

COURSE TITLE - INTITULE DU COURS

Course title - Intitulé du cours	Stochastic methods for optimization and sampling
Level / Semester - Niveau /semestre	M1 S2
Teacher - Enseignant responsable	Julien Chhor
Other teacher(s) - Autre(s) enseignant(s)	
Lecture Hours - Volume Horaire CM	30
TA Hours - Volume horaire TD	
TP Hours - Volume horaire TP	
Course Language - Langue du cours	English
TA and/or TP Language - Langue des TD et/ou TP	Python

Teaching staff contacts - Coordonnées de l'équipe pédagogique :

Julien Chhor

Course's Objectives - Objectifs du cours :

This course focuses on stochastic optimization and sampling methods, with an emphasis on mathematical proofs and theoretical analysis. Homework assignments will be given to help you implement the algorithms discussed in class using Python. The final grade will be based on the homework and a final written exam.

Part 1: Stochastic Optimization

The first part of the course, on stochastic optimization, is a continuation of the first-semester optimization course. We will study state-of-the-art optimization methods based on variations of stochastic gradient descent, widely used in modern machine learning.

We will explore the following algorithms, discussing their appropriate applications and the assumptions under which they operate:

- Stochastic gradient descent
- Minibatch stochastic gradient descent
- Proximal stochastic gradient descent
- Variance reduction techniques (e.g., SVRG)
- Momentum
- Algorithms with adaptive step sizes (Adagrad, RMSprop, Adam)

For these algorithms, we will focus on deriving rates of convergence under assumptions of convexity or strong convexity. Additionally, we will cover stochastic approximation and analyze the almost sure convergence of the Robbins-Monro algorithm.

Part 2: Sampling Methods

The second part of the course focuses on sampling methods (i.e. techniques for generating random variables from a given probability distribution). We will study the following methods:

- Simulation of random variables with classical probability distributions (Bernoulli, binomial, multinomial, Poisson, exponential)
- Inversion of the CDF method
- Rejection method
- Simulation of normally distributed random variables (Box-Muller method, Cholesky decomposition)
- Monte Carlo methods and confidence intervals
- Importance sampling (variance reduction, simulation of rare events)
- Markov Chain Monte Carlo (MCMC) methods (Metropolis-Hastings algorithm, Gibbs sampling)

Prerequisites - Pré requis :

Basic knowledge of differential calculus, probability theory, and knowledge of gradient descent algorithms is required.

Practical information about the sessions - Modalités pratiques de gestion du cours :

Laptops are allowed during the class.

Grading system - Modalités d'évaluation :

Written final exam, homework.

Bibliography/references - Bibliographie/références :

Learning theory from first principles, F. Bach, https://www.di.ens.fr/%7Efbach/lfp_book.pdf

Lecture notes, S. Bubeck <http://sbubeck.com/book.html>

Monte-Carlo methods, C. Robert <https://link.springer.com/book/10.1007/978-1-4757-4145-2>

A complete set of lecture notes is provided.