

Module Handbook

for the

Master Programme “Computer Science”

at

Rheinischen Friedrich-Wilhelms-Universität Bonn

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The curriculum of the master programme is divided into four sub-curricula, each corresponding to one of the four main areas of competence in research of the Bonn Institute of Computer Science:

1. Algorithmics
2. Graphics, Vision, Audio
3. Information and Communication Management
4. Intelligent Systems

Module numbers **MA-INF ASXY** have been assigned according to the following key: vergeben:

- **A** = number of the area of competence
- **S** = semester within the master curriculum
- **XY** = sequential number within the semester and the respective area of competence (two digits)

According to the curriculum, all modules ought to be taken between the first and the third semester. The fourth semester is reserved for preparing the master thesis.

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1 Algorithmics

| | | | | |
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| MA-INF 1304 | Sem2 | 4 CP | Seminar Computational Geometry | 35 |
| MA-INF 1305 | | 6 CP | Graduate Seminar on Applied Combinatorial Optimization | 36 |
| MA-INF 1307 | Sem2 | 4 CP | Seminar Advanced Algorithms | 37 |
| MA-INF 1308 | Lab4 | 9 CP | Lab Algorithms for Chip Design | 38 |
| MA-INF 1309 | Lab4 | 9 CP | Lab Efficient Algorithms: Design, Analysis and Implementation | 39 |
| MA-INF 1314 | L4E2 | 9 CP | Online Motion Planning | 41 |
| MA-INF 1315 | Lab4 | 9 CP | Lab Computational Geometry | 42 |
| MA-INF 1316 | Lab4 | 9 CP | Lab Cryptography | 43 |
| MA-INF 1322 | Sem2 | 4 CP | Seminar Focus Topics in High Performance Computing | 44 |
| MA-INF 1323 | L4E2 | 9 CP | Computational Topology | 45 |

MA-INF 1102 Combinatorial Optimization

| Workload | Credit points | Duration | Frequency | | |
|--|---------------------------------------|------------|---------------------|-----|--|
| 270 h | 9 CP | 1 semester | at least every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Jens Vygen | All lecturers of Discrete Mathematics | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 1. or 2. | | | |
| Learning goals: technical skills | | | | | |
| Advanced knowledge of combinatorial optimization. Modelling and development of solution strategies for combinatorial optimization problems | | | | | |
| Learning goals: soft skills | | | | | |
| Mathematical modelling of practical problems, abstract thinking, presentation of solutions to exercises | | | | | |
| Contents | | | | | |
| Matchings, b-matchings and T-joins, optimization over matroids, submodular function minimization, travelling salesman problem, polyhedral combinatorics, NP-hard problems | | | | | |
| Prerequisites | | | | | |
| none | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |
| Graded exams | | | | | |
| Oral exam | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| The completion of regularly provided exercise sheets. The work can be done individually or in groups of two students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions twice. | | | | | |
| Literature | | | | | |
| <ul style="list-style-type: none">• B. Korte, J. Vygen: Combinatorial Optimization: Theory and Algorithms. Springer, 6th edition, 2018• A. Schrijver: Combinatorial Optimization: Polyhedra and Efficiency. Springer, 2003• W. Cook, W. Cunningham, W. Pulleyblank, A. Schrijver: Combinatorial Optimization. Wiley, 1997• A. Frank: Connections in Combinatorial Optimization. Oxford University Press, 2011 | | | | | |

MA-INF 1103 Cryptography

| Workload | Credit points | Duration | Frequency |
|-------------------------|--------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Dr. Michael Nüsken | Dr. Michael Nüsken | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Understanding of security concerns and measures, and of the interplay between computing power and security requirements. Mastery of the basic techniques for cryptosystems and cryptanalysis, including modelling security and reducing security to basic assumptions.

Learning goals: soft skills

Competences: Ability to assess, present and explain schemes and their use in applications, orally and written. Critical assessment of applications in terms of security, social and ethical context and more.

Contents

Basic private-key and public-key cryptosystems: AES, RSA, group-based. Security reductions. Key exchange, cryptographic hash functions, signatures, identification; factoring integers and discrete logarithms; lower bounds in structured models.

Prerequisites

Recommended:

Basics in elementary number theory, groups and complexity theory -in particular, reductions- are helpful.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. Each student must present a solution to an exercise in the exercise sessions twice.

Literature

- Jonathan Katz & Yehuda Lindell (2015/2008). Introduction to Modern Cryptography, CRC Press.
- Course notes

MA-INF 1105 Algorithms for Data Analysis

| Workload | Credit points | Duration | Frequency |
|-------------------------|------------------------|------------|------------------------|
| 180 h | 6 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Petra Mutzel | Prof. Dr. Petra Mutzel | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Ability to independently design and analyze efficient algorithms and data structures, in particular using methods and techniques of modern algorithmics with respect to big data and/or analytics tasks;

Learning goals: soft skills

Presentation of solutions and methods; critical discussion of applied methods and techniques clearly and in accordance with academic standards; ability to analyze problems theoretically and to find efficient as well as practical solutions; to examine one's solutions and results critically; to classify new problems into the state-of-the-art of the respective area;

Contents

Advanced algorithmic techniques and data structures relevant to analytic tasks for big data, i.e., algorithms for efficiently computing centrality indices for networks, theoretical and practical approaches to graph similarity, parallel algorithms, external data structures, and streaming algorithms.

Prerequisites

Recommended:

Essential is knowledge of:

- fundamental algorithms and algorithmic paradigms (e.g., graph algorithms, greedy algorithms, divide and conquer, dynamic programming), data structures (e.g., balanced search trees, hash tables)
- mathematical foundations of algorithm analysis (e.g., Big O notation, recurrence relations, proof techniques, running-time analysis)
- computational complexity (e.g., NP-hardness, reductions)

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam (30 minutes)

Ungraded coursework (required for admission to the exam)

It is necessary to pass one of two written tests during the semester. Moreover, the completion of regularly provided exercise sheets is required. The work can be done in groups. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions twice. At the beginning of each exercise session, all participants mark on a list which (sub)exercises they have completed successfully and for which they wish to receive credit. The tutor then selects, for each (sub)exercise, one participant to present it. For more complex exercises, a written solution is required, which can be uploaded during the presentation.

MA-INF 1107 Foundations of Quantum Computing

| Workload | Credit points | Duration | Frequency |
|------------------------------------|------------------------------------|------------|---------------|
| 180 h | 6 CP | 1 semester | every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr.-Ing. Christian Bauckhage | Prof. Dr.-Ing. Christian Bauckhage | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 3. | |

Learning goals: technical skills

Upon successful completion of this module, students should be able to describe fundamental concepts and techniques (qubits, quantum registers, quantum gates, quantum circuits) in quantum computing. Students will be equipped with specific, quantum computing related programming know-how; based on knowledge and skills acquired, students should be able to

- devise quantum computing algorithms for basic computational tasks
- run these algorithms on (simulated) quantum computers

Learning goals: soft skills

In the exercises, students will have the opportunity to put their knowledge into practice, since they will realize small projects on computing with quantum gates and their solutions using quantum inspired methods or genuine quantum methods. This requires teamwork; upon successful completion of the module, students should be able to

- draft and implement basic quantum computing algorithms
- apply quantum computing (simulations) to test these algorithms
- prepare and give oral presentations about their work in front of an audience

Contents

Boolean algebras and Boolean lattices; cellular automata; classical digital computing; classical reversible computing; mathematical foundations of quantum computing (complex vector spaces, tensor products, unitary operators, Hermitian operators, qubits, superposition, entanglement); quantum gate computing; quantum circuits

Prerequisites

Recommended:

Good working knowledge of theory and practice of linear algebra

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to five students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Forms of media

- lecture slides / lecture notes are made available online
- notebooks with programming examples are made available online

Literature

- L. Susskind, A. Friedman, “Quantum Mechanics: The Theoretical Minimum”, Penguin, 2015
 - M.A. Nielsen, I.L Chuang, “Quantum Computation and Quantum Information”, Cambridge University Press, 10th Anniversary edition, 2010
 - P. Wittek, “Quantum Machine Learning”, Academic Press, 2016
 - M. Schuld, F. Petruccione, “Machine Learning with Quantum Computers”, Springer, 2nd edition, 2021
 - S. Ganguly, “Quantum Machine Learning: An Applied Approach”, Apress, 2021
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MA-INF 1108 Introduction to High Performance Computing: Architecture Features and Practical Parallel Programming

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Estela Suarez | Prof. Dr. Estela Suarez | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Understanding principles of computer architecture of modern HPC systems at component (processor, accelerators) and system level (system architecture, network, memory hierarchy) and their implication for application programming. Ability to program parallel computers, employing multi-core and multi-node features. Programming CPU and GPUs. Understanding the quality of performance and scaling behaviour, and applying the measures needed to improve them.

Learning goals: soft skills

Critical assessment of hardware and applications in terms of performance and efficiency.

Contents

- Computer architectures, system components (CPU, memory, network) and their interrelation.
- Software environment
- Access to HPC compute resources at the Jülich Supercomputing Centre
- Practical use of parallel programming paradigms (MPI, OpenMP, CUDA)
- Performance of applications and scaling behavior, understanding and strategies for improvement
- Current challenges in HPC

Prerequisites

Required:

MA-INF 1108 replaces MA-INF 1106 and cannot be taken after completing MA-INF 1106.

Recommended:

Knowledge of a modern programming language (ideally C/C++ and Python) is required.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|-------------|-----|---------------------------|
| Lecture | | 2 | 30 T / 45 S | 2.5 | T = face-to-face teaching |
| Exercises | | 2 | 30 T / 75 S | 3.5 | S = independent study |

Graded exams

Written exam (90 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Forms of media

Laptop and projector

Literature

- John L. Hennessy, David A. Patterson: Computer Architecture - A Quantitative Approach. Morgan Kaufmann Publishers, 2012
- David A. Patterson, John L. Hennessy: Computer Organization and Design - The Hardware / Software Interface. Morgan Kaufmann Publishers, 2013
- Message Passing Interface Forum: MPI: A Message-Passing Interface Standard, Version 3.1
- OpenMP Application Programming Interface, Version 4.5, November 2015

MA-INF 1110 Elliptic Curves and their Applications in Cryptography

| Workload | Credit points | Duration | Frequency |
|-------------------------|------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Michael Meier | Dr. Gerhard Schabhüser | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-3. | |

Learning goals: technical skills

After completion of the modul students will understand the theory of elliptic Curves and their applications in cryptography. The students will learn, why elliptic curves have useful properties in Cryptography (at least as long as there are no powerful Quantum-Computers in place).

The relevant mathematical background will be developed and specific applications like ECC-Pseudo-Random-Number-Generators, ECC-Public-KC-Protocols and-Algorithms or Algorithms used in Cryptoanalysis will be presented.

In addition to the mathematical perspective the implementation-perspective especially concerning secure implementation will be addressed.

Learning goals: soft skills

Students will get the competence of understanding the mathematical background of elliptic curves, they will be sensible for the need of secure implementation of cryptographic algorithms and -protocols. They will be aware, that understanding the mathematics of cryptography has the capability to support secure implementation in cryptography their knowledge for secure implementation.

Contents

Algebraic Background

- algebraic Structures
- Introduction to Number theory
- Finite Fields

Basic Arithmetic Algorithms.

- Exponentiation.
- Integer arithmetic.
- Finite fields arithmetic.

Geometry und arithmetic of algebraic curves.

- Affine space.
- Projective space.

Elliptic Curves.

- Arithmetic.
- Points of finite order.
- Group of rational points.

Cubic curves over finite fields.

- Arithemetic.
- Rational points.
- A theorem of Gauß.
- Points of finite order (revisor).

Elliptic curve cryptography.

- Factorisation of integers.
- Discrete logarithm.
- Diffie-Hellman-protocol.
- El-Gamal-signatures.
- EC-DSA.

Implementing ECC-arithmetic.

- Timing attacks.
- Power consumption attacks.
- Secure implementations using Mathematics.

Prerequisites

Recommended:

Recommended : linear algebra, basic knowledge in algebra.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam (30 min).

Ungraded coursework (required for admission to the exam)

Participation in one written achievement test. At least 50% of the points much be achieved.

Literature

- Henri Cohen, Gerhard Frey et. al. (2005). Handbook of Elliptic and hyperelliptic Curve Cryptography.
- Joseph Silverman and John Tate. Rational Points on Elliptic Curves.
- Joseph Silverman. The Arithmetic of Elliptic Curves. 2nd Edition.

MA-INF 1201 Approximation Algorithms

| Workload | Credit points | Duration | Frequency |
|-------------------------|---|------------|---------------------|
| 270 h | 9 CP | 1 semester | at least every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Jens Vygen | All lecturers of Discrete Mathematics, Senior Prof. Dr. Marek Karpinski | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Introduction to design and analysis of most important approximation algorithms for NP-hard combinatorial optimization problems, and various techniques for proving lower and upper bounds, probabilistic methods and applications

Learning goals: soft skills

Presentation of solutions and methods, critical discussion of applied methods and techniques

Contents

Approximation Algorithms and Approximation Schemes. Design and Analysis of Approximation algorithms for selected NP-hard problems, like Set-Cover, and Vertex-Cover problems, MAXSAT, TSP, Knapsack, Bin Packing, Network Design, Facility Location. Introduction to various approximation techniques (like Greedy, LP-Rounding, Primal-Dual, Local Search, randomized techniques and Sampling, and MCMC-Methods), and their applications. Analysis of approximation hardness and PCP-Systems.

Prerequisites

Recommended:

Introductory knowledge of foundations of algorithms and complexity theory is essential.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | T = face-to-face teaching S = independent study |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions twice.

Literature

- S. Arora, C. Lund: Hardness of Approximations. In: Approximation Algorithms for NP-Hard Problems (D. S. Hochbaum, ed.), PWS, 1996
- M. Karpinski: Randomisierte und approximative Algorithmen für harte Berechnungsprobleme, Lecture Notes (5th edition), Universität Bonn, 2007
- B. Korte, J. Vygen: Combinatorial Optimization: Theory and Algorithms (6th edition), Springer, 2018
- V. V. Vazirani: Approximation Algorithms, Springer, 2001
- D. P. Williamson, D. B. Shmoys: The Design of Approximation Algorithms, Cambridge University Press, 2011

MA-INF 1202 Chip Design

| Workload | Credit points | Duration | Frequency |
|-------------------------|---------------------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Jens Vygen | All lecturers of Discrete Mathematics | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Knowledge of the central problems and algorithms in chip design. Competence to develop and apply algorithms for solving real-world problems, also with respect to technical constraints. Techniques to develop and implement efficient algorithms for very large instances.

Learning goals: soft skills

Mathematical modelling of problems occurring in chip design, development of efficient algorithms, abstract thinking, presentation of solutions to exercises

Contents

Problem formulation and design flow for chip design, logic synthesis, placement, routing, timing analysis and optimization

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | T = face-to-face teaching S = independent study |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions twice.

Literature

- C.J. Alpert, D.P. Mehta, S.S. Sapatnekar: The Handbook of Algorithms for VLSI Physical Design Automation. CRC Press, New York, 2008.
- S. Held, B. Korte, D. Rautenbach, J. Vygen: Combinatorial optimization in VLSI design. In: "Combinatorial Optimization: Methods and Applications" (V. Chvátal, ed.), IOS Press, Amsterdam 2011, pp. 33-96
- S. Held, J. Vygen: Chip Design. Lecture Notes (distributed during the course)
- L. Lavagno, I.L. Markov, G. Martin, and L.K. Scheffer, eds.: Electronic Design Automation for IC Implementation, Circuit Design, and Process Technology. CRC Press, 2nd edition, 2016

MA-INF 1203 Discrete and Computational Geometry

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Anne Driemel | Prof. Dr. Anne Driemel, PD Dr. Elmar Langetepe, Dr. Herman Haverkort | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-4. | |

Learning goals: technical skills

Knowledge of fundamental theorems and concepts in the area of discrete and computational geometry; design and analysis of geometric algorithms; combinatorial analysis of the complexity of geometric configurations; to apply this knowledge autonomously in solving new problems.

Learning goals: soft skills

Social competence (communication, presenting one's own solutions, goal-oriented discussions in teams), methodical competence (analysis, abstraction, proofs), individual competence (commitment and willingness to learn, creativity, endurance).

Contents

Fundamentals of convex sets, Voronoi diagrams, hyperplane arrangements, well-separated pair decomposition, spanners, metric space embedding, dimension reduction, VC-dimension, epsilon-nets, visibility, point location, range searching, randomized incremental construction, geometric distance problems in dimension two and higher.

Prerequisites

Recommended:

BA-INF 114 – Grundlagen der algorithmischen Geometrie

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | T = face-to-face teaching S = independent study |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved.

Literature

- Jiri Matousek. Lectures on Discrete Geometry. Springer Graduate Texts in Mathematics. ISBN 0-387-95374-4.
- Mark de Berg, Otfried Cheong, Marc van Kreveld, and Mark Overmars. Computational Geometry — Algorithms and Applications (Third Edition). Springer. ISBN 978-3-540-77973-5.
- Narasimhan/Smid, Geometric Spanner Networks
- Klein, Concrete and Abstract Voronoi Diagrams

MA-INF 1205 Graduate Seminar Discrete Optimization

| Workload | Credit points | Duration | Frequency | | |
|--|---------------------------------------|------------|--------------|----|--|
| 180 h | 6 CP | 1 semester | every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Jens Vygen | All lecturers of Discrete Mathematics | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. | | | |
| Learning goals: technical skills | | | | | |
| Competence to understand new research results based on original literature, to put such results in a broader context and present such results and relations. | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to read and understand research papers, abstract thinking, presentation of mathematical results in a talk | | | | | |
| Contents | | | | | |
| A current research topic in discrete optimization will be chosen each semester and discussed based on original literature. | | | | | |
| Prerequisites | | | | | |
| Recommended: MA-INF 1102 – Combinatorial Optimization | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 4 | 60 T / 120 S | 6 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |
| Literature | | | | | |
| The topics and the relevant literature will be announced towards the end of the previous semester. | | | | | |

MA-INF 1206 Seminar Randomized and Approximation Algorithms

| Workload | Credit points | Duration | Frequency | | |
|--|---|------------|-------------|----|--|
| 120 h | 4 CP | 1 semester | every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Heiko Röglin | Prof. Dr. Anne Driemel, Prof. Dr. Thomas Kesselheim, Prof. Dr. Heiko Röglin, PD Dr. Elmar Langetepe, Dr. Herman Haverkort, Senior Prof. Dr. Marek Karpinski | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. | | | |
| Learning goals: technical skills | | | | | |
| Ability to perform individual literature search, critical reading, understanding, and clear presentation. | | | | | |
| Learning goals: soft skills | | | | | |
| Presentation of solutions and methods, critical discussion of applied methods and techniques | | | | | |
| Contents | | | | | |
| Current topics in design and analysis of randomized and approximation algorithms based on latest research literature | | | | | |
| Prerequisites | | | | | |
| none | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |
| Literature | | | | | |
| The relevant literature will be announced in time. | | | | | |

MA-INF 1209 Seminar Advanced Topics in Cryptography

| Workload | Credit points | Duration | Frequency |
|-------------------------|--------------------|------------|----------------|
| 120 h | 4 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Dr. Michael Nüsken | Dr. Michael Nüsken | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in the area of cryptography.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of cryptography; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media at academic standards, well-structured and didactically effective, and motivate the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

We discuss cutting-edge papers from current cryptographic research literature.

Prerequisites

Recommended:

Basic knowledge in cryptography is highly recommended, eg. by MA-INF 1103 – Cryptography.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

Current cryptographic literature.

MA-INF 1213 Randomized Algorithms and Probabilistic Analysis

| Workload | Credit points | Duration | Frequency |
|-------------------------|------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Heiko Röglin | Prof. Dr. Heiko Röglin | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 4. | |

Learning goals: technical skills

Understanding of models and techniques for the probabilistic analysis of algorithms as well as for the design and analysis of randomized algorithms

Learning goals: soft skills

Oral and written presentation of solutions and methods, abstract thinking

Contents

Design and analysis of randomized algorithms

- complexity classes
- Markov chains and random walks
- tail inequalities
- probabilistic method

smoothed and average-case analysis

- simplex algorithm
- local search algorithms
- clustering algorithms
- combinatorial optimization problems
- multi-objective optimization

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. A total of 25% of the points must be achieved.

Literature

- lecture notes
- research articles
- Motwani, Raghavan, Randomized Algorithms, Cambridge University Press, 1995
- Mitzenmacher, Upfal, Probability and Computing, Cambridge University Press, 2nd edition, 2017

MA-INF 1217 Seminar Theoretical Foundations of Data Science

| Workload | Credit points | Duration | Frequency |
|--|--|------------|------------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Heiko Röglin | Prof. Dr. Anne Driemel, Prof. Dr. Thomas Kesselheim, Prof. Dr. Heiko Röglin, PD Dr. Elmar Langetepe, Dr. Herman Haverkort | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |
| Learning goals: technical skills | | | |
| Ability to understand new research results presented in original scientific papers. | | | |
| Learning goals: soft skills | | | |
| Ability to present and to critically discuss these results in the framework of the corresponding area. | | | |
| Contents | | | |
| Current conference and journal papers | | | |
| Prerequisites | | | |
| none | | | |
| Course meetings | | | |
| Teaching format | Group size | h/week | Workload[h] CP |
| Seminar | 10 | 2 | 30 T / 90 S 4 |
| T = face-to-face teaching S = independent study | | | |
| Graded exams | | | |
| Oral presentation, written report | | | |
| Ungraded coursework (required for admission to the exam) | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | |

MA-INF 1218 Algorithms and Uncertainty

| Workload | Credit points | Duration | Frequency | | |
|--|-----------------------------|------------|------------------------|--|-----|
| 270 h | 9 CP | 1 semester | at least every 2 years | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Thomas Kesselheim | Prof. Dr. Thomas Kesselheim | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. or 3. | | | |
| Learning goals: technical skills | | | | | |
| Understanding approaches for modeling uncertainty in algorithmic theory. Designing and analyzing algorithms with performance guarantees in the context of uncertainty. | | | | | |
| Learning goals: soft skills | | | | | |
| Oral and written presentation of solutions and methods | | | | | |
| Contents | | | | | |
| <ul style="list-style-type: none">• Advanced Online Algorithms• Markov Decisions Processes• Stochastic and Robust Optimization• Online Learning Algorithms and Online Convex Optimization | | | | | |
| Prerequisites | | | | | |
| Recommended: Solid background in algorithms, calculus, and probability theory. Specialized knowledge about certain algorithms is not necessary. | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] CP | T = face-to-face teaching S = independent study | |
| Lecture | | 4 | 60 T / 105 S | | 5.5 |
| Exercises | | 2 | 30 T / 75 S | | 3.5 |
| Graded exams | | | | | |
| Oral exam | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Each student must present a solution to an exercise in the exercise sessions once. | | | | | |
| Literature | | | | | |
| lecture notes, research articles | | | | | |

MA-INF 1219 Seminar Algorithmic Game Theory

| Workload | Credit points | Duration | Frequency | | |
|--|-----------------------------|------------|-------------|----|--|
| 120 h | 4 CP | 1 semester | every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Thomas Kesselheim | Prof. Dr. Thomas Kesselheim | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. or 3. | | | |
| Learning goals: technical skills | | | | | |
| Ability to understand new research results presented in original scientific papers. | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to perform individual literature search, critical reading, and clear didactic presentation | | | | | |
| Contents | | | | | |
| Advanced topics in Algorithmic Game Theory and Algorithmic Mechanism Design based on current conference and journal papers | | | | | |
| Prerequisites | | | | | |
| none | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |

T = face-to-face teaching
S = independent study

MA-INF 1220 Seminar Algorithms for Computational Analytics

| Workload | Credit points | Duration | Frequency |
|--|------------------------|------------|--|
| 120 h | 4 CP | 1 semester | at least every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Petra Mutzel | Prof. Dr. Petra Mutzel | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |
| Learning goals: technical skills | | | |
| Ability to perform individual literature search, critical reading, understanding, and clear didactic presentation. | | | |
| Learning goals: soft skills | | | |
| Ability to present and to critically discuss these results in the framework of the corresponding area. | | | |
| Contents | | | |
| Current topics in algorithms for computational analytics based on recent research literature. | | | |
| Prerequisites | | | |
| Recommended: Interest in Algorithms | | | |
| Course meetings | | | |
| Teaching format | Group size | h/week | Workload[h] CP |
| Seminar | 10 | 2 | 30 T / 90 S 4 |
| | | | T = face-to-face teaching S = independent study |
| Graded exams | | | |
| Oral presentation, written report | | | |
| Ungraded coursework (required for admission to the exam) | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | |
| Literature | | | |
| The relevant literature will be announced in time. | | | |

MA-INF 1221 Lab Computational Analytics

| Workload | Credit points | Duration | Frequency |
|-------------------------|------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Petra Mutzel | Prof. Dr. Petra Mutzel | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Ability to independently design, theoretically analyze, implement, and experimentally evaluate algorithms and efficient data structures for computational analytics problems; gain experience with software development techniques, tools and standards and the scientifically clean documentation of the students own work (including the written report and software).

Learning goals: soft skills

- Knowledge of scientific approach to problem solving;
- ability to scientifically present solutions and methods;
- critical discussion of applied methods and techniques clearly and in accordance with academic standards;
- ability to analyze problems theoretically and to find efficient as well as practical solutions;
- to examine one's solutions and results critically;
- to classify new problems into the state-of-the-art of the respective area.

Contents

We will design efficient exact and approximate algorithms and data structures for computational analytics problems. We study a (set of) selected combinatorial optimization problem(s) with the goal to design new algorithmic approaches. Often, we focus on solving (graph) problems for selected applications (e.g., in cartography, geodesy, neurosciences, chemistry, or others). Typically, we start with a literature search on State-of-the-Art approaches; based on that, we adapt selected approaches

to our studied problem(s) or we design new approaches. We then theoretically analyze and implement our adapted/new algorithms. This is followed by an extensive experimental evaluation including a discussion of the results on benchmark instances. Often, the analysis triggers improvements of the algorithms. This is also called the Algorithm Engineering cycle.

Prerequisites

Recommended:

Essential are knowledge of:

- fundamental algorithms and algorithmic paradigms (e.g., graph algorithms, greedy algorithms, divide and conquer, dynamic programming), data structures (e.g., balanced search trees, hash tables)
- mathematical foundations of algorithm analysis (e.g., Big O notation, recurrence relations, proof techniques, running-time analysis)
- computational complexity (e.g., NP-hardness, reductions).

It is recommended to first complete at least one of the following modules:

- MA-INF 1105 Algorithms for Data Analysis
- MA-INF 1201 Approximation Algorithms
- MA-INF 1203 Discrete and Computational Geometry
- MA-INF 1213 Randomized Algorithms and Probabilistic Analysis
- MA-INF 1218 Algorithms and Uncertainty
- MA-INF 1301 Algorithmic Game Theory
- MA-INF 4112 Algorithms for Data Science

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

The relevant literature will be announced in time.

MA-INF 1222 Lab High Performance Optimization

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Petra Mutzel | Prof. Dr. Petra Mutzel, Dr. Sven Mallach | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

- Ability to independently design, theoretically analyze, implement, and experimentally evaluate algorithms and efficient data structures for computational analytics problems;
- understanding and using parallel programming paradigms and high-level programming languages;
- using performance analysis tools, understanding performance bottlenecks and measures to improve them;
- acquisition of knowledge about software development and standards;
- gain experience with the documentation of the students own work (including the written report and software);

Learning goals: soft skills

- Knowledge of scientific approach to problem solving;
- ability to scientifically present solutions and methods;
- critical discussion of applied methods and techniques clearly and in accordance with academic standards;
- ability to analyze problems theoretically and to find efficient as well as practical solutions;
- to examine one's solutions and results critically;
- to classify new problems into the state-of-the-art of the respective area;

Contents

We will design efficient exact and approximate algorithms and data structures for optimization problems on big data with the focus of using high performance computing (HPC) systems (like, e.g. the HPC clusters Marvin or Bender). We study a (set of) selected optimization problem(s) with the goal to design new parallel algorithms that scale well on HPC systems. Often, we focus on solving (graph) problems for selected applications (e.g., physics, chemistry, neurosciences, geodesy, or others).

Typically, we start with an introduction into parallel algorithms and an introduction into the relevant API for developing parallel programs. A literature search yields State-of-the-Art techniques; based on that, we adapt selected approaches to our studied problem(s) or we design new approaches with the goal that they scale well on HPC systems. We then theoretically analyze and implement our adapted/new parallel algorithms using parallel programming paradigms and high-level programming languages. This is followed by an extensive experimental evaluation using performance analysis tools and understanding performance bottlenecks. Often, this triggers improvements of the parallel algorithms and/or the implementation.

Prerequisites

Recommended:

Essential are knowledge of:

- fundamental algorithms and algorithmic paradigms (e.g., graph algorithms, greedy algorithms, divide and conquer, dynamic programming), data structures (e.g., balanced search trees, hash tables)
- mathematical foundations of algorithm analysis (e.g., Big O notation, recurrence relations, proof techniques, running-time analysis)
- computational complexity (e.g., NP-hardness, reductions)

It is recommended to complete at least one the following modules first:

- MA-INF 1105 Algorithms for Data Analysis
- MA-INF 1108 Introduction to High Performance Computing: Architecture Features and Practical Parallel Programming
- MA-INF 1201 Approximation Algorithms
- MA-INF 1203 Discrete and Computational Geometry
- MA-INF 1213 Randomized Algorithms and Probabilistic Analysis
- MA-INF 1218 Algorithms and Uncertainty
- MA-INF 1301 Algorithmic Game Theory

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

The relevant literature will be announced in time.

MA-INF 1223 Privacy Enhancing Technologies

| Workload | Credit points | Duration | Frequency |
|-------------------------|--------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Dr. Michael Nüsken | Dr. Michael Nüsken | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Knowledge: Cryptographic schemes for enhancing privacy, underlying security notions, applications and restrictions.

Skills: Secure application of sophisticated cryptographic schemes. Evaluation of their correctness, efficiency and security in an application setting.

Learning goals: soft skills

Competences: Ability to assess, present and explain schemes and their use in applications, orally and written. Critical assessment of applications in terms of security, social and ethical context and more.

Contents

With more and more data available a clear separation of sensitive data is necessary and needs to be protected. Some of that data must stay within strict environments, for examples hospitals must store certain highly sensitive medical information about patients but they are not allowed to store it outside its own facilities. Some of that data is stored or collected in a cloud environment in encrypted form, say data from a medical device or a smart home. But it shall still be possible to derive important conclusions from it, for example to send immediate help to a patient suffering a heart attack.

Innovative solutions are needed in this area of tension. The research in cryptography provides some highly sophisticated tools for solving the like problems.

- Fully homomorphic encryption (FHE).
- Zero-Knowledge techniques, in particular: Non-interactive zero-knowledge proof (NIZKs).
- Secure multi-party computations (MPC).
- Anonymisation, TOR. Pseudonymization. Blinding.
- Weaker privacy notions, like differential privacy.

Prerequisites

Recommended:

Basic knowledge in cryptography (for example from MA-INF 1103) is highly recommended.

A profound mathematical background does help. In particular, precise mathematical formulation and reasoning are important, but also topics like elementary number theory and discrete mathematics, especially lattices, are interesting.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. Each student must present twice in the tutorial.

MA-INF 1224 Quantum Computing Algorithms

| Workload | Credit points | Duration | Frequency |
|-------------------------------|-------------------------------|------------|---------------|
| 180 h | 6 CP | 1 semester | every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Christian Bauckhage | Prof. Dr. Christian Bauckhage | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Upon successful completion of this module, students should be able to describe fundamental concepts behind working quantum algorithms.

Students acquire quantum computing programming know-how; based on knowledge and skills acquired, students should be able to

- run quantum algorithms on (simulated) quantum computing platforms
- devise their own algorithms for optimization or classification problems that can be solved on quantum computers

Learning goals: soft skills

In the exercises, students can put their quantum computing knowledge into practice and realize small projects involving the implementation of quantum algorithm. This requires teamwork; upon successful completion of the module, students should be able to

- draft and implement basic quantum computing algorithms
- apply quantum computing (simulations) to test these algorithms
- prepare and give oral presentations about their work in front of an audience

Contents

quantum gate algorithms such as Deutsch-Jozsa, Bernstein-Vazirani, Simon, Shor, Grover; phase kick-back, amplitude amplification; swap tests; Hamiltonian simulation, Trotterization, variational quantum computing for optimization

Prerequisites

Required:

MA-INF 1107 - Foundations of Quantum Computing

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to five students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Forms of media

- lecture slides / lecture notes are made available online
- notebooks with programming examples are made available online

Literature

M.A. Nielsen, I.L. Chuang, “Quantum Computation and Quantum Information”, Cambridge University Press, 10th Anniversary edition, 2010

P. Wittek, “Quantum Machine Learning”, Academic Press, 2016

M. Schuld, F. Petruccione, “Machine Learning with Quantum Computers”, Springer, 2nd edition, 2021

S. Ganguly, “Quantum Machine Learning: An Applied Approach”, Apress, 2021

MA-INF 1225 Lab Exploring HPC technologies

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------------------|
| 270 h | 9 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Estela Suarez | Prof. Dr. Estela Suarez | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Understanding a use case from complex code developed. Adapting and running applications to different kinds of processing units, taking into account their specific architecture characteristic and programming environments. Understanding and using parallel programming paradigms and high-level programming languages. Designing and executing a benchmarking campaign. Using performance analysis tools, understanding performance bottlenecks and measures to improve them. Software development skills and standards.

Learning goals: soft skills

Ability to analyze computational problems and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to produce good quality software, prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to aim at long-range goals under limited resources; to work under pressure.

Contents

The students carry out a practical task (project) in High Performance Computing (HPC), including test of different hardware architectures and software tools, documentation of the implemented software/system. Contents: HPC systems: access/use of compute resources at Jülich Supercomputing Centre; Use of different processor architectures; Software environment, performance analysis tools; Parallel programming; Benchmarking tools/procedures; Performance of applications and scaling behavior, strategies for improvement.

Prerequisites

Required:

- Passed the exam of MA-INF 1108 Introduction to High Performance Computing: Architecture Features and Practical Parallel Programming (or its precursor MA-INF 1106).
- Knowledge of modern programming languages (C/C++, Python).
- Willingness to stay for at least 2 days per week during 4 weeks at the Jülich Supercomputing Centre, dates to be discussed.

Remarks

Registration first via direct mail communication with the lecturer, in order to identify suitable dates for the stay at JSC.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 2 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Forms of media

Own laptop to connect and program on the supercomputers.

Literature

- John L. Hennessy, David A. Patterson: Computer Architecture - A Quantitative Approach. Morgan Kaufmann Publishers, 2012
 - David A. Patterson, John L. Hennessy: Computer Organization and Design - The Hardware / Software Interface. Morgan Kaufmann Publishers, 2013
 - Message Passing Interface Forum: MPI: A Message-Passing Interface Standard, Version 3.1
 - OpenMP Application Programming Interface, Version 4.5, November 2015
-

MA-INF 1226 Applications of Computational Topology in Information Theory

| Workload | Credit points | Duration | Frequency |
|-------------------------|---|------------|---------------|
| 180 h | 6 CP | 1 semester | every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Anne Driemel | Dr. Felix Jonathan Boes, Dr. Benedikt Kolbe | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-4. | |

Learning goals: technical skills

Upon successful completion of the module, students should have the ability to, in the treated topics, verify the validity of propositions from original literature independently and to question research results critically. Students acquire the competency to engage in independent study on current research topics.

Learning goals: soft skills

Social competence (communication, presenting one's own solutions, goal-oriented discussions in teams), methodical competence (analysis, abstraction, proofs), individual competence (commitment and willingness to learn, creativity, endurance).

Contents

The course treats the usage of tools and algorithms from algebraic topology, particularly (co)homology theory, for problems in computer science. Topics covered include: Symmetries as groups, (co)homology, equivariant cohomology, topology in the modeling of the problem, algorithmic properties. The main focus is the connection of error correcting codes, manifolds with involution and lattices.

Special features

The course will cover the use of advanced mathematical machinery (e.g. cohomology) from topology in applications in computer science.

Prerequisites

Recommended:

- MA-INF1323 Computational Topology
- MA-INF1315 Lab Computational Geometry
- MA-INF1203 Discrete and Computational Geometry

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

Participation in an achievement test (midterm exam). At least 50% of the points must be achieved on this test.

MA-INF 1227 Hardness of Approximation

| Workload | Credit points | Duration | Frequency |
|-------------------------|--------------------------------------|------------|------------------------|
| 150 h | 5 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. László Végh | Prof. Dr. László Végh, Matthias Kaul | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-4. | |

Learning goals: technical skills

Knowledge and understanding of techniques, concepts and results for establishing hardness of approximation results in complexity theory. Analyzing approximability lower bounds and the ability to relate them to important hardness assumptions. Being able to apply methods related to probabilistically checkable proofs, constraint satisfaction problems, Fourier analysis, and Unique Games Conjecture.

Learning goals: soft skills

Problem solving skills, critical discussion of applied methods and techniques

Contents

Hardness of Approximation is one of the most active subfields of complexity theory and has been making steady progress in establishing which problems admit polynomial time approximation algorithms (up to reasonable hardness assumptions). For many problems, matching lower and upper bounds on their polynomial-time approximability have been shown, proving that often very simple algorithms -such as the algorithm of Goemans-Williamson or random sampling of a solution- achieve best-possible approximation ratios.

This course will focus on giving a working understanding of the current state of the field, focusing on some standout results that represent well the standard techniques, as well as some applications of these foundational theorems.

Concretely the goal is to work on the following tentative list of topics:

- Irit Dinur's proof of the PCP-theorem
- Håstad's tight inapproximability theorems for some MaxCSPs
- Fourier Analysis of Boolean Functions and Dictatorship Testing
- Tight inapproximability of Max-Cut up to the Goemans-Williamson threshold under the Unique Games Conjecture

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lecture | | 2 | 30 T / 120 S | 5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

Literature

- Irit Dinur. The PCP theorem by gap amplification. Journal of the ACM (2007)
- Johan Håstad. Some optimal inapproximability results. Journal of the ACM (2001)
- Subash Khot, Guy Kindler, Elchanan Mossel, Ryan O'Donnell. Optimal Inapproximability Results for MAX-CUT and Other 2-variable CSPs? Siam Journal on Computing (2007)
- Ryan O'Donnell. Analysis of Boolean Functions. Cambridge University Press (2014); ArXiv 2021

MA-INF 1228 Graduate Seminar on Algorithms and Optimization

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------------------|
| 180 h | 6 CP | 1 semester | at least every 2 years |

| Module coordinator | Lecturer(s) |
|-----------------------|-----------------------|
| Prof. Dr. László Végh | Prof. Dr. László Végh |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2-4. |

Learning goals: technical skills

Ability to undertake independent study of an advanced topic in discrete optimization using specialized literature. Assessment, evaluation and presentation of results from algorithms and optimization. Didactic preparation and presentation as a seminar talk and in the form of a manuscript covering the contents of the talk. Competence in scientific discussions.

Learning goals: soft skills

Contents

A current, active research topic in algorithms and optimization chosen on a rotational basis will be treated in depth by studying the relevant literature.

Prerequisites

Recommended:

- MA-INF 1102 - Combinatorial Optimization

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Seminar | 10 | 4 | 60 T / 120 S | 6 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 1301 Algorithmic Game Theory

| Workload | Credit points | Duration | Frequency |
|-----------------------------|---|------------|---------------|
| 270 h | 9 CP | 1 semester | every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Thomas Kesselheim | Prof. Dr. Thomas Kesselheim, Senior Prof. Dr. Marek Karpinski | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Knowledge of fundamental results in (algorithmic) game theory and (algorithmic) mechanism design. Techniques and methods related to mathematical modeling of strategic agents. Analyzing and designing systems of strategic agents, with a focus on computational efficiency and performance guarantees.

Learning goals: soft skills

Presentation of solutions and methods, critical discussion of applied methods and techniques

Contents

- basic game theory
- computability and hardness of equilibria
- convergence of dynamics of selfish agents
- (bounds on the) loss of performance due to selfish behavior
- designing incentive-compatible auctions
- maximizing revenue
- designing mechanisms for stable and fair allocations without money

Prerequisites

Recommended:

Introductory knowledge of foundations of algorithms and complexity theory is essential.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|--------------|-----|---------------------------|
| Lecture | | 4 | 60 T / 105 S | 5.5 | T = face-to-face teaching |
| Exercises | | 2 | 30 T / 75 S | 3.5 | S = independent study |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. Each student must present a solution to an exercise in the exercise sessions once.

Literature

- N. Nisan, T. Roughgarden, E. Tardos, V.V. Vazirani (ed.): Algorithmic Game Theory, Cambridge Univ. Press, 2007
- T. Roughgarden, Twenty Lectures on Algorithmic Game Theory, Cambridge Univ. Press, 2016
- A. Karlin, Y. Peres, Game Theory, Alive, AMS, 2017
- Y. Shoham, K. Leyton-Brown, Multiagent Systems, Cambridge Univ. Press, 2009
- D. M. Kreps: A Course in Microeconomic Theory, Princeton Univ. Press, 1990
- M. J. Osborne, A. Rubinstein: A Course in Game Theory, MIT Press, 2001

MA-INF 1304 Seminar Computational Geometry

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Anne Driemel | Prof. Dr. Anne Driemel, PD Dr. Elmar Langetepe, Dr. Herman Haverkort | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-4. | |

Learning goals: technical skills

To independently study problems at research level, based on research publications, to prepare a concise summary, to present the summary in a scientific talk, to lead a critical discussion with other seminar participants.

Learning goals: soft skills

Contents

Current topics in computational geometry.

Prerequisites

Recommended:

BA-INF 114 – Grundlagen der algorithmischen Geometrie

MA-INF 1203 – Discrete and Computational Geometry

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Forms of media

Multimedia projector, black board.

Literature

The relevant literature will be announced.

MA-INF 1305 Graduate Seminar on Applied Combinatorial Optimization

| Workload | Credit points | Duration | Frequency | | |
|---|---------------------------------------|------------|--------------|----|--|
| 180 h | 6 CP | 1 semester | every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Jens Vygen | All lecturers of Discrete Mathematics | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 3. | | | |
| Learning goals: technical skills | | | | | |
| Competence to understand new theoretical results and practical solutions in VLSI design and related applications, as well as presentation of such results | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to read and understand research papers, abstract thinking, presentation of mathematical results in a talk | | | | | |
| Contents | | | | | |
| Current topics in chip design and related applications | | | | | |
| Prerequisites | | | | | |
| Recommended: At least 1 of the following: MA-INF 1102 – Combinatorial Optimization MA-INF 1202 – Chip Design | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 4 | 60 T / 120 S | 6 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |
| Literature | | | | | |
| The topics and the relevant literature will be announced towards the end of the previous semester | | | | | |

MA-INF 1307 Seminar Advanced Algorithms

| Workload | Credit points | Duration | Frequency | | |
|---|--|------------|-------------|----|--|
| 120 h | 4 CP | 1 semester | every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Thomas Kesselheim | Prof. Dr. Anne Driemel, Prof. Dr. Thomas Kesselheim, Prof. Dr. Heiko Röglin, PD Dr. Elmar Langetepe, Dr. Herman Haverkort | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 3. | | | |
| Learning goals: technical skills | | | | | |
| Presentation of selected advanced topics in algorithm design and various applications | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to perform individual literature search, critical reading, understanding, and clear didactic presentation | | | | | |
| Contents | | | | | |
| Advanced topics in algorithm design based on newest research literature | | | | | |
| Prerequisites | | | | | |
| none | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |
| Literature | | | | | |
| The relevant literature will be announced in time. | | | | | |

MA-INF 1308 Lab Algorithms for Chip Design

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|----------------------|---------------------------------------|
| Prof. Dr. Jens Vygen | All lecturers of Discrete Mathematics |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 3. |

Learning goals: technical skills

Competence to implement algorithms for VLSI design, efficient handling of very large instances, testing, documentation. Advanced software techniques.

Learning goals: soft skills

Efficient implementation of complex algorithms, abstract thinking, modelling of optimization problem in VLSI design, documentation of source code

Contents

A currently challenging problem will be chosen each semester. The precise task will be explained in a meeting in the previous semester.

Prerequisites

Recommended:

At least 3 of the following:

MA-INF 1102 – Combinatorial Optimization

MA-INF 1202 – Chip Design

MA-INF 1205 – Graduate Seminar Discrete Optimization

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

The topics and the relevant literature will be announced towards the end of the previous semester

MA-INF 1309 Lab Efficient Algorithms: Design, Analysis and Implementation

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|---------------------|
| 270 h | 9 CP | 1 semester | at least every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Heiko Röglin | Prof. Dr. Anne Driemel, Prof. Dr. Thomas Kesselheim, Prof. Dr. Heiko Röglin, PD Dr. Elmar Langetepe, Dr. Herman Haverkort | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-3. | |

Learning goals: technical skills

Ability to independently design, analyze and implement efficient algorithms and data structures for selected computational problems

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time; to aim at long-range goals under limited resources; to work under pressure.

Contents

Design of efficient exact and approximate algorithms and data structures for selected computational problems.

Prerequisites

Recommended:

Knowledge of:

- fundamental algorithms and algorithmic paradigms (e.g., graph algorithms, greedy algorithms, divide and conquer, dynamic programming), data structures (e.g., balanced search trees, hash tables)
- mathematical foundations of algorithm analysis (e.g., Big O notation, recurrence relations, proof techniques, running-time analysis)
- computational complexity (e.g., NP-hardness, reductions)

It is recommended to take at least one of the following modules first:

- MA-INF 1102 Combinatorial Optimization
- MA-INF 1103 Cryptography
- MA-INF 1105 Algorithms for Data Analysis
- MA-INF 1107 Foundations of Quantum Computing
- MA-INF 1108 Introduction to High-Performance Computing: Architecture Features and Practical Parallel Programming
- MA-INF 1201 Approximation Algorithms
- MA-INF 1202 Chip Design
- MA-INF 1203 Discrete and Computational Geometry
- MA-INF 1213 Randomized Algorithms and Probabilistic Analysis
- MA-INF 1218 Algorithms and Uncertainty
- MA-INF 1227 Hardness of Approximation
- MA-INF 1301 Algorithmic Game Theory
- MA-INF 1314 Online Motion Planning
- MA-INF 1323 Computational Topology

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

The relevant literature will be announced in time.

MA-INF 1314 Online Motion Planning

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|------------------------|--|
| PD Dr. Elmar Langetepe | Prof. Dr. Rolf Klein, PD Dr. Elmar Langetepe |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 1-4. |

Learning goals: technical skills

To acquire fundamental knowledge on topics and methods in online motion planning

Learning goals: soft skills

Contents

Search and exploration in unknown environments (e.g., graphs, cellular environments, polygons, streets), online algorithms, competitive analysis, competitive complexity, functional optimization, shortest watchman route, tethered robots, marker algorithms, spiral search, approximation of optimal search paths.

Prerequisites

Recommended:

BA-INF 114 – Grundlagen der algorithmischen Geometrie

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|--------------|-----|---------------------------|
| Lecture | | 4 | 60 T / 105 S | 5.5 | T = face-to-face teaching |
| Exercises | | 2 | 30 T / 75 S | 3.5 | S = independent study |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. A total of 25% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Forms of media

Java applets of geometry lab

Literature

Scientific research articles will be recommended in the lecture.

MA-INF 1315 Lab Computational Geometry

| Workload | Credit points | Duration | Frequency |
|--|--|------------|------------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Anne Driemel | Prof. Dr. Anne Driemel, PD Dr. Elmar Langetepe, Dr. Herman Haverkort | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. | |
| Learning goals: technical skills | | | |
| Ability to design, analyze, implement and document efficient algorithms for selected problems in computational geometry. | | | |
| Learning goals: soft skills | | | |
| Ability to properly present, defend and discuss design and implementation decisions, to document software according to given rules and to collaborate with other students in small groups. | | | |
| Contents | | | |
| Various problems in computational geometry. | | | |
| Prerequisites | | | |
| none | | | |
| Course meetings | | | |
| Teaching format | Group size | h/week | Workload[h] CP |
| Lab | 8 | 4 | 60 T / 210 S 9 |
| T = face-to-face teaching S = independent study | | | |
| Graded exams | | | |
| Oral presentation, written report | | | |
| Ungraded coursework (required for admission to the exam) | | | |
| Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | |
| Literature | | | |
| The relevant literature will be announced in time. | | | |

MA-INF 1316 Lab Cryptography

| Workload | Credit points | Duration | Frequency |
|-------------------------|--------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Dr. Michael Nüsken | Dr. Michael Nüsken | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

The students will carry out a practical task (project) in the context of Cryptography, including test and documentation of the implemented software/system.

Learning goals: soft skills

Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify ones own results into the state-of-the-art of the resp. area.

Contents

Front of research topics in cryptography, in particular, related to fully homomorphic encryption, multi-party computation, automated security verification.

The target of the lab is to understand how cryptography may work in one particular application that we are choosing together. Ideally, we can come up with a novel solution for performing an unconsidered algorithm. We study the tasks and tools, select algorithms, find a protocol, prototype an implementation, perform a security analysis, present an evaluation.

Prerequisites

Recommended:

Good knowledge in cryptography is vital, eg. by

- MA-INF 1103 - Cryptography
- MA-INF 1223 - Privacy Enhancing Technologies
- MA-INF 1209 - Seminar Advanced Topics in Cryptography.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 1322 Seminar Focus Topics in High Performance Computing

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Estela Suarez | Prof. Dr. Estela Suarez | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge on topics and trends in the area of high performance computing.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of the corresponding research area; to execute peer-review processes, both to review work from others and to write rebuttal letters to reply reviewer reports; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media in a way that adheres to academic standards, that is well-structured and didactically effective, and that motivates the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

General topics and trends in high performance computing, based on recent review and research literature

Prerequisites

Recommended:

MA-INF 1108 Introduction to High Performance Computing: Architecture Features and Practical Parallel Programming

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

Literature and further information about this seminar will be announced in time in the website of lecturer.

MA-INF 1323 Computational Topology

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------------------|
| 270 h | 9 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Anne Driemel | Prof. Dr. Anne Driemel, Dr. Benedikt Kolbe | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Knowledge of fundamental theorems and concepts in the area of computational topology in particular, persistent homology and topological data analysis; design and analysis of combinatorial algorithms in topological contexts; analysis of the complexity; to apply this knowledge autonomously to solving new problems and analysing new data sets.

Learning goals: soft skills

Social competence (communication, presenting one's own solutions, goal-oriented discussions in teams), methodical competence (analysis, abstraction, proofs), individual competence (commitment and willingness to learn, creativity, perseverance).

Contents

Fundamental concepts of relative homology and cohomology theory and persistence theory in computational settings, category theory in this context, algorithms for the computation of (persistent) homology, (extended) persistence modules and their decompositions, Morse theory, duality theorems, quiver representation theory, stability of persistence diagrams and barcodes, algebraic stability, topological filtrations, multiparameter persistence, invariants of persistence, topological data analysis, applications to shape pattern recognition, machine learning, identification of geometric objects.

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Literature

- Herbert Edelsbrunner, John Harer (2010). Computational Topology: An Introduction. American Mathematical Society.
- Steve Oudot (2015). Persistence Theory: From Quiver Representations to Data Analysis (Vol. 209). American Mathematical Society.
- Magnus Bakke Botnan, Michael Lesnick (2022). An Introduction to Multiparameter Persistence.
- Allen Hatcher (2002). Algebraic Topology (Vol. 44). Cambridge University Press.

2 Graphics, Vision, Audio

| | | | | |
|-------------|------|------|--|----|
| MA-INF 2113 | L2E2 | 6 CP | Foundations of Audio Signal Processing | 47 |
| MA-INF 2114 | L2E4 | 6 CP | Foundations of 4D/6D Object Capture for Virtual Environments | 48 |
| MA-INF 2115 | L4E2 | 9 CP | Computational Medical Imaging | 50 |
| MA-INF 2201 | L4E2 | 9 CP | Computer Vision | 52 |
| MA-INF 2202 | L4E2 | 9 CP | Computer Animation | 53 |
| MA-INF 2206 | Sem2 | 4 CP | Seminar Vision | 54 |
| MA-INF 2207 | Sem2 | 4 CP | Seminar Graphics | 55 |
| MA-INF 2208 | Sem2 | 4 CP | Seminar Audio | 56 |
| MA-INF 2209 | L4E2 | 9 CP | Advanced Topics in Computer Graphics I | 57 |
| MA-INF 2210 | Sem2 | 4 CP | Seminar Computer Animation | 59 |
| MA-INF 2212 | L2E2 | 6 CP | Pattern Matching and Machine Learning for Audio Signal Processing | 60 |
| MA-INF 2213 | L3E1 | 6 CP | Advanced Computer Vision | 61 |
| MA-INF 2214 | L2E2 | 6 CP | Computational Photography | 62 |
| MA-INF 2215 | Sem2 | 4 CP | Seminar Digital Material Appearance | 63 |
| MA-INF 2216 | Lab4 | 9 CP | Lab Visual Computing | 64 |
| MA-INF 2218 | L2E2 | 6 CP | Video Analytics | 65 |
| MA-INF 2219 | Sem2 | 4 CP | Seminar Visualization and Medical Image Analysis | 66 |
| MA-INF 2220 | Lab4 | 9 CP | Lab Visualization and Medical Image Analysis | 67 |
| MA-INF 2221 | Sem2 | 4 CP | Seminar Visual Computing | 68 |
| MA-INF 2222 | L4E2 | 9 CP | Visual Data Analysis | 69 |
| MA-INF 2225 | L2E2 | 6 CP | Discrete Models for Visual Computing | 70 |
| MA-INF 2226 | Lab4 | 9 CP | Lab Geometry Processing | 71 |
| MA-INF 2227 | Lab4 | 9 CP | Lab 3D Animation | 72 |
| MA-INF 2228 | Sem2 | 4 CP | Seminar Vision and Graphics (Role-Based) | 73 |
| MA-INF 2229 | Sem2 | 4 CP | Seminar Recent Advances in Geometry Processing | 74 |
| MA-INF 2230 | Lab4 | 9 CP | Lab Computational Medical Imaging | 75 |
| MA-INF 2307 | Lab4 | 9 CP | Lab Vision | 77 |
| MA-INF 2308 | Lab4 | 9 CP | Lab Graphics | 78 |
| MA-INF 2309 | Lab4 | 9 CP | Lab Audio | 79 |
| MA-INF 2310 | L4E2 | 9 CP | Advanced Topics in Computer Graphics II | 80 |
| MA-INF 2311 | Lab4 | 9 CP | Lab Computer Animation | 82 |
| MA-INF 2312 | L3E1 | 6 CP | Image Acquisition and Analysis in Neuroscience | 83 |
| MA-INF 2316 | Lab4 | 9 CP | Lab Digital Material Appearance | 84 |
| MA-INF 2317 | L2E2 | 6 CP | Numerical Algorithms for Visual Computing and Machine Learning | 85 |
| MA-INF 2318 | Sem2 | 4 CP | Seminar Computational Medical Imaging | 86 |

MA-INF 2113 Foundations of Audio Signal Processing

| Workload | Credit points | Duration | Frequency |
|----------------------------|---|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| apl. Prof. Dr. Frank Kurth | apl. Prof. Dr. Frank Kurth, Prof. Dr. Michael Clausen | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

- Introduction to basic concepts of analog and digital signal processing: Acquire basic knowledge on modeling and representing audio content; learn fundamental concepts of analog and digital signal processing, in particular mathematical models of signal spaces and apply them to the audio domain; learn methods for analog to digital conversion, frequency analysis, time-frequency analysis and digital filtering.
- Applications in the field of Audio Signal Processing: Learn typical application domains of audio signal processing techniques and how to apply the acquired methods in solving applications problems from those domains. Important examples are basic signal manipulation and filtering.
- Solving basic Signal Processing Problems: Learn basic signal processing algorithms for performing the Fourier Transform and a time-frequency analysis, as well as for performing filter operations and fundamental types of signal manipulations.
- Implementing basic Signal Processing Algorithms using state-of-the-art software frameworks: In the exercises, the introduced methods and algorithms have to be implemented and applied to basic applications problems. Hence knowledge in the practical implementation of digital signal processing methods in standard programming environments such as Python, Matlab or Octave is acquired.

Learning goals: soft skills

Capability to analyze; Time management; Presentation skills; Discussing own solutions and solutions of others, and working in groups.

Contents

Theoretical introduction to analog and digital Signal Processing; Fourier Transforms; Analog to digital Conversion; Digital Filters; Audio Signal Processing Applications; Filter banks; Windowed Fourier Transform; 2D-Signal Processing

Prerequisites

Recommended:

Solid basic knowledge on Linear Algebra and Analysis on the level acquired in Bachelor in Computer Science programmes, including proficiency in using complex numbers.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of two to four students. A total of 50% of the points must be achieved.

Forms of media

Slides, Blackboard, Whiteboard

MA-INF 2114 Foundations of 4D/6D Object Capture for Virtual Environments

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|----------------|
| 180 h | 6 CP | 1 semester | every semester |

| Module coordinator | Lecturer(s) |
|--------------------------|--|
| Prof. Dr. Reinhard Klein | Prof. Dr. Reinhard Klein, Dr. Patrick Stotko |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 1-2. |

Learning goals: technical skills

- Knowledge about 3D/4D/6D data capturing and how to apply state-of-the art models and scene representations to effectively process these data
- Make proper use and integrate solutions in game engines like Unity and Unreal Engine and standard tools like Blender for practical applications
- Development and realization of individual state-of-the-art graphics and vision approaches

Learning goals: soft skills

- Communicative Skills: Written and oral presentation of solutions, discussing ideas in small teams, and preparing structured written documents.
- Self-Competences: include time management, goal-oriented work, the ability to analyze problems theoretically, and finding practical solutions
- Social Skills: involves effective teamwork, collaborating with others, accepting and formulating criticism, and critical examination of research results
- Practical Skills: ability to implement practical solutions, present and defend design decisions, and prepare readable documentation of software or projects

Contents

This intensive course offers an overview of the latest techniques and trends in 3D/4D/6D visual data processing and demonstrates how these basic concepts can be applied to game engines and standard graphics tools. The covered topics will be:

- Foundations of Computer Graphics and Vision
- Use of Deep Learning techniques in visual data processing
- Data acquisition techniques for Graphics and Vision
- Human model representations
- Motion data processing
- Geometry processing techniques
- Differentiable rendering for 3D/4D/6D reconstruction and model optimization
- Neural Radiance Fields and Gaussian Splatting as efficient scene representations
- Dynamic scene representations

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 4 | 60 T / 45 S | 3.5 | |

Graded exams

Written exam in three parts

Ungraded coursework (required for admission to the exam)

Successful participation in the exercise requires a minimum of 50% correct unit tests for the programming assignments in each 5-day period

Literature

Supplemental readings will be provided before the lecture starts.

MA-INF 2115 Computational Medical Imaging

| Workload | Credit points | Duration | Frequency |
|--------------------------|----------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Thomas Schultz | Prof. Dr. Shadi Albarqouni | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 3. | |

Learning goals: technical skills

- Learn the fundamental paradigms and mathematical foundations of computational medical imaging.
- Understand image formation processes (e.g., CT/MRI physics), and how they translate into discrete reconstruction algorithms.
- Master classical and modern algorithms for: ? Image Segmentation (e.g., region-growing, atlas-based, clustering; CNN-based methods) ? Image Registration (e.g., affine, deformable, diffeomorphic; learning-based registration) ? Feature Extraction & Quantitative Imaging (e.g., intensity? and texture?based radiomics) ? Machine-Learning & Deep-Learning in Medical Imaging (e.g., UNet, GANs for medical tasks)
- Formulate imaging problems as optimization tasks; derive and implement relevant cost functions and solvers.
- Analyze performance measures and evaluation protocols used in research and clinical practice.

Learning goals: soft skills

- Develop social competences through group exercises and in?class discussions.
- Enhance communicative skills via in?lecture question sessions and short presentations.
- Write concise algorithmic descriptions in reports; present technical material to peers.

Contents

Lecture (4 h/week).

- Introduction to Medical Imaging Modalities (CT physics, MRI basics, ultrasound principles).
- Segmentation Techniques (graph?cuts, level sets, statistical shape models, deep segmentation).
- Registration & Alignment (rigid vs. nonrigid, mutual information, Demons, SyN, learning?based registration).
- Quantitative Imaging & Radiomics (feature engineering, dimensionality reduction, classifiers).
- Machine Learning Foundations (supervised vs. unsupervised, loss functions, cross?validation in medical data).
- Deep Learning Architectures (CNN fundamentals, U-Net, GANs, Vision Transformers applied to medical data).
- Uncertainty & Bias in Medical Imaging (Bayesian networks, domain adaptation, causal inference).
- Ethical, Regulatory & Clinical Translation (data privacy, FDA/EMA guidelines, explainability, fairness).
- Emerging Topics (federated learning in healthcare, multimodal imaging, large language models in radiology).

Exercises (2 h/week)

- Hands-on segmentation tasks with public datasets (e.g., Brain MRI Tumor Segmentation), compare classical vs. CNN approaches.
- Registration exercise using SimpleITK (perform rigid and nonrigid registration, compute registration error).
- Implement a small end-to-end deep learning pipeline (data loading, model training, evaluation) for a simple classification or segmentation task.
- Evaluation metrics: compute Dice coefficient, Hausdorff distance, ROC/AUC for a provided dataset.

Prerequisites

Recommended:

- Basic knowledge of linear algebra, analysis, Matlab, and Python.
- MA-INF 2312 – Image Acquisition and Analysis in Neuroscience (or equivalent knowledge of medical imaging modalities) und/oder:
- MA-INF 2222 – Visual Data Analysis (or equivalent knowledge of statistical data analysis).

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam

Ungraded coursework (required for admission to the exam)

Successful exercise participation

MA-INF 2201 Computer Vision

| Workload | Credit points | Duration | Frequency |
|-------------------------|-----------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Jürgen Gall | Prof. Dr. Jürgen Gall | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Students will be able to understand and explain mathematical descriptions of methods in publications from Computer Vision. Students will be able to implement the discussed Computer Vision algorithms, apply them, and choose the right approach and hyper-parameters for a given problem.

Learning goals: soft skills

Productive work in small teams, development and realization of individual approaches and solutions, critical reflection of competing methods, discussion in groups.

Contents

The class will cover a number of mathematical methods and their applications in computer vision. For example, linear filters, edges, derivatives, Hough transform, segmentation, graph cuts, mean shift, active contours, level sets, MRFs, expectation maximization, background subtraction, temporal filtering, active appearance models, shapes, optical flow, 2d tracking, cameras, 2d/3d features, stereo, 3d reconstruction, 3d pose estimation, articulated pose estimation, deformable meshes, RGBD vision.

Prerequisites

Recommended:

Basic knowledge of linear algebra, analysis, probability theory, Python programming

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved.

Literature

- R. Hartley, A. Zisserman: Multiple View Geometry in Computer Vision
- R. Szeliski: Computer Vision: Algorithms and Applications
- S. Prince: Computer Vision: Models, Learning, and Inference

MA-INF 2202 Computer Animation

| Workload | Credit points | Duration | Frequency |
|-------------------------|------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Björn Krüger | Prof. Dr. Björn Krüger | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-3. | |

Learning goals: technical skills

Students will learn fundamental paradigms used in computer animation. They will learn the mathematical foundations and basic algorithms to solve problems in the areas of motion capturing, motion synthesis, and motion analysis.

Learning goals: soft skills

Social competences (work in groups), communicative skills (written and oral presentation)

Contents

Fundamentals of computer animation; kinematics; representations of motions; motion capturing; motion editing; motion synthesis; facial animations

Prerequisites

Recommended:

Basic knowledge of linear algebra, analysis, Matlab and Python

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam (30 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. A total of 50% of the points must be achieved.

Literature

- Dietmar Jackel, Stephan Neunreither, Friedrich Wagner: Methoden der Computeranimation, Springer 2006
- Rick Parent: Computer Animation: Algorithms and Techniques, Morgan Kaufman Publishers 2002
- Frederic I. Parke, Keith Waters: Computer Facial Animation. A K Peters, Ltd. 199
- Grünvogel Stefan, Einführung in die Computer Animation, Springer 2024

MA-INF 2206 Seminar Vision

| Workload | Credit points | Duration | Frequency | | |
|--|-----------------------|------------|----------------|----|--|
| 120 h | 4 CP | 1 semester | every semester | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Jürgen Gall | Prof. Dr. Jürgen Gall | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. or 3. | | | |
| Learning goals: technical skills | | | | | |
| Ability to understand new research results presented in original scientific papers. | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to present and to critically discuss these results in the framework of the corresponding area. | | | | | |
| Contents | | | | | |
| Current conference and journal papers. | | | | | |
| Prerequisites | | | | | |
| Recommended: MA-INF 2201 – Computer Vision or MA-INF 2213 - Advanced Computer Vision | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |

MA-INF 2207 Seminar Graphics

| Workload | Credit points | Duration | Frequency | | |
|--|--------------------------|------------|----------------|----|--|
| 120 h | 4 CP | 1 semester | every semester | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Reinhard Klein | Prof. Dr. Reinhard Klein | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. or 3. | | | |
| Learning goals: technical skills | | | | | |
| Ability to understand new research results presented in original scientific papers. | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to present and to critically discuss these results in the framework of the corresponding area. | | | | | |
| Contents | | | | | |
| Current conference and journal papers. | | | | | |
| Prerequisites | | | | | |
| Recommended: Mathematical background (multidimensional analysis and linear algebra, basic numerical methods) Basic knowledge in Computer Graphics | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |

T = face-to-face teaching
S = independent study

MA-INF 2208 Seminar Audio

| Workload | Credit points | Duration | Frequency | | |
|--|---|------------|----------------|----|--|
| 120 h | 4 CP | 1 semester | every semester | | |
| Module coordinator | Lecturer(s) | | | | |
| apl. Prof. Dr. Frank Kurth | apl. Prof. Dr. Frank Kurth, Dr. Michael Clausen | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. | | | |
| Learning goals: technical skills | | | | | |
| Ability to understand new research results presented in original scientific papers. | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to present and to critically discuss these results in the framework of the corresponding area. | | | | | |
| Contents | | | | | |
| Current conference and journal papers in the area of audio signal processing. | | | | | |
| Prerequisites | | | | | |
| Recommended: MA-INF 2113 - Audio Signal Processing | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |

MA-INF 2209 Advanced Topics in Computer Graphics I

| Workload | Credit points | Duration | Frequency |
|--------------------------|--------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Reinhard Klein | Prof. Dr. Reinhard Klein | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Analytical formulation of problems related to rendering. Knowledge of principles, techniques and algorithms to

- recognize and understand the physical quantities of light transport
- explain a range of surface and volumetric material models
- explain the rendering and radiative transfer equations
- design and implement methods to solve these equations, especially Monte Carlo methods
- Assess / Evaluate the performance and conceptual limits of the implemented simulation code

Learning goals: soft skills

Based on the knowledge and skills acquired students should be able to

- read and judge current scientific literature in the area of rendering
- identify the major literature concerning a given problem in rendering and gain an overview of the current state of the art
- discuss problems concerning rendering with researchers from different application fields
- present, propose and communicate different solutions and work in a team to solve a rendering problem

Contents

This course introduces the basic physical quantities as well as the mathematical and algorithmic tools required to understand and simulate the light interaction with objects and different materials in a 3D scene. We will discuss how to solve the mathematical problem numerically in order to create realistic images. Advanced topics include participating media, material models for sub-surface light transport, and Markov Chain Monte Carlo Methods. Topics among others will be

- rendering and radiative transfer equation
- methods and algorithms to solve these equations, radiosity, Monte Carlo, photon mapping
- analytical and data driven surface and subsurface material models, especially BRDF, BSSRDF models
- differentiable rendering

In addition, results from state-of-the-art research will be presented.

Prerequisites

Recommended:

Recommended but not enforced: basic knowledge in computer graphics, (numerical) analysis and linear algebra, C++

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved. For 70% of the exercise sheets, 50% of the points must be achieved for each sheet. The exercises are divided into theoretical and practical exercises, and the points to be achieved apply separately to both categories.

Literature

- M. Pharr, W. Jakob, and G. Humphreys, Physically Based Rendering: From Theory to Implementation (3rd edition), 2018
 - L. Szirmay-Kalos: Monte-Carlo Methods in Global Illumination, Institute of Computer Graphics, Vienna University of Technology, Vienna, 1999 URL: <https://cg.iit.bme.hu/~szirmay/script.pdf>
 - P. Dutre, K. Bala, P. Bekaert: Advanced Global Illumination, 2nd ed., B&T, 2006
 - D'Eon, Eugene. A Hitchhiker's Guide to Multiple Scattering, 2016
-

MA-INF 2210 Seminar Computer Animation

| Workload | Credit points | Duration | Frequency |
|--------------------------|------------------------|------------|------------------------|
| 120 h | 4 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Reinhard Klein | Prof. Dr. Björn Krüger | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. | |

Learning goals: technical skills

Ability to understand new research results presented in original scientific papers.

Learning goals: soft skills

Ability to present and to critically discuss these results in the framework of the corresponding area.

Contents

Current conference and journal papers.

Prerequisites

Recommended:

At least 1 of the following:

MA-INF 2202 – Computer Animation

MA-INF 2311 – Lab Computer Animation

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2212 Pattern Matching and Machine Learning for Audio Signal Processing

| Workload | Credit points | Duration | Frequency |
|----------------------------|---|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| apl. Prof. Dr. Frank Kurth | apl. Prof. Dr. Frank Kurth, Prof. Dr. Michael Clausen | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

- Introduction into selected topics of digital signal processing: Acquire basic knowledge on representing and manipulating 1D-time series. Learn basic methods for time-frequency analysis and signal processing methods for feature extraction.
- Applications in the field of Audio Signal Processing: Learn typical application domains of audio signal processing techniques and how to apply the acquired methods in solving applications problems. Important examples are filtering, signal/object detection and classification tasks.
- Methods of Automatic Pattern Recognition and Machine Learning: Learn methods for Feature Extraction, Automatic Pattern Recognition and Machine Learning for the context of Audio Signal Processing. Be able to apply those fundamental methods (method list: see "Contents" section) in particular for solving applications tasks.

Learning goals: soft skills

Audio Signal Processing Applications; Extended programming skills for signal processing applications; Capability to analyze; Time management; Presentation skills; Discussing own solutions and solutions of others, and working in groups.

Contents

The lecture is presented in modular form, where each module is motivated from the application side. The presented topics are: Windowed Fourier transforms; Audio Identification; Audio Matching; Signal Classification; Applications of ML/DL concepts, in particular HMMs, SVMs and Neural Networks to Audio Signal processing tasks.

Prerequisites

Recommended:

Solid basic knowledge on Linear Algebra, Analysis and Stochastics, including proficiency in using complex numbers. Having attended MA-INF 2113 Foundations of Audio Signal Processing is highly recommended, as fundamental material from (Digital) Signal Processing and Audio Processing are introduced there in depth. Basic knowledge in time series data analysis is helpful but not mandatory.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of two to four students. A total of 50% of the points must be achieved.

Forms of media

Slides, Blackboard, Whiteboard

MA-INF 2213 Advanced Computer Vision

| Workload | Credit points | Duration | Frequency |
|-------------------------|-----------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Jürgen Gall | Prof. Dr. Jürgen Gall | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Students will be able to implement the discussed machine learning algorithms for Computer Vision, apply them, and choose the right approach and hyper-parameters for a given problem.

Learning goals: soft skills

Productive work in small teams, development and realization of individual approaches and solutions, critical reflection of competing methods, discussion in groups.

Contents

The class will cover a number of computer vision applications. For example, image classification, object detection, action recognition, pose estimation, face analysis, tracking, image synthesis, vision-language models.

Prerequisites

Recommended:

MA-INF 2201 – Computer Vision

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Lecture | | 3 | 45 T / 45 S | 3 | |
| Exercises | | 1 | 15 T / 75 S | 3 | |

Graded exams

Oral exam (20 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved.

MA-INF 2214 Computational Photography

| Workload | Credit points | Duration | Frequency |
|---------------------------|---------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Matthias Hullin | Prof. Dr. Matthias Hullin | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Foundations in optics and image sensors. Signal processing and inverse problems in imaging. Color spaces and perception. Image alignment and blending. High-dimensional representations of light transport (light fields, reflectance fields, reflectance distributions). Computational illumination.

Learning goals: soft skills

- to read and understand current literature in the field
- to implement standard computational photography techniques
- to propose and implement solutions to a given problem
- to follow good scientific practice by planning, documenting and communicating their work

Contents

- Image sensors
- Optics
- Panoramas
- Light fields
- Signal processing and inverse problems
- Color, perception and HDR
- Reflectance fields and light transport matrices

Prerequisites

Required:

Basic knowledge in computer graphics, data structures, multidimensional analysis und linear algebra, numerical analysis and numerical linear algebra, C++ or MATLAB

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

(i) The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved. The exercises are divided into theoretical and practical exercises, and the points to be achieved apply separately to both categories. Each student must present a solution to an exercise in the exercise sessions twice. (ii) The completion of a programming project. The work is done in groups of two to four students, depending on the total number of students taking the course. The results of the programming project must be presented in class.

MA-INF 2215 Seminar Digital Material Appearance

| Workload | Credit points | Duration | Frequency | | |
|--|---------------------------|------------|-------------|----|--|
| 120 h | 4 CP | 1 semester | every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Matthias Hullin | Prof. Dr. Matthias Hullin | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. | | | |
| Learning goals: technical skills | | | | | |
| Ability to understand new research results presented in original scientific papers. | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to present and to critically discuss these results in the framework of the corresponding area. | | | | | |
| Contents | | | | | |
| Current conference and journal papers | | | | | |
| Prerequisites | | | | | |
| none | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |

T = face-to-face teaching
S = independent study

MA-INF 2216 Lab Visual Computing

| Workload | Credit points | Duration | Frequency |
|---------------------------|---------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Florian Bernard | Prof. Dr. Florian Bernard | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

- Getting into a selected topic of visual computing
- Implementation and practical application of current visual computing methods
- Experimental evaluation and visualisation of results
- Scientific research and writing

Learning goals: soft skills

- self-organisation
- ability to analyze problems theoretically and to find creative and practical solutions
- critical thinking: examine one's solutions and results critically
- to classify own results into the state-of-the-art of the respective area
- to prepare readable documentation of software and research results
- to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards

Contents

This lab introduces visual computing methods and applications. You will get a chance to study the methods in depth by implementing them and running experiments. At the end of the semester, you will present the method, give a short demonstration and hand in a report describing the method and experimental outcomes. Potential topics include deep learning (e.g. graph neural networks, unsupervised learning, 3D deep learning), mathematical optimization (e.g. linear/convex/non-convex programming, graph-based algorithms) and other methods involving mathematical modeling of visual computing problems.

Prerequisites

Recommended:

Basic knowledge in mathematics (e.g. linear algebra, calculus, optimization) and programming (e.g. python, in particular pytorch or tensorflow, C++, or Matlab). In addition:

- MA-INF 2317: Numerical Algorithms for Visual Computing and Machine Learning, or
- MA-INF 2225: Discrete Models for Visual Computing

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2218 Video Analytics

| Workload | Credit points | Duration | Frequency |
|-------------------------|-----------------------|------------|------------------------|
| 180 h | 6 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Jürgen Gall | Prof. Dr. Jürgen Gall | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-3. | |

Learning goals: technical skills

Students will be able to implement the discussed machine learning algorithms for video understanding, apply them, and choose the right approach and hyper-parameters for a given problem.

Learning goals: soft skills

Productive work in small teams, development and realization of a state-of-the-art system for video analysis.

Contents

The class will discuss state-of-the-art methods for several tasks of video analysis. For example, action recognition, hidden Markov models, 3D convolutional neural networks, temporal convolutional networks, recurrent neural networks, temporal action segmentation, weakly supervised learning, self-supervised learning, anticipation and forecasting.

Prerequisites

Recommended:

MA-INF 2201 – Computer Vision

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam (20 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. A total of 50% of the points must be achieved.

MA-INF 2219 Seminar Visualization and Medical Image Analysis

| Workload | Credit points | Duration | Frequency |
|--------------------------|--------------------------|------------|------------------------|
| 120 h | 4 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Thomas Schultz | Prof. Dr. Thomas Schultz | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in the area of visualization and medical image analysis.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of the corresponding research area; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media in a way that adheres to academic standards, that is well-structured and didactically effective, and that motivates the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

Recent research topics in visualization and medical image analysis based on journal and conference publications. Relevant journals include Medical Image Analysis, IEEE Transactions on Medical Imaging, IEEE Transactions on Visualization and Computer Graphics; relevant conferences include Medical Image Computing and Computer-Assisted Intervention (MICCAI), IEEE/CVF Computer Vision and Pattern Recognition (CVPR) IEEE VIS, EuroVis.

Prerequisites

Recommended:

At least one of the following:

- MA-INF 2222 – Visual Data Analysis
- MA-INF 2312 – Image Acquisition and Analysis in Neuroscience

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2220 Lab Visualization and Medical Image Analysis

| Workload | Credit points | Duration | Frequency |
|--------------------------|--------------------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Thomas Schultz | Prof. Dr. Thomas Schultz | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Students acquire a deep understanding of a specific problem in visualization and medical image analysis, and technical knowledge about state-of-the-art algorithmic approaches to solving it. This involves problem identification; data processing; selection, design, implementation, and application of suitable algorithms; communication of results.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the

respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time; to aim at long-range goals under limited resources.

Contents

The students will carry out a practical task (project) in the context of data visualization and visual analytics or medical image analysis, including test and documentation of the implemented software/system. Projects are often based on journal and conference publications. Relevant journals include Medical Image Analysis, IEEE Transactions on Medical Imaging, IEEE Transactions on Visualization and Computer Graphics; relevant conferences include Medical Image Computing and Computer-Assisted Intervention (MICCAI), IEEE/CVF Computer Vision and Pattern Recognition (CVPR) IEEE VIS, EuroVis.

Prerequisites

Recommended:

At least one of the following:

- MA-INF 2222 – Visual Data Analysis
- MA-INF 2312 – Image Acquisition and Analysis in Neuroscience.

A solid background in programming is required, preferably in Python. Most projects also require basic knowledge in linear algebra, calculus, probability theory, and/or numerical algorithms.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2221 Seminar Visual Computing

| Workload | Credit points | Duration | Frequency | | |
|---|---------------------------|------------|---------------------|----|--|
| 120 h | 4 CP | 1 semester | at least every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Florian Bernard | Prof. Dr. Florian Bernard | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. or 3. | | | |
| Learning goals: technical skills | | | | | |
| Ability to understand new research results presented in original scientific papers. | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to present and to critically discuss these results in the framework of the corresponding area. | | | | | |
| Contents | | | | | |
| Current conference and journal papers. | | | | | |
| Prerequisites | | | | | |
| Required: No formal requirements. Participants are expected to have some previous exposure to at least one of the following: - visual computing (e.g. computer vision, computer graphics, 3D shape analysis, image analysis, etc.), - mathematical optimisation (e.g. combinatorial/continuous, convex/non-convex, etc.), or - machine learning. | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |

MA-INF 2222 Visual Data Analysis

| Workload | Credit points | Duration | Frequency |
|--------------------------|--------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Thomas Schultz | Prof. Dr. Thomas Schultz | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Ability to design, implement, and make proper use of systems for visual data analysis. Knowledge of algorithms and techniques for the visualization of multi-dimensional data, graphs, as well as scalar, vector, and tensor fields.

Learning goals: soft skills

Productive work in small teams, self-dependent solution of practical problems in the area of visual data analysis, critical reflection on visualization design, presentation of solution strategies and implementations, self management

Contents

This class provides a broad overview of principles and algorithms for data analysis via interactive visualization. Specific topics include perceptual principles, color spaces, visualization analysis and design, integration of visual with statistical data analysis and machine learning, as well as specific algorithms and techniques for the display of multidimensional data, dimensionality reduction, graphs, geospatial data, neural networks, as well as scalar, vector and tensor fields.

Prerequisites

Recommended:

Students are recommended to have a basic knowledge in linear algebra and calculus, as well as proficiency in programming.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Literature

- A.C. Telea, Data Visualization: Principles and Practice. CRC Press, Second Edition, 2015
- M. Ward et al., Interactive Data Visualization: Foundations, Techniques, and Applications. CRC Press, 2010
- T. Munzner, Visualization Analysis and Design, A K Peters, 2015

MA-INF 2225 Discrete Models for Visual Computing

| Workload | Credit points | Duration | Frequency |
|---------------------------|---------------------------|------------|------------------------|
| 180 h | 6 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Florian Bernard | Prof. Dr. Florian Bernard | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

- Ability to implement basic visual computing algorithms, understanding their strengths and shortcomings
- Mathematical modelling of computational problems in visual computing
- Gain an intuition which algorithm is best applied for which problem in visual computing, so that practical problems in these areas can be solved

Learning goals: soft skills

- Problem solving skills: ability to identify and utilise analogies between new problems and previously seen ones
- Analytical and abstract thinking: develop a general intuition of computational problems, being able to adopt different perspectives of particular concepts

Contents

This module focuses on discrete models that frequently occur in the field of visual computing (VC). In addition to algorithms, this module will also cover modelling aspects that are relevant for solving practical problems in VC. The contents include:

- Graph-based models (e.g. linear and quadratic assignment, network flows, product graph formalisms, dynamic programming and their application)
- Continuous algorithms for discrete problems (e.g. convex & spectral relaxations, projection methods, path-following and their application)
- Deep Learning for discrete domains (e.g. differentiable programming, graph neural networks, deep learning on meshes)

Prerequisites

Recommended:

Participants are expected to have a high level of mathematical maturity (in particular, a good working knowledge of linear algebra and calculus/analysis is essential). A basic understanding of graph theory is advantageous.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved.

MA-INF 2226 Lab Geometry Processing

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------------------|
| 270 h | 9 CP | 1 semester | at least every 2 years |

| Module coordinator | Lecturer(s) |
|-----------------------------|-----------------------------|
| Jun. Prof. Dr. Zorah Lähner | Jun. Prof. Dr. Zorah Lähner |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 1-3. |

Learning goals: technical skills

Ability to handle complex geometric data types; to extract implementation details from research publications; to implement and visualize geometric data.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time.

Contents

Mesh deformation, point cloud meshing, pytorch3D, shape correspondence, reconstruction, 2D-to-3D transfer. This lab introduces methods and applications in the field of geometry processing. You will get a chance to study the methods in depth by implementing them and running experiments. At the end of the semester, you will present the method, give a short demonstration and hand in a report describing the method and experimental outcomes.

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2227 Lab 3D Animation

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |

| Module coordinator | Lecturer(s) |
|---------------------|---------------------|
| Prof. Dr. Ina Prinz | Prof. Dr. Ina Prinz |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 1-3. |

Learning goals: technical skills

The students will learn to carry out a practical task (project) in the context of 3D animation, containing modelling, preparing a screenplay, realizing an animation related to real physical laws, rendering and creating a video.

Learning goals: soft skills

Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify ones own results into the state-of-the-art of the resp. area.

Contents

Varying selected topics close to current research in the area of the history of computing and the mechanization of computing as well as deep understanding of mechanical and technical functions and its presentation in a representative 3D animation video, contains technical visualization and didactic skills.

Prerequisites

Recommended:

For students who did not take BA-INF 108 Geschichte des maschinellen Rechnens I and BA-INF 126 Geschichte des maschinellen Rechnens II in their Bachelor's studies, recommended reading includes:

- Aspray, W.: Computing before Computers. Ames, 1990.
- Bauer, Friedrich L.: Origins and Foundations of Computing. Berlin 2010.
- Ceruzzi, Paul E.: A History of Modern Computing. Cambridge, 2003.
- Goldstine, H.: The Computer from Pascal to von Neumann. Princeton, 1972.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report, presentation of the video

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2228 Seminar Vision and Graphics (Role-Based)

| Workload | Credit points | Duration | Frequency |
|-----------------------------|-----------------------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Jun. Prof. Dr. Zorah Lähner | Jun. Prof. Dr. Zorah Lähner | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-4. | |

Learning goals: technical skills

- reading and understanding of research publications in the area of computer vision and computer graphics
- learning about different roles in the research community and taking their point of view

Learning goals: soft skills

- Critical thinking: ability to put research into wider context and analyze it from different perspectives
- Communication: oral and written presentation of scientific content, high level discussion about a new topic
- Self-Competence: time management, focusing on essential aspects, creativity

Contents

Students will study a variety of publications in the area of computer vision and graphics, and will be assigned a specific role which determines how to interact with the work.

The roles include but are not limited to:

- Scientific Peer Reviewer
- Academic Researcher
- Archaeologist (putting the paper into context regarding previous and subsequent work)
- Industry Practitioner

Prerequisites

Recommended:

A background in visual computing through lectures from the Graphics, Vision, Audio subfield is highly recommended.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). Participation in each type of assigned role in-presence at least once.

MA-INF 2229 Seminar Recent Advances in Geometry Processing

| Workload | Credit points | Duration | Frequency |
|-----------------------------|-----------------------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Jun. Prof. Dr. Zorah Lähner | Jun. Prof. Dr. Zorah Lähner | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-4. | |

Learning goals: technical skills

This module examines recent topics in geometry processing. The students learn to do independent, in-depth study of state-of-the-art scientific literature, discuss them with their peers and present in a form suited for a scientific audience.

Learning goals: soft skills

Communication skills: oral and written presentation of scientific content

Self-competence: the ability to analyze problems, time management, creativity

Contents

Algorithmic and learning-based methods for geometry processing, including typical applications like shape correspondence, 3D reconstruction, geometry evaluation, differential geometry, statistical modeling as well differences for methods using implicit and explicit geometry representations.

Prerequisites

Recommended:

MA-INF 2310 Advanced Topics in Computer Graphics II

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2230 Lab Computational Medical Imaging

| Workload | Credit points | Duration | Frequency |
|--------------------------|----------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Thomas Schultz | Prof. Dr. Shadi Albarqouni | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

- Acquire a deep understanding of a selected problem in computational medical imaging: from problem identification to data processing, algorithm design, implementation, and evaluation.
- Implement, test, and validate state-of-the-art image-analysis algorithms (e.g., segmentation, registration, reconstruction, classification) on real medical data.
- Develop proficiency in using libraries and toolkits commonly used in medical imaging (e.g., ITK, SimpleITK, PyTorch for deep learning, nibabel/dipy).
- Learn to document software systematically (API documentation, code comments, unit tests) and to generate reproducible experiments (version control, containerization).

Learning goals: soft skills

- Collaborate effectively in small groups over the entire semester, dividing tasks (e.g., data curation, algorithmic implementation, evaluation).
- Prepare clear, concise technical documentation and design rationales.
- Present project progress and final results in oral form (midterm demo, final demo).
- Critically assess one's own results and position them within the state-of-the-art in computational medical imaging.

Contents

Project-based lab: Students work in groups (max 3 per group) to carry out a semester-long project in computational medical imaging. Possible project topics (chosen or proposed by the instructors) include:

- Anatomical Structure Segmentation (e.g., multi-atlas, CNN-based)
- Deformable Registration (e.g., classic demons, learning-based registration)
- Lesion/Anomaly Detection (e.g., out-of-distribution detection in X-ray)
- Radiomics & Quantitative Biomarker Extraction (e.g., texture features, deep radiomics)
- Uncertainty Estimation in Deep Learning (e.g., MC-Dropout, Bayesian networks)
- Causality & Bias Analysis in Medical Datasets (e.g., domain shift, fairness)

Each group will:

- Identify a well-defined problem and collect or be provided a suitable dataset (publicly available or hospital data under ethics approval).
- Perform a literature review to select baseline methods.
- Implement baseline and at least one novel or improved approach.
- Evaluate quantitatively (e.g., Dice, Hausdorff, MSE, classification accuracy) and qualitatively (expert review where possible)
- Document the software (README, API docs) and provide a reproducible environment (Docker/Singularity).
- Present midterm progress (oral demonstration + short written summary) and final results (oral + poster or full report).

Prerequisites

Recommended:

At least one of the following:

- MA-INF 2222 – Visual Data Analysis.
- MA-INF 2312 – Image Acquisition and Analysis in Neuroscience.
- MA-INF 2220 – Lab Visualization and Medical Image Analysis (or equivalent).

A solid background in programming (Python and/or C++), basic linear algebra, calculus, probability theory, and/or numerical algorithms is required. Familiarity with deep learning frameworks is highly recommended.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation (final demo + Q&A, 20 minutes per group). Written report (12–16 pages, including background, methods, results, discussion).

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2307 Lab Vision

| Workload | Credit points | Duration | Frequency | | |
|--|-----------------------|------------|----------------|----|--|
| 270 h | 9 CP | 1 semester | every semester | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Jürgen Gall | Prof. Dr. Jürgen Gall | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. or 3. | | | |
| Learning goals: technical skills | | | | | |
| The students will carry out a practical computer vision task (project). | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify ones own results into the state-of-the-art of the resp. area | | | | | |
| Contents | | | | | |
| Computer Vision: research topics and applications | | | | | |
| Prerequisites | | | | | |
| Required: Good C++ or Python programming skills | | | | | |
| Recommended: MA-INF 2201 – Computer Vision or MA-INF 2213 - Advanced Computer Vision | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Lab | 8 | 4 | 60 T / 210 S | 9 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |

MA-INF 2308 Lab Graphics

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |

| Module coordinator | Lecturer(s) |
|--------------------------|--------------------------|
| Prof. Dr. Reinhard Klein | Prof. Dr. Reinhard Klein |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2. or 3. |

Learning goals: technical skills

The students will learn to carry out a practical task (project) in the context of geometry processing, rendering, scientific visualization or human computer interaction, including test and documentation of the implemented software/system.

Learning goals: soft skills

Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify ones own results into the state-of-the-art of the resp. area

Contents

Varying selected topics close to current research in the area of geometry processing, rendering, scientific visualization or human computer interaction.

Prerequisites

Recommended:

At least one of the following:

- MA-INF 1108 Introduction to High Performance Computing
- MA-INF 2202 Computer Animation
- MA-INF 2222 Visual Data Analysis

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2309 Lab Audio

| Workload | Credit points | Duration | Frequency |
|----------------------------|---|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| apl. Prof. Dr. Frank Kurth | apl. Prof. Dr. Frank Kurth, Prof. Dr. Michael Clausen | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Proficiency in implementing signal processing concepts introduced in selected scientific publications or research reports. Proficiency in collecting and maintaining data sets, in particular signals and corresponding metadata, and performing scientific evaluations of signal processing methods based on data sets and implemented algorithms.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time; to pursue long-range goals under a given resource budget.

Contents

In the lab a medium-sized programming project related to digital audio signal processing has to be solved during the period of one semester. For this, initial literature, usually in form of one or two scientific papers or reports, will be provided at the beginning of the lab. Also, resources regarding the audio signal data to be used, are given. Typical programming tasks consist of implementing either general signal processing algorithms such as fundamental frequency estimation or of implementing algorithms for solving application problems such as speaker detection or classification. For participants with interest in topics of pattern recognition, machine and deep learning, programming projects from those areas, with application to audio processing, can be selected.

Prerequisites

Recommended:

Solid basic proficiency in imperative programming (e.g. knowledge of C/C++, Java, Python). Knowledge of the material from MA-INF 2113 Foundations of Audio Signal Processing is highly recommended. Knowledge of material from MA-INF 2212 Pattern Matching and Machine Learning for Audio is helpful but not necessary.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2310 Advanced Topics in Computer Graphics II

| Workload | Credit points | Duration | Frequency |
|--------------------------|--------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Reinhard Klein | Prof. Dr. Reinhard Klein | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 3. | |

Learning goals: technical skills

Analytical formulation of problems related to geometry processing:

- apply methods of geometry processing
- apply basic concepts of statistical shape analysis and shape spaces to real world applications
- Design and implement novel application software in this area

Learning goals: soft skills

Based on the knowledge and skills acquired students should be able to

- read and judge current scientific literature in the area of geometry processing and gain an overview of the current state of the art
- identify the major literature relevant for solving a given problem in geometry processing
- present, propose and communicate different solutions and work in a team to solve geometry processing problems
- discuss geometry processing problems with researchers from different application fields

Contents

This course will first introduce the mathematical and algorithmic tools required to represent, model, and process 3D geometric objects. The second part discusses the latest mathematical, algorithmic, and statistical tools required for the analysis and modeling of 3D shape variability, which can facilitate the creation of 3D models. Topics among others will be

- classical and discrete differential geometry of curves and surfaces
- mesh data structures and generation of meshes from point clouds
- Laplacian operator and optimization techniques with applications to denoising, smoothing, decimation, shape fitting, shape descriptors, geodesic distances
- parameterization and editing of surfaces
- point cloud registration
- correspondences
- shape spaces and statistical shape analysis

In addition, results from state-of-the-art research will be presented.

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|-----|--|
| Lecture | | 4 | 60 T / 105 S | 5.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved. For 70% of the exercise sheets, 50% of the points must be achieved for each sheet. The exercises are divided into theoretical and practical exercises, and the points to be achieved apply separately to both categories.

Literature

- M. Botsch, L. Kobbelt, M. Pauly, P. Alliez, B. Levy, Polygon Mesh, Processing, A K Peters, 2010
 - Laga, Hamid, Yulan Guo, Hedi Tabia, Robert B. Fisher, and Mohammed Bennamoun. 3D Shape analysis: fundamentals, theory, and applications. John Wiley & Sons, 2018.
 - Solomon, Justin. Numerical Algorithms. Textbook published by AK Peters/CRC Press, 2015
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MA-INF 2311 Lab Computer Animation

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------------------|
| 270 h | 9 CP | 1 semester | at least every 2 years |

| Module coordinator | Lecturer(s) |
|--------------------------|------------------------|
| Prof. Dr. Reinhard Klein | Prof. Dr. Björn Krüger |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 3. |

Learning goals: technical skills

The students will carry out a practical task (project) in the context of computer animation, including test and documentation of the implemented software/system.

Learning goals: soft skills

Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify ones own results into the state-of-the-art of the resp. area

Contents

Varying selected topics close to current research in the area of computer animation.

Prerequisites

Recommended:

At least 1 of the following:

MA-INF 2202 – Computer Animation

MA-INF 2302 – Physics-based Modelling

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2312 Image Acquisition and Analysis in Neuroscience

| Workload | Credit points | Duration | Frequency |
|--------------------------|--------------------------|------------|------------------------|
| 180 h | 6 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Thomas Schultz | Prof. Dr. Thomas Schultz | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-4. | |

Learning goals: technical skills

Students will learn about image acquisition and analysis pipelines which are used in neuroscience. They will understand algorithms for image reconstruction, artifact removal, image registration and segmentation, as well as relevant statistical and machine learning techniques. A particular focus will be on data from Magnetic Resonance Imaging and on mathematical models for functional and diffusion MRI data.

Learning goals: soft skills

Productive work in small teams, self-dependent solution of practical problems in the area of biomedical image processing, presentation of solution strategies and implementations, self management, critical reflection of conclusions drawn from complex experimental data.

Contents

This course covers the full image formation and analysis pipeline that is typically used in biomedical studies, from image acquisition to image processing and statistical analysis.

Prerequisites

Recommended:

Mathematical background (calculus, linear algebra, statistics); imperative programming.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Lecture | | 3 | 45 T / 45 S | 3 | |
| Exercises | | 1 | 15 T / 75 S | 3 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Literature

- B. Preim, C. Botha: Visual Computing for Medicine: Theory, Algorithms, and Applications. Morgan Kaufmann, 2014
- R.A. Poldrack, J.A. Mumford, T.E. Nichols: Handbook of Functional MRI Data Analysis. Cambridge University Press, 2011
- D.K. Jones: Diffusion MRI: Theory, Method, and Applications, Oxford University Press, 2011

MA-INF 2316 Lab Digital Material Appearance

| Workload | Credit points | Duration | Frequency |
|---------------------------|---------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Matthias Hullin | Prof. Dr. Matthias Hullin | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

The students will carry out a practical task (project) in the context of the corresponding area, including test and documentation of the implemented software/system.

Learning goals: soft skills

Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify ones own results into the state-of-the-art of the resp. area

Contents

Within the lab, a computational imaging and/or digital material appearance technique is implemented. This can be a newly developed approach, an improvement of an existing technique, or an implementation of a paper. Each participant selects a topic, defines an objective, and presents a work plan at the beginning of the project. At the end of the lab, each project is presented within a seminar and a written report.

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 2317 Numerical Algorithms for Visual Computing and Machine Learning

| Workload | Credit points | Duration | Frequency |
|---------------------------|---------------------------|------------|------------------------|
| 180 h | 6 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Florian Bernard | Prof. Dr. Florian Bernard | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

- ability to implement basic numerical algorithms, understanding their strengths and shortcomings
- mathematical modelling of computational problems in visual computing and machine learning
- gain an intuition which algorithm is best applied for which problem in visual computing and machine learning, so that practical problems in these areas can be solved

Learning goals: soft skills

- problem solving skills: ability to identify and utilise analogies between new problems and previously seen ones
- analytical and abstract thinking: develop a general intuition of computational problems, being able to adopt different perspectives of particular concepts

Contents

This module focuses on numerical methods that frequently occur in the fields visual computing (VC) and machine learning (ML). In addition to algorithms, this module will also cover modelling aspects that are relevant for solving practical problems in VC and ML. The contents include:

- Error analysis and conditioning of problems
- Linear systems (solvability, algorithms, stability, regularisation), and applications and modelling in VC and ML (e.g. linear regression, image alignment, deconvolution)
- Spectral methods (eigenvalue decomposition, singular value decomposition, respective algorithms), and their applications and modelling in VC and ML (e.g. clustering, Procrustes analysis, point-cloud alignment, principal components analysis)
- Numerical optimisation (gradient-based methods, second-order methods, large-scale optimisation) and applications and modelling in VC and ML.

Prerequisites

Recommended:

Participants are expected to have a high level of mathematical maturity (in particular, a good working knowledge of linear algebra and calculus/analysis is essential). A basic understanding of mathematical optimisation is advantageous.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved.

MA-INF 2318 Seminar Computational Medical Imaging

| Workload | Credit points | Duration | Frequency |
|--------------------------|----------------------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Thomas Schultz | Prof. Dr. Shadi Albarqouni | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

- Ability to understand, survey, and critically appraise current research results in computational medical imaging – including both classical algorithms and deep learning-based methods.
- Deepen one's grasp of topics such as medical image segmentation, registration, classification, uncertainty quantification, and bias/causality in medical images.
- Learn to extract the core contributions of a paper, identify strengths and limitations of proposed methods, and relate them to the state-of-the-art in the field.

Learning goals: soft skills

- Develop competence in independent literature search, paper selection, and reading state-of-the-art scientific publications.
- Acquire skills to present complex material in a didactically effective manner (both written and oral), including selecting appropriate visual media (slides, diagrams).
- Practice critical discussion and defense of one's assessments in a knowledgeable scientific audience.
- Manage one's time under relatively open assignments and long-ranging deadlines; formulate and accept constructive criticism.

Contents

Seminar topics cover recent research in computational medical imaging drawn from top journals and conferences. Typical subject areas include:

- Segmentation & Classification (e.g., anatomical structure delineation, lesion detection)
- Registration & Alignment (e.g., atlas-based, diffeomorphic registration)
- Quantitative Imaging & Radiomics (e.g., feature extraction from images, prognostic modeling)
- Uncertainty Quantification & Bias (e.g., Bayesian deep learning, causal analysis, dataset shift)
- Deep Learning Architectures (e.g., U-Nets, GANs, Vision Transformers)
- Ethical, Regulatory, and Clinical Translation Considerations

Relevant journals:

- Nature Machine Intelligence.
- Medical Image Analysis (MedIA).
- IEEE Transactions on Medical Imaging (TMI).
- European Radiology, Radiology: AI, IEEE Journal of Biomedical and Health Informatics.

Relevant conferences:

- MICCAI (Medical Image Computing & Computer-Assisted Intervention).
- IEEE/CVF Computer Vision and Pattern Recognition (CVPR).
- MIDL (Medical Imaging with Deep Learning).
- ISBI (International Symposium on Biomedical Imaging).
- RSNA (Radiological Society of North America Annual Meeting).

Prerequisites

Recommended:

At least one of the following:

- MA-INF 2222 – Visual Data Analysis.
- MA-INF 2312 – Image Acquisition and Analysis in Neuroscience.

A solid background in programming (preferably Python), as well as basic knowledge of linear algebra, probability, and numerical algorithms, is required.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation (20 minutes per student, including Q&A). Written seminar report (8–10 pages summarizing each student's topic and critical evaluation).

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

3 Information and Communication Management

| | | | | |
|-------------|------|------|---|-----|
| MA-INF 3108 | L2E2 | 6 CP | Secure Software Engineering | 89 |
| MA-INF 3109 | L2E2 | 6 CP | Quantum Algorithms: Introduction and Data Fusion Examples | 90 |
| MA-INF 3110 | Lab4 | 9 CP | Lab Basics of iOS-Development | 92 |
| MA-INF 3202 | L2E2 | 6 CP | Mobile Communication | 93 |
| MA-INF 3209 | Sem2 | 4 CP | Seminar Selected Topics in Communication Management | 94 |
| MA-INF 3216 | Sem2 | 4 CP | Seminar Sensor Data Fusion | 95 |
| MA-INF 3229 | Lab4 | 9 CP | Lab IT-Security | 96 |
| MA-INF 3233 | L2E2 | 6 CP | Advanced Sensor Data Fusion in Distributed Systems | 97 |
| MA-INF 3236 | L2E2 | 6 CP | IT Security | 98 |
| MA-INF 3237 | L2E2 | 6 CP | Array Signal and Multi-channel Processing | 100 |
| MA-INF 3238 | L2E2 | 6 CP | Side Channel Attacks | 101 |
| MA-INF 3239 | L2E2 | 6 CP | Malware Analysis | 102 |
| MA-INF 3241 | L3E1 | 6 CP | Practical Challenges in Human Factors of Security and Privacy | 104 |
| MA-INF 3242 | L2E2 | 6 CP | Security of Distributed and Resource-constrained Systems | 105 |
| MA-INF 3246 | L2E2 | 6 CP | Security in Digital Supply Chains | 106 |
| MA-INF 3304 | Lab4 | 9 CP | Lab Communication and Communicating Devices | 107 |
| MA-INF 3310 | L2E2 | 6 CP | Introduction to Sensor Data Fusion - Methods and Applications | 108 |
| MA-INF 3312 | Lab4 | 9 CP | Lab Sensor Data Fusion | 109 |
| MA-INF 3317 | Sem2 | 4 CP | Seminar Selected Topics in IT Security | 110 |
| MA-INF 3319 | Lab4 | 9 CP | Lab Usable Security and Privacy | 111 |
| MA-INF 3320 | Lab4 | 9 CP | Lab Security in Distributed Systems | 112 |
| MA-INF 3321 | Sem2 | 4 CP | Seminar Usable Security and Privacy | 113 |
| MA-INF 3322 | L2E2 | 6 CP | Applied Binary Exploitation | 114 |
| MA-INF 3323 | Lab4 | 9 CP | Lab Fuzzing | 115 |

MA-INF 3108 Secure Software Engineering

| Workload | Credit points | Duration | Frequency |
|-------------------------|------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Dr. Christian Tiefenau | Dr. Christian Tiefenau | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-3. | |

Learning goals: technical skills

The students will learn how to integrate security aspects into the phases of a Software Development Lifecycle. They will learn:

- Methods for identifying threats and vulnerabilities (threat modeling and risk analysis).
- How to design secure architectures using fundamental design principles (e.g., STRIDE).
- Secure coding practices and common vulnerability types.
- Key considerations when using cryptographic methods in software.
- How to assess the severity of a vulnerability.
- Best practices for system configuration, deployment, and maintenance.

Learning goals: soft skills

In the exercises, the students will conduct practical tasks to strengthen the understanding of the methods within the secure software engineering lifecycle. Through this, the abilities teamwork, organization and critical discussion of their own and others' results are strengthened.

Contents

- Threat modeling
- Risk analysis
- Architectural security
- Secure coding
- Applied Cryptography
- Secure configuration and deployment
- Updates and maintenance

Prerequisites

Recommended:

Basic knowledge of software engineering and IT Security-concepts is advantageous but not mandatory.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (90 minutes)

Ungraded coursework (required for admission to the exam)

none

Literature

Software Security: Building Security In by Gary McGraw

MA-INF 3109 Quantum Algorithms: Introduction and Data Fusion Examples

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Wolfgang Koch | Prof. Dr. Wolfgang Koch, Dr. Felix Govaers, Dr. Martin Ulmke | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Quantum algorithms for data fusion may become game changers as soon as quantum processing kernels embedded in hybrid processing architectures with classical processors will exist. While emerging quantum technologies directly apply quantum physics, quantum algorithms do not exploit quantum physical phenomena as such, but rather use the sophisticated framework of quantum physics to deal with “uncertainty”. Although the link between mathematical statistics and quantum physics has long been known, the potential of physics-inspired algorithms for data fusion has just begun to be realized. While the implementation of quantum algorithms is to be considered on classical as well as on quantum computers, the latter are anticipated as well-adapted “analog computers” for unprecedentedly fast solving data fusion and resources management problems. While the development of quantum computers cannot be taken for granted, their potential is nonetheless real and has to be considered by the international information fusion community.

Learning goals: soft skills

- Problem solving
- Adaptability
- Critical thinking

Contents

- Introduction with Examples
- Short introduction to quantum mechanics
- Introduction to quantum computing
- Quantum computing hardware
- Quantum inspired tracking
- Particle filtering and fermionic target tracking
- The data association problem
- Track extraction and sensor management
- Quantum computing for multi target tracking data association
- Quantum computing for resources management
- Quantum many particle systems and boson sampling
- Path Integrals

Prerequisites

Recommended:

One of the following:

- BA-INF 137 – Einführung in die Sensordatenfusion
- MA-INF 3310 – Introduction to Sensor Data Fusion - Methods and Applications

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

50% of the possible points for the exercises. The points are acquired by a small programming exercise with a workload of about 15 hours and some theoretical exercises with a workload of 10 hours. The solution has to be submitted individually or in groups of up to three students and will be rated by points.

MA-INF 3110 Lab Basics of iOS-Development

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Stephan Jonas | Prof. Dr. Stephan Jonas | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-3. | |

Learning goals: technical skills

Students acquire the ability to design and develop iOS applications while critically evaluating current research and best practices in mobile computing. They learn to compare different frameworks and architectural approaches, justify their decisions based on literature, and reflect on the advantages and limitations of various solutions. In addition to implementation, emphasis is placed on critical analysis and integration of current research findings, e.g., in the areas of usability, accessibility, performance, and security.

Students learn how to conduct literature research related to digital medicine application development and to critically evaluate scientific sources in mobile app development and human-computer interaction. They learn to document and justify design and development decisions with reference to scientific findings and empirical evidence. Furthermore, students learn to communicate results in a scientifically grounded project report and oral presentation.

Learning goals: soft skills

- Self-competences: Work and time management, handling feedback, and adapting to changing requirements.
- Develop scientific thinking and research literacy by critically evaluating sources, documenting decisions, and reflecting on the app development process in an evidence-based manner.

Contents

- Usage of Xcode
- Basic understanding of the programming language Swift.
- UI development with SwiftUI.
- Design of User Interfaces and Prototyping.
- Local data persistence on the devices.
- Git: Branches, Pull Requests, Code Review.

Prerequisites

Recommended:

Experience in object-oriented programming

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation (individually graded), written project documentation / report.

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Forms of media

Projection, videos, interactive exercises.

The lectures and exercises are based on interaction. We expect active participation! To take part in the exercises, a MacBook (with macOS 15 or later) is required. Please bring your own device or contact us in advance if you need to borrow one.

Literature

- Human Interface Guidelines (<https://developer.apple.com/design/human-interface-guidelines>).
- SwiftUI Dokumentation (<https://developer.apple.com/documentation/swiftui/>).

MA-INF 3202 Mobile Communication

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|-------------------------|---|
| Prof. Dr. Peter Martini | Prof. Dr. Peter Martini, Dr. Matthias Frank |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 1. or 2. |

Learning goals: technical skills

After completion of the module students will be able to cope with challenges and problems arising in design and operation of wireless and mobile communication systems. They can choose suitable protocols or design new ones. They are able to select mechanisms from different architectural layers, integrate them into a new complete architecture and justify their selection and integration decisions.

Learning goals: soft skills

Theoretical exercises support in-depth understanding of lecture topics and stimulate discussions; practical exercises in teamwork support time management, targeted organisation of practical work and critical discussion of own and others' results

Contents

Mobility Management in the Internet, Wireless Communication Basics, Wireless Networking Technologies (like Bluetooth, Wireless LAN, LoRa/LoRaWAN, focus on system architecture and medium access), Cellular/Mobile Communication Networks (voice and data communication, 2G, 4G, ...).

Prerequisites

Recommended:

Bachelor level knowledge of basics of communication systems and Internet protocols. Students may receive access to lecture slides in English language of our Bachelor module BA-INF 101 "Kommunikation in Verteilten Systemen" as a reference. Contact the lecturer in advance of the course, and information will also be given in the first lecture.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|-------------|-----|---------------------------|
| Lecture | | 2 | 30 T / 45 S | 2.5 | T = face-to-face teaching |
| Exercises | | 2 | 30 T / 75 S | 3.5 | S = independent study |

Graded exams

Written exam (90 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. A total of 50% of the points must be achieved. For 70% of the exercise sheets, 20% of the points must be achieved for each sheet.

Literature

- Jochen Schiller: Mobile Communications, Addison-Wesley, 2003
- William Stallings: Wireless Communications and Networking, Prentice Hall, 2002
- Further up-to-date literature will be announced in due course before the beginning of the lecture

MA-INF 3209 Seminar Selected Topics in Communication Management

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|----------------|
| 120 h | 4 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Peter Martini | Prof. Dr. Peter Martini, Prof. Dr. Michael Meier, Dr. Matthias Frank | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in the area of communication systems and Internet protocols.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of the corresponding research area; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media in a way that adheres to academic standards, that is well-structured and didactically effective, and that motivates the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

Current research topics in communication systems and Internet protocols based on conference and journal papers.

Prerequisites

Recommended:

Successful completion of at least one of the following lectures:

- MA-INF 3202 Mobile Communication
- MA-INF 3236 IT Security
- MA-INF 3239 Malware Analysis

Bachelor level knowledge of basics of communication systems and Internet protocols, e.g. OSI model, medium access of wired and wireless LAN technologies, IP addressing and routing, transport protocols UDP and TCP.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

The relevant literature will be announced towards the end of the previous semester

MA-INF 3216 Seminar Sensor Data Fusion

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Wolfgang Koch | Prof. Dr. Wolfgang Koch, Dr. Felix Govaers | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in state estimation and object tracking.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of the corresponding research area; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media in a way that adheres to academic standards, that is well-structured and didactically effective, and that motivates the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

The seminar focuses on specific research papers in the field of sensor data fusion, which may include topics like non-linear state estimation, deep learning for sensor perception, or multi object tracking.

Prerequisites

Recommended:

- MA-INF 3310 Introduction to Sensor Data Fusion – Methods and Applications.
- It is assumed that the participants know linear algebra and have basic knowledge in probability theory.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

The relevant literature will be announced at the beginning of the seminar.

MA-INF 3229 Lab IT-Security

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Michael Meier | Prof. Dr. Michael Meier | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

After completion of the lab module students have completed a practical task in the context of IT security. The students will have gained experience in the typical technical skills like the design and implementation of software, test and documentation of the software, and performance evaluation (e.g. by measurements, simulation, analysis) and presentation of performance results.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time; to aim at long-range goals under limited resources; to work under pressure.

Contents

Selected topics close to current research in the area of IT security.

Prerequisites

Recommended:

Foundational knowledge in

- IT security: security terminology, authentication, access control, applied cryptography (symmetric encryption, asymmetric encryption, hashing, key management)
- Networks: OSI model, addressing, routing, protocols.

It is recommended to take MA-INF 3236 IT Security first.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 3233 Advanced Sensor Data Fusion in Distributed Systems

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Wolfgang Koch | Dr. Felix Govaers | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Students will be able to describe the advanced principles of sensor data fusion for state estimation and object tracking based on tracks from multiple sensors in distributed systems. They will be aware of the correlation problem in track-to-track fusion and know several algorithms to cope with it. They will know the assumptions, advantages and disadvantages of different algorithms and be able to select and apply suitable candidates in practical applications.

Learning goals: soft skills

Mathematical derivation of algorithms, application of mathematical results on estimation theory.

Contents

Tracklet fusion, the Bar-Shalom-Campo formula, the Federated Kalman Filter, naive fusion, the distributed Kalman filter and the least squares estimate, Accumulated State Densities, Decorrelated fusion, product representation.

For challenging state estimation tasks, algorithms which enhance the situational awareness by fusing sensor information are inevitable. Nowadays it has become very popular to improve the performance of systems by linking multiple sensors. This implies some challenges to the sensor data fusion methodologies such as sensor registration, communication delays, and correlations of estimation errors. In particular, if the communication links have limited bandwidth, data reduction techniques have to be applied at the sensor sites, that is local tracks have to be computed. Once received at a fusion center (FC), the tracks then are fused to reconstruct a global estimate.

Prerequisites

Recommended:

Basic knowledge about the Kalman filter is required (see also recommended literature).

Students who did not take BA-INF 137 – Einführung in die Sensordatenfusion in their Bachelor's are advised to first take MA-INF 3310 – Introduction to Sensor Data Fusion - Methods and Applications.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam (30 minutes)

Ungraded coursework (required for admission to the exam)

50% of the maximum achievable points in the practical programming exercises are required. There is one practical exercise, which is a workload of about 15h. The delivery of the programmed solution is done individually or in group work of up to three students. A total of 10 points will be awarded, 50% of which will have been achieved if the Distributed Kalman filter has been programmed in an executable and consistent manner.

Forms of media

Power Point

Literature

W. Koch: "Tracking and Sensor Data Fusion: Methodological Framework and Selected Applications", Springer, 2014.
D. Hall, C.-Y. Chong, J. Llinas, and M. L. II: "Distributed Data Fusion for Network-Centric Operations", CRC Press, 2014.

MA-INF 3236 IT Security

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Michael Meier | Prof. Dr. Michael Meier | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Knowledge of a variety of active research fields in IT security including motivation, challenges and objectives in these fields as well as selected fundamental knowledge and methods helping students to deepen their knowledge in their upcoming studies. In detail, participants will know

- advanced cryptographic constructions and low-level programming in offensive and defensive scenarios;
- how to apply program analysis techniques to IT security;
- how to achieve security by and security of methods from the area of machine learning.

Learning goals: soft skills

Working in small groups on exercises, critical discussion of own and others' results, time management, transferring theoretical knowledge to practical scenarios

Contents

The contents vary but usually include

- Privacy
- Cryptographic Protocols
- Network Security
- Supply Chain Attacks
- Management of Identity Data
- Low-level software analysis
- Software testing
- Side Channel Attacks
- Anomaly Detection
- Human Factor in Security

Prerequisites

Recommended:

Foundational knowledge in

- IT security: security terminology, authentication, access control, applied cryptography (symmetric encryption, asymmetric encryption, hashing, key management)
- Low-level/OS-level programming: x86 assembly, C programming, OS-level programming for Linux, buffer overflows, sockets
- Networking: OSI model, modulation, addressing, routing, udp, tcp

You find useful information on these topics in the following books (available through library search portal bonnus):

- M. Bishop: Computer Security: Art and Science, Pearson Education, 2018.
- J. Streib: Guide to Assembly Language: A Concise Introduction. Springer, 2020.
- W. Stevens: UNIX Network Programming – The Sockets Networking API, Prentice Hall International, 3rd Edition, 2003
- Tanenbaum: Computer Networks, Pearson Education, 4th Edition, 2002

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. For 70% of the exercise sheets, 50% of the points must be achieved for each sheet.

MA-INF 3237 Array Signal and Multi-channel Processing

| Workload | Credit points | Duration | Frequency |
|-------------------------|-----------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Wolfgang Koch | Dr. Marc Oispuu | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-3. | |

Learning goals: technical skills

Students will be able to describe the central principles of array signal and multi-channel processing and to name their advantages and disadvantages as well as to illustrate their relevance in application examples such as wireless communication, acoustics, radar, sonar or seismology. Furthermore, they will be able to implement suitable methods of direction finding, spatial filtering and bearings-only localization and to apply them to electromagnetic or acoustic signals and to evaluate the achieved results in terms of their performance.

Learning goals: soft skills

Mathematical derivation of algorithms, applications of mathematical results on estimation theory

Contents

Estimation theory, Sensor model, Cramér-Rao analysis, conventional beamforming, Multiple Signal Classification (MUSIC), sensor calibration, Bearings-only localization, Direct Position Determination (DPD), Applications

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral Exam (30 minutes)

Ungraded coursework (required for admission to the exam)

50% of the maximum achievable points in the practical programming exercises are required. There is one practical exercise, which is a workload of about 10h. The delivery of the programmed solution is done individually or in group work of up to three students. A total of 10 points will be awarded, 50% of which will have been achieved if the basic signal processing algorithms for array sensors have been implemented.

Forms of media

Power Point

Literature

H. L. van Trees, Optimum Array Processing. Part IV of Detection, Estimation, and Modulation Theory. New York: Wiley-Interscience, 2002.

MA-INF 3238 Side Channel Attacks

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|--------------------|----------------|
| Dr. Felix Boes | Dr. Felix Boes |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2. or 3. |

Learning goals: technical skills

- Students are introduced to theoretical and practical side channel effects of modern hardware.
- Students learn techniques to utilize these effects to circumvent security mechanisms.
- This includes covert channels as well as side channel attacks and microarchitectural attacks on modern CPUs.

Learning goals: soft skills

Theoretical exercises to support in-depth understanding of lecture topics and to stimulate discussions, practical exercises in teamwork to support time management, targeted organization of practical work and critical discussion of own and others' results.

Contents

- Theoretical foundations of side channel effects and attacks as well as
- covert channels,
- differential power analysis,
- padding oracle,
- RSA timing attacks,
- cache based side channel effects,
- microarchitectural attacks (Spectre)

Prerequisites

Recommended:

Fundamental knowledge about IT Security, operating systems and statistics is advantageous but not mandatory.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written Exam (90 minutes)

Ungraded coursework (required for admission to the exam)

Participation in two achievement tests. In total, at least 50% of the points must be achieved on these tests.

MA-INF 3239 Malware Analysis

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Peter Martini | Prof. Dr. Elmar Padilla | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

The students should be able to analyze the functional scope of a binary file independently and to describe its damage potential. In addition, the students should be able to carry out detailed analyzes of given aspects and to partially automate these with the help of scripts.

Learning goals: soft skills

Presentation of solutions and methods, critical discussion of applied methods and techniques.

Contents

In the course, the skills acquired so far in binary analysis will first be deepened and adapted to the peculiarities of malware analysis. Different malware samples are used to explain the techniques used by malware authors. These priorities include:

- Characteristics of malware
- Persistence
- Network communication
- Encryption
- Dynamic malware analysis
- Debugging
- Behavioral obfuscation
- Virtual analysis environments
- Static malware analysis
- Control flow obfuscation
- Automation of common analysis steps
- Reconstruction of binary algorithms

The event begins with several lectures that provide the basics for the students to work independently later. In the course of this, the students will work on practical topics from the field of malware analysis during the semester. Since these subject areas can turn out to be very specific, it is necessary to be willing to deal with the subject outside of the lecture and exercise times.

Prerequisites

Recommended:

Basic knowledge of operating systems (kernel, threads, virtual memory), network communication (protocols, architectures), binary analysis (assembler, endianness, semantic gap, coding), software development (programming, semantics, scripting in Python)

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral exam (30 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved.

Literature

The relevant literature will be announced at the beginning of the lecture

MA-INF 3241 Practical Challenges in Human Factors of Security and Privacy

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Matthew Smith | Prof. Dr. Matthew Smith | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-3. | |

Learning goals: technical skills

Students are introduced to a variety of current challenges in security and privacy which contain human aspects and have societal relevance. Students learn about the motivation, challenges and objectives in these areas and select one for the semester topic. They then learn how to design, conduct and evaluate user studies to tackle the selected challenge. Additionally, they get to know selected fundamental knowledge and methods helping them to deepen their knowledge on human factors research.

Learning goals: soft skills

Breaking down complex topics into manageable components, critical discussion of own and others' results, time management, transferring theoretical knowledge to practical scenarios

Contents

The course begins with several lectures that provide an overview and discussion of current societal challenges in the area of human factors in security and privacy. The students will select a semester topic and together with the lecturer explore this topic using user studies. Since these subject areas can turn out to be very specific, it is beneficial to be willing to deal with the subject outside of the lecture and exercise times. Topics can include surveillance, age verification, anonymity, online abuse, fake news, etc.

Prerequisites

Recommended:

It is recommended that students have experience with designing and evaluating survey and interview-based user studies. It is recommended to check the material of BA-INF 145 Usable Security and Privacy (available in English).

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Lecture | | 1 | 15 T / 45 S | 2 | |
| Exercises | | 3 | 45 T / 75 S | 4 | |

Graded exams

electronic exam (90 minutes, pass/fail)

Ungraded coursework (required for admission to the exam)

The participation in at least 80% of regularly provided exercises.

MA-INF 3242 Security of Distributed and Resource-constrained Systems

| Workload | Credit points | Duration | Frequency |
|-------------------------|----------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Michael Meier | Dr. Thorsten Aurisch | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Ability to understand and analyse theoretical and practical cyber security challenges of distributed and resource-constrained systems, as well as the ability to select and apply appropriate solutions.

Learning goals: soft skills

Working in small groups on exercises, critical discussion of own and others' results, time management, transferring theoretical knowledge to practical scenarios.

Contents

- Group communication with IP multicast
- Group key management
- Broadcast encryption
- Public key infrastructure
- Web of trust
- Multicast infrastructure protection
- Distributed security mechanisms
- Cyber resilience in groups
- Distributed ledger technology
- Cyber security in software-defined networks
- Artificial intelligence in cyber security
- Security for IoT

Prerequisites

Recommended:

Foundational knowledge in

- IT security: security terminology, authentication, access control, applied cryptography (symmetric encryption, asymmetric encryption, hashing, key management)
- Low-level/OS-level programming: x86 assembly, C programming, OS-level programming for Linux, buffer overflows, sockets
- Networking: OSI model, modulation, addressing, routing, udp, tcp

You find useful information on these topics in the following books (available through library search portal bonnus):

- M. Bishop: Computer Security: Art and Science, Pearson Education, 2018.
- J. Streib: Guide to Assembly Language: A Concise Introduction. Springer, 2020.
- W. Stevens: UNIX Network Programming – The Sockets Networking API, Prentice Hall International, 3rd Edition, 2003
- Tanenbaum: Computer Networks, Pearson Education, 4th Edition, 2002

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|-------------|-----|---------------------------|
| Lecture | | 2 | 30 T / 45 S | 2.5 | T = face-to-face teaching |
| Exercises | | 2 | 30 T / 75 S | 3.5 | S = independent study |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

Participation in an achievement test. At least 50% of the points must be achieved on this test.

MA-INF 3246 Security in Digital Supply Chains

| Workload | Credit points | Duration | Frequency |
|-------------------------|---------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Dr. Marc Ohm | Dr. Marc Ohm | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-3. | |

Learning goals: technical skills

This module introduces the challenges and risks of digital supply chains in the context of cybersecurity. It focuses on recent developments in the software supply chain and the artificial intelligence supply chain. Additionally, it will present threat intelligence methodologies.

Learning goals: soft skills

Presentation of solutions and methods, critical discussion of own and others' results.

Contents

- Threat Actors
- Threat Intelligence
- Attack vector of Software Supply Chains
- Adversarial Machine Learning
- Prevention and mitigation strategies
- Regulations and compliance

Prerequisites

Recommended:

- MA-INF 3236 IT-Security
- MA-INF 4204 Technical Neural Nets

An understanding of the basic concepts of software development, artificial intelligence and IT security.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|-------------|-----|---------------------------|
| Lecture | | 2 | 30 T / 45 S | 2.5 | T = face-to-face teaching |
| Exercises | | 2 | 30 T / 75 S | 3.5 | S = independent study |

Graded exams

Written exam

Ungraded coursework (required for admission to the exam)

Participation in a performance test. At least 50% of the points must be achieved on this test.

MA-INF 3304 Lab Communication and Communicating Devices

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Peter Martini | Prof. Dr. Peter Martini, Prof. Dr. Michael Meier, Dr. Matthias Frank | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

After completion of the lab module students have completed a practical task in the context of communication and networked systems. The students will have gained experience in the typical technical skills like the design and implementation of communication software/networked systems, test and documentation of the software, and performance evaluation (e.g. by measurements, simulation, analysis) and presentation of performance results.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time; to aim at long-range goals under limited resources; to work under pressure.

Contents

Selected topics close to current research in the area of communication systems, network security, mobile communication and communicating devices.

Prerequisites

Recommended:

Foundational knowledge in networks: OSI model, addressing, routing, protocols;

Successful completion of at least one of the following lectures:

- MA-INF 3202 Mobile Communication
- MA-INF 3236 IT Security
- MA-INF 3239 Malware Analysis

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

The relevant literature will be announced towards the end of the previous semester.

MA-INF 3310 Introduction to Sensor Data Fusion - Methods and Applications

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Wolfgang Koch | Prof. Dr. Wolfgang Koch | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Students will be able to describe the central principles of sensor data fusion for state estimation and object tracking based on error-prone and ambiguous measurements. They will be able to apply the Kalman filter and to formulate sensor and dynamics models for different kind of sensors and objects. Furthermore, they will know the concept of probabilistic data association and a computationally feasible approximation using Gaussian mixture densities.

Learning goals: soft skills

Mathematical derivation of algorithms, application of mathematical results on estimation theory.

Contents

Gaussian probability density functions, Kalman filter, Unscented Kalman Filter, Extended Kalman Filter, Particle Filter, Multi-Hypothesis-Tracker, Extended Target Tracking, Road Tracking, Interacting Multiple Model Filter, Retrodiction, Smoothing, Maneuver Modeling.

The lecture starts with preliminaries on how to handle uncertain data and knowledge within analytical calculus. Then, the fundamental and well-known Kalman filter is derived. Based on this tracking scheme, further approaches to a wide spectrum of applications will be shown. All algorithms will be motivated by examples from ongoing research projects, industrial cooperations, and impressions of current demonstration hardware.

Because of inherent practical issues, every sensor measures certain properties up to an error. This lecture shows how to model and overcome this error by an application of theoretical tools such as Bayes' rule and further derivations. Moreover, solutions to possible false-alarms, miss-detections, maneuvering phases, and much more will be presented.

Prerequisites

Recommended:

It is assumed that the participants know linear algebra and have basic knowledge in probability theory.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|-------------|-----|---------------------------|
| Lecture | | 2 | 30 T / 45 S | 2.5 | T = face-to-face teaching |
| Exercises | | 2 | 30 T / 75 S | 3.5 | S = independent study |

Graded exams

Oral exam

Ungraded coursework (required for admission to the exam)

50% of the possible points for the exercises. The points are acquired by a small programming exercise with a workload of about 15 hours and some theoretical exercises with a workload of 10 hours. The solution has to be submitted individually or in groups of up to three students and will be rated by points.

Literature

- W. Koch: "Tracking and Sensor Data Fusion: Methodological Framework and Selected Applications", Springer, 2014.
- Y. Bar-Shalom: "Estimation with Applications to Tracking and Navigation", Wiley-Interscience, 2001.

MA-INF 3312 Lab Sensor Data Fusion

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Wolfgang Koch | Prof. Dr. Wolfgang Koch | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in state estimation and object tracking.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time; to aim at long-range goals under limited resources; to work under pressure.

Contents

In the lab, the students apply methods from the sensor data fusion and state estimation theory to practical examples in order to get experience in the application and implementation. The exemplary scenarios and application examples vary each year but may be for instance on a simulated radar network for multi object tracking, camera image processing, heterogeneous sensor fusion, or array sensor bearing processing.

The students shall work together in a team. Everyone is responsible for a specific part in the context of a main goal. Results will be exchanged and integrated via software interfaces.

Prerequisites

Recommended:

- MA-INF 3310 Introduction to Sensor Data Fusion – Methods and Applications;
- knowledge of linear algebra and basic knowledge in probability theory.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

The relevant literature will be announced at the beginning of the lab.

MA-INF 3317 Seminar Selected Topics in IT Security

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|----------------|
| 120 h | 4 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Michael Meier | Prof. Dr. Michael Meier, Prof. Dr. Peter Martini | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in the area of IT Security.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of the corresponding research area; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media in a way that adheres to academic standards, that is well-structured and didactically effective, and that motivates the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

Current research topics in IT security based on conference and journal papers.

Prerequisites

Recommended:

Foundational knowledge in

- IT security: security terminology, authentication, access control, applied cryptography (symmetric encryption, asymmetric encryption, hashing, key management)
- Networks: OSI model, addressing, routing, protocols.

It is recommended to take MA-INF 3236 IT Security first.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 3319 Lab Usable Security and Privacy

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Matthew Smith | Prof. Dr. Matthew Smith | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Ability to carry out a practical task (project) in the context of human factors of security and privacy, including user studies and their evaluation. This includes selecting variables of interest, designing measurement instruments, such as interviews, surveys or prototypes, recruiting participants, executing and evaluating the user-study.

Learning goals: soft skills

Ability to work in small teams and cooperate with other teams in a group; ability to make design decisions in a practical task; present and discuss (interim and final) results in the team/group and to other students; prepare written documentation of the work carried out

Contents

The students will select and carry out a practical task (project) in the context of human factors of security and privacy, including user studies and their evaluation. Topics for the project are close to current research in the area of human aspects of security and privacy. Focus topics include but are not limited to: Attitudes towards Surveillance, S&P Ethics, Privacy technology, Authentication, Encryption, Gamification, Age verification, etc.

Prerequisites

Recommended:

Knowledge on how to run and evaluate user studies is required. It is recommended to check the material of the Bachelor's course BA-INF 145 Usable Security and Privacy (available in English) and to take:

- MA-INF 3241 Practical Challenges in Human Factors of Security and Privacy.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 3320 Lab Security in Distributed Systems

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Matthew Smith | Prof. Dr. Matthew Smith | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Ability to carry out a practical task (project) in the context of distributed security using modern software engineering processes, including testing and documentation of the implemented software/system.

Learning goals: soft skills

Ability to work in small teams and cooperate with other teams in a group; ability to make design decisions in a practical task; present and discuss (interim and final) results in the team/group and to other students; prepare written documentation of the work carried out.

Contents

The students will carry out a practical task (project) in the context of distributed security, including documentation of the implemented software/system. Topics are selected topics close to current research in the area of distributed systems security and privacy. Focus topics include but are not limited to: Authentication, Encryption, Gamification, Age verification, Data management, Study platforms, etc. The students will build software systems using modern software engineering processes. They will test them either programmatically or with a small user studies. They will document their software.

Prerequisites

Recommended:

Strong programming skills are required. It is recommended to take MA-INF 3242 Security of Distributed and Resource-constrained Systems first.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 3321 Seminar Usable Security and Privacy

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|----------------|
| 120 h | 4 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Matthew Smith | Prof. Dr. Matthew Smith | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in the area of human aspects of security and privacy.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of the corresponding research area; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media in a way that adheres to academic standards, that is well-structured and didactically effective, and that motivates the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

Current conference and journal papers in the area of human aspects of security and privacy. This includes but is not limited to: Attitudes towards Surveillance, S&P Ethics, Privacy technology, Authentication, Encryption, Gamification, Age verification, etc.

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 3322 Applied Binary Exploitation

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Peter Martini | Prof. Dr. Elmar Padilla | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-3. | |

Learning goals: technical skills

recognition of vulnerabilities in binary programs, static reverse engineering of binary programs (Ghidra, IDA Free, Linux command line tools), debugging of binary programs with gdb/pwndbg, Python programming with pwntools, application of exploit strategies such as overwriting return addresses/function pointers, return-oriented programming (ROP, SROP, ret2csu), shellcoding, glibc heap exploitation techniques (Use-After-Free, Unlink Exploit, House of Orange), understanding a complex real-world exploit, usage of git/GitLab and Docker for the exercises.

Learning goals: soft skills

Frustration tolerance when working with binary representations and trying to apply taught techniques, focused working on technically challenging problems, simultaneously applying knowledge from different areas of computer science.

Contents

This university course covers various topics related to software security and exploitation techniques. It starts with an introduction to finding vulnerabilities in C programs and binaries. The course then delves into stack-based buffer overflows and the mitigations used to prevent them. Students will also learn about circumventing these mitigations and explore return-oriented programming. The course continues with a focus on manual crafting of shellcode and understanding the internals of the glibc heap. Students will gain knowledge about heap exploitation techniques, including use-after-free exploits, heap unlink exploits, and the house of orange exploit. The course concludes with a complex case study on the Exim RCE exploit, providing students with a practical understanding of real-world vulnerabilities. Additionally, guest lectures will be held to provide further insights into the field of software security.

Please note that basic skills in static and dynamic binary analysis (e. g. read disassembled/decompiled code or debug a binary program with gdb) are required to successfully participate in this lecture.

Prerequisites

Recommended:

- Binary Analysis skills (as taught in the Bachelor's module BA-INF 155 Angewandte Binäranalyse; English slides available)
- Basic knowledge of the Linux operating system
- System Programming skills in C
- Basic Python programming skills

This module is best taken after or together with MA-INF 3239 Malware Analysis.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Oral Examination (30 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. The exercises are divided into group tasks and tasks to be completed individually. For each category of tasks, at least 50% of the points must be achieved.

Literature

The relevant literature will be announced at the beginning of the lecture

MA-INF 3323 Lab Fuzzing

| Workload | Credit points | Duration | Frequency | | |
|--|------------------------|------------|--------------|----|--|
| 270 h | 9 CP | 1 semester | every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Prof. Dr. Matthew Smith | Dr. Christian Tiefenau | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. or 3. | | | |
| Learning goals: technical skills | | | | | |
| The students will carry out a practical task (project) in the context of fuzz testing, including test and documentation of the implemented software/system. | | | | | |
| Learning goals: soft skills | | | | | |
| Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify ones own results into the state-of-the-art of the resp. area | | | | | |
| Contents | | | | | |
| The lab aims at understanding and extending current fuzzers (AFL++, libFuzzer, syzkaller, kafi and Jazzer). | | | | | |
| Prerequisites | | | | | |
| none | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Lab | 8 | 4 | 60 T / 210 S | 9 | |
| Graded exams | | | | | |
| Oral presentation, written report | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6). | | | | | |

4 Intelligent Systems

| | | | | |
|-------------|------|------|---|-----|
| MA-INF 4111 | L2E2 | 6 CP | Principles of Machine Learning | 117 |
| MA-INF 4112 | L2E2 | 6 CP | Algorithms for Data Science | 119 |
| MA-INF 4113 | L2E2 | 6 CP | Cognitive Robotics | 120 |
| MA-INF 4114 | L2E2 | 6 CP | Robot Learning | 121 |
| MA-INF 4115 | L3E1 | 6 CP | Introduction to Natural Language Processing | 122 |
| MA-INF 4116 | Sem2 | 4 CP | Seminar AI Ethics | 124 |
| MA-INF 4117 | L2E2 | 4 CP | Mining Media Data I | 125 |
| MA-INF 4201 | L2E2 | 6 CP | Artificial Life | 126 |
| MA-INF 4204 | L2E2 | 6 CP | Technical Neural Nets | 127 |
| MA-INF 4208 | Sem2 | 4 CP | Seminar Vision Systems | 129 |
| MA-INF 4209 | Sem2 | 4 CP | Seminar Principles of Data Mining and Learning Algorithms | 130 |
| MA-INF 4211 | Sem2 | 4 CP | Seminar Cognitive Robotics | 131 |
| MA-INF 4213 | Sem2 | 4 CP | Seminar Humanoid Robots | 132 |
| MA-INF 4214 | Lab4 | 9 CP | Lab Humanoid Robots | 133 |
| MA-INF 4215 | L2E2 | 6 CP | Humanoid Robotics | 134 |
| MA-INF 4216 | L2E2 | 6 CP | Biomedical Data Science and AI | 135 |
| MA-INF 4217 | Sem2 | 4 CP | Seminar Machine Learning Methods in the Life Sciences | 136 |
| MA-INF 4226 | Lab4 | 9 CP | Lab Parallel Computing for Mobile Robotics | 137 |
| MA-INF 4228 | L4E2 | 9 CP | Foundations of Data Science | 138 |
| MA-INF 4230 | L2E2 | 6 CP | Advanced Methods of Information Retrieval | 139 |
| MA-INF 4231 | Sem2 | 4 CP | Seminar Advanced Topics in Information Retrieval | 141 |
| MA-INF 4232 | Lab4 | 9 CP | Lab Information Retrieval in Practice | 142 |
| MA-INF 4235 | L2E2 | 6 CP | Reinforcement Learning | 143 |
| MA-INF 4236 | L2E2 | 4 CP | Advanced Methods for Text Mining | 144 |
| MA-INF 4237 | Lab4 | 9 CP | Lab Natural Language Processing | 146 |
| MA-INF 4238 | L2E2 | 6 CP | Dialog Systems | 147 |
| MA-INF 4240 | Lab4 | 9 CP | Lab Hybrid Learning and Applications | 149 |
| MA-INF 4241 | Lab4 | 9 CP | Lab Cognitive Modelling of Biological Agents | 151 |
| MA-INF 4242 | L2E2 | 6 CP | Self-supervised Learning | 152 |
| MA-INF 4243 | L2E2 | 4 CP | Mining Media Data II | 153 |
| MA-INF 4304 | Lab4 | 9 CP | Lab Cognitive Robotics | 154 |
| MA-INF 4306 | Lab4 | 9 CP | Lab Development and Application of Data Mining and Learning Systems | 155 |
| MA-INF 4308 | Lab4 | 9 CP | Lab Vision Systems | 156 |
| MA-INF 4322 | Lab4 | 9 CP | Lab Machine Learning on Encrypted Data | 157 |
| MA-INF 4324 | Sem2 | 4 CP | Seminar Advanced Topics in Data Science | 158 |
| MA-INF 4325 | Lab4 | 9 CP | Lab Data Science in Practice | 159 |
| MA-INF 4326 | L2E2 | 6 CP | Explainable AI and Applications | 160 |
| MA-INF 4327 | Lab4 | 9 CP | Lab Biomedical Data Science | 162 |
| MA-INF 4328 | L2E2 | 6 CP | Spatio-Temporal Data Analytics | 163 |
| MA-INF 4329 | Sem2 | 4 CP | Seminar Biological Intelligence | 164 |
| MA-INF 4330 | Lab4 | 9 CP | Lab Explainable AI and Applications | 165 |
| MA-INF 4331 | Lab4 | 9 CP | Lab Perception and Learning for Robotics | 167 |
| MA-INF 4332 | Sem2 | 4 CP | Seminar Large Language Models | 168 |
| MA-INF 4333 | L2E2 | 6 CP | Geometric Deep Learning | 169 |
| MA-INF 4334 | L2E2 | 6 CP | Computational neuroscience: cognition and behaviour | 170 |
| MA-INF 4335 | Lab4 | 9 CP | Lab AI Alignment | 171 |
| MA-INF 4336 | Sem2 | 4 CP | Seminar Selected Topics in Natural Language Processing | 173 |

MA-INF 4111 Principles of Machine Learning

| Workload | Credit points | Duration | Frequency |
|------------------------------------|------------------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr.-Ing. Christian Bauckhage | Prof. Dr.-Ing. Christian Bauckhage | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1-2. | |

Learning goals: technical skills

Upon successful completion of this module, students should be able to describe fundamental methods, algorithms, and use cases of machine learning. Students acquire knowledge about supervised and unsupervised learning; based on the knowledge and skills acquired, students should be able to

- Implement, algorithms for optimization and parameter estimation in model training and machine learning tasks.
- Adopt the fundamental methods they learned about to a wide range of problems in automated intelligent data analysis.

Learning goals: soft skills

In the exercises, students can put their knowledge about theoretical concepts, mathematical methods, and algorithmic approaches into practice and realize small projects involving the implementation and evaluation of machine learning algorithms. This requires teamwork; upon successful completion of the module, students should be able to

- draft and implement basic machine learning algorithms for various practical problem settings
- prepare and give oral presentations about their work in front of an audience

Contents

Fundamental machine learning models for classification and clustering, model training via minimization of loss functions, fundamental optimization algorithms, model regularization, kernel methods for supervised and unsupervised learning, probabilistic modeling and inference, dimensionality reduction and latent factor models, the basic theory behind neural networks and neural network training; This course is intended to lay the foundation for more advanced courses on modern deep learning and reinforcement learning.

Prerequisites

Recommended:

Linear algebra, statistics, probability theory, calculus, python programming

Remarks

At most 150 participants.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | 150 | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to five students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Forms of media

- lecture slides / lecture notes are made available online
- notebooks with programming examples are made available online

Literature

- D.J.C MacKay: Information Theory, Inference and Learning Algorithms, Cambridge University Press, 2003
 - C.M. Bishop: Pattern Recognition and Machine Learning, Springer, 2006
 - S. Haykin: Neural Networks and Learning Machines, Pearson, 2008
-

MA-INF 4112 Algorithms for Data Science

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Stefan Wrobel | Dr. Tamas Horvath, Prof. Dr. Stefan Wrobel | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

In this module the students will learn algorithms for data science as well as implement and practice selected algorithms from this field. The module concentrates on basic algorithms in association rule mining, graph mining, and data streams. At the end of the module, students will be capable of analyzing formal properties of this kind of algorithms and choosing appropriate pattern discovery and data stream algorithms.

Learning goals: soft skills

Communicative skills (oral and written presentation of solutions, discussions in teams), self-competences (ability to accept and formulate criticism, ability to analyse, creativity in the context of an "open end" task), social skills (effective team work and project planning).

Contents

The module is offered every year, each time concentrating on one or more specific issues, such as frequent, closed and maximal frequent itemset mining, frequent subgraph mining algorithms for forests and for other graph classes beyond forests, frequent items and frequency moments in data streams, and graph stream algorithms.

Prerequisites

Recommended:

Knowledge of standard notions and results from complexity theory, propositional logic, hashing, probability theory, and calculus, all on the bachelor level, are required.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | T = face-to-face teaching S = independent study |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to five students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Forms of media

lectures, exercises

Literature

- Avrim Blum, John Hopcroft, Ravindran Kannan: Foundations of Data Science. Cambridge University Press, 2020.
- Jiawei Han, Micheline Kamber, Jian Pei: Data Mining: Concepts and Techniques. Morgan Kaufmann Publishers, 2012.
- David J. Hand, Heikki Mannila and Padhraic Smyth: Principles of Data Mining. The MIT Press, 2001.

MA-INF 4113 Cognitive Robotics

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Sven Behnke | Prof. Dr. Sven Behnke, Prof. Dr. Maren Bennewitz | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

This lecture is one of two introductory lectures on Robotics of the intelligent systems track. The lecture covers cognitive capabilities of robots, like self-localization, mapping, object perception, and action-planning in complex environments.

This module complements MA-INF 4114 and can be taken before or after that module.

Learning goals: soft skills

Communicative skills (oral and written presentation of solutions, discussions in small teams), self competences (ability to accept and formulate criticism, ability to analyze problems)

Contents

Probabilistic approaches to state estimation (Bayes Filters, Kalman Filter, Particle Filter), motion models, sensor models, self-localization, mapping with known poses, simultaneous mapping and localization (SLAM), iterated closest-point matching, path planning, place- and person recognition, object recognition.

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved.

Literature

- S. Thrun, W. Burgard and D. Fox: Probabilistic Robotics. MIT Press, 2005.
- B. Siciliano, O. Khatib (Eds.): Springer Handbook of Robotics, 2008.
- R. Szeliski: Computer Vision: Algorithms and Applications, Springer 2010.

MA-INF 4114 Robot Learning

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Sven Behnke | Prof. Dr. Sven Behnke, Dr. Nils Goerke | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

This lecture is one of two introductory lectures on Robotics of the intelligent systems track. Creating autonomous robots that can learn to assist humans in situations of daily life is a fascinating challenge for machine learning. The lecture covers key ingredients for a general robot learning approach to get closer towards human-like performance in robotics, such as reinforcement learning, learning models for control, learning motor primitives, learning from demonstrations and imitation learning, and interactive learning.

This module complements MA-INF 4113 and can be taken before or after that module.

Learning goals: soft skills

Communicative skills (oral and written presentation of solutions, discussions in small teams), self competences (ability to accept and formulate criticism, ability to analyze problems)

Contents

Reinforcement learning, Markov decision processes, dynamic programming, Monte Carlo methods, temporal-difference methods, function approximation, linear quadratic regulation, differential dynamic programming, partially observable MDPs, policy gradient methods, inverse reinforcement learning, imitation learning, learning kinematic models, perceiving and handling of objects.

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to two students. A total of 50% of the points must be achieved.

Literature

- R. Sutton and A. Barto: Reinforcement Learning, MIT-Press, 1998.
- O. Sigaud and J. Peters (Eds.): From Motor Learning to Interaction Learning in Robots. Springer, 2010.

MA-INF 4115 Introduction to Natural Language Processing

| Workload | Credit points | Duration | Frequency |
|-------------------------|----------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Lucie Flek | Prof. Dr. Lucie Flek | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

This class provides a technical perspective on NLP ? methods for building computer software that understands and manipulates human language. Contemporary data-driven approaches are emphasized, focusing on machine learning techniques. The covered applications vary in complexity, including for example Entity Recognition, Argument Mining, or Emotion Analysis.

Learning goals: soft skills

Group work during programming exercises will allow students to work on real-world NLP application projects. The final project offers you the chance to apply your newly acquired skills towards an in-depth application using different frameworks such as PyTorch and spaCy and present it in a poster session.

Contents

Through lectures, exercises, and a final project, you will gain a thorough introduction to cutting-edge research in NLP, from the linguistic basis of computational language methods to recent advances in deep learning and large language models. This course provides:

- An overview of NLP goals, challenges, and applications
- Text representation (Words, sentences, paragraphs, documents), word embeddings, word2vec, BERT, word similarity
- Machine learning / deep learning algorithms for text classification, Transformers
- Basics of neural language modeling
- Basics of computational linguistics
- Transforming words to their base forms (tokenization, stemming, lemmatization)
- Syntactic analysis (part of speech tagging, chunking, and parsing)
- Techniques for extracting meaning from text (semantic analysis), use of lexical resources in NLP
- NLP applications and projects (e.g., Sentiment Analysis, Named Entity Recognition, Question Answering, Summarization, Fake news detection, Plagiarism detection, Abusive language detection, Opinion mining...)

Prerequisites

Recommended:

- Basics of statistics recommended.
- Basic programming knowledge in Python is of advantage.
- Basics of machine learning are of advantage.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Lecture | | 3 | 45 T / 45 S | 3 | |
| Exercises | | 1 | 15 T / 75 S | 3 | |

Graded exams

Written exam (60 %); Project work (40 %)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work must be done individually. A total of 50% of the points must be achieved.

Forms of media

- Lecture slides
- Exercise slides
- Notebooks with programming examples

Literature

- J. Eisenstein: Introduction to Natural Language Processing
 - Jurafsky, Daniel, and James H. Martin. "Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition."
 - S. Bird, E. Klein, E. Loper; Natural Language Processing with Python
-

MA-INF 4116 Seminar AI Ethics

| Workload | Credit points | Duration | Frequency |
|-------------------------|----------------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Lucie Flek | Prof. Dr. Lucie Flek | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

The seminar aims to introduce students to the ethical dilemmas of artificial intelligence. Students will develop skills in assessing AI systems, identifying ethical dilemmas and social impacts, reasoning through ethical and social issues, and communicating their reasoning.

Learning goals: soft skills

Students will learn about the design of ethical and socially responsible systems. They will gain practice engaging with multidisciplinary perspectives from behavioral and social science. At the end of the course, students will write a final term essay on one of the course topics.

Contents

We study artificial intelligence and the ethical dilemmas associated with the research, design, deployment, and interaction with AI systems.

Six broad modules structure the seminar:

- Foundations of AI and AI ethics
- Bias & fairness
- Privacy & data privacy
- Social networks & civility of communication
- Politics & policy
- AI for “social good”

A typical lecture will consist of 2-3 student presentations that focus on a research article and the broad context of its topic.

Following each presentation, we discuss the work with a focus on assessing relevant ethical issues and potential approaches for ethical design and engineering.

Prerequisites

Required:

No previous knowledge is required.

Recommended:

Previously attended classes in machine learning, robotics, data mining, or related, can be useful for understanding the topics but are not a must.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 4117 Mining Media Data I

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Rafet Sifa | Prof. Dr. Rafet Sifa, Dr. Lorenz Sparrenberg | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

By the end of this course, students will be able to:

- Analyze and extract meaningful relationships from large-scale media datasets using advanced data mining techniques.
- Develop and implement predictive and descriptive models for applications such as recommender systems, trend analysis, and outlier detection.
- Apply mathematical optimization methods to create interpretable and efficient machine learning models.
- Integrate theoretical concepts with practical tools to address challenges in digital forensics, behavioral profiling, and marketing strategy design.

Learning goals: soft skills

Contents

This course provides a comprehensive exploration of advanced data mining techniques tailored for media data analysis. Students will delve into methods like affinity mining, latent pattern mining, neural networks, and archetypal analysis to uncover insights in behavioral profiling, recommender systems, and outlier detection. Emphasis is placed on theoretical understanding and practical application through mathematical optimization, interpretable models, and real-world case studies, enabling participants to harness data for impactful digital marketing, fraud detection, and content personalization.

Prerequisites

Recommended:

Basic knowledge of data science, machine learning, and pattern recognition; programming skills; linear algebra.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 1 | 15 T / 30 S | 1.5 | |

Graded exams

Written exam (120 minutes) or oral exam.

Ungraded coursework (required for admission to the exam)

(i) The completion of regularly provided exercise sheets. The work can be done in groups of up to five students. A total of 50% of the points must be achieved. (ii) The completion of a programming project. The work is done in groups of up to five students. The results of the programming project must be presented in class.

Literature

- Rafet Sifa (2019). Matrix and Tensor Factorization for Profiling Player Behaviour. Independently pressed.
- Jiawei Han, Jian Pei, Micheline Kamber (2012). Data Mining: Concepts and Techniques. 3rd Ed., Elsevier Inc.
- Christopher Manning, Prabhakar Raghavan, Hinrich Schütze (2008). Introduction to Information Retrieval. Cambridge University Press.
- Michael Negnevitsky (2019), Artificial Intelligence: A Guide to Intelligent Systems. 3rd Ed., Pearson.
- Ian Goodfellow, Yoshua Bengio, Aaron Courville (2016). Deep Learning. MIT Press..
- Lecture notes of the instructors.

MA-INF 4201 Artificial Life

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|-----------------------|-----------------|
| Prof. Dr. Sven Behnke | Dr. Nils Goerke |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 1-3. |

Learning goals: technical skills

Detailed understanding of the most important approaches and principles of artificial life. Knowledge and understanding of the current state of research in the field of artificial life. The students can judge and explain if an Artificial Life approach is feasible for a given class of problems. They can estimate the necessary effort to implement and shape the Artificial Life paradigm w.r.t. the task, and can give an educated estimation of the possible outcome and foreseeable limitations of the approach. They can implement the basic fundamental Artificial Life paradigms.

Learning goals: soft skills

Capability to identify the state of the art in artificial life, and to present and defend the found solutions within the exercises in front of a group of students. Critical discussion of the results of the homework.

Contents

Foundations of artificial life, cellular automata, Conway's "Game of Life"; mechanisms for structural development; foundations of nonlinear dynamical systems, Lindenmeyer-systems, evolutionary methods and genetic algorithms, reinforcement learning, artificial immune systems, adaptive behaviour, self-organising criticality, multi-agent systems, and swarm intelligence, particle swarm optimization.

Prerequisites

Recommended:

Basic knowledge of linear algebra, analysis, logic, automata, and complexity analysis of deterministic and randomised algorithms.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|-------------|-----|---------------------------|
| Lecture | | 2 | 30 T / 45 S | 2.5 | T = face-to-face teaching |
| Exercises | | 2 | 30 T / 75 S | 3.5 | S = independent study |

Graded exams

Written exam (100 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to four students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions twice.

Forms of media

Pencil and paper work, explain solutions in front of the exercise group, implementation of small programs, use of simple simulation tools.

Literature

- Christoph Adami: Introduction to Artificial Life, The Electronic Library of Science, TELOS, Springer-Verlag
- Eric Bonabeau, Marco Dorigo, Guy Theraulaz: Swarm Intelligence: From Natural to Artificial Systems, Oxford University Press, Santa Fe Institute Studies in the Science of Complexity.
- Andrzej Osyczka: Evolutionary Algorithms for Single and Multicriteria Design Optimization, Studies in Fuzzyness and Soft Computing, Physica-Verlag, A Springer-Verlag Company, Heidelberg

MA-INF 4204 Technical Neural Nets

| Workload | Credit points | Duration | Frequency |
|-------------------------|-----------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Dr. Nils Goerke | Dr. Nils Goerke | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

Detailed knowledge of the most important neural network approaches and learning algorithms and its fields of application. Knowledge and understanding of technical neural networks as Non-Von Neumann computer architectures similar to concepts of brain functions at different stages of development. The students can judge and explain if a neural network approach is feasible for a given class of problems. They can estimate the necessary effort to implement and shape the neural approach for a given task and can give an educated estimation of the possible outcome and foreseeable limitations of that approach. They can implement the basic neural network approaches and neural learning paradigms.

Learning goals: soft skills

The students will be capable to propose several paradigms from neural networks that are capable to solve a given task. They can discuss the pro and cons with respect to efficiency and risk. They will be capable to plan and implement a small project with state of the art neural network solutions. Capability to identify the state of the art in neural network research. Capability to present and defend the found solutions within the exercises in front of a group of students. Critical discussion of the results of the homework.

Contents

Multi-layer perceptron, radial-basis function nets, Hopfield nets, self organizing maps (Kohonen), adaptive resonance theory, learning vector quantization, recurrent networks, back-propagation of error, reinforcement learning, Q-learning, support vector machines, pulse processing neural networks. Exemplary applications of neural nets: function approximation, prediction, quality control, image processing, speech processing, action planning, control of technical processes and robots. Implementation of neural networks in hardware and software: tools, simulators, analog and digital neural hardware.

Prerequisites

Recommended:

Basic knowledge of linear algebra, analysis, logic, automata, complexity analysis of deterministic and randomised algorithms, and practical and theoretical foundations of machine learning.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (100 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to four students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions twice.

Forms of media

Pencil and paper work, explaining solutions in front of the exercise group, implementation of small programs, use of simple simulation tools

Literature

- Christopher M. Bishop: Neural Networks for Pattern Recognition, Oxford University Press, ISBN-10: 0198538642, ISBN-13: 978-0198538646
 - Ian T. Nabney: NETLAB. Algorithms for Pattern Recognition, Springer, ISBN-10: 1852334401, ISBN-13: 978-1852334406
 - David Kriesel: A brief Introduction on Neural Networks, http://www.dkriesel.com/en/science/neural_networks
 - David Kriesel: Ein kleiner Überblick über Neuronale Netze, http://www.dkriesel.com/science/neural_networks
 - Simon Haykin: Neural Networks, and Learning Machines, 3rd Edition, Prentice Hall International Editions.
-

MA-INF 4208 Seminar Vision Systems

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|----------------|
| 120 h | 4 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Sven Behnke | Prof. Dr. Sven Behnke, Dr. Nils Goerke | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

- Knowledge in advanced topics in the area of technical vision systems, such as image segmentation, feature extraction, and object recognition.
- Ability to understand new research results presented in original scientific papers and to present them in a research talk as well as in a seminar report.

Learning goals: soft skills

Self-competences (time management, literature search, self-study), communication skills (preparation and clear didactic presentation of research talk, scientific discussion, structured writing of seminar report), social skills (ability to formulate and accept criticism, critical examination of research results).

Contents

Current research papers from conferences and journals in the field of vision systems covering fundamental techniques and applications.

Prerequisites

Recommended:

At least one of the following:

- MA-INF 2201 - Computer Vision
- MA-INF 4111 – Principles of Machine Learning
- MA-INF 4204 – Technical Neural Nets

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- R. Szeliski: Computer Vision: Algorithms and Applications, Springer 2010.
- C. M. Bishop: Pattern Recognition and Machine Learning, Springer 2006.
- D. A. Forsyth and J. Ponce: Computer Vision: A Modern Approach, Prentice Hall, 2003.

MA-INF 4209 Seminar Principles of Data Mining and Learning Algorithms

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Stefan Wrobel | Prof. Dr. Stefan Wrobel, PD Dr. Michael Mock, Dr. Florian Seiffarth, Dr. Tamas Horvath | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in the area of machine learning and data mining.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of the corresponding research area; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media in a way that adheres to academic standards, that is well-structured and didactically effective, and that motivates the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

Theoretical, statistical and algorithmical principles of data mining and learning algorithms. Search and optimization algorithms. Specialized learning algorithms from the frontier of research. Fundamental results from neighbouring areas.

Prerequisites

Recommended:

Knowledge of basic notions and algorithms from machine learning and data mining. It is recommend to first take at least one of the following modules:

- MA-INF 4111 – Principles of Machine Learning
- MA-INF 4112 – Algorithms for Data Science

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Forms of media

Scientific papers and websites, interactive presentations.

Literature

The relevant literature will be announced towards the end of the previous semester.

MA-INF 4211 Seminar Cognitive Robotics

| Workload | Credit points | Duration | Frequency |
|-------------------------|---|------------|----------------|
| 120 h | 4 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Sven Behnke | Prof. Dr. Sven Behnke, Dr. Raphael Memmesheimer | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Knowledge in advanced topics in the area of cognitive robotics, such as robot perception, action planning, and robot learning.

Ability to understand new research results presented in original scientific papers and to present them in a research talk as well as in a seminar report.

Learning goals: soft skills

Self-competences (time management, literature search, self-study), communication skills (preparation and clear didactic presentation of research talk, scientific discussion, structured writing of seminar report), social skills (ability to formulate and accept criticism, critical examination of research results).

Contents

Current research papers from conferences and journals in the field of cognitive robotics covering fundamental techniques and applications.

Prerequisites

Recommended:

At least 1 of the following:

- MA-INF 4113 – Cognitive Robotics
- MA-INF 4114 – Robot Learning

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- S. Thrun, W. Burgard and D. Fox: Probabilistic Robotics. MIT Press, 2005.
- B. Siciliano, O. Khatib (Eds.): Springer Handbook of Robotics, 2008.
- Selected papers.

MA-INF 4213 Seminar Humanoid Robots

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|----------------|
| 120 h | 4 CP | 1 semester | every semester |

| Module coordinator | Lecturer(s) |
|---------------------------|---------------------------|
| Prof. Dr. Maren Bennewitz | Prof. Dr. Maren Bennewitz |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2. or 3. |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in the area of humanoid robotics, such as perception, state estimation, navigation, manipulation, and motion planning.

Learning goals: soft skills

Self-competences (time management, literature search, self-study), communication skills (preparation of the talk, clear didactic presentation of techniques and experimental results, scientific discussion, structured writing of summary), social skills (ability to formulate and accept criticism, critical examination of algorithms and experimental results).

Contents

Current research papers from conferences and journals in the field of humanoid robotics covering fundamental techniques and applications.

Prerequisites

Recommended:

At least 1 of the following:

- MA-INF 4215 – Humanoid Robotics
- MA-INF 4113 – Cognitive Robotics

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP |
|-----------------|------------|--------|-------------|----|
| Seminar | 10 | 2 | 30 T / 90 S | 4 |

T = face-to-face teaching
S = independent study

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- S. Thrun, W. Burgard and D. Fox: Probabilistic Robotics. MIT Press
- B. Siciliano, O. Khatib (Eds.): Springer Handbook of Robotics
- K. Harada, E. Yoshida, K. Yokoi (Eds.), Motion Planning for Humanoid Robots, Springer
- Selected papers.

MA-INF 4214 Lab Humanoid Robots

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |

| Module coordinator | Lecturer(s) |
|---------------------------|---------------------------|
| Prof. Dr. Maren Bennewitz | Prof. Dr. Maren Bennewitz |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2. or 3. |

Learning goals: technical skills

Design and implementation of perception, state estimation, navigation, manipulation, and motion planning techniques for humanoid robots.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time;

Contents

Robot middleware, perception, state estimation, navigation, manipulation, and motion planning for humanoid robots.

Prerequisites

Recommended:

At least 1 of the following:

- MA-INF 4215 – Humanoid Robotics
- MA-INF 4113 – Cognitive Robotics

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- S. Thrun, W. Burgard and D. Fox: Probabilistic Robotics. MIT Press
- B. Siciliano, O. Khatib (Eds.): Springer Handbook of Robotics
- K. Harada, E. Yoshida, K. Yokoi (Eds.), Motion Planning for Humanoid Robots, Springer
- Selected papers.

MA-INF 4215 Humanoid Robotics

| Workload | Credit points | Duration | Frequency |
|---------------------------|---------------------------|------------|------------------------|
| 180 h | 6 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Maren Bennewitz | Prof. Dr. Maren Bennewitz | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

This lecture covers techniques for humanoid robots such as perception, navigation, and motion planning. After the lecture, the students will be able to understand and implement techniques that enable humanoid robots to autonomously navigate in human environments as well as perceive, represent, and manipulate objects.

Learning goals: soft skills

Communicative skills (oral and written presentation of solutions, discussions in small teams), ability to analyze problems.

Contents

Sensing and perception, environment representations, active perception, inverse kinematics, motion planning, grasping, balance control, walking, and footstep planning.

Prerequisites

Recommended:

MA-INF 4113 – Cognitive Robotics

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (90 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. A total of 50% of the points must be achieved.

Literature

- S. Thrun, W. Burgard and D. Fox: Probabilistic Robotics. MIT Press, 2005.
- B. Siciliano, O. Khatib (Eds.): Springer Handbook of Robotics
- K. Harada, E. Yoshida, K. Yokoi (Eds.), Motion Planning for Humanoid Robots, Springer
- Selected research papers.

MA-INF 4216 Biomedical Data Science and AI

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|---------------------|---------------------|
| Dr. Holger Fröhlich | Dr. Holger Fröhlich |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 3. |

Learning goals: technical skills

- understanding and knowledge of fundamental data mining and machine learning methods
- understanding of their application in bioinformatics

Learning goals: soft skills

- communication: oral and written presentation of solutions to exercises
- self-competences: ability to analyze application problems and to formulate possible solutions
- practical skills: ability to practically implement solutions
- social skills: working in a small team with other students

Contents

This lecture gives a broad overview about frequently used statistical techniques as well as data mining and machine learning algorithms in bioinformatics. The use of the respective methods to solve problems in bioinformatics is explained. The goal is to understand the explained methods, being able to apply them correctly and partially implement them. More detailed, the following topics are covered in the context of their application in bioinformatics:

- Short introduction to Bioinformatics and Biomedicine
- Statistical Basics: Probability distributions and Bayesian inference, statistical hypothesis testing, linear models, logistic regression, Principal Component Analysis
- Clustering
- Hidden Markov Models
- Supervised Machine Learning
- Elastic Net

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam

Ungraded coursework (required for admission to the exam)

(i) The completion of regularly provided exercise sheets. The work can be done in groups of up to three students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once. (ii) Participation in an achievement test. On the test, at least 50% of the points must be achieved.

Literature

T. Hastie, R. Tibshirani, J. Friedman, The Elements of Statistical Learning, Springer, 2008
 S. Boslaugh, P. Watters, Statistics in a Nutshell, O'Reilly, 2008
 N. Jones, P. Pevzner, An Introduction to Bioinformatics Algorithms, MIT Press, 2004

MA-INF 4217 Seminar Machine Learning Methods in the Life Sciences

| Workload | Credit points | Duration | Frequency |
|-------------------------|---------------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Dr. Holger Fröhlich | Dr. Holger Fröhlich | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 4. | |

Learning goals: technical skills

- understanding and knowledge of machine learning methods and their application in modern life sciences, e.g. biomedicine

Learning goals: soft skills

- communication: oral scientific presentation of a defined topic
- self-competences: ability to identify relevant literature for a given topic; ability to read, understand and analyze scientific publications
- social skills: ability to discuss a scientific topic with other students and the staff

Contents

Machine learning techniques play a crucial role in modern life sciences, including biomedicine. The goal of this seminar is to discuss a variety of machine learning techniques in the context of their application to solve real-world problems in biomedicine.

Topics will be selected from the following areas:

- Ensemble learning
- Survival and disease progression models
- Bayesian Networks
- Stochastic processes, e.g. Gaussian Processes, Dirichlet Process Mixture Models
- MCMC methods
- Deep learning methods, e.g. DNNs, CNNs, Deep Belief Networks
- feature selection and non-linear embedding methods
- multi-modal data fusion techniques

Attendees will be asked to perform research about their topic in a self-responsible manner.

Prerequisites

Recommended:

MA-INF 4216 – Data Mining and Machine Learning Methods in Bioinformatics

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Forms of media

powerpoint

Literature

selected journal and conference papers

MA-INF 4226 Lab Parallel Computing for Mobile Robotics

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------------------|
| 270 h | 9 CP | 1 semester | at least every 2 years |

| Module coordinator | Lecturer(s) |
|---------------------------|---------------------------|
| Prof. Dr. Maren Bennewitz | Prof. Dr. Maren Bennewitz |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2. |

Learning goals: technical skills

Students will make practical experience with the design and implementation of parallelized algorithms in the context of motion planning and navigation.

Learning goals: soft skills

Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify ones own results into the state-of-the-art of the resp. area

Contents

Parallel programming on the GPU, CUDA, shortest path planning, collision checking, visibility graph, A* algorithm

Prerequisites

Recommended:

C++, Linux.

Since the exercises revolve around path planning, one of those courses might be helpful:

MA-INF 4203: Autonomous Mobile Systems

MA-INF 4113: Cognitive Robotics

MA-INF 4310: Lab Mobile Robots

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 4228 Foundations of Data Science

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|----------------------|----------------------|
| Prof. Dr. Lucie Flek | Prof. Dr. Lucie Flek |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 1-3. |

Learning goals: technical skills

Knowledge: Peculiarities of high dimensional spaces in geometry and probabilities. Singular vector decomposition. Basics in machine learning and clustering.

Skills: Understanding of mathematical tools.

Competences: Application to data science problems and ability to assess similar methods.

Learning goals: soft skills

Oral presentation (in tutorial groups), written presentation (of exercise solutions), team collaboration in solving homework problems, critical assessment

Contents

Data science aims at making sense of big data. To that end, various tools have to be understood for helping in analyzing the arising structures.

Often data comes as a collection of vectors with a large number of components. To understand their common structure is the first main objective of understanding the data. The geometry and the linear algebra behind them becomes relevant and enlightening. Yet, the intuition from low-dimensional space turns out to be often misleading. We need to be aware of the particular properties of high-dimensional spaces when working with such data. Fruitful methods for the analysis include singular vector decomposition from linear algebra and supervised and unsupervised machine learning.

Prerequisites

Recommended:

Basic skills in linear algebra and stochastics.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|-----------------|------------|--------|--------------|-----|---------------------------|
| Lecture | | 4 | 60 T / 105 S | 5.5 | T = face-to-face teaching |
| Exercises | | 2 | 30 T / 75 S | 3.5 | S = independent study |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions twice.

Literature

Avrim Blum, John Hopcroft, and Ravindran Kannan (2018+). Foundations of Data Science.

MA-INF 4230 Advanced Methods of Information Retrieval

| Workload | Credit points | Duration | Frequency |
|--------------------------|--------------------------|------------|------------------------|
| 180 h | 6 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Elena Demidova | Prof. Dr. Elena Demidova | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

This module introduces the students to the advanced methods, data structures, and algorithms of information retrieval for structured and semi-structured data (including, for example, knowledge graphs, relational data, and tabular data).

At the end of the module, the students will be capable of choosing appropriate data structures and retrieval algorithms for specific applications and correctly apply relevant statistical and machine learning-based information retrieval procedures.

Learning goals: soft skills

Communication skills: oral and written presentation and discussion of solutions.

Self-competences: ability to analyse and solve problems.

Contents

The module topics include data structures, ranking methods, and efficient algorithms that enable end-users to effectively obtain the most relevant search results from structured, heterogeneous, and distributed data sources. Furthermore, we will study the corresponding evaluation techniques as well as novel applications.

Prerequisites

Recommended:

Basic knowledge of data science and machine learning; programming skills. Recommended reading:

- Sarah Boslaugh. Statistics in a Nutshell. A Desktop Quick Reference, O'Reilly Media, Inc., 2nd Edition, (2012).
- Ethem Alpaydin. Machine Learning. The MIT Press (2021).

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three, four or five students, depending on the total number of students taking the course. A total of 50% of the points must be achieved. For 80% of the exercise sheets, 40% of the points must be achieved for each sheet. Each student must present a solution to an exercise in the exercise sessions once.

Literature

Selected chapters from:

- Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, Introduction to Information Retrieval, Cambridge University Press. 2008.
- Bhaskar Mitra and Nick Craswell (2018), "An Introduction to Neural Information Retrieval ", Foundations and Trends^{so} in Information Retrieval: Vol. 13: No. 1, pp 1-126.
- Ridho Reinanda, Edgar Meij and Maarten de Rijke (2020), "Knowledge Graphs: An Information Retrieval Perspective", Foundations and Trends^{so} in Information Retrieval: Vol. 14: No. 4, pp 289-444.
- Jeffrey Xu Yu, Lu Qin, Lijun Chang. Keyword Search in Databases. Synthesis Lectures on Data Management. Morgan & Claypool Publishers. 2009.

Further references to relevant material will be provided during the lecture.

MA-INF 4231 Seminar Advanced Topics in Information Retrieval

| Workload | Credit points | Duration | Frequency |
|--------------------------|--------------------------|------------|------------------------|
| 120 h | 4 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Elena Demidova | Prof. Dr. Elena Demidova | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in the area of information retrieval, including understanding of information retrieval process, specialized data representation methods, advanced retrieval methods, evaluation techniques, and domain-specific applications.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of the corresponding research area; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media in a way that adheres to academic standards, that is well-structured and didactically effective, and that motivates the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

Statistical and machine learning-based information retrieval methods, including typical steps of the information retrieval process: data collection, feature extraction, indexing, retrieval, ranking, and evaluation. Specialized data representation and retrieval methods for selected data types and applications in specific domains.

Prerequisites

Recommended:

MA-INF 4230 - Advanced Methods of Information Retrieval.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

Selected chapters from:

- Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, Introduction to Information Retrieval, Cambridge University Press. 2008.
- Bhaskar Mitra and Nick Craswell (2018), "An Introduction to Neural Information Retrieval ", Foundations and TrendsSM in Information Retrieval: Vol. 13: No. 1, pp 1-126.

Further relevant literature will be announced at the beginning of the seminar.

MA-INF 4232 Lab Information Retrieval in Practice

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|--------------------------|--------------------------|
| Prof. Dr. Elena Demidova | Prof. Dr. Elena Demidova |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2. or 3. |

Learning goals: technical skills

This module concentrates on practical experience in information retrieval. Participants acquire basic knowledge and practical experience in designing and implementing information retrieval systems for specific data types and applications.

Learning goals: soft skills

Communication skills: the ability to work in teams.

Self-competences: the ability to analyse problems and find practical solutions. Time management, creativity, presentation of results.

Contents

Practical application of information retrieval methods to solve retrieval problems on real-world data and evaluate proposed solutions.

Prerequisites

Recommended:

MA-INF 4230 - Advanced Methods of Information Retrieval

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

Selected chapters from:

- Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, Introduction to Information Retrieval, Cambridge University Press. 2008.
- Bhaskar Mitra and Nick Craswell (2018), "An Introduction to Neural Information Retrieval ", Foundations and TrendsSM in Information Retrieval: Vol. 13: No. 1, pp 1-126.

Further references to relevant material will be provided during the lab.

MA-INF 4235 Reinforcement Learning

| Workload | Credit points | Duration | Frequency |
|------------------------------------|------------------------------------|------------|---------------|
| 180 h | 6 CP | 1 semester | every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr.-Ing. Christian Bauckhage | Prof. Dr.-Ing. Christian Bauckhage | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-3. | |

Learning goals: technical skills

Upon successful completion of this module, students should be able to describe fundamental methods, algorithms, and use cases of reinforcement learning. Students acquire knowledge about underlying mathematical models and corresponding algorithms; based on the knowledge and skills acquired, students should be able to:

- implement algorithms for reinforcement learning problems;
- adopt the fundamental methods they learned about to a wide

range of problems in policy optimization.

Learning goals: soft skills

In the exercises, students can put their knowledge about theoretical concepts, mathematical methods, and algorithmic approaches into practice and realize small projects involving the implementation and evaluation of search- and policy learning algorithms. This requires teamwork; upon successful completion of the module, students should be

able to:

- draft and implement basic reward functions and policy learning algorithms for various practical problem settings;
- prepare and give oral presentations about their work in front of an audience.

Contents

State space models, tree search algorithms, Monte Carlo tree search, Markov chain models, Markov decision processes, value functions, reward functions, Bellman equations, policy learning, TD learning Q learning, deep Q learning

Prerequisites

Required:

Linear algebra, statistics, probability theory, python programming

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to five students. A total of 50% of the points must be achieved. Each student must present a solution to an exercise in the exercise sessions once.

Forms of media

- lecture slides / lecture notes are made available online
- notebooks with programming examples are made available online

Literature

R.S. Sutton and A.G. Barto: Reinforcement Learning, 2nd ed., MIT Press, 2018

MA-INF 4236 Advanced Methods for Text Mining

| Workload | Credit points | Duration | Frequency |
|-------------------------|----------------------|------------|------------------------|
| 120 h | 4 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Rafet Sifa | Prof. Dr. Rafet Sifa | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Knowledge: Students will learn about the basic as well as the advanced methods for processing textual data, including necessary preprocessing steps such as stemming and lemmatization. They will also learn about representation learning methods, such as TF-IDF, Latent Semantic Indexing, Global Vectors, Recurrent Neural Networks, Transformer Networks, as well as the variants of the last such as Generative Pre-trained Transformers and Bidirectional Encoder Representations from Transformers, to extract meaningful embeddings for downstream tasks. The students will gain knowledge on how to build predictive and prescriptive methods for a variety of objectives, including text classification, outlier detection, and recommender systems. Additionally, they will learn how to categorize these methods based on their complexities and their applicability to different text mining problems, such as sentiment analysis, natural language inference, computational argumentation, information extraction, named entity recognition, text summarization, opinion mining, text segmentation, event detection, and more.

Skill: Students should be able to analyze, design as well as reason about existing and new data mining algorithms, theoretically compare algorithms, strengthen their analytical thinking to solve difficult modelling problems, have acquired the necessary mathematical as well as programming/IT skills to systematically plan, design and implement text and data mining projects.

Competences: Based on the knowledge and skills acquired in this module, the students will be able to assess certain characteristics of the already existing text mining methods as well as build new solutions to emerging problems. Additionally, the students will be able to transfer their knowledge to other data science areas involving modelling data with sequential dependencies.

Learning goals: soft skills

critical discussion in groups of one's own and others'/competing results/solutions, time management, transferring theoretical knowledge to practical scenarios, presentation of solutions and methods, productive work in small teams

Contents

Neural Networks, Text Mining Pipelines, Stemming, Lemmatization, TF-IDF, Latent Semantic Indexing, Global Vectors, Recurrent Neural Networks, Transformer Networks, Generative Pre-trained Transformers, Bidirectional Encoder Representations, Prompt Analysis, Sentiment Analysis, Natural Language Inference, Computational Argumentation, Information Extraction, Named Entity Recognition, Text Summarization, Opinion Mining, Text Segmentation, Event Detection, Representation Learning and Applications

Prerequisites

Recommended:

Basic knowledge of AI, data science, machine learning, and pattern recognition; programming skills; good working knowledge in statistics, linear algebra, and optimization.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 1 | 15 T / 30 S | 1.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets, on which a total of 50% of the points must be achieved, and the successful completion and presentation of a programming project. The work can be done in group of up to four students.

Literature

- Introduction to Information Retrieval, Christopher D. Manning, Prabhakar Raghavan and Heinrich Schütze
 - Aggarwal, C. C. (2018). Machine learning for text (Vol. 848). Cham: Springer.
 - Lecture notes of the instructors
-

MA-INF 4237 Lab Natural Language Processing

| Workload | Credit points | Duration | Frequency |
|-------------------------|----------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Lucie Flek | Prof. Dr. Lucie Flek | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-3. | |

Learning goals: technical skills

The Natural Language Processing (NLP) Lab course provides students with a detailed look at the recent advancements in NLP, covering various aspects such as large language models (LLMs), conversational systems, and computational social science. The course emphasizes a practical approach and offers you the opportunity to gain hands-on experience in developing NLP-based systems, allowing you to deepen your understanding of NLP technologies and apply theoretical knowledge to real-world scenarios.

Learning goals: soft skills

Through tutorials and a final project, you will gain practical skills in NLP techniques and have this chance to apply this knowledge to a various interesting project. Students will collaborate in small teams (a group of two students) and implement NLP applications over the course of the term. Each team is advised by one researcher of the CAISA Lab.

Contents

The course emphasizes a practical approach and offers you the opportunity to gain hands-on experience in developing NLP-based systems, allowing you to deepen your understanding of NLP technologies and apply theoretical knowledge to real-world scenarios.

Prerequisites

Required:

MA-INF 4115: Introduction to Natural Language Processing

Recommended:

- Basic programming knowledge in Python and Machine Learning
- Basics of Machine Learning
- Basic knowledge of Python Libraries for ML (NumPy, Scikit-Learn, Pandas)
- Basics of Probability, Linear Algebra and Statistics

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 4238 Dialog Systems

| Workload | Credit points | Duration | Frequency |
|-------------------------|----------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Lucie Flek | Prof. Dr. Lucie Flek | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-3. | |

Learning goals: technical skills

In this course, students will learn:

- The differences between types of dialog systems and their purposes
- How to ethically design dialog systems using contemporary methods
- To determine how to know if a system is performing well
- How to implement various methods of dialog control and generation
- How linguistic processes contribute to the foundations and capabilities of dialog models and language understanding

Learning goals: soft skills

Group work during programming exercises will allow students to work on real-world dialog systems application projects. The final project offers you the chance to apply your newly acquired skills towards in-depth applications and valuable datasets.

Contents

This course is a detailed introduction to the architecture of conversational systems (chatbots). We will introduce the main components of dialog systems and show approaches to their implementation, including natural language understanding, natural language generation, and dialog sequence management. This course will briefly discuss speech-related components and multi-modal systems, but will primarily focus on text processing and language understanding. The lab sessions will be dedicated to implementing a simple dialog system and selected components (via weekly homework assignments).

Prerequisites

Recommended:

The following is recommended:

- Introduction to Natural Language Processing
- Introduction to Machine Learning
- Basics of statistics
- Basics of programming (Python)

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (60%), Project work (40%)

Ungraded coursework (required for admission to the exam)

Forms of media

- Lecture slides
- Exercise slides
- Notebooks with programming examples

Literature

- Jurafsky, D., & Martin, J. E. Speech & Language Processing, an Introduction to Natural Language Processing, Computational Linguistics & Speech Recognition
 - Goodfellow, I., Bengio, Y., & Courville, A. Deep Learning. MIT Press.
 - McTear, M. Spoken Dialogue Technology: Enabling the Conversational User Interface. ACM.
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MA-INF 4240 Lab Hybrid Learning and Applications

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Rafet Sifa | Prof. Dr. Rafet Sifa, Dr. Lorenz Sparrenberg | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-4. | |

Learning goals: technical skills

- Studying a self-selected research topic
- Reproducing important results
- Elaborating findings based on own research
- Applying theoretical knowledge to real-world problems
- Familiarity with external research work

Learning goals: soft skills

- Own idea generation
- Project completion within self-defined scope and timeline
- Adapting relevant aspects to own projects
- Communication skills through structured presentations

Contents

This lab offers a comprehensive introduction to using hybrid learning, merging machine learning and deep learning techniques to address complex problems. By integrating foundation models with downstream tasks using various machine learning methods, students explore a range of fascinating applications. They are encouraged to select and research their own project topics, gaining hands-on experience in data preprocessing, model building, evaluation, and optimization. This course is designed to equip students with practical skills to design and implement effective hybrid learning solutions.

Schedule:

1. organization meeting
2. presentation of the research idea and its application (1 week later)
3. midterm presentation of results
4. final presentation
5. Student paper

Prerequisites

Required:

- Independent work required

Recommended:

- A basic understanding of machine learning is helpful
- Students should bring their own ideas.

Remarks

Due to the limit of 10 participants, students must send their participation request and a few sentences about their research idea to amllab@bit.uni-bonn.de before the first appointment. Places will be allocated according to the date of receipt and the quality of the idea submitted.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- Topic dependent and specified or researched by the student
 - Lecture notes of the instructor (Advanced methods for text mining by Prof. Dr. Rafet Sifa, SS24)
-

MA-INF 4241 Lab Cognitive Modelling of Biological Agents

| Workload | Credit points | Duration | Frequency |
|----------------------------|----------------------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Dr. Dominik Bach | Prof. Dr. Dr. Dominik Bach | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

- Cognitive modelling workflow in computational neuroscience.
- Analysis of real-life cognitive tasks.
- Reasoning about different problem solutions.
- Understanding constraints of biological systems.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time; to aim at long-range goals under limited resources; to work under pressure.

Contents

The goal of cognitive modelling in computational neuroscience is to reverse-engineer how a real neural system solves a given cognitive task, often using reinforcement learning theory as a starting point. This lab covers the entire cognitive modelling workflow as used in computational neuroscience. Students will address an interesting cognitive problem by (a) developing rational solutions drawing on reinforcement learning, or descriptive solutions drawing on cognitive science and mathematical psychology, (b) derive behavioural signatures of this solution by mathematical analysis or computational simulation, (c) design efficient experiments to disambiguate these solutions from real behaviour, and (d) potentially analyse existing data sets. The course emphasises a practical, application-focused approach. Students collaborate in teams of 2, each supervised by a CAIAN researcher.

Prerequisites

Recommended:

One out of:

- MA-INF 4113 Cognitive Robotics
- MA-INF 4114 Robot Learning
- MA-INF 4215 Humanoid Robotics
- MA-INF 4235 Reinforcement Learning

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 4242 Self-supervised Learning

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| JProf. Dr. Hermann Blum | JProf. Dr. Hermann Blum | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Students can list and explain different fundamental unsupervised, self-supervised machine learning models and can justify a choice of model for a given problem. Students can list and explain different techniques of self-supervision and semi-supervision. For a given data source and task, they can evaluate if a technique is applicable and implement it based on established software frameworks.

Learning goals: soft skills

Communicative skills (discussions in small teams), self competences (ability to accept and formulate criticism, ability to analyze problems).

Contents

The course covers a broad range of methods to learn from unlabelled data with a focus on deep neural networks and hybrid methods.

Models: Nearest Neighbors, Clustering, Autoencoders, (pretrained) Neural Networks, Generative Models

Self-Supervision Techniques: Denoising, Masking, Pre-text Tasks, Distillation, Cycleconsistency, Contrastive Learning, Pseudo-Labeling, System-level Self-Supervision.

Prerequisites

Recommended:

It is recommended that the students have:

- knowledge of foundations of artificial intelligence and deep learning.

It is recommended to first complete the following module:

- MA-INF 4111 Principles of Machine Learning.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 min)

Ungraded coursework (required for admission to the exam)

none

Literature

- scikit-learn User Guide.
- I. Goodfellow, Y. Bengio and A. Courville: Deep Learning. MIT Press, 2016.
- Balestrierio et al.: A Cookbook of Self-Supervised Learning, 2023.

MA-INF 4243 Mining Media Data II

| Workload | Credit points | Duration | Frequency |
|--------------------|---------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2. or 3. |

Learning goals: technical skills

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

- Understand and implement advanced data mining techniques for predictive and prescriptive analytics.
- Employ large language models and transformer-based architectures for tasks like text analysis, classification, and summarization.
- Apply knowledge distillation techniques to optimize and deploy machine learning models in resource-constrained environments.
- Analyze media data effectively to derive insights and support decision-making in real-world applications, including digital marketing and fraud detection.
- Address challenges in media analytics, such as ethical considerations, model interpretability, and efficient resource use.

Learning goals: soft skills

Contents

This course explores advanced techniques in data mining, emphasizing predictive and prescriptive methods applied to media data. Students will learn to analyze large and complex datasets using state-of-the-art machine learning methodologies, including behavioral prediction, knowledge distillation, and large language models (LLMs). The curriculum includes foundational concepts, text representation learning, transformer architectures, and practical applications in media analytics, such as recommendation systems and information extraction. The course combines theoretical instruction with hands-on exercises to develop both technical and analytical skills relevant to industry and research.

Prerequisites

Recommended:

Basic knowledge of data science, machine learning, and pattern recognition; programming skills; linear algebra. Completion of MA-INF 4117 - Mining Media Data I is recommended but not mandatory.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 1 | 15 T / 30 S | 1.5 | |

Graded exams

Written exam (120 min) or oral exam.

Ungraded coursework (required for admission to the exam)

(i) The completion of regularly provided exercise sheets. The work can be done in groups of up to five students. A total of 50% of the points must be achieved. (ii) The completion of a programming project. The work is done in groups of up to five students. The results of the programming project must be presented in class.

MA-INF 4304 Lab Cognitive Robotics

| Workload | Credit points | Duration | Frequency |
|-------------------------|---|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Sven Behnke | Prof. Dr. Sven Behnke, Dr. Raphael Memmesheimer | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Participants acquire practical experience and in-depth knowledge in the design and implementation of perception and control algorithms for complex robotic systems. In a small group, they analyze a problem, realize a state-of-the-art solution, and evaluate its performance.

Learning goals: soft skills

Self-competences (time management, goal-oriented work, ability to analyze problems and to find practical solutions), communication skills (Work together in small teams, oral and written presentation of solutions, critical examination of implementations)

Contents

Robot middleware (ROS), simultaneous localization and mapping (SLAM), 3D representations of objects and environments, object detection and recognition, person detection and tracking, action recognition, action planning and control, mobile manipulation, human-robot interaction.

Prerequisites

Recommended:

At least 1 of the following:

- MA-INF 4113 – Cognitive Robotics
- MA-INF 4114 – Robot Learning

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- S. Thrun, W. Burgard and D. Fox: Probabilistic Robotics. MIT Press, 2005.
- B. Siciliano, O. Khatib (Eds.): Springer Handbook of Robotics, 2008.
- Selected research papers.

MA-INF 4306 Lab Development and Application of Data Mining and Learning Systems

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Stefan Wrobel | Prof. Dr. Stefan Wrobel | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Students will acquire in-depth knowledge in the design, implementation, and experimental evaluation of machine learning and data mining systems. They learn how to work with existing state-of-the-art machine learning and data mining algorithms and apply them to real-world and synthetic datasets, usually extending them for the requirements of their particular learning/mining task.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time; to aim at long-range goals under limited resources; to work under pressure.

Contents

Design, adaptation, implementation, and systematic experimental evaluation of specialised data mining and learning algorithms, from classical to state-of-the-art, from all areas of machine learning and data mining. Search and optimization algorithms. Common open source libraries for machine learning and data mining.

Prerequisites

Recommended:

Basic notions and algorithms from machine learning and data mining are required. It is recommended to take at least one of the following courses first:

- MA-INF 4111 – Principles of Machine Learning
- MA-INF 4112 – Algorithms for Data Science

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Forms of media

Computer Software, Documentation, Research Papers.

Literature

The relevant literature will be announced towards the end of the previous semester.

MA-INF 4308 Lab Vision Systems

| Workload | Credit points | Duration | Frequency |
|-------------------------|-----------------------|------------|----------------|
| 270 h | 9 CP | 1 semester | every semester |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Sven Behnke | Prof. Dr. Sven Behnke | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Students will acquire knowledge of the design and implementation of parallel algorithms on GPUs. They will apply these techniques to accelerate standard machine learning algorithms for data-intensive computer vision tasks.

Learning goals: soft skills

Self-competences (time management, goal-oriented work, ability to analyze problems and to find practical solutions), communication skills (Work together in small teams, oral and written presentation of solutions, critical examination of implementations)

Contents

Basic matrix and vector computations with GPUs (CUDA). Classification algorithms, such as multi-layer perceptrons, support-vector machines, k-nearest neighbors, linear-discriminant analysis. Image preprocessing and data handling. Quantitative performance evaluation of learning algorithms for segmentation and categorization.

Prerequisites

Recommended:

At least 1 of the following:

MA-INF 2201 - Computer Vision

MA-INF 4111 – Intelligent Learning and Analysis Systems: Machine Learning

MA-INF 4204 – Technical Neural Nets

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- R. Szeliski: Computer Vision: Algorithms and Applications, Springer 2010.
- C. M. Bishop: Pattern Recognition and Machine Learning, Springer 2006.
- NVidia CUDA Programming Guide, Version 4.0, 2011.

MA-INF 4322 Lab Machine Learning on Encrypted Data

| Workload | Credit points | Duration | Frequency |
|-------------------------|--------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Dr. Michael Nüsken | Dr. Michael Nüsken | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

The students will carry out a practical task (project) in the context of Cryptography, including test and documentation of the implemented software/system.

Learning goals: soft skills

Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify one's own results into the state-of-the-art of the resp. area

Contents

With the rise of more and more mechanisms and installations of data science methodology to automatically analyze large amounts of possibly privacy infringing data we have to carefully understand how to protect our data. Also more and more fake data shows up and we have to find ways to distinguish faked from trustable data. At the same time we want to allow insightful research and life-easing analyzes to be possible. This seeming contradiction has lead to various efforts for unifying both: protecting data and allowing analyzes, at least to some extent and possibly under some restrictions.

The target of the lab is to understand how computations on encrypted data may work in one particular application that we are choosing together. Ideally, we can come up with a novel solution for performing an unconsidered algorithm. We study the tasks and tools, select algorithms, find a protocol, prototype an implementation, perform a security analysis, present an evaluation.

Prerequisites

Recommended:

Good knowledge in cryptography is vital, e.g. by one or more modules out of:

- MA-INF 1103 - Cryptography,
- MA-INF 1223 - Privacy Enhancing Technologies, and
- MA-INF 1209 - Seminar Advanced Topics in Cryptography.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 4324 Seminar Advanced Topics in Data Science

| Workload | Credit points | Duration | Frequency |
|--------------------------|--------------------------|------------|------------------------|
| 120 h | 4 CP | 1 semester | at least every 2 years |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Elena Demidova | Prof. Dr. Elena Demidova | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Enhanced and in-depth knowledge in specialized topics in the data science, including understanding of the data science process, statistical and machine learning-based data analytics methods, specialized data representation techniques, evaluation methods, and domain-specific applications.

Learning goals: soft skills

Acquire the competence to independently search for and study state-of-the-art scientific literature in depth, read critically, identify the most relevant content, and assess research results in the context of the corresponding research area; to discuss research results with a knowledgeable scientific audience; to present prior work by others in writing and in presentations with visual media in a way that adheres to academic standards, that is well-structured and didactically effective, and that motivates the audience to participate; to formulate and accept criticism; to manage one's time with relatively open assignments and long-ranging deadlines.

Contents

Statistical and machine learning-based methods of data analytics, including typical steps of the data science process: data generation, integration, cleaning, exploration, modelling and evaluation. Specialized data representation and analytics methods for selected data types and applications in specific domains.

Prerequisites

Recommended:

MA-INF 4328 - Spatio-Temporal Data Analytics

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

Relevant literature will be announced at the beginning of the seminar

MA-INF 4325 Lab Data Science in Practice

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|--------------------------|---|
| Prof. Dr. Elena Demidova | Prof. Dr. Elena Demidova, Dr. Rajjat Dadwal |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2. or 3. |

Learning goals: technical skills

This module concentrates on practical experience in data analytics. Participants acquire basic knowledge and practical experience in the design and implementation of data science workflows for specific data types and applications.

Learning goals: soft skills

- Communication skills: the ability to work in teams.
- Self-competences: the ability to analyse problems and find practical solutions. Time management, creativity, presentation of results.

Contents

Practical application of statistical and machine learning-based methods to solve data analytics problems on real-world datasets and evaluate proposed solutions.

Prerequisites

Recommended:

MA-INF 4328 - Spatio-Temporal Data Analytics

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 4326 Explainable AI and Applications

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Dr. Rafet Sifa | Prof. Dr. Rafet Sifa, Dr. Lorenz Sparrenberg | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

- Know the dual-model functioning of the human mind, and two main AI paradigms
- Develop white-box neural AI systems
- Understand the problems and limitations of Blackbox Deep-Learning systems, and Know the state-of-the-art Methods for Interpreting Deep-Learning systems (XAI)

Learning goals: soft skills

- Know System 1 and 2 of the mind, pros and cons of symbolic AI and connectionist AI
- Develop neural-geometric systems that have both good features of symbolic AI and connectionist AI
- Know the limitation of famous Deep-Learning systems, such as GPT3, self-driving. Know standard methods to explore the explainability of Deep-Learning systems

Contents

1. Introduction: fates of large Deep-Learning systems, e.g. Watson, GPT, self-driving cars
2. Dual-system theories (System 1 and 2), nine laws of cognition, criteria of semantic models
3. The target and the state-of-art methods of XAI
4. Neural-symbolic AI
5. Cognitive maps, Collages, Mental Spatial Representation, Events
6. Qualitative Spatial Representation and Reasoning
7. Rotating Sphere Embedding: A New Wheel for Neural-Symbolic Unification
8. Neural Syllogistic Reasoning
9. Recognizing Variable Environments
10. Humor Understanding
11. Rotating Spheres as building-block semantic components for Language, Vision, and Action

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (120 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to four students. A total of 50% of the points must be achieved.

Literature

- Kahneman, D. (2011). Thinking fast and slow. Farrar, Straus and Giroux.
 - Gaedenfors, P. (2017). The Geometry of Meaning. MIT Press.
 - Attardo, Hempelmann, Maio (2003). Script Oppositions and Logical Mechanisms: Modeling Incongruities and their Resolutions, HUMOR 15(1)3–46
 - Tversky, B. (2019). Mind in Motion. Basic Books, New York.
 - Dong, et al. (2020). Learning Syllogism with Euler Neural-Networks. arXiv:2007.07320
 - Dong, T. (2021). A Geometric Approach to the Unification of Symbolic Structure and Neural Networks. Springer.
 - Knauff and Spohn (2021). Handbook of Rationality. MIT Press, Cambridge, MA, USA.
 - Samek et.al. (2019), Explainable AI: Interpreting, Explaining and Visualizing Deep Learning. Springer.
 - Greg Dean (2019). Step by Step to Stand-Up Comedy (Revised Edition). ISBN: 978-0-9897351-7-9
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MA-INF 4327 Lab Biomedical Data Science

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|---------------------------|---------------------------|
| Prof. Dr. Holger Fröhlich | Prof. Dr. Holger Fröhlich |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 3. |

Learning goals: technical skills

The students will carry out a practical task (project) in the context of biomedical data science, including test and documentation of the implemented software/system.

Learning goals: soft skills

Ability to properly present and defend design decisions, to prepare readable documentation of software; skills in constructively collaborating with others in small teams over a longer period of time; ability to classify ones own results into the state-of-the-art of the resp. area

Contents

Varying selected topics close to current research in the area of biomedical data science.

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 4328 Spatio-Temporal Data Analytics

| Workload | Credit points | Duration | Frequency |
|--------------------------|---|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Elena Demidova | Dr. Rajjat Dadwal, Prof. Dr. Elena Demidova | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 1. or 2. | |

Learning goals: technical skills

This module introduces the students to the advanced methods, data structures, and data analytics algorithms for spatio-temporal data. At the end of the module, the students will be capable of choosing appropriate data representations, data structures and algorithms for specific applications and correctly applying relevant statistical and machine learning-based data analytics procedures.

Learning goals: soft skills

Communication skills: oral and written presentation and discussion of solutions. Self-competences: the ability to analyze and solve problems.

Contents

The module topics include data structures, data representation and analysis methods, and algorithms that enable analyzing spatio-temporal data and building predictive models effectively and effectively. Furthermore, we will study the corresponding evaluation techniques and novel applications.

Prerequisites

Recommended:

Basic knowledge of data science and machine learning; programming skills. Recommended reading:

- Sarah Boslaugh. Statistics in a Nutshell. A Desktop Quick Reference, O'Reilly Media, Inc., 2nd Edition, (2012).
- Ethem Alpaydin. Machine Learning. The MIT Press (2021).

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam (90 minutes)

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to three, four or five students, depending on the total number of students taking the course. A total of 50% of the points must be achieved. For 80% of the exercise sheets, 40% of the points must be achieved for each sheet. Each student must present a solution to an exercise in the exercise sessions once.

MA-INF 4329 Seminar Biological Intelligence

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |

| Module coordinator | Lecturer(s) |
|----------------------------|----------------------------|
| Prof. Dr. Dr. Dominik Bach | Prof. Dr. Dr. Dominik Bach |

| Programme | Mode | Semester |
|-------------------------|----------|----------|
| M. Sc. Computer Science | Optional | 2. or 3. |

Learning goals: technical skills

Ability to understand new research results presented in original scientific papers.

Learning goals: soft skills

Communication skills: oral and written presentation of scientific content. Self-competences: the ability to analyze problems, time management, creativity

Contents

Humans and other animals outperform artificial agents in various tasks and domains. This includes but is not limited to: learning and planning in unstructured domains; learning from sparse data, observation, and play; generalisation and transfer; causal reasoning; intuitive physics and psychology; language use; any time planning; continuous planning; spatial navigation; dynamic memory and active forgetting. This seminar provides background on some of the underlying biological skills, and computational theories that seek to explain them. We will discuss implications for designing and/or constraining artificial agents.

Prerequisites

none

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 10 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

MA-INF 4330 Lab Explainable AI and Applications

| Workload | Credit points | Duration | Frequency |
|-------------------------|--|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Rafet Sifa | Prof. Dr. Rafet Sifa, Dr. Lorenz Sparrenberg | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-4. | |

Learning goals: technical skills

Independent Research: Students will select a research paper focused on representation learning, replicate its findings, and use techniques from the "Explainable AI and Applications" course to deepen their understanding of the concepts and potentially enhance the results. This process also teaches students to manage and complete a project within a defined scope and timeline.

Practical Application: The lab emphasizes the application of theoretical knowledge to real-world problems, encouraging deeper understanding and innovation. Students will become familiar with external research, apply, and adapt the relevant research code to their projects.

Communication Skills: Students will develop their ability to present complex ideas clearly and effectively through structured presentations and written reports. The course also covers scientific writing, literature review, proper citation, and best practices in academic research.

Learning goals: soft skills

Contents

The lab focuses on enhancing students' understanding of Explainable AI and its applications through hands-on exercises and active participation in presentation meetings. Students explore recent research on the topic of latent representations (e. g. text or image embeddings, sentiment analysis) aiming to reproduce existing research. Then, they apply techniques learned in the lecture "Explainable AI and Applications" (e. g. neurosymbolic representation learning) to get a better understanding of these representations. The results will be presented and discussed in a presentation as well as in a student paper (5-8 pages, given template). There is an opportunity to publish excellent ideas that go beyond the state of the art and brilliant experimental results.

Schedule:

1. organization (April)
2. presentation of the research idea and its application (1 week later)
3. midterm presentation of results (June)
4. final presentation (September)
5. Student paper (September)

Prerequisites

Recommended:

Basic knowledge of machine learning, and pattern recognition, Python programming

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Intermediate presentation (25%), final presentation (25%), student paper (50%)

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- Topic dependent to be researched by the student.
 - Lecture notes of the instructors (Explainable AI and Applications by Dr. Tiansi Dong, WS23/24)
-

MA-INF 4331 Lab Perception and Learning for Robotics

| Workload | Credit points | Duration | Frequency |
|-------------------------|-------------------------|------------|---------------------|
| 270 h | 9 CP | 1 semester | at least every year |
| Module coordinator | Lecturer(s) | | |
| JProf. Dr. Hermann Blum | JProf. Dr. Hermann Blum | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Participants learn how to practically approach a robot perception problem. They learn how to critically read a research paper, how to conduct experiments in the context of robot perception, and how to report and present scientific findings.

Learning goals: soft skills

Ability to analyze problems theoretically and to find creative and practical solutions; to examine one's solutions and results critically; to classify one's own results into the state-of-the-art of the respective area; to prepare readable documentation of software and research results; to present, defend and discuss design decisions and results in the team/group and to other students clearly and in accordance with academic standards; to collaborate constructively with others in small teams over a longer period of time; to aim at long-range goals under limited resources; to work under pressure.

Contents

In small groups, students apply their knowledge of robot perception, deep learning, and computer vision to a novel problem. They analyze the problem, read into relevant literature, propose and implement a solution, and empirically test it. They then refine their approach based on an analysis of the experimental outcomes. The course projects are related to one of multiple of the following topics: Robot localization, planning, navigation, manipulation; Practical aspects of Deep Learning; Sensor models, calibration, capture, processing. Software deployment.

Prerequisites

Recommended:

Students are expected to have general programming skills and prior experience with python. Students will need to operate linux terminal systems such as the university's GPU cluster.

It is recommended to first take two of the following modules:

- MA-INF 2201 Computer Vision
- MA-INF 2213 Advanced Computer Vision
- MA-INF 2218 Video Analytics
- MA-INF 4113 Cognitive Robotics

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- S. Thrun, W. Burgard and D. Fox: Probabilistic Robotics. MIT Press, 2005
- I. Goodfellow, Y. Bengio and A. Courville: Deep Learning. MIT Press, 2016
- Per-project assigned literature

MA-INF 4332 Seminar Large Language Models

| Workload | Credit points | Duration | Frequency |
|----------------------------------|----------------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Lucie Flek | Prof. Dr. Lucie Flek | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-4. | |
| Learning goals: technical skills | | | |

| Learning goals: soft skills |
|-----------------------------|
|-----------------------------|

Contents

Large Language Models (LLMs), such as GPT-4, Gemini, and their successors, have had an enormous impact on various domains, including natural language processing, machine learning, and artificial intelligence. These models have redefined what's possible in applications such as text generation, translation, summarization, sentiment analysis, and more. The aim of this seminar is to explore cutting-edge research, insights, and trends in the field of LLMs, such as:

- hallucination reduction and factual grounding
- explainability, reasoning, faithfulness
- safety, toxicity, fairness and bias
- social and moral alignment of LLMs
- style control and personalization
- sustainability, compression, model size reduction, knowledge distillation
- multilinguality and multimodality
- LLMs as planning agents
- and more

Prerequisites

none

Remarks

At most 35 participants

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 35 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- Bommasani, Rishi: On the opportunities and risks of foundation models
- Devlin, Jacob, et al.: Bert: Pre-training of deep bidirectional transformers for language understanding
- Brown, Tom, et al.: Language models are few-shot learners
- WX Zhao, et al.: A survey of large language models
- Yang, Jingfeng, et al.: Harnessing the power of LLMs in practice: A survey on ChatGPT and beyond

MA-INF 4333 Geometric Deep Learning

| Workload | Credit points | Duration | Frequency | | |
|---|-----------------------------|------------|-------------|-----|--|
| 180 h | 6 CP | 1 semester | every year | | |
| Module coordinator | Lecturer(s) | | | | |
| Jun. Prof. Dr. Zorah Lähner | Jun. Prof. Dr. Zorah Lähner | | | | |
| Programme | Mode | Semester | | | |
| M. Sc. Computer Science | Optional | 2. or 3. | | | |
| Learning goals: technical skills | | | | | |
| <ul style="list-style-type: none">• Understanding advanced topics in the design of neural networks using geometric data• Mathematical modelling of invariances and non-Euclidean domains in deep learning and guarantees that can be derived from these• Gain an overview of practical applications in which this theory can be applied | | | | | |
| Learning goals: soft skills | | | | | |
| <ul style="list-style-type: none">• Problem solving skills: ability to identify and utilize analogies between new problems and previously seen ones• Analytical and abstract thinking: develop a general intuition of computational problems, being able to adopt different perspectives of particular concepts | | | | | |
| Contents | | | | | |
| This lecture will cover advanced topics in deep learning focusing on theory related to geometric data and the incorporation of invariances in network architectures. Topics include, among others, permutation invariance, differential geometry, the curse of dimensionality, neural fields and physics-informed neural networks. Students will learn how to process a variety of geometric data structures and implement deep learning algorithms on these related to applications in visual computing, physics and graph processing. | | | | | |
| Prerequisites | | | | | |
| Recommended: Students are recommended to have basic knowledge about deep learning and computer vision, for example gained in <ul style="list-style-type: none">• MA-INF 4111 Principles of Machine Learning,• MA-INF 2201 Computer Vision, or• MA-INF 2222 Visual Data Analysis, and proficiency in python. | | | | | |
| Course meetings | | | | | |
| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |
| Graded exams | | | | | |
| Written exam (120 minutes) | | | | | |
| Ungraded coursework (required for admission to the exam) | | | | | |
| none | | | | | |

MA-INF 4334 Computational neuroscience: cognition and behaviour

| Workload | Credit points | Duration | Frequency |
|----------------------------|----------------------------|------------|------------|
| 180 h | 6 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Dr. Dominik Bach | Prof. Dr. Dr. Dominik Bach | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2-3. | |

Learning goals: technical skills

- Conceptual knowledge and mathematical understanding of common behavioural and cognitive models from computational neuroscience
- Knowledge of common experimental methods used to develop and disambiguate such models
- Basic knowledge of fundamentals in neuroscience, cognitive/perceptual psychology and microeconomics
- In the exercises, students will learn to implement models and how to use them as benchmarks for bottom-up computational neuroscience models, and for automatic signature-testing of AI algorithms

Learning goals: soft skills

- Teamwork (exercises)
- Oral presentation in front of audience (exercises)

Contents

The two dominant paradigms in computational neuroscience are bottom-up (starting from the spontaneous behaviour of constituent elements of the nervous system) and top-down (starting from known functions of biological agents). This lecture introduces important topdown models of behaviour and cognition from three perspectives: computational (problem definition and optimal solutions), algorithmic (rational/engineering/descriptive solutions) and implementation (neural hardware). The lecture covers the following domains:

- decision-making with noisy information (value-based, time-integrated, multi-channel, sequential)
- information representation under resource constraints
- memory formation and storage in biological neural networks
- movement planning
- spatial navigation

Prerequisites

Recommended:

Recommended one out of:

- MA-INF 4113 Cognitive Robotics
- MA-INF 4114 Robot Learning
- MA-INF 4215 Humanoid Robotics
- MA-INF 4235 Reinforcement Learning

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|-----|--|
| Lecture | | 2 | 30 T / 45 S | 2.5 | |
| Exercises | | 2 | 30 T / 75 S | 3.5 | |

Graded exams

Written exam

Ungraded coursework (required for admission to the exam)

The completion of regularly provided exercise sheets. The work can be done in groups of up to four students. A total of 50% of the points must be achieved. Each group must present a solution to an exercise in the exercise sessions once.

MA-INF 4335 Lab AI Alignment

| Workload | Credit points | Duration | Frequency |
|-------------------------|----------------------|------------|------------|
| 270 h | 9 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Lucie Flek | Prof. Dr. Lucie Flek | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

Through tutorials and a final project, you will gain hands-on experience in AI alignment techniques and have this chance to apply this knowledge to various interesting projects. Students will collaborate in small teams (a group of 3-4 students) and implement small research projects over the course of the term, advised by a researcher from the CAISA lab. Students will learn to reproduce important results from the field, study the scientific literature, generate and implement their own research ideas, and present their results as a presentation and as a paper.

Learning goals: soft skills

Contents

As AI systems such as Large Language Models become increasingly capable and start to be used in high-stakes scenarios, ensuring that they act safely is gaining importance. The research field of AI alignment studies methods to align the behavior and values of AI systems with the user and broader society in a robust, scalable, and interpretable way. The aim of this course is to explore cutting-edge research, insights, and trends in the field of AI alignment.

Schedule:

- Week 0: Organization meeting
- Week 1-5: Lectures and programming exercises
- Week 6: Presentation of project ideas
- Week 12: midterm presentation of results
- Final presentation
- Student paper

Concrete research topics are 1) value alignment, 2) emergent misalignment, 3) scalable oversight, and 4) mechanistic interpretability, among others.

Prerequisites

Recommended:

One of the following courses is recommended:

- MA-INF 4115 - Introduction to Natural Language Processing,
- MA-INF 4235 - Reinforcement Learning,
- MA-INF 4204 - Technical Neural Nets.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|--------------|----|--|
| Lab | 8 | 4 | 60 T / 210 S | 9 | |

Graded exams

Oral presentation, written report

Ungraded coursework (required for admission to the exam)

Project work; attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- Hendrycks, Dan: Introduction to AI Safety, Ethics, and Society.
 - Ouyang, Long et al.: Training language models to follow instructions with human feedback.
 - Bowman, Sam et al.: Measuring Progress on Scalable Oversight for Large Language Models.
 - Li, Nathaniel et al.: Measuring and Reducing Malicious Use With Unlearning.
 - Bricken, Trenton et al.: Towards monosemanticity: Decomposing language models with dictionary learning.
-

MA-INF 4336 Seminar Selected Topics in Natural Language Processing

| Workload | Credit points | Duration | Frequency |
|-------------------------|----------------------|------------|------------|
| 120 h | 4 CP | 1 semester | every year |
| Module coordinator | Lecturer(s) | | |
| Prof. Dr. Lucie Flek | Prof. Dr. Lucie Flek | | |
| Programme | Mode | Semester | |
| M. Sc. Computer Science | Optional | 2. or 3. | |

Learning goals: technical skills

In this course, students will learn to engage with technical research papers and other material that study the state-of-the-art approaches to Natural Language Processing. They will learn to synthesize, critically assess, and build upon the material by conducting required readings, weekly discussions. In particular:

- to read and examine the scientific literature critically,
- to identify and present examples of relevant real-world application fields of the scientific publication,
- to give a good scientific presentation to peers that is precise, informative, and engaging,
- to summarize and write a concise technical report including a critical discussion of the research paper (with additional literature research).

Learning goals: soft skills

Contents

In this weekly seminar, students will learn about selected research topics in natural language processing and its applications. In addition, it is an introduction to reading scientific papers, learning how to give a good presentation, and how to write a technical report.

To better explore how state-of-the-art research presentations can be constructed, as a part of the seminar students will also have a chance to attend and discuss presentations of researchers on more senior level presenting their papers (e.g. guest speakers).

Prerequisites

Recommended:

One of the following courses is recommended (but not obligatory):

- MA-INF 4115 - Introduction to Natural Language Processing,
- MA-INF 4235 - Reinforcement Learning,
- MA-INF 4204 - Technical Neural Nets.

Remarks

At most 20 participants

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | 20 | 2 | 30 T / 90 S | 4 | |

Graded exams

Oral presentation, written report.

Ungraded coursework (required for admission to the exam)

Attendance in course sessions in accordance with the exam regulations of 2023, § 12(6).

Literature

- Jurafsky & Martin, Speech and Language Processing: <https://web.stanford.edu/~jurafsky/slp3/> .

5 Master Thesis

| | | | |
|-------------|-------|----------------------|-----|
| MA-INF 0401 | 30 CP | Master Thesis | 175 |
| MA-INF 0402 | 2 CP | Master Seminar | 176 |

MA-INF 0401 Master Thesis

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|----------------|
| 900 h | 30 CP | 1 semester | every semester |

| Module coordinator | Lecturer(s) |
|-----------------------|-----------------------------------|
| The Examination Board | All lecturers of computer science |

| Programme | Mode | Semester |
|-------------------------|------------|----------|
| M. Sc. Computer Science | Compulsory | 4. |

Learning goals: technical skills

Ability to solve a well-defined, significant research problem under supervision, but in principle independently

Learning goals: soft skills

Ability to write a scientific documentation of considerable length according to established scientific principles of form and style, in particular reflecting solid knowledge about the state-of-the-art in the field

Contents

Topics of the thesis may be chosen from any of the areas of computer science represented in the curriculum

Prerequisites

Required:

By the examination regulations of 2023, the Master's thesis project can only commence after 60 credits in other modules of the programme have been obtained. Before you start on the project, you must obtain the approval of the exam committee and register the starting date of the project. Please check the website of the examination office for forms and procedures.

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | |
|---|------------|--------|-------------|----|--|
| Independent preparation of a scientific thesis with individual coaching | | 0 | 900 S | 30 | T = face-to-face teaching S = independent study |

Graded exams

Master Thesis

Ungraded coursework (required for admission to the exam)

None

Literature

Individual bibliographic research required for identifying relevant literature (depending on the topic of the thesis)

MA-INF 0402 Master Seminar

| Workload | Credit points | Duration | Frequency |
|----------|---------------|------------|----------------|
| 60 h | 2 CP | 1 semester | every semester |

| Module coordinator | Lecturer(s) |
|-----------------------|-----------------------------------|
| The Examination Board | All lecturers of computer science |

| Programme | Mode | Semester |
|-------------------------|------------|----------|
| M. Sc. Computer Science | Compulsory | 4. |

Learning goals: technical skills

Knowledge of the state-of-the-art in research in the respective area and how the thesis results relate to that.

Learning goals: soft skills

Ability to identify the most relevant content for a knowledgeable scientific audience; ability to present and defend one's work in a presentation with visual media in a way that adheres to academic standards; ability to anticipate, accept and answer critical questions.

Contents

Topic, scientific context, and results of the master thesis

Prerequisites

Required:

The Master Seminar accompanies the Master Thesis project, see MA-INF 0401 for prerequisites.

Recommended:

None

Course meetings

| Teaching format | Group size | h/week | Workload[h] | CP | T = face-to-face teaching S = independent study |
|-----------------|------------|--------|-------------|----|--|
| Seminar | | 2 | 30 T / 30 S | 2 | |

Graded exams

Oral presentation of final results

Ungraded coursework (required for admission to the exam)

None

Literature

Individual bibliographic research required for identifying relevant literature (depending on the topic of the thesis)