

Task 10:

Mining Time Interval Temporal Patterns For Anomaly Detection in ICS

PI: Dr. Nir Nissim (BGU)

Our Goals and Approach

- Goal:

Developing an accurate anomaly detection model for ICS based on multivariate time series data (MTSD).

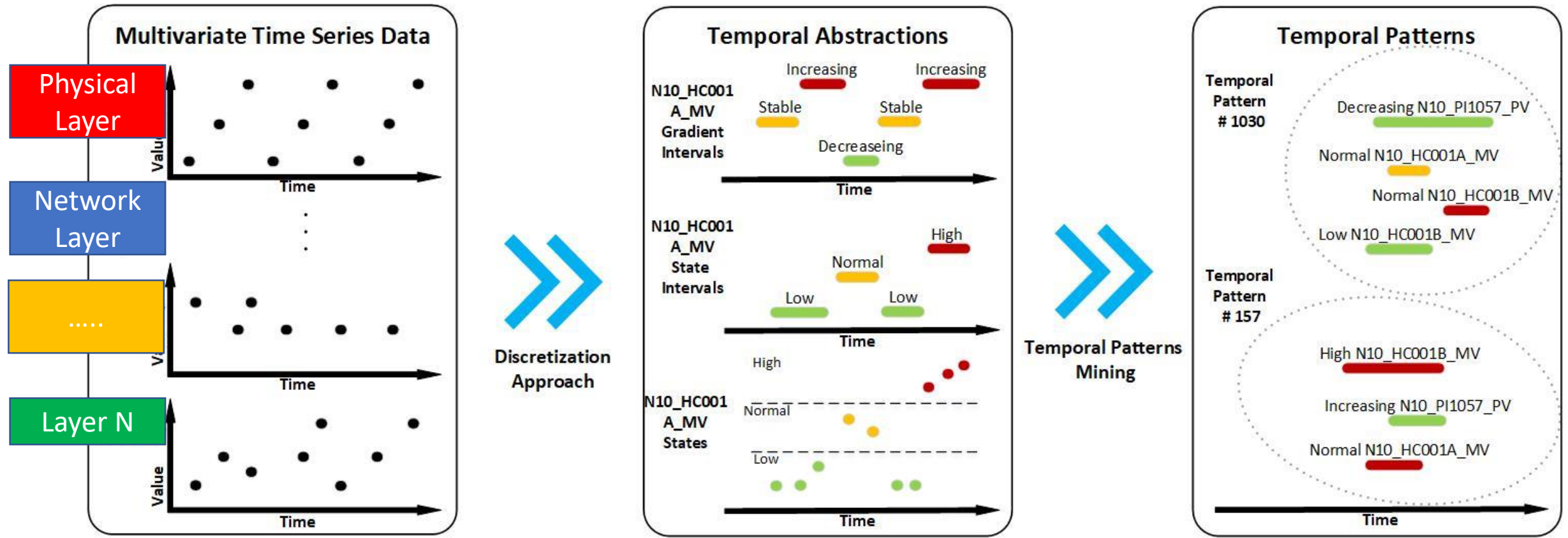
- Our proposed approach:

- Exploiting and Fusing multiple ICS data sources (Physical layer, Network layer etc.)
- Mining Time Interval temporal patterns that capture the temporal interaction (B. layers and variables)
- Induce an ML based detection model that well profile normal ICS behavior over time
- Detect Anomalous behaviors in ICS based on the profiles we have learned

- Current sub goals:

- Fully understanding the data that we were provided with (Delek, Otorio, DLC)
- Exploring whether the data is enough for our needs
- Raising our gaps\inputs regarding the data
- Receiving further data that meets our needs
- Designing and Developing our proposed detection model based on the updated data we'll receive

Optimal Case: Temporal Patterns Mining from Multiples Sources



Note: vision can be achieved only if all data sources (layers) will be concurrently recorded from same ICS

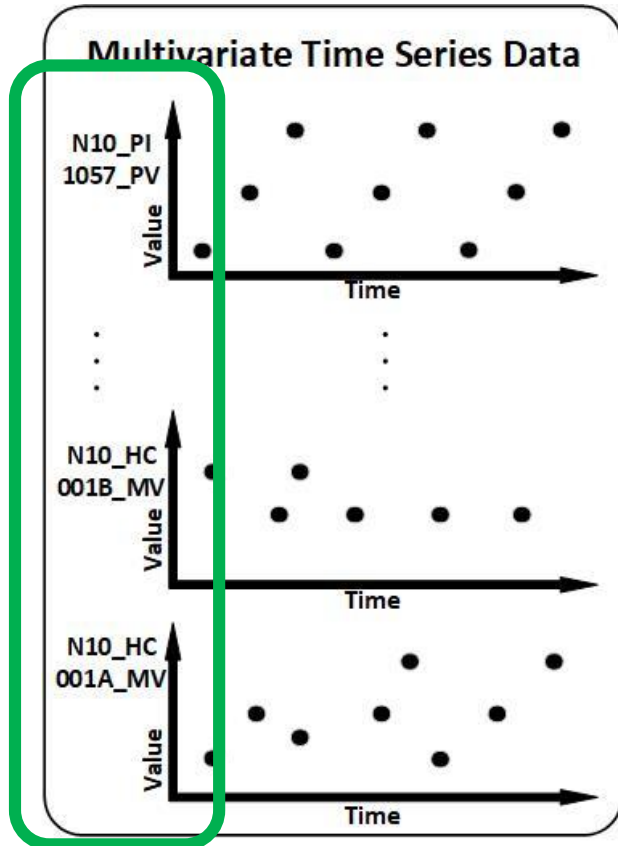
Current Data: Temporal Patterns Mining from one source separately

Delek-US PI - Multivariate Time Series Data (MTSD)

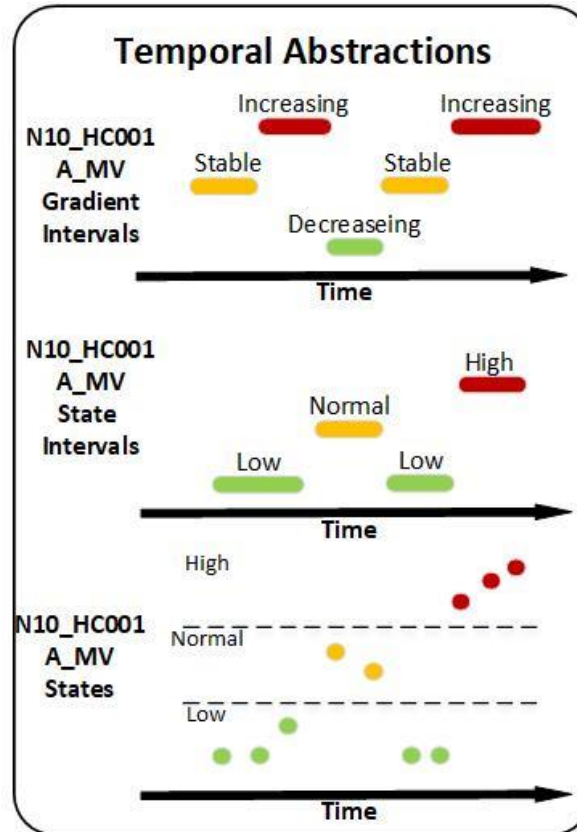
- A Recording of a Single ICS entity (Physical layer)
- Timestamped data, collected from hundreds of sensors via the PI framework 556 Raw Features (different sensor)
- Recording duration ~12 months
- Sampling rate every 30 minutes
- 17521 Timestamped values (in total from all data sources\ sensors)
- Our inputs and gaps to be filled:
 - More explanations and descriptions are required regarding the data (Bob?)
 - Higher Sampling rate is required (much lesser than 30 current minutes, e.g. every minute)
 - Data recorded from more layers are required to better Profile a Generic Normal Behavior
 - Malicious or Anomalous data should be provided to evaluate the model

	DateTime	DateTime_Elapsed	DateTime_year	DateTime_month	DateTime_day	DateTime_hour	DateTime_minute	DateTime_second	DateTime_weekday	N10_HC001A_MV	...	N10_F11053_PV
0	2860.39990	0.000000	2017	10	31	9	35	45	3	58.999939	...	5.422828
1	2860.42065	0.020833	2017	10	31	10	5	45	3	58.999939	...	5.188814
2	2860.44141	0.041667	2017	10	31	10	35	45	3	58.999939	...	4.270872
3	2860.46240	0.062500	2017	10	31	11	5	45	3	58.999939	...	5.009398
4	2860.48315	0.083333	2017	10	31	11	35	45	3	58.999939	...	4.636016

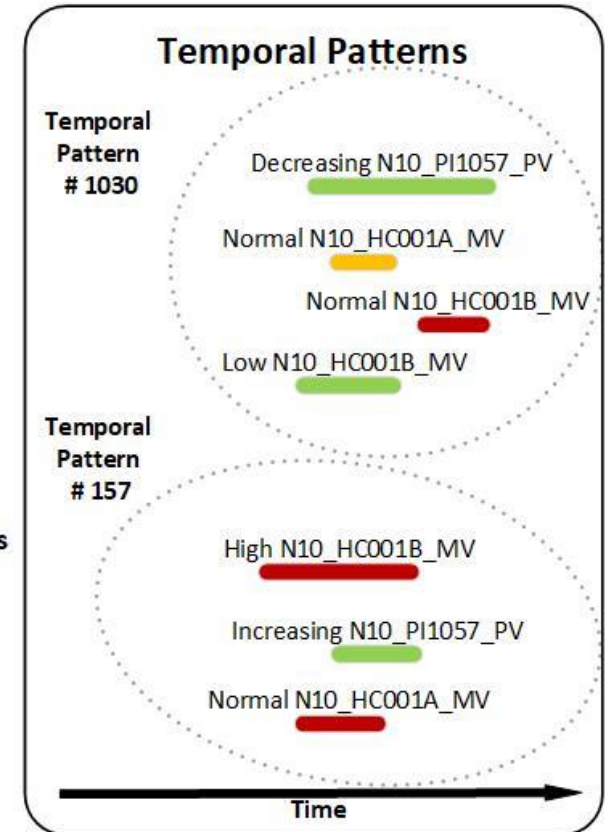
Temporal Patterns Mining – Delek-US MTSD Example



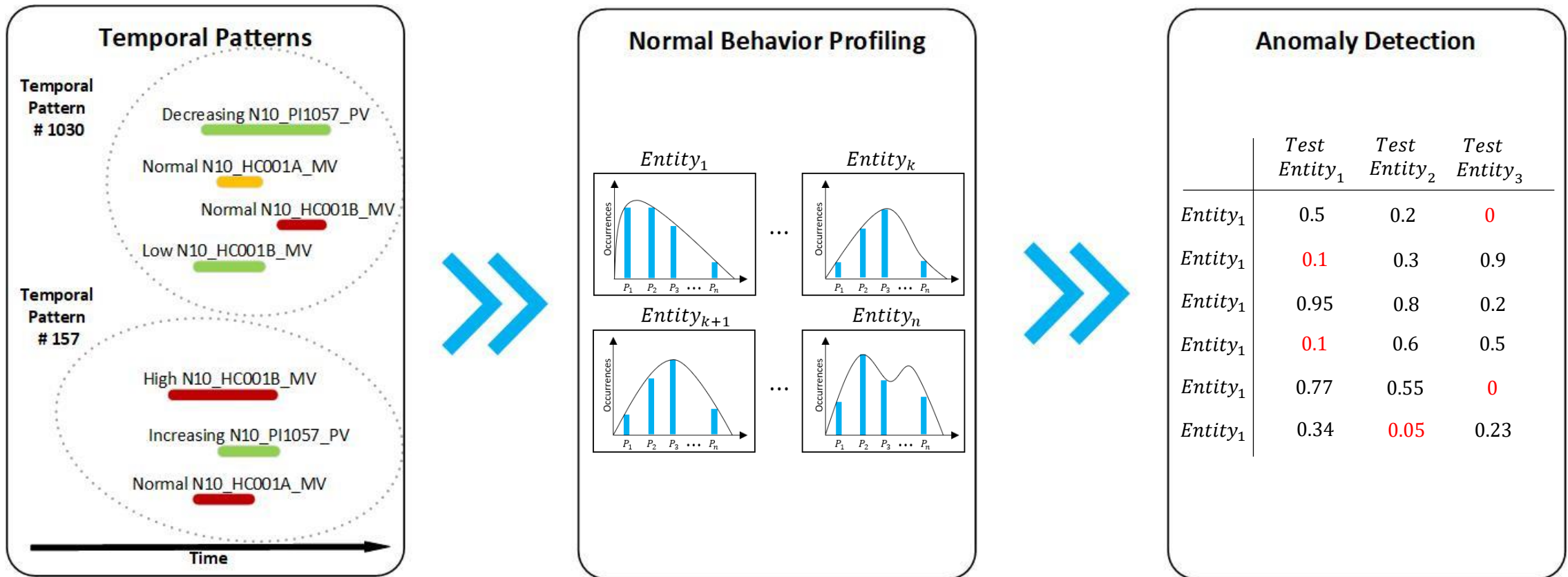
Discretization Approach



Temporal Patterns Mining



Temporal Patterns For Anomaly Detection – Delek-US MTSD Example



Task 12:

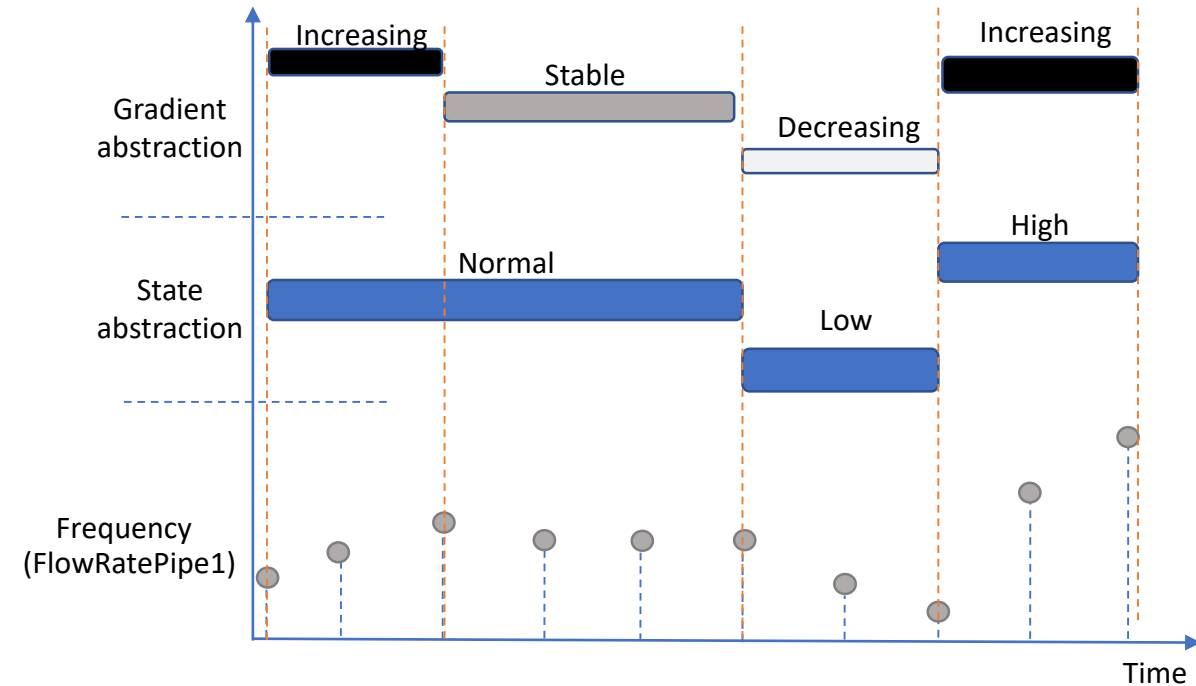
Temporal Explainability of ICS behavior based on Mined Time Interval Temporal Patterns

PI: Dr. Nir Nissim (BGU)

Temporal Patterns Explainability – Developing KBTA for ICS

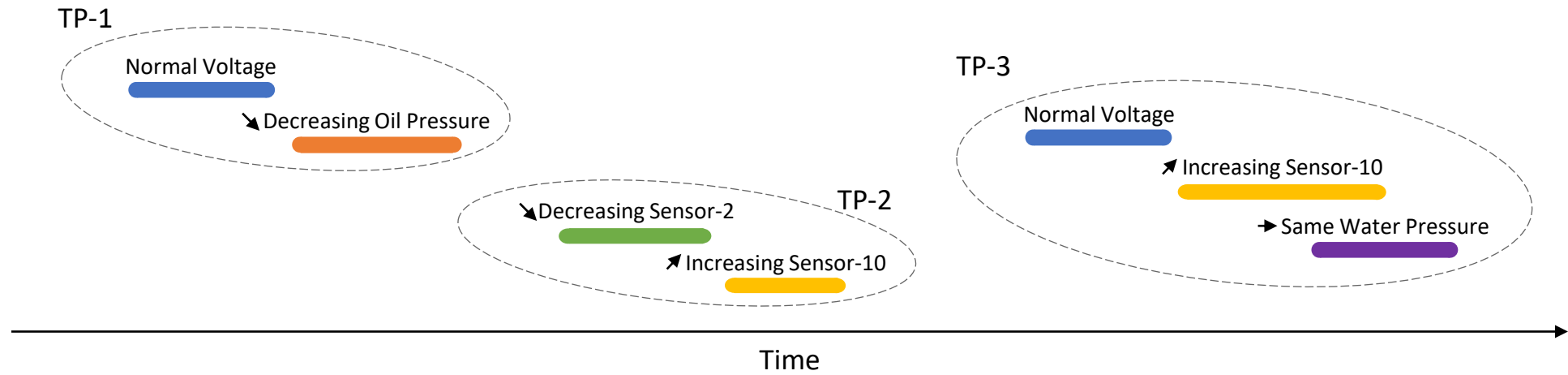
Knowledge Based Temporal Abstraction of an example feature from the WADI Dataset

Feature	Description	Low <	High >	Gradient Trend
FlowRatePipe1	Rate of flow of water into pipe 1 in the testbed	10 m/s	15 m/s	$ \Delta \geq 1$
FlowRatePipe2	Rate of flow of water into pipe 2 in the testbed	8 m/s	12 m/s	$ \Delta \geq 1.5$
FlowRatePipe3	Rate of flow of water into pipe 3 in the testbed	20 m/s	30 m/s	$ \Delta \geq 4$
Boiler1_Temp	Temperature of boiler 1	40° C	110° C	$ \Delta \geq 0.05$
Tank1_Pressure	Pressure of water tank 1	1e6 Pa	2e6 Pa	$ \Delta \geq 1e5$

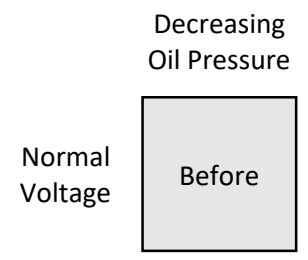


Temporal Patterns Explainability – Developing Exploration & Visualization Module

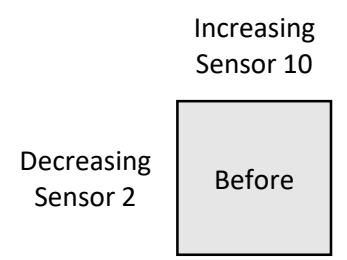
Highlighting and visualizing interesting TPs across time, one can easily explain temporal behaviors.



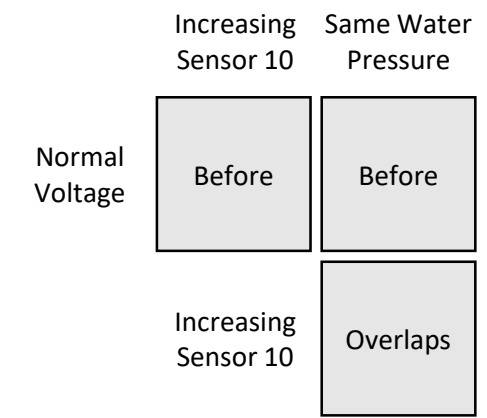
Temporal Pattern 1



Temporal Pattern 2



Temporal Pattern 3



Experiments and Current Results

for Tasks 10 and 12

Based on WADI Dataset

WADI - Multivariate Time Series Data (MTSD)

- The WADI dataset (Ahmed et al. 2017) is a water distribution testbed related data.
- WADI consists of a total of five stages:
 - Three stages controlled by Programmable Logic Controllers (PLCs)
 - Two stages controlled via Remote Terminal Units (RTUs).
- The recorded data consists of:
 - 16 days of sampling (14 normal days ; 2 days containing attack scenarios)
 - 123 **measurements** (continuous as well as categorical) regarding the testbed:
 - Actuators (valves etc.) related
 - Sensors (pH etc.) related
 - **Sampling rates: 60 Hz (each second)**
 - 14 different malicious attacks on different **parts (e.g. Sensors, Valves, Pumps)** of the testbed
 - High class imbalance – 94% of the data is “no-attack” and 6% is “attack”

Data preprocessing:

- Data splitting according to the shortest attack duration (88 seconds)
- 1,980 samples: 120 are related to 1 of 14 attacks , 1880 samples are “no-attack” (Normal)
→ A class balance of 94% Vs. 6%.

Temporal Abstraction & Temporal Patterns mining:

- State abstraction (only) using Equal Frequency Discretization (EFD)
- A vertical support of 50%
- Mining Temporal Patterns of up to size 3 (including)

Machine Learning Algorithms:

- Feature representation using Horizontal Support , Binary
- Feature selection using: Entropy, Gini;
- Selecting different amounts of temporal patterns: 25, 50, 100, 200, 300, 400, 500 and All
- Variety of ML algorithms; RF, SVM (Linear & RBF kernels), KNN, ANN, NB, and LR.

Goal:

- Evaluate the detection capability of our proposed detection method
- Given new (unlabeled) time series of ICS data our method should correctly classify to “attack” or “normal”

Experimental Design:

- The learning methods were evaluated using a stratified 5 folds CV
- Classification performance checked correctness of classifying a given new time series an attack or not.
- Classification performance was averaged across the folds and reported on next slide

Temporal Patterns Mining

- A total of 121,500 time interval temporal patterns have been discovered
 - A total of 105,000 in the “Attack” class of which around 41,000 are exclusive
 - A total of 80,600 in the “No-Attack” class of which around 16,800 are exclusive
 - A total of 63,700 were mutual for both “Attack” and “No-Attacks”

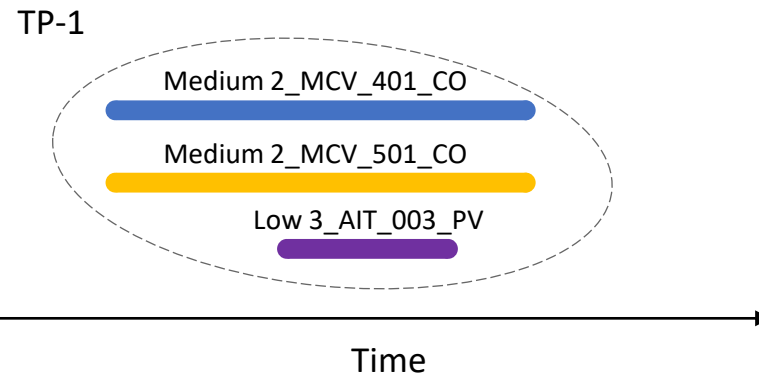
Classification performance (best results are in red)

Method	Precision	Recall (TPR)	F1-Score
KNN (k=5), All TPs, Horizontal Support – Best Precision setup	66.26%	74.43%	75.89%
KNN (k=5), Top 100 TPs, Binary, Entropy FS – Best Recall setup	49.21%	87.4%	52.1%
KNN (k=5), All TPs, Horizontal Support – Best F1-Score setup	66.26%	74.43%	75.89%
MAD-GAN (Li et al. 2019) – Best Precision setup	46.98%	24.58	32%
MAD-GAN (Li et al. 2019) – Best Recall setup	6.46%	99%	12%
MAD-GAN (Li et al. 2019) – Best F1-Score setup	41.44%	33.92%	37%

WADI - TPs Explainability

Highlighting and visualizing interesting TPs across time, one can easily explain temporal behaviors.

Attack Exclusive TP

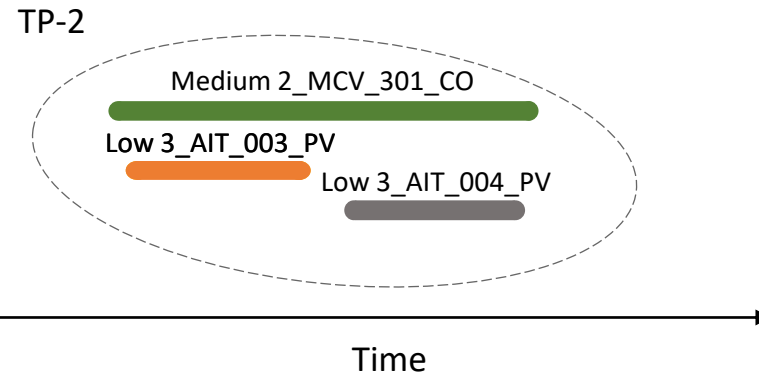


Temporal Pattern 1

	Medium 2_MCV_501 _CO	Low 3_AIT_003 _PV
Medium 2_MCV_401 _CO	Equal	Contain
	Medium 2_MCV_501 _CO	Contain

MCV = Motorized Consumer Valve
AIT = Sensor to asses compounds in the water

No-Attack Exclusive TP



Temporal Pattern 2

	Low 3_AIT_003 _PV	Low 3_AIT_004 _PV
Medium 2_MCV_301 _CO	Contain	Contain
	Low 3_AIT_003 _PV	Before

WADI data collection (Water Distribution):

Data preprocessing:

- Split the data differently and tune for the best split
- Reduce the number of features using feature selection on the raw data

Temporal Abstraction & Temporal Patterns mining:

- Leverage different discretization approaches (EWD, TD4C or other)
- Leverage additional temporal abstractions (states, gradients)

Machine Learning Algorithms:

- Evaluate additional algorithms as well as TPs dedicated ones (TPF, STF-Mine etc.)

Machine Learning Task:

- Anomaly detection – extend our supervised model

SWAT Data set (Secure Water Treatment)