Automated, fast, multi-timescale, Time Series AI

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APCSM Conference 2022

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Falkonry: Making Smart *Easy*

Automatically watch time series data to identify events you can't see and speed up action

Find complex events

Understand hidden causes

Extremely fast

Forbes AI50 TOP AI FIRMS TO WATCH 2021

AFWERX

AI 100 CBINSIGHTS 2020

JMP EFFICIENT 50

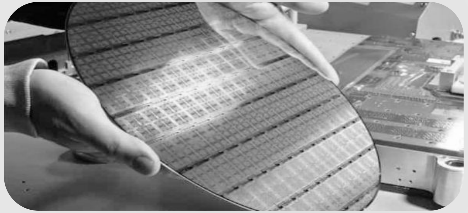
APCSM Conference 2022

Smart factory use cases in semi fabs

PREDICTIVE MAINTENANCE

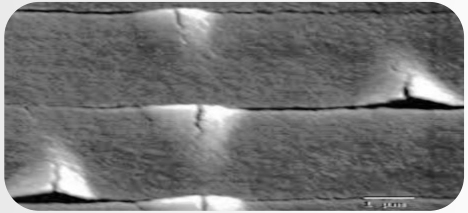
Etching, CMP, Deposition

VIRTUAL METROLOGY



Defectivity Analysis

ROOT CAUSE ANALYSIS

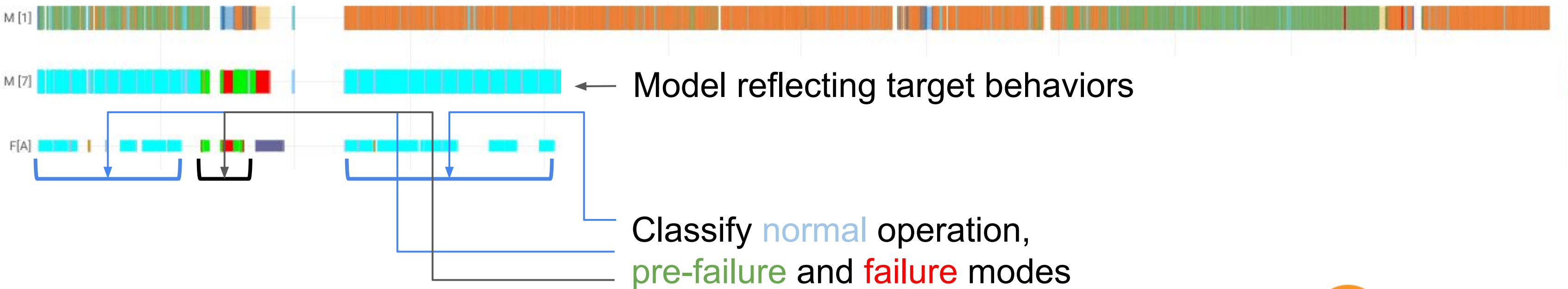


Delamination (Deposition)

Previous Smart Factory approach was ground truth dependent

Failure Prediction Workflow:

1) Collect sensor and ground truth data
2) Understand historical system behavior
3) Separate pre-failure from normal behavior
4) Verify on a different known event
5) Deploy against streaming data



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Outline of our talk

1. Motivation
   a. Smart Factory needs and challenges
   b. Conventional FDC approach
   c. Data science makes it worse

2. Goals and objectives
   a. Better FDC automation goals
   b. AI FDC approach

3. Time Series AI
   a. Autoencoder approach
   b. AI inputs and
   c. Learning data volume

4. Time Series AI results
   a. Time-oriented anomaly
   b. Time-frequency anomaly
   c. Frequency anomaly

5. Conclusions
   a. AI to improve human productivity
   b. Advantages of Time Series AI
   c. Future Work

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Needs and challenges for Smart Factory in fabs

Push to increase engineer productivity

Severe shortage of manufacturing talent, especially in U. S. requires higher analytics automation

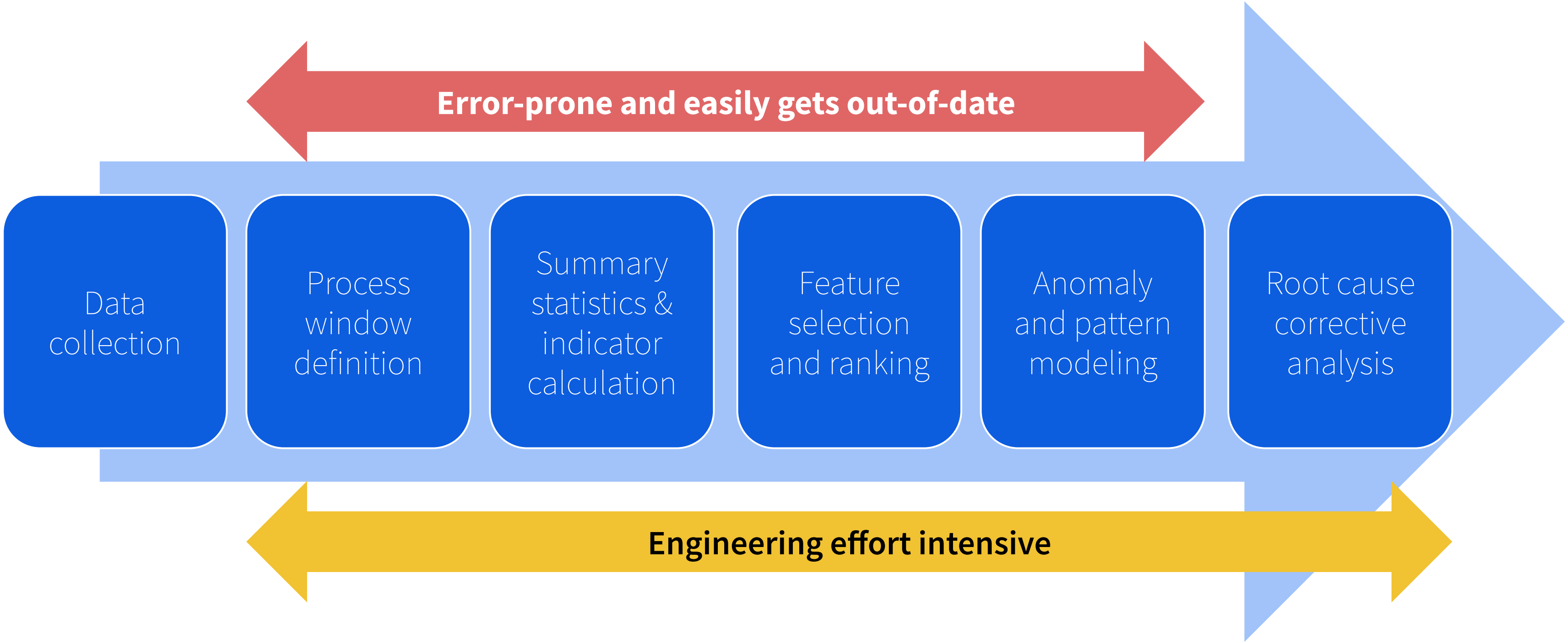
High Complexity of fabs and products

1,000,000s of signal-step-recipe indicators to monitor in mid-sized fabs

Restricted compute technology options

Operational economics do not permit unreliable or non-standard computing resources

Structure of conventional FDC approaches



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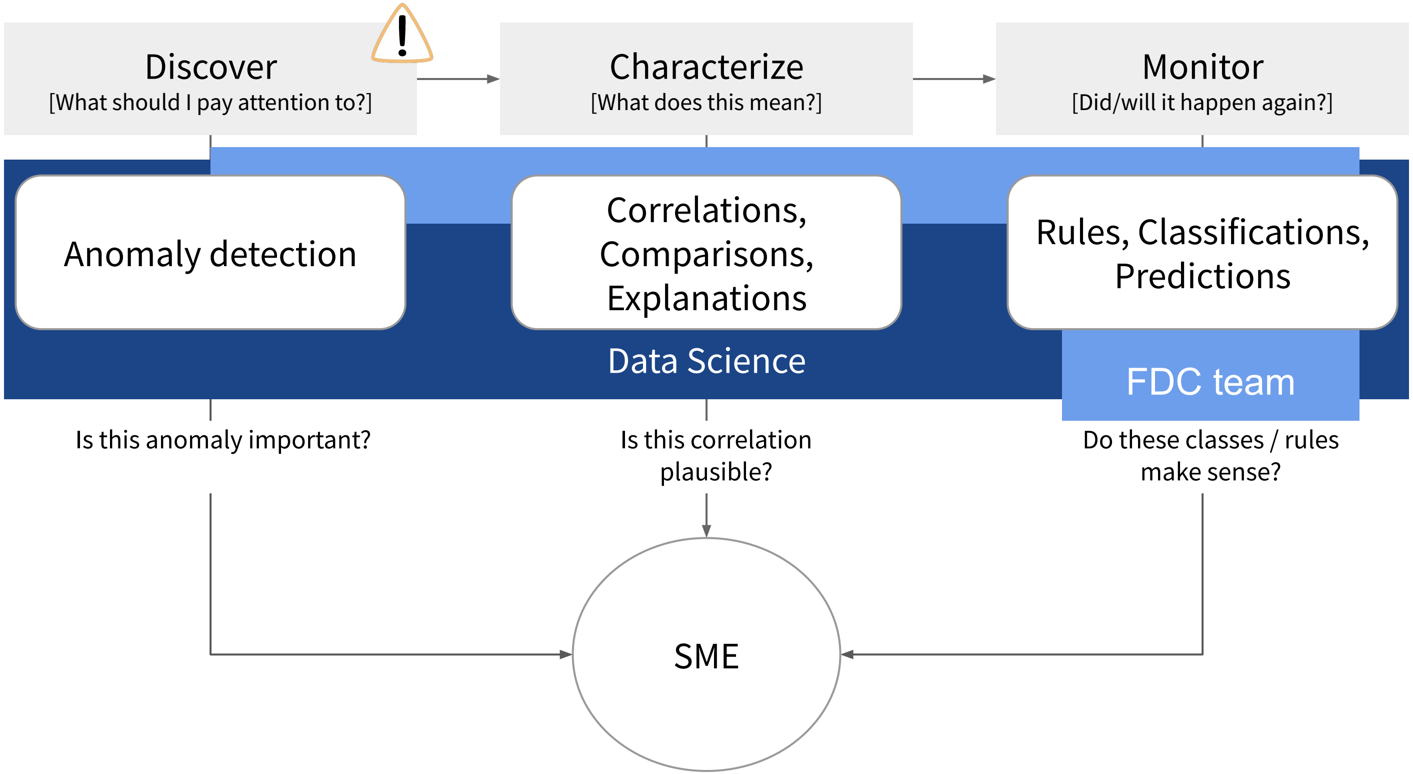
Data science to current FDC functions



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Better FDC automation means

Engineer productivity

1. No human labeling or anomaly detection setup
2. No human involvement on window and indicator definitions

Process complexity

1. Work across tools and products
2. Continuously learns even as recipes change

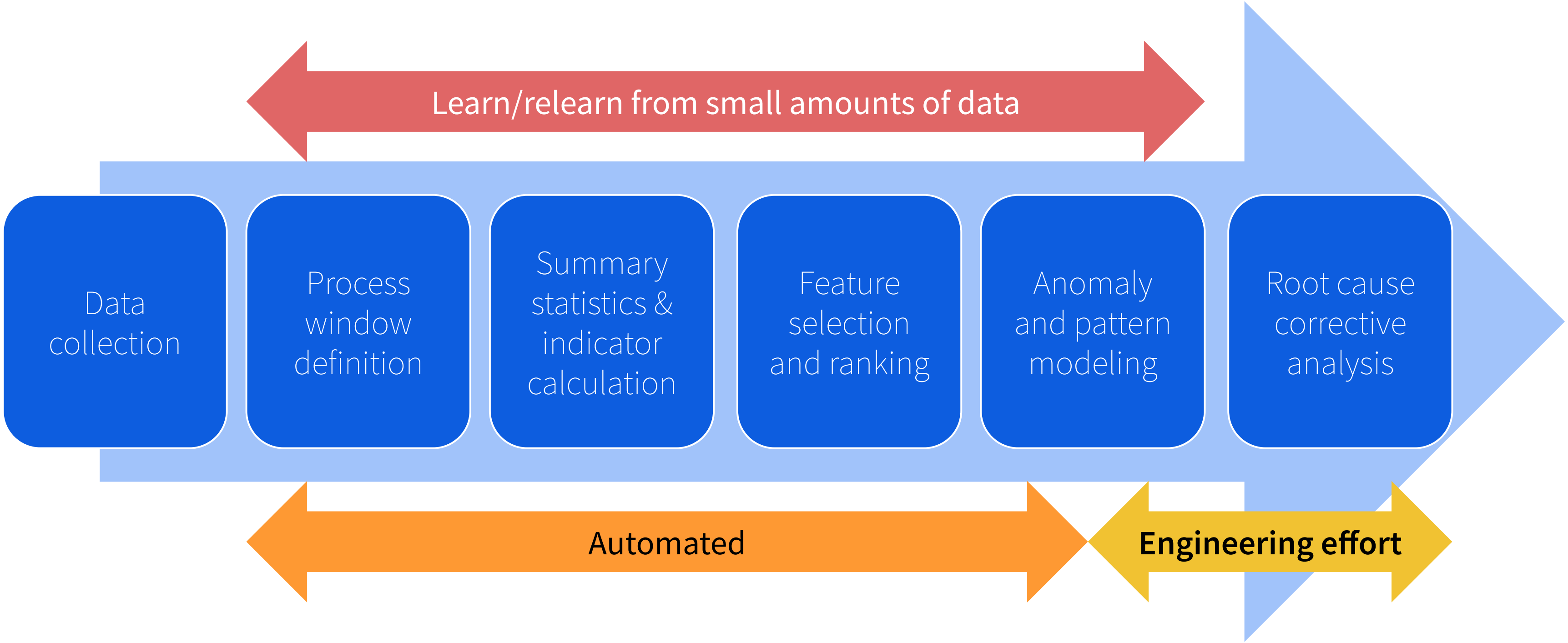
Result quality

1. Anomaly alerts: High accuracy and reasonable false alerts
2. Rare condition classification: High accuracy from low counts

Knowledge digitalization

1. Isolate interesting failure modes
2. Precise findings against specific time steps

Time Series AI approach and reduction of engineering effort



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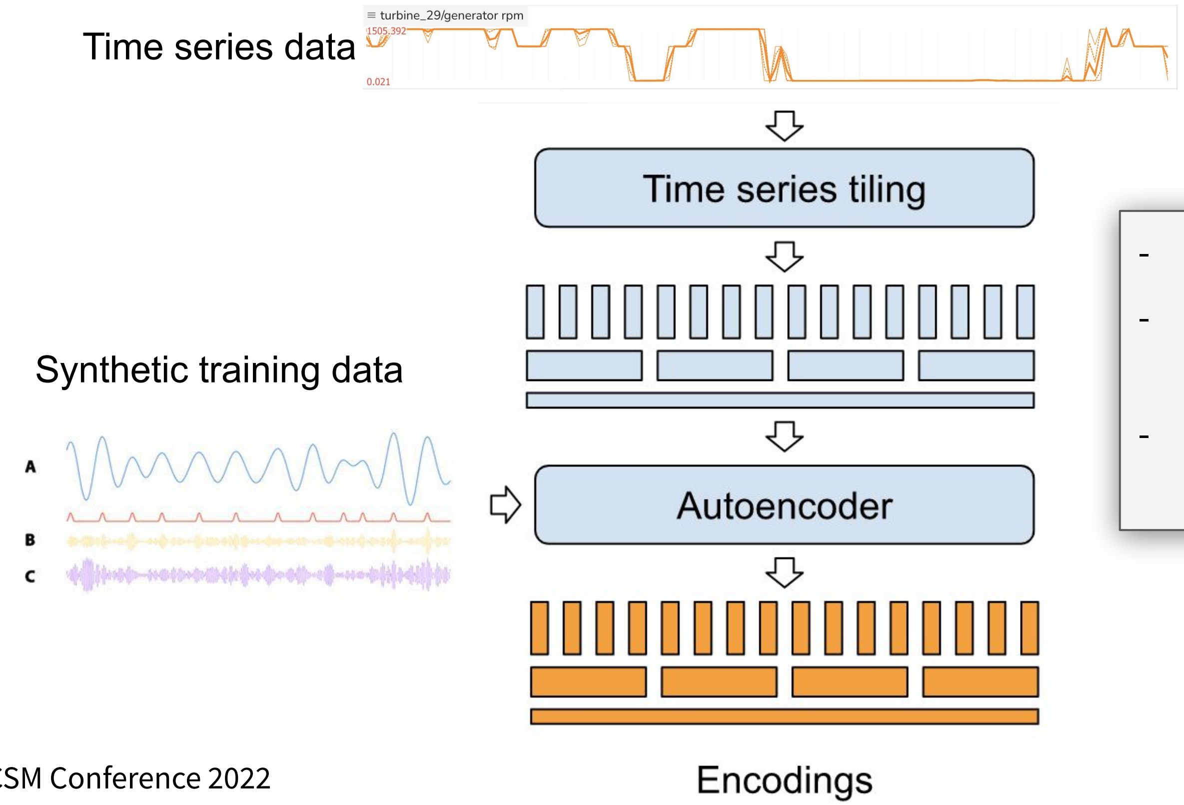
Falkonry Time Series AI: A human efficient time series learner



- Automated: no data set up efforts
- Rapid learning: historical data not needed
- Fast inference: independent of signal sampling

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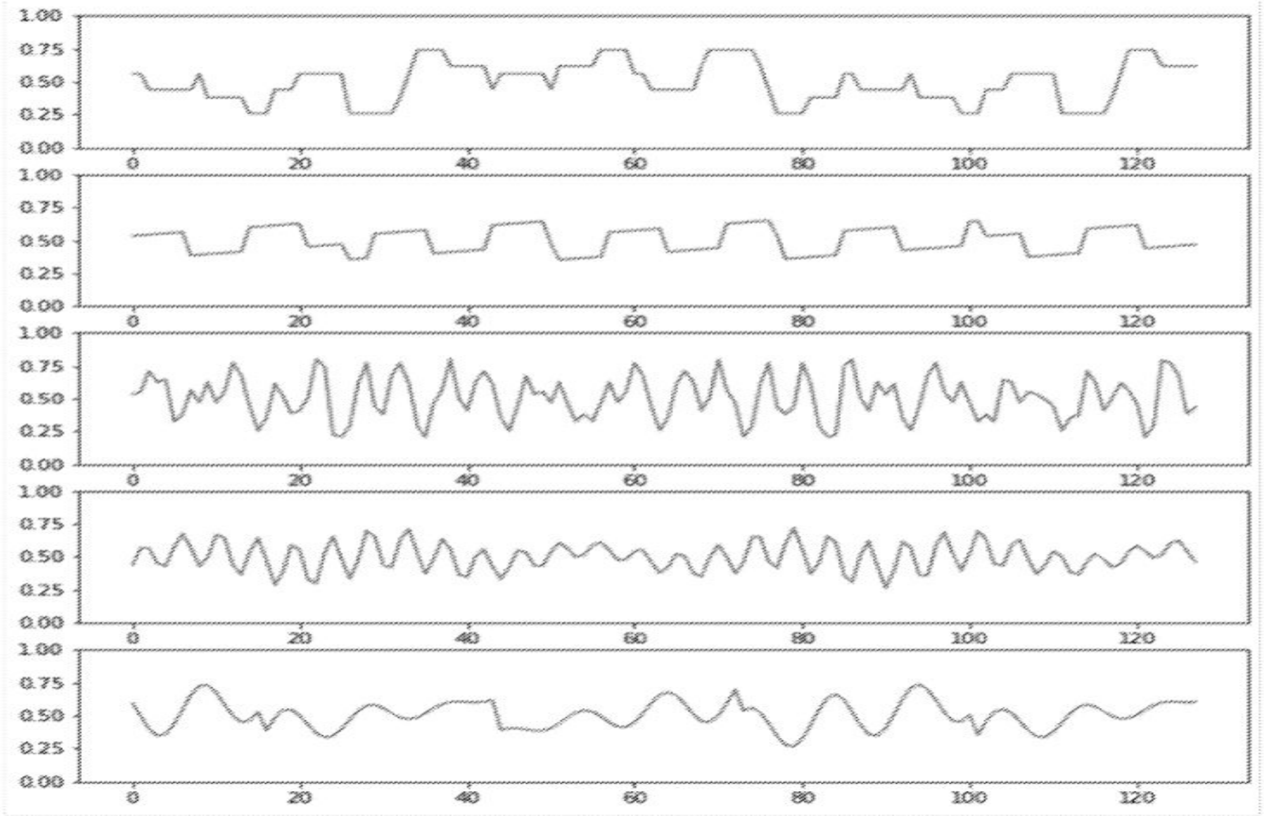
Autoencoder seeded with ramps, sines, and sawtooths



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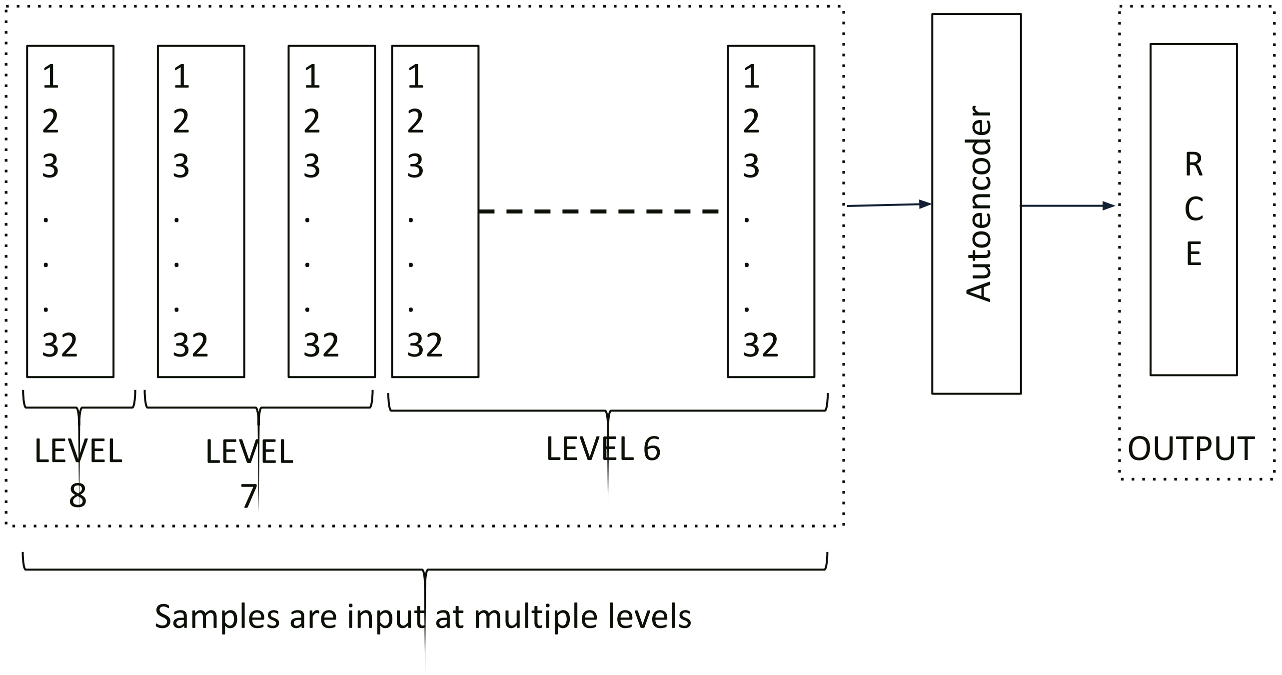
Organize data into tiles at every order of time magnitude

US Patent: [11295414B2]

CVAE needs context to learn: Tiles provide adjacent values



Final learning requires small amounts of data

Approximate extent of data for learning	Sampling frequency (resolution)
A few seconds	1kHz (1 ms)
A few minutes	100Hz (10 ms)
Many minutes	10Hz (100 ms)
A few hours	1Hz (1 s)

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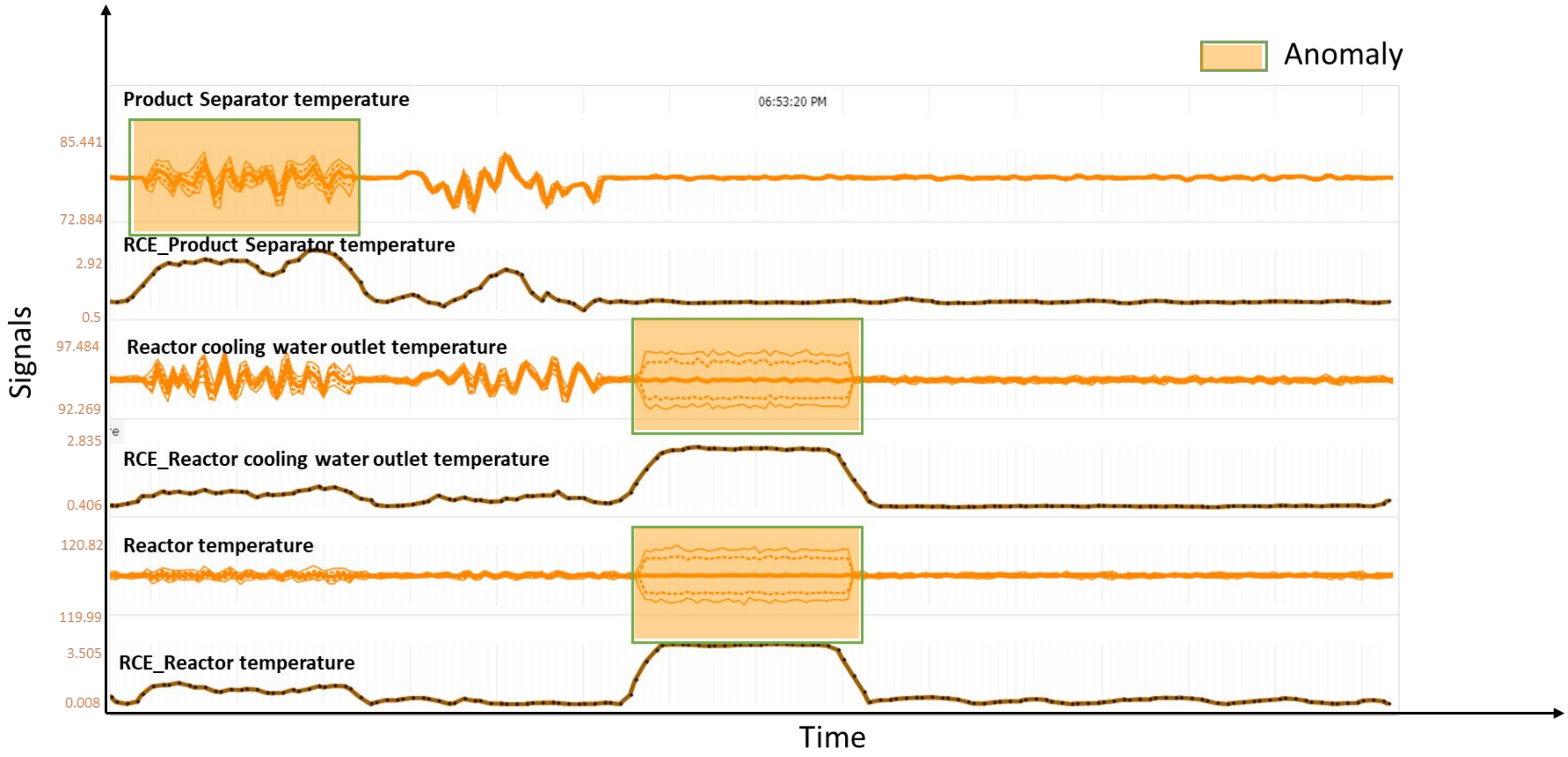
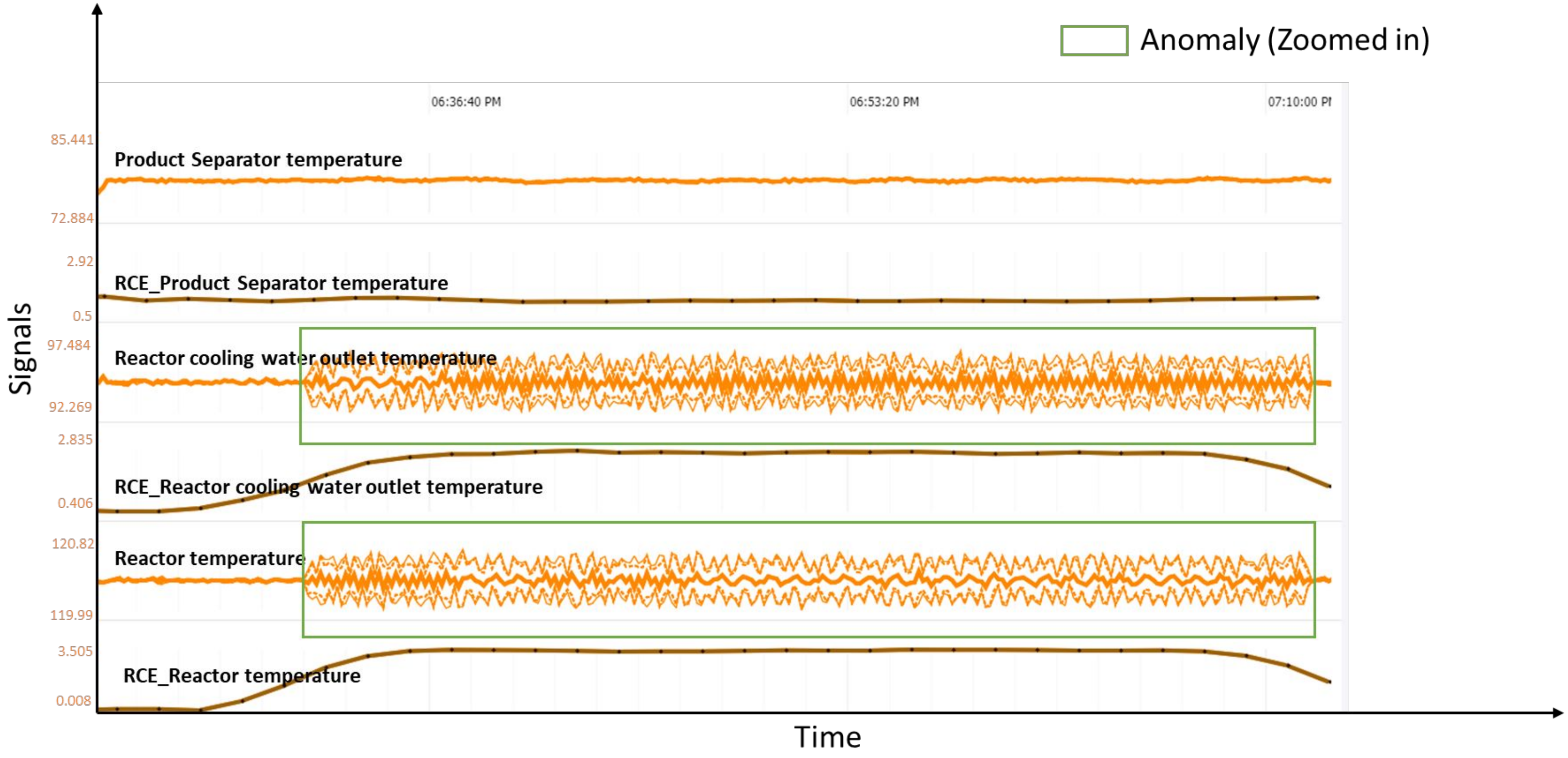
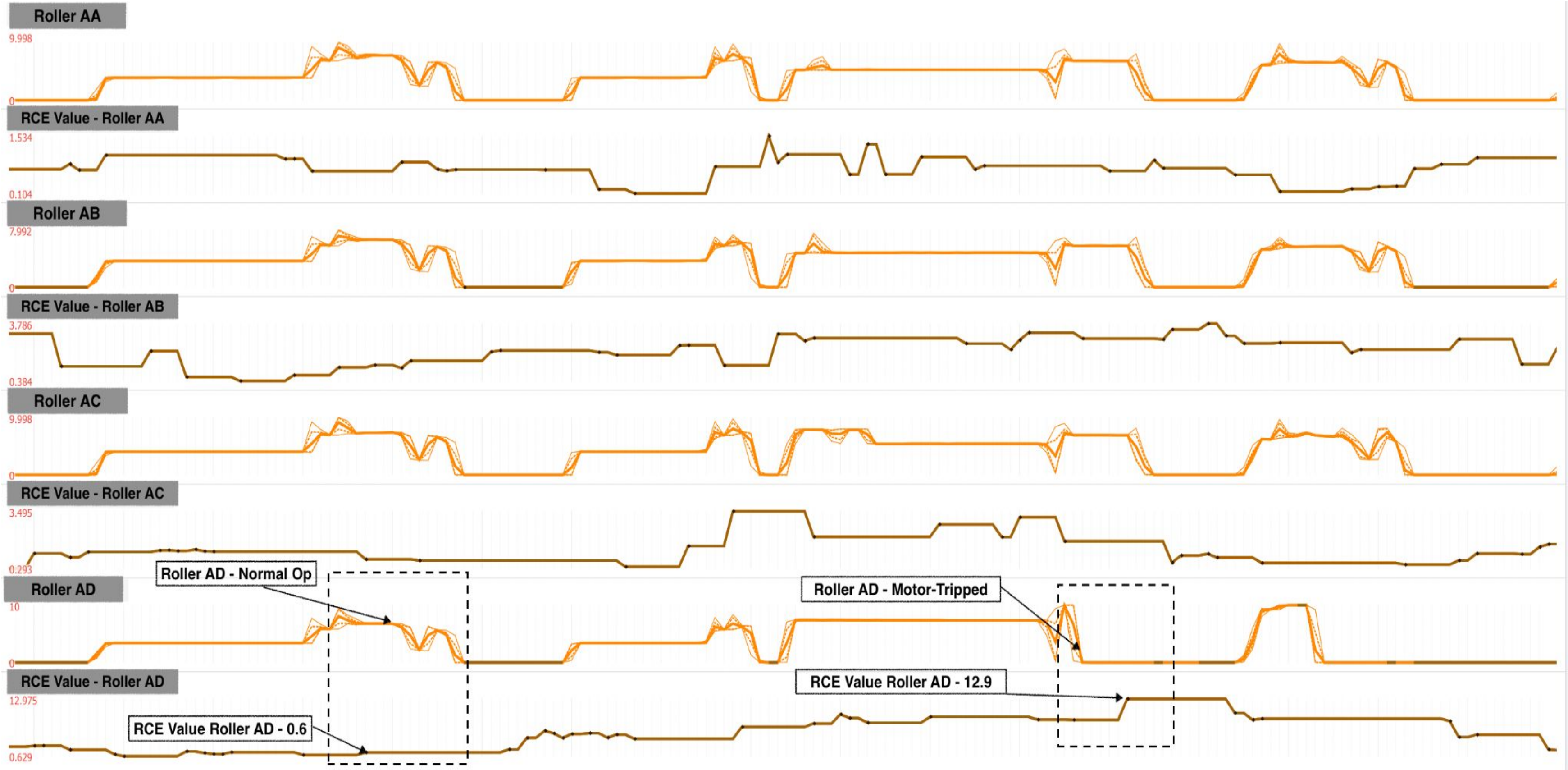
Anomaly spotting in unsegmented data from continuous operations



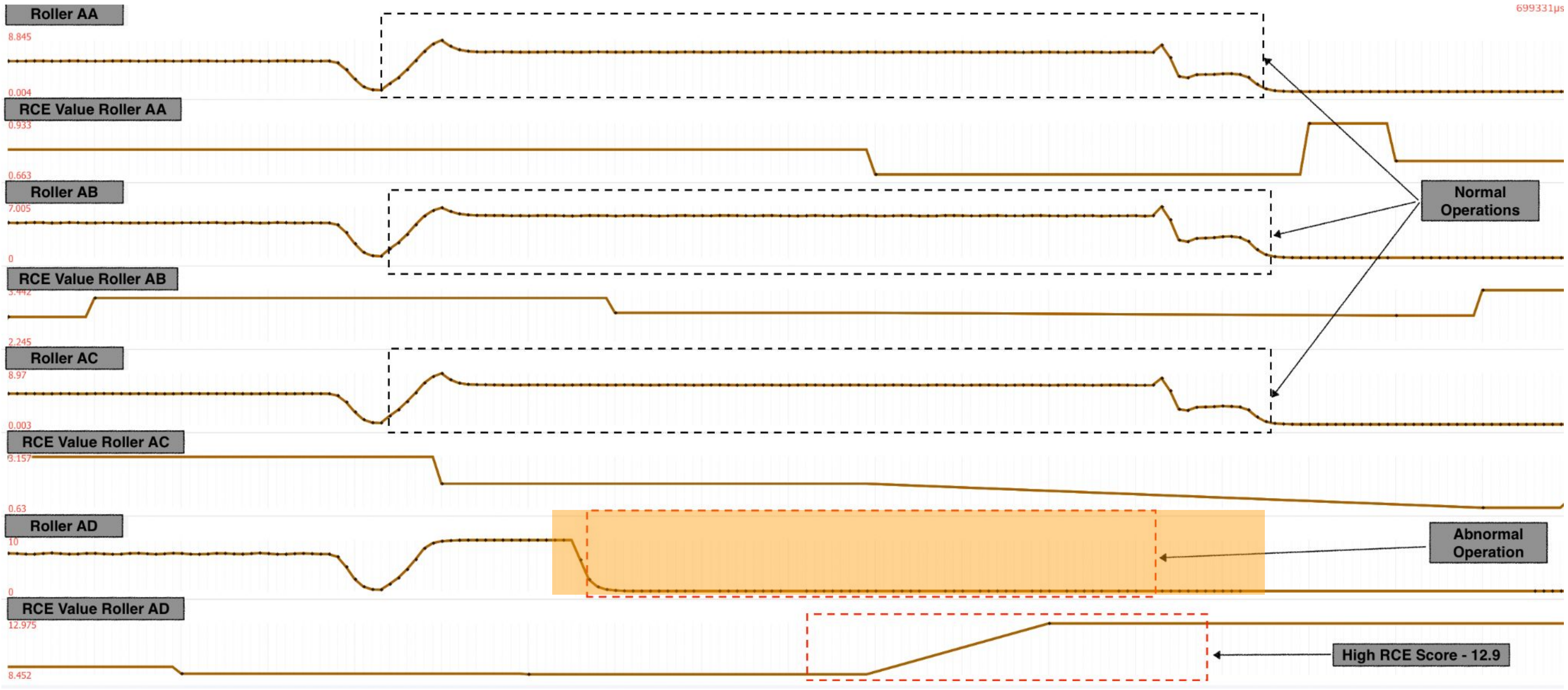
More severe anomaly in reactor temp than cooling water outlet temp



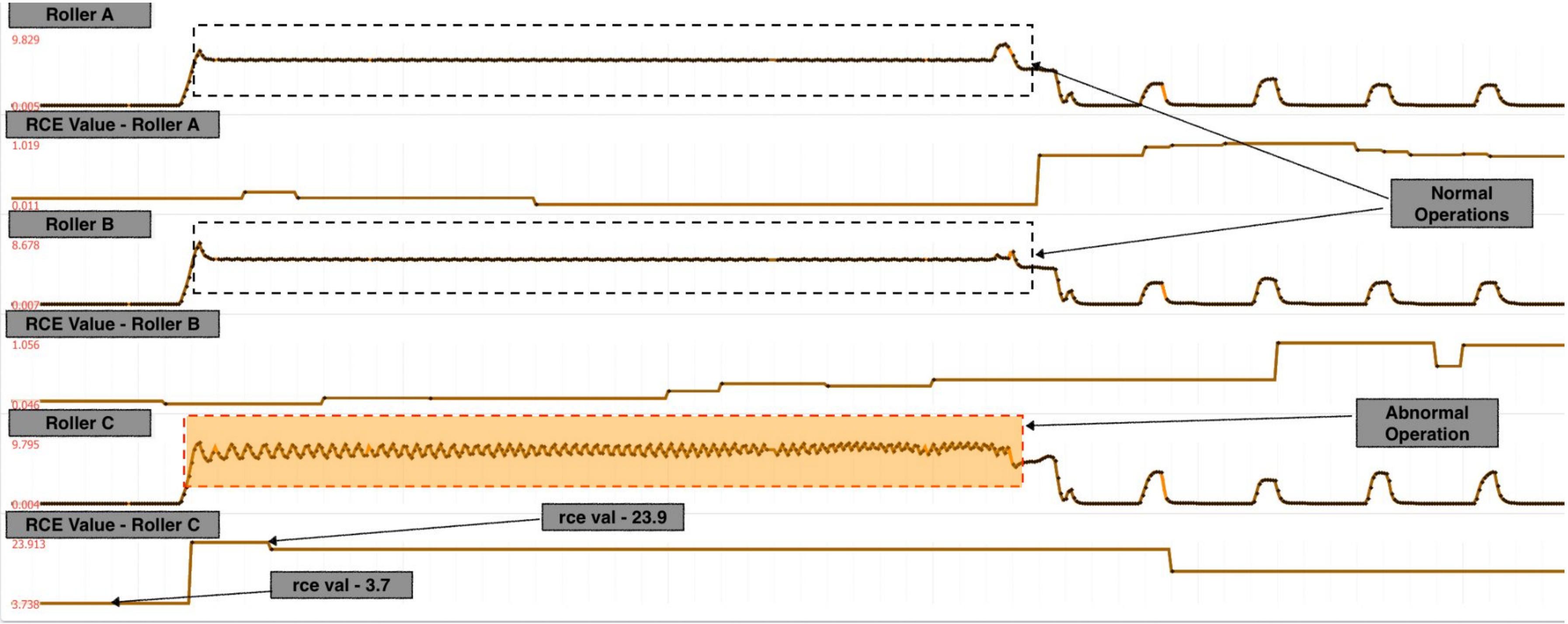
Electrical signal anomaly analysis



Time-oriented anomaly



Time-frequency-oriented anomaly



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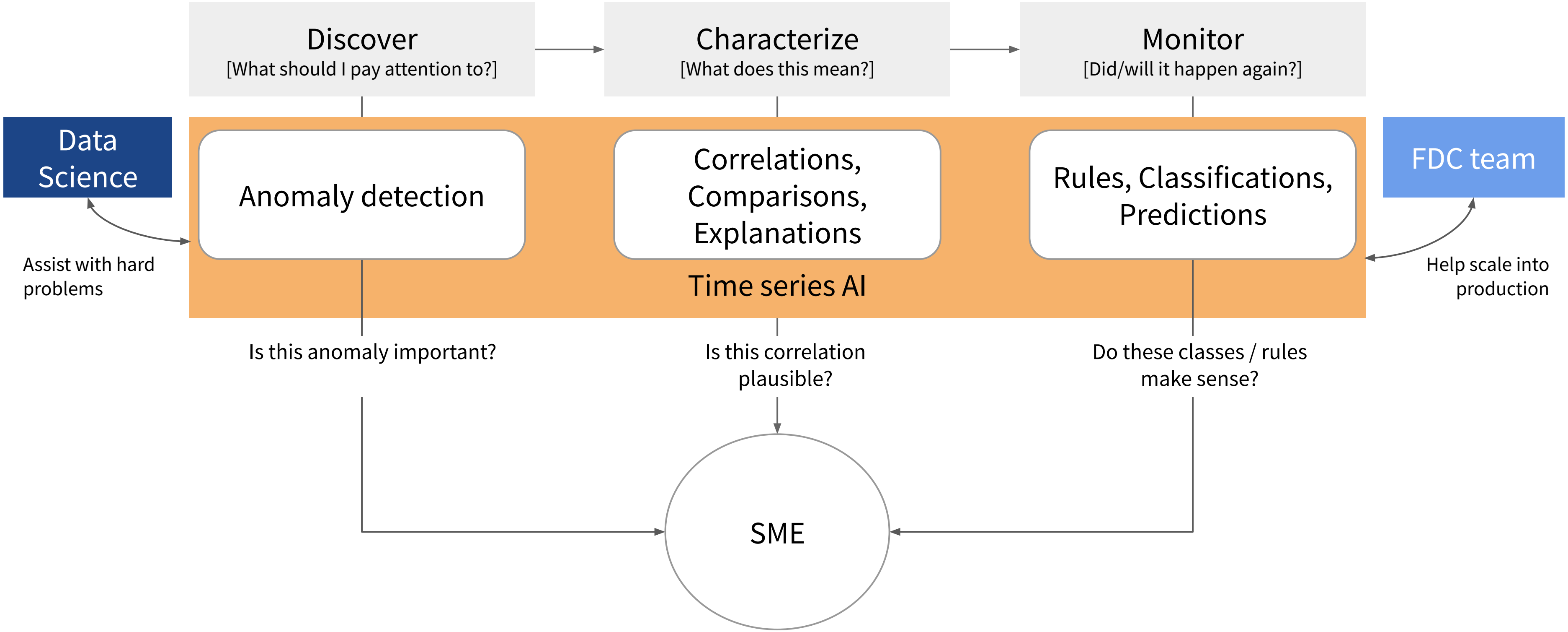
Time Series AI makes SMEs more productive with data



Advantages of Falkonry Time Series AI

Engineer productivity

- ✅ No human labeling or anomaly detection setup
- ✅ No set up/tuning segment boundaries, indicators or parameter bands

Process complexity

- ✅ Work across tools and products with normalized anomaly score
- ✅ Learns continuously and independently of recipes and products
- ✅ Ignored anomalies are learned as normal

Compute efficiency

- ✅ Single pass learning
- ✅ Compute scales linearly with signals
- ✅ Works against > 1kHz signals
- ✅ Uses well tested CVAE and GPU Tensor RT infra

Knowledge digitalization

- ✅ Precise findings against specific time steps
- ✅ Isolates previously unobserved faults without labeling

Future Work

Speed anomaly comprehension

Simplify understanding of anomalies over time and signals through grouping, multivariate analysis, and step marking

Rare condition classification

Use embeddings as feature vectors to create classifiers from two or three failure instances

Search for similar behavior

Assist in root cause analysis by finding similar behavior based on embedding similarity

Field deployment

Field deployed architecture reduces data transmission need and provides immediate awareness of problems