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Machine learning and applications

Course information

Machine Learning is about the construction and study of systems that can automatically learn from data. With the emergence of massive datasets commonly encountered today, the need for powerful machine learning is of acute importance. Examples of successful applications include effective web search, anti-spam software, computer vision, robotics, practical speech recognition, and a deeper understanding of the human genome. In this course, we will give an introduction to this exciting field. We will focus on supervised learning, such as classification and ranking, and unsupervised learning problems, such as clustering and dimension reduction. We will study classical algorithms, and introduce tools to measure their performance, as well as their computational complexity.

Related courses

- CR07 Algorithms for Molecular Biology
- CR08: Combinatorial Scientific Computing
- CR16: Data analysis and processing for networks

Evaluation

- homeworks (1/3)
- project (2/3)

Course outline

Introduction

- Empirical risk minimization
- Risk convexification and regularization
- Bias-variance trade-off, and risk bounds

Supervised learning

- Ridge regression
- Logistic regression
- Perceptron and neural networks
- Support vector machines
- Other methods: nearest-neighbors, kernel methods, etc.

Unsupervised learning

- Principal component analysis
- Data clustering
- Other methods: canonical correlation analysis, sparse coding, etc.

Reading material

Machine Learning and Statistics

- Vapnik, The nature of statistical learning theory. Springer
- Hastie, Tibshirani, Friedman, The elements of statistical learning. (free online)
- Devroye, Gyorfi, Lugosi, A probabilistic theory of pattern recognition. Springer
- Dubashi, Panconesi, Concentration of measure for analysis of randomized algorithms, Cambridge University Press
- J Shawe-Taylor, N Cristianini. Kernel methods for pattern analysis. 2004.
- Slides by Jean-Philippe Vert on kernel methods.

Optimization

- S. Boyd and L. Vandenberghe. Convex Optimization. 2004. (free online)
- D. Bertsekas. Nonlinear Programming. 2003.

Calendar

Date	Lecturer	Topic	Scribes
12/09	LJ	Introduction + Bias-variance tradeoff. slides Scribe notes	Sebastien Jonglez Stephane Durand
19/09	LJ	Supervised Learning - SVM slides Scribe notes	Raphael Bournhonesque

26/09	LJ	Empirical risk minimization - cross validation slides Scribe notes	Martin Privat
03/10	JM	Convex optimization principles - Non-parametric estimation Scribe notes	Antoine Pouille
10/10	JM	Introduction to kernels and RKHS Scribe notes	Sebastian Scheibner
24/10	JM	Kernels methods and kernel examples Scribe notes	Guinard Brieuc Emma Prudent
14/11	JS	Unsupervised learning	Mouhcine Mendil
21/11	JS	Unsupervised learning Scribe notes	Aurore Alcolei

Scribe notes

For each course, a duo of students commit to turn their notes into latex format. A cool package, due to students from last year can be found here.

Homeworks

There will be three homeworks given during the course. Each of them should be returned within three weeks. (no need to use LateX here).

- **Homework 1: due October 24th**: pdf, code in R, data.
- **Homework 2: due November 25th**: pdf.
- **Homework 3: due December 17th**: pdf.

Projects

The project consists of implementing an article, doing some experiments, and writing a small report (less than 10 pages). It is also possible to study a theoretical paper instead of implementing a method. All reports should be written in LateX, and a pdf should be sent to the lecturers before **January 5th**. You can either comes with your own idea and discuss it with us, or we can give you some suggestions. You can also pick up one article in the list below, or look at the projects from last year.

- Learning using large datasets
- Spectral ranking using seriation
- Graphical lasso
- Intersecting singularities for multi-structured estimation
- Convolution and local alignment kernel
- Distributed robust learning
- Optimization with quadratic penalties
- Safe feature elimination for the Lasso
- Bayesian model averaging

- Speaker recognition
- Graph kernels for biology
- Text categorization

So far, the project courses chosen by the students are

Project	Student(s)	Coach
Supervised text classification	Aurore Alcolei	JM
Prediction in social Networks article	Guinard Brieuc	LJ
Distributed robust learning	Mendil Mouhcine	JS
Audio processing and machine learning	Emma Prudent	JS
Latency prediction in TCP networks	Baptiste Jonglez	JM
Speaker Recognition	Raphael Bournhonesque	LJ
Text analysis	Martin Privat	JM
Safe feature elimination for the Lasso	Antoine Pouille	JS
Graph kernel for biology	Sebastian Scheibner	LJ

Jobs / Internships Opportunities

We have different intern/PhD opportunities in machine learning, image processing, bioinformatics and computer vision. It is best to discuss that matter early with us since the number of places is limited.

Lecturers

- **Laurent Jacob** LBBE, CNRS
- **Julien Mairal** LEAR, INRIA
- **Joseph Salmon** STA, Telecom ParisTech

Kernel Methods for Statistical Learning

INVENTEURS DU MONDE NUMÉRIQUE

Course information

Statistical learning is about the construction and study of systems that can automatically learn from data. With the emergence of massive datasets commonly encountered today, the need for powerful machine learning is of acute importance. Examples of successful applications include effective web search, anti-spam software, computer vision, robotics, practical speech recognition, and a deeper understanding of the human genome. This course gives an introduction to this exciting field, with a strong focus on kernels as a versatile tool to represent data, in combination with (un) supervised learning techniques that are agnostic to the type of data that is learned from. The learning techniques that will be covered include regression, classification, clustering and dimension reduction. We will cover both the theoretical underpinnings of kernels, as well as a series of kernels that are important in practical applications.

Evaluation

- For UJF: homeworks 1,2,3 (1/2) + project (1/2)
- For ENSIMAG: homework 1 (1/4) + project (3/4)

Course outline

Introduction

- Motivating example applications
- Empirical risk minimization
- Bias-variance trade-off, and risk bounds

Supervised learning with linear models and kernels

- Risk convexification and regularization
- Ridge regression
- Logistic regression
- Support vector machines
- Kernels for non-linear models

Unsupervised learning

- Principal component analysis
- Data clustering
- Other methods: canonical correlation analysis, sparse coding, etc.

Kernels for probabilistic models

- Fisher kernels
- Probability product kernels

Reading material

Machine Learning and Statistics

- Vapnik, The nature of statistical learning theory. Springer
- Hastie, Tibshirani, Friedman, The elements of statistical learning. (free online)
- Devroye, Gyorfi, Lugosi, A probabilistic theory of pattern recognition. Springer
- J Shawe-Taylor, N Cristianini. Kernel methods for pattern analysis. 2004.
- Bishop, Pattern recognition & machine learning. 2006.
- Slides by Jean-Philippe Vert on kernel methods.

Optimization

- S. Boyd and L. Vandenberghe. Convex Optimization. 2004. (free online)
- D. Bertsekas. Nonlinear Programming. 2003.

Calendar

Date	Room	Lecturer	Topic	Homework
07/10	H104	JV	Introduction + Bias-variance tradeoff. slides	
14/10	H201	JV	Penalized empirical risk minimization, linear classifiers, introduction kernels. slides	Homework 1
21/10	H201	JM	Reproducing kernel Hilbert spaces (RKHS)	
04/11	H201	JV	The kernel trick, supervised kernel methods, and Fisher kernels. slides	Homework 2
25/11	H201	JM		

2/12	H201	JM

Homeworks

There will be three homeworks given during the course, at lecture 2, 4, and 6. Each of them should be returned within three weeks. Either use LateX, or make sure you write very clearly. Homework has to be done individually. ENSIMAG students only have to handin the first homework, since they get less credits for the course.

Projects

The project consists of implementing an article, doing some experiments, and writing a small report (less than 10 pages). It is also possible to study a theoretical paper instead of implementing a method. All reports should be written in LateX, and a pdf should be sent to the lecturers before **January 5th**. Projects can be done alone, or in groups of two people. You can either come with your own idea and discuss it with us, or we can give you some suggestions. To give you an idea, these are projects of a related course.

Project	Student(s)	Coach
Supervised classification of text documents. material	Vera Shalaeva and Manon Lukas	
Predicting Molecular Activity with Graph Kernels. material	Phivos Valougeorgis	
Speaker Recognition. material	Li Liu	
Supervised classification of Flickr images. material	Leonardo Gutierrez Gomez	
Fast string kernels using inexact matching for protein sequences material		
Semigroup kernels on measures material	Julien Alapetite	
Kernel change-point analysis material		
Fast global alignment kernels material		
Multiple kernel learning, conic duality, and the SMO algorithm material		
Predictive low-rank decomposition for kernel methods material		
Image classification with segmentation graph kernels material		

Image Classification with the Fisher Vector: Theory and Practice **material**	Jerome Lesaint

Jobs / Internships Opportunities

We have different intern/PhD opportunities in machine learning, image processing, bioinformatics and computer vision. It is best to discuss that matter early with us since the number of places is limited.

Lecturers

- **Julien Mairal** LEAR, INRIA
- **Jakob Verbeek** LEAR, INRIA