Stellar spectra exhibit wider range of spectral features as the stars move along the evolutionary track. These variations are caused by different physical processes continuously happening throughout the star. Yet the underlying factors that shape them can be summarized into two physical parameters, the temperature and the gas pressure, towards the outer layer of the stars. Close inspection of the spectra not only reveals the physical processes behind their wizard appearance but also provide powerful means to know a lot about the Interstellar medium (ISM). It provides a basic tool to measure the interstellar extinction and the composition of ISM, amongst various other things. Absolute or differential photometry is the standard method to find the interstellar reddening. However, exploration of stellar spectra using machine learning tools has greatly facilitated both classification and extinction measurement. In the present chapter, we discuss UV features of different stellar types and present results of classification obtained by employing artificial neural network (ANN)
3.1 Stellar Spectral Features and Classification

The ANN has been used in this chapter, for the automated stellar classification of IUE database and to measure the interstellar extinction in terms of \( E(B - V) \) magnitudes. While earlier works in this field have used the full stellar spectra, the present work uses the simulated band data, as expected from the TAUVEX satellite, for the purpose.

3.1 Stellar Spectral Features and Classification

Spectra of different stars present different features based on the prevailing physical conditions in them, as was discussed in section §1.1.1. At the onset of the astronomical classification, when only the optical window (4500Å-7500Å) of the electromagnetic radiation was accessible to mankind, the stellar classification was done based on the optical features only. In those days, the lack of technology kept the spectra limited in the optical window with low-resolution spectra, recorded on photographic plates. The signal to noise (S/N) ratio used to be low for these spectra. The boundary between the spectral types were drawn by the presence or absence of different absorption or emission lines.

For example, the O spectral class was originally defined by the presence of absorption lines of He II at blue-violet wavelengths, particularly the Pickering series [85], although these lines are now well detected up to B0.5 in modern high S/N data [86]. Fig.3.1 shows the optical spectra of stars with different spectral types according to the MK classification system. The figure describes specific features of each of the spectral types. The MK classification system is based on two fundamental ideas, (i) ionization equilibrium and (ii) pressure broadening of hydrogen lines due to the Stark and the Zeeman effects [87].
Accordingly, stars are classified as O, B, A, F, G, K, M, L in the decreasing order of temperature at stellar surface layer.

<table>
<thead>
<tr>
<th>Temperature (K)</th>
<th>Spectrum Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>650 nm</td>
<td>Hydrogen</td>
</tr>
<tr>
<td>400 nm</td>
<td></td>
</tr>
<tr>
<td>30,000 K</td>
<td>O</td>
</tr>
<tr>
<td>20,000 K</td>
<td>B</td>
</tr>
<tr>
<td>10,000 K</td>
<td>A</td>
</tr>
<tr>
<td>7000 K</td>
<td>B</td>
</tr>
<tr>
<td>6000 K</td>
<td>A</td>
</tr>
<tr>
<td>4000 K</td>
<td>G</td>
</tr>
<tr>
<td>3000 K</td>
<td>M</td>
</tr>
</tbody>
</table>

Many molecules

Figure 3.1: Spectral classification in optical. Adapted from http://zebu.uoregon.edu
The lines in a spectrum change with temperature due to the balance between ionization and excitation states of atoms in the outer layers of a star. Among many other factors, the one that most influentially determines the shape of spectral feature is the pressure broadening.

Figure 3.2: Hertzsprung-Russel diagram  Adapted from http://www4.nau.edu/meteorite/Meteorite/Images/Hertzsprung-Russell.jpg

With the average density ranging between $10^{-8}$ and $10^6$ times $M_\odot$, smaller size stars have greater surface pressure or greater surface gravity. Hence atoms
3.1 Stellar Spectral Features and Classification

and electrons are more closely packed for those stars. This leads to the perturbation of energy levels resulting in the broadening of the spectral lines. Accordingly, each of the spectral types are further classified into luminosity classes I, II, III, IV, V, VI, VII in the increasing order of surface gravity. Thus, the MK-classification system is a two dimensional (2D) classification system. The scatter distribution of stars in a 2D space is known as the Hertzsprung-Russell diagram, or more commonly, as HR diagram; this is depicted in Fig 3.2, and a description can be found in any standard textbook on stellar astrophysics.

Later access to the shorter wavelength windows, viz., ultra-violet (UV), X-ray up-to gamma-ray (γ-ray) and in the longer wavelength side, viz., infra-red, radio has brought a different era in the field of astronomy. This has facilitated, for astronomers, access to almost the entire range of electromagnetic radiation. The following section discusses spectra of different classes of stars in the light of optical and UV information. The spectra have been normalized to unity at the maximum intensity of each spectra separately. Such normalization clearly displays the changes in UV flux as temperature decreases. The spectra are taken from the *International Ultraviolet Explorer (IUE) low resolution spectra reference atlas, normal stars, ESASP-1052* by Heck et al. [88]. The strongest feature captured by the satellite was Lyman-α line at λ 1216Å. The other lines of the series, being weaker in intensity, were not easily discerned by the satellite. For stars cooler than the Sun, chromospheric and coronal activities increase and photospheric contribution in the ultraviolet decreases. Besides temperature and gravity, the chromospheric and coronal activities are affected by other factors also, such as, rotation and magnetic field of the star. Because of this reason, the emission lines induced in the chromospheric and the coronal regions cannot be used for MK spectral or luminosity classification, the
classification being based only on the temperature and the pressure condition of a star. In the following subsections we have presented some of the salient features of stars of different spectral types in the ultra-violet waveband and they have been subsequently used for classification using ANN.

3.1.1 O-type

The O-type stars are the young stars. Their effective temperature is higher than 30,000K with dominant emission in the ultra-violet wavelength. Because of this UV radiation, which gets most effected by dust, the O-type stars are playing a major role in the study of interstellar medium (ISM), galactic evolution etc. O-type of stars show most of the characteristic features in the range of wavelength 1200-2000Å. The main features present in this range are, three
major wind profiles accompanied by three minor ones at the resonance doublets NV $\lambda\lambda 1239\text{Å}, 1243\text{Å}$; Si IV $\lambda\lambda 1394\text{Å}, 1403\text{Å}$; C IV $\lambda\lambda 1548\text{Å}, 1551\text{Å}$, and the subordinate lines OV $\lambda 1371\text{Å}$, He II $\lambda 1640\text{Å}$, N IV $\lambda 1718\text{Å}$, respectively. Among these Si wind profile suffers the most dramatic changes as wind density increases with luminosity, modulo the ionization potentials of the specific features [89, 90]. On the other hand, N V and C IV wind profiles get saturated at all luminosity in early O spectra. But at later O type spectra, when the profiles get weakened, they start showing analogous luminosity effects. Additionally, another wind profile of OV $\lambda 1371\text{Å}$ is a unique signature of O2-O3 giant and supergiant spectra. Fig. 3.3 shows the normalized spectra of O5V star.

**3.1.2 B-type**

B-type star temperature ranges from 10,000-28,000 K. This stellar type exhibits medium strength Balmer lines of hydrogen and of neutral helium in blue-violet spectra, see Fig. 3.4. The lines are shallower and narrower at higher luminosity due to the *Stark effect*. In ultra-violet, characteristic lines are Si II $\lambda 1264\text{Å}, 1265$ Si III $\lambda 1299\text{Å}$, $\lambda\lambda 1341\text{Å}, 1343\text{Å}$, C II $\lambda\lambda 1334\text{Å}, 1335\text{Å}$, C III $\lambda\lambda 175\text{Å}, 1176\text{Å}$, Al II $\lambda 1671\text{Å}$, Al III $\lambda 1863\text{Å}$. The Lyman-$\alpha$ line strengthens considerably towards the later types whereas He II $\lambda 1640\text{Å}$ line disappears at about B2. However, this limit is dependent on the resolution of observation. Other strong features present in the B-type stellar spectra include, the resonance lines of C IV $\lambda 1550\text{Å}$, Si IV $\lambda 1400\text{Å}$ and N V $\lambda 1240\text{Å}$. These lines basically arise in the stellar wind.

It is to be mentioned that the study of B-type stars has played a major role in early development of astrophysics. By providing a simple radiative atmosphere, this stellar class has facilitated the early development of stellar-
3.1 Stellar Spectral Features and Classification

Figure 3.4: Normalized spectra of B3V star

atmosphere model and later in the development of non-local thermodynamic equilibrium (NLTE) atmosphere models as well as theories of spectral-line formation. Another important result from the study of the B-type stars is the discovery and mapping of spiral structure of the Milky-Way galaxy [86].

3.1.3 A-type

The temperature of A-type star ranges from 7500-10,000 K. This stellar type shows the most speculating varieties in characters among all spectral classes. They may be normal stars with strong hydrogen lines of the Balmer series or may be peculiar stars with large abundance or under-abundance of some chemical elements. When all heavy elements are enhanced in stellar atmosphere, then those A-type stars are known as the Am or metallic line stars. In some
other cases, only selected elements have greatly enhanced abundance. Those stars are known as the Ap or the peculiar A-type stars. In reality, most of the Ap stars are actually B-type stars in terms of effective temperature [86]. The emissions from the convective zone starts from this type of stars onwards. In any case, besides the Balmer line, the blue-violet features include the Ca II lines strengthening towards the later types and general metallic-line spectrum showing similar nature like Ca II. The UV spectra of A-type stars are more analogous to optical spectra of K-type stars with high density of lines with visibly no continuum. The other features to be mentioned include Mg II h & k blend at λ 2580Å and λ 2860Å. These lines change their behavior similar to that of Ca II lines. The doublet profile at λ1848Å changes to a tooth-like feature towards late type A-stars. The morphology of λ2375Å feature also

Figure 3.5: Normalized spectra of A5V star
changes into a flat-bottomed broad absorption features by early F-type stars

### 3.1.4 F-type

In F-type stars, convective zone expands and deepens beyond the photospheric layer and by late F/early G type, the atmosphere becomes almost entirely convective.

![Normalized spectra of F3V star](image)

**Figure 3.6:** Normalized spectra of F3V star

The convection mixes stellar atmosphere and the underlying convective envelope thoroughly. Molecular bands start appearing in optical wavelength. However, the shorter wavelength side lacks sufficient spectral features. Because of this, only some initial attempts have been taken to set up a classification system in UV range. Heck et al., for example, have classified the IUE low
3.1 Stellar Spectral Features and Classification

dispersion UV spectra [88].

In UV, spectral energy distribution of F-type stars is strongly dependent on metallicity. Spectra shows strong features of neutral and ionized lines of magnesium and iron. The Mg II line at $\lambda$ 2880Å continues to increase in strength and width as one moves towards the G-type stars. Other features include a blend of Fe I and Fe II features at $\lambda$ 2745Å, and Mg I line at $\lambda$ 2852Å. In late F-type stars, a strong Si I line appears at $\lambda$ 2881Å and a relatively weak, but broad feature develops towards short wavelength side of Fe II, Fe I $\lambda 2745$Å blend. While these Mg/Fe/Si features provide the spectral classification there are hardly any positive features for the luminosity classification. In optical wavelength, the luminosity criteria are provided by ionized iron and titanium. High resolution UV spectra from upcoming missions can be hoped to provide sufficient features for luminosity classification. Fig 3.6 shows the UV spectra of F-type stars.

3.1.5 G-type

The temperature for G-type star ranges from 5,000-6,000 K. Our Sun is a G-type giant star. The boundary between G-type stars and F-type stars is not a distinct one. In G stellar type, the G-band characteristically dominates over other features. Fig.3 7 shows the UV spectrum of a giant G-type star. Like F-type stars, as has been mentioned in §3.1.4, no formal attempt has yet been made to set a classification scheme for this spectral type, as they lack sufficient spectral features [86] in UV. Nevertheless, preliminary investigation of the IUE spectra has revealed metals as the main cause of opacity in UV range. The Mg II h & k lines developed in F-type stars continue to increase both in strength and width into this stellar type. Molecular features develop at $\lambda$ 3066Å and $\lambda$
3.1 Stellar Spectral Features and Classification

3.1.6 K-type

These stars are orange to red in color. Their temperature ranges between 3,500 - 5,000 K. Their spectra are dominated by H and K lines of calcium, and lines of neutral iron and titanium. Molecular bands are due to cyanogen (CN) and titanium dioxide (TiO). These features become increasingly prominent at the cooler end of the range. Figure 3.8 shows UV spectrum of K type giant stars.
3.2 Automated Stellar Spectral Classification

Although spectroscopy is the most commonly used and widely known technique for classification, it is not the only technique. Multicolor photometry is an alternate technique used for classification. In photometry, measurement of the stellar fluxes are done in preferred spectral bands. Isolation of selected band fluxes are carried out with glass and/or interference filters depending on the purpose of the scientific study at hand. Accordingly, different missions design their own photometric filters. Still, so far the most widely used filter system is the Johnson UBV system \cite{91}. Figure 3.9 shows the transmission curves of Johnson and Morgan UBV filter system. While spectral classification
is based on the distribution of line spectrum, multicolor photometry extract information by extracting the continuum features in a spectra. For example, in UBV system, U-V and B-V indices, where U, B and V are stellar fluxes in the U, V and B filters respectively measured in units of magnitude, are sensitive to the Balmer jump and slope of the Paschen continuum. Therefore, the indices give measure of the effective temperature leading to stellar spectral classification of stars. However, unlike spectral classification, the limitation of photometric classification lies in the fact that even the best designed photometric system is not completely free from degeneracies. Because of these degeneracies, stellar types with quite different physical parameters overlap in the color-color diagram [92]. Additionally, combined effect of different nonlinear phenomena, like interstellar reddening, rotation, metallicity etc, also leads
into confusion in translation of photometric indices to MK types. Craw et al. [93] and Gray et al. [92] have reviewed the issues in detail and have concluded that photometry is complementary to the MK spectral classification.

Another modern technique for classification of large data base is to automatize the process. Such technique has the benefit of recursive use. The method consumes less time and provides a more objective classification of objects. Fig 3.10 provides a flowchart of data handling in two cases, such as, when data volume is smaller and when it is a bigger one. There are mainly two approaches to achieve this goal, viz., the metric-distance technique and the Artificial Neural Network (ANN) based technique. The metric-distance technique assumes that the features are represented in a vector space. For example, for a digitized spectrum with \( n \) number of resolution elements, the metric-distance method considers the spectrum as an \( n \)-element vector and defines the metric distance between a program spectrum \( X \) and a standard \( S \) as

\[
d_{xs} = \frac{1}{n} \sqrt{\sum_{i=1}^{n} \alpha^2 (X_i - S_i)^2}
\]  

(3.1)

where the weighting factors \( \alpha^2 \) is defined in such a way that the highest weights are given to those features that most strongly discriminates the final spectral type from other surrounding spectral types [94]. This method is quite close to the original philosophy of the MK system. However, the method demands the removal of the shape of the continuum from the spectra. This makes it difficult to use the technique for late-type stars. On the other hand a ANN based scheme does not require the spectra to be rectified. Because of this reason, ANN have been used extensively for different classification systems.
The present work has made use of the Back-propagation algorithm based ANN in hierarchical fashion for stellar classification and extinction measurement. The back-propagation algorithm has two distinct properties, namely, (a) the computation involved is simple, and (b) it performs stochastic gradient descent in weight space. Because of these properties, backpropagation algorithm has emerged as the most popular algorithm for supervised training of multilayer perceptrons [57].

The main disadvantage of the hierarchical ANN, employed in the work of the present chapter (and also in the next chapter), is that the error can propagate from one stage to the next stage of operation. An alternative way to avoid hierarchy is to go for the principal component analysis (PCA). PCA
reduces the number of parameters in the network and hence the volume of computation required. But the disadvantage of this method is that the very weak features having very small correlation across the data can be lost in a PCA reconstruction.

3.2.1 ANN architecture

We have already discussed about the working principle of back propagation algorithm in section §2.3. This section describes the architecture of ANN used for classification, the generation and pre-processing of the data required to train and test the network, methodology and the performance result of ANN.

In defining topology of ANN, there are two decisions to be taken, namely, the number of hidden layers that the network must have, and secondly, the number of hidden neurons that must be associated with each of these layers. But unfortunately, there is no any well established theoretical limit on this number. However, earlier works have found that while a single hidden layer network can approximate any function that contains a continuous mapping from one finite space to another, a two hidden layers network can represent an arbitrary decision boundary to arbitrary accuracy with rational activation functions and can approximate any smooth mapping to any accuracy [95]. Also, there are disagreements regarding number of hidden nodes that a hidden layer must have. Too few nodes can lead to under fitting and too many nodes can lead the system towards memorizing the patterns in data. According to Kolmogorov's theorem, twice the number of input nodes plus one number of hidden nodes is sufficient to compute any arbitrary continuous function [96]. Wanas et al. [97] claim that the best results, in terms of both performance and computation time, occurs when the number of hidden nodes is equal to log (n),
3.2 Automated Stellar Spectral Classification

\( n \) being the number of training samples. However, there is no real consensus on this matter in literature. There are many other methods, essentially based on rule-of-thumb for determining number of neurons to use in hidden layers, such as, (a) the number of hidden neurons should be between the size of the input layer and the size of the output layer, (b) the number of hidden neurons should be \( 2/3 \) the size of the input layer, plus the size of the output layer, (c) the number of hidden neurons should be less than twice the size of the input layer [95]. These rules provide a starting point only, the ultimate selection of a network architecture will essentially boil down to trial and error only.

For stellar classification and finding interstellar reddening, we have considered a back propagation algorithm [5, 13, 98, 99] based supervised neural network with 2 hidden layers and 64 nodes each. The number of input nodes is equal to the size of an input pattern presented to the network. On the other hand, the number of output nodes is the number of classes or groups into which one wants to classify the data. Thus, in stellar classification, the number of output nodes is 58 (equal to the number of spectral classes) and in determining the interstellar reddening the number of output nodes is 21 (equal to the number of \( E(B-V) \) values). Training has been done using both full spectra as well as band integrated data as expected from the TAUVEX satellite. The two cases correspond to 40 and 4 input nodes respectively. The generation of simulated data and their pre-processing are described in §3.2.2.

As discussed in section §2.1.1, response of a neuron depends on the activation function used to control output of the neuron. The function must be continuous, as its derivative is taken during training. The activation function used in the present ANN architecture is the Logistic Function. It is mathe-
matically defined as

\[ f(x) = \frac{1}{1 + \exp(-ax)} \]  
(3.2)

The function normalizes the input parameter in the interval \([0,1]\).

Figure 3.11: Gradient descent rule in error \((2+1)\) curve

Error has been minimized using the gradient descent rule, the error surface being a \((m+1)\) dimensional surface, as shown in fig 3.11. Here the number \(m\) correspond to total number of weight connections in the network and the \(m + 1\) -th dimension is the error vector in the surface. The weights get modified according to equation 2.12. Table 3.1 and table 3.2 summarize the ANN parameters of the two configurations.

Here we found that smaller values of \(\alpha\) and \(\eta\) give better classification
3.2 Automated Stellar Spectral Classification

Table 3.1: ANN parameters for spectral classification

<table>
<thead>
<tr>
<th>Parameters</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>number of input nodes</td>
<td>40 (full spectra mode)</td>
</tr>
<tr>
<td></td>
<td>4 (band integrated spectra mode)</td>
</tr>
<tr>
<td>number of hidden layers</td>
<td>2</td>
</tr>
<tr>
<td>hidden layer nodes</td>
<td>64</td>
</tr>
<tr>
<td>output nodes</td>
<td>58</td>
</tr>
<tr>
<td>activation function</td>
<td>$1/[1 + \exp(-x)]$</td>
</tr>
<tr>
<td>gain parameter ($\eta$)</td>
<td>0.1</td>
</tr>
<tr>
<td>momentum parameter ($\alpha$)</td>
<td>0.1</td>
</tr>
<tr>
<td>threshold value</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

Table 3.2: ANN parameters for extinction measurement

<table>
<thead>
<tr>
<th>Parameters</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>number of input nodes</td>
<td>40 (full spectra mode)</td>
</tr>
<tr>
<td></td>
<td>4 (band integrated spectra mode)</td>
</tr>
<tr>
<td>number of hidden layers</td>
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</tr>
<tr>
<td>hidden layer nodes</td>
<td>64</td>
</tr>
<tr>
<td>output nodes</td>
<td>21</td>
</tr>
<tr>
<td>activation function</td>
<td>$1/[1 + \exp(-x)]$</td>
</tr>
<tr>
<td>gain parameter ($\eta$)</td>
<td>0.1</td>
</tr>
<tr>
<td>momentum parameter ($\alpha$)</td>
<td>0.1</td>
</tr>
<tr>
<td>threshold value</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

results and it consumes approximately 3 hours in training the network using 64 bit 8 x 4 AlphaServer ES45 68/1250 Systems @ 1.25 GHz.

3.2.2 Simulated data generation for Train set

The training sets for ANN are generated from two independent sources of spectra. One is the stellar flux calculator from TAUVEX website (http://tauves.iap.res.in/htmls/tools/fluxcalc/) containing 286 spectro-luminosity classes and the other is the UVBLUE fluxes [100] (http://www.bo.astro.it/~eps/uvblue/uvblue.html). Metallicity of the stars are same as that of the solar type stars with $[M/H] = 0$ dex. Based on the spectral type and luminosity class of
3.2 Automated Stellar Spectral Classification


Fig 3.12 shows a sample of normalized simulated spectra of different spectral types compared to the real spectra of the same spectral type. The plot presents the discrepancies between the theoretical and the real data very clearly. In the early-type stars i.e. O and B, the main discrepancy between observed and theoretical is near 1500 Å. This is a consequence of the physical origin of the CIV line that gets strongly affected by stellar winds and mass-loss processes in massive stars. For F-type stars the metallic features at 2400 Å (Fe III), 2500 Å (Fe I/Si I), 2800 Å (Mg II) are more enhanced in the simulated spectra. In G-type stars the chromospheric activities increase and thus trigger prominent Mg core emissions. However, this feature is not seen in the simulated spectra as the chromospheric activities are not accounted for in the Kurucz's model [100].

The above generated fluxes need to be processed via a common flux integration program provided at the TAUVE tools site to form two sets of band data. Each of the two sets of data contain four fluxes corresponding to the four TAUVEX bands (SF1, SF2, SF3 and NBF3) and they constitute the simulated
3.2 Automated Stellar Spectral Classification

band data set for the ANN training sets.

We have also obtained two sets of fluxes (with 50Å resolution and 40 data bins covering the spectral region of 1250–3220Å) aimed at preparing the ANN tools for another Indian scientific mission satellite ASTROSAT (http://www.rri.res.in/astrosat/) which will have gratings to provide slit-less spectra for spatially resolved stars. It will also prepare us for the future GAIA mission (http://gaia.esa.int/science-e/www/area/index.cfm?fareaid=26).

![Figure 3.12: IUE and TAUVEX Simulated fluxes for 6 sample stars at a resolution of 50Å.](image)

While making the train and test sets, one has to ensure that the number
of spectral fluxes at the respective wavelengths and the starting and ending wavelengths are identical. Also the spectral resolution needs to be same and for this, the spectral libraries had to be convolved with appropriate Gaussian functions to bring them at par with each other. The fluxes are normalized to unity with respect to maximum flux in each spectrum before sending to the ANN inputs. The spectra for 286 TAUVEK spectral types generated in the range 1250-3200\AA have a resolution of 10\AA which we have degraded to 50\AA using Lagrange's interpolation method. The resolution of 277 UVBLUE spectral types have been degraded similarly using the relevant online IDL program code with some modification to incorporate the appropriate need in the data structure. These set of spectra are then reddened using the analytical model of Seaton[36] at the IUE wavelength. This model uses $A_V/(B - V) = 3.10$ and is close to the preferred curve of Savage and Mathis [110] except near the 2200 \AA "bump", where it deviates by 5% [19]. The observed flux is related to the emitted one by equation 1.10 as,

$$f_{\text{obs}}(\lambda) = f_{\text{int}}(\lambda)10^{-0.4A_\lambda} \quad (3.3)$$

where, $f_{\text{obs}}, f_{\text{int}}$ are the observed and the intrinsic fluxes and

$$A_\lambda \approx E(\lambda - V) = \left(\frac{E(\lambda - V)}{E(B - V)}\right)E(B - V) \quad (3.4)$$

The $E(B - V)$ values are added in the range of 0.00-1.00 mag. Fig.3.13 is the Seaton's curve and the comparison curve for the O4V type stars with and without extinction. We describe below the details of the procedure adopted for generation of training sets for the two hierarchical stages, from the reddened spectra.
3.2 Automated Stellar Spectral Classification

Figure 3.13: (a) Seaton's Curve, (b) Comparison Curve

Figure 3.14: Filter response curve of TAUVEX satellite.

The procedure adopted for generating the band integrated train and test set
is described with reference to the TAUVEX filter response. For the TAUVEX mission, the observations will be available from 1250Å to 3220Å spectral region using five filters, namely BBF, SF1, SF2, SF3 and NBF3, in the five UV bands.

Fig. 3.14 shows the total response of each of the TAUVEX filters in units of Effective Area cm$^2$ and their approximate characteristics are summarized in Table 3.3.

Table 3.3: TAUVEX filters specifications

<table>
<thead>
<tr>
<th>Filter</th>
<th>Wavelength</th>
<th>Width</th>
<th>Normalized transmission</th>
</tr>
</thead>
<tbody>
<tr>
<td>BBF</td>
<td>2300</td>
<td>1000</td>
<td>80%</td>
</tr>
<tr>
<td>SF1</td>
<td>1750</td>
<td>400</td>
<td>20%</td>
</tr>
<tr>
<td>SF2</td>
<td>2200</td>
<td>400</td>
<td>45%</td>
</tr>
<tr>
<td>SF3</td>
<td>2600</td>
<td>500</td>
<td>40%</td>
</tr>
<tr>
<td>NBF3</td>
<td>2200</td>
<td>200</td>
<td>30%</td>
</tr>
</tbody>
</table>

Generating data set for Spectral Type determination:

In the first stage, to accomplish the task of spectral classification, reddening values are added to simulated data, using Eqn 3.3, in steps of $E(B - V) = 0.20$ magnitudes. The 0.20 step is chosen for computational convenience. For example, the TAUVEX simulated data set consists of 286 different classes with 58 spectral types, each having 5 luminosity classes (except for O6.5V). If one wants to classify the spectral type, luminosity class and the reddening value in a single run, reddening these 286 data sets with reddening value from 0.00-1.00, even at a step of 0.1 leads to $286 \times 11 = 3146$ number of distinct classes. However, this is not possible with our current computational facilities and the
present version of our ANN. Instead, we go for the hierarchical scheme, wherein all the luminosity classes are merged in the first run. For example, instead of considering O3I-O3V as five separate classes, the ANN will be trained to learn all the five different patterns as single O3 spectral type only, though the variation in all the five spectra still go as input to the ANN. The process thus reduces the number of distinct classes from 286 to only 58 classes, making the computation fast. When the learning process is completed, ANN can separate different Spectral types, thus making it possible to find out the reddening values in the next stage.

Generating data set for evaluation of reddening:

In the second stage, reddening values are added in step sizes of $E(B-V) = 0.05$ to the simulated data. The separation of the available spectra into different groups O, B, A, F, G, K etc. in the first stage, makes it possible to select this finer precession of step size of 0.05. In our work we have not classified the luminosity classes separately, however, this can be done easily by adding one more stage in the hierarchical scheme.

After addition of extinction only, the fluxes are processed via the above mentioned flux integration program to form two sets of band data. One set corresponds to the TAUVEK simulated spectra and the other set corresponds to the UVBLUE library spectra. Each of the two sets have four flux values corresponding to four filters SF1, SF2, SF3 and NBF. As the BBF filter aggregates over other four filters, it does not provide any new pattern to the ANN. Hence the BBF filter is not taken into account in finding out the band data.

Fig 3.15 shows the discrepancy between the theoretically simulated data and the real observation spectra in term of band data. The discrepancy is more
3.2 Automated Stellar Spectral Classification

clearly visible towards the late type stars.

![Figure 3.15: Integrated IUE and Simulated TAUVEX fluxes for the same 6 sample stars in NBF, SF1, SF2 and SF3 filters along with the residues in the corresponding lower panels.](image)

The final training set thus contains (a) the spectra in the form shown in Fig 3.12 and (b) 4 flux values in the 4 bands of TAUVEX in the form shown in Fig.3.15 – for each of the 286 TAUVEX spectra (277 spectra for the UVBLUE case) with reddening in the range of 0.00 to 1.00 mag with a step of 0.2 mag.

Fig.3.16, fig.3.17 shows a block diagram of the flow chart for preparing these two training sets for spectral type classification and extinction measurement.
Figure 3.16: A block diagram showing the flow chart for creating the ANN train set for spectral classification with TAUVEX and UVBLUE simulated sources.
3.2 Automated Stellar Spectral Classification

![Block Diagram](image)

Figure 3.17: A block diagram showing the flow chart for creating the ANN train set for extinction classification for both simulated sources i.e. TAUVEX and UVBLUE.

3.2.3 ANN test sets

The test spectra were taken from the IUE low resolution spectra: reference atlas, normal stars, ESA SP-1052 by Heck et al. [88]
3.2 Automated Stellar Spectral Classification

Figure 3.18: A block diagram showing the flow chart for creating the ANN test set for spectral classification corresponding to the fig 3.16.

The atlas contains 229 low-dispersion flux calibrated spectra of O to K spectral type. The spectra are available online on the CDS (Centre de Données astronomiques de Strasbourg) webpage (http://cdsarc.u-strasbg.fr/viz-bin/Cat?target=http&cat=III%2F83&). The spectra have been trimmed in range...
3.2 Automated Stellar Spectral Classification

1250-3220Å. The original resolution of 6Å of spectra have been brought down to 50Å by convolving with appropriate Gaussian function and then the spectra have been processed via a common integration program as discussed in the training set generation section. Fig.3.18 shows the block diagram of the flow chart for generating this IUE test set for spectral classification and fig.3.19 shows the corresponding block diagram of the flow chart for creating the IUE test set for extinction measurement respectively.

The performance of a machine learning algorithm depends on an appropriate knowledge representation for the input presented to the program. Table 3.4 shows the number of spectra per spectral type used in this analysis. The numbers in the 2nd and 3rd column are the basic sets for training sessions of the ANN. The hierarchical ANN scheme we have used works in two stages as has already been mentioned before viz the 1st stage which performs the spectral type classification and for this these numbers get multiplied by 6, and the 2nd stage which performs the color excess classification; in this case, these numbers get multiplied by 21. Further, in order to have a uniform number of spectra per spectral type, classes which have just one example are duplicated during the training session.

Table 3.4: Number of Spectra for each data set according to the spectral types.

<table>
<thead>
<tr>
<th>Spectral Class</th>
<th>TAUVEK</th>
<th>UVBLUE</th>
<th>IUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>O</td>
<td>36</td>
<td>36</td>
<td>42</td>
</tr>
<tr>
<td>B</td>
<td>50</td>
<td>41</td>
<td>115</td>
</tr>
<tr>
<td>A</td>
<td>50</td>
<td>50</td>
<td>48</td>
</tr>
<tr>
<td>F</td>
<td>50</td>
<td>50</td>
<td>20</td>
</tr>
<tr>
<td>G</td>
<td>50</td>
<td>50</td>
<td>3</td>
</tr>
<tr>
<td>K</td>
<td>50</td>
<td>50</td>
<td>1</td>
</tr>
</tbody>
</table>

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Figure 3.19: A block diagram showing the flow chart for creating the ANN test set for extinction classification corresponding to the fig 3.17.
3.3 ANN performance and Classification Results

Fig 3.20 and fig 3.21 represent the learning curves when the ANN has been trained with the UVBLUE library spectra and TAUVEX simulated spectra respectively. The learning curve is a plot of root mean-squared error vs number of epochs.

The stable part of the learning curves ($\Delta \text{error} \approx 10^{-4} < \text{threshold value}$) are presented in miniwindows of the respective plots. Once the learning is over the weights at the nodes are frozen and the network is now ready for testing on IUE spectra.

The results of spectral classification are depicted in the Fig 3.22. The
3.3 ANN performance and Classification Results

Figure 3.21: Learning curve of ANN with TAUVEX training set in full spectra mode

numbers on the axes of this figure refer to the spectral coding. This is done to make the network understand different spectral classes and the luminosity classes in terms of the numerical values. The coding system is briefly as follows:

The main spectral classes are represented by numerical values (MSp) from 1000 to 6000 in the decreasing order of temperature. To the main spectral type the sub-spectral types are added in units of 100. Finally the luminosity classes are represented, such that, I = 1.5, II = 3.5, III = 5.5, IV = 7.5 and V = 9.5. This gives the final numerical code as MSp + SubC + (1.5 + 2 * LC). For example, the Sun is a G2V star. For it MSp = 5000, SubC = 200 and LC = 9.5 yielding the numerical code as 5209.5.

A classification error of 500 in the scatter plot implies deviation of two sub-classes, for example, a G2 star can, at worse, be classified either as F7 or G7 spectral type.
Figure 3.22: Scatter plots of classification of the 229 IUE stars with TAUVEK bands and fluxes and with UVBLUE bands and fluxes. The classification accuracy values $\sigma$ are shown for each case in units of sub-spectral types.

Figure 3.23 shows the scatter plots for pre-classified IUE stars (in O, B, A and F spectral types) for UVBLUE fluxes with their color excess estimates $\sigma$ in units of magnitudes. Figure 3.24 shows the scatter plots for pre-classified IUE stars (in O, B, A and F spectral types) for UVBLUE bands with their color excess estimates $\sigma$ in units of magnitudes. Figures 3.25 & 3.26 show the
3.3 ANN performance and Classification Results

corresponding classification results for TAUVE fluxes and bands respectively

\[ \begin{align*}
\text{O-Type (UVBLUE Flux)} & \quad \sigma = 0.11 \\
\text{B-Type (UVBLUE Flux)} & \quad \sigma = 0.08 \\
\text{A-Type (UVBLUE Flux)} & \quad \sigma = 0.14 \\
\text{F-Type (UVBLUE Flux)} & \quad \sigma = 0.18
\end{align*} \]

Figure 3.23: Scatter plot of classification of 229 IUE stars (pre-classified into O, B, A and F spectral types) with UVBLUE fluxes for colour excess estimates. The classification accuracy values \( \sigma \) are shown for each case in units of E(B-V) magnitudes.

In these 3D scatter plots, the 'Cat' and 'ANN' denote the catalog and ANN classes respectively. Further, the vertical axis in the plots gives the number of stars (N) present for a particular color excess value and are re-scaled as the square root of the actual number (i.e. \( N^{1/2} \)) for better representation; otherwise in the cases where this number is large, the corresponding points for single stars would look too small on the plots.

It is important to see that in the spectral classification scheme, the outliers in the all the four panels of Fig.3.22 belong to G and K type, they being misclassified as the F type stars. This can be attributed to the discrepancies mentioned in section §3.22. In the two exceptional cases G8 gets classified as
3.3 ANN performance and Classification Results

O2 type in FLUX UVBLUE panel whereas A2 gets classified as K3 in FLUX TAUVE panel. The misclassification of G8 as O2 may be because as G8 IUE spectra shows a moderate UV excess compared to the theoretical one as mentioned in Rodriguez-Merino et al. (2005) [100].

![Figure 3.24](image)

**Figure 3.24:** Scatter plot of classification of 229 IUE stars (pre-classified into O, B, A and F spectral types) with UVBLUE bands for colour excess estimates. The classification accuracy values $\sigma$ are shown for each case in units of E(B-V) magnitudes.

From the Figs.3.23, 3.24, 3.25 & 3.26 we see an overall colour excess estimate accuracy in the range of 0.20 in the worst case of F-Type spectra with band data to 0.06 in the best case for B-Type spectra with band data. The results with band data show better accuracies in comparison to the fluxes which may indicate that band data is a better estimator for colour excess than the fluxes.

The ANN inputs take most of the information in terms of absorption fea-
3.3 ANN performance and Classification Results

Figure 3.25: Scatter plot of classification of 229 IUE stars (pre-classified into O, B, A and F spectral types) with TAUVEX fluxes for colour excess estimates. The classification accuracy values $\sigma$ are shown for each case in units of $E(B-V)$ magnitudes.

...which are embedded in the full range of spectral fluxes (or the integrated fluxes in the band data) for performing the classification. Thus information is available for the hot stars like O, B and A but lacks in F or later spectral types. Due to this reason, the ANNs do not provide a good estimate of reddening for these late type stars. Thus we have not estimated the colour excess for the G and K type IUE spectra (the 3 G star and 1 K star of the IUE test set mentioned in Table 3.4 have no reddening). Table 3.5 summarizes the results for both spectral type classification and colour excess estimation. It is seen from the table that for stellar classification and extinction measurement the band data configuration performs better than the full spectra configuration in terms of the error.
3.3 ANN performance and Classification Results

Figure 3.26: Scatter plot of classification of 229 IUE stars (pre-classified into O, B, A and F spectral types) with TAUVEX bands for colour excess estimates. The classification accuracy values $\sigma$ are shown for each case in units of E(B-V) magnitudes.

Table 3.5: Summary of Classification results.

<table>
<thead>
<tr>
<th>Simulated Source: Simulated Source:</th>
<th>TAUVE</th>
<th>UVBLUE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Flux</td>
<td>Band</td>
</tr>
<tr>
<td></td>
<td>3.97</td>
<td>3.84</td>
</tr>
</tbody>
</table>

Colour Excess E(B-V) Error

<table>
<thead>
<tr>
<th>Spectral Type</th>
<th>TAUVE Flux</th>
<th>TAUVE Band</th>
<th>UVBLUE Flux</th>
<th>UVBLUE Band</th>
</tr>
</thead>
<tbody>
<tr>
<td>O-Type</td>
<td>0.10</td>
<td>0.09</td>
<td>0.11</td>
<td>0.09</td>
</tr>
<tr>
<td>B-Type</td>
<td>0.09</td>
<td>0.07</td>
<td>0.08</td>
<td>0.06</td>
</tr>
<tr>
<td>A-Type</td>
<td>0.10</td>
<td>0.08</td>
<td>0.14</td>
<td>0.09</td>
</tr>
<tr>
<td>F-Type</td>
<td>0.10</td>
<td>0.16</td>
<td>0.18</td>
<td>0.20</td>
</tr>
</tbody>
</table>
3.4 Summary

Stellar spectra show wide range of variations on the course of their evolution. The underlying factors that shape them are the effective temperature and the gas pressure at the outer surface of the star. The classification of stellar spectra based on these two parameters leads to a two dimensional scheme, known as the MK classification system. In the present chapter, we have studied stellar spectra in the ultra-violet waveband. The task of setting up a ANN based scheme for stellar classification and for determination of the interstellar extinction in terms of the $E(B-V)$ has been accomplished in this chapter.

Till now several studies have demonstrated that the ANN schemes can reliably and successfully classify stellar spectral data as well as extract fundamental stellar parameters in the visible region. The extension of applicability of this scheme to UV region has been less prevalent mainly because of non-availability of abundant data in this region. Nevertheless, some attempts have been made in the past to automate the process of classification of spectral data from the IUE satellite. In this work, we have demonstrated that the ANN can be successfully employed to classify stellar photometric (band) data.

We have shown that the ANN tools developed by us can successfully classify the 229 IUE spectra reduced to the four TAUVEX bands to an accuracy in the range of 3-4 sub-spectral types. We have also estimated the colour excess for the hot stars (O, B and A types) to an accuracy of up to 0.1 magnitudes in terms of $E(B-V)$ colours. Thus, even with the limitation of data from just photometric bands, ANNs have not only classified the stars, but also provided satisfactory estimates for interstellar extinction.

In the actual post launch of TAUVEX when the real data will be available,
the scheme applied to estimate the colour excess will have to run the ANN in two stages i.e. in a hierarchical manner such that, the first stage classifies the test set (IUE database or the expected TAUVEX database) into the spectral classes and then a second ANN stage performs the colour excess estimation.