

PLS regression and PARAFAC2

Less used but useful

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Outline

The short version!

1. Multiway regression
2. PARAFAC2



TRICAP 2003



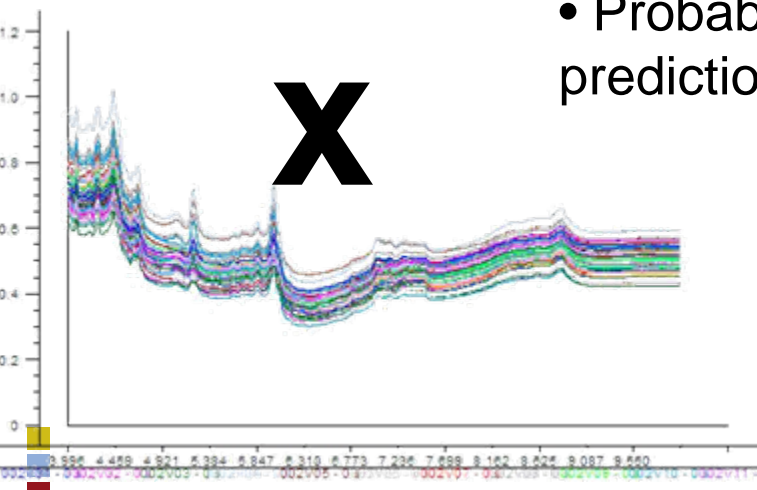
Chemometric Regression

$$\min_b \|y - Xb\|_F^2$$

Example: Online determination of activity of antidepressant

$b = X^+y$ does not work

- Collinearity
- X is probably around rank 10-20 plus some 40 pure noise components
- Probably only a rank 4-10 part is needed for optimal predictions



Fast method for determination measuring directly on the tablet
Near infrared spectra (X, 780 variables) - 10000-4000 cm⁻¹ (1000-2500 nm), Water content from lab (y)
Courtesy, Lundbeck A/S

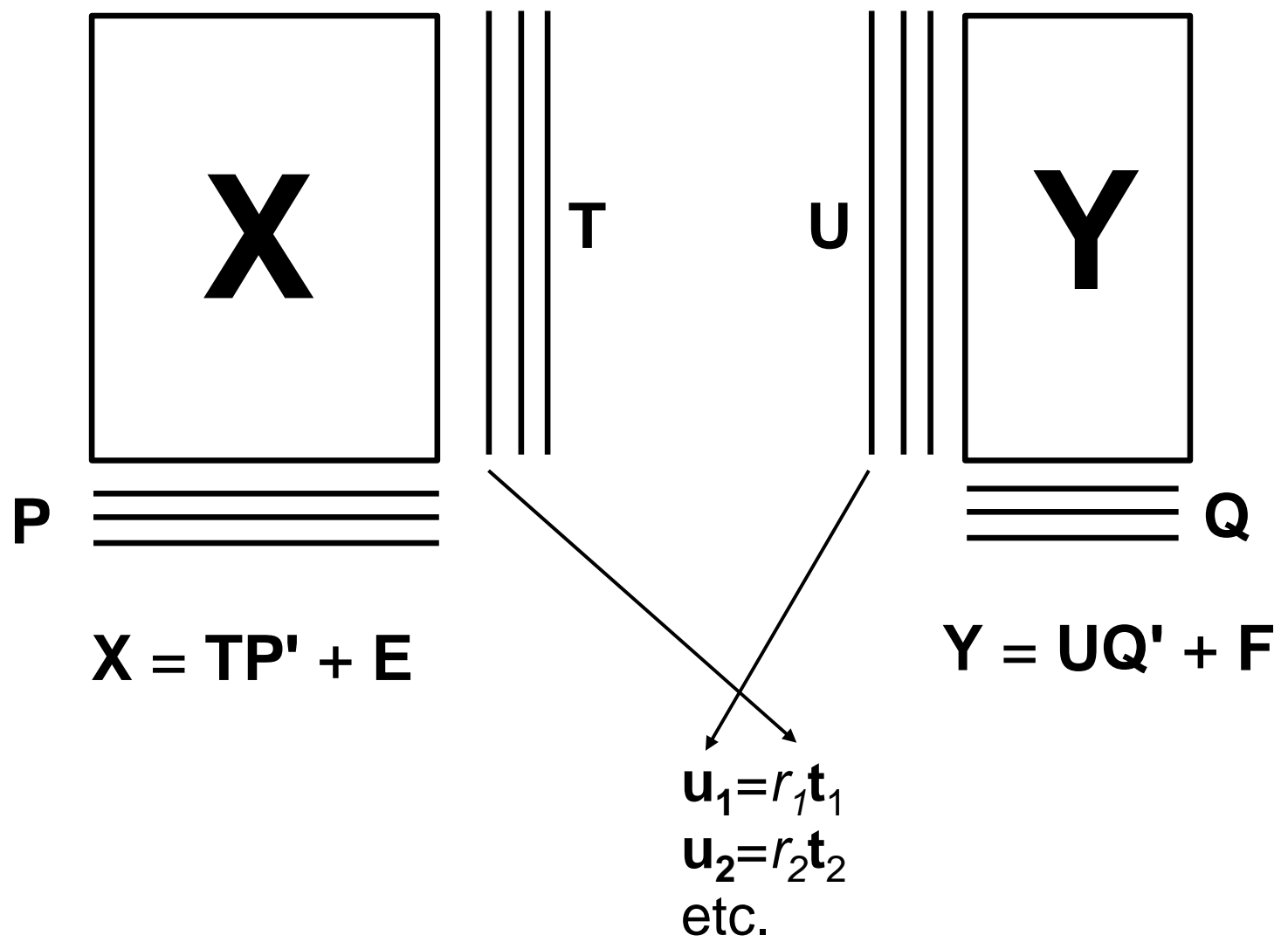
PLS regression

Two-way PLS principle

- Find \mathbf{w} ($\|\mathbf{w}\|=1$) and \mathbf{q} ($\|\mathbf{q}\|=1$) such that the one-component models of $\mathbf{X} = \mathbf{t}\mathbf{w}' + \mathbf{E}_x$ and $\mathbf{Y} = \mathbf{u}\mathbf{q}' + \mathbf{E}_y$ have maximal covariance ($\mathbf{t}'\mathbf{u}$)
- Predict \mathbf{u} from \mathbf{t} (t_r)
- Subtract the model from \mathbf{X} ($\mathbf{t}\mathbf{w}'$) and predictions from \mathbf{Y} ($\mathbf{t}\mathbf{r}\mathbf{q}'$)
- Proceed with the next component from residuals



PLS – Partial Least Squares regression



PLS – Partial Least Squares regression

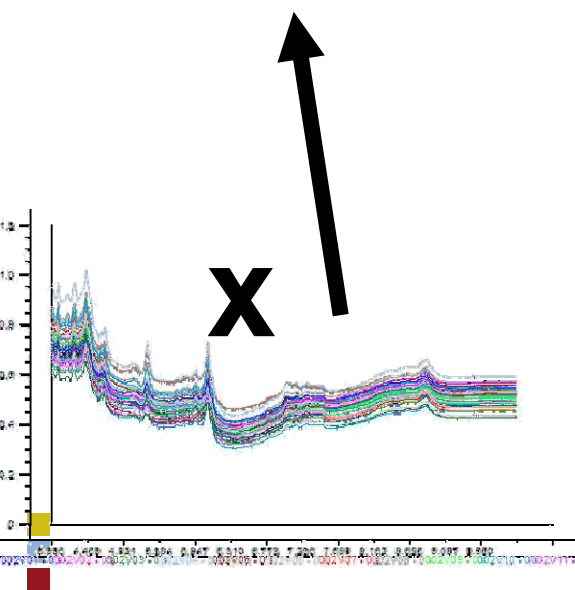
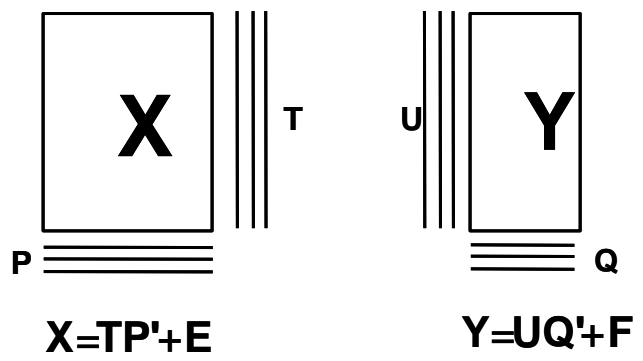
Two-way PLS: how to do it - one y.

$$\begin{aligned} & \max_w \left[\text{cov}(\mathbf{t}, \mathbf{y}) \mid \mathbf{t} = \mathbf{X}\mathbf{w} \right] = \text{Max covariance} \\ & \max_w \left[\mathbf{t}'\mathbf{y} \mid \mathbf{t} = \mathbf{X}\mathbf{w} \right] = \text{LS model} \\ & \max_w \left[\mathbf{y}'\mathbf{X}\mathbf{w} \right] = \\ & \max_w \left[\mathbf{z}'\mathbf{w} \right] \Rightarrow \\ & \mathbf{w} = \frac{\mathbf{X}'\mathbf{y}}{\|\mathbf{X}'\mathbf{y}\|} \end{aligned}$$

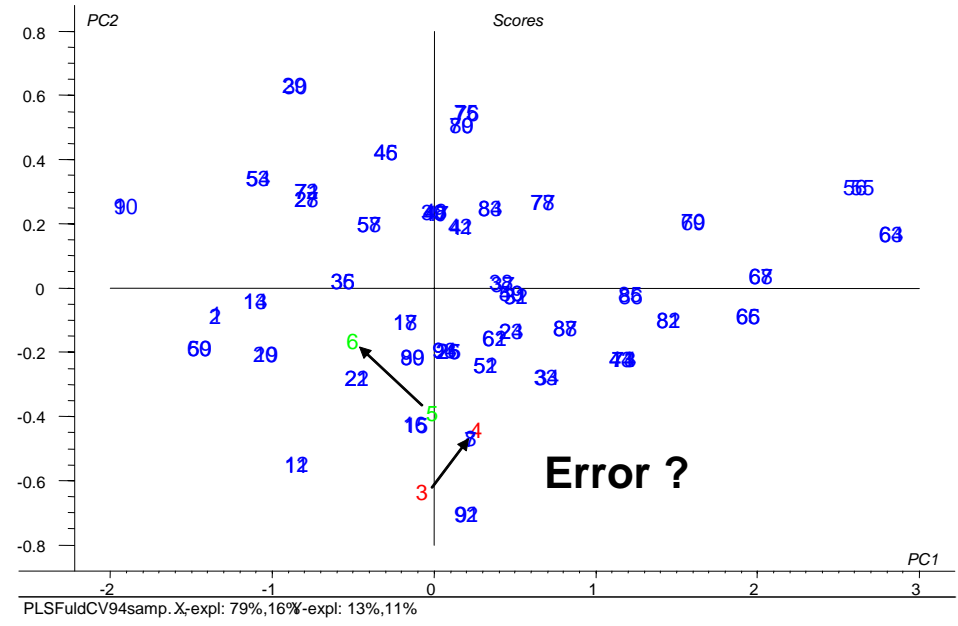


PLS – what's the advantage

Outlier check
 Plus variable importance
 Plus much more



T(:,2)



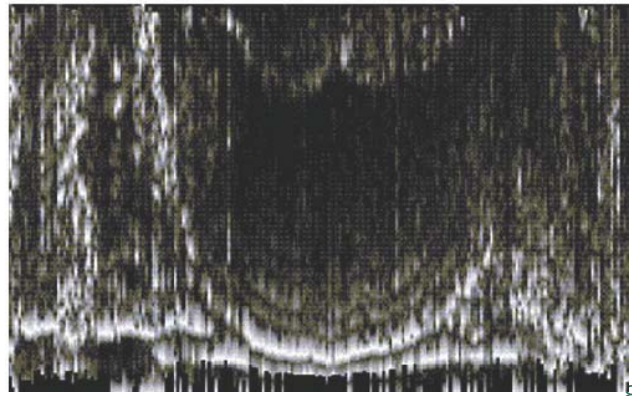
T(:,1)

Chemometric Regression

Another typical example

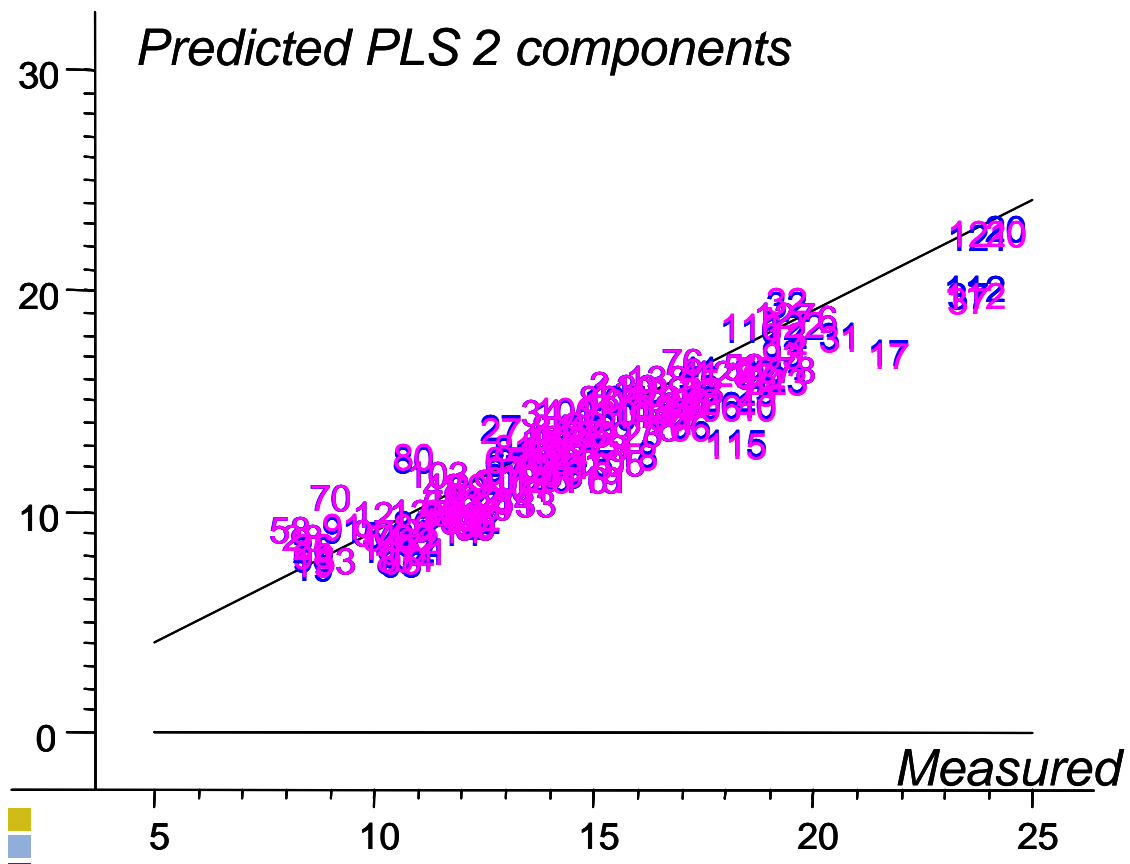
Up to 1200 carcasses per hour

One sample of ??

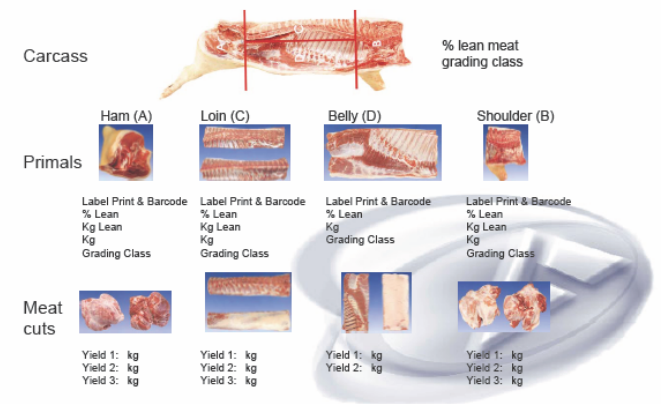


Chemometric Regression

Fat Thickness



AutoFom - Concept



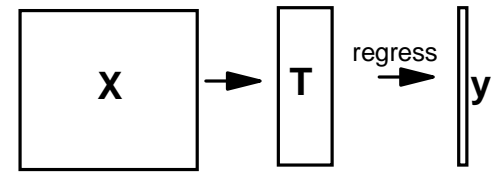
Extending PLS to multi-way

N-PLS (N-way PLS)

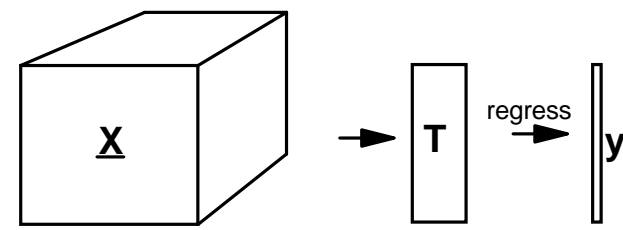
N-PLS

- For two-way data a bilinear model is used
- For three-way data a trilinear model is used

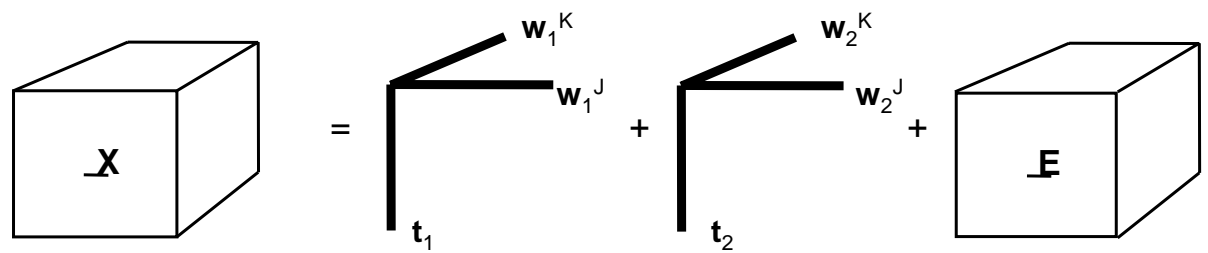
PLS



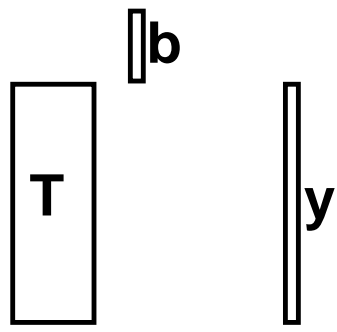
N-PLS



Three-way PLS regression



- Use a trilinear (PARAFAC-like) model of X but such that the scores are predictive of y .



PLS – Partial Least Squares regression

Two-way PLS: how to do it - one y.

$$\max_w \left[\text{cov}(\mathbf{t}, \mathbf{y}) \mid \mathbf{t} = \mathbf{X}\mathbf{w} \right] =$$

Max covariance

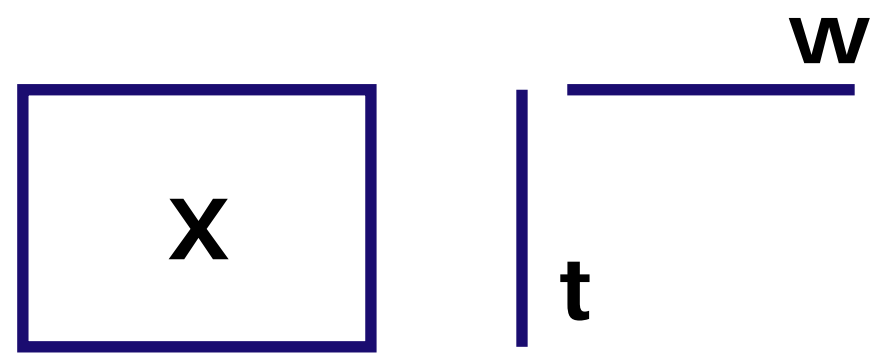
LS model

$$\max_w \left[\mathbf{t}'\mathbf{y} \mid \mathbf{t} = \mathbf{X}\mathbf{w} \right] =$$

$$\max_w \left[\mathbf{y}'\mathbf{X}\mathbf{w} \right] =$$

$$\max_w \left[\mathbf{z}'\mathbf{w} \right] \Rightarrow$$

$$\mathbf{w} = \frac{\mathbf{X}'\mathbf{y}}{\|\mathbf{X}'\mathbf{y}\|}$$



PLS - Partial Least Squares regression

Three-way PLS

Two-way PLS: how to do it - one y.

Same thing but now there are two weight vectors for each component, one for each variable mode

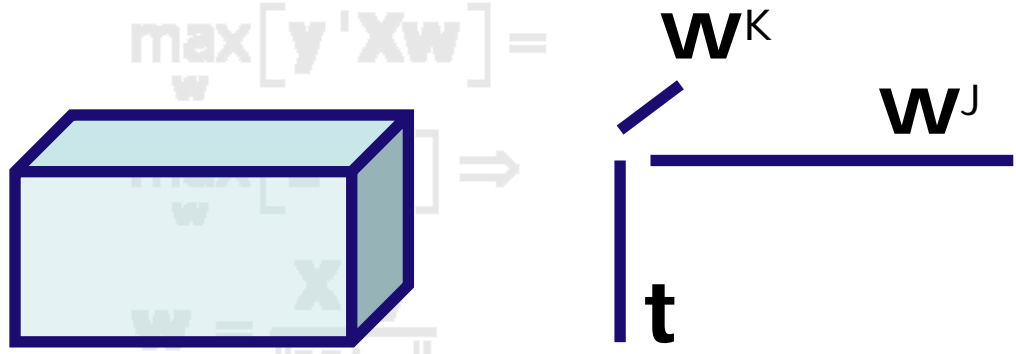
$$\max_w [\text{cov}(t, y) \mid t = Xw] =$$

Max covariance

$$\max_w [t'y \mid t = Xw] =$$

LS model

$$\max_w [y'Xw] =$$



Three-way PLS regression

Three-way PLS: how to do it - one y .

$$\max_{\mathbf{w}^J \mathbf{w}^K} \left[\text{cov}(\mathbf{t}, \mathbf{y}) \mid t_i = \mathbf{w}^J \mathbf{X}_i \mathbf{w}^K \right] =$$

$$\max_{\mathbf{w}^J \mathbf{w}^K} \left[\mathbf{t}^T \mathbf{y} \mid t_i = (\mathbf{w}^J)^T \mathbf{X}_i \mathbf{w}^K \right] =$$

$$\max_{\mathbf{w}^J \mathbf{w}^K} \left[(\mathbf{w}^J)^T \mathbf{Z} \mathbf{w}^K \mid z_{jk} = \mathbf{y}^T \mathbf{x}_{jk} \right] \Rightarrow$$

SVD on \mathbf{Z}

Three-way PLS: how to do it - one y.

Table 1. Matlab code for tri-PLS1 regression of y ($I \times 1$) on (centred) X ($I \times JK$)

```

e=y;                                % initialize
for lv=1:LV                          % for each factor
    Z=reshape(e'*X,J,K);              % vector of covariances→matrix
    [wJ, wK]=svd(Z);                  % find weights maximizing covariance
    WJ=[WJ wJ(:,1)];                  % save weights J-mode
    WK=[WK wK(:,1)];                  % save weights K-mode
    T=[T X*kron(wK(:,1),wJ(:,1))];    % save scores I-mode
    b=inv(T'*T)*T'*y;                 % y loadings wrt T
    e=y - T*b;                         % residual y
end
bNPLS=0;
for 1v=1:LV
    bNPLS=bNPLS+kron(WK(:,1v),WJ(:,1v))*b(1v); %regression coeffs
end

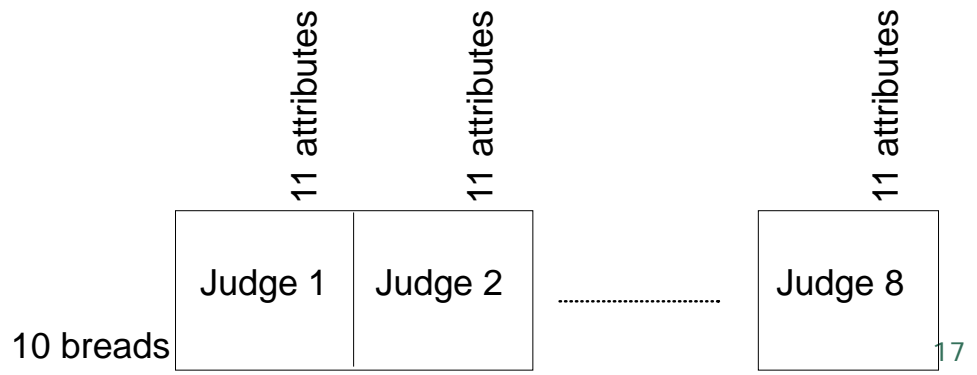
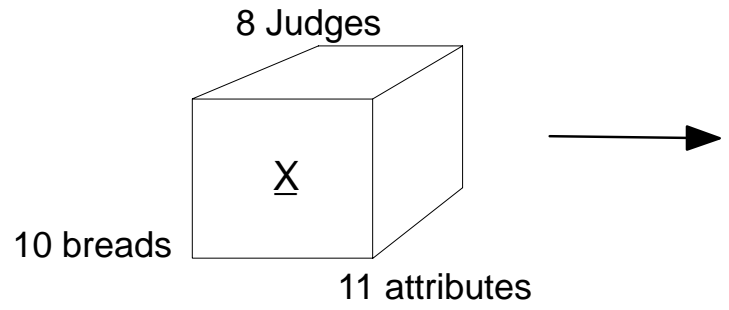
```

N-PLS regression

Example sensory data

Three-way, two-way:
Does it make a difference?

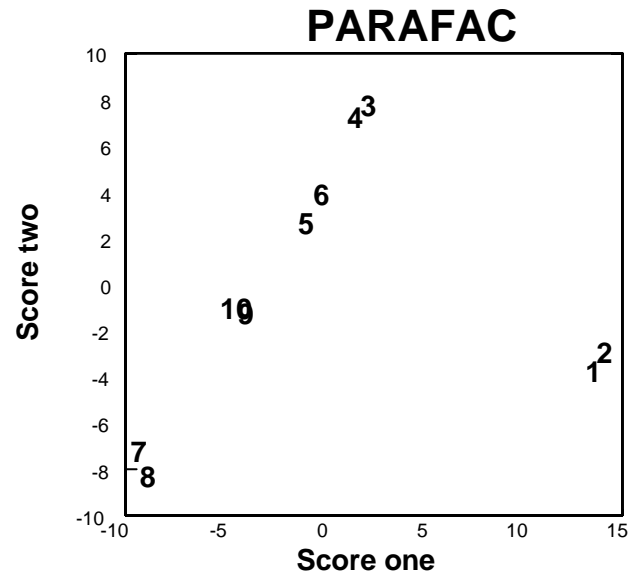
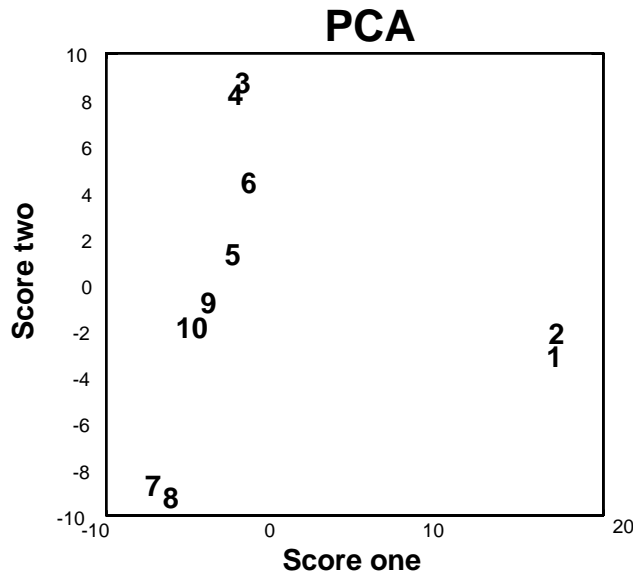
5 breads (in replicates) × 11 attributes × 8 judges
Data due to Magni Martens



Sensory data

Scores from bilinear PCA and trilinear PARAFAC

Three-way more robust because of 'stronger' structural model

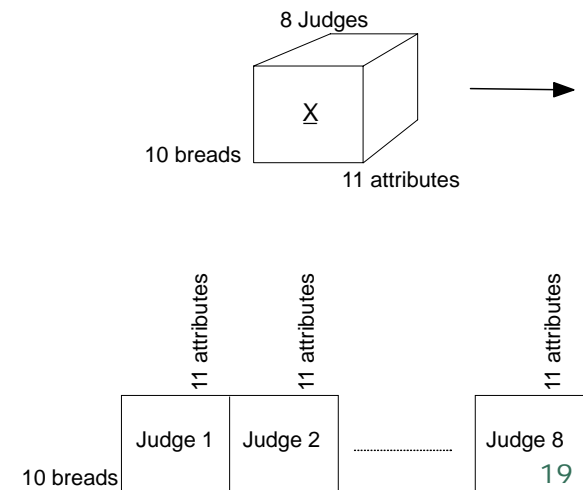


Similar but note that replicates are closer for PARAFAC

Cross-validation

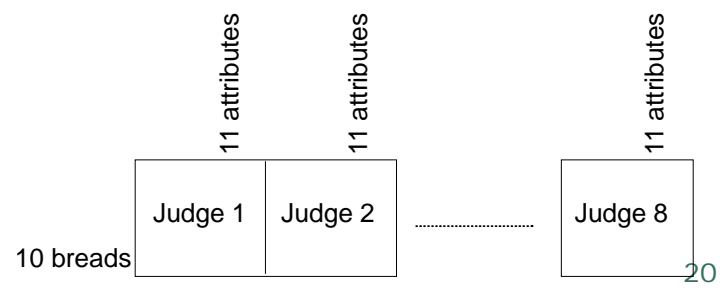
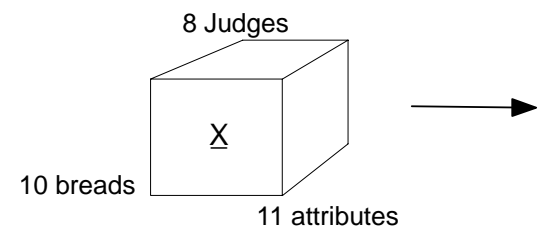
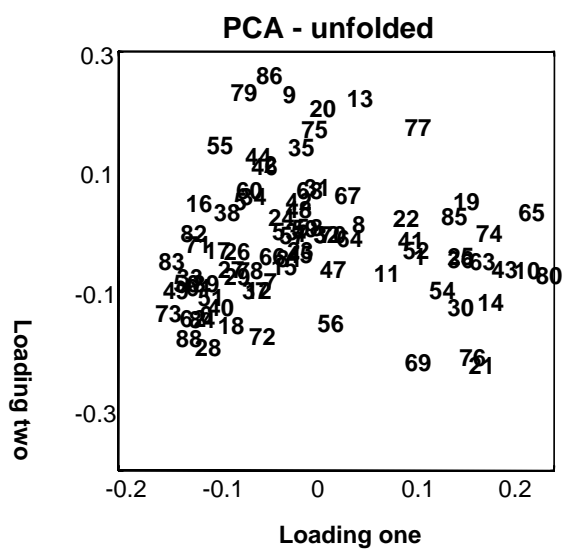
- PARAFAC fits worse but provide best predictions
- Thus nothing gained going to more complex PCA

Number of components	PARAFAC		PCA	
	<i>Fit</i>	<i>Cross-val</i>	<i>Fit</i>	<i>Cross-val</i>
1	35.3	14.5	44.6	13.2
2	49.2	26.2	65.8	26.5
3	57.4	32.9	74.3	18.6



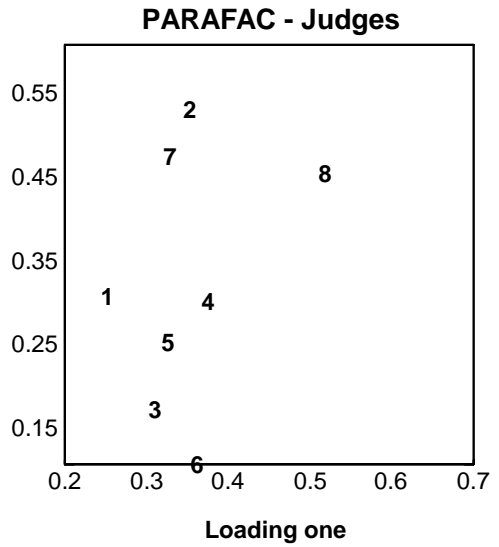
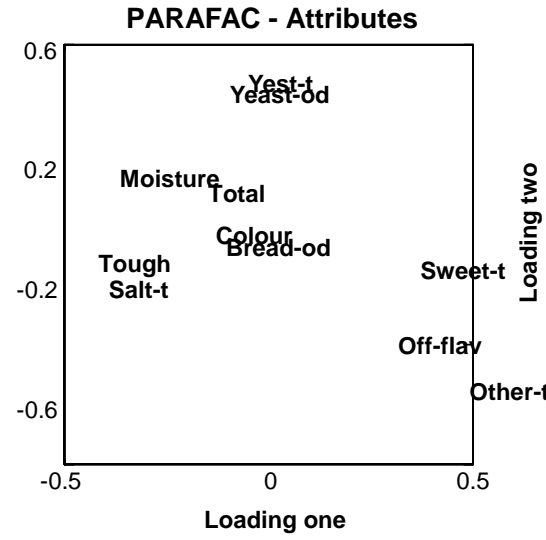
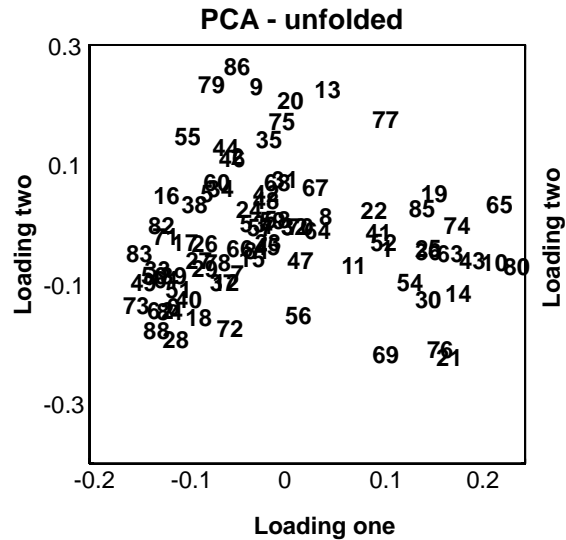
Sensory data

Loadings from bilinear PCA



Sensory data

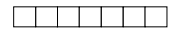
Loadings from bilinear PCA and trilinear PARAFAC



PARAFAC 19 loading-elements per component
PCA 88 loading-elements per component!

Sensory data

- Calibration - predict salt content



unfold-PLS





Trilinear PLS



Sensory data

- Calibration - predict salt content
 - 25% improvement!!

	LV	Variation explained /%				RMSE	
		X cal.	X val.	Y cal.	Y val.	Y cal.	Y val.
 unfold-PLS	1	43	25	80	62	0.21	0.29
	2	61	38	95	76	0.10	0.23
	3	74	49	100	84	0.03	0.19
 Trilinear PLS	1	31	22	75	60	0.23	0.30
	2	46	36	93	82	0.12	0.20
	3	54	44	98	91	0.07	0.15

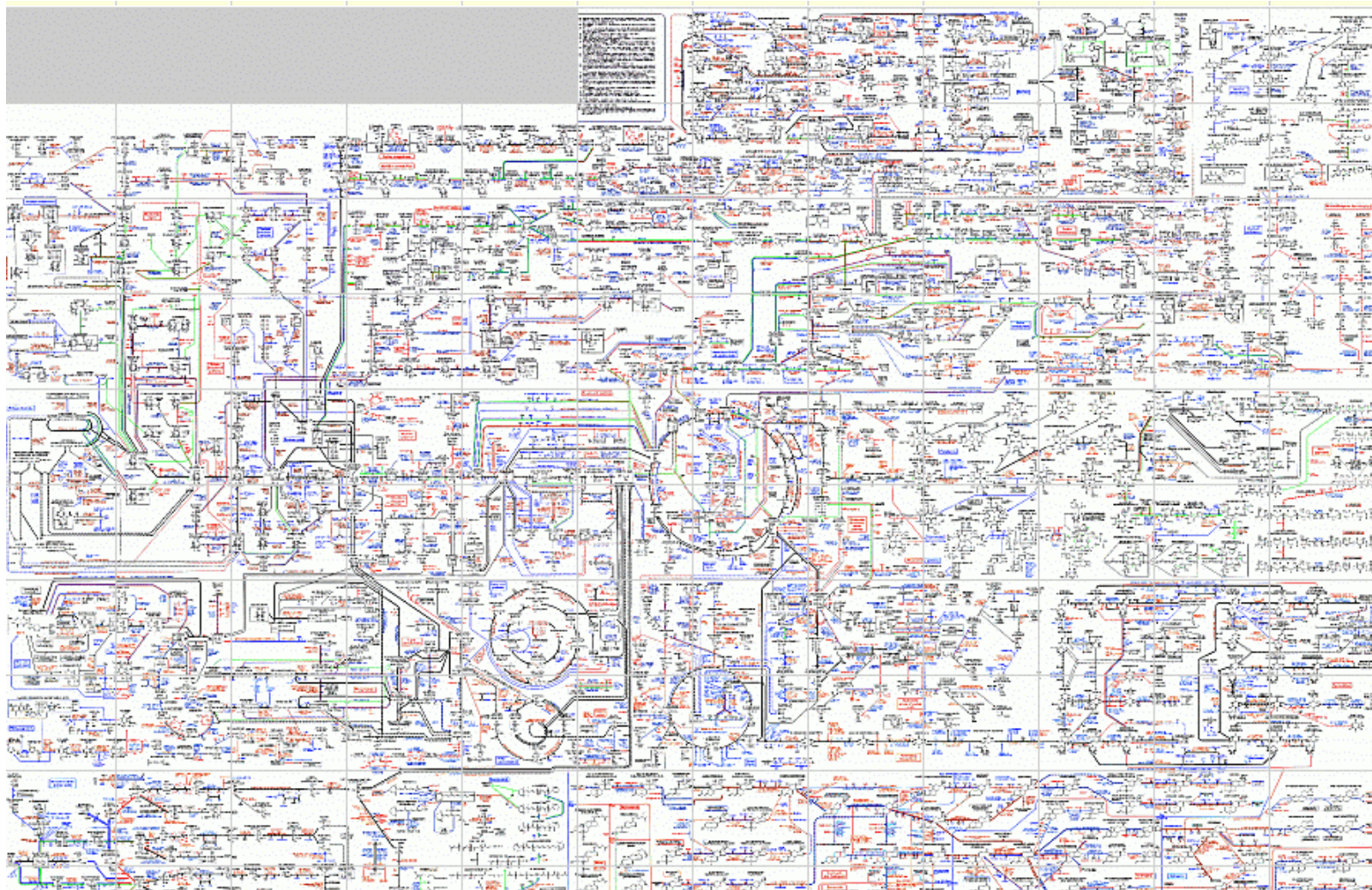
Three-way more predictive
because less overfit



Multi-way analysis in metabonomics

Metabonomics “the systematic study of the unique chemical fingerprints that specific cellular processes leave behind”.

A simplified view on
metabolic pathways



Herbal medicine

Exploring hypericum

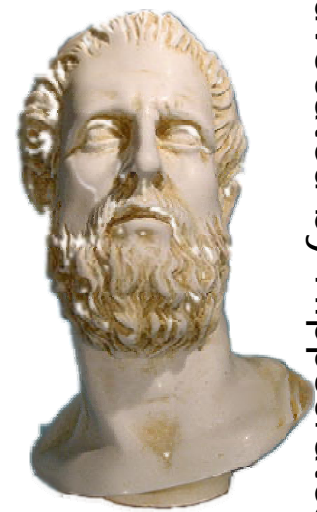
The mechanism by which St. John's Wort acts as an antidepressant is not fully understood.

The antidepressant or mood elevating effects of St. John's Wort were originally thought to be due solely to hypericin

http://www.holistic-online.com/Herbal-Med/_Herbs/h20.htm



Hypericum perforatum = St. John's wort



Advocated by Hippocrates

Herbal medicine



Available online at www.sciencedirect.com
SCIENCE @ DIRECT®
Life Sciences 73 (2003) 627–639

Life Sciences
www.elsevier.com/locate/lifescie

Several compounds seem essential

Step by step removal of hyperforin and hypericin: activity profile of different *Hypericum* preparations in behavioral models

Veronika Butterweck^{a,*}, Volker Christoffel^c, Adolf Nahrstedt^b, Frank Peterleit^b,
Barbara Spengler^c, Hilke Winterhoff^a

time in a dosage of 500 mg/kg after acute as well as after repeated treatment. The present results clearly show that an SJW extract free of hyperforin and hypericin exerts antidepressant activity in behavioral models, supporting our working hypothesis that flavonoids are part of the constituents responsible for the therapeutic

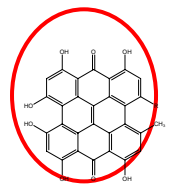
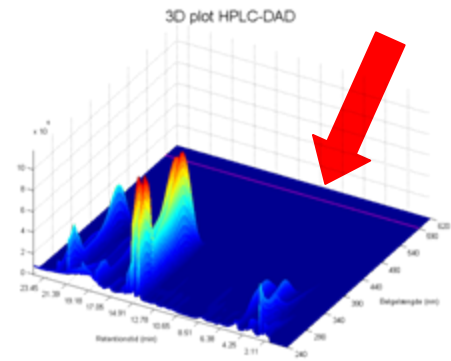
Rutin is Essential for the Antidepressant Activity of *Hypericum perforatum* Extracts in the Forced Swimming Test



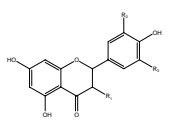
Rapid Co

Herbal medicine

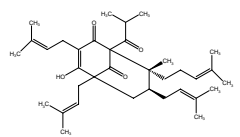
of clinical trials on the antidepressant effects of *Hypericum* for Hypericum extracts. This study evaluates the antidepressant standardized to contain 0.3% hypericin in comparison with different doses of two Hypericum extracts, of hypericin to detail immobile and active behaviors of rats during



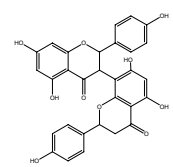
Naphthodianthrones
e.g. hypericin



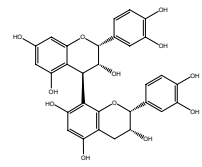
Flavonol glycosides
e.g. hyperoside



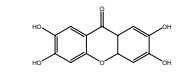
Phloroglucinol
e.g. hyperforin



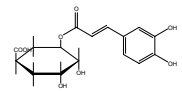
Biflavones
e.g. 13,118-biapigenin



Protoanthocyanidins
e.g. procyanidin B2



Xanthones
e.g. 1,3,6,7-tetrahydroxanthone



Propylalkans
e.g. chlorogenic acid

Still standardization of hypericum is done *only* with respect to hypericin!!

Problem:

Find a more satisfactory model of the relation between biochemistry and clinical effect

Solution:

Measure many different extracts with chemical fingerprinting (NMR,

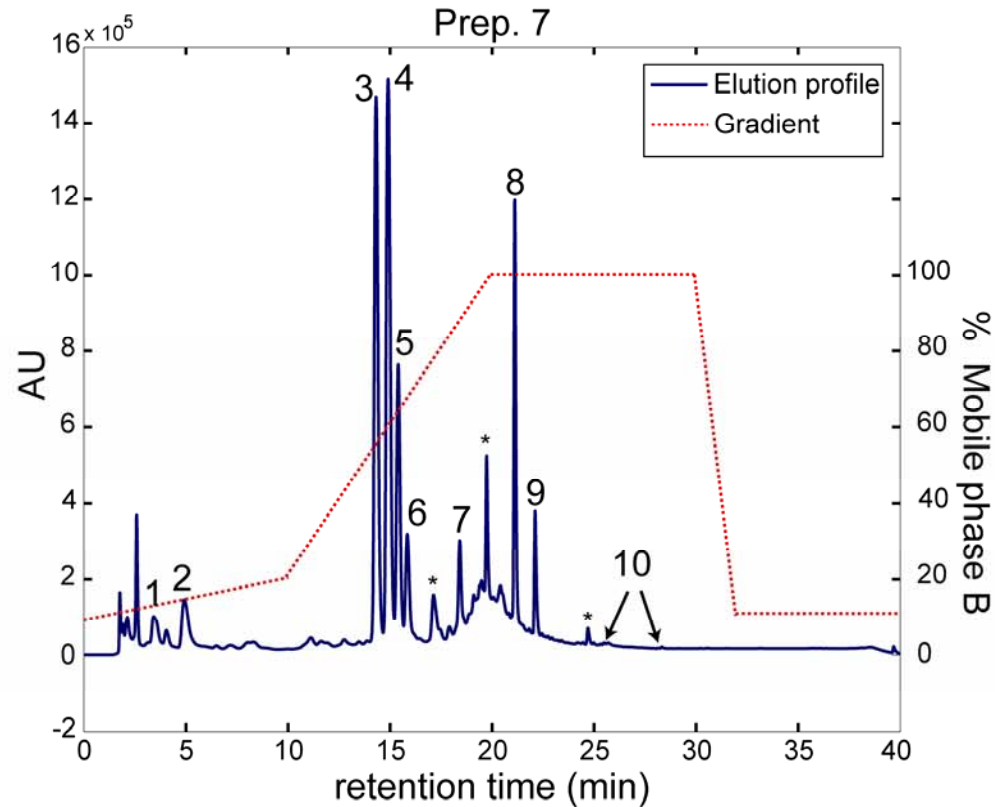
chromatography, etc.) and correlate to physiological effect

Here:

Chromatographic data are complicated and need special care

Herbal medicine

HPLC-UVVis for separation and identification



Mobile phases.

A: MeCN:H₂O 5:95 + 0.1% HCOOH

B: MeCN:H₂O 95:5 + 0.1% HCOOH

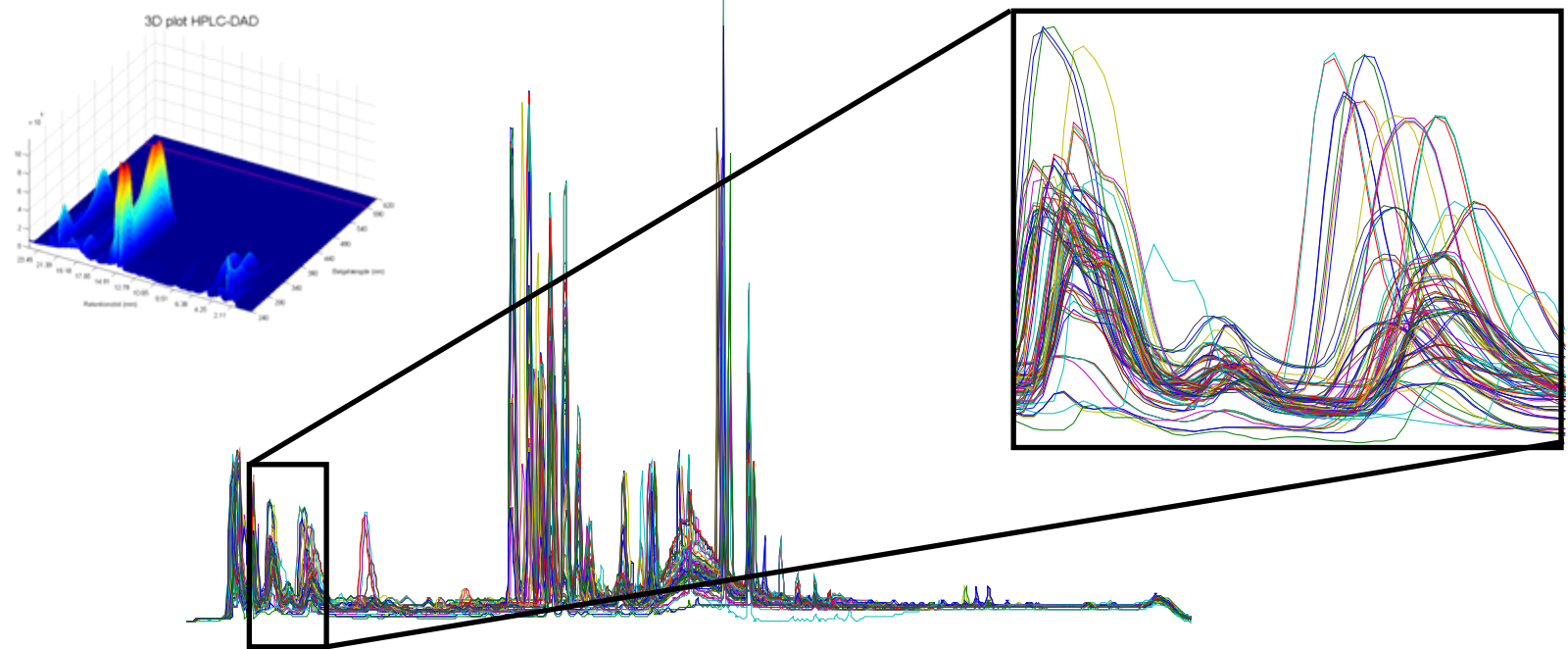
Assignment.

1. Chlorogenic acid derivative (extract structure unknown)
2. Chlorogenic acid
3. Rutin
4. Hyperoside
5. Isoquercetin
6. Quercetrin
7. Quercetin
8. I3-I8-biapigenin
9. Hypericins (extracts structures unknown)

* Structure unknown

Herbal medicine

Most peaks are identified but some are difficult

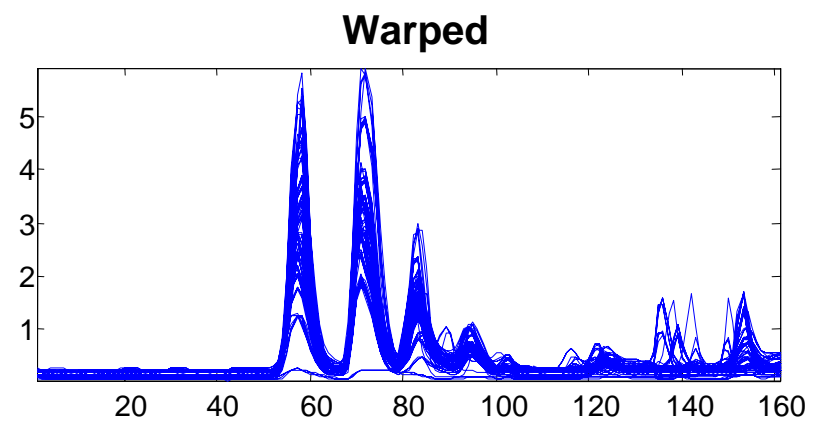
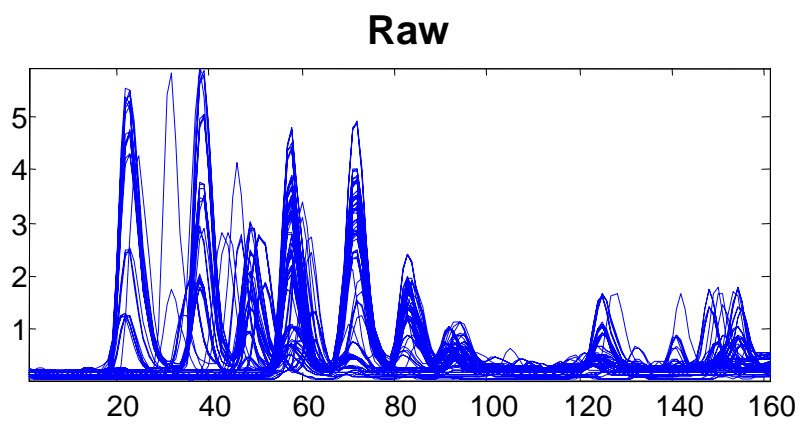


Summed profile of all samples



Herbal medicine

Warping to eliminate shift problems



JOURNAL OF CHEMOMETRICS
J. Chemometrics 2004; 18: 231-241
Published online 16 July 2004 in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/cem.859

Correlation optimized warping and dynamic time warping as preprocessing methods for chromatographic data

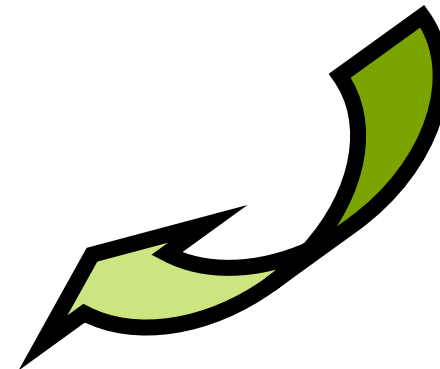
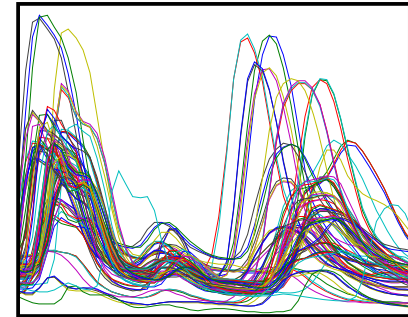
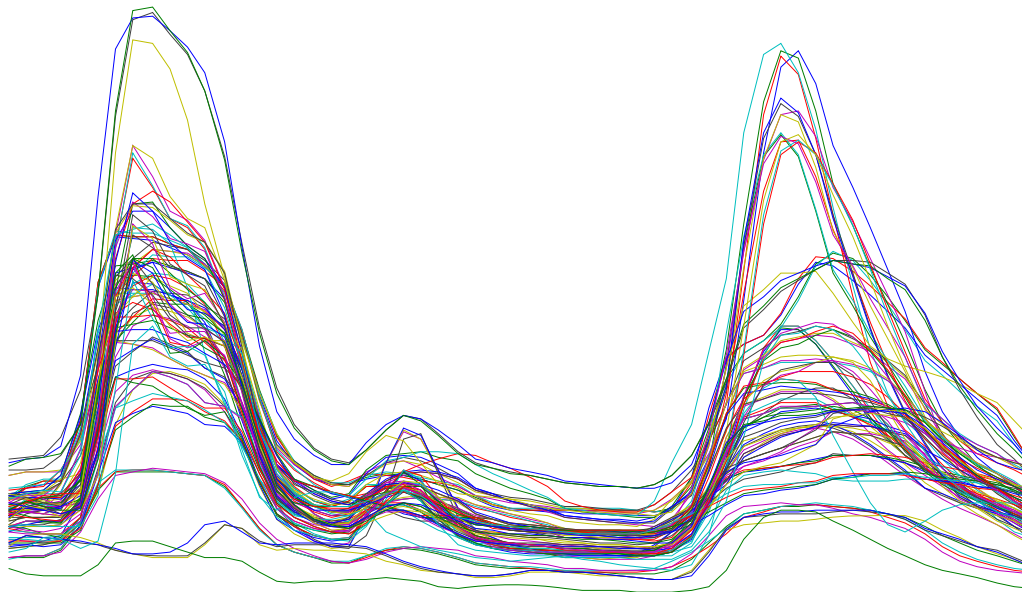
Giorgio Tomasi*, Frans van den Berg and Claus Andersson



Herbal medicine

Warping not always enough

2D warped data still have shape-difference



Herbal medicine

PARAFAC can not handle shifts and shape changes



PARAFAC(1) $\mathbf{X}_k = \mathbf{A}\mathbf{D}_k\mathbf{B}^T$



Herbal medicine

**Actually it is more general than shifts but it's a feasible approximation to what PARAFAC2 can handle*

PARAFAC2 for handling shifts*



PARAFAC2 $\mathbf{X}_k = \mathbf{A} \mathbf{D}_k \mathbf{B}_k^T$ subject to $\mathbf{B}_k^T \mathbf{B}_k$ constant

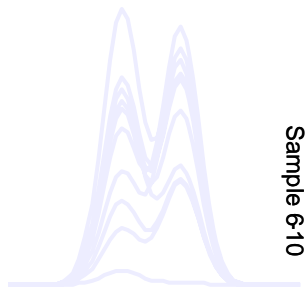
PARAFAC(1) $\mathbf{X}_k = \mathbf{A} \mathbf{D}_k \mathbf{B}^T$

R. A. Harshman. *UCLA working papers in phonetics* 22: 30-47, 1972.
H. A. L. Kiers, J. M. F. ten Berge, R. Bro. *J. Chemom.* 13:275-294, 1999.
R. Bro, C. A. Andersson, H. A. L. Kiers. *J. Chemom.* 13:295-309, 1999.



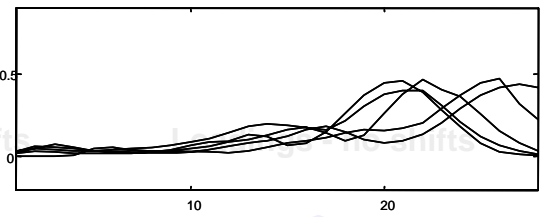
Herbal medicine

Elution profiles - no shifts

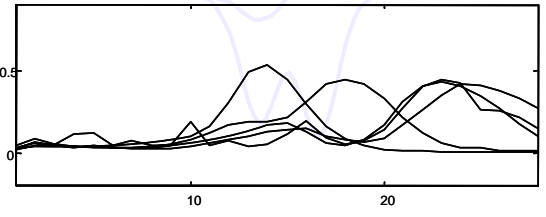


Sample 1-5

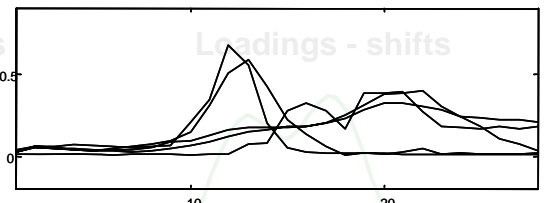
Reference



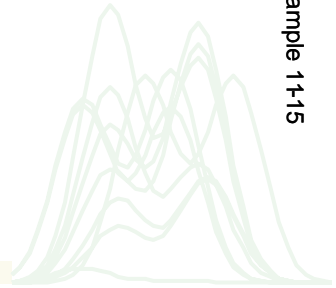
Sample 6-10



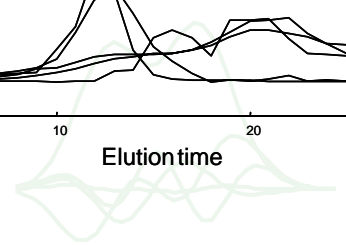
Sample 11-15



Elution profiles - shifts

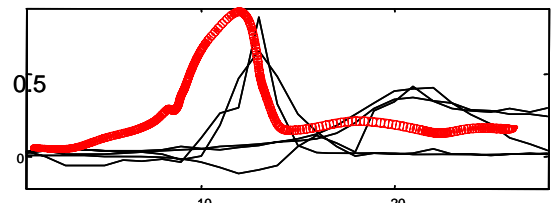
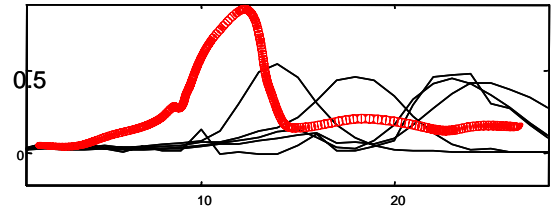
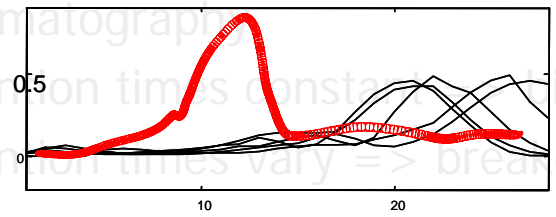


Loadings - shifts



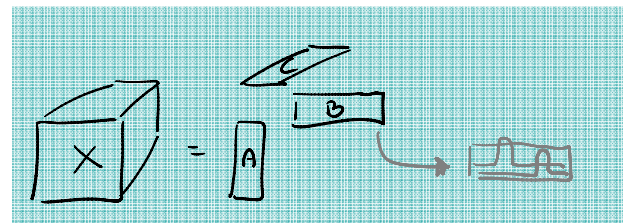
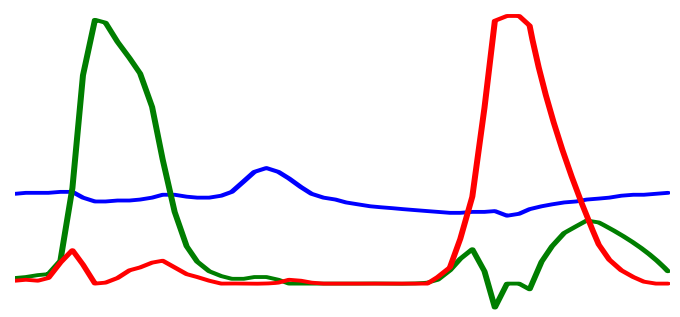
Two-way shifts Four-way PARAFAC2

- Chromatography
- Retention times constant => linear data
- Retention times vary => breakdown

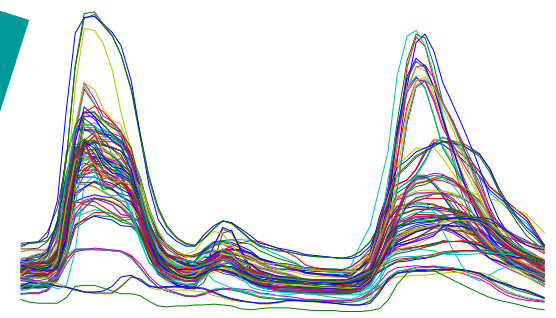
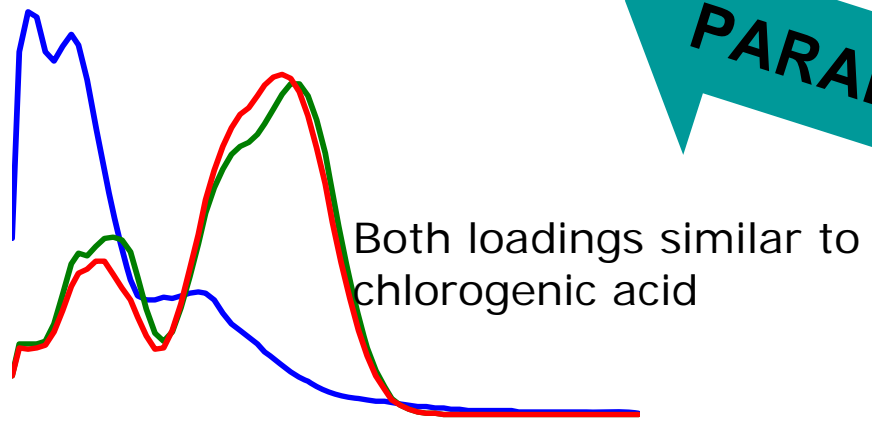


Herbal medicine

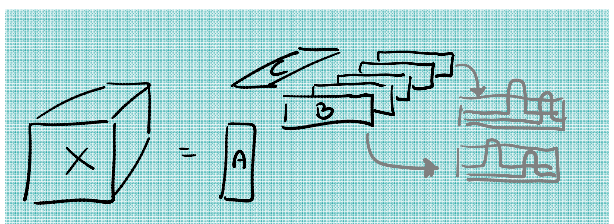
PARAFAC shows one eluent and two almost identical spectral peaks



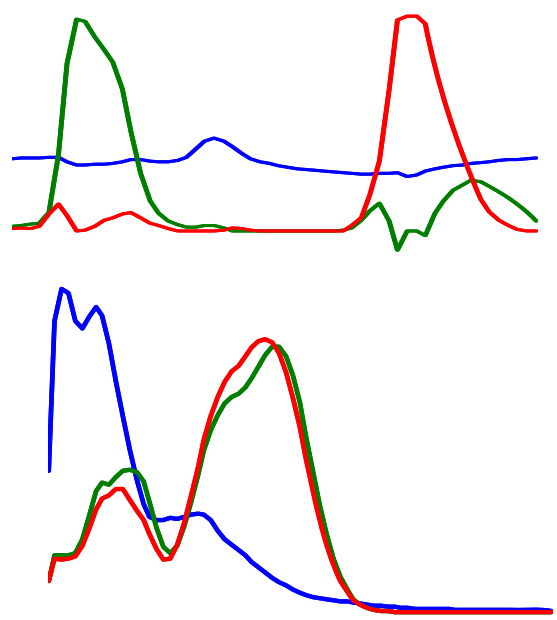
PARAFAC



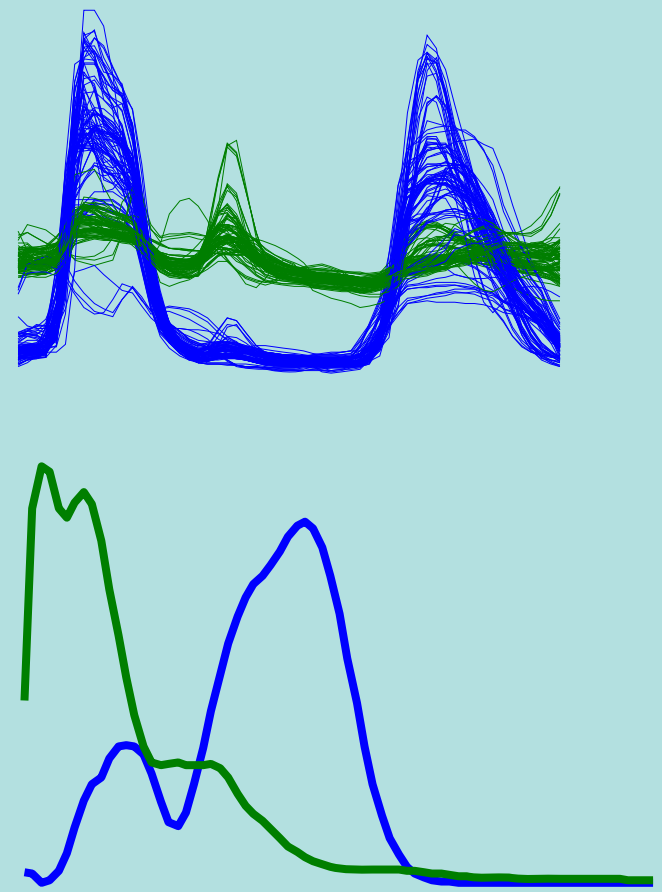
Herbal medicine



PARAFAC result from 93 samples



PARAFAC2 result from 93 samples



Herbal medicine

Next step:

Use PARAFAC,
Warping, PARAFAC2
to get concentrations
of specific chemicals

Perform clinical tests
and relate to
measured patterns

Perform verifying tests
based on results



The end

N-PLS Regression

Combines good predictions with powerful visual tools

PARAFAC2

Makes it possible to fit PARAFAC even when it's impossible!!!

**Multi-way papers, dissertations etc. available at
www.models.kvl.dk/tricap2006.zip**