# Detecting and measuring the redshift of galaxies in MUSE hyperspectral data

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## I. Context

The Multi Unit Spectroscopic Explorer (MUSE) [1] is an Integral Field spectrograph.

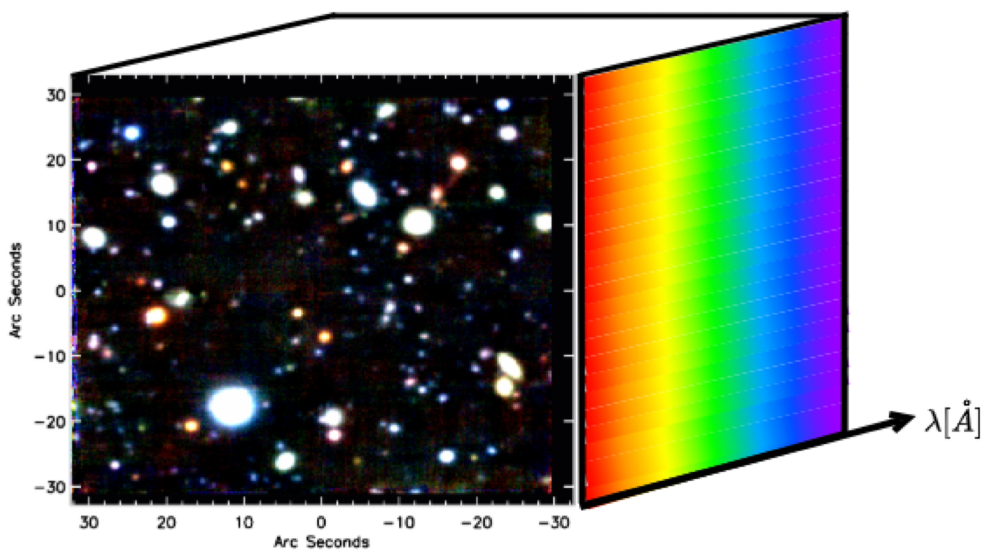



Fig:Sketch of a MUSE datacube

**Challenges:**

- (automatically) Detect all galaxies
- (automatically) Measure their redshift

## II. Data

$\sim 9200$ Galaxy spectra from $5$ MUSE surveys with a measured redshift, transformed to the rest frame.

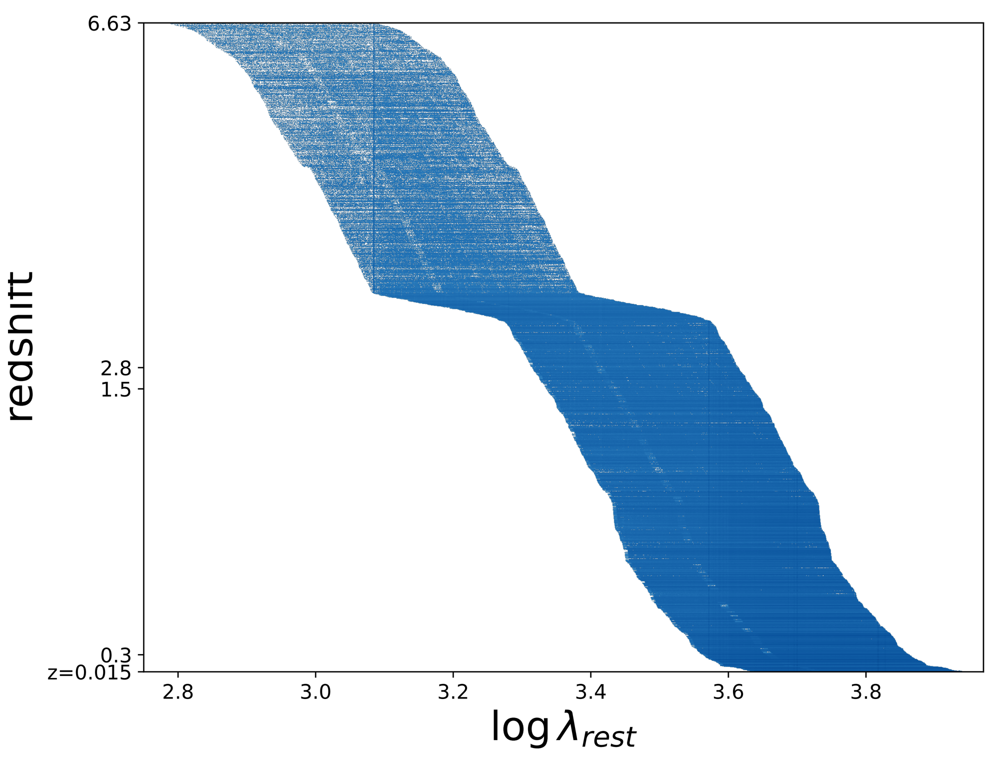



Fig:MUSE galaxy spectra stacked in increasing redshift from bottom to top

Split into $80\%$ (learn)/ $20\%$ (test) configuration

## III.1 Method: Non-negative Matrix Factorization (NMF) [3] [4] [2]

Learn a low-rank representation of a large set of spectra

$X \simeq WH$

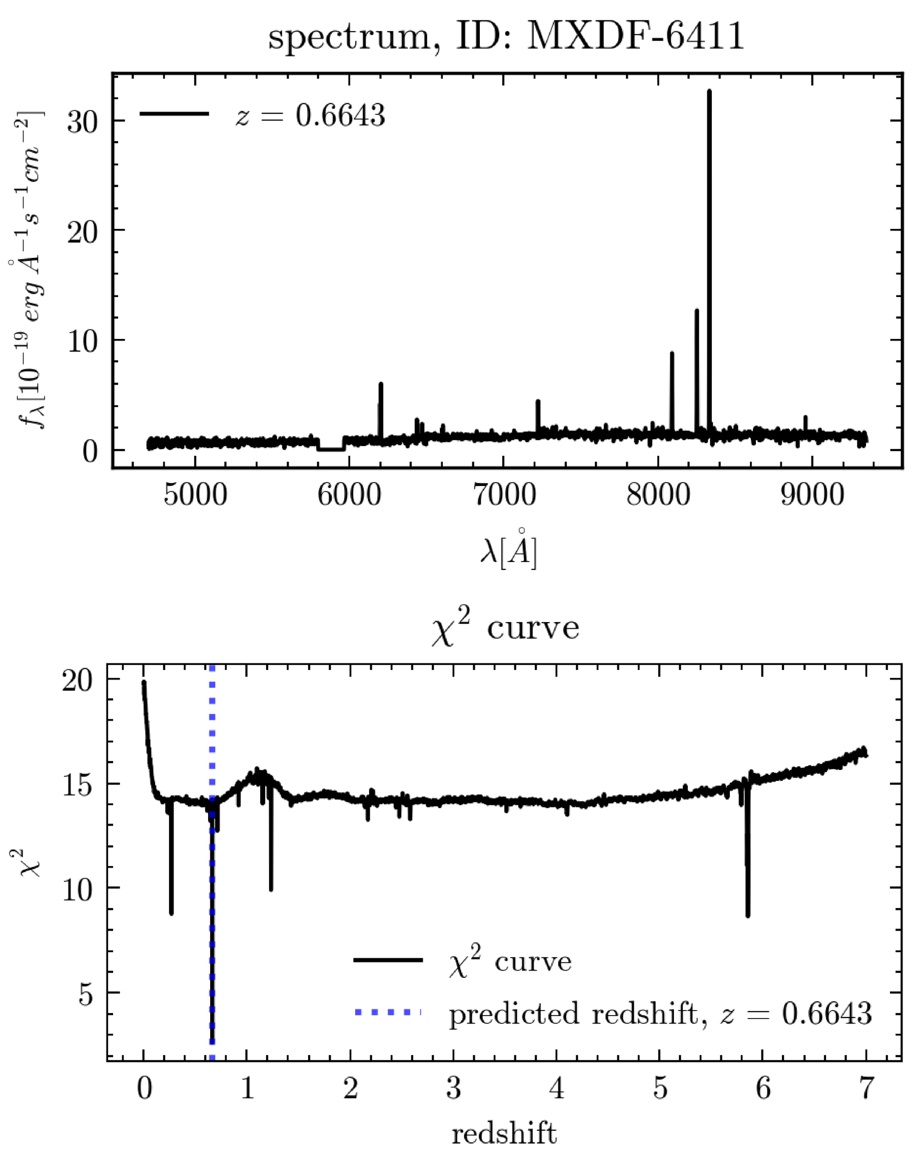
with: $X \in R^{n\times l}, W \in R_+^{n\times k}, H \in R_+^{k\times l}$

Rank $k$ is a free parameter, we fine-tune it using a K-fold cross-validation.

## III.2 Application: Redshift prediction

We test all redshifts from $0$ to $7$ with a step of $0.001$. For each test redshift $z_{test}$ we:

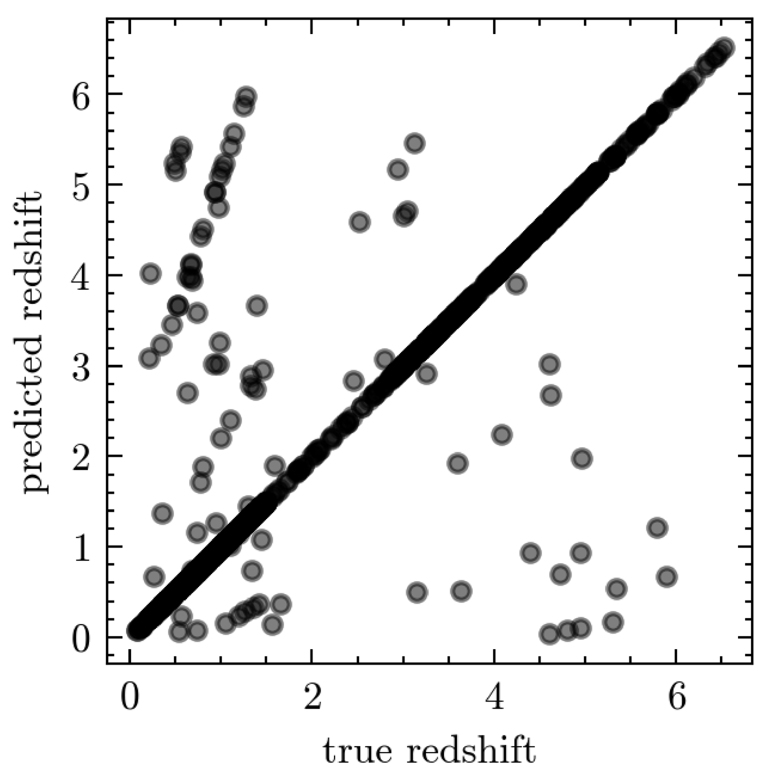
- De-reshift the spectrum assuming $z_{test}$.
- Reconstruct de-redshifted spectrum using basis vectors (non-negative least squares)
- Quantify reconstruction error with a $\chi^2$ metric.



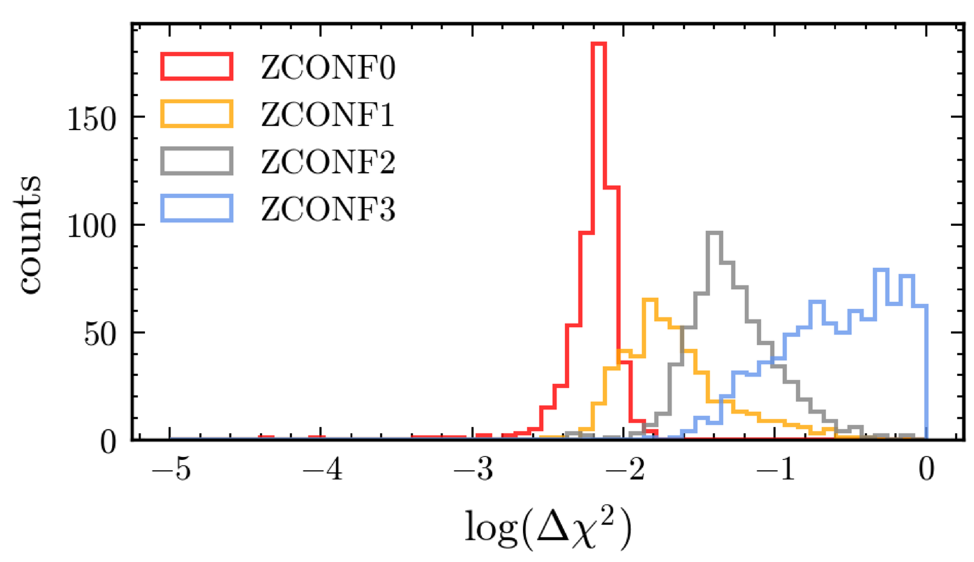

We characterize each redshift with a significance score $\Delta\chi^2$ (deviation from the $\chi^2$ curve baseline)

## IV. Results

1. We achieve a $\mathbf{94}\%$ fraction of good predictions on the test set (with $k = 10$ ). Bad predictions come mainly from blended sources and artifacts



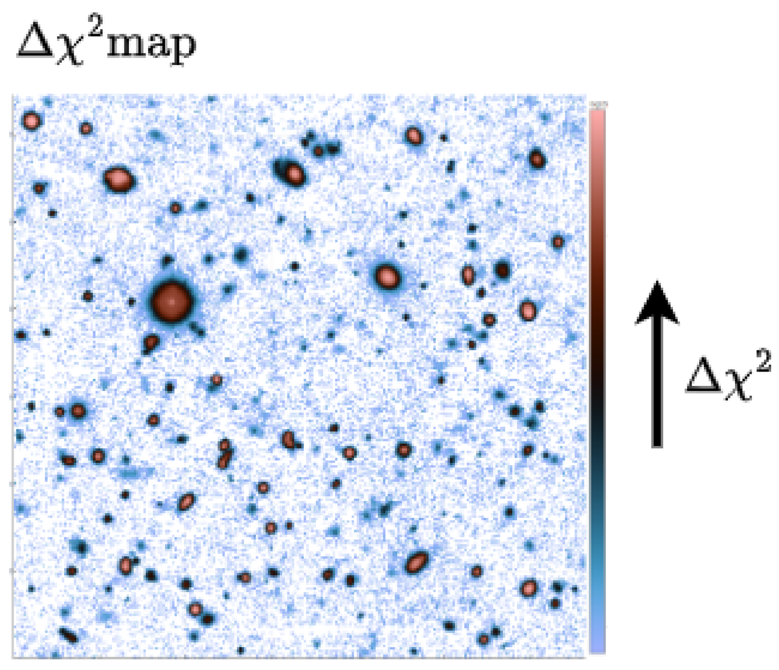

2. $\Delta\chi^2$ correlates with redshift confidence scores.

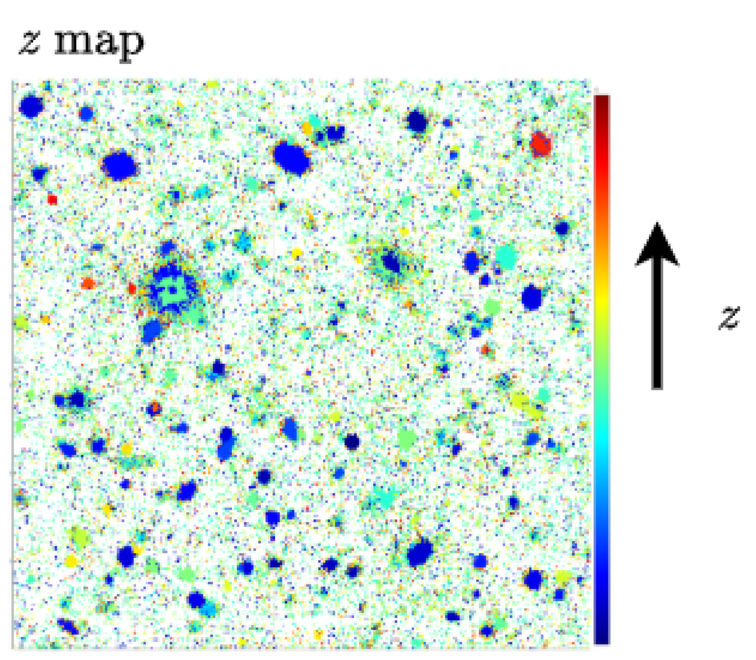



## V. Conclusion & perspectives

Our NMF-based approach outperforms classical methods( based on Principal Component Analysis and template matching)

Applying NMF on the full cube provides a $\Delta\chi^2$ and a redshift map simultaneously, offering a new approach for detection.




### References

[1] Roland Bacon et al. "The MUSEHubbleUltra Deep Field surveys: Data release II". In: *Astronomy amp; Astrophysics* 670 (Jan. 2023), A4. ISSN: 1432-0746. DOI: 10.1051/0004-6361/202244187. URL: http://dx.doi.org/10.1051/0004-6361/202244187.

[2] Dylan Green et al. *Algorithms for Non-Negative Matrix Factorization on Noisy Data With Negative Values*. 2024. arXiv: 2311.04855 [astro-ph.IM]. URL: https://arxiv.org/abs/2311.04855.

[3] Daniel D. Lee et al. "Learning the parts of objects by non-negative matrix factorization". In: *Nature* 401.6755 (1999), pp. 788–791. DOI: 10.1038/44565. URL: https://doi.org/10.1038/44565.

[4] Guangtun Zhu. "Nonnegative Matrix Factorization (NMF) with Heteroscedastic Uncertainties and Missing data". In: *arXiv e-prints*, arXiv:1612.06037 (Dec. 2016), arXiv:1612.06037. DOI: 10.48550/arXiv.1612.06037. arXiv: 1612.06037 [astro-ph.IM].

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