Module Code	t.BA.DS.NLP.20HS						
ECTS Credits	4						
Language of Instruction/Examination	German						
Organizational Unit	CAI						
Module Coordinator	Mark Cieliebak						
Legal Framework	The module description is part of the legal basis in addition to the general academic regulations. It is binding. During the first week of the semester a written and communicated supplement can specify the module description in more detail.						
Module Characteristic	Type 2a						
	4 consecutive lecture lessons per semester week and class						
Module Description	This module introduces the basic methods and technologies of Natural Language Processing (NLP). Typical tasks and solution approaches are presented and implemented based on practice-oriented projects.						
	generation (e.g., abstractive summarization). For each task, the relevant solution approaches are presented. These include, but are not limited to, the following topics - Preprocessing of the data: Tokenization, stemming, etc Representation of the data: Vector-Space Models, TF-IDF, Pretrained Language Models/Embeddings etc Machine Learning Models and Algorithms: SVM, Neural Networks, etc Evaluation methods: Precision/Recall, F-Score, ROUGE etc Established tools and frameworks e.g. nltk, Pytorch, huggingface etc Experimental setup and documentation of resul For each task, students will develop a solution individually or in small groups of up to 3 people. The documentation of the solution will be assessed afterwards.						
	approaches are presented. These include, but are not - Preprocessing of the data: Tokenization, stemming, e data: Vector-Space Models, TF-IDF, Pretrained Langua Machine Learning Models and Algorithms: SVM, Neura methods: Precision/Recall, F-Score, ROUGE etc Esta e.g. nltk, Pytorch, huggingface etc Experimental setu For each task, students will develop a solution individu	limited to, the foll etc Representat ge Models/Ember Il Networks, etc Iblished tools and p and document Jally or in small g	owing topics: ion of the ddings etc · Evaluation d frameworks ation of result roups of up to				
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Prerequisite Knowledge Learning Objectives (Competences)	approaches are presented. These include, but are not   - Preprocessing of the data: Tokenization, stemming, edata: Vector-Space Models, TF-IDF, Pretrained Langua   Machine Learning Models and Algorithms: SVM, Neura   methods: Precision/Recall, F-Score, ROUGE etc Estate.g. nltk, Pytorch, huggingface etc Experimental setur   For each task, students will develop a solution individu   3 people. The documentation of the solution will be assisted   Students   The students know typical tasks in the field of NLP.   Students can integrate existing technical solutions for a problem into their problem solving.   Students can plan and document machine-based	limited to, the foll etc Representat ge Models/Ember al Networks, etc ablished tools and p and document ually or in small g sessed afterward Competencies F F, M	owing topics: ion of the ddings etc · Evaluation d frameworks ation of result roups of up to is. Taxonomies K1, K2 K1, K2, K3				
Learning Objectives	approaches are presented. These include, but are not i   - Preprocessing of the data: Tokenization, stemming, e   data: Vector-Space Models, TF-IDF, Pretrained Langua   Machine Learning Models and Algorithms: SVM, Neura   methods: Precision/Recall, F-Score, ROUGE etc Esta   e.g. nltk, Pytorch, huggingface etc Experimental setu   For each task, students will develop a solution individu   3 people. The documentation of the solution will be as:   Vectors can integrate existing technical solutions for a problem into their problem solving.   Students can plan and document machine-based experiments on textual data in a structured way.   The students can document their results in the form of a	limited to, the foll etc Representat ge Models/Ember Il Networks, etc ablished tools and p and document ually or in small g sessed afterward	owing topics: ion of the ddings etc Evaluation d frameworks ation of result roups of up to is. Taxonomies K1, K2 K1, K2, K3 K1, K2, K3				

Module description	on: Introducti	on to Na	tural Lan	iguage	Proce	ssing			
Performance Assessment	End-of-module exam	Assessment	Length (min.)	Weighting	Form				
	report	Grade	0	60	acc. to module agreement				
	Performance assessment during the semester		Assessment	Length (min.)	Weighting	Form			
	report		Grade	0	20	acc. to module agreement			
	report		Grade	0	20	acc. to module agreement			
Classroom Attendance Requirement	None								
Learning material	The necessary material is provided during in class.								
Comments	Individual performance can also have an influence on individual grades in group work, i.e. not all group members must always receive the same grade.								