Machine Learning for Computational Economics

EDHEC Business School — Spring 2026

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Location: EDHEC (E-learning room) | Course site: TBA

Course schedule: Thu 01/15 09:00–12:15 & 14:45–18:00; Fri 01/16 09:00–12:15 & 13:45–18:00; Sat 01/17 09:00–12:15.

Course Description

This course combines classical numerical methods in economics and finance with modern machine-learning approaches for solving and estimating dynamic models. Students learn to connect discrete- and continuous-time dynamic programming with neural-network approximations and gradient-based optimization. The course culminates with the *Deep Policy Iteration (DPI)* algorithm and higher-order extensions for high-dimensional diffusion models. Each module blends theory, implementation, and live coding in Julia/Pluto.

Learning Outcomes

By the end of the five modules, you will be able to:

- Solve dynamic optimization problems in discrete and continuous time.
- Implement stable numerical schemes (finite differences, collocation) and verify convergence.
- Build, train, and interpret shallow/deep neural networks; choose and tune SGD variants (Momentum, RMSProp, Adam/AdamW).
- Apply *Deep Policy Iteration* (DPI) to solve high-dimensional continuous-time models (policy/value nets, drift estimation, control updates without closed-form FOCs).
- Prototype diffusion-estimation pipelines that scale in state dimension using ML surrogates for scores, drifts, and likelihood components.

By the end of the course, students will be able to solve and estimate complex dynamic models that arise in macroeconomics, asset pricing, and corporate finance using modern ML methods.

Prerequisites

Graduate-level macroeconomics or asset pricing. Familiarity with dynamic optimization and basic statistics is expected. All computations are done in Julia. Prior experience is helpful but not required. To prepare, review the "Getting Started with Julia" section of the QuantEcon tutorial (`https://julia.quantecon.org/intro.html`).

Texts & References

The main reference are the lecture notes **"Machine Learning for Computational Economics"** developed for this course. The notes go through the theory and implementation of the methods in detail. It includes a lot of examples and guided implementations of the different methods in Julia.

Additional reading: There are several useful references that complement the lecture notes. The handbook chapter on numerical methods by Fernández-Villaverde, Rubio-Ramírez and Schorfheide (2016) is a great summary of the classical methods for solving dynamic models. For the fundamentals of machine learning, the classic books by Hastie, Tibshirani and Friedman (2009) and Goodfellow, Bengio and Courville (2016) are great references. My discussion of fundamentals of Machine Learning is closer to Prince (2023). The material on the DPI method is based on *"Machine Learning Methods for Continuous-Time Finance"* by Duarte, Duarte and Silva (2024), and the discussion of estimation of high-dimensional diffusion models is based on Duarte, Duarte and Silva (2025).

High-Level Schedule (5 x 3h)

Module	**Theme**	**Core Topics & In-Class Activities**
01	Discrete-Time Methods	Bellman equation; contraction mapping; EGM vs. policy iteration; interpolation (Chebyshev, splines); monotone schemes; *hands-on:* consumption–savings baseline, Tauchen & policy updates.
02	Continuous-Time Methods	From Bellman to HJB; diffusions & jumps; stationary HJB; boundary conditions; FD vs. collocation; viscosity solutions; stability/consistency/monotonicity; *hands-on:* Solving continuous-time consumption–savings problem.
03	Fundamentals of ML	Supervised pipeline; linear models as baseline; SNN/DNN; activation functions; SGD, Momentum, RMSProp, Adam/AdamW; Lux.jl model building; *hands-on:* training runs, loss landscapes, breakpoint adaptivity.
04	Deep Policy Iteration (DPI) for CT Finance	Three curses and DPI: (i) drift evaluation in high-d; (ii) NN approximations (value/policy); (iii) control update without closed-form FOCs; implementation loop; *applications:* Lucas orchard, Hennessy–Whited, high-d portfolio choice; diagnostics & ablations.
05	ML for High-Dimensional Diffusion Estimation	Standard simulation/perturbation methods; computing nested drifts; higher-order DPI variants; *hands-on:* mini pipeline on synthetic diffusions.

Detailed Module Plan

Module 01: Discrete-Time Methods (3h)

- Bellman equation; fixed-point arguments; value vs. policy iteration.
- Endogenous Grid Method (EGM) and relation to CT limits.
- Approximation: grids, Chebyshev nodes, interpolation error.
- *Lab:* implement consumption–savings; compare VFI vs. PFI vs. EGM.

Recommended reading: Course notes on *Discrete-Time Methods*.

Module 02: Continuous-Time Methods (3h)

- From discrete time to HJB; diffusion terms; transversality; steady state.
- Numerics: FD schemes, collocation, stability/consistency, viscosity notion.
- *Lab:* baseline HJB and extension with risky return term.

Recommended reading: Course notes on *Continuous-Time Methods*.

Module 03: Fundamentals of ML (3h)

- SNN/DNN expressivity; universal approximation (width/depth versions).
- Optimization: SGD family (Momentum, RMSProp, Adam/AdamW); regularization.
- Lux.jl basics; training loops; monitoring; generalization checks.
- *Lab:* fit SNN on piecewise functions; DNN on polynomial target; optimiser comparison.

Recommended reading: Course notes on *ML Fundamentals*.

Module 04: Deep Policy Iteration (DPI) (3h)

- DPI loop: value/policy networks; drift evaluation; argmax without closed-form controls.
- Practicalities: scaling, batching, AD details, stability, and stopping.
- *Applications:* Lucas orchard, Hennessy–Whited corporate model, high-d portfolio choice.
- *Lab:* skeleton DPI implementation; replicate a simplified application.

Recommended reading: Course notes on *DPI Method* and Duarte et al. (2024).

Module 05: ML for Diffusion Estimation (3h)

- The challenges of estimating high-dimensional diffusion models.
- Approximation through nested drifts; automatic differentiation with hyper-duals.
- *Lab:* toy high-d diffusion estimation pipeline.

Recommended reading: Course notes on *Estimation of High-Dimensional Diffusion Models* and Duarte et al. (2025).

This syllabus may be updated to reflect pacing and student feedback; any changes will be announced in class and on the course site.

References

Duarte, Victor, Diogo Duarte, and Dejanir H. Silva, "Machine Learning for Continuous-Time Finance," *The Review of Financial Studies*, 2024, *37* (11), 3217–3271.

_ , _ , and _ , "Estimation of High-Dimensional Diffusion Models: A Hyper-Dual Approach," 2025.

Fernández-Villaverde, Jesús, Juan Francisco Rubio-Ramírez, and Frank Schorfheide, "Solution and estimation methods for DSGE models," in "Handbook of Macroeconomics," Vol. 2, Elsevier, 2016, pp. 527–724.

Goodfellow, Ian, Yoshua Bengio, and Aaron Courville, *Deep Learning*, MIT Press, 2016.

Hastie, Trevor, Robert Tibshirani, and Jerome Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2 ed., New York, NY: Springer, 2009.

Prince, Simon J. D., *Understanding Deep Learning*, Cambridge, UK: Cambridge University Press, 2023.