Machine Learning in Economics (D200)

Syllabus (Lent 2025)

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Course Code and Title: Machine Learning in Economics (D200)
Term: Lent Term 2025
Lecturer: Dr. Stefan Bucher
Office Hours: Thu 11.30am-12.30pm. Sign up here

Lectures: Fri 9.00-11.00am in Meade Room, weeks 1-9
Classes: (some) Thu 4.00-6.00pm in Room 7 (Lecture Block), weeks 3, 5-7, and 9.
Teaching Assistant: Cheuk Ng (cfn24@cam.ac.uk)

Course Website: https://github.com/MLecon/ML-in-Economics
Assignment Submission: Github Classroom
Readings: Zotero Group Library
Recordings of further interest: Youtube Playlist

Course Overview

Course Description

Machine Learning is in the process of transforming economics as well as the business world. This course aims to provide a graduate-level introduction to machine learning equipping students with a solid and rigorous foundation necessary to understand the key techniques of this fast-evolving field and apply them to economic problems. The curriculum bridges theoretical foundations with practical implementations and strives to remain relevant by teaching a conceptual understanding that transcends the implementation details of current state-of-the art methods.

Specific Topics Covered

The course covers key methods in

- supervised learning, including regression, classification, and neural networks
- unsupervised learning, including clustering and dimensionality reduction
- reinforcement learning, including bandit problems
- applications to economics.

Course Aims and Objectives

By the end of this course, students will be equipped with:

- a foundational understanding of the most relevant ML tools and how they are reshaping economic analysis
- the ability to work with ML models using popular software environments such as PyTorch and scikit-learn, and to adapt them for economic problems
- critical skills in interpreting and explaining sophisticated ML models in economic contexts

Lecture Materials

Lecture materials will be posted to the course website. The course loosely follows the textbook of Prince [2023] which is freely available at https://udlbook.github.io/udlbook/. The material may be complemented by chapters from further classic textbooks, including Bishop [2006], Hastie et al. [2009], Goodfellow et al. [2016], MacKay [2003], Murphy [2022], and Sutton and Barto [2018]. These are not required reading.

All readings are also organized in a Zotero Group Library. A Youtube Playlist curates videos of further interest to the course's topics.

Computing Environment

The lectures and classes feature examples in Jupyter Notebooks for use on Google Colab. Students with a demonstrated need can request HPC access (e.g. for the project) after consulting with the instructor.

Prerequisites

Linear Algebra, calculus, probability theory and statistics, as well as programming skills (ideally in Python) are required.

Contents and Schedule

Introduction and Foundations - Week 1 (24 January)

- A brief overview of AI, ML, and Deep Learning [Prince, 2023, Chapter 1]
- Probability and information theory fundamentals [Prince, 2023, Appendix C]

Part 1: Supervised Machine Learning

Prediction and Linear Regression - Week 2 (31 January)

- Linear Regression: Minimizing mean-squared error using matrix notation [Prince, 2023, Chapter 2]
- Optimization and stochastic gradient descent [Prince, 2023, Chapter 6]
- Model Evaluation: Bias-variance tradeoff and overfitting, training/test set and cross-validation, double descent [Prince, 2023, Chapter 8]
- sklearn
- PyTorch

Classification and Logistic Regression - Week 3 (7 February)

- Multinomial Logit and Discrete Choice
- Loss functions [Prince, 2023, Chapter 5]
- Regularization [Prince, 2023, Chapter 9]
- Multi-Layer Perceptron
- Support Vector Machines (SVM)
- Decision/classification trees
- Ensemble Methods: Boosting and bagging, random forests, gradient boosting machines

Artificial Neural Networks and Deep Learning - Week 4 (14 February)

- Deep learning as a nonlinear model (like GLM) [Prince, 2023, Chapter 3]
- Feedforward neural networks (=multi-layer perceptrons) [Prince, 2023, Chapter 4]
- Backprop and stochastic gradient descent [Prince, 2023, Chapter 7]

Representation Learning and Natural Language Processing (NLP) - Week 5 (21 February)

- Convolutional neural networks (CNN) [Prince, 2023, Chapter 10]
- Transformers and Large Language Models (LLM) [Prince, 2023, Chapter 12.1-12.6]
- Extra: Sequence and time series modeling: Recurrent neural networks (RNN), Hopfield network, LSTM
- Extra: Word embedding (e.g. Word2Vec)

Part 2: Unsupervised Machine Learning

Generative AI - Week 6 (28 February)

- Introduction to Research Project

- Generative Pre-trained Transformers (GPT) [Prince, 2023, Chapter 12.7-12.10]
- Unsupervised Learning [Prince, 2023, Chapter 14]
- Gaussian Mixture Models, Expectation Minimization (vs gradient descent)
- Clustering: K-means
- Dimensionality reduction: PCA and ICA
- Variational Autoencoders (VAE), variational Bayesian methods, ELBO [Prince, 2023, Chapter 17]
- Diffusion Models [Prince, 2023, Chapter 18]
- *Generative Adversarial Networks (GANs) [Prince, 2023, Chapter 15]

Part 3: Reinforcement Learning

Reinforcement Learning - Week 7 (7 March)

- Reinforcement Learning [Prince, 2023, Chapter 19]
- Hidden Markov Models (HMM) and Markov Decision Processes
- Multi-armed bandit testing
- Bandit Gradient Algorithm as Stochastic Gradient Descent
- Q-Learning
- SOTA RL algorithm (e.g. PPO)
- Deep Q-Networks
- Silver et al. [2016]
- Schrittwieser et al. [2020]
- Inverse Reinforcement Learning

Part 4: ML and Economics

ML and Economics - Week 8 (14 March)

- Review and synthesis: The information-theoretic lens as a unifying principle [Alemi, 2024]
- ML and Economics [Athey and Imbens, 2019]
- Brief remarks on causal inference (separate module)
- Matrix completion problem: Consumer choice modeling and application to recommender systems

Project Presentations - Week 9 (21 March)

- Project presentations

Classes and Problem Sets

Classes are meant to discuss problem sets and questions arising from the lectures as well as (towards the end of the term) the research projects. Problem sets are to be submitted in groups of 4 students (of varying configuration) on Github Classroom.

Assessment

Assessment in the course is based entirely on the completion of a small-scale research project.

The grade is composed of three submissions, due at 12 noon UK time.

- 10% Proposal (due 10th March 2025): 1-page description of the proposed project, clearly articulating the research questions and the methods to be used.
- 30% Draft (due 24th March 2025): Complete draft of the project report.
- 60% Submission (due 7th April 2025): Final project report incorporating feedback received in response to the draft.

The project report should be around 4 single-spaced pages, approximately 2000-2500 words.

Key Dates

24 Jan First Lecture
4 Feb Problem Set 1 due
18 Feb Problem Set 2 due
4 Mar Problem Set 3 due
10 Mar Project proposal due
21 Mar Project presentations (last lecture)
24 Mar Draft of project report due
7 Apr Final project report due

Policies

Attendance Regular attendance at lectures and classes is mandatory.
Plagiarism All work submitted must be original. Plagiarism will result in serious academic penalties in line with University policy.
Use of Large Language Models Submitted work must not be direct output from Large Language Models such as ChatGPT, and may be checked accordingly.
Late Submissions Assignments submitted after the deadline will be penalized (unless an extension is granted in advance) by 10% per 24 hours (additively, i.e. a submission received 49 hours after the deadline will receive 70% of full marks).

Support

Students are encouraged to use office hours to discuss any academic or personal issues related to the course. Additional support services are available through the university's counseling and academic support centers.

Feedback

Feedback of any kind is most welcome. To suggest improvements (e.g. typos) on the teaching material, please open a Github issue.

Resources and Reading Materials

Alex Alemi. KL is All You Need. https://blog.alexalemi.com/kl-is-all-you-need.html, January 2024.

Susan Athey and Guido W. Imbens. Machine Learning Methods That Economists Should Know About. *Annual Review of Economics*, 11:685–725, 2019.

Christopher M. Bishop. *Pattern Recognition and Machine Learning*. Information Science and Statistics. Springer, New York, 2006. ISBN 978-0-387-31073-2.

Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. Adaptive Computation and Machine Learning. The MIT Press, Cambridge, Massachusetts, 2016. ISBN 978-0-262-03561-3.

Trevor Hastie, Robert Tibshirani, and J. H. Friedman. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer Series in Statistics. Springer, New York, NY, 2nd ed edition, 2009. ISBN 978-0-387-84857-0 978-0-387-84858-7.

David J. C. MacKay. *Information Theory, Inference, and Learning Algorithms*. Cambridge University Press, Cambridge, 22nd printing edition, 2003. ISBN 978-0-521-64298-9.

Kevin P. Murphy. *Probabilistic Machine Learning: An Introduction*. Adaptive Computation and Machine Learning Series. The MIT Press, Cambridge, Massachusetts, 2022. ISBN 978-0-262-04682-4.

Simon J. D. Prince. *Understanding Deep Learning*. The MIT Press, Cambridge, Massachusetts, 2023. ISBN 978-0-262-04864-4.

Julian Schrittwieser, Ioannis Antonoglou, Thomas Hubert, Karen Simonyan, Laurent Sifre, Simon Schmitt, Arthur Guez, Edward Lockhart, Demis Hassabis, Thore Graepel, Timothy Lillicrap, and David Silver. Mastering Atari, Go, chess and shogi by planning with a learned model. *Nature*, 588(7839):604–609, December 2020. ISSN 1476-4687. doi: 10.1038/s41586-020-03051-4.

David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel, and Demis Hassabis. Mastering the game of Go with deep neural networks and tree search. *Nature*, 529(7587): 484–489, January 2016. ISSN 1476-4687. doi: 10.1038/nature16961.

Richard S. Sutton and Andrew G. Barto. *Reinforcement Learning: An Introduction*. Adaptive Computation and Machine Learning Series. The MIT Press, Cambridge, Massachusetts, second edition edition, 2018. ISBN 978-0-262-03924-6.