# Interpretable, Online Soft Sensors for Process Control

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Introduction – problem description

Technique for development of adaptive transparent models for process control

Conclusions and further steps

# Motivation: Why explanatory modeling?

Benefits of **data-driven explanatory** models:

- Improvement of understanding of the process
- Possibility for comparison with expert knowledge
- Aid in overcoming barriers to uptake a soft sensor – soft sensor acceptance

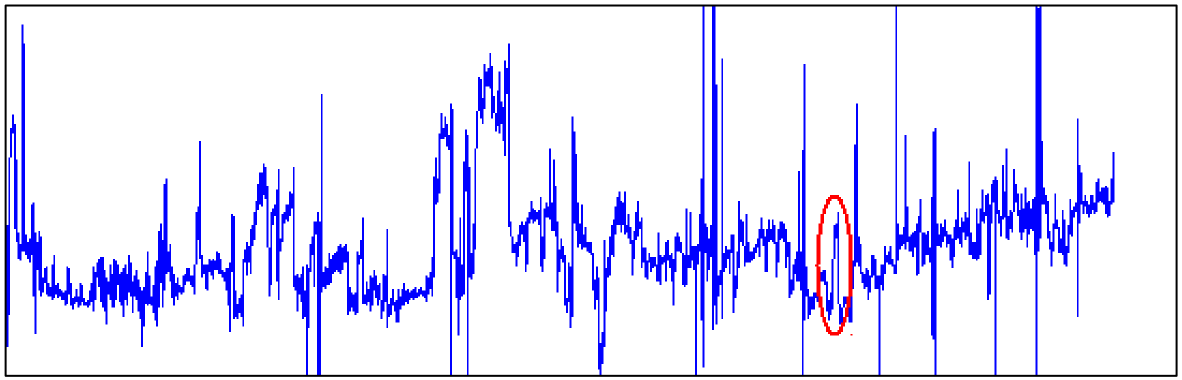
Above points needs to be fulfilled when the soft sensor has to be used for **process control** (inferential control)

# Case study: Analysis of states in reactive distillation column

In this plant the occurrence of sub-optimal states should be analysed and the cause identified

A lot of data is available - 2 years of data were analysed

Process is heavily instrumented with high number of sensors - 85 used in this study



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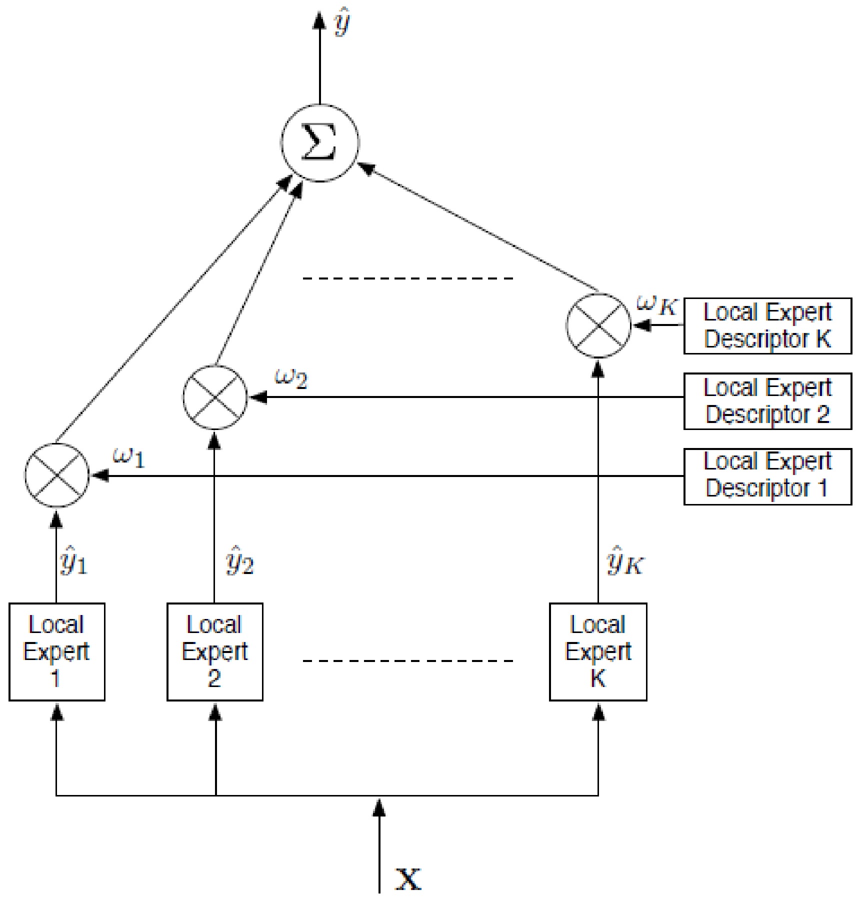
# Explanatory model structure: Soft sensor framework using ensemble methods and local learning



# Explanatory model structure: Local experts

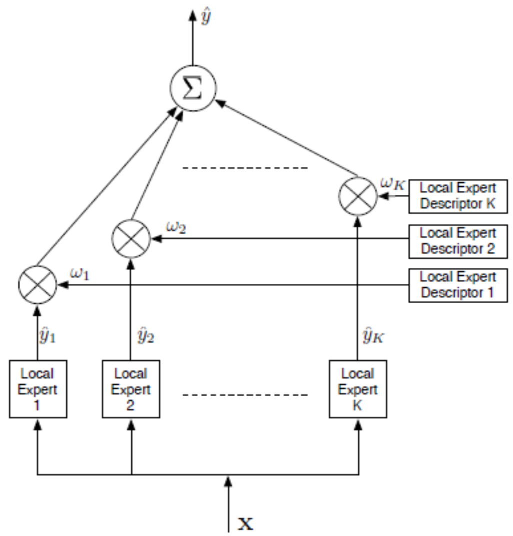
Can be any predictive model

Constraints on the models in this work:

- Have to be transparent
- Have to be adaptive

Suitable techniques:

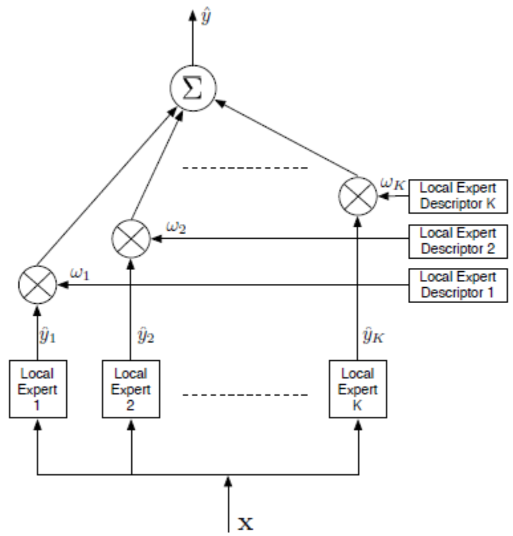
- Recursive Partial Least Squares
- Adaptive decision trees



# Explanatory model structure: Adaptive decision trees

- Using variance reduction as splitting rule
- Incremental updates in each node as new data arrives possible
- Requires only the sum of observations falling to left of each potential split for the updates
- Rebuilding the tree only below the node where optimal split significantly changes

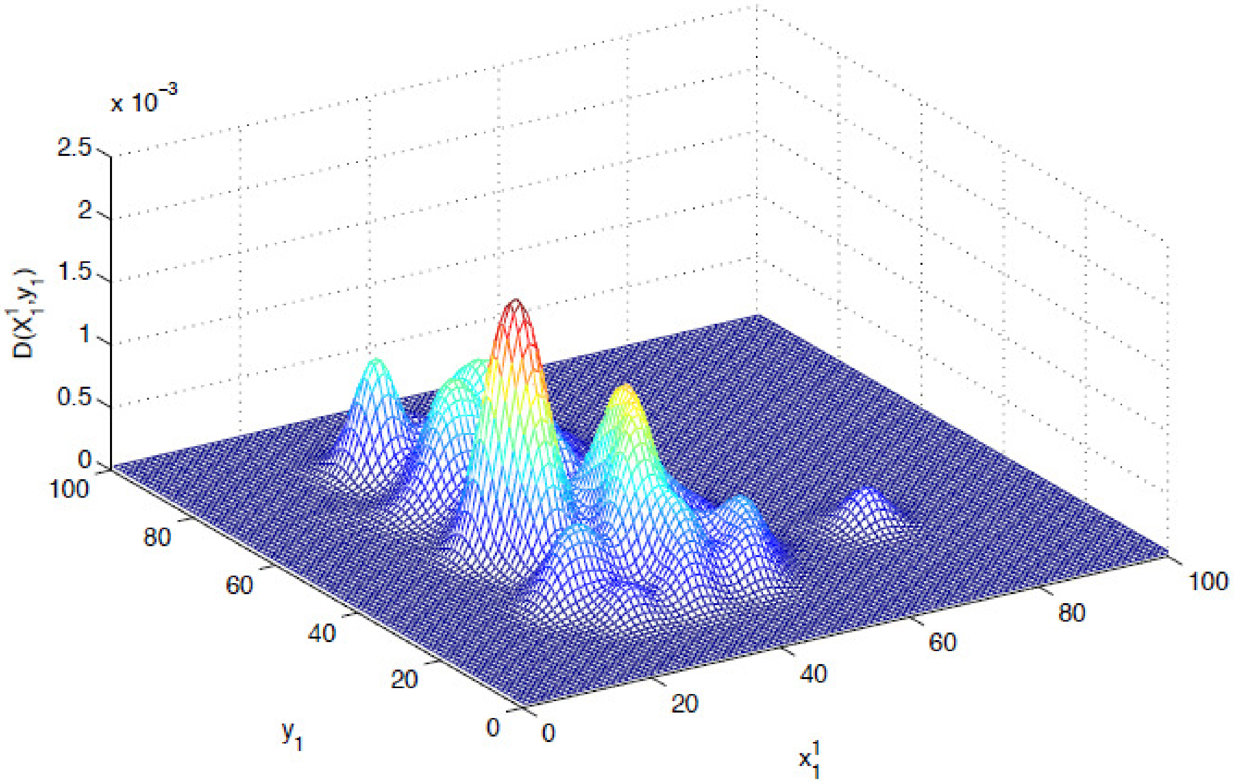
$$R = |\nu_p| V(\nu_P) - |\nu_L| V(\nu_L) - |\nu_R| V(\nu_R)$$
$$= \left(\sum_P y^2 - \sum_L y^2 - \sum_R y^2\right) + \frac{1}{|\nu_P|}\left(\sum_P y\right)^2 - \frac{1}{|\nu_L|}\left(\sum_L y\right)^2 - \frac{1}{|\nu_R|}\left(\sum_R y\right)^2$$

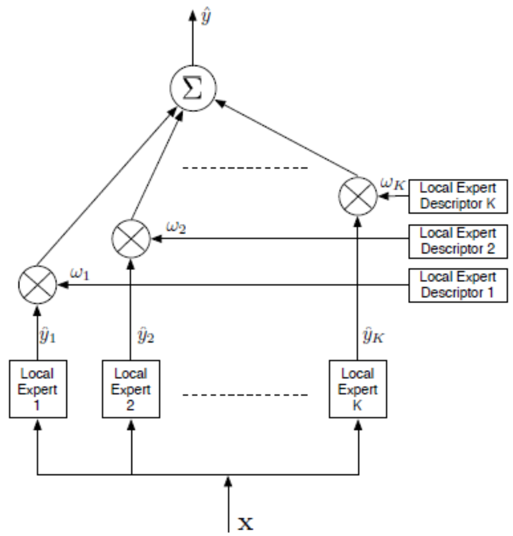



**Contribution plots indicating the significance of the variables can be extracted**

$$C_i = \sum_{\nu \in N_i} \left(1 - 2I(\mathbf{E}_{\nu_L} y > \mathbf{E}_{\nu_R} y)\right) |\nu| R_\nu$$

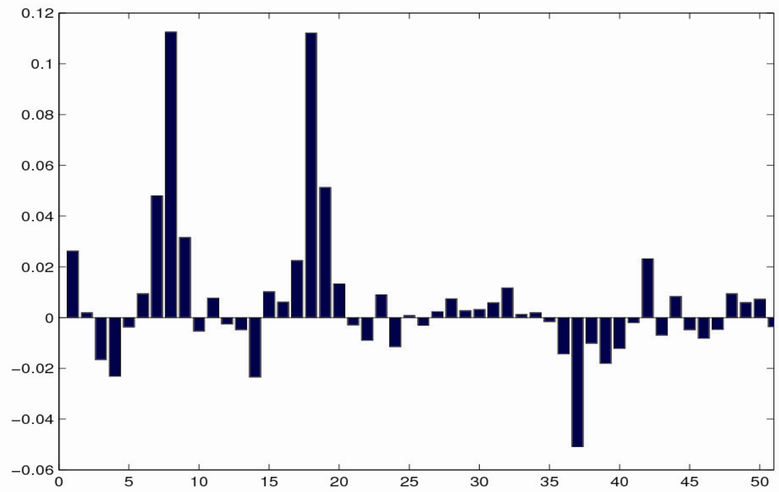
# Adaptive soft sensing algorithm – Local Expert Descriptors



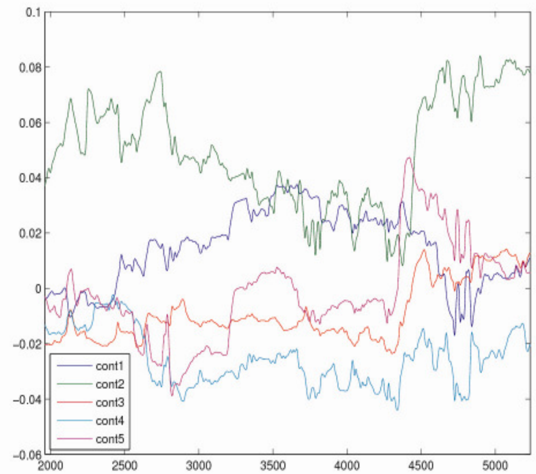



## Results of the study

Contribution plots extracted from the decision trees




Due to the adaptive nature of the model, the changes during the time can be observed



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# Conclusions

Previously available framework used for development of adaptive explanatory models

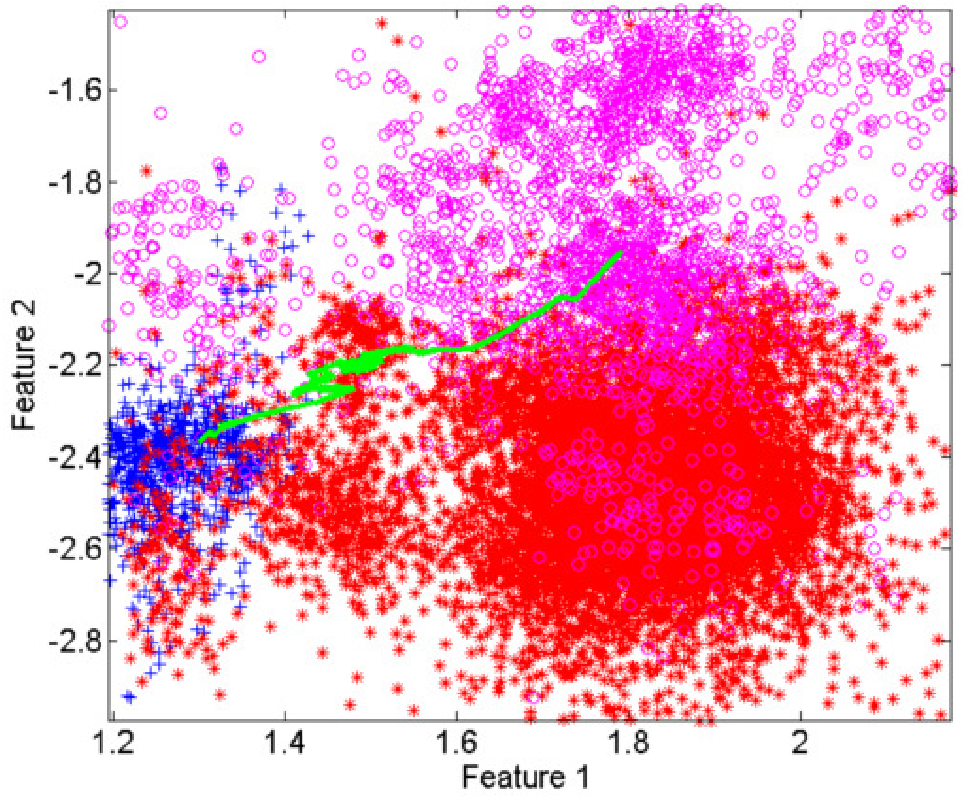
Tested using two techniques – one standard (PLS), one novel (adaptive regressive decision trees)

Gained information:

- Influence of the input data on the target variable
- Dynamic changes of the influence

# Further steps

Development of recommendation engine for avoiding the sub-optimal states:



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