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 biology 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.
Learning Sciences		Opt.
Life Sciences Engineering	MA1, MA3	Opt.
Managmt, tech et entr.	MA1, MA3	Opt.
Neuro-X minor	H	Opt.
Neuro-X	MA1, MA3	Opt.
Quantum Science and Engineering	MA1, MA3	Opt.
Robotics, Control and Intelligent Systems		Opt.
SC master EPFL	MA1, MA3	Obl.

Language of teaching	English
Credits	8
Session	Winter
Semester	Fall
Exam	Written
Workload	240h
Weeks	14
Hours	**6 weekly**
Lecture	4 weekly
Exercises	2 weekly
Number of positions	

Summary

Machine learning methods 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, k-NN, SVMs and kernel methods*
2. *Fundamental concepts: cost-functions and optimization, cross-validation and bias-variance trade-off, curse of dimensionality.*
3. *Neural Networks: Representation power, backpropagation, activation functions, CNN, regularization, data augmentation, dropout*
4. *Unsupervised learning: k-means clustering, gaussian mixture models and the EM algorithm. Basics of self-supervised learning*
5. *Dimensionality reduction: PCA and matrix factorization, word embeddings*
6. *Advanced methods: Adversarial learning, Generative adversarial networks*

Keywords

• *Machine learning, pattern recognition, deep learning, neural networks, 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 machine learning (CS-233)*
• *...or similar bachelor lecture from other sections*

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
• Conduct a real-world interdisciplinary machine learning project, in collaboration with application domain experts
• Define the following basic machine learning models: Regression, classification, clustering, dimensionality reduction, neural networks, time-series analysis

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

- Written final exam
- Continuous control (Course projects)

Supervision

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
- Understanding Machine Learning / Shalev-Shwartz
- Neural Networks and Deep Learning / Nielsen
- Machine Learning: A Probabilistic Perspective / Murphy
- Pattern Recognition and Machine Learning / Bishop

Notes/Handbook

https://github.com/epfml/ML_course

Websites

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

Moodle Link

- https://go.epfl.ch/CS-433