	UE-ML3: Deep Learning	
	UE-ML3: Deep Learning	Semester 1
Contributes to	MICAS	

Coordinators:	Hadi GHAUCH, Telecom Paris Mansoor YOUSEFI, Telecom Paris	
Volume:	30h	**3 ects**
Hours:	Lectures: 27h, Seminars: 3h	
Assessment:	2 Assignments, 1 Paper Presentation, and Final Project	
Language:	English	

Objectives:

The course offers an in-depth study on the mathematical foundations of deep neural networks (DNNs), which are at the heart of the AI revolution. The first part of the course covers the fundamental aspects of statistical learning and large-scale convex and non-convex optimization methods for modern machine learning tasks. We then focus on learning by a DNN, pose the resulting learning problem as an empirical risk minimization, discuss state-of-the-art methods of large-scale training. Finally, we describe common DNN architectures/types such as deep convolutional/recurrent neural networks.

Outcomes:

On completion of the course students should be able to:

- Understand fundamental theories on large-scale convex optimization, and non-convex optimization, which underpin deep learning
- Understand state-of-the art training methods being used at the forefront of deep learning research
- Acquire theoretical background (and practical skills) needed to do research in deep learning, or to apply these techniques to their field of expertise

Prerequisite

- Linear algebra
- Introduction to Convex Optimization
- Introduction to Probability and Statistics

Syllabus

- Fundamentals of deep neural networks (DNNs): mathematical models, feedforward neural networks, derivations of BackPropagation algorithm
- Large-scale training of DNNs: challenges in DNN training, loss surface, state of the art training methods(AdaGrad, RMPProp, ADAM)
- Recurrent neural networks (RNN) for sequence modeling: mathematical models for RNNs, training RNNs (with BPTT), challenges with learning long-term dependencies
- Long-short term memory networks: Motivation, mathematical models, training (with BPTT)
- Convolutional neural networks
- Factor models and manifold learning

Bibliography:

- Goodfellow, Y. Bengio and A. Courville,"Deep Learning", MIT press, 2016.
- L. Bottou, F. Curtis and J. Norcedal, "Optimization Methods for Large-Scale Machine Learning", SIAM Rev., 60(2), 223–311, 2018.
- M. Hong, M. Razaviyayn, Z. Q. Luo and J. S. Pang, "A Unified Algorithmic Framework for Block-Structured Optimization Involving Big Data: With applications in machine learning and signal processing", in IEEE Signal Processing Magazine, vol. 33, no. 1, pp. 57–77, Jan. 2016.