

# DATA-DRIVEN SPECTRAL MODELS FOR APOGEE M DWARFS

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**ABSTRACT:** The Cannon [1,2] is a flexible, **data-driven spectral modeling** and parameter inference framework, demonstrated on high-resolution Apache Point Galactic Evolution Experiment (**APOGEE**;  $\lambda/\Delta\lambda \sim 22,500$ , 1.5–1.7  $\mu\text{m}$ ) spectra of giant stars to estimate stellar labels (Teff, logg, [Fe/H], and chemical abundances) to precisions higher than the model-grid pipeline. The lack of reliable stellar parameters reported by the APOGEE pipeline for temperatures less than  $\sim 3550\text{K}$  [4], motivates the extension of this approach to M dwarf stars. Using a training set of **51 M dwarfs with spectral types ranging M0-M9** obtained from SDSS optical spectra, we demonstrate that The Cannon can **infer spectral types to a precision of 0.6 types**. We then use **30 M dwarfs ranging  $3072 < \text{Teff} < 4131\text{K}$ , and  $-0.48 < [\text{Fe}/\text{H}] < 0.49$**  to train a two-parameter model **precise to 44K and 0.05 dex** respectively. Additionally we discuss the extension of a model to other labels, and the scientific objectives a data-driven pipeline could enable.

## DATA-DRIVEN APPROACH

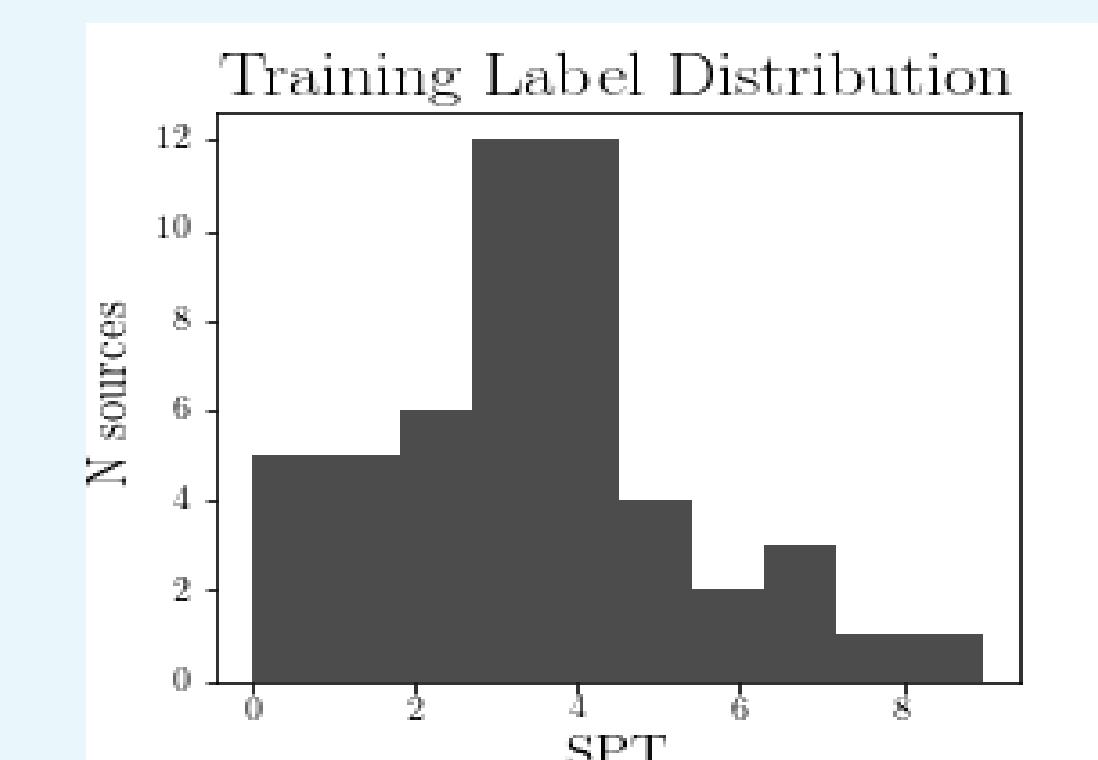
## SPECTRAL TYPE MODEL

### MODEL INPUT

#### MODEL ASSUMPTIONS:

1. Sources with identical labels have near-identical flux at each pixel.
2. Expected flux at each pixel varies continuously with change in label.

**INPUT:** Set of **training sources** w/ known **reference labels**, and a label vector.



**TRAINING SAMPLE:** West et al. 2011  
51 sources, M0-M9

**REFERENCE LABELS:**  
SPT from SDSS optical spectra  
using The Hammer.

**QUADRATIC MODEL:**

$$l_n \equiv [1, SPT, SPT^2]$$

### TRAINING STEP

#### GENERATIVE MODEL:

$$f_{n\lambda}^L = g(l_n^A | \theta_\lambda) + \text{noise}$$

$$f_{n\lambda}^L = \theta_\lambda^T \cdot l_n^A + [s_\lambda^2 + \sigma_{n\lambda}^2] \varepsilon_n$$

noise

Solving for the coefficients and scatter:

$$\ln p(f_{n\lambda} | \theta_\lambda^T, \ell_n, s_\lambda^2) = -\frac{1}{2} \frac{|f_{n\lambda} - \theta_\lambda^T \cdot \ell_n|^2}{s_\lambda^2 + \sigma_{n\lambda}^2} - \frac{1}{2} \ln(s_\lambda^2 + \sigma_{n\lambda}^2)$$

$$\theta_\lambda, s_\lambda \leftarrow \underset{\theta_\lambda, s_\lambda}{\operatorname{argmax}} \sum_{n=1}^N \ln p(f_{n\lambda} | \theta_\lambda^T, \ell_n, s_\lambda^2)$$

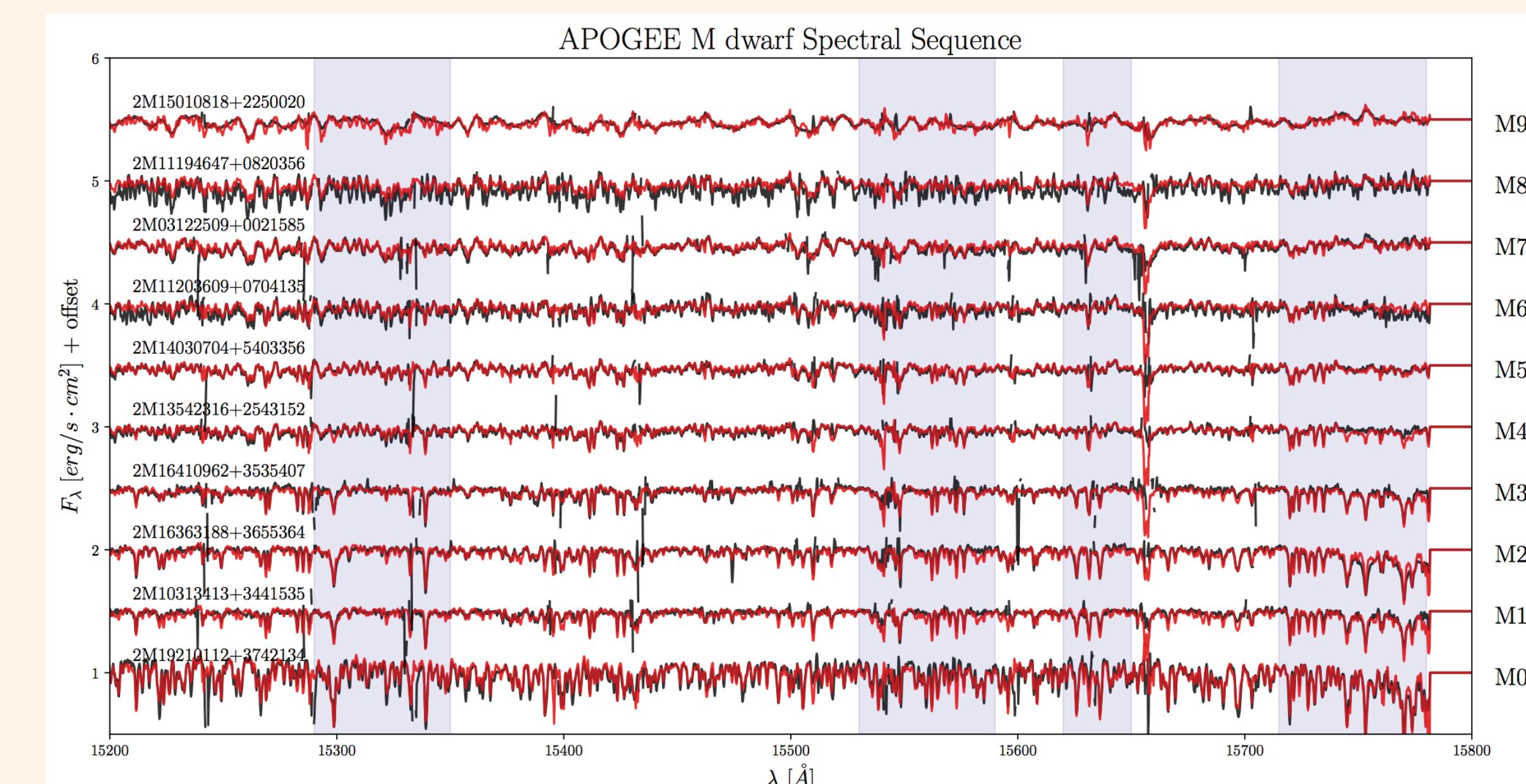


Figure 1: Spectral sequence of dwarfs in training set M0-M9; chip 1 of APOGEE spectrum with highlighted spectral type sensitive regions identified in [3].

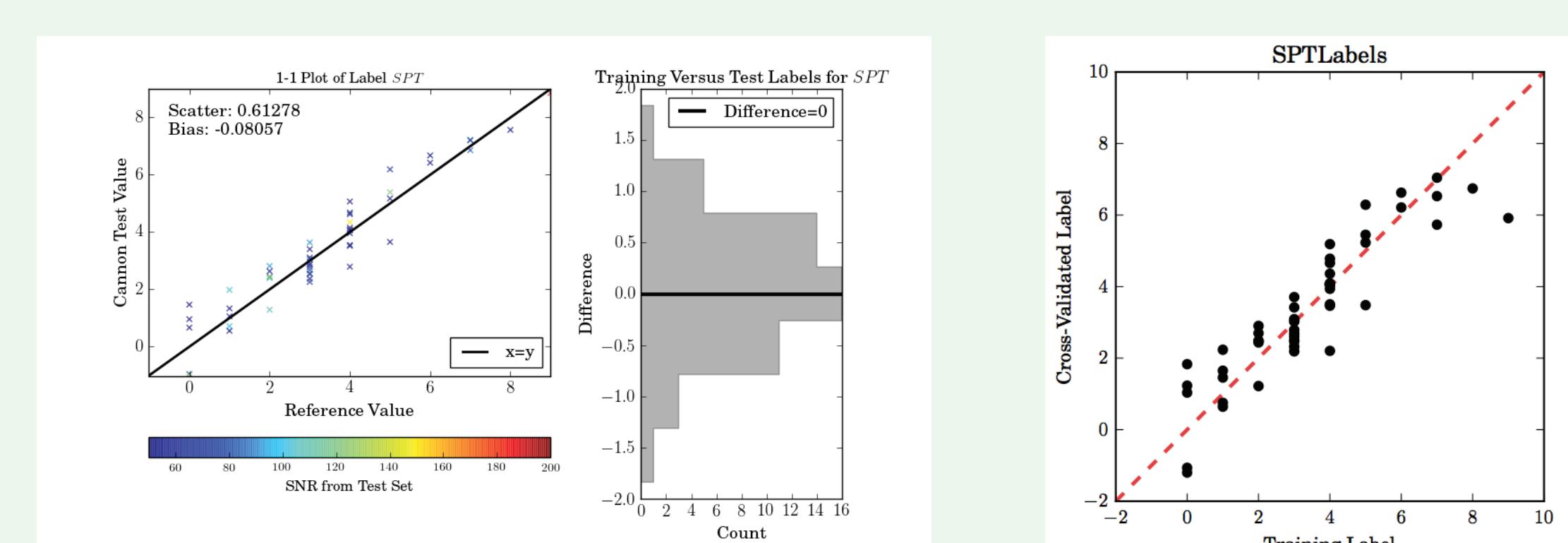
### TEST STEP

**INFERRING LABELS:** optimize labels for each star, using  $\theta_\lambda$  &  $s_\lambda$  from training step:

$$\{\ell_{mk}\} \leftarrow \underset{\{\ell_{mk}\}}{\operatorname{argmax}} \sum_{\lambda=1}^{N_{\text{pix}}} \ln p(f_{m\lambda} | \theta_\lambda^T, \ell_m, s_\lambda^2)$$

**VALIDATION:** Model consistency tested by self-test (training vs test labels), and leave-one-out cross validation.

(See [1] - Ness et al. 2015)



Figures 4-5: Label self-test (left) and cross validation (right) for West-trained model.

## THE APOGEE SURVEY

#### SPECIFICATIONS:

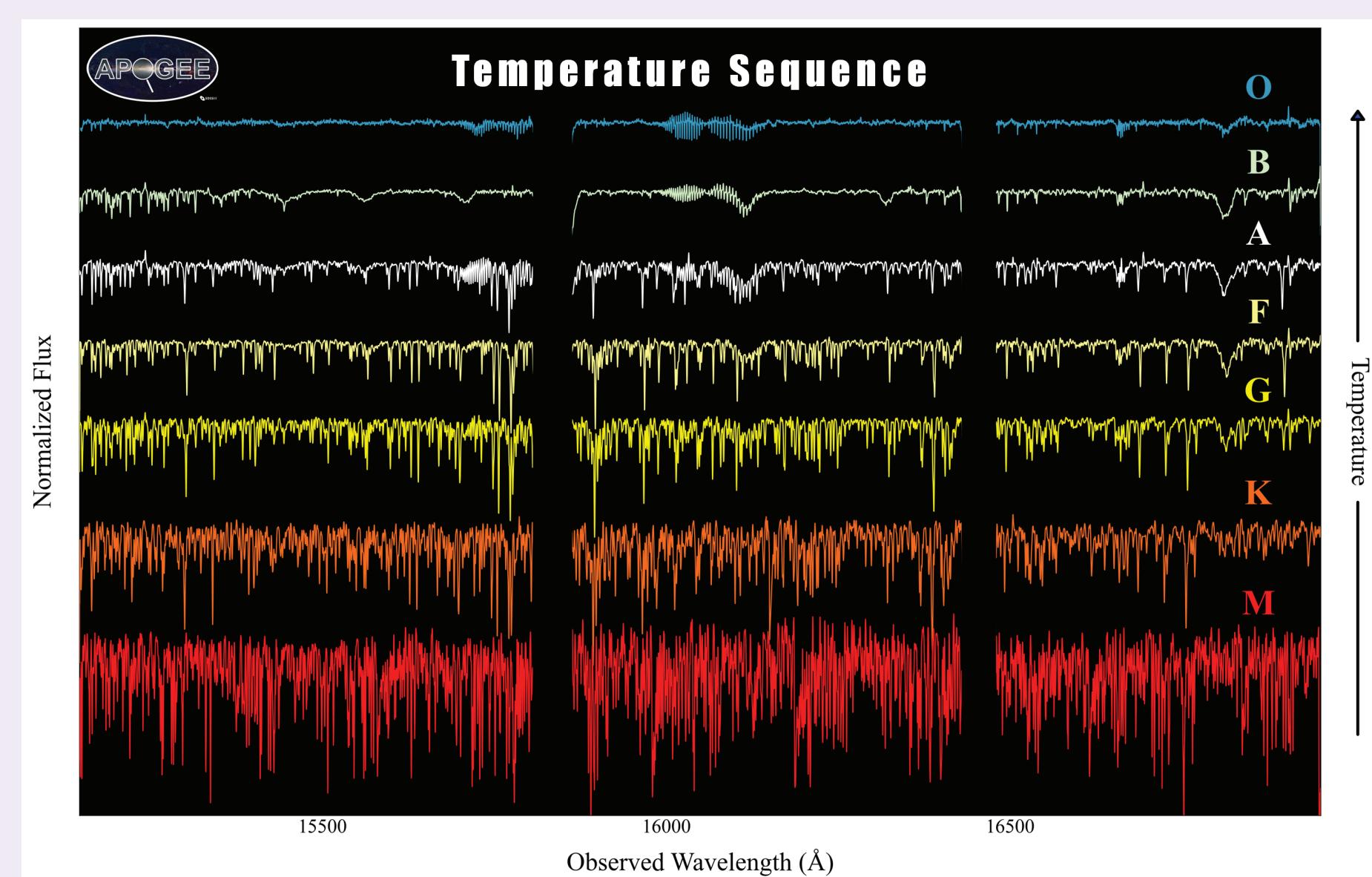
R $\sim 22,500$ , 1.5–1.7  $\mu\text{m}$ ; Targeted mainly at giant sources with the objective of studying galactic structure [11].

#### M DWARF CHALLENGE:

ASPCAP pipeline fails to deliver reliable parameters for sources cooler than  $\sim 3550\text{K}$  [4].

Numerous overlapping features present in sources this cool make it infeasible to use equivalent width methods [5].

Spectral synthesis with precomputed model grids has produced some stellar parameter estimates of the warmer sources ( $> M5$ ) [5,10].



## WHY DATA-DRIVEN MODELS?

#### WORK WITH THE CANNON:

The Cannon has been used on APOGEE giants to infer stellar parameters (Teff, logg, [Fe/H]) [1] and 15 elemental abundances [2] to higher precisions than ASPCAP.

**SOLUTION:** Data-driven models take away the challenge of directly inferring labels from a survey [3]—instead we **transfer labels** from another (more accurate/easier-to-model) survey.

**BENEFITS:** Fast computation time; flexible model labels (can train on any parameters that you have reference labels for); flexible label vectors (can specify degree of polynomial). Enables systematic search for lines/features that vary strongly with change in parameter.

Accurate training parameters + very precise label transfer = high quality label inference!

## FUTURE WORK

**IMPROVE THE MODEL:** Expand training sets by either (1) obtaining more reference labels for other APOGEE M dwarfs (expanding Mann's sample or observing sources w/ SpeX/NIRSPEC), or (2) obtaining APOGEE spectra for more known M dwarfs. Also, construct a training set with more reference labels (logg, abundances).

**M DWARF PIPELINE FOR APOGEE:** Identify, classify and label all of the (probably 1000s of) M dwarfs in the APOGEE survey, which do not have reliable parameters from the ASPCAP pipeline—will require training additional Cannon models to discriminate M stars from hotter stars, and dwarfs from giants.

**SCIENTIFIC GOALS:** strong match to features => precise radial velocity measurements (look at rv variations over multiple epochs, and velocity distributions in galaxy); chemical abundance analysis; line analysis and comparison to theoretical models (i.e. BT-Settl, PHOENIX).

## REFERENCES:

- [1] Ness et al. 2015, ApJ, 808, 16
- [2] Casey et al. 2016, ApJ, 840, 1
- [3] Ho et al. 2016, ApJ, 808, 1
- [4] Schmidt et al. 2016, MNRAS, 460, 2611
- [5] Deshpande et al. 2013, AJ, 146, 156
- [6] Mann A. W., et al. 2015, ApJ, 804, 64
- [7] West et. al. 2011, AJ, 141, 97
- [8] Burgasser et. al. 2014, ASICS, 10, 1-10
- [9] Souto et al. 2017, ApJ, 835, 239
- [10] Rajpurohit et al. 2017, A&A, arXiv:1708.06211
- [11] Majewski et. al. 2015, AJ, arXiv:1509.05420

