



JAGIELLONIAN UNIVERSITY
IN KRAKÓW

AIRA SEMINAR

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24.04.2025

**Enhancing concept drift detection,
explanation and adaptation to changes
in industrial data streams**

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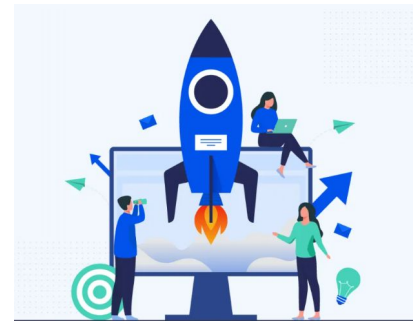
MOTIVATION

Daily life challenges in industry

NEW
PRODUCTION
LINES



NEW/ RARE
PRODUCTS



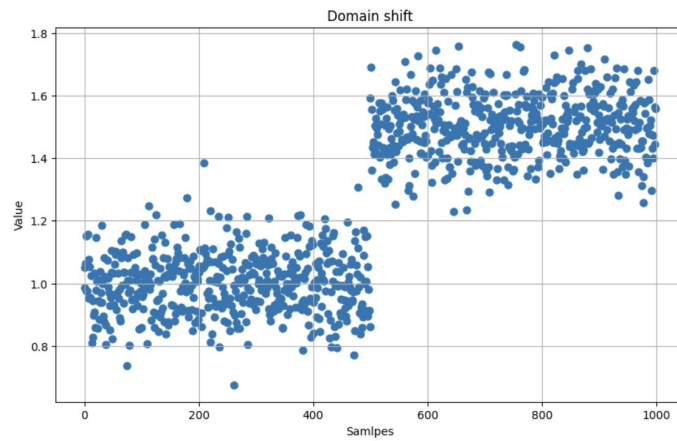
RENOVATIONS/
CALIBRATION



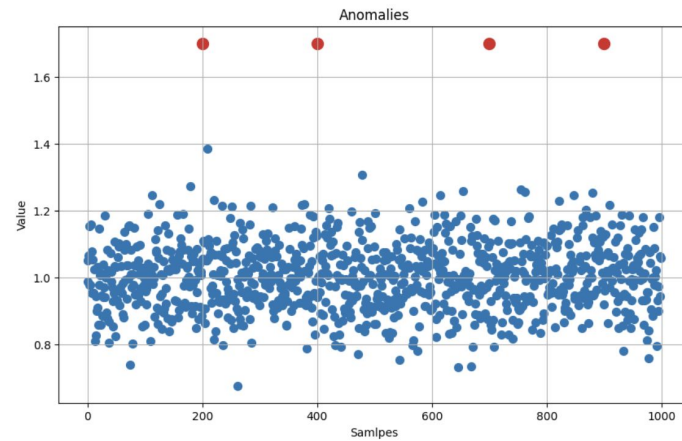
MOTIVATION

Challenges in industrial data streams

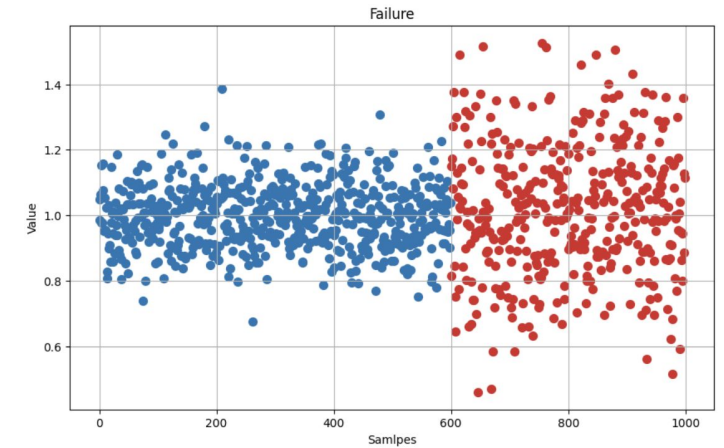
Domain Shifts



Anomalies



Failures



Problems?

1. **Domain shifts violate the i.i.d** (independence and identity) assumptions -> decrease in model performance
2. **Small domains are treated as anomalies by anomaly detectors** -> decrease in production quality, many false alarms
3. **Failures can look like domain shifts** -> no failure detection, adaptation to failures

MOTIVATION



Rapid detection and adaptation to changes in data distribution



Good representation of even small groups of data



Explanation of the changes in data streams



Addressing **Representation** **and Aggregation Biases** in Streaming Anomaly Detection through Domain Adaptation and Data Shift Detection

Natalia Wojak-Strzelecka, Szymon Bobek, Sepideh
Pashami, Grzegorz J. Nalepa

submitted to ECML2025 journal track

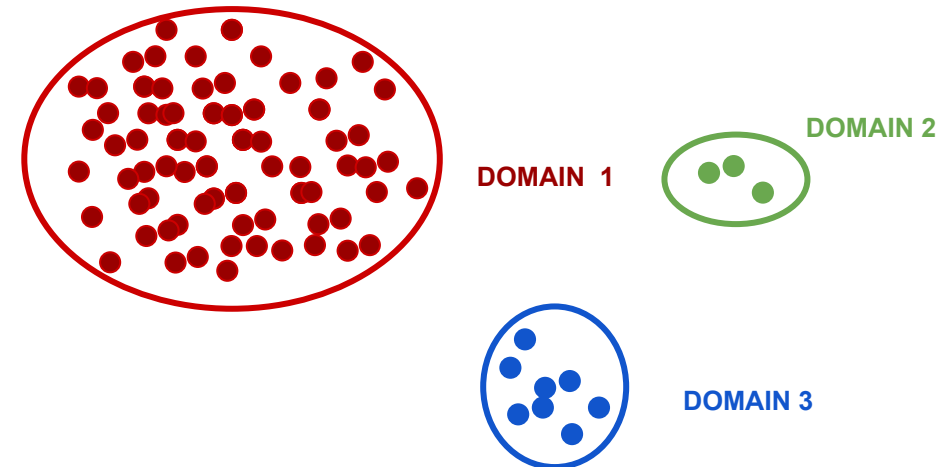
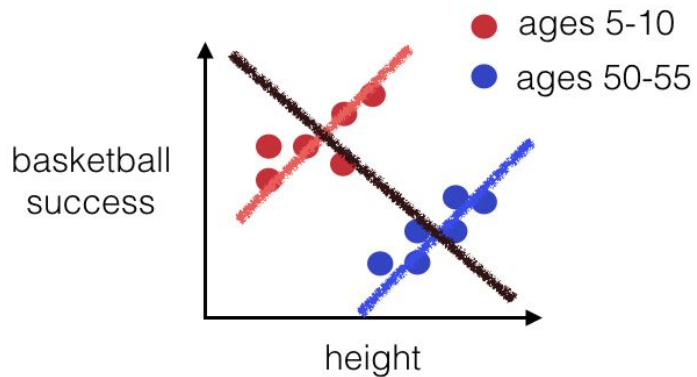
DEALING WITH DOMAIN SHIFTS

ONE MODEL FOR ALL DOMAINS

SEPARATE MODELS FOR ALL DOMAINS

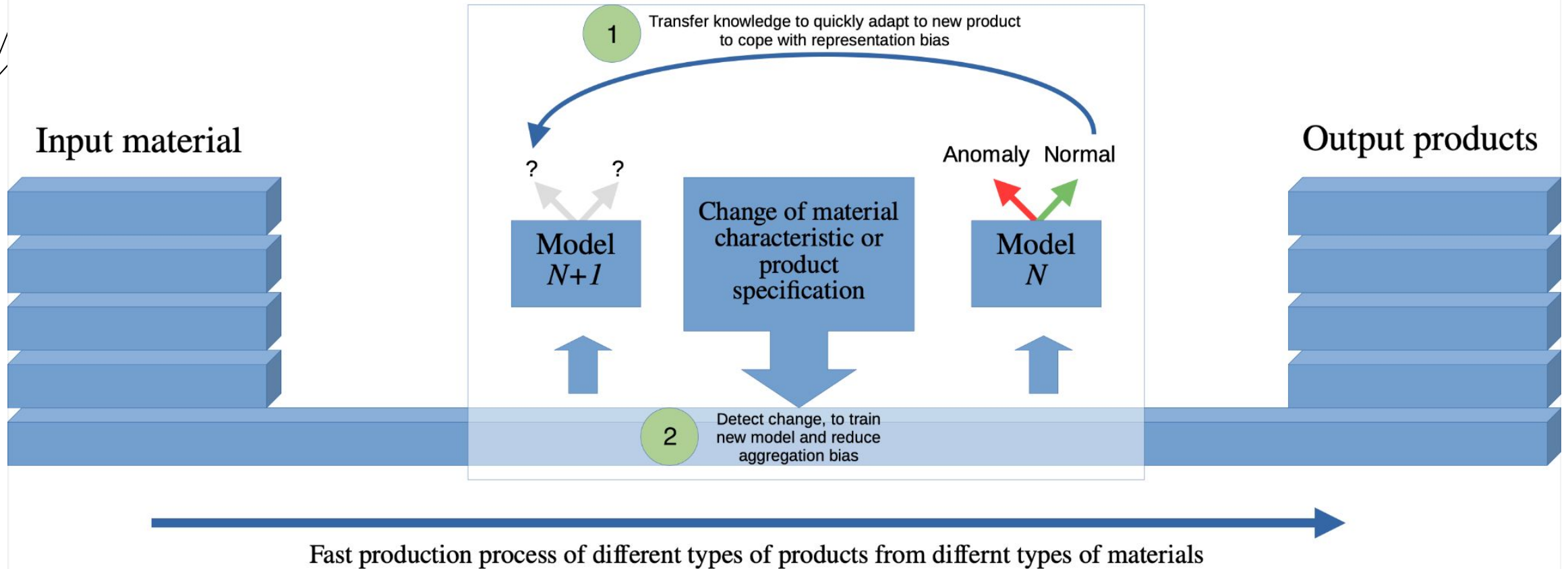
AGGREGATION BIAS

REPRESENTATION BIAS



PROPOSED APPROACH

Product quality management system that detects anomalies in streaming data from the industrial process

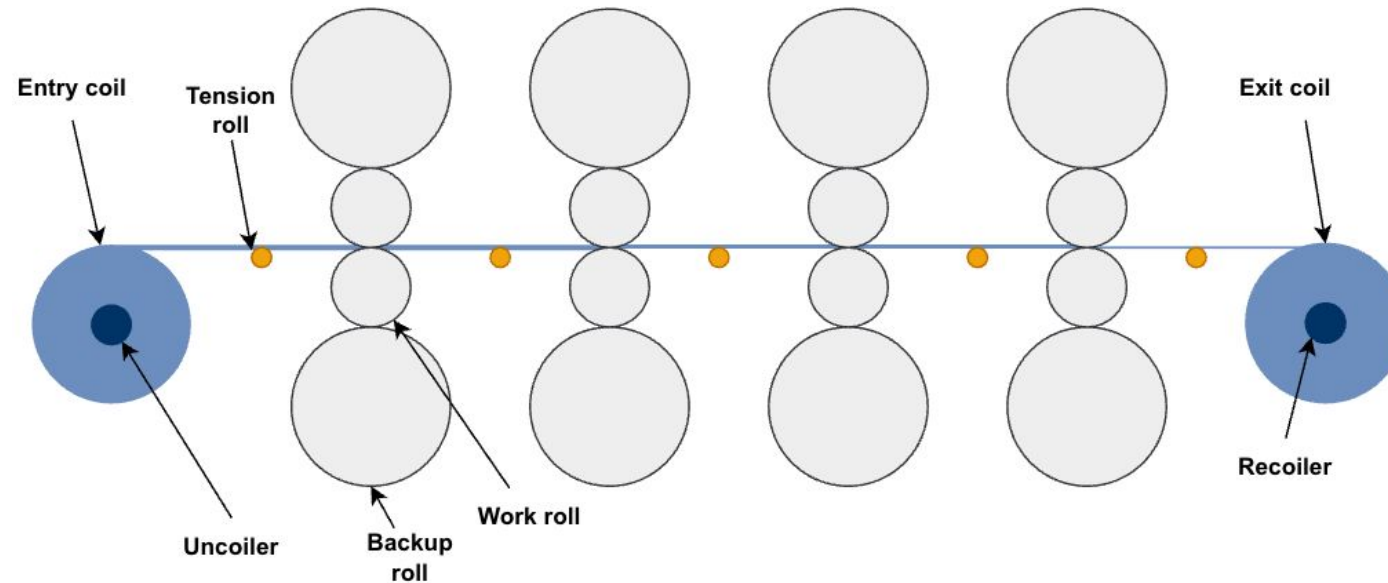


- 1 How to deal with representation bias, where separate models for different products cannot be trained effectively due to lack of enough data
- 2 How to deal with aggregation bias, where one single model cannot be used to handle all types of products efficiently

COLD ROLLING

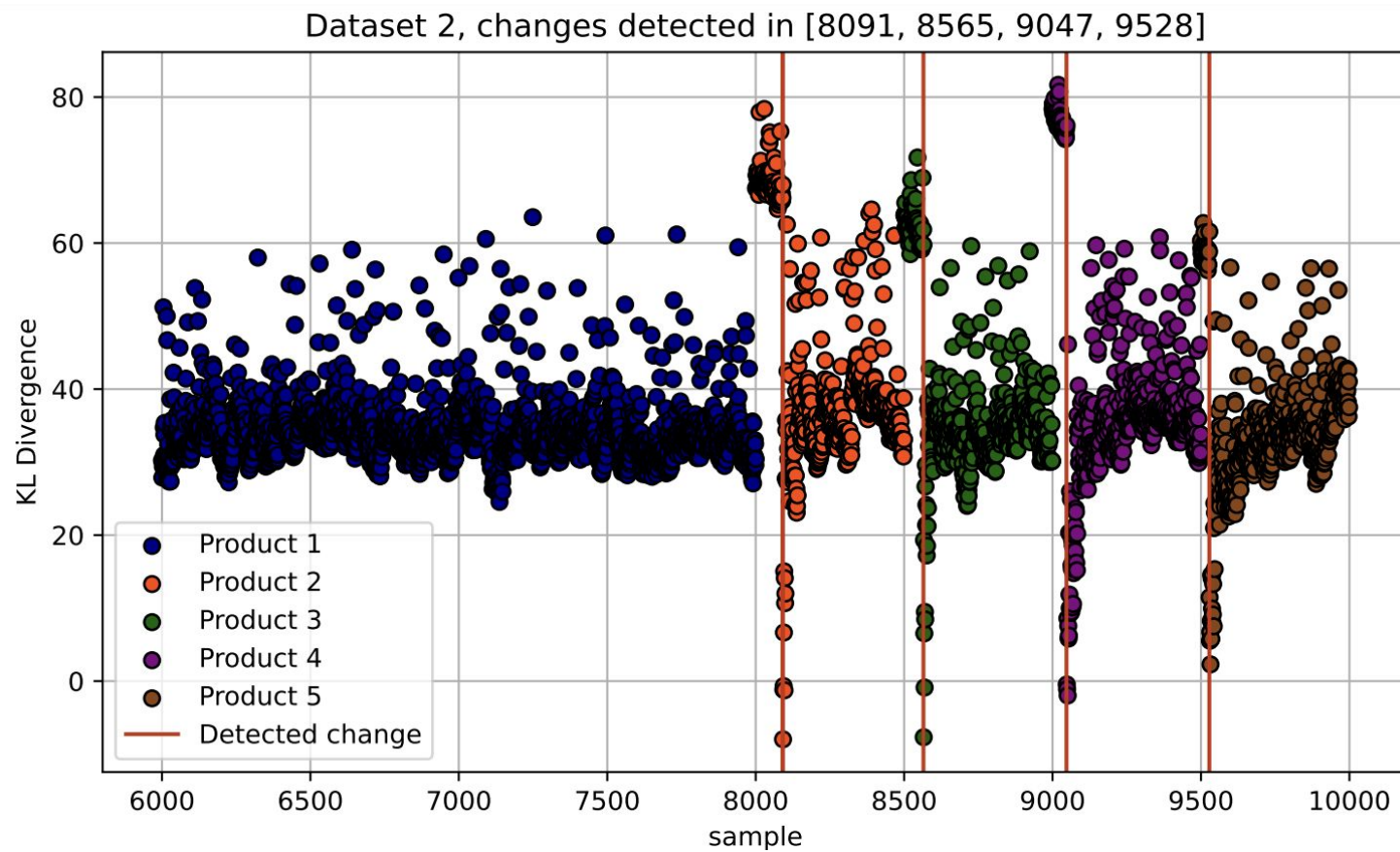
The cold rolling process aims to reduce the steel thickness to a satisfactory level, making the product ready to be sold to customers.

- **Domain shifts** – represents a change in the data characteristics
- **Anomalies** – Short-lasting deviations in process



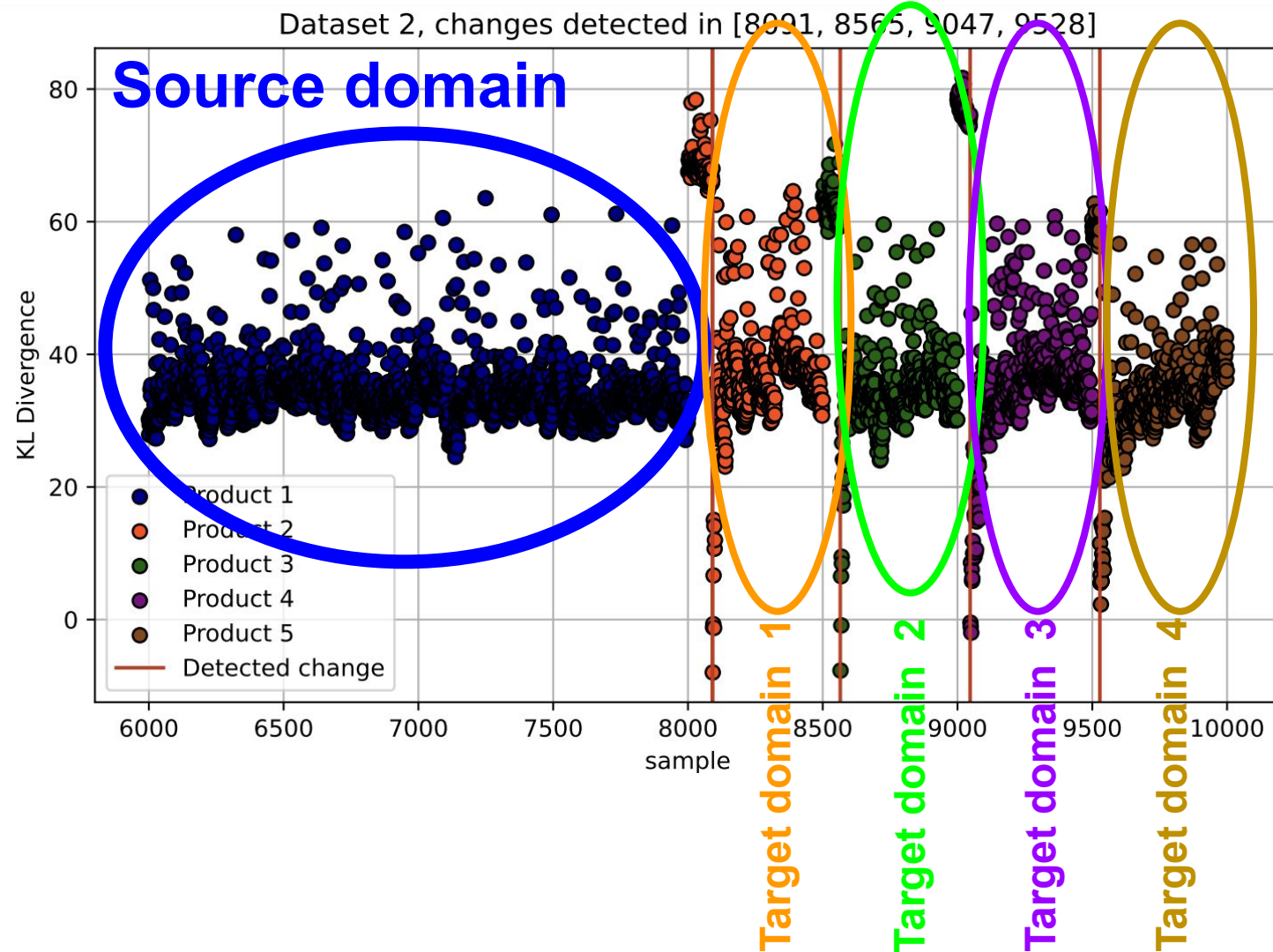
DOMAIN SHIFT DETECTOR

KL Divergence + Page Hinkley

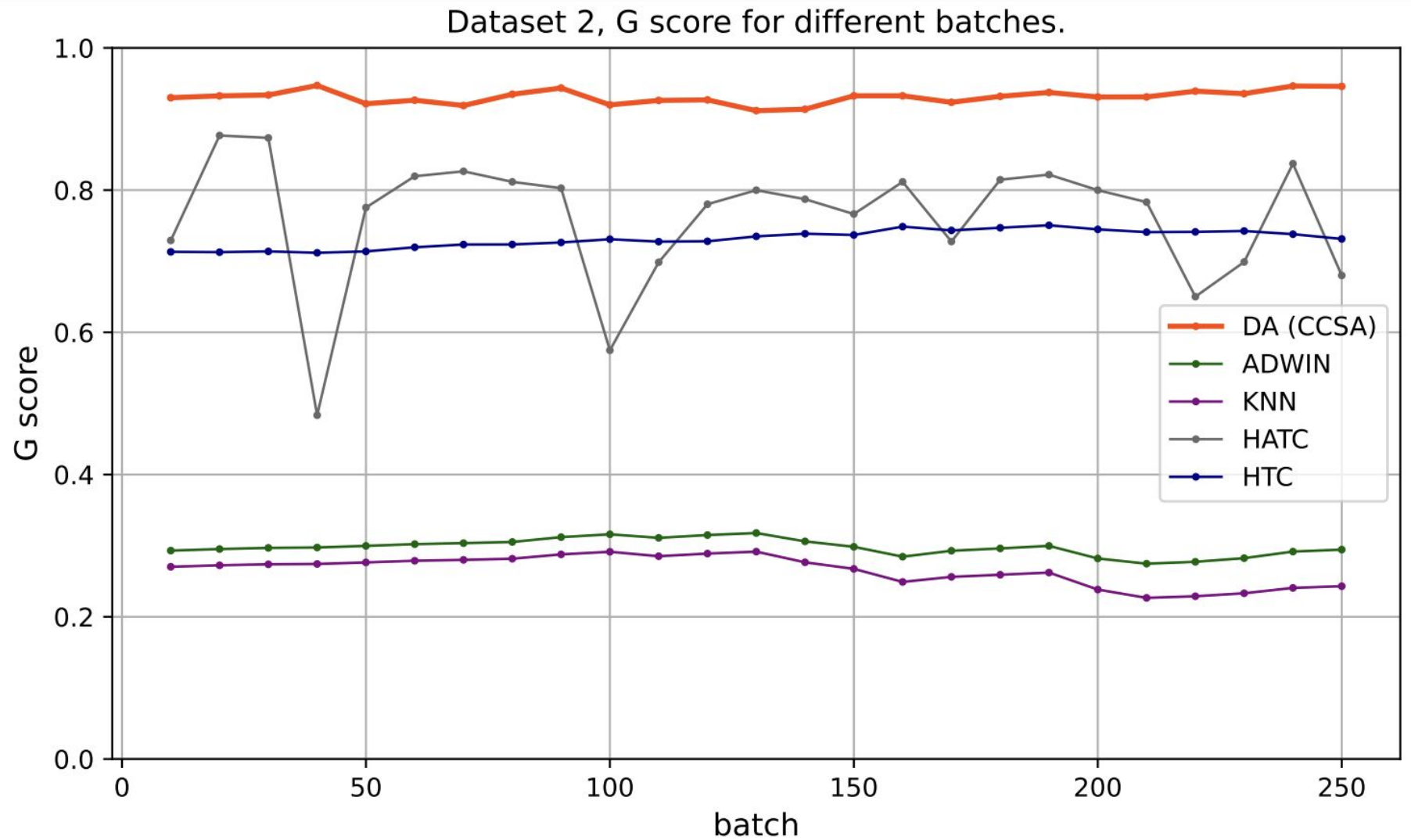


DOMAIN ADAPTATION CLASSIFIER

CCSA (Classification and Contrastive Semantic Alignment) Model



DOMAIN ADAPTATION CLASSIFIER





Towards Differentiating Between **Failures** and **Domain Shifts** in Industrial Data Streams

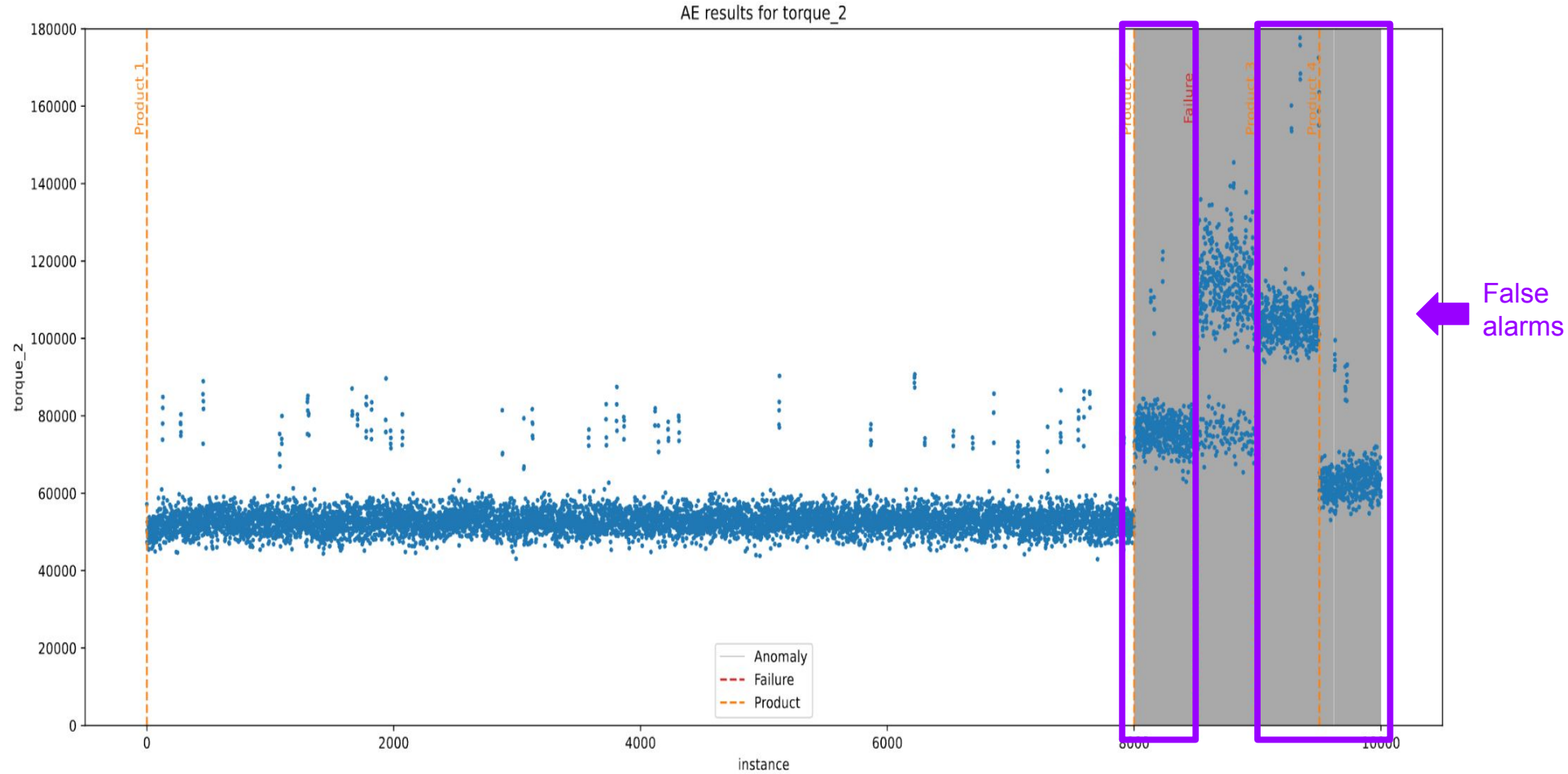
Natalia Wojak-Strzelecka, Szymon Bobek, Grzegorz J.
Nalepa, Jerzy Stefanowski

published on ECAI 2024

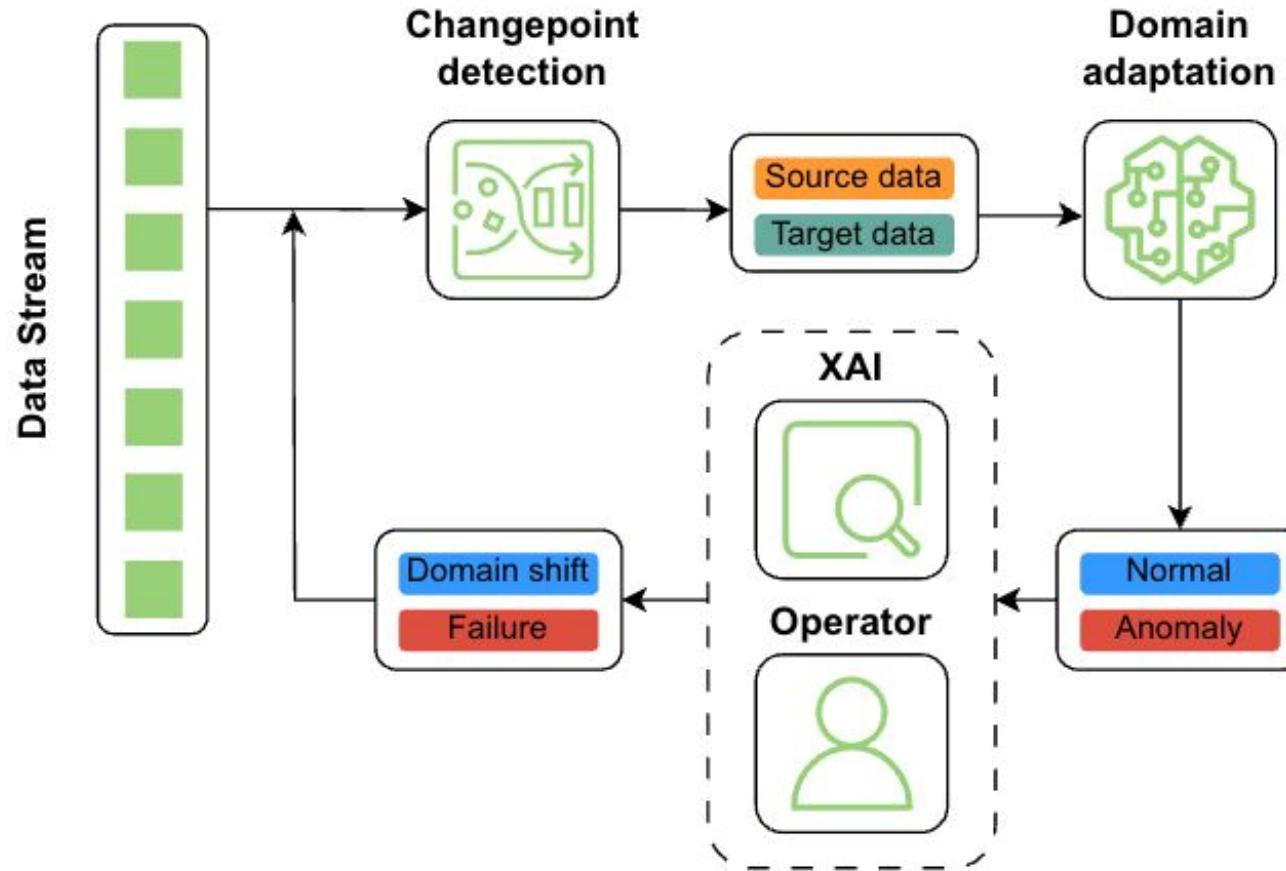
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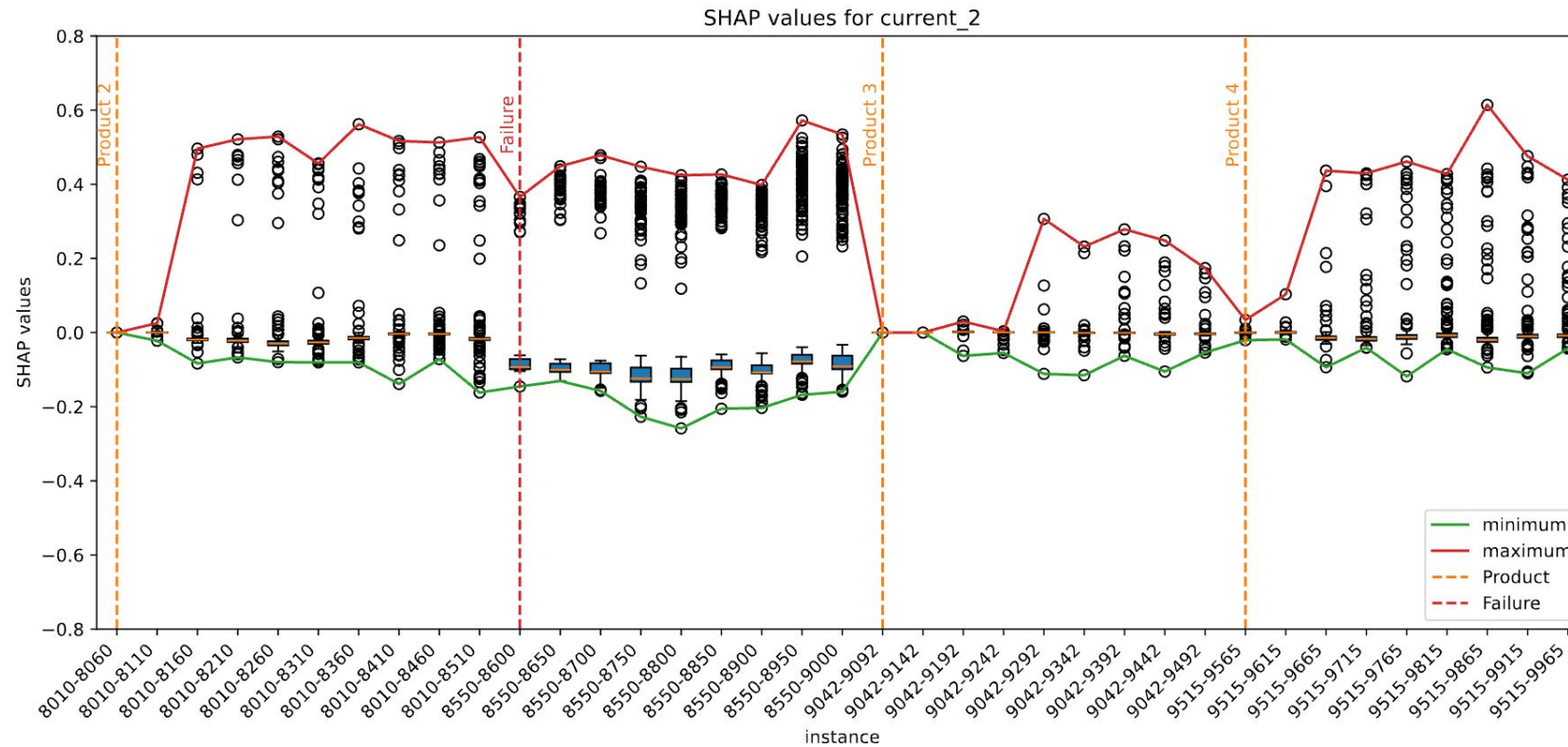
DOMAIN SHIFT VS FAILURE



PROPOSED APPROACH



EXPLANATION OF THE CHANGES OF MODEL BEHAVIOR BETWEEN CHANGEPOINTS





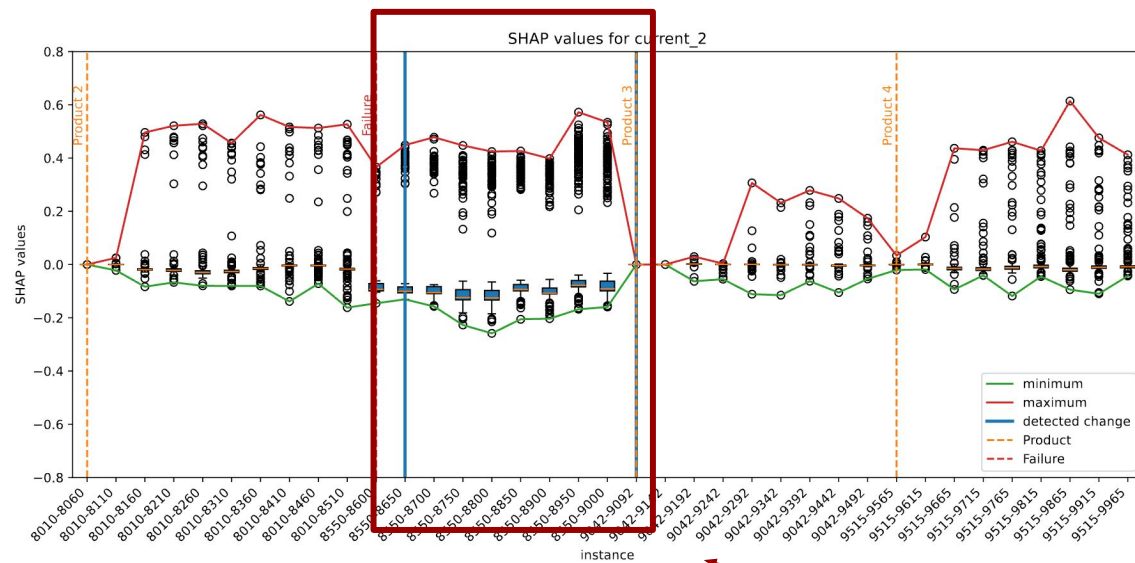
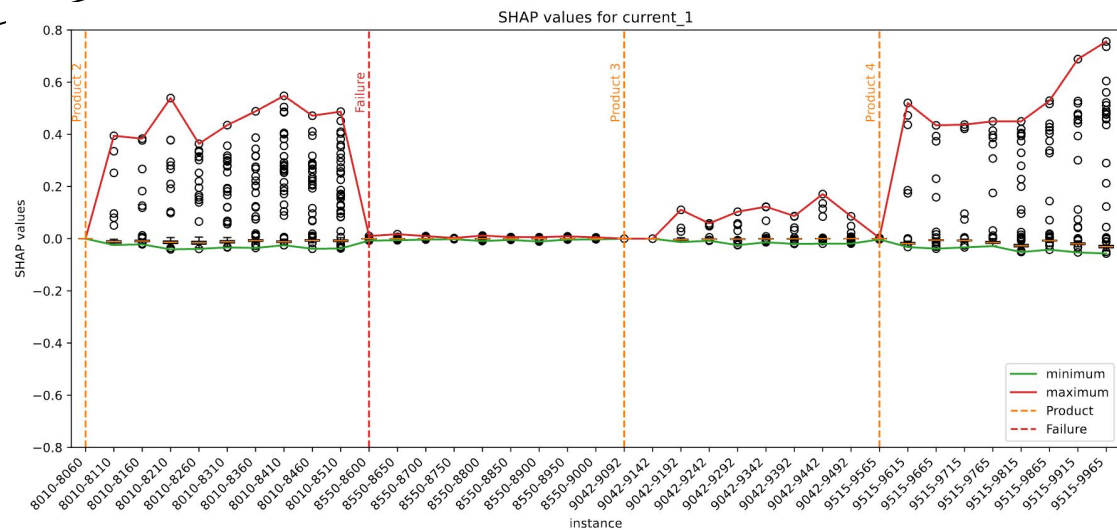
COLD ROLLING MILL DATASET



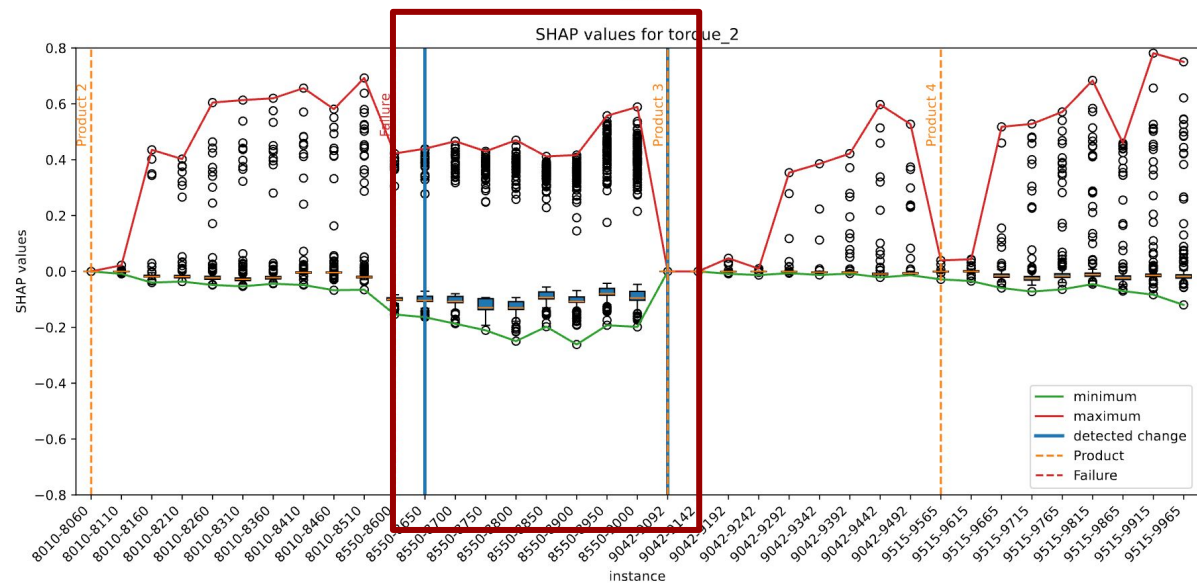
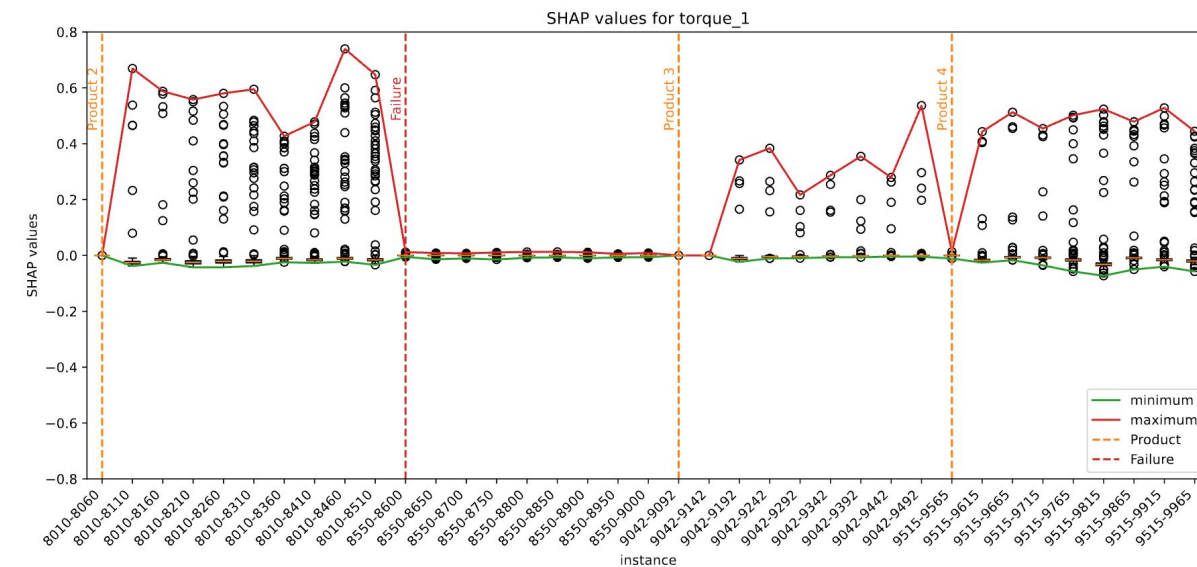
RESULTS

COLD ROLLING MILL DATASET

current

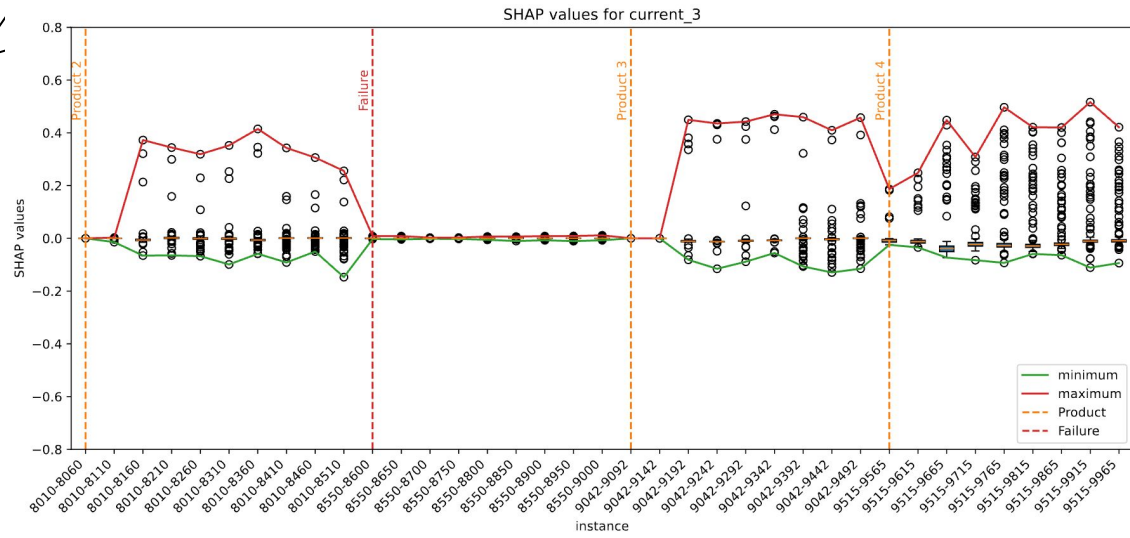


torque

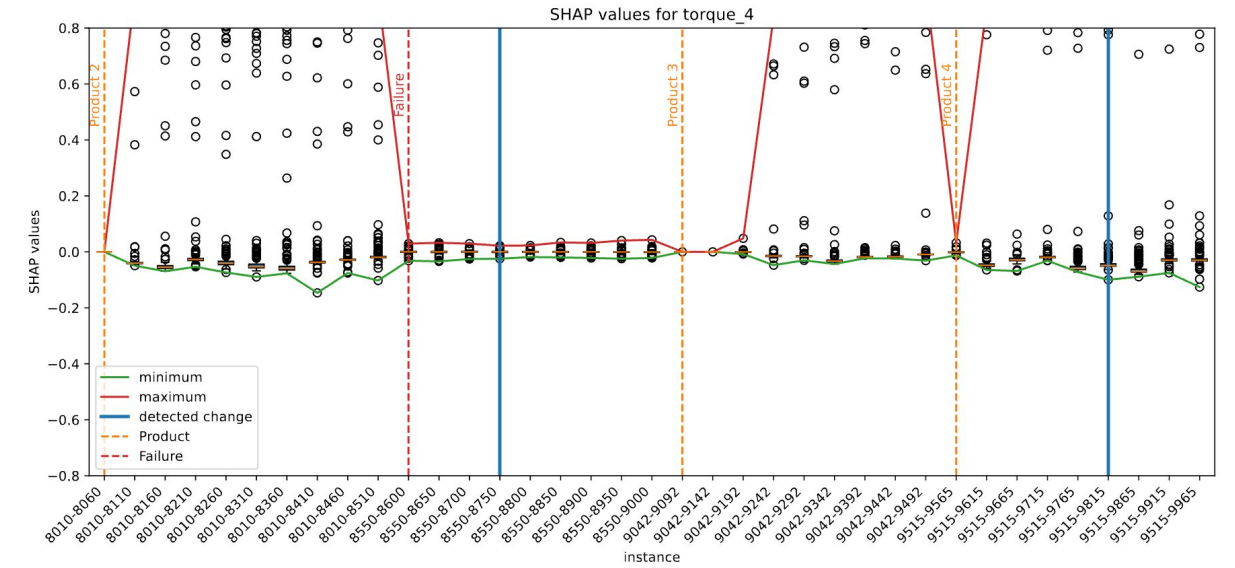
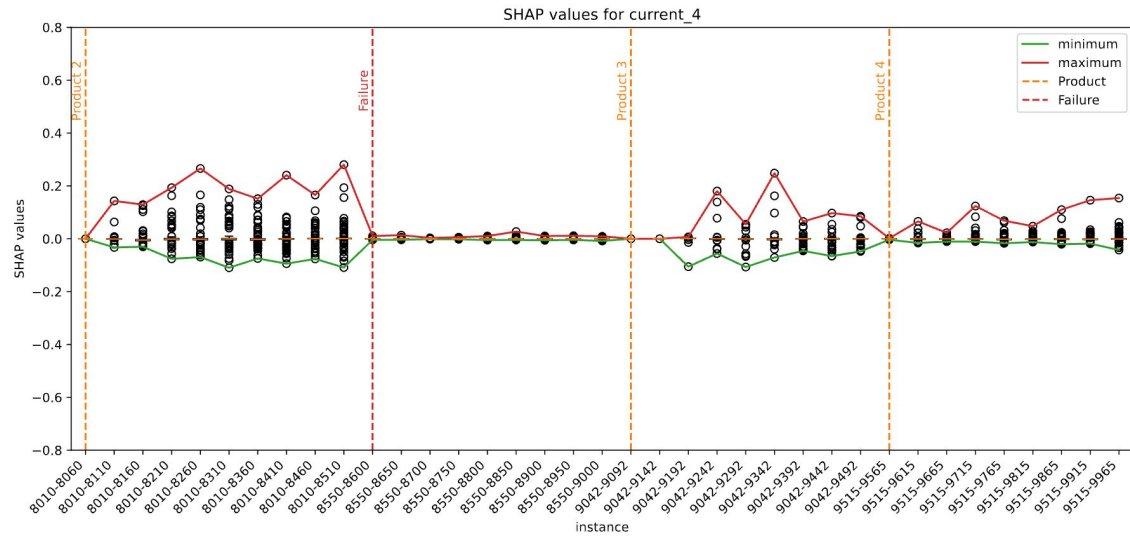
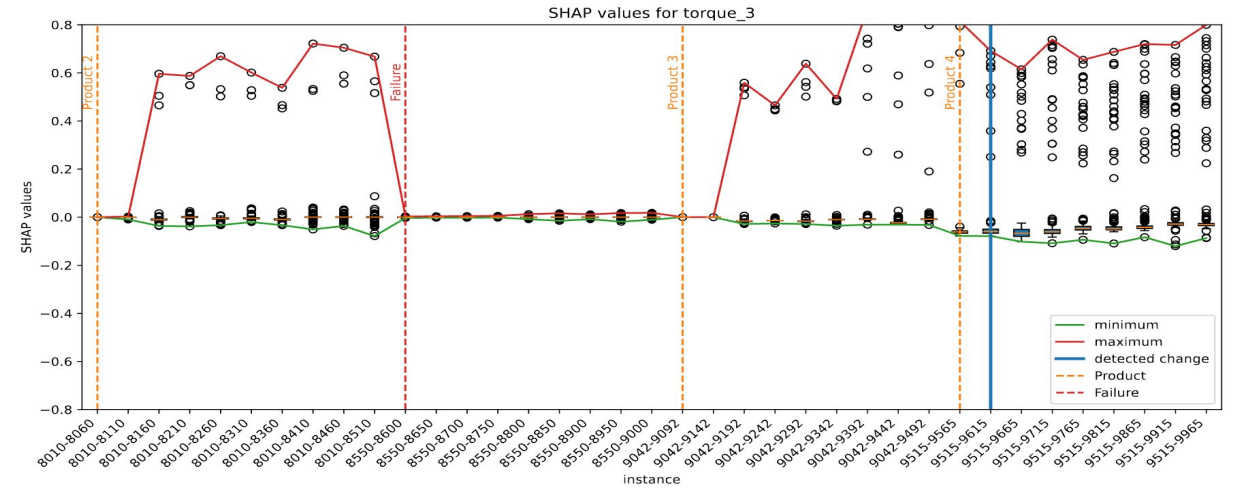


Failure

current



torque



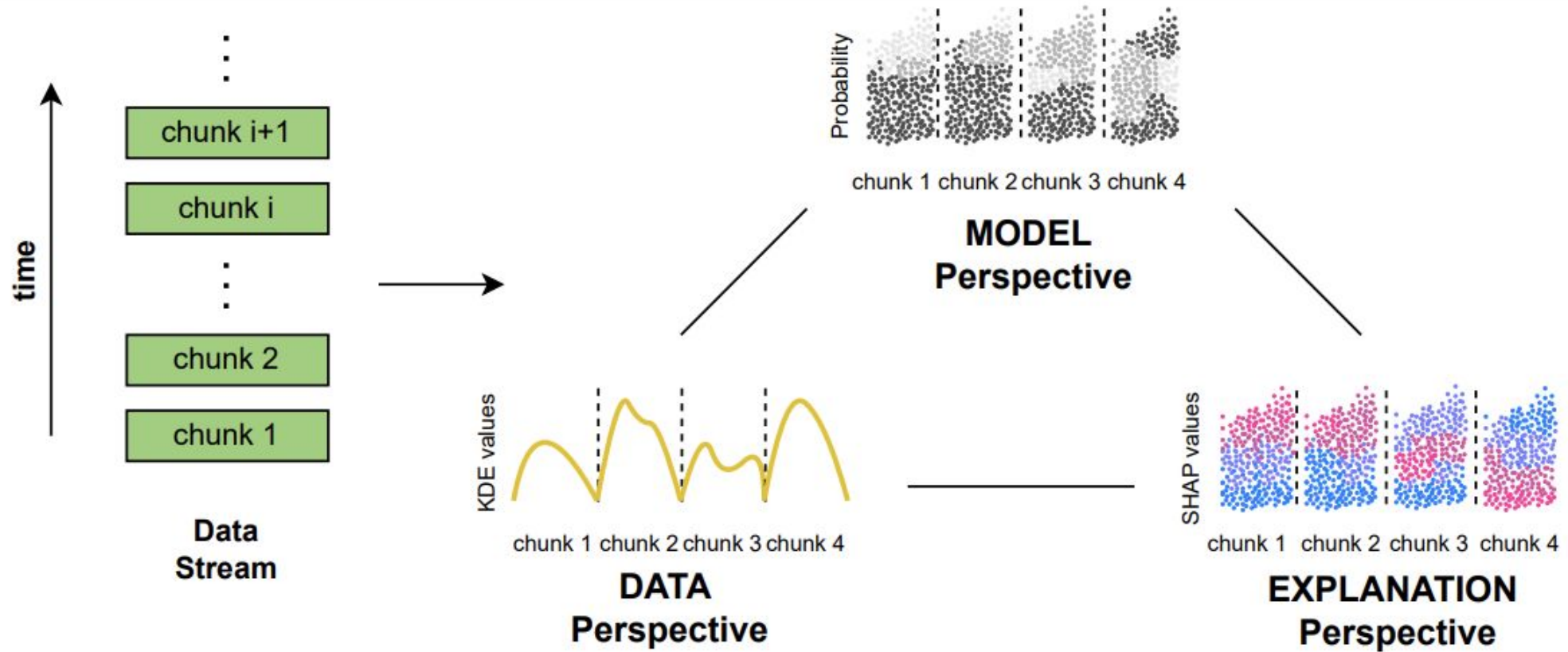


Proposing **multi-perspective approach** for detecting and explaining concepts drifts in evolving data

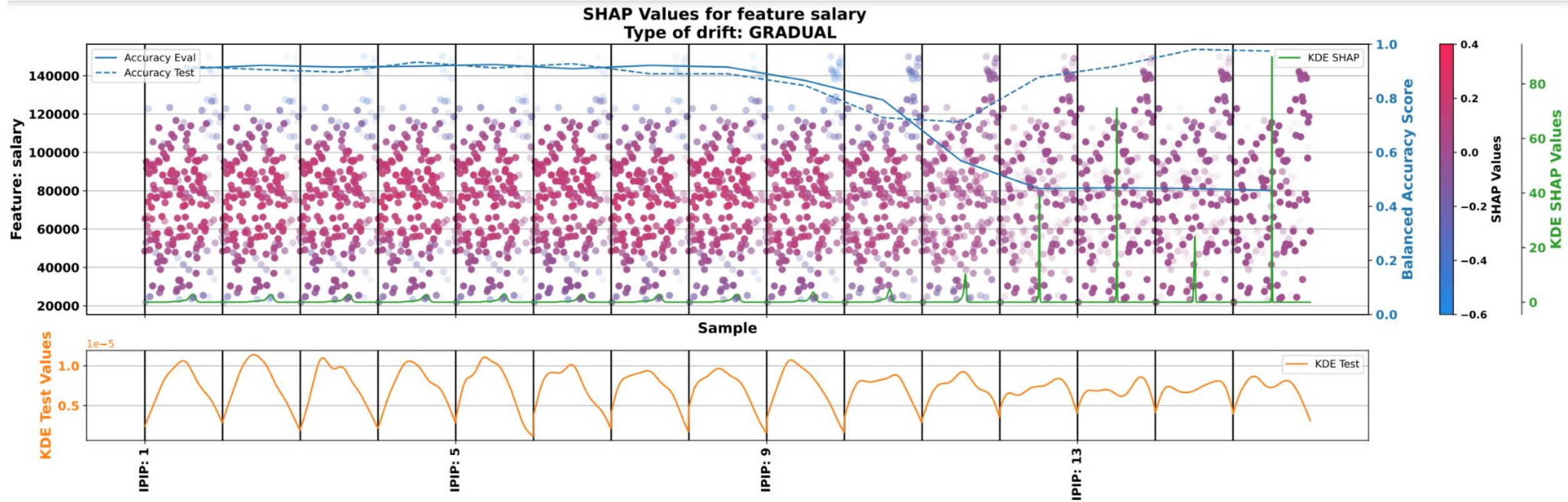
Natalia Wojak-Strzelecka, Antonio Guillén-Teruel,
Szymon Bobek, Grzegorz J. Nalepa, José Palma, Juan
A. Botía

submitted to ECML2025 research track

FLOWCHART of MPF (multi-perspective framework)



EXAMPLE OF VISUALIZATION



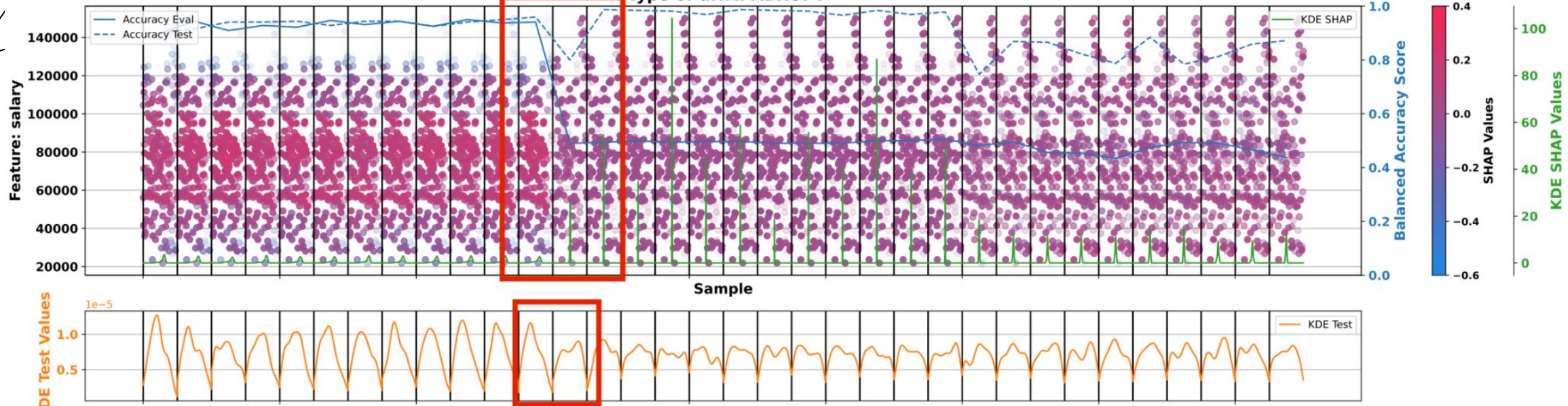
RESULTS

AGRAWAL DATASET

- Data stream with nine features, including six numerical and three categorical attributes.
- Assign binary class labels, likely indicating whether a loan should be approved.
- Data stream divide into 34 chunks.
- Concept **drift around 12 and 24 chunk.**

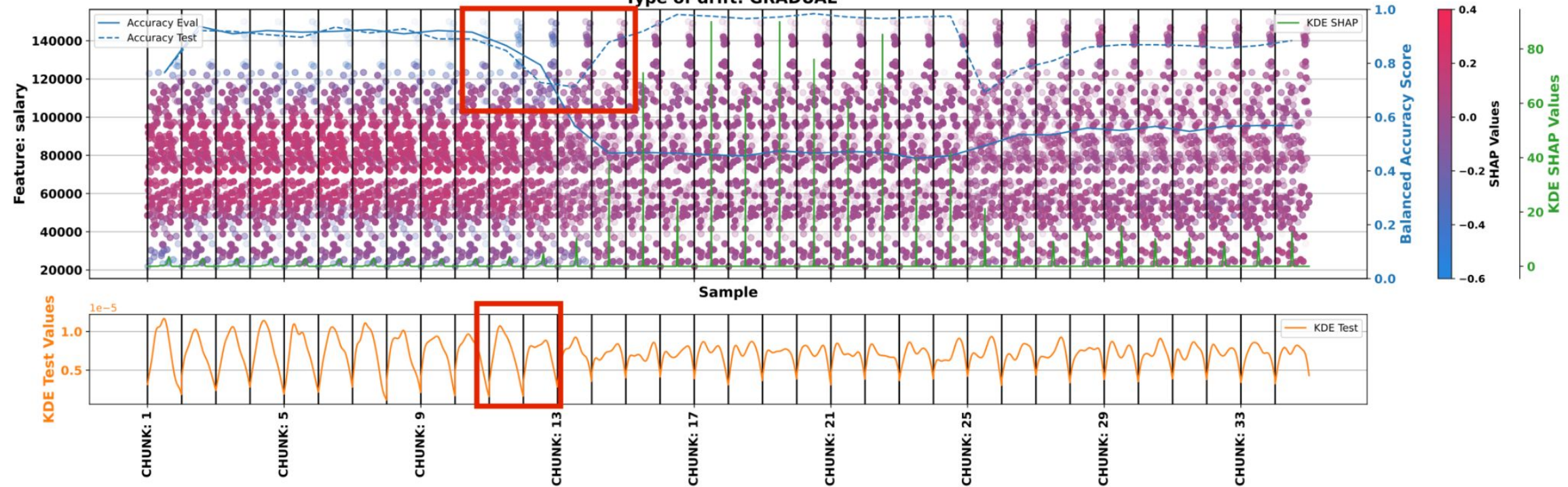
SHAP Values for feature salary

Type of drift: ABRUPT

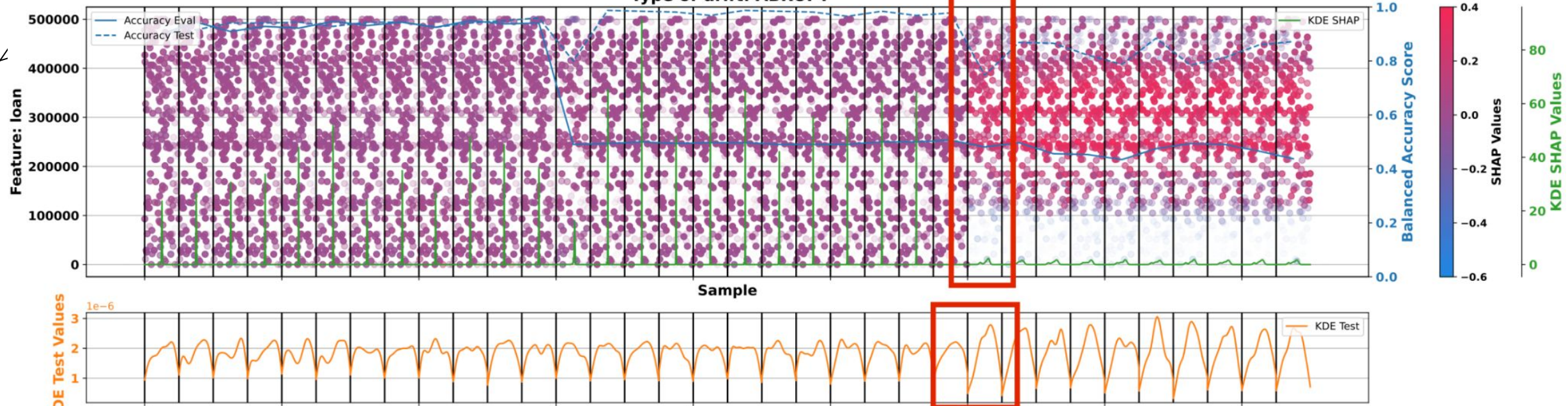


SHAP Values for feature salary

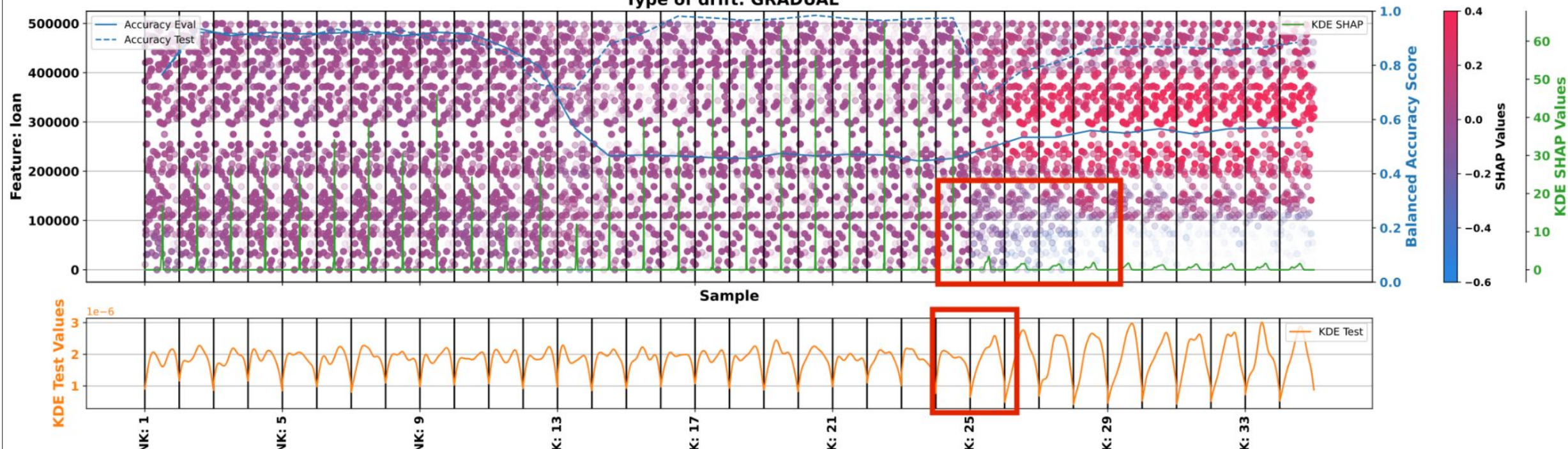
Type of drift: GRADUAL



SHAP Values for feature loan
Type of drift: ABRUPT



SHAP Values for feature loan
Type of drift: GRADUAL

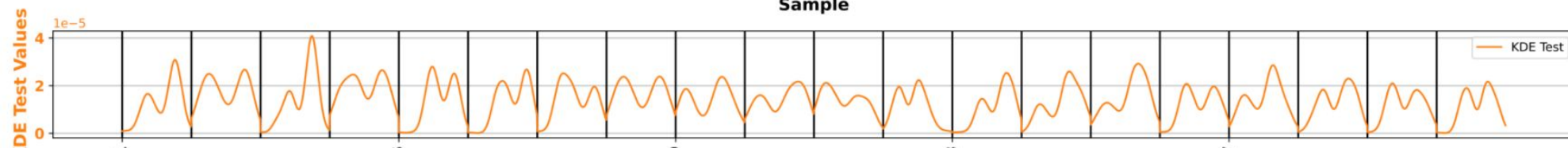
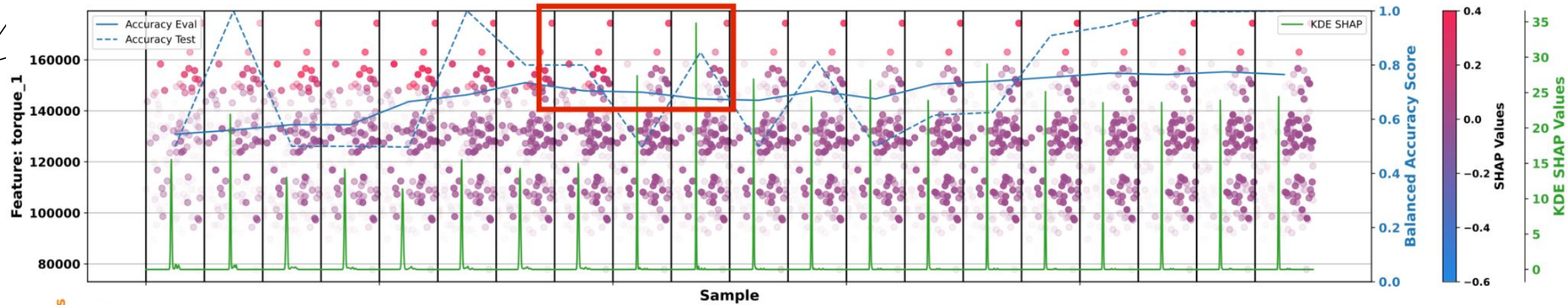


RESULTS

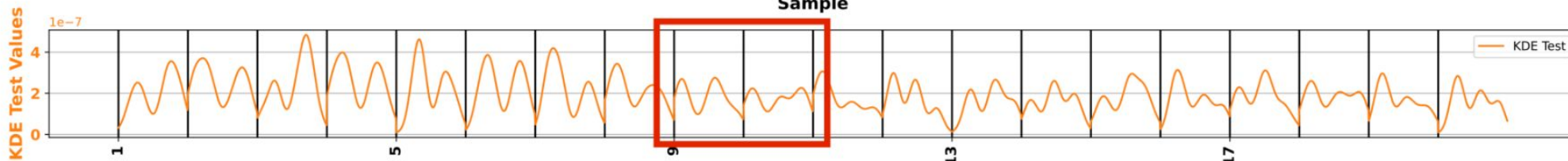
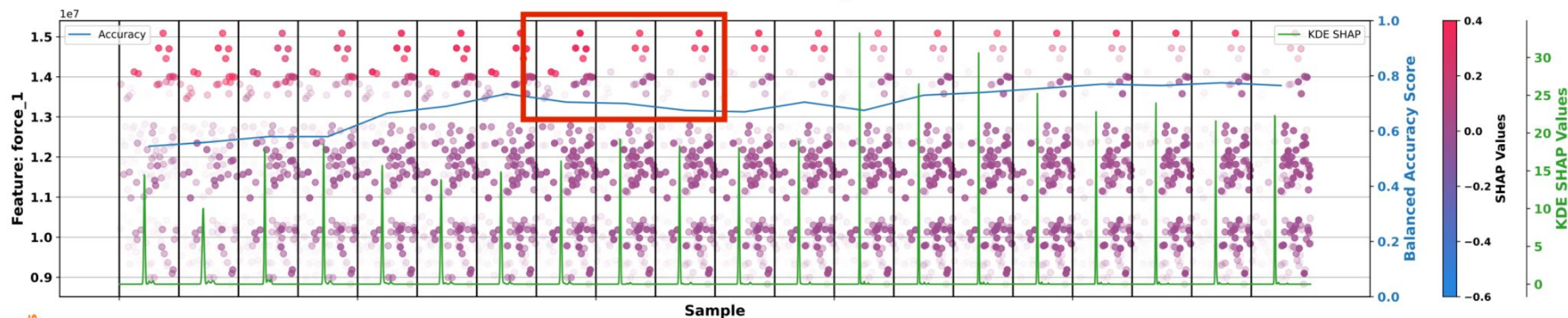
COLD ROLLING MILL DATASET

- Five-stand cold rolling mill simulator.
- Binary labels indicating normal or anomalous behavior.
- The dataset was divided into 20 equally sized chunks.
- **Two drifts:**
 - First, a **drift associated with the introduction of previously unseen product types** (around chunk 8).
 - Second, a **drift related to increased production capacity** is introduced (around chunk 16).

SHAP Values for feature torque_1



SHAP Values for feature force_1



CHUNK: 1

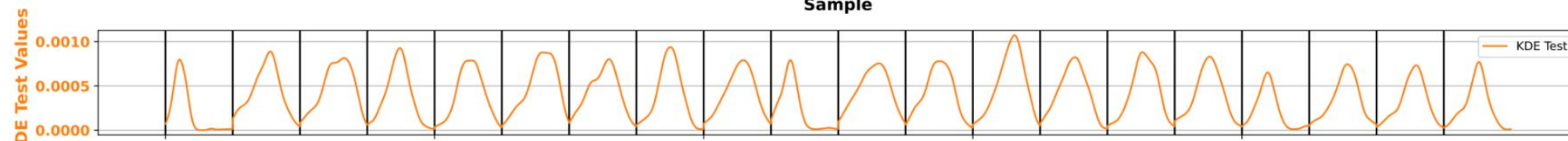
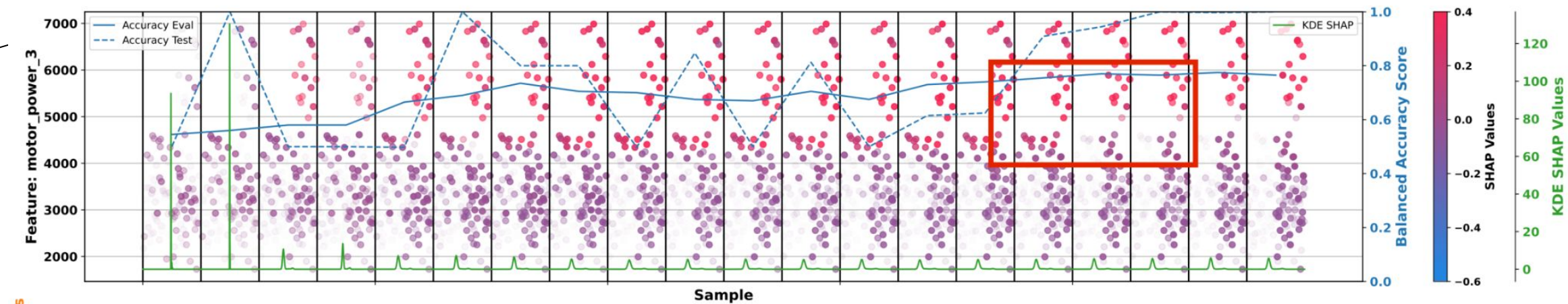
CHUNK: 5

CHUNK: 9

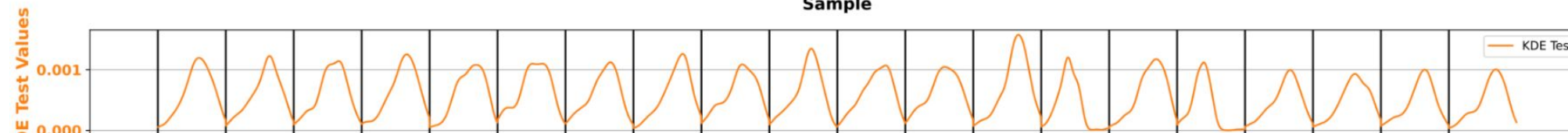
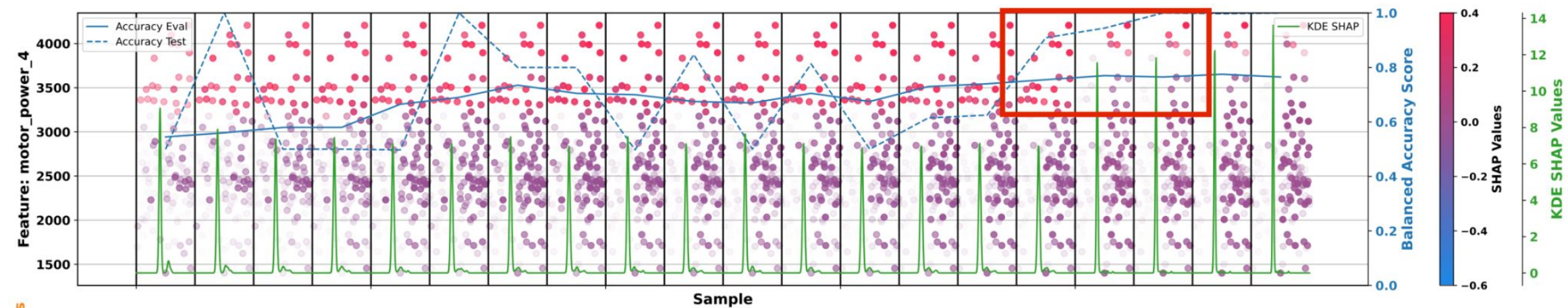
HUNK: 13

HUNK: 17

SHAP Values for feature motor_power_3



SHAP Values for feature motor_power_4



IPIP: 1

IPIP: 5

IPIP: 9

IPIP: 13

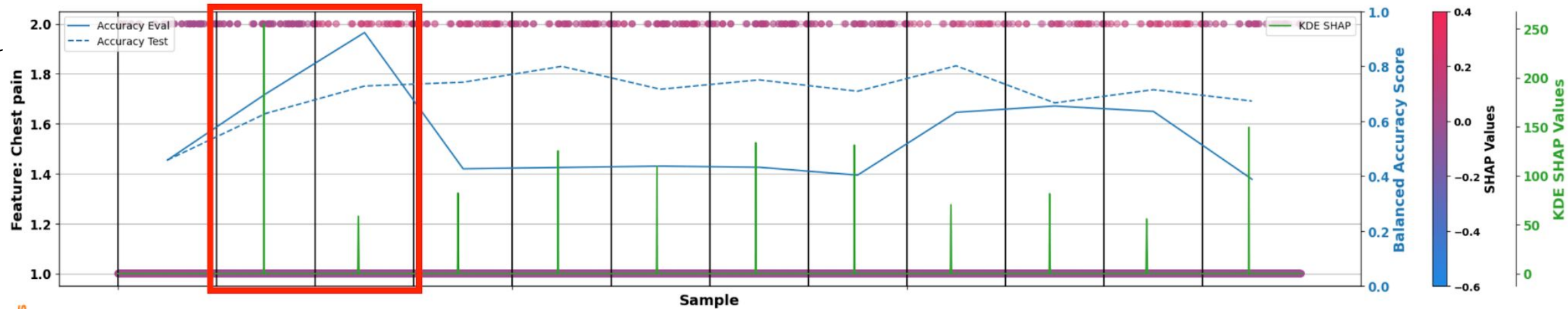
IPIP: 17

RESULTS

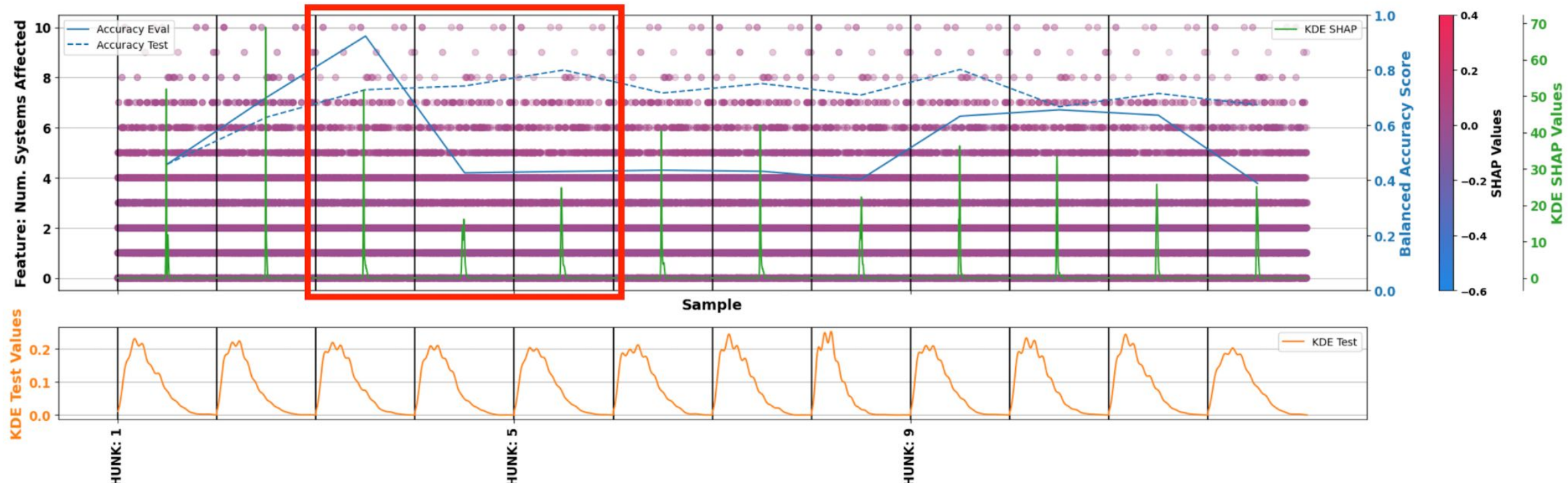
SMS COVID-19 DATASET

- These data were collected from electronic medical records of the Regional Health System (SMS) from the Region of Murcia (Spain).
- Binary classification problem - if a patient would need to be hospitalized or not .
- The dataset was divided into 13 equally sized chunks, each 2 months of data, starting from March 2020.
- **Two drifts:**
 - First, connected with the **variables responsible for hospitalization** (around chunk 2).
 - Second, connected with **changes affected by vaccination and different COVID variant** (around chunk 9).

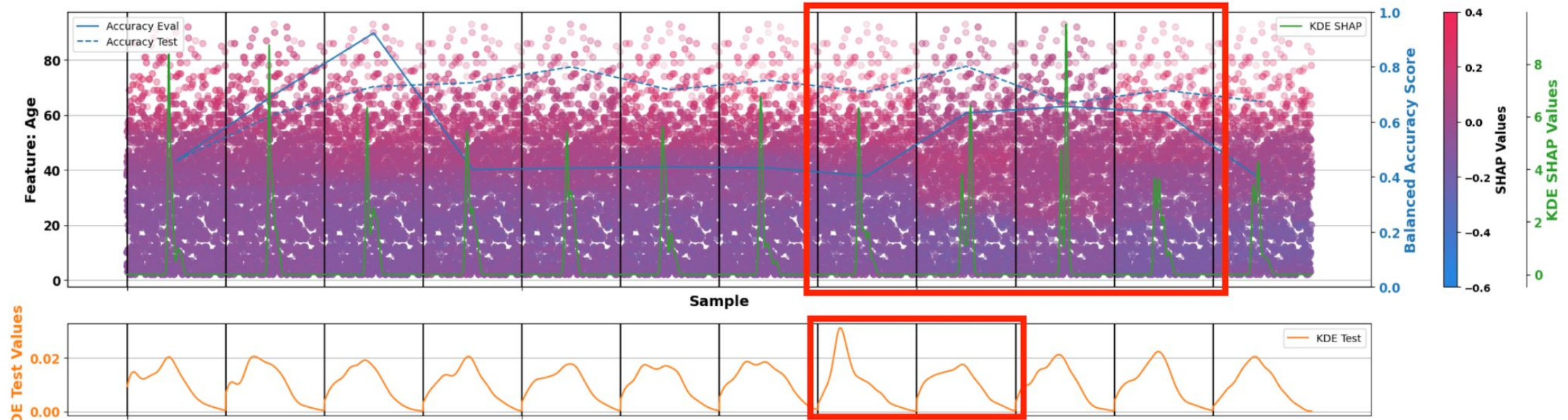
SHAP Values for feature Chest pain



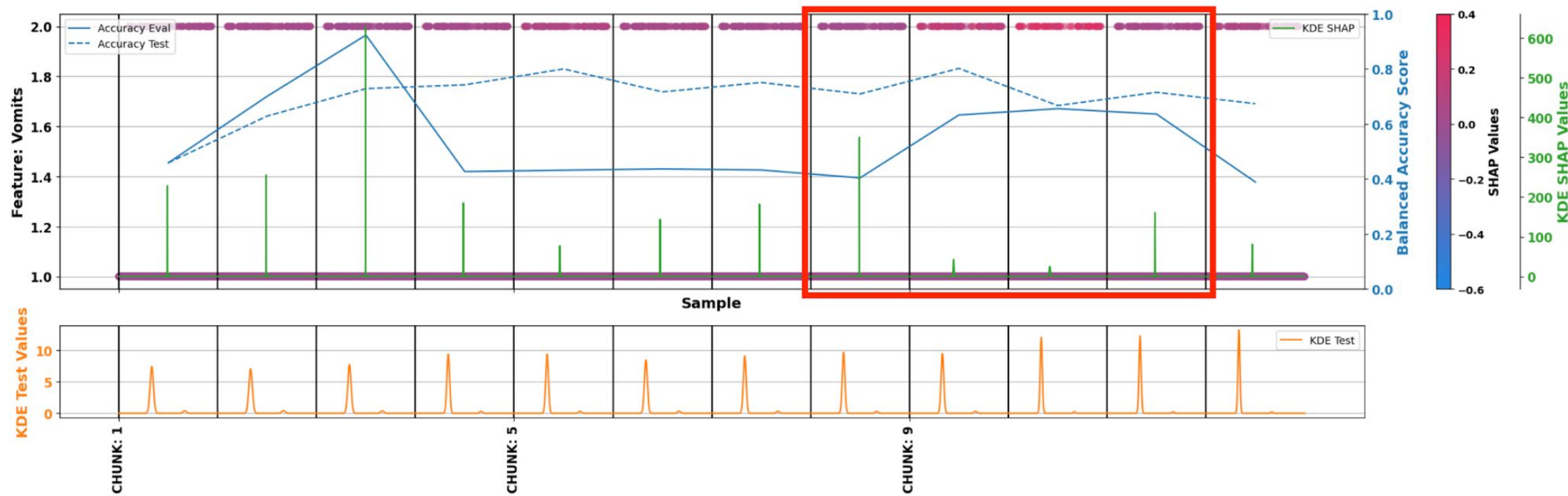
SHAP Values for feature Num. Systems Affected



SHAP Values for feature Age



SHAP Values for feature Vomits



FUTURE DIRECTIONS

UNSUPERVISED DOMAIN ADAPTATION

Extend the current supervised domain adaptation method to unsupervised or semi-supervised settings.

DRIFT TYPE DETECTION AND CLASSIFICATION

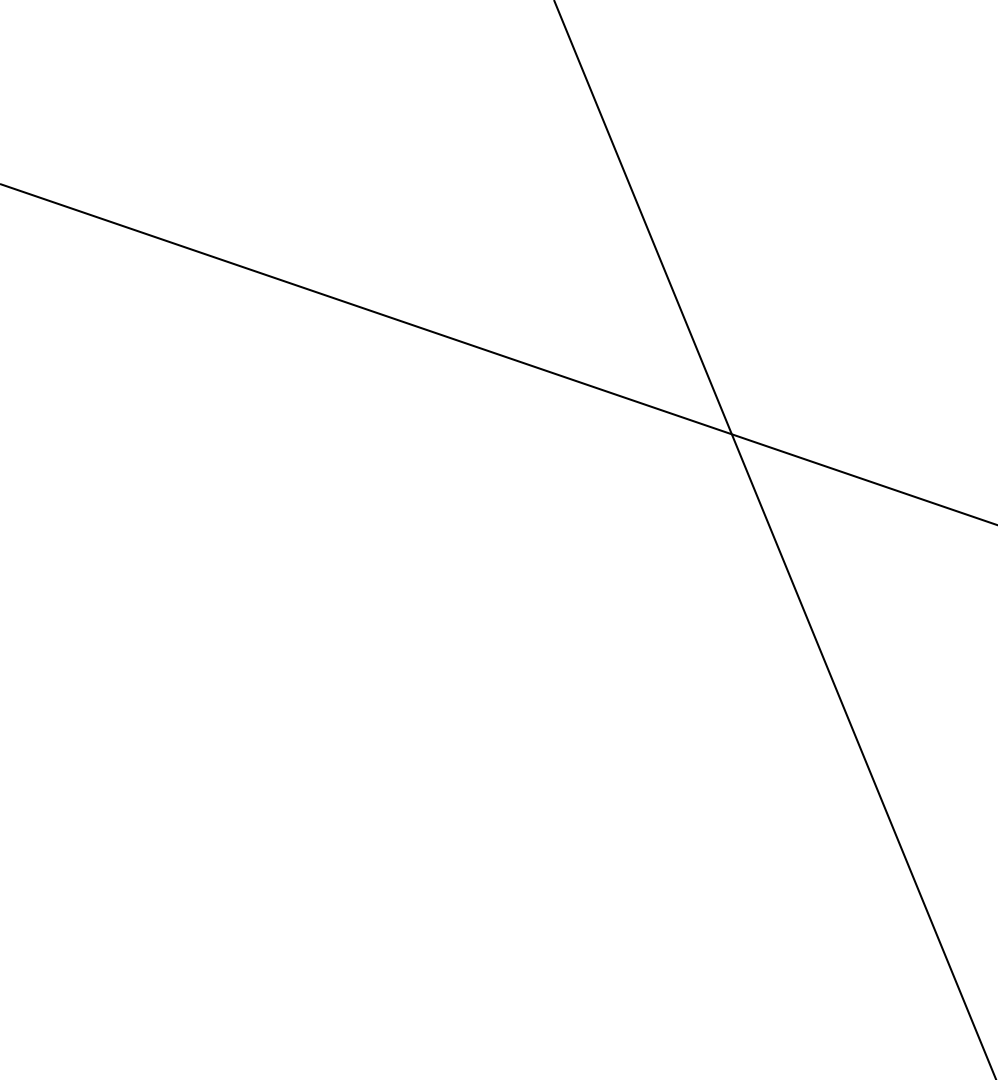
Introduce a module that automatically detect classifies the type of drift (e.g., sudden, gradual, recurring) based on SHAP trends and model performance indicators

ACTIVE LEARNING

Strategies to query for the most informative labels when drift is suspected, optimizing labeling cost.

HUMAN IN THE LOOP

User-friendly tools for non-experts to visualize the drift



Thank you for attention!

MEET THE TEAM

<https://www.geist.re/start>