EPFL

CS-433

# Machine learning

Flammarion Nicolas, Jaggi Martin

| Cursus | Sem. | Type |
|---|---|---|
| Biocomputing minor | H | Opt. |
| Civil & Environmental Engineering | | Opt. |
| Communication systems minor | H | Opt. |
| Computational Neurosciences minor | H | Opt. |
| Computational science and Engineering | MA1, MA3 | Opt. |
| Computer and Communication Sciences | | Opt. |
| Computer science minor | H | Opt. |
| Computer science | MA1, MA3 | Obl. |
| Cybersecurity | MA1, MA3 | Obl. |
| Data Science | MA1, MA3 | Obl. |
| Data science minor | H | Opt. |
| Digital Humanities | MA1, MA3 | Opt. |
| Electrical Engineering | | Opt. |
| Electrical and Electronical Engineering | MA1, MA3 | Opt. |
| Financial engineering | MA1, MA3 | Opt. |
| Life Sciences Engineering | MA1, MA3 | Opt. |
| Managmt, tech et entr. | MA1, MA3 | Opt. |
| Robotics, Control and Intelligent Systems | | Opt. |
| SC master EPFL | MA1, MA3 | Obl. |
| Sciences du vivant | MA3 | Opt. |

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|---|---|
| Language of teaching | English |
| Credits | 7 |
| Session | Winter |
| Semester | Fall |
| Exam | Written |
| Workload | 210h |
| Weeks | 14 |
| **Hours** | **6 weekly** |
| Courses | 4 weekly |
| Exercises | 2 weekly |
| **Number of positions** | |

## Summary

Machine learning and data analysis are becoming increasingly central in many sciences and applications. In this course, fundamental principles and methods of machine learning will be introduced, analyzed and practically implemented.

## Content

1. *Basic regression and classification concepts and methods: Linear models, overfitting, linear regression, Ridge regression, logistic regression, and k-NN.*
2. *Fundamental concepts: cost-functions and optimization, cross-validation and bias-variance trade-off, curse of dimensionality.*
3. *Unsupervised learning: k-Means Clustering, Gaussian mixture models and the EM algorithm.*
4. *Dimensionality reduction: PCA and matrix factorization, word embeddings*
5. *Advanced methods: generalized linear models, SVMs and Kernel methods, Neural networks and deep learning*

## Keywords

- *Machine learning, pattern recognition, deep learning, data mining, knowledge discovery, algorithms*

## Learning Prerequisites

### Required courses

- Analysis I, II, III
- Linear Algebra
- Probability and Statistics (MATH-232)
- Algorithms (CS-250)

### Recommended courses

- *Introduction to differentiable optimization (MATH-265)*
- *Linear Models (MATH-341)*

### Important concepts to start the course

- *Basic probability and statistics (conditional and joint distribution, independence, Bayes rule, random variables, expectation, mean, median, mode, central limit theorem)*
- *Basic linear algebra (matrix/vector multiplications, systems of linear equations, SVD)*
- *Multivariate calculus (derivative w.r.t. vector and matrix variables)*
- *Basic Programming Skills (labs will use Python)*

## Learning Outcomes

By the end of the course, the student must be able to:

- Define the following basic machine learning problems: Regression, classification, clustering, dimensionality reduction, time-series
- Explain the main differences between them
- Implement algorithms for these machine learning models
- Optimize the main trade-offs such as overfitting, and computational cost vs accuracy
- Implement machine learning methods to real-world problems, and rigorously evaluate their performance using cross-validation. Experience common pitfalls and how to overcome them
- Explain and understand the fundamental theory presented for ML methods

## Teaching methods

- Lectures
- Lab sessions
- Course Projects

## Expected student activities

Students are expected to:

- attend lectures
- attend lab sessions and work on the weekly theory and coding exercises
- work on projects using the code developed during labs, in small groups

## Assessment methods

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• Written final exam
• Continuous control (Course projects)

## Supervision

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|---|---|
| Office hours | Yes |
| Assistants | Yes |
| Forum | Yes |

## Resources

### Virtual desktop infrastructure (VDI)

No

### Bibliography

• Christopher Bishop, Pattern Recognition and Machine Learning
• Kevin Murphy, Machine Learning: A Probabilistic Perspective
• Shai Shalev-Shwartz, Shai Ben-David, Understanding Machine Learning
• Michael Nielsen, Neural Networks and Deep Learning
• (Jerome Friedman, Robert Tibshirani, Trevor Hastie, The elements of statistical learning : data mining, inference, and prediction)

### Ressources en bibliothèque

• Linear algebra and learning from data
• The elements of statistical learning : data mining, inference, and prediction / Friedman
• Pattern Recognition and Machine Learning / Bishop
• Neural Networks and Deep Learning / Nielsen
• Machine Learning: A Probabilistic Perspective / Murphy
• Understanding Machine Learning / Shalev-Shwartz

### Notes/Handbook

https://github.com/epfml/ML_course

### Websites

• https://www.epfl.ch/labs/mlo/machine-learning-cs-433/