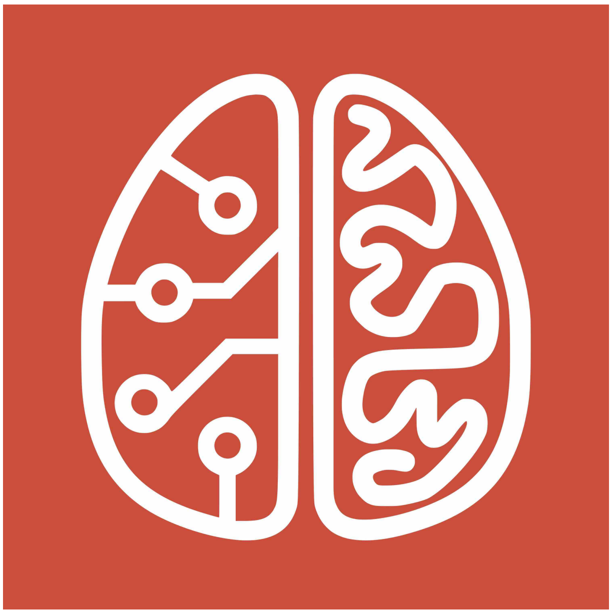
Department of Computer Science
Faculty of Mathematics and Science
Eberhard Karls University Tübingen

Module handbook

Machine Learning

Master of Science (M.Sc.)



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EBERHARD KARLS
UNIVERSITÄT
TÜBINGEN

MATHEMATISCH-
NATURWISSENSCHAFTLICHE
FAKULTÄT

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Preface

Structure and Subject Matter

This handbook describes the modules that make up the Master's program Machine Learning at the Department of Computer Science (Faculty of Science, Eberhard Karls University Tübingen). The Master's program consists of elective-compulsory modules ("Foundations of Machine Learning"), a large variety of elective modules in the area of machine learning ("Diverse Topics in Machine Learning") and more computer science in general ("General Computer Science"), as well as completely free modules ("Expanded perspectives"). Descriptions for the modules and additional areas of studies are given below, containing among other information the number of credit points required in each. Credit point requirements in a studies area are fulfilled by completing one or more modules belonging to that area and adding up credit points earned. Which module belongs to which area(s) can be seen from this handbook's appendix, the modules list.

Credit Points

Study areas and modules earn credit points (also: ECTS points based on the European Credit Transfer System, or simply credits). Credit points measure a student's time investment. Following national as well as international standards (in Germany: Resolution of the Standing Conference of the Minsters of Education and Cultural Affairs, 24 October 1997), a credit point represents a workload of 30 hours in attended classes and autonomous study performed by the student. The overall per-semester workload (including nonterm periods) ought not to exceed 900 hours, resulting in approximately 30 credit points required of the student each semester. Credit points represent not only time spent physically attending classes, but also time spent on preparing for and processing classes, as well as autonomous activities such as preparation for exam, writing the master thesis, and practical projects. Credit points are earned by attending and participating in courses that make up the modules, and require the completion of course-related tasks.

Types of Courses

Below we detail the general types of courses in the Master's program (note that some individual courses might give alternative information in their course descriptions).

Lectures, with and without tutorials In lectures, transfer of knowledge takes the form of a series of talks by the teacher. Lectures often go hand in hand with tutorials that deepen the students' understanding and knowledge about the subject matter and apply the techniques presented in class to concrete examples and scenarios. Homework commonly accompany this course type. Often, programming and other practical exercises, in which tasks are completed under direct supervision, form an important part. Typically, performance measurement and grading is based on a written (or more rarely oral) exam at the end of term.

Practical training are courses in which students finish assigned tasks in small teams, autonomously or under supervision. Study and exam performance are usually evaluated based on active participation, a presentation of results and in written reports.

Research projects are intended to give students an opportunity to get engaged in the ongoing research conducted in one of the groups and labs participating in this study program, for the duration of one semester. This course type aims to closely link the Master's program to current research, and to thoroughly prepare students for their upcoming Master's thesis. Study and exam performance are usually evaluated based on active participation, a presentation of results and in written reports. If applicable, students can participate in scientific publications.

Seminars are a series of classes in which students take up a specific assigned subject matter and give a presentation about it in front of their teacher and other co-participants. Usually, handing in a written version is an additional requirement. Performance is measured and grades assigned based on the presentation, the written report, and the student's active participation in class.

Grading

Modules will, as a rule, always be graded. Grades are determined by taking an examination of some sort – in the case of lectures, this is typically a written test. In certain instances, grading can be based on a multi-part examination. Details are given in the module descriptions. Grading is performed by the teachers of individual modules. According to our examination regulations, the grades of each module enter into the cumulative grade (Master's degree final grade), weighted by the module's credit points. An exception are modules within in ML-EXP (Expanded Perspectives) area of studies: credit points earned here can be used to fulfill overall credit requirements according to Examination Regulations, §3 (Structure), but grades earned in this area do not enter into the calculation of the cumulative grade for the Master's program. This gives students the possibility to extend their horizons by attending courses that are out of their comfort zone, without risking a dip in their overall grade.

Master's Program Machine Learning

General Information

Subjects

The international Master's Program Machine Learning will enable graduates to analyze, implement, leverage, and modify techniques of machine learning. As future actors and deciders in the field, they will be competent in all basic and many advanced areas of machine learning, understanding and suitably applying this increasingly essential tool for dealing with large datasets, be it in science, industry or alternative domains.

The studies program deals both with generic methods and their applications to specific fields, making it highly relevant for new career and job market purposes, both in science and industry. Education in problem solving capabilities is a central training objective.

To pick up on scientific trends and make the best use of the current state of research, the curriculum relies heavily on the strong research presence on site, in machine learning as well as the wider field of computer science: top-level researchers in all major methodological branches of machine learning are present in Tübingen – personnel that will actively engage in teaching for the Master's Program Machine Learning. Since the field is obviously very young and currently developing extremely rapidly, training will naturally be based on the most recent insights and the most pressing research questions of these teaching researchers.

Project work and the Master's thesis will offer students the opportunity to develop code for research purposes and their own scientific projects. In this whole Master program, besides professional expertise, graduates will also acquire language skills and intercultural competence due to the program's international nature.

Qualification Objectives

The Master's Program Machine Learning promotes a focus on research. It expands and deepens methodological and technical knowledge, enables graduates to work scientifically, provides the basis for advancing the field, and prepares graduates for subsequent PhD studies. The program specifically empowers graduates to take up responsible leading roles and emphasizes a scientific, research-oriented mindset based on independent thought, judgement and decision-making.

The program explicitly aims to cover the full breadth of the field, ranging from fundamental skills in mathematics and data handling to advanced methods of data analysis using a variety of methods of machine learning. We will particular train students to be able to quickly take up new research developments in the field of machine learning. Alongside aiming for breadth, the program also encourages specialization, in that modules within one area of studies can be freely combined. In their Master's thesis, graduates can take machine learning approaches and methods to tackle a freely chosen area in computer science or an adjoining field such as bioinformatics or medical informatics. The requisite depth of knowledge to do so will be obtained due to the program's consecutive studies plan, which is based on a B.Sc. in computer science or a neighbouring discipline.

Qualification objectives of this Master's program are as follows:

Graduates...

1. ...have further developed the qualifications obtained in their B.Sc. studies in an ongoing process of academic maturation. They have transferred learned skills to the field of machine learning and gained facility in applying and implementing technical and non-technical knowledge.
2. ...have obtained expert knowledge in a chosen focus field in the wider area of machine learning. .
3. ...have the necessary breadth as well as depth to quickly acquaint themselves with new developments in their own area of expertise and its adjacent areas.
4. ...are able to successfully utilize, to critically examine and to further advance machine learning methods in order to formulate and solve complex problems of research and development in the industry as well as research.
5. ...have acquired a diverse technical and social skillset (abstraction, analytical and systematic thinking, teamwork, communication, international and intercultural competence etc.), empowering them to seek positions of leadership.
6. ...are optimally prepared not only for functions related to research and development, but also for further responsible and leading positions in the industry or public administration.

Areas of Studies and Modules

Foundations of Machine Learning (ML-FOUND): this study area covers the basic, foundational directions in the field of machine learning that every student is supposed to learn. The modules in this area are elective modules, and altogether 24 CPs have to be earned in this area.

Diverse Topics in Machine Learning (ML-DIV): this study area contains many different courses of various aspects of machine learning, ranging from theory, generic methods, implementation details and fields of applications. Students can choose freely from this area of studies, and thereby set their own focus. All in all, 36 CPs need to be earned in this area of studies.

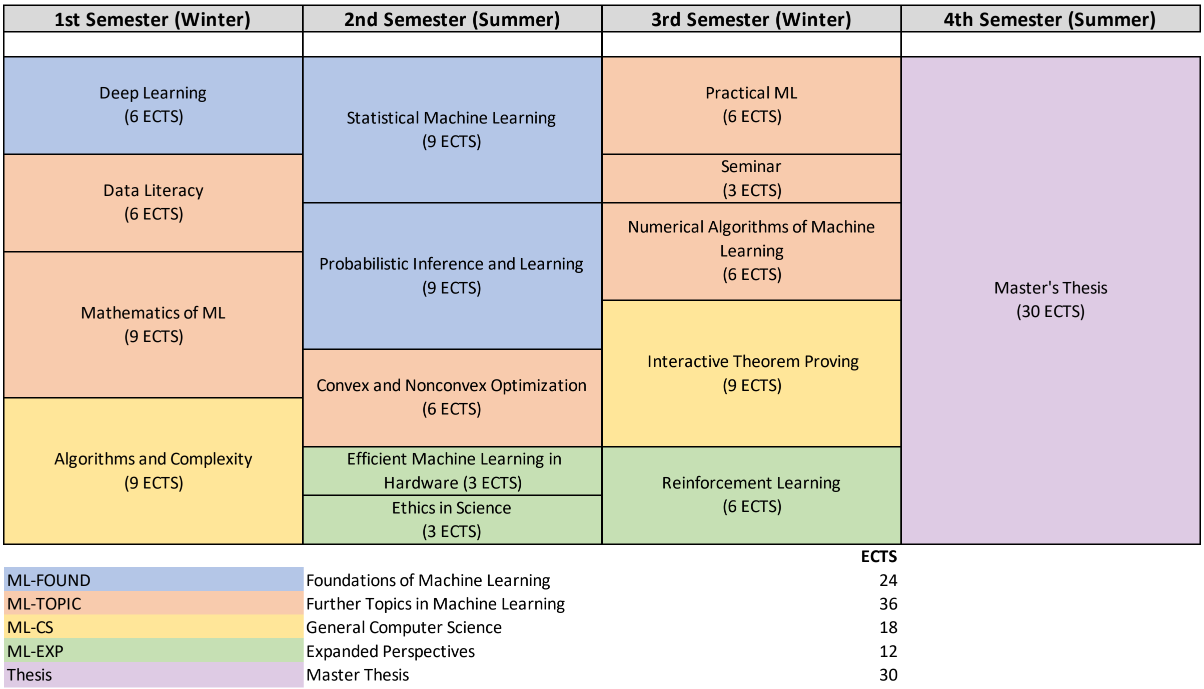
General computer science (ML-CS): In this study area students can take part in other courses offered by the Department of Computer science, for example to broaden their knowledge in a technique they feel they are still lacking (e.g., databases), or in application domains (e.g., computer vision, bioinformatics). Students choose courses of a total of 18 CPs.

Expanded Perspectives (ML-EXP): In this study area, students can choose courses freely from almost all courses (except for sports courses) offered at the University of Tübingen. It is meant to give students the opportunity to learn about particular application fields (e.g., geoscience, linguistics), improve their language skills in German (for foreign students) or English (for German students), or learn to reflect upon ethical or philosophical challenges brought by machine learning. Altogether 12 CPs in this field have to be fulfilled. Courses taken in this area need to be graded ones, and the grades will show up on the transcript of records, but the grades will not be taken into account for the cumulative grade of the Master's program, as stated above.

Structuring and Organizing Your Studies

The Examination Regulations, §3 (Structure), provides details on how to structure the studies in the Master's Program Machine Learning over four semesters. Overall, the program requires 120 credit points to be obtained. More information on modules and types of courses can be found within this module handbook. Figures 1-3 below show examples of study plans as examples of how one may organize one's studies; the ability to freely combine modules within areas of studies ensures that a wide range of studies plans are viable.

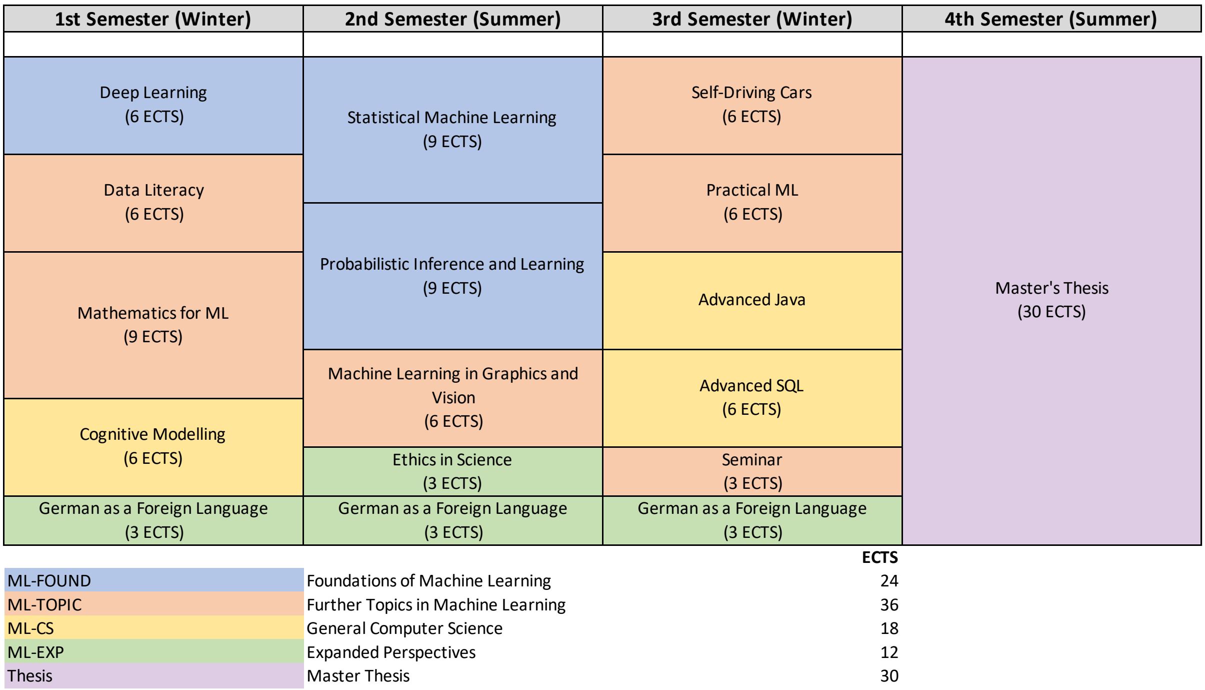
For students who plant to spend a semester abroad we recommend to do this in the third semester.



1st Semester (Winter)	2nd Semester (Summer)	3rd Semester (Winter)	4th Semester (Summer)
Deep Learning (6 ECTS)	Statistical Machine Learning (9 ECTS)	Practical ML (6 ECTS)	Master's Thesis (30 ECTS)
Data Literacy (6 ECTS)	Probabilistic Inference and Learning (9 ECTS)	Seminar (3 ECTS)	
Mathematics of ML (9 ECTS)	Convex and Nonconvex Optimization (6 ECTS)	Numerical Algorithms of Machine Learning (6 ECTS)	
Algorithms and Complexity (9 ECTS)	Efficient Machine Learning in Hardware (3 ECTS)	Interactive Theorem Proving (9 ECTS)	
	Ethics in Science (3 ECTS)	Reinforcement Learning (6 ECTS)	

		ECTS
ML-FOUND	Foundations of Machine Learning	24
ML-TOPIC	Further Topics in Machine Learning	36
ML-CS	General Computer Science	18
ML-EXP	Expanded Perspectives	12
Thesis	Master Thesis	30

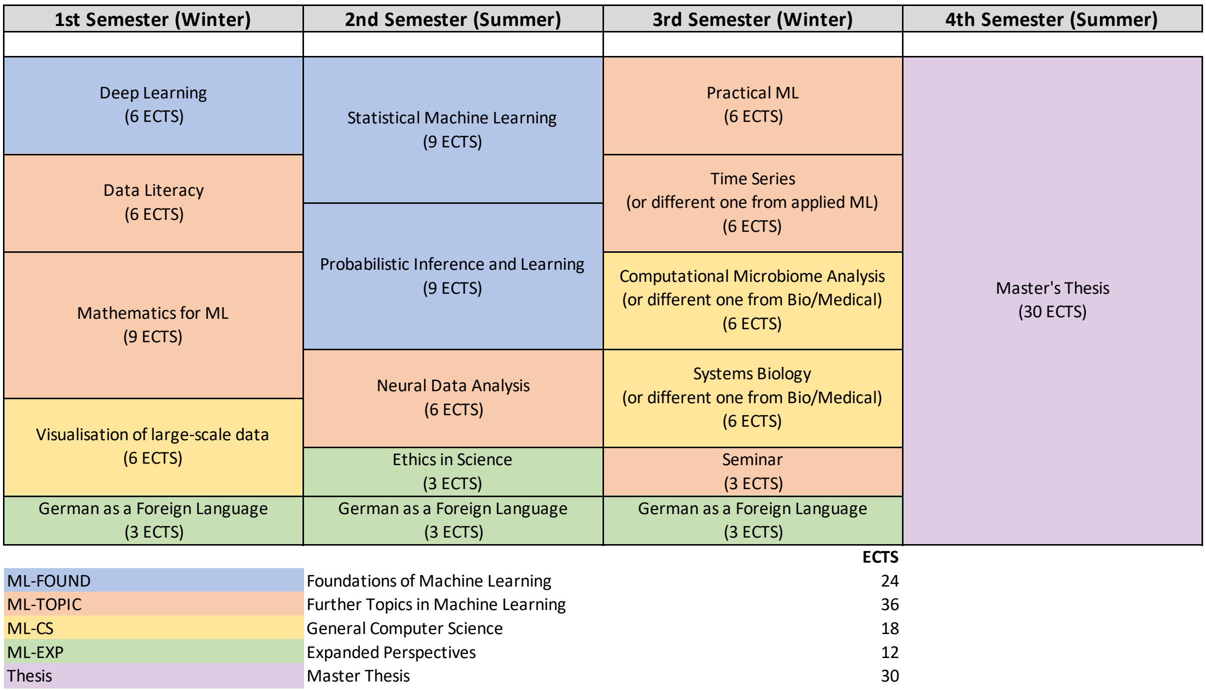
Figure 1: Study plan with focus on theory



1st Semester (Winter)	2nd Semester (Summer)	3rd Semester (Winter)	4th Semester (Summer)
Deep Learning (6 ECTS)	Statistical Machine Learning (9 ECTS)	Self-Driving Cars (6 ECTS)	Master's Thesis (30 ECTS)
Data Literacy (6 ECTS)	Probabilistic Inference and Learning (9 ECTS)	Practical ML (6 ECTS)	
Mathematics for ML (9 ECTS)	Machine Learning in Graphics and Vision (6 ECTS)	Advanced Java	
Cognitive Modelling (6 ECTS)	Ethics in Science (3 ECTS)	Advanced SQL (6 ECTS)	
German as a Foreign Language (3 ECTS)	German as a Foreign Language (3 ECTS)	Seminar (3 ECTS)	
		German as a Foreign Language (3 ECTS)	

		ECTS
ML-FOUND	Foundations of Machine Learning	24
ML-TOPIC	Further Topics in Machine Learning	36
ML-CS	General Computer Science	18
ML-EXP	Expanded Perspectives	12
Thesis	Master Thesis	30

Figure 2: Study plan with focus on practical (e.g. industrial) applications



1st Semester (Winter)	2nd Semester (Summer)	3rd Semester (Winter)	4th Semester (Summer)
Deep Learning (6 ECTS)	Statistical Machine Learning (9 ECTS)	Practical ML (6 ECTS)	Master's Thesis (30 ECTS)
Data Literacy (6 ECTS)		Time Series (or different one from applied ML) (6 ECTS)	
Mathematics for ML (9 ECTS)	Probabilistic Inference and Learning (9 ECTS)	Computational Microbiome Analysis (or different one from Bio/Medical) (6 ECTS)	
Visualisation of large-scale data (6 ECTS)	Neural Data Analysis (6 ECTS)	Systems Biology (or different one from Bio/Medical) (6 ECTS)	
	Ethics in Science (3 ECTS)	Seminar (3 ECTS)	
German as a Foreign Language (3 ECTS)	German as a Foreign Language (3 ECTS)	German as a Foreign Language (3 ECTS)	

		ECTS
ML-FOUND	Foundations of Machine Learning	24
ML-TOPIC	Further Topics in Machine Learning	36
ML-CS	General Computer Science	18
ML-EXP	Expanded Perspectives	12
Thesis	Master Thesis	30

Figure 3: Study plan with focus on biomedical applications

Module catalogue for the Master's degree program Machine Learning

Notes

This **module catalogue** is an appendix to the module handbook for the Master's degree programs Bioinformatics and Medical Informatics of the Computer Science Department at the Eberhard Karls University Tübingen.

The modules in this catalogue are arranged according to degree program, and within the degree programs according to the topically grouped required elective modules. For details regarding these required elective modules see the module handbook.

The academic council of the Computer Science Department provides an updated version of the module catalogue at the beginning of each semester.

Legend

Abbreviations	Meaning
Type	L = Lecture S = Seminar T = Tutorial P = Practical course R = Research project
Status	c = compulsory o = optional
CH	Credit hours
CP	Credit points (= ECTS points)
Type of exam	wt = written test ot = oral test tp = term paper op = oral presentation
Duration of exam	in minutes
Evaluation	g = graded ug = ungraded (pass / fail) nt = no test
Calculation of modules	possible percentage weighting of grades

Study Area: Foundations of Machine Learning

Module Number: ML-4103	**Module title** Deep Learning		**Module** elective
ECTS	6		
Work load **- Contact time** **- Self study**	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Lecture type	Lecture with tutorials		
Duration	1 semester		
Frequency	Regularly once a year		
Language of instruction	English		
Type of Exam	Written exam (in case of a small number of participants: oral exam)		
Content	Within the last decade, deep neural networks have emerged as an indispensable tool in many areas of artificial intelligence including computer vision, computer graphics, natural language processing, speech recognition and robotics. This course will introduce the (practical and theoretical) principles of deep neural networks and give an overview over the most established training and regularization techniques. The lecture will further discuss the most important network variants, including convolutional neural networks, generative neural networks, recurrent neural networks and deep reinforcement learning. Furthermore, the course will give an overview over the most important architectures (hourglass networks, skip connections, dense connections, dilated convolutions, permutation invariant networks, siamese networks, etc.). In addition, applications from various fields will be presented throughout the course. The tutorials will deepen the understanding of deep neural networks by implementing, training and applying them using modern deep learning frameworks.		
Objectives	Students gain an understanding of the practical and theoretical concepts of deep neural networks including, optimization, inference, various architectures and application domains. After this course, students should be able to develop and train deep neural network architectures for a particular task and understand the potentials and pitfalls when applying deep neural networks in practice.		

(still ML-4103)

Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Lecture	L	o	2	3	W	90	g	100
	Tutorial	T	o	2	3				
Requirement for participation	Basic math (linear algebra & analysis) and coding skills (Python).								
Lecturer	Andreas Geiger, Andreas Zell								
Literature	Related literature will be listed throughout the lecture.								

<table>
<tr><td>Module Number:
ML-4201</td><td colspan="2">Module title
Statistical Machine Learning</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">9</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
270 h</td><td>Class time
90 h / 6 CH</td><td>Self-Study
180 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="3">Regularly once a year</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="3">The focus of this lecture is on algorithmic and theoretical aspects of statistical machine learning. We will cover many of the standard algorithms, learn about the general principles for building good machine learning algorithms, and analyze their theoretical and statistical properties. The following topics will be covered: Supervised machine learning, for example linear methods; regularization; SVMs; kernel methods. Bayesian decision theory, loss functions,
Unsupervised learning problems, for example dimension reduction, kernel PCA, multi-dimensional scaling, manifold methods; spectral clustering and spectral graph theory.
Introduction to statistical learning theory: no free lunch theorem; generalization bounds; VC dimension; universal consistency;
Evaluation and comparison of machine learning algorithms.
Advanced topics in statistical learning, for example low rank matrix completion, compressed sensing, ranking, online learning.</td></tr>
<tr><td>Objectives</td><td colspan="3">Students get to know the most important classes of statistical machine learning algorithms. They understand why certain algorithms work well and others don’t. They can evaluate and compare the results of different learning algorithms. They can model machine learning applications and get a feeling for common pitfalls. They can judge machine learning algorithms from a theoretical point of view.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3">
<table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>4</td><td>6</td><td>W</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td><td></td><td></td><td></td><td></td></tr>
</table>
</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Students need to know the contents of the basic math classes, in particular linear algebra and probability theory.</td></tr>
<tr><td>Lecturer</td><td colspan="3">Matthias Hein, Ulrike von Luxburg</td></tr>
<tr><td>Literature</td><td colspan="3">The literature for this lecture will be provided at the beginning of the semester.</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4202</td><td colspan="5">Module title
Probabilistic Machine Learning</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">9</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
270 h</td><td colspan="3">Class time
90 h / 6 CH</td><td colspan="4">Self-Study
180 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">Regularly once a year</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="9">Probabilistic inference is a foundation of scientific reasoning, statistics, and machine learning. The lecture course begins with a general introduction to basic principles (rules of probability theory, graphical models), then covers the probabilistic view on many standard settings, like supervised regression and classification, and unsupervised dimensionality reduction and clustering. In a parallel thread through the lecture, we will also encounter a number of popular algorithms for inference in probabilistic models, including exact inference in Gaussian models, sampling, and free-energy methods. At specific points, connections and differences to non-probabilistic frameworks will be made.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students gain an intuitive, as well as a mathematical and algorithmic understanding of probabilistic reasoning. They acquire a mental toolbox of probabilistic models for various problem classes, along with the algorithms required for their concrete implementation. Over the course of the lecture, they also become proficient in the fundamental concept of uncertainty, and the philosophical challenges and pitfalls associated with it. They are empowered to build, analyse, and use their own probabilistic models for concrete use cases.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>4</td><td>6</td><td rowspan="2">W</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">basic math, in particular linear algebra. Code examples and coding exercises use python.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Philipp Hennig, Nico Pfeifer</td></tr>
<tr><td>Literature</td><td colspan="9">Literature will be listed at the beginning of the semester.</td></tr>
</table>

Study Area: Diverse Topics in Machine Learning

Module Number: ML-4101	**Module title** Mathematics of Machine Learning		**Module** elective
ECTS	9		
Work load **- Contact time** **- Self study**	Work load 270 h	Class time 90 h / 6 CH	Self-Study 180 h
Lecture type	Lecture with tutorials		
Duration	1 semester		
Frequency	every year		
Language of instruction	English		
Type of Exam	Written exam (in case of a small number of participants: oral exams)		
Content	The lecture will repeat and introduce basic notions of mathematics used in machine learning • **Calculus:** multivariate calculus (gradient and Hessian), Taylor expansion etc. • **Linear Algebra:** eigenvectors, eigenvalues (including variational characterization), singular value decomposition and best low rank approximation, inverse and pseudo-inverse, norms, basic algorithms and their complexity (solving linear equations, matrix inversion, eigenvectors (power method)) etc. • **Probability:** discrete and continuous probability measures (and mixed ones), basic notions, generation of random variables, conditional expectation and independence, law of large numbers and concentration inequalities for rates of convergence, central limit theorem etc. • **Statistics:** parametric and non-parametric tests • **Optimization:** Lagrangian and dual optimization problem, popular optimization techniques and their properties • **Optional:** basic functional analysis and approximation theory, curse of dimensionality		

(still ML-4101)

<table>
<tr><td>Objectives</td><td>Students learn the mathematical foundations for the latter machine learning courses. In particular,
they know multivariate calculus and linear algebra as needed in machine learning lectures
they can apply probability and statistics and are able to prove basic properties
they have an overview of existing optimization techniques and are able to reformulate equivalent constrained optimization problems</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td><table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">W</td><td rowspan="2">90</td><td rowspan="2">b</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
</table></td></tr>
<tr><td>Requirement for participation</td><td>Students need to have basic knowledge in analysis and linear algebra on the level of the bachelor lectures “Mathematik für Informatiker I-III”</td></tr>
<tr><td>Lecturer</td><td>Ulrike von Luxburg, Matthias Hein</td></tr>
<tr><td>Literature</td><td>The literature for this lecture will be provided at the beginning of the semester.</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4102</td><td colspan="6">Module title
Data Literacy</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">Regularly once a year</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="9">This course equips students with the concepts and tools that should be familiar to anyone who works with (large) data. It is centered around the following five central topics: conceptual framework of data, data collection, data management, data evaluation, and data application. Based on practical experiments and examples, frequently encountered pitfalls and problems are discussed alongside best practices. We will encounter common datatypes, and techniques for data preparation and cleaning. Several forms of bias are studied. Basic tools for data analysis and visualization are introduced and used hands-on. We will also discuss best practices for scientific data presentation and documentation—how to make expressive figures and tables and perform reproducible experiments—and explore ethical and technical considerations in the context of privacy and transparency.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students develop a sensitivity for common problems and misconceptions in empirical work with data. They understand the mathematical, epistemological, ethical, technical and social challenges surrounding the use of data, and know best practices to address them. They also collect a concrete box of software tools to collect, document, explore, visualize, and draw conclusions from structured, large, small, corrupted and expensive data.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">W</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">basic math and coding skills. The practical part will use several different, and largely open-source software packages.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Kay Nieselt, Philipp Hennig</td></tr>
<tr><td>Literature</td><td colspan="9">Literature will be listed at the beginning of the semester.</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4301</td><td colspan="6">Module title
Numerical Algorithms of Machine Learning</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="9">The computational cost of machine learning is almost entirely caused by numerical computations: <i>Optimization</i> for training and fitting of point estimates; <i>integration</i> for marginalization and conditioning in probabilistic models; <i>simulation</i>, i.e. the solution of differential equations for predictions of the future, and <i>linear algebra</i> as the base case of all of the above. These tasks are often solved with “black-box” tools, but those who want to build highly performant, scalable, professional solutions need to know how these tools worn and adapt them to the specific task. This course introduces basic and advanced tools for the aforementioned tasks. It develops a holistic view of computation in the context of, and within the conceptual framework of machine learning, moving from classic concepts to recent developments.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students develop both an intuitive and mathematical understanding of numerical methods for optimization, integration, linear algebra, and the solution of differential equation. They know how to adapt the tools to the challenges of the task at hand, such as high dimensionality, stochasticity in computation, numerical stability, non-convexity, efficient tuning of algorithmic parameters, and uncertainty calibration for imprecise computation. Experience in the design and use of numerical tools is a highly sought-after skill in industry, and distinguishes the expert engineer from the amateur user.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">W</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Linear algebra is a core theme. Knowledge of probabilistic machine learning is valuable for this course. Prior experience with numerical analysis is helpful but not required. The practical parts use python and various recent python libraries.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Philipp Hennig</td></tr>
<tr><td>Literature</td><td colspan="9">Literature will be listed at the beginning of the semester.</td></tr>
</table>

<table>
<tr><th>**Module Number:**
ML-4302</th><th colspan="2">**Module title**
Statistical Learning Theory</th><th>**Module**
elective</th></tr>
<tr><td>**ECTS**</td><td colspan="3">6</td></tr>
<tr><td>**Work load**
- Contact time
- Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>**Lecture type**</td><td colspan="3">Lecture with tutorials</td></tr>
<tr><td>**Duration**</td><td colspan="3">1 semester</td></tr>
<tr><td>**Frequency**</td><td colspan="3">Irregularly</td></tr>
<tr><td>**Language of instruction**</td><td colspan="3">English</td></tr>
<tr><td>**Type of Exam**</td><td colspan="3">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>**Content**</td><td colspan="3">Part 1: basic results in statistical learning theory:
• Statistical setup, estimation and approximation error, consistency
• Negative results: No free lunch theorem, slow rates of convergence
• Consistency of k nearest neighbor algorithms and partitioning algorithms
• Concentration inequalities: Hoeffding and Chernov
• Simple generalization bounds, for example with shattering coefficients and VC dimension
• Advanced generalization bounds, for example using Rademacher complexities, algorithmic stability, sample compression, ...
• Regularization and its consistency
Part 2: advanced results in statistical learning theory. This part of the lecture changes, depending on the interests of the audience and the current state of the art in the field and covers some of the recent results on learning theory. It could cover topics like online learning, theory of unsupervised learning, theory of deep learning, etc.</td></tr>
<tr><td>**Objectives**</td><td colspan="3">Students get to know the standard tools and approaches in statistical learning theory. They understand positive and negative results in learning theory, in particular what are the fundamental limitations of machine learning, and which properties are important to make a machine learning algorithm work.</td></tr>
<tr><td>**Requirement for Credit Points / Grade**</td><td colspan="3">
<table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td>W</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td><td></td><td></td><td></td><td></td></tr>
</table>
</td></tr>
</table>

(still ML-4302)

Requirement for participation	Students need to know the contents of the basic math classes, in particular linear algebra and probability theory.
Lecturer	Ulrike von Luxburg
Literature	The literature for this lecture will be provided at the beginning of the semester.

Module Number:	**Module title**	**Module**
ML-4303	Convex and Nonconvex Optimization	elective

ECTS	9

Work load **- Contact time** **- Self study**	Work load	Class time	Self-Study
	270 h	90 h / 6 CH	180 h

Lecture type	Lecture with tutorials
Duration	1 semester
Frequency	every two years
Language of instruction	English
Type of Exam	Written test (in case of a small number of participants: oral tests)
Content	Convex optimization problems arise quite naturally in many application areas like signal processing, machine learning, image processing, communication and networks and finance etc. The course will give an introduction into convex analysis, the theory of convex optimization such as duality theory, algorithms for solving convex optimization problems such as interior point methods but also the basic methods in general nonlinear unconstrained minimization, and recent first-order methods in non-smooth convex optimization. We will also cover related non-convex problems such as d.c. (difference of convex) programming, biconvex optimization problems and hard combinatorial problems and their relaxations into convex problems. While the emphasis is given on mathematical and algorithmic foundations, several example applications together with their modeling as optimization problems will be discussed. The course requires a good background in linear algebra and multivariate calculus, but no prior knowledge in optimization is required.
Objectives	Students learn the foundations of convex analysis and how to formulate and transform optimization problems. After the lecture they know a variety of methods for solving convex and non-convex optimization problems and have guidelines which method to choose for which problem.

Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Lecture	L	o	4	6	W	90	g	100
	Tutorial	T	o	2	3				

Requirement for participation	Students need to know the contents of the basic math classes, in particular linear algebra and multivariate calculus. No prior background in optimization is required.
Lecturer	Matthias Hein
Literature	The lecture does not follow a specific book. The literature for this lecture will be provided at the beginning of the semester.

<table>
<tr><td>Module Number:
ML-4310</td><td colspan="5">Module title
Data Mining and Probabilistic Reasoning</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
90 h</td><td colspan="3">Class time
30 h / 2 CH</td><td colspan="4">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">regularly in the winter</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="9">The lecture gives an introduction into the basics of probability theory, statistics, information theory, data (pre-)processing and indexing techniques, graph representations and link analysis, classification, clustering and topic models, probabilistic inference in graphical models.</td></tr>
<tr><td>Objectives</td><td colspan="9">The students acquire extensive knowledge in theory and application of methods from the field of data science.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>1</td><td>2</td><td rowspan="2">W</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>1</td><td>1</td></tr>
<tr><td>Requirement for participation</td><td colspan="9"></td></tr>
<tr><td>Lecturer</td><td colspan="9">Gjergji Kasneci</td></tr>
<tr><td>Literature</td><td colspan="9">Will be supplied (book chapters and papers in English)</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4320</td><td colspan="6">Module title
Time Series</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="9">A time series is an extremely wide-spread type of empirical data: a (potentially multivariate) set of observations that evolves over a univariate and thus ordered index space—time. Examples include stock prices, inventory levels, sports statistics, sensor readings in scientific equipment, cars and machinery, and many more. Time series often require real-time processing, and can potentially be infinitely long. But their univariate domain also allows for a crucial property of the model: <i>Markovianity</i>, the ability to locally store all aspects of the model necessary for inference in a time-local memory of fixed and finite size. This course introduces a range of models and algorithms for efficient and flexible inference in time series. Starting from famous concepts from the areas of signal processing and control, we will move to recent and contemporary models for structured, high-dimensional, non-linear and irregular time series. Alongside data and models, efficient algorithms for approximate inference are a core focus.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students develop an understanding for key algorithmic and modelling challenges in the analysis of, and practical inference with time-ordered processes and data. They can implement and debug basic and advanced models for such data, including for production-level, large-scale applications, and for areas demanding high quality predictions, such as scientific analysis.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture
Tutorial</td><td>L
T</td><td>o
o</td><td>2
2</td><td>3
3</td><td>wo</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Basic linear algebra. Knowledge of probabilistic concepts in machine learning is valuable. Some of the practical exercises use python.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Philipp Hennig</td></tr>
<tr><td>Literature</td><td colspan="9">Literature will be listed at the beginning of the semester.</td></tr>
</table>

<table>
<tr><td>**Module Number:**
ML-4330</td><td colspan="2">**Module title**
Machine Learning in Graphics and Vision</td><td>**Module**
elective</td></tr>
<tr><td>**ECTS**</td><td colspan="3">6</td></tr>
<tr><td>**Work load**
- Contact time
- Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>**Lecture type**</td><td colspan="3">Lecture with tutorials</td></tr>
<tr><td>**Duration**</td><td colspan="3">1 semester</td></tr>
<tr><td>**Frequency**</td><td colspan="3">Regularly once a year in the summer semester</td></tr>
<tr><td>**Language of instruction**</td><td colspan="3">English</td></tr>
<tr><td>**Type of Exam**</td><td colspan="3">Oral Exam</td></tr>
<tr><td>**Content**</td><td colspan="3">This course covers basic machine learning concepts that are relevant in the context of computer vision and computer graphics. The focus of this course is to establish the connections between machine learning and concrete applications in computer vision and computer graphics for which learning from large (annotated) datasets is relevant. Topics in machine learning include supervised learning, unsupervised learning, classification, regression, random forests, support vector machines, deep neural networks, generative adversarial networks, graphical models, structured prediction and deep structured models. Topics in computer vision and graphic cover image classification, semantic segmentation, stereo, multi-view stereo, optical flow, image denoising, image deblurring, rendering of faces and global illumination.</td></tr>
<tr><td>**Objectives**</td><td colspan="3">Students develop an understanding for the challenges of several important computer vision and computer graphics problems and how to tackle these challenges using large datasets and machine learning techniques. They understand the basic concepts of machine learning that are relevant to these applications and are able to apply them using common deep learning frameworks.</td></tr>
<tr><td>**Requirement for Credit Points / Grade**</td><td colspan="3"><table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td>o</td><td>30</td><td>g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td><td></td><td></td><td></td><td></td></tr>
</table></td></tr>
<tr><td>**Requirement for participation**</td><td colspan="3">Basic math and coding skills. Experience with deep learning (e.g., course “Deep Neural Networks”) is an advantage but not a must. The necessary deep learning frameworks will be briefly introduced in the first tutorials of this lecture.</td></tr>
<tr><td>**Lecturer**</td><td colspan="3">Andreas Geiger, Hendrik Lensch</td></tr>
<tr><td>**Literature**</td><td colspan="3">Related literature will be listed throughout the lecture.</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4340</td><td colspan="6">Module title
Self-Driving Cars</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">Regularly once a year</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Oral Exam</td></tr>
<tr><td>Content</td><td colspan="9">Within the last years, driverless cars have emerged as one of the major workhorses in the field of artificial intelligence. Given the large number of traffic fatalities, the limited mobility of elderly and handicapped people as well as the increasing problem of traffic jams and congestion, self-driving cars promise a solution to one of our socities most important problems: the future of mobility. However, making a car drive on its own in largely unconstrained environments requires a set of algorithmic skills that rival human cognition, thus rendering the task very hard. This course we will cover the most dominant paradigms of self-driving cars: modular pipeline-based approaches as well as deep-learning based end-to-end driving techniques. Topics include camera, lidar and radar-based perception, localization, navigation, path planning, vehicle modeling/control, imitation learning and reinfocement learning. The tutorials will deepen the acquired knowledge through the implementation of several deep learning based approaches to perception and sensori-motor control in the context of autonomous driving. Towards this goal, we will build upon existing simulation environments and established deep learning frameworks.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students develop an understanding of the capabilities and limitations of state-of-the-art autonomous driving solutions. They gain a basic understanding of the entire system comprising perception, learning and vehicle control. In addition, they are able to implement and train simple models for sensori-motor control.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">o</td><td rowspan="2">30</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Basic math and coding skills. Experience with deep learning frameworks is an advantage but not a must. The necessary deep learning frameworks will be briefly introduced in the first tutorials of this lecture.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Andreas Geiger</td></tr>
</table>

(still ML-4340)

Literature	Related literature will be listed throughout the lecture.

<table>
<tr><td>Module Number:
ML-4350</td><td colspan="2">Module title
Reinforcement Learning</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Lecture, Tutorial</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="3">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Oral presentation and written project report</td></tr>
<tr><td>Content</td><td colspan="3">Introduction to Machine Learning
Supervised Learning and Optimization
Intro Reinforcement Learning (RL) and Markov Decision Processes
Dynamic Programming, prediction and control
Value Function Approximation
Policy Gradient
Deep RL, control in continuous state-action domains
Optimal Control and Model-based RL
Advanced topics in RL</td></tr>
<tr><td>Objectives</td><td colspan="3">Students can phrase a problem in the reinforcement learning framework and can select an appropriate algorithm for solving it. Students are able to implement a set of algorithms and analyse their behavior.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3"><table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td>o</td><td>30</td><td>g</td><td>50</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td><td>p</td><td></td><td>g</td><td>50</td></tr>
</table></td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Recommended to attend basic Machine learning class before.</td></tr>
<tr><td>Lecturer</td><td colspan="3">Georg Martius</td></tr>
<tr><td>Literature</td><td colspan="3">Reinforcement learning by Sutton and Barto <code>http://incompleteideas.net/book/bookdraft2017nov5.pdf</code>
Pattern Recognition and Machine Learning by C.M. Bishop, Chap. 3 and 5
Deep Learning by Goodfellow, Bengio and Courville <code>https://www.deeplearningbook.org</code></td></tr>
</table>

<table>
<tr><th>Module Number:
ML-4410</th><th colspan="6">Module title
Neural Data Analysis</th><th colspan="3">Module
elective</th></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
120 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture, Tutorial</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">regularly in the summer term</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written report and cumulative oral exam</td></tr>
<tr><td>Content</td><td colspan="9">In recent years experimental methods to record brain activity have been revolutionized. As the complexity of the data acquired in neuroscience increases, neural data analysis becomes ever more important: The complex multidimensional signals recorded with e.g. multielectrode arrays or two-photon imaging can no longer be interpreted by eye, but rigorous data analytic techniques are needed.
In this course we will cover a selection of topics related to the analysis of different kinds of neural data based on concepts of machine learning: time series analysis, spike sorting, spike triggered average/covariance, dimensionality reduction techniques and information theory. The focus will be on applying state-of-the-art concepts in hands-on data analysis of real data sets.</td></tr>
<tr><td>Objectives</td><td colspan="9">In this course students will acquire the techniques necessary to analyze multidimensional discrete (spike trains) and continuous (cellular voltage/calcium signals, LFP, EEG, etc.) neural signals. Students will acquire hands-on knowledge and learn to deal with the difficulties of applying those techniques to real data.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td>o</td><td>30</td><td>g</td><td>50</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td><td></td><td></td><td>g</td><td>50</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Some knowledge of basic neuroscience is helpful, but not a must.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Prof. Dr. Philipp Berens, Dr. Alexander Ecker</td></tr>
</table>

(still ML-4410)

Literature	Emery N Brown, Robert E Kass, und Partha P Mitra, „Multiple neural spike train data analysis: state-of-the-art and future challenges“, Nat Neurosci 7, Nr. 5 (Mai 2004): 456-461. Robert E. Kass, Valérie Ventura, und Emery N. Brown, „Statistical Issues in the Analysis of Neuronal Data“, Journal of Neurophysiology 94, Nr. 1 (Juli 1, 2005): 8 -25. Dayan and Abbott: Theoretical Neuroscience. MIT Press. Rieke, Warland, Ruyter van Stevenik and Bialek: Spikes – Exploring the neural code. MIT Press.

<table>
<tr><td>Module Number:
INFO-4366</td><td colspan="6">Module title
Advanced Topics in Neural Networks</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
45 h / 3 CH</td><td colspan="3">Self-Study
135 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Seminar</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Will be announced at the beginning of the seminar</td></tr>
<tr><td>Content</td><td colspan="9">The seminar deals with yearly changing topics of artifical neural networks, e.g. deep convolutional neural networks, recurrent neural networks, neural networks for image classification or image segmentation, neural network for control, hybrid classical - neural systems, etc.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students may choose a topic in the field of mobile robots, perform a scientific analysis of the chosen topic and present their results in written and oral form.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Seminar</td><td>S</td><td>o</td><td>3</td><td>6</td><td>wt</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">none</td></tr>
<tr><td>Lecturer</td><td colspan="9">Zell</td></tr>
<tr><td>Literature</td><td colspan="9">Will be announced in the pre-lecture meeting.</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4492</td><td colspan="6">Module title
Special Topics in Learning Theory</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English or German, depending on the participants</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="9">In this module we discuss advanced results and approaches in learning theory and current research results in the area of machine learning in general.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students get to know about advanced results in learning theory. They can judge whether an algorithm is well designed, both from an algorithmic and statistical point of view. They understand about the fundamental limitations of machine learning. They can reflect current research questions. After this module they are well-prepared to write a master thesis in the area of learning theory.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">wt</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Solid knowledge in maths (linear algebra, probability theory); Basic knowledge in machine learning</td></tr>
<tr><td>Lecturer</td><td colspan="9">von Luxburg</td></tr>
<tr><td>Literature</td><td colspan="9">will be announced in the lecture</td></tr>
</table>

Module Number: INFO-4493	**Module title** Learning Theory		**Module** elective
ECTS	3		
Work load **- Contact time** **- Self study**	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h
Lecture type	Seminar		
Duration	one semester		
Frequency	irregularly		
Language of instruction	English or German, depending on the participants		
Type of Exam	Oral presentation, written report.		
Content	In this seminar we discuss current research papers in the area of machine learning theory, in the form of student's presentations and guided discussions.		
Objectives	Students are able to read and reflect upon current research papers in the area of learning theory. They can critically assess the contributions of such a paper. They can present current research results to other students and researchers and can lead research discussions. They can summarize and evaluate the results of a paper in form of a written research report.		

Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Seminar	S	o	2	3	R	45	g	100

Requirement for participation	Basic knowledge in machine learning.
Lecturer	von Luxburg
Literature	will be announced in the lecture

<table>
<tr><td>Module Number:
ML-4420</td><td colspan="2">Module title
Efficient Machine Learning in Hardware</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
90 h</td><td>Class time
30 h / 2 CH</td><td>Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Lecture</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="3">regularly in the summer, every two years</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Oral Exam</td></tr>
<tr><td>Content</td><td colspan="3">The recent breakthroughs in using deep neural networks for a large variety of machine learning applications have been strongly influenced by the availability of high performance computing platforms. In contrast to its biological origin, however, high performance of artificial neural networks critically relies on much higher energy demands. While the average energy consumption of the entire human brain is comparable to that of a Laptop computer (i.e. 20W), artificial intelligence often resorts to large HPCs with several orders of magnitude higher energy demand. This lecture will discuss this problem and show solution how to build energy and resource efficient architectures for machine learning in hardware. In this context, the following topics will be addressed:
• Hardware architectures for machine learning: GPUs, FPGAs, overlay architectures, SIMD architectures, domain-specific architectures, custom accelerators, in/near memory computing, architectures for training vs. architectures for inference
• Energy-efficient machine learning
• Optimized mapping of deep neural networks to hardware and pipelining techniques
• Word length optimization (binary, ternary, integer, floating point)
• Scalable application specific architectures
• New switching devices to implement neural networks (Memristors, PCM)
• Neuromorphic computing</td></tr>
<tr><td>Objectives</td><td colspan="3">Students gain in-depth knowledge about the challenges associated with energy-efficient machine learning hardware and respective state-of-the-art solutions. Different hardware architectures will be compared regarding the trade-off between their energy consumption, complexity, computational speed and the specificity of their applicability. The main goals of the course are learning what kinds of hardware architectures are used for machine learning, understanding the reasons why a particular architecture is suitable for a particular application and how to efficiently implement machine learning algorithms in hardware.</td></tr>
</table>

(still ML-4420)

		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Requirement for Credit Points / Grade	Lecture	L	o	2	3	ot	30	g	100
Requirement for participation									
Lecturer	Bringmann								
Literature	Will be announced in the first lecture								

<table>
<tr><td>Module Number:
ML-4510</td><td colspan="5">Module title
Practical Machine Learning</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="4">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Practical Course</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">every semester</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Oral presentation, written report, lab journal</td></tr>
<tr><td>Content</td><td colspan="9">The practical course consists of finishing assigned tasks in small teams, autonomously or under supervision. Study and exam performance are usually evaluated based on active participation, a presentation of results and in written reports.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students will gain practical experience in designing and programming methods / software /tools for ML. They will be able to use libraries and frameworks, and will acquire knowledge or extend their knowledge of various programming languages. By working together in groups, students obtain teamwork and collaboration skills, and they will learn about project organization and presentation techniques. Students will know about the strengths and weaknesses and about the limitations of various methods for evaluating complex and high-dimensional data, and will be able to describe and evaluate these methods.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Practical</td><td>P</td><td>o</td><td>4</td><td>6</td><td>wo</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9"></td></tr>
<tr><td>Lecturer</td><td colspan="9">All lecturers in the programme</td></tr>
<tr><td>Literature</td><td colspan="9">-</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4501</td><td colspan="6">Module title
Machine Learning Seminar</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
90 h</td><td colspan="4">Class time
30 h / 2 CH</td><td colspan="3">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Seminar</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">regularly in the winter/summer</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Oral presentation and written report</td></tr>
<tr><td>Content</td><td colspan="9">In this module we discuss advanced results and approaches in machine learning theory and application and current research results in the area of machine learning in general.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students get to know about advanced results in machine learning theory and applications. They can judge for example whether an algorithm is well designed, both from an algorithmic and statistical point of view. They understand about the fundamental limitations of machine learning. They can reflect current research questions. Students will be able to acquire knowledge about current findings through comprehensive literature search. They will know the importance of current topics in the area of machine learning, and will be aware that there are still many open questions. Students will not only have improved their study and reading skills, but will also have enhanced their capability of working independently. The teaching method in this seminar aims at boosting the students' confidence (oral presentation), and at enhancing their communication skills and enabling them to accept criticism (discussion session following their presentation. After this module they are well-prepared to write a master thesis in the area of machine learning.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Seminar</td><td>S</td><td>o</td><td>2</td><td>3</td><td>wo</td><td>30</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9"></td></tr>
<tr><td>Lecturer</td><td colspan="9">All lecturers in the computer science department</td></tr>
<tr><td>Literature</td><td colspan="9">Will be handed out in the course</td></tr>
</table>

Module Number:	**Module title**	**Module**
ML-4998	Research Project Machine Learning	elective

ECTS	9		
Work load **- Contact time** **- Self study**	Work load 270 h	Class time 30 h / 2 CH	Self-Study 240 h
Lecture type	Independent research project		
Duration	1 semester		
Frequency	each semester		
Language of instruction	English		
Type of Exam	Essay		
Content	The research project serves to deepen theoretical and practical knowledge in a specific field of machine learning. Students are working on a research project with the main focus of the research group.		
Objectives	The students • get an insight into scientific work, • learn how to independently pursue a research question, • learn independently to identify and compile scientific literature for the question to be worked on, • are able to work in a team in an international scientific environment, • deepen their problem-solving skills, • can give a scientific lecture		

Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Research Project	R	o	2	9	tp		g	100

Requirement for participation	Excellent academic grades in Master Machine Learning. There are only a few research projects that are offered semester by semester. A written application, including letter of motivation, CV and Transcript of Records should be sent to the research group leader of the offered research project.
Lecturer	All professors in Machine learning
Literature	Scientific literature/publications relevant to the research topic to be addressed

Study Area: General Computer Science

Module Number: INFO-4165	**Module title** Discrete Optimization for Image Analysis		**Module** elective
ECTS	3		
Work load **- Contact time** **- Self study**	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h
Lecture type	Lecture		
Duration	1 semester		
Frequency	Regularly once a year		
Language of instruction	English		
Type of Exam	e.g. Oral or written exam		
Content	This lecture introduces fundamental tasks in the field of image analysis through their mathematical abstraction in the form of discrete optimization problems. The tasks include image classification, image and video segmentation, multiple object recognition and multiple object tracking. The problems include the unconstrained binary quadratic program, graph decomposition and node labeling problems. The course establishes the computational complexity of these problems by reduction techniques. It introduces algorithms for computing feasible solutions, partial solutions and bounds. An emphasis is on efficient algorithms that are practical for image analysis, including local search, bounded reverse search and network flow.		
Objectives	Participants get to know fundamental problems in the field of image analysis. They develop a rigorous understanding of these problems and their complexity. Participants also get to know practical algorithms for computing feasible solutions, partial solutions and bounds. Finally, they develop the scholarly communication skills in English.		

(still INFO-4165)

Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Lecture	L	o	2	3	wt or ot	90 or 30	g	100
Requirement for participation									
Lecturer	Björn Andres								
Literature	e.g. Related literature will be listed throughout the lecture.								

<table>
<tr><td>Module Number:
INFO-4315</td><td colspan="5">Module title
Advanced Topics in Embedded Systems</td><td colspan="4">Module
Elective Module</td></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
90 h</td><td colspan="3">Class time
30 h / 2 CH</td><td colspan="3">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">each summer semester</td></tr>
<tr><td>Language of instruction</td><td colspan="9">German, Englisch</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Oral exam (in case of a large course written exam)</td></tr>
<tr><td>Content</td><td colspan="9">This lecture discusses current topics and trends in embedded system research with special focus on design, analysis and verification of embedded systems and Systems-on-Chip. The lecture starts with an introduction into embedded systems architectures and electronic system level design. Then, the latest developments in analysis of non-functional properties like timing, power dissipation, and energy consumption are discussed. The lesson on verification addresses formal, semi-formal and dynamic techniques and give insights into run-time verification using different languages for formal property specification. The lecture finally covers advanced semiconductor technologies as well as reliability and functional safety aspects.</td></tr>
<tr><td>Objectives</td><td colspan="9">Participants will acquire the necessary knowledge to upcoming aspects in embedded systems as well as the necessary skills to design, analyse, and verify embedded systems under safety constraints. They will gain hands-on experience in embedded system design and to avoid common pitfalls.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td>OR</td><td>30</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">none</td></tr>
<tr><td>Lecturer</td><td colspan="9">Bringmann</td></tr>
<tr><td>Literature</td><td colspan="9">Will be announced during the first lecture.</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4194</td><td colspan="5">Module title
Behavior and Learning</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="4">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="9">Based on our knowledge about how animals and humans plan their behavior, make behavioral decisions, control their behavior, and progressively optimize and adapt it, behavioral decision making, control, optimization, and adaptation algorithms are introduced. In particular, the lecture introduces spatial representations for behavioral control, forward-inverse control models, including the learning of such representations and models. Also the encoding and the learning of motor control primitives and motor complexes is considered. Last but not least, self-motivated artificial systems are considered that strive to maintain internal homeostasis and to maximize information gain.</td></tr>
<tr><td>Objectives</td><td colspan="9">Know how intelligent behavior can be generated and learned in artificial systems. Knowledge about reinforcement learning (RL), including hierarchical RL and factored RL; dynamic motion primitives and their optimization; information-gain driven behavior; sensorimotor-grounded spatial representations and machine learning principles to learn such representations; developing artificial systems that learn to behave effectively and goal-directedly in artificial (virtual) environments.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td>wt</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td><td></td><td></td><td></td><td>0</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Introductory course knowledge about machine learning, artificial neural networks, robotics, or artificial intelligence is required.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Butz</td></tr>
<tr><td>Literature</td><td colspan="9">Will be supplied (book chapters and papers in English)</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4210</td><td colspan="2">Module title
Advanced Artificial Neural Networks</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Lecture with tutorial</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="3">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="3">Advanced ANN topics. First, revisiting backpropagation and backpropagation through time; then: Advanced Recurrent Neural Networks (LSTM); Deep Learning; Convolution; Reservoir Computing; Dynamic NNs; Hierarchical Vision Architectures; Restricted Boltzmann Machines; Predictive Encoding & Free Energy; Gain Fields and Switching Networks</td></tr>
<tr><td>Objectives</td><td colspan="3">Know about and how to apply advanced artificial neural networks in various domains including data classification, image recognition, language processing, spatially-invariant recognition, spatial transformations, and spatial mappings.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3">
<table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td>tp</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td><td></td><td></td><td></td><td>0</td></tr>
</table>
</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Introductory course knowledge about machine learning, artificial neural networks, robotics, or artificial intelligence is required.</td></tr>
<tr><td>Lecturer</td><td colspan="3">Butz</td></tr>
<tr><td>Literature</td><td colspan="3">Will be supplied (book chapters and paper in English)</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4212</td><td colspan="5">Module title
Artificial Neural Networks</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
180 h</td><td colspan="4">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Practical course</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Final Project Presentation and Report</td></tr>
<tr><td>Content</td><td colspan="9">Programming enhanced functionalities in ANN Software, evaluating performance, analyzing the system.</td></tr>
<tr><td>Objectives</td><td colspan="9">Know how to work with artificial neural networks..</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>4</td><td>6</td><td>tp</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Solid Knowledge in Programming. Knowledge about artificial neural networks or machine learning.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Butz</td></tr>
<tr><td>Literature</td><td colspan="9"><i>keine</i></td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4213</td><td colspan="5">Module title
Advanced Artificial Neural Networks Project</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
90 h</td><td colspan="3">Class time
30 h / 2 CH</td><td colspan="4">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Practical course</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Final Project Presentation and Report</td></tr>
<tr><td>Content</td><td colspan="9">Working with ANN Software, evaluating performance, & analyzing the system.</td></tr>
<tr><td>Objectives</td><td colspan="9">Know how to evaluate and analyze artificial neural networks.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td><td>tp</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Solid Knowledge in Programming. Knowledge about artificial neural networks or machine learning.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Butz</td></tr>
<tr><td>Literature</td><td colspan="9"><i>keine</i></td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4214</td><td colspan="5">Module title
Cognitive Modeling</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="4">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="9">Various cognitive models including descriptive, qualitative, quantitative and neural models are introduced and contrasted. Moreover, techniques to compare models as well as to interpret and evaluate model parameters are introduced. Also parameter optimization is covered. All techniques are closely related to cognitive processes, mechanisms, and learning in the brain. However, the covered techniques may also be applied in other domains where data is analyzed, interpreted, and modeled.</td></tr>
<tr><td>Objectives</td><td colspan="9">Know how to model cognitive processes, mechanisms, and learning at different levels. Know techniques to compared different models qualitatively and quantitatively. Know how to validate and falsify cognitive models. Know how to interpret cognitive models. Know about different types of neuro-computational cognitive models.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td>wt</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td><td></td><td></td><td></td><td>0</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Introductory course knowledge about machine learning, artificial neural networks, robotics, cognitive architectures, or artificial intelligence is required.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Butz</td></tr>
<tr><td>Literature</td><td colspan="9">Book: S. Lewandowsky & S. Farrell (2011). Computational Modeling in Cognition. Additional papers and book chapters will be supplied.</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4211</td><td colspan="6">Module title
Avatars in Virtual Realities</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Practical course</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Final Project Presentation and Report</td></tr>
<tr><td>Content</td><td colspan="9">Programming and design of intelligent, realistic, interesting, behaving avatars in virtual realities.</td></tr>
<tr><td>Objectives</td><td colspan="9">Know how to work with virtual realities and how to develop animated, autonomous avatars in these environments.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>4</td><td>6</td><td>tp</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Solid Knowledge in Programming. General knowledge about simulation software.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Butz</td></tr>
<tr><td>Literature</td><td colspan="9"><i>keine</i></td></tr>
</table>

<table>
<tr><th>Module Number:
INFO-4250</th><th colspan="5">Module title
Information Processing for Perception and Action</th><th colspan="4">Module
elective</th></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
90 h</td><td colspan="3">Class time
30 h / 2 CH</td><td colspan="3">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Seminar</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">Deutsch, English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Wird zu Beginn des Semesters bekanntgegeben / Will be announced at beginning of semester</td></tr>
<tr><td>Content</td><td colspan="9">Humans as well as complex technical systems process sensory information to interact with the environment. These actions have consequences which (again) create sensory events that can be processed and used to improve the interaction with the environment. We will discuss advanced topics of this full ’perception–action’ loop; in humans as well as in technical systems. A special focus will be on the experimental literature from the Cognitive– and Neurosciences and on advanced statistical methods.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students will know current views on biological information processing and on the interaction of humans with technical systems. They will also learn and understand advanced statistical and empirical methods that were used to generate this knowledge. This expertise will help them to apply their knowledge in interdisciplinary working environements, whenever empirical studies on human performance and actions are required.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Seminar</td><td>S</td><td>c</td><td>2</td><td>3</td><td>tp,op</td><td>45</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">No formal requirements, but students should have a good background in statistics and should have attended introductory/mid–level courses in Cognitive Science/Neuroscience.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Franz</td></tr>
<tr><td>Literature</td><td colspan="9">Wird zu Beginn des Semesters bekanntgegeben / Will be announced at beginning of semester</td></tr>
</table>

Module Number: INFO-4152	**Module title** Advanced Statistics		**Module** elective
ECTS	3		
Work load **- Contact time** **- Self study**	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h
Lecture type	Lecture, Tutorials		
Duration	1 semester		
Frequency	irregularly		
Language of instruction	English		
Type of Exam	Pass/fail depending on performance in homework (every 4th session is a tutorial for which we expect participants to have prepared and handed in homework; typically some implementation in R/SPSS; for each session we expect participants to have read the relevant literature).		
Content	Advances in neuroscientific methodology give rise to the accumulation of huge amounts of data. Analysing these data poses new problems that are typically not covered by the classical introductory statistics courses and also increase the need to master classic statistical topics as, for example, statistical power and required sample sizes, problems of multiple testing, correlational structure of repeated measures, etc. In short, solid statistical knowledge beyond standard tests and ANOVAs are very important for anyone working in the neurosciences today. Moreover, in recent years, alternative approaches to data analysis have received increasing attention because they can solve specific problems and inconsistencies of classical statistics. E.g. Bayesian approaches makes use of our previous knowledge about the data, and non-parametric permutation statistics/Bootstrap have the advantage of being relatively free of assumptions about the underlying distribution of the data. This course will present these statistical methods in a way that focuses on understanding the guiding principals as well as the practical applications of these methods in real neuroscientific data. Further details: `http://www.ecogsci.cs.uni-tuebingen.de/teach.php`		
Objectives	Being able to understand and apply somewhat advanced statistical methods to empirical research questions in the life-sciences/neuroscience.		
Requirement for participation	Basic/intermediate knowledge of classic statistics. You should feel comfortable with basic statistical topics as between-groups ANOVA, t-tests, regression analysis, basics of repeated-measures ANOVA, and the rationale/mathematics behind these procedures. You should also feel comfortable (or be willing to learn rapidly) with implementing these basic methods either in the programming language R or in the SPSS macro language (‘syntax mode’).		
Lecturer	Franz and Gaiss (Medical Faculty)		
Literature	Literature will be announced during the course.		

<table>
<tr><td>Module Number:
INFO-4149</td><td colspan="2">Module title
Selected Topics in Database Systems: Advanced SQL</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="3">one semester</td></tr>
<tr><td>Frequency</td><td colspan="3">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English or German, depending on attendees</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Written exam (or oral exam if number of attendees is small)</td></tr>
<tr><td>Content</td><td colspan="3">We study established as well as recent topics in the design, implementation, and applications of database system technology, with a focus on relational database systems. This includes the evaluation of data-intensive algorithms close to the source data, i.e., inside the database system itself: database systems provide much more than dumbed down table storage.</td></tr>
<tr><td>Objectives</td><td colspan="3">Students gain insights into the internals of modern database systems, including physical data layout and storage, data indexing, query optimization, and processing. Attendees will be able to properly position database systems in larger system architectures and know about their particular strengths as well as the bottlenecks they may introduce. Students will understand database systems as capable data processors that can play a central role in data-intensive computation. The course provides the ideal introduction for a continued deeper study of database systems and prepares students for subsequent research and master thesis projects in this field.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3">
<table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>4</td><td>wr</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>2</td><td></td><td></td><td></td><td></td></tr>
</table>
</td></tr>
<tr><td>Requirement for participation</td><td colspan="3"><i>none</i></td></tr>
<tr><td>Lecturer</td><td colspan="3">Grust</td></tr>
<tr><td>Literature</td><td colspan="3">To be announced during the semester, typically a selection of classical and recent scientific articles that define the field.</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4381</td><td colspan="6">Module title
Advanced Topics in Perception Engineering</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
90 h</td><td colspan="4">Class time
30 h / 2 CH</td><td colspan="3">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Seminar</td></tr>
<tr><td>Duration</td><td colspan="9">one semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written report (essay)</td></tr>
<tr><td>Content</td><td colspan="9">Eye movements are not only a rich source of information about a person's intention and perception but, above all, the most intuitive form of interaction. Although eye-tracking is still in its infancy, the technology offers the greatest potential for novel communication solutions and applications across industries, such as medicine, automotive, education, advertisement, sports or security. This course tackles challenges and benefits associated with eye tracking that can pave the way for new gaze-based technology in everyday life.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students will read and reflect upon current research in the area of perception engineering. They can present current research results to other students and researchers as well as lead research discussions. They can summarize and evaluate the results of a paper in the form of a written research report.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Seminar</td><td>S</td><td>o</td><td>2</td><td>3</td><td>op</td><td>30</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">none</td></tr>
<tr><td>Lecturer</td><td colspan="9">Kasneci</td></tr>
<tr><td>Literature</td><td colspan="9"><i>keine</i></td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4412</td><td colspan="6">Module title
Algorithms and Complexity</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">9</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
270 h</td><td colspan="3">Class time
90 h / 6 CH</td><td colspan="3">Self-Study
180 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture, Tutorial</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">regularly in the winter, every year</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written Exam (Oral Exam at small number of participants), grades in the tutorial might be included to the final grade as bonus</td></tr>
<tr><td>Content</td><td colspan="9">Topics amongst others are:
• Matching
• MinCostFlow
• Approximation Schemes
• Network Analysis
• Clustering
• Algorithmic Geometry
• Discussions about complexity, e.g. lower bounds</td></tr>
<tr><td>Objectives</td><td colspan="9">Students gain in-depth knowledge about algorithmic techniques in different fields of problems. This includes the application of sophisticated graph algorithms, the proficiency in strategies for network analysis as well as the ability to apply and develop approximation methods. Regarding the field of complexity, the students can judge the difficulty level of problems and also prove their judgements by techniques learned in this course.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>4</td><td>6</td><td rowspan="2">W</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Requirement for participation</td><td colspan="9"></td></tr>
<tr><td>Lecturer</td><td colspan="9">Kaufmann</td></tr>
</table>

(still INFO-4412)

Literature	Raghavan, Magnati, Orlin: Randomized Algorithms Mehlhorn, Näher: LEDA - A platform for combinatorial and geometric computation Papadimitriou, Steiglitz: Combinatorial optimization : algorithms and complexity

<table>
<tr><td>Module Number:
INFO-4241</td><td colspan="6">Module title
Programming Languages II</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">about every two years</td></tr>
<tr><td>Language of instruction</td><td colspan="9">Englisch or German, depending on the participants</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written or oral examination. Participation in exercises is required for exam participation.</td></tr>
<tr><td>Content</td><td colspan="9">This lecture is about the semantics and type systems of modern programming languages. We discuss the foundations of programming languages using formal semantics (such as small-step operational semantics), formal type systems and their properties, and different variants of typed lambda calculi that constitute the foundation for modern type systems.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students will be able to discuss and analyze modern programming languages in terms of the properties of their theoretical foundations. They will understand the design space and tradeoffs of type systems for these languages.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">wt or ot</td><td rowspan="2">90 or 30</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Programming Languages I is helpful, but not required.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Ostermann</td></tr>
<tr><td>Literature</td><td colspan="9">Benjamin C. Pierce. Types and Programming Languages. MIT Press, 2003.</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4242</td><td colspan="6">Module title
Programming Languages III</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture, Practical exercises</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written or oral exam</td></tr>
<tr><td>Content</td><td colspan="9">This course is on advanced programming techniques and programming language features. Possible topics include: Partial evaluation and staging, dependently-typed programming, type-level programming, object algebras, generic programming, embedding techniques for domain-specific languages, metaprogramming.</td></tr>
<tr><td>Objectives</td><td colspan="9">The students are able to recognize the need for and apply advanced programming in their programs.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">wt or ot</td><td rowspan="2">90 or 30</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Programming Languages I and II is helpful, but not required</td></tr>
<tr><td>Lecturer</td><td colspan="9">Ostermann</td></tr>
<tr><td>Literature</td><td colspan="9">Will be published on the course homepage.</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4246</td><td colspan="5">Module title
Programming with Dependent Types</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
120 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="4">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Practical Course</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">German or English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Project, Presentation and Documentation</td></tr>
<tr><td>Content</td><td colspan="9">Dependent types are types that can depend on values: arrays of length 25, 20-by-20 matrices, or integers larger than -3. Agda and Idris are two dependently typed languages. Dependent types are good for many things -— from eliminating ArrayIndexOutOfBoundsException to mechanically verified programs and proving mathematical theorems -— yet the idea itself originates from the foundational crisis of mathematics at the turn of the 19th century. Dependent types carry their own coding patterns and caveats. In this seminar, we learn to program effectively with dependent types: How to make hard things possible, how to not make simple things hard, and a bit of how things work under the hood.</td></tr>
<tr><td>Objectives</td><td colspan="9">The students can use a dependently-typed language such as Agda or Coq and use dependent types to express and prove non-trivial program properties.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Practical</td><td>P</td><td>o</td><td>4</td><td>6</td><td>tpt</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Participation in Programming Languages I, II or III is helpful but not required..</td></tr>
<tr><td>Lecturer</td><td colspan="9">Ostermann</td></tr>
<tr><td>Literature</td><td colspan="9">will be announced during the course</td></tr>
</table>

Module Number: INFO-4247	**Module title** Algorithmic Trading		**Module** elective
ECTS	9		
Work load **- Contact time** **- Self study**	Work load 270 h	Class time 90 h / 6 CH	Self-Study 180 h
Lecture type	Lecture, Seminar and Programming Project		
Duration	1 semester		
Frequency	irregularly		
Language of instruction	English		
Type of Exam	Oral exam, seminar presentation, project		
Content	This course starts with a crash course on quantitative methods in computational finance (such as quantitative financial modelling), econometrics (such as time series analysis), and trading strategies (such as statistical arbitrage trading). In the second part of the course, the seminar part, the participants prepare presentations on practical software tools for algorithmic trading, such as the quantmod and PerformanceAnalytics packages for R, or the Quantopian framework for trading with Python. In the third part of the course, the project part, the participants program their own trading algorithm with languages and tools of their choice. The algorithms will be back-tested with real data.		
Objectives	The students know what algorithmic trading is and how it connects to common computer science topics, such as event processing systems or machine learning algorithms. They can use common tools to program trading algorithms.		
Requirement for participation	Programming skills in Python, R or Scala are helpful.		
Lecturer	Ostermann		
Literature	Will be published on the course homepage.		

Module Number: INFO-4248	**Module title** Interactive Theorem Proving		**Module** elective
ECTS	9		
Work load **- Contact time** **- Self study**	Work load 270 h	Class time 90 h / 6 CH	Self-Study 180 h
Lecture type	Lecture with tutorials		
Duration	1 semester		
Frequency	about every two years		
Language of instruction	English		
Type of Exam	Written or oral examination. Participation in exercises is required for exam participation.		
Content	This course is an introduction to interactive theorem programming and advanced functional programming, mostly using the Coq proof assistant. This course is for students interested in: 1. The foundational theories of mathematics, most notably type theory and logic 2. Practical interactive theorem proving in a state-of-the-art proof assistant 3. Advanced functional programming languages and their relation to constructive mathematics via the "Curry-Howard Isomorphism" 4. Program verification and "certified programming" 5. Programming Language Semantics		
Objectives	Students will be able to write programs and prove theorems in the Coq proof assistant. Students understand the theoretical underpinnings of interactive theorem provers and get basic insights into the semantics and formal properties of programming languages.		
Requirement for participation	A background in functional programming is helpful. Experience with mathematical proofs is helpful.		
Lecturer	Ostermann		
Literature	Volume 1 and 2 of the "Software Foundations" series available at `https://softwarefoundations.cis.upenn.edu/`. A. Chlipala, Certified Programming with Dependent Types, MIT Press		

<table>
<tr><td>**Module Number:**
INFO-4467</td><td colspan="6">**Module title**
Advanced Mathematical Logic</td><td colspan="3">**Module**
elective</td></tr>
<tr><td>**ECTS**</td><td colspan="9">6</td></tr>
<tr><td>**Work load**
- Contact time
- Self study</td><td colspan="2">Work load
180 h</td><td colspan="4">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>**Lecture type**</td><td colspan="9">Lectures + tutorials</td></tr>
<tr><td>**Duration**</td><td colspan="9">1 semester</td></tr>
<tr><td>**Frequency**</td><td colspan="9">every year</td></tr>
<tr><td>**Language of instruction**</td><td colspan="9">English</td></tr>
<tr><td>**Type of Exam**</td><td colspan="9">Written or oral examination, with bonus points from assessed exercises of the tutorials</td></tr>
<tr><td>**Content**</td><td colspan="9">Advanced topics in mathematical logic including Gödel's theorems, intuitionistic (constructive) logic, elements of proof theory</td></tr>
<tr><td>**Objectives**</td><td colspan="9">Students should master basic methods and results of mathematical logic that go beyond standard first-order logic, in particular topics relevant to computer science.</td></tr>
<tr><td rowspan="3">**Requirement for Credit Points / Grade**</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lectures</td><td>L</td><td>o</td><td>2</td><td>4</td><td rowspan="2">W</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorials</td><td>T</td><td>o</td><td>2</td><td>2</td></tr>
<tr><td>**Requirement for participation**</td><td colspan="9">Solid knowledge of first-order logic (for example, INF3481)</td></tr>
<tr><td>**Lecturer**</td><td colspan="9">Schroeder-Heister</td></tr>
<tr><td>**Literature**</td><td colspan="9">To be made available on the web</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4469</td><td colspan="2">Module title
Special Topics in Mathematical Logic</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Lectures + tutorials</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="3">no regular intervals</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Written or oral examination, with bonus points from assessed exercises of the tutorials</td></tr>
<tr><td>Content</td><td colspan="3">Varying topics from the area of mathematical logic, for which no dedicated module has been defined. Examples: Nonclassical logics, many-valued and fuzzy logics, nonmonotonic logic, categorial logic, proof-theoretic semantics.</td></tr>
<tr><td>Objectives</td><td colspan="3">Students acquire basic knowledge of logical methodology and applications of logic for a special topic.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3">
<table>
<tr><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lectures</td><td>L</td><td>o</td><td>2</td><td>4</td><td rowspan="2">W</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorials</td><td>T</td><td>o</td><td>2</td><td>2</td></tr>
</table>
</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Solid knowledge of first-order logic (for example, INF3481)</td></tr>
<tr><td>Lecturer</td><td colspan="3">Schroeder-Heister</td></tr>
<tr><td>Literature</td><td colspan="3">To be made available on the web</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4482</td><td colspan="6">Module title
Proof Theory</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lectures + Tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">no regular interval</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written or oral examination, with bonus points from assessed exercises of the tutorials</td></tr>
<tr><td>Content</td><td colspan="9">Proof theory studies the structure of mathematical proofs. Due to the parallelism between proving and computing it is of particular relevance for computer science. Besides the structure of proofs, the discipline investigates the relative strengh of formal systems, for example with respect to the induction principles available or the power of inductive definitions that can be formulated within the system. The course presents basic methods and results for first- and second-order logic, formal arithmetic and constructive type theory.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students obtain an overview of a way to formally study mathematical proofs. Apart from its intrinsic interest, this course shows how to approach reasoning in general in a mathematically precise way.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>4</td><td rowspan="2">wt</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>2</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Solid knowledge of first-order logic (for example, INF3481)</td></tr>
<tr><td>Lecturer</td><td colspan="9">Schroeder-Heister</td></tr>
<tr><td>Literature</td><td colspan="9">To be provided on the web</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4654</td><td colspan="5">Module title
Mathematical Logic</td><td colspan="4">Module
Elective</td></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
90 h</td><td colspan="3">Class time
30 h / 2 CH</td><td colspan="3">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Seminar</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">(almost) every semester</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Oral and written presentation (essay)</td></tr>
<tr><td>Content</td><td colspan="9">Advanced topics of mathematical logic</td></tr>
<tr><td>Objectives</td><td colspan="9">Besides extending their knowledge of mathematical logic (in addition to the lecture course “Advanced Mathematical Logic”, INF4467), students should autonomously acquire competence in a special topic of mathematical logic and present it both in form of a lecture and by means of an essay in a precise way.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Seminar</td><td>S</td><td>o</td><td>2</td><td>3</td><td>tp</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Solid knowledge of first-order logic (for example, INF3481)</td></tr>
<tr><td>Lecturer</td><td colspan="9">Schroeder-Heister</td></tr>
<tr><td>Literature</td><td colspan="9">To be provided on the web</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4462</td><td colspan="2">Module title
Communication, Mobility, Parallelism: Introduction to the Pi-Calculus</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Lectures + tutorials</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="3">no regular intervals</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Written or oral examination, with bonus points from assessed exercises of the tutorials</td></tr>
<tr><td>Content</td><td colspan="3">The Pi-calculus serves for the description of the behavior of interacting mobile processes. Here, “behavior” is not merely the input-output relationship of a classical automaton, but stands for state-transformations of parallel interacting automata (“processes”), which are formalized in detail. Applications of the Pi-calculus reach from the description of high-level handshakes in communication networks over the modelling of the runtime-behavior of object-oriented programming languages to the presentation of evaluation strategies in functional programming languages. The course covers both the theoretical foundations of the Pi-calculus as well as a selection of significant applications.</td></tr>
<tr><td>Objectives</td><td colspan="3">Students acquire knowledge of an extension of the concept of automaton that is particularly useful for the description of interaction and parallelism. This gives them basic theoretical tools for the modelling of communication networks.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3"><table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>4</td><td>wt</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>2</td><td></td><td></td><td></td><td></td></tr>
</table></td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Some knowledge of first-order logic (for example, INF3481) is useful, but not absolutely necessary.</td></tr>
<tr><td>Lecturer</td><td colspan="3">Schroeder-Heister, Arndt</td></tr>
<tr><td>Literature</td><td colspan="3">R. Milner, Communicating and Mobile Systems: The Pi-Calculus, Cambridge University Press, 1999 D. Sangiorgi & D. Walker, The Pi-Calculus. A Theory of Mobile Processes, Cambridge University Press, 2001. Further sources will be made available on the web.</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4466</td><td colspan="5">Module title
Logics for Programs and Processes</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lectures + tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">no regular intervals</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written or oral examination, with bonus points from assessed exercises of the tutorials</td></tr>
<tr><td>Content</td><td colspan="9">Foundations of “dynamic logic”, which allows for the specification of programs and processes by means of techniques from modal and temporal logics.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students acquire a theoretical instrument to deal not only with states, but also with dynamic procedures, and thus gain basic knowledge of the theoretical modelling of processes. The ethods exemplified are useful in many fields of practical and technical informatics.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>4</td><td>wt</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>2</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Solid knowledge of first-order logic (for example, INF3481)</td></tr>
<tr><td>Lecturer</td><td colspan="9">Schroeder-Heister, Arndt</td></tr>
<tr><td>Literature</td><td colspan="9">D. Harel, D. Kozen & J. Tiuryn, Dynamic Logic, MIT Press, 2000. Further materials will be made available on the web.</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4465</td><td colspan="6">Module title
Lambda Calculus and Combinatory Logic</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lectures + tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">no regular intervals</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written or oral examination, with bonus points from assessed exercises of the tutorials</td></tr>
<tr><td>Content</td><td colspan="9">The Lambda calculus is a fundamental prerequisite for the abstract modelling of functions and is absolutely central not only for functional programming but for any computational topic in which the notion of function plays a significant role. The course presents the basic variants of the calculus (typed, untyped, polymorph) as well as its relationship to combinatory logic, in which the dealing with bound variables is replaced with the handling of operators called “combinators”. Central topics cover confluence, normalization, typing algorithms as well as the relationship to deductive logic (“Curry-Howard correspondence”).</td></tr>
<tr><td>Objectives</td><td colspan="9">Students acquire basic issues of one of the most fundamental formal tools in theoretical computer science, which has many applications also in other disciplines which use the concept of function such as, for example, mathematics and linguistics.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>4</td><td rowspan="2">wt</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>2</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Some knowledge of first-order logic (for example, INF3481) is useful, but not absolutely necessary.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Schroeder-Heister, Arndt, Piecha</td></tr>
<tr><td>Literature</td><td colspan="9">J. Hindley, P. Seldin: Lambda-Calculus and Combinators: An Introduction, Cambridge University Press 2008, course notes by P. Schroeder-Heister (in German, see homepage). Further sources will be made available on the web.</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4468</td><td colspan="5">Module title
Theoretical Foundations of Logic Programming</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="4">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lectures + Tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">no regular interval</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written or oral examination, with bonus points from assessed exercises of the tutorials</td></tr>
<tr><td>Content</td><td colspan="9">Logic programming is a declarative programming paradigm that has special application, for example, in linguistics. This course is devoted to its theoretical foundations, which are mathematically near to the theory of inductive definitions, and in computer science near to (aspects of) database theory. Programs in a programming language such as PROLOG are clauses of a fragment of first-order logic, which are evaluated according to a specific procedure (unification, resolution, backtracking). Particular emphasis is put on the handling of hypothetical and negative information. The techniques used in logic programming overlap with certain techniques in automated theorem proving. Thus students interested in the latter subject can benefit from this course.</td></tr>
<tr><td>Objectives</td><td colspan="9">Knowledge of a particular way to computationally frame reasoning logically encoded knowledge, which is relevant in many areas inside and outside of computer science.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>4</td><td rowspan="2">wt</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>2</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Solid knowledge of first-order logic (for example, INF3481)</td></tr>
<tr><td>Lecturer</td><td colspan="9">Schroeder-Heister, Piecha</td></tr>
<tr><td>Literature</td><td colspan="9">To be provided on the web</td></tr>
</table>

<table>
<tr><td>Module Number:
BIO-4376</td><td colspan="2">Module title
Biomedical data management</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Lecture, Seminar</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="3">yearly</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Oral exam (in case of high number of participants: written exam); successful seminar participation is a prerequisite for the exam.</td></tr>
<tr><td>Content</td><td colspan="3">Topics will be the various high-throughput technologies that are used to generate data in biomedical research (e.g., omics, imaging, screening), methods for the processing and the analysis of high-throughput data. We will discuss standardization and data sharing. You will be introduced to data and metadata models, state-of-the-art data storage and general data management concepts (e.g., database systems, data warehouses and web interfaces) and data visualization. Furthermore, we will introduce concepts for automated data integration and automated workflows in general.
The lecture provides the technical basis of the topics and the seminar provides their applications. Students will present and discuss original scientific articles of the technologies outlined in the lecture.</td></tr>
<tr><td>Objectives</td><td colspan="3">The model teaches the technical basis for the professional handling of biomedical high-throughput data. Students will learn methods to implement bioinformatics workflows for data processing and statistical methods for data evaluation. Students will be proficient in handling big data and in data management systems (e.g., OpenBIS) and their applications. As part of the seminar, students will learn to present and defend scientific topics, as well as written scientific articles that relate to data management and biomedicine.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3"><table>
<tr><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>O</td><td>2</td><td>3</td><td>O</td><td>30</td><td>g</td><td>50</td></tr>
<tr><td>Seminar</td><td>S</td><td>O</td><td>2</td><td>3</td><td></td><td></td><td></td><td>50</td></tr>
</table></td></tr>
<tr><td>Requirement for participation</td><td colspan="3">-</td></tr>
<tr><td>Lecturer</td><td colspan="3">Nahnsen</td></tr>
<tr><td>Literature</td><td colspan="3">-</td></tr>
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<table>
<tr><td>**Module Number:**
BIO-4242</td><td colspan="6">**Module title**
Advanced Java in Bioinformatics</td><td colspan="3">**Module**
elective</td></tr>
<tr><td>**ECTS**</td><td colspan="9">6</td></tr>
<tr><td>**Work load**
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>**Lecture type**</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>**Duration**</td><td colspan="9">1 semester</td></tr>
<tr><td>**Frequency**</td><td colspan="9">yearly</td></tr>
<tr><td>**Language of instruction**</td><td colspan="9">English</td></tr>
<tr><td>**Type of Exam**</td><td colspan="9">Written or oral exam</td></tr>
<tr><td>**Content**</td><td colspan="9">In this course, we study the latest features of Java to address challenging programming problems in bioinformatics. Topics include JavaFx, two- and third-dimensional graphics, properties and bindings, animation, concurrent programming and webprogramming.</td></tr>
<tr><td>**Objectives**</td><td colspan="9">The aim of this course is to enable students to address challenging programming problems in bioinformatics using advanced features of Java.</td></tr>
<tr><td rowspan="2">**Requirement for Credit Points / Grade**</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>f</td><td>4</td><td>6</td><td>w or o</td><td>90 or 30</td><td>g</td><td>100</td></tr>
<tr><td>**Requirement for participation**</td><td colspan="9">BIO-4110 Sequence Bioinformatics</td></tr>
<tr><td>**Lecturer**</td><td colspan="9">Huson</td></tr>
<tr><td>**Literature**</td><td colspan="9">Programming literature</td></tr>
</table>

<table>
<tr><th>Module Number:
BIO-4311</th><th colspan="6">Module title
Phylogenetic Trees and Networks</th><th colspan="3">Module
elective</th></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test or oral test</td></tr>
<tr><td>Content</td><td colspan="9">In this course, we introduce students to advanced computational aspects of phylogenetic trees and networks. We look at both unrooted and rooted trees and networks, and discuss the technical details of many of the methods used to compute them.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students are introduced to advanced concepts and methods in phylogeny. They are enabled who to apply such methods to questions in systematics.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>c</td><td>4</td><td>6</td><td>wt</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">BIO-4110 Sequence Bioinformatics</td></tr>
<tr><td>Lecturer</td><td colspan="9">Huson</td></tr>
<tr><td>Literature</td><td colspan="9">Huson, Rupp and Scornavacca, Phylogenetic Networks, CUP 2011. Steel, Phylogenetics, 2016</td></tr>
</table>

<table>
<tr><td>Module Number:
BIO-4361</td><td colspan="5">Module title
Advanced Sequence Analysis</td><td colspan="4">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="2">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="4">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">every two years</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test or oral test</td></tr>
<tr><td>Content</td><td colspan="9">In this course, we look at advanced topics in sequence analysis, such as fast string matching, multiple string matching, approximate string matching, and advanced data-structures such as suffix trees, suffix arrays and the Burrows-Wheeler index.</td></tr>
<tr><td>Objectives</td><td colspan="9">The aim of this course is to provide students with detailed knowledge of advanced topics in sequence analysis.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>4</td><td>6</td><td>wt</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">BIO-4110 Sequence Bioinformatics</td></tr>
<tr><td>Lecturer</td><td colspan="9">Huson</td></tr>
<tr><td>Literature</td><td colspan="9">Detailed script, original articles</td></tr>
</table>

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<table>
<tr><td>Module Number:
BIO-4331</td><td colspan="6">Module title
Advances in Computational Transcriptomics</td><td colspan="3">Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="9">Lecture, tutorial</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="9">Offered at irregular intervals</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test, or oral test (in case of a small group)</td></tr>
<tr><td>Content</td><td colspan="9">Functional genomics, i.e. the interpretation of a genome to determine the biological function of the gene and of gene interaction, is one of the most important fields of modern biology. In addition to DNA microarrays, next-generation sequencing techniques are increasingly applied which allow simultaneous measurement of the expression of thousands of genes. This results in new challenges in bioinformatics with regard to algorithms and software. This lecture covers topics such as NGS technologies, especially RNA-Seq and ChIP-Seq technologies, fast to ultra fast alignment techniques from short reads, mapping-based and de-novo assembly of genomes and transcriptomes, peak calling, splicing and gene models, motif search, differential expression, visualization of NGS data, and other current topics. In the tutorial, the focus is on scientific working and writing; the tutorial will also make use of blended learning techniques.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students will know about the latest findings in bioinformatics concerning expression analysis and current sequencing techniques, and will be able to identify the challenges of these new technologies for the bioinformatics field. They will familiar with the algorithms for quantifying expression data, with statistical methods and machine learning techniques for calculating differential expressions and for classification, and with methods for analyzing expression data in the network context. Students will be able to analyze real microarray and RNA-Seq experiments, and will have expanded their knowledge in R. They will also know about the possibilities and the limitations of various methods in this area of bioinformatics. In addition, students will be able to scientifically analyze problems and summarize their findings in written form. Special focus is on promoting intrinsic motivation and encouraging students to work independently.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>c</td><td>2</td><td>4</td><td rowspan="2">wt</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>c</td><td>2</td><td>2</td></tr>
</table>

(still BIO-4331)

Requirement for participation	BIOINF3331 Microarray bioinformatics (recommended)
Lecturer	Nieselt
Literature	Scripts by the lecturer and selected articles.

<table>
<tr><td>Module Number:
BIO-4210</td><td colspan="2">Module title
Practical Transcriptomics</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
90 h</td><td>Class time
30 h / 2 CH</td><td>Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Practical course</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="3">Offered at irregular intervals</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">The final grade is based on performance, a written report on each day of the practical course, and one or two short oral presentations.</td></tr>
<tr><td>Content</td><td colspan="3">The focus is on the practical analysis of so-called next generation sequencing data. Students learn the use of tools for evaluating this data. This practical course uses real-life data; the focus is on the entire process of evaluating experimental data, from quality analyses to in-depth statistical analyses; various methods are compared. Topics include de-novo assembly, expression count calculation, normalization and clustering, machine learning methods and their application to expression data, statistical methods for calculating differential expressions, visualization methods, and enrichment methods.</td></tr>
<tr><td>Objectives</td><td colspan="3">Students will gain practical experience in designing and programming bioinformatics software for analyzing NGS data. They will be able to use libraries and frameworks, and will acquire knowledge or extend their knowlege of Java or C++ and R. By working together in groups, students obtain teamwork and collaboration skills, and they will learn about project organization and presentation techniques. Students will know about the strenghts and weaknesses and about the limitations of various methods for evaluating high-throuput transcriptomic data, and will be able to describe and evaluate these methods.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3"><table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Practical course</td><td>P</td><td>c</td><td>3</td><td>3</td><td>wt</td><td>90</td><td>g</td><td>100</td></tr>
</table></td></tr>
<tr><td>Requirement for participation</td><td colspan="3">BIOINF4110, BIOINF4120, BIOINF4331 Advances in Computational Transcriptomics (recommended), BIOINF3331 Microarray bioinformatik (recommended)</td></tr>
<tr><td>Lecturer</td><td colspan="3">Nieselt</td></tr>
<tr><td>Literature</td><td colspan="3">Will be provided at the beginning of the course, if necessary.</td></tr>
</table>

<table>
<tr><td>Module Number:
BIO-4363</td><td colspan="2">Module title
RNA Bioinformatics</td><td>Module
elective</td></tr>
<tr><td>ECTS</td><td colspan="3">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
90 h</td><td>Class time
30 h / 2 CH</td><td>Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Seminar</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="3">Offered at irregular intervals</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Oral presentation and written report</td></tr>
<tr><td>Content</td><td colspan="3">This seminar covers current topics concerning computer-based RNA bioinformatics, such as folding: RNA structure, thermodynamics, basic folding; RNA abstract shapes; comparative structure prediction: structure comparison, alignment folding, consensus shapes; structure comparison: structure metrics, tree alignment, multiple structure alignment; RNA gene prediction: prediction from models, prediction from folding, prediction from comparisons; miRNAs: miRNA prediction, miRNA target prediction; stochastic models: HMMs, SCFGs, model training; 3D modelling; cofolding; RNA motifs and other topics concerning current research.</td></tr>
<tr><td>Objectives</td><td colspan="3">Students will be able to acquire knowledge about current findings in bioinformatic RNA biology through comprehensive literature search. They will know the importance of this area of bioinformatics, and will be aware that there are still many open questions. Students will not only have improved their study and reading skills, but will also have enhanced their capability of working independently. The teaching method in this seminar aims at boosting the students' confidence (oral presentation), and at enhancing their communication skills and enabling them to accept criticism (discussion session following their presentation).</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3">
<table>
<tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr>
<tr><td>Seminar</td><td>S</td><td>o</td><td>2</td><td>3</td><td>op</td><td>45</td><td>g</td><td>50</td></tr>
<tr><td>Seminar</td><td>S</td><td>o</td><td></td><td></td><td>wr</td><td></td><td>g</td><td>50</td></tr>
</table>
</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">-</td></tr>
<tr><td>Lecturer</td><td colspan="3">Nieselt</td></tr>
<tr><td>Literature</td><td colspan="3">Latest scientific publications dealing with the topic in question</td></tr>
</table>

Module Number:	**Module title**		**Module**
BIO-4364	Visualisation of Biological Data		elective
ECTS	6		
Work load **- Contact time** **- Self study**	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Lecture type	Lecture, tutorial		
Duration	1 semester		
Frequency	Offered at irregular intervals		
Language of instruction	English		
Type of Exam	Oral test, or written test (in case of a large group)		
Content	With the continuous increase in the volume of biological data, biology is shifting from a hypothesis-driven to a more data-driven science. At the same time, data exploration is gaining in importance. This lecture will first provide students with a general introduction in visualization, and then introduce modern visualization methods for biological data, with special focus on visual analytics. Topics are e.g. fundamentals of visualization, fundamentals of biological data visualization, methods for visualizing genomic and transcriptomic data, visualization of structures, network visualization etc. In the tutorial, the focus is on scientific working and writing; the tutorial will also make use of blended learning techniques.		
Objectives	Students will understand the process of visual analytics. They will know about the basic possibilities (do's) and limitations (don't's) of visualization. They will be familiar with methods for visualizing large genomic data volumes, and they will be able to apply methods for visualizing transcriptional abundance and regulation. They will also be familiar with the challenges of visualizing GWAS and eQTL data. In addition, students will be able to scientifically analyze problems and summarize their findings in written form. Special focus is on promoting intrinsic motivation and encouraging students to work independently.		

Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Lecture	L	o	2	4	ot or wt	30 or 90	g	100
	Tutorial	T	o	2	2				

Requirement for participation	-
Lecturer	Krone, Nieselt

(still BIO-4364)

Literature	Tamara Munzner ‘Visualization Analysis and Design’, Nature Methods Supplement ‘Visualizing biological data’, several ’Points of View’ Nature Methods, and scripts by the lecturer.

Module Number: MEDZ-4991	**Module title** Medical Data Science		**Module** elective
ECTS	6		
Work load **- Contact time** **- Self study**	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Lecture type	Lecture, tutorial		
Duration	1 semester		
Frequency	once per year		
Language of instruction	English		
Type of Exam	Oral Exam		
Content	This lecture comprises different areas of Medical Data Science. Data Science or statistical machine learning methods have the potential to transform personal health care over the coming years. Advances in the technologies have generated large biological data sets. In order to gain insights that can then be used to improve preventive care or treatment of patients, these big data have to be stored in a way that enables fast querying of relevant characteristics of the data and consequently building statistical models that represent the dependencies between variables. These models can then be utilized to derive new biomedical principals, provide evidence for or against certain hypotheses, and to assist medical professionals in their decision process. Specific topics are: • Gaining new insights from medical data • Modeling uncertainty in medical data science models • Making medical findings available through interpretable decision support systems Method-wise, the lecture introduces methods for GWAS analyses (e.g., LMMs), methods for sequence analysis (e.g., kernel methods), methods for “small n problems” (e.g., domain adaptation, transfer learning, and multitask learning), methods for data integration (advanced unsupervised learning methods), methods for learning probabilistic Machine Learning models (e.g., graphical models), methods for large data sets (e.g., deep learning models).		
Objectives	The students are capable of explaining the most important terms, methods and theories in the data science area with focus on the analysis of biomedical data. They are enabled to decide which type of methods fit to which kind of data sets and see where current shortcomings of the methods are to potentially come up with ideas for extending or improving the methods.		

(still MEDZ-4991)

		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Requirement for Credit Points / Grade	Lecture	L	c	2	4	wt	90	g	100
	Tutorial	T	c	2	2				
Requirement for participation	recommended: Machine learning: theory and algorithms								
Lecturer	Pfeifer								
Literature	Trevor Hastie, Robert Tibshirani, Jerome Friedman: The Elements of Statistical Learning, Springer Series in Statistics. Further books will be announced in the first lecture.								

Study Area: Expanded Perspectives

Module Number: ML-5001	**Module title** Expanded Perspectives		**Module** Study Area
ECTS	12		
Work load **- Contact time** **- Self study**	Work load 360 h	Class time 120 h / 8 CH	Self-Study 240 h
Lecture type	Lecture, Tutorial, Seminars		
Duration	3 semester		
Frequency	every semester		
Language of instruction	English		
Type of Exam	Oral or written exams, presentation, essays, reports		
Content	In this study area, students can choose courses freely from almost all courses (except for sports courses) offered at the University of Tübingen. In particular also all courses offered in the area of 'diverse topics in machine learning' or 'general computer science' can be taken. It is also meant to give students the opportunity to learn about particular application fields (e.g., geoscience, linguistics), improve their language skills in German (for foreign students) or English (for German students), or learn to reflect upon ethical or philosophical challenges brought by machine learning. Altogether 12 CPs in this field have to be fulfilled. Courses taken in this area need to be graded ones, and the grades will show up on the transcript of records, but the grades will not be taken into account for the cumulative grade of the Master's program, as stated above. Due to the high, interdisciplinary flexibility of the courses that can be taken in this study area, the expected performance in the respective courses are checked separately, depending on the format.		
Objectives	These depend on the format and content of the courses taken.		
Requirement for participation	-		
Lecturer	-		
Literature	-		

Module Master Thesis

Module Number: ML-4999	**Module title** Master thesis		**Module** compulsory
ECTS	30		
Work load **- Contact time** **- Self study**	Work load 900 h	Class time 60 h / 4 CH	Self-Study 840 h
Lecture type	Independent research work, Master's thesis (in written form) and oral presentation		
Duration	1 semester		
Frequency	Every semester		
Language of instruction	English		
Type of Exam	Written thesis and oral presentation		
Content	The Master's thesis is the final stage of the Master's degree program, and comprises completing a project in machine learning, evaluating and processing the results obtained, and finally preparing a written detailed presentation of these results. The results should be of scientific value. In addition, students will give an oral presentation of their thesis' topic.		
Objectives	Students • are able to become familiar with a current research issue within a given time frame. They are able to apply scientific methods and present their results in a scientifically appropriate manner; • are able to independently handle a complex scientific issue, applying their knowledge of machine learning methods; • gain a deeper understanding of how to solve problems, and are able to apply their knowledge of methods; • are able to work in teams in an international scientific setting; • are able to present and defend their evidence before an audience in English.		

(still ML-4999)

Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Master's thesis	R	o	–	27	w		g	100
	Oral presentation	-	o	–	3				
Requirement for participation	If any conditions have been set for admission to a Master's degree course, students must prove that these conditions have been met prior to registering a thesis topic.								
Lecturer	Lecturers of the Department of Computer Science								
Literature	Depends on the topic								