SYLLABUS

REGARDING THE QUALIFICATION CYCLE FROM 2023TO 2025

ACADEMIC YEAR 2024/2025

1. BASIC COURSE/MODULE INFORMATION

Course/Module title	*Elective Course 3: Application of Aggregations in Machine Learning*
Course/Module code *	
Faculty (name of the unit offering the field of study)	*College of Natural Sciences*
Name of the unit running the course	*Institute of Computer Science*
Field of study	*Computer Science*
Qualification level	2^{nd} degree
Profile	*general academic profile*
Study mode	*full-time studies*
Year and semester of studies	*year 2, semester 3*
Course type	*major subject to elect*
Language of instruction	English
Coordinator	Urszula Bentkowska, PhD DSc
Course instructor	Urszula Bentkowska, PhD DSc; Aleksander Wojtowicz, MSc Eng

* - as agreed at the faculty

1.1. Learning format – number of hours and ECTS credits

Semester (no.)	Lectures	Classes	Colloquia	Lab classes	Seminars	Practical classes	Internships	others	**ECTS credits**
3	15			30					4

1.2. Course delivery methods

conducted in a traditional way

1.3. Course/Module assessment

pass with a grade

2. PREREQUISITES

Elements of Logic and Set Theory, Mathematical Analysis, Artificial Intelligence in the field of Machine Learning, Fuzzy Systems in the field of fuzzy reasoning

3. OBJECTIVES, LEARNING OUTCOMES, COURSE CONTENT, AND INSTRUCTIONAL METHODS

3.1. Course/Module objectives

O1	To familiarize students with the basic issues and concepts used to create and analyze the operation of machine learning models using aggregation functions.
O2	Developing students' skills in using libraries for modelling and analyzing machine learning models created using the aggregation function.
O3	Developing students' skills in selecting the appropriate analysis and modelling method based on aggregation functions.

3.2. Course/Module Learning Outcomes

Learning Outcome	The description of the learning outcome defined for the course/module	Relation to the degree programme outcomes
LO_01	Student knows in-depth issues related to the use of aggregations applied in machine learning and data mining and knows examples of libraries using aggregations to create data mining models.	K_W01
LO_02	Student is able to properly design and implement a machine learning model using aggregations and select the appropriate aggregations for the type of data and model being analyzed. Student is able to interpret the obtained results and draw correct conclusions. Student can also modify and tune machine learning models.	K_U02
LO_03	Student recognizes the importance of mathematics, in particular the aggregation function in solving problems related to data mining, and is able to use the opinions of experts in case of difficulties in solving the problem on their own.	K_K01

3.3. Course content

A. Lectures

Numerical and interval-valued aggregations
Examples of aggregation classes: quasi-arithmetic mean, Choquet integral, Choquet-like integral CF i $CF_{1,2}$, Sugeno integral and generalizations, t-norm and t-conorm, OWA operator, penalty function, moderate deviation function, *N-overlap*
Application of moderate deviation functions to measure similarity of the data
Application of penalty functions in aggregation of data
Application of Choquet-like integrals in classification systems based on fuzzy rules
The use of interval-valued aggregations in selected image processing issues
The use of interval-valued aggregations in classification of data with large number of missing values

B. Classes, tutorials/seminars, colloquia, laboratories, practical classes

Use of basic data classification methods - repetition
Using sample libraries offering aggregation functions to create ensembles of classifiers
Using sample libraries offering interval-valued aggregation functions to create ensembles of classifiers
Using sample libraries to measure data similarity
The use of penalty functions in data aggregation
Using sample libraries offering aggregations, e.g. Choquet-like integrals, to create classification systems based on fuzzy rules

3.4. Methods of Instruction

Lecture: a lecture supported by a multimedia presentation
Laboratory classes: individual and group work designing and conducting experiments using sample libraries

4. ASSESSMENT TECHNIQUES AND CRITERIA

4.1. Methods of evaluating learning outcomes

Learning outcome	Methods of assessment of learning outcomes (e.g. test, oral exam, written exam, project, report, observation during classes)	Learning format (lectures, classes,…)
LO-01	observation during classes, project	lecture, lab
LO-02	observation during classes, project	lecture, lab
LO-03	observation during classes, project	lecture, lab

4.2. Course assessment criteria

The condition for passing the course is a positive grade from the laboratory, including knowledge from the lecture and practical skills acquired during laboratory classes.

The condition for passing the laboratory is to obtain a positive grade for the practical project involving the description and analysis of the operation of the proposed model using aggregation methods.

The project will be assessed on points:
positive assessment >50% of points,
dst (3.0) in case of obtaining 51-60% of points,
dst plus (3.5) in case of obtaining 61-70% of points,
db (4.0) in case of obtaining 71-80% of points,
db plus (4.5) in case of obtaining 81-90% of points,
very good (5.0) if 91-100% of points are obtained.

5. TOTAL STUDENT WORKLOAD NEEDED TO ACHIEVE THE INTENDED LEARNING OUTCOMES – NUMBER OF HOURS AND ECTS CREDITS

Activity	Number of hours
Scheduled course contact hours	45
Other contact hours involving the teacher (consultation hours, examinations)	20
Non-contact hours - student's own work (preparation for classes or examinations, projects, etc.)	35
Total number of hours	100
Total number of ECTS credits	4

* One ECTS point corresponds to 25-30 hours of total student workload

6. INTERNSHIPS RELATED TO THE COURSE/MODULE

Number of hours	------
Internship regulations and procedures	------

7. INSTRUCTIONAL MATERIALS

Compulsory literature:

[1] A.H. Altalhi, J.I. Forcén, M. Pagola, E. Barrenechea, H. Bustince, Z. Takáč, Moderate deviation and restricted equivalence functions for measuring similarity between data, Information Sciences 501, 19-29, 2019.

[2] G. Beliakov, H. Sola, T. Calvo, A practical guide to averaging functions, vol. 329, Springer, 2016.

[3] U. Bentkowska, Interval-valued methods in classifications and decisions, vol. 378, Springer, 2020.

[4] U. Bentkowska, M. Mrukowicz, Parameterized Interval-Valued Aggregation Functions in Classification of Data with Large Number of Missing Values, in: Atanassov, K.T., et al. Uncertainty and Imprecision in Decision Making and Decision Support - New Advances, Challenges, and Perspectives, pp. 85-94, vol 793, Springer, Cham, 2023.

[5] H. Bustince, G. Beliakov, G.P. Dimuro, B. Bedregal, R. Mesiar, On the definition of penalty functions in data aggregation, Fuzzy Sets and Systems 323, 1-18, 2017.

[6] A. Jurio, M. Pagola, R. Mesiar, G. Beliakov, H. Bustince, Image Magnification Using Interval Information, IEEE Transactions on Image Processing 20 (11), 3112-3123, 2011.

[7] G. P. Pereira Dimuro, G. Lucca, B. Bedregal, R. Mesiar, J. A. Sanz, C.-T. Lin, H. Bustince, Generalized CF1F2-integrals: From Choquet-like aggregation to ordered directionally monotone functions, Fuzzy Sets and Systems 378, 44-67, 2020.

[8] https://github.com/furoDMGroup/IWIFSGN2022

[9] HTTPS://PYPI.ORG/PROJECT/FANCY-AGGREGATIONS/

[10] HTTPS://PYPI.ORG/PROJECT/AGGREGATIONSLIB/

Complementary literature:

[1] J. Fumanal-Idocin, Y. -K. Wang, C. -T. Lin, J. Fernández, J. A. Sanz and H. Bustince, Motor-Imagery-Based Brain–Computer Interface Using Signal Derivation and Aggregation Functions, *IEEE Transactions on Cybernetics* 52 (8), 7944-7955, 2022.

[2] K. Kuratowski, Rachunek różniczkowy i całkowy, PWN, Warszawa 2023.

[3] L. Rutkowski, Metody i techniki sztucznej inteligencji, PWN, Warszawa 2018.

Approved by the Head of the Department or an authorised person