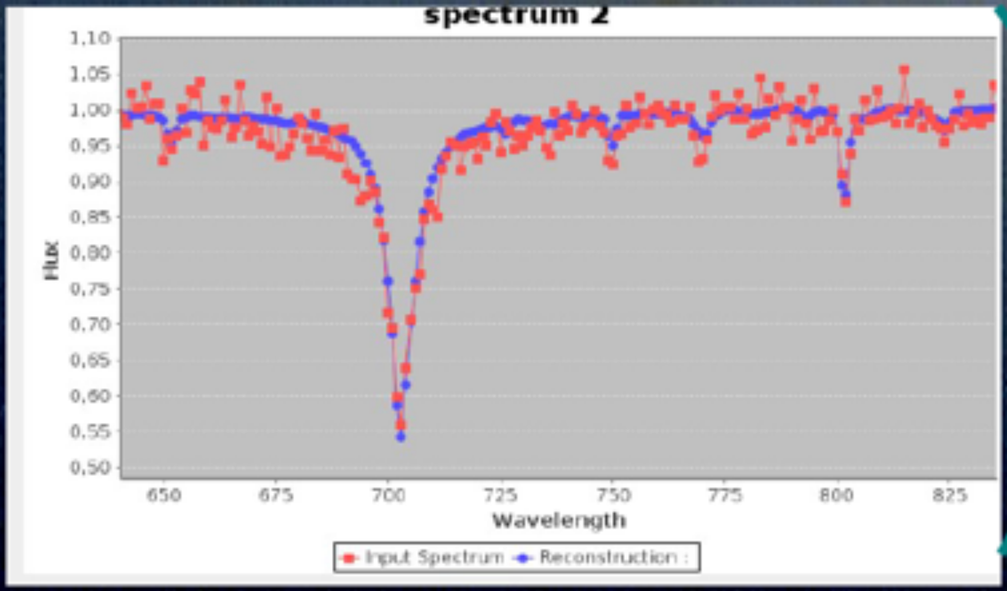
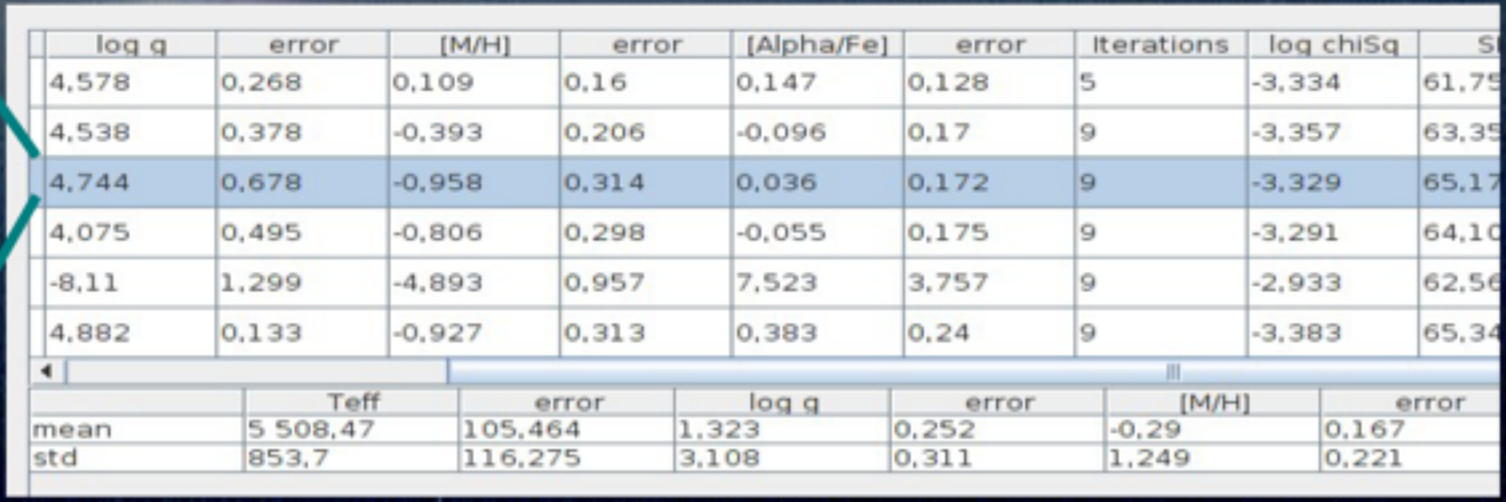
Automated spectrum analysis of stellar spectra: a possibility for MOONS





log g	error	[M/H]	error	[Alpha/Fe]	error	Iterations	log chiSq	S
4,578	0,268	0,109	0,16	0,147	0,128	5	-3,334	61,7
4,538	0,378	-0,393	0,206	-0,096	0,17	9	-3,357	63,3
4,744	0,678	-0,958	0,314	0,036	0,172	9	-3,329	65,17
4,075	0,495	-0,806	0,298	-0,055	0,175	9	-3,291	64,1
-8,11	1,299	-4,893	0,957	7,523	3,757	9	-2,933	62,5
4,882	0,133	-0,927	0,313	0,383	0,24	9	-3,383	65,3

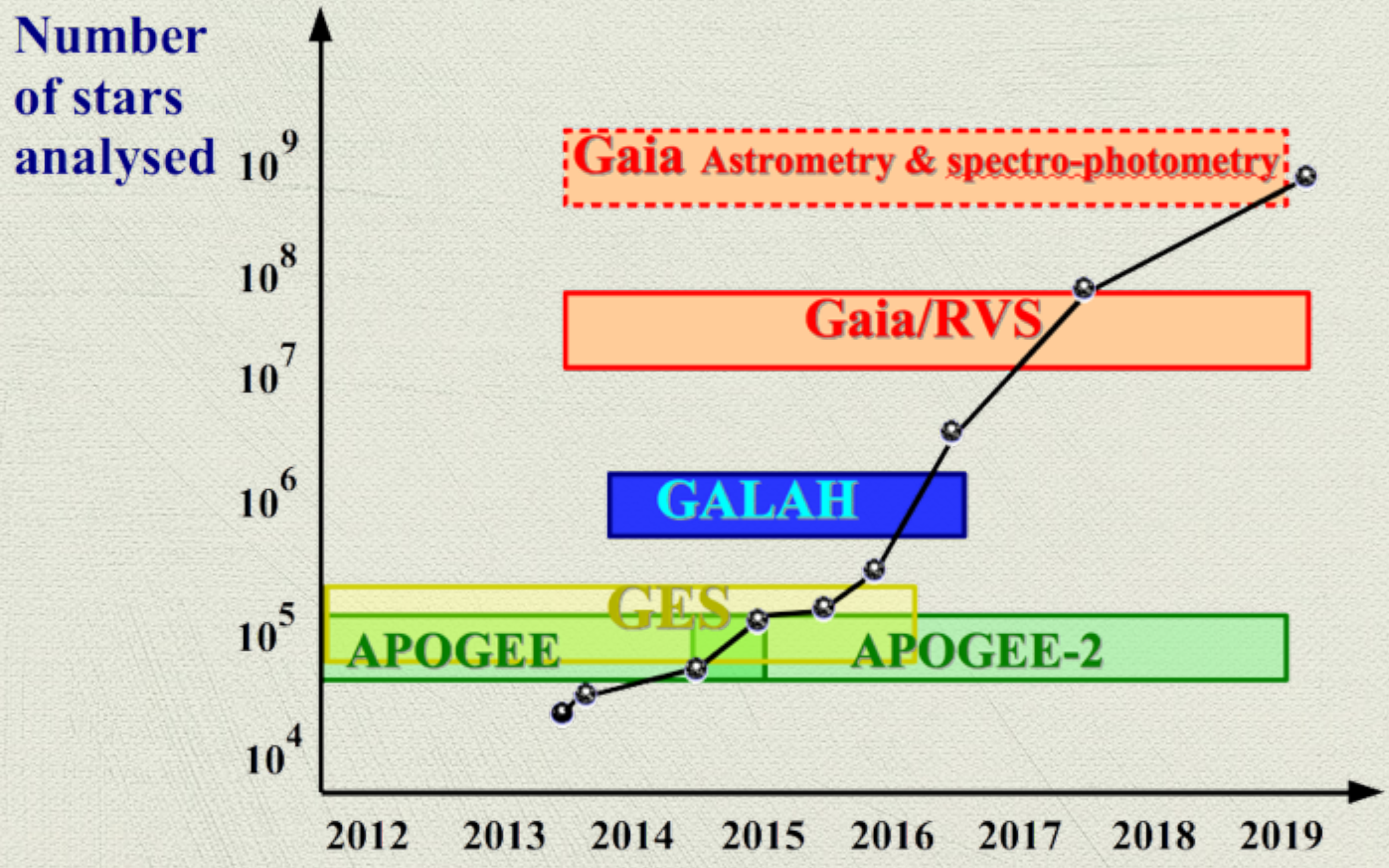
	Teff	error	log g	error	[M/H]	error
mean	5 508,47	105,464	1,323	0,252	-0,29	0,167
std	853,7	116,275	3,108	0,311	1,249	0,221

Alejandra Recio-Blanco

Observatoire de la Côte d'Azur (France)

Automated spectrum analysis

Huge numbers of spectra: automated analysis procedures needed

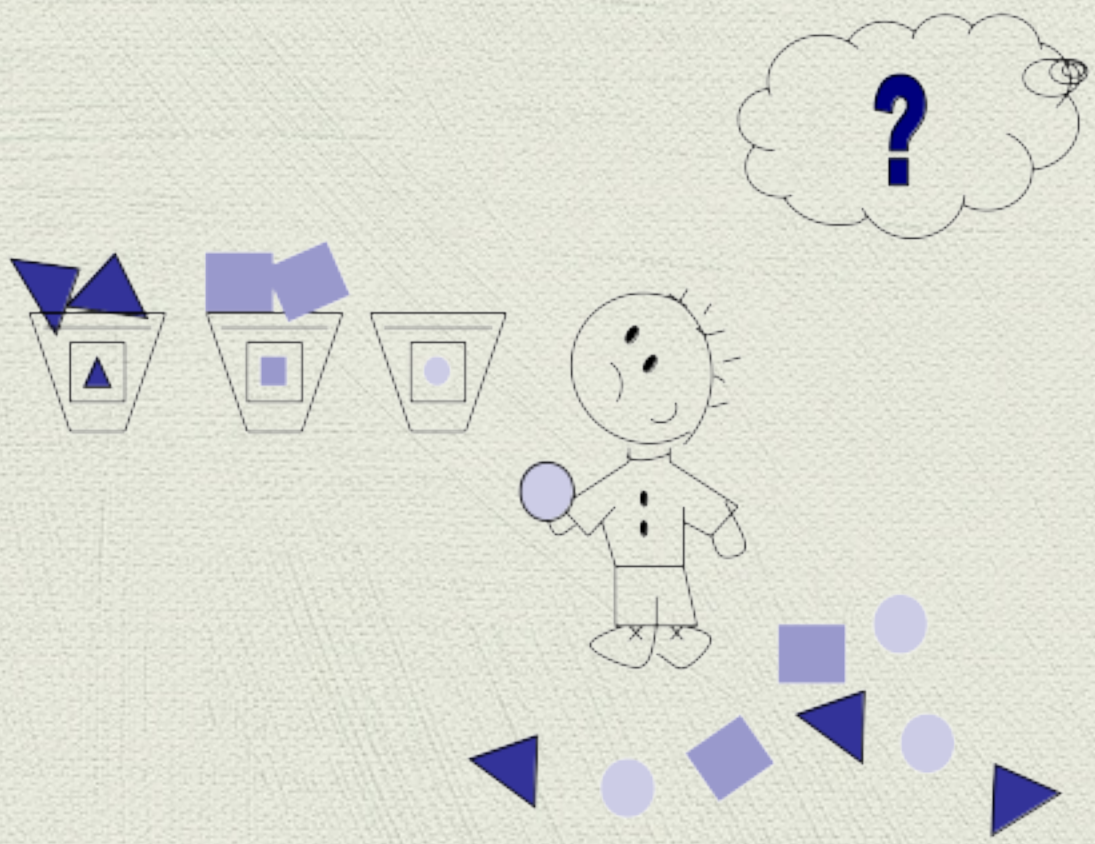


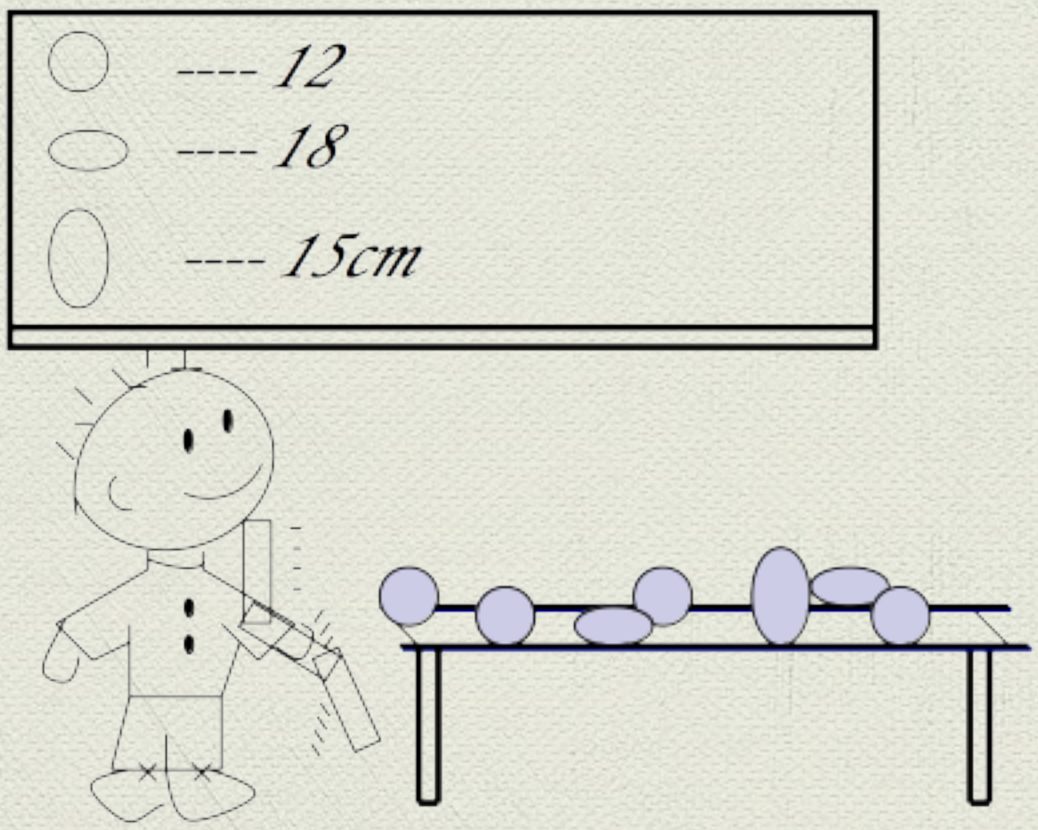
Automated spectrum analysis

Data mining approaches:

depend on the **degree of knowledge of the scientific targets**

Classification → **Parameterization**



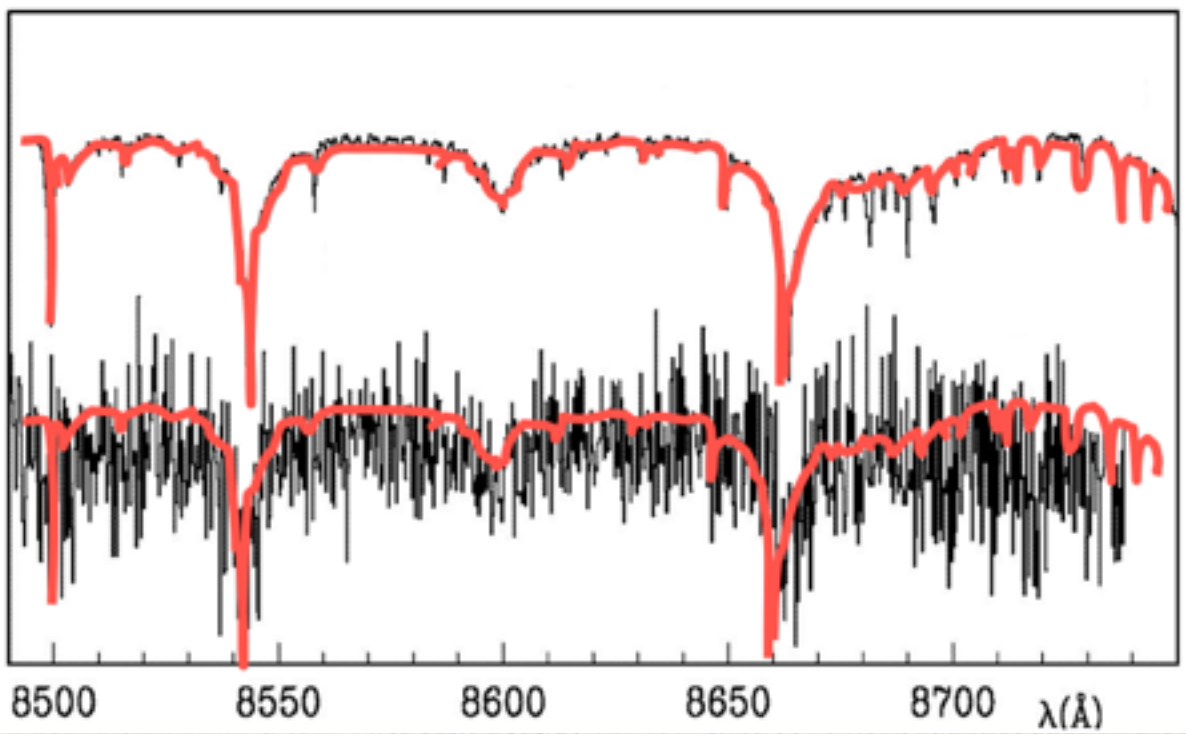


Pictures from Allende Prieto

Automated spectrum analysis

Parametrisation

To determine the stellar parameters (effective temperature, surface gravity, global metallicity, chemical abundances) **that best fit an observed spectrum with a reference (synthetic) one.**



Distance minimization:

$$D(\Theta) = \sum_{l=1,L} [O(l) - S(l,\Theta)]^2.$$

Complex physics -> No analytical solutions -> Need of reference spectra

Automated spectrum analysis

Parametrisation

Need of reference spectra

Understanding of the physics?

No	Yes
Data driven	Model driven

- **Morgan-Keenan classification**
  Sun -> G2V
- **The Cannon** **(Ness et al. 2015)**
  Parameters of training data are assigned by a different (model driven) approach

Close **environnement of knowledge**

- **Different mathematical approaches**

Open **environnement of knowledge**

Automated spectrum analysis

Mathematical approaches of parametrisation

Optimization

Parameters derived through a distance minimization

e.g. Minimum distance, Nelder-Mead, Gauss-Newton (**GAUGUIN**), Penalized chi2, The Cannon

Projection

Spectra projected into vectors derived during learning phase

e.g. **MATISSE**, PCA (MOPED, MaX)

Classification

Pattern recognition problem

e.g. Decision trees (**DEGAS**), Neural networks, Support vector machines

Automated spectrum analysis

Mathematical approaches of parametrisation

Optimisation	Projection	Pattern Recognition
GAUGUIN, Bijaoui, Recio-Blanco et al. 2012 (AMBRE, GES/GIRAFFE, Gaia/RVS) FERRE, Allende Prieto et al. 2006 (SEGUE, GES/GIRAFFE, APOGEE) SME, Valenti & Piskunov 1996 (GES/UVES +GIRAFFE) ARES, Sousa et al. 2008 (GES/UVES) Boeche et al. 2011 (RAVE) GALA, Mucciarelli et al. 2013 (GES/UVES) ROTFIT, Frasca et al. 2006 (GES/UVES +GIRAFFE) UlySS, Koleva et al. 2009 (LEGUE) CANNON Ness et al. 2015 (APOGEE)	**MATISSE, Recio-Blanco et al. 2006** (AMBRE, GES/UVES +GIRAFFERAVE, CoRoT/GIRAFFE, Gaia/RVS)	**DEGAS, Kordopatis, Recio-Blanco et al. 2011a** (RAVE, GES/GIRAFFE, Gaia/RVS) Re Fiorentin et al. 2007 (SEGUE)

Automated spectrum analysis

Mathematical approaches of parametrisation

Comparison with reference models (flux as a function of lambda) through:

Computation time ↑

- **On the fly computations:**
  - Spectral Synthesis
  - Equivalent widths
- **Pre-computed spectra grid:**
  - Without training
  - With training

Automated spectrum analysis

- **MATISSE** : Recio-Blanco et al. 2006

Projection method. Local multilinear regression

Stellar parameters
Teff, logg, [M/H], [alpha/Fe]

Observed spectrum

$$\hat{\theta}_i = \sum_{\lambda} B_{\theta_i}(\lambda) O(\lambda).$$

Synthetic grid spectra

$$B_{\theta_i}(\lambda) = \sum_{j} \alpha_{ij} S_j(\lambda)$$

Correlation matrix
$c_{ij} = S_i S_j$

$$\Theta_i = C\alpha_i.$$

Application phase

Training phase

Automated spectrum analysis

- **DEGAS** : **Kordopatis, Recio-Blanco et al. 2011**

Pattern recognition method. Oblique k-d decision tree

Decisions = projection of data into <u>node vectors Dn</u>

Observed spectrum

$$c_i = \boldsymbol{O}_i \cdot \boldsymbol{D}_n$$

Synthetic grid spectra

$$c_j = \boldsymbol{S}_j \cdot \boldsymbol{D}_n$$

Median of spectra with $c_j <$ median (c_j)

Median of spectra with $c_j >$ median (c_j)

$$\boldsymbol{D} = \boldsymbol{M}_1 - \boldsymbol{M}_2$$

Application phase

Training phase

Automated spectrum analysis

- **GAUGUIN** : Bijaoui, Recio-Blanco et al. 2012

Optimization method. Gauss-Newton algorithm

Linearization around a parameter set Θ associated to a theoretical spectrum $\mathbf{S}_0$. Corrections obtained with:

Observed spectrum

Synthetic spectrum

$$\delta\Theta = (\mathbf{J}^T\mathbf{J})^{-1}\mathbf{J}^T(\mathbf{O} - \mathbf{S}_0)$$

Jacobian matrix $[\partial S(l, \Theta(0))/\partial\theta i]$

Used after MATISSE, DEGAS or photometric parameters

Automated spectrum analysis

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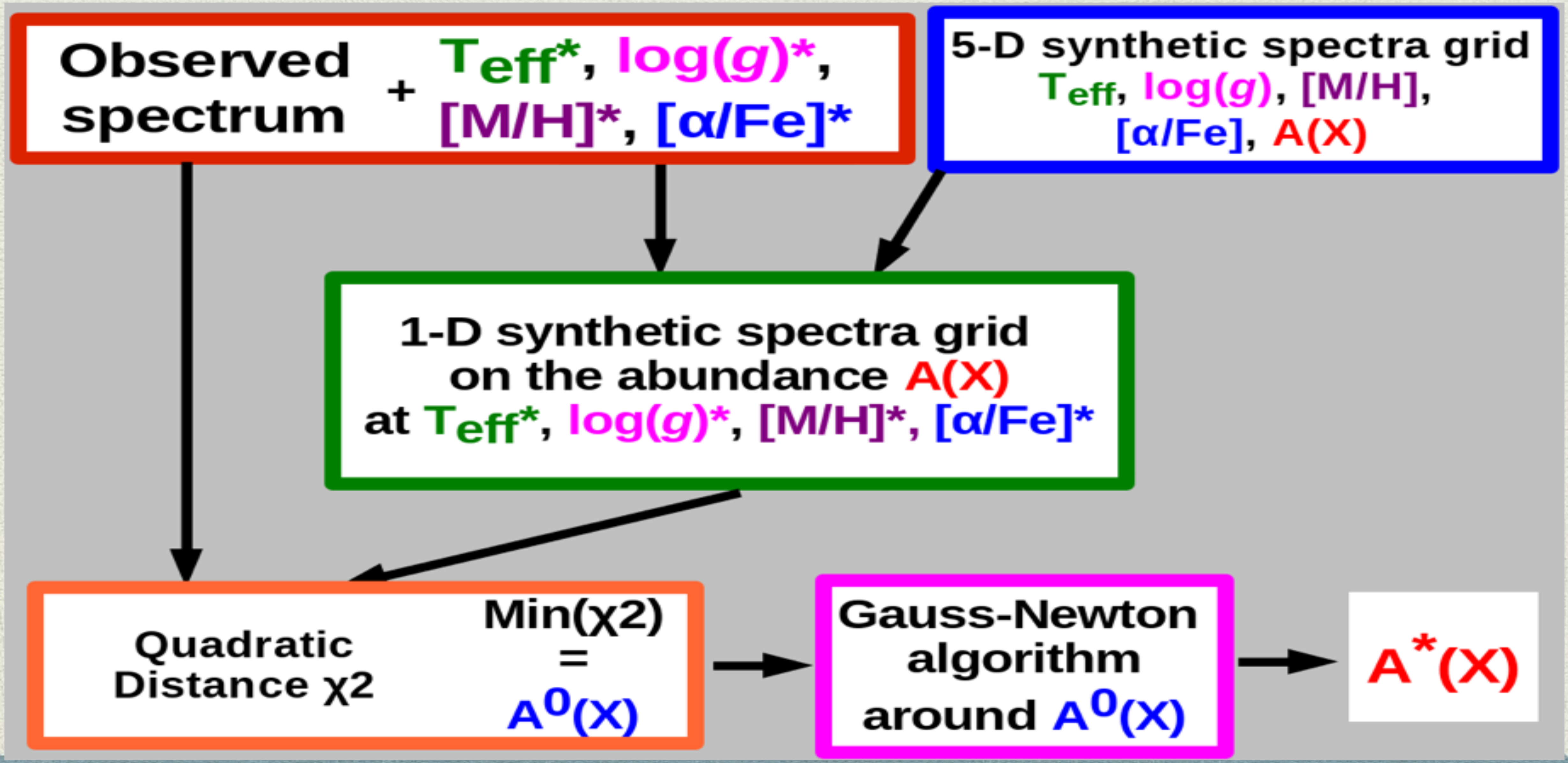
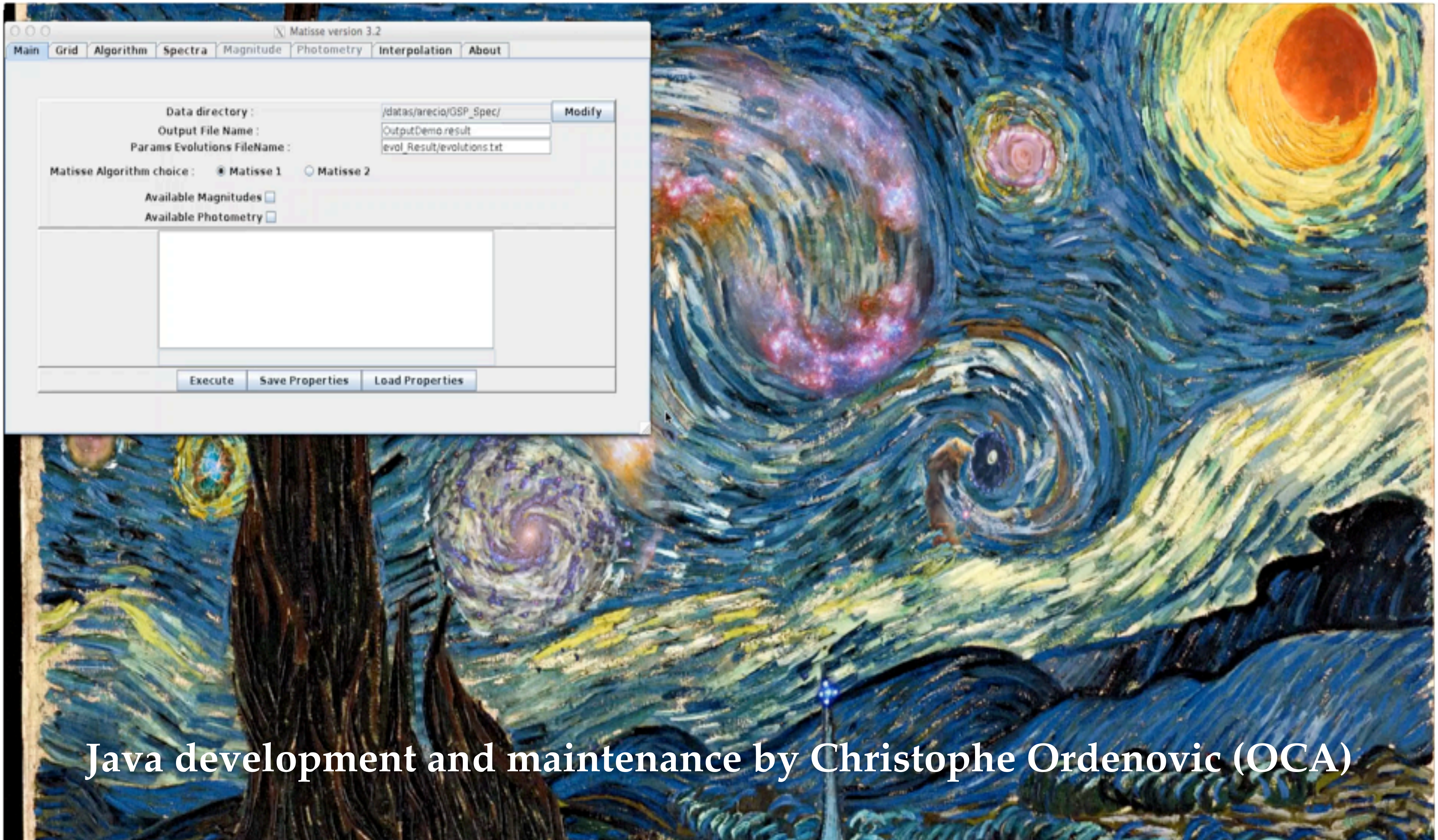


Automated spectrum analysis



Java development and maintenance by Christophe Ordenovic (OCA)

Automated spectrum analysis

Pipelines already developped with Nice tools for :

CoRot follow up: 1300 spectra

Disc archaeology (VLT PI programme): 700 spectra

Gaia-ESO Survey (Giraffe HR10, 21; UVES): 200 000 spectra

ESO archival spectra (AMBRE project): 200 000 spectra

RAVE survey: 430 000 spectra

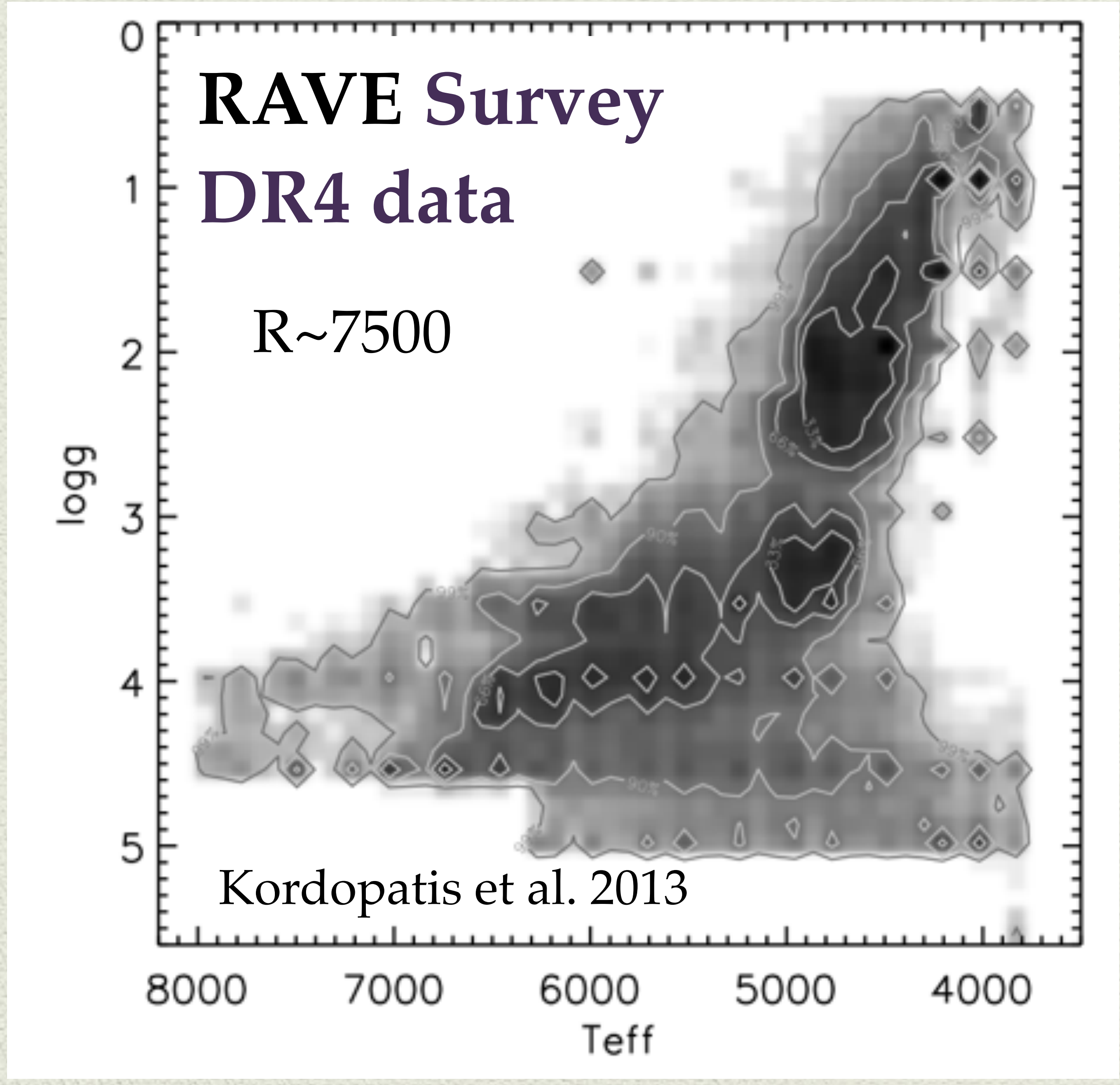
Gaia/RVS : ~150 million spectra

Under testing for: **4MOST@VISTA pipeline**

Automated spectrum analysis

P.I. M. Steinmentz

DR4 & DR5 data



Automated spectrum analysis

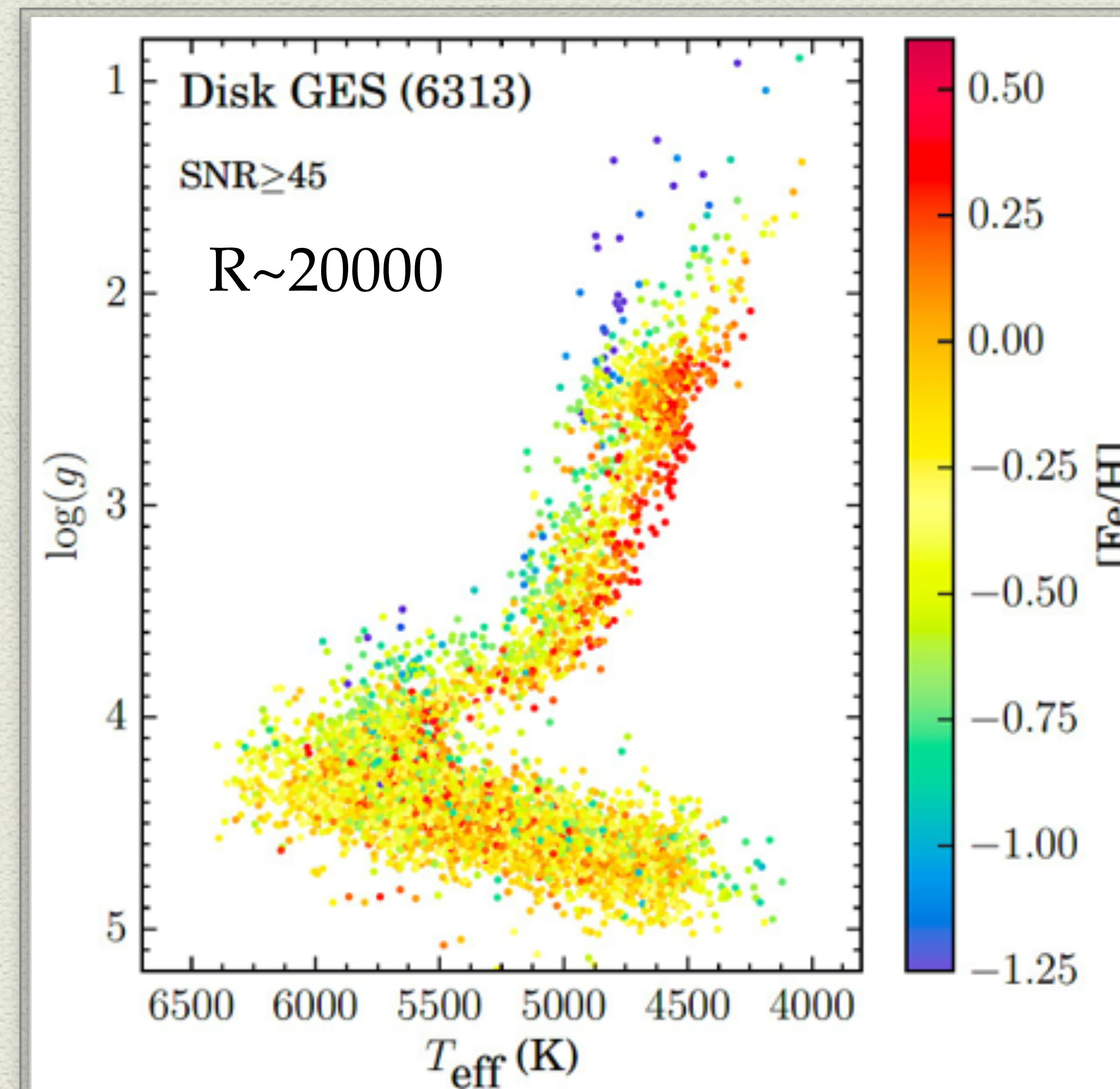
Gaia-ESO Survey

(P.I. G. Gilmore & S. Randich)

Giraffe data

Co-responsible of WG10

A. Recio-Blanco



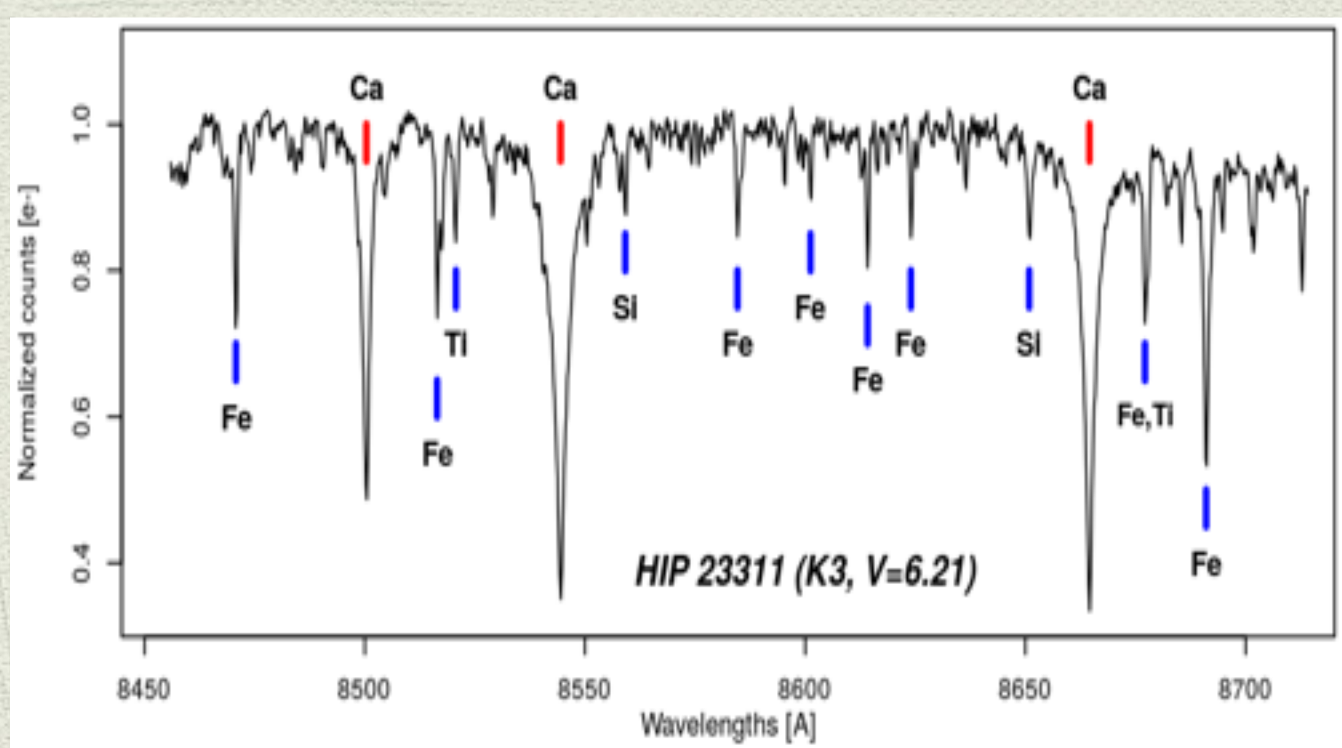
Recio-Blanco et al. in prep.

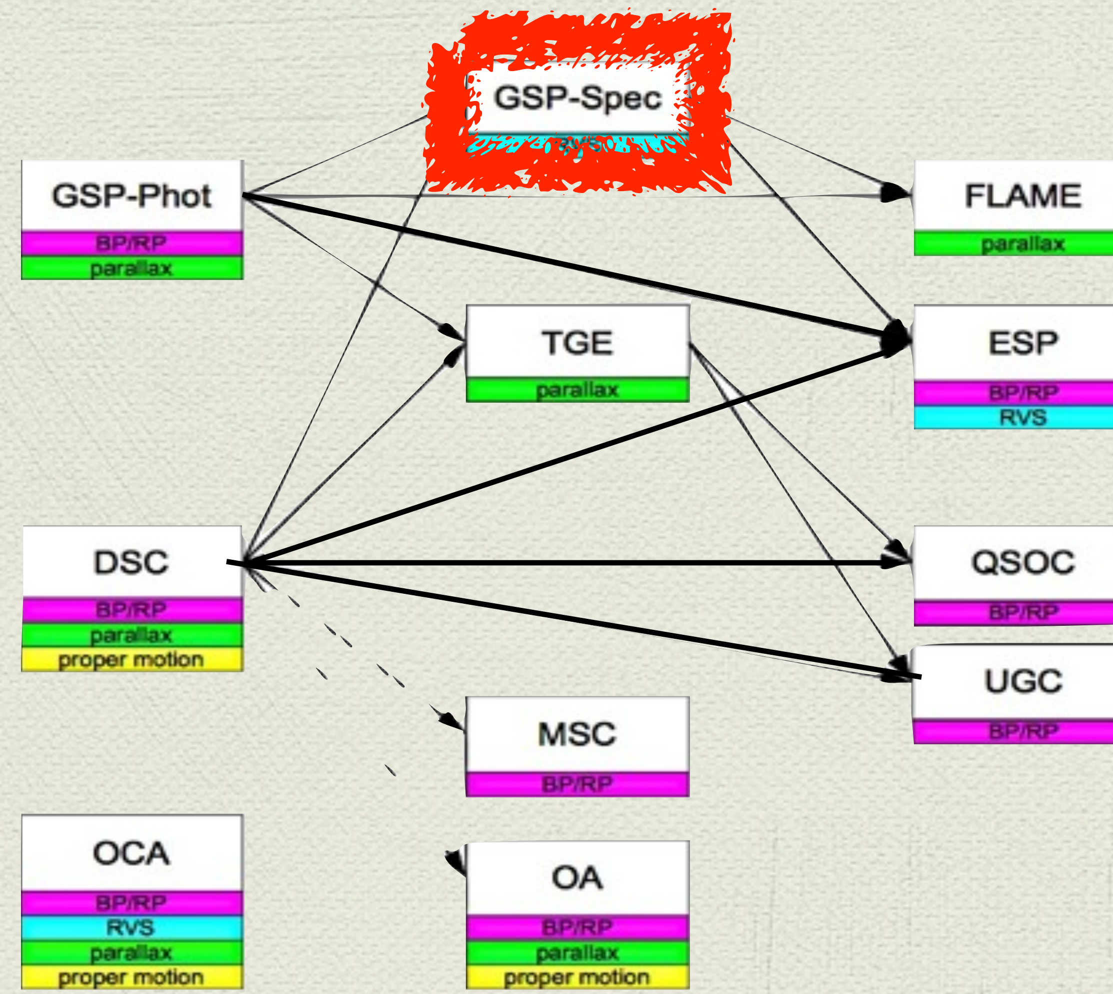
Automated spectrum analysis

Gaia DPAC APSIS pipeline (CU8)

GSPspec module

Parametrisation of Gaia/RVS stellar spectra





Automated spectrum analysis

Gaia DPAC APSIS pipeline (CU8)

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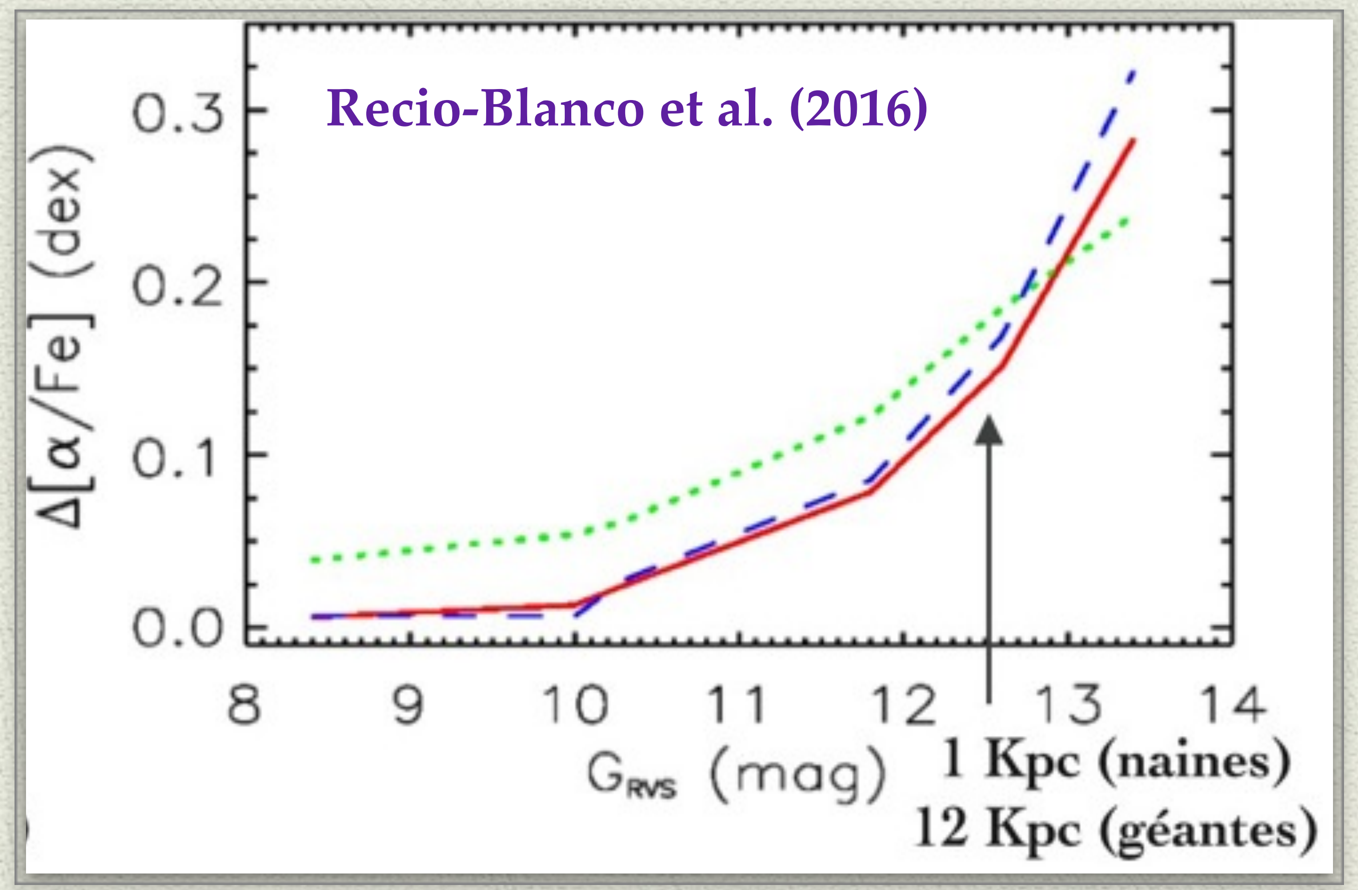
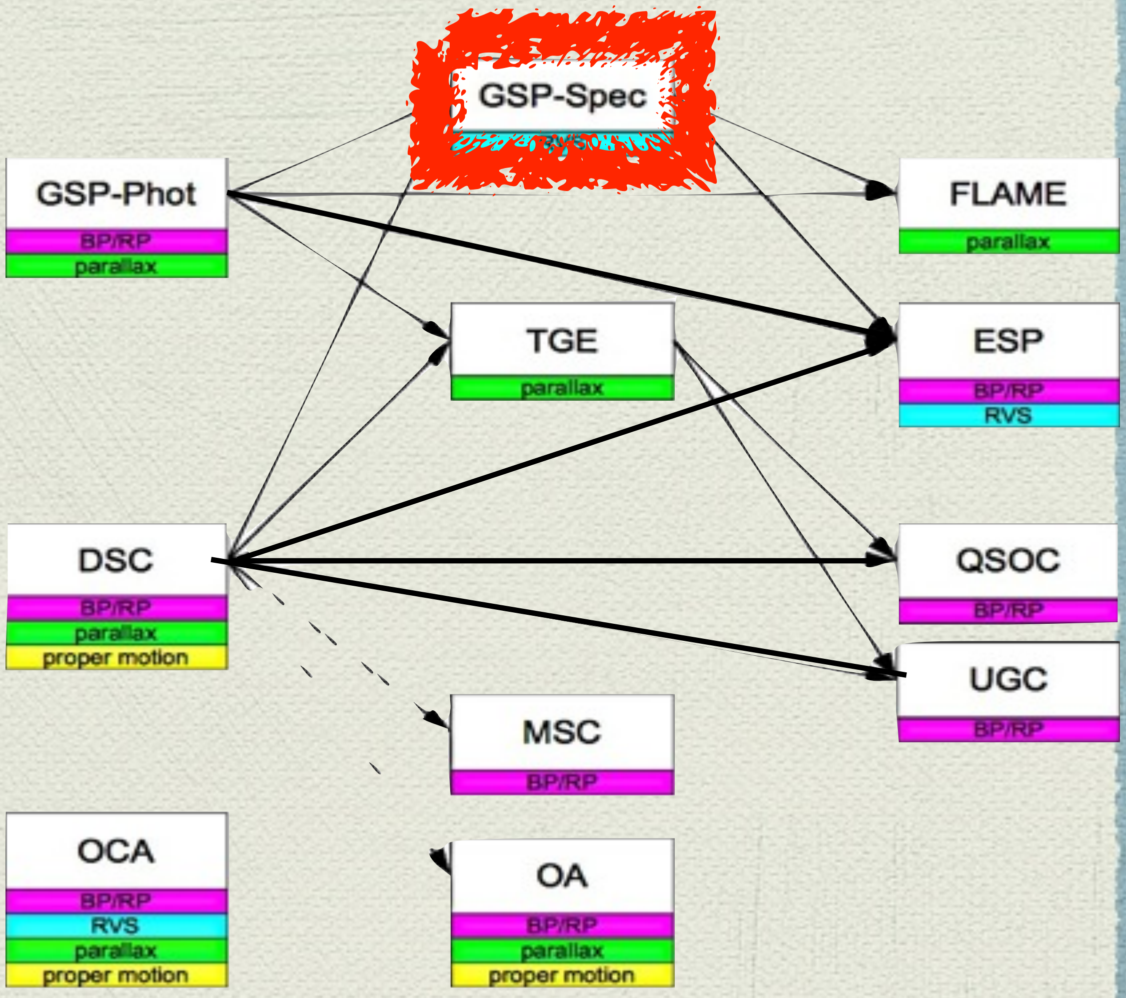


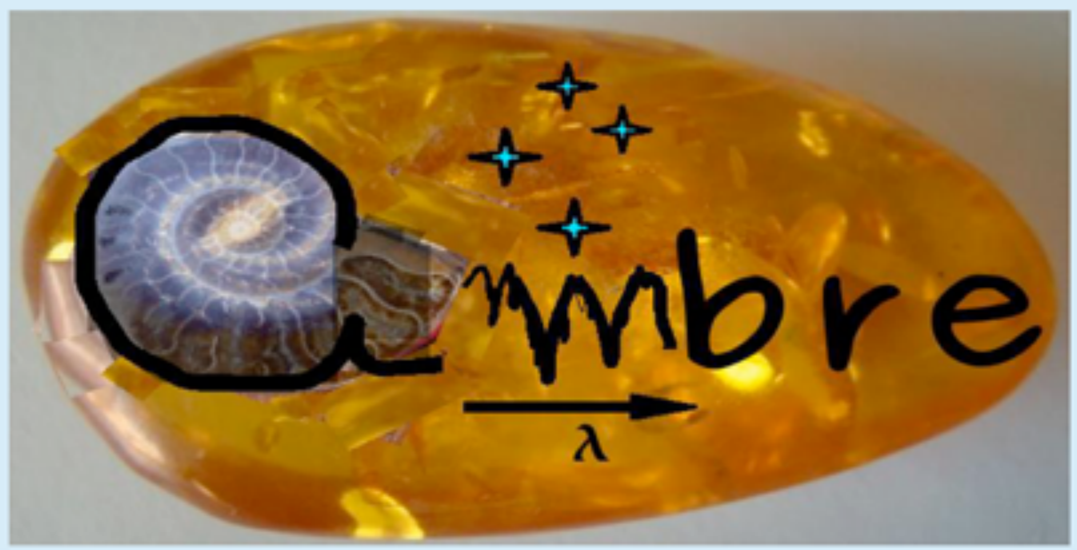


Automated spectrum analysis

Agreement between the Observatoire de la Côte d'Azur and ESO (2009)

Observatoire de la CÔTE d'AZUR

ESO



Primary Goal to provide advanced data products for the ESO archive

- **Homogeneous determination** of stellar parameters for archived spectra
- Available to the entire astronomical community → **ESO Archive**

Automated spectrum analysis

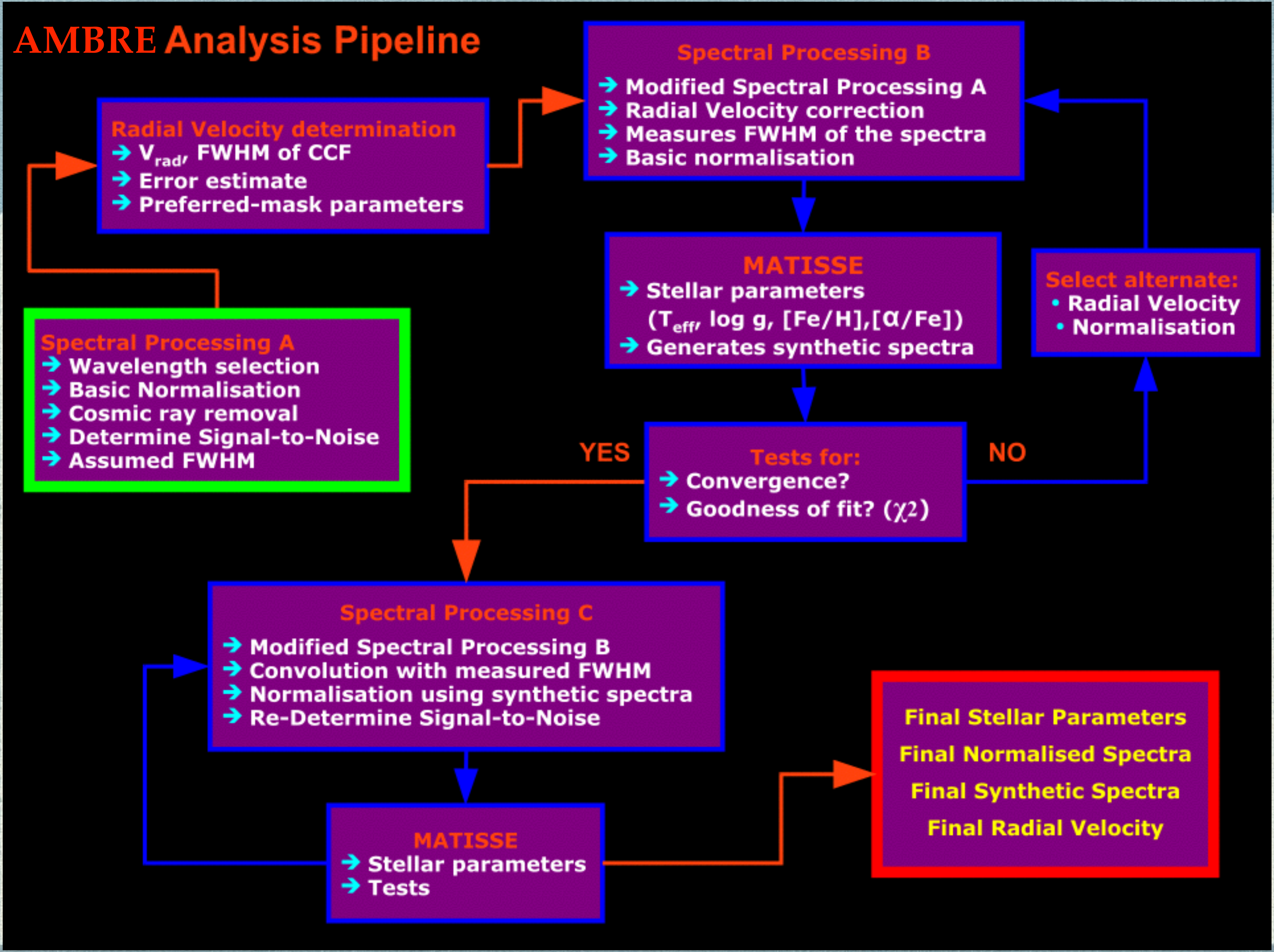
Methodology Parametrisation pipeline

for Vrad, Teff, log(g), [M/H], [α/Fe]

- MATISSE algorithm (Recio-Blanco et al., 2006)
- FGKM-type spectra grid (de Laverny et al. 2012)

Fully parametrised samples

- 6 508 FEROS spectra (Worley et al., 2012)
- 93 116 HARPS spectra (de Pascale+2014)
- 12 403 UVES spectra (Worley et al. 2016)

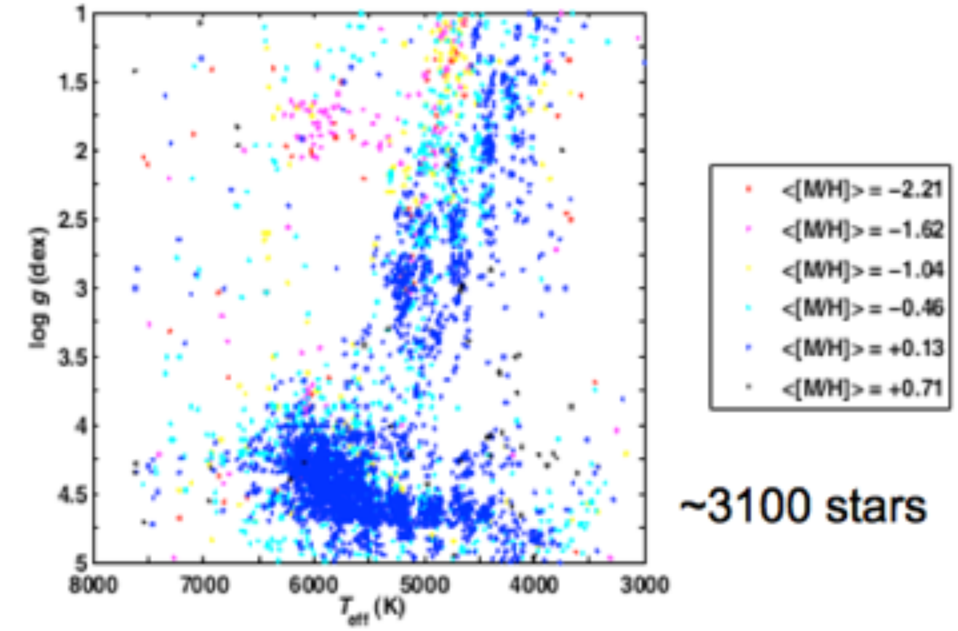

AMBRE Analysis Pipeline
Spectral Processing B
Modified Spectral Processing A
Radial Velocity correction
Measures FWHM of the spectra
Basic normalisation
Radial Velocity determination
V_{rad}, FWHM of CCF
Error estimate
Preferred-mask parameters
MATISSE
Stellar parameters
(T_{eff}, log g, [Fe/H],[α/Fe])
Generates synthetic spectra
Select alternate:
Radial Velocity
Normalisation
Spectral Processing A
Wavelength selection
Basic Normalisation
Cosmic ray removal
Determine Signal-to-Noise
Assumed FWHM
YES
Tests for:
Convergence?
Goodness of fit? (χ2)
NO
Spectral Processing C
Modified Spectral Processing B
Convolution with measured FWHM
Normalisation using synthetic spectra
Re-Determine Signal-to-Noise
Final Stellar Parameters
Final Normalised Spectra
Final Synthetic Spectra
Final Radial Velocity
MATISSE
Stellar parameters
Tests

Automated spectrum analysis

AMBRE pipeline : MATISSE method
+ Int. Err. (repeats) + Ext. Err + Quality + ...

FEROS spectra Worley et al., 2012

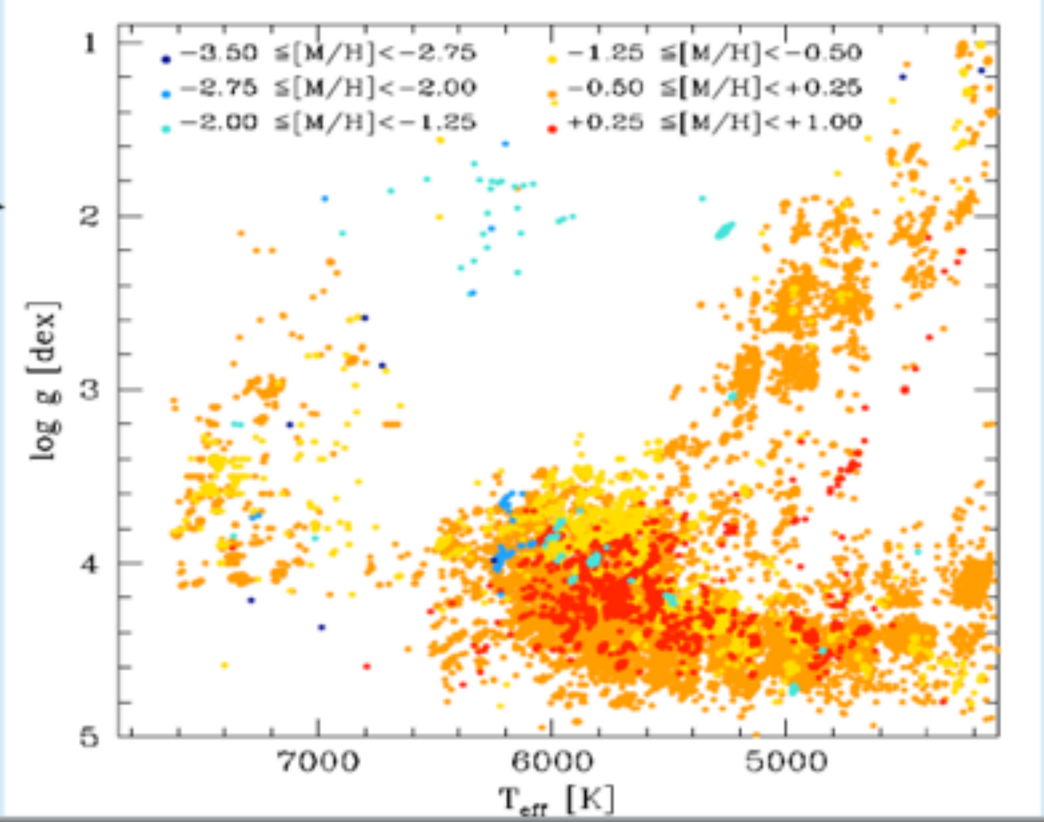
21 551 spectra : ¼ fully parametrized

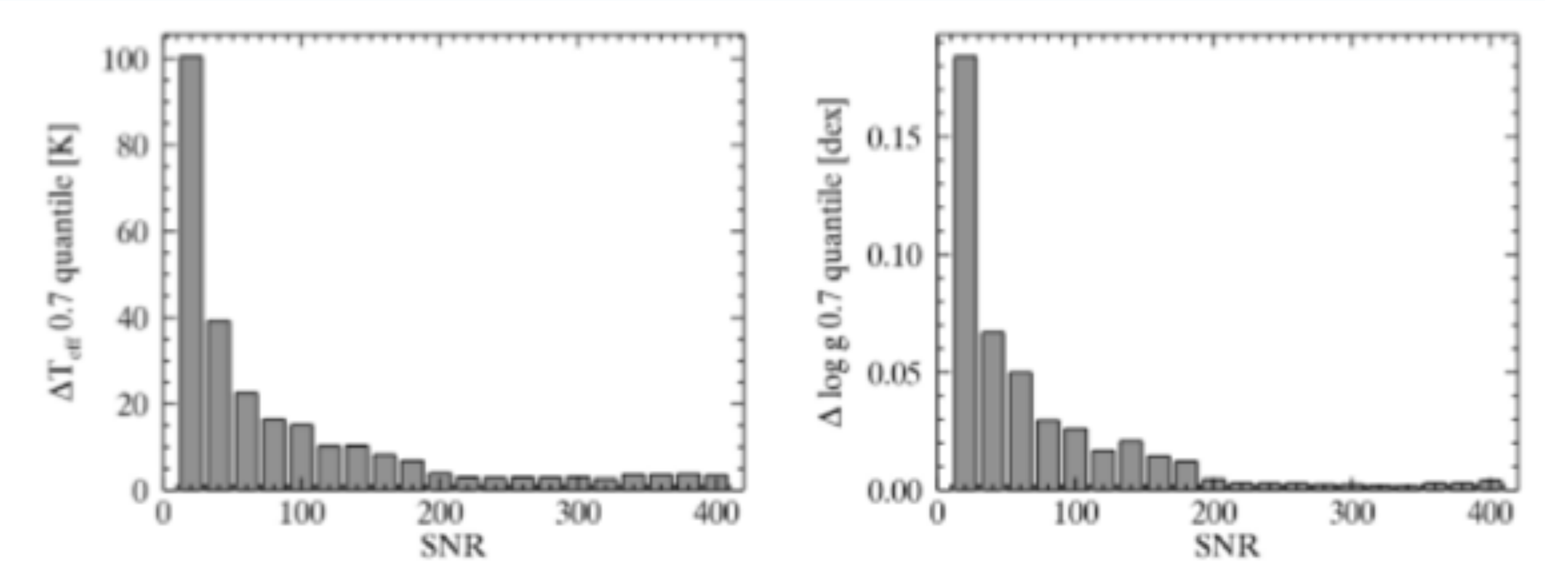


~3100 stars

HARPS spectra de Pascale et al., 2014

127 000 spectra : 3/4 fully parametrized





Automated spectrum analysis

AMBRE pipeline : MATISSE method
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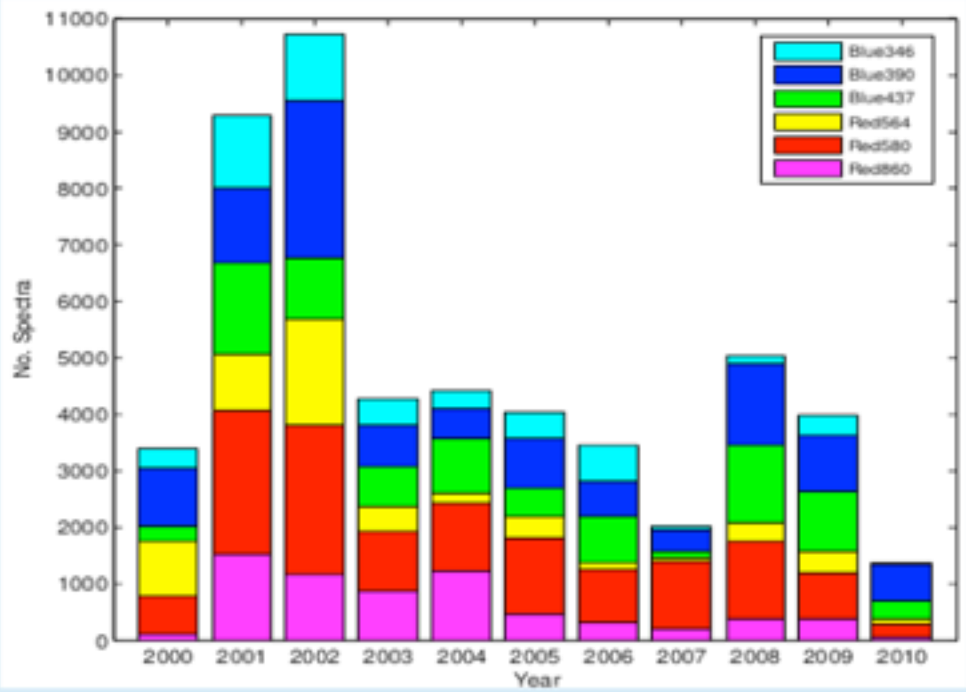
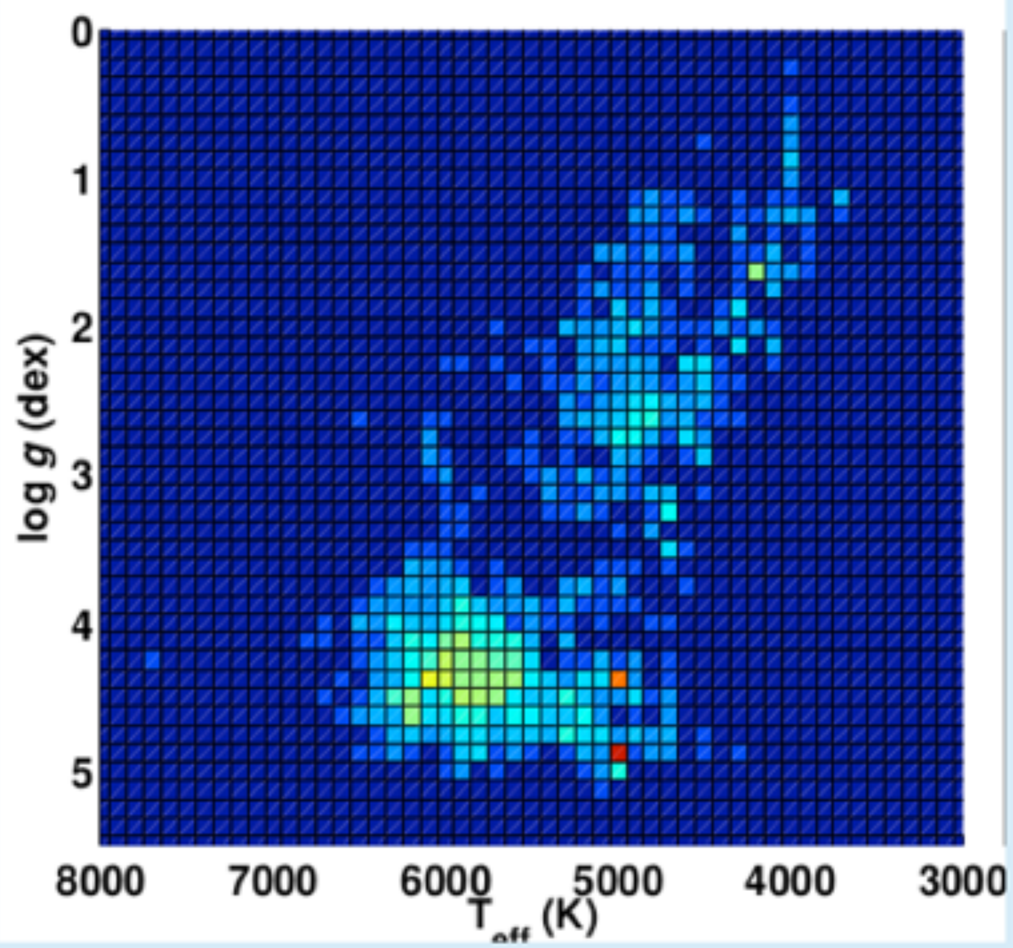
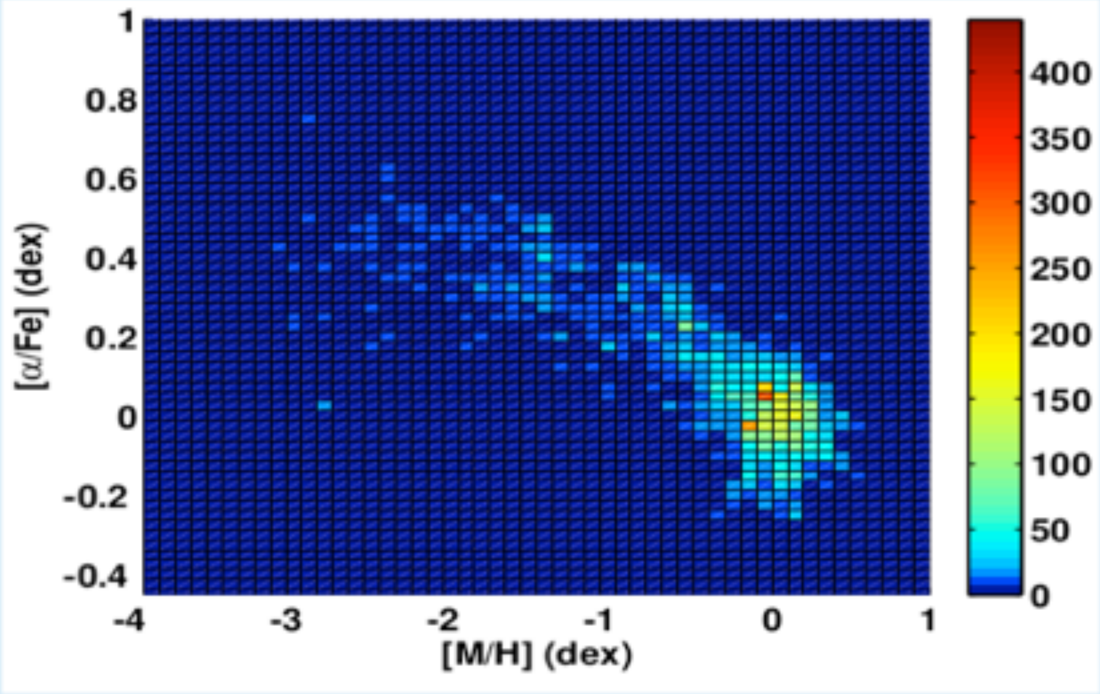


UVES spectra

Worley et al., 2016

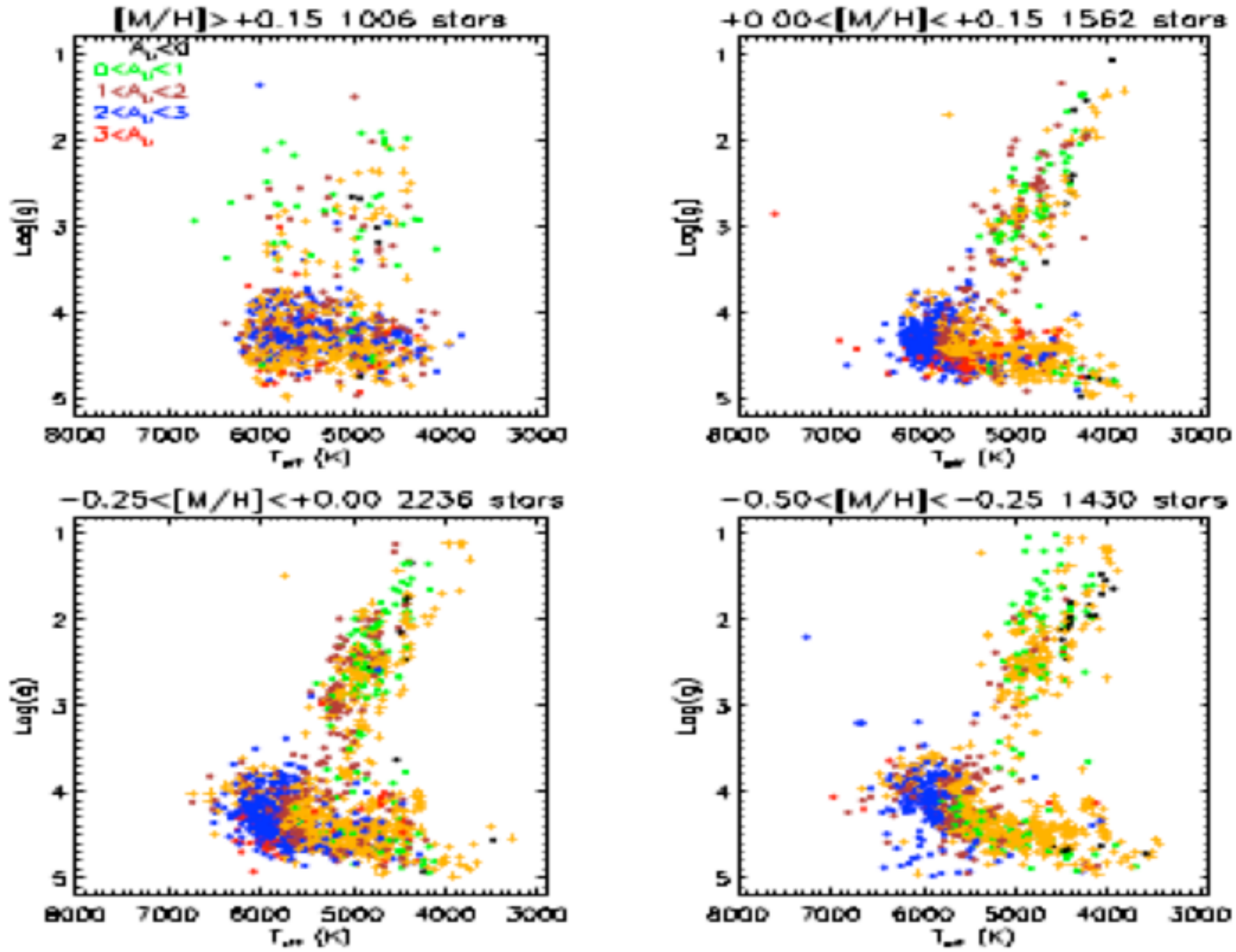
51 921 spectra : ¼ fully parametrized (3800 stars)





Automated spectrum analysis

AMBRE pipeline for chemical abundances (GAUGUIN)



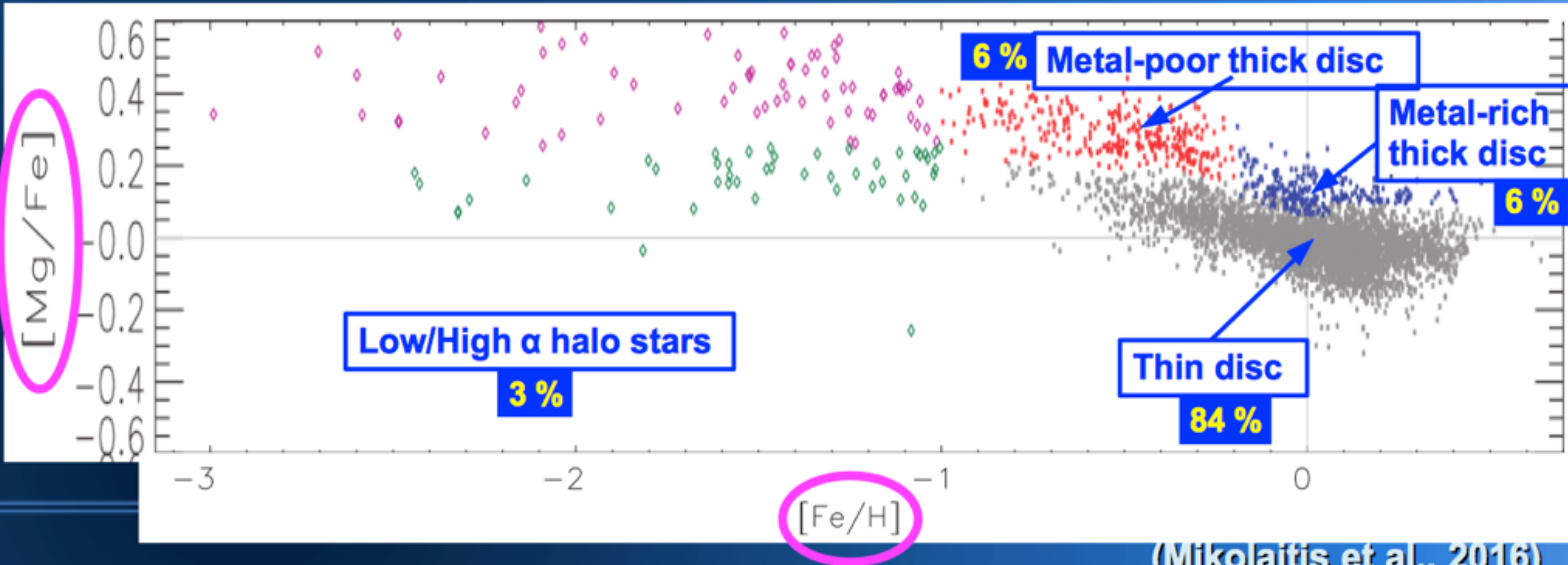
Lithium abundance for 7800 stars

Guiglion et al., 2016

Automated spectrum analysis

LTE abundances for 4 666 stars **Mg, Mn, Fe, Ni, Cu, Zn**

Chemical separation of the Galactic substructures



(Mikolaitis et al., 2016)

Automated spectrum analysis

- Experience on automated stellar parameterisation

- APOGEE data can be used to start exploring /implementing the MOONS analysis

- Proposal of collaboration with Oscar González

- MOONS consortium framework to be defined.