Towards Automatic Batch Phase Detection
First Results using Machine Learning

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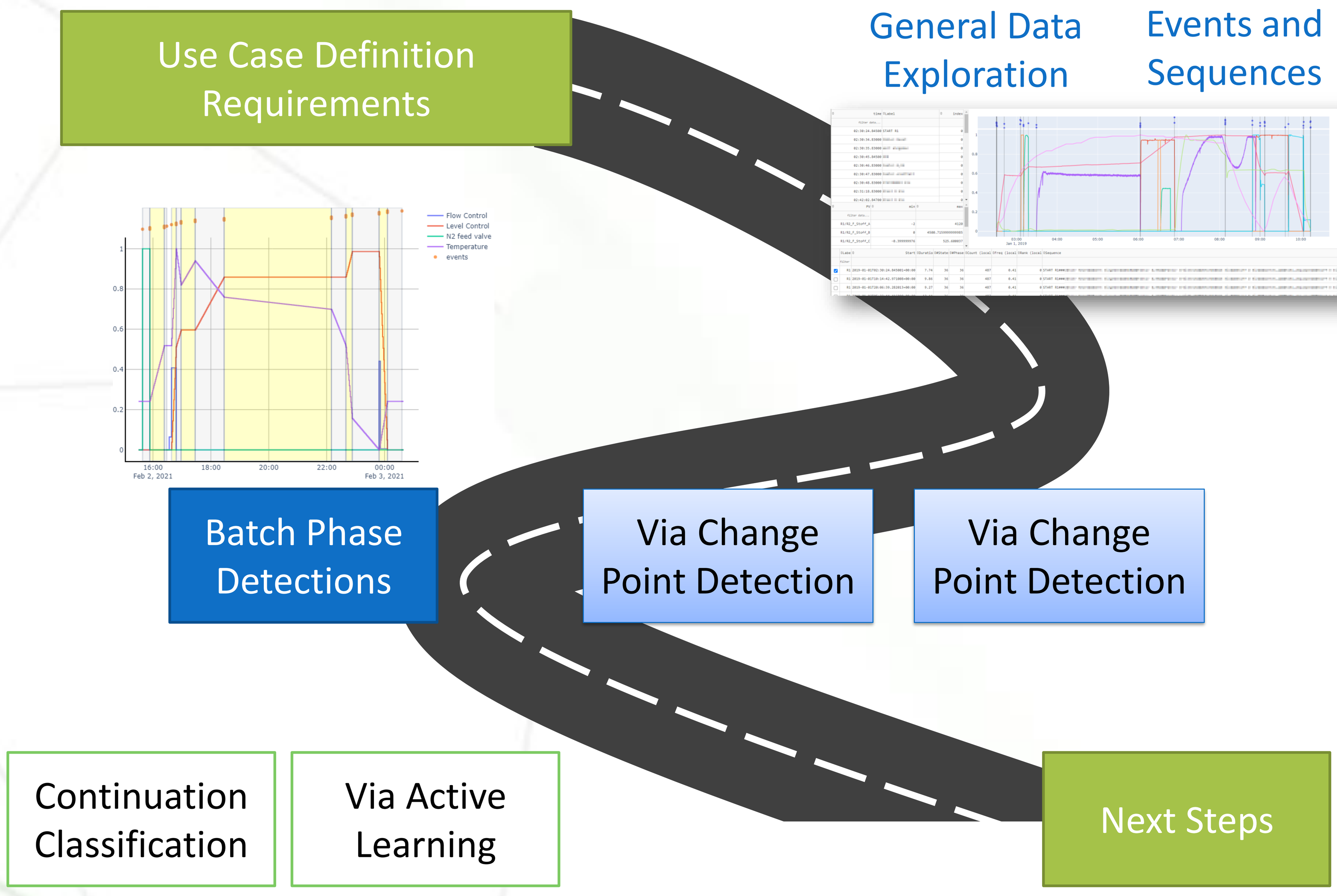
Motivation

- Batch phase statistics make batch process data and analyses accessible
- They have a wide range of use cases
  - Data analysis, process modelling (scheduling, planning, retrofit optimization), but also realtime-hard process monitoring
- Batch phase statistics (start, end, attributes) are not always archived automatically, and not always at high quality, especially in
  - Old plants, systems with islands of automation, manually operated plants
- Timeseries values of measurements are more often archived
- The inherent reproducibility of batch recipes makes automatic posterior batch phase identification based on timeseries values a promising task for ML
  - ML can help to distinguish recurrent & irregular behaviors as well as noise

Roadmap



Detection of Start and End Times of Batch Phases [1]

- How easy or hard is it to identify batch phases?
  - Given labelled information to train on
  - Without labels and looking for candidates
- Simple classification works extremely good on ideal data from simulation
  - Real-World Data need further work
- Performance of Change Point Detection depends on the characteristics of timeseries
  - Overall relevant / interesting parts can be identified

Results Classification

- 2 approaches for the classification of batch phases were tested:
  - Random forest classification on sensor measurements
  - Random forest classification on statistical features [2]
- Experiments were made on:
  - Simulated data with 4 variables and 13 different phases
  - Real data with 8 variables and 43 different phases

Accuracy of prediction	Simulated data	Real plant data
Classification on sensor measurements	99.94%	69.92%
Classification on statistical features	99.94%	58.49%

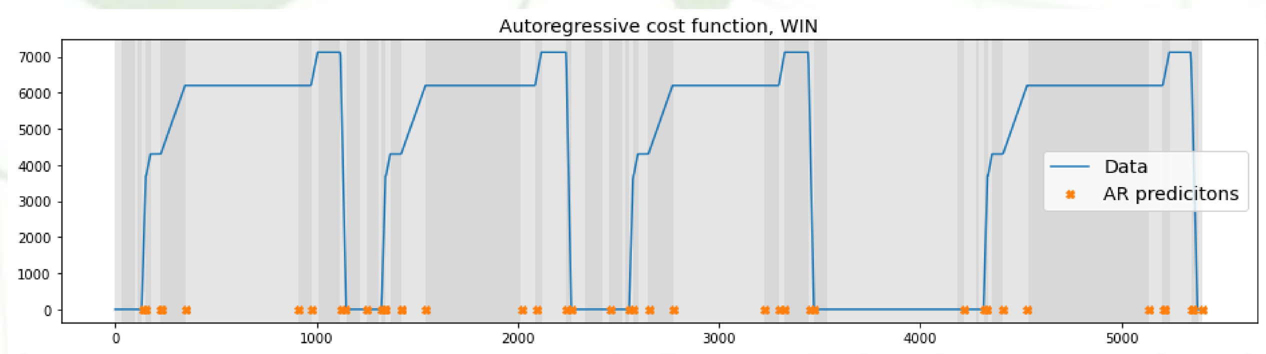
Results - Change Point Detection

- Unsupervised CPD as an optimization problem:

$$\min_{\tau} V(\tau) + pen(\tau) \;=\; \min_{\tau} \sum_{t \in \tau} c(\,y_{t_j:t_{j+1}}\,) + \beta|\tau|$$

τ: change points; y: original signal;
V: criterion function for all segments ; pen: penalty; c: cost function

- Results for automatic batch phase detection



- Findings: cost function influences the performance of CPD and should be chosen according to the characteristic of the data.

Next Steps

- Batch phase classification (5.2)
  - Multivariate optimization to create better classification results
  - Removal of erroneous batches
  - Refine feature creation to achieve better results
  - Include sequences in classification
- Active Learning (5.4)
  - Evaluation of Idea - Provide few exact labels (via Experts)
  - Comparison with classification / Supervised Learning
  - Improve the visualization of the prediction quality during active learning interaction

[1] S. Merkelbach, R. Tan, F. Bähner, M. Gärtler, J. Gatter, R. Gedda, L. Urbas: Automatic Detection of start and end times of batch phases for the process industry, AUTOMATION 2021, accepted (2021)

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[2] B. Esmael, R. K. Fruhwirth, and G. Thonhauser, "A Statistical Features Based Approach for Operations Recognition in Drilling Time Series," vol. 5, p. 4545, 2013.

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