

<b>Study program: Artificial intelligence</b>			
<b>Name of the subject: Distributed Optimization with Applications</b>			
<b>Teacher(s): Dušan Jakovetić</b>			
<b>Status of the subject: obligatory</b>			
<b>Number of ECTS credits: 6</b>			
<b>Conditions: none</b>			
<b>Subject goal</b>			
<ul style="list-style-type: none"> <li>- Understanding of a wide range of modern optimization methods for large scale, parallel, and distributed optimization</li> <li>- Ability to select appropriate algorithms for the problem at hand</li> <li>- Ability to implement the taught algorithms in MATLAB</li> </ul>			
<b>Outcome of the subject</b>			
<ul style="list-style-type: none"> <li>- Ability and experience in applying the taught algorithms on real-world problems</li> <li>- Ability to apply the taught algorithms on research problems from a wide variety of application areas</li> <li>- Ability to synthesize and analyze efficient distributed algorithms for a given application</li> </ul>			
<b>Subject content</b>			
<i>Theory</i>			
Modern first-order methods for large-scale optimization: proximal gradient; accelerated Nesterov gradient; accelerated gradient for non-smooth optimization (FISTA); Randomized methods: randomized coordinate gradient; stochastic/online gradient; online gradient method under privacy constraints; Parallel and distributed methods: primal decomposition; dual decomposition; augmented Lagrangian; ADMM; distributed gradient; distributed dual averaging; distributed approximate Newton.			
<i>Practical learning</i>			
Application examples in telecom, electric grid (smart grid), machine learning, sensor networks, etc.; Implementation of the taught methods in MATLAB; Application of selected methods on real-world examples through the course project.			
<b>Literature</b>			
Main:			
<ol style="list-style-type: none"> <li>1. Nedic, Ozdaglar, Distributed Subgradient Methods For Multi-agent Optimization, Ieee Transactions On Automatic Control, Volume: 54, Issue:1 [1], Jan. 2009</li> <li>2. S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, Distributed optimization and statistical learning via the alternating direction method of multipliers, Foundations and Trends in Machine Learning, 2011</li> <li>3. Soummya Kar And Jose M. F. Moura, "Distributed Consensus Algorithms In Sensor Networks: Link Failures And Channel Noise" Ieee Transactions On Signal Processing, 57:1, Pp. 355-369, January 2009</li> <li>4. Wei Shi ; Qing Ling ; Kun Yuan ; Gang Wu ; Wotao Yin, On The Linear Convergence Of The Admm In Decentralized Consensus Optimization, Ieee Transactions On Signal Processing ( Volume: 62, Issue: 7 2014)</li> </ol>			
Textbooks (additional):			
<ol style="list-style-type: none"> <li>1. S. Boyd and L. Vandenberghe: Convex Optimization, Cambridge University Press, 2004</li> <li>2. D. Bertsekas, Nonlinear Programming, Athena Scientific, 2004</li> <li>3. D. Bertsekas and J. Tsitsiklis: Parallel and Distributed Computation: Numerical Methods, Prentice-Hall, 1989</li> </ol>			
<b>Number of active teaching classes</b>		<b>Theoretical teaching: 3</b>	<b>Practical teaching: 2</b>
<b>Method of carrying out the teaching</b>			
Lectures; revisions of the material; active students' participation in problem solving; knowledge tests – colloquia; application of the taught material on real-world examples within the course project.			
<b>Evaluation of knowledge (maximum number of points 100)</b>			
<b>Pre-exam obligations</b>	points	<b>Final exam</b>	points
Colloquia	30	Written exam	40
Course project	30		