Artificial Intelligence in Industry 4.0: Data, Models, and Knowledge

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GEIST research group

http://GEIST.re

JAGIELLONIAN UNIVERSITY
IN KRAKÓW

AIRA seminar (online)
2021.12.02

GEIST research group 2017-currently (est. 2009)

Cooperation within projects and researchers from international universities in areas of:

- Semantic knowledge engineering
- Knowledge graphs
- Context-aware systems
- Data mining
- Ambient intelligence
- Sensor data analysis
- Affective computing
- Industrial AI
- Explainable AI (XAI)
- AI and Law
- Semantic data mining

Research staff mobility and position “upgrade”.
In 2020 we moved from AGH to Jagiellonian!

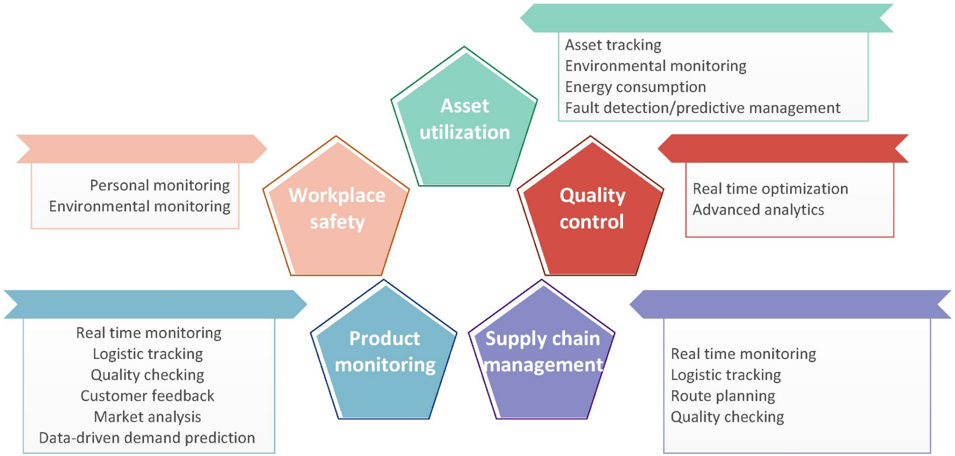
Industry 4.0: ideas & opportunities - Smart Factory

Fourth Industrial Revolution introduced through the World Economic Forum in 2015.

Themes, concepts: Interconnection, Information transparency, Technical assistance, Decentralized decisions.

Technologies: Mobile computing, cloud computing, 5G, big data, IoT, CyberPhSys.

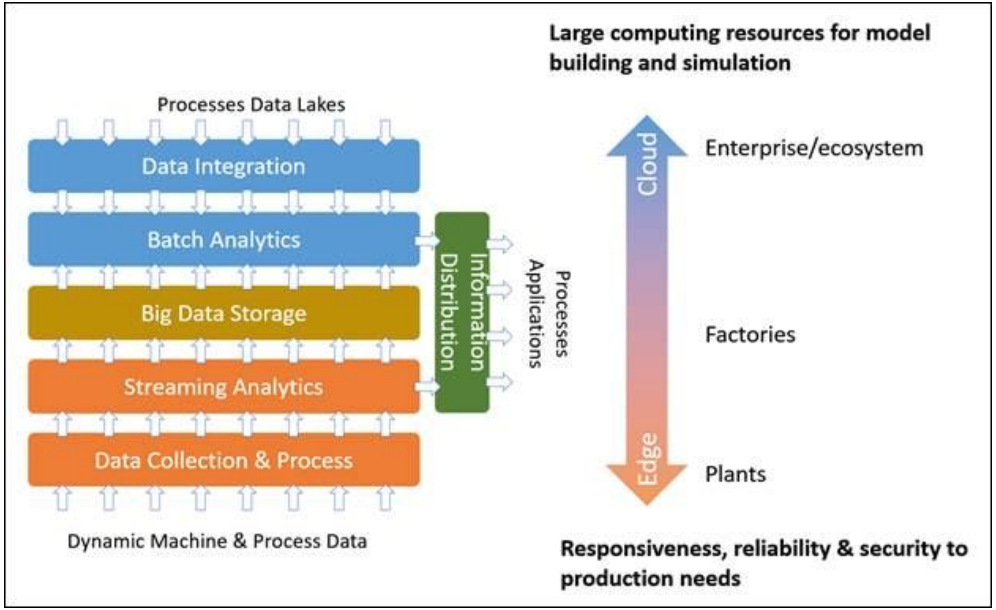
Yang Lu, Industry 4.0: A survey on technologies, applications and open research issues, Journal of Industrial Information Integration, Volume 6, 2017, Pages 1-10 https://doi.org/10.1016/j.jii.2017.04.005



Application domains of I40 *after: Pilloni, V. How Data Will Transform Industrial Processes: Crowdsensing, Crowdsourcing and Big Data as Pillars of Industry 4.0. Future Internet 2018, 10, 24. https://doi.org/10.3390/fi10030024*

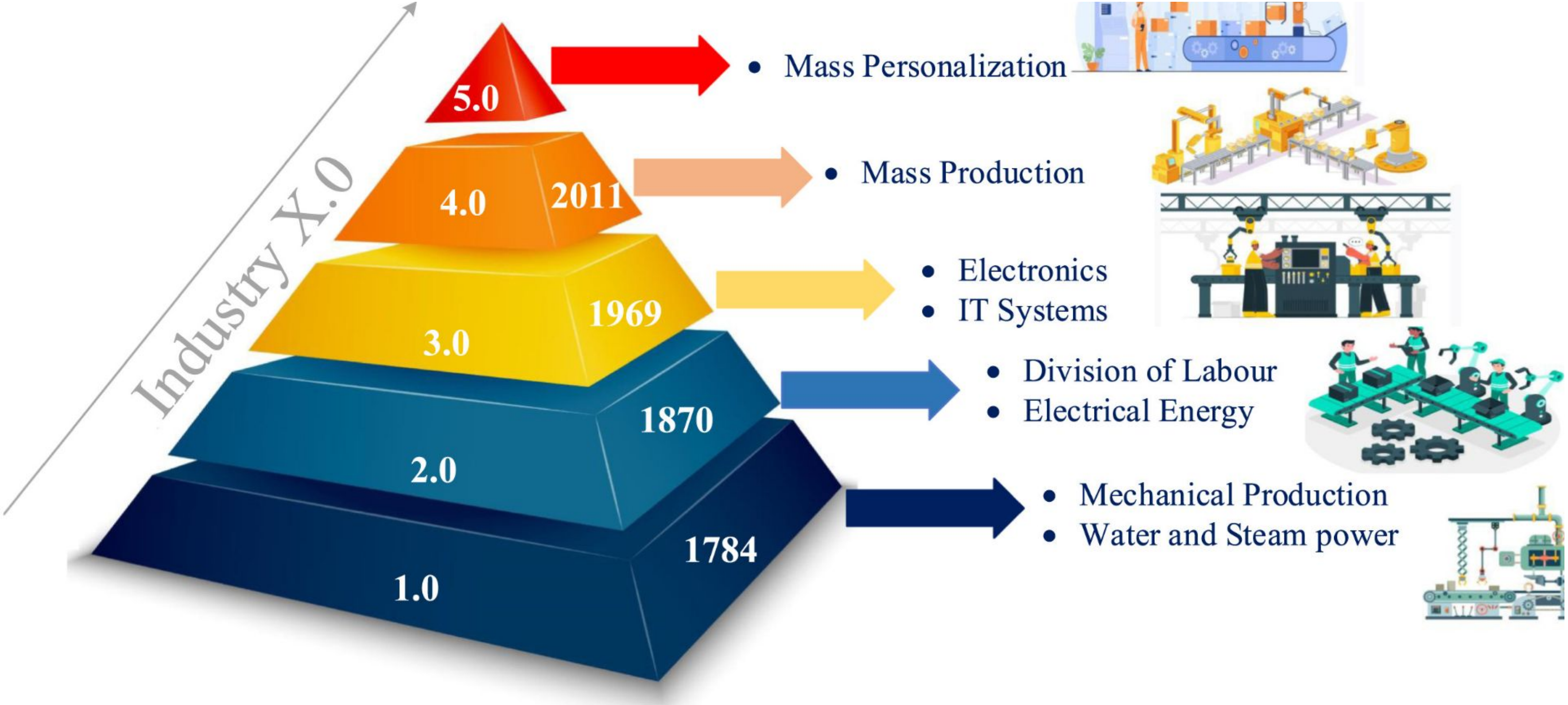
Industry 4.0: big data challenges

- I40 poses important BD challenges on a especially large scale.
- Many industrial installations are in fact being transformed into smart factories, thus incremental integration is especially difficult.
- Artificial Intelligence solutions for data analysis, integration and interpretation are gaining rapid adoption.
- Most recently XAI solutions are used due to safety and trustworthiness.
- Proper use of industrial domain knowledge remains a challenge.



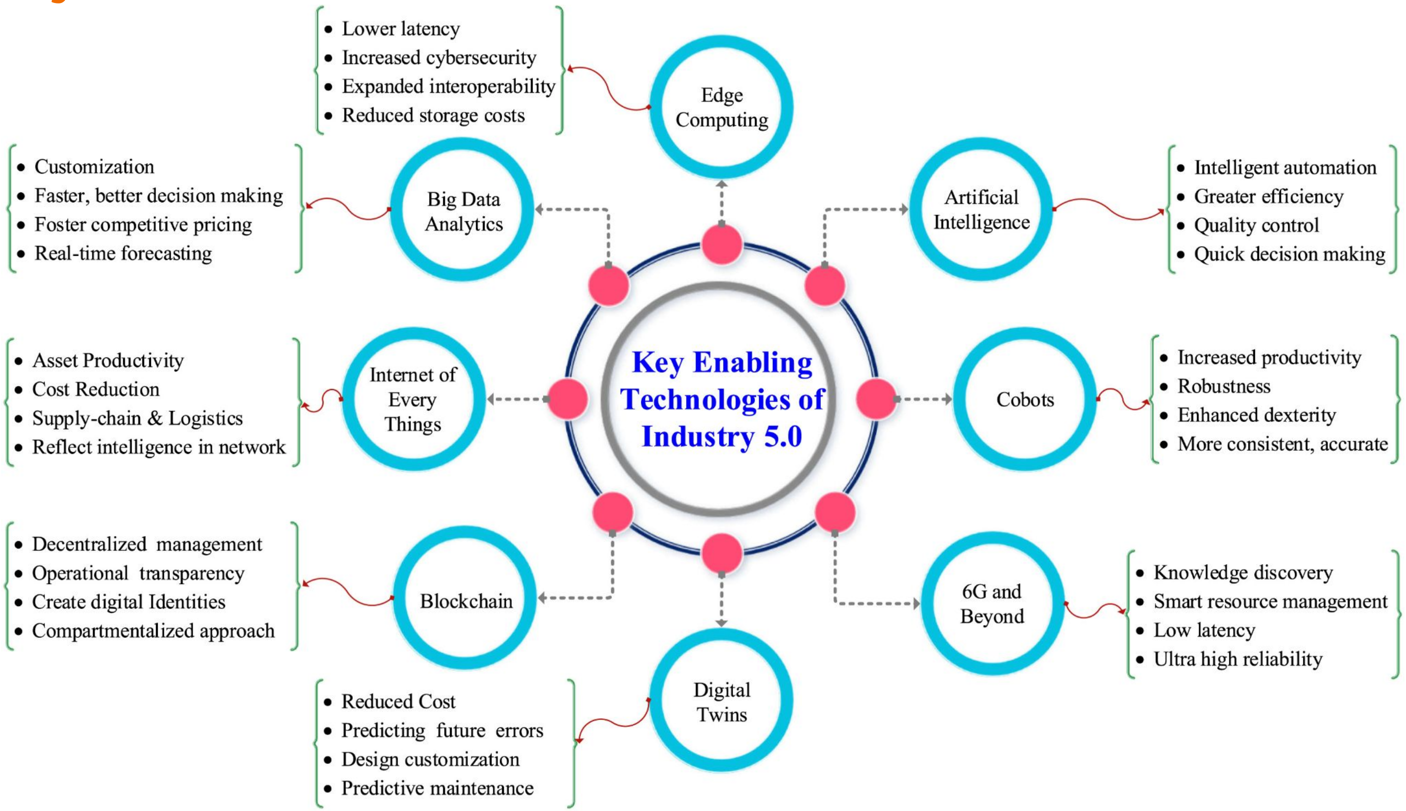
Shi-Wah Lin, IIoT for Smart Manufacturing part 3 – A New Digitalization Architecture, October 16, 2017, https://industrial-iot.com/2017/10/iiot-smart-manufacturing-part-3-new-digitalization-architecture

Industry X.0



Praveen Kumar (et al.) Industry 5.0: A survey on enabling technologies and potential applications, Journal of Industrial Information Integration, 2021, 100257

Industry 5.0



Praveen Kumar (et al.) Industry 5.0: A survey on enabling technologies and potential applications, Journal of Industrial Information Integration, 2021, 100257

GEIST involvement in I4.0 via CHIST-ERA calls

2019 Call XAI: Explainable Machine Learning-based Artificial Intelligence:

- Novel, ambitious and reliable technologies for explainable machine learning-based AI;
- AI systems with integrated explanations in a variety of application areas;
- Frameworks for integrating explainability into AI (Explainability by Design);
- Methods for putting explainability into current AI systems;
- Use cases in specific application areas.

2017 Call BDSI: Big Data and Process Modelling for Smart Industry:

- Large-scale, complex systems in dynamic environments;
- Designing conceptual models for autonomous or semi-autonomous decision support;
- Intelligent fusion of multiple data streams;
- Integration of heterogeneous, structured and unstructured data;
- Combining a priori knowledge and models with empirically derived data.

PACMEL from: CHIST-ERA CALL 2017 BDSI

Big Data and Process Modelling for Smart Industry

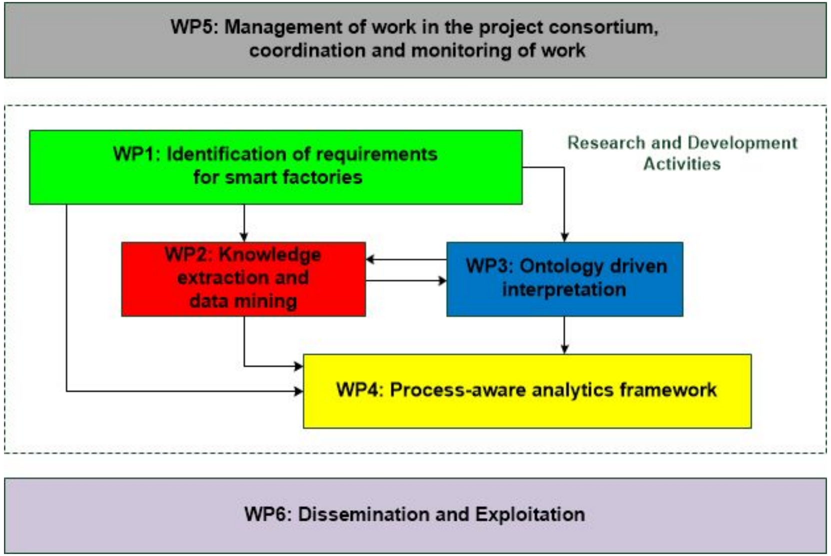
- Large-scale, complex systems in dynamic environments;
- Designing conceptual models for autonomous or semi-autonomous decision support;
- Intelligent fusion of multiple data streams;
- Integration of heterogeneous, structured and unstructured data;
- Combining a priori knowledge and models with empirically derived data;

PACMEL

Process-aware Analytics Support based on Conceptual Models for Event Logs

PACMEL consortium and structure

1. Poland: AGH University of Science and Technology, G. J. Nalepa, E. Brzychczy
2. Italy: Free University of Bozen-Bolzano, Diego Calvanese
3. Spain: Universidad Autónoma de Madrid, David Camacho



Project Impacts: scientific and industrial

1. Method for the use of *hidden knowledge about processes from sensor data*, which cannot be extracted without appropriate analytic tools

2. Extensions of *industrial analytics methods based on sensor data*, (process-oriented)

3. Support for analysis of complex processes, enabling process improvement in the BPM cycle or process redesign during re-engineering

4. Improved monitoring of the process execution and decision-making flow.

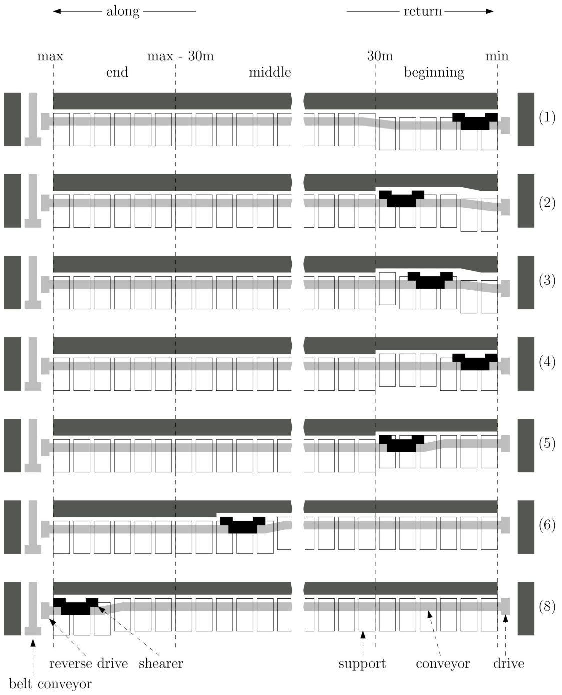
1. In depth analysis of process performance at various abstraction levels of event logs.

2. Wider acceptance of process mining toolkits and process exploratory analysis for industrial event logs created based on various abstraction level of sensor data

3. Strengthening of cooperation between academia and selected specific industrial partners who expressed their interest in the exploitation of projects results

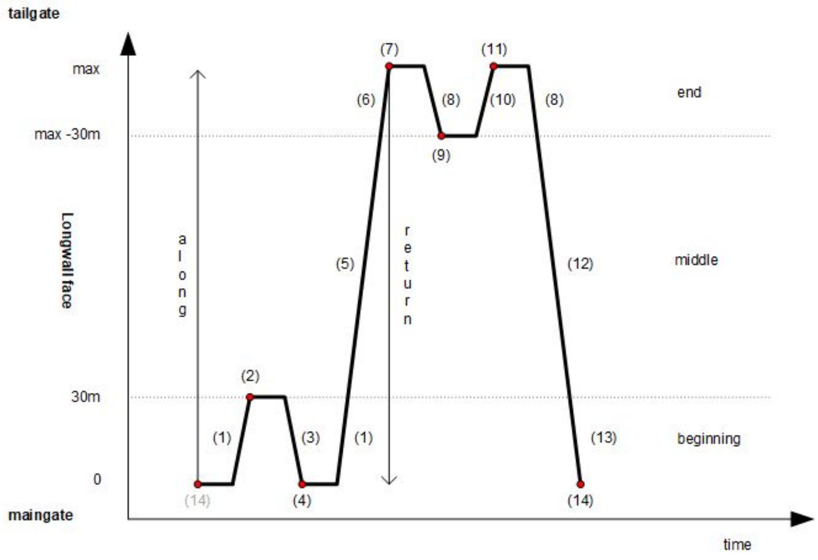
Underground mine use case

- Data was delivered by project partner the Famur S.A. company
- Coal sheerer moves along longwall excavating coal
- About 300 different measurements every second
- Expert rules for extracting basic machinery states

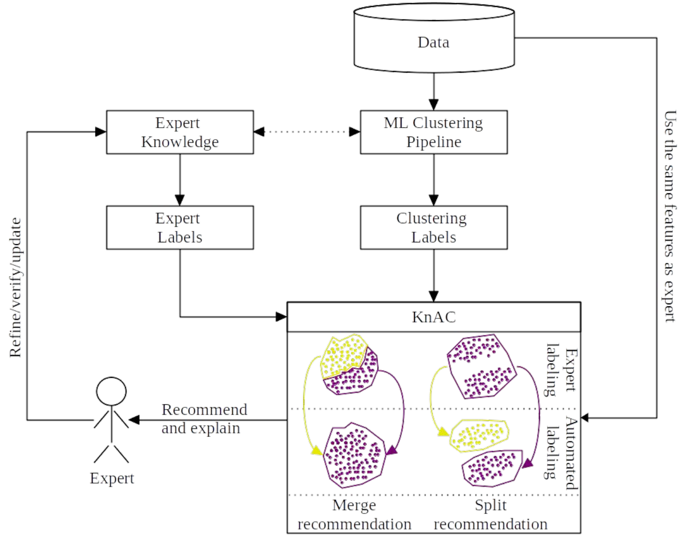


Underground mine use case

- Coal sheerer moves along longwall excavating coal
- About 300 different measurements every second
- Expert rules for extracting basic machinery states
- We would like to have a mechanism that assist experts in verifying their labelling



Framework for expert knowledge extension (KnAC)

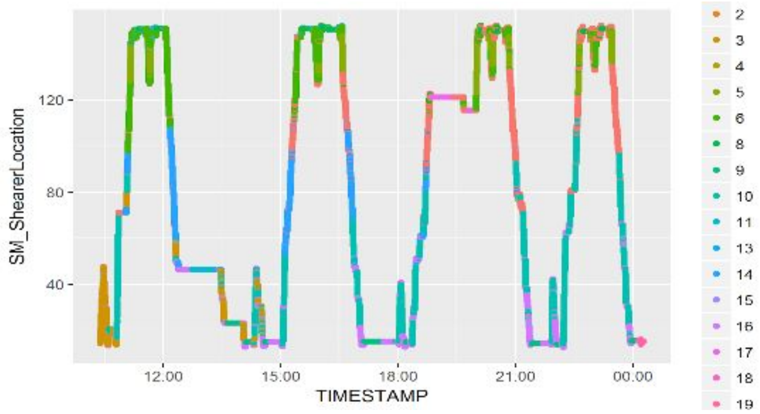


- Clustering pipeline embedded with split/merge recommendations
- No limits on the clustering methods used
- Clustering transformed to classification task (cluster label as target)
- Recommend split/merge
- Explain why clusters should be merged/split

S. Bobek, A. Trzcionkowska, E. Brzychczy, G. J. Nalepa, *Cluster Discovery from Sensor Data Incorporating Expert Knowledge*, Workshop of Knowledge Representation & Representation Learning, ECAI 2020 in Santiago de Compostela, June 2020

Automated state discovery

- We added artificial features to capture temporal character of the process
- Dimensionality reduction with PCA (we reduced dimensions from 170 to 10)
- Clustering with K-means (19 clusters discovered)
- Best clustering was selected based on silhouette score and homogeneity, completeness wrt. expert labels



Expert labels vs. Clustering labels

Expert labels vs. Discovered clusters	1	2	3	4	5	6	8	9	10	11	13	14	15	16	17	18	19
Cutting_into_tailgate_along	0	0	262	0	0	0	0	0	708	0	0	0	17	306	0	33	5
Return_to_maingate_along	0	5	371	0	0	0	0	0	354	0	0	0	23	614	0	35	6
Cutting_middle_along	437	0	43	2	0	69	0	0	769	0	0	670	9	51	0	0	0
Cutting_into_tailgate_end_along	241	0	0	3	210	429	0	0	5	0	3	0	0	0	0	0	0
Cutting_into_maingate_return	1210	0	0	0	274	1374	0	0	0	0	92	0	0	0	0	0	0
Return_to_tailgate_return	446	0	0	1	113	1426	0	0	0	0	85	0	0	0	0	0	0
Cutting_middle_return	759	0	74	0	0	43	0	0	735	0	0	745	14	107	0	0	0
Cutting_into_maingate_beginning_return	0	0	214	0	0	0	0	0	358	0	0	0	1	459	0	0	0
Moving	152	0	0	0	0	91	0	0	0	0	29	0	0	3	0	0	0
Reversion_along	81	1	74	0	8	16	0	0	44	0	0	32	25	48	0	0	0
Reversion_return	73	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0
Stoppage_in_ON_mode_beginning_along	0	278	46	0	0	0	0	6403	21	0	0	0	7	4292	0	3	473
Stoppage_in_ON_mode_beginning_return	0	0	0	0	0	0	0	1458	0	0	0	0	0	820	0	0	0
Stoppage_in_ON_mode_end_along	1364	0	3	0	6	3	0	0	0	0	17	0	0	2	2923	0	0
Stoppage_in_ON_mode_end_return	2224	0	0	0	55	265	5628	0	1	0	956	0	0	0	0	0	0
Stoppage_in_ON_mode_middle_along	1470	25	1	0	1	0	0	0	6	0	0	1	0	937	0	0	0
Stoppage_in_ON_mode_middle_return	883	0	0	0	0	0	0	0	4	2465	0	1	0	2066	0	0	0

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

Results - merges

Expert labels vs. Discovered clusters	1	2	3	4	5	6	8	9	10	11	13	14	15	16	17	18	19
Cutting_into_tailgate_along	0	0	262	0	0	0	0	0	708	0	0	0	17	306	0	33	5
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Stoppage_in_ON_mode_middle_along	1470	25	1	0	1	0	0	0	6	0	0	1	0	937	0	0	0
Stoppage_in_ON_mode_middle_return	883	0	0	0	0	0	0	0	4	2465	0	1	0	2066	0	0	0

```
Return_to_maingate_along
    MERGE WITH Cutting_into_maingate_beginning_return (0.97)
Return_to_tailgate_return
    MERGE WITH Cutting_into_maingate_return (0.85)
```

Results - splits

Expert labels vs. Discovered clusters	1	2	3	4	5	6	8	9	10	11	13	14	15	16	17	18	19
Cutting_into_tailgate_along	0	0	262	0	0	0	0	0	708	0	0	0	17	306	0	33	5
Return_to_maingate_along	0	5	271	0	0	0	0	0	354	0	0	0	22	614	0	35	6
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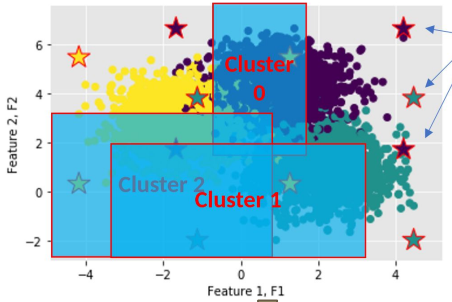
Stoppage_in_ON_mode_middle_along	1470	25	1	0	1	0	0	0	6	0	0	1	0	937	0	0	0
Stoppage_in_ON_mode_middle_return	883	0	0	0	0	0	0	0	4	2465	0	1	0	2066	0	0	0

```
Cutting_middle_along SPLIT TO [(10, 14), 0.38]
Cutting_into_maingate_return SPLIT TO [(1, 6), 0.42]
Cutting_into_maingate_beginning_return SPLIT TO [(10, 16), 0.40]
Moving SPLIT TO [(1, 6), 0.41]
Stoppage_in_ON_mode_middle_along SPLIT TO [(1, 16), 0.49]
```

Recent results: Explainable clustering with multidimensional bounding boxes



Bounding box

Use bounding boxes to generate rules

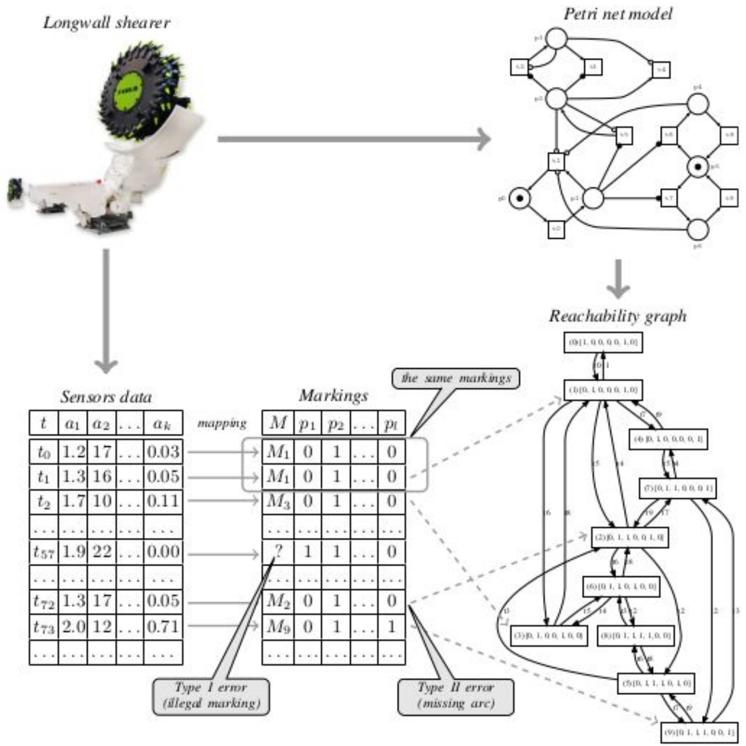
Rule no.	Rule	Cluster	Certainty
1	F1 > 0.68 and F2 > 2.99	0	0.48
2	0.68 < F1 ≤ 1.77 and F2 > 1.64	0	0.64
3	-1.14 < F1 ≤ 1.77 and F2 > 1.64	0	0.54
4	F1 > 0.68 and F2 ≤ 2.99	1	0.44
5	F1 > -1.14 and F2 ≤ 1.64	1	0.68
6	F1 ≤ -1.14	2	0.25
7	F1 ≤ 0.68 and F2 ≤ 2.99	2	0.43

- The explanations are represented as HEARTDROID rules
- They are executable and can be integrated with additional rule-based knowledge
- Uncertainty of an explanation can be computes in terms of coverage and precision of rules

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.

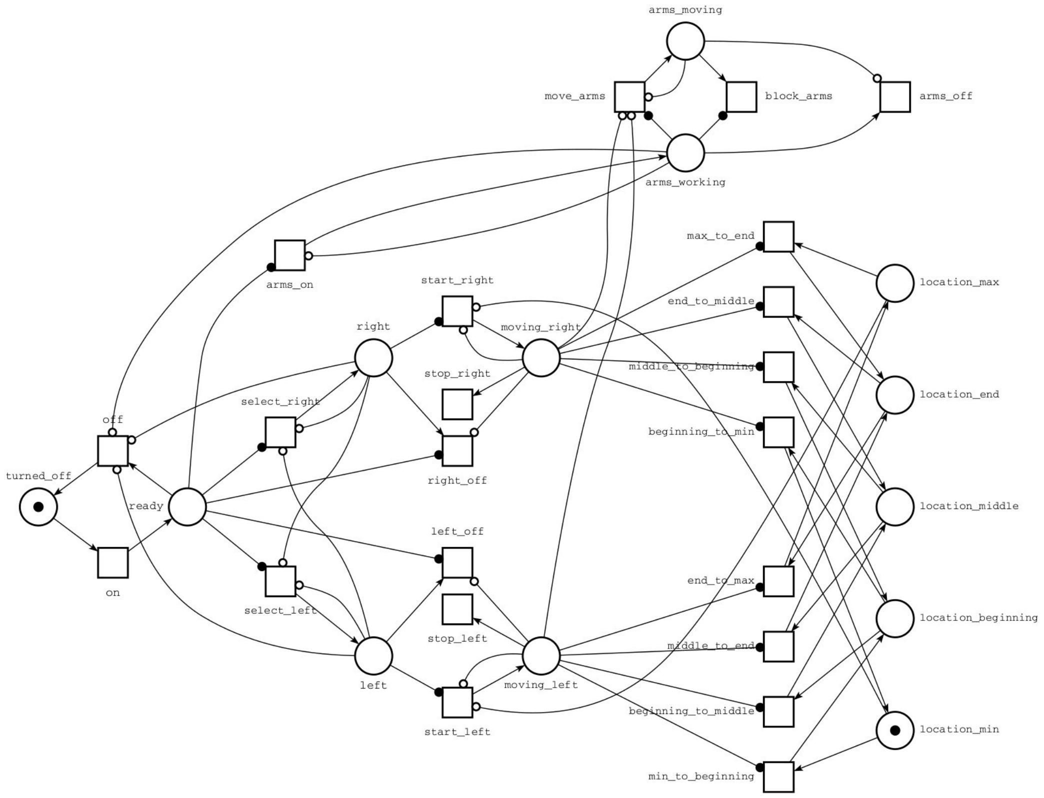
Formal modeling

- Formal methods: Petri nets, SMV (nuXMv), process algebras
- High abstraction level - shearer phases
- Low abstraction level: simulation of the process, data generation
- Formalized verification wrt certain properties, e.g. using logics LTL, CTL, mu; tools: CADP, nuXmv)



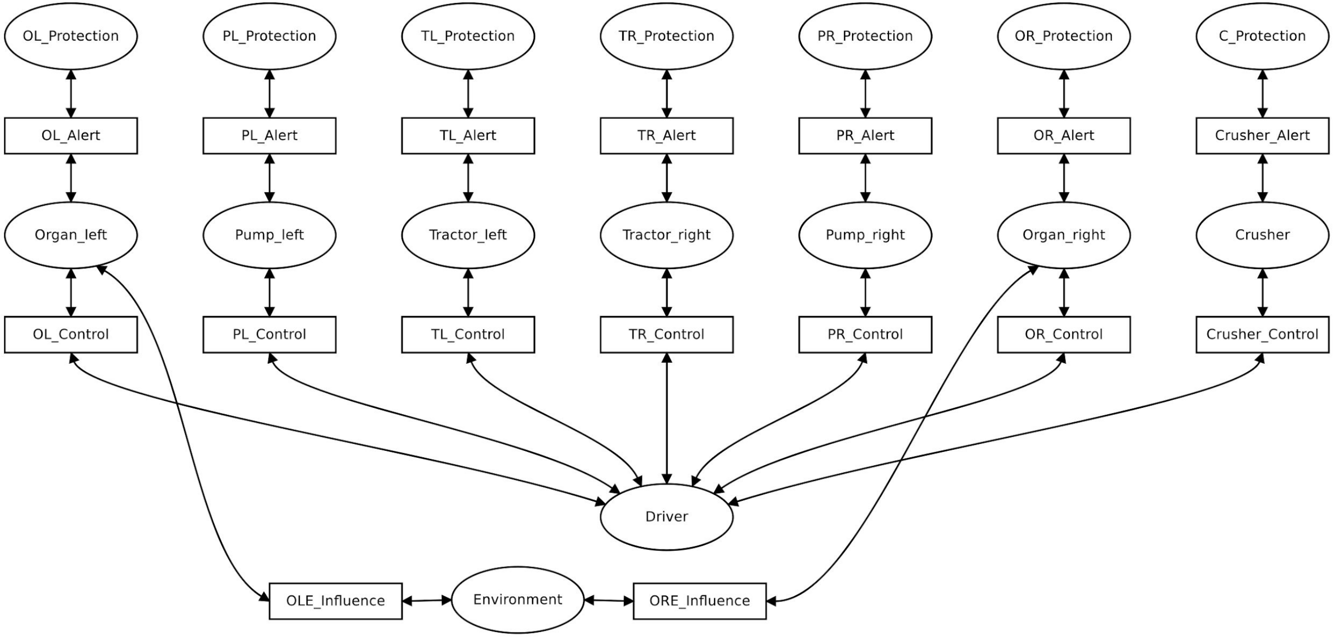
M. Szpyrka, E. Brzychczy, A. Napieraj, J. Korski, G. J. Nalepa *Conformance checking of a longwall shearer operation based on low-level events* Energies 2020, 13, 6630 https://doi.org/10.3390/en13246630

Petri Net - model of longwall shearer operation



- High level of abstraction
- Represents operation phases
- Representation of the location in the longwall
- Interactive simulation
- Labeled state space
- Integration with numeric data from the sensors

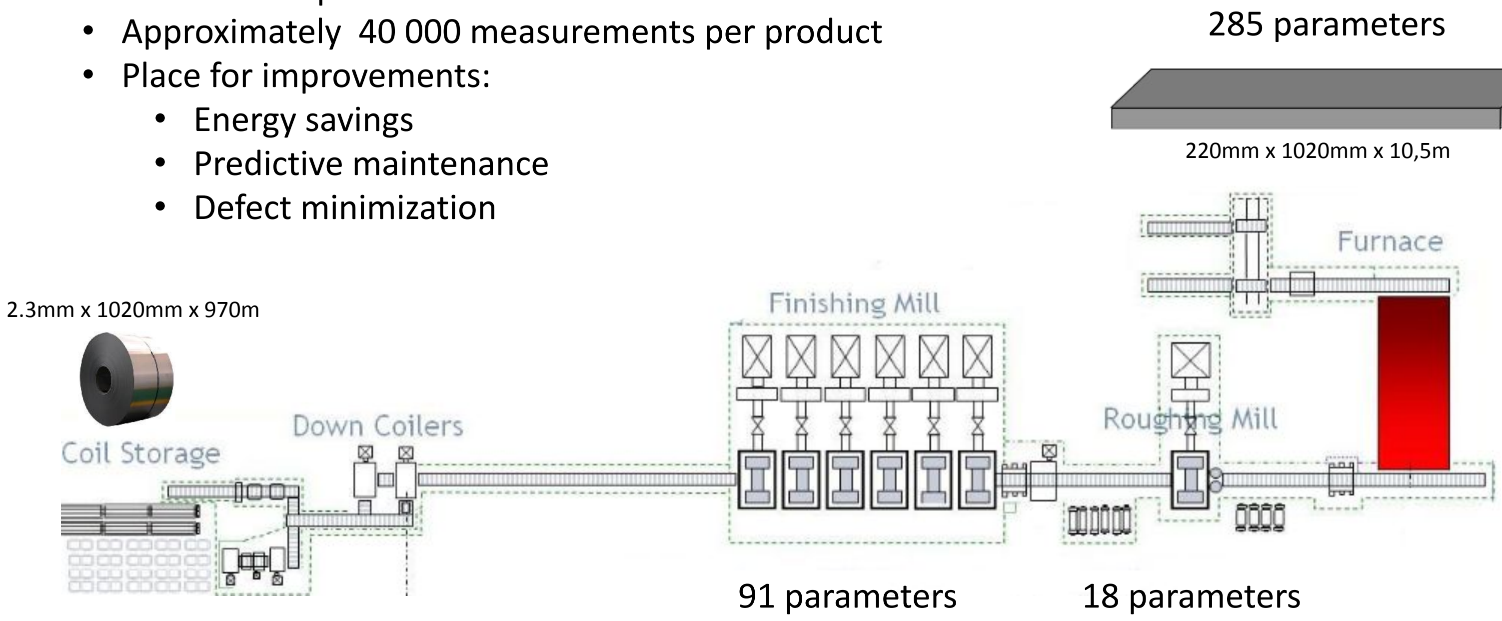
Colored Petri Net - model of longwall shearer



- Hierarchical model
- Simulation of the device operation
- Generation of numerical data
- Simulation of device sensors

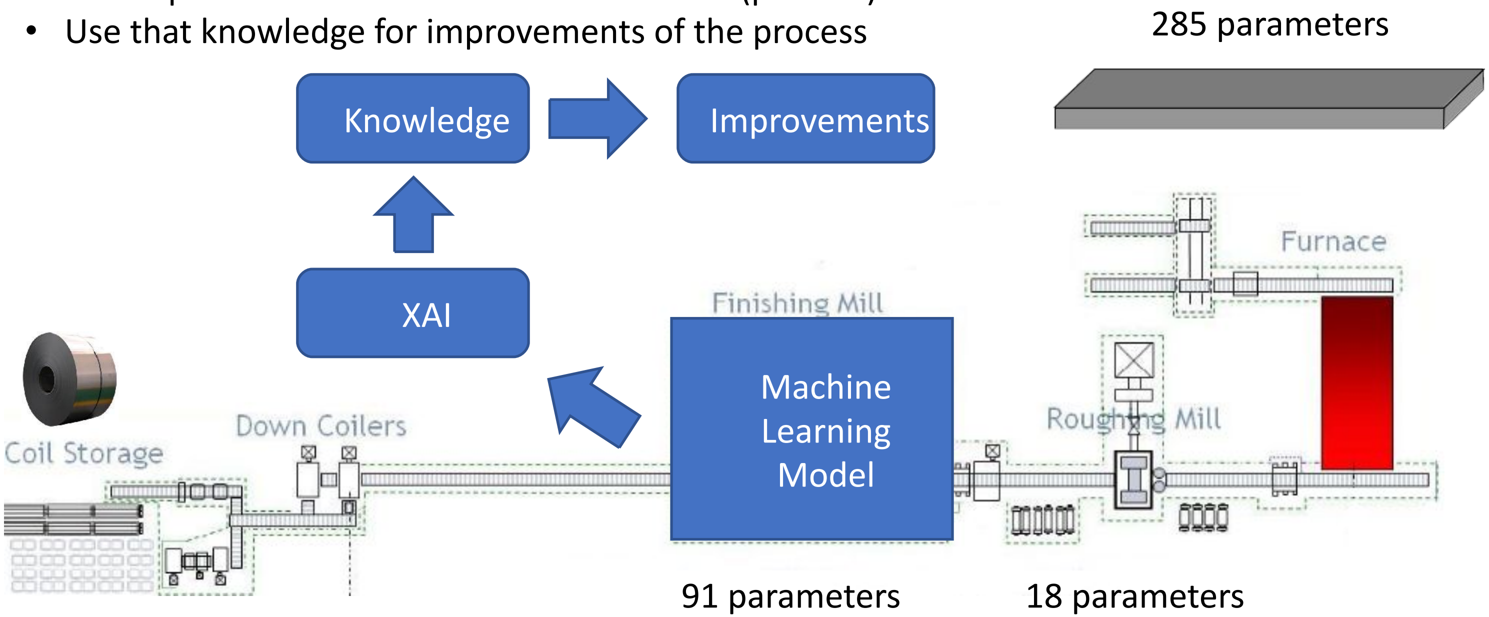
Hot Rolling Industrial Process (ArcelorMittal Poland)

- Fully automated process
- Hundreds of parameters involved
- Approximately 40 000 measurements per product
- Place for improvements:
    - Energy savings
    - Predictive maintenance
    - Defect minimization



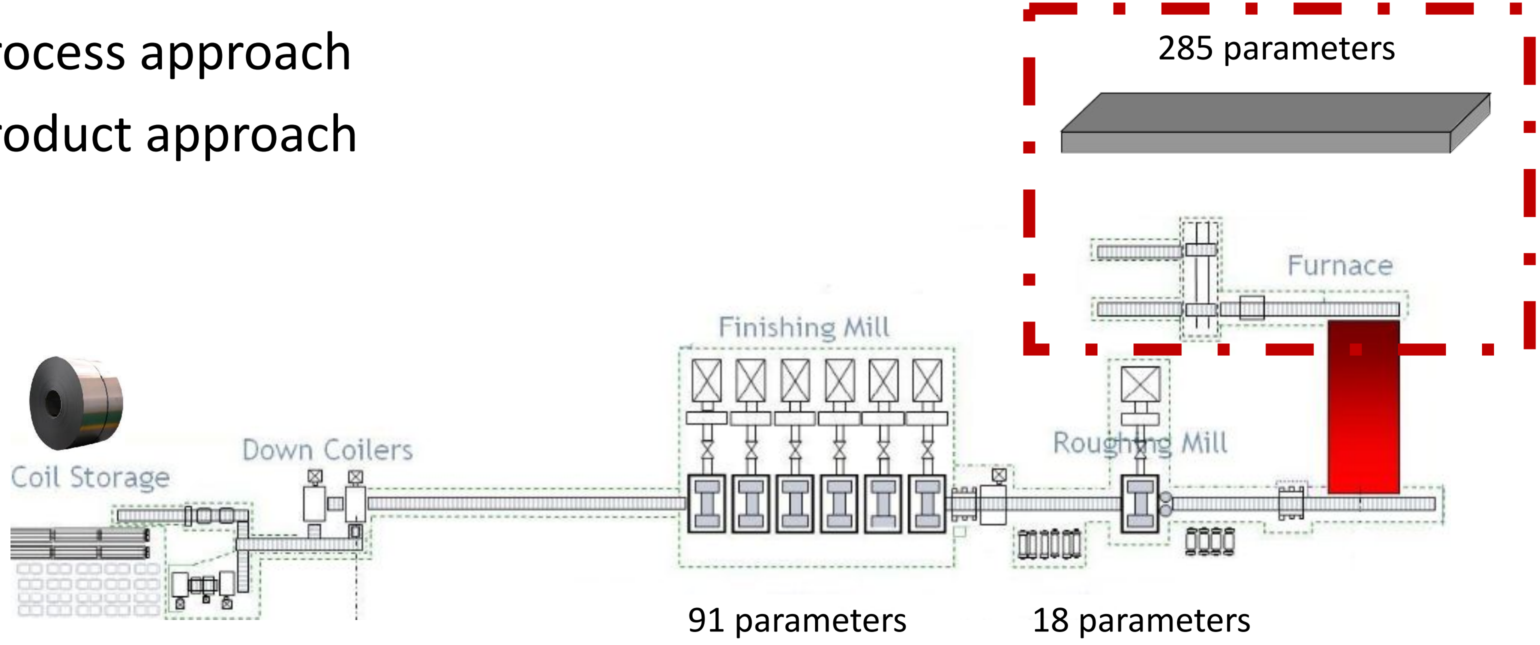
Hot Rolling Industrial Process

- Use machine learning to learn the process
- Use eXplainable AI to understand the model (process)
- Use that knowledge for improvements of the process



Three complementary approaches

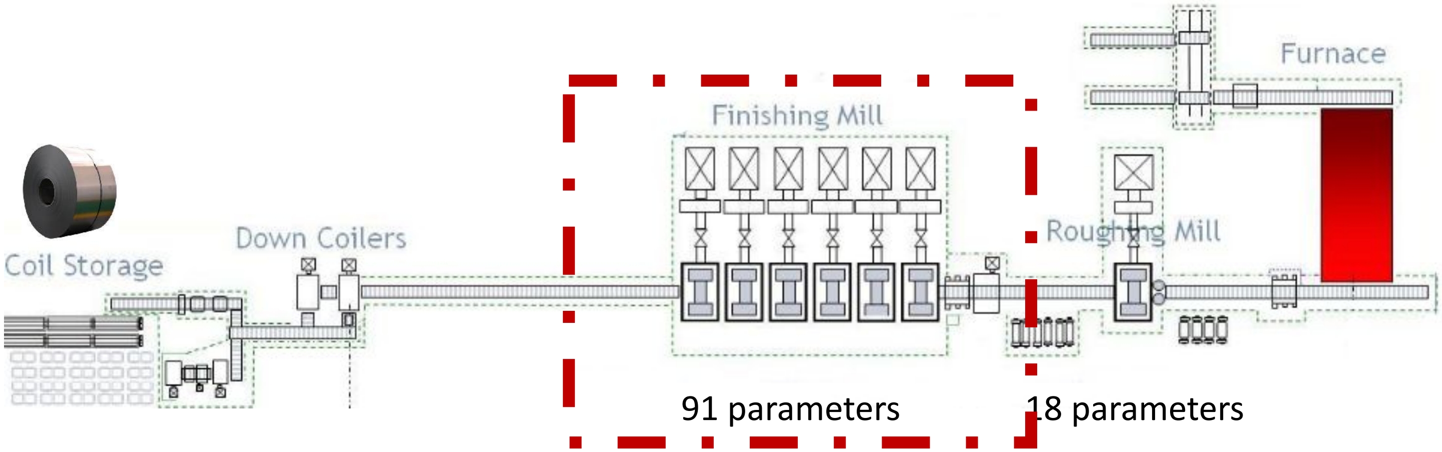
- Static parameters analysis
- Process approach
- Product approach



Three complementary approaches

- Static parameters analysis
- Process approach
- Product approach

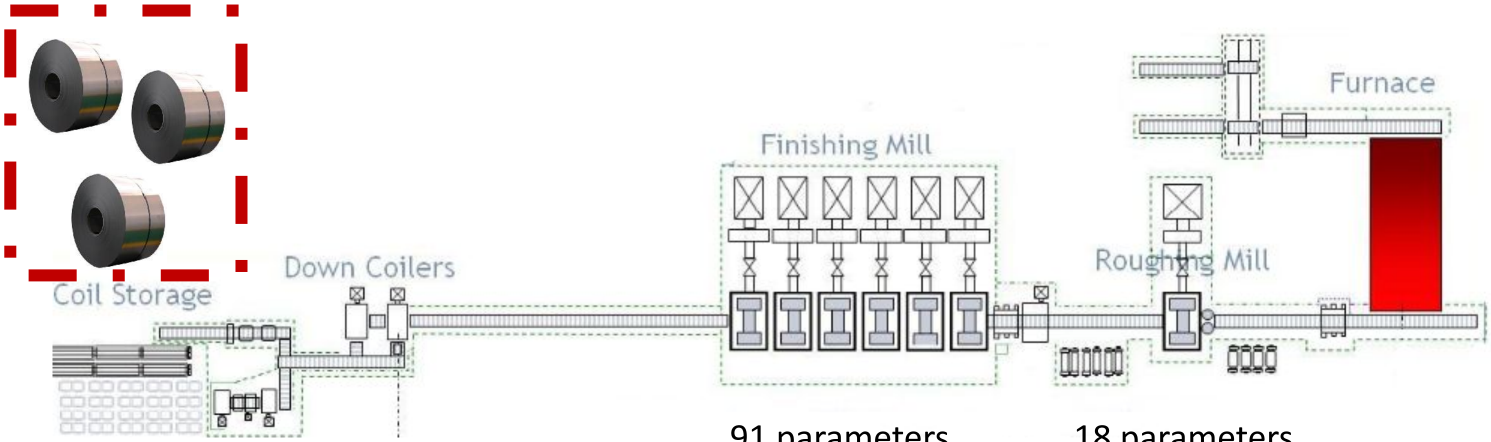
285 parameters



Three complementary approaches

- Static parameters analysis
- Process approach
- Product approach

285 parameters

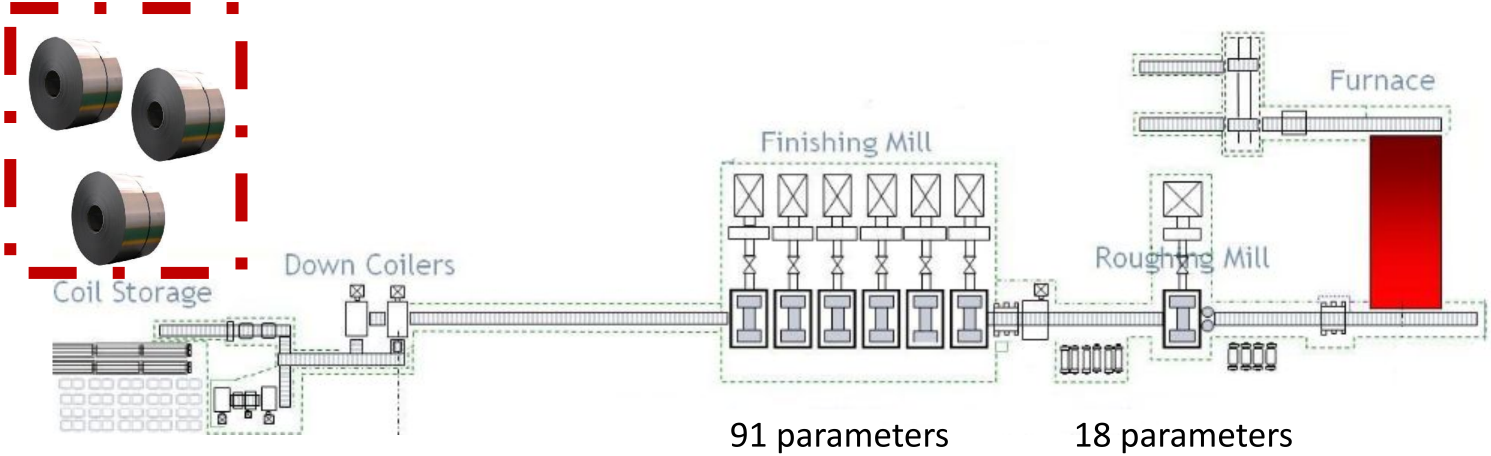


91 parameters

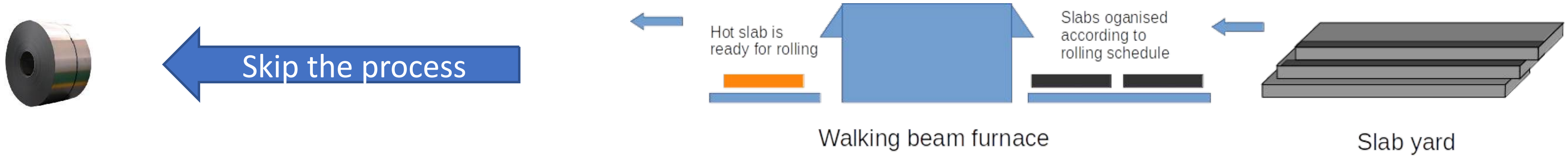
18 parameters

Three complementary approaches

- Static parameters analysis (9513 products/70 features)
- Process approach (9513 products/39 (196) features)
- Product approach (317 products/39 (196) features)



Static parameters analysis – how meta-parameters affect thickness

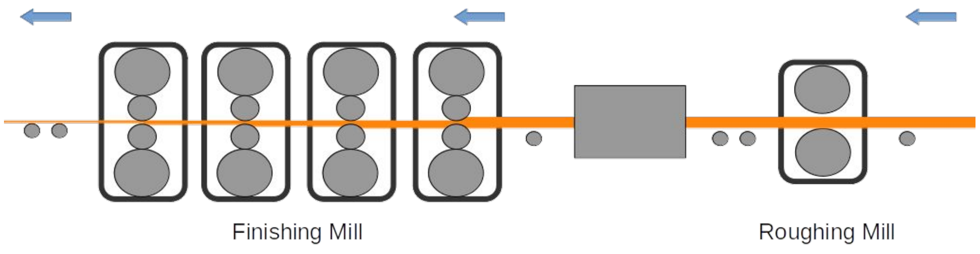


- Use static (not process) data as independent variables
- Use average thickness of a product as target
- Use Random forest regressor
- Feature importance as explanation
- Results: MAE: 0.1482

Param. Numb.	Importance	Description
52	0.3581	Targeted (calculated) width of the transfer bar.
67	0.3314	Entrance length of the transfer bar on each pass.
20	0.0653	Theoretical slab thickness.
27	0.0595	Measured coil weight.
60	0.0825	Targeted end rolling temperature.

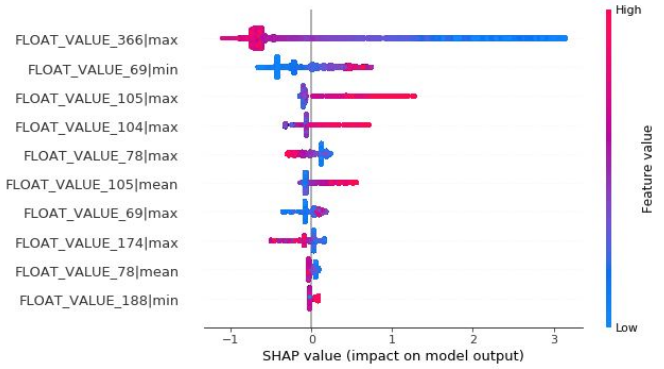
M. Szelążek, S. Bobek, A. Gonzalez-Pardo, G. J. Nalepa, *Towards the Modeling of the Hot Rolling Industrial Process. Preliminary Results,* 21st International Conference on Intelligent Data Engineering and Automated Learning - IDEAL 2020, November 2020

Process approach – how process affects thickness



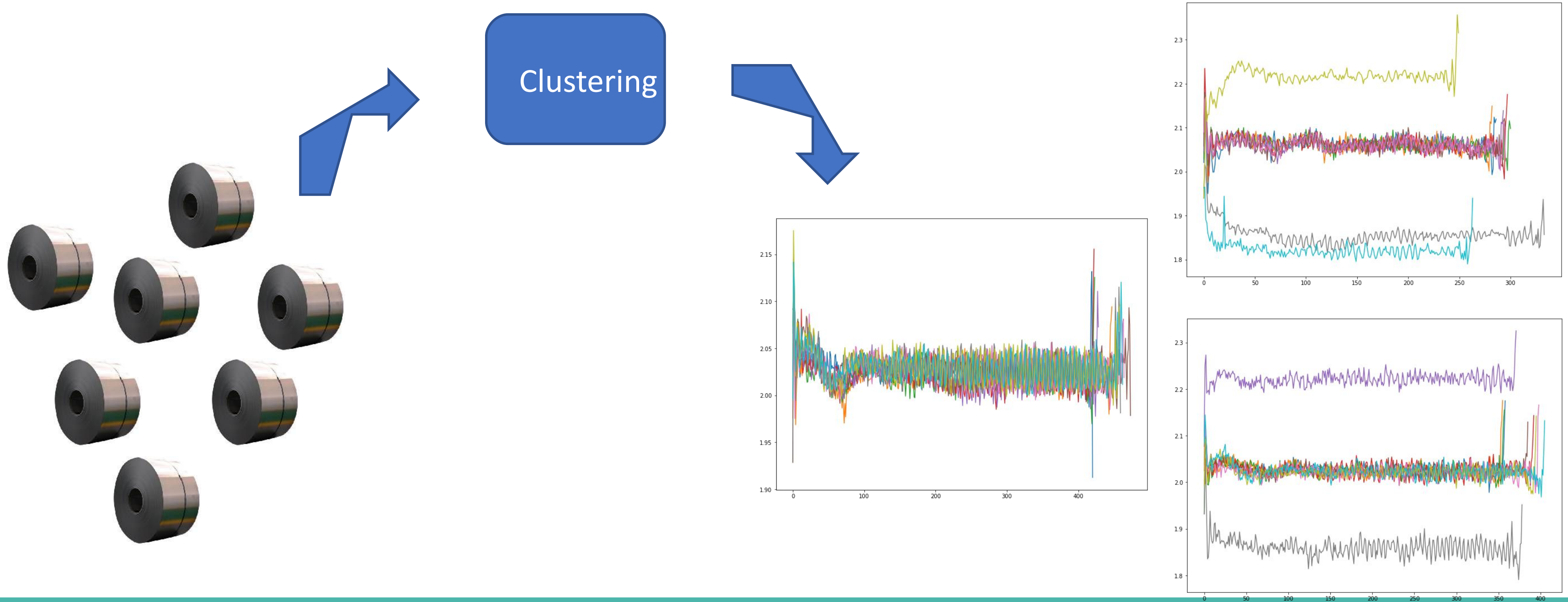
Param. Numb.	Description
366	Coiling speed.
69	Strip tension between 6 stand and coiler.
105	Strip wedge (after FM).
104	Strip profile (after FM).
78	Roller pressure force DS (FM 2).
174	Rolling speed (stand 1).
188	Loop position (stand 4).

- Cleaning data
- Synchronizing measurements (stands have different clocks)
- Averaging measurements in sliding window
- Calculating features (statistical properties)
- Use XGBoost as a regressor
- Use SHAP as explainer
- Results: R2 0.90



Product approach – what makes products different

- Features as simple statistical properties
- Features by ROCKET
- Features by TSFRESH

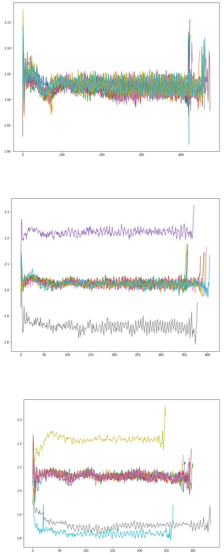


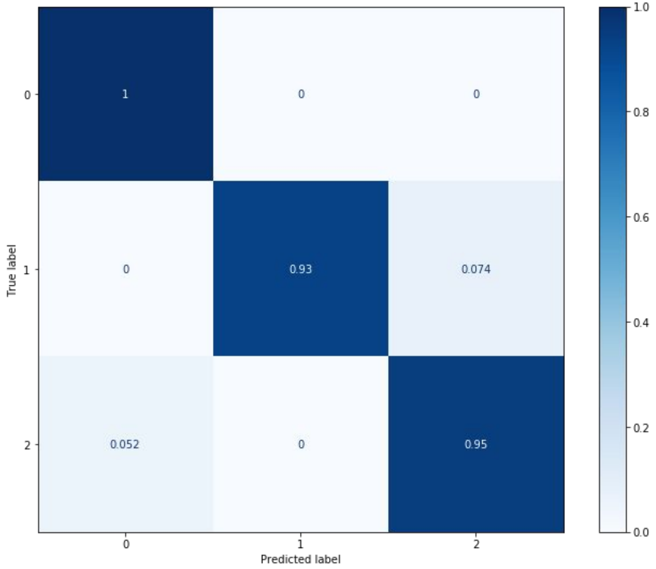
Product approach – what makes products different

Classification XGBoost

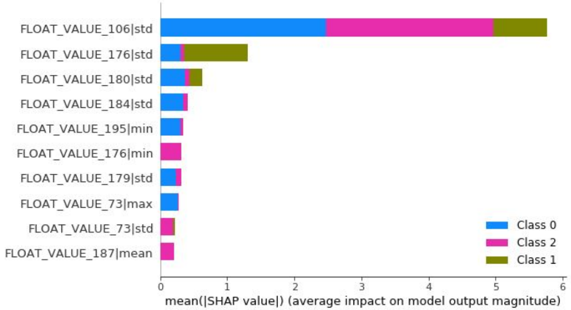
F1 score = 0.98

XAI





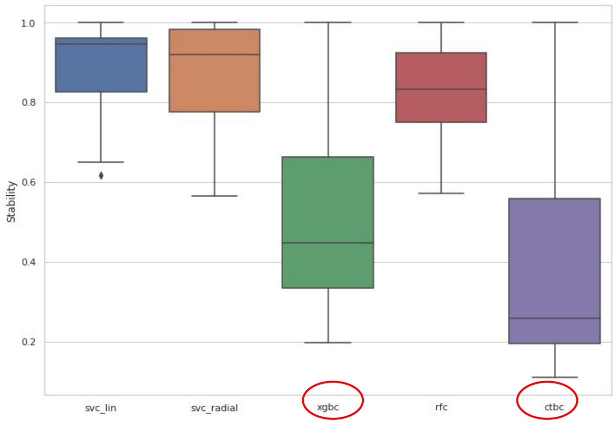
Param. Numb.	Description
106	Rolling finish temperature.
176	Loop position (stand 1).
180	Loop position (stand 2).
184	Loop position (stand 3).
195	Acceleration (stand 6).
179	Acceleration (stand 2).
73	Roller pressure force - DS - (FM 1).
187	Acceleration (stand 4).

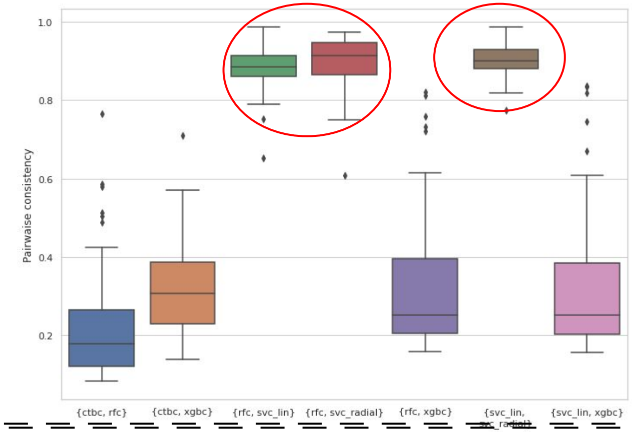


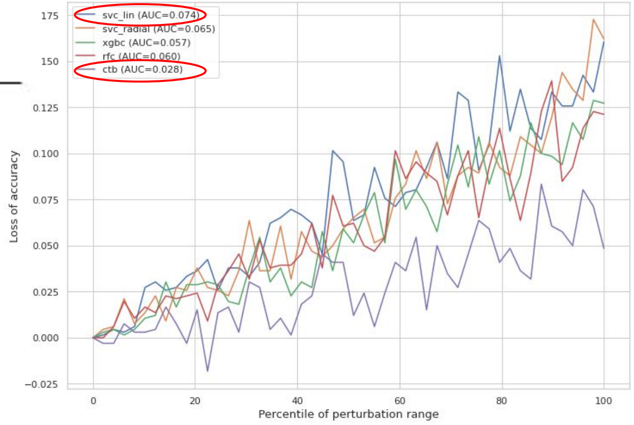
Recent results: Explanation-Driven Model Stacking

model	model abbreviation	accuracy score	F1-score class "0"	F1-score class "1"
SVMClassifier with RBF kernel	svc_radial	0.76	0.78	0.73
SVMClassifier with linear kernel	svc_lin	0.82	0.83	0.80
XGBClassifier	xgbc	0.74	0.76	0.72
RandomForestClassifier	rfc	0.74	0.77	0.70
CatBoostClassifier	ctbc	0.65	0.66	0.65

Combines models through lenses of their explanation capabilities and performance

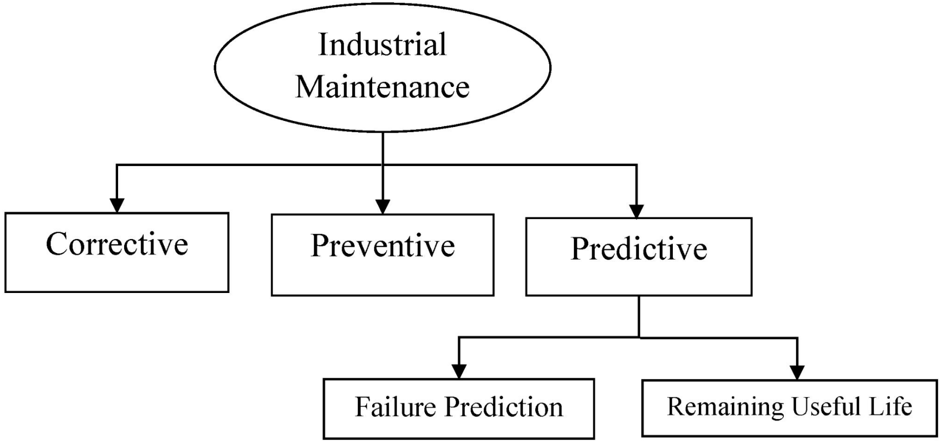


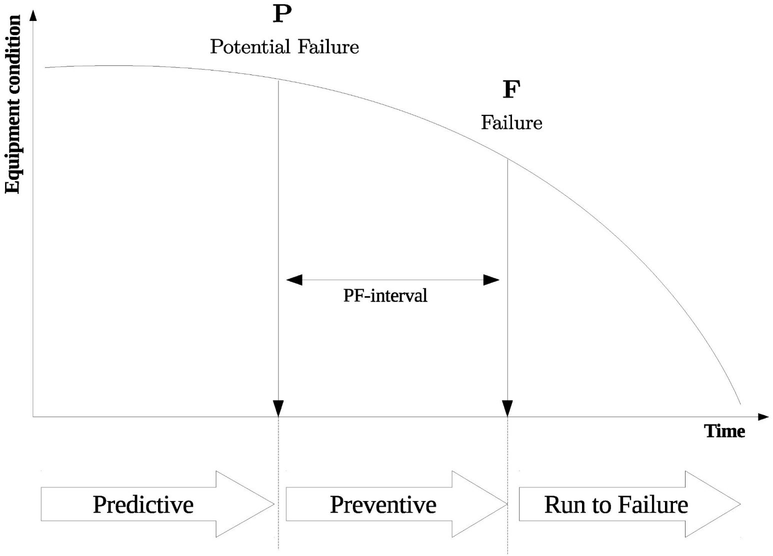




S. Bobek, M. Mozolewski, G. J. Nalepa, Explanation-Driven Model Stacking *ICCS 2021. Lecture Notes in Computer Science, vol 12747. Springer, Cham. https://doi.org/10.1007/978-3-030-77980-1_28*

Industry 4.5: Predictive Maintenance (PdM)





PdM was proposed as a part of I40 and is being emphasized in I50. It is made possible mostly thanks to advanced AI methods.

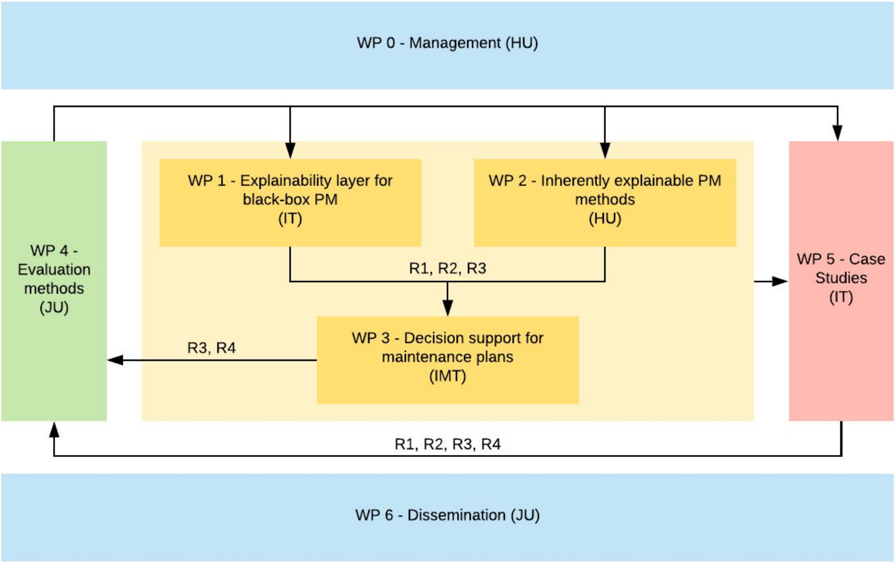
Davari, N.; Veloso, B.; Costa, G.d.A.; Pereira, P.M.; Ribeiro, R.P.; Gama, J. A Survey on Data-Driven Predictive Maintenance for the Railway Industry. Sensors 2021, 21, 5739. https://doi.org/10.3390/s21175739

XPM project - CHIST-ERA 2019 XAI - objectives

- O1: novel methods for creating explanations for AI decisions within the PdM domain
  - SO1a: Develop a novel post hoc explainability layer for black-box PdM models
  - SO1b: Develop novel algorithms for creating inherently explainable PdM models
- O2: framework for evaluation of explanations within the XPM setting:
  - SO2a: Propose multi-faceted evaluation metrics for PdM explanations
  - SO2b: Design an interactive decision support system based on explainable PdM

XPM consortium and structure

1. Sweden: Halmstad University, Sławomir Nowaczyk
2. Portugal: Inesc Tec, João Gama
3. Poland: Jagiellonian University, Grzegorz J. Nalepa
4. France: IMT Lille-Douai, Moamar Sayed-Mouchaweh



Main project impacts

Scientific:

1. *novel post hoc explainability layer* for black-box PdM models, supporting their proper selection and parameterisation
2. *new glass models in PdM,* i.e., inherently explainable models, incorporating domain expert knowledge
3. *new metrics for explainable PdM* models, combining quantitative performance measures with qualitative human expert evaluation,
4. *linking the explanations to the decision support system* through the design of an interactive human-machine tool.

Industrial:

1. *improved decision-making process in the industries* currently using black-box PM, through explanations supporting maintenance plans,
2. *increased awareness of the pros&cons of glass models* as an alternative to black-box ones,
3. *efficient maintenance methods* through a better understanding of the product life cycle.

Societal: trustworthiness of AI systems in the industry resulting from:

1. increasing their understandability on the technical level,
2. legal analysis of liability norms related to the development and operation of the AI systems,
3. guidelines, standards and criteria for evaluation and certification,
4. integration of human expert-based decision making with the AI operation.

Industrial partners and case studies

Steel factory: XPM will apply explainers to be used by the quality control in a steel factory. We will associate flaws in steel sheet production by associating those flaws with misbehaving components or steps based on explanations using the data from Hot Rolling Mill.
Poland: ArcelorMittal

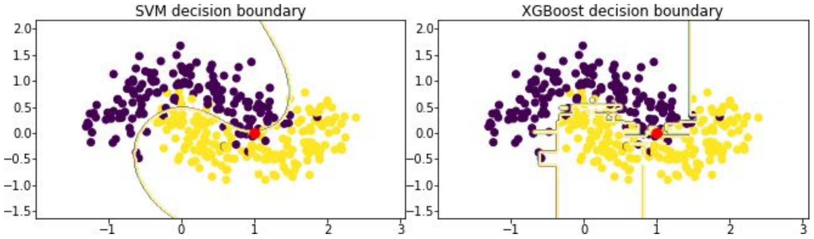
Electric heavy-duty vehicles: We will monitor battery health degradation for individual vehicles, based on each one's specific usage patterns and external operating conditions. XPM will use explainers to detect anomalies and their severity, enabling cost-effective predictive and prescriptive maintenance at the right time.
Sweden: Volvo Group

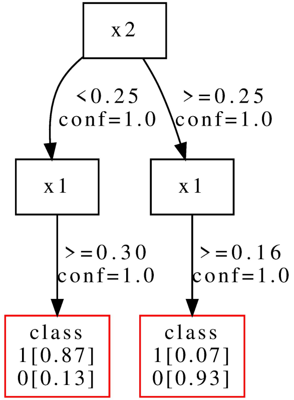
Wind farms: XPM will focus on early detection of critical failures, e.g. the generator or drivetrain, key to reduce the maintenance costs and related production losses. Explainers will be used to predict failures and their severity and facilitate the establishment of a maintenance plan.
France: ENGIE Group

Case study: Metro Porto: To help maintenance teams to evolve their working procedures, incorporating the info provided by Failure Prediction systems to manage maintenance cycles, which requires failure explainability capabilities and time-to-fail forecast from multiple subsystems in the whole metro fleet.
Portugal: Metro do Porto

Recent results: Introducing Uncertainty into Explainable AI Methods (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

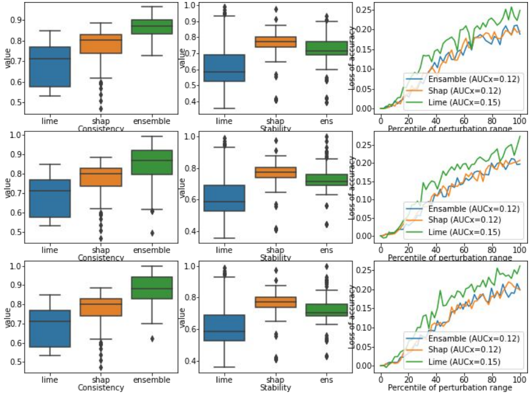




Uncertainty of decision model transferred to explanation model

S. Bobek, G.J. Nalepa *Introducing Uncertainty into Explainable AI Methods,* In M. Paszynski, D. Kranzlmuller, V. V. Krzhizhanovskaya, J. J. Dongarra, and P. M. A. Sloot, editors, Computational Science – ICCS 2021, pages 444-457, Cham, 2021. Springer International Publishing

Recent results: Towards Model-Agnostic Ensemble Explanations



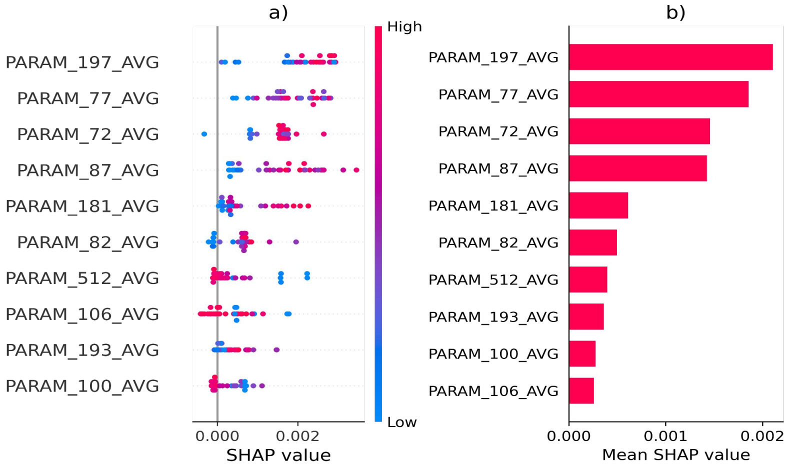
Multiple models rated through metrics

Ensamble explanation

S. Bobek, G.J. Nalepa *Towards Model-Agnostic Ensemble Explanations,* In M. Paszynski, D. Kranzlmuller, V. V. Krzhizhanovskaya, J. J. Dongarra, and P. M. A. Sloot, editors, Computational Science – ICCS 2021, pages 39-51, Cham, 2021. Springer International Publishing

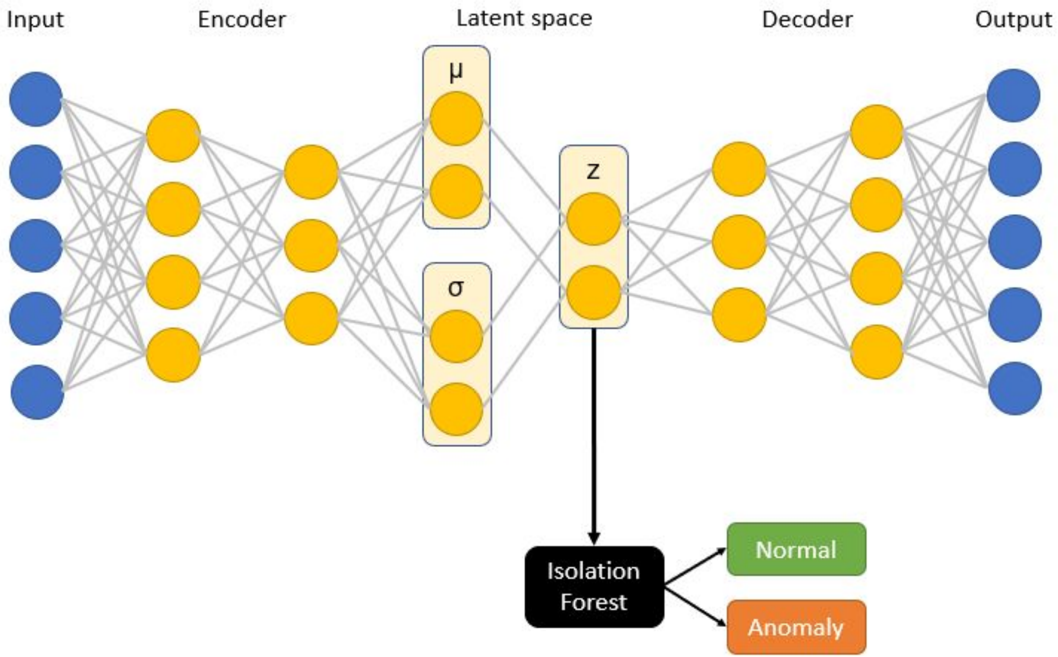
Recent results: Explainable anomaly detection for Hot-rolling industrial process

- LSTM-based autoencoder trained on industrial data
- Reconstruction error as anomaly
- Detected anomalies used for training classifier
- SHAP for explanations of causes of anomalies



J. Jakubowski, P. Stanisz, S. Bobek and G. J. Nalepa, Explainable anomaly detection for Hot-rolling industrial process, 2021 IEEE 8th International Conference on Data Science and Advanced Analytics (DSAA), 2021, pp. 1-10, doi: 10.1109/DSAA53316.2021.9564228.

Recent results: Anomaly detection in asset (...)



- Variational LSTM-based autoencoder
- Anomaly detection in latent space
- Visible improvements in F1 score comparing to previous results

Metric	AE	VAE
Accuracy	98.1%	98.7%
Precision	94.2%	95.7%
Recall	93.4%	95.6%
F1	93.8%	95.7%

J. Jakubowski, S. Bobek, P. Stanisz and G. J. Nalepa, Anomaly detection in asset degradation process using variational autoencoder and explanations, 2021 (submitted to Sensors).

Recent results: Explainability in the AI Act

- After a few years of work by various teams, the European Commission published a project of the Artificial Intelligence Act (AI Act or AIA) in April 2021.
- The project aims to be the first international regulation of issues connected with AI, setting standards for other legislations to follow in the future.
- It is a part of an elaborate EU strategy for AI "Commission’s two-pronged policy has been to make the EU a world-class hub for AI, while ensuring that AI is human-centric and trustworthy."
- There are many reasons to question if AIA grants effective tools for fulfilling these goals...

R. Pałosz, M. Araszkiewicz and G. J. Nalepa, Explainability in the Artificial Intelligence Act, 2021 (submitted to XAILA@JURIX).

Semantic Data Mining coop. w/ Martin Atzmueller

Open Access Review

Semantic Data Mining in Ubiquitous Sensing: A Survey

by Grzegorz J. Nalepa [1,2,*], Szymon Bobek [1,2], Krzysztof Kutt [1] and Martin Atzmueller [3,*]

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Academic Editor: Mehmet Rasit Yuce

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Data Mining Process and KDD

The general goal of data mining (DM) is to uncover novel, interesting, and ultimately understandable patterns i. e., relating to valuable, useful and implicit knowledge.

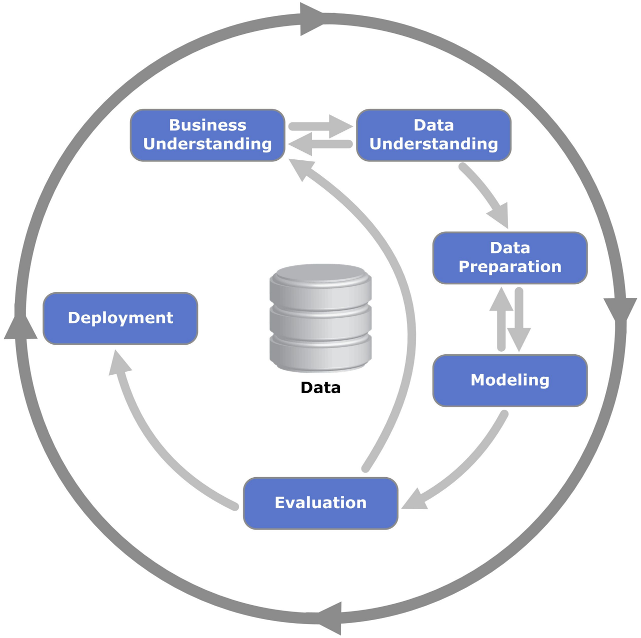
Long time tradition of Knowledge Discovery from Databases (KDD)

See: Fayyad, U.M. Data Mining and Knowledge Discovery: Making Sense Out of Data.
IEEE Expert 1996, 11, 20–25.
doi:10.1109/64.539013.

CRISP (Cross-industry standard process for DM)

1. Business Understanding (defining the goals of DM),
2. Data Understanding (making sure that data is applicable and clarifies semantics),
3. Data Preparation (transforming and cleaning the data, including feature engineering)
4. Modeling (the central phase: regularities and patterns are extracted from the data for constructing the data mining model),
5. Evaluation (where the quality of the mined model needs to be assessed),
6. Deployment (where the model is applied, e. g., for prediction, classification, or clustering).

#3 usually needs about 80% of the total effort!



Extensions (selected) of CRISP DM

SAS Institute proposed its own SEMMA (Sample, Explore, Modify, Model, and Assess) sequential approach for DM

IBM proposed its own extension to the original CRISP-DM process, called ASUM-DM to focus more on the operations side of implementing DM projects

However, these two approaches remain sequential, and do not notice the role of the domain knowledge, nor the explanative aspect.

Most recently the so-called Model Development Process was proposed. It extends the ideas of Rational Unified Process, and partially notices the needs for introducing explanations.

Semantic, Knowledge-Based, and Declarative DM

The main aspect of *semantic DM* is the explicit integration of *background knowledge* into the DM and KDD modeling step, where the algorithms for data mining/modeling or post-processing make use of the formalized knowledge to improve the overall results.

Several toolkits allow for *embedding declarative knowledge* into the learning process, e.g. graph embedding.

An idea for *declarative data analysis* specifically targets declarative problem formulation in DM.

In the area of *constraint programming* there have been approaches re-framing a DM method using constraint-based programming. These approaches actually are about specifying what the ML or DM task is about rather than utilizing contextual domain knowledge in a declarative way.

Explainability and Interpretability in Data Mining

- Explanations are a central component for advanced data mining approaches.
- Especially relevant when considering complicated black-box models providing recommendations and predictions in sensitive application contexts like medicine, Industry 4.0 etc.
- Intransparent methods and models make it more difficult to spot errors mistakes and can thus lead to biased decisions.
- Particularly important in the light of the EU GDPR and the “right to explanation”.
- As the challenges of XAI are mostly related to ML models and their use in the DM process, two main cases are considered: different levels of transparent ML models, and post-hoc explainers for black-box ML models.
- Interpretability goes far beyond the model itself, and needs to be considered in the scope of the whole process of designing a system.

Our research and focus

- Integration of domain/ background/ expert knowledge into DM
- Enhancements of the DM process towards SDM
- Hybrid approaches combining transparent ML models and post-hoc explainers for black-boxes

Applications in:

- Ubiquitous sensing
- Industrial AI
- Affective computing
- Interdisciplinary: AI & Law

Future works, activities, and developments

- Industrial AI: ML, KR, XAI and Predictive Maintenance
- Sensor data analysis in human and industrial context
- Introducing knowledge-based approaches for Data Mining
- The Semantic Data Mining (SEDAMI) Workshop http://sedami.geist.re
- Practical applications of eXplainable Artificial Intelligence methods (PRAXAI) Workshop http://praxai.geist.re
- The EXplainable & Responsible AI in Law (XAILA) Workshop http://xaila.geist.re
- On a more applied front: working with SMEs in the area of Internet marketing & logistics
- *JAHCAI lab: Jagiellonian Human-Centered AI Lab*
- Sensors SI: "Machine Learning from Heterogeneous Condition Monitoring Sensor Data for Predictive Maintenance and Smart Industry"
- To boldly go, where no one has gone before...

GJN in Alicante in 2018

Thank you for your attention!

GEIST Research Group

Some take away messages:

- *Big pictures and multidisciplinary work might be challenging yet very satisfying*
- *Everyone does XAI now, not so many of them know how and why.*

Maybe we will? :)

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