

# **Modulhandbuch**

für den Studiengang Master Artificial Intelligence

Fakultät für Informatik und Wirtschaftsinformatik

gültig für das Sommersemester 2024 und Wintersemester 2024

## Inhaltsverzeichnis

<b>Semester 1</b> .....	<b>3</b>
Artificial Intelligence and Machine Learning.....	4
Artificial Neural Networks and Cognitive Models.....	6
Mathematical Foundations of AI.....	8
Parallel Programming.....	9
Project Module 1.....	10
Project Module 2.....	11
Reasoning and Decision Making under Uncertainty.....	12
<b>Semester 1,2</b> .....	<b>14</b>
Cloud Native.....	15
Entrepreneurship for Engineers.....	17
Ethics and Regulation of AI.....	18
<b>Semester 2</b> .....	<b>20</b>
Ausgewählte Kapitel der Embedded Systems.....	21
Fundamentals of Mobile Robotics.....	23
Learning of structured data.....	24
Project Module II.....	26
Scientific seminar.....	27
Semantic data processing and representation.....	29
Trustworthy AI and AI regulations.....	31
<b>Semester 2,3</b> .....	<b>33</b>
Competitive Programming.....	34
Computational Creativity.....	35
Unsupervised Deep Learning.....	37
<b>Semester 3</b> .....	<b>39</b>
Bayesian Statistics and Learning.....	40
Computational Mechanization of Reasoning.....	41
Master Thesis.....	42
<b>Modulverzeichnis</b> .....	<b>43</b>

# Semester 1

## Artificial Intelligence and Machine Learning (5171020)

### Artificial Intelligence and Machine Learning

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Sommersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Ivan Yamshchikov		
<b>Dozierende</b>	Prof. Dr. Ivan Yamshchikov		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Schriftliche Prüfung <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Upon completion of the module students: <ul style="list-style-type: none"> <li>• knowing traditional AI techniques, how they evolved and how they are linked to current approaches</li> <li>• understand basic types of problems to which machine learning algorithms can be applied and can compare them in terms of data that the algorithm expects to receive and the objectives they use for training</li> <li>• have a general overview of key machine learning methods, understand their mechanism and major pros and cons, and can use these (relying on existing implementations) to solve typical learning problems by developing own pipelines and models</li> <li>• can evaluate results of learning exercises and compare different methods in terms of their accuracy as well as computational efficiency and can report on these in oral as well as written form using appropriate tools for expert or more general audience (e.g. via Jupyter Notebooks)</li> <li>• can follow and grasp formal description of standard machine learning algorithms and translate these into a working implementation in standard machine learning software</li> <li>• can critically assess data analytical and machine learning exercises in terms of quality of the experimentation pipeline and the clarity and transparency of the experimental protocol</li> </ul>		
<b>Modulinhalte</b>	<ul style="list-style-type: none"> <li>• Introduction in Artificial Intelligence</li> <li>• overview of the development of AI within the last few decades</li> <li>• introduction into symbolic vs sub-symbolic concepts of AI</li> <li>• classical AI methods (perceptron, boltzman machine, hopfield network, cellular automata and alike)</li> <li>• brief introduction to semantic knowledge representation with links to (fuzzy-) logic, ontologies</li> <li>• Main concepts and principles of machine learning</li> <li>• Basic types of machine learning (supervised/ unsupervised / reinforcement learning) and their use</li> <li>• Main learning goals (prediction - regression/ classification, knowledge discovery – clustering / density estimation, etc.)</li> <li>• Formalism of the learning problem</li> <li>• Ethical and societal impacts of machine learning</li> <li>• Foundations of learning from data</li> <li>• Objective (loss) function</li> <li>• Expected/ empirical risk</li> <li>• Model complexity (over-/ under-fitting)</li> <li>• Model training/ validation/ testing</li> </ul>		

	<ul style="list-style-type: none"> <li>• Model evaluation/ selection</li> <li>• Selected key machine learning algorithms</li> <li>• Linear models for regression/classification</li> <li>• Regularization, ridge regression</li> <li>• Variable selection, sparse models (lasso)</li> <li>• Mixture models (k-means clustering, Gaussian mixtures)</li> <li>• Non-parametric methods (kernels, trees, forests)</li> <li>• Programming for machine learning</li> <li>• Matlab / Python and packages (Numpy, Pandas, Sci-kit learn, Jupyter Notebooks, and other)</li> </ul>
<p><b>Literatur</b></p>	<ol style="list-style-type: none"> <li>1. Bishop, Christopher M. Pattern Recognition and Machine Learning. Information Science and Statistics. New York: Springer, 2006.</li> <li>2. Murphy, Kevin P. Machine Learning: A Probabilistic Perspective. Adaptive Computation and Machine Learning Series. Cambridge, MA: MIT Press, 2012.</li> <li>3. Hastie, Trevor, Robert Tibshirani, and Jerome Friedman. The Elements of Statistical Learning. Springer Series in Statistics. New York, NY, USA: Springer New York Inc., 2001.</li> <li>4. Russel, S, Norwig, P. Artificial Intelligence: A Modern Approach, Pearson, 2022</li> </ol>

## Artificial Neural Networks and Cognitive Models (5171030)

### Artificial Neural Networks and Cognitive Models

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Sommersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Magda Gregorová		
<b>Dozierende</b>	Prof. Dr. Magda Gregorová		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO</i> : keine <i>empfohlen</i> : keine		
<b>Prüfung</b>	<i>Art der Prüfung</i> : Portfolio <i>Art der Note</i> : Differenzierte Note		
<b>Lernergebnisse</b>	Upon completion of the module students: <ul style="list-style-type: none"> <li>• can place artificial neural networks within the broader area of machine learning, understand their major advantages and disadvantages, and are aware of major applications of ANN as well as selected advanced models under research and their fundamental ideas</li> <li>• understand and assess the critical differences between the basic ANN architectures (MLP, CNN, RNN), can implement them in standard deep learning software packages, and can train, test, and evaluate the ANN models over real data</li> <li>• building on the experience of working with their own ANN implementations, can reuse publicly available implementations of more complex models to carry out experiments over real datasets, can compare the performance of these across various models and their hyperparameter setups</li> <li>• understand the importance of transparency and reproducibility in deep learning experimentation and can present in written as well as oral their learning and evaluation pipeline including relevant description of the selected software and hardware configuration</li> <li>• are aware of the ethical and societal impacts of machine learning and deep learning and can critically assess deep learning reports along these lines</li> </ul>		
<b>Modulinhalte</b>	<ul style="list-style-type: none"> <li>• Artificial neural networks (ANN) in machine learning (ML)</li> <li>• Basic concepts of learning algorithms and typical tasks</li> <li>• Model development workflow, hyperparameter tuning, performance measures and model selection</li> <li>• Ethical and societal aspects (open access, data governance, fairness, transparency, reproducibility, safety and robustness, interpretability and human oversight/trust, ecological footprint)</li> <li>• Basic ANN architectures</li> <li>• Multilayer perceptron (feed forward)</li> <li>• Convolutional neural networks</li> <li>• Recurrent neural networks</li> <li>• ANN model regularization</li> <li>• Norm penalties</li> <li>• Data augmentation</li> <li>• Early stopping</li> <li>• Dropout</li> <li>• ANN model optimization</li> <li>• (Stochastic) gradient descent</li> <li>• Backpropagation</li> <li>• Momentum methods</li> </ul>		

	<ul style="list-style-type: none"><li>• Learning rate scheduling</li><li>• Major ANN applications and selected advanced models</li><li>• Computer vision (object detection, image classification, style transfer)</li><li>• Natural language processing (word2vec, BERT)</li><li>• Autoencoders</li><li>• Generative models</li><li>• Deep learning software packages (one of these)</li><li>• PyTorch</li><li>• Tensorflow</li></ul>
<b>Literatur</b>	<ol style="list-style-type: none"><li>1. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. Deep Learning. MIT Press, 2016</li><li>2. Zhang, Aston, Zachary C. Lipton, Mu Li, and Alexander J. Smola. Dive into Deep Learning. <a href="https://d2l.ai/">https://d2l.ai/</a>, 2021</li></ol>

## Mathematical Foundations of AI (5172010)

### Mathematical Foundations of AI

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Sommersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Martin Storath		
<b>Dozierende</b>	Prof. Dr. Martin Storath		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Schriftliche Prüfung <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	<ul style="list-style-type: none"> <li>• Students refresh and develop further their knowledge and skills on the necessary mathematical foundations for understanding and developing algorithms for AI; in particular, linear algebra, calculus, probability.</li> <li>• Students understand the principles of continuous optimization (constrained and unconstrained), are able to select appropriate approaches and they apply them for problems in AI.</li> <li>• Students are able to apply and evaluate the principles of probabilistic modelling and inference, and they create probabilistic models for frequently occurring kinds of data.</li> <li>• Students use the acquired mathematical skills to design and create frequently occurring building blocks of AI systems, such as linear regression, PCA, Gaussian mixture models and support vector machines.</li> </ul>		
<b>Modulinhalte</b>	<ol style="list-style-type: none"> <li>1. Advanced Vector Calculus                         <ul style="list-style-type: none"> <li>• Multivariate derivatives and chain rule</li> <li>• Backpropagation and automatic differentiation</li> <li>• Linearization and multivariate Taylor series</li> </ul> </li> <li>2. Advanced Linear Algebra                         <ul style="list-style-type: none"> <li>• Eigenvalues and eigenvectors</li> <li>• Singular value decomposition</li> <li>• Matrix approximation</li> </ul> </li> <li>3. Continuous Optimization                         <ul style="list-style-type: none"> <li>• Gradient descent</li> <li>• Constrained optimization and Lagrange multipliers</li> <li>• Convex Optimization</li> </ul> </li> <li>4. Models and Data                         <ul style="list-style-type: none"> <li>• Change of variables</li> <li>• Empirical risk minimization</li> <li>• Parameter estimation</li> <li>• Probabilistic modelling and inference</li> <li>• Model selection</li> </ul> </li> </ol>		
<b>Literatur</b>	<ol style="list-style-type: none"> <li>1. M. P. Deisenroth, A. A. Faisal, Cheng Soon Ong: Mathematics for Machine Learning, Cambridge University Press, 2020</li> <li>2. C. M. Bishop: Pattern Recognition and Machine Learning, Springer, 2006</li> <li>3. G. James, D. Witten, T. Hastie, R. Tibshirani: An Introduction to Statistical Learning, Second Edition, Springer, 2021</li> </ol>		



## Parallel Programming (5171510)

### Parallel Programming

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Unregelmäßig	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Kai Diethelm		
<b>Dozierende</b>	Prof. Dr. Kai Diethelm		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine  <i>empfohlen:</i> Fundamental knowledge in programming in a higher programming language, e.g. C or C++.		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio  <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Students have a firm knowledge of the concepts and methods of parallel programming. They are aware of the capabilities and limitations of these concepts. They can select appropriate approaches for given applications and apply them to the problems at hand.		
<b>Modulinhalte</b>	The module will address the following topics: <ul style="list-style-type: none"> <li>• Basic ideas of parallel computing</li> <li>• Hardware concepts for parallel computers (shared memory systems, distributed memory systems, GPU-based systems)</li> <li>• Amdahl's law</li> <li>• SISD, SIMD and MIMD software</li> <li>• Introduction to the programming paradigms OpenMP, MPI and CUDA</li> <li>• Code performance analysis and optimization (bottlenecks etc.)</li> </ul> All parts of the module are accompanied by a significant amount of practical work on a high performance compute cluster that provides all the required hardware.		
<b>Literatur</b>	1. Thomas Rauber and Gudula Rünger: Parallel Programming for Multicore and Cluster Systems, 2nd ed. Springer, Heidelberg, 2013 2. Timothy G. Mattson, Yun (Helen) He and Alice E. Koniges: The OpenMP Common Core. MIT Press, Cambridge, 2019 3. David Kirk and Wen-mei W. Hwu: Programming Massively Parallel Processors – A Hands-on Approach, 3rd ed. Morgan Kaufmann, Waltham, 2016 4. William Gropp, Ewing Lusk and Anthony Skjellum: Using MPI, 3rd ed. MIT Press, Cambridge, 2014 5. Georg Hager and Gerhard Wellein: Introduction to High Performance Computing for Scientists and Engineers. CRC Press, Boca Raton, 2011		

## Project Module 1 (5172050)

### Project Module 1

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Semester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1	<b>Lehr- und Lernformen</b> Projekt
<b>Modulverantwortung</b>	Prof. Dr. Magda Gregorová		
<b>Dozierende</b>	Prof. Dr. Arndt Balzer, Prof. Dr. Magda Gregorová		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Students can methodically process and solve comprehensive tasks. The students can develop and implement suitable solution strategies in a team. They know how team processes work and can assess how to contribute their own personality. The students can independently set up, implement, accompany and present a small AI project in a team. They can select and use appropriate development technologies and test and document their code.		
<b>Modulinhalte</b>	The students will work in groups to solve projects using AI techniques (supervised by at least one professor). The topics are provided by professors of the FIW, other faculties or external partners. In general the project will contain a software development (potentially accompanied by a technical solution) and a respective documentation or other form or presentation.		
<b>Literatur</b>	<ol style="list-style-type: none"> <li>1. Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, A.Geron, O'Reilly, 2019</li> <li>2. The Data Science Design Manual, S. Skiena, Springer, 2017</li> <li>3. Deep Learning, I. Goodfellow, MIT Press, 2016</li> </ol> Further literature will be given based on the respective project tasks.		

## Project Module 2 (5172060)

### Project Module 2

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Semester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1	<b>Lehr- und Lernformen</b> Projekt
<b>Modulverantwortung</b>	Prof. Dr. Magda Gregorová		
<b>Dozierende</b>	Prof. Dr. Arndt Balzer, Prof. Dr. Magda Gregorová		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Students can methodically process and solve comprehensive tasks. The students can develop and implement suitable solution strategies in a team. They know how team processes work and can assess how to contribute their own personality. The students can independently set up, implement, accompany and present a small AI project in a team. They can select and use appropriate development technologies and test and document their code.		
<b>Modulinhalte</b>	The students will work in groups to solve projects using AI techniques (supervised by at least one professor). The topics are provided by professors of the FIW, other faculties or external partners. In general the project will contain a software development (potentially accompanied by a technical solution) and a respective documentation or other form or presentation.		
<b>Literatur</b>	<ol style="list-style-type: none"> <li>1. Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, A.Geron, O'Reilly, 2019</li> <li>2. The Data Science Design Manual, S. Skiena, Springer, 2017</li> <li>3. Deep Learning, I. Goodfellow, MIT Press, 2016</li> </ol> Further literature will be given based on the respective project tasks.		

## Reasoning and Decision Making under Uncertainty (5171040)

### *Reasoning and Decision Making under Uncertainty*

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Sommersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Frank Deinzer		
<b>Dozierende</b>	Prof. Dr. Frank Deinzer		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	<ul style="list-style-type: none"> <li>• Students develop further knowledge and skills on the necessary mathematical foundations for understanding and developing algorithms for AI.</li> <li>• Students can apply the principles of Reinforcement Learning algorithms</li> <li>• Students can use the principles of modelling gents, environments and rewards.</li> <li>• Students understand the necessity of function approximations in learning.</li> <li>• Students understand the concepts of statistical sensor fusion</li> <li>• Students can realize sensor fusion applications</li> <li>• Students build on their acquired knowledge to master learning problems.</li> </ul>		
<b>Modulinhalte</b>	The course is composed of 2 thematic blocks. Block A: Reinforcement Learning <ol style="list-style-type: none"> <li>1. Basic Reinforcement Learning Concepts                             <ul style="list-style-type: none"> <li>• Actions and States</li> <li>• Goals, Rewards, Returns and Episodes</li> <li>• Policies and Value Functions</li> </ul> </li> <li>2. Basic Reinforcement Learning Methods                             <ul style="list-style-type: none"> <li>• Finite Markov Decision Processes</li> <li>• Dynamic Programming</li> <li>• Monte Carlo Methods</li> </ul> </li> <li>3. Advanced tabular learning Methods                             <ul style="list-style-type: none"> <li>• Temporal-Difference Learning</li> <li>• Bootstrapping Methods</li> </ul> </li> <li>4. Learning in Continuous State and Action Spaces                             <ul style="list-style-type: none"> <li>• On-Policy Approximation</li> <li>• Value-function Approximation</li> <li>• Off-Policy Approximation</li> <li>• Approximate Eligibility Traces</li> </ul> </li> <li>5. Value Function Approximation Case Studies                             <ul style="list-style-type: none"> <li>• Computer Vision: Action planning</li> <li>• Mastering Games: Backgammon, Go</li> </ul> </li> <li>6. Applications and Exercises</li> </ol> Block B: Sensor Fusion <ol style="list-style-type: none"> <li>1. Using Bayes for Sensor Data Fusion                             <ul style="list-style-type: none"> <li>• Modeling and Estimation of Densities</li> <li>• Sensor Fusion over Time</li> </ul> </li> <li>2. Hidden Markov Models and Viterbi Algorithm</li> <li>3. Recursive State Estimation</li> </ol>		

	<ul style="list-style-type: none"><li>• Gaussian Filters</li><li>• Nonparametric Filters</li></ul> 4. Applications
<b>Literatur</b>	<ol style="list-style-type: none"><li>1. Sutton, Barto. Reinforcement Learning - An Introduction. Bradford Books, 2018</li><li>2. Thorp. Beat the Dealer. Random House. 1966</li><li>3. Mitchell. Data Fusion: Concepts and Ideas. Springer. 2014</li><li>4. Thrun, Burgard, Fox: Probabilistic Robotics. MIT Press. 2005</li><li>5. Johnson, Freund, Miller. Miller &amp; Freund's Probability and Statistics for Engineers. Pearson</li></ol> Further specialized literature will be announced in the course.

# Semester 1,2

## Cloud Native (5171512)

### Cloud Native

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Unregelmäßig	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1,2	<b>Lehr- und Lernformen</b> Seminar
<b>Modulverantwortung</b>	Prof. Dr. Pascal Meißner		
<b>Dozierende</b>	Harald Philipp Gerhards		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> Basic skills in programming are needed		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Schriftliche Prüfung <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Upon completion of the module, students will: <ul style="list-style-type: none"> <li>• have an overview of the evolution of cloud computing and new architectures.</li> <li>• Be able to understand the architectural patterns of cloud native platforms and applications.</li> <li>• Be able to develop applications for container platforms on behalf of containerization principles.</li> <li>• Be able to understand vertical and horizontal scaling of applications.</li> <li>• Be able to maintain and configure monitoring and security components of Kubernetes platforms.</li> <li>• Be able to critically access approaches to versioning software artifacts and develop appropriate strategies for agile software projects.</li> <li>• Know the concepts of asynchronous communication using Apache Kafka.</li> <li>• Have solidified their knowledge on cloud native tools like Docker, Kubernetes, Helm, Apache Kafka and Git</li> </ul>		
<b>Modulinhalte</b>	Main Concepts of Cloud Computing <ul style="list-style-type: none"> <li>• Definition of "cloud native"</li> <li>• Historical background</li> <li>• Cloud Native and Open Source</li> <li>• Major players (CNCF, Linux Foundation, Apache Foundation)</li> </ul> Cloud Native Architecture <ul style="list-style-type: none"> <li>• Principles and paradigms</li> <li>• Distributed systems</li> <li>• Representation Concepts (C4, UML)</li> </ul> Containerization & Virtualization Principles <ul style="list-style-type: none"> <li>• Container vs. Virtual Machine</li> <li>• Emergence of Docker</li> <li>• Container Images</li> <li>• Image Build</li> <li>• Composing Containers</li> </ul> Container Orchestration <ul style="list-style-type: none"> <li>• Horizontal and vertical scaling</li> <li>• Kubernetes artifacts</li> <li>• Cluster Network</li> <li>• Persistence in Kubernetes</li> <li>• Templating for Kubernetes</li> <li>• Monitoring and Logging</li> <li>• Kubernetes Management</li> </ul>		

	<ul style="list-style-type: none"><li>• Service Mesh</li></ul> <p>Pub-Sub-Messaging Concepts</p> <ul style="list-style-type: none"><li>• Apache Kafka</li><li>• Distributed logs</li><li>• Stream processing</li></ul> <p>Versioning</p> <ul style="list-style-type: none"><li>• Commit strategies</li><li>• Branching strategies</li></ul> <p>Development Operation Principles</p> <ul style="list-style-type: none"><li>• DevOps</li><li>• DevSecOps</li><li>• CI/CD</li><li>• GitOps</li></ul>
<b>Literatur</b>	Literature will be announced in the course.



## Entrepreneurship for Engineers (5171514)

### Entrepreneurship for Engineers

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Unregelmäßig	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1,2	<b>Lehr- und Lernformen</b> Projekt
<b>Modulverantwortung</b>	Prof. Dr. Ivan Yamshchikov		
<b>Dozierende</b>	Prof. Dr. Ivan Yamshchikov		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Projektarbeit <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	<ul style="list-style-type: none"> <li>— Students learn how to apply the principles of technological entrepreneurship.</li> <li>— Students can create a Minimal Viable Prototype (MVP) by applying principles of paper prototyping.</li> <li>— Students can create and implement a customer development pipeline can evaluate product market fit and unit economics of the technological product.</li> <li>— Students can create a pitch deck for their project from scratch, evaluate the quality of the early-stage venture capital, and implement a fund-raising plan.</li> <li>— Students understand the overall properties of venture capital markets.</li> </ul>		
<b>Modulinhalte</b>	<p>1 What is venture capital? — a brief history of venture investment — probabilistic approach to venture investment — venture capital and technological development</p> <p>2 What is a product? — Why is technology not a product? — Paper prototyping and product market fit — Customer development for engineers</p> <p>3 What is a pitch deck? — What are the key structural components of a good pitch? — Unit economics — Storytelling for engineers</p> <p>4 How do you make decisions under stress? — Managing small teams — Trade-off between discipline and creativity — Empathy for engineers</p>		
<b>Literatur</b>	<p>B. Horowitz \\\\\"The Hard Thing About Hard Things: Building a Business When There Are No Easy Answers\\\\\\\"</p> <p>P. Thiel \\\\\"Zero to One: Notes on Startups, or How to Build the Future\\\\\\\"</p> <p>Optional literature:</p> <p>M. Weber \\\\\"Protestant Ethic and the Spirit of Capitalism\\\\\\\"</p> <p>K.F. Lee \\\\\"AI Superpowers: China, Silicon Valley and the New World Order\\\\\\\"</p> <p>\\\"</p> <p>B. Christian, T. Griffiths \\\\\"Algorithms to Live By\\\\\\\"</p>		

## Ethics and Regulation of AI (5171519)

### Ethics and Regulation of AI

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Sommersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 1,2	<b>Lehr- und Lernformen</b> Seminar
<b>Modulverantwortung</b>	Prof. Dr. Markus Oermann		
<b>Dozierende</b>	Prof. Dr. Markus Oermann		
<b>Verwendbarkeit</b>	Master Artificial Intelligence, Master Digital Business Systems		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	<p>Participants</p> <ul style="list-style-type: none"> <li>• have profound insights regarding the central clusters of ethical challenges of AI</li> <li>• know the basic requirements on AI by established ethical guidelines by the UNESCO, the Council of Europe, the G7 etc.</li> <li>• know how to integrate an ethical assessment in professional workstreams/development processes</li> <li>• know the basics of the new legal framework for AI in the EU that will be established by the AI Act</li> <li>• have insights on current legal discussions on the use of copyright protected material as training data and on the protection of AI's output in terms of intellectual property</li> <li>• get insights on the next phase of the EU's regulation of AI which will address the question of liability</li> <li>• are thereby able to better communicate and cooperate with ethical and legal professionals in their future work environment</li> </ul>		
<b>Modulinhalte</b>	<ul style="list-style-type: none"> <li>• AI, a dazzling concept - basic definitions of AI by OECD and EU</li> <li>• basics on ethics in general</li> <li>• clusters of ethical challenges related to AI: <ul style="list-style-type: none"> <li>- power and responsibility</li> <li>- agency and human/machine relation</li> <li>- biases and discrimination</li> <li>- data ownership/data protection</li> <li>- copyright/intellectual property</li> <li>- job displacement/transformation of work</li> </ul> </li> <li>• selected established ethical guidelines and their take on these challenges: <ul style="list-style-type: none"> <li>- UNESCO</li> <li>- Council of Europe</li> <li>- G7</li> <li>- Blechtlely Parc Declaration</li> <li>- special sector codes: IEEE, ILO</li> <li>- self regulatory codes: Open AI safety guidelines</li> </ul> </li> <li>• approaches and standards on how to integrate ethical assessment in professional workstreams/development of AI and AI applications</li> <li>• overview on the new legal framework for AI by the upcoming EU AI Act</li> <li>• further current legal discussions on AI: <ul style="list-style-type: none"> <li>- how to deal with the use of copyright protected material as training data</li> <li>- how to deal with AI's output in terms of copyright law</li> </ul> </li> </ul>		

---

	- next step of regulation: the planned reform of the liability regime for AI by the European Commission
<b>Literatur</b>	Coeckelbergh, Mark (2021): AI ethics, Cambridge, MA: MIT Press. Further basic texts will be announced or made available in the first session

# Semester 2

## Ausgewählte Kapitel der Embedded Systems (5071038)

### Selected Topics in Embedded Systems

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Deutsch/Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Wintersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2	<b>Lehr- und Lernformen</b> Seminar
<b>Modulverantwortung</b>	Prof. Dr. Arndt Balzer		
<b>Dozierende</b>	Prof. Dr. Arndt Balzer, Prof. Dr. Andreas Lehrmann		
<b>Verwendbarkeit</b>	Master Artificial Intelligence, Master Digital Business Systems		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> Affinität zu technischen Anwendungen		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Referat, Kolloquium <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Die Studierenden sind in der Lage <ul style="list-style-type: none"> <li>• Notwendigkeit, Marktrelevanz und das Potential Eingebetteter (mobiler) Systeme zu bewerten,</li> <li>• Herausforderungen bei Bau autonomen fahrender Systeme beurteilen und Lösung entwerfen zu können,</li> <li>• Aufbau und Funktionsweise der Hard- und Software von Regelungssystemen am Beispiel eines Quadropters zu beschreiben, einschließlich der Echtzeitanforderungen,</li> <li>• Teile der Systemsoftware zu implementieren,</li> <li>• eingesetzte mathematische Methoden zu beurteilen,</li> <li>• Ansätze zur Verbesserung der Signalverarbeitung zu entwerfen.</li> </ul>		
<b>Modulinhalte</b>	Die Inhalte der Lehrveranstaltung werden aktuellen Erfordernissen angepasst. Seit 2020 ist der Schwerpunkt die Entwicklung von Software für ein autonom fahrendes Fahrzeug auf Basis von NVIDIA Hardware Grundlagen des maschinellen Lernen, dabei u.a. künstliche neuronale Netze Maschinelles Sehen, "klassische" Bildverarbeitung Bis 2019 war der Schwerpunkt: Entwicklung von Software zur Steuerung eines Quadropters Programmierung von Embedded Systems Regelungstechnik, insbesondere PID Regler Sensorik, Telemetrie Mathematische Grundlagen: Kartesische und Polar Koordinaten, Euler Winkel, komplexe Zahlen, Quaternionen, Vektoralgebra Signalverarbeitung: Zustandsschätzer, Bayes-, Gauss-, Kalman-Filter Lageregelung, Yaw Regelung, Telekommandos Bei Bedarf: Entwicklung von Software für MCU mit aktuellen IDEs, teil-autonomes Fahren		
<b>Literatur</b>	Tom M. Mitchell, Machine Learning, <a href="http://www.cs.cmu.edu/~tom/mlbook.html">http://www.cs.cmu.edu/~tom/mlbook.html</a> Christopher M. Bishop, Pattern Recognition and Machine Learning, online Trevor Hastie et al., The Elements of Statistical Learning, online Kevin P. Murphy, Machine learning, online S. Thrun, W. Burgard, D. Fox: Probabilistic Robotics, The MIT Press, 2005 Unterlagen der Uni Würzburg / Emqopter, 2019 A. Gelb, Applied Optimal Estimation, MIT Press, 1974 R. Kalman, A New Approach to Linear Filtering and Prediction Problems, Transaction of the ASME—Journal of Basic Engineering, 1960 P. Marwedel: Embedded System Design - Foundations of Cyber-Physical Systems, Springer, 2011		

---

D. Gajski, F. Vahid: Specification and Design if Embedded Systems, Pearson, 2008 J. McClellan. R. Schafer: Signal Processing First, Pearson, 2003
--

## Fundamentals of Mobile Robotics (5172080)

### Fundamentals of Mobile Robotics

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Wintersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Pascal Meißner		
<b>Dozierende</b>	Prof. Dr. Pascal Meißner		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Mündliche Prüfung <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	<ul style="list-style-type: none"> <li>• Apply the Bayes (filter) formula and sample from probability density functions</li> <li>• Determine and apply probabilistic sensor and motion models</li> <li>• Discuss the steps and components of realizations of Bayes filters</li> <li>• Implement realizations of Bayes filters and compute location estimates for robots</li> <li>• Build and analyze grid maps</li> <li>• Differentiate between localization and SLAM systems as well as outline auxiliary techniques for SLAM solutions</li> <li>• Assess and implement components of landmark- and grid-based solutions to the SLAM problem</li> <li>• Differentiate between different path planning techniques and discuss the steps of collision avoidance solutions</li> <li>• Apply and implement graph-search techniques for path planning</li> <li>• Assess the Markov Decision Process definition as well as the concepts of Utility and Policy</li> <li>• Apply dynamic programming on Markov Decision Problems to compute value functions and optimal policies</li> </ul>		
<b>Modulinhalte</b>	01. Introduction – Nomenclature, history, state of the art, module logistics 02. Linear Algebra and Probability Primer – Vectors and operations, matrices and operations, axioms of probability, independent events, Bayes rule 03. Bayes Filter – Recursive Bayesian updating, state transitions, Markov property, derivation 04. Probabilistic Modelling – Odometry- and velocity-based motion models, beam- and scan-based sensor models 05. Localization with Nonparametric Filters – Discrete Bayes filter, importance sampling, particle filter 06. Localization with Gaussian Filters – Kalman filter, Extended Kalman filter 07. Mapping with Known Poses – Occupancy maps, reflection probability maps 08. Landmark-based SLAM – SLAM problem, EKF SLAM, loop closing, Rao-Blackwellization, FastSLAM 09. Grid-based SLAM – Scan matching, FastSLAM, improved proposals, selective resampling 10. Motion and Path Planning – Configuration spaces, combinatorial planning, search algorithms, A* with extensions, collision avoidance 11. Markov Decision Processes – MDP definition, utility, value iteration, policy iteration		
<b>Literatur</b>	<ul style="list-style-type: none"> <li>• Probabilistic Robotics, Sebastian Thrun and Wolfram Burgard and Dieter Fox, MIT Press, 978-0262201629, 2005</li> <li>• Artificial Intelligence: A Modern Approach, Stuart Russell and Peter Norvig, 4th ed. Prentice Hall, 978-0136042594, 2021</li> </ul>		

## Learning of structured data (5171100)

### Learning of structured data

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Wintersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Dominik Seuß		
<b>Dozierende</b>	Prof. Dr. Dominik Seuß, Prof. Dr. Andreas Lehrmann		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> <ul style="list-style-type: none"> <li>Hands-on knowledge from the modules:                             <ul style="list-style-type: none"> <li>Mathematical (and Theoretical) Foundations of AI</li> <li>Artificial Intelligence and Machine Learning</li> <li>Artificial Neural Networks and Cognitive Models</li> </ul> </li> </ul>		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	<ul style="list-style-type: none"> <li>being able to evaluate and to apply modelling techniques for non-standard data</li> <li>being able to analyse non-vectorial data and to derive and improve predictive models</li> <li>knowing how to evaluate and assess respective representation techniques</li> <li>being able to implement pipelines for non-vectorial data analysis</li> <li>learn the how-to of proximity based learning</li> <li>learn how to assess, use and potentially extend the respective frameworks</li> <li>Students know how to characterize, choose, evaluate, assess and construct practical tools for structured data analysis and respective application fields</li> <li>learn how to use scientific literature and to understand, derive, implement and potentially extend the presented methods</li> </ul>		
<b>Modulinhalte</b>	The module explains the generic analysis and processing of non-vectorial or structured data like graphs, trees, sequential data or alike. We discuss algebraic methods as well as neural network based techniques. The algorithmic part is shown in matlab, numpy/python or by use of other numerical frameworks. Exemplary the following key topics are addressed: <ul style="list-style-type: none"> <li>Particularities of non-vectorial, compositional and structured data</li> <li>General proximity measures and implications on mathematical models</li> <li>Mathematical concepts like information theoretic measures, non-euclidean spaces, local and global embedding approaches</li> <li>Representation by proximity measures and simple learning methods</li> <li>Particular algebraic and neural network based Embedding techniques</li> <li>Evaluation methods for the representation of non-vectorial data</li> <li>Exemplary implementations and applications</li> </ul>		
<b>Literatur</b>	<ul style="list-style-type: none"> <li>The Dissimilarity Representation for Structural Pattern Recognition, Pekalska &amp; Duin, World Scientific, 2005</li> <li>Graph Classification And Clustering Based On Vector Space Embedding, Bunke et al., 2010</li> <li>Kernels For Structured Data, Gartner, 2008</li> <li>Graph Representation Learning, Hamilton, 2020</li> </ul>		



- 
- |  |  |
|--|--|
|  | <ul style="list-style-type: none"><li>• Recent publications on learning of structured data are provided / suggested during the lecture</li></ul> |
|--|--|

## Project Module II (5172060)

### Project Module II

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Wintersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2	<b>Lehr- und Lernformen</b> Projekt
<b>Modulverantwortung</b>	Prof. Dr. Magda Gregorová		
<b>Dozierende</b>	Prof. Dr. Arndt Balzer, Prof. Dr. Frank Deinzer, Prof. Dr. Frank-Michael Schleif, Prof. Dr. Magda Gregorová, Prof. Dr. Pascal Meißner, Prof. Dr. Ivan Yamshchikov		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> Project Module I <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Students can methodically process and solve comprehensive tasks. The students can develop and implement suitable solution strategies in a team. They know how team processes work and can assess how to contribute their own personality. The students can independently set up, implement, accompany and present a small AI project in a team. They can select and use appropriate development technologies and test and document their code.		
<b>Modulinhalte</b>	The students will work in groups to solve projects using AI techniques (supervised by at least one professor). The topics are provided by professors of the FIW, other faculties or external partners. In general the project will contain a software development (potentially accompanied by a technical solution) and a respective documentation or other form or presentation.		
<b>Literatur</b>	Literature will be distributed based on the respective project tasks.		

## Scientific seminar (5171110)

### Scientific seminar

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Wintersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2	<b>Lehr- und Lernformen</b> Seminar
<b>Modulverantwortung</b>	Prof. Dr. Magda Gregorová		
<b>Dozierende</b>	Prof. Dr. Magda Gregorová		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Upon completion of the seminar students: <ul style="list-style-type: none"> <li>• can write English academic texts on AI topics taking into account the expected format (using appropriate mathematical typographical software - LaTeX), structure, and the target audience; can adapt the language and visual support accordingly (article vs. presentation, etc.).</li> <li>• understand the importance of good academic conduct, the boundaries and consequences of plagiarism, and the benefits of open science, transparency and reproducibility, they can design their communication strategy accordingly (open access / open source, experimental documentation, etc.)</li> <li>• can conduct relevant literature search, analyze the quality of texts, can create and maintain a relevant bibliography in standard software tools and correctly reference previous work in their academic outputs</li> <li>• are aware of selected recent trends in AI research and main opportunities and challenges in transferring them to practical applications</li> <li>• can critically analyse academic text and provide constructive feedback, can interact with senior researchers in an informed discussion</li> </ul>		
<b>Modulinhalte</b>	Practical research and scientific work skills and principles of good scientific conduct. <ul style="list-style-type: none"> <li>• Academic writing on AI topics in English (for non-native speakers)</li> <li>• Standard structure of academic texts – theses, technical reports, research articles, academic CV</li> <li>• Specific grammar features and word choices of English academic text and common pitfalls for non-native speakers</li> <li>• Good conduct in academic writing (citations, acknowledgments, plagiarism), open science, transparency, reproducibility</li> <li>• Literature review (dblp, google scholar, journals and conferences, predatory publishers)</li> <li>• Visual support of technical text (visual display of quantitative data, visual communication), academic presentations and poster design</li> <li>• Analysis of academic text, critical evaluation, peerreview process and principles</li> <li>• Academic and research support software tools and bibliography systems (Zotero, Mendeley, ...)</li> <li>• Academic talk structure, audience targeting, academic exchange of knowledge and experience, constructive feedback and academic research discussion</li> </ul> The seminar will be enriched by a series of invited talks and events. Through these the students will learn about: <ul style="list-style-type: none"> <li>• Current trends and topics in AI research and real-life applications</li> <li>• Transferability of theoretical research results to practical applications in company context</li> </ul>		

	<ul style="list-style-type: none"><li>• Opportunities, open questions and challenges for AI research and applications (technical, societal, ethical, economic, entrepreneurship, etc.)</li><li>• Networking, establishing and fostering collaborations, job search, formal/ informal interaction with senior researchers and company practitioners</li></ul>
<b>Literatur</b>	To be defined in seminar

## Semantic data processing and representation (5171090)

### *Semantic data processing and representation*

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Wintersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Ivan Yamshchikov		
<b>Dozierende</b>	Prof. Dr. Ivan Yamshchikov		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 30	<i>Selbststudium</i> 120
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> Mathematical Foundations of AI Artificial Intelligence and Machine Learning Artificial Neural Networks and Cognitive Models		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	After successfully completing the module: <ul style="list-style-type: none"> <li>• students are able to apply the basic methods of Natural Language Processing and related applications. The students are able to develop result-oriented applications that integrate Natural Language Processing methods. These methods can be based in whole or in part on various forms of artificial neural networks (deep neural networks).</li> <li>• students are able to analyse concrete tasks in the field of natural language processing from applied science or industrial practice and evaluate and select suitable methods and software components from the field of natural language processing. In particular, students are also able to describe and develop suitable Deep Learning architectures.</li> <li>• students are also able to describe, implement and present a corresponding overall software architecture. In doing so, they draw on common frameworks from the field of deep learning (e.g. KERAS, TensorFlow, PyTorch, etc.). They organise themselves and their team independently in the application of learned methods of Natural Language Processing.</li> </ul>		
<b>Modulinhalte</b>	<ul style="list-style-type: none"> <li>— Introduction and Natural Language Processing Applications</li> <li>— Text and Speech Basics</li> <li>— Reading scientific papers</li> <li>— Tokenization</li> <li>— Embeddings</li> <li>— Verbal Intelligence</li> <li>— Semantic Representations</li> <li>— Distributed Representations / Word Embeddings</li> <li>— Language Models</li> <li>— Transformers</li> <li>— Large Language Models</li> <li>— Frontiers of modern NLP</li> </ul> The model is implementing a learning-by-doing approach. The students read a variety of scientific publications that are fundamental for the topic, present and discuss these contributions as the course unfolds.		
<b>Literatur</b>	<ul style="list-style-type: none"> <li>• Kamath, Uday, John Liu, and James Whitaker. Deep learning for NLP and speech recognition. Vol. 84. Cham: Springer, 2019.</li> </ul>		

- 
- |  |  |
|--|--|
|  | <ul style="list-style-type: none"><li>• Chris Manning and Hinrich Schütze, Foundations of Statistical Natural Language Processing, MIT Press. Cambridge, MA: May 1999.</li></ul> |
|--|--|

## Trustworthy AI and AI regulations (5171070)

### Trustworthy AI and AI regulations

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Wintersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Markus Oermann		
<b>Dozierende</b>	Prof. Dr. Markus Oermann		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Schriftliche Prüfung <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	<p>After the module participants will</p> <ul style="list-style-type: none"> <li>• have profound insights regarding central clusters of ethical challenges of AI</li> <li>• know how to integrate an ethical assessment in professional workstreams/AI development processes</li> <li>• have gained insights on data protection law requirements for AI and the shortcomings of the EU's General Data Protection Regulation</li> <li>• know the basic requirements on AI by established international ethical guidelines</li> <li>• know the basics of the new legal framework for AI in the EU that will be established by the AI Act</li> <li>• have insights on current legal discussions on the use of copyright protected material as training data and on the protection of AI's output in terms of intellectual property</li> <li>• know the basic structures of civil liability and have insights on the next phase of the EU's regulation of AI which will address the liability regime</li> <li>• are thereby well prepared to communicate and cooperate with ethical and legal professionals in their future work environment</li> </ul>		
<b>Modulinhalte</b>	<ul style="list-style-type: none"> <li>• "Trustworthy AI", a dazzling concept - basic definitions of AI by OECD and EU</li> <li>• Ethics 101 and the traditional schools of Ethics</li> <li>• Clusters of ethical challenges related to AI: <ul style="list-style-type: none"> <li>- agency and human/machine relation</li> <li>- power and responsibility</li> <li>- biases and discrimination</li> <li>- data ownership/data protection (including basics structures of data protection law)</li> <li>- democracy, election integrity, free discourse and the problem of AI driven malinformation, disinformation and deep fakes</li> <li>- AI vs. sustainability (?)</li> <li>- AI as catalyst of radical transformation?: job displacement/transformation of work</li> </ul> </li> <li>• Approaches and standards on how to integrate ethical assessment in professional workstreams/development of AI and AI applications</li> <li>• Selected established international ethical guidelines and their take on these challenges: EU, OECD, UNESCO, Council of Europe, G7</li> <li>• Self-regulation vs. state regulation (?)</li> <li>• Overview on the new legal framework for AI by the EU's AI Act</li> <li>• Further current legal and regulatory discussions on AI: <ul style="list-style-type: none"> <li>- How to deal with the use of copyright protected material as training data?</li> <li>- How to deal with AI's output in terms of copyright law?</li> <li>- What's ahead: the planned reform of the liability regime for AI in the EU</li> </ul> </li> </ul>		

---

<b>Literatur</b>	Coeckelbergh, Mark (2021): AI ethics, Cambridge, MA: MIT Press. Dignum, Virginia (2019): Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way, Cham: Springer Int. Publ. Further basic texts will be announced or made available in the first session
------------------	--



# Semester 2,3

## Competitive Programming (5171521)

### Competitive Programming

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Unregelmäßig	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2,3	<b>Lehr- und Lernformen</b> Seminar
<b>Modulverantwortung</b>	Prof. Dr. Ivan Yamshchikov		
<b>Dozierende</b>	Pavel Chizhov		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> Understanding of algorithms and data structures, full command of Python, knowledge of other languages such as C/C++ is a plus. Rust programming for safety-critical systems or Sicher Programmieren in Rust. Algorithmen und Datenstrukturen 1/2.		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	After the completion of the course the participants will obtain: — Ability to rapidly prototype in a stressful and challenging environment; — Deeper understanding of algorithms and computational complexity; — Ability to critically assess the proposed solutions, choose the optimal one, and efficiently implement it in code; — Efficient skills of interaction within a team of software developers.		
<b>Modulinhalte</b>	The module mostly consists of Hands-on prototyping and code-reviewing. However, certain topics will be covered in flash-lectures. — Basics of algorithms, i.e. sorting, binary search, dynamic programming, greedy algorithms, graph algorithms, etc. — Data structures, i.e. stacks, sets, hashmaps, heaps, graphs, binary search trees, priority queues, etc. — Complexity theory, in particular, big-O notation. The focus of the course is programming practice in solving programming problems, specifically the ones offered at ICPC. The methodology implies follow-up discussions after every set of problems that allow to extend the variety of possible solutions and outlines the optimal ones. The best team will take part in the North European ICPC.		
<b>Literatur</b>	Thomas H. Cormen, Charles E. Leiserson, Introduction to Algorithms. 2022. Fourth Edition.		

## Computational Creativity (5171522)

### Computational Creativity

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Unregelmäßig	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2,3	<b>Lehr- und Lernformen</b> Seminar
<b>Modulverantwortung</b>	Prof. Dr. Ivan Yamshchikov		
<b>Dozierende</b>	Prof. Dr. Ivan Yamshchikov		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> Full command of Python and "Artificial Neural Networks and Cognitive Models" are prerequisites for the course.		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Schriftliche Prüfung <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	This course explores the intersection of artificial intelligence and creative processes. It introduces students to the fundamentals of computational creativity, discussing how AI can be used to simulate or replicate human-like creative abilities in various domains such as art, music, engineering, and problem-solving. Course Objectives: — Understand the theoretical foundations of computational creativity. — Explore various AI techniques used in creative processes. — Analyze case studies where AI has been applied in creative industries. Upon completion of the course, the students develop and implement AI models that demonstrate creative behaviour or have certain artistic merit.		
<b>Modulinhalte</b>	Module Structure: Introduction to Computational Creativity — Definition and history — Key concepts and challenges — Overview of the field and its importance in AI Theoretical Foundations — Models of creativity in psychology and cognitive science — Computational models of creative thinking — Philosophical aspects of creativity and AI Technologies and Algorithms — Machine learning techniques in creativity — Natural language processing for creative writing — Evolutionary algorithms and their creative applications — Neural networks (e.g., GANs, RNNs) in art and music generation Creative Domains and Applications — Visual arts: automated image and video generation — Music: composition and performance enhancements — Literature: poetry and prose generation Practical Workshops and Projects — Group projects to design a creative AI model — Weekly iteration of the project and a final showcase gallery The selected projects might be presented at the Deutsche Technische Museum Bonn.		

---

<b>Literatur</b>	Machado, Romero and Greenfield. Artificial Intelligence and the Arts: Computational Creativity, Artistic Behavior, and Tools for Creatives (Computational Synthesis and Creative Systems). Levin and Brain. Code as Creative Medium: A Handbook for Computational Art and Design
------------------	---

## Unsupervised Deep Learning (5171523)

### *Unsupervised Deep Learning*

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Wintersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 2,3	<b>Lehr- und Lernformen</b> Seminar
<b>Modulverantwortung</b>	Prof. Dr. Magda Gregorová		
<b>Dozierende</b>	Prof. Dr. Magda Gregorová		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> Finished the following courses with grade better than 2.5: <ul style="list-style-type: none"> <li>• Artificial Neural Networks and Cognitive Models</li> <li>• Mathematical Foundations of AI</li> </ul> <i>empfohlen:</i> excellent knowledge of probability theory basics fluency in implementing and training neural networks in PyTorch		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Portfolio <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Upon taking up the course students shall understand the differences between supervised, unsupervised and self-supervised learning and be able to name their primary usage and pros/cons. Students shall be aware of the variety of possible approaches and shall be able to explain the main ideas underlying the five main deep unsupervised learning paradigms. Students shall understand the mathematical formulations underlying the models and shall be able to build on this understanding when exploring independently more complex versions of the models. Students shall be able to implement and train the basic versions of the main deep unsupervised models and shall be able to appreciate the intricacies of implementing and training more complex versions of the models. Students shall be aware of classical as well as recent use-cases for the models, their challenges and strategies to tackle them, as well as of current limitations for the models.		
<b>Modulinhalte</b>	In this course we shall cover the fundamental ideas of deep unsupervised learning, generative modelling and self-supervised learning. We will explore the main types of models for deep unsupervised learning: autoregressive models, flow models, latent variable models, generative adversarial networks and diffusion models. We will discuss their motivation, mathematical description as well as their practical implementation. We will investigate the the strengths and weaknesses of the models for various tasks and data modalities. We will put the models into the context of modern AI and establish the links to foundational models, unsupervised distribution alignment, compression and AI for science. The course will be organized as a seminar with strong focus on independent work of the students. Students will be expected to follow pre-recorded videos and read recommended papers which will be further discussed in the class. An important part of the course will be coding homeworks, where students shall implement and train the main unsupervised deep learning architectures.		

	Throughout the whole course students will be supported by common discussion and question&answer sessions, online discussion forum as well as the possibility for one-on-one consultation sessions.
<b>Literatur</b>	Videos and slides of the Berkeley course on deep unsupervised learning - <a href="https://sites.google.com/view/berkeley-cs294-158-sp24/home">https://sites.google.com/view/berkeley-cs294-158-sp24/home</a> Papers referred to in the Berkeley course Material (slides, papers and other artifacts) distributed in the class

# Semester 3

## Bayesian Statistics and Learning (5171518)

### *Bayesian Statistics and Learning*

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Sommersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 3	<b>Lehr- und Lernformen</b> Seminaristischer Unterricht
<b>Modulverantwortung</b>	Prof. Dr. Martin Storath		
<b>Dozierende</b>	Prof. Dr. Martin Storath		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> Mathematical Foundations of AI must be completed		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Schriftliche Prüfung <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	<ul style="list-style-type: none"> <li>• Develop a comprehensive understanding of statistical methods including Bayes's Theorem, various probability distributions, hypothesis testing, and regression analysis.</li> <li>• Gain expertise in Bayesian statistics, covering concepts like conjugate priors, Markov Chain Monte Carlo (MCMC) techniques, and approximate Bayesian computation.</li> <li>• Acquire skills to apply statistical methods to real-world scenarios using Python.</li> </ul>		
<b>Modulinhalte</b>	<ul style="list-style-type: none"> <li>• Distributions and conjugate priors</li> <li>• Estimation techniques</li> <li>• Decision analysis</li> <li>• Testing</li> <li>• Classification techniques</li> <li>• Inference</li> <li>• Computational methods</li> </ul>		
<b>Literatur</b>	Allen B. Downey, Think Bayes 2, online publication B. Lambert, A student's guide to Bayesian Statistics, SAGE Publications, 2018 G. James, D. Witten, T. Hastie, R. Tibshirani: An Introduction to Statistical Learning, Second Edition, Springer, 2021		



## Computational Mechanization of Reasoning (5171520)

### Computational Mechanization of Reasoning

<b>Art des Moduls</b> Wahlpflichtmodul	<b>Sprache</b> Englisch	<b>SWS</b> 4	<b>ECTS</b> 5
<b>Häufigkeit</b> Jedes Sommersemester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 3	<b>Lehr- und Lernformen</b> Seminar
<b>Modulverantwortung</b>	Prof. Dr. Pascal Meißner		
<b>Dozierende</b>	Dr. Alex Goeßmann		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 150	<i>Präsenzzeit</i> 60	<i>Selbststudium</i> 90
<b>Voraussetzungen</b>	<i>nach SPO:</i> keine <i>empfohlen:</i> keine		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Mündliche Prüfung <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	Students will be enabled to <ul style="list-style-type: none"> <li>• understand the principles of logical and probabilistic reasoning</li> <li>• apply tensor networks to design efficient reasoning algorithms</li> <li>• learn and infer graphical models such as Markov Logic Networks</li> <li>• design Knowledge Graphs respecting Semantic Web Standards</li> <li>• work on research topics of the ENEXA project</li> </ul>		
<b>Modulinhalte</b>	The module is an introduction to the research topics of the ENEXA project ( <a href="https://enexa.eu">https://enexa.eu</a> ). Starting with the principles of logical and probabilistic reasoning we will apply the formalism of tensor networks to mechanize reasoning in an efficient way. In particular the following topics will be treated: <ul style="list-style-type: none"> <li>• Principles of Logical Reasoning: Syntax, Semantics, Inference algorithms</li> <li>• Tensor Networks for Logical Reasoning: Representation of Semantics, Sparsity of Sentences</li> <li>• Graphical Models: Tensor Network representation, Bayesian Networks, Markov Logic Networks</li> <li>• Principles of Probabilistic Reasoning: Variable Elimination, Gibbs Sampling</li> <li>• Knowledge Graphs: Semantic Web Standards, Description Logic Reasoners</li> <li>• Inductive Reasoning: Inductive Logic Programming, Maximum Likelihood Estimation</li> </ul> All topics will be accompanied by demonstrations and exercises based on the python library <code>tnreason</code> (developed within ENEXA).		
<b>Literatur</b>	<ul style="list-style-type: none"> <li>• Russel, Norvig: Artificial Intelligence - A Modern Approach (Fourth Edition), Pearson Education 2021</li> <li>• Kolda, Bader: Tensor Decompositions and Applications, SIAM 2009</li> <li>• Koller, Friedman: Probabilistic Graphical Models - Principles and Techniques, MIT Press 2009</li> <li>• Murphy: Machine Learning - A Probabilistic Perspective, MIT 2012</li> <li>• Brachman, Levesque: Knowledge Representation and Reasoning, Morgan Kaufman 2004</li> </ul>		

## Master Thesis (5171130)

### Master Thesis

<b>Art des Moduls</b> Pflichtmodul	<b>Sprache</b> Deutsch/Englisch	<b>SWS</b> 0	<b>ECTS</b> 25
<b>Häufigkeit</b> Jedes Semester	<b>Dauer</b> 1 Semester	<b>Studiensemester</b> 3	<b>Lehr- und Lernformen</b>
<b>Modulverantwortung</b>	Prof. Dr. Pascal Meißner		
<b>Dozierende</b>	Prof. Dr. Arndt Balzer, Prof. Dr. Frank Deinzer, Prof. Dr. Frank-Michael Schleif, Prof. Dr. Magda Gregorová, Prof. Dr. Pascal Meißner, Prof. Dr. Ivan Yamshchikov		
<b>Verwendbarkeit</b>	Master Artificial Intelligence		
<b>Aufwand</b>	<i>Gesamt</i> 750	<i>Präsenzzeit</i> 0	<i>Selbststudium</i> 750
<b>Voraussetzungen</b>	<i>nach SPO:</i> 50 ECTS points  <i>empfohlen:</i> Regarding the actual writing of the thesis it is strongly recommended that the \ "Scientific seminar\" is already completed.		
<b>Prüfung</b>	<i>Art der Prüfung:</i> Thesis  <i>Art der Note:</i> Differenzierte Note		
<b>Lernergebnisse</b>	With the submission of a Master's thesis and the successful assessment, students document that they have understood the teaching content of the previous semesters and are able to apply it to tasks independently and successfully. They are able to derive an innovative research question on a selected research area, which includes a sufficiently significant and as yet unresearched research field. They can work on this research question largely independently with an appropriate and meaningful research design and lead to an objectively comprehensible, reliable and valid result. The written result is at the level of international standards of scientific publications and, upon successful completion, demonstrates the competences in terms of connectivity in the direction of doctoral projects.		
<b>Modulinhalte</b>	Independent preparation of a thesis and processing of a theoretical or practical task according to scientific methods.		
<b>Literatur</b>	Is provided based on the topic, but needs also to be identified by the student as part of the master thesis.		

## Modulverzeichnis

Artificial Intelligence and Machine Learning.....	4
Artificial Neural Networks and Cognitive Models.....	6
Ausgewählte Kapitel der Embedded Systems.....	21
Bayesian Statistics and Learning.....	40
Cloud Native.....	15
Competitive Programming.....	34
Computational Creativity.....	35
Computational Mechanization of Reasoning.....	41
Entrepreneurship for Engineers.....	17
Ethics and Regulation of AI.....	18
Fundamentals of Mobile Robotics.....	23
Learning of structured data.....	24
Master Thesis.....	42
Mathematical Foundations of AI.....	8
Parallel Programming.....	9
Project Module 1.....	10
Project Module 2.....	11
Project Module II.....	26
Reasoning and Decision Making under Uncertainty.....	12
Scientific seminar.....	27
Semantic data processing and representation.....	29
Trustworthy AI and AI regulations.....	31
Unsupervised Deep Learning.....	37