MASTER OF SCIENCE IN ENGINEERING

Module Description

Machine Learning

General Information

Number of ECTS Credits

3

Module code

TSM_MachLe

Responsible of module

Dr. Thilo Stadelmann, ZHAW

Language

Explanations regarding the language definitions for each location:

- Instruction is given in the language defined below for each location/each time the module is held.
- Documentation is available in the languages defined below. Where documents are in several languages, the percentage distribution is shown (100% = all the documentation).
- The examination is available 100% in the languages shown for each location/each time it is held.

	Berne	Lausanne			Lugano	Zurich		
Instruction	☐ E 100%	☐ E 100%		☑ F 100%	☐ E 100%	☑ E 100%		☐ D 100%
Documentation	☐ E 100%	☐ E 100%	☑ E 100%	☐ F %	☐ E 100%	☑ E 100%	☐ E %	☐ D %
Examination	☐ E 100%	☐ E 100%	☑ E 100%	☑ F 100%	☐ E 100%	☑ E 100%	☐ E 100%	☐ D 100%

Module category

☐ FTP Fundamental theoretical principles

☑ TSM Technical/scientific specialization module

☐ CM Context module

Lessons

2 lecture periods and 1 tutorial period per week

Entry level competencies

Prerequisites, previous knowledge

- **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)

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 ensemble methods.

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 in**to** 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, ensemble learning, graphical models (Bayesian networks)
- **Unsupervised learning** (3 weeks): Learning without labels
  Algorithms: e.g., dimensionality reduction, 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 (e.g., in Python 3)

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)

None (completion of labs and attendance of lectures strongly encouraged)

Basic principle for exams:
All the standard final exams for modules are written exams.
The repetition exams can be either written or oral.

Standard final exam for a module and written repetition exam

Kind of Exam	written
Duration of exam	120 minutes
Permissible aids	☐ No aids
	☑ Permissible aids:
	☐ Electronical aids: none
	☐ Hardcopy form: none
	☑ **1 A4 page** (front and back) of **handwritten** notes (no book, no slides, no further notes)

Special case: Repetition exam as an oral exam

If an oral exam is set (only possible for ≤ 4 students), the following applies:

Kind of Exam	oral
Duration of exam	30 minutes
Permissible aids	No aids