# Syllabus: "Advanced Methods in Computational Economics"

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To be held from 14.11.2022 - 25.11.2022 at CREST/ENSAE

**Abstract**

This course is intended to confront M.sc. and Ph.D. students in economics, finance, and related fields with recent tools developed in applied mathematics, machine learning, computational science, and the computational economics literature to solve and estimate state-of-the-art models. The lectures will be centered around sparse grids, adaptive sparse grids, two types of machine learning methods (Gaussian Processes and Deep Neural Networks), and will be showcased in the context of application in climate change economics, macroeconomics, and finance. The lectures will be interactive, in a workshop-like style, that is, a mix of theory and actively playing with code examples (delivered in Python and deployed on a cloud computing infrastructure).

## 1 Detailed topics of the mini-course

There will be four lectures that will cover the following topics:

### Lecture 1 – Monday 14/11

Sparse Grids, Adaptive Sparse Grids, High-dimensional model reduction, and high-performance computing Python libraries (if time permits).

### Lecture 2 – Thursday 17/11

Gaussian Processes, Bayesian active learning, and active subspace methods for solving dynamic stochastic models.

### Lecture 3 – Monday 21/11

Deep Learning basics.

### Lecture 4 – Thursday 24/11

Deep Equilibrium Nets, Deep structural estimation, and some applications to climate economics and finance.

## 2 Pre-requisites

- Graduate-level mathematics (see, e.g., "Mathematics for Machine Learning". The book is freely downloadable here: https://mml-book.github.io).
- Solid coding skills in Python (see, e.g., https://python-programming.quantecon.org/intro.html, Sections 1 - 7).
- Some working knowledge of recursive methods (see, e.g., Stokey et al. [1989], Ljungqvist and Sargent [2000]).

## 3 Evaluation

Participants who take the course for credits are expected to propose a small project where they apply some of the methods learned to an application (e.g., apply deep learning to a data set, solve a dynamic model, etc.). The deliverable that will be graded is a short write-up (4-6 pages maximum), the data set (if any), and the code on which the presented results in the report were based. The participants will have four weeks' time after the course is finished to complete the task.

## 4 Some related literature

- Sparse grids in general: Bungartz and Griebel [2004]
- Sparse grids in economics: Brumm and Scheidegger [2017], Brumm et al. [2021]
- High-dimensional model representation: Yang et al. [2012]
- High-dimensional dynamic stochastic model representation: Eftekhari and Scheidegger [2020]
- Gaussian processes in general: Rasmussen [2004]
- Gaussian processes in economics and finance: Scheidegger and Bilionis [2019], Renner and Scheidegger [2018]
- Active subspaces: Constantine [2015]
- Active subspaces in economics: Scheidegger and Bilionis [2019], Kubler and Scheidegger [2018]
- Deep learning in general: Goodfellow et al. [2016]
- Deep equilibrium nets: Azinovic et al. [2022]
- Deep structural estimation: Chen et al. [2021]

## Bibliographies

Marlon Azinovic, Luca Gaegauf, and Simon Scheidegger. Deep equilibrium nets. *International Economic Review*, 2022. doi: https://doi.org/10.1111/iere.12575. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/iere.12575`.

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Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning.* MIT Press, 2016. `http://www.deeplearningbook.org`.

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L. Ljungqvist and T.J. Sargent. *Recursive macroeconomic theory.* Mit Press, 2000. ISBN 9780262194518. URL `http://books.google.ch/books?id=3LmXQgAACAAJ`.

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Simon Scheidegger and Ilias Bilionis. Machine learning for high-dimensional dynamic stochastic economies. *Journal of Computational Science*, 33:68 – 82, 2019. ISSN 1877-7503. doi: https://doi.org/10.1016/j.jocs.2019.03.004. URL `http://www.sciencedirect.com/science/article/pii/S1877750318306161`.

Nancy L. Stokey, Robert E. Lucas, and Edward C. Prescott. *Recursive Methods in Economic Dynamics.* Harvard University Press, 1989. ISBN 9780674750968. URL `http://www.jstor.org/stable/j.ctvjnrt76`.

Xiu Yang, Minseok Choi, Guang Lin, and George Em Karniadakis. Adaptive anova decomposition of stochastic incompressible and compressible flows. *Journal of Computational Physics*, 231(4):1587 – 1614, 2012. ISSN 0021-9991. doi: https://doi.org/10.1016/j.jcp.2011.10.028. URL `http://www.sciencedirect.com/science/article/pii/S0021999111006280`.