

A deep space photograph showing a vast field of stars and galaxies. In the foreground, there are several bright, yellowish-white stars. In the background, there are numerous smaller, fainter stars and several galaxies, including a prominent spiral galaxy in the lower right quadrant and a few elliptical galaxies scattered throughout the field.

Deciphering the hidden side of galaxies with full-spectral fitting



J. Falcón-Barroso

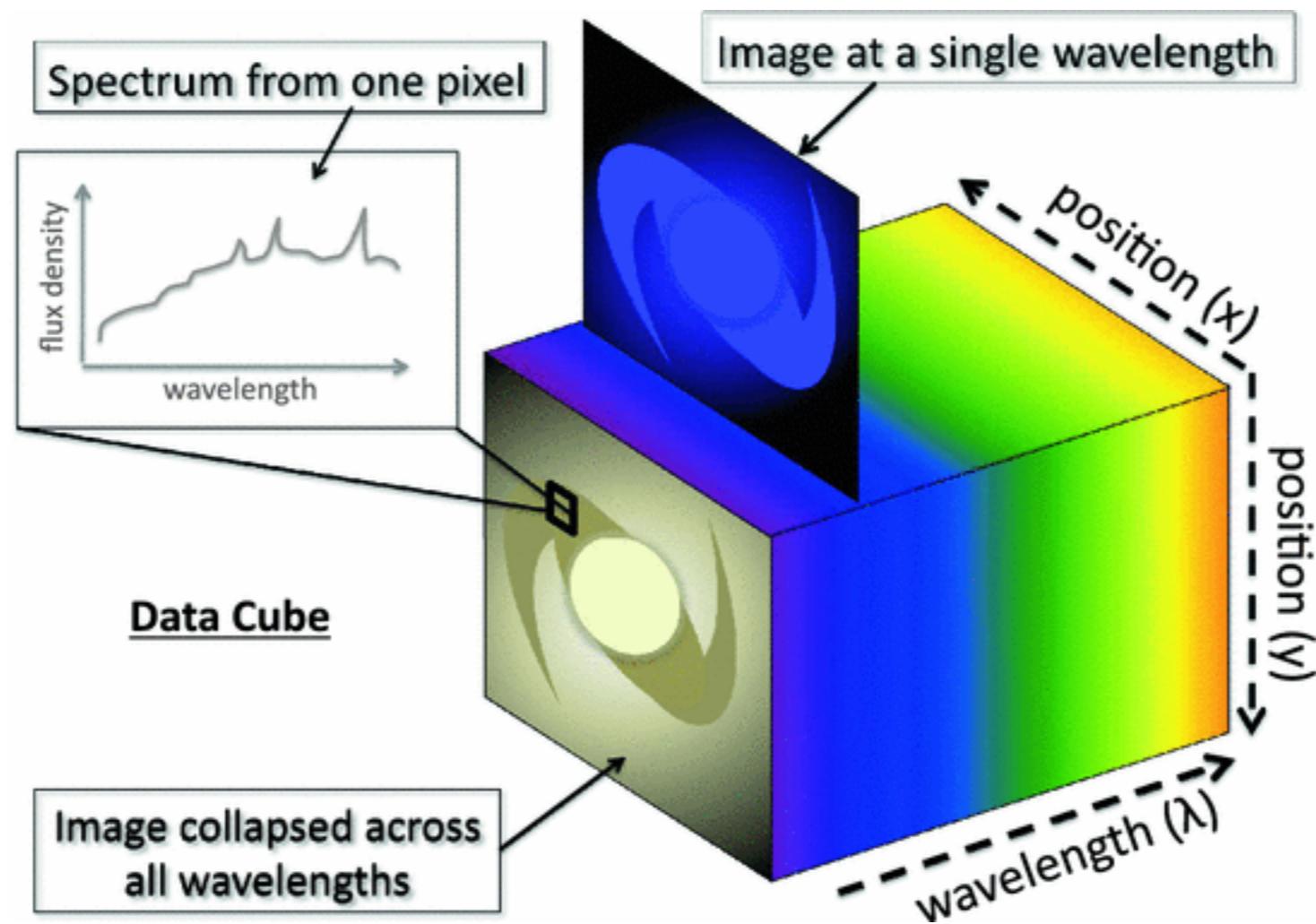
ML meeting - Ringberg Castle (9 -13 December 2019)

Learning from the fossil-record

- Galaxy spectra holds fundamental info about:
 - The way the stars move (stellar kinematics)
 - Their chemical composition (stellar populations)
- Both tracers have retain dynamical and population memory of galaxy evolution
- Extraction of those parameters is poised with degeneracies that are not necessarily easy to control



The Data



How do we retrieve that info?

$$G_{model}(\lambda) = \sum_1^K [w_k \cdot T_k(\lambda)] \star B$$

Populations weights (red box) points to w_k .
 Library of K template spectra (blue box) points to $T_k(\lambda)$.
 convolution (blue box) points to \star .
 LOSVD Kinematics (red box) points to B .
 Galaxy model spectrum (blue box) points to $G_{model}(\lambda)$.

Residuals

$$r_n = \frac{G_{model}(\lambda_n) - G(\lambda_n)}{\Delta G(\lambda_n)}$$

Minimisation

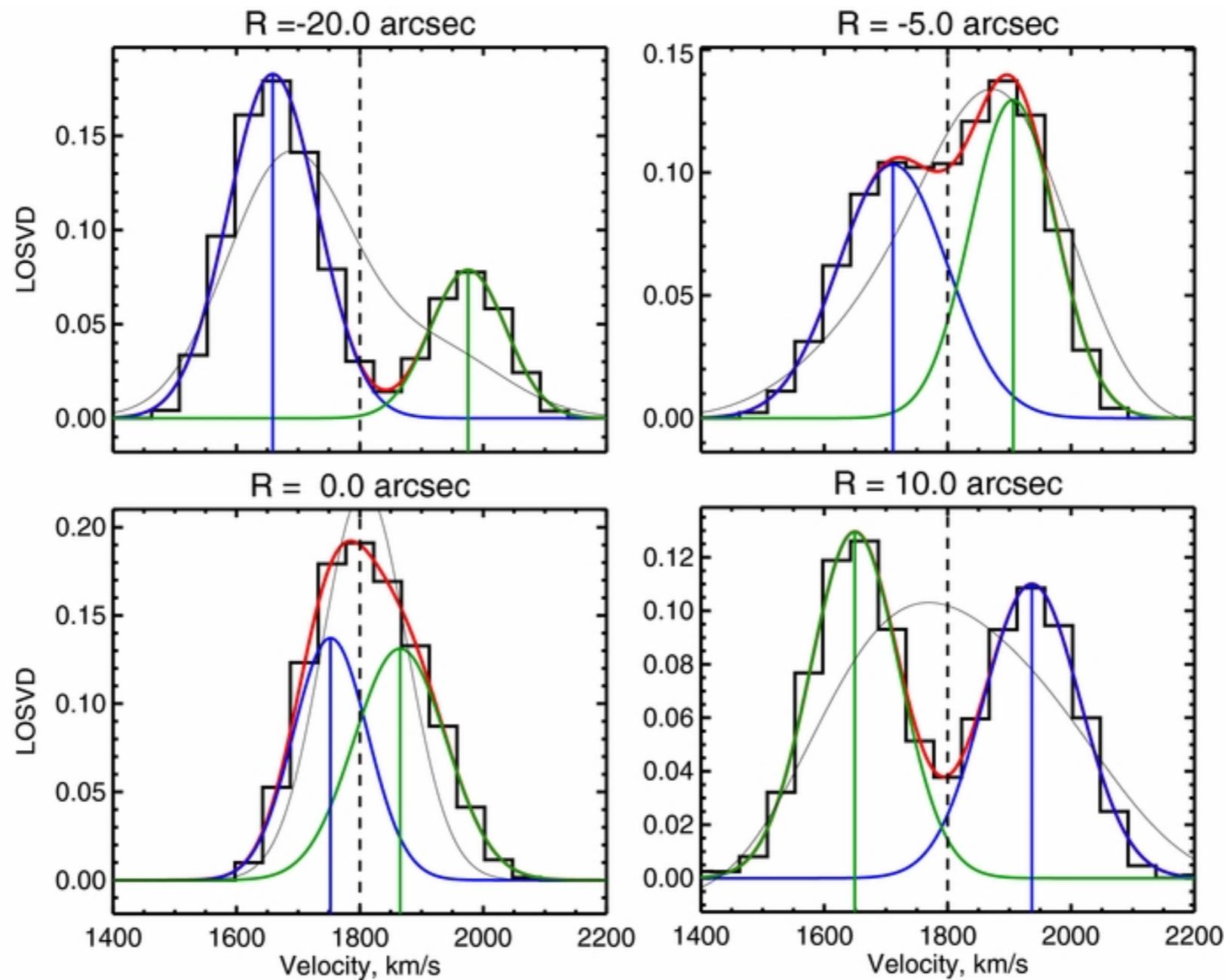
$$\chi^2 = \sum_1^N r_n^2$$



The LOSVD

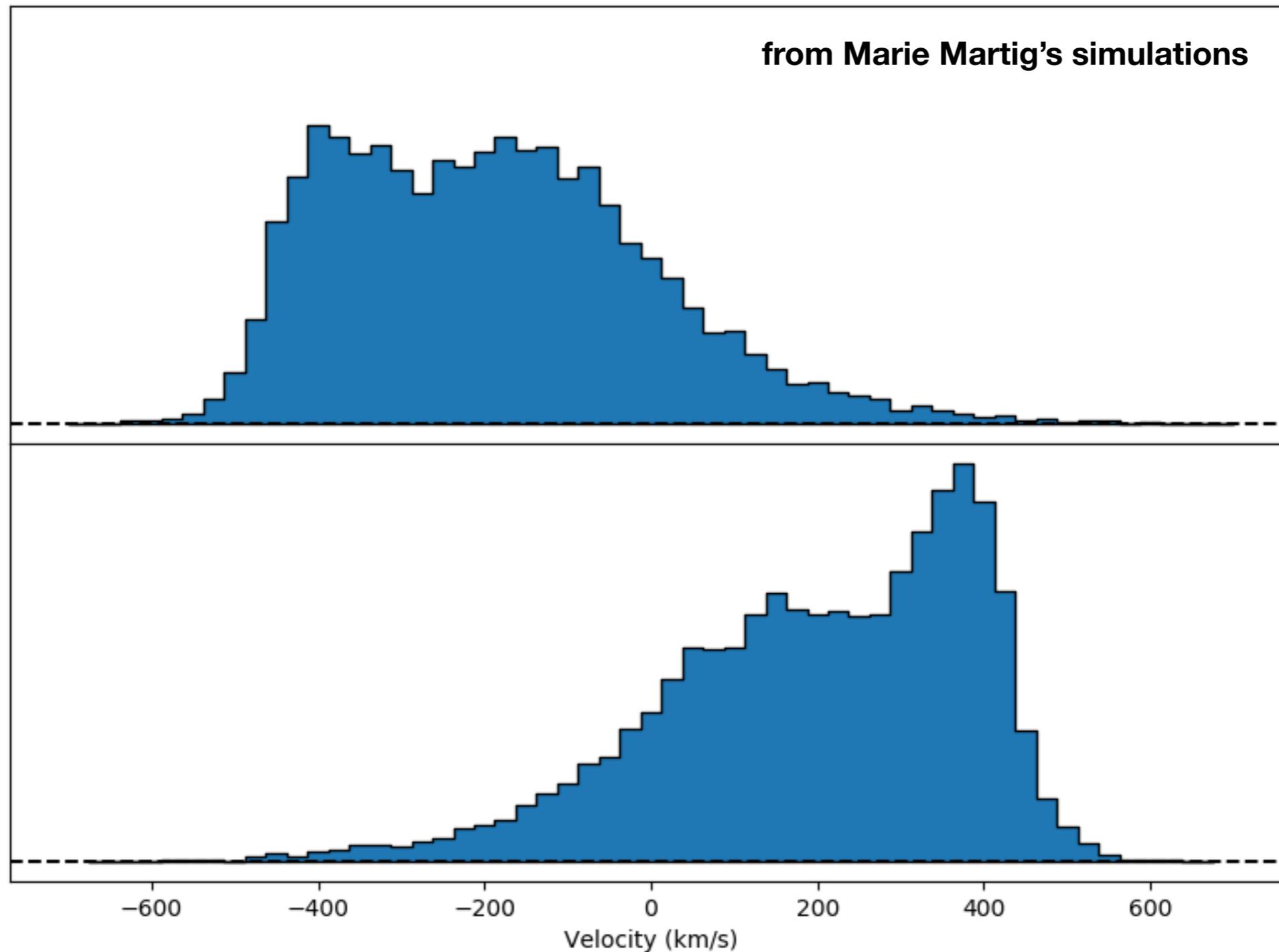
The LOSVD

- Observations can show complex LOSVDs...



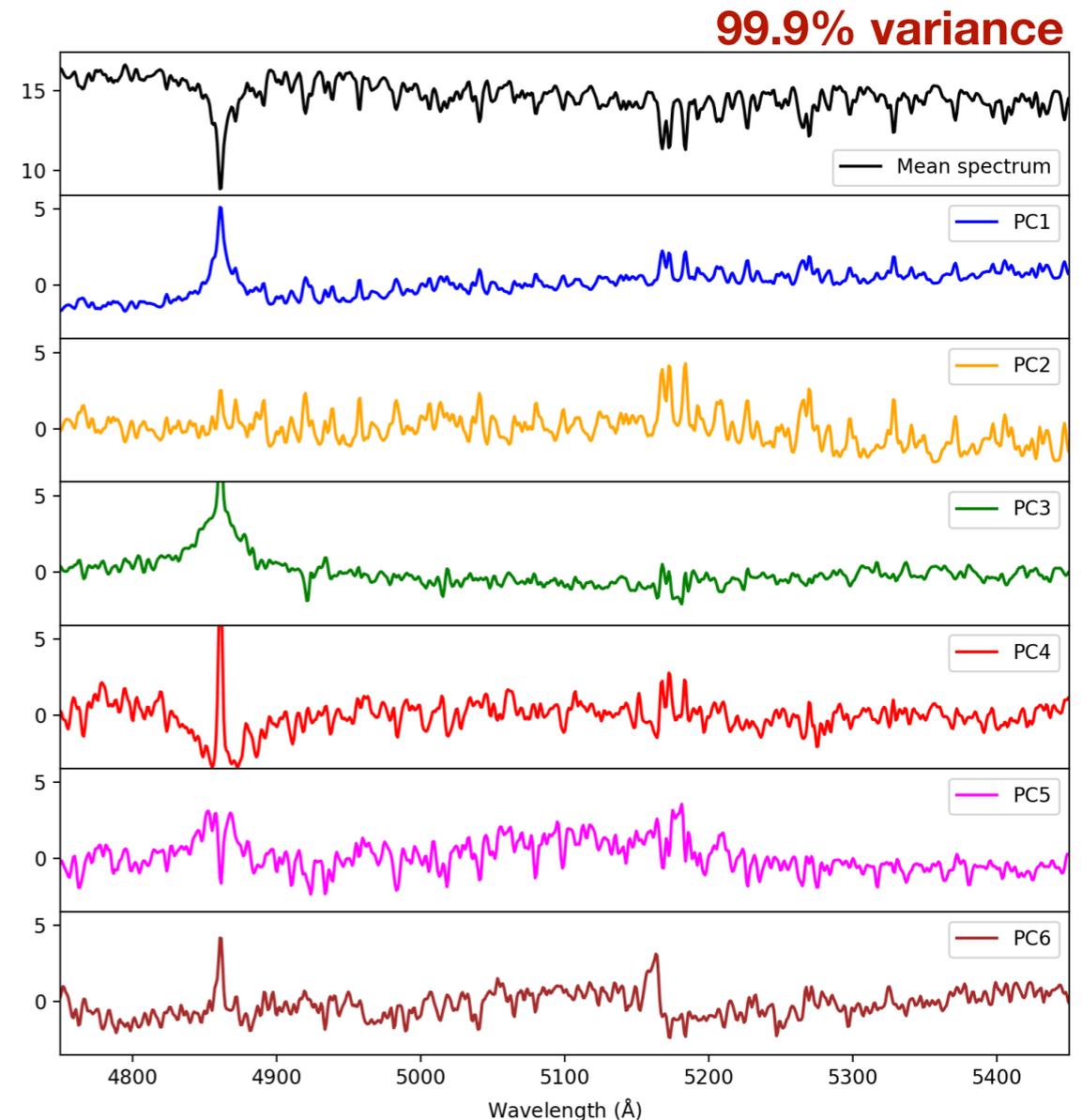
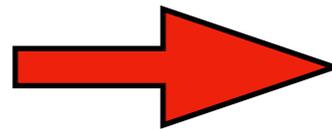
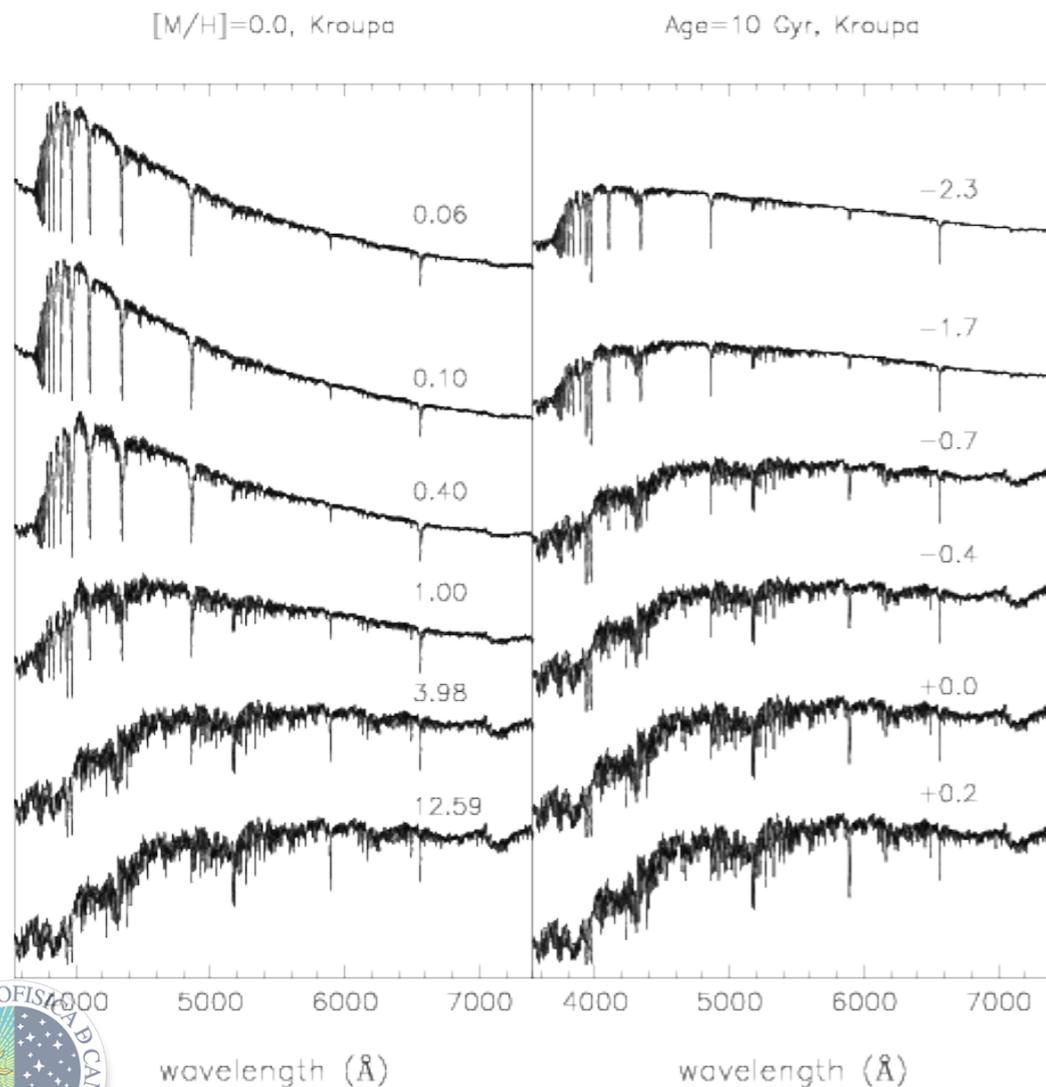
The LOSVD

- And numerical simulations too!



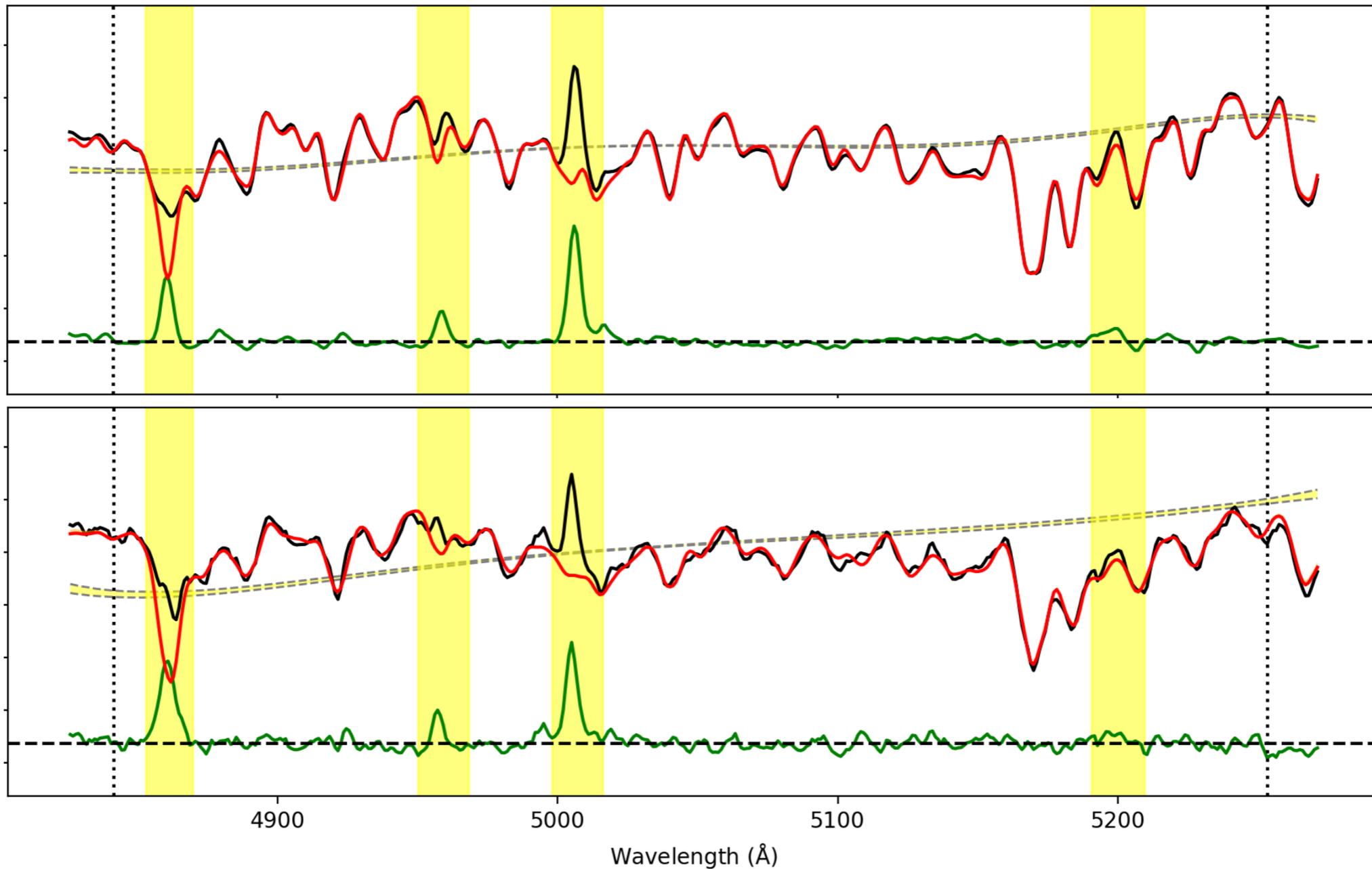
LOSVD recovery

- Difficult to characterise the uncertainties in the recovered LOSVD
- Bayesian frameworks deal with this, but still slow because number of templates can be large
- Typical template libraries contain ~ 1000 spectra with 5000 pixels
- This is extremely time consuming for any sampler
- Dimensionality reduction of the input template library helps (e.g. PCA)



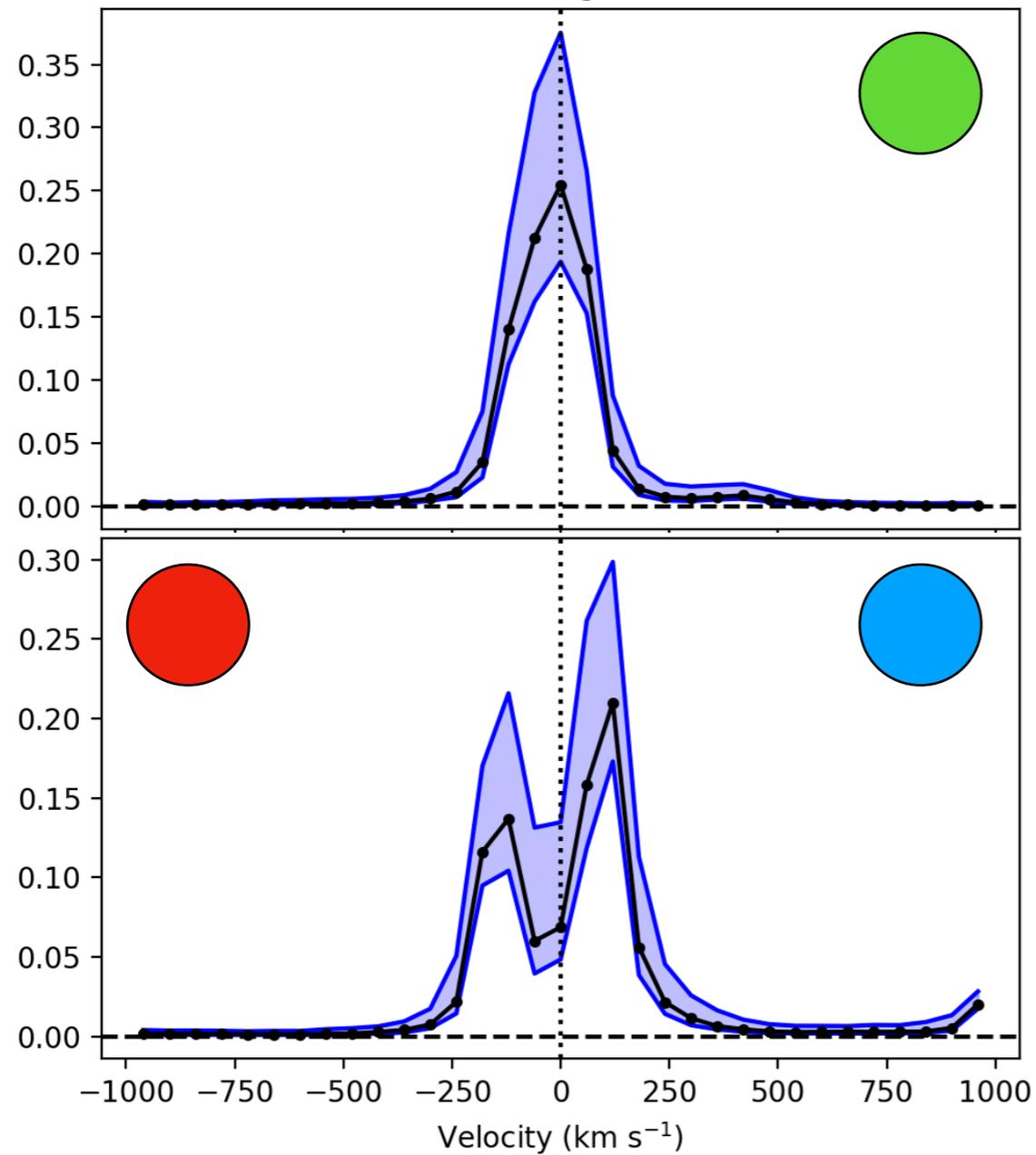
BAYES-LOSVD

- A Bayesian non-parametric recovery of the LOSVD using  <http://mc-stan.org/>

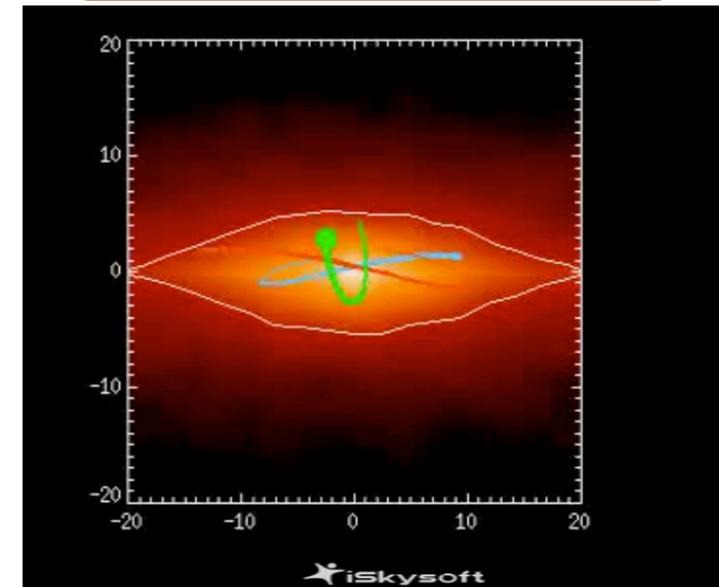


BAYES-LOSVD

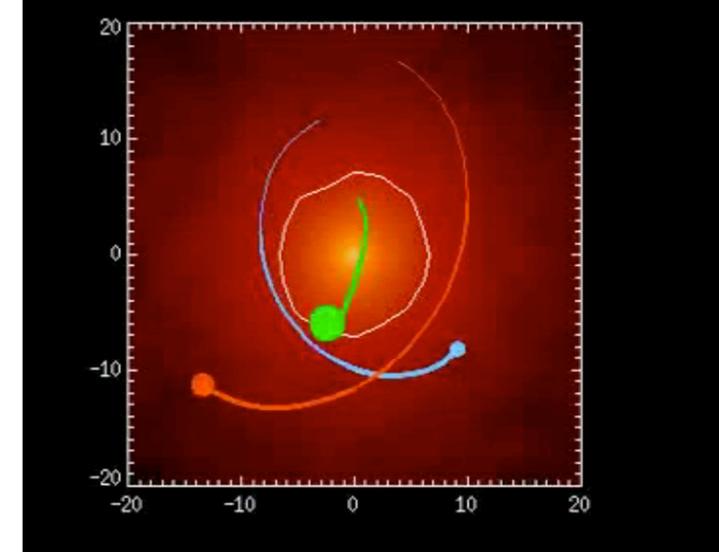
LOSVD recovery for NGC4550



Edge-on



Face-on



(Credit R. van den Bosch)



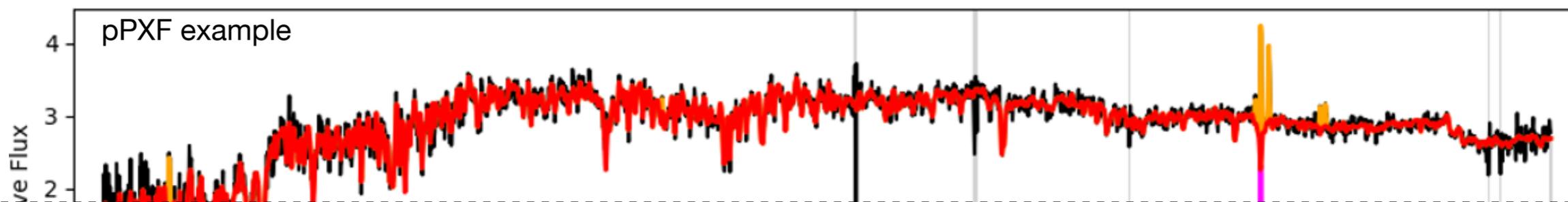
Stellar Populations

recovery

Stellar Populations recovery

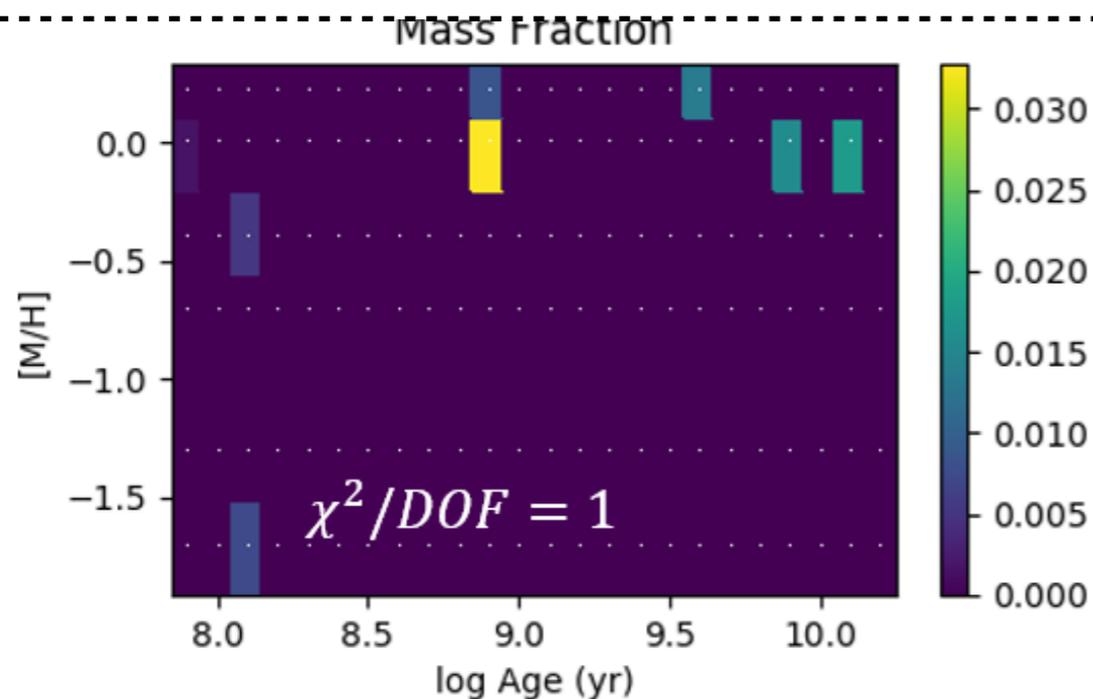
Regularisation

- The weights associated to each template tells you something about the star formation history and chemical evolution of a galaxy
- NNLS estimators are relatively quick. They can handle 1000s of templates.
- Regularisation is typically involved to obtain more physically meaningful solutions



Can we avoid regularisation?

Can we let the data tell us how much regularisation is allowed?



No regularised

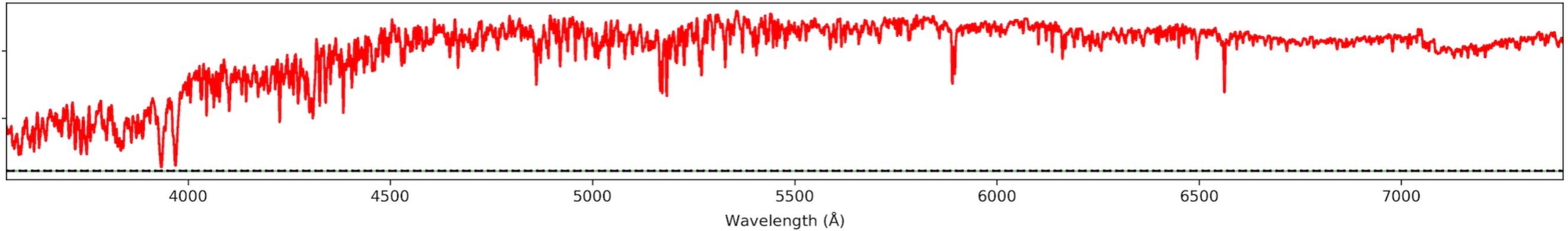
Regularised



Stellar Populations recovery

Robustness of the solution

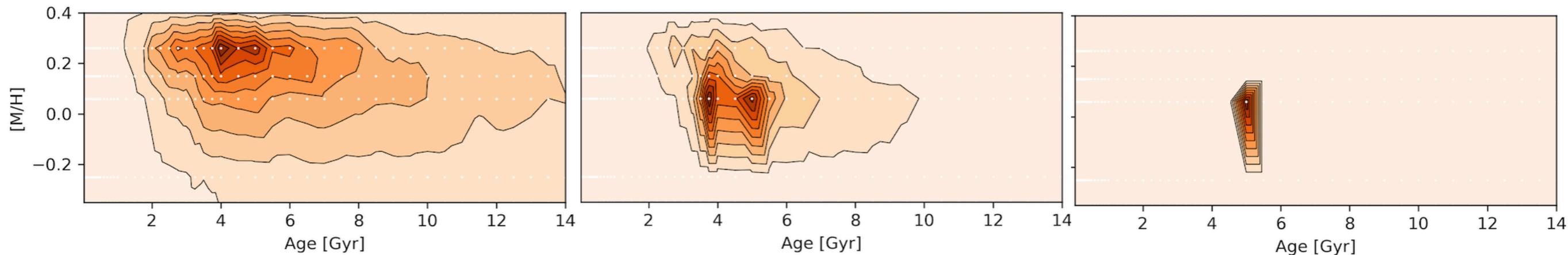
Age = 5 Gyr [M/H] = +0.06 dex



SNR = 50

SNR = 100

SNR = 1000



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How can we get more robust solutions for intermediate SNR levels?

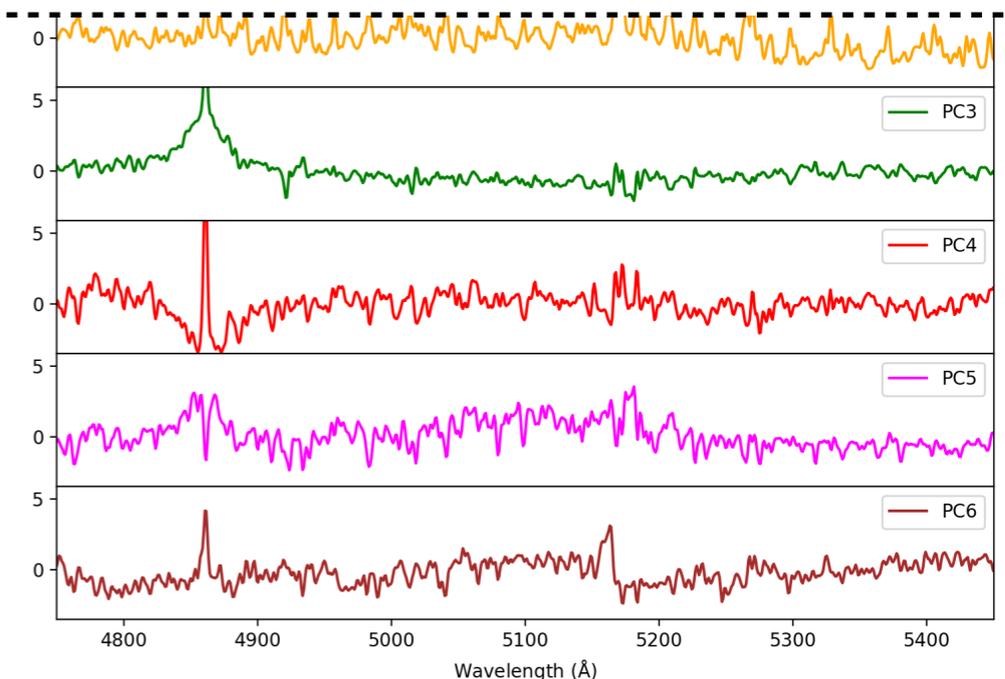
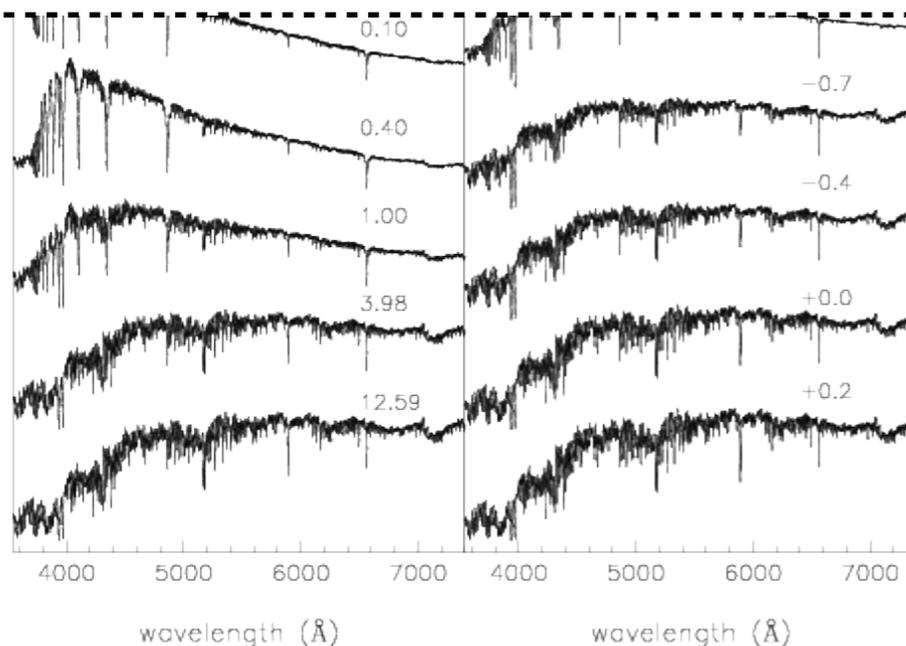


Stellar Populations recovery

Dimensionality reduction on templates

- Using full library of templates is extremely time consuming
- PCA, ICA, NNMF, reduce dimensionality, so it could help
- Inversion produces non-physical solutions (i.e. negative weights)
- Can we perform the fitting in some latent (lower dimensional) space that allows to reverse the process? *(see Prashin's talk tomorrow)*

Can dimensionality reduction help speeding up computation without a strong penalty on robustness of the solution?



Summary

- Life of galaxies is encoded in their spectra
- Kinematics and populations hold the key information
- Bayesian frameworks give robust accounts of degeneracies in the recovery of both LOSVD and stellar populations, but not very fast
- Stellar populations more difficult to unveil: regularisation, robustness, speed
- Eventually we want to work with IFU data and fit all spectra simultaneously, but we need to get the correct solutions for single spectra first
- How can Machine Learning help handling these issues?

