Using ML and XAI for decision support in Business Intelligence analysis.

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Agenda

1. Machine Learning as element of Business Intelligence - background
2. Interpretation of explainability (XAI) scores
3. Incorporating business assumptions into analytical process
4. Contextualisation of the XAI results
5. Conclusions

Area of intrests

1. Align business objectives with technical aspects of ML procedure

2. Add context for interpretation of XAI results to enhance usefulness of predictions

Challenges

Technical perspective

- Performance
- Features selection
- Evaluation criteria

Usability perspective

- Evaluation understandability
- Tailored visualization of the results
- Usefulness

Inefficient model → **wrong conclusions**

Unclear results → **no conclusions**

Usability of ML in Business Intelligence

Motivations for investment in Industry 4.0 and similar ideas - Company **profit**

Revenue

Cost optimisation

Time optimisation

Quality optimisation

ML in Business Intelligence

Mimic current abilities

- Automation of human tasks
- Data processing, features extraction
- Statistical analyzes => ML algorithms

Evaluation:
Interpretable and consistent with domain knowledge.

Enhance current abilities

- Multidimentional analyses
- Estimations
- rule-based solutions => adaptive Smart systems

Evaluation:
Need of new metrics, and context for new results interpretation

Opportunities to expand current capabilities of analytical process

Inclusion of **external knowledge**:

- Additional set of descriptive features
- Assumptions and restrictions for analyses workflow

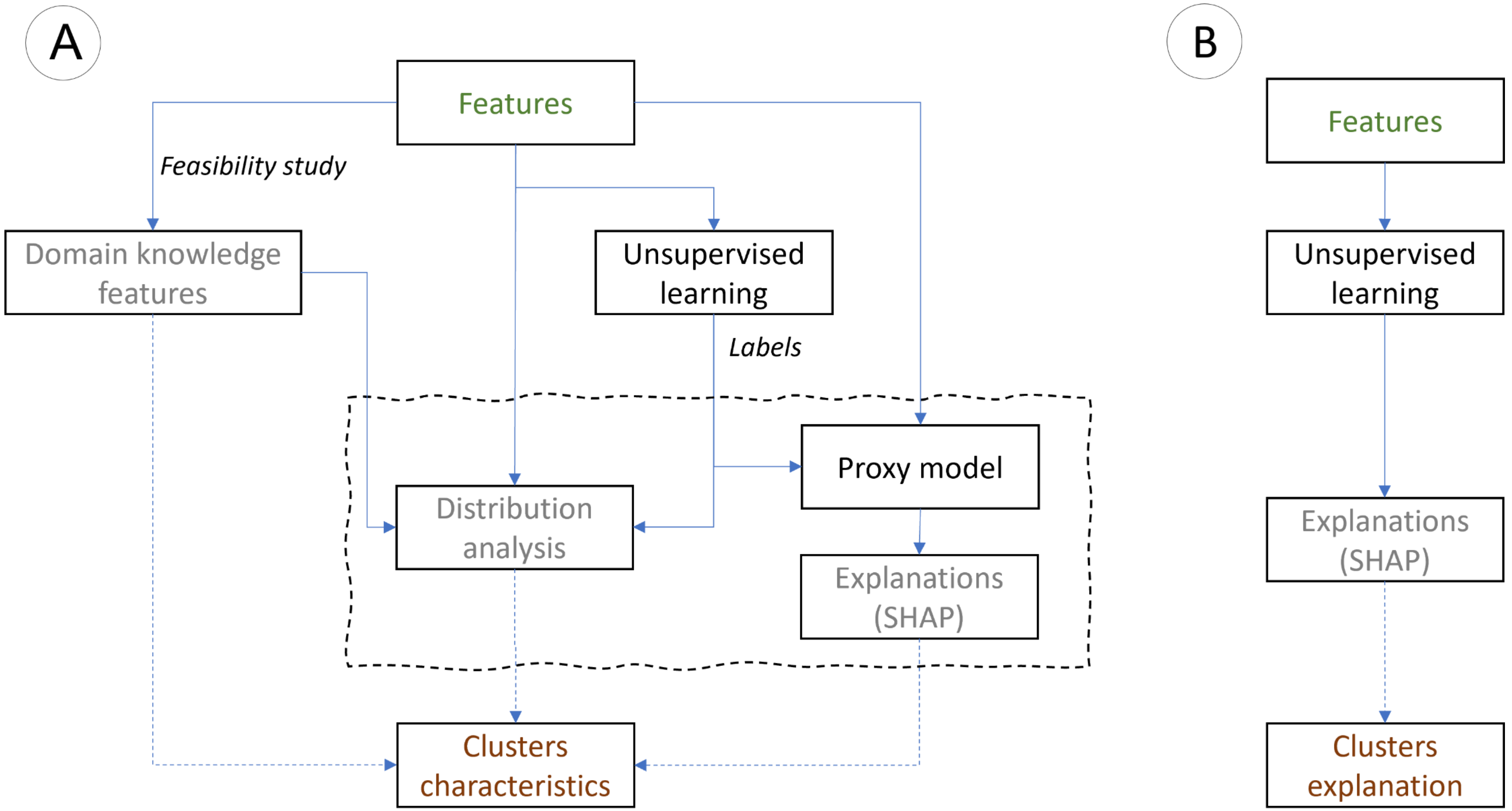
Inclusion of **explainability results**:

- Planning the meaning of XAI through a set of analysis assumptions and the form of the ML model
- Interpretation of XAI in connection with other elements of the analysis

  (input values, predictions, labels)

„Improving understandability of explanations with a usage of expert knowledge – unsupervised learning”

Maciej Szelążek, Szymon Bobek, Grzegorz J. Nalepa SEDAMI @ ECAI 2023



Pima diabetes dataset

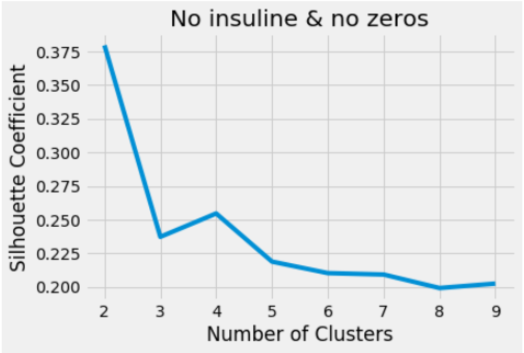
- 768 entries
- 9 features

- Females
- Age > 21
- Pima Indian heritage

Amount of null values

Pregnancies	0
Glucose	5
BloodPressure	35
SkinThickness	227
Insulin	374
BMI	11
DiabetesPedigreeFunction	0
Age	0
Outcome	0

Silhouette score



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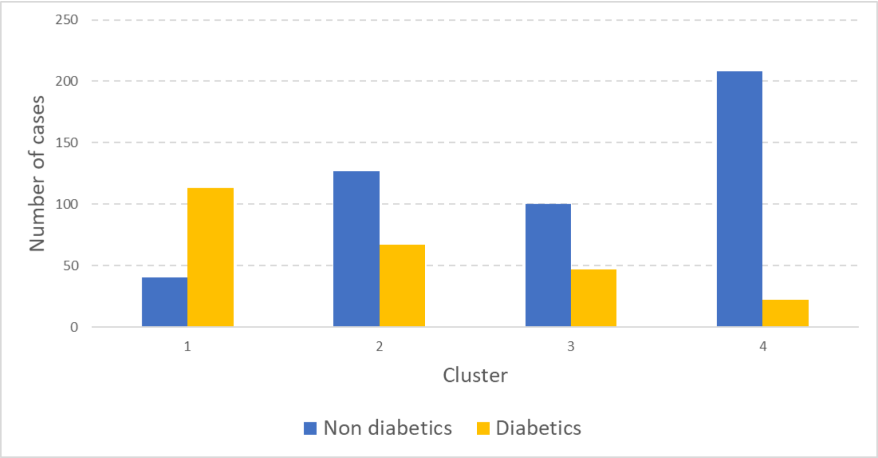
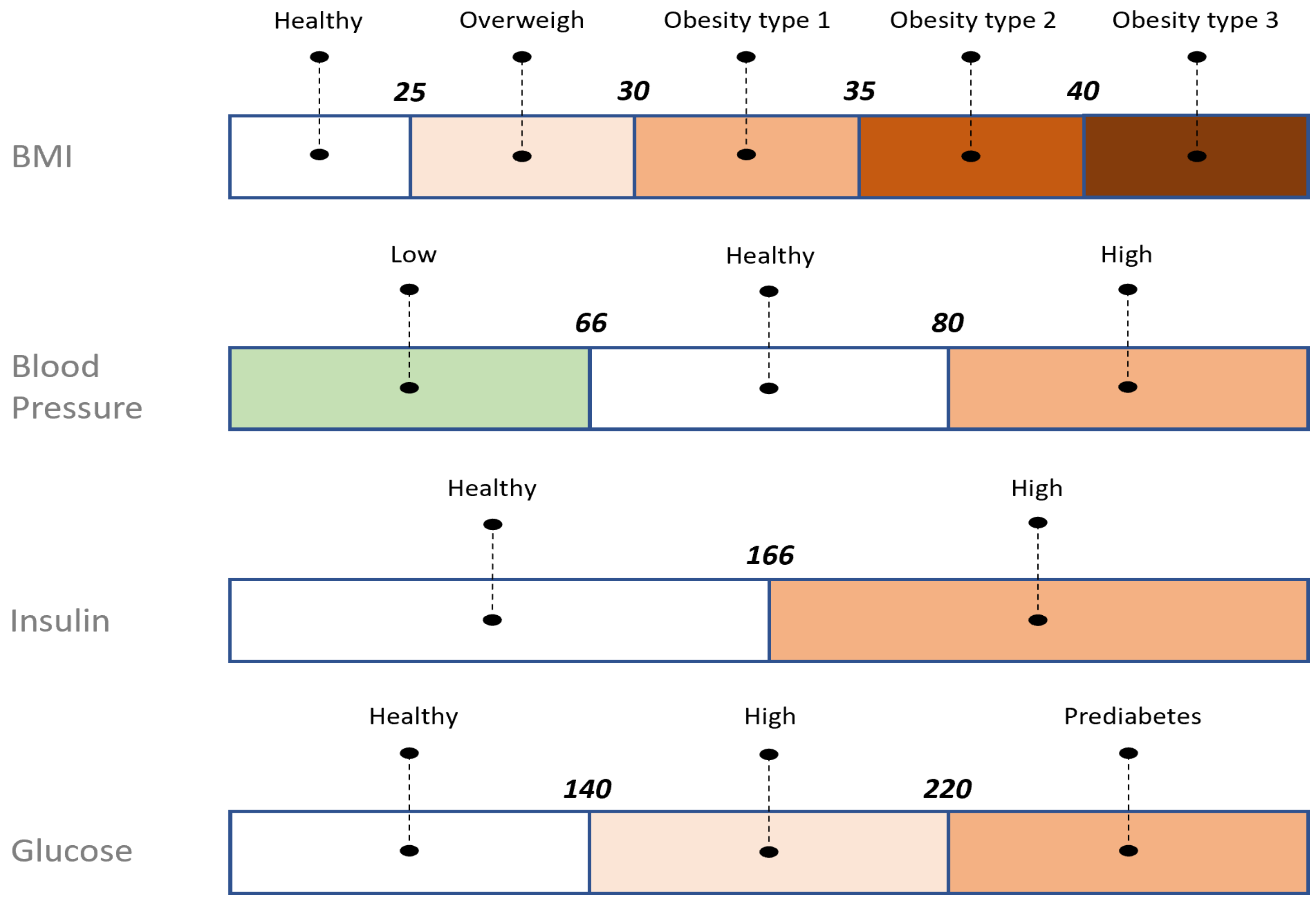


Unsupervised learning base characteristics

Cluster	Sum	Outcome	Quantity
0	153	0	40
		1	113
1	194	0	127
		1	67
2	147	0	100
		1	47
3	230	0	208
		1	22

Feasibility study of domain knowledge



Rules for segmentation patients inside the clusters

IF:

Set of rules

BMI

$$\text{IF} \sum_{i=0}^{n} x_i > BMI\_limit_i \quad \text{then} \quad BMI\_category_i$$

- Healthy BMI
- Overweight
- Obesity type 1
- Obesity type 2
- Obesity type 3

AND

Blood pressure

$$\text{IF} \sum_{i=0}^{n} x_i > BP\_limit_i \quad \text{then} \quad BP\_category_i$$

- Healthy blood pressure
- High blood pressure
- Low blood pressure

AND

Insulin

$$\text{IF} \sum_{i=0}^{n} x_i > Insulin\_limit_i \quad \text{then} \quad Insulin\ category_i$$

- Healthy insulin
- High insulin

AND

Glucose

$$\text{IF} \sum_{i=0}^{n} x_i > Glucose\_limit_i \quad \text{then} \quad Glucose\ category_i$$

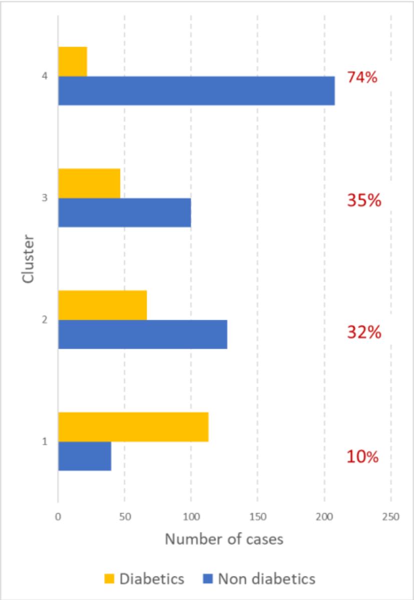
- Healthy glucose
- High glucose
- Prediabetes glucose

Then:

Health score

3 data sources for describing clusters

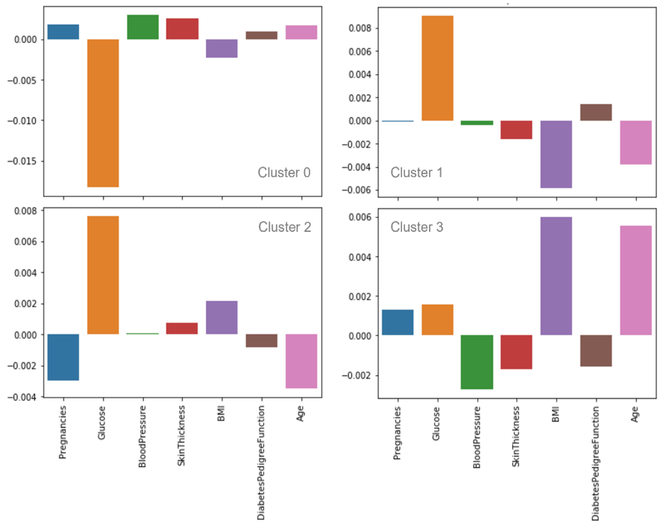
Share of diabetes in **clusters**



Domain features characteristics

Cluster	BMI_obese3	BMI_obese2	BMI_obese1	BMI_overweight	Glucose_hi	BloodPressure_hi	BloodPressure_lo
0	32	33	57	20	**153**	**54**	24
1	**34**	**53**	**58**	40	16	51	46
2	12	18	42	42	16	40	25
3	12	37	55	**64**	0	18	**111**

SHAP characteristics

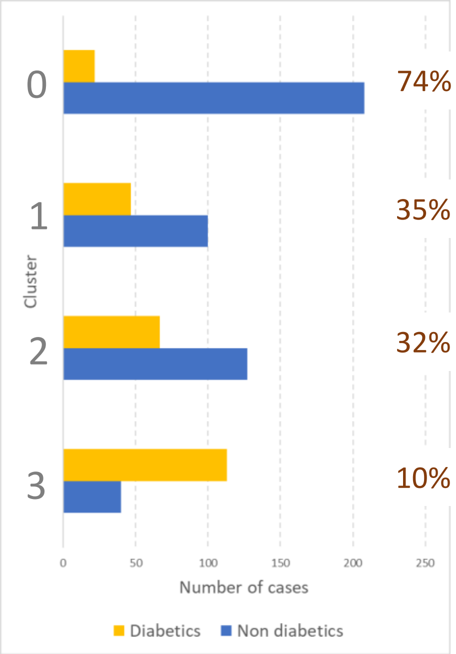


Input features characteristics

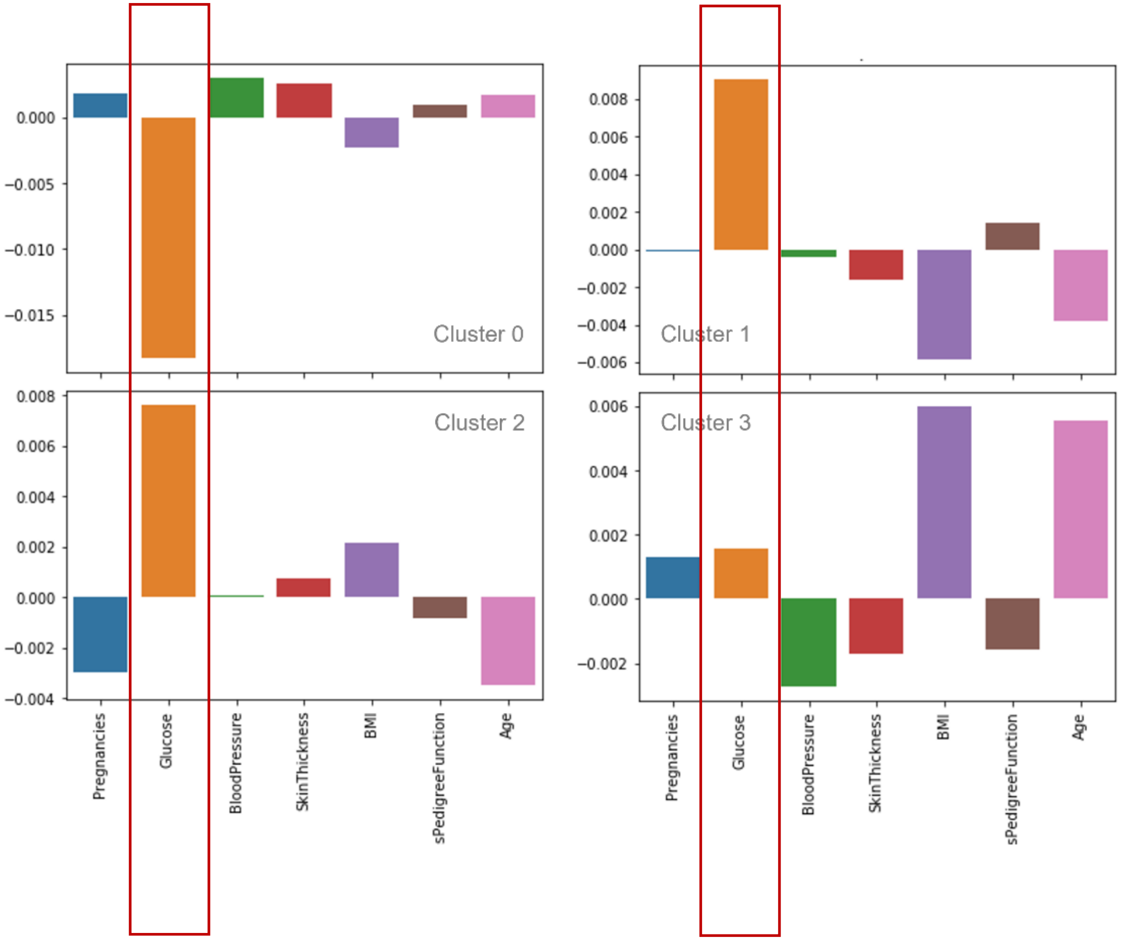
Cluster	Pregnancies	Glucose	BloodPressure	SkinThickness	BMI	DiabetesPedigreeFunction	Age
0	**5,0**	**168,7**	**76,6**	25,1	**35,1**	**0,55**	**38,7**
1	3,5	121,7	73,7	**33,6**	34,9	0,50	31,9
2	4,6	121,9	75,9	*2,3*	30,7	*0,42*	37,7
3	*2,9*	*90,8*	*66,2*	21	*29,8*	0,44	*28,2*

Explainability interpretation - Glucose

- No proportional relationship between SHAP importance and input values
- For cluster 0 results are more than 2x higher than for clusters 1 and 2, and significantly lowest in cluster
- Negative sign is related to cluster with highest glucose values

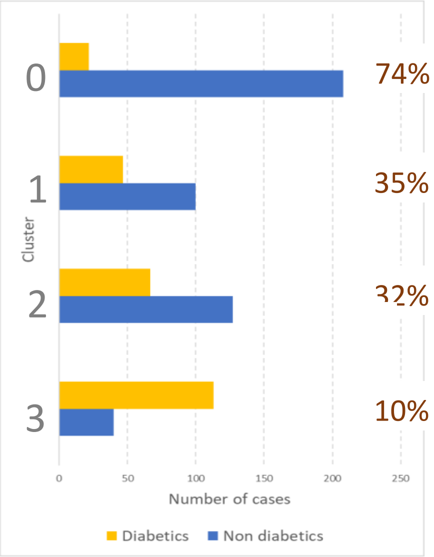


Cluster	Glucose	Glucose_hi
0	**168,7**	**153**
1	121,7	16
2	121,9	16
3	*90,8*	0



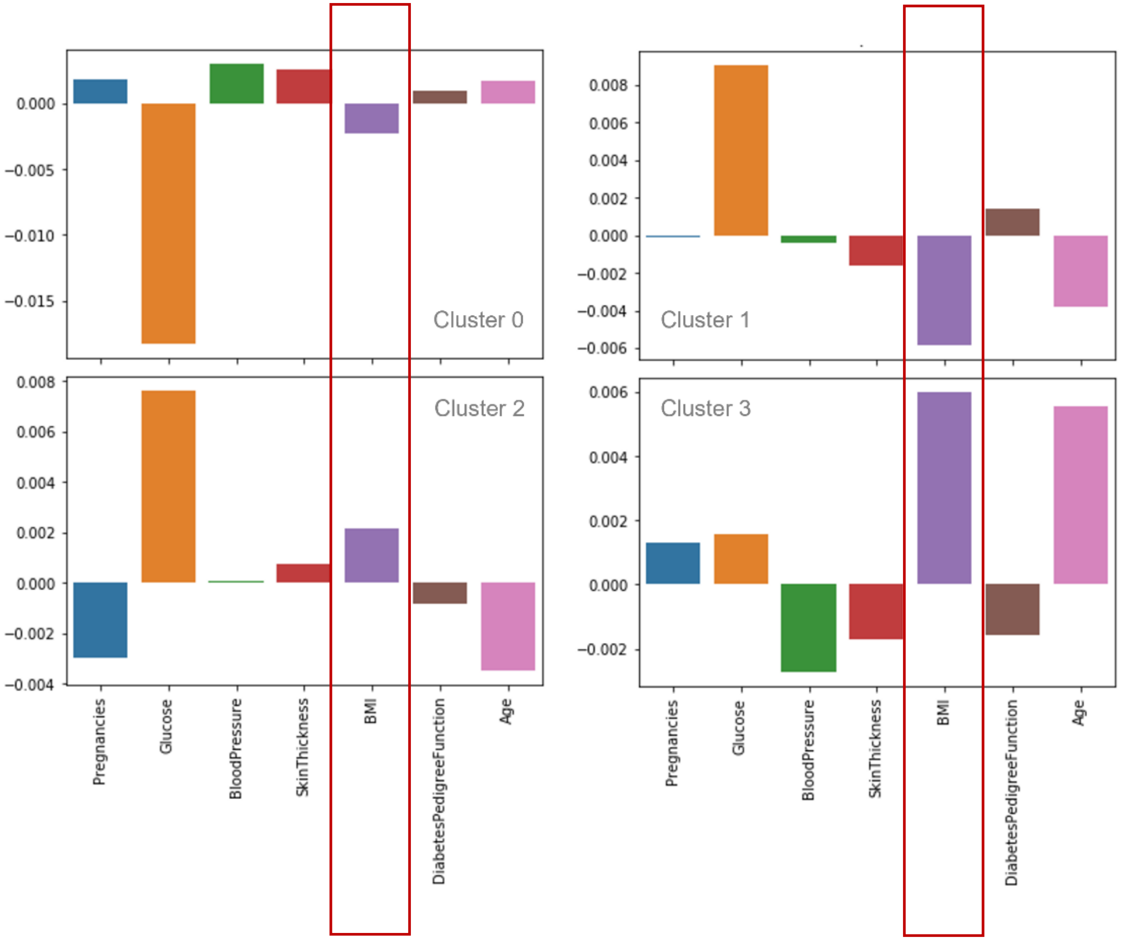
Explainability interpretation - BMI

- Negative sign is related to cluster with largest share of high BMI values
- The highest SHAP score is for cluster 3



Cluster	BMI	Glucose
0	**35,1**	**168,7**
1	34,9	121,7
2	30,7	121,9
3	*29,8*	*90,8*

Cluster	BMI_obese3	BMI_obese2	BMI_obese1	BMI_overweight
0	32	33	57	20
1	**34**	**53**	**58**	40
2	12	18	42	42
3	12	37	55	**64**



Conclusions

SHAP values have no explicit relationship with **input** data **values.**
Relation needs to be defined by context.

Incorporation of the **external knowledge** could be use as adittional set of **descriptive features** in context of the results evaluation

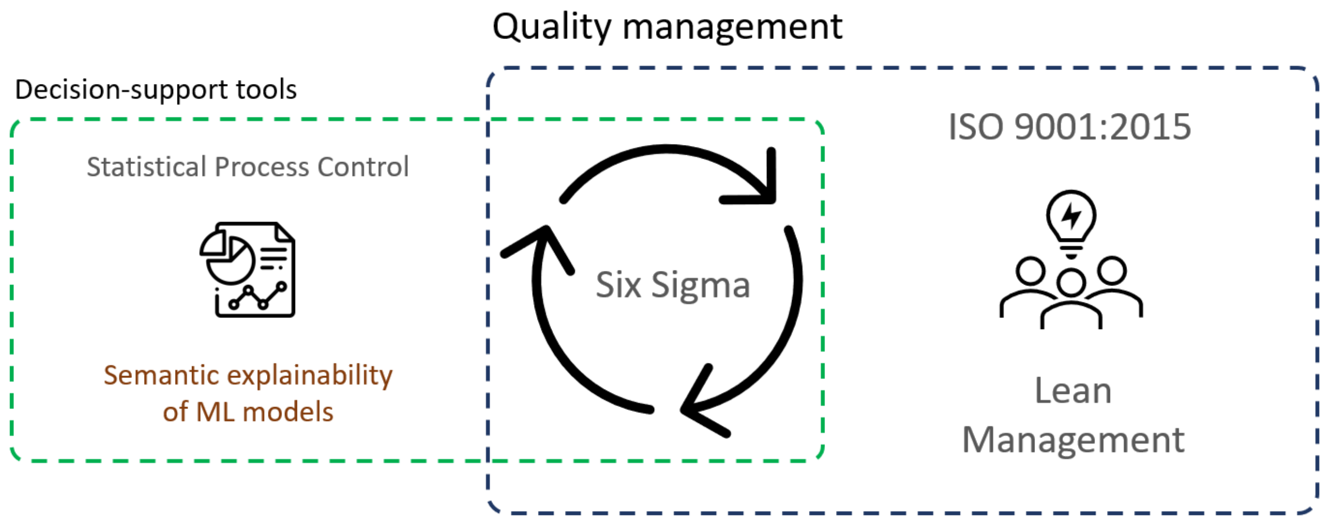
A way to extend the evaluation of **clusters** created via unsupervised learning is to analyze the **distributions of subgroups** within clusters.

„Smantic Data Mining based decision support for quality assessment in steel industry”

Maciej Szelążek, Szymon Bobek, Grzegorz J. Nalepa; Expert Systems 2022

Integration of machine learning approach with ruled-based quality management systems

Semantic compatibility with current support decision systems



ISO 9001:2015 norm

International standard that specifies the requirements for companies quality management systems

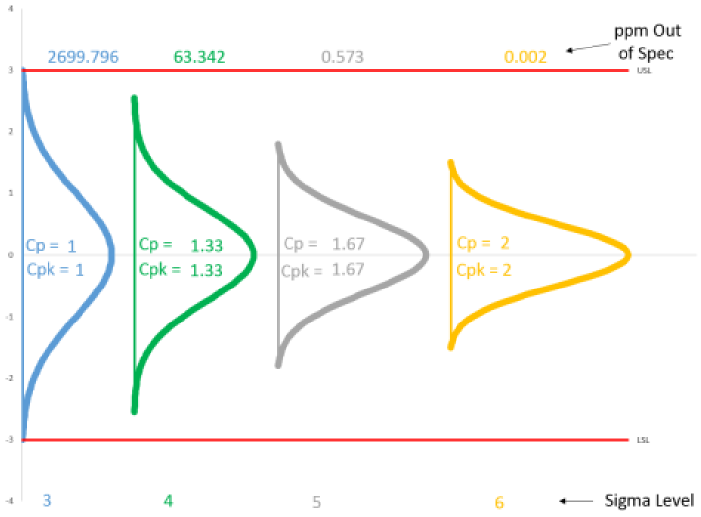
The most important conclusion:

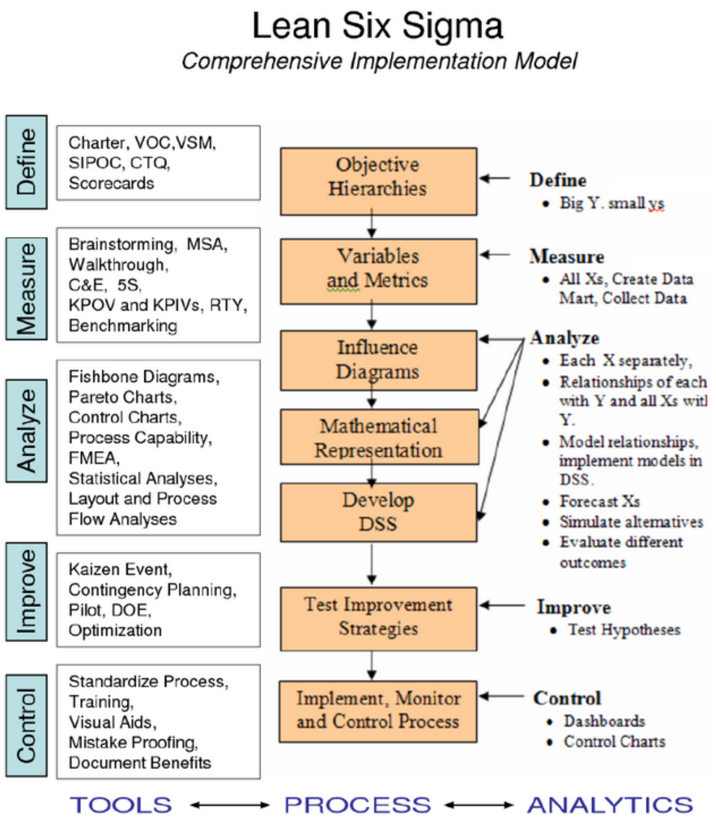
- Results will be used by different groups of specialists
- The most effective form is the simplest one

Six Sigma

Six Sigma – registered trademark of Motorola

Well-tested set of instruments and sophisticated techniques aimed at reducing the variability (tolerance) and defectiveness of a product and process.





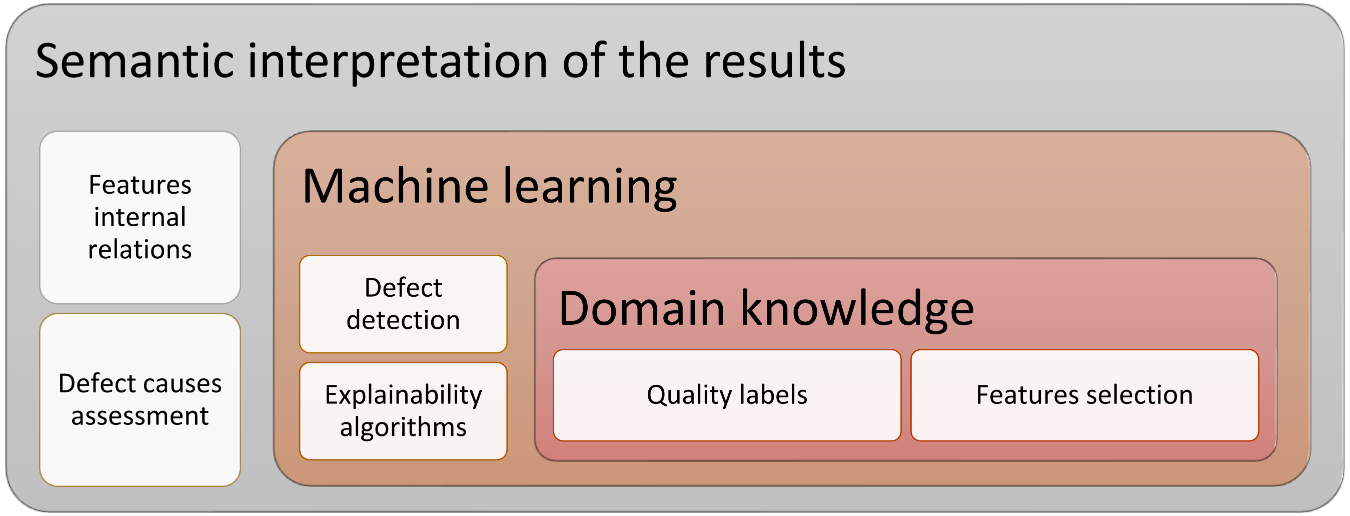
https://www.researchgate.net/publication/333648011_Quality_a_Key_Value_Driver_in_Value_Based_Management
https://lablean.blogspot.com/2015/03/dmaic-applied-to-biopmanufacturing.html

Semantic Data Mining – supervised learning

Data mining is the proces of uncover novel, interesting and understandable patterns related to valuable, useful, and implicit knowledge.

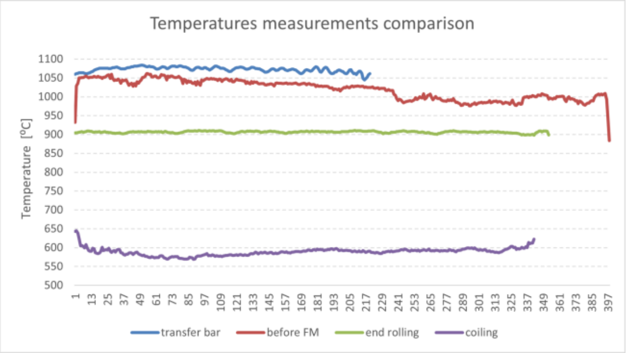
Semantic Data Mining is a knowledge-based analysis approach.

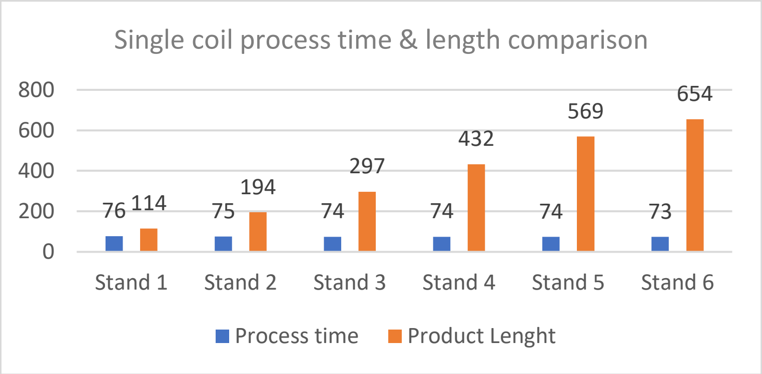
Focused on exploiting the formalized information in order to enhance interpretability of the applied data mining models

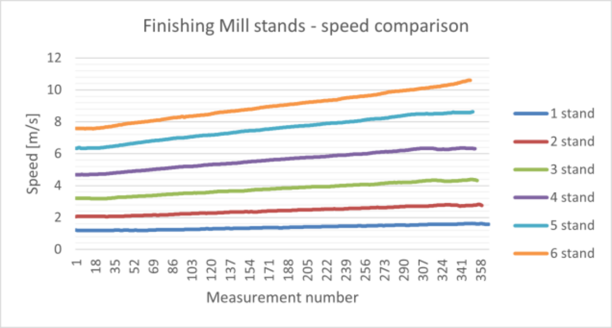


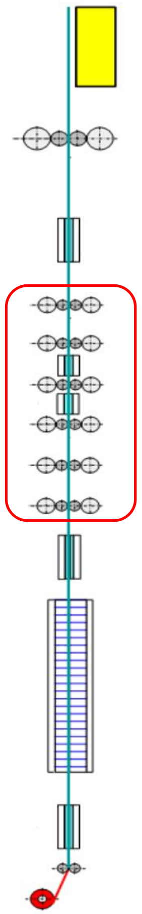
Hot Rolling process

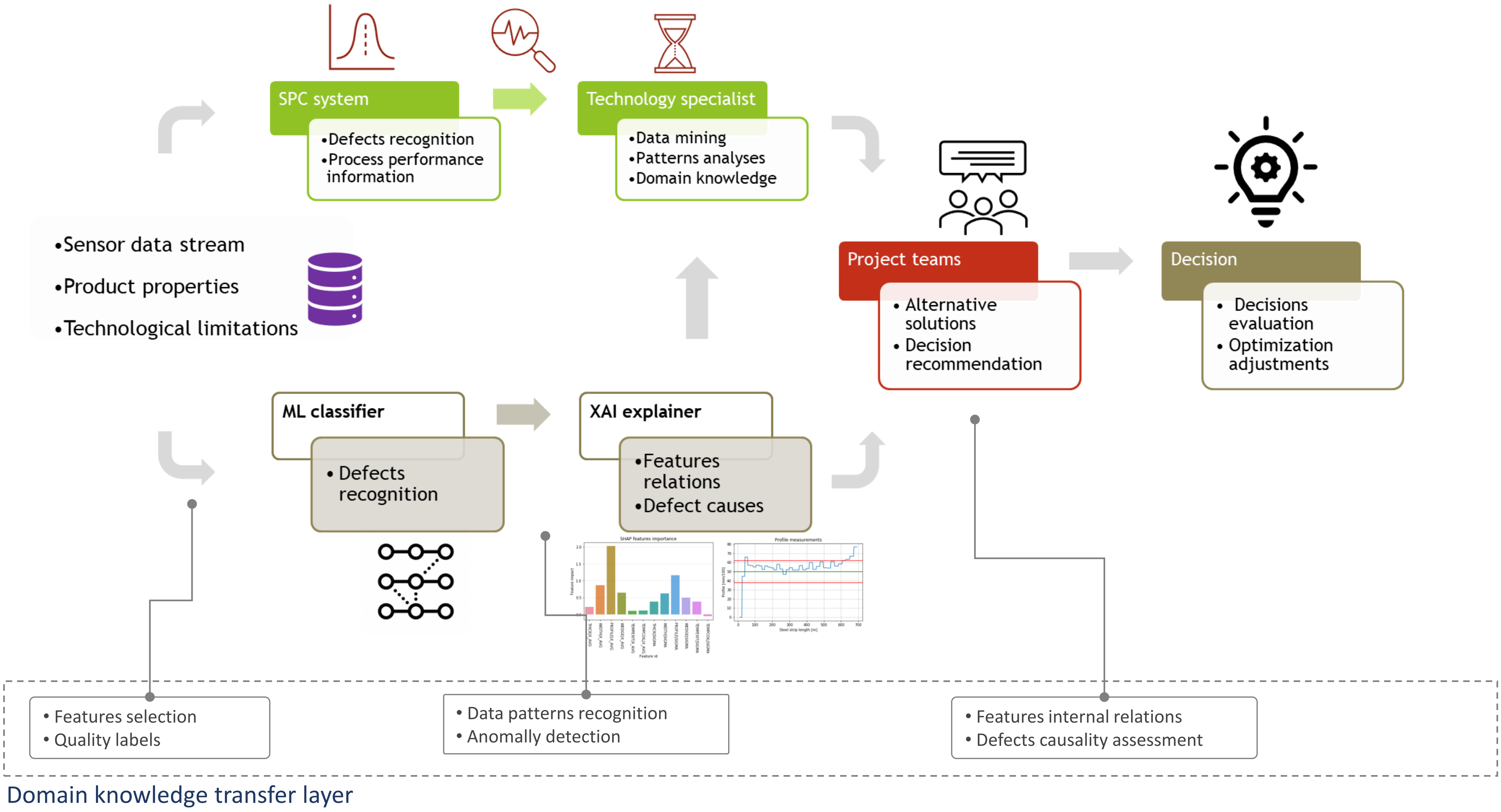
- 100 s of rolling
- Over 40 times thickness reduction
- 3.5 min whole process
- 4 mln tonnes/year production capability










SPC system
•Defects recognition
•Process performance information
Technology specialist
•Data mining
•Patterns analyses
•Domain knowledge
•Sensor data stream
•Product properties
•Technological limitations
Project teams
• Alternative solutions
• Decision recommendation
Decision
• Decisions evaluation
• Optimization adjustments
ML classifier
• Defects recognition
XAI explainer
•Features relations
•Defect causes
SHAP features importance
Profile measurements
• Features selection
• Quality labels
• Data patterns recognition
• Anomally detection
• Features internal relations
• Defects causality assessment
Domain knowledge transfer layer

Podsumowanie SDM

Compliance with existing standards in the company is an important prerequisite for the successful implementation of an analytical solution based on ML

The interpretation of the XAI results can be determined by the conditions that define the ML model procedure:

- Analysis of rules in the existing rule-based system => ML input data and labels
- As a result XAI values associated with 'rules' are complementary with original system

Use of model explainability as actionable Decision–Support for data series analysis

Maciej Szelążek, Szymon Bobek, Grzegorz J. Nalepa; ICCS 2024

Goal: Add context for interpretation of XAI results

- Contextualisation - Presentation of XAI in the context of quality indicators consistent with the current methodology of quality management in the organization
- Actionability
  - Automation of the procedure
  - Universal KPIs - The procedure allows for any dependent variable (quality metric), regardless of the input data
- Visualisation
  - Present the results in a way that can be understood by a diverse range of audiences

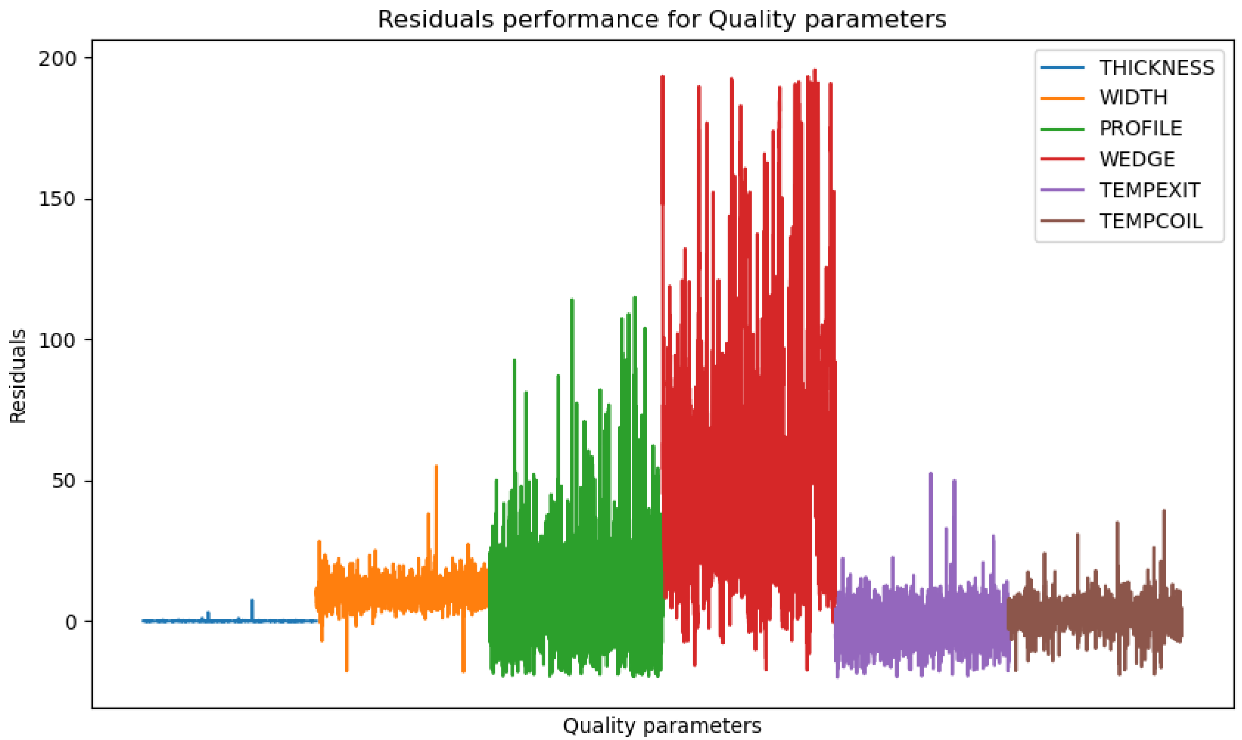
Data

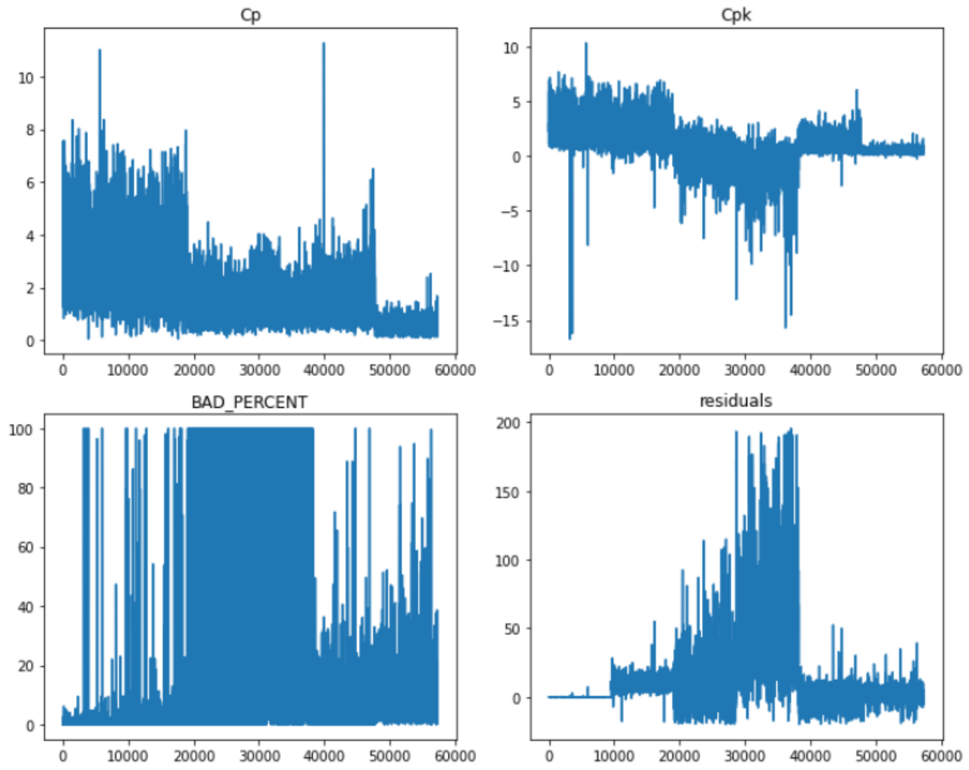
Process measurements:

- 6 features
- Time series (200-250 measurements)
- 10 000 products

Quality KPIs

- Capability factors
- Bad percent
- Residuals





KPIs - Capability factors

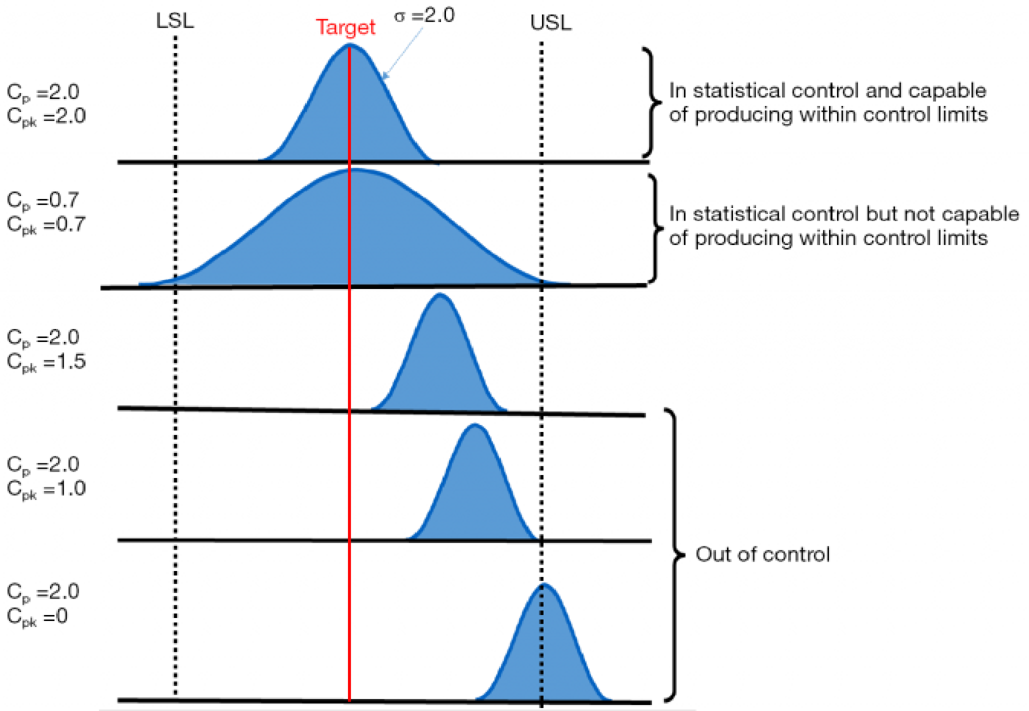
Process capability – Cp : tolerance width divided by the total spread of process (6 Sigma).

Cp	Defects amount
1	2700 ppm
1,33	63 ppm
1,67	0,57 ppm
2	0,002 ppm

Calculation of Process Capability (Cp) :

$$Cp = \frac{\text{Design Tolerance}}{6\sigma} = \frac{USL - LSL}{6\sigma}$$

USL = Upper Specification Limit, **LSL** = Lower Specification Limit



Process Capability Index – Cpk: indicates shifting of the process, the minimum of Cpk upper and Cpk lower.

Calculation of Process Capability Index (Cpk) :

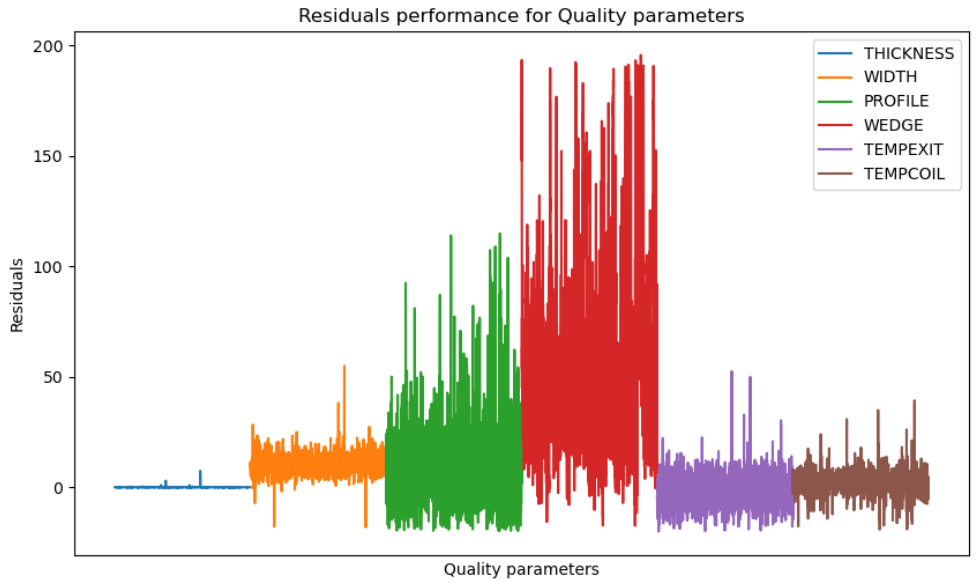
$$Cpk_U = \frac{USL - \bar{\bar{X}}}{3\sigma} \quad \text{and} \quad Cpk_L = \frac{\bar{\bar{X}} - LSL}{3\sigma}$$

https://www.doriane-copar.com/process-capability-index-cpk/

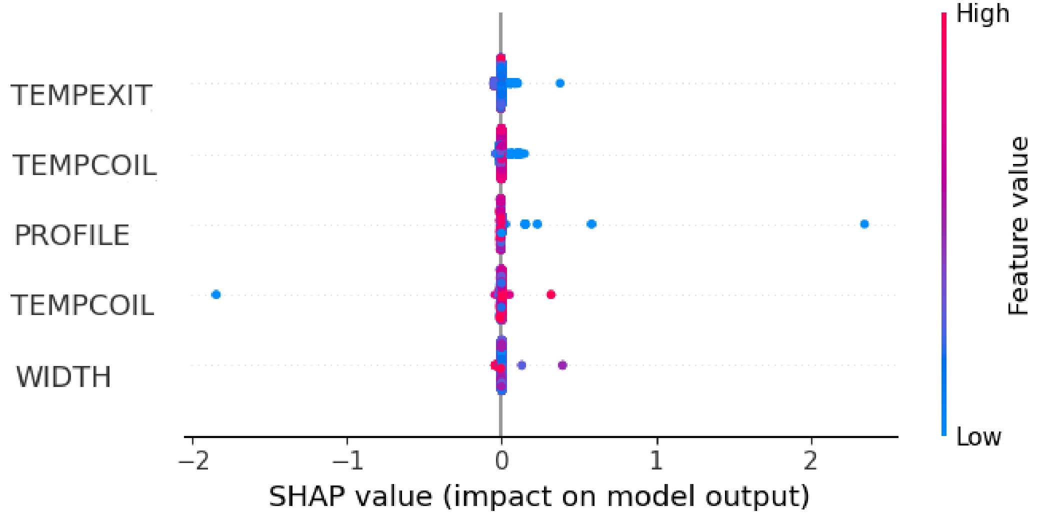
https://techqualitypedia.com/cp-and-cpk/

Issue – how to interpret XAI results

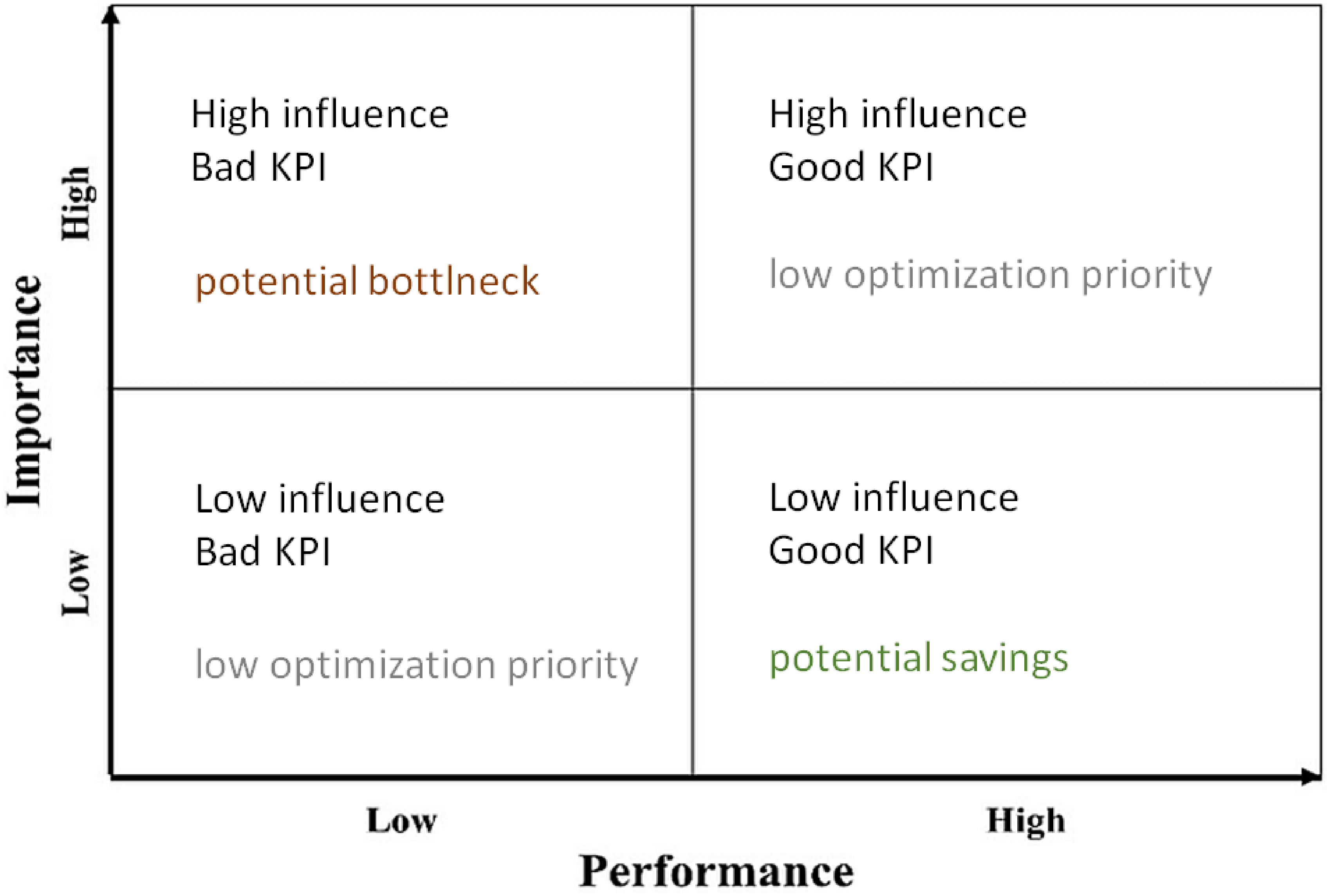
Lots of information based on analysis of KPI residuals:
- Different levels of overruns – amplitude
- Trends above and below target – density
- Cases significantly different from natural variability - outliers



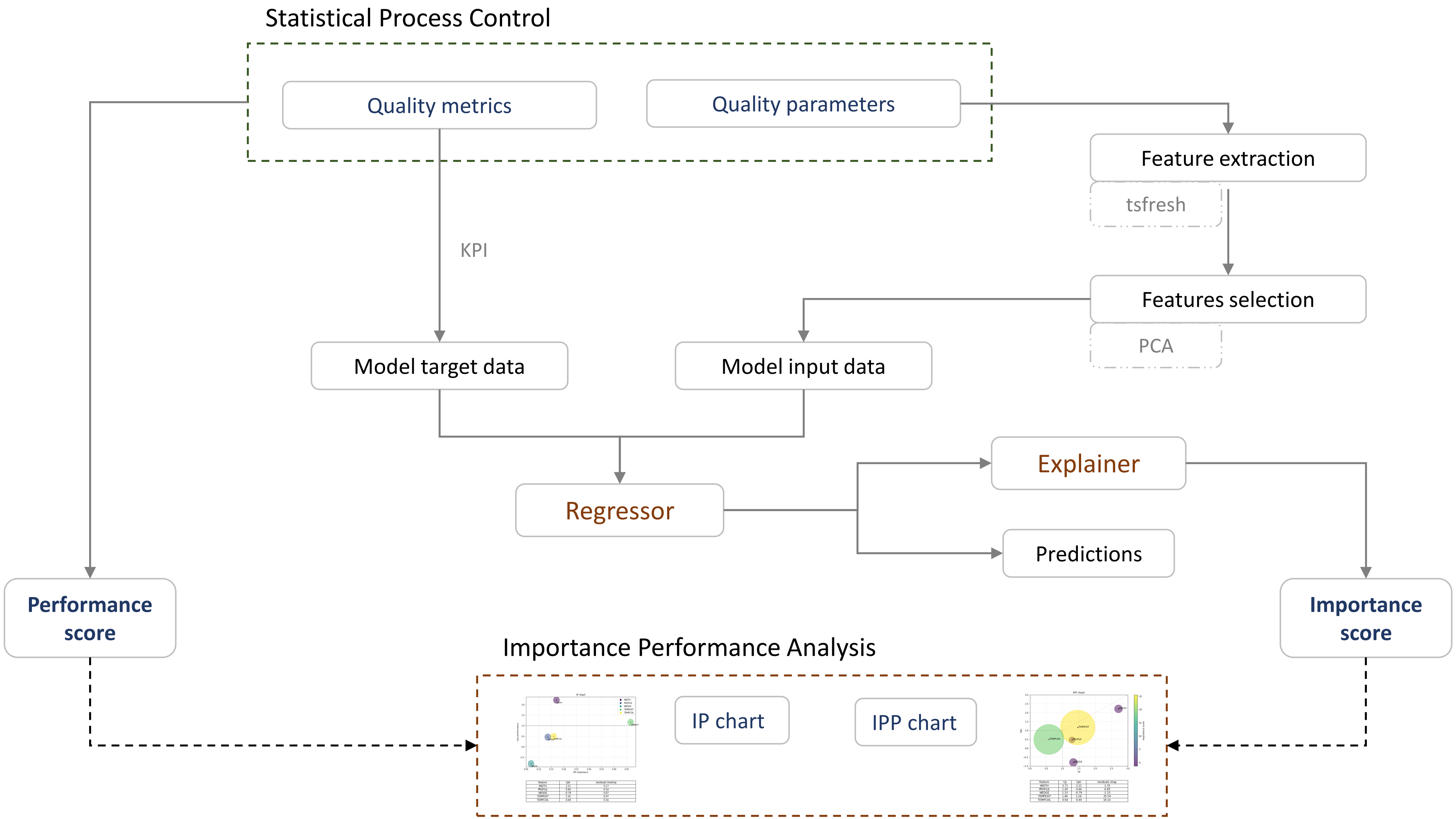
SHAP
- Similar XAI values for extremely different feature values
- No clear relationships between XAI values for different features



Importance Performance Analysis



Workflow


Statistical Process Control
Quality metrics
Quality parameters
Feature extraction
tsfresh
KPI
Features selection
PCA
Model target data
Model input data
Explainer
Regressor
Predictions
Performance score
Importance score
Importance Performance Analysis
IP chart
IPP chart

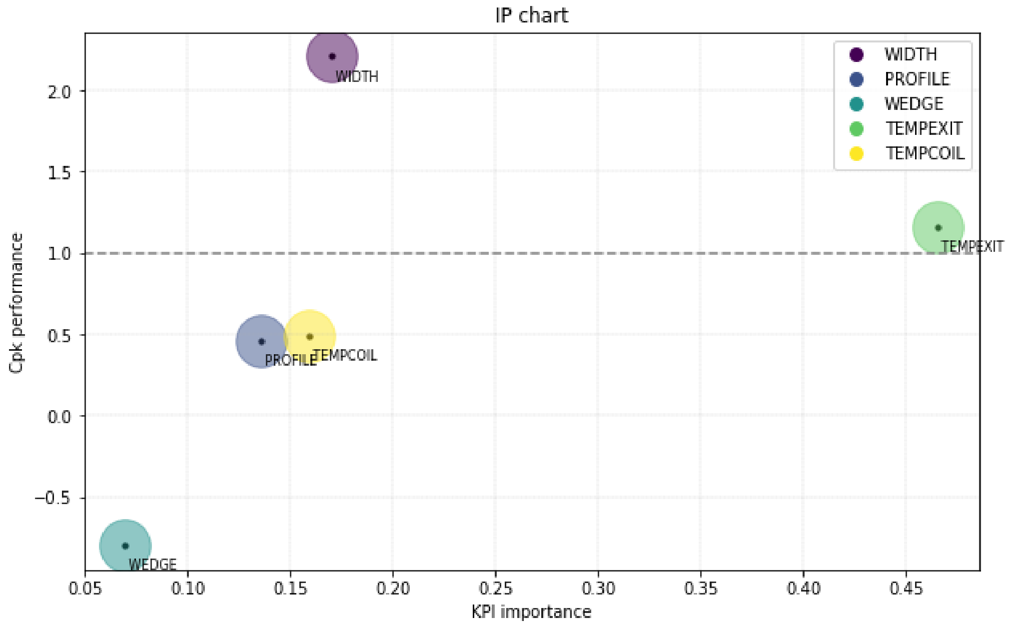
Results - IP chart

Contextualisation

Actionability

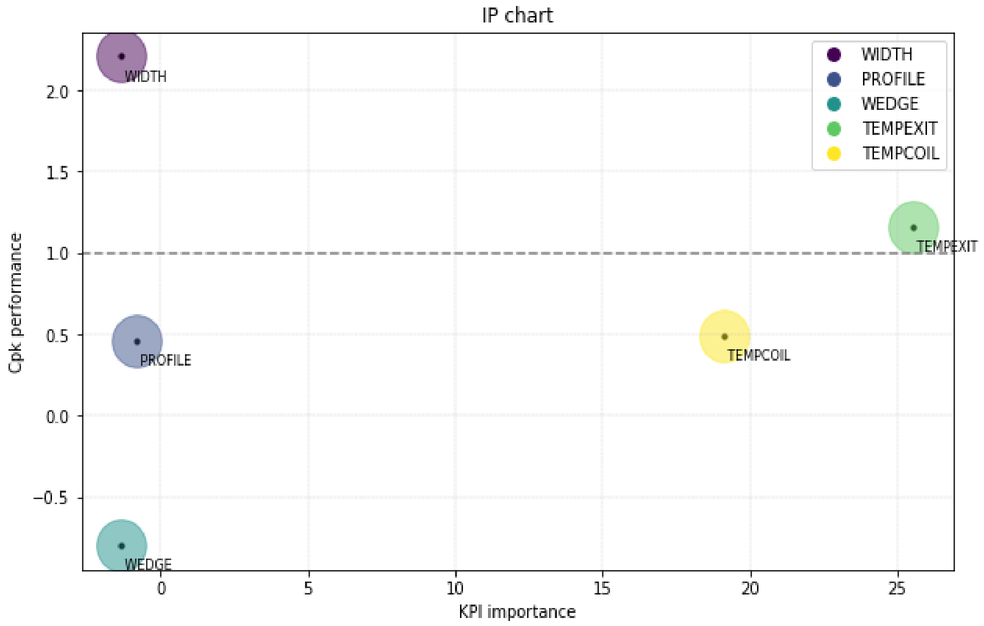
Visualisation

Tree Importance score



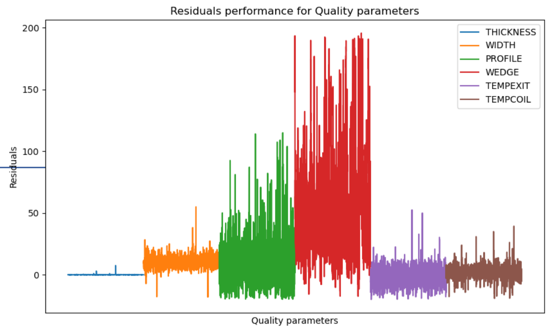
Feature	Cpk	residuals treeImp
WIDTH	2.21	0.17
PROFILE	0.46	0.14
WEDGE	-0.79	0.07
TEMPEXIT	1.16	0.47
TEMPCOIL	0.49	0.16

SHAP



Feature	Cpk	residuals shap
WIDTH	2.21	-1.35
PROFILE	0.46	-0.83
WEDGE	-0.79	-1.33
TEMPEXIT	1.16	25.54
TEMPCOIL	0.49	19.10

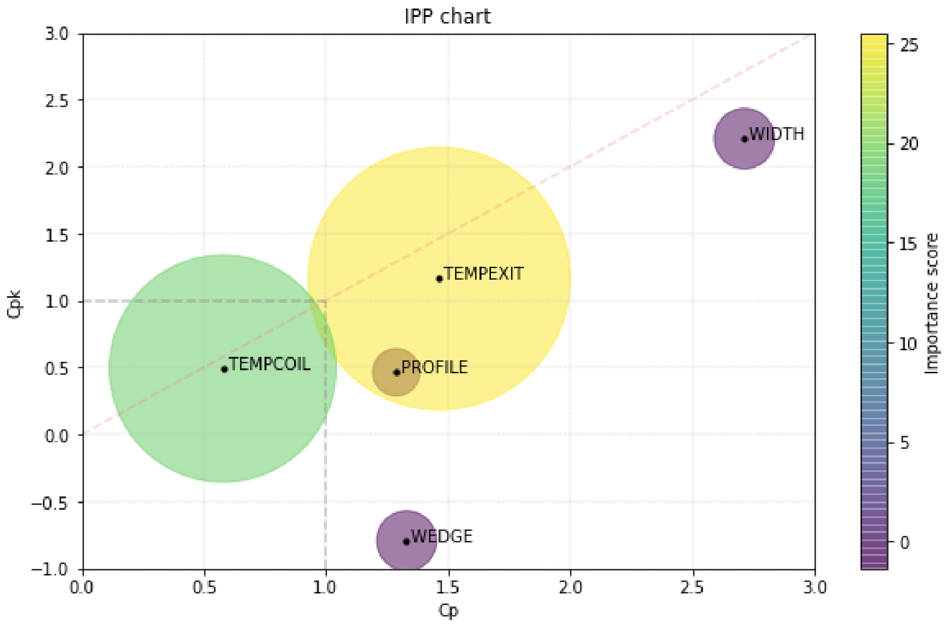
Results - IPP chart



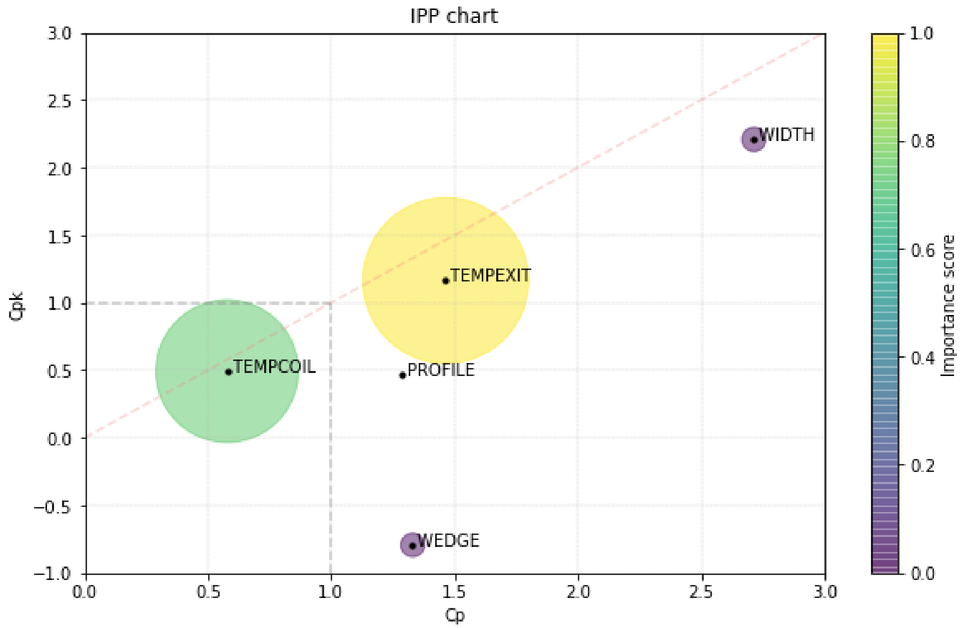
The closer to the **red line** the more centered the process

The further outside the gray lines the narrower distribution (Capability Index).

The table shows the sign of the XAI score, and the precise scale of differences between the features importances.



Feature	Cp	Cpk	residuals shap
WIDTH	2.71	2.21	-1.35
PROFILE	1.29	0.46	-0.83
WEDGE	1.33	-0.79	-1.33
TEMPEXIT	1.46	1.16	25.54
TEMPCOIL	0.58	0.49	19.10



Feature	Cp	Cpk	residuals shap
WIDTH	2.71	2.21	0.02
PROFILE	1.29	0.46	0.00
WEDGE	1.33	-0.79	0.02
TEMPEXIT	1.46	1.16	1.00
TEMPCOIL	0.58	0.49	0.74

Final conclusions

Incorporation of domain knowledge into BI analysis:

- Additional set of rules
- Compliance with company standards
- Extension of existing standards, maintaining compatibility with previous solutions

Incorporation of Explainability scores into BI analysis:

- **SHAP values** have no explicit relationship with **input** data **values.**
  - Use of explainability algorithms as part of data-mining analysis requires relating results to input data
- The interpretation of the XAI results can be determined by the conditions that define the ML model procedure

Published papers

lp	Title	Authors	Conference / Journal	Date
1	Enhanced Explanations for Knowledge-Augmented Clustering using Subgroup Discovery	Maciej Szelążek, Daniel Hudson, Szymon Bobek, Grzegorz J. Nalepa and Martin Atzmueller	DSAA 2023	2023.10
2	Improving understandability of explanations with a usage of expert knowledge.	Maciej Szelążek, Szymon Bobek, Grzegorz J. Nalepa	SEDAMI @ ECAI 2023	2023.10
3	Poster: Application of knowledge transfer to ML–based Quality Decision Support practice in the steel manufacturing process.	Maciej Szelążek, Szymon Bobek, Grzegorz J. Nalepa	CHItaly 2023	2023.09
4	Visual patterns in an interactive app for analysis based on control charts and SHAP values	Iwona Grabska-Gradzińska, Maciej Szelążek, Szymon Bobek and Grzegorz J. Nalepa	SEDAMI @ ECAI 2023	2023.09
5	Why Industry 5.0 Needs XAI 2.0?	Szymon Bobek, Sławomir Nowaczyk, Joao Gama, Sepideh Pashami, Rita P. Ribeiro, Zahra Taghiyarrenani, Bruno Veloso, Lala Rajaoarisoa, Maciej Szelążek, and Grzegorz J. Nalepa	xAI 2023	2023.07
6	Improving understandability of explanations with a usage of expert knowledge.	Maciej Szelążek, Szymon Bobek, Grzegorz J. Nalepa	PP-RAI 2023	2023.04
7	BIRAFFE2, a multimodal dataset for emotion-based personalization in rich affective game environments.	Krzysztof Kutt, Dominika Drążyk, Laura Żuchowska, Maciej Szelążek, Szymon Bobek & Grzegorz J. Nalepa	Scientific Data	2022.06
8	Semantic Data Mining Based Decision Support for Quality Assessment in Steel Industry	Maciej Szelążek, Szymon Bobek, Grzegorz J. Nalepa	Expert Systems	2022.05
9	Enhancing cluster analysis with explainable AI and multidimensional cluster prototypes	Szymon Bobek, Michał Kuk, Maciej Szelążek, Grzegorz J. Nalepa	IEEE Access	2022.01
10	The BIRAFFE2 Experiment. Study in Bio-Reactions and Faces for Emotion-based Personalization for AI Systems	Krzysztof Kutt, Dominika Drążyk, Maciej Szelążek, Szymon Bobek, Grzegorz J. Nalepa	Human-AI Interaction Workshop @ ECAI 2020	2020.11
11	Towards the modeling of the hot rolling industrial process : preliminary results	Maciej Szelążek, Szymon Bobek, Antonio Gonzalez-Pardo & Grzegorz J. Nalepa	IDEAL 2020	2020.10
12	Explaining machine learning models of emotion using the BIRAFFE dataset	Szymon Bobek, Magdalena M. Tragarz, Maciej Szelążek, Grzegorz J. Nalepa	ICAISC 2020	2020.10

Thank you for your attention