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

Module handbook

Machine Learning

Master of Science (M.Sc.)

Released by the Academic Commission of the Department of Computer Science
(updated January 16, 2021)

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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 crtedit 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 plan to spend a semester abroad we recommend to do this in the third semester.

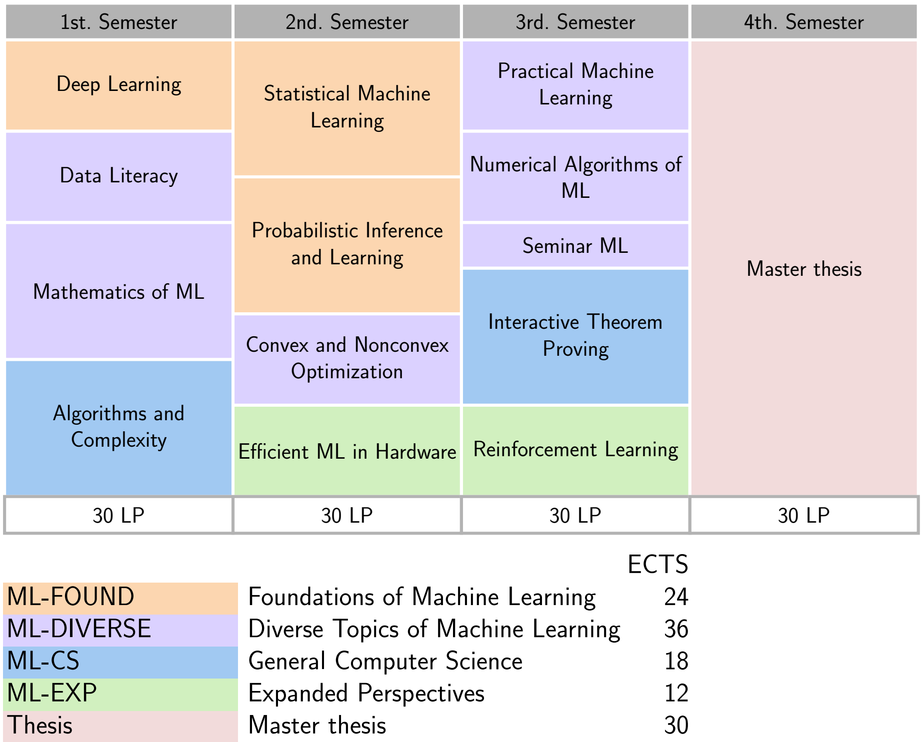

Figure 1: Study plan with focus on theory

1st. Semester	2nd. Semester	3rd. Semester	4th. Semester
Deep Learning	Statistical Machine Learning	Practical Machine Learning	Master thesis
Data Literacy	Probabilistic Inference and Learning	Self-Driving Cars	
Mathematics of ML	ML in Graphics and Vision	Seminar ML	
Cognitive Modelling	Ethics in Science	Advanced Java	
German as Foreign Language	German as Foreign Language	Advanced SQL	
		German as Foreign Language	
30 LP	30 LP	30 LP	30 LP

		ECTS
ML-FOUND	Foundations of Machine Learning	24
ML-DIVERSE	Diverse Topics of 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	2nd. Semester	3rd. Semester	4th. Semester
Deep Learning	Statistical Machine Learning	Practical Machine Learning	Master thesis
Data Literacy	Probabilistic Inference and Learning	Time Series	
Mathematics of ML	Neural Data Analysis	Seminar ML	
Visualisation of large-scale data	Ethics in Science	Computational Microbiome Analysis	
German as Foreign Language	German as Foreign Language	Systems Biology	
		German as Foreign Language	
30 LP	30 LP	30 LP	30 LP

		ECTS
ML-FOUND	Foundations of Machine Learning	24
ML-DIVERSE	Diverse Topics of 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

The following module list specifies the courses offered for the Master Program in Machine Learning, describes each of them using an abstract of the subject matter, qualification aims, and exam modalities, and associates them with individual required study areas.

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 Lecture with tutorials
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 theoretical and practical concepts of deep neural networks including optimization, inference, architectures and applications. After this course, students should be able to develop and train deep neural networks, reproduce research results and conduct original research in this area.		

(still ML-4103)

		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	wt/ot	90	g	100
	Tutorial	T	o	2	3				
Usability (modules)	Foundations of ML;								
Requirement for participation	Basic math (linear algebra & analysis, probability and information theory) and coding knowledge (variables, functions, loops, classes, algorithms). Experience in Python is recommended.								
Lecturer	Geiger, Zell								
Literature	Related literature will be listed throughout the lecture.								

Module Number: ML-4201	**Module title** Statistical Machine Learning	**Module** Lecture with tutorials
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	Regularly once a year
Language of instruction	English
Type of Exam	Written test (in case of a small number of participants: oral tests)
Content	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.
Objectives	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.

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				

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

<table>
<tr><th>Module Number:
ML-4202</th><th colspan="2">Module title
Probabilistic Inference and Learning</th><th>Module
Lecture with tutorials</th></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">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.
Apart from mathmatical derivations, the exercises put a focus on practical programming. In particular, they contain implementations of some content of the lectures.</td></tr>
<tr><td>Objectives</td><td colspan="3">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>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>Usability (modules)</td><td colspan="3">Foundations of ML; General Computer Science; Expanded Perspectives</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Standard undergraduate knowledge of mathematics is required, to the extent that is provided, for example, by the course on Mathematics for Machine Learning (ML 4101).</td></tr>
<tr><td>Lecturer</td><td colspan="3">Hennig, Macke</td></tr>
<tr><td>Literature</td><td colspan="3">Literature will be listed at the beginning of the semester.</td></tr>
</table>

Study Area: Diverse Topics in Machine Learning

Lectures

Module Number: ML-4101	Module title Mathematics of Machine Learning		Module Lecture with tutorials
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)

Objectives	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								
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	b	100
	Tutorial	T	o	2	3				
Usability (modules)	Diverse Topics in ML;								
Requirement for participation	Students need to have basic knowledge in analysis and linear algebra on the level of the bachelor lectures “Mathematik für Informatiker I-III”								
Lecturer	von Luxburg, Hein								
Literature	The literature for this lecture will be provided at the beginning of the semester.								

<table>
<tr><th>Module Number:
ML-4102</th><th colspan="8">Module title
Data Literacy</th><th colspan="3">Module
Lecture with tutorials</th></tr>
<tr><td>ECTS</td><td colspan="11">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="4">Class time
60 h / 4 CH</td><td colspan="4">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="11">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="11">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="11">Regularly once a year</td></tr>
<tr><td>Language of instruction</td><td colspan="11">English</td></tr>
<tr><td>Type of Exam</td><td colspan="11">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="11">This course equips students with concepts and tools that should be familiar to anyone working with (large) data. Based on practical experiments and examples, frequently encountered pitfalls and problems are discussed alongside best practices. We encounter basic statistical notions and problems of bias, testing and experimental design. Foundational methods of machine learning and statistical data analysis are employed to employ these ideas in practice. 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 fairness and transparency.
Apart from mathmatical derivations, the exercises put a focus on practical programming. In particular, they contain implementations of some content of the lectures.</td></tr>
<tr><td>Objectives</td><td colspan="11">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 colspan="3"></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 colspan="3">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 colspan="3">Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Usability (modules)</td><td colspan="11">Diverse Topics in ML; General Computer Science; Expanded Perspectives</td></tr>
<tr><td>Requirement for participation</td><td colspan="11">only basic math and coding skills as provided by the BSc Computer Science.</td></tr>
<tr><td>Lecturer</td><td colspan="11">Hennig</td></tr>
<tr><td>Literature</td><td colspan="11">Literature will be listed at the beginning of the semester.</td></tr>
</table>

Module Number: ML-4301	**Module title** Numerical Algorithms of Machine Learning	**Module** Lecture with tutorials
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	irregularly	
Language of instruction	English	
Type of Exam	Written test (in case of a small number of participants: oral tests)	
Content	The computational cost of machine learning is almost entirely caused by numerical computations: *Optimization* for training and fitting of point estimates; *integration* for marginalization and conditioning in probabilistic models; *simulation*, i.e. the solution of differential equations for predictions of the future, and *linear algebra* 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. Apart from mathmatical derivations, the exercises put a focus on practical programming. In particular, they contain implementations of some content of the lectures.	
Objectives	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.	
Requirement for Credit Points / Grade	see below	
Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives	
Requirement for participation	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.	
Lecturer	Hennig	
Literature	Literature will be listed at the beginning of the semester.	

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				

Module Number: ML-4302	Module title Statistical Learning Theory		Module Lecture with Tutorials
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	Irregularly		
Language of instruction	English		
Type of Exam	Written exam (in case of a small number of participants: oral exams)		
Content	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 • 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.		
Objectives	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.		

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				

Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives
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: ML-4303	Module title Convex and Nonconvex Optimization			Module Lecture with tutorials
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 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				

Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives
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	Hein
Literature	The lecture does not follow a specific book. The literature for this lecture will be provided at the beginning of the semester.

Module Number: ML-4310	Module title Data Mining and Probabilistic Reasoning								Module Lecture with tutorials
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 with tutorials								
Duration	1 semester								
Frequency	regularly in the winter term								
Language of instruction	English								
Type of Exam	Written test (in case of a small number of participants: oral tests)								
Content	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.								
Objectives	(1) The students acquire extensive knowledge in theory and application of methods from the field of data science. (2) The students acquire various data science techniques for conceptual thinking, problem formalization and problem solving. (3) The students are introduced to challenging research questions from the field of data science.								
Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Lecture	L	o	1	2	W	90	g	100
	Tutorial	T	o	1	1				
Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives								
Requirement for participation									
Lecturer	Gjergji Kasneci								
Literature	Will be supplied (book chapters and papers in English)								

<table>
<tr><td>Module Number:
ML-4320</td><td colspan="9">Module title
Time Series</td><td colspan="3">Module
Lecture with tutorials</td></tr>
<tr><td>ECTS</td><td colspan="12">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="4">Work load
180 h</td><td colspan="5">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="12">Lecture with tutorials</td></tr>
<tr><td>Duration</td><td colspan="12">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="12">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="12">English</td></tr>
<tr><td>Type of Exam</td><td colspan="12">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="12">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: Markovianity, 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.
Apart from mathmatical derivations, the exercises put a focus on practical programming. In particular, they contain implementations of some content of the lectures.</td></tr>
<tr><td>Objectives</td><td colspan="12">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. Apart from mathmatical derivations, the exercises put a focus on practical programming. In particular, they contain implementations of some content of the lectures.</td></tr>
<tr><td rowspan="3">Requirement for Credit Points / Grade</td><td colspan="4"></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 colspan="4">Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">wo</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td colspan="4">Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Usability (modules)</td><td colspan="12">Diverse Topics in ML;</td></tr>
<tr><td>Requirement for participation</td><td colspan="12">Knowledge of the material provided in the course Probabilistic Machine Learning (ML-4202) is required.f</td></tr>
<tr><td>Lecturer</td><td colspan="12">Hennig, Tronarp</td></tr>
<tr><td>Literature</td><td colspan="12">Literature will be listed at the beginning of the semester.</td></tr>
</table>

Module Number: ML-4340	**Module title** Self-Driving Cars	**Module** Lecture with tutorials
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 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 societies 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 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.	
Objectives	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.	
Requirement for Credit Points / Grade	see table below	
Usability (modules)	Foundations of ML;	
Requirement for participation	Basic math (linear algebra, probabilities) and coding (Python) skills. Experience with deep learning (e.g., course “Deep Learning”). Experience in PyTorch is recommended.	
Lecturer	Andreas Geiger	
Literature	Related literature will be listed throughout the lecture.	

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/ot	90	g	100
Tutorial	T	o	2	3				

Module Number: ML-4360	Module title Computer Vision			Module Lecture with tutorials
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	The goal of computer vision is to compute geometric and semantic properties of the three-dimensional world from digital images. Problems in this field include reconstructing the 3D shape of an object, determining how things are moving and recognizing objects or scenes. This course will provide an introduction to computer vision, with topics including image formation, camera models, camera calibration, feature detection and matching, motion estimation, geometry reconstruction, object detection and tracking, and scene understanding. Applications include building 3D maps, creating virtual avatars, image search, organizing photo collections, human computer interaction, video surveillance, self-driving cars, robotics, virtual and augmented reality, simulation, medical imaging, and mobile computer vision. Modern computer vision relies heavily on machine learning in particular deep learning and graphical models. This course therefore assumes prior knowledge of deep learning (e.g., deep learning lecture) and introduces the basic concepts of graphical models and structured prediction where needed.			
Objectives	Students gain an understanding of the theoretical and practical concepts of computer vision including image formation, camera models, feature detection, multiple view geometry, 3D reconstruction, motion estimation, object recognition, scene understanding and structured prediction using deep neural networks and graphical models. After this course, students should be able to understand and apply the basic concepts of computer vision in practice, develop and train computer vision models, reproduce research results and conduct original research in this area.			

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/ot	90	g	100
Tutorial	T	o	2	3				

Usability (modules)	Foundations of ML;
Requirement for participation	Basic math (linear algebra, probabilities) and coding (Python) skills. Experience with deep learning (e.g., course “Deep Learning”). Experience in PyTorch is recommended.
Lecturer	Andreas Geiger
Literature	Related literature will be listed throughout the lecture.

Module Number: ML-4601	Module title Introduction to Game Theory with Application to Multi-Agent Systems		Module Lecture
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		
Duration	1 semester		
Frequency	regularly in the winter semester		
Language of instruction	English		
Type of Exam	Written Exam		
Content	This module is about game theory and mechanism design, with an emphasis on applications in different domains. The students study the essential concepts in game theory such as equilibrium, belief, best-response dynamics, and the like. Besides, they learn about strategic- and extensive form games, achieving equilibrium in repeated games, games with incomplete and imperfect information. Also, they obtain knowledge regarding other topics such as the Nash bargaining solution, auctions, and computational models of human decision-making. In brief, the students obtain broad knowledge about different branches of game theory such as competitive-, cooperative-, and behavioral game theory, in addition to studying detailed mathematical results, e.g., regarding the existence and uniqueness of equilibrium in well-known scenarios. Besides theoretical foundations, the students become familiar with the connection between game theory and distributed control, and they gain experience in modeling and solving different applied problems using game theory.		
Objectives	After the lectures, the students have a broad and profound knowledge of essential concepts of game theory. Therefore, they can identify the problems in the applied domains that can be modeled based on game theory. The students possess the ability to solve such problems by using the mathematical tools that they have learned in this module. Besides, they have a high level of proficiency in selecting, reading, analyzing, and criticizing scientific results, preparing technical presentations, holding talks, and participating in discussions. Finally, the students are independent learners and can expand their knowledge to advanced levels in various topics of game theory.		
Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives		
Requirement for participation			
Lecturer	Maghsudi		

(still ML-4601)

Literature	• Mas-Colell and M.D. Whinston, and J.R. Green, Microeconomic Theory, Oxford University Press, 1995 • Ozduglar, Game Theory with Engineering Application, MIT OpenCourseWare, 2009 • Fudenberg and D. Levine, The Theory of Learning in Games, MIT Press, 1998 • Fudenberg and J. Tirole, Game Theory, MIT Press, 1991 • Vijay, Auction Theory, Harvard University Press, 2008

Module Number: ML-4350	Module title Reinforcement Learning		Module Lecture, Tutorial
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	irregularly		
Language of instruction	English		
Type of Exam	Oral presentation and written project report		
Content	• 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		
Objectives	) Students can phrase a problem in the reinforcement learning framework and can select an appropriate algorithm for solving it. (2) Students are able to implement a set of deep reinforcement learning algorithms and analyse their behavior. (3) Students can explain the challenges in reinforcement learning and assess and characterize new reinforcement learning methods.		
Usability (modules)	General Computer Science; Expanded Perspectives		
Requirement for participation	Recommended to attend basic Machine learning class before.		
Lecturer	Martius		
Literature	Reinforcement learning by Sutton and Barto http://incompleteideas.net/book/bookdraft2017nov5.pdf Pattern Recognition and Machine Learning by C.M. Bishop, Chap. 3 and 5 Deep Learning by Goodfellow, Bengio and Courville https://www.deeplearningbook.org		

Module Number: ML-4410	Module title Neural Data Analysis		Module Lecture, Tutorial
ECTS	6		
Work load - Contact time - Self study	Work load 120 h	Class time 60 h / 4 CH	Self-Study 60 h
Lecture type	Lecture, Tutorial		
Duration	1 semester		
Frequency	regularly in the summer term		
Language of instruction	English		
Type of Exam	Written report and cumulative oral exam		
Content	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.		
Objectives	1) In this course students will acquire knowledge of basic and advanced techniques necessary to analyze discrete (spike trains) and continuous (cellular voltage/calcium signals, LFP, EEG) neural signals. (2) Students will implement important techniques (Filtering, MoG, STA, etc) and evaluate them on artificial and real data. (3) Students will learn how to work with real neural data and cope with the challenges this brings about.		
Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives		
Requirement for participation	Some knowledge of basic neuroscience is helpful, but not a must.		
Lecturer	Berens		
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.		

Module Number: INFO-4492	**Module title** Special Topics in Learning Theory								**Module** Lecture, Tutorials
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, Tutorials								
Duration	1 semester								
Frequency	irregularly								
Language of instruction	English or German, depending on the participants								
Type of Exam	Written exam (in case of a small number of participants: oral exams)								
Content	In this module we discuss advanced results and approaches in learning theory and current research results in the area of machine learning in general.								
Objectives	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.								
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	K	90	b	100
	Tutorial	T	o	2	3				
Usability (modules)	General Computer Science; Expanded Perspectives								
Requirement for participation	Solid knowledge in maths (linear algebra, probability theory); Basic knowledge in machine learning								
Lecturer	von Luxburg								
Literature	will be announced in the lecture								

Module Number: ML-4420	Module title Efficient Machine Learning in Hardware		Module Lecture
ECTS	6		
Work load - Contact time - Self study	Work load 180 h	Class time 32 h / 4 CH	Self-Study 208 h
Lecture type	Lecture		
Duration	1 semester		
Frequency	regularly in the summer, every two years		
Language of instruction	English		
Type of Exam	Oral exam		
Content	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 solutions on 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: GPU, FPGA, SIMD architectures, domain-specific architectures, custom accelerators, in/near memory computing, training vs. inference architectures • 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		
Objectives	The students gain in-depth knowledge about the challenges associated with energy-efficient machine learning hardware and respective state-of-the-art solutions. They can compare different hardware architectures regarding the trade-off between energy consumption, complexity, computational speed and the specificity of their applicability. The students learn what kinds of hardware architectures are used for machine learning, understand the reasons why a particular architecture is suitable for a particular application, and can efficiently implement machine learning algorithms in hardware.		
Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives		
Requirement for participation	Knowledge about foundations in machine learning		
Lecturer	Bringmann		
Literature	Will be announced in the first lecture		

Seminars

Module Number: ML-4501	**Module title** Machine Learning Seminar								**Module** Seminar
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	1 semester								
Frequency	regularly in the winter/summer								
Language of instruction	English								
Type of Exam	Oral presentation and written report								
Content	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.								
Objectives	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.								
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	wo	30	g	100
Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives								
Requirement for participation									
Lecturer	All lecturers in the computer science department								
Literature	Will be handed out in the course								

<table>
<tr><th>Module Number:
ML-4503</th><th colspan="2">Module title
Explainable Machine Learning</th><th>Module
Seminar</th></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">regularly in the winter 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 Presentation (about 30 minutes) and written elaboration (approx. 10 pages), leading the discussion once</td></tr>
<tr><td>Content</td><td colspan="3">In this seminar, we will discuss research papers related to explainable machine learning focusing on generating visual and textual explanations for classification decision of machine learning models.
From a methodological perspective, we will discuss about popular perceptual modules of machine learning models, integrated attention mechanisms as well as memory based natural language processing methods tailored towards explanation generation.
General knowledge on Statistical Machine Learning
General knowledge on Deep Learning
General knowledge on Computer Vision
General knowledge on Natural Language Processing is a plus</td></tr>
<tr><td>Objectives</td><td colspan="3">Students are able to read and reflect upon current research papers in this research area. 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. The form of learning used in the seminar is intended to help the students to develop self-confidence (presentation) and the ability to criticise and communicate (in the subsequent discussion).</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>wo</td><td>30</td><td>g</td><td>100</td></tr></table></td></tr>
<tr><td>Usability (modules)</td><td colspan="3">Diverse Topics in ML; General Computer Science; Expanded Perspectives</td></tr>
<tr><td>Requirement for participation</td><td colspan="3"></td></tr>
<tr><td>Lecturer</td><td colspan="3">Akata</td></tr>
<tr><td>Literature</td><td colspan="3">Will be announced in the first meeting</td></tr>
</table>

Module Number: INFO-4493	Module title Learning Theory								Module Seminar
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	b	100
Usability (modules)	General Computer Science; Expanded Perspectives								
Requirement for participation	Basic knowledge in machine learning.								
Lecturer	von Luxburg								
Literature	will be announced in the lecture								

Module Number: ML-4502	Module title Machine learning methods for scientific discovery		Module Seminar
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	1 semester		
Frequency	irregularly		
Language of instruction	English		
Type of Exam	Oral presentation, written report		
Content	In this seminar, we will discuss current and classical research papers which describe machine learning methods for applications in the natural sciences. From a methodological perspective, a particular focus will be on ‘simulation-based inference approaches’, as these provide a bridge between data-driven machine learning methods, and theory-driven scientific modelling, as well as on latent-variable models for inferring dynamical systems from data.		
Objectives	Students are able to read and reflect upon current research papers in this research area. 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	wo	30	g	100

Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives
Requirement for participation	Basic knowledge probabilistic machine learning
Lecturer	Macke
Literature	Will be announced in the first meeting

Practical Courses and Research Project

Module Number: ML-4510	**Module title** Practical Machine Learning		**Module** Practical Course
ECTS	6		
Work load - Contact time - Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Lecture type	Practical Course		
Duration	1 semester		
Frequency	every semester		
Language of instruction	English		
Type of Exam	Oral presentation, written report, lab journal		
Content	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.		
Objectives	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.		

Requirement for Credit Points / Grade

	Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Practical	P	o	4	6	wo		g	100

Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives
Requirement for participation	
Lecturer	All lecturers in the programme
Literature	-

Module Number: ML-4998	Module title Research Project Machine Learning		Module Independent research project
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

Usability (modules)	Diverse Topics in ML;
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-4315	Module title Advanced Topics in Embedded Systems		Module Lecture
ECTS	6		
Work load **- Contact time** **- Self study**	Work load 180 h	Class time 30 h / 2 CH	Self-Study 150 h
Lecture type	Lecture		
Duration	1 semester		
Frequency	regularly in the summer term (block course)		
Language of instruction	English		
Type of Exam	Oral exam (written exam in case of a large number of participants)		
Content	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 (SoCs). 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 lectures on verification addresses cyber-physical systems, safety verification, and robustness optimization of machine-learning based embedded systems. The lecture finally covers advanced hardware architectures for low-power implementation of deep learning approaches in hardware. Between the lectures, practical exercises in form of programming assignments will take place. The lecturers will present the relevant basics as well as recent research results in each topic.		
Objectives	Participants will acquire in-depth knowledge to different 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 in order to avoid common pitfalls. The students will get a deeper practical understanding by working on topic-specific programming assignments.		

(still INFO-4315)

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	MP	30	b	100
	Practical	P	o	2	2				
Usability (modules)	General Computer Science; Expanded Perspectives								
Requirement for participation	Prerequisites are the lectures “Entwurf und Synthese Eingebetteter Systeme” or “Modellierung und Analyse Eingebetteter Systeme”								
Lecturer	Bringmann								
Literature	Will be announced during the first lecture.								

<table>
<tr><th>Module Number:
INFO-4194</th><th colspan="2">Module title
Behavior and Learning</th><th>Module
Lecture, Tutorials</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
32 h / 4 CH</td><td>Self-Study
208 h</td></tr>
<tr><td>Lecture type</td><td colspan="3">Lecture, 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 (oral exam if number of participants allows)</td></tr>
<tr><td>Content</td><td colspan="3">This lecture builds on the available knowledge how animals and humans plan, decide on, and control their behavior and how they progressively optimize and adapt their behavior over time. Accordingly, algorithms are introduced for behavioral decision making, control, optimization, and adaptation. 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="3">Students know how intelligent behavior can be generated and learned in artificial systems. They can apply reinforcement learning (RL), including hierarchical RL, factored RL, and actor-critic approaches to the appropriate problems. Moreover, they are aware of the contrast between model-free and model-based RL approaches. They know about dynamic motion primitives and know how to optimize them. Moreover, they know about Gaussian Mixture Models, including how to learn and optimize them. They can implement information-gain driven and self-motivated behavior and are aware of the exploration-exploitation dilemma. Moreover, they are aware of model-predictive control, of options to learn suitable model-predictive structures, and of options to suitably abstract such structures. Finally, they know how sensorimotor-grounded spatiotemporal representations can be learned, stored as episodic memory units, and can be abstracted into cognitive maps, enabling model-based RL.</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>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>
</table>
</td></tr>
<tr><td>Usability (modules)</td><td colspan="3">General Computer Science; Expanded Perspectives</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Introductory course 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 papers in English)</td></tr>
</table>

Module Number: INFO-4210	Module title: Recurrent and Generative Artificial Neural Networks								Module: Lecture, Tutorials
ECTS	6								
Work load - Contact time - Self study	Work load 180 h				Class time 32 h / 4 CH				Self-Study 208 h
Lecture type	Lecture, Tutorials								
Duration	1 semester								
Frequency	irregularly								
Language of instruction	English								
Type of Exam	Written (oral exam if number of participants allows)								
Content	Advanced ANN topics. First, revisiting backpropagation and backpropagation through time; then: Advanced Recurrent Neural Networks (LSTM, GRU); Very Deep Learning and Generative Adversarial Networks; Spatial and Temporal Convolution; Reservoir Computing; Neuroevolution; Attention and Routing Networks; Autoencoders and Restricted Boltzmann Machines; Gain Fields and Switching Networks; Latent Space Visualization techniques; Generative Inference								
Objectives	Students know about and how to apply generative and typically recurrent artificial neural networks in various domains including data classification, image recognition, language processing, spatially-invariant recognition, spatial transformations, and spatial mappings. They can apply complex, generative artificial neural networks from scratch as well as with available tools. They know how to optimize weights and network structures by means of gradient descent as well as by alternative methods. They can use complex recurrent network structures to selectively process aspects of the data. They know how to apply generative networks as model-predictive neural controllers and as well as long-range temporal predictors. They can combine retrospective latent state and motor inference techniques with prospective motor control.								
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	90	g	100
	Tutorial	T	o	2	3				0
Usability (modules)	Diverse Topics in ML; General Computer Science; Expanded Perspectives								
Requirement for participation	Knowledge about machine learning, artificial neural networks, deep learning, or artificial intelligence is required.								
Lecturer	Butz								
Literature	Will be supplied (book chapters and paper in English)								

Module Number: INFO-4212	Module title Artificial Neural Networks								Module Practical Course
ECTS	6								
Work load - Contact time - Self study	Work load 180 h		Class time 60 h / 4 CH				Self-Study 120 h		
Lecture type	Practical Course								
Duration	1 semester								
Frequency	irregularly								
Language of instruction	English								
Type of Exam	Final Project Presentation and Report								
Content	Programming enhanced functionalities in ANN Software, evaluating performance, analyzing the system.								
Objectives	Know how to work with, implement, and enhance complex artificial neural networks..								
Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Practical	P	o	2	3	tp		g	100
Usability (modules)	General Computer Science; Expanded Perspectives								
Requirement for participation	Solid Knowledge in Programming. Knowledge about artificial neural networks or machine learning.								
Lecturer	Butz								
Literature	*none*								

<table>
<tr><th>Module Number:
INFO-4213</th><th colspan="5">Module title
Advanced Artificial Neural Networks Project</th><th colspan="4">Module
Practical Course</th></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, program, 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>Practical</td><td>P</td><td>o</td><td>2</td><td>3</td><td>tp</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Usability (modules)</td><td colspan="9">General Computer Science; Expanded Perspectives</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">none</td></tr>
</table>

Module Number: INFO-4214	**Module title** Cognitive Modeling		**Module** Lecture, Tutorials
ECTS	6		
Work load - Contact time - Self study	Work load 180 h	Class time 32 h / 4 CH	Self-Study 208 h
Lecture type	Lecture, Tutorials		
Duration	1 semester		
Frequency	irregularly		
Language of instruction	English		
Type of Exam	Written (oral exam if number of participants allows)		
Content	Cognitive models covering learning, action and perception are presented and discussed, including descriptive, qualitative, quantitative and neural models. In addition, parameter optimization as well as techniques to compare models and to interpret and evaluate model parameters are introduced. All techniques are shown in the context of concrete models of cognitive processes. Moreover, the necessary statistical methods are introduced in a practical, application-oriented manner.		
Objectives	Students know the most important principles and techniques of cognitive modeling. They know how to model cognitive processes, mechanisms, and learning at different levels of complexity. They can apply various cognitive models and modeling approaches in a goal-directed manner. Moreover, they can evaluate, compare, and contrast different modeling approaches as well as modeling results. They are able to judge whether a model is falsifiable and they know how to validate and interpret cognitive models. Finally, they can use statistical methods to quantitatively compare different cognitive models.		

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	90	g	100
Tutorial	T	o	2	3				0

Usability (modules)	General Computer Science; Expanded Perspectives
Requirement for participation	Introductory course knowledge about machine learning, artificial neural networks, robotics, cognitive architectures, or artificial intelligence is required.
Lecturer	Butz
Literature	Book: S. Lewandowsky & S. Farrell (2011). Computational Modeling in Cognition. Additional papers and book chapters will be supplied.

Module Number: INFO-4211	**Module title** Avatars in Virtual Realities		**Module** Practical Course
ECTS	6		
Work load - Contact time - Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Lecture type	Practical Course		
Duration	1 semester		
Frequency	Irregularly		
Language of instruction	English		
Type of Exam	Final Project Presentation and Report		
Content	In this project-oriented practical course, students learn how to design realistic, interesting, behaving avatars in virtual realities. Typically the focus lies in developing user interfaces, and new options for interacting with the VR and acting upon objects or other entities within the VR. Alternatively, experimental setups will be programmed and optimized in order to run real-world psychological and evaluative experiments in which users control avatars in VR.		
Objectives	Students know how to work with virtual realities (VRs) and how to develop animated, autonomous avatars in these environments. They are able to create and use suitable interfaces to enable users to effectively interact with VRs and control avatars within.		

Requirement for Credit Points / Grade

	Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Practical	P	o	4	6	tp		g	100

Usability (modules)	General Computer Science; Expanded Perspectives
Requirement for participation	Solid Knowledge in Programming. General knowledge about simulation software.
Lecturer	Butz
Literature	*none*

Module Number: INFO-4250	Module title Information Processing for Perception and Action		Module Seminar
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	1 semester		
Frequency	irregularly		
Language of instruction	Deutsch, English		
Type of Exam	Wird zu Beginn des Semesters bekanntgegeben / Will be announced at beginning of semester		
Content	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.		
Objectives	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.		

Requirement for Credit Points / Grade

	Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Seminar	S	f	2	3	tp	45	g	100

Usability (modules)	General Computer Science; Expanded Perspectives
Requirement for participation	No formal requirements, but students should have a good background in statistics and should have attended introductory/mid–level courses in Cognitive Science/Neuroscience.
Lecturer	Franz
Literature	Wird zu Beginn des Semesters bekanntgegeben / Will be announced at beginning of semester

Module Number: INFO-4152	**Module title** Advanced Statistics		**Module** Lecture, Tutorials
ECTS	3		
Work load - Contact time - Self study	Work load 90 h	Class time 2 h / 2 CH	Self-Study 88 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 4. 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.		
Usability (modules)			
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.		

Module Number: INFO-4149	Module title Selected Topics in Database Systems		Module Lecture, Tutorials
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, Tutorials		
Duration	one semester		
Frequency	irregularly		
Language of instruction	English (or German, depends on participants)		
Type of Exam	Written exam (oral exam for small number of participants), exercise points can be included in the exam as bonus points.		
Content	Changing in-depth topics from the various areas of the Research field database systems. Use of database systems for the realisation of demanding applications (*Advanced SQL*).		
Objectives	The students have knowledge of research methodology in the field of database systems. The focus is mainly on the use of SQL as database language, their efficient translation, as well as their use for Implementation of very complex applications. The participants are familiar with the preparation of scientific papers, particularly in sub-areas of the research field of database systems Students can focus specifically on Master's theses and research projects.		

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	W	90	g	100
Tutorial	T	o	2	2				

Usability (modules)	General Computer Science; Expanded Perspectives
Requirement for participation	INF3131 Introduction to Relational Database Systems (DB1)
Lecturer	Grust
Literature	Classical and current research literature on the subject area.

Module Number: INFO-4381	**Module title** Advanced Topics in Human-Computer Interaction								**Module** Seminar
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								
Type of Exam	Oral presentation of at least 30 minutes and written report (essay at least 8 pages)								
Content	This seminar covers current and varying topics from research and application in the field of (multimodal) human-machine interaction.								
Objectives	Students will read and reflect upon current research in the area of human-computer interaction. 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.								
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	tp	30	g	100
Usability (modules)	General Computer Science; Expanded Perspectives								
Requirement for participation	none								
Lecturer	Kasneci								
Literature	*none*								

Module Number: INFO-4412	**Module title** Algorithms and Complexity								**Module** Lecture, Tutorial
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, Tutorial								
Duration	1 semester								
Frequency	regularly in the winter, every year								
Language of instruction	English								
Type of Exam	Written Exam (Oral Exam at small number of participants), grades in the tutorial might be included to the final grade as bonus								
Content	Topics amongst others are: • Matching • MinCostFlow • Approximation Schemes • Network Analysis • Clustering • Algorithmic Geometry • Discussions about complexity, e.g. lower bounds								
Objectives	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.								
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				
Usability (modules)	General Computer Science; Expanded Perspectives								
Requirement for participation									
Lecturer	Kaufmann								
Literature	Raghavan, Magnati, Orlin: Randomized Algorithms Mehlhorn, Näher: LEDA - A platform for combinatorial and geometric computation Papadimitriou, Steiglitz: Combinatorial optimization : algorithms and complexity								

Module Number: INFO-4241	Module title Programming Languages II		Module Lecture, Tutorials
ECTS	6		
Work load - Contact time - Self study	Work load 180 h	Class time 32 h / 4 CH	Self-Study 208 h
Lecture type	Lecture, Tutorials		
Duration	1 semester		
Frequency	about every two years		
Language of instruction	English or German dependent on participants)		
Type of Exam	Written or oral examination. Participation in exercises is required for exam participation.		
Content	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.		
Objectives	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.		
Usability (modules)	General Computer Science; Expanded Perspectives		
Requirement for participation	Programming Languages I is helpful, but not required.		
Lecturer	Ostermann		
Literature	Benjamin C. Pierce. Types and Programming Languages. MIT Press, 2003.		

Module Number: INFO-4246	Module title Programming with Dependent Types		Module Practical Course
ECTS	6		
Work load - Contact time - Self study	Work load 120 h	Class time 60 h / 4 CH	Self-Study 60 h
Lecture type	Practical Course		
Duration	1 semester		
Frequency	irregularly		
Language of instruction	English or German, depends on participants		
Type of Exam	Project 50 %, Presentation and Documentation 50 %		
Content	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.		
Objectives	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.		
Usability (modules)	General Computer Science; Expanded Perspectives		
Requirement for participation	Participation in Programming Languages I, II or III is helpful but not required.		
Lecturer	Ostermann		
Literature	will be announced at beginning of course		

Module Number: INFO-4248	Module title Interactive Theorem Proving		Module Lecture, Tutorials
ECTS	9		
Work load - Contact time - Self study	Work load 270 h	Class time 34 h / 6 CH	Self-Study 296 h
Lecture type	Lecture, Tutorials		
Duration	1 semester		
Frequency	about every two years		
Language of instruction	Englisch, if all participants agree, else German		
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.		
Usability (modules)	General Computer Science; Expanded Perspectives		
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		

Module Number: BIO-4242	Module title Advanced Java in Bioinformatics								Module Lecture and tutorials
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 and tutorials								
Duration	1 semester								
Frequency	every two years								
Language of instruction	English								
Type of Exam	Programming project								
Content	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. We will build a full-featured, interactive bioinformatics program.								
Objectives	The students are able to design and implement a fully featured bioinformatics program. They are able to analyze a computational problem and to develop an appropriate solution. They are aware of both the possibilities and the limitations of the application of Java to solve computational tasks. They are able to analyse problems on a scientific level and summarise them in writing. In particular, a high degree of intrinsic motivation and personal responsibility is encouraged.								
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
Usability (modules)	General Computer Science; Expanded Perspectives								
Requirement for participation	BIOINF4110 Sequence Bioinformatics								
Lecturer	Huson								
Literature	Programming and bioinformatics literature								

Module Number: BIO-4311	Module title Microbiome analysis		Module Lecture, Tutorials
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, Tutorials		
Duration	1 semester		
Frequency	every two years		
Language of instruction	English		
Type of Exam	Written or oral exam		
Content	This course provides an in-depth introduction to microbiome analysis. Topics include: Sequencing technologies. Community profiling using the SSU rRNA gene. Community profiling using shotgun sequencing. Alignment-free and alignment-based taxonomic profiling. Functional analysis and profiling. Sample comparison and time-series analysis.		
Objectives	The students are familiar with recent bioinformatics findings on microbiome analysis. They can formulate the challenges of microbiome analysis for bioinformatics. They know algorithms for taxonomic and functional analysis of microbiome sequencing data, statistical methods for comparison and methods for community profiling using 16S sequences. Students can analyse microbiome sequencing data and perform profiling and comparison. They are aware of both the possibilities and the limitations of different methods in this subfield of bioinformatics. They are able to analyse problems on a scientific level and summarise them in writing. In particular, a high degree of intrinsic motivation and personal responsibility is encouraged.		

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	W	90	g	100
Tutorial	T	o	2	2				

Usability (modules)	General Computer Science; Expanded Perspectives
Requirement for participation	BIO-4110 Sequence Bioinformatics
Lecturer	Huson
Literature	Lecture notes and scientific publications

Module Number: BIO4364	**Module title** Visualization of Biological Data		**Module** Lecture, Tutorials
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, Tutorials		
Duration	1 semester		
Frequency	Regularly in the winter semester		
Language of instruction	English		
Type of Exam	Oral Exam (or written exam if number of participants is large)		
Content	As biological datasets increase in size and complexity, we are moving more and more from an hypothesis-driven research paradigm to a data-driven one. As a result, the visual exploration of that data has become even more crucial than in the past. The aim of this lecture is to familiarize the participants with modern methodologies of Information Visualization and Visual Analytics. Information Visualization is concerned with methods for the visualization of abstract data that has no inherent spatial structure (the visualization of spatial data is covered in INF3145 - Scientific Visualization). The lecture imparts how to apply these methods to biological data using practical examples and provides hands-on training during the tutorials. Questions such as 'what is data visualization', 'what is visual analytics', and 'how can we visualise (biological) data to gain insight in them, so that hypotheses can be generated or explored and further targeted analyses can be defined' are discussed. No prior knowledge of biology is required, that is, the lecture is also suitable for students from other fields such as computer science or media/medical informatics.		
Objectives	Students understand the visual analysis process. They know basic methods of information visualization and the 'do's' and 'don'ts' of visualization. The know methods to visualize diverse biological data like genomics or transcriptomics data. They are able to chose suitable visualizations based on the type of data and the given analysis task. The students will be able to design and develop complex, interactive visual analytics applications in small teams.		

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	O	30	g	100
Tutorials	T	o	2	2				

Usability (modules)	General Computer Science; Expanded Perspectives
Requirement for participation	-
Lecturer	Krone, Nieselt
Literature	Lecture slides will be provided for download. Tamara Munzner 'Visualization Analysis and Design', A K Peters, 2014. Nature Methods Supplement 'Visualizing biological data', various Nature Methods 'Points of View' articles.

<table>
<tr><td>Module Number:
BIO-4331</td><td colspan="8">Module title
Advances in Computational Transcriptomics</td><td colspan="2">Module
Lecture, Tutorials</td></tr>
<tr><td>ECTS</td><td colspan="10">6</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td colspan="3">Work load
180 h</td><td colspan="5">Class time
60 h / 4 CH</td><td colspan="2">Self-Study
120 h</td></tr>
<tr><td>Lecture type</td><td colspan="10">Lecture, Tutorials</td></tr>
<tr><td>Duration</td><td colspan="10">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="10">once a year</td></tr>
<tr><td>Language of instruction</td><td colspan="10">English</td></tr>
<tr><td>Type of Exam</td><td colspan="10">Written exam (oral exam for small number of participants)</td></tr>
<tr><td>Content</td><td colspan="10">Functional genomics, i.e. the interpretation of a genome to determine the biological function of genes and gene interactions, is one of the most important fields in modern biology. Today, "next-generation" sequencing technologies are increasingly being used to measure the expression of thousands of genes simultaneously. This results in new challenges for bioinformatics, both algorithmically and software-wise. In the lecture the following topics will be discussed among others: NGS technologies, in particular RNA-Seq and ChIP-Seq technologies, fast to ultrafast alignment methods of 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 exercises, especially scientific work and scientific writing is encouraged. The exercises are also supplemented with blended learning methods</td></tr>
<tr><td>Objectives</td><td colspan="10">The students are familiar with the new bioinformatics findings on expression analysis and the newer sequencing technologies. They can formulate the challenges of the new technologies for bioinformatics. They know algorithms for the quantification of expression data, statistical methods and machine learning procedures for the calculation of differential expression and classification as well as methods for the analysis of expression data in a network context. Students can analyse real microarray experiments as well as RNA-Seq experiments and have deepened their R knowledge. The students are aware of the possibilities but also the limitations of different methods in this subfield of bioinformatics. They are able to analyse problems on a scientific level and summarise them in writing. In particular, a high degree of intrinsic motivation and personal responsibility is encouraged.</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 colspan="2">Calculation of Module (%)</td></tr>
<tr><td>Vorlesung</td><td>V</td><td>o</td><td>2</td><td>4</td><td>K</td><td>90</td><td>b</td><td colspan="2">100</td></tr>
<tr><td>Übung</td><td>Ü</td><td>o</td><td>2</td><td>2</td><td></td><td></td><td></td><td colspan="2"></td></tr>
<tr><td>Usability (modules)</td><td colspan="10">General Computer Science; Expanded Perspectives</td></tr>
<tr><td>Requirement for participation</td><td colspan="10">BIOINF3331 recommended</td></tr>
<tr><td>Lecturer</td><td colspan="10">Nieselt</td></tr>
</table>

(still BIO-4331)

Literature	Own lecture notes and selected articles

<table>
<tr><td>Module Number:
BIO-4210</td><td colspan="3">Module title
Practical Transcriptomics</td><td colspan="5">Module
Practical course</td></tr>
<tr><td>ECTS</td><td colspan="8">3</td></tr>
<tr><td>Work load
- Contact time
- Self study</td><td>Work load
90 h</td><td colspan="2">Class time
30 h / 2 CH</td><td colspan="5">Self-Study
60 h</td></tr>
<tr><td>Lecture type</td><td colspan="8">Practical course</td></tr>
<tr><td>Duration</td><td colspan="8">1 semester</td></tr>
<tr><td>Frequency</td><td colspan="8">Offered at irregular intervals</td></tr>
<tr><td>Language of instruction</td><td colspan="8">English</td></tr>
<tr><td>Type of Exam</td><td colspan="8">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="8">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="8">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 knowledge 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 strengths and weaknesses and about the limitations of various methods for evaluating high-throughput transcriptomic 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 course</td><td>P</td><td>c</td><td>3</td><td>3</td><td>H.R</td><td></td><td>b</td><td>100</td></tr>
<tr><td>Usability (modules)</td><td colspan="8">-</td></tr>
<tr><td>Requirement for participation</td><td colspan="8">BIOINF4110, BIOINF4120, BIOINF4331 Advances in Computational Transcriptomics (recommended), BIOINF3331 Expression Bioinformatik (recommended)</td></tr>
<tr><td>Lecturer</td><td colspan="8">Nieselt</td></tr>
<tr><td>Literature</td><td colspan="8">Will be provided at the beginning of the course, if necessary.</td></tr>
</table>

Module Number: BIO-4363	Module title RNA Bioinformatics		Module Seminar
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	1 semester		
Frequency	irregularly		
Language of instruction	English		
Type of Exam	Presentation (about 30 minutes) and written elaboration (approx. 10 pages), leading the discussion once		
Content	In this seminar, current topics related to computer-aided RNA bioinformatics will be discussed. These can be, among others, the following: 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 supplemented by current research.		
Objectives	The students can independently work with supervision on a challenging topic through systematic research. Students gain experience in giving a technical presentation and producing a technical writeup in bioinformatics. They summarize, assess, classify, scientifically correctly represent and present concepts and methods of bioinformatic RNA biology. On the one hand, the students will get an overview of modern knowledge in the field of bioinformatic RNA biology and thus the importance of this subfield of bioinformatics. On the other hand, they will know that there are still many open research questions in this field. By studying current articles, the students have not only improved their reading and learning skills, but also their personal responsibility. The form of learning used in the seminar is intended to help the students to develop self-confidence (presentation) and the ability to criticise and communicate (subsequent discussion).		
Requirement for Credit Points / Grade	(see table below)		
Usability (modules)			
Requirement for participation	-		
Lecturer	Nieselt		
Literature	Articles / scientific publications for each individual topic		

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	b	100
Seminar	S	o			H			

Module Number: MEDZ-4991	Module title Medical Data Science								Module Lecture, Tutorial
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	Written 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. The students can critically reflect on shortcomings of state-of-the-art methods to potentially come up with ideas for extending or improving the methods.								
Requirement for Credit Points / Grade		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
	Vorlesung	V	o	2	4	K	90	b	100
	Übung	Ü	o	2	2				
Usability (modules)	General Computer Science; Expanded Perspectives								

(still MEDZ-4991)

Requirement for participation	recommended: Machine learning: theory and algorithms or Introduction to Statistical Machine Learning for Bioinfos and Medicine Infos
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 Lecture, Tutorial, Seminars
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.		
Usability (modules)			
Requirement for participation	-		
Lecturer	-		
Literature	-		

Module Master Thesis

Module Number: ML-4999	Module title Master thesis		Module Independent research work, Master's thesis (in written form) and oral presentation
ECTS	30		
Work load - Contact time - Self study	Work load 900 h	Class time 30 h / 2 CH	Self-Study 870 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)

		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Requirement for Credit Points / Grade	Master's thesis	R	o	–	27	w		g	100
	Oral presentation	-	o	–	3				
Usability (modules)	-								
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								