Department
MATHEMATIK

FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG
NATURWISSENSCHAFTLICHE
FAKULTÄT

Module handbook

for the study programme

Data Science (M.Sc.)

Summer semester 2022

Stand: 02.05.2022

Notes:

Further information on the individual study programs (study and examination regulations, student advisory, etc.) can be found at www.math.fau.de/studium.

- For updates on courses offered in this and the next semester, please visit the UnivIS portal.
- Modules of a study program are defined in the respective examination regulations. This collection includes all modules offered by the Department of Computer Science, the Department of Data Science, and the Department of Mathematics for this study programme.
- Modules from application subjects and technical qualifications will not explicitly be mentioned in this handbook.
- Please also refer to the module catalogues to get an overview of all modules which are offered for this study programme.
- This module handbook was handcrafted in dedication by Jutta Zintchenko and Daniel Tenbrinck.

Descriptions to the following modules taught in **English** can be found in the module handbook of the M.Sc. study programme Computational and Applied Mathematics (CAM):

- Practical Course: Modeling, Simulation, Optimization (MoSi)
- Mathematische Grundlagen zu Künstliche Intelligenz, Neuronale Netze und Data Analytics II (MathKINN II)

Descriptions to the following modules taught in **German** can be found in the respective module handbook of the M.Sc. study programmes Mathematics and Economics and Mathematics:

- Projektseminar Optimierung (ProO)

Table of Content

English modules

1	**Module name**	**Advanced Solution Techniques (AdSolTech)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (1 SWS)	
3	**Lectures**	Dr. Stefan Metzger stefan.metzger@fau.de	
4	**Module coordinator**	Prof. Dr. Eberhard Bänsch baensch@math.fau.de	
5	**Content**	This course covers: • Krylov subspace methods for large non-symmetric systems of equations • Multilevel methods, especially multigrid (MG) methods, nested and non-nested grid hierarchies • Parallel numerics, especially domain decomposition methods • Inexact Newton/Newton-Krylov methods for discretized nonlinear partial differential equations • Preconditioning and operator-splitting methods	
6	**Learning objectives and skills**	Students • are able to design application-specific own MG algorithms with the theory of multigrid methods and decide for which problems the MG algorithm is suitable to solve large linear systems of equations, • are able to solve sparse nonlinear/non-symmetric systems of equations with modern methods (also with parallel computers), • are able to develop under critical assessment complete and efficient methods for application-orientated problems.	
7	**Prerequisites**	Recommended: Advanced Discretization Techniques	
8	**Integration into curriculum**	in 2nd semester	
9	**Module compatibility**	Mandatory elective module for: • M.Sc. Computational and Applied Mathematics • M.Sc. Data Science • M.Sc. Mathematics • M.Sc. Industrial Mathematics • M.Sc. Economics and Mathematics	
10	**Method of examination**	Oral exam (15 min.)	
11	**Grading Procedure**	Oral exam (100 %)	
12	**Module frequency**	Summer semester (annually)	
13	**Workload**	Workload: 150h distributed as: • Contact hours: 112.5h • Independent study: 37.5h	
14	**Module duration**	One semester	
15	**Teaching and examination language**	English	

16	**Recommended reading**	• Quarteroni & A. Valli: Numerical Approximation of Partial Differential Equations • P. Knabner & L. Angermann: Numerical Methods for Elliptic and Parabolic Differential Equations • Further literature and scientific publications are announced during the lectures

1	**Module name**	**Artificial Intelligence II (KI II)**	**7.5 ECTS**
2	**Courses/lectures**	Lectures (4 SWS) Exercises (2 SWS)	
3	**Lecturers**	Prof. Dr. Michael Kohlhase michael.kohlhase@fau.de	
4	**Module coordinator**	Prof. Dr. Michael Kohlhase michael.kohlhase@fau.de	
5	**Content**	This course covers the foundations of Artificial Intelligence (AI), in particular reasoning under uncertainty, machine learning and (if there is time) natural language processing . This course builds on the course Artificial Intelligence I from the preceding winter semester and continues it.	
6	**Learning objectives and skills**	**Technical, Learning, and Method Competencies:** • Knowledge: The students learn foundational representations and algorithms in AI. • Application: The concepts learned are applied to examples from the real world (homeworks) • Analysis: By modeling human cognitive abilities, students learn to assess and understand human intelligence better. **Social Competencies**: • Students work in small groups to solve a machine learning challenge/competition.	
7	**Prerequisites**	Artificial Intelligence I	
8	**Integration into curriculum**	in 2nd semester	
9	**Module compatibility**	Mandatory elective module for: • M.Sc. Artificial Intelligence • B.Sc. Computational Engineering • B.Sc./M.Sc. Computer Science • B.Sc./M.Sc. Data Science • M.Sc. International Information Systems • B.Sc. Mathematics • B.Sc./M.Sc. Mechatronics • M.Sc. Medical Technology • B.Sc. Business Informatics	
10	**Method of examination**	Written exam (90 min.)	
11	**Grading Procedure**	Written exam (100%); Up to 10% bonus points can be achieved by completing the exercise sheets.	
12	**Module frequency**	Summer semester (annually)	
13	**Workload**	Workload: 225h distributed as: • Contact hours: 90h • Independent study: 135h	
14	**Module duration**	One semester	
15	**Teaching and examination language**	English	

16	**Recommended reading**	The course follows the following textbook: Stuart Russell and Peter Norvig: Artificial Intelligence: A Modern Approach. Prentice Hall, 3rd edition, 2009ISBN: 978-3-8273-7089-1

1	**Module name**	**CML: Control, Machine Learning and Numerics (CML)**	**10 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Practical exercises (3 SWS)	
3	**Lecturers**	Prof. Dr. Enrique Zuazua enrique.zuazua@fau.de Dr. Yongcun Song yongcun.song@fau.de	
4	**Module coordinator**	Prof. Dr. Enrique Zuazua enrique.zuazua@fau.de	
5	**Content**	This course covers: • several topics related to the control of Ordinary Differential Equations (ODE) and Partial Differential Equations (PDE), including controllability, observability, and some of the most fundamental work that has been done in the subject in recent years. • an introduction to Machine Learning, focusing mainly on the use of control techniques for the analysis of Deep Neural Networks as a tool to address, for instance, the problem of Supervised Learning. • some classical computational techniques related to the control of ODE and PDE, and machine learning.	
6	**Learning objectives and skills**	Students are able to: • understand some basic theory on control and machine learning. • learn about recent advances on control and machine learning. • implement some computational techniques using their own or specified software and critically evaluate the results, • set out their approaches and results in a comprehensible and convincing manner, making use of appropriate presentation techniques.	
7	**Prerequisites**	Basic knowledge of calculus, linear algebra, ODE and PDE. Familiarity with scientific computing is helpful.	
8	**Integration into curriculum**	in 2nd semester	
9	**Module compatibility**	Mandatory elective module for: • M.Sc. Computational and Applied Mathematics • M.Sc. Data Science	
10	**Method of examination**	Project work with presentation and report	
11	**Grading Procedure**	• Presentation (50%) • Report (50%)	
12	**Module frequency**	Summer semester (annually)	
13	**Workload**	Workload: 300h distributed as: • Contact hours: 75h • Independent study: 225h	
14	**Module duration**	One semester	
15	**Teaching and examination language**	English	

16	**Recommended reading**	[1] L. Bottou, F. E. Curtis, and J. Nocedal, Optimization methods for large-scale machine learning. SIAM Review, 60 (2) (2018), 223-311. [2] J. M. Coron, Control and Nonlinearity, Mathematical Surveys and Monographs, 143, AMS, 2009. [3] I. Goodfellow, Y. Bengio, & A. Courville, Deep Learning. MIT press, 2016. [4] R. Glowinski, J. L. Lions, and J. He, Exact and Approximate Controllability for Distributed Parameter Systems: A Numerical Approach, Encyclopedia Math. Appl., Cambridge University Press, Cambridge, UK, 2008. [5] C. F. Higham, and D. J. Higham, Deep learning: An introduction for applied mathematicians. SIAM Review, 61 (4) (2019), 860-891. [6] J. Nocedal, and S. Wright, Numerical Optimization. Springer Science & Business Media, 2006. [7] D. Ruiz-Balet, and E. Zuazua, Neural ODE control for classification, approximation and transport. arXiv preprint arXiv:2104.05278, (2021). [8] E. Zuazua, Propagation, observation, and control of waves approximated by finite difference methods, SIAM Review, 47 (2) (2005), 197-243. [9] E. Zuazua, Controllability and observability of partial differential equations: some results and open problems, in Handbook of Differential Equations: Evolutionary Equations. Vol. 3. North-Holland, 2006. 527-621.

1	**Module name**	**Computational Complexity (CC)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (1 SWS)	
3	**Lecturers**	Prof. Dr. Yiannis Giannakopoulos yiannis.giannakopoulos@fau.de	
4	**Module coordinator**	Prof. Dr. Yiannis Giannakopoulos yiannis.giannakopoulos@fau.de	
5	**Content**	This course covers: • P, NP, and NP-completeness • Complexity classes and reductions • Boolean circuits • The polynomial-time hierarchy • Space complexity • Randomized computation • Counting complexity • Introduction to the PCP theorem and hardness of approximation • Average-case complexity	
6	**Learning objectives and skills**	Upon successful completion of the module, students are able to: • have a rigorous understand of the concept of computation and its formal limitations • have knowledge of the fundamental complexity classes (including P, NP and PSPACE) • understand the notion of completeness and are able to design and understand reductions between these classes • are exposed to various formal computation models, including Boolean circuits and randomness	
7	**Prerequisites**	Undergraduate-level course in algorithms and/or discrete optimization. Basic knowledge of analysis, linear algebra, and probability.	
8	**Integration into curriculum**	from 1st semester	
9	**Module compatibility**	Mandatory elective module for: • M.Sc. Artificial Intelligence • M.Sc. Computational and Applied Mathematics • B.Sc. Computer Science • M. Sc. Data Science • M. Sc. Mathematics • M. Sc. Economics and Mathematics	
10	**Method of examination**	Oral exam (30 min.)	
11	**Grading Procedure**	Oral exam (100%)	
12	**Module frequency**	Annually (summer semester)	
13	**Workload**	Workload: 150h distributed as: • Contact hours: 45h • Independent study: 105h	

14	**Module duration**	One semester
15	**Teaching and examination language**	English
16	**Recommended reading**	• Oded Goldreich. “Computational Complexity: A Conceptual Perspective”. Cambridge University Press, 2008. • Sanjeev Arora and Boaz Barak. “Computational Complexity: A Modern Approach”. Cambridge University Press, 2009 • Christos H. Papadimitriou. “Computational Complexity”. Addison-Wesley, 1994.

1	**Module name**	**Data Structure Engineering (DSE)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (2 SWS)	
3	**Lecturers**	Prof. Dr. Viktor Leis viktor.leis@fau.de	
4	**Module coordinator**	Prof. Dr. Viktor Leis viktor.leis@fau.de	
5	**Content**	Data structures are often crucial for overall performance. On modern hardware a low asymptotic complexity does not guarantee good performance. To achieve good performance in practice, one must also take features of today's processors, such as caches and the abundant parallelism, into account when designing and implementing data structures. This course teaches principles for engineering of high-performance data structures on modern hardware. It first introduces the necessary hardware background, before studying different variants of data structures such as hash tables, search trees, and tries. Finally, a number of synchronization protocols for concurrent access are presented.	
6	**Learning objectives and skills**	Students can implement efficient data structures. They are capable of designing custom, domain-specific data structure variants and of synchronizing them for multi-core processors in a scalable fashion.	
7	**Prerequisites**	Recommended: • Algorithms and Data Structures • System programming • Good programming skills in C or C++	
8	**Integration into curriculum**	from 1st semester	
9	**Module compatibility**	Mandatory elective module in: • M.Sc. Computer Science • M.Sc. Data Science • M.Sc. Information and Communication Technology	
10	**Method of examination**	Oral exam (30 min.)	
11	**Grading Procedure**	Oral exam (100%)	
12	**Module frequency**	Summer semester (annually)	
13	**Workload**	Workload: 150h distributed as: • Contact hours: 60h • Independent study: 90h	
14	**Module duration**	One semester	
15	**Teaching and examination language**	English	
16	**Recommended reading**		

1	**Module name**	**Discrete Optimization II (DiskOpt II)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (1 SWS)	
3	**Lecturers**	Prof. Dr. Alexander Martin alexander.martin@fau.de	
4	**Module coordinator**	Prof. Dr. Alexander Martin alexander.martin@fau.de	
5	**Content**	In this lecture, we cover theoretical aspects and solution strategies for difficult integer and mixed-integer optimization problems. First, we show the equivalence between separation and optimization. Then, we present solution strategies for large-scale optimization problems, e.g., decomposition methods and approximation algorithms. Finally, we deal with conditions for the existence of integer polyhedra. We also discuss applications for example from the fields of engineering, finance, energy or public transport.	
6	**Learning objectives and skills**	Students are able to: • use basic terms of discrete optimization • model real-world discrete optimization problems, determine their complexity and solve them with appropriate mathematical methods.	
7	**Prerequisites**	Recommended: • Knowledge in linear and combinatorial optimization • Discrete optimization I	
8	**Integration into curriculum**	in 2nd semester	
9	**Module compatibility**	Mandatory elective module in: • M.Sc. Artificial Intelligence • M.Sc. Computational and Applied Mathematics • B.Sc./M.Sc. Computer Science • M.Sc. Data Science • M.Sc. Economics and Mathematics • M.Sc. Industrial Mathematics • M.Sc. Mathematics	
10	**Method of examination**	Oral exam (20 min.)	
11	**Grading Procedure**	Oral exam (100%)	
12	**Module frequency**	Summer semester (annually)	
13	**Workload**	Workload: 150h distributed as: • Contact hours: 45h • Independent study: 105h	
14	**Module duration**	One semester	
15	**Teaching and examination language**	English	

16	**Recommended reading**	• Lecture notes • Bertsimas, Weismantel: Optimization over Integers, Dynamic Ideas, 2005 • Conforti, Cornuéjols, Zambelli: Integer Programming, Springer 2014 • Nemhauser, Wolsey: Integer and Combinatorial Optimization, Wiley 1994 • Schrijver: Combinatorial optimization Vol. A - C, Springer 2003 • Schrijver: Theory of Linear and Integer Programming, Wiley, 1986 • Wolsey: Integer Programming, Wiley, 2021

1	**Module name**	**Introduction to Material and Shape Optimization (MSOpt)**	**10 ECTS**
2	**Courses/lectures**	Lectures (4 SWS)	
3	**Lecturers**	Prof. Dr. Michael Stingl michael.stingl@fau.de	
4	**Module coordinator**	Prof. Dr. Michael Stingl michael.stingl@fau.de	
5	**Content**	This course covers: • shape-, material- and topology optimization models • linear elasticity and contact problems • existence of solutions of shape, material and topology optimization problems • approximation of shape, material and topology optimization problems by convergent schemes	
6	**Learning objectives and skills**	Students are able to: • derive mathematical models for shape-, material and topology optimization problems, • apply regularization techniques to guarantee to existence of solutions, • approximate design problems by finite dimensional discretizations, • derive algebraic forms and solve these by nonlinear programming techniques.	
7	**Prerequisites**	Recommended: • Knowledge in nonlinear optimization, • Basic knowledge in numerics of partial differential equations	
8	**Integration into curriculum**	2nd semester	
9	**Module compatibility**	Mandatory elective module in: • M.Sc. Computational an Applied Mathematics • M.Sc. Data Science • M.Sc. Economics and Mathematics • M.Sc. Mathematics	
10	**Method of examination**	Oral exam (20 min.)	
11	**Grading Procedure**	Oral exam (100%)	
12	**Module frequency**	Summer semester (annually)	
13	**Workload**	Workload: 300h distributed as: • Contact hours: 60h • Independent study: 240h	
14	**Module duration**	One semester	
15	**Teaching and examination language**	English	

16	**Recommended reading**	• J. Haslinger & R. Mäkinen: Introduction to shape optimization, SIAM, • M. P. Bendsoe & O. Sigmund: Topology Optimization: Theory, Methods and Applications, Springer.

1	**Module name**	**Introduction to Random Matrix Theory (RMT)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (1 SWS)	
3	**Lecturers**	Prof. Dr. Thorsten Neuschel neuschel@math.fau.de	
4	**Module coordinator**	Prof. Dr. Thorsten Neuschel neuschel@math.fau.de	
5	**Content**	The course introduces fundamental concepts of the theory by covering • Wigner's semicircle law for self-adjoint random matrices • Method of moments and the corresponding combinatorics • Convergence of random spectral measures • Distribution of eigenvalues of Gaussian orthogonal and unitary ensembles	
6	**Learning objectives and skills**	The students • understand and explain basic principles for the spectral behavior of high-dimensional random matrices • learn the application of the method of moments • bring together knowledge from Analysis, Linear Algebra, Measure Theory and Probability to describe the spectral properties of the most important classes of random matrices	
	Prerequisites	It is recommended to have a background in Analysis, Linear Algebra, Measure Theory and Probability.	
8	**Integration into curriculum**	1st to 3rd semester	
9	**Module compatibility**	Mandatory elective module in • M.Sc. Data Science • M.Sc. Mathematik • M.Sc. Technomathematik • M.Sc. Wirtschaftsmathematik	
10	**Method of examination**	Oral exam (approx. 15-20 Minutes) or written exam (120 Minutes), will be decided at the beginning	
11	**Grading Procedure**	Oral exam (100%) or written exam (100%)	
12	**Module frequency**	Summer semester	
13	**Workload**	Workload 150 h distributed as: • Contact hours: 45h • Independent study: 105h	
14	**Module duration**	One semester	
15	**Teaching and examination language**	English	

16	**Recommended reading**	Anderson, Guionnet, Zeitouni: An Introduction to Random Matrices, Cambridge University Press.

1	**Module name**	**Knowledge Discovery in Databases with Exercises (KKDmUe)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (2 SWS)	
3	**Lecturers**	M.Sc. Dominik Probst, M.Sc. Melanie Bianca Sigl dominik.probst@fau.de, melanie.sigl@fau.de	
4	**Module coordinator**	Prof. Dr. Richard Lenz richard.lenz@fau.de	
5	**Content**	This course covers: **Theoretical knowledge** on: • Why data mining? • What is data mining? • A multi-dimensional view of data mining • What kinds of data can be mined? • What kinds of patterns can be mined? • What technologies are used? • What kinds of applications are targeted? • Major issues in data mining • A brief history of data mining **Practical exercises** on: • Introduction to Pandas & scikit-learn • Data analysis & data preprocessing • Frequent Pattern • Classification • Clustering • Outliers	
6	**Learning objectives and skills**	The students: • know the typical KDD process; • know procedures for the preparation of data for data mining; • know the definition of distance or similarity functions for the different kinds of attributes; • define distance and similarity functions for a particular dataset; • check attributes of a dataset for their meaning with reference to an analysis and transform attribute values accordingly, if required. • know how a typical data warehouse is structured; • are familar with the principle of the Apriori algorithm for the identification of frequent itemsets; • know the FP-growth algorithm for a faster identification of frequent itemsets: • present the definitions of support and confidence for association rules; • describe the construction of association rules based on frequent itemsets; • are capable of describing the course of action in classification tasks; • present the construction of a decision tree based on a training dataset; • present the principle of Bayes' classification; • enumerate different clustering procedures; • describe the steps of k-means clustering; • know the different kinds of outliers. • are able to practically apply the various steps of a KDD process.	

7	**Prerequisites**	
8	**Integration into curriculum**	in 2nd semester
9	**Module compatibility**	Mandatory elective module in: • M.Sc. Computer Science • M.Sc. Data Science
10	**Method of examination**	Written exam (90 min.)
11	**Grading Procedure**	Written exam (100%)
12	**Module frequency**	Summer semester (annually)
13	**Workload**	Workload: 150h distributed as: • Contact hours: 60h • Independent study: 90h
14	**Module duration**	One semester
15	**Teaching and examination language**	English
16	**Recommended reading**	The lecture is based on the following book: • J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques, 3rd. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2011, ISBN: 0123814790 Also interesting and related textbooks are: • A. Géron, Hands-on machine learning with Scikit-Learn and TensorFlow: concepts, tools, and techniques to build intelligent systems, 2nd ed. O'Reilly Media, 2017, ISBN: 978-1491962299 • H. Du, Data Mining Techniques and Applications: An Introduction. Cengage Learning EMEA, May 2010, p. 336, ISBN: 978-1844808915 • I. H. Witten, E. Frank, M. A. Hall, et al., Data Mining, Fourth Edition: Practical Machine Learning Tools and Techniques, 4th. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2016, ISBN: 0128042915

1	**Module name**	**Lab Course Machine Learning in Signal Processing (LabMLISP)**	**2.5 ECTS**
2	**Courses/lectures**	Practical sessions (4 SWS)	
3	**Lecturers**	M.Sc. Kamal Gopikrishnan Nambiar kamal.nambiar@fau.de	
4	**Module coordinator**	Prof. Dr. Andrè Kaup andre.kaup@fau.de	
5	**Content**	This is an advanced-level lab course in machine learning. Imagine a car driving on an autobahn in automatic mode. Among other things, the car needs to steer itself to keep driving in its lane. To accomplish this, the central problem is to detect the road-lane markings. These are the white solid or dashed lines that are drawn on each side of the lane. The standard modern approach to solve this type of problem is to take a large dataset of labeled examples and train a deep neural network model to accomplish the task. This is how car and pedestrian detection algorithms are developed. The difficulty with the road-lane markings is that there is no labeled dataset of them and creating such a dataset would be very expensive. In this lab course we will solve this problem using transfer learning and mathematical modeling: • Create cartoon-like artificial images of a road with known locations for the lane markings. • Train deep neural networks on these artificial images with heavy data augmentations that mimic real-world images. • Create a dataset of unlabeled real-life videos by downloading and organizing examples from YouTube. • Create a machine learning pipeline for working with these videos efficiently. • Apply the neural network that has been trained on artificial data to real-world videos. • Analyze the quality of results produced by the network. • Use mathematical modeling to correct the outputs of the network. • Retrain the network on the dataset composed of the corrected outputs. • Measure and analyze the quality of the results. The software will be written in Python using the JupyterLab development framework. Access to modern GPU servers will be provided. The best students will have the opportunity to contribute to the creation of a state-of-the-art lane detection system for self-driving cars during or after the course.	
6	**Learning objectives and skills**	Students are able to: • Independently design machine learning pipelines to solve complex problems in artificial intelligence. • Choose appropriate algorithms for the problem at hand. • Use standard packages for machine learning in Python: NumPy, scikit-learn, PyTorch. • Debug and calibrate machine learning algorithms. Develop modification to the standard algorithms as appropriate to the problem at hand. • Explain the theoretical aspects of deep learning.	
7	**Prerequisites**	Knowledge of Python programming language is required. Basic theoretical knowledge in machine learning is assumed: consider taking the Machine Learning in Signal Processing (MLISP) course.	

8	**Integration into curriculum**	from 1st semester
9	**Module compatibility**	Mandatory elective module in: • M.Sc. Advanced Signal Processing & Communications Engineering • M.Sc. Communications and Multimedia Engineering • M.Sc. Data Science • M.Sc. Information and Communication Technology • M.Sc. Mechatronics
10	**Method of examination**	Students must present a: • Well-documented algorithm that detects lanes on a driving video. • Video demonstration showing the functioning of the algorithm. • Short report (up to 3 pages).
11	**Grading Procedure**	Ungraded
12	**Module frequency**	Summer and winter semester
13	**Workload**	Workload: 75h distributed as: • Contact hours: 60h • Independent study: 15h
14	**Module duration**	One Semester
15	**Teaching and examination language**	English
16	**Recommended reading**	

1	**Module name**	**Mathematics of Learning (MoL)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (2 SWS)	
3	**Lecturers**	Prof. Dr. Frauke Liers frauke.liers@math.uni-erlangen.de	
4	**Module coordinator**	Prof. Dr. M. Burger martin.burger@fau.de	
5	**Content**	This course covers: • Machine learning: empirical risk minimization, kernel methods and variational models • Mathematical aspects of deep learning • Ranking problems • Mathematical models of network interaction	
6	**Learning objectives and skills**	Students are able to: • develop understanding of modern big data and state of the art methods to analyze them, • apply state of the art algorithms to large data sets, • derive models for network / graph structured data.	
7	**Prerequisites**	Recommended: Basic knowledge in numerical methods and optimization	
8	**Integration into curriculum**	in 1st or 3rd semester	
9	**Module compatibility**	Mandatory module for: • M.Sc. Data Sciences Mandatory elective module for: • M.Sc. Computational and Applied Mathematics • M.Sc. Economics and Mathematics • M.Sc. Mathematics	
10	**Method of examination**	Written exam (60 min.)	
11	**Grading Procedure**	Written exam (100%)	
12	**Module frequency**	Winter semester (annually) Summer semester (exceptionally)	
13	**Workload**	Workload: 150h distributed as: • Contact hours: 60h • Independent study: 90h	
14	**Module duration**	One Semester	
15	**Teaching and examination language**	English	
16	**Recommended reading**	• Courville, Goodfellow, Bengio, Deep Learning, MIT Press, 2015 • Hastie, Tibshirani, Friedman, The Elements of Statistical Learning, 2008	

1	**Module name**	**Numerical Aspects of Linear and Integer Programming (NALIP)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (1 SWS)	
3	**Lecturers**	Dr. Andreas Bärmann andreas.baermann@math.uni-erlangen.de	
4	**Module coordinator**	Prof. Dr. Alexander Martin alexander.martin@fau.de	
5	**Content**	This course covers: • Revised Simplex (with bounds) • Simplex Phase I • Dual Simplex • LP Presolve/Postsolve • Scaling • MIP Solution Techniques	
6	**Learning objectives and skills**	Students are able to explain and use methods and numerical approaches for solving linear and mixed-integer programs in practice.	
7	**Prerequisites**	Recommended: Knowledge in linear algebra and combinatorial optimization	
8	**Integration into curriculum**	in 2nd semester	
9	**Module compatibility**	Mandatory elective module for: • M.Sc. Artificial Intelligence • B.Sc./M.Sc. Computer Science • B.Sc./M.Sc. Data Science • M.Sc. Economics and Mathematics • M.Sc. Mathematics • M.Sc. Industrial Mathematics	
10	**Method of examination**	Oral exam (15 min.)	
11	**Grading Procedure**	Oral exam (100%)	
12	**Module frequency**	Summer semester (irregularly) To check whether the course is offered, see UnivIS or the module handbook of the current semester.	
13	**Workload**	Contact hours: 45h Independent study: 105h Total: 150h	
14	**Module duration**	One semester	
15	**Teaching and examination language**	English	
16	**Recommended reading**	• V. Chvátal: Linear Programming, W. H. Freeman and Company, New York, 1983 • L.A. Wolsey: Integer Programming, John Wiley and Sons, Inc., 1998	

1	**Module name**	**Quality of Service in Communications (DKS)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (2 SWS)	
3	**Lecturers**	Prof. Dr. Reinhard German reinhard.german@fau.de	
4	**Module coordinator**	Prof. Dr. Reinhard German reinhard.german@fau.de	
5	**Content**	We introduce the term quality-of-service (QoS), discuss important approaches to achieve certain degrees of QoS, and show how the implementation in computer networks. Then a number of methodologies to assess and design systems with respect to their QoS: • network planning and optimization, • network simulation, • stochastic analysis (Markov chains, non-Markovian models, queuing systems), • deterministic analysis with network calculus to determine QoS guarantees • measurements (hardware, software, and hybrid monitoring, benchmarks). All methods are illustrated by examples.	
6	**Learning objectives and skills**	Goals: • Basic understanding of Quality-of-Service (QoS) in networking • An umbrella for quantitative metrics which are essential in networking • Techniques for achieving QoS • Methodology for performance evaluation and dimensioning: • measurements, modeling, analysis, optimization, simulation • Methods for assuring QoS guarantees	
7	**Prerequisites**	Recommended: • Computer communication • Communication systems • Basic programming skills, ideally in C++ and R	
8	**Integration into curriculum**	from 1st semester	
9	**Module compatibility**	Mandatory elective module for: • M.Sc. Advanced Signal Processing & Communications Engineering • B.Sc./M.Sc. Computer Science • M.Sc. Data Science • M.Sc. Information and Communication Technology • M.Sc. International Information Systems • M.Sc. Economics and Mathematics • B.Sc. Mathematics	
10	**Method of examination**	If there are more than 20 participants, the examination will be written (90 min.) otherwise oral (30 min.)	
11	**Grading Procedure**	Written or oral exam (100%)	
12	**Module frequency**	Summer semester (annually)	

13	**Workload**	Workload: 150h distributed as: • Contact hours: 60h • Independent study: 90h
14	**Module duration**	One semester
15	**Teaching and examination language**	English
16	**Recommended reading**	• Kurose, Ross. Computer Networking: A Top-Down Approach Featuring the Internet. 6th Ed., Addison Wesley, 2013 • W. Stallings. Data and Computer Communications, 10th ed., Pearson Education, 2014 • W. Stallings. Foundations of Modern Networking: SDN, NFV, QoE, IoT, and Cloud, Pearson Education, 2016

1	**Module name**	**Partial Differential Equations Based Image Processing (PDE based Image Processing)**	**5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (0.5 SWS)	
3	**Lecturers**	Prof. Dr. Martin Burger, Dr. Lea Föcke martin.burger@fau.de, lea.foecke@fau.de	
4	**Module coordinator**	Dr. Michael Fried fried@math.fau.de	
5	**Content**	This course covers: • basics of image processing • variational methods in image processing including total variation • deblurring using different partial differential equations • basics of image reconstruction	
6	**Learning objectives and skills**	Students are able to: • explain mathematical and algorithmic methods for image processing, • apply above image processing methods in computerised practical exercises, • apply analytical techniques to evaluate the qualitative characteristics of the above methods.	
7	**Prerequisites**	Recommended: Basic knowledge in functional analysis and numerical methods for PDEs	
8	**Integration into curriculum**	in 2nd semester	
9	**Module compatibility**	Mandatory elective module for: • M.Sc. Computational and Applied Mathematics • M.Sc. Data Science • M.Sc. Mathematics	
10	**Method of examination**	Oral exam (15 min.)	
11	**Grading Procedure**	Oral exam (100%)	
12	**Module frequency**	Summer semester every second year To check whether the course is offered, see UnivIS or the module handbook of the current semester.	
13	**Workload**	Workload: 150h distributed as: • Contact hours: 37.5h • Independent study: 112.5h	
14	**Module duration**	One semester	
15	**Teaching and examination language**	English	
16	**Recommended reading**	• G. Aubert & P. Kornprobst: Mathematical problems in image processing, Springer • Bredies & Lorenz, Mathematical Image Processing, Springer • Burger & Osher, Level Set and PDE based reconstruction methods, Springer	

1	**Module name**	**Pattern Analysis (PA)**	**5 ECTS**
2	**Courses/lectures**	Lectures (3 SWS) Exercises (1 SWS)	
3	**Lecturers**	PD Dr. Christian Riess christian.riess@fau.de	
4	**Module coordinator**	PD Dr. Christian Riess christian.riess@fau.de	
5	**Content**	This module introduces the design of pattern analysis systems as well as the corresponding fundamental mathematical methods. The topics comprise: • clustering methods: soft and hard clustering • classification and regression trees and forests • parametric and non-parametric density estimation: maximum-likelihood (ML) estimation, maximum-a-posteriori (MAP) estimation, histograms, Parzen estimation, relationship between folded histograms and Parzen estimation, adaptive binning with regression trees • mean shift algorithm: local maximization using gradient ascent for non-parametric probability density functions, application of the mean shift algorithm for clustering, color quantization, object tracking • linear and non-linear manifold learning: curse of dimensionality, various dimensionality reduction methods: principal component analysis (PCA), multidimensional scaling (MDS), isomaps, Laplacian eigenmaps • Gaussian mixture models (GMM) and hidden Markov models (HMM): expectation maximization algorithm, parameter estimation, computation of the optimal sequence of states/Viterbi algorithm, forward-backward algorithm, scaling • Markov random fields (MRF): definition, probabilities on undirected graphs, clique potentials, Hammersley-Clifford theorem, inference via Gibbs sampling and graph cuts	
6	**Learning objectives and skills**	The students are able to: • explain the discussed methods for classification, prediction, and analysis of patterns, • compare and analyze methods for manifold learning and select a suited method for a given set of features and a given problem, • compare and analyze methods for probability density estimation and select a suited method for a given set of features and a given problem, • apply non-parametric probability density estimation to pattern analysis problems, • apply dimensionality reduction techniques to high-dimensional feature spaces, • explain statistic modeling of feature sets and sequences of features, • explain statistic modeling of statistical dependencies, • implement presented methods in Python, • supplement autonomously the mathematical foundations of the presented methods by self-guided study of the literature, • discuss the social impact of applications of pattern analysis solutions.	
7	**Prerequisites**	Prior participation in the course "Pattern Recognition" is strongly recommended.	

8	**Integration into curriculum**	in 2nd semester
9	**Module compatibility**	Mandatory elective module in: • M.Sc. Advanced Optical Technologies • M.Sc. Advanced Signal Processing & Communications Engineering • M.Sc. Artificial Intelligence • M.Sc. Communications and Multimedia Enginnering • M.Sc. Computational Engineering • M.Sc. Computer Science • M.Sc. Data Science • M.Sc. Information and Communication Technology • M.Sc. International Information Systems • B.Sc./M.Sc. Mechatronics • M.Sc. Medical technology
10	**Method of examination**	Written exam (60 min)
11	**Grading Procedure**	Written exam (60 min.)
12	**Module frequency**	Summer semester (annually)
13	**Workload**	Workload: 150h distributed as: • Contact hours: 60h • Independent study: 90h
14	**Module duration**	One Semester
15	**Teaching and examination language**	English
16	**Recommended reading**	• C. Bishop: Pattern Recognition and Machine Learning, Springer Verlag, Heidelberg, 2006 • T. Hastie, R. Tibshirani und J. Friedman: The Elements of Statistical Learning, 2nd Edition, Springer Verlag, 2009 • A. Criminisi and J. Shotton: Decision Forests for Computer Vision and Medical Image Analysis, Springer, 2013

1	**Module name**	**Simulation and Modeling 2 (SaM 2)**	**7.5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (2 SWS)	
3	**Lecturers**	Prof. Dr.-Ing. Reinhard German reinhard.german@fau.de	
4	**Module coordinator**	Prof. Dr.-Ing. Reinhard German reinhard.german@fau.de	
5	**Content**	The class is project-oriented: participants conduct one larger simulation project in a team (3-4 students). The simulation project covers all typical phases including project planning, requirements analysis, data collection, input modeling, conceptual modeling, verification, validation, simulation runs, output analysis, result presentation and documentation. The lecture covers: • simulation project management, presentation, and documentation techniques • detailed simulation project case studies, • advanced topics in simulation such as variance reduction techniques, rare event simulation, parallel and distributed simulation. The project teams also present their results in the lectures. The exercises are used for team meetings. Implementations, simulation runs, etc. can be performed on computing facilities of the Computer Science 7 Group with commercial/academic simulation packages (e.g., AnyLogic/OMneT++/ns-3) in reserved computer hours. Possible projects encompass but are not restricted to: elevators, university canteen (Mensa), crossing with traffic lights, gas station, supermarket, hospital emergency reception, flexible manufacturing system, houses or neighborhood with renewable energy systems, battery powered devices, time sensitive networking e.g., in train communications, industrial communications. Own project ideas are possible and welcome.	
6	**Learning objectives and skills**	Students get • hands-on experience in applying the theory of “Simulation and Modelling I” and in realizing simulation studies • skills in using professional (both commercial and/or academic) simulation software • skills in project and team work • training in simulation project management, presentations, documentation • knowledge of advanced topics in simulation such as variance reduction, distributed simulation, validation techniques	
7	**Prerequisites**	Simulation and Modeling 1	
8	**Integration into curriculum**	in 2nd semester	
9	**Module compatibility**	Mandatory elective module in: • M.Sc. Data Science	

10	**Method of examination**	• Oral exam (30 min.) • Written report, acquired by successful participation in the project and submission of a project report (about 20 pages).
11	**Grading Procedure**	• Oral exam (50%) • Written report (50%)
12	**Module frequency**	Summer semester (anually)
13	**Workload**	Workload: 225h distributed as: • Contact hours: 60h • Independent study: 165h
14	**Module duration**	One Semester
15	**Teaching and examination language**	English
16	**Recommended reading**	Averill Law: "Simulation Modeling and Analysis", 5th ed., McGraw Hill, 2014

1	**Module name**	**Simulation and Scientific Computing 2 (SiWiR2)**	**7.5 ECTS**
2	**Courses/lectures**	Lectures (2 SWS) Exercises (2 SWS) Tutorial (2 SWS)	
3	**Lecturers**	Prof. Dr. Christoph Pflaum christoph.pflaum@fau.de	
4	**Module coordinator**	Prof. Dr. Christoph Pflaum christoph.pflaum@fau.de	
5	**Content**	Simulations are becoming more and more important in various fields of engineering as a fast, cheap and flexible alternative to real-world experiments. In order to successfully carry out such simulations, a profound knowledge of the respective physical models, numerical discretization and solution methods, and performance-aware programming techniques is indispensable. The course "Simulation and Scientific Computing 2" covers these essential aspects of simulations in detail on the basis of typical engineering problems: • Introduction to multigrid methods • Concept and implementation of the finite element method • discretization grids and interpolation • Computational fluid dynamics: Finite difference discretization and lattice Boltzmann method • Computational mechanics: finite elements for linear elasticity • Computational electromagnetics: FTDT for Maxwell's equations	
6	**Learning objectives and skills**	Students learn • techniques for optimizing algorithms in the field of scientific computing • to implement and optimize algorithms on parallel computers • to analyze the stability of numerical algorithms	
	Prerequisites	The participants should have a sound background in engineering mathematics and a higher programming language (preferably C/C++).	
8	**Integration into curriculum**	in 2nd semester	
9	**Module compatibility**	Mandatory Module in: • B.Sc. Computational Engineering Mandatory elective module in: • M.Sc. Computer Science • M.Sc. Data Sciences	
10	**Method of examination**	• 50% of exercise points needed (ungraded) • Written exam (90 min)	
11	**Grading Procedure**	Written exam (100%)	
12	**Module frequency**	Summer semester (annually)	
13	**Workload**	Workload: 225h distributed as: • Contact hours: 90h • Independent study: 135h	
14	**Module duration**	One semester	

15	**Teaching and examination language**	English
16	**Recommended reading**	• Briggs, Henson, McCormick - A Multigrid Tutorial. SIAM. • Axelsson, Barker - Finite Element Solution of Boundary Value Problems. SIAM. • Braess - Finite elements. Cambridge University Press. • Grossmann, Roos, Stynes - Numerical treatment of partial differential equations. Springer. • Timm Krüger, and others. The Lattice Boltzmann Method: Principles and Practice. Springer. • Allen Taflove and Susan C. Hagness. Computational Electrodynamics: The • Finite-Difference Time-Domain Method. Artech House.

German modules

1	**Modulbezeichnung**	**Einführung in die Darstellungstheorie (EDT)**	**10 ECTS**
2	**Lehrveranstaltungen**	Vorlesung (4 SWS) Übung (2 SWS)	
3	**Lehrende**	Prof. Dr. Wolfgang Ruppert ruppert@mi.uni-erlangen.de	
4	**Modulverantwortung**	Prof. Dr. Peter Fiebig fiebig@math.fau.de	
5	**Inhalt**	• Darstellungen endlicher Gruppen • Moduln über Ringen • Halbeinfache Ringe • Kategorien und Funktoren • Anwendungen Die Präsentation des Stoffes erfolgt in Vorlesungsform. Die weitere Aneignung der wesentlichen Begriffe und Techniken erfolgt durch wöchentliche Hausaufgaben.	
6	**Lernziele und Kompetenzen**	Die Studierenden • nennen und erläutern die grundlegenden Begriffe der Darstellungstheorie anhand beispielhaft ausgewählter Kapitel und erkennen und erklären deren Zusammenhänge; • ordnen Methoden aus der Algebra in einen übergreifenden Kontext ein und wenden diese an; • analysieren und bewerten algebraische Strukturen und erkennen Zusammenhänge; • klassifizieren und lösen selbstständig algebraische Probleme	
7	**Voraussetzungen für die Teilnahme**	empfohlen: Modul Algebra	
8	**Einpassung in Musterstudienplan**	im 1. bis 3. Semester	
9	**Verwendbarkeit des Moduls**	Wahlpflichtmodul in • M.Sc. Data Science • B.Sc. Mathematik • B.Sc. Wirtschaftsmathematik	
10	**Studien- und Prüfungsleistung**	• Übungsleistung (wöchentliche Hausaufgaben, unbenotet) • mündliche Prüfung (benotet, 20 Min.)	
11	**Berechnung Modulnote**	mündliche Prüfung (100%)	
12	**Turnus des Angebots**	jährlich im Sommersemester	
13	**Arbeitsaufwand**	Workload: 300h davon: • Vorlesung: 4 SWS x 15 Wochen = 60 h • Übung: 2 SWS x 15 Wochen = 30 h • Selbststudium: 210h	
14	**Dauer des Moduls**	ein Semester	

15	**Unterrichts- und Prüfungssprache**	Deutsch
16	**Literaturhinweise**	• C. Meusburger, Vorlesungsskript "Einführung in die Darstellungstheorie" • S. Sternberg, "Group Theory and Physics", CUP 1994 • M. Artin, "Algebra", Pearson, 2011.

1	**Modulbezeichnung**	**Kolloquiumsvorlesung Digitale Souveränität (KvDS)**	**5 ECTS**
2	**Lehrveranstaltungen**	Vorlesung (4 SWS) (Anwesenheitspflicht bei den Vorträgen)	
3	**Lehrende**	Prof. Dr. Johannes Helbig, Prof. Dr. Georg Glasze johannes.helbig@fau.de, georg.glasze@fau.de	
4	**Modulverantwortung**	Prof. Dr. Johannes Helbig johannes.helbig@fau.de	
5	**Inhalt**	Die Digitalisierung verändert unsere Welt, disruptiv, umfassend und unumkehrbar: Sie ändert die strukturellen Voraussetzungen für unsere Wirtschaft, unsere Gesellschaft und unser Verständnis von uns selbst. Digitale Souveränität adressiert die Frage, wie wir diesem Umbruch Gestaltung und Führung geben können, nach eigenem Willen und eigenen Wertvorstellungen. Das betrifft insbesondere die Freiheitlichkeit, die soziale Gerechtigkeit und die wirtschaftliche Leistungsfähigkeit der Gesellschafts- und Wirtschaftsordnungen der Zukunft. Viele Disziplinen müssen dazu beitragen, keine kann diese Aufgabe *innerhalb* des eigenen Horizonts lösen. Die Veranstaltung ist entsprechend in hohem Maße multidisziplinär. Sie richtet sich an fortgeschrittene Studierende aus mathematisch-naturwissenschaftlichen und technischen Studiengängen, aus Wirtschafts-, Sozial- und Rechtswissenschaften sowie aus Philosophie und Ethik. Die Veranstaltung ist als Ringvorlesung mit internen und externen Gästen konzipiert. Auf einen Kolloquiumsvortrag folgt jeweils ein diskursiver Abschnitt in Breakout-Gruppen. Themenschwerpunkte umfassen: • Zukunft der Wertschöpfung und Wettbewerbsfähigkeit • Innere und äußere Sicherheit • Meinungsbildung und öffentlicher Raum • Konstruktive Anpassung des Rechtssystems • Zukunft der Arbeit und partizipative Nutzenverteilung • Strukturvoraussetzungen demokratischer politischer Prozesse und Systeme • Leistungsfähige Bildung • Trustworthy Artificial Intelligence • Souveräne digitale Infrastrukturen • Neue Narrative für die Basis gesellschaftlicher Solidarität • Menschenbild, Weltbild und ethische Reflektion Die Veranstaltung wird ergänzt durch vertiefende Seminare zu ausgewählten Einzelthemen; diese können auch jeweils eigenständig belegt werden.	
6	**Lernziele und Kompetenzen**	Die Studierenden • kennen die disruptiven Auswirkungen der Digitalisierung in unterschiedlichen Domänen • verstehen zugrundeliegende Veränderungen der strukturellen Voraussetzungen und ihre Wirkzusammenhänge und erkennen wiederkehrende Muster • können Handlungsfelder einschätzen und exemplarisch Maßnahmenansätze entwickeln und beurteilen • kennen Denkansätze, Begriffsbildungen und Paradigmen benachbarter Disziplinen und können sie im Dialog miteinander in Beziehung setzen • können eigenständig und im Team ein Teilthema eigenständig und vertiefend erschließen und Gestaltungsansätze entwickeln	
7	**Voraussetzungen für die Teilnahme**		

8	**Einpassung in Musterstudienpl**	ab 1. Semester
9	**Verwendbarkeit des Moduls**	Wahlpflichtmodul in: • M.Sc. Data Science
10	**Studien- und Prüfungsleistung**	• schriftliche Abschlussarbeit (maximal 10 Seiten)
11	**Berechnung Modulnote**	• schriftliche Abschlussarbeit (65%) • Beteiligung in den Diskussionen (35%)
12	**Turnus des Angebots**	jährlich im Sommersemester
13	**Arbeitsaufwand**	Workload: 150h davon: • Vorlesung: 4 SWS x 15 = 60h • Selbststudium: 10h • Abschlussarbeit: 80h
14	**Dauer des Moduls**	ein Semester
15	**Unterrichts- und Prüfungssprache**	Deutsch, bei Bedarf auch Englisch
16	**Literaturhinweise**	wird vom Lehrenden in der Vorlesung bekannt gegeben

1	**Modulbezeichnung**	**Lie-Gruppen (LieG)**	**10 ECTS**
2	**Lehrveranstaltungen**	Vorlesung (4 SWS) Übung (2 SWS)	
3	**Dozenten/-innen**	Prof. Dr. Karl-Hermann Neeb neeb@mi.uni-erlangen.de	
4	**Modulverantwortung**	Prof. Dr. Karl-Hermann Neeb neeb@mi.uni-erlangen.de	
5	**Inhalt**	• Lie-Algebra einer Lie-Gruppe, Exponentialfunktion • Abgeschlossene Untergruppen, Quotienten, homogene Räume • Überlagerungen von Lie-Gruppen, Strukturtheorie, Integrationsprobleme • Elementare Anwendungen in der Darstellungstheorie Die Präsentation des Stoffes erfolgt in Vorlesungsform. Die weitere Aneignung der wesentlichen Begriffe und Techniken erfolgt in den Übungen.	
6	**Lernziele und Kompetenzen**	Die Studierenden verwenden die grundlegenden Methoden der Lie'schen Gruppentheorie und insbesondere den Übersetzungsmechanismus von Lie-Algebra zur Gruppe mittels der Exponentialfunktion. Sie ordnen Methoden aus den Bereichen Algebra, Geometrie und Analysis in einen übergreifenden Kontext ein und wenden sie dort an.	
7	**Voraussetzungen für die Teilnahme**	empfohlen: • Grundkenntnisse über Mannigfaltigkeiten (Vektorfelder, Flüsse), • Grundkenntnisse in Topologie (Bogenzusammenhang, Überlagerungen)	
8	**Einpassung in Musterstudienplan**	im 1. bis 3. Semester	
9	**Verwendbarkeit des Moduls**	Wahlpflichtmodul in: • M.Sc. Data Science Wahlmodul in: • M.Sc. Mathematik • M.Sc. Technomathematik • M.Sc. Wirtschaftsmathematik Kern-/Forschungsmodul in: • M.Sc. Mathematik	
10	**Studien- und Prüfungsleistung**	mündliche Prüfung (20 Min.)	
11	**Berechnung Modulnote**	mündliche Prüfung (100 %)	
12	**Turnus des Angebots**	zweijährlich im Sommersemester (siehe Modulverzeichnis im **UnivIS)**	

13	**Arbeitsaufwand**	Workload: 300h davon • Vorlesung: 4 SWS x 15 = 60h • Übung: 2 SWS x 15 = 30h • Selbststudium: 210h
14	**Dauer des Moduls**	ein Semester
15	**Unterrichtssprache**	Deutsch oder Englisch. Die Unterrichtssprache können Sie dem Modulverzeichnis im **UnivIS** entnehmen.
16	**Vorbereitende Literatur**	• Vorlesungsskript zu diesem Modul • Hilgert/Neeb, Structure and Geometry of Lie Groups

1	**Modulbezeichnung**	**Masterseminar (MaSe)**	**5 ECTS**
2	**Lehrveranstaltungen**	1. Seminar Spin Glasses with Applications to Deep Learning	
3	**Lehrende**	1. Prof. Dr. Thorsten Neuschel thorsten.neuschel@fau.de	
4	**Modulverantwortung**	Studiendekan/in studiendekan@math.fau.de	
5	**Inhalt**	Die aktuell angebotenen Themen werden von den Dozenten rechtzeitig bekannt gegeben.	
6	**Lernziele und Kompetenzen**	Die Studierenden • erarbeiten sich vertiefende Fachkompetenzen in einem Teilgebiet der Mathematik; • analysieren Fragestellungen und Probleme aus dem gewählten Teilgebiet der Mathematik und lösen diese mit wissenschaftlichen Methoden; • verwenden relevante Präsentations- und Kommunikationstechniken und präsentieren die mathematischen Sachverhalte in mündlicher und schriftlicher Form; • tauschen sich untereinander und mit den Dozenten über Informationen, Ideen, Probleme und Lösungen auf wissenschaftlichem Niveau aus.	
7	**Voraussetzungen für die Teilnahme**	nach Vorgabe der Dozentin/des Dozenten	
8	**Einpassung in Musterstudienplan**	im 3. Semester	
9	**Verwendbarkeit des Moduls**	Pflichtmodul in: • M.Sc. Data Science • M.Sc. Mathematik • M.Sc. Wirtschaftsmathematik	
10	**Studien- und Prüfungsleistung**	• Vortrag (90 Min.) • schriftliche Ausarbeitung (5–10 Seiten)	
11	**Berechnung Modulnote**	• Vortrag (50%) • schriftliche Ausarbeitung (50%)	
12	**Turnus des Angebots**	jedes Semester	
13	**Arbeitsaufwand**	Workload: 150h davon: • Seminar: 2 SWS x 15 = 30h • Selbststudium: 120h	
14	**Dauer des Moduls**	ein Semester	
15	**Unterrichts- und Prüfungssprache**	Deutsch oder Englisch	
16	**Literaturhinweise**	nach Vorgabe der Dozentin/des Dozenten	

1	**Modulbezeichnung**	**Modul MS: Mathematische Statistik** (englische Bezeichnung: Mathematical Statistics)	**5 ECTS**
2	**Lehrveranstaltungen**	Vorlesung mit Übung (3 SWS)	
3	**Lehrende**	Prof. Dr. Christoph Richard richard@math.fau.de	
4	**Modulverantwortung**	Prof. Dr. Christoph Richard richard@math.fau.de	
5	**Inhalt**	• Parameterschätzung • Konfidenzbereiche • Hypothesentests Die Präsentation des Stoffes erfolgt in Vorlesungsform. In der Übung vertiefen Lösungen typischer Beispiele das Verständnis des Vorlesungsstoffs.	
6	**Lernziele und Kompetenzen**	Die Studierenden erklären und verwenden mathematische Grundlagen der Statistik. Sie entwickeln Lösungsmethoden für einfache statistische Problemstellungen eigenständig.	
7	**Voraussetzungen für die Teilnahme**	Stochastische Modellbildung sowie Maßtheorie (Analysis III), Grundkenntnisse in Wahrscheinlichkeitstheorie	
8	**Einpassung in Musterstudienplan**	im 1. bis 3. Semester	
9	**Verwendbarkeit des Moduls**	Wahlplichtmodul in • M.Sc. Data Science • M.Sc. Mathematik • M.Sc. Wirtschaftsmathematik	
10	**Studien- und Prüfungsleistung**	mündliche Prüfung (15 Min.)	
11	**Berechnung Modulnote**	mündliche Prüfung (100%)	
12	**Turnus des Angebots**	jährlich im Sommersemester	
13	**Arbeitsaufwand**	Workload: 150h davon • Vorlesung mit Übung: 3 SWS x 15 = 45h • Selbststudium: 105h	
14	**Dauer des Moduls**	ein Semester	
15	**Unterrichts- und Prüfungssprache**	Deutsch	
16	**Literaturhinweise**	• Georgii, Stochastik • Casella, Berger, Statistical Inference	

1	**Modulbezeichnung**	**Partielle Differentialgleichungen II (PDG II)**	**10 ECTS**
2	**Lehrveranstaltungen**	Vorlesung (4 SWS) Übung (2 SWS)	
3	**Lehrende**	Prof. Dr. Hannes Meinlschmidt hannes.meinlschmidt@math.fau.de	
4	**Modulverantwortung**	Prof. Dr. Günther Grün gruen@math.fau.de	
5	**Inhalt**	• direkte Methoden der Variationsrechnung, Existenz im konvexen Fall, Hölder-Regularität • Die Wärmeleitungsgleichung und andere parabolische Gleichungen • Die Wellengleichung und andere hyperbolische Gleichungen • Weitere ausgewählte Themen, z.B.: • Energiemethoden • Viskositätslösungen • skalare Erhaltungsgleichungen • parabolische p-Laplace und poröse Mediengleichung (Regularität, qualitative Eigenschaften, usw.) • Gleichungen vierter Ordnung Die Präsentation des Stoffes erfolgt in Vorlesungsform. Die weitere Aneignung der wesentlichen Begriffe und Techniken erfolgt durch wöchentliche Hausaufgaben	
6	**Lernziele und Kompetenzen**	Die Studierenden wenden Methoden für Existenzbeweise bei nichtlinearen Gleichungen an, und erweitern ihr Methodenspektrum für Lösungskonzepte und Eindeutigkeitsresultate.	
7	**Voraussetzungen für die Teilnahme**	Partielle Differentialgleichungen I	
8	**Einpassung in Musterstudienplan**	im 2. oder 3. Semester	
9	**Verwendbarkeit des Moduls**	Wahlpflichtmodul in • M.Sc. Mathematik • M.Sc. Technomathematik • M.Sc. Wirtschaftsmathematik	
10	**Studien- und Prüfungsleistung**	mündliche Prüfung (20 Min.)	
11	**Berechnung Modulnote**	mündliche Prüfung (100 %)	
12	**Turnus des Angebots**	jährlich im Sommersemester	
13	**Arbeitsaufwand**	Workload: 300h davon • Vorlesung: 4 SWS x 15 = 60h • Übung: 2 SWS x 15 = 30h • Selbststudium: 210 h	

14	**Dauer des Moduls**	ein Semester
15	**Unterrichts- und Prüfungssprache**	Deutsch oder Englisch
16	**Literaturhinweise**	• L. C. Evans, Partial Differential Equations, AMS 1997 • D. Gilbarg, N. S. Trudinger, Elliptic Partial Differential Equations, Springer 1983 • E. DiBenedetto, Partial Differential Equations, Birkhäuser 2001 • E. Giusti, Direct methods in the calculus of variations. *World Scientific Publishing* 2003 • Vorlesungsskriptum

1	**Modulbezeichnung**	**Wahrscheinlichkeitstheorie (WT)**	**10 ECTS**
2	**Lehrveranstaltungen**	Vorlesung (4 SWS) Übung (2 SWS) Zentralübung (1 SWS)	
3	**Lehrende**	Prof. Dr. Torben Krüger tk@math.ku.dk	
4	**Modulverantwortung**	Prof. Dr. Torben Krüger tk@math.ku.dk	
5	**Inhalt**	• Mengensysteme, messbare Abbildungen, Maße, Integrationstheorie • Podukträume, unabhängige Zufallsvariablen und gekoppelte Experimente • Maße mit Dichten • Bedingte Erwartungen und Martingale • Stochastische Ungleichungen und Grenzwertsätze • Grundlagen stochastischer Prozesse Die Präsentation des Stoffes erfolgt in Vorlesungsform online. Die weitere Aneignung der wesentlichen Begriffe und Techniken erfolgt durch Präsenzübungen.	
6	**Lernziele und Kompetenzen**	Die Studierenden • erkennen und erklären die formale maßtheoretische Grundlage der Wahrscheinlichkeitstheorie und übertragen diese. • erfassen und formulieren zufällige Phänomene mit mathematisch komplexeren Strukturen. • nennen und erklären die wichtigsten stochastischen Prozesse, die in den Anwendungen eine Rolle spielen. • sammeln und bewerten relevante Informationen und erkennen Zusammenhänge zu anderen mathematischen Themenfeldern. • klassifizieren und lösen selbstständig Probleme analytisch.	
7	**Voraussetzungen für die Teilnahme**	empfohlen: Stochastische Modellbildung und Grundlagen in Analysis	
8	**Einpassung in Musterstudienplan**	im 1. bis 3. Semester	
9	**Verwendbarkeit des Moduls**	Wahlpflichtmodul in: • M.Sc. Data Science • B.Sc. Mathematik • B.Sc. Wirtschaftsmathematik	
10	**Studien- und Prüfungsleistung**	• Übungsleistungen (wöchentliche Hausaufgaben, unbenotet) • Klausur (benotet, 90 Min.)	

11	**Berechnung Modulnote**	Klausur (100%)
12	**Turnus des Angebots**	jährlich im Sommersemester
13	**Arbeitsaufwand**	Workload: 300h davon • Vorlesung: 4 SWS x 15 = 60h • Übung: 2 SWS x 15 = 30h • Zentralübung: 1 SWS x 15 = 45h • Selbststudium: 195 h
14	**Dauer des Moduls**	ein Semester
15	**Unterrichts- und Prüfungssprache**	Deutsch
16	**Literaturhinweise**	• Bauer: Einführung in die Wahrscheinlichkeitstheorie • Breiman: Probability • Durrett: Probability • Klenke: Wahrscheinlichkeitstheorie