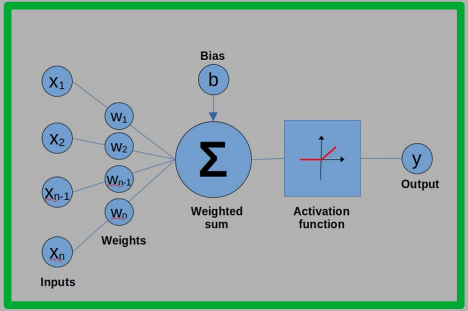
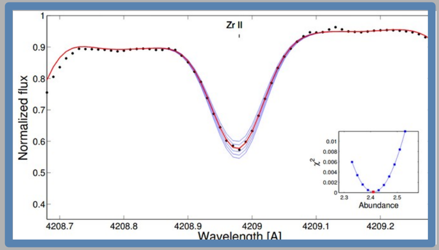
Machine learning for stellar chemical composition studies

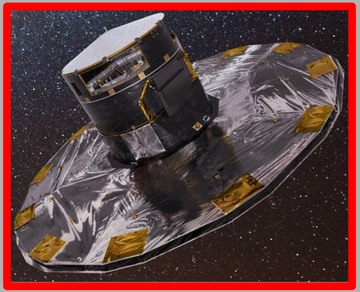
Guillaume Guiglion (G, GG ; MPIA, guiglion@mpia.de)

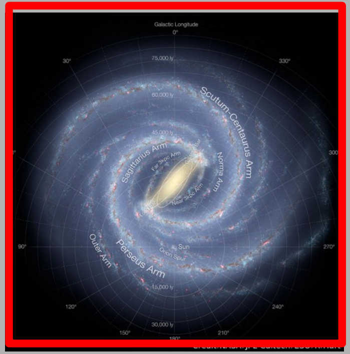
Europlanet Summer School 2023, Moletai, 8-18 Aug. 2023



Machine Learning for stellar chemical composition Studies







C. Chiappini

M. Valentini

M. Steinmetz

G. Matijevič

Š. Mikolaitis

I. Minchev

S. Nepal

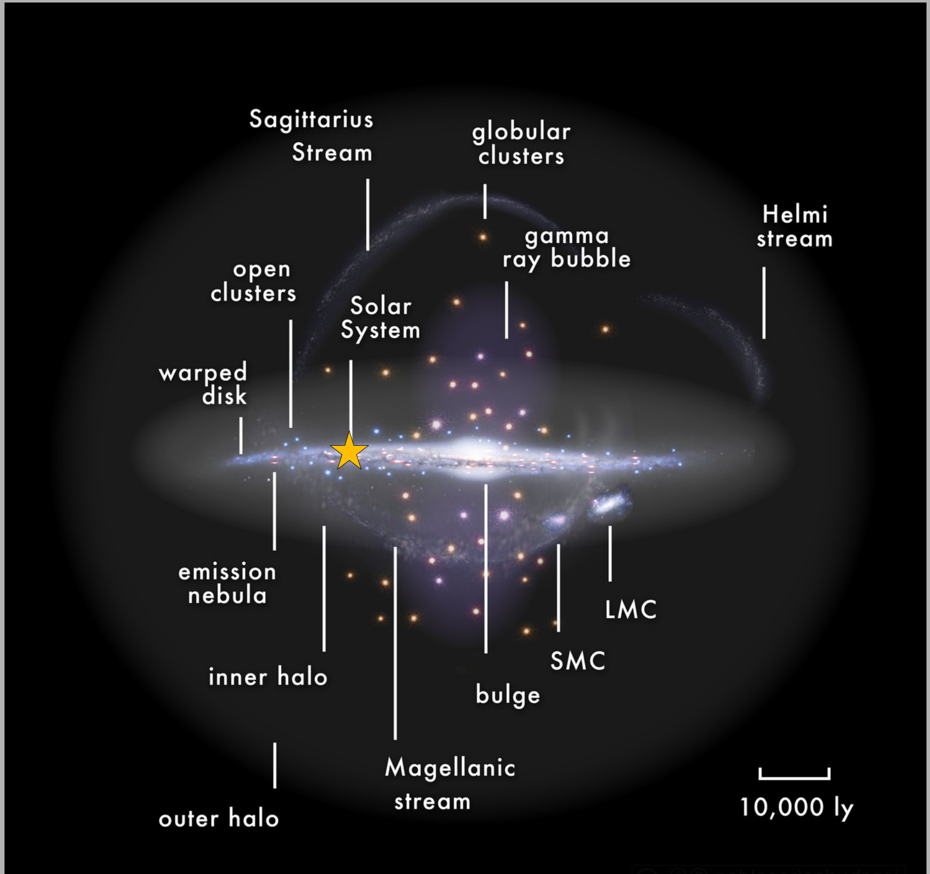
A. Queiroz

M. Ambrosch

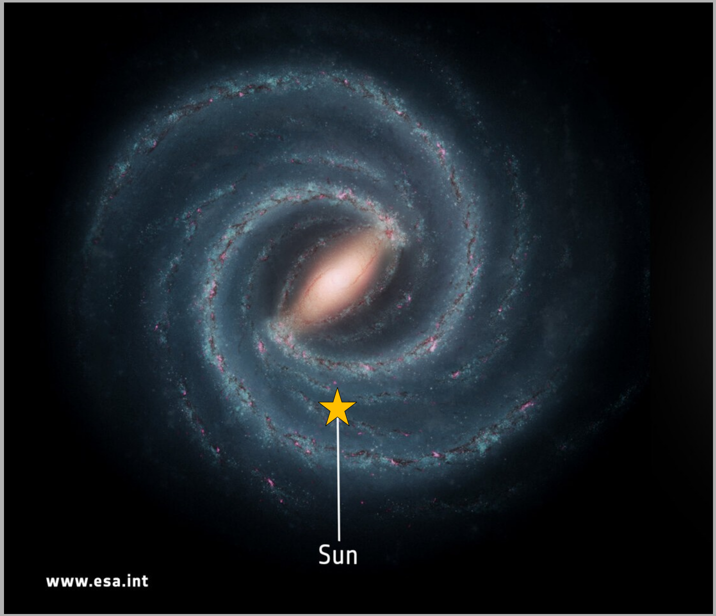
M. Bergemann

Galactic Archaeology

→ studying the formation and evolution of the Milky Way and it’s local volume



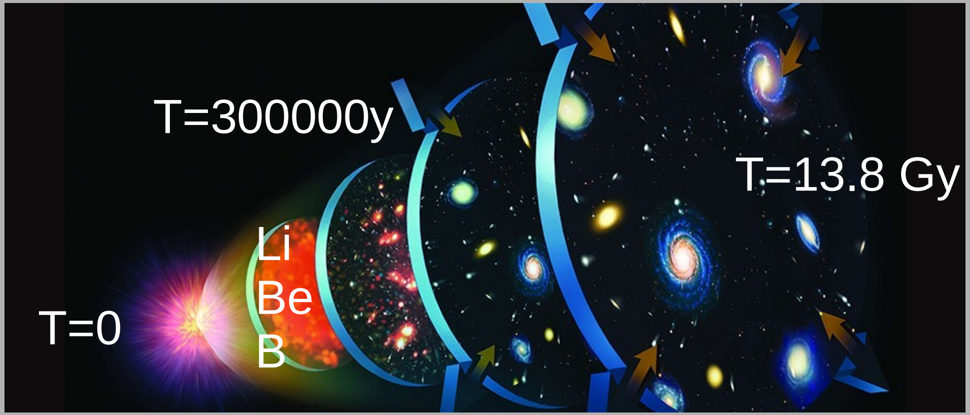
https://en.wikipedia.org/wiki/Milky_Way



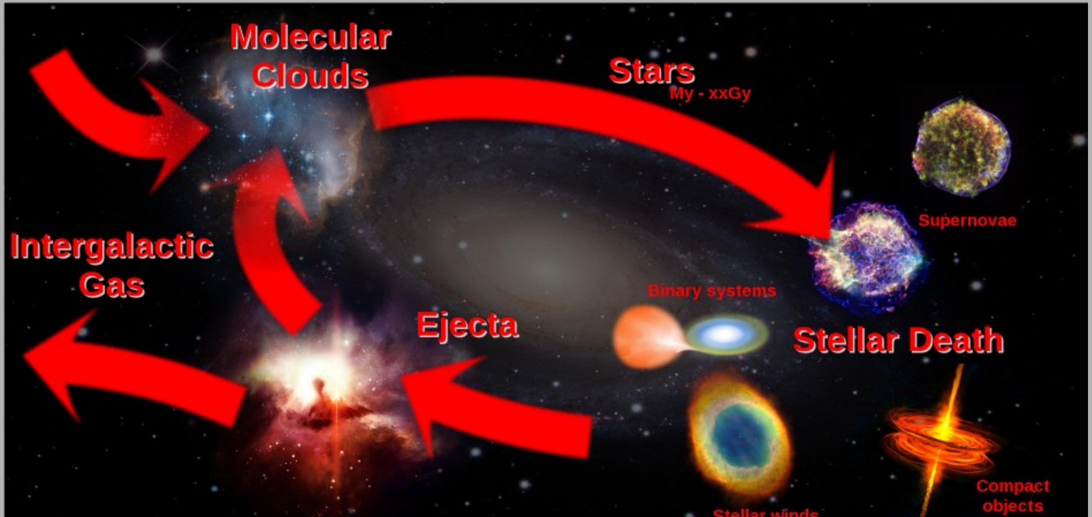
→ **Stellar chemistry in essential for Galactic Archaeology**

→ **Low-mass stars as fossil records of the interstellar medium**

→ **From Big Bang to today**



→ **Chemical enrichment of the interstellar medium**

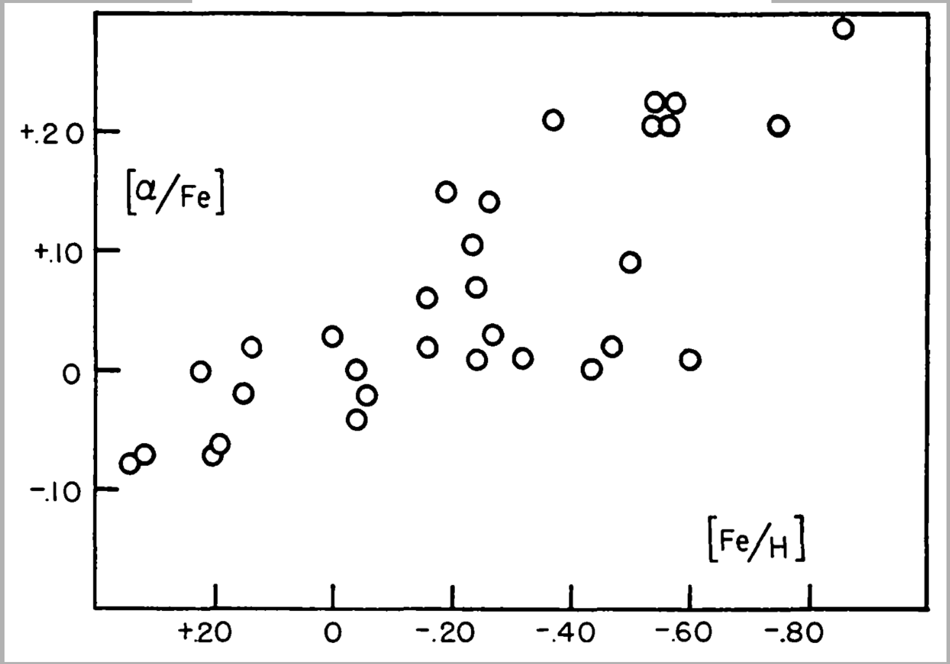


Bovy J. Dynamics and Astrophysics of Galaxies. Princeton, NJ (in preparation)

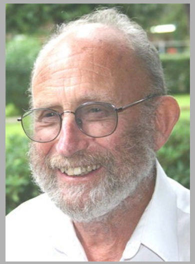
→ **Stellar chemistry in essential for Galactic Archaeology**

→ **The Tinsley-Wallerstein diagram**

30 stars from Wallerstein (1962)



Beatrice Tinsley



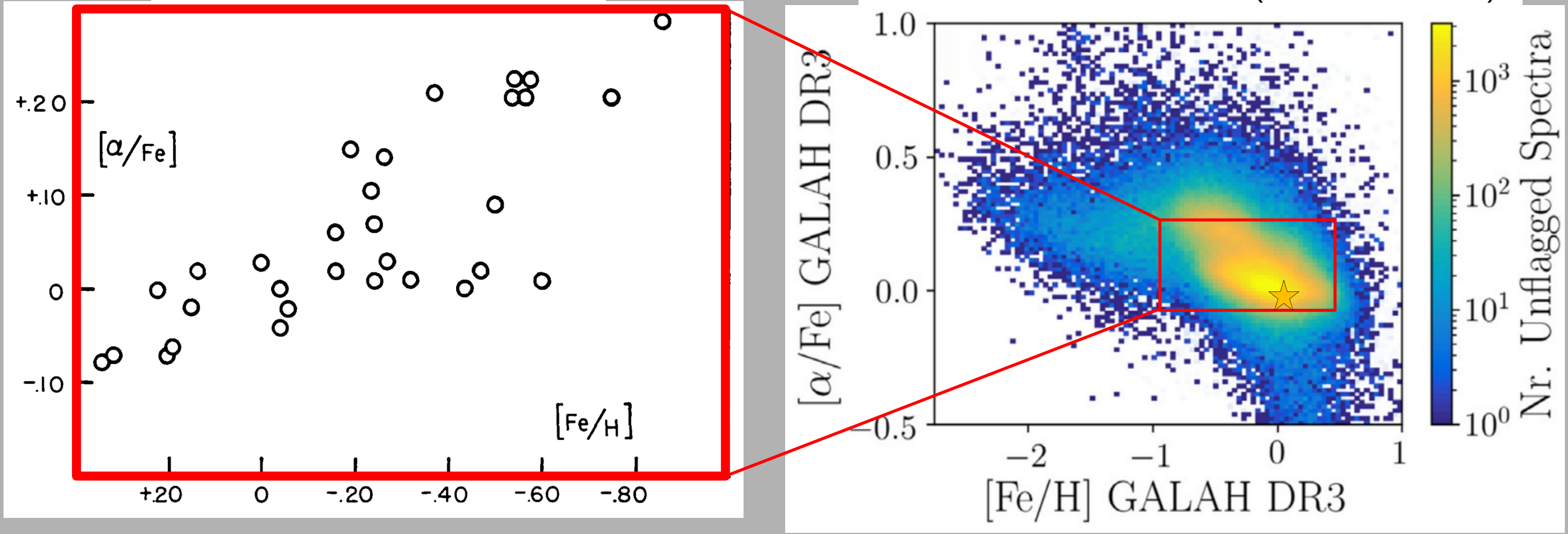
George Wallerstein

→ **Stellar chemistry in essential for Galactic Archaeology**

→ **The Tinsley-Wallerstein diagram**

30 stars from Wallerstein (1962)

~500000 stars from GALAH (Buder et al. 2021)



Other types of elements:

→ α-like: Ca, Ma, Ti, Si, O, Ne, S

→ Fe-peak: Z, Cu, Ni, Co, Fe, Mn, Cr, V

→ neutron-capture: Sr, Y, Zr, Ba, La, Ce, Pr, Sm, Eu, Gd, Dy, ...

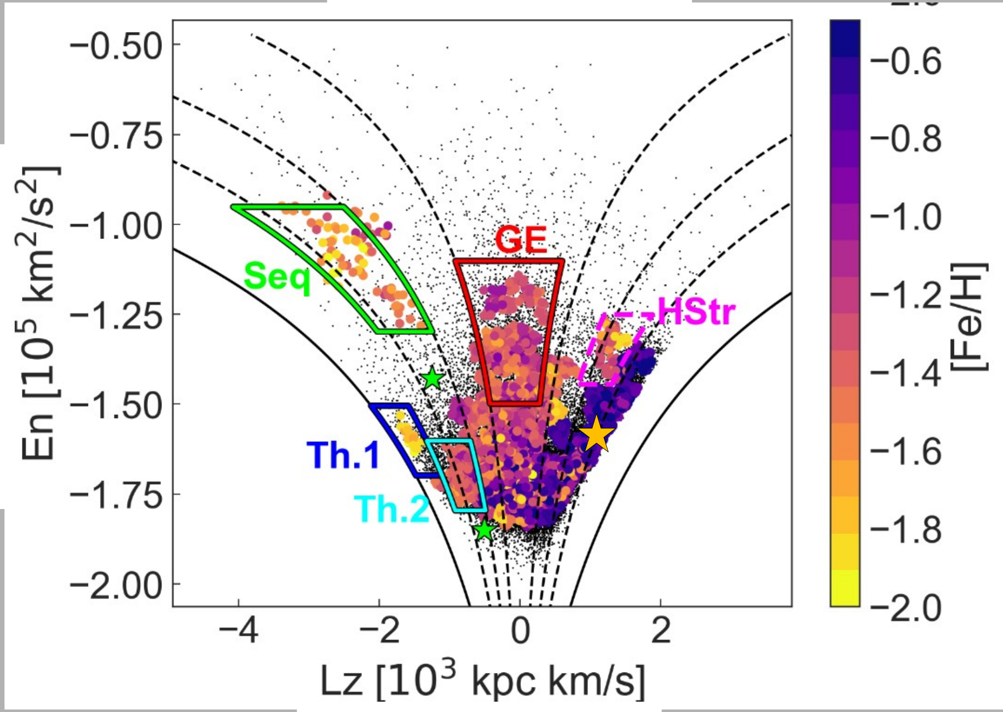
→ Light: Li, B, Be, C, N

→ Odd-Z: Sc, K, Al, Na

→ Stellar chemistry in essential for Galactic Archaeology

→ But stellar kinematics and stellar ages too :)

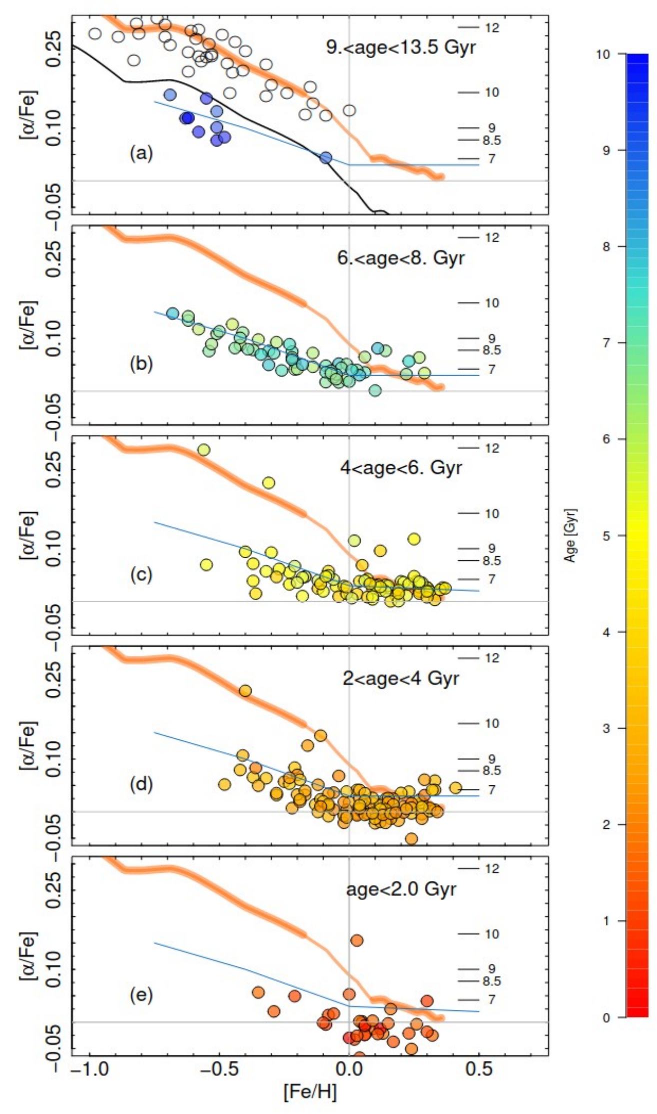
Koppelmann et al. 2019



(Energy)

(Angular momentum)

Haywood et al. 2019



The need for large spectroscopic surveys

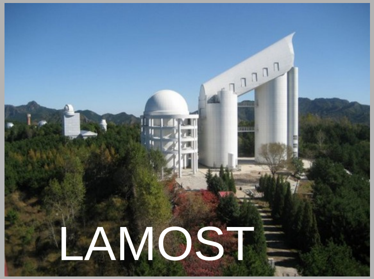
5x10^5 stars

10^5 stars

>10^4 stars

>5x10^6 spec

>10^6 stars



10^6 stars

>5x10^5 stars

>10^6 stars

>10^6 stars

>5x10^5 stars

30x10^6 stars

>10^6 stars

Gaia: Gaia Collaboration, Vallenari et al. 2022
AMBRE/ESO: Guiglion et al. 2016
LAMOST: Zhang et al. 2021
***Gaia*-ESO:** Romano et al. 2021
GALAH: Gao et al. 2020
APOGEE: Abdurro'uf et al. 2022
4MOST: de Jong et al. 2019
WEAVE: Jin et al. 2022
MSE: Bergemann et al. 2019
MOONS: Cirasuolo et al. 2020

What we measure from a star:

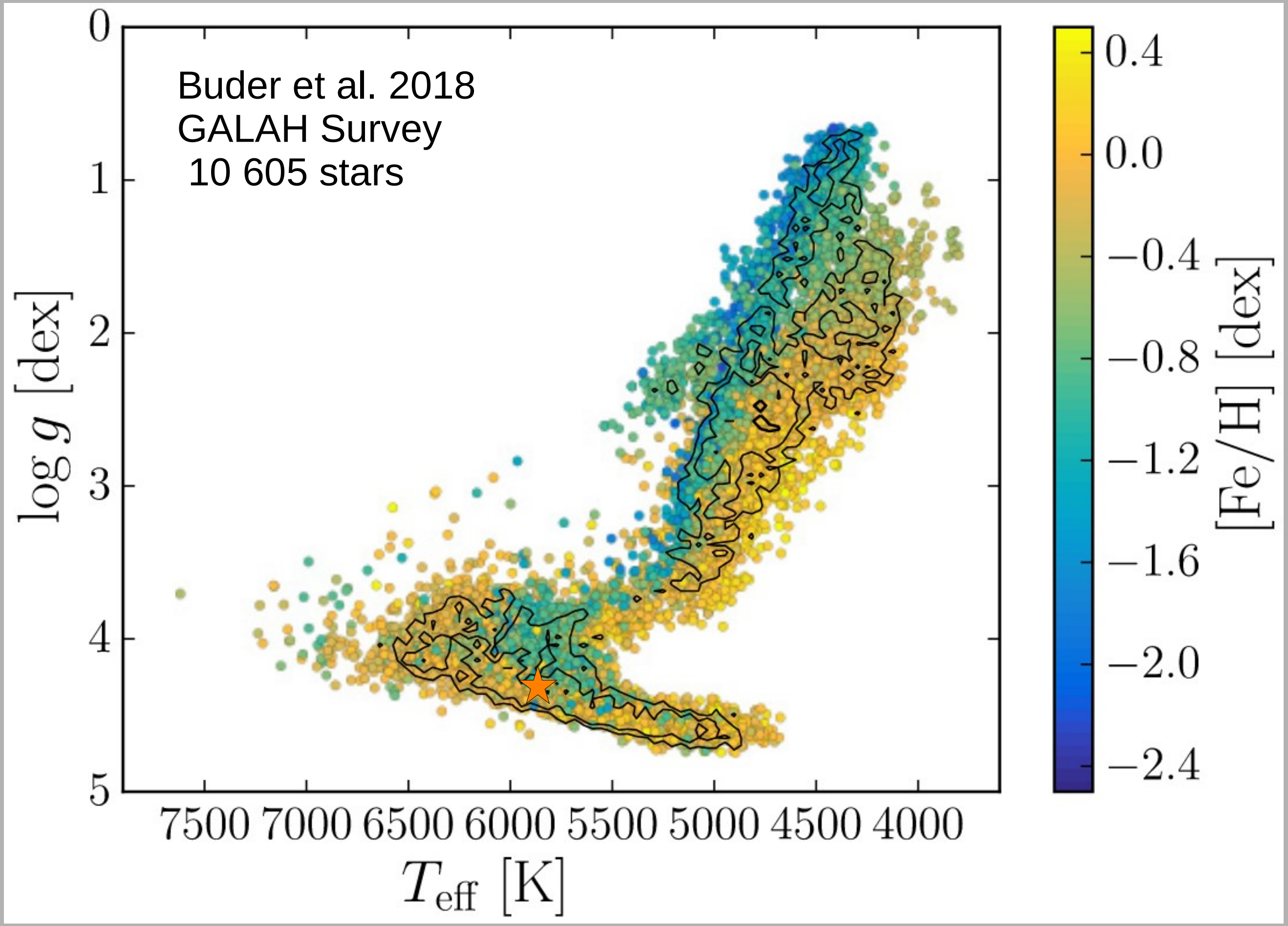
→ **Atmospheric parameters:**
  → Effective temperature **T_{eff}**
  → Surface gravity **log(g)**
  → Overall metallicity **[M/H]**

→ **Average abundance ratios**
  → For instance **[α/M]** with α goes for α-elements (Mg, Si, Ca, O, Ti, Ne, S)

→ **Individual chemical abundances**
  → **[X/Fe] with X = {Mg, Si, Ti, Ni, Fe, Ba, Eu, ….}**

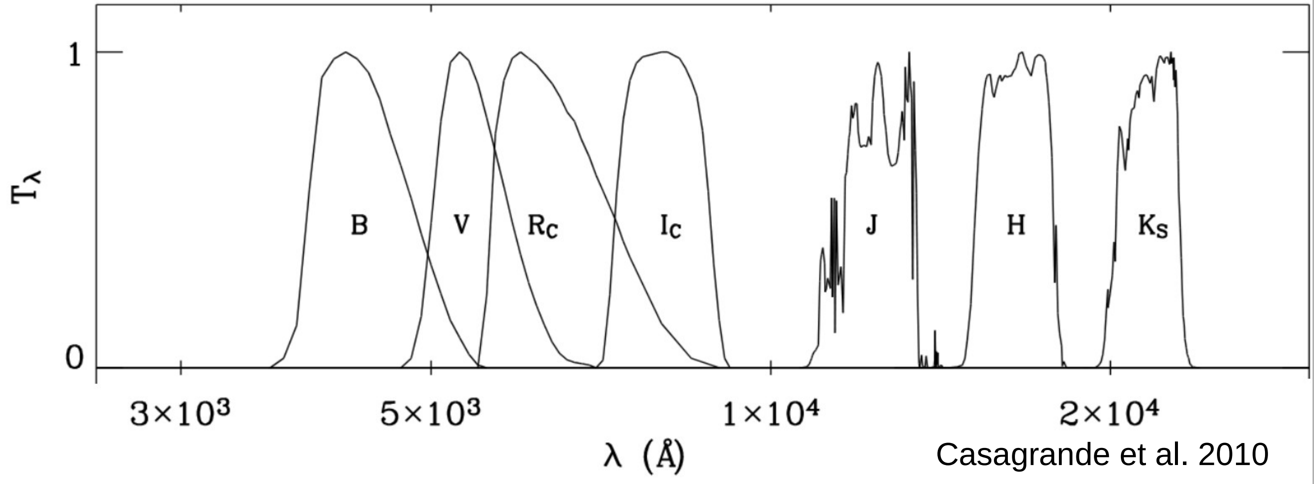
Many other parameters, such as rotation, activity, mass, age ...

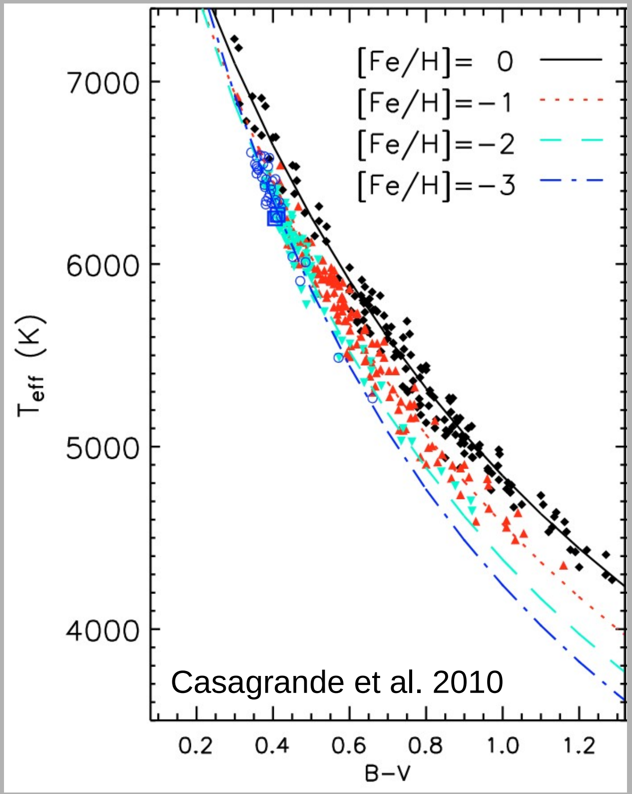
What type of stars are we interested in ?



How do we measure astrophysical quantities?

→ **Using stellar photometry (magnitudes)**



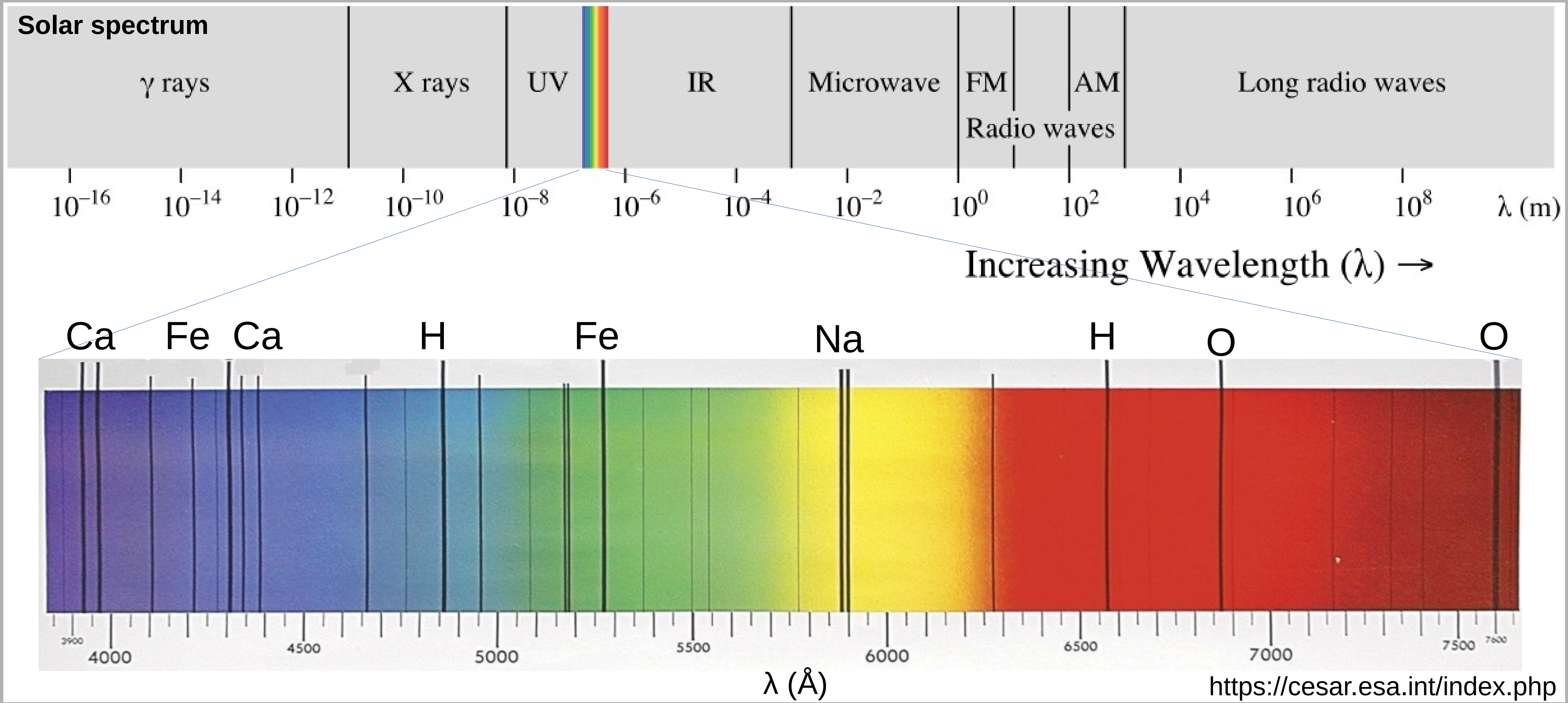


→ **See also Casagrande et al. 2021 (+ references there-in)**

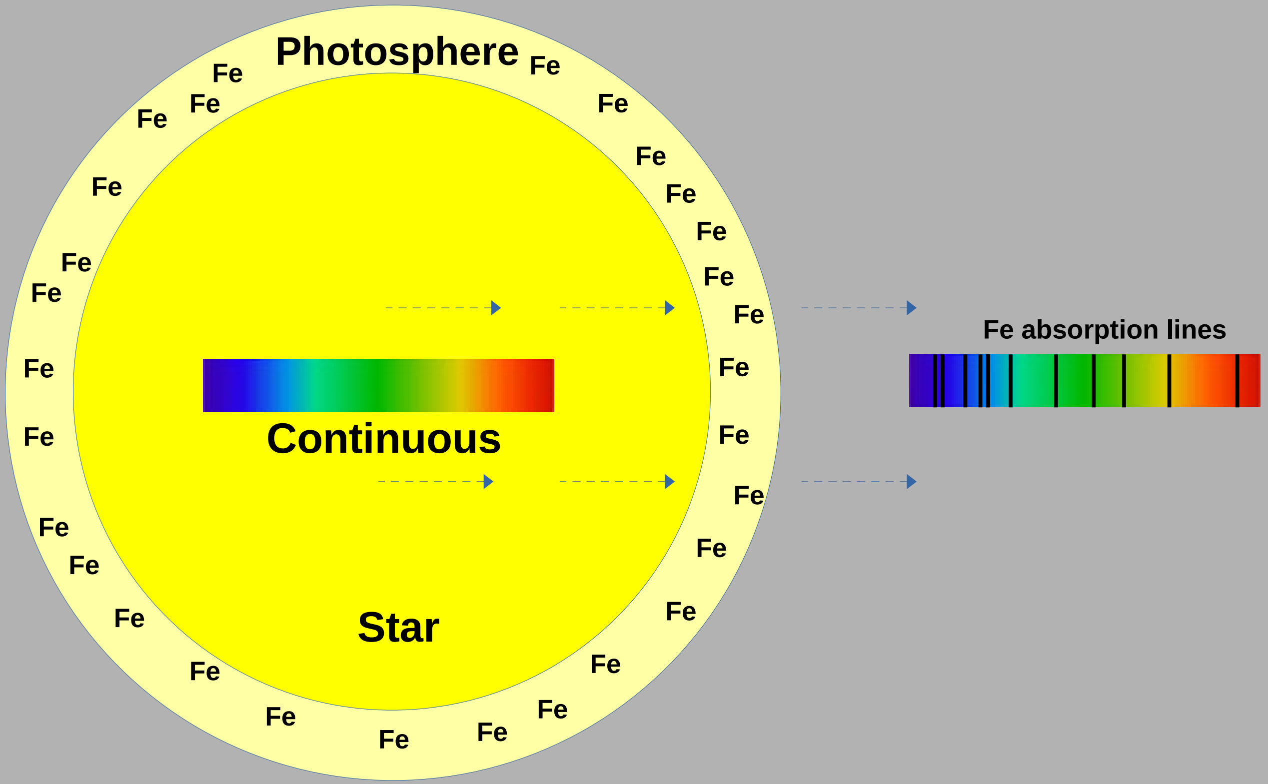
→ **Using stellar evolutionary models + magnitudes + parallaxes (distances)**
- → **Can measure T_{eff}, log(g), [M/H]**
- → **StarHorse code: Queiroz et al (2018, 2020, 2023), Anders et al. (2019, 2022)**

How do we measure astrophysical quantities?

→ **Using stellar spectra**



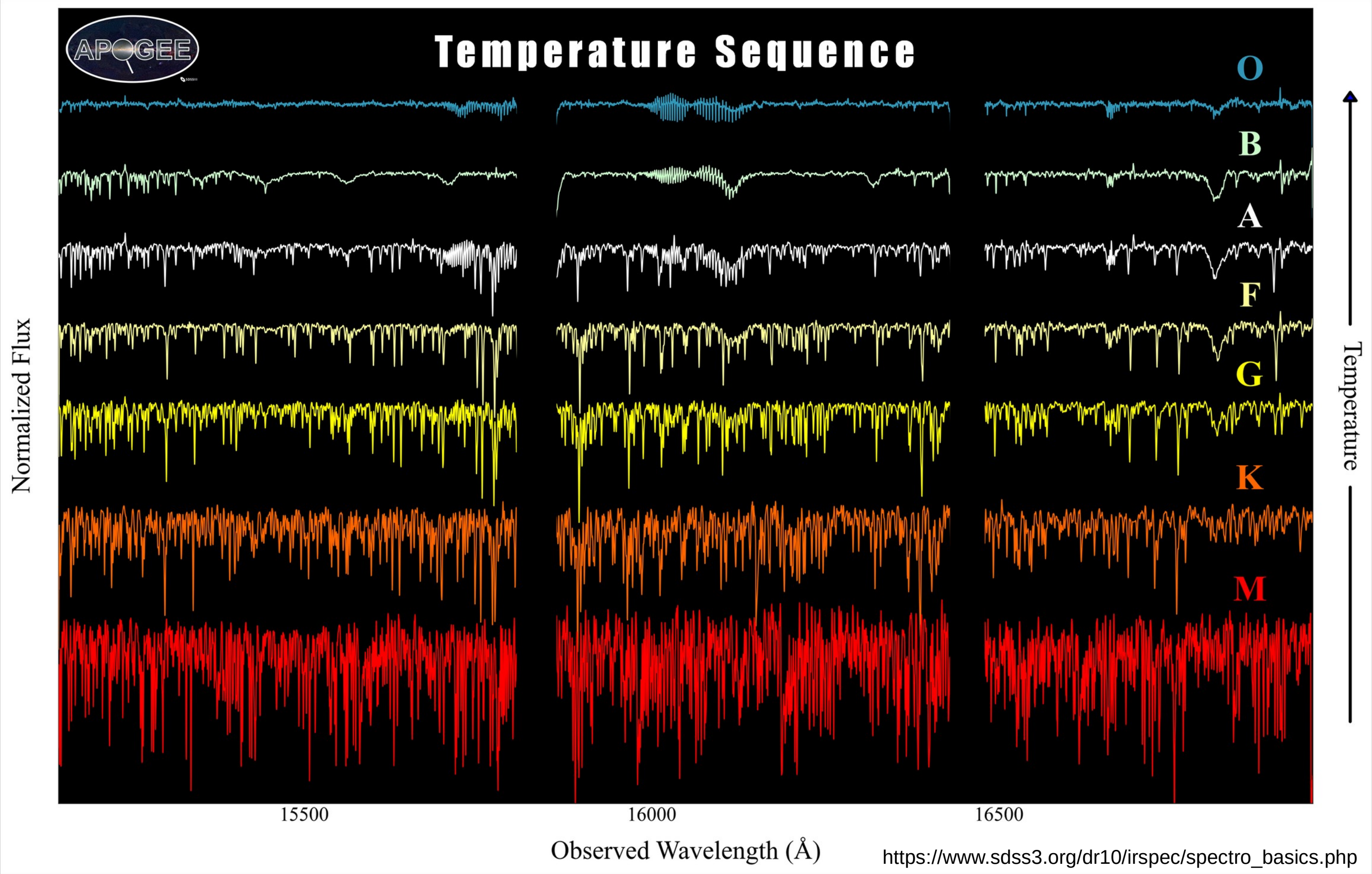
How do we form stellar absorption spectra ?



→ **More on stellar spectroscopy:**
  - → **D. F. Gray “The Observation and Analysis of Stellar Photospheres ” (2021)**
  - → **R. J. Rutten “Radiative Transfer in Stellar Atmospheres” (2003)**

How do stellar spectra correlate with astrophysical parameters ?

→ Example: effective temperature



https://www.sdss3.org/dr10/irspec/spectro_basics.php

T_{eff} (K)

> 20000

[10000-20000]

[7500-1000]

[6000-7500]

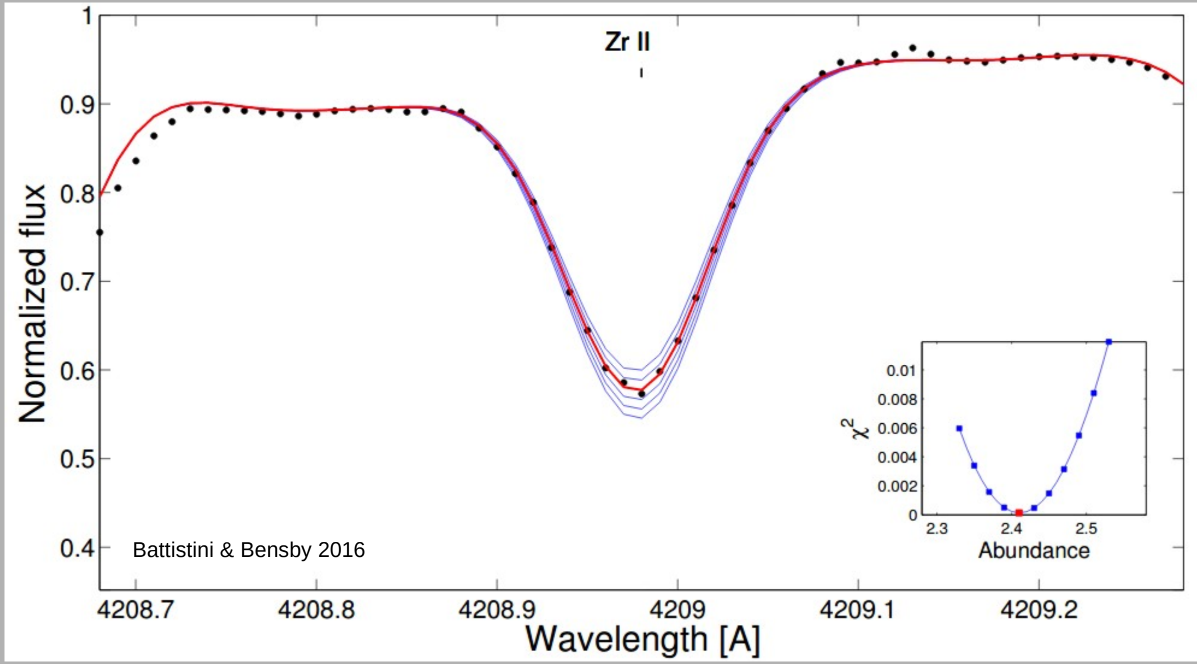
[4500-6000]

[3000-4500]

< 3000

How do we measure chemical abundances ?

→ One popular method: spectral fitting



To create model spectra, we need:

Model atmosphere

+

Radiative transfer code

+

T_{eff}
log(g)
[M/H]

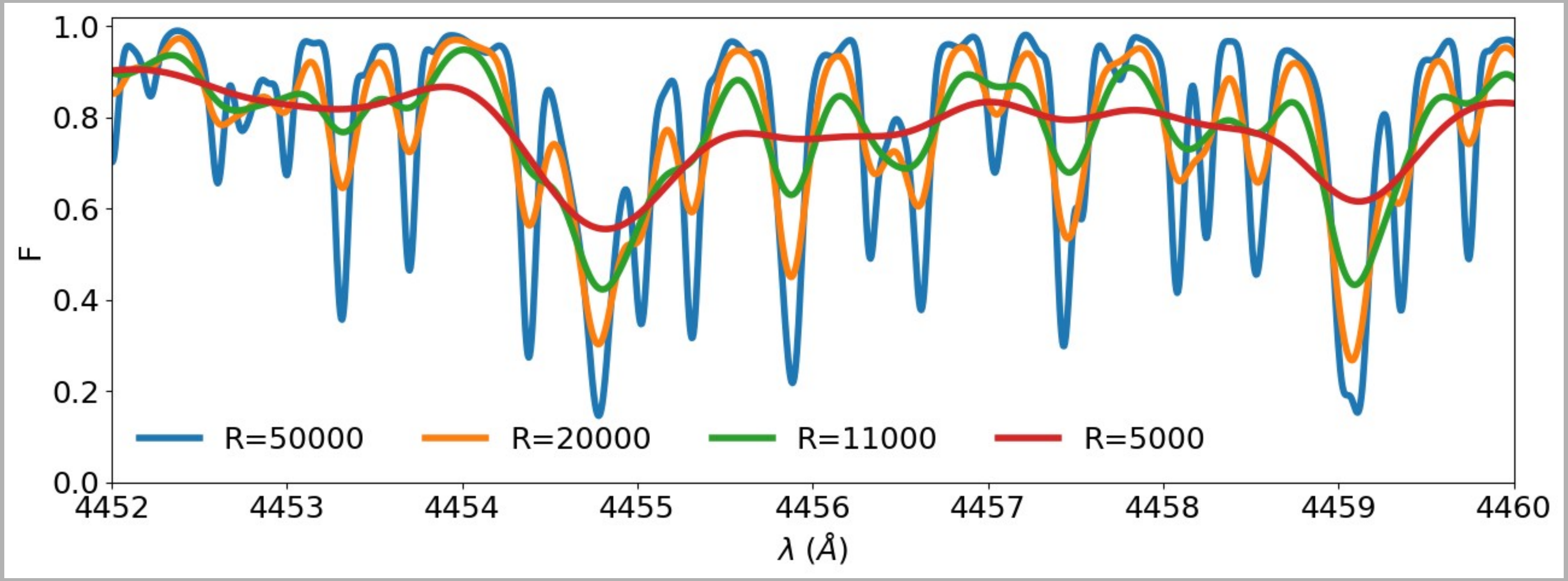
+

Atomic data

Challenges to face:
1D vs 3D
LTE vs. NLTE
(Lind et al. 2009, Wang et al. 2021)
Low-res vs. High-res
Blends
Rotation, Turbulence

More details on chemical abundance derivation:
→ Jofré, Heiter, and Soubiran (2019)

The impact of spectral resolution on abundance determination



→ **Lower spectral resolution:**
- → **Less clean spectral features to rely on**
- → **Less elements to be measured**
- → **Lower precision**

A few examples of spectral analysis codes

→ **Ispec**

(Blanco-Cuaresma et al. 2014)
https://www.blancocuaresma.com/s/iSpec

Download

If you use iSpec, we thank you to cite these two articles: A&A (2014) and MNRAS (2019).

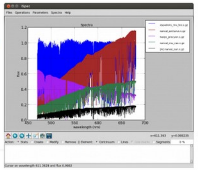
Installation and usage | Ask to be informed about updates!

* Guide translated to Chinese (中文使用手册): Main | Mirror

iSpec

iSpec is a tool for the treatment and analysis of stellar spectra. Some of the main functionalities for spectra treatment are the following:

- Cosmic rays removal
- Continuum normalization
- Resolution degradation
- Radial velocity determination and correction
- Telluric lines identification
- Re-sampling



Atmospheric parameters and chemical abundances.

iSpec is capable of determining atmospheric parameters (i.e effective temperature, surface gravity, metallicity, micro/macroturbulence, rotation) and individual chemical abundances for AFGKM stars by using two different approaches: synthetic spectra fitting technique or equivalent widths method. iSpec integrates MARCS and ATLAS model atmospheres together with the following radial transfer codes:

- SPECTRUM R. O. Gray
- Turbospectrum Bertrand Plez
- SME Valenti & Piskunov
- MOOG Chris Sneden
- Synthe/WIDTH9 Kurucz/Atmos

Python 3 powered automatized analyses.

The user-friendly interface is perfect for learning and testing. However, to take advantage of the full potential, iSpec can be used from Python 3. This is the recommended way to use iSpec for complex scientific studies, it ensures reproducibility and give access to a wider range of functionalities and options.

→ **Spectroscopy Made Easy (SME)**

(Valenti & Piskunov 1996, Piskunov & Valenti 2017)
https://www.stsci.edu/~valenti/sme.html

Home SME IDL Jeff Valenti

Spectroscopy Made Easy (SME) is IDL software and a compiled external library that fits an observed high-resolution stellar spectrum with a synthetic spectrum to determine stellar parameters. The original paper describing SME is Valenti & Piskunov (1996). Subsequent enhancements of the package are described in Piskunov & Valenti (2016).

SME Releases

Version	Size	Release Date
574	1276 MB	2020-Feb-22
522	414 MB	2016-Jul-15
423	294 MB	2014-May-15
412	294 MB	2014-Mar-04
342	102 MB	2013-Mar-25
312	81 MB	2012-Oct-26

Release 574 introduced a serious bug that caused SME to overestimate the concentration of several negative ions. This resulted in underestimated electron concentration, H^- concentration, and H^- opacity. This error is particularly serious for M dwarfs. A new version will be released soon. Release 574 includes automatic continuum matching, more non-LTE grids, improved UV continuous opacities, and additional methods for extracting information from the external library.

Each release includes the SME User Handbook and an SME tutorial. Version 412 and later include a technical note that describes major changes to the way model atmosphere information is stored in SME structures. Each release includes the SME external library, compiled for Linux, OSX, and Windows systems.

Atomic and molecular line data formatted for SME may be obtained from VALD3, which supersedes the previous version of VALD. SME understands extended van der Waals encoding, which is enabled in the VALD3 unit selection configuration page. SME can solve for empirical log(gf) and damping parameters, using an observed spectrum of a star (usually the Sun) as a constraint.

Using empirical line data for wavelength ranges 5164-5190 (Mg b triplet) and 6000-6180 Å, Valenti & Fischer (2005) obtained spectroscopic parameters for 1040 cool stars. Damping wings of the Mg b lines are a useful gravity constraint for dwarfs cooler than about 6200 K. Mass, radius, gravity, and especially age in Table 9 were revised shortly after publication when a software bug was fixed.

→ **MOOG**

(Sneden et al. 2012)
https://www.as.utexas.edu/~chris/moog.html

MOOG

HOME | TEACHING | HALOSTARS | DISKSTARS | LABDATA | MOOG | SPECTRE | MISC

MOOG is a code that performs a variety of LTE line analysis and spectrum synthesis tasks. The typical use of MOOG is to assist in the determination of the chemical composition of a star. The basic equations of LTE stellar line analysis are followed, in particular using the formulation of F. N. Edmonds, Jr. (1969, *JQSRT*, **9**, 1427). Much of the MOOG code follows in a general way the WIDTH and SYNTHE codes of R. L. Kurucz (see his web site: http://kurucz.harvard.edu/). Below are instructions on downloading MOOG. If you have trouble grabbing or decoding the code please email me at chris@verdi.as.utexas.edu.

The coding is in various subroutines that are called from a few *driver* routines; these routines are written in standard FORTRAN. The standard MOOG version has been developed on unix, linux and macintosh computers.

One of the chief assets of MOOG is its ability to do on-line graphics. This means that the plotting commands are given within the FORTRAN code. MOOG uses the graphics package *SM*, chosen for its ease of implementation in FORTRAN codes. Plotting calls are concentrated in just a few routines, and it should be possible for users of other graphics packages to substitute other appropriate FORTRAN commands.

The current MOOG release (November 2019) is the only code that is actively supported. See below for downloading instructions of this code.

Finally, financial support from the US National Science Foundation and NASA for many years in development of this code is gratefully acknowledged.

Take home messages:

- Chemical abundances and kinematics are essential for Galactic Archaeology studies

- The analysis of stellar spectra is the only way to get detailed and precise chemical abundances

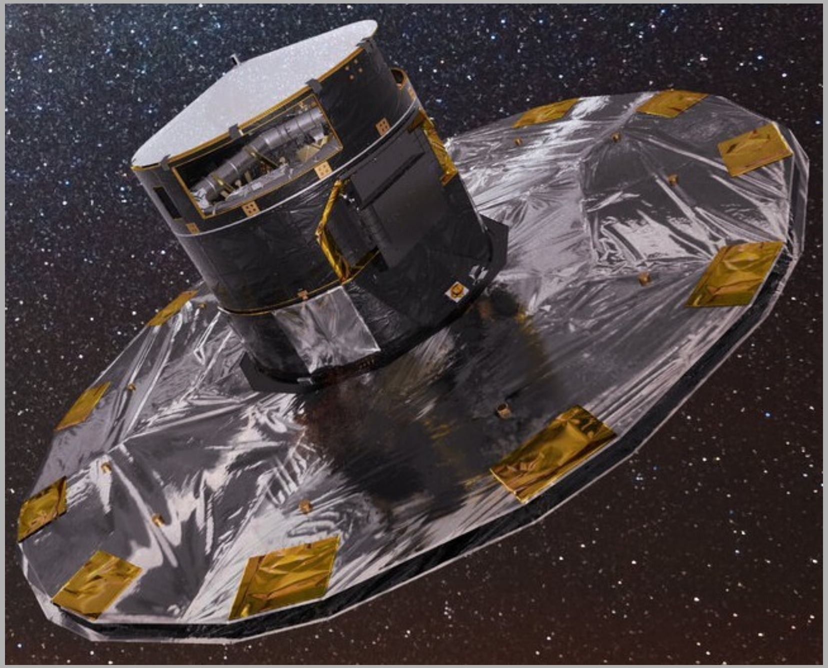
- Large spectroscopic surveys are required (many stars, many Galactic components surveyed, as many elements as possible)

- Standard spectroscopic pipelines are essential algorithms but can be slow (few tens of spectra analysed per second)

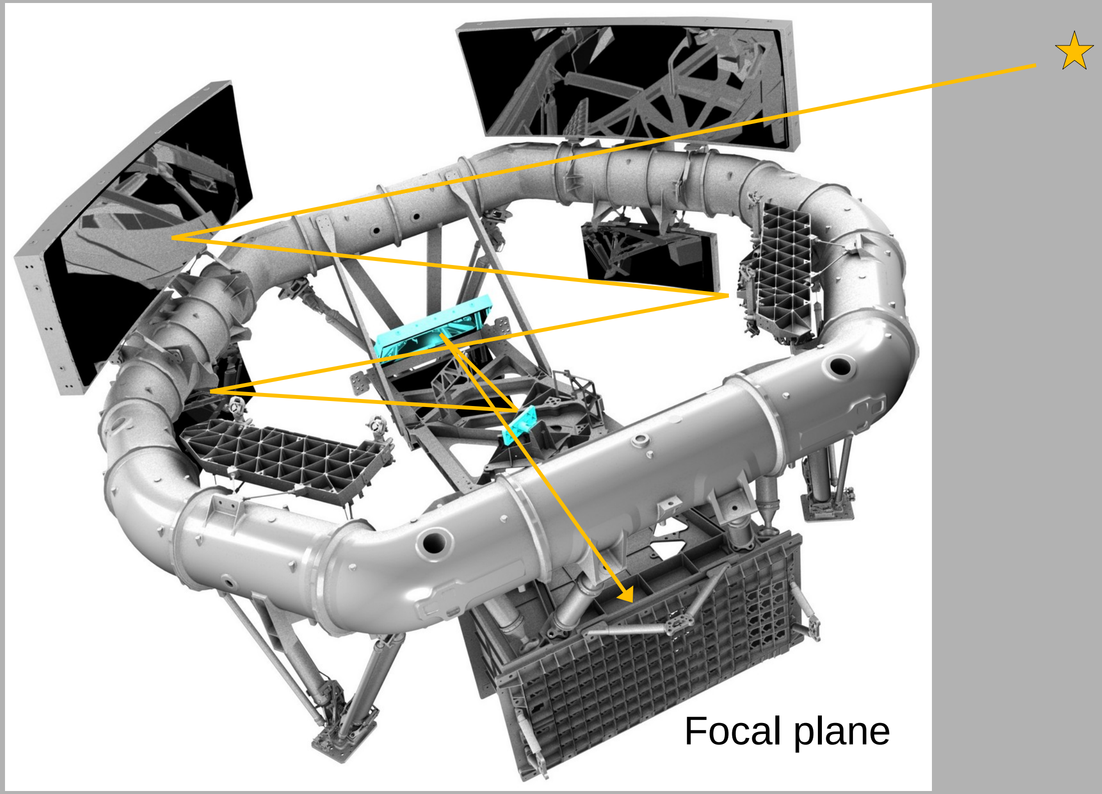
- Data analysis challenge for on-going and future surveys (>10^7 stars)

A fantastic machine for Galactic Archaeology: The ESA *Gaia* space mission

Gaia: ESA's billion star surveyor



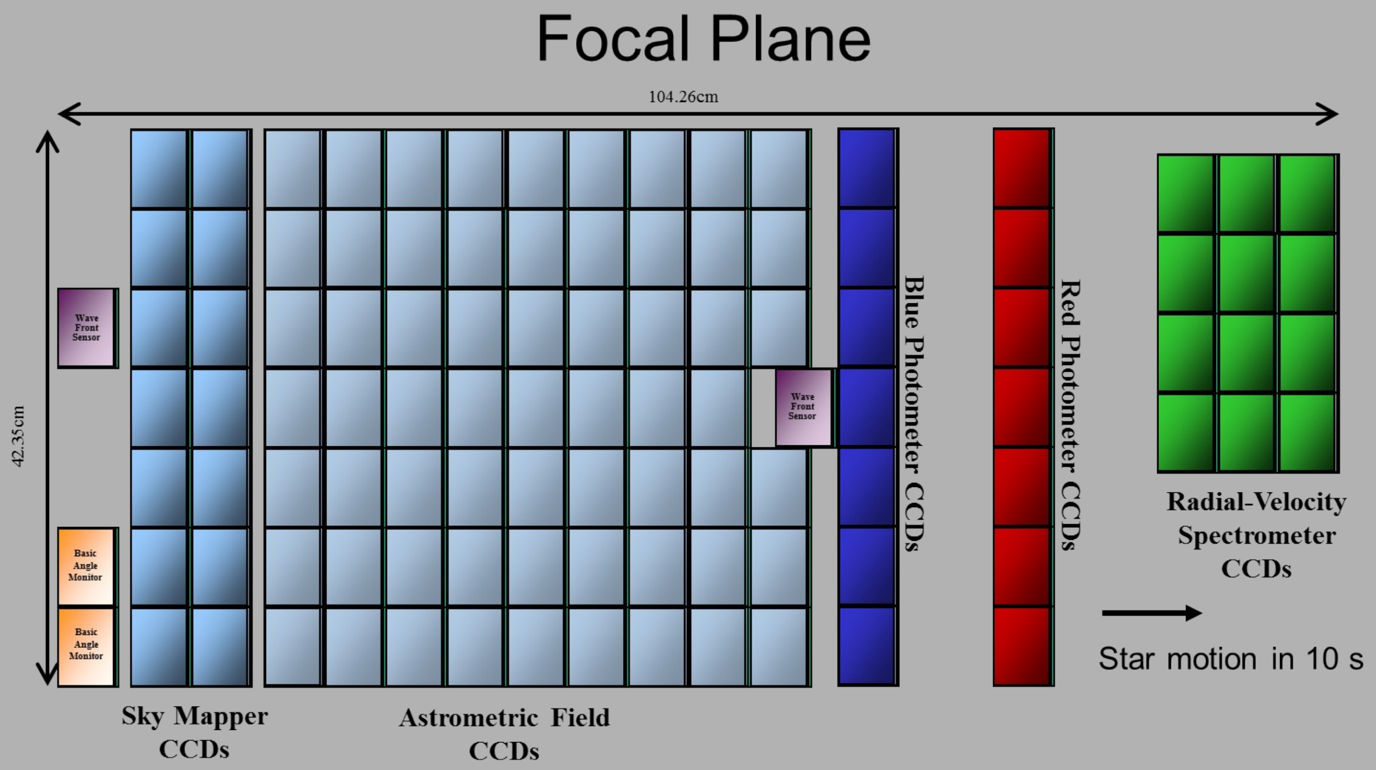
https://www.esa.int/Enabling_Support/Operations/Gaia_s_biggest_operation_since_launch



https://www.cosmos.esa.int/web/gaia/instruments

Useful link:
https://www.esa.int/Science_Exploration/Space_Science/Gaia

Gaia: ESA's billion star surveyor



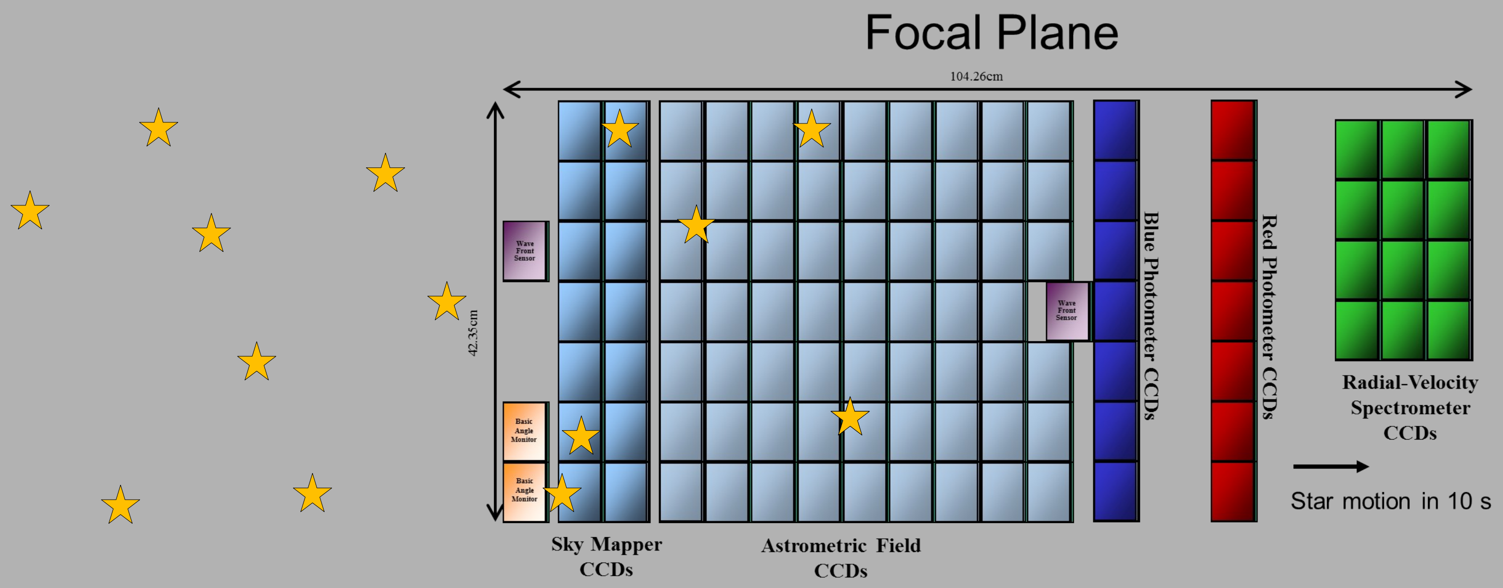
Position & Brightness

Low-resolution Spectra (Blue & Red)

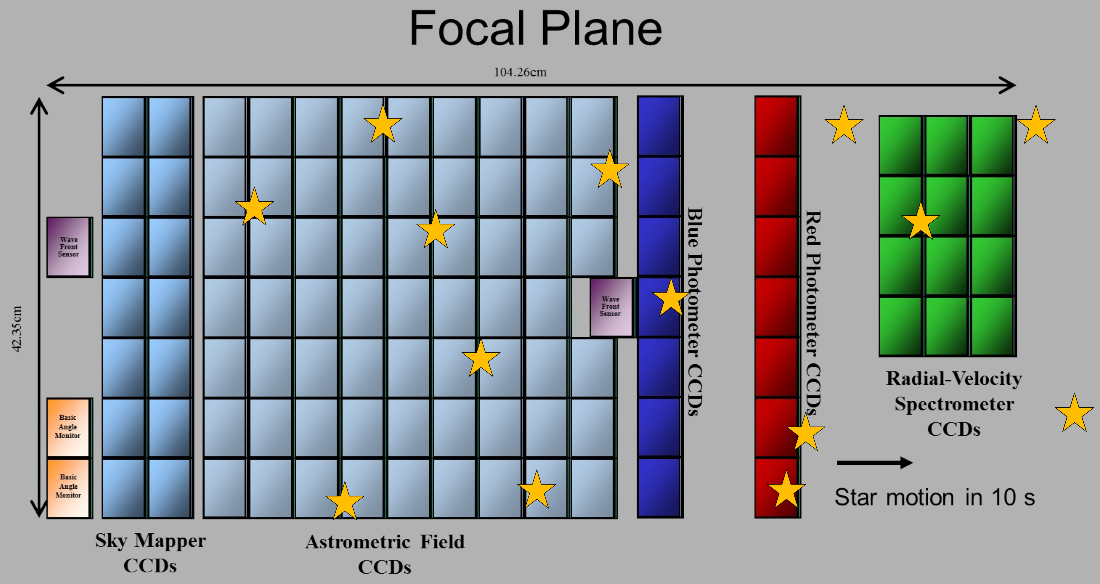
Intermediate-resolution spectra (abundances :))

Useful link:
https://www.cosmos.esa.int/web/gaia/payload-module

Gaia: ESA's billion star surveyor



Gaia: ESA's billion star surveyor



→ **2 million stars per hours are measured !!**

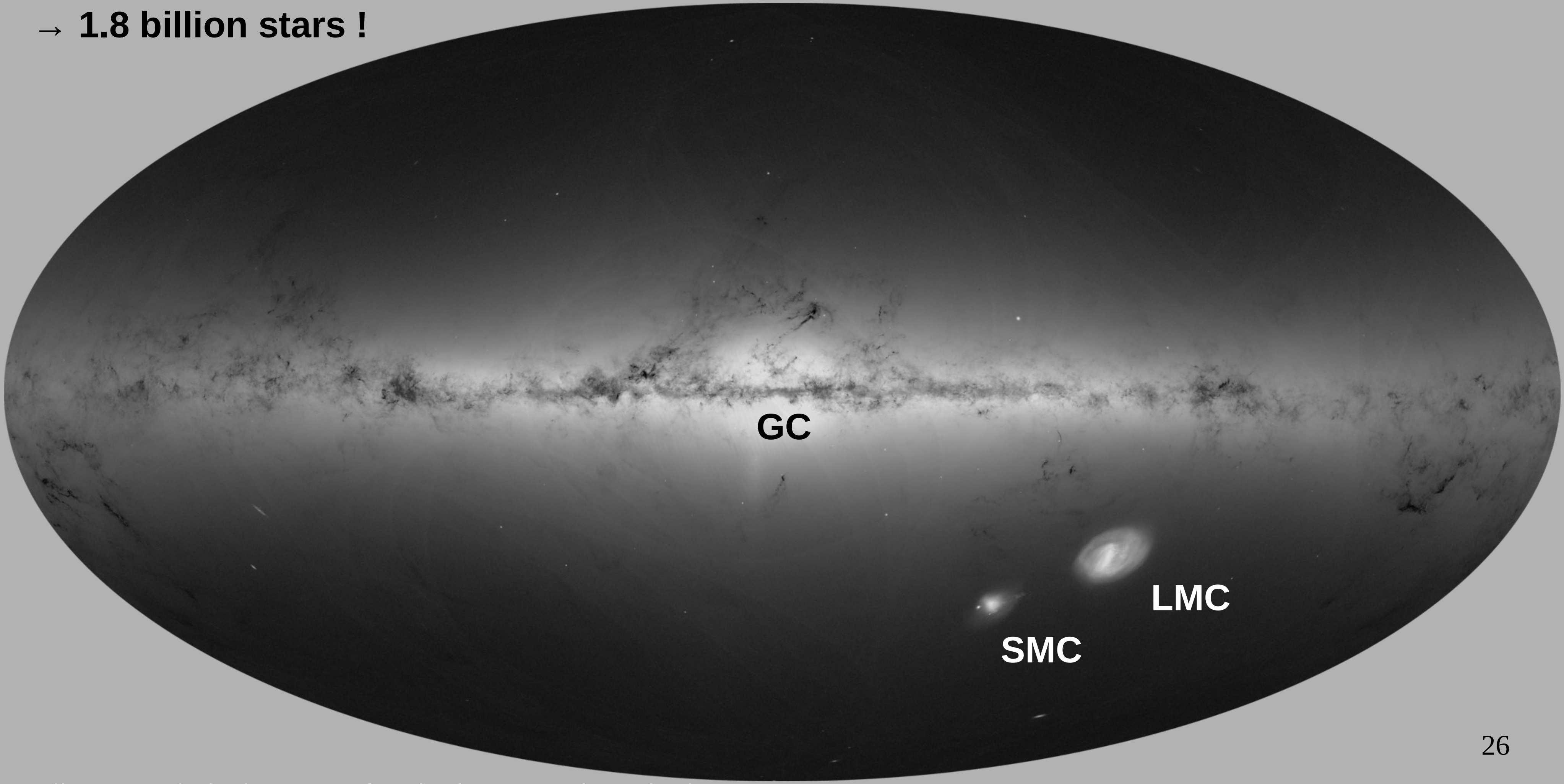
Content of *Gaia* DR3: tremendous amount of data

	# sources in Gaia DR3	# sources in Gaia DR2	# sources in Gaia DR1
Total number of sources	**1,811,709,771**	**1,692,919,135**	**1,142,679,769**
	Gaia Early Data Release 3		
Number of sources with full astrometry	1,467,744,818	1,331,909,727	2,057,050
Number of 5-parameter sources	585,416,709		
Number of 6-parameter sources	882,328,109		
Number of 2-parameter sources	343,964,953	361,009,408	1,140,622,719
Gaia-CRF sources	1,614,173	556,869	2191
Sources with mean G magnitude	1,806,254,432	1,692,919,135	1,142,679,769
Sources with mean G_{BP}-band photometry	1,542,033,472	1,381,964,755	-
Sources with mean G_{RP}-band photometry	1,554,997,939	1,383,551,713	-
	New in Gaia Data Release 3	Gaia DR2	Gaia DR1
Sources with radial velocities	33,812,183	7,224,631	-
Sources with mean G_{RVS}-band magnitudes	32,232,187	-	-
Sources with rotational velocities	3,524,677	-	-
Mean BP/RP spectra	219,197,643	-	-
Mean RVS spectra	999,645	-	-
Variable-source analysis	10,509,536	550,737	3,194

Gaia DR3 content:
https://www.cosmos.esa.int/web/gaia/dr3
Gaia DR3 papers:
https://www.cosmos.esa.int/web/gaia/dr3-papers

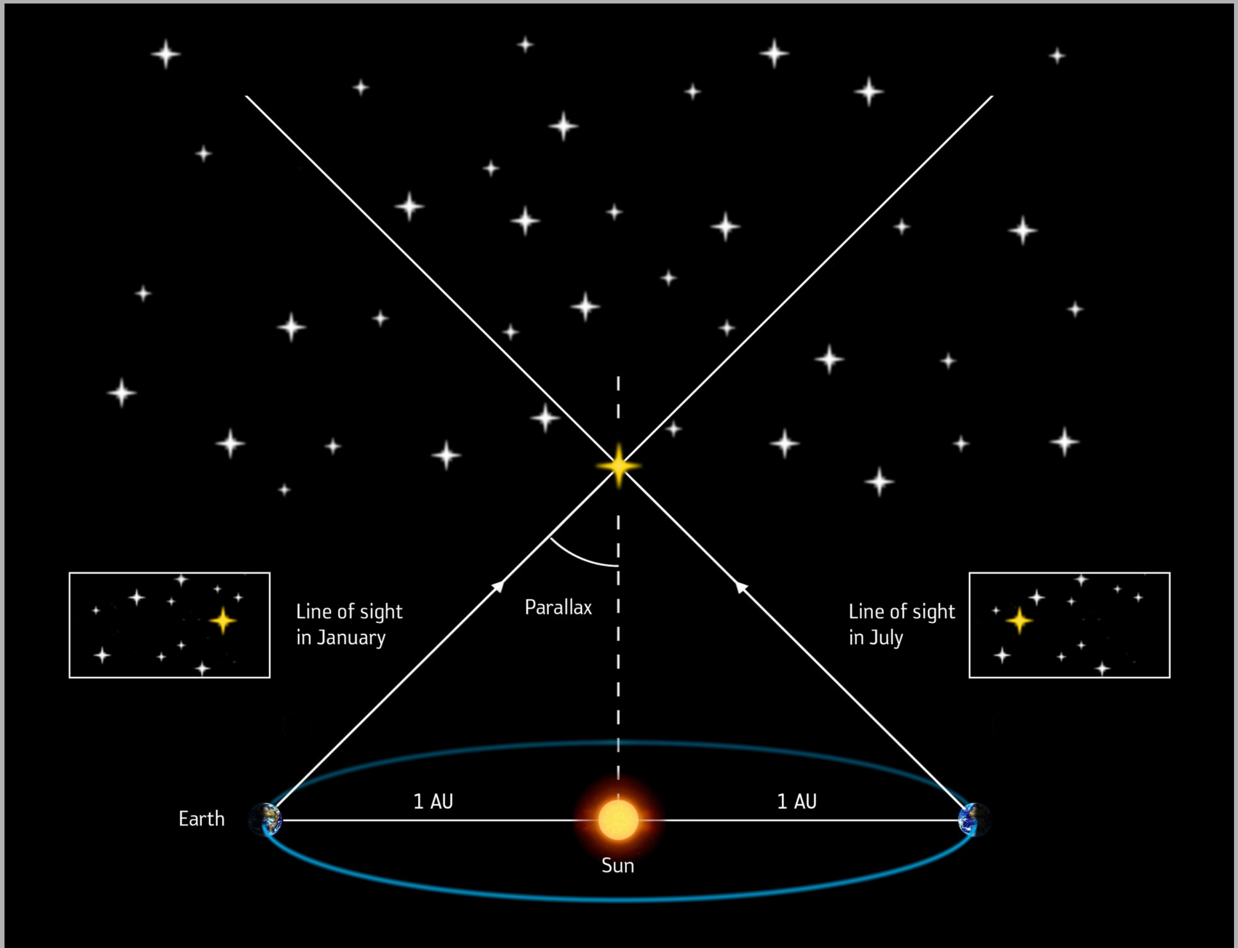
Map of stellar magnitudes from *Gaia's* Early Data Release 3

→ **1.8 billion stars !**



https://www.esa.int/Science_Exploration/Space_Science/Gaia

One major output of Gaia: parallaxes (and distances)



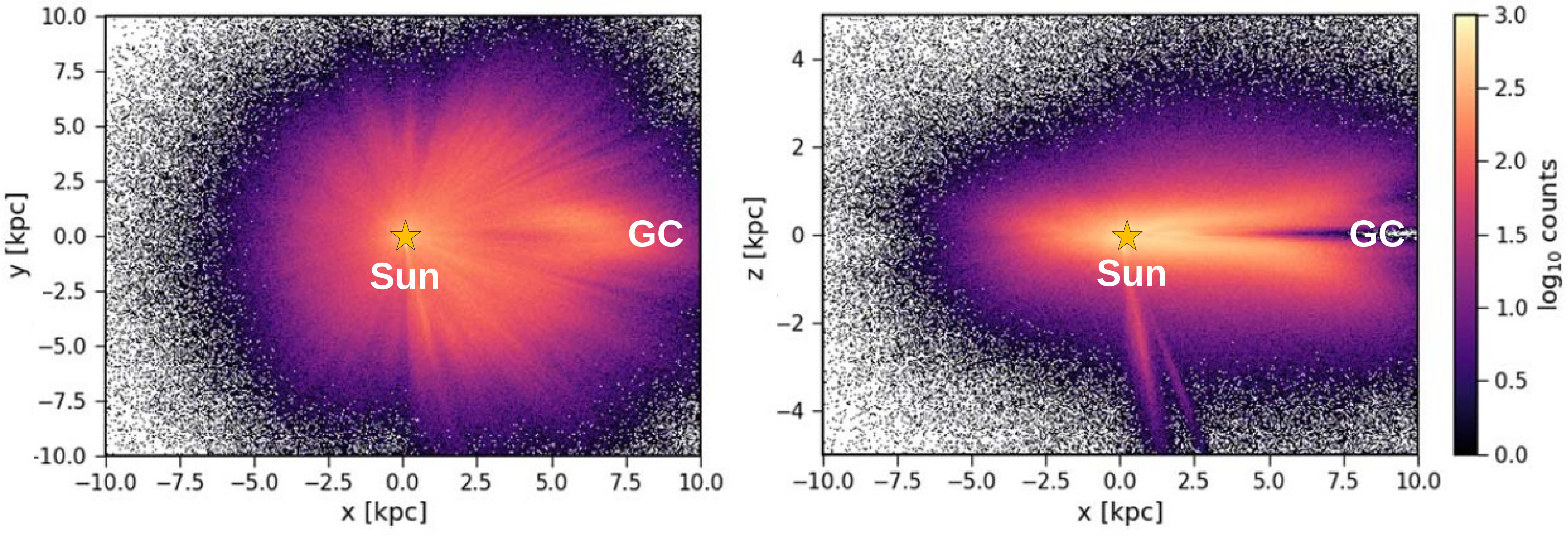
https://www.esa.int/Science_Exploration/Space_Science/Gaia/Parallax

→ **distance ≈ 1 / parallax**

One major output of Gaia: parallaxes (and distances)

Estimating Distances from Parallaxes. V. Geometric and Photogeometric Distances to 1.47 Billion Stars in Gaia Early Data Release 3

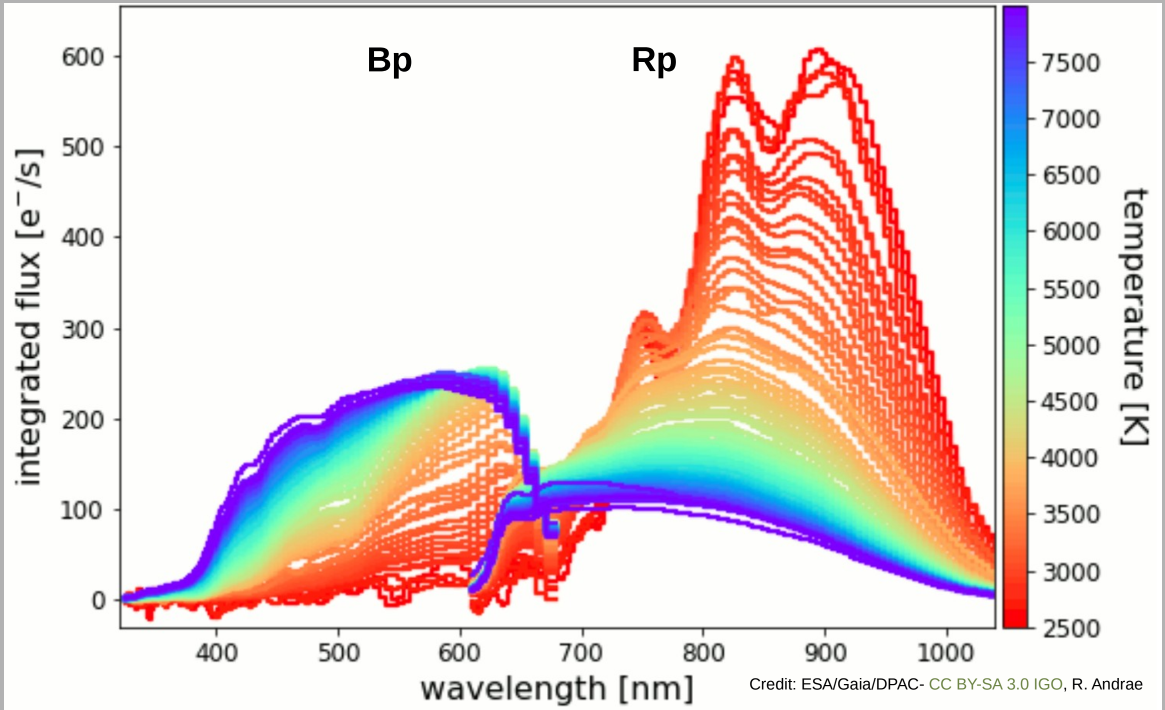
C. A. L. Bailer-Jones[1], J. Rybizki[1], M. Fouesneau[1], M. Demleitner[2], and R. Andrae[1]
[1] Max Planck Institute for Astronomy, Heidelberg, Germany
[2] Astronomisches Rechen-Institut, Zentrum für Astronomie der Universität Heidelberg, Germany
Received 2020 December 9; revised 2020 December 30; accepted 2020 December 31; published 2021 February 25



Gaia Rp, Rp spectra

→ **220 millions spectra available**

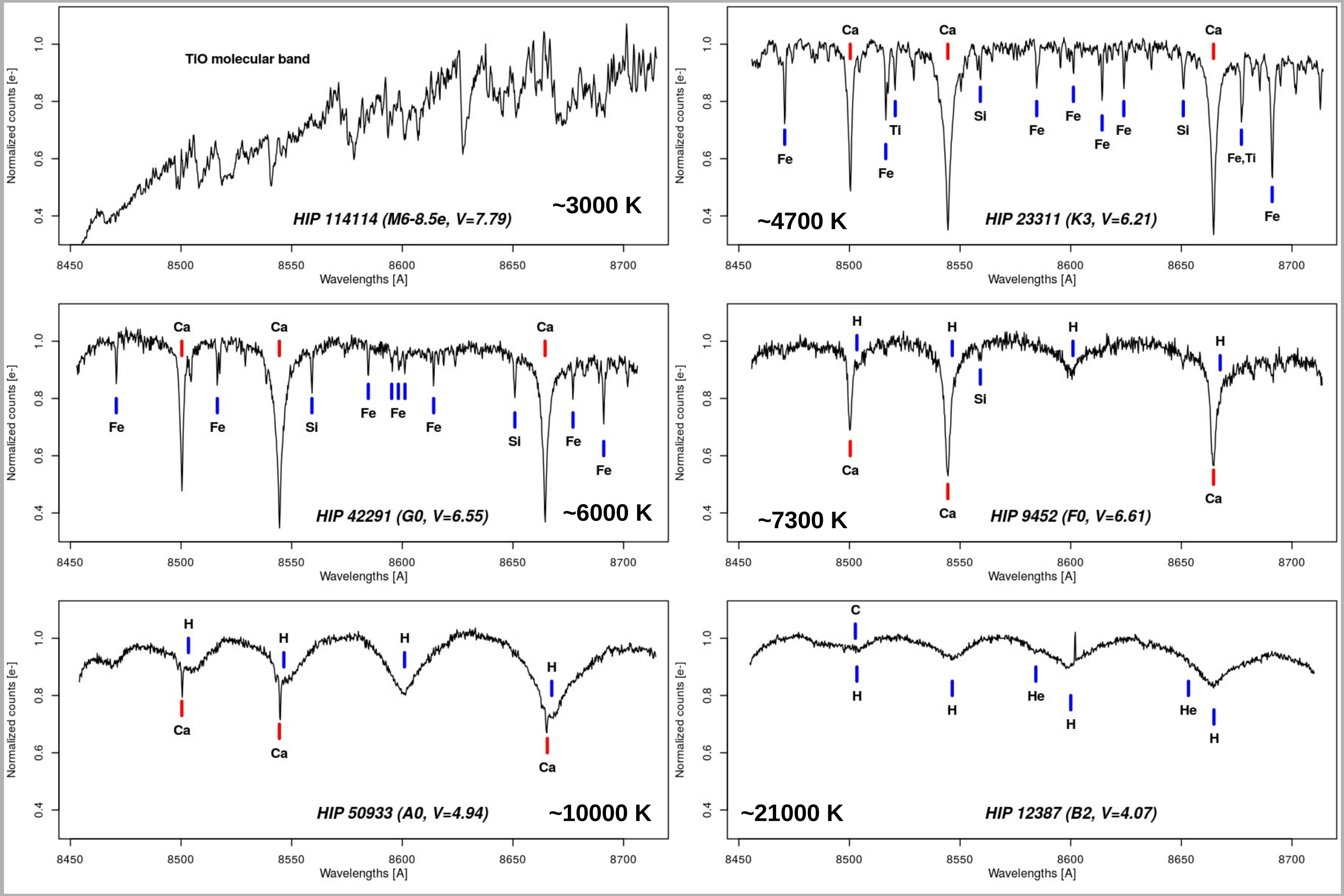
R~30-100 (De Angeli et al. 2022)



Credit: ESA/Gaia/DPAC- CC BY-SA 3.0 IGO, R. Andrae

Useful link:
https://www.cosmos.esa.int/web/gaia/dr3-what-colour-do-they-have

Gaia RVS spectra → 1 million spectra available, R~11500 (Katz et al. 2022)



ESA/Gaia/DPAC/Observatoire de Paris-Meudon/Olivier Marchal & David Katz

Can we exploit in a homogeneous way *Gaia* spectra (RVS + BP/RP) magnitudes (G, Bp, Rp) and parallaxes for supercharged stellar parametrization ?

- → **Answer after 3 minutes break**
- → **Spoiler: yes. Method: modern techniques**

Modern techniques **==** **Machine Learning**

The world of machine-learning

Supervised Learning			Unsupervised Learning	
Regression	Classification	Neural networks	Clustering	Dimensionality Reduction
Linear Regression	Logistic Regression	Convolutional Neural Networks (CNN)	K-means	t-Distributed Stochastic Neighbor Embedding (t-SNE)
K-Nearest Neighbors Regression (KNN)	K-Nearest Neighbors Classification (KNN)	Generative Adversarial Networks (GAN)	Gaussian Mixture Models (GMM)	Locally Linear Embedding (LLE)
Random Forest Regression	Random Forest Classification	Long Short Term Memory Networks (LSTM)	Hierarchical Agglomerative Clustering (HAC)	Uniform Manifold Approximation and Projection (UMAP)
Decision Tree Regression (CART)	Decision Tree classification (CART)	Gated Recurrent Units (GRU)	Density-Based spatial Clustering of Applications with Noise (DBSCAN)	Multidimensional Scaling (MDS)
Support Vector Regression (SVR)	Support Vector Machines (SVM)	Feedforward Neural Networks (FFNN)		Principal Component Analysis (PCA)
Multivariate Adaptive regression Splines (MARS)	Extreme Gradient Boosting (XGBoost)			Isomap Embedding
	Gradient Boosted Trees			
	Naive Bayes			

Webb & Good 2023

→ In the current talk, I will discuss only on Convolutional Neural-Networks

Why are we interested in Convolutional Neural Networks ?

- Very versatile

- Allow to combine large datasets of different types

- Adapted for large datasets

- Allows to provide fast parametrization

- Able to learn from the noise in the data

Basic concepts of Convolutional Neural-Networks (CNN)
→ Practical example: Cat and dog classification

→ Dog ?

→ Step 1: build a training sample

Data

Labels

Cat
Dog
...
Dog
Cat

→ Step 2: generate a model between data and labels

Data → CNN = High-dimensional non-linear function → **Labels**

→ Step 3: predict the type of animal on a picture

→ CNN model → **Dog**

Basic concepts of Convolutional Neural-Networks (CNN)
→ Practical example: Cat and dog classification

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Dog
Cat

→ Step 2: generate a model between data and labels

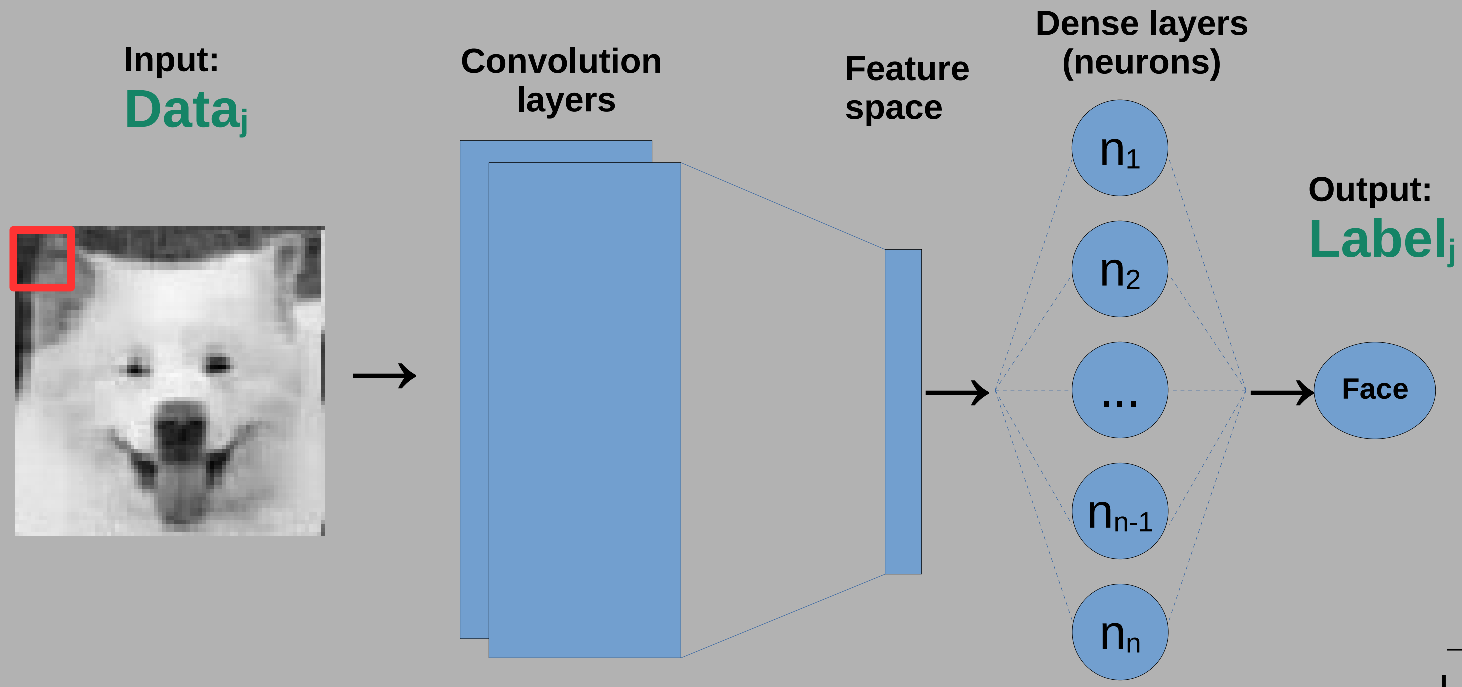
Data → CNN = High-dimensional non-linear function → **Labels**

???

→ Step 3: predict the type of animal on a picture

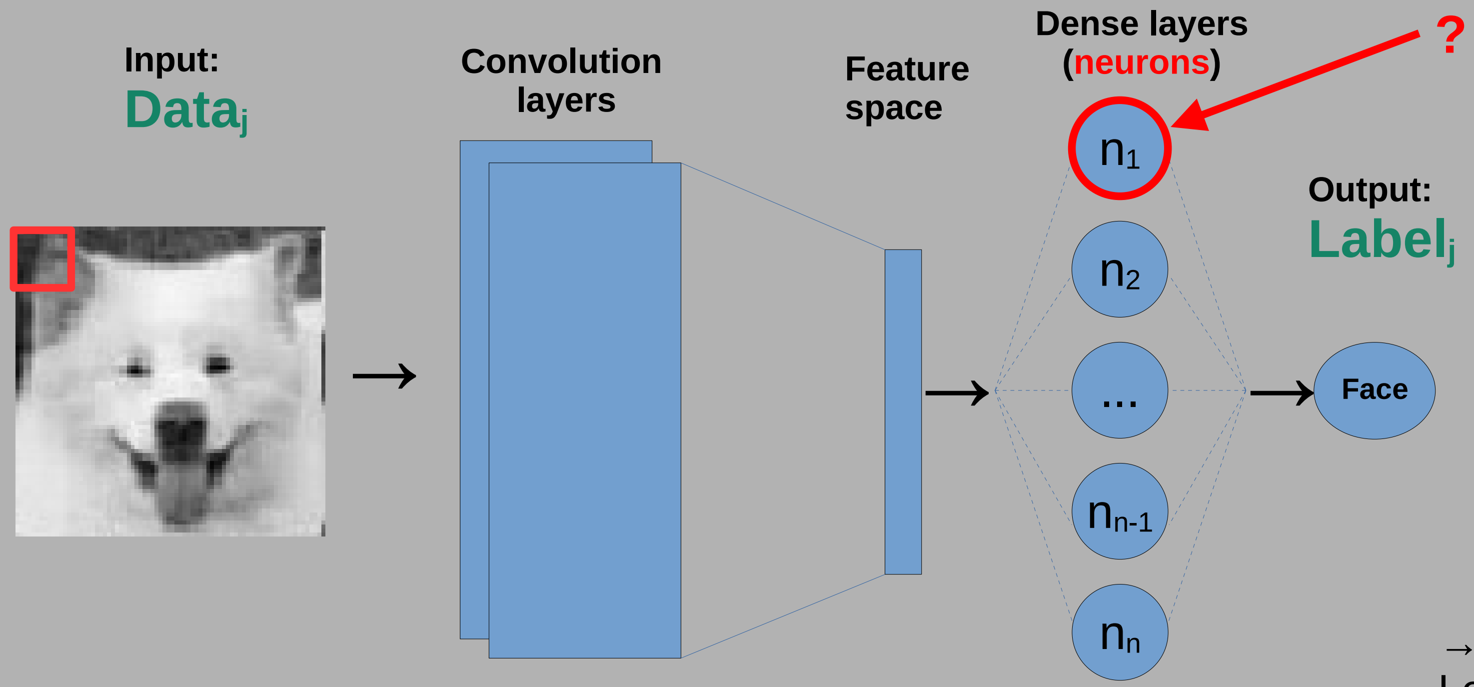
→ CNN model → **Dog**

Basic concepts of Convolutional-Neural Networks



→ Some literature:
LeCun et al. 1989
LeCun & Bengio 1995
Ciresan et al. 2011

Basic concepts of Convolutional-Neural Networks



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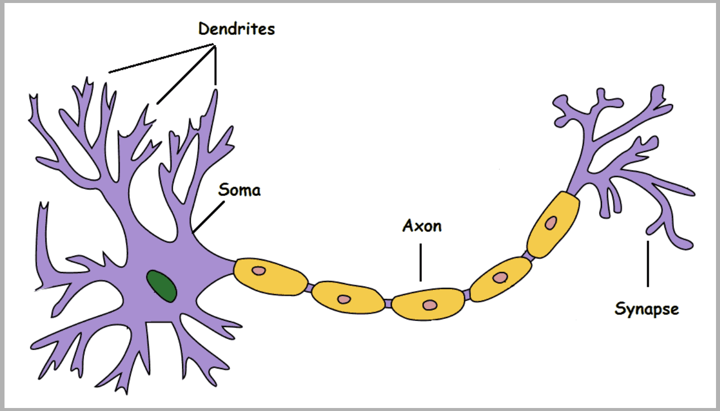
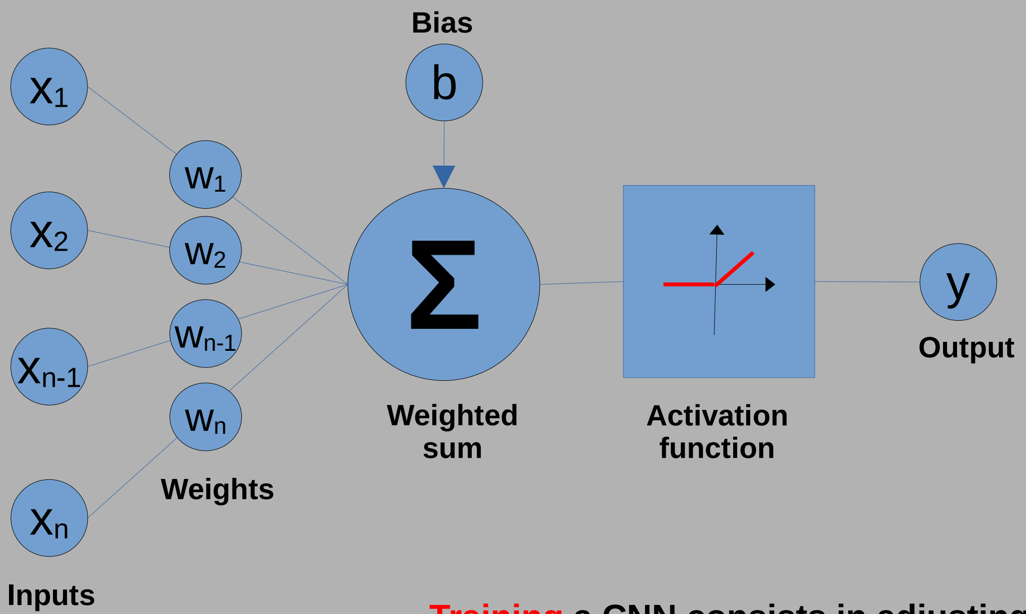
Basic concepts of Convolutional-Neural Networks



https://teksands.ai/blog/evolution-of-design-of-artificial-neuron

What is a neuron?

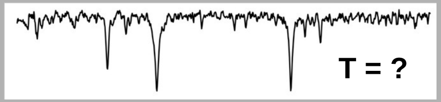
→ Computer representation of human neuron
→ "Perceptron"
→ Linear threshold function
→ First implemented on machine by in 1958 by Frank Rosenblatt



→ **Training** a CNN consists in adjusting the weights and biases of neurons in all layers, to minimize the loss function (mean squared error between truth and prediction)

CNNs for stellar spectroscopy

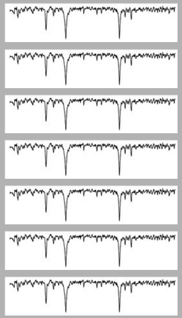
→ **Example: Measuring temperature of the star which spectrum is**



→ Step 1: build a training set

(with labels determined from standard spectroscopic methods)

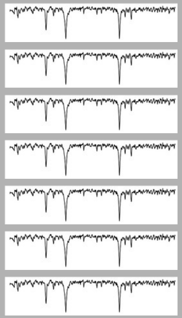
Data = spectra **Labels = T_{eff}**



5234
4834
2730
7598
…
…
…

→ Step 2: train a CNN

Input: spectra

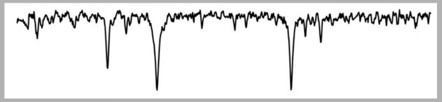


→ CNN →

Output: Labels

5234
4834
2730
7598
…
…
…

→ Step 3: predict temperature of



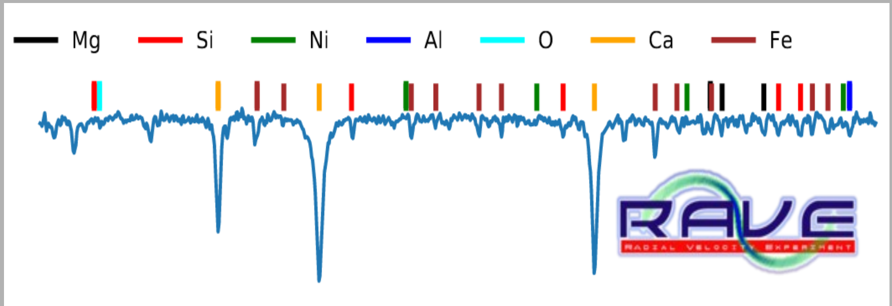
→ Trained CNN → **T_{eff} = 5812 K**

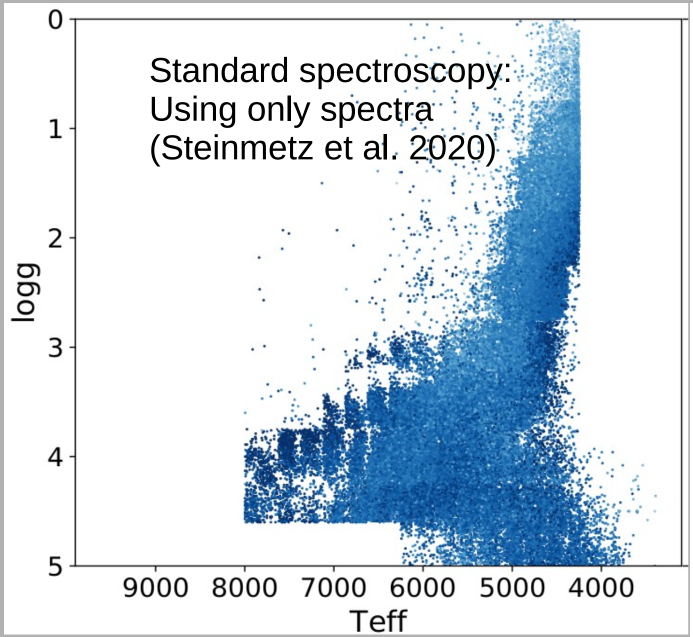
CNN for stellar spectroscopy:

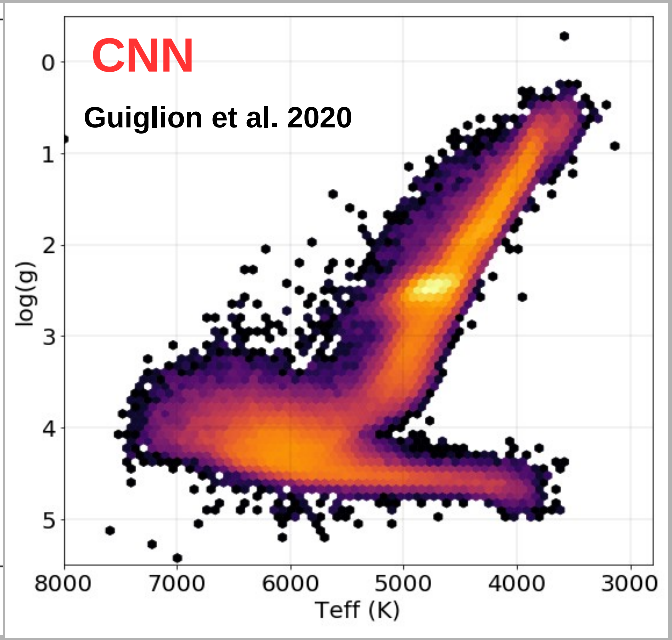
Bailer-Jones et al. 1997
Leung & Bovy 2019
Fabbro et al. 2018
Zhang et al. 2019
Bialek et al. 2020

Our experience with CNNs and *Gaia*-like spectra

→ 1st application of CNNs combining RAVE spectra, *Gaia* magnitudes, and parallaxes
→ Training set: 4000* with labels from APOGEE DR16 (R~22000)
→ Transfer high-quality labels to low-resolution RAVE spectra (R~7500)







→ Such particular combination of data allows to break the spectral degeneracies inherent to RAVE spectra (and likely to be present in *Gaia* RVS spectra)

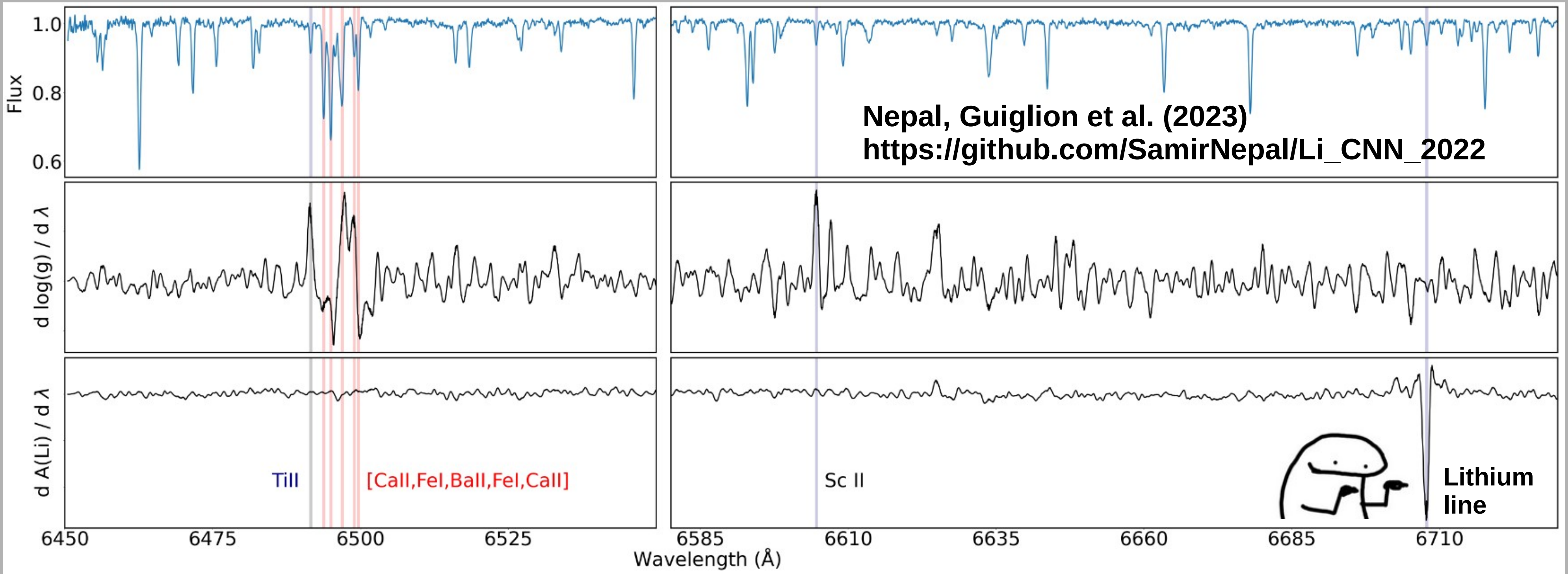
Chemical evolution of lithium with CNN from stellar spectra

S. Nepal (AIP)

→ **Why is lithium important ?**

→ **Chemical evolution of Li in the Milky Way still unclear (e.g. Guiglion et al. 2019)**

→ **Training set: 7000 stars with *Gaia*-ESO spectra, to derive T_{eff}, log(g), [Fe/H], A(Li)**



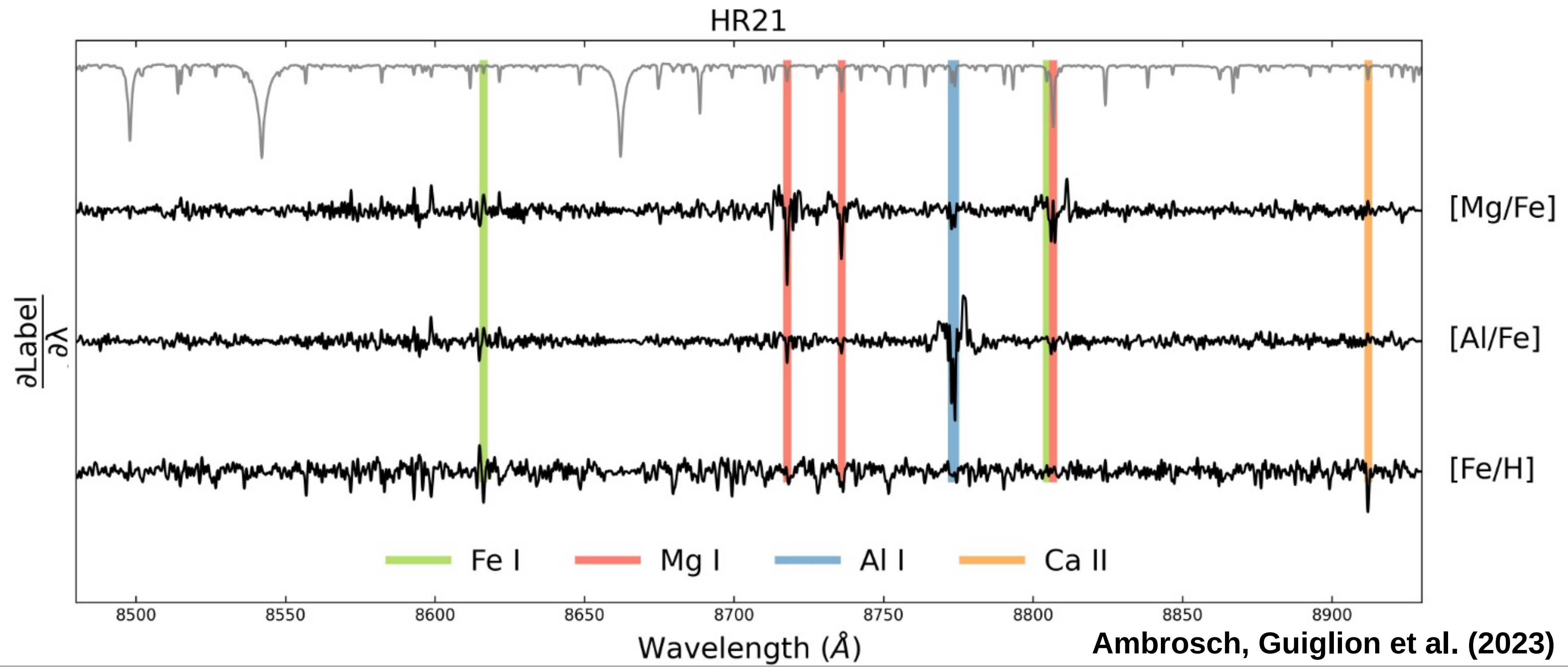
→ **CNN learns efficiently from relevant spectral features !!**

→ **CNN well suited for Li derivation (good insigths for next surveys like 4MOST)**

Are we sure that CNN is not measuring abundance correlations ?

→ [Al/Fe] and [Mg/Fe] ratios are anti-correlated in Globular Clusters (e.g. Pancino et al. 2017)
→ Training set: 14637 stars with *Gaia*-ESO spectra.
Labels: T_{eff}, log(g), [Fe/H], [Al/Fe], [Mg/Fe]

M. Ambrosch



Ambrosch, Guiglion et al. (2023)

→ We know how to properly use CNNs for abundance measurements

Analysis of the 1 million *Gaia* RVS-spectra with CNNs

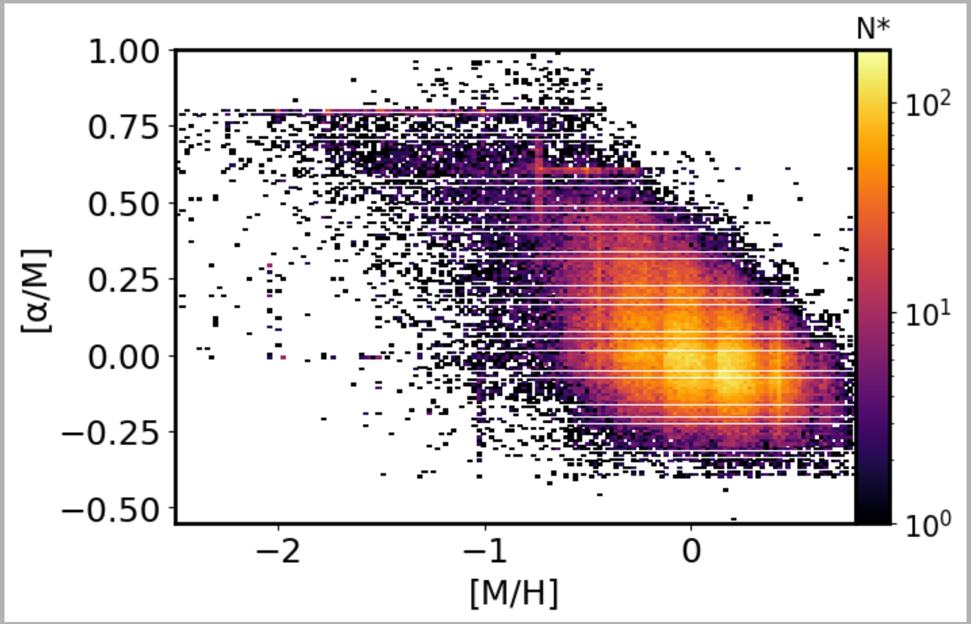
Beyond *Gaia* DR3: tracing the $[\alpha/M] - [M/H]$ bimodality from the Inner to the outer Milky Way disc with *Gaia* RVS and Convolutional Neural-Networks

G. Guiglion[1], S. Nepal[2,3], C. Chiappini[2], S. Khoperskov[2], G. Traven[4], A. B. A. Queiroz[2], M. Steinmetz[2], M. Valentini[2], Y. Fournier[2], A. Vallenari[5], K. Youakim[6], M. Bergemann[1], S. Mészáros[7,8], S. Lucatello[9,10], R. Sordo[5], S. Fabbro[11], I. Minchev[2], G. Tautvaišienė[12], Š. Mikolaitis[12], J. Montalbán[13]

Analysis of the 1 million *Gaia* RVS-spectra with CNNs

Motivations and goals:

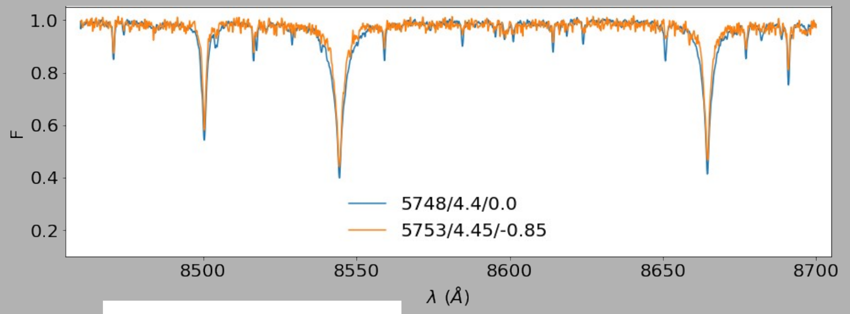
→ Use homogeneously the full Gaia data product
→ Provide more precise and accurate atmospheric parameters and abundances than the standard Gaia spectroscopic pipeline (GSP-Spec)



Method: GSP-Spec
Data: spectra with 15<S/N<25
Results from Recio-Blanco et al. 2022

→ Set the machine-learning path for Gaia data analysis (DR4 in 2025, DR5 in 2027)
→ Provide robust chemical estimates for low-S/N spectra (300000 spectra with 15<S/N<25 !!!!)

Analysis of the 1 million *Gaia* RVS-spectra with CNNs



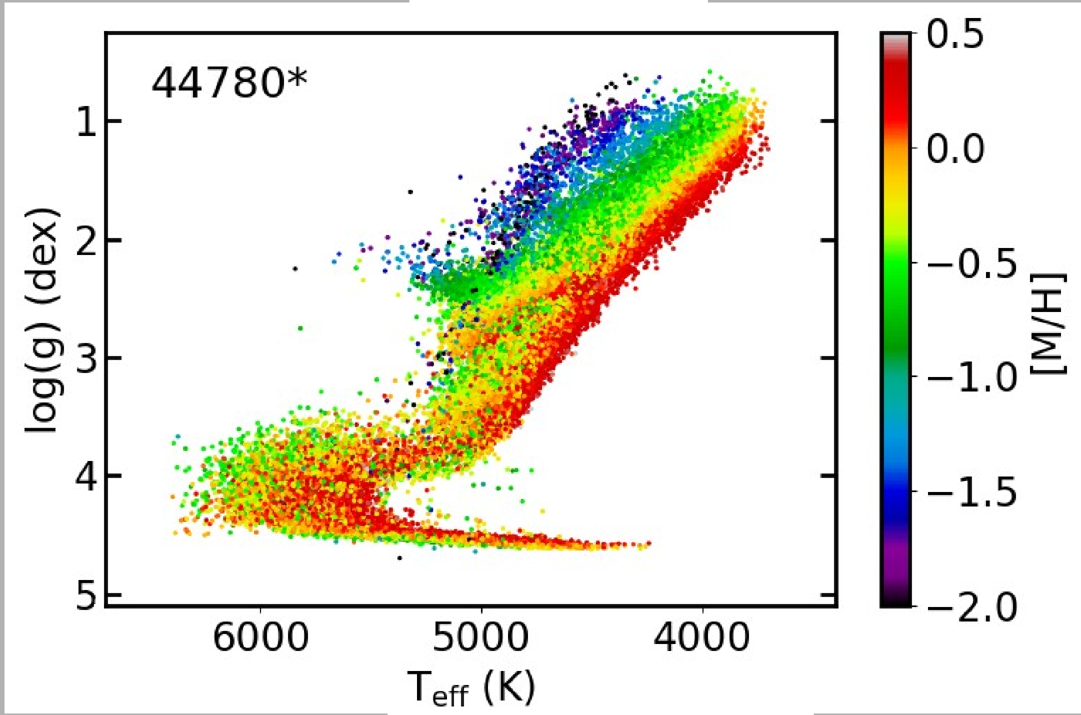
→ **Labels we aim at deriving: T_{eff}, log(g), [M/H], [α/M], [Fe/H]**
→ **Building a robust training set**

R~22000

Knowledge transfer from high-quality high-res APOGEE labels to intermediate-res RVS

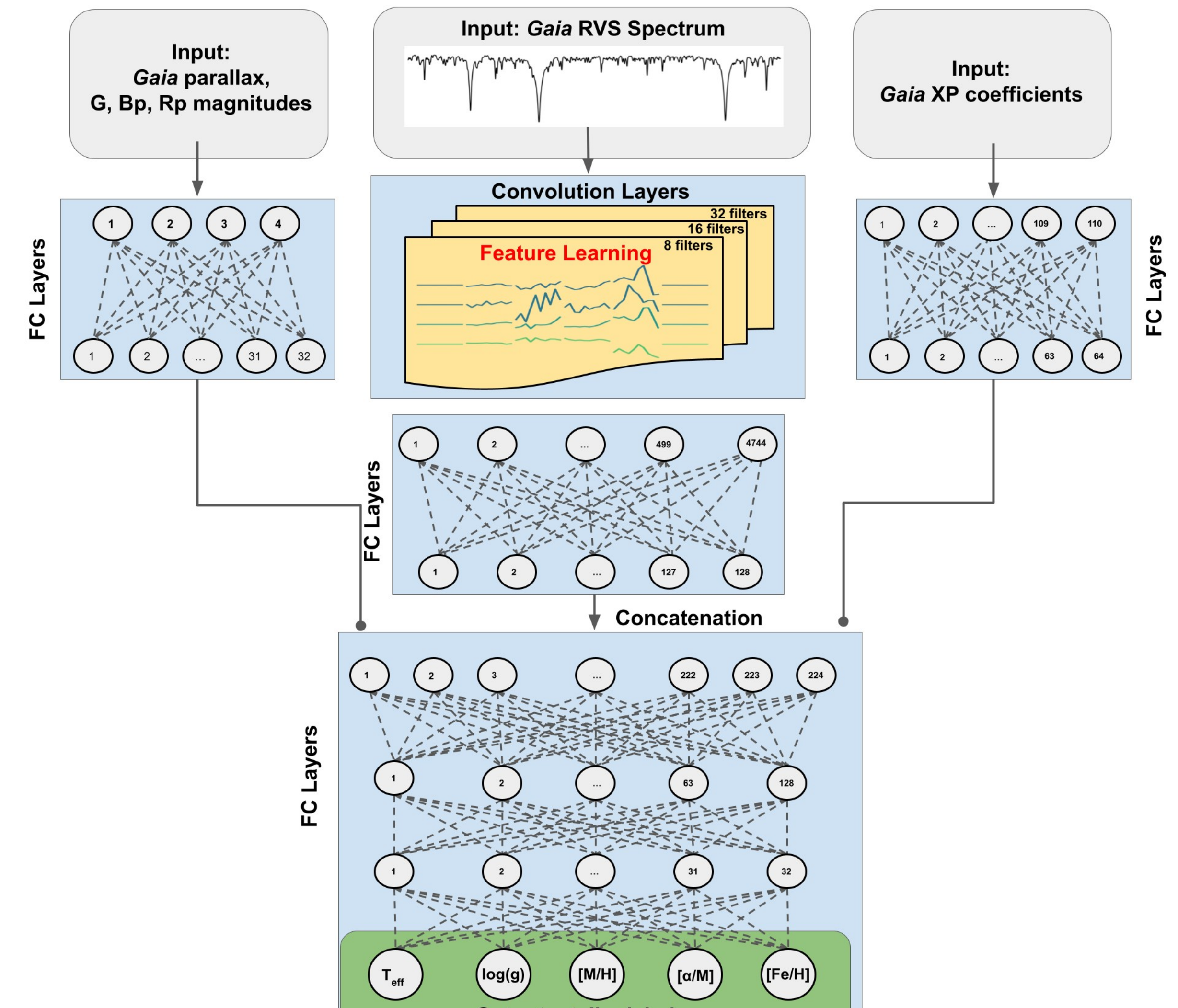
R~11000

Training sample



Guiglion, Nepal et al. 2023

A hybrid Convolutional Neural-Network for *Gaia*-RVS analysis



Guiglion, Nepal et al. 2023

→ **CNN combines *Gaia* G, Bp, Rp magnitudes, Parallaxes, RVS spectra, and XP data**

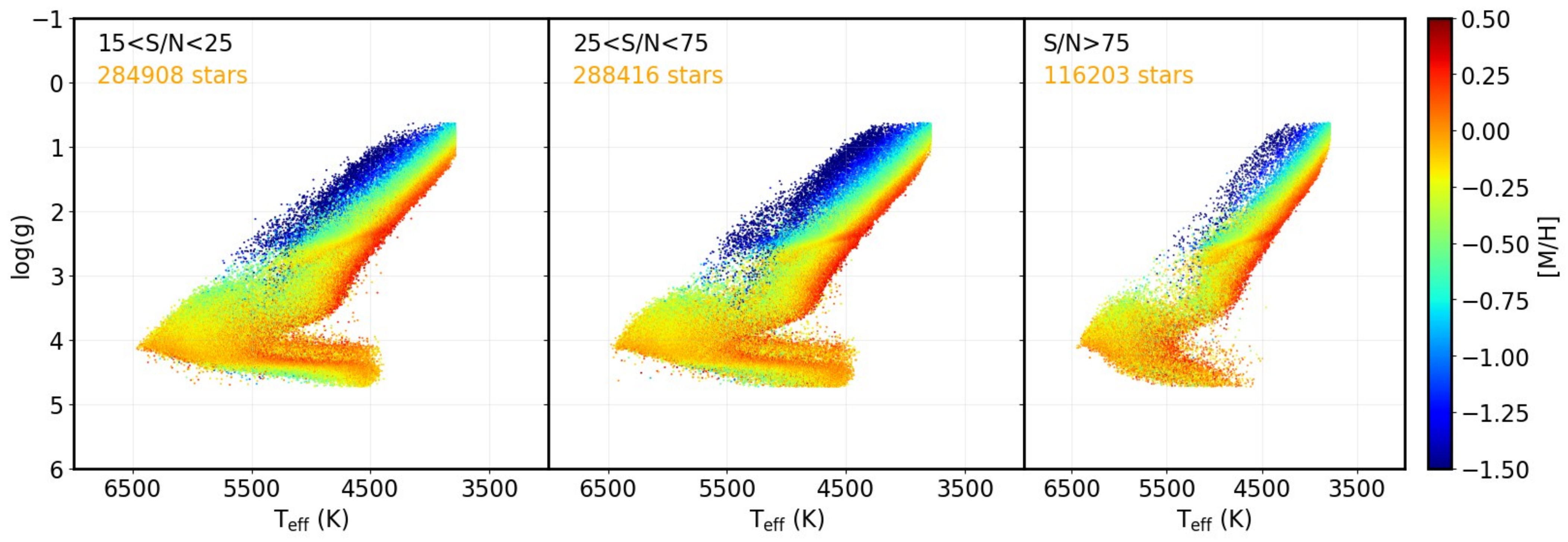
→ **Labels derived:**
T_{eff}, log(g), [M/H], [α/M], [Fe/H]

→ **Prediction time**
4 labels in 3300 stars / second

→ **Deep ensemble approach to derive uncertainties.**

Robust estimates of T_{eff}, log(g), [M/H] for 690000 *Gaia* stars

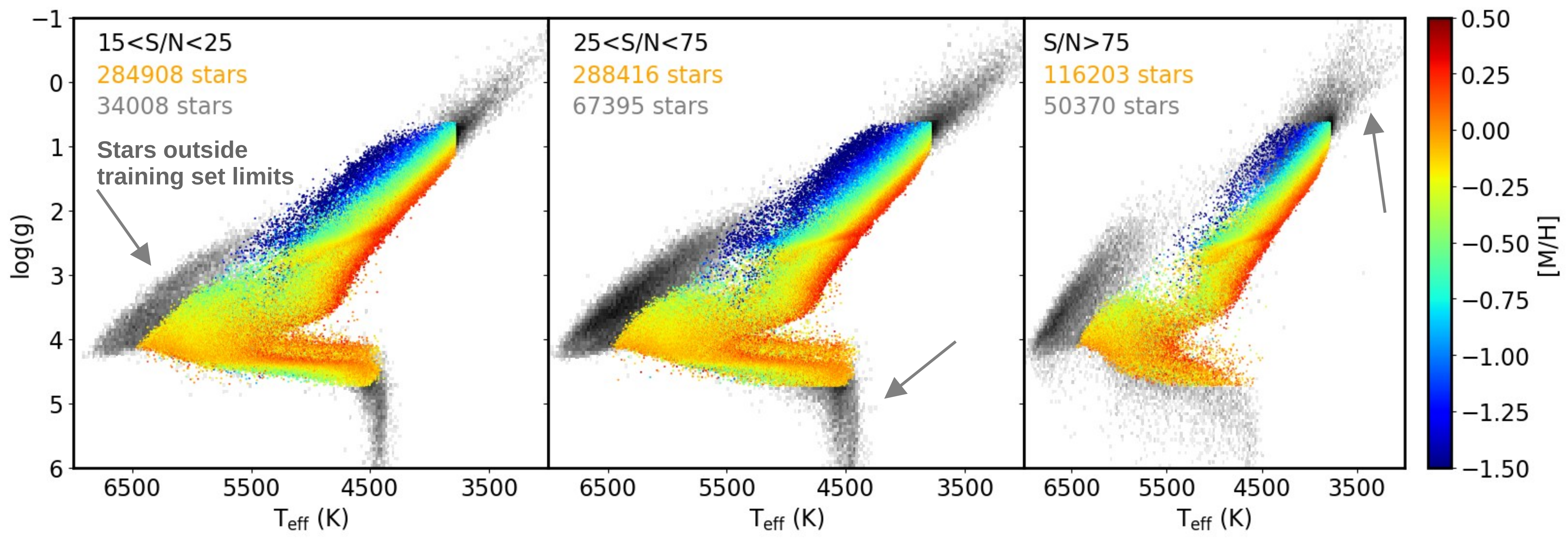
Guiglion, Nepal et al. 2023



→ By adding magnitudes, parallaxes and XP data, CNN is able to break spectral degeneracies in *Gaia* RVS spectra.

Robust estimates of T_{eff}, log(g), [M/H] for 690000 *Gaia* stars

Guiglion, Nepal et al. 2023

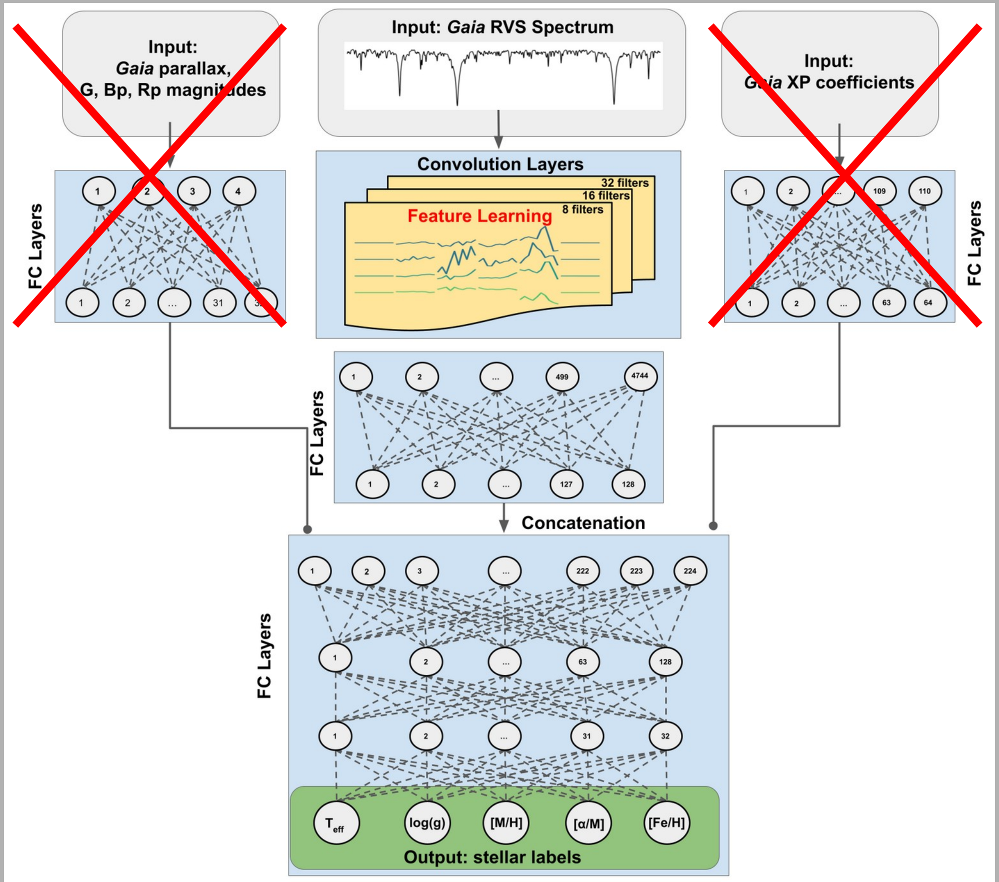


→ By adding magnitudes, parallaxes and XP data, CNN is able to break spectral degeneracies in *Gaia* RVS spectra.

→ CNN results are as good as the training set can be.

Are we really breaking the RVS degeneracies by using mag., parallaxes and XP data ?

→ Test: Training CNN only using RVS spectra (no mags, no parallaxes, no XP)



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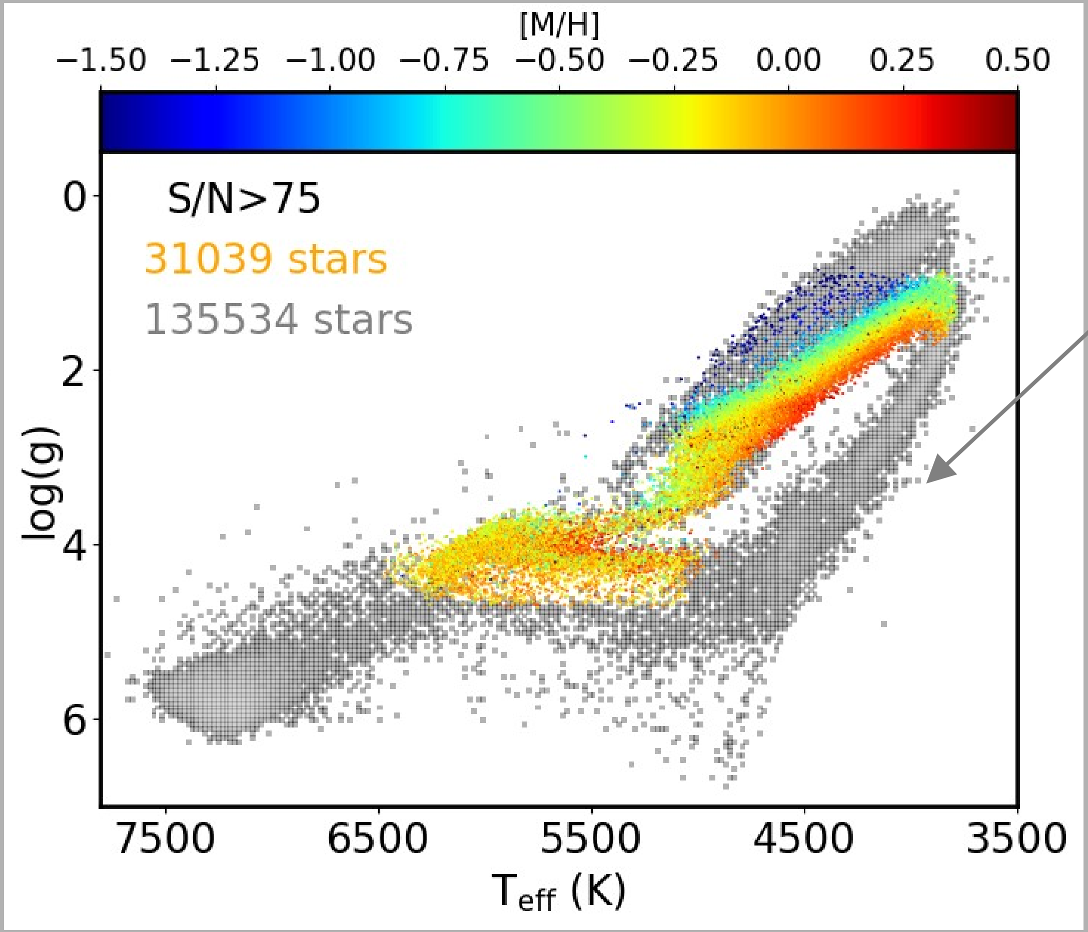
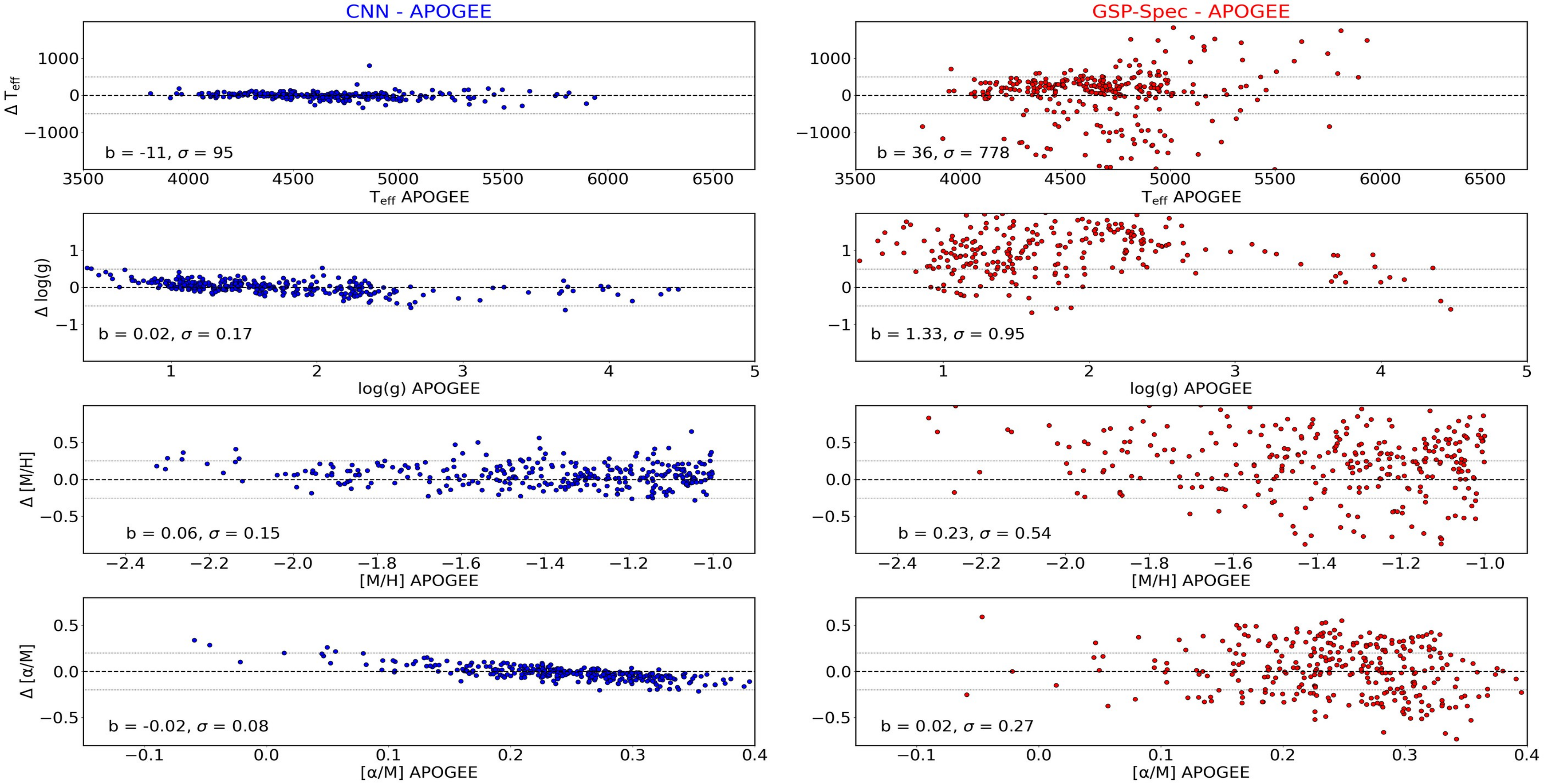


→ **Hard for CNN to differentiate between cool dwarfs and cool giants (same for GSP-Spec)**

→ **Large uncertainties for >75% of the sample**

→ **Thus, combining spectra, magnitudes, parallaxes, and XP data is required for precise and accurate parametrization**

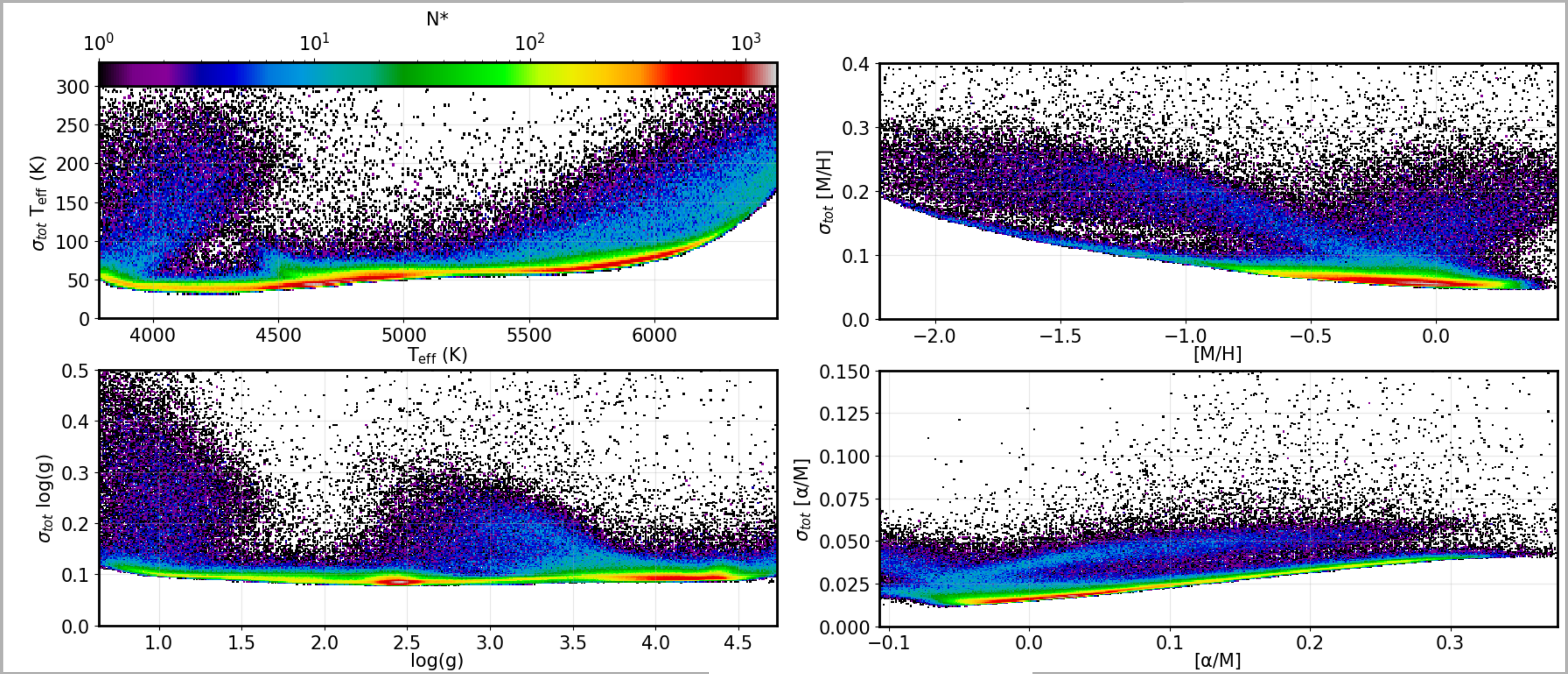
How does CNN compare to *Gaia* GSP-Spec (standard spectroscopy) for halo stars ?



Guiglion, Nepal et al. 2023

→ CNN provides precise and accurate labels down to [M/H]=-2.4 dex

CNN uncertainties

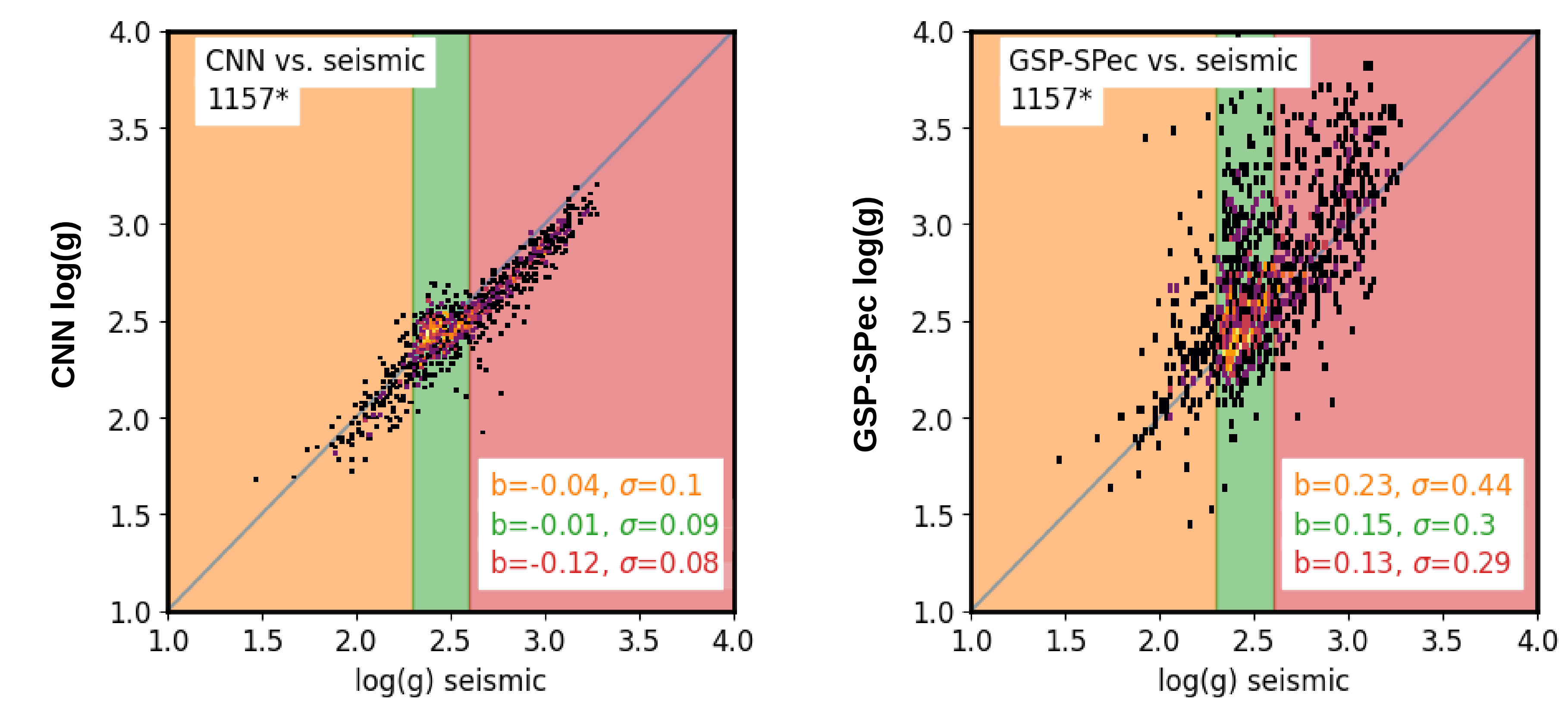


Guiglion, Nepal et al. 2023

→ **We provide realistic uncertainties thanks to a deep ensemble approach**

How does CNN gravities compare to precise asteroseismic ages ?

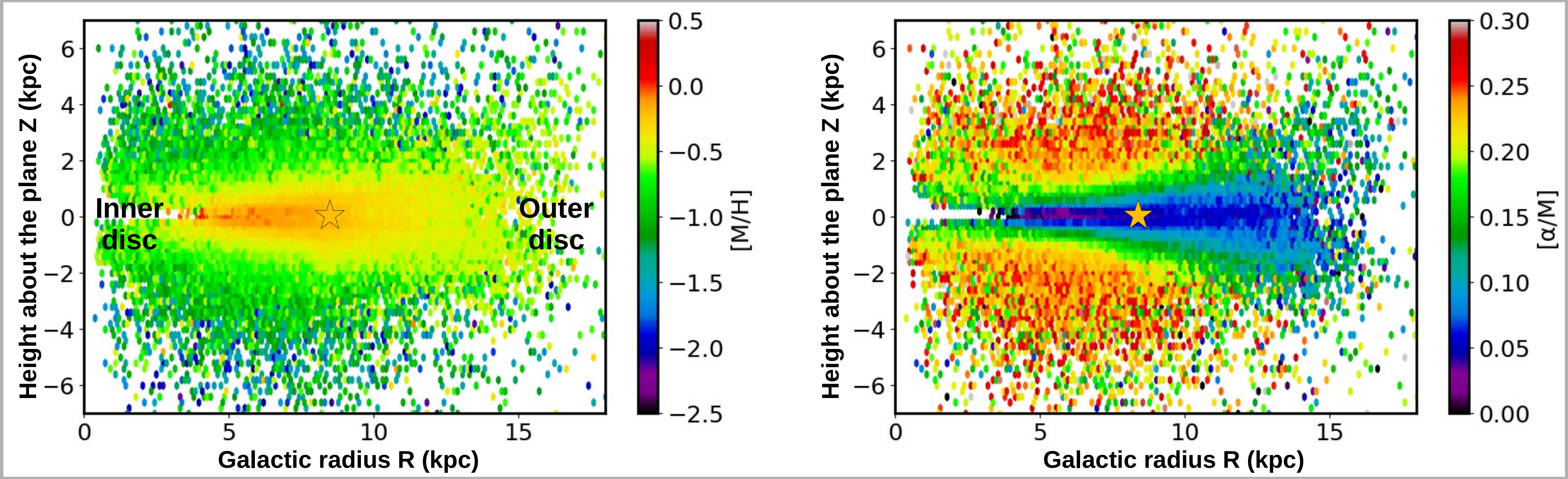
- → Asteroseismology relies on stellar oscillations (Chaplin & Miglio 2013)
- → Widely used for validation purposes (eg. in RAVE; Valentini et al. 2017)
- → We use here Zinn et al. (2022) asteroseismic data for validation



Guiglion, Nepal et al. 2023

Chemical cartography of the Milky Way, for Inner to Outer regions with *Gaia* and CNN

→ We selected giants, to probe large distances, and limit possible systematics → 147416 stars
→ Galactic radius and Height adopted from Nepal et al. In prep. (using StarHorse distances).



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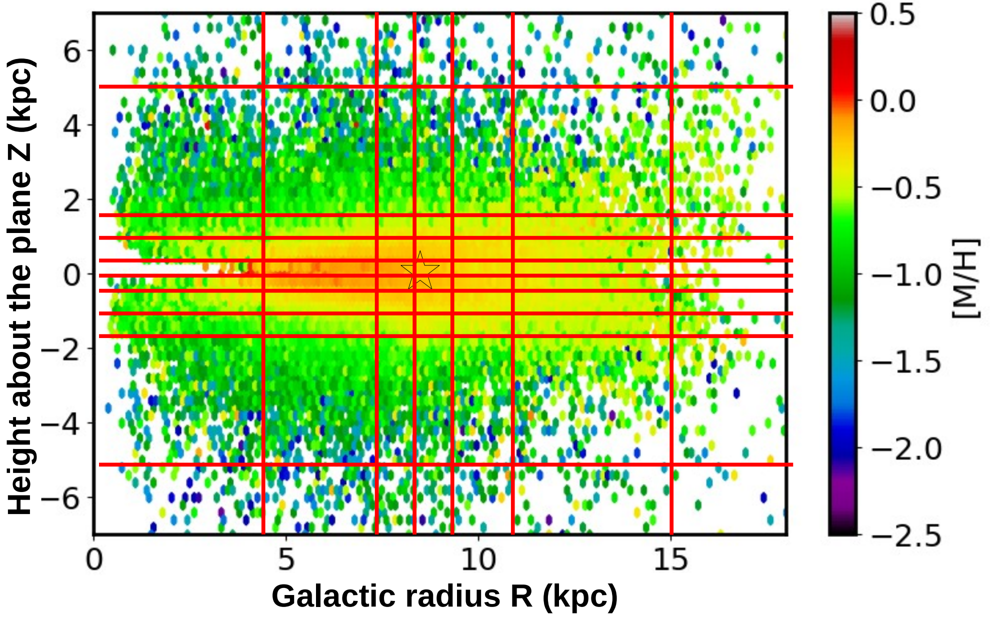
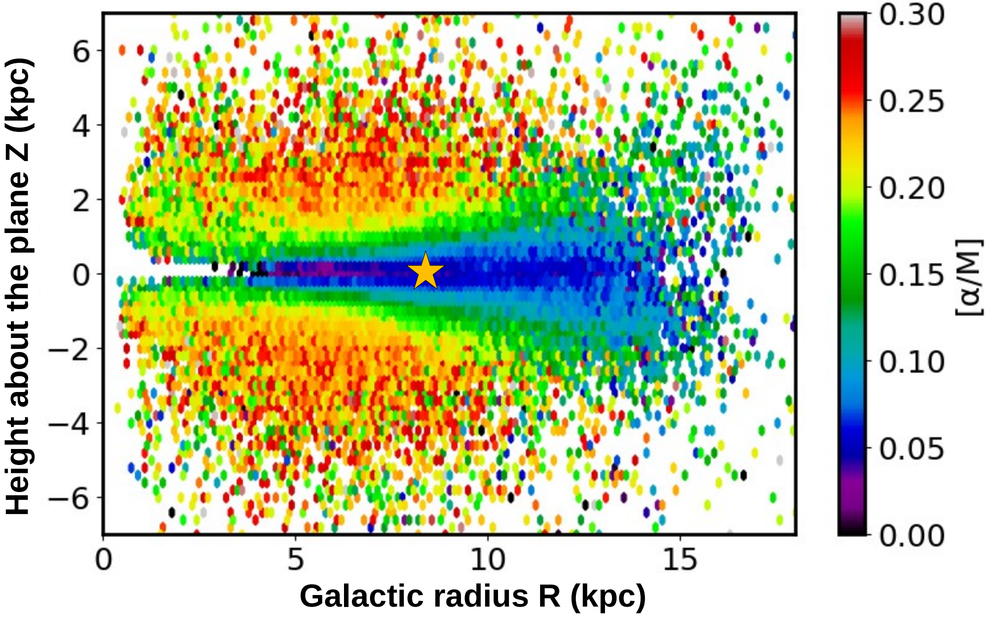
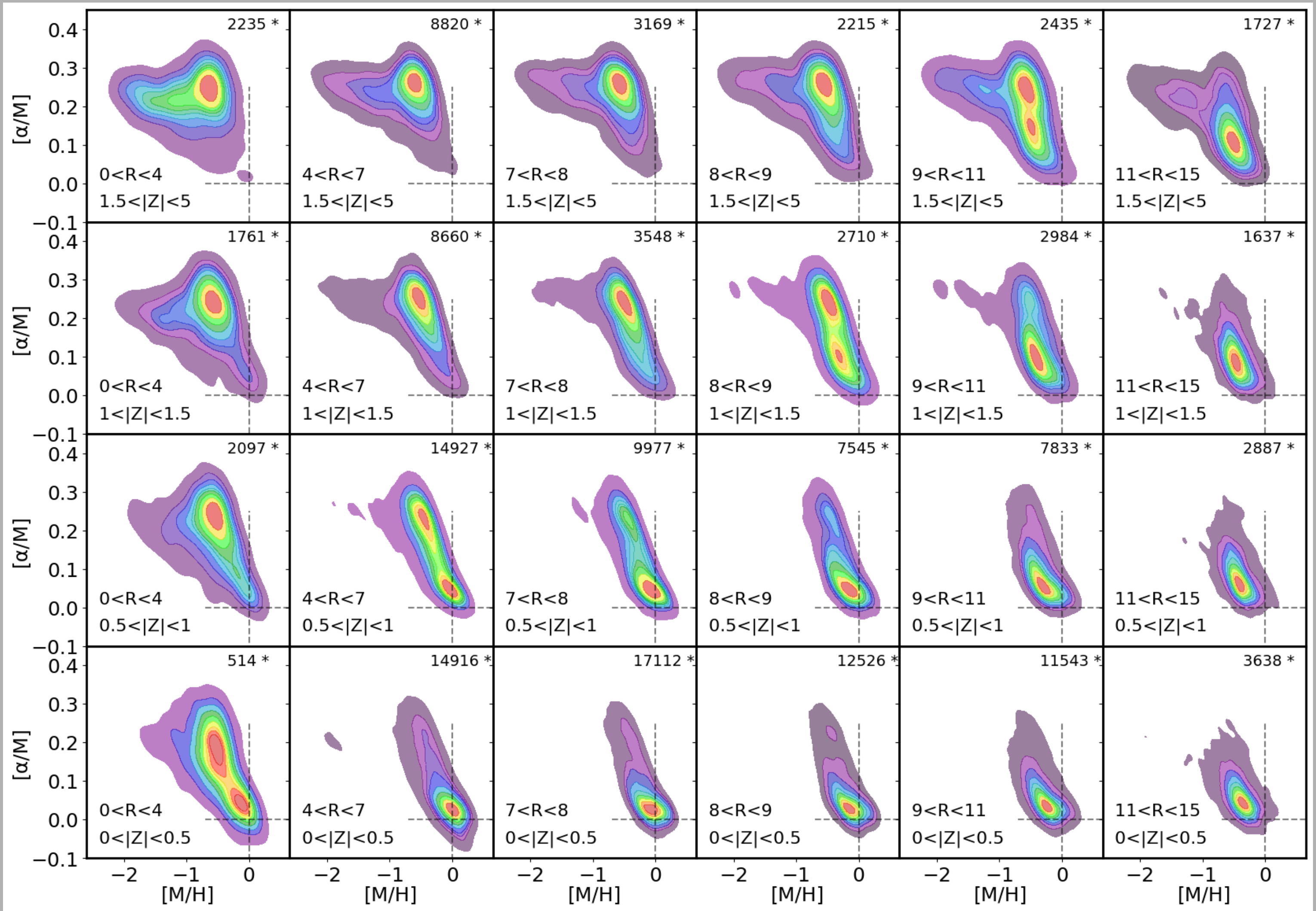


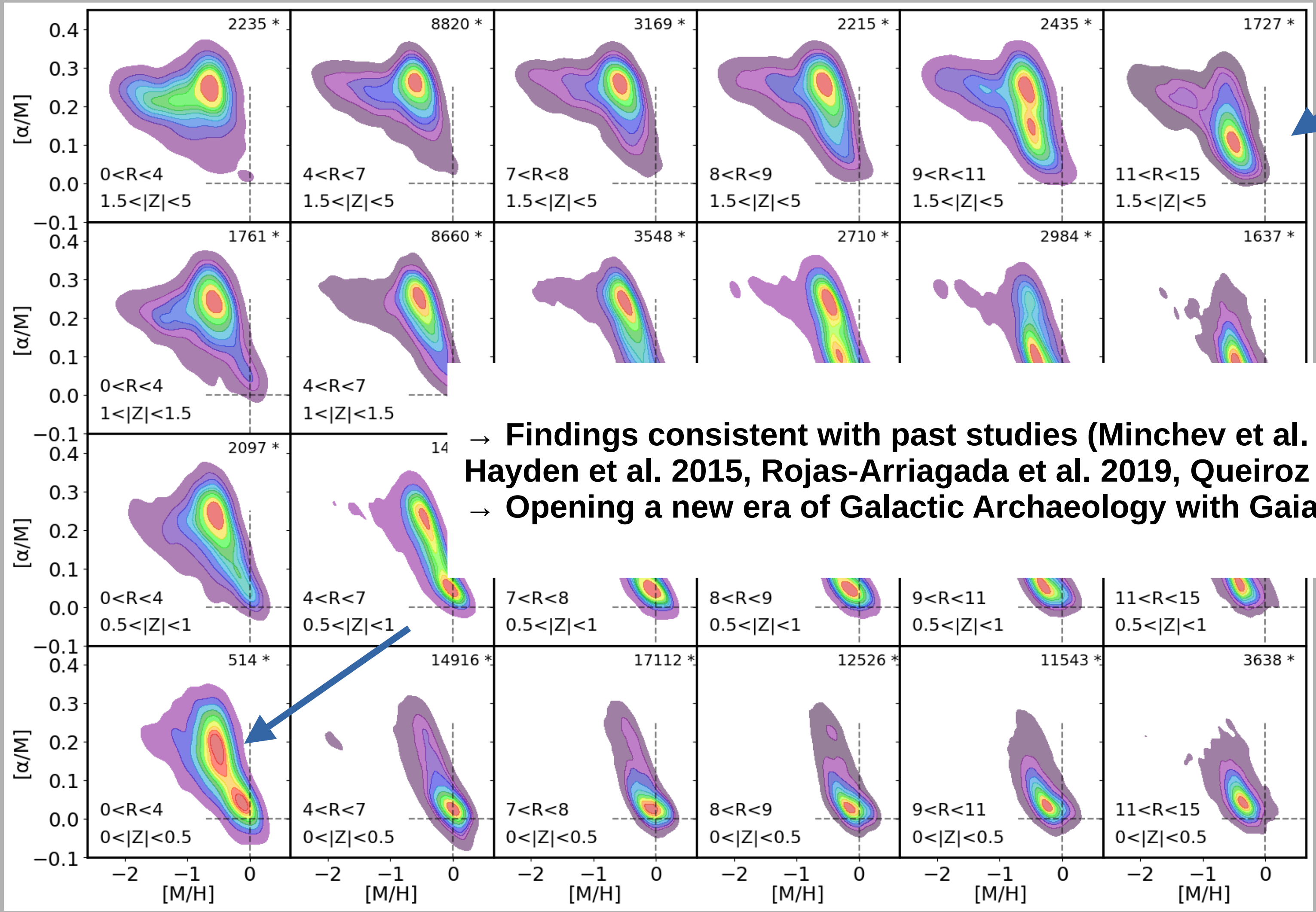


→ Studying the chemical abundance pattern [α/M] vs. [M/H] as function of R and Z

Chemical cartography of the Milky Way, for Inner to Outer regions with *Gaia* and CNN



Chemical cartography of the Milky Way, for Inner to Outer regions with *Gaia* and CNN



→ Findings consistent with past studies (Minchev et al. 2015, Anders et al. 2014, Hayden et al. 2015, Rojas-Arriagada et al. 2019, Queiroz et al. 2020, 2021).

→ Opening a new era of Galactic Archaeology with Gaia-RVS (Nepal et al. in prep a,b)

Last take home messages:

- Convolutional Neural-Networks (CNN) are well suited for stellar parametrization

- CNN parametrization is mainly reliable within the training sample limits

- Modern techniques are essential for providing training sample labels

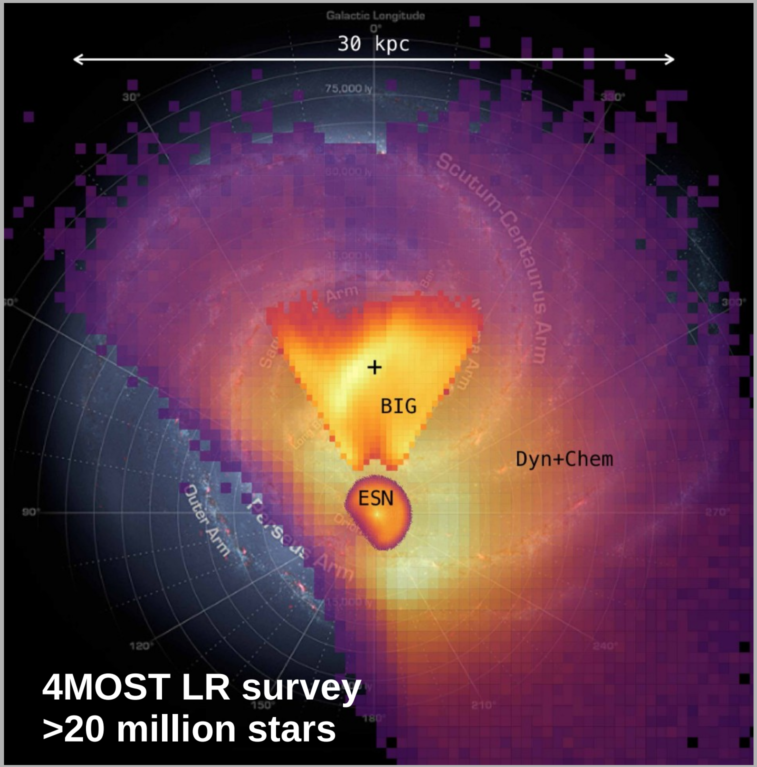
- CNN parametrization is fast and robust (several 10^3 stars per second)

- The training sample should be built in a pro-active way

- Future spectroscopic surveys will strongly benefit from such algorithms

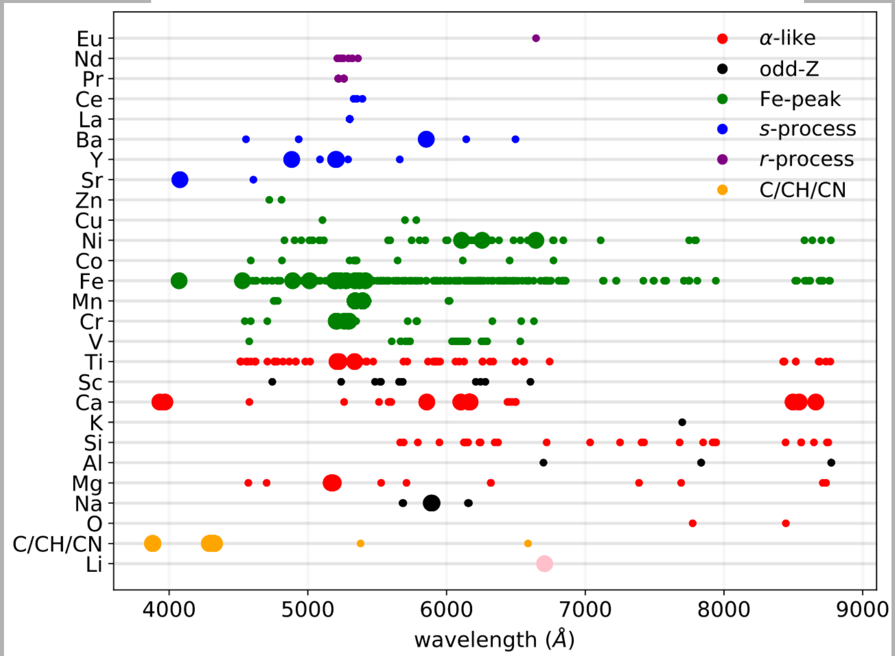
An example of future spectroscopic survey: 4MOST

→ **Survey description:** de Jong et al. 2019
→ **Survey strategy:** Guiglion et al. 2019
→ **MW Halo surveys:** Helmi et al. 2019, Christlieb et al. 2019
→ **MW Disc and bulge surveys:** Chiappini et al. 2019, Bensby et al. 2019
→ **Magellanic clouds:** Cioni et al. 2019



4MIDABLE-LR ESO proposal 2020

>20 elements to be measured at R=5000



4MIDABLE-LR ESO proposal 2020

→ CNN is currently one of the tested ML algorithm for the 4MOST Galactic pipeline