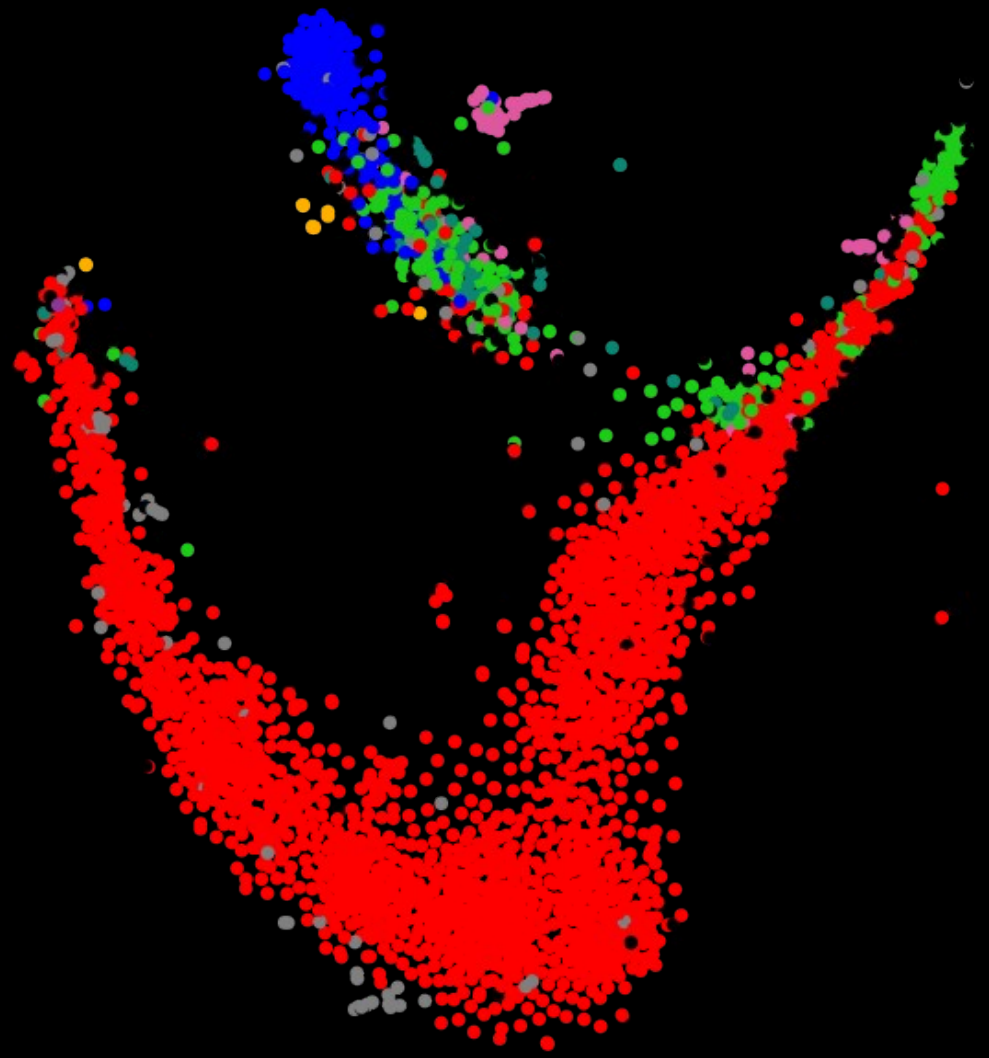
Spectral Classification of White Dwarfs by Dimensionality Reduction

Xander Byrne

Amy Bonsor – Laura Rogers – Christopher Manser

Outline

- Spectroscopic surveys
- White dwarfs
- Dimensionality reduction (DR)
- Variation: focus on spectral lines



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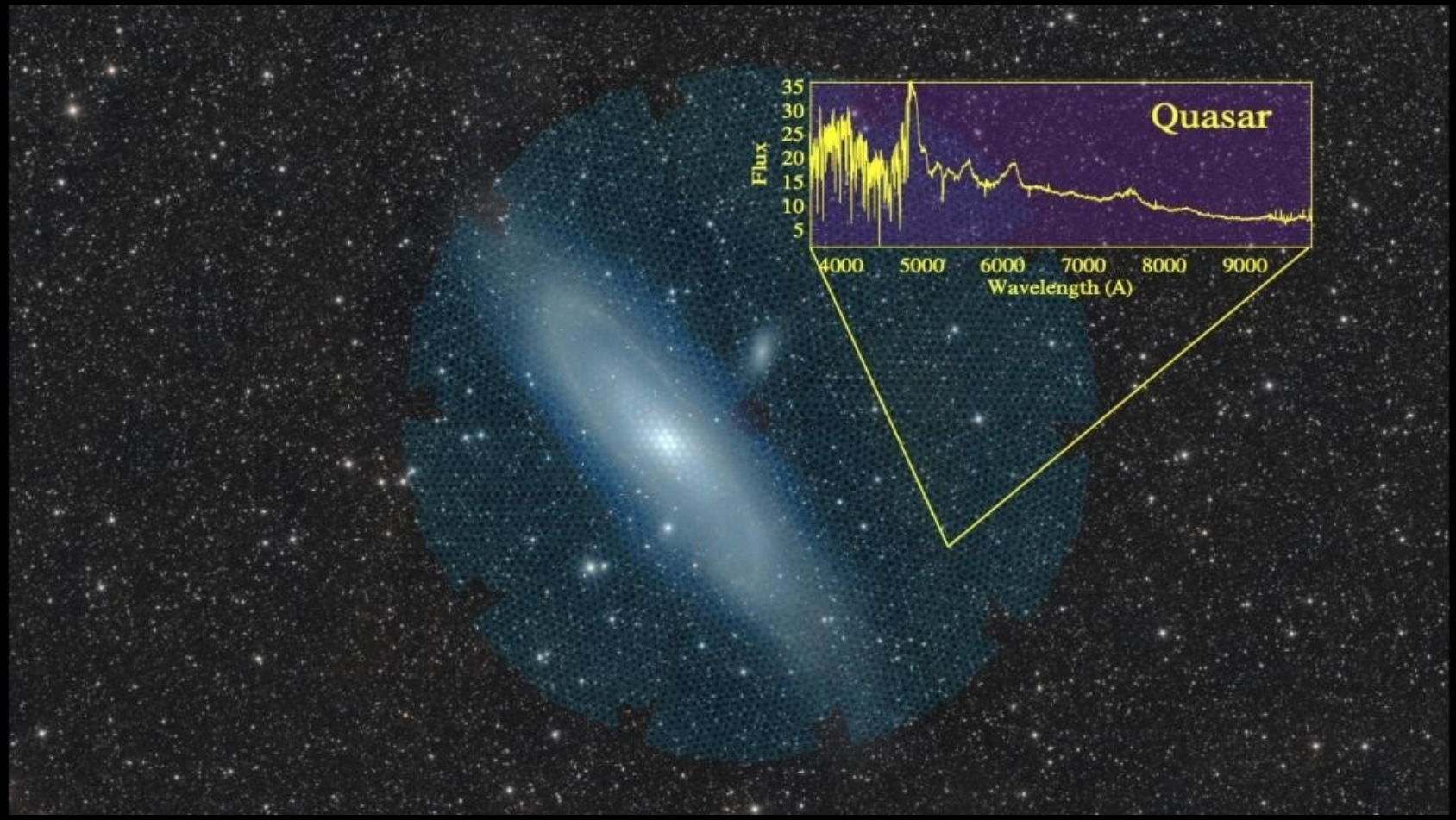

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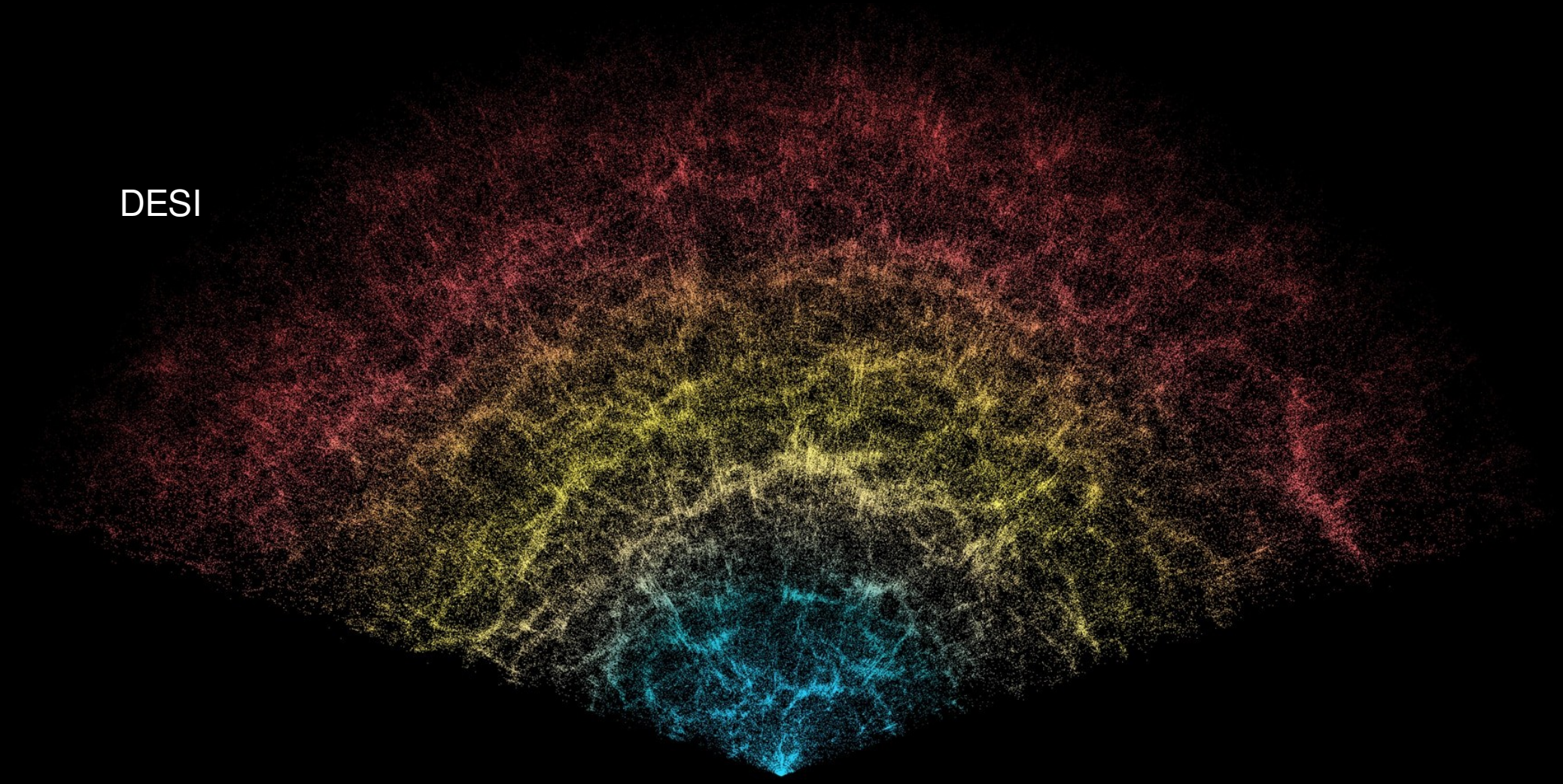
DESI



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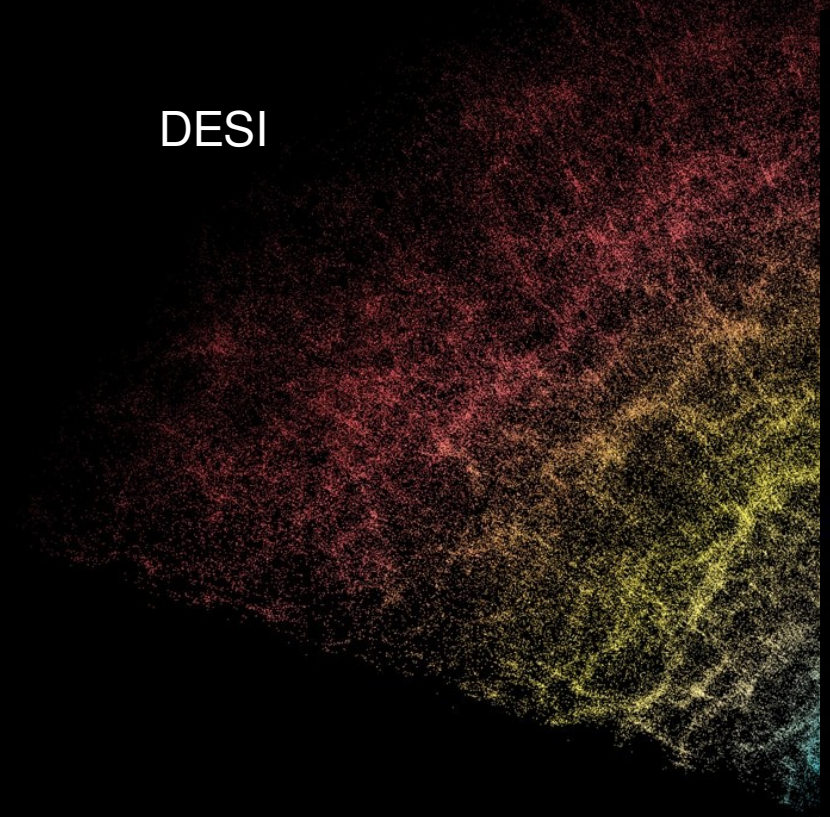

GALAH

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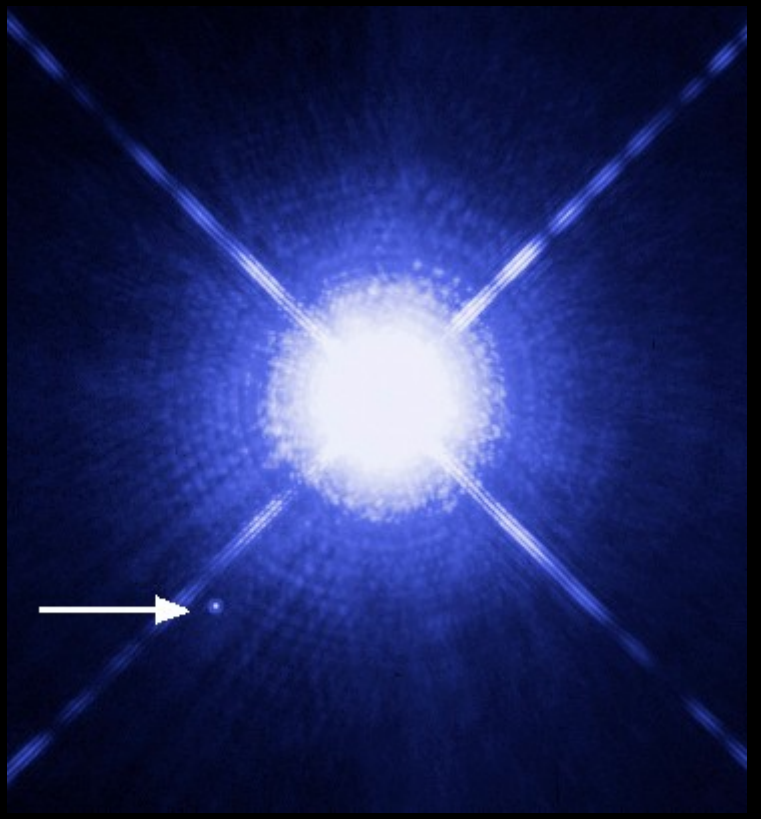

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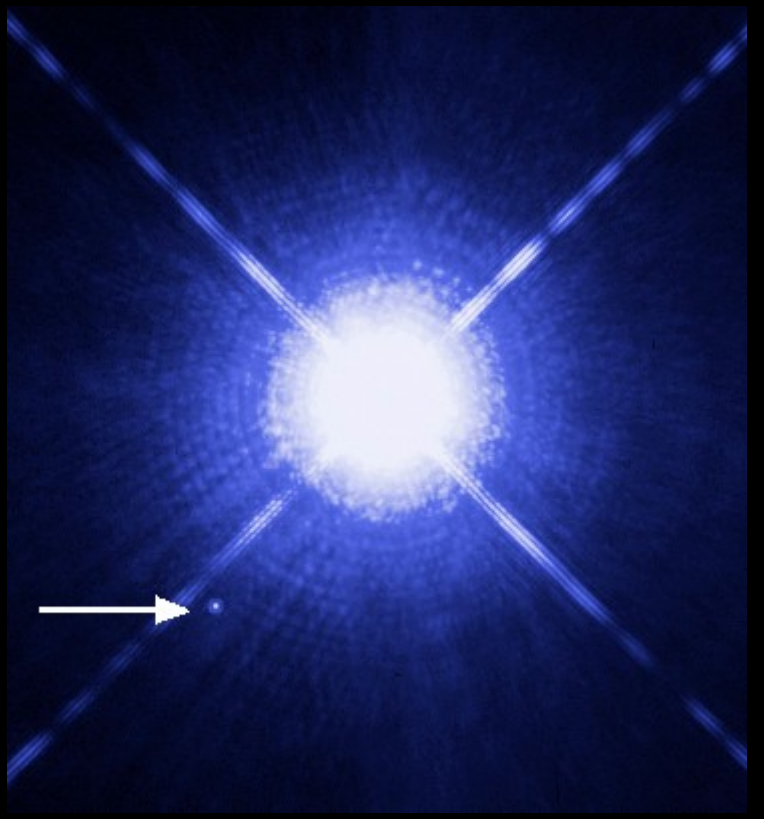

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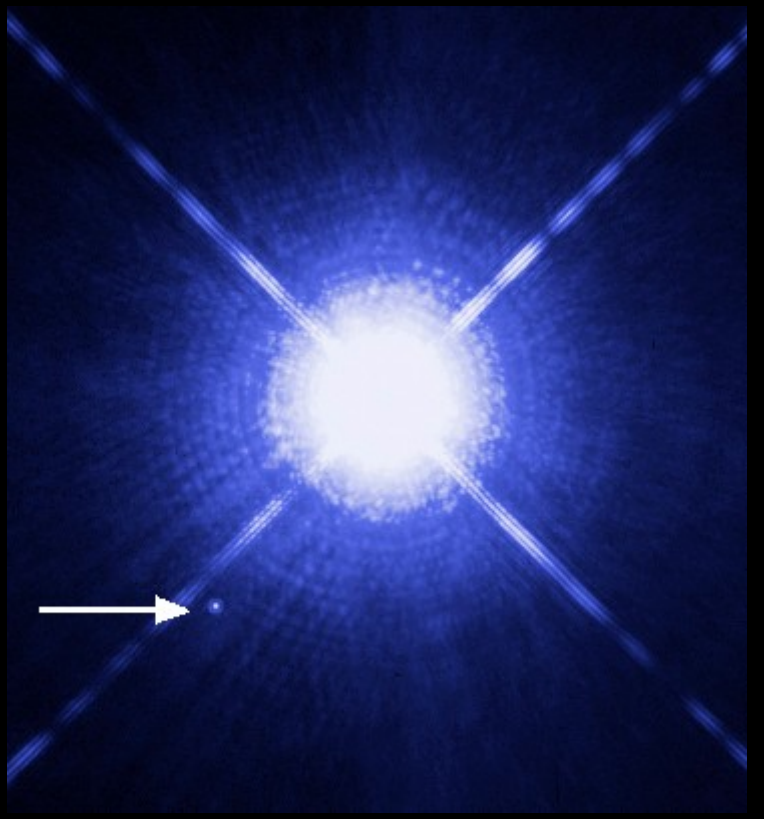

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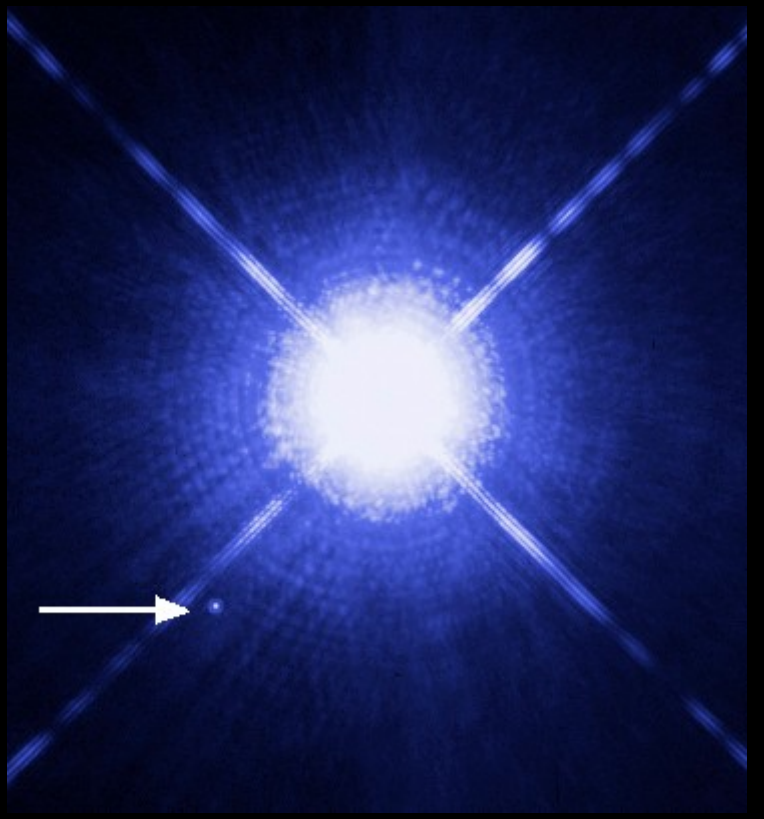

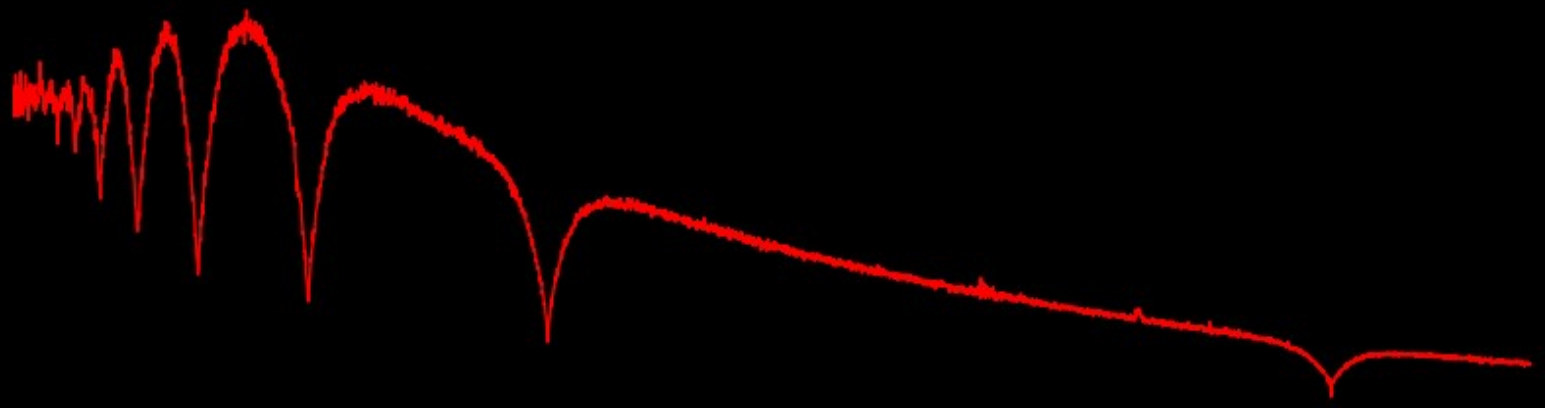

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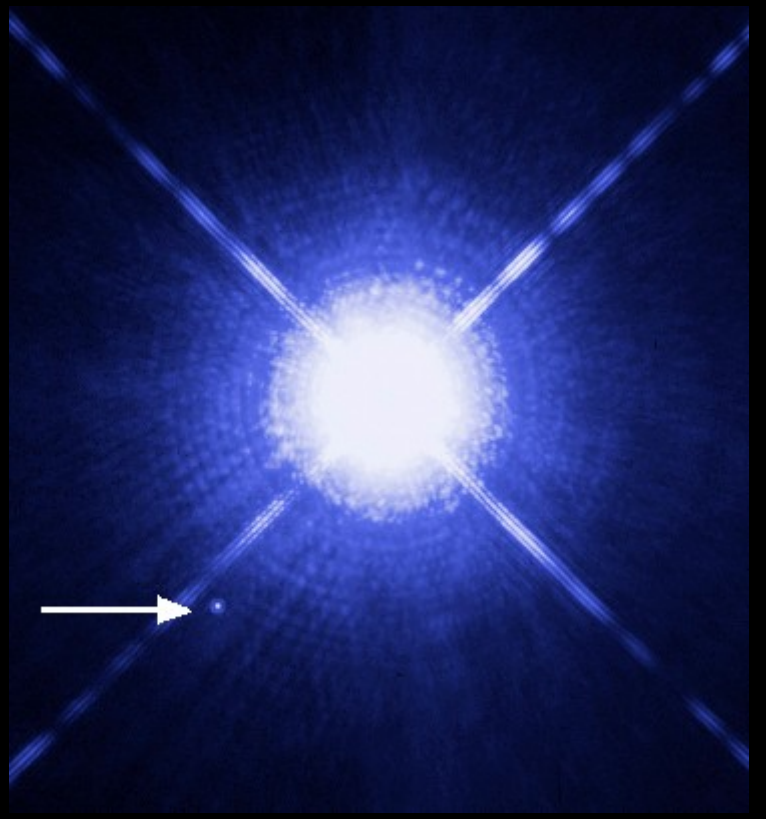

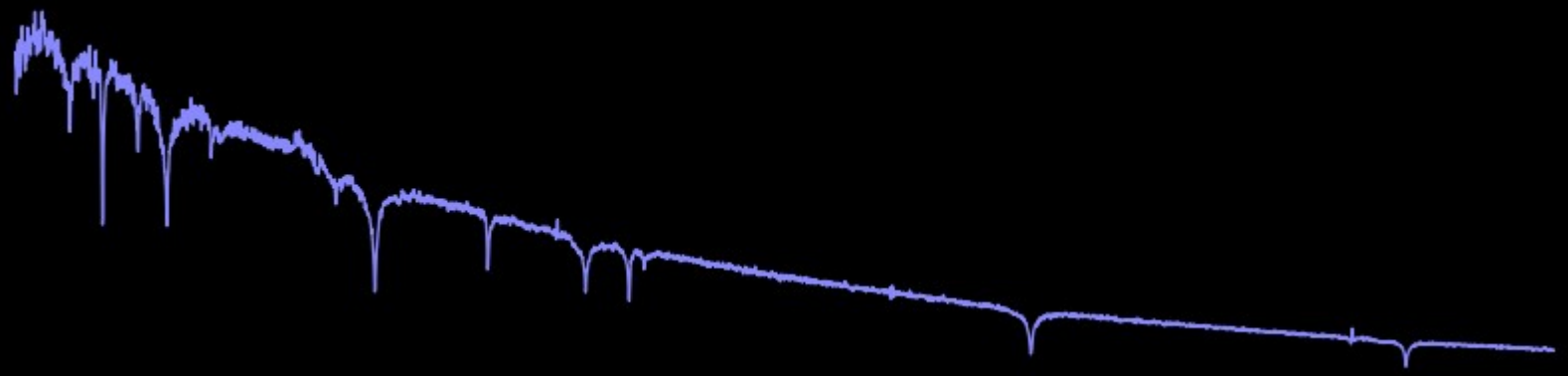

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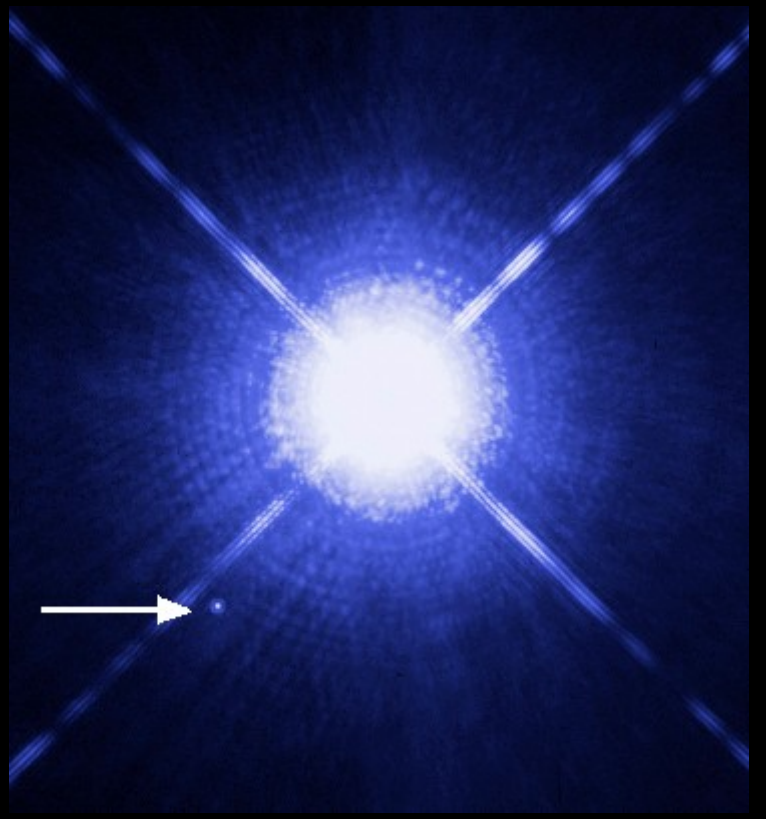

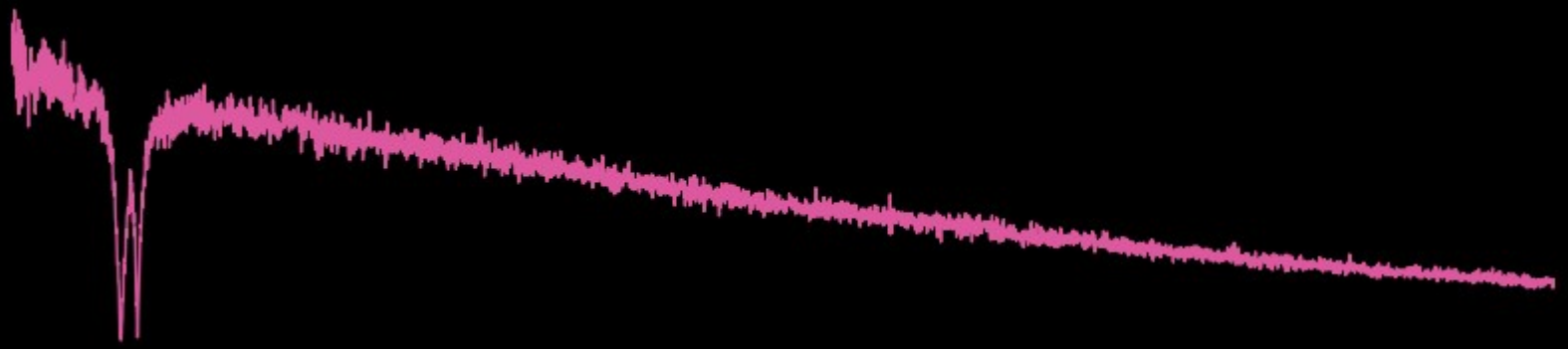

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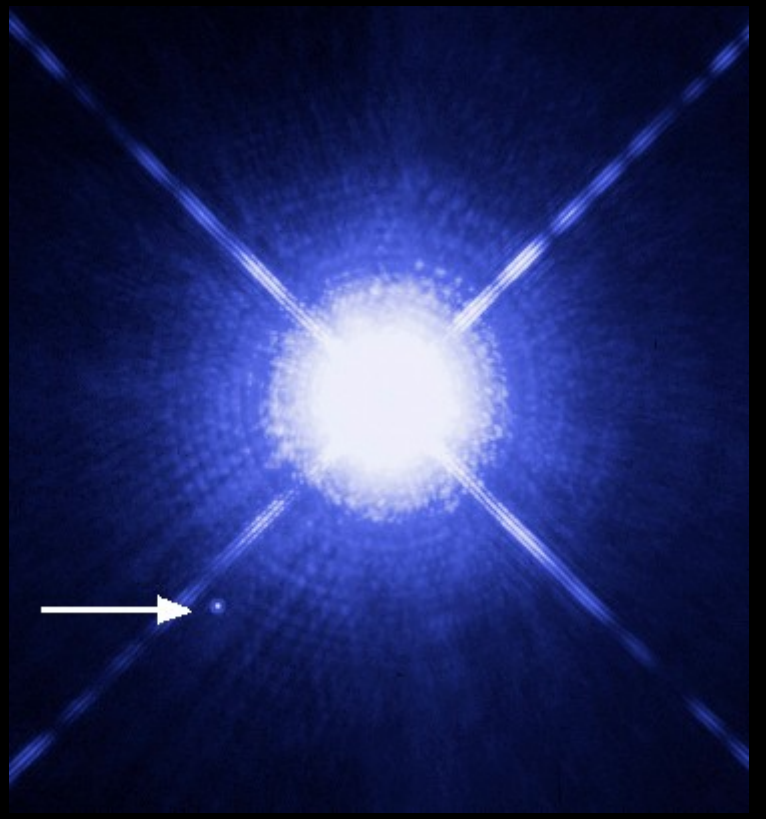

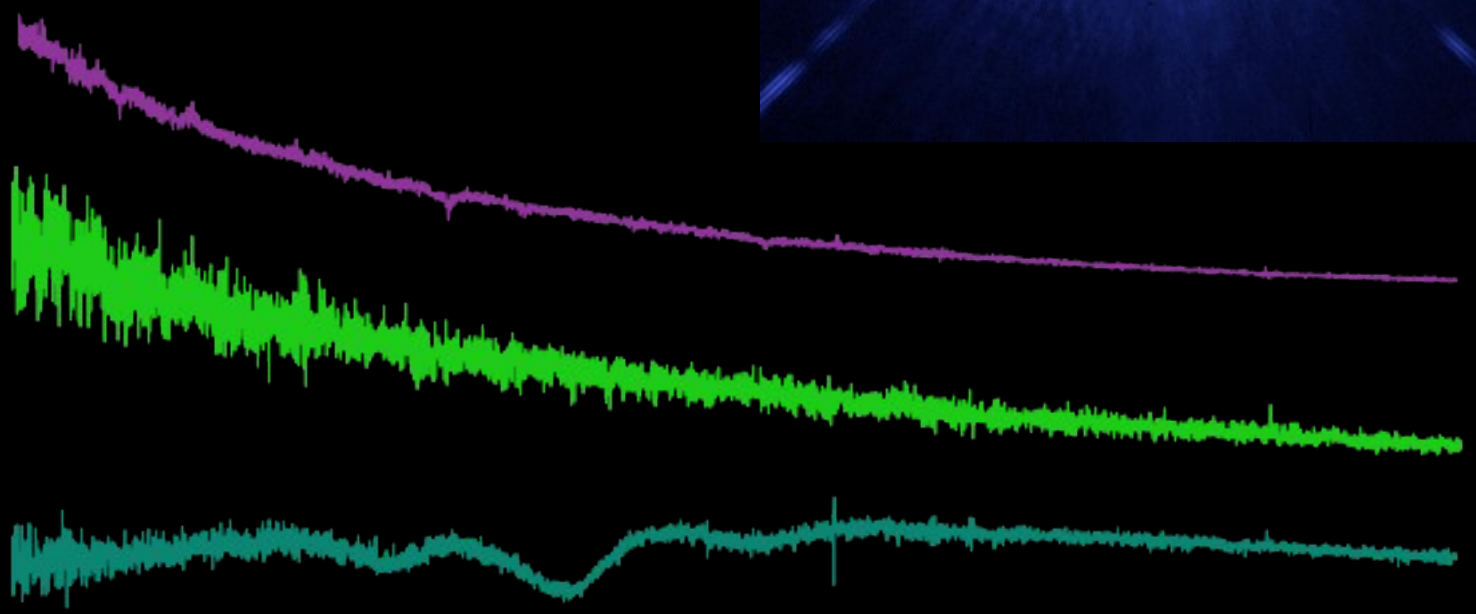

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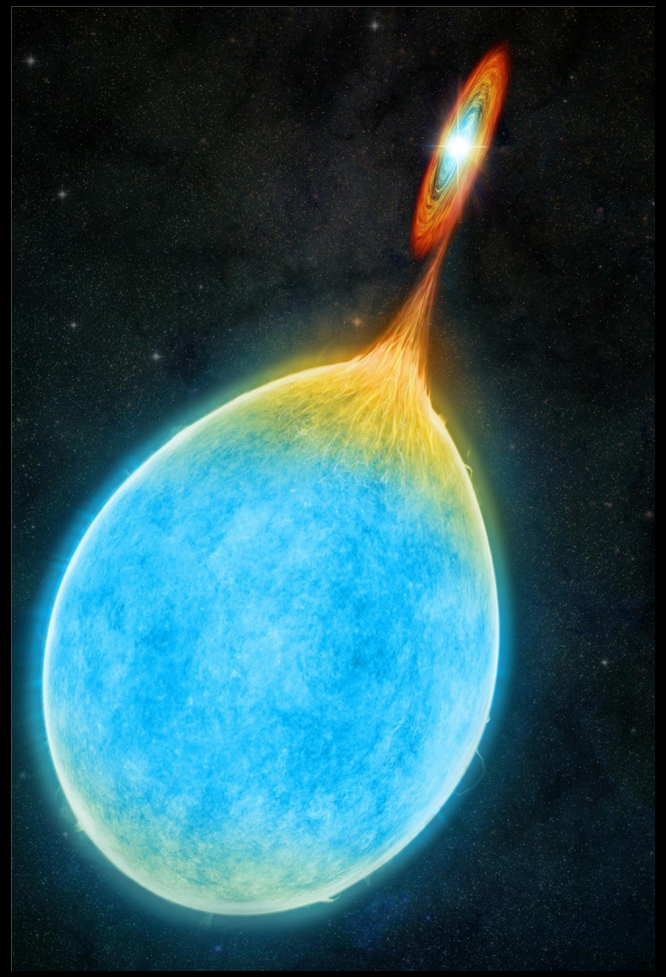
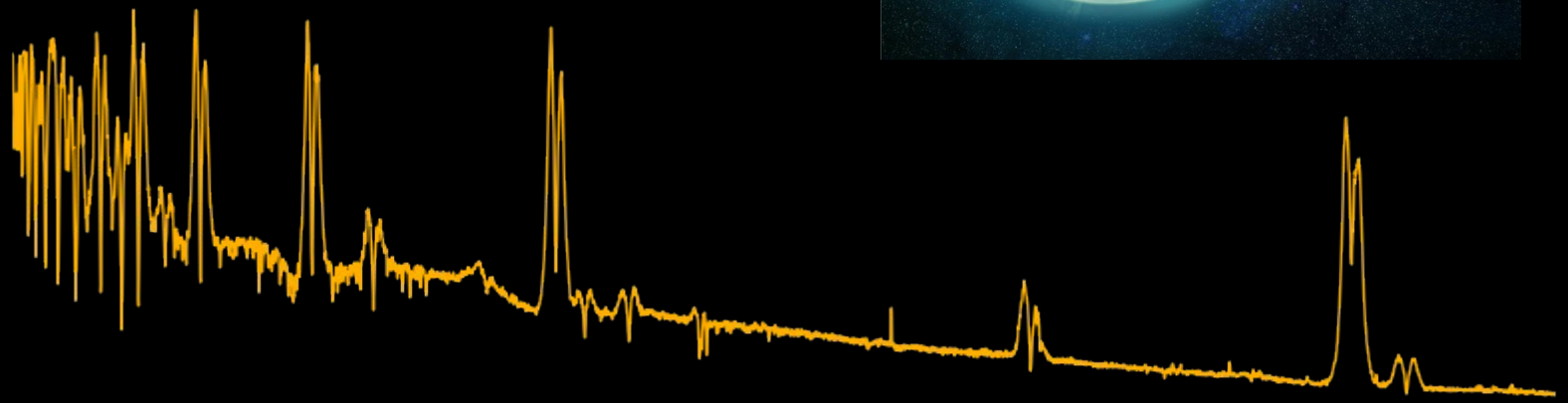


M. Weiss / CfA



~{ Interlude: Astrocolonialism }~

- DESI is on the Mayall 4m telescope at **Iolkam Du’ag / Kitt Peak**

- This site is leased (dubiously?) from the **Tohono O’odham Nation**

- astrobites:
  ‘A tale of two observatories’

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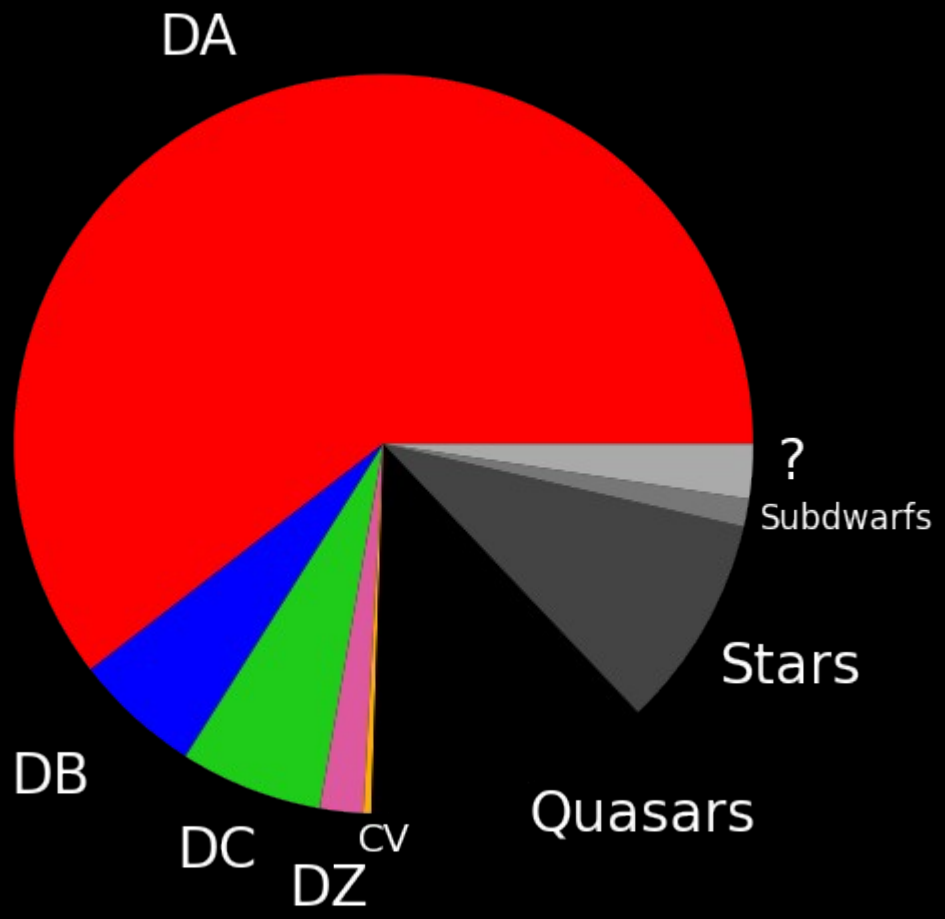

Manser+24

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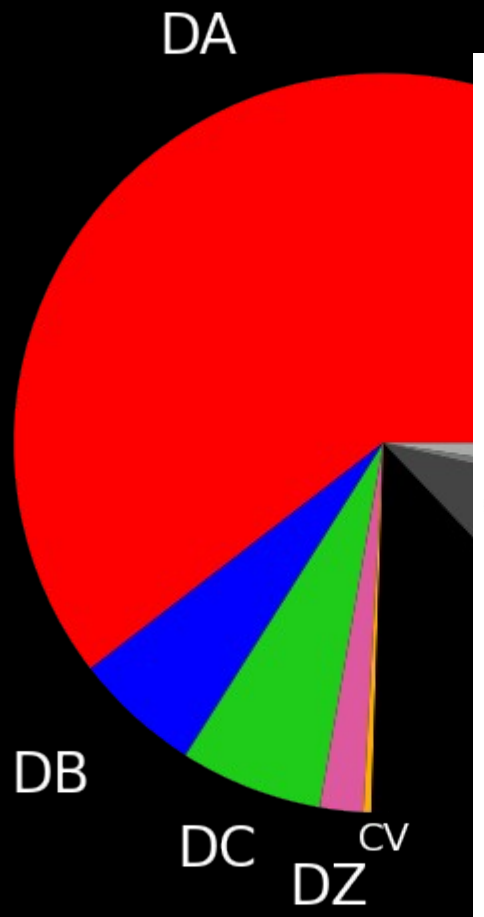

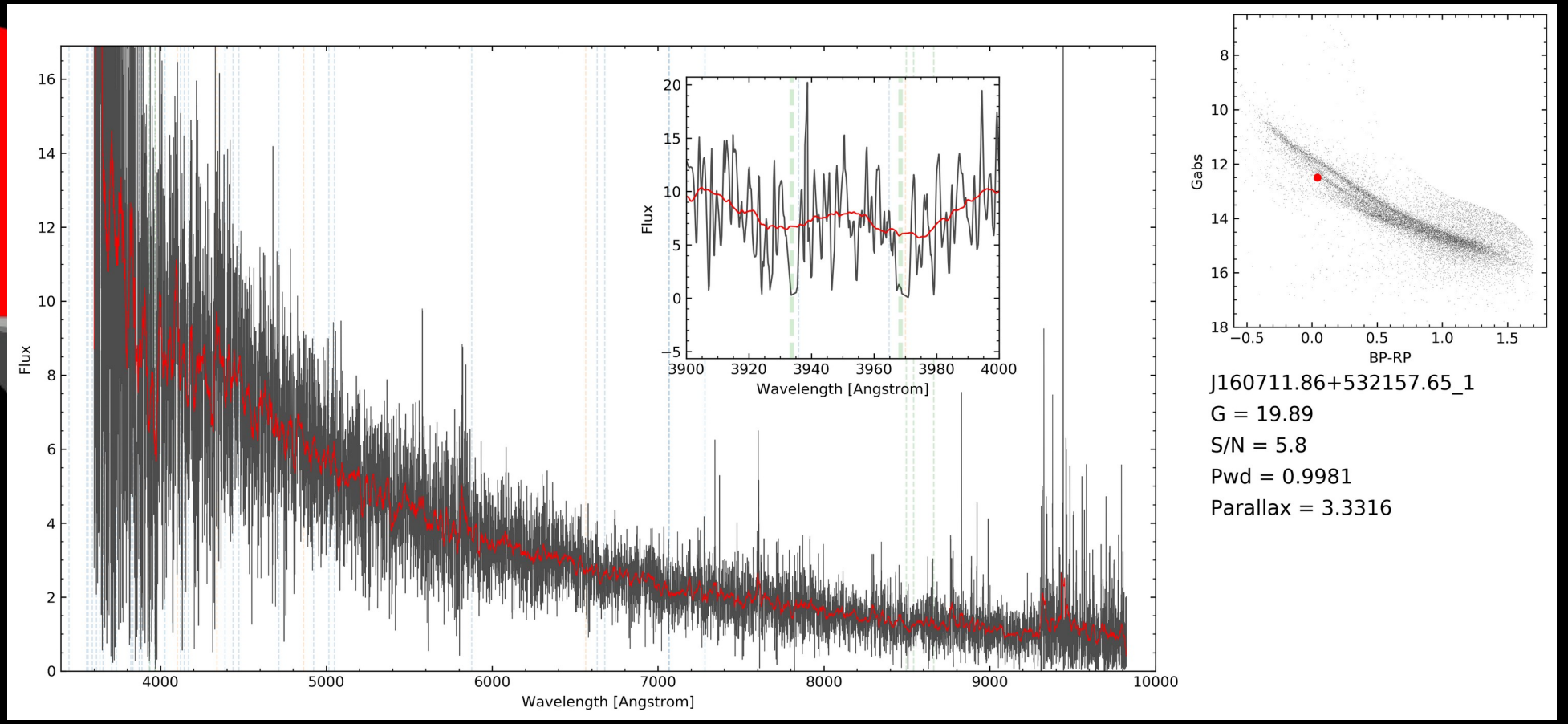

Manser+24

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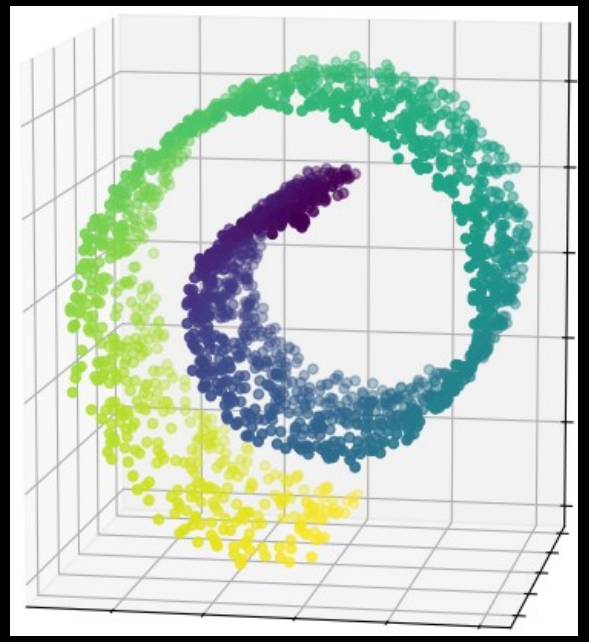

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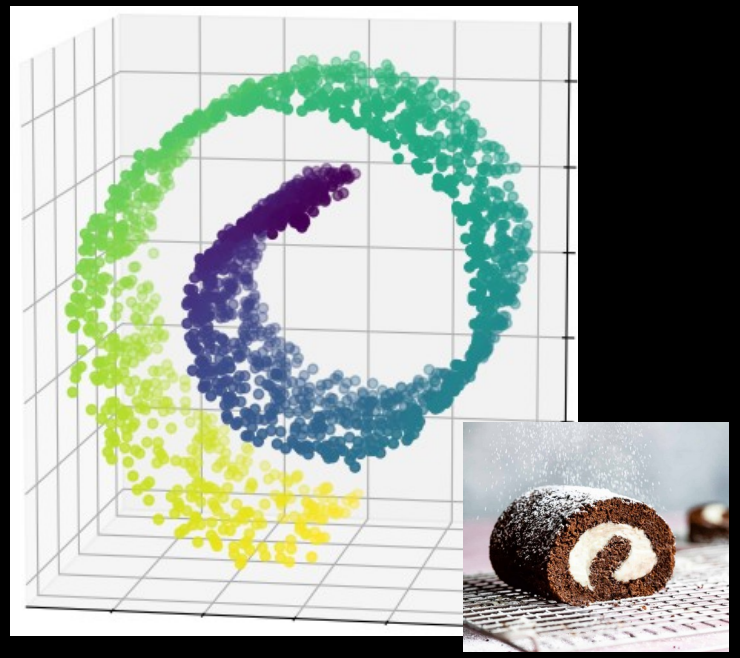

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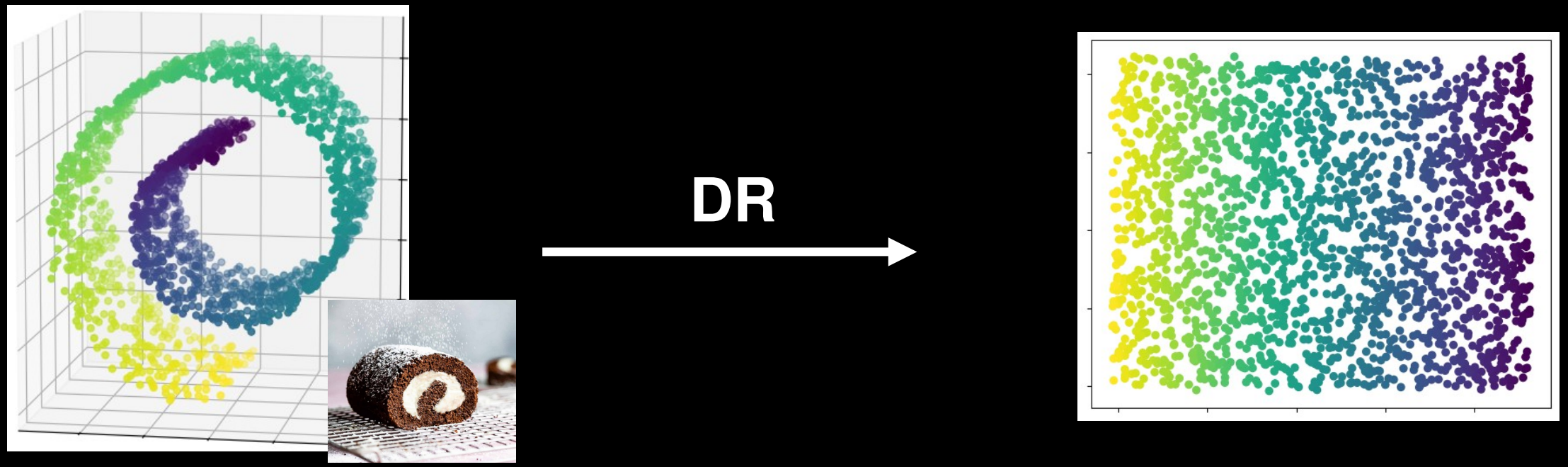
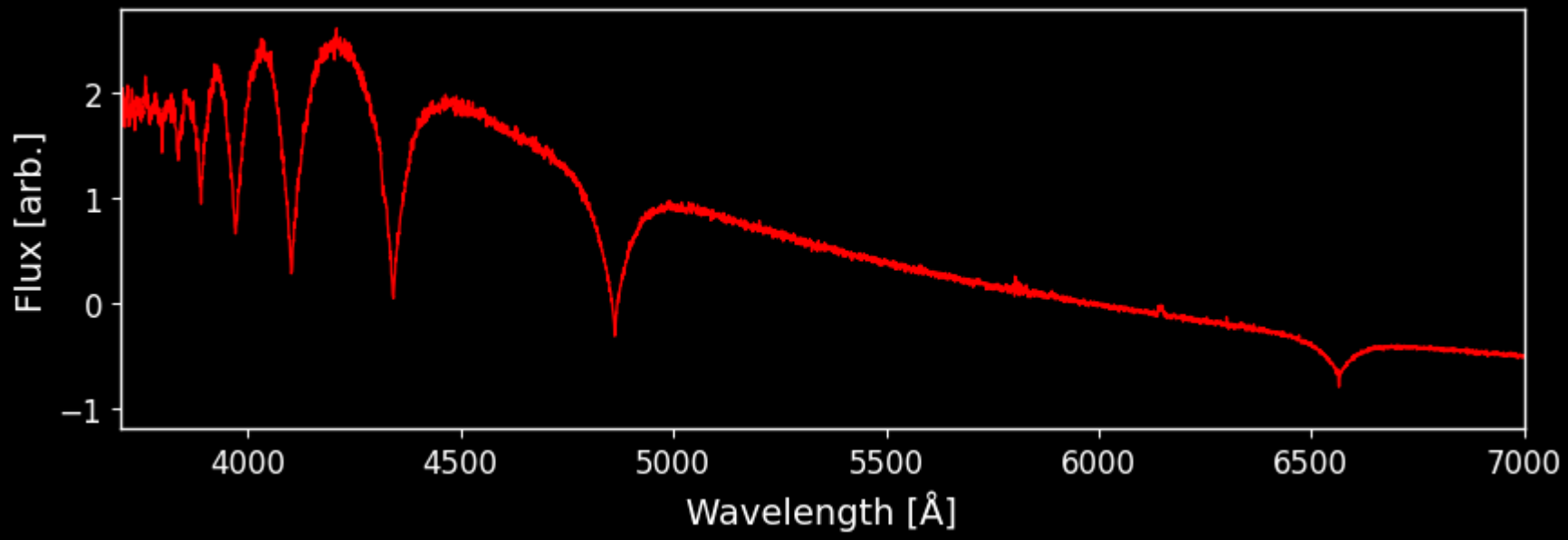


DR on a spectroscopic survey

- Each data point (e.g. spectrum) **converted to a vector**:



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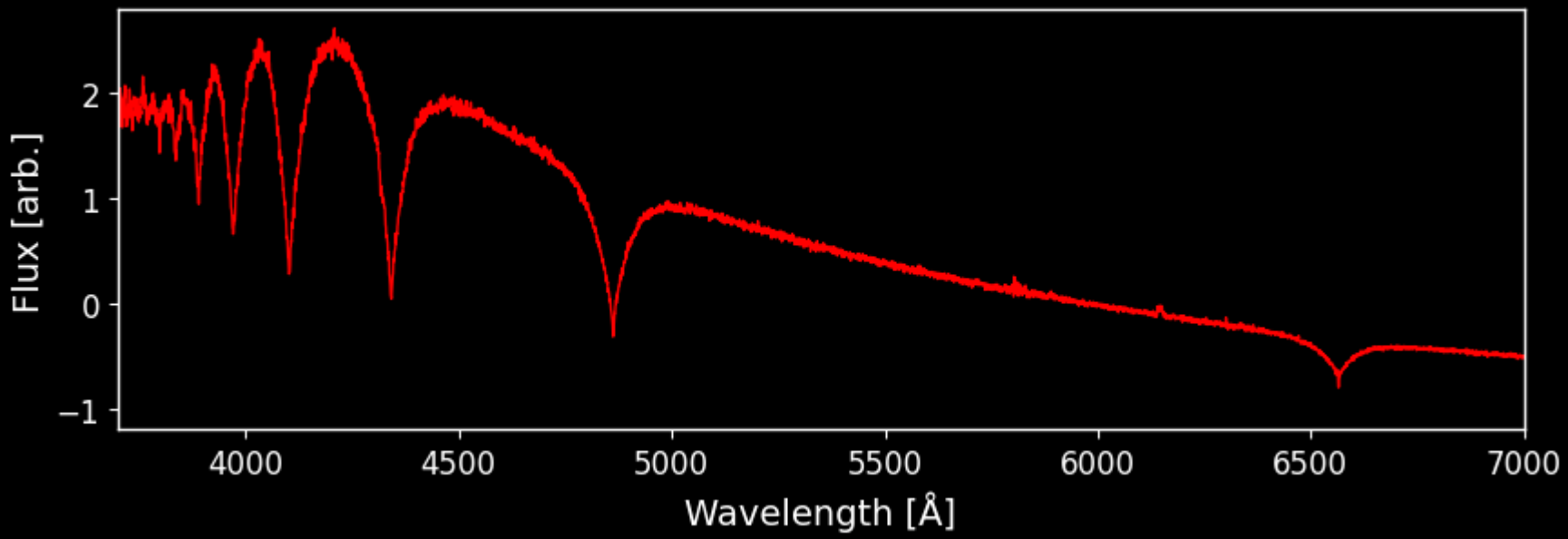

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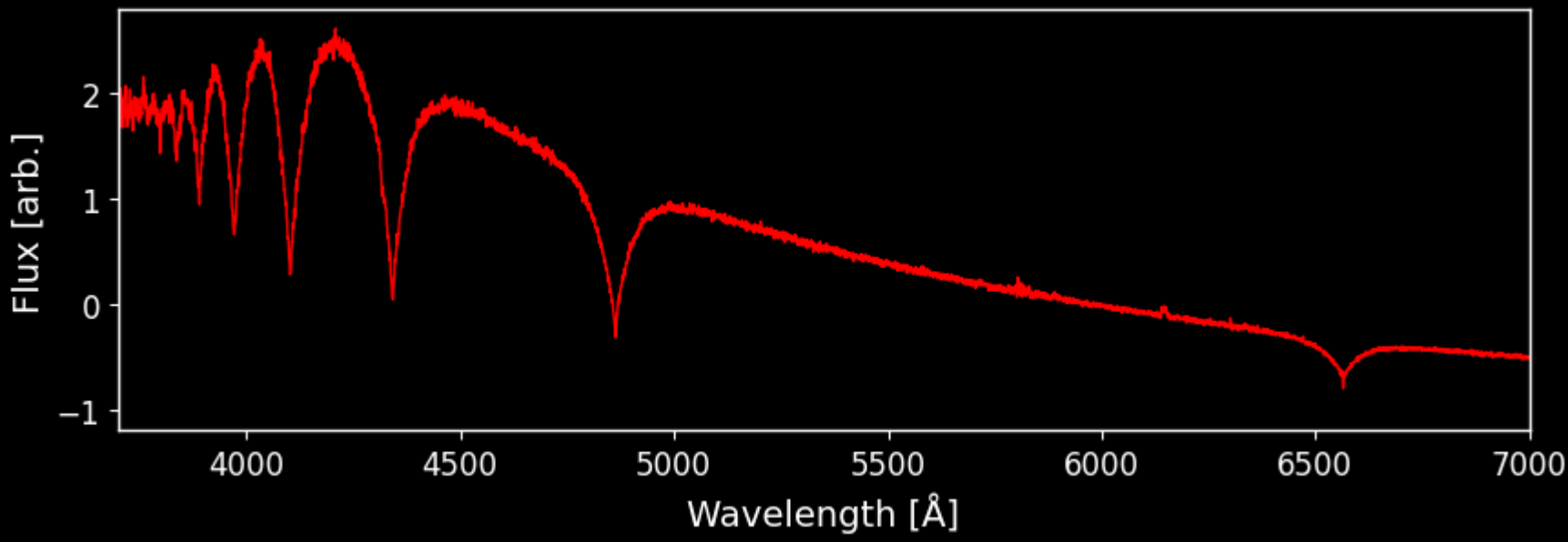
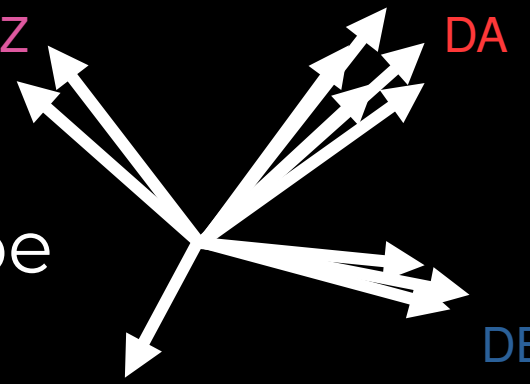
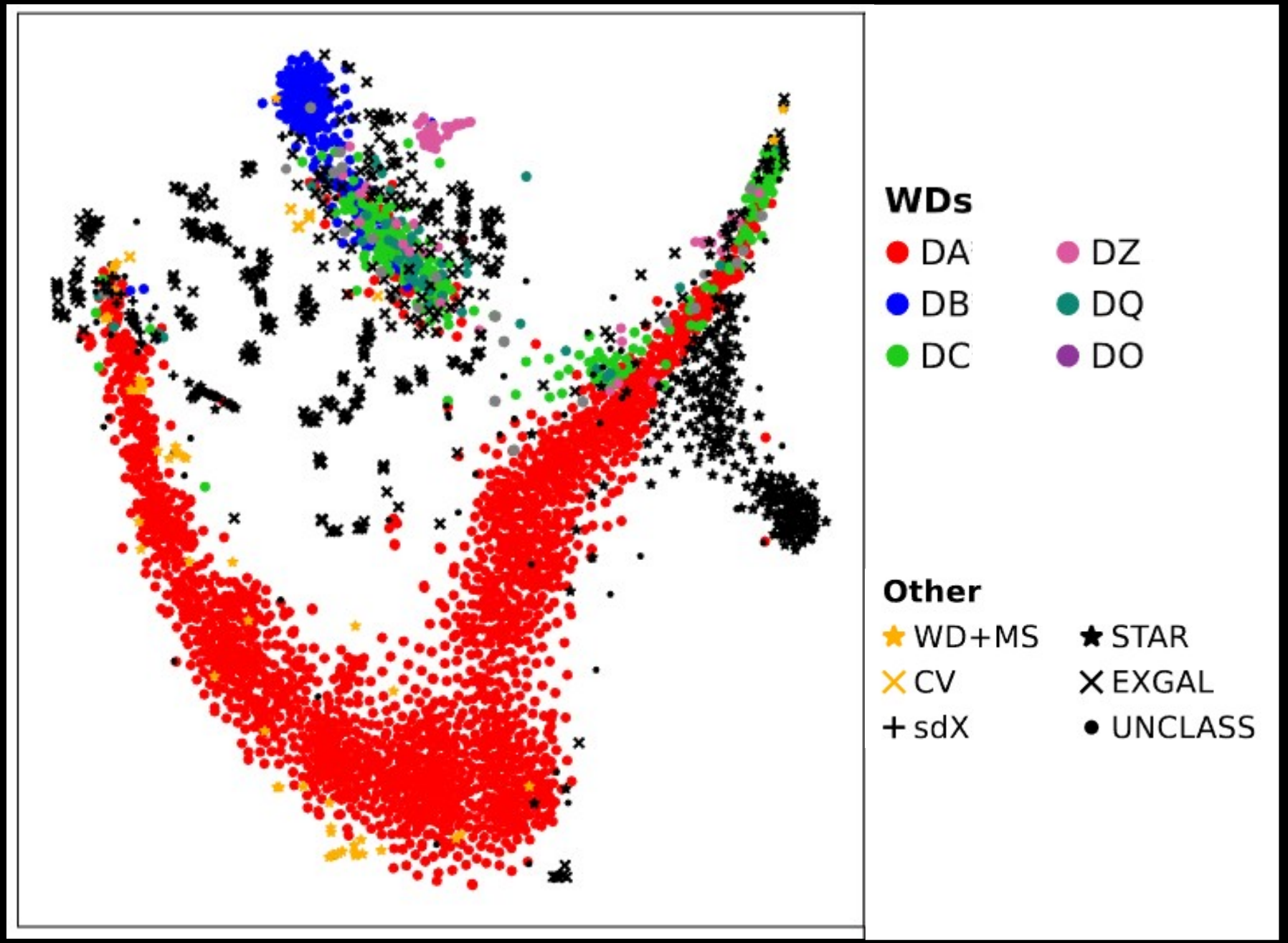


- => a dataset of ~8000D vectors, arranged by type





Byrne+, in rev.

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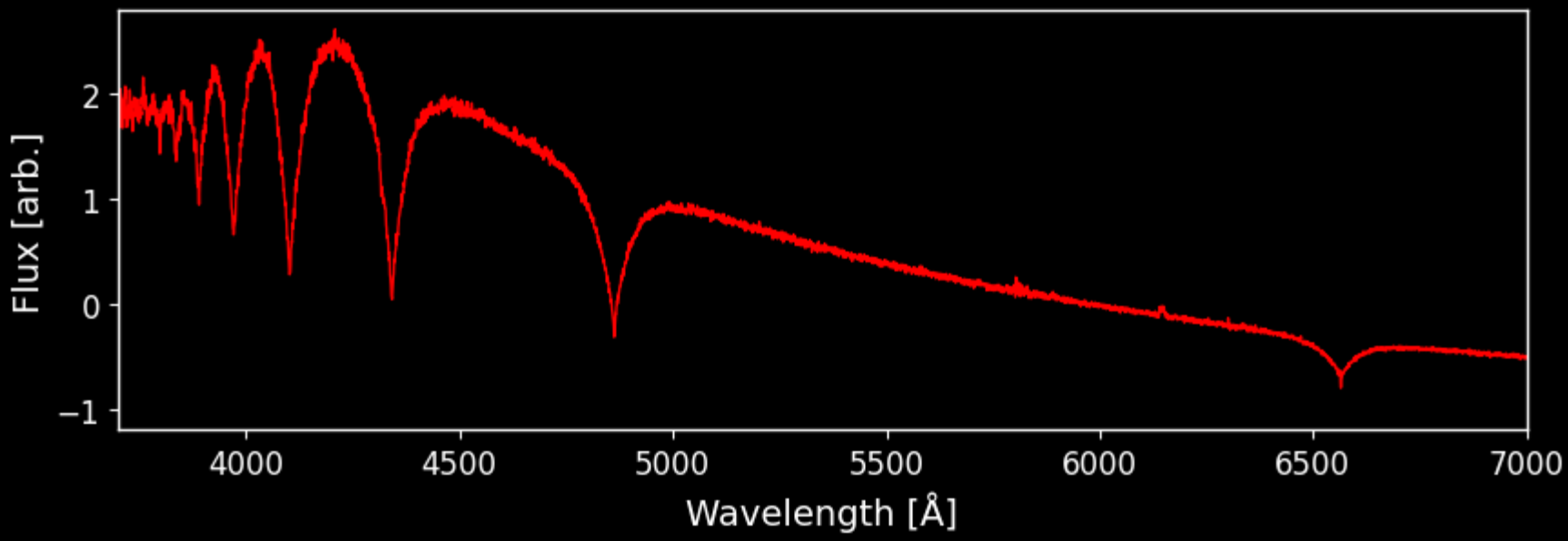
- **Objective** – doesn’t rely on human interpretation

Focusing on spectral lines



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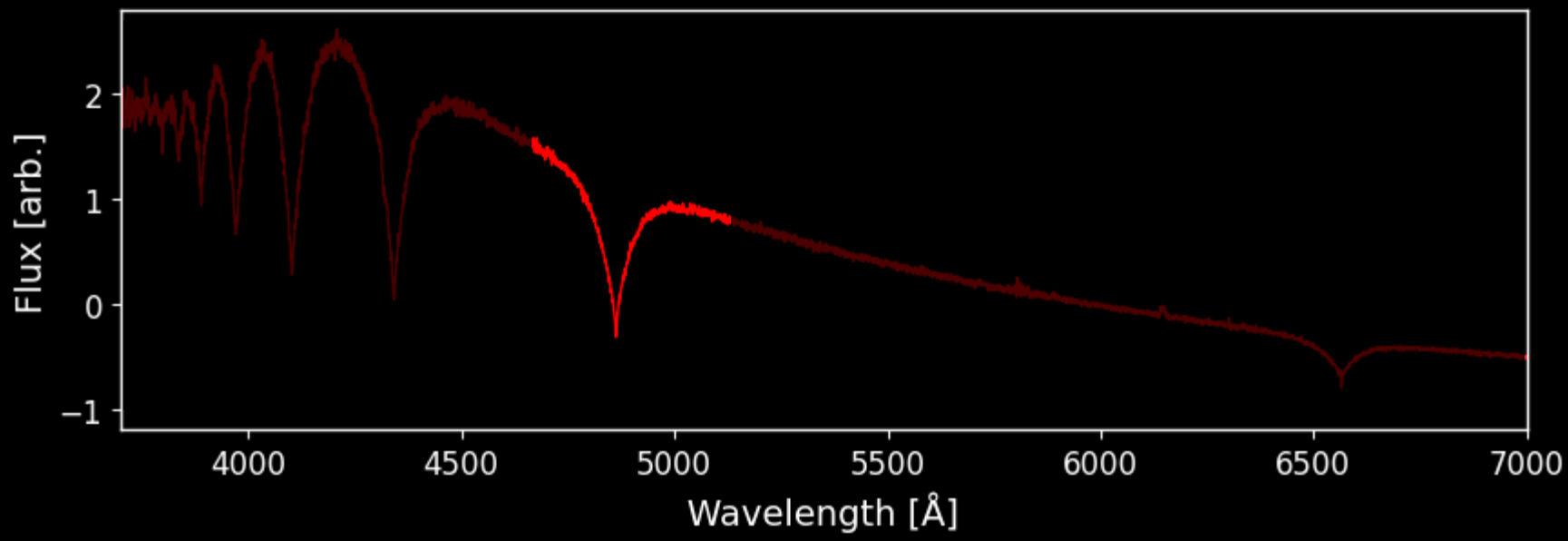

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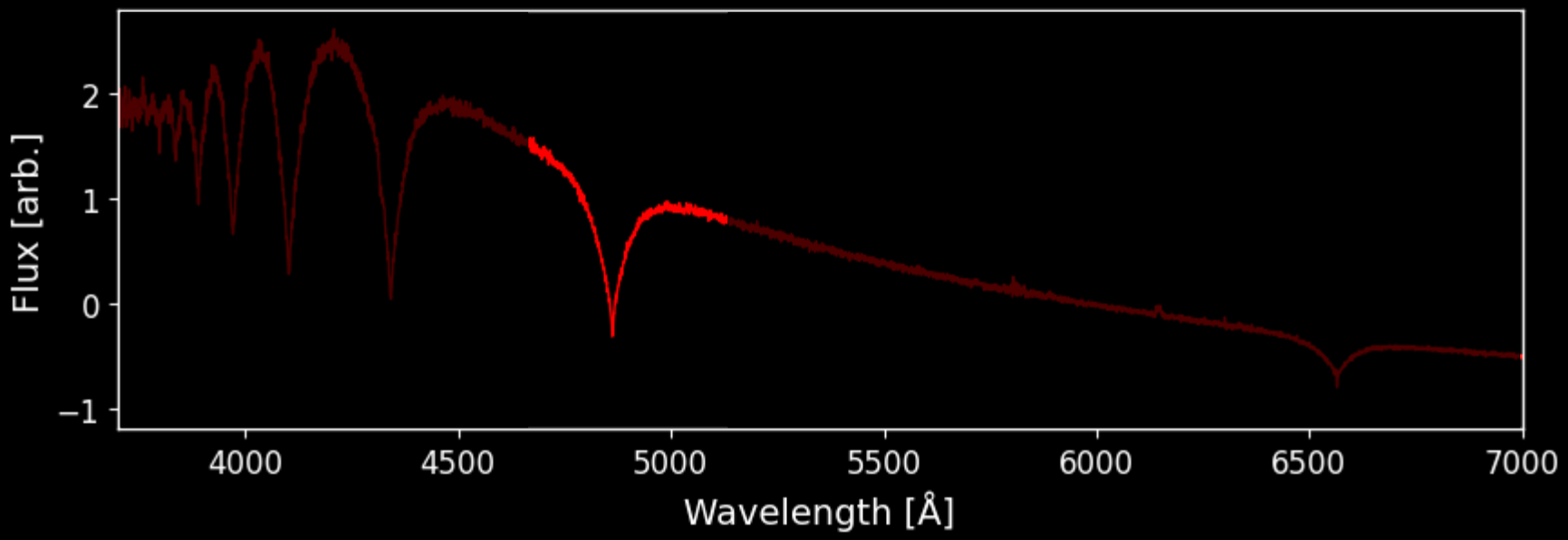

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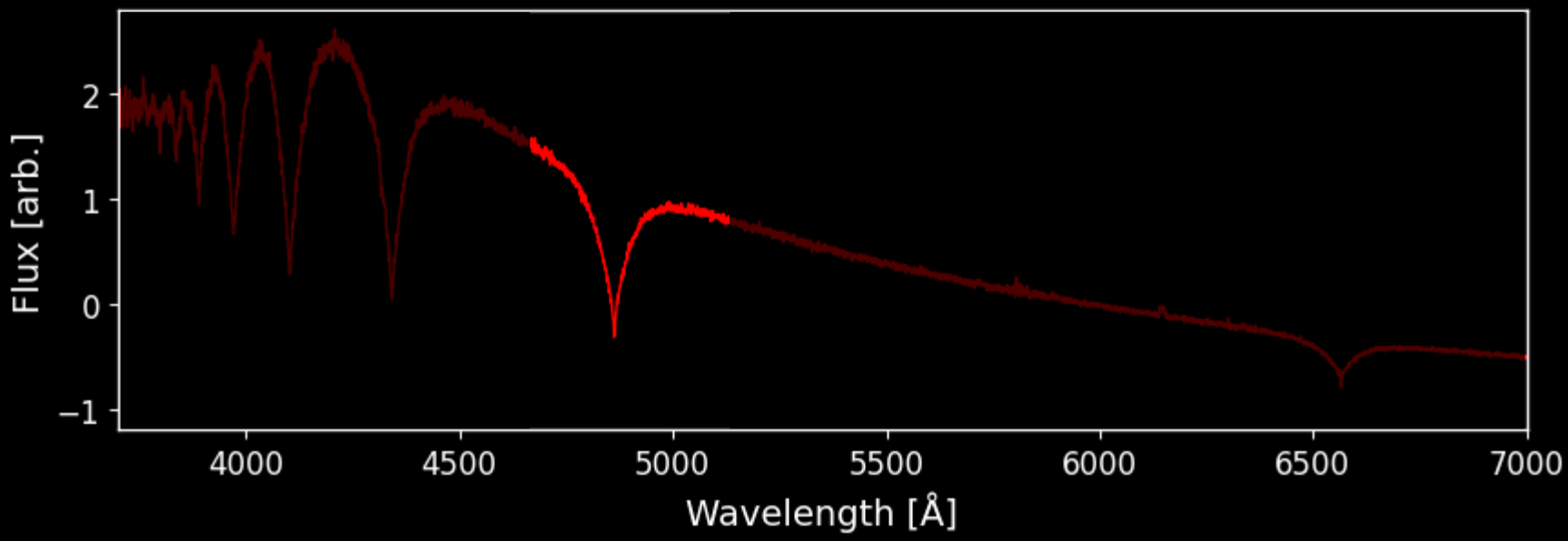

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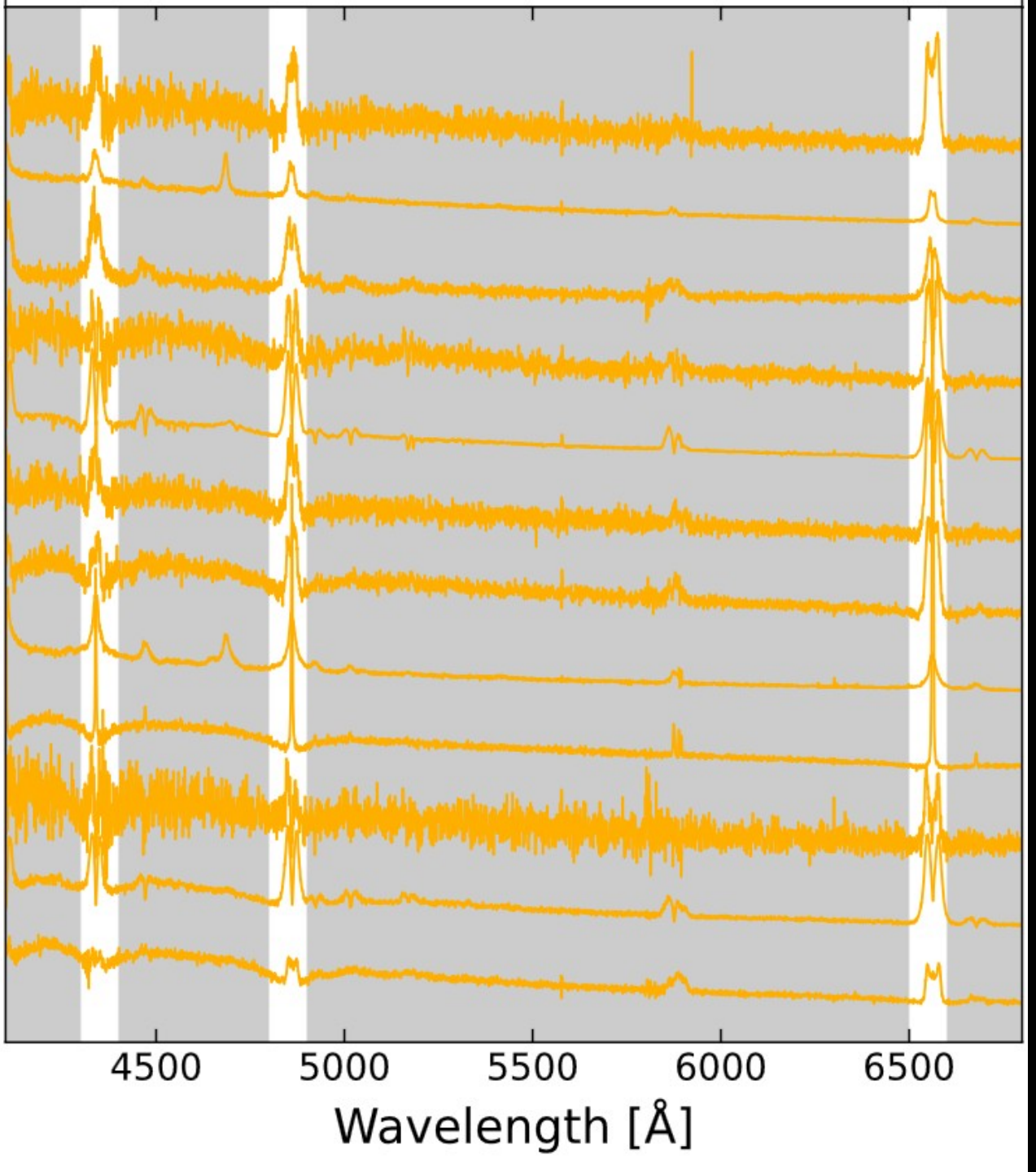
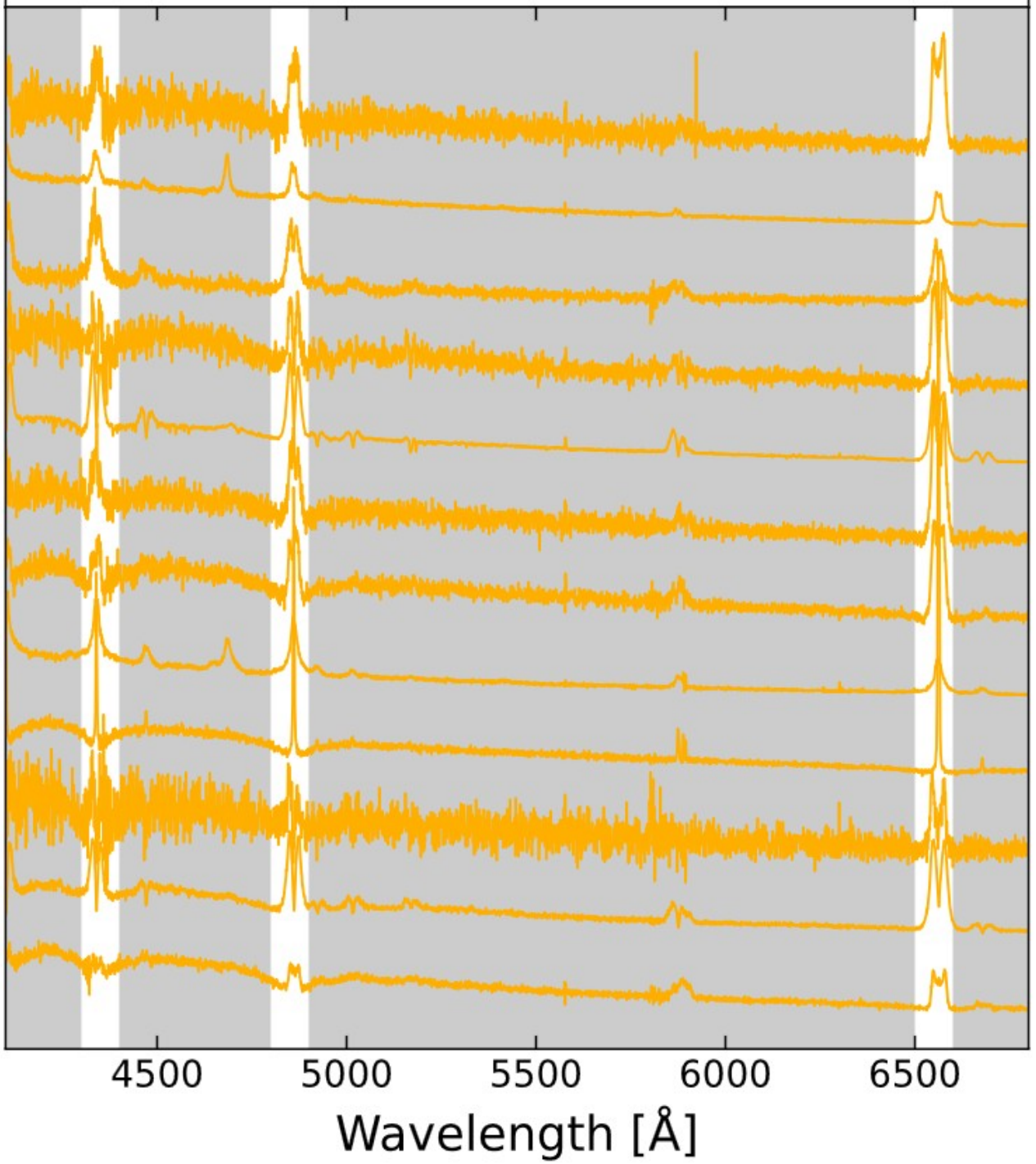
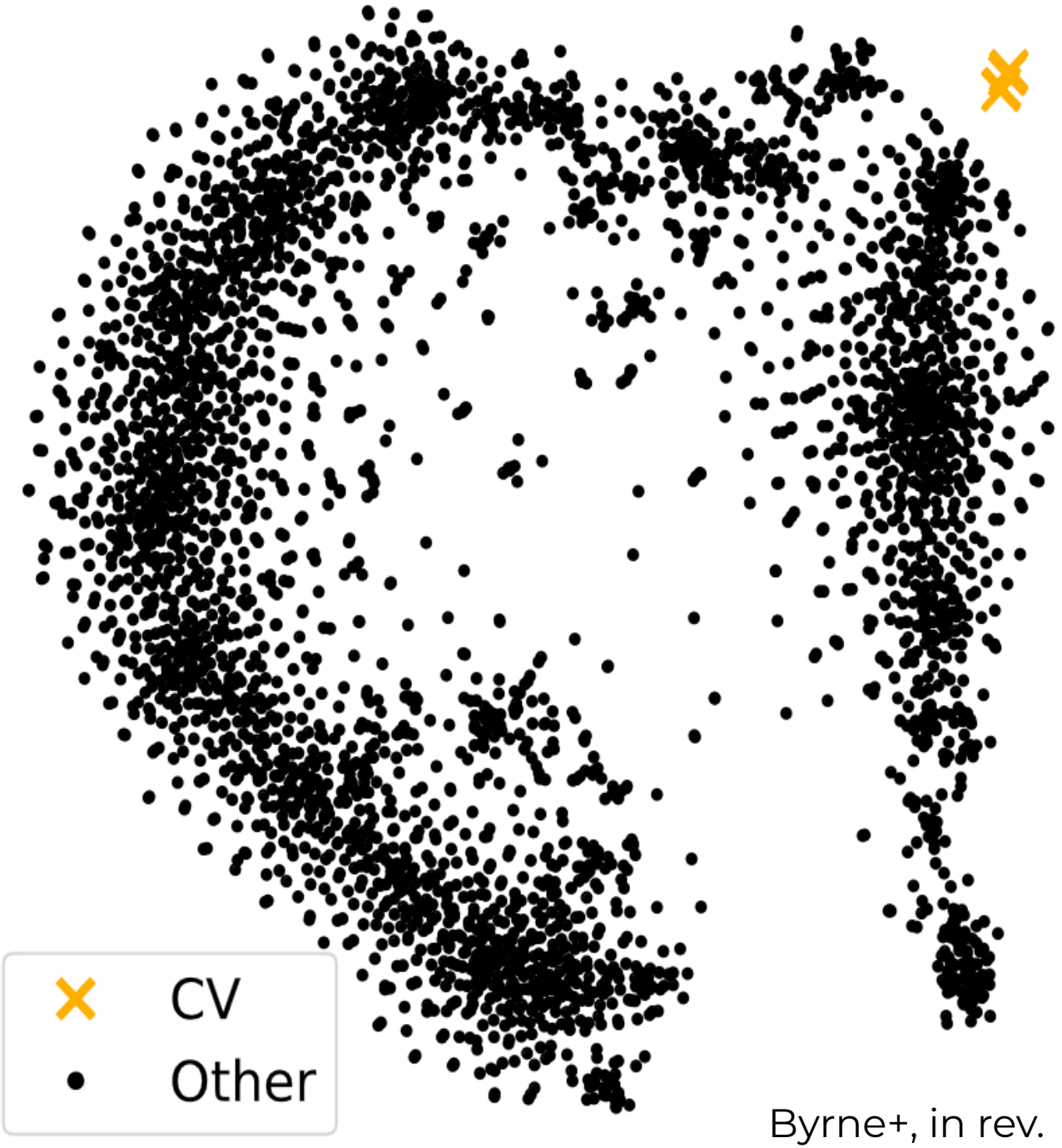
- Vectors now clustered based on a spectral feature
- Removes ‘distraction’ of rest of the spectrum



Byrne+, in rev.





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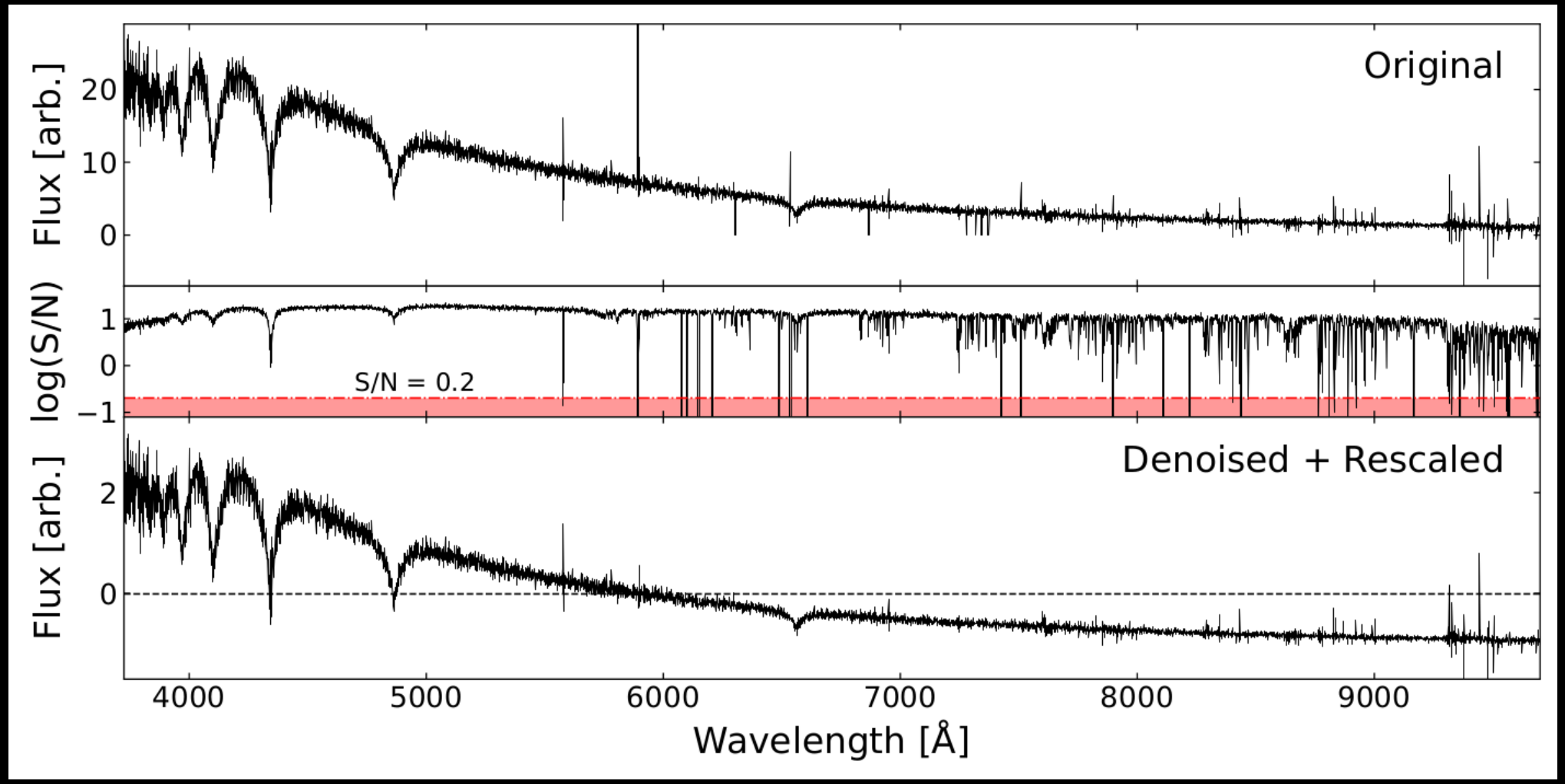
Conclusions

- Spectroscopic surveys return valuable data for WD science
- Dimensionality reduction is a useful classification tool for spectroscopic surveys
- Focusing on spectral lines can improve classification power

Extra slides

Preprocessing



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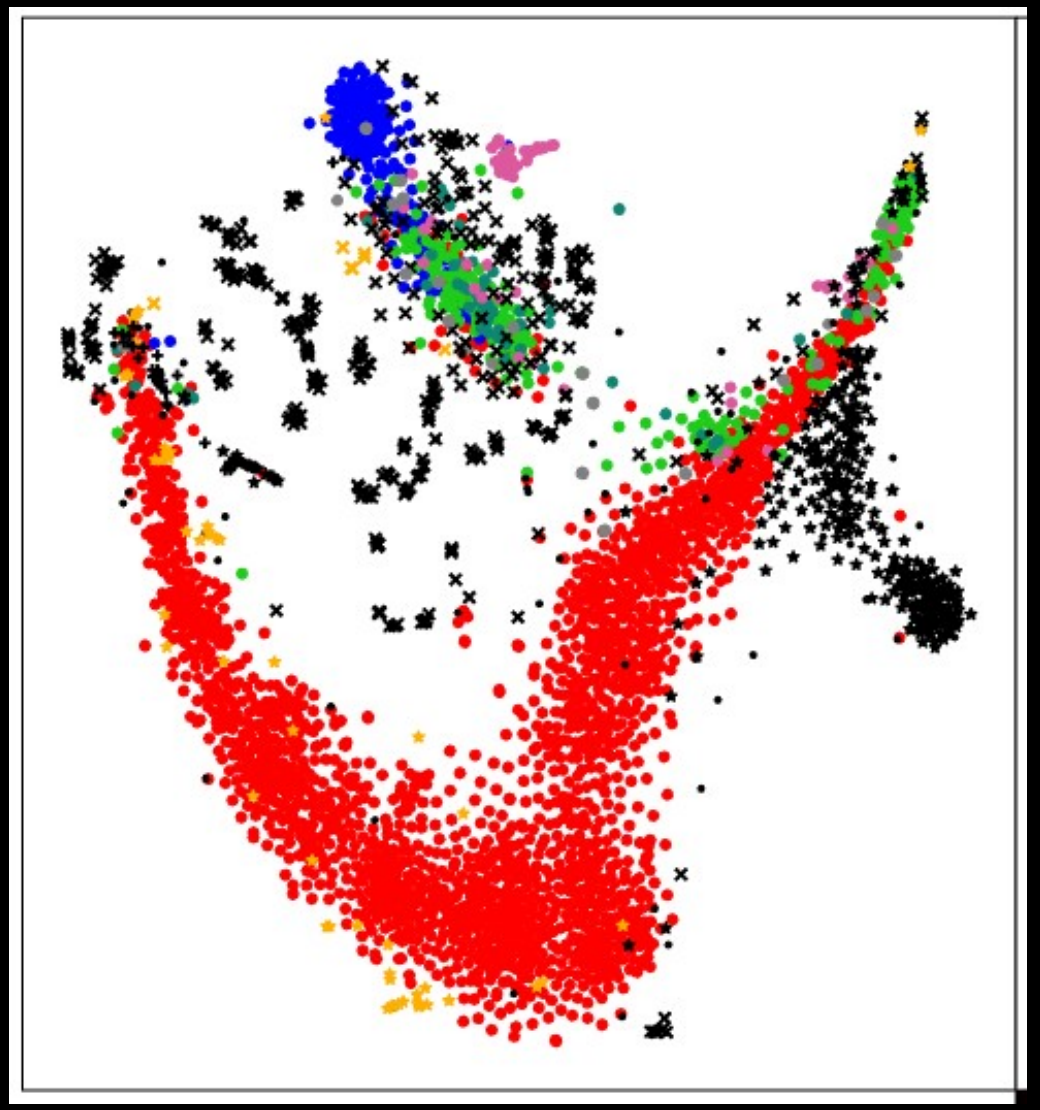

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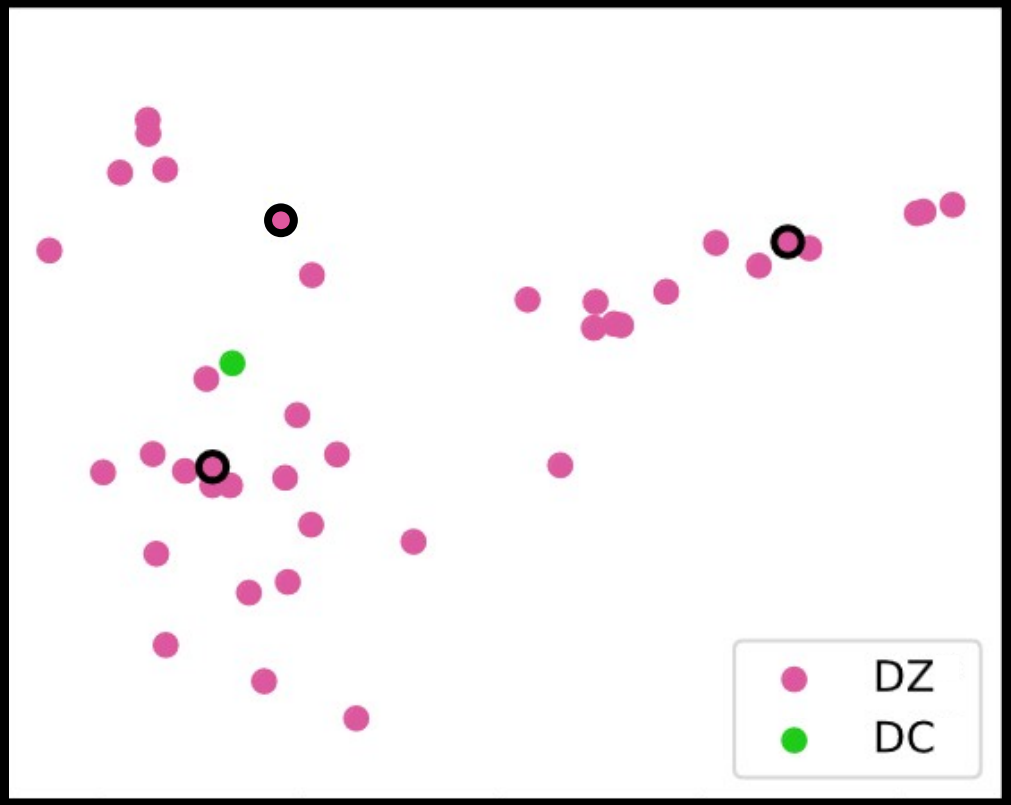

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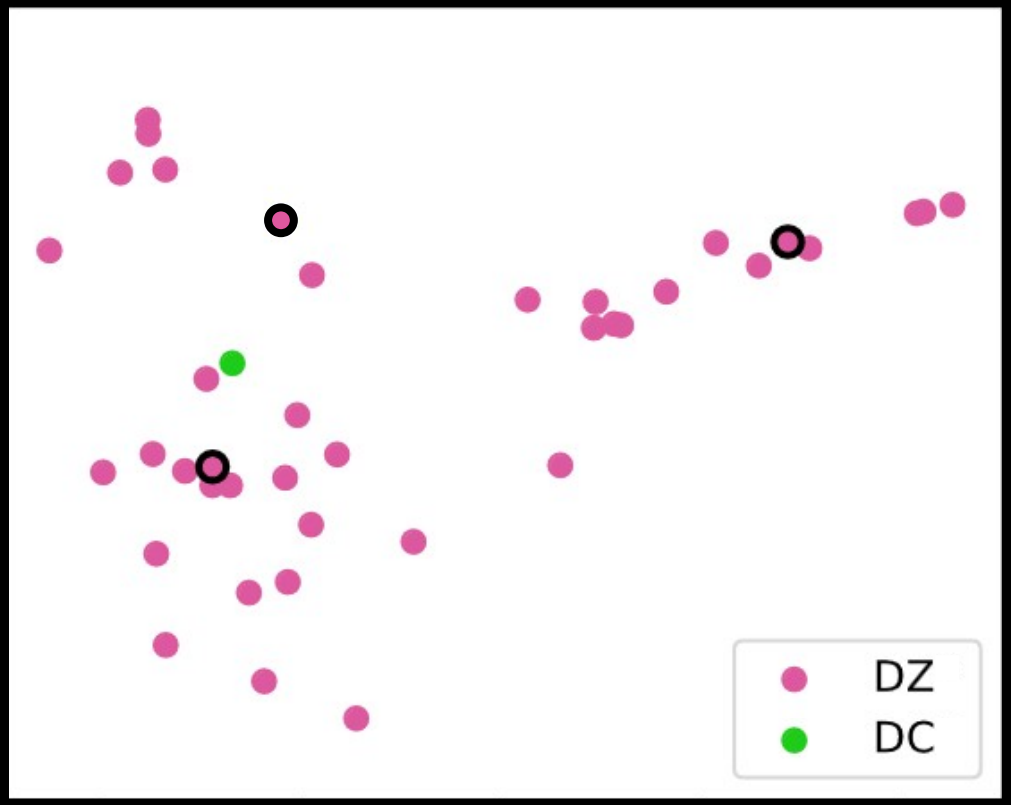

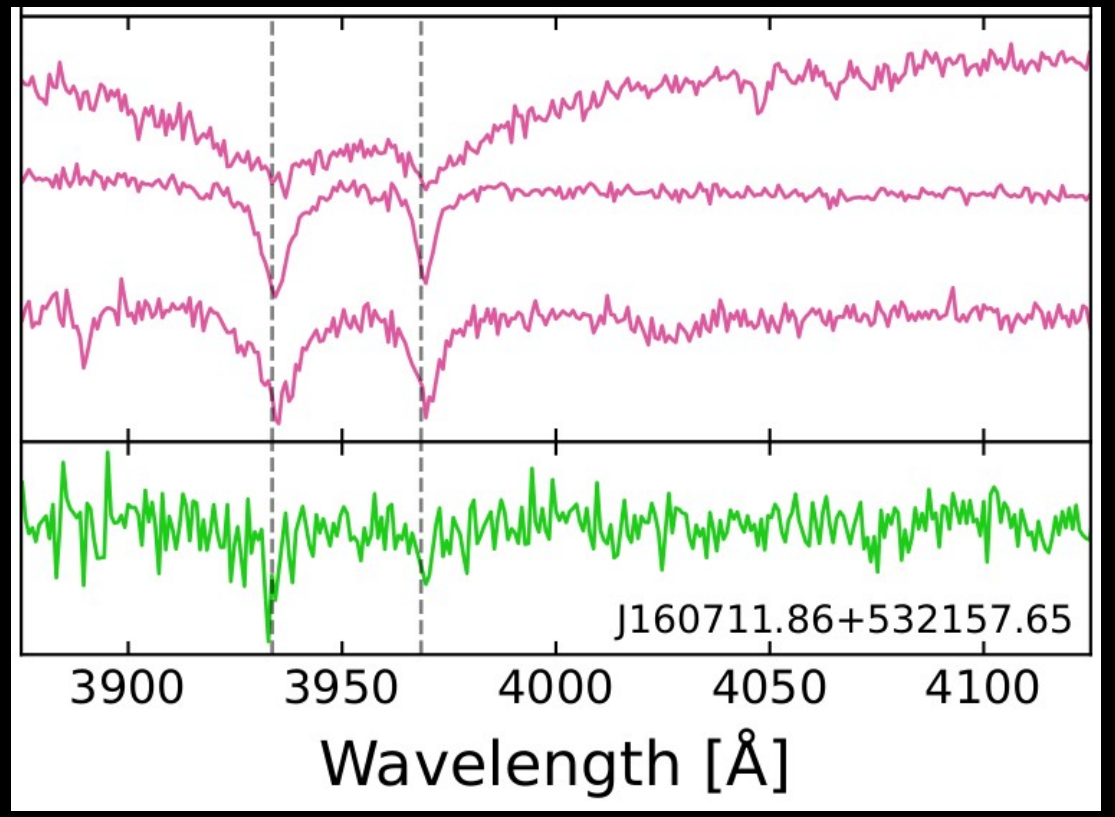

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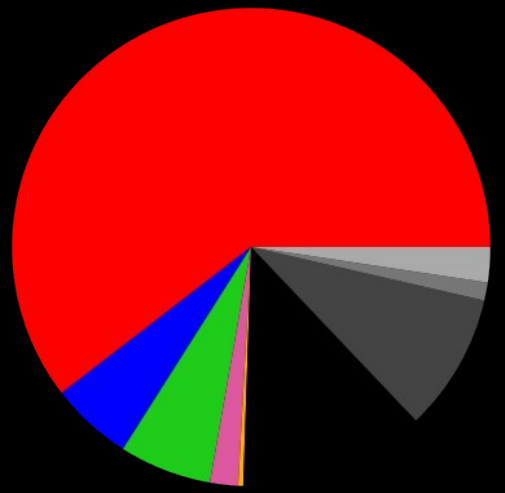

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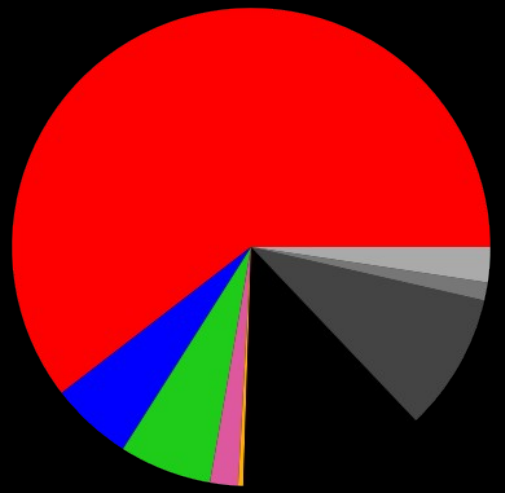

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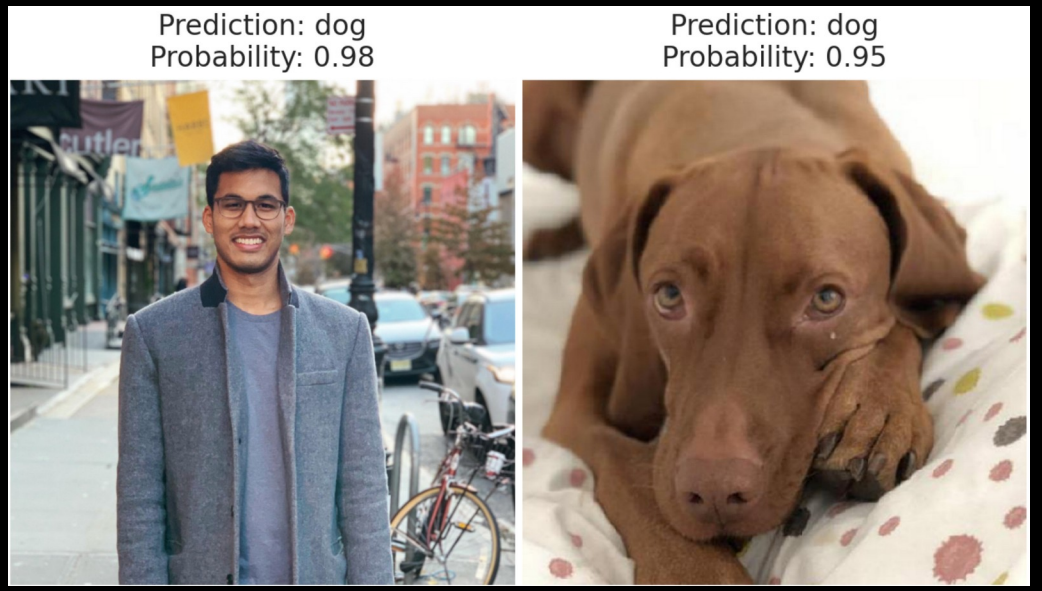
- Also, sometimes **weirdly confident**



Jonathan Ramkissoon

Unsupervised Methods

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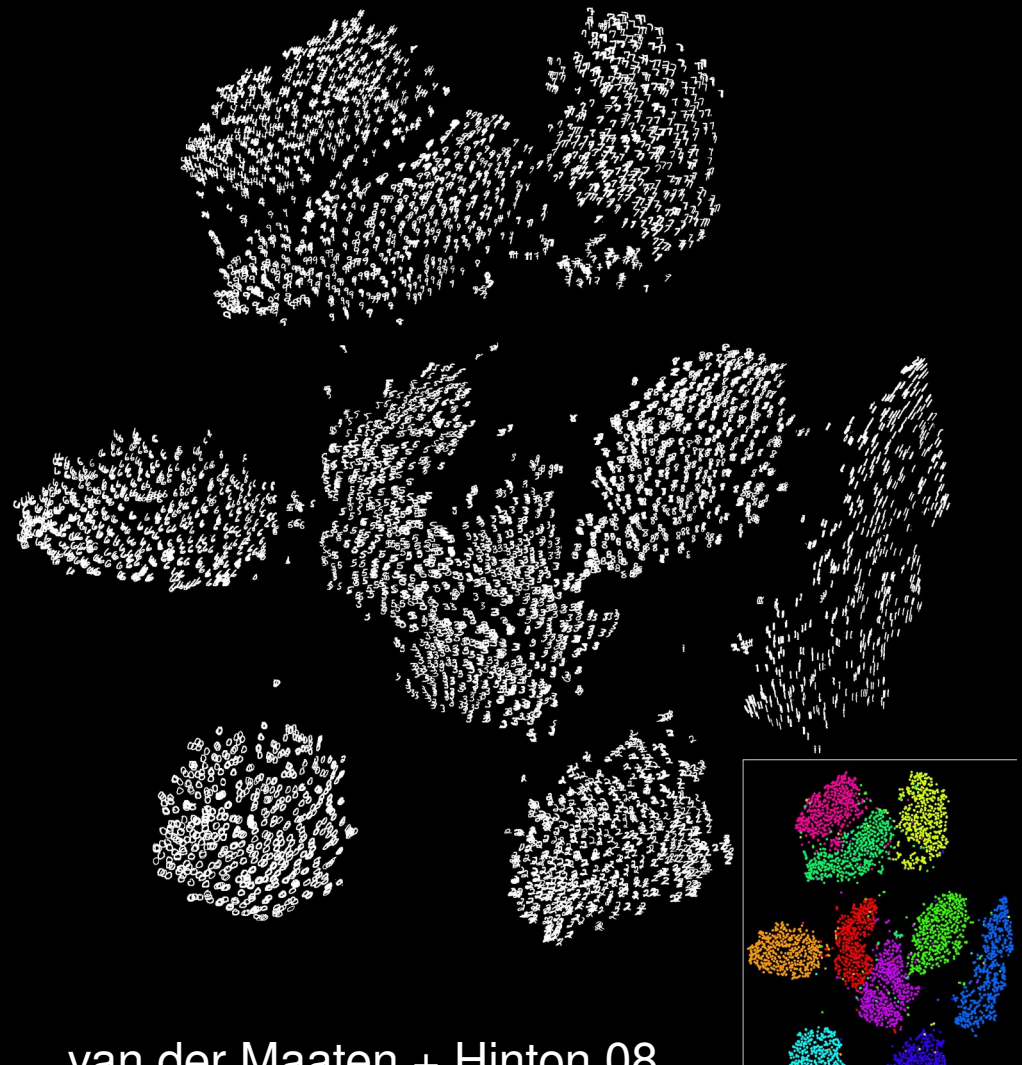

van der Maaten + Hinton 08

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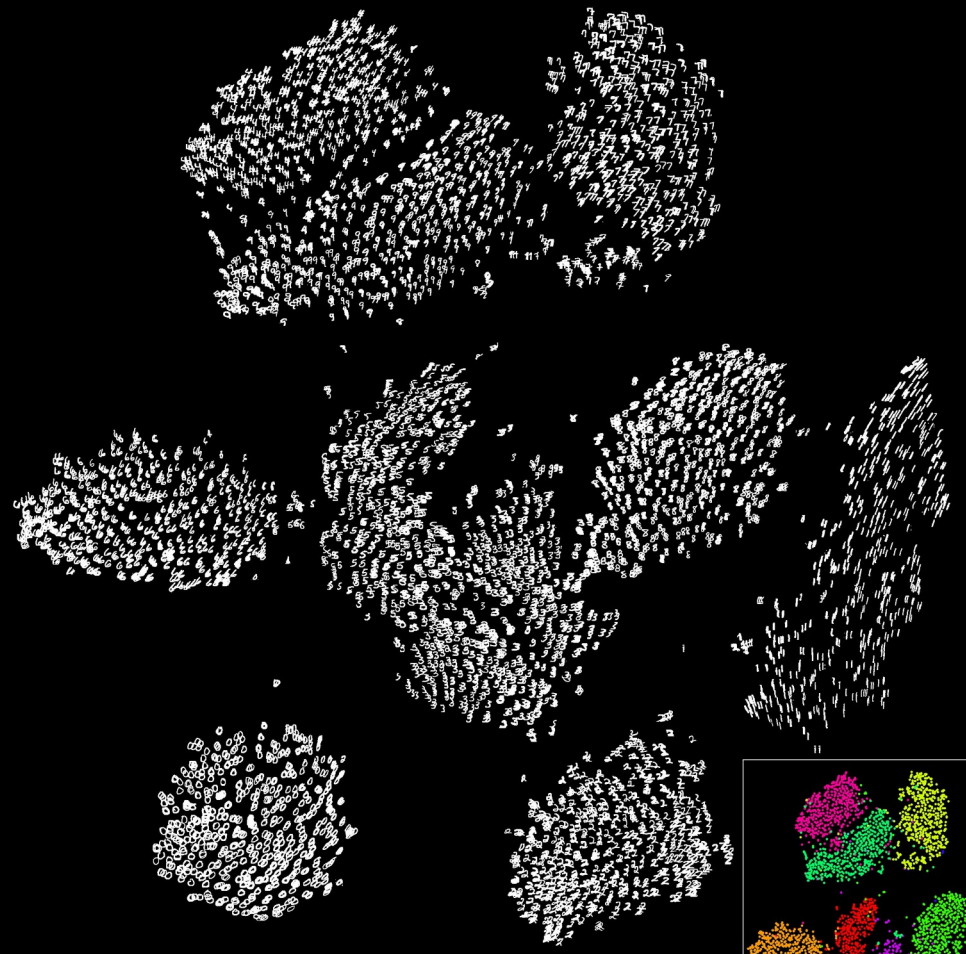
- Usually involves **comparing data points to each other**



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