GDAŃSK UNIVERSITY OF TECHNOLOGY

Subject card

Subject name and code	Detecting Anomalies in Processes, PG_00068082		
Field of study	Automatic Control, Cybernetics and Robotics		
Date of commencement of studies	October 2025	Academic year of realisation of subject	2027/2028
Education level	first-cycle studies	Subject group	Optional subject group Subject group related to scientific research in the field of study
Mode of study	Full-time studies	Mode of delivery	at the university
Year of study	3	Language of instruction	Polish
Semester of study	6	ECTS credits	2.0
Learning profile	general academic profile	Assessment form	assessment
Conducting unit	Department of Decision Systems and Robotics -> Faculty of Electronics Telecommunications and Informatics -> Wydziały Politechniki Gdańskiej		
Name and surname of lecturer (lecturers)	Subject supervisor	dr inż. Mariusz Domżalski	
	Teachers	dr inż. Mariusz Domżalski	

Lesson types and methods of instruction	Lesson type	Lecture	Tutorial	Laboratory	Project	Seminar	SUM
	Number of study hours	15.0	0.0	15.0	0.0	0.0	30
	E-learning hours included: 0.0						

Learning activity and number of study hours	Learning activity	Participation in didactic classes included in study plan	Participation in consultation hours	Self-study	SUM
	Number of study hours	30	2.0	18.0	50

Subject objectives	The objective of the course is to familiarize students with the theoretical and practical aspects of anomaly detection in process data and time series. Students will learn a range of methods, from classical statistical techniques and machine learning algorithms to advanced deep learning models (recurrent neural networks, transformers). The course emphasizes the practical application of the acquired knowledge in solving real-world engineering problems, such as failure prediction, IoT system monitoring, or medical data analysis.

Learning outcomes

Course outcome	Subject outcome	Method of verification
[K6_U07] can apply methods of process and function support, specific to the field of study	Is able to select an appropriate anomaly detection method based on data characteristics and problem specifics (e.g., static data vs. time series), and subsequently interpret the results to support the decision-making process (e.g., for fault identification).	[SU4] Assessment of ability to use methods and tools [SU1] Assessment of task fulfilment
[K6_W01] knows and understands, to an advanced extent, mathematics necessary to formulate and solve simple issues related to the field of study	Is able to implement and test selected anomaly detection algorithms (statistical, clustering-based, autoencoder-based) using dedicated programming libraries (e.g., Scikit-learn, TensorFlow/ PyTorch) to analyze process data and time series.	[SW3] Assessment of knowledge contained in written work and projects
[K6_U04] can apply knowledge of programming methods and techniques as well as select and apply appropriate programming methods and tools in computer software development or programming devices or controllers using microprocessors or programmable elements or systems specific to the field of study	Understands the mathematical and statistical foundations underlying the covered anomaly detection methods, including the concepts of probability distributions, distance metrics, and optimization principles used in machine learning models.	[SU3] Assessment of ability to use knowledge gained from the subject [SU2] Assessment of ability to analyse information
[K6_W21] knows and understands the basic methods of decision making as well as methods and techniques of design and operation of automatic regulation and control systems, computer applications for controlling and monitoring dynamic systems.	Knows and understands the role and application of anomaly detection methods in the context of monitoring dynamic systems, predictive maintenance, and ensuring process safety.	[SW1] Assessment of factual knowledge

Subject contents

1. Introduction to Anomaly Detection: Definition of anomalies, significance in Industry 4.0, medicine, and cybersecurity. Characteristics of process data and time series. Anomaly classification: point, contextual, and collective.

2. Statistical Methods: Parametric models (hypothesis tests, Gaussian distribution) and non-parametric models (histograms, Kernel Density Estimation). Detection based on static and dynamic thresholding.

3. Time Series Analysis and Predictive Models: Signal decomposition (trend, seasonality). Utilizing regression models (e.g., ARIMA) for prediction and detecting deviations from the forecast.

4. Unsupervised Machine Learning: Density-based algorithms (DBSCAN, LOF) and clustering (k-means). Isolation-based methods (Isolation Forest). Application of autoencoders for signal reconstruction and anomaly detection.

5. Deep Learning in Sequence Analysis: Recurrent neural network architectures (RNN, LSTM, GRU) for modeling dynamic processes. Utilizing Transformer networks for analyzing long-range dependencies in data.

6. Advanced Techniques and Applications: Utilizing GANs for generating normal data and detecting anomalies. Applications in industrial process monitoring (predictive maintenance), ECG/EEG signal analysis, IoT systems, and cybersecurity. Summary and development trends.

Prerequisites and co-requisites

Assessment methods and criteria

Subject passing criteria	Passing threshold	Percentage of the final grade
Lab grade	50.0%	50.0%
Written colloquium	50.0%	50.0%

Recommended reading

Basic literature	1. Aggarwal C. C., Outlier Analysis, Springer, 2nd ed., 2017. 2. Chandola V., Banerjee A., Kumar V., Anomaly detection: A survey, ACM computing surveys, 2009. 3. McKinney W., Python for Data Analysis, O'Reilly Media, 2nd ed., 2017. 4. Library documentation: Scikit-learn, TensorFlow, PyTorch.
Supplementary literature	1. Goodfellow I., Bengio Y., Courville A., Deep Learning, MIT Press, 2016. 2. Hyndman R.J., Athanasopoulos G., Forecasting: principles and practice, OTexts, 3rd ed., 2021. 3. Research papers from conferences (e.g., NeurIPS, ICML) and journals (e.g., IEEE Transactions) concerning anomaly detection.
eResources addresses	

Example issues/ example questions/ tasks being completed	**Sample theoretical questions:** 1. Define and provide examples of a point anomaly, a contextual anomaly, and a collective anomaly in the context of industrial process data. 2. Explain how an autoencoder can be used for anomaly detection. What serves as the anomaly score in this approach, and how can a decision threshold be determined? 3. Compare the k-means and DBSCAN algorithms in terms of their suitability for anomaly detection. In which scenarios would one have an advantage over the other? 4. Describe how recurrent neural networks (e.g., LSTM) are used for anomaly detection in time series. What are the advantages of this approach compared to statistical methods? **Sample tasks implemented in the laboratory:** 1. Implement an anomaly detection algorithm in Python based on the moving average and standard deviation method (3-sigma rule). Test it on a provided time-series dataset and visualize the detected anomalies. 2. Use the Scikit-learn library to apply the Isolation Forest algorithm to a financial transaction dataset to detect potential fraud. Evaluate the model's performance. 3. Build and train a simple autoencoder in TensorFlow/Keras on a dataset of "normal" samples (e.g., simulated sensor data). Then, use the reconstruction error to identify anomalies in a test set containing unusual samples.
Work placement	Not applicable

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