Année universitaire 2025/2026

Intelligence Artificielle, Systèmes, Données - Mathématiques - 2e année de Master

Responsables pédagogiques :

- CHRISTIAN **ROBERT** - https://dauphine.psl.eu/recherche/cvtheque/robert-christian-p
- JUDITH **ROUSSEAU** - https://dauphine.psl.eu/recherche/cvtheque/rousseau-judith

Crédits ECTS : 60

LES OBJECTIFS DE LA FORMATION

Une formation complète de "Data Scientist". L'objectif de la **2e année du Master Mathématiques et Applications parcours Intelligence Artificielle, Systèmes, Données (IASD) - Mathématiques** (anciennement MASH) est d'offrir à des étudiants et étudiantes issus d'un cursus mathématique une formation solide en apprentissage statistique dont les applications sont centrées sur l'économie numérique, les sciences et les humanités au sens large. Porté par la croissance exponentielle du flot de données générées par des applications aussi variées que la biologie, la médecine, le commerce en ligne, l'imagerie, la vidéo ou le traitement du langage. Le master comporte deux parcours distincts, **IASD - Mathématiques** et **IASD - Informatique**, qui partagent la majorité des cours mais se distinguent par des cours de tronc commun spécifiques à chaque parcours. Les deux parcours conduisent à des diplômes de master dans les mentions, respectivement, Informatique et Mathématiques et applications

Les objectifs de la formation :

- Maîtriser des fondations théoriques de l'apprentissage : méthodes de noyaux, apprentissage supervisé et non supervisé, optimisation, modèles graphiques, etc. ;
- Maîtriser des méthodes statistiques fondamentales : simulation, estimation, détection, etc.;
- Ouvrir aux applications de l'apprentissage en marketing, santé, journalisme, politiques publiques, etc.;
- Acquérir des compétences opérationnelles dans un certain nombre de langages informatiques clés : Python (notamment le package scikit-learn), HADOOP, R, MATLAB, Julia, etc.;
- Développer un savoir-faire pratique dans la manipulation des jeux de données issus d'applications et de projets.

Les cours sont dispensés au 16 bis rue de l'Estrapade, 75005 Paris.

MODALITÉS D'ENSEIGNEMENT

Les cours sont dispensés au 16 bis rue de l'Estrapade, 75005 Paris. **Les Modalités des Contrôles de Connaissances (MCC) détaillées sont communiquées en début d'année.** Le Master IASD commence par un semestre de tronc commun consacré aux disciplines fondamentales de l'IA et des sciences des données, qui comprend quatre cours communs et trois cours spécifiques à chaque parcours. À la fin du premier semestre, les étudiants choisissent six cours d'approfondissement pour le second semestre, dont une semaine intensive PSL permettant l'ouverture thématique vers d'autres disciplines ou applications. L'année se poursuit par un stage effectué dans un laboratoire de recherche académique ou industriel et se conclut en septembre par la rédaction d'un mémoire et sa soutenance publique. Le Master IASD se compose d'un semestre de tronc commun sur les disciplines fondamentales de l'IA (de septembre à décembre ; 7 cours obligatoires, soit 168h de formation - 28 ECTS) suivi d'un semestre d'options (de janvier à mars ; 6 cours optionnels, 140h de formation - 22 ECTS) et d'un stage de recherche (d'avril à septembre ; 10 ECTS) effectué dans un laboratoire académique ou une entreprise. Le tronc commun comporte sept cours obligatoires tandis que le second semestre permet d'approfondir six matières à choisir parmi une vingtaine d'options, dont une semaine intensive PSL rattachée au programme transverse DATA. Des cours optionnels de remise à niveau sur les fondements probabilistes et la programmation sont proposés avant le début des cours de tronc commun au début du mois de septembre. Les parcours IASD - Mathématiques et IASD - Informatique partagent quatre cours communs au premier semestre et se distinguent par trois cours qui sont spécifiques à chaque parcours. Les cours spécifiques d'un parcours peuvent éventuellement être choisis comme option dans l'autre parcours, dans la limite de deux options, au maximum, suivies au premier semestre.

ADMISSIONS

Titulaires d'un diplôme BAC+4 (240 crédits ECTS) ou équivalent à Dauphine, d'une université, d'une école d'ingénieur ou d'un autre établissement de l'enseignement supérieur dans le domaine des mathématiques appliquées.

POURSUITE D'ETUDES

Le Master **Intelligence Artificielle, Systèmes, Données (IASD) - Mathématiques** est une formation d'excellence ouvrant vers des carrières de recherche et développement dans des laboratoires de recherche publics ou privés ou des entreprises innovantes.

PROGRAMME DE LA FORMATION

- Semestre 3 - 28 ECTS
  - Cours introductifs obligatoires
    - A review of probability theory foundations
  - UE fondamentales 3
    - Bayesian statistics
    - Data Science Lab
    - Foundations of Machine Learning
    - High-dimensional statistics
    - Optimal transport
    - Optimization for Machine Learning
    - Reinforcement learning
- Semestre 4 - 20 ECTS
  - UE optionnelles (5 UE à choisir)
    - Advanced machine learning
    - Bayesian case studies
    - Bayesian machine learning
    - Computational social choice
    - Computational statistics methods and MCMC
    - Dimension reduction and manifold learning
    - Data acquisition, extraction and storage
    - Deep learning for image analysis
    - Graph analytics
    - Incremental learning, game theory and applications
    - Introduction to causal inference
    - Knowledge graphs, description logics, reasoning on data
    - Large language models
    - LLM for code and proof
    - Machine learning on Big Data
    - Machine learning with kernel method
    - Mathematics of deep learning
    - Monte-Carlo search and games
    - Non-convex inverse problems
    - NoSQL databases
    - Point cloud and 3D modelling
    - Topics in trustworthy machine learning
  - PSL week - 2 ECTS
    - PSL Week
  - Bloc stage - 10 ECTS
    - Stage

DESCRIPTION DE CHAQUE ENSEIGNEMENT

SEMESTRE 3 - 28 ECTS

Cours introductifs obligatoires

A review of probability theory foundations

Langue du cours : Anglais

Volume horaire : 15

Description du contenu de l'enseignement :

- Measure theory and integration
- Random variables, independence, inequalities
- Convergence of random variables, limit theorems
- Conditioning
- Stochastic processes, stopping times, martingales
- Gaussian vectors
- Brownian motion

Compétences à acquérir :

- Measure theory and integration
- Random variables, independence, inequalities
- Convergence of random variables, limit theorems
- Conditioning
- Stochastic processes, stopping times, martingales
- Gaussian vectors
- Brownian motion

UE fondamentales 3

Bayesian statistics

ECTS : 4

Enseignant responsable : JUDITH **ROUSSEAU** (https://dauphine.psl.eu/recherche/cvtheque/rousseau-judith)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

This course will cover the foundations of Bayesian statistics: including Bayesian decision theory, Bayesian tests and model selection, credible measures and will cover also the fundamental results of Bayesian asymptotics: Posterior contraction and consistency, parametric Bernstein von Mises theorem, BIC formula and Laplace approximation

Compétences à acquérir :

The aim of this course is to introduce the foundations of Bayesian statistics , mostly from a theoretical perspective. The students should then be fluent in Bayesian decision theory and understand the mechanisms underlying Bayesian asymptotic theory; with its implications and its limitations.

Pré-requis obligatoires

Probability theory: conditional distributions, limit theorems, measures
Statistics: likelihood, estimators, confidence regions

Bibliographie, lectures recommandées :

Bayesian choice, C.P. Robert The fundamentals of Bayesian nonparametrics, S. Ghosal and A. van der Vaart

Data Science Lab

ECTS : 4

Enseignant responsable : Alexandre **VERINE** (https://dauphine.psl.eu/recherche/cvtheque/verine-alexandre)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Students enrolled in this class will form groups and choose one topic among a list of proposed topics in the core areas of the master such as supervised or unsupervised learning, recommendation, game AI, distributed or parallel data-science, etc. The topics will generally consist in applying a well-established technique on a novel data-science challenge or in applying recent research results on a classical data-science challenge. Either way, each topic will come with its own novel scientific challenge to address. At the end of the module, the students will give an oral presentation to demonstrate their methodology and their findings. Strong scientific rigor as well as very good engineering and communication skills will be necessary to complete this module successfully.

Compétences à acquérir :

The goal of this module is to provide students with a hands-on experience on a novel data-science/AI challenge using state-of-the-art tools and techniques discussed during other classes of this master.

Foundations of Machine Learning

ECTS : 4

Enseignant responsable : FRANCIS **BACH**

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

The course will introduce the theoretical foundations of machine learning, review the most successful algorithms with their theoretical guarantees, and discuss their application in real-world problems. The covered topics are:

- **Part 1**: Supervised Learning Theory: the batch setting
  - Intro
  - Surrogate Losses
  - Uniform Convergence and PAC Learning
    - Empirical Risk Minimization and ill-posed problems
    - Concentration Inequalities
    - Universal consistency, PAC Learnability
    - VC Dimension
    - Rademacher complexity
  - Non Uniform Learning and Model Selection
    - Bias-variance Tradeoff
    - Structural Minimization Principle and Minimum Description Length Principle
    - Regularization
- **Part 2**: Supervised Learning Theory and Algorithms in the Online Setting
  - Foundations of Online Learning
  - Beyond the Perceptron Algorithm
- **Partie 3**: Ensemble Methods and Kernels Methods
  - SVMs, Kernels
  - Kernel Approximation Algorithms in the Primal
  - Ensemble Methods: Bagging, Boosting, Gradient Boosting, Random Forests
- **Partie 4**: Algorithms for Unsupervised Learning
  - Dimensionality Reduction: PCA, ICA, Kernel PCA, ISOMAP, LLE
  - Representation Learning
  - Expectation Maximization, Latent Models and Variational Methods

Compétences à acquérir :

The aim of this course is to provide the students with the fundamental concepts and tools for developing and analyzing machine learning algorithms.

Pré-requis obligatoires

- Linear Algebra

- Statistics and Probability

Pré-requis recommandés

- Linear models

Mode de contrôle des connaissances :

- Each student will have to have the role of scribe during one lecture, taking notes during the class and sending the notes to the teacher in pdf.
- Final exam

Bibliographie, lectures recommandées :

The most important book: - Shalev-Shwartz, S., & Ben-David, S. (2014). Understanding machine learning: From theory to algorithms. Cambridge University Press. Also: - Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2012). Foundations of machine learning. MIT press. - Vapnik, V. (2013). The nature of statistical learning theory. Springer science & business media. - Bishop Ch. (2006). Pattern recognition and machine learning. Springer - Friedman, J., Hastie, T., & Tibshirani, R. (2001). The elements of statistical learning (Vol. 1, No. 10). New York, NY, USA: Springer series in statistics. - James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112). New York: Springer.

High-dimensional statistics

ECTS : 4

Enseignant responsable : VINCENT **RIVOIRARD** (https://www.ceremade.dauphine.fr/~rivoirar/)

Langue du cours : Anglais

Volume horaire : 24

Optimal transport

ECTS : 4

Enseignant responsable : GABRIEL **PEYRE**

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Optimal transport (OT) is a fundamental mathematical theory at the interface between optimization, partial differential equations and probability. It has recently emerged as an important tool to tackle a surprisingly large range of problems in data sciences, such as shape registration in medical imaging, structured prediction problems in supervised learning and training deep generative networks. This course will interleave the description of the mathematical theory with the recent developments of scalable numerical solvers. This will highlight the importance of recent advances in regularized approaches for OT which allow one to tackle high dimensional learning problems. The course will feature numerical sessions using Python.

- Motivations, basics of probabilistic modeling and matching problems.
- Monge problem, 1D case, Gaussian distributions.
- Kantorovich formulation, linear programming, metric properties.
- Schrödinger problem, Sinkhorn algorithm.
- Duality and c-transforms, Brenier's theory, W1, generative modeling.
- Semi-discrete OT, quantization, Sinkhorn dual and divergences

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Optimization for Machine Learning

ECTS : 4

Enseignant responsable : Clement **ROYER** (https://www.lamsade.dauphine.fr/~croyer/cours.html)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Optimization has long been a fundamental component for modeling and solving classical machine learning problems such as linear regression and SVM classification. It also plays a key role in the training of neural networks, thanks to the development of efficient numerical tools tailored to deep learning. This course is concerned with developing optimization algorithms for learning tasks, and will consist of both lectures and hands-on sessions in Python. The course will begin by an introduction to the various problem formulations arising in machine and deep learning, together with a refresher on key mathematical concepts (linear algebra, convexity, smoothness). The course will then describe the main algorithms for optimization in data science (gradient descent, stochastic gradient) and their theoretical properties. Finally, the course will focus on the challenges posed by implementing these methods in a deep learning and large-scale environment (automatic differentiation, distributed calculations, regularization).

Compétences à acquérir :

- Understand the nature and structure of optimization problems arising in machine learning.
- Select an algorithm tailored to solving a particular instance among those seen in class based on theoretical and practical concerns.
- Experience the practical challenges in implementing an optimization scheme in a learning setting.

Bibliographie, lectures recommandées :

- L. Bottou, F. E. Curtis and J. Nocedal. Optimization Methods for Large-Scale Machine Learning. SIAM Review, 2018.
- S. J. Wright and B. Recht. Optimization for Data Analysis. Cambridge University Press, 2022.

Reinforcement learning

ECTS : 4

Enseignant responsable : OLIVIER **CAPPE**

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

- Models: Markov decision processes (MDP), multiarmed bandits and other models
- Planning: finite and infinite horizon problems, the value function, Bellman equations, dynamic programming, value and policy iteration
- Basic learning tools: Monte Carlo methods, temporal-difference learning, policy gradient
- Probabilistic and statistical tools for RL: Bayesian approach, relative entropy and hypothesis testing, concentration inequalities
- Optimal exploration in multiarmed bandits: the explore vs exploit tradeoff, lower bounds, the UCB algorithm, Thompson sampling
- Extensions: Contextual bandits, optimal exploration for MDP

Compétences à acquérir :

Reinforcement Learning (RL) refers to scenarios where the learning algorithm operates in closed-loop, simultaneously using past data to adjust its decisions and taking actions that will influence future observations. Algorithms based on RL concepts are now commonly used in programmatic marketing on the web, robotics or in computer game playing. All models for RL share a common concern that in order to attain one's long-term optimality goals, it is necessary to reach a proper balance between exploration (discovery of yet uncertain behaviors) and exploitation (focusing on the actions that have produced the most relevant results so far).

The methods used in RL draw ideas from control, statistics and machine learning. This introductory course will provide the main methodological building blocks of RL, focussing on probabilistic methods in the case where both the set of possible actions and the state space of the system are finite. Some basic notions in probability theory are required to follow the course. The course will imply some work on simple implementations of the algorithms, assuming familiarity with Python.

Mode de contrôle des connaissances :

- Individual homework (in Python)
- Final exam

Bibliographie, lectures recommandées :

Bibliographie, lectures recommandées

- M. Puterman. Markov Decision Processes: Discrete Stochastic Dynamic Programming. John Wiley & Sons, 1994.
- R. Sutton and A. Barto. Introduction to Reinforcement Learning. MIT Press, 1998.
- C. Szepesvari. Algorithms for Reinforcement Learning. Morgan & Claypool Publishers, 2010.
- T. Lattimore and C. Szepesvari. Bandit Algorithms. Cambridge University Press. 2019.

SEMESTRE 4 - 20 ECTS

UE optionnelles (5 UE à choisir)

Advanced machine learning

ECTS : 4

Enseignant responsable : YANN **CHEVALEYRE** (https://dauphine.psl.eu/recherche/cvtheque/chevaleyre-yann)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

This research-oriented module will focus on advanced machine learning algorithms, in particular in the Bayesian setting 1) Bayesian Machine Learning (with Moez Draief, chief data scientist CapGemini)   - Bayesian linear regression   - Gaussian Processes (i.e. kernelized Bayesian linear regression)   - Approximate Bayesian Inference   - Latent Dirichlet Allocation 2) Bayesian Deep Learning (with Julyan Arbel, CR INRIA)   - MCMC methods   - variationnal methods 3) Advanced Recommandation Techniques (with Clement Calauzene, Criteo)

Compétences à acquérir :

Probabilistic, Bayesian ML and recommandation systems

Mode de contrôle des connaissances :

- Chaque étudiant devra présenter un papiers de recherche

Bayesian case studies

ECTS : 4

Enseignant responsable : JULIEN **STOEHR** (https://www.ceremade.dauphine.fr/~stoehr/)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

1. Bayesian Modelling Foundations: learn the principle of Bayes formulation, the choice of a prior distribution (conjugate prior, Jeffreys prior, non-informative and weekly informative prior) and model selection (Bayes Factor)
2. Bayesian Inference: insights on sampling methods such as importance sampling, Markov Chain Monte Carlo methods, Approximate Bayesian Computation methods
3. Variable Selection: learn about Gibbs Sampler, model averaging and Zellner's Prior
4. Bayesian Workflow: apply the Bayesian workflow on examples using R and stan

Compétences à acquérir :

- Learn Bayesian thinking in practice, not just theory
- Build statistical models that are interpretable and robust
- Apply simulation algorithms
- Perform model selection
- Hands-on with real data using R and Stan

Mode de contrôle des connaissances :

Final written examination including a practical part on R

Bibliographie, lectures recommandées :

Bayesian Essentials with R, Jean-Michel Marin, Christian P. Robert (2014)

Bayesian machine learning

ECTS : 4

Enseignant responsable : GUILLAUME **KON KAM KING** (https://sites.google.com/site/guillaumekonkamking/courses)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Bayesian Nonparametrics:

- Introduction
- The Dirichlet Process
- Infinite Mixture models
- Posterior Sampling
- Models beyond the Dirichlet Process
- Gaussian Processes
- Selected applications

Bayesian Deep Learning

- Why do we want parameter uncertainty
- Priors for Bayesian neural networks
- Posterior inference
- Martingale Posteriors and generalised Bayesian Inference

Compétences à acquérir :

Essentials of Bayesian Nonparametrics, main concepts for Bayesian Deep Learning

Pré-requis obligatoires

- Bayesian statistics
- Markov Chain Monte Carlo

Mode de contrôle des connaissances :

Final exam and homework

Bibliographie, lectures recommandées :

- Hjort NL, Holmes C, Müller P, Walker SG, editors. Bayesian nonparametrics. Cambridge University Press; 2010 Apr 12.
- Ghosal S, Van der Vaart AW. Fundamentals of nonparametric Bayesian inference. Cambridge University Press; 2017 Jun 26.
- Williams CK, Rasmussen CE. Gaussian processes for machine learning. Cambridge, MA: MIT press; 2006.
- Many references at https://www.gatsby.ucl.ac.uk/~porbanz/npb-tutorial.html
- Murphy KP. Probabilistic machine learning: Advanced topics. MIT press; 2023 Aug 15.
- Fong E, Holmes C, Walker SG. Martingale posterior distributions. Journal of the Royal Statistical Society Series B: Statistical Methodology. 2023 Nov;85(5):1357-91.

Computational social choice

ECTS : 4

Enseignant responsable : JEROME **LANG** (https://www.lamsade.dauphine.fr/~lang/)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

The aim of this course is to give an overview of the problems, techniques and applications of computational social choice, a multidisciplinary topic at the crossing point of computer science (especially artificial intelligence, operations research, theoretical computer science, multi-agent systems, computational logic, web science) and economics. The course consists of the analysis of problems arising from the aggregation of preferences of a group of agents from a computational perspective. On the one hand, it is concerned with the application of techniques developed in computer science, such as complexity analysis or algorithm design, to the study of social choice mechanisms, such as voting procedures or fair division algorithms. On the other hand, computational social choice is concerned with importing concepts from social choice theory into computing. The course will focus on normative aspects, computational aspects, and real-world applications (including some case studies). Program: 1. Introduction to social choice and computational social choice. 2. Preference aggregation, Arrow's theorem and how to escape it. 3. Voting rules: informational basis and normative aspects. 4. Voting rules : computation. Voting on combinatorial domains. 5. Strategic issues: strategyproofness, Gibbard and Satterthwaite's theorem, computational resistance to manipulation, other forms of strategic behaviour. 6. Multiwinner elections. Public decision making and participatory budgeting. 7. Communication issues in voting: voting with incomplete preferences, elicitation protocols, communication complexity, low-communication social choice. 8. Fair division. 9. Matching under preferences. 10. Specific applications and case studies (varying every year): rent division, kidney exchange, school assignment, group recommendation systems…

Compétences à acquérir :

N/S

Pré-requis obligatoires

none

Pré-requis recommandés

Prerequisite-free. Basics of discrete mathematics (especially graph theory) and algorithmics is a plus.

Mode de contrôle des connaissances :

Written exam by default.

Bibliographie, lectures recommandées :

References: * Handbook of Computational Social Choice (F. Brandt, V. Conitzer, U. Endriss, J. Lang, A. Procaccia, eds.), Cambridge University Press, 2016. Available for free online. * Trends in Computational Social Choice (U. Endriss, ed), 2017. Available for free online.

Computational statistics methods and MCMC

ECTS : 4

Enseignant responsable : CHRISTIAN **ROBERT** (https://dauphine.psl.eu/recherche/cvtheque/robert-christian-p)

Langue du cours : Anglais

Volume horaire : 24

Dimension reduction and manifold learning

ECTS : 4

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Modern machine learning typically deals with high-dimensional data. The fields concerned are very varied and include genomics, image, text, time series, or even socioeconomic data where more and more unstructured features are routinely collected. As a counterpart of this tendency towards exhaustiveness, understanding these data raises challenges in terms of computational resources and human understandability. Manifold Learning refers to a family of methods aiming at reducing the dimension of data while preserving certain of its geometric and structural characteristics. It is widely used in machine learning and experimental science to compress, visualize and interpret high-dimensional data. This course will provide a global overview of the methodology of the field, while focusing on the mathematical aspects underlying the techniques used in practice.

Compétences à acquérir :

- Curse of dimensionality, manifold hypothesis and intrinsic dimension(s)
- Multidimensional scaling
- Linear dimension reduction (random projections, principal component analysis)
- Non-linear spectral methods (kernel PCA, ISOMAP, MVU, Laplacian eigenmaps)

- Ad-hoc distance-preserving methods (diffusion maps, LLE)
- Probabilistic dimension reduction and clustering (SNE, UMAP)
- Neural network-based dimensionality reduction

Pré-requis obligatoires

Linear algebra, basic probability theory, statistics, Python coding

Bibliographie, lectures recommandées :

- Ghojogh, B., M. Crowley, F. Karray, and A. Ghodsi (2023). Elements of dimensionality reduction and manifold learning
- Lee, J. A., M. Verleysen, et al. (2007). Nonlinear dimensionality reduction

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Data acquisition, extraction and storage

ECTS : 4

Enseignant responsable : Pierre **SENELLART** (https://pierre.senellart.com/)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

The objective of this course is to present the principles and techniques used to acquire, extract, integrate, clean, preprocess, store, and query datasets, that may then be used as input data to train various artificial intelligence models. The course will consist on a mix of lectures and practical sessions. We will cover the following aspects:

- Web data acquisition (Web crawling, Web APIs, open data, legal issues)
- Information extraction from semi-structured data
- Data cleaning and data deduplication
- Data formats and data models
- Storing and processing data in databases, in main memory, or in plain files
- Introduction to large-scale data processing with MapReduce and Spark
- Introduction to the management of uncertain data

Compétences à acquérir :

Understanding:

- how to acquire data from a variety of sources and in a variety of formats
- how to extract structured data from unstructured or semi-structured data
- how to format, integrate, clean data sets
- how to store and access data sets

Pré-requis obligatoires

Basics of computer science and computer engineering (algorithms, databases, programming, logics, complexity).

Mode de contrôle des connaissances :

Project (50% of the grade) and in-class written assessment (50% of the grade)

En savoir plus sur le cours :https://moodle.psl.eu/course/view.php?id=34943

Deep learning for image analysis

ECTS : 4

Enseignant responsable : Etienne **DECENCIERE**

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Deep learning has achieved formidable results in the image analysis field in recent years, in many cases exceeding human performance. This success opens paths for new applications, entrepreneurship and research, while making the field very competitive.

This course aims at providing the students with the theoretical and practical basis for understanding and using deep learning for image analysis applications.

Program to be followed
The course will be composed of lectures and practical sessions. Moreover, experts from industry will present practical applications of deep learning.
Lectures will include:

- Artificial neural networks, back-propagation algorithm
- Convolutional neural networks
- Design and optimization of a neural architecture
- Analysis of neural network function
- Image classification and segmentation
- Auto-encoders and generative networks
- Transformers
- Current research trends and perspectives

During the practical sessions, the students will code in Python, using Keras or Pytorch. They will be confronted with the practical problems linked to deep learning: architecture design; optimization schemes and hyper-parameter selection; analysis of results.

Compétences à acquérir :

Deep learning for image analysis: theoretical foundations and applications

Pré-requis obligatoires

- Linear algebra, basic probability and statistics
- Python

Mode de contrôle des connaissances :

Practical session and exam

Graph analytics

ECTS : 4

Enseignant responsable : DANIELA **GRIGORI** (https://dauphine.psl.eu/recherche/cvtheque/grigori-daniela)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

The objective of this course is to give students an overview of the field of graph analytics. Since graphs form a complex and expressive data type, we need methods for representing graphs in databases, manipulating, querying, analyzing and mining them. Moreover, graph applications are very diverse and need specific algorithms. The course presents new ways to model, store, retrieve, mine and analyze graph-structured data and some examples of applications. Lab sessions are included allowing students to practice graph analytics: modeling a problem into a graph database and performing analytical tasks over the graph in a scalable manner.   Program - Graph analytics - Network properties and models - Link Analysis: PageRank and its variants - Community detection - Frameworks for parallel graph analytics - Pregel - a model for parallel-graph computing - GraphX Spark - unifying graph- and data -parallel computing - Machine learning with graphs - Applications: process mining and analysis Practical work: graph analytics with GraphX and Neo4J

Compétences à acquérir :

Modeling a problem into a graph model and performing analytical tasks over the graph in a scalable manner.

Bibliographie, lectures recommandées :

References   Ian Robinson, Jim Weber, Emil Eifrem, Graph Databases, Editeur : O'Reilly (4 juin 2013), ISBN-10: 1449356265   Eric Redmond, Jim R. Wilson, Seven Databases in Seven Weeks - A Guide to Modern Databases and the NoSQL Movement, Publisher: Pragmatic Bookshelf   Grzegorz Malewicz, Matthew H. Austern, Aart J.C Bik, James C. Dehnert, Ilan Horn, Naty Leiser, and Grzegorz Czajkowski. 2010. Pregel: a system for large-scale graph processing, SIGMOD '10, ACM, New York, NY, USA, 135-146   Xin, Reynold & Crankshaw, Daniel & Dave, Ankur & Gonzalez, Joseph & J. Franklin, Michael & Stoica, Ion. (2014). GraphX: Unifying Data-Parallel and Graph-Parallel Analytics.   Michael S. Malak and Robin East, Spark GraphX in Action, Manning, June 2016

Incremental learning, game theory and applications

ECTS : 4

Enseignant responsable : YANNICK **VIOSSAT** (https://dauphine.psl.eu/recherche/cvtheque/viossat-yannick)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

This course focuses on the behavior of learning algorithms when several agents interacts : specifically, what happens when an agent that follows an online learning algorithm interacts with one or several agents doing the same? The natural language to frame such questions is that of game theory. The course will begin with a short introduction to the topic : normal form games (in particular zero-sum, potential, and stable games), solution concepts (elimination of dominated strategies/rationalizability, Nash equilibrium, correlated and coarse correlated equilibrium, evolutionary stable strategies), and some extensions (Blackwell approachability). Subsequently, we will examine the long-term behavior of a variety of online learning algorithms (fictitious play, regret-matching, exponential weights, etc.). Time allowing, we will discuss links with evolutionary game dynamics, as well as applications to generative adversarial networks (GANs), traffic routing, prediction, or online auctions.

Compétences à acquérir :

- Basic of game theory: representation of strategic interactions, solution concepts, important classes of games.
- Long-run performance of learning procedures when several agents are playing against each other
- Familiarity with game dynamics

Pré-requis recommandés

A basic acquaintance with game theory is beneficial but the course is accessible to students who never studied game theory.

Mode de contrôle des connaissances :

To be discussed with students

Bibliographie, lectures recommandées :

1. Nicolò Cesa-Bianchi and Gábor Lugosi, Prediction, learning, and games, Cambridge University Press, 2006.
2. Drew Fudenberg and David K. Levine, The theory of learning in games, Economic learning and social evolution, vol. 2, MIT Press, Cambridge, MA, 1998.
3. Sergiu Hart and Andreu Mas-Colell, Simple adaptive strategies: from regret matching to uncoupled dynamics, World Scientific Series in Economic Theory - Volume 4, World Scientific Publishing, 2013.
4. Vianney Perchet, Approachability, regret and calibration: implications and equivalences, Journal of Dynamics and Games 1 (2014), no. 2, 181–254.
5. Shai Shalev-Shwartz, Online learning and online convex optimization, Foundations and Trends in Machine Learning 4 (2011), no. 2, 107–194.

Introduction to causal inference

ECTS : 4

Enseignant responsable : FABRICE **ROSSI** (https://www.ceremade.dauphine.fr/en/members/detail-cv/profile/fabrice-rossi.html)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

This course provides an introduction to causal inference. It covers both the Neyman–Rubin potential outcomes framework and Pearl's do-calculus. The former is used to introduce the fundamental problem of causal inference and the notion of counterfactuals. The core hypotheses needed for causal identification of average treatment effects are presented: (conditional) exchangeability, positivity, and consistency. Estimation based on generalised linear models and on machine learning approaches is explored, including the double-machine learning approach.

The second part of the course covers Pearl's do-calculus. The course introduces graphical models, with a focus on directed models, followed by structural causal models. The simple Markovian case is used to link this framework to the potential outcomes one and to derive classical techniques such as the back-door criterion. The semi-Markovian case is then explored as the general way of representing causal hypotheses in the presence of unobserved confounding variables. Identification is revisited in the light of the do-calculus and of the IDC algorithm.

The final part of the course reviews causal discovery algorithms and open research questions.

Compétences à acquérir :

This course is an introduction to causal inference with a strong emphasis on the use of graphical models. After the course, the students should be able

- to apply consistent average treatment effect estimation procedures
- to turn causal hypotheses into structural causal models
- to analyse graphical models to determine independence structures
- to use do-calculus and the IDC algorithm to identify causal estimands

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Knowledge graphs, description logics, reasoning on data

ECTS : 4

Enseignant responsable : Michael **THOMAZZO**

Langue du cours : Français et anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Introduction to Knowledge Graphs, Description Logics and Reasoning on Data.
Knowledge graphs are a flexible tool to represent knowledge about the real world. After presenting some of the existing knowledge graphs (such as DBPedia, Wikidata or Yago) , we focus on their interaction with semantics, which is formalized through the use of so-called ontologies. We then present some central logical formalism used to express ontologies, such as Description Logics and Existential Rules. A large part of the course will be devoted to study the associated reasoning tasks, with a particular focus on querying a knowledge graph through an ontology. Both theoretical aspects (such as the tradeoff between the expressivity of the ontology language versus the complexity of the reasoning tasks) and practical ones (efficient algorithms) will be considered.

Program:
1. Knowledge Graphs (history and uses)
2. Ontology Languages (Description Logics, Existential Rules)
3. Reasoning Tasks (Consistency, classification, Ontological Query Answering)
4. Ontological Query Answering (Forward and backward chaining, Decidability and complexity, Algorithms, Advanced Topics)

Compétences à acquérir :

Capacity to read and understand a research article on logical foundations of knowledge graphs.

Pré-requis recommandés

First order logic; complexity.

Mode de contrôle des connaissances :

Research article presentation

Bibliographie, lectures recommandées :

-- The description logic handbook: theory, implementation, and applications. Baader et al., Cambridge University Press

-- Foundations of Semantic Web Technologies, Hitzler et al., Chapman&Hall/CRC

-- Web Data Management, Abiteboul et al., Cambridge University Press

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Large language models

ECTS : 4

Enseignant responsable : ALEXANDRE **ALLAUZEN** (https://allauzen.github.io/)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

The course focuses on modern and statistical approaches to NLP. Natural language processing (NLP) is today present in so many applications because people communicate almost everything in language : post on social media, web search, advertisement, emails and SMS, customer service exchange, language translation, etc. While NLP heavily relies on machine learning approaches and the use of large corpora, the peculiarities and diversity of language data imply dedicated models to efficiently process linguistic information and the underlying computational properties of natural languages. Moreover, NLP is a fast evolving domain, in which cutting-edge research can nowadays be introduced in large scale applications in a couple of years. The course focuses on modern and statistical approaches to NLP: using large corpora, statistical models for acquisition, disambiguation, parsing, understanding and translation. An important part will be dedicated to deep-learning models for NLP. - Introduction to NLP, the main tasks, issues and peculiarities - Sequence tagging: models and applications - Computational Semantics - Syntax and Parsing - Deep Learning for NLP: introduction and basics - Deep Learning for NLP: advanced architectures - Deep Learning for NLP: Machine translation, a case study

Compétences à acquérir :

- Skills in Natural Language Processing using deep-learning
- Understand new architectures

Pré-requis recommandés

PyTorch

Bibliographie, lectures recommandées :

References - Costa-jussà, M. R., Allauzen, A., Barrault, L., Cho, K., & Schwenk, H. (2017). Introduction to the special issue on deep learning approaches for machine translation. Computer Speech & Language, 46, 367-373. - Dan Jurafsky and James H. Martin. Speech and Language Processing (3rd ed. draft): https://web.stanford.edu/~jurafsky/slp3/ - Yoav Goldberg. A Primer on Neural Network Models for Natural Language Processing: http://u.cs.biu.ac.il/~yogo/nnlp.pdf - Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep Learning: http://www.deeplearningbook.org/

LLM for code and proof

ECTS : 4

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Recent advances in large language models (LLMs) have enabled remarkable progress in program synthesis and code generation. This course explores the foundations and methodologies behind modern neural code generation, with a particular focus on Transformer-based architectures and LLM techniques.

Compétences à acquérir :

The course has two main objectives: (1) to provide students with a deep understanding of the core techniques for training and fine-tuning neural models for code generation, including inference strategies and evaluation metrics specific to code, and (2) to introduce current research in neural program synthesis, highlighting applications in software engineering, reasoning, and formal verification.

Pré-requis obligatoires

Mastery of Python and Pytorch

Mode de contrôle des connaissances :

Homeworks and projects

Machine learning on Big Data

ECTS : 4

Enseignant responsable : DARIO **COLAZZO** (https://dauphine.psl.eu/recherche/cvtheque/dario-colazzo)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

This course focuses on the typical, fundamental aspects that need to be dealt with in the design of machine learning algorithms that can be executed in a distributed fashion, typically on Hadoop clusters, in order to deal with big data sets, by taking into account scalability and robustness. Nowadays there is an ever increasing demand of machine learning algorithms that scales over massives data sets. In this context, this course focuses on the typical, fundamental aspects that need to be dealt with in the design of machine learning algorithms that can be executed in a distributed fashion, typically on Hadoop clusters, in order to deal with big data sets, by taking into account scalability and robustness. So the course will first focus on a bunch of main-stream, sequential machine learning algorithms, by taking then into account the following crucial and complex aspects. The first one is the re-design of algorithms by relying on programming paradigms for distribution and parallelism based on map-reduce (e.g., Spark, Flink, ….). The second aspect is experimental analysis of the map-reduce based implementation of designed algorithms in order to test their scalability and precision. The third aspect concerns the study and application of optimisation techniques in order to overcome lack of scalability and to improve execution time of designed algorithm. The attention will be on machine learning technique for dimension reduction, clustering and classification, whose underlying implementation techniques are transversal and find application in a wide range of several other machine learning algorithms. For some of the studied algorithms, the course will present techniques for a from-scratch map-reduce implementation, while for other algorithms packages like Spark ML will be used and end-to-end pipelines will be designed. In both cases algorithms will be analysed and optimised on real life data sets, by relying on a local Hadoop cluster, as well as on a cluster on the Amazon AWS cloud. References: - Mining of Massive Data sets http://www.mmds.org - High Performance Spark - Best Practices for Scaling and Optimizing Apache Spark Holden Karau, Rachel Warren O'Reilly

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Machine learning with kernel method

ECTS : 4

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Reproducing kernel Hilbert spaces et le "kernel trick" Théorème de représentation Kernel PCA Kernel ridge regression Support vector machines Noyaux sur les semigroupes Noyaux pour le texte, les graphes, etc.

Compétences à acquérir :

Présenter les bases théoriques et des applications des méthodes à noyaux en apprentissage.

Mathematics of deep learning

ECTS : 4

Enseignant responsable : BRUNO **LOUREIRO** (https://brloureiro.github.io/)

Langue du cours : Anglais

Volume horaire : 24

Monte-Carlo search and games

ECTS : 4

Enseignant responsable : TRISTAN **CAZENAVE** (https://dauphine.psl.eu/recherche/cvtheque/tristan-cazenave)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

Introduction to Monte Carlo for computer games. Monte Carlo Search has revolutionized computer games. It works well with Deep Learning so as to create systems that have superhuman performances in games such as Go, Chess, Hex or Shogi. It is also appropriate to address difficult optimization problems. In this course we will present different Monte Carlo search algorithms such as UCT, GRAVE, Nested Monte Carlo and Playout Policy Adaptation. We will also see how to combine Monte Carlo Search and Deep Learning. The validation of the course is a project involving a game or an optimization problem. La recherche Monte-Carlo a révolutionné la programmation des jeux. Elle se combine bien avec le Deep Learning pour créer des systèmes qui jouent mieux que les meilleurs joueurs humains à des jeux comme le Go, les Échecs, le Hex ou le Shogi. Elle permet aussi d'approcher des problèmes d'optimisation difficiles. Dans ce cours nous traiterons des différents algorithmes de recherche Monte-Carlo comme UCT, GRAVE ou le Monte-Carlo imbriqué et l'apprentissage de politique de playouts. Nous verrons aussi comment combiner recherche Monte-Carlo et apprentissage profond. Le cours sera validé par un projet portant sur un jeu ou un problème d'optimisation difficile.

Bibliographie, lectures recommandées :

Bibliographie : Intelligence Artificielle Une Approche Ludique, Tristan Cazenave, Editions Ellipses, 2011.

Non-convex inverse problems

ECTS : 4

Enseignant responsable : IRENE **WALDSPURGER** (https://dauphine.psl.eu/recherche/cvtheque/waldspurger-irene)

Langue du cours : Anglais

Volume horaire : 24

Description du contenu de l'enseignement :

An inverse problem is a problem where the goal is to recover an unknown object (typically a vector with real coordinates, or a matrix), given a few ``measurements'' of this object, and possibly some information on its structure. In this course, we will discuss examples of such problems, motivated by applications as diverse as medical imaging, optics and machine learning. We will especially focus on the questions: which algorithms can we use to numerically solve these problems? When and how can we prove that the solutions returned by the algorithms are correct? These questions are relatively well understood for convex inverse problems, but the course will be on non-convex inverse problems, whose study is much more recent, and a very active research topic.

The course will be at the interface between real analysis, statistics and optimization. It will include theoretical and programming exercises.

Compétences à acquérir :

Understand what is a non-convex inverse problems; get some familiarity with the most classical algorithms to solve them, and with algorithms for general non-convex optimization

NoSQL databases

ECTS : 4

Enseignant responsable : PAUL **BONIOL**

Langue du cours : Anglais

Volume horaire : 24

Point cloud and 3D modelling

ECTS : 4

Enseignant responsable : FRANCOIS **GOULETTE**

Langue du cours : Anglais

Volume horaire : 24

Topics in trustworthy machine learning

ECTS : 4

Enseignant responsable : OLIVIER **CAPPE**

Langue du cours : Anglais

Volume horaire : 24

PSL week - 2 ECTS

PSL Week

Langue du cours : Français

Bloc stage - 10 ECTS

Stage

ECTS : 10

Langue du cours : Français

Description du contenu de l'enseignement :

4 à 6 mois de stage
