Module catalogue

of the module handbook for the

Bioinformatics Master's degree programs

for the exam regulations valid as of 1 October 2021

Last updated: March 3, 2022

Computer Science Department

EBERHARD KARLS
UNIVERSITÄT
TÜBINGEN

MATHEMATISCH-
NATURWISSENSCHAFTLICHE
FAKULTÄT

Contents

Notes

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

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

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

Legend

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

Required elective modules: INFO-INFO

Computer Science

Module Number: INFO-4214	Module title Cognitive Modeling		Lecture types Lecture, Tutorials
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Duration	1 semester		
Frequency of offer	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.		

(noch INFO-4214)

		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Requirement for Credit Points / Grade	Lecture	L	f	2	3	wt	90	g	100
	Tutorial	T	f	2	3				0
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-4152	Module title Advanced Statistics		Lecture types Lecture, Tutorials
ECTS	3		
Work load -Contact time -Self study	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h
Duration	1 semester		
Frequency of offer	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.		
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-4250	**Module title** Information Processing for Perception and Action			**Lecture types** Seminar
ECTS	3			
Work load -Contact time -Self study	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h	
Duration	1 semester			
Frequency of offer	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 environenements, whenever empirical studies on human performance and actions are required.			
Requirement for Credit Points / Grade	(see table below)			
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			

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	45	g	100

Module Number: INFO-4173	Module title: Massively Parallel Computing									Lecture types: Vorlesung, Übungen
ECTS	6									
Work load -Contact time -Self study	Work load 180 h				Class time 60 h / 4 CH					Self-Study 120 h
Duration	1 semester									
Frequency of offer	every summer semester									
Language of instruction	Englisch									
Type of Exam	Mündliche Prüfung (bei großer Teilnehmerzahl Klausur), durch erfolgreiche Übungen kann ein Notenbonus erarbeitet werden.									
Content	Die Vorlesung führt die nötigen Konzepte der parallelen Verarbeitung ein, und gibt einen Überblick über die augenblicklich verfügbare Hardware. Weiterhin werden grundlegende parallele Algorithmen, z.B. Map, Reduce, Prefix-Sum, Branching, aber auch parallele Anwendungen wie FFT, Partikelsysteme und Simulationen etc. behandelt. Um für neue Probleme effiziente, parallele Lösungen zu entwickeln, werden entsprechende Herangehensweisen und Komplexitätsanalysen vermittelt.									
Objectives	Ein aktueller Trend aller Chip-Hersteller ist es, mehr und mehr Recheneinheiten auf einem Chip zu integrieren, z.B. mit mehreren hundert Prozessoren auf einer Grafikkarte. Um diese Architekturen effizient zu nutzen, müssen geeignete Algorithmen gewählt und die Probleme hinsichtlich der Speicherbandbreite optimiert werden. (1) Ziel der Vorlesung ist es, die Studenten in die Lage zu versetzen, ein gegebenes Problem hinsichtlich der möglichen Effizienzsteigerung durch Parallelisierung zu analysieren. (2) Sie können geignete Algorithmen entwickeln, um ein möglichst schnelle massiv-parallele Implementierung zu erarbeiten. (3) Sie sind in der Lage, durch Profiling ihre Programme hinsichtlich der Speicherbandbreite, der Auslastung der GPU und der Register zu optimieren.									
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	3	MP	25	b	100	
	Übung	Ü	O	2	3					
Requirement for participation	-									
Lecturer	Lensch									
Literature	Hubert Nguyen: GPU Gems 3, Addison Wesley; T. Mattson, B. Sanders, B. Massingill: Patterns for Parallel Programming, Addison Wesley ; gpgpu.org - General-Purpose Computation Using Graphics Hardware; NVIDIA CUDA page; NVIDIA CUDA Programming Guide ; Vorlesungsfolien werden bereitgestellt									

<table>
<tr><td>Module Number:
INFO-4174</td><td colspan="8">Module title
Massively Parallel Computing</td><td colspan="2">Lecture types
Praktikum</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="4">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Duration</td><td colspan="10">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="10">jährlich</td></tr>
<tr><td>Language of instruction</td><td colspan="10">Englisch</td></tr>
<tr><td>Type of Exam</td><td colspan="10">Präsentation und Ausarbeitung des Projektes</td></tr>
<tr><td>Content</td><td colspan="10">Es werden die effiziente Implementierung und die Umsetzung von Algorithmen aus den unterschiedlichen Bereichen der Informatik oder angrenzender Fachbereiche auf massiv-parallelen Architekturen vermittelt. Weiterhin wird die Programmierung von massiv-parallelen Rechnersystemen GPU, und die damit verbundenen Herausforderungen wie Speicherverwaltung, Branching, Synchronisation behandelt. Neben der Programmierung von GPUs steht auch das Messen und Vergleichen der Performanz paralleler Anwendungen im Fokus.</td></tr>
<tr><td>Objectives</td><td colspan="10">Die Studierenden können selbständig (in kleinen Gruppen) die Umsetzung rechenintensiver Aufgaben auf massiv-parallelen Rechnern planen, implementieren und durchführen. Sie sind in der Lage, die Laufzeit von parallelen Anwendungen zu messen und zu analysieren.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td colspan="2"></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="2">Praktikum</td><td>P</td><td>O</td><td>3</td><td>6</td><td>H</td><td></td><td>b</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="10">INFO-4173 Massively Parallel Computing (auch parallel)</td></tr>
<tr><td>Lecturer</td><td colspan="10">Lensch</td></tr>
<tr><td>Literature</td><td colspan="10">Entwicklungsumgebung wird zur Verfügung gestellt, NVIDIA CUDA page</td></tr>
</table>

Module Number: INFO-4241	Module title Programming Languages II		Lecture types Lecture, Tutorials
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 90 h / 4 CH	Self-Study 90 h
Duration	1 semester		
Frequency of offer	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.		
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		**Lecture types** Practical Course
ECTS	6		
Work load **-Contact time** **-Self study**	Work load 120 h	Class time 30 h / 4 CH	Self-Study 90 h
Duration	1 semester		
Frequency of offer	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.		
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		**Lecture types** Lecture, Tutorials
ECTS	9		
Work load -Contact time -Self study	Work load 270 h	Class time 135 h / 6 CH	Self-Study 135 h
Duration	1 semester		
Frequency of offer	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.		
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: MEDZ-4310	**Module title** Selected Topics in Medical Informatics		**Lecture types** Lecture, Tutorials
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Duration	1 semester		
Frequency of offer	once a year		
Language of instruction	English		
Type of Exam	Oral or written test		
Content	The focus of this lecture is on the relationship between Medical Informatics and Bioinformatics; it is a fundamental lecture for the research-oriented MSc in Medical Informatics.		
Objectives	Introducing current research fields, students learn to perceive the relationship between Medical Informatics and Bioinformatics.		
Requirement for participation	–		
Lecturer	Academic staff of Medical Informatics		
Literature	*none*		

Module Number: MEDZ-4320	**Module title** Selected Topics in Medical Informatics		**Lecture types** Lecture, Tutorials
ECTS	9		
Work load -Contact time -Self study	Work load 270 h	Class time 90 h / 6 CH	Self-Study 180 h
Duration	1 semester		
Frequency of offer	once a year		
Language of instruction	English		
Type of Exam	Oral test		
Content	The focus of this lecture is on the relationship between Medical Informatics and Bioinformatics; it is a fundamental lecture for the research-oriented MSc in Medical Informatics.		
Objectives	Introducing current research fields, students learn to perceive the relationship between Medical Informatics and Bioinformatics.		
Requirement for participation	MEDZ-RES MEDZ-BIOMED		
Lecturer	Academic staff of Medical Informatics		
Literature	*none*		

Module Number: MEDZ-4410	**Module title** Seminar Selected Topics in Medical Informatics		**Lecture types** Seminar
ECTS	3		
Work load -Contact time -Self study	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h
Duration	1 semester		
Frequency of offer	once a year		
Language of instruction	English		
Type of Exam	Oral presentation (30 minutes), written elaboration (8-10 pages)		
Content	Varying current scientific topics of the different fields of Medical Informatics. Students learn to work with and use scientific primary literature sources and present a summary of the content to their fellow student colleagues.		
Objectives	Students will be able to work with and use scientific primary literature sources for complex research topics in Medical Informatics. They have learned to provide a summary of the content both in written and oral form. In addition to having extended and deepened their knowledge, students have also improved social skills such as communication capabilities, moderation skills, rhetorical skills as well as handling criticism.		
Requirement for participation	–		
Lecturer	Academic staff of Medical Informatics		
Literature	Current research articles related to the research topic		

Technical Computer Science

Module Number: INFO-4313	Module title Embedded Systems		Lecture types Seminar
ECTS	3		
Work load -Contact time -Self study	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h
Duration	1 semester		
Frequency of offer	regularly in the summer term		
Language of instruction	English		
Type of Exam	Oral presentation and written report		
Content	Embedded systems have become a fundamental part of many technical systems and are already integral part of everyday life, e.g. in mobile communications, medical technology, consumer electronics, smart homes and autonomous vehicles as well as in industrial automation and Internet of Things (IoT). The manifold dependencies between software and the underlying hardware architecture require a holistic approach in design, analysis, and verification of embedded systems. This seminar examines modelling, analysis and verification approaches for distributed embedded systems, highlights the latest research trends in computer architecture and machine learning, and discusses their applicability in future embedded systems. The students choose a seminar topic from the given topic list, examine the topic in substance, and present the elaborated content by an oral seminar presentation and a written report.		
Objectives	Students are able to read, reflect, and examine the topic in substance upon current research papers in the area of embedded systems and can critically assess the contributions of 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 research papers in form of a oral presentation and a written report.		

Requirement for Credit Points / Grade

	Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Seminar	S	c	2	3	tp+op	30	g	100

Requirement for participation	none
Lecturer	Bringmann
Literature	Will be announced in the pre-lecture meeting.

Module Number: INFO-4315	**Module title** Advanced Topics in Embedded Systems		**Lecture types** Lecture
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 45 h / 2 CH	Self-Study 135 h
Duration	1 semester		
Frequency of offer	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.		

Requirement for Credit Points / Grade

	Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Lecture	L	c	2	3	ot	30	g	100
Lecture	L	c	2	4	ot	30	g	100
Tutorial	T	c	2	2				

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-4349</th><th colspan="6">Module title
Communication Networks (Seminar)</th><th colspan="3">Lecture types
Seminar</th></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="3">Work load
90 h</td><td colspan="3">Class time
30 h / 2 CH</td><td colspan="3">Self-Study
60 h</td></tr>
<tr><td>Duration</td><td colspan="9">one semester</td></tr>
<tr><td>Frequency of offer</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">Oral presentation and written report</td></tr>
<tr><td>Content</td><td colspan="9">This seminar covers current and varying topics from research and application in the field of communication networks.</td></tr>
<tr><td>Objectives</td><td colspan="9">Students are able to read, reflect, and examine the topic in substance upon current research papers in the area of communication networks. They can critically assess the contributions of 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 research papers in form of a oral presentation and a written report.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Seminar</td><td>S</td><td>c</td><td>2</td><td>3</td><td>tp+op</td><td>30</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">INF4348 Communication Technologies or another Communication Networks master lecture</td></tr>
<tr><td>Lecturer</td><td colspan="9">Menth</td></tr>
<tr><td>Literature</td><td colspan="9">none</td></tr>
</table>

Machine Learning

<table>
<tr><td>Module Number:
ML-4503</td><td colspan="8">Module title
Explainable Machine Learning</td><td colspan="2">Lecture types
Seminar</td></tr>
<tr><td>ECTS</td><td colspan="10">3</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="3">Work load
90 h</td><td colspan="5">Class time
30 h / 2 CH</td><td colspan="2">Self-Study
60 h</td></tr>
<tr><td>Duration</td><td colspan="10">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="10">regularly in the winter semester</td></tr>
<tr><td>Language of instruction</td><td colspan="10">English</td></tr>
<tr><td>Type of Exam</td><td colspan="10">Oral Presentation (about 30 minutes) and written elaboration (approx. 10 pages), leading the discussion once</td></tr>
<tr><td>Content</td><td colspan="10">• 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="10">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 rowspan="2">Requirement for Credit Points / Grade</td><td colspan="2"></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="2">Seminar</td><td>S</td><td>o</td><td>2</td><td>3</td><td>wt,ot</td><td>30</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="10"></td></tr>
<tr><td>Lecturer</td><td colspan="10">Akata</td></tr>
<tr><td>Literature</td><td colspan="10">Will be announced in the first meeting</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4505</td><td colspan="2">Module title
Learning with Limited Labeled Data</td><td>Lecture types
Seminar</td></tr>
<tr><td>ECTS</td><td colspan="3">3</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td>Work load
90 h</td><td>Class time
30 h / 2 CH</td><td>Self-Study
60 h</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency of offer</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">Two oral presentations based on a paper selected from a set of suggested research papers (approx. 15 minutes each).</td></tr>
<tr><td>Content</td><td colspan="3">In this seminar, we will discuss research papers related to visual learning with limited labeled data, including deep learning methods for zero-shot and few-shot learning, semi-supervised learning, unsupervised pre-training, and self-supervised learning.
From a methodological perspective, we will discuss popular zero-shot learning and few-shot learning methods and applications, as well as different families of semi-supervised and unsupervised learning models, such as consistency regularization, self-training, and deep generative models.
General knowledge on Statistical Machine Learning
General knowledge on Deep Learning
General knowledge on Computer Vision</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 participate to 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><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr><tr><td>Seminar</td><td>S</td><td>o</td><td>2</td><td>3</td><td>tp+op</td><td>30</td><td>g</td><td>100</td></tr></table></td></tr>
<tr><td>Requirement for participation</td><td colspan="3">none</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:	**Module title**		**Lecture types**
ML-4309	Data Compression with Deep Probabilistic Models		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
Duration	1 semester		
Frequency of offer	Regularly once a year		
Language of instruction	English		
Type of Exam	In addition to solving weekly problem sets, students will be required to work on individual course projects in small groups and under occasional supervision by the lecturer or an assigned PhD student. Students will be graded based on a writeup and a presentation of their course project in lieu of a final exam.		
Content	This course unites concepts from probabilistic machine learning, information theory, and source coding theory into practical methods for developing highly effective compression codecs. Recently, established compression codecs (e.g., for images and videos) have been outperformed by a new class of codecs that employ probabilistic machine learning models. This course will introduce the information theoretical foundations of data compression. Students will then learn some basic knowledge of deep probabilistic models, various entropy coding algorithms, and how the two can be combined to develop and evaluate novel compression codecs.		
Objectives	From the theory side, students learn information theoretical bounds for lossless compression and the concept of rate-distortion performance in lossy compression. They learn the general concept of entropy coding, specific instances of entropy coding algorithms, and their respective advantages and disadvantages. In order to apply these concepts in practice, students learn some basic concepts of (deep) probabilistic models and (approximate) Bayesian inference. From the practical side, students learn about existing machine learning based compression codecs and obtain hands-on experience in implementing, training, and evaluating a new and practically usable codec		

Requirement for Credit Points / Grade

	Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Lecture	L	o	3	4.5			g	
Tutorial	T	o	1	1.5				

Requirement for participation	Students should have a sound understanding of multivariate calculus, some practical experience with the training of machine learning models, and proficiency with Python and at least one compiled language (e.g., Rust, C, C++). Parallel attendance of the course "Probabilistic Machine Learning" is encouraged but not strictly required.
Lecturer	Bamler
Literature	Literature will be listed at the beginning of the semester.

Module Number: ML-4506	**Module title** Machine Learning for Medical Image Analysis								**Lecture types** Seminar
ECTS	3								
Work load -Contact time -Self study	Work load 90 h		Class time 30 h / 2 CH					Self-Study 60 h	
Duration	1 semester								
Frequency of offer	Offered at irregular intervals								
Language of instruction	English								
Type of Exam	Oral presentation and graded participation in paper discussion								
Content	The seminar starts with an introductory lecture to provide a compact overview of the research field (machine learning for medical image analysis), as well as a tutorial on critical analysis and presentation of research papers. Throughout the remainder of the course, each student presents a paper from a collection of seminal work in the field. To foster engaging scientific exchange, each presented paper will have designated critics who are also tasked with studying the paper and preparing questions for its discussion.								
Objectives	The learning objectives of this seminar consist of three parts: (1) the students will gain a solid understanding of key contributions to the field of machine learning for medical image analysis, (2) the students learn to critically read and analyse original research papers and judge their impact, and (3) the students will improve their scientific communication skills with an oral presentation and participation in discussions sessions.								
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+op	30	g	100
Requirement for participation									
Lecturer	Baumgartner,Koch								
Literature	Will be provided in the course								

<table>
<tr><th>Module Number:
ML-4420</th><th colspan="2">Module title
Efficient Machine Learning in Hardware</th><th>Lecture types
Lecture</th></tr>
<tr><td>ECTS</td><td colspan="3">6</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="3">regularly in the summer, every two years</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Oral exam</td></tr>
<tr><td>Content</td><td colspan="3">The recent breakthroughs in using deep neural networks for a large variety of machine learning applications have been strongly influenced by the availability of high performance computing platforms. In contrast to its biological origin, however, high performance of artificial neural networks critically relies on much higher energy demands. While the average energy consumption of the entire human brain is comparable to that of a laptop computer (i.e. 20W), artificial intelligence often resorts to large HPCs with several orders of magnitude higher energy demand. This lecture will discuss this problem and show 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
</td></tr>
<tr><td>Objectives</td><td colspan="3">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.</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Knowledge about foundations in machine learning</td></tr>
<tr><td>Lecturer</td><td colspan="3">Bringmann</td></tr>
<tr><td>Literature</td><td colspan="3">Will be announced in the first lecture</td></tr>
</table>

<table>
<tr><td>Module Number:
INFO-4194</td><td colspan="5">Module title
Behavior and Learning</td><td colspan="4">Lecture types
Lecture, Tutorials</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="2">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="4">Self-Study
120 h</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written (oral exam if number of participants allows)</td></tr>
<tr><td>Content</td><td colspan="9">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="9">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 rowspan="3">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>f</td><td>2</td><td>3</td><td rowspan="2">wt</td><td rowspan="2">90</td><td rowspan="2">g</td><td>100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>f</td><td>2</td><td>3</td><td>0</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Introductory course about machine learning, artificial neural networks, robotics, or artificial intelligence is required.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Butz</td></tr>
<tr><td>Literature</td><td colspan="9">Will be supplied (book chapters and papers in English)</td></tr>
</table>

Module Number: INFO-4210	**Module title** Recurrent and Generative Artificial Neural Networks		**Lecture types** Lecture, Tutorials
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Duration	1 semester		
Frequency of offer	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	f	2	3	wt	90	g	100
Tutorial	T	f	2	3				0

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 papers in English)

<table>
<tr><td>Module Number:
INFO-4211</td><td colspan="8">Module title
Avatars in Virtual Realities</td><td>Lecture types
Practical Course</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="2">Work load
180 h</td><td colspan="4">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency of offer</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">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.</td></tr>
<tr><td>Objectives</td><td colspan="9">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.</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>f</td><td>4</td><td>6</td><td>tp</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Solid Knowledge in Programming. General knowledge about simulation software.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Butz</td></tr>
<tr><td>Literature</td><td colspan="9">none</td></tr>
</table>

Module Number: INFO-4212	**Module title** Artificial Neural Networks								**Lecture types** Practical Course
ECTS	6								
Work load -Contact time -Self study	Work load 180 h			Class time 60 h / 4 CH			Self-Study 120 h		
Duration	1 semester								
Frequency of offer	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	f	2	3	tp		g	100
Requirement for participation	Solid Knowledge in Programming. Knowledge about artificial neural networks or machine learning.								
Lecturer	Butz								
Literature	*none*								

Module Number: INFO-4213	**Module title** Advanced Artificial Neural Networks Project								**Lecture types** Practical Course
ECTS	3								
Work load -Contact time -Self study	Work load 90 h			Class time 30 h / 2 CH					Self-Study 60 h
Duration	1 semester								
Frequency of offer	irregularly								
Language of instruction	English								
Type of Exam	Final Project Presentation and Report								
Content	Working with ANN Software, evaluating performance, & analyzing the system.								
Objectives	Know how to evaluate, program, and analyze 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	f	2	3	tp		g	100
Requirement for participation	Solid Knowledge in Programming. Knowledge about artificial neural networks or machine learning.								
Lecturer	Butz								
Literature	*none*								

Module Number: ML-4103	**Module title** Deep Learning								**Lecture types** 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
Duration	1 semester								
Frequency of offer	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.								
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				
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.								

<table>
<tr><td>Module Number:
ML-4340</td><td colspan="2">Module title
Self-Driving Cars</td><td>Lecture types
Lecture with tutorials</td></tr>
<tr><td>ECTS</td><td colspan="3">6</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency of offer</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 exam (in case of a small number of participants: oral exam)</td></tr>
<tr><td>Content</td><td colspan="3">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.</td></tr>
<tr><td>Objectives</td><td colspan="3">Students develop an understanding of the capabilities and limitations of state-of-the-art autonomous driving solutions. They gain a basic understanding of the entire system comprising perception, learning and vehicle control. In addition, they are able to implement and train simple models for sensori-motor control.</td></tr>
<tr><td>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 rowspan="2">wt/ot</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
</table>
</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Basic math (linear algebra, probabilities) and coding (Python) skills. Experience with deep learning (e.g., course “Deep Learning”). Experience in PyTorch is recommended.</td></tr>
<tr><td>Lecturer</td><td colspan="3">Andreas Geiger</td></tr>
<tr><td>Literature</td><td colspan="3">Related literature will be listed throughout the lecture.</td></tr>
</table>

<table>
<tr><th>Module Number:
ML-4360</th><th>Module title
Computer Vision</th><th>Lecture types
Lecture with tutorials</th></tr>
<tr><td>ECTS</td><td colspan="2">6</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="2"><table><tr><td>Work load
180 h</td><td>Class time
60 h / 4 CH</td><td>Self-Study
120 h</td></tr></table></td></tr>
<tr><td>Duration</td><td colspan="2">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="2">Regularly once a year</td></tr>
<tr><td>Language of instruction</td><td colspan="2">English</td></tr>
<tr><td>Type of Exam</td><td colspan="2">Written exam (in case of a small number of participants: oral exam)</td></tr>
<tr><td>Content</td><td colspan="2">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.</td></tr>
<tr><td>Objectives</td><td colspan="2">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.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="2"><table><tr><th></th><th>Type of Class</th><th>Status</th><th>CH</th><th>CP</th><th>Type of Exam</th><th>Duration of Exam</th><th>Evaluation</th><th>Calculation of Module (%)</th></tr><tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">wt/ot</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr><tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr></table></td></tr>
<tr><td>Requirement for participation</td><td colspan="2">Basic math (linear algebra, probabilities) and coding (Python) skills. Experience with deep learning (e.g., course “Deep Learning”). Experience in PyTorch is recommended.</td></tr>
<tr><td>Lecturer</td><td colspan="2">Andreas Geiger</td></tr>
<tr><td>Literature</td><td colspan="2">Related literature will be listed throughout the lecture.</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4101</td><td colspan="2">Module title
Mathematics of Machine Learning</td><td>Lecture types
Lecture with tutorials</td></tr>
<tr><td>ECTS</td><td colspan="3">9</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td>Work load
270 h</td><td>Class time
90 h / 6 CH</td><td>Self-Study
180 h</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="3">every 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 exam (in case of a small number of participants: oral exams)</td></tr>
<tr><td>Content</td><td colspan="3">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
</td></tr>
<tr><td>Objectives</td><td colspan="3">Students learn the mathematical foundations for the latter machine learning courses. In particular,

they know multivariate calculus and linear algebra as needed in machine learning lectures
they can apply probability and statistics and are able to prove basic properties
they have an overview of existing optimization techniques and are able to reformulate equivalent constrained optimization problems
</td></tr>
</table>

(noch ML-4101)

		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	90	g	100
	Tutorial	T	o	2	3				
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.								

Module Number: ML-4201	Module title: Statistical Machine Learning		Lecture types: 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
Duration	1 semester		
Frequency of offer	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	see table below		
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.		

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	wt	90	g	100
Tutorial	T	o	2	3				

<table>
<tr><td>Module Number:
ML-4303</td><td colspan="2">Module title
Convex and Nonconvex Optimization</td><td>Lecture types
Lecture with tutorials</td></tr>
<tr><td>ECTS</td><td colspan="3">9</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td>Work load
270 h</td><td>Class time
90 h / 6 CH</td><td>Self-Study
180 h</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="3">every two years</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="3">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.</td></tr>
<tr><td>Objectives</td><td colspan="3">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.</td></tr>
<tr><td>Requirement for Credit Points / Grade</td><td colspan="3">

	Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Lecture	L	o	4	6	wt	90	g	100
Tutorial	T	o	2	3				

</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">Students need to know the contents of the basic math classes, in particular linear algebra and multivariate calculus. No prior background in optimization is required.</td></tr>
<tr><td>Lecturer</td><td colspan="3">Hein</td></tr>
<tr><td>Literature</td><td colspan="3">The lecture does not follow a specific book. The literature for this lecture will be provided at the beginning of the semester.</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4102</td><td colspan="9">Module title
Data Literacy</td><td colspan="3">Lecture types
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>Duration</td><td colspan="12">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="12">Regularly once a year</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">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="12">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="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">wt</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>Requirement for participation</td><td colspan="12">only basic math and coding skills as provided by the BSc Computer Science.</td></tr>
<tr><td>Lecturer</td><td colspan="12">Hennig</td></tr>
<tr><td>Literature</td><td colspan="12">Literature will be listed at the beginning of the semester.</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4202</td><td colspan="2">Module title
Probabilistic Inference and Learning</td><td>Lecture types
Lecture with tutorials</td></tr>
<tr><td>ECTS</td><td colspan="3">9</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td>Work load
270 h</td><td>Class time
90 h / 6 CH</td><td>Self-Study
180 h</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency of offer</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>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></td></tr>
</table>
</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>

<table>
<tr><td>Module Number:
ML-4301</td><td colspan="9">Module title
Numerical Algorithms of Machine Learning</td><td colspan="3">Lecture types
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>Duration</td><td colspan="12">1 semester</td></tr>
<tr><td>Frequency of offer</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">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.</td></tr>
<tr><td>Objectives</td><td colspan="12">Students develop both an intuitive and mathematical understanding of numerical methods for optimization, integration, linear algebra, and the solution of differential equation. They know how to adapt the tools to the challenges of the task at hand, such as high dimensionality, stochasticity in computation, numerical stability, non-convexity, efficient tuning of algorithmic parameters, and uncertainty calibration for imprecise computation. Experience in the design and use of numerical tools is a highly sought-after skill in industry, and distinguishes the expert engineer from the amateur user.</td></tr>
<tr><td rowspan="2">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 colspan="2">Calculation of Module (%)</td></tr>
<tr><td colspan="3">Lecture
Tutorial</td><td>L
T</td><td>o
o</td><td>2
2</td><td>3
3</td><td>wt</td><td>90</td><td>g</td><td colspan="2">100</td></tr>
<tr><td>Requirement for participation</td><td colspan="12">Linear algebra is a core theme. Knowledge of probabilistic machine learning is valuable for this course. Prior experience with numerical analysis is helpful but not required. The practical parts use python and various recent python libraries.</td></tr>
<tr><td>Lecturer</td><td colspan="12">Hennig</td></tr>
<tr><td>Literature</td><td colspan="12">Literature will be listed at the beginning of the semester.</td></tr>
</table>

<table>
<tr><td>Module Number:
ML-4320</td><td colspan="5">Module title
Time Series</td><td colspan="4">Lecture types
Lecture with tutorials</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="2">Work load
180 h</td><td colspan="3">Class time
60 h / 4 CH</td><td colspan="4">Self-Study
120 h</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written test (in case of a small number of participants: oral tests)</td></tr>
<tr><td>Content</td><td colspan="9">A time series is an extremely wide-spread type of empirical data: a (potentially multivariate) set of observations that evolves over a univariate and thus ordered index space—time. Examples include stock prices, inventory levels, sports statistics, sensor readings in scientific equipment, cars and machinery, and many more. Time series often require real-time processing, and can potentially be infinitely long. But their univariate domain also allows for a crucial property of the model: 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="9">Students develop an understanding for key algorithmic and modelling challenges in the analysis of, and practical inference with time-ordered processes and data. They can implement and debug basic and advanced models for such data, including for production-level, large-scale applications, and for areas demanding high quality predictions, such as scientific analysis. 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></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture</td><td>L</td><td>o</td><td>2</td><td>3</td><td rowspan="2">tp+op</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td>Tutorial</td><td>T</td><td>o</td><td>2</td><td>3</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Knowledge of the material provided in the course Probabilistic Machine Learning (ML-4202) is required.</td></tr>
<tr><td>Lecturer</td><td colspan="9">Hennig, Tronarp</td></tr>
<tr><td>Literature</td><td colspan="9">Literature will be listed at the beginning of the semester.</td></tr>
</table>

Module Number: ML-4310	**Module title** Data Mining and Probabilistic Reasoning			**Lecture types** Lecture with tutorials
ECTS	3			
Work load -Contact time -Self study	Work load 90 h	Class time 45 h / 2 CH		Self-Study 45 h
Duration	1 semester			
Frequency of offer	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	wt	90	g	100
Tutorial	T	o	1	1				

Requirement for participation	
Lecturer	Gjergji Kasneci
Literature	Will be supplied (book chapters and papers in English)

Module Number: ML-4302	Module title Statistical Learning Theory		Lecture types 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
Duration	1 semester		
Frequency of offer	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	wt	90	g	100
Tutorial	T	o	2	3				

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

<table>
<tr><td>Module Number:
ML-4502</td><td colspan="8">Module title
Machine learning methods for scientific discovery</td><td colspan="2">Lecture types
Seminar</td></tr>
<tr><td>ECTS</td><td colspan="10">3</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="3">Work load
90 h</td><td colspan="5">Class time
30 h / 2 CH</td><td colspan="2">Self-Study
60 h</td></tr>
<tr><td>Duration</td><td colspan="10">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="10">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="10">English</td></tr>
<tr><td>Type of Exam</td><td colspan="10">Oral presentation, written report</td></tr>
<tr><td>Content</td><td colspan="10">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.</td></tr>
<tr><td>Objectives</td><td colspan="10">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.</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 colspan="2">Calculation of Module (%)</td></tr>
<tr><td>Seminar</td><td>S</td><td>o</td><td>2</td><td>3</td><td>wp+tp</td><td>30</td><td>g</td><td colspan="2">100</td></tr>
<tr><td>Requirement for participation</td><td colspan="10">Basic knowledge probabilistic machine learning</td></tr>
<tr><td>Lecturer</td><td colspan="10">Macke</td></tr>
<tr><td>Literature</td><td colspan="10">Will be announced in the first meeting</td></tr>
</table>

Module Number: ML-4601	**Module title** Introduction to Game Theory with Application to Multi-Agent Systems		**Lecture types** Lecture
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Duration	1 semester		
Frequency of offer	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.		
Requirement for participation			
Lecturer	Maghsudi		

(noch 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

<table>
<tr><td>Module Number:
MEDZ-4110</td><td colspan="2">Module title
Advanced Medical Informatics</td><td>Lecture types
Lecture, Tutorial</td></tr>
<tr><td>ECTS</td><td colspan="3">9</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td>Work load
270 h</td><td>Class time
90 h / 6 CH</td><td>Self-Study
180 h</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="3">once per year</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">Oral Exam</td></tr>
<tr><td>Content</td><td colspan="3">This lecture comprises different areas of Medical Informatics. The focus is on data integration, medical data privacy, artificial intelligence and data mining for health data, and treatment decision support systems. Specific topics are:
statistical machine learning basics
state-of-the-art in decision support systems and beyond
differential privacy
k-anonymity
privacy-preserving record linkage
federated learning approaches and GO-FAIR
genome privacy
FHIR
openEHR
data warehouses and no-SQL data bases
map reduce</td></tr>
<tr><td>Objectives</td><td colspan="3">The students are capable of explaining the most important terms, methods and theories of clinical decision support systems, medical data privacy, and data integration and analysis. 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.</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">recommended: Grundlagen der Medizininformatik</td></tr>
<tr><td>Lecturer</td><td colspan="3">Pfeifer</td></tr>
<tr><td>Literature</td><td colspan="3">Eta S. Berner: Clinical Decision Support Systems - Theory and Practice, A. Gkoulalas-Divanis and G. Loukides: Medical Data Privacy Handbook, P. Lake and P. Crowther: Concise guide to databases</td></tr>
</table>

Module Number: INFO-4492	Module title: Special Topics in Learning Theory	Lecture types: Lecture, Tutorials

ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Duration	1 semester		
Frequency of offer	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	c	2	3	wt	90	g	100
Tutorial	T	c	2	3				

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

<table>
<tr><th>Module Number:
INFO-4493</th><th colspan="8">Module title
Learning Theory</th><th>Lecture types
Seminar</th></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="3">Work load
90 h</td><td colspan="3">Class time
30 h / 2 CH</td><td colspan="3">Self-Study
60 h</td></tr>
<tr><td>Duration</td><td colspan="9">one semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="9">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English or German, depending on the participants</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Oral presentation, written report.</td></tr>
<tr><td>Content</td><td colspan="9">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.</td></tr>
<tr><td>Objectives</td><td colspan="9">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.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Seminar</td><td>S</td><td>c</td><td>2</td><td>3</td><td>op</td><td>45</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">Basic knowledge in machine learning.</td></tr>
<tr><td>Lecturer</td><td colspan="9">von Luxburg</td></tr>
<tr><td>Literature</td><td colspan="9">will be announced in the lecture</td></tr>
</table>

Module Number: INFO-4381	**Module title** Advanced Topics in Human-Computer Interaction									**Lecture types** Seminar
ECTS	3									
Work load -Contact time -Self study	Work load 90 h			Class time 30 h / 2 CH						Self-Study 60 h
Duration	one semester									
Frequency of offer	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	
Requirement for participation	none									
Lecturer	Kasneci									
Literature	*none*									

Module Number: ML-4501	Module title Machine Learning Seminar								Lecture types Seminar
ECTS	3								
Work load -Contact time -Self study	Work load 90 h			Class time 30 h / 2 CH			Self-Study 60 h		
Duration	1 semester								
Frequency of offer	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	tp+op	30	g	100
Requirement for participation									
Lecturer	All lecturers in the computer science department								
Literature	Will be handed out in the course								

Required elective modules: BIO-BIO

Module Number: BIO-4103	Module title Group Project Bioinformatics		Lecture types Small Team project
ECTS	3		
Work load -Contact time -Self study	Work load 90 h	Class time 15 h / 1 CH	Self-Study 75 h
Duration	1 semester		
Frequency of offer	each Semester		
Language of instruction	English		
Type of Exam	Written Report		
Content	The group project serves to deepen the knowledge in a specific area of bioinformatics that have been introduced in either of the two lectures “Sequence Bioinformatics” (BIO-4110) oder “Structure and Systems Bioinformatics” (BIO-4120). Students work in small groups (4 students) and work on a project with the thematic focus of either of the lectures. The project topics encompass algorithmic problems, literature investigations, or application of tools to biological data. The idea is to apply gained knowledge to real biological data/tasks. Student have the opportunity to suggest a topic.		
Objectives	The students • gain insight into scientific work, • learn how to independently pursue a research question, • learn to independently identify and compile scientific literature for the research question to be worked on, • are able to work in a team, • deepen their problem-solving skills.		
Requirement for participation	BIO-4110 or BIO-4120		
Lecturer	The lecturers of either BIO-4110 or BIO-4120		
Literature	Scientific literature/publications relevant for the topic to be worked on		

Module Number: BIO-4998	Module title Research Project Bioinformatics		Lecture types Research Project
ECTS	9		
Work load -Contact time -Self study	Work load 270 h	Class time 90 h / 2 CH	Self-Study 180 h
Duration	1 semester		
Frequency of offer	each semester		
Language of instruction	English		
Type of Exam	Presentation and written report (either as a scientific paper or as a report (15-20 pages))		
Content	The research project aims to deepen theoretical and practical knowledge in a specific area of bioinformatics. Students participate in a research project with the thematic focus of the research group.		
Objectives	The students • gain insight into scientific work, • learn how to independently pursue a research question, • learn to independently identify and compile scientific literature for the research question to be worked on, • are able to work in a team in a scientific international environment, • deepen their problem-solving skills.		

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,op		g	100

Requirement for participation	Excellent academic grades in the Master of Bioinformatics. There are only a few research projects offered on a semester basis. A written application, including a letter of motivation, CV and Transcript of Records should be sent to the research group leader of the offered research project.
Lecturer	All lecturers in bioinformatics or medical informatics
Literature	Scientific literature/publications relevant to the research topic being addressed.

Module Number: BIO-4382	Module title Machine Learning for Single Cell Biology		Lecture types Lecture, Tutorial
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Duration	1 semester		
Frequency of offer	every year		
Language of instruction	English		
Type of Exam	Oral test		
Content	Single-cell technologies in conjunction with machine learning approaches are transforming the life sciences and the understanding of complex diseases like cancer. This lecture provides an introduction into (1) the biological and medical questions that can be uniquely addressed by such single-cell approaches, (2) state-of-the-art single-cell technologies such as high dimensional mass-/flow cytometry, multi-omic and/or spatial single-cell sequencing/imaging, and (3) (un-)supervised machine learning and dynamic modeling approaches to address afore questions on the basis of high dimensional single-cell data.		
Objectives	• Overview state-of-the-art single-cell technologies • Translation of biological/medical research questions into machine learning problems • Unsupervised/Supervised/Weakly-supervised machine learning models for characterization of cellular composition of tissues and their association with health/disease states • Dynamic models for cellular systems		
Requirement for participation	Programming skills in Python		
Lecturer	Claassen		
Literature	TBD		

Module Number: BIO-4383	Module title: Advanced Topics in Machine Learning for Single Cell Biology		Lecture types: Seminar
ECTS	3		
Work load -Contact time -Self study	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h
Duration	1 semester		
Frequency of offer	every year		
Language of instruction	English		
Type of Exam	Presentation (about 30 minutes) and written elaboration (approx. 10 pages), leading the discussion once		
Content	This seminar builds on the lecture 'Machine Learning for Single Cell Biology' (BIO-4382) and discusses current scientific publications on machine learning method development and application for basic science and translational single-cell biology studies.		
Objectives	• Reading and comprehension of state-of-the-art publications in the field Machine Learning for Single Cell Biology • Presentation of publications • Discussion of study results • Deepening of Unsupervised/Supervised/Weakly-supervised and dynamic system machine learning models in single-cell biology		
Requirement for participation	BIO-4382 or equivalent course		
Lecturer	Claassen		
Literature	Articles / scientific publications for each individual topic		

Module Number: BIO-4242	**Module title** Advanced Java in Bioinformatics		**Lecture types** 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
Duration	1 semester		
Frequency of offer	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	wt	90	g	100

Requirement for participation	BIOINF4110 Sequence Bioinformatics
Lecturer	Huson
Literature	Programming and bioinformatics literature

<table>
<tr><td>Module Number:
BIO-4311</td><td colspan="8">Module title
Microbiome analysis</td><td>Lecture types
Lecture, Tutorials</td></tr>
<tr><td>ECTS</td><td colspan="9">6</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="3">Work load
180 h</td><td colspan="4">Class time
60 h / 4 CH</td><td colspan="2">Self-Study
120 h</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="9">every two years</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">Written or oral exam</td></tr>
<tr><td>Content</td><td colspan="9">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.</td></tr>
<tr><td>Objectives</td><td colspan="9">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.</td></tr>
<tr><td rowspan="2">Requirement for Credit Points / Grade</td><td></td><td>Type of Class</td><td>Status</td><td>CH</td><td>CP</td><td>Type of Exam</td><td>Duration of Exam</td><td>Evaluation</td><td>Calculation of Module (%)</td></tr>
<tr><td>Lecture
Tutorial</td><td>L
T</td><td>o
o</td><td>2
2</td><td>4
2</td><td>wt</td><td>90</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">BIO-4110 Sequence Bioinformatics</td></tr>
<tr><td>Lecturer</td><td colspan="9">Huson</td></tr>
<tr><td>Literature</td><td colspan="9">Lecture notes and scientific publications</td></tr>
</table>

<table>
<tr><th>Module Number:
BIO-4399</th><th colspan="8">Module title
Advanced Topics in Bioinformatics</th><th colspan="3">Lecture types
Lectures and tutorials</th></tr>
<tr><td>ECTS</td><td colspan="11">6</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="4">Work load
180 h</td><td colspan="4">Class time
60 h / 4 CH</td><td colspan="3">Self-Study
120 h</td></tr>
<tr><td>Duration</td><td colspan="11">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="11">every two years</td></tr>
<tr><td>Language of instruction</td><td colspan="11">English</td></tr>
<tr><td>Type of Exam</td><td colspan="11">Written exam or oral exam</td></tr>
<tr><td>Content</td><td colspan="11">In this course, we explore new and important developments in bioinformatics. This can be driven by new technologies, new biological questions with a computational angle, or new methodologies. Typically, in the first third of the course we will cover the background and introductory material. We then study the new developments in detail in the second third of the course. In the final third, we discuss open problems and possible solutions.</td></tr>
<tr><td>Objectives</td><td colspan="11">The students are familiar with an advanced topic in bioinformatics. They can formulate the main challenges in that topic. They can analyse data that arises in that topic. They are aware of both the possibilities and the limitations of different methods in the topic. 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 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>4</td><td rowspan="2">wt</td><td rowspan="2">90</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td colspan="3">Tutorial</td><td>T</td><td>o</td><td>2</td><td>2</td></tr>
<tr><td>Requirement for participation</td><td colspan="11">BIO-4110 Sequence Bioinformatics</td></tr>
<tr><td>Lecturer</td><td colspan="11">Huson</td></tr>
<tr><td>Literature</td><td colspan="11">Lecture notes and scientifict publications</td></tr>
</table>

Module Number: BIO-4371	**Module title** Structure-Based Drug Design		**Lecture types** Lecture, Tutorial, Project
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Duration	1 semester		
Frequency of offer	regularly		
Language of instruction	English		
Type of Exam	Oral exam or, in case of too many students, written exam. 50% of the achievable points from the assignments and the project, individually, are required for exam admission. Points achieved in excess of 50% serve as a bonus for the final exam.		
Content	Starting with a broad introduction of the pharmaceutical drug development process, the lecture conveys key concepts of structure-based computer-aided drug design (CADD). Required basics on pharmaceutical key concepts are discussed followed by basic concepts for modeling of 3D structures (ligands and proteins). In the second part key physicochemical interactions between proteins and ligands are presented, forming the basis to discuss strategies to predict protein-ligand binding with a strong focus on algorithms for protein-ligand docking. Finally, the challenging task of estimating binding affinities between proteins and ligands *in silico* is introduced, leading to the discussion of scoring functions, which are developed und used for that purpose.		
Objectives	Students have a working knowledge on the pharmaceutical development process. They are familiar with protein and ligand structures, with standard methods to resolve them experimentally, with methods to model 3D structures, and are able to identify relevant physicochemical interactions between them. They have detailed knowledge of algorithmic techniques to predict protein-ligand binding (docking and scoring). The students are able to implement methods to work with protein-ligand structures and to develop simple CADD tools. Project work strengthened their ability to work in a team and to write down and to present scientific work.		
Requirement for participation	No formal requirements. Basic knowledge of protein structure, organic chemistry, and programming skills in Python are recommended.		
Lecturer	Kohlbacher		
Literature	Lecture slides and additional materials will be provided in electronic form, handouts of the slides are provided in the lecture. Recommended textbooks: - Leach A. "Molecular Modelling", Prentice Hall 2001 - Schlick T. "Molecular Modeling and Simulation", Springer 2010 - Klebe G. "Wirkstoffdesign", Springer 2009		

Module Number: BIO-4372	Module title Cheminformatics		Lecture types Lecture, Tutorial, Project
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Duration	1 semester		
Frequency of offer	irregularly		
Language of instruction	English		
Type of Exam	Oral exam or, in case of too many students, written exam. 50% of the achievable points from the assignments and the project, individually, are required for exam admission. Points achieved in excess of 50% serve as a bonus for the final exam.		
Content	Starting with an overview of its main application area, namely drug design, the lecture teaches how computer science methods can be used to work with chemical data, strongly focusing on small organic molecules (compounds). Representation of compounds (graphs, line notations, file formats) is followed by most important ways of topological comparison (identity, substructure, similarity). Relevant applications of topological similarity are introduced (searching, clustering, library generation). Quantitative Structure-Activity Relationship (QSAR) is introduced as the cheminformatics branch for predictive modeling of chemical properties. Finally, the prediction of 3D-structures from topology and similarity methods for compounds with 3D coordinates are introduced.		
Objectives	Students know how different kinds of chemical data can be handled with computers, how to represent and to analyse that data with methods from computer science, and they have an overview of the main application area drug design. Having understood the fundamental "Similar Property Principle" they are able to handle and to analyse experimental screening data and to implement and apply ligand-based screening methods. Students have a solid knowledge on standard tools and software libraries for cheminformatics. Project work strengthened their ability to work in a team and to write down and to present scientific work.		
Requirement for participation	No formal requirements. Basic knowledge of organic chemistry, graph theory, and programming skills in Python are recommended.		
Lecturer	Kohlbacher		
Literature	Lecture slides and additional materials will be provided in electronic form, handouts of the slides are provided in the lecture. Recommended textbooks: - Leach A., Gillet V. "An Introduction To Chemoinformatics", Springer 2007 - Faulon J.-L., Bender A. (Eds.) "Handbook Of Chemoinformatics Algorithms", CRC Press 2010 - Engel T., Gasteiger J. (Eds.) "Chemoinformatics", Wiley-VCH 2018 - Optional: Klebe G. "Wirkstoffdesign", Springer 2009		

Module Number: BIO-4364	**Module title** Visualization of Biological Data								**Lecture types** Lecture, Tutorials
ECTS	6								
Work load -Contact time -Self study	Work load 180 h			Class time 60 h / 4 CH					Self-Study 120 h
Duration	1 semester								
Frequency of offer	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	ot	30	g	100
	Tutorials	T	o	2	2				
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.								

Module Number: BIO-4331	Module title Advances in Computational Transcriptomics		Lecture types Lecture, Tutorials
ECTS	6		
Work load -Contact time -Self study	Work load 180 h	Class time 60 h / 4 CH	Self-Study 120 h
Duration	1 semester		
Frequency of offer	once a year		
Language of instruction	English		
Type of Exam	Written exam (oral exam for small number of participants)		
Content	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		
Objectives	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.		

Requirement for Credit Points / Grade

	Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)
Lecture	L	c	2	4	wt	90	g	100
Tutorial	T	c	2	2				

Requirement for participation	BIOINF3331 recommended
Lecturer	Nieselt
Literature	Own lecture notes and selected articles

Module Number: MEDZ-4991	Module title: Medical Data Science								Lecture types: Lecture, Tutorial
ECTS	6								
Work load -Contact time -Self study	Work load 180 h			Class time 60 h / 4 CH				Self-Study 120 h	
Duration	1 semester								
Frequency of offer	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 (%)
	Lecture	L	c	2	4	wt	90	g	100
	Tutorial	T	c	2	2				

(noch 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.

Required elective modules: BIO-SEM

Module Number: BIO-4383	**Module title** Advanced Topics in Machine Learning for Single Cell Biology		**Lecture types** Seminar
ECTS	3		
Work load -Contact time -Self study	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h
Duration	1 semester		
Frequency of offer	every year		
Language of instruction	English		
Type of Exam	Presentation (about 30 minutes) and written elaboration (approx. 10 pages), leading the discussion once		
Content	This seminar builds on the lecture 'Machine Learning for Single Cell Biology' (BIO-4382) and discusses current scientific publications on machine learning method development and application for basic science and translational single-cell biology studies.		
Objectives	• Reading and comprehension of state-of-the-art publications in the field Machine Learning for Single Cell Biology • Presentation of publications • Discussion of study results • Deepening of Unsupervised/Supervised/Weakly-supervised and dynamic system machine learning models in single-cell biology		
Requirement for participation	BIO-4382 or equivalent course		
Lecturer	Claassen		
Literature	Articles / scientific publications for each individual topic		

Module Number: BIO-4322	**Module title** Metagenomics									**Lecture types** Seminar
ECTS	3									
Work load -Contact time -Self study	Work load 90 h			Class time 30 h / 2 CH						Self-Study 60 h
Duration	1 semester									
Frequency of offer	annually									
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, we look at current research topics in the area of microbiome analysis, such as metagenomics, meta-transcriptomics and meta-proteomics. We will focus, to a degree, on the human microbiome. We provide a number of topics and associated publications to choose from and each participant delivers an oral presentation and a writeup of their chosen topic.									
Objectives	The students can independently work with supervision on a challenging topic through systematic research. They summarize, assess, classify and scientifically correctly represent and present concepts and methods in the context of microbiome analysis. On the one hand, students will obtain an overview of modern knowledge in the field of microbiome analysis. On the other hand, students 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		Type of Class	Status	CH	CP	Type of Exam	Duration of Exam	Evaluation	Calculation of Module (%)	
	Seminar	S	c	2	3	tp+op		g	100	
Requirement for participation	BIO-4110 Sequence Bioinformatics									
Lecturer	Huson									
Literature	Scientific publications									

<table>
<tr><td>Module Number:
BIO-4362</td><td colspan="2">Module title
Algorithms in Bioinformatics</td><td>Lecture types
Seminar</td></tr>
<tr><td>ECTS</td><td colspan="3">3</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td>Work load
90 h</td><td>Class time
30 h / 2 CH</td><td>Self-Study
60 h</td></tr>
<tr><td>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="3">annually</td></tr>
<tr><td>Language of instruction</td><td colspan="3">English</td></tr>
<tr><td>Type of Exam</td><td colspan="3">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 look at current research topics in bioinformatics, for example, fast alignment methods or single sequencing assembly. We provide a number of topics and associated publications to choose from and each participant delivers an oral presentation and a writeup of their chosen topic.</td></tr>
<tr><td>Objectives</td><td colspan="3">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 algorithms in bioinformatics. On the one hand, the students will get an overview of the state of the art of algorithms in bionformatics. 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).</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>c</td><td>2</td><td>3</td><td>op</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Seminar</td><td>S</td><td>c</td><td></td><td></td><td>tp</td><td></td><td></td><td></td></tr>
</table>
</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">BIO-4110 Sequence Bioinformatics</td></tr>
<tr><td>Lecturer</td><td colspan="3">Huson</td></tr>
<tr><td>Literature</td><td colspan="3">Scientific publications</td></tr>
</table>

<table>
<tr><td>Module Number:
BIO-4363</td><td colspan="8">Module title
RNA Bioinformatics</td><td colspan="3">Lecture types
Seminar</td></tr>
<tr><td>ECTS</td><td colspan="11">3</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="3">Work load
90 h</td><td colspan="5">Class time
30 h / 2 CH</td><td colspan="3">Self-Study
60 h</td></tr>
<tr><td>Duration</td><td colspan="11">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="11">irregularly</td></tr>
<tr><td>Language of instruction</td><td colspan="11">English</td></tr>
<tr><td>Type of Exam</td><td colspan="11">Presentation (about 30 minutes) and written elaboration (approx. 10 pages), leading the discussion once</td></tr>
<tr><td>Content</td><td colspan="11">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.</td></tr>
<tr><td>Objectives</td><td colspan="11">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).</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">Seminar</td><td>S</td><td>c</td><td rowspan="2">2</td><td rowspan="2">3</td><td>op</td><td rowspan="2">45</td><td rowspan="2">g</td><td rowspan="2">100</td></tr>
<tr><td colspan="3">Seminar</td><td>S</td><td>c</td><td>tp</td></tr>
<tr><td>Requirement for participation</td><td colspan="11">-</td></tr>
<tr><td>Lecturer</td><td colspan="11">Nieselt</td></tr>
<tr><td>Literature</td><td colspan="11">Articles / scientific publications for each individual topic</td></tr>
</table>

<table>
<tr><th>Module Number:
BIO-4373</th><th colspan="9">Module title
Bioinformatics and Machine Learning</th><th colspan="3">Lecture types
Seminar</th></tr>
<tr><td>ECTS</td><td colspan="12">3</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="4">Work load
90 h</td><td colspan="4">Class time
30 h / 2 CH</td><td colspan="4">Self-Study
60 h</td></tr>
<tr><td>Duration</td><td colspan="12">1 semester</td></tr>
<tr><td>Frequency of offer</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">Presentation (about 30 minutes) and written elaboration (approx. 10 pages), leading the discussion once</td></tr>
<tr><td>Content</td><td colspan="12">In this seminar, machine learning approaches with applications to bioinformatics will be discussed. These can be, among others, the following: supervised classification; deep learning in bioinformatics, support vector machines for classification; dimension reduction methods; probabilistic graphical models; applications to the fields of genomics, transcriptomics, evolution, systems biology, text mining and other topics supplemented by current research will be discussed.</td></tr>
<tr><td>Objectives</td><td colspan="12">The students can independently work with supervision on a challenging topic through systematic research. They summarize, assess, classify, scientifically correctly represent and present concepts and methods of machine learning that are applied to bioinformatics problems. On the one hand, students will get an overview of modern knowledge in the field of machine learning and their importance for various questions in bioinformatics. On the other hand, students 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).</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">Seminar</td><td>S</td><td>c</td><td>2</td><td>3</td><td>op</td><td>45</td><td>g</td><td>100</td></tr>
<tr><td colspan="4">Seminar</td><td>S</td><td>c</td><td></td><td></td><td>tp</td><td></td><td></td><td></td></tr>
<tr><td>Requirement for participation</td><td colspan="12">-</td></tr>
<tr><td>Lecturer</td><td colspan="12">Nieselt</td></tr>
<tr><td>Literature</td><td colspan="12">Articles / scientific publications for each individual topic</td></tr>
</table>

<table>
<tr><th>Module Number:
MEDZ-4520</th><th colspan="2">Module title
Biomedical Informatics Methods for Infection Research</th><th>Lecture types
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>Duration</td><td colspan="3">1 semester</td></tr>
<tr><td>Frequency of offer</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">Talk (30 minutes) and report (8-10 pages)</td></tr>
<tr><td>Content</td><td colspan="3">This seminar covers different aspects of biomedical informatics methods for infection research. This includes computer science methods to support research in the following areas:
Pathogen-host interactions
Diversity of pathogens and its relevance for human infections
Analysis of viral epitopes
Support for vaccine development
Predicting drug resistance
Assessing the efficacy of combination drug therapies</td></tr>
<tr><td>Objectives</td><td colspan="3">Successful students know the most important terms, theories and methods in the field of fighting infections with computer science methods and know how to critically reflect on them.</td></tr>
<tr><td>Requirement for participation</td><td colspan="3">recommended: Machine learning: theory and algorithms or Introduction to Statistical Machine Learning for Bioinfos and Medicine Infos</td></tr>
<tr><td>Lecturer</td><td colspan="3">Pfeifer</td></tr>
<tr><td>Literature</td><td colspan="3">The papers will be announced at the first meeting.</td></tr>
</table>

Module Number: MEDZ-4522	Module title Machine Learning for Health		Lecture types Seminar
ECTS	3		
Work load -Contact time -Self study	Work load 90 h	Class time 30 h / 2 CH	Self-Study 60 h
Duration	1 semester		
Frequency of offer	irregularly		
Language of instruction	Englisch		
Type of Exam	Talk (30 minutes) and report (8-10 pages)		
Content	This seminar covers different state-of-the-art machine learning methods on biomedical data to answer medical questions of interest. This can include: • Graphical model structure learning and causality in medicine • Deep learning approaches in medicine • Machine learning methods for small sample sizes		
Objectives	Successful students know the most important terms, theories and methods in the field of fighting infections with computer science methods and know how to critically reflect on them.		
Requirement for participation	recommended: Machine learning: theory and algorithms or Introduction to Statistical Machine Learning for Bioinfos and Medicine Infos		
Lecturer	Pfeifer		
Literature	The papers will be announced at the first meeting.		

Required elective modules: BIO-PRAK

Module Number: BIO-4240	**Module title** Bioinformatics Tools		**Lecture types** Practical course
ECTS	3		
Work load **-Contact time** **-Self study**	Work load 90 h	Class time 80 h / 3 CH	Self-Study 10 h
Duration	Two week block course semester		
Frequency of offer	every semester		
Language of instruction	English		
Type of Exam	The final grade is based on performance, a written report on each day of the practical course, and one or two short oral presentations.		
Content	In this practical course, students work on a mini research project in the area of genomics, metagenomics or phylogenetics. Working in teams, the participants use state-of-the-art bioinformatics tools to address a series of typical computational questions. During the course, students read up on different methods and introduce the methods to each other in short presentations.		
Objectives	Students will gain practical experience in application of bioinformatics software for analyzing NGS data in the context of genomics, metagenomics or phylogenetics. They will be able to use libraries and frameworks, and will acquire knowledge or extend their knowledge of Java and Python. 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 molecular sequence 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 course	P	c	3	3	tp+op		g	100
Requirement for participation	BIO-4110								

(noch BIO-4240)

Lecturer	Huson
Literature	Scientific publications

<table>
<tr><td>Module Number:
BIO-4220</td><td colspan="6">Module title
Integrative Bioinformatics</td><td colspan="3">Lecture types
Practical course</td></tr>
<tr><td>ECTS</td><td colspan="9">3</td></tr>
<tr><td>Work load
-Contact time
-Self study</td><td colspan="3">Work load
90 h</td><td colspan="3">Class time
80 h / 3 CH</td><td colspan="3">Self-Study
10 h</td></tr>
<tr><td>Duration</td><td colspan="9">two-weeks block course during lecture-free time semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="9">every semester</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">A written report is to be submitted after the course. Performance during the course will also be integrated into the final grade.</td></tr>
<tr><td>Content</td><td colspan="9">The basics of modelling biological data and integration of heterogeneous datasets are conveyed and applied on concrete examples in this practical course. Using the scripting language Python the data is parsed and consolidated in a database. Biologically relevant, demonstrative analyses are performed on this integrated data. Data integration, exploration, visualization, statistical tests and machine learning are applied on a dataset of genomic, transcriptomic, metabolomic and phenomic data from genetically equal samples.</td></tr>
<tr><td>Objectives</td><td colspan="9">(1)The students learn how to parse and integrate heterogeneous biological data into databases. (2) They learn how to perform statistical analyses on biological data and to summarize and illustrate their results visually. (3) They learn how to interpret the results of integrative analyses and report on these results in a concise manner.</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>tp+op</td><td>-</td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">BIO-4120</td></tr>
<tr><td>Lecturer</td><td colspan="9">Kohlbacher</td></tr>
<tr><td>Literature</td><td colspan="9">Will be supplied during the course.</td></tr>
</table>

<table>
<tr><th>Module Number:
BIO-4210</th><th colspan="6">Module title
Practical Transcriptomics</th><th colspan="3">Lecture types
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="3">Work load
90 h</td><td colspan="3">Class time
80 h / 2 CH</td><td colspan="3">Self-Study
10 h</td></tr>
<tr><td>Duration</td><td colspan="9">1 semester</td></tr>
<tr><td>Frequency of offer</td><td colspan="9">Offered at irregular intervals</td></tr>
<tr><td>Language of instruction</td><td colspan="9">English</td></tr>
<tr><td>Type of Exam</td><td colspan="9">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="9">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="9">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>tp,op</td><td></td><td>g</td><td>100</td></tr>
<tr><td>Requirement for participation</td><td colspan="9">BIOINF4110, BIOINF4120, BIOINF4331 Advances in Computational Transcriptomics (recommended), BIOINF3331 Expression Bioinformatik (recommended)</td></tr>
<tr><td>Lecturer</td><td colspan="9">Nieselt</td></tr>
<tr><td>Literature</td><td colspan="9">Will be provided at the beginning of the course, if necessary.</td></tr>
</table>