2ND YEAR

SEMESTER 3 — 30 ECTS

Mandatory	***12 ECTS***
Bayesian Learning	*3 ECTS*
Advanced deep learning	*3 ECTS*
Introduction to Information Theory	*3 ECTS*
Model-Based statistical learning	*3 ECTS*

Advanced Machine Learning	***9 ECTS***
Research Project	*6 ECTS*
Student has to choose one of the following courses :	
Stochastic models in neurocognition and their statistical inference	*3 ECTS*
Reasoning and decision making	*3 ECTS*
Federated Learning - Data Privacy	*3 ECTS*
Interactions with Big Data Analytics - Natural Languages	*3 ECTS*

Advanced Methods in AI	***9 ECTS***
Student has to choose three of the following courses :	
Advanced Learning : functional, mixed and text data	*3 ECTS*
Foundation of geometric methods in data analysis	*3 ECTS*
Inverse problems in image processing	*3 ECTS*
Deep learning for computer vision	*3 ECTS*
Statistical analysis of graph	*3 ECTS*
Medical Images	*3 ECTS*

SEMESTER 4 — 30 ECTS

Internship

ADVANCED MACHINE LEARNING 9 ECTS

RESEARCH PROJECT	6 ECTS

Student has to choose one of the following courses :

FEDERATED LEARNING - DATA PRIVACY	3 ECTS
REASONING AND DECISION MAKING	3 ECTS
INTERACTIONS WITH BIG DATA ANALYTICS - NATURAL LANGUAGES	3 ECTS
STOCHASTIC MODELS IN NEUROCOGNITION AND THEIR STATISTICAL INFERENCE	3 ECTS

REASONING AND DECISION MAKING

Level : M2	Semester : S3	Code : AIEDA310	ECTS : 3	Elective

Professors

Giuseppe ATTANASI, Agnès FESTRÉ and Éric GUERCI

Pre-requisites to the course

Notions of game theory
Notions of statistics and probability

Acquired skills/Course description

In this course, we introduce the field of behavioral and experimental economics from a historical and methodological perspective. We then discuss various models of decision making in both non-strategic and strategic environments. The former will be based on the literature and recent advancement of Decision Theory, the latter will be based on Game Theory. In discussing these models, we will refer to the experimental literature that has tested the implications of these models, and motivated new theoretical developments. Furthermore, we will also discuss findings from the literature on heuristics used in decision making. The course adopts an hands-on training approach. Some lectures will be given at the CoCoLab experimental laboratory. Students will participate to ad hoc laboratory experiments and will be encouraged to discuss about the outcomes of the experiments.

Course program

Part 1 (Agnès FESTRÉ): THE COGNITIVE/EXPERIMENTAL TURN IN ECONOMICS
Lecture 1. History and evolution of the relation between psychology and economics
Lecture 2. Economic experiments: methodological issues and debates
Lecture 3. Behavioral economics: theoretical foundations and their operationalization into public policies

PART 2 (Giuseppe ATTANASI): PSYCHOLOGICAL AND SOCIAL « BIASES » IN INDIVIDUAL AND STRATEGIC DECISION MAKING
Lecture 4. Psychological bias and heuristics in choice under risk
Lecture 5. Psychological bias and heuristics in choice under ambiguity
Lecture 6. Social preferences in strategic decision making

PART 3 (Eric GUERCI): AN « UNHORTODOX » VIEW ON REASONING AND DECISION MAKING
Lecture 7. The three major types of reasoning: deductive / inductive / abductive.
Lecture 8. Trade-off between stability and variability in the decision making and the role of emotions.
Lecture 9. Human vs Artificial: from prediction to decision-making.

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Group assignment (Group Task) with a presentation (possibly during a Friday Meeting) – 25% of final mark
Written exam – 75% of final mark

STOCHASTIC MODELS IN NEUROCOGNITION AND THEIR STATISTICAL INFERENCE

Level : M2	Semester : S3	Code :	ECTS : 3	Elective

Professors

Patricia Reynaud-Bouret (LJAD) and Etienne Tanré (Inria)

Acquired skills/Course description

The objective is to describe the main stochastic models (Markov Chains, Integrate and Fire, point processes [...]) used in neuroscience and cognition and their main mathematical properties. The pros and cons of each of them is discussed especially in terms of the modeling and the statistical inference of real data.

Course program

Approximate order :

C3 sessions with P. Reynaud-Bouret about i.i.d. models and more advanced statistical methods, in particular likelihood, contrast, model slection, cross-validation, bootstrap

2 Sessions with E. Tanré about Markov Chains and Poisson processes

1 session with P. Reynaud-Bouret about Statistics for Poisson processes

2 sessions with E. Tanré about Piecewise Deterministic Markov Processes and Brownian motion

1 session with P. Reynaud-Bouret about more complex point processes in particular Hawkes process (useful for functional connectivity)

1 session with E. Tanré about mean-field approximation

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About each week, you will have some tutorial to do at home. If you have problems doing it (and this will be the usual case), you should ask us questions by e-mails at
Patricia.Reynaud-Bouret@univ-cotedazur.fr
Etienne.Tanré@inria.fr
For the ones who need a grade at the end, please note that one of the two grades will be about your investment in the tutorials and in particular your evolution along the weeks (and not just the fact that you get a correct answer). It also means that you have to send your questions and final answers of the tutorials before we put the correction in the moodle. This will also help you to keep up with the rhythm of the course.

The other grade will be a final exam, in class.

FEDERATED LEARNIG DATA PRIVACY

Level : M2	Semester : S3	Code :	ECTS : 3	Elective

Professor

Giovanni Neglia (Inria), Chuan Xu (UCA), Angelo Rodio (3IA)

Programming Language(s) :

Python

Main Libraries :

PyTorch

Pre-requisites to the course

Familiarity with gradient-based optimization methods.

Acquired skills/Course description

Course 1 : Introduction to federated learning (FL): motivations, cross-device, and cross-silo settings,differences with distributed training in clustering. A look at the classic federated averaging algorithm (FedAvg). An overview of existing software frameworks and benchmarks for FL.

Course 2 : Optimization Algorithms for FL: convergence results under iid and non-iid data.

Course 3 : Practical session: introduction to the use of PyTorch, Colab, and GPU on a cluster.

Course 4 : Model personalization to address statistical heterogeneity (different local data distributions) and system heterogeneity (different clients' capabilities).

Course 5 : Practical session: Implementation of distributed gradient descent using the parameter-server architecture.

Course 6 : Communication: topology selection, sampling schemes, and compression.

Course 7 : Practical session: Implementation of algorithms for cross-device and cross-silo federated learning.

Course 8 : Privacy issues in FL. Introduction to possible attacks when the server or the participant is malicious, e.g., membership inference attack, model inversion attack, and data poisioning attack. State-of-the-art privacy-preserving mechanisms to prevent such attacks, including differential private algorithms and Byzantine-Resilient algorithms.

Course 9: Practical session: implementation of FedAvg with differential privacy and evaluation of its ability to defend from a specific attack.

Course 10 : Exam

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30% classwork (a 10 minutes test very lesson, only 4 best marks will be considered), 45% theoretical exam, 25% lab evaluation

ADVANCED METHODS IN AI — 9 ECTS

Student has to choose three of the following courses :

ADVANCED LEARNING : FUNCTIONAL, MIXED AND TEXT DATA	3 ECTS
FOUNDATION OF GEOMETRIC METHODS IN DATA ANALYSIS	3 ECTS
INVERSE PROBLEMS IN IMAGE PROCESSING	3 ECTS
DEEP LEARNING FOR COMPUTER VISION	3 ECTS
STATISTICAL ANALYSIS OF GRAPH	3 ECTS
MEDICAL IMAGES	3 ECTS

FOUNDATION OF GEOMETRIC METHODS IN DATA ANALYSIS

Level : M2	Semester : S3	Code : AIEDA310	ECTS : 3	Elective

Professors

Frederic Cazals, Mathieu Carrière, Jean-Daniel Boissonnat

Programming Language(s) :

Python, C++

Main Libraries :

Gudhi
https://gudhi.inria.fr/python/latest/

Pre-requisites to the course

Basics of linear and abstract algebra (vector spaces, group theory). Basics of data science and machine learning (optional). Basics of point-set topology (optional).

Acquired skills/Course description

Theory and algorithms of Geometric and Topological Data Analysis, including : dimensionality reduction, manifold learning, nearest neighbors, density estimation, persistent homology and statistical topological inference. This course reviews fundamental constructions related to the manipulation of point clouds, mixing ideas from computational geometry and topology, statistics, and machine learning. The emphasis is on methods that not only come with theoretical guarantees, but also work well in practice. In particular, software references and example datasets will be provided to illustrate the constructions.

Course program

Course 1	Nearest neighbors in Euclidean and metric spaces: data structures and algorithms
Course 2	Nearest neighbors in Euclidean and metric spaces: analysis
Course 3	Computational Topology (I): Simplicial Complexes
Course 4	Computational Topology (II): (Persistent) Homology
Course 5	Manifold Learning
Course 6	Topological Machine Learning (I)
Course 7	Topological Machine Learning (II)
Course 8	Reeb spaces and Mapper
Course 9	Dimensionality reduction algorithms
Course 10	Sampling high dimensional distributions with Markov chains

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This course will be validated with research projects involving manipulation and analysis of real data sets with the methods seen in class. The grade will be assessed from the obtained results and a written report describing the student's scientific approach.

INVERSE PROBLEMS IN IMAGE PROCESSING

Level : M2	Semester : S3	Code : AIEDA311	ECTS : 3	Elective

Professors

Laure Blanc-Féraud, Luca Calatroni, Vasiliki Stergiopoulou, Marta Lazzaretti

Programming Language(s) :

Python

Main Libraries :

NumPy, Scipy, PyLops, scikit-learn, PyTorch

Pre-requisites to the course

Basic knowledge on functional analysis, differentiation, convolution, optimization.

Acquired skills/Course description

The aim of this course is to present the problem of image reconstruction which is frequently encountered in a large number of imaging applications such as biomedical, satellite and seismic imaging. The study of this type of problems requires the use of advanced notions of image processing such as sparse reconstruction, anisotropic and non-linear diffusion-type PDEs, representation in wavelet bases, non-smooth optimization etc. The methodology described further involves the use of tools frequently encountered in general high-dimensional data processing and often used in several model and variable selection problems, as well as the design of smooth and non-smooth optimization algorithms (e.g. proximal gradient type) for which a parallel with deep learning methods will be made.

Course program

Course 1 : Introduction to inverse problems, convolution/deconvolution, Fourier transforms. Continuum VS discrete convolution. Matrix-vector product. Noise modelling. Likelihood functions. Ill-posedness / bad conditioning of forward matrix
Course 2 : Basics on convex optimization. Smooth/non-smooth (e.g. l_1) optimisation, subgradients, proximal operators, forward-backward splitting algorithm.
Course 3 : Wavelet transform for image compression and denoising. Hard/soft thresholding for different WT, artefacts due to non-translation invariance.
Course 4 : Regularization of inverse problems by smooth/sparsity-promoting regularisers (Tikhonov, TV, Wavelets), ADMM. Importance of parameter selection. Choice of regularisation and noise models.
Course 5 : Image processing by partial differential equations (PDEs), connection with heat equation and non-linear diffusion (TV). Isotropic/anisotropic diffusion
Course 6 : Non-smooth optimization, Forward-backward splitting. ISTA. Acceleration techniques, FISTA. Comparison with FBS
Course 7 : Stochastic gradient descent, connection to deep learning methods (activation functions), comparison between SG, SGA and SAG
Course 8 : Sparse l0 reconstruction + Non convex optimization. Use in deconvolution/sper-resolution: FBS, MCP, CEL0
Course 9 : CNN and algorithmic unrolling main ideas. LISTA.
Course 10 : Algorithmic unrolling for sparse representation. Application to super-resolution

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DEEP LEARNING FOR COMPUTER VISION

Level : M2	Semester : S3	Code : AIEDA313	ECTS : 3	Elective

Professor

François Bremond

Programming Language(s) :

C++, Python

Main Libraries :

PyTorch, TensorFlow, Keras

Pre-requisites to the course

Basic Knowledge on Computer Vision and on Deep Neural Network frameworks (PyTorch, TensorFlow, Keras). Strong background in C++/Python programming. Knowledge on the following topics is a plus : Machine learning, Probabilistic Graphical Models and Optimization techniques, Mathematic (Geometry, Graph theory, Optimization), Artificial intelligence, Image processing.

Acquired skills/Course description

This course studies Computer Vision (CV) algorithms together with their visual representations learnt through Deep Learning (DL) techniques. The studied algorithms are intended to solve traditional CV tasks, including classification, object detection and tracking, retrieval, face detection, image/video generation, emotion and action recognition and are illustrated through a panel of applications, such as video retrieval from the web, visual-surveillance, autonomous driving, merchandising, assisted living and robotics. The course discusses state-of-the-art methods from low-level description to high-level representation, and their dependence on the related CV tasks. The focus of the course is on recent, state of the art methods and large-scale applications. Cutting-edge topics will be studied, such as Convolutional Neural Networks, Recurrent Neural Networks and Generative Adversarial Networks. You will learn also to build projects in PyTorch/TensorFlow using CoLab.

Course program

Course 1 :	Introduction. Neural Networks Basic
Course 2 :	Convolutional Neural Networks Architecture
Course 3 :	Object Detection 1
Course 4 :	Object Detection 2
Course 5 :	Video classification: RNN, LSTM, GRU
Course 6 :	Action Recognition: 3D CNN, TCN
Course 7 :	Attention mechanisms: SEN, Self-attention, VPN, PDAN, Transformer, ViT, ViviT
Course 8 :	Generative Adversarial Networks (GANs): CGan, Image2Image translation, DCGan, CycleGan, StyleGan, BigGan, Video Generation, Deep Fake
Course 9 :	Generative Adversarial Networks (GANs): VAE, GAN evaluation
Course 10 :	Final Project Presentations

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Class involvement + Final Project

STATISTICAL ANALYSIS OF NETWORKS

Level : M2	Semester : S3	Code :	ECTS : 3	Elective

Professor

Konstantin Avrachenkov

Programming Language(s) :

Python

Main Libraries :

Networkx

Pre-requisites to the course

Linear Algebra, Basic Probability and Statistics.

Acquired skills/Course description

This course will provide statistical tools to study and analyze complex networks.

Since interactions between agents arise in various situations, networks have an exceptional impact on both science and society. We can mention the various interactions between people (communication networks, social networks), between proteins (biological networks), between particles (statistical physics), or between economic agents (countries, companies, etc.). Many of these real networks are very large (Twitter, Facebook, etc.), and data might not always be fully available (or its access is restricted via API, like Twitter).

We will begin by introducing the classic random graphs models (Erdos-Renyi, Configuration Model, Preferential Attachment, etc.). Then, we will give some standard algorithms for community detection (Spectral Clustering, Louvain, Modularity, etc.). Last, we propose to describe and analyze methods to sample average or maximal values of network functions, such as degree, population opinion, or rating. Half of the course hours will be spent on implementing the methods in Python (using the package networkX).

Course program

Main course parts :

1. Random graph models (Erdős–Rényi graphs, stochastic block models, preferential attachment model, configuration model);

2. Community detection (cut-based methods, modularity, centrality, statistical physics methods, game-theoretic methods, distributed methods for community detection);

3. Sampling on graphs (estimation of graph parameters such as the average degree, approximate counting of motifs in a graph, inference of opinion in an online social network).

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One mid-term exam and one final exam.

MEDICAL IMAGES

Level : M2	Semester : S3	Code :	ECTS : 3	Elective

Professors

Hervé Delingette, Xavier Pennec

Programming Language(s) :

Python

Main Libraries :

simpleITK, scikit-image

Pre-requisites to the course

Solid notions of linear algebra (spectral analysis, linear system of equations), and calculus calculus (derivatives and integral calculus). Basic knowledge of machine learning (regression and classification problems). Knowledge of differential geometry, image processing, deep learning is a plus.

Acquired skills/Course description

The course is an advanced introduction to the mathematical and computing tools used in medical image analysis, ranging from generic image analysis such as image registration and image segmentation to more advanced techniques in statistical and mechanical modeling for computational anatomy and physiology. After following this course, students should be able to read and understand most state of art research papers in the field of computer vision and medical image analysis.

Course program

Course 1 : Introduction to Medical Image Acquisition, Medical Image Registration
Course 2 : Image Filtering & main concepts in image Segmentation
Course 3 : Riemanian Geometry and Statistics
Course 4 : Image Segmentation based on Clustering
Course 5 : Image Segmentation based on connexity and Shape Constraints
Course 6 : Image analysis based on biophysical modeling
Course 7 : Analysis in the space of Covariance Matrices
Course 8 : Diffeomorphic Registration and Computational Anatomy
Course 9 : Examination

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The course will be validated based on the written and oral presentation of a research article and a multiple choice questionnaire