Challenges in Explainable Artificial Intelligence for Industry 4.0

Szymon Bobek

AIRA seminar
13 January 2022

JAGIELLONIAN UNIVERSITY
IN KRAKÓW

https://geist.re

AGH University of Science and Technology

The presentation covers several different works founded from the PACMEL (NCN 2018/27/Z/ST6/03392) and XPM (NCN UMO-2020/02/Y/ST6/00070) projects funded by the National Science Centre, Poland under CHIST-ERA program .

GEIST (https://geist.re)

Group for Engineering of Intelligent Systems and Technologies

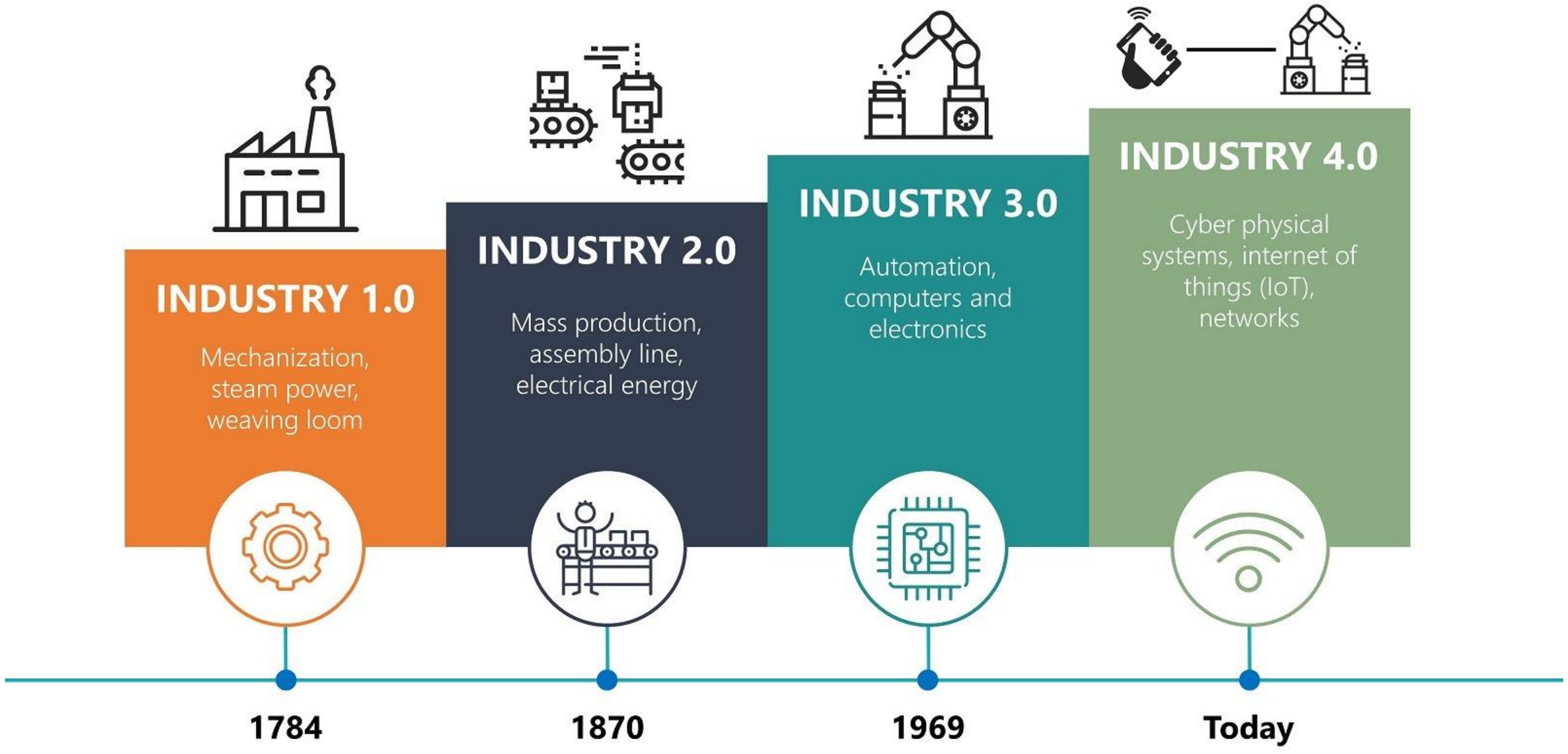
Welcome to GEIST Research Group Webpage!

GEIST is a research group that includes number of senior and postdocoral researchers as well as PhD and master students. The work of the group is coordinated by Grzegorz J. Nalepa. GEIST researchers mostly work at the Jagiellonian University (UJ.edu.pl) as well as the AGH University of Science and Technology (AGH.edu.pl) in Kraków, Poland.

The group is active in the general area of intelligent systems. We work in Explainable AI (XAI), Knowledge and Software Engineering (KE/SE), Business Intelligence (BI), Ambient Intelligence (AmI), and Affective Computing (AfC), (see the group's **research profile**).

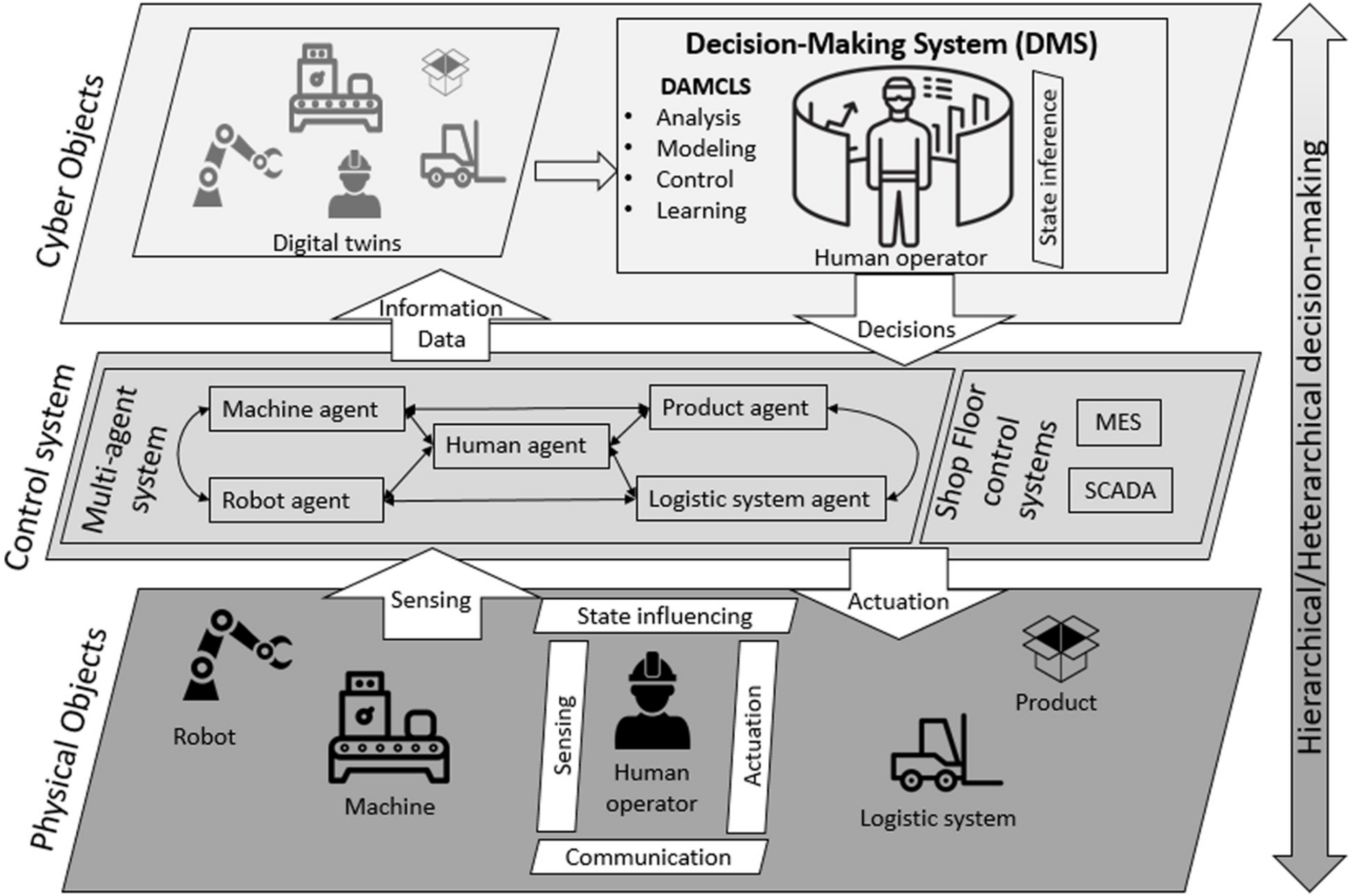
GEIST has been involved in number of projects. For more information see **recent activity**, **publications** and **software**.

Industry 4.0



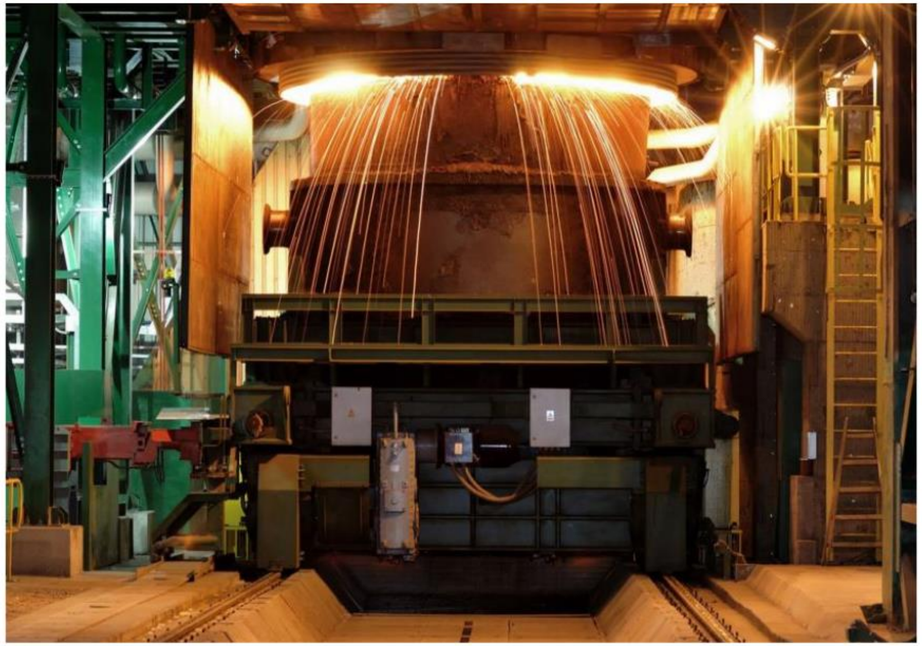
Source: https://www.presentationpoint.com/blog/data-signals-triggers-industry-4-0/ (Accessed 12.01.2021)

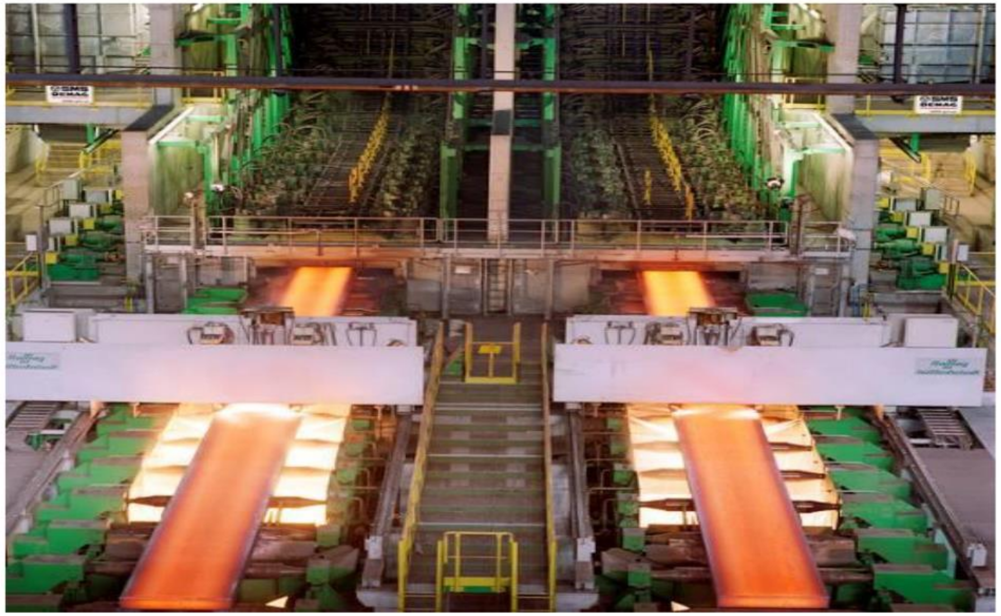
Let us have an Industry 4.0 factory!



Source: Cimini, C.; Pirola, F.; Pinto, R.; Cavalieri, S. A human-in-the-loop manufacturing control architecture for the next generation of production systems. Journal of Manufacturing Systems 2020, 54, 258–271. doi:https://doi.org/10.1016/j.jmsy.2020.01.002.


Source: Presentation @ DSAA2021

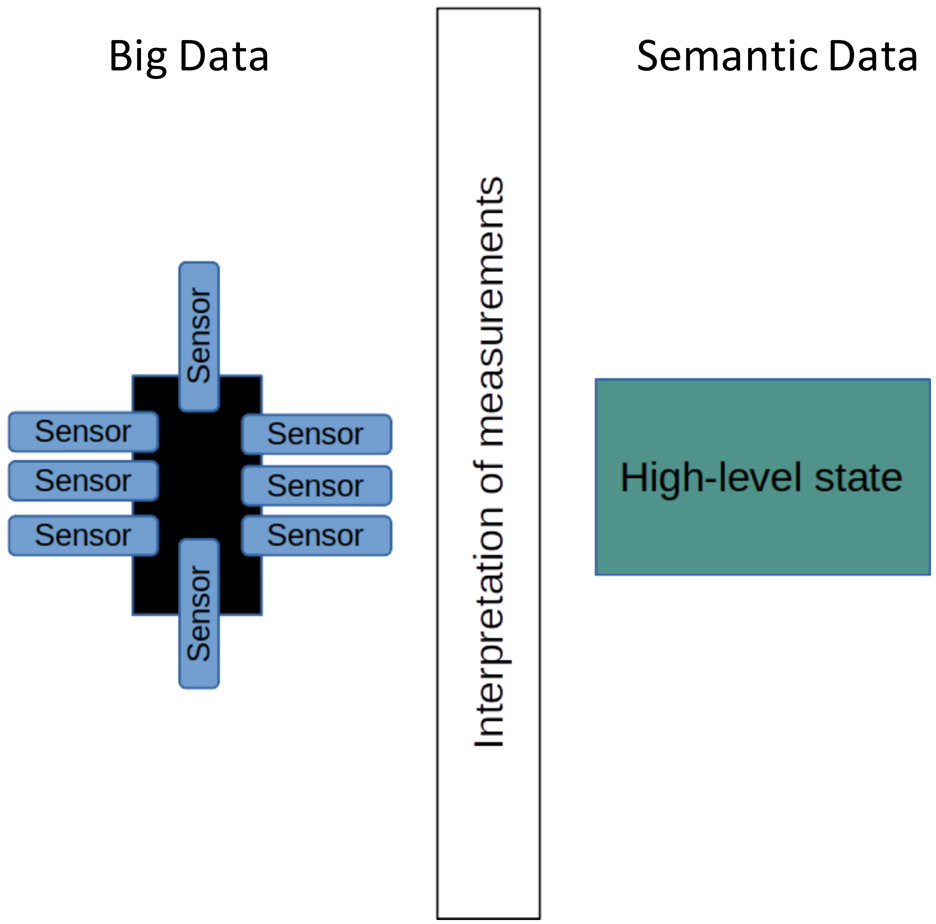





Source: https://www.mdpi.com/1996-1073/13/24/6630/htm

Knowledge discovery from industrial logs

- PACMEL Project (http://pacmel.geist.re)
- Industry 4.0: everything is measured
- Low-level measurements to higher-level states
- Expert-defined states vs. Automatically discovered states
  - Data comes with no labels
  - Expert may be to general, or too specific
  - There is a lot of measurements



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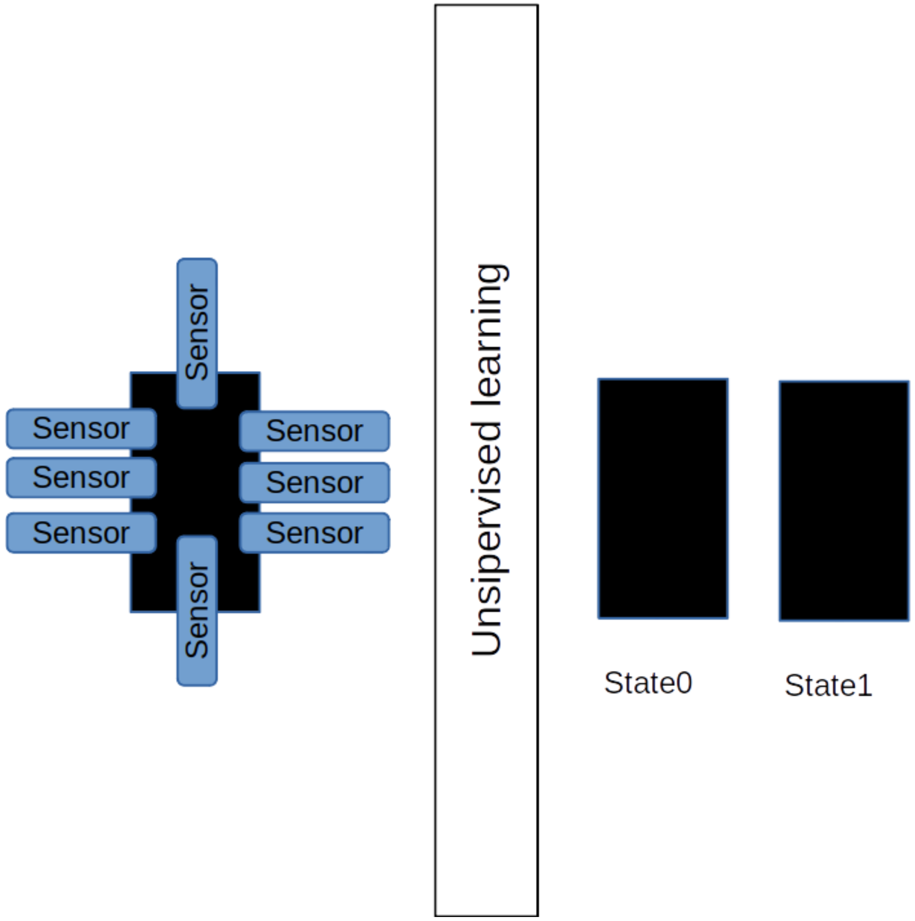

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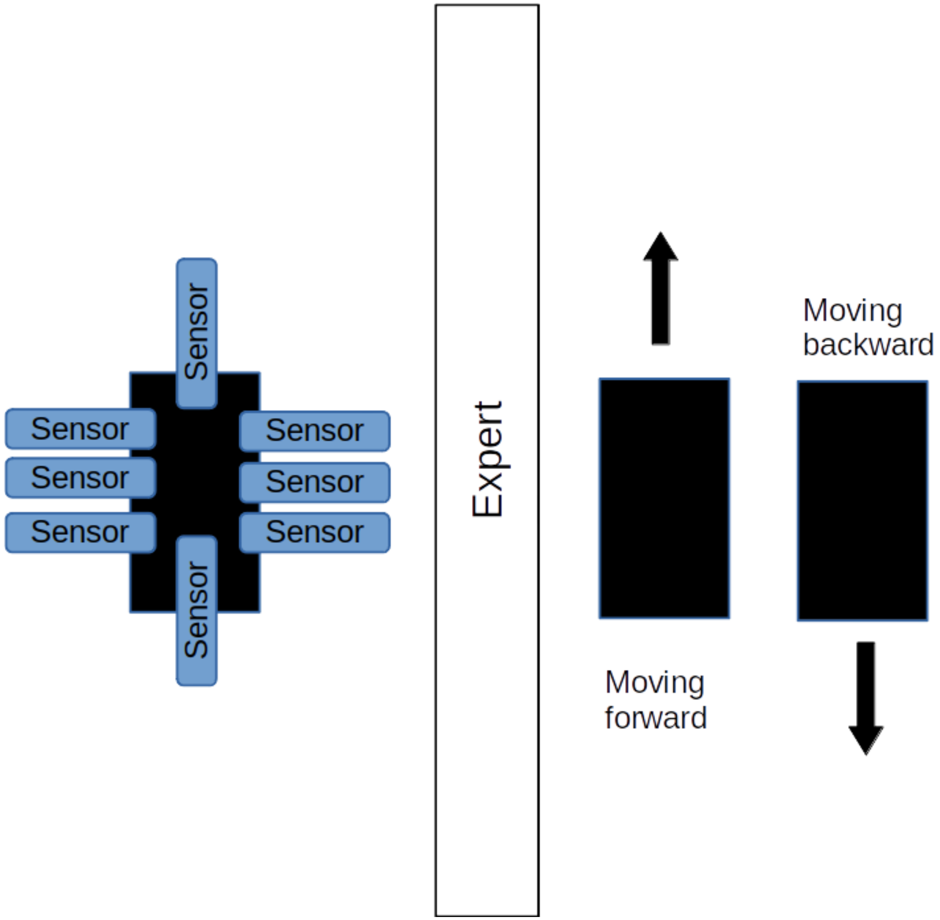

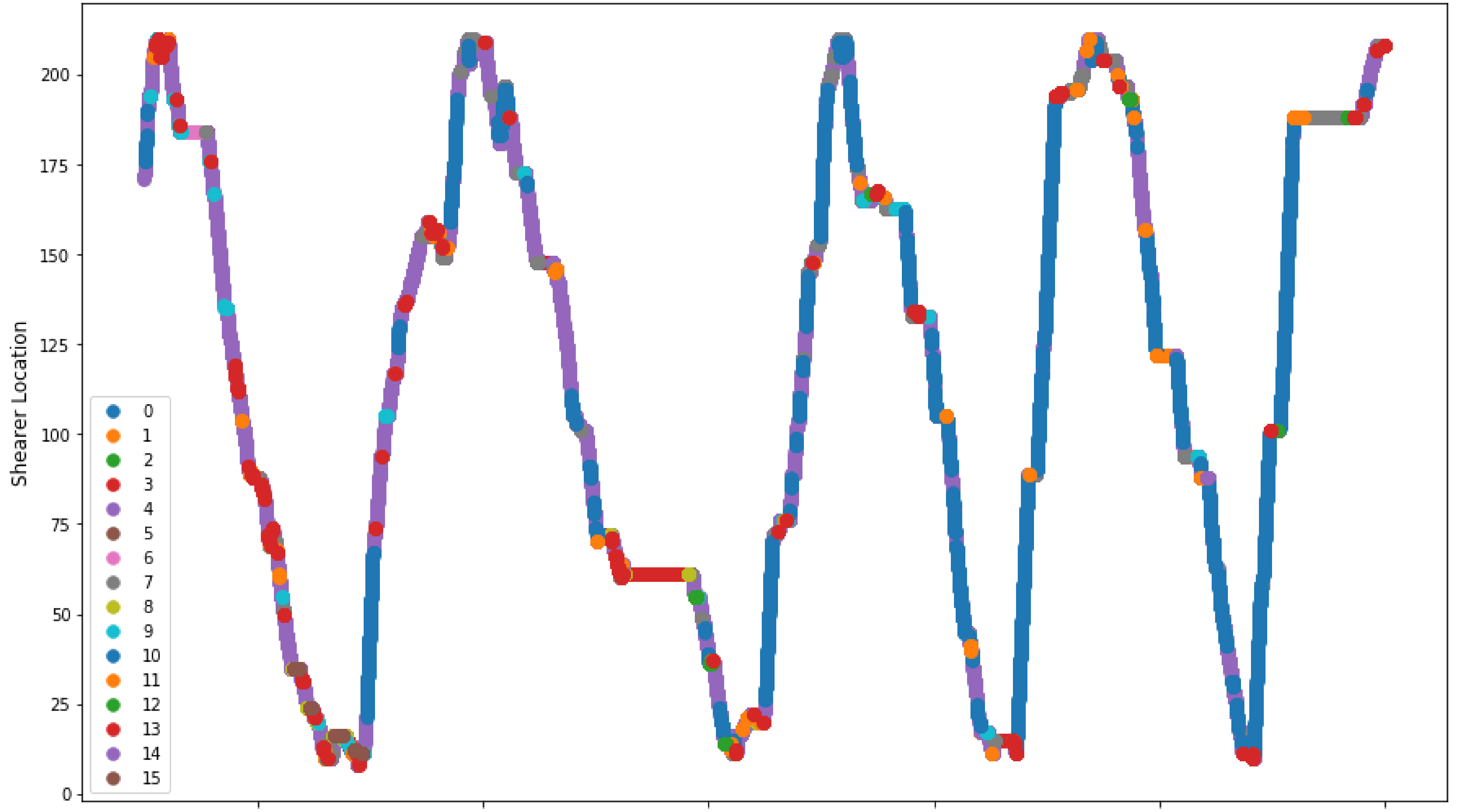

Shearer Location
0
25
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75
100
125
150
175
200
0
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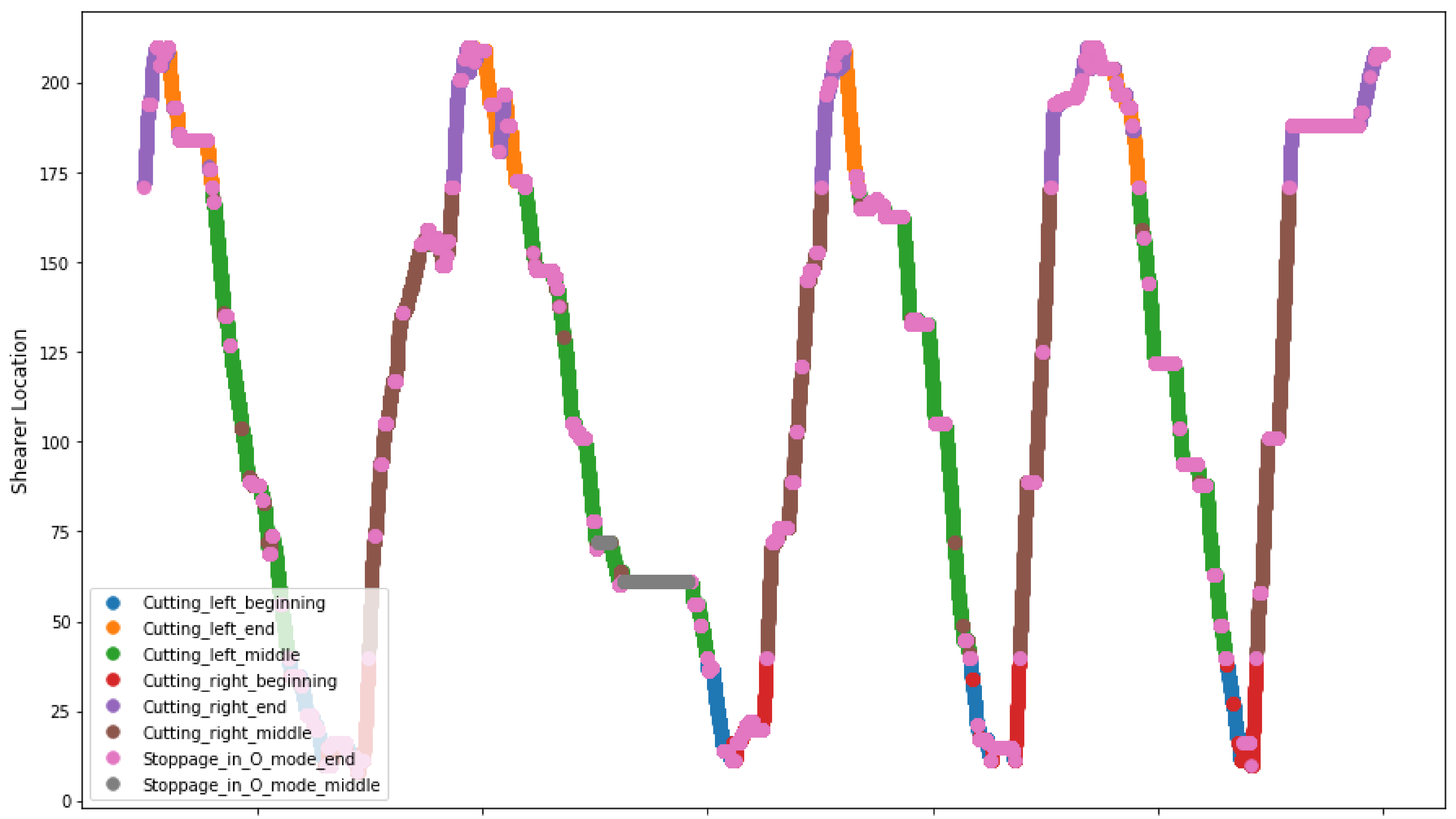
12
13
14
15

Theoretical states are given by the expert

					State	#
= 0	> 0	= 0	= 1	= any	set movingLeft	1
= 0	> 0	= 0	= 0	= any	set movingRight	1
> 0	> 0	= any	= 1	< 40	set cuttingLeftBegining	1
> 0	> 0	= any	= 1	∈ [40 .. 180]	set cuttingLeftMiddle	1
> 0	> 0	= any	= 1	>= 180	set cuttingLeftEnd	1
> 0	> 0	= any	= 0	< 40	set cuttingRightBeginning	1
> 0	> 0	= any	= 0	∈ [40 .. 180]	set cuttingRightMiddle	1
> 0	> 0	= any	= 0	> 180	set cuttingRightEnd	1
= any	= any	= any	≠ any	< 40	set stoppageInOModeBeginn…	1
= any	= any	= any	≠ any	< 180	set stoppageInOModeMiddle	1
= any	= any	= any	≠ any	>= 180	set stoppageInOModeEnd	1

expertLabeling

Add condition | Add decision | Add rule



Shearer Location
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75
100
125
150
175
200
Cutting_left_beginning
Cutting_left_end
Cutting_left_middle
Cutting_right_beginning
Cutting_right_end
Cutting_right_middle
Stoppage_in_O_mode_end
Stoppage_in_O_mode_middle

Knowledge discovery from industrial logs

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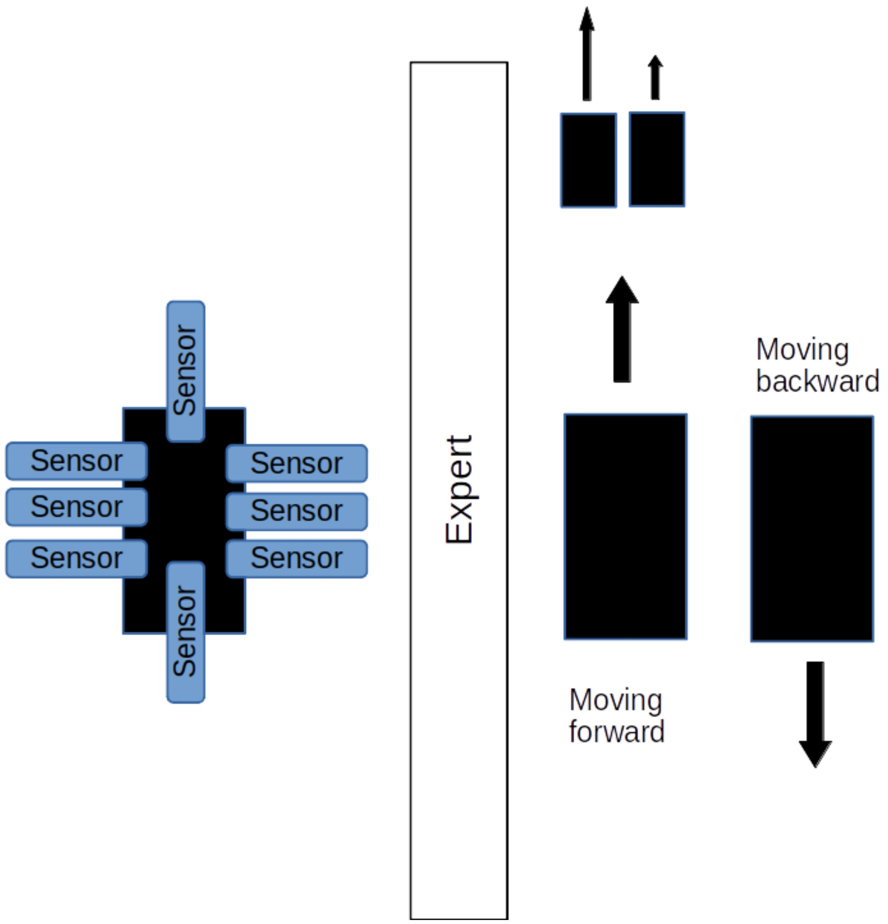

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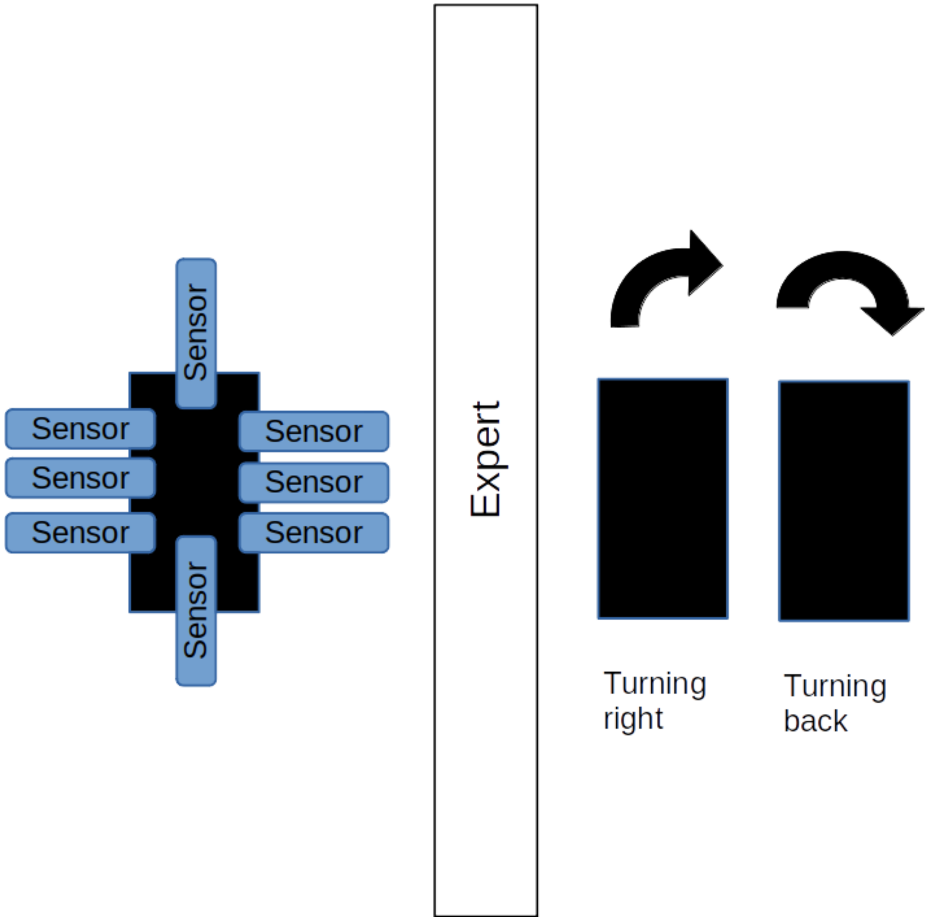

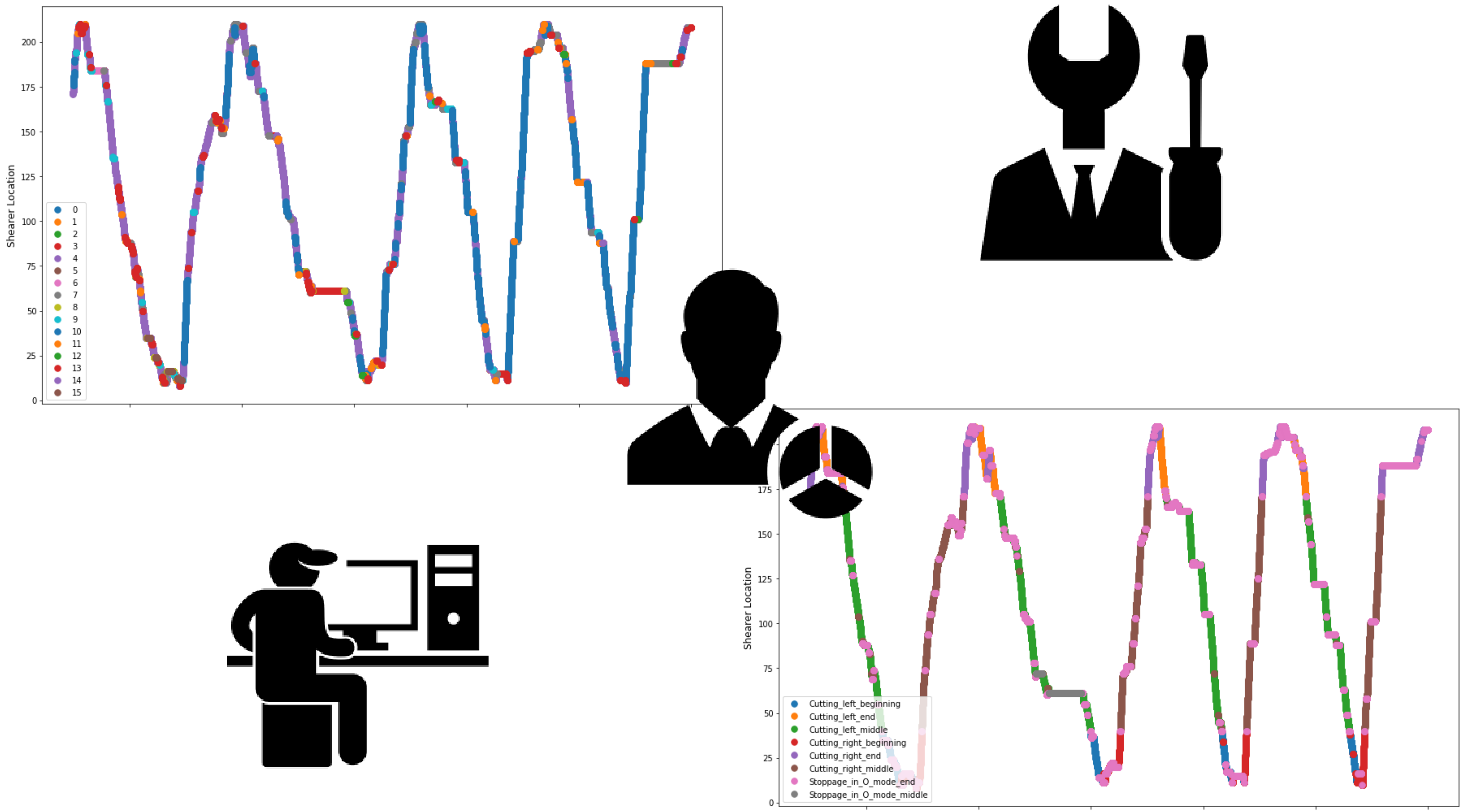

Shearer Location
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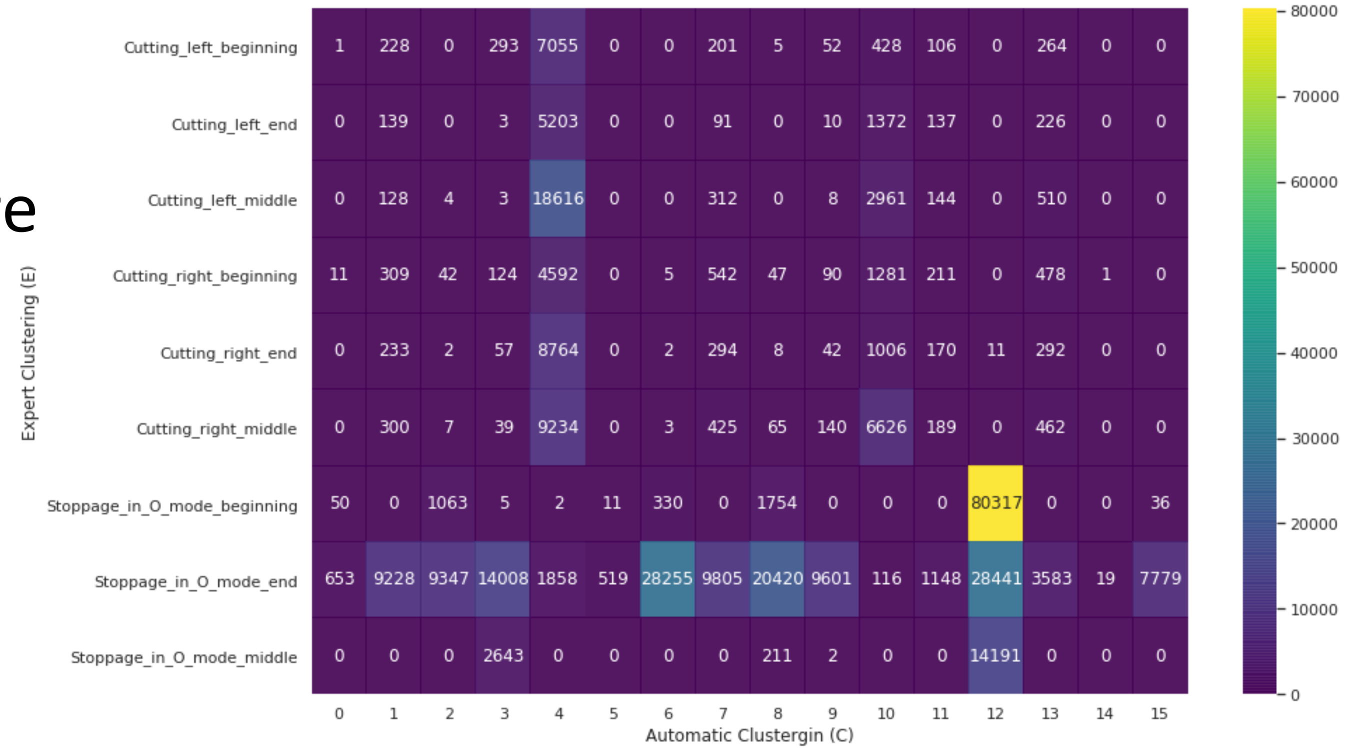
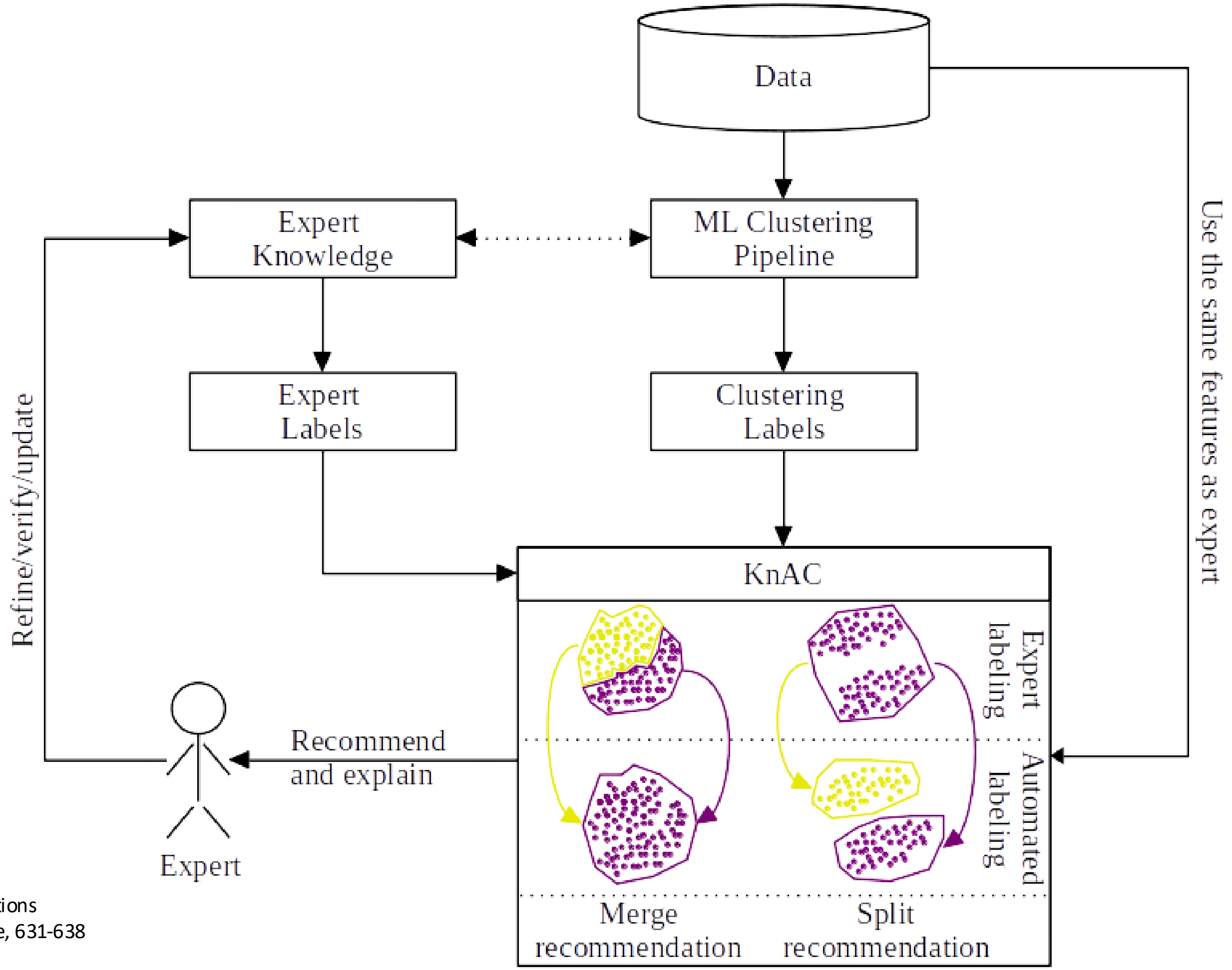
Cutting_right_end
Cutting_right_middle
Stoppage_in_O_mode_end
Stoppage_in_O_mode_middle

How to confront expert and automatic labelling?

- Analysis of each of the states separately via contingency matrix
- Adjusted rand score
- Adjusted mutual info score
- Homogeneity
- Consistency
- V-measure
- …



Knowledge Augmented Clustering (KnAC)



Augmenting Au tomatic Clustering with Expert Knowledge and Explanations
S Bobek, GJ Nalepa, International Conference on Computational Science, 631-638

KnAC: an approach for enhancing cluster analysis with background knowledge and explanations
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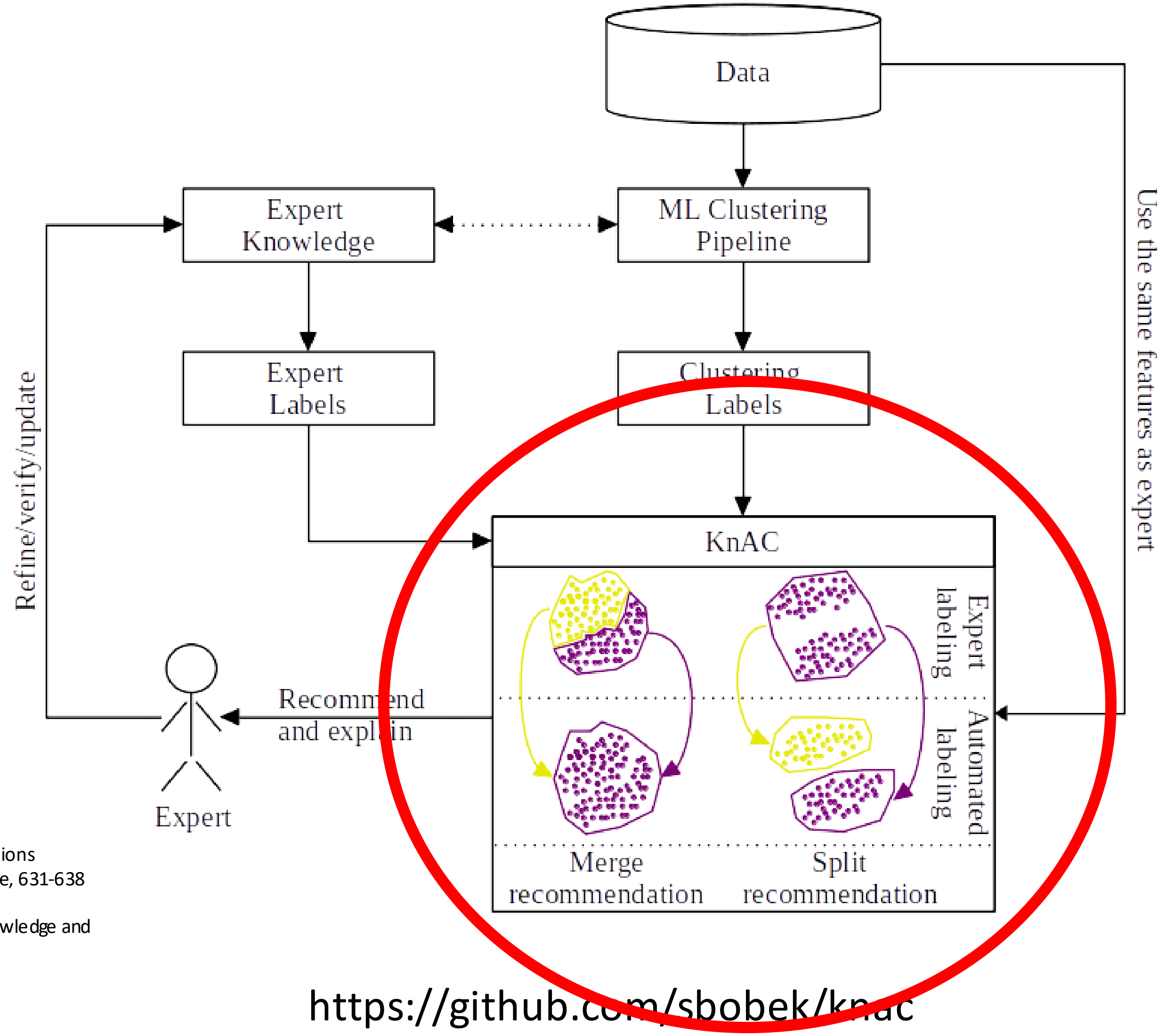

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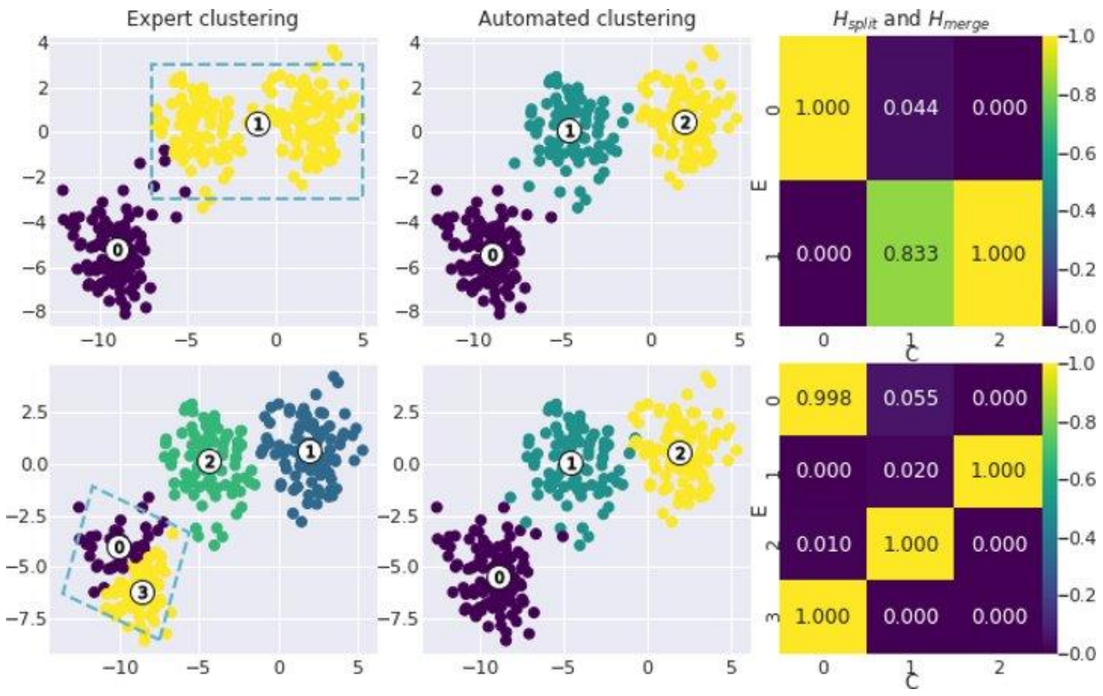
Expert labels vs. Clustering labels



- Split expert clusters into more specific ones
- Merge expert clusters that seem to be simillar
- It is an iterative approach

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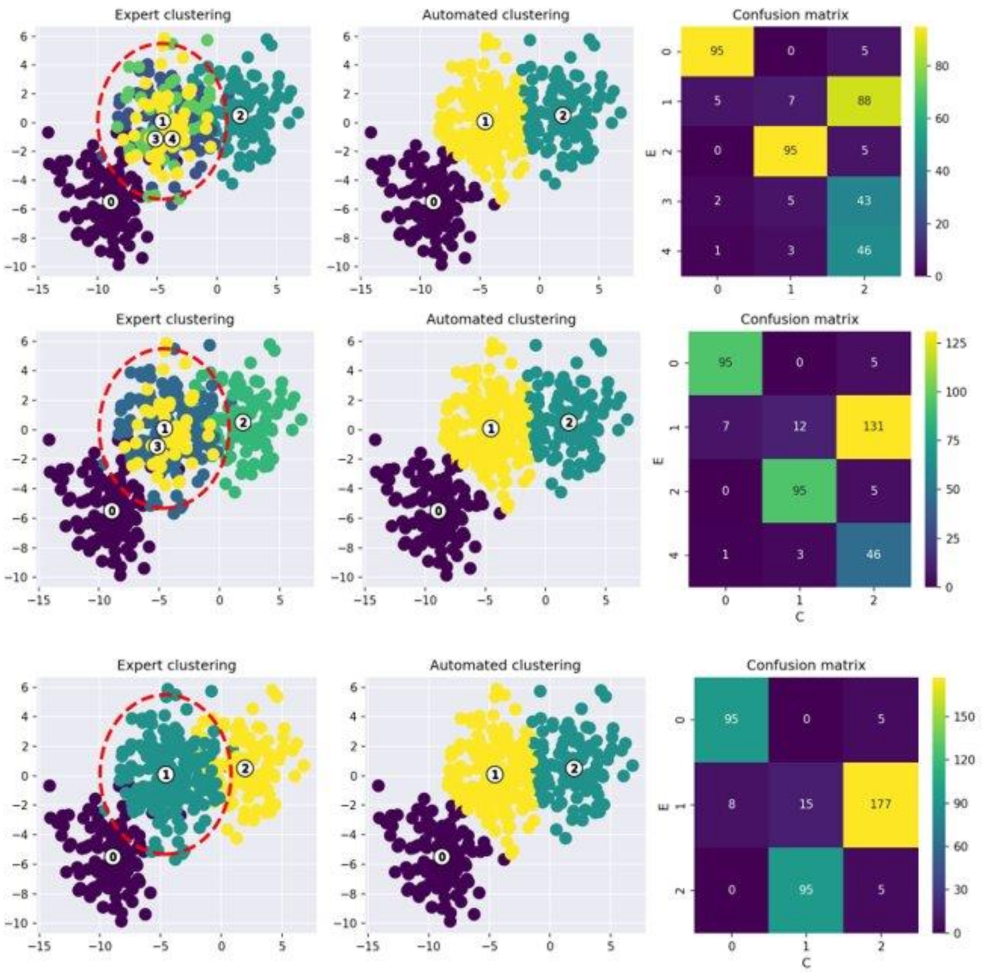

- Split expert clusters into more specific ones
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Splitting expert cluster

- We calculated entropy of each cluster distribution with respect to expert labels
- We scaled rows of distribution matrix to deal with different sized expert clusters
- We divided normalized matrix with entropy values
- The split confidence was calcculated by averaging each row of such matrix

	C1	C2	C3	C4
Expert Cluster 1	400	0	1	..
Expert Cluster 2	1000	1000	1000	..
Expert Cluster 3	200	0	3	..
Expert Cluster 4	600	0	10	..

$$H_{i,j}^{split} = \frac{M_{i,j}}{||M_i||_2 \left[\frac{H(M_i)}{log2(||E||)} + 1\right]}$$

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Expert Cluster 3	0	0	3	..
Expert Cluster 4	0	60	0	60

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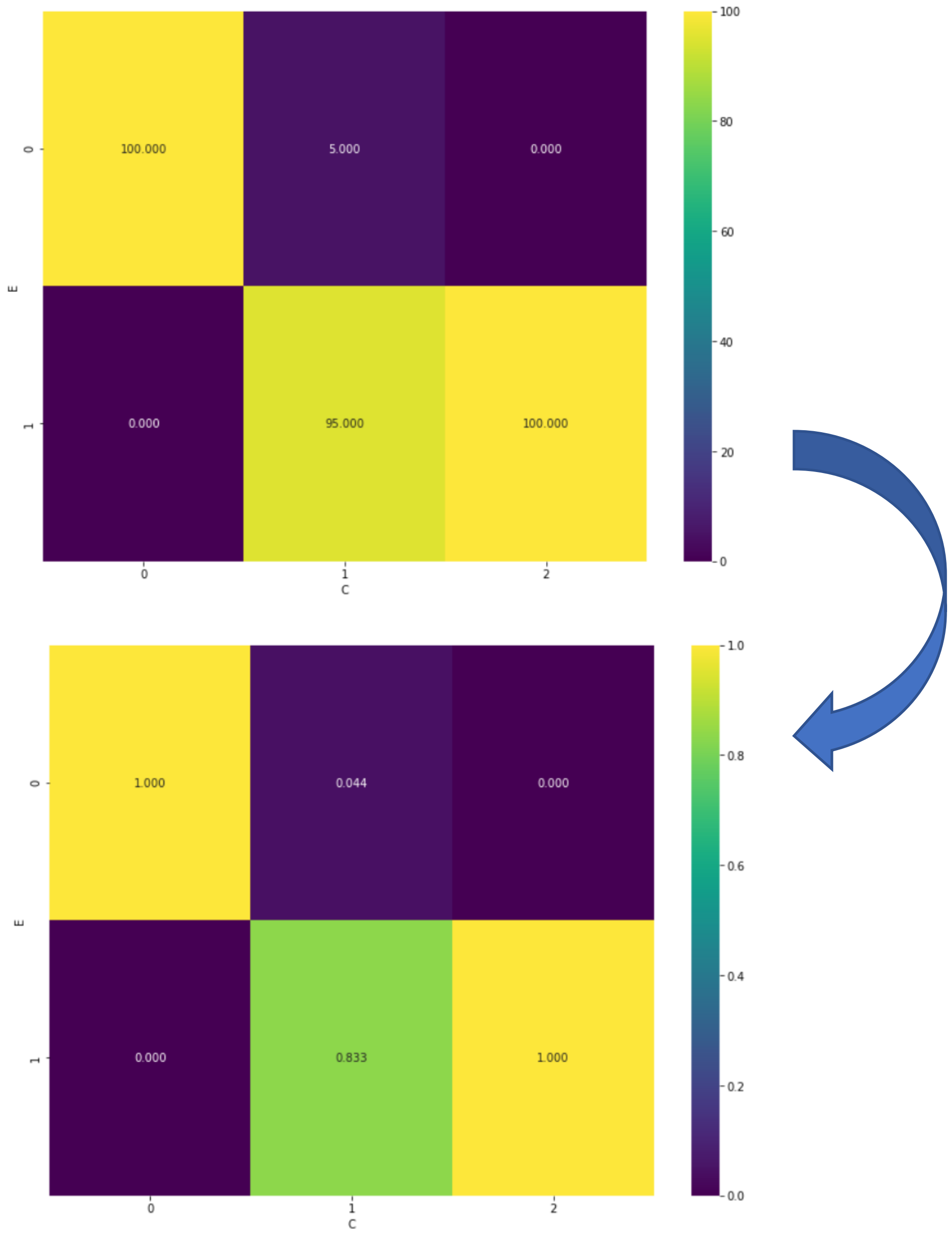

Merging expert cluster

- We calculated *l2* normalized distribution matrix
- We calculated cosine similarity between rows to denote expert clusters that were similarly splitted with automated method

	C1	C2	C3	C4
Expert Cluster 1	400	0	1	..
Expert Cluster 2	1000	0	1000	0
Expert Cluster 3	0	0	3	..
Expert Cluster 4	60	0	60	0

$$H_{i,j}^{merge} = \frac{M_{i,j}}{||M_i||_2}$$

Expert Clusters 2 and 4 are simmilar in their distribution in automated clustering

Merging expert cluster

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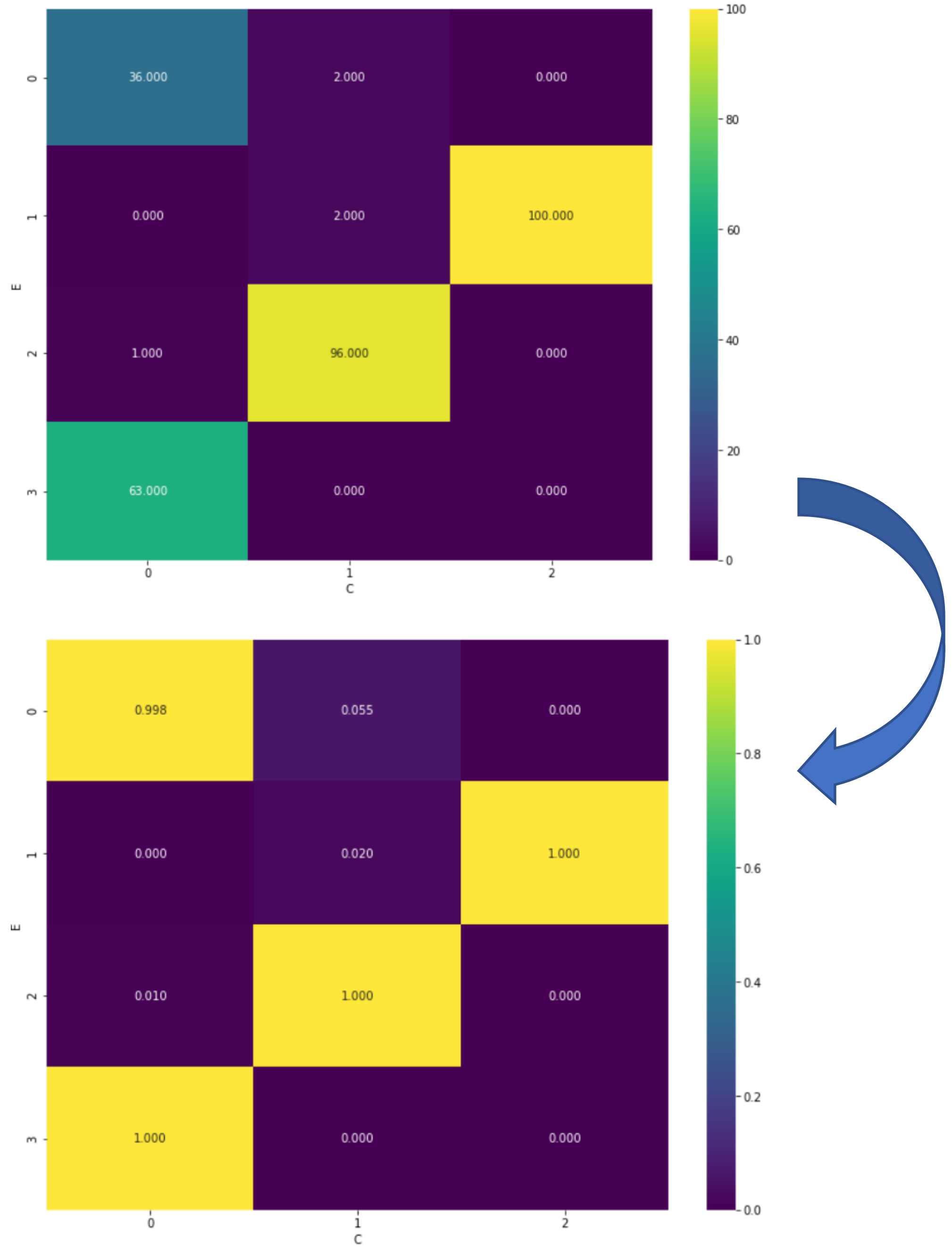
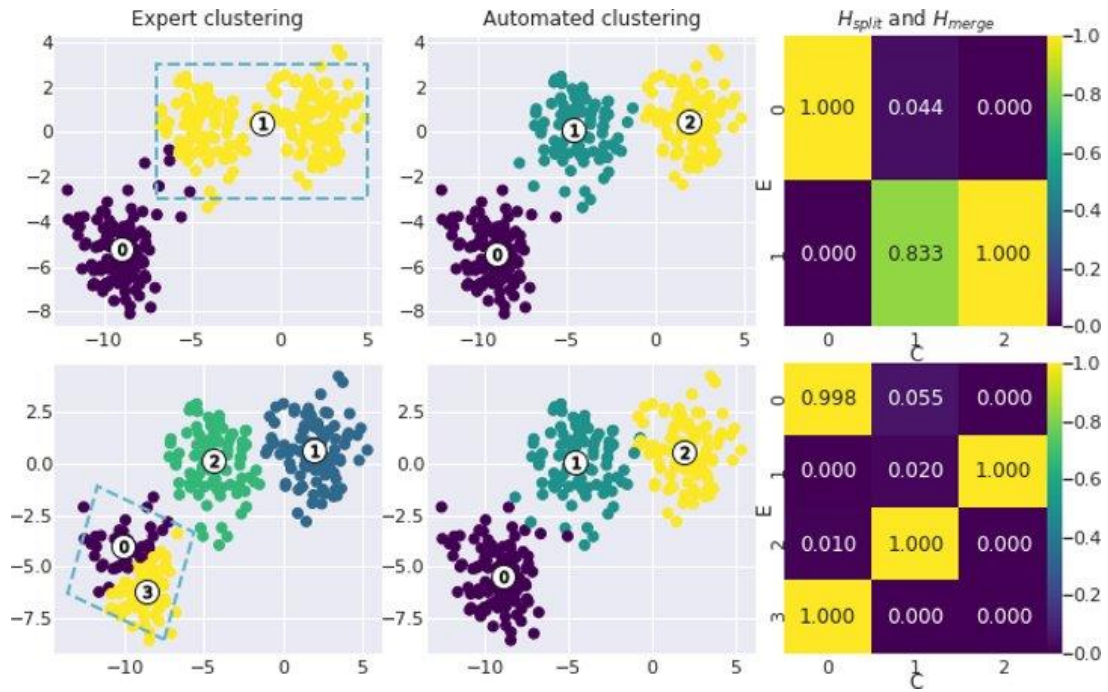
- We calculated cosine similarity between rows to denote expert clusters that were similarly splitted with automated method



Results - splits

$$C_i^{split} = \left\{ c_j \in H_i^{split} : \frac{c_j}{1-\lambda^s} > \varepsilon_s \right\}$$



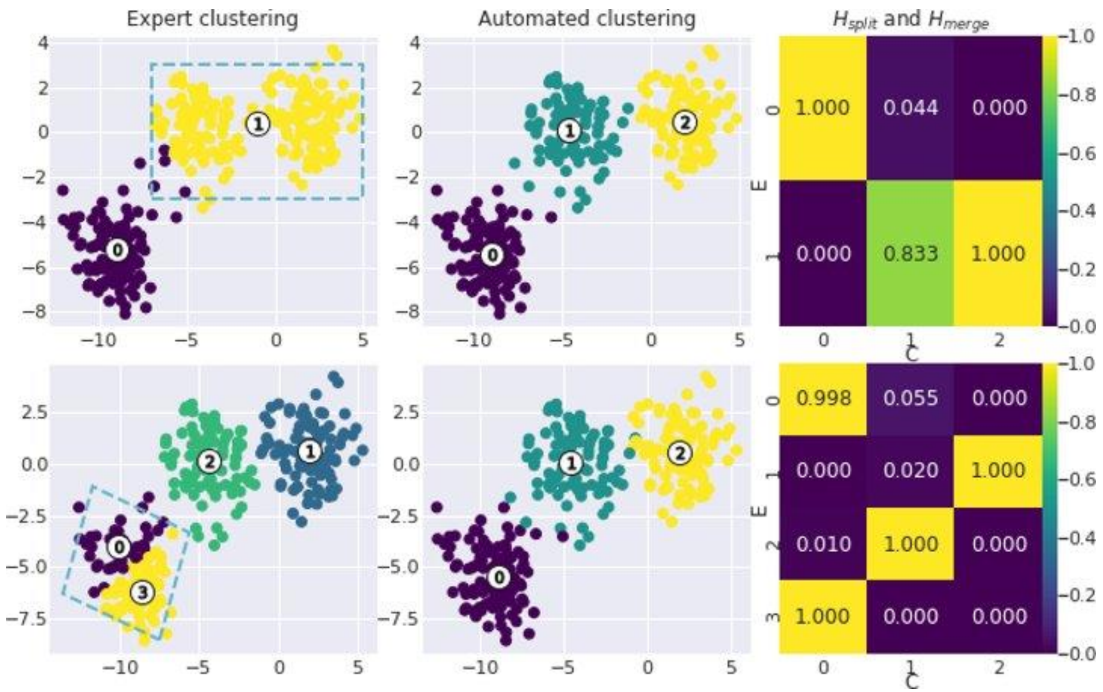
Decrease in silhouette score between splitted clusters

$$Conf(C_i^{split}) = \left\{ (1-\lambda^s)c_j + \lambda^s(S^{dec}(C_i^{split})) : c_j \in C_i^{split} \right\}$$

Assuming $\lambda^s = 0.1$

```
SPLIT EXPERT CLUSTER
  E_1
INTO CLUSTERS
  [(C_1, C_2)]
(Confidence 0.87)
```

Results - merges



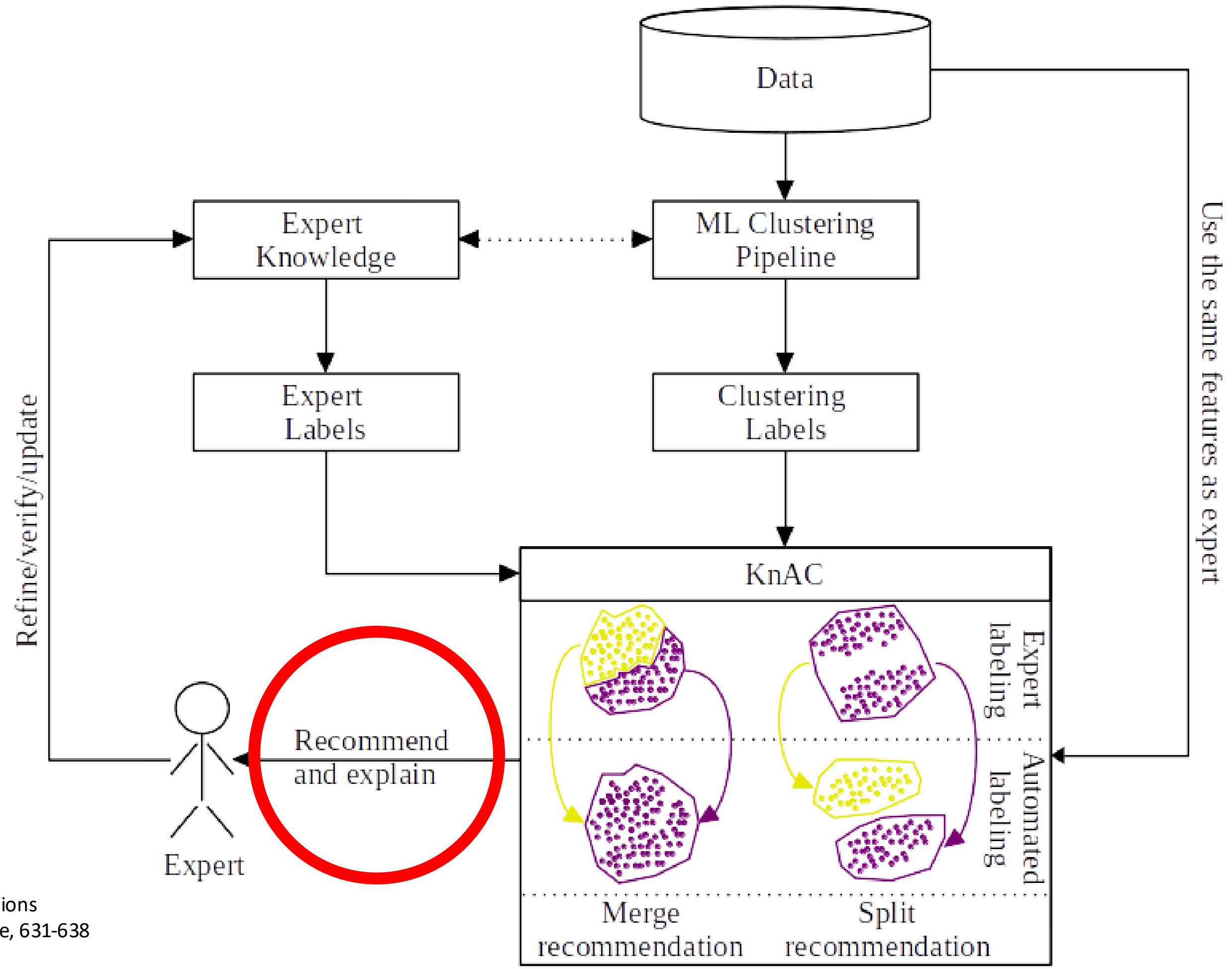
Linkage distance between merged clusters

$$C^{merge}_{j,k} = \left\{ E \ni E_j, E_k : (1-\lambda^m) H^{sim}_{j,k} + \lambda^m (1 - D^{linkage}_{j,k}) > \varepsilon_m \right\}$$

Assuming $\lambda^m = 0.2$

MERGE
EXPERT CLUSTER E_0
WITH
EXPERT CLUSTER E_3
INTO
CLUSTER C_0 # (Confidence 0.98)

Knowledge Augmented Clustering (KnAC)



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eXplainable Artificial Intelligence (XAI)

To explain an event is to provide some information about its causal history. In an act of explaining, someone who is in possession of some information about the causal history of some event - explanatory information, I shall call it - tries to convey it to someone else. - David Lewis

Different approaches

- Intelligibility of the system
- Interpretability of models
- Explainability of ML models

Old topic

- Expert systems
- Recommender systems
- Context-aware systems
- Machine learning

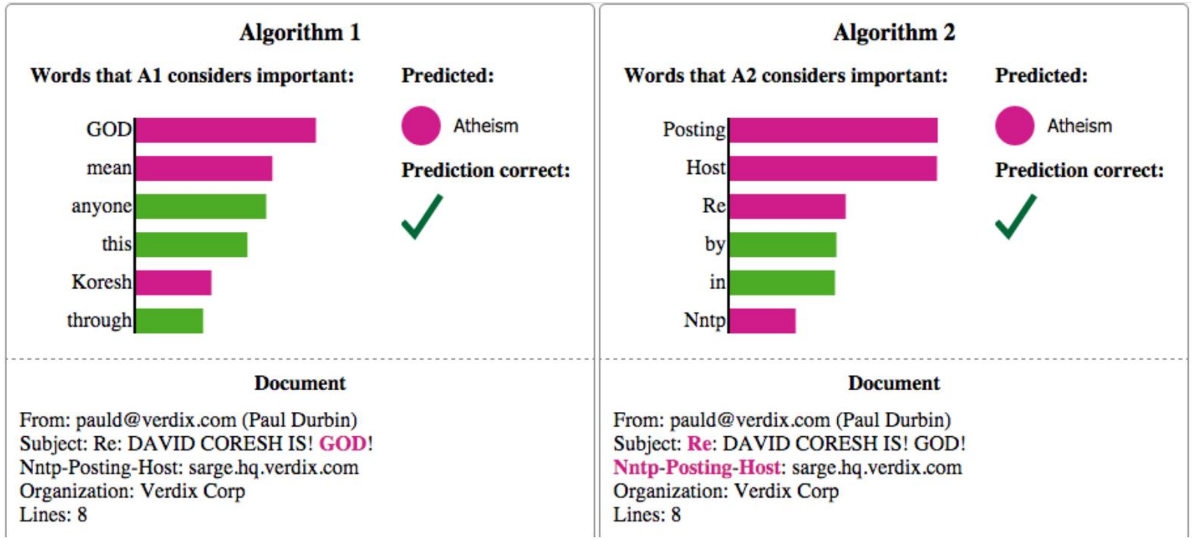
DARPA. Broad agency announcement – explainable artificial intelligence (XAI). DARPA-BAA-16-53, August 2016. https://www.darpa.mil/program/explainable-artificial-intelligence

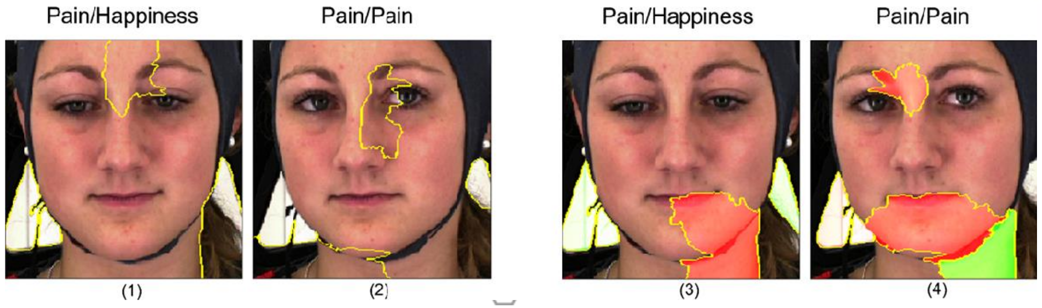
C. Molnar.Interpretable Machine Learning.E-book – Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License, 2019. https://christophm.github.io/interpretable-ml-book/

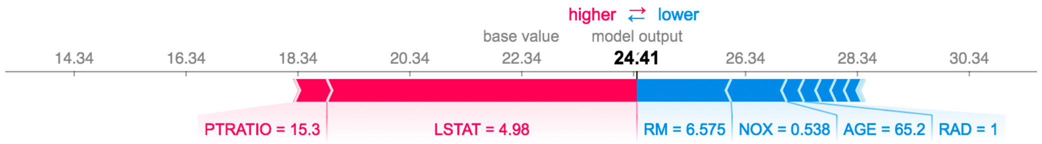
Rudin, C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nat Mach Intell* **1,** 206–215 (2019). https://doi.org/10.1038/s42256-019-0048-x

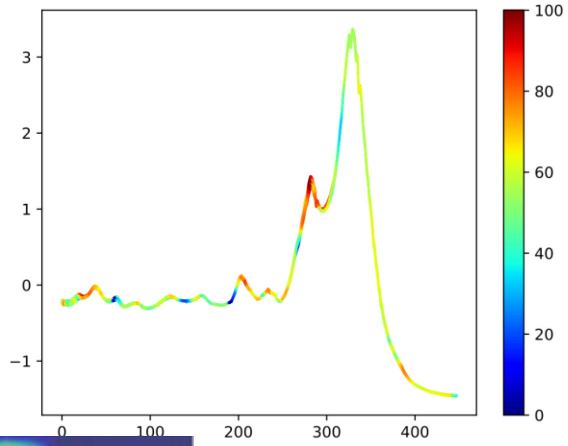
A. Barredo Arrieta, N. D´ıaz-Rodr´ıguez, J. Del Ser, A. Bennetot, S. Tabik, A. Bar-bado, S. Garcia, S. Gil-Lopez, D. Molina, R. Benjamins, R. Chatila, and F. Her-rera. Explainable artificial intelligence (xai): Concepts, taxonomies, opportunitiesand challenges toward responsible ai.Information Fusion, 58:82 – 115, 2020.

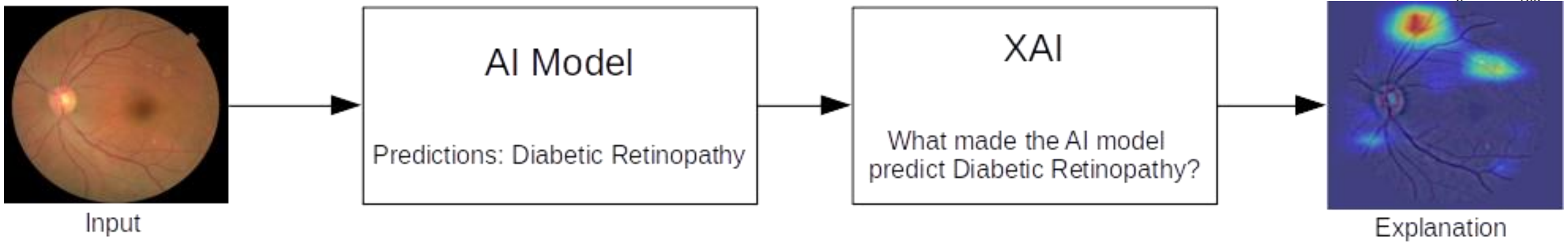
Examples of XAI



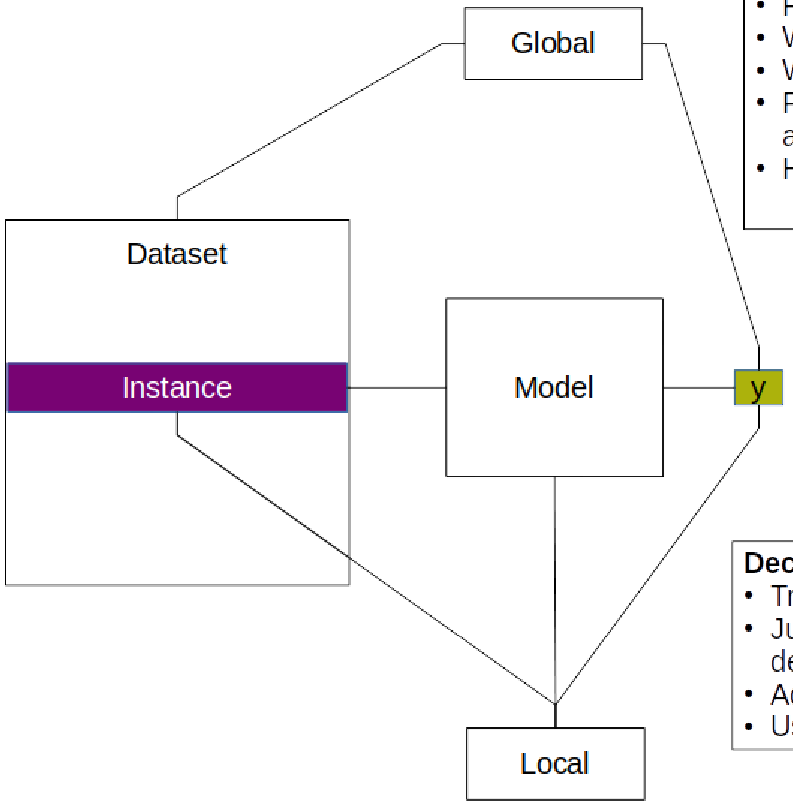








General Goals of XAI



Training:
- For feature selection
- Which model is better
- What is wrong with my dataset
- Prevention from adversarial attacks
- Help in domain understanding

Decision making:
- Transparency
- Justification of uncertain decisions
- Adversarial actions
- User-system trust

Why XAI is non trivial

*In an **act** of explaining, **someone** who is in possession of **some information***

Artificial intelligence

Feature contribution

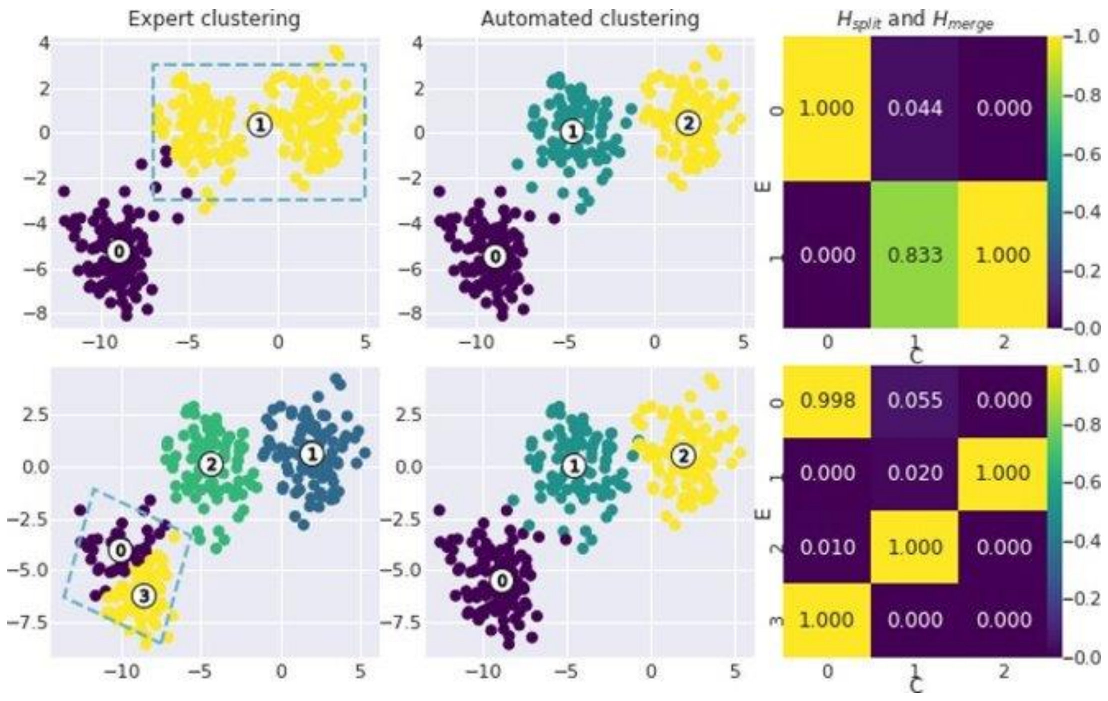
*about the **causal history of some event** - explanatory information,*

Why input to the model generated such output

*I shall call it - tries to **convey it to someone else**.*

Human

How to use XAI in KnAC?



- Split: What makes the two new clusters different from each other to convince expert they are different entities?
- Merge: What makes the two expert clusters different from each other to convince expert that they are the same entity (difference is irrelevant)

From clustering to classification

Data

- Transformations
- Feature extraction

Clustering

- Deciding on number of clusters
- No limits on the clustering algorithm

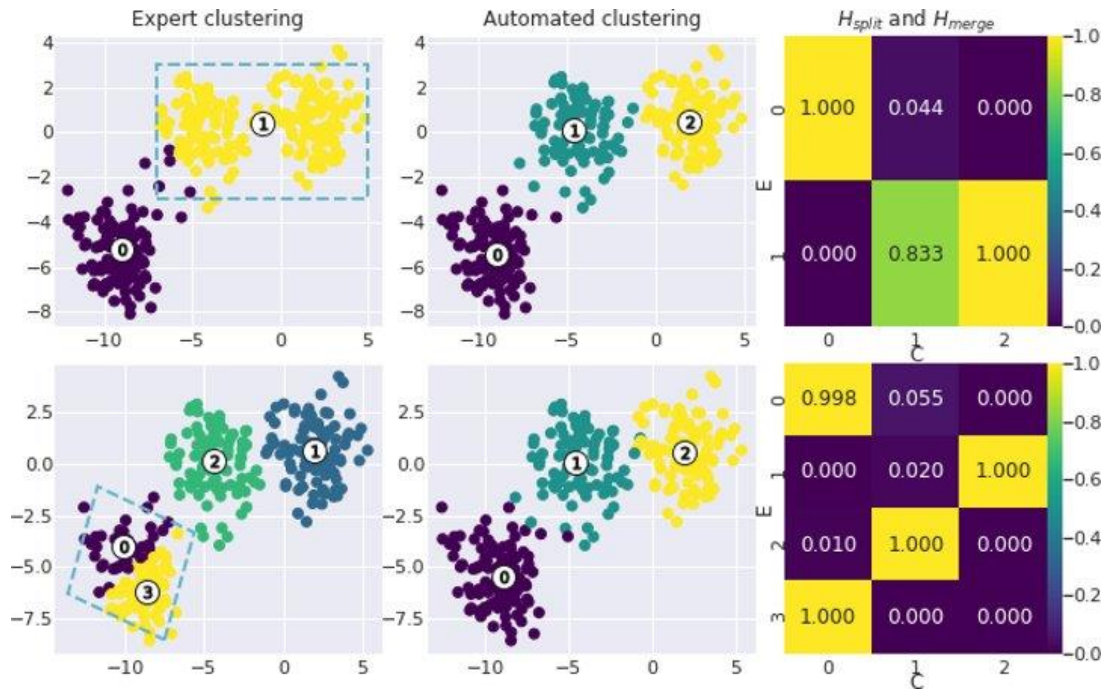
Classification

- Transform clustering into classification
- Use cluster labels as target class
- Use features understandable by the user

Explanation

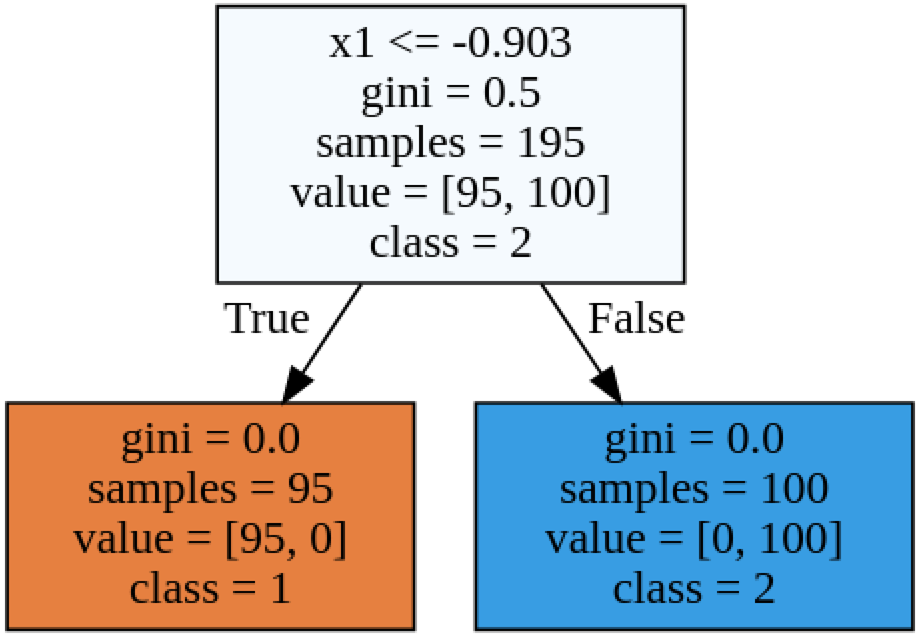
- Apply XAI methods to obtain reason why two clusters are different

Explanations of splits

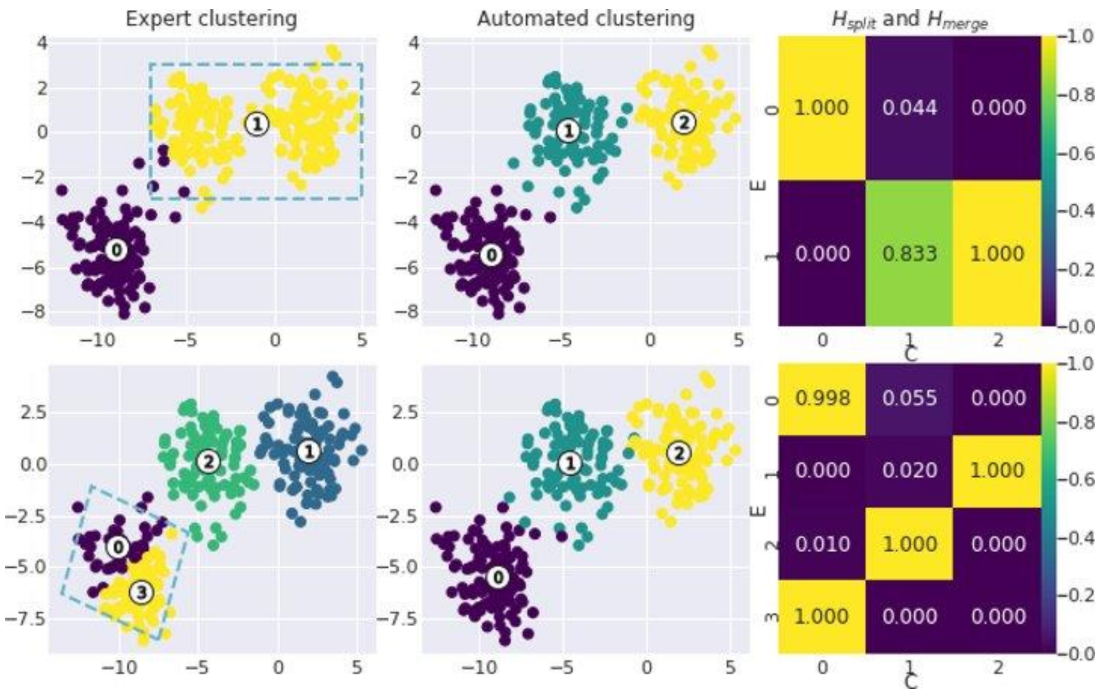



```
C_1: x1 <= -0.30 (Precision: 0.99, Coverage: 0.49)
C_2: x1 > -0.30 (Precision: 1.00, Coverage: 0.49)
```

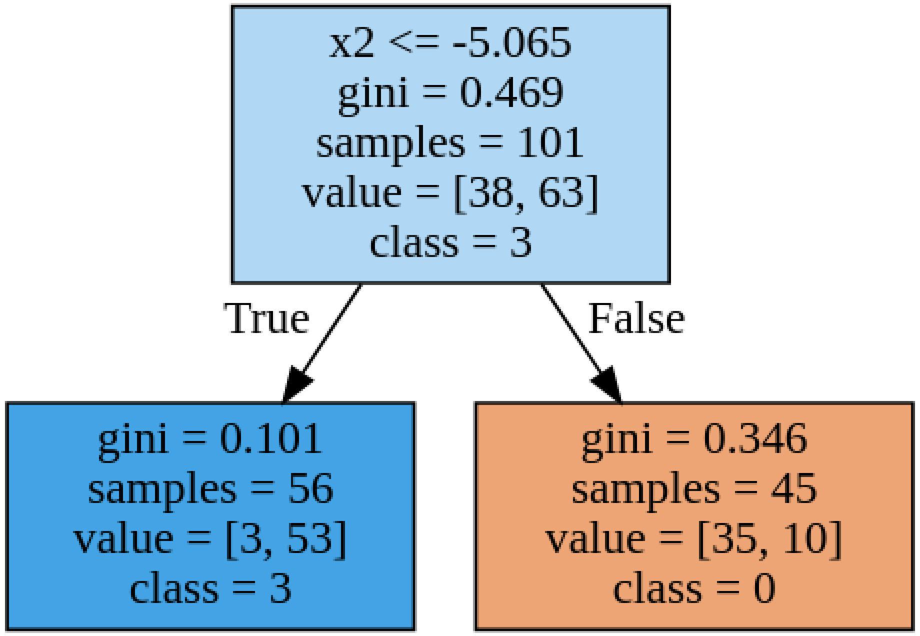
```
SPLIT EXPERT CLUSTER
  E_1
INTO CLUSTERS
  [(C_1, C_2)]
(Confidence 0.87)
```



Explanations of merges

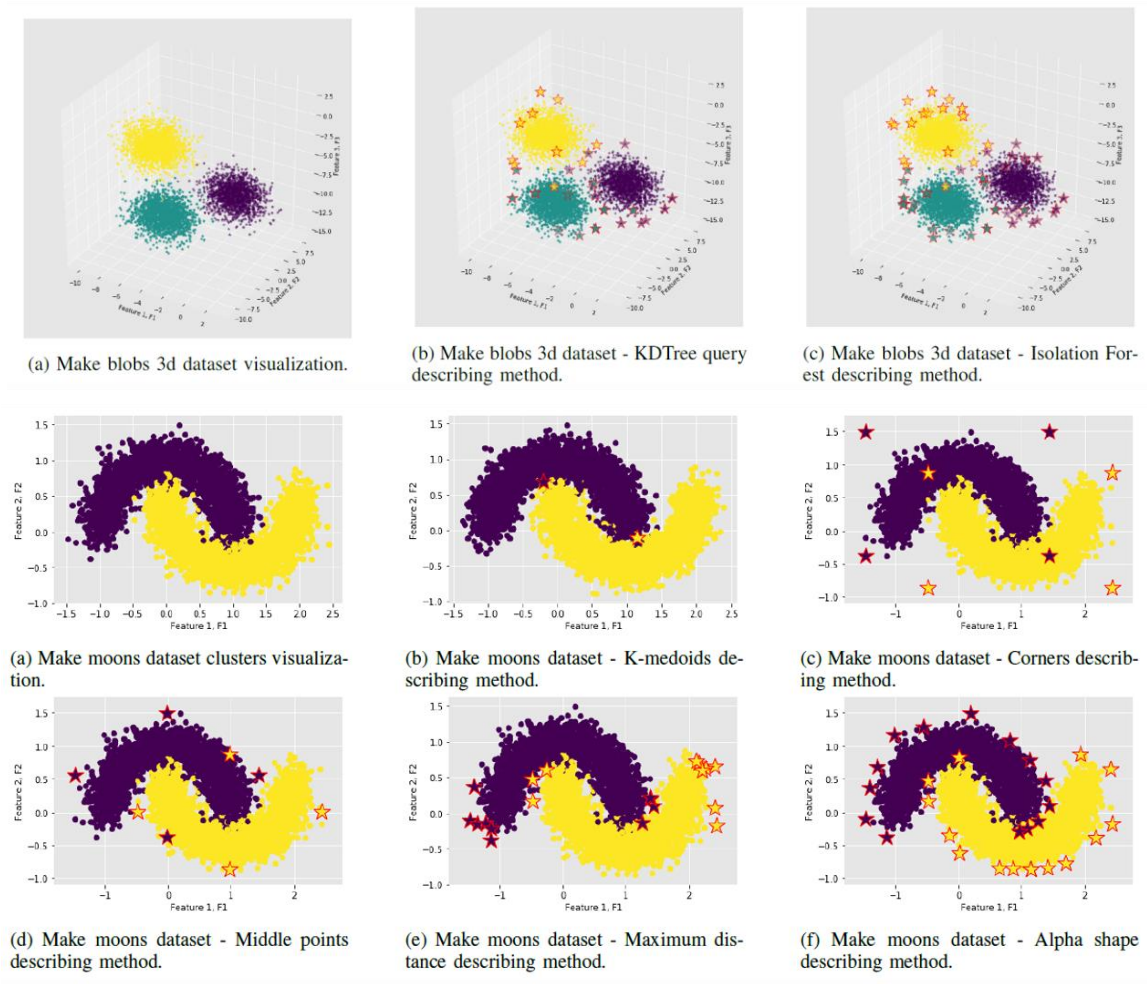


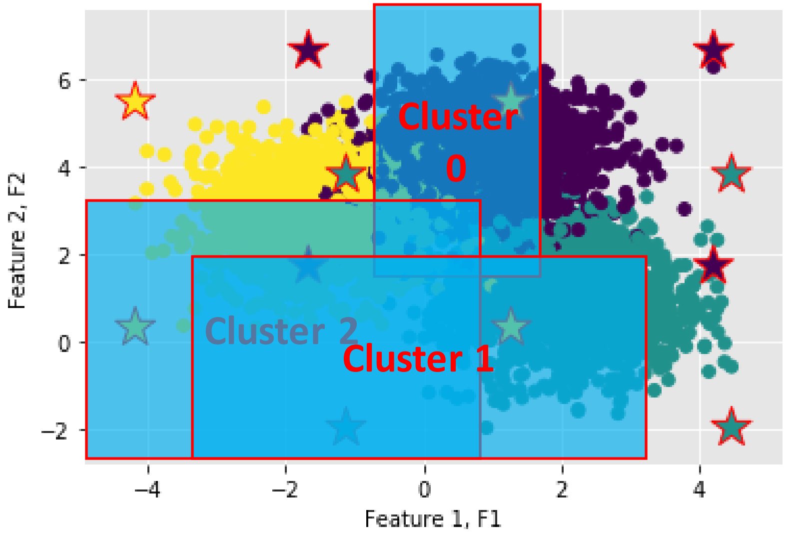
MERGE
EXPERT CLUSTER E_0
WITH
EXPERT CLUSTER E_3
INTO
CLUSTER C_0 # (Confidence 0.98)




```
E_0: x1 <= -8.20 AND x2 > -4.34 (Precision: 1.00, Coverage: 0.07)
E_1: x1 <=-4.34(Precision: 0.90, Coverage: 0.25)
```

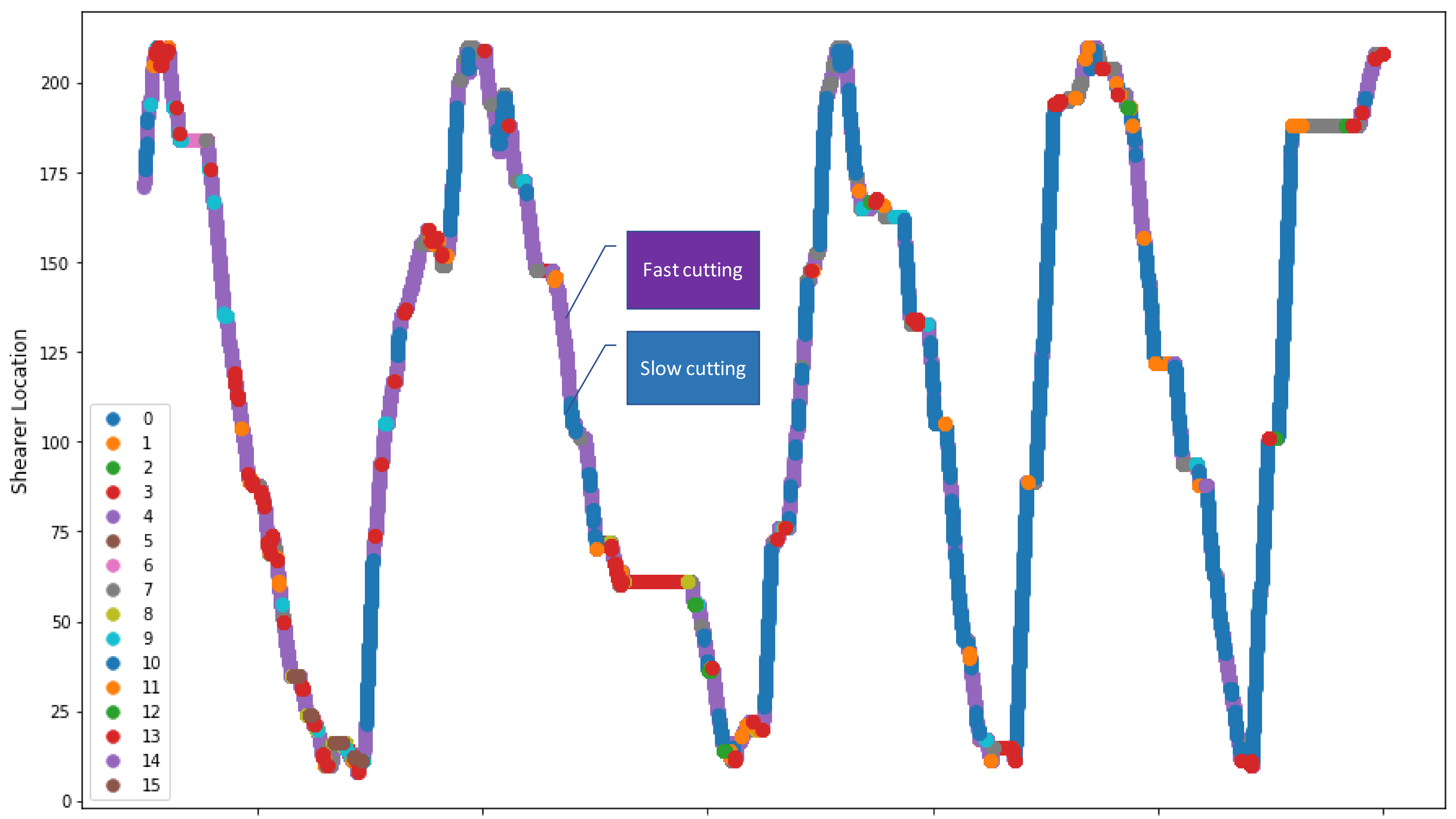
Explainable clusters





Rule no.	Rule	Cluster	Certainty
1	F1 > 0.68 and F2 > 2.99	0	0.48
2	0.68 < F1 ≤ 1.77 and F2 > 1.64	0	0.64
3	-1.14 < F1 ≤ 1.77 and F2 > 1.64	0	0.54
4	F1 > 0.68 and F2 ≤ 2.99	1	0.44
5	F1 > -1.14 and F2 ≤ 1.64	1	0.68
6	F1 ≤ -1.14	2	0.25
7	F1 ≤ 0.68 and F2 ≤ 2.99	2	0.43

M. Kuk, S. Bobek and G. J. Nalepa, "Explainable clustering with multidimensional bounding boxes," *2021 IEEE 8th International Conference on Data Science and Advanced Analytics (DSAA)*, 2021, pp. 1-10, doi: 10.1109/DSAA53316.2021.9564220.



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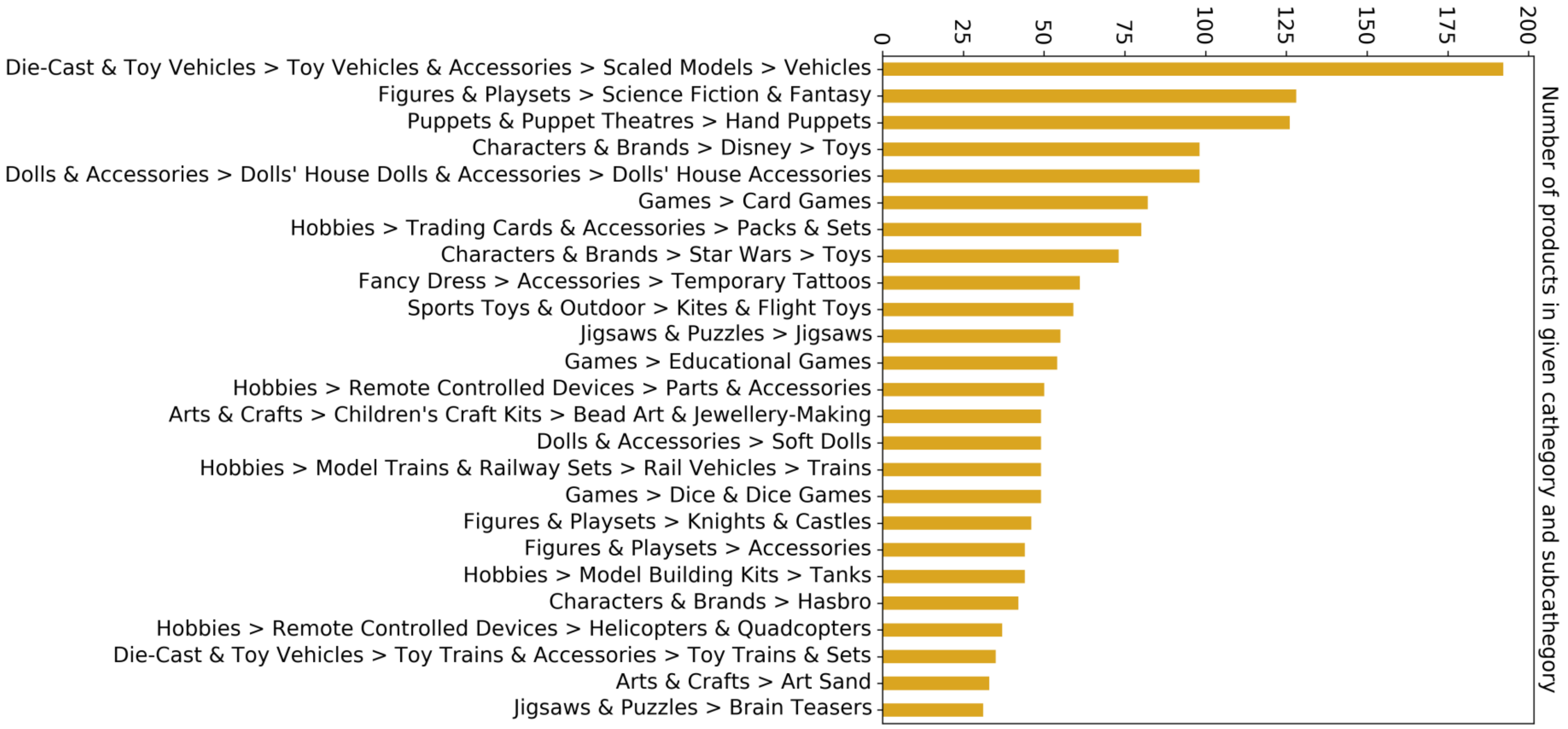
0
25
50
75
100
125
150
175
200
Fast cutting
Slow cutting
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15

E-commerce and coal mine

Product to category

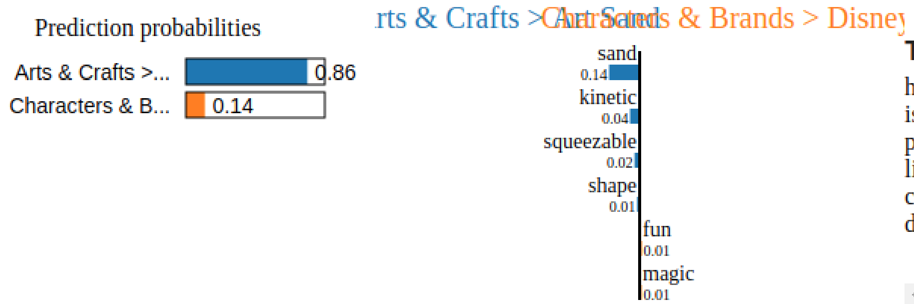


Chuggington is an action-packed contemporary animated train series for pre-schoolers that follows the exciting adventures of three young trainees: Wilson, Brewster and Koko. In each energetic, vibrant episode, the trainees ride the rails through the world of Chuggington, exploring many locations and taking on exciting challenges that test their courage, speed and determination. With the help support and guidance of the more experienced Chuggers, they learn positive values, including respect and loyalty, and new skills such as teamwork and patience, empowering them to be the best trainees they can be. Box Contains 1 x Chuggington Train ”

E-commerce and coal mine

See the results at online tutorial: **https://github.com/sbobek/knac**

```
Justification for Arts & Crafts > Art Sand
[('sand', -0.14062779721924024), ('kinetic', -0.04427780308500065), ('squeezable', -0.023407082689875347), ('shape', -0.011500639821694475), ('fun', 0.01030430901487353
```



Text with highlighted words

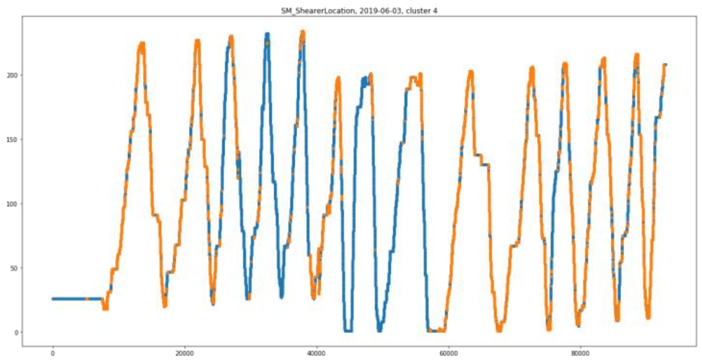
have hours of fun with this magic sand playset creating brilliant sand shapes or create your own sculptures the magic sand is the squeezable sand where you can feel the fun pack it pull it shape it and love it motion sand is so incredible you can put it down it kinetic meaning it sticks to itself and not to you it easy to shape and mould and flows through your fingers like slow moving liquid but leaves them completely dry kinetic sand stimulates children creative skills allowing them to create anything they can imagine it never dries out and is gluten free this soft and stretchy sand easily cleans up while delivering non stop fun it squeezable sand you can put down for ages years and over

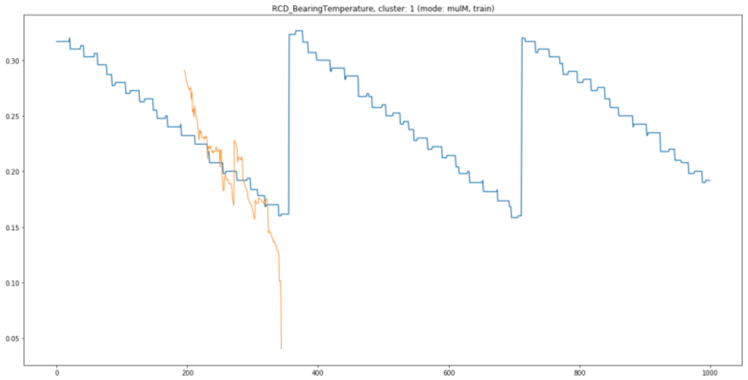
```
Justification for Characters & Brands > Disney > Toys
[('disney', 0.027092040859663918), ('soft', -0.008068585098757642), ('character', 0.006040355286770795), ('characters', 0.004645787316197593), ('kids', 0.00434906686059
```

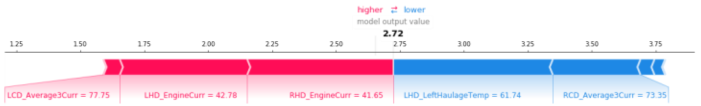
Text with highlighted words

product description whether at home on the road or in the air your favourite disney character can provide great companyand comfort these soft colourful cushions can be easily transformed into disney character soft toy by simply opening and closing the velcro loved by children of all ages these classic disney characters will keep kids entertained for hours and when sleepy just rest your head on the cushion and dream away all our disney character cushions are washable please read washing label for further instructions box contains x

How to explain? Which explanation should we trust?

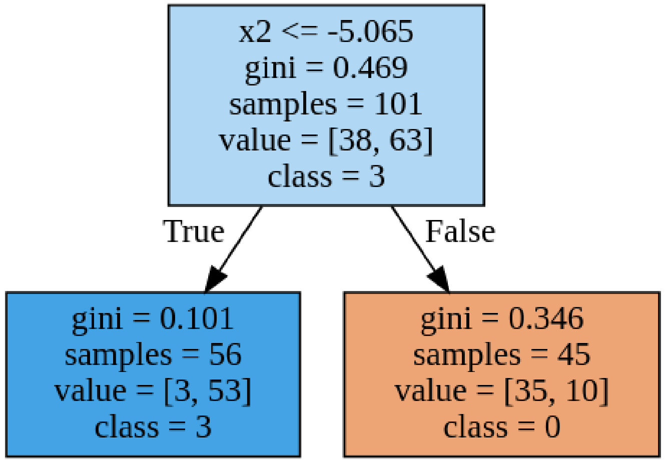


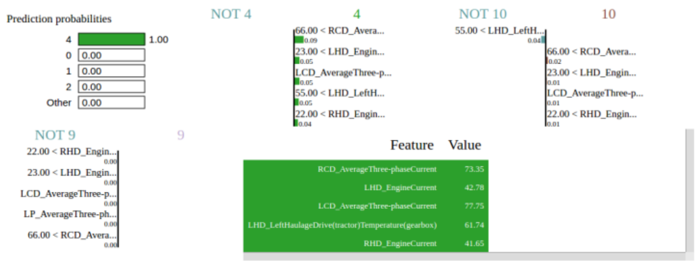




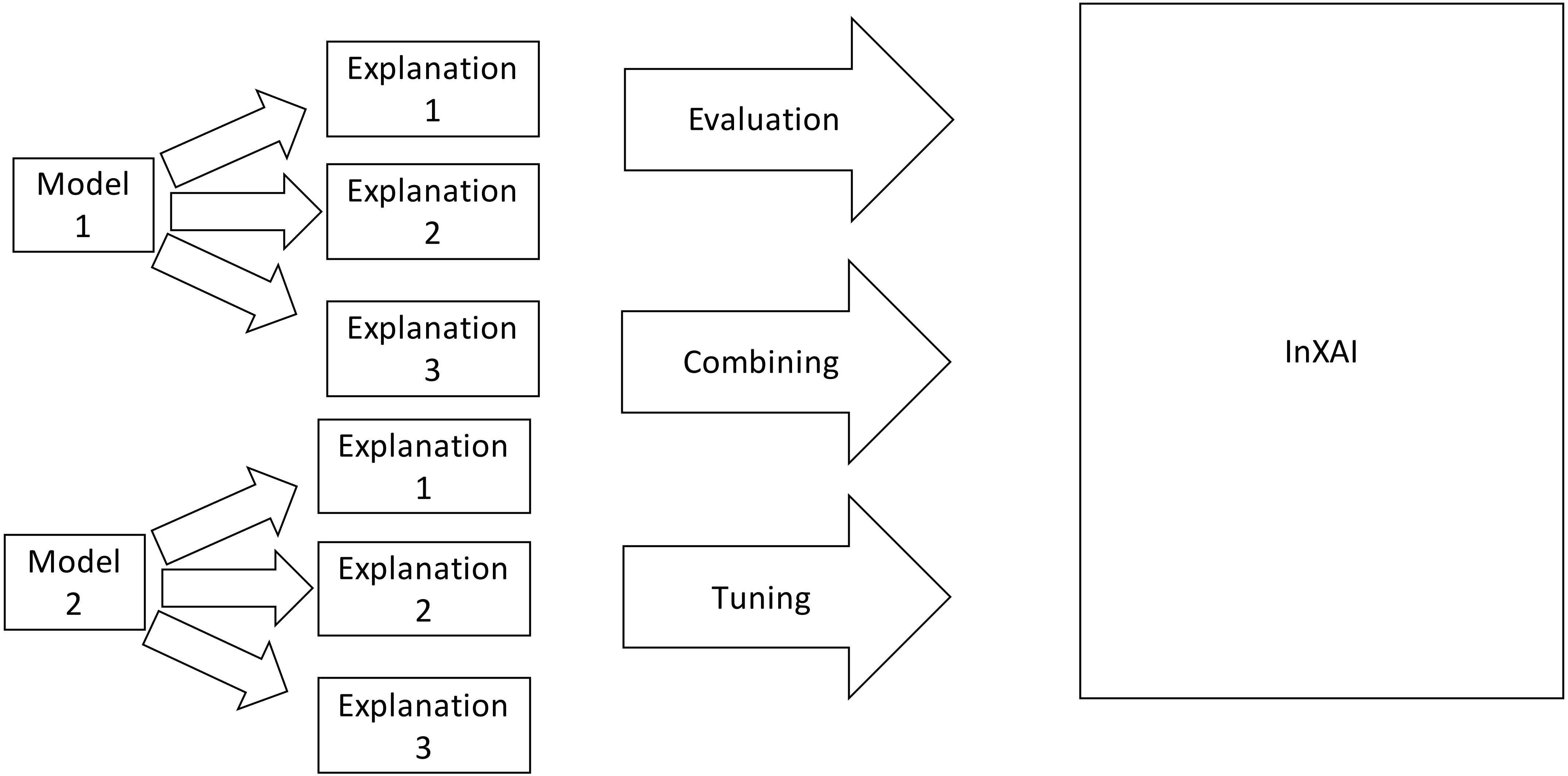
ANCHOR

SM_ShearerSpeed <= 2.00 AND
(RCD_AverageThree-phaseCurrent_LOW OR
RCD_AverageThree-phaseCurrent_MEDIUM OR
RCD_AverageThree-phaseCurrent_HIGH OR
RCD_AverageThree-phaseCurrent_OVERLOAD) AND
(RHD_EngineCurrent_IDLE OR
RHD_EngineCurrent_LOW) AND
(LCD_AverageThree-phaseCurrent_IDLE OR
LCD_AverageThree-phaseCurrent_LOW) AND
RHD_RightHaulageDrive(tractor)Temperature(gearbox) > 0.00 AND
(LHD_EngineCurrent_IDLE OR LHD_EngineCurrent_LOW) AND
43.00 < LA_LeftArmTemperature <= 52.00 AND
LHD_LeftHaulageDrive(tractor)Temperature(gearbox) > 65.00 AND
RA_RightArmTemperature <= 54.00 AND LP_AverageThree-phaseCurrent
<= 4.00 AND
57.00 < RCD_BearingTemperature <= 64.00





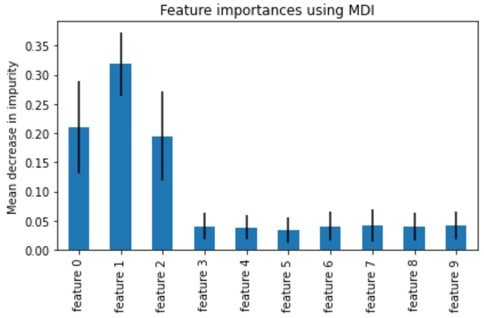
Intelligible XAI (InXAI)

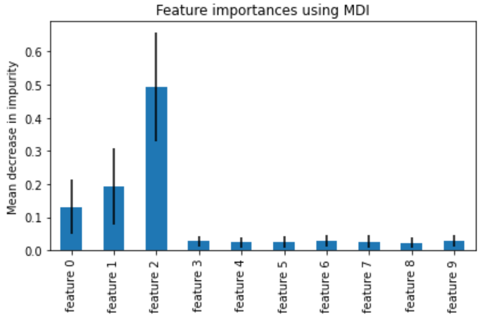


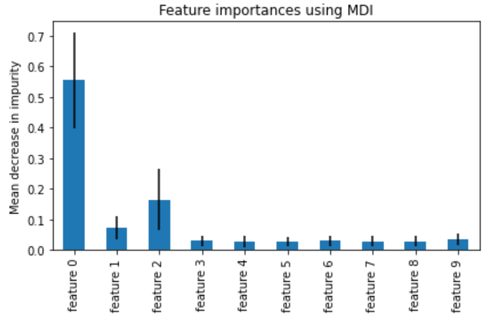
https://github.com/sbobek/inxai

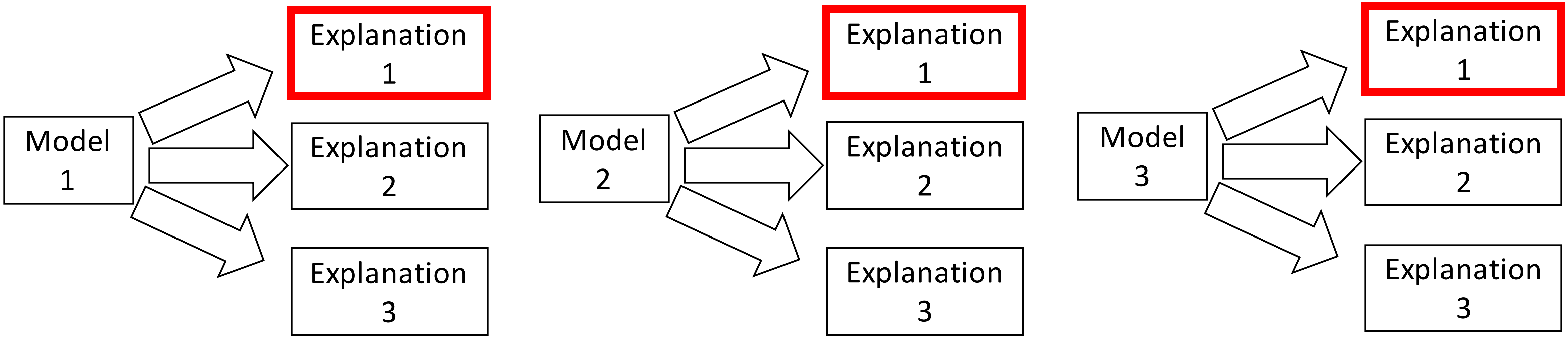
Consistency between explanations for diferent models (or explainers)

$$C(\Phi^{e \to m_1}, \Phi^{e \to m_2}, \ldots, \Phi^{e \to m_n}) = \frac{1}{\max\limits_{a,b \in m_1, m_2, \ldots, m_n} ||\Phi_j^{e \to m_a} - \Phi_j^{e \to m_b}||_2 + 1}$$



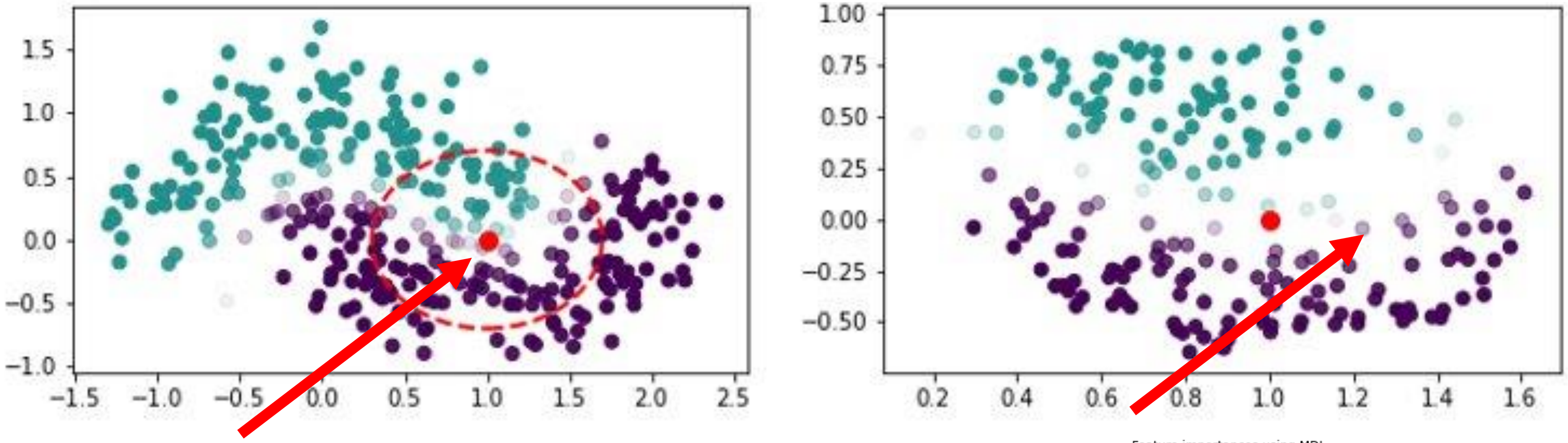


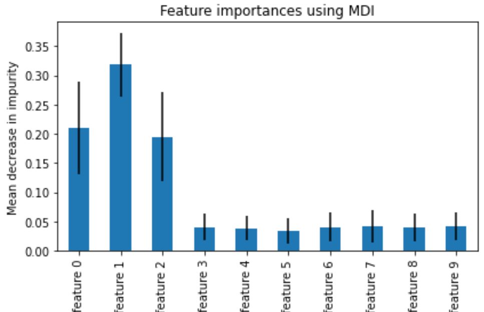


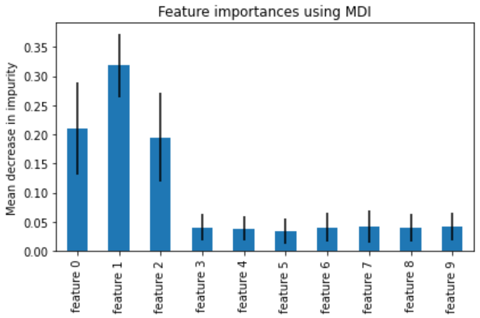


Stability of explanations for similar instances

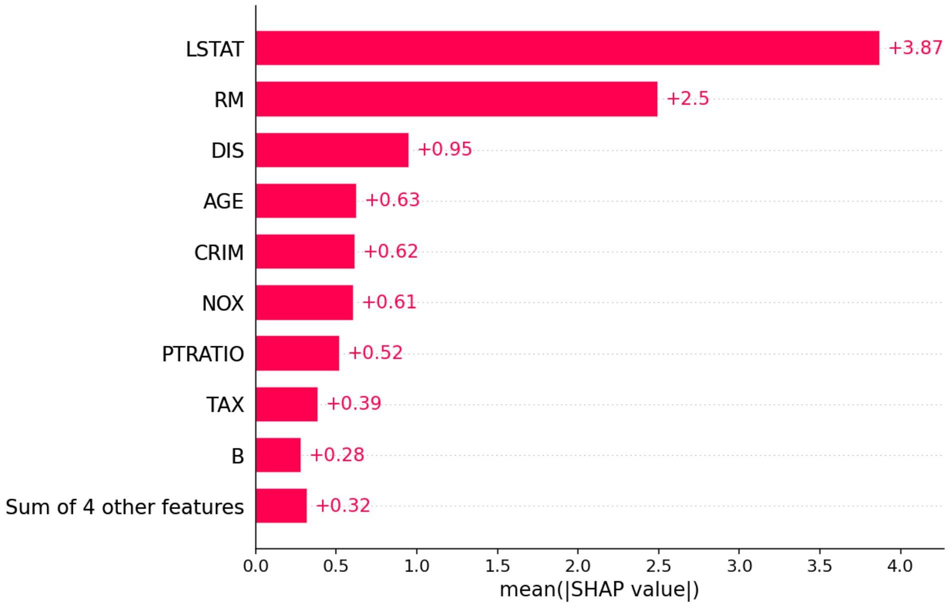
$$\hat{L}(\Phi^{e\rightarrow m}, X) = \max_{x_j \in N_\epsilon(x_i)} \frac{||x_i - x_j||_2}{||\Phi_i^{e\rightarrow m} - \Phi_j^{e\rightarrow m}||_2 + 1}$$



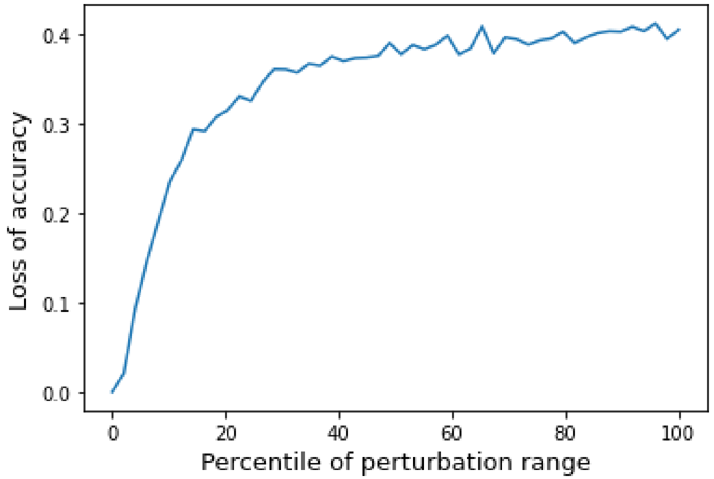


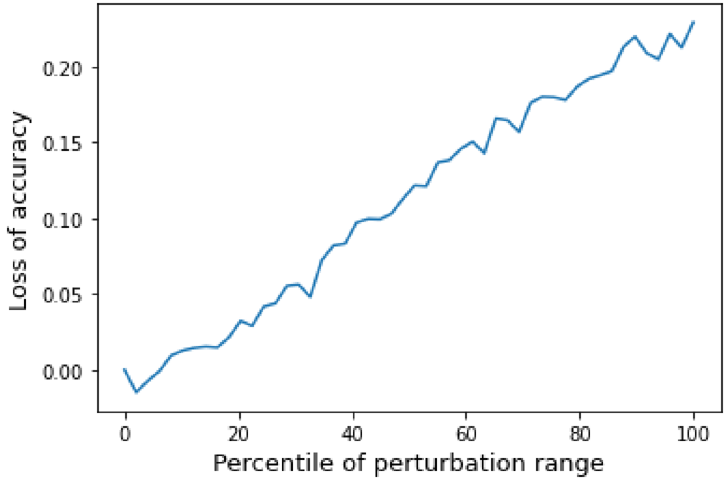


Quality Loss (AUCx)

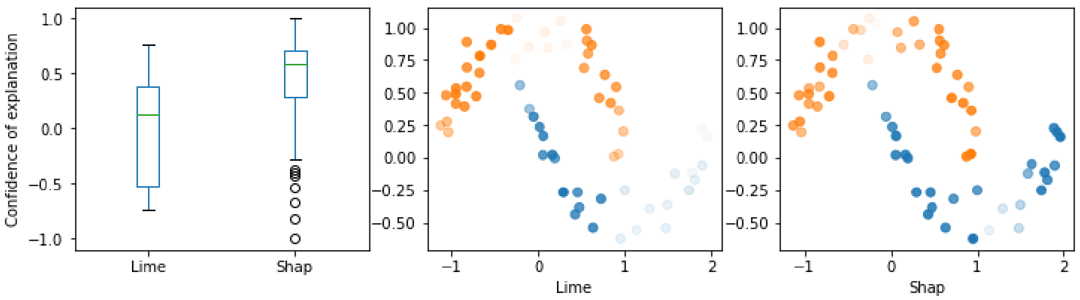


Perturb
data accordingly





Ensemble explanations

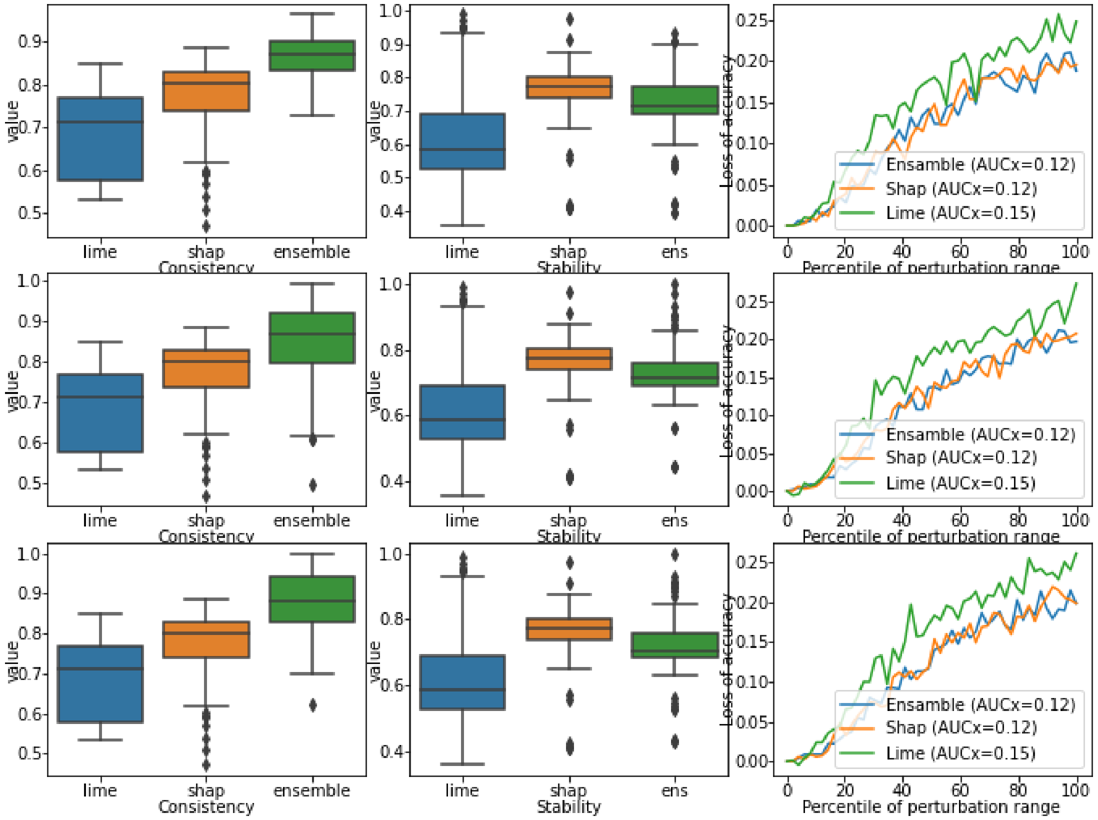


$$C(\Phi^{e\to m_1}, \Phi^{e\to m_2}, \dots, \Phi^{e\to m_n}) = \frac{1}{\max\limits_{a,b \in m_1, m_2, \dots, m_n} ||\Phi_j^{e\to m_a} - \Phi_j^{e\to m_b}||_2 + 1}$$

$$\hat{L}(\Phi^{e\to m}, X) = \max_{x_j \in N_\epsilon(x_i)} \frac{||x_i - x_j||_2}{||\Phi_i^{e\to m} - \Phi_j^{e\to m}||_2 + 1}$$

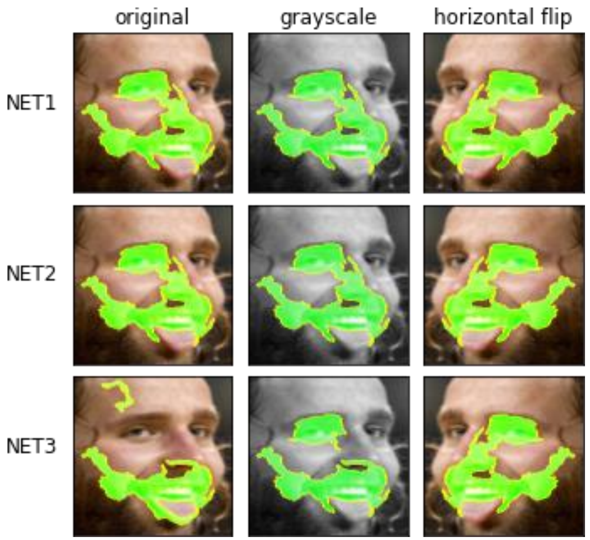
$$ES(M, w) = \sum w_i \cdot M_i$$

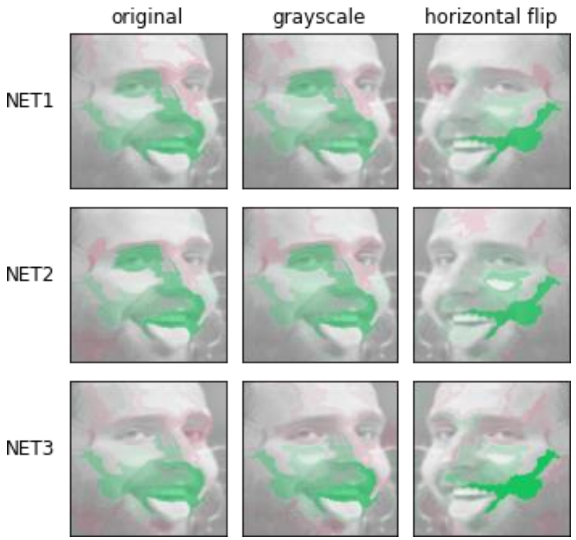
$$\Phi^{ens} = \frac{ES(M,w) \cdot [\gamma_1 \Phi^{e_1}, \gamma_2 \Phi^{e_2}, \dots, \gamma_n \Phi^{e_n}]}{\sum_{i=1}^{n} ES_i(M,w)}$$

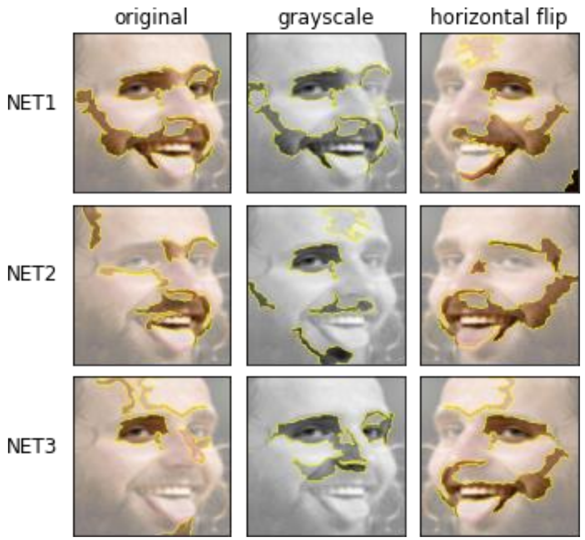


https://github.com/sbobek/inxai

Ensemble explanations

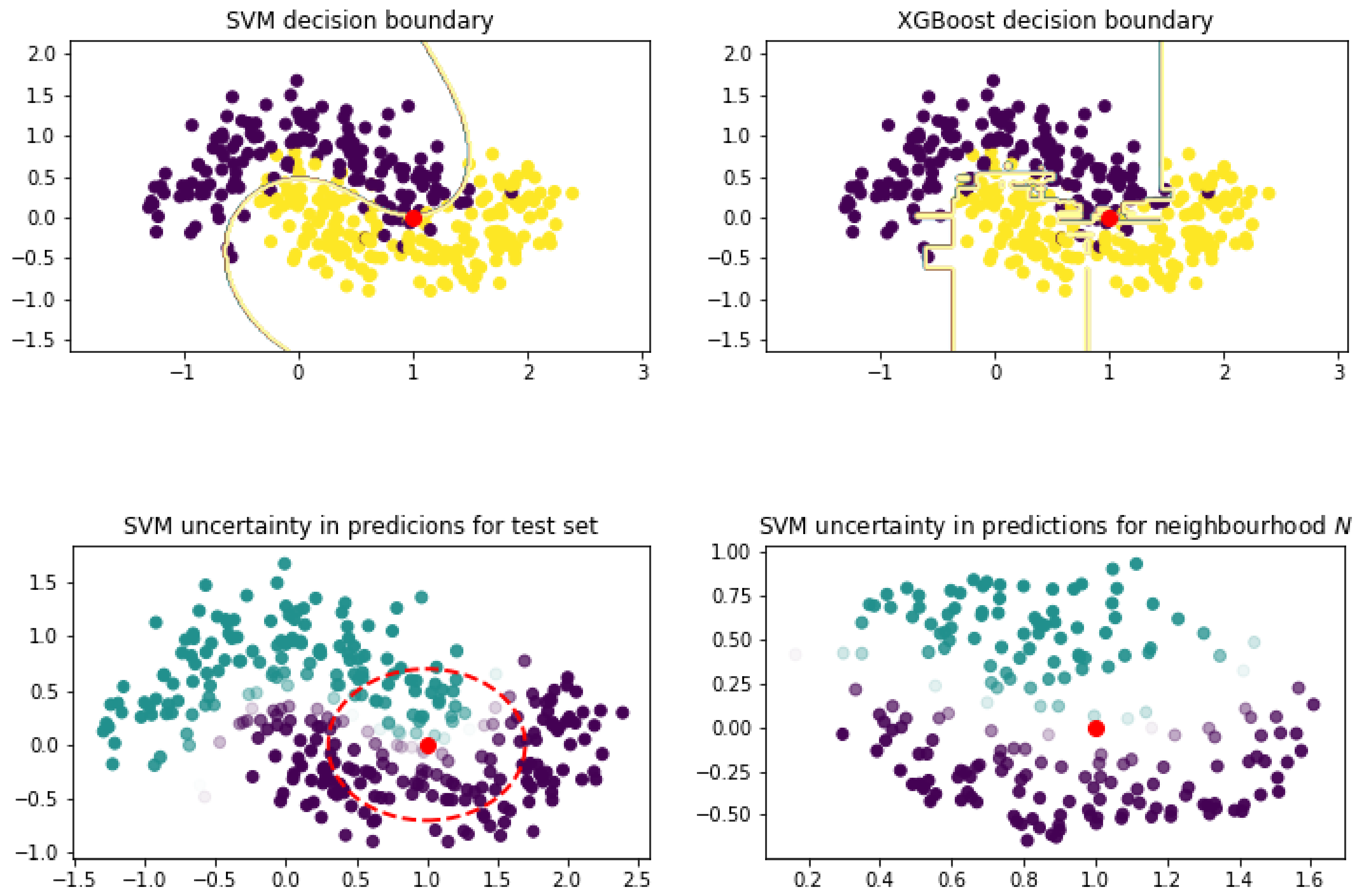






Local Uncertain Explanations

- Machine learning model we explain is **uncertain**
- **Target variable** for training local interpretable model **is uncertain**
- **Neighbourhood** (training data for local explainable model) is **uncertain**

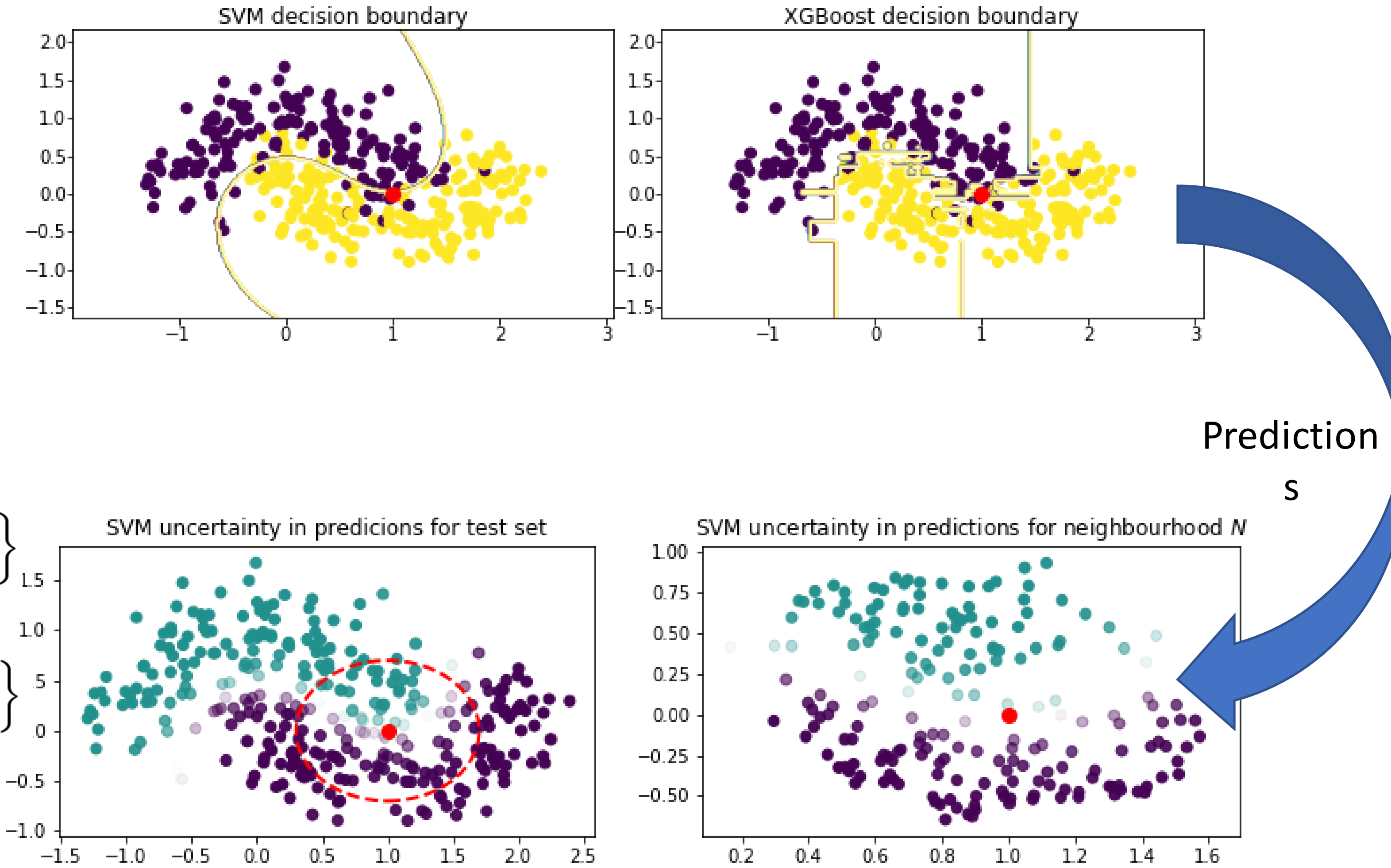


Local Uncertain Explanations

- We use neighbourhood as uncertain dataset
- Instead of probability calculated as frequency, we average the probability obtained from ML model
- We modify Information Gain split criteron to use these measure and build decision tree

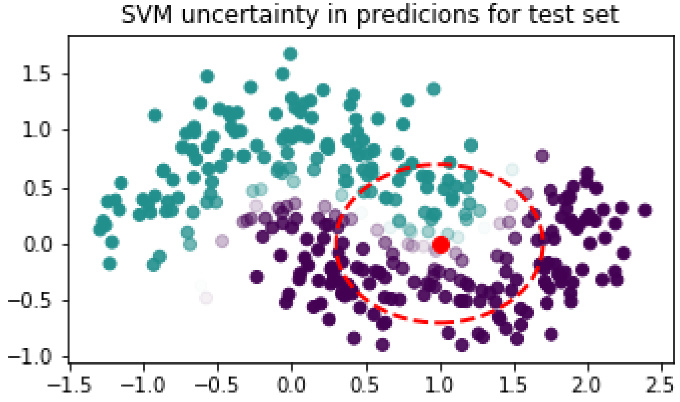
$$N(x^{(i)}, K) = \left\{ x^{(k)} \in X : d(x^{(i)}, x^{(k)}) \leq D_i^{(K)} \right\}$$

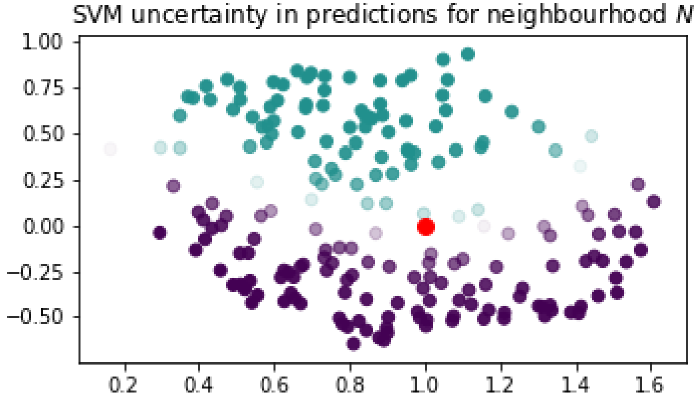
$$D_i = \left\{ d(x^{(i)}, x^{(1)}), d(x^{(i)}, x^{(2)}), \ldots, d(x^{(i)}, x^{(m)}) \right\}$$



Local Uncertain eXplanations (LUX)

- We use neighbourhood as uncertain dataset
- Instead of probability calculated as frequency, we average the probability obtained from ML model
- We modify Information Gain split criterion to use these measure and build decision tree



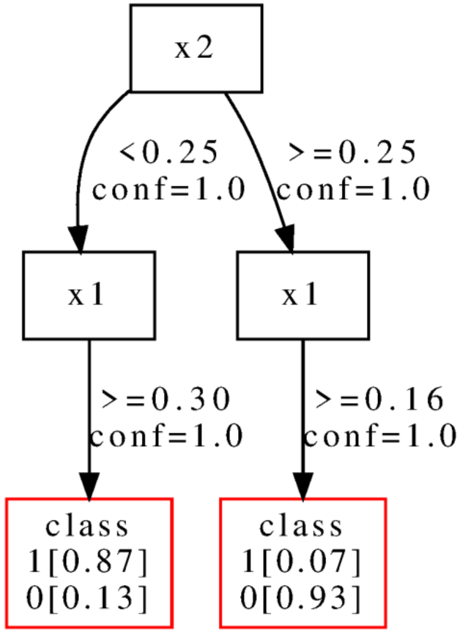


$$H^U(X) = -\sum_{v \in Domain(C)} P_{total}(C = v) \log_2 P_{total}(C = v)$$

$$P_{total}(A_i = v_j^i) = \frac{1}{k} \sum_{X_t \ni P_{j=1\ldots n}} P_j(A_i = v_j^i)$$

$$Gain^U(A) = H^U(X) - \sum_{v \in Domain(A)} P_{total}(A = v) H^U(X_v)$$

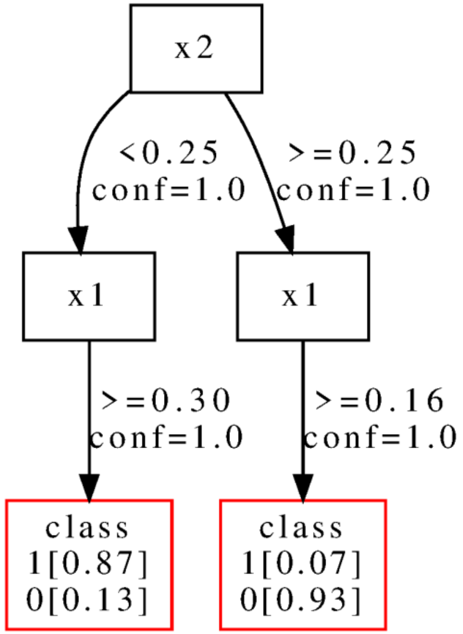
```
@relation lux
@attribute x1 @REAL
@attribute x2 @REAL
@attribute class {1,0}
@data
0.94,0.01,1[0.48]
0.87,-0.04,1[0.64]
1.02,-0.16,1[0.78]
1.14,0.08,1[0.37]
1.01,-0.21,1[0.83]
1.10,-0.19,1[0.81]
0.80,-0.13,1[0.81]
0.91,-0.23,1[0.87]
0.77,-0.12,1[0.83]
1.01,-0.28,1[0.89]
0.97,-0.28,1[0.89]
...
```



https://github.com/sbobek/lux

[Introducing Uncertainty into Explainable AI Methods](#)
S Bobek, GJ Nalepa
International Conference on Computational Science, 444-457

Local Uncertain Explanations (LUX)



- Translate branches to rules (XTT2 format)
- XTT2 format is a **knowledge** representation that is
  - **extensible (HWEd editor),**
  - **formalized (ALSV(FD) logic),**
  - **executable (HeaRTDrtoid engine)**
- **Get the uncertainty of an explanation that is transferred from uncertainty of data and model prediction**

x1	x2	class	#
>= 0.30	< 0.25	set 1	0,8
>= 0.16	>= 0.25	set 0	0,9

tree

Add condition Add decision Add rule

Summary

- Knowledge Augmented Clustering (KnAC)
- Local Uncertain eXplanbations (LUX)
- Intelligible XAI (InXAI)
- Technology needs to be human-centric
- Explanations are important for unsupervised methods (KnAC/Explainable clusters)
- *The truth is out there*

Open Challenges in XAI for (not only) Industry 4.0

- Mediating explanations between human and XAI system.
  - Explanation is an act of conveying knowledge
  - Technology needs to be human-centric. Good explanation does not always mean useful or understandable
- Defining mediatable information granules via human-in-the-loop conceptualization.
  - Semantic gap between XAI and different explanation addresse (stakeholders)
- Multi-faced continuous assessment of quality of explanations.
  - Why should I trust... your explanation
  - Correlation does not mean causation

Thank you for your attention!

Give us a feedback @ https://github.com/sbobek/knac

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AND TECHNOLOGY