe}/\text{H}) \approx 0.2$ dex.

2. A FEW LESSONS LEARNED

Here we offer a few comments on lessons we have learned in applying ANNs to the problems of spectral classification and parameterization:

- Classification in spectral type and parameterization in T_{eff} are easy, the ANNs have little trouble finding a good global solution, and the results are generally precise to less than a spectral subtype or 200 K.
- Luminosity classification and $\log(g)$ parameterization are possible, but more difficult. Both require spectra with an adequate combination of resolution, wavelength coverage, and S/N. This spectral quality is just achieved with classical MK objective prism resolution and wavelength coverage.
- ANNs are best suited to stellar classification/parameterization when a single wavelength range and resolution are used for a particular ANN.
- If low S/N spectra are used, besides the higher random errors, ANNs may make systematic errors unless they have been trained on low S/N spectra (Snider et al. 2001).
- Supervised ANNs treat spectra as patterns with a known correlation between those patterns and answers, and attempt to learn that relationship. The better one can homogenize the training data so that the ANN does not find spurious correlations between the input catalog and the answers the better results one achieves. Larger catalogs always help in this regard, as do uniform data sets. Spurious correlations caused by real astrophysics can also be a problem. As an example of this phenomenon, the Houk catalog is magnitude-limited with $V_{\text{limit}} = 10\text{--}11$. This magnitude limit creates a correlation between spectral type and luminosity class, i.e., the catalog contains mostly early type dwarfs and late type giants. Without proper scrutiny one might believe a trained ANN has achieved true luminosity classification using such a catalog when the ANN could have learned to classify luminosity statistically based on spectral type.
- Principle Component Analysis (PCA) can be used to compress stellar spectra or to remove spurious signals (e.g., Storrie-Lombardi et al. 1995). PCA also bears a strong resemblance to ANNs (Lahav 1995), and is a good pedagogical tool to gaining a heuristic understanding of ANNs. By creating a series of vectors, a linear combination of which will recreate any star in the library, PCA recasts a stellar spectral library in much the same way as the hidden nodes in a single hidden layer ANN.
- Spectral classification errors are a function of spectral type, based largely on the number of examples and variance within a given type or range of types. For example, Bailer-Jones et al. (1998) found $\sigma(\text{SpT})=0.5$ for B3 to A0 stars and $\sigma(\text{SpT})=0.8$ for F3 to G1 stars. The lower errors for the B and A stars are probably the result of reduced sensitivity of their spectra to abundance differences.
- It is easiest to build multiple ANNs, each specializing in a specific dimension, when solving multi-dimensional spectral classification or parameterization problems. Not only are the ANNs more likely to converge on a good global solution, but less data are required for this approach. For example, Snider et al. (2001) built ANNs specializing in each of T_{eff} , $\log(g)$, and $[\text{Fe}/\text{H}]$. Weaver (2000) has also found it helpful to use one ANN for initial rough classifications, followed by specialist ANNs, trained on a limited spectral type ranges, to refine the classifications.

3. PROPOSED CLASSIFICATION AND PARAMETERIZATION FOR THE MASSES

Can we build automated spectral classifiers for general use? For some time Bob Garrison has pointed out that we could build stellar classifiers for particular spectrographs. Users of such spectrographs might have a near real-time reduction pipeline, immediately following which they would receive a stellar classification. This is certainly possible. In fact, if the data were obtained in a standard manner, the only reduction steps required prior to ANN classification would be spectral extraction and wavelength calibration.

In practice, neither we nor, to the best of our knowledge, any other group has taken this approach. The difficulties are not technical, but rather the time-consuming nature of building multiple such classification machines for the many possible spectrographs in use by stellar spectroscopists. Certainly, if a stellar spectroscopic survey of sufficient size were to be undertaken which would create a uniform data set of sufficient quality, we and others would be motivated to build a tailor-made stellar classification or parameterization machine for that instrument/survey.

We propose instead a thematically related approach. Instead of building ANN classification/parameterization machines for particular spectrographs, we propose to build such machines for particular combinations of wavelength coverage, resolution, and S/N, and make these available for use via the web. It would be up to the user to process their data onto a linear flux and wavelength scale at one of the resolutions and wavelength ranges supported by our web site algorithms. Users would upload their spectra, run the classification or parameterization ANNs, and receive a spectral type and luminosity class and/or the stellar astrophysical parameters, along with the associated uncertainties.

We hope to develop such a tool first by beginning with stellar parameterization based on model atmospheres. Our entire approach would be modular and would initially support a single resolution and wavelength range, while covering the parameter range $4500 \leq T_{\text{eff}} \leq 8000$, $2 \leq \log(g) \leq 5$, $-4.5 \leq [\text{Fe}/\text{H}] \leq +0.5$, and $0 \leq \text{microturbulence} \leq 1/2$ the stellar rotation break-up velocity. Our initial resolution and wavelength range have not been finalized, but would probably be $R \approx 2000$ and 150 \AA around $\text{H}\beta$, respectively. This would allow anyone with higher resolution spectra or spectra with a broader range of wavelengths to take advantage of our first automated parameterization algorithms. As we move to support a wider range of spectral resolutions and wavelength coverages we also intend to add modules to increase our effective temperature range to $T_{\text{eff}} = 50,000$, decrease our surface gravity range to $\log(g) = 1$, include different relative O, Mg, and Ca abundances, and begin spectral classification on the MK system for stars of near solar metallicity. Eventually we hope to push the stellar parameters into the M, L, and T dwarf regimes. We recognize that model atmospheres are never perfectly accurate and that they improve with time. From time to time, where meaningful advances have been made for a particular range of stellar atmospheres, we will upgrade our parameterization modules.

Our anticipated users are spectroscopists doing fine-abundance analysis who want a starting point or a sanity check on their result, those conducting surveys who need classifications or parameterizations for statistical or pre-selection purposes, and those wanting independent determinations of the classifications/parameters for their program stars for a wide variety of studies.

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