Leveraging Human-Centered Machine Learning to Create More Explainable Machine Learning Models

Bahavathy Kathirgamanathan, Fraunhofer IAIS, Bonn Germany

Partner institutions:

technische universität dortmund

Fraunhofer IAIS

UNIVERSITÄT BONN

Fraunhofer IML

Institutionally funded by:

Bundesministerium für Bildung und Forschung

Ministerium für Kultur und Wissenschaft des Landes Nordrhein-Westfalen

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Domain knowledge insertion to create more explainable models

Motivation

- Machine Learning models developed in a purely data-driven way may perform well, however they have some limitations
- Data (e.g., numeric values at fine-grained time steps) used for training may not be meaningful to a human

Challenge: The model cannot be sensibly explained

- Standard numeric measures of model quality lack domain-specific meaning

Challenge: They do not help to detect problems and find ways to improve

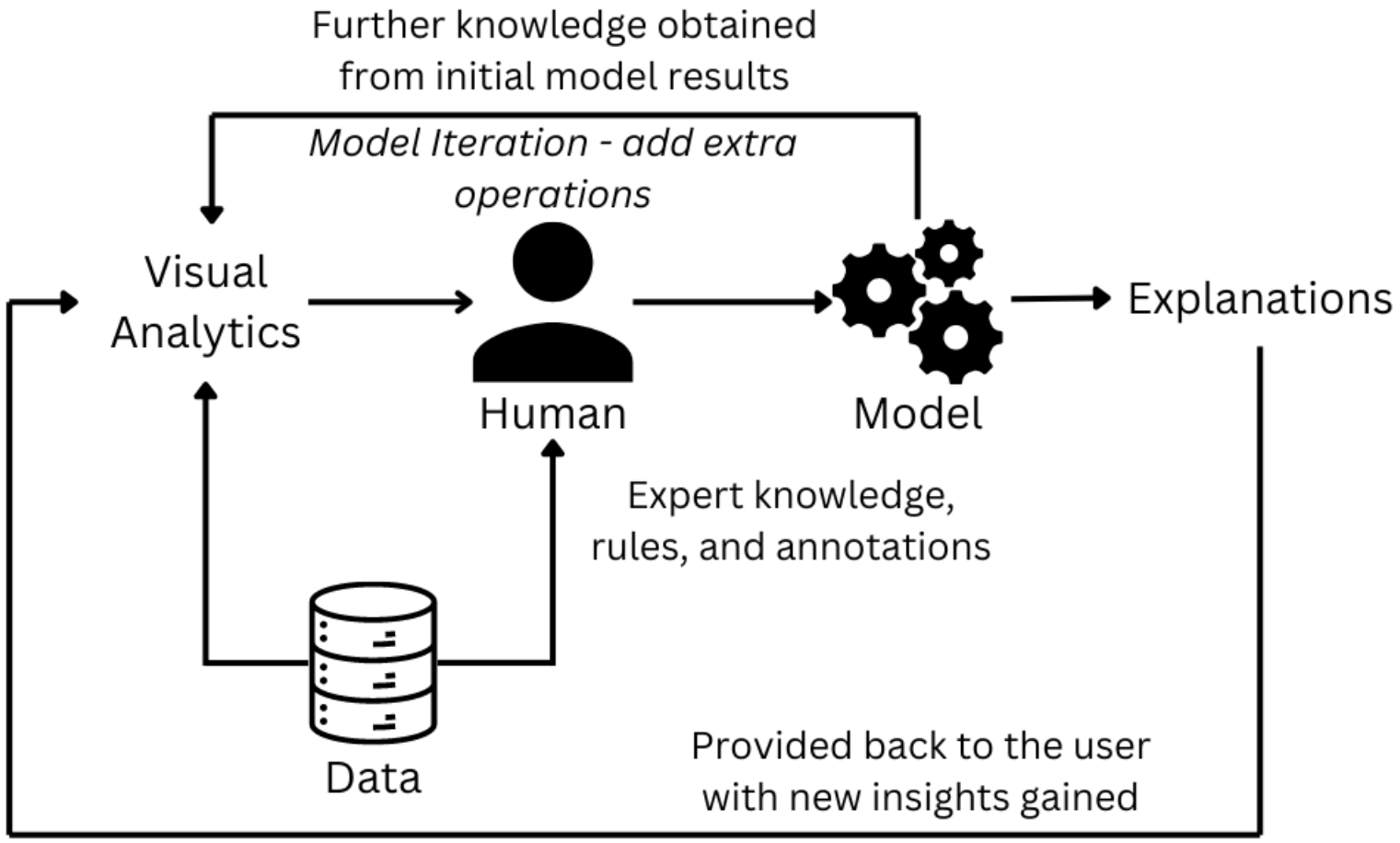
Human-centric machine learning combines computational power with human intelligence and creates explainable and accountable models aligned with human knowledge and logic

Our approach

Employ **interactive visual interfaces** to involve **human expertise** in the model building process

- **Transform raw data** to meaningful structures that match domain concepts
- Investigate model output and provide **expert feedback** for iterative model refinement

The approach is designed to be suitable to be used with a variety of ML algorithms.



Augmenting the model with human knowledge

1. Data abstraction and definition of appropriate units

Time series data –> Time intervals
Geographic data -> Spatial Areas
Social data -> Groups

2. Contextualization

Time series data -> preceding values or trends
Geographic data -> neighboring areas or regions
Social data -> strongly connected nodes

3. Synoptic Feature Generation

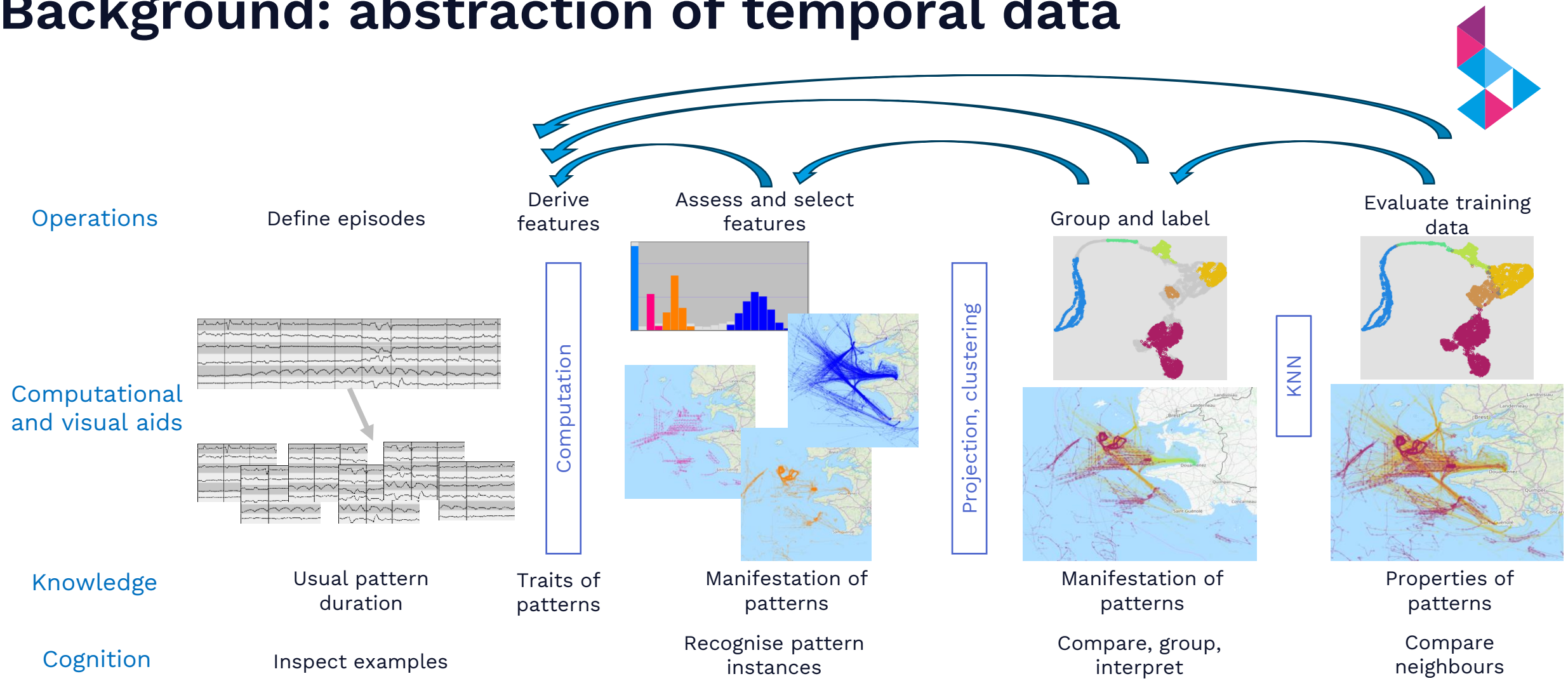
Time series data -> statistical summaries, trend indicators
Geographic data -> internal composition or densities
Social data -> aggregate measures about characteristics of a group

4. Iterative, Human-Controlled Workflow and Insight Injection

For all data types:

- *Correct issues with raw data*
- *introduce new features or adjust based on insights*
- *Validate that the data and model aligns with domain knowledge*

Background: abstraction of temporal data



Natalia Andrienko, Gennady Andrienko, Alexander Artikis, Periklis Mantenoglou, Salvatore Rinzivillo
Human-in-the-Loop: Visual Analytics for Building Models Recognising Behavioural Patterns in Time Series
IEEE Computer Graphics & Applications , 2024, **44**(3), 14-29 https://doi.org/10.1109/MCG.2024.3379851

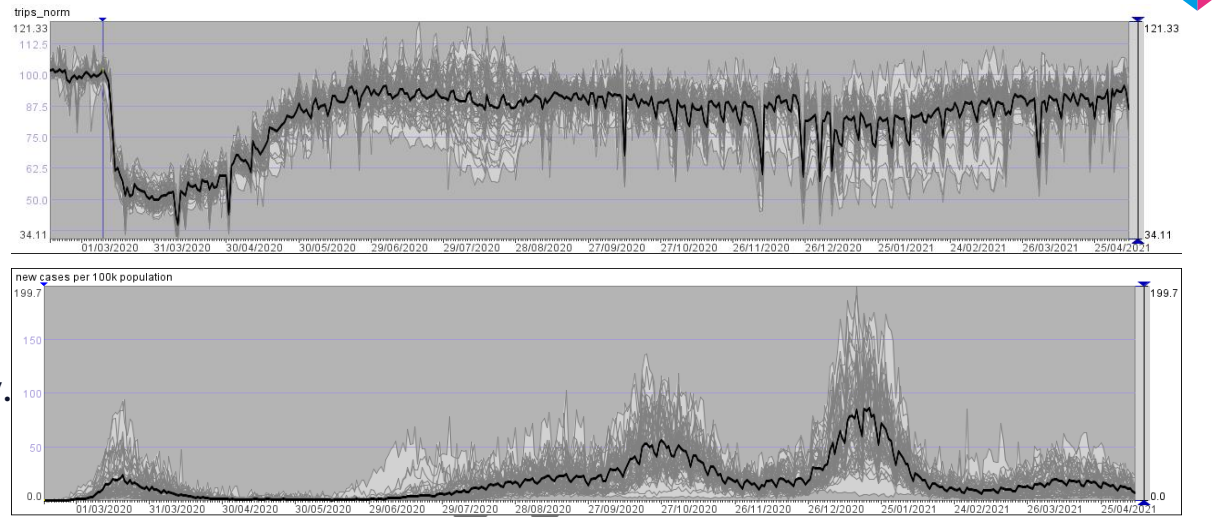
However, this framework focuses on data preparation without addressing model development

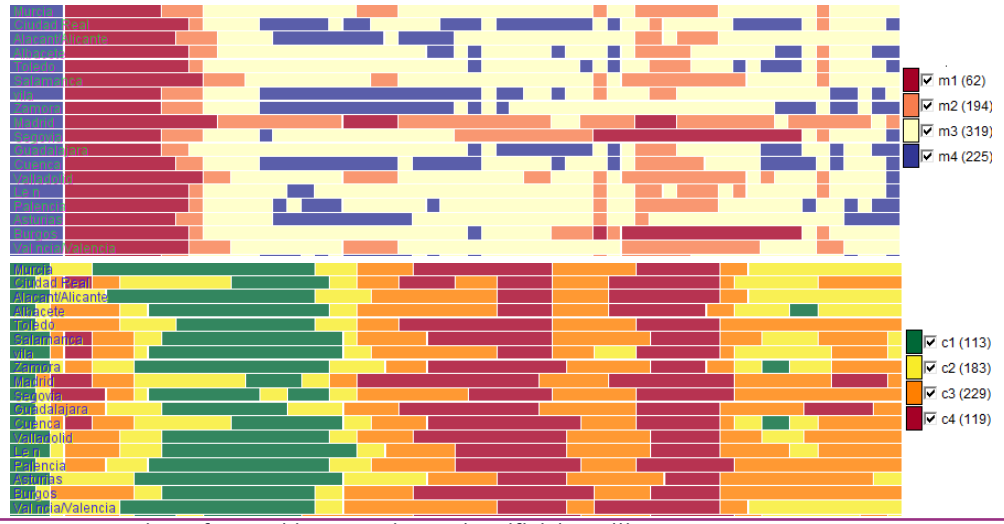
Case Study: Two-way relationships between population mobility behavior and the development of the COVID-19 pandemic

Data: Time series of daily values of Mobility and COVID cases for the provinces of Spain for the period from 17/02/2020 to 09/05/2021 [1,2]

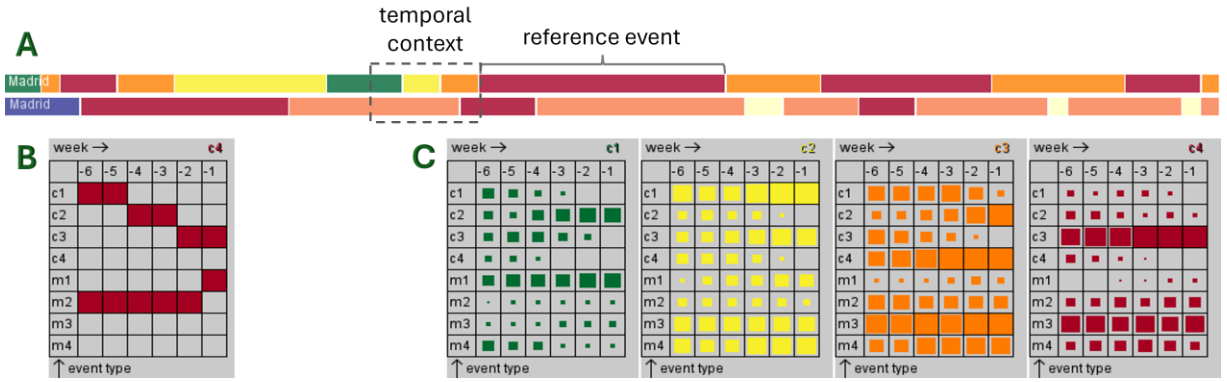
Data Pre-processing: Smoothed and divided into episodes with a length of 7 days.

Temporal abstraction: Each episode is assigned a class based on the (1) level of COVID-19 and (2) level of mobility. Sequences of same class episodes united into *events*.





Created features: Temporal contexts of COVID-19 events



Case Study: Initial Model Development

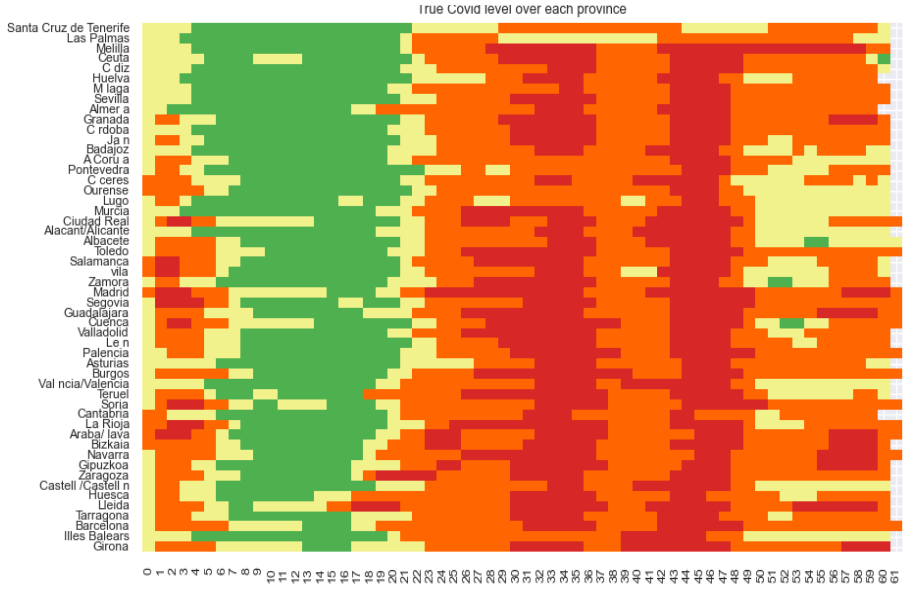
Modelling Task: Use historical data from the prior six weeks of event contexts to predict the current level of COVID-19.

Machine Learning Model used: Random Forest model using a 5-fold cross validation strategy

Model Output: Base model accuracy of 0.71

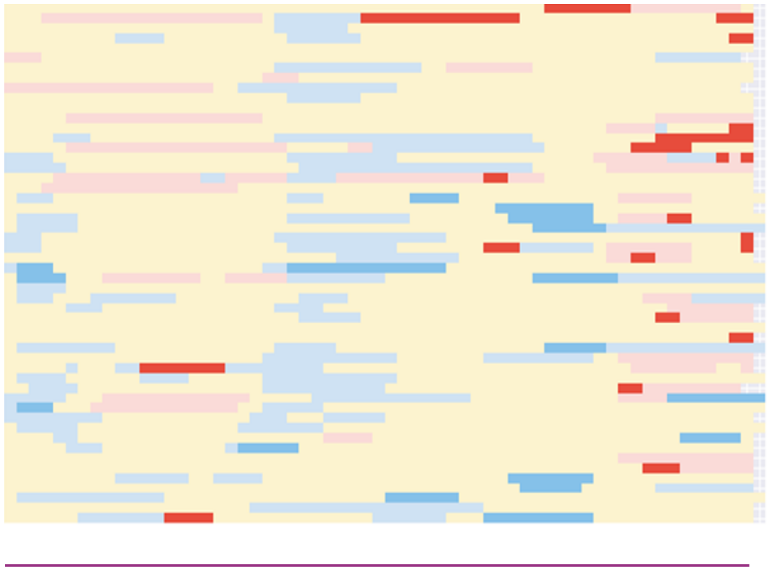
Visual analytics techniques are used to explore the spatio-temporal distribution of the model errors. Detected patterns provide clues to help a human understand what and how to improve.

True classes



Predicted classes

Differences



Iterative Model Development

Summary of the models tested

- Human insights are incorporated into the model through data operations, aiming for compatibility with common ML techniques.

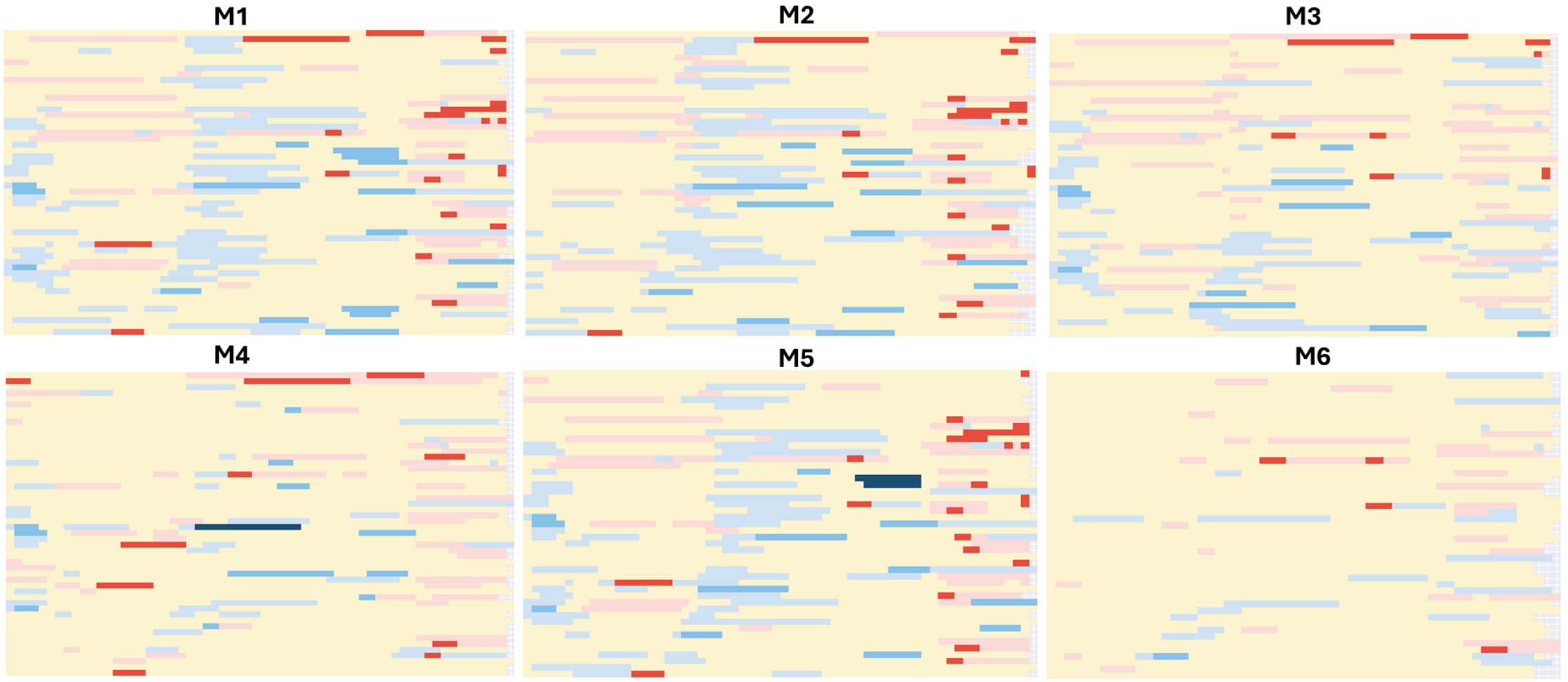
- The operations on the data guided by the iterative visual exploration and human feedback finally led to an improvement of model accuracy from 0.71 to 0.86

Model	Operations Undertaken	5-Fold CV Mean Accuracy
M1	Basic Model – No extra operations	0.71244 ± 0.041
M2	First 30 days removed	0.71827 ± 0.016
M3	Number of weeks since the start added as a feature	0.74798 ± 0.047
M4	Duration of the event added as a feature	0.78847 ± 0.019
M5	All island provinces are removed	0.71636 ± 0.041
M6	All of the above operations	0.86334 ± 0.036

Table 1. A summary of the operations applied during the iterative Model development

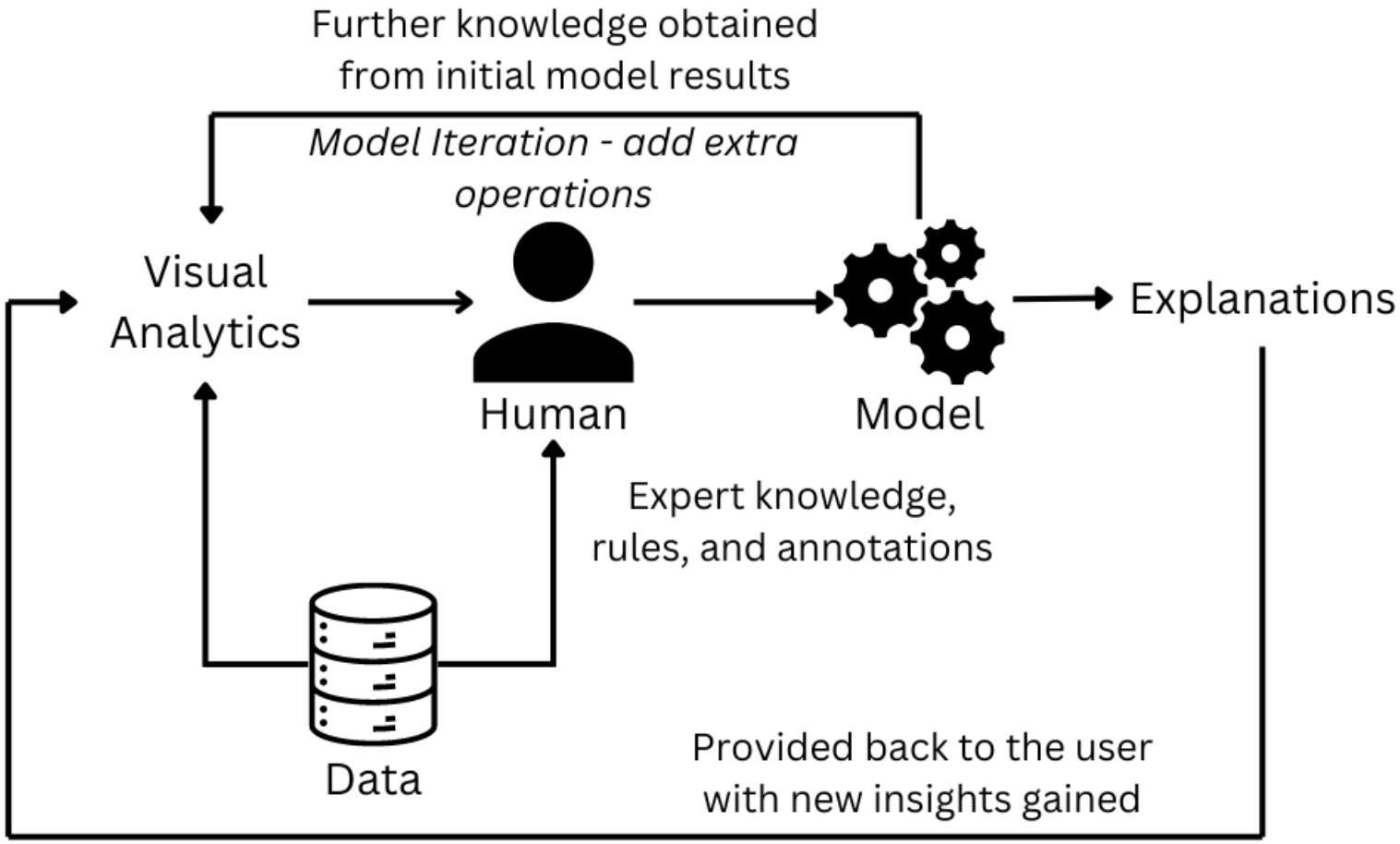
Iterative Model Development

Reducing errors and removing patterns in the error distribution



Proposed General Framework

- Model will be refined based on insights obtained from visualizing the data and/or the model results
- Human knowledge gained can also be used to provide explanations
- Key idea: Visual Analytics enables humans to understand and organize data and define relevant concepts to be used in the ML algorithm and for explanation



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A Hybrid Human-Centric approach to combining Rule-based and Attribute based explanations

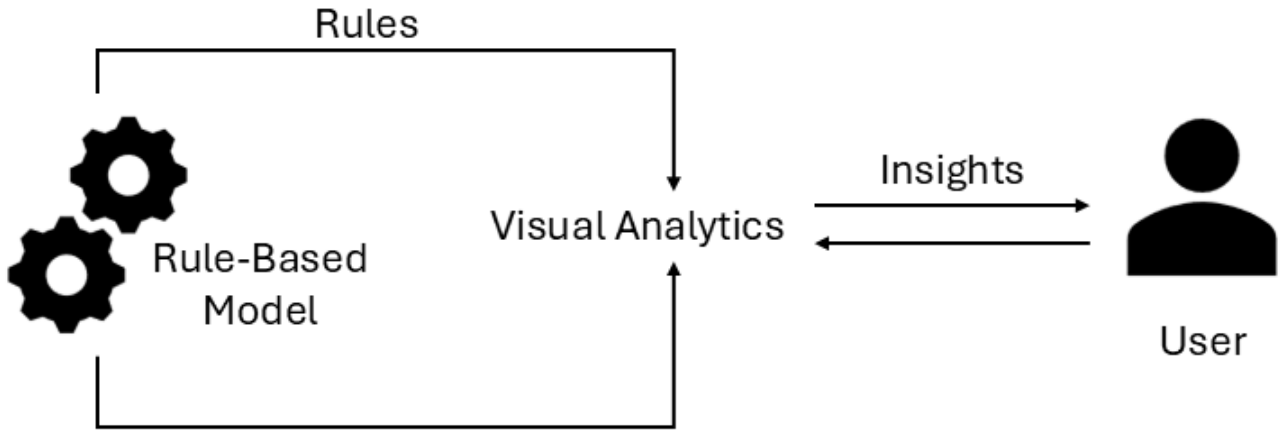
Motivation

- Rule based and Feature attribution methods have distinct strengths and weaknesses.

- Hypothesis: By using them both together, the overall user trust and model interpretability can be improved further

- Motivation:
  - Enhance interpretability
  - Support interactive exploration and alignment

+ Intuitive and align with human reasoning
+ Stable results
- Does not scale well



+ Quantitative values are available
+ Can be summarized simply for any amount of data
- Do not align with human reasoning
- Results may be instable

Proposed Workflow

1. Visualise Rules

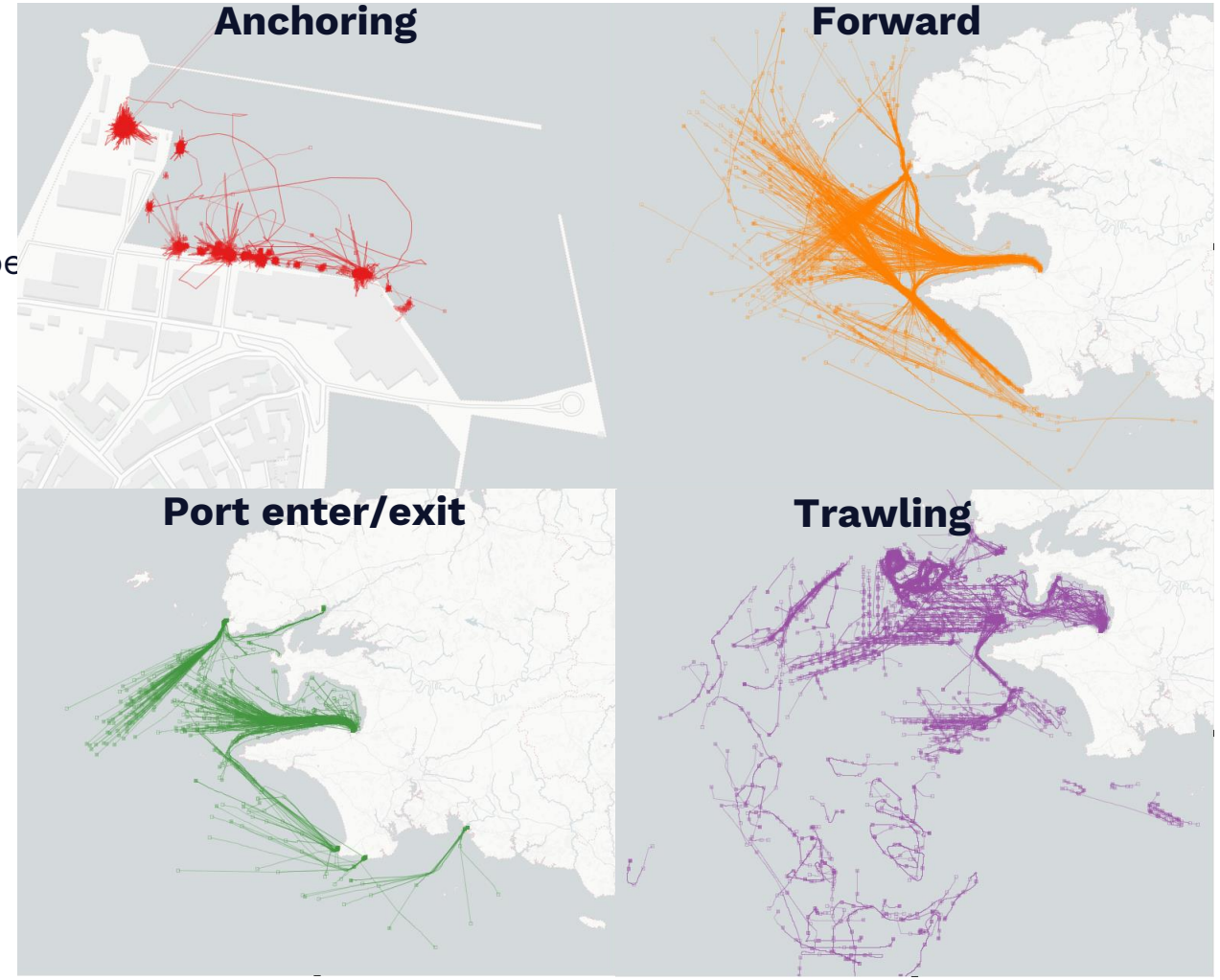
2. Compute and Visualise Feature Attribution Scores

3. Interactively Explore the Ruleset

4. Iterate

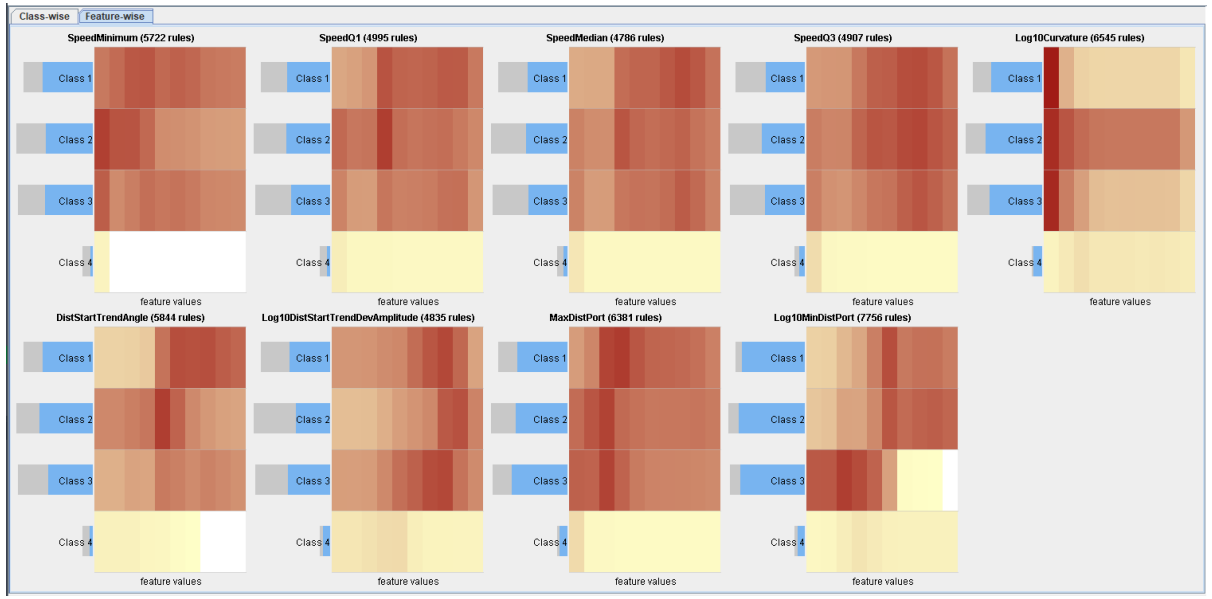
Case Study – Movement Vessel Dataset

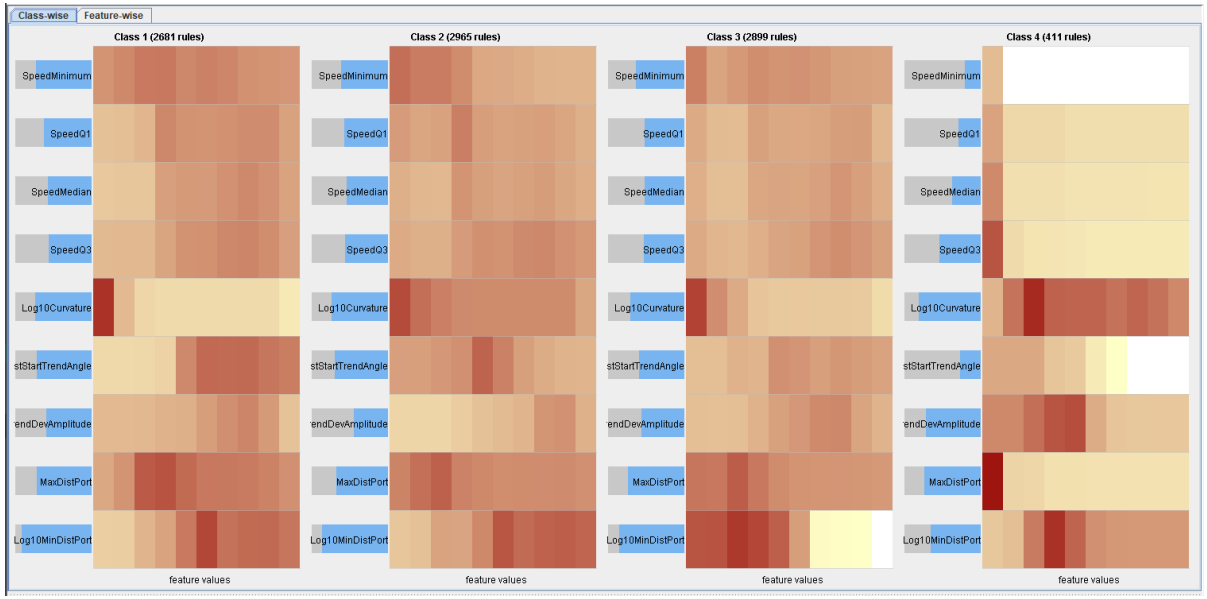
- Dataset with trajectories from fishing vessels in France
- Each episode was represented by 9 features which characterize the speed, trajectory shape and the proximity to the port
- Episodes were classified into four activity classes.
- A random forest classifier was trained achieving an accuracy of **0.97**



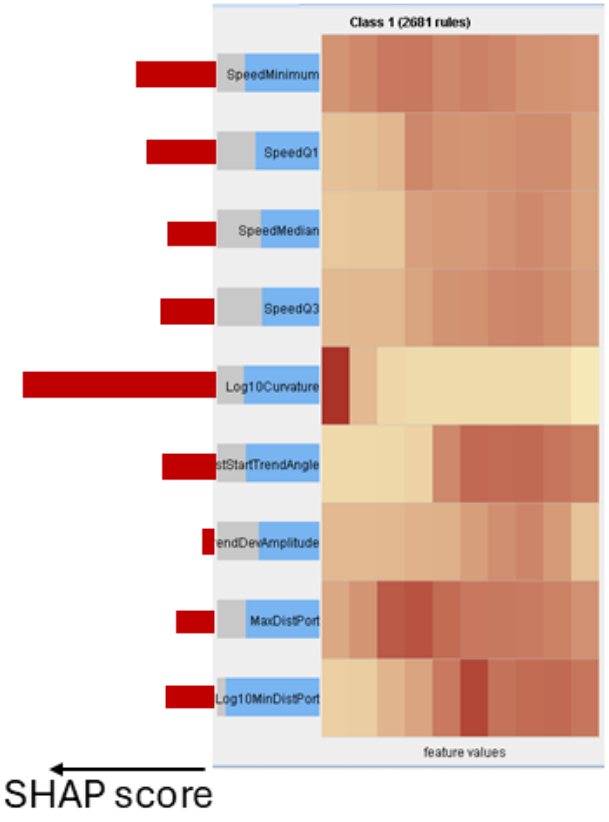
Rule-based explorer

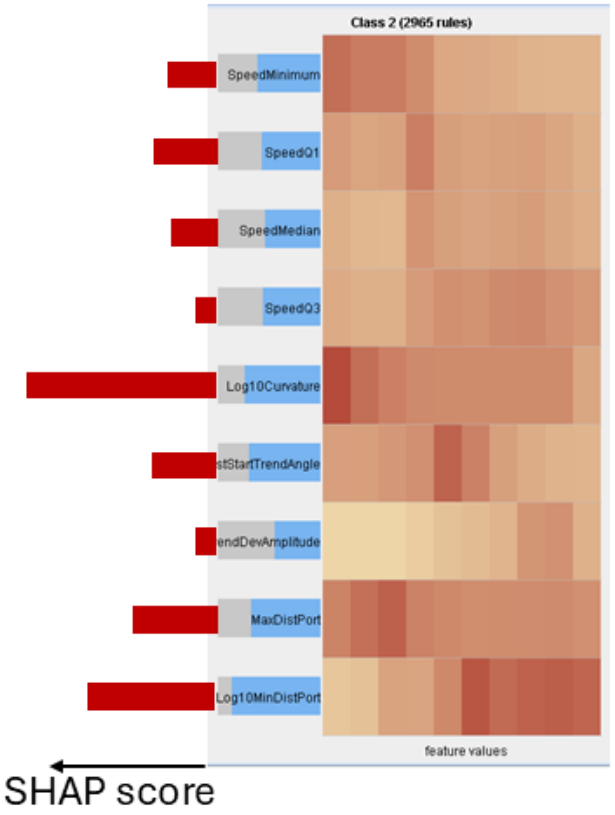
- RuleExplorer – a software prototype to visualize and interact with rules

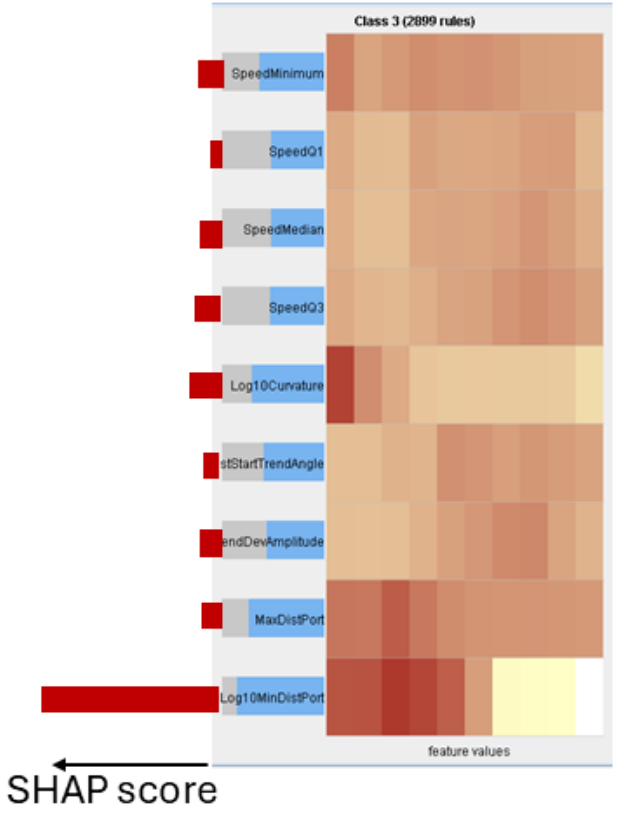


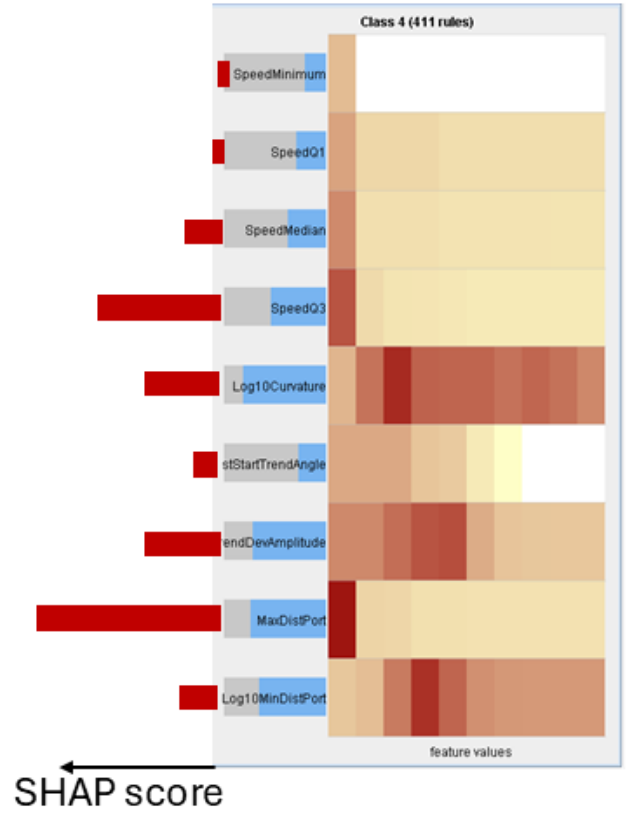


Hybrid View – feature attribution + Rules









Key Objectives

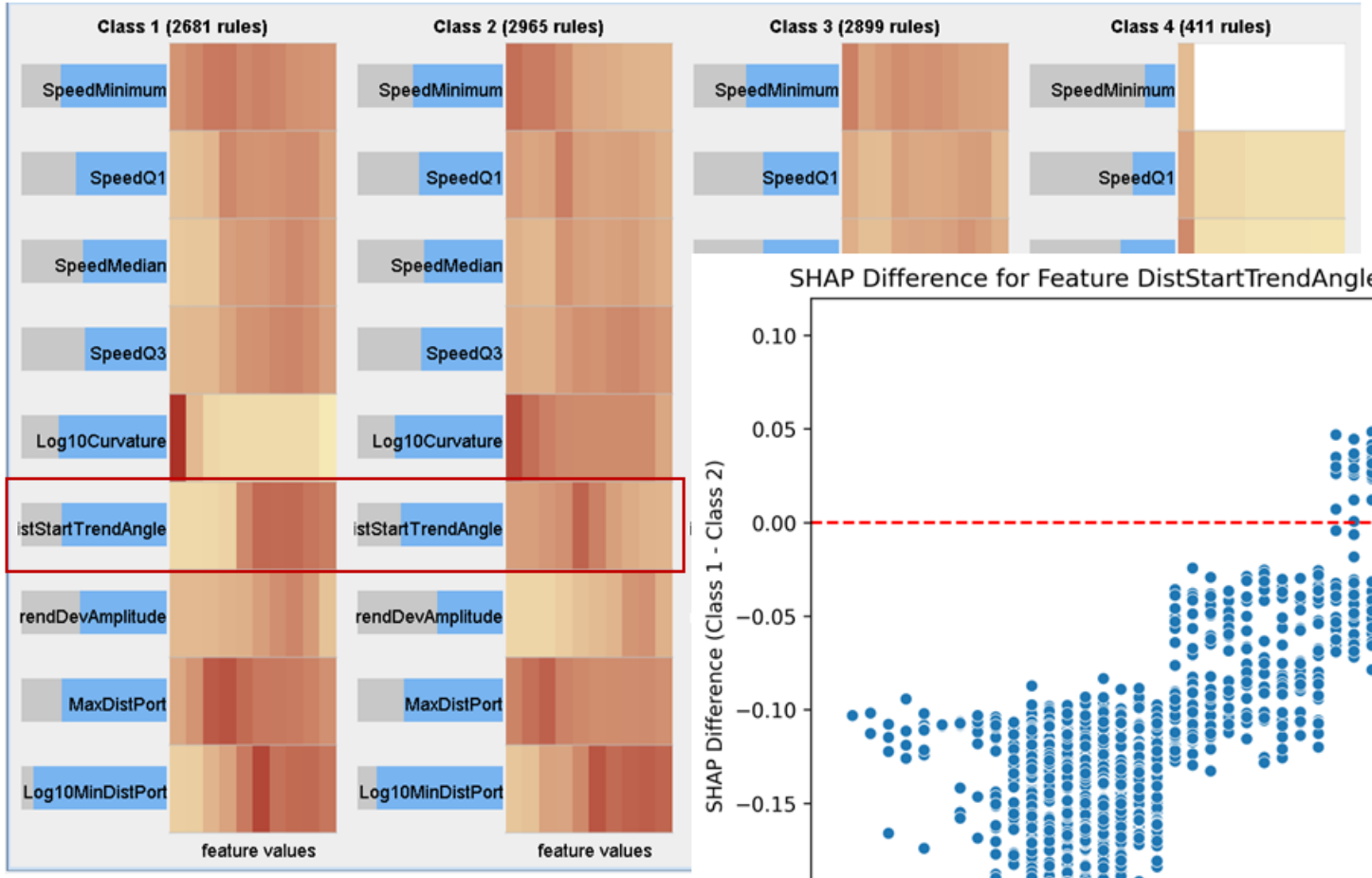
Enhancing interpretability of model behavior:

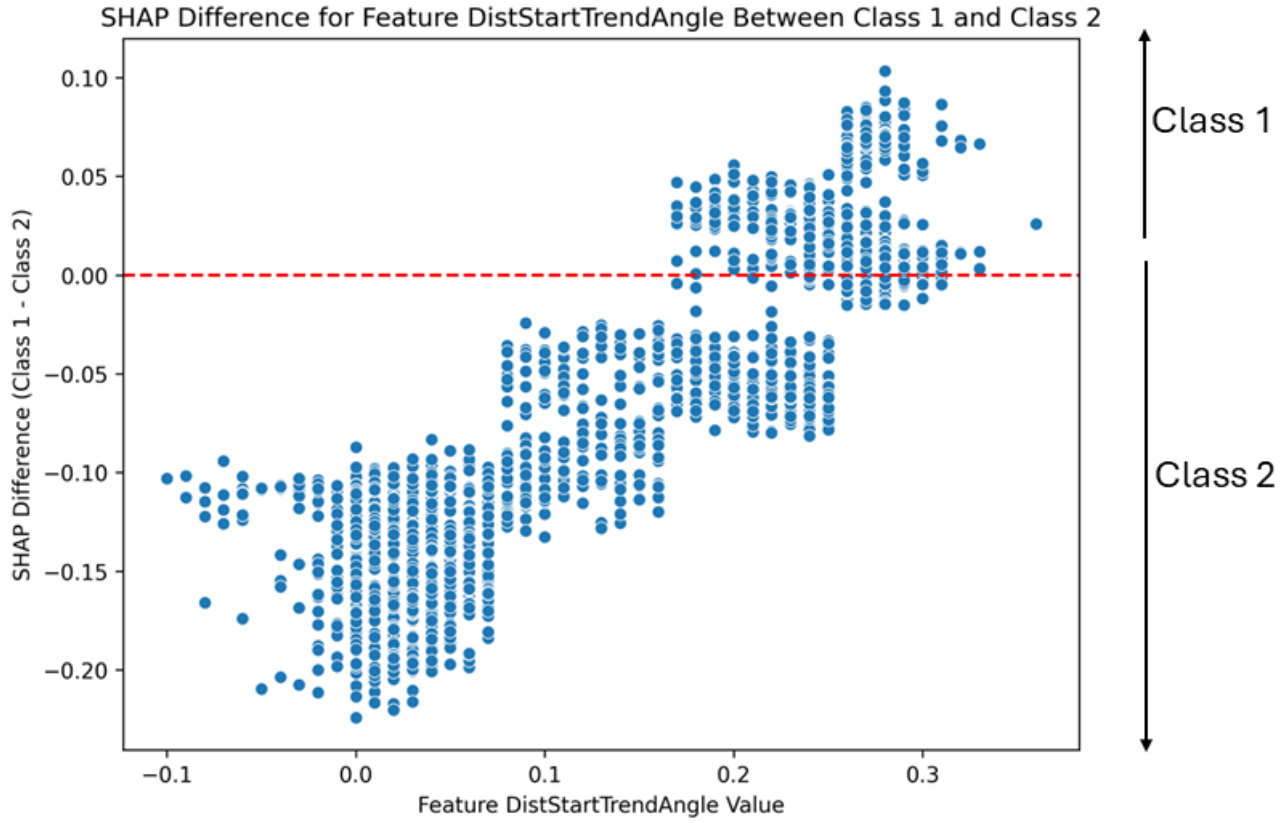
- Feature impact scores provide complementary information that is not directly accessible from rule-based explanations alone.
- By quantifying the contribution of individual features to model predictions, they support a more detailed understanding of the model's reasoning and foster greater transparency.

Supporting interactive exploration:

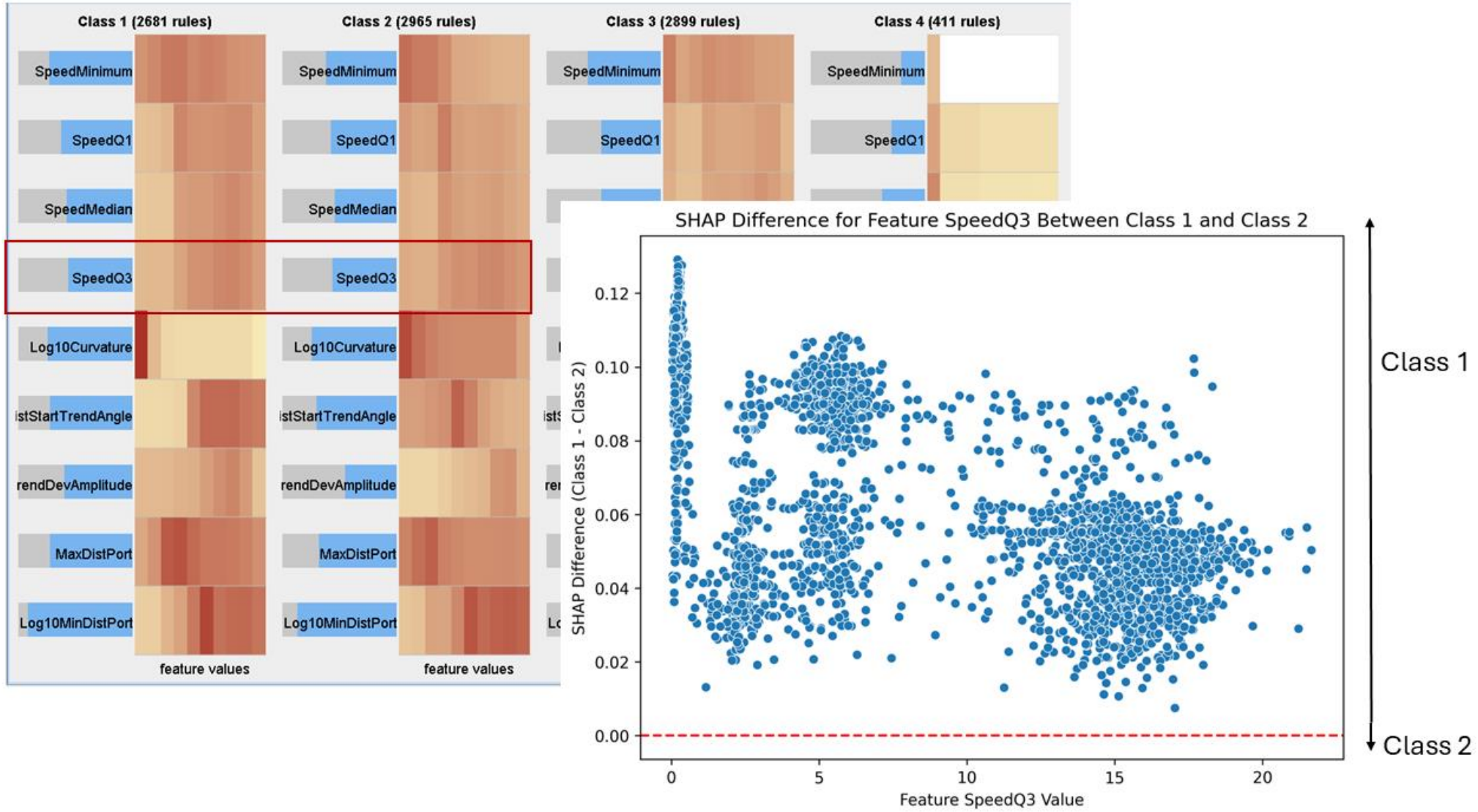
- Awareness of feature importance enables users to more effectively navigate and interrogate the rule space, prioritizing rules that include or omit key features.
- The comparison of rule-based and attribution-based explanations allows users to identify discrepancies and improve mutual trust in the system.

Enhancing Interpretability

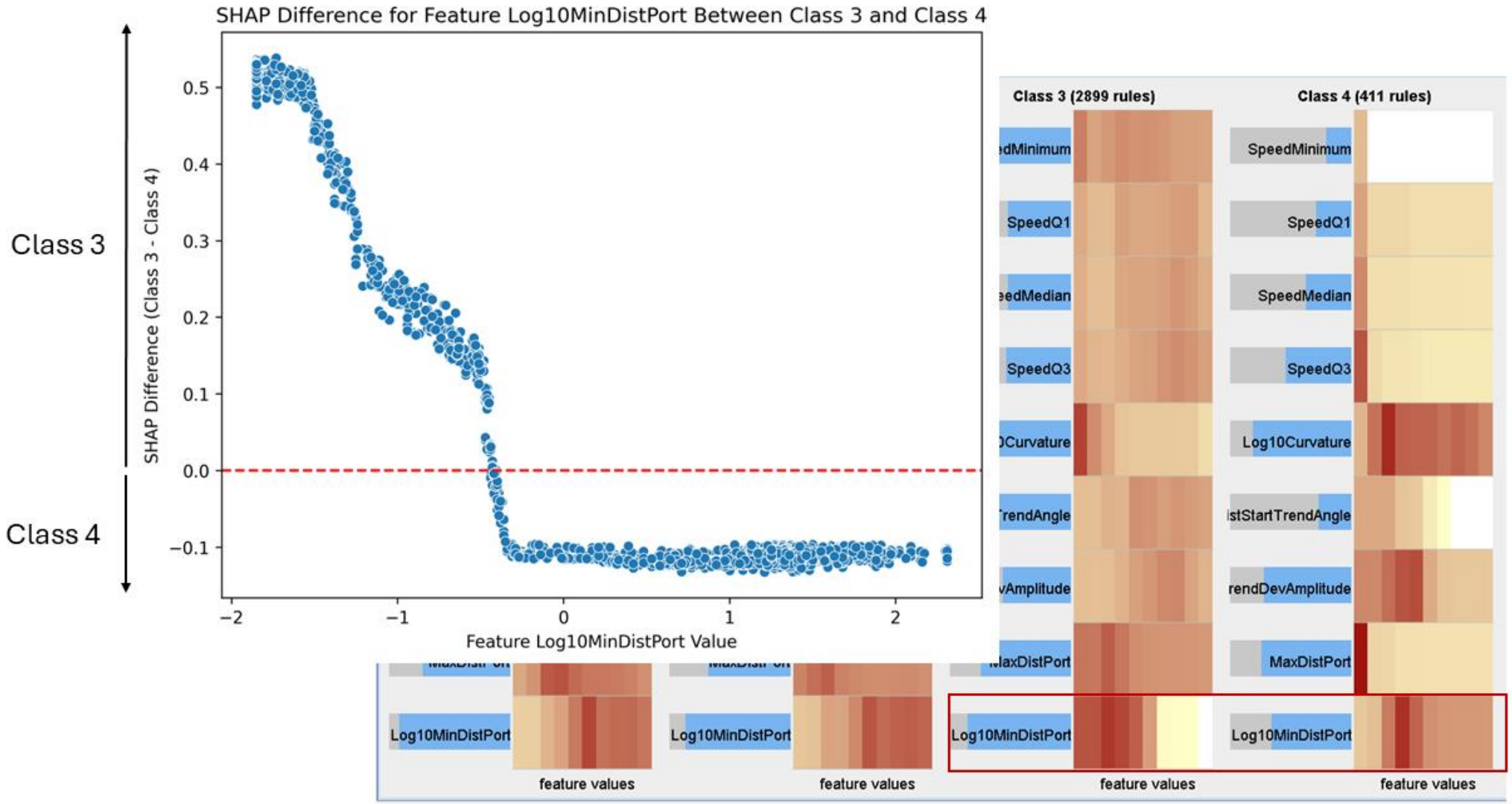




Enhancing Interpretability



Enhancing Interpretability



Limitations and Future work

- Shap stability – Explore stabilization techniques
- Refine visualization of feature attributions
- Generalisation and Validation – look at further datasets
- Provide Local Explanations

Ideas for Collaboration

- Interesting datasets to apply our techniques ?
  - Particularly temporal or spatio-temporal datasets
- Ideas for improving the framework?
- Techniques to compliment the framework?

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The Team:

Prof. Dr. Natalia Andrienko

Prof. Dr. Gennady Andrienko

Dr. Bahavathy Kathirgamanathan

Institute: Fraunhofer IAIS, Sankt Augustin, Germany



References

[1] Ponce-de Leon et al., **COVID-19 Flow-Maps an open geographic information system on COVID-19 and human mobility for Spain**. Scientific Data 8(1), 310 (Nov 2021).

[2] Ponce-de Leon et al., **COVID19 Flow-Maps daily cases reports** (2021). https://doi.org/10.5281/zenodo.5217386

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Contact

Dr. Bahavathy Kathirgamanathan
Scientific Coordinator, Lamarr Human Centered AI Systems

Email:
bahavathy.kathirgamanathan@iais.fraunhofer.de

www.lamarr-institute.org

Partner institutions:

technische universität dortmund

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Institutionally funded by:

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