Local PLSR averaging

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The unit

Projet scientifique

Produits et publications

Enseignement et formation

Livestock Systems and Animal Products Management

The SELMET research unit is an international group focused on livestock production in Mediterranean and tropical areas. The unit has approximately 100 permanent and contractual staff drawn from CIRAD, INRAE and the Institut Agro Montpellier. SELMET offers research, teaching and expertise to support sustainable transitions in livestock activities.

NIR Laboratory

- Spectrometry → Foss, Bruker, Asd
- Chemical analyses

Compositions

- Forages
- Feed
- Feces (digestibility)

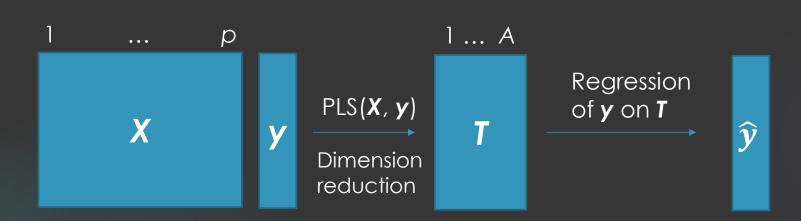
European and tropical

1. PLSR averaging

2. Extension to a method of local PLSR

3. Illustration: forages and feed dataset

1. PLSR

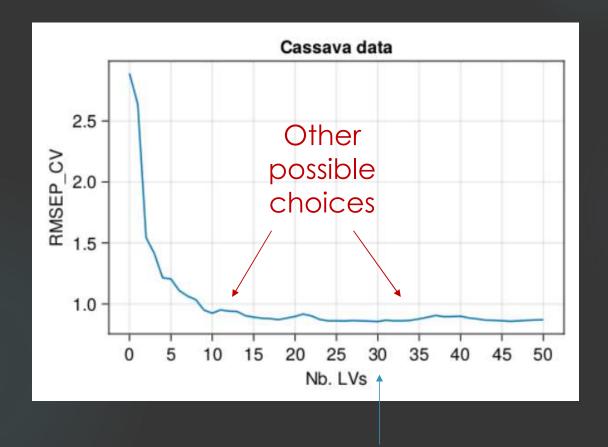


PLS scores = LVs

Required step: Tuning A = nb. LVs

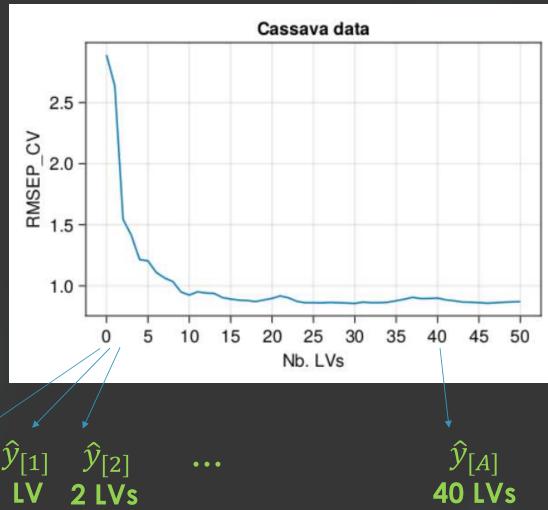
Which value for A?

One usual tuning approach: Cross-validation



$$a_{opt} = 30 \text{ LVs}$$

Prediction $\Rightarrow \hat{y}_{[a \ opt]}$



Average

$$\hat{y}_{avg,[A]} = \frac{\hat{y}_{[0]} + \hat{y}_{[1]} + \dots + \hat{y}_{[A-1]} + \hat{y}_{[A]}}{A+1}$$

Final prediction

= PLSR averaging with uniform weighting

More elaborated weighting

$$\hat{y}_{avg,[A]} = \theta_0 \ \hat{y}_{[0]} + \theta_1 \hat{y}_{[1]} + \dots + \theta_A \hat{y}_{[A]}$$

$$\sum_{a=0}^{A} \theta_a = 1$$

~ Confidence given to model [a]

- Probability (Bayes)
- Model performance
 - RMSEP-CV
 - AIC
 - etc.

More the model is performant, higher is θ_a

One variant: Stacking

 $\frac{\theta_a}{a}$ are estimated from a meta-regression model

$$\sum_{a=0}^{A} \theta_a \neq 1$$

 $PLSR \Rightarrow PLSR-AVG$

Natural extension

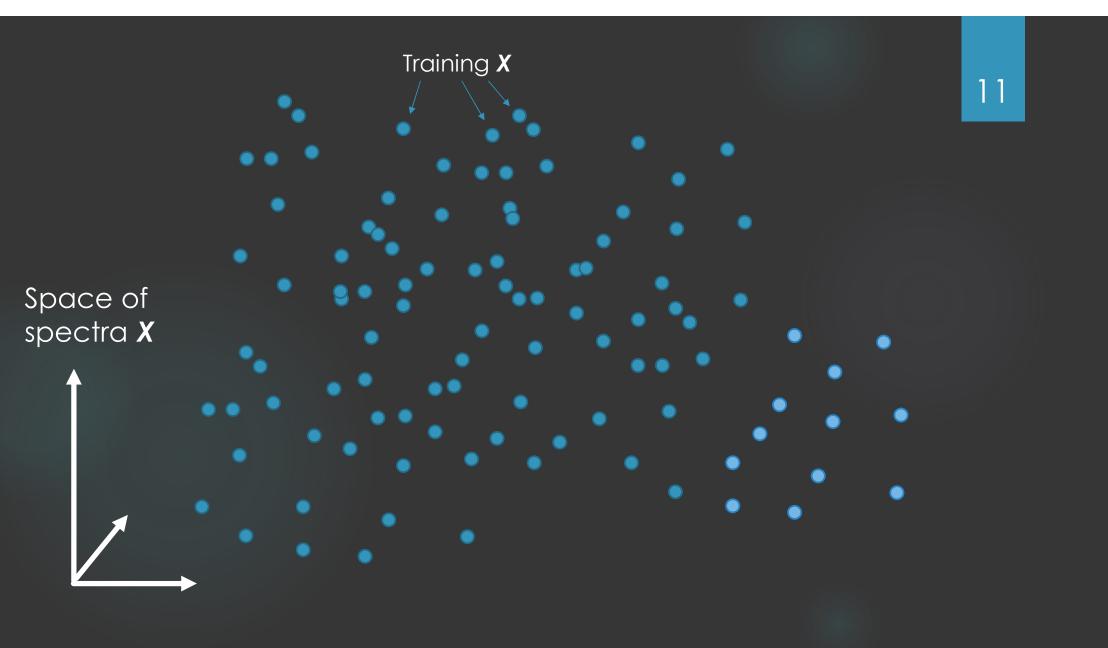
Local PLSR ⇒ Local PLSR-AVG

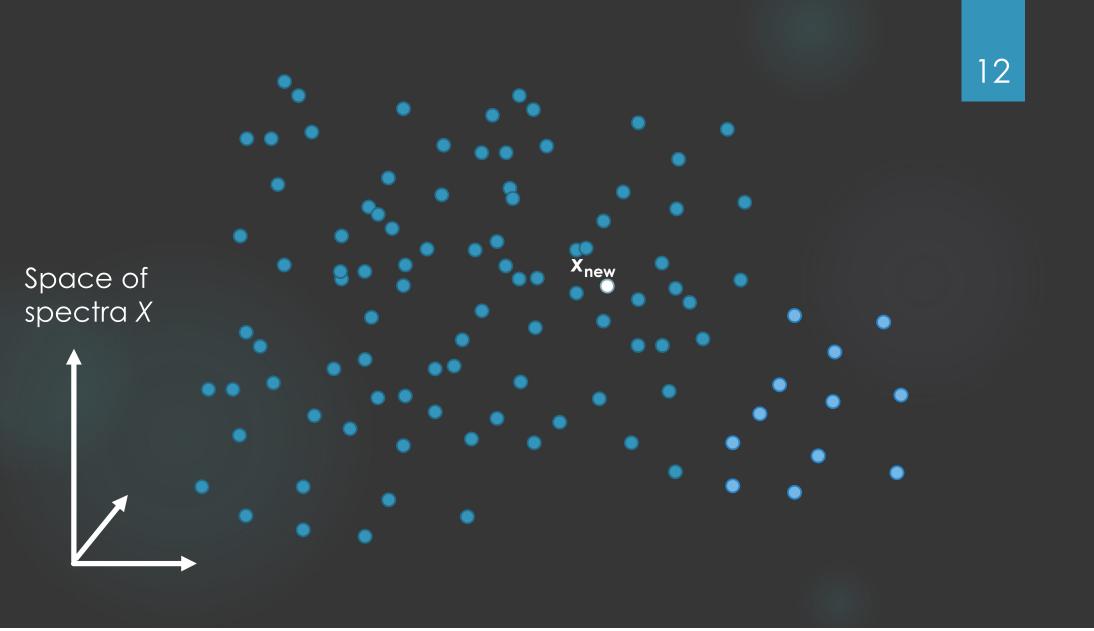
2. One local PLSR pipeline (*): kNN-LWPLSR

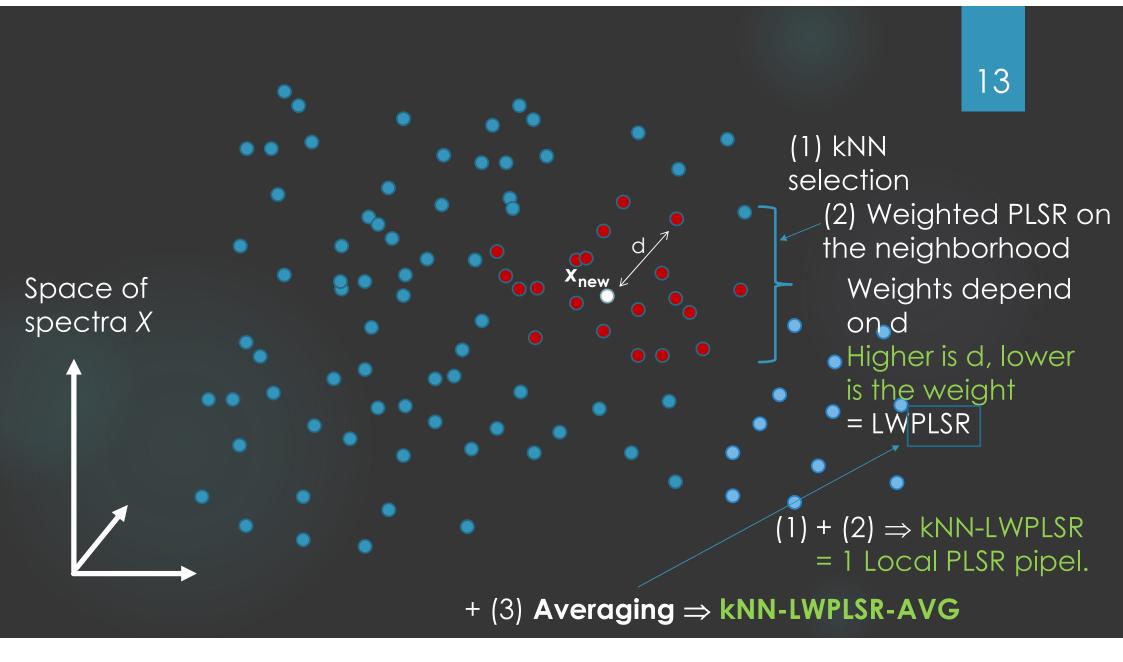
k nearest neighbors - locally weighted PLSR

Lesnoff et al. 2020 J. Chemometrics https://doi.org/10.1002/cem.3209

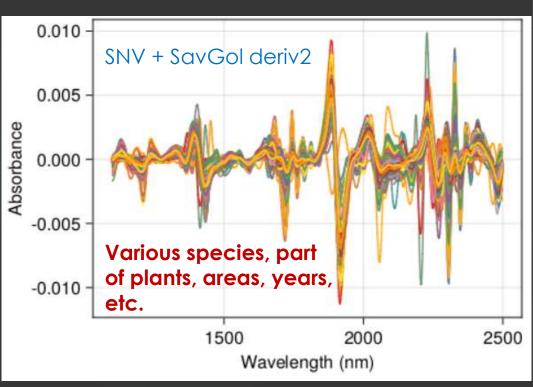
(*) Many other pipelines are possible

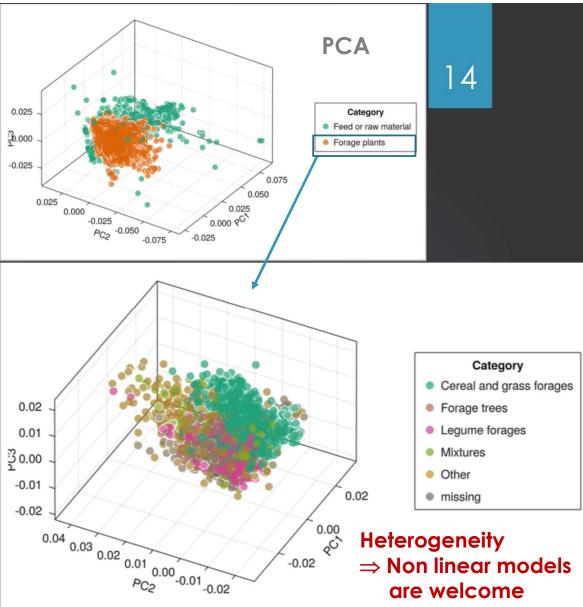






NIR Foss 1100-2498 nm step = 2 nm





Available

12 variables to predict (chemical composition)

Abbreviation	Unit	Variable	N
DM	%	Dry matter	17714
ASH	%DM	Mineral matter	17299
CP	%DM	Crude protein	16295
EE	%DM	Crude fat	7004
CF	%DM	Crude fiber	13006
NDF	DM	Neutral detergent fiber	10414
ADF	%DM	Acid detergent fiber	11097
ADL	%DM	Acid detergent lignin	10809
DMDCELL	%DM	DM enzymatic digestibility	9043
OMDCELL	%DM	OM enzymatic digestibility	8713
STARCH	%DM	Starch	1919
SUGARS	%DM	Total sugars	2014

Compared models

I. knn-lwplsr

Usual CV tuning

⇒ Optimize Nb. LVs in the local PLSR models

II. kNN-LWPLSR-AVG Averaging over 0-20 LVs

For each variable

Available data $N \Rightarrow \text{Train} + 20\% \text{ Test} \text{ (random)}$

Train ⇒ Cal + 20% Val (random)
 Tuning

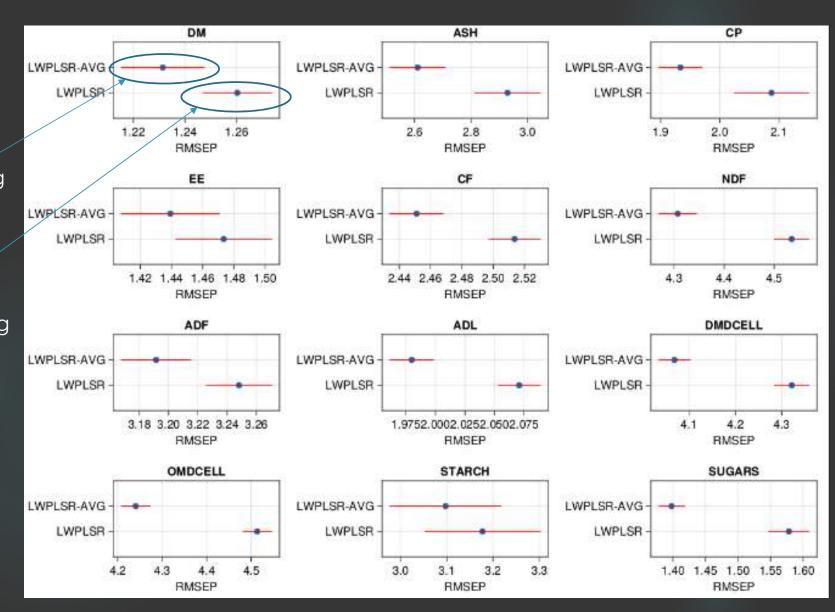
Test error (RMSEP_{test})

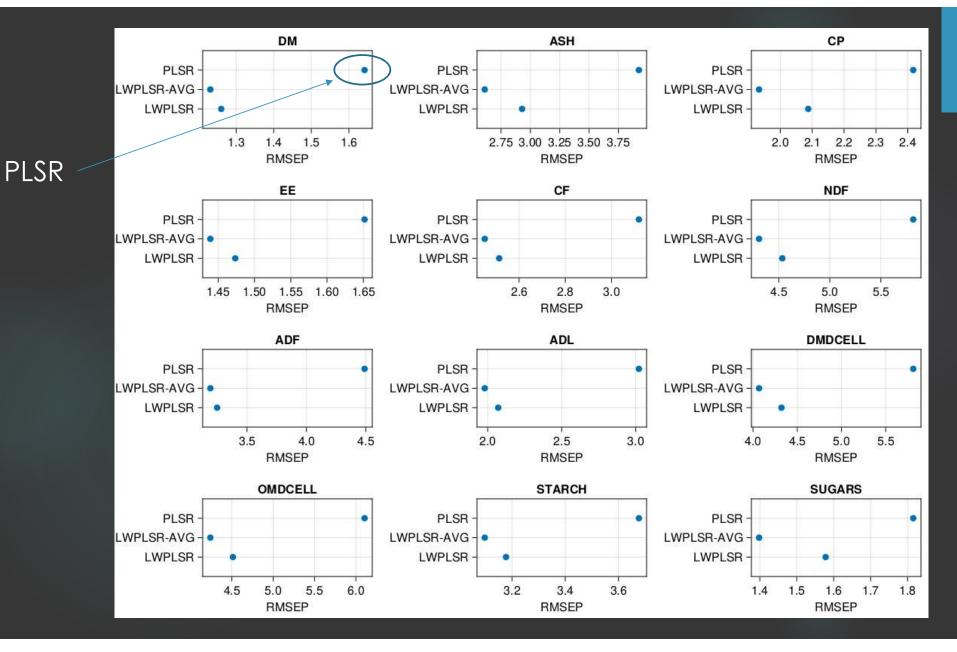
30 replica-

Test errors

Averaging 0-20 LVs

Usual CV No averaging





Averaging in PLSR is not very new ...

- Shenk, J., Westerhaus, M., Berzaghi, P., 1997 Investigation of a LOCAL calibration procedure for near
 infrared instruments. Journal of Near Infrared Spectroscopy 5, 223. https://doi.org/10.1255/jnirs.115
- Zhang, M.H.; Xu, Q.S.; Massart, D.L. 2004 Averaged and Weighted Average Partial Least Squares. Anal. Chim. Acta, 504, 279–289
- Silalahi, D.D.; Midi, H.; Arasan, J.; Mustafa, M.S.; Caliman, J.-P. **2020** Automated Fitting Process Using Robust Reliable Weighted Average on Near Infrared Spectral Data Analysis. *Symmetry*, 12, 2099
- Lesnoff, M., Andueza, D., Barotin, C., Barre, P., Bonnal, L., Fernández Pierna, J.A., Picard, F., Vermeulen, P., Roger, J.-M., **2022** Averaging and Stacking Partial Least Squares Regression Models to Predict the Chemical Compositions and the Nutritive Values of Forages from Spectral Near Infrared Data. *Applied Sciences* 12, 7850

Six datasets of tropical and European forages

⇒ demonstrates PLSR-AVG efficiency for forages data

The present study confirmed the results

PLSR averaging belongs to a general frame:

"model averaging"

model 1 \hat{y}_1

model 2 \hat{y}_2

model 3 \hat{y}_3

• • •

 $model K \hat{y}_K$

$$\hat{y}_{avg} = \theta_0 \ \hat{y}_{[0]} + \theta_1 \hat{y}_{[1]} + \dots + \theta_A \hat{y}_{[A]}$$

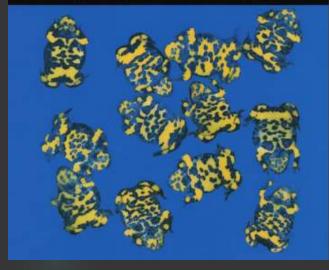
Often

 $Var(\hat{y}_{avg,i}) < Var(\hat{y}_{[k],i})$



MODEL SELECTION AND MULTIMODEL INFERENCE
A Practical Information-Theoretic Approach
SECOND EDITION

KENNETH P. BURNHAM . DAVID R. ANDERSON



Conclusions

- Averaging in local PLSR is in general beneficial
 - For heterogeneous materials such as mixed plants (information everywhere over the wavelengths)
 - Less efforts of tuning interesting when automatized prediction platforms
 - Fast algorithm if uniform weighting
- Can also be used for (a) multivariate Y (PLS2),
 and (b) kNN-LWPLSDA (but I observed less performance gains)



Available in package Jchemo

https://github.com/mlesnoff/Jchemo.jl

« Dimension reduction, Regression and Discrimination for Chemometrics »

lwplsr
lwmlr
lwplsr
lwmlr_s
lwplsr_s
lwplsravg kNN-LWPLSR-AVG

Local regression pipelines

Can be installed from the official Julia repo

Exists also on R Cran Package rchemo

(slower)



Thank you for your attention