Module Description, available in: EN

**Machine Learning**

**General Information**

<table>
<thead>
<tr>
<th></th>
<th>Berne</th>
<th>Lausanne</th>
<th>Lugano</th>
<th>Zurich</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Instruction</strong></td>
<td>X E 100%</td>
<td></td>
<td></td>
<td>X E 100%</td>
</tr>
<tr>
<td><strong>Documentation</strong></td>
<td>X E 100%</td>
<td>X E 100%</td>
<td></td>
<td>X E 100%</td>
</tr>
<tr>
<td><strong>Examination</strong></td>
<td>X E 100%</td>
<td></td>
<td></td>
<td>X E 100%</td>
</tr>
</tbody>
</table>

**Module Category**

FTP Fundamental theoretical principles

**Lessons**

2 lecture periods and 1 tutorial period per week

**Entry level competences**

- **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 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, 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**

- 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**

Module does not use certification requirements

**Basic principle for exams**

As a rule, all the standard final exams for modules and also all resit exams are to be in written form
**Standard final exam for a module and written resit exam**

**Kind of exam**
written

**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 handwritten notes (no book, no slides, no further notes)

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

**Kind of exam**
oral

**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 handwritten notes (no book, no slides, no further notes)