EE-622

Computational Optimal Transport (2019)

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Cursus	Sem.	Type
Electrical Engineering		Obl.

Language of teaching	English
Credits	1
Session	
Exam	Project report
Workload	30h
Hours	**17**
Courses	13
TP	4
Number of positions	**60**

Frequency

Only this year

Remark

Only this year: 24th, 25th, 26th June, 2019

Summary

In this short course, I will review numerical approaches for the approximate resolution of optimization problems related to optimal transport. I will also give some insight on how to apply these methods to imaging sciences and machine learning problems.

Content

Optimal transport (OT) has become a fundamental mathematical tool at the interface between calculus of variations, partial differential equations and probability. It took however much more time for this notion to become mainstream in numerical applications. This situation is in large part due to the high computational cost of the underlying optimization problems. There is a recent wave of activity on the use of OT-related methods in fields as diverse as computer vision, computer graphics, statistical inference, machine learning and image processing.
In this short course, I will review numerical approaches for the approximate resolution of optimization problems related to optimal transport. I will also give some insight on how to apply these methods to imaging sciences and machine learning problems. The course will feature a numerical session using Python. Material for the course (including a small book, slides
and computational resources) can be found online at https://optimaltransport.github.io/.

Course 1: Foundations of Optimal Transport
- The basics of Optimal Transport
- Overview of applications in imaging and learning
- Special cases: 1-D, Gaussians
- Network flows solvers
- Semi-discrete, auction

Course 2: Entropic regularization

- Regularization and approximation
- Sinkhorn's algorithm
- Hilbert's metric, Perron-Frobenius
- Extensions: multimarginal, unbalanced

Course 3: Variational Wasserstein problems
- Wasserstein barycenters
- Gradient flows
- Gromov-Wasserstein

Course 4: Density fitting and generative modeling
- Statistical divergences

- Sample complexity
- Minimum Kantorovich Estimator
- Deep learning and generative models

Note

Students will be required to bring their own laptops to the lab session with an updated version of Python 3 installed via an Anaconda distribution (installation instructions can be found at docs.anaconda.com/anaconda/install/).

Keywords

- Optimal Transport
- Machine Learning

Learning Outcomes

By the end of the course, the student must be able to:

- Expound the basics of OT
- Implement sinkhorn-based methods
- Expound how to apply OT to imaging and ML problems

Assessment methods

Project report.

Resources

Bibliography

Gabriel Peyré and Marco Cuturi, Computational Optimal Transport, ArXiv:1803.00567, 2018.

Websites

- https://optimaltransport.github.io/