

# Selective Standard Normal Variate

G. Rabatel<sup>1</sup>, F. Marini<sup>2</sup>, B. Walczak<sup>3</sup>, **J-M. Roger<sup>1</sup>**

<sup>1</sup> ITAP, Irstea Montpellier Centre, BP 5095 34196 Montpellier cedex 5, France. [gilles.rabatel@irstea.fr](mailto:gilles.rabatel@irstea.fr)

<sup>2</sup> Department of Chemistry, Univeristy of Rome “La Sapienza”, P.le Aldo Moro 5, I-00185 Rome, Italy

<sup>3</sup> Silesian University, 9 Szkolna Street, 40-006 Katowice, Poland



# Outline

- Introduction / theory
- Example on simulated data
- Example on real data
- Conclusion

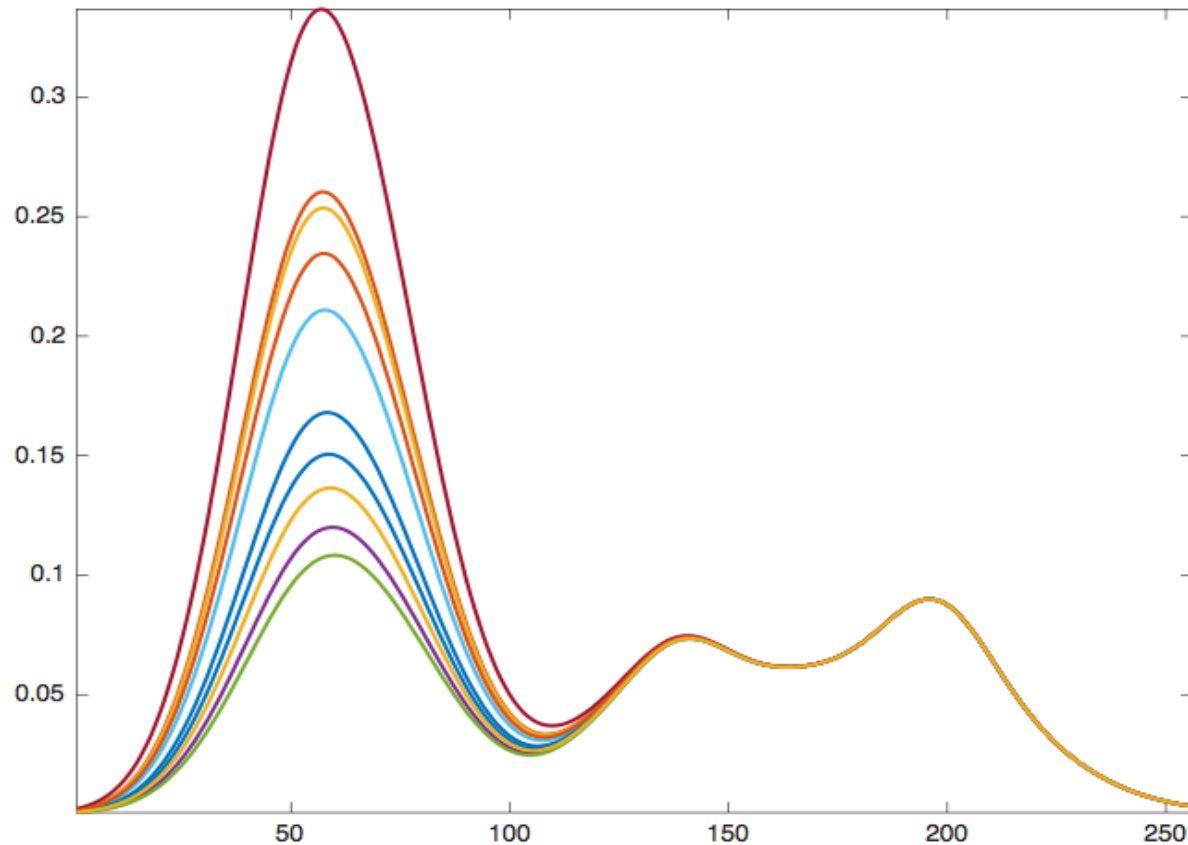
# Introduction

- Beata Walczak told you at Genève in 2015
- Tom Fearn told you again at Namur in 2016

The normalisation must be used with caution

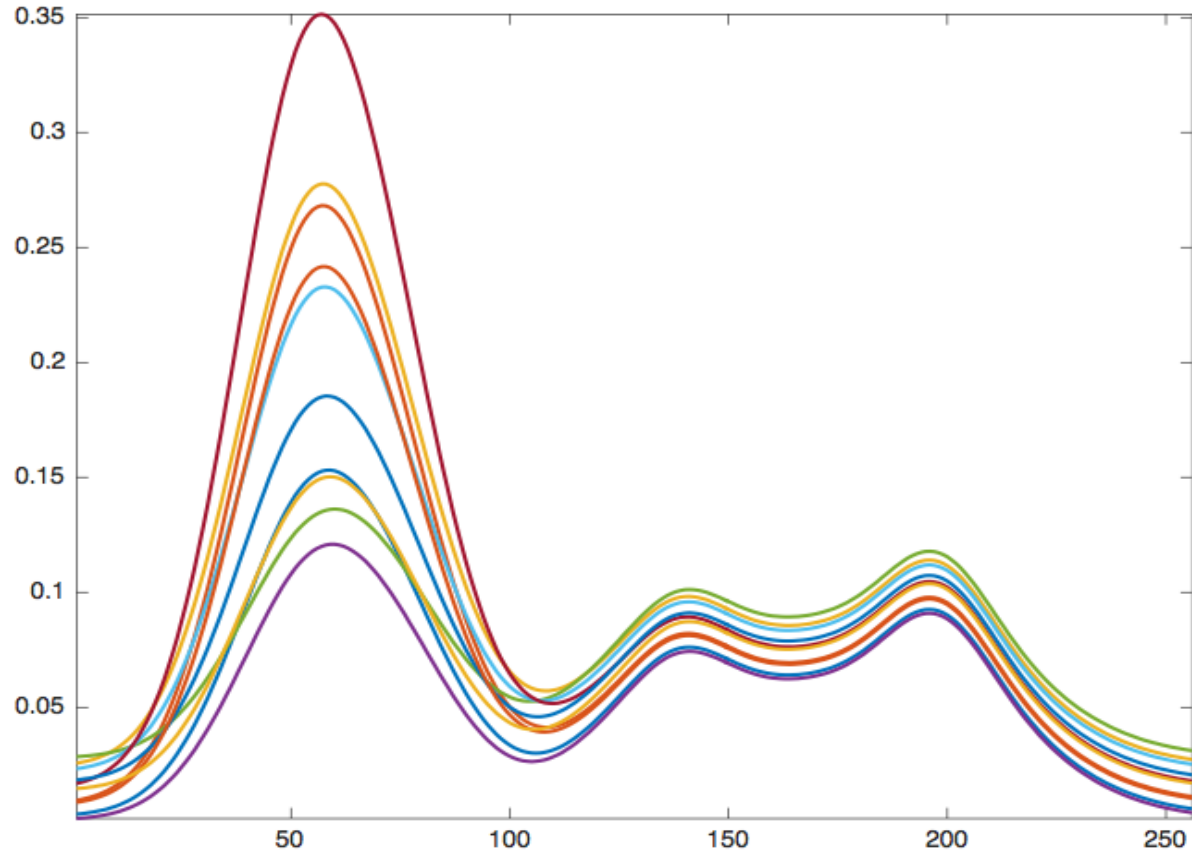
Because it has side effects !!

# Introduction: a simulated example



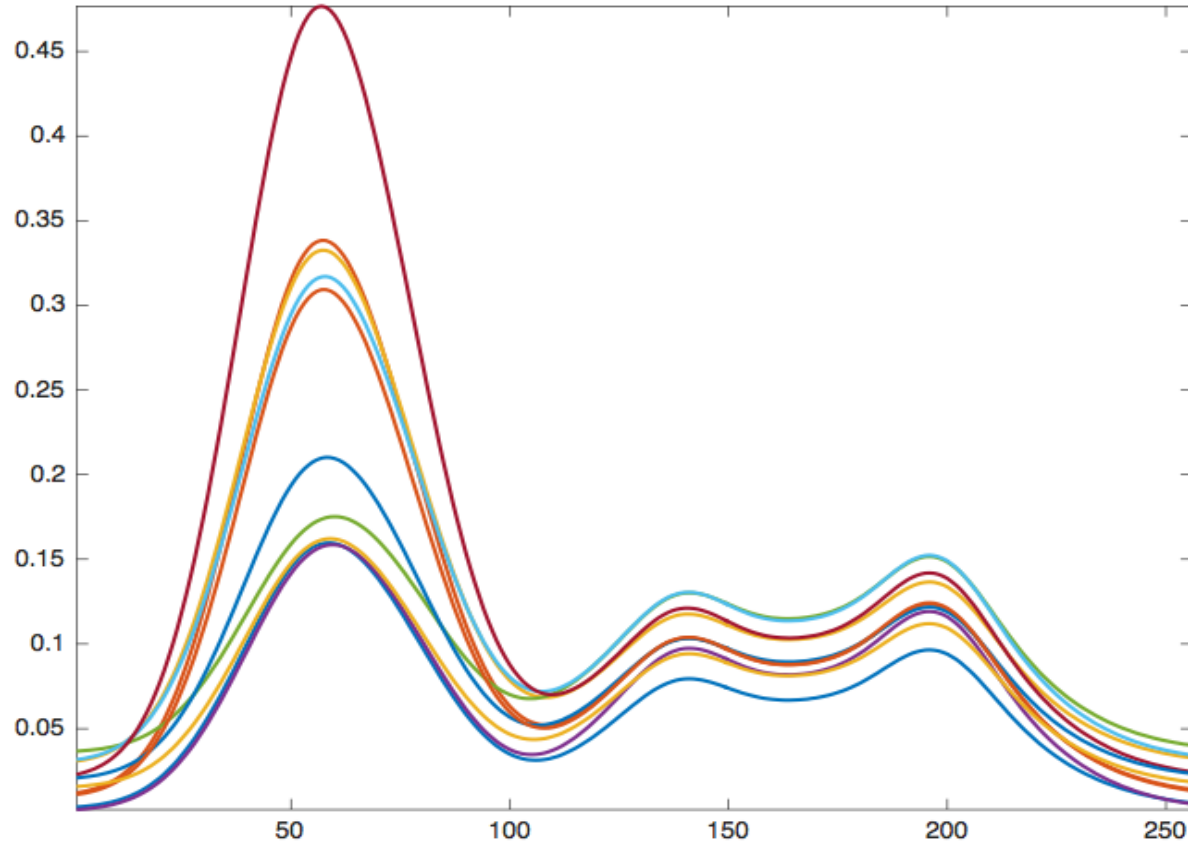
Spectra without any additive or multiplicative effect  
One peak related to Y, two not

# Introduction: a simulated example



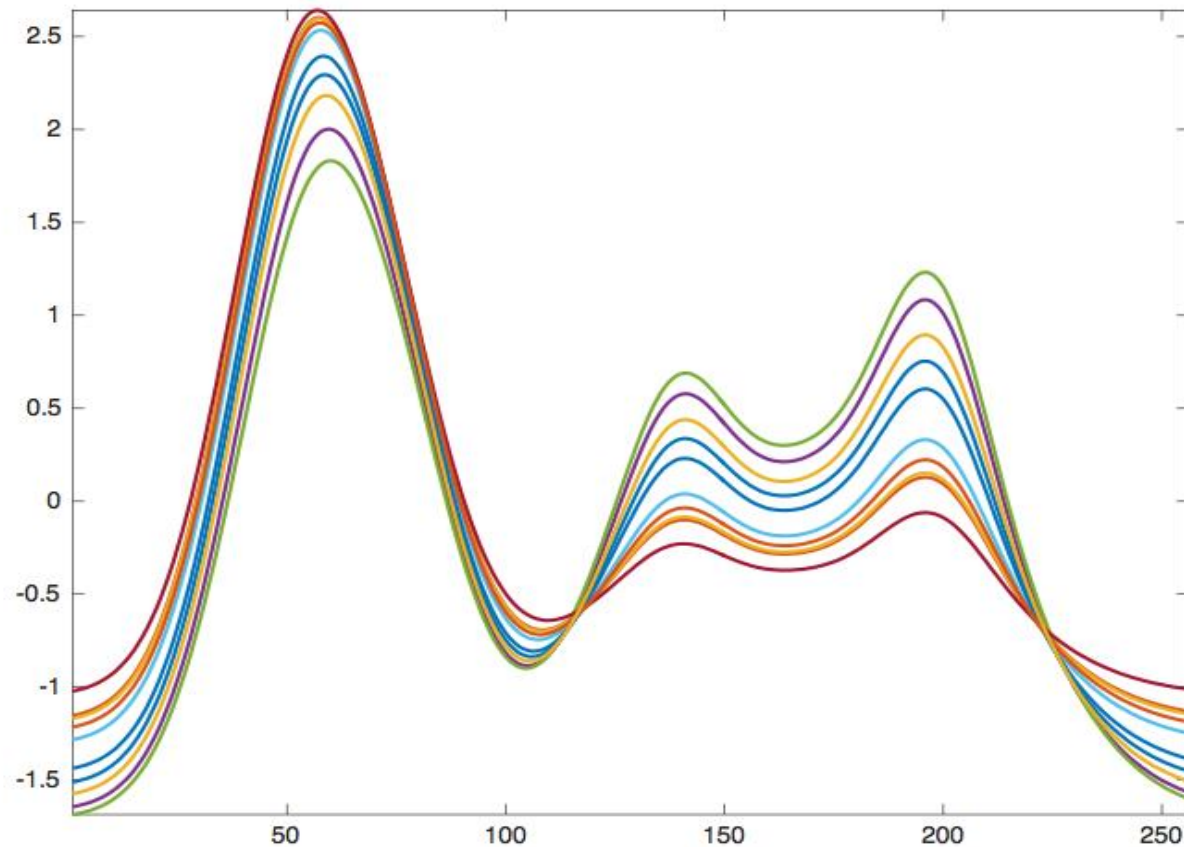
Let add baselines

# Introduction: a simulated example



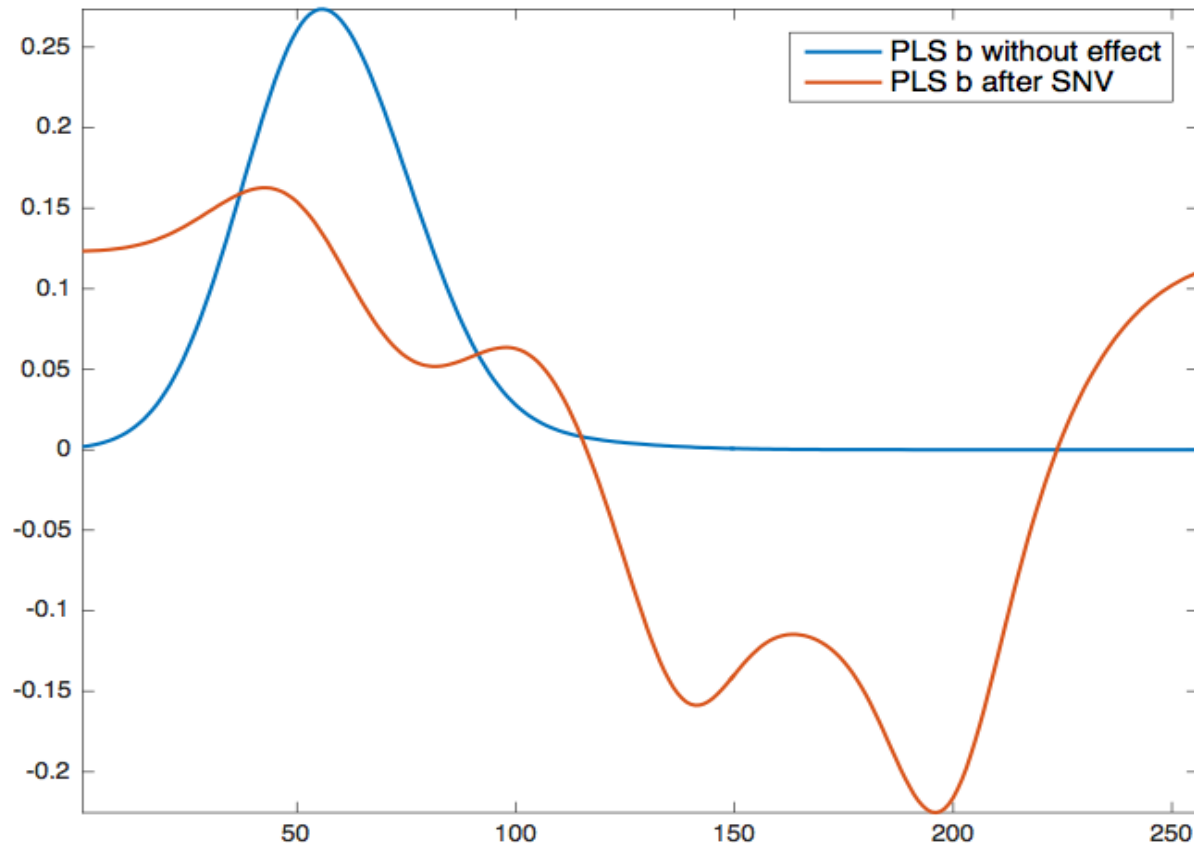
And a multiplicative effect

# Introduction: a simulated example



And let apply SNV

# Introduction: a simulated example



Model performances are good (on calibration set)  
But the model itself is erroneous



# Theory

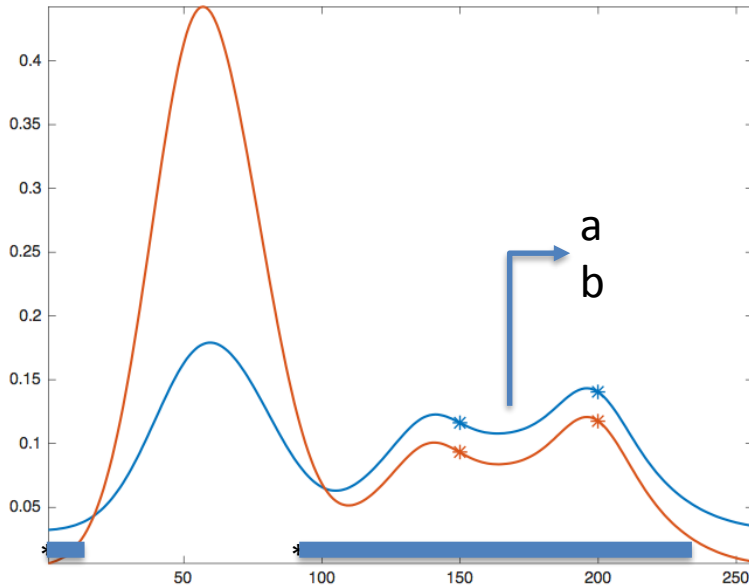
- What happens?
- SNV estimates :
  - the multiplicative effect as the standard deviation of the spectrum
  - the additive effect as the mean of the spectrum
- But these statistics depend also on Y
- SNV tends to dilute the information along the whole spectrum

# Theory

- A solution :
  - To calculate standard deviation and mean on wavelengths little related to  $\mathbf{Y}$
  - To normalize the spectrum with these values
- Or, more generally:
  - To calculate diagonal matrix  $\mathbf{W}$  of weights between 0 (no selection) and 1 (complete selection)
  - To calculate the normalisation on  $\mathbf{W}\mathbf{x}$  and apply it to  $\mathbf{x}$

# An algorithm using RANSAC

(Fischler and Bolles, 1981)



Let take a couple of spectra  $i, j$

Let take a couple of wavelengths  $k, l$

Calculate coefficients  $a, b$   
so that  $(x_{ik}, x_{il}) = a(x_{jk}, x_{jl}) + b$

Retrieve the set of wavelengths that respect  
the same relationship, given a tolerance

After some iterations, retain the largest set

One gets a partition of the wavelengths in two subsets:

the INLIERS, which all share the same coefficients

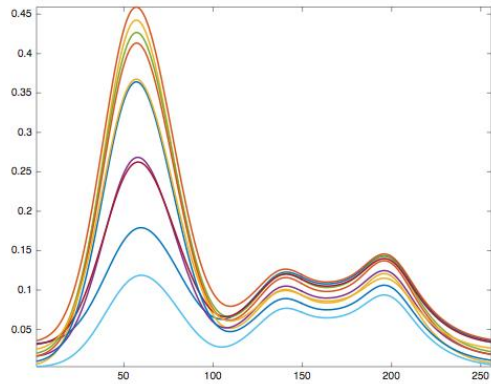
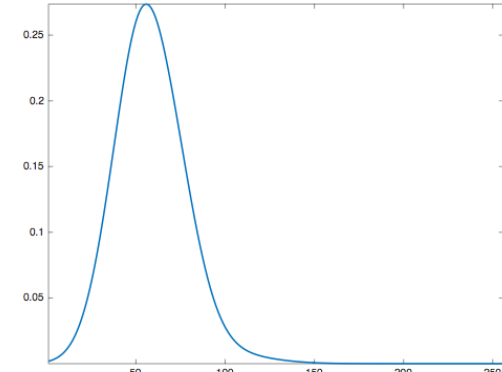
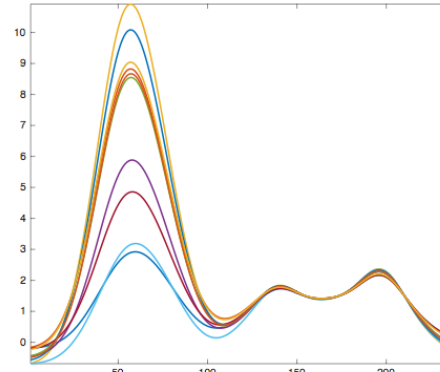
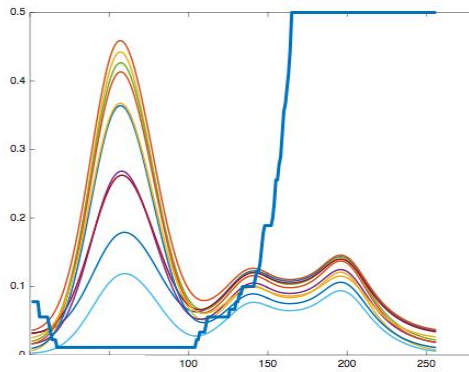
the OUTLIERS

We propose to calculate  $w_i = p(\text{wavelength } i \text{ is an INLIER})$

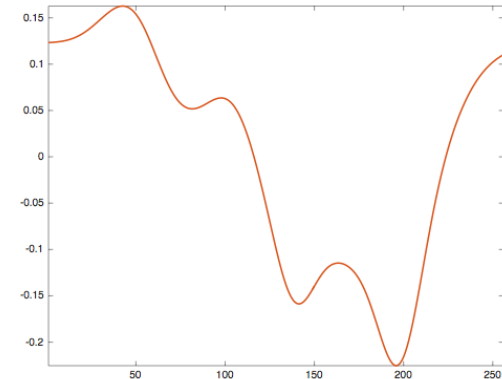
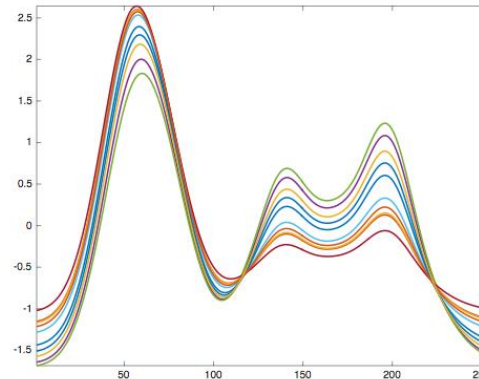
One estimate this probability by drawing couples of spectra in  $\mathbf{X}$

# Results on simulated data

weighted SNV  
tol = 0.001



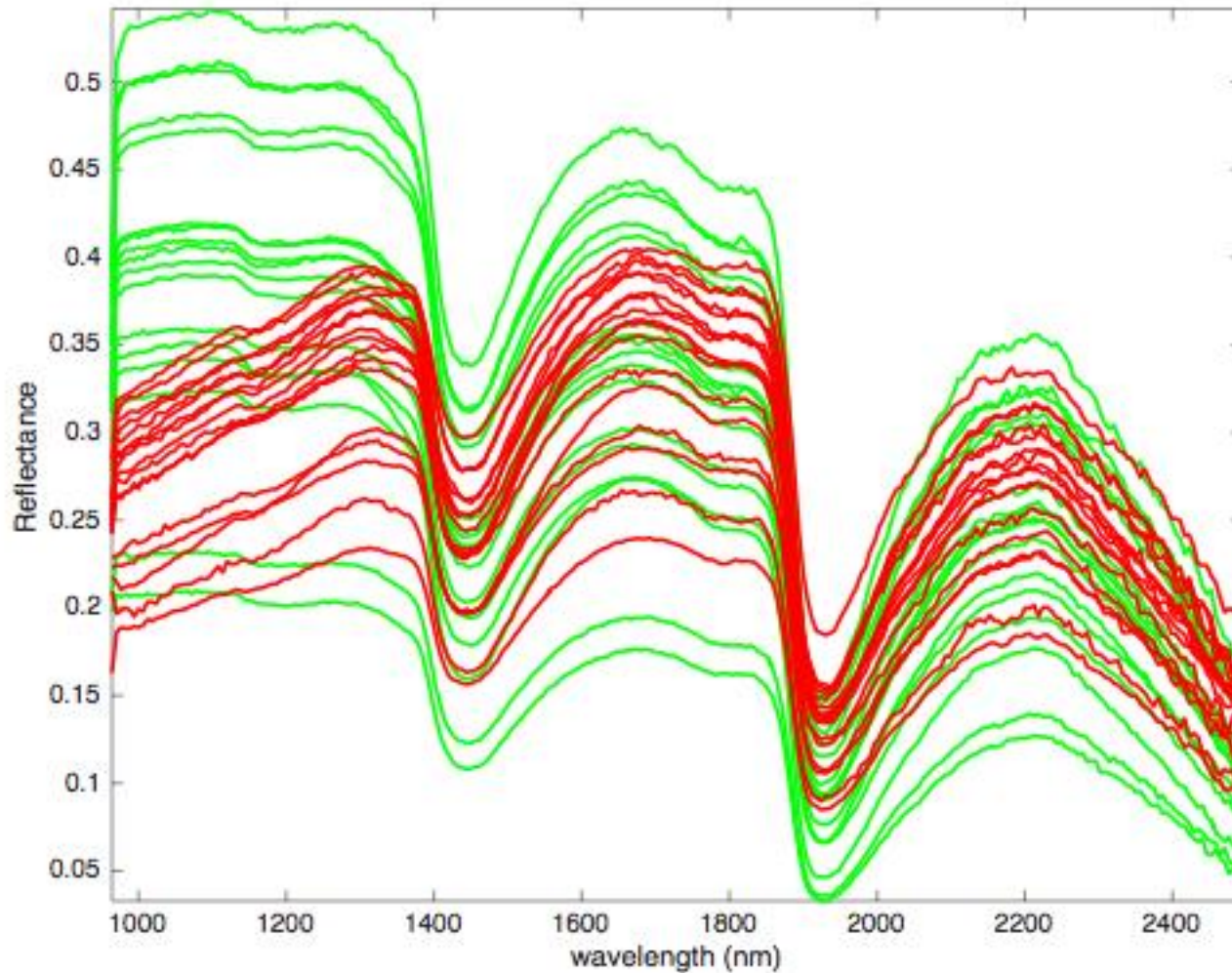
classical SNV



# Real example

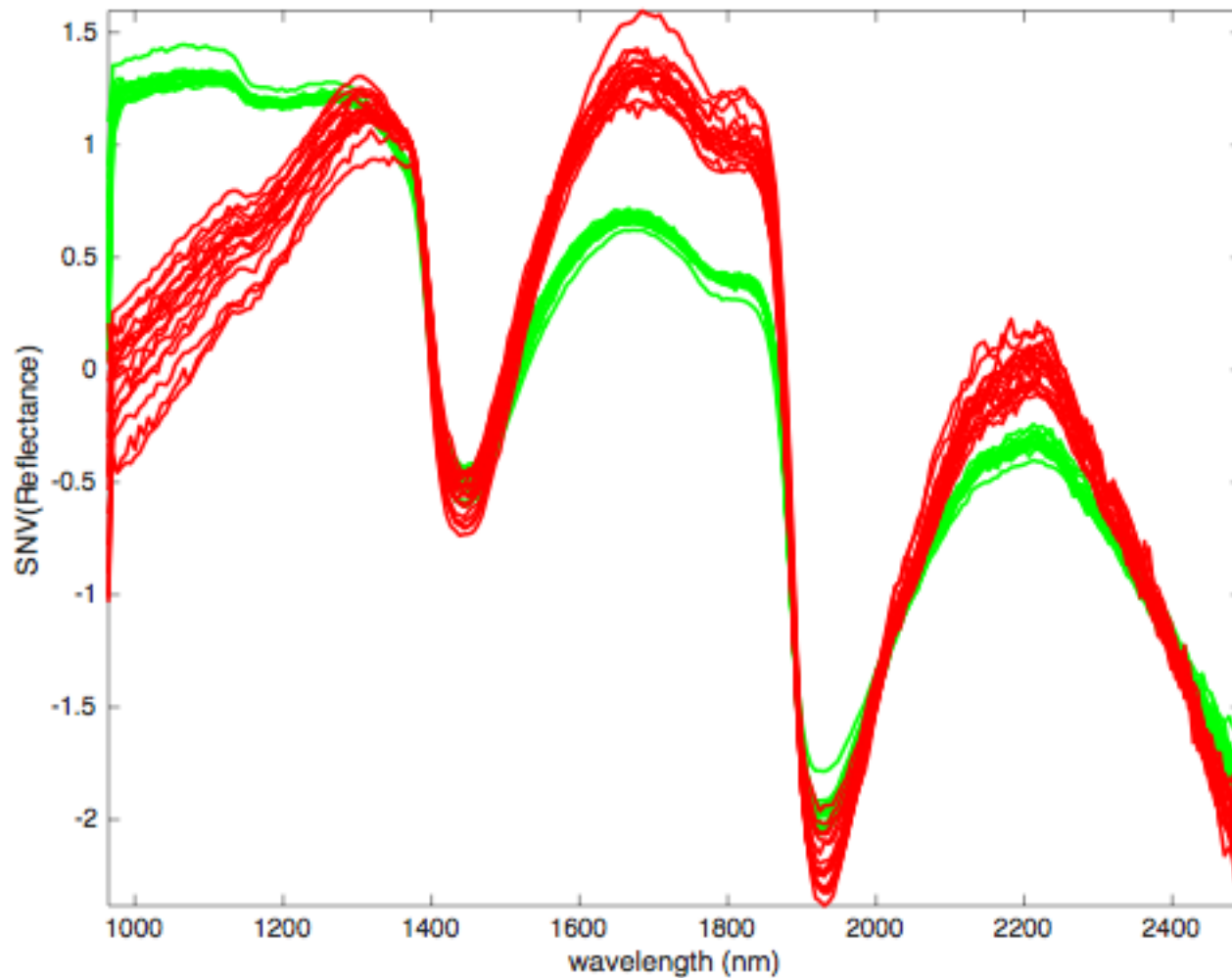
- Data : apple tree leaf spectra
- Images acquired with an NEO SWIR hyperspectral camera; 1000 - 2500 nm
- Each spectrum is the mean of pixels from an area
- Two classes :
  - healthy
  - scab disease spot

# Real example



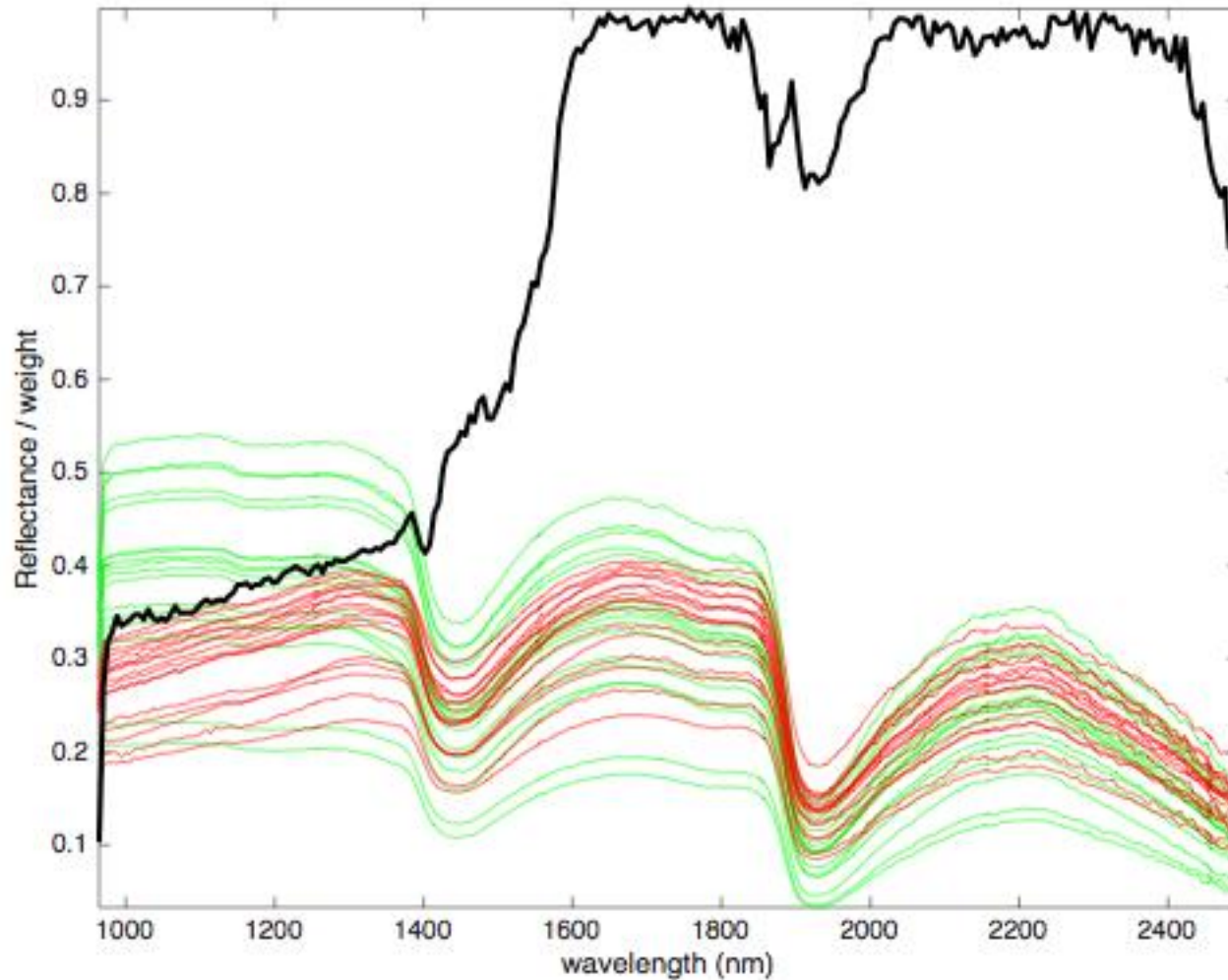
healthy (green) and scab (red) spectra

# Real example



spectra processed by classical SNV

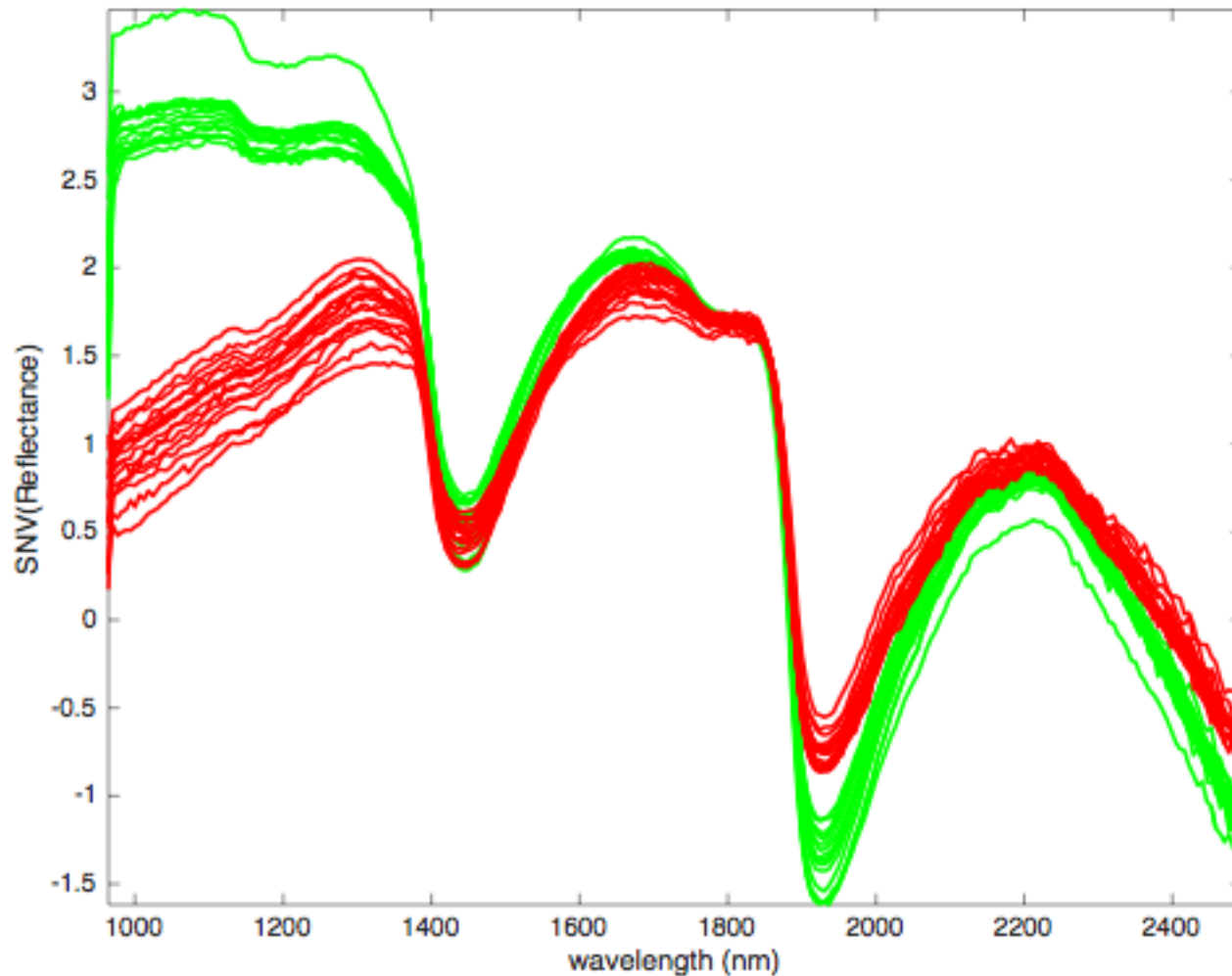
# Real example



weights yielded by the algorithm ; tol = 0.01

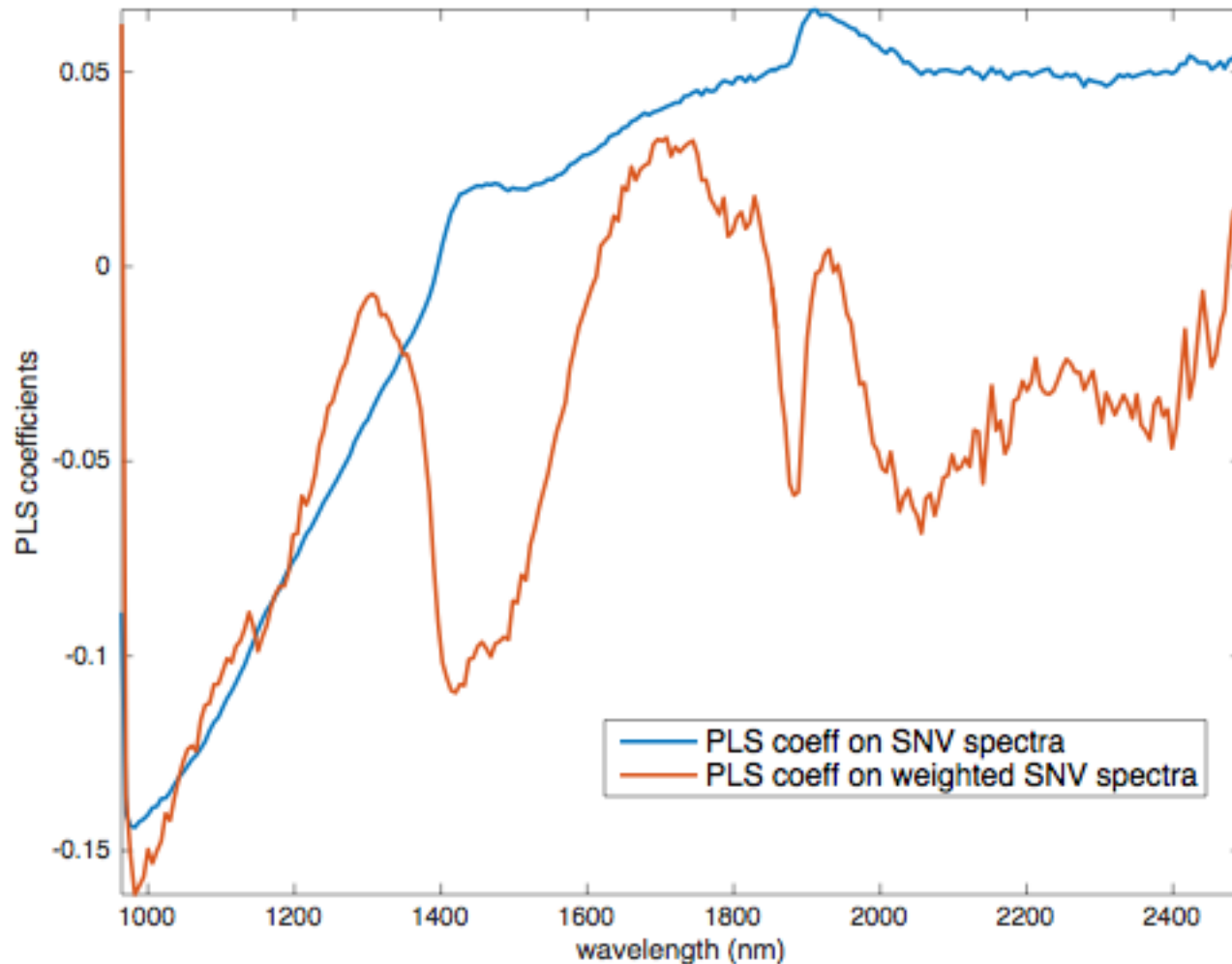


# Real example



spectra processed by weighted SNV

# Real example



PLS models on the two sets, (2 latent variables)

# Conclusions

- The normalisation (e.g. SNV) induces undesirable alterations
- This does not change the model performances, but can severely affect the loadings
- A solution consists of weighting the variables regarding the normalisation
- An algorithm is proposed
  - Results are satisfactory
  - Do not need reference spectrum, as MSC, PQN, ...
  - The weights found can be easily applied to new spectra
  - It must be compared to other methods, as those using robust regressions (p.ex. RSNV, Guo et al, 1999)
  - It should be adapted to other type of effects
  - It must be optimized and automatized

Thanks for your attention