

# HARPSpec: Using Machine Learning to Find Chemical Compositions of Stars from Their Spectra

Joseph Hand, Ian J.M. Crossfield

University of Kansas, ExoLab

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# Background

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- Weight: Machine learning model degree of freedom



# What is HARPSpec?

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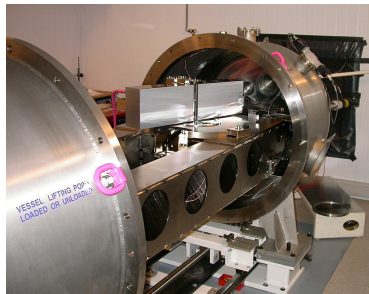


Image courtesy of ESO

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- Will use publicly available spectra from HARPS (pictured)
  - Located at La Silla, Chile
  - High resolution, optical
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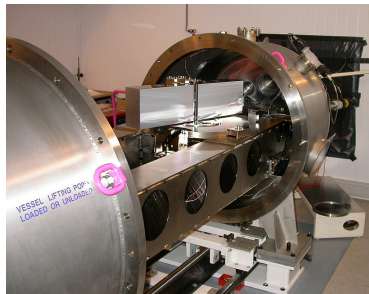


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- Will use the Cannon
  - Supervised machine learning library
  - Fast and efficient

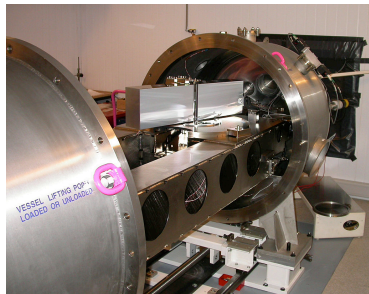


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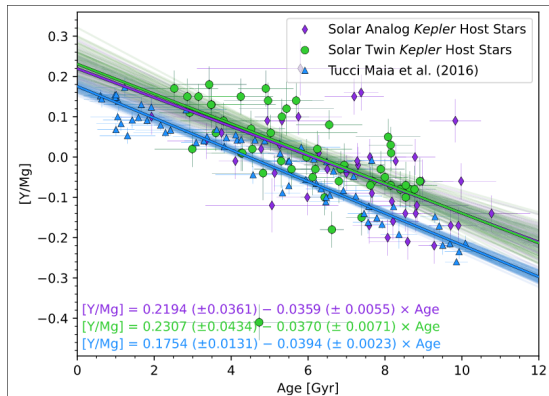
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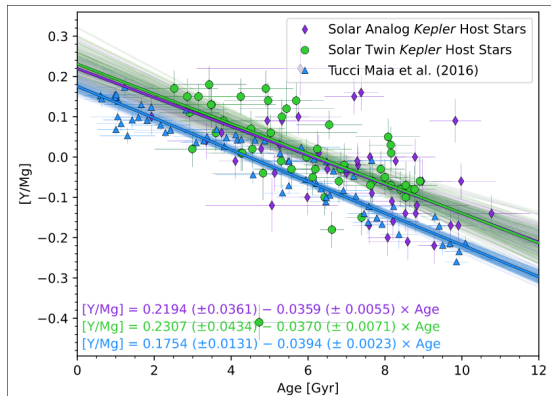


Berger et al. (2022)

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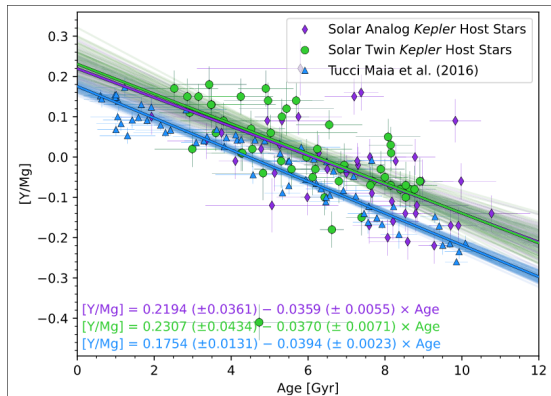


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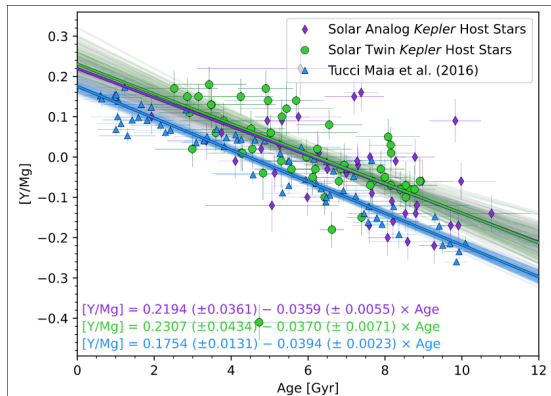
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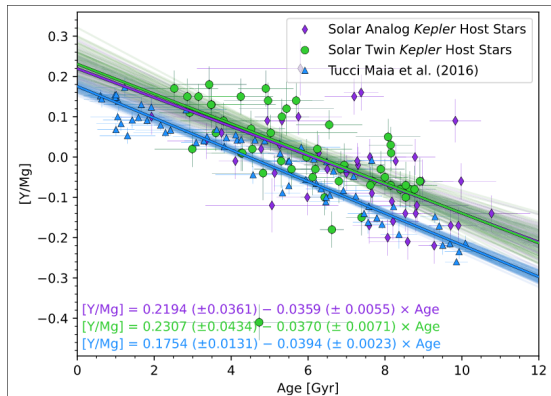


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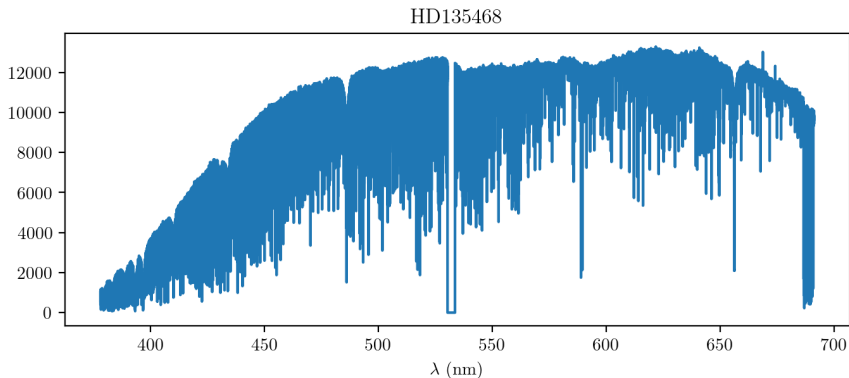
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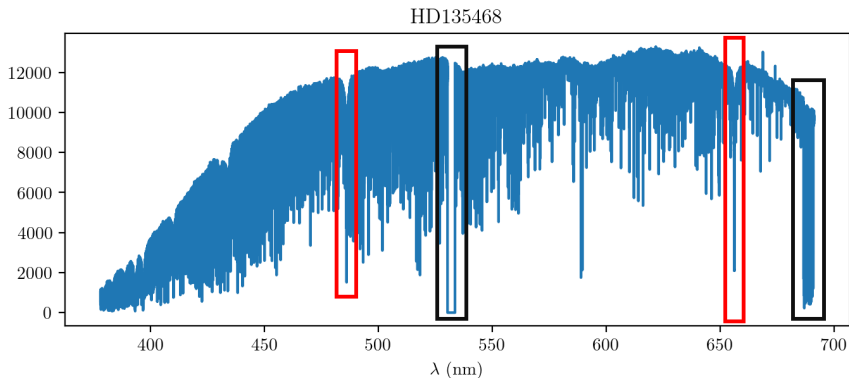
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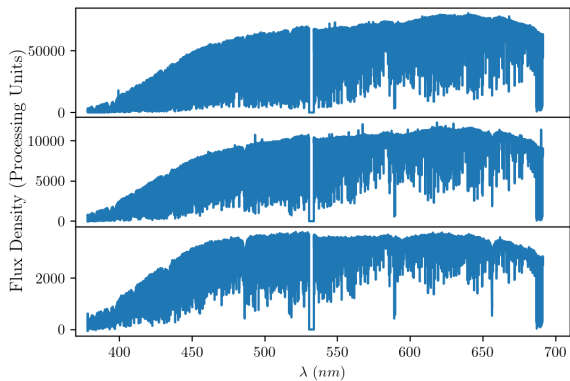


- Overall shape due to instrument sensitivity
- Absorption lines (Red)
- A few artifacts (Black)

# Data

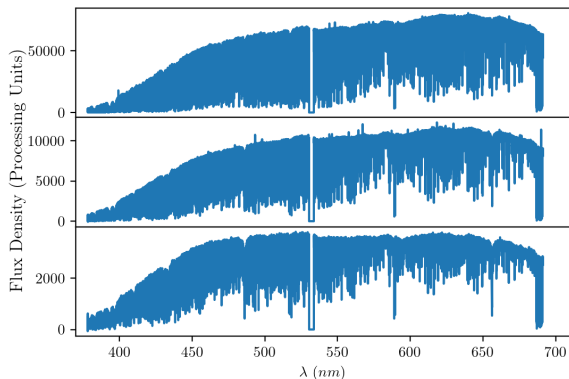
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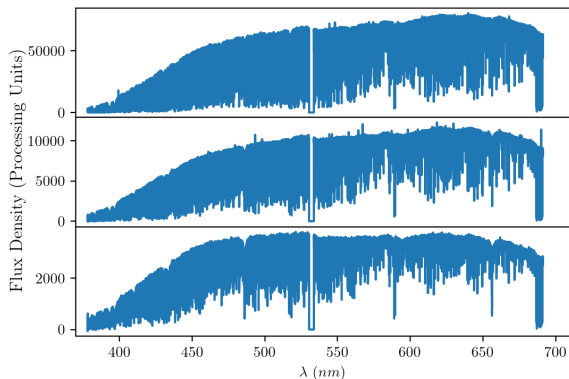
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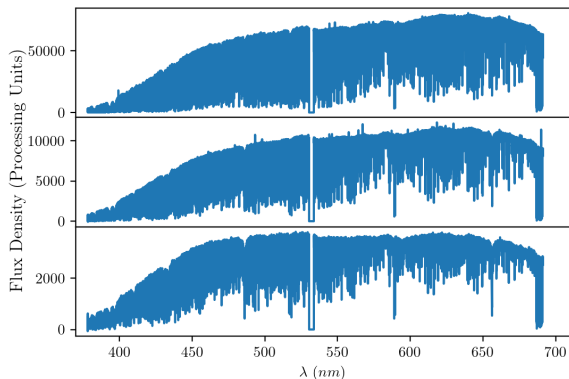
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- All spectra are publicly available



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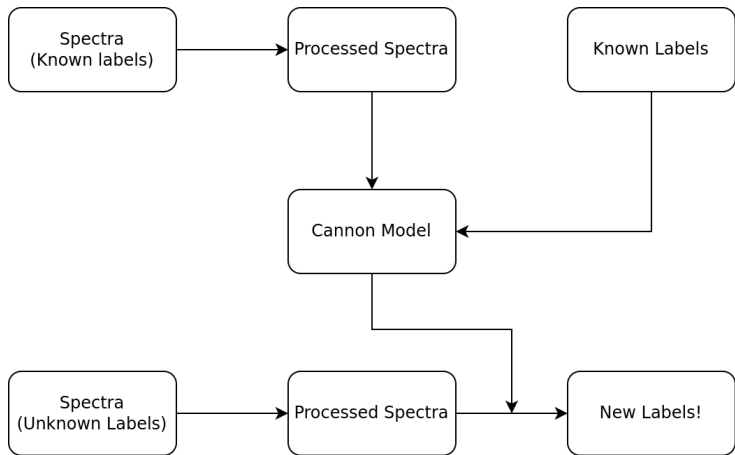
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## Abundances from:

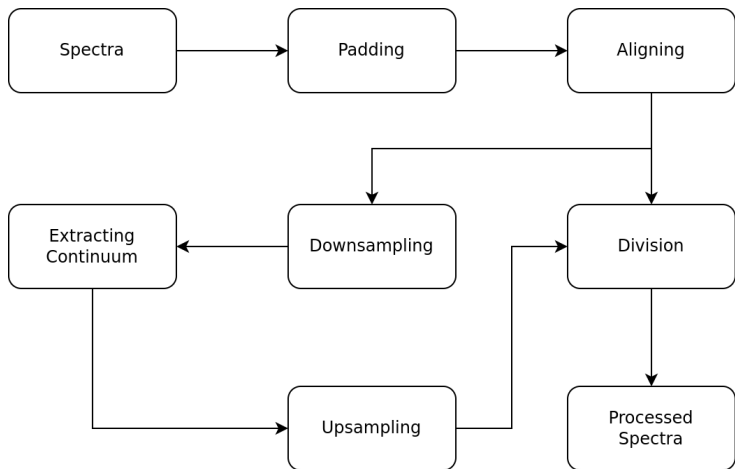
- Adibekyan et al. (2012)
- Bertran et al. (2015)
- Costa Silva et al. (2020)
- Delgado Mena et al. (2010, 2017, 2021)
- Suarez Andres et al. (2017)

# HARPSpec

# Overview of HARPSpec



# Spectral Processing

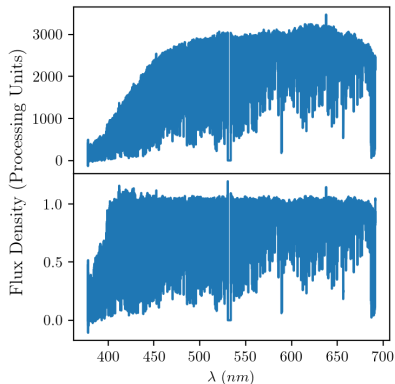




# Continuum Normalization

Basic technique:

- Identify continuum pixels
- Fit curve to continuum
- Divide spectra by this fit



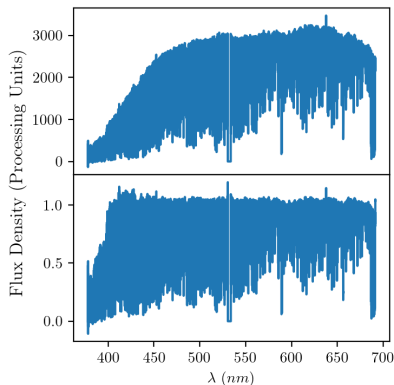
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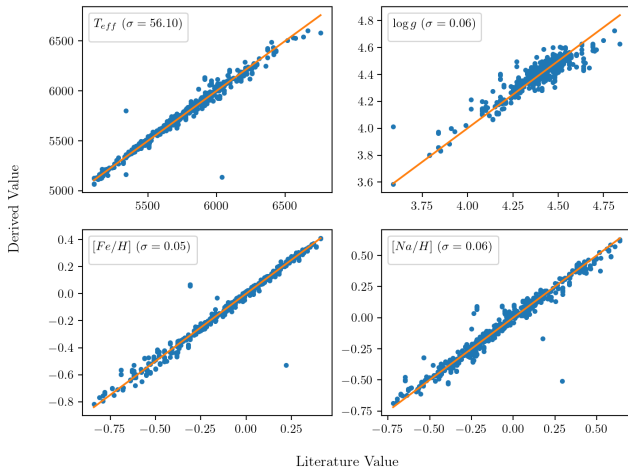
Some details:

- Spectral resolution is too large to do this quickly.
- First two steps done on downsampled spectra

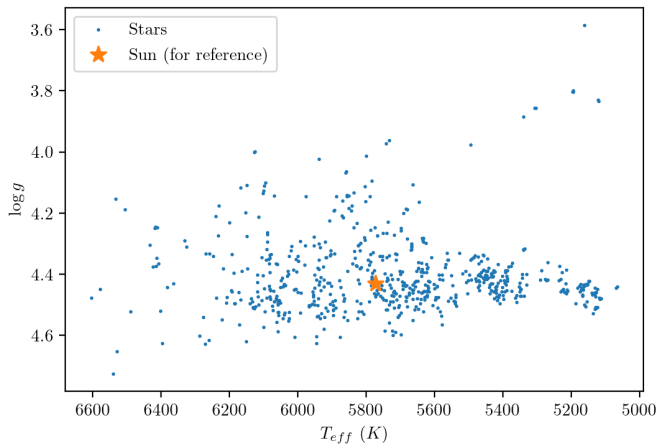


# Current Results

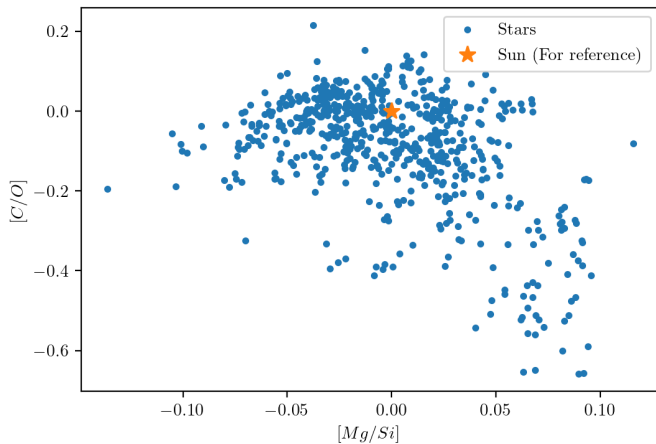
# HARPSpec Performance



# Temperature vs. Surface Gravity



# [C/O] vs. [Mg/Si]



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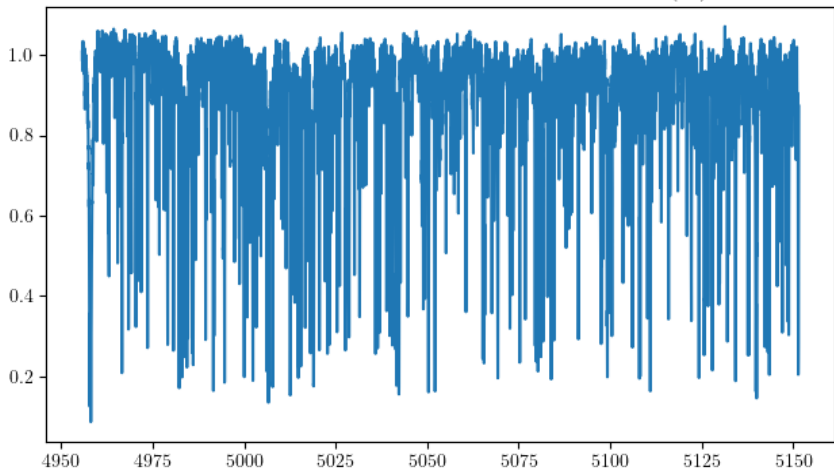
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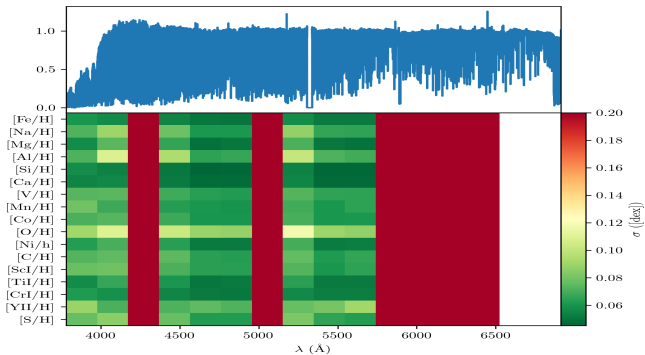
Questions?



HD149396\_HARPS.2006-05-31T05:03:14.850\_s1d\_A (88)



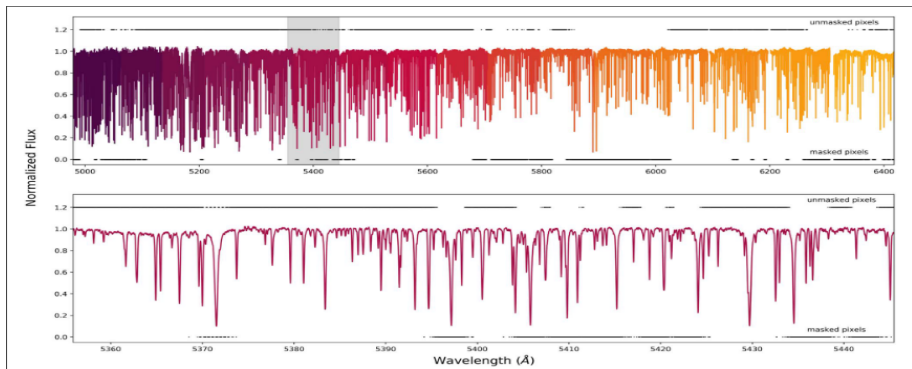




# Current Issues

- Resource Usage
  - 500GB RAM when training on the full dataset
  - Cutting spectra into 16 parts
  - This is not a permanent solution
  - Possible solutions include:
    - Binning down spectra
    - Getting more RAM
- Stability Issues
  - Occasional math errors with certain spectra
  - Very inaccurate labels for these spectra
  - Still unknown what is going wrong here

# Telluric Masking

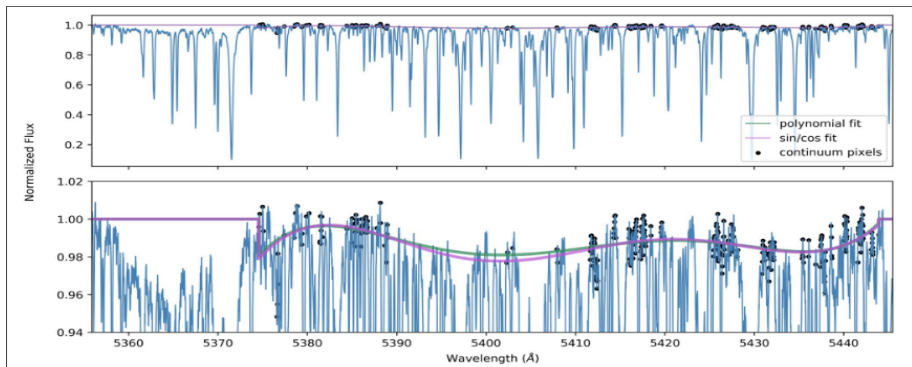


Rice & Brewer (2020)

- Ignore wavelengths affected by Earth's atmosphere
- Absorption lines from Earth's atmosphere confuse the Cannon



# Data-Driven Continuum Normalization



Rice & Brewer (2020)

- Use the Cannon itself to identify continuum pixels
- Improve continuum-fitting algorithms (e.g. Ness et al. 2015)