

Frankfurt School Exchange Student Information

Overview of Winter Semester 2026

MSc Modules

Master of Artificial Intelligence & Data Science *

(formerly – Master of Applied Data Science)

Please note that some combinations of courses might not be possible.
These incompatibilities will be indicated on the selection platform.

Quarter Schedules courses:

Quarter 1: Academic period: 27 August – 17 October 2026

Exam Week: 19 October – 24 October 2026

Quarter 2: Academic period: 26 October – 12 December 2026

Exam Week: 14 December – 19 December 2026

Course	Quarter
Quantitative Fundamentals	1
Algorithms & Data Structures	1
Introduction to Data Analytics in Business*	1+2
Computational Statistics & Probability	2
The Language of Business	2
Strategy and Performance Management	1
Deep Learning	1
Natural Language Processing	2

**This course is scheduled across Q1 and Q2*

Quantitative Fundamentals [QUM71140]

Module Coordinator		Nagler, Jan			
Programme(s)		Master of Artificial Intelligence & Data Science			
Term		Semester 1 Q1			
Module Duration		1 Semester			
Compulsory/Elective Module		Compulsory Module			
Credits:		6			
Frequency		Annually			
Language		English			
Total Workload	150 h	Academic Teaching Hours:	44	Remaining Workload:	Self-study
		One academic teaching hour corresponds to 45 minutes.			
		Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.			
Prerequisites		Mathematics on high-school level, in particular algebra and analysis. Very basic knowledge in Python including NumPy, available, e. g., at Github, http://cs231n.github.io/python-numpy-tutorial/			

Content	<p>Part 1: Linear Algebra</p> <ol style="list-style-type: none"> 1. Scalars, Vectors, Matrices, and Tensors 2. Matrix and Vector Multiplication 3. Identity and Inverse Matrices 4. Linear Dependence and Span 5. Norms <ul style="list-style-type: none"> • Measuring the size of a vector with L_p • The Euclidean norm (L_2) • The max norm (L_1) • Frobenius norm 1. Special kinds of matrices <ul style="list-style-type: none"> • Diagonal • Symmetric • Unit vector & unit norm • Orthogonal vectors and orthogonal matrices 1. Eigendecomposition 2. Singular Value Decomposition 3. The Moore-Penrose Pseudoinverse 4. The Trace Operator and Determinant <p>Part 2: Useful functions, Iterated maps and Convergence Problems</p> <ol style="list-style-type: none"> 1. Sigmoid function 2. Softplus 3. Derivatives 4. Simple maps 5. Chaotic maps 6. Convergence Problems <p>Part 3: Probability</p> <ol style="list-style-type: none"> 1. Introduction to Probability <ul style="list-style-type: none"> • Discrete variables and probability mass functions • Continuous variables and probability density functions • Marginal and conditional probability • Chain rule • Independence and conditional Independence • Bayes rule • Expectation, Variance and Covariance • Transformation of random variables 1. Common Probability Distributions <ul style="list-style-type: none"> • Bernoulli distribution • "Multinoulli" distributions • Gaussian distribution • Exponential and Laplace • Dirac distribution and cumulative distributions 1. Bayesian networks 2. Self-information & Entropy
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<p>Intended Learning Outcomes</p>	<p>Knowledge: The students will acquire a basic understanding of linear algebra, convergence problems, probability theory, and their use in machine learning and data science.</p> <p>Skills: Upon the successful completion of the course, students are able to</p> <ul style="list-style-type: none"> • represent and perform numerical operations on systems of linear equations in linear algebraic terms • critically assess and select appropriate norms for measuring vector length • construct, calculate, and critically assess common forms of probabilistic and statistical reasoning • construct, calculate, and critically assess common forms of information theoretic methods • use matrices to formulate problems • use matrix algebra to determine solubility within a given problem formulation • use matrix algebra to solve problems • use norms to formulate and measure distances in datasets • identify parameters to quantification of numerical convergence • formulate and modify convergence criteria and overcome computational convergence difficulties • identify distributions that properly describe a given probabilistic problem • formulate and solve problems formulated in sets of conditional probabilities • identify and formulate conditionally dependences and independences to reduce problem complexity • solve problems with correlated stochastic variables and data • formulate and solve causal models 								
<p>Forms of teaching, methods and support</p>	<p>The course will consist in theoretical lectures, where theory and theoretical insights are covered. In addition, there will be tutorials and Python exercises, where students will begin work on that week's programming assignment, which will be completed outside of class. The Professor will be available to help students.</p>								
<p>Type of Assessment(s) and performance</p>	<table border="1"> <thead> <tr> <th>Type of Assessment</th> <th>Duration</th> <th>Performance Points</th> <th>Due Date or Date of Exam</th> </tr> </thead> <tbody> <tr> <td>Written exam</td> <td>120 minutes</td> <td>120</td> <td>Exam Week</td> </tr> </tbody> </table>	Type of Assessment	Duration	Performance Points	Due Date or Date of Exam	Written exam	120 minutes	120	Exam Week
Type of Assessment	Duration	Performance Points	Due Date or Date of Exam						
Written exam	120 minutes	120	Exam Week						
<p>Recommended Literature</p>	<ul style="list-style-type: none"> • Gentle, J.E. (2017). Matrix Algebra: Theory, Computations, and Applications in Statistics, 2nd. Ed. Springer. • Savov, I. (2017). No Bullshit Guide to Linear Algebra. 2nd Ed. Minireference Co. • Murphy, K. P. (2012). Machine Learning: A Probabilistic Perspective, MIT Press. • Cover, T. M and Thomas, J. A. (2006). Elements of Information Theory, 2nd Edition. Wiley. 								

Module Structure	Session Topic Preparation 1 Scalars, Vectors, Matrices, Tensors, Matrix and Vector Multiplication 2 Identity and Inverse Matrices, Linear Dependence and Span 3 Norms 4 Special kinds of matrices 5 Eigendecomposition, Singular Value Decomposition 6 The Moore-Penrose Pseudoinverse, The Trace Operator and Determinant 7 Useful functions 8 Iterated maps and Convergence Problems 9 Introduction to Probability: Discrete variables and probability mass functions, Continuous variables and probability density functions, Marginal and conditional probability, Chain rule, Independence and Conditional Independence, Bayes rules, Expectation, Variance and Covariance 10 Common Probability Distributions 11 Bayesian networks Self-Information & Entropy
Usability in other Modules/Programmes	Machine Learning 1, Machine Learning 2, Thesis
Last Approval Date	2026/04/14

Algorithms & Data Structures [QUM71141]

Module Coordinator		Andonians Salmas, Vahe			
Programme(s)		Master of Artificial Intelligence & Data Science			
Term		Semester 1 Q1			
Module Duration		1 Semester			
Compulsory/Elective Module		Compulsory Module			
Credits:		6			
Frequency		Annually			
Language		English			
Total Workload	150 h	Academic Teaching Hours:	44	Remaining Workload:	Self-study
		One academic teaching hour corresponds to 45 minutes.			
		Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.			
Prerequisites		Students need a laptop with Python 3 installed (preferably using Anaconda)			

Content	<p>Introduction to algorithms</p> <ul style="list-style-type: none"> • Introduction to Python <ul style="list-style-type: none"> • Expressions • Variables • Conditions • Iterations • Functions, scoping, and abstraction in Python <ul style="list-style-type: none"> • Functions and scoping • Global Variables • Files • Modules • Analyzing algorithms • Introduction to git • Sorting <ul style="list-style-type: none"> • Merge Sort • Quicksort • Object oriented programming • Elementary data structures <ul style="list-style-type: none"> • Stacks and queues • Linked lists • Hash tables • Binary search trees • Structured types in Python <ul style="list-style-type: none"> • Tuples • Dictionaries • Classes • Functions as objects • Introduction to NumPy • Introduction to Pandas
Intended Learning Outcomes	<p>Knowledge: By the time students finish the module, they can define algorithms and data structures recognize algorithms and data structures explain algorithms and data structures which build the foundation of software engineering</p> <p>Skills: Students practice the programming language Python Students design basic computational algorithms as narrative Students analyze basic computational algorithms as narrative Students implement basic computational algorithms in Python</p> <p>Competence: On successful completion of this module, students can demonstrate theory and practice of software engineering apply theory and practice of software engineering illustrate theory and practice of software engineering solve an unknown problem theoretically using algorithms</p>
Forms of teaching, methods and support	Theory is explained during class and broadcasted using Zoom, students will apply this during class in individual and group assignments

Type of Assessment(s) and performance	Type of Assessment	Duration	Performance Points	Due Date or Date of Exam
	Individual assignments	Five days per assignment	50	5 assignments during courses
	Group assignments	Five days per assignment	20	2 assignments during the course
	Final exam	50 minutes	50	During exam week
Recommended Literature	<p>Students will be provided with the necessary material during the course. For students, who would like to dive deeper into Algorithms and Data Structures following book would be useful: Heineman, George T., Stanley Selkow. Algorithms in a Nutshell (In a Nutshell (O'Reilly)) (Kindle Locations 3-6). O'Reilly Media. (for preparation chapters</p>			
Module Structure	<p>Session Topic Preparation</p> <ol style="list-style-type: none"> 1 Introduction to algorithms 2 Introduction to Python 3 Functions, scoping, and abstraction in Python; 4 Analyzing algorithms; sorting algorithms 5 Introduction to git; sorting algorithms 6 Object Oriented Programming 7 Object Oriented Programming 8 Elementary data structures 9 Elementary data structures 10 Structured data types in Python 11 Introduction to NumPy and Pandas 			
Usability in other Modules/Programmes	<p>This introductory course to Software Engineering using Python builds the foundation for all other courses using programming.</p>			
Last Approval Date	2026/04/20			

Introduction to Data Analytics [INF71125]

Module Coordinator		Böttcher, Lucas			
Programme(s)		Master of Artificial Intelligence & Data Science			
Term		Semester 1 Q1			
Module Duration		-			
Compulsory/Elective Module		Compulsory Module			
Credits:		6			
Frequency		Annually			
Language		English			
Total Workload	150 h	Academic Teaching Hours:	44	Remaining Workload:	Self-study
		One academic teaching hour corresponds to 45 minutes.			
		Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.			
Prerequisites		programming knowledge (Python); version control (git); probability theory; calculus; linear algebra (This course will *not* provide an introduction to programming/python. If you feel that you need additional learning material w.r.t. programming/python basics, I refer you to freely available course material from other sources like https://et.lecturers.inf.ethz.ch/viewer/courses .)			
Content		<p>This course provides an introduction to different aspects of data analytics, covering computational techniques for identifying and analyzing patterns in large-scale and high-dimensional datasets. Topics to be covered include dimensionality reduction, regression models, model selection, classification algorithms, network analysis, and recommender systems. Students will implement and apply methods using Python.</p> <p>In addition to in-class exercises, students will work on group projects that focus on a specific data science topic of their interest.</p>			

Intended Learning Outcomes	<p>Knowledge: Students will acquire a comprehensive understanding of different data-analysis frameworks. They can:</p> <ul style="list-style-type: none"> • Explain differences between various data-analysis frameworks • Apply problem-specific data-analysis models <p>Skills: Students learn to analyze datasets, select appropriate modeling techniques, and construct models for decision support. They also learn how to implement different data analytics algorithms using Python. They are able to:</p> <ul style="list-style-type: none"> • Select appropriate computational methods • Process and analyze large-scale and high-dimensional datasets • Implement and develop custom data analytics algorithms • Train and tune algorithms to achieve desired results <p>Competence: Students are qualified to identify and analyze patterns in large-scale and high-dimensional datasets and to translate data-driven insights into informed decision-making. They acquire a fundamental background to fulfill the demands of a modern data scientist. They are able to:</p> <ul style="list-style-type: none"> • Identify relevant datasets • Distinguish between different computational methods to analyze large-scale and high-dimensional data • Apply appropriate computational techniques to efficiently analyze datasets • Visualize results and translate data-driven insights into informed decision-making 															
Forms of teaching, methods and support	Lecture with in-class and home assignments.															
Type of Assessment(s) and performance	<table border="1"> <thead> <tr> <th>Type of Assessment</th> <th>Duration</th> <th>Performance Points</th> <th>Due Dte or Date of Exam</th> </tr> </thead> <tbody> <tr> <td>Graded individual in-class assignment</td> <td>40 min (30 min + 10 min reading time)</td> <td>30</td> <td>tba</td> </tr> <tr> <td>Group project including written report and presentation</td> <td>At least two weeks</td> <td>90</td> <td>tba</td> </tr> </tbody> </table>				Type of Assessment	Duration	Performance Points	Due Dte or Date of Exam	Graded individual in-class assignment	40 min (30 min + 10 min reading time)	30	tba	Group project including written report and presentation	At least two weeks	90	tba
Type of Assessment	Duration	Performance Points	Due Dte or Date of Exam													
Graded individual in-class assignment	40 min (30 min + 10 min reading time)	30	tba													
Group project including written report and presentation	At least two weeks	90	tba													

Recommended Literature	<p><u>Data and information sciences:</u></p> <ul style="list-style-type: none"> • Leskovec, Jure, Anand Rajaraman, and Jeffrey David Ullman. <i>Mining of massive data sets</i>. Cambridge University Press, 2020. • Géron, Aurélien. <i>Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems</i>. O'Reilly Media, 2019. • Friedman, Jerome, Trevor Hastie, and Robert Tibshirani. <i>The Elements of Statistical Learning: Data Mining, Inference, and Prediction</i>. Vol. 2. New York: Springer Series in Statistics, 2009. • Bishop, Christopher M. <i>Pattern Recognition and Machine Learning</i>. Springer, 2006 <p><u>Network analysis and related concepts:</u></p> <ul style="list-style-type: none"> • Newman, Mark. <i>Networks</i>. Oxford University Press, 2018. • Böttcher, Lucas and Hans J. Herrmann. <i>Computational Statistical Physics</i>. Cambridge University Press, 2021. <p><u>Programming:</u></p> <ul style="list-style-type: none"> • Martin, Robert C. <i>Clean Code: A Handbook of Agile Software Craftsmanship</i>. Upper Saddle River, NJ: Prentice Hall, 2009.
Module Structure	<ol style="list-style-type: none"> 1. Standard tools and problems in data analytics 2. Data preparation, feature transformation, and dimensionality reduction 3. Regression models and model selection 4. Classification algorithms 5. Large-scale data analysis with PySpark 6. Network analysis 7. Recommender systems 8. Student presentations
Usability in other Modules/Programmes	All computational modules in the following semesters. Thesis.
Last Approval Date	2026/03/31

Computational Statistics & Probability
[INF71126]

Module Coordinator		Wheeler, Gregory			
Programme(s)		Master of Artificial Intelligence & Data Science			
Term		Semester 1 Q2			
Module Duration		1 Semester			
Compulsory/Elective Module		Compulsory Module			
Credits:		6			
Frequency		Annually			
Language		English			
Total Workload	150 h	Academic Teaching Hours:	44	Remaining Workload:	Self-study
		One academic teaching hour corresponds to 45 minutes.			
		Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.			
Prerequisites		Quantitative Fundamentals			
Content		<p>This course is an introduction to Bayesian generalized linear multi-level models. The course starts with the basics of regression and proceeds to advanced multilevel models, all from a hands-on, computational-Bayesian perspective. The course uses much more computer code (in R) than formal mathematics to impart the fundamental concepts of Bayesian statistics. Doing so in an introductory course teaches students from the beginning to recognize fundamental issues that arise from using different methods to implement the same mathematical statistical model.</p>			
Intended Learning Outcomes		<p>Upon successfully completing the module, each student can:</p> <ul style="list-style-type: none"> • construct, fit and interpret Bayesian multilevel regression models using R • execute prior predictive simulations • plot and interpret posterior distributions • compare models by their predictive accuracy using cross-validation and information criteria • use graphical causal modeling to perform variable selection • estimate unknown posterior distributions with quadratic approximation • estimate unknown posterior in high-dimensional problems with Markov chain Monte Carlo (MCMC) methods 			

Forms of teaching, methods and support	The course consists of lectures, where theory and implementation examples are covered, and tutorials, where students begin working on programming assignments that are then completed outside of class.			
Type of Assessment(s) and performance	Type of Assessment	Duration	Performance Points	Due Date oder Date of Exam
	Four (4) Programming Assignments	3 days per assignment	70	During Module
	Written Exam	50 min	50	During Exam Week
In order to fully assess the students competences in both theory and practice, more than one type of assessment is necessary.				
Recommended Literature	<p>Required</p> <ul style="list-style-type: none"> • McElreath, R. (2020). <i>Statistical Rethinking: A Bayesian Course with Examples in R and Stan, 2nd Edition</i>, Chapman Hall/CRC Press. <p>Recommended</p> <ul style="list-style-type: none"> • Pearl, J., Glymour, M., and Jewell, N. (2016). <i>Causal Inference in Statistics: A Primer</i>, Wiley. <p>In addition, students may wish also to consult the following resources for programming in R:</p> <ul style="list-style-type: none"> • Wickham & Garrett Golemund (2017). <i>R for Data Science</i>, O' Reilly. 			
Module Structure	<p>The module structure consists of four components:</p> <ol style="list-style-type: none"> 1. Preparation for each lecture by reading the assigned material prior to class 2. Attend all tutorials with a laptop with all necessary software installed and ready prior to class. 3. Complete all programming assignments and submit them before deadline, correctly formatted, and following the instructions for submission. 4. A final exam. 			
Usability in other Modules/Programmes	Machine Learning I, Machine Learning II, Generative AI and Agentic Systems, Company Project, Thesis			
Last Approval Date	2026/04/08			

The Language of Business [ACC71158]

Module Coordinator		Ramasubramanian, Hari			
Programme(s)		Master of Artificial Intelligence & Data Science			
Term		Semester 1 Q2			
Module Duration		1 Semester			
Compulsory/Elective Module		Compulsory Module			
Credits:		6			
Frequency		Annually			
Language		English			
Total Workload	150 h	Academic Teaching Hours:	44	Remaining Workload:	Self-study
		One academic teaching hour corresponds to 45 minutes.			
		Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.			
Prerequisites		Basic understanding of statistics. Interest in understanding balance sheets and connection thereof with market pricing. Interest in connecting coding skills with balance sheet and financial market analysis. The course is taught interactively. For full credit participation is necessary.			

<p>Content</p>	<p>This module serves as an introduction to accounting as a business language and a data-generating system, with applications in financial analysis and data-driven decision-making.</p> <p>At a very basic level, financial statements are a primary source of systematic public information about companies and form the basis for answering many relevant questions. How are business transactions recorded and transformed into financial statements? How do financial statements reflect the underlying business model of a firm? How can accounting data be structured and analyzed for decision-making purposes? What is the relationship between financial statement information and market prices? How can data science and analytical tools be applied to accounting data? These are key questions, which will be answered in this module. They also form the basis for the development of digital transformation in the financial sector. The basis of the course are the first 3 topics of the agenda. This is due to the fact that a fundamental understanding of the topics must be achieved before you can start to think about the use of digital tools.</p> <p>In parallel, students apply these concepts in practical exercises and projects, including the use of programming tools (e.g., Python) to analyze financial data and derive insights.</p> <p>Accounting is essentially a form of standardization of communication between enterprises and their stakeholders that facilitates both their preparation and interpretation. In many cases, accounting and the resulting financial statements are the only source of publicly available and reliable information about a company itself, but also about its customers, suppliers and competitors.</p> <p>Consequently, it is relevant for the students to gain an understanding of the underlying accounting principles as well as its practical implementation.</p> <p>Likewise it is important to understand the interplay between balance sheet and market pricing. This interplay is illustrated using practical examples.</p> <p>The module focuses on the following areas: Balance sheet entries and generating data to attain those Optimization of accounting processes and data handling using analytical tools Understanding connection between balance sheet entries and market pricing Application of data analysis techniques to evaluate financial statements Students will work with financial data to construct datasets and perform analysis to measure constructs using financial statements.</p>
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	<p>In all these cases, several specialist departments are involved (e.g. accounting, tax department, IT, trading, auditors), combining different fields of expertise. In order to ensure an efficient project progress, experts are required to act as negotiator and translators between IT and the respective specialists. The course aims to prepare students to act as intermediaries between financial, technical, and analytical stakeholders in mixed-specialty teams.</p> <p>Setting the scene in the digital architecture: The student gets insight into the practice including its interfaces to the following lectures in the remaining curriculum of MADS</p>
<p>Intended Learning Outcomes</p>	<p>Upon completion of the module, the student can:</p> <p>Understand and account for transactions based on accounting conventions (knowledge).</p> <p>Describe how the business model of a company is represented in annual financial statements and explain why and how the accounting data is audited by the auditors (understanding).</p> <p>Reconcile the path from a business question to the collection of raw data, construct datasets, and apply analytical approaches using accounting information for decision-making (synthesis).</p> <p>Critically evaluate the individual business transactions accordingly (evaluation).</p> <p>Assess the importance of accounting data as a rare source of reliable firm-level information.</p> <p>Understand the use of accounting information for decision making within firms (knowledge).</p> <p>Evaluate a firm's strategy based on its financial statements (evaluation).</p> <p>Understand the link between accounting and market prices (knowledge).</p> <p>Apply basic programming tools (e.g., Python) to analyze financial data and derive insights.</p> <p>Transform accounting data into structured datasets suitable for analysis.</p> <p>Communicate analytical findings effectively to both technical and non-technical stakeholders.</p>
<p>Forms of teaching, methods and support</p>	<ul style="list-style-type: none"> • Lecture with interactive case studies and related discussions • Practical exercises / presentations. Divided into small groups of about 4 participants including presentation of the solution • Group-based analytical and programming exercises integrated throughout the course • Python session / deep dive

Type of Assessment(s) and performance	Type of Assessment	Duration	Performance Points	Due Date or Exam Date
	Quizzes	10-20 min	20	During the course
	Small project incl. presentation	approx. 1-2 weeks	60	during the course
	Oral participation / exam	n/a	20	during course / end of course
	group wide programming exercise (single contribution)	approx 1-2 weeks	20	during the course
Recommended Literature	International Financial Reporting Standards (IFRS) 2021: English & German edition of the official standards approved by the EU, Wiley – March 10, 2021. Financial Accounting an international introduction “David Alexander&Christopher Nobes”, 7th edition Financial Literacy, R.A. Lambert			
Module Structure	Module outline (tentative): Session Topic(s) 1 Introduction 2 Accounting in general 3 Income statement, Balance sheet, and Cash flow statement 4 Ratio analysis 5 Cost behavior 6 Breakeven analysis 7 Budgeting and forecasting 8 Accounting and Strategy 9 Capital Asset Pricing Model (CAPM)			
Usability in other Modules/Programmes	Within the MADS programme, the course provides foundational knowledge for financial management.			
Last Approval Date	2026/04/21			

**Strategy and Performance Management
[MGT73373]**

Module Coordinator		Mahlendorf, Matthias			
Programme(s)		Master in Applied Data Science			
Term		Semester 3 Q1			
Module Duration		1 Semester			
Compulsory/Elective Module		Compulsory Module			
Credits:		6			
Frequency		Annually			
Language		English			
Total Workload	150 h	Academic Teaching Hours:	44	Remaining Workload:	Self-study
		One academic teaching hour corresponds to 45 minutes.			
		Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.			
Prerequisites		All previous modules of the programme			
Content		<p><i>“However beautiful the strategy, you should occasionally look at the results” — Sir Winston Churchill</i></p> <p>This course equips students in with advanced analytical tools for strategic business decision-making. Students learn to apply machine learning and econometric techniques, such as difference-in-difference analyses, to interpret complex financial and non-financial data. They gain practical experience with AI tools, text analytics and innovative data sources to enhance performance management. The course emphasizes strategic positioning, effective design and implementation of A/B tests, and field experiments to optimize business initiatives. Students become proficient in selecting relevant performance indicators and understanding how these metrics influence managerial decisions. Graduates are prepared for data science positions supporting company executives, AI consulting, and other jobs that analyze data to improve firm performance.</p> <p>Throughout the course, we will aim for both, understanding business concepts (“How do executives think?”) as well as analysing business data (“How can AI and data science help the organization to be successful?”).</p>			

Intended Learning Outcomes

This course provides students with comprehensive knowledge, skills, and competencies required for data-driven strategic decision-making in business contexts.

Knowledge: Having completed this course, students will know:

- How a company identifies and sustains competitive advantage.
- The opportunities and risks associated with AI agents.
- How data science supports strategic implementation.
- Machine learning and generative AI (GenAI) techniques for analyzing textual data to derive insights for performance management.
- Econometric analysis methods, including difference-in-difference panel data analyses with fixed effects, lagged effects, and clustered standard errors.
- Methods for improving decision-making through analyses of financial and non-financial data for various business contexts.
- Principles for designing and implementing A/B testing and field experiments to systematically analyze and optimize company initiatives and investments.

Skills: Upon successful completion of the course, students will acquire the ability to:

- Analyze a company's strategic positioning.
- Select performance indicators aligned with short-term and long-term strategic goals.
- Utilize statistical methods to identify performance drivers and inform organizational decisions.
- Analyze ratings and text reviews from online platforms, such as employer ratings, using causal inference techniques including exogenous shocks, staggered introductions, and difference-in-differences designs.
- Develop and implement effective performance management systems aligned with company strategy.
- Critically evaluate real business scenarios to understand how performance measures influence managerial decision-making and control.

Competence: Upon successful completion, students will be qualified to:

- Evaluate company performance through detailed analyses of financial and non-financial data.

Career Opportunities: This course content directly supports career paths such as:

- In general, understanding business decisions will be useful for almost any career path (e.g., even a "pure AI researcher" needs to convince others to provide funding/capital)
- More specifically, the course will be particularly relevant for jobs related to AI consulting and corporate positions which help organizations leverage AI (and AI agents) to improve performance
- Data scientists supporting strategic management roles, including responsibility for strategy formulation, execution, and performance management.

	<ul style="list-style-type: none"> • Data-oriented positions in Finance, monitoring and interpreting financial and non-financial performance metrics for strategic management. • Data strategists and individuals interested in leveraging diverse data sources, including accounting data, employee insights, and customer feedback, to enhance organizational effectiveness and decision-making. 																
Forms of teaching, methods and support	Lectures Python programming exercises Excel exercises Case studies Simulation Games Practitioner guest lectures Final project with real world/company data																
Type of Assessment(s) and performance	<table border="1"> <thead> <tr> <th>Type of Assessment</th> <th>Duration</th> <th>Performance Points</th> <th>Due Date oder Date of Exam</th> </tr> </thead> <tbody> <tr> <td>Assignments</td> <td>360 minutes</td> <td>60</td> <td>Before, during and after classes</td> </tr> <tr> <td>Class participation</td> <td>n.a.</td> <td>10</td> <td>During each class</td> </tr> <tr> <td>Final project (in teams)</td> <td>50 minutes</td> <td>50</td> <td>During the quarter with a presentation at the end of the quarter</td> </tr> </tbody> </table>	Type of Assessment	Duration	Performance Points	Due Date oder Date of Exam	Assignments	360 minutes	60	Before, during and after classes	Class participation	n.a.	10	During each class	Final project (in teams)	50 minutes	50	During the quarter with a presentation at the end of the quarter
Type of Assessment	Duration	Performance Points	Due Date oder Date of Exam														
Assignments	360 minutes	60	Before, during and after classes														
Class participation	n.a.	10	During each class														
Final project (in teams)	50 minutes	50	During the quarter with a presentation at the end of the quarter														
Recommended Literature	<p>Note: Additional supporting literature for each lecture will be provided in Canvas when the course starts.</p> <ul style="list-style-type: none"> • Nick Huntington-Klein (2021). The Effect: An Introduction to Research Design and Causality. Free online access: https://theeffectbook.net/ • Besanko, D. Dranove, D., Shanley, M., Schaefer (2017). Economics of Strategy. 7th edition, Wiley. • Rumelt, R. (2011). Good Strategy Bad Strategy. Random House. • Wouters et al. (2012). Cost Management: Strategies for Business Decisions. <p>As an entertaining "soft learning" approach I recommend the following podcasts:</p> <ul style="list-style-type: none"> • Dwarkesh Podcast Podcast on Spotify https://open.spotify.com/show/4JH4tybY1zX6e5hjCwU6gF • Lex Fridman Podcast Podcast on Spotify https://open.spotify.com/show/2MAi0BvDc6GTFvKFPXnkCL 																

Module Structure	<ol style="list-style-type: none"> 1. Analyzing ratings and text reviews from online platforms 2. Identifying causal effects: Exogenous shocks, staggered introduction & difference-in-difference designs 3. Interaction effects 4. Alternative and innovative data usecases 5. Analyzing firm performance drivers 6. Panel data analyses: Lagged effects, fixed effects 7. Collecting and analyzing survey data: Understanding employees and customers 8. A/B testing / field experiments 9. AI Agents and Digitalization of Internal Controls 10. Strategic investments: Discounted cash flows, scenarios, real options, Monte Carlo 11. Growing a Platform Business: Simulation Game <p>Note that this structure can be subject to changes.</p>
Usability in other Modules/Programmes	Thesis module
Last Approval Date	2026/04/10

Deep Learning [MGT75025]

Module Coordinator		Szabados, Levente			
Programme(s)		Master in Applied Data Science			
Term		Semester 3 Q1			
Module Duration		1 Semester			
Compulsory/Elective Module		Compulsory Module			
Credits:		6			
Frequency		Annually			
Language		English			
Total Workload	150 h	Academic Teaching Hours:	44	Remaining Workload:	Self-study
		One academic teaching hour corresponds to 45 minutes.			
		Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.			
Prerequisites		Machine Learning I and II			
Content		<p>This module covers deep neural networks, which are currently the “workhorse” of machine learning and most commonly used method.</p> <p>We start with a quick recap of simple neural networks, which were only of limited success in their applications and then move on to introduce the theory of deep neural networks and why, in contrast, they have been so successful. Our main purpose will be to understand the theoretical background necessary to employ deep neural networks to solve problems of image recognition and language processing. Particularly, we focus on different theoretical concepts behind deep neural networks that are essential for building successful applications. This includes the working and effect of stochastic gradient decent and mini batch, activation functions, such as ReLu (rectifier linear unit), drop out and regularization, as well as different architectures (Convolutional Neural Networks as well as Long Short Term Memory neural networks and Transformers).</p> <p>The module has a practical focus, taking theory and then applying it immediately in each class. After an initial introduction, participants will be asked to form teams to solve a practical machine learning problem using deep learning methods.</p>			

Intended Learning Outcomes	<p>At the end of the module students should be able to:</p> <ul style="list-style-type: none"> List the most important deep learning approaches Recognize modern deep neural network machine learning methods Explain modern deep neural network machine learning methods Apply deep neural networks to a number of practical problems using appropriate algorithmic structures and optimization Analyze optimization metrics for a solution they have defined in order to distinguish whether neural network learning proceeded correctly Evaluate which of a series of models performs best Evaluate why this is so, particularly why increasing model complexity should (or should not) add predictive accuracy 																
Forms of teaching, methods and support	<p>Most of the content that we are going to use will be in Jupyter notebooks. For each class, you will have to complete a small programming assignment in the Jupyter notebook.</p>																
Type of Assessment(s) and performance	<table border="1"> <thead> <tr> <th>Type of examination</th> <th>Duration or length</th> <th>Performance Points</th> <th>Due date or date of exam</th> </tr> </thead> <tbody> <tr> <td>Individual assignments</td> <td>six weeks</td> <td>40</td> <td>There is one assignment for each lecture of the class. The assignments are due 2 weeks after the class.</td> </tr> <tr> <td>Continuous assignments</td> <td>two weeks</td> <td>40</td> <td>Two weeks after the final class</td> </tr> <tr> <td>Exam</td> <td>40 minutes</td> <td>40</td> <td>Exam week</td> </tr> </tbody> </table>	Type of examination	Duration or length	Performance Points	Due date or date of exam	Individual assignments	six weeks	40	There is one assignment for each lecture of the class. The assignments are due 2 weeks after the class.	Continuous assignments	two weeks	40	Two weeks after the final class	Exam	40 minutes	40	Exam week
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Recommended Literature	<p>There is no mandatory reading, only the provided class material. Optional reading: Goodfellow, I., Bengio, Y., & Courville, A. (2016). <i>Deep Learning</i>. MIT Press. Available online at: http://www.deeplearningbook.org</p>																

Module Structure	<p>Session Topic</p> <p>Recap of neural network basics - Perceptron model, perceptron update rule</p> <ul style="list-style-type: none"> - XOR Problem - Basic feed forward neural networks - Regularising neural networks - Hyperparameter optimisation methods <p>Problem of generalization -Bias-Variance trade-off</p> <ul style="list-style-type: none"> - Overfitting - Regularisation methods <p>Training setup for neural networks - Introduction to TensorFlow</p> <ul style="list-style-type: none"> - Getting data into TensorFlow - TensorFlow Core and train APIs - Debugging and visualisation, - Tensor Board - Keras <p>Current neural architectures and their application - Problem domains, datasets and baselines</p> <ul style="list-style-type: none"> - Convolutional neural networks and recurrent neural networks <p>Neural Scaling Laws - Foundational principles of modern neural scaling</p> <p>Unsupervised learning with neural models - Representation learning techniques</p> <p>Transfer learning - Practical need for transfer</p> <ul style="list-style-type: none"> - Methods and catastrophic forgetting <p>Deploying deep neural networks - Learning models</p> <ul style="list-style-type: none"> - Project design principles - Architecture concerns - Validation, Performance <p>Outlook Large Language Models and Agentic AI foundations</p>
Usability in other Modules/Programmes	Frontiers of AI; Master's Thesis
Last Approval Date	2026/04/09

Natural Language Processing [MGT73326]

Module Coordinator		Andonians Salmas, Vahe			
Programme(s)		Master in Applied Data Science			
Term		Semester 3 Q2			
Module Duration		1 Semester			
Compulsory/Elective Module		Compulsory Module			
Credits:		6			
Frequency		Annually			
Language		German			
Total Workload	150 h	Academic Teaching Hours:	44	Remaining Workload:	Self-study
		One academic teaching hour corresponds to 45 minutes.			
		Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.			
Prerequisites		Introduction to Machine Learning I and II and Deep Learning			
Content		<p>This module is focused on applying machine learning techniques to gain language understanding. Natural language processing is one of the main sub-fields of machine learning and has driven major algorithmic breakthroughs in recent years. Language is a form of time series so breakthroughs in natural language processing such as LSTM networks have been closely connected to advances in machine learning in general.</p> <p>The module is thus taking a twofold approach. On the one hand we will introduce general machine learning techniques that can deal with time series and show how they can be effectively applied to give computers language understanding. On the other hand, we will combine these techniques with domain specific applications such as word embedding, semantic distance and dependency tree parsing.</p> <p>The module takes a practical approach combining theory with practice, so roughly 50% of the module will be theory and 50% will be practice.</p>			

Intended Learning Outcomes	<p>After completion of this class students should be able to</p> <ul style="list-style-type: none"> • Recognize the latest machine learning techniques to gain language understanding through computational techniques. • Translate the knowledge gained on NLP algorithms to novel language processing problems. • Apply natural language processing techniques to business problems to better understand the sentiment of customers, their needs and how they may be persuaded. • Analyze the most advanced machine learning techniques such as LSTM networks in a domain specific context, in our case natural language processing. • Evaluate which model is most appropriate for a problem, based on accuracy and convergence metrics of the optimization. 																		
Forms of teaching, methods and support	<p>Most of the content that we are going to use will be in Jupyter notebooks. For each class, you will have complete a small programming assignment in the Jupyter notebook.</p>																		
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Recommended Literature	<p>Speech and Language Processing (3rd ed. draft) Dan Jurafsky and James H. Martin</p> <p>available at: https://web.stanford.edu/~jurafsky/slp3/</p>																		
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Usability in other Modules/Programmes	<p>AI - The Frontier</p>																		
Last Approval Date	<p>2026/04/20</p>																		