Leibniz-Institut für Astrophysik Potsdam

Parametrization of stellar spectra based on Convolutional Neural Network

G. Guiglion

Leibniz-Institut für Astrophysik Potsdam (AIP)

My collaborators

AIP Leibniz-Institut für Astrophysik Potsdam

C. Chiappini

H. Enke

G. Matijevic

I. Minchev

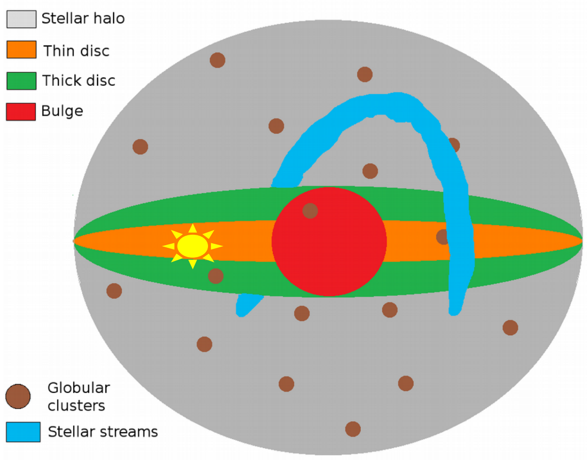
A. Queiroz

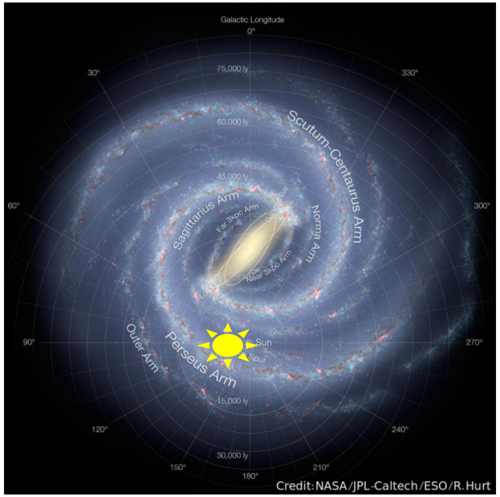
M. Steinmetz

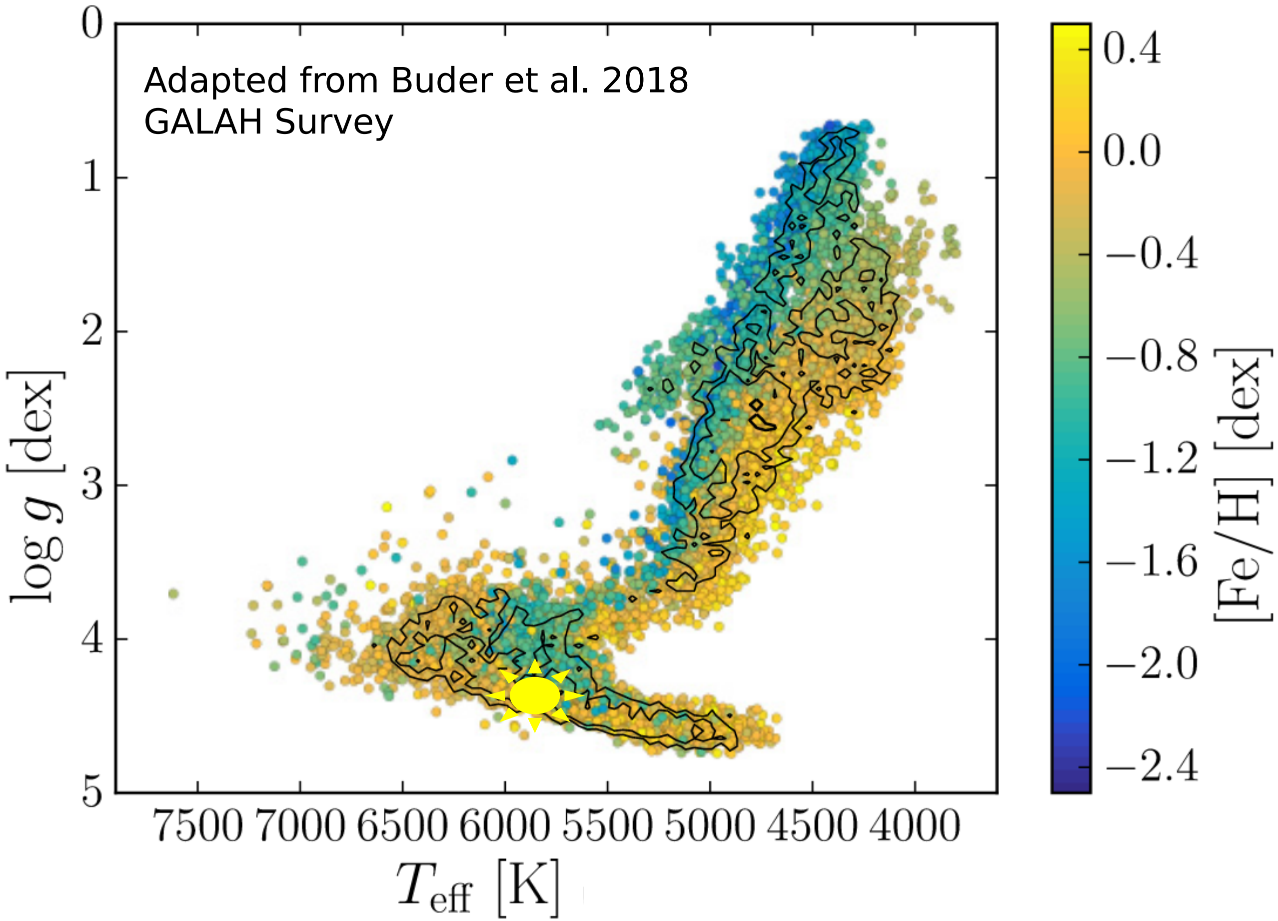
M. Valentini

Some context

Why do we care about chemical abundances ?







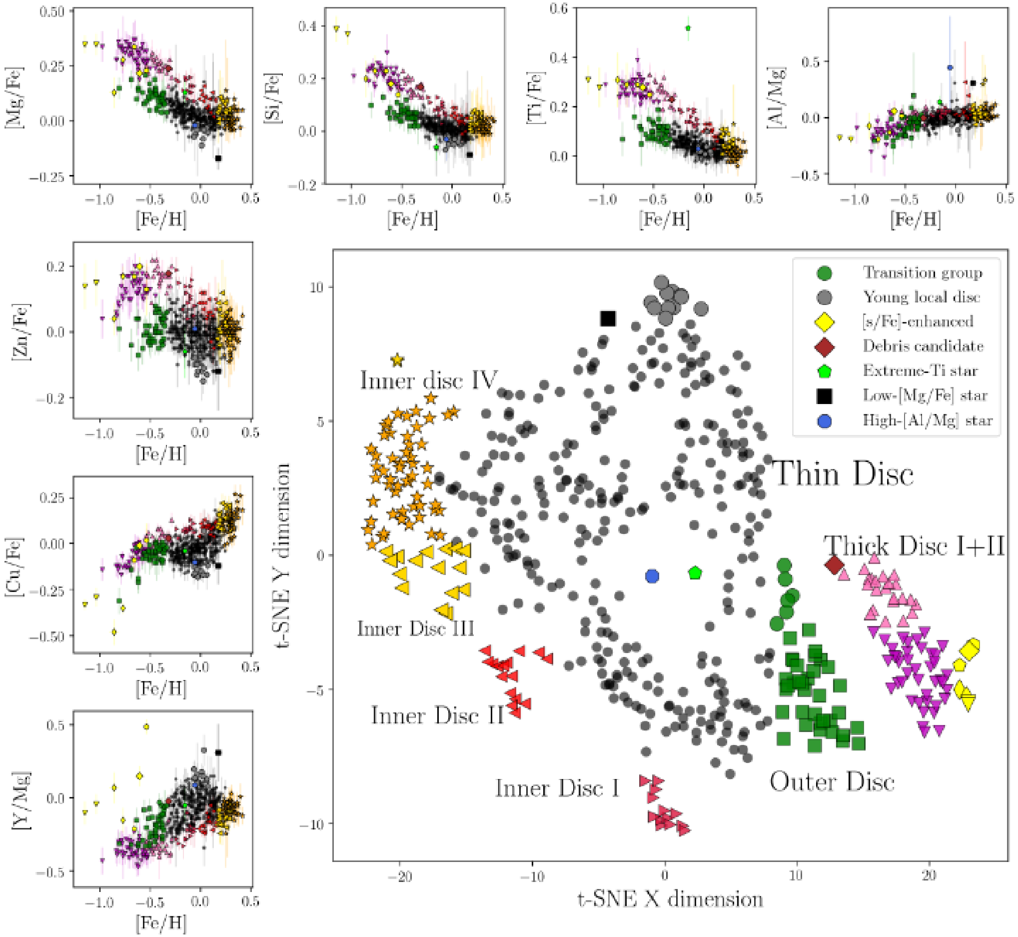
Why do we care about chemical abundances ?

→ Photospheric chemical composition
= ISM composition at τ_{birth}
(Wyse & Gilmore 1988)

→ Most used tracers: α-elements
(O, Ne, Mg, Si, Ti …)
(Adibekyan *et al.* 2013)

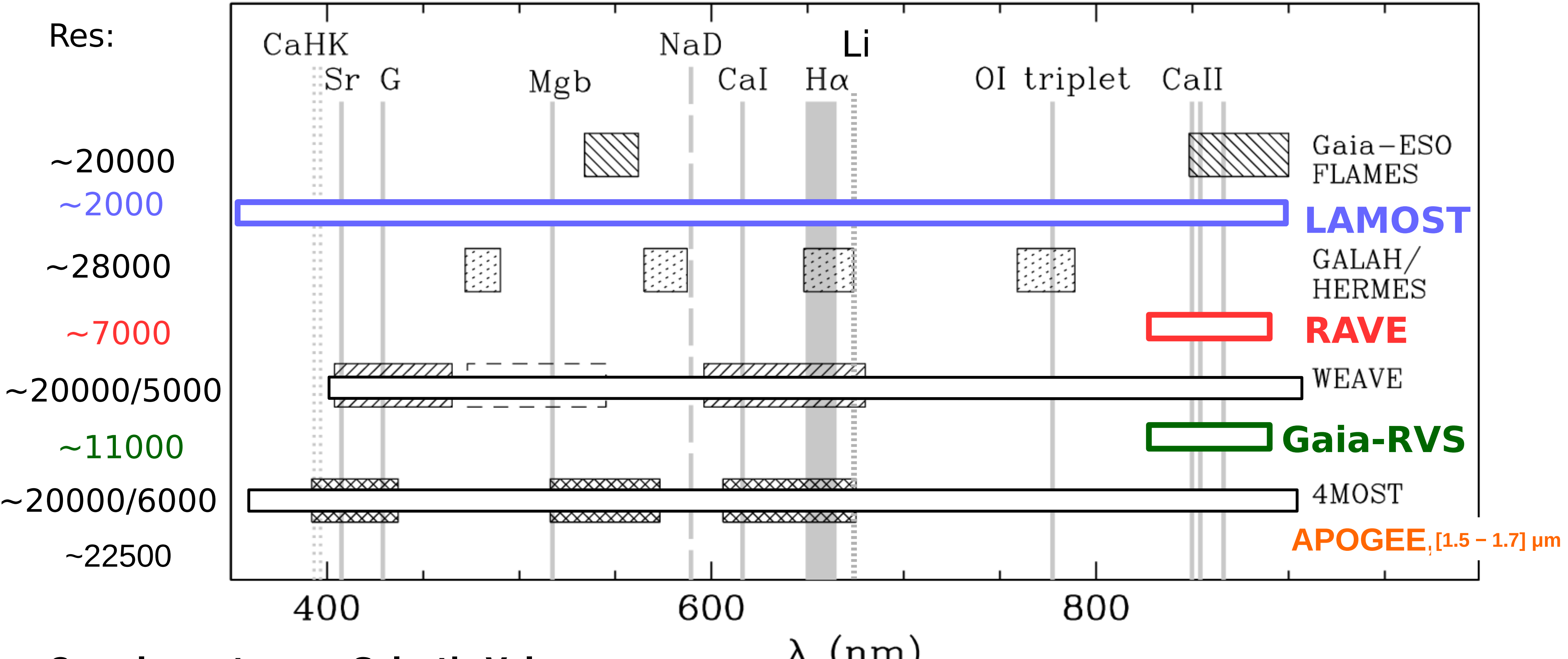
→ Other elements: lithium, 'r' and
's'-processes
(Guiglion et al. 2016, 2018)

Anders et al. 2018, with HR data from Delgado-Mena et al. 2017



Spectroscopic surveys

Adapted from Feltzing et al. (2018)



→ **Complementary:** ≠ **Galactic Volume**
≠ **Chemical elements**
≠ **Stellar populations (Bulge, disc, halo, ...)**

Deriving chemical abundances from stellar spectra

Classical pipelines:

Space (Boeche et al. 2011, **RAVE, LAMOST**), **SME** (Valenti & Piskunov 2012 **GES, GALAH**),
FERRE (Allende-Prieto et al. 2006, **PRISTINE, APOGEE**), **GAUFRE** (Valentini et al. 2013, **RAVE**),
Synspec (Mikolaitis et al. 2015, **GES, AMBRE**), **ATHOS** (Hanke et al. 2018),
MATISSE (Recio-blanco et al. 2006 **GES, AMBRE, RAVE, Gaia-RVS**),
GAUGUIN (Guiglion et al. 2016 **GES, AMBRE, RAVE, Gaia-RVS**)

↓ ↓

TRAINING SAMPLE
Stellar labels: Atmosph. Params + Abundances
Stellar spectra: Real or Synthetic

↓ ↓

Supervised machine learning:

The Cannon: Ness et al. 2015 (**APOGEE**), Buder et al. 2018 (**GALAH**)

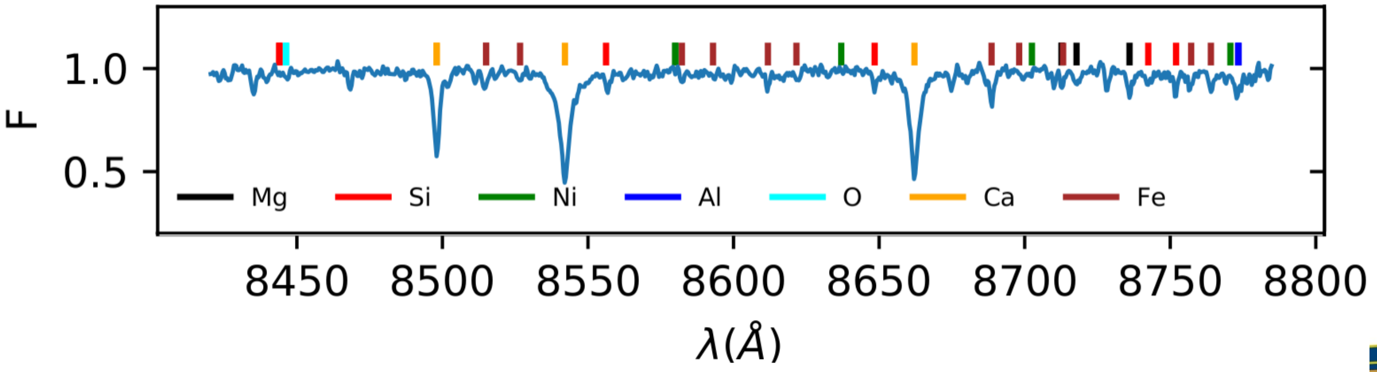
The Payne: Ting et al. 2019 (**APOGEE**), Xiang et al. 2019 (**LAMOST**)

Convolutional Neural-Network: Bialek et al. 2019 (**GES UVES**) Leung & Bovy 2019 (**APOGEE**), Zhang et al. 2019 (**LAMOST**), Guiglion et al. 2020 (**RAVE**)

Convolutional Neural Network application to

RAVE
RADIAL VELOCITY EXPERIMENT

Guiglion, Matijevic, Queiroz, Valentini, Steinmetz, Chiappini et al. 2020
in press (arxiv : 2004.12666)



→ **Extend the scientific output of RAVE spectra (atmospheric parameters + chemical abundances)**

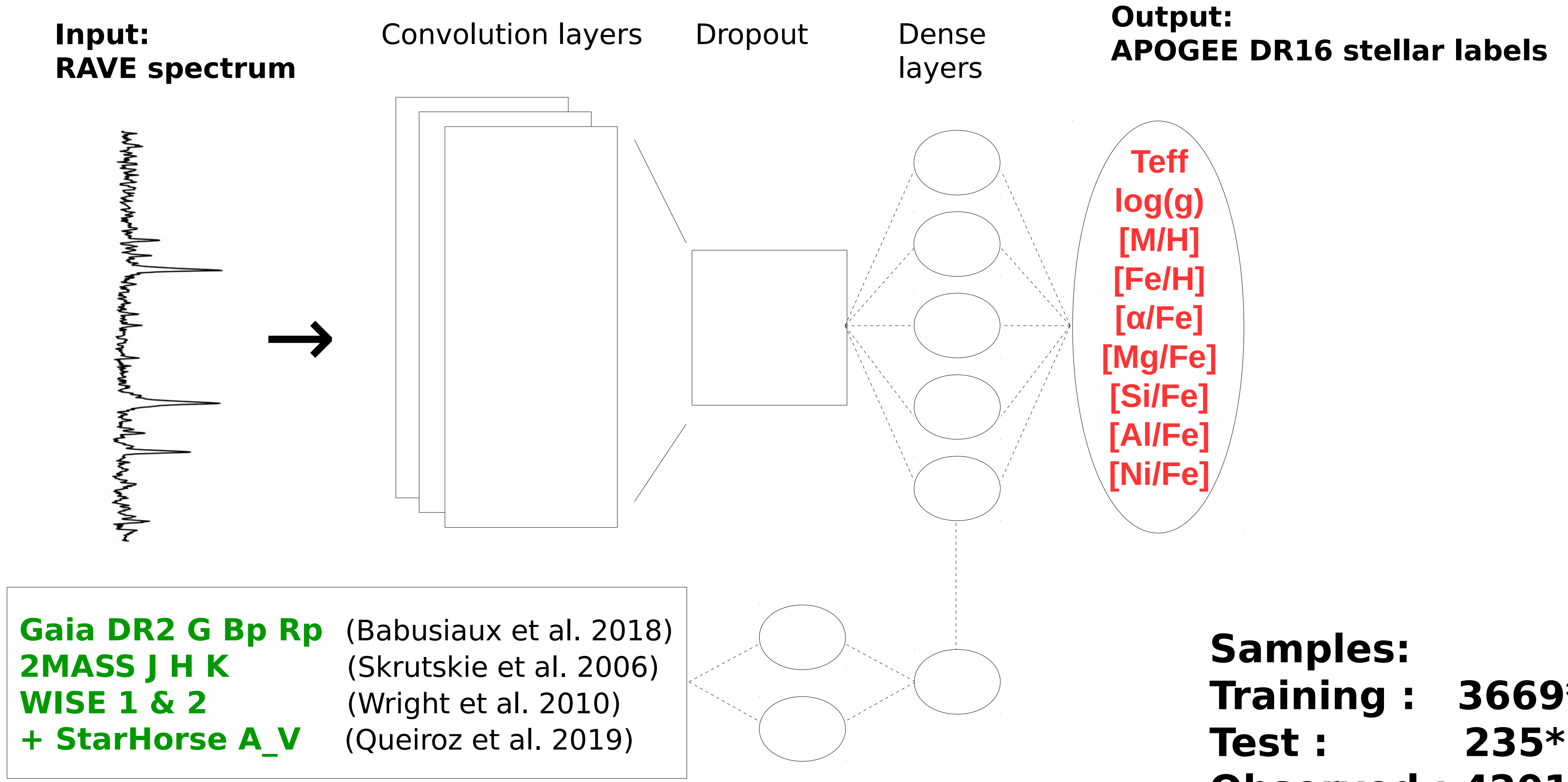
→ **Transfer knowledge from High-res survey (APOGEE) to lower-res different survey (RAVE).**

→ **Deal with correlated noise efficiently.**

→ **Combine spectra with photom. & astrom. smoothly.**

→ **Rely only on observables.**

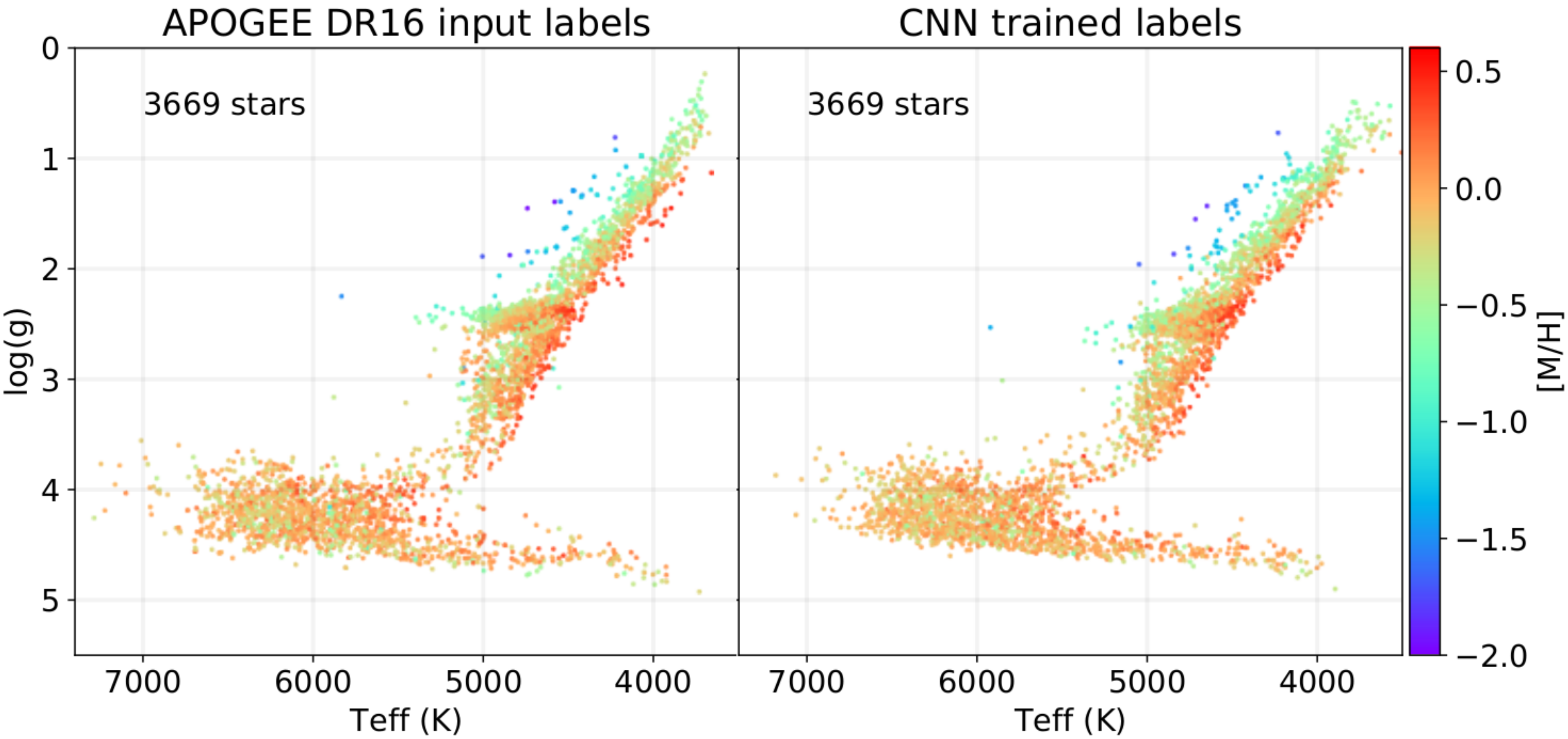
→ **Develop a pipeline that is reusable.**



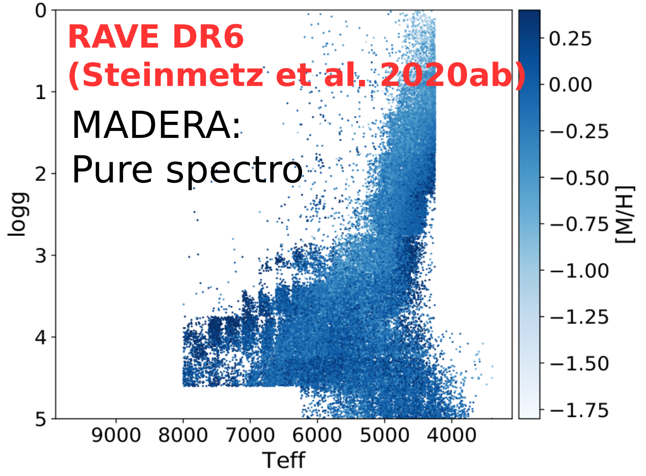
Samples:
Training : 3669*
Test : 235*
Observed : 420165*

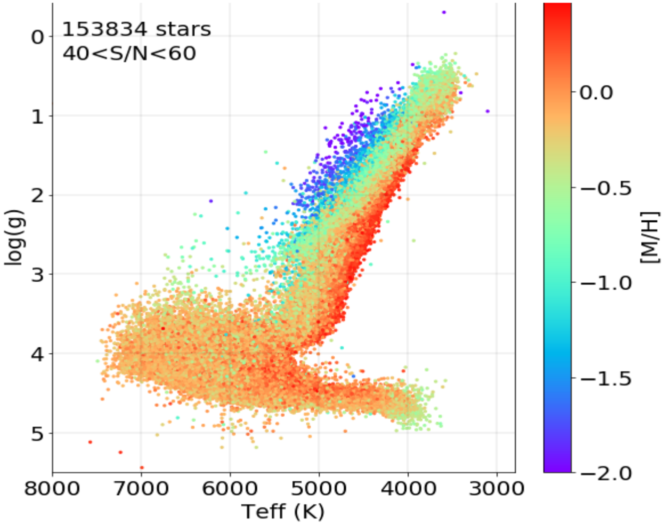
→ **Parallax errors < 20% for 94% of RAVE stars**

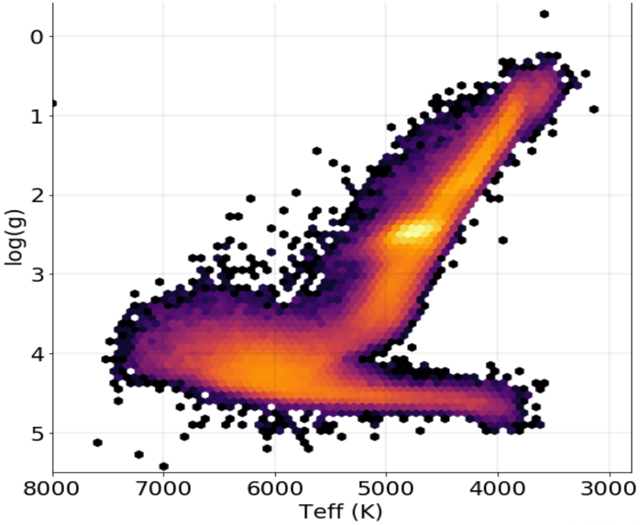
Training the Neural-Network



Kiel diagram of the observed sample







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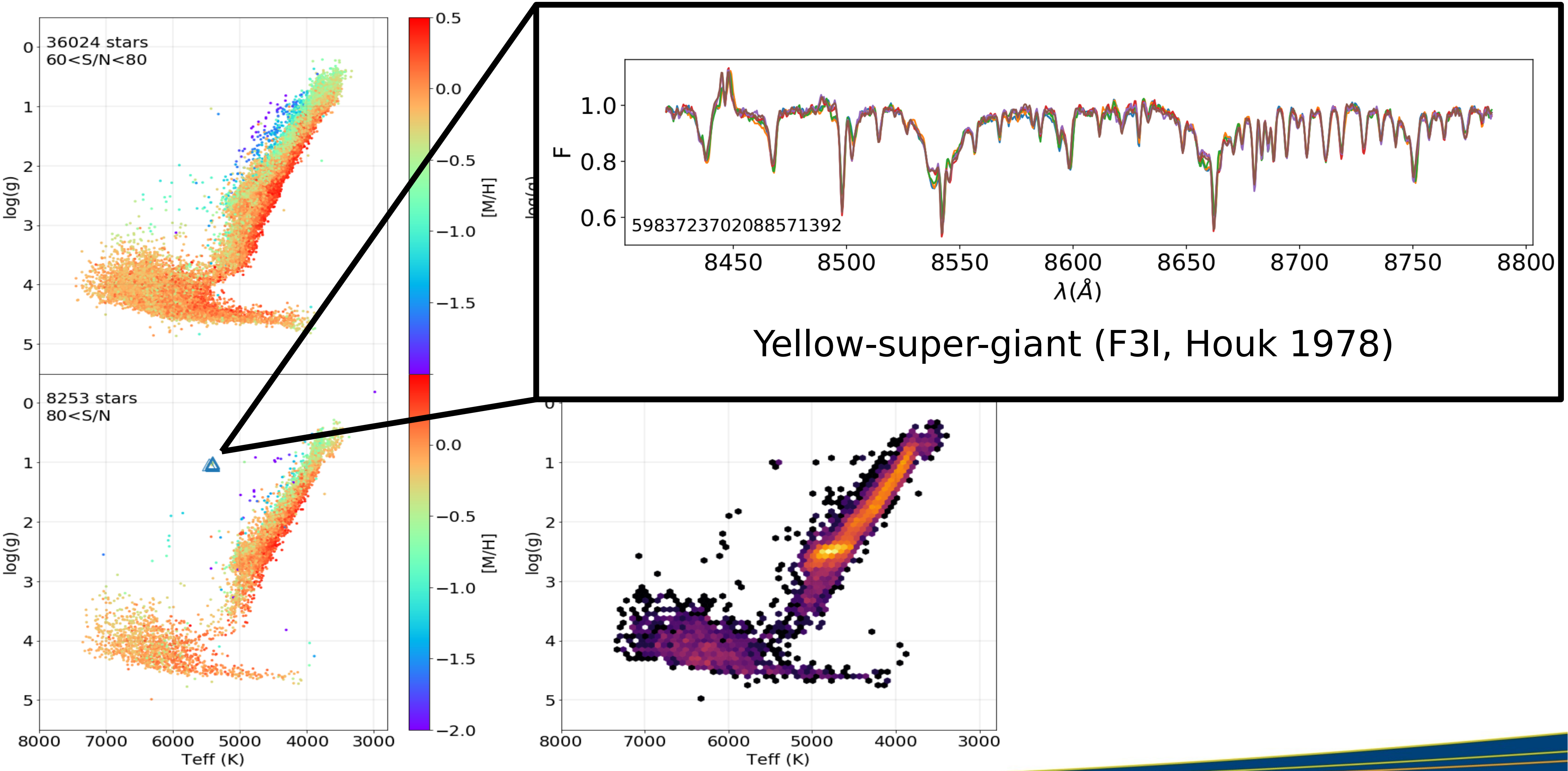
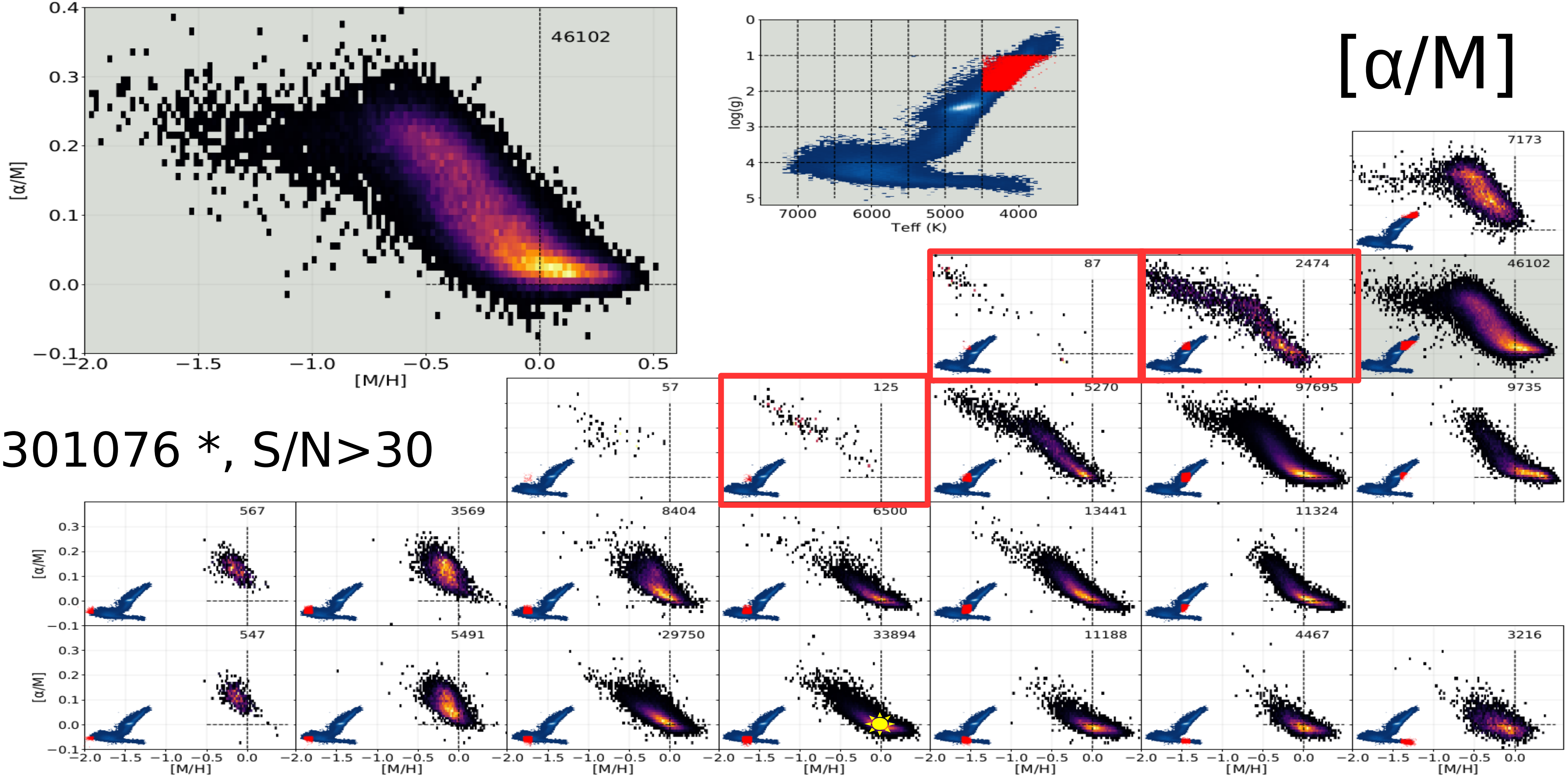
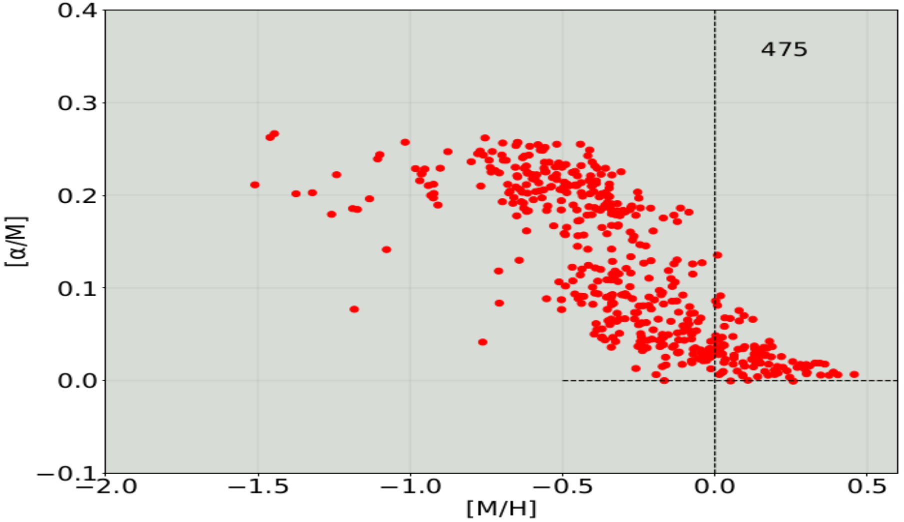


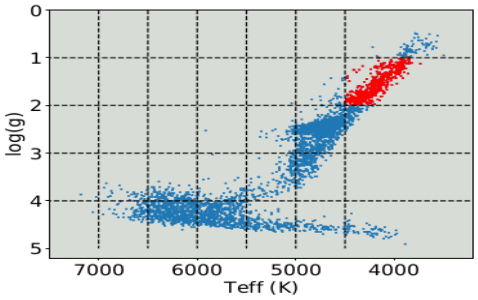
[α/M]

301076 *, S/N>30

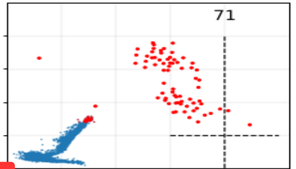


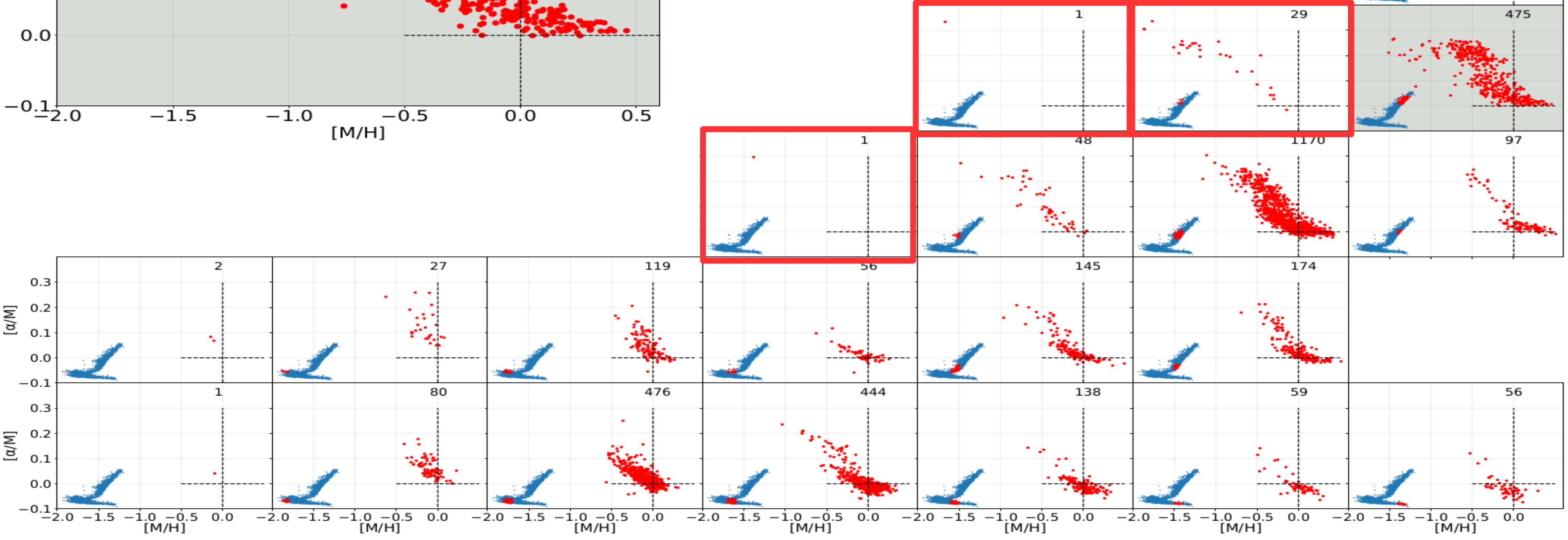
Guiglion et al., 2020, in press





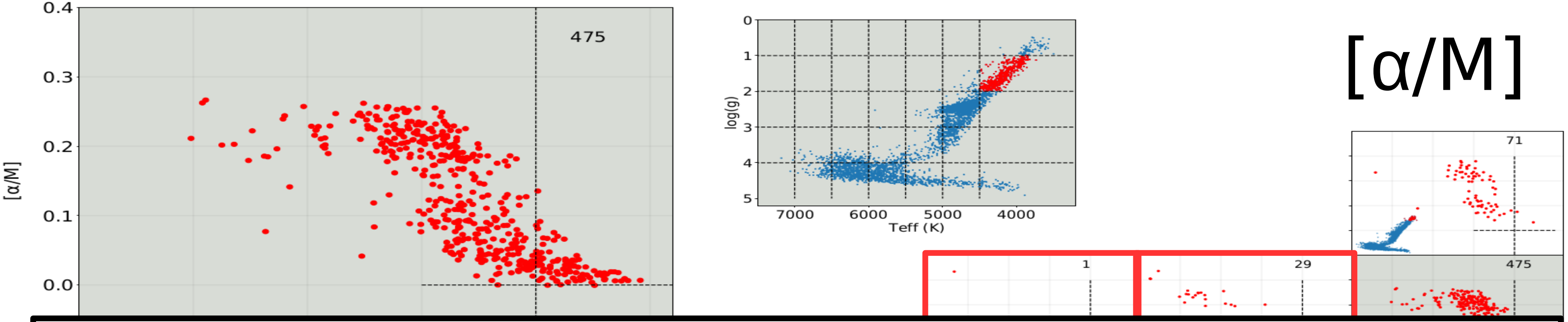
[α/M]



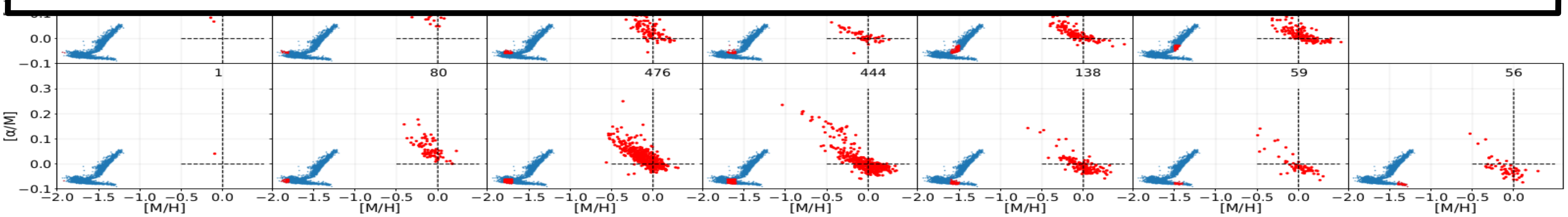


Guiglion et al., 2020, in press

[α/M]

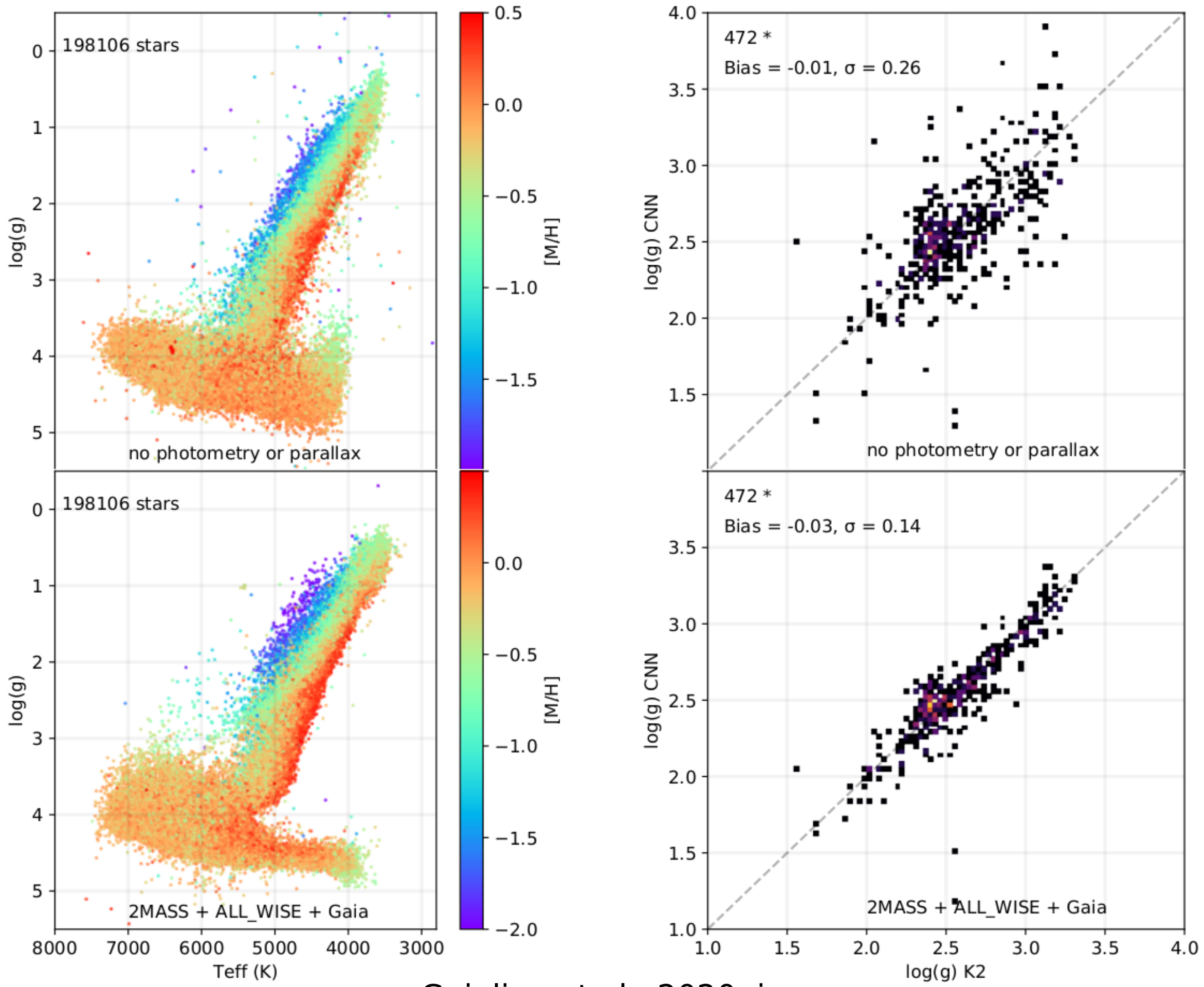


Need to understand better the selection effects and get a training sample as complete as possible !!!



Guiglion et al., 2020, in press

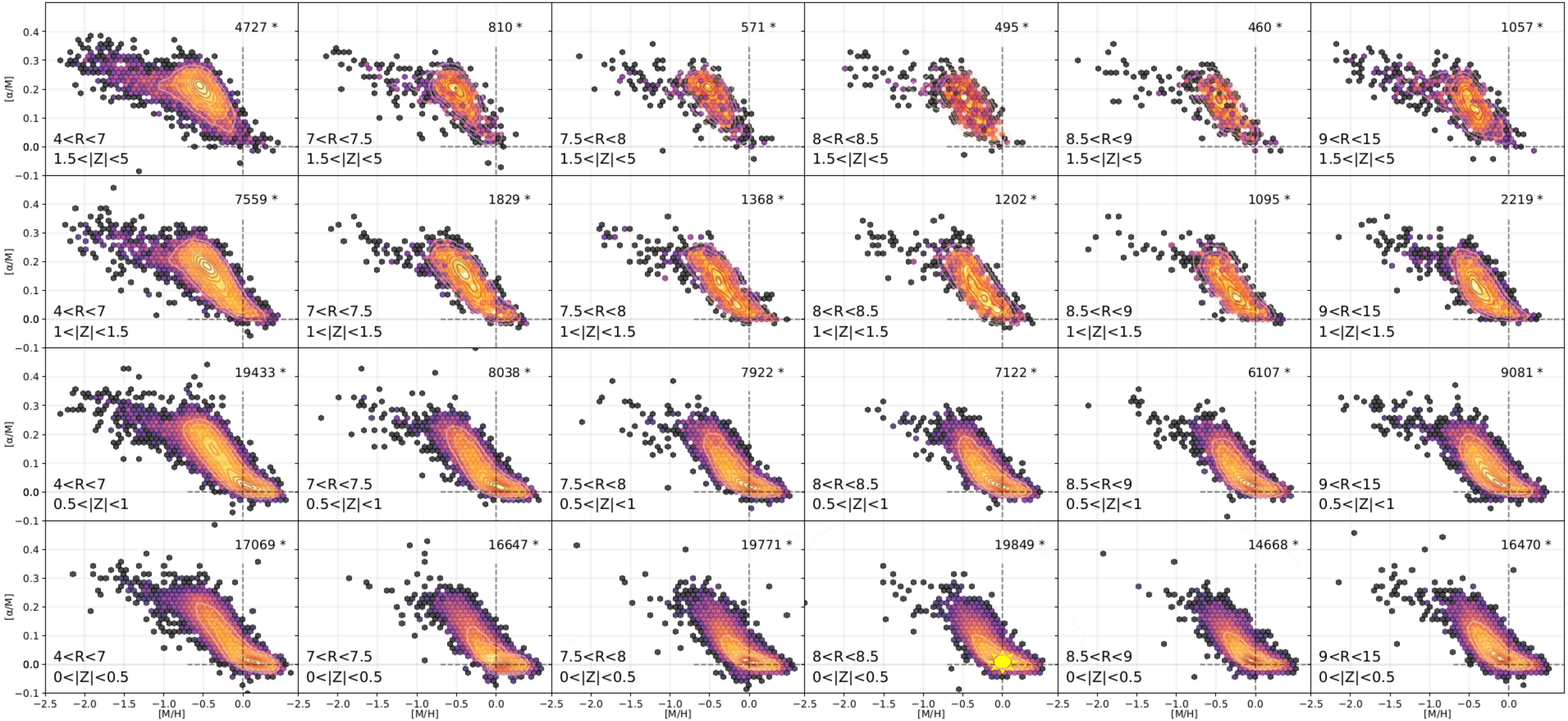
To use or not to use Absolute magnitudes ?



Valentini et al. in prep.
(see also Valentini et al. 2017)

Guiglion et al., 2020, in press

Chemical cartography of [α/Fe] with RAVE 185000 stars



Inner disc

Outer disc

Guiglion et al., 2020, in press

Take-home messages:

→ Labels are based on stellar physics → "Stellar labels"

→ Training samples: need to understand better the selection effects and get a training sample as complete as possible !!!

→ Smooth combination of spectra, photometry and astrometry ?
- → Convolutional Neural Networks !
- → Applicable to future spectroscopic surveys like WEAVE, 4MOST, Gaia RVS.

→ Working now on CNN with RAVE/GALAH, 4MOST, and Gaia-ESO Survey (Samir Nepal, master project)