

# AI/ML - applications to stars and stellar population studies

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# Outline

- Stellar classification
- Stellar parameterization
- Stellar abundance estimation
- Chemical tagging
- Future direction

# Why are we interested in stars?

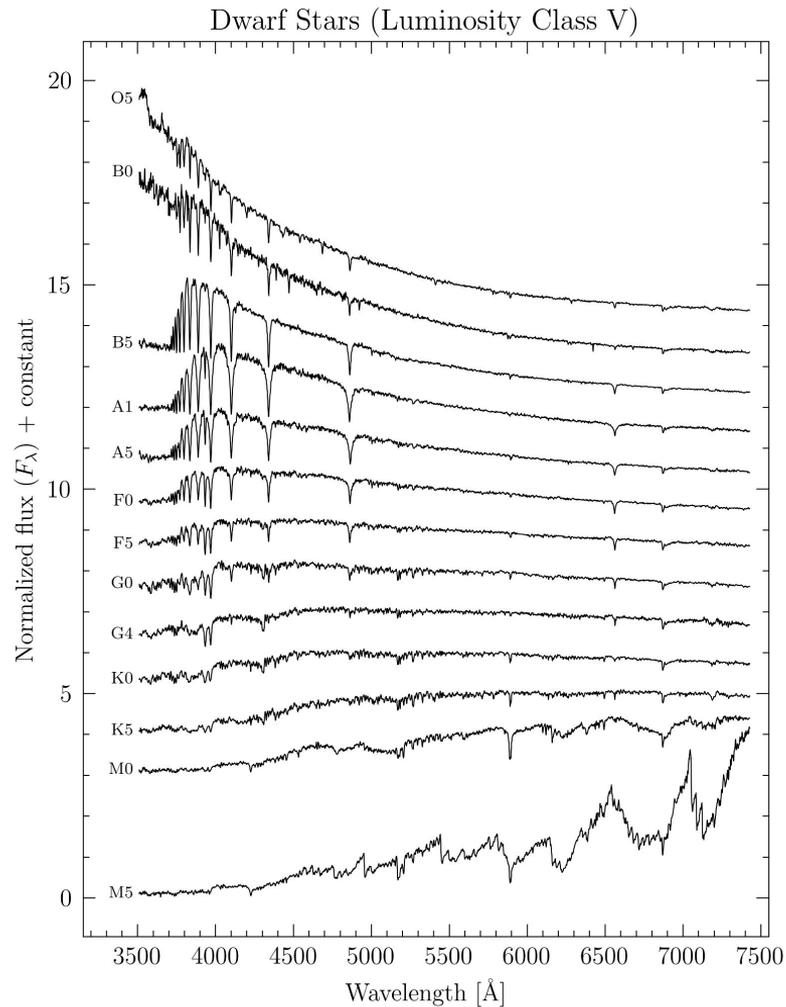
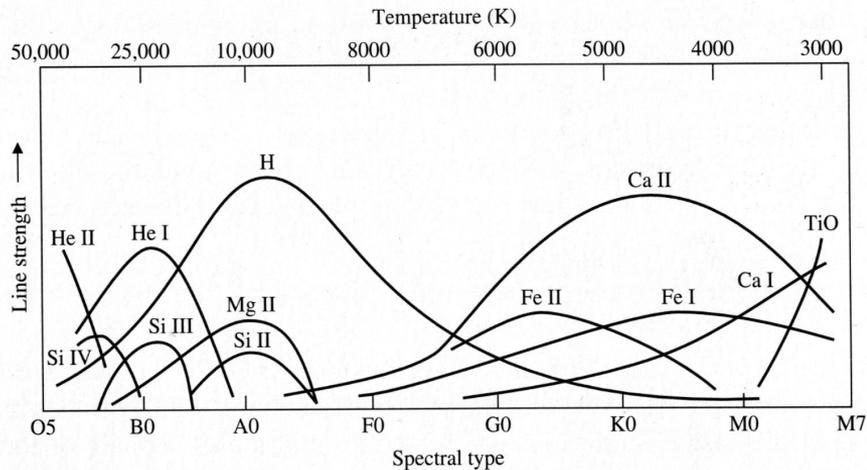
To understand the Sun, its formation and evolution and as part of the Galaxy

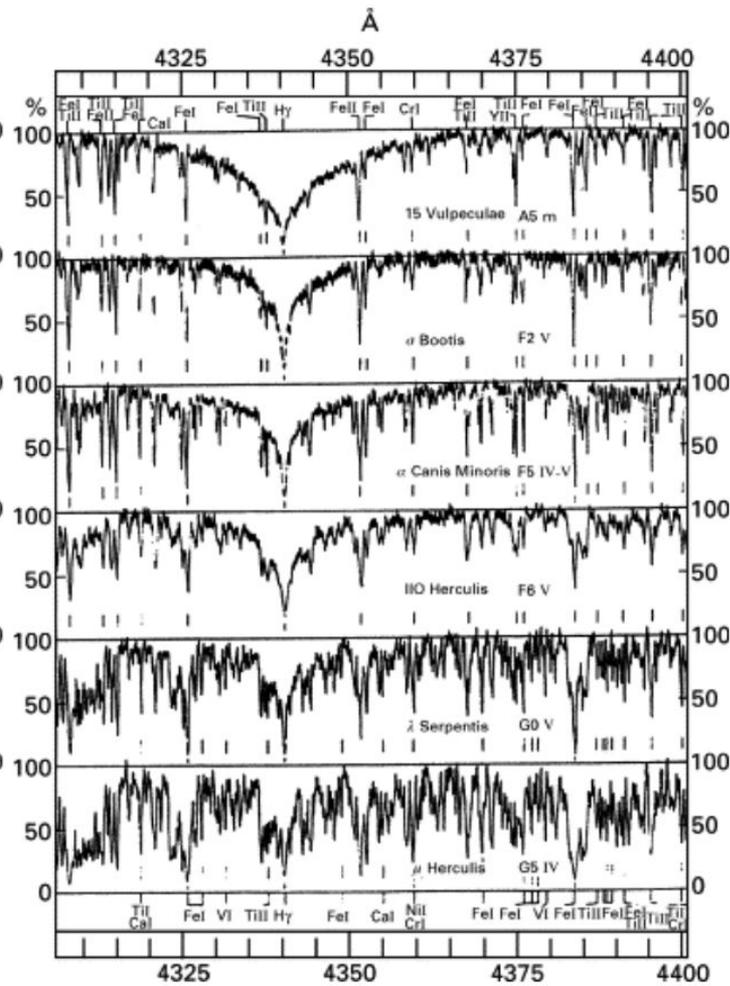
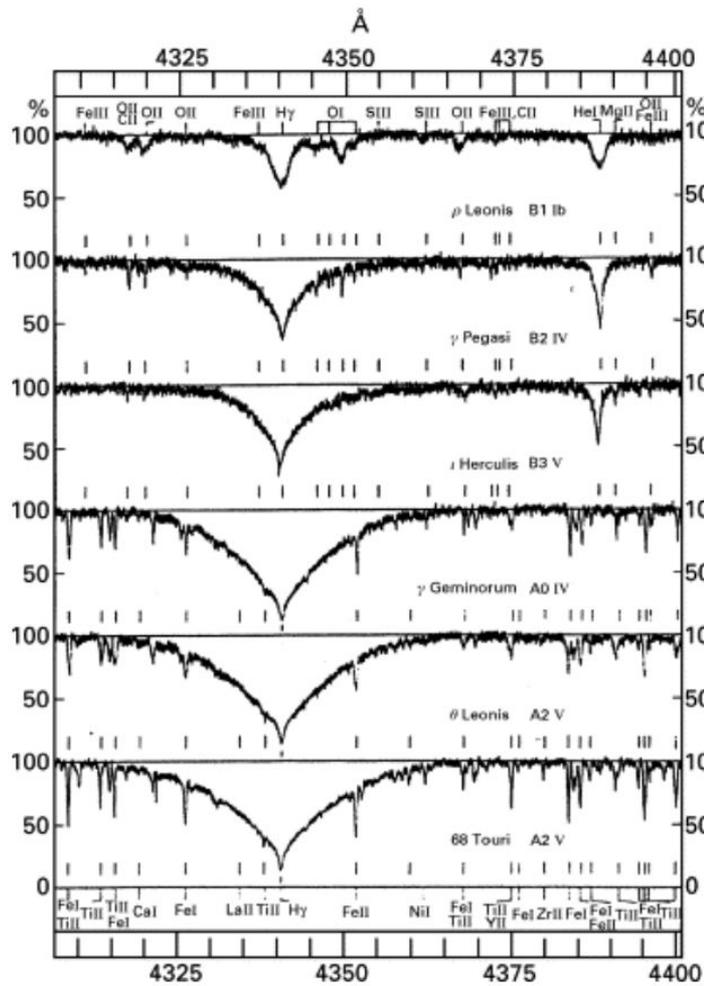
Use stars as to tool to study galaxies.  $\Rightarrow$  Stars contribute to the most of the visible wavelength emission of a galaxy

# MK spectral classification -2D

Spectral class - OBAFGKMLT

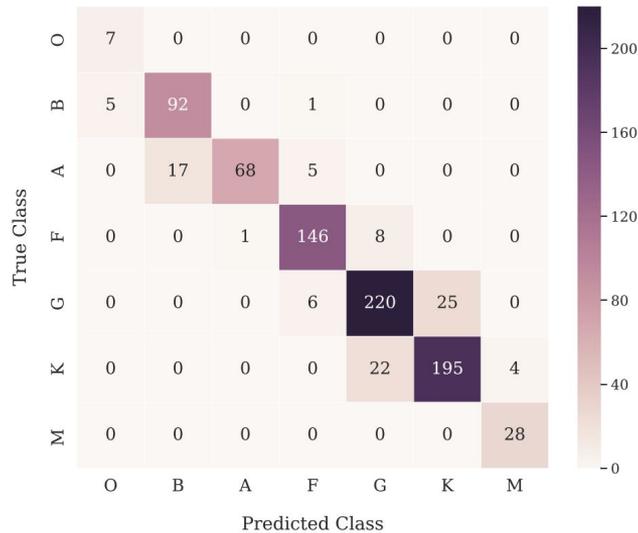
Luminosity class - I,II,III,IV,V





# Spectral classification

Autoencoders, CNN, Sharma et al. 2020

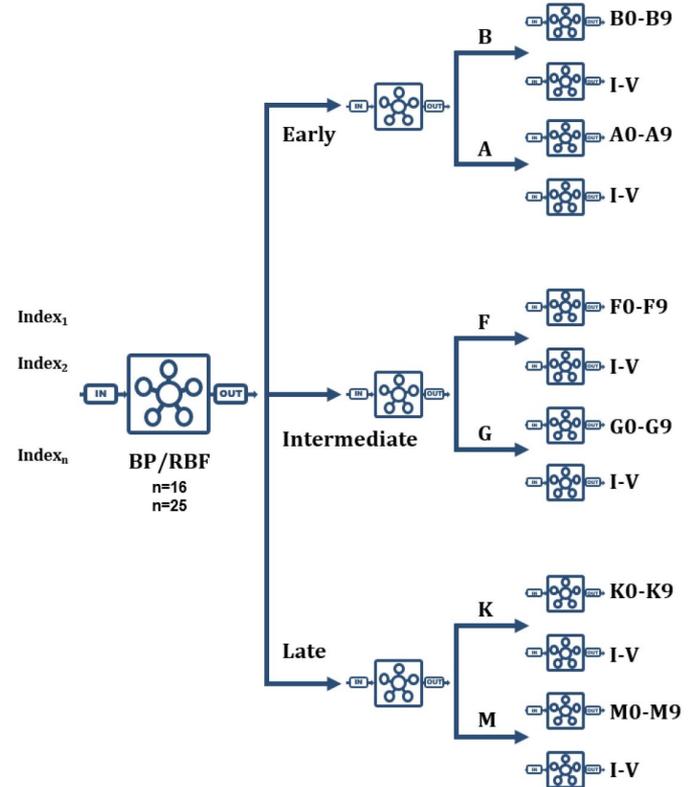
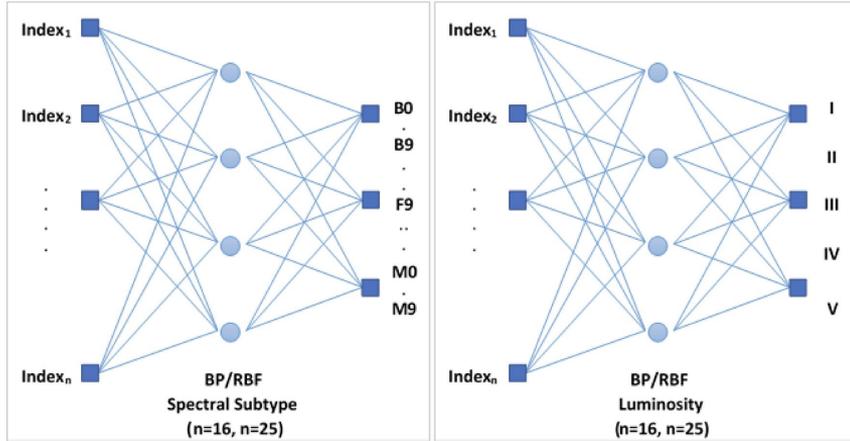


**Figure 12.** Confusion matrix for the main spectral classes computed for the CFLIB library using 1D CNN classification model.

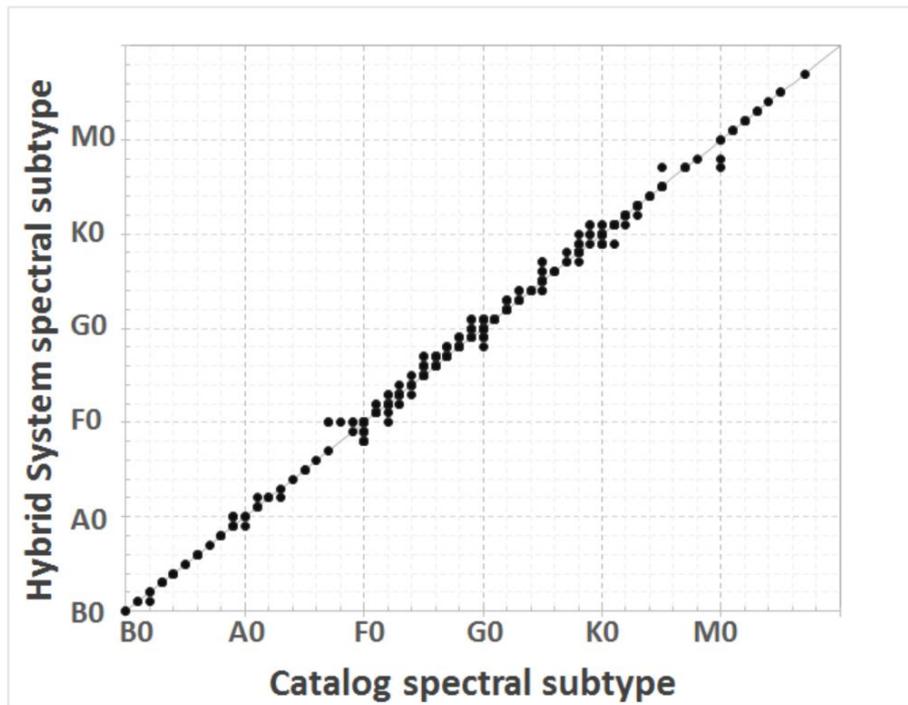


**Figure 14.** Confusion matrix for luminosity classification on CFLIB using 1D CNN.

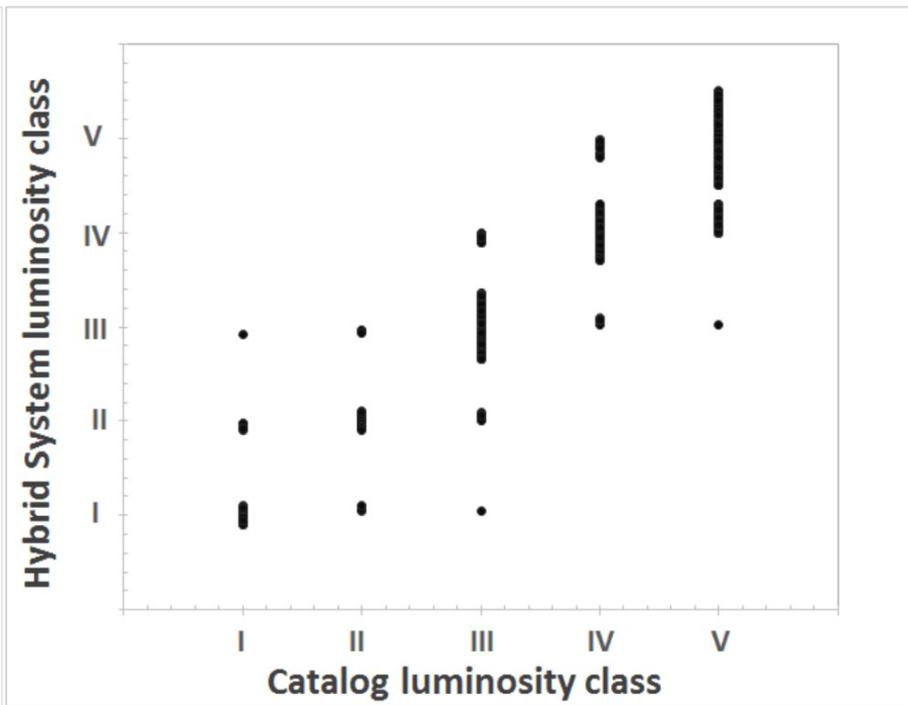
# Spectral classification - Hybrid approach - Dafonte et al.



# Spectral classification - Hybrid approach - Dafonte et al.



(a)

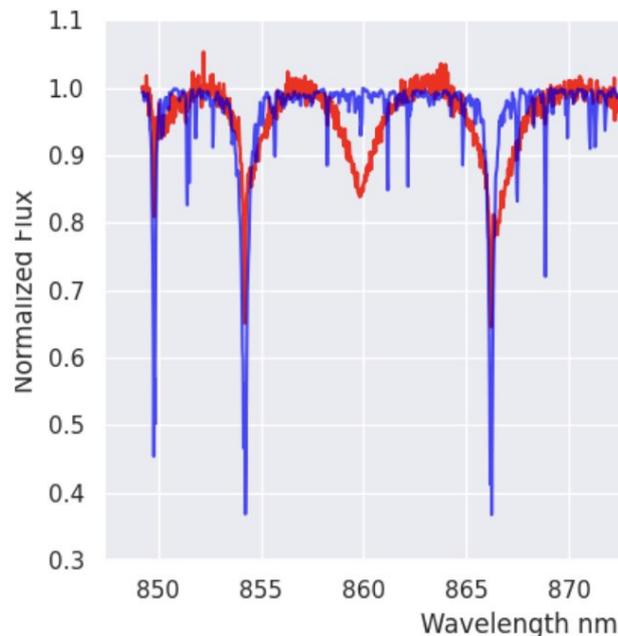


(b)

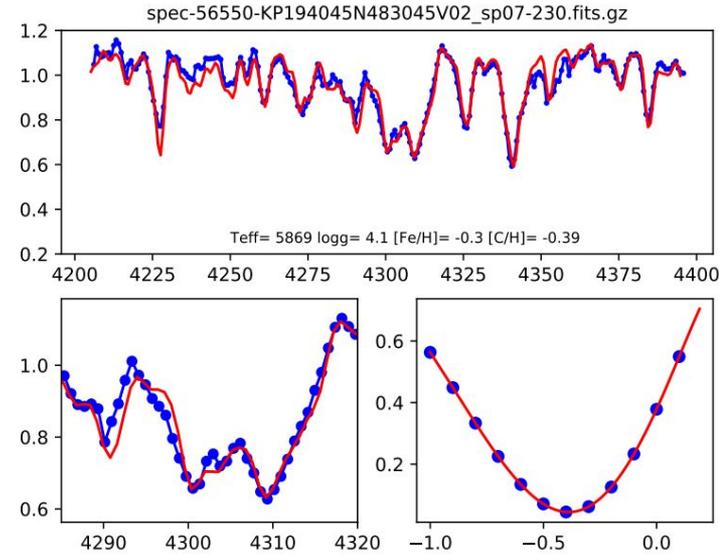
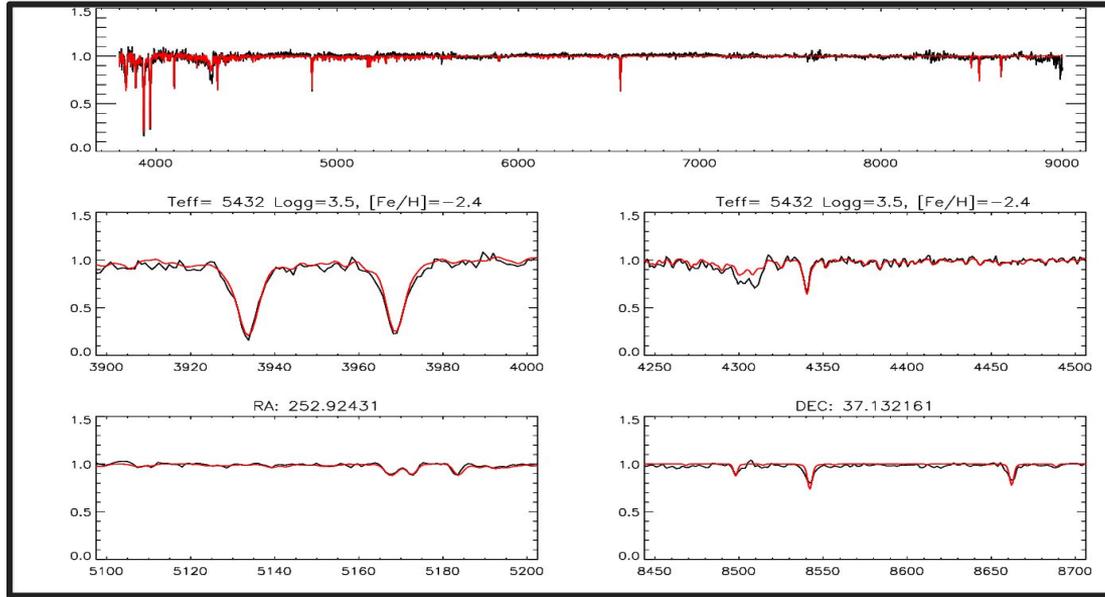
# Spectral classification

Matching with the set of benchmark training stars to get luminosity and distances

Finding rare objects - similarity index and twins - identifying Metal poor stars from Gaia-XP spectra – APOGEE, LAMOST is used to train Gaia XP spectra



# Stellar parameterisation

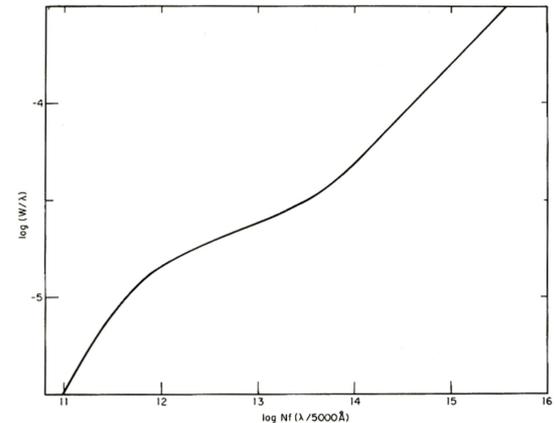
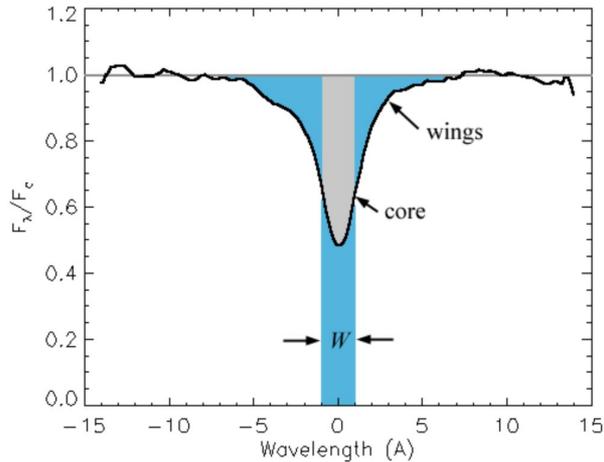


Estimation of physical parameters,  $T_{\text{eff}}$ ,  $\text{logg}$ ,  $[\text{Fe}/\text{H}]$ , matching with synthetic spectra using global optimizer Simulated Annealing. Issue: Degeneracy between  $T_{\text{eff}}$  and  $\text{logg}$ .

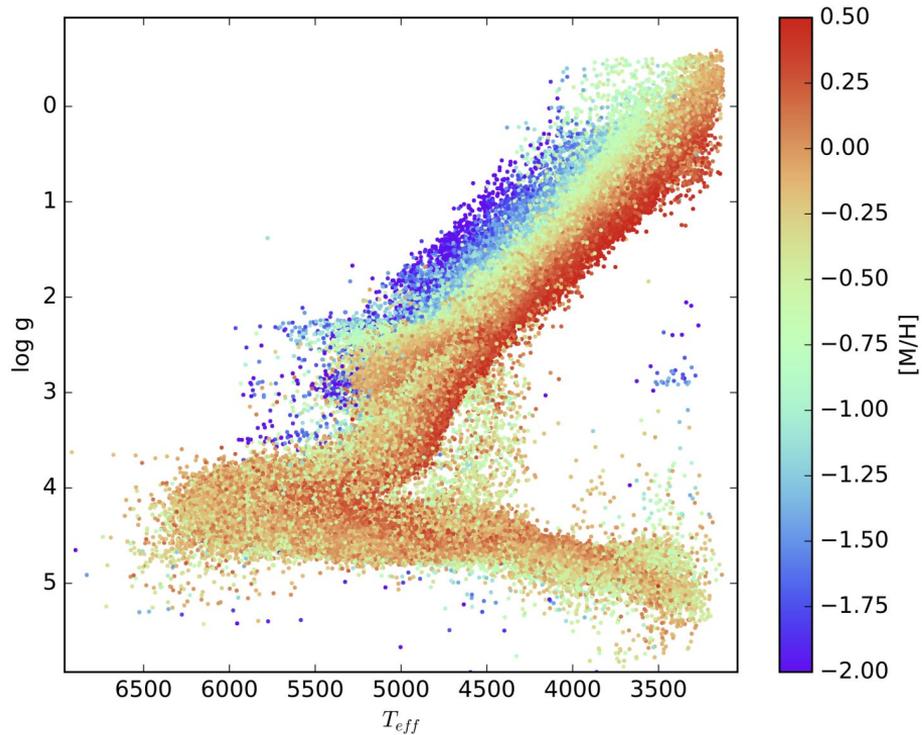
Stellar parameterization suffers from degeneracies

Most surveys use empirical calibration to match high resolution spectroscopy  
or Trained on high resolution

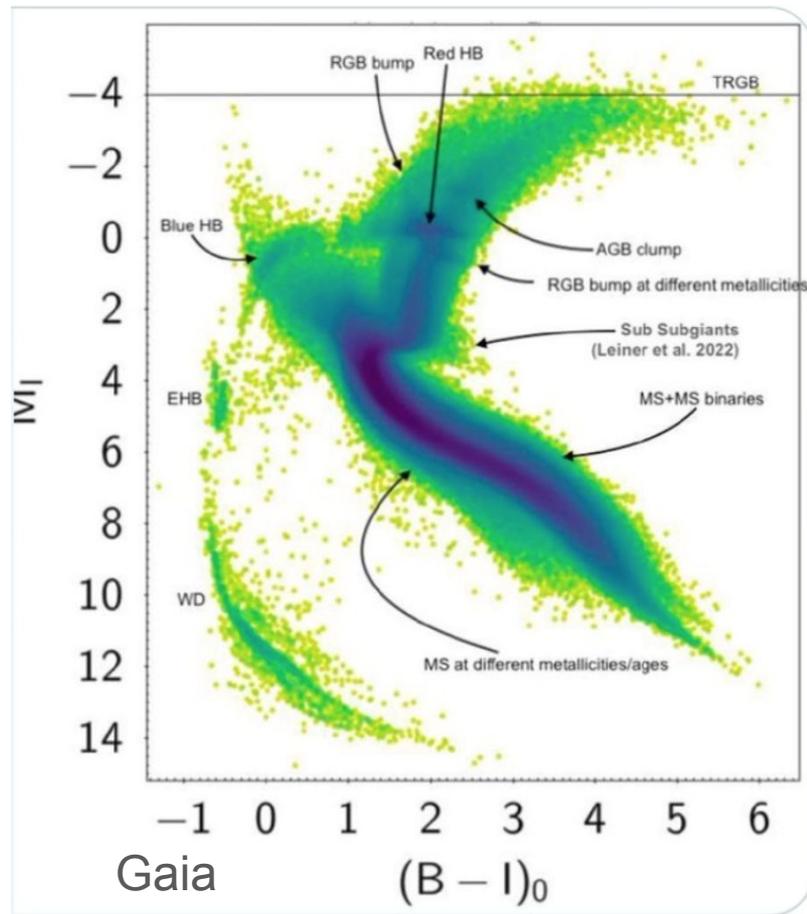
High resolution uses weak lines, low resolution uses strong lines, affected by microturbulence and line broadening, nonlinear dependency of optical depth. Carefully using wings of the lines would work better.

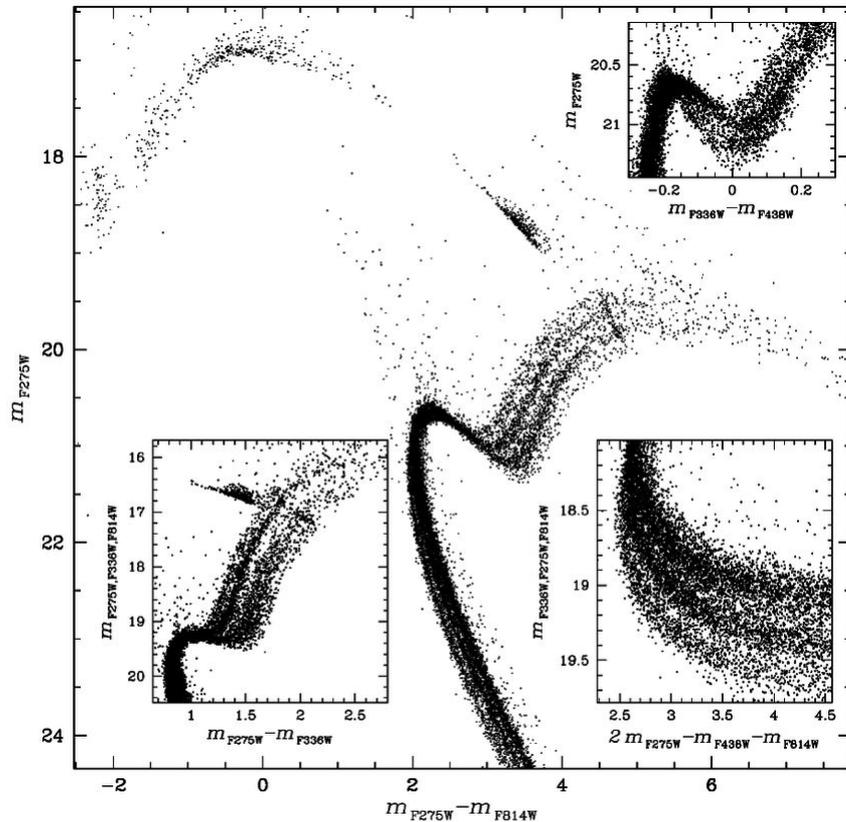
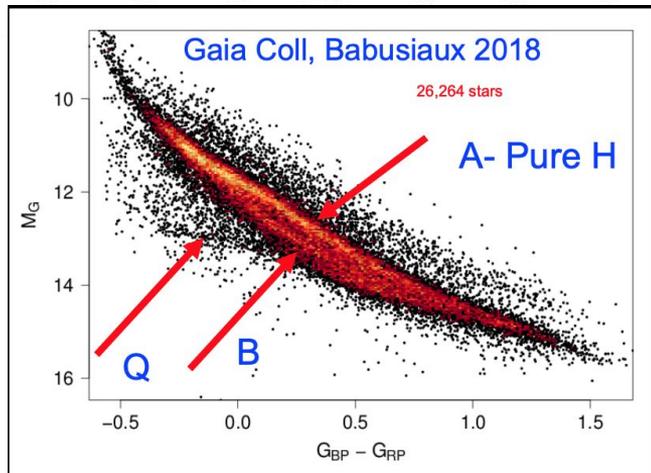
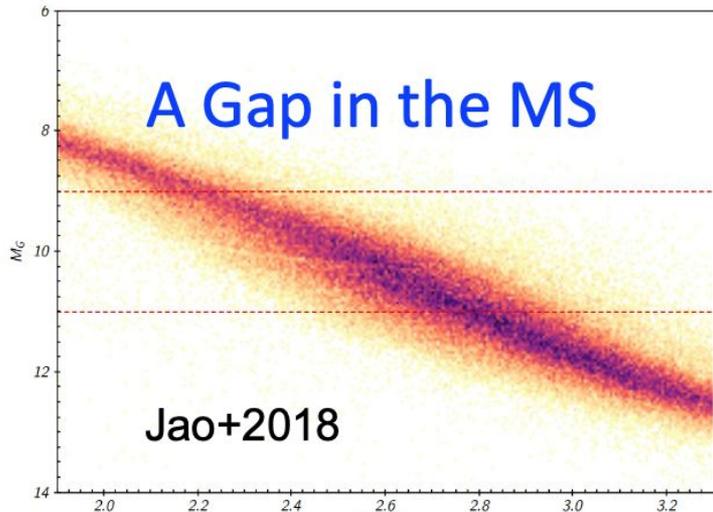


# Comparison of observed and derived HR diagram



APOGEE

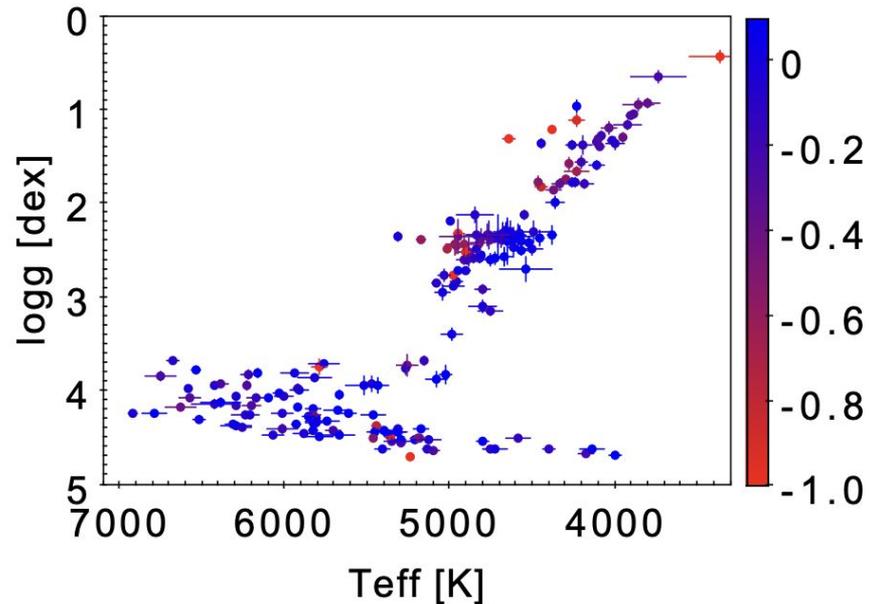




# Towards precision spectroscopy - Bridge the gap between models and observations

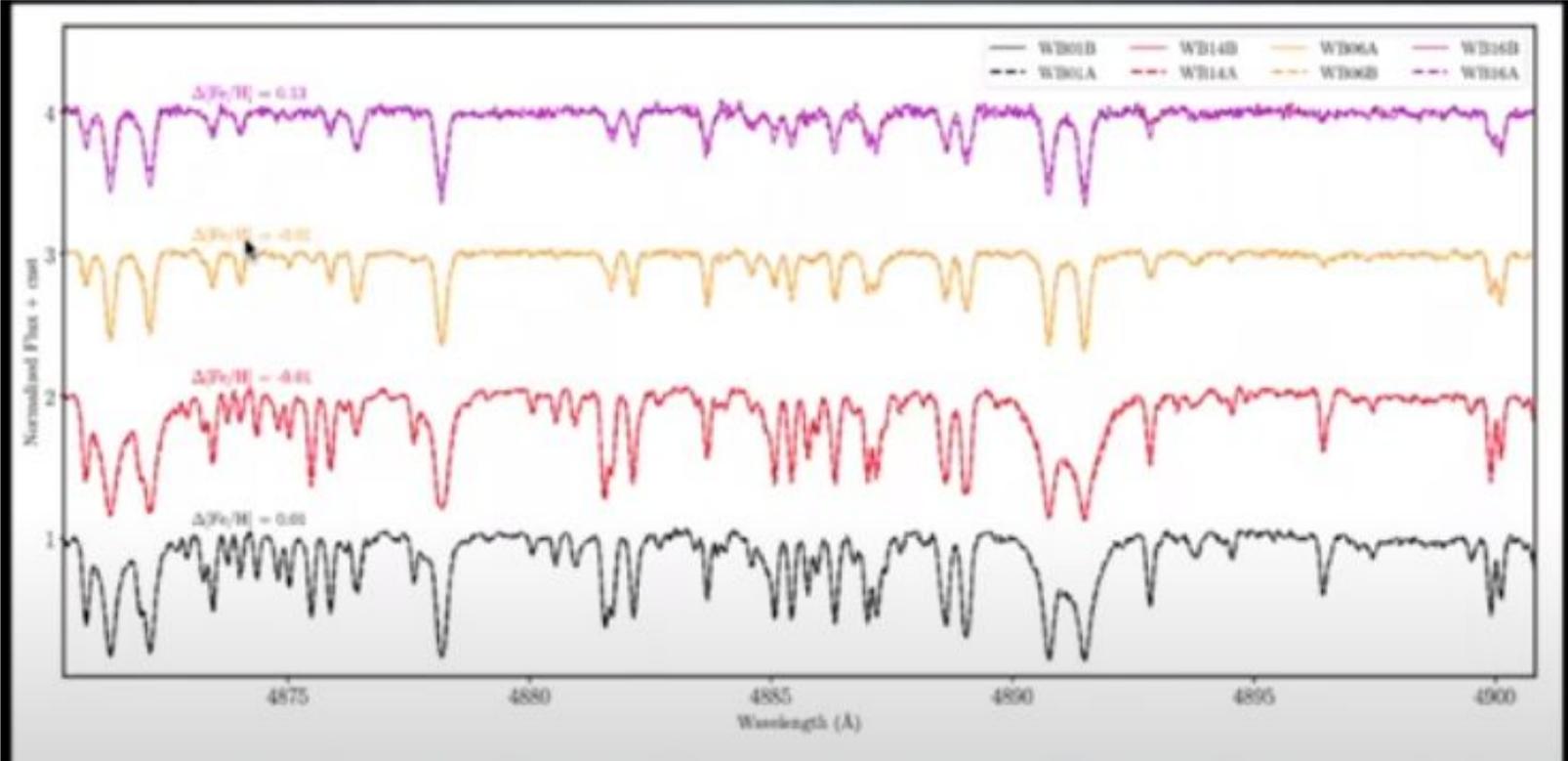
Teff and log g through the fundamental relations with a minimum of assumptions and theoretical modelling

Gaia benchmark stars - 200 stars, stellar diameters and parallax

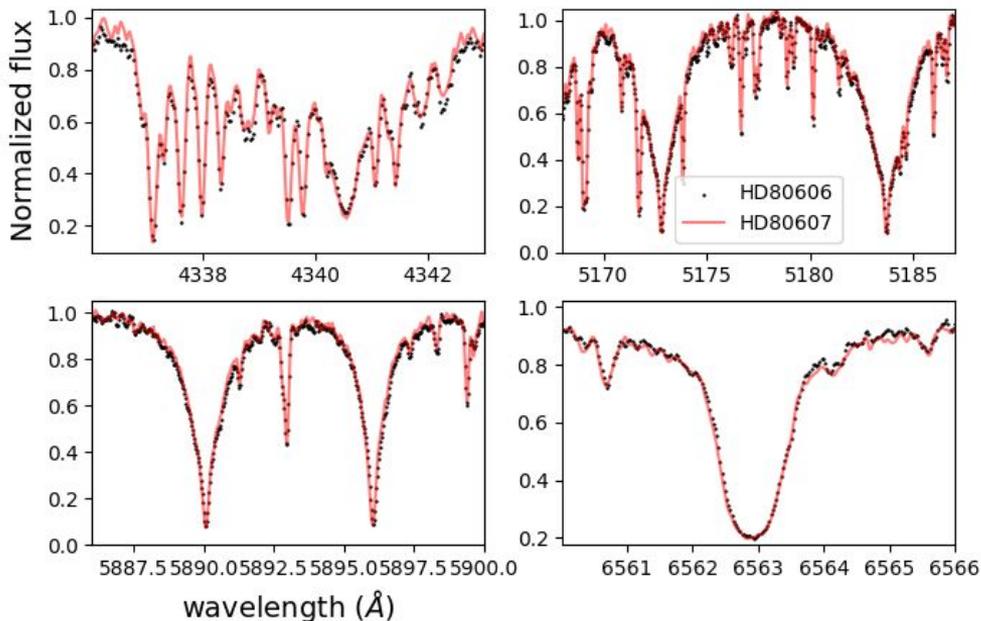


Soubiran et al (2024)

# Differential Abundance Stellar twins



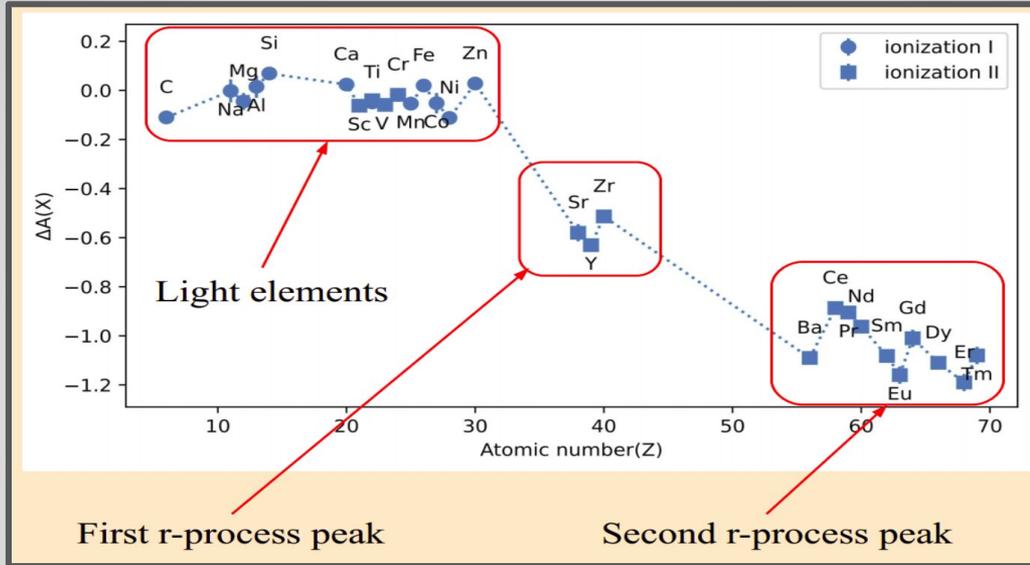
# Differential approach for solar twins



Parameter estimated	HD 80606	HD 80607
<b>Teff (k)</b>	<b>Δ 37 K</b>	<b>5650 K</b>
<b>logg</b>	<b>Δ 0.03</b>	<b>4.4</b>
<b>[Fe/H]</b>	<b>Δ 0.012 dex</b>	<b>0.32 dex</b>
<b>εt (km/s)</b>	<b>Δ 0.3</b>	<b>1.30</b>

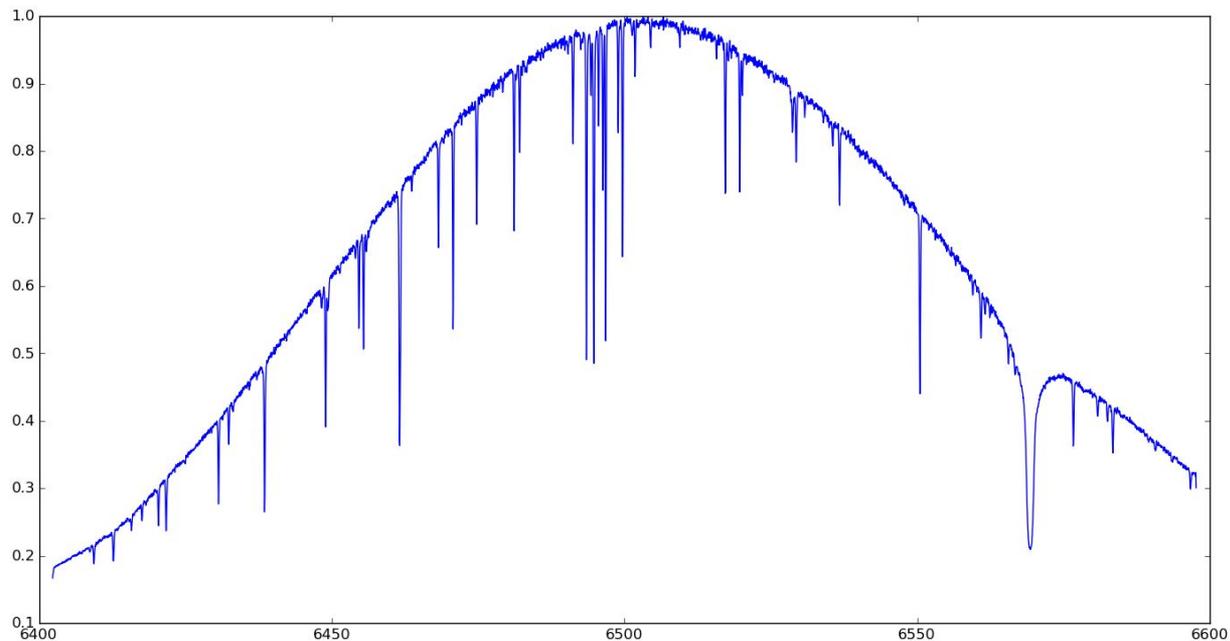
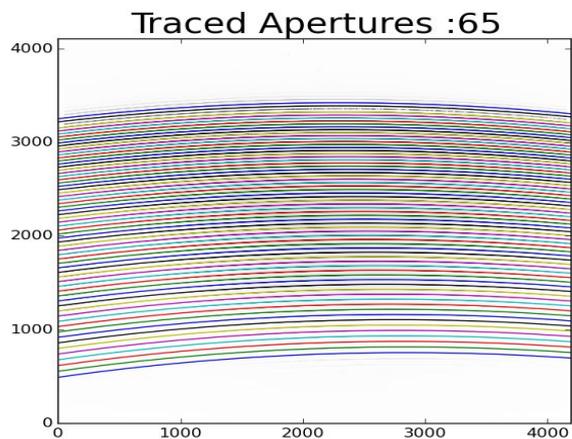
Unni et al. in preparation

# Is r-process pattern universal?



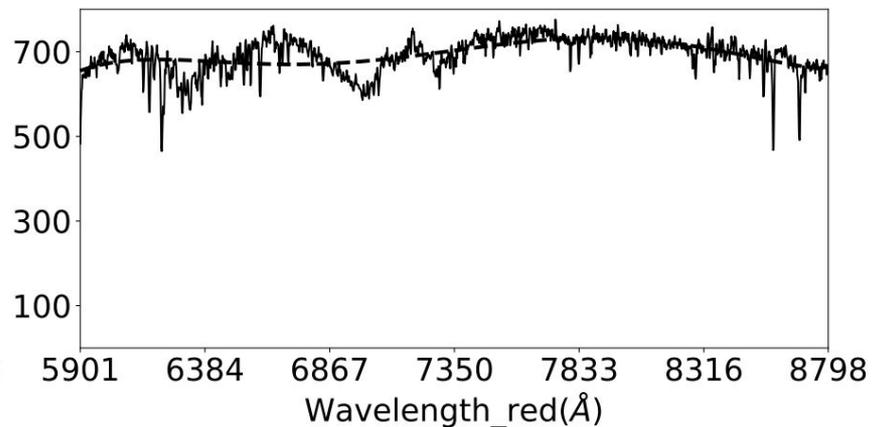
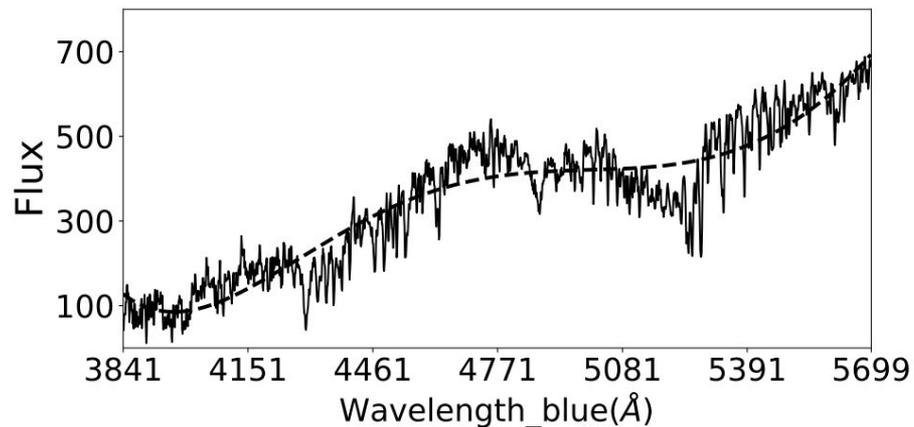
- Alpha and Fe-peak elements in r-I and r-II stars come from same site that does not produce n-capture elements.
- Lighter n-capture elements (Sr, Y, Zr) need additional production site compared to heavy n-capture elements (Ba, Eu, ...)
- Even among the main r-process elements there is significant difference (0.1 – 0.2 dex) between r-I and r-II stars.

# Going down a step into data reduction and applying data driven approach

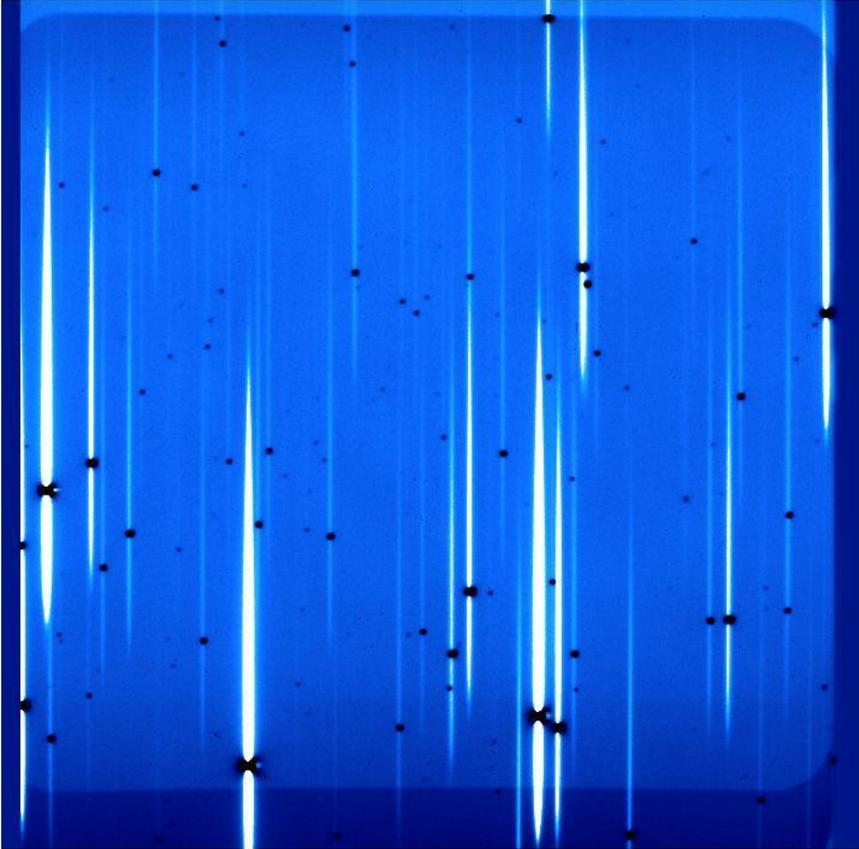


Instrument model based extraction and calibration – Stability places a crucial role  
Chanumolu et al. 2015, 2016

# Continuum fitting in LAMOST



# Data driven approach to Background subtraction slitless spectroscopy

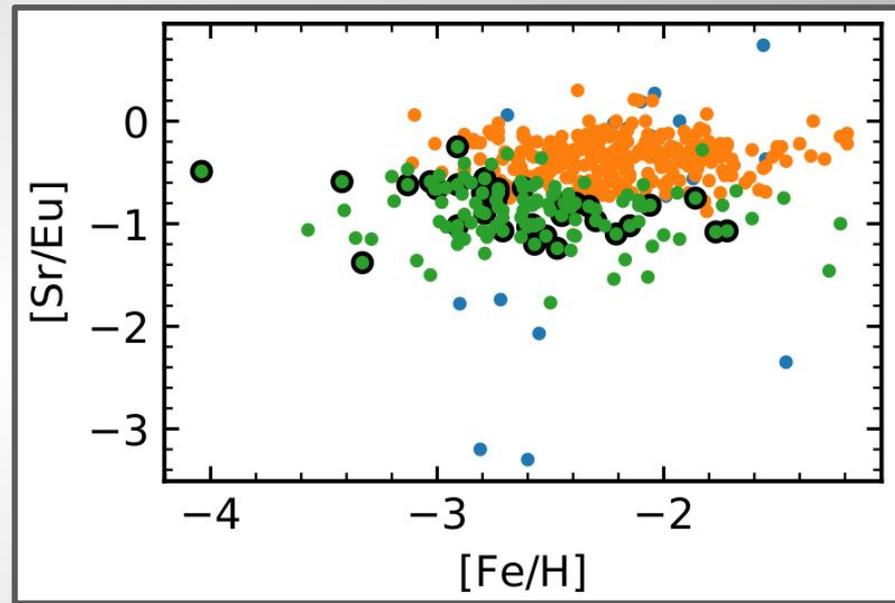
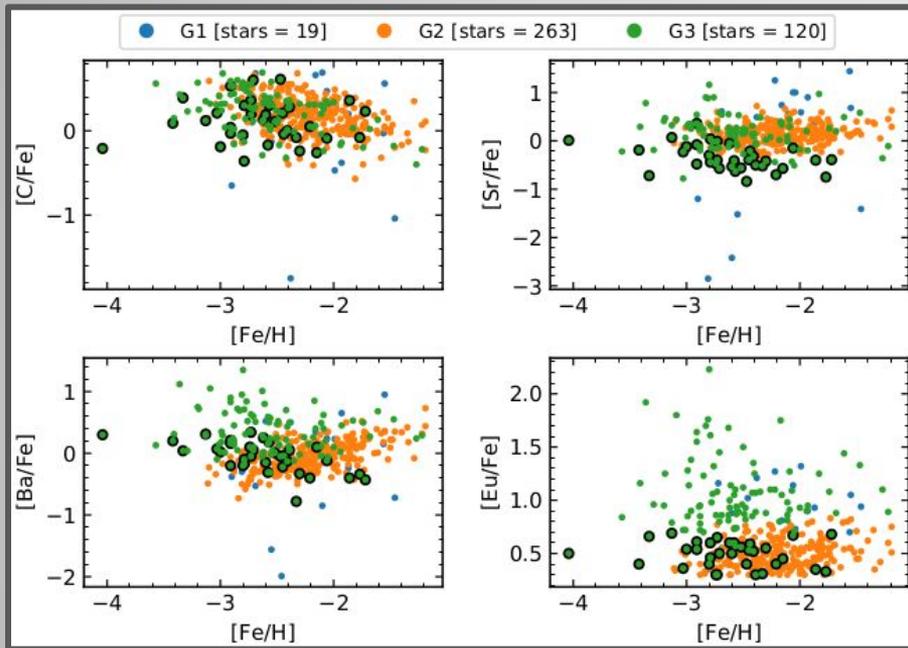


Divakar et al. in preparation

# Application at the higher level

Description	Definition	Abbreviation
Population III stars	Postulated first stars, formed from metal-free gas	Pop III
Population II stars	Old (halo) stars formed from low-metallicity gas	Pop II
Population I stars	Young (disk) metal-rich stars	Pop I
Super-metal-rich	$[\text{Fe}/\text{H}] > 0.0$	MR
Solar	$[\text{Fe}/\text{H}] = 0.0$	None
Metal-poor	$[\text{Fe}/\text{H}] < -1.0$	MP
Very metal-poor	$[\text{Fe}/\text{H}] < -2.0$	VMP
Extremely metal-poor	$[\text{Fe}/\text{H}] < -3.0$	EMP
Ultra-metal-poor	$[\text{Fe}/\text{H}] < -4.0$	UMP
Hyper-metal-poor	$[\text{Fe}/\text{H}] < -5.0$	HMP
Mega-metal-poor	$[\text{Fe}/\text{H}] < -6.0$	MMP
Septa-metal-poor	$[\text{Fe}/\text{H}] < -7.0$	SMP
Octa-metal-poor	$[\text{Fe}/\text{H}] < -8.0$	OMP
Giga-metal-poor	$[\text{Fe}/\text{H}] < -9.0$	GMP
Ridiculously metal-poor	$[\text{Fe}/\text{H}] < -10.0$	RMP

# Data driven classification



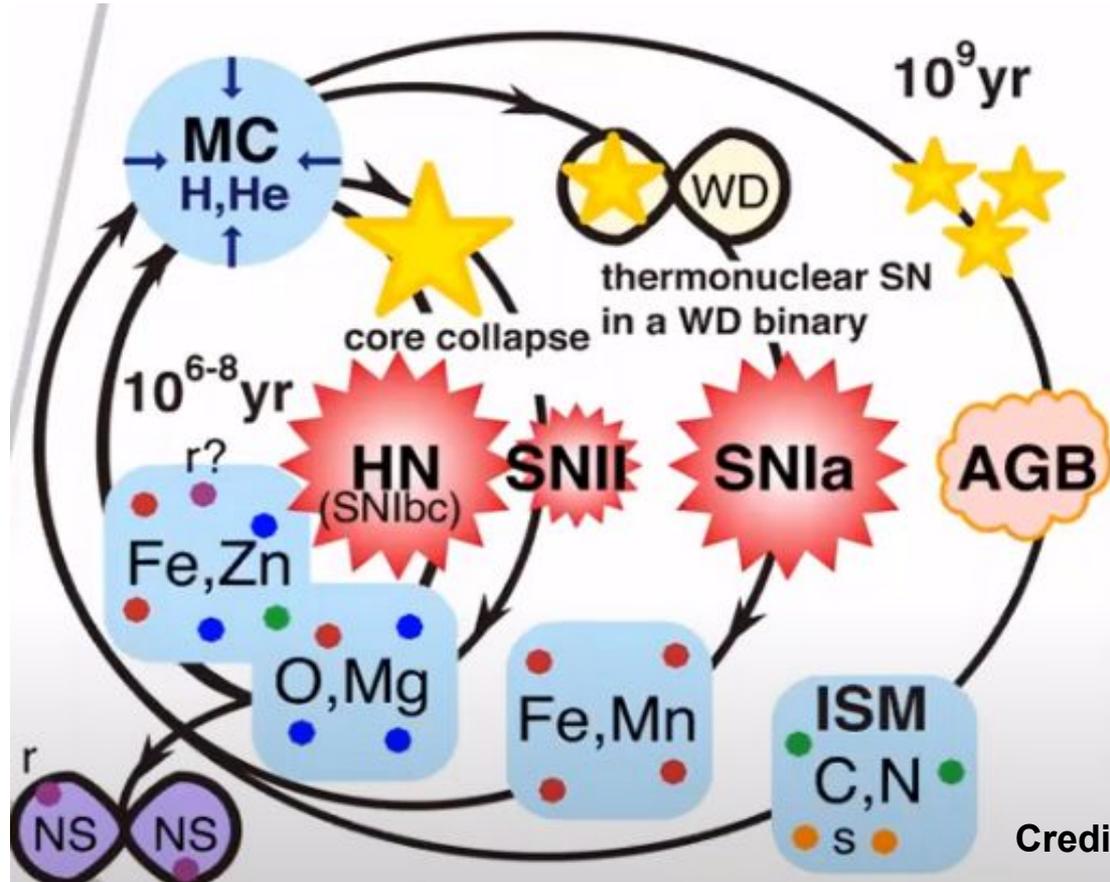
group G1: % of r-I = 31.58  
          % of r-II = 68.42

group G2: % of r-I = 92.02  
          % of r-II = 7.98

group G3: % of r-I = 29.17  
          % of r-II = 70.83

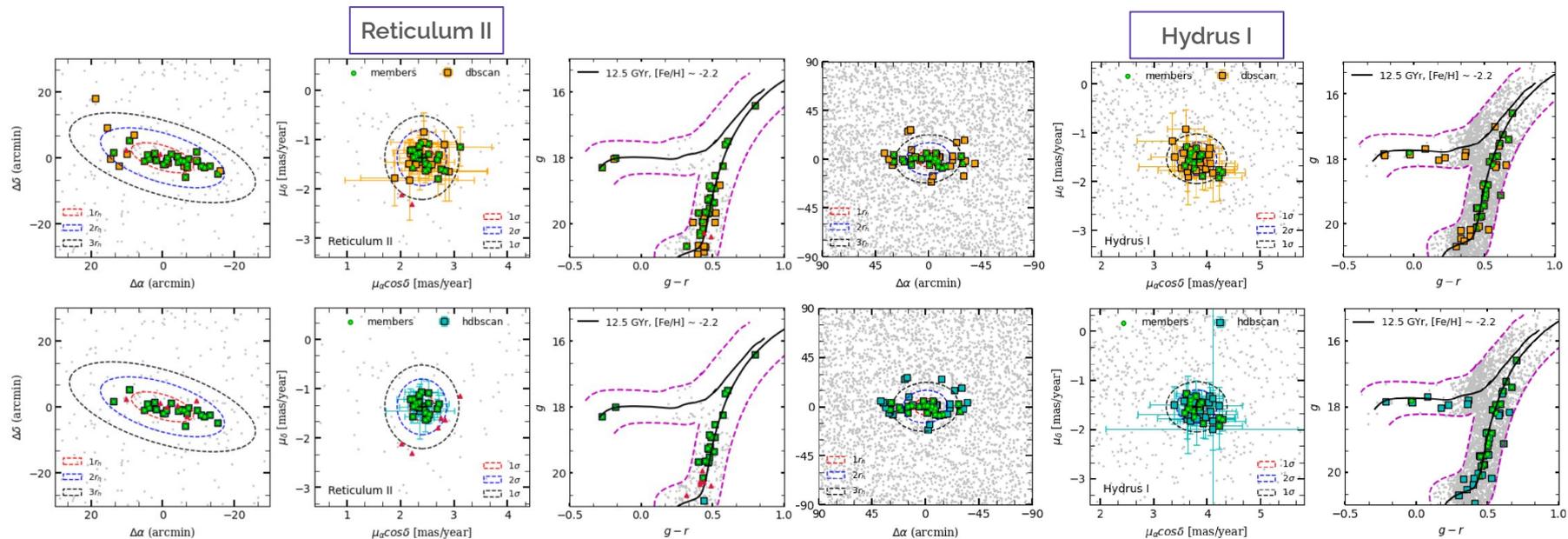
Saraf et al. 2024

# Data driven approach to chemical tagging



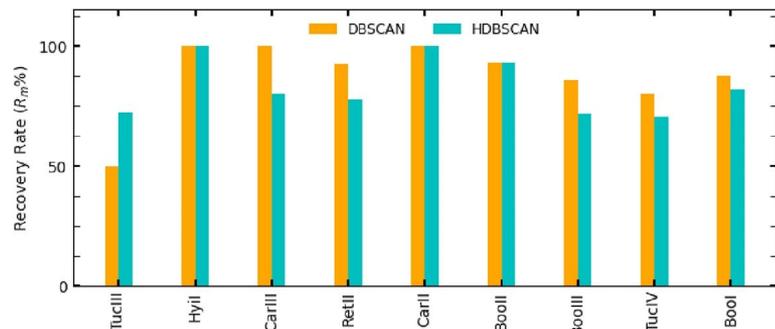
Credit: Kobhayashi

# Machine Learning Techniques to find new members of UFDs - Results

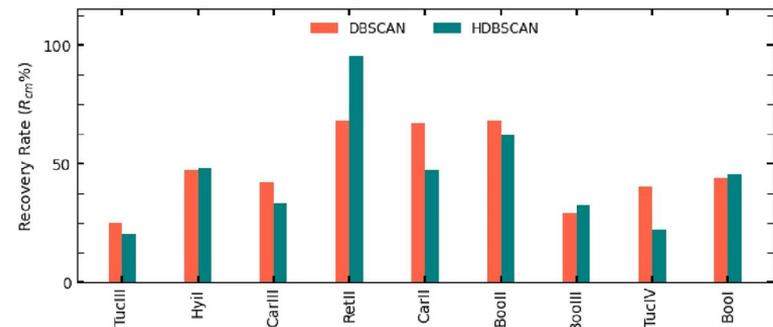


Green squares are known spectroscopic members, Yellow squares are identified new candidates using DBSCAN, Blue squares are identified new new candidates using HDBSCAN

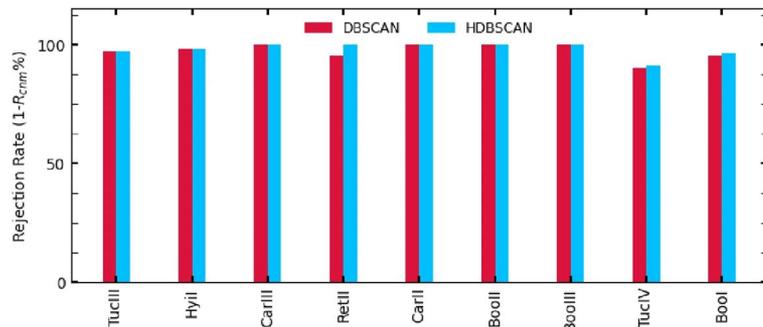
# Performance of DBSCAN



> 75% of spectroscopic member retrieval

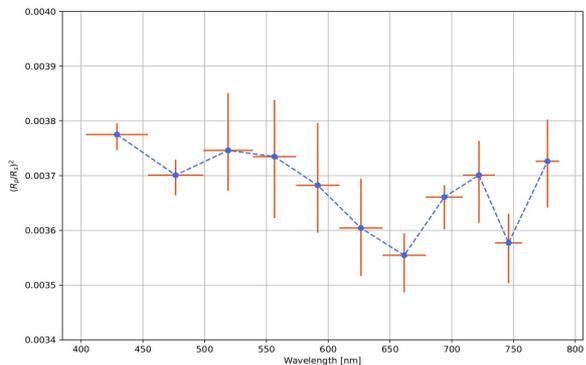
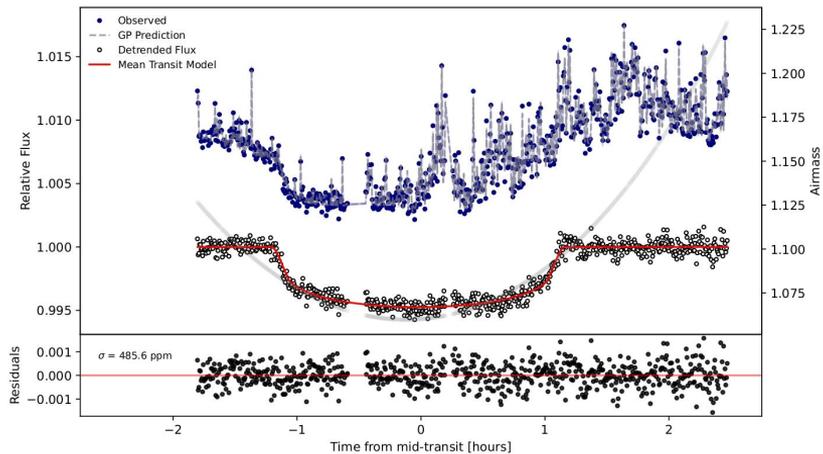


DBSCAN in terms of candidate member retrieval

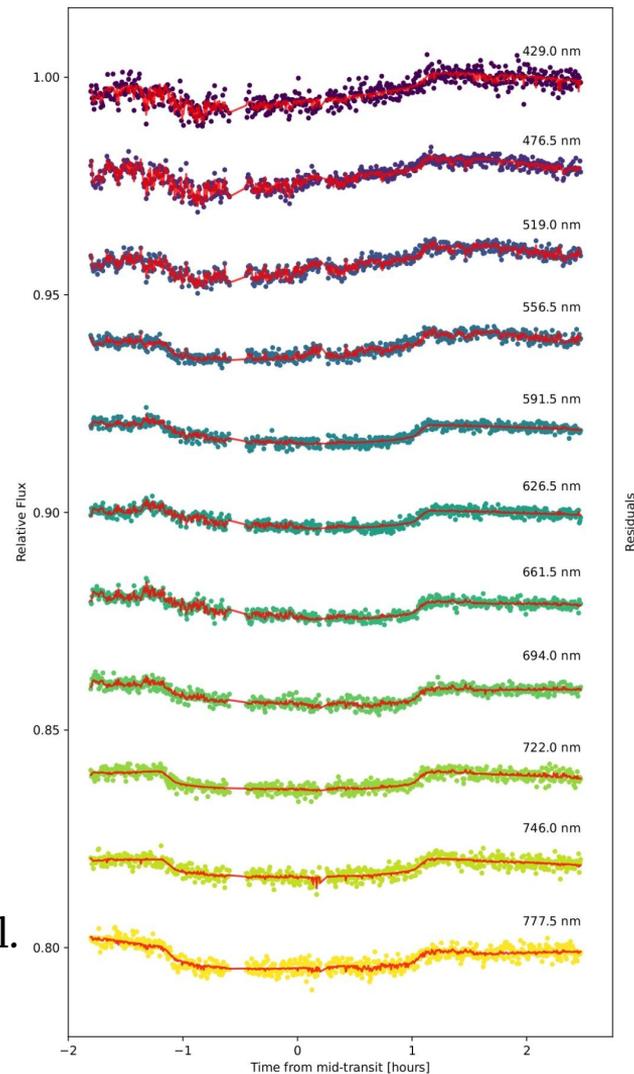


> 95% of non-member rejection

# Exoplanet Transit spectroscopy 2D Gaussian process regression

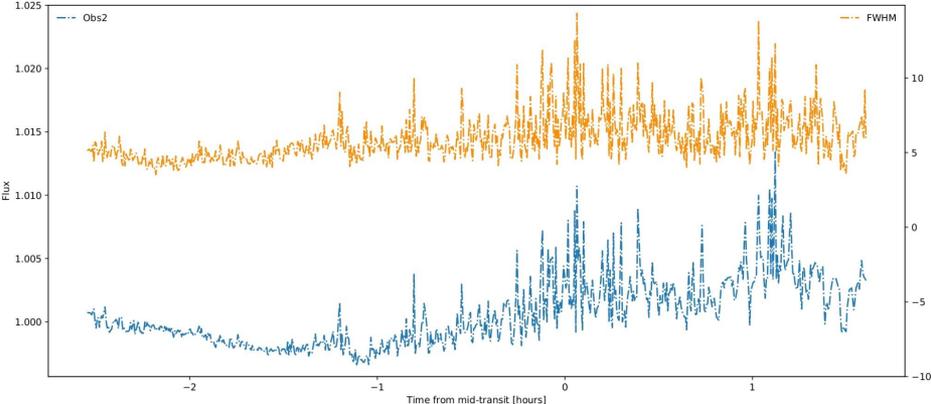
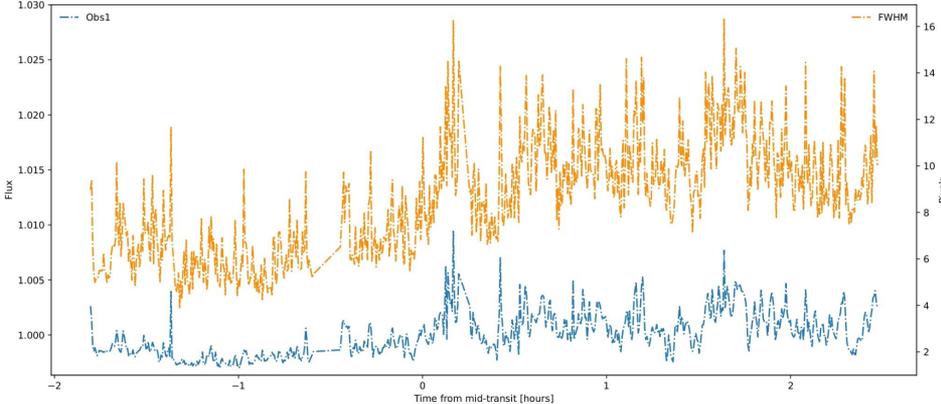


Manickavasaham et al.  
in preparation



# Comparison of WLC systematics and FWHM of spectral profile

August 30, 2016



September 25, 2017

# Summary and future direction

Even with lot of data, high resolution and high SNR, we are yet to reach high precision stellar abundances

Information content in stellar spectra at different spectral resolution

Exoplanet host star studies has added more data, to obtain time resolved and disk resolved spectroscopy for stars, this adding more information and complexity

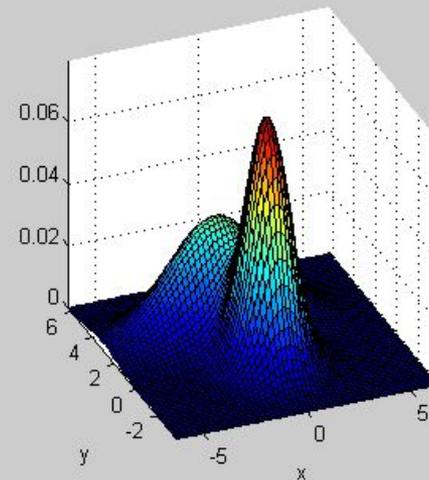
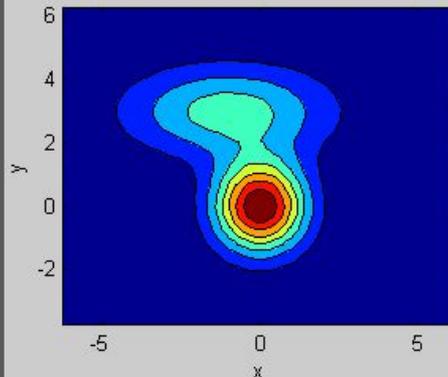
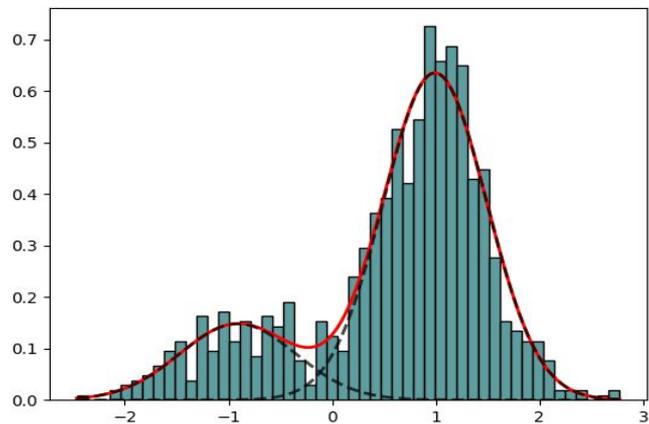
Astrophysical sites of elements production and chemical tagging of stars

Chemical evolutionary models

Data driven approach to theoretical stellar models and improve the atomic and molecular data

Thank You!

# What is GMM (Gaussian Mixture Model)?



# Information content of stellar spectra at different resolution

# Forward model - Retrieval

Models incomplete physics,

Incomplete molecular atomic data. Even wrong data

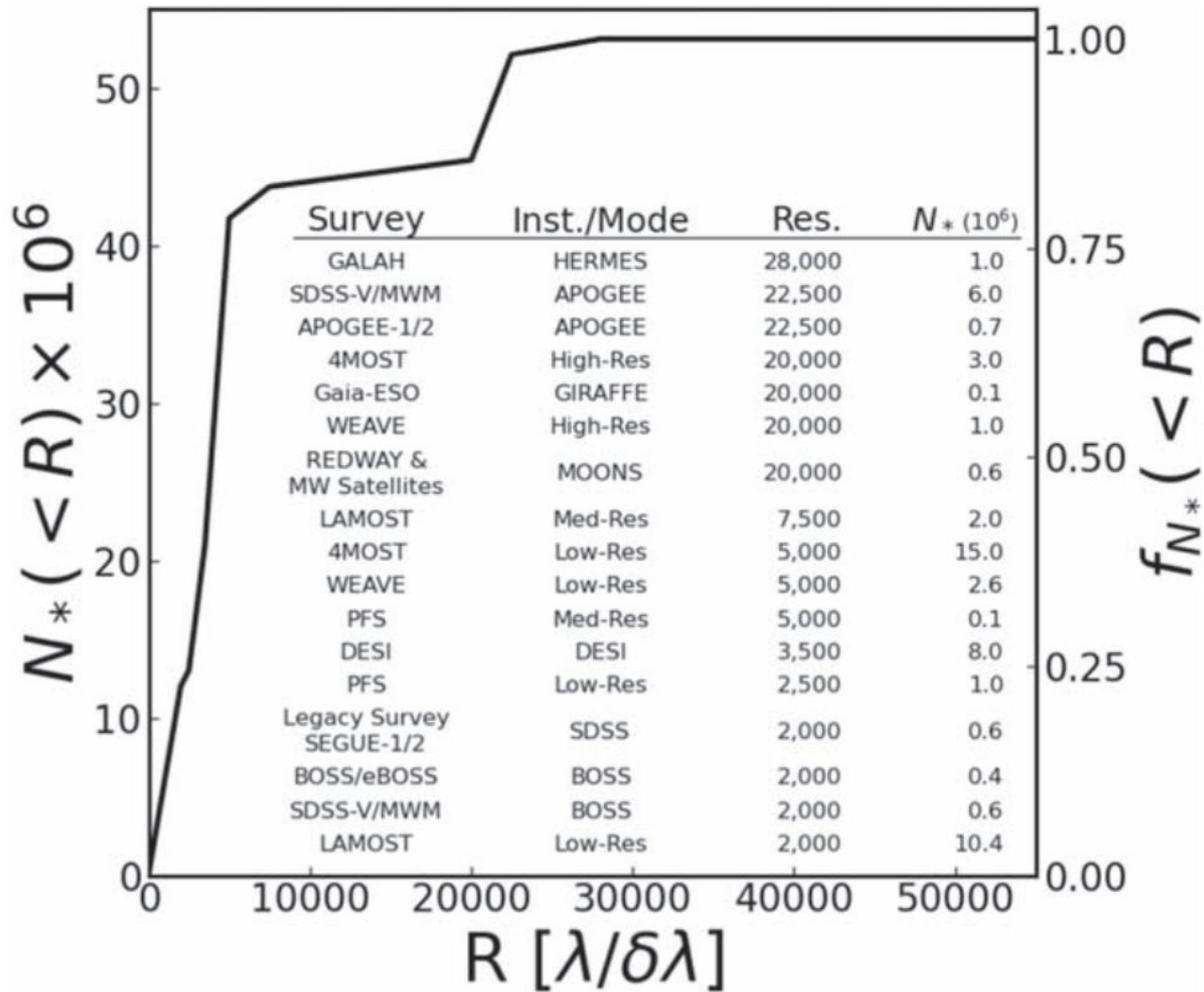
Telluric subtraction, Continuum fitting

# Data processing

Normalisation – Continuum fitting or renormalisation (dividing by median) ⇒  
Instrument stability

# Stellar classification and Stellar Parametrisation

Apache Point Observatory Galactic Evolution Experiment (APOGEE) (Prieto et al. 2010), the Galactic Archaeology with HERMES Survey (GALAH) (De Silva et al. 2015), the Large Sky Area Multi-Object Fibre Spectroscopic Telescope (LAMOST) Experiment for Galactic Understanding and Exploration (LEGUE) (Deng et al. 2012; Zhao et al. 2012), The Gaia-ESO Public Spectroscopic Survey (GaiaESO) (Gilmore et al. 2012), the Sloan Extension for Galactic Understanding and Exploration (SEGUE) (Yanny et al. 2009), the RAdial Velocity Experiment (RAVE) (Steinmetz et al. 2006)



Stanford et al.  
2023, ApJS, 267

