

## Module Description

<b>Module name</b>					
<b>Data Assimilation for Fluid Dynamics</b>					
<b>Module no.</b>	<b>Credit Points</b>	<b>Workload</b>	<b>Self-study</b>	<b>Duration</b>	<b>Frequency</b>
04-10-0622/en	5 CP	150 h	105 h	1 Semester	Irregularly
<b>Language of Instruction</b>			<b>Person responsible for the Module</b>		
English			Prof. Dr. rer. nat. Moritz Egert		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0622-vu	Data Assimilation for Fluid Dynamics	0	Lecture and Exercise	3
<b>2</b>	<b>Study Content</b>				
	<p>Dynamical systems and control theory, feedback control (nudging approach), observational measurements, asymptotic stability, reference solutions, reconstruction of solutions without initial data.</p> <p>Classical data assimilation algorithms (Kalman filter, AOT), resolution of spatial mesh, nodal interpolation.</p> <p>Fundamental equations in fluid dynamics, Boussinesq approximation.</p>				
<b>3</b>	<b>Learning Outcomes</b>				
	<p>Students understand and are able to apply the notions, methods and results treated in the course. They develop an advanced level of understanding of partial differential equations through the methodology of data assimilation and are able to extend their knowledge in this field.</p>				
<b>4</b>	<b>Requirements for Participation</b>				
	Recommended: Functional Analysis, Partial Differential Equations I				
<b>5</b>	<b>Form of Examination</b>				
	<p>Final Module Examination:</p> <p style="padding-left: 40px;"><input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 60 min, Standard)</p> <p>Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated</p>				

	during the first two weeks of the lecture, based on the prospective number of students taking the exam.
<b>6</b>	<b>Requirements on the Award of Credit Points</b> Passing Technical Examination („Fachprüfung“)
<b>7</b>	<b>Grading</b> Final Module Examination:    <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)
<b>8</b>	<b>Usability of the Module</b> M. Sc. Mathematics, Mathematics in Data Science
<b>9</b>	<b>Literature</b> M. Tucsnak, G. Weiss: Observation and Control for Operator Semigroups (Springer) T.-P. Tsai: Lectures on Navier-Stokes Equations (AMS) S. Reich, C. Cotter: Probabilistic Forecasting and Bayesian Data Assimilation (Cambridge University Press)
<b>10</b>	<b>Comment</b>

## Module Description

<b>Module name</b>					
<b>Partial Differential Equations I</b>					
<b>Module no.</b> 04-10-0626/en	<b>Credit Points</b> 9 CP	<b>Workload</b> 270 h	<b>Self-study</b> 180 h	<b>Duration</b> 1 Semester	<b>Frequency</b> Every 2. semester
<b>Language of Instruction</b> English			<b>Person responsible for the Module</b> Prof. Dr. rer. nat. Matthias Hieber		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0626-vu	Partial Differential Equations I	0	Lecture and Exercise	6
<b>2</b>	<b>Study Content</b> Classical treatment of important types of equations (e.g. elliptic, parabolic, hyperbolic, dispersive), variational formulation of elliptic problems, regularity of solutions, theory of Sobolev spaces, Galerkin methods, fixed-point methods for non-linear elliptic and parabolic equations, theory of weak solutions for equations in fluid mechanics				
<b>3</b>	<b>Learning Outcomes</b> Students understand and are able to apply the notions, methods and results treated in the course. They develop an advanced level of understanding of partial differential equations and are able to extend their knowledge in this field.				
<b>4</b>	<b>Requirements for Participation</b> Recommended: Functional Analysis				
<b>5</b>	<b>Form of Examination</b> Final Module Examination:    <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 90 min, Standard)  Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated during the first two weeks of the lecture, based on the prospective number of students taking the exam.				
<b>6</b>	<b>Requirements on the Award of Credit Points</b> Passing the Technical Examination („Fachprüfung“)				

7	<b>Grading</b> Final Module Examination:    <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)
8	<b>Usability of the Module</b> M. Sc. Mathematics, Mathematics in Data Science
9	<b>Literature</b> L.C. Evans: Partial Differential Equations (AMS) D. Gilbarg, N.S. Trudinger: Elliptic Partial Differential Equations of Second Order (Springer) M. Renardy, R.C. Rogers: An Introduction to Partial Differential Equations (Springer)
10	<b>Comment</b>

## Module Description

<b>Module name</b>					
<b>Machine Learning for Fluid Dynamics</b>					
<b>Module no.</b>	<b>Credit Points</b>	<b>Workload</b>	<b>Self-study</b>	<b>Duration</b>	<b>Frequency</b>
04-10-0627/en	5 CP	150 h	150 h	1 Semester	Irregularly
<b>Language of Instruction</b>			<b>Person responsible for the Module</b>		
English			Prof. Dr. rer. nat. Dieter Bothe		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0627-vu	Machine Learning for Fluid Dynamics	0	Lecture and Exercise	0
<b>2</b>	<b>Study Content</b>				
	Navier-Stokes Equations (NSE) for two-phase incompressible flows with mass transfer. The unstructured Finite Volume method. The ALE and VOF methods for simulating incompressible two-phase flows. Deep Learning (DL) for general function approximation. Deep Learning for segregated solution algorithms for NSE. Physics-informed Machine Learning (Pi-ML) - a collocation method with Artificial Neural Networks. Designing Pi-ML models for segregated solution algorithms for NSE, and curvature approximation for two-phase flows.				
<b>3</b>	<b>Learning Outcomes</b>				
	The students can derive Navier-Stokes equations for two-phase incompressible flows with mass transfer from first principles, they can discretize PDEs using the unstructured finite volume method, and describe the relevant algorithms of the ALE and VOF two-phase flow simulation methods. The students can describe the training process of a Deep Neural Network, and the construction and training of a Physics-Informed Neural Network for (coupled) Partial Differential Equations. In exercises, students gather hands-on experiences in simulating incompressible two-phase flows using OpenFOAM, and designing and training (Pi-)ML models for fluid dynamics problems.				
<b>4</b>	<b>Requirements for Participation</b>				
	Recommended: Partial Differential Equations				
<b>5</b>	<b>Form of Examination</b>				
	Final Module Examination:				
	<input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 60 min, Standard)				
	Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an				

	oral exam. The decision about the form of the exam is taken and communicated during the first two weeks of the lecture, based on the prospective number of students taking the exam.
<b>6</b>	<b>Requirements on the Award of Credit Points</b> Passing the Technical Examination („Fachprüfung“)
<b>7</b>	<b>Grading</b> Final Module Examination:    □ • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)
<b>8</b>	<b>Usability of the Module</b> M. Sc. Mathematics, Mathematics in Data Science
<b>9</b>	<b>Literature</b> Moukalled, F., Mangani, L., Darwish, M. (2016). The finite volume method. In The finite volume method in computational fluid dynamics (pp. 103-135). Springer, Cham.  Maric, Tomislav, Jens Hopken, and Kyle Mooney. "The OpenFOAM technology primer." (2014).  Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., Yang, L. (2021). Physics-informed machine learning. Nature Reviews Physics, 3(6), 422-440.  Physics-Based ML in OpenFOAM - OpenFOAM Workshop Training: <a href="https://youtu.be/uKo3RD3yYrU?list=PLwSEyKg12dVYbpC2wy_RT2_azGUwZPCQ9">https://youtu.be/uKo3RD3yYrU?list=PLwSEyKg12dVYbpC2wy_RT2_azGUwZPCQ9</a>  OpenFOAM Data-Driven Technical Committee source code repositories: <a href="https://github.com/OFFDataCommittee">https://github.com/OFFDataCommittee</a>
<b>10</b>	<b>Comment</b>

## Module Description

<b>Module name</b>					
<b>Efficient Methods for Data Assimilation</b>					
<b>Module no.</b>	<b>Credit Points</b>	<b>Workload</b>	<b>Self-study</b>	<b>Duration</b>	<b>Frequency</b>
04-10-0619/en	5 CP	150 h	105 h	1 Semester	Irregularly
<b>Language of Instruction</b>			<b>Person responsible for the Module</b>		
English			Prof. Dr. rer. nat. Jan Giesselmann		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0619-vu	Efficient Methods for Data Assimilation	0	Lecture and Exercise	3
<b>2</b>	<b>Study Content</b>				
	Bayesian Formulation of Data Assimilation problems, Kalman smoothing, Markov-Chain Monte-Carlo method, Variational approaches (4DVar), Sequential approaches and 3DVar, Kalman filter and Ensemble Kalman filter; nudging methods (e.g. Luenberger observer) , model reduction methods; implementation of the above methods				
<b>3</b>	<b>Learning Outcomes</b>				
	The students know the most important methods of variational and sequential data assimilation. They understand their properties and numerical challenges arising when these methods are used in practise. They can choose appropriate data assimilation methods for specific applications and they can implement and analyse these methods.				
<b>4</b>	<b>Requirements for Participation</b>				
	Recommended: Einführung in die Stochastik (Introduction to Stochastics), Gewöhnliche Differentialgleichungen (Ordinary Differential Equations), Einführung in die Numerische Mathematik (Introduction to Numerical Analysis)				
<b>5</b>	<b>Form of Examination</b>				
	Final Module Examination:  <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 60 min, Standard)  Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated during the first two weeks of the lecture, based on the prospective number of students taking the exam.				

6	<b>Requirements on the Award of Credit Points</b> Passing Technical Examination („Fachprüfung“)
7	<b>Grading</b> Final Module Examination:   □ • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)
8	<b>Usability of the Module</b> M. Sc. Mathematics, Mathemaics in Data Science
9	<b>Literature</b> Kody Law, Andrew Stuart, Konstantinos Zygalakis; Data Assimilation: A mathematical introduction, Springer, 2015 Mark Asch, Marc Bocquet, Maelle Nodet; Data Assimilation: Methods, Algorithms and Applications, SIAM 2016
10	<b>Comment</b>



## Module Description

<b>Module name</b>					
<b>Numerics of PDEs with Uncertain Data</b>					
<b>Module no.</b>	<b>Credit Points</b>	<b>Workload</b>	<b>Self-study</b>	<b>Duration</b>	<b>Frequency</b>
04-10-0620/en	9 CP	270 h	180 h	1 Semester	Irregularly
<b>Language of Instruction</b>			<b>Person responsible for the Module</b>		
English			Prof. Dr. rer. nat. Jens Lang		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0620-vu	Numerics of PDEs with Uncertain Data	0	Lecture and Exercise	6
<b>2</b>	<b>Study Content</b>				
	<p>Examples of PDEs, weak solutions of elliptic PDEs, finite element method, error estimates, strong formulations of elliptic PDEs with uncertain data, Monte Carlo finite elements, multi-level Monte Carlo finite elements, weak formulations of elliptic PDEs with uncertain data, stochastic Galerkin method, Karhunen-Loeve expansion, weak solutions of parabolic PDEs, Method of Lines or Rothe Method with finite elements,</p> <p>implementation of the above methods</p>				
<b>3</b>	<b>Learning Outcomes</b>				
	<p>Students will be able to describe, explain and apply the main design principles of numerical solution methods for linear elliptic and parabolic partial differential equations with deterministic as well as uncertain data. They will be able to analyze, evaluate, implement and compare the methods.</p>				
<b>4</b>	<b>Requirements for Participation</b>				
	<p>Recommended: Introduction to Numerical Analysis, Numerical Methods for Ordinary Differential Equations</p>				
<b>5</b>	<b>Form of Examination</b>				
	<p>Final Module Examination:</p> <p style="text-align: center;">  <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 90 min, Standard)</p>				

	Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated during the first two weeks of the lecture, based on the prospective number of students taking the exam.
<b>6</b>	<b>Requirements on the Award of Credit Points</b> Passing Technical Examination („Fachprüfung“)
<b>7</b>	<b>Grading</b> Final Module Examination:    <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)
<b>8</b>	<b>Usability of the Module</b> M. Sc. Mathematics, Mathemaics in Data Science
<b>9</b>	<b>Literature</b> S. Brenner, R. Scott: Mathematical Theory of Finite Element Methods, Texts in Applied Mathematics, Vol. 15, Springer, 2008  S. Larsson, V. Thomée: Partial Differential Equations with Numerical Methods. Texts in Applied Mathematics, Vol. 45, Springer 2003.  G. J. Lord, C. E. Powell, and T. Shardlow. An Introduction to Computational Stochastic PDEs. Cambridge University Press, 2014.
<b>10</b>	<b>Comment</b>

## Module Description

<b>Module name</b>					
<b>Scalable Linear Solvers for Data Science</b>					
<b>Module no.</b>	<b>Credit Points</b>	<b>Workload</b>	<b>Self-study</b>	<b>Duration</b>	<b>Frequency</b>
04-10-0621/en	5 CP	150 h	105 h	1 Semester	Irregularly
<b>Language of Instruction</b>			<b>Person responsible for the Module</b>		
English			Prof. Dr. rer. nat. Jens Lang		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0621-vu	Scalable Linear Solvers for Data Science	0	Lecture and Exercise	3
<b>2</b>	<b>Study Content</b>				
	Preconditioning of linear systems of equations, conjugate gradient method, linear iterative methods, preconditioning with incomplete decompositions, subspace correction methods, hierarchical bases and multigrid methods, bandwidth minimisation				
<b>3</b>	<b>Learning Outcomes</b>				
	Students will be able to describe, explain and apply the main design principles of scalable linear solvers for Data Science. They will be able to analyze, evaluate, implement and compare the methods.				
<b>4</b>	<b>Requirements for Participation</b>				
	Recommended: Introduction to Numerical Analysis				
<b>5</b>	<b>Form of Examination</b>				
	Final Module Examination:				
	<input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 60 min, Standard)				
	Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated during the first two weeks of the lecture, based on the prospective number of students taking the exam.				
<b>6</b>	<b>Requirements on the Award of Credit Points</b>				
	Passing Technical Examination („Fachprüfung“)				

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7	<b>Grading</b> Final Module Examination:    □ • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)
8	<b>Usability of the Module</b> M. Sc. Mathematics, Mathemaics in Data Science
9	<b>Literature</b> Wolfgang Hackbusch, Iterative Solution of Large Sparse Systems of Equations, 2nd ed. 2016, Applied Mathematical Sciences Vol. 95, Springer International Publishing, 2016
10	<b>Comment</b>

## Module Description

<b>Module name</b>					
<b>Deep Learning Lab</b>					
<b>Module no.</b>	<b>Credit Points</b>	<b>Workload</b>	<b>Self-study</b>	<b>Duration</b>	<b>Frequency</b>
04-10-0618/en	5 CP	150 h	105 h	1 Semester	Irregularly
<b>Language of Instruction</b>			<b>Person responsible for the Module</b>		
English			Prof. Dr. Yann Disser		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0618-vu	Deep Learning Lab	0	Lecture and Exercise	3
<b>2</b>	<b>Study Content</b>				
	introduction to deep learning, mathematical foundations, Keras and TensorFlow, classification, convolutional neural nets, adversarial deep learning, text generation Possible societal implications will be addressed in the lecture				
<b>3</b>	<b>Learning Outcomes</b>				
	The students know and understand the concepts and methods taught in the course and can apply them. They have a thorough understanding of the formal foundations of deep learning. They are able to independently expand their knowledge of the field and pursue supervised research projects. Students are able to contextualize subject matter within the social context, critically assess the consequences, and act ethically and responsibly accordingly.				
<b>4</b>	<b>Requirements for Participation</b>				
	Recommended: Algorithmic Discrete Mathematics Einführung in die Optimierung (Introduction to optimization) programming expertise (ideally Python)				
<b>5</b>	<b>Form of Examination</b>				
	Final Module Examination:  <input type="checkbox"/> • Module Examination (Study Examination, Paper, Standard)  Study Examination („Studienleistung“): Presentation				
<b>6</b>	<b>Requirements on the Award of Credit Points</b>				
	Passing Study Examination („Studienleistung“)				
<b>7</b>	<b>Grading</b>				

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	Final Module Examination:   <input type="checkbox"/> • Module Examination (Study Examination, Paper, Weight: 0%, Standard)
<b>8</b>	<b>Usability of the Module</b> M. Sc. Mathematics, Mathematics in Data Science
<b>9</b>	<b>Literature</b> Deep Learning with Python (2nd edition) - François Chollet
<b>10</b>	<b>Comment</b>

## Module Description

<b>Module name</b>					
<b>Optimization Methods for Maschine Learning</b>					
<b>Module no.</b> 04-10-0624/en	<b>Credit Points</b> 5 CP	<b>Workload</b> 150 h	<b>Self-study</b> 105 h	<b>Duration</b> 1 Semester	<b>Frequency</b> Every 2. semester
<b>Language of Instruction</b> English			<b>Person responsible for the Module</b> Prof. Dr. rer. nat. Marc Pfetsch		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0624-vu	Optimization Methods for Maschine Learning	0	Lecture and Exercise	3
<b>2</b>	<b>Study Content</b> Foundations of Maschine learning, Classification (Support Vector Maschines), Matrix Completion, Sparse Regression, Lasso, Neural Networks (Deep Learning)				
<b>3</b>	<b>Learning Outcomes</b> After taking the course, the students have insight into machine learning. In particular, they know which mathematical optimization methods can be applied in this context and know their properties.				
<b>4</b>	<b>Requirements for Participation</b> Recommended: Introduction to Optimization, Discrete Optimization or Nonlinear Optimization				
<b>5</b>	<b>Form of Examination</b> Final Module Examination:  <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 60 min, Standard)  Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated during the first two weeks of the lecture, based on the prospective number of students taking the exam.				
<b>6</b>	<b>Requirements on the Award of Credit Points</b> Passing Technical Examination („Fachprüfung“)				
<b>7</b>	<b>Grading</b>				

	<p>Final Module Examination:</p> <p>  □ • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)</p>
<b>8</b>	<p><b>Usability of the Module</b></p> <p>M.Sc. Mathematics, Mathematics in Data Science</p>
<b>9</b>	<p><b>Literature</b></p> <p>Hastie, Tibshirani, Friedman: The Elements of Statistical Learning, Springer 2000</p> <p>Mitchell: Machine Learning. Mcgraw-Hill 1997</p> <p>Murphy: Machine Learning: A Probabilistic Perspective, MIT Press 2012</p> <p>Sra, Nowozin, Wright: Optimization for Machine Learning, MIT Press, 2012</p> <p>Miroslav Kubat: An Introduction to Machine Learning. Springer, 2015.</p>
<b>10</b>	<p><b>Comment</b></p>



## Module Description

<b>Module name</b>					
<b>Optimization Methods in Data Science</b>					
<b>Module no.</b> 04-10-0625/en	<b>Credit Points</b> 5 CP	<b>Workload</b> 150 h	<b>Self-study</b> 105 h	<b>Duration</b> 1 Semester	<b>Frequency</b> Every 2. semester
<b>Language of Instruction</b> English			<b>Person responsible for the Module</b> Prof. Dr. rer. nat. Marc Pfetsch		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0625-vu	Optimization Methods in Data Science	0	Lecture and Exercise	3
<b>2</b>	<b>Study Content</b> data preprocessing, (sparse) principal component analysis; clustering, k-means, semidefinite models; generative and adversarial models; sparse optimization				
<b>3</b>	<b>Learning Outcomes</b>				
<b>4</b>	<b>Requirements for Participation</b> Recommended: Introduction to Optimization; Discrete Optimization or Nonlinear Optimization				
<b>5</b>	<b>Form of Examination</b> Final Module Examination:  <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 60 min, Standard)  Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated during the first two weeks of the lecture, based on the prospective number of students taking the exam				
<b>6</b>	<b>Requirements on the Award of Credit Points</b> Passing the Technical Examination („Fachprüfung“)				
<b>7</b>	<b>Grading</b> Final Module Examination:				

	<ul style="list-style-type: none"> <li>□• Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)</li> </ul>
<b>8</b>	<b>Usability of the Module</b> M. Sc. Mathematics, Mathematics in Data Science
<b>9</b>	<b>Literature</b> Hastie, Tibshirani, Friedman: The Elements of Statistical Learning, Springer 2000 Mitchell: Machine Learning. Mcgraw-Hill 1997 Murphy: Machine Learning: A Probabilistic Perspective, MIT Press 2012 Sra,Nowozin, Wright: Optimization for Machine Learning, MIT Press, 2012 Miroslav Kubat: An Introduction to Machine Learning.Springer, 2015.
<b>10</b>	<b>Comment</b>

## Module Description

<b>Module name</b>					
<b>First-order methods for optimization in data analytics</b>					
<b>Module no.</b>	<b>Credit Points</b>	<b>Workload</b>	<b>Self-study</b>	<b>Duration</b>	<b>Frequency</b>
04-10-0623/en	5 CP	0 h	0 h	1 Semester	Irregularl
<b>Language of Instruction</b>			<b>Person responsible for the Module</b>		
English			Prof. Dr. rer. nat. Stefan Ulbrich		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0623-vu	First-order methods for optimization in data analytics	0	Lecture and Exercise	0
<b>2</b>	<b>Study Content</b>				
	<p>First-order methods are a highly active research field in optimization, in particular for applications in data analytics. They often combine primal-dual decomposition approaches with relatively simple iteration schemes and provide very efficient structure-exploiting algorithms for challenging large scale problems. This course gives an introduction into the design and theory of first-order proximal point and primal-dual optimization methods.</p>				
<b>3</b>	<b>Learning Outcomes</b>				
	<p>The students are able to apply and investigate important classes of first-order optimization methods, in particular proximal point and primal-dual methods. They are prepared for studying scientific developments and applications in this field independently.</p>				
<b>4</b>	<b>Requirements for Participation</b>				
	Recommended: Introduction to Optimization; Nonlinear Optimization				
<b>5</b>	<b>Form of Examination</b>				
	<p>Final Module Examination:</p> <p style="padding-left: 40px;"><input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 60 min, Standard)</p> <p>Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated during the first two weeks of the lecture, based on the prospective number of students taking the exam.</p>				
<b>6</b>	<b>Requirements on the Award of Credit Points</b>				

	Passing the Technical Examination („Fachprüfung“)
7	<p><b>Grading</b></p> <p>Final Module Examination:</p> <p>      <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)</p>
8	<p><b>Usability of the Module</b></p> <p>M. Sc. Mathematics, Mathematics in Data Science</p>
9	<p><b>Literature</b></p> <p>Stephen Boyd, Neal Parikh, Eric Chu, Borja Peleato, Jonathan Eckstein: Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers, Foundations and Trends in Machine Learning Vol. 3, No. 1 (2010), 1–122.</p> <p>Antonin Chambolle, Thomas Pock: A First-Order Primal-Dual Algorithm for Convex Problems with Applications to Imaging, Journal of Mathematical Imaging and Vision, Vol. 40, No. 1 (2011), 120-145.</p> <p>Christian Clason, Tuomo Valkonen: Intoduction to Nonsmooth Analysis, arXiv:2001.00216v3, <a href="https://doi.org/10.48550/arXiv.2001.00216">https://doi.org/10.48550/arXiv.2001.00216</a></p>
10	<b>Comment</b>

## Module Description

<b>Module name</b>					
<b>Mathematical Statistics</b>					
<b>Module no.</b> 04-10-0616/en	<b>Credit Points</b> 9 CP	<b>Workload</b> 270 h	<b>Self-study</b> 180 h	<b>Duration</b> 1 Semester	<b>Frequency</b> Every 3. semester
<b>Language of Instruction</b> English			<b>Person responsible for the Module</b> Prof. Dr. rer. nat. Michael Kohler		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0616-vu	Mathematical Statistics	0	Lecture and Exercise	6
<b>2</b>	<b>Study Content</b> Estimation of distributions, VC theory, density estimation, point estimates, statistical tests, confidence intervals.  Possible societal implications will be addressed in the lecture.				
<b>3</b>	<b>Learning Outcomes</b> The students know and understand the above mentioned concepts, methods and results, and are able to apply them. They have a deep understanding of Mathematical Statistics and are able to learn new knowledge in this field by themselves. Students are able to contextualize subject matter within the social context, critically assess the consequences, and act ethically and responsibly accordingly.				
<b>4</b>	<b>Requirements for Participation</b> recommended: Probability theory				
<b>5</b>	<b>Form of Examination</b> Final Module Examination:  <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 90 min, Standard)  Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated				

	during the first two weeks of the lecture, based on the prospective number of students taking the exam.
<b>6</b>	<b>Requirements on the Award of Credit Points</b> Passing the Technical Examination („Fachprüfung“);
<b>7</b>	<b>Grading</b> Final Module Examination:    <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)
<b>8</b>	<b>Usability of the Module</b> M. Sc. Mathematics, Mathematics in Data Science
<b>9</b>	<b>Literature</b> Lehmann, Romano: Testing Statistical Hypotheses. Devroye, Lugosi: Combinatorial methods in density estimation
<b>10</b>	<b>Comment</b>

## Module Description

<b>Module name</b>					
<b>Statistical theory for Deep Learning</b>					
<b>Module no.</b> 04-10-0617/en	<b>Credit Points</b> 9 CP	<b>Workload</b> 270 h	<b>Self-study</b> 180 h	<b>Duration</b> 1 Semester	<b>Frequency</b> Every 3. semester
<b>Language of Instruction</b> English			<b>Person responsible for the Module</b> Prof. Dr. rer. nat. Michael Kohler		
<b>1</b>	<b>Courses of the Module</b>				
	<b>Course no.</b>	<b>Course name</b>	<b>Workload (CP)</b>	<b>Form of Teaching</b>	<b>Contact Hours per Week</b>
	04-10-0617-vu	Statistical theory for Deep Learning	0	Lecture and Exercise	6
<b>2</b>	<b>Study Content</b> types of neural networks, nonparametric regression and image classification, gradient descent, approximation results for feed forward neural networks, rate of convergence for least squares neural network estimates, analysis of neural networks learned by gradient descent  Possible societal implications will be addressed in the lecture				
<b>3</b>	<b>Learning Outcomes</b> The students know and understand the above mentioned concepts, methods and results, and are able to apply them. They have a deep understanding of Deep Learning and are able to learn new knowledge in this field by themselves. Students are able to contextualize subject matter within the social context, critically assess the consequences, and act ethically and responsibly accordingly.				
<b>4</b>	<b>Requirements for Participation</b> recommended: Probability theory				
<b>5</b>	<b>Form of Examination</b> Final Module Examination:  <input type="checkbox"/> • Module Examination (Technical Examination, oral / written Examination, Duration 90 min, Standard)  Usually the exam is taken in form of a written test, except when there are only a small number of potential participants. In this case, the exam can be taken in the form of an oral exam. The decision about the form of the exam is taken and communicated				

	during the first two weeks of the lecture, based on the prospective number of students taking the exam.
<b>6</b>	<b>Requirements on the Award of Credit Points</b> Passing the Technical Examination („Fachprüfung“);
<b>7</b>	<b>Grading</b> Final Module Examination:    □ • Module Examination (Technical Examination, oral / written Examination, Weight: 100%, Standard)
<b>8</b>	<b>Usability of the Module</b> M. Sc. Mathematics, Mathematics in Data Science
<b>9</b>	<b>Literature</b> Goodfellow, Bengio, Courville: Deep Learning. Györfi, Kohler, Krzyzak, Walk: A distribution - free theory of nonparametric regression
<b>10</b>	<b>Comment</b>