**Module Description, available in: EN**

# *Machine Learning*

## General Information

**Number of ECTS Credits**

3

**Module code**

FTP_MachLe

**Valid for academic year**

2026-27

**Last modification**

2024-11-08

**Coordinator of the module**

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**Explanations regarding the language definitions for each location:**

- Instruction is given in the language specified for each location and module execution.
- Documentation is available in the language(s) listed for each location and module execution. If the documentation is in multiple languages, the percentage distributed is indicated (100% = all documentation provided).
- The examination, including both questions and answers, is provided entirely (100%) in the language(s) specified for each location and module execution. The exams are on-site.

| | Lausanne | | | Lugano | Zurich | | |
|---|---|---|---|---|---|---|---|
| **Instruction** | **X** E 100% | | | | **X** E 100% | | |
| **Documentation** | **X** E 100% | | | | **X** E 100% | | |
| **Examination** | **X** E 100% | | | | **X** E 100% | | |

**Module Category**

FTP Fundamental theoretical principles

**Profile Recommendations**

This module is recommended for the following profiles:

| | Lausanne | Zurich |
|---|---|---|
| **Profile** | CS, DS, ICS | EIE, ICS, Med, Avi |

**Lessons**

2 lecture periods and 1 tutorial period per week

## Entry level competences

**Prerequisites, previous knowledge**

- **Math**: basic calculus / linear algebra / probability calculus (e.g., derivatives, matrix multiplication, normal distribution)
- **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, 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-trend of digitalization. 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 competencies to be acquired

- Students **know** the **background and taxonomy** of machine learning methods
- On this basis, they **formulate** given problems as l**earning 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

### Module content with weighting of different components

- **Introduction** (ca. 2 weeks): Convergence for participants with different backgrounds
- **Supervised learning** (ca. 7 weeks): Learn from labeled data
  *Cross-cutting topics*: such as feature engineering; ensemble learning; instance vs. model-based approaches, debugging ML systems
  *Algorithms*: e.g. kNN, decision tree, SVM, ensemble learning (bagging, boosting), graphical models (Bayesian networks), gradient based approaches
  *bias-variance tradeoff*: hyperparameter tuning, cross-validation, performance metrics
- **Unsupervised learning** (ca. 3 weeks): Learning without labels
  *Algorithms*: e.g., clustering, dimensionality reduction, anomaly detection, archetypal analysis
- **Special chapters** (ca. 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, Jupyter notebooks, Orange)

### Literature


- Aurélien Géron: "*Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*", Concepts, Tools, and Techniques to Build Intelligent Systems, O’Reilley Media, 2022
- T. Mitchell, “*Machine Learning*”, 1997
- C. M. Bishop, “*Pattern Recognition and Machine Learning*”, 2006
- Simon Rogers, Mark Girolami: “*A First Course in Machine Learning*”, ISBN-13: 978-0367574642, Chapman and Hall/CRC; 2. Edition, 2016
- G. James et al., “*An Introduction to Statistical Learning*”, 2014


## Assessment

### Additional performance assessment during the semester

The module does not contain an additional performance assessment during the semester

### Basic principle for exams

**As a rule, all standard final exams are conducted in written form. For resit exams, lecturers will communicate the exam format (written/oral) together with the exam schedule.**

### Standard final exam for a module and written resit exam

**Kind of exam**

Written exam

**Duration of exam**

120 minutes

**Permissible aids**

*Aids permitted as specified below:*

**Permissible electronic aids**

No electronic aids permitted

**Other permissible aids**

1 A4 page (front and back) of personally compiled notes (no book, no slides, no further notes)

**Exception: In case of an electronic Moodle exam, adjustments to the permissible aids may occur. Lecturers will announce the final permissible aids prior to the exam session.**

**Special case: Resit exam as oral exam**

**Kind of exam**

Oral exam

**Duration of exam**

30 minutes

**Permissible aids**

*Aids permitted as specified below:*

**Permissible electronic aids**

No electronic aids permitted

**Other permissible aids**

1 A4 page (front and back) of personally compiled notes (no book, no slides, no further notes)