

Module Description

Machine Learning

General Information**Number of ECTS Credits**

3

Abbreviation

TSM_MachLe

Version

27.06.2016

Responsible of module

Dr. Thilo Stadelmann, ZHAW

Language

	Lausanne	Bern	Zurich
Instruction	<input type="checkbox"/> E <input checked="" type="checkbox"/> F	<input type="checkbox"/> D <input type="checkbox"/> E <input type="checkbox"/> F	<input type="checkbox"/> D <input checked="" type="checkbox"/> E
Documentation	<input checked="" type="checkbox"/> E <input type="checkbox"/> F	<input type="checkbox"/> D <input type="checkbox"/> E <input type="checkbox"/> F	<input type="checkbox"/> D <input checked="" type="checkbox"/> E
Examination	<input checked="" type="checkbox"/> E <input checked="" type="checkbox"/> F	<input type="checkbox"/> D <input type="checkbox"/> E <input type="checkbox"/> F	<input type="checkbox"/> D <input checked="" type="checkbox"/> E

Module category

- Fundamental theoretical principles - FTP
- Technical/scientific specialization module - TSM
- Context module - CM

Lessons

- 2 lecture periods and 1 tutorial period per week
- 2 lecture periods per week

Brief course description of module objectives and content

Machine learning (ML) emerged out of artificial intelligence and computer science as the academic discipline concerned with *“giving computers the ability to learn without being explicitly programmed”* (A. Samuel, 1959). Today, it is the methodological driver behind the mega-trends of big data and data science. ML experts are highly sought after in industry and academia alike.

This course builds upon basic knowledge in math, programming and analytics/statistics as is typically gained in respective undergraduate courses of diverse engineering disciplines. From there, it teaches the foundations of modern machine learning techniques in a way that focuses on practical applicability to real-world problems. The complete process of building a learning system is considered:

- formulating the task at hand as a learning problem;
- extracting useful features from the available data;
- choosing and parameterizing a suitable learning algorithm.

Covered topics include cross-cutting concerns like ML system design and debugging (how to get intuition into learned models and results) as well as feature engineering; covered algorithms include (amongst others) Support Vector Machines (SVM) and the emerging champion of ML methods, supervised and unsupervised deep learning techniques.

Aims, content, methods**Learning objectives and acquired competencies**

- Students **know** the **background and taxonomy** of machine learning methods
- On this basis, they **formulate** given problems as **learning tasks** and **select a proper learning method**
- Students **are able to convert** a data set into a proper **feature set** fitting for a task at hand
- They **evaluate** the chosen **approach** in a structured way using proper design of experiment
- Students **know how** to select models, and „**debug**“ features and learning algorithms if results do not fit expectations
- Students are able to leverage on the evaluation framework to **tune the parameters** of a given system and **optimize** its performances
- Students **have seen examples** of **different data** sources / problem types and **are able to acquire additional expert knowledge** from the scientific literature

Contents of module with emphasis on teaching content

- **Introduction** (2 weeks): Convergence for participants with different backgrounds
- **Supervised learning** (7 weeks): Learn from labeled data
Cross-cutting topics: Feature engineering; ensemble learning; debugging ML systems
Algorithms: e.g. SVM, deep (convolutional) neural networks, graphical models (Bayesian networks)
- **Unsupervised learning** (3 weeks): Learning without labels
Algorithms: e.g., unsupervised feature learning, anomaly detection, archetypal analysis
- **Special chapters** (2 weeks):
Algorithms: e.g., reinforcement learning, recommender systems, hidden Markov / Gaussian mixture models

Teaching and learning methods

Classroom teaching; programming exercises

Prerequisites, previous knowledge, entrance competencies

- **Math:** basic calculus / linear algebra / probability calculus (e.g., derivatives, matrix multiplication, normal distribution, Bayes' theorem)
- **Statistics:** basic descriptive statistics (e.g., mean, variance, co-variance, histograms, box plots)
- **Programming:** good command of any structured programming language (e.g., Python, Matlab, R, Java, C, C++)
- **Analytics:** basic data analysis methods (data pre-processing, decision trees, k-means clustering, linear & logistic regression)

Literature

T. Mitchell, *"Machine Learning"*, 1997
C. M. Bishop, *"Pattern Recognition and Machine Learning"*, 2006
G. James et al., *"An Introduction to Statistical Learning"*, 2014
K. Murphy, *"Machine Learning – A Probabilistic Perspective"*, 2012

Assessment**Certification requirements for final examinations (conditions for attestation)**

75% of homework passed

Written module examination

Duration of exam: 120 minutes
Permissible aids: 1 A4 page (front and back) of handwritten notes; no electronic aids