Frankfurt School of Finance & Management
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Frankfurt School Exchange Student Information

Overview of Winter Semester 2024 MSc Modules

Master in Applied Data Science*

Please note that some combinations of core courses and concentrations courses might not be compatibles. These incompatibilities will be indicated on the selection platform. A maximum of two sessions overlap between courses are allowed for international students to enrich the courses portfolio.

Quarter Schedules for courses:

Quarter 1:	Academic period:	02 September – 19 October 2024
	Exam Week:	21 October – 26 October 2024
Quarter 2:	Academic period:	28 October – 14 December 2024
	Exam Week:	16 December – 21 December 2024

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

**This course is scheduled across Q1 and Q2*

If you combine in your selection core courses and concentrations, it may happen that there will be a clash as they belong to two different intakes. A maximum of two sessions overlap between courses are allowed for international students to enrich the courses portfolio.

**Current as of June 2024. This module catalogue is subject to change.*

Quantitative Fundamentals [QUM71131]

<table>
<tr><td colspan="2">Module Coordinator</td><td colspan="4">Nagler, Jan</td></tr>
<tr><td colspan="2">Programme(s)</td><td colspan="4">Master in Applied Data Science</td></tr>
<tr><td colspan="2">Term</td><td colspan="4">Semester 1 Q1</td></tr>
<tr><td colspan="2">Module Duration</td><td colspan="4">1 Semester</td></tr>
<tr><td colspan="2">Compulsory/Elective Module</td><td colspan="4">Compulsory Module</td></tr>
<tr><td colspan="2">Credits:</td><td colspan="4">6</td></tr>
<tr><td colspan="2">Frequency</td><td colspan="4">Annually</td></tr>
<tr><td colspan="2">Language</td><td colspan="4">English</td></tr>
<tr><td>Total Workload</td><td>150 h</td><td>Academic Teaching Hours:</td><td>44</td><td>Remaining Workload:</td><td>Self-study</td></tr>
<tr><td colspan="2" rowspan="2"></td><td colspan="4">One academic teaching hour corresponds to 45 minutes.</td></tr>
<tr><td colspan="4">Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.</td></tr>
<tr><td colspan="2">Prerequisites</td><td colspan="4">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/</td></tr>
</table>

Content	**Part 1: Linear Algebra** 1. Scalars, Vectors, Matrices, and Tensors 2. Matrix and Vector Multiplication 3. Identity and Inverse Matrices 4. Linear Dependence and Span 5. Norms • Measuring the size of a vector with Lp • The Euclidean norm (L2) • The max norm (L1) • Frobenius norm 1. Special kinds of matrices • 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 **Part 2: Useful functions, Iterated maps and Convergence Problems** 1. Sigmoid function 2. Softplus 3. Derivatives 4. Simple maps 5. Chaotic maps 6. Convergence Problems **Part 3: Probability** 1. Introduction to Probability • Discrete varibales and probability mass functions • Continuous cariables 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 • Bernoulli distribution • "Multinoulli" distributions • Gaussian distribution • Exponential and Laplace • Dirac distribution and cumulative distributions 1. Bayesian networks 2. Self-information & Entropy

Intended Learning Outcomes	***Knowledge:*** The students will acquire a basic understanding of linear algebra, convergence problems, probability theory, and their use in machine learning and data science. ***Skills:*** Upon the successful completion of the course, students are able to • represent and perform numercial 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
Forms of teaching, methods and support	The course will consist in theoretical lectures, where theory and theoretcial 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 completed outside of class. The Professor will be available to help students.
Type of Assessment(s) and performance	Type of Assessment / Duration / Performance Points / Due Date or Date of Exam: Written exam / 120 minutes / 120 / Exam Week
Recommended Literature	• 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	2024/03/27

Algorithms & Data Structures [QUM71132]

Module Coordinator		Andonians Salmas, Vahe			
Programme(s)		Master in Applied 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	***Introduction to algorithms***
	• ***Introduction to Python***
	  ◦ *Expressions*
	  ◦ *Variables*
	  ◦ *Conditions*
	  ◦ *Iterations*
	• ***Functions, scoping, and abstraction in Python***
	  ◦ *Functions and scoping*
	  ◦ *Global Variables*
	  ◦ *Files*
	  ◦ *Modules*
	• ***Analyzing algorithms***
	• ***Introduction to git***
	• ***Sorting***
	  ◦ *Merge Sort*
	  ◦ *Quicksort*
	• ***Object oriented programming***
	• ***Elementary data structures***
	  ◦ *Stacks and queues*
	  ◦ *Linked lists*
	  ◦ *Hash tables*
	  ◦ *Binary search trees*
	• ***Structured types in Python***
	  ◦ *Tuples*
	  ◦ *Dictionaries*
	  ◦ *Classes*
	  ◦ *Functions as objects*
	• ***Introduction to NumPy***
	• ***Introduction to Pandas***

Intended Learning Outcomes	*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 *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 *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
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	<table><tr><td>Type of Assessment</td><td>Duration</td><td>Performance Points</td><td>Due Date or Date of Exam</td></tr><tr><td>Individual assignments</td><td>Five days per assignment</td><td>50</td><td>5 assignments during courses</td></tr><tr><td>Group assignments</td><td>Five days per assignment</td><td>20</td><td>2 assignments during the course</td></tr><tr><td>Final exam</td><td>50 minutes</td><td>50</td><td>During exam week</td></tr></table>
Recommended Literature	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
Module Structure	Session Topic Preparation 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	This introductory course to Software Engineering using Python builds the foundation for all other courses using programming.
Last Approval Date	2024/05/28

Introduction to Data Analytics in Business
[INF71119]

Module Coordinator		Böttcher, Lucas			
Programme(s)		Master in Applied 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		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		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. In addition to in-class exercises, students will work on group projects that focus on a specific data science topic of their interest.			

Intended Learning Outcomes	*Knowledge:* Students will acquire a comprehensive understanding of different data-analysis frameworks. They can: • Explain differences between various data-analysis frameworks • Apply problem-specific data analysis models *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: • 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 *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: • 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	(see table below)

Type of Assessment	Duration	Performance Points	Due Dte or Date of Exam
Group project including written report and presentation	At least two weeks	120	Oct 31 and Nov 1

Recommended Literature	Data and information sciences: • Leskovec, Jure, Anand Rajaraman, and Jeffrey David Ullman. *Mining of massive data sets*. Cambridge University Press, 2020. • Géron, Aurélien. *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems*. O'Reilly Media, 2019. • Friedman, Jerome, Trevor Hastie, and Robert Tibshirani. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Vol. 2. New York: Springer Series in Statistics, 2009. • Bishop, Christopher M. *Pattern Recognition and Machine Learning*. Springer, 2006 Network analysis and related concepts: • Newman, Mark. *Networks*. Oxford University Press, 2018. • Böttcher, Lucas and Hans J. Herrmann. *Computational Statistical Physics*. Cambridge University Press, 2021. Programming: • Martin, Robert C. *Clean Code: A Handbook of Agile Software Craftsmanship*. Upper Saddle River, NJ: Prentice Hall, 2009.
Module Structure	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 quantitative modules in the following semesters. Thesis.
Last Approval Date	2024/04/22

Computational Statistics & Probability
[INF71121]

Module Coordinator		Wheeler, Gregory			
Programme(s)		Master in Applied 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		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.			
Intended Learning Outcomes		Upon successfully completing the module, each student can: • 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 Gibbs Sampling • estimate unknown posterior in high-dimensional problems with Markov chain Monte Carlo (MCMC) methods			

<table>
<tr><td>Forms of teaching, methods and support</td><td>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.</td></tr>
<tr><td>Type of Assessment(s) and performance</td><td>
<table>
<tr><td>Type of Assessment</td><td>Duration</td><td>Performance Points</td><td>Due Date oder Date of Exam</td></tr>
<tr><td>Five (5) Programming Assignments</td><td>3 days per assignment</td><td>70</td><td>During Module</td></tr>
<tr><td>Written Exam</td><td>50 min</td><td>50</td><td>During Exam Week</td></tr>
</table>

In order to fully assess the students competences in both theory and practice, more than one type of assessment is necessary.</td></tr>
<tr><td>Recommended Literature</td><td>Required
McElreath, R. (2020). Statistical Rethinking: A Bayesian Course with Examples in R and Stan, 2nd Edition, Chapman Hall/CRC Press.
Recommended
Pearl, J., Glymour, M., and Jewell, N. (2016). Causal Inference in Statistics: A Primer, Wiley.
In addition, students may wish also to consult the following resources for programming in R:
Wickham & Garrett Grolemund (2017). R for Data Science, O’ Reilly.
Wickham (2016), ggplot2: Elegant Graphics for Data Analysis, 2nd Edition, Springer.</td></tr>
<tr><td>Module Structure</td><td>The module structure consists of four components:
Preparation for each lecture by reading the assigned material prior to class
Attend all tutorials with a laptop with all necessary software installed and ready prior to class.
Complete all programming assignments and submit them before deadline, correctly formatted, and following the instructions for submission.
A final exam.</td></tr>
<tr><td>Usability in other Modules/Programmes</td><td>Machine Learning I, Machine Learning II, Text Mining and Natural Language Processing, Company Project, Thesis</td></tr>
<tr><td>Last Approval Date</td><td>2024/04/11</td></tr>
</table>

The Language of Business [ACC71156]

<table>
<tr><td colspan="2">Module Coordinator</td><td colspan="4">Dengler, Heike</td></tr>
<tr><td colspan="2">Programme(s)</td><td colspan="4">Master in Applied Data Science</td></tr>
<tr><td colspan="2">Term</td><td colspan="4">Semester 1 Q2</td></tr>
<tr><td colspan="2">Module Duration</td><td colspan="4">1 Semester</td></tr>
<tr><td colspan="2">Compulsory/Elective Module</td><td colspan="4">Compulsory Module</td></tr>
<tr><td colspan="2">Credits:</td><td colspan="4">6</td></tr>
<tr><td colspan="2">Frequency</td><td colspan="4">Annually</td></tr>
<tr><td colspan="2">Language</td><td colspan="4">English</td></tr>
<tr><td>Total Workload</td><td>150 h</td><td>Academic Teaching Hours:</td><td>44</td><td>Remaining Workload:</td><td>Self-study</td></tr>
<tr><td colspan="2" rowspan="2"></td><td colspan="4">One academic teaching hour corresponds to 45 minutes.</td></tr>
<tr><td colspan="4">Self-study includes lesson preparation and follow-up activities, reading assignments, assessment preparation, take-home assignments, etc.</td></tr>
<tr><td colspan="2">Prerequisites</td><td colspan="4">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 tought interactively. For full credit participation is necessary.</td></tr>
</table>

Content	The module serves as an introduction **to accounting as a business language** and its various purposes and applications. 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. What does bookkeeping mean? => Data basis for Data analytics Which is the link between bookkeeping and annual financial statement? What is the process of preparing an annual financial statement? => process understanding what is the benefit of unsing Data Science/Analytics in this area => using coding skills to evaluate balance sheets, financial statements and market analytics. in what way are balance sheets of banks particular What is the connection between balance sheet /financial statement entries and market prices What is the benefit by using Data Sciences/ Analytics in this area?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. Nevertheless, a dedicated project using programming skills and also teaching the essential coding skills where required, is run in parallel from the beginning of the course. 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. Consequently, it is relevant for the students to gain an understanding of the underlying accounting principles as well as its practical implementation. Likewise it is important to understand the interplay between balance sheet and market pricing. The can be understood best using balance sheet of banks. The module focuses on the following areas: Balance sheet entries and generating data to attain those How can we optimize the process and how can we us Data Sciences/ Analytics Understanding connection between balance sheet entries and market pricing How can we use Data Science/Analytics to that end? 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 at preparing the students to fill such an intermediary role in mixed-specialty teams. 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
Intended Learning Outcomes	Upon completion of the module, the student can: Understand and account for transactions based on accounting conventions (knowledge). 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). Is this still applicable: Reconcile the path from a question to the collection of raw data, constructing datasets and setting up test designs that make use of accounting information for corporate decision-making (synthesis). Critically evaluate the individual business transactions accordingly (evaluation). Assess the importance of accounting data as a rare source of reliable firm-level information. Connect accounting data to market prices and understand differences make predictions about future accounting entries given market developments
Forms of teaching, methods and support	• 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 wide programming exercise run in parallel from the start of the lecture • Python session / deep dive

Type of Assessment(s) and performance	<table><tr><td>Type of Assessment</td><td>Duration</td><td>Performance Points</td><td>Due Date or Exam Date</td></tr><tr><td>Quizzes</td><td>10-20 min</td><td>20</td><td>During the course</td></tr><tr><td>Small project incl. presentation</td><td>approx. 1-2 weeks</td><td>60</td><td>during the course</td></tr><tr><td>Oral participation / exam</td><td>n/a</td><td>20</td><td>during course / end of course</td></tr><tr><td>group wide programming exercise (single contribution)</td><td>approx 1-2 weeks</td><td>20</td><td>during the course</td></tr></table>
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 balance sheet entries 4 Financial Reporting 5 Bank Balance sheets - practical aspects 6 market prices and balance sheet entires 7 market liquidity and impact on future balance sheet entries 8 Practical exercises
Usability in other Modules/Programmes	Within the MADS programme, the course provides foundational knowledge for financial management.
Last Approval Date	2024/05/06

Strategy and Performance Management
[MGT73367]

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	*“However beautiful the strategy, you should occasionally look at the results” — Sir Winston Churchill* *“Strategy Execution is the responsibility that makes or breaks executives” — Alan Branche and Sam Bodley-Scott* Every successful business needs to develop a strategy and manage its performance. Strategy defines the potential sources for future corporate success and performance management helps companies to successfully implement strategy and to monitor its success. To be able to make the right decisions, managers need to understand the drivers of their strategic advantage, revenues, costs, and the profitability of different services, products, and customers. To achieve this goal, this course provides you with the latest insights, tools and recent examples from corporate practice on strategic decisions, monitoring strategy execution and managing performance. This course covers all important steps of managing the performance within the companies. Starting with strategic investment decisions, followed by implementing and communicating the strategy, measuring the achieved performance and closing the learning loop by adjusting future investment decisions based on prior performance. Throughout the course, we will aim for both, understanding business concepts (“How do executives think?”) as well as analysing business data (“How can data analytics help the organization to be successful?”.

Intended Learning Outcomes	*Knowledge:* Having taken the course, students can: • Illustrate how a company develops and sustains competitive advantage, • Improve decision making by conducting suitable analyses of financial and non-financial data for a variety of business decisions • Utilize various methods that help to analyze the successes of strategy implementation. *Skills:* With successful completion of the course managerial accounting, you will be able to • Analyze the strategic positioning of a company, • Select performance indicators which support the achievement of short and long-term objectives, • Use statistical methods to understand performance drivers within an organization improve decision making by conducting suitable analyses of financial and non-financial data for a variety of business decisions • Design and implement an adequate performance management system to implement the company´s strategy • Judge in real business cases how managerial decision making is shaped by using performance measures for decision-making and control. • Discuss with top executives, people in the finance function as well as other employees information, ideas, problems, and solutions according to their respective area using appropriate terms and economic language. *Competence:* On successful completion you become qualified to: • Assess how different types of data sources can help firms for a variety of strategic questions • Analze different types of data with appropriate methods • Suggest actions for a firm based on the analysis of financial and nonfinancial data The content of this course will be useful for the following career paths: • Data scientist that work on business related topics • General management (being responsible for strategy development and execution, as well as managing the performance of a business function, a business unit, or a non-profit organization and understanding the pitfalls of using incentives) • Entrepreneurs and consultants (identifying strategic niches, making investment decisions, analyzing and improving profitability) • Analysts, investors and board members (understanding financial and non-financial performance measures for monitoring strategy execution by company management) • Anyone who is interested in understanding how analyzing data from different sources such as accounting, employees and customers can help to run organizations better

Forms of teaching, methods and support	Case studies Lectures Exercises Simulation Games Practitioner guest lectures Final project
Type of Assessment(s) and performance	<table><tr><td>Type of Assessment</td><td>Duration</td><td>Performance Points</td><td>Due Date oder Date of Exam</td></tr><tr><td>Assignments</td><td>360 minutes</td><td>60</td><td>Usually before each class</td></tr><tr><td>Final project (in teams)</td><td>60 minutes</td><td>60</td><td>During the quarter with a project submission at the end of the quarter</td></tr></table>
Recommended Literature	Note: A comprehensive reading list will be provided in the course syllabus. • 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. • March, J. G. (2010). The ambiguities of experience. Cornell University Press. • Rumelt, R. (2011). Good Strategy Bad Strategy. Random House. • Wouters et al. (2012). Cost Management: Strategies for Business Decisions.
Module Structure	1. Strategic disruption - Product portfolio (BCG Matrix) 2. Strategic investments - Sony simulation 3. ESG performance - Causal inference 4. Predicting cost and profit 5. Digitalizing controls - Working capital optimization 6. Survey data - Measuring strategy execution 7. Balanced scorecard simulation 8. Target ratcheting - Alternative data 9. Service and customer profitability Note that this structure can be subject to changes.
Usability in other Modules/Programmes	Thesis module
Last Approval Date	2024/05/07

Deep Learning [MGT75023]

Module Coordinator		Ellsaesser, Florian			
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		This module covers deep neural networks, which are currently the “workhorse” of machine learning and most commonly used method. 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). 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.			

<table>
<tr><td>Intended Learning Outcomes</td><td>At the end of the module students should be able to:

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
</td></tr>
<tr><td>Forms of teaching, methods and support</td><td>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.</td></tr>
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<table>
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<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>
</table>
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</table>

Module Structure	**Session Topic** **Recap of neural network basics** - Perceptron model, perceptron update rule - XOR Problem - Basic feed forward neural networks - Regularising neural networks - Hyperparameter optimisation methods **Problem of generalization** -Bias-Variance trade-off - Overfitting - Regularisation methods **Training setup for neural networks** - Introduction to TensorFlow - Getting data into TensorFlow - TensorFlow Core and train APIs - Debugging and visualisation, - Tensor Board - Keras **Current neural architectures and their application** - Problem domains, datasets and baselines - Convolutional neural networks and recurrent neural networks **Memory networks - Motivation** - Extension of temporal architectures - Neural Turing Machine **Unsupervised learning with neural models** **Transfer learning** - Practical need for transfer - Methods and catastrophic forgetting **Deploying deep neural networks** - Learning models - Project design principles - Architecture concerns - Validation,Performance **Practical application case study**
Usability in other Modules/Programmes	Frontiers of AI; Master's Thesis
Last Approval Date	2024/05/06

Frankfurt School of Finance & Management
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Natural Language Processing [MGT73324]

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		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 break-throughs in recent years. Language is a form of time series so break throughs in natural language processing such as LSTM networks have been closely connected to advances in machine learning in general. 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. The module takes a practical approach combining theory with practice, so roughly 50% of the module will be theory and 50% will be practice.			

<table>
<tr><td>Intended Learning Outcomes</td><td>After completion of this class students should be able to
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.</td></tr>
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1 Introduction Read lecture material
2 Part of Speech Tagging, Dependency Parsing Read lecture material
3 Semantics I Read lecture material
4 Semantics II Read lecture material
5 Sequence to Sequence Modelling Read lecture material</td></tr>
<tr><td>Usability in other Modules/Programmes</td><td>AI - The Frontier</td></tr>
<tr><td>Last Approval Date</td><td>2024/05/28</td></tr>
</table>