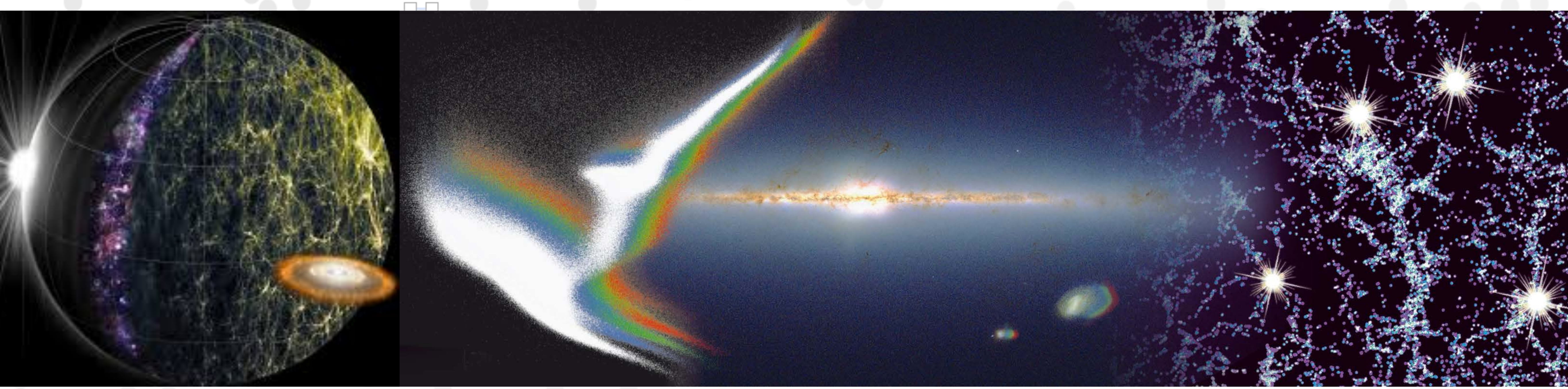

Galactic Archaeology with SPHEREx & SDSS-V (all the stars)

Melissa Ness, Columbia University, Feb 24, 2020
SPHEREx workshop @ Flatiron

1

Who am I?

1) Survey Scientist – *SDSS V's Milky Way Mapper*
2) I derive measurements from stellar spectra (Teff, logg, age, chemical abundances): use these to say things (about Galaxy's formation)
3) Build (simple) data-driven (generative) models: R=30,000 to 1800

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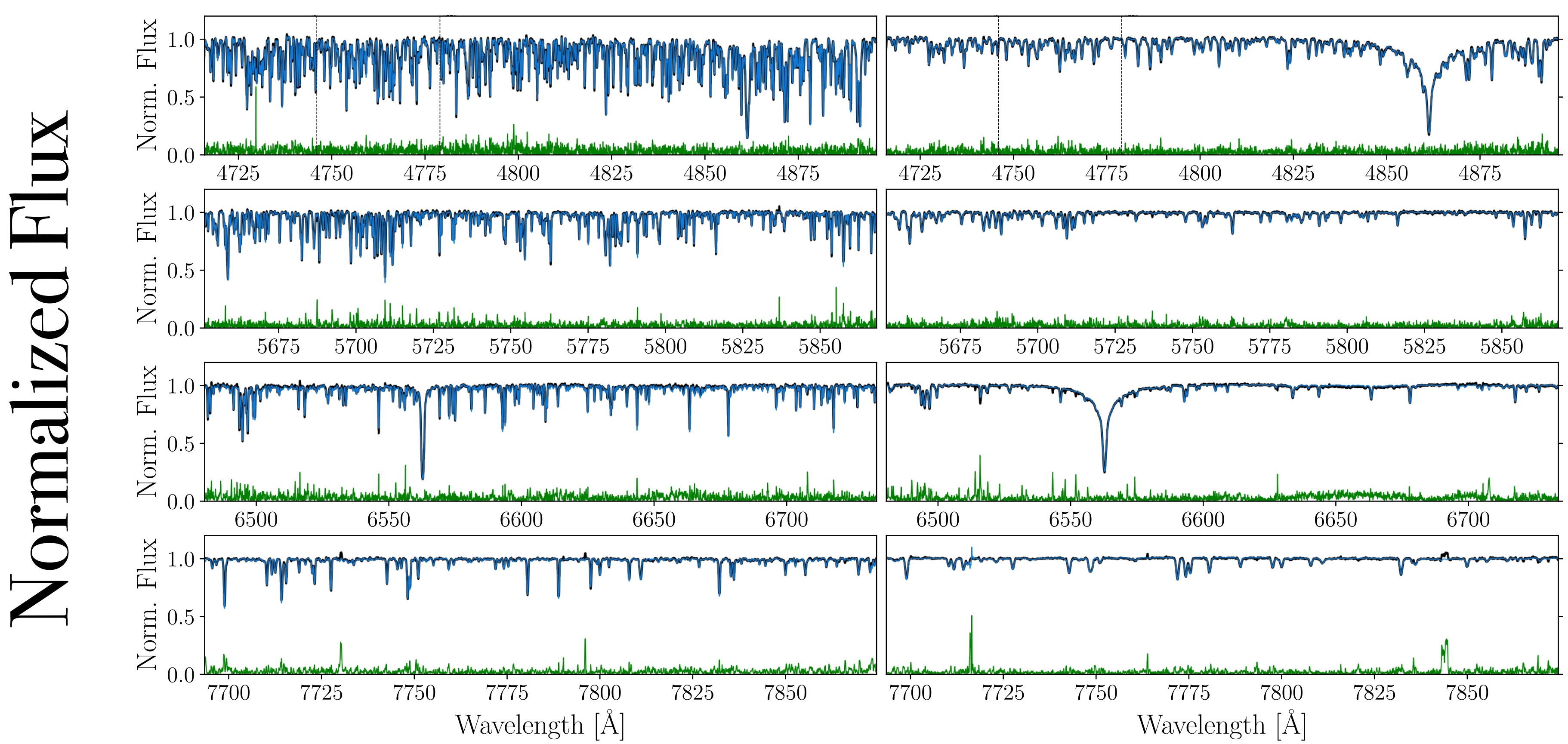

GALAH, Buder+ 2018

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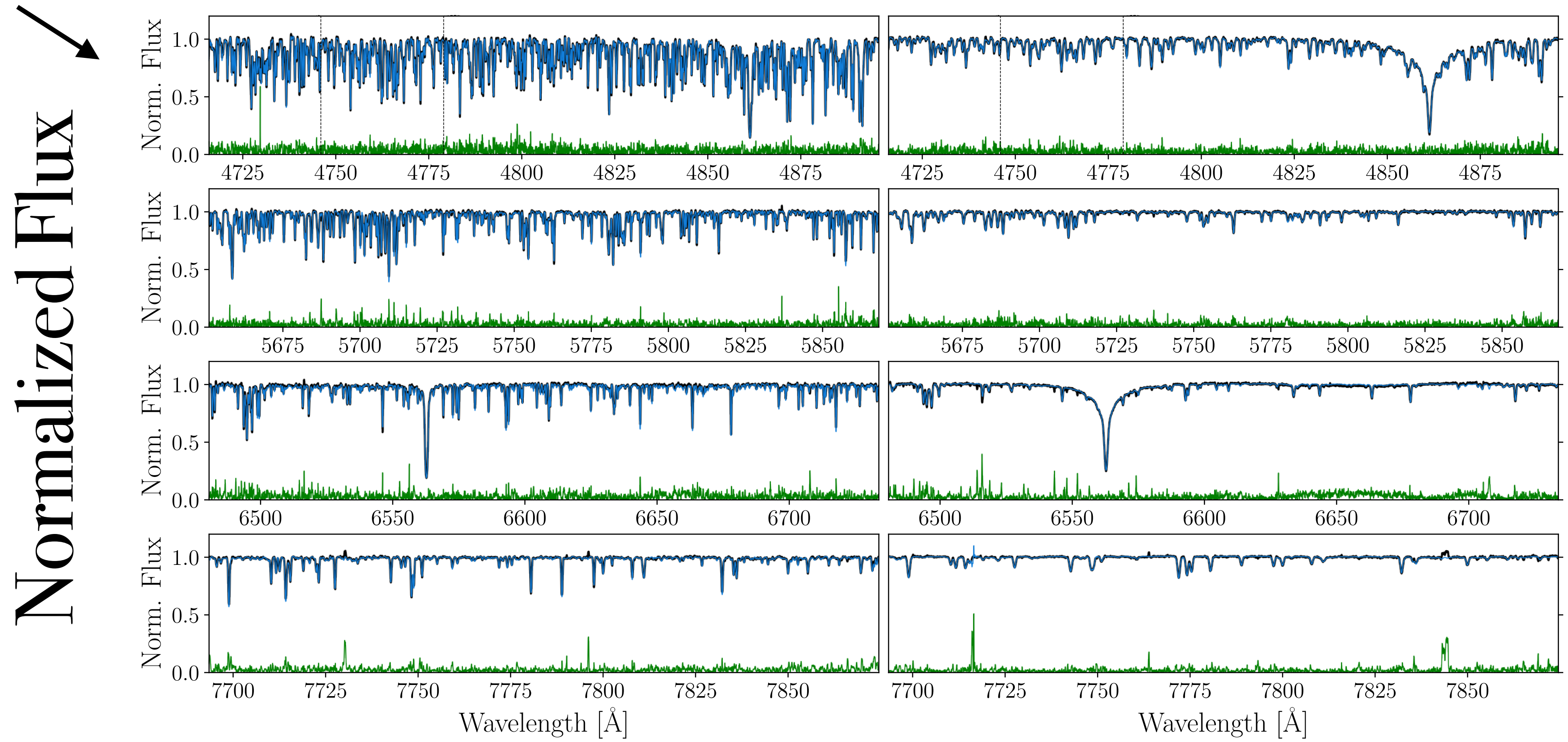

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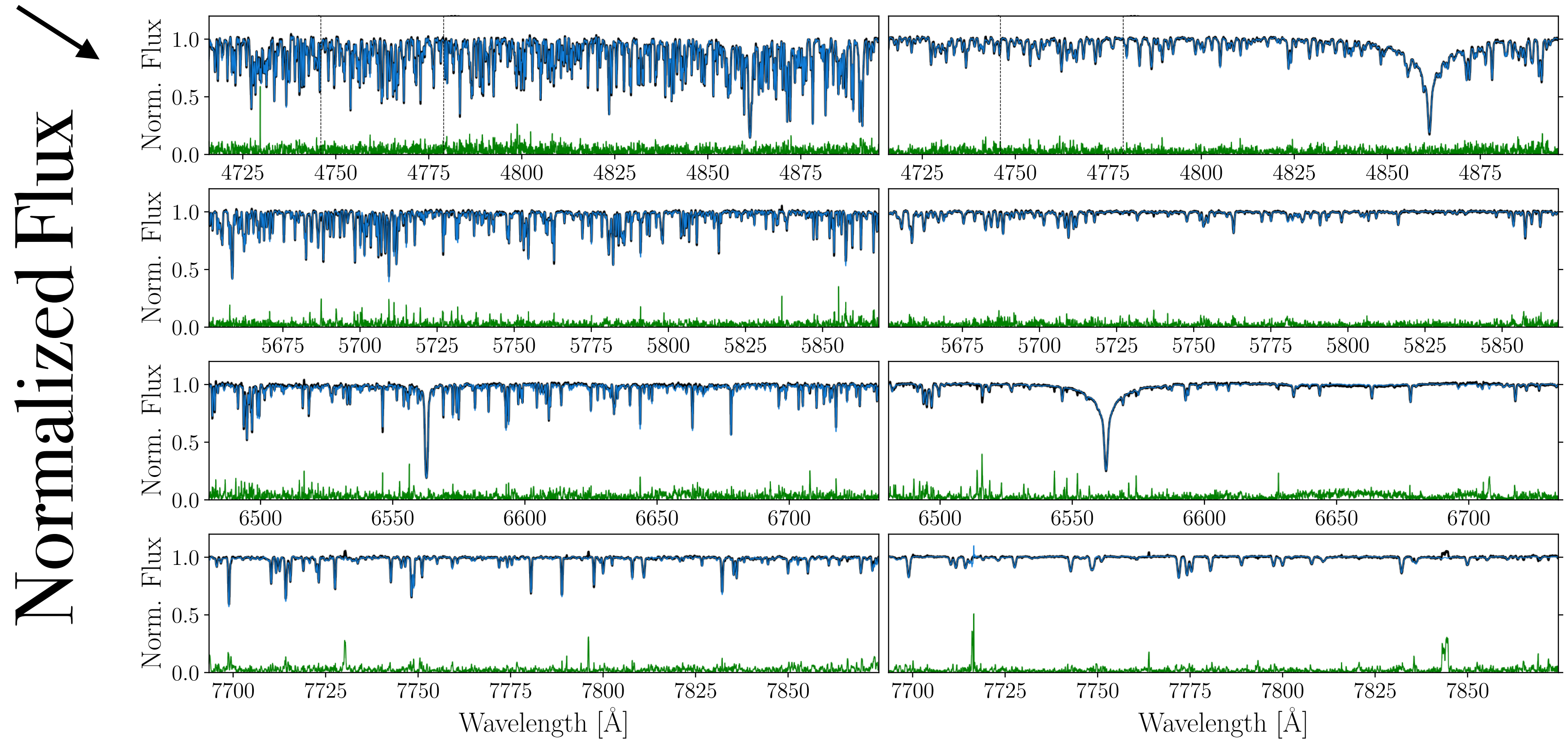

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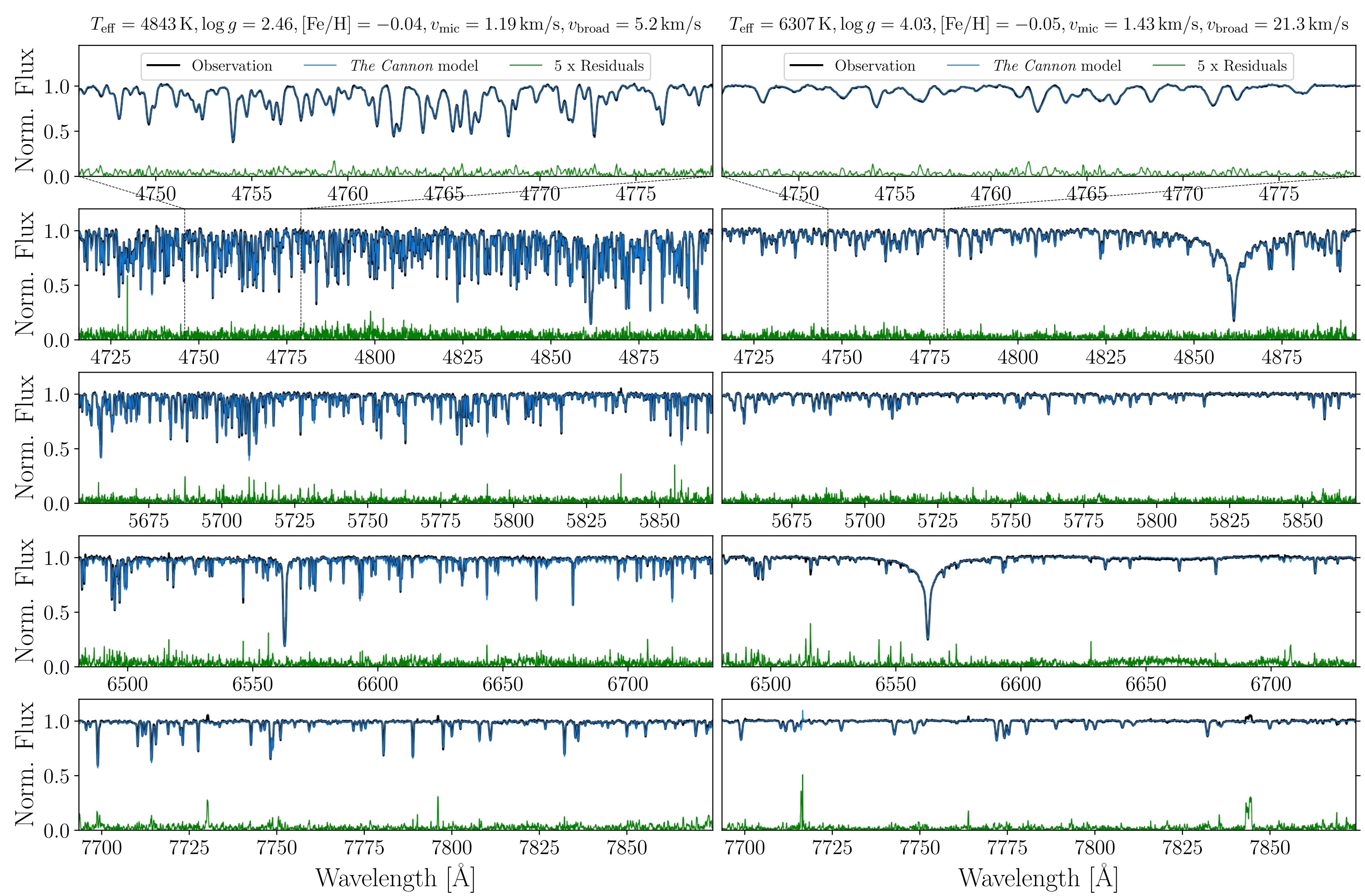
Normalized Flux



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GALAH, Buder+ 2018

What am I going to propose?

Now

Later

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Characterise **what** information we can recover from *SPHEREx* (stellar) data

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→ Non-stellar features in the spectrum (dust, molecules in ISM)

→ Peculiar chemical composition (dynamical interactions, planet ingestion)

SDSS-V

5 year program starting 2020 - both hemispheres

3 Science Programs

1) Milky Way Mapper (stars)
2) Black Hole Mapper
3) Local Volume Mapper (galaxies)

2 Infrastructure Investments

1) Fiber Positioning System
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Kollmeier et al., 2017 – http://adsabs.harvard.edu/abs/2017arXiv171103234K

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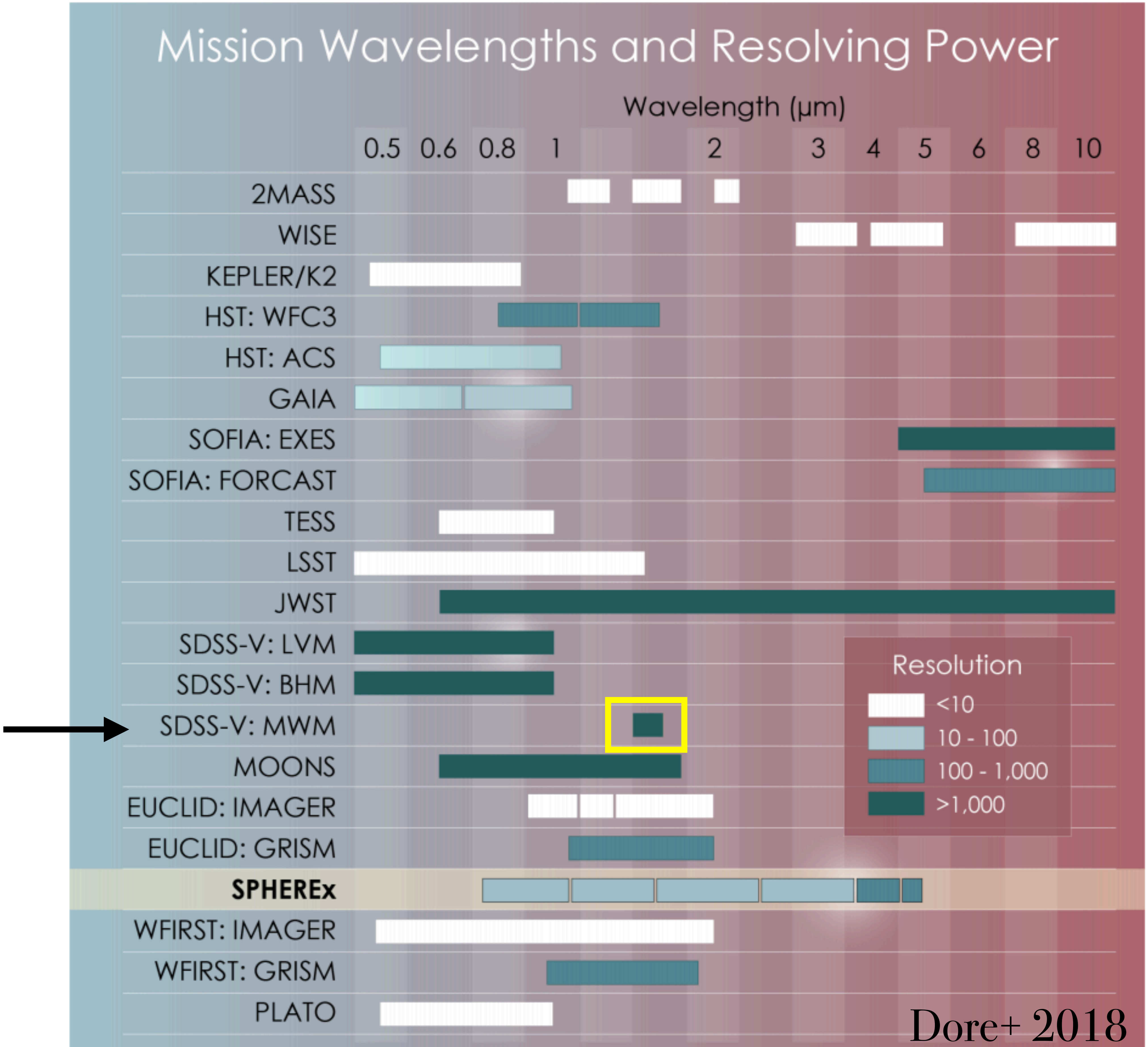

Mission Wavelengths and Resolving Power
Wavelength (μm)
0.5
0.6
0.8
1
2
3
4
5
6
8
10
2MASS
WISE
KEPLER/K2
HST: WFC3
HST: ACS
GAIA
SOFIA: EXES
SOFIA: FORCAST
TESS
LSST
JWST
SDSS-V: LVM
SDSS-V: BHM
SDSS-V: MWM
MOONS
EUCLID: IMAGER
EUCLID: GRISM
SPHEREx
WFIRST: IMAGER
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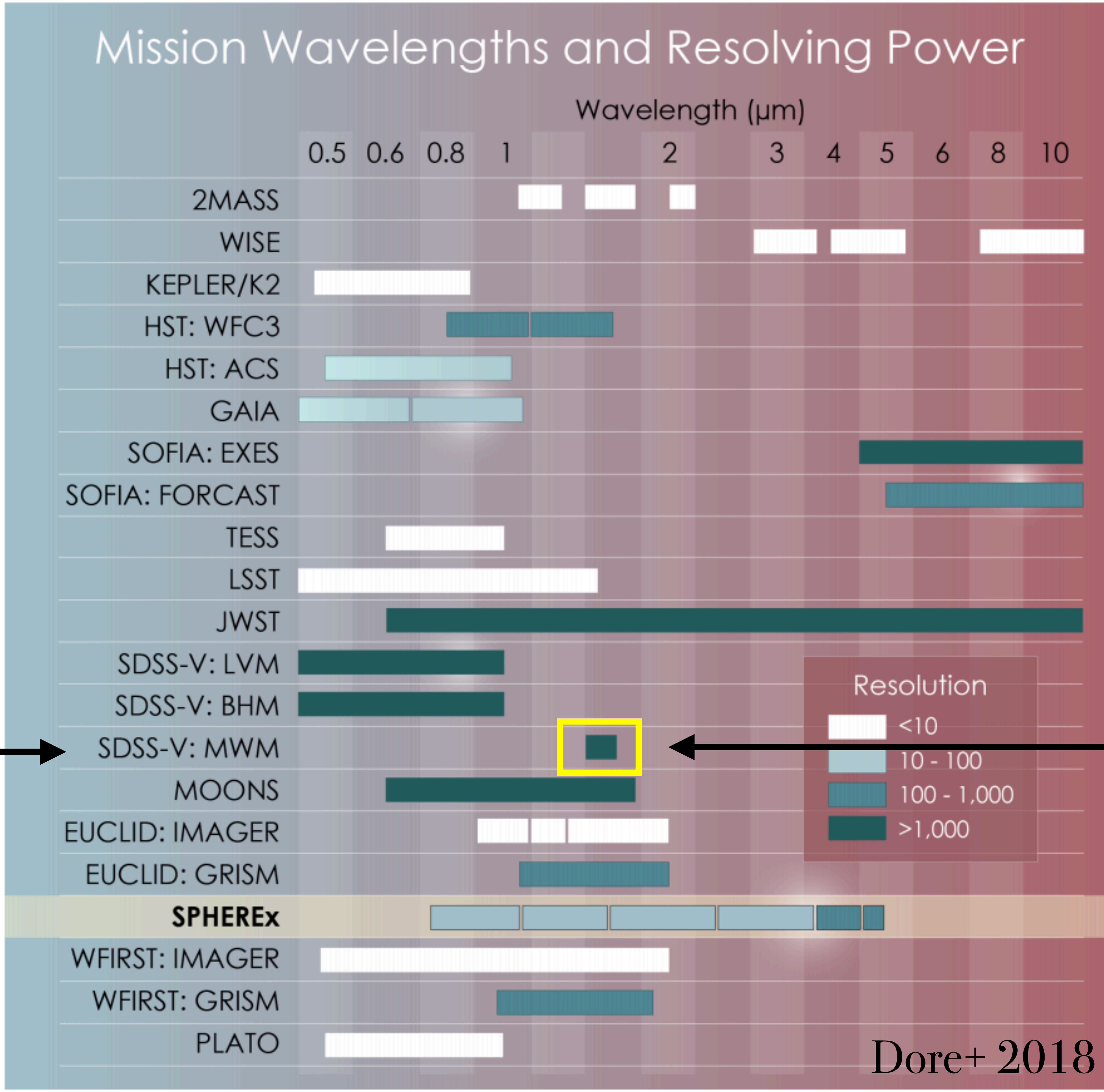
PLATO
Resolution
<10
10 - 100
100 - 1,000
>1,000
Dore+ 2018



R=22,500
1.5-1.7μm

R=1800
0.4-0.9μm

SDSS-V's Milky Way Mapper

- Target 5 million stars in the Milky Way with H < 11, G-H > 3.5
- Spans a spatial area of ~ 3000 deg^2

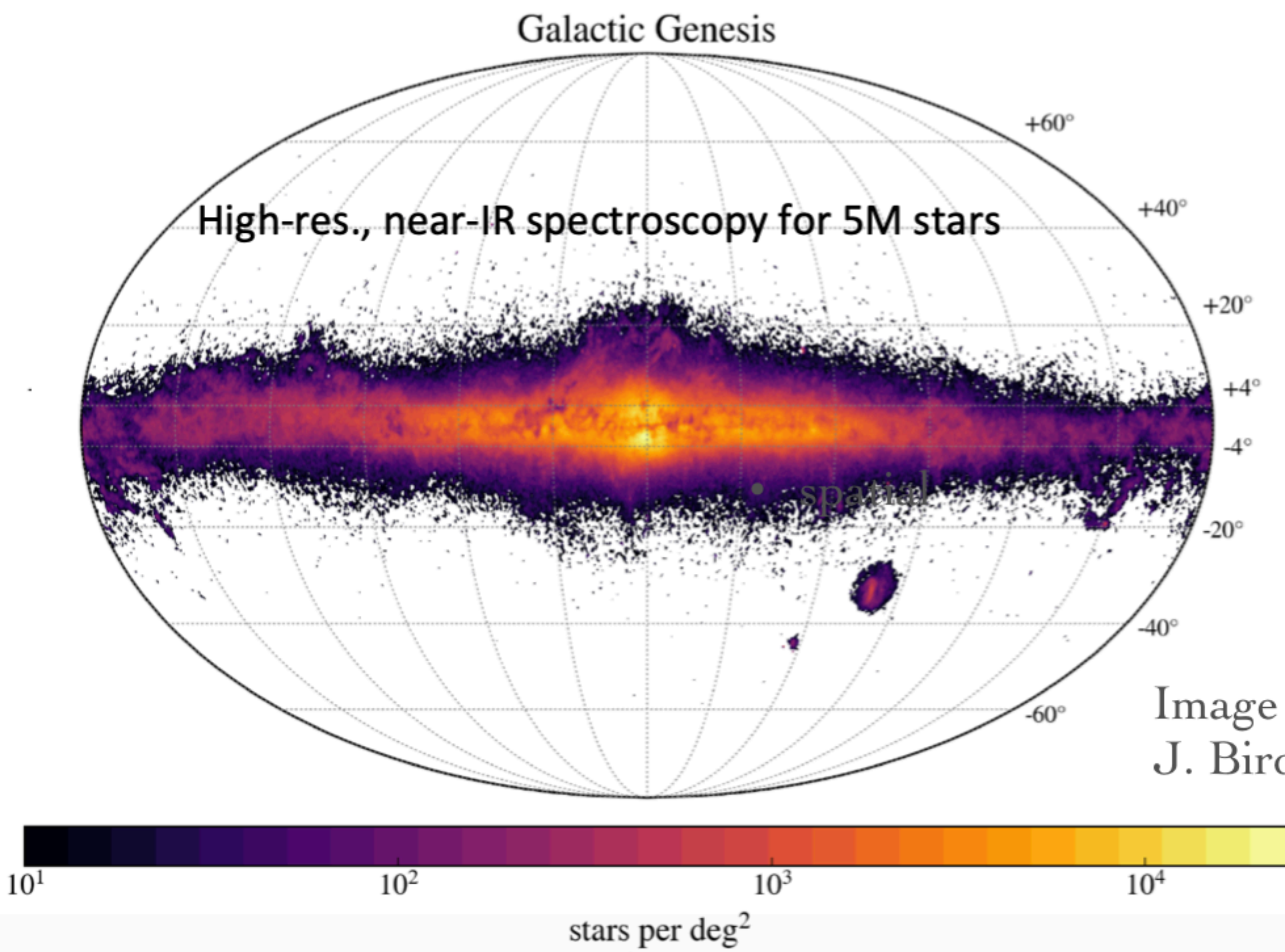


Image credit:
J. Bird (Vanderbilt)

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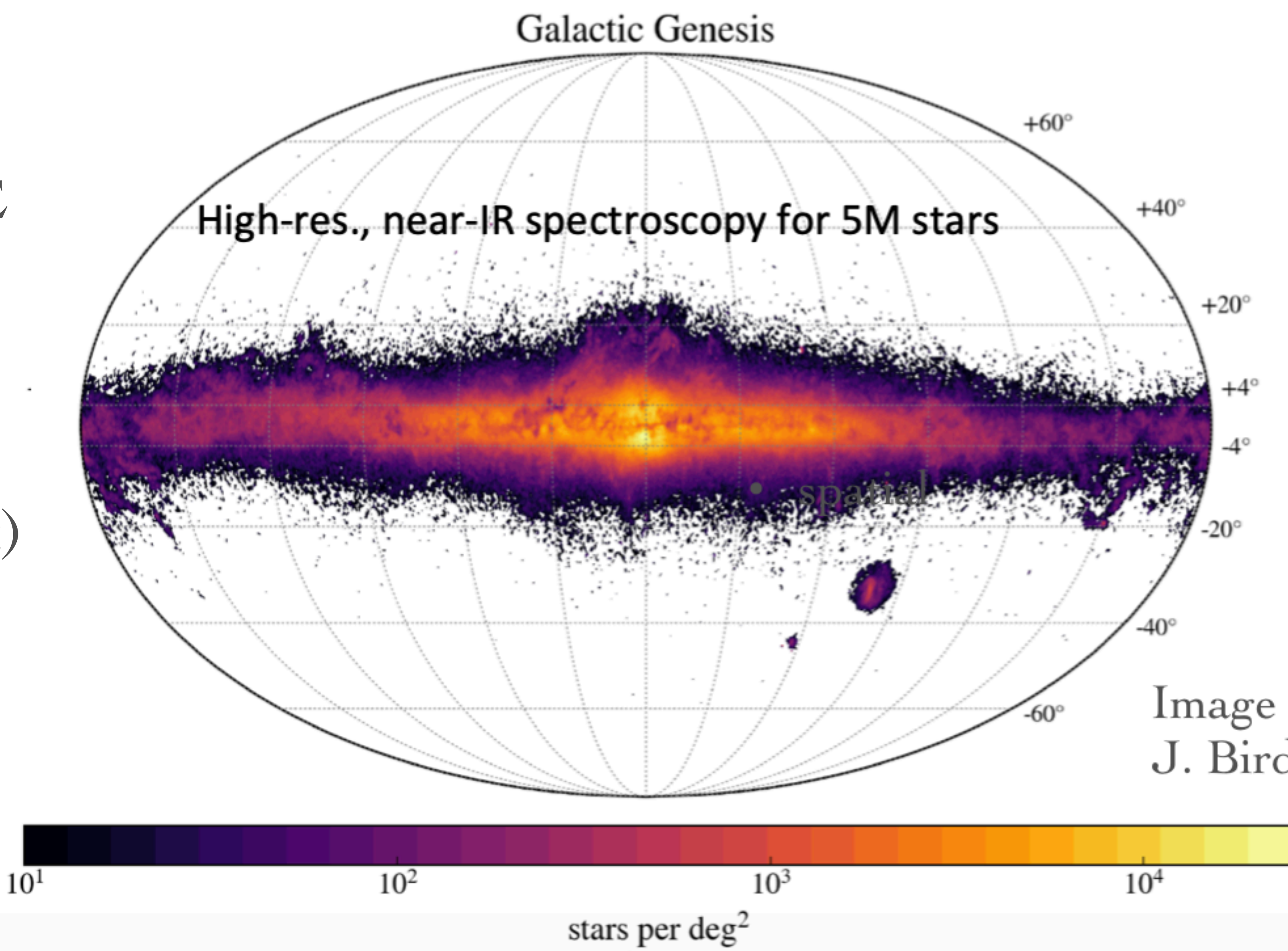
<u>Spectra</u>
R=22,500 -APOGEE
(R=1800 - BOSS)

<u>Measure</u>
Teff, logg,[Fe/H],
25 x [X/Fe] (0.05dex)
mass (age) (< 40%)
distances (< 20%)



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Data-Driven Modeling of Stars

Approach to infer stellar parameters and individual abundances for stars in large surveys

[The Cannon (Ness+2015), The Payne (Ting+ 2017), AstroNN (Leung+ 2019)]

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- **Precise** (2-3 times higher precision than previous approaches)
- **Computationally fast**
- Understand **where/how** information distributed

Data-Driven Modeling

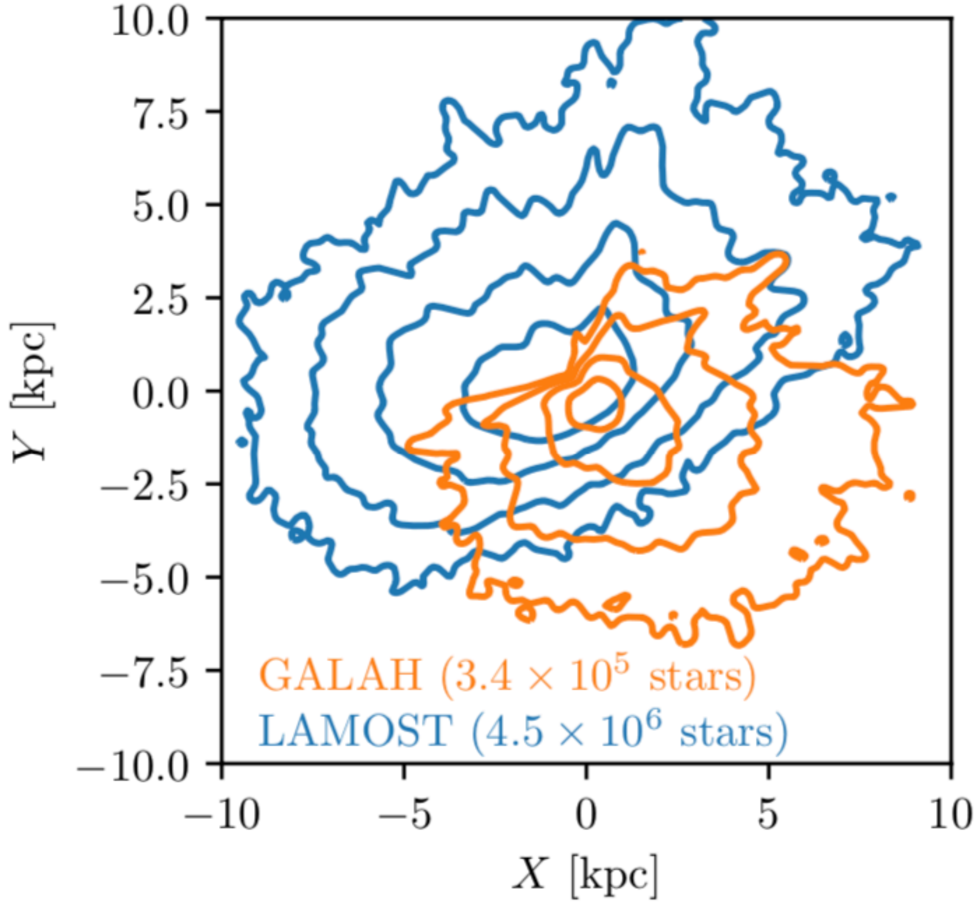
Approach to “betterize" spectra in large surveys — de-noise and in-paint missing regions

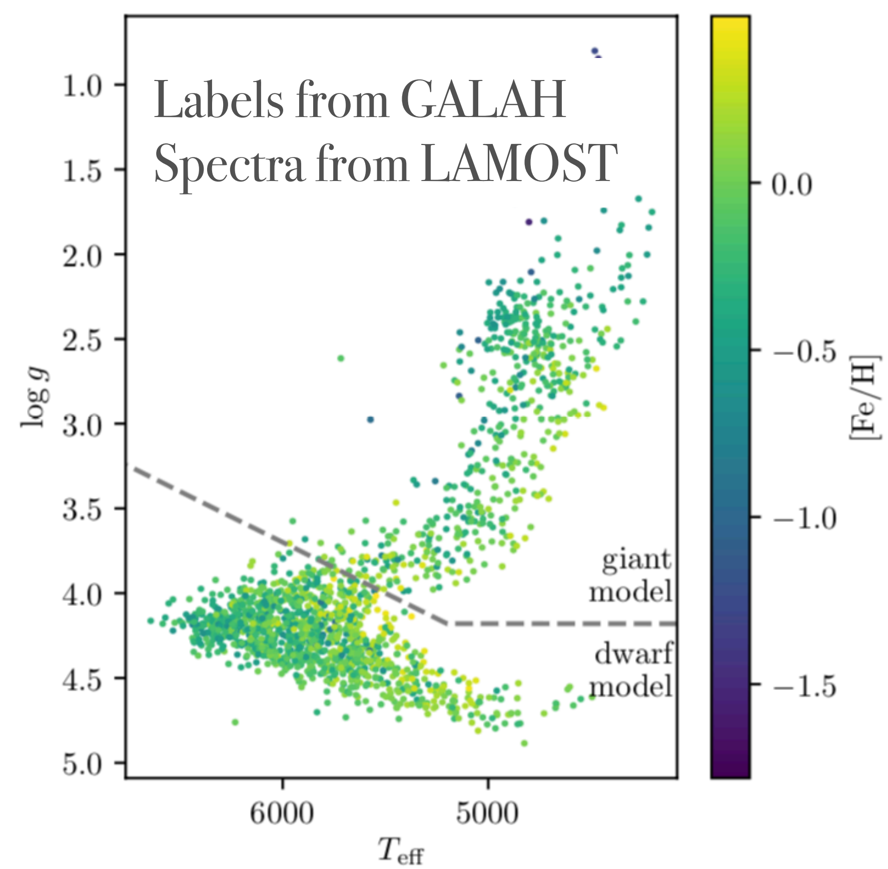
SSSpaNG! (Feeney, Wandelt, Ness 2020)

Spectra as data-driven non-Gaussian processes

The Cannon (for label transfer)

Determined [X/Fe] labels for LAMOST (R=1800) – using stars in common with GALAH (R=28,000)





Adam Wheeler, Ness+ 2020

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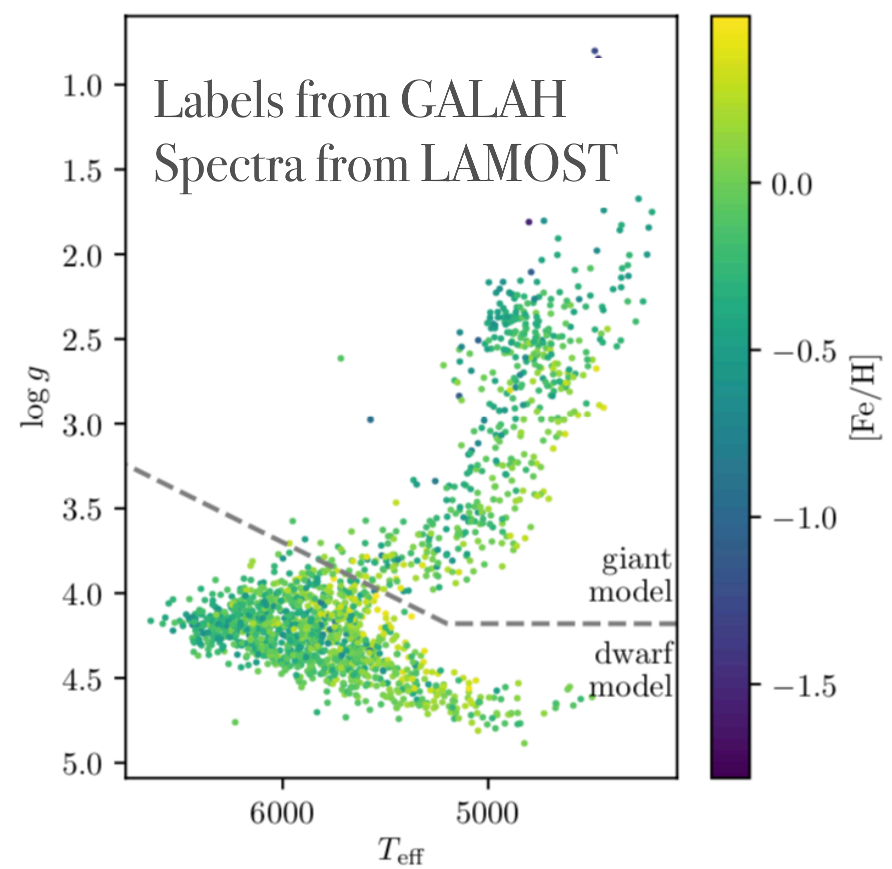

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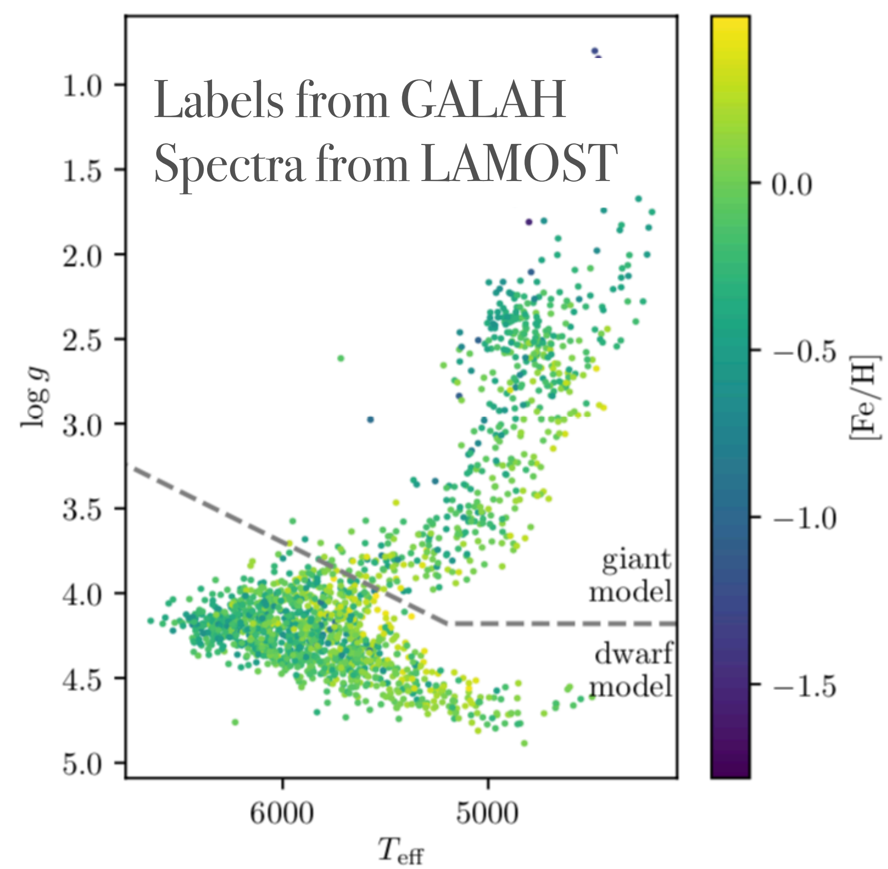

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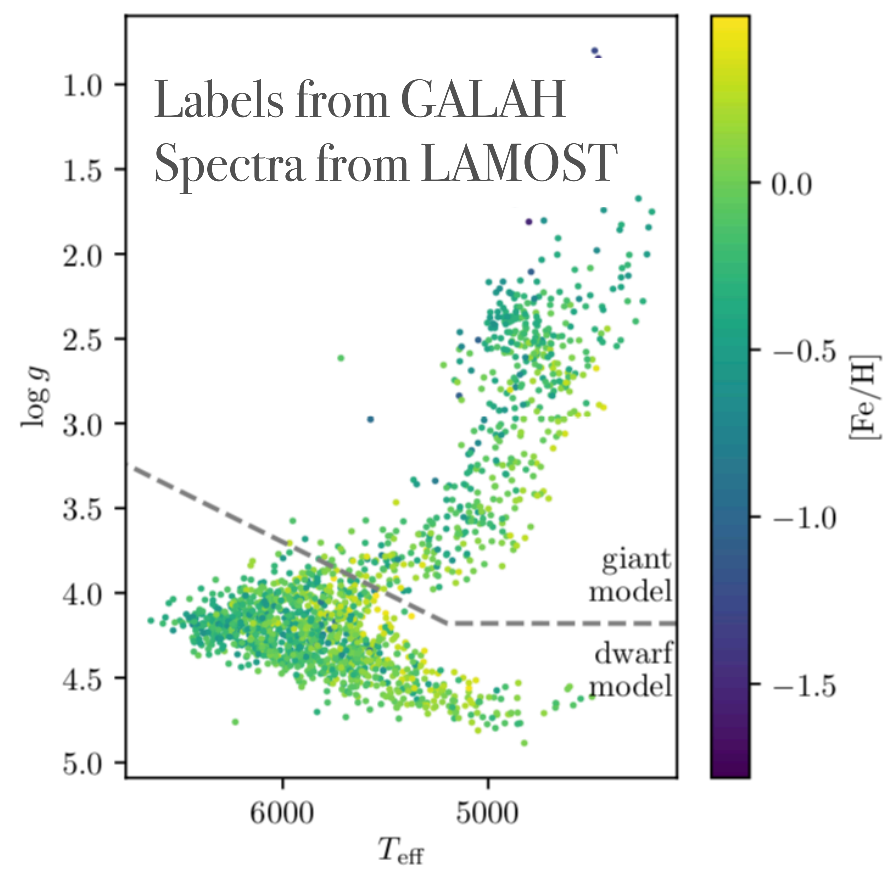

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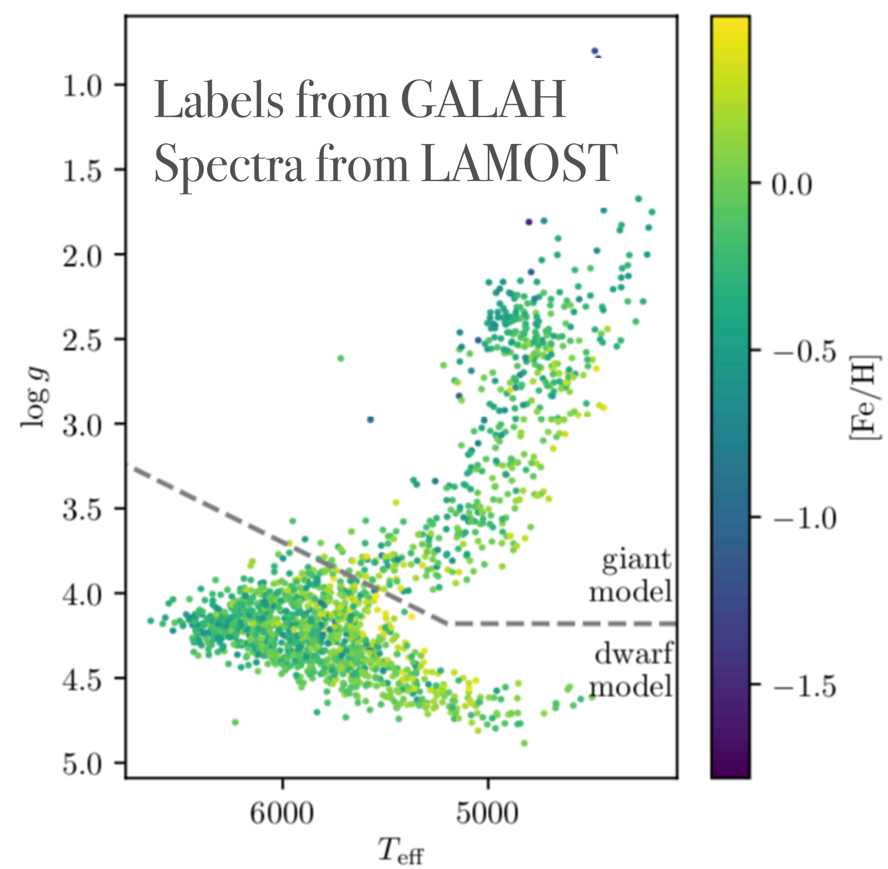

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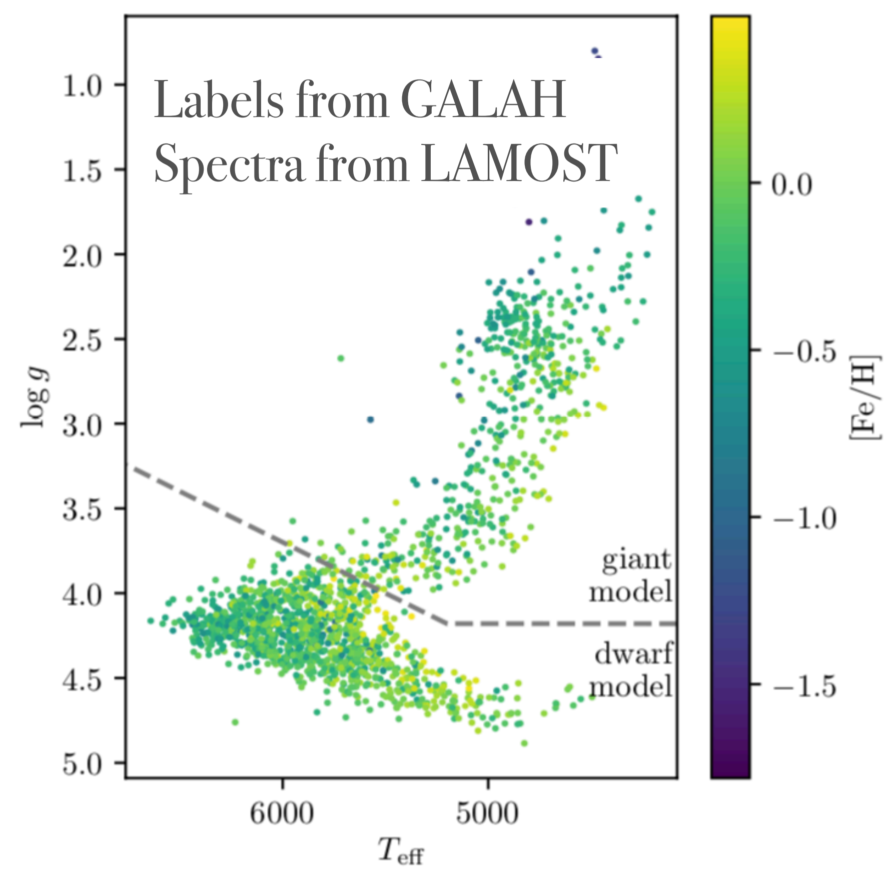

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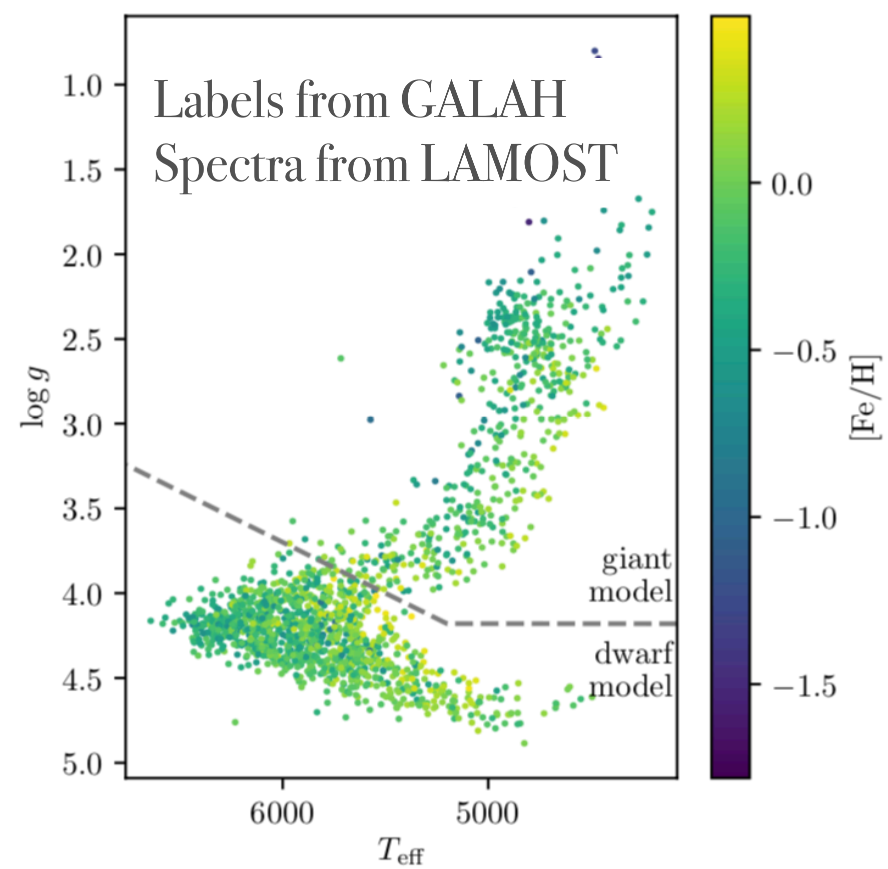

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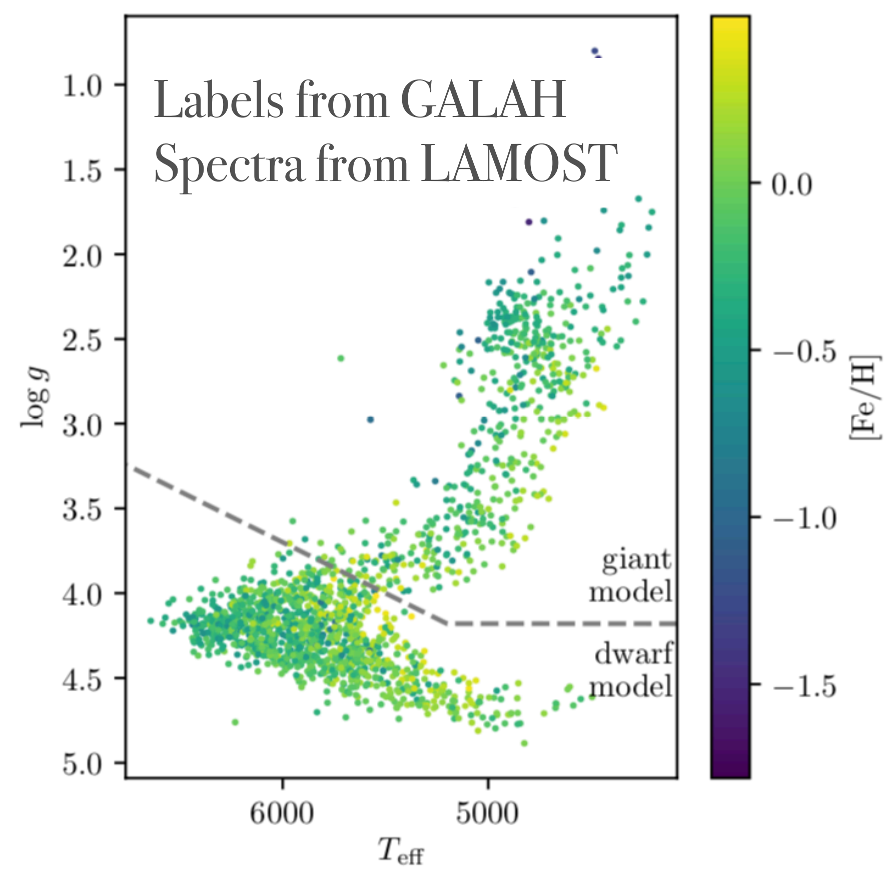

Adam Wheeler, Ness+ 2020

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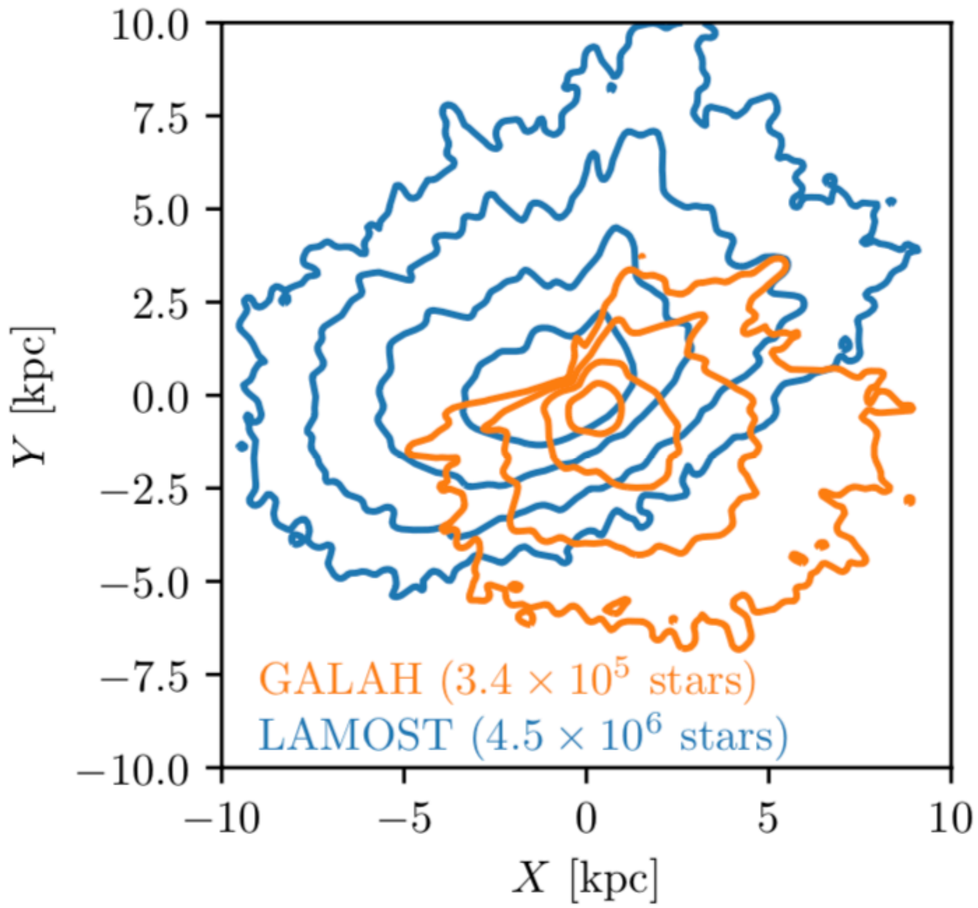

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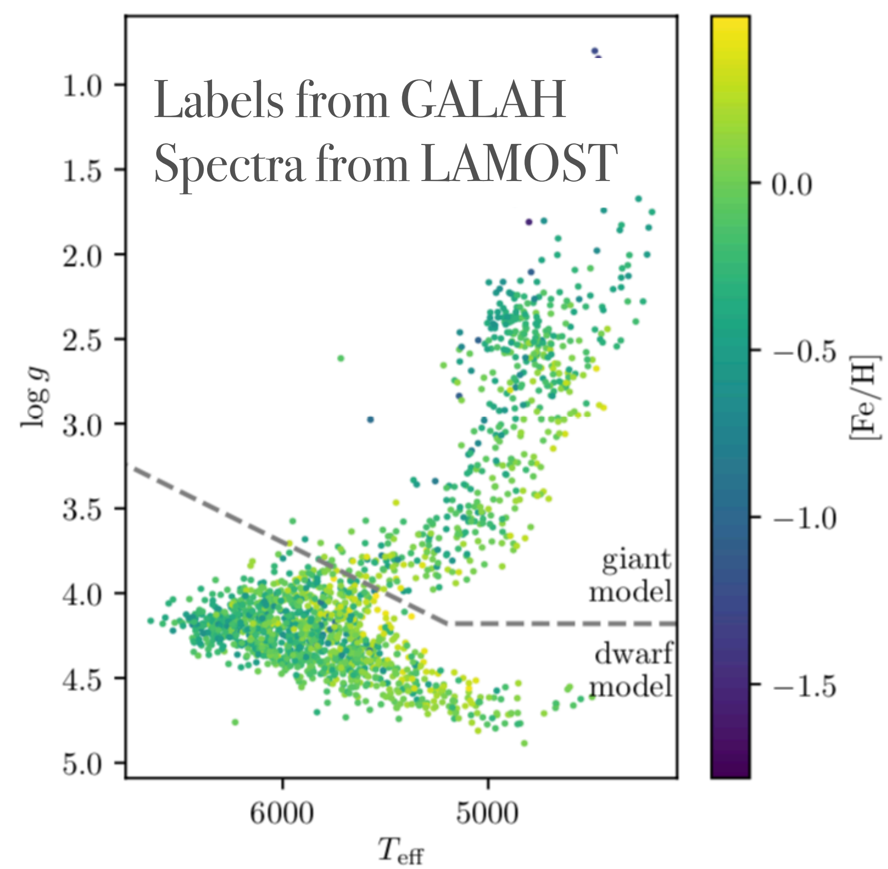

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GALAH labels

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Wheeler,
Ness+ 2020

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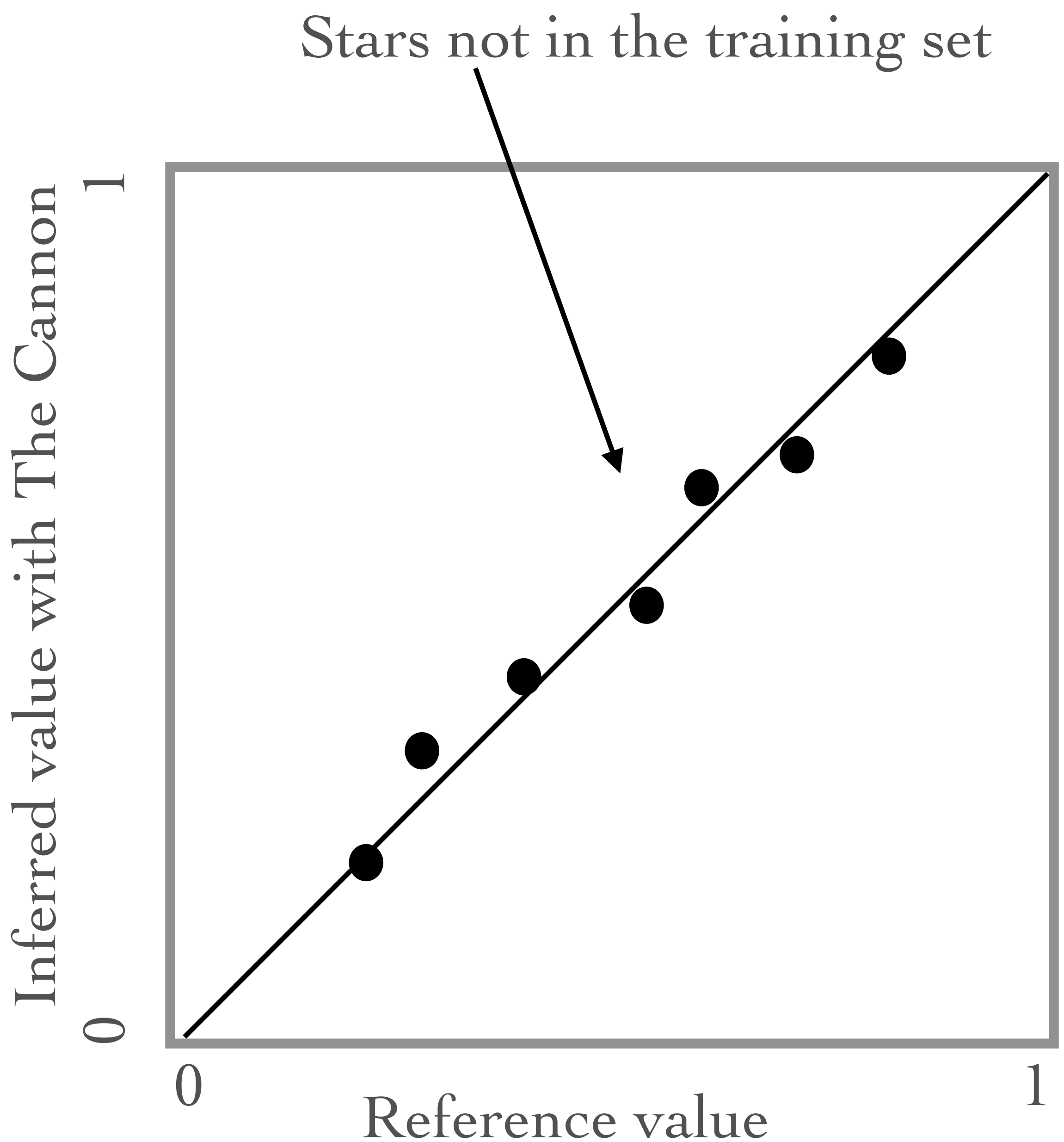
Wheeler, Ness+ 2020

Validation



Adam
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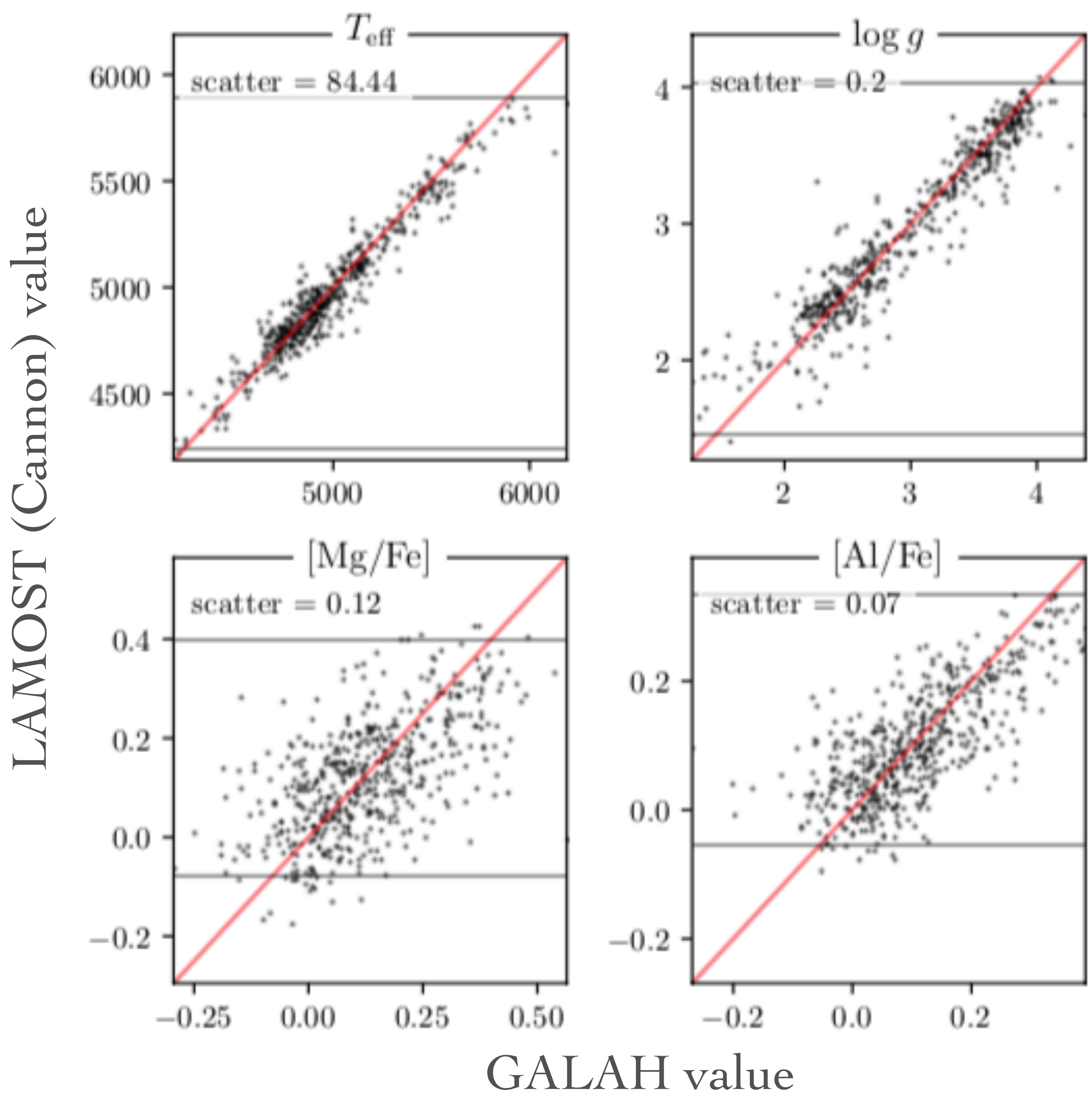

Adam Wheeler, Ness+ 2020

Data-Driven Modeling with SPHEREx

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- Propagate labels between SPHEREx and Sloan V data

Data-Driven Modeling with SPHEREx

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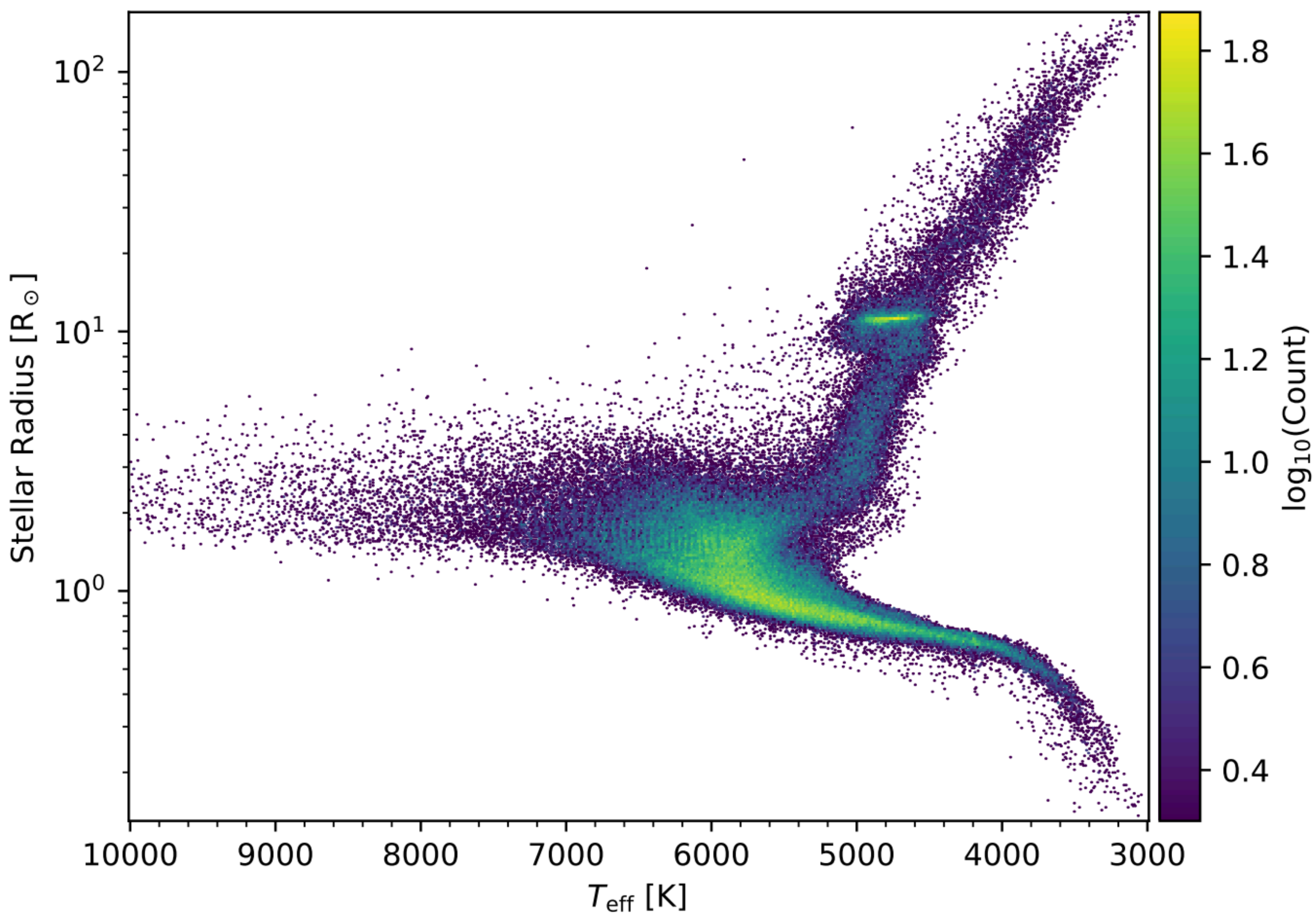
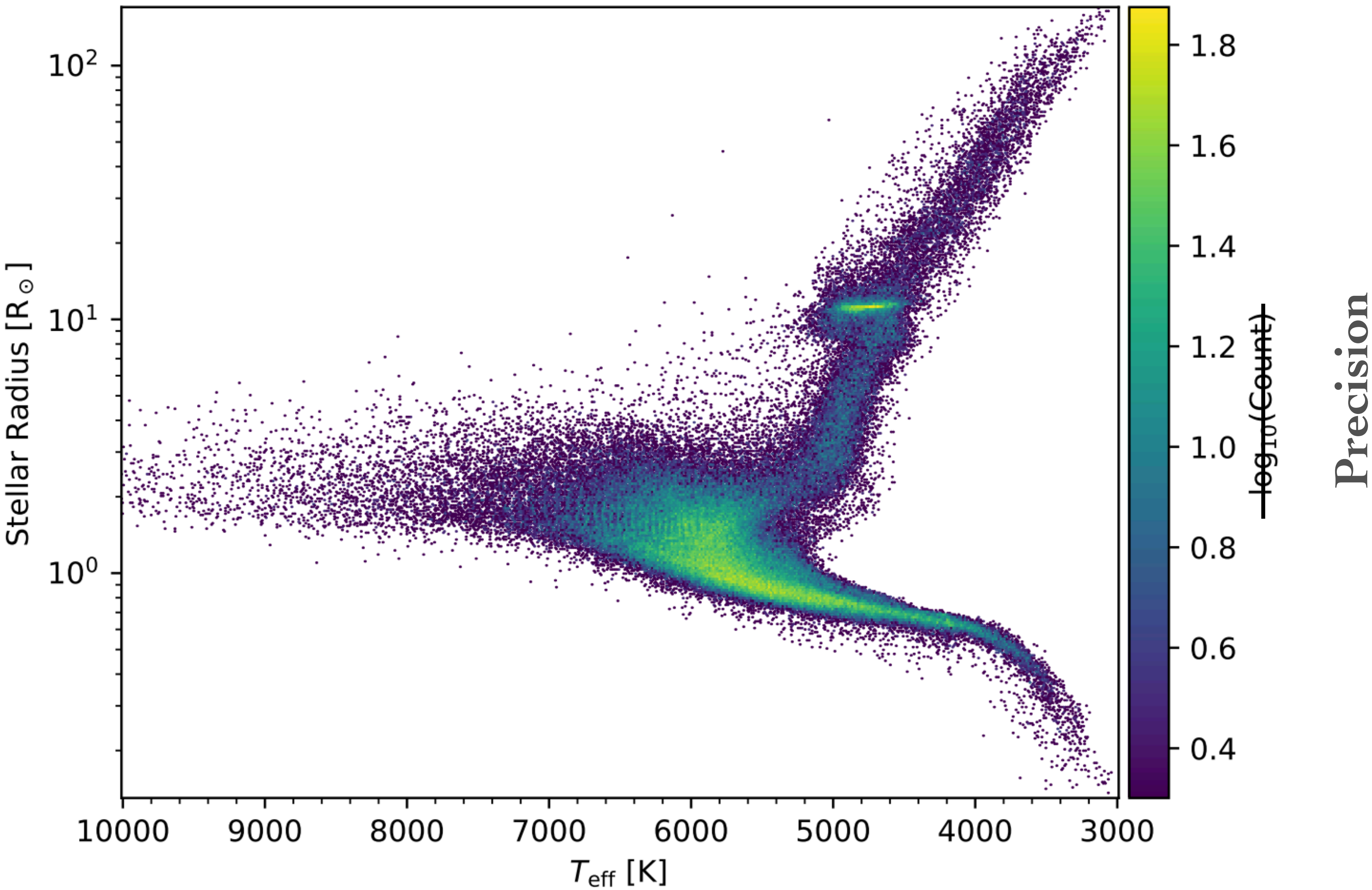


Berger+ 2019

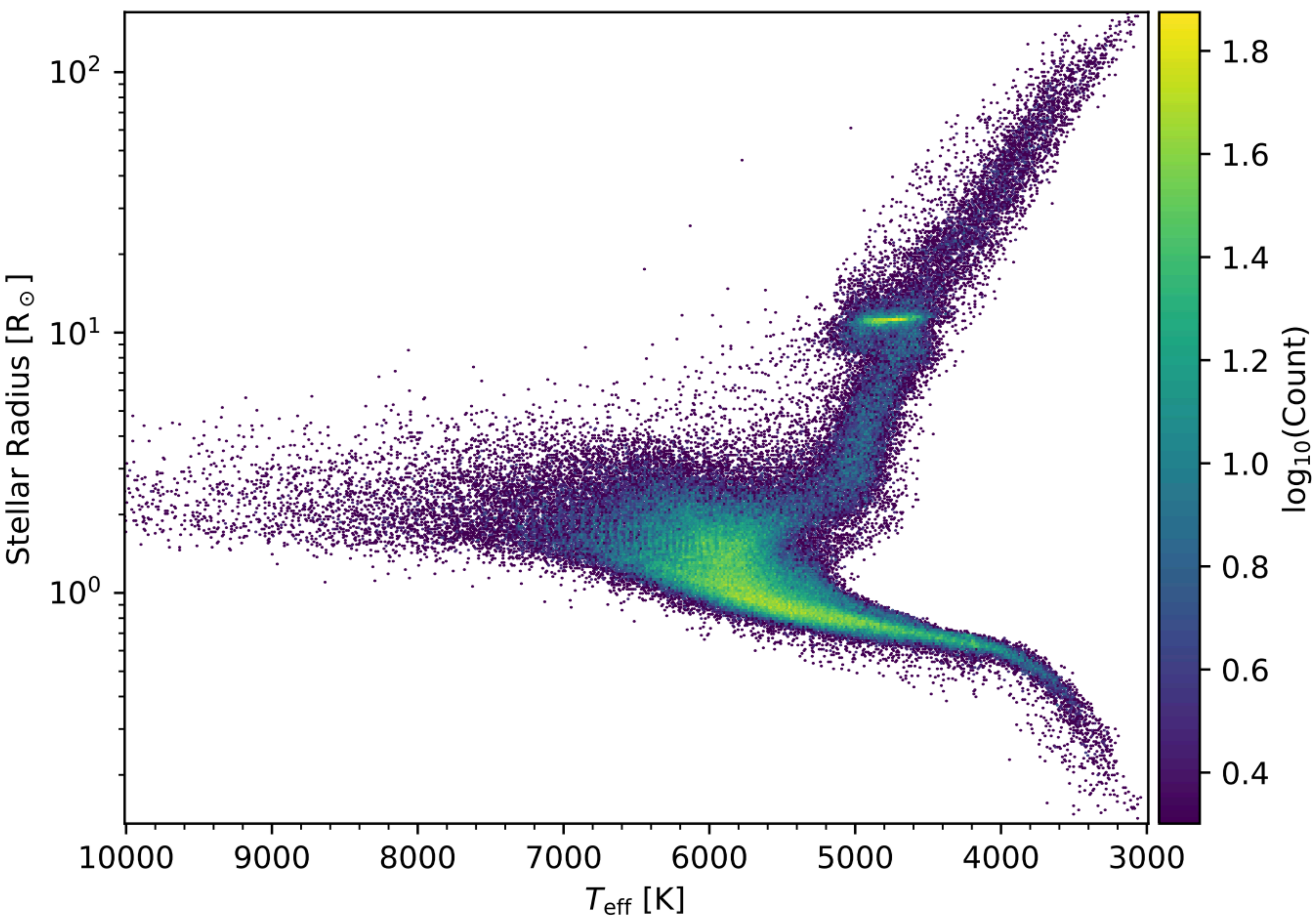
Data-Driven Modeling with SPHEREx

- Propagate labels between SPHEREx and Sloan V data
- What labels can we infer from SPHEREx spectra and to what precision
- What does stellar SPHEREx data look like?



Berger+ 2019

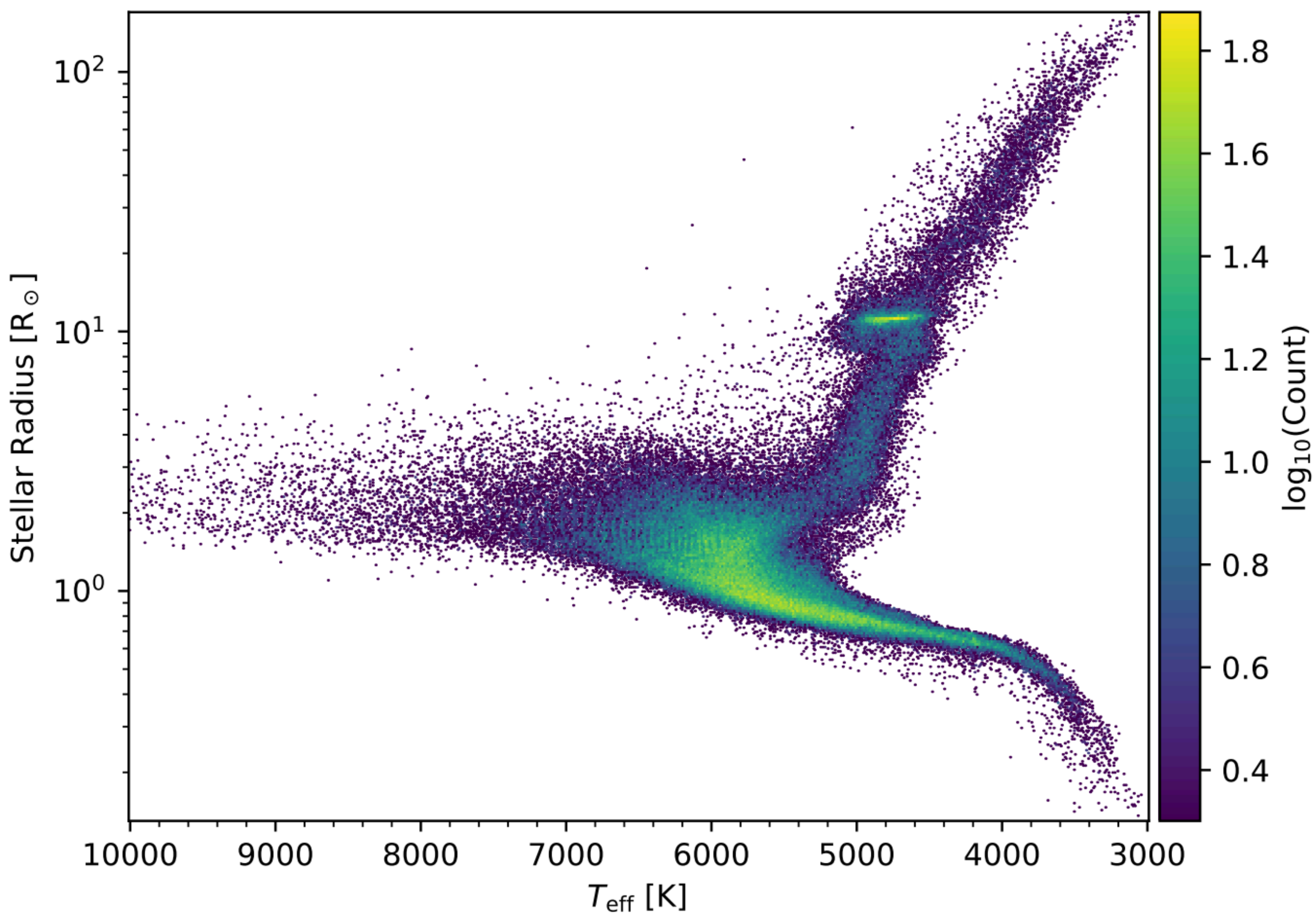
Stars as seen by SPHEREx?



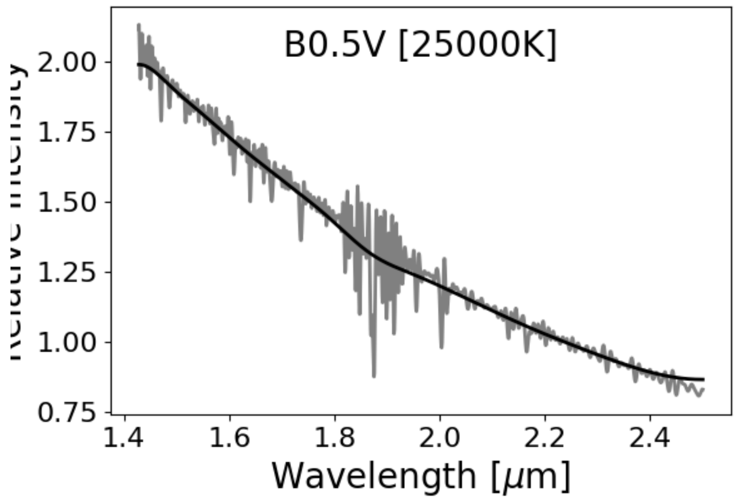
Berger+ 2019

Stars as seen by SPHEREx?

Lacon+ 1996 Near-IR spectra for 56 stars across the HR diagram R= 500 (grey)



Berger+ 2019



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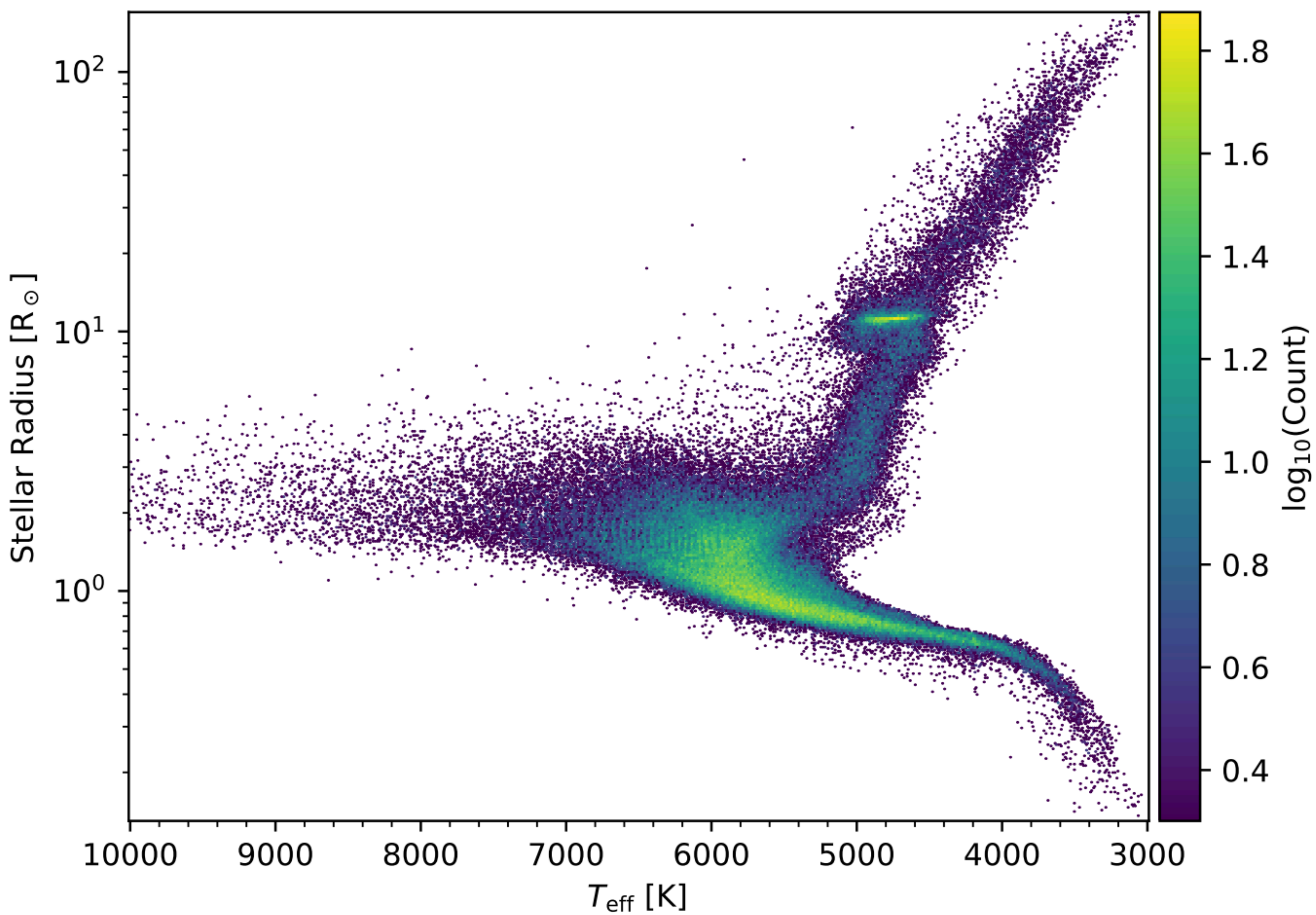

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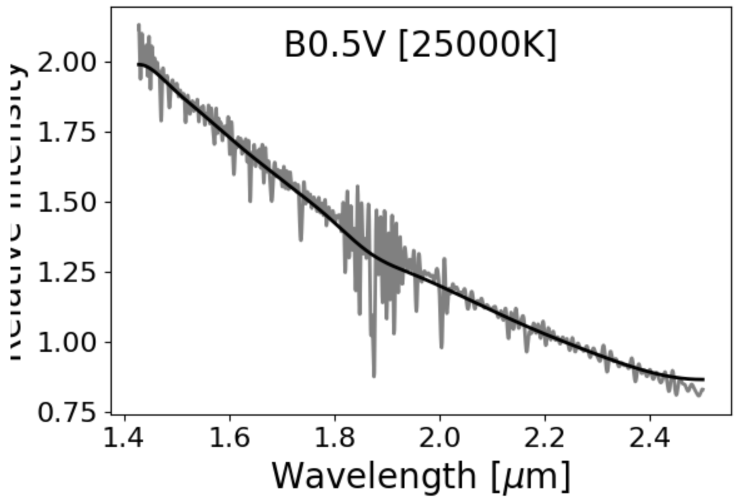

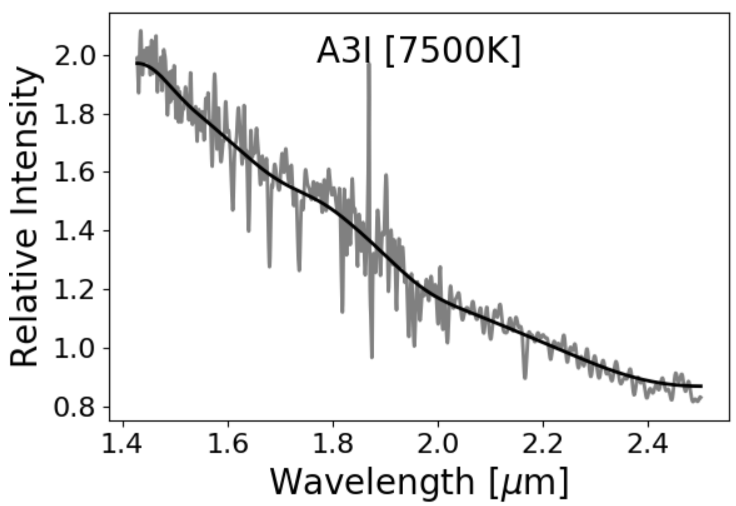

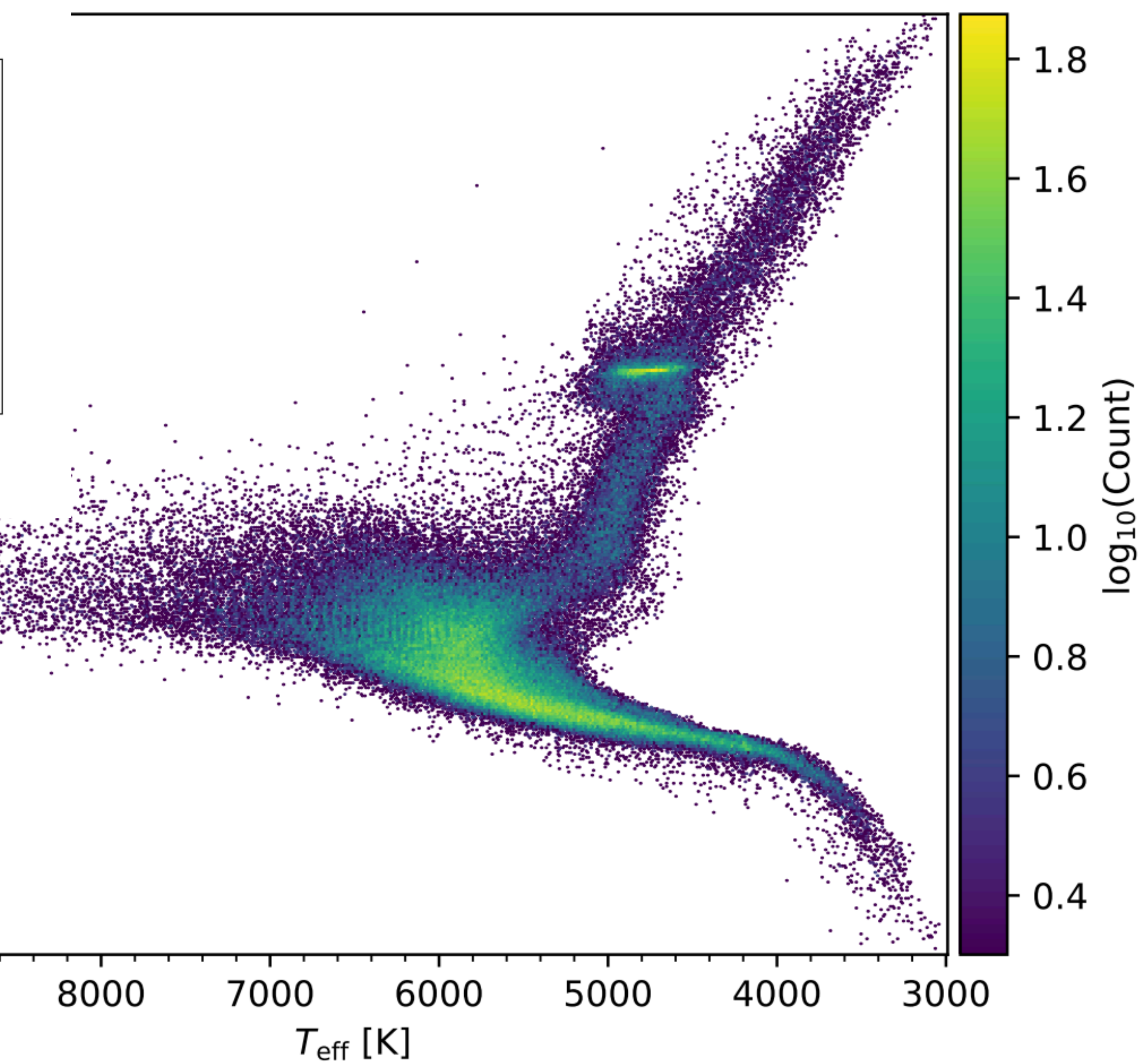

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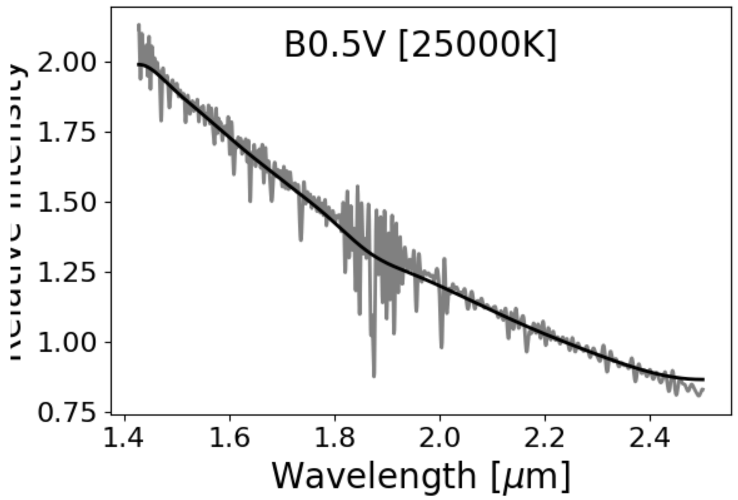

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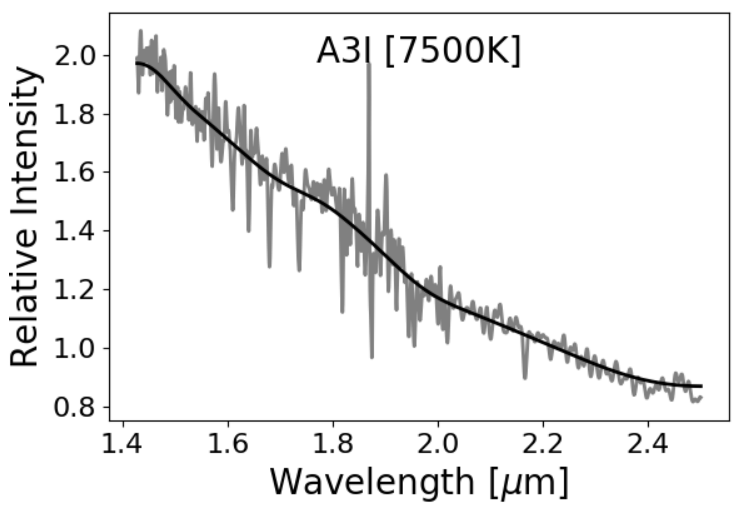

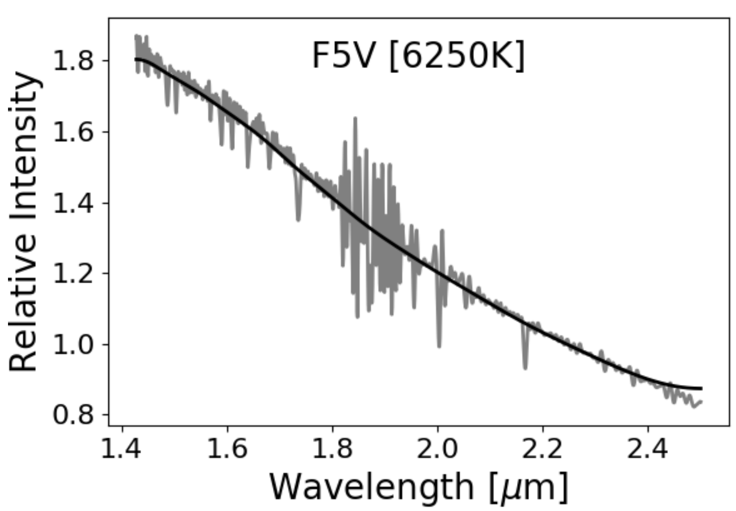

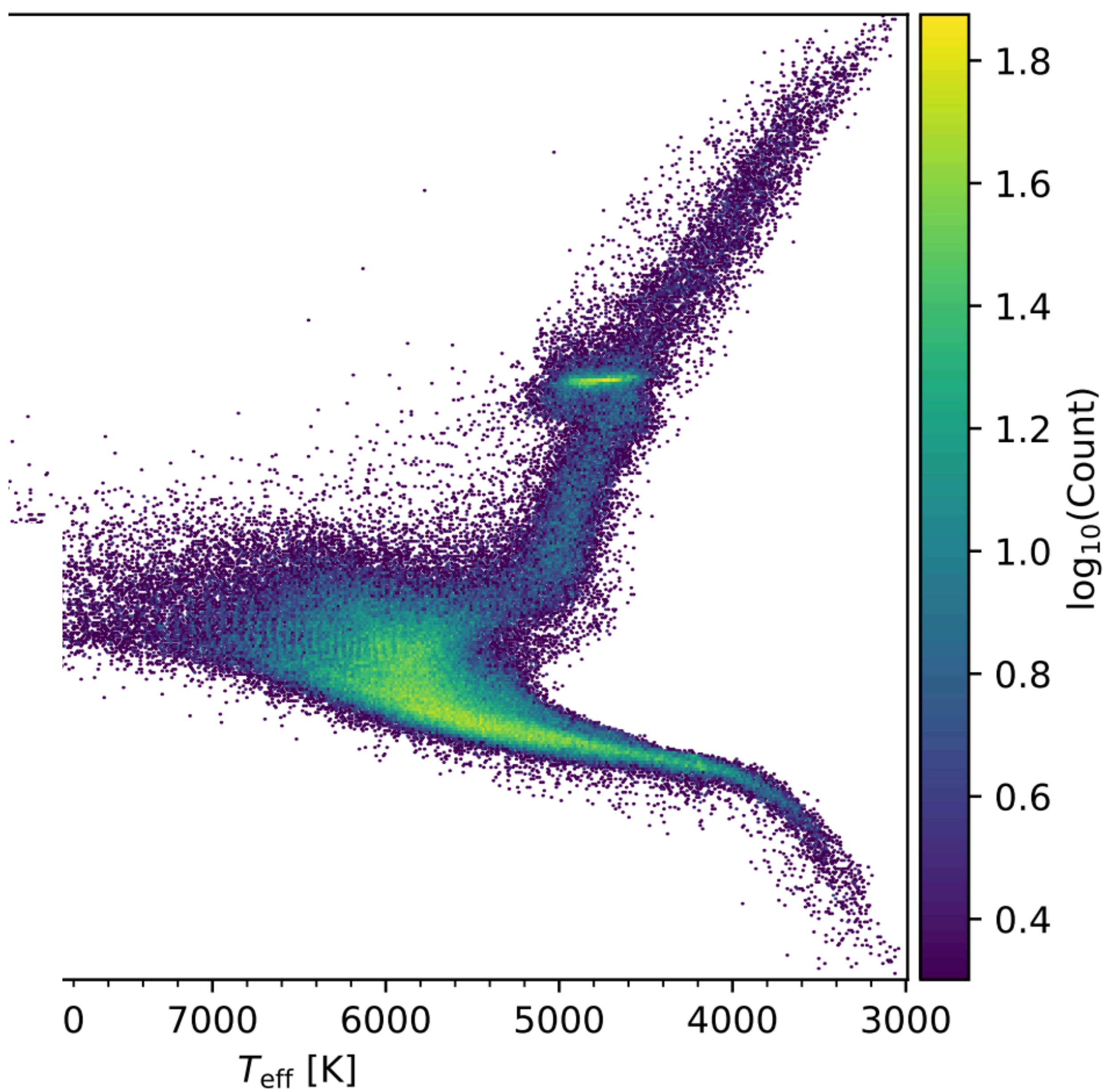

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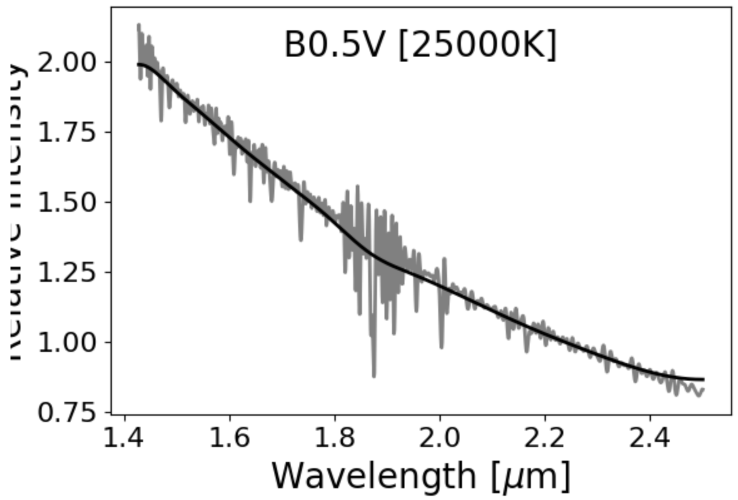

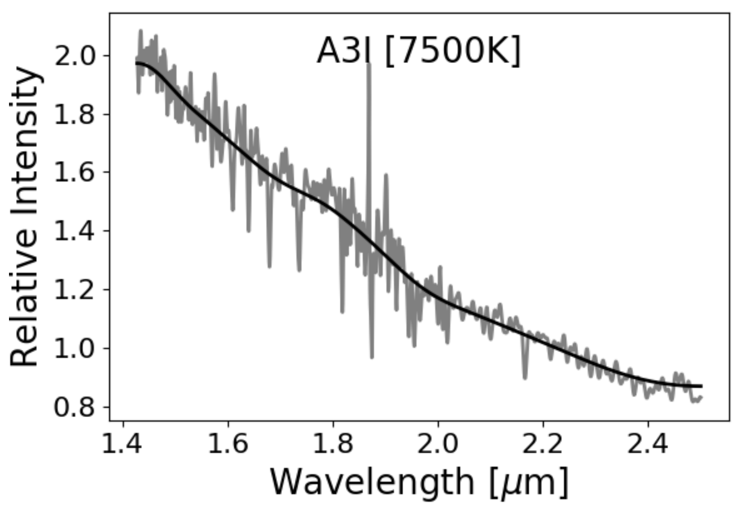

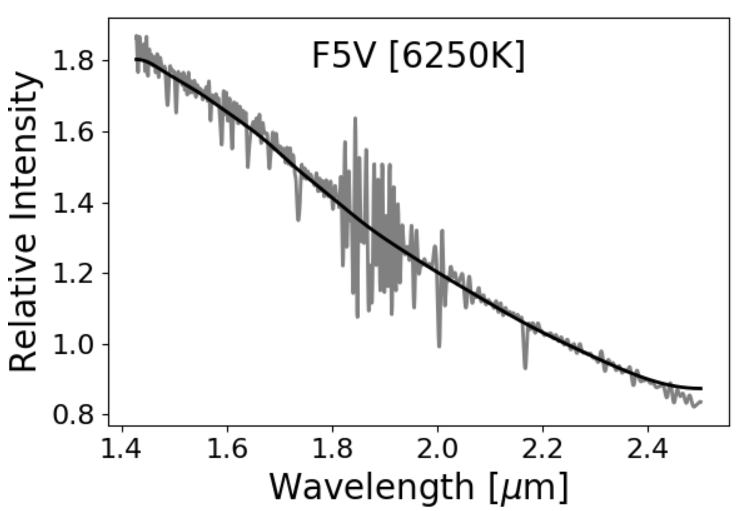

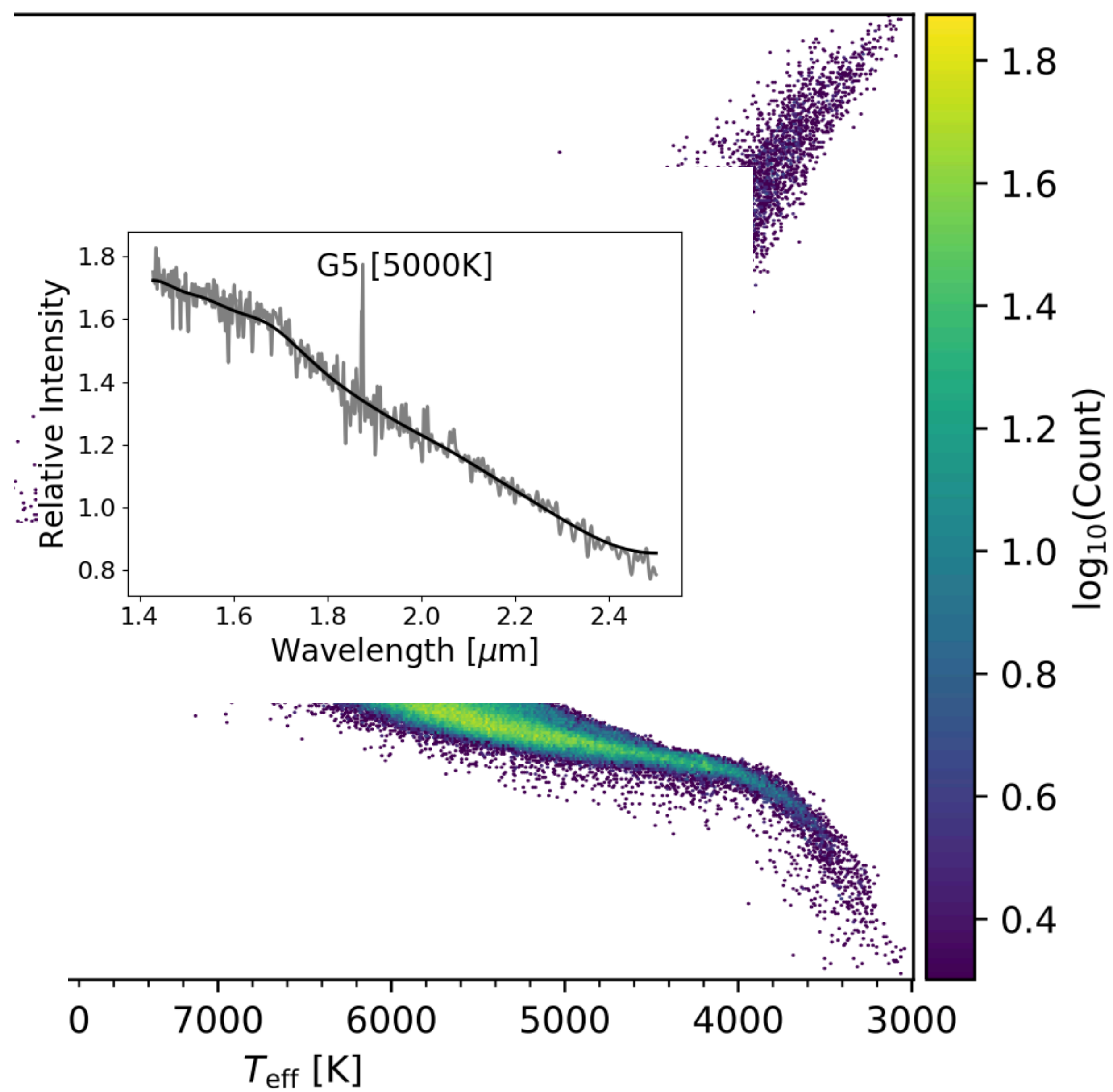

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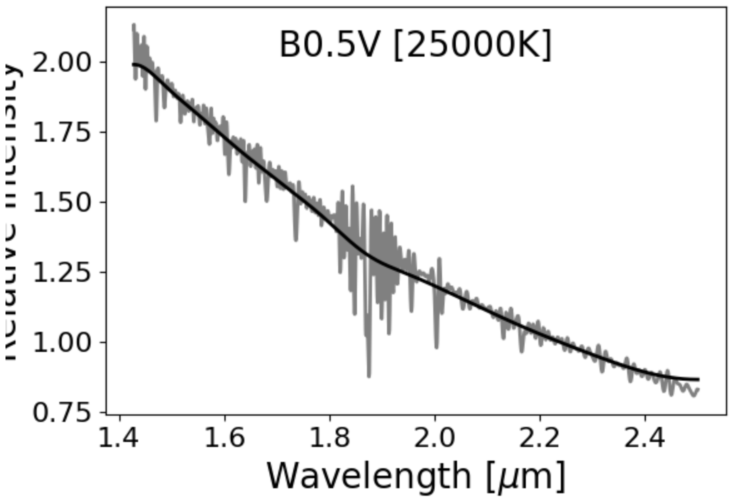
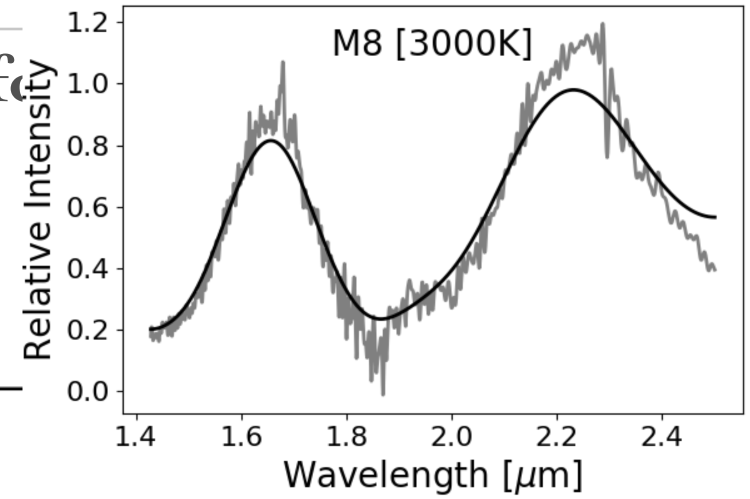
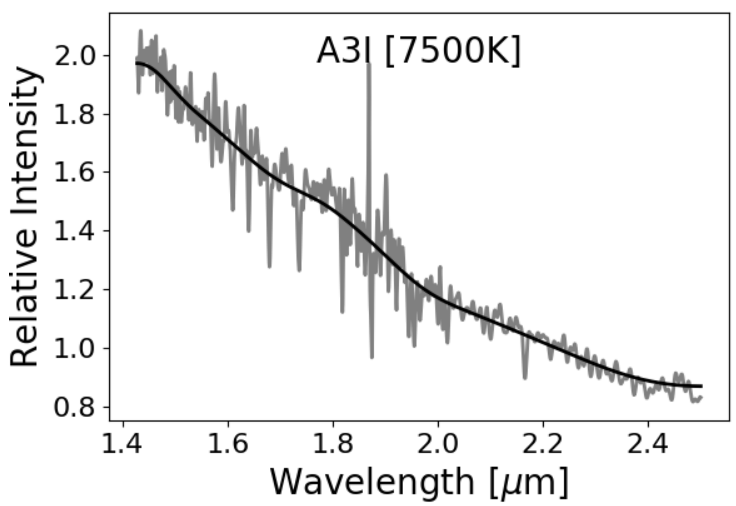
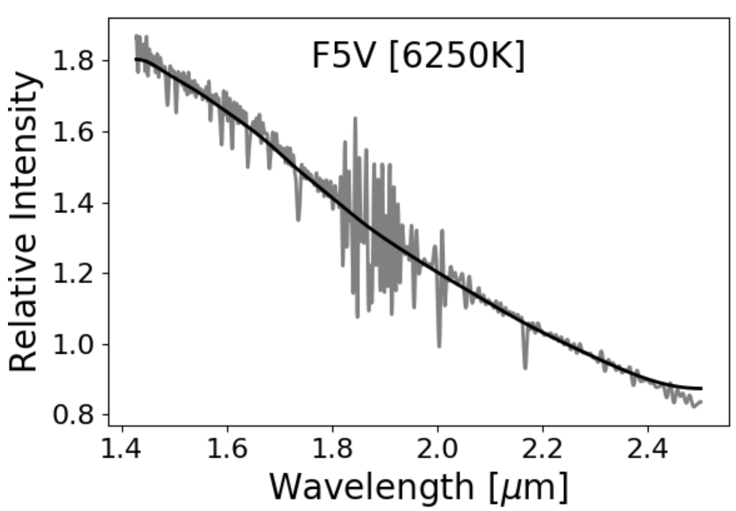
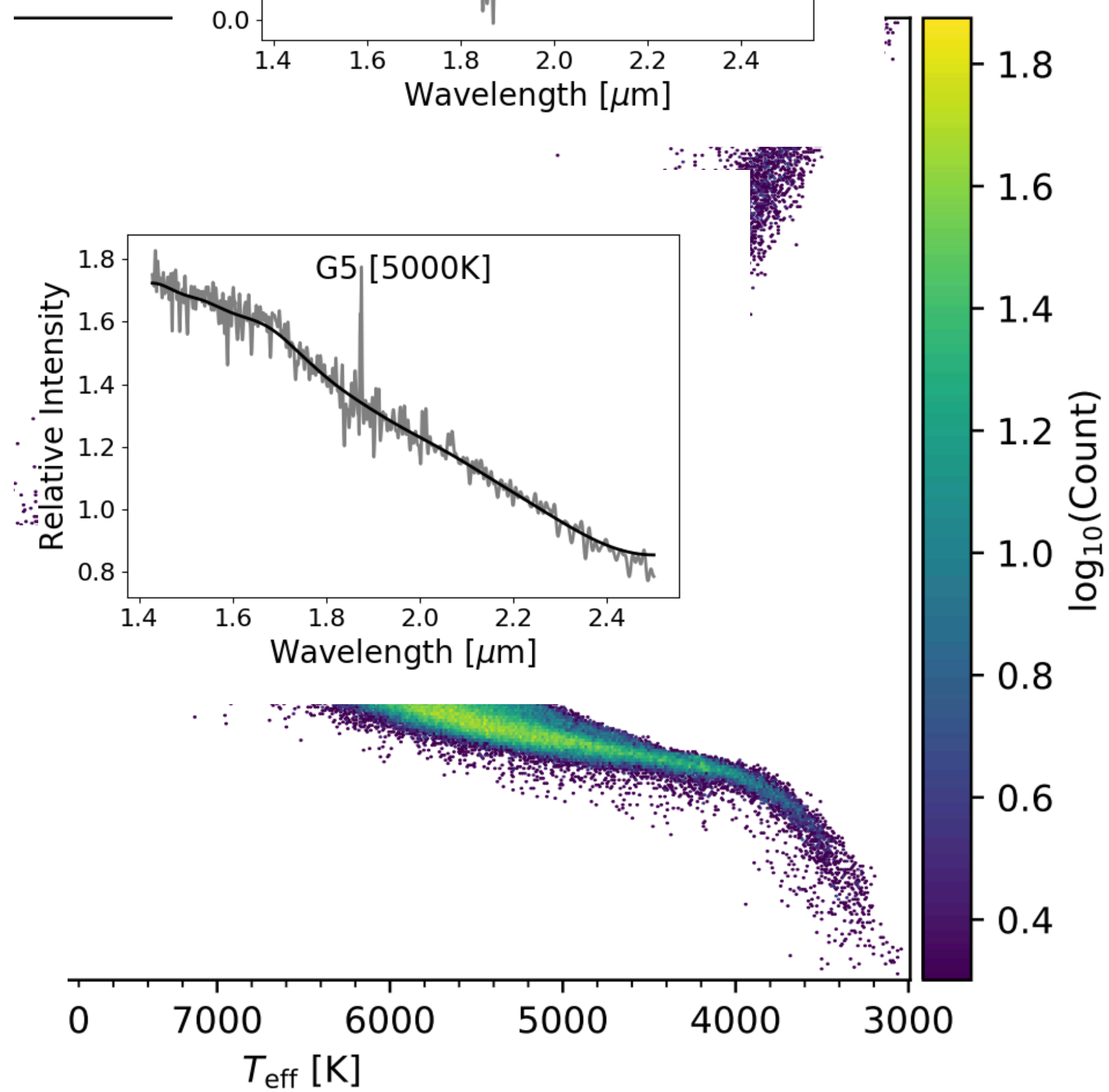






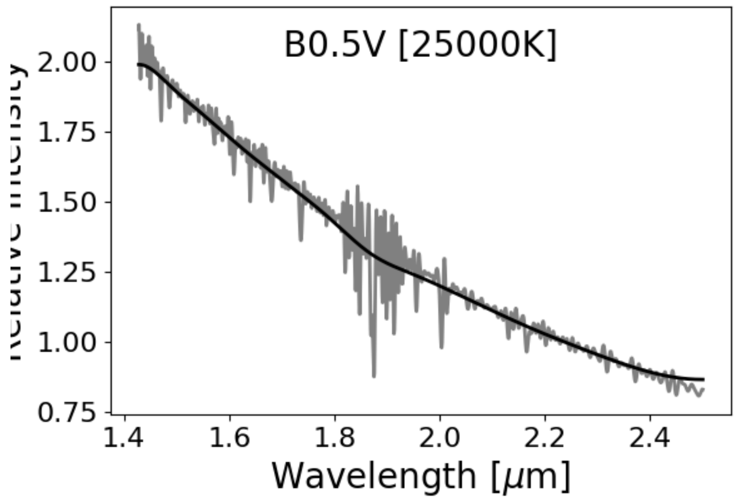


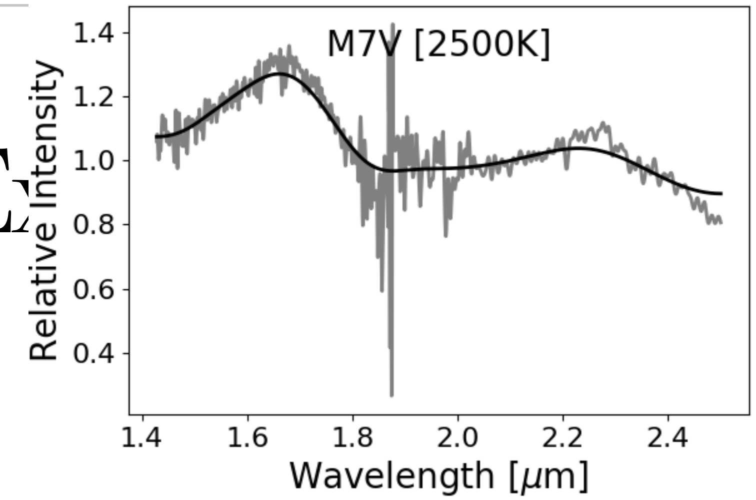


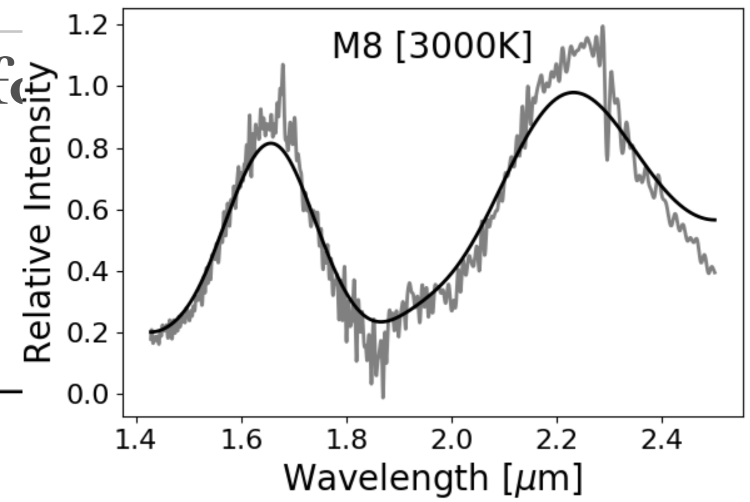
Berger+ 2019

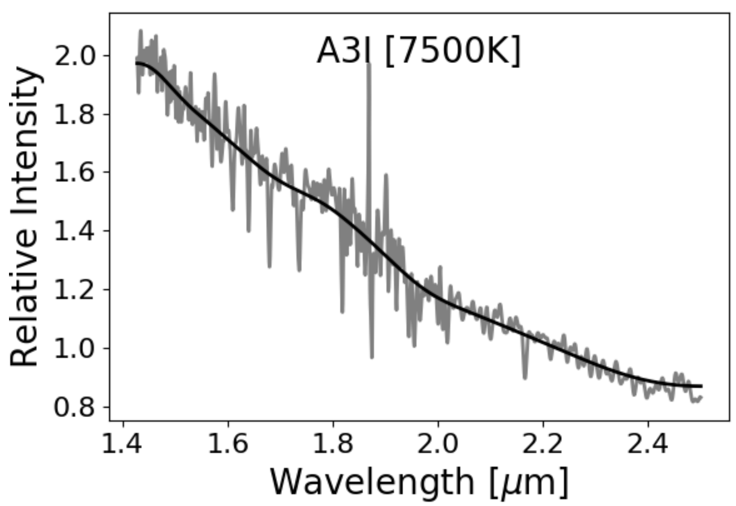
ars as seen by SPHERE

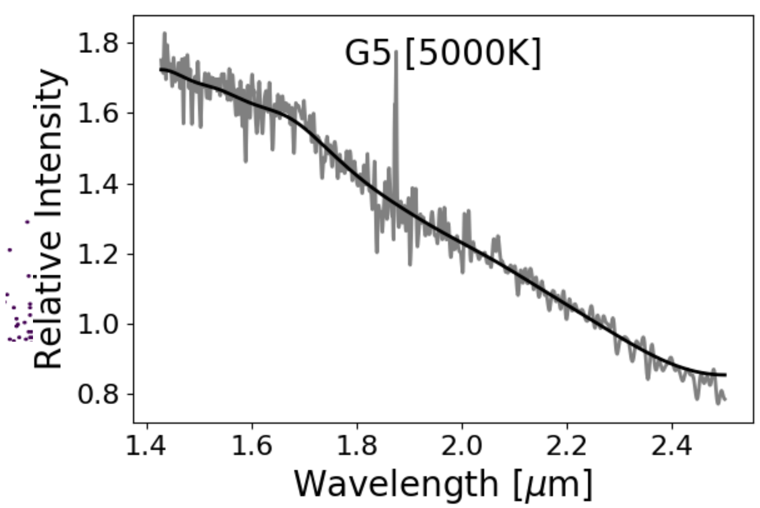
spectra f

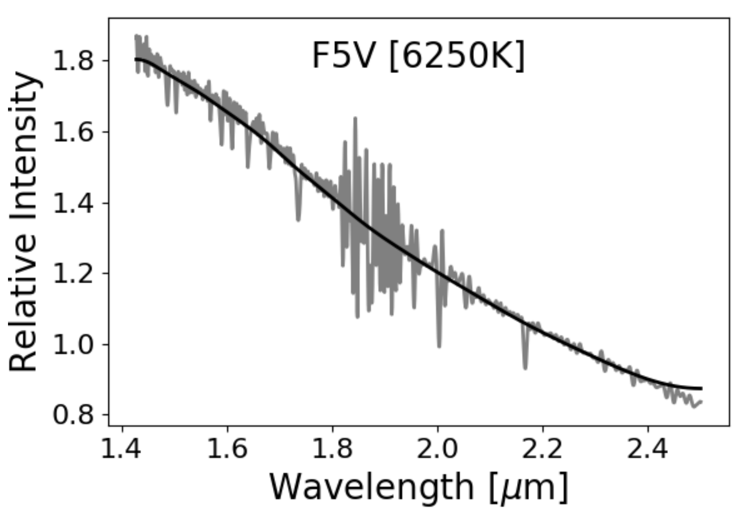


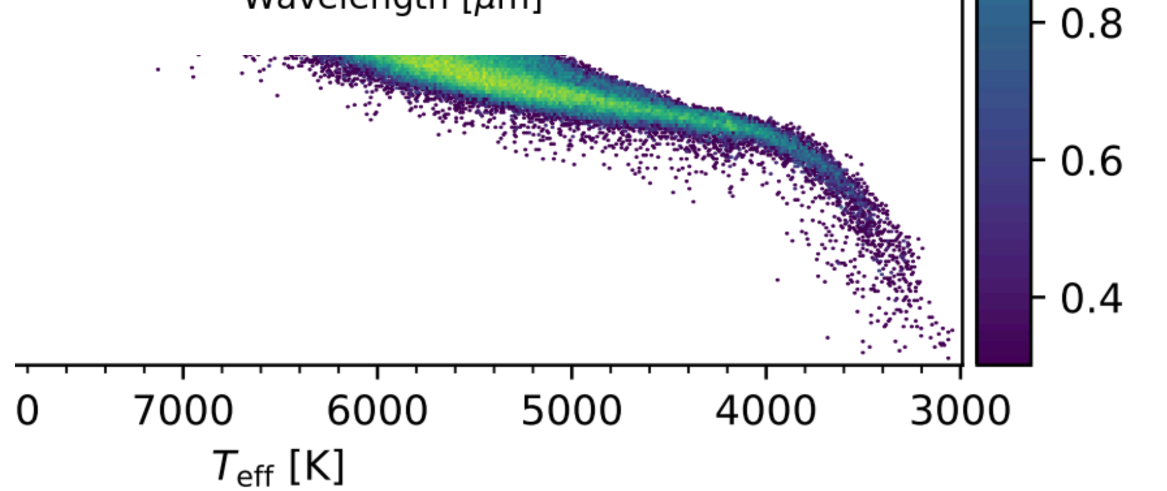








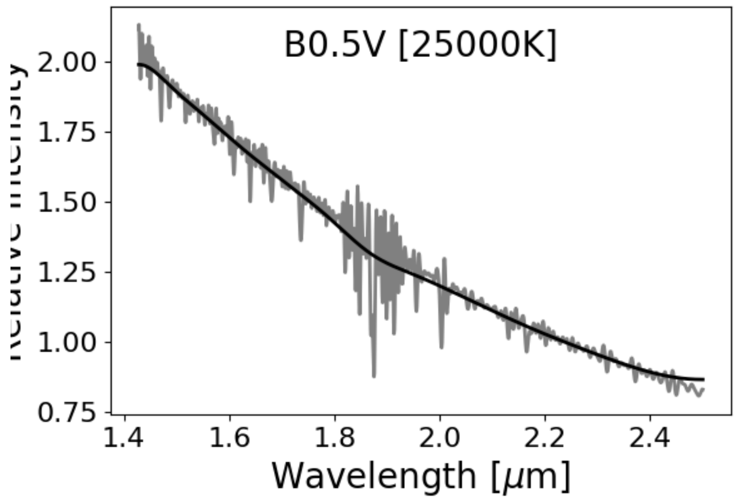


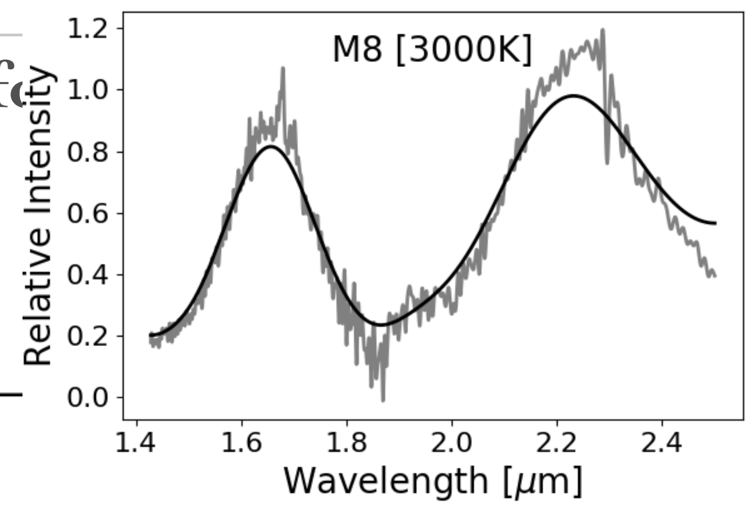


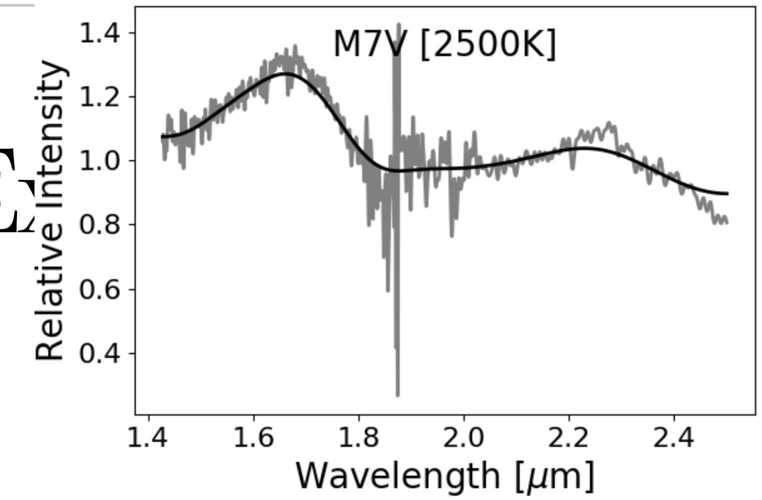
Berger+ 2019

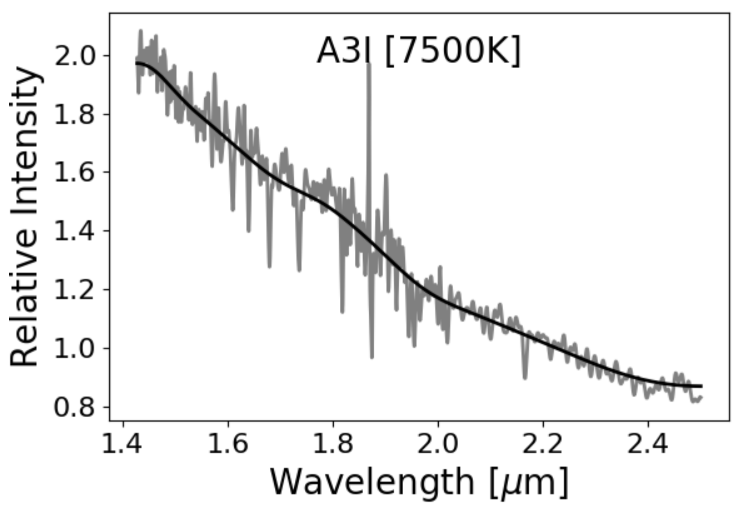
ars as seen by SPHERE

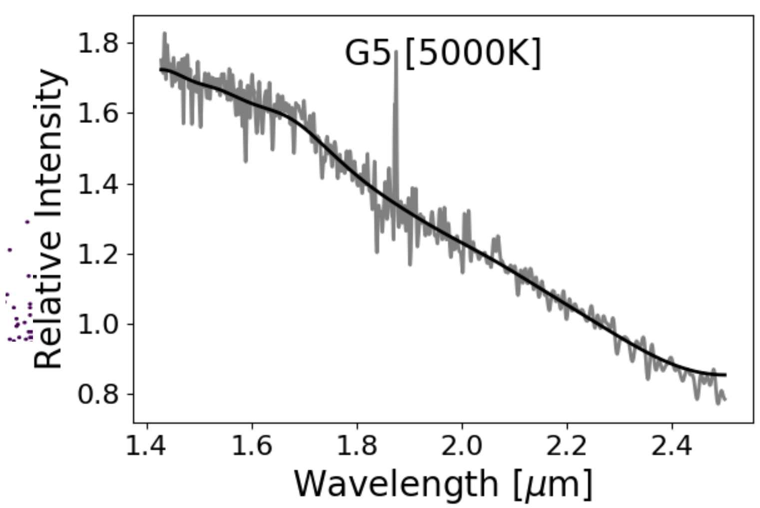
spectra fo

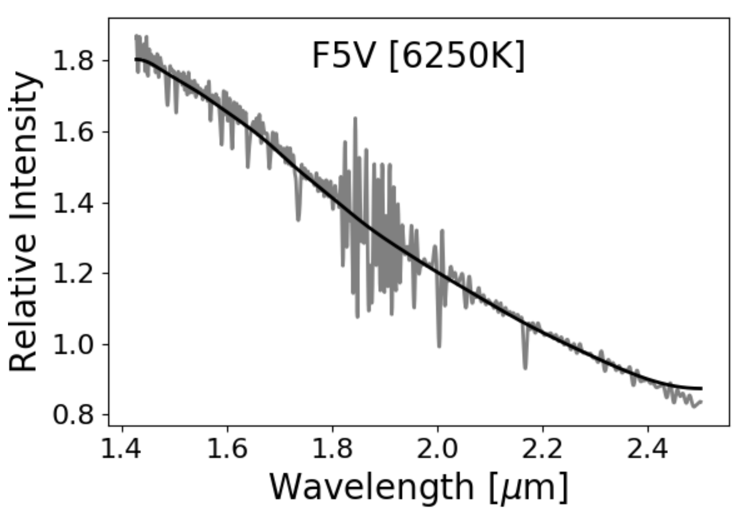


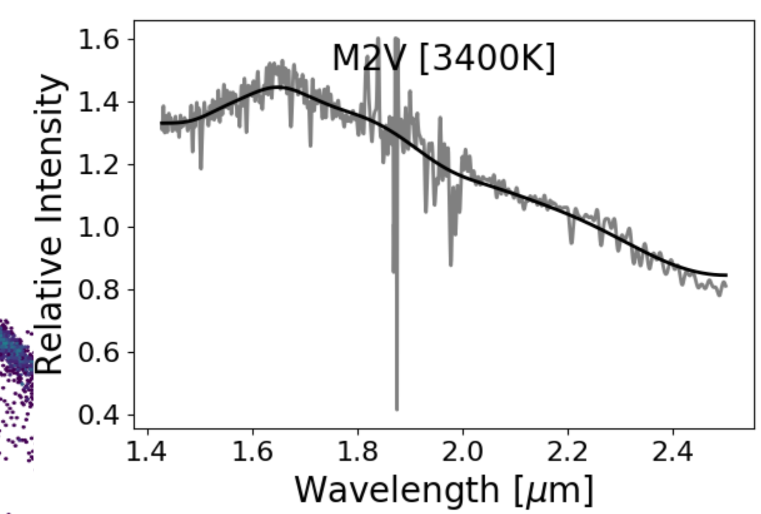


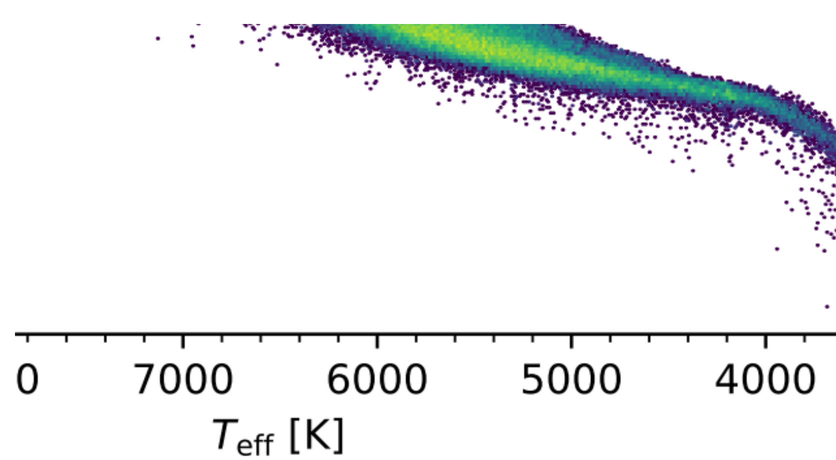












Berger+ 2019

Action item

→ Build a theoretical / empirical / semi-empirical stellar SPHEREx library

→ Characterise **what** information we can recover from *SPHEREx* (stellar) data

→ precision of inferred (Teff, logg, [M/H]) across (evolutionary state, SNR)

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Now

Apply (data-driven) methods developed within SDSS to SPHEREx

Future action item

Future action item

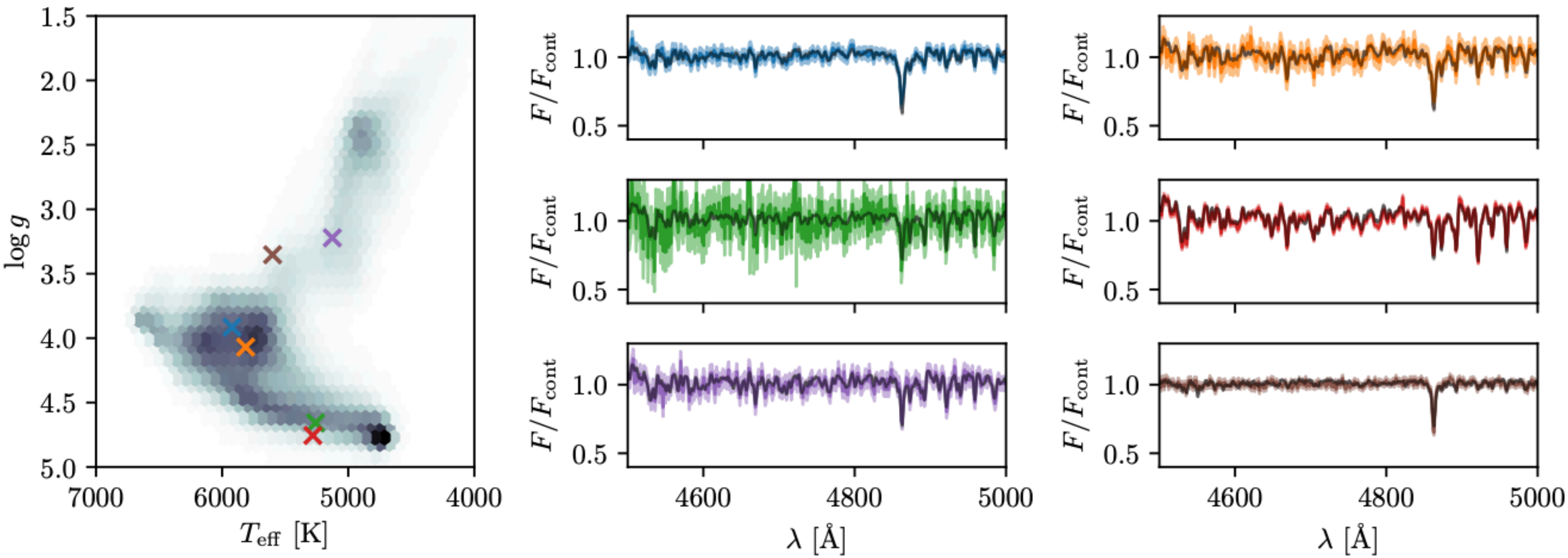
Where do data-driven models *not* match the data?

Future action item

Where do data-driven models *not* match the data?

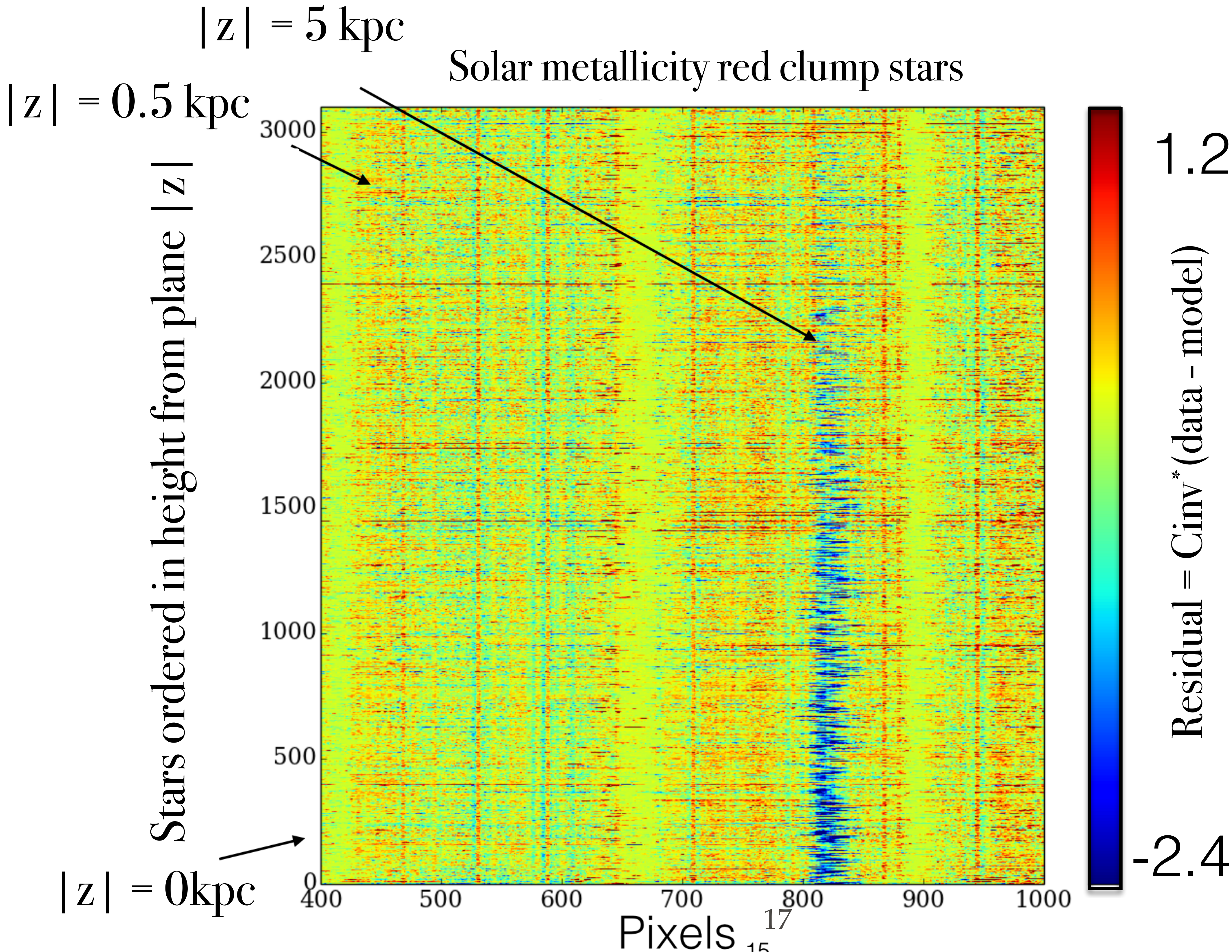
→ Non-stellar features in the spectrum (dust, molecules in ISM)
→ Peculiar chemical composition (dynamical interactions, planet ingestion)

The Cannon provides a remarkable match to the data



Wheeler,
Ness+ 2020

Failures: non-stellar



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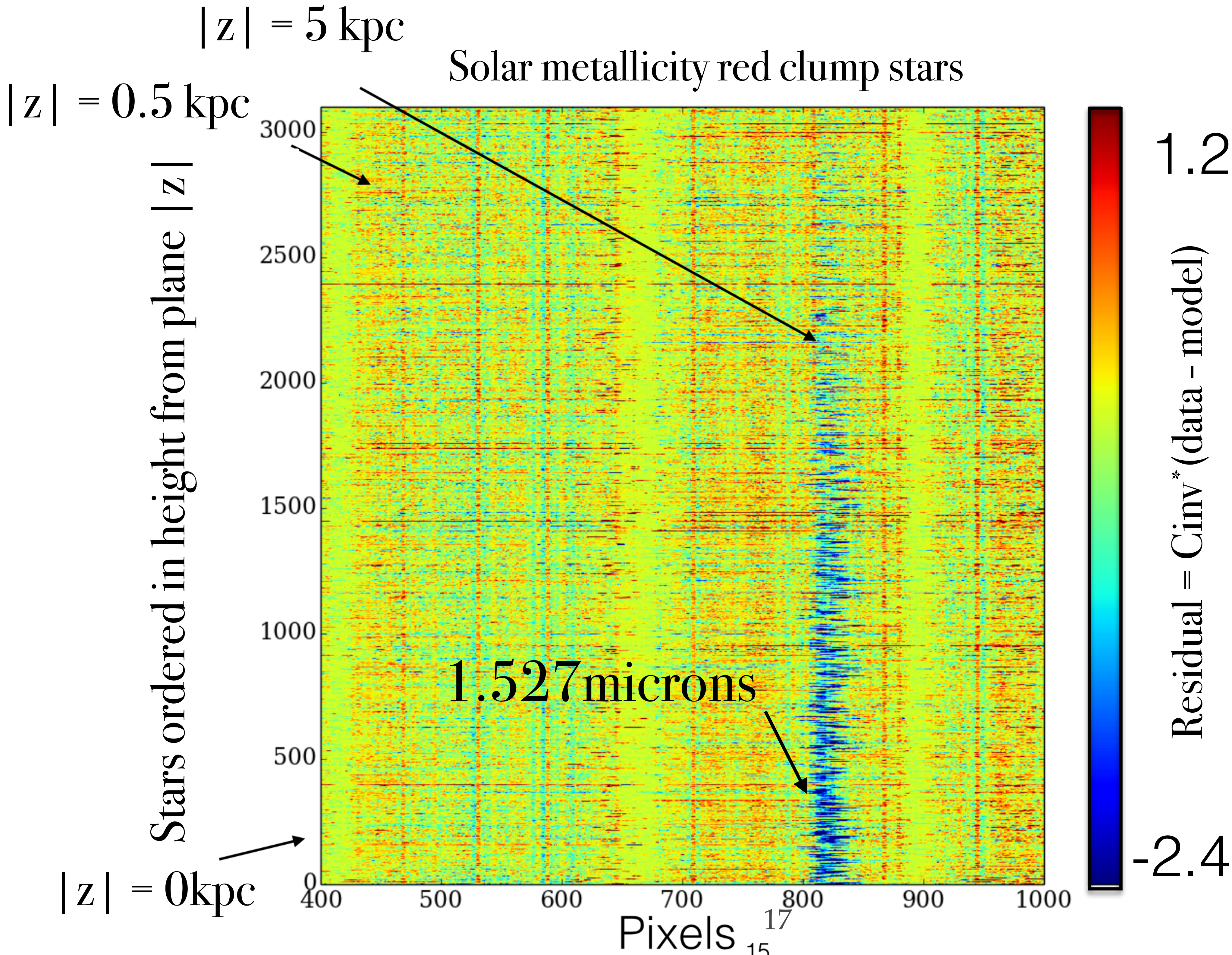

Failures: non-stellar

MAPPING THE INTERSTELLAR MEDIUM WITH NEAR-INFRARED DIFFUSE INTERSTELLAR BAND

G. Zasowski[1,11], B. Ménard[1,2,12], D. Bizyaev[3,4], D. A. García-Hernández[5,6], A. E. García Pérez[7], M. R. Hayden
J. Holtzman[4], J. A. Johnson[8], K. Kinemuchi[4], S. R. Majewski[7], D. L. Nidever[9], M. Shetrone[10], and J. C. Wilson
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[2] Kavli Institute for the Physics and Mathematics of the Universe, University of Tokyo, Kashiwa 277-8583, Japan
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[7] Department of Astronomy, University of Virginia, Charlottesville, VA 22904, USA
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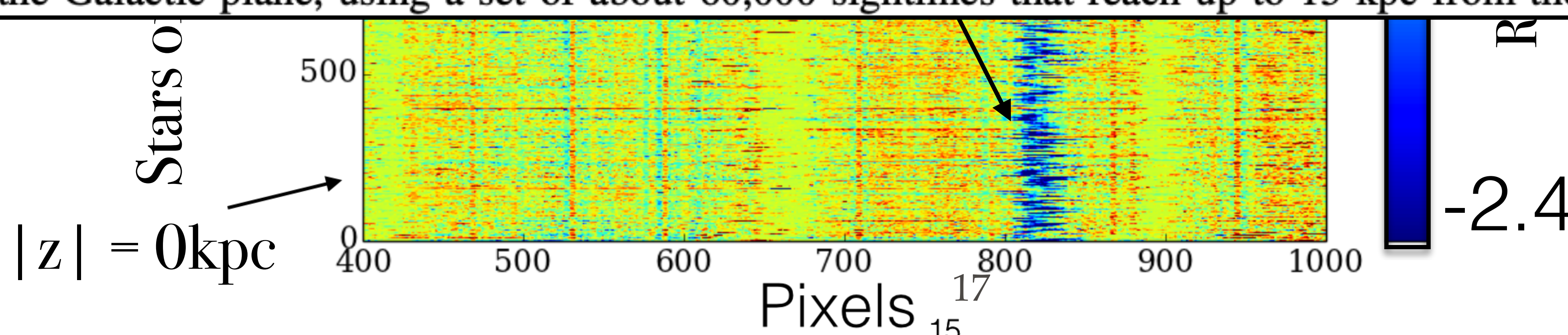
Received 2014 June 4; accepted 2014 October 20; published 2014 December 18

ABSTRACT

We map the distribution and properties of the Milky Way's interstellar medium as traced by diffuse interstellar bands (DIBs) detected in near-infrared stellar spectra from the SDSS-III/APOGEE survey. Focusing exclusively on the strongest DIB in the *H* band, at $\lambda \sim 1.527\ \mu$m, we present a projected map of the DIB absorption field in the Galactic plane, using a set of about 60,000 sightlines that reach up to 15 kpc from the Sun and probe up to



Failures: peculiar stars

Where data-driven model fails (around labels **not** modeled)

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LAMOST - two **Lithium** features

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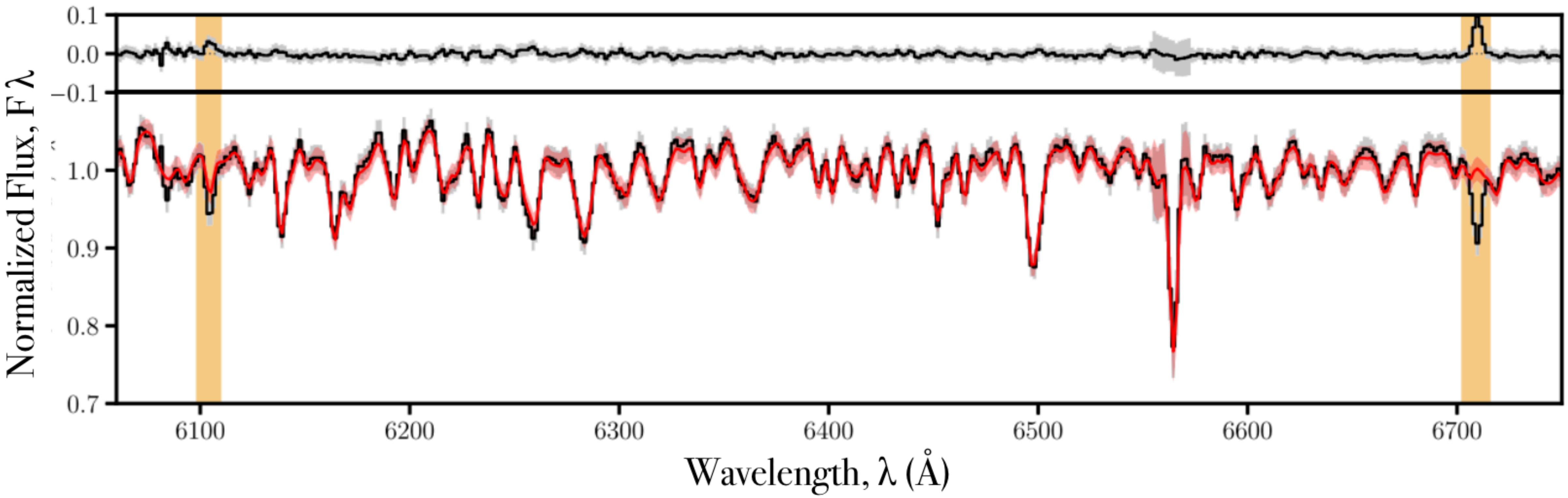
LAMOST - two **Lithium** features



2300 Lithium rich giants discovered in LAMOST (Casey+ 2019, Ho+ 2017)
looking where Li lines >> data-driven model (no Li modeled),
signature of tidal spin up and in some cases planet consumption (Soares-Furtado+ 2020)

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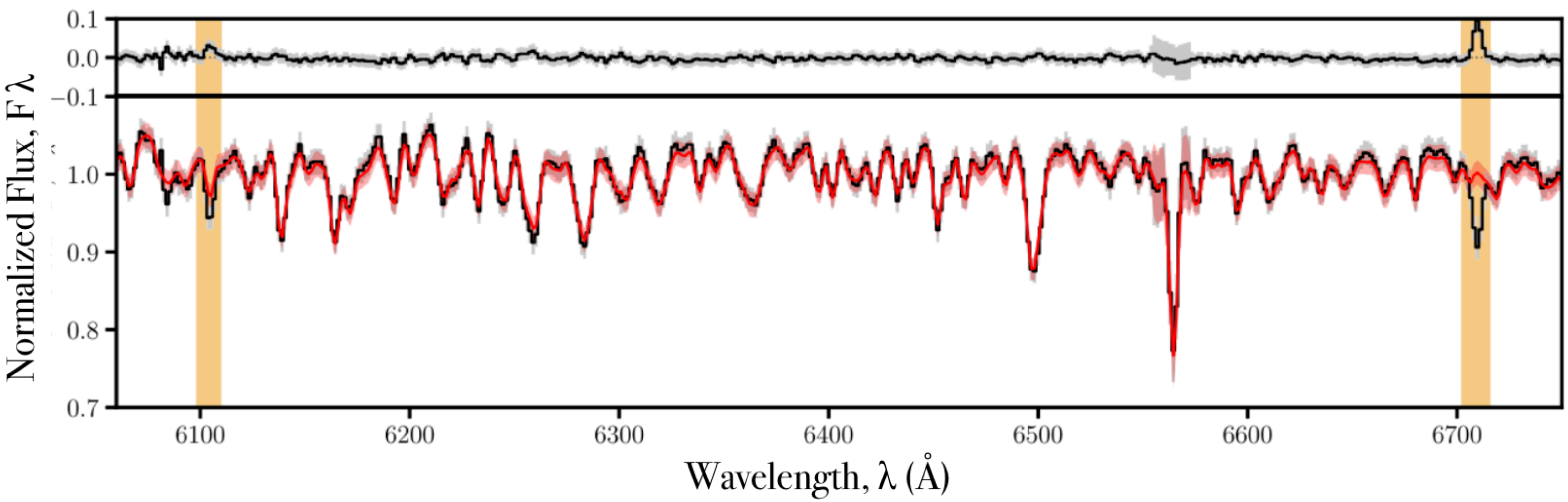

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Wheeler in prep (unsupervised)

What I proposed today

Now

Later

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Characterise **what** information we can recover from *SPHEREx* (stellar) data

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→ *Build a stellar SPHEREx library*

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Where do data-driven models *not* match the data?

→ *Non-stellar features in the spectrum (dust, molecules in ISM)*

→ *Peculiar spectra due to perturbations (external work, planet ingestion, mass exchange, extra-galactic)*

Large coverage of the disk

APOGEE: 250K stars

Milky Way Mapper:
5 million stars

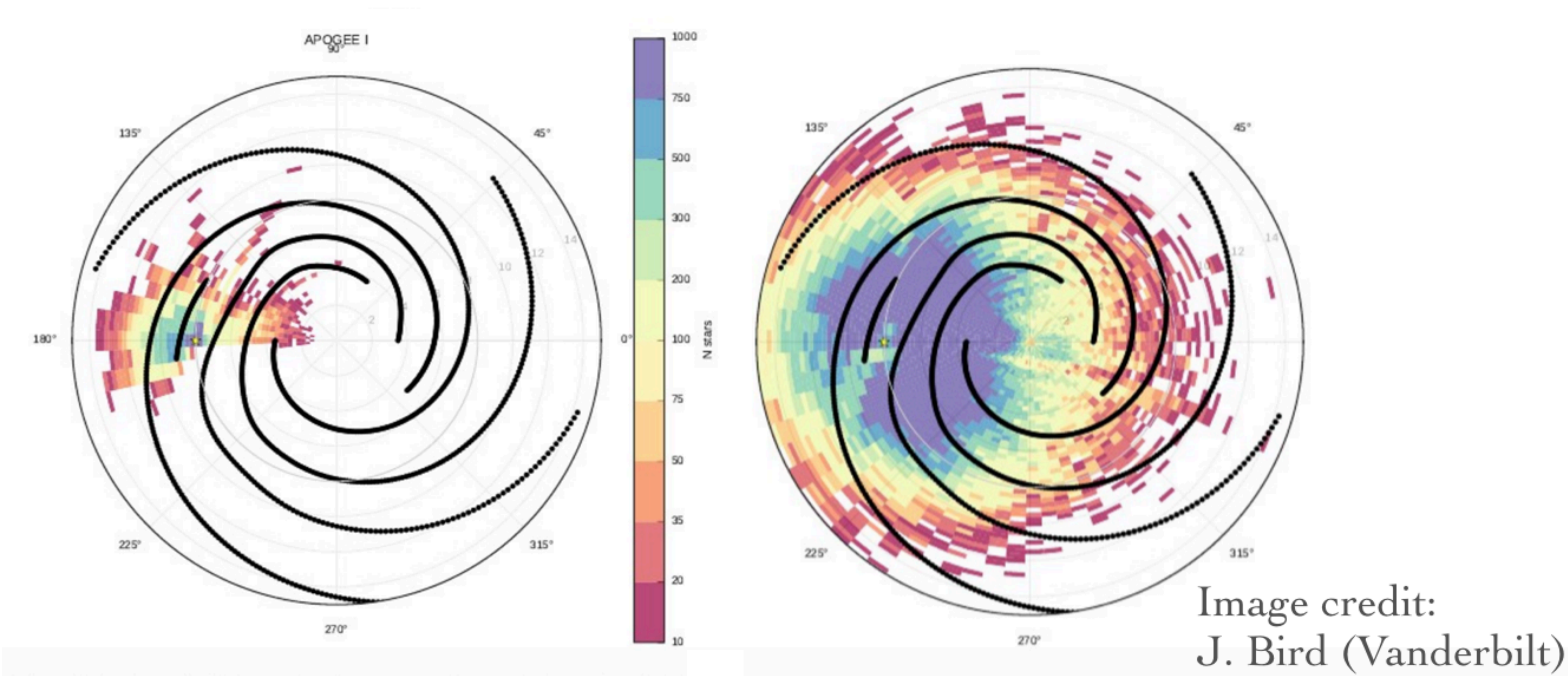

Image credit:
J. Bird (Vanderbilt)

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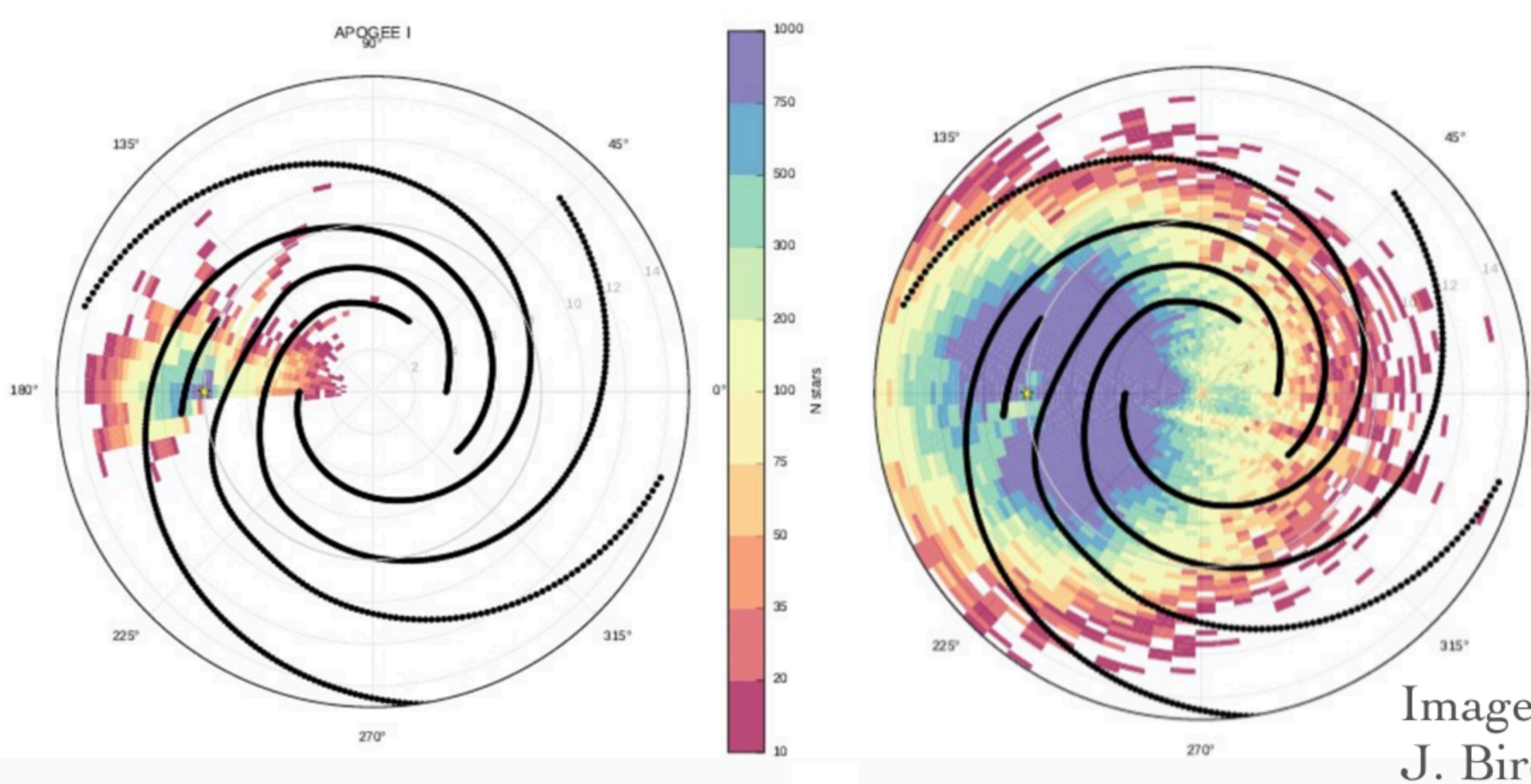

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Spectrophotmetric distances with data-driven models (in dust obscured crowded disk)
(Hogg+2019, Eilers+2019, Leung+2019)