ZENTRUM FÜR ASTRONOMIE

Deutsche Forschungsgemeinschaft
German Research Foundation

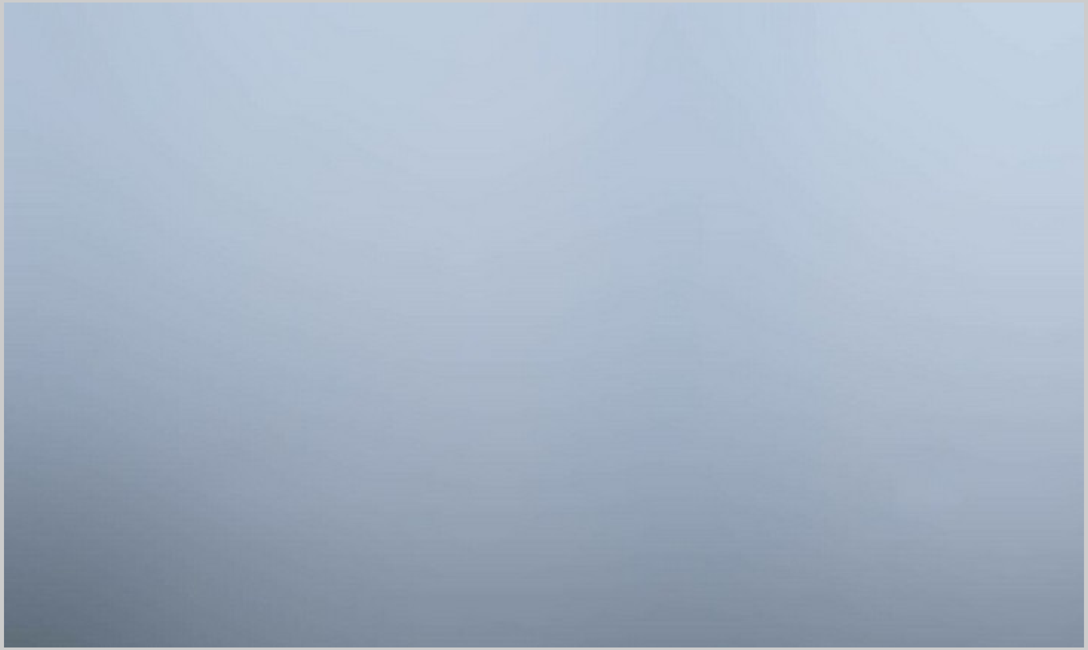
Max-Planck-Institut für Astronomie Heidelberg
Max Planck Institute for Astronomy Heidelberg

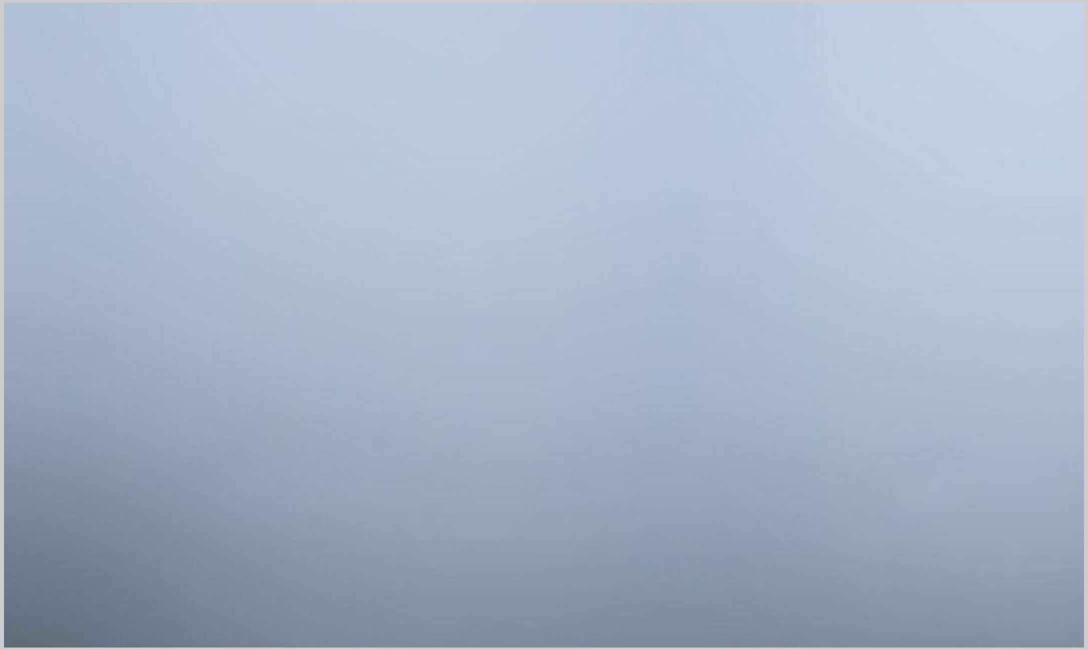
Realising the potential of large spectroscopic surveys with machine-learning

Guillaume Guiglion (GG)

with S. Nepal, C. Chiappini, M. Ambrosch, M. Steinmetz, M. Valentini, G. Matijevič and R. de Jong

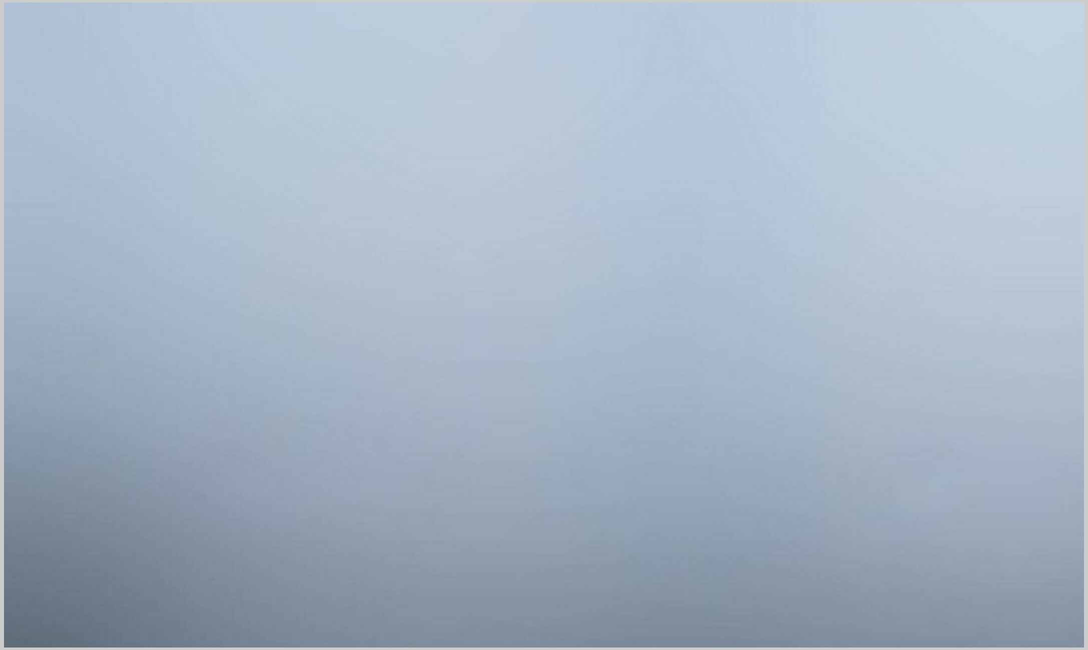
IAUS395 – Paraty - 21/11/24





MPIA

Paraty



MPIA

Paraty

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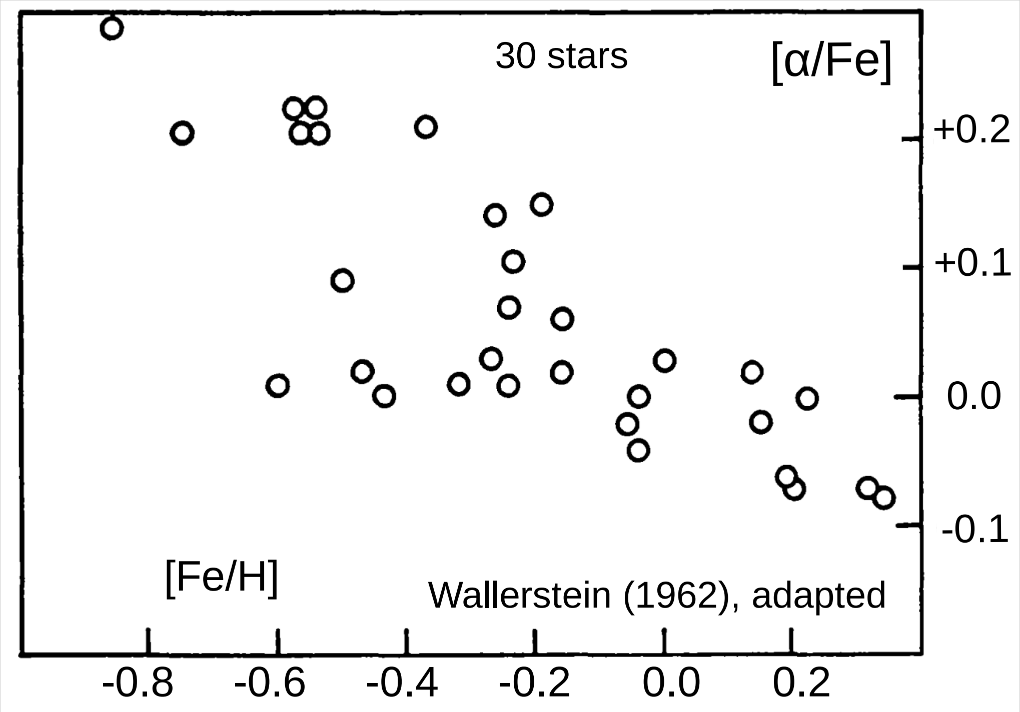
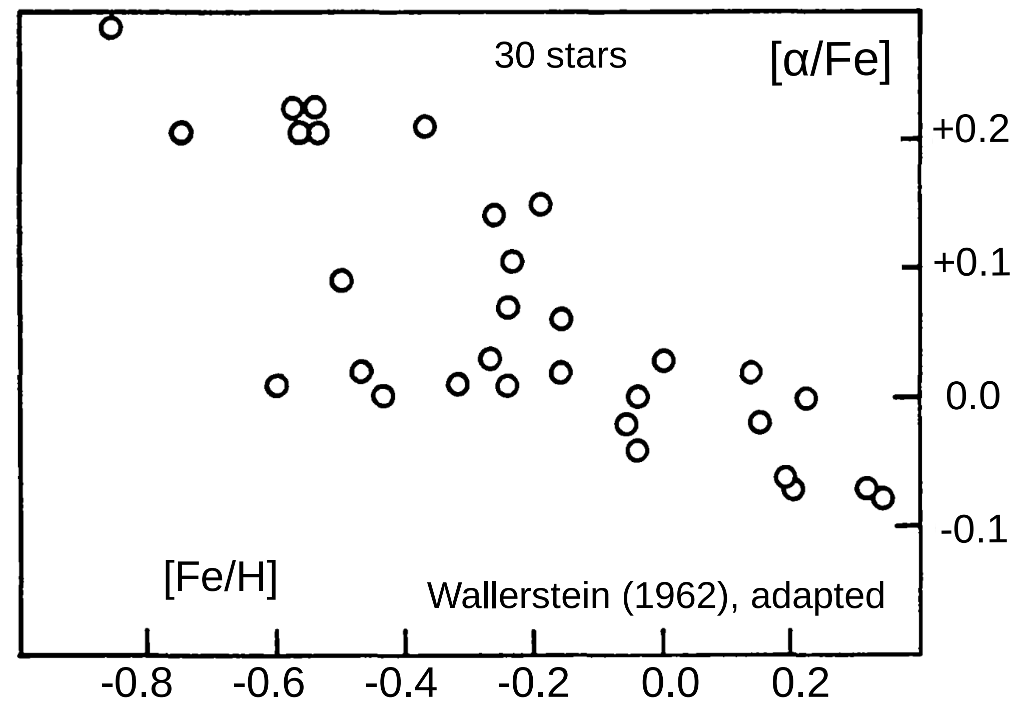
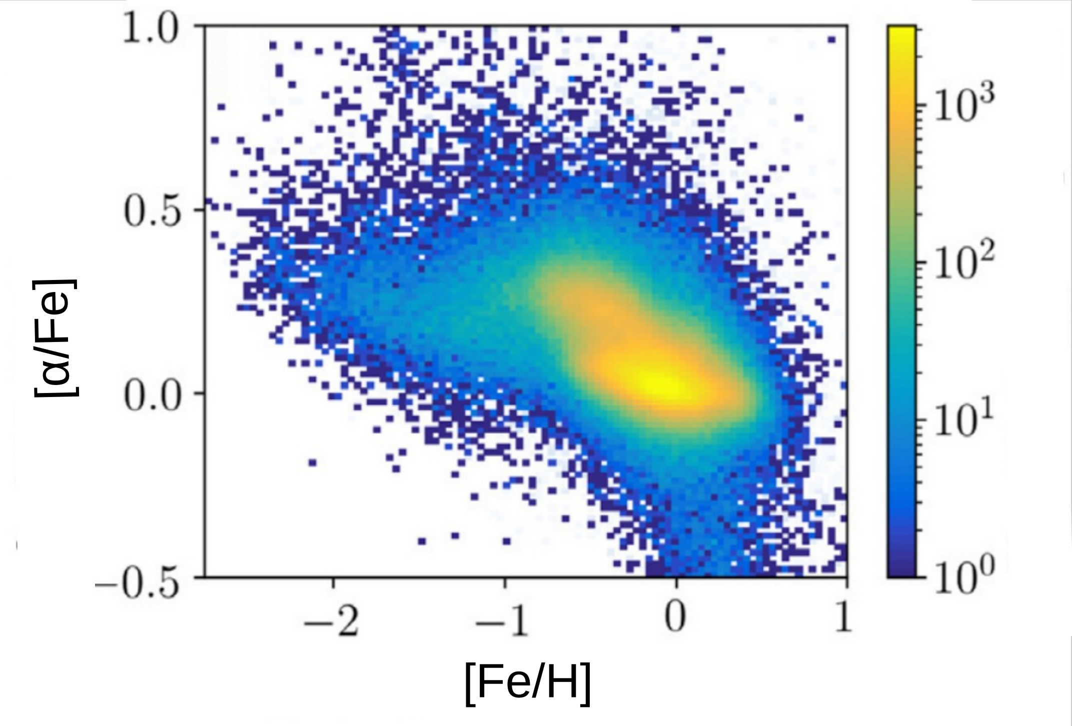
Stellar abundances for Galactic Archaeology



Stellar abundances for Galactic Archaeology



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



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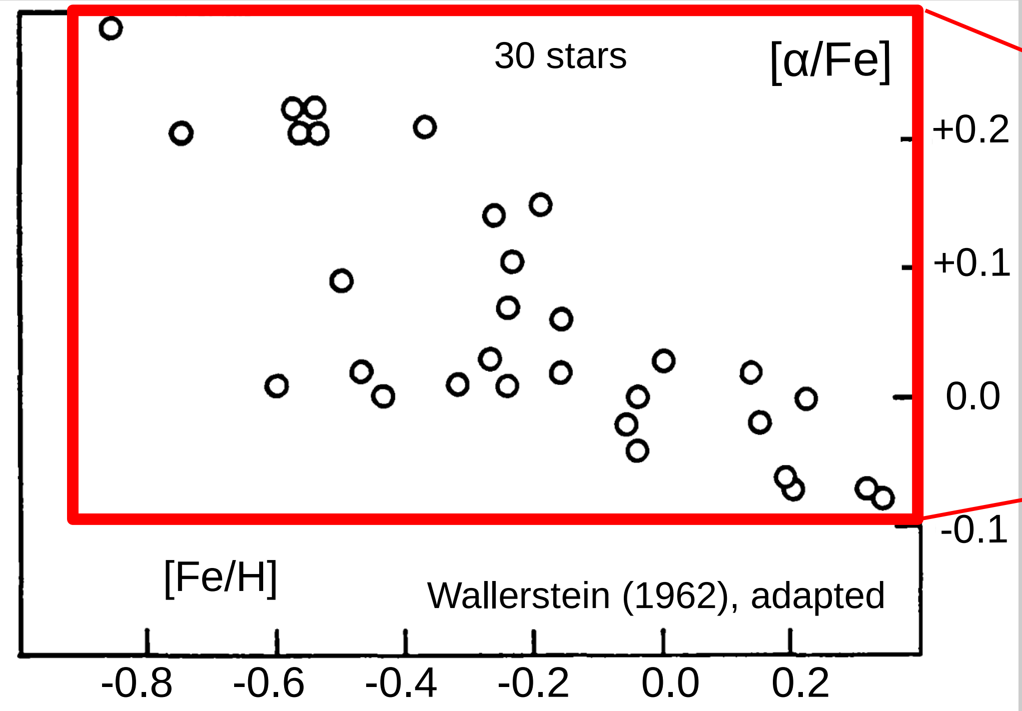

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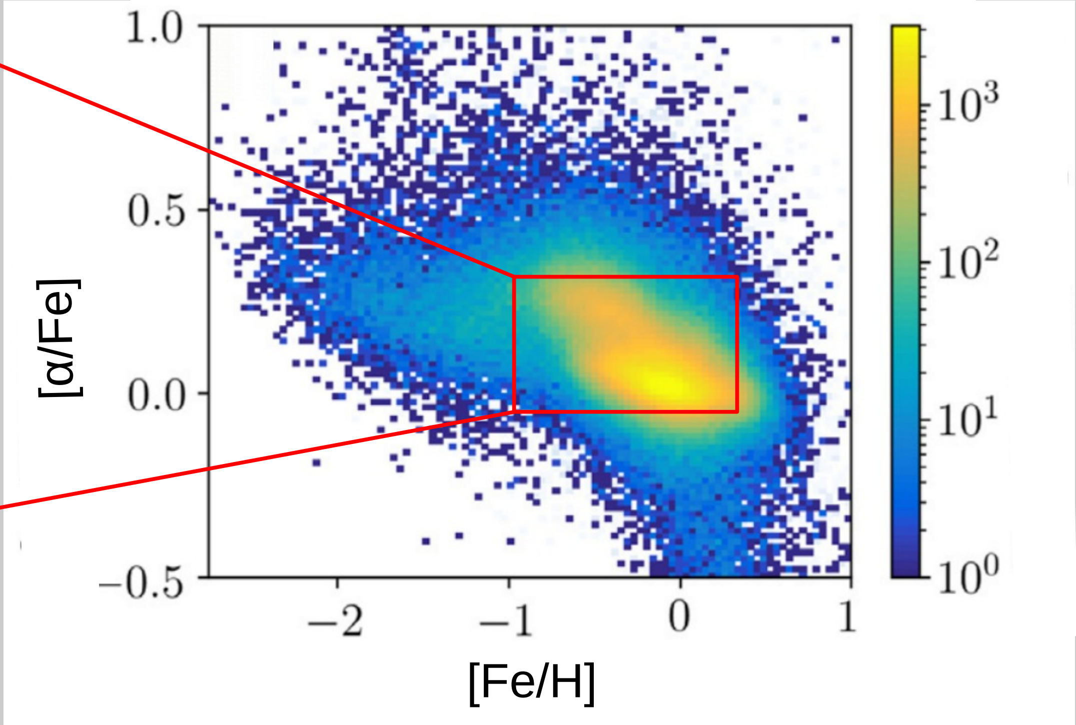


The need for large spectroscopic surveys

RAVE
RADIAL VELOCITY EXPERIMENT

5×10^5

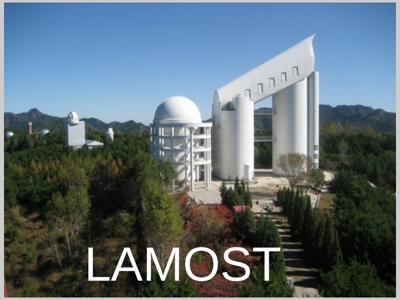
GaiaESO

10^5

ESO

Ambre

$>10^4$



10^6

GALAH

5×10^5

APOGEE

SDSSIII

$>5 \times 10^5$

gaia

10^6

The need for large spectroscopic surveys

RAVE — RADIAL VELOCITY EXPERIMENT

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GaiaESO

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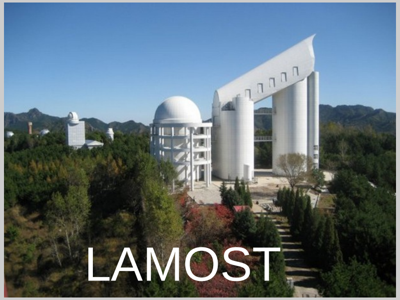

10^6

GALAH

10^6

4MOST

$>10^7$

MOONS — Multi Object Optical and Near-infrared Spectrograph

$>10^6$

APOGEE SDSSIII

10^6

gaia

10^7

WST

$>10^7$

For stellar parametrization:

→ One can use standard spectroscopy

e.g.:

- **SME** (Valenti & Piskunov; @GALAH)
- **FERRE** (Allende-Prieto et al. 2006; @PRISTINE)
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  - → Leung & Bovy 2019 (@APOGEE)
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  - → GG et al. 2020 (@RAVE)
  - → Ambrosch, GG et al. 2023 (@GES HR10&21)
  - → Nepal, GG et al. 2023 (@GES HR15)
  - → GG et al. 2024 (@*Gaia* RVS)

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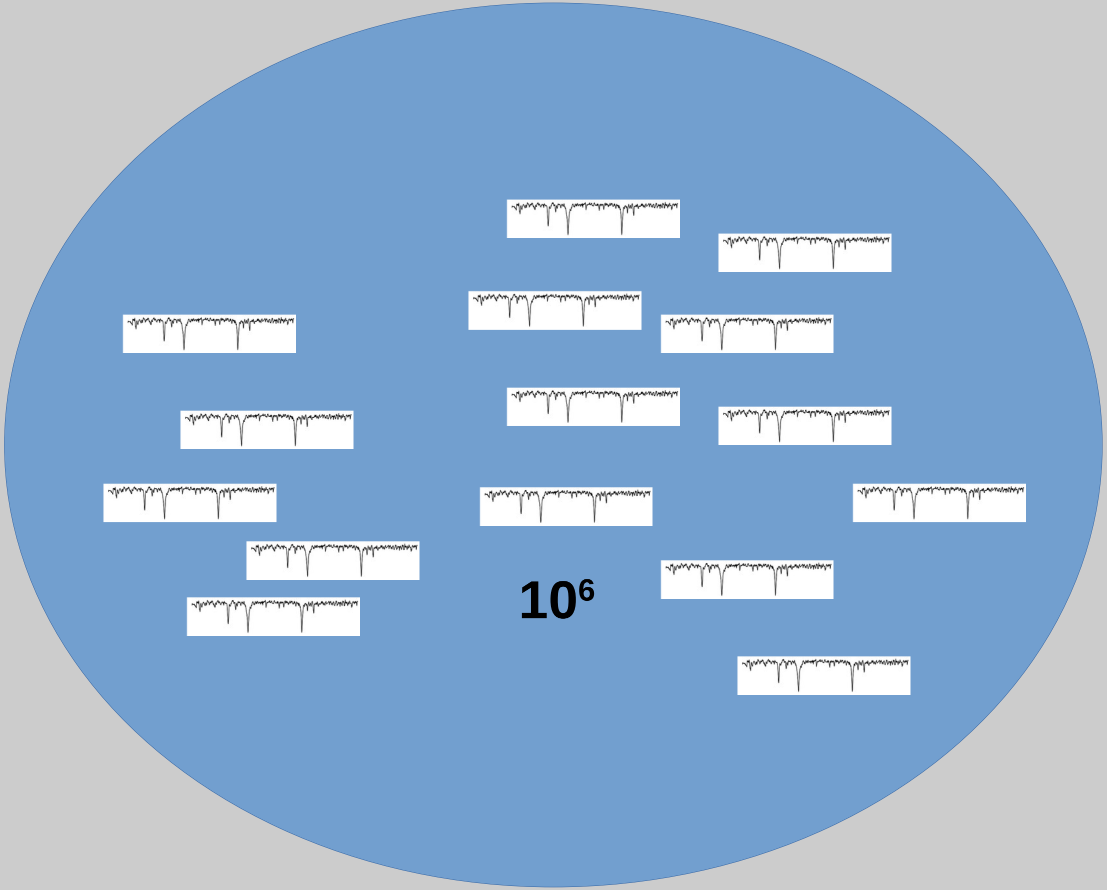
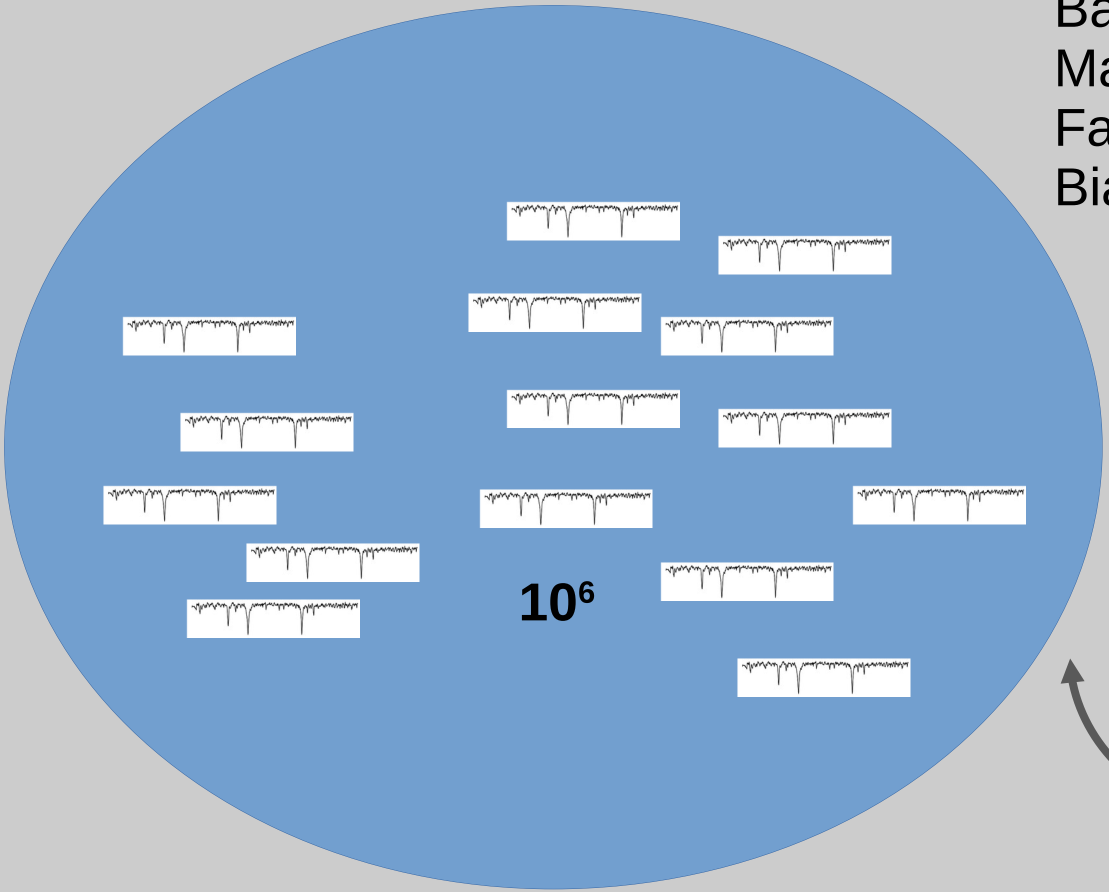
E.g. measuring T_{eff}, log(g), [Fe/H] in:



E.g. measuring T_{eff}, log(g), [Fe/H] in:

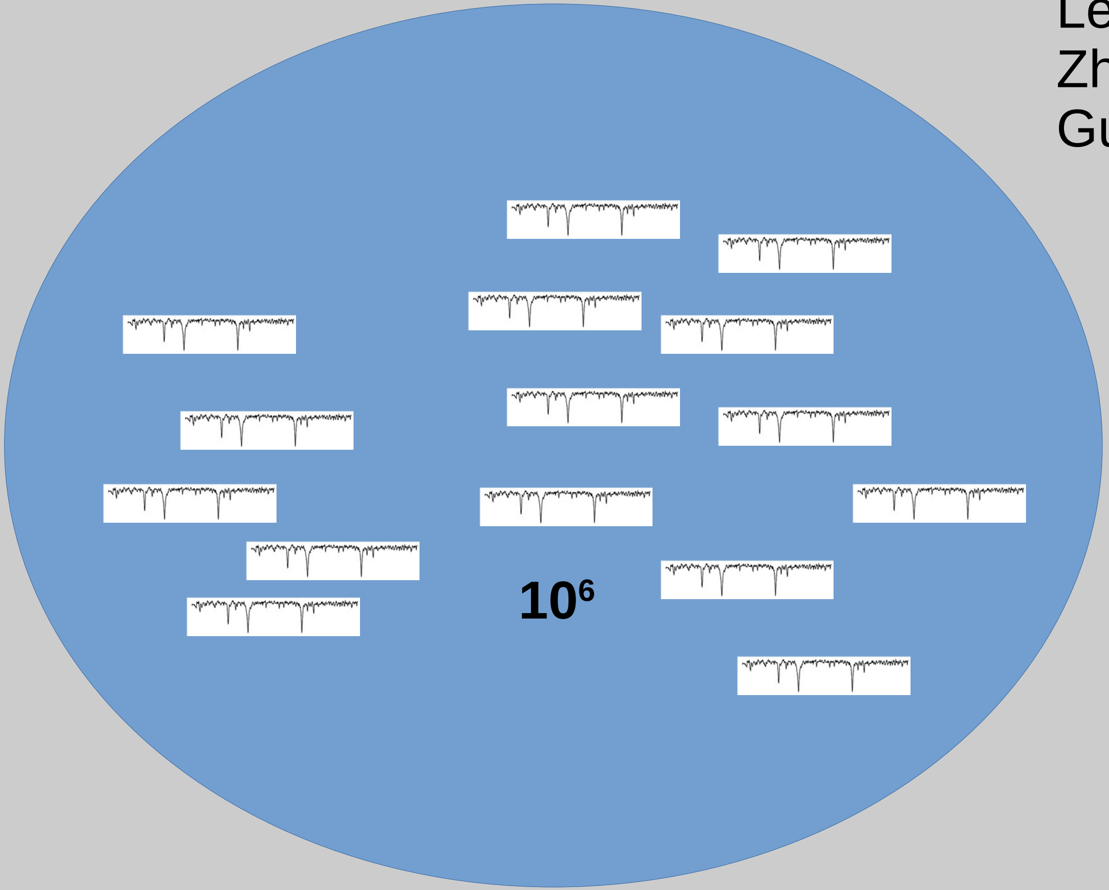
Model driven:
Bailer-Jones et al. 1997
Manteiga et al. 2010
Fabbro et al. 2018
Bialek et al. 2020



Grid of synthetic spectra

CNN

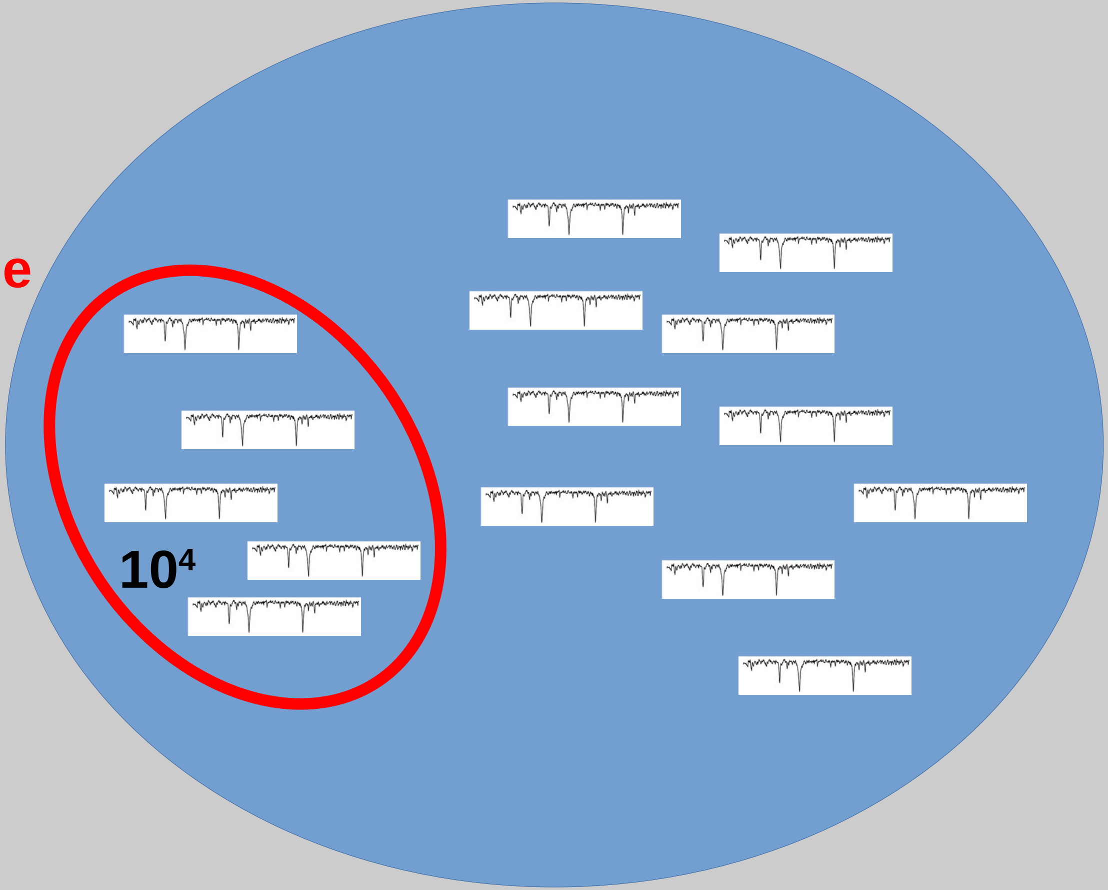
E.g. measuring T_{eff}, log(g), [Fe/H] in:



Data driven:
Leung & Bovy 2019
Zhang et al. 2019
Guiglion et al. 2020

E.g. measuring T_{eff}, log(g), [Fe/H] in:

T_{eff}, log(g), [M/H]
from standard
spectroscopy
→ **Training sample**



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Observed sample:
T_{eff}, log(g), [M/H]
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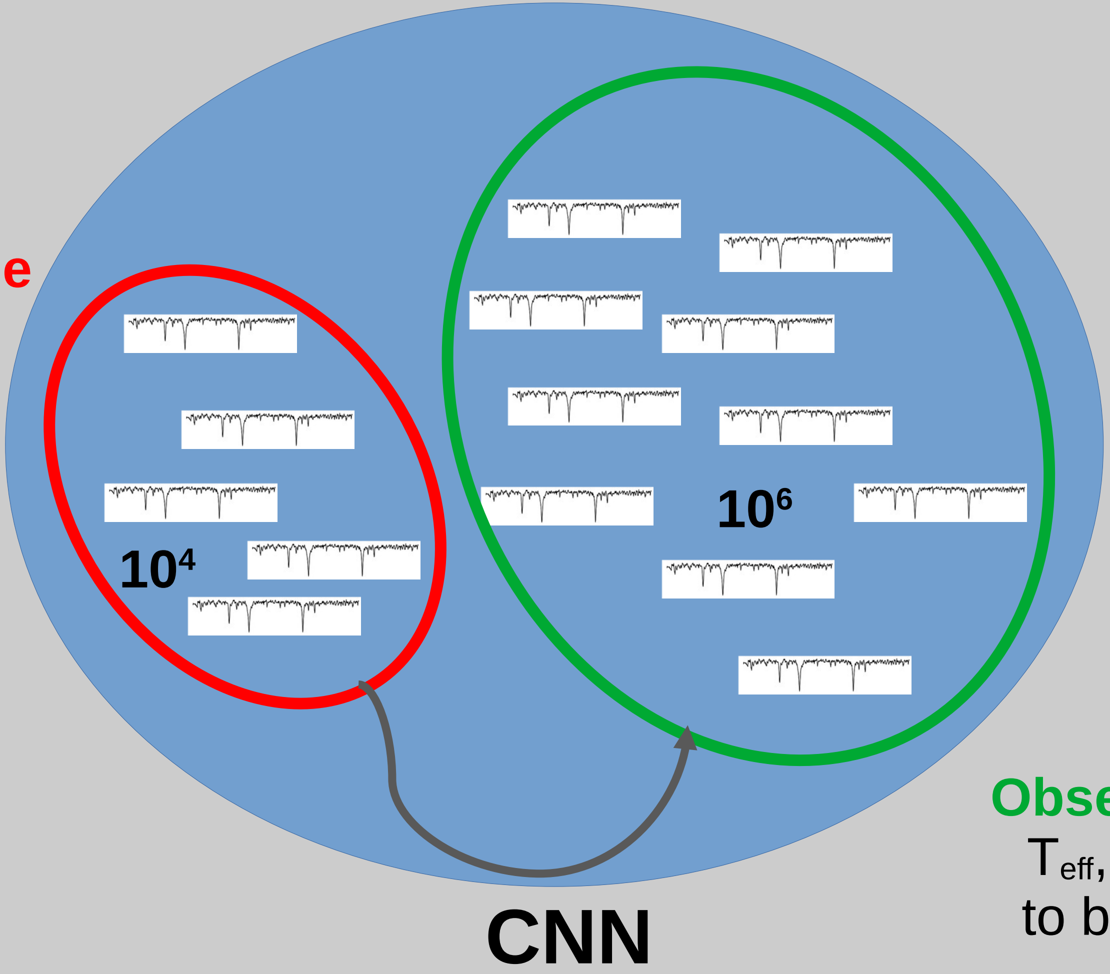

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How is CNN learning?

CNN for *Gaia*-ESO

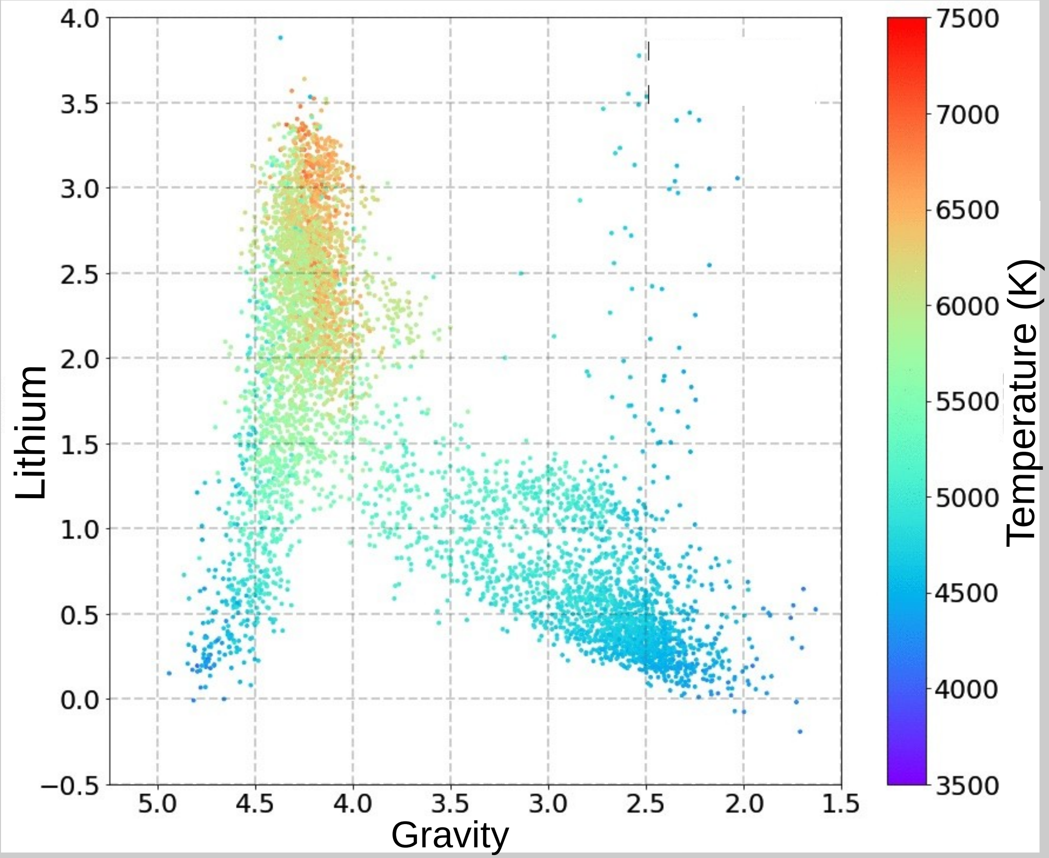
A&A 671, A61 (2023)
https://doi.org/10.1051/0004-6361/202244765

The *Gaia*-ESO Survey: Preparing the ground for 4MOST and WEAVE galactic surveys

Chemical evolution of lithium with machine learning★,★★,★★★

S. Nepal[1,2], G. Guiglion[3,1], R. S. de Jong[1], M. Valentini[1], C. Chiappini[1], M. Steinmetz[1], M. Ambrosch[4], E. Pancino[5], R. D. Jeffries[6], T. Bensby[7], D. Romano[8], R. Smiljanic[9], M. L. L. Dantas[9], G. Gilmore[10], S. Randich[5], A. Bayo[11], M. Bergemann[12,3], E. Franciosini[5], F. Jiménez-Esteban[13], P. Jofré[14], L. Morbidelli[5], G. G. Sacco[5], G. Tautvaišienė[4], and S. Zaggia[15]

Measurements of lithium in Milky Way stars with CNN & GES



Nepal et al. 2023

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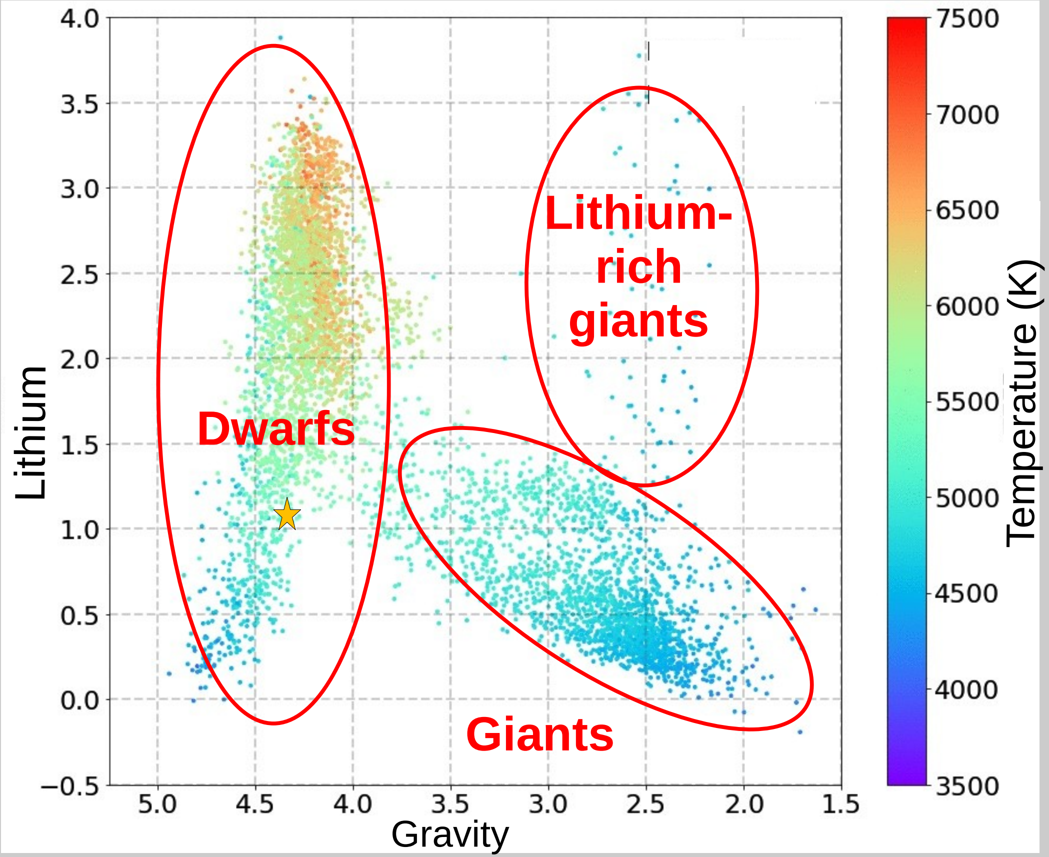

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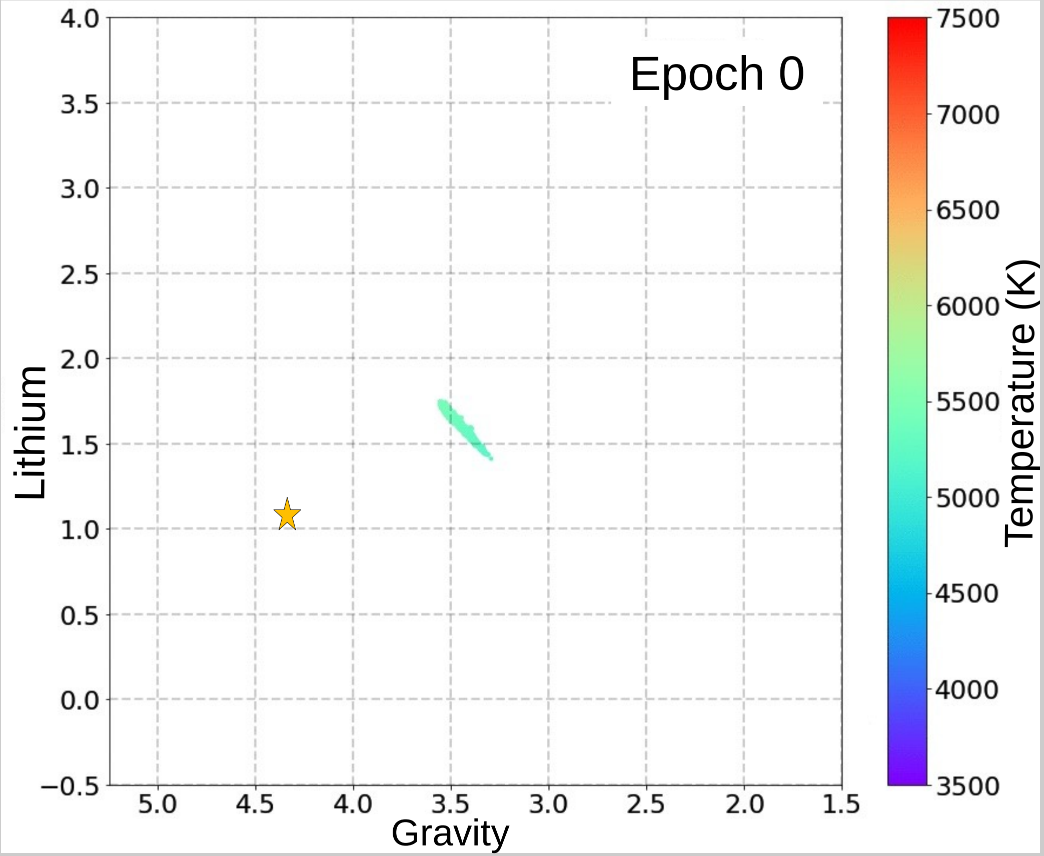

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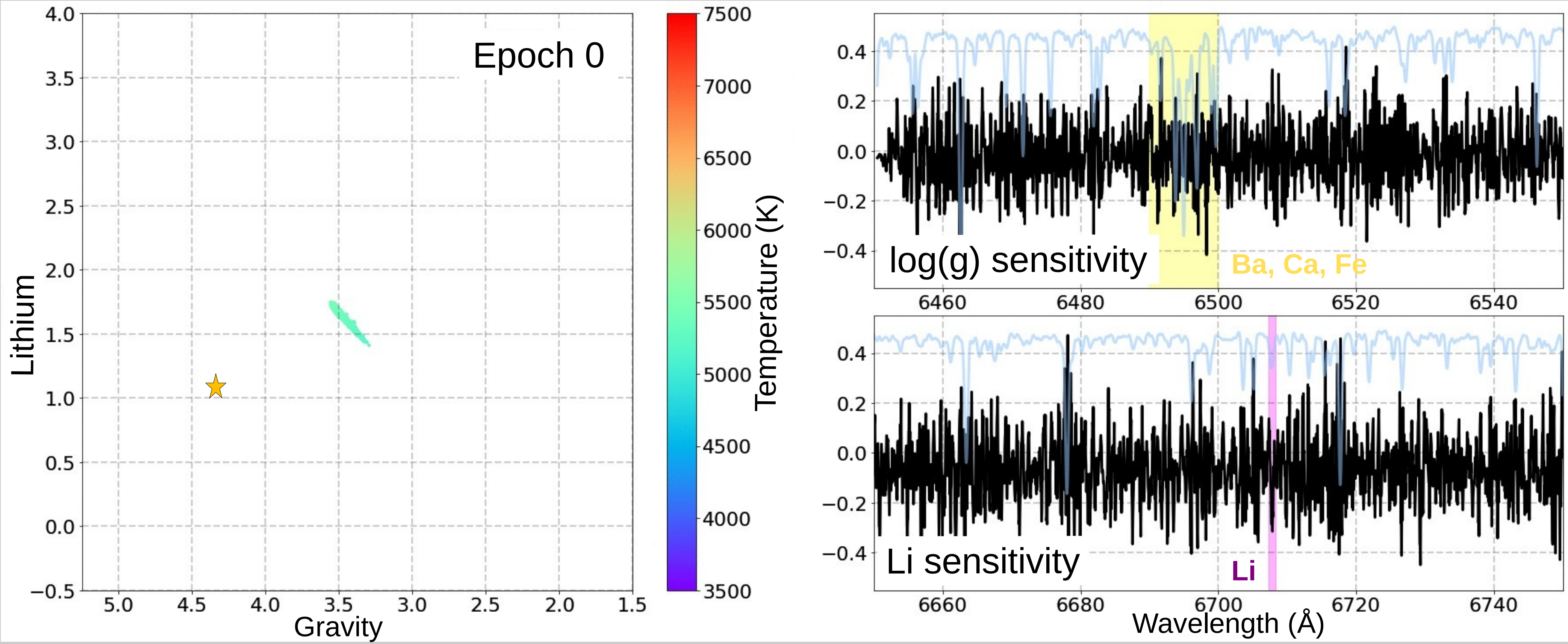

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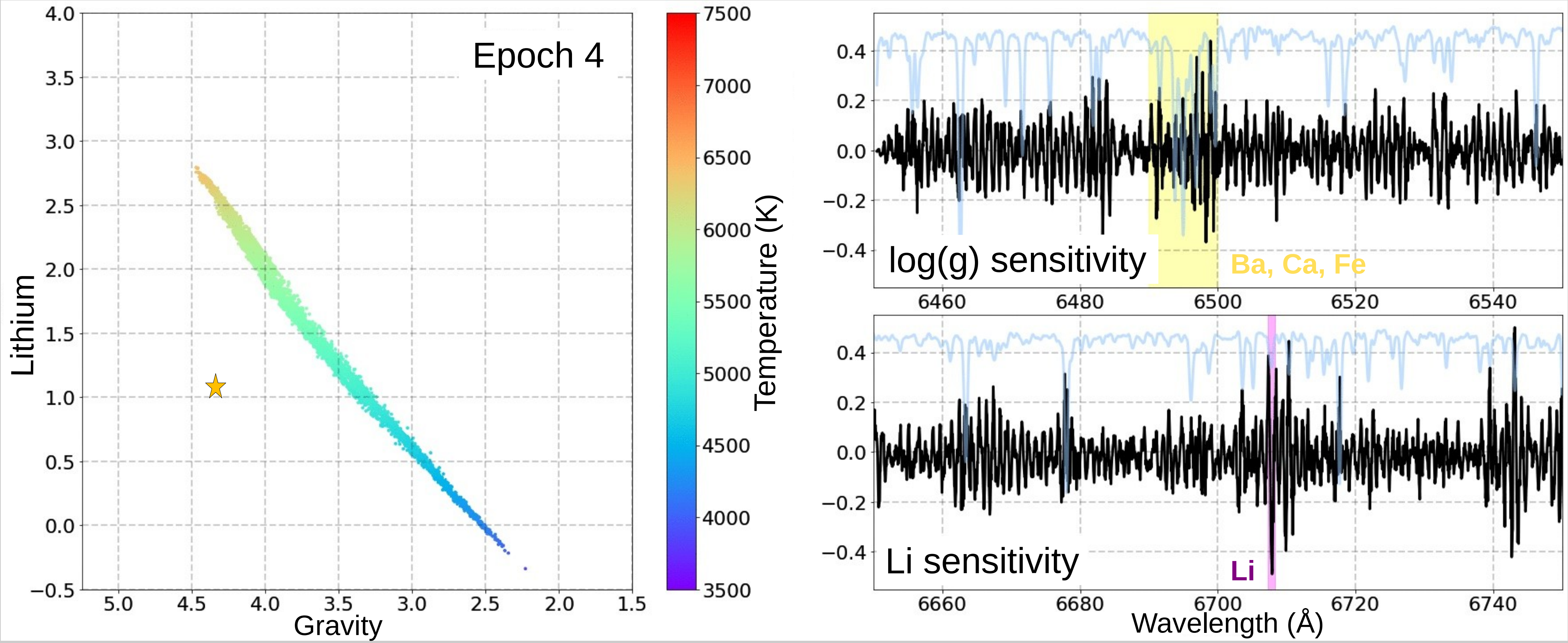

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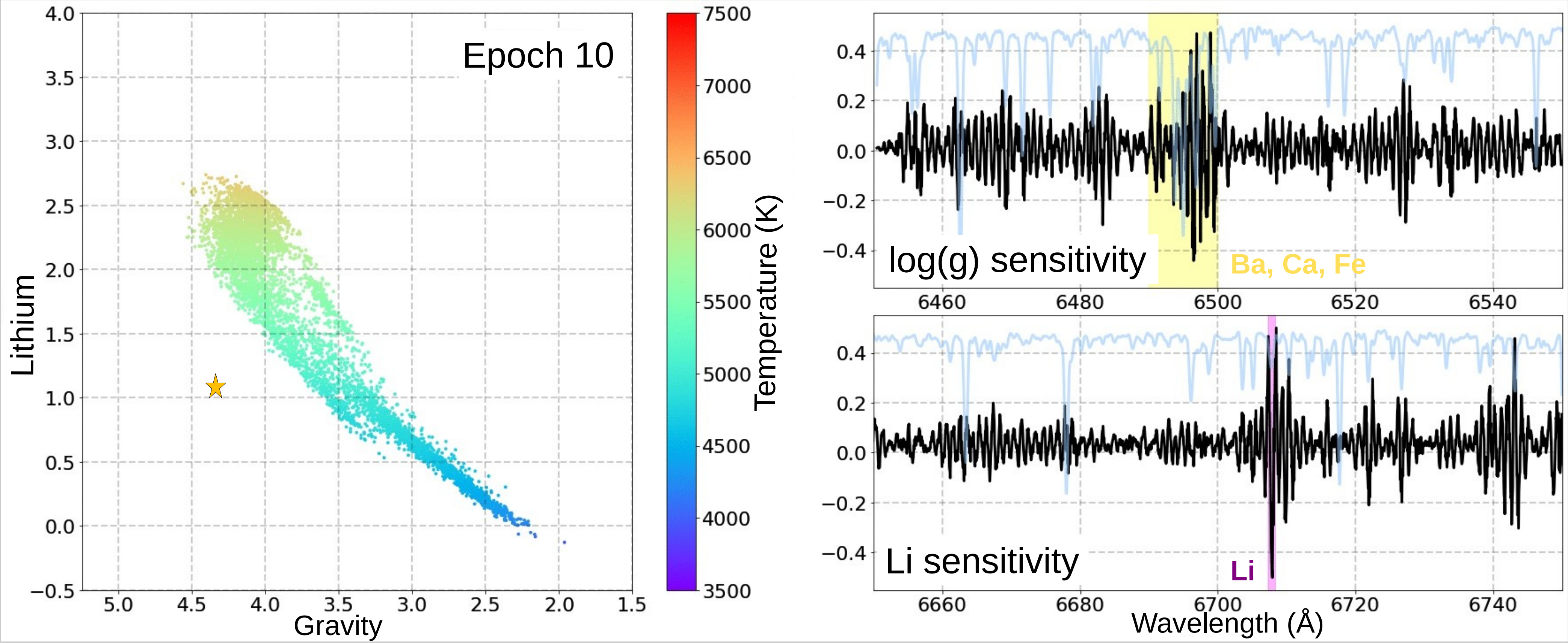

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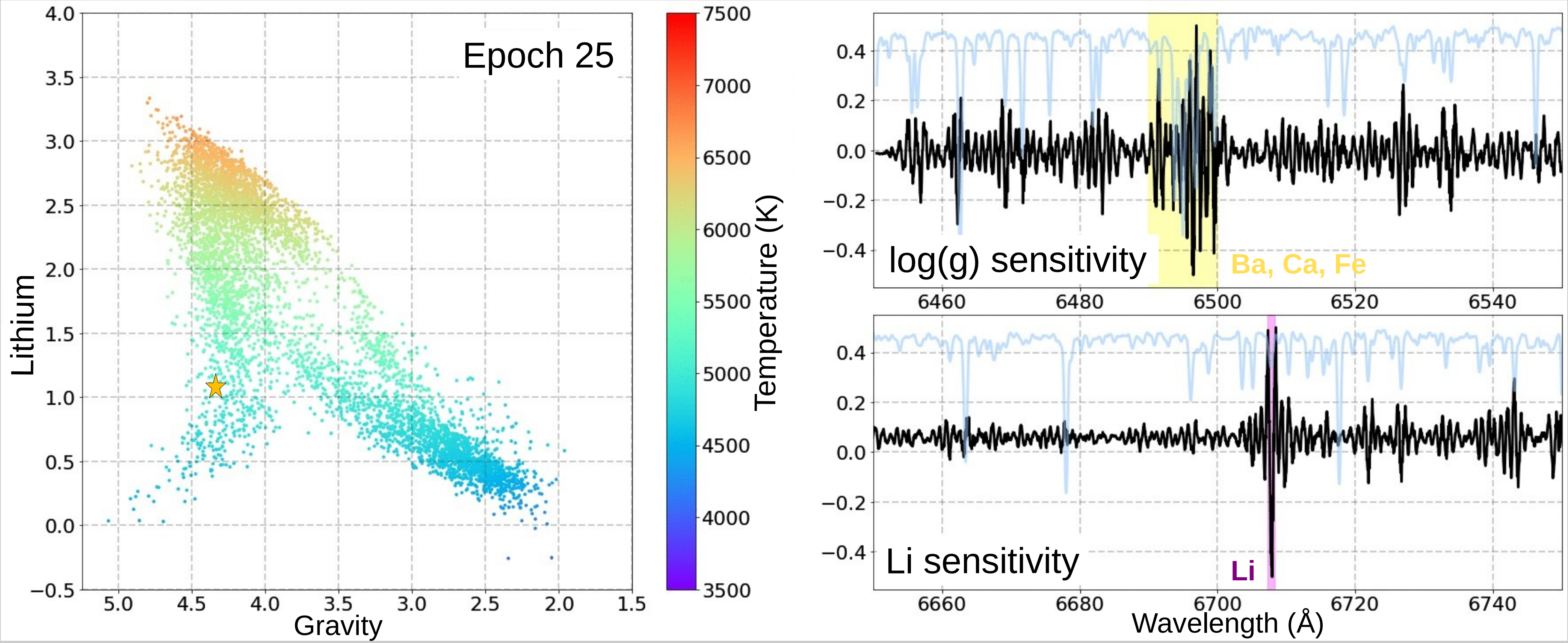

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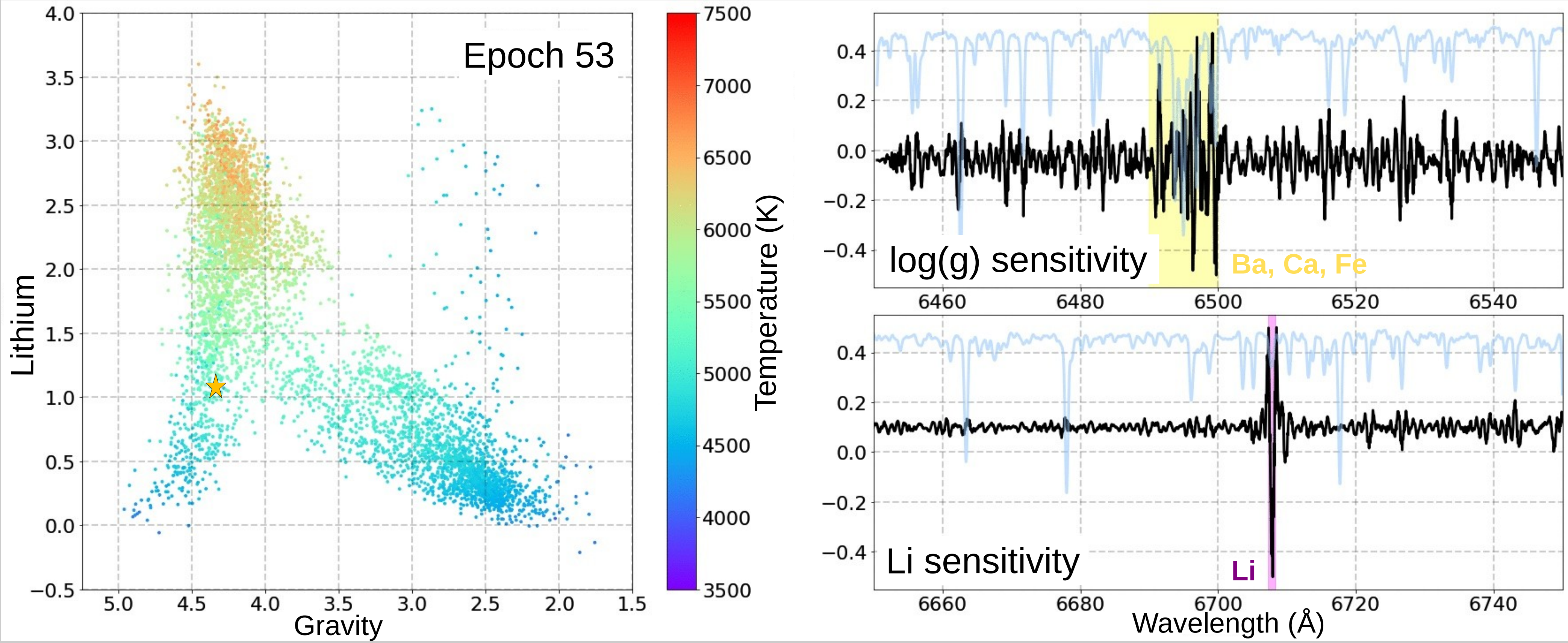

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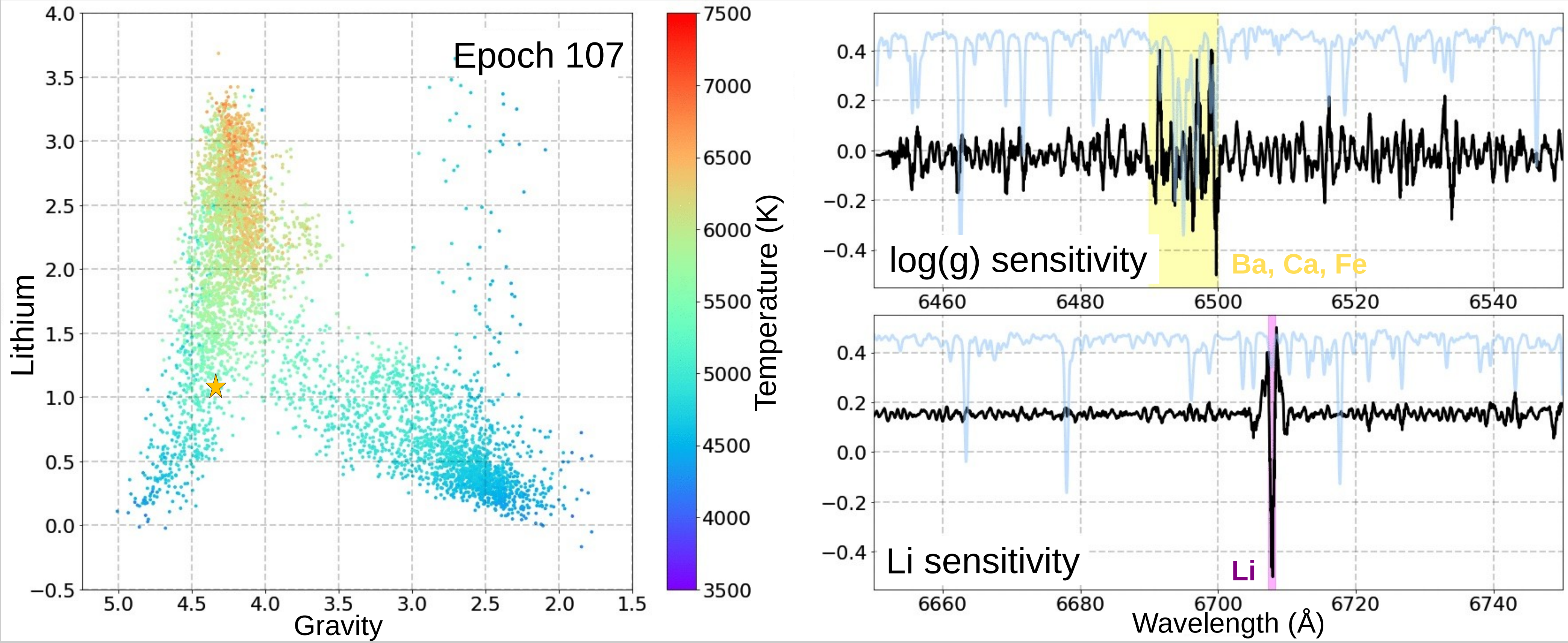

Nepal et al. 2023

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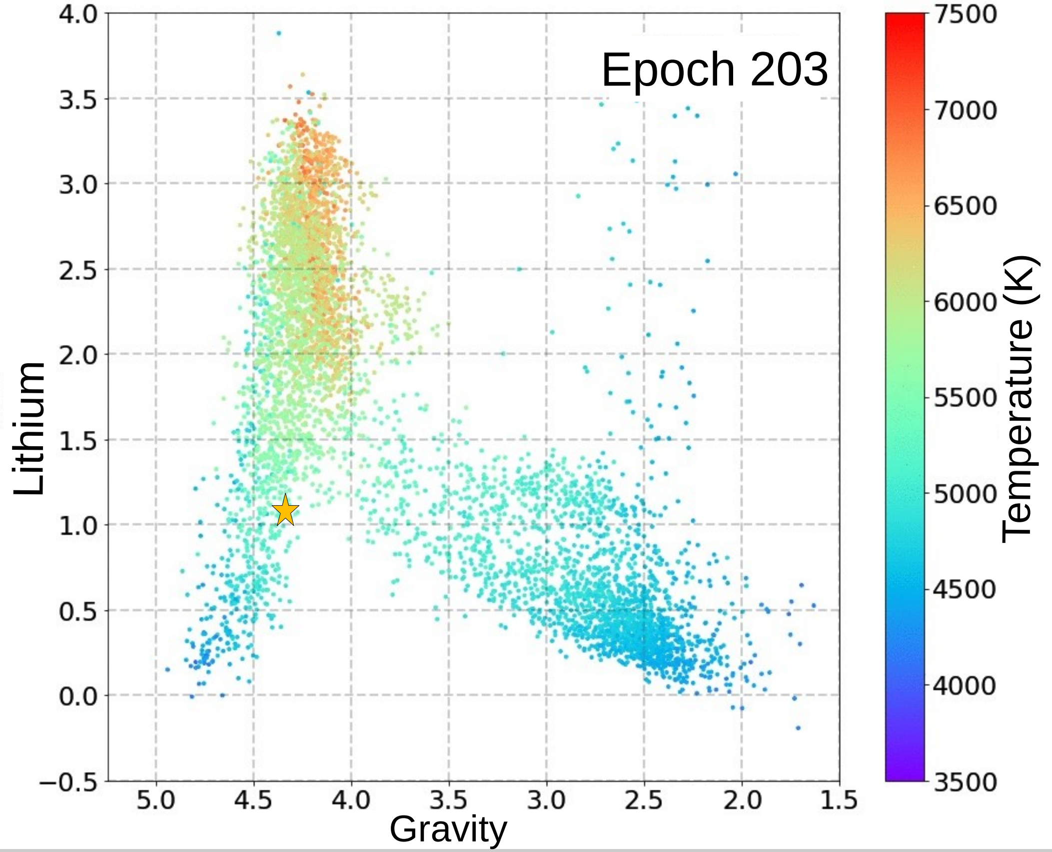

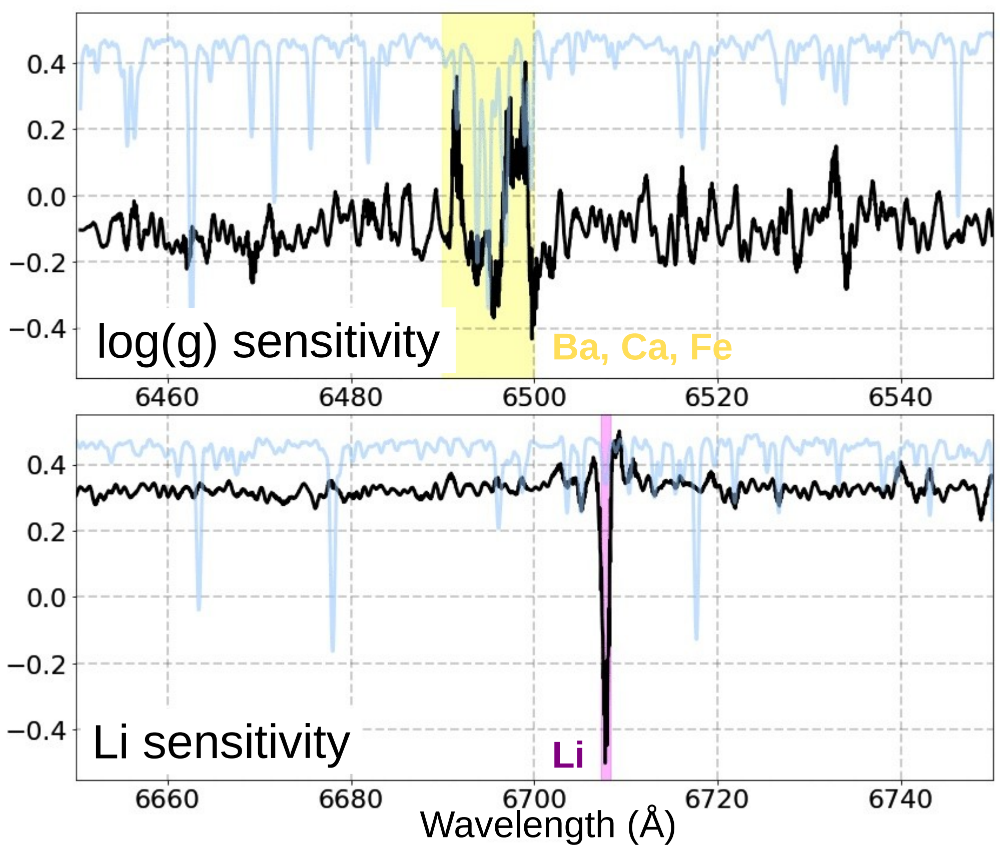

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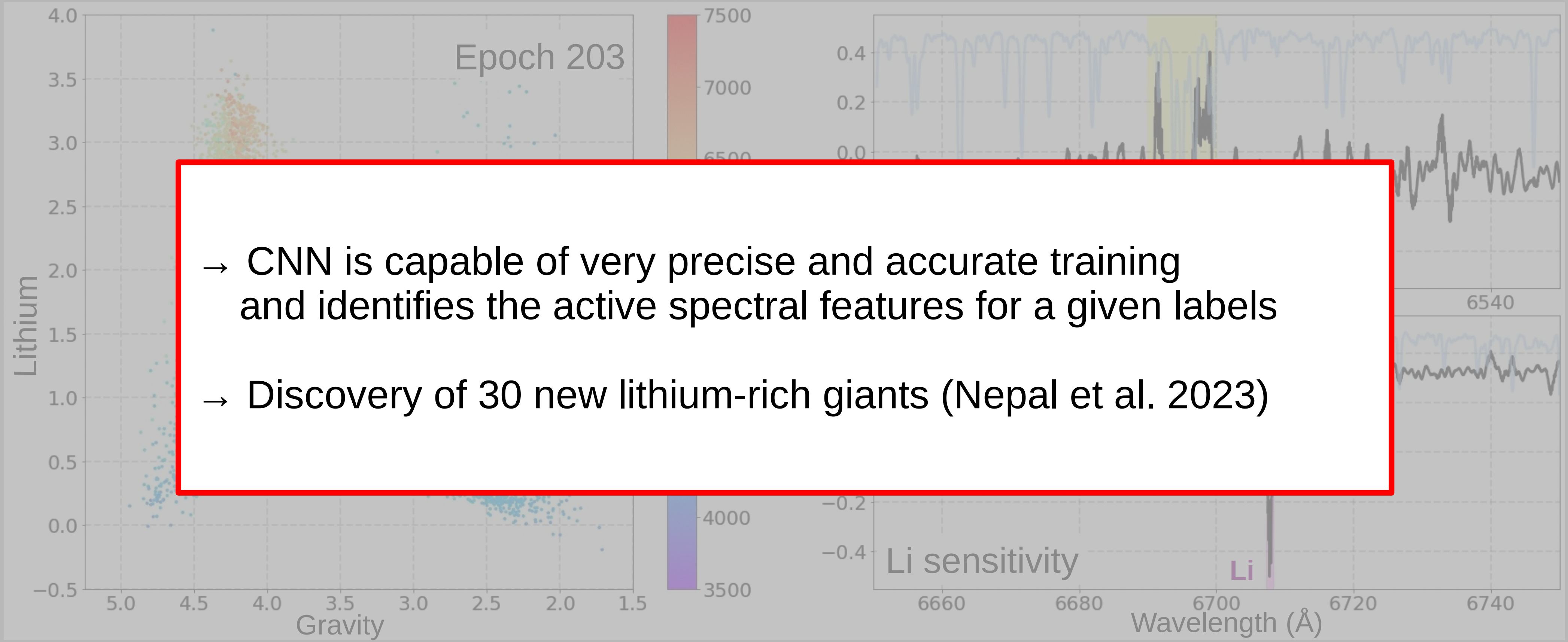


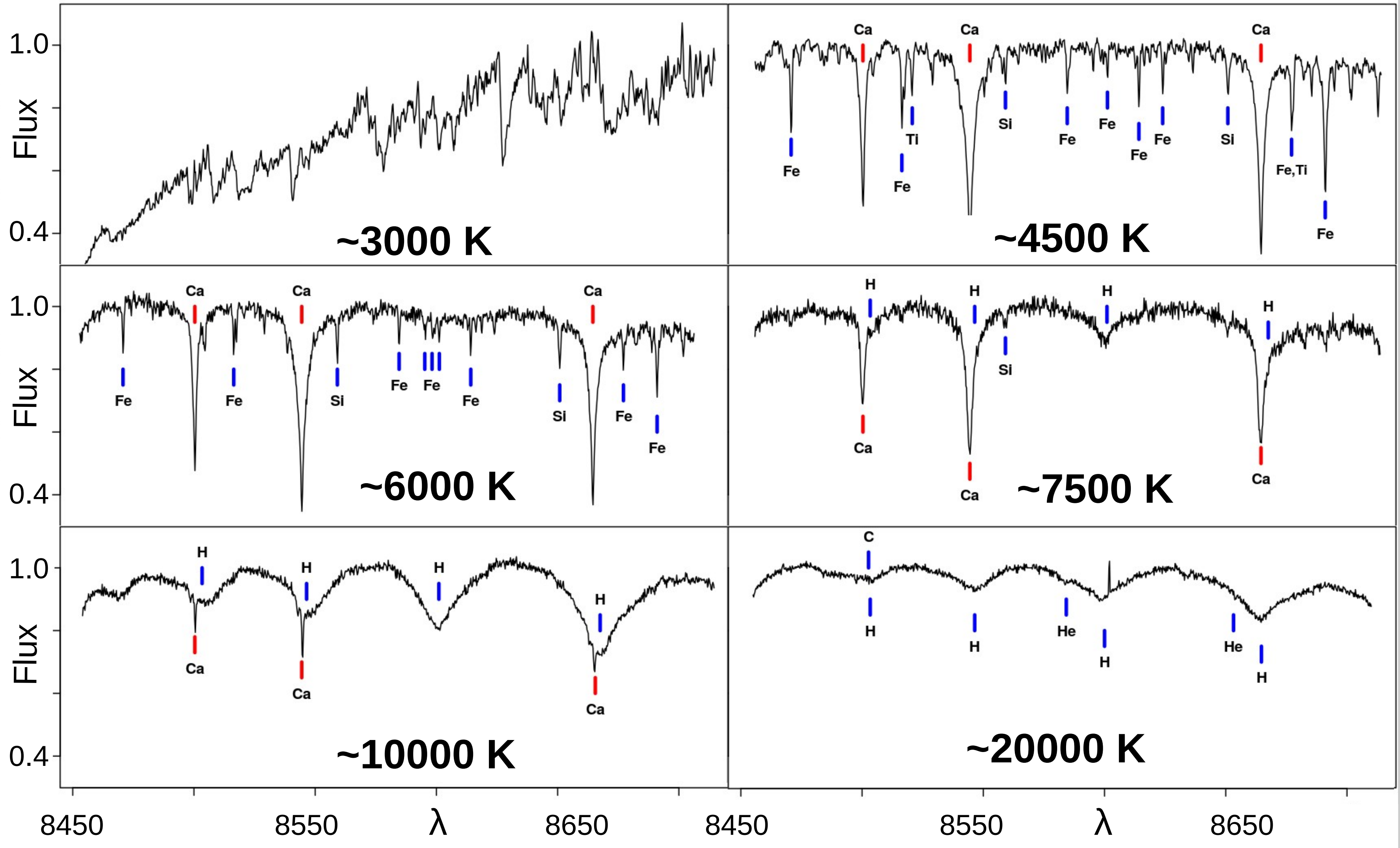
→ CNN is capable of very precise and accurate training
and identifies the active spectral features for a given labels

→ Discovery of 30 new lithium-rich giants (Nepal et al. 2023)

Nepal et al. 2023

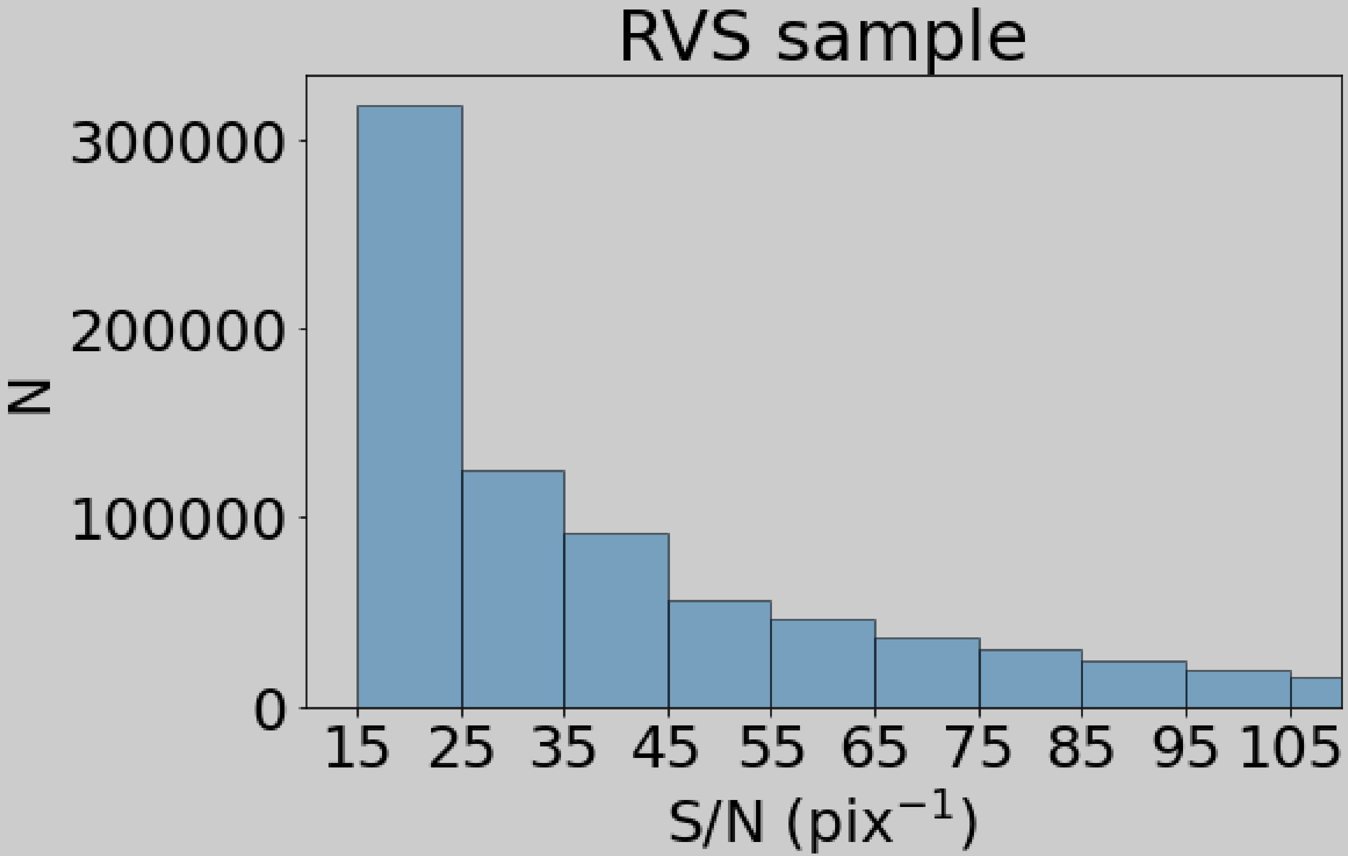
gaia RVS + CNN

Gaia DR3 June 2022: 10^6 RVS spectra, R~11500 (Katz et al. 2022)



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

Motivations



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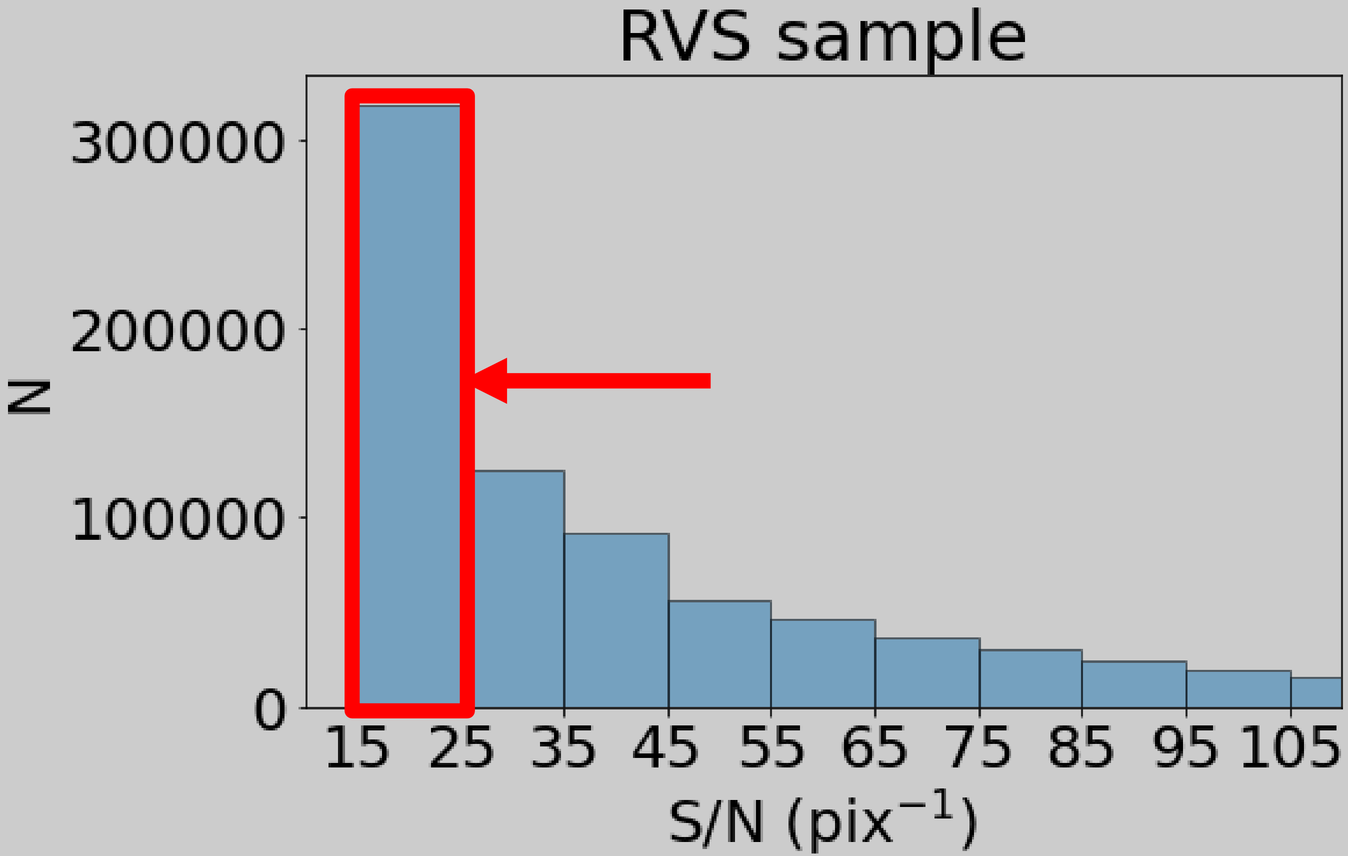
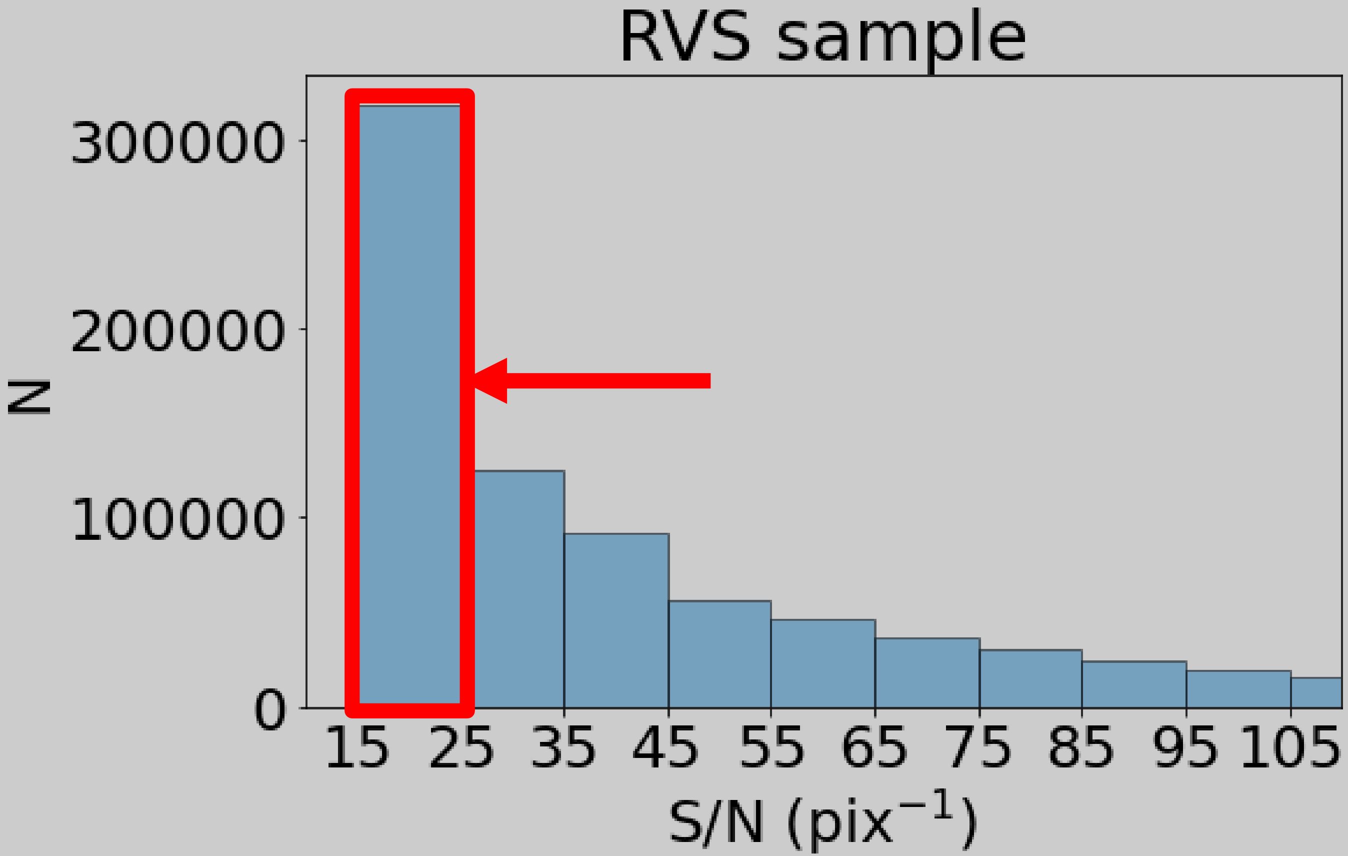


gaia

Motivations



No GSP-Spec labels with 13 “good” flags within 15<S/N<25

→ **Leverage the low-S/N RVS sample**

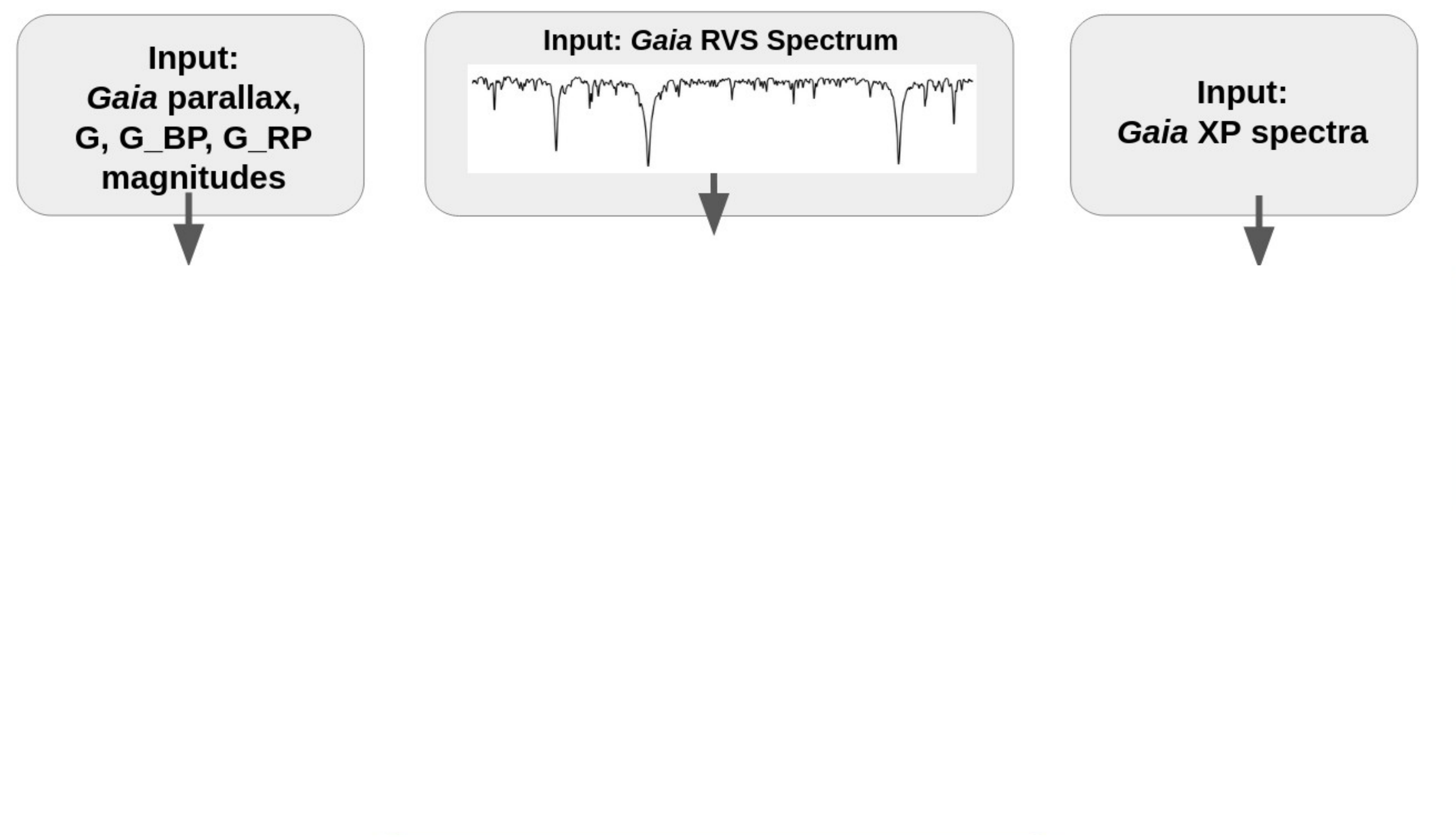
A&A, 682, A9 (2024)
https://doi.org/10.1051/0004-6361/202347122

Astronomy & Astrophysics

Beyond *Gaia* DR3: Tracing the [α/M] – [M/H] bimodality from the inner to the outer Milky Way disc with *Gaia*-RVS and convolutional neural networks★

G. Guiglion[1,2,3], S. Nepal[3,4], C. Chiappini[3], S. Khoperskov[3], G. Traven[5], A. B. A. Queiroz[3], M. Steinmetz[3], M. Valentini[3], Y. Fournier[3], A. Vallenari[6], K. Youakim[7], M. Bergemann[2], S. Mészáros[8,9], S. Lucatello[10,11], R. Sordo[6], S. Fabbro[12], I. Minchev[3], G. Tautvaišienė[13], Š. Mikolaitis[13], and J. Montalbán[14]

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



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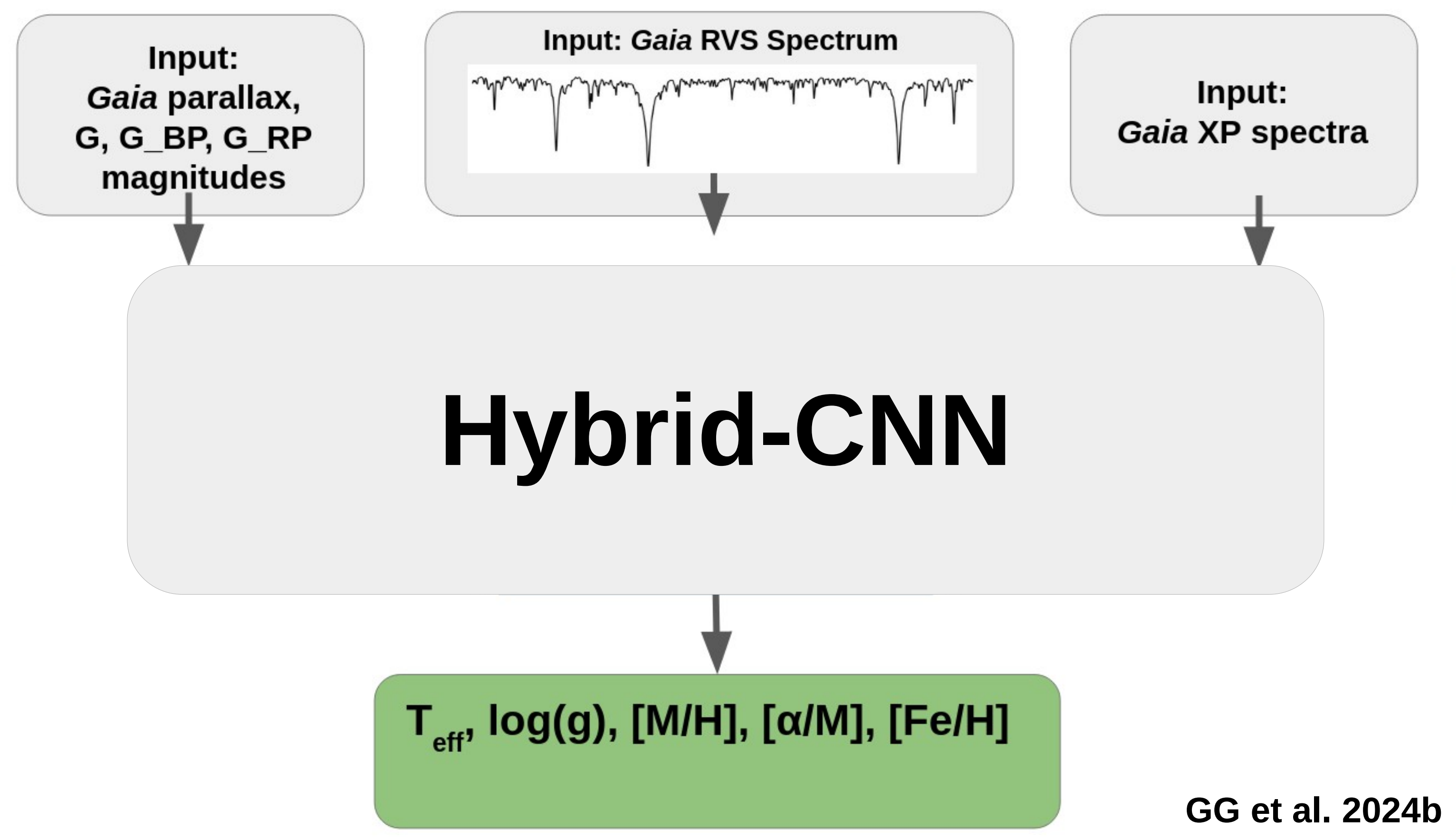

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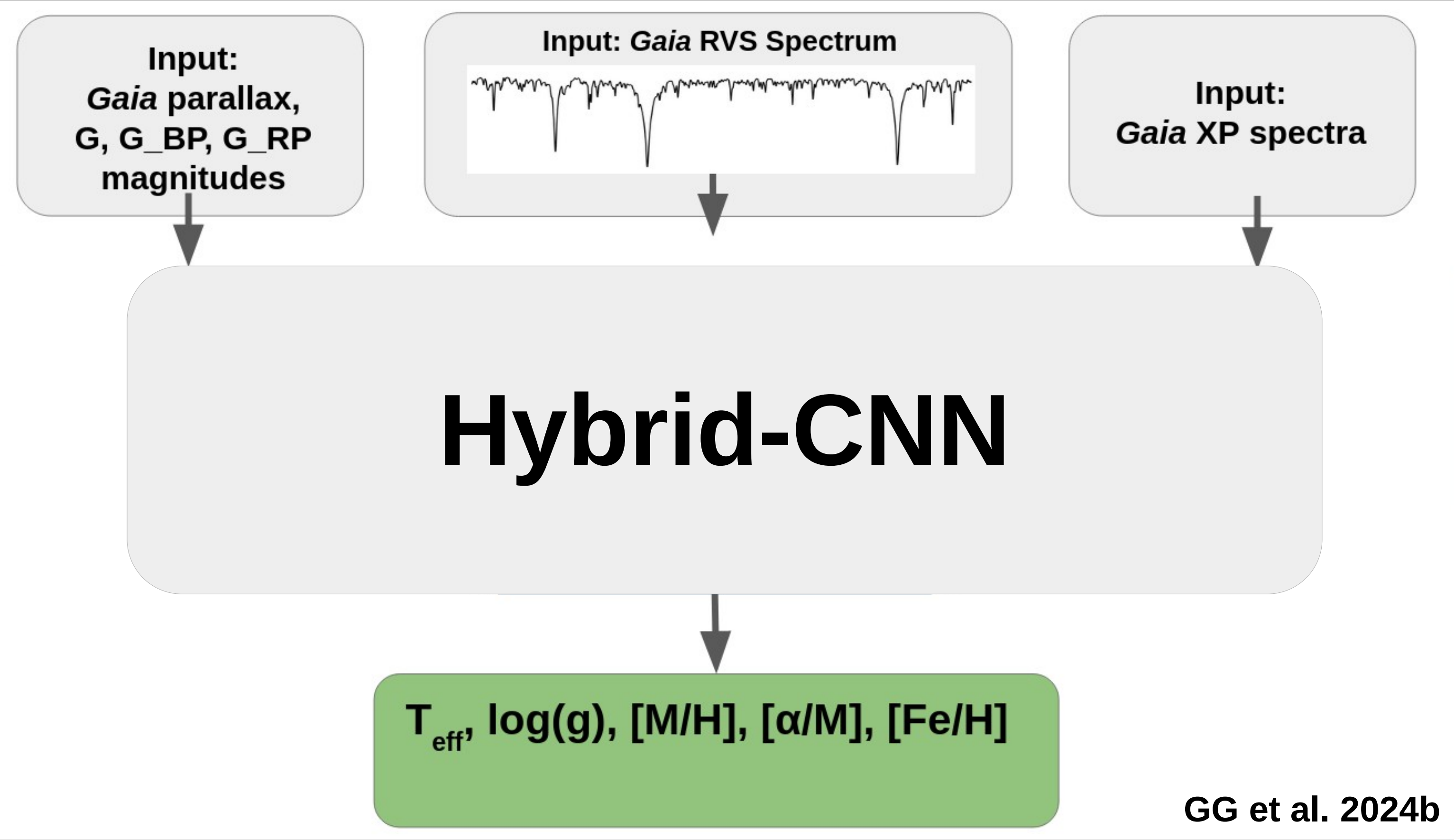


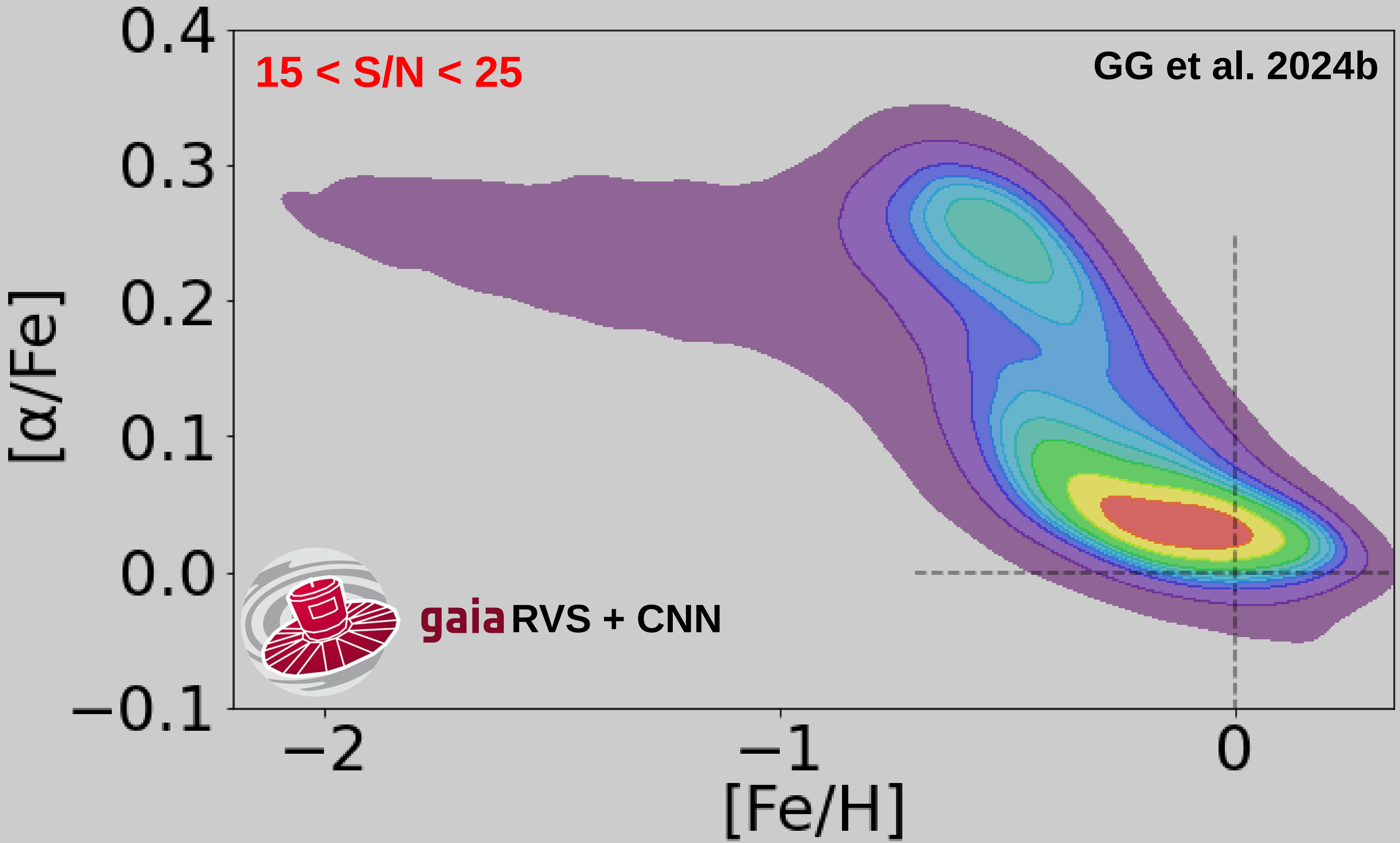
Training sample labels

APOGEE

R~22000

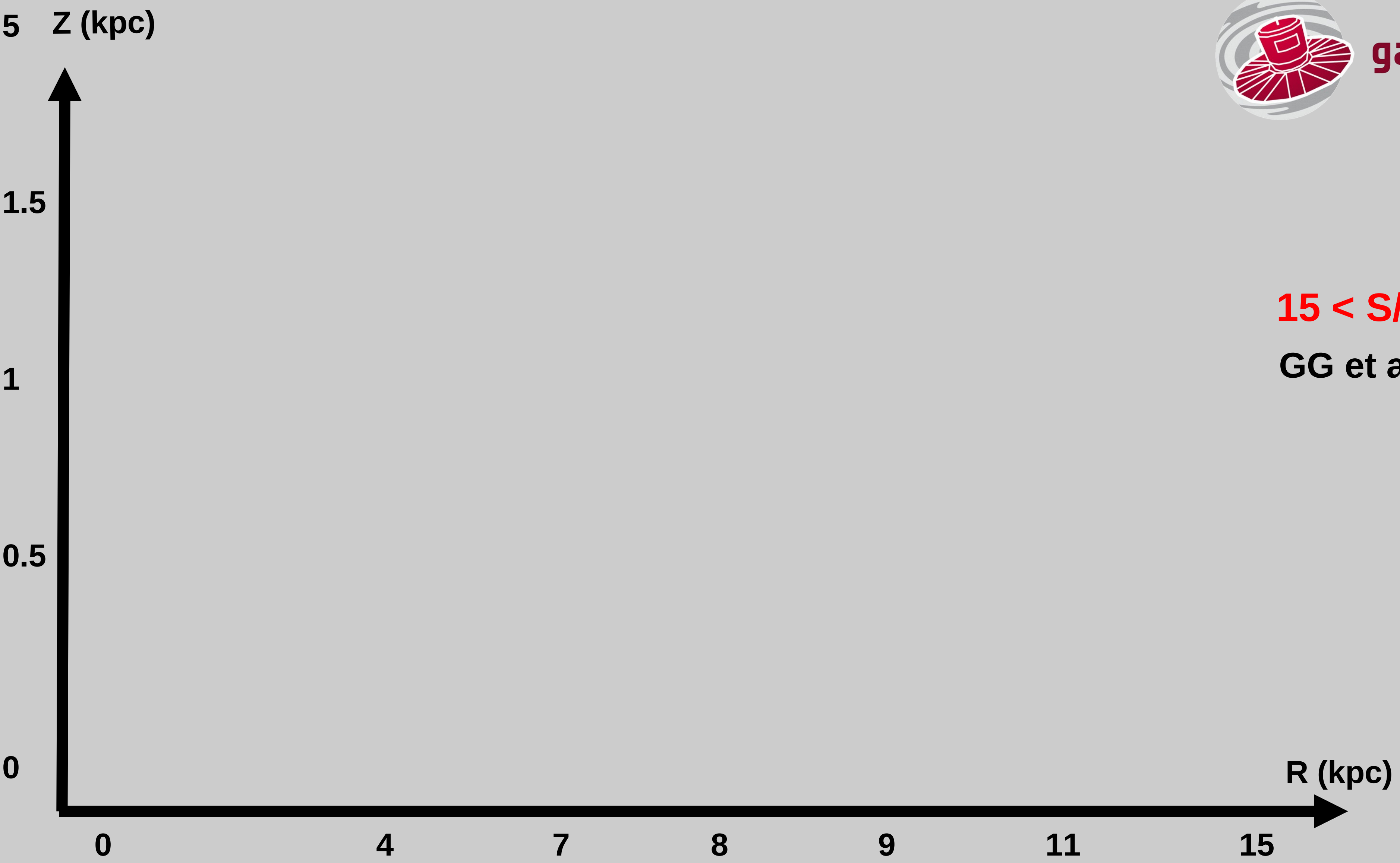
**→ Observed sample:
841300 RVS stars**

**→ Prediction time
3300 stars / second**



15 < S/N < 25
GG et al. 2024b
gaia RVS + CNN
[α/Fe]
[Fe/H]
0.4
0.3
0.2
0.1
0.0
−0.1
−2
−1
0

gaia RVS
+
CNN



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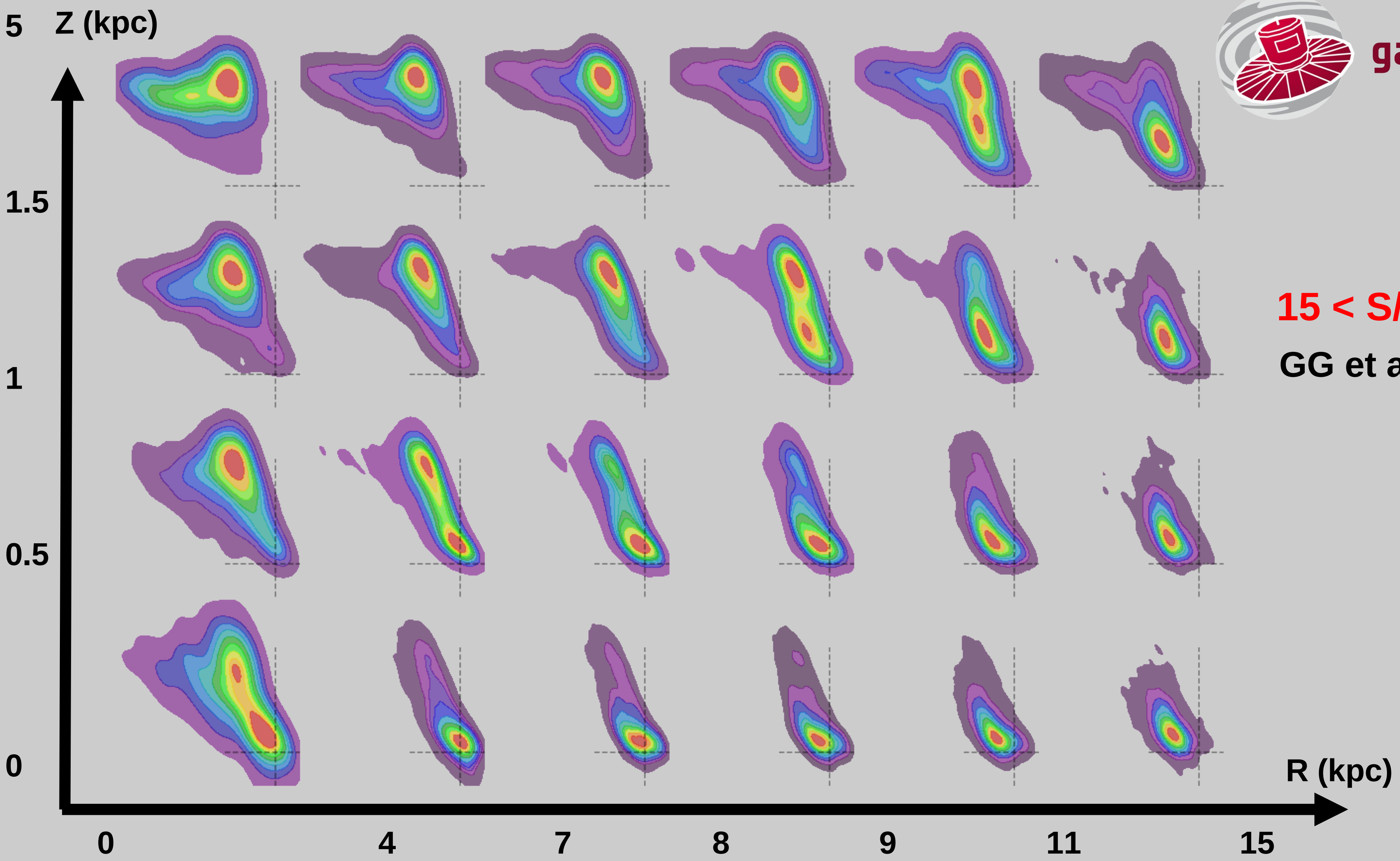
GG et al. 2024b



gaia RVS
+
CNN

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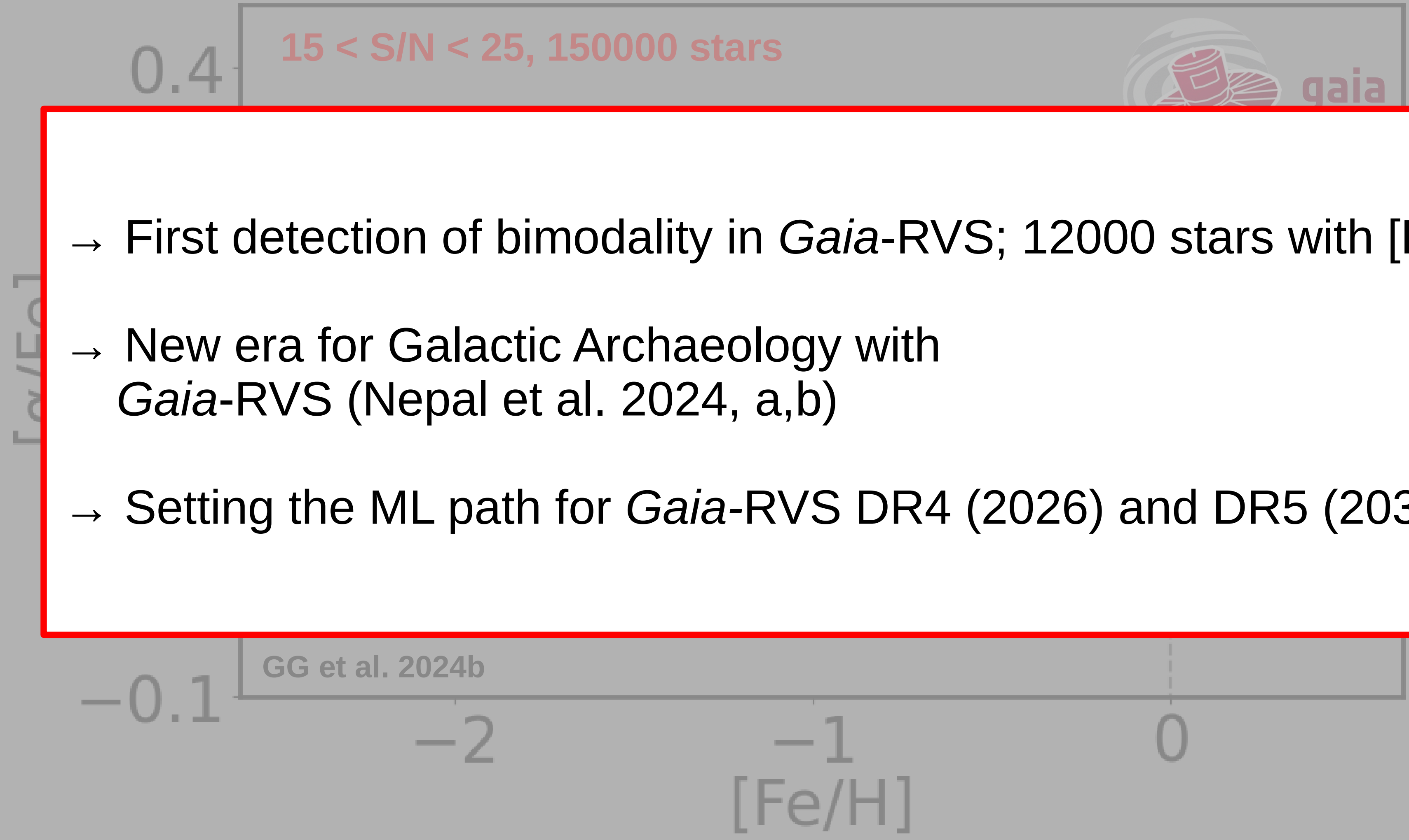
GG et al. 2024b

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



→ First detection of bimodality in *Gaia*-RVS; 12000 stars with [Fe/H]<-1.

→ New era for Galactic Archaeology with *Gaia*-RVS (Nepal et al. 2024, a,b)

→ Setting the ML path for *Gaia*-RVS DR4 (2026) and DR5 (2030).

Take-home messages

- Standard and ML spectroscopic methods complement each other !

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- CNN performs extremely well for abundance measurements (RAVE, *Gaia*-ESO, *Gaia*-RVS)

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- CNN performs extremely well for abundance measurements (RAVE, *Gaia*-ESO, *Gaia*-RVS)

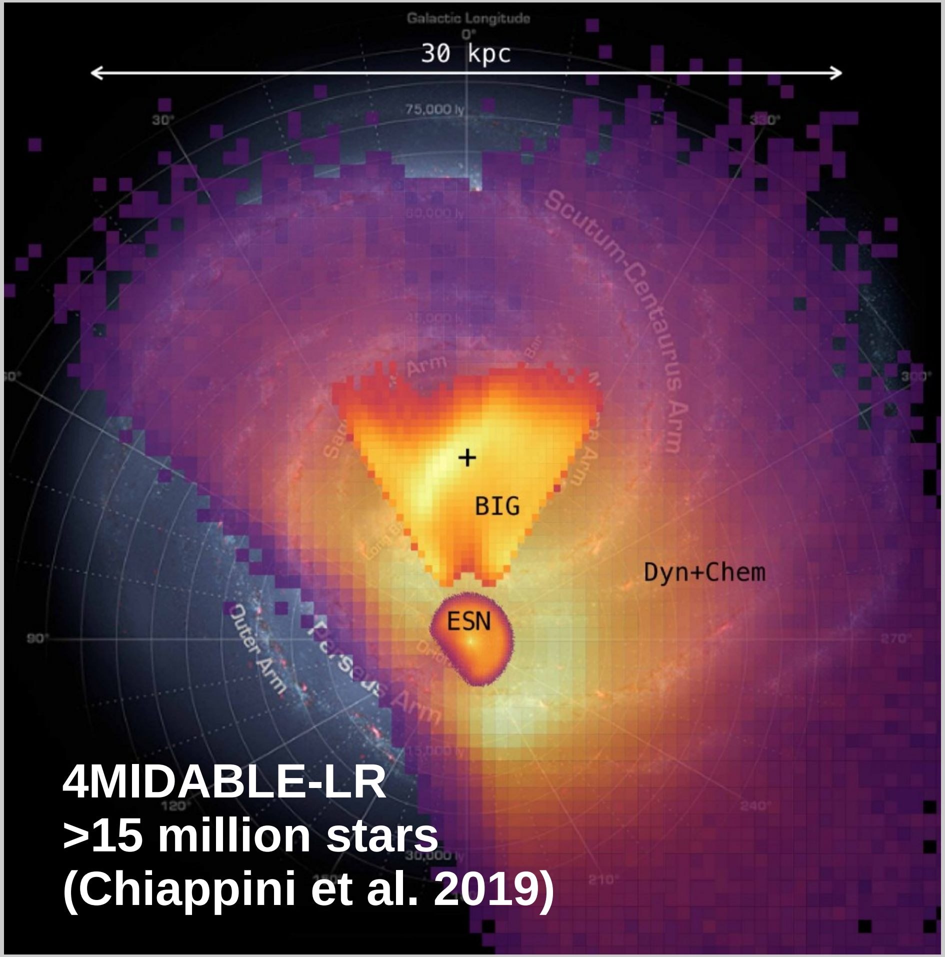
- CNN in the context of the future large datasets !

(2024-2030) (2025-2030) gaia (2026) (2030) (>2030)

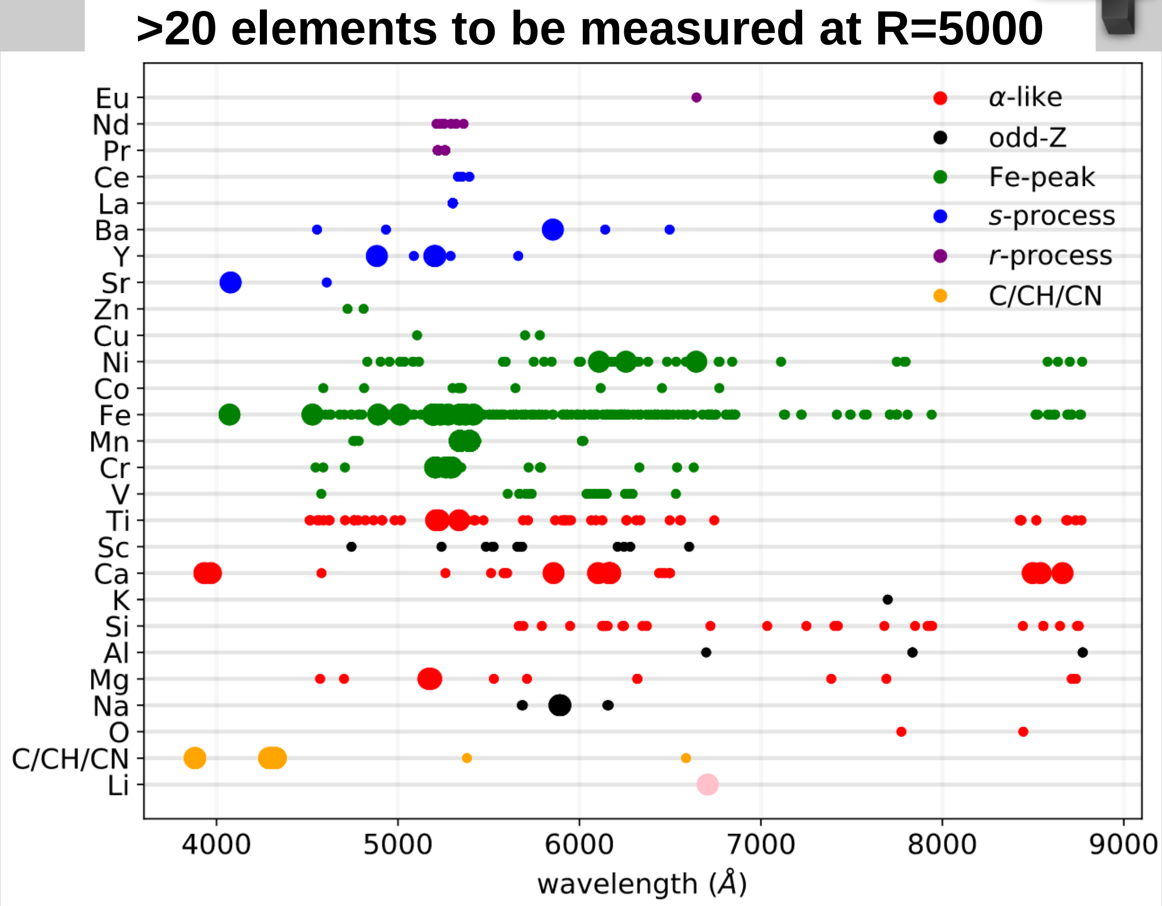
CNN part of the Galactic Pipeline ! @4MIDABLE-LR

BONUS SLIDES

Why using CNN on low-res spectra ?

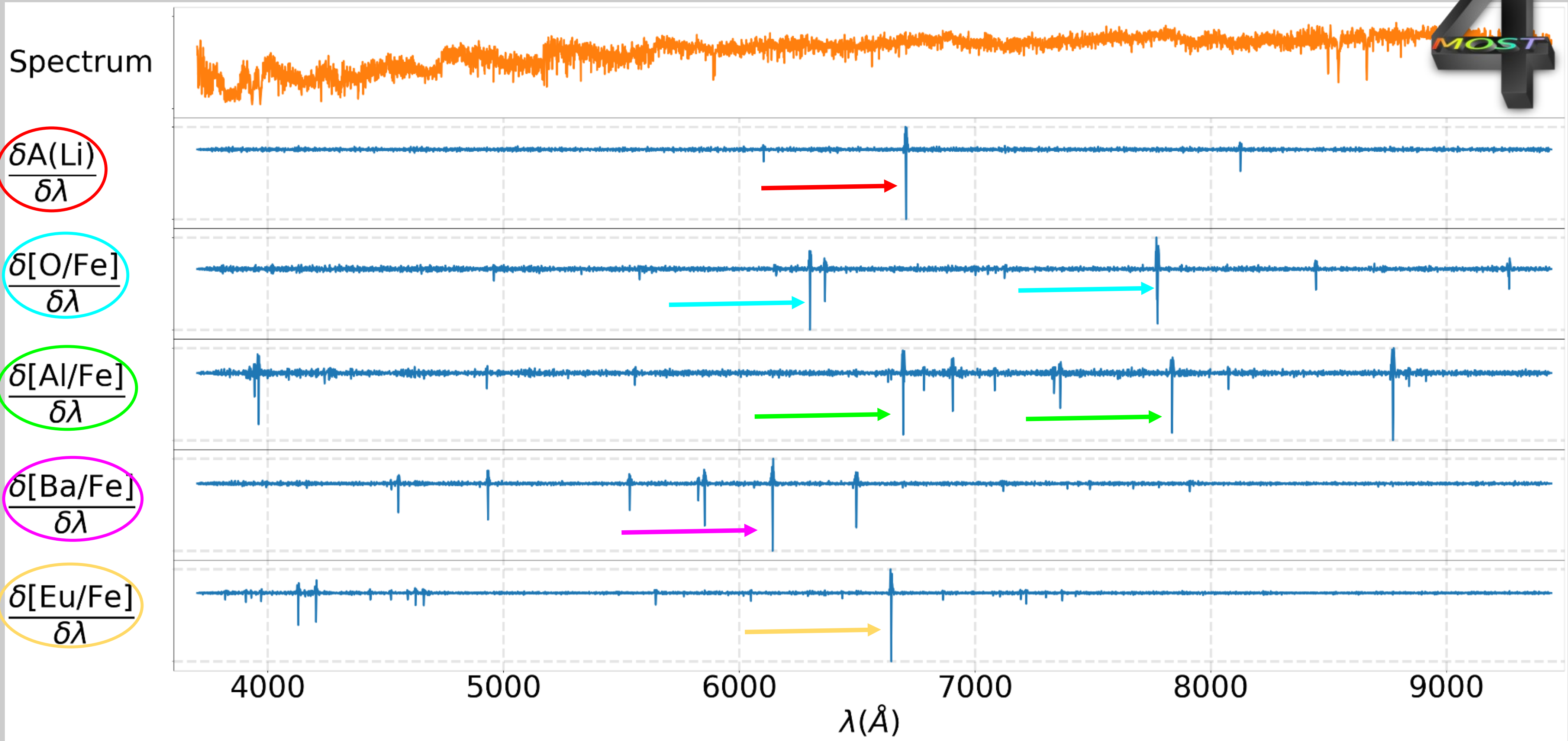


4MIDABLE-LR ESO proposal 2020

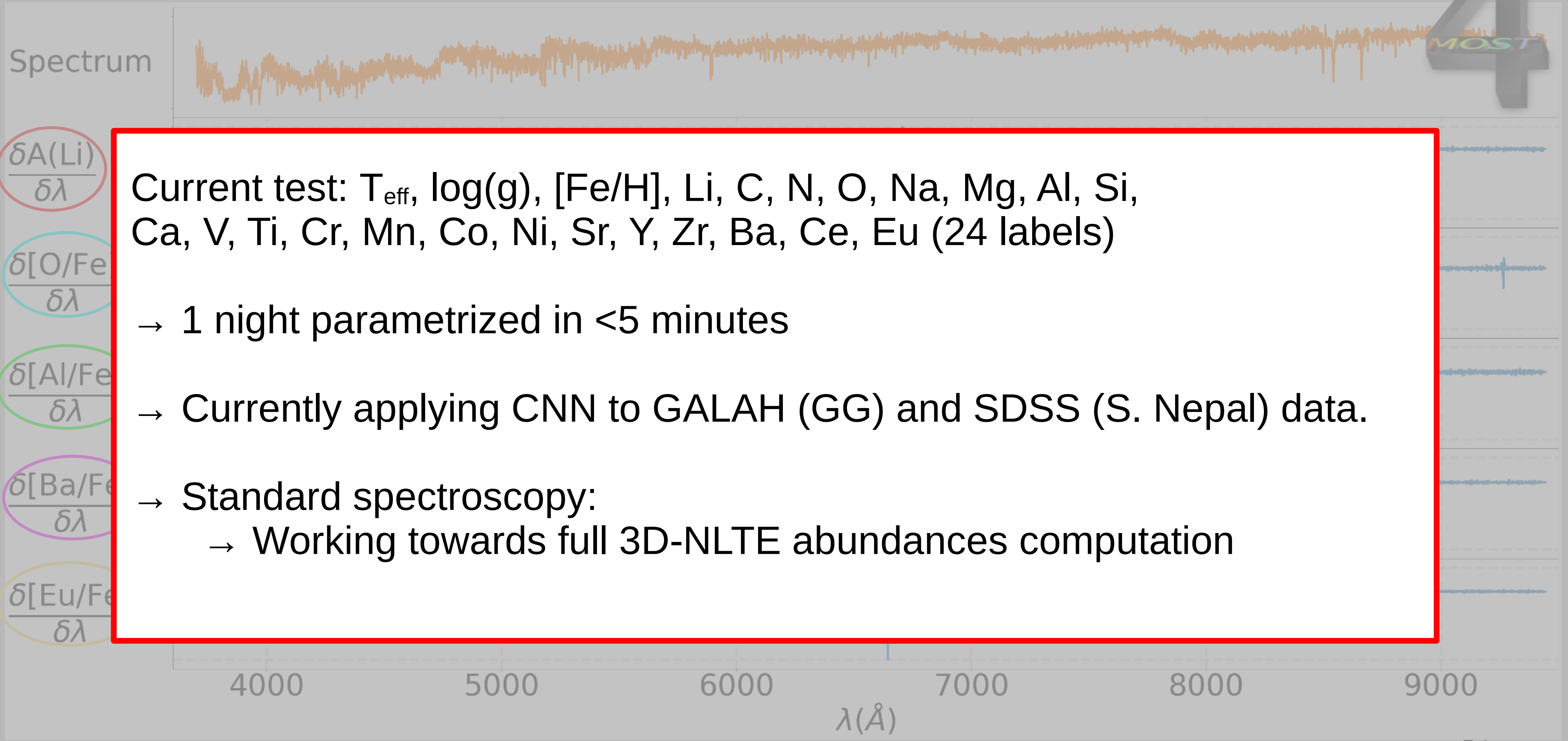


4MIDABLE-LR ESO proposal 2020

Developing CNN for 4MOST



Developing CNN for 4MOST



Current test: T_{eff}, log(g), [Fe/H], Li, C, N, O, Na, Mg, Al, Si, Ca, V, Ti, Cr, Mn, Co, Ni, Sr, Y, Zr, Ba, Ce, Eu (24 labels)

→ 1 night parametrized in <5 minutes

→ Currently applying CNN to GALAH (GG) and SDSS (S. Nepal) data.

→ Standard spectroscopy:
  → Working towards full 3D-NLTE abundances computation

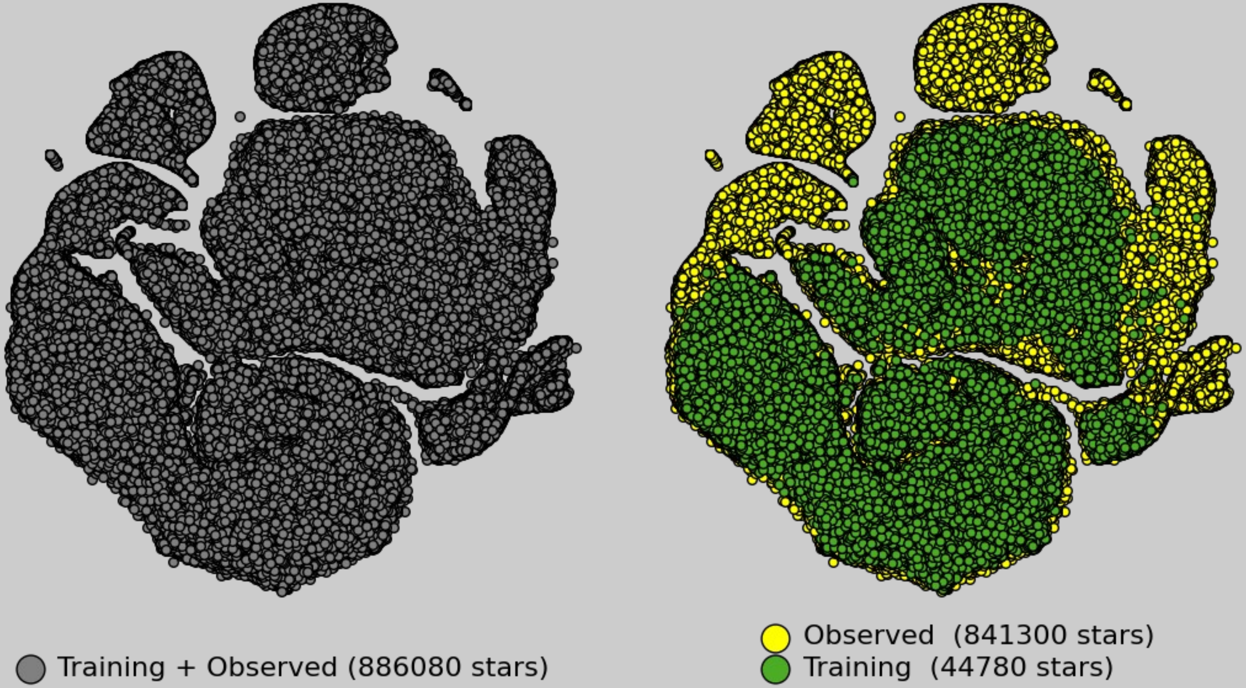
Selecting stars within the training sample limits

→ t-SNE classification of RVS spectra (adapted from Ambrosch, GG et al. 2023)

GG et al. 2024b

Selecting stars within the training sample limits

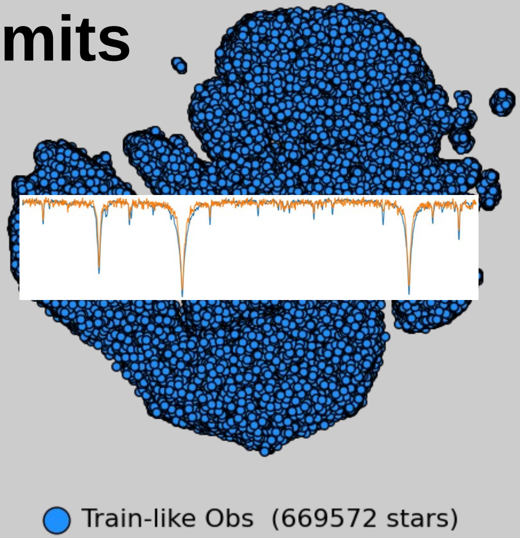
→ t-SNE classification of RVS spectra
(adapted from Ambrosch, GG et al. 2023)

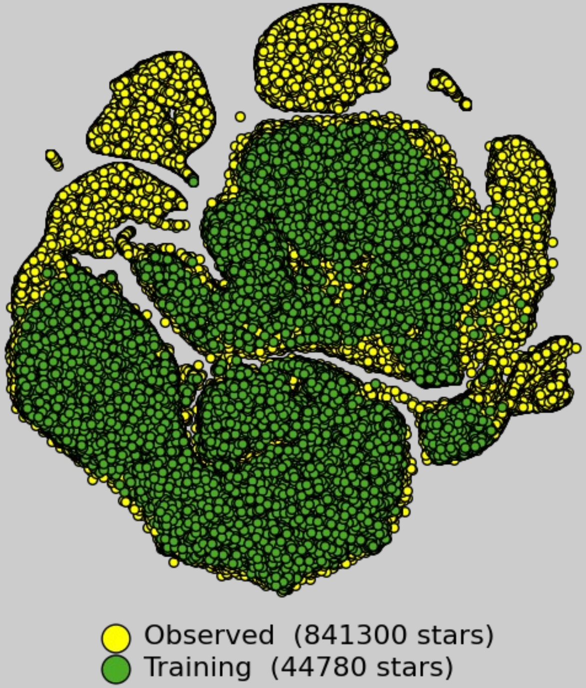


GG et al. 2024b

Selecting stars within the training sample limits

→ t-SNE classification of RVS spectra (adapted from Ambrosch, GG et al. 2023)

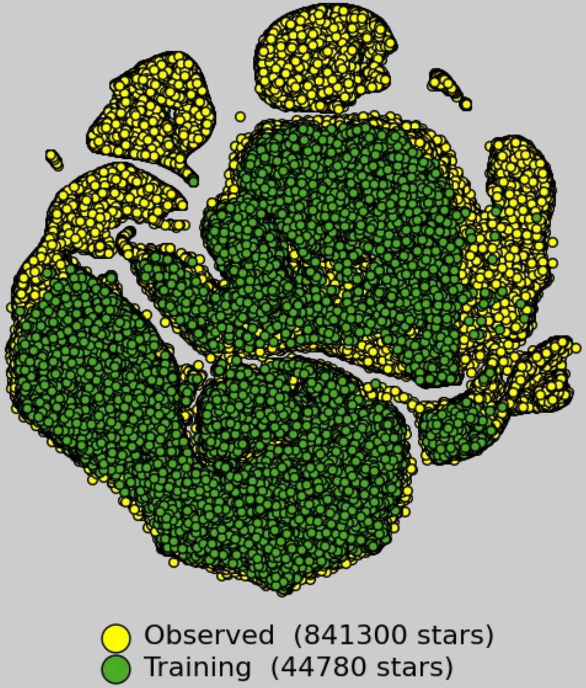


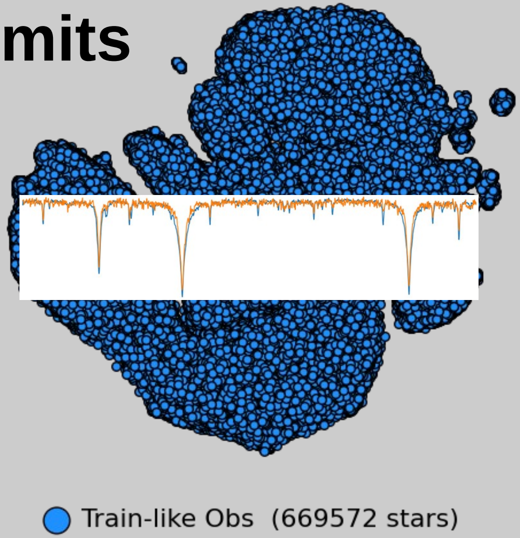


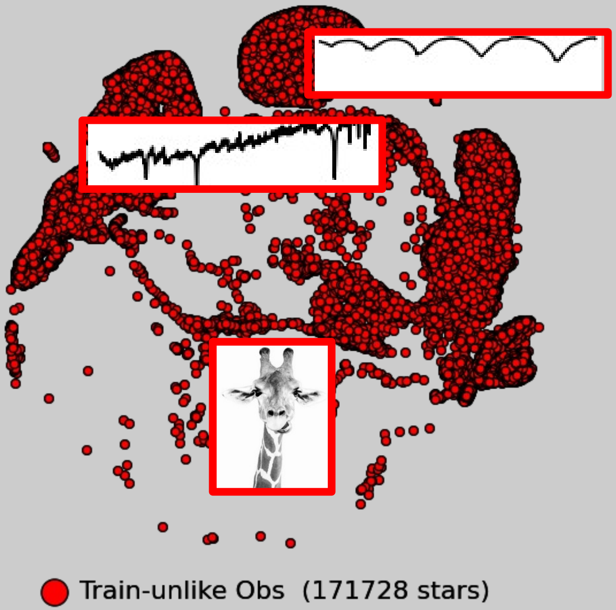
GG et al. 2024b

Selecting stars within the training sample limits

→ **t-SNE classification of RVS spectra (adapted from Ambrosch, GG et al. 2023)**



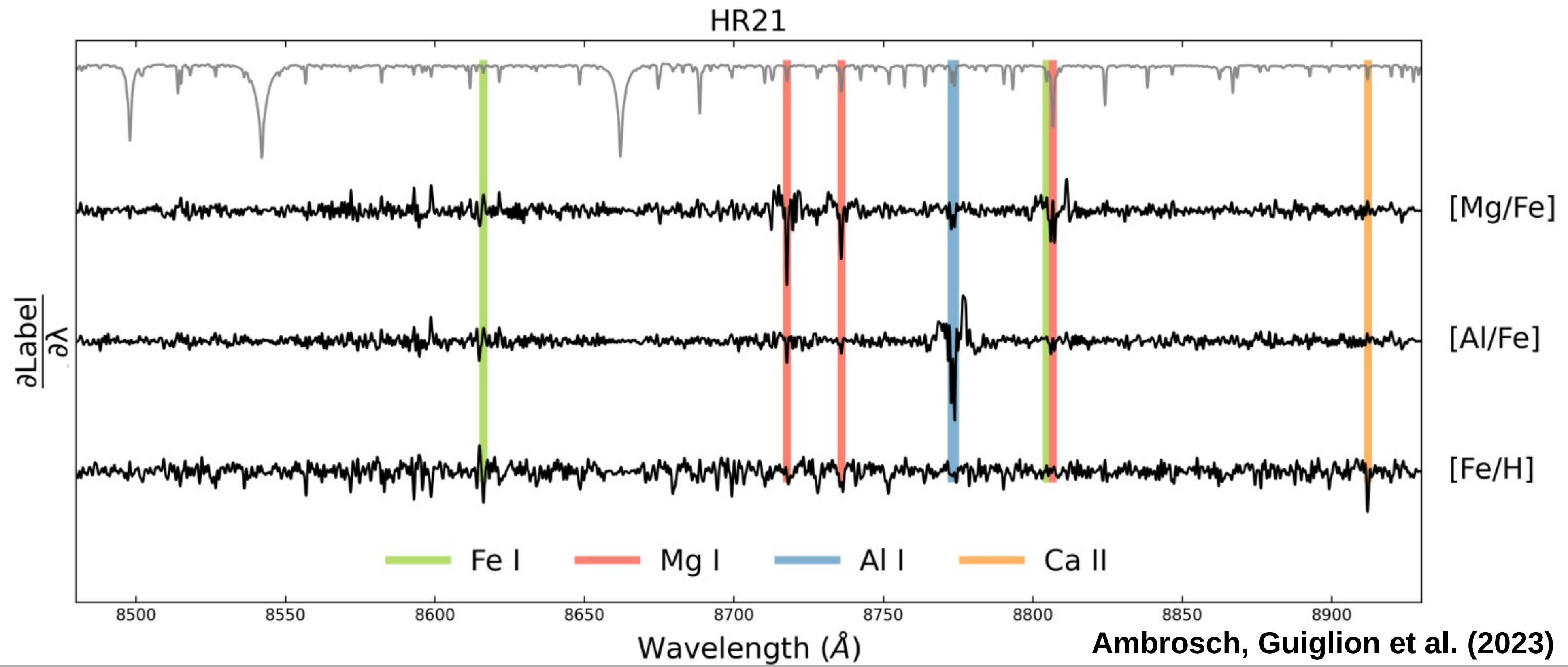




GG et al. 2024b

Are we sure that CNN is not measuring abundance correlations ?

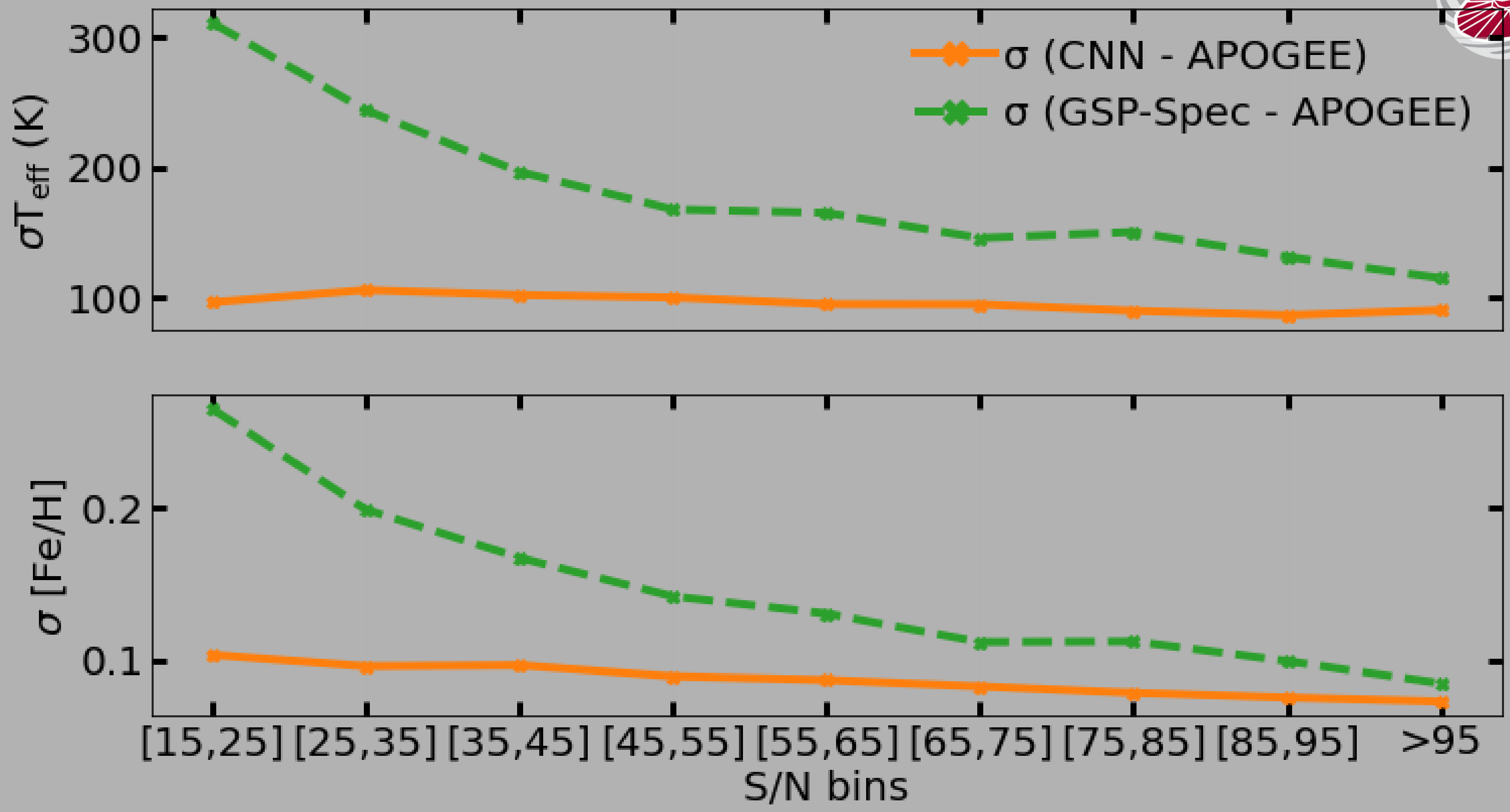
→ [Al/Fe] and [Mg/Fe] ratios are anti-correlated in Globular Clusters (e.g. Pancino et al. 2017)
→ Training set: 14637 stars with *Gaia*-ESO spectra.
Labels: T_{eff}, log(g), [Fe/H], [Al/Fe], [Mg/Fe]



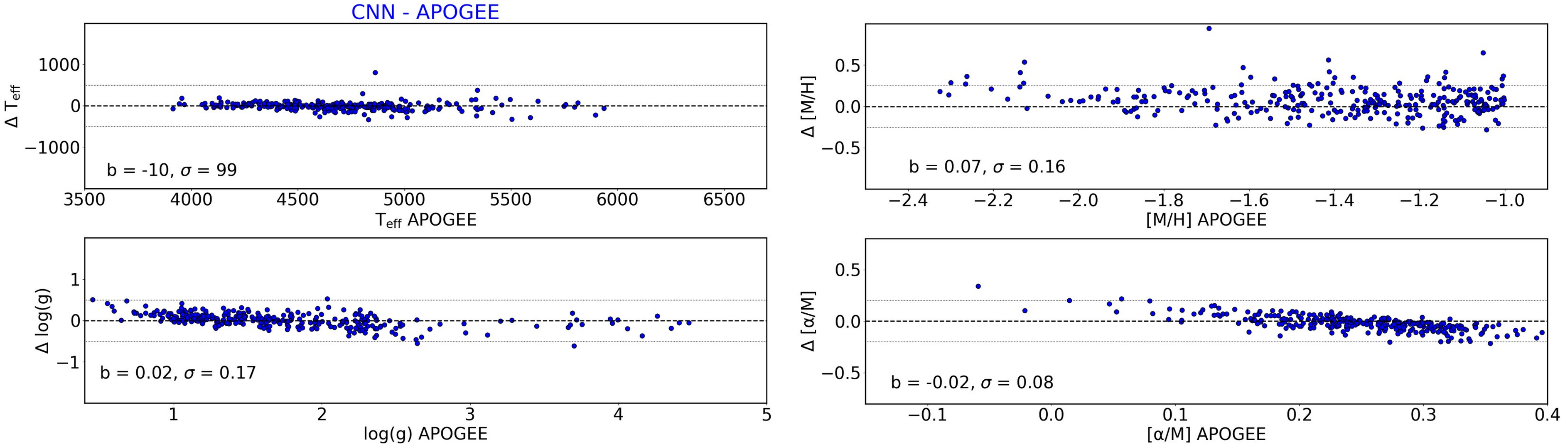
Ambrosch, Guiglion et al. (2023)

→ **We know how to properly use CNNs for abundance measurements**

Robustness of CNN with noise



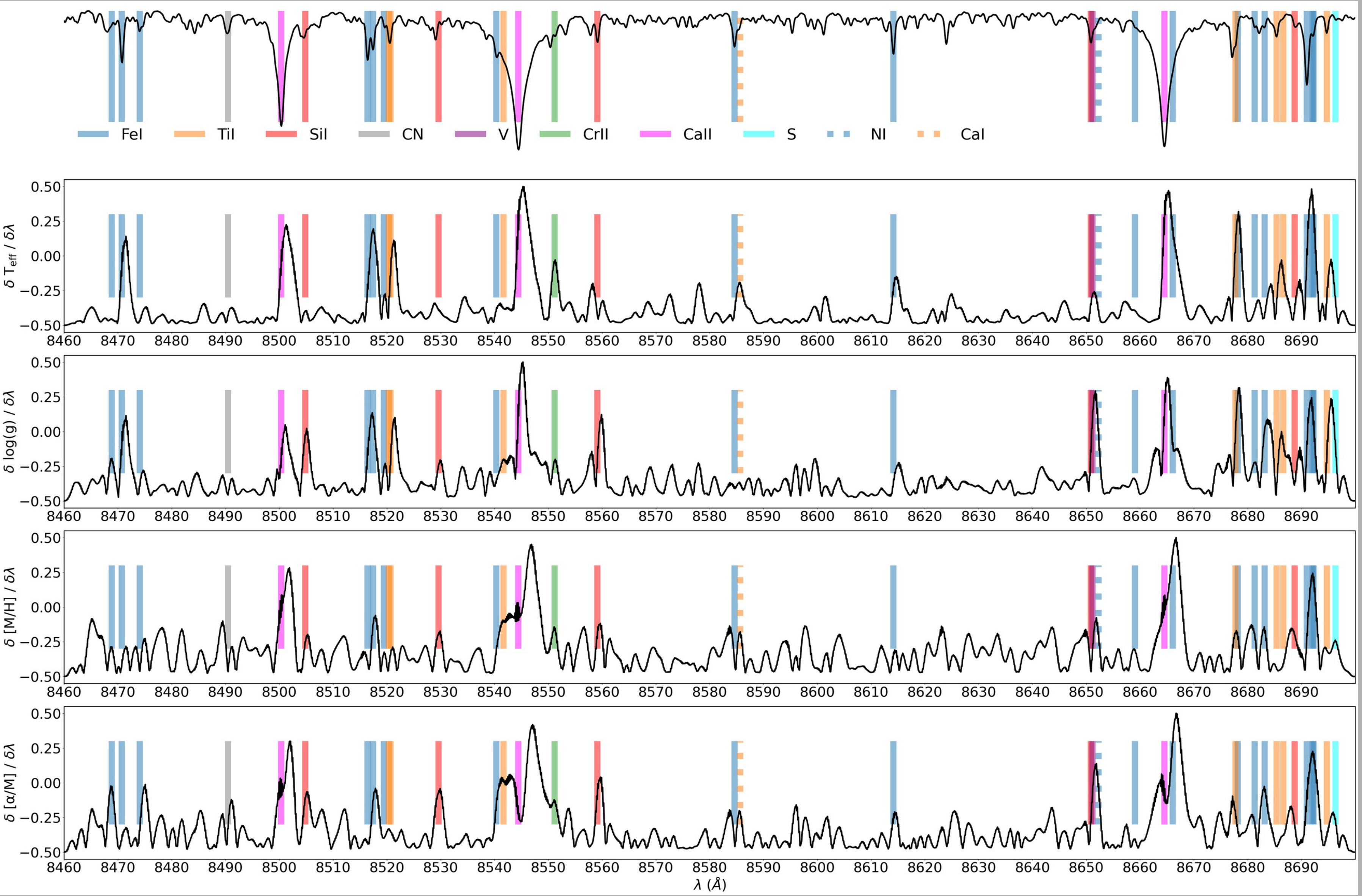
CNN performances for halo stars
→ 15<S/N<25



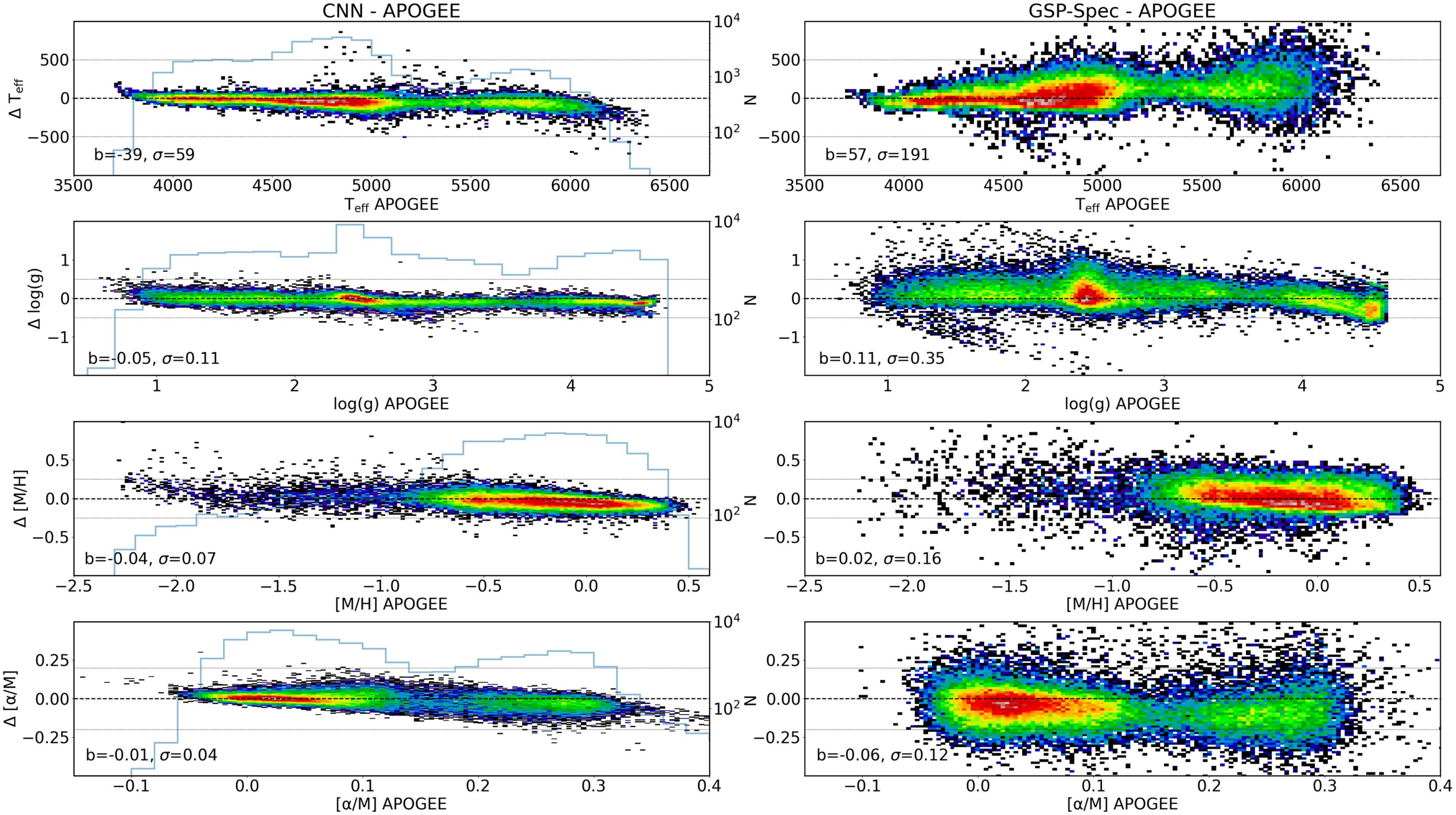
GG et al. 2023

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

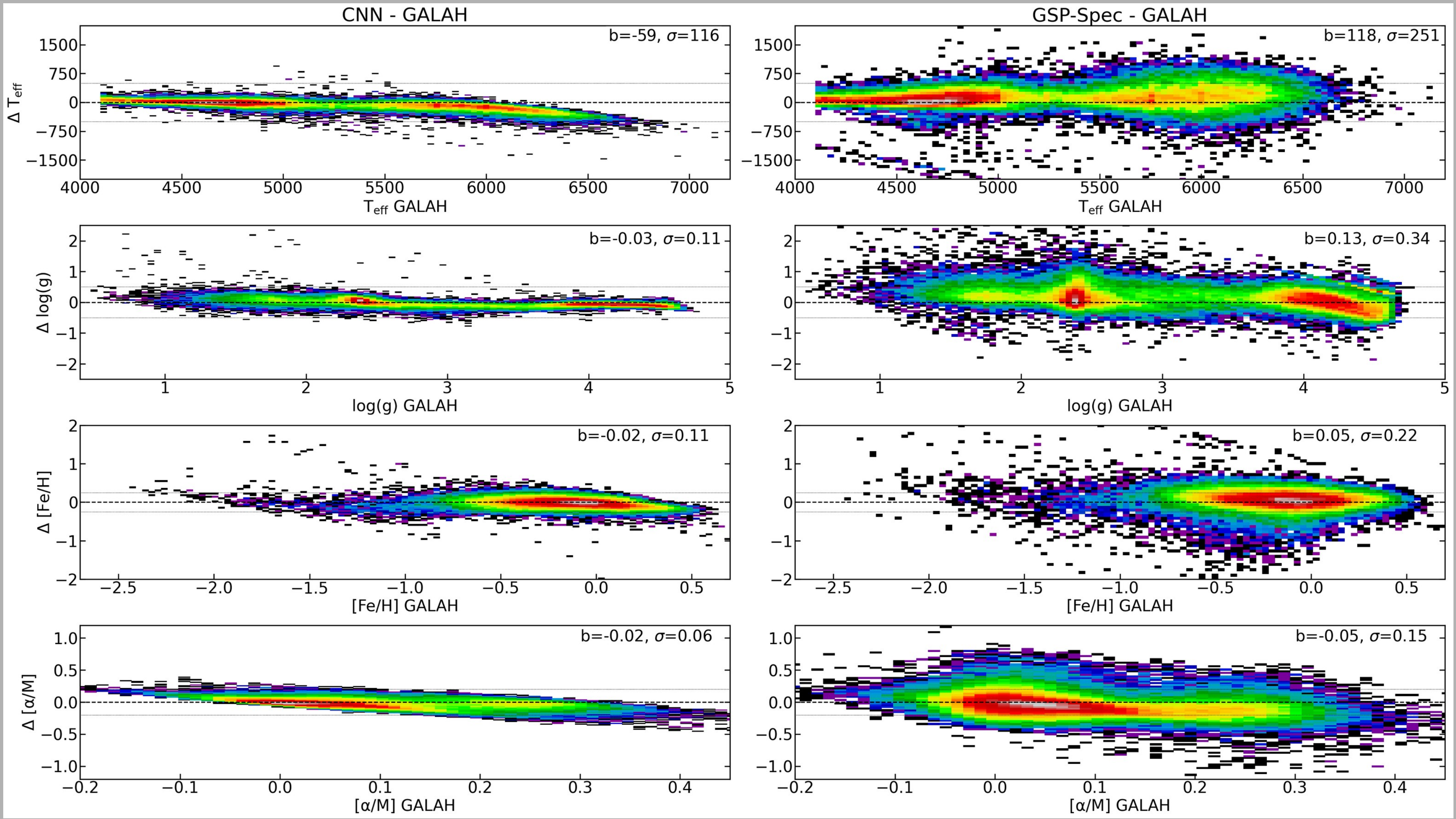
→ More external validation with GALAH, OCs, and GSP-Phot



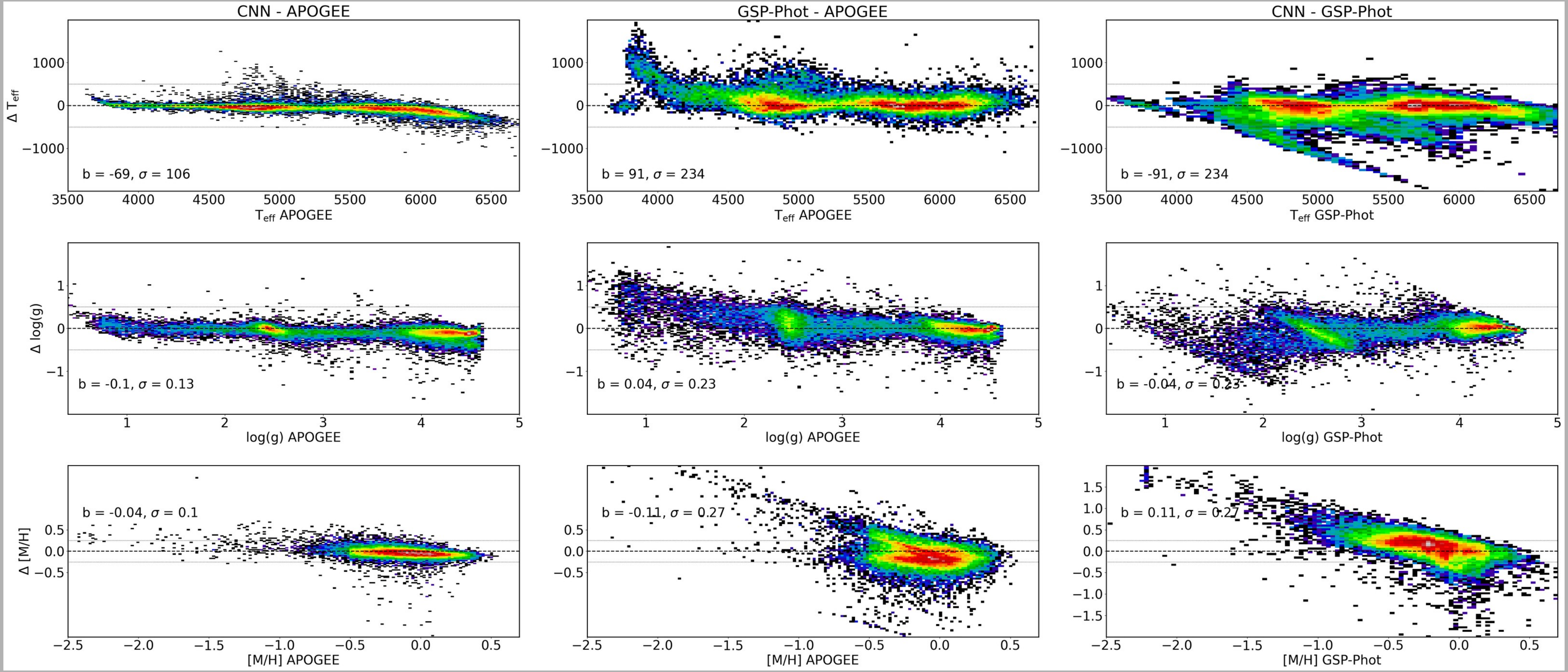
FeI
TiI
SiI
CN
V
CrII
CaII
S
NI
CaI
δ T_eff / δλ
δ log(g) / δλ
δ [M/H] / δλ
δ [α/M] / δλ
λ (Å)

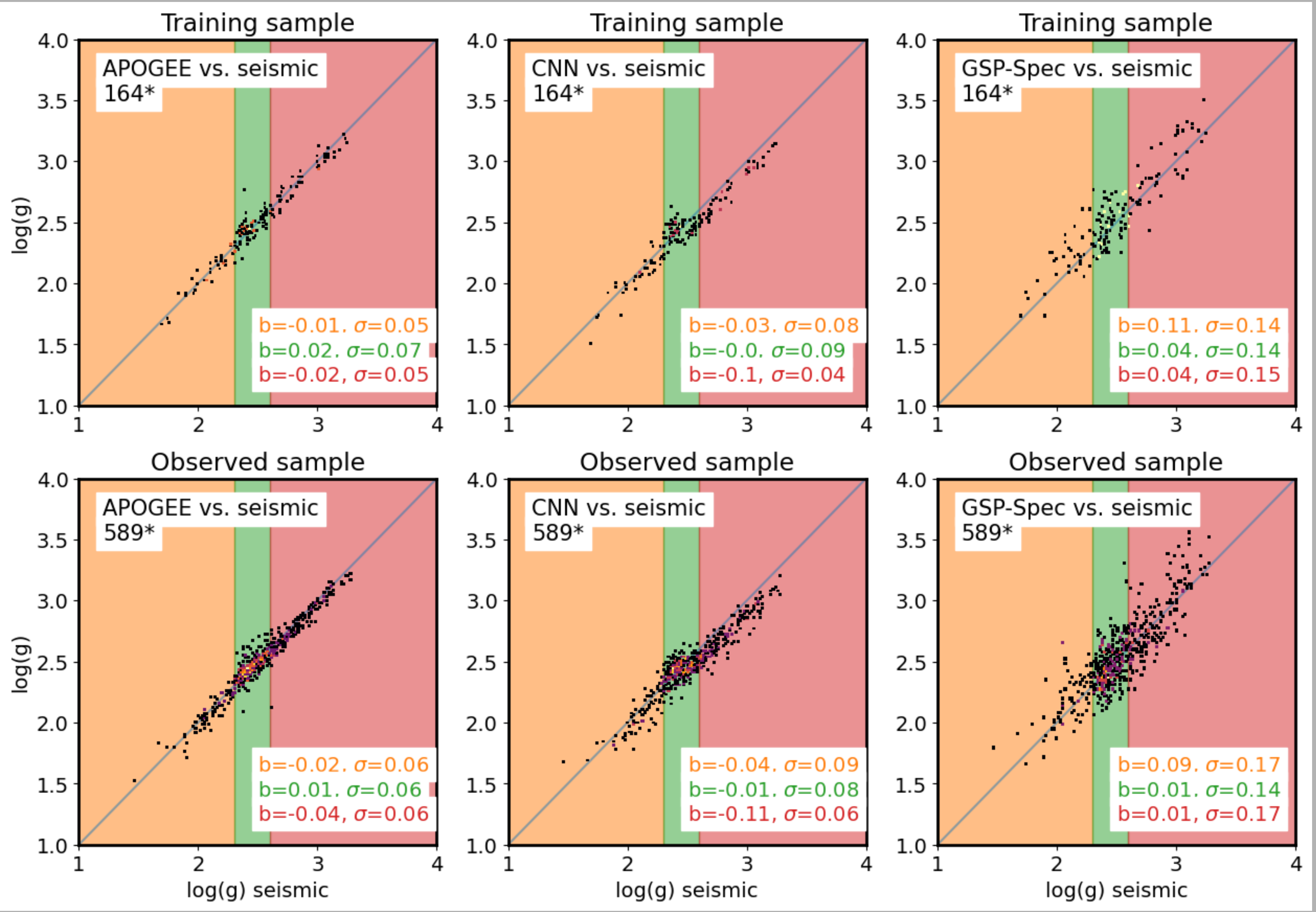


CNN - APOGEE
GSP-Spec - APOGEE
Δ T_eff
T_eff APOGEE
b=-39, σ=59
b=57, σ=191
Δ log(g)
log(g) APOGEE
b=-0.05, σ=0.11
b=0.11, σ=0.35
Δ [M/H]
[M/H] APOGEE
b=-0.04, σ=0.07
b=0.02, σ=0.16
Δ [α/M]
[α/M] APOGEE
b=-0.01, σ=0.04
b=-0.06, σ=0.12
N



CNN - GALAH
GSP-Spec - GALAH
b=-59, σ=116
b=118, σ=251
Δ T_eff
T_eff GALAH
b=-0.03, σ=0.11
b=0.13, σ=0.34
Δ log(g)
log(g) GALAH
b=-0.02, σ=0.11
b=0.05, σ=0.22
Δ [Fe/H]
[Fe/H] GALAH
b=-0.02, σ=0.06
b=-0.05, σ=0.15
Δ [α/M]
[α/M] GALAH


CNN - APOGEE
GSP-Phot - APOGEE
CNN - GSP-Phot
Δ Teff
Teff APOGEE
Teff GSP-Phot
b = -69, σ = 106
b = 91, σ = 234
b = -91, σ = 234
Δ log(g)
log(g) APOGEE
log(g) GSP-Phot
b = -0.1, σ = 0.13
b = 0.04, σ = 0.23
b = -0.04, σ = 0.23
Δ [M/H]
[M/H] APOGEE
[M/H] GSP-Phot
b = -0.04, σ = 0.1
b = -0.11, σ = 0.27
b = 0.11, σ = 0.27



Training sample
APOGEE vs. seismic
164*
b=-0.01, σ=0.05
b=0.02, σ=0.07
b=-0.02, σ=0.05
Training sample
CNN vs. seismic
164*
b=-0.03, σ=0.08
b=-0.0, σ=0.09
b=-0.1, σ=0.04
Training sample
GSP-Spec vs. seismic
164*
b=0.11, σ=0.14
b=0.04, σ=0.14
b=0.04, σ=0.15
Observed sample
APOGEE vs. seismic
589*
b=-0.02, σ=0.06
b=0.01, σ=0.06
b=-0.04, σ=0.06
Observed sample
CNN vs. seismic
589*
b=-0.04, σ=0.09
b=-0.01, σ=0.08
b=-0.11, σ=0.06
Observed sample
GSP-Spec vs. seismic
589*
b=0.09, σ=0.17
b=0.01, σ=0.14
b=0.01, σ=0.17
log(g)
log(g) seismic