



ESCAPE

European Science Cluster of Astronomy &
Particle physics ESFRI research Infrastructures

Task 4.3 Summary and Status

Martino Romaniello, Nima Sedaghat, Felix Stoehr
Jon Carrick, FX Pineau, Henri Boffin



WP4 Tasks

Task 4.1 Integration of astronomy VO data and services into the EOSC

Lead: Marco Molinaro (INAF)

Task 4.2 Implementation of FAIR principles for ESFRI data through the Virtual Observatory

Lead: François Bonnarel (CDS CNRS Université de Strasbourg)

Task 4.3 Adding value to trusted content in astronomy archives

Co-leads: Mark Allen (CNRS-ObAS) & Martino Romaniello (ESO)



Task 4.3 Adding value to trusted content in astronomy archives

*Next generation functionalities for creation and publication of **high-level, value-added data products** from ESFRIs*

- Assessment and application of **new techniques** – machine learning analytics. (connection to WP3)
 - *Specific example applied to ESO archives data products: spectra, cubes, source catalogues*
- Identification of **stewardship best practices**
 - *Curation and publication of next-generation data products via ESFRI archives*
 - *Technical and human aspects*



Major milestones

D4.5 Release of prototype machine learning enabled archive services providing value-added content to archives (Demonstration)	Month 30 (+6) January 2022
D4.8 Final analysis report on use of IVOA standards for FAIR ESFRI and community data and best stewardship practices for value-added data (Report) <i>(includes report of feedback on prototype services developed for D4.5)</i>	Month 40 (+6?) November 2022 (?)



Deep Learning & Data Archives

- Scope: provide archive users with novel ways to identify data
 - Beyond traditional approach of specifying query parameters
 - Revolutionary extension of recent move from instrument to data keywords (e.g. exposure time to signal-to-noise)
- Target: the different data types in the ESO Science Archives
 - Spectra
 - Cubes
 - Source catalogues
- Let the data speak ... on a massive scale
 - Huge data variety: impractical, and not desirable, to impose preconceived interpretations



Deep Learning on 1D spectra: HARPS

- Scope: Deep Learning analysis of the entire HARPS archive
 - High-resolution, high-stability spectrograph
 - Main science case: discovery and characterization of exoplanets
 - ~270,000 spectra, ~300,000 wavelengths channels each
 - 1D spectra, pipeline-reduced to high accuracy
- Different approaches
 - HITS: fully-connected autoencoder with 2 latent dimensions, down sampled spectral resolution
 - Agile architecture for speed and interactivity
 - ESO: combination of convolutional and fully-connected layers with between 4 to 8192 latent dimensions, full spectral resolution
 - Find minimal representation which preserves all the relevant information



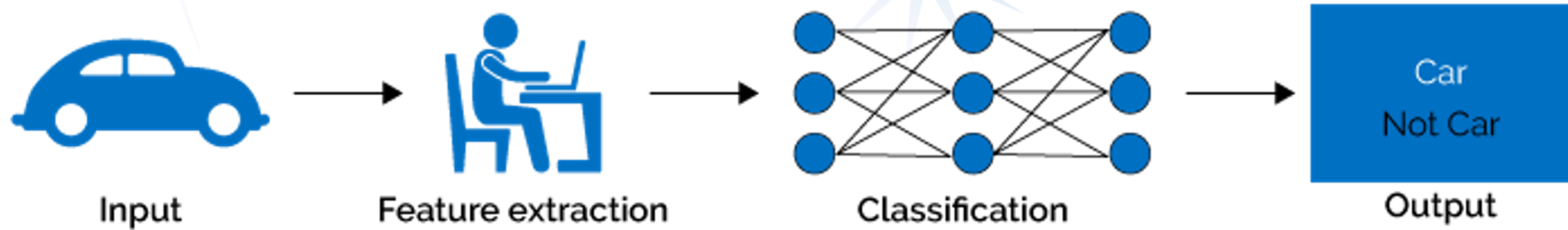
So now, how to turn this into user services?

- These techniques have the potential of being a game-changer, BUT:
 - The results have to be meaningful
 - Interaction with the results has to be user-friendly
- In practice:
 - What makes spectra similar?
 - What are the uses and limitations of a similarity service?
 - Can spectra be tagged with some physical properties of the celestial object?
 - If so, what are they?
 - What are the uses and limitations?
 - What is the best way to present and interact with the results?
 - Services for the few or for the many?
 - About half of the astronomical community uses the ESO Science Archives

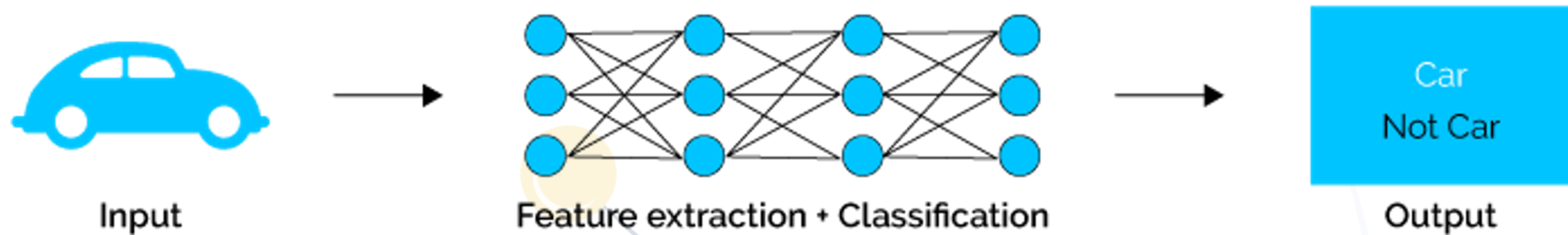


From Hand-Crafted Features to Representation Learning

Machine Learning



Deep Learning



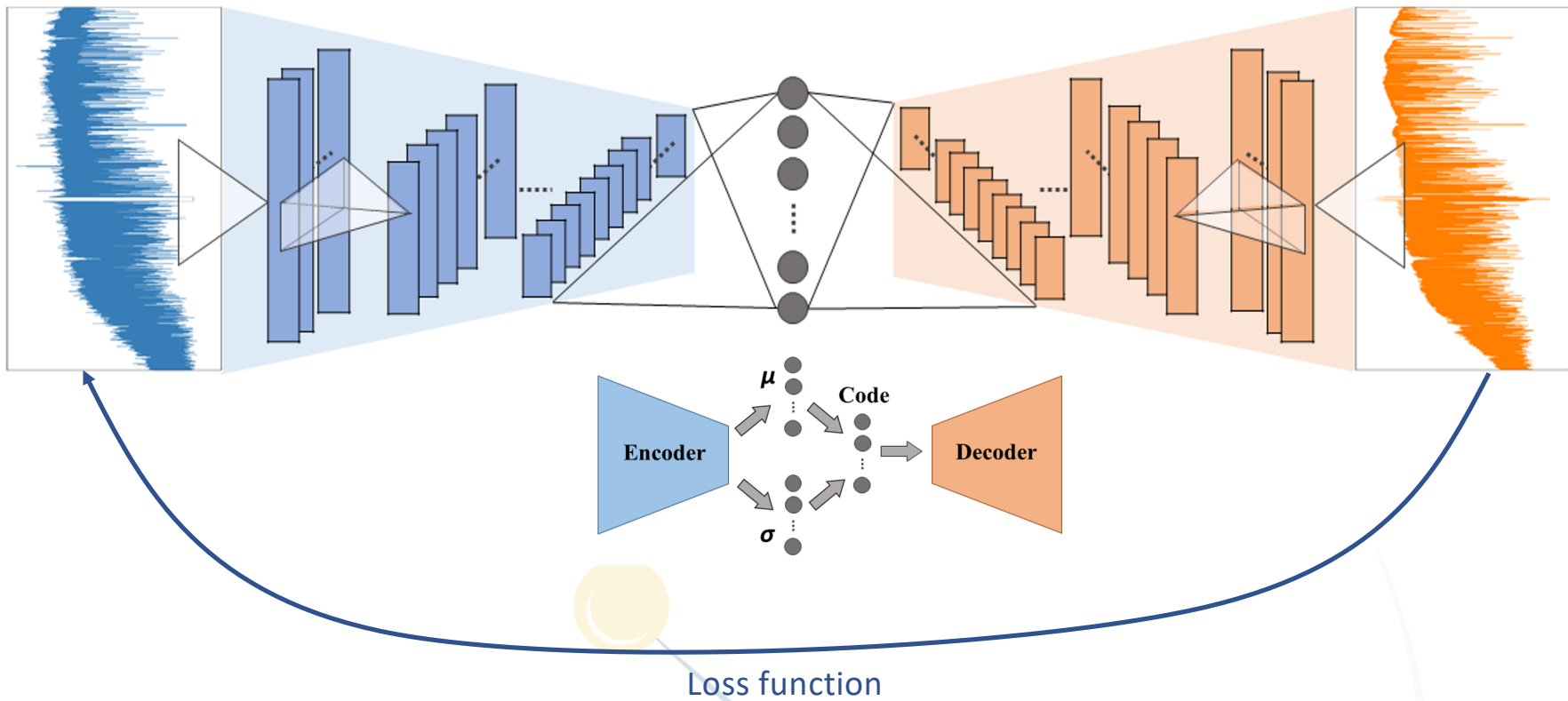
Let the Data Speak for itself!

- Define the problem and data carefully
- Design your own network (with inspiration from existing ones)
- Train it
- Try to interpret how the network solved the problem

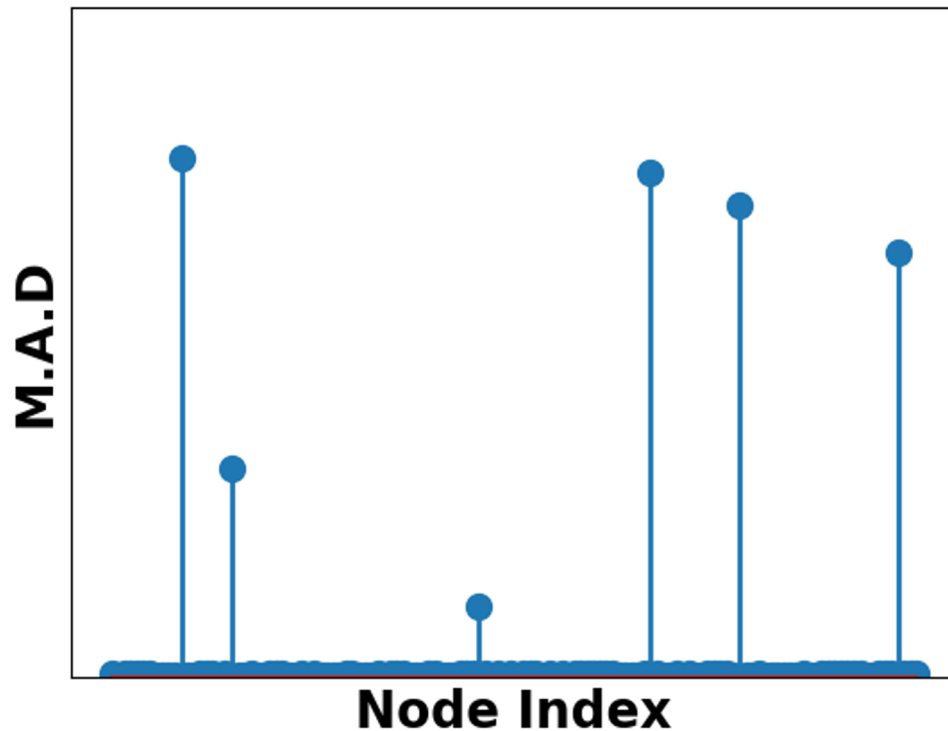
- Let's see how a network chooses to perceive big data
- Push for disentangled representations
 - Facilitates interpretation



Network schematics



Not all dimensions are informative



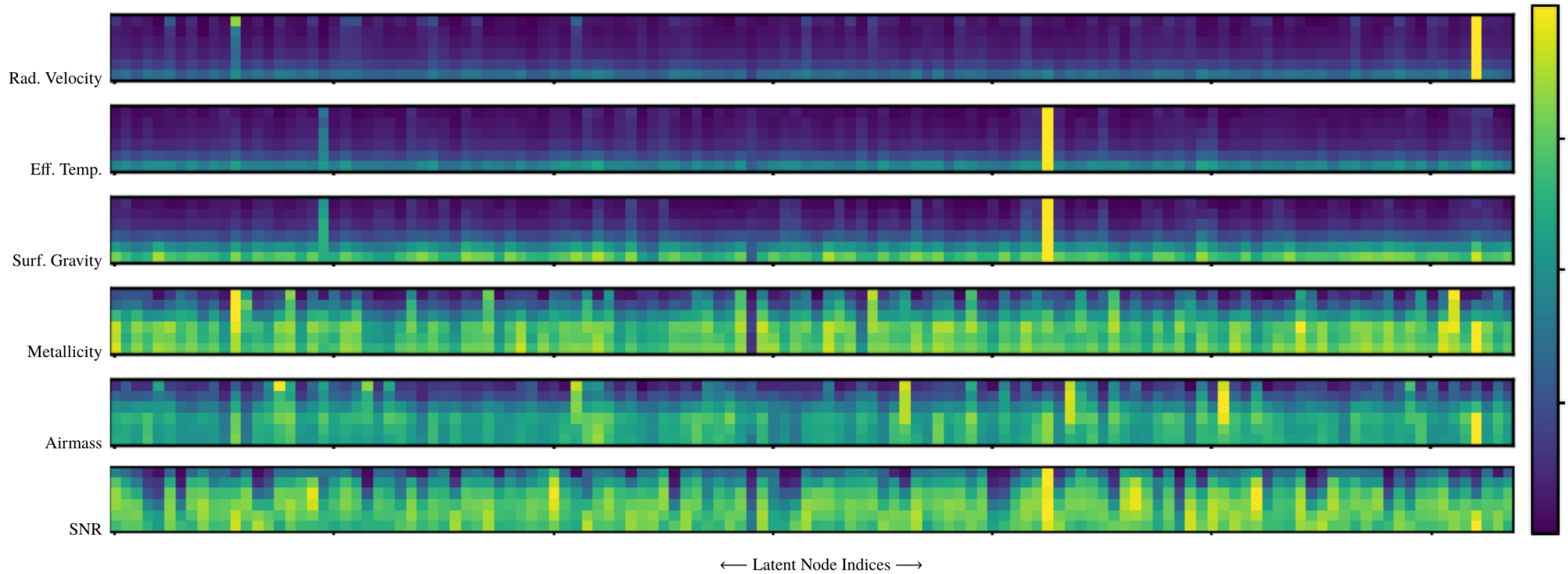
Only 6 dimensions out of 128 carry information



So now, are they physically interpretable?



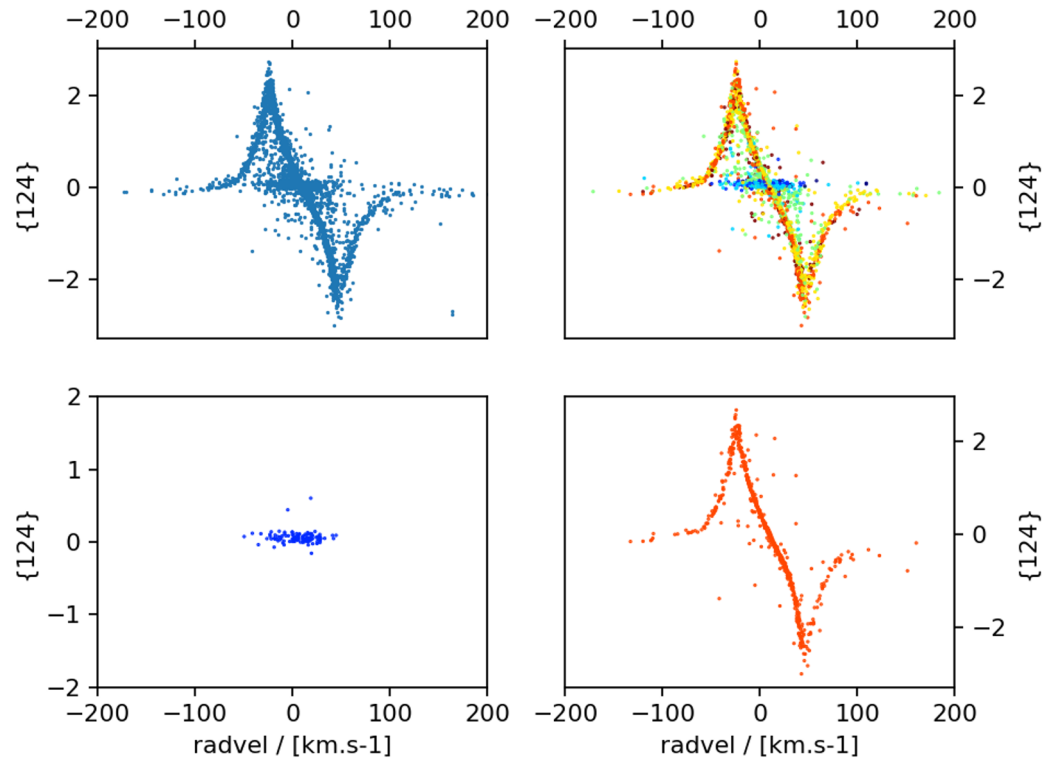
Mutual Information with Stellar Parameters



Sedaghat, MR, Carrick, Pineau 2021, MNRAS, 501, 6026



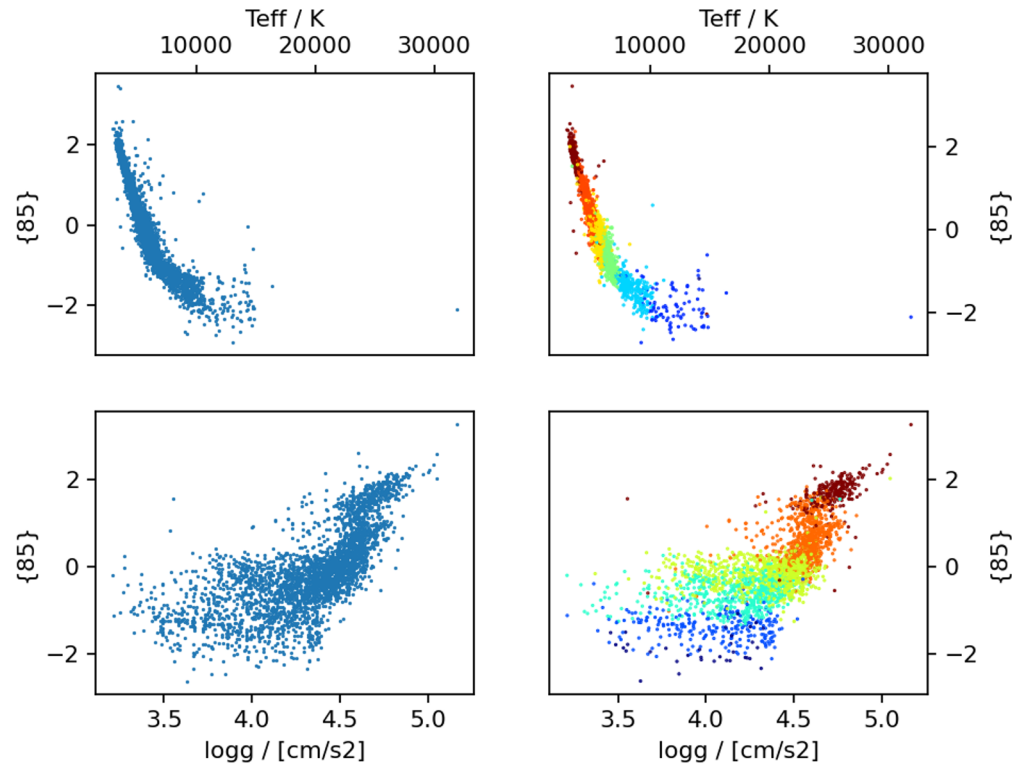
Mutual Information with Stellar Parameters



Sedaghat, MR, Carrick, Pineau 2021, MNRAS, 501, 6026



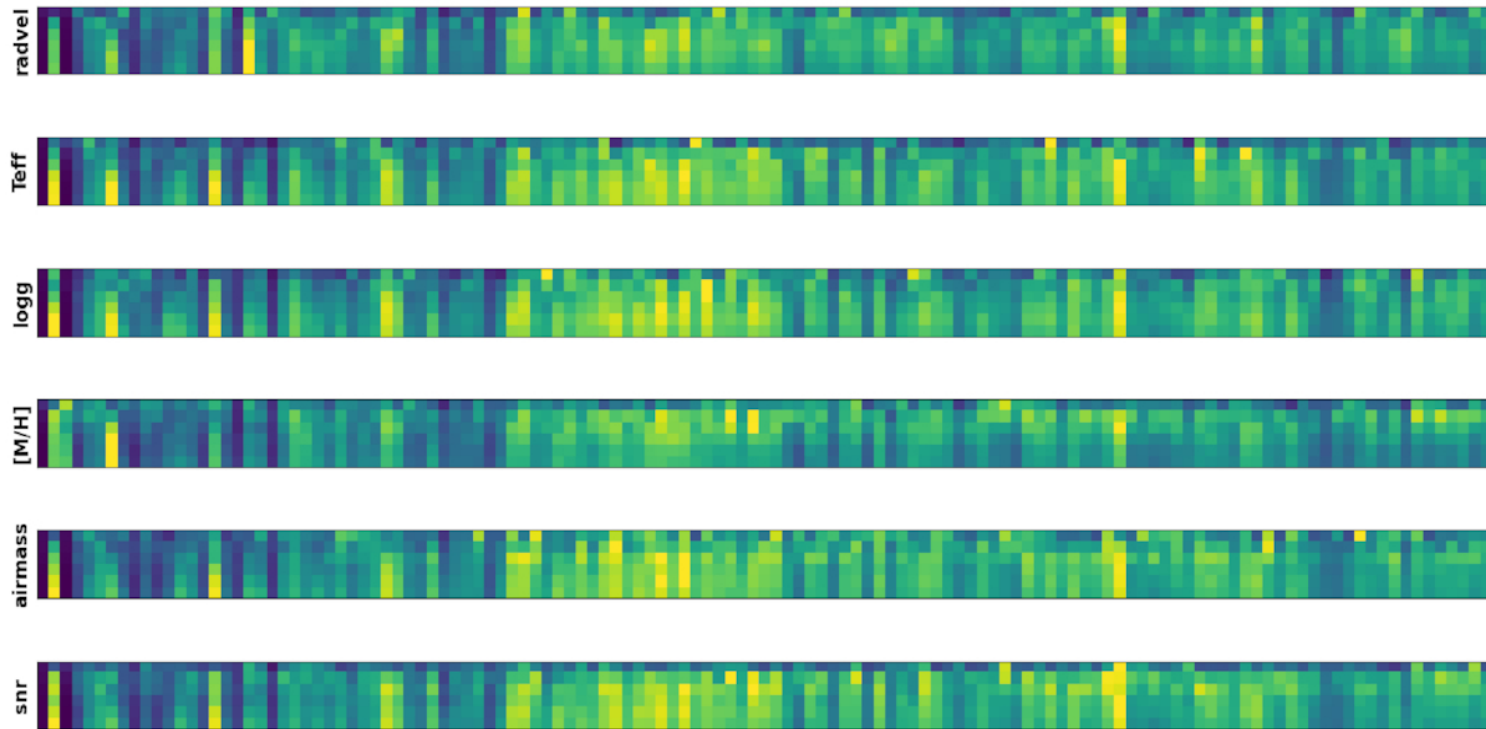
Mutual Information with Stellar Parameters



Sedaghat, MR, Carrick, Pineau 2021, MNRAS, 501, 6026



PCA: no one-to-one mapping with physical features



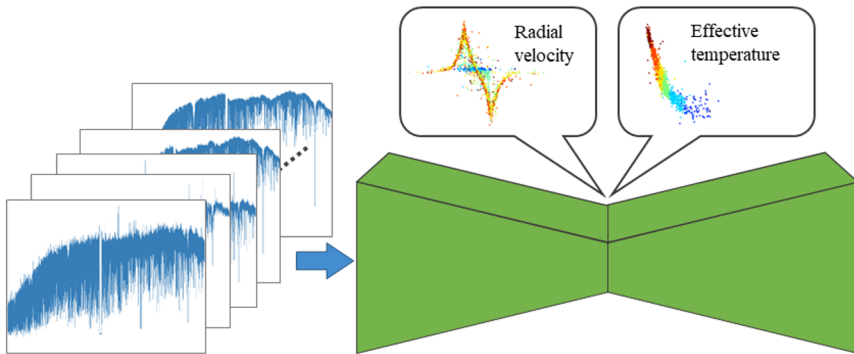
Sedaghat, MR, Carrick, Pineau 2021, MNRAS, 501, 6026



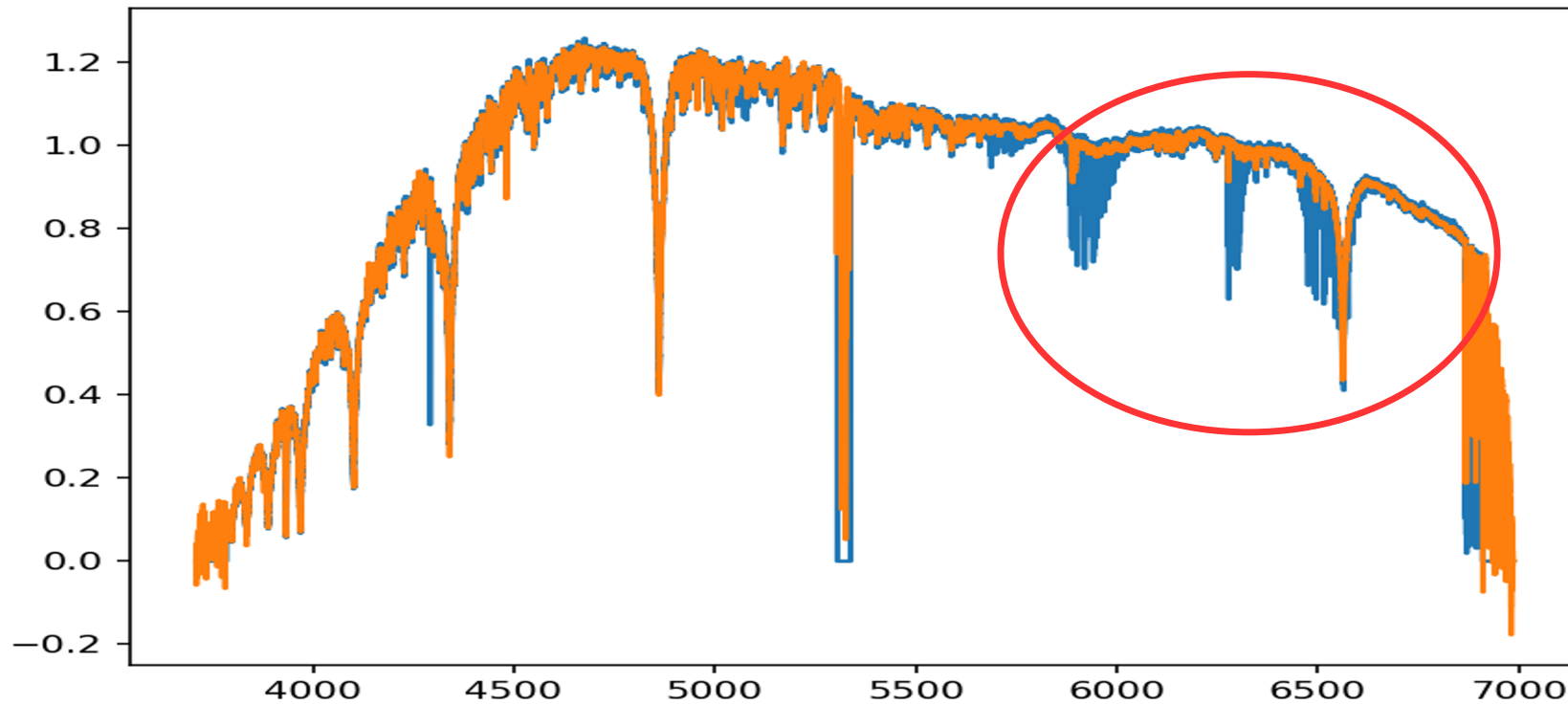
The first step is taken: the basic idea works

Next steps

- What physical parameters are the other significant dimensions linked to?
 - Why isn't RV representation monotonic?
- Extension to different spectral datasets
 - Stellar: RAVE, GALA (non-ESO)
 - Non-stellar: UVES, X-Shooter
- Extension to images/cubes: ALMA
- Source separation
 - Stellar vs telluric features



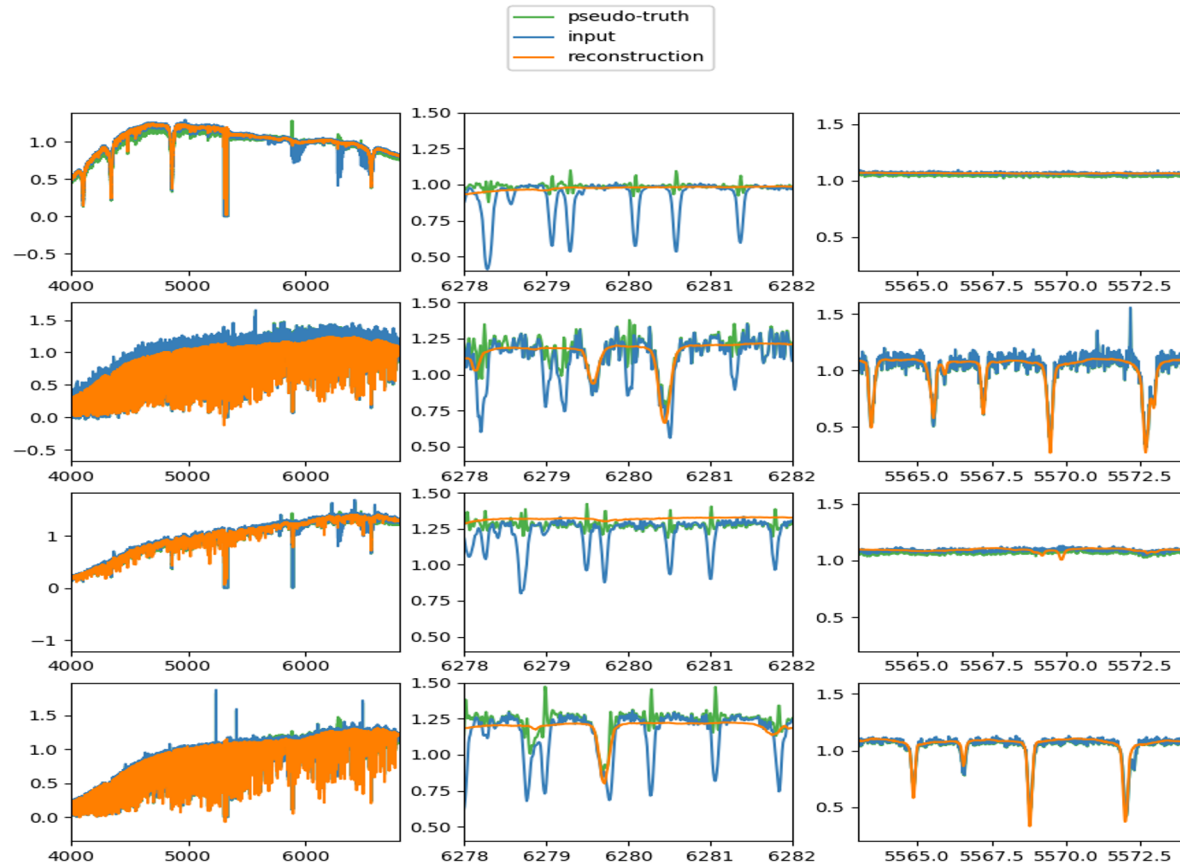
Source separation: stellar vs telluric features



Sedaghat, MR et al, in preparation



Source separation: stellar vs telluric features



Sedaghat, MR et al, in preparation

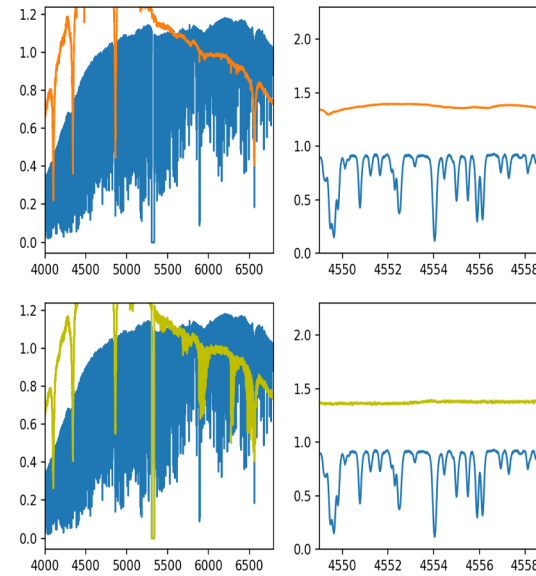


WIP: ALMA cubes and images

- ALMA generates 3D data cubes: 2 spatial + 1 spectral dimensions
- The cubes themselves unfortunately are not homogeneous enough along the spectral dimension to be readily fed to the Deep Learning machinery
- We started from 2D images with the spectral dimension compressed (“continuum images”), running them through the same machinery as the spectra
- WIP ...



User tools: “Sliders” for exploration of the latent space



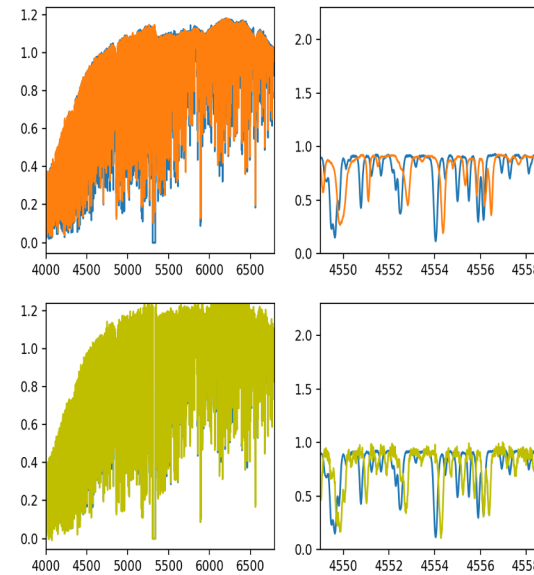
Spectral Class:
RadVel: 0.03600,
Class: PM*,
Teff: 6119.8,
logg: 4.1479,
Mass: 1.15,
[M/H]: 0.1241,
E(B-V): nan
[-0.98 -0.2 0.01 -0.54 -0.87 0.48]

Spectral Class:
RadVel: -25.00000,
Class: PM*,
Teff: 9234.0,
logg: nan,
Mass: nan,
[M/H]: nan,
E(B-V): nan
[-0.98 -0.01 -0.08 -2.08 -0.84 -0.03]

<https://www.eso.org/~nsedagha/universe/#astromachines>



User tools: “Sliders” for exploration of the latent space



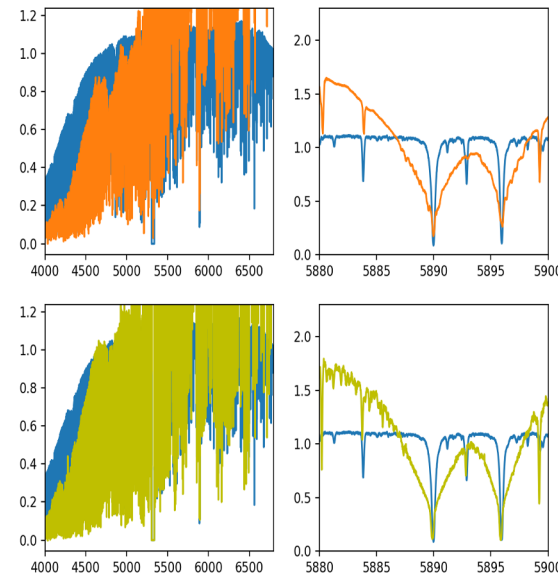
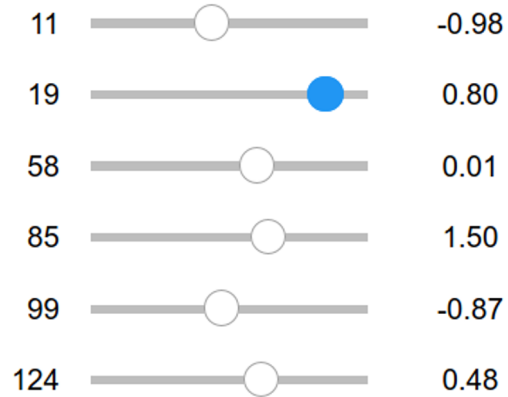
Spectral Class,
RadVel: 0.03600,
Class: PM*,
Teff: 6119.8,
logg: 4.1479,
Mass: 1.15,
[M/H]: 0.1241,
E(B-V): nan
[-0.98 -0.2 0.01 -0.54 -0.87 0.48]

Spectral Class,
RadVel: 15.77000,
Class: PM*,
Teff: 6124.7,
logg: 4.3664,
Mass: 1.16,
[M/H]: 0.18,
E(B-V): nan
[-1.03 -0.13 -0. -0.52 -0.8 -0.25]

<https://www.eso.org/~nsedagha/universe/#astromachines>



User tools: “Sliders” for exploration of the latent space



Spectral Class:
RadVel: 0.03600,
Class: PM*,
Teff: 6119.8,
logg: 4.1479,
Mass: 1.15,
[M/H]: 0.1241,
E(B-V): nan

[-0.98 -0.2 0.01 -0.54 -0.87 0.48]

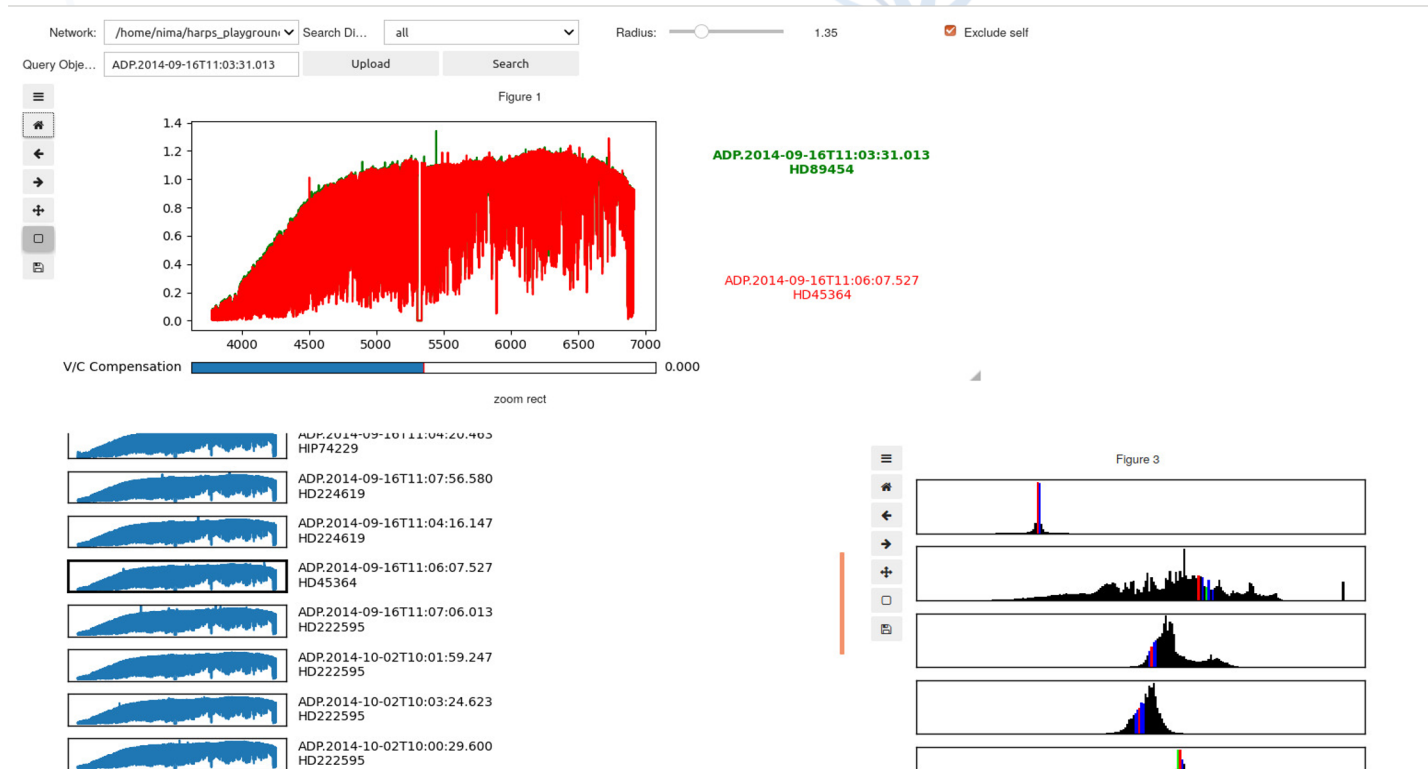
Spectral Class:
RadVel: -3.45700,
Class: RotV*,
Teff: 4023.0,
logg: 4.5969,
Mass: 0.63,
[M/H]: nan,
E(B-V): nan

[-1.13 0.68 -0.03 1.31 -0.83 0.64]

<https://www.eso.org/~nsedagha/universe/#astromachines>



User tools: RETR-SPECT, a Retrieval engine for Spectra



<https://www.eso.org/~nsedagha/universe/#retrspect>



<http://www.eso.org/~nsedagha/universe>

martino.romaniello@eso.org
nima.sedaghat@eso.org

