

# SARTORIUS

## Simplifying Progress

### OPLS<sup>®</sup> in Process Modeling

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Senior Lecturer and Principal Data Scientist

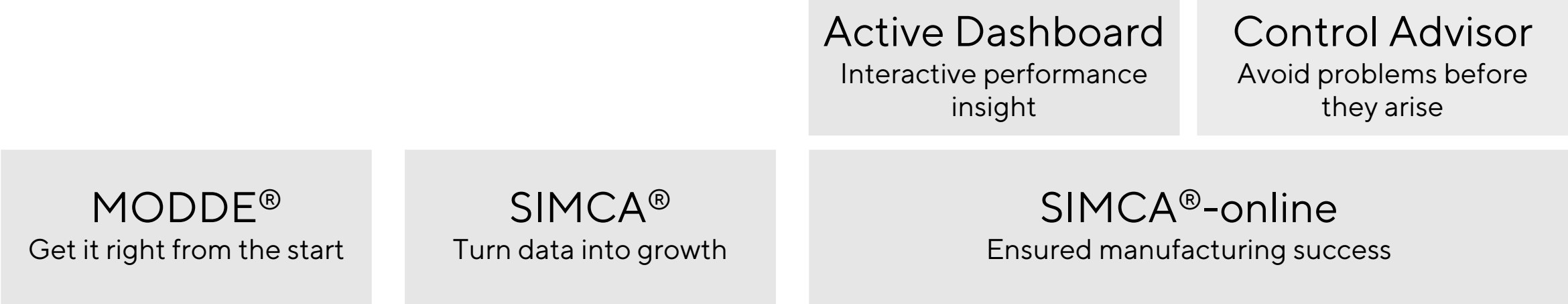


# Born in Data Analytics



- Company founded in 1987 by Professor Svante Wold, in Umeå, Sweden
  - Originator of Chemometrics and the SIMCA® Methodology
- Patented technologies in Design of Experiments and Multivariate Data Analysis
- We help our customers bring high-quality products to market faster
- Part of Sartorius Stedim Biotech since April 2017
- Products like MODDE®, SIMCA® and SIMCA®-online
- Global strength with local presence

# Business Growth Through the Entire Product Lifecycle



## Umetrics® Suite

Education/training and consulting  
Transferring expertise to you

# Upcoming Webinars

(<https://www.sartorius.com/en/company/exhibition-conferences>)

The screenshot displays a webinars page with a navigation bar at the top containing 'UPCOMING EVENTS', 'PAST EVENTS', 'CALENDAR', and 'SCHEDULE'. A search bar is located below the navigation. The main content area is divided into two columns of webinar cards. Each card features a green square icon, a 'STANDARD' tag, the webinar title, and the date and time. A vertical ellipsis menu is on the right of each card.

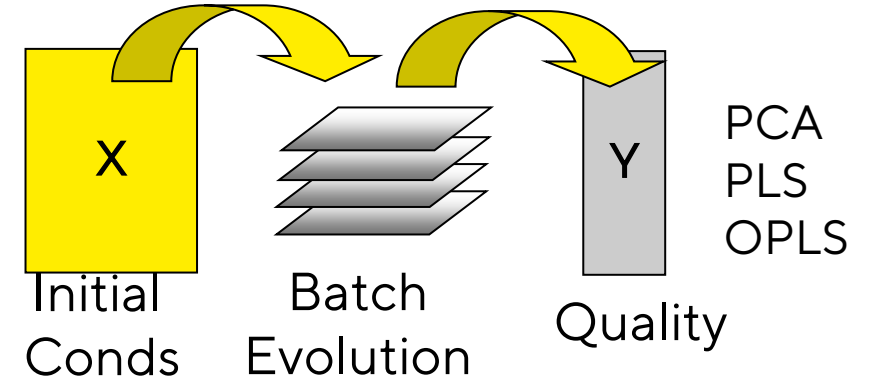
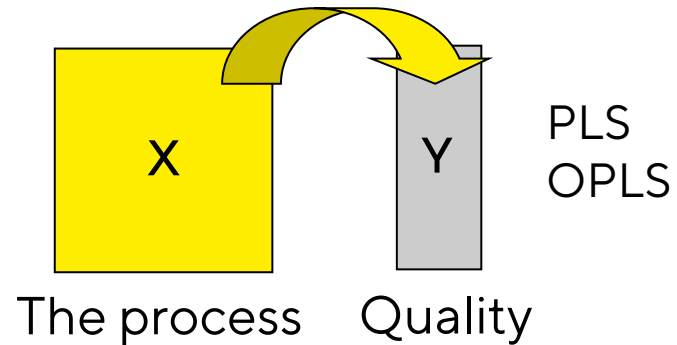
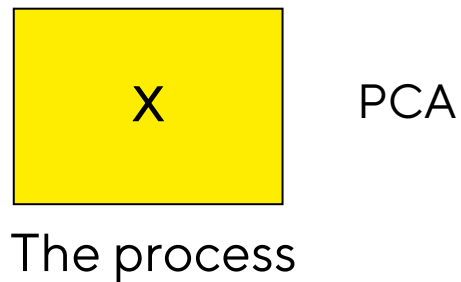
| Webinar Title   | Date              | Time                    |
|---|-------------------|-------------------------|
| Design of Experiments (DOE) for the Beginner  | TUE, JAN 26, 2021 | 03:00 PM - 04:00 PM CET |
| Multivariate Data Analysis (MVDA) for the Beginner                                  | THU, JAN 28, 2021 | 03:00 PM - 04:00 PM CET |
| Lean-and-clean DOE using One-click analysis   | TUE, FEB 16, 2021 | 03:00 PM - 04:00 PM CET |
| OPLS® in process modeling   | THU, FEB 18, 2021 | 03:00 PM - 04:00 PM CET |
| Robust optimization made easy   | TUE, MAR 2, 2021  | 03:00 PM - 04:00 PM CET |
| Analyzing batch process data, a step-by-step guide                                  | THU, MAR 4, 2021  | 03:00 PM - 04:00 PM CET |
| From Design of Experiments to Design Space Estimation                               | TUE, MAR 23, 2021 | 03:00 PM - 04:00 PM CET |
| Multiblock Orthogonal Component Analysis (MOCA) – A Novel Tool for Data Integration | THU, MAR 25, 2021 | 03:00 PM - 04:00 PM CET |

# Multivariate Process Data

- Monitoring a process
  - Early warning of disturbances
  - Diagnostics - finding "assignable causes"

- Modelling a process output
  - Monitor Quality of final product

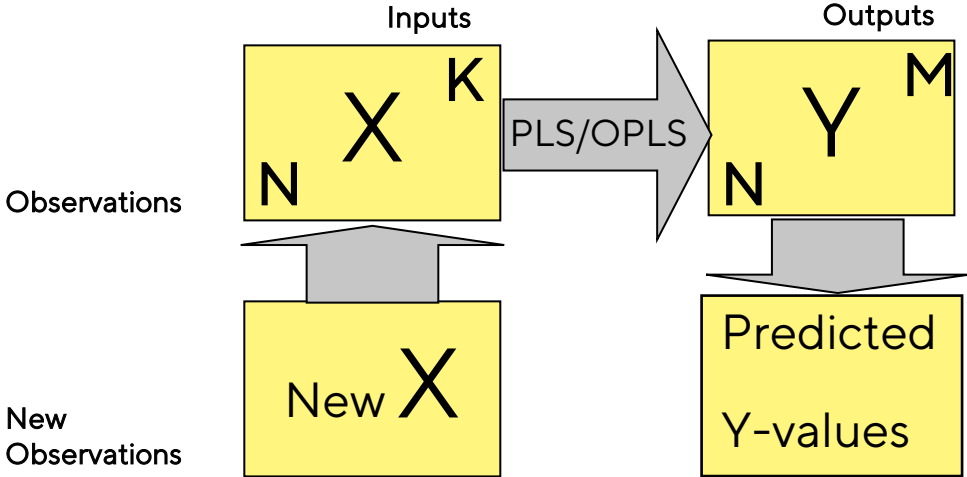
- Modelling Batch Processes
  - Majority of industrial processes
  - More complex analysis



# Schematic View of the Regression Problem

- Find relationships between sets of multivariate data X and Y

X - Inputs:  
Chemical measurements  
in Situ data  
Spectra  
Process data  
Chemical Composition data

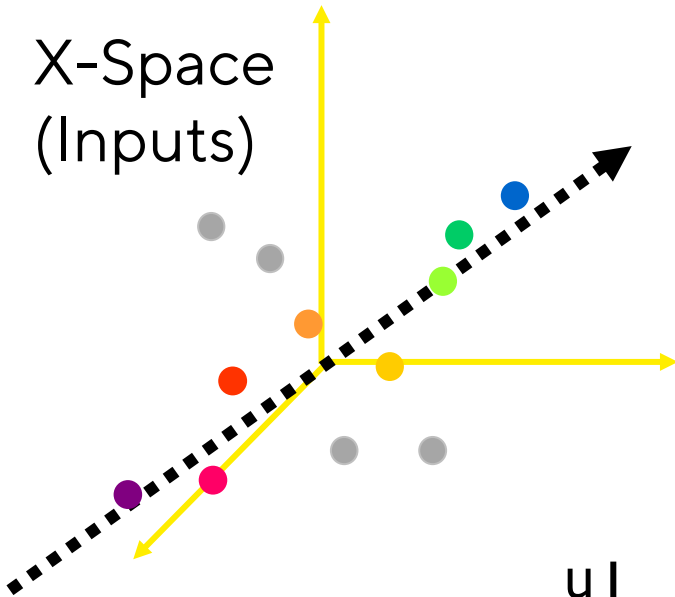


Y - Outputs:  
Yield  
Purity  
Quality  
Metrology  
Biological data

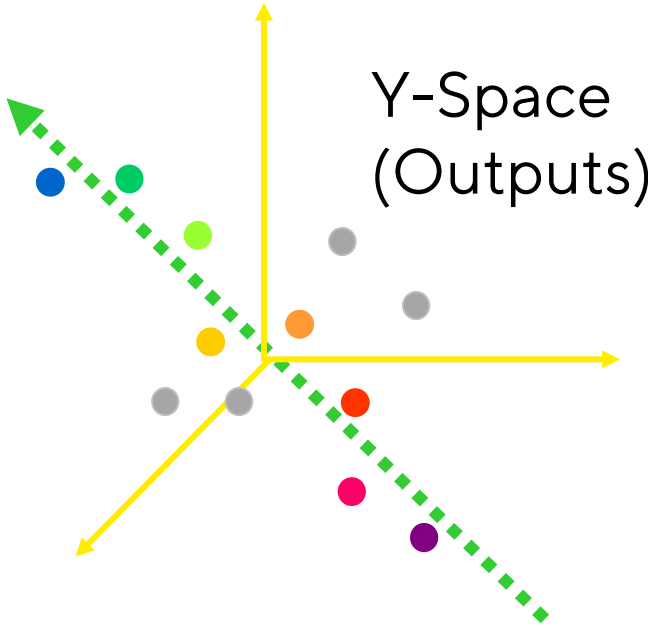
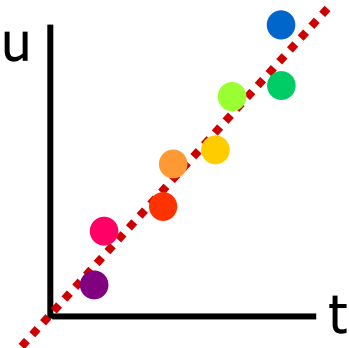
# Introduction to PLS/OPLS

- Relationships between two blocks of data (often called X and Y) can be explored by regression extensions of PCA, i.e. PLS and OPLS
- PLS (= Partial Least Squares) was originated around 1975
  - Refined around 1982-83
- An improvement called OPLS (= Orthogonal PLS) was presented 2002
  - OPLS offers enhanced model interpretation
  - PLS and OPLS models for single-Y are identical wrt to prediction

# Projection-Based Regression Modeling



Finds directions (here: colors) in X which are predictive of directions in Y

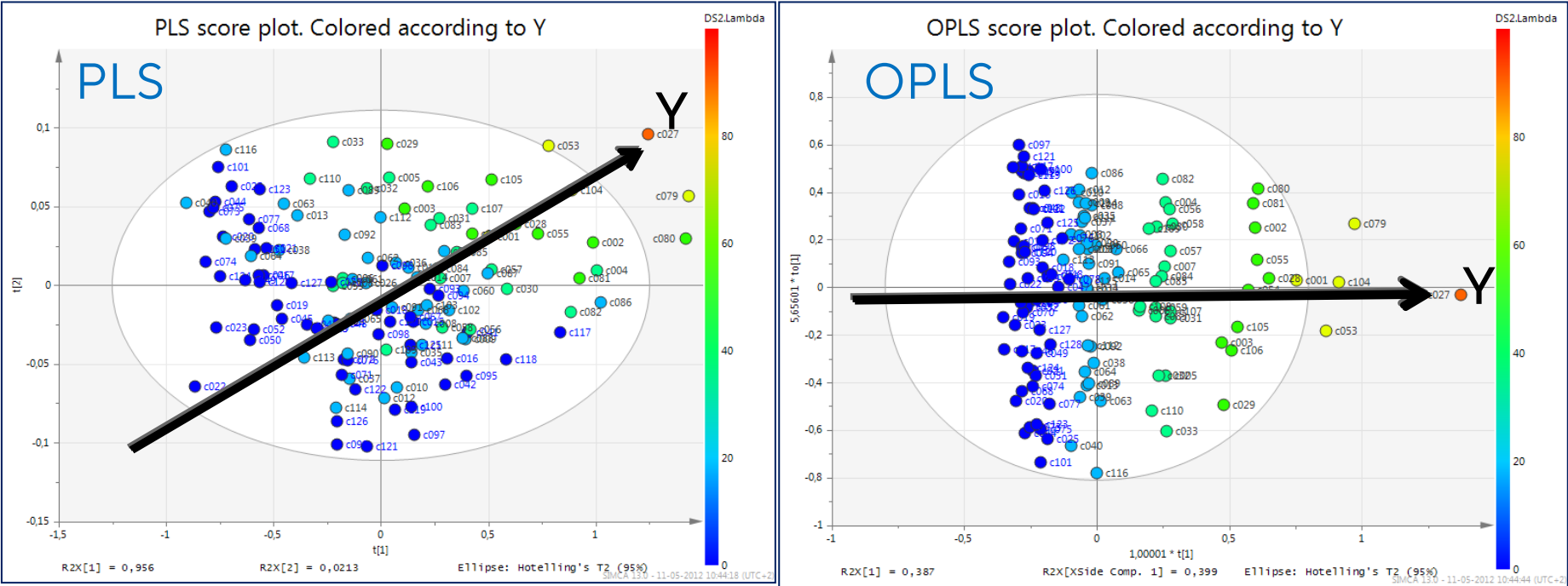


PLS works well when colored structures dominate; when gray structures dominate OPLS is needed to filter it out



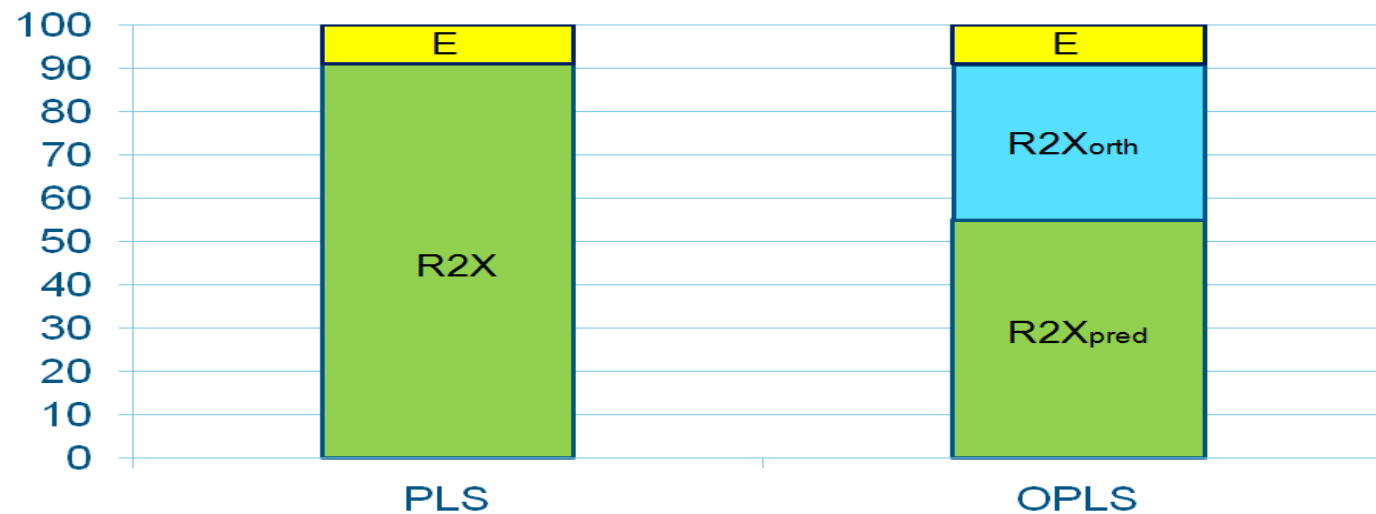
# Orthogonal-PLS (OPLS)

- A rotation or “transformation” of the PLS solution
  - OPLS and PLS models with single-Y and same number of components are equivalent; same predictive power

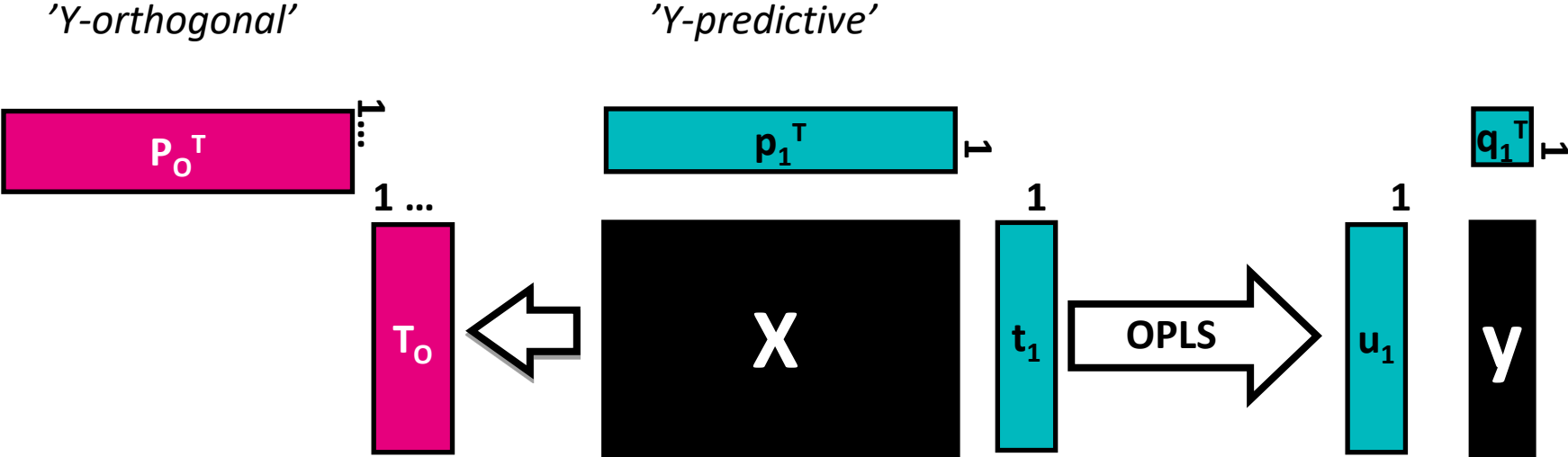


# OPLS Terminology

- PLS divides the variability in the X-matrix in two parts, the systematic variability and the residual variability.
- OPLS further splits the systematic variability,  $R^2X$ , in two parts, the part that is correlated (predictive) to Y and the part that is uncorrelated (orthogonal) to Y.



# OPLS Model Structure (Single-Y)



OPLS Model

$$\begin{cases} X = t_1 p_1^T + T_0 P_0^T + E \\ Y = t_1 q_1^T + F \end{cases}$$

# Example: Binary Powder I

- Mixing two powders with similar particle sizes which represents a common situation in pharmaceutical production
  - The two model powders are lactose and salicylic acid.
- Sample mixtures were prepared using salicylic acid/lactose mixtures in the range 45/55% (w/w) to 55/45% (w/w).
- Main reference: O Berntsson, LG Danielsson, MO Johansson, and S Folestad, Quantitative determination of content in binary powder mixtures using diffuse reflectance near infrared spectrometry and multivariate data analysis. *Analytica Chimica Acta*, 419 (2000) 45-54.

# Multivariate Process Data

- Monitoring a process

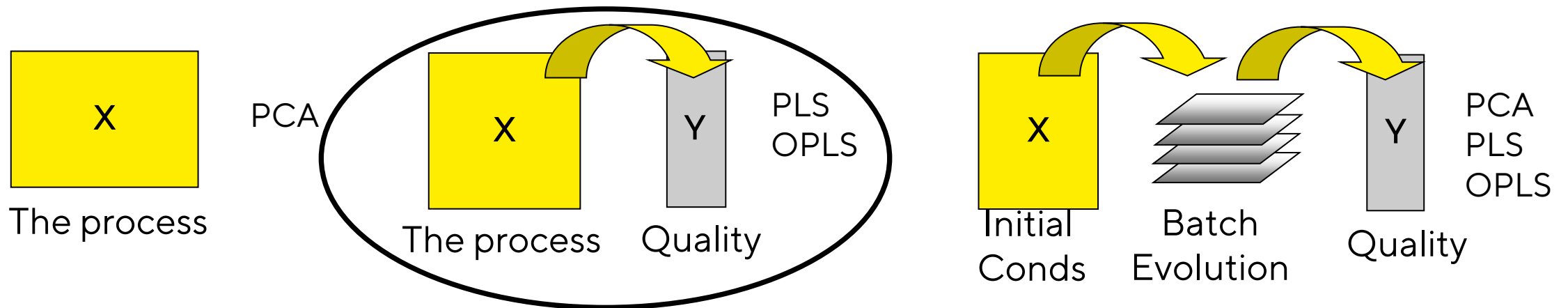
- Early warning of disturbances
- Diagnostics - finding "assignable causes"

- Modelling a process output

- Monitor Quality of final product

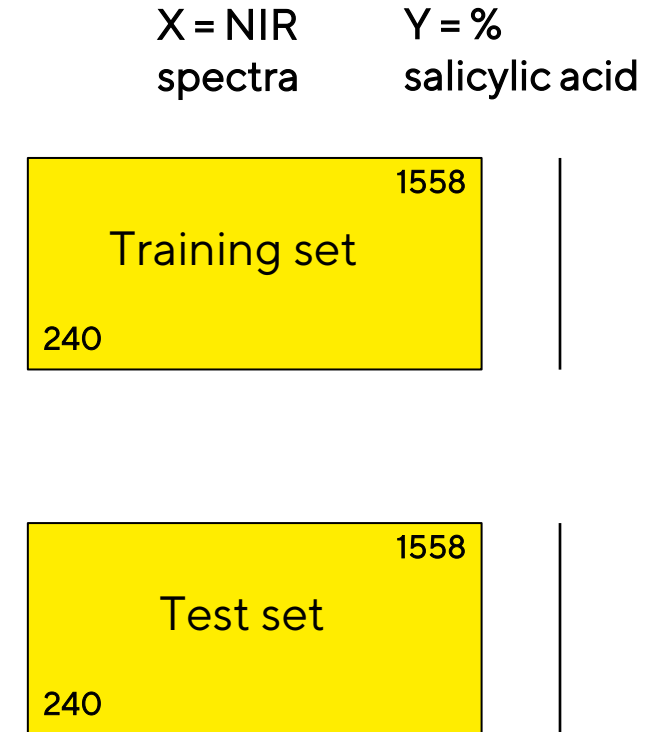
- Modelling Batch Processes

- Majority of industrial processes
- More complex analysis

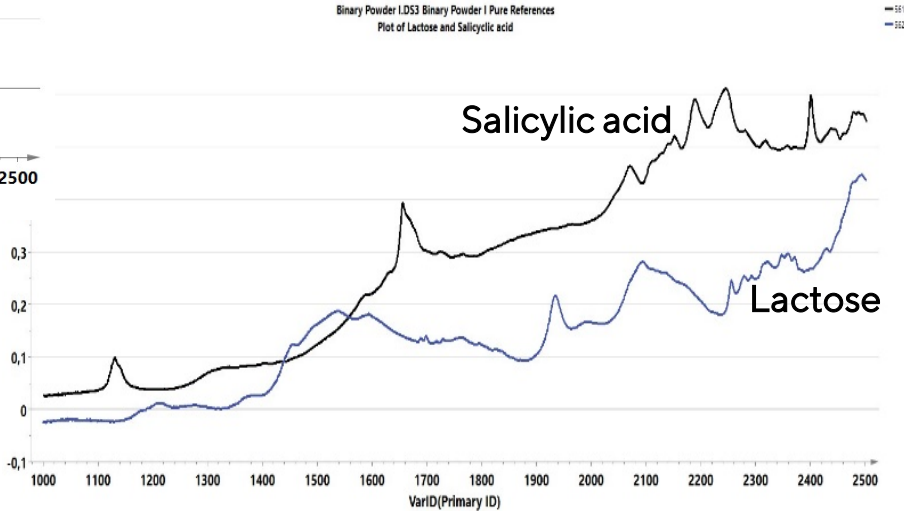
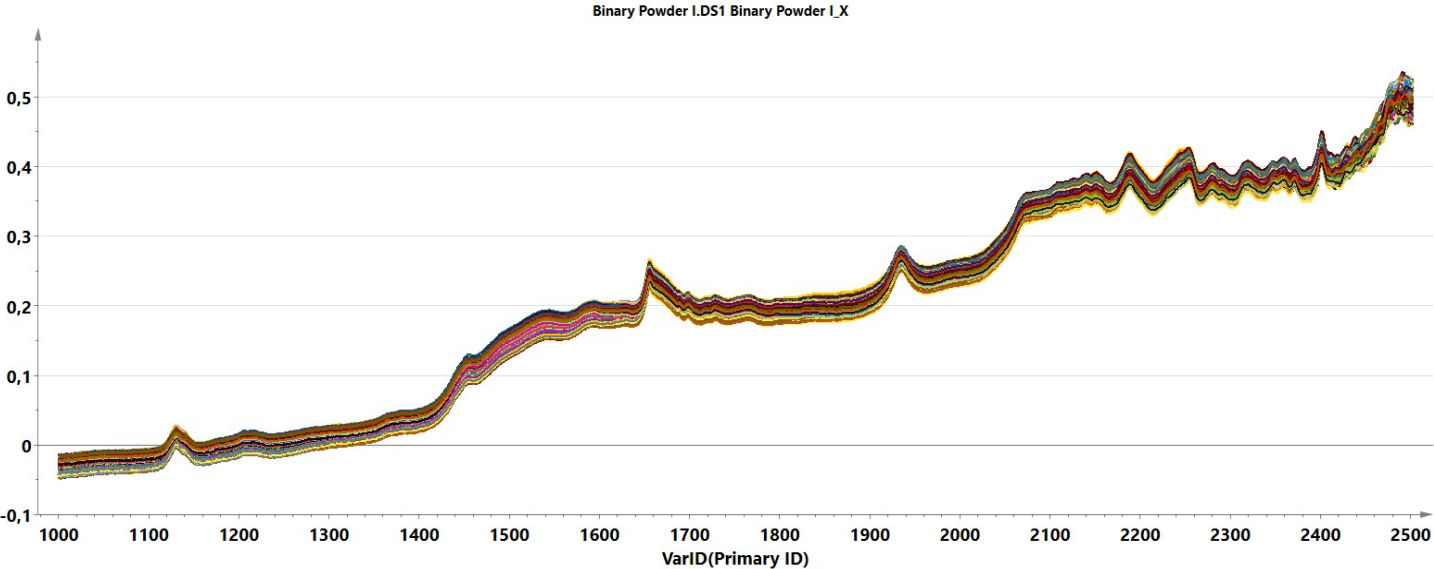


# Data

- The data consists of 12 batches of powders with salicylic acid content ranging from 45% to 55%.
  - 6 batches used as training set and 6 batches used as test set
- For each batch, 40 NIR spectra were acquired by holding the fibre-optic probe against the powder surface in 40 randomly chosen positions.
  - $12 \times 40 = 480$  observations; divided 240/240
- NIR spectra were obtained as  $\log(1/R)$  in the 1000-2500nm range giving a total of 1558 X-variables.



# Spectra of Training Set Samples



# OPLS Model

- The PLS and OPLS models have identical performance
- However, the additional insight provided by the OPLS model is that only 22% of the variation in the NIR data is connected to the variation in the levels of salicyclic acid
- 77% of NIR variance systematic but not predictive to Y

**Binary Powder I - M4**  
Title: OPLS odd batches  
Type: OPLS-Class(1) Observations (N)=240, variables (K)=1559 (X=1558, Y=1)

| Component              | R2X    | R2X(cum) | Eigenvalue | R2    | R2(cum) | Q2    | Limit | Q2(cum) | R2Y | R2Y(cum) | EigenvalueY | Significance |
|------------------------|--------|----------|------------|-------|---------|-------|-------|---------|-----|----------|-------------|--------------|
| Model                  | 0,989  |          |            | 0,972 |         |       |       | 0,956   | 1   |          |             |              |
| Predictive             | 0,22   |          |            | 0,972 |         |       |       | 0,956   | 1   |          |             |              |
| L P1                   | 0,22   | 0,22     | 52,8       | 0,972 | 0,972   | 0,956 | 0,01  | 0,956   | 1   | 1        | 1           | R1           |
| Orthogonal in X(OP...) | 0,769  |          |            | 0     |         |       |       |         |     |          |             |              |
| O1                     | 0,6... | 0,699    | 168        | 0     | 0       |       |       |         |     |          |             | R1           |
| O2                     | 0,0... | 0,743    | 10,4       | 0     | 0       |       |       |         |     |          |             | R1           |
| O3                     | 0,0... | 0,753    | 2,52       | 0     | 0       |       |       |         |     |          |             | R1           |
| O4                     | 0,0... | 0,761    | 1,78       | 0     | 0       |       |       |         |     |          |             | R1           |
| O5                     | 0,0... | 0,765    | 0,959      | 0     | 0       |       |       |         |     |          |             | R1           |
| O6                     | 0,0... | 0,769    | 0,945      | 0     | 0       |       |       |         |     |          |             | R1           |

**Binary Powder I - M2**  
Title: PLS odd batches  
Type: PLS-Class(1) Observations (N)=240, variables (K)=1559 (X=1558, Y=1)

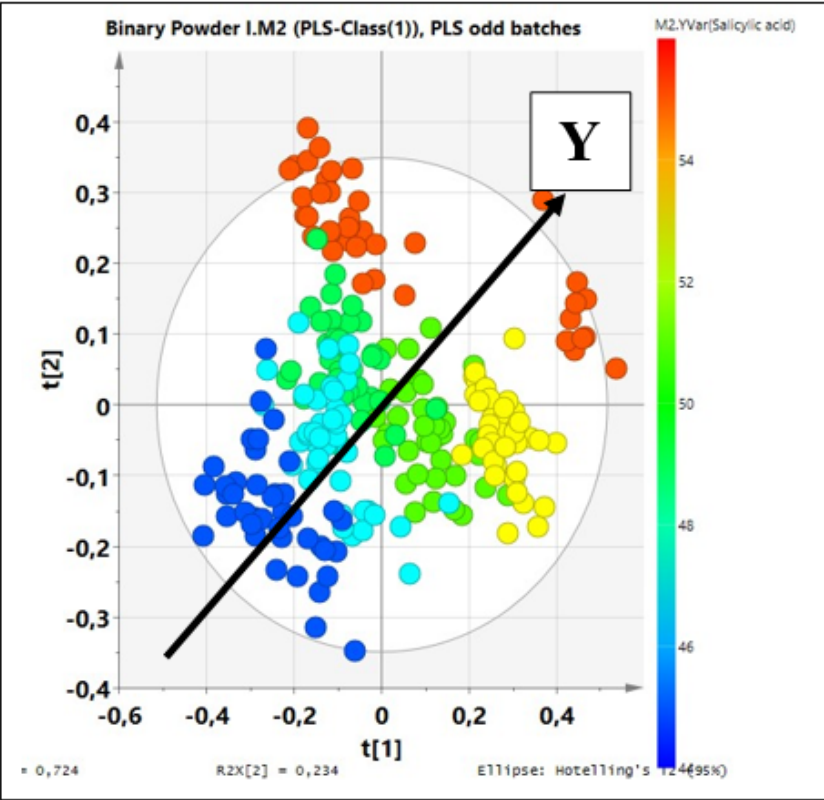
| Component | R2X      | R2X(cum) | Eigenvalue | R2Y    | R2Y(cum) | Q2      | Limit | Q2(cum) | Significance | Iterations |
|-----------|----------|----------|------------|--------|----------|---------|-------|---------|--------------|------------|
| 0         | Cent.    |          |            |        |          |         |       |         |              |            |
| 1         | 0,724    | 0,724    | 174        | 0,425  | 0,425    | 0,422   | 0     | 0,422   | R1           | 1          |
| 2         | 0,234    | 0,958    | 56,2       | 0,406  | 0,831    | 0,705   | 0     | 0,829   | R1           | 1          |
| 3         | 0,0218   | 0,98     | 5,22       | 0,0698 | 0,901    | 0,402   | 0     | 0,898   | R1           | 1          |
| 4         | 0,0026   | 0,983    | 0,624      | 0,0311 | 0,932    | 0,195   | 0     | 0,918   | R1           | 1          |
| 5         | 0,004... | 0,987    | 1,03       | 0,0127 | 0,945    | 0,155   | 0     | 0,931   | R1           | 1          |
| 6         | 0,001... | 0,988    | 0,279      | 0,0110 | 0,957    | 0,09... | 0     | 0,937   | R1           | 1          |
| 7         | 0,000... | 0,989    | 0,106      | 0,0152 | 0,972    | 0,121   | 0     | 0,945   | R1           | 1          |



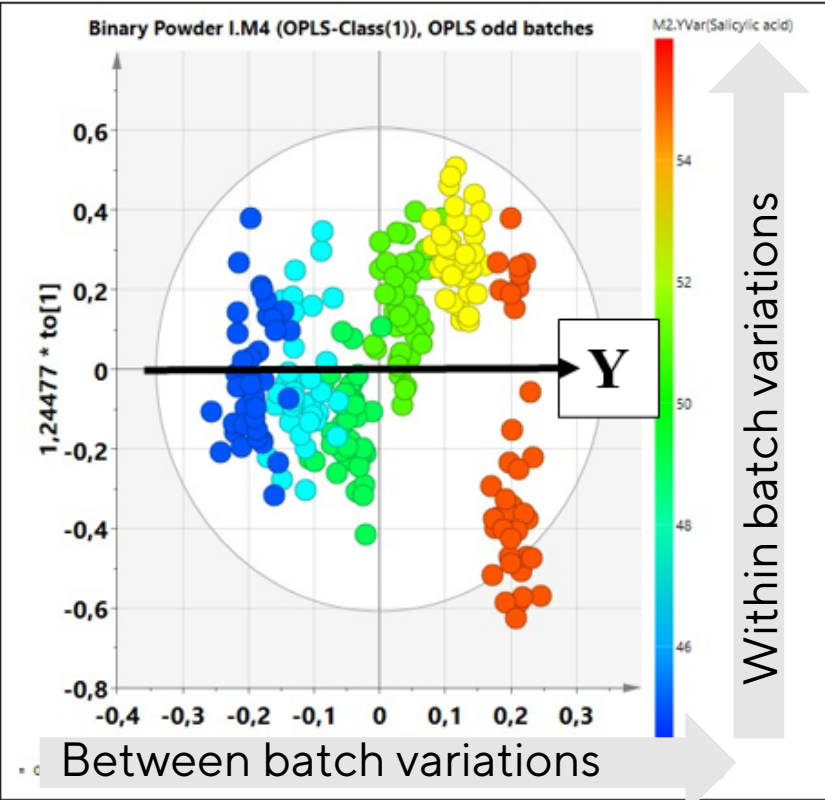
# Rotation of Projection Towards Y

■

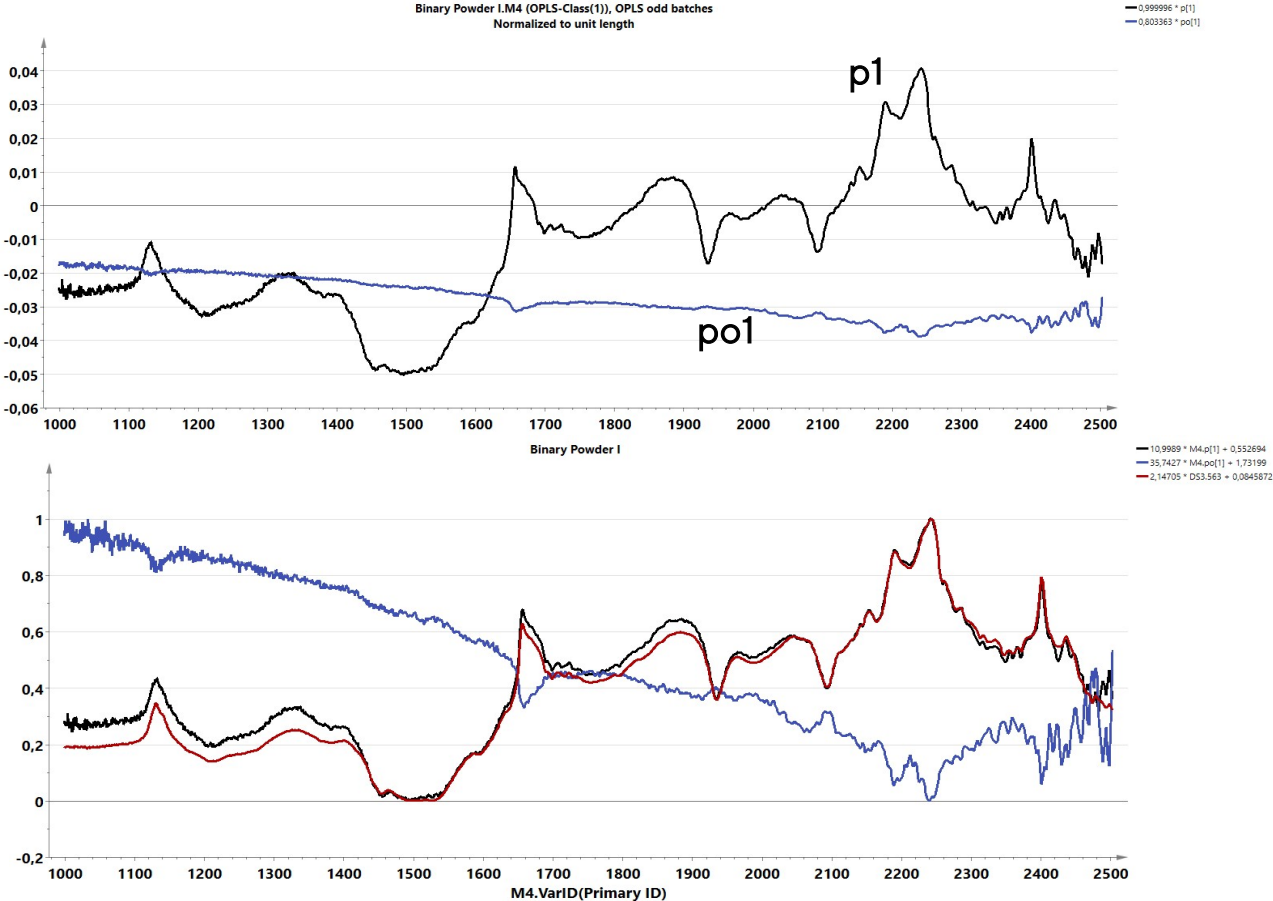
PLS



OPLS

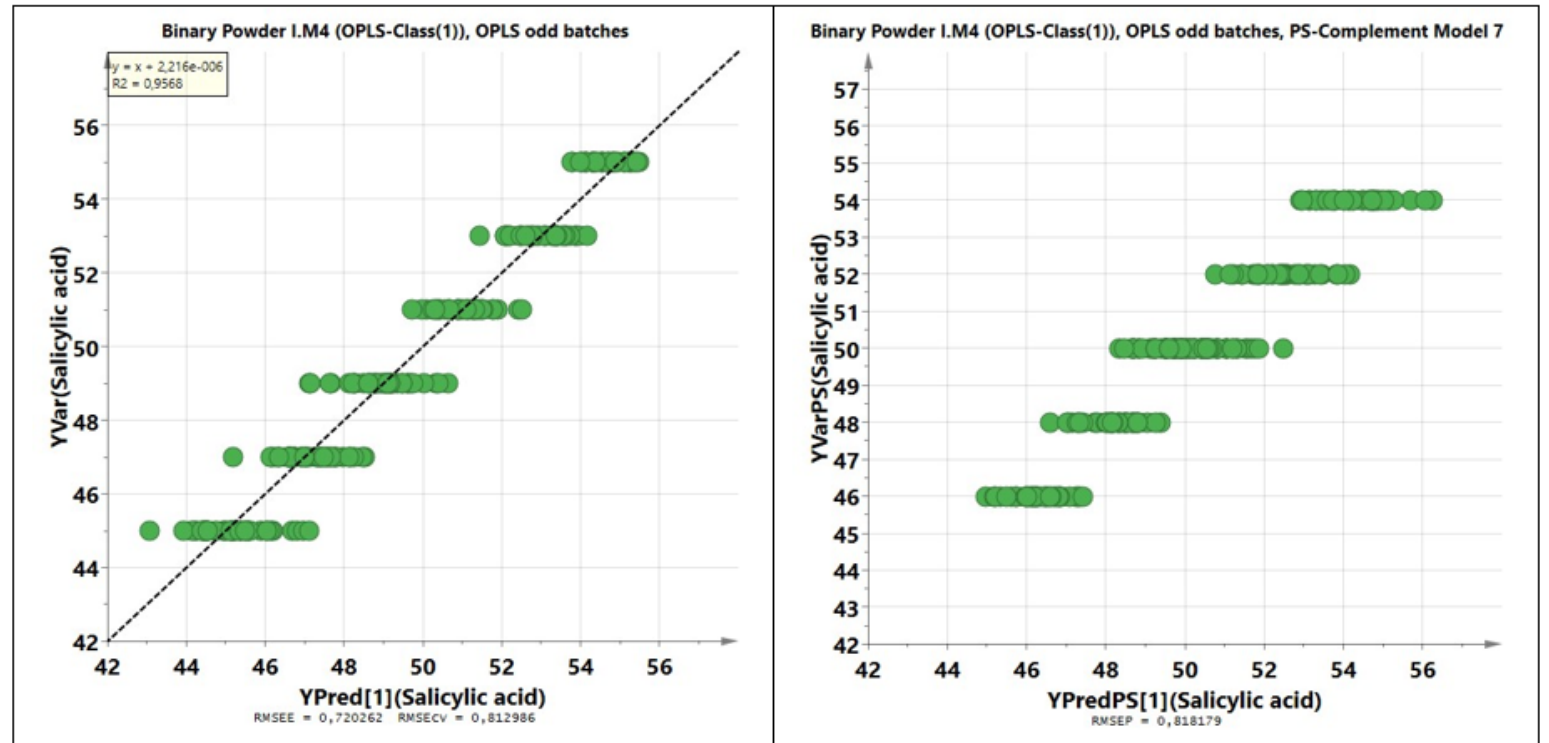


# Interpretation of Predictive and Orthogonal Components (No Mixing)



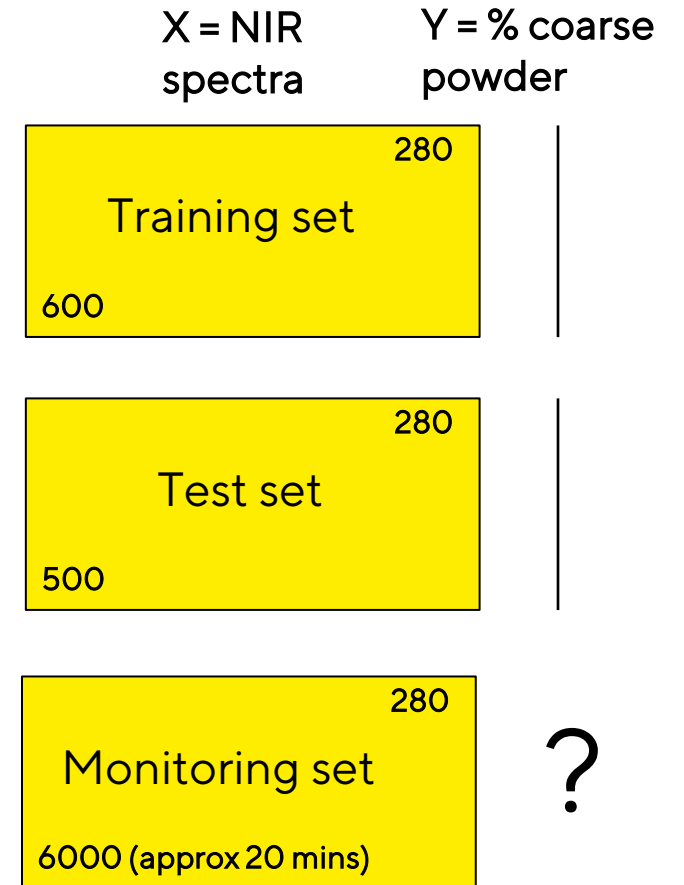
# Prediction For Test Set

- Good agreement between fit and prediction measures
- RMSEE = 0.72, RMSE<sub>cv</sub> = 0.81, RMSEP = 0.82.



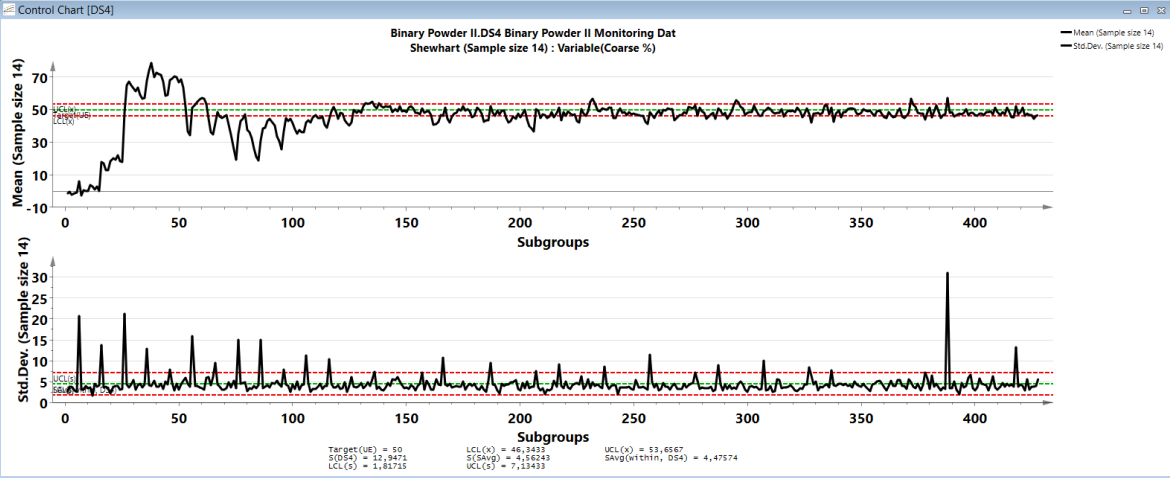
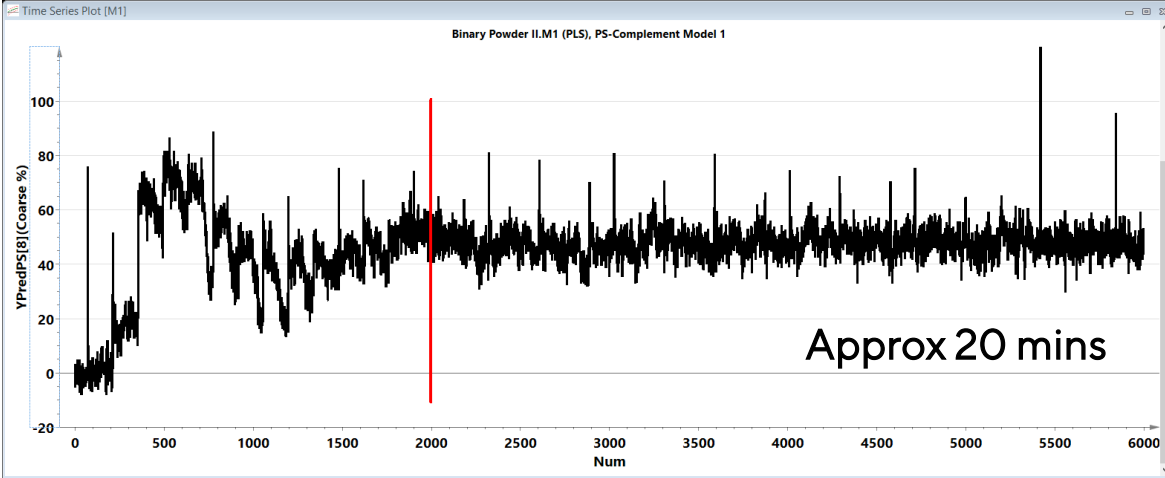
# Example: Binary Powder II

- Mixing two powders with dissimilar particle sizes
  - 0 - 100% coarse powder
- Training set 6\*100 = 600 spectra
- Test set 5\*100 = 500 spectra
- Monitoring set = 6000 spectra
- Spectral range: 1082-2025 nm  
(→ 280 variables)
- Scenario: In the monitoring experiment, equal amounts of the coarse and fine powders were loaded into a vertical cone mixer with the coarse powder on top.
- Question: When is mixing complete?



# When Is Mixing Complete?

- Mixing complete about 1/3 into the sampling period
- Effect of orbiting screw seen every 140th spectrum



# Batch Example: Hydrogenation Reaction

- PLS and OPLS are available for BEM and BLM
- PLS maximizes covariance between X and Y; risk is that undesired X-variability is picked up by BEM in terms of more components (more control charts to monitor)
- OPLS divides systematic SS of X in two parts, pred and orth; this may affect trajectory estimations and confidence intervals



OPLS in batch monitoring – Opens up new opportunities

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<sup>a</sup> Computational Life Science Cluster (CLIC), Department of Chemistry, Umeå University, Sweden

<sup>b</sup> MKS Umetrics, Umeå, Sweden

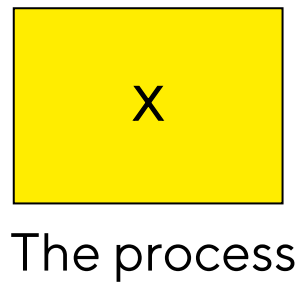


# Multivariate Process Data

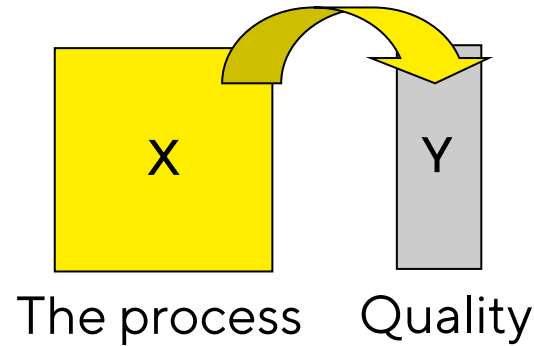
- Monitoring a process
  - Early warning of disturbances
  - Diagnostics - finding "assignable causes"

- Modelling a process output
  - Monitor Quality of final product

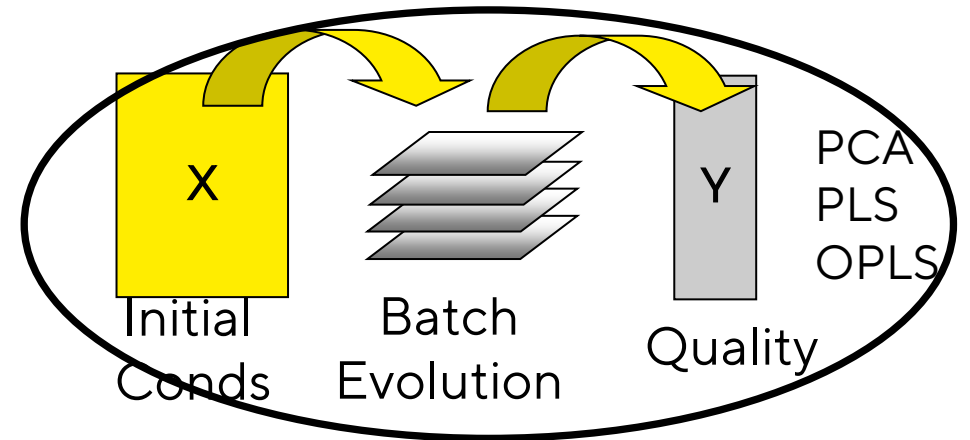
- Modelling Batch Processes
  - Majority of industrial processes
  - More complex analysis



PCA



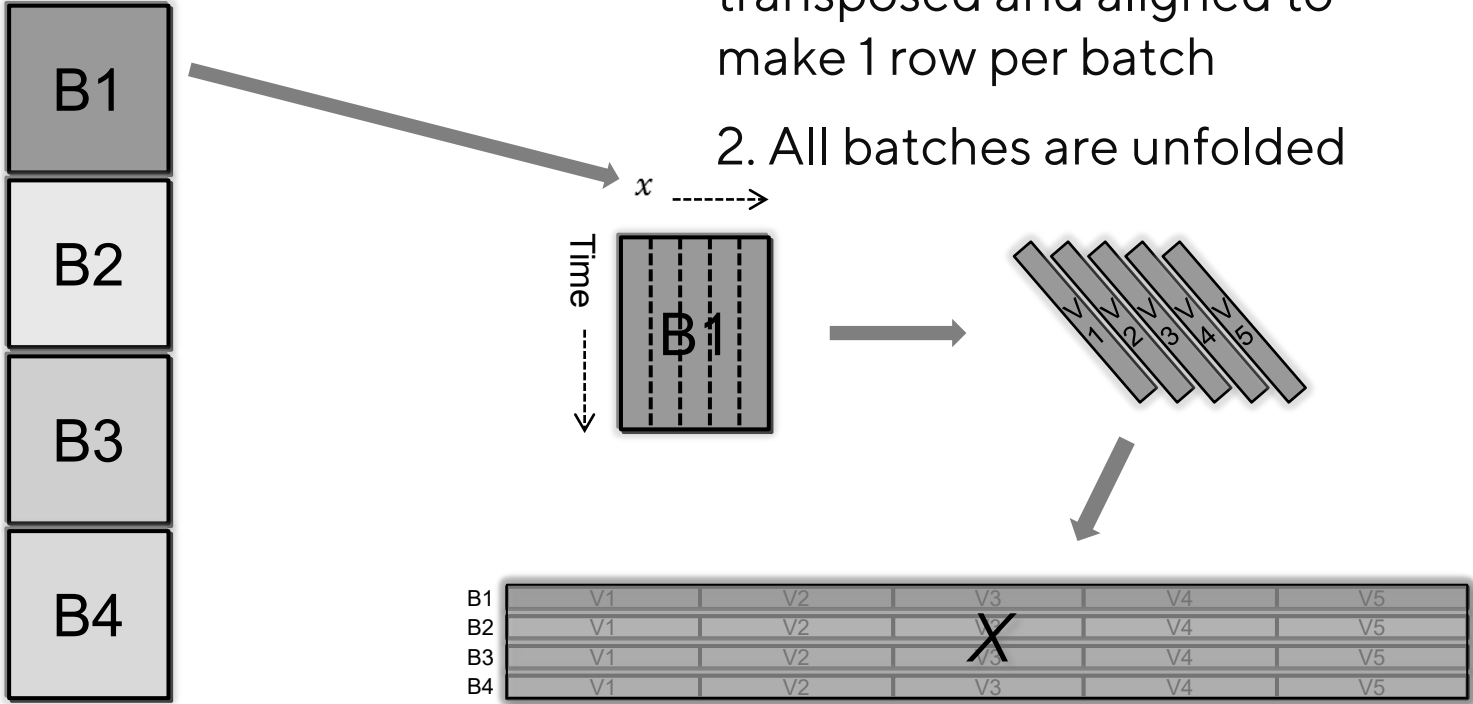
PLS  
OPLS



PCA  
PLS  
OPLS

# Batch Data; BEM and BLM

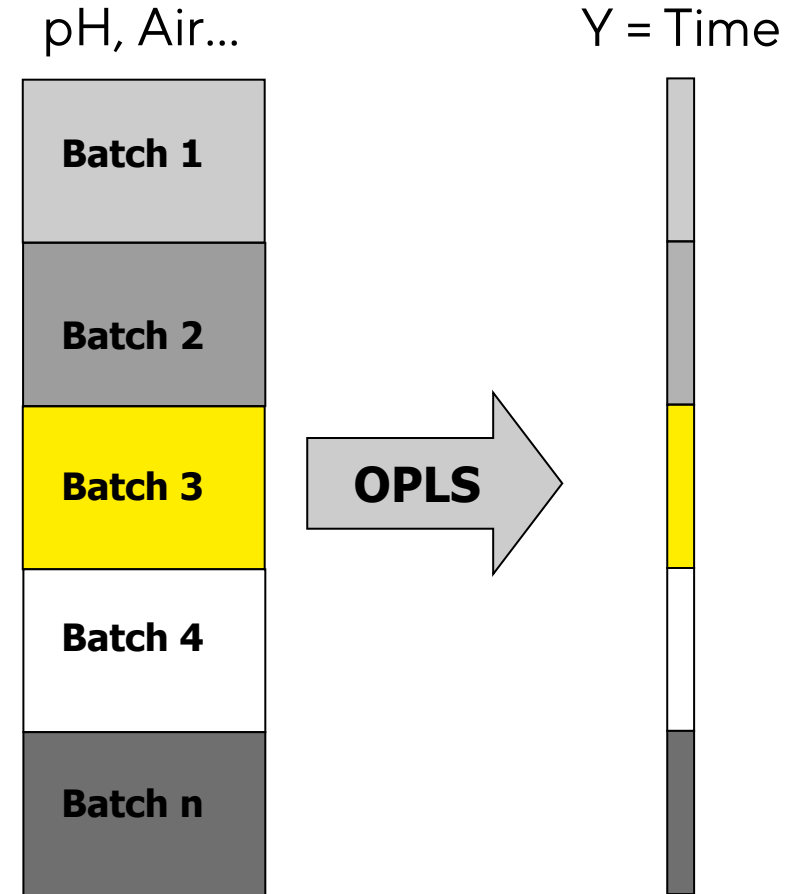
- Batch data has time dependency
  - A table of data is generated for each batch
  - Variables measured over time





# The Batch Evolution Model (BEM)

- Time (or maturity) is used as a Y-variable to give the model a direction
- Maturity need not be time. It could be say, for example, be Ethanol in beer brewing



# Example: Hydrogenation Reaction

- 6 centerpoint batches, NOC batches, used for model training
- 5 additional batches used for model testing
  - 3 corners of DOE (one corner missing)
  - 2 PD, process disturbances, batches (process upsets induced)
- 87 variables, 80 spectral (UV 200-300 nm, 1st derivative) and 7 process variables
  - reactor temp, reactor pressure, gas feed, jacket-in temp, jacket-out temp, flow rate of oil, and stirrer speed

J. Gabrielsson, H. Jonsson, J. Trygg, C. Airiau, B. Schmidt, R. Escott, *AIChE J.* 52 (2006) 3164–3172.

# Example: Hydrogenation Reaction (Nitrobenzene to Aniline)

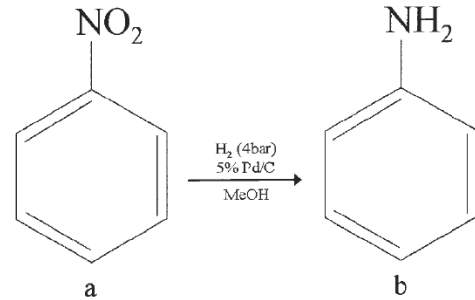


Figure 2. Reaction scheme for the conversion of Nitrobenzene (a) to Aniline (b).

## X data

- 1st der UV data (200-300 nm)
- Process data
  1. Reactor temperature,
  2. Reactor pressure
  3. gas feed
  - 4-7 jacket temp and stirrer speed

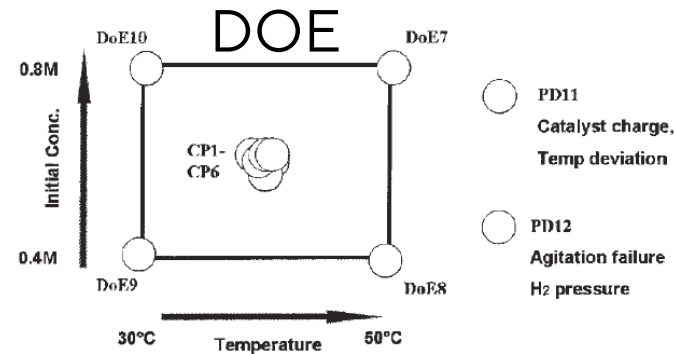


Figure 1. Illustration of the  $2^2$  full factorial design that was implemented in the study.

Table 1. Factor Settings for the  $2^2$  Full Factorial Experimental Design for the Conversion of Nitrobenzene to Aniline

| Batch Name (abbreviation)   | Reaction Temperature (°C) | Initial Conc. (mol/L) | Duration (min) |
|-----------------------------|---------------------------|-----------------------|----------------|
| Center point 1 (CP1)        | 40                        | 0.6                   | 45.7           |
| Center point 2 (CP2)        | 40                        | 0.6                   | 39.1           |
| Center point 3 (CP3)        | 40                        | 0.6                   | 37.8           |
| Center point 4 (CP4)        | 40                        | 0.6                   | 37.9           |
| Center point 5 (CP5)        | 40                        | 0.6                   | 38.9           |
| Center point 6 (CP6)        | 40                        | 0.6                   | 37.3           |
| Experiment 7 (DoE7)         | 50                        | 0.8                   | 24.1           |
| Experiment 8 (DoE8)         | 50                        | 0.4                   | —              |
| Experiment 9 (DoE9)         | 30                        | 0.4                   | 66.1           |
| Experiment 10 (DoE10)       | 30                        | 0.8                   | 45.4           |
| Process deviation 11 (PD11) | 40                        | 0.6                   | 47.6           |
| Process deviation 12 (PD12) | 40                        | 0.6                   | 33.9           |

Included also are six center points and two batches with introduced process deviations (explained in detail in Table 2). The resulting duration of each batch is given in min.

# BEM Results

- 3 PLS components
- 1+2 OPLS components
  - R2Xpred = 65%
  - R2Xorth = 19%,
  - Xres = 16%

Hydrogenation\_SIMCA 14 - M1

Workset... Options... Title: Untitled

Type: PLS Observations (N)=1188, variables (K)=92 (X=91, Y=1), included batches: 6

| Component | R2X    | R2X(cum) | Eigenvalue | R2Y     | R2Y(cum) | Q2      | Limit | Q2(cum) | Significance | Iterations |  |
|-----------|--------|----------|------------|---------|----------|---------|-------|---------|--------------|------------|--|
| 0         | Cent.  |          |            |         |          |         |       |         |              |            |  |
| 1         | 0,669  | 0,669    | 60,9       | 0,93    | 0,93     | 0,93    | 0     | 0,93    | RB1          | 1          |  |
| 2         | 0,0578 | 0,727    | 5,26       | 0,0227  | 0,953    | 0,325   | 0     | 0,953   | RB1          | 1          |  |
| 3         | 0,111  | 0,838    | 10,1       | 0,003.. | 0,956    | 0,06... | 0     | 0,956   | RB1          | 1          |  |

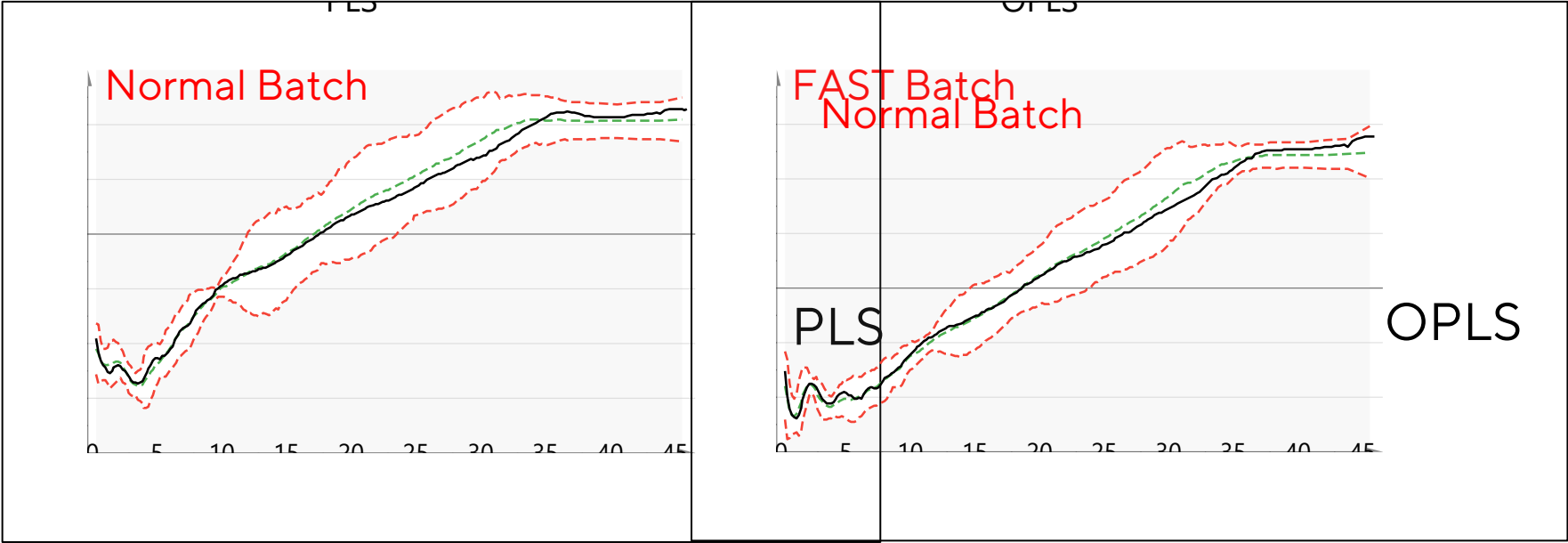
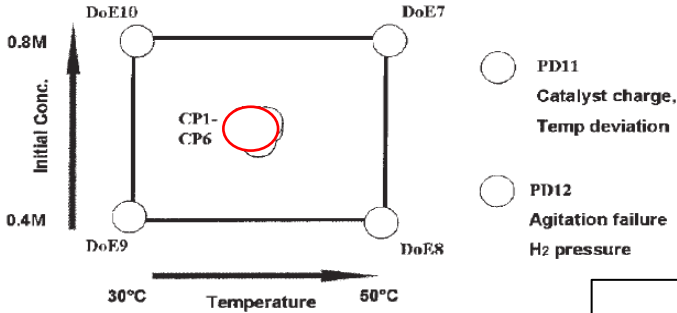
Hydrogenation\_SIMCA 14 - M2

Workset... Options... Title: Untitled

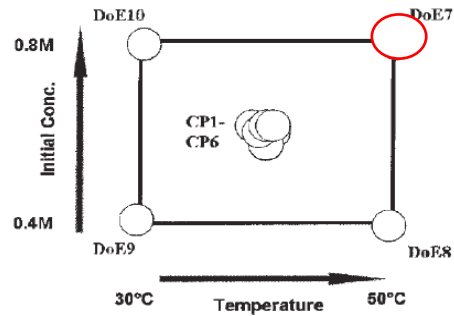
Type: OPLS Observations (N)=1188, variables (K)=92 (X=91, Y=1), included batches: 6

| Component              | R2X    | R2X(cum) | Eigenvalue | R2    | R2(cum) | Q2    | Limit | Q2(cum) | R2Y | R2Y(cum) | EigenvalueY | Significance |
|------------------------|--------|----------|------------|-------|---------|-------|-------|---------|-----|----------|-------------|--------------|
| Model                  |        | 0,838    |            |       | 0,956   |       |       | 0,956   |     | 1        |             |              |
| Predictive             |        | 0,65     |            |       | 0,956   |       |       | 0,956   |     | 1        |             |              |
| └ P1                   | 0,65   | 0,65     | 59,2       | 0,956 | 0,956   | 0,956 | 0,01  | 0,956   | 1   | 1        | 1           | R1           |
| Orthogonal in X(OP...) |        | 0,188    |            |       | 0       |       |       |         |     |          |             |              |
| └ O1                   | 0,0... | 0,0747   | 6,8        | 0     | 0       |       |       |         |     |          |             | R1           |
| └ O2                   | 0,1... | 0,188    | 10,3       | 0     | 0       |       |       |         |     |          |             | NS           |

# Control Charts Representing NOC

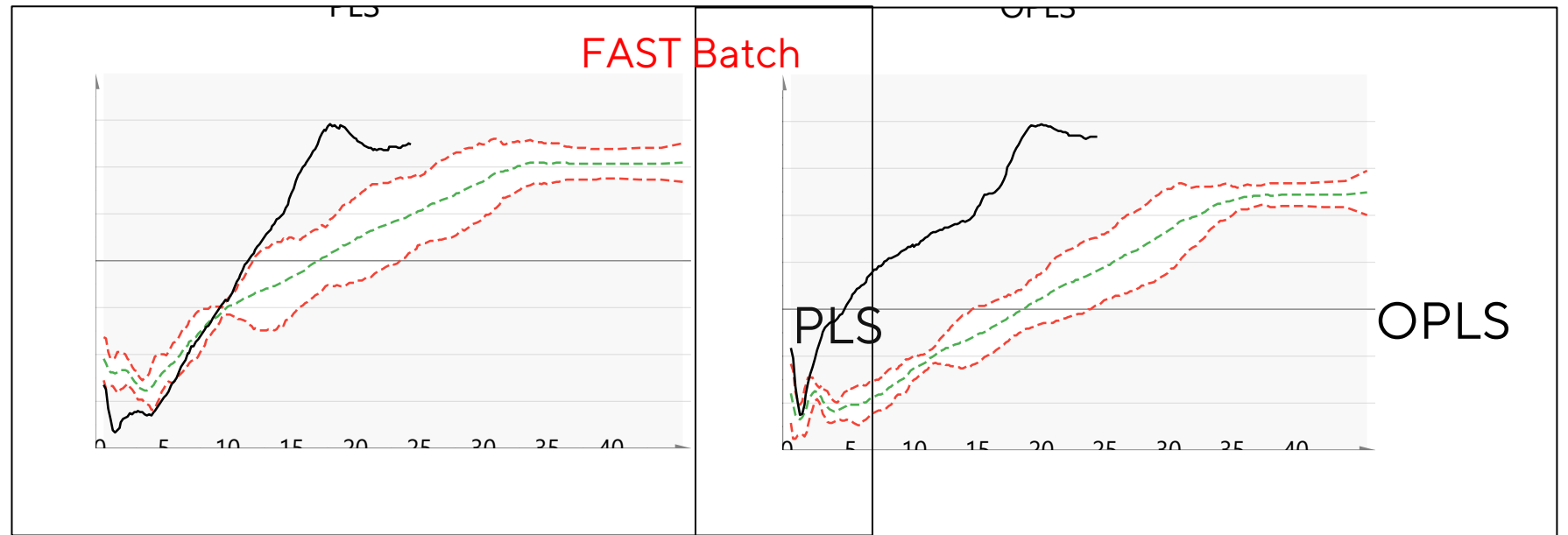


# Prediction of Batch DOE7 (tps1) – High Temp / High Initial Conc.

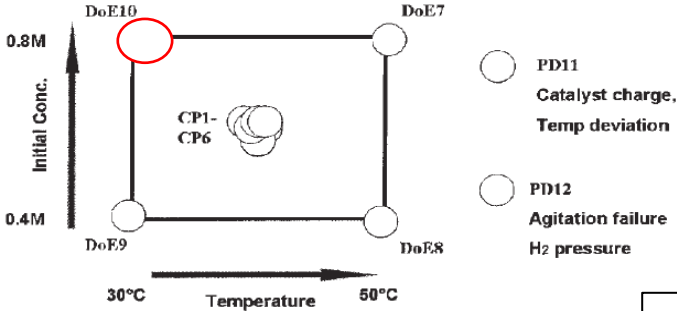


- PD11  
Catalyst charge,  
Temp deviation
- PD12  
Agitation failure  
H<sub>2</sub> pressure

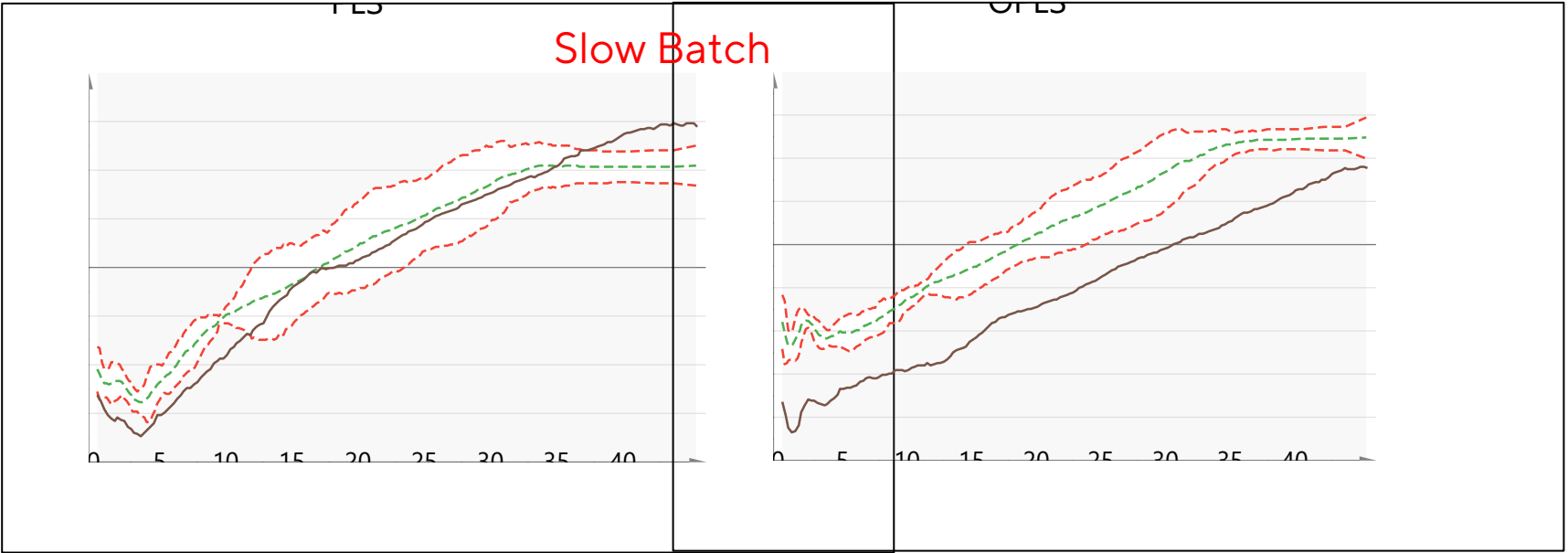
Reaction fast and high amount of product  
OPLS consistently shows this in score plot  
PLS not as sharp and capable



# Prediction of Batch DOE10 (tps1) – Low Temp / High Initial Conc.

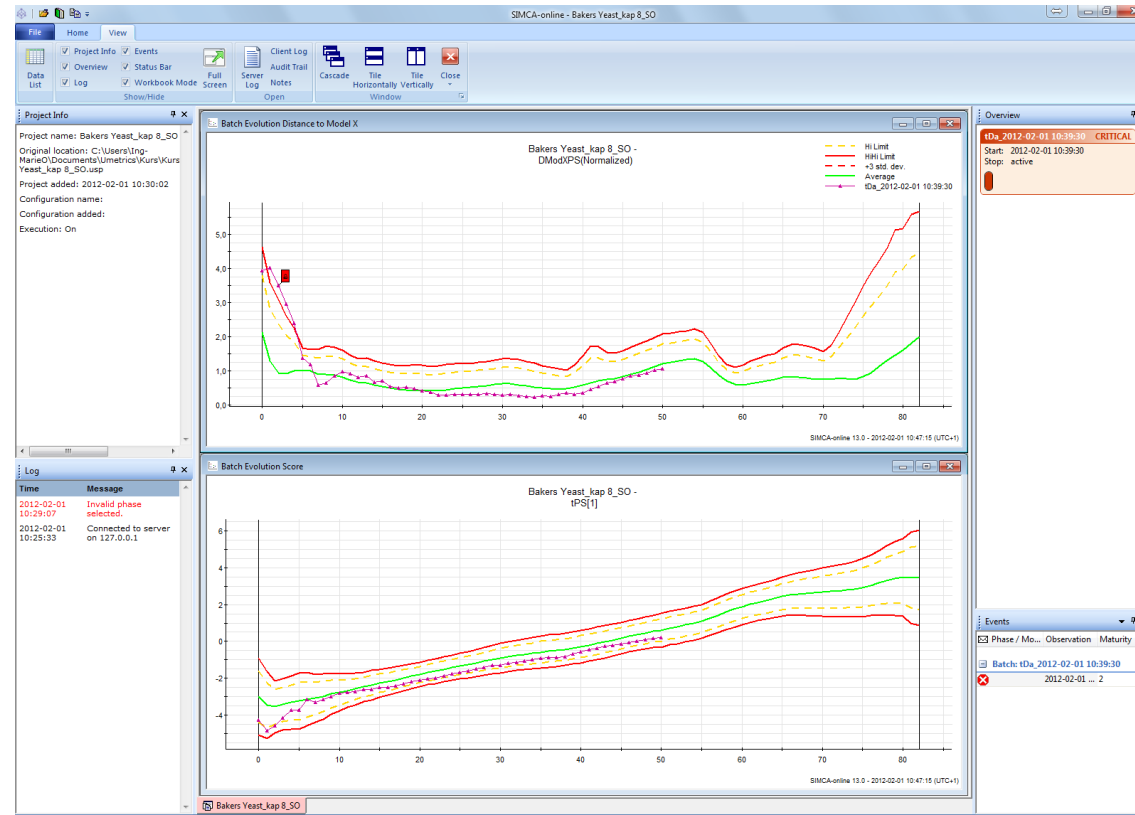


Reaction slow and low amount of product  
 OPLS consistently shows this in score plot  
 PLS not as sharp and capable



# SIMCA<sup>®</sup>-online

- Once the model is created and validated it is ready for online deployment







Demo

CONNECTION  
ANALYSIS  
DATA  
SEARCHING  
VERIFICATION

SARTORIUS

# Conclusions OPLS

- A single-Y PLS and a single-Y OPLS model with the same number of components are mathematically equivalent.
- Predictions, residuals,  $R^2$ ,  $R^2$  per variable,  $DModX$ , etc, are the same for PLS and OPLS.
- Loadings and scores are different for PLS compared to OPLS.
- Interpretation is easier with OPLS, since the user has a clearer understanding of what the different components mean

# Upcoming Webinars

(<https://www.sartorius.com/en/company/exhibition-conferences>)

The screenshot displays a web interface for Sartorius webinars. At the top, there are navigation tabs: 'UPCOMING EVENTS' (selected), 'PAST EVENTS', 'CALENDAR' (with a calendar icon), and 'SCHEDULE' (with a plus icon). Below the tabs is a search bar with a magnifying glass icon and the text 'Search'. The main content area is divided into two columns of event cards. Each card features a teal square icon, a 'STANDARD' tag, the event title, and the date and time. A vertical ellipsis menu is located to the right of each card.

| Event Title   | Date              | Time                    |
|---|-------------------|-------------------------|
| Design of Experiments (DOE) for the Beginner  | TUE, JAN 26, 2021 | 03:00 PM - 04:00 PM CET |
| Multivariate Data Analysis (MVDA) for the Beginner                                  | THU, JAN 28, 2021 | 03:00 PM - 04:00 PM CET |
| Lean-and-clean DOE using One-click analysis   | TUE, FEB 16, 2021 | 03:00 PM - 04:00 PM CET |
| OPLS® in process modeling   | THU, FEB 18, 2021 | 03:00 PM - 04:00 PM CET |
| Robust optimization made easy   | TUE, MAR 2, 2021  | 03:00 PM - 04:00 PM CET |
| Analyzing batch process data, a step-by-step guide                                  | THU, MAR 4, 2021  | 03:00 PM - 04:00 PM CET |
| From Design of Experiments to Design Space Estimation                               | TUE, MAR 23, 2021 | 03:00 PM - 04:00 PM CET |
| Multiblock Orthogonal Component Analysis (MOCA) - A Novel Tool for Data Integration | THU, MAR 25, 2021 | 03:00 PM - 04:00 PM CET |

# Launch Webinar – SIMCA® 17

- <https://www.sartorius.com/en/company/exhibition-conferences>

22 Feb 21 Webinar Launch Webinar - SIMCA® 17: Unlock the Full Potential of Spectroscopy Using SIMCA! [Link to Event](#)