1. Introduction

Spectroscopy is a cornerstone of modern astronomy. Our understanding of the composition of stars, molecular clouds, nebulae, and exoplanetary atmospheres is determined via spectroscopy. Spectroscopy is used to search for and to characterize binary companions and exoplanets, to study the environments around stars and galaxies, and to map the distances to galaxies and quasars.

Stellar spectroscopy allows for the measurement of stellar radial velocities (RVs), key for the study of galactic archaeology and evolution, as well as for the study of binary stellar systems and their evolution. Modern spectroscopic instruments and telescopes can determine RVs from the tug of exoplanets around other stars. In the case of double-lined spectroscopic binaries (SB2), spectroscopy can reveal not only the presence of a binary system but information on its individual components. Accurate and rapid stellar classification is crucial to extract physics from stellar spectroscopy, especially in the era of large surveys.

The current spectral classification system, the Harvard system, classifies stars into letter classes that follow a temperature scale. The current classes of O, B, A, F, G, K, M, L, T, and Y represent stars and brown dwarfs across the stellar temperature range. O stars have the highest temperatures found in stars, and the M, L, T, and Y dwarfs are the coolest (and most abundant; see Bochanski et al. 2010) spectral types that span the change from stars to brown dwarfs. While the majority of stars fall into these types, there are a few other common spectral types commonly found in large surveys, including the carbon (C) and white dwarf (WD) stars. The expanded Morgan–Keenan system (Morgan et al. 1943) adds additional luminosity (i.e., giant, dwarf, and sub-dwarf) classes to the spectral typing scheme.

In recent years, there have been numerous implementations of automated spectral typing algorithms and software. These have included the principal component analysis of large spectroscopic surveys like the Sloan Digital Sky Survey (SDSS; McGurk et al. 2010; Blanton et al. 2017), neural networks (Singh et al. 1998; Sharma et al. 2020), the fitting of synthetic spectra from model atmospheres, and comparisons to spectral line in stellar templates like PyHammer (Kesseli et al. 2017).

These automatic spectral typing methods have come about as a direct need of current and future large spectroscopic survey campaigns like SDSS and the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (Cui et al. 2012). These surveys have already produced spectra for millions of stars, and with the beginning of the SDSS-V (Kollmeier et al. 2017), millions more will be observed with repeat, time-domain spectroscopy. These surveys represent an enormous, only partly exploited, resource for astronomy. With the coming of age of time-domain astronomy and large scale, all-sky photometric surveys, like the Zwicky Transient Facility (ZTF; Bellm et al. 2019; Graham et al. 2019; Masci et al. 2019) and the Rubin Observatory Legacy Survey of Space and Time (LSST; Ivezić et al. 2019), the need for efficient and accurate stellar spectral typing is only going to become more relevant.

In addition to large spectroscopic surveys, further advances are needed to spectrally type binary stars, particularly close interacting binary stars. Recent surveys have shown that almost half (46%) of solar-type stars are in multiple systems (Raghavan et al. 2010). Higher multiplicities can be found for earlier-type stars, while later-type stars are found to have a lower multiplicity—near 27% for M dwarfs (Winters et al. 2019). Many of these systems are spatially unresolved and therefore undetected. However, the spectrum contains the light from both components and can tell us information about each one. In some cases, these components are of sufficiently
different spectral type that the spectrum is visually striking as an SB2 (e.g., M+WD binaries). However, the majority of SB2 components are in spectral types that are closer together in the MK system (e.g., G+K). While there have been advances in “disentangling” SB2 spectra (Sablowski & Weber 2017; Sablowski et al. 2019), these methods have generally relied on high-resolution, high signal-to-noise ratio (S/N), and multi-epoch spectra. These high-quality spectra require significant dedicated telescope time.

Motivation for this work came from the combination of a large scale spectroscopic survey with a large fraction of stars being possible binary systems. The SDSS-IV’s Time Domain Spectroscopic Survey (TDSS; Morganson et al. 2015; Ruan et al. 2016; MacLeod et al. 2018; S. F. Anderson et al. 2020, in preparation) is a large survey spectral designed to collect optical spectra for a large sample of variable objects. The TDSS observed optical spectra for approximately 81,000 variable sources (quasars and stars) selected based on being spatially unresolved in SDSS imaging and photometrically variable, without further regard, e.g., for the color or type of variability (S. F. Anderson et al. 2020, in preparation). One of the TDSS’s main goals is the study of variable stars with a combination of spectroscopy and photometry. Approximately half of the periodic stellar systems in this sample are likely to be binaries but do not show clear eclipses. These undetected binaries and their properties led to the motivation for the work detailed here. More details of the TDSS variable star survey can be found in B. R. Roulston et al. (2020, in preparation).

Here we present the newest version of PyHammer, a Python spectral typing suite. PyHammer has the advantage of needing only a single epoch of spectroscopy to perform spectral typing, including the new SB2 typing abilities detailed here. We also present a new library of empirically derived, luminosity-normalized spectral templates. These luminosity spectra are used to create SB2 templates, which have also been added to PyHammer. This version has also been extended to include single carbon and DA WD stars.

2. PyHammer

2.1. PyHammer v1.0

PyHammer (Kesseli et al. 2017; https://github.com/BU-hammerTeam/PyHammer) is a Python based spectral typing suite that is based on the IDL program the Hammer (Covey et al. 2007; http://myweb.facstaff.wwu.edu/coveyk/thehammer.html).

In v1.0 of PyHammer, spectral types were assigned by measuring spectral indices (similar to equivalent widths) for 34 atomic and molecular lines and by comparing the measured indices to those of the templates. The best-matching spectral type was selected as the one that minimized the χ² difference between spectral indices. Because proper flux calibration across the full wavelength range of optical spectra can often be a significant challenge to achieve observationally, the use of spectral indices offers a distinct advantage for accurate classification of typical spectra.

The templates used by PyHammer are for single stars spanning types: O, B, A, F, G, K, M, and L. Each of these classes contains a variety of subtypes and metallicities that are simultaneously compared. All of these templates were created from the co-addition of SDSS (Blanton et al. 2017) optical spectra, as detailed in Kesseli et al. (2017).

The v1.0 PyHammer release extended the Hammer by including new templates to allow for spectral typing across different metallicities. It also provided a Python package that is easy to install and begin spectral typing without requiring IDL.⁵

2.2. PyHammer v2.0: SB2

In our new release of PyHammer, available on GitHub,⁶ we add two new single star spectral types for main-sequence carbon stars (i.e., dwarf carbon (dC)) and DA WDs, defining spectral indices for the C2 and CH bandheads. The new dC stars span a range of broadband colors (and likely effective temperatures from classic “G-“ to “M-“ type stars, while the WDs span a range of temperatures from 7000 K to 100,000 K.

While the Balmer line spectral indices were included in PyHammer v1.0, we include a second set that spans wider Balmer line wavelength regions to help aid in the classification of the WDs.

PyHammer v2.0 now also has the ability to detect some combinations of spectroscopic binaries. The details of the SB2 templates are discussed in Section 5.

3. Carbon Star and WD Templates

3.1. Carbon Star Templates

This release of PyHammer includes three new single star dC star templates. These new dC star templates are made using dC stars and were created in a similar method as the stellar library of Kesseli et al. (2017), involving the co-addition of individual spectra to make each subtype.

The individual spectra used to make the dC star templates are from the SDSS sample of Green (2013). Green (2013) identified carbon stars by visual inspection of single-epoch SDSS spectra compiled from the union of (1) SDSS data release 7 (DR7) spectra (Abazajian et al. 2009) having strong cross-correlation coefficients with the SDSS carbon star templates and with (2) SDSS spectra with a DR8 pipeline class of “STAR” and subclasses including the word carbon (Aihara et al. 2011). The subsample with main-sequence luminosities (the dCs) were identified by their high proper motions.

The spectra used to make the new dC star templates were all selected from the SDSS DR16 (Ahumada et al. 2020), which includes a combination of SDSS-I/SDSS-II and SDSS-III/SDSS-IV spectroscopic data. SDSS-I/SDSS-II spectra were taken with the legacy SDSS spectrograph, spanning a wavelength range of 3900–9100 Å with a resolution of R ~ 2000. The newer extended Baryon Oscillation Spectroscopic Survey (eBOSS) spectrograph (Smee et al. 2013) used in SDSS-III/SDSS-IV covers the 3600–10400 Å range at a resolution of R ~ 2500.

From the Green (2013) dC star sample, we made a series of quality cuts as follows: (1) SDSS 15.0 < r < 17.0 mag to ensure the SDSS sources are neither saturated nor have large uncertainties (Fukugita et al. 1996), (2) average S/N > 5 for the SDSS spectrum, (3) Gaia DR2 (Gaia Collaboration et al. 2018) matches within 2", (4) Gaia DR2 distance (Bailer-Jones et al. 2018) S/N > 5, (5) any dC stars known to be in binaries

⁵ https://www.harrisgeospatial.com/Swiftware-Technology/IDL

⁶ https://github.com/BU-hammerTeam/PyHammer

⁷ Our original cut on the parallax (σ/σparallax > 5) did not translate to a distance S/N > 5 for all objects. The cut on the distance S/N ensures, however, that parallax and distance both have an S/N > 5.
From this sample of 260,000 high-confidence WD candidates, we selected stars using the following quality cuts: (1) DA classification by Gentile Fusillo et al. (2019), (2) SDSS 15.0 < r < 17.0 mag, (3) an existing SDSS spectrum with (4) mean S/N > 5, and (5) a Gaia DR2 distance (Bailer-Jones et al. 2018) S/N > 5. Similarly to the dC star templates, after these selection cuts were made each individual spectrum was visually inspected to check for bad flux regions and artifacts, removing stars with bad regions. The remaining stars were grouped by temperature, taken from model fits by Gentile Fusillo et al. (2019), and co-added to create the 10 final DA templates, which were chosen to represent a reasonably spaced temperature grid from 7000 to 1000,000 K. Each individual spectrum was assigned to the template nearest in temperature (e.g., the $T_{\text{eff}} = 10,000$ K template is made of WDs with 9500 K < $T_{\text{eff}} \leq 12,500$ K).

The naming of the DA templates follow the system and effective-temperature indicator introduced by Sion et al. (1983), where we also follow the half-integer steps of Wesemael et al. (1993).

Table 2 shows the resulting set of DA templates, their temperatures, and the number of individual spectra averaged to make them. As with the new dC star templates, these new DA templates are listed as [Fe/H] = 0.0. Although this is not valid for WDs, a metallicity value is required by the PyHammer software.

Figure 2 shows these new DA single star PyHammer templates, illustrating the variety of the DA temperatures included.

PyHammer v1.0 used Balmer line indices for spectral typing; however, the featureless spectra of the new DA WDs were almost always confused with A and F star templates in v1.0. To distinguish WDs, additional Balmer line indices of varying widths were added as well as additional fitting methods. Details of these can be found in Section 3.3.

3.3. PyHammer Spectral Indices

In addition to the new dC and DA WD templates, corresponding dC and DA line indices have been added to the list that PyHammer measures. The entire list, including new lines, is shown in Table 3. This table shows the line and the comparison wavelength regions for the spectral index numerator and denominator.

For the dC stars, we include the C$_2$ molecular bands in the blue and CN bands in the red. This allows for C bands to be calculated for either the bluer “G-type” carbon stars or the redder “M types.”

We have added a second set of Balmer line indices specifically for the DA WDs. These new “WD Balmer” line indices add a wider wavelength region to the previously included narrow Balmer line indices. Since the DA WD Balmer lines are broadened due to strong pressure broadening—this helps both with line detection—and to distinguish the DA WD indices from those of main-sequence stars with Balmer absorption. However, these wider Balmer line indices alone were not enough to consistently differentiate between DA WDs and hot stars of A and F types. Therefore, an additional line width measurement for the H$_\alpha$ line was added to the typing routine. This involved fitting the H$_\alpha$ line with a Gaussian profile if the type is initially either A, F, or DA WD. It then compares the fit width ($\sigma$) with that measured for most DA WDs; if the fit width is sufficiently large ($\sigma > 15\AA$), PyHammer classifies the spectrum as a DA.

3.2. WD Templates

We have created new DA WD templates and added them to v2.0 of PyHammer. These WD templates were created using the same method as for the original single star PyHammer templates and new dC star templates. We used spectra from the Gentile Fusillo et al. (2019) WD sample, which used spectroscopically confirmed WDs from the SDSS to create selection criteria and color cuts to select WDs from Gaia DR2.

| Table 1 | dC Star Template Colors |
|---|---|
| Template | g − r | r − i | BP − RP | N$_{spec}$ | S/N |
| dCG | 0.68 | 0.47 | 1.35 | 3 | 59 |
| dCK | 1.30 | 0.56 | 1.64 | 5 | 54 |
| dCM | 1.77 | 0.61 | 1.92 | 9 | 64 |

Notes. Properties of the new dC star templates. Colors are the unweighted average of SDSS and Gaia colors of the component spectra and were used to help separate stars into the three dC star template classes (along with visual inspection). The templates for dCG, dCK, and dCM correspond to “G,” “K,” and “M” type dC stars, respectively.

$^a$ Number of individual stellar spectra combined to create template.

with a WD are removed (i.e., those with evident DA/dC composite spectra Heber et al. 1993; Liebert et al. 1994; Green 2013; Si et al. 2014), and (6) any stars marked as giant in Green (2013) are removed.

After these cuts, we visually inspected each individual spectrum and removed those with bad flux regions and artifacts, which can happen due to background contamination, errors during the pipeline reduction, or a fiber not being correctly placed. During this visual inspection, the “type” of dC star was noted (i.e., going progressively redder from “G” to “K” to “M” types) based on continuum shape and strength of the CN bands.

We then placed the remaining dC stars into three groups based on the “type” given during the visual inspection. Then using the average SDSS colors of g − r and r − i and Gaia BP − RP, we removed any sources that fell outside of the color locus for a given template. The breakdown of these colors can be found in Table 1. The resulting templates (dubbed dCG, dCK, and dCM) correspond approximately by color to “G,” “K,” and “M” types and were made from the co-addition of 3, 5, and 9 C star spectra, respectively.

This co-addition follows the same method as used in Kesseli et al. (2017) for the original PyHammer: creating a wavelength grid that is logarithmically spaced (with 5 km s$^{-1}$ spacing), interpolating each component spectrum onto this grid, and then adding all the components together. The resulting template is then normalized so that the flux at 8000 Å is unity.

The new dC star templates are listed as [Fe/H] = 0.0, although their metallicity information is unknown. Both higher-resolution spectra and well-tested model atmospheres would be needed but are not yet available for dC stars.

The most striking features of dC stars are their prominent C$_2$ and CN bandheads. These can be seen in Figure 1, which shows the three new dC star PyHammer templates. This figure also shows the variety of the dC class. The C$_2$ and CN molecular bandheads are marked, as well as the H$_\alpha$ atomic line wavelength. These bandheads allow for accurate spectral typing, given that additional spectral indices are added to PyHammer. Details of these can be found in Section 3.3.

3.2. WD Templates

We have created new DA WD templates and added them to v2.0 of PyHammer. These WD templates were created using the same method as for the original single star PyHammer templates and new dC star templates. We used spectra from the Gentile Fusillo et al. (2019) WD sample, which used spectroscopically confirmed WDs from the SDSS to create selection criteria and color cuts to select WDs from Gaia DR2.
temperatures from 7000 to 100,000 K and all have an S
Notes.
Properties of the 10 new DA WD templates. These templates span
DA7 7000 0.19 0.05 0.52 16 164
DA6.5 8000 0.05
−
DA6 9000
−
DA5.5 10,000
−
DA5 10,000
−
DA4.5 15,000 0.02 0.35 20 154
DA4 20,000
−
DA3.5 30,000
−
DA3 40,000
−
DA2.5 50,000
−
DA2 60,000
−
DA1.5 80,000
−
DA1 10,000
−
DA0.5 100,000
−
We also show the new spectral index regions used by PyHammer for the automatic typing. There are 10 new dC star lines (4 C2 and 6 CN), each consisting of a wavelength region within an absorption line or band, and a comparison “continuum” region near the line region. The line regions and continuum regions are shown with dark and light gray shading, respectively. Each subtype has been offset in flux for better visualization.

Figure 1. New PyHammer single star dC star templates. Each of these subtype templates is averaged from a sample of luminosity-normalized single-epoch SDSS spectra. The striking and prominent C2 and CN bandheads are visible across the dC stars. These bandheads, as well as Hα, are marked and labeled with dashed lines. We also list the new spectral index regions used by PyHammer for the automatic typing. There are 10 new dC star lines (4 C2 and 6 CN), each consisting of a wavelength region within an absorption line or band, and a comparison “continuum” region near the line region. The line regions and continuum regions are shown with dark and light gray shading, respectively. Each subtype has been offset in flux for better visualization.

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Table 2
DA WD Templates

| Template | $T_{\text{eff}}$ | $g - r$ | $r - i$ | $BP - RP$ | $N_{\text{spec}}$ | S/N |
|----------|----------------|--------|--------|----------|-----------------|-----|
| DA0.5    | 100,000        | −0.53  | −0.38  | −0.55    | 6               | 102 |
| DA1      | 50,000         | −0.53  | −0.37  | −0.55    | 12              | 120 |
| DA1.5    | 40,000         | −0.51  | −0.36  | −0.51    | 18              | 175 |
| DA2      | 30,000         | −0.47  | −0.34  | −0.45    | 61              | 301 |
| DA2.5    | 20,000         | −0.39  | −0.30  | −0.30    | 100             | 421 |
| DA3.5    | 15,000         | −0.30  | −0.25  | −0.15    | 99              | 325 |
| DA5      | 10,000         | −0.14  | −0.17  | 0.06     | 44              | 230 |
| DA5.5    | 9000           | −0.02  | −0.07  | 0.24     | 28              | 164 |
| DA6.5    | 8000           | 0.05   | −0.02  | 0.35     | 20              | 154 |
| DA7      | 7000           | 0.19   | 0.05   | 0.52     | 16              | 164 |

Notes. Properties of the 10 new DA WD templates. These templates span temperatures from 7000 to 100,000 K and all have an S/N above 100. The reported colors are from SDSS and Gaia DR2 where the value is the unweighted average of all the spectra used to make each template.

4. Luminosity Stellar Templates

To create single star templates that can then be combined to create realistic spectroscopic binary templates, we built a library of luminosity-normalized spectra,8 in units of erg s$^{-1}$ Å$^{-1}$. To do this, we sought optical spectral libraries with precise flux calibrations that allow transformation into luminosity units using well-measured distances. We created this by selecting O, B, A, and F main-sequence stars from Pickles (1998); G, K, and M stars from the SDSS-IV MaStar program (Yan et al. 2019) program; dC stars from Green (2013); and DA WDs from Gentile Fusillo et al. (2019).

The MaStar survey uses fiber bundles, which can achieve much more accurate flux calibration than the normal SDSS survey. However, the MaStar sample (DR16) lacks O, B, A, and F stars that meet our quality cuts. For those spectral types, we used the Pickles (1998) library. This library also is well flux calibrated and has a similar resolution to SDSS and MaStar (R $\sim$2000).

There are no public digital libraries of precisely flux-calibrated C and WD star spectra. For these spectral types, we used the same libraries that we made their single star templates from. Our Gaia distance quality cuts ensure accurate distances to perform the flux-to-luminosity transformation.

The O, B, A, and F stars from Pickles (1998) have excellent relative flux calibrations but are presented in normalized units where each spectrum is normalized to 1.0 at 5556 Å. Since absolute magnitudes $M_V$ are reported for each, we used the V-band filter response function from Bessell (1990) to perform synthetic photometry, thereby finding the appropriate scale factor to convert these templates into luminosity units of erg s$^{-1}$ Å$^{-1}$.

For the G, K, and M spectral types we matched each MaStar star to Gaia DR2 and selected the best spectrum for each spectral type and subtype. This best spectrum was chosen as having the best combination of Gaia DR2 parallax S/N and Gaia $G$ magnitude S/N. After selecting those with Gaia DR2 $\alpha/\alpha_{\text{err}} > 10$, we then chose the best S/N spectrum in each subtype bin. Then, using the Gaia DR2 distance, we converted these flux spectra into luminosity spectra in units of erg s$^{-1}$ Å$^{-1}$.

For the dC and DA WD stars, we used a similar method as the GKM stars. However, since these objects are from the main SDSS-IV survey, some may have poorer absolute flux calibrations due, e.g., to suboptimal individual fiber placement or transmissivity. We mitigate this by averaging. We converted each of the individual spectra for each template into luminosity

8 Here luminosity-normalized refers to spectra in luminosity units, not to be confused with luminosity classes from the MK system.
Spectral indices for v2.0 of PyHammer. For the indices that have two numerator regions, the weight for each numerator is shown. Atomic and molecular lines

| Subtype | Numerator (A) | Denominator (A) |
|---------|---------------|-----------------|
| Ca II K | 3924.8–3944.8 | 3944.8–3954.8   |
| Ca I λ6421 | 4087.9–4117.9 | 4137.9–4177.2   |
| Ca I λ4217 | 4217.9–4237.9 | 4237.9–4257.2   |
| G band | 4286.2–4316.2 | 4356.2–4371.2   |
| WD Hγ | 4290.0–4405.0 | 4430.0–4460.0   |
| Hγ | 4333.7–4348.7 | 4356.2–4371.2   |
| C2 λ4382 | 4350.0–4380.0 | 4450.0–4600.0   |
| Fe I λ4383 | 4379.8–4389.8 | 4356.2–4371.2   |
| Fe I λ4404 | 4401.0–4411.0 | 4416.0–4426.0   |
| C2 λ4737 | 4650.0–4730.0 | 4750.0–4850.0   |
| WD Hβ | 4823.0–4900.0 | 4945.0–4980.0   |
| Hβ | 4848.4–4878.3 | 4818.3–4848.4   |
| C2 λ5165 | 5028.0–5165.0 | 5210.0–5380.0   |
| Mg I | 5154.1–5194.1 | 5101.4–5151.4   |
| C2 λ5636 | 5400.0–5630.0 | 5650.0–5800.0   |
| NaD | 5881.6–5906.6 | 5911.6–5936.6   |
| Ca I λ6125 | 6151.7–6176.7 | 6121.7–6146.7   |
| WD Hα | 6519.0–6609.0 | 6645.0–6700.0   |
| Hα | 6549.8–6579.8 | 6584.6–6614.8   |
| CaII | 6815.9–6847.9 | 7043.9–7074.9   |
| CN λ6926 | 6935.0–7035.0 | 6850.0–6900.0   |
| CaH | 6961.9–6991.9 | 7043.9–7074.9   |
| CN λ7088 | 7075.0–7233.0 | 7039.0–7075.0   |
| TiO5 | 7127.9–7136.9 | 7043.9–7074.9   |
| CN λ7259 | 7233.0–7382.0 | 7382.0–7425.0   |
| VOλ4344 | 7432.0–7472.0 | 7552.0–7572.0   |

Note. Spectral indices for v2.0 of PyHammer. For the indices that have two numerator regions, the weight for each numerator is shown. Atomic and molecular lines are in increasing wavelength order. Some color region indices, separated from the atomic and molecular line indices at the bottom of the right set of indices, are also in increasing wavelength order.

units using the Gaia DR2 distances. Then, we co-added and averaged to get an average luminosity spectrum for each spectral type.

Although PyHammer contains single L templates, we do not make L star spectral luminosity templates, because the L templates are constructed from very faint spectra (r > 21), outside our range.
of quality criteria. These L spectra likely have poor flux calibrations that are not suitable for transforming into luminosity units. This luminosity-normalized digital spectral library allows for a variety of useful applications. The templates can be combined to create templates for spectroscopic binaries as described in the next section. Another important application is using these templates for flux calibration. Once an observed spectrum has been typed using PyHammer, one can divide the appropriate template by the observed spectrum, fit with a low-order polynomial, and then multiply the polynomial by the observed spectrum to get a luminosity-normalized observed spectrum.

Figure 3 shows all of the luminosity spectra from our library that we then used to create spectroscopic binary templates. All of the luminosity spectra are in units of erg s\(^{-1}\) Å\(^{-1}\) and have been smoothed by a boxcar of 10 pixels to aid in visualization.

This luminosity-normalized spectral library can be found on Zenodo\(^9\) in FITS format.

5. Spectroscopic Binary Templates

Using the luminosity library from Section 4, we were able to combine these spectra to create a library of main-sequence spectroscopic binary templates. This can be done by adding the component spectra together on a common wavelength axis to form a combined SB2 spectrum (the common wavelength axis we use is the PyHammer template wavelength grid, which is logarithmically spaced between 3550 Å and 10,500 Å with spacing of 5 km s\(^{-1}\)).

Not all combinations of our main-sequence luminosity templates make useful SB2 templates, as the more luminous stars easily overpower the faintest ones (e.g., an A5+M2 binary would be useless as the A star would be almost 10\(^3\) times more luminous than the M star and no M star features would be visible).

To limit the combinations to those with some realistic hope of detection, we require that at least 20% of the pixels of the two constituent spectra be within 20% of the luminosity of each other.

For practical reasons of classification accuracy detailed in Section 6, we only build SB2 combinations from constituents of different main spectral types (i.e., no A+A, F+F, etc.). This results in the following combinations of main SB2 spectral types: A + F, F + G, F + K, G + K, G+dC, G+DA, K + M, K+dC, K+DA, M+dC, M+DA, and dC+DA.

We have created and included these new SB2 templates to allow PyHammer the ability to spectral type SB2s based on a

\(^9\) doi:10.5281/zenodo.3900328
single epoch of optical spectroscopy. The SB2s generated and studied in the current work do not include any giant stars.

### 5.1. SB2 RVs

In addition to spectral typing, PyHammer has the ability to measure the RV of an input spectrum. As detailed in Kesseli et al. (2017), PyHammer uses a cross-correlation method across three wavelength regions. Kesseli et al. (2017) report that the original PyHammer has an RV accuracy of 7–10 km s$^{-1}$ for mid-temperature and low-temperature stars and 10–15 km s$^{-1}$ for high-temperature stars.

In the process of this work, we also considered adding the ability to PyHammer to fit the RV of each of the SB2 component spectra. This would involve using our luminosity spectral library to create SB2 composite templates on the fly, fitting the SB2 to the input spectrum with the RVs for both components as free parameters. This would be useful to find SB2s with components of similar spectral types (e.g., M2+M3 or F5+F6, etc.) where PyHammer v2.0 likely will classify the system as a single star. However, in such cases, there may often be widening or even separation of spectral lines due to the radial components of orbital motion of the components, potentially allowing RV fitting to detect the RVs of both stars.

In practice, however, this proved difficult for a variety of reasons. Mainly, the S/N of most SDSS spectra is not high enough to allow for this robust of a fitting routine, and our attempts at recovering simulated RV shifts were unsuccessful. After implementing and testing a few methods, our retrieved RV measurements for simulated SB2s have, so far, been unreliable and so we do not include this tool in PyHammer v2.0. Stars determined to be best fit by an SB2 template will have an RV reported by the software as not a number. The ability to calculate RVs for single stars, however, remains the same as with the original PyHammer (including for the new C and WD templates).

![Figure 4](image)

**Figure 4.** Classification accuracy for single stars for two different sets of SB2 combinations. The lower panel shows the accuracy rates for single stars typed as single stars when including same main spectral type SB2s (e.g., A+A or G+G). The upper panel shows the accuracy rates for single stars typed as single stars when same main spectral type binaries are excluded from PyHammer. For each spectral type there are four bars for four S/N bins (left to right); S/N < 5, 5 ≤ S/N < 10, 10 ≤ S/N < 20, and S/N ≥ 20. Note that not all spectral types have all S/N bins. Given the strong degradation in accuracy for single stars when allowing the same main type SB2s, we exclude them from the software.

![Figure 5](image)

**Figure 5.** SB2 accuracy based on subtype, S/N, and accuracy criteria. Each primary+secondary combination has four bars for four S/N bins (left to right): S/N < 5, 5 ≤ S/N < 10, 10 ≤ S/N < 20, and S/N ≥ 20. Each bar then has three stacked components representing the previously described accuracy criteria (using criterion 0, 1, or 2). Criterion 0 is represented by the most transparent bars (single diagonal hatching), criterion 1 by the middle transparent bars (double diagonal hatching), and criterion 2 by solid color bars (no hatching).

### 6. Accuracy

Our initial SB2 templates included all templates those met the requirement that 20% of the pixels of the two constituent spectra be within 20% of the luminosity of each other, including SB2s wherein both the primary and secondary were of the same main spectral type (e.g., A2+A3 and M2+M4).

However, after initial accuracy tests, we found that the classification accuracy rates for single stars dropped significantly when SB2s with the same main spectral type were included in PyHammer. For example, a single F5 star is unlikely to be misclassified as an F2+G2 SB2 but is quite likely to be misclassified as, e.g., an F2+F5 SB2.

Figure 4 shows the classification accuracy for single stars being typed as single stars when including SB2s with the same main spectral type. The bottom panel shows the accuracy when including same main spectral type SB2s and the top panel shows the accuracy rate when excluding same main spectral type SB2s. This figure shows how strongly the single star...
accuracy rates are affected by including same main spectral type SB2s.

One possible reason that these same main spectral type SB2s negatively affect the single star accuracy rates is that there are two nearly equivalent templates in terms of spectral indices. For example, when typing an F5 spectrum it could be equally well-matched to an F5 template or an F4+F5 template. This results in single stars that have lower S/N or a noisy spectrum to be best typed by an SB2 with the same main spectral types.

For this reason, we do not include these same main spectral type SB2s templates in PyHammer v2.0, limiting to SB2s that have different main spectral types.

However, all possible SB2 combinations meeting the 20% criteria outlined in Section 5 are included in the Zenodo library for completeness, whether or not they combine the same main spectral types. This includes some types, like dC+dC, which would be expected to be extremely rare in the cosmos for reasons of stellar evolution, as well as DA+DA types, which could be extremely interesting but difficult to detect with PyHammer.

We have tested our new SB2 templates for their accuracy and their dependence on the input spectral S/N. We tested accuracies for all templates across a range of S/N. We did this by degrading each template by varying the levels of noise. We created a Gaussian distribution for each pixel centered at the pixel’s flux with the standard deviation given by an integer multiple of the template error at that pixel. We then used these distributions to draw new noisy spectra for integer multiples between 1σ and 50σ. Using PyHammer, we typed each noisy test spectrum at each degradation level. To better represent the

The accuracies detailed here are representative of SDSS spectra and may not reflect results for spectra of different resolutions, wavelength coverages, relative flux calibration, or quality.
accuracies for different use cases, we selected three “criteria” of classification accuracy to test.

The first criterion (criterion 0) is the least stringent, allowing any combination of subtypes as long as the two main spectral types are correct. For example, an M2+DA3.5 would be correct even if labeled as an M1+DA7 because the main spectral types are correctly M and DA, but if it were labeled as K7+DA0.5, it would be counted as incorrect.

The second criterion (criterion 1) increases the requirements to count correct typing as only those SB2s classified by our code to be within one subtype, in either or both of the components. In this case, an M2+DA3.5 would be counted correct if labeled as M2+DA2.5 (or M3+DA5, etc.), but would be incorrect if labeled as M2+DA6.

The third and most stringent criterion (criterion 2) counts the classification as correct if (and only if) the exact spectral types and subtypes for both components of the SB2 are correct. An example is an M2+DA3.5 that would be classified correct only if labeled as M2+DA3.5; if labeled as M2+DA2.5, it would be incorrect.

11 Accuracy criterion 0 may be imprecise because it has discontinuous jumps at spectral type boundaries. For example, an F9+G9 classified as F9+K0 would be incorrect, even though a G9 is just one subtype away from K0. However, this affects only a small percentage of our SB2 combinations.

Figure 5 shows the accuracy for each of the SB2 groups in PyHammer 2.0. Each of the panels shows the accuracy for one of the six possible primary spectral types (A, F, G, K, M, and dC). Each panel then shows the accuracies for the possible combinations of secondary types (e.g., A+F or dC+DA). Each primary+secondary combination has four bars for four S/N bins (left to right): S/N < 5, 5 ≤ S/N < 10, 10 ≤ S/N < 20, and S/N ≥ 20. Each bar then has three stacked components representing the previously described accuracy criteria (0, 1, or 2). Criterion 0 is represented by the most transparent (single diagonal hatching), criterion 1 by the partially transparent (double diagonal hatching), and criterion 2 by the solid color (no hatching) bars.

From Figure 5, we see that PyHammer’s accuracy with SB2 stars is dependent both on the input spectrum’s S/N and on the spectral type combination. As expected, the lowest S/N has the lowest accuracy, which holds across all three “criteria” for counting accuracy. We also can see that early-type stellar combinations (i.e., A+F, F+G, and F+K) tend to be less reliable. This is expected, as the early types of A and F are spectrally similar, with the main features being the Balmer lines. In contrast, late-type combinations (e.g., G+dC, K+M, M+dC, etc.) are much more—in some cases nearly 100%—accurate. This is likely due to the strong difference in visible atomic and molecular lines and bands within these spectral
structures. These rates are for $S/N < 5$ and only represent the accuracy and error rates between the single star and SB2 star template groups (i.e., this does not represent the total true accuracy rate because it only accounts for errors between the single and SB2 star classes). For each spectral type shown, the rate shown is the percentage of all test spectra in that primary–secondary type bin that were classified correctly as an SB2 for SB2 stars (and single for single stars).

| SB2 Type | $N_{\text{spec}}$ | Accuracy |
|----------|----------------|----------|
| A + F    | 424            | 90.3     |
| F + G    | 769            | 90.8     |
| F + K    | 65             | 94.6     |
| G + K    | 1665           | 88.2     |
| G+dC     | 253            | 94.5     |
| G+DA     | 72             | 88.9     |
| K + M    | 375            | 95.7     |
| K+dC     | 433            | 98.4     |
| K+DA     | 580            | 95.7     |
| M+dC     | 203            | 95.1     |
| M+DA     | 1686           | 100.0    |
| dC+DA    | 708            | 90.4     |
| SB2 average | 602     | 93.5     |

| Single type | $N_{\text{spec}}$ | Accuracy |
|-------------|----------------|----------|
| O           | 187            | 100.0    |
| B           | 421            | 99.5     |
| A           | 1406           | 94.5     |
| F           | 2140           | 96.4     |
| G           | 2278           | 90.1     |
| K           | 1653           | 91.0     |
| M           | 1507           | 97.9     |
| L           | 250            | 94.4     |
| dC          | 137            | 96.4     |
| DA          | 412            | 99.8     |
| Single average | 1039     | 96.0     |

Note. Accuracy and misclassification rates between the single and SB2 star classes. These rates are for $S/N < 5$ and only represent the accuracy and error rates between the single star and SB2 star template groups (i.e., this does not represent the total true accuracy rate because it only accounts for errors between the single and SB2 star classes). For each spectral type shown, the rate shown is the percentage of all test spectra in that primary–secondary type bin that were classified correctly as an SB2 for SB2 stars (and single for single stars).

types (e.g., TiO bands in M dwarfs, and CN and CH, and $C_2$ bands in dC stars). PyHammer is particularity good at identifying binaries of late-type stars with a DA companion (i.e., G+DA, K+DA, M+DA, and C+DA) due to the strong WD Balmer lines shown in blue with strong late-type stellar features shown in red. These types are all nearly 100% accurate across all $S/N$ bins and accuracy criteria.

Figure 6 shows the accuracy for specific SB2 combinations. These accuracies are for criterion 0 (main types correct) and are an average of the degraded test spectra for that SB2 type that falls within the given $S/N$ range. The figure shows two $S/N$ ranges, with the $1.8 < S/N < 5$ bin given above the diagonal in the upper triangle and the $5 < S/N < 15$ bin given below the diagonal in the lower triangle. This figure shows again that late-type combinations and those combinations with a DA WD component tend to be the most accurate at low $S/N$. However, at higher $S/N$ (above ~10), most combinations are above 90% accurate in all three criteria of accuracy.

We also report the accuracy of PyHammer v2.0 in identifying between the single star and SB2 star templates. Table 4 shows these accuracy rates between the single star and SB2 star classes. These rates are calculated from the total average across all $S/N$ and across all spectral types and SB2 combinations. Here, an accurate typing is counted whenever a single star is typed as a single star or an SB2 is typed as an SB2. All other combinations are counted as incorrect (i.e., a single star classified as an SB2 or an SB2 classified as a single star).

These accuracies give the rates at which, on average, we expect PyHammer to mistype between single and SB2 star templates. There is a dependence on both the spectral type and $S/N$, with these misclassifications all occurring for $S/N < 5$ and 32% being for A or F types. Misclassifications of A and F types are again not surprising, as those classes are very similar with predominant Balmer lines only. With low $S/N$, it is hard for PyHammer to distinguish between a low $S/N$ A star and an A+F SB2. Overall, as shown in Table 4, PyHammer has about 95% accuracy in correctly identifying between the single and SB2 star classes.

7. PyHammer GUI

The graphical user interface (GUI) for PyHammer v2.0 is functionally similar to the GUI in v1.0 of PyHammer. We have made a few minor updates and included the new functionality needed for classification using the SB2 templates.

PyHammer uses a $\chi^2$ method to compare the spectral indices of the input spectrum to that of the templates. We now show and report this raw “distance” measure on the GUI screen as LineDist to aid users when visually checking the classifications. Along with this statistic, we also report the residual between the chosen template and the input spectrum as well as the residual weighted by the errors. These allow the user to easily see the statistical change in the fit of each template in addition to a visual check.

There are now two additional sliders and a toggle for SB2 templates. The toggle will turn on to include both single and SB2 templates or off to include only single star templates. The additional sliders allow the user to select a secondary star’s spectral type and subtype based on the selected primary types. Only valid combinations from our list of SB2 templates are allowed, with unavailable options grayed out. Figure 7 shows the new GUI in PyHammer v2.0 for the example of a dC+DA binary spectrum. The new secondary stellar type sliders are visible, showing how the sliders limit the possible SB2 combinations.

8. Summary

We have extended the PyHammer spectral typing software to include new carbon and DA WD single star templates. These new templates were created in a similar method as the original PyHammer stellar templates via the co-addition of SDSS optical spectra. These new templates cover a range of effective temperatures across both dC and DA WD classes, providing spectral typing abilities for unique and important stellar types.

In addition, we have also created a new luminosity-normalized spectral library that consists of stars across the MK classification types. These luminosity templates are based on two libraries of accurately flux-calibrated optical spectra and using the Gaia DR2 to convert to luminosity units of erg s$^{-1}$ Å$^{-1}$. This luminosity library allowed us to create combinations of double-lined (SB2 templates that we have also added to this v2.0 of PyHammer.

Fast and accurate automatic spectral typing is important for individual observers but also for large-scale all-sky surveys of today and the future. Surveys such as the SDSS-IV (Blanton et al. 2017) and the upcoming SDSS-V (Kollmeier et al. 2017) need accurate stellar spectral types in their reduction pipelines. These surveys often use stellar templates based on synthetic spectra and model atmospheres that require assumptions and simplifications. The stellar templates presented here allow for
accurate spectral typing for situations in which accurate stellar models do not exist and would normally be left out of synthetic template libraries, such as dC stars (Green 2013).

PyHammer is also easily extendable to any spectral class in the future. The requirements are only that enough correctly typed spectra exist to create a template and that there are measurable spectral line features characteristic of that type. Examples of future PyHammer extensions could be CVs, T Tauri stars, quasi-stellar objects (QSOs), or other classes of galaxies. It is also possible that PyHammer could be extended to other wavelengths—for example, to encompass infrared (IR) spectra. This type of extension would only require additional spectral indices in the desired wavelength ranges and would be useful for IR spectral surveys such as the Apache Point Observatory Galactic Evolution Experiment (Majewski et al. 2017).

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Facility: Sloan 2.5 m.

Software: astropy (Astropy Collaboration et al. 2018), matplotlib (Hunter 2007), numpy (Oliphant 2006), PyHammer (Kesseli et al. 2017), scipy (van der Walt et al. 2011; Virtanen et al. 2020).

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