Using Machine-Learning to Predict Stellar Parameters

Overview: In this work, we investigate using a machine learning technique to predict physical parameters of variable stars in SDSS. Our work is based on the paper, "A Machine-Learning Method to Infer Fundamental Stellar Parameters from Photometric Light Curves" by Miller et al. (2015). We use the same data as this paper, but instead use a Neural Network rather than a random forest (RF) algorithm.

Methods: Our dataset is the University of Washington Variable Star Catalog (UWVSC), which we split into a training, test, and validation dataset for our neutral network. We use the standard Keras Python package with a Tensorflow backend. We perform the predictions of three physical parameter: $T_{\rm eff}$ (effective temperature), $\log g$ (surface gravity), and $Z = [{\rm Fe/H}]$ (metallicity) using the data from Table 3 of Miller et al (2015) obtained from SDSS spectra as a ground truth. For each physical parameter, we use the colors ($u - g, g - r, r - i$), light curve metrics (g-band amplitude, r-band amplitude, i-band amplitude, and period P), and both colors + light curve metrics combined as our features. We use a simple neural network with two hidden laters, 64 nodes, and one output to predict each physical parameter individually. Then, we use a combined architecture to predict all physical parameters at once.

Results: In general, our results perform as well as or slightly better than the RF method in the paper. Our primary metric of evaluation is the root-mean-squared error (RMSE) of the predicted versus actual physical parameters. We plot the loss curves for each of our models to check that we are not over-fitting. We also tried adding more hidden layers and a dropout layer to our natural network, but found it did not improve the results significantly. We used standard z-score normalization of our data before feeding it into the neural network.

Lessons Learned: We found that, while most of our results were consistent with the RF performance presented in the paper, we failed to use the light curve metrics to predict $T_{\rm eff}$ as effectively as Miller et al (2015). This may be because the normalization removes amplitude information between the different bands. In future work, we may use the full light curves in a convolutional neural network. We may also split the dataset into sub-classes of variable stars (e.g. RR Lyrae, Cepheid variable, etc.) to improve performance.

Contributions:
Sreevani Jarugula: Implemented the neural network and plotting code in Keras. Implemented neural network for predicting all physical parameters and made network architecture plots. *Performed prediction on color features and combined predictions.*
Colin Burke: Gathered prediction data from paper. Edited code for easier usage, added loss curve plots. Improved plotting code, color maps, added RMSE metric. *Performed prediction on light curve features.*
Breanna Lucero: Investigated the physical interpretation of the stellar parameters. Put together the presentation. *Performed prediction on light curve + color features.*