Unsupervised classification of galaxy spectra up to z~1.2

Towards galaxy spectral evolution ?

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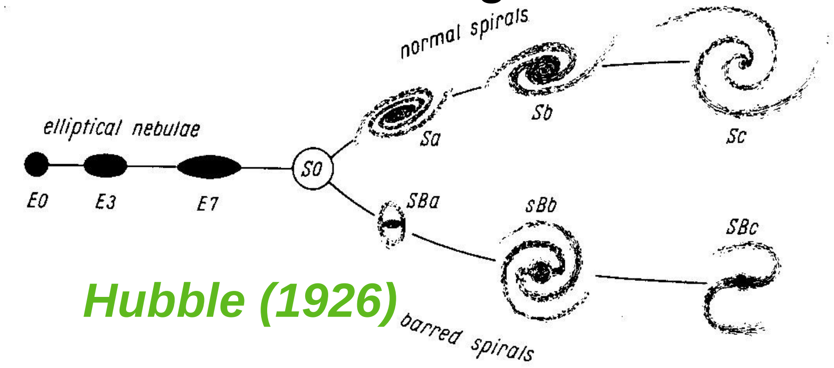
Julien Dubois *(PhD student)*
Cécilia Beissière-Thygesen *(Master student)*

Classification of galaxies

The Hubble tuning fork



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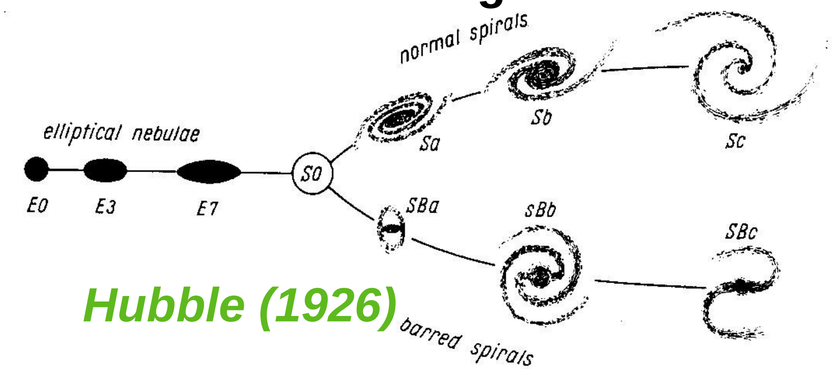

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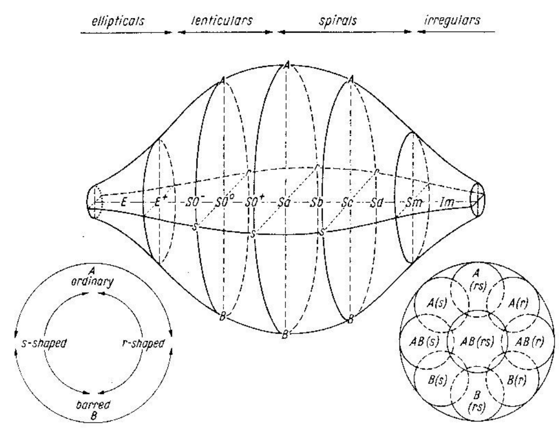

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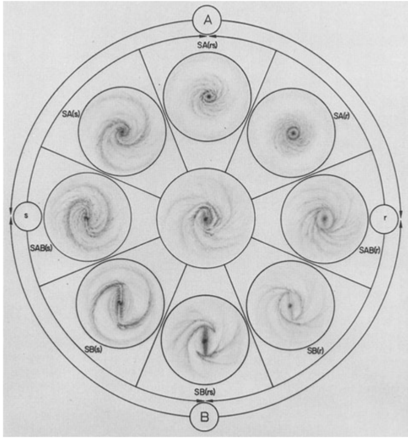

G. and A. De Vaucouleurs (1963)

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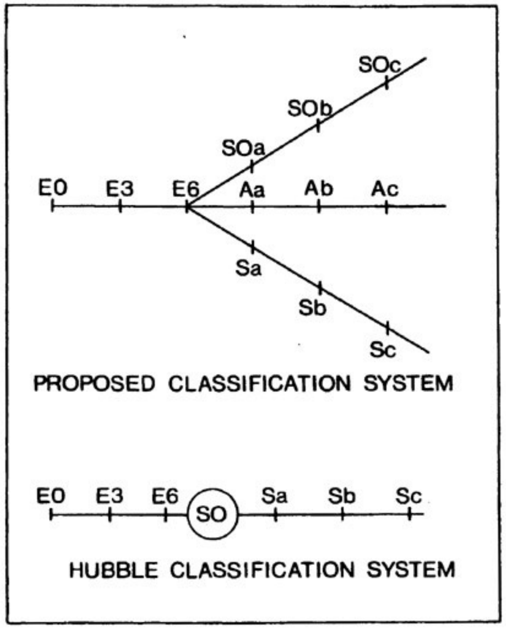

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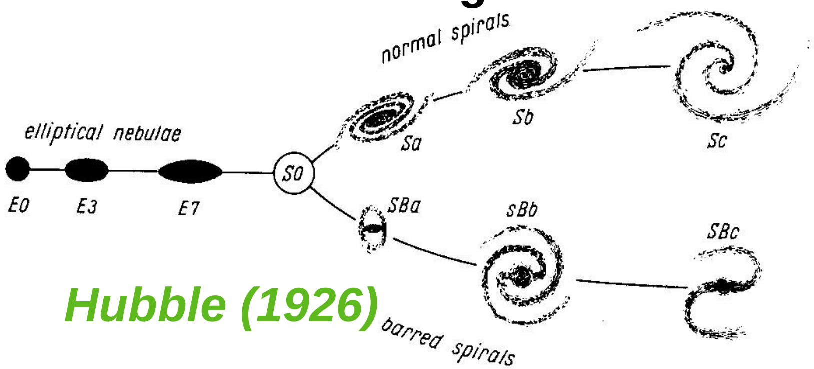

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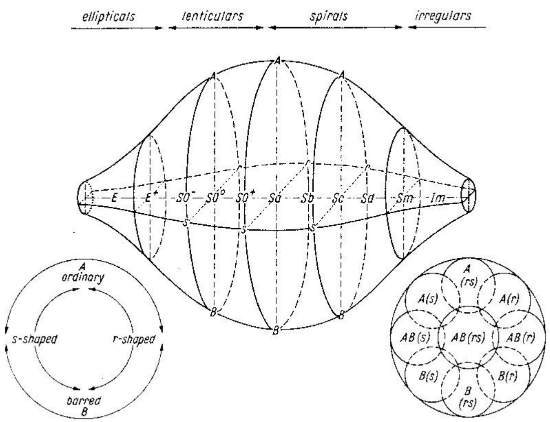

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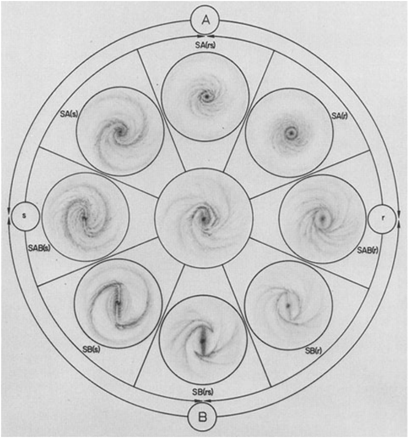

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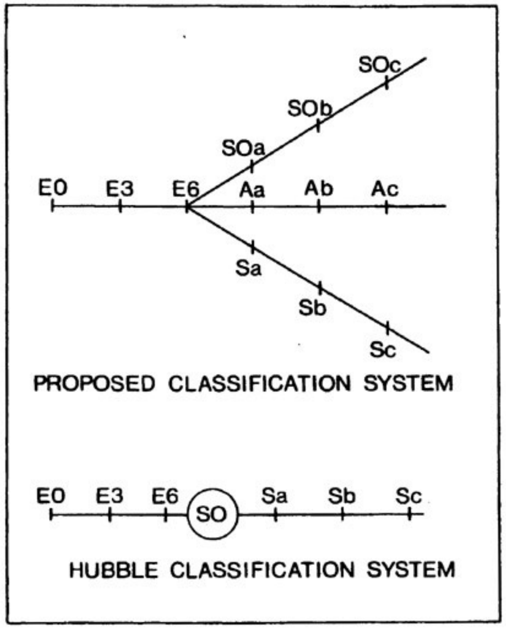

→ **Morphologies**

Classification of galaxies

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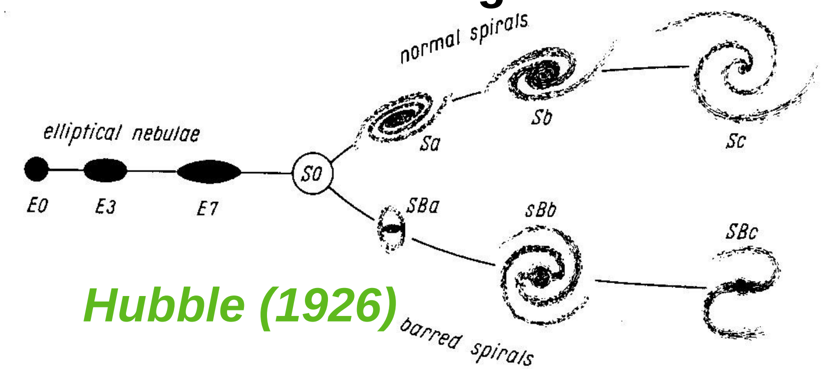

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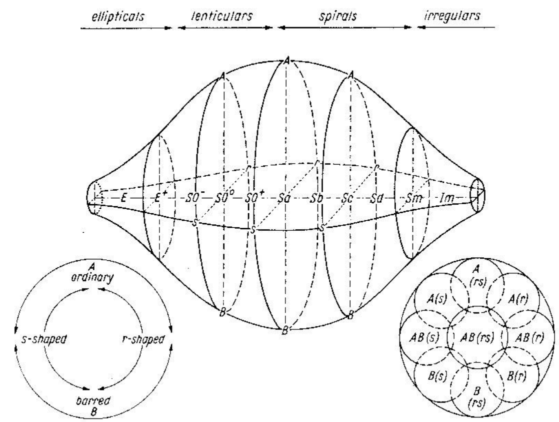

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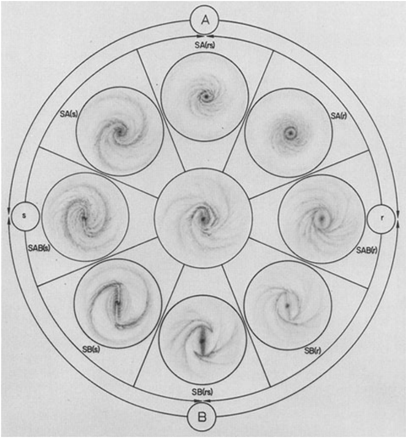

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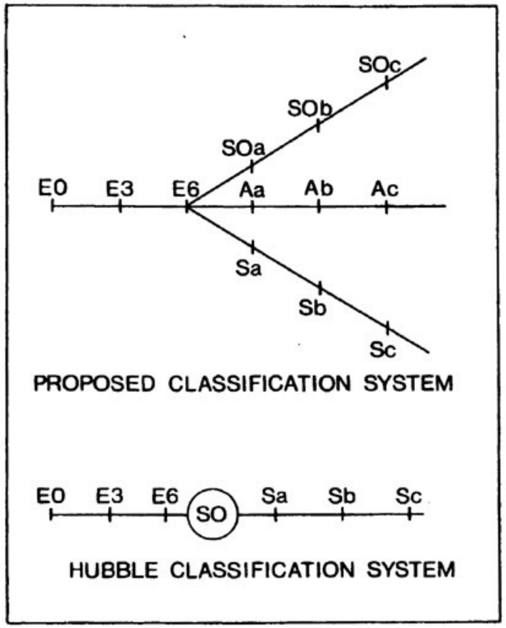

… Automated classification with Machine Learning and Deep Learning

e.g : ***Fraix-Burnet (2023) , Zhang et al (2022), Cavanagh et al. (2021), Cheng et al. (2020), Khramtsov et al. (2019) ...***

Morphologies

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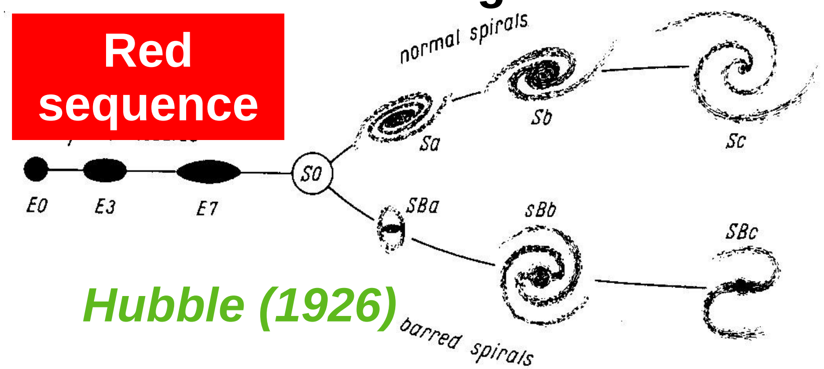
Red sequence



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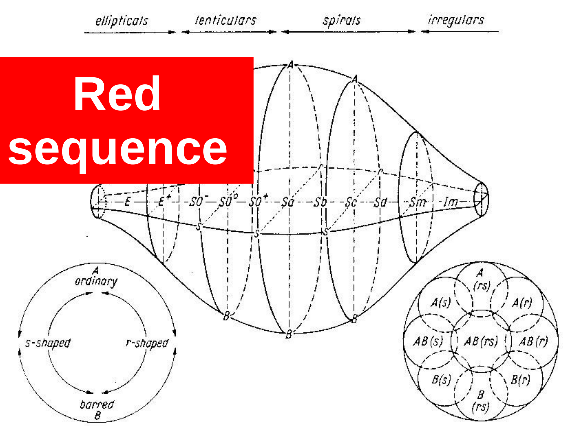

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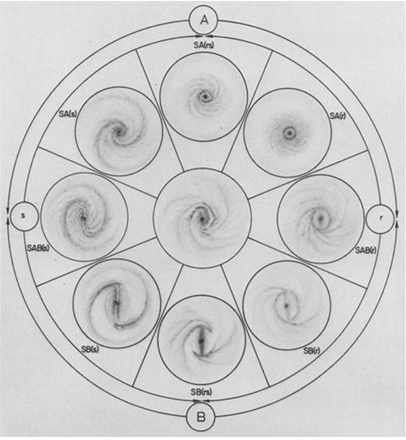

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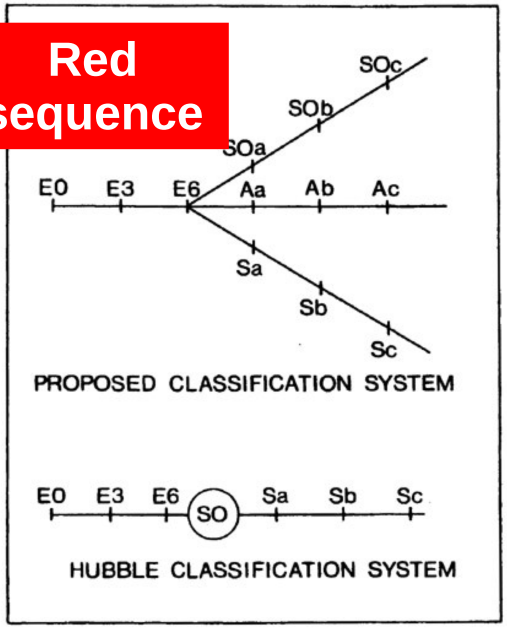

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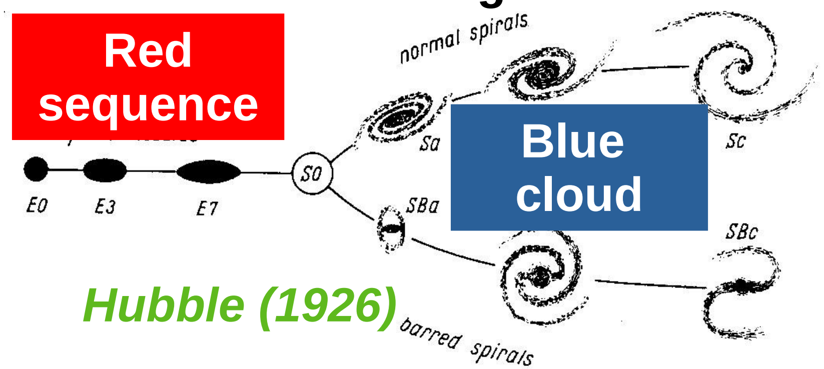

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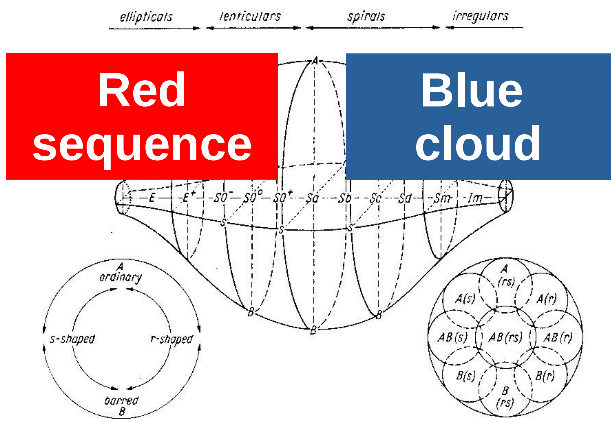

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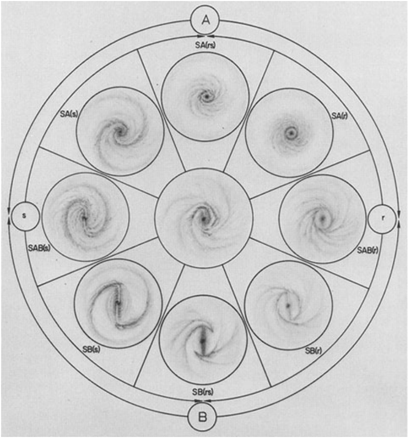

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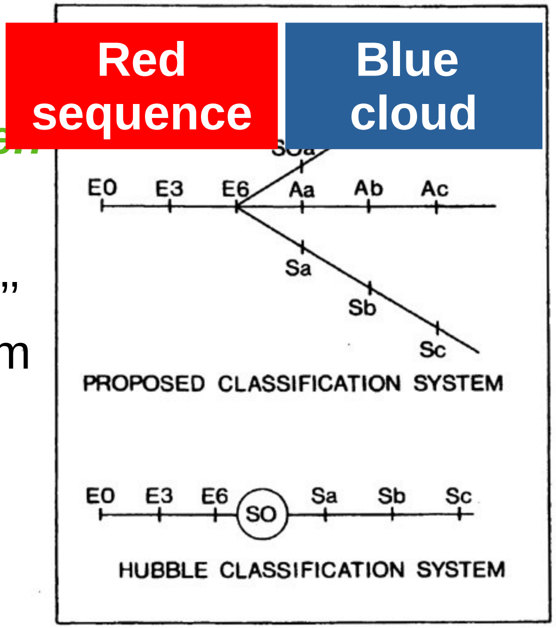

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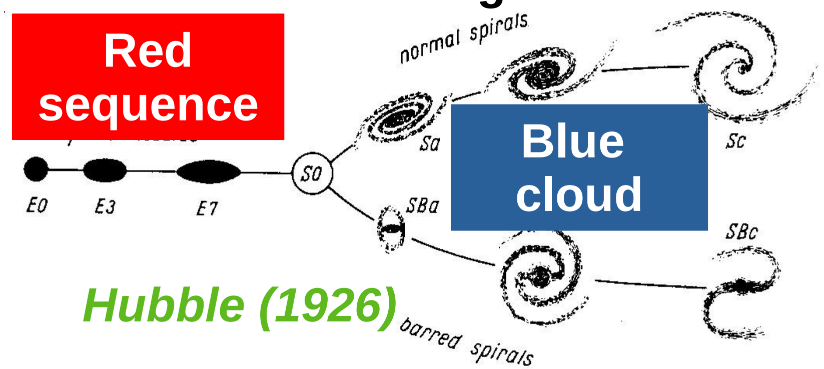
Red sequence

Blue cloud



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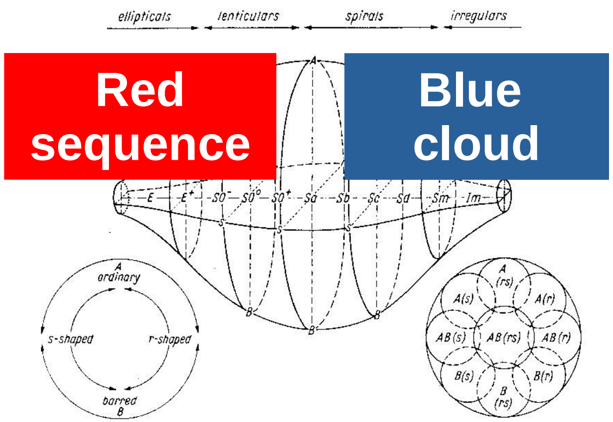

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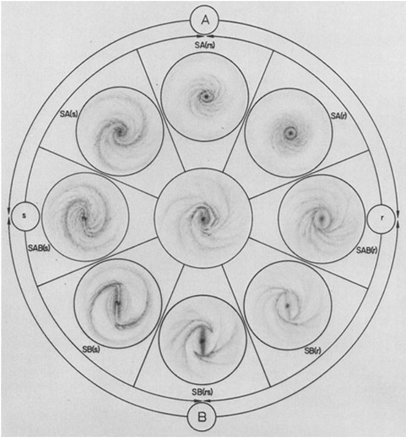

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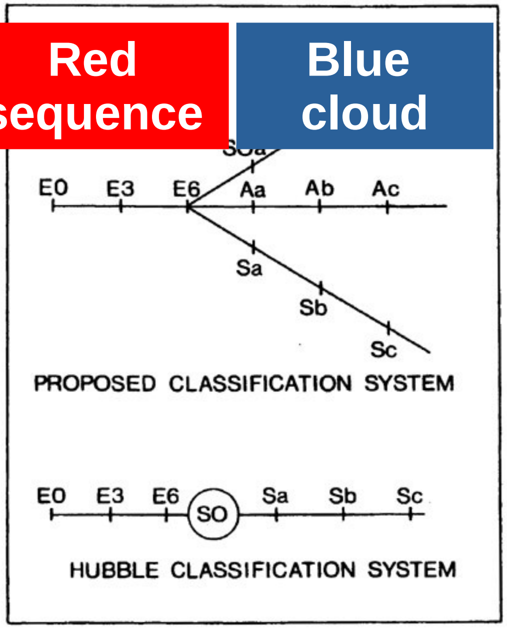

Bimodal distribution of galaxies

What about spectral classification ?

Visual inspection

Morgan & Mayall (1957), Veron (1976), Kennicut (1992), Dobos et al. (2012), Wang et al. (2017) ...

Automatic inspection (Machine Learning)

Sanchez Almeida et al . (2010) : 700 000 (SDSS DR7) using K-means method

De et al. (2016) : Canopy clustering algorithm

… This talk

Not much has been done

Our goal

Make a classification of spectra of galaxies at different redshifts to :

- Improve galaxy classification across cosmic times by **constraining their physics**
- Find **unknown classes** of galaxy spectra ➡ Refine the bimodal distribution of galaxies

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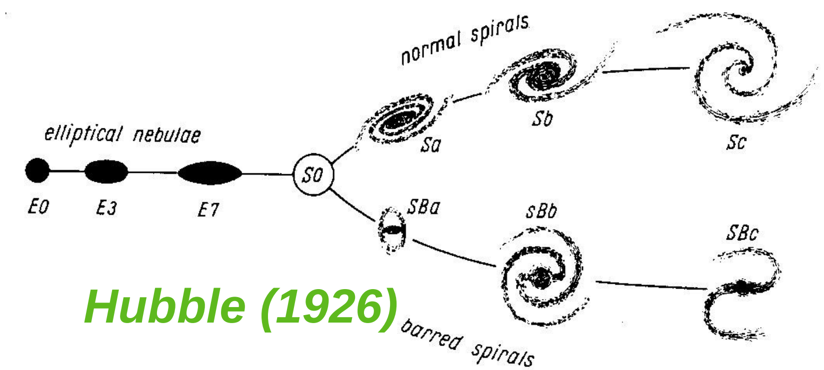
Just like ...



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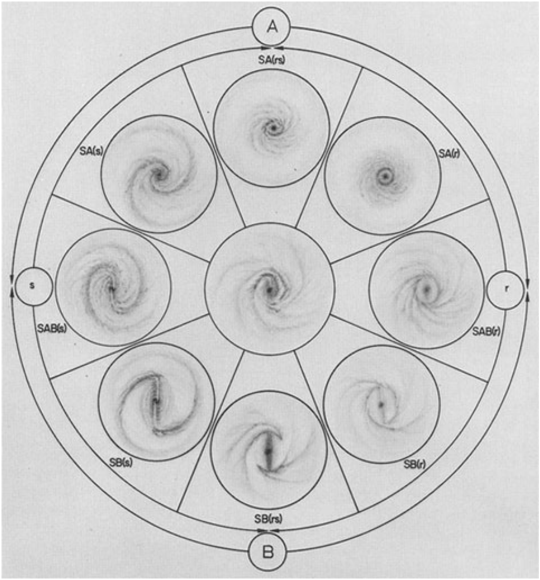

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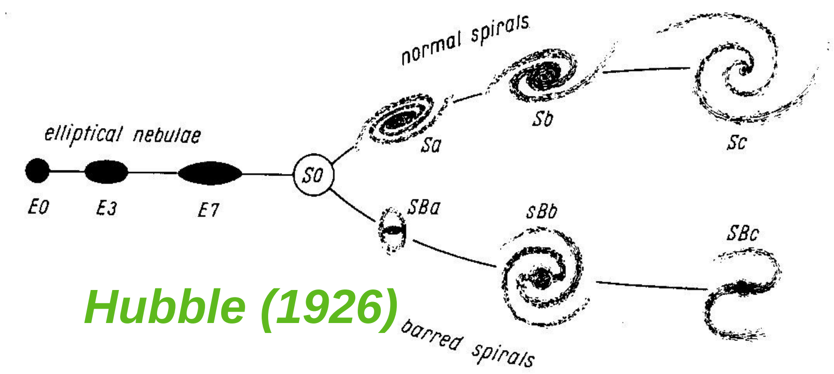

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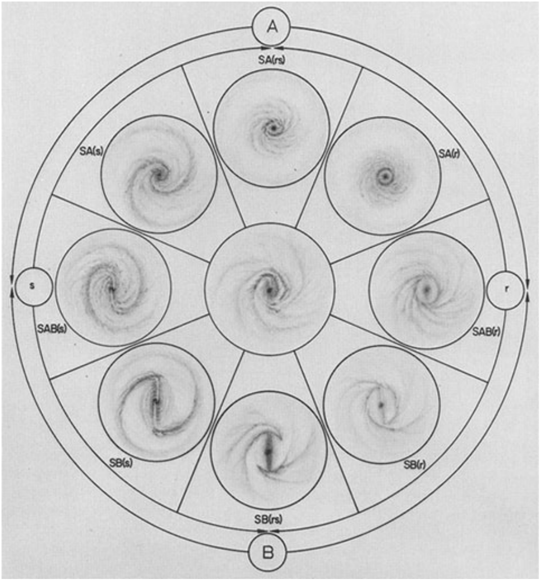
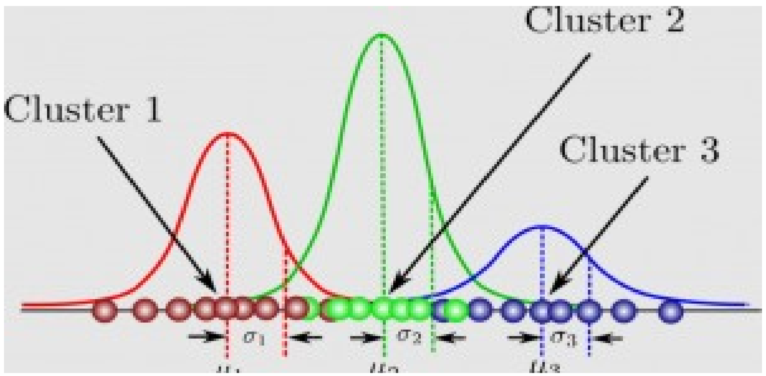


G. & A. De Vaucouleurs (1963)

→ Derive **templates** of galaxy **spectra** that may be used as training templates for supervised approaches of ML ...

Fisher-EM algorithm

Bouveyron, C., & Brunet, C. 2012a, Stat. Comput., 22, 301



Gaussian Mixture Model (GMM)

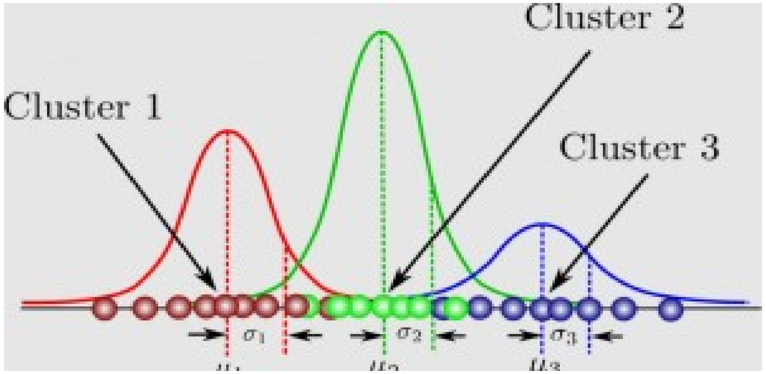
Fisher-EM algorithm

Bouveyron, C., & Brunet, C. 2012a, Stat. Comput., 22, 301

First guess (**GMM**)

Number of classes **K**

Input



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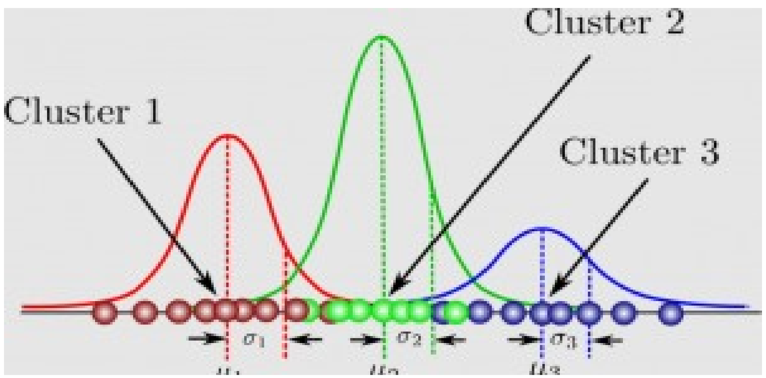

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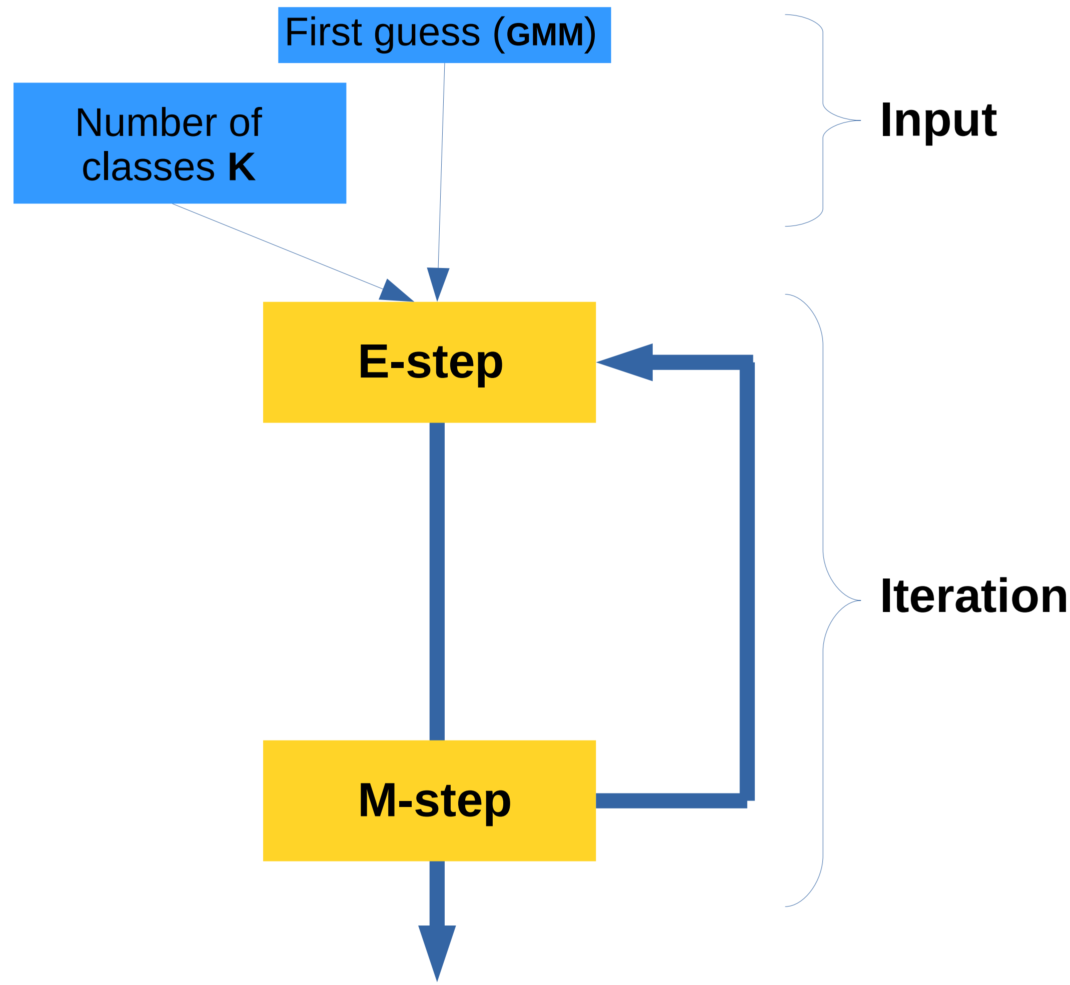

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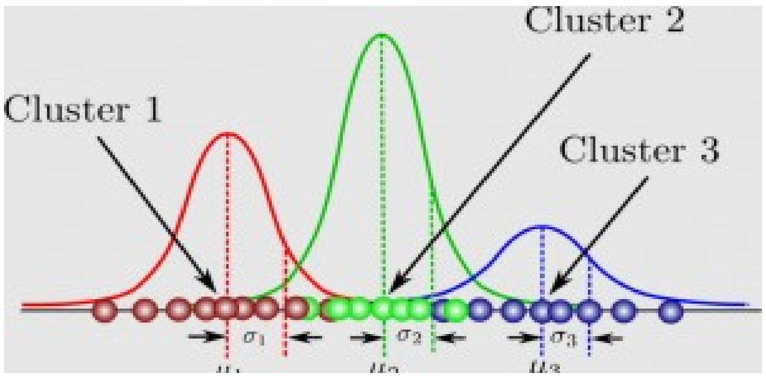

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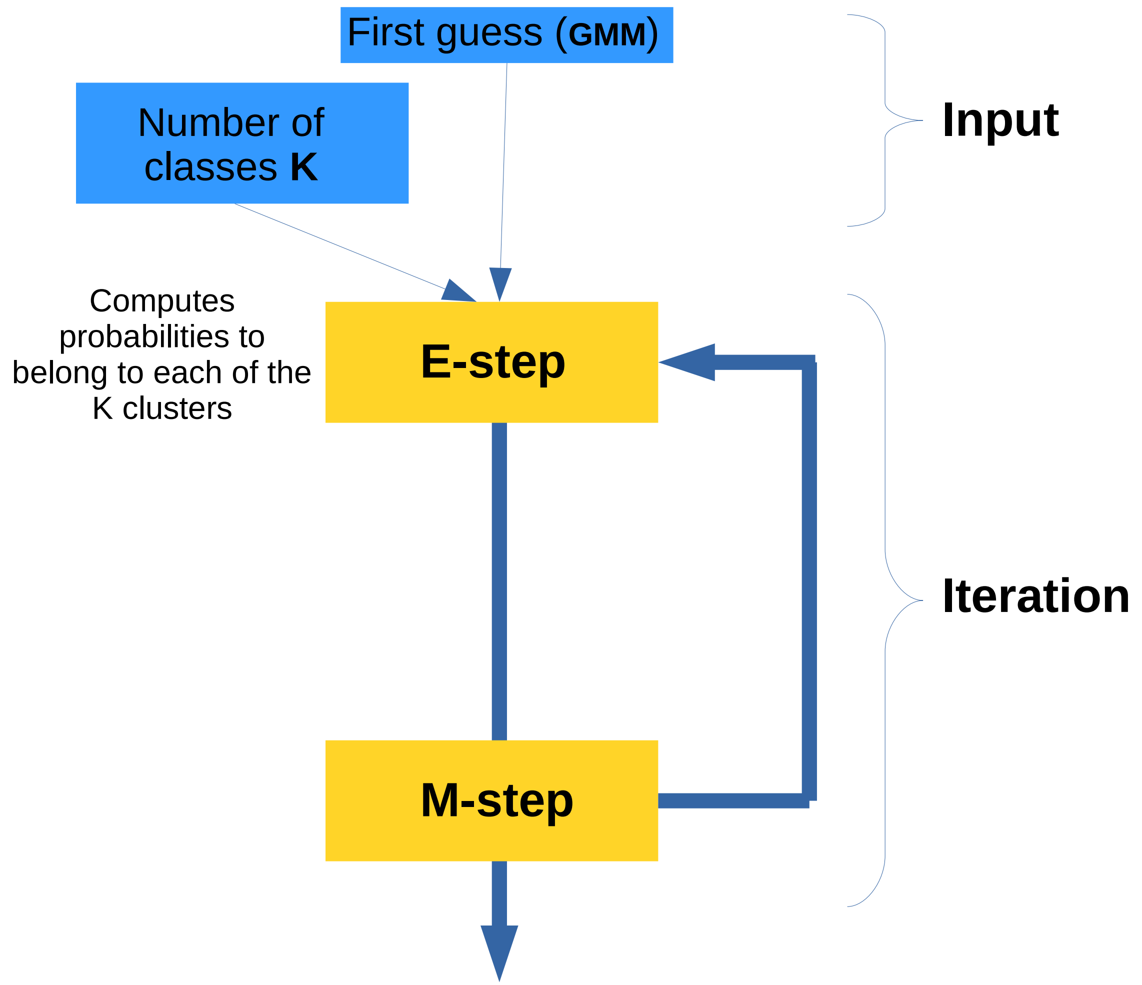

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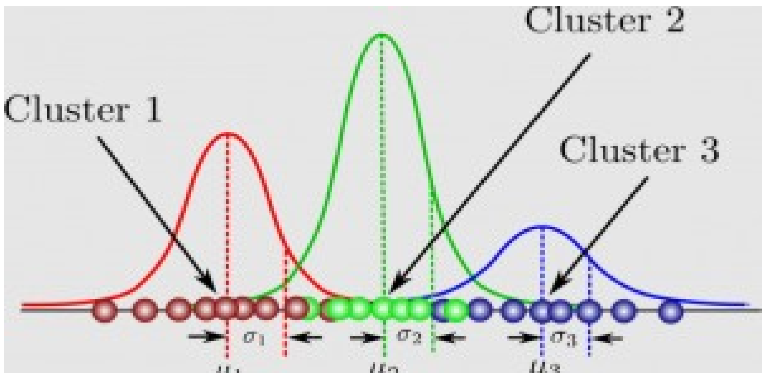

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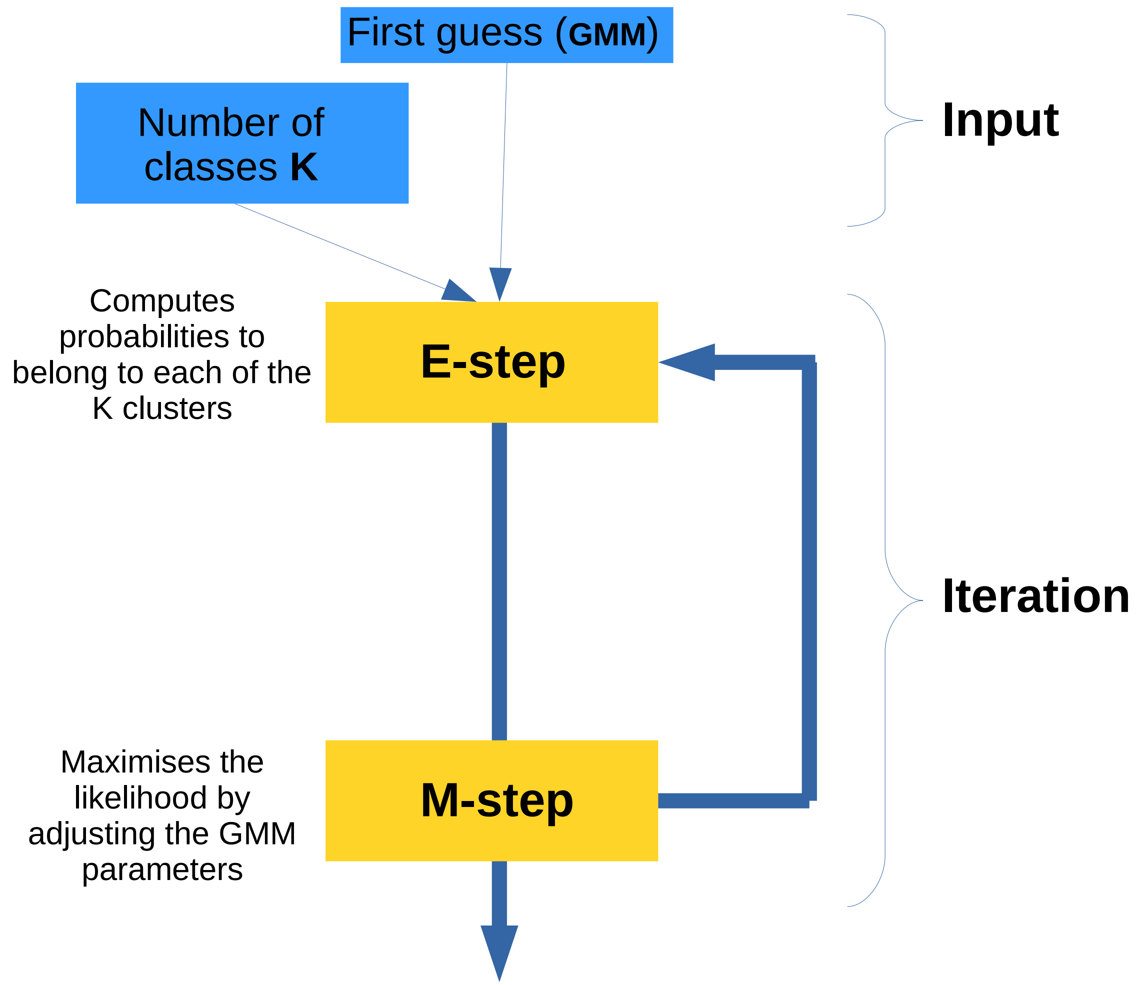

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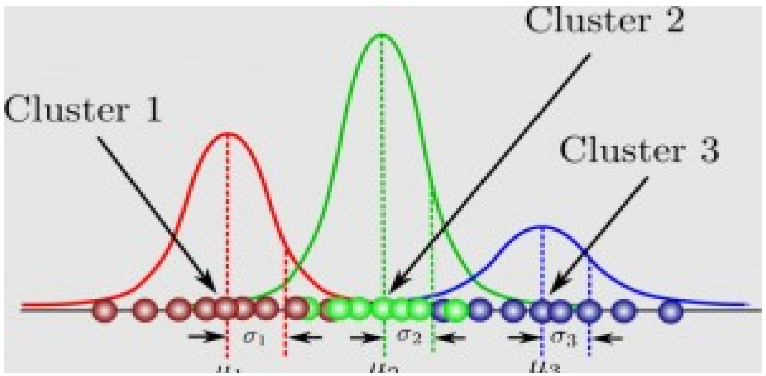

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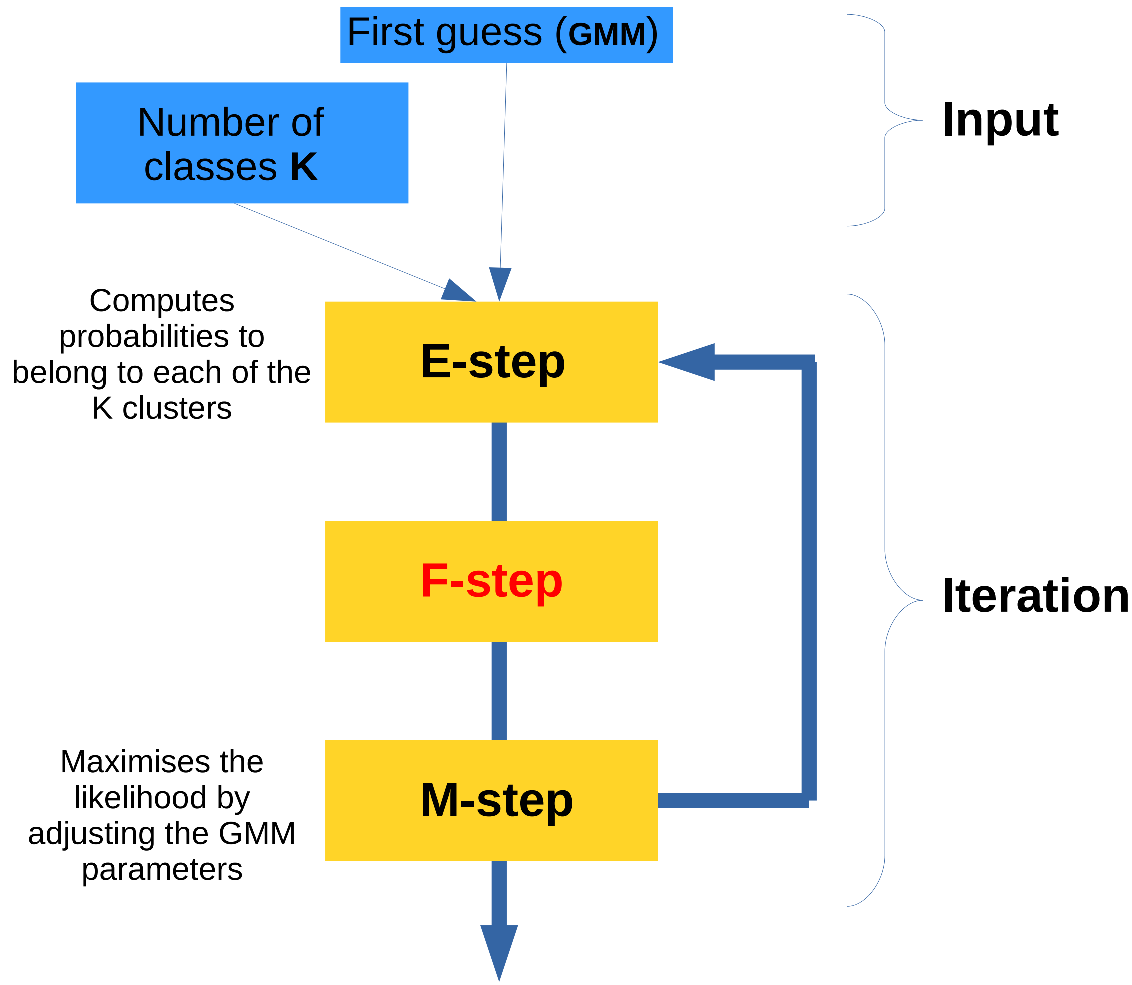

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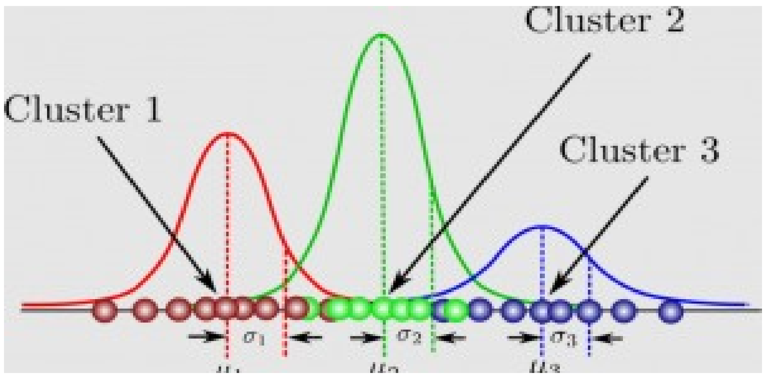

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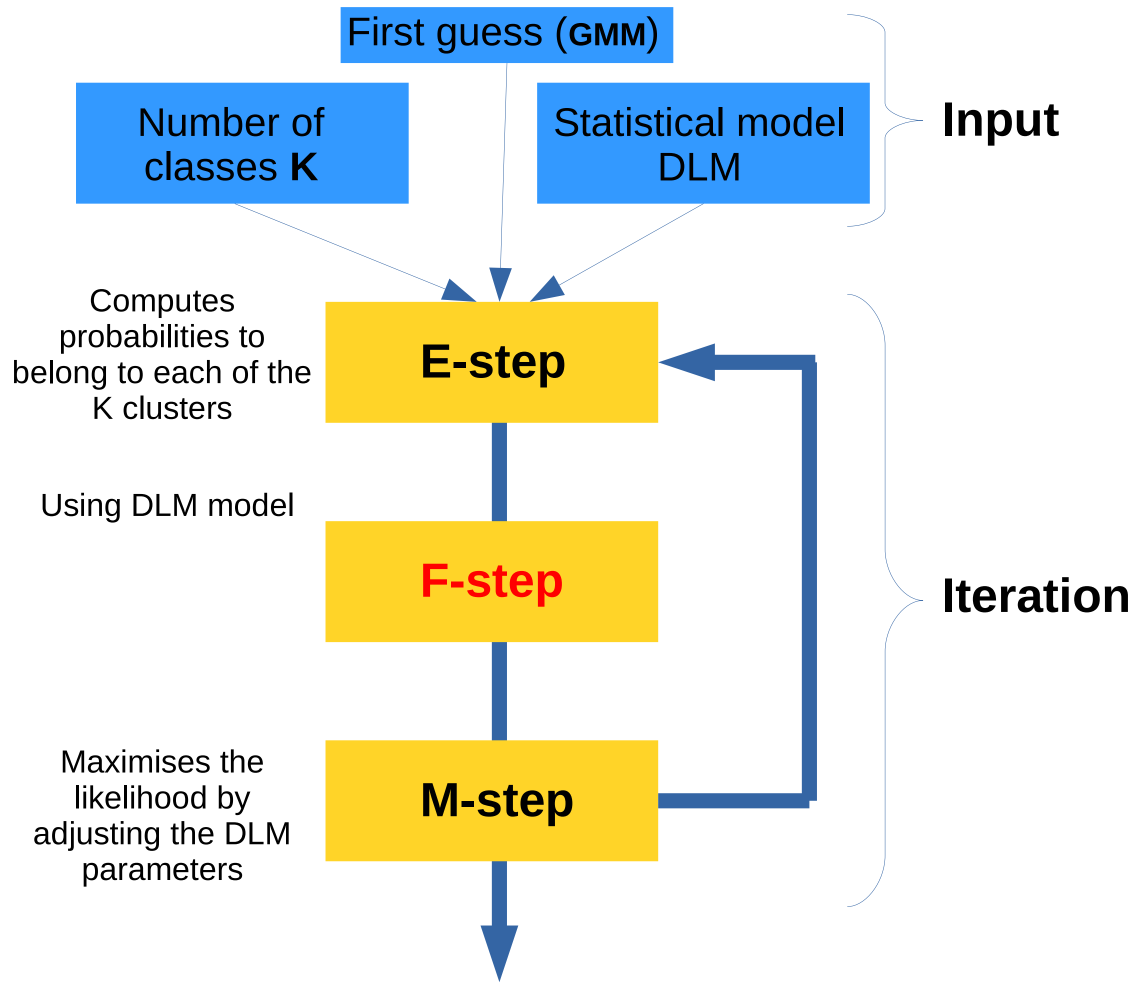

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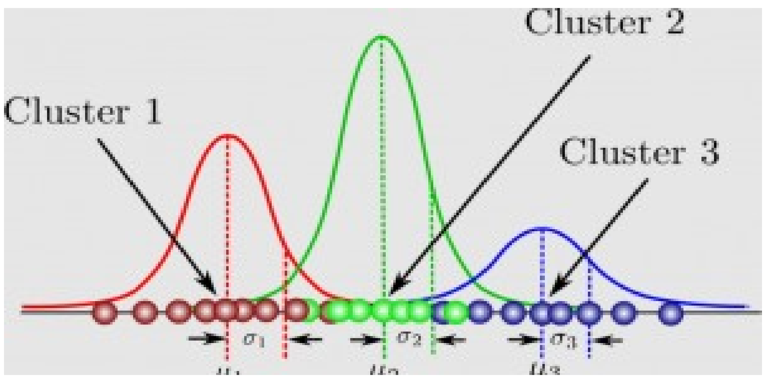
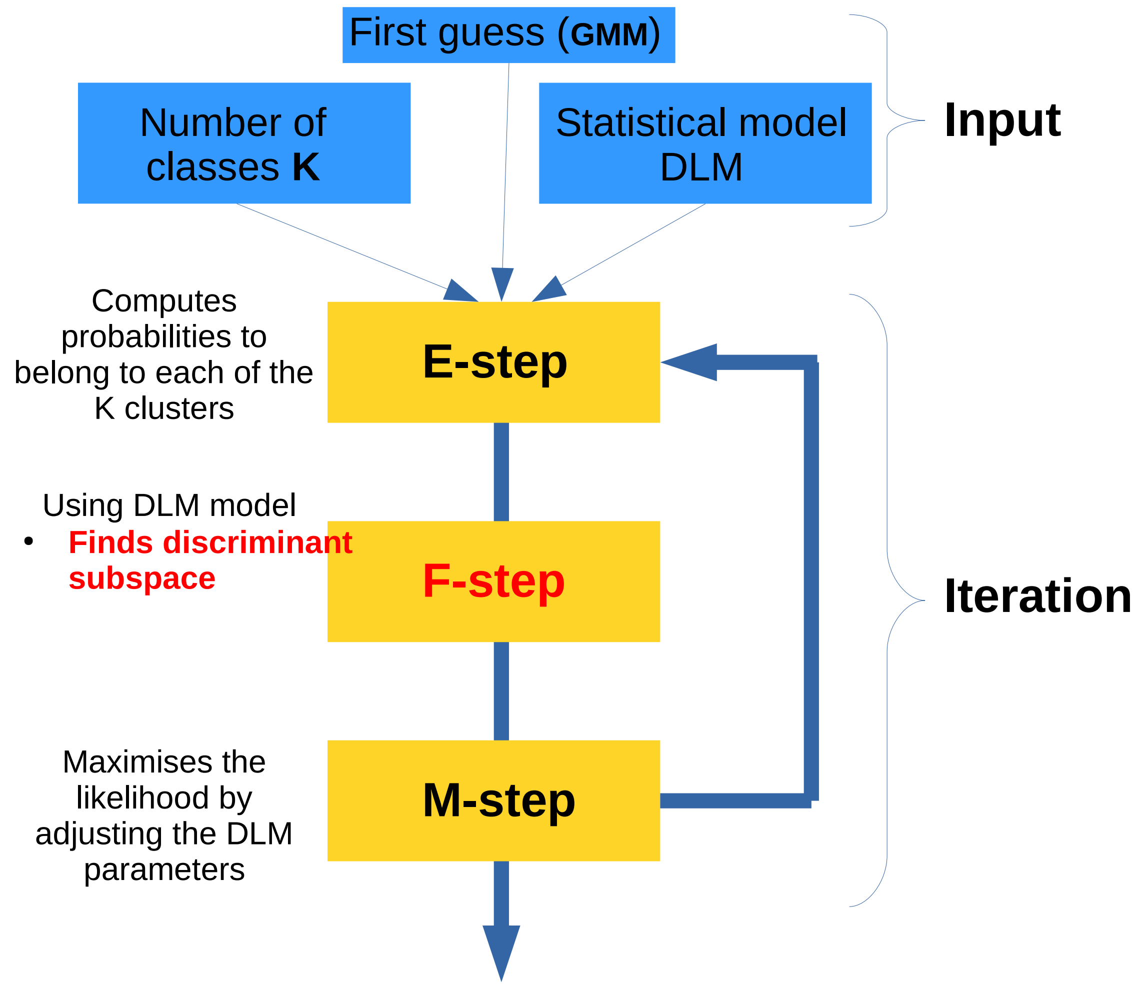


Gaussian Mixture Model (GMM)

in a subspace of smaller dimension than phys. parameter space, the « latent subspace »



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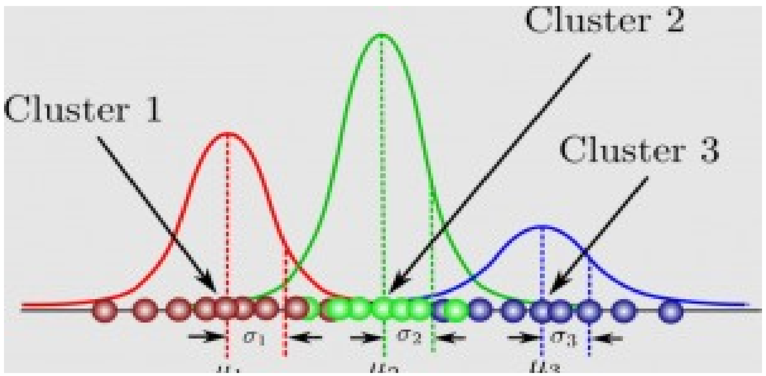

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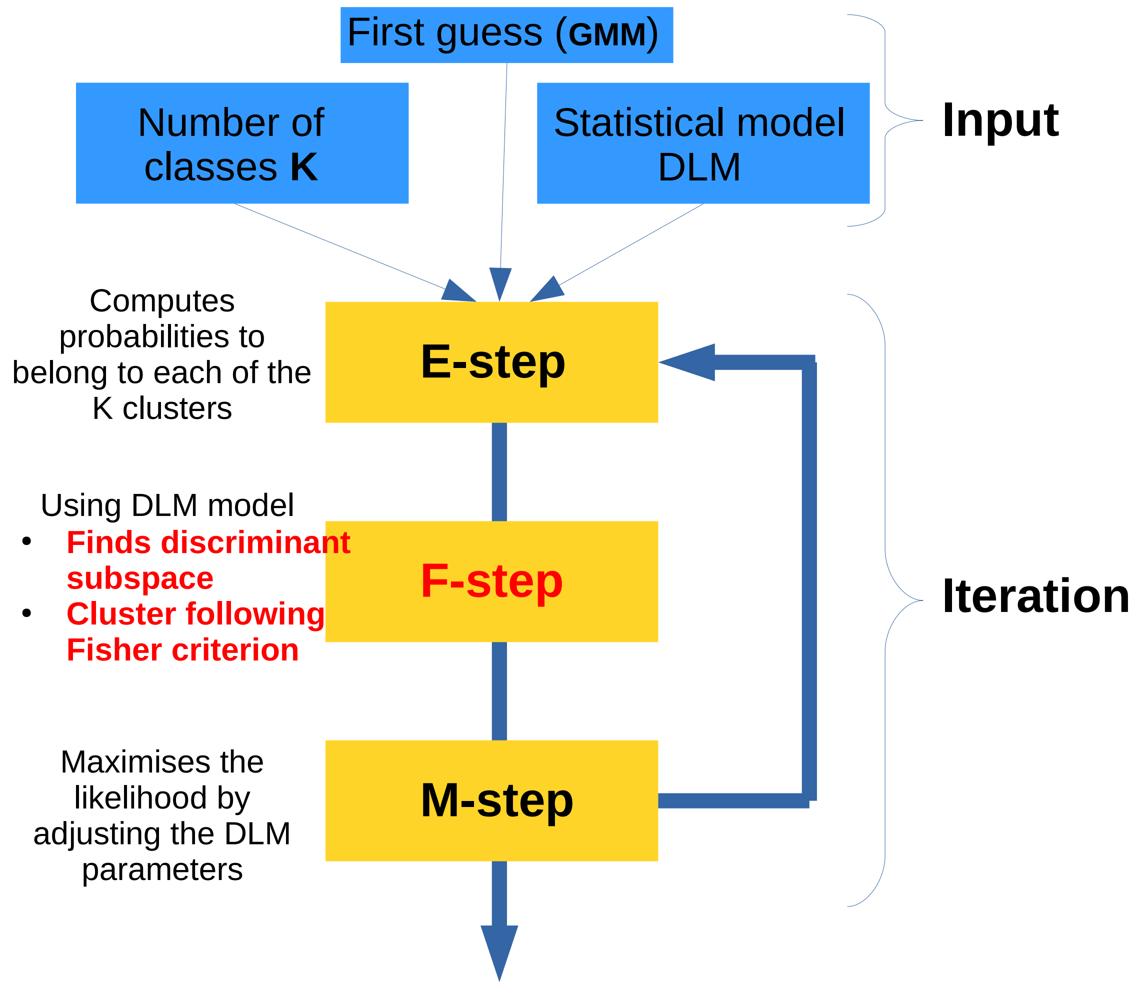

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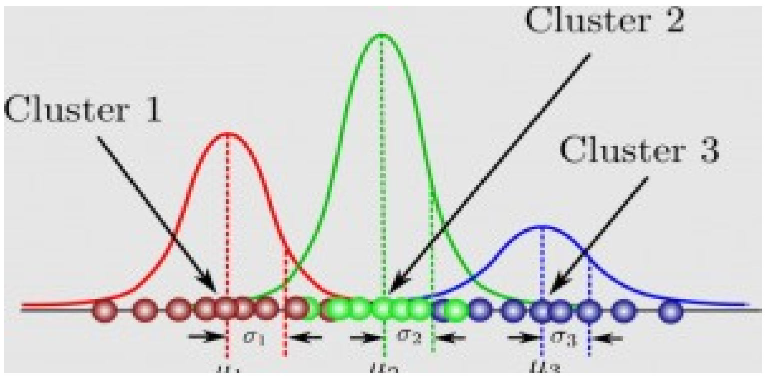

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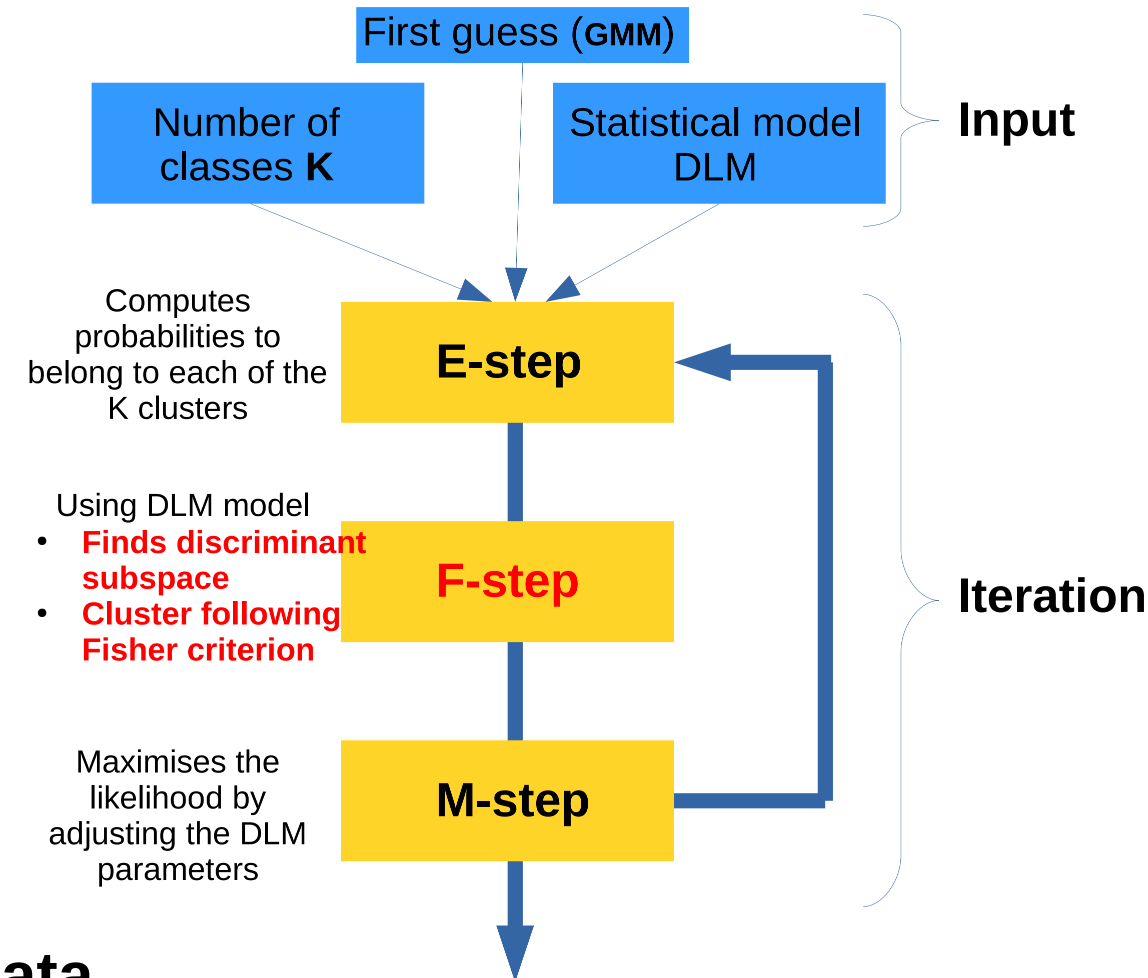
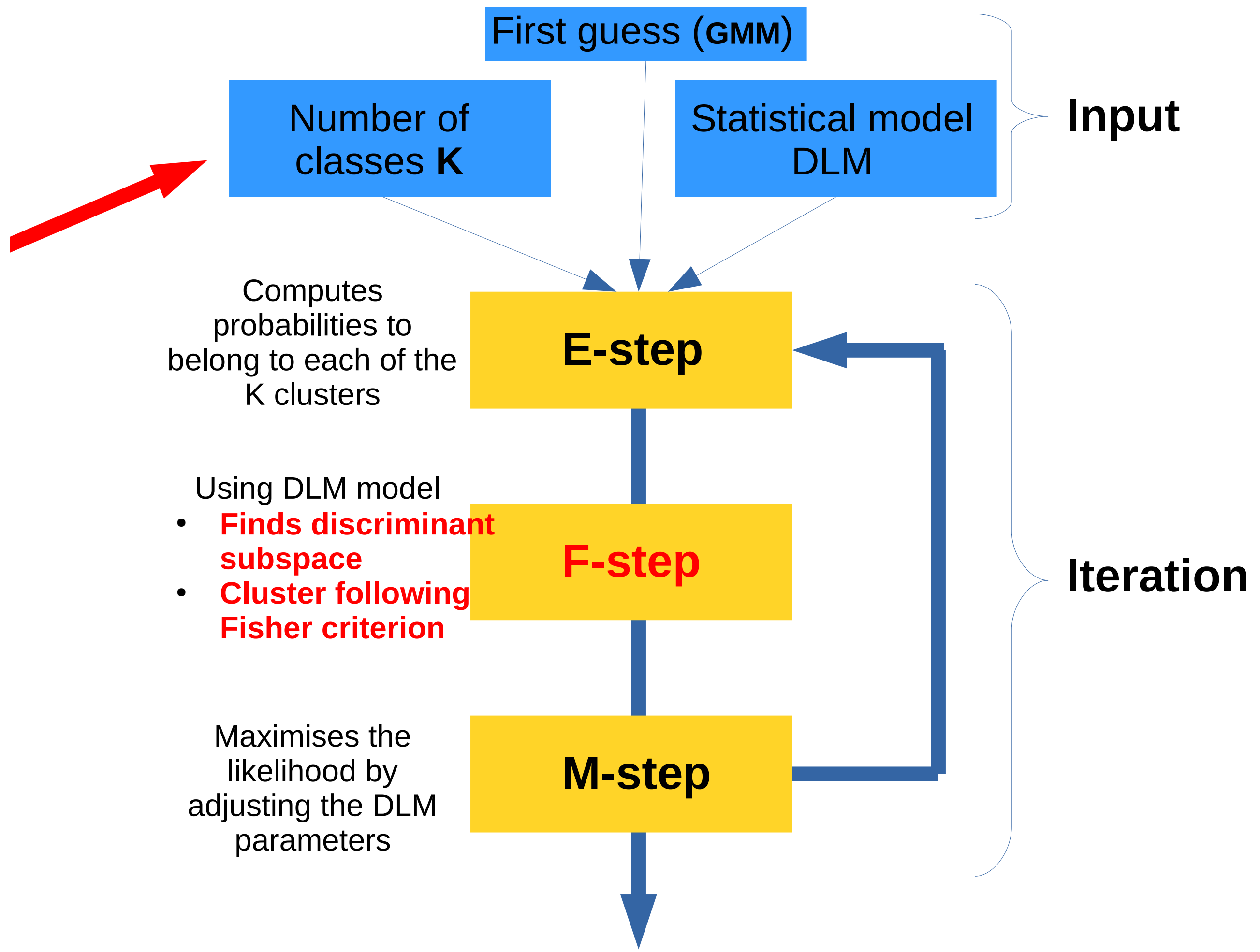


High-dimensional data

Fisher-EM algorithm

Bouveyron, C., & Brunet, C. 2012a, Stat. Comput., 22, 301

The best DLM model and optimal K are those maximising the Integrated Completed Likelihood (ICL) statistical criterion



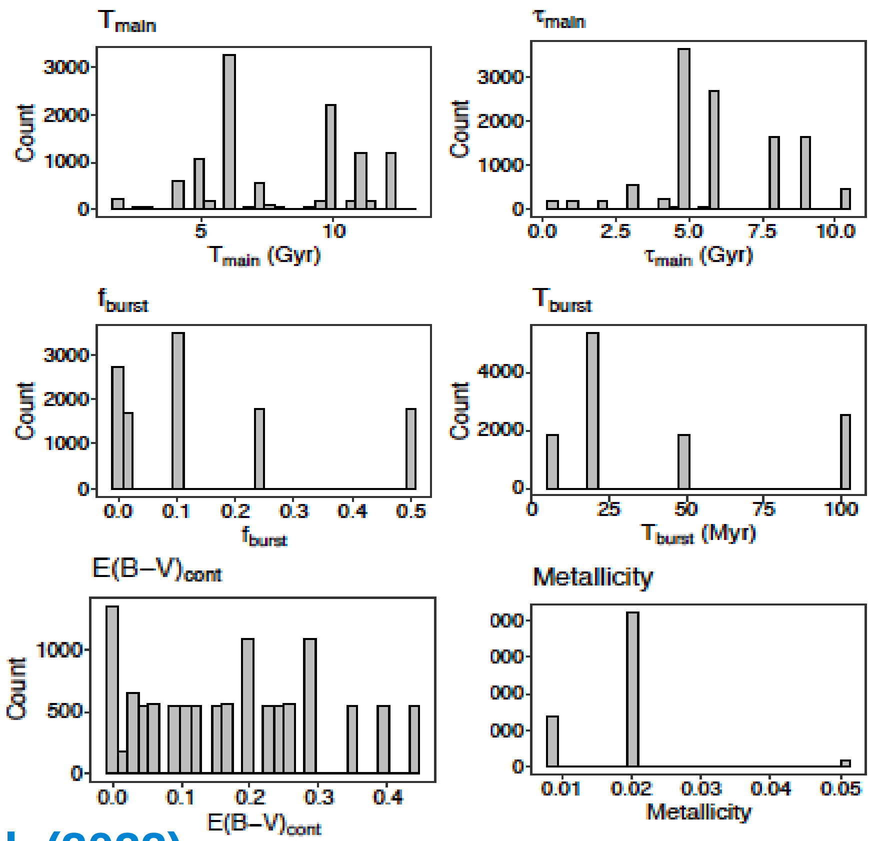
Fisher-EM on simulated spectra

Optical simulated spectra of 11000 galaxies with CIGALE ***Burgarella et al. (2005)***

SFH : Main population and a later burst (same metallicity)

➡ **6 physical parameters :**

- **Age** & **e-folding time** of the main SP (Myr)
- **Age** & stellar **mass fraction** of the burst (Myr)
- **Metallicity**
- **Reddening**



Dubois et al. (2022)

Distribution of parameters

Fisher-EM on simulated spectra

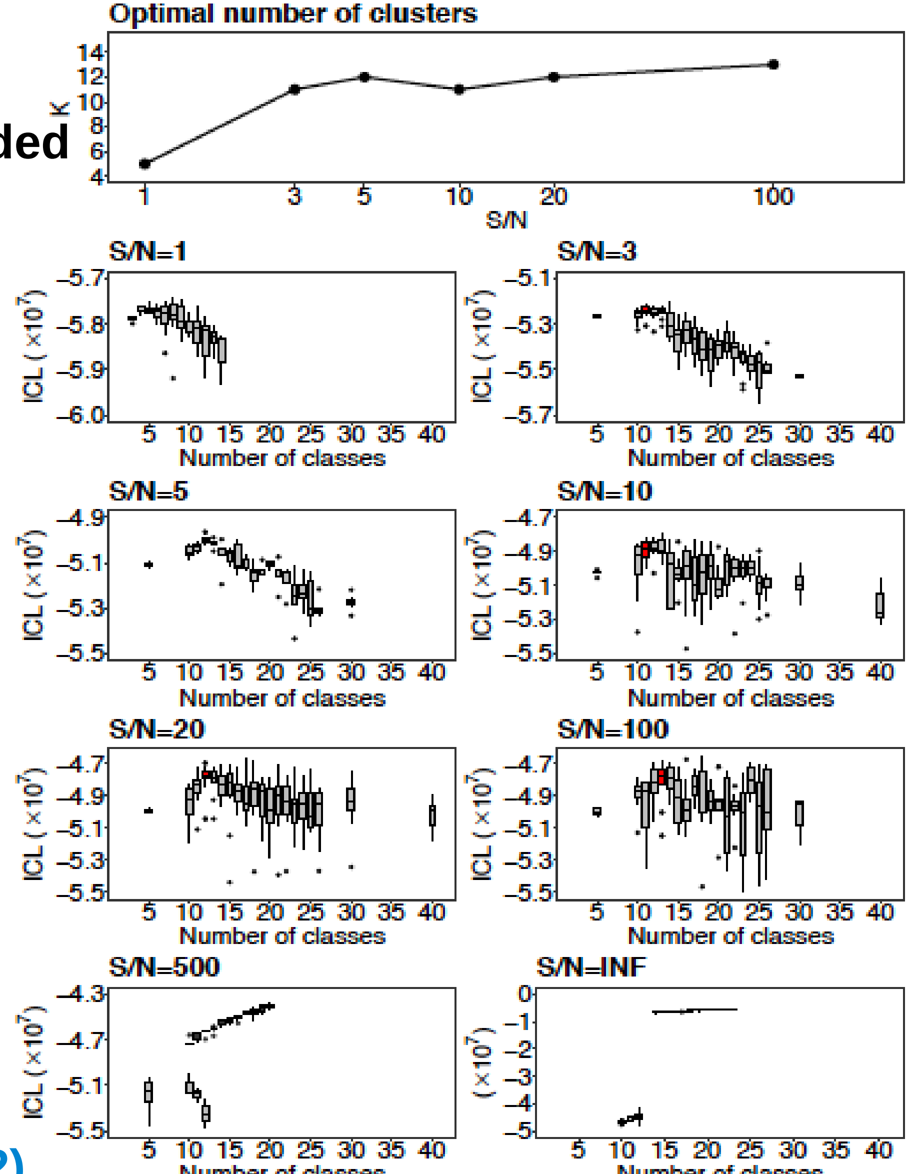
- **Classification of sample without noise**
- **Classifications of samples with different added noise levels (S/N = 1, 3, 5, 10, 20, 100, 500)**

For SNR < 500 :

→ Best solution for K=12 (**Robust** results)
→ Well **discriminated phys. parameters** (but less discrimination at higher noise)

Convergence issues for SNR >= 500

→ Due to coverage of parameter space, sparsity
→ Noise insufficient to blur data sparsity



Dubois et al. (2022)

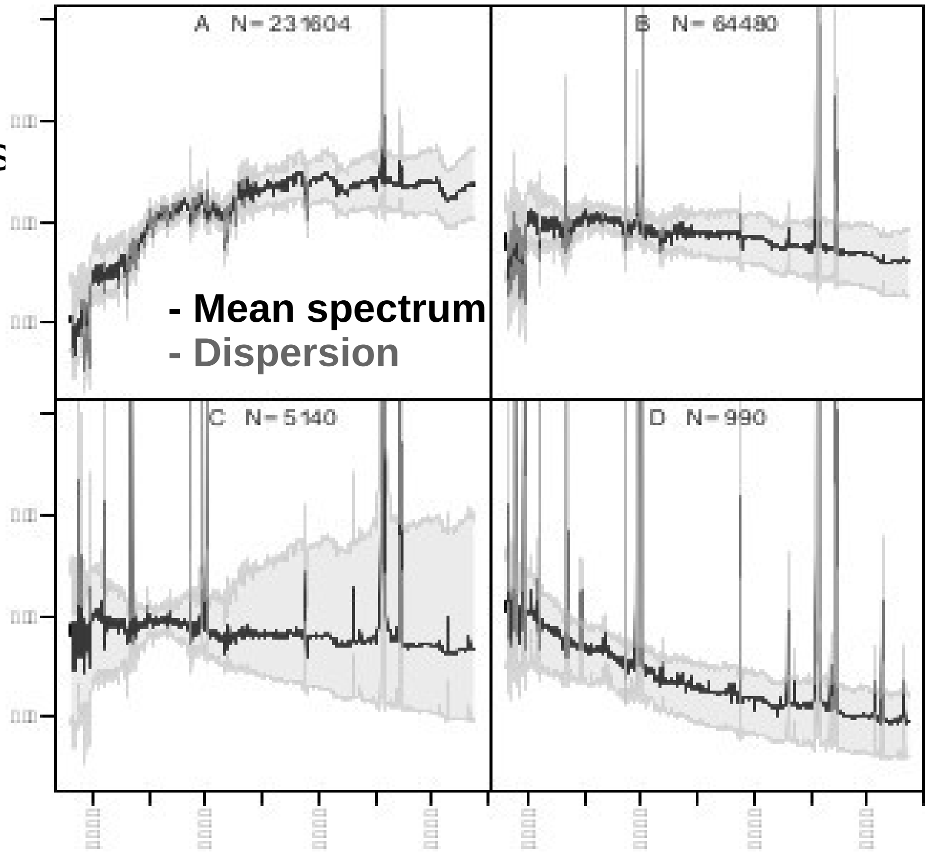
Fisher-EM on SDSS spectra

About 700,000 spectra of galaxies and quasars from SDSS DR7 with z < 0.25 (corrected for redshift, resampled, rebinned and normalised)

Different steps : FEM applied on subsamples

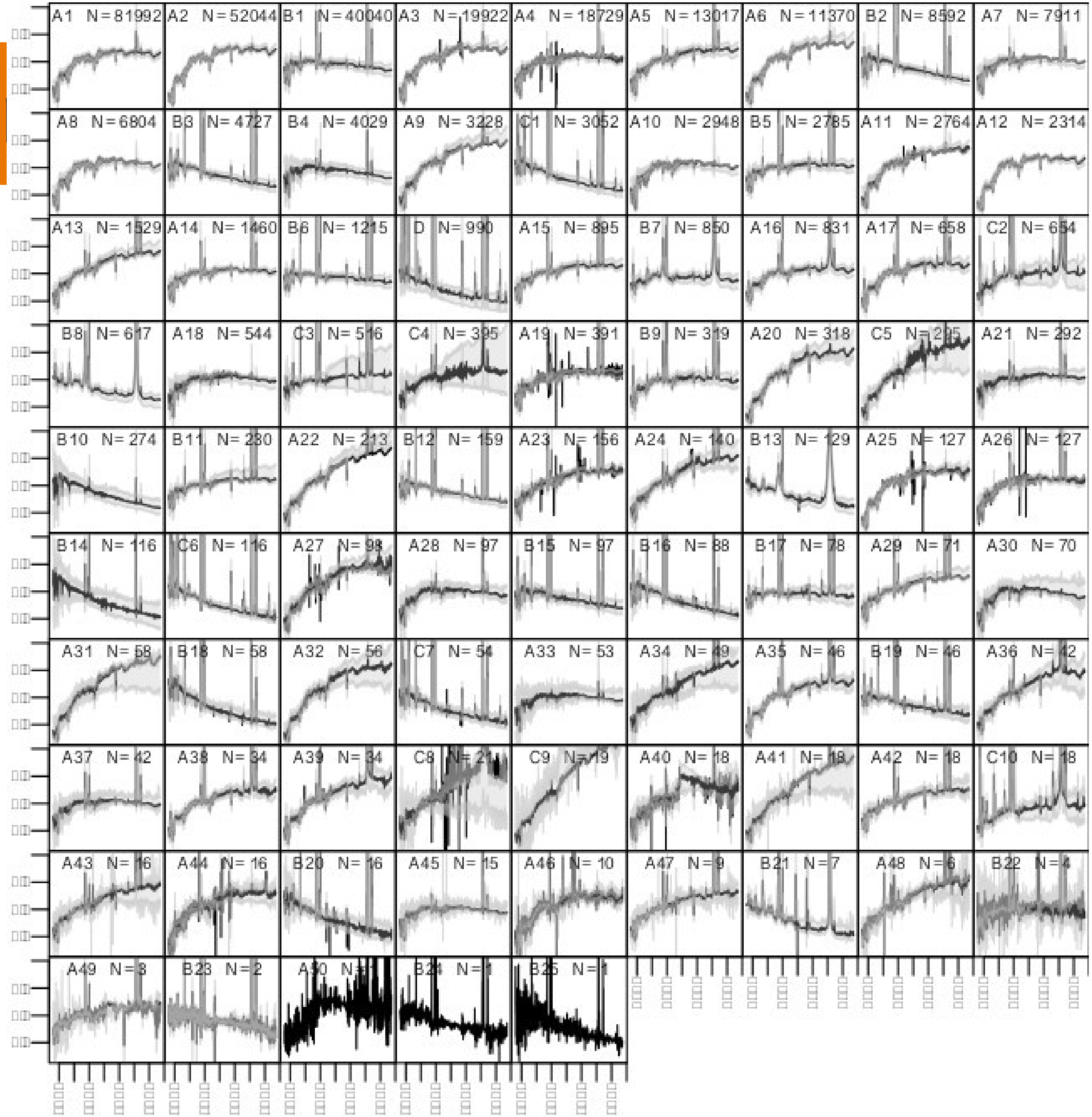
→ 4 main classes : A,B,C,D

→ Subclassification



Fraix-Burnet et al. (2021)

Fishe



86 final classes

Fraix-Burnet et al. (2021)

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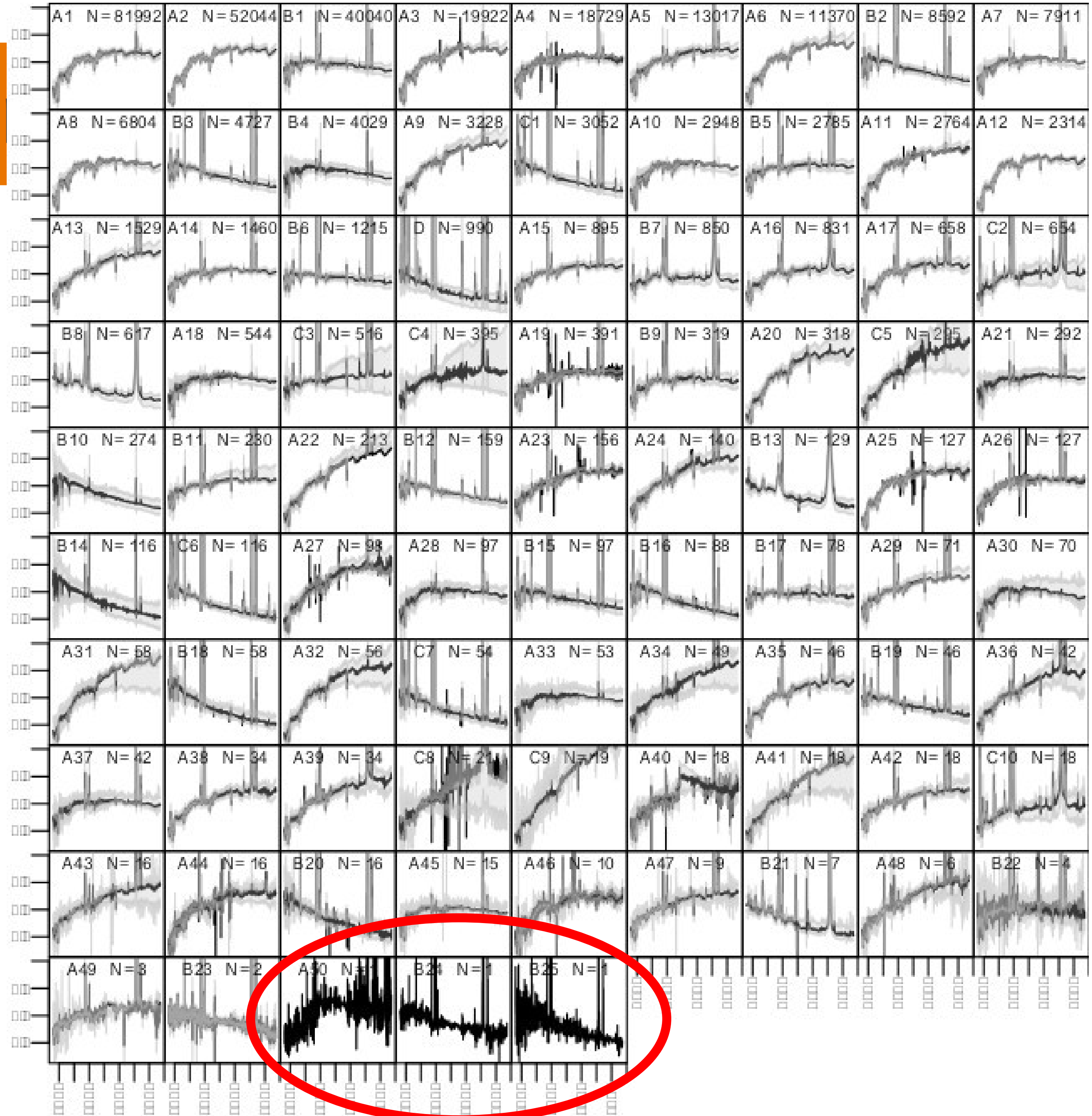

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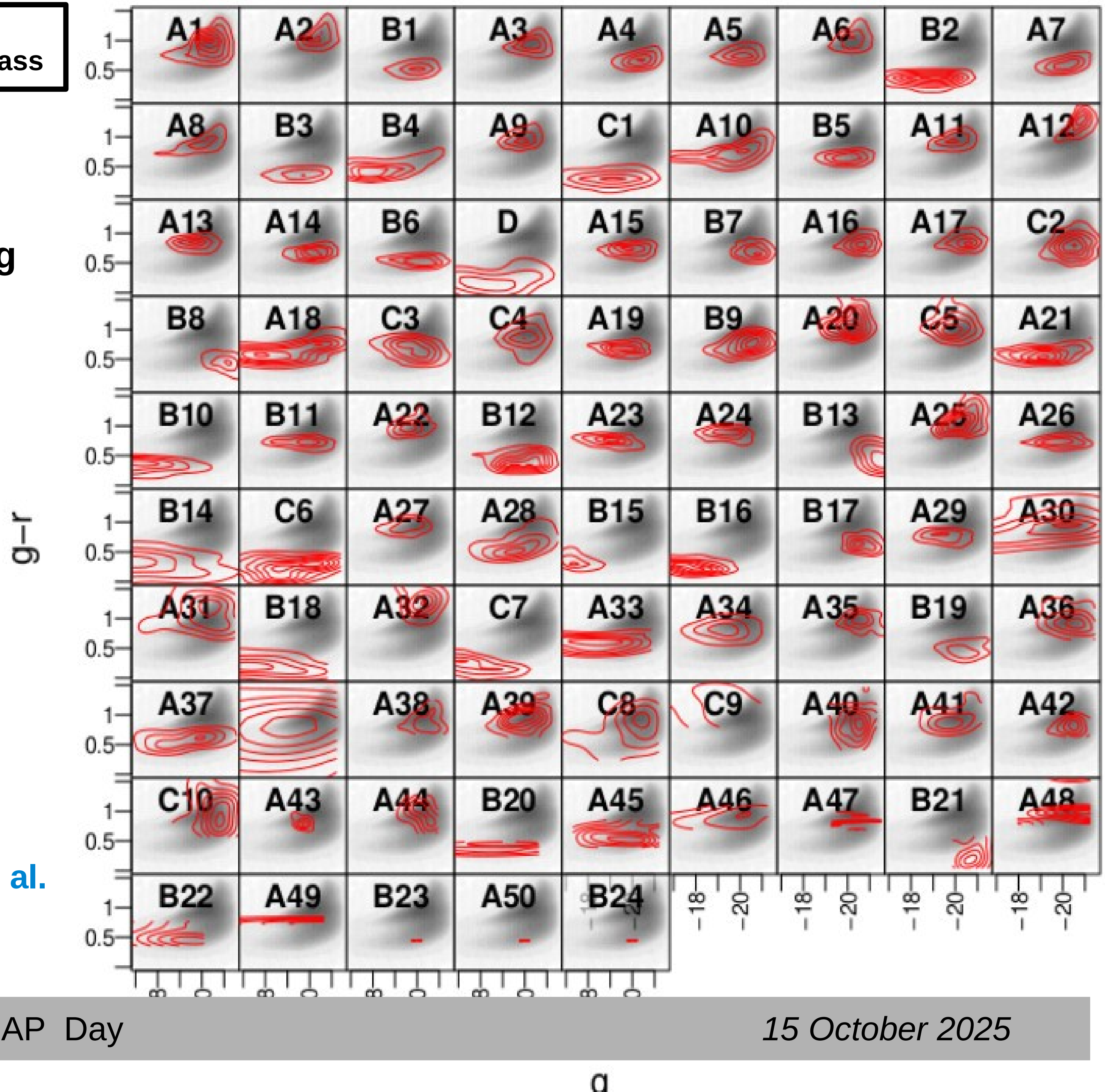
Fraix-Burnet et al. (2021)

Grey: whole sample
Red: spectra of the class

Color-mag diagram



Fraix-Burnet et al. (2021)

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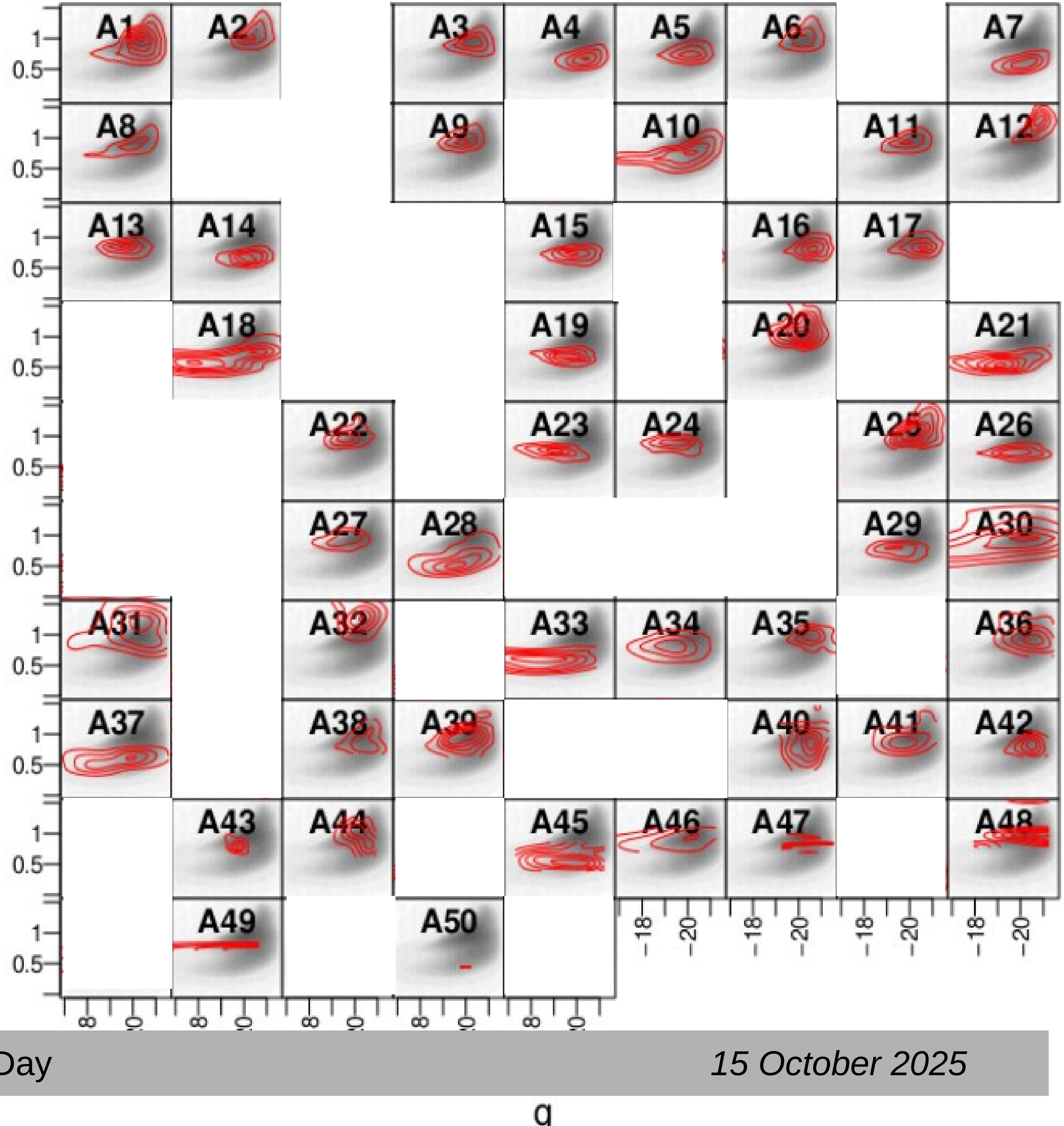
Class A

Red sequence



Fraix-Burnet et al. (2021)

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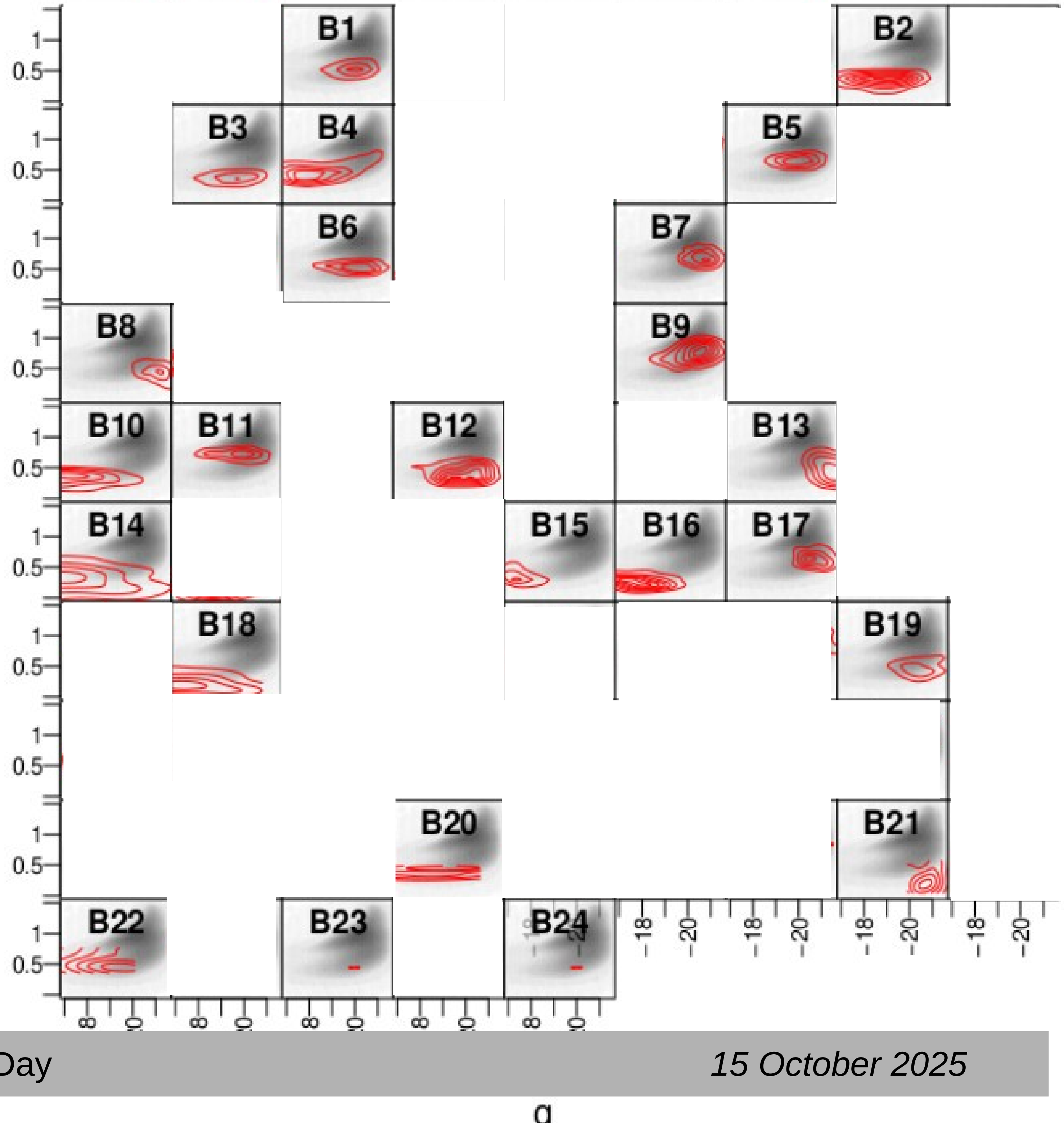
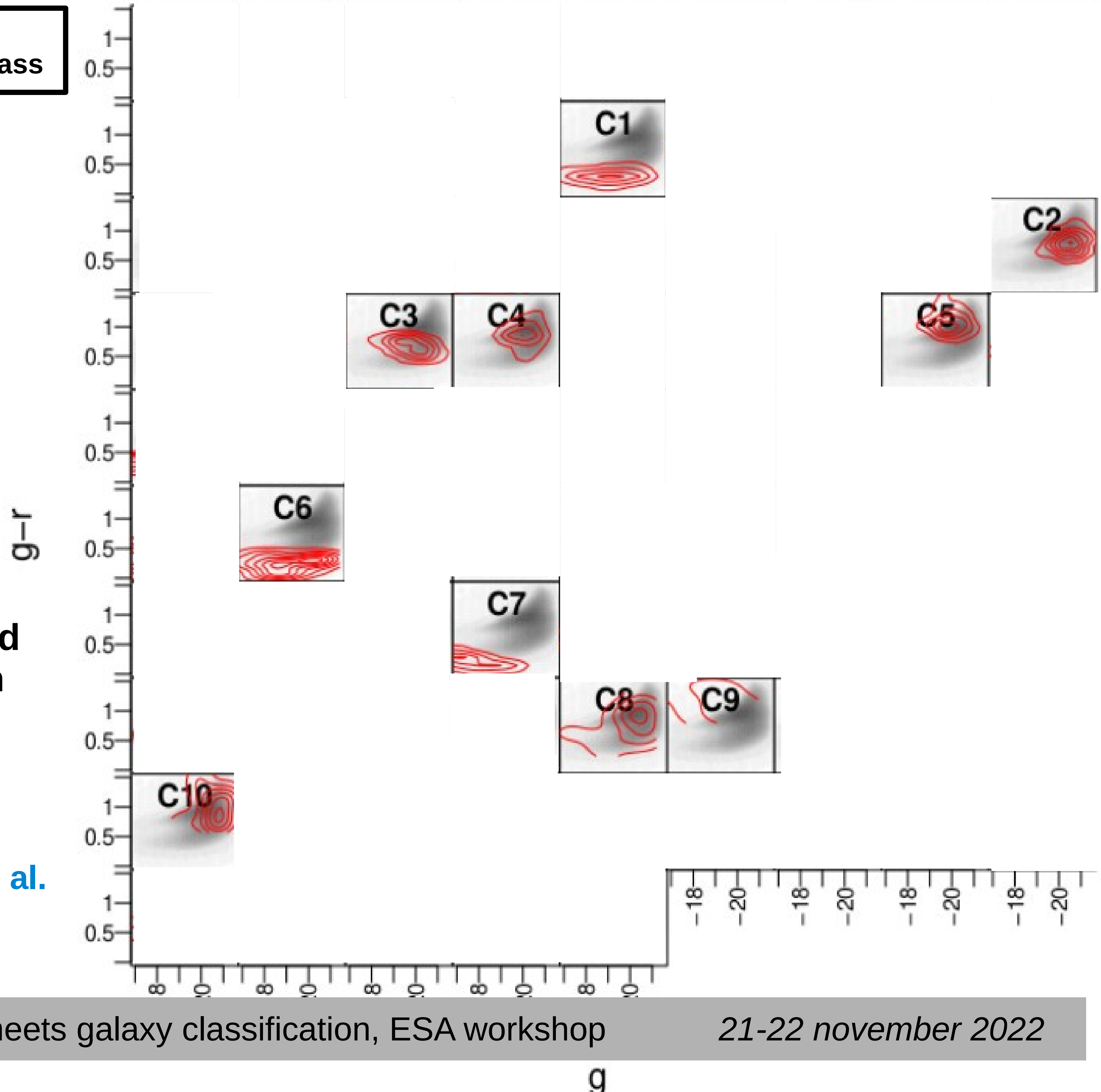
Class B

Blue sequence



Fraix-Burnet et al. (2021)

Grey: whole sample
Red: spectra of the class



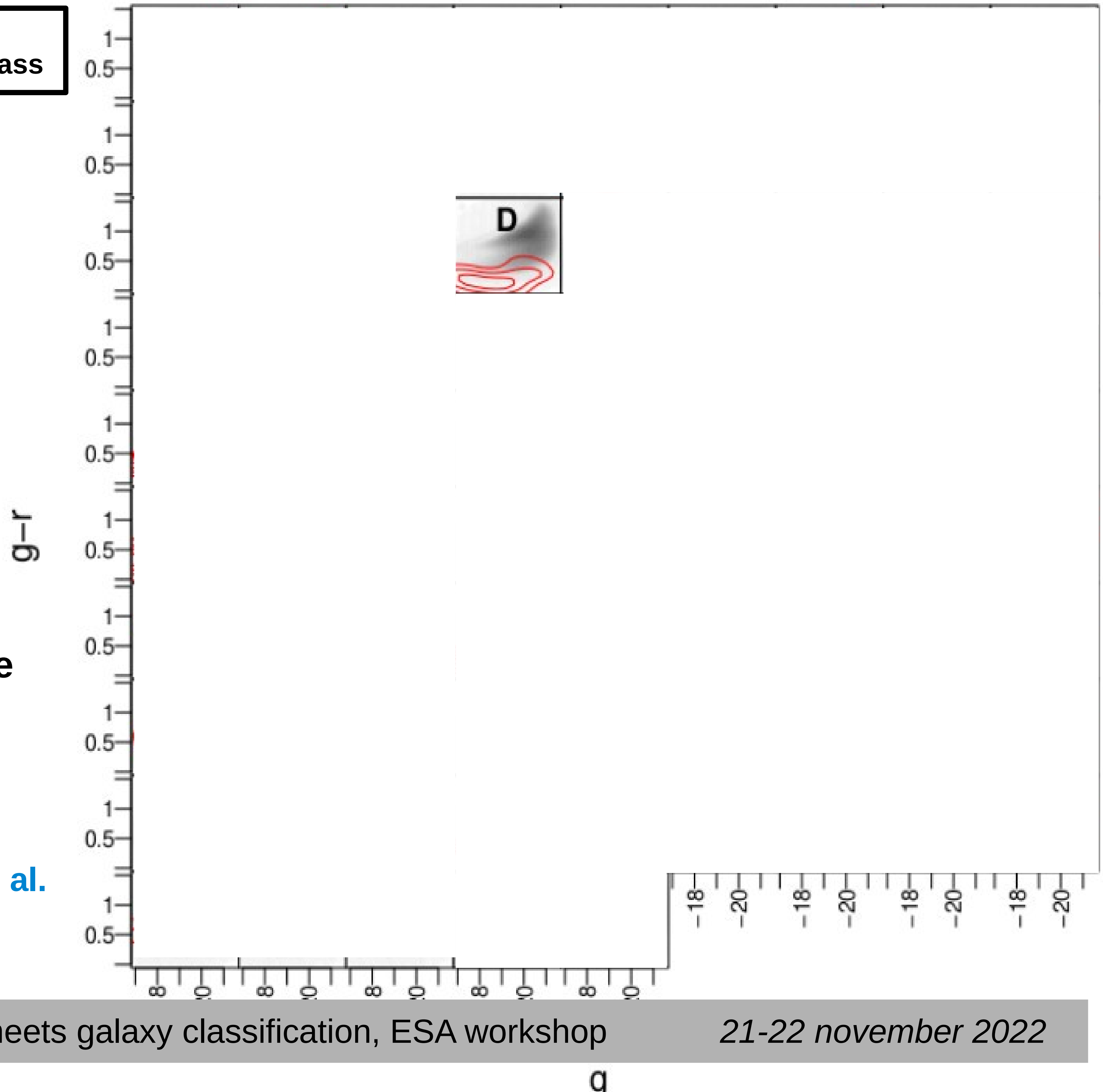
Class C

Diverse

Characterized by emission lines

Fraix-Burnet et al. (2021)

Grey: whole sample
Red: spectra of the class



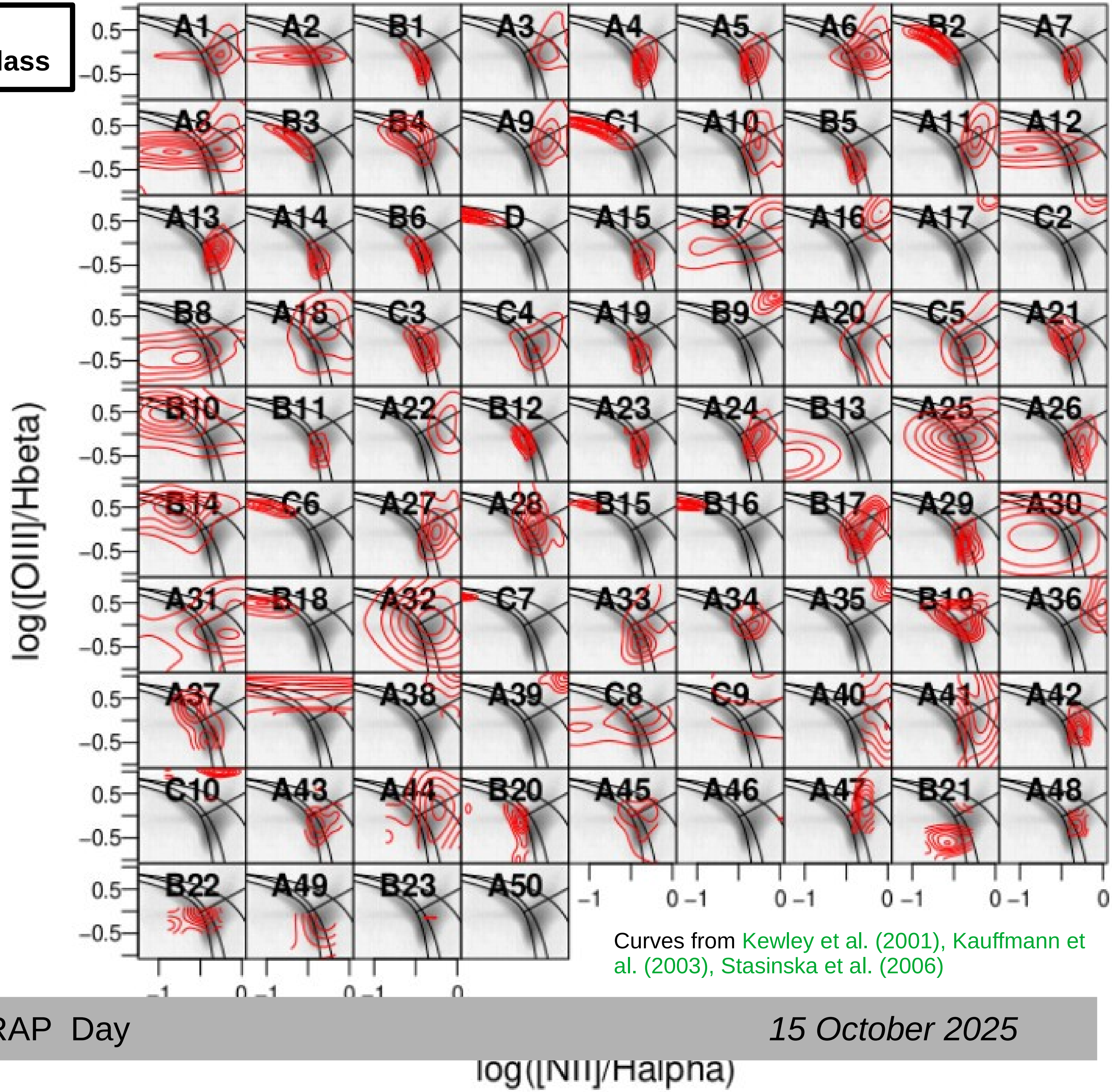
Class D

Extremely blue

Fraix-Burnet et al. (2021)

Grey: whole sample
Red: spectra of the class

BPT diagrams



Curves from Kewley et al. (2001), Kauffmann et al. (2003), Stasinska et al. (2006)

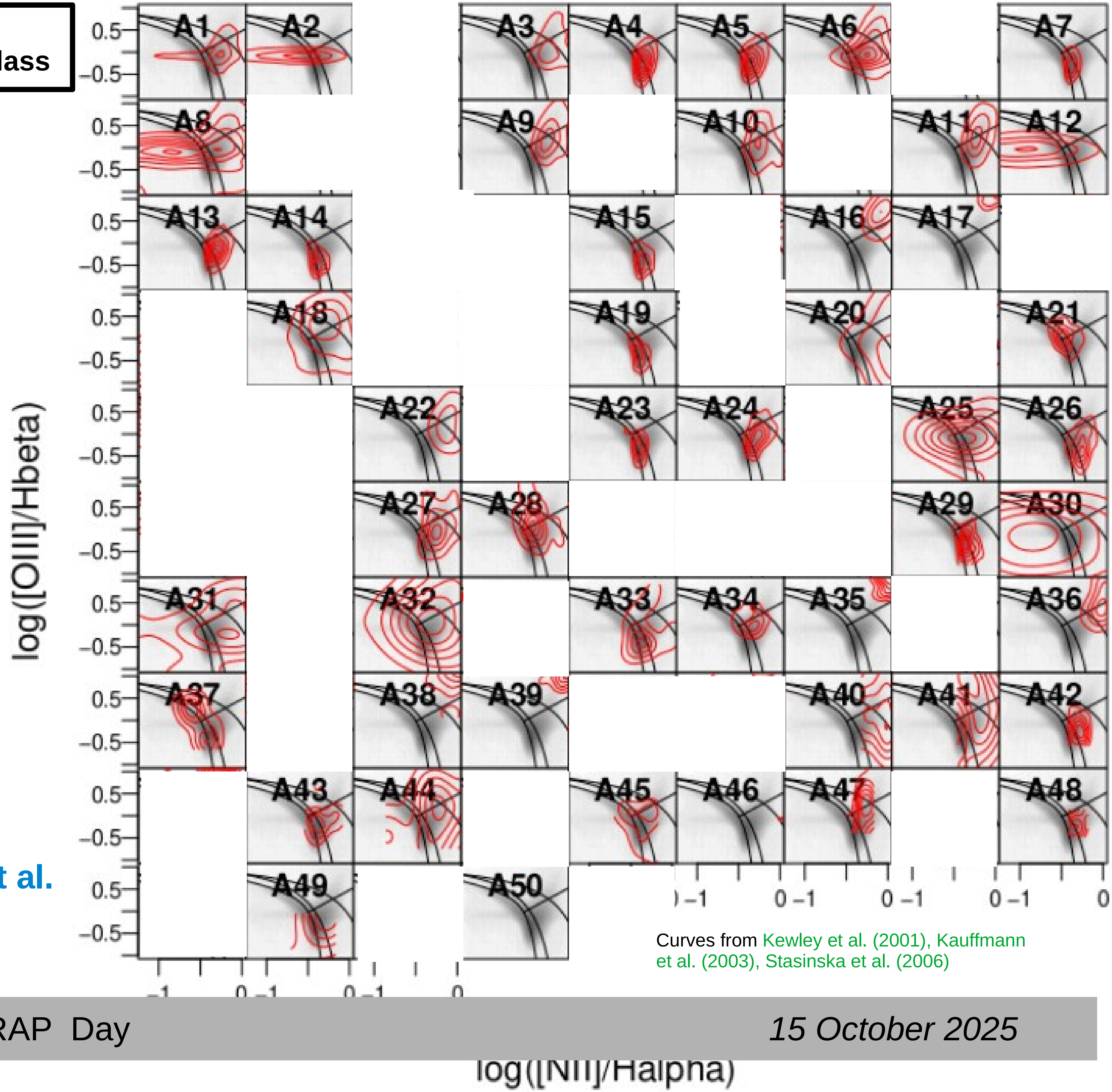
Grey: whole sample
Red: spectra of the class

BPT diagrams

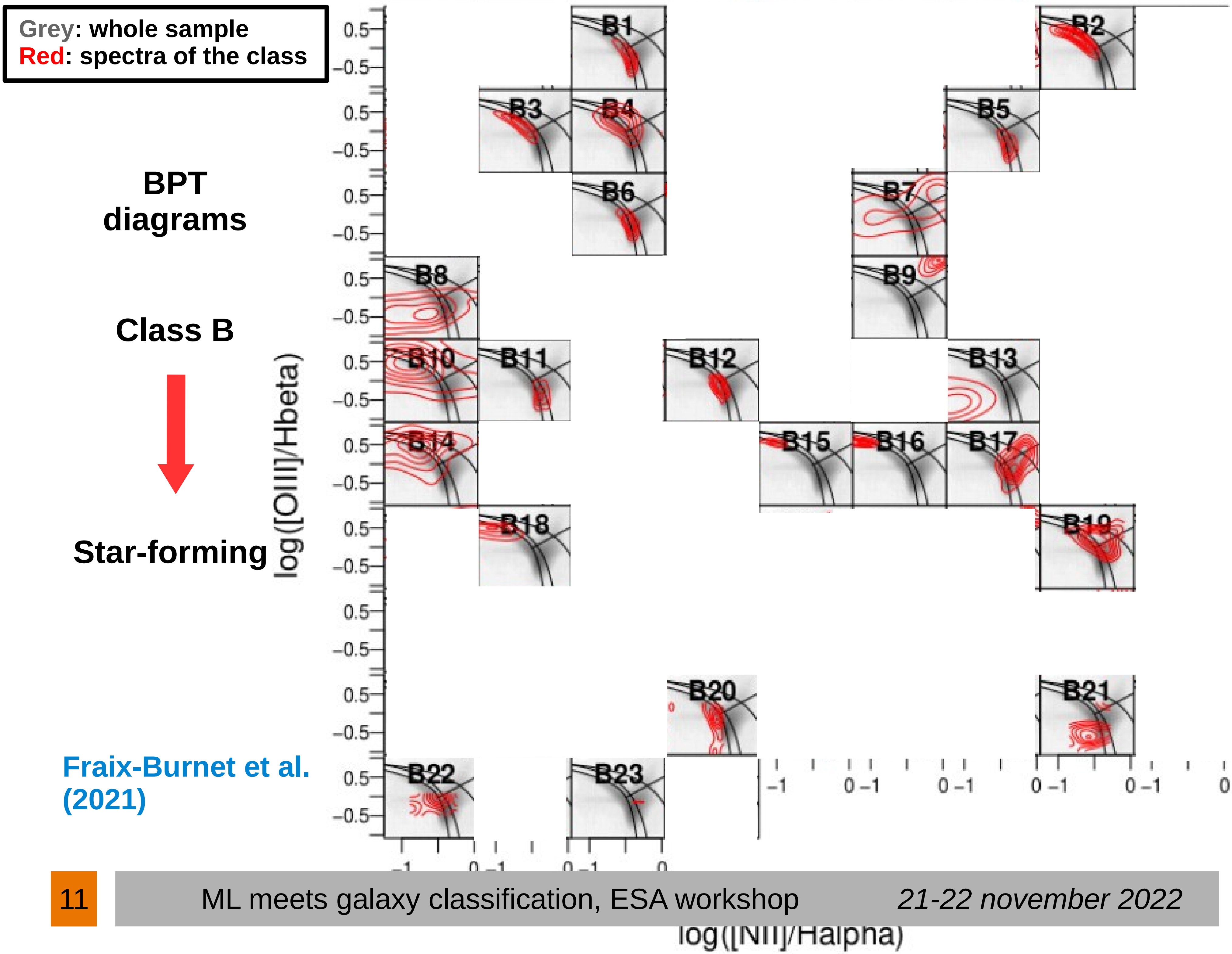
Class A

Seyferts or LINER galaxies

Fraix-Burnet et al. (2021)



Curves from Kewley et al. (2001), Kauffmann et al. (2003), Stasinska et al. (2006)



BPT diagrams

Class B

Star-forming

Fraix-Burnet et al. (2021)

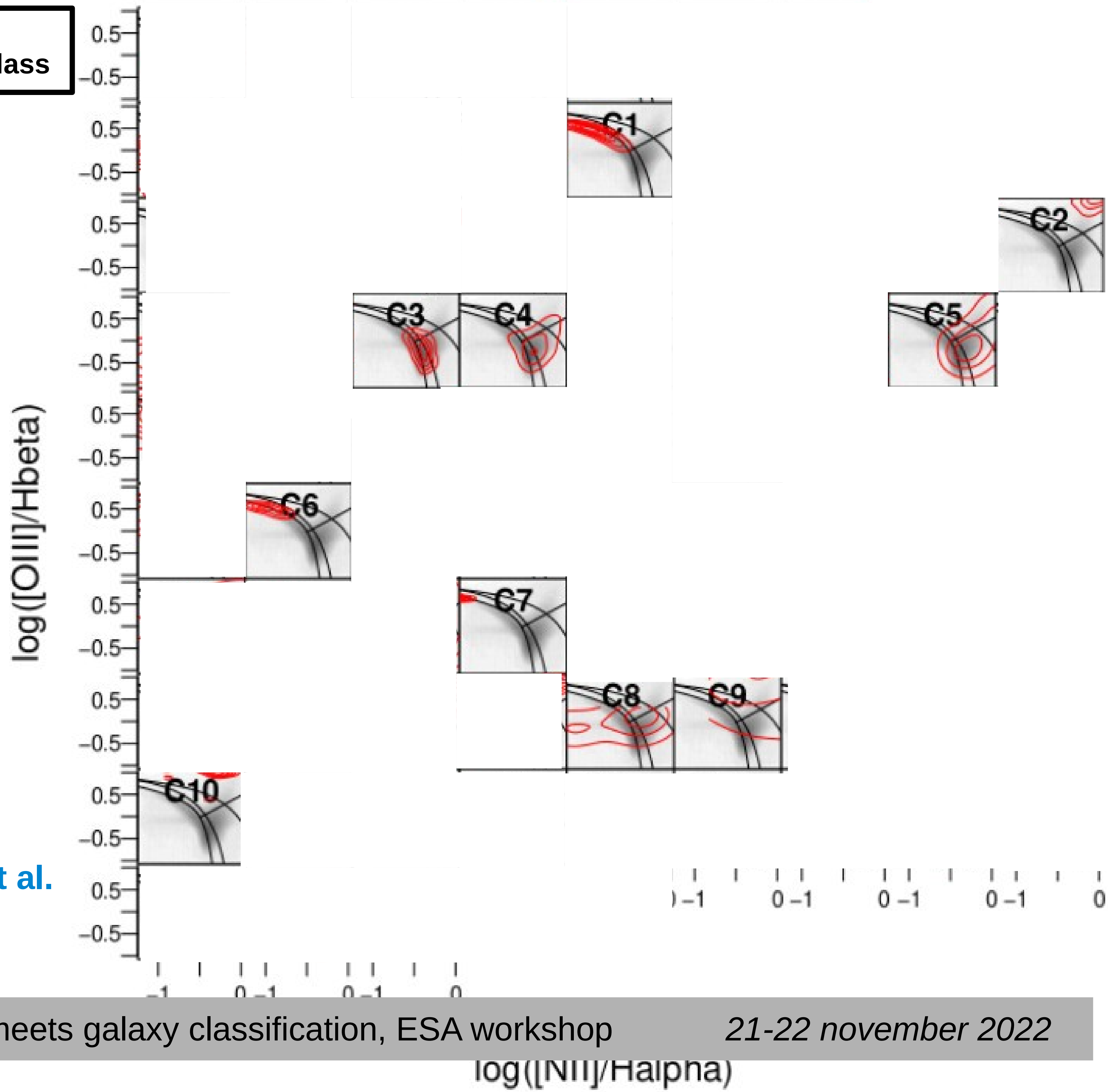
Grey: whole sample
Red: spectra of the class

BPT diagrams

Class C

Star formation & Nuclear activity

Fraix-Burnet et al. (2021)



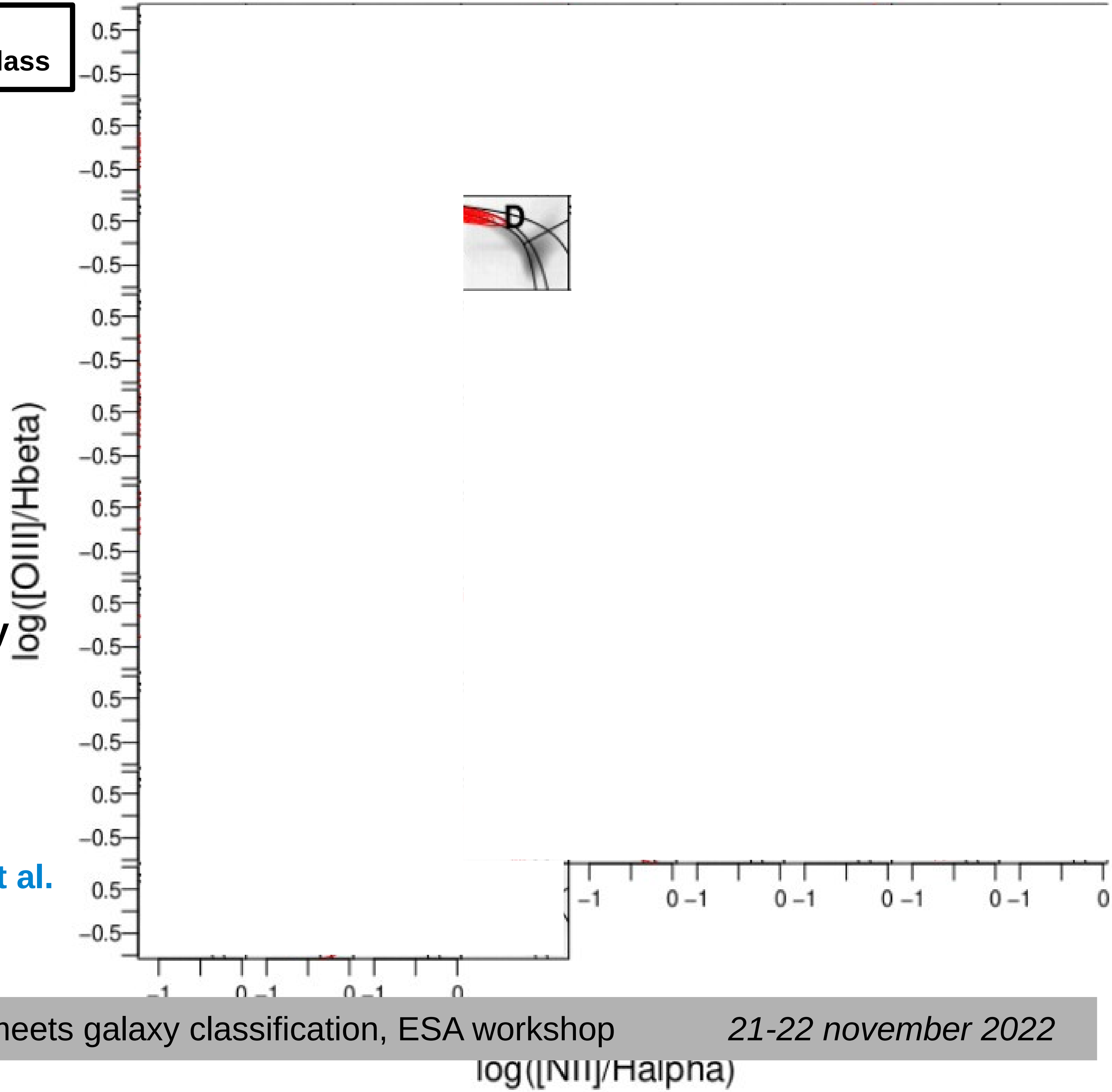
Grey: whole sample
Red: spectra of the class

BPT diagrams

Class D

High activity of Star formation

Fraix-Burnet et al. (2021)



Fisher-EM on SDSS spectra

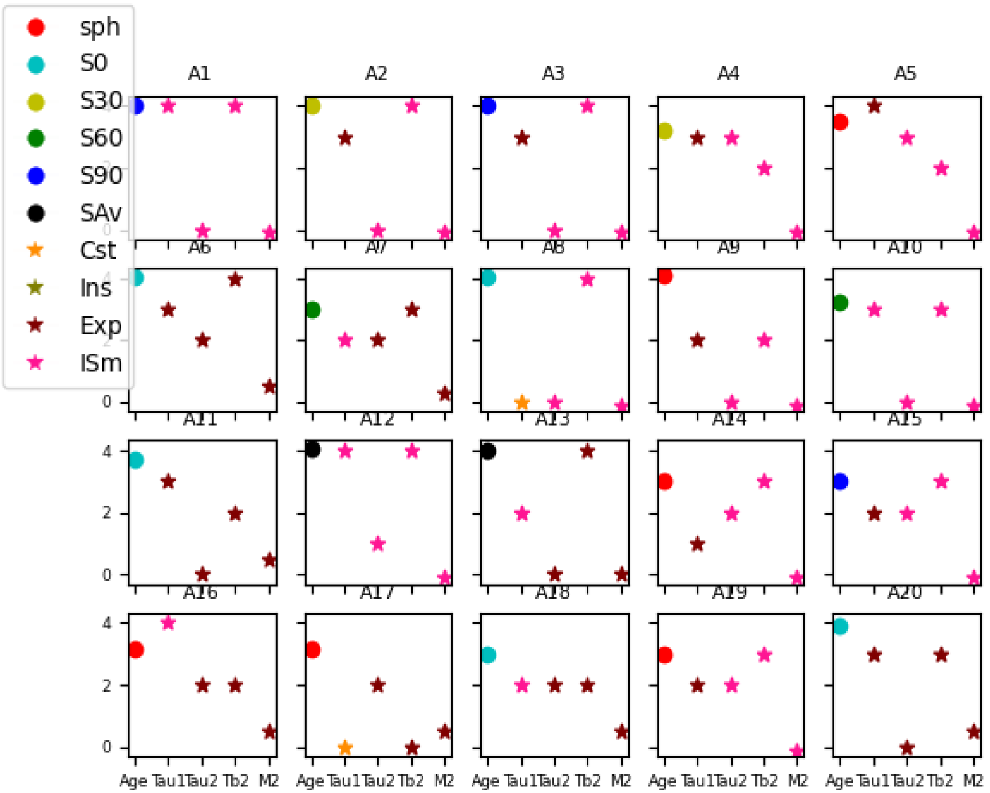
Next step → **Label** the mean spectra of the 86 classes

Mean spectra fitted by modeled stellar population models with PEGASE3 (***Fioc & Rocca-Volmerange 2019***)

Parameters :

- 2 stell. pop. (ages, e-folding times, burst mass)
- 4 SFR shapes
- 6 morphological types

→ **Each class has a distinct SP scenario**



Labeling example of the first A classes

Moultaka et al. (in prep)

Fisher-EM on GAMA survey

Two samples of galaxies from GAMA survey (***Driver et al. 2009***) :

- Sample of **5 physical parameters** of **7338 galaxies** from ***Turner et al. 2019 (T19)*** :

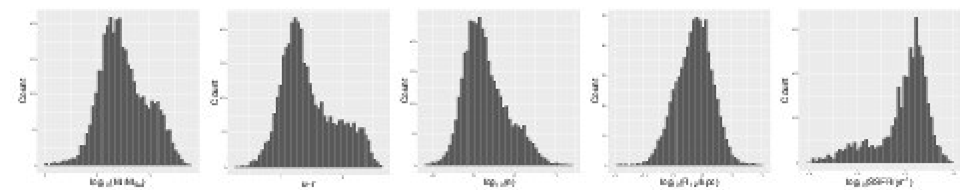
    -Stellar mass (**M***)

    -Color (**u-r**)

    -Sérsic index (**n**)

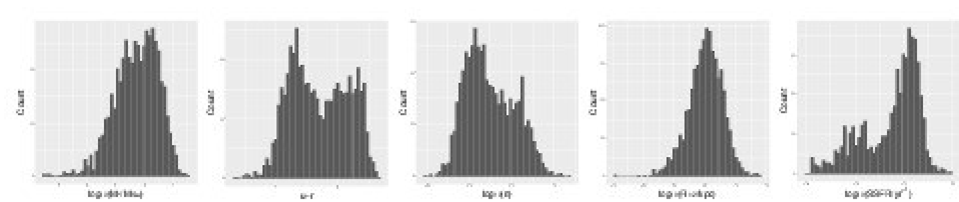
    -Effective radius (**$R_{1/2}$**)

    -Specific star formation rate (**sSFR**)



M* **u-r** **n** **$R_{1/2}$** **sSFR**

- Subsample of **spectra** of **2550 galaxies** taken from the previous sample for which **SDSS optical spectra** are available.



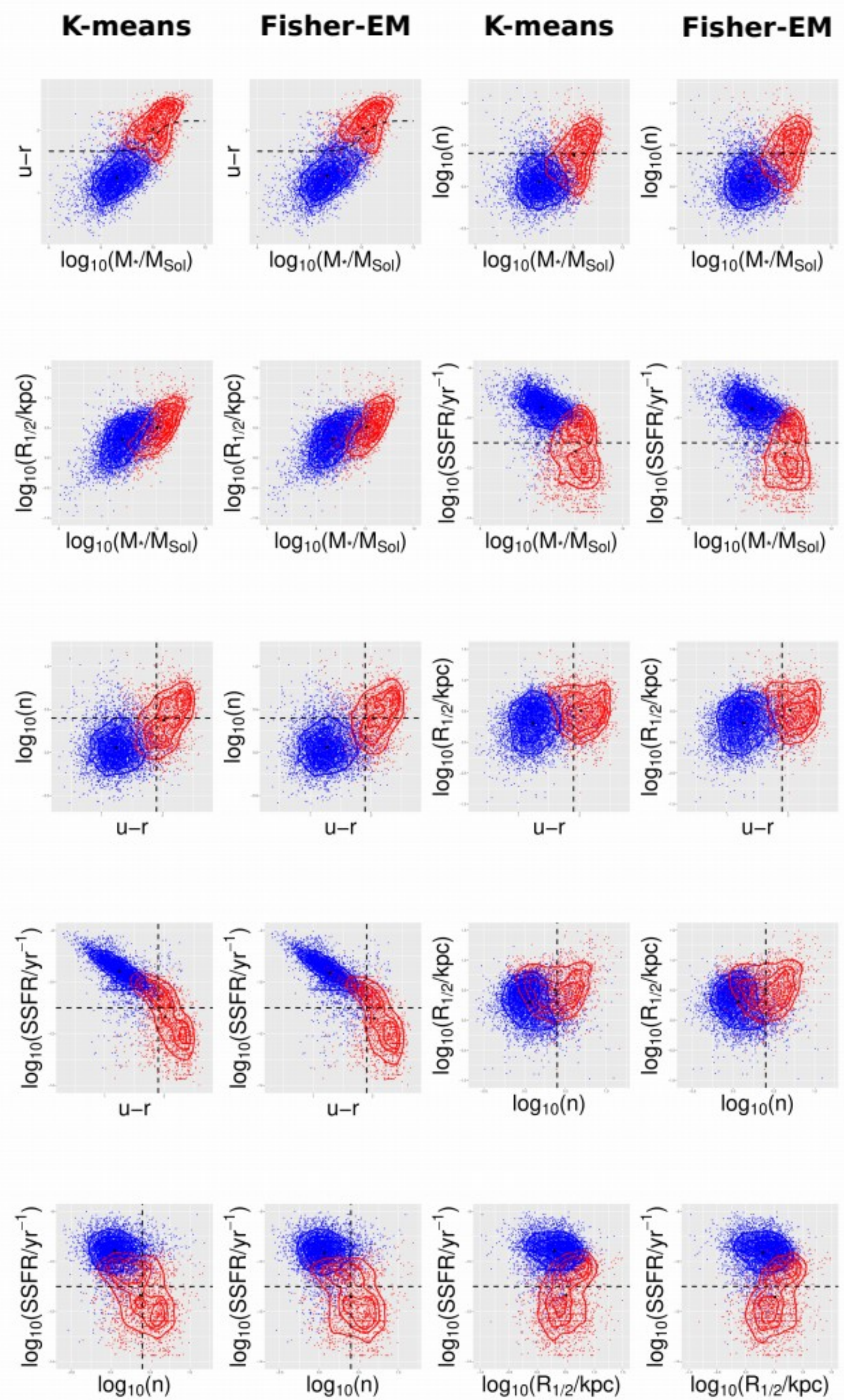
Distribution of the samples in the 5-physical parameter space

Beissière & Moultaka (in prep)

Fisher-EM

Comparison of the classifications obtained with K-means and Fisher-EM of the sample of physical parameters for K = 2

Equivalent solutions

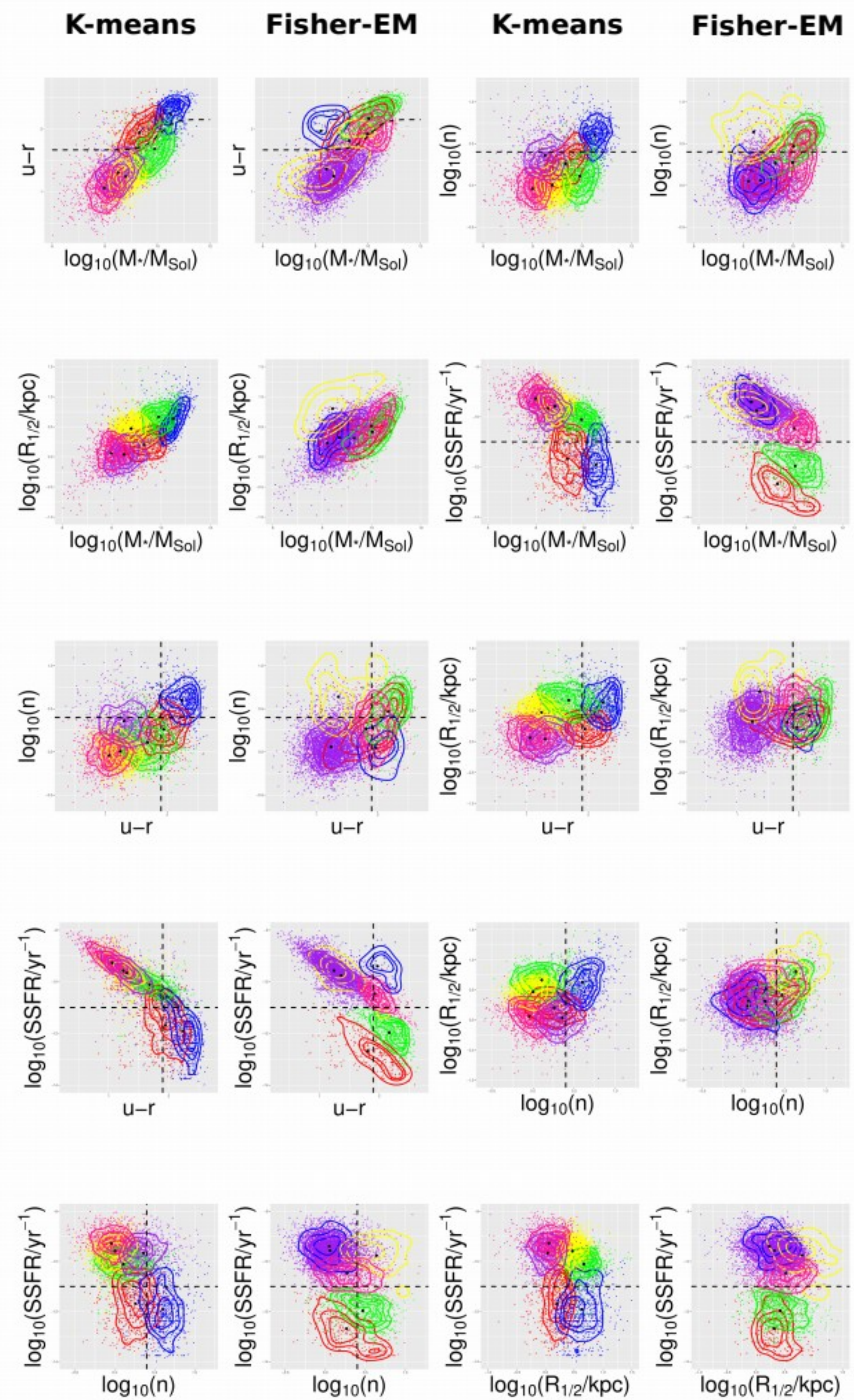


Beissière & Moultaka (in prep)

Fisher-EM

Comparison of the classifications obtained with K-means and Fisher-EM of the sample of physical parameters for K=6

Fisher-EM solutions are more physical

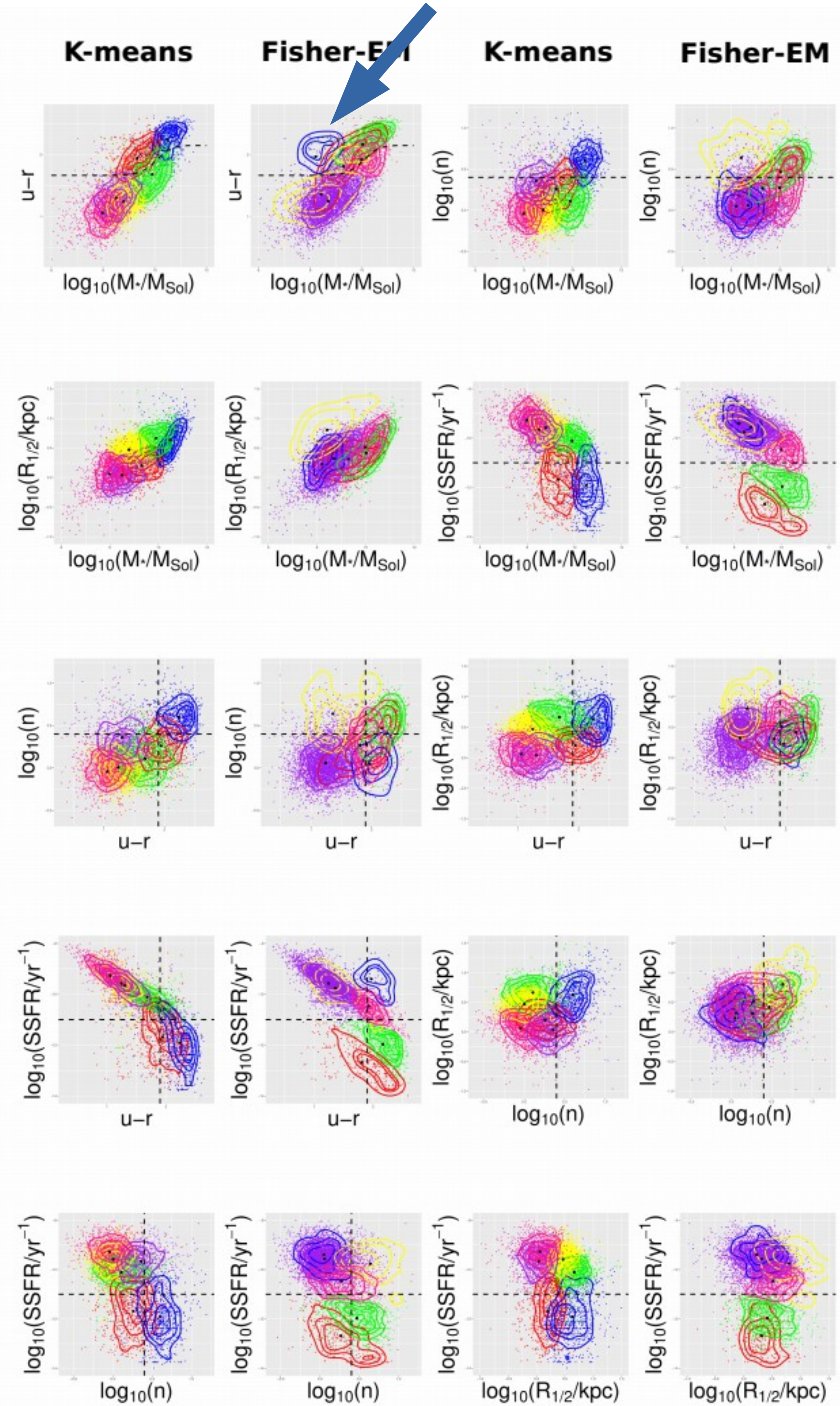


Beissière & Moultaka (in prep)

Fisher-EM

Comparison of the classifications obtained with K-means and Fisher-EM of the sample of physical parameters for K=6

Fisher-EM solutions are more physical

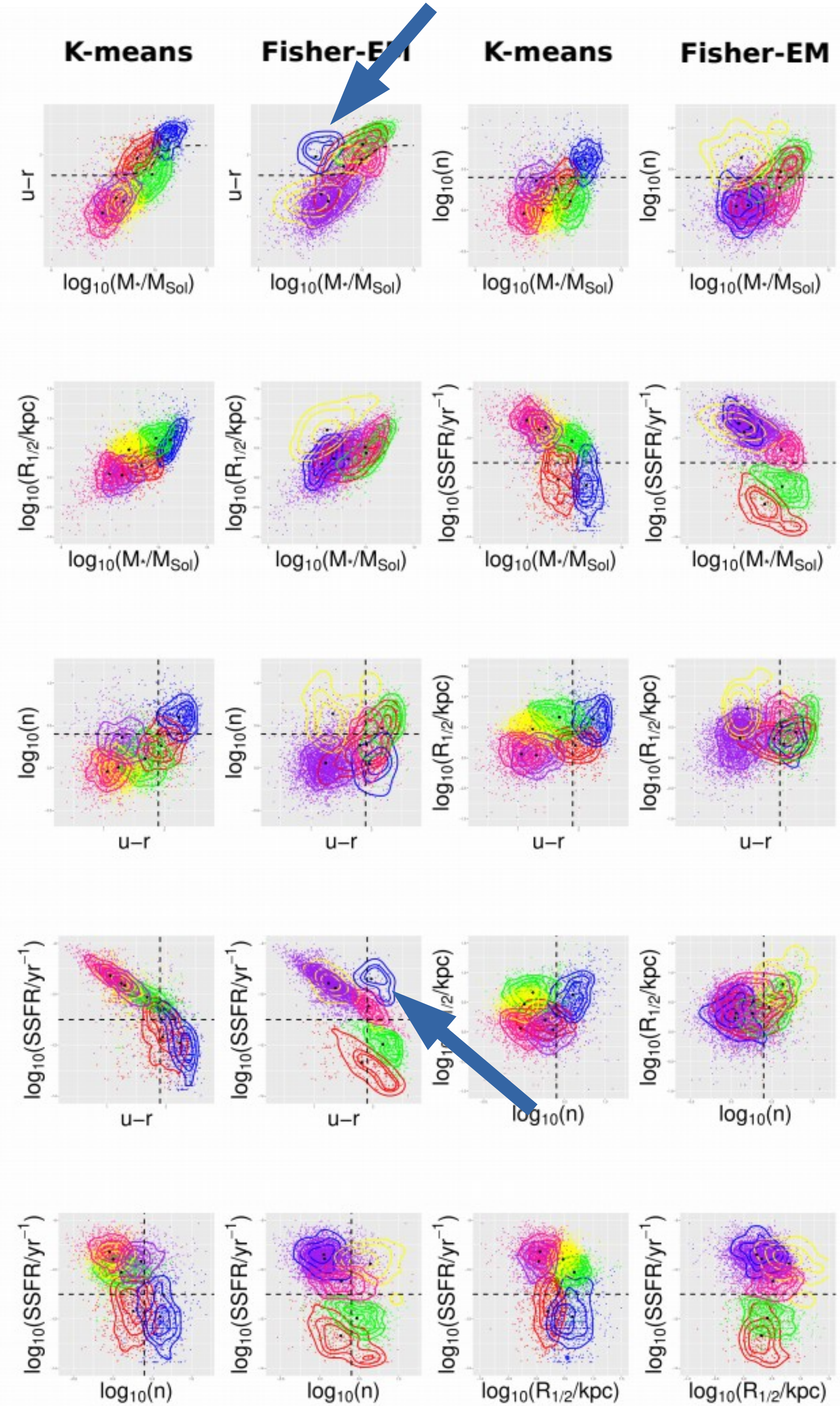


Beissière & Moultaka (in prep)

Fisher-EM

Comparison of the classifications obtained with K-means and Fisher-EM of the sample of physical parameters for K=6

Fisher-EM solutions are more physical

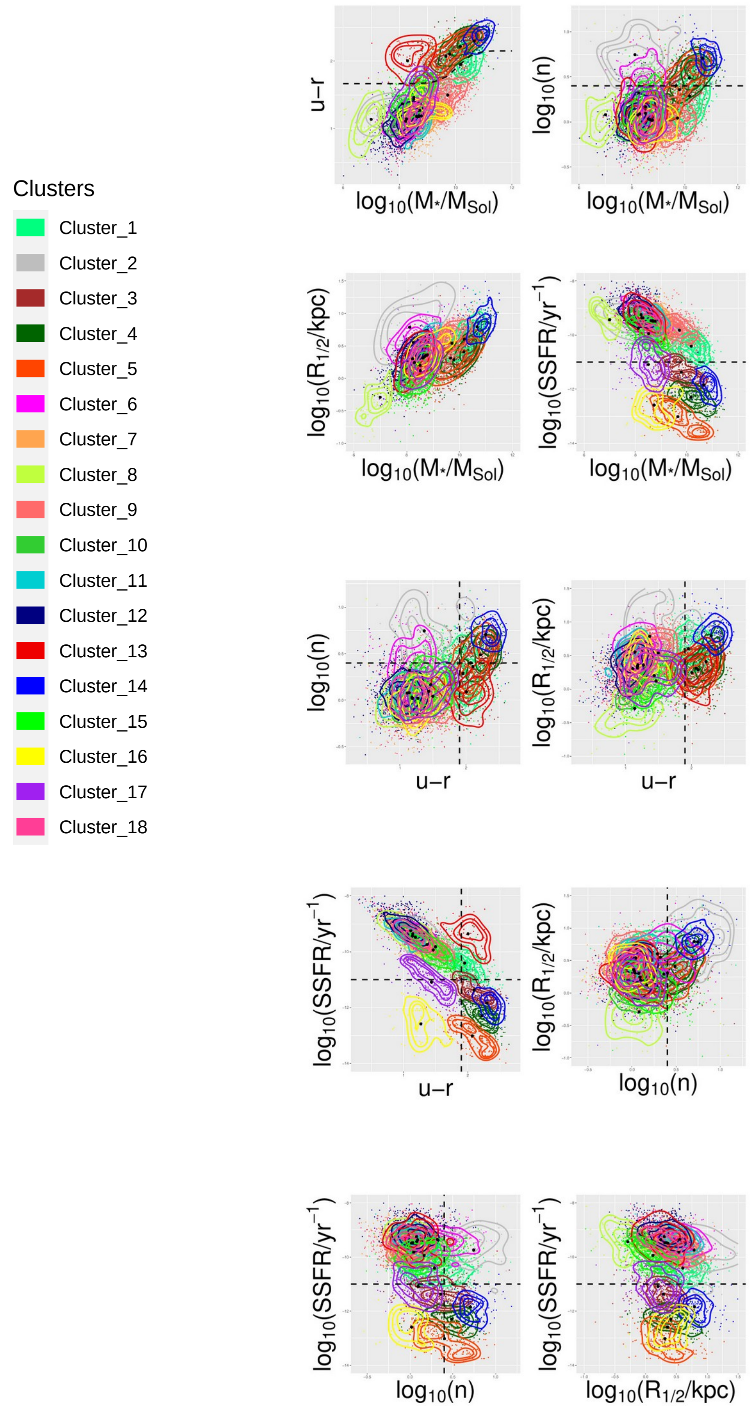


Beissière & Moultaka (in prep)

Fisher-EM

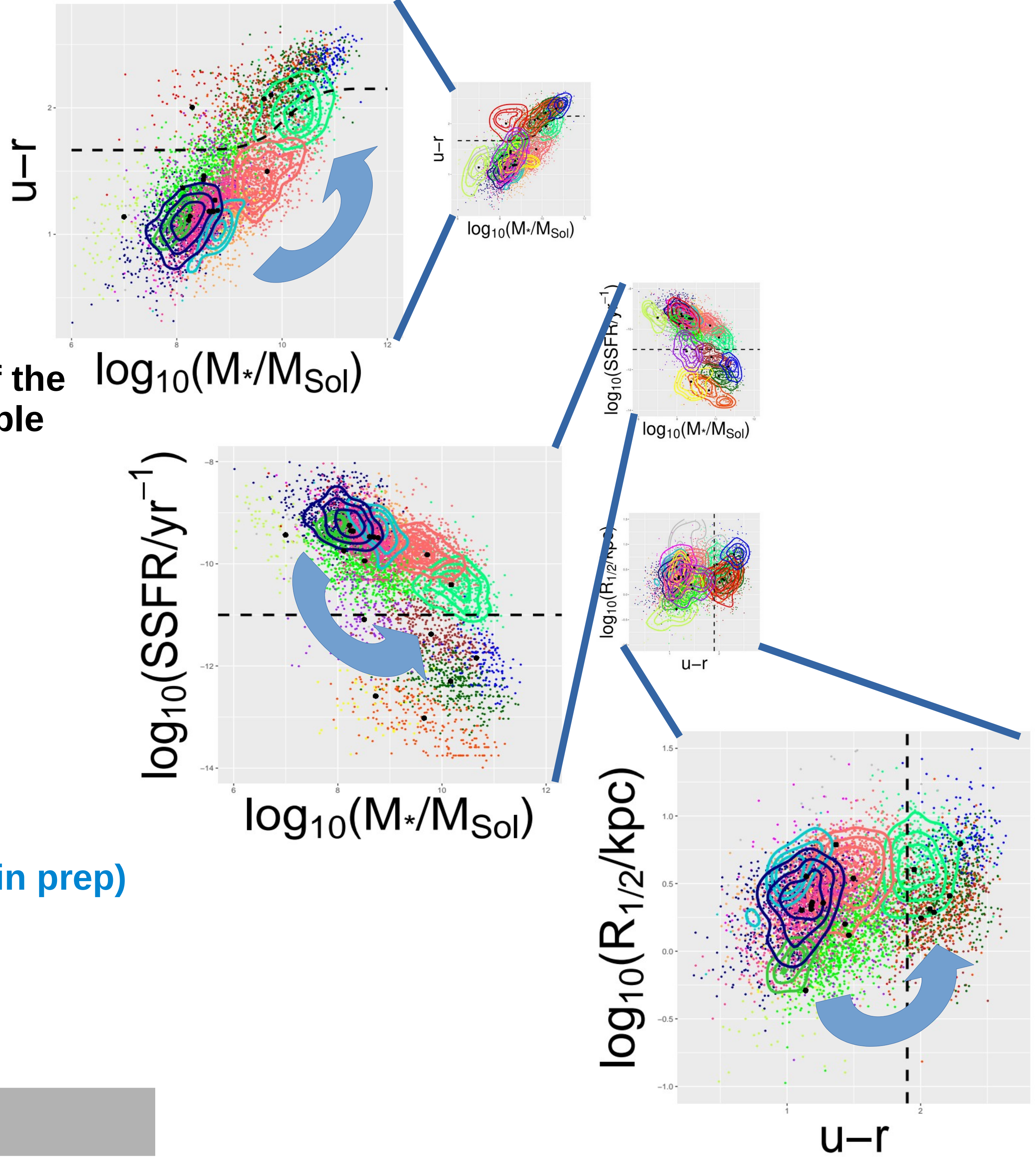
Optimal solution of the 5-parameter sample

K= 18



Beissière & Moultaka (in prep)

Fisher



Optimal solution of the 5-parameter sample

K= 18

Pathways from blue to red galaxies

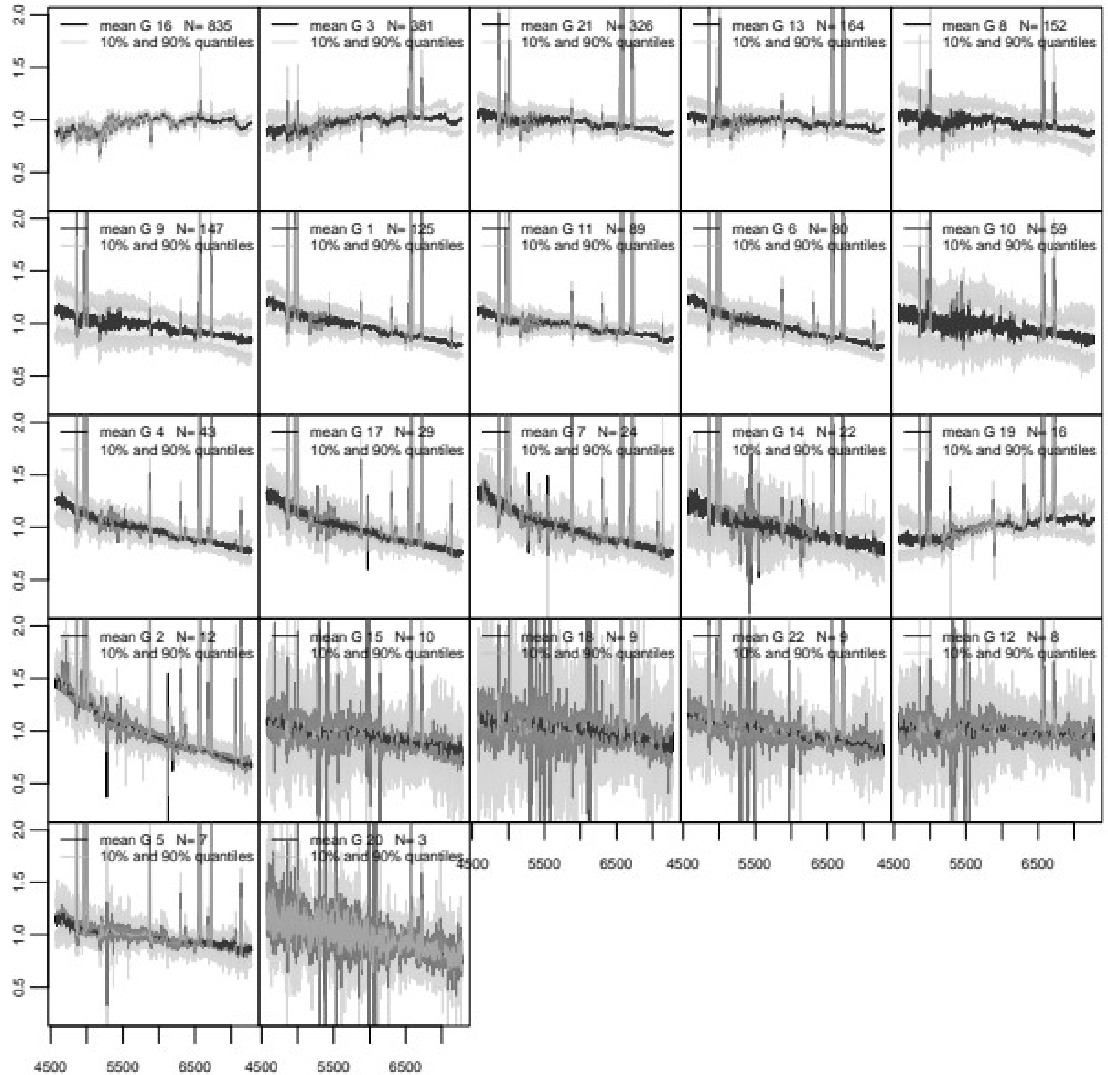
Beissière & Moultaka (in prep)

Fisher-EM on GAMA survey

Optimal solution of the sample of spectra

↓

K = 22

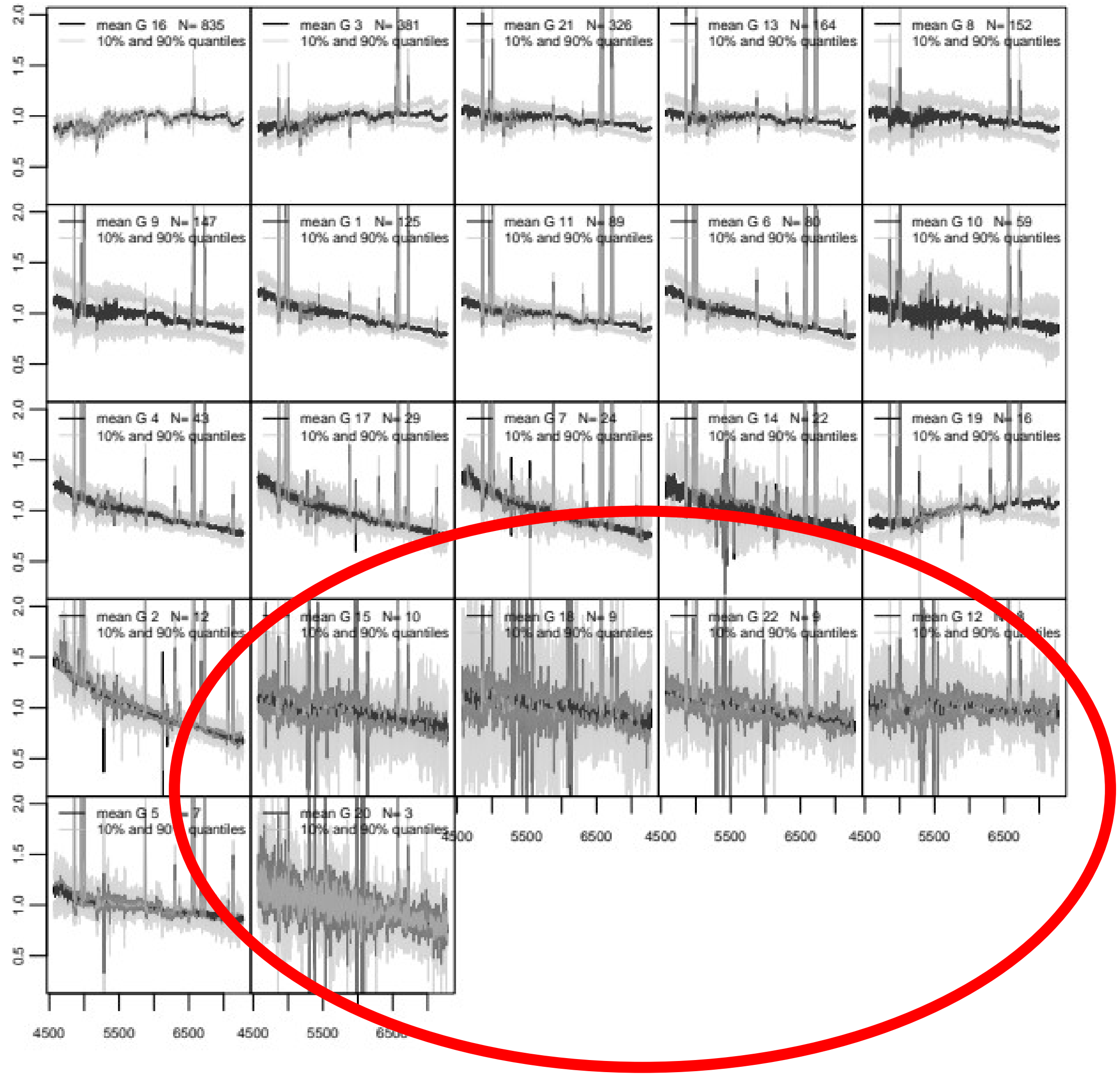


Beissière & Moultaka (in prep)

Fisher-EM on GAMA survey

Optimal solution of the sample of spectra

K = 22



Beissière & Moultaka (in prep)

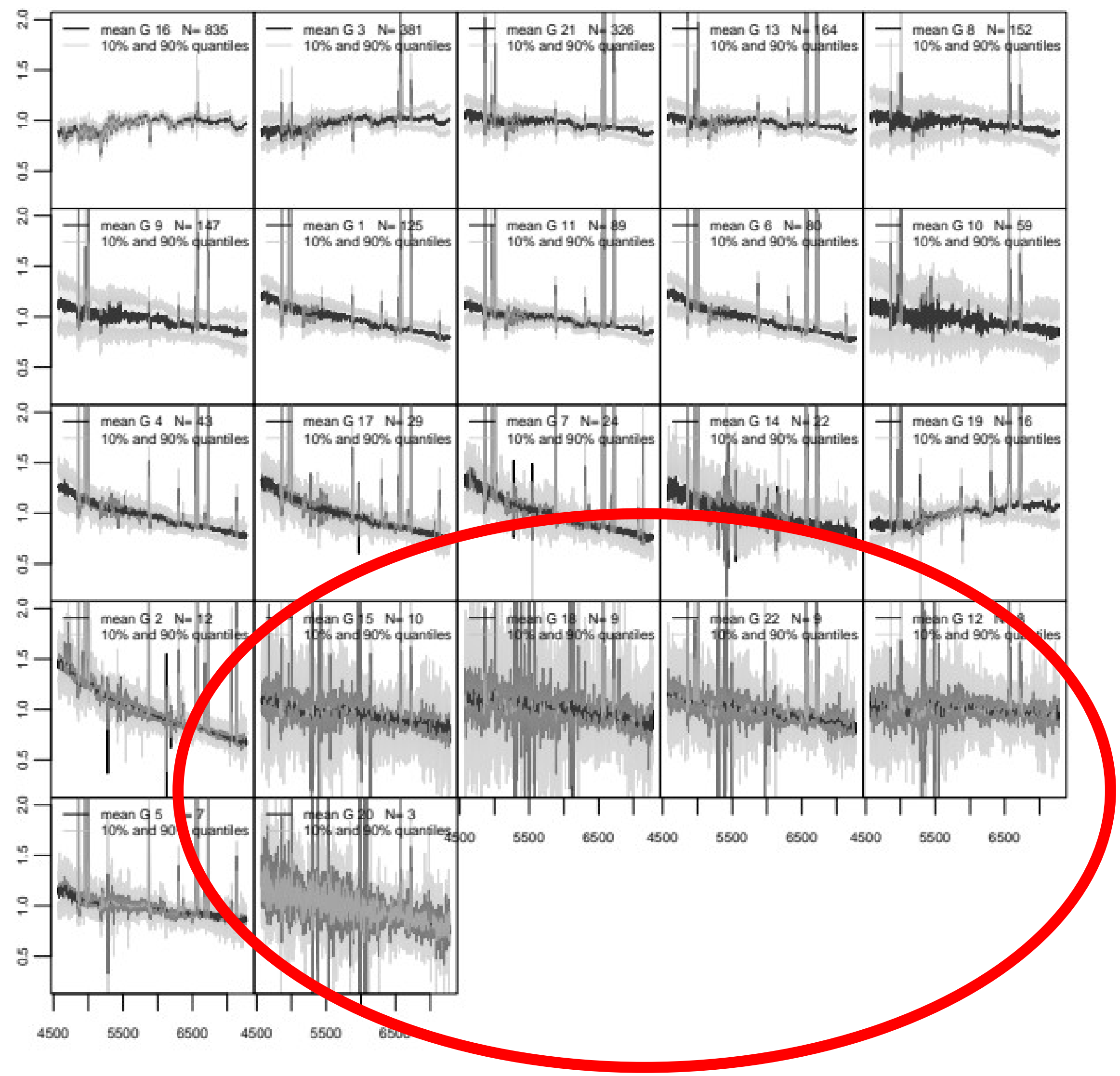
Fisher-EM on GAMA survey

Optimal solution of the sample of spectra

K = 22

K = 17

Beissière & Moultaka (in prep)



Fisher-EM on GAMA survey

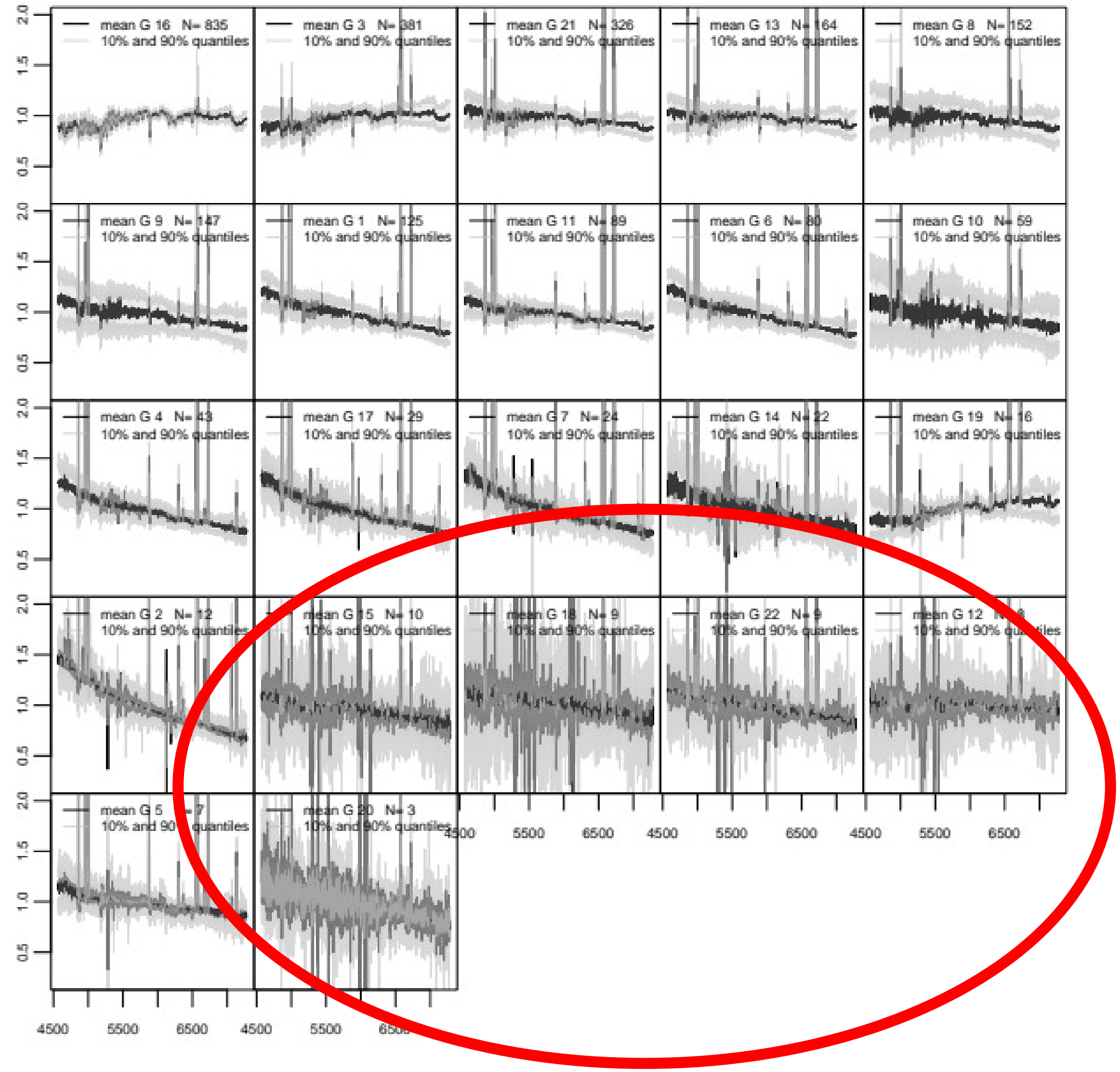
Optimal solution of the sample of spectra

K = 22

K = 17

Beissière & Moultaka (in prep)

To be continued ...

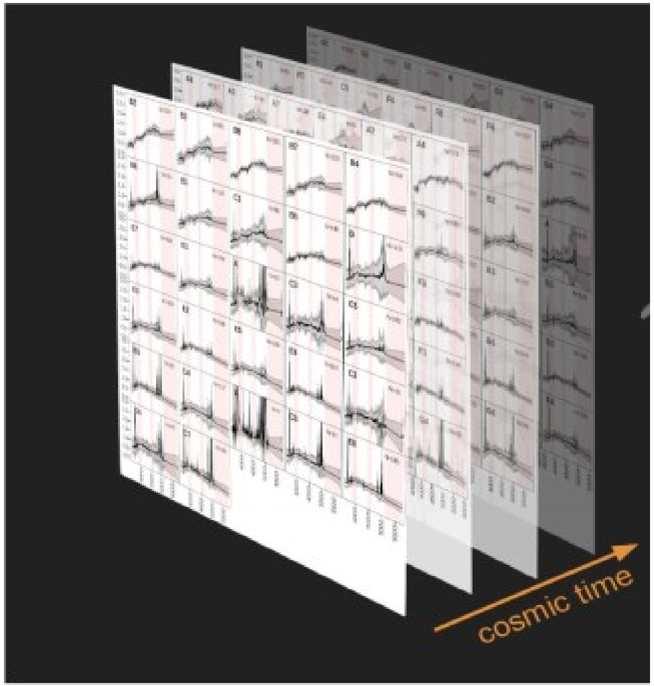


Fisher-EM on VIPERS spectra

79 000 spectra of galaxies from VIPERS survey ($0.4 < z < 1.2$)

(corrected for redshift and masked, homogeneously sampled)

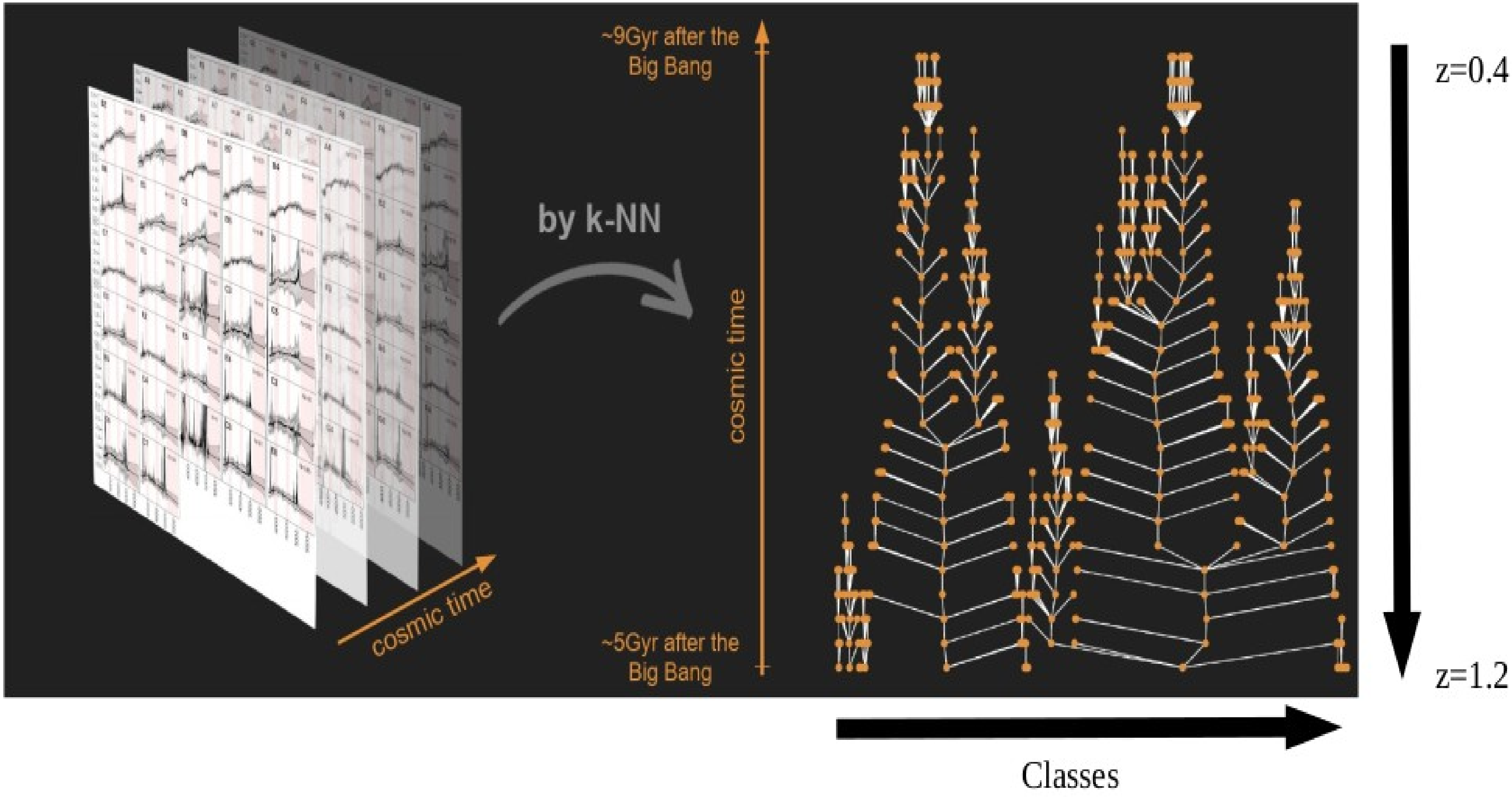
- Divided into 26 bins of redshifts → constant step of cosmic time
- Classification at each redshift bin → 26 classifications



Dubois et al. (2024)

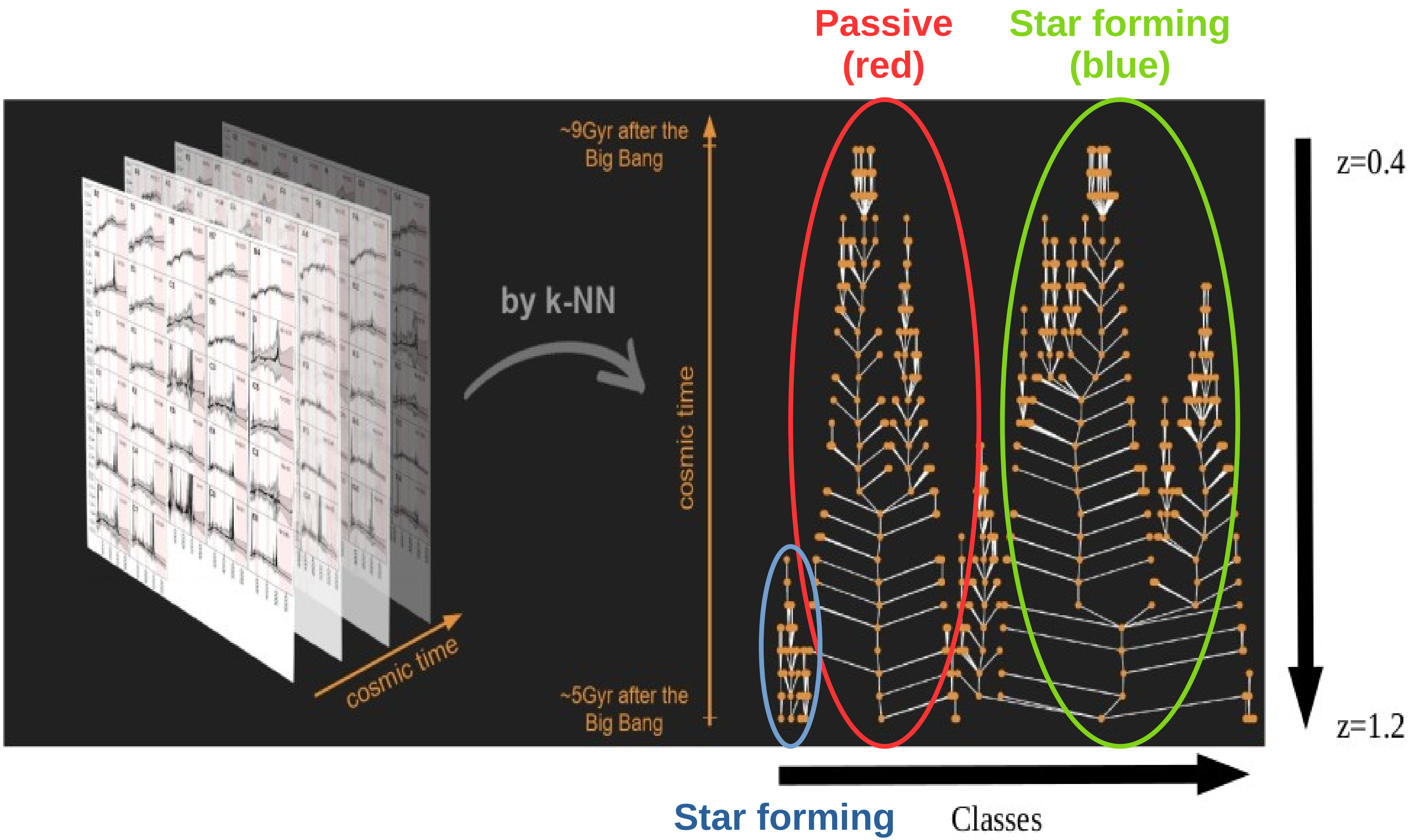
Link classes of successive epochs using k-NN algorithm → **Evolutionary tree**

Fisher-EM on VIPERS spectra



Dubois et al. (2024)

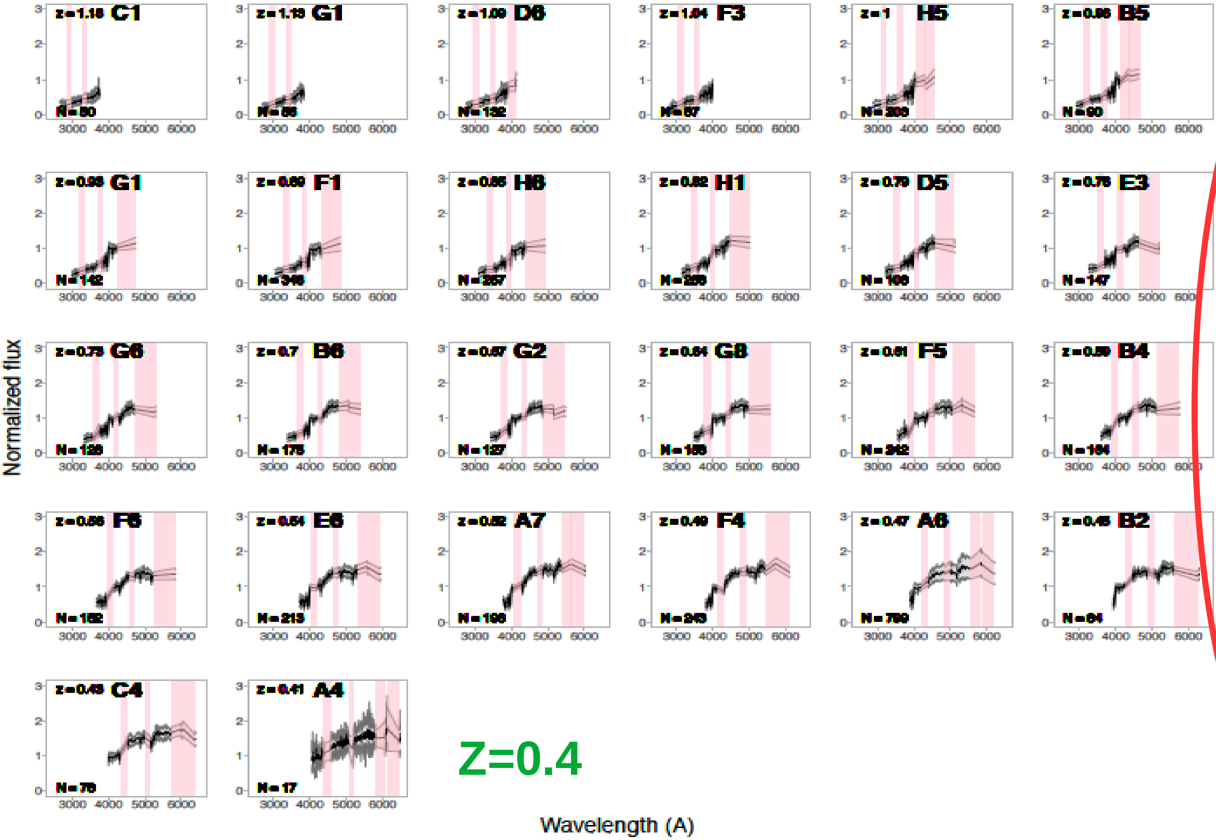
Fisher-EM on VIPERS spectra



Dubois et al. (2024)

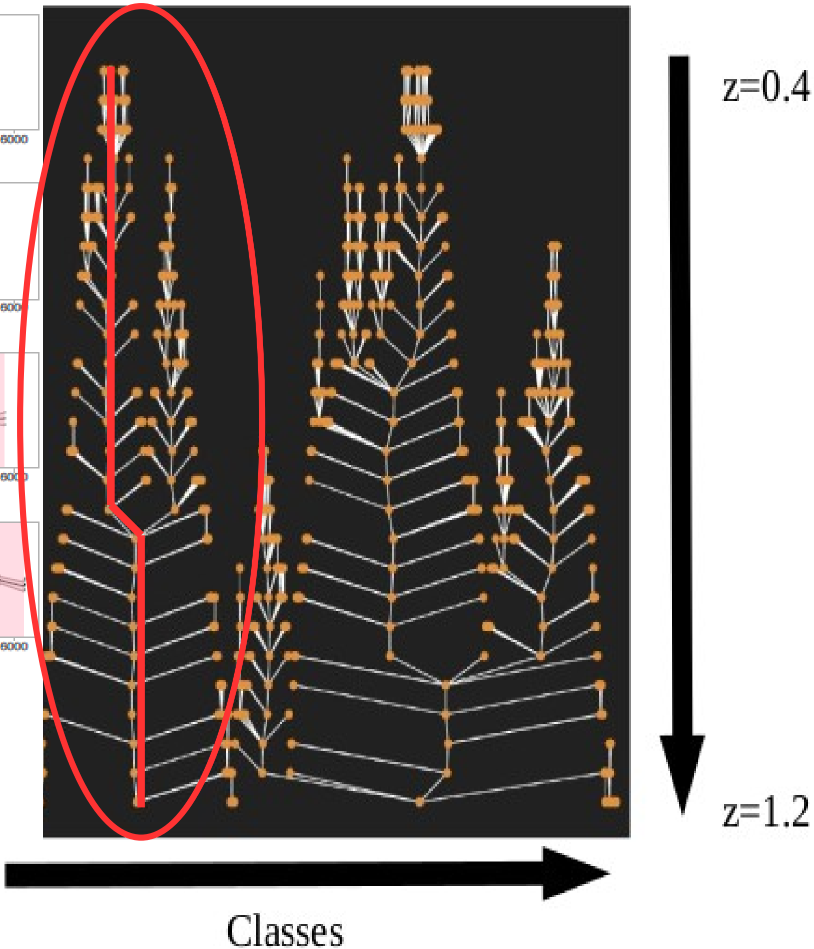
Fisher-EM on VIPERS spectra

Z=1.2



Z=0.4

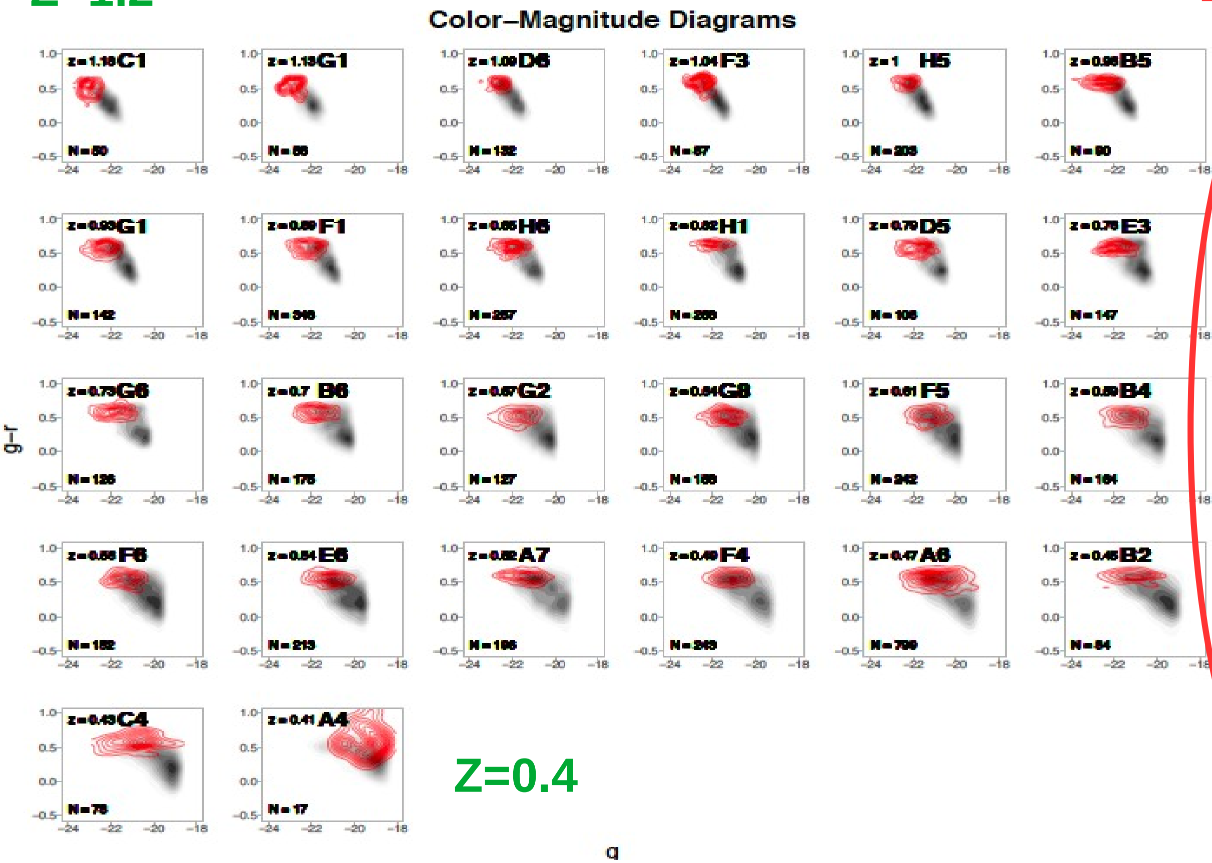
Passive Branch



Dubois et al. (2024)

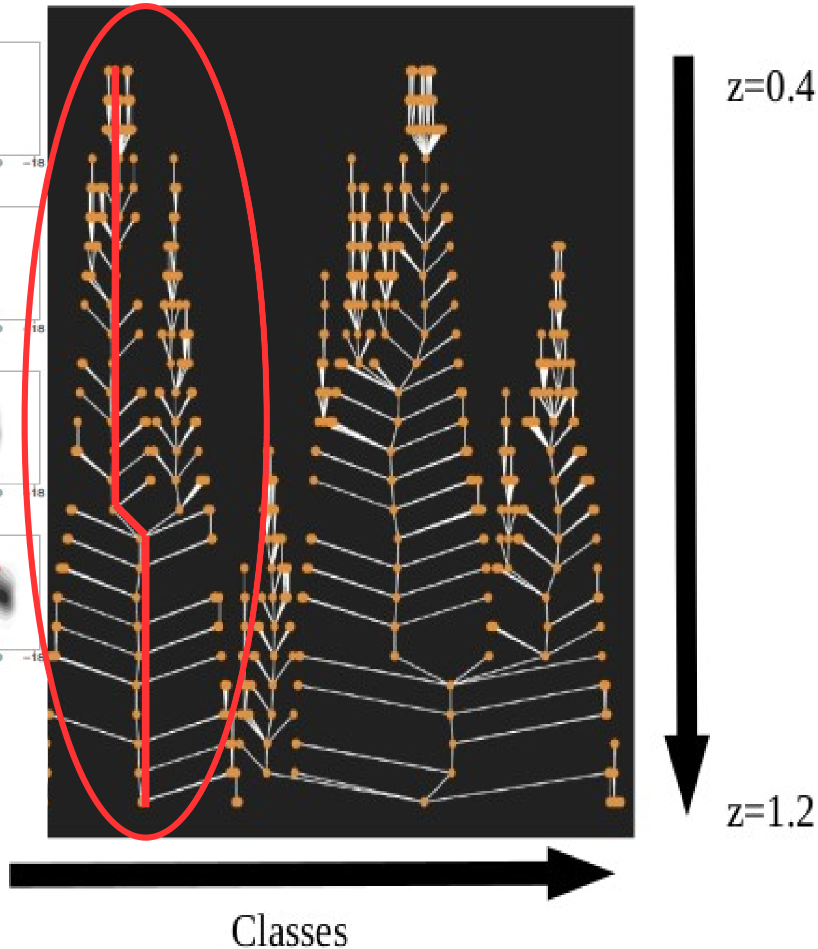
Fisher-EM on VIPERS spectra

Z=1.2



Z=0.4

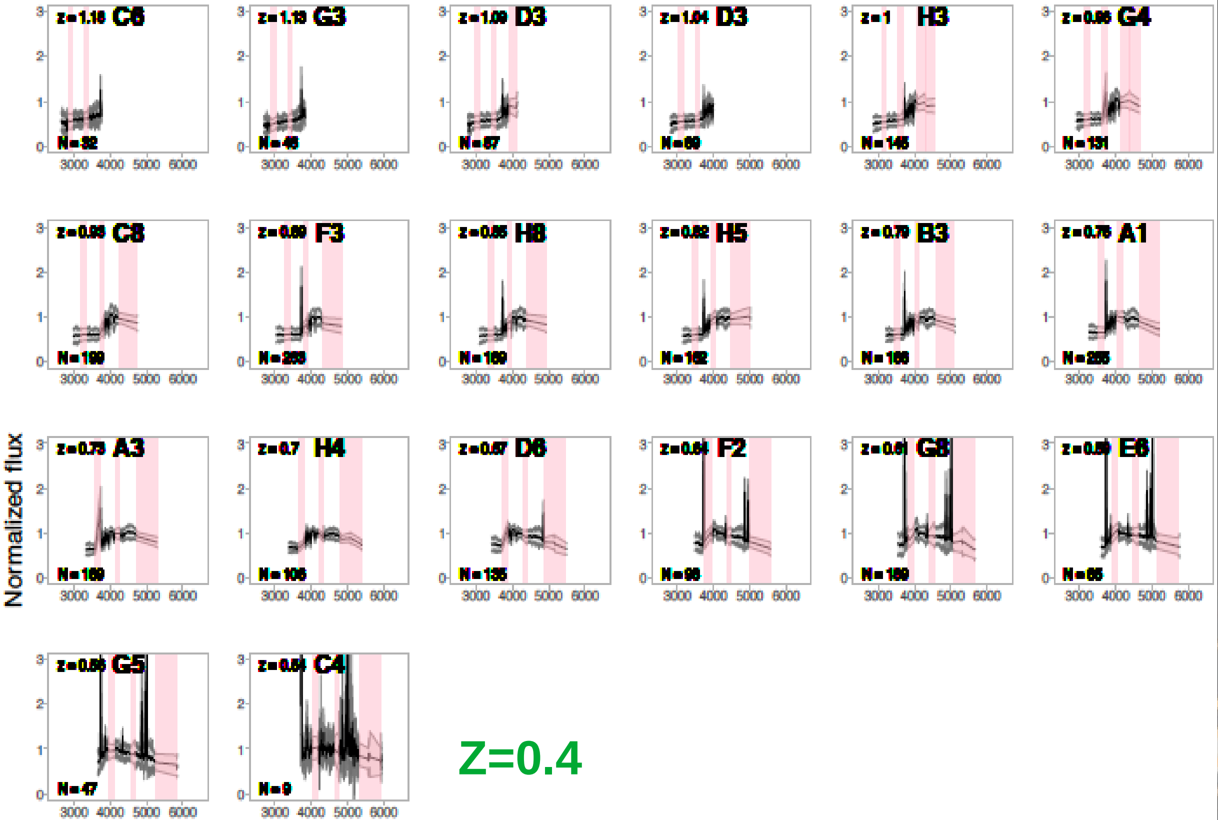
Passive Branch



Dubois et al. (2024)

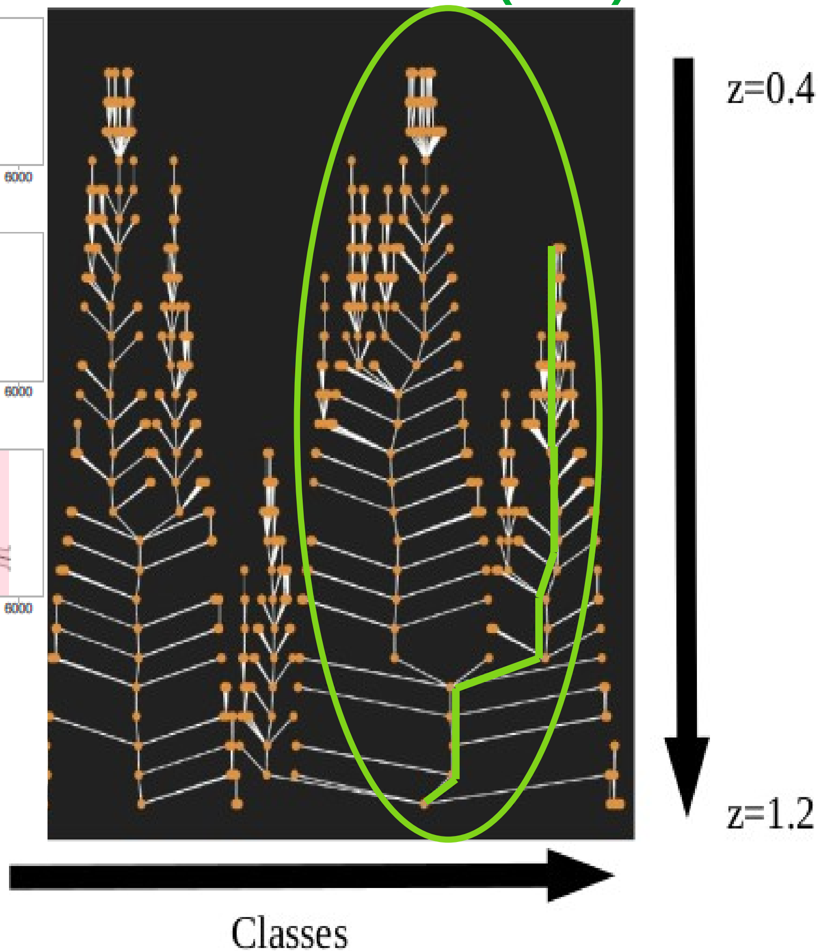
Fisher-EM on VIPERS spectra

Z=1.2



Z=0.4

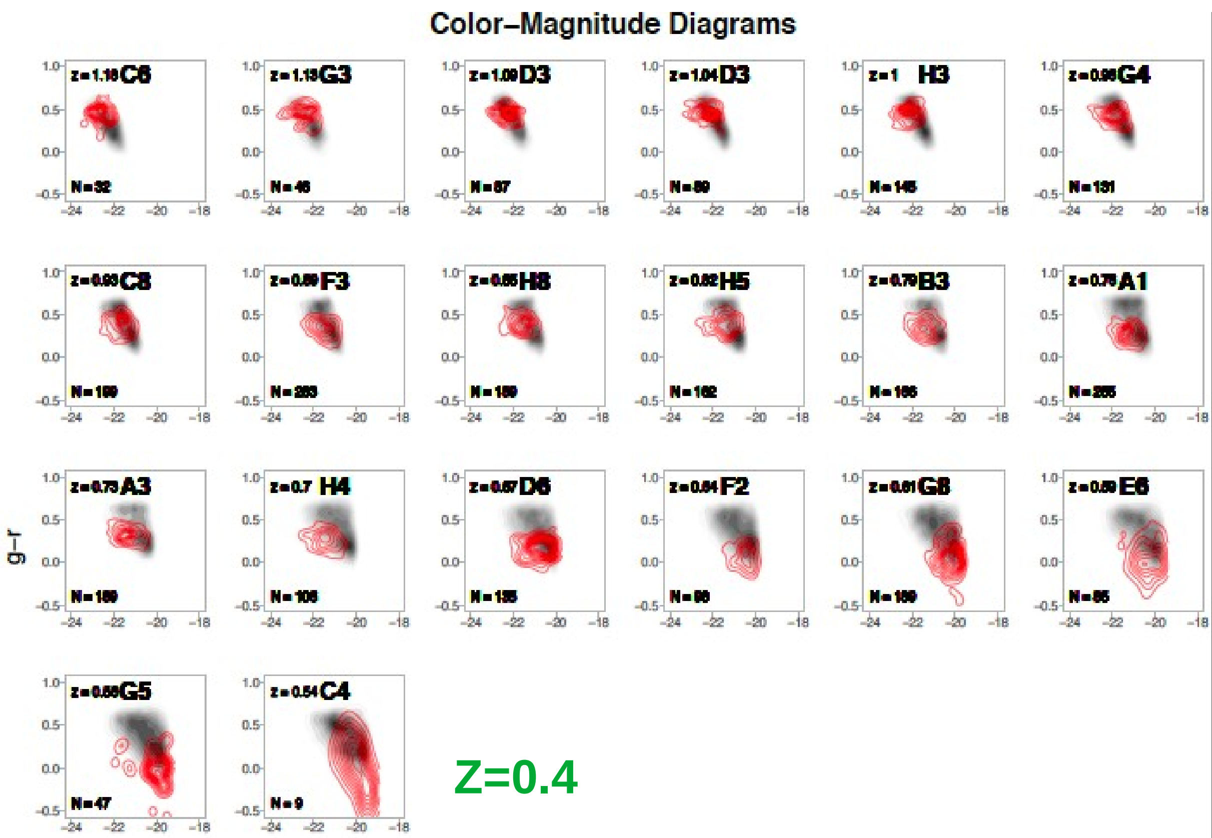
Star forming (blue)



Dubois et al. (2024)

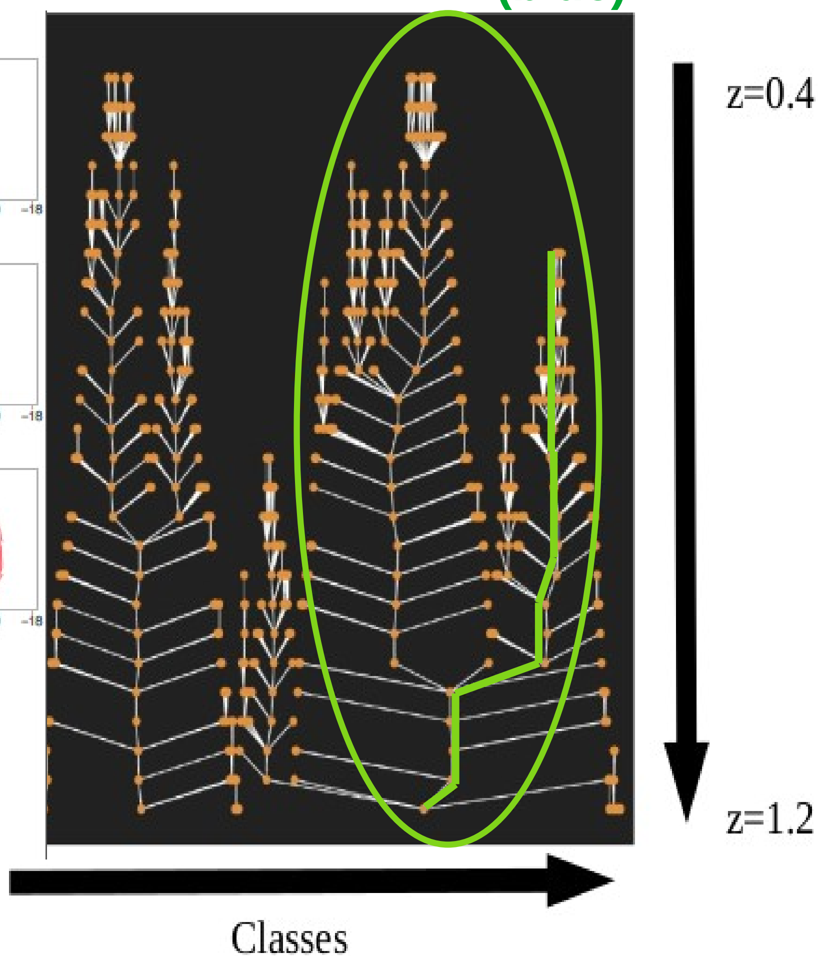
Fisher-EM on VIPERS spectra

Z=1.2



Z=0.4

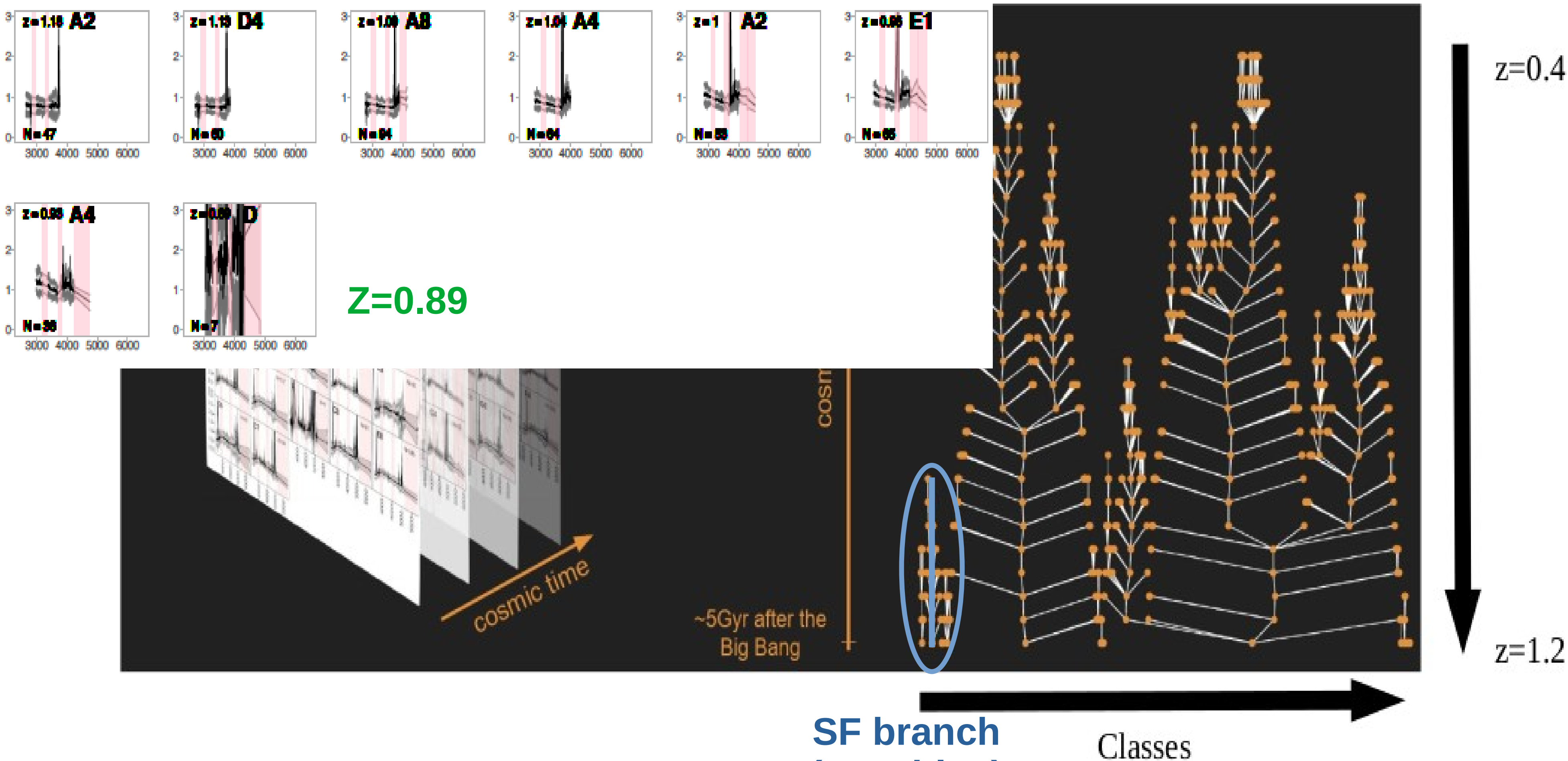
Star forming
(blue)



Dubois et al. (2024)

Fisher-EM on VIPERS spectra

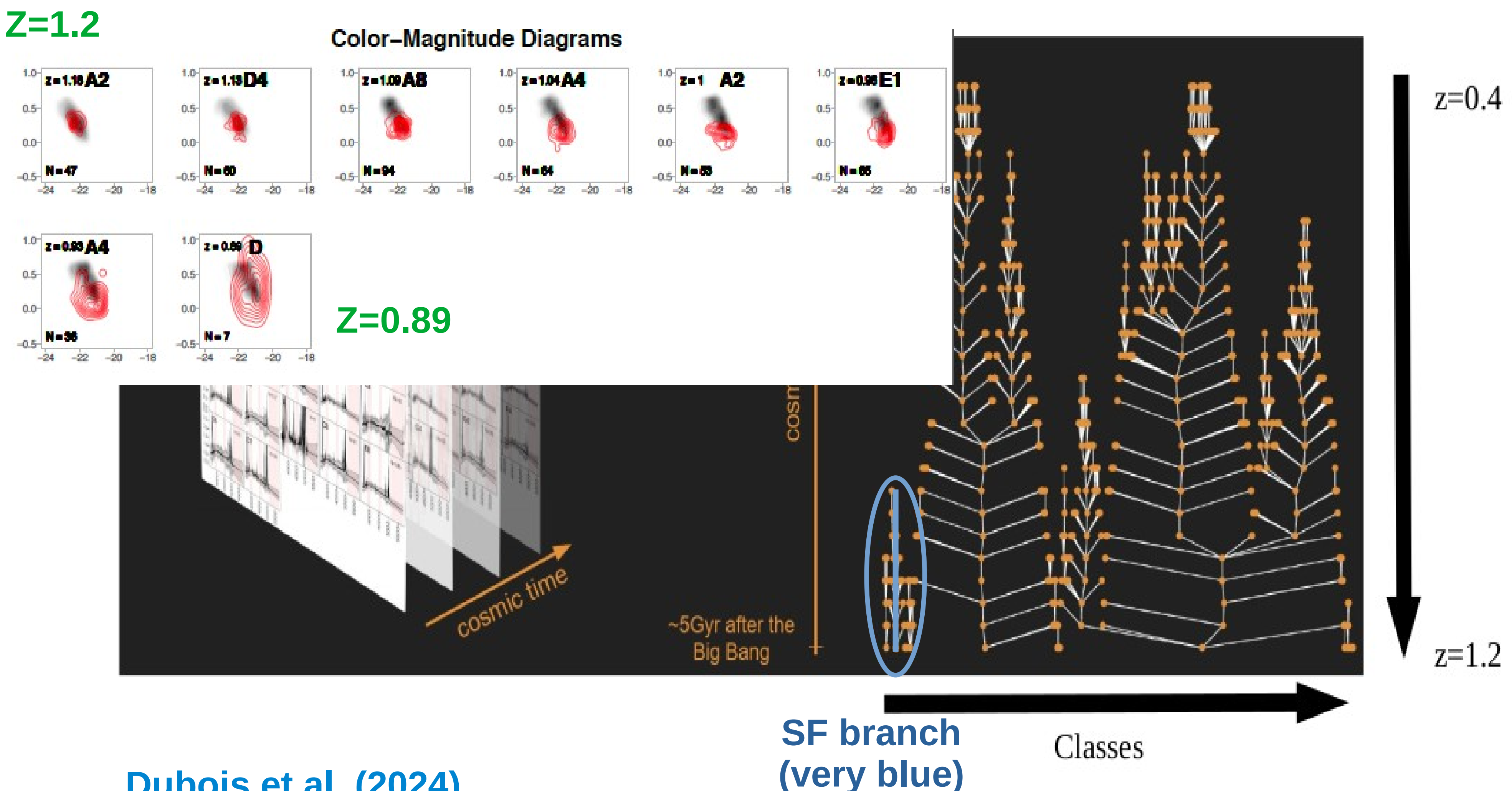
Z=1.2



SF branch
(very blue)

Dubois et al. (2024)

Fisher-EM on VIPERS spectra



Dubois et al. (2024)

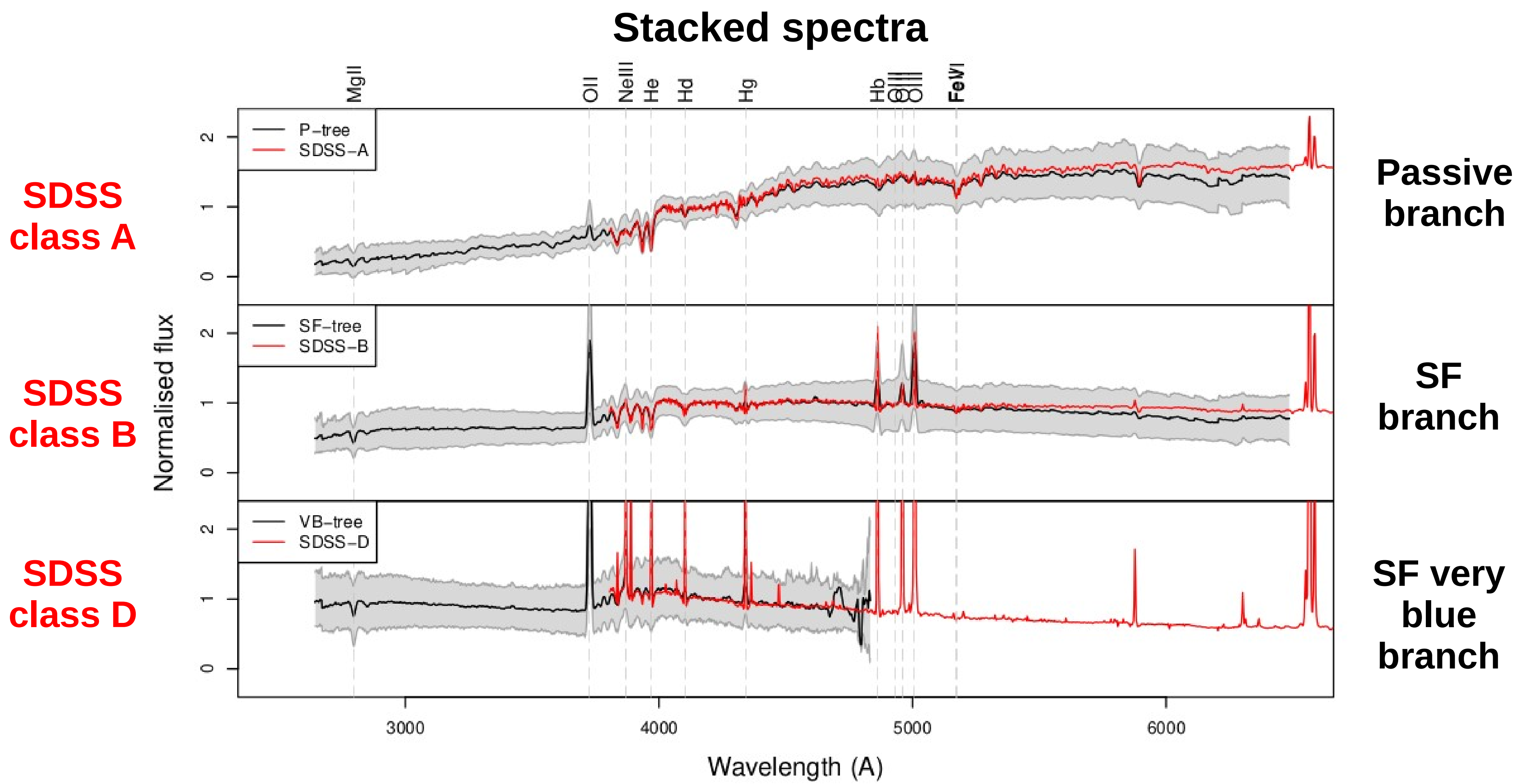
Conclusion

- Demonstrate the **power of unsupervised approach**
- **Fisher-EM** is a reliable method for unsupervised classification at **high dimension**
- **Discriminates** physical parameters of galaxies from their spectra
- Provides a meaningful **physical classification of optical spectra** at low redshift galaxies
- **Distinguishes pathways** in the parameter spaces of the classical **bimodal distribution** of galaxies
- Seems to discriminate **evolutionary sequences** of galaxy spectra through the cosmic ages

What’s next ?

Probe other redshifts, wavelength ranges and physical observables

Fisher-EM on VIPERS spectra



Dubois et al. (2024)