Mathematical and Theoretical Foundations of AI (5171010)

Englischer Titel	Mathematical and Theoretical Foundations of AI					
Art des Moduls	Pflichtmodul		**Modulverantwortliche(r)**		Prof. Dr. Frank-Michael Schleif	
Dozent(in)	Prof. Dr. Martin Storath, Prof. Dr. Kai Diethelm					
Sprache	Englisch		**Studiensemester**		1	
SWS	4		**Lehr- und Lernformen**		Seminaristischer Unterricht	
ECTS-Punkte	5		**Art der Prüfung**		Schriftliche Prüfung	
Bonusleistungen						
Arbeitsaufwand	**Gesamt**	150	**Präsenzzeit**	60	**Selbststudium**	90
Dauer	1 Semester		**Angeboten**		Sommersemester	
Art der Note	Differenzierte Note		**Verwendbarkeit**		Artificial Intelligence	
Voraussetzungen nach SPO	None					
Empfohlende Voraussetzungen						
Lernergebnis des Moduls	- 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. - Students understand the principles of continuous optimization (constrained and unconstrained), are able to select appropriate approaches and they apply them for problems in AI. - 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. - 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.					
Inhalte des Moduls	1. Advanced Vector Calculus • Multivariate derivatives and chain rule • Backpropagation and automatic differentiation • Linearization and multivariate Taylor series 2. Advanced Linear Algebra • Eigenvalues and eigenvectors • Singular value decomposition • Matrix approximation 3. Continuous Optimization • Gradient descent • Constrained optimization and Lagrange multipliers • Convex Optimization 4. Models and Data • Change of variables • Empirical risk minimization • Parameter estimation • Probabilistic modelling and inference • Model selection 5. Basic Applications for AI systems • Linear Regression • Dimensionality Reduction with Principal Component Analysis (PCA) • Density Estimation with Gaussian Mixture Models					
Literatur	1. M. P. Deisenroth, A. A. Faisal, Cheng Soon Ong: Mathematics for Machine Learning, Cambridge University Press, 2020 2. C. M. Bishop: Pattern Recognition and Machine Learning, Springer, 2006 3. G. James, D. Witten, T. Hastie, R. Tibshirani: An Introduction to Statistical Learning, Second Edition, Springer, 2021					

Artificial Intelligence and Machine Learning (5171020)

<table>
<tr><td>Englischer Titel</td><td colspan="6">Artificial Intelligence and Machine Learning</td></tr>
<tr><td>Art des Moduls</td><td colspan="2">Pflichtmodul</td><td colspan="2">Modulverantwortliche(r)</td><td colspan="2">Prof. Dr. Frank-Michael Schleif</td></tr>
<tr><td>Dozent(in)</td><td colspan="6">Prof. Dr. Frank-Michael Schleif</td></tr>
<tr><td>Sprache</td><td colspan="2">Englisch</td><td colspan="2">Studiensemester</td><td colspan="2">1</td></tr>
<tr><td>SWS</td><td colspan="2">4</td><td colspan="2">Lehr- und Lernformen</td><td colspan="2">Seminaristischer Unterricht</td></tr>
<tr><td>ECTS-Punkte</td><td colspan="2">5</td><td colspan="2">Art der Prüfung</td><td colspan="2">Schriftliche Prüfung</td></tr>
<tr><td>Bonusleistungen</td><td colspan="6"></td></tr>
<tr><td>Arbeitsaufwand</td><td>Gesamt</td><td>150</td><td>Präsenzzeit</td><td>60</td><td>Selbststudium</td><td>90</td></tr>
<tr><td>Dauer</td><td colspan="2">1 Semester</td><td colspan="2">Angeboten</td><td colspan="2">Sommersemester</td></tr>
<tr><td>Art der Note</td><td colspan="2">Differenzierte Note</td><td colspan="2">Verwendbarkeit</td><td colspan="2">Artificial Intelligence</td></tr>
<tr><td>Voraussetzungen nach SPO</td><td colspan="6">None</td></tr>
<tr><td>Empfohlende Voraussetzungen</td><td colspan="6"></td></tr>
<tr><td>Lernergebnis des Moduls</td><td colspan="6">Upon completion of the module students:
• 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
• 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
• 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)
• can follow and grasp formal description of standard machine learning algorithms and translate these into a working implementation in standard machine learning software
• 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</td></tr>
<tr><td>Inhalte des Moduls</td><td colspan="6">• Main concepts and principles of machine learning
- Basic types of machine learning (supervised/ unsupervised / reinforcement learning) and their use
- Main learning goals (prediction - regression/ classification, knowledge discovery – clustering / density estimation, etc.)
- Formalism of the learning problem
- Ethical and societal impacts of machine learning
• Foundations of learning from data
- Objective (loss) function
- Expected/ empirical risk
- Model complexity (over-/ under-fitting)
- Model training/ validation/ testing
- Model evaluation/ selection
• Selected key machine learning algorithms
- Linear models for regression/classification
- Regularization, ridge regression
- Variable selection, sparse models (lasso)
- Mixture models (k-means clustering, Gaussian mixtures)
- Non-parametric methods (kernels, trees, forests)
• Programming for machine learning
- Python and packages (Numpy, Pandas, Sci-kit learn, Jupyter Notebooks, and other)</td></tr>
<tr><td>Literatur</td><td colspan="6">1. Bishop, Christopher M. Pattern Recognition and Machine Learning. Information Science and Statistics. New York: Springer, 2006.
2. Murphy, Kevin P. Machine Learning: A Probabilistic Perspective. Adaptive Computation and Machine Learning Series. Cambridge, MA: MIT Press, 2012.
3. Hastie, Trevor, Robert Tibshirani, and JeromeFriedman. The Elements of Statistical Learning. Springer Series in Statistics. New York, NY, USA: Springer New York Inc., 2001.</td></tr>
</table>

Artificial Neural Networks and Cognitive Models (5171030)

<table>
<tr><td>Englischer Titel</td><td colspan="6">Artificial Neural Networks and Cognitive Models</td></tr>
<tr><td>Art des Moduls</td><td colspan="2">Pflichtmodul</td><td colspan="2">Modulverantwortliche(r)</td><td colspan="2">Prof. Dr. Magda Gregorová</td></tr>
<tr><td>Dozent(in)</td><td colspan="6">Prof. Dr. Magda Gregorová</td></tr>
<tr><td>Sprache</td><td colspan="2">Englisch</td><td colspan="2">Studiensemester</td><td colspan="2">1</td></tr>
<tr><td>SWS</td><td colspan="2">4</td><td colspan="2">Lehr- und Lernformen</td><td colspan="2">Seminaristischer Unterricht</td></tr>
<tr><td>ECTS-Punkte</td><td colspan="2">5</td><td colspan="2">Art der Prüfung</td><td colspan="2">Portfolio</td></tr>
<tr><td>Bonusleistungen</td><td colspan="6"></td></tr>
<tr><td>Arbeitsaufwand</td><td>Gesamt</td><td>150</td><td>Präsenzzeit</td><td>60</td><td>Selbststudium</td><td>90</td></tr>
<tr><td>Dauer</td><td colspan="2">1 Semester</td><td colspan="2">Angeboten</td><td colspan="2">Sommersemester</td></tr>
<tr><td>Art der Note</td><td colspan="2">Differenzierte Note</td><td colspan="2">Verwendbarkeit</td><td colspan="2">Artificial Intelligence</td></tr>
<tr><td>Voraussetzungen nach SPO</td><td colspan="6">None</td></tr>
<tr><td>Empfohlende Voraussetzungen</td><td colspan="6"></td></tr>
<tr><td>Lernergebnis des Moduls</td><td colspan="6">Upon completion of the module students:
• 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
• 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
• 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
• 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
• are aware of the ethical and societal impacts of machine learning and deep learning and can critically assess deep learning reports along these lines</td></tr>
<tr><td>Inhalte des Moduls</td><td colspan="6">• Artificial neural networks (ANN) in machine learning (ML)
- Basic concepts of learning algorithms and typical tasks
- Model development workflow, hyperparameter tunning, performance measures and model selection
- Ethical and societal aspects (open access, data governance, fairness, transparency, reproducibility, safety and robustness, interpretability and human oversight/trust, ecological footprint)
• Basic ANN architectures
- Multilayer perceptron (feed forward)
- Convolutional neural networks
- Recurrent neural networks
• ANN model regularization
- Norm penalties
- Data augmentation
- Early stopping
- Dropout
• ANN model optimization
- (Stochastic) gradient descent
- Backpropagation
- Momentum methods
- Learning rate scheduling
• Major ANN applications and selected advanced models
- Computer vision (object detection, image classification, style transfer)
- Natural language processing (word2vec, BERT)
- Autoencoders
- Generative models
• Deep learning software packages (one of these)
- PyTorch
- Tensorflow</td></tr>
<tr><td>Literatur</td><td colspan="6">1. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. Deep Learning. MIT Press, 2016
2. Zhang, Aston, Zachary C. Lipton, Mu Li, and Alexander J. Smola. Dive into Deep Learning. https://d2l.ai/, 2021</td></tr>
</table>

Reasoning and Descision Making under Uncertainty (5171040)

<table>
<tr><td>Englischer Titel</td><td colspan="6">Reasoning and Descision Making under Uncertainty</td></tr>
<tr><td>Art des Moduls</td><td colspan="2">Pflichtmodul</td><td colspan="2">Modulverantwortliche(r)</td><td colspan="2">Prof. Dr. Frank Deinzer</td></tr>
<tr><td>Dozent(in)</td><td colspan="6">Prof. Dr. Frank Deinzer</td></tr>
<tr><td>Sprache</td><td colspan="2">Englisch</td><td colspan="2">Studiensemester</td><td colspan="2">1</td></tr>
<tr><td>SWS</td><td colspan="2">4</td><td colspan="2">Lehr- und Lernformen</td><td colspan="2">Seminaristischer Unterricht</td></tr>
<tr><td>ECTS-Punkte</td><td colspan="2">5</td><td colspan="2">Art der Prüfung</td><td colspan="2">Portfolio</td></tr>
<tr><td>Bonusleistungen</td><td colspan="6"></td></tr>
<tr><td>Arbeitsaufwand</td><td>Gesamt</td><td>150</td><td>Präsenzzeit</td><td>60</td><td>Selbststudium</td><td>90</td></tr>
<tr><td>Dauer</td><td colspan="2">1 Semester</td><td colspan="2">Angeboten</td><td colspan="2">Sommersemester</td></tr>
<tr><td>Art der Note</td><td colspan="2">Differenzierte Note</td><td colspan="2">Verwendbarkeit</td><td colspan="2">Artificial Intelligence</td></tr>
<tr><td>Voraussetzungen nach SPO</td><td colspan="6">Keine</td></tr>
<tr><td>Empfohlende Voraussetzungen</td><td colspan="6"></td></tr>
<tr><td>Lernergebnis des Moduls</td><td colspan="6">- Students develop further knowledge and skills on the necessary mathematical foundations for understanding and developing algorithms for AI.
- Students can apply the principles of Reinforcement Learning algorithms
- Students can use the principles of modelling gents, environments and rewards.
- Students understand the necessity of function approximations in learning.
- Students understand the concepts of statiscal sensor fusion
- Students can realize sensor fusion applications
- Students build on their acquired knowledge to master learning problems.</td></tr>
<tr><td>Inhalte des Moduls</td><td colspan="6">The course is composed of 2 thematic blocks.

Block A: Reinformcement Learning
1. Basic Reinforcement Learning Concepts
- Actions and States
- Goals, Rewards, Returns and Episodes
- Policies and Value Functions
2. Basic Reinforcement Learning Methods
- Finite Markov Decision Processes
- Dynamic Programming
- Monte Carlo Methods
3. Advanced tabular learning Methods
- Temporal-Difference Learning
- Bootstrapping Methods
4. Learning in Continuous State and Action Spaces
- On-Policy Approximation
- Value-function Approximation
- Off-Policy Approximation
- Approximate Eligibility Traces
5. Value Function Approximation Case Studies
- Computer Vision: Action planning
- Mastering Games: Backgammon, Go
6. Applications and Exercises

Block B: Sensor Fusion
1. Using Bayes for Sensor Data Fusion
- Modeling and Estimation of Densities
- Sensor Fusion over Time
2. Hidden Markov Models and Viterbi Algorithm
3. Recursive State Estimation
- Gaussian Filters
- Nonparametric Filters
4. Applications</td></tr>
<tr><td>Literatur</td><td colspan="6">1. Sutton, Barto. Reinforcement Learning - An Introduction. Bradford Books, 2018
2. Thorp. Beat the Dealer. Random House. 1966
3. Mitchell. Data Fusion: Concepts and Ideas. Springer. 2014
4. Thrun, Burgard, Fox: Probabilistic Robotics. MIT Press. 2005

Further specialized literature will be announced in the course.</td></tr>
</table>

Parallel Programming (5171510)

<table>
<tr><td>Englischer Titel</td><td colspan="6">Parallel Programming</td></tr>
<tr><td>Art des Moduls</td><td colspan="2">Wahlpflichtmodul</td><td colspan="2">Modulverantwortliche(r)</td><td colspan="2">Prof. Dr. Frank-Michael Schleif</td></tr>
<tr><td>Dozent(in)</td><td colspan="6">Prof. Dr. Kai Diethelm</td></tr>
<tr><td>Sprache</td><td colspan="2">Englisch</td><td colspan="2">Studiensemester</td><td colspan="2">1</td></tr>
<tr><td>SWS</td><td colspan="2">4</td><td colspan="2">Lehr- und Lernformen</td><td colspan="2">Seminaristischer Unterricht, Seminar</td></tr>
<tr><td>ECTS-Punkte</td><td colspan="2">5</td><td colspan="2">Art der Prüfung</td><td colspan="2">Portfolio</td></tr>
<tr><td>Bonusleistungen</td><td colspan="6"></td></tr>
<tr><td>Arbeitsaufwand</td><td>Gesamt</td><td>150</td><td>Präsenzzeit</td><td>60</td><td>Selbststudium</td><td>90</td></tr>
<tr><td>Dauer</td><td colspan="2">1 Semester</td><td colspan="2">Angeboten</td><td colspan="2">Unregelmäßig</td></tr>
<tr><td>Art der Note</td><td colspan="2">Differenzierte Note</td><td colspan="2">Verwendbarkeit</td><td colspan="2">Artificial Intelligence</td></tr>
<tr><td>Voraussetzungen nach SPO</td><td colspan="6">None</td></tr>
<tr><td>Empfohlende Voraussetzungen</td><td colspan="6"></td></tr>
<tr><td>Lernergebnis des Moduls</td><td colspan="6">None</td></tr>
<tr><td>Inhalte des Moduls</td><td colspan="6">• Parallel computers (shared memory, distributed memory)
• SISD, SIMD, MIMD
• OpenMP, MPI
• Code analysis and optimization (bottlenecks etc.)</td></tr>
<tr><td>Literatur</td><td colspan="6">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</td></tr>
</table>

Conversational AI – Virtual Assistants und Chatbots (IBM Watson Chatbot

<table>
<tr><td>Englischer Titel</td><td colspan="6">Conversational AI – Virtual Assistants and Chatbots (IBM Watson Chatbot Challenge 2022)</td></tr>
<tr><td>Art des Moduls</td><td colspan="2">Wahlpflichtmodul</td><td colspan="2">Modulverantwortliche(r)</td><td colspan="2">Prof. Dr. Christian Bachmeir</td></tr>
<tr><td>Dozent(in)</td><td colspan="6">Prof. Dr. Christian Bachmeir</td></tr>
<tr><td>Sprache</td><td colspan="2">Deutsch/Englisch</td><td colspan="2">Studiensemester</td><td colspan="2">1,2</td></tr>
<tr><td>SWS</td><td colspan="2">4</td><td colspan="2">Lehr- und Lernformen</td><td colspan="2">Seminar, Projekt</td></tr>
<tr><td>ECTS-Punkte</td><td colspan="2">5</td><td colspan="2">Art der Prüfung</td><td colspan="2">Projektarbeit</td></tr>
<tr><td>Bonusleistungen</td><td colspan="6"></td></tr>
<tr><td>Arbeitsaufwand</td><td>Gesamt</td><td>150</td><td>Präsenzzeit</td><td>60</td><td>Selbststudium</td><td>90</td></tr>
<tr><td>Dauer</td><td colspan="2">1 Semester</td><td colspan="2">Angeboten</td><td colspan="2">Unregelmäßig</td></tr>
<tr><td>Art der Note</td><td colspan="2">Differenzierte Note</td><td colspan="2">Verwendbarkeit</td><td colspan="2">Informationssysteme, Artificial Intelligence</td></tr>
<tr><td>Voraussetzungen nach SPO</td><td colspan="6">keine</td></tr>
<tr><td>Empfohlende Voraussetzungen</td><td colspan="6"></td></tr>
</table>

Lernergebnis des Moduls	1) Overall objective • Students can explain conversational systems by using conversational terms such as: entities, intents, utterances, context, slots/parameters, actions, dialogue design, disambiguation, digression, events, response, broadcast/push notifications and fulfilment • Students can describe how knowledge-based systems and knowledge engineering could help to increase the natural language understanding (NLU) • Students can describe how machine learning, intent matching, entity extraction, dialogue design and context can increase the user experience and containment • Students can identify and solve a business case applying the Enterprise Design Thinking methodology, can train and integrate a virtual assistant • Students identify the cost, benefit, flexibility, and risk factors that affect the investment decision, can explain ROI and indicate the PV, NPV 2) Objective: Professional skills • Students can execute a requirements elicitation phase for an AI-powered virtual assistant • Students can design and construct a conversational system • Students develop a data model • Students train the virtual assistant with client data • Students can construct and implement a conversational AI prototype, pilot or proof-of-concept • Students can integrate backend services or APIs in the client environment or external webpage • Students can address and integrate virtual assistant systems and other channels • Students solve a client use case 3) Objective: Problem-solving and critical thinking Students can identify use case by exercising Enterprise AI Design Thinking • Students should be able to analyze and answer complex questions about the structure and dynamics of conversational flows • Students can justify an overall conversational architecture based on a prior requirements analysis and/or design process • Students should be able to assess the strengths and weaknesses of their work • Students can outline further implementation flavors • Students can identify potential for further enhancements of the virtual assistant depending on the use case (e. g. encorporating further Watson Services, connecting to an IVR system, adding more user languages, preprocessing the user utterance, process automation, incorporating webservices, etc.) 4) Objective: Method skills • Understand and apply the core concepts of conversational analysis by structuring and infusing the data into Watson Assistant • Solve a business case by identifying the appropriate tools and services that support a user-oriented solution 5) Objective: Communication skills • Students can communicate best practices for building a conversational AI solution • Students understand the client’s requirements and know how to translate those into milestones • Students can manage the client’s expectations • Students can demonstrate and explain their solution to a non-technical audience 6) Objective: Interpersonal skills • Students can investigate self-directedly further machine learning and/or knowledge engineering methods based on the conversational scenario • Students will work cooperatively within their teams in order to solve the business problem together • Students will take over responsibility and accountability for the work that they have committed themselves

Inhalte des Moduls	Conversational artificial intelligence (AI) is no longer science fiction, but an increasingly mainstream capability with which consumers interact daily in their homes, workplaces, and on the go. Usually known as bots, chatbots, or virtual assistants, this conversational AI makes up a crowded and confusing enterprise market, leading buyers with many “bot” versions that may not talk to each other effectively. Watson Assistant is IBM’s virtual assistant solution that allows users to interact with business systems using natural human language. IBM has married a technically robust conversational platform with developer and line-of-businessfriendly tools with the breadth of the broader Watson portfolio. Enterprises can build and train the AI solution to serve a wide range of use cases across applications, devices, and channels. The module aims are to design enterprise-specific conversational use cases and implement them using state-of-the-art frameworks of IBM Watson Assistant. You will get insights into: * the conversational design, * natural language processing (NLP) * in general and specifically in natural language understanding (NLU) and generation (NLG) * as well as dialogue design. Further, you will get a glimpse into machine learning and knowledge engineering depending on the group project requirements and students preferences. The assessment is a group project focussing in a cross-functional team on a provided or real use case and a prototypical implementation during the course. These virtual assistants aim to create and solve a real business case of real companies. They are presented and evaluated by the companies at a final presentation. In this independent study module, 20% of the classroom time will be coaching; the first two sessions will be classical/ directed input and hands-on lecture; later the learning is self-directed by working on the group work. There will be a mid-term checkpoint to ensure the milestones of the project are on track. Contents 1) Motivation and history • Enterprise AI Design Thinking • AI and non-AI Methods for Chatbot/Virtual Assistant • Conversational AI and Bot Lifecycle • Conversational Design and Engineering Process • Use Case Ideation and/or Requirements Gathering • Conversational and User Experience (UX) • General approach to Cognitive Computing - Cognitive Computing flavours • Introduction into Piloting and MVP • Integration of Conversational Channels • Introduction into Watson Assistant 2) Core concepts and methods • Fundamental concepts of AI • Provision of service instances in IBM Cloud account • Introduction to Watson Assistant main concepts • Conversational Prototyping and Implementation • Data model (Intents & Entities) • Ground truth (Training Data) • Basic Conversational dialogue design • Designing Multi-turn interactions • Optional: Search Skill • Decision trees and dialog features • Conversational Service Integration and Fulfillment 3) Advanced topics • Programing User Interface • REST API calls • Analytics and conversation analysis • Integration (Chat Widget / Webhooks) • Handing over the conversation to an agent (Triage) • Connecting other Watson Services for preprocessing data • Testing methods for accuracy and containment 4) Application • Introduction to Watson Conversation concepts • Chatbot Challenge Introduction and description • Client introduction • Instructions (Cooperation with client / Professors) • Criteria's to evaluate each team • Collecting use case requirements • Managing expectation • Defining goals and milestones

Literatur	* Slides with methodological requirements and optional further readings will be handed out to sTudents at the beginning of the semester. * Online resources: IBM Cloud, Watson Assistant, Watson Discovery

Project Module (5171060)

<table>
<tr><td>Englischer Titel</td><td colspan="6">Project Module</td></tr>
<tr><td>Art des Moduls</td><td colspan="2">Pflichtmodul</td><td colspan="2">Modulverantwortliche(r)</td><td colspan="2">Prof. Dr. Frank-Michael Schleif</td></tr>
<tr><td>Dozent(in)</td><td colspan="6">Prof. Dr. Frank-Michael Schleif</td></tr>
<tr><td>Sprache</td><td colspan="2">Englisch</td><td colspan="2">Studiensemester</td><td colspan="2">1,2</td></tr>
<tr><td>SWS</td><td colspan="2">8</td><td colspan="2">Lehr- und Lernformen</td><td colspan="2">Projekt</td></tr>
<tr><td>ECTS-Punkte</td><td colspan="2">10</td><td colspan="2">Art der Prüfung</td><td colspan="2">Projektarbeit</td></tr>
<tr><td>Bonusleistungen</td><td colspan="6"></td></tr>
<tr><td>Arbeitsaufwand</td><td>Gesamt</td><td>300</td><td>Präsenzzeit</td><td>120</td><td>Selbststudium</td><td>180</td></tr>
<tr><td>Dauer</td><td colspan="2">2 Semester</td><td colspan="2">Angeboten</td><td colspan="2">Jedes Semester</td></tr>
<tr><td>Art der Note</td><td colspan="2">Differenzierte Note</td><td colspan="2">Verwendbarkeit</td><td colspan="2">Artificial Intelligence</td></tr>
<tr><td>Voraussetzungen nach SPO</td><td colspan="6">None</td></tr>
<tr><td>Empfohlende Voraussetzungen</td><td colspan="6"></td></tr>
<tr><td>Lernergebnis des Moduls</td><td colspan="6">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.</td></tr>
<tr><td>Inhalte des Moduls</td><td colspan="6">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.</td></tr>
<tr><td>Literatur</td><td colspan="6">1. Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, A.Geron, O’Reilly, 2019
2. The Data Science Design Manual, S. Skiena, Springer, 2017
3. Deep Learning, I. Goodfellow, MIT Press, 2016
Further literature will be given based on the respective project tasks.</td></tr>
</table>

Cloud Native (5171512)

Englischer Titel	Cloud Native						
Art des Moduls	Wahlpflichtmodul		**Modulverantwortliche(r)**		Prof. Dr. Frank-Michael Schleif		
Dozent(in)	Dr. Harald Gerhards						
Sprache	Englisch		**Studiensemester**		1,2		
SWS	4		**Lehr- und Lernformen**		Seminar		
ECTS-Punkte	5		**Art der Prüfung**		Schriftliche Prüfung		
Bonusleistungen							
Arbeitsaufwand	**Gesamt**	150	**Präsenzzeit**	60	**Selbststudium**	90	
Dauer	1 Semester		**Angeboten**		Unregelmäßig		
Art der Note	Differenzierte Note		**Verwendbarkeit**		Artificial Intelligence		
Voraussetzungen nach SPO	none						
Empfohlende Voraussetzungen							
Lernergebnis des Moduls	Upon completion of the module, students will: • have an overview of the evolution of cloud computing and new architectures. • Be able to understand the architectural patterns of cloud native platforms and applications. • Be able to develop applications for container platforms on behalf of containerization principles. • Be able to understand vertical and horizontal scaling of applications. • Be able to maintain and configure monitoring and security components of Kubernetes platforms. • Be able to critically access approaches to versioning software artifacts and develop appropriate strategies for agile software projects. • Know the concepts of asynchronous communication using Apache Kafka. • Have solidified their knowledge on cloud native tools like Docker, Kubernetes, Helm, Apache Kafka and Git						

Inhalte des Moduls	Main Concepts of Cloud Computing • Definition of \"cloud native\" • Historical background • Cloud Native and Open Source • Major players (CNCF, Linux Foundation, Apache Foundation) Cloud Native Architecture • Principles and paradigms • Distributed systems • Representation Concepts (C4, UML) Containerization & Virtualization Principles • Container vs. Virtual Machine • Emergence of Docker • Container Images • Image Build • Composing Containers Container Orchestration • Horizontal and vertical scaling • Kubernetes artifacts • Cluster Network • Persistence in Kubernetes • Templating for Kubernetes • Monitoring and Logging • Kubernetes Management • Service Mesh Pub-Sub-Messaging Concepts • Apache Kafka • Distributed logs • Stream processing Versioning • Commit strategies • Branching strategies Development Operation Principles • DevOps • DevSecOps • CI/CD • GitOps
Literatur	Literature will be announced in the course.