

ALS Scheme using Extent-based Constraints for the Analysis of Chemical Reaction Systems

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Outline

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- Use of implicit calibration in ALS
- Use of extents in ALS
 - A brief introduction to Extents
 - Constraints based on Extents
 - An initialization based on conc. submatrices and local rank information
 - ALS algorithm with Extents and implicit calibration
- Simulated case study
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Introduction and Motivation

Introduction

ALS algorithm leads to a solution (\mathbf{C} , \mathbf{E}) for the factorization of L -dim. spectroscopic data \mathbf{A} of S species at K times, so that $\mathbf{A} = \mathbf{C} \mathbf{E}$.

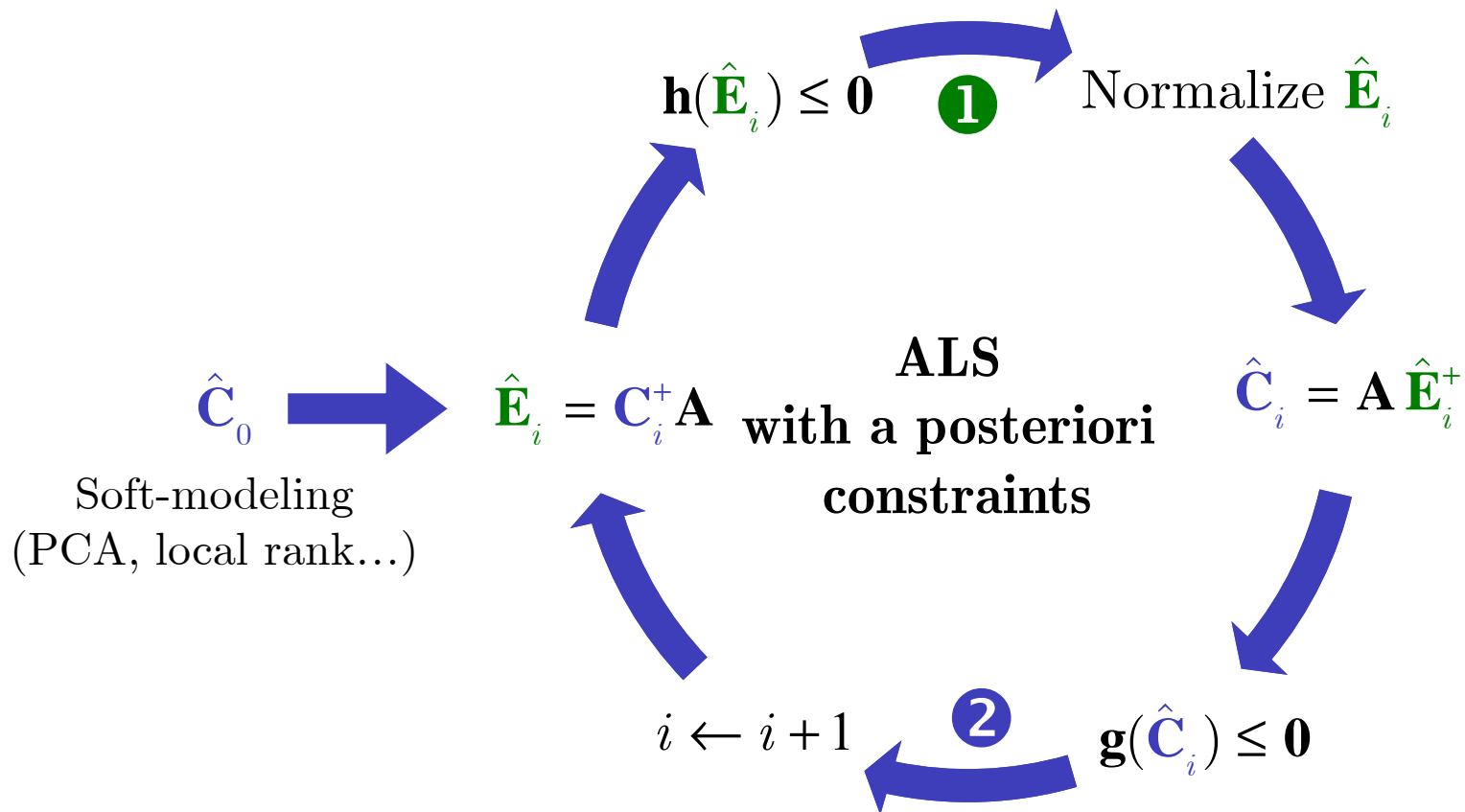
Motivation

- Working in a d -dim. space with $d \leq S$ ($\mathbf{C} \rightarrow$ extents \mathbf{X})
- Constraints in \mathbf{X} are numerous and stronger than in \mathbf{C}
- More constraints in the *time* direction (on \mathbf{X}) means fewer constraints in the *wavelength* direction (on \mathbf{E}).

Scope of this work

Absorbance data measured under batch and fed-batch conditions

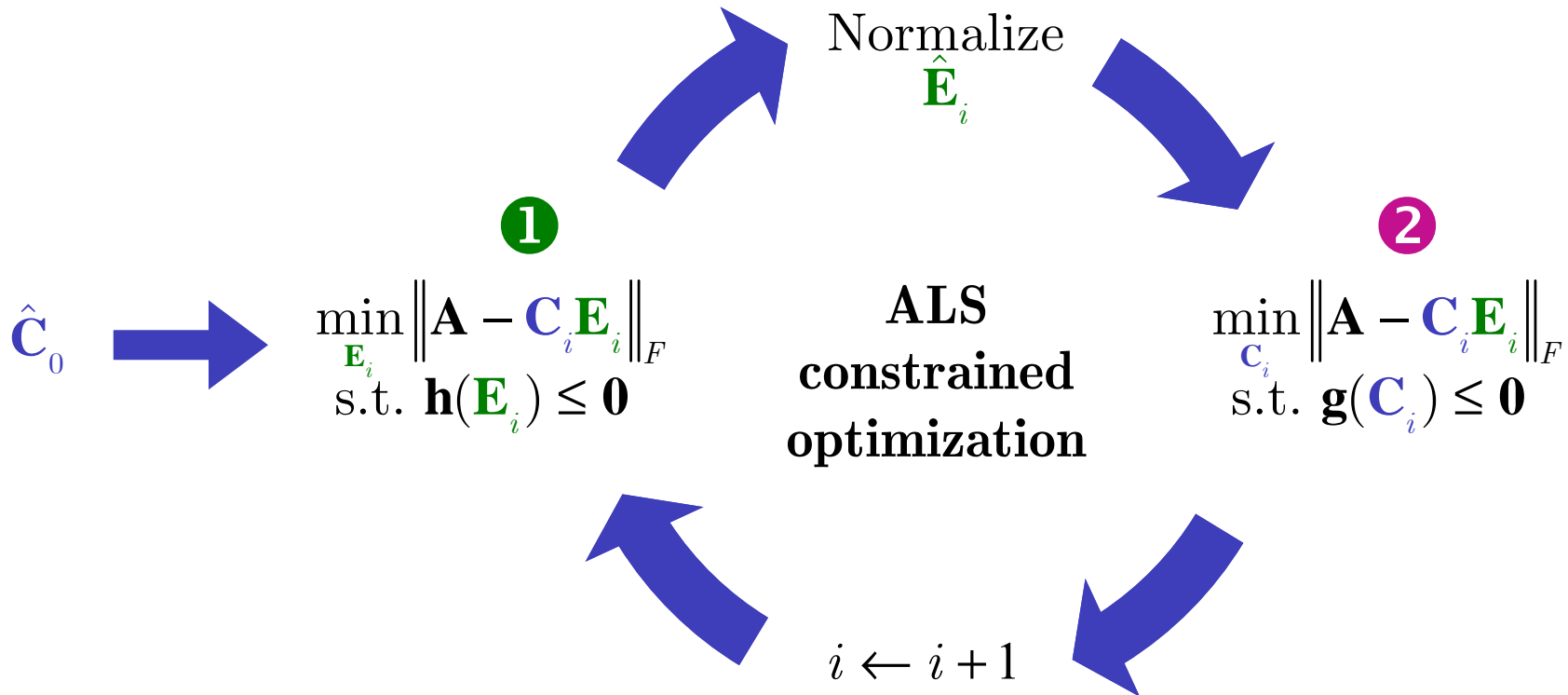
ALS algorithm with a posteriori constraints



☹ Estimates at points **1** and **2** are not least-squares estimates!

☛ Problems of convergence

ALS algorithm with constrained optimization



☺ Estimates at points 1 and 2 are least-squares estimates!

ALS algorithm with implicit calibration

- Solve the problem of finding \mathbf{C} and \mathbf{E} as a **combined constrained optimization problem** where only \mathbf{C} is adjusted and \mathbf{E} is estimated by **implicit calibration** ($\mathbf{E} = \mathbf{C}^+ \mathbf{A}$)

$$\min_{\mathbf{C}} \|\mathbf{A} - \mathbf{C} \mathbf{E}\|_F$$

$$\text{s.t. } \mathbf{E} = \mathbf{C}^+ \mathbf{A}$$

$$\mathbf{g}(\mathbf{C}) \leq \mathbf{0},$$

$$\mathbf{h}(\mathbf{E}) \leq \mathbf{0}$$

Normalize \mathbf{E}

- Typical constraints
 - $\mathbf{g}(\mathbf{C})$: nonnegativity, monotonicity, unimodality, closure
 - $\mathbf{h}(\mathbf{E})$: nonnegativity
- **Constraints and normalization of \mathbf{E} are required, as well as $\text{rank } \mathbf{C} = \text{rank } \mathbf{E} = S$!**

Concept of Extents

Homogeneous reaction systems with inlets

- Material balance in terms of numbers of moles \mathcal{N} ($K \times S$)

$$\dot{\mathbf{n}}(t) = \mathbf{N}^T \mathbf{r}(t) + \mathbf{C}_{in} \mathbf{q}_{in}(t), \quad \mathbf{n}(0) = \mathbf{n}_0$$

- S numbers of moles $\mathcal{N} \rightarrow \boxed{d = R + p \leq S}$ extents \mathbf{X}

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}_r & \mathbf{X}_{in} \end{bmatrix} = \left(\mathcal{N} - \mathbf{1}_{nt} \mathbf{n}_0^T \right) \mathbf{T} \quad \text{with} \quad \mathbf{T} = [\mathbf{N}; \mathbf{C}_{in}^T]^+$$

$$\dot{\mathbf{x}}_r(t) = \mathbf{r}(t), \quad \mathbf{x}_r(0) = \mathbf{0}_R$$

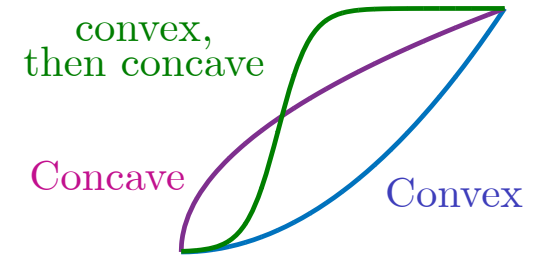
$$\dot{\mathbf{x}}_{in}(t) = \mathbf{q}_{in}(t), \quad \mathbf{x}_{in}(0) = \mathbf{0}_p$$

- Reconstruction equation

$$\mathcal{N} = \mathbf{X}_r \mathbf{N} + \mathbf{X}_{in} \mathbf{C}_{in}^T + \mathbf{1}_{nt} \mathbf{n}_0^T$$

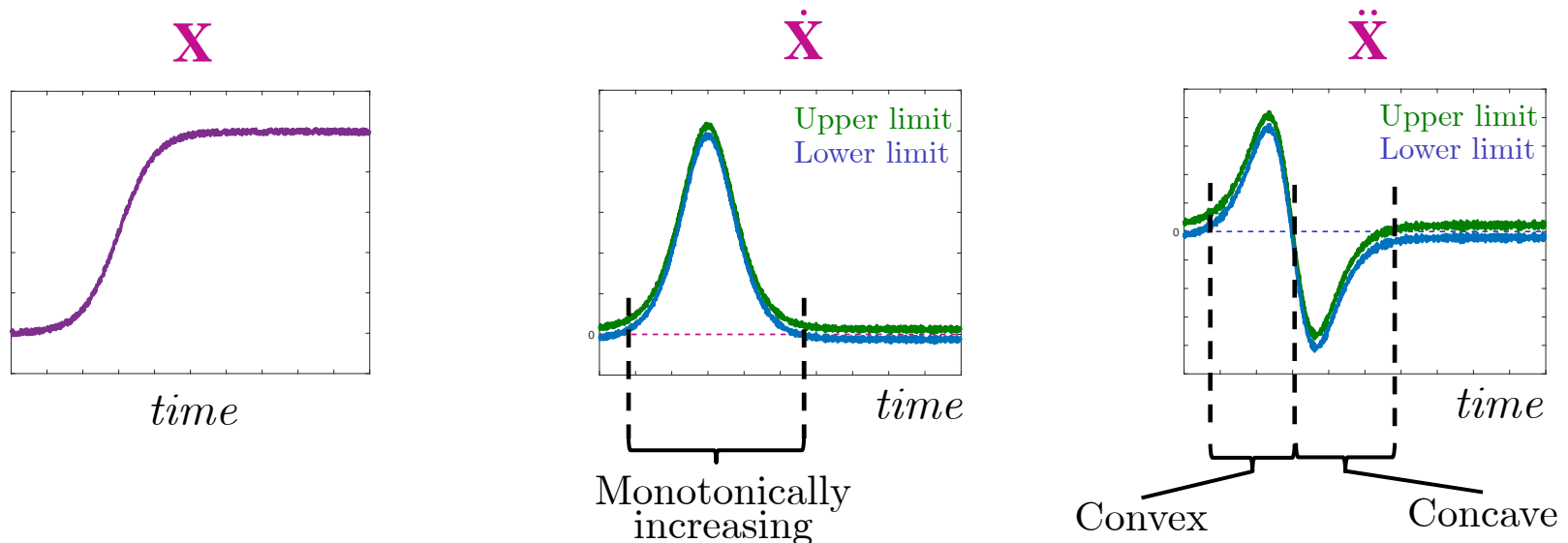
Constraints on Extents based on prior knowledge

- $\mathbf{x}(0) = \mathbf{0}_d$ (initial conditions of \mathbf{X})
- $\mathbf{X} \geq \mathbf{0}_{K \times d}$ and $\mathcal{N}(\mathbf{X}) \geq \mathbf{0}_{K \times S}$ (nonnegative)
- \mathbf{X}_{in} monotonically increasing,
 $x_{in,j}(t)$ concave (convex) if $q_{in,j}$ monotonically decreasing (increasing)
- \mathbf{X}_r monotonically increasing (for *irreversible reactions*)
 $x_{r,i}(t)$ concave (convex) if $r_i(t)$ monotonically decreasing (increasing)
- Initial and Terminal equality constraints on $\mathcal{N}(\mathbf{X})$ are enforced
 $\mathbf{n}_0 = \mathbf{n}_k(0)$ and $\mathbf{n}(\mathbf{x}(t_{end})) = \mathbf{n}_k(\mathbf{x}_k(t_{end}))$, sub k indicates a known value
- Path equality constraints on \mathbf{X} can be enforced
 $\mathbf{x}_i(t) = \mathbf{x}_{i,k}(t)$ (e.g. an extent is known a priori to be zero)



Constraints on Extents based on measurements

1. Estimate numerically the 1st and 2nd time derivatives of \mathbf{X} , i.e. $\dot{\mathbf{X}}$ and $\ddot{\mathbf{X}}$
2. Design **convex/concave constraints** based on the sign of $\ddot{\mathbf{X}}$
3. If step 2 failed, design **monotonicity constraints** based on the sign of $\dot{\mathbf{X}}$



Remark: this approach could also be applied to concentration profiles to detect regions where monotonicity and/or unimodality constraints apply.

Initialization with Concentration submatrices and local rank information

- ① Assumption: The **initial** and **final concentrations** of $S_a \geq d$ species are known for any experiment
- ① The $(S - S_a)$ remaining conc. are reconstructed via the extents
- ② **E** is estimated via $N = \frac{1}{2}(S + S \bmod 2)$ experiments
- ③ \mathcal{N}_0 and \mathbf{X}_0 are computed from the estimate of **E**,

$$\begin{array}{c}
 \mathcal{N}_{c,a} = \begin{bmatrix} [\mathbf{n}_{0,a}^{(1)}; \mathbf{n}_{f,a}^{(1)}]^\top \\ \vdots \\ [\mathbf{n}_{0,a}^{(j)}; \mathbf{n}_{f,a}^{(j)}]^\top \\ \vdots \\ [\mathbf{n}_{0,a}^{(N)}; \mathbf{n}_{f,a}^{(N)}]^\top \end{bmatrix} \xrightarrow{\mathbf{T}_a} \mathbf{X}_c \xrightarrow{\mathbf{T}^+} \mathcal{N}_c \xrightarrow{\mathbf{A}_{v,c}} \hat{\mathbf{E}} = \mathcal{N}_c^+ \mathbf{A}_{v,c} \rightarrow \hat{\mathcal{N}}_0 = \mathbf{A}_v \hat{\mathbf{E}}^+ \xrightarrow{\mathbf{T}} \hat{\mathbf{X}}_0 \\
 \begin{array}{ccccccc}
 (2N \times S_a) & & (2N \times d) & (2N \times S) & & (K \times S) & (K \times d) \\
 \textcircled{1} & & \textcircled{1} & \textcircled{2} & & \textcircled{3} &
 \end{array}
 \end{array}$$

c : calibration, a : available species, f : final conditions

ALS algorithm with Extents and implicit calibration

- $\mathbf{A} = \mathbf{C}\mathbf{E} \rightarrow \mathbf{A}_v := \mathbf{V}\mathbf{A} = \mathcal{N}\mathbf{E}$, with \mathbf{V} the volume
- Solve the **constrained optimization** where \mathbf{X} is adjusted and \mathbf{E} is estimated by **implicit calibration** ($\mathbf{E} = \mathcal{N}(\mathbf{X})^+ \mathbf{A}_v$).

$$\min_{\mathbf{X}} \left\| \mathbf{A}_v - \mathcal{N}(\mathbf{X}) \mathbf{E} \right\|_F$$

$$\text{s.t. } \mathbf{E} = \mathcal{N}(\mathbf{X})^+ \mathbf{A}_v$$

$$\mathbf{f}(\mathbf{X}) \leq \mathbf{0},$$

$$\mathbf{g}(\mathcal{N}(\mathbf{X})) \leq \mathbf{0}$$

- Typical constraints
 - $\mathbf{f}(\mathbf{X})$: nonnegativity, monotonicity, convexity/concavity, path constraints
 - $\mathbf{g}(\mathcal{N}(\mathbf{X}))$: nonnegativity, initial and final equality constraints
- No constraints on \mathbf{E} are required!

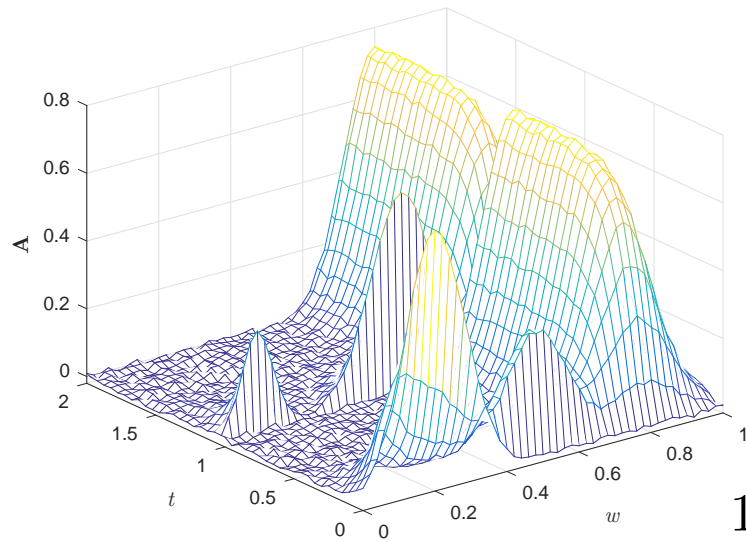
Simulated case study

Difference absorbance spectra



2 combined experiments:

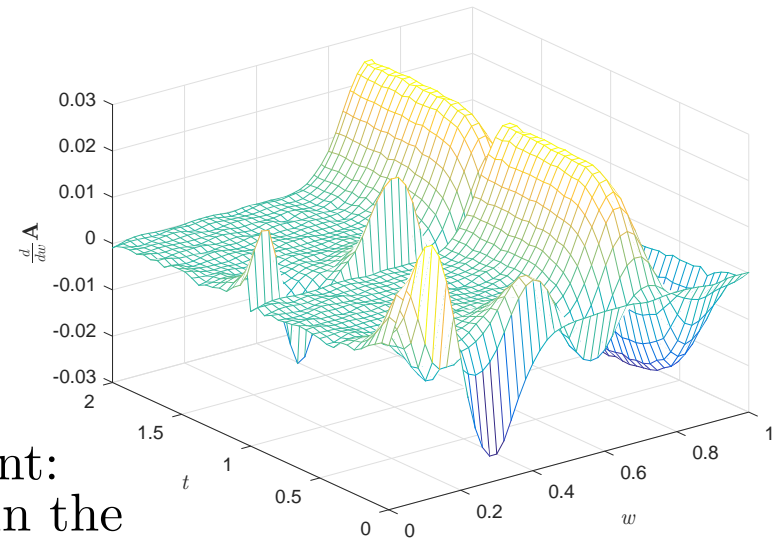
- Experiment 1 (only A initially present)
- Experiment 2 (only B initially present)



Noise:
1% uniformly distributed



Pretreatment:
1st derivative in the
wavelength direction



Simulated case study

Constraints applied

- Regular ALS does not work as \mathbf{E} cannot be constrained positively
- ALS based on \mathbf{X} with **implicit calibration** resolves both the rotational and intensity ambiguities with the following constraints:
 - Initialization \mathbf{X}_0 from **conc. submatrices** and **local rank information**
 - **Constraints on Experiment 1**
 - Initial and terminal \mathbf{n} 's imposed
 - \mathbf{x}_1 and \mathbf{x}_2 monotonically increasing
 - \mathbf{x}_1 concave, \mathbf{x}_2 convex then concave
 - **Constraints on Experiment 2**
 - Initial and terminal \mathbf{n} 's imposed
 - $x_1(t) = 0, \forall t$ (path constraint)
 - \mathbf{x}_2 concave

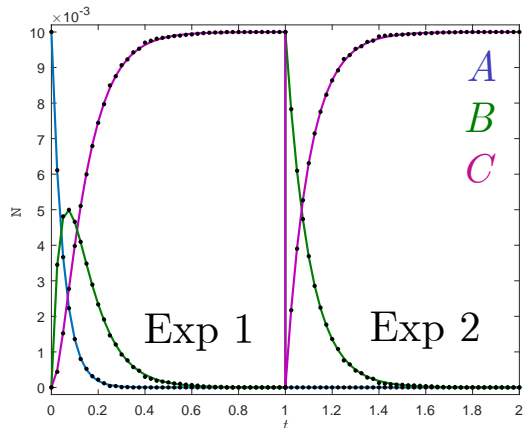
Remarks: No constraint or normalization on \mathbf{E} is required!

Constraints $\mathbf{X}_0 \geq \mathbf{0}$, $\mathcal{N}(\mathbf{X}) \geq \mathbf{0}$ are not even necessary!

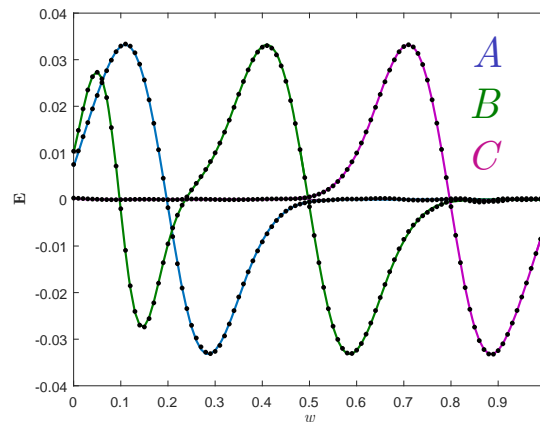
Simulated case study

ALS based on X with implicit calibration

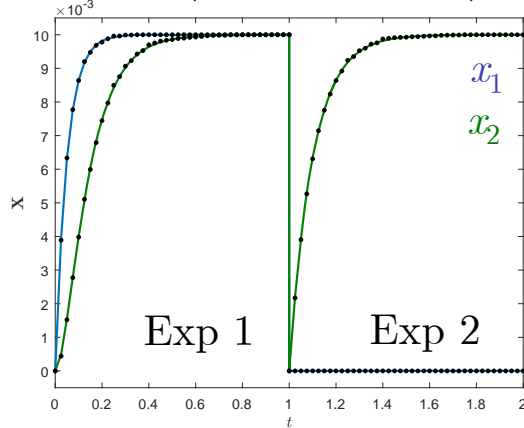
\mathcal{N} (ssq 7.5×10^{-8})



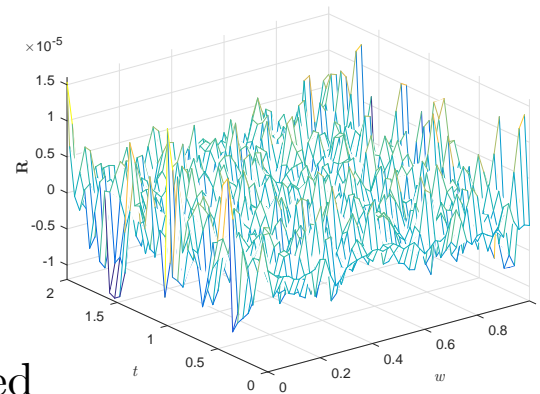
\mathbf{E} (ssq 1.4×10^{-5})



\mathbf{X} (ssq 4.6×10^{-4})



Residuals (ssq 1.6×10^{-7})



— true
● ALS-estimated

Conclusion

ALS with extents and implicit calibration

- **Optimization in a reduced space**
 - $S \cdot K$ decision variables in **C** versus $d \cdot K$ in **X**, with $d \leq S$
- **Better handling of the constraints**
 - Simpler constraints formulation
 - Large number of constraints based on prior knowledge
 - Stronger constraints (concavity/convexity vs unimodality)
- **No constraints on **E****
 - Use of data pre-treatment along *wavelength* direction (e.g. 1st derivative correction...)

Perspectives

ALS with extents and implicit calibration

- **Analysis of rank-deficient data**
 - Subtraction of the initial and inlet contributions
 $\mathbf{A} \rightarrow \mathbf{H} = \mathbf{X}_r (\mathbf{N}\mathbf{E}) \rightarrow$ ALS on \mathbf{X}_r and $(\mathbf{N}\mathbf{E})$ with rank $R < S$
- **Use of hard constraints in terms of extents**
 - Each extent of reaction represents the effect of a single reaction independently of all the others. The use of hard constraints in terms of extents should allow a constant diagnosis of each postulated kinetic step.

Final word

Thank you for your attention

References

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