<table>
<tr><td colspan="3">Institute of Applied Mathematics</td><td colspan="4">Semester 2. of the curriculum
2025-26-2</td></tr>
<tr><td rowspan="2">Name of the subject:</td><td rowspan="2">Code of the subject:</td><td rowspan="2">Credits:</td><td colspan="4">Weekly hours:</td></tr>
<tr><td></td><td>lec</td><td>sem</td><td>lab</td></tr>
<tr><td>Mathematical Methods for Data Science</td><td>NMXMM1EMNF</td><td>5</td><td>full-time</td><td>2</td><td>2</td><td>0</td></tr>
<tr><td colspan="3">Responsible person for the subject: Gábor CSISZÁR PhD</td><td colspan="4">Classification: habilitated associate professor</td></tr>
<tr><td colspan="7">Subject lecturer(s): Gábor CSISZÁR PhD</td></tr>
<tr><td>Prerequisites:</td><td>-</td><td colspan="5">-</td></tr>
<tr><td>Way of the assessment:</td><td>Exam</td><td></td><td colspan="4"></td></tr>
<tr><td colspan="7">Course description</td></tr>
<tr><td>Goal:</td><td colspan="6">Learning objective of the course Mathematical Methods for Data Science is to develop students’ problem-solving skills, foster critical thinking, and advance their competence in data-driven decision-making. A core goal is to strengthen students’ technical proficiency in programming, statistical analysis, and machine learning. Through the knowledge and skills acquired in the course, students will be able to effectively meet the practical demands of industry.
The course material further includes the development of analytical and quantitative reasoning, while cultivating a mindset of lifelong learning. The overarching aim of the course is to equip students with the essential mathematical foundations of data science, enabling them to rigorously communicate their results and to explain the significance of their technical knowledge in a way that is understandable both to domain experts and to non-specialists. A key objective is to empower students to make their work interpretable and accessible — not only in technical terms, but also for a broader audience, highlighting the real-world relevance and impact of data science.</td></tr>
<tr><td>Course description:</td><td colspan="6">Linear systems: LU decomposition, QR decomposition.
Fitting methods: Least Squares Method (LSM), Pattern-Fitting Method (PFM), and spline-based fitting.
Optimization techniques — derivative-based and derivative-free: Golden-Section Search (GSS), Successive Parabolic Interpolation (SPI), Gradient Descent.
Iterative solvers: Jacobi method.
Numerical differentiation and numerical integration.
Initial-Value Problems (IVPs), Boundary-Value Problems (BVPs).
Finite-difference discretization.
Time- and space-stepping schemes (temporal/spatial marching methods).
Fourier analysis: Fourier series in complex form, Gibbs phenomenon.
Fourier transform (FT) and its properties, Parseval’s theorem, Parseval/energy identity.
Discrete Fourier Transform (DFT), DFT vs FFT, Short-Time / Windowed Fourier Transform, spectrograms, Gabor (Gábor) transform.
Laplace transform and its properties.
Matrix decompositions by singular values over real and complex fields: SVD, SVD properties, SVD computation.
Principal Component Analysis (PCA).
Linear classification: Perceptron algorithm.
Linear and quadratic discriminant analysis (LDA, QDA).
Linear and quadratic classifiers, including discriminant analysis.</td></tr>
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Lecture schedule	
Education week	Topic
1.	Linear systems: LU decomposition, QR decomposition. Fitting methods: Least Squares Method (LSM), Pattern-Fitting Method (PFM), and spline-based fitting.
2.	Optimization techniques — derivative-based and derivative-free: Golden-Section Search (GSS), Successive Parabolic Interpolation (SPI), Gradient Descent. Iterative solvers: Jacobi method.
3.	Numerical differentiation and numerical integration. Initial-Value Problems (IVPs), Boundary-Value Problems (BVPs).
4.	Finite-difference discretization, Time and Space Stepping Schemes
5.	Fourier analysis: Fourier series in complex form, Gibbs phenomenon. Fourier transform (FT) and its properties, Parseval's theorem, Parseval/energy identity.
6.	Discrete Fourier Transform (DFT), DFT vs FFT, Short-Time / Windowed Fourier Transform, spectrograms, Gabor (Gábor) transform.
7.	1st Midterm test
8.	Laplace transform and its properties.
9.	Matrix decompositions by singular values over real and complex fields: SVD
10.	SVD properties, SVD computation
11.	Principal Component Analysis (PCA).
12.	Linear classification: Perceptron algorithm.
13.	Linear and quadratic discriminant analysis (LDA, QDA).
14.	2nd Mid-term Test
exam period, 1st week	Make-up mid-term test

Mid-term requirements	
Conditions for obtaining a mid-term grade/signature	**A minimum of 70% class attendance and at least a passing (grade 2 – satisfactory) mid-term test result is required. A successful test is mandatory to acquire grade.**

Assessment schedule	
Education week	Topic
7.	1st Midterm test
14.	2nd Midterm test
exam period, 1st week	Make-up mid-term test

Method used to calculate the *mid-term grade* (to be filled out only for subjects with mid-term grades)
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Type of the replacement	
Type of the replacement of written test/mid-term grade/signature	**During the signature make-up week, the mid-term test may be retaken — for a fee — on one of the first 10 working days of the exam period.**

Type of the exam (to be filled out only for subjects with exams)	
Oral exam	
Calculation of the exam mark (to be filled only for subjects with exams)	
Final grade calculation methods:	
The final grade will be calculated using the following scale:	

Achieved result	Grade
91% - 100%	excellent (5)
75%- 90%	good (4)
61% -74%	satisfactory (3)
51% - 60%	pass (2)
0 - 50 %	failed (1)

References	
Obligatory:	• Materials for presentations and lecture notes related to in-class sessions
Recommended:	• Gilbert Strang, *Computational Science and Engineering*, Wellesley-Cambridge Press, 2019. • Gilbert Strang, *Linear Algebra and Learning from Data*, Wellesley-Cambridge Press, 2019. • Gilbert Strang, and Truong Nguyen, *Wavelets and Filter Banks*, Wellesley-Cambridge Press, 1996.
Other references:	• https://elearning.uni-obuda.hu/