

DOES THE MODEL THINK AS WE EXPECT?

EXPLORING ML MODEL LOGIC THROUGH DECISION RULES

Natalia Andrienko, Gennady Andrienko, Bahavathy Kathirgamanathan

Fraunhofer Institute IAIS (Intelligent Analysis and Information Systems), Germany

Lamarr Institute for Machine Learning and Artificial Intelligence, Germany

Research Area: Human-Centred AI

INTRODUCTION

- **Key question:** ML models can be accurate, but do they reason as we expect?
- **Why This Matters:**
 - Trust in ML models is not just about accuracy – it's about understanding *why* they make decisions.
 - A model may produce correct predictions while relying on reasoning that differs from human logic.
 - This misalignment can affect model adoption, interpretation, and decision-making in critical applications.
- **Additional question:** Can we use a ML model to understand the data and phenomena it captures?
- **Our goal:** support exploring model's internal workings and logic.
 - We consider models represented by systems of decision rules.

INTERPRETABILITY OF ML MODELS

- A model is **interpretable** if a person can understand its internal mechanics and capture relevant knowledge concerning relationships between inputs and outputs.
- Interpretability is essential for trust, transparency, debugging, and domain insight.

Inherently Interpretable Models (contrasted with “black box” models):

- **Linear Models** – simple mathematical expressions with coefficients showing direct feature influence.
- **Decision Trees** – visualize decisions as a sequence of understandable splits.
- **Rule-Based Models** – express decisions as explicit IF–THEN rules.
 - Decision trees can be transformed to equivalent rule-based models.
- A common approach to explain black-box models is to approximate their behaviour with an interpretable surrogate, such as a decision tree or rule set.

VISUALISATION OF A RULE-BASED MODEL: RULEMATRIX

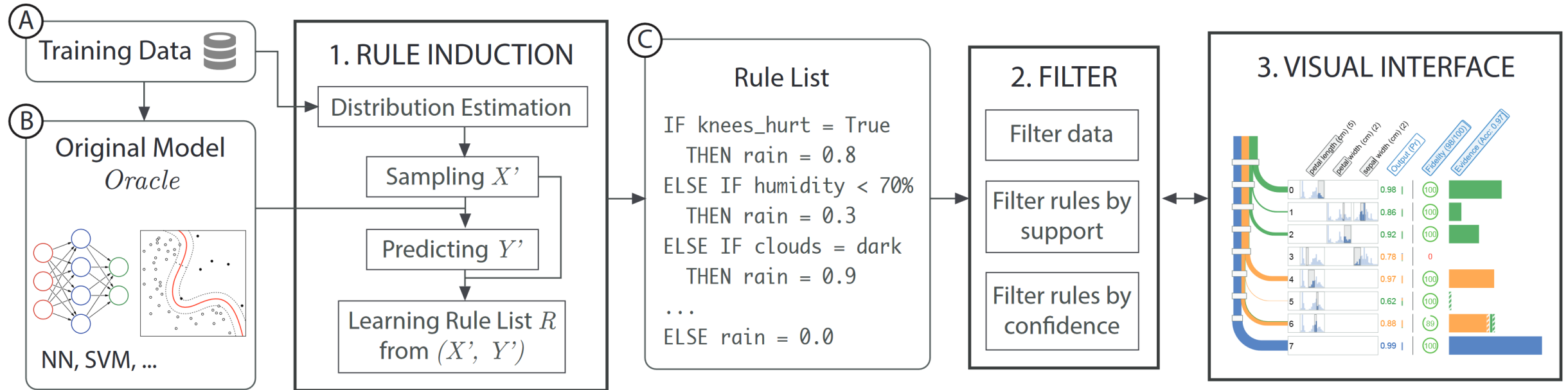
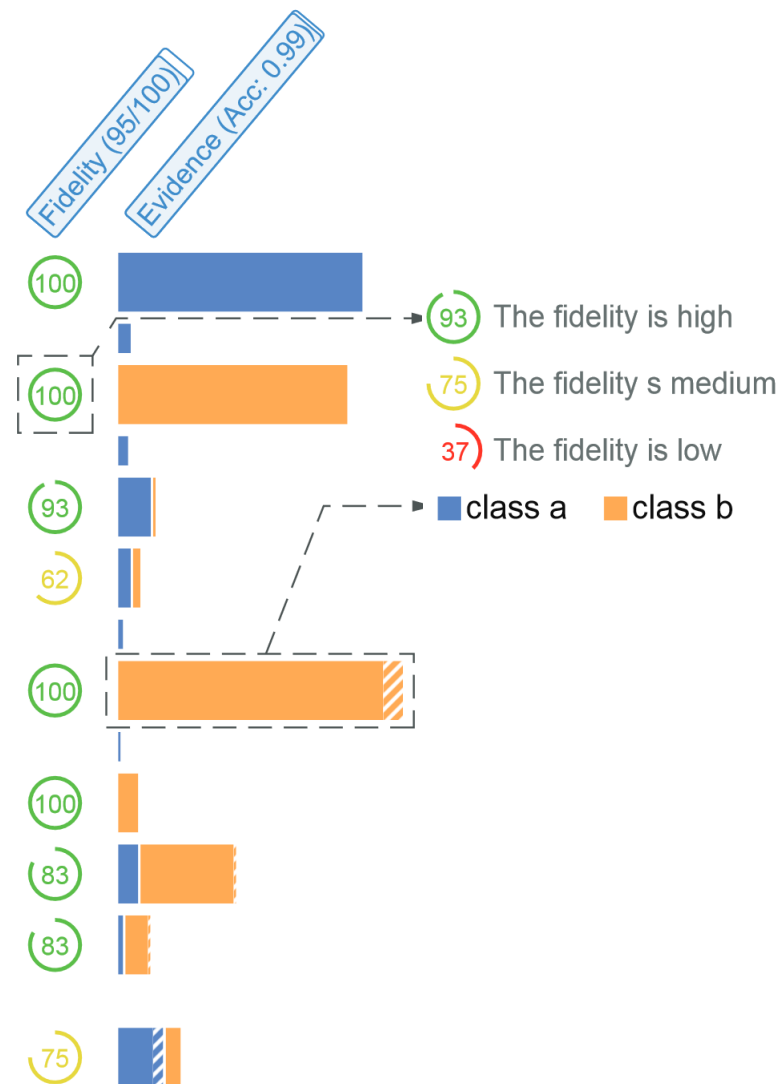
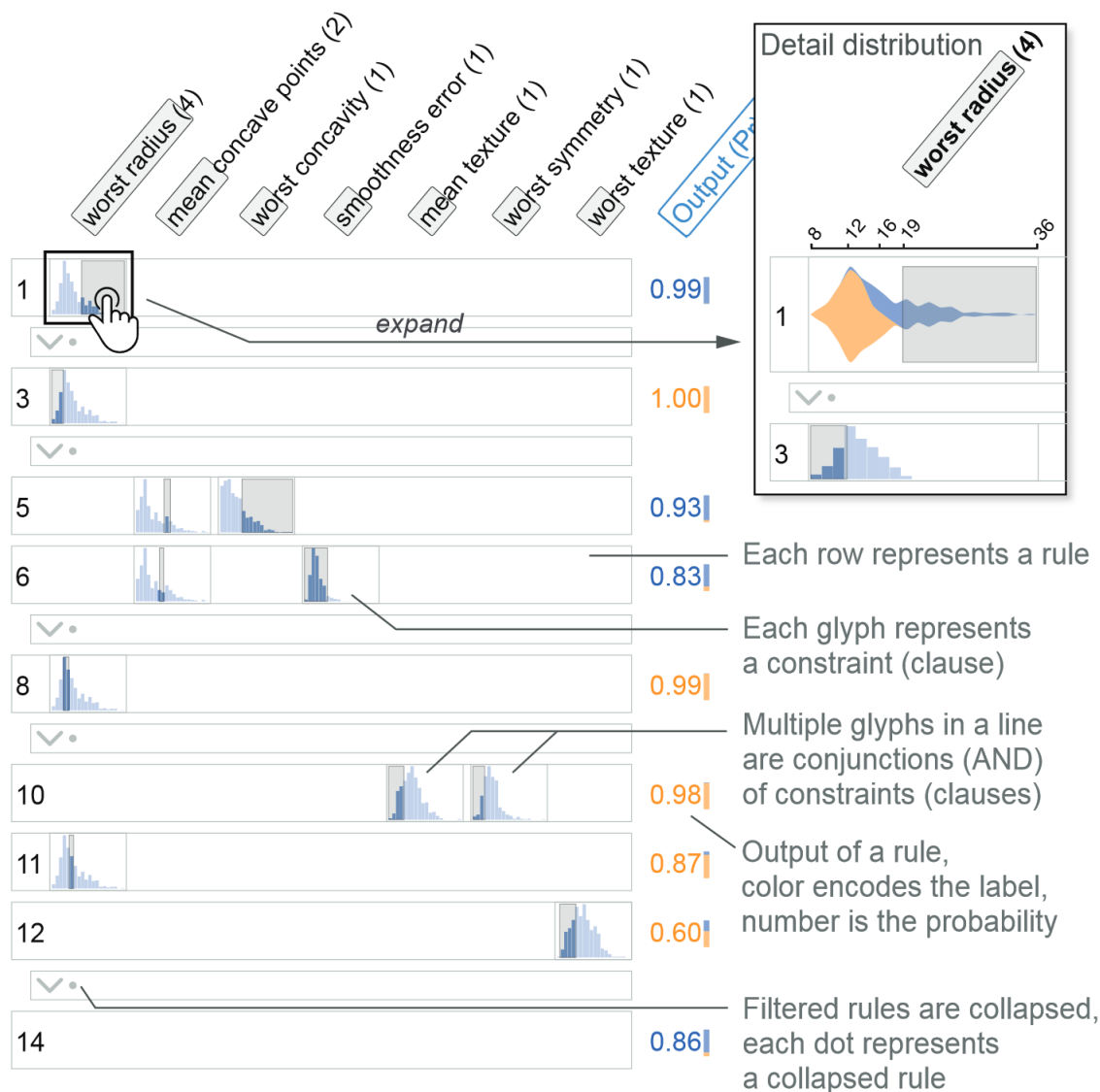
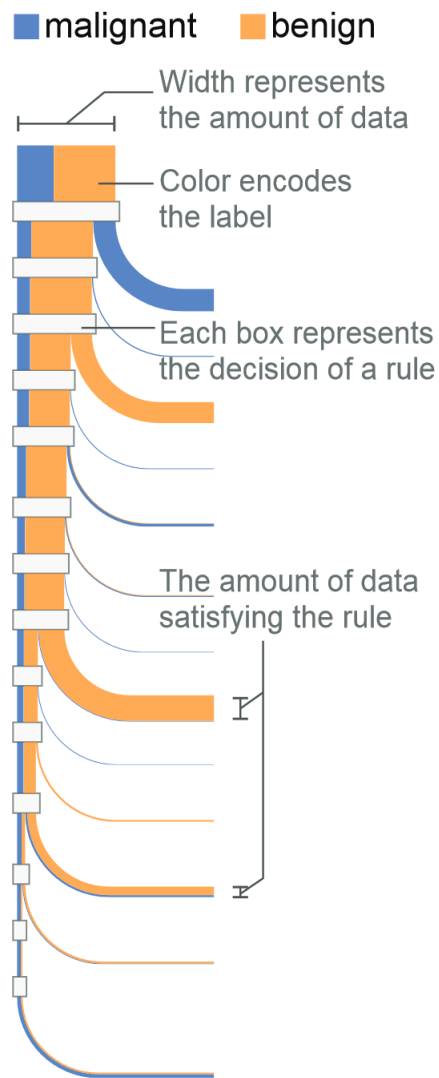


Fig. 2. The pipeline for creating a rule-based explanation interface. The rule induction step (1) takes (A) the training data and (B) the model to be explained as input, and produces (C) a rule list that approximates the original model. Then the rule list is filtered (2) according to user-specified thresholds of support and confidence. The rule list is visualized as RuleMatrix (3) to help users navigate and analyze the rules.

Ming, Y., Qu, H., & Bertini, E. (2018).
RuleMatrix: Visualizing and Understanding Classifiers with Rules.
IEEE Transactions on Visualization and Computer Graphics, 25, 342-352.

RULEMATRIX



Our previous work:

EXPLAINING RULE-BASED MODEL'S LOGIC USING A SIMPLIFIED DESCRIPTIVE MODEL

Adilova, L., Kamp, M., Andrienko, G. and Andrienko, N.
“Re-interpreting rules interpretability”.
International Journal of Data Science and Analytics (2023).
doi:10.1007/s41060-023-00398-5.

PROBLEM STATEMENT

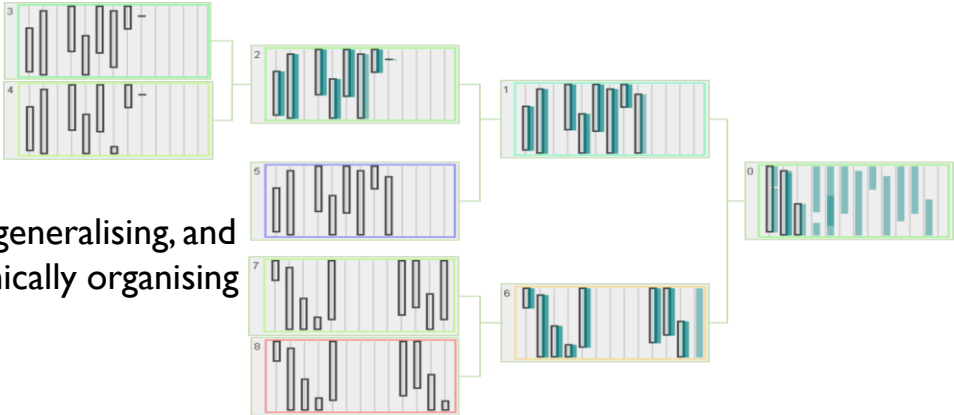
- Given: a rule-based model with a large number of decision rules
- Task: facilitate human's comprehension of the logic of the entire model
 - Challenge: although decision rules and decision trees are considered “inherently interpretable”, comprehension of a large system of rules or decision tree may be beyond human perceptual and cognitive capacity.
 - Aspects of complexity:
 - Number of rules
 - Number of conditions in a rule

APPROACH: AGGREGATE – GENERALISE – CREATE A SIMPLER DESCRIPTIVE MODEL

Visualisation of a rule-based model



Joining, generalising, and hierarchically organising rules



Aggregated rules (11), N conditions (45), Total uses (402); obtained with coherence threshold 1.000 and max Q difference 0.35000

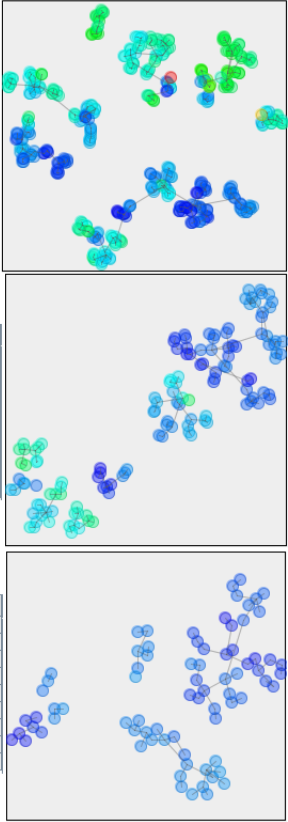
Q min..max	N right co...	N...	Rule	percent_at...	alpha	ecn_bon...	c	b_c	ecn_bond...	percent_a...	percent_ato...	gamma
0.000..0.322	133	1	0 0 0 0 0 0 0 0 0 0									
0.010..0.315	46	4	0 0 0 0 0 0 0 0 0 0									
0.021..0.364	61	3	0 0 0 0 0 0 0 0 0 0									
0.056..0.361	62	4	0 0 0 0 0 0 0 0 0 0									
0.082..0.159	6	5	0 0 0 0 0 0 0 0 0 0									
0.103..0.103	1	5	0 0 0 0 0 0 0 0 0 0									
0.137..0.282	19	6	0 0 0 0 0 0 0 0 0 0									
0.166..0.479	49	5	0 0 0 0 0 0 0 0 0 0									
0.253..0.398	17	3	0 0 0 0 0 0 0 0 0 0									
0.612..0.612	1	6	0 0 0 0 0 0 0 0 0 0									
0.768..0.768	1	3	0 0 0 0 0 0 0 0 0 0									

Aggregated rules (9), N conditions (40), Total uses (138); obtained with coherence threshold 1.000 and max Q difference 0.15000

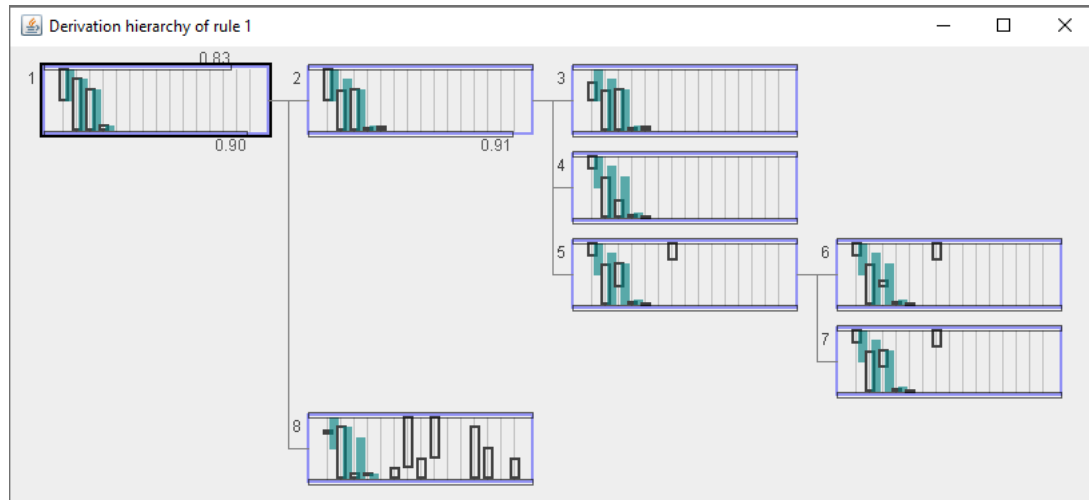
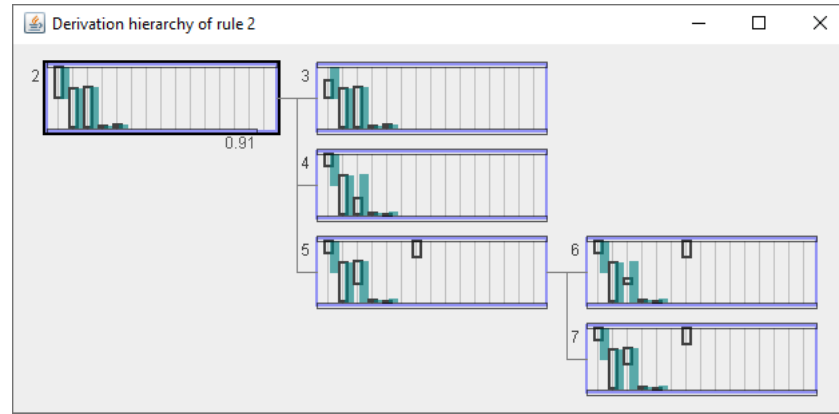
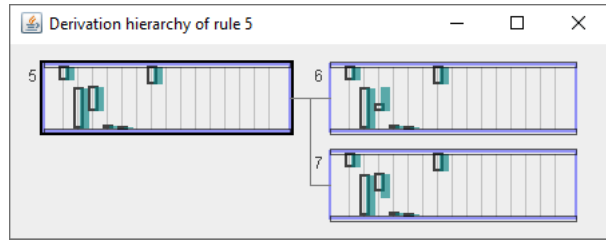
Q min..max	N right c...	N...	Rule	percent_ato...	a	gamma	percent_ato...	a_c	ecn_bond...	vol_per_atom	a_b
0.000..0.115	57	3	0 0 0 0 0 0 0 0 0 0								
0.000..0.109	10	3	0 0 0 0 0 0 0 0 0 0								
0.082..0.202	24	2	0 0 0 0 0 0 0 0 0 0								
0.082..0.082	1	7	0 0 0 0 0 0 0 0 0 0								
0.090..0.147	5	6	0 0 0 0 0 0 0 0 0 0								
0.161..0.294	15	7	0 0 0 0 0 0 0 0 0 0								
0.181..0.286	10	5	0 0 0 0 0 0 0 0 0 0								
0.199..0.316	10	4	0 0 0 0 0 0 0 0 0 0								
0.322..0.322	1	3	0 0 0 0 0 0 0 0 0 0								

Aggregated rules (9), N conditions (42), Total uses (81); obtained with coherence threshold 1.000 and max Q difference 0.07500

Q min..max	N right ...	N...	Rule	percen...	a	gamma	a_c	c	a_b	Natoms	perce...	ecn_b...	vol_pe...	ecn_b...	alpha	ecn_b...
0.000..0.044	15	4	0 0 0 0 0 0 0 0 0 0													
0.000..0.039	7	4	0 0 0 0 0 0 0 0 0 0													
0.038..0.091	21	4	0 0 0 0 0 0 0 0 0 0													
0.074..0.116	21	4	0 0 0 0 0 0 0 0 0 0													
0.082..0.101	6	3	0 0 0 0 0 0 0 0 0 0													
0.082..0.082	1	7	0 0 0 0 0 0 0 0 0 0													
0.089..0.106	3	4	0 0 0 0 0 0 0 0 0 0													
0.090..0.096	2	7	0 0 0 0 0 0 0 0 0 0													
0.114..0.114	1	5	0 0 0 0 0 0 0 0 0 0													



KEY IDEA: AGGREGATE AND GENERALISE SIMILAR RULES



Visual representation of one rule

Features → vertical axes

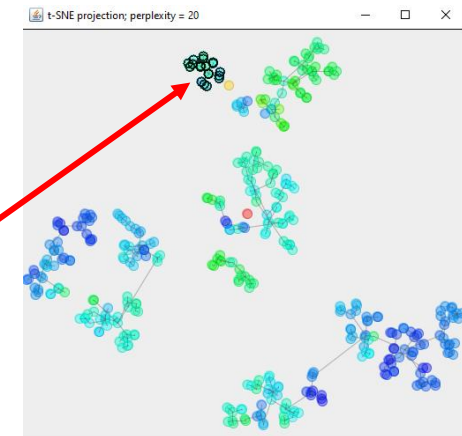


Intervals of feature values → bars

Rough rules
(have exceptions)

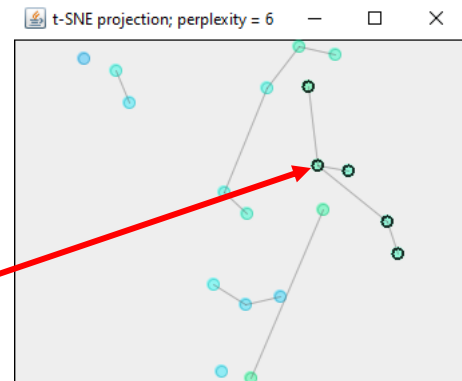
Highly generalised rule set

Q min...max	N u...	N +	N -	+/-	N d...	Order	Clus...	N co...	N ri...	N wr...	Coh...	N uni...	Depth...	Rule	perc...	alpha	ecn...	c	b_c	ecn...	perc...	perc...	gam...
0.040..0.315	47	47	0	1.00...	47	9	-1	4	46	0	100....	90	10	□□□□□□□□□□									
0.103..0.103	1	1	0	1.00...	1	10	-1	5	1	0	100....	0	1	□□□□□□□□□□									
0.000..0.322	138	138	0	1.00...	138	3	-1	1	133	0	100....	264	16	□□□□□□□□□□									
0.082..0.159	6	6	0	1.00...	6	7	-1	5	6	0	100....	10	5	□□□□□□□□□□									
0.056..0.361	62	62	0	1.00...	62	4	-1	4	62	0	100....	122	14	□□□□□□□□□□									
0.024..0.364	61	61	0	1.00...	61	0	-1	3	61	0	100....	120	15	□□□□□□□□□□									
0.137..0.282	19	19	0	1.00...	19	5	-1	6	19	0	100....	36	10	□□□□□□□□□□									
0.253..0.398	17	17	0	1.00...	17	2	-1	3	17	0	100....	32	8	□□□□□□□□□□									
0.156..0.479	49	49	0	1.00...	49	8	-1	5	49	0	100....	96	14	□□□□□□□□□□									
0.612..0.612	1	1	0	1.00...	1	6	-1	6	1	0	100....	0	1	□□□□□□□□□□									
0.768..0.768	1	1	0	1.00...	1	1	-1	3	1	0	100....	0	1	□□□□□□□□□□									



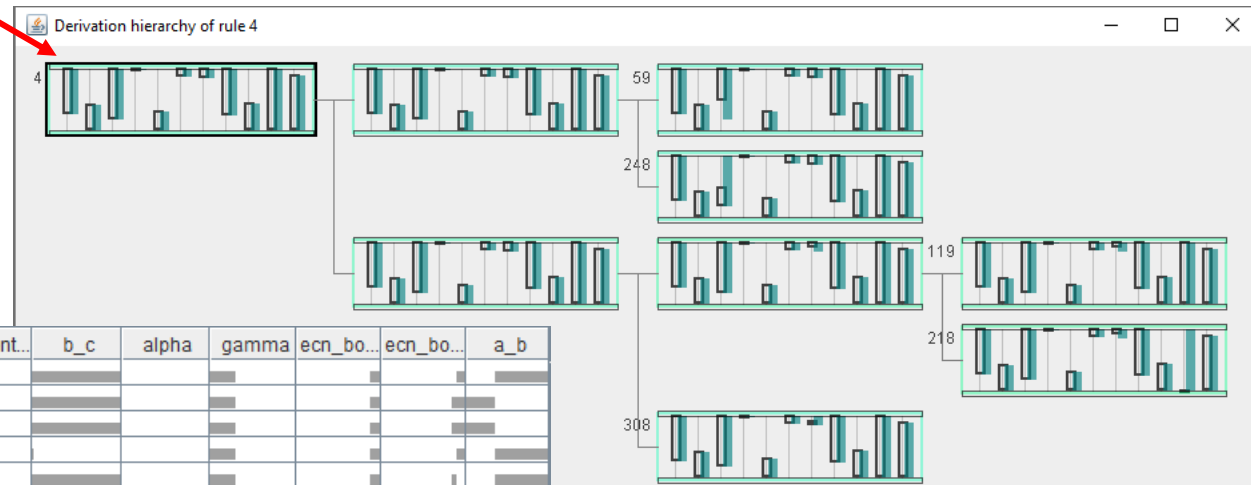
Refinement of a selected generalised rule

Q min..max	N u...	N +	N -	+/-	N d...	Order	Clu...	N co...	N ri...	N wr...	Coh...	N u...	Dep...	Rule	perc...	c	perc...	alpha	ga...	ecn...	ecn...	vol_...	perc...	b_c	ecn...
0.137..0.137	1	1	0	1.00...	1	6	-1	9	1	0	100....	0	1	□□□□□□□□□□											
0.156..0.197	3	3	0	1.00...	3	4	-1	7	3	0	100....	4	3	□□□□□□□□□□											
0.174..0.174	1	1	0	1.00...	1	3	-1	9	1	0	100....	0	1	□□□□□□□□□□											
0.176..0.214	2	2	0	1.00...	2	5	-1	9	2	0	100....	2	2	□□□□□□□□□□											
0.213..0.253	5	8	2	0.80...	5	0	-1	9	8	2	80.0...	8	4	□□□□□□□□□□											
0.248..0.284	5	5	0	1.00...	5	1	-1	11	5	0	100....	8	4	□□□□□□□□□□											
0.272..0.282	2	2	0	1.00...	2	2	-1	8	2	0	100....	2	2	□□□□□□□□□□											



Viewing original rules included in the selected rule

Id	N con...	N right...	N wro...	Coher...	N unit...	Depth...	Rule	percent...	c	percent...	vol_per...	ecn_bo...	percent...	b_c	alpha	gamma	ecn_bo...	ecn_bo...	a_b
119	12	1	0	100.00...	0	1	□□□□□□□□□□												
59	12	1	0	100.00...	0	1	□□□□□□□□□□												
248	12	1	0	100.00...	0	1	□□□□□□□□□□												
218	12	1	0	100.00...	0	1	□□□□□□□□□□												
308	12	1	0	100.00...	0	1	□□□□□□□□□□												



SUMMARY

- Problem: practical incomprehensibility of theoretically interpretable models due to large size and complexity
- Goal: facilitate comprehension by creating a smaller and simpler *descriptive model*
- Approach: iterative aggregation and generalisation
 - Rough rules with exceptions
 - Approximate rules for representing regression models
- 👉 Limited degree of simplification for models optimised for compactness
- 👉 Required: domain semantics-based grouping and aggregation of features

Our current work:

SEEKING MORE SCALABLE APPROACHES TO SUPPORTING INTERACTIVE VISUAL EXPLORATION OF LARGE RULE-BASED ML MODELS

Such as rules extracted from Random Forest models

RANDOM FOREST

- Ensemble learning method that creates many decision trees.
- Based on the principle of “wisdom of the crowd” – **multiple weak learners** form a strong predictor.

How it works:

- Each tree is trained on a random subset of the data (bagging).
- At each split, a random subset of features is considered.
- Final prediction is made by **majority vote** (classification) or **average** (regression).

Key features:

- 👍 Handles non-linear relationships and high-dimensional data well.
- 👍 Robust to overfitting due to randomization and averaging.
- 👎 Still a **black-box model** – hard to interpret due to large size, redundancy, and possible inconsistencies.

RUNNING EXAMPLE:VESSEL MOVEMENT PATTERN RECOGNITION

- **Goal:** Classify vessel movement segments into behavior types (class 1 – *Forward movement*, class 2 – *Trawling*, class 3 – *Port enter/exit*, class 4 – *Anchoring*)
- **Data:** Segments of vessel trajectories derived from AIS (Automatic Identification System) records and described by engineered *time interval-based features*:
 - *SpeedMinimum, SpeedQ1, SpeedMedian, SpeedQ3* – represent speed distribution over time interval.
 - *Log10Curvature* – logarithm of the curvature of the time series of the vessel's distance from the starting point computed as the ratio between the sum of absolute consecutive changes and the amplitude of values.
 - *DistStartTrendAngle, Log10DistStartTrendDevAmplitude* – angle of the linear trend fitted to the time series of the vessel's distance from the starting point and logarithm of the amplitude of deviations from the trend line.
 - *MaxDistPort, Log10MinDistPort* –maximum and log-transformed minimum distance from the nearest port.
- **Model:** Random Forest classifier transformed into a **rule-based model** for interpretability
 - **100** decision trees transformed to **9,939** rules with **56,838** conditions in total

Tree Id	Class	N conditions	Rule	SpeedMinimum	SpeedQ1	SpeedMedian	SpeedQ3	Log10Curvature	DistStartTrend...	Log10DistStar...	MaxDistPort	Log10MinDistP...
0	3	6										
0	4	6										
19	3	6										
19	2	7										
35	2	7										
35	3	6										
0	3	7										
35	3	6										
81	2	8										
3	3	5										
80	3	8										
3	2	5										
3	3	5										
19	3	7										
35	3	7										
81	3	8										
35	3	6										
81	3	6										
81	2	5										
0	4	5										
81	3	5										
0	2	6										
0	2	7										
6	3	6										
26	3	5										
26	3	7										
28	2	6										
15	3	6										
15	2	7										
15	2	7										
15	3	7										
15	3	7										
15	3	7										
6	3	6										
6	3	6										
6	4	6										
15	2	6										

Contradictory rules

Redundant rules

AN EXAMPLE OF A CONTRADICTORY RULE

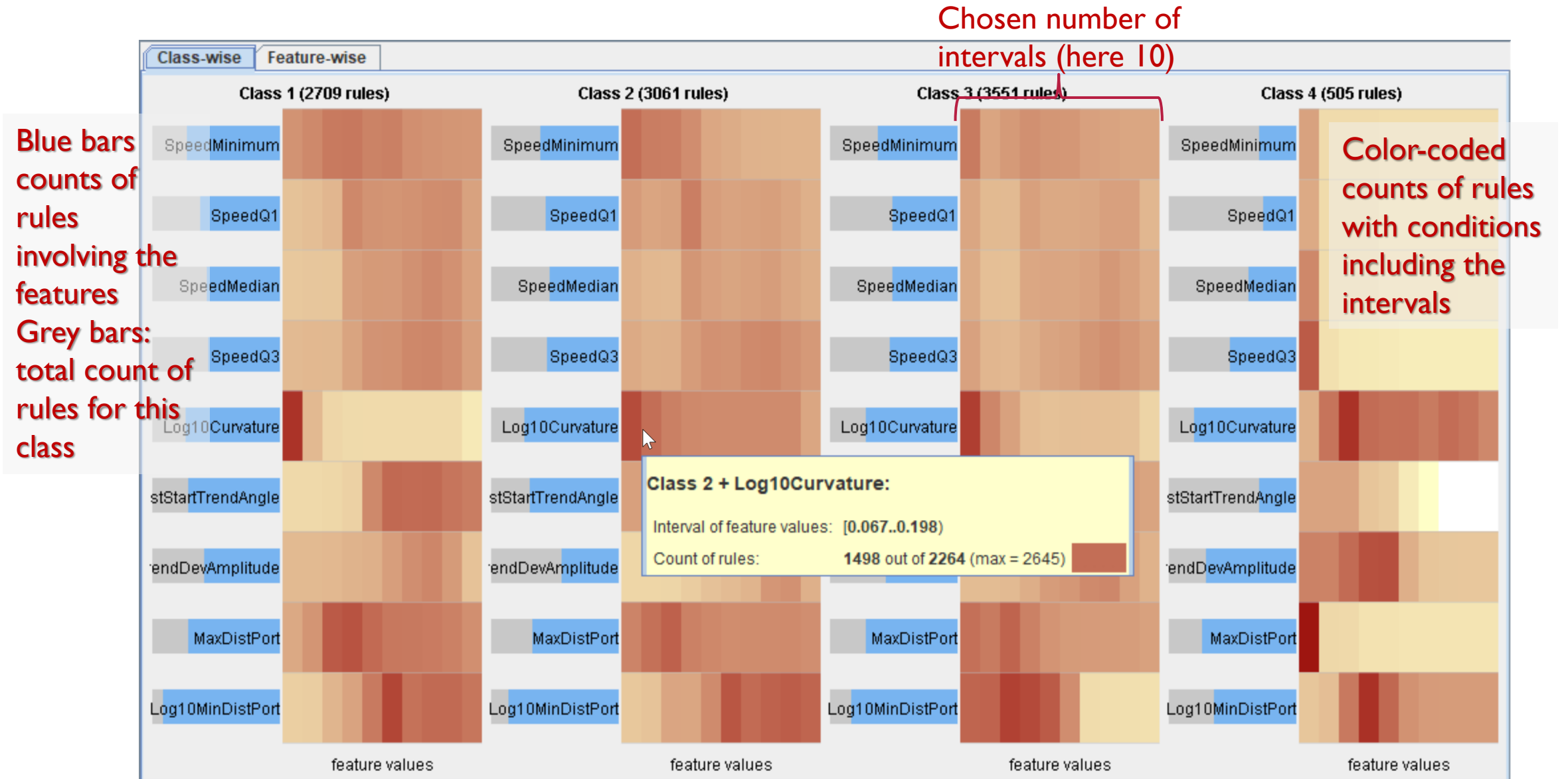
Tree Id	Class	N conditions	Rule	SpeedMinimum	SpeedQ1	SpeedMedian	SpeedQ3	Log10Curvat...	DistStartTrendA...	Log10DistSta...	MaxDistPort	Log10MinDistPort
2	3	2										
2	3	2										
91	3	3										
39	3	3										
47	3	3										
89	3	3										
84	3	4										
91	4	4										
1	3	5										
1	4	5										
21	3	6										
21	4	6										
23	3	6										
67	3	5										
91	3	4										
67	4	5										

The combination of the conditions of the topmost rule is more general than in the remaining rules shown. Some of the remaining rules predict another class than the topmost rule.

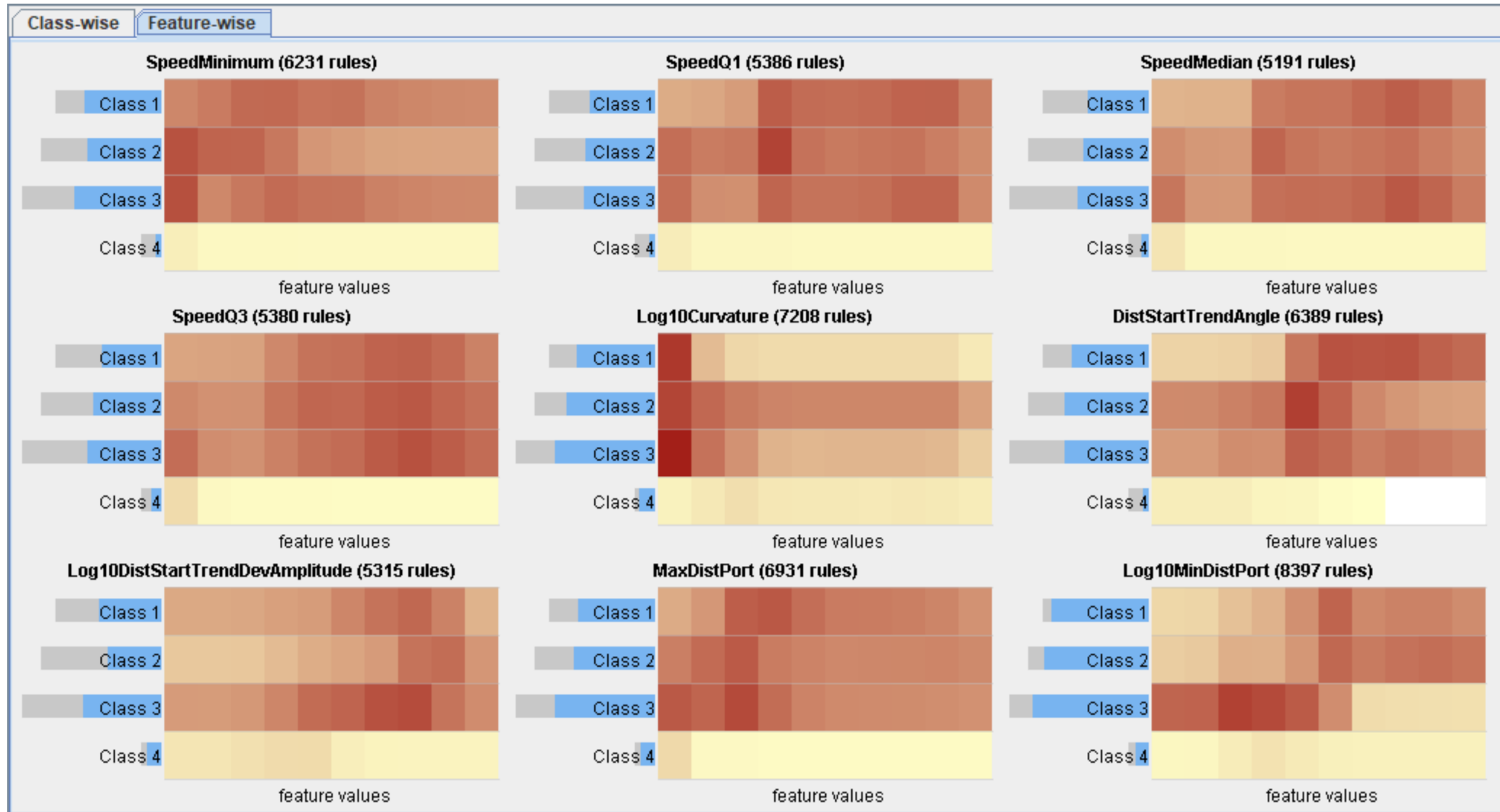
INITIAL CLEANING

- Automatically detect and remove contradictory rules – 113 rules removed
- Automatically detect and remove redundant rules (either same as or fully covered by other rules) – 311 rules removed

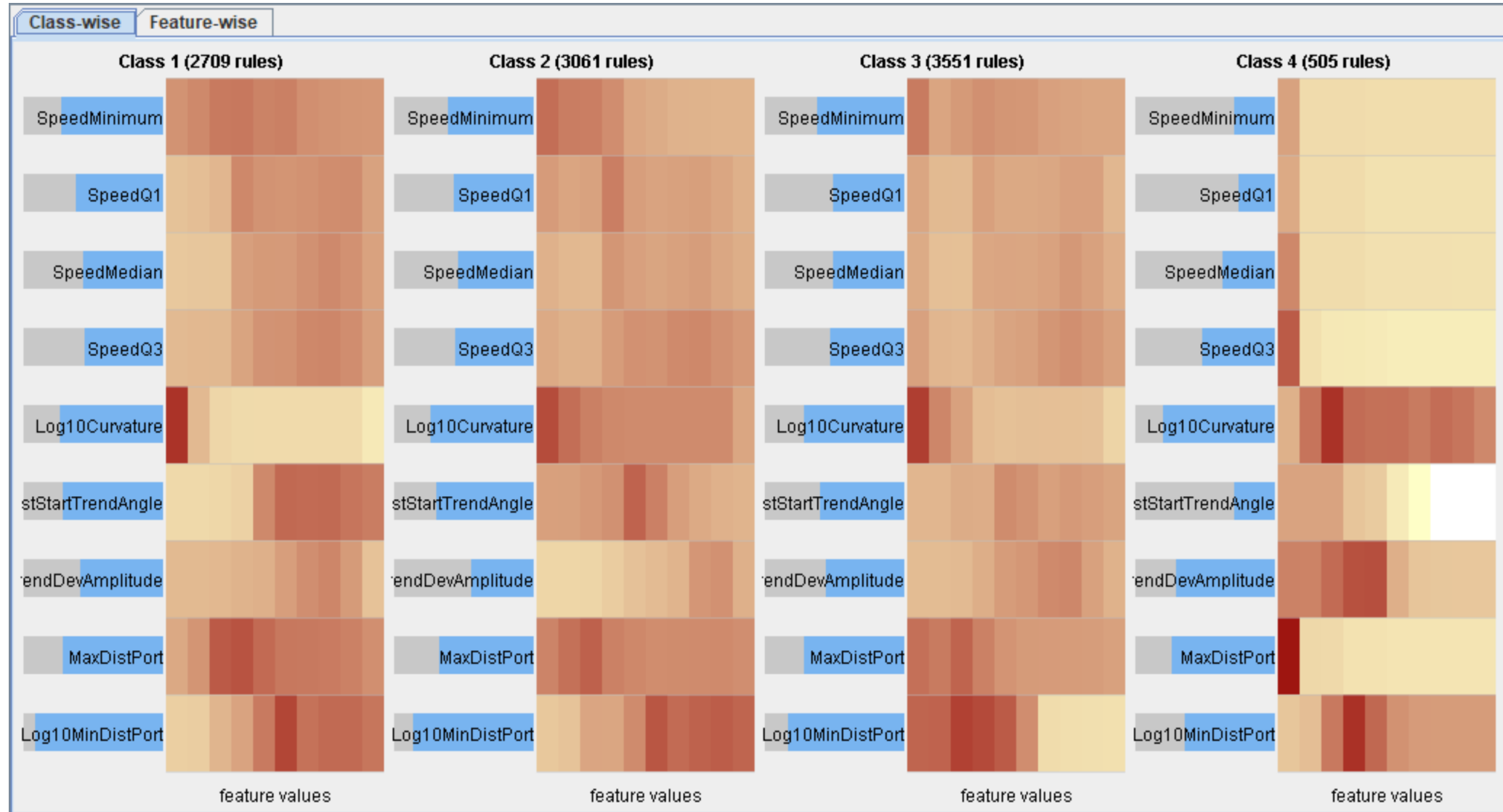
DISTRIBUTIONS OF FEATURES AND THEIR VALUE INTERVALS



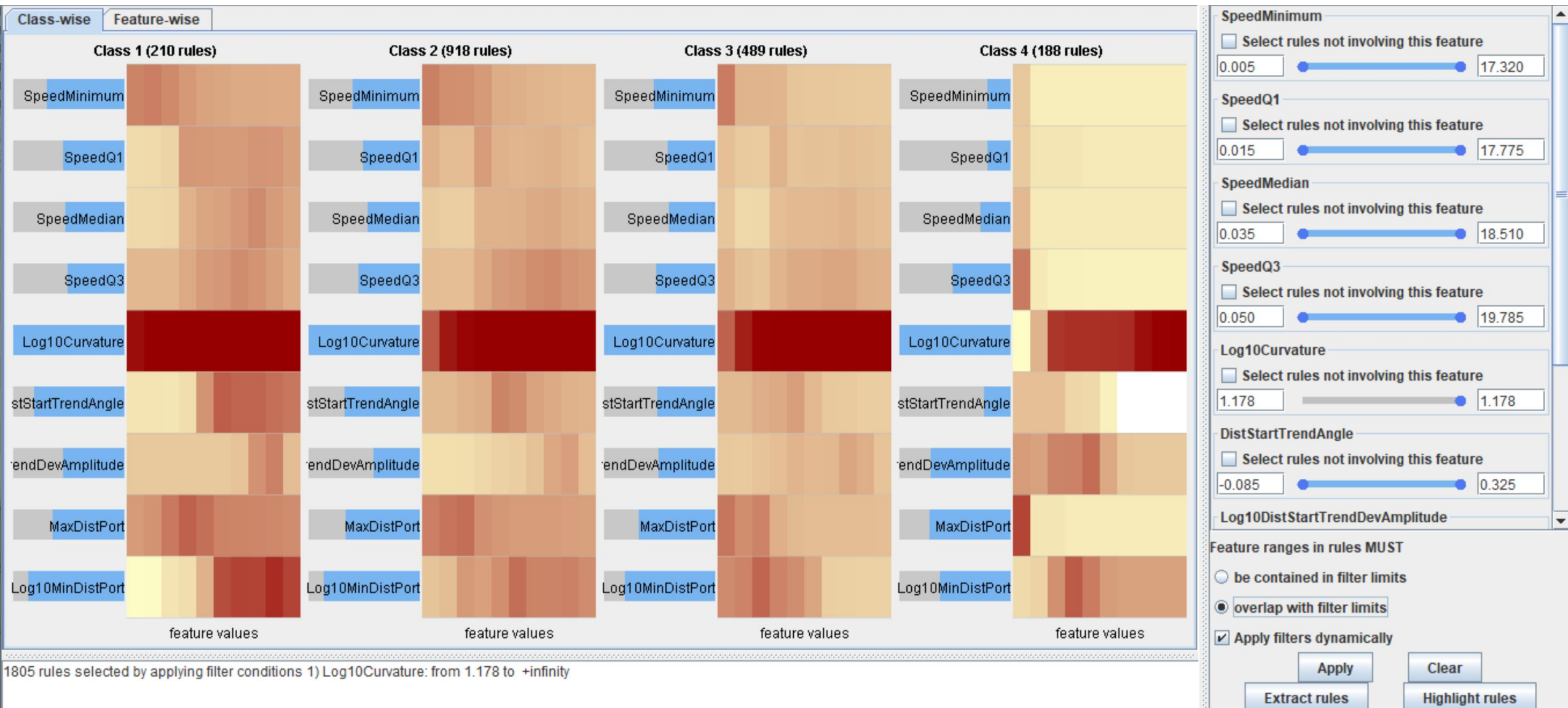
HOW DOES THE MODEL USE THE FEATURES?



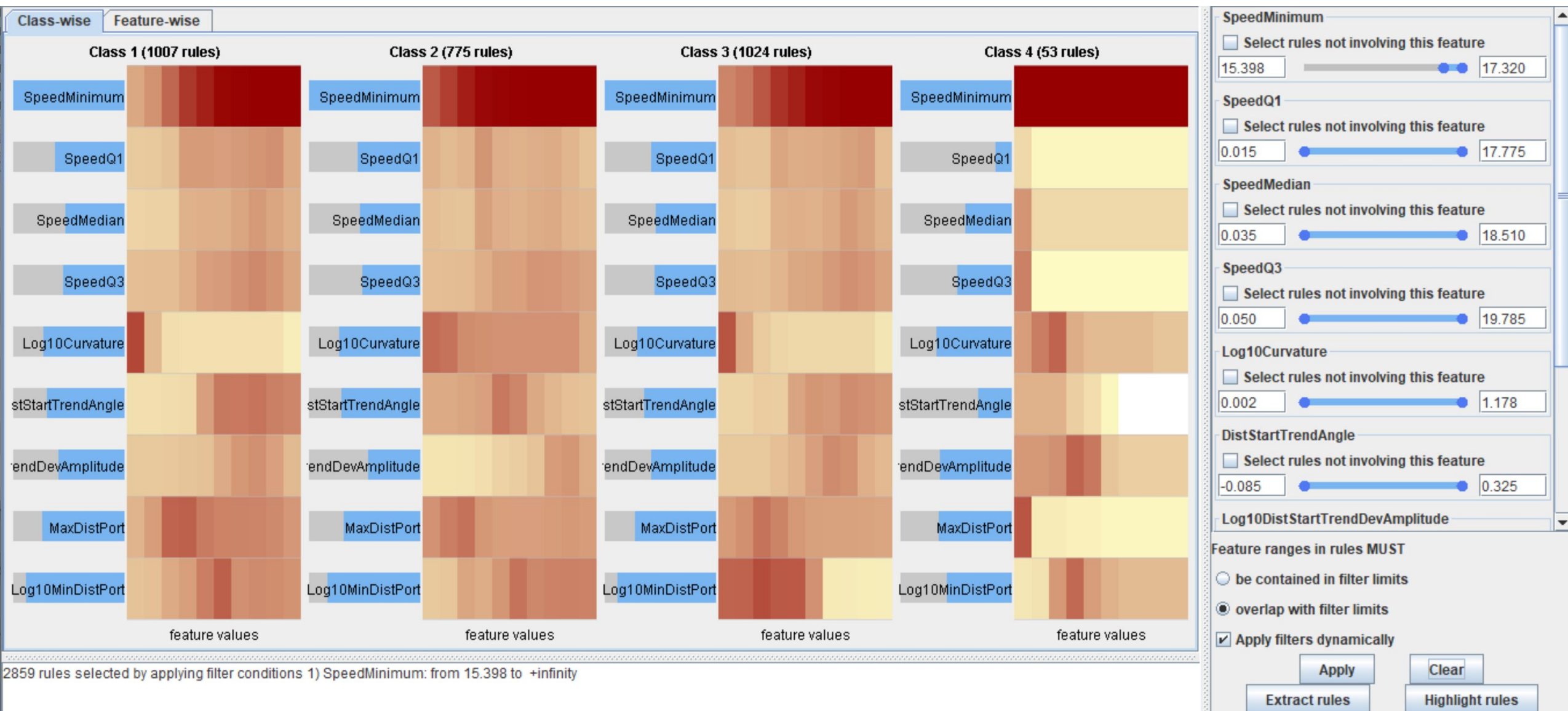
DO THE DISTRIBUTIONS ALIGN WITH OUR EXPECTATIONS?



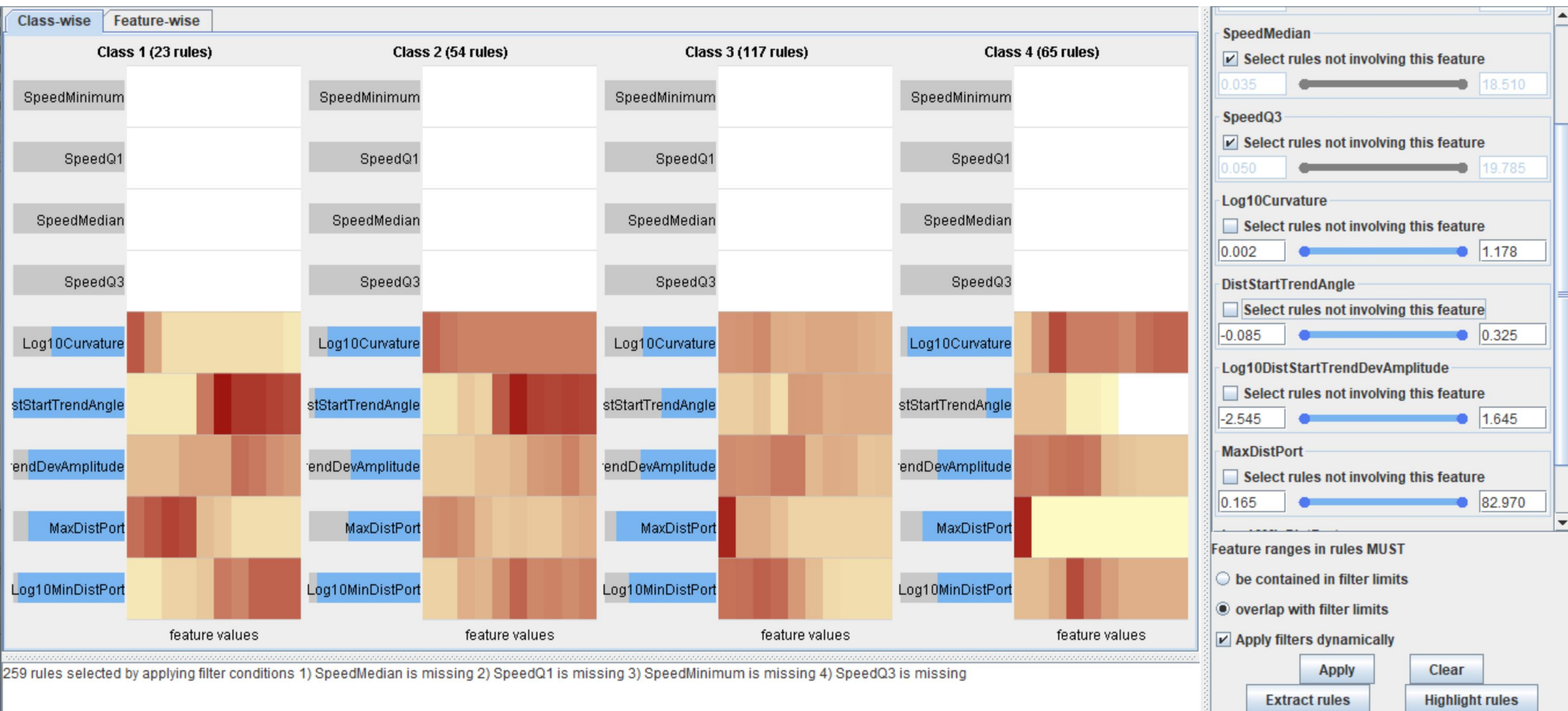
Controls for interactive filtering



There are rules allowing high curvature for forward movement patterns (class 1)



There are rules allowing high minimal speed for anchoring patterns (class 4)



There are rules ignoring the speed distribution features

Further filtering: rules with negative trend angle of the distances from the start

Class-wise

Feature-wise

Class 1 (2 rules)

Class 2 (6 rules)

Class 3 (20 rules)

Class 4 (15 rules)

SpeedMinimum

SpeedQ1

SpeedMedian

SpeedQ3

Log10Curvature

DistStartTrendAngle

Log10DistStartTrendDevAmplitude

MaxDistPort

Log10MinDistPort

feature values

feature values

feature values

feature values

0.035

18.510

SpeedQ3

☒ Select rules not involving this feature

0.050

19.785

Log10Curvature

☐ Select rules not involving this feature

0.002

1.178

DistStartTrendAngle

☐ Select rules not involving this feature

-0.085

-0.01

Log10DistStartTrendDevAmplitude

☐ Select rules not involving this feature

-2.545

1.645

MaxDistPort

☐ Select rules not involving this feature

0.165

82.970

Log10MinDistPort

☐ Select rules not involving this feature

-1.845

1.815

Feature ranges in rules MUST

☐ be contained in filter limits

☒ overlap with filter limits

☒ Apply filters dynamically

Apply

Clear

Extract rules

Highlight rules

Contradict to our expectations for forward movement

43 rules selected by applying filter conditions 1) SpeedMedian is missing 2) DistStartTrendAngle: from -infinity to -0.010 3) SpeedQ1 is missing 4) SpeedMinimum is missing 5) SpeedQ3 is

INTERACTIVE CLEANING THROUGH FILTERING AND TESTING ON LABELLED DATA

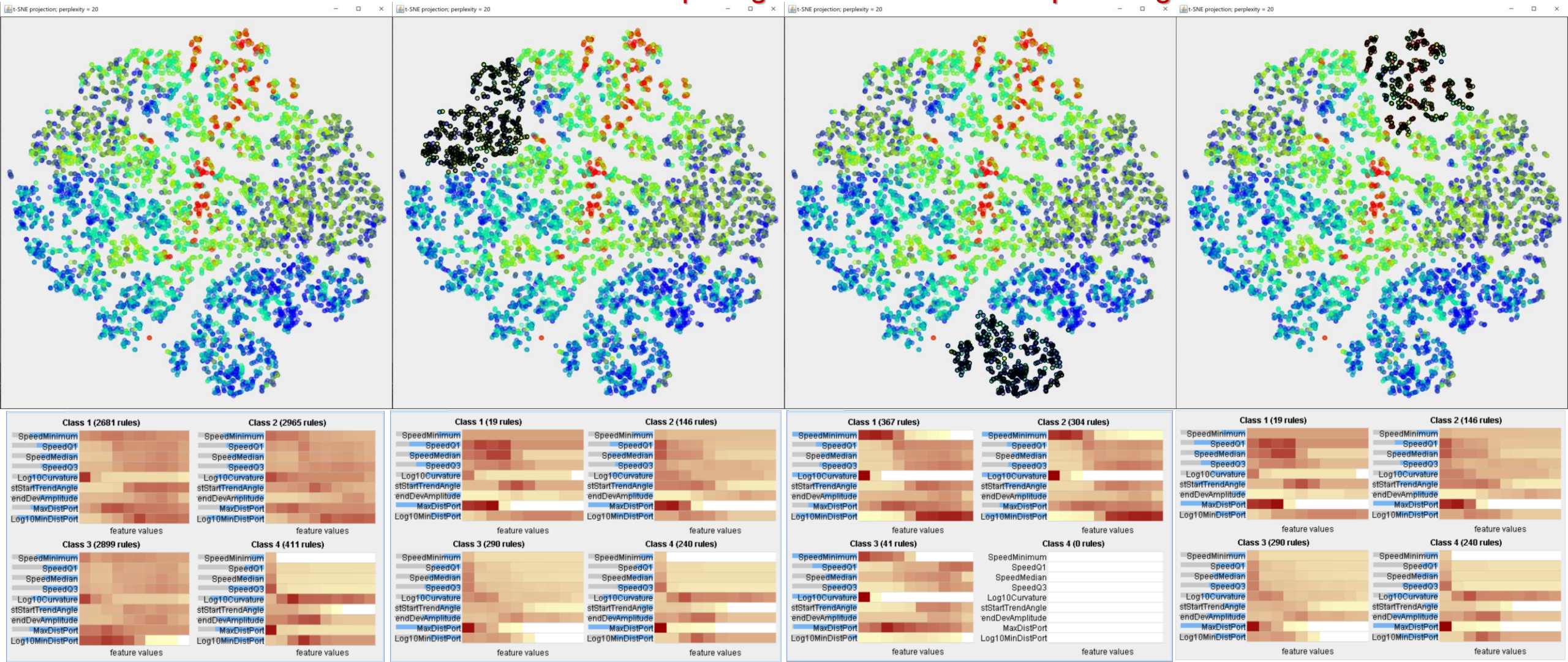
- 2 rules for class 1 (forward movement) ignoring speed distribution and allowing negative distance trend
- 7 rules for class 2 (trawling) that allow high values of *SpeedMinimum*
- 144 rules for class 3 (port entering or exiting) ignoring both *MaxDistPort* and *Log10MinDistPort*
- 353 rules for class 3 (port entering or exiting) not restricting *Log10MinDistPort*
- 53 rules for class 4 (anchoring) that do not limit *SpeedMinimum*

Result:

- 8,956 rules, no loss of accuracy

2D PROJECTION OF THE RULES BASED ON CONDITIONS SIMILARITY

Exploring subsets of similar rules predicting distinct classes



SUMMARY: INTERACTIVE RULE EXPLORATION

What we saw:

- Filtering and testing rules reveals inconsistencies that can be removed to improve model logic
- Better alignment with domain knowledge can be achieved without hurting accuracy

But ...

- Interpretability gains come at the cost of expert time and effort

Possible future research direction:

- Develop a smart expert UI to:
 - Define domain constraints
 - Automatically flag rule violations
 - Support semi-automated model refinement

TOPIC MODELLING TO REVEAL FEATURE INTERACTIONS

Encoding the rules:

Attribute	Min	Max	Count o...	Count o...	Mode	Number o...	Class Intervals
SpeedMinimum	0.005	15.395	586	7049	Quantiles	3	[2.0549998, 6.7825003]
SpeedQ1	0.015	17.775	594	5906	Quantiles	3	[5.255, 13.21]
SpeedMedian	0.035	18.51	636	5619	Quantiles	3	[7.9925003, 14.327499]
SpeedQ3	0.05	19.785	586	5712	Quantiles	3	[11.24, 15.03]
Log10Curvature	0.002	1.178	320	7551	Quantiles	3	[0.08400001, 0.212]
DistStartTrendAngle	-0.085	0.325	80	6780	Quantiles	3	[0.075, 0.19749999]
Log10DistStartTrendDevAmplitude	-2.545	1.645	411	5705	Quantiles	3	[0.125, 0.78499997]
MaxDistPort	0.165	82.97	809	8150	Quantiles	3	[15.842501, 24.9225]
Log10MinDistPort	-1.845	1.815	590	10193	Quantiles	3	[-0.5675, 0.1425]

ruleAsText

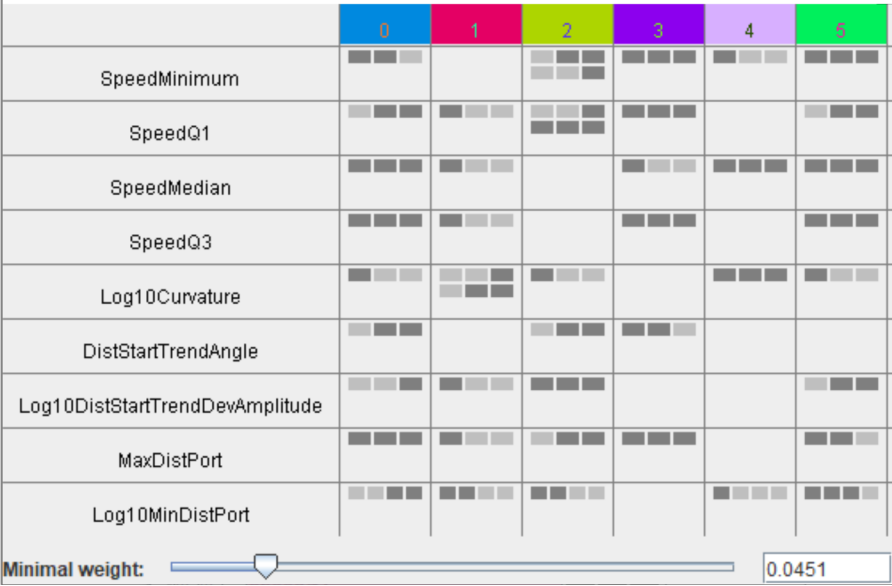
conditionsAsMasks

SpeedMedian:[7.184999942779541..Inf] Log10Curvature:[-Inf..0.04300001263618469] DistStartTrendAngle:[SpeedMedian__111 Log10Curvature__100 DistStartTrendAngle__011 Log10MinDistPort__1000
SpeedMedian:[7.184999942779541..Inf] Log10Curvature:[-Inf..0.014999997802078724] Log10MinDistPort:[SpeedMedian__111 Log10Curvature__100 Log10MinDistPort__0001
Log10Curvature:[1.003999948501587..Inf] => 4
Log10Curvature:[-Inf..0.24549999833106995] MaxDistPort:[-Inf..0.5699994564056396] Log10MinDistPort:[-Inf..0.5699994564056396] Log10Curvature__111 MaxDistPort__100 Log10MinDistPort__0111
Log10Curvature:[0.24549999833106995..Inf] Log10DistStartTrendDevAmplitude:[-2.5450000762939453..Inf] Log10Curvature__001 Log10DistStartTrendDevAmplitude__111 MaxDistPort__100 Log10MinDistPort__1100
Log10Curvature:[-Inf..0.25] MaxDistPort:[-Inf..0.3000001907348633] => 4
Log10DistStartTrendDevAmplitude:[-Inf..0.7750000357627869] MaxDistPort:[-Inf..0.170000359416008] => 3
SpeedMinimum:[-Inf..0.2800000309944153] SpeedQ1:[5.90500020980835..Inf] Log10Curvature:[-Inf..0.0019999996602535248..Inf] DistStartTrendAngle:[0.10499999672174454..Inf] MaxDistPort
Log10Curvature:[0.0019999996602535248..Inf] DistStartTrendAngle:[0.10499999672174454..Inf] MaxDistPort
SpeedQ1:[5.90500020980835..Inf] Log10Curvature:[0.010500003583729267..Inf] DistStartTrendAngle:[0.15199999999999999..Inf] SpeedQ1__011 Log10Curvature__111 DistStartTrendAngle__011 Log10DistStartTrendDevAmplitude__001 MaxDistPort__01:
SpeedMedian:[-Inf..0.07500005513429642] Log10Curvature:[-Inf..0.24549999833106995] DistStartTrendAngle:[-Inf..0.07500005513429642] SpeedMedian__100 Log10Curvature__111 DistStartTrendAngle__110 MaxDistPort__100
SpeedQ3:[-Inf..0.6550000905990601] Log10Curvature:[-Inf..0.17299999296665192] DistStartTrendAngle:[-Inf..0.17299999296665192] SpeedQ3__100 Log10Curvature__110 DistStartTrendAngle__111
SpeedQ3:[-Inf..0.6550000905990601] Log10Curvature:[0.17299999296665192..Inf] Log10MinDistPort:[-Inf..0.17299999296665192] SpeedQ3__100 Log10Curvature__011 Log10MinDistPort__1000
SpeedQ3:[-Inf..0.6550000905990601] Log10Curvature:[0.17299999296665192..Inf] Log10MinDistPort:[-1.6119999999999999..Inf] SpeedQ3__100 Log10Curvature__011 Log10MinDistPort__1000
SpeedMinimum:[3.190000057220459..Inf] SpeedQ1:[15.854999542236328..Inf] SpeedQ3:[18.399999618533333..Inf] SpeedMinimum__011 SpeedQ1__001 SpeedQ3__001 Log10Curvature__110 Log10MinDistPort__1100
SpeedMinimum:[3.190000057220459..Inf] SpeedQ3:[14.1899995803833..Inf] Log10Curvature:[0.06800000033333333..Inf] SpeedMinimum__011 SpeedQ3__011 Log10Curvature__111 Log10MinDistPort__0011
SpeedMinimum:[-Inf..9.529999732971191] DistStartTrendAngle:[-Inf..0.044999998062849045] MaxDistPort:[SpeedMinimum__111 DistStartTrendAngle__100 MaxDistPort__111 Log10MinDistPort__0011
SpeedMedian:[0.08499997109174728..Inf] SpeedQ3:[-Inf..2.0949997901916504] Log10Curvature:[0.25699999999999999..Inf] SpeedMedian__111 SpeedQ3__100 Log10Curvature__001 MaxDistPort__100
SpeedQ1:[5.755000114440918..Inf] SpeedMedian:[-Inf..6.994999885559082] Log10MinDistPort:[1.0449999999999999..Inf] SpeedQ1__011 SpeedMedian__100 Log10MinDistPort__0001
SpeedMinimum:[0.6450000405311584..Inf] Log10Curvature:[0.027000000700354576..Inf] DistStartTrendAngle:[-Inf..0.027000000700354576] SpeedMinimum__111 Log10Curvature__111 DistStartTrendAngle__011 Log10MinDistPort__0111
MaxDistPort:[-Inf..0.46999967098236084] Log10MinDistPort:[-Inf..0.8700000047683716] => 3
SpeedQ1:[-Inf..0.07499993592500687] Log10Curvature:[-Inf..0.17299999296665192] MaxDistPort:[-Inf..0.46999967098236084] SpeedQ1__100 Log10Curvature__110 MaxDistPort__100
SpeedQ1:[5.90500020980835..Inf] Log10Curvature:[0.17000000178813934..Inf] MaxDistPort:[0.46999967098236084..Inf] SpeedQ1__011 Log10Curvature__011 MaxDistPort__111 Log10MinDistPort__1000
Log10Curvature:[0.09150000661611557..Inf] DistStartTrendAngle:[0.10499999672174454..Inf] MaxDistPort:[Log10Curvature__011 DistStartTrendAngle__011 MaxDistPort__111 Log10MinDistPort__0111
MaxDistPort:[-Inf..0.1650005728006363] => 3
SpeedQ3:[-Inf..0.5400001406669617] Log10Curvature:[-Inf..0.24549999833106995] DistStartTrendAngle:[0.15199999999999999..Inf] SpeedQ3__100 Log10Curvature__111 DistStartTrendAngle__111

TOPICS

Term-prefix ▲	Term-suffix	topic=0: Topic...	topic=1: Topic...	topic=2: Topic...	topic=3: Topic...	topic=4: Topi...	topic=5: Topi...
DistStartTrendAngle							
DistStartTrendAngle							
Log10Curvature							
Log10Curvature							
Log10Curvature							
Log10Curvature							
Log10DistStartTrendDevAmplitude							
Log10DistStartTrendDevAmplitude							
Log10DistStartTrendDevAmplitude							
Log10DistStartTrendDevAmplitude							
Log10MinDistPort							
Log10MinDistPort							
Log10MinDistPort							
Log10MinDistPort							
MaxDistPort							
MaxDistPort							
MaxDistPort							
MaxDistPort							
SpeedMedian							
SpeedMedian							
SpeedMinimum							
SpeedMinimum							
SpeedMinimum							
SpeedMinimum							
SpeedMinimum							
SpeedQ1							
SpeedQ1							
SpeedQ1							
SpeedQ1							
SpeedQ3							
SpeedQ3							

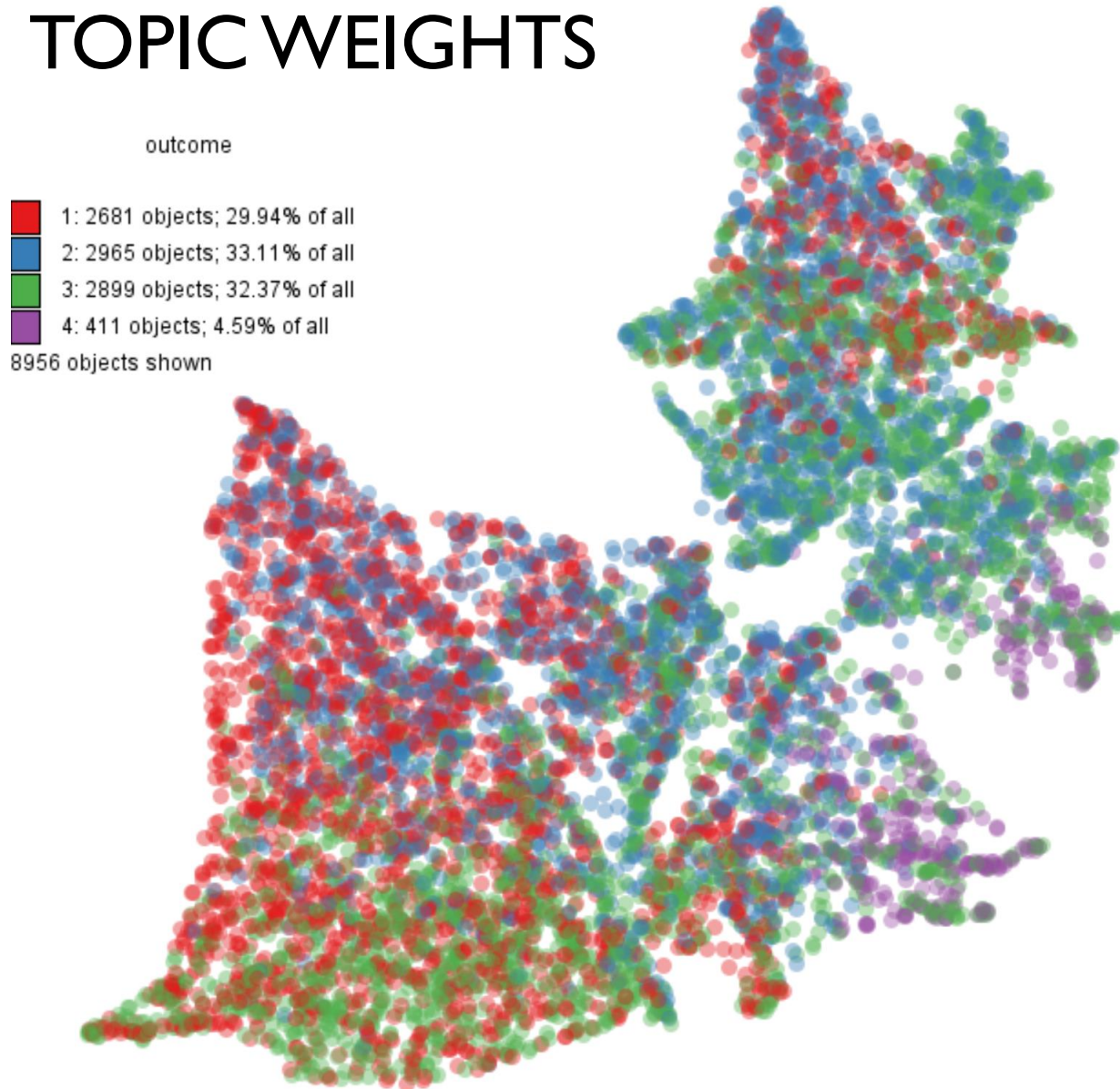
Most significant “terms” defining the topics:



Topics represent re-occurring combinations of similar conditions

Topics defined as vectors of weights of the “terms”, i.e., encoded conditions

APPLYING DIMENSIONALITY REDUCTION TO VECTORS OF TOPIC WEIGHTS



- Each rule receives a multidimensional vector of topic weights.
- We apply dimensionality reduction (e.g., UMAP) to obtain a 2D projection.
- Each rule is represented by a point in the projection space.
- We represent the rule outcomes (predicted classes) by colours of dot marks.
- We see that the classes are not separated by the topic weights.

☒ Representation method:
Pies

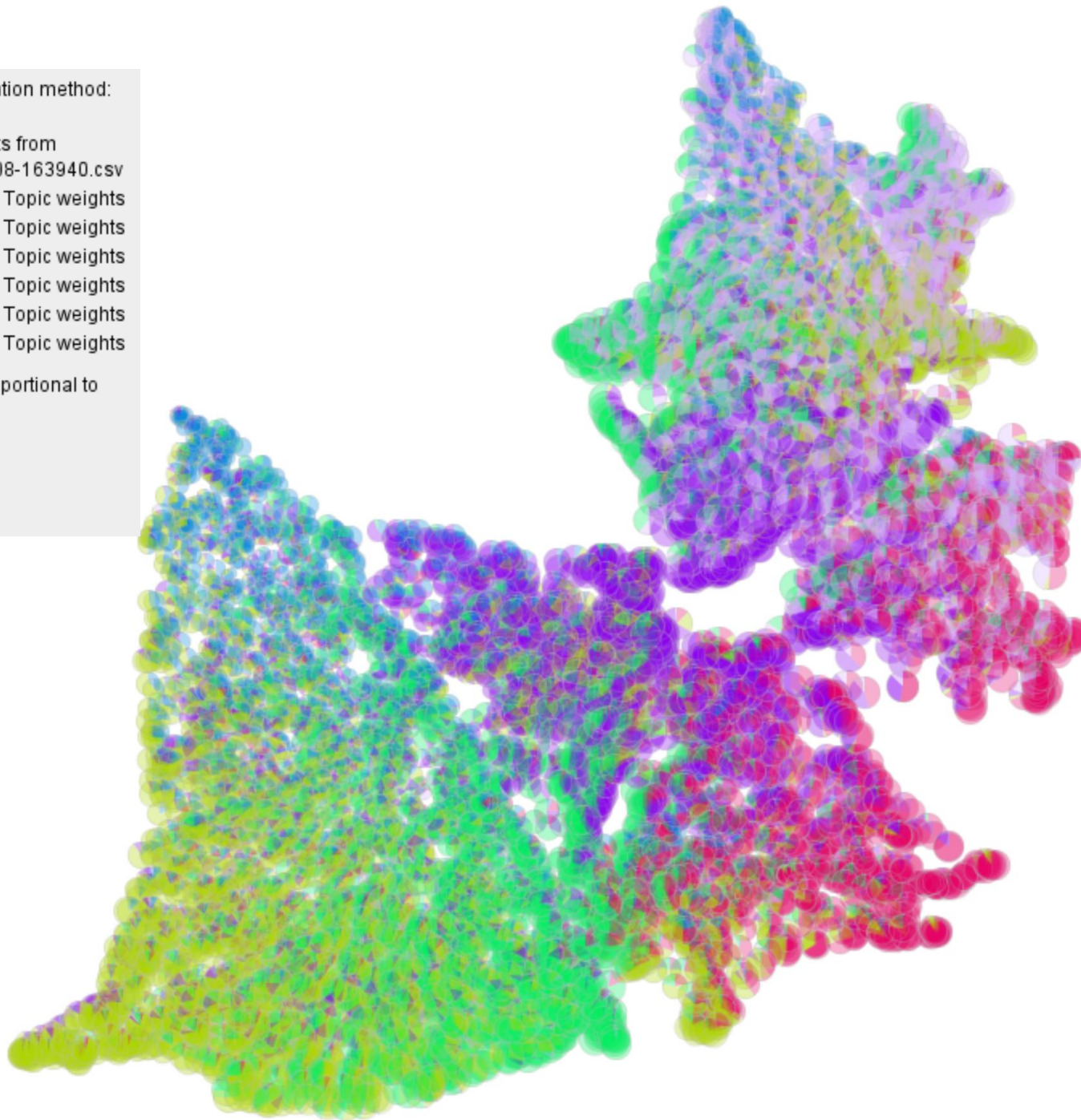
Points from
TM_20250508-163940.csv

- topic=0: Topic weights
- topic=1: Topic weights
- topic=2: Topic weights
- topic=3: Topic weights
- topic=4: Topic weights
- topic=5: Topic weights

Pie area is proportional to sum:

- 0.0282
- 0.3228

8956 objects

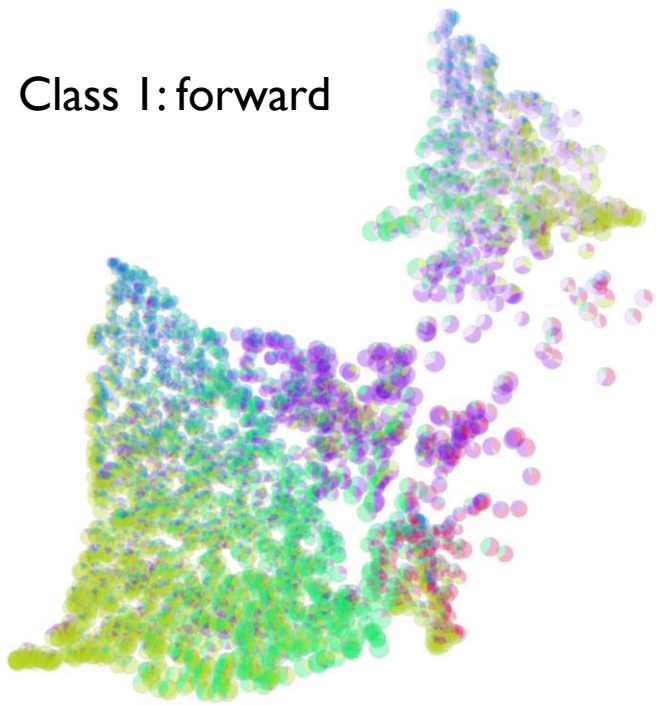


- Pie charts represent compositions of topics characterizing the rules.
- In the projection map we see areas (= groups of rules) dominated by specific topics.

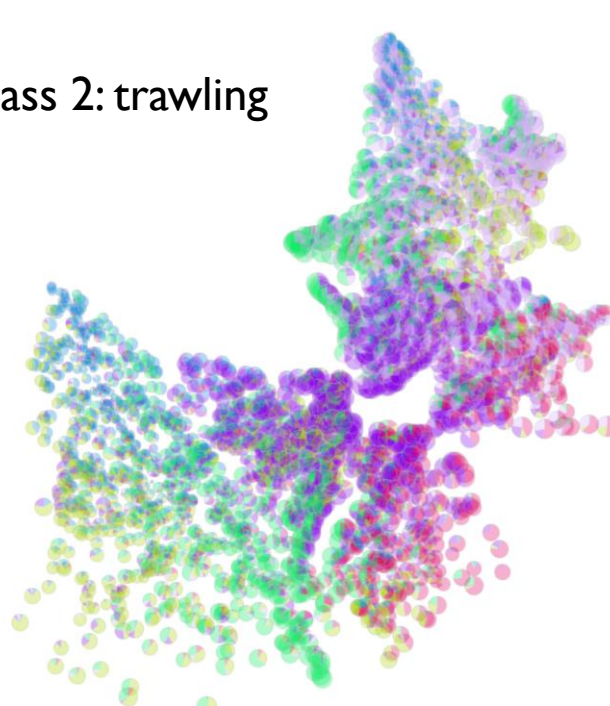
	0	1	2	3	4	5
SpeedMinimum	■■■■		■■■■	■■■■	■■■■	■■■■
SpeedQ1	■■■■	■■■■	■■■■	■■■■		■■■■
SpeedMedian	■■■■	■■■■		■■■■	■■■■	■■■■
SpeedQ3	■■■■	■■■■		■■■■		■■■■
Log10Curvature	■■■■	■■■■	■■■■		■■■■	■■■■
DistStartTrendAngle	■■■■		■■■■	■■■■		
Log10DistStartTrendDevAmplitude	■■■■		■■■■			■■■■
MaxDistPort	■■■■	■■■■	■■■■	■■■■		■■■■
Log10MinDistPort	■■■■	■■■■	■■■■		■■■■	■■■■

Minimal weight:

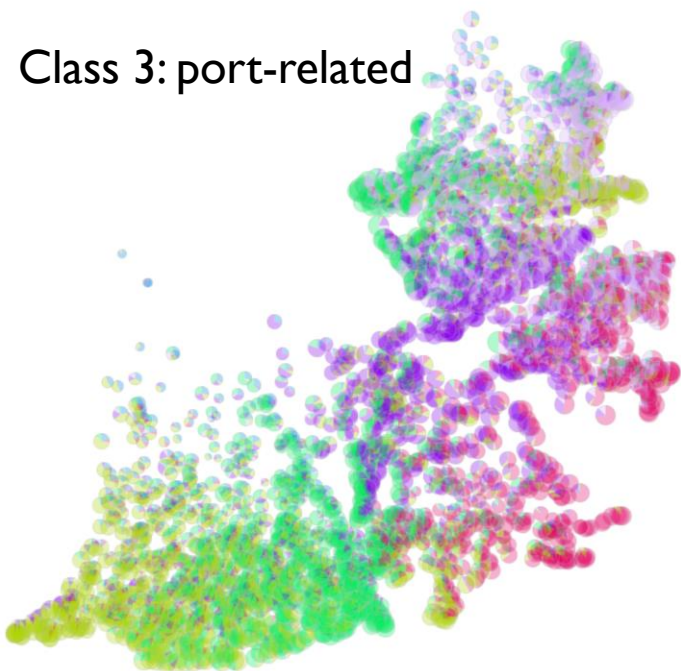
Class 1: forward



Class 2: trawling



Class 3: port-related



Class 4: anchoring



Topic association tendencies:

- Topic 0: forward movement and trawling
- Topic 1: high association with anchoring, weak association with trawling and port-related
- Topic 2: forward movement and port-related
- Topic 3: medium association with trawling but also co-occurs with the other classes
- Topic 4: medium association with trawling but co-occurs with the others
- Topic 5: medium association with port-related and forward movement, less with trawling

	0	1	2	3	4	5
SpeedMinimum	■ ■ ■		■ ■ ■	■ ■ ■	■ ■ ■	■ ■ ■
SpeedQ1	■ ■ ■	■ ■ ■	■ ■ ■	■ ■ ■		■ ■ ■
SpeedMedian	■ ■ ■	■ ■ ■		■ ■ ■	■ ■ ■	■ ■ ■
SpeedQ3	■ ■ ■	■ ■ ■		■ ■ ■		■ ■ ■
Log10Curvature	■ ■ ■	■ ■ ■	■ ■ ■		■ ■ ■	■ ■ ■
DistStartTrendAngle	■ ■ ■		■ ■ ■	■ ■ ■		
Log10DistStartTrendDevAmplitude	■ ■ ■	■ ■ ■	■ ■ ■			■ ■ ■
MaxDistPort	■ ■ ■	■ ■ ■	■ ■ ■	■ ■ ■		■ ■ ■
Log10MinDistPort	■ ■ ■	■ ■ ■	■ ■ ■		■ ■ ■	■ ■ ■
Minimal weight:	<input type="range"/>					0.0451

SUMMARY: TOPIC MODELING FOR RULE ANALYSIS

- **No simple pattern:** Except for Class 4, classes are not defined by distinct recurring rule conditions
 - Random forests lack interpretable, consistent class definitions
- What Topic Modelling Adds:
 - Reveals feature interdependencies and co-occurring conditions
 - Helps to see key feature interactions in rule subsets
 - Provides a common space for comparing all rules enabling 2D projections, clustering, and identification of subgroups
- **Takeaway:**
 - Topic modelling complements visual filtering and rule inspection
 - Supports higher-level understanding beyond individual rules

CONCLUSIONS: KEY INSIGHTS & CONTRIBUTIONS

- **Focus on logical consistency** of rule-based models with respect to human reasoning and domain knowledge, not just accuracy or performance.
- **Exposing model's internal workings:** synoptic and detailed views for navigating complex rule sets.
- **Feature interdependency analysis:** topic modelling and similarity metrics reveal collective effects.
- **Logic-focused refinement:** tools for detecting and testing rule inconsistencies and model cleaning.
- **Domain knowledge integration:** supporting expert-driven improvements that enhance model transparency and reasoning.
- **Main limitation:** high reliance on expert judgment – manual and time-intensive.
- **Direction for future work:** automation of domain constraint enforcement.

CLOSING REFLECTIONS & OPEN QUESTIONS

- Trustworthiness is not just about accuracy—it's about ***understanding why*** the model makes decisions.
- How can we *incorporate human logic* into the interpretation and explanation of data-driven models?
- Should ML models be adjusted to better *reflect human reasoning*, even if accuracy slightly decreases?
- Can domain knowledge be integrated *during model development*, rather than only in post hoc analysis?
Can *visual analytics* help to achieve this?
- How can we scale interpretability work via *semi-automated expert-guided interfaces*?