Lab Rotations

Responsible for the Module Prof. Dr. Markus Kollmann			Date 01.11.2019
Lecturer(s) All group leaders offering Lab Rotations			**Semester** 2./3.
Language: English			**Modus** Obligatory Course
Work Load 300 h	**Credits** 10 CP	**Contact Time** 60 h	**Self-study** 240 h
Course Practical Work	**Turnus** each year	**Group Size** –	**Duration** 6 Weeks

Learning results & Competences

Students can work independently on a specific Data Science / AI project within a larger research group. They understand how the data they work on have been generated and preprocessed. They understand the goals of the research project and how the data analysis is connected to it. They are able to identify suitable algorithms to analyse the data and know their limitations. They can benchmark algorithms against each other and can carry out statistical analysis of their performance. They are able to present the results of their work to an audience that has different scientific background.

Content

The co-supervisors agree on a lab rotation project based on the tasks to be carried out. The project can involve all steps of a data analysis pipeline – e.g. data cleaning, data preprocessing, data analysis, data postprocessing, data visualization – but not data generation. Ideally, these tasks should be realized by self-written code. Special emphasis in a lab rotation should be given to sensitise students for the peculiarities of the involved data and that students give understandable presentations of their results.

Teaching

Students can apply to research groups that generate/analyse data to carry out a lab rotation. The group leaders offering lab rotation places may choose among applicants according to their suitability. Lab rotations can also be carried out outside the university in R&D environments that generate/analyse sufficiently large data sets. The lab rotation requires permanent physical presence of the student within the chosen research group. The student is co-supervised by a member of the chosen research group and a lecturer that is involved in a theoretical module in the Master’s Program „Artificial Intelligence and Data Science“.

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination

None.

Prerequisites for receiving credit points Permanent presence in the chosen research/development group Active participation at research/development work Giving a seminar talk
Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs No
Weight in overall rating None
Further Information

Master Thesis

Responsible for the Module Prof. Dr. Markus Kollmann			**Date** 01.11.2019
Lecturer(s) All group leaders offering projects for Master Thesis			**Semester** 4.
Language: English			**Modus** Obligatory Course
Work Load 900 h	**Credits** 30 CP	**Contact Time** 60 h	**Self-study** 840 h
Course Practical Work	**Turnus** –	**Group Size** –	**Duration** 6 Month

Learning results & Competences
With the written thesis, the students prove that they are able to carry out scientific work independently on a topic in the field of Artificial Intelligence and Data Science within a given period of time (6 months). They are able to develop their findings concisely and to evaluate or interpret them competently. The Master's thesis must be written in English and presented in an oral presentation.

Content
The content of the master thesis is defined by the supervisor.

Teaching
Students can apply to any research group that offers data science projects for a Master Thesis. Ideally, the thesis should be carried out in one of the two groups where a Lab Rotations has been completed. If the Master Thesis is carried out outside the computer science department the student is co-supervised by a member of the chosen research group and a lecturer that is involved in a theoretical module in the Master Program „Artificial Intelligence and Data Science“.

Prerequisites for attending
Formal: Starting a Master Thesis requires at least 60CP of passed courses within the program „Artificial Intelligence and Data Science“.
Contentual: none

Examination
Grading of the content of Master Thesis and its oral presentation

Prerequisites for receiving credit points
(1) Successful work on the topic and on-time submission of the thesis
(2) Giving an oral presentation of the content of the thesis

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information

Advanced Topics in Bayesian Data Analysis

Responsible for the Module Prof. Dr. Martin Lercher, Dr. Pablo Verde			**Date** 18.10.2021
Lecturer(s) Dr. Pablo Verde			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 50 h	**Self-study** 100 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** each winter term	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

The course teaches the role of computer simulations and Bayesian methods for real modelling. Students that completed this module have a profound knowledge in using R and WinBUGS for Bayesian modelling.

Content

Introduction to Bayesian hierarchical (linear and generalized) models, Bayesian inference and empirical Bayesian inference, Monte-Carlo techniques and MCMC-computations, Bayesian meta-analysis, in particular for diagnostic test data. Evidence synthesis for deterministic models. Explorative data analysis of multi-step and logitudinal data. Bayesian models for statistical regression problems. Linear regression with a large number of covariates. Variable selection. Explorative multivariate analysis. A-priori distributions for variance-covariance-matrices. Bayesian treatment of missing (random and non-random) variables. Survival modelling. Bayesian nonparametric models, mixed models. Statistical modelling with Dirichlet-process mixtures.

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Examination

Written exam

Prerequisites for receiving credit points

Regular and active participation in the exercises

Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

M.Sc. Informatik

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Advanced Programming and Algorithms

Responsible for the Module Dr. Anja Rey			**Date** 16.08.2022
Lecturer(s) Dr. Anja Rey			**Semester** 1.
Language: English			**Modus** Obligatory Course
Work Load 300 h	**Credits** 10 CP	**Contact Time** 120 h	**Self-study** 180 h
Course Lecture: 4 SWS Exercises: 4 SWS	**Turnus** each winter term and each summer term	**Group Size** 40	**Duration** 2 Semesters

Learning results & Competences

After completing the first part the students can
- reproduce algorithmic and programming principles, and explain technical terms and basic methods,
- describe known algorithms and new algorithms based on pseudocode and Python code and apply them exemplarily to adequate problem settings,
- implement algorithms in Python and apply selected software engineering tools,
- distinguish between data structures (theoretically and in Python) and apply them in adequate contexts,
- interpret and visualise different types of data,
- analyse algorithms (e.g., compute and classify their running time) and prove their correctness,
- test their code and apply test driven development,
- evaluate code and apply refactoring techniques in order to improve code quality,
- operate a version control system and develop in groups,
- evaluate the quality of a given piece of code and provide reviews for improvement,
- create reproducible environments and build data science workflows, and
- design and develop algorithms based on known methods.

After completing the second part the students can:
- reproduce further algorithms, programming principles, and data structures,
- implement further algorithms in Python and apply selected software engineering tools,
- match algorithms to different algorithmic design paradigms and apply them exemplarily,
- adapt algorithms and data structures and transfer them to new contexts,
- design algorithms according to adequate design paradigms,
- classify and evaluate algorithms according to further analysis techniques, and
- classify algorithmic problems according to basic complexity classes.

Content

This course consists of two parts about algorithm design and programming. It provides an insight into algorithmic and programming tools, combining theoretical and practical methods

that build a foundation for further courses in the Master of Articficial Intelligence and Data Science programme.
Winter term:
- Algorithmic foundations and data structures
- Introduction to the Python programming language
- Algorithm analysis (running time analysis, correctness proofs)
- Software engineering methods for code quality (software testing, code review, refactoring)
- Version control systems (e.g., git) and continuous integration
- Classic algorithms (e.g., sorting algorithms, graph algorithms) and data streams
- Selected packages (e.g., numpy, matplotlib, pandas)
- Data science workflows (e.g. snakemake), reproducible environments (e.g. docker)
Summer term:
- Algorithmic design principles (recursion, divide-and-conquer, dynamic programming, greedy algorithms) and their analysis
- Further application of Python programming and software development methods
- Further algorithms (e.g., sorting, search, graph algorithms, pattern matching)
- Further data structures (e.g., search trees, splay trees, B-trees, suffix trees, heaps, hashing)
- Object oriented programming
- Computational complexity (e.g., P vs. NP, NP-completeness)

Teaching
Lecture with (theoretical and practical) exercises

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination
Written examination after both courses about content of lectures and exercises

Prerequisites for receiving credit points
(1) Regular and active participation in the exercises
(2) Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points

Further Information

Advanced Programming and Algorithms (deprecated)

Responsible for the Module Dr. Anja Rey			**Date** 26.01.2021
Lecturer(s) Dr. Marcel Schweitzer, Dr. Timo Dickscheid			**Semester** 1.
Language: English			**Modus** Obligatory Course
Work Load 300 h	**Credits** 10 CP	**Contact Time** 100 h	**Self-study** 200 h
Course Lecture: 4 SWS Exercises: 2 SWS	**Turnus** each winter term	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

Students know the basic toolbox of algorithm design and analysis. They can prove correctness of algorithms and analyze their running time and space requirements using O-Notation. They know the differences between basic complexity classes and can prove NP-completeness using reduction techniques. They know and can apply the major algorithmic design principles. They know algorithms for classic problems such as sorting, searching and pattern matching as well as important data structures for dictionaries and text indexing. They are able to work with graphs and understand and can apply and analyze classic graph algorithms.
On the practical side, students can work with the Unix shell, implement algorithms in Python and create data science workflows using Snakemake. Students can use a version control system (e.g. git) and docker to create reproducible execution environments. Students know how to test their code and are able to apply test driven development. Students can evaluate the quality of a given piece of code and provide feedback for improvement. Students are able to apply refactoring techniques in order to improve code quality. They are able to use a debugger to identify errors in code.

Content

Lecture:
Algorithmic Problems. Algorithms and algorithmic problems, correctness proofs and running time analysis, O-Notation, computational complexity. The traveling salesman problem.
Programming and Software Engineering. Introduction to the Python programming language. Data science workflows with Snakemake. Version Control Systems, Creating reproducible execution environments, Software testing, Code Review, Code Quality, Refactoring, Debugging.
Algorithmic design principles. Brute force, recursion, divide-and-conquer, dynamic programming, branch-and-bound, greedy algorithms, heuristics. Approximation.
Classic algorithms and data structures. Quicksort/Mergesort/Heapsort, binary search, search trees, splay trees, B-trees, pattern matching, suffix trees, hashing.
Graph theory and graph algorithms. Graphs, topological sort, DFS/BFS, connectivity, shortest paths, minimum spanning trees

Exercises: In the exercises the content of the lecture is applied and deepened in theoretical exercises. In addition, the students will implement selected algorithms and data structures in Python and will build algorithmic workflows using Snakemake. They will apply basic software engineering tools.
Teaching Lecture with (theoretical and practical) exercises
Prerequisites for attending Formal: Admission to master studies in „Artificial Intelligence and Data Science". Contentual: none
Examination Written examination about content of lectures
Prerequisites for receiving credit points (1) Regular and active participation in the exercises (2) Passing the examination
Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points
Further Information Superseded by the two courses Advanced Programming and Algorithms I and II

Algorithmic Game Theory

Responsible for the Module			Date
Prof. Dr. Jörg Rothe			17.06.2019
Lecturer(s)			**Semester**
Prof. Dr. Jörg Rothe			variable
Language:			**Modus**
English			Elective Course
Work Load	**Credits**	**Contact Time**	**Self-study**
300 h	10 CP	100 h	200 h
Course	**Turnus**	**Group Size**	**Duration**
Lecture: 4 SWS Exercises: 2 SWS	irregular	–	1 Semester

Learning results & Competences

The goal of this module is to introduce into the most important topics, results, models, and methods of algorithmic game theory, which is a central theoretical foundation of numerous applications in artificial intelligence and multiagent systems. The students will get to know central game-theoretic problems and algorithms solving them; they will be able to modify and apply these algorithms; they learn how to describe strategic scenarios by cooperative or noncooperative games, and to formally characterize concepts of stability and equilibria in these games. They will also be able to analyse the corresponding decision and optimization problems (in suitable compact representations) in terms of their computational complexity.

Content

Noncooperative Game Theory:
– Foundations
 • Normal form games, dominant strategies, and equilibria
 • Two-person games
– Nash equilibria in mixed strategies
 • Definition and properties of mixed Nash equilibria
 • Existence of Nash equilibria in mixed strategies
– Checkmate: Trees for games with perfect information
 • Sequential two-player games
 • Equilibria in game trees
– Full house: Games with incomplete information
 • The Monty Hall problem
 • Analysis of a simple poker variant
– How hard is it to find a Nash equilibrium?
 • Nash equilibria in zero-sum games
 • Nash equilibria in general normal form games
Cooperative Game Theory
– Foundations

- Cooperative games with transferable utility
- Superadditive games
- Stability concepts for cooperative games

– Simple games

- The core of a simple game
- Counting and representing simple games
- Weighted voting games
- Dimensionality
- Power indices
- The Shapley-Shubik index and the Shapley value
- The Banzhaf indices

– Complexity of problems for succinctly representable games

- Games on graphs
- Weighted voting games
- Hedonic games

Teaching
Lecture „Algorithmic Game Theory“: 4 SWS, Exercises: 2 SWS

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination
written examination

Prerequisites for receiving credit points
Regular and active participation in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points

Further Information
Literature

- Jörg Rothe (ed.): Economics and Computation: An Introduction to Algorithmic Game Theory, Computational Social Choice, and Fair Division, Springer-Verlag, 2015.

A shorter German version of this book appeared as:

- Jörg Rothe, Dorothea Baumeister, Claudia Lindner und Irene Rothe: Einführung in Computational Social Choice. Individuelle Strategien und kollektive Entscheidungen beim Spielen, Wählen und Teilen, Spektrum Akademischer Verlag (Springer), 2011.

Additional literature

- Bezalel Peleg and Peter Sudhölter: Introduction to the Theory of Cooperative Games, Kluwer Academic Publishers, 2003.

- Martin J. Osborne and Ariel Rubinstein: A Course in Game Theory, MIT Press, 1994.
- Georgios Chalkiadakis, Edith Elkind, and Michael Wooldridge: Computational Aspects of Cooperative Game Theory, Morgan and Claypool Publishers, 2011.
- Noam Nisan, Tim Roughgarden, Eva Tardos, and Vijay V. Vazirani (eds.): Algorithmic Game Theory, Cambridge University Press, 2008.

Algorithms for Sequence Analysis

Responsible for the Module Prof. Dr. Tobias Marschall			Date 24.06.2021
Lecturer(s) Prof. Dr. Tobias Marschall			**Semester** variable
Language: English			**Modus** Elective Course
Work Load 300 h	**Credits** 10 CP	**Contact Time** 100 h	**Self-study** 200 h
Course Lecture: 4 SWS Exercises: 2 SWS	**Turnus** each summer term	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences
This course enables students to understand advanced algorithmic concepts in sequence analysis and to apply them in practice. In particular, this course will provide the algorithmic foundation to develop modern tools to process DNA sequencing data. However, the focus is on general algorithmic concepts and hence the scope of applications is not limited to biological sequence analysis.

Content
Sequence information is ubiquitous in many application domains –and collections strings are one important data type in modern Data Dcience. DNA sequencing data are one example that motivates this lecture, but the focus of this course is on algorithms and concepts that are not specific to bioinformatics. This lecture ad-dresses classic as well as recent advanced algorithms for the analysis of large sequence databases. Topics include: full text search without index; approximate pattern matching; index structures such as suffix trees and enhanced suffix arrays, Burrows-Wheeler transform and the FM index; De Bruijn graphs; data compres-sion; multiple sequence alignment; Positional Burrows-Wheeler Transform; and Locality Sensitive Hashing.

Teaching
Lecture with (theoretical and practical) exercises

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: Advanced Programming and Algorithms

Examination
usually oral exam

Prerequisites for receiving credit points
Regular and active participation in the exercises: 50% of the programming exercises and 50% of the theoretical exercises need to be solved.
Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Informatik

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Applications of Transformer Networks in Bio- and Cheminformatics

Responsible for the Module Dr. Alexander Kroll			**Date** 16.10.2023
Lecturer(s) Dr. Alexander Kroll			**Semester** 2.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** 30	**Duration** 1 Semester

Learning results & Competences

The course teaches how to apply Transformer Networks to problems in bioinformatics and cheminformatics. Students will learn best practices for (i) training and fine-tuning Transformer Networks with molecules (proteins or small molecules) as input, (ii) using the generated numerical representations to make predictions for chemical and biological tasks, (iii) training multimodal Transformer Networks that can process more than one molecule modality/type at a time, and (iv) visualising what Transformer Networks learn and how this information can be used to gain biological insight.

Content

-Detailed description of Transformer Networks (TNs)
-Implementation and training of TNs in Pytorch: Self-supervised learning on molecule representations
-Application of TNs to protein amino acid sequences and small molecule SMILES strings (including coverage of the Alphafold, ESM-1b and ChemBERTa models)
-Gradient boosting models (xgboost) and their application to numerical molecular representations
-Best practices for fine-tuning pre-trained TNs
-Multimodal TNs: processing more than one molecule modality simultaneously
-Visualising what TNs learn

Teaching

Lectures with exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: None.

Examination

Written or oral examination

Prerequisites for receiving credit points

Regular and active participation in the exercises Passing the examination
Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs M.Sc. Computer Science
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information

Approximation Algorithms for Clustering Problems

Responsible for the Module Prof. Dr. Melanie Schmidt			**Date** 06.04.2023
Lecturer(s) Prof. Dr. Melanie Schmidt			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size**	**Duration** 1 Semester

Learning results & Competences

After completing the course, students are able to
- model discussed and new clustering problems as linear programs,
- describe advanced analysis techniques for discussed clustering problems,
- explain discussed algorithmic ideas for clustering problems, and
- analyze the approximation guarantee of discussed and slightly varified clustering procedures.

Content

This course is a lecture on advanced algorithms and deals with clustering algorithms. The focus lies on approximation algorithms. In particular, we discuss the following topics:
- LP-based techniques
- local search
- approximation algorithms for the k-median problem and for the k-means problem
- clustering in the Euclidean space
- dimensionality reduction and data stream algorithms for clustering problems

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: It is helpful to know the contents of the modules Approximation Algorithms and Combinatorial Algorithms for Clustering Problems from the M.Sc. Computer Science

Examination

written or oral examination

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs M.Sc. Artificial Intelligence and Data Science
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information There is a manuscript and more literature will be given in the first class.

Category Theory in Machine Learning and Data Science

Responsible for the Module Dr. Peter Arndt			**Date** 18.1.2022
Lecturer(s) Dr. Peter Arndt			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 60 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 30 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** limited to 24	**Duration** 1 Semester

Learning results & Competences

The students know the basic notions of category theory. They know how to phrase concepts from Machine Learning, Data Science and probability theory using the language of category theory. They have a principled approach to the analysis of Machine Learning situations and can use this to design new approaches.

Content

Category theory is a unifying language and tool for analyzing and relating mathematical situations. Originally coming from pure mathematics, it is now being applied to many fields, including Machine Learning and Data Science. The categorical formulation of probability theory can be used for the semantics of probabilistic programming languages.
Basic notions:
Categories, functors, natural transformations, monoidal categories, string diagrams, monads
Further topics will be chosen from the recent literature, e.g.
Categorical view on gradient descent and backpropagation, lenses and learners,
Categorical probability theory, Markov categories and applications, Semantics of probabilistic programming, categorical interpretation of KL-divergence, functorial clustering,
Databases and data migration as functors, categorical understanding of persistent homology, toposes in information theory

Teaching

Seminar talks and discussions

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: None

Examination

Assessment of the presentation

Prerequisites for receiving credit points

(1) Active presence in the seminar

(2) Presentation of a topic
(3) Active participation in discussions
(4) Written summary of the topic

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
B.Sc. Mathematik und Anwendungsgebiete

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Causality

Responsible for the Module			Date
Prof. Dr. Dominik Heider			17.06.2019
Lecturer(s) Prof. Dr. Dominik Heider			**Semester** variable
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 64 h	**Self-study** 86 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** yearly	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

After successfully finishing the course, the student
* can understand and can explain the theoretical foundations of causal inference
* can implement and apply algorithms of causal inference

Content

This module teaches foundational knowledge about:
* Directed acyclic graphs, causal graphs
* Conditional independence
* PC algorithm
* Structural equation models
* Additive noise models
* Interventions
* Counterfactuals
* Markov equivalence
* Faithfulness
* Distinguishing cause and effect

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination

Written examination

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points

Further Information
Literature:
Main text book is:
* Peters/Janzing/Schölkopf, Elements of Causal inference, MIT
Additionally, the following books are helpful:
* Spirtes/Glymour/Scheines, Causation, Prediction, and Search, MIT 2000
* Pearl: Causality, Cambridge 2000

Clinical Decision Support Systems (CDSS)

Responsible for the Module Prof. Dr. Dominik Heider			**Date** 18.01.2024
Lecturer(s) Dr. Oluwafemi A. Sarumi			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** –	**Duration** 1 Semester

Learning results & Competences

After completing this course, students should be able to:

- describe the process of DSS including their principles, functionalities, and applications in healthcare settings.
- integrate DSS seamlessly with EHR systems, fostering interoperability and efficient data utilization.
- apply CDSS in real-world scenarios, addressing practical design and implementation challenges.
- understanding the regulatory landscape and compliance requirements for decision support systems

Content

In this course, students will learn the theoretical foundations of Decision Support Systems (DSS) and explore their integration with electronic health record (EHR) systems. The curriculum covers essential concepts such as decision rule modeling, representation, design, and implementation. Also, students will gain insights into the technology of clinical decision support systems and its broader applications. Additionally, the course will delve into ethical considerations, and strategies for evaluating Clinical Decision Support Systems (CDSS).

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science".
Contentual: none

Examination

written examination or oral examination

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information
Recommended Literature

- Greenes, R. A., Greenes, R., & Del Fiol, G. (Eds.). (2023). Clinical decision support and beyond : progress and opportunities in knowledge-enhanced health and healthcare (Third edition.). Academic Press
- Berner E. (eds). (2016) Clinical Decision Support Systems Theory and Practice. Health Informatics. Springer, Cham
- Further literature will be announced in the course.

Computational Linguistics

Responsible for the Module Prof. Dr. Laura Kallmeyer (kallmeyer@phil.hhu.de)			**Date** 17.05.2019
Lecturer(s) the lecturers of the Department of Computational Linguistics, Prof. Dr. Stefan Conrad			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Seminar: 4 SWS	**Turnus** every year	**Group Size** –	**Duration** 1 Semester

Learning results & Competences

Students will understand the intricacies of modeling a specific linguistic phenomenon in such a way that it can be processed automatically. Furthermore, they will get to know different techniques

a) for learning such a model from language data,
b) for applying it to new data and
c) for evaluating it in order to assess its adequacy with respect to the phenomenon one wanted to model.

This can include frameworks and representation formats for modeling syntax (the structure of sentences and texts) and semantics (the meaning of sentences and text) and various machine learning and deep learning techniques applied to this.

Content

Teaching

Advanced seminar (depending on the topic including practical exercises besides theoretical sessions)
It is possible to take two seminars of 2 SWS each instead of a single one of 4 SWS

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination

Written examination or oral examination or term paper

Prerequisites for receiving credit points

Passing examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points
Further Information

Computer Vision

Responsible for the Module Prof. Dr. Paul Swoboda			**Date** 18.01.2023
Lecturer(s) Prof. Dr. Paul Swoboda, Prof. Dr. Timo Dickscheid			**Semester** 2.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** every summer term	**Group Size** –	**Duration** 1 Semester

Learning results & Competences

After successful completion of the course, participants will be able to

- Explain the geometric foundations of image formation with a digital camera
- Train deep neural network models for detecting objects of interest in images
- Implement algorithms for inferring 3D information about a scene from a set of overlapping images

Content

Computer vision is a research field which aims to enable machines to interpret and understand visual information from the world around them, in similar ways that humans see. This implies algorithms and mathematical models to analyze and process digital images and videos in order to extract useful information. Typical tasks are object recognition, 3D reconstruction, scene understanding, or motion tracking. Computer vision has become an increasingly important area of research with applications in domains such as medical imaging, autonomous driving, surveilance, virtual and augmented reality, process automation, or optical inspection.

In recent years, the rapid advances in machine learning and deep learning had a great impact on the field of computer vision, and learning algorithms replace many classical solutions to computer vision problems and often provide superior performance.

In this course, we will introduce you to this exciting field. We will cover

- History of computer vision
- Formation of digital images
- 3D geometry and projective geometry
- Classification, segmentation, and object detection
- Stereo reconstruction
- Structure from motion
- Shape reconstruction

In the practical work, we will study a selection of recent scientific papers from this field and apply a selection of approaches to real-world problems.

Teaching
Lectures with exercises

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none.

Examination
Written or oral examination

Prerequisites for receiving credit points
Regular and active participation in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information
Literature:

- Szeliski, Computer vision, Springer 2010
- Goodfellow I, Bengio Y, Courville A. Deep Learning. The MIT Press; 2016.
- Recent publications will be provided during the course

Create Your Tech Startup

Responsible for the Module Prof. Dr. Steffi Haag			**Date** 23.02.2022
Lecturer(s) Prof. Dr. Steffi Haag			**Semester** 1.-4.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS, Exercise: 2 SWS	**Turnus** Each summer term	**Group Size** Limited to 30	**Duration** 1 Semester

Learning results & Competences

Students can

- model, analyze, and discuss digital business models and its components
- assess the specific opportunities for and challenges of technology-based businesses
- create, plan, and implement novel tech startups
- pitch their startup idea in front of peers and experts
- present, assess, and give feedback to novel tech business models
- assess their entrepreneurial skills
- collaborate with interdisciplinary peers comprising various competences.

Content

Students explore the entrepreneurial process using a learning by doing methodology.
The lecture and case studies sessions provide and discuss tools and methods of creating, visualizing, and analyzing digital business models (e.g., business model canvas, lean startup, design thinking).
In a group project, students transfer and apply those tools and methods to create, evaluate, plan, and pitch their own tech startup ideas.

Teaching

Lecture „Create Your Tech Startup“, Case Study sessions

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: None

Examination

Business plan, presentations in groups, and class participation

Prerequisites for receiving credit points

Presentations in groups
Written documentation of a business plan
Active class participation in discussions

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information
See website/LSF for details on the application process.
Literature:
Blank, S.; Dorf, B. (2012): The Startup Owner's Manual: The Step-By-Step Guide for Building a Great Company, K & S Ranch
Osterwalder, A; Pigneur, Y. (2010): Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers, John Wiley & Sons
Osterwalder, A; Pigneur, Y.; Bernarda, G; Smith, A. (2014): Value Proposition Design: How to Create Products and Services Customers Want, John Wiley & Sons
Ries, E. (2011): The Lean Startup: How Constant Innovation Creates Radically Successful Businesses, Portfolio Penguin, London.
Further literature is provided in the course sessions.

Data & Knowledge Engineering (DKE)

Responsible for the Module Prof. Dr. Stefan Dietze			**Date** 17.06.2019
Lecturer(s) Prof. Dr. Stefan Dietze			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** –	**Duration** 1 Semester

Learning results & Competences

Application of W3C Standards (RDF, SPARQL) for using and extracting Knowledge Graphs, Linked Data and structured Data in the Web
Basic understanding of Information- und Knowlege Extraction Methods
Generation of formal Knowledge Representions and Knowledge Databases using Description Logics
Understanding and applying structured Web Markup (RDFa, Microdata, schema.org)

Content

Understanding and interpreting heterogeneous data, in particular in distributed settings such as the Web, remains a challenging task. State-of-the-art Web applications such as Web search engines rely on a combination of approaches for making sense of data, involving both explicit knowledge, for instance, through knowledge graphs such as Wikidata or the Google knowledge graph and semi-structured Web markup, as well as statistical and machine-learning based approaches.
This course provides an introduction to data and knowledge engineering methods and principles, with a particular focus on the Web. This includes methods related to knowledge graphs and formal data & knowledge representation (RDF, OWL, Description Logics), data integration and linking, information extraction, Web data sharing practices (Linked Data, Semantic Web and affiliated W3C standards such as RDF, RDFa, Microdata), as well as emerging approaches in the context of distributional semantics, such as word and entity embeddings. Attention will also be paid to applications of taught techniques to facilitate data sharing and reuse on the Web.

Teaching

Lecture „Data & Knowledge Engineering“, 2 SWS (in English)
Excercise, 2 SWS (in English)

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination
written examination

Prerequisites for receiving credit points
Regular and active participation in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points

Further Information
Literature:
“Artificial Intelligence: A Modern Approach” by Stuart Russell and Peter Norvig (2nd edition, Prentice-Hall, 2003)
“A Semantic Web Primer” by Grigoris Antoniou and Frank van Harmelen (MIT Press, 2004)
“Foundations of Semantic Web Technologies”, P. Hitzler, M. Krötzsch, S. Rudolph:, CRC Press, 2009.
“Linked Data – Evolving the Web into a Global Data Space”, T. Heath, Ch. Bizer, Morgan & Claypool, 2011.
Doing Data Science – Straight Talk from the Frontline, Cathy O’Neil, Rachel Schutt, O’Reilly Media

Deep Learning: Generative Models

Responsible for the Module Prof. Dr. Markus Kollmann			**Date** 01.05.2019
Lecturer(s) Prof. Dr. Markus Kollmann			**Semester** 2.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 50 h	**Self-study** 100 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** Summer Semester	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

Students know how to implement machine learning algorithms in Pytorch and to run it on HPC. They understand central concepts of Machine Learning and are familiar with common Neural Network architectures, based on convolutional and/or attention layers. They know how to implement Deep Generative Models such as Variational Autoencoder, Autoregressive Networks, Normalizing Flow based Networks, and Score based Generative Models. They understand the conceptional differences between the generative models, their advantages, and their shortcomings.

Content

Lectures and Practical Work:
We start with a brief introduction to common neural network structures, such as Convolutional Neural Networks in general and ResNets in particular and show how to implement and train them. We introduce different concepts of generative models and the training objectives behind them. We apply generative models to toy data sets and to the important problem of Protein/RNA folding.

Teaching

Lecture with (theoretical and practical) exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: Decent understanding of Machine Learning

Examination

written examination

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science, M.Sc. Biology, M.Sc Biochemistry

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information
Students from Biology and Biochemistry will be assigned 7CP for the course as it takes them significantly more time to carry out the programming exercises

Deep Learning: Representation Learning

Responsible for the Module Prof. Dr. Markus Kollmann			**Date** 01.05.2019
Lecturer(s) Prof. Dr. Markus Kollmann			**Semester** 2.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 50 h	**Self-study** 100 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** Winter Semester	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

Students know how to implement machine learning algorithms in Pytorch and to run it on HPC. They understand central concepts of Machine Learning and are familiar with common Neural Network architectures, such as Convolutional Neural Networks. The understand the difference between Maximum Likelihood Learning and Contrastive Learning. They are familiar with data augmentation methods and simple sampling methods.

Content

Lectures and Practical Work:

We start with a brief introduction to common neural network structures, such as Convolutional Neural Networks in general and ResNets in particular and show how to implement and train them. We show how to construct loss functions and how to find analytical expressions for the asymptotically optimal solutions, using Variational Calculus. We introduce Contrastive Learning -- and Self-supervised Learning in general -- as methods for Representation Learning. We introduce Autoencoders -- and Generative Models in general -- as methods for learning the data hyperplane. We discuss why including prior knowledge is the key for the success of Machine Learning Methods in diagnostic and therapeutic applications.

In the practical work we apply Representation Learning to detect heart arrhythmias from real time series data of patients and anomalies in (medical) image data.

Teaching

Lecture with (theoretical and practical) exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.

Contentual: Decent understanding of Machine Learning

Examination

written examination

Prerequisites for receiving credit points

Regular and active participation in the exercises

Passing the examination
Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs M.Sc. Computer Science, M.Sc. Biology, M.Sc Biochemistry
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information Students from Biology and Biochemistry will be assigned 7CP for the course as it takes them significantly more time to carry out the programming exercises

Deep Learning

Responsible for the Module Prof. Dr. Stefan Harmeling			**Date** 17.06.2019
Lecturer(s) Prof. Dr. Stefan Harmeling			**Semester** 2./3.
Language: English			**Modus** Obligatory Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** yearly	**Group Size** –	**Duration** 1 Semester

Learning results & Competences

After successfully finishing the course, the student
* can understand and can explain the theoretical foundations of deep learning
* can implement and apply algorithms of deep learning

Content

This module teaches foundational knowledge about:
* Loss functions and optimization
* Neural networks / backpropagation
* Deep learning software
* Convolutional neural networks
* Generative models
* Recurrent neural networks

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination

written examination

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

M.Sc. Computer Science

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points

Further Information

No special text book is used, the following book is helpful:

* Goodfellow et al, "Deep learning", MIT

Game Theory

Responsible for the Module Prof. Dr. Hans-Theo Normann			Date 16.08.2022
Lecturer(s) Prof. Dr. Hans-Theo Normann and teaching/research assistants of the DICE			**Semester** 2-4
Language: English			**Modus** elective course
Work Load 240 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 90 h
Course Lectures and tutorial: 2+2 SWS	**Turnus** each summer term	**Group Size** limited to 25	**Duration** 1 semester

Learning results & Competences

By the end of the module, students will be able to
- repeat and exemplify fundamental and advanced concepts of the game theory which will be used in the following master degree programme;
- represent and exemplify strategic behaviour of players and their interactions by means of the game theory;
- apply the gained knowledge exemplary on chosen areas of economics;
- simplify complex economic issues by the means of the game theory;
- adopt and transact the gained expertise of course 1 by the means of practical tasks.

Content

Course 1: Game Theory
1. static games with complete information
2. dynamic games with complete information
3. evolutionary game theory
4. static games with incomplete information
5. dynamic games with incomplete information

Course 2: Game Theory – tutorial
Cf. contents of course 1.

Teaching

Game Theory

Prerequisites for attending

A good understanding of Microeconomics and previous knowledge in Mathematics

Examination

Written exam at the end of the summer semester (60 minutes)

Prerequisites for receiving credit points

Successful participation in the exam. The exam will be passed if the grade is at least sufficient (4,0).

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Business Administration; M. Sc. Economics; M.Sc. Mathematics

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information
Current information can be found at the website of the DICE.

Generative Models and Sampling Methods

Responsible for the Module Prof. Dr. Markus Kollmann			**Date** 01.05.2019
Lecturer(s) Prof. Dr. Markus Kollmann			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

Students know the basic concepts of deep generative models and manifold learning. They understand the concepts of Variational Autoencoders, Autoregressive Networks, and Generative Adversarial Networks and can point out their pros and cons. The can implement generative models in Tensorflow/Pytorch. They understand the concepts of sampling methods, such as importance sampling, MCMC sampling, Gibbs sampling, and can implement these concepts in Python. They understand how deep generative models can strongly improve sampling efficiency and understand the connection to reinforcement learning

Content

Lecture:
Variational Autoencoders: Variational objectives, Posterior, Encoder, Decoder, Latent space models, manifold learning,
Autoregressive Models: autoregressive concept (PixelCNN, Transformer), exposure bias
Generative Adversarial Networks: Discriminators, Stability Problems, Progressive growing GANs.
Sampling Methods: (Hamilton) MCMC, Metropolis Hastings, Gibbs, Importance Sampling, Monte Carlo Tree Seach.
Exercises:
In the exercises the content of the lecture is applied and deepened in theoretical exercises. In addition, the students will implement the central concepts in Python and apply them to real and self-generated data.

Teaching

Lecture with (theoretical and practical) exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination

written examination

Prerequisites for receiving credit points Regular and active participation in the exercises Passing the examination
Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information

Growth Mechanics

Responsible for the Module Prof. Dr. Martin Lercher, Dr. Hugo Dourado			Date 08.04.2022
Lecturer(s) Dr. Hugo Dourado			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 50 h	**Self-study** 100 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** Winter and summer term	**Group Size** Not limited	**Duration** 1 Semester

Learning results & Competences

Students understand the principles of mathematic modeling of cellular reaction networks. They can give various examples on how physical constraints on cellular growth and replication can be modeled.
Students are able to build and analyze self-replicator cellular models using the GNU R or Python programming languages.
Basic concepts behind linear and nonlinear numerical optimization are known and the course participants are able to highlight the specific differences and computational challenges.

Content

- Introduction to the mathematical modeling and analysis of cellular reaction networks as a resource allocation problem
- The main physical constraints on cellular growth and replication
- Growth modeling: self-replicator models and nonlinear optimization
- The Singular Value Decomposition (SVD) of the normalized stoichiometric matrix: Fundamental Modes
- Growth Economy and Control Analysis: the marginal value of reactions and specific costs and benefits
- Growth Balance Analysis: the analytical conditions for optimal cellular growth
- Principles of nonlinear numerical optimization

With the help of selected examples, the course describes the modeling and analysis of cellular reaction networks, combining multidisciplinary methods from Mathematics, Biology, Physics, Chemistry, and Computer Science.

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Students should be comfortable with the fundamentals of multivariate Calculus and Linear Algebra, and should be proficient with a programming language. The language of the course is

English.
Examination Written exam
Prerequisites for receiving credit points 50 percent of total points in the exercises Passing the examination
Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs M.Sc. Informatik
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information Information about literature will be given during the course.

Information Theory

Responsible for the Module Dr. Peter Arndt			Date 15.12.2020
Lecturer(s) Dr. Peter Arndt			**Semester** 2.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** 20	**Duration** 1 Semester

Learning results & Competences

In this module students get to know fundamental and advanced concepts of information theory, their relation to coding, data compression and signal transmission. They get a better understanding of randomness, as captured by the concepts of entropy, information loss and Kolmogorov complexity. They obtain a principled view on general assumptions and techniques in machine learning, like the information bottleneck. They know applications to statistics and machine learning.

Content

Entropy, conditional, joint and relative entropy, mutual information and their interrelations, Source Coding Theorem, characterizations of entropy and relative entropy, Renyi and Tsallis entropy, universal source coding, Kolmogorov complexity and connection to entropy, applications of Kolmogorov complexity, entropy of stochastic processes, channel capacity and Channel Coding Theorem, differential entropy, Gaussian channel, maximum entropy distributions, higher information theoretic invariants, applications.

Teaching

Lectures with exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science".
Contentual: None.

Examination

written or oral examination

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
B.Sc. Mathematik und Anwendungsgebiete

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Discrete Optimization: Theory and Applications

Responsible for the Module Prof. Dr. Gunnar Klau (gunnar.klau@hhu.de)			**Date** 1.05.2019
Lecturer(s) Prof. Dr. Gunnar Klau			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 300 h	**Credits** 10 CP	**Contact Time** 90 h	**Self-study** 210 h
Course Lecture: 4 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** –	**Duration** 1 Semester

Learning results & Competences

Foundations of Linear Programming. Students know the definitions of linear programs (LPs), and their standard forms. They can solve low-dimensional LPs geometrically. They understand and can apply the Simplex method and the fundamental theorem of Linear Programming. They understand and can apply the concept and proofs of weak and strong duality.
Integer Linear Programming. Students know the definition of integer linear programs (ILPs) and the fundamental difference to LPs in terms of computational complexity. They understand the relation to combinatorial optimization problems. They know and can apply different methods to solve ILPs: Branch-and-Bound based on the LP relaxation, cutting planes, Branch-and-Cut and Lagrangian relaxation. They understand the concept of separation.
Network Flows. Students understand the concepts of networks and flows in networks. They can distinguish different variants and special cases of flow problems. They can compute maximum flows with the augmented path method (Ford-Fulkerson) and can prove why the method works. They understand the relation to duality in form of the max-flow-min-cut theorem.
Applications. Students can apply different modeling techniques to develop ILP formulations for combinatorial optimization problems. Examples include maximum clique, phylogeny reconstruction and the traveling salesman problem. They can solve real-world instances of these problems with self-written Python code using external optimization libraries.

Content

Lecture:
Foundations of Linear Programming. Linear Programs and their geometric interpretation. Duality. The Simplex method.
Integer Linear Programming. Linear programming-based Branch-and-Bound. Cutting planes. Branch-and-Cut. Lagrange relaxation.
Network Flows. Theory and algorithms.
Applications. Selected applications of linear optimization techniques from bioinformatics and other fields.

Exercises:
In the exercises the content of the lecture is applied and deepened. For that the exercises contain theoretical as well as practical elements. The students use professional linear and integer linear programming modeling software and solvers to build solve applied programming exercises.

Teaching
Lecture with theoretical and practical exercises

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination
written examination or oral examination

Prerequisites for receiving credit points
Regular and active participation in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Introduction to Logic Programming

Responsible for the Module			Date
Prof. Dr. Michael Leuschel (michael.leuschel@hhu.de)			10.4.2019
Lecturer(s) Prof. Dr. Michael Leuschel (michael.leuschel@hhu.de)			**Semester** 3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 90 h	**Self-study** 60 h
Course Practical: 4 SWS Lectures: 2 SWS	**Turnus** Every winter term	**Group Size** 30	**Duration** 1 Semester

Learning results & Competences

To understand and be able to use the main concepts of propositional and predicate logic
To understand the logic programming paradigm and be able to use it for problem solving
To be able to write Prolog programs in a logical style
To be able to use informed search algorithms (A*) and develop AI algorithms for game playing (Minimax)

Content

An important part of this unit is devoted to the study of logic. The discipline of logic is concerned both with proving theorems and also with drawing inferences from existing knowledge. The unit covers basic programming concepts of logical systems, resolution logic and horn clauses. This logical development provides a foundation for introducing the main concepts of logic programming. The unit also includes a practical introduction to the main features of Prolog, the language which implements this style of programming. Theoretical and practical topics are interleaved, the course as a whole dividing roughly equally between logic and theory and practical programming. The course covers many AI topics such as informed search algorithms (A*), constraint satisfaction and game playing (Minimax, Alpha-Beta pruning).

Teaching

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: Foundations of software development and programming

Examination

Written examination (80% of grade)
Assessment of practical work (20% of grade)

Prerequisites for receiving credit points

Successful participation at the practical work
Passed written examination

Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs B.Sc. Informatik
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points
Further Information

Introduction to Statistical Analysis through Computer Simulations

Responsible for the Module Prof. Dr. Martin Lercher, Dr. Pablo Verde			**Date** 25.2.2022
Lecturer(s) Dr. Pablo Verde			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 50 h	**Self-study** 100 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** each summer term	**Group Size**	**Duration** block course, 2 weeks

Learning results & Competences

Students are able to use the statistical programming language R and the software OpenBUGS for Bayesian reasoning. They understand the significance of computer simulations and Bayesian methods for modelling. They can classify different simulation methods.

Content

Introduction to Bayesian reasoning: Probability Theory and introduction to computer simulations, introduction to Bootstrap, introduction to Bayesian modelling, introduction to multivariate distributions and multiple parameter models
Monte Carlo simulation methods: Monte Carlo method for computing integrals, Rejection Sampling, Importance Sampling, Sampling Importance Resampling
Markov chain Monte Carlo methods: Introduction to Markov chains, Metropolis-Hastings algorithm, directed acyclic graphs, Gibbs sampling, MCMC output analysis
Statistical Modelling: Regression modelling, analysis of multiple contingency tables, introduction to hierarchical models

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Examination

Written exam

Prerequisites for receiving credit points

Regular and active participation in the exercises, solving the exercises
Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

M.Sc. Informatik, M.Sc. Biology

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Machine Learning

Responsible for the Module Prof. Dr. Stefan Harmeling			**Date** 17.06.2019
Lecturer(s) Prof. Dr. Stefan Harmeling			**Semester** 1.
Language: English			**Modus** Obligatory Course
Work Load 300 h	**Credits** 10 CP	**Contact Time** 100 h	**Self-study** 200 h
Course Lecture: 4 SWS Exercises: 2 SWS	**Turnus** each winter term	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

After successfully finishing the course, the student

* can understand and can explain the theoretical foundations of machine learning.
* can explain the foundations in mathematical terms and can do proofs about it
* can implement and apply algorithms of machine learning

Content

This module teaches foundational knowledge about the following topics:

* Probability, frequentist statistics, Bayesian statistics
* Supervised learning, unsupervised learning
* Generative vs discriminative models
* Linear regression, linear discriminant analysis
* Gaussian processes
* Support vector machines
* Kernel trick, kernel PCA
* Graphical models
* Neural networks

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.

Contentual: none

Examination

written examination

Prerequisites for receiving credit points

Regular and active participation in the exercises

Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

B.Sc. Computer Science

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

No special text book is used, the following books are helpful:

* Murphy, Machine Learning: A Probabilistic Perspective
* MacKay, Information Theory, Inference, and Learning Algorithms, Cambridge 2003
* Barber, Bayesian Reasoning and Machine Learning, Cambridge 2012
* Rasmussen/Williams, Gaussian Processes for Machine Learning, MIT 2006
* Bishop, Pattern Recognition and Machine Learning, Springer 2007
* Schölkopf/Smola, Learning with Kernels, MIT 2001
* Jaynes, Probability Theory – the Logic of Science, Cambridge 2003

Markov Chains (Ausgewählte Kapitel der Stochastik)

Responsible for the Module Prof. Dr. Peter Kern (kern@hhu.de)			**Date** 01.04.2019
Lecturer(s) Prof. Dr. Peter Kern, Prof. Dr. Axel Bücher			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 45 h	**Self-study** 105 h
Course Lecture: 2 SWS Exercises: 1 SWS	**Turnus** Summer term, irregular	**Group Size** 20	**Duration** 1 semester

Learning results & Competences

The students overcome with the basic principles and the basic mathematical theory of Markov chains. They are able to argue on the basis of mathematical definitions and theorems to solve selected problems independently and to present their solution. They gain methods of systematic and efficient knowledge acquisition. The students will reach a deep understanding of basic techniques and convergence results for Markov models. They will be able to adapt algorithms based on Markov chains to data, to apply these and to discuss the results critically.

Content

Lecture

The first part of the lecture covers the basic mathematical theory of Markov chains: Markov property, random walk, transition matrices, transition graphs, Chapman-Kolmogorov equation, classification of states, irreducibility, periodicity, recurrence and transience, renewal equation, strong Markov property, equilibrium distribution, ergodic theorems. The second part of the lecture focusses on practical aspects of these methods: branching processes, time to absorption, Markov chain Monte Carlo (MCMC) method, Metropolis sampler, Gibbs sampler, Ising model, simulated annealing, cooling schedules.

Exercise course

The lectures are accompanied by weekly exercise courses in which exercises concerned with the practical applications of selected problems and with the aim of a deeper understanding of the mathematical theory of Markov chains are discussed. These problems are first solved by the students independently, and afterwards the corrected homework is presented and discussed in the exercise courses.

Teaching

Lecture with exercise course.

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.

Contentual: Passed exam in „Mathematical and Statistical Foundations in Data Science“. It is further recommended to have taken a course on stochastics previous to this course.

Examination
Learning portfolio consisting of:
(1) Competence area knowledge (100% of final mark): Written exam on the contents of lectures and exercise classes.
(2) Application of acquired knowledge (40% of exercise points as admission to the final exam): Practical exercises during the semester.

Prerequisites for receiving credit points
(1) Passing the exam.
(2) Regular and active attendance to exercises.

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
B.Sc. Mathematik und Anwendungsgebiete, B.Sc. Finanz- und Versicherungsmathematik

Weight in overall rating
The mark will contribute to the final grade in relation to its credit points.

Further Information

Master's Seminar Advanced Mathematical and Numerical Methods in Data Science

Responsible for the Module			Date
Dr. Marcel Schweitzer			03.10.2020
Lecturer(s) Dr. Marcel Schweitzer			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** 20	**Duration** 1 Semester

Learning results & Competences

Students acquire knowledge about state of the art numerical algorithms at the core of data science methods, or about advanced mathematical concepts and models used to structure or analyze data.

Content

Efficient numerical algorithms are an important ingredient of almost all applications in machine learning and data science. However, these algorithms are often more or less invisible to the user as they lie at the very core of data science methods. This seminar focuses on these algorithms and how they enable and improve methods in various applications across machine learning and data science. Another possible direction of this seminar is the discussion of advanced mathematical concepts that are aimed directly at structuring data or revealing structure within data.

Possible topics for the seminar:

Interpretable matrix decomposition methods in data science

Numerical linear algebra for second-order methods in deep learning

Randomized numerical algorithms

Tensor representations for high-dimensional data

Mathematical analysis of complex networks

Teaching

Seminar

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.

Contentual: none

Examination

Graded seminar talk

Prerequisites for receiving credit points

Presence and active participation in the seminar

Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information

Master's Seminar Advances in Data Science

Responsible for the Module Prof. Dr. Stefan Dietze			**Date** 01.05.2019
Lecturer(s) Prof. Dr. Stefan Dietze			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 60 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 30 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** –	**Duration** 1 Semester

Learning results & Competences
Students have in depth understanding about actual methods and their applications in Data Science.

Content
Learning from data in order to gain useful insights is an important task, generally covered under the data science umbrella. This involves a wide variety of fields such as statistics, artificial intelligence, effective visualization, as well as efficient (big) data engineering, processing and storage, where efficiency and scalability often play crucial roles in order to cater for the quantity and heterogeneity of data.
The goal of this seminar is to deepen the understanding about data science & engineering techniques through studying and critically evaluating state-of-the-art literature in the field. Participants will be introduced to the critical assessment and discussion of recent scientific developments, thereby learning about emerging technologies as well as gaining the ability to evaluate and discuss focused scientific works. Participants will be given recent literature covering relevant data science areas. Each participant will review independently 1-2 publications and present and discuss its content and contribution, which are then presented and discussed with the entire student participants.

Teaching
Seminar „Advances in Data Science“

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination
Assessment of presentation

Prerequisites for receiving credit points
Active presence in seminar

Study Program

M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs M.Sc. Computer Science
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information Literature: •R for Data Science (by Garrett Grolemund and Hadley Wickham) O’Reilly Media •Statistics in a Nutshell, 2nd Edition, A Desktop Quick Reference, Sarah Boslaugh, O’Reilly Media •Doing Data Science – Straight Talk from the Frontline, Cathy O’Neil, Rachel Schutt, O’Reilly Media •Data Analytics with Hadoop, Benjamin Bengfort & Jenny Kim, O‘Reilly Media •Deep Learning by Ian Goodfellow and Yoshua Bengio and Aaron Courville

Master-Seminar: Algorithmic Data Analysis

Responsible for the Module			Date
Prof. Dr. Melanie Schmidt			01.03.2022
Lecturer(s)			**Semester**
Prof. Dr. Melanie Schmidt			2./3.
Language:			**Modus**
English			Elective Course
Work Load	**Credits**	**Contact Time**	**Self-study**
150 h	5 CP	30 h	120 h
Course	**Turnus**	**Group Size**	**Duration**
Seminar: 2 SWS	irregular	–	1 Semester

Learning results & Competences
After completion the students can
- structure, plan and give a talk
- do basic data analysis with Python

Content
Different methods for algorithmic data analysis (e.g., SVMs, clustering). The students learn about the topic both from literature and from a tutorial which is provided to them.

Teaching
Weekly seminar sessions

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science".
Contentual: none

Examination
Assessment of the abstract and the presentation

Prerequisites for receiving credit points
- talk on the chosen topic
- successful completion of the tutorial
- written feedback on the tutorial

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information
Literature:

Different for the topics and provided to the students at the beginning of the semester.

Master's Seminar Combinatorial Optimization in Bioinformatics

Responsible for the Module Prof. Dr. Gunnar Klau			Date 03.10.2020
Lecturer(s) Prof. Dr. Gunnar Klau, Eline van Mantgem			Semester 2./3.
Language: English			Modus Elective Course
Work Load 150 h	Credits 5 CP	Contact Time 30 h	Self-study 120 h
Course Seminar: 2 SWS	Turnus irregular	Group Size 20	Duration 1 Semester

Learning results & Competences

Students acquire knowledge about state-of-the-art combinatorial optimization algorithms in bioinformatics. They learn and practice how to read, understand, discuss, present and write about scientific literature and further develop their critical thinking skills.

Content

Many problems in bioinformatics can be formulated as combinatorial optimization problems. This module provides advanced knowledge for identifying, formulating, and solving such problems. Based on a selection from current bioinformatics topics – usually by studying recent conference papers – students learn about the application of important optimization tools and techniques such as dynamic programming, graph algorithms, linear and integer linear programming, Lagrangian relaxation, parameterized algorithms and satisfiability solving.

Teaching

Seminar

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination

Graded participation, presentation and final report

Prerequisites for receiving credit points

Presence and active participation in the seminar. Passing grades for participation, presentation and report.

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.
Further Information

Master's Seminar: Computational Argumentation

Responsible for the Module Jun. Prof. Gabriella Lapesa			**Date** 12.10.2023
Lecturer(s) Jun. Prof. Gabriella Lapesa			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** 26	**Duration** 1 Semester

Learning results & Competences

After this course the students students will be familiar with the conceptual building blocks of computational argumentation (e.g., claim, stance, evidence) and with the challenges and interdisciplinary applications of the NLP modeling of arguments in text. Beyond the specific topic, an important meta-skill that we will practice in class will having a critical attitude towards scientific texts, both at the level of the write-up (strength, clarity) and at the level of its content (reproducibility, ethical issues).

Content

Argument mining is a highly interdisciplinary field in Natural Language Processing. Given a linguistic unit (a speech, an essay, forum post, or a tweet), its goal is to determine what is the position adopted by the author/speaker on a certain topic/issue (i.e., whether or not vaccinations should be enforced), and to identify the evidence (if any) provided by the speaker for its position. In this seminar we will read and discuss recent papers in Argument Mining, based on a selection structured along three main coordinates: the core notion of Argument Quality (How do we recognise good arguments?); the modeling challenges related to the automatic extraction of argument structures (multilingualism; bias; evaluation of different modeling architectures); applications (computational social science; education).

Teaching

Seminar „Master’s Seminar on Computational Argumentation“

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science" or "Computer Science"

Contentual: none, but having attended the lecture „Natural Language Processing“ is highly recommended

Examination

Assessment of the presentation and coursework

Prerequisites for receiving credit points

(1) Active presence in the seminar
(2) Presentation of a paper
(3) Active participation in discussions
(4) Review of 4 papers in the seminar reading list

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Master's Seminar Computational Multiomics

Responsible for the Module Prof. Dr. Tobias Marschall			**Date** 24.06.2021
Lecturer(s) Prof. Dr. Tobias Marschall			**Semester** variable
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 50 h	**Self-study** 100 h
Course Seminar: 2 SWS	**Turnus** each winter term	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

Participants will be given an insight into high-throughput technologies and the kind of data gathered in such experiments. A key skill that is taught in this course is the art of transducing biological questions into compu-tational problems that can be efficiently solved. Further, participants have the opportunity to increase their proficiency in the critical dissemination of scientific papers and giving oral presentations.

Content

Modern laboratory equipment enables high-throughput experiments that provide detailed insights into molecular biology. These give rise to several branches of research including genomics, transcriptomics, proteomics, metabolomics, epigenomics, and metagenomics, with -omics meaning “the total of some sort”. Omics experiments produce massive amounts of data that are subject of a variety of challenging computational problems. In this class, computational problems and their solutions for the analysis of multiomics experiments are presented and discussed.Participants will be assigned individual topics. The selection and matching between topics and participants will be determined in the first meeting of the seminar.

Teaching

Seminar talks.

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: Advanced Programming and Algorithms

Examination

Graded seminar talk

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs M.Sc. Informatik
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information

Master’s Seminar: Digital Innovation and Entrepreneurship

Responsible for the Module Prof. Dr. Steffi Haag			**Date** 12.10.2022
Lecturer(s) Prof. Dr. Steffi Haag			**Semester** 1.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Seminar: 2 SWS	**Turnus** Irregular	**Group Size** Limited to 30	**Duration** 1 Semester

Learning results & Competences

After completing the course, students are able to
independently prepare and interpret the most important theories, concepts, methods, and results related to the field of digital innovation and entrepreneurship,
analyze scientific literature in order to independently define relevant research problems,
apply conceptual, quantitative, or qualitative research methods to analyze these problems,
write and review seminar papers,
critically reflect, present, and discuss the topic, research design, and results in the context of the seminar,
provide appropriate feedback on complex challenges, and
develop teamwork skills through collaboration with fellow students.

Content

The seminar covers a selection of current research topics in the area of Digital Innovation and Entrepre- neurship.
Students learn theories, concepts, processes, tools, and methods surrounding IT-based innovation, business models, user experience, and entrepreneurship.
Topics will be introduced and assigned in the first session.
During the semester, students will work on their seminar paper.
The results will be presented and discussed in the middle and at the end of the semester.
In addition, an introduction to scientific writing is given at the beginning.

Teaching

Seminar „Digital Innovation and Entrepreuneurship“, Session on scientific writing

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: None

Examination

Seminar paper, presentations in groups, and class participation

Prerequisites for receiving credit points

Written elaboration of the topic to be worked on (if necessary in groups)

Presentation of the topic (if necessary in groups)

Active class participation in discussions

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

M.Sc. Computer Science

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points

Further Information

Master's Seminar on Ethics in NLP

Responsible for the Module Jun. Prof. Gabriella Lapesa			**Date** 12.10.2023
Lecturer(s) Jun. Prof. Gabriella Lapesa			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** 26	**Duration** 1 Semester

Learning results & Competences

After this course, the students will be familiar with the literature on the reflection on ethical issues in NLP, fro the perspective of specific task and applications but also, at a higher level, on the dynamics of the debate regarding what needs to be done to solve these issues (Who are the stakeholders? what are the measures already in place, and do they work?, etc.) Beyond the specific topic, an important meta-skill that we will practice in class will having a critical attitude towards scientific texts, both at the level of the write-up (e.g., strength, clarity) and at the level of its content (e.g., reproducibility).

Content

Natural Language Technologies and, more broadly, Machine Learning, are everywhere, so embedded in everyday life that we, users, sometimes lose awareness of their presence. As scientists as researchers, however, our role is to keep track of the potential dangerous outcomes of these technologies, and to act as an interface between them and the general public. In the course, we will go through a selection of papers on ethical issues related ot NLP (e.g., bias, manipulation, privacy, etc.) with the goal of building together our taxonomy of these issues, along with our reflection on the steps to be taken to address them.

Teaching

Seminar „Master’s Seminar on Ethics in NLP“

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science" or "Computer Science"
Contentual: none.

Examination

Assessment of the presentation and coursework

Prerequisites for receiving credit points

(1) Active presence in the seminar
(2) Presentation of a paper

(3) Active participation in discussions

(4) Review of 4 papers in the seminar reading list

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

M.Sc. Computer Science

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Master's Seminar on Limits of Computation

Responsible for the Module Prof. Dr. Melanie Schmidt			**Date** 19.06.2022
Lecturer(s) Abhiruk Lahiri (PhD)			**Semester** 2-3
Language: English			**Modus** elective course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** –	**Duration** 1 semester

Learning results & Competences

Upon completion of the course, students will be expected to:

 know about different classes of computationally hard problems
 analyse the running time of algorithms through rigorous argument
 acquire a broad overview of existing literature on hard problems
 successfully perform reduction techniques to map a problem of interest onto another problem of known hardness
 demonstrate the ability to comprehend and effectively communicate the contents of assigned topics, both in written and oral formats

Content

Understanding the limits of computation is paramount in comprehending the provable accuracy of algorithms. Impossibility results and hypotheses delineate the boundaries within which algorithmic improvements can be anticipated. This understanding is increasingly crucial in our current era, where algorithms assume decision-making responsibilities in intricate processes on our behalf. The objective of this module is to familiarise students with significant research areas. Through this module, students will delve into topics such as NP-hardness, approximation hardness, Exponential Time Hypothesis and hardness within polynomial time algorithms.

Teaching

Seminar sessions every week

Prerequisites for attending

Formal: Admission to master studies in 'Artificial Intelligence and Data Science'
Contentual: Advanced Programming and Algorithms

Examination

Assessment of the write-up and the presentation

Prerequisites for receiving credit points

Preparation of a report on a topic within the scope of the module;

giving twenty minutes presentation on the chosen topic
peer review two other reports and provide feedback;
taking active participation during other presentations.

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
Grading will be based on the performance in the final presentation and quality of the submitted write-up. The mark given will contribute to the final grade in proper relation to its credit points.

Further Information
Literature:
Computers and Intractability: A Guide to the Theory of NP-Completeness, Michael Garey and David S. Johnson, W. H. Freeman, 1979, https://archive.org/details/computersintract0000gare
Parameterised Algorithms, Marek Cygan, Fedor V. Fomin, Łukasz Kowalik, Daniel Lokshtanov, Dániel Marx, Marcin Pilipczuk, Michał Pilipczuk, Saket Saurabh, Springer 2015, https://doi.org/10.1007/978-3-319-21275-3
On some fine-grained questions in algorithms and complexity, Virginia Vassilevska Williams, Proceedings of the International Congress of Mathematicians (ICM 2018), 3447– 3487, https://doi.org/10.1142/9789813272880_0188

Master's Seminar: NLP for Political Science

Responsible for the Module Jun. Prof. Gabriella Lapesa			Date 18.01.2024
Lecturer(s) Jun. Prof. Gabriella Lapesa			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** 28	**Duration** 1 Semester

Learning results & Competences

After this course, the students will be familiar with the literature on the application of Natural Language Processing methods to address Political Science questions. While the core of the course is on the NLP methods, the students will also benefit from the exposure to Political Science literature on the selected issues. Beyond the specific topic, an important meta-skill that we will practice in class will having a critical attitude towards scientific texts, both at the level of the write-up (e.g., strength, clarity) and at the level of its content (e.g., reproducibility).

Content

In this seminar, we will explore the potential of the application of Natural Language Processing methods to a selection of questions coming from Political Science (PolSci). The selection of papers will be structured along three main coordinates. The first coordinate has to do with the phenomena that have been investigated at this interdisciplinary intersection, e.g., media manipulation strategies like agenda-setting (the targeted selection of what is reported in the news, as a distraction factor) or framing (the targeted selection of certain aspects of a phenomenon, to bias the public towards a certain conceptualization of it); the dynamics of policy debates (discussions regarding the set of laws to be adopted in a certain domain, i.e., immigration) are another PolSci phenomenon which has been investigated with the support of NLP methods. The second coordinate has to do with the textual typology on which the analysis takes place: policy debates, for example, take place in a parliament, are summarized in newspapers, and widely debated on the social media. The third coordinate is methodological: What are the challenges of the interdisciplinary synergy between NLP and PolSci? What are the potential for the use of Large Language Models on this type of research questions? How about the risks?

Teaching

Seminar „Master’s Seminar on NLP for Political Science“

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science" or "Computer Science"

Contentual: none.

Examination
Assessment of the presentation and coursework

Prerequisites for receiving credit points
(1) Active presence in the seminar
(2) Presentation of a paper
(3) Active participation in discussions
(4) Review of 4 papers in the seminar reading list

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Master's Seminar: Property Testing

Responsible for the Module Dr. Anja Rey			**Date** 01.03.2022
Lecturer(s) Dr. Anja Rey			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** –	**Duration** 1 Semester

Learning results & Competences

After completion the students can

- extract significant contents of a given topic and to reproduce them in a written and oral form,
- evaluate the readability and technical quality of other abstracts,
- plan and hold a presentation, and
- ask and answer adequate questions and to give and take constructuctive feedback.

Content

We study algorithmic techniques that allow us to solve relaxed decision problems efficiently such as testing whether a sparse graph is connected or „far away“ from being connected in sublinear time. Individual topics can include state of the art research in this area.

Teaching

Weekly seminar sessions

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination

Assessment of the abstract and the presentation

Prerequisites for receiving credit points

- write an abstract about a given topic
- provide feedback via a peer review
- present your topic
- ask and answer questions

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

M.Sc. Computer Science

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Literature:

Oded Goldreich. Introduction to Property Testing. Cambridge University Press, 2017

Further literature will be announced in the beginning of the seminar according to the individual topics.

Master's Seminar: Subjectivity in NLP

Responsible for the Module Jun. Prof. Gabriella Lapesa			**Date** 18.01.2024
Lecturer(s) Jun. Prof. Gabriella Lapesa			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** 28	**Duration** 1 Semester

Learning results & Competences

After this course, the students will be familiar with a range of dimensions of individual variation (socio-demographics, personality traits, systems of morals and values) and with the conceptual, ethical and technical challenges that the NLP modeling of subjectivity implies. Beyond that, an important meta-skill that we will practice in class will having a critical attitude towards scientific texts, both at the level of the write-up (e.g., strength, clarity) and at the level of its content (e.g., reproducibility).

Content

This course will focus on the defining features of individuals, on what makes them unique or establishes their membership to a specific group, and on the challenges that these features pose to the development and use of Natural Language Processing models.

In the first part of the seminar, we will focus on the NLP modeling of what defines individuals: our obvious departure point will be socio-demographic variables, and we will then further proceed to personality traits and systems of morals and values.

The second part of the seminar will take a closer look at Large Language Models. What are the methods and challenges to define the socio-demographics of LLMs? Humans exhibit a wide range of psychological diversity: which humans do LLMs resemble?

In the third part of the seminar, we will take a methodological angle and review research on the "learning from disagreements" challenge. NLP approaches which rely on gold standards typically average annotators' perspectives; however, in particular when it comes to highly subjective phenomena, disagreements are a feature to take into account in the modeling, and not a bug to fix.

Teaching

Seminar „Master's Seminar on Subjectivity in NLP"

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science" or "Computer Science"
Contentual: none.

Examination
Assessment of the presentation and coursework

Prerequisites for receiving credit points
(1) Active presence in the seminar
(2) Presentation of a paper
(3) Active participation in discussions
(4) Review of 4 papers in the seminar reading list

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Master's Seminar on Information Theory, Inference, and Learning Algorithms

Responsible for the Module Prof. Dr. Stefan Harmeling			**Date** 01.10.2020
Lecturer(s) Prof. Dr. Stefan Harmeling			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 60 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 30 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** Limited to 24	**Duration** 1 Semester

Learning results & Competences

After completion students have in-depth understanding of various methods and techniques from the areas of Information Theory, Inference and Learning Algorithms. They improve their presentational skills and understanding of the covered topics.

Content

The Seminar aims to build upon and enhance the understanding of the lecture „Machine Learning“. Students will independently review and prepare 1-2 chapters from the Book „Information Theory, Inference, and Learning Algorithms“ by David MacKay, or other books or scientific publications related to the topic. Each week, 1-2 of the participants of the seminar will give a presentation, followed by a discussion involving all participants, focussing on content as well as the delivery of a good scientific presentation. In addition, each presenter is required to hand in a short summary of their presentation afterwards.

Teaching

Seminar „Information Theory, Inference, and Learning Algorithms“

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: Lecture „Machine Learning“

Examination

Assessment of the presentation

Prerequisites for receiving credit points

(1) Active presence in the seminar
(2) Presentation of a topic
(3) Active participation in discussions
(4) Written summary of the topic

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

M.Sc. Computer Science
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information Literature: Including David J.C.MacKay, „Information Theory, Inference, and Learning Algorithms“, Cambridge, PDF freely available on the author’s website.

Master's Seminar on Machine Learning

Responsible for the Module Prof. Dr. Stefan Harmeling			**Date** 01.10.2020
Lecturer(s) Prof. Dr. Stefan Harmeling			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 60 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 30 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** Limited to 24	**Duration** 1 Semester

Learning results & Competences

After completion students have in-depth understanding of various methods and typical applications from the area of Machine Learning. They can independently review and evaluate scientific publications and improve their presentational skills.

Content

Machine Learning has gained large influence in many scientific areas and branches as a method of detecting patterns and structure in data and deriving decisions and predictions from those. In particular the ever-growing masses of data in companies, research and the internet has led to a broad demand for experts in this field. Because of the quick evolution and discovery of new methods, a constant occupation with the newest findings is necessary. This seminar aims to build upon and enhance the learnings from the lecture „Machine Learning“ by independent study of such scientific publications. Each week, 1-2 of the participants of the seminar will give a presentation, followed by a discussion involving all participants, focussing on content as well as the delivery of a good scientific presentation. In addition, each presenter is required to hand in a short summary of their presentation afterwards.

Teaching

Seminar „Master’s Seminar on Machine Learning“

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: Lecture „Machine Learning“

Examination

Assessment of the presentation

Prerequisites for receiving credit points

(1) Active presence in the seminar
(2) Presentation of a topic
(3) Active participation in discussions
(4) Written summary of the topic

Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs M.Sc. Computer Science
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information

Master’s Seminar on Privacy-preserving Machine Learning

Responsible for the Module Prof. Dr. Milica Gašić			**Date** 23.2.2022
Lecturer(s) Prof. Dr. Milica GasicGašić			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 60 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 30 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** Limited to 24	**Duration** 1 Semester

Learning results & Competences

After completion students have in-depth understanding of various methods and typical applications from the area of privacy-preserving Machine Learning. They can independently review and evaluate scientific publications and improve their presentational skills.

Content

This seminar series will cover several classic papers in the topic of privacy preserving machine learning (PPML). PPML is a new area of Machine Learning that explores mechanisms to protect the owners of data from their data being leaked, while simultaneously allowing for insights to be gathered. Example applications include enabling models to be trained on data from private remote data, such as data on phones or in hospitals, and executing models on data without leaking the contents of the model. Example techniques include homomorphic encryption, secure multi-party computation, differential privacy and federated learning. This seminar aims to build upon and enhance the learnings from the lectures such as „Machine Learning“ and „Deep Learning” by independent study of such scientific publications. Each week, 1-2 of the participants of the seminar will give a presentation, followed by a discussion involving all participants, focussing on content as well as the delivery of a good scientific presentation. In addition, each presenter is required to hand in a short summary of their presentation afterwards.

Teaching

Seminar „Master’s Seminar on Privacy-preserving Machine Learning“

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: Lecture „Machine Learning“ and/or „Deep Learning“

Examination

Assessment of the presentation

Prerequisites for receiving credit points

(1) Active presence in the seminar

(2) Presentation of a topic
(3) Active participation in discussions
(4) Written summary of the topic

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Master’s Seminar on Word Embedding Spaces

Responsible for the Module Dr. Benjamin Ruppik Prof. Dr. Milica Gašić	**Date** 23.2.2022
Lecturer(s) Dr. Benjamin Ruppik	**Semester** 2./3.
Language: English	**Modus** Elective Course

Work Load 60 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 30 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** Limited to 26	**Duration** 1 Semester

Learning results & Competences

After completion students

have in-depth understanding of various methods and techniques for constructing word embeddings,

can name applications for word embeddings in natural language processing and dialog systems,

can independently review and evaluate scientific publications and improve their presentational skills.

Content

In a word embedding we encode language by associating to each word a vector in some ambient space, such that words which have similar meaning are close together in the space. When words are modelled as vectors or points in an ambient high-dimensional space, this is called an embedding.

Words which are used in similar contexts usually have similar meanings: The distributional hypothesis states that words which frequently appear in similar contexts are similar themselves. This makes it possible to acquire meaningful representations from unlabelled data such as text from Wikipedia, books, or news headlines.

In this seminar, we will study recently published techniques for finding both static and contextual embeddings: In a static embedding there is one fixed embedding for each word in the vocabulary. In a contextual embedding the vector we associate to a word is distinct if it is used in a different context. Another important, but challenging aspect is evaluating the quality of a word embedding, which form the basis of many natural language processing tasks such as document search, document classification, information retrieval, language translation and sentiment analysis.

•Static word embeddings: Frequency based methods, word2vec, GloVe, fastText

•Contextual word embeddings: ELMo, Transformer, BERT, Sentence Embeddings

•Evaluation of word embeddings, Geometry of the word embedding space, Bias in word embeddings, Sentiment, Multi-lingual word embeddings

•Topological Data Analysis

Teaching
Seminar „Master’s Seminar on Word Embedding Spaces“

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: Lecture „Machine Learning“

Examination
Assessment of the presentation

Prerequisites for receiving credit points
(1) Active presence in the seminar
(2) Presentation of a topic
(3) Active participation in discussions
(4) Written summary of the topic (“extended abstract”, maximum 2 pages)

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Master Seminar Reproducibility in Bioinformatics Research

Responsible for the Module Prof. Dr. Gunnar Klau			**Date** 03.10.2020
Lecturer(s) Prof. Dr. Gunnar Klau, Eline van Mantgem			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Seminar: 2 SWS	**Turnus** irregular	**Group Size** 20	**Duration** 1 Semester

Learning results & Competences

Students learn about the reproducibility crisis in computational research and reasons why it exists. In group work they practice how to read, understand, discuss, present and write about scientific literature and further develop their critical thinking skills. They will advance their practical programming and data analysis skills by reproducing published research. They will learn how to use tools like Conda, Snakemake and Docker to produce highly reproducible research.

Content

Scientific data analysis is becoming increasingly important in research. In bioinformatics in particular, the combination of enormously growing data volumes, lack of standards and incentives and poor programming practices has led to a reproducibility crisis. Scientific software is too often inadequately documented, inefficiently programmed, and unmaintained. In this seminar, we will highlight these flaws by attempting to reproduce the data analysis of selected original papers. In addition, we will learn how to do it correctly by implementing these analyses using tools like Conda, Snakemake and Docker and, if successful, making them availlable on certified online storage services.

Teaching

Seminar

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science".
Contentual: none

Examination

Graded participation, presentation and final report

Prerequisites for receiving credit points

Presence and active participation in the seminar. Passing grades for participation, presentation and report.

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Mathematical and Statistical Foundations of Data Science

Responsible for the Module Dr. Peter Arndt			**Date** 01.05.2019
Lecturer(s) Dr. Peter Arndt			**Semester** 1.
Language: English			**Modus** Obligatory Course
Work Load 300 h	**Credits** 10 CP	**Contact Time** 100 h	**Self-study** 200 h
Course Lecture: 4 SWS Exercises: 2 SWS	**Turnus** each winter term	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

Students know the basic concepts of linear algebra, convex optimization, Bayesian statistics, and information theory. They know the principles behind matrix differential calculus. They understand the difference between likelihood and posterior probability and can apply these concepts to solve (generalized) linear regression problems. They can apply Gaussian process priors to regression problems. They are familiar with regularization techniques to control overfitting. They know convex optimization problems and understand the techniques to solve them efficiently.
The students are familiar with the basic concepts of information theory. They understand the concept of discrete stochastic processes and their applications to sequential data. They know the concept of continuous time stochastic process. They are familiar with sampling methods and their application to Bayesian statistics.

Content

Lecture:
Linear Algebra. Eigenvalue problems, Singular value decomposition, Low rank approximation, matrix differential calculus.
Regression. Linear models, generalized linear models, regularization.
Stochastic Processes. Markov property, Markov chains, state space models.
Convex Optimisation. Primal-dual-problem, Lagrangian, duality gap, KKT conditions, regularizing conditions.
Bayesian Statistics. A priori and a posteriori distributions, conjugate priors, Gaussian Process regression/classification, importance sampling rejection sampling, Markov Chain Monte Carlo, Metropolis Hastings, Gibbs sampling.
Information Theory. Jensen's inequality, Entropy, KL-divergence, Rate distortion theory, differential entropy, minimum description length.
Exercises:
The content of the lecture is applied and deepened in theoretical exercises. In addition, the students will implement the central concepts in Python and apply them to real and self-

generated data.

Teaching
Lecture with (theoretical and practical) exercises

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination
written examination

Prerequisites for receiving credit points
Regular and active participation in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Methods for Population Genetics

Responsible for the Module Prof. Dr. Tobias Marschall			**Date** 06.07.2023
Lecturer(s) Prof. Dr. Tobias Marschall			**Semester** variable
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 45 h	**Self-study** 105 h
Course Lecture: 2 SWS Exercises: 1 SWS	**Turnus** each winter term	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

After completing the course, students are able to
- explain the fundamental principles and terms used in population genetics,
- analyze and compare the effects of mutation, migration and selection on genotypes in a population,
- describe analyses of genetic variation in the context of phenotypic traits, and
- apply the algorithmic and statistical concepts of population genetics to modern sequencing data sets.

Content

Population Genetics studies the distribution of genetic information across populations under varying conditions. This lecture provides the necessary methods to answer questions such as: Is there evidence for selection pressure on a certain gene? How can ancient migration patterns be retraced based on genetic information? How can quantitative traits such as disease susceptibility be attributed to genetic loci?
- Hardy-Weinberg principle
- Genetic drift and Wright-Fisher model
- Kolmogorov forward and backward equations
- Mutation and selection
- Linkage disequilibrium
- Population structure and inbreeding
- Haplotype phasing and imputation
- Genome-wide association studies and quantitative traits

Teaching

Lecture with (theoretical and practical) exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: None

Examination
oral exam

Prerequisites for receiving credit points
Regular and active participation in the exercises: 50% of the points from the exercise sheets.
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Artificial Intelligence and Data Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Natural Language Processing

Responsible for the Module Prof. Dr. Stefan Conrad (stefan.conrad@uni-duesseldorf.de)			**Date** 17.04.2019
Lecturer(s) Prof. Dr. Stefan Conrad			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** –	**Duration** 1 Semester

Learning results & Competences

Natural Language Processing (NLP). Students understand basic methods and algorithms for NLP and can explain them. They are able to design a NLP pipeline for a dedicated task and to implement it using adequate libraries. The students know how to evaluate NLP algorithms and whole pipelines and are able to interpret the results of such evaluations.

Information Retrieval. Students know basic retrieval models and information retrieval concepts and can explain them in the context of natural language processing.

Content

Lecture:
– Introduction into Natural Language Processing (NLP) and Information Retrieval (IR) concepts
– NLP pipeline and basic NLP methods/algorithms
– Evaluation principles and measurements
– Selected applications for NLP

Exercises:
In the exercises the content of the lecture is applied and deepened. For that the exercises contain theoretical as well as practical elements. In particular, the development of NLP algorithms and the design of NLP pipelines can be practically carried out.

Teaching
Lecture with (theoretical and pratical) exercises

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination

Written or oral examination

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Neuroimaging and Precision Medicine

Responsible for the Module Prof. Dr. S. B. Eickhoff (S.Eickhoff@fz-juelich.de) Prof. Dr. S. Caspers (svenja.caspers@hhu.de) PD Dr. S. Weis (S.Weis@fz-juelich.de)			**Date** 01.04.2019
Lecturer(s) Prof. Dr. S. Eickhoff, Prof. Dr. C. Caspers, PD Dr. S. Weis			**Semester** 3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 45 h	**Self-study** 105 h
Course Lectures: 2 SWS Seminar: 1 SWS	**Turnus** Every Winter Term	**Group Size** 25	**Duration** 1 Semester

Learning results & Competences

Neuroimaging

Students will be able to describe the basic principles of cognitive neuroimaging of the human brain as a basis for the subsequent application of Big Data and AI approaches. For all important imaging modalities, they can explain the relationship between neuronal activity and the measured signal. They will be able to evaluate strengths and weaknesses of the different modalities to address specific research questions. They will be able to explain the basics of experimental design and the statistical analysis of neuroimaging studies. In particular, they will be able to decide which approaches to the data analysis of brain imaging data are suitable for answering specific questions.

Precision Medicine

Students will have an understanding of how the collection and analysis of very large datasets (so-called "big data") can be used to study functional brain organization in the healthy brain and its disorders. They will understand how AI and data science can be used to draw conclusions about individual differences in the brain organization and identify biomarkers. Students will have an overview of clinical applications of the above methods for specific neurological and psychiatric disorders such as Parkinson's disease, Alzheimer's disease or schizophrenia.

Content

Lectures

Lectures start with an introduction to the main methods of structural and functional neuroimaging. Students learn the necessary steps for pre-processing and statistical analysis of the data. The usual methods of data analysis, such as case studies, group studies and correlation analyses, are discussed to give students an insight into what conclusions can be drawn from the various types of analysis and which methodological approaches are suitable for addressing which questions. In the second part of the lectures methodical approaches for the

analysis of "Big Data" and for conclusions about individual differences in the structural and functional brain organization are discussed. In particular, prediction and classification analyses are presented using brain imaging data. The lecture also deals with applications and results of these methods in the clinical context as well as with studies on the identification of individual biomarkers.
Seminars
It is the aim of the seminars to familiarize students with current research questions in the field of AI / Data Sciences in the Neuroscience and in Precision Medicine, and to encourage critical reflection of such issues. To this end, a series of current research topics in these areas will be discussed in the form of presentations prepared by the students themselves. The possible subject areas are varied, and the individual interests of the students can be taken into account. To give a comprehensive overview of the topic, the articles will be suggested by the lecturers.

Teaching
Lectures and Seminars

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination
Oral examination

Prerequisites for receiving credit points
Oral Presentation
Active presence in seminars

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Numerical Methods for Data Science

Responsible for the Module Prof. Dr. Christiane Helzel (christiane.helzel@hhu.de)			**Date** 01.05.2019
Lecturer(s) Prof. Dr. Christiane Helzel			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 45 h	**Self-study** 105 h
Course Lecture: 2 SWS Exercises: 1 SWS	**Turnus** irregular	**Group Size** 20	**Duration** 1 Semester

Learning results & Competences

The students will acquire knowledge on different numerical methods that are used to compute the solution of linear systems, least square problems, eigenvalue problems and the singular value decomposition. They will learn which algorithms are used in various situations.

Content

Lecture:

The class covers several powerful numerical linear algebra techniques that are used in various applications in data mining and pattern recognition. We first review basic linear algebra concepts and matrix decompositions, in particular the LU and the QR decomposition and use these techniques to solve linear systems and least square problems. Furthermore, we study different algorithms for computing eigenvalues and the singular value decomposition. Finally we will see how these concepts are used in different applications such as text mining, page ranking and face recognition. Throughout the course, the presented methods will be illustrated by test problems that are carried out in Matlab or Python.

Exercises:

The lectures are accompanied by exercise courses in which the students apply the different numerical methods that are covered in the lectures. Exercise problems are solved by the students independently, and are afterwards presented and discussed in the exercise courses.

Teaching

Lecture with (theoretical and practical) exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.

Contentual: none

Examination

written examination

Prerequisites for receiving credit points

Regular and active participation in the exercises

Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

B.Sc. Mathematics

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Literature:

J.W.Demmel, Applied Numerical Linear Algebra, SIAM

L.Elden, Matrix Methods in Data Mining and Pattern Recognition, SIAM

Probabilistic Machine Learning

Responsible for the Module Prof. Dr. Paul Swoboda			**Date** 09.10.2023
Lecturer(s) Prof. Dr. Paul Swoboda			**Semester** 3.
Language: English			**Modus** Elective Course
Work Load 300 h	**Credits** 10 CP	**Contact Time** 90 h	**Self-study** 210 h
Course Lecture: 4 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

The students will obtain a theoretical understanding of Probabilistic Machine Learning tools, that is Probabilistic Graphical Models and various generative models. The students will obtain the capabilities to implement and apply the covered techniques. They will understand the probabilistic foundations of the field. They will understand their numerical implementation and their application to problems in machine learning.

Content

Probabilistic Graphical Models, Directed & Undirected Graphical Models, Exact, Approximate and Variational Inference, Sampling, Learning Probabilistic Graphical Models,
Generative Models, including Variational Autoencoders, autoregressive models, normalizing flows, energy-based models and diffusion models.
Probabilistic Basics needed for Probabilistic Machine Learning, ELBO, divergence measures

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Formal: none
Contentual: Machine Learning, Deep Learning

Examination

written or oral examination

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

B.Sc. Mathematik und Anwendungsgebiete

M.Sc. Computer Science

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Philosophy of Intelligence

Responsible for the Module			Date
Prof. Dr. Gottfried Vosgerau (vosgerau@hhu.de)			01.03.2019
Lecturer(s) Prof. Dr. Gottfried Vosgerau, Prof. Dr. Frank Dietrich, and further staff of the Institute of Philosophy			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lectures: 2 SWS Exercises: 2 SWS	**Turnus** Every second Summer term	**Group Size** 20	**Duration** 1 Semester

Learning results & Competences

Concepts and Measurements of Intelligence. Students are able to explain and criticize different conceptions of intelligence in Psychology and Philosophy. Students are able to connect the different conceptions to specific ways of measuring intelligence and to evaluate the theoretical soundness of the measurements in relation to the different conceptions. Cognitive Models of Intelligence. Students are able to explain the theoretical foundations of cognitive modelling and cognitive architecture. They are able to name the most important cognitive faculties and to describe functional interdependencies. They are able to explain and criticize representationalist and anti-representationalist conceptions of the mind.

Goals and Limits of Cognitive Modelling. Students are able to describe the different possible goals of cognitive modelling within the cognitive sciences. They are able to identify the limits of different approaches in relation to the according epistemological goals.

The Ethics of Artificial Intelligence. Students know the most important ethical questions arising in the context of developing and implementing AI systems. They are able to discuss these questions against the background of different ethical theories.

Content

Lectures

The lecture starts with an historical overview of the different conceptions of intelligence in Psychology and Philosophy. The theoretical basis of these conceptions is introduced along with the proposed measurement of intelligence. The students learn to criticize the different approaches on the basis of the theoretical conceptions and to name their limits. Then, the relation between theories in Cognitive Science and cognitive modelling is introduced and discussed. A focus will be set on connectionist models in contrast to classical symbol- and rule-based models. The discussion of the different models will especially highlight the different cognitive faculties that favor one or the other model of explanation. With concrete examples, the interdependency between the explanatory goals and the virtues and limits of cognitive modelling are introduced. Finally, a systematic overview of the most important ethical

questions arising in the context of developing and implementing AI systems will be given. Based on prominent examples, different ethical theories are illustrated.
Exercise
The exercise will consist in the critical reading and discussion of key texts pertinent to the topics of and in parallel with the lecture.

Teaching
Vorlesung mit Lektüre-Übungen

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination
A written online-exam about the contents of the module.

Prerequisites for receiving credit points
(1) Passing the exam
(2) Regular and active participation in the exercise

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Practical: Implementing Transformer Models

Responsible for the Module Prof. Dr Milica Gašić			**Date** 27.06.2023
Lecturer(s) Carel van Niekerk			**Semester** 2-3
Language: English			**Modus** elective course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 30 h	**Self-study** 120 h
Course Practical: 2 SWS	**Turnus** irregular	**Group Size** limited to 24	**Duration** 1 semester

Learning results & Competences

By the end of the module, students will be able to:

- interpret the architectural nuances and computational aspects of Transformer models, including the attention mechanism and multi-head attention layers.
- adopt scientific research skills, such as setting up independent projects, implementing models based on academic literature, and producing scientifically sound, reproducible results.
- apply knowledge of optimal GPU utilisation, including the setup and management of parallel training environments and effective resource allocation for machine learning training.

Content

- Detailed study and implementation of the Transformer model, building an intuitive understanding of its unique architecture and the attention mechanism.
- Practical application of computational aspects of the Transformer model, including the scaling of dot products and shared parameter mechanisms, such as embedding vectors.
- Training a Transformer model tailored for machine translation, including the preparation and pre-processing of a translation dataset.
- Exploration of GPU utilisation, parallel training strategies and effective resource allocation for machine learning training.

Teaching

Practical Sessions

Prerequisites for attending

Examination

Presentation and final report

Prerequisites for receiving credit points

Active participation in the practical. Passing grades for presentation and report.

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs M.Sc. Computer Science
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information Attention is all you need. (https://arxiv.org/pdf/1706.03762.pdf)

Reinforcement Learning

Responsible for the Module			Date
Prof. Dr. Stefan Harmeling			17.06.2019
Lecturer(s)			**Semester**
Prof. Dr. Stefan Harmeling			2./3.
Language:			**Modus**
English			Elective Course
Work Load	**Credits**	**Contact Time**	**Self-study**
150 h	5 CP	60 h	90 h
Course	**Turnus**	**Group Size**	**Duration**
Lecture: 2 SWS Exercises: 2 SWS	irregular	–	1 Semester

Learning results & Competences

After successfully finishing the course, the student

* can understand and can explain the theoretical foundations of reinforcement learning.
* can implement and apply algorithms of reinforcement learning.

Content

* The reinforcement learning problem
* Multi-armed bandits
* Markov Decision processes
* Dynamic programming
* Monte Carlo Methods
* Temporal-difference learning
* On- and off-policy methods
* Elligibility traces
* Policy gradients

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.

Contentual: none

Examination

written examination

Prerequisites for receiving credit points

Regular and active participation in the exercises?

Passing the examination?

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information
Literature
Richard Sutton, Andrew Barto, "Reinforcement Learning: An Introduction", 2018, MIT press, draft online available

Relational Databases and Data Analysis

Responsible for the Module			Date
Prof. Dr. Stefan Conrad (stefan.conrad@uni-duesseldorf.de)			17.04.2019
Lecturer(s) Prof. Dr. Stefan Conrad			**Semester** 3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** –	**Duration** 1 Semester

Learning results & Competences

Relational Databases.

Students understand the relational model for databases together with its foundations (e.g. relational algebra). They are able to design relational databases and to express simple and complex database queries using SQL.

Data warehouses.

Students know the basic architecture and central concepts of data warehouses and can explain them. They can design relational data warehouses using multi-dimensional modelling.

OLAP and complex database queries.

Students are able to understand, analysis and formulate complex OLAP and database queries using the SQL query language and its OLAP extension.

Content

Lecture:

– Introduction into the relational database model and relational data warehouses;
– Design of relational databases
– Multi-dimensional modelling for (relational) data warehouses
– SQL
– OLAP
– Complex OLAP queries in SQL for data analysis

Exercises:

In the exercises the content of the lecture is applied and deepened. For that the exercises contain thoeretical as well as practical elements. In particular, the development of complex OLAP and database queries using the language SQL can practically be carried out using a database system provided to the students.

Teaching
Lecture with (theoretical and practical) exercises

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: none

Examination
Written examination or oral examination

Prerequisites for receiving credit points
(1) Regular and active participation in the exercises
(2) Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points

Further Information

Spectral Graph Theory and Graph Signal Processing

Responsible for the Module Dr. Peter Arndt			**Date** 03.10.2020
Lecturer(s) Dr. Peter Arndt			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** 20	**Duration** 1 Semester

Learning results & Competences

In this module, students learn about different matrix representations of graphs and how the eigenvalues and eigenvectors of those matrices reveal combinatorial properties of the graph and subsequently help analyzing and structuring the underlying data. Additionally it is discussed how concepts from classical signal processing (like convolution and the Fourier transform) can be adapted to signals on graphs. After covering these basic concepts, the main focus is on applying them to real-world complex networks from various application areas.

Content

Classical spectral graph theory:
• Adjacency matrices
• The graph Laplacian
• Algebraic connectivity and the Fiedler vector
• The Cheeger constant and Cheeger's inequality
• Spectral clustering
• Graph coloring, the chromatic number and Wilf's theorem
• Centrality measures based on spectral information

Graph Signal processing:
• Signals on graphs
• Frequencies on graphs and the graph Fourier transform
• Interpreting graph frequencies
• Shifts and convolutions on graphs
• Total variation on graphs
• Diffusion processes on graphs
• Learning graphs from data

Applications:
• Community detection in complex networks

• Spreading of infectious diseases
• Efficient exploration of large networks
• Finding consensus in multi-agent systems via network dynamics
• Fake image detection with Forensic Similarity Graphs

Teaching
Lecture with (theoretical and practical) exercises

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“
Contentual: Advanced Programming and Algorithms

Examination
Written examination or oral examination

Prerequisites for receiving credit points
(1) Regular and active participation in the exercises
(2) Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Spoken Dialogue Systems

Responsible for the Module Prof. Dr Milica Gasic			**Date** 25.06.2019
Lecturer(s) Prof. Dr Milica Gasic			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 300 h	**Credits** 10 CP	**Contact Time** 120 h	**Self-study** 180 h
Course Lecture: 4 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

On completion of this module, students should understand:
The purpose and operation of the main components of a spoken dialogue system
How the framework of partially observable Markov decision processes can be used to model a spoken dialogue system
How classification, regression, sequence-to-sequence models and reinforcement learning can be used to implement a spoken dialogue system. The various options for optimizing and adapting a statistical spoken dialogue system, both off-line and on-line, and how deep learning can be utilised to achieve state of the art results in dialogue modelling.

Content

Introduction: architecture of a spoken dialogue system, dialogue acts, turn management issues
Semantic decoding: representing and decoding meaning from user inputs, semantic decoding as a classification task, semantic decoding as a sequence-to-sequence learning task
Dialogue state tracking: tracking beliefs over multiple turns, classical generative and discriminative approaches, recent deep learning approaches, integration of decoding and tracking.
Dialogue Management: modelling via Markov Decision Processes, reinforcement learning, gradient methods, Gaussian Processes
Response Generation: template methods, generative models, recent neural network approaches
Current research topics: incremental dialogue, towards open-domain systems, end-to-end neural network architectures
Practical Work:
Students will be provided with a set of Python tools which will enable them to configure and test a simple spoken dialogue system. They will be asked to implement a simple dialogue state tracker and a reinforcement learning algorithm and optimize the dialogue manager in interaction with a simulated user. This will give them an opportunity to explore a practical example of reinforcement learning.

Teaching
Lecture with (theoretical and practical) exercises

Prerequisites for attending
Formal: none
Contentual: none

Examination
Assessment:
Written report of 2000 words covering the practical [100%]

Prerequisites for receiving credit points
Regular and active participation in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points

Further Information
Recommended Reading Page:

S. Young (2013). "Talking to Machines" Royal Academy of Engineering Ingenia, 54:40-46
S. Young, M. Gasic, B. Thomson and J. Williams (2013). "POMDP-based Statistical Spoken Dialogue Systems: a Review." Proc IEEE, 101(5):1160-1179

Statistical Data Analysis

Responsible for the Module Prof. Dr. Holger Schwender (holger.schwender@hhu.de)			**Date** 01.04.2019
Lecturer(s) Prof. Dr. Holger Schwender, Prof. Dr. Axel Bücher			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 45 h	**Self-study** 105 h
Course Lecture: 2 SWS Exercises: 1 SWS	**Turnus** About every fourth semester	**Group Size** 20	**Duration** 1 Semester

Learning results & Competences

The students will be able to perform statistical analyses of different types of data and to use the statistical software environment and language R for these data analyses. The students will acquire knowledge on different types of statistical methods such as testing procedures, analysis of variance, and regression methods, on how to use these methods for a statistical data analysis, and on good practice in planning a study, in preparing data sets for a statistical analysis, as well as in presenting the results of a statistical analysis using, e.g., graphical data presentations. They will be able to decide which of the statistical methods to use in which situation and to apply these procedures to the data.

Content

Lecture

The lecture covers a wide range of statistical methods focusing on the practical aspects of these methods and their application to different types of data. Since the statistical software environment and language R is the most popular, advanced software for statistical analysis, R is mainly used in the lecture to exemplify the application of the statistical procedures. Therefore, the lecture starts with a basic, practical introduction to R. This knowledge on R is successively extended during the semester (in both the lectures and the exercise courses). It is discussed how graphics and descriptive statistics can be generated in R and should be generated in general to present and summarizing the data and the results of a data analysis in a best practice way. Moreover, good practice in preparing a data set for a statistical data analysis in, e.g., R is discussed. Prior to the actual data analysis an important step is the preprocessing of the data including checking the data for plausibility or errors, determining whether input variables should be transformed and how they could be transformed, as well as handling missing values in the data. Therefore, these issues will be discussed in the lecture in a practical way. Afterwards, the general principle of statistical testing and multiple statistical testing as well as testing procedures for the most important testing situations are taught. It is discussed how to apply these tests to data, how to check the assumptions of these tests, and how to select the most appropriate test for a particular testing situations. The rest of the course is dedicated to one- and multi-way analysis of variance as wells as different regression methods including linear regression, generalized linear models (especially, logistic regression), regularized regression (e.g., ridge regression and Lasso), (generalized) linear mixed models, Cox proportional hazard models, and nonparametric regression models (e.g., kernel smoothing, smoothing splines, or neural nets from a regression perspective). Besides the Cox regression, survival analysis is also considered in general. Again, in the discussion of the analysis of variance and the regression methods, emphasis will be placed on practical aspects of the application of these methods to data, considering different types of data sets.

Exercise course

The lectures are accompanied by exercise courses in which exercises concerned with the practical application of the statistical procedures taught in the lectures to data sets from different fields of application are discussed. These data analysis problems are solved by the students independently, and afterwards, presented and discussed in the exercise courses.

Teaching

Lecture with exercise course.

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science“.

Contentual: Passed exam in „Mathematical and Statistical Foundations in Data Science“. It is recommended to have taken a course on stochastics previous to this course.

Examination

Typically, a written examination about the content of this course.

Prerequisites for receiving credit points

Passing the exam.

Regular and active attendance of the practicals.

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

B.Sc. Mathematics

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Statistical Learning

Responsible for the Module Prof. Dr. Axel Bücher (axel.buecher@hhu.de)			**Date** 20.06.2019
Lecturer(s) Prof. Dr. Axel Bücher, Prof. Dr. Holger Schwender			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 45 h	**Self-study** 105 h
Course Lecture: 2 SWS Exercises: 1 SWS	**Turnus** irregular	**Group Size** 20	**Duration** 1 Semester

Learning results & Competences

The students will acquire knowledge on different types of statistical learning methods, with an emphasis on dimensionality reduction, clustering and classification. They will be able to apply those methods independently to different types of data, to present their solution and to discuss the results critically. The students gain profound knowledge in using the statistical software environment and language R for the data analyses. They gain methods of systematic and efficient knowledge acquisition.

Content

Lecture

The lecture covers some of the most important statistical learning methods, with an emphasis on dimensionality reduction, clustering and classification, as well as on the application to different types of data. The lecture serves as a complement to the module „Statistical Data Analysis“, but may be attended without any knowledge from that module.

The lecture starts by discussing the most common approaches to dimensionality reduction, in particular principal component analysis and factor analysis based on latent variable models. The second part covers clustering methods, in particular hierarchical clustering algorithms based on similarity and dissimilarity measures and k-means clustering. The third part covers basic supervised learning methods for classification: classical approaches like linear and quadratic discriminant analysis and logistic regression, K-nearest Neighbors, classification trees (CART algorithm, weakest link pruning), ensemble methods like bagging and random forests, support vector machines, as well as model evaluation based on cross-validation.

Throughout the course, the presented methods will be illustrated by exemplarily applications carried out within the statistical software environment and language R, the nowadays most popular software for advanced statistical analysis. The knowledge on R is successively extended during the semester (in both the lectures and the exercise courses).

Exercise course

The lectures are accompanied by exercise courses in which exercises concerned with the practical application of the statistical learning methods to data sets from different fields of

application are discussed. These data analysis problems are solved by the students independently, and are afterwards presented and discussed in the exercise courses.
Teaching Lecture with exercise course.
Prerequisites for attending Formal: Admission to master studies in „Artificial Intelligence and Data Science“. Contentual: Passed exam in „Mathematical and Statistical Foundations in Data Science“. It is further recommended to have taken a course on stochastics previous to this course.
Examination Typically, a written examination about the content of this course.
Prerequisites for receiving credit points Passing the exam. Regular and active attendance of the practical work.
Study Program M.Sc. Artificial Intelligence and Data Science
Module accessible for other Study Programs B.Sc. Mathematics
Weight in overall rating The mark given will contribute to the final grade in proper relation to its credit points.
Further Information

Stochastic Models of Biological Systems

Responsible for the Module			Date
Prof. Dr. Martin Lercher, Dr. Adélaïde Raguin			06.04.2023
Lecturer(s) Dr. Adélaïde Raguin			**Semester** 2./3.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** Winter and summer term	**Group Size** Not limited	**Duration** 1 Semester

Learning results & Competences

After completing the course, students are able to
- distinguish and recognise key biological features that justify the use of the models studied,
- explain modelling approaches based on the underlying biology,
- develop and implement stochastic algorithms using the programming language C++,
- simulate the dynamics of the systems studied and critically evaluate the quality of their results,
- reproduce all analytical calculations executed in the course,
- explain physico-chemical parameters that influence the dynamics of the processes studied.

Content

- Cell birth-and-death, moment-generating functions.
- Diffusion models and Brownian dynamics, comparison of deterministic versus stochastic approaches.
- Protein production, the Totally Asymmetric Simple Exclusion Process, its analytical solution in mean field.
- Cytoskeletal transport, directed transport properties of three dimensional structures.
- Polysaccharide synthesis, complex enzymatic processes.

The course describes the stochastic modelling (analytical and numerical) of the biological systems from cell biology above listed. Key algorithms used throughout the module are Monte Carlo and Gillespie, implemented in C. The module is highly interdisciplinary and includes knowledge and methods from Mathematics, Biology, Physics, and Chemistry, with a strong focus on algorithms and programming in the tutorials. The methods and tools learnt during this course also apply to other fields than Biology. Specifically, they are used in theoretical Physics of both dilute and condensed systems, and Engineering. The programming language C is widely spread in these fields since it is well suited for computer intensive numerical methods.

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Examination
Written exam, usually 90 minutes

Prerequisites for receiving credit points
50 percent of total points in the exercises
Passing the examination

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Artificial Intelligence and Data Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information

Topological Data Analysis

Responsible for the Module			Date
Prof. Dr. Marcus Zibrowius, Dr. Peter Arndt			14.10.2020
Lecturer(s)			**Semester**
Prof. Dr. Marcus Zibrowius, Dr. Peter Arndt			2.
Language:			**Modus**
English			Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 64 h	**Self-study** 86 h
Course Lecture: 2 SWS Exercises: 2 SWS	**Turnus** irregular	**Group Size** 40	**Duration** 1 Semester

Learning results & Competences

The students know the general idea of algebraic topology and the notions of metric spaces, simplicial complexes, homotopy and (co)homology. They know how a point cloud gives rise to a filtered simplicial complex, via the Cech complex and the Vietoris-Rips complex constructions. They know the concept of persistent homology of a filtered simplicial complex. They know the mapper algorithm. They know software tools to perform topological data analysis in practice.

Content

Simplicial complexes, triangulability, Simplicial homology, Cech complex & Vietoris-Rips complex, Decomposition of persistence modules, Barcodes & persistence diagrams, Persistent images, persistence landscapes and other approaches to feed persistence into machine learning, mapper algorithm, practical topological data analysis

Teaching

Lecture with theoretical and practical exercises

Prerequisites for attending

Formal: Admission to master studies in „Artificial Intelligence and Data Science".
Contentual: none

Examination

written or oral examination

Prerequisites for receiving credit points

Regular and active participation in the exercises
Passing the examination

Study Program

M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs

B.Sc. Mathematik und Anwendungsgebiete

Weight in overall rating

The mark given will contribute to the final grade in proper relation to its credit points.
Further Information

User Experience (UX) Design and Management

Responsible for the Module Prof. Dr. Steffi Haag			Date 2.9.2022
Lecturer(s) Prof. Dr. Steffi Haag			**Semester** 1.--4.
Language: English			**Modus** Elective Course
Work Load 150 h	**Credits** 5 CP	**Contact Time** 60 h	**Self-study** 90 h
Course Lecture: 2 SWS Exercise: 2 SWS	**Turnus** Each winter term	**Group Size** Limited to 30	**Duration** 1 Semester

Learning results & Competences

After completing the course, students are able to

define, discuss, and apply the concepts, methods, and tools of analyzing and managing the experiences users perceive in interaction with new digital technologies of startups/established companies,

measure and analyze user experiences of novel technologies and infer recommendations for technology and policy design and development,

assess and reflect the social and ethical implications of designing, evaluating, and implementing digital technologies,

present user research results towards peers, and

develop skills in collaborative interaction with peers.

Content

Students explore the user perspective on interacting with digital technologies, thereby becoming more aware of users' needs during product development. Designing and maintaining great user experience (UX) is the best way for both startups and established companies to build trust, retention, and loyalty of staff and customers alike.

The lecture

teaches the key concepts, methods, and approaches that help design, measure, and manage total UX across organizations and drive value propositions of digital business models.

discusses established and new methods of UX research for (further) developing digital technologies.

introduces frameworks to build and lead teams of UX researchers, designers, engineers, product managers.

employs case studies to transfer and discuss the application of UX design, research, and management in practice.

In the practice sessions, (groups of) students

practically apply UX research methods and tools (e.g., user interviews, A/B testing, or emotion detection) to investigate users' experiences in interaction with state-of-the-art digital

technology prototypes and to deduce implications for product and organizational strategy, development, and design.
present the results towards peers and experts from research and industry.

Teaching
Lecture „User Experience (UX) Design & Management“, Case study sessions, Project sessions

Prerequisites for attending
Formal: Admission to master studies in „Artificial Intelligence and Data Science“.
Contentual: None

Examination
Project report in groups, presentations in groups, and class participation

Prerequisites for receiving credit points
Presentations in groups
Written documentation of a project report
Active class participation in discussions

Study Program
M.Sc. Artificial Intelligence and Data Science

Module accessible for other Study Programs
M.Sc. Computer Science

Weight in overall rating
The mark given will contribute to the final grade in proper relation to its credit points.

Further Information
Please see LSF for details on the application process.