

The Chinese University of Hong Kong

ECON5170 Computational Methods in Economics Spring, 2021-2022

Instructor Naijia Guo (guonaijia@cuhk.edu.hk, ELB 913)

Lecture Hours and Location

Time: January 12th - April 20th, every Wednesday 3:30pm - 6:15pm

Venue: ELB916(first four weeks)/ELB403(the rest of the weeks)

Office hours: By appointment

Course Description

In modern economic research, computers enhance our capacity of solving complex problems. Computation is particularly important in fields involving massive data. The objective of this course is to introduce graduate students to computational approaches for solving economic models, with an emphasis on dynamic programming and simulation-based econometric methods. We will formulate economic problems in computationally tractable form and use techniques from numerical analysis to solve them. The substantive applications will cover a wide range of problems including labor, industrial organization, macroeconomics, and international trade.

Learning outcomes

Computational economics has not been part of the core curriculum of postgraduate-level economics education, whereas programming skill is critical for a postgraduates success in academia and industry. This course intends to teach students computational methods for solving economic problems, and expose students to extensive programming exercises. We expect that at the end of the course a student would proficiently use at least one programming language (Stata, Matlab, R, etc). Moreover, we aim to equip the students with the computational ability to tackle problems of their own research areas.

Assessment

Midterm	30%	A small take-home exercise.
Final	70%	A group project. Form a group of 2-3 people. Write a computer program to solve one of the two problems (micro or macro). Present the results on April 20th or later (30% of the total score). Hand in the report with codes and results by May 20th (40% of the total score). In the final report, clarify the contribution of each group member.

Class Schedule

Date	Content
12 Jan	Stata I (ELB916, Computer Lab)
19 Jan	Stata II (ELB916, Computer Lab)
26 Jan	Matlab I (ELB916, Computer Lab)
2 Feb	No class (Lunar New Year)
9 Feb	Matlab II (ELB916, Computer Lab)
16 Feb	Linear Equations
23 Feb	Optimization
2 Mar	Nonlinear Equations
9 Mar	Monte Carlo Simulation
16 Mar	Numerical Integration and Differentiation
23 Mar	Function Approximation and Projection Methods
30 Mar	Dynamic Programming I
6 Apr	Dynamic Programming II
13 Apr	Preparation of group projects (no class)
20 Apr (TBA)	Presentation of group projects

Required Readings

- Judd, Kenneth (1998): Numerical Methods in Economics, the MIT Press
- Efron, Bradley and Hastie, Trevor (2016): Computer Age Statistical Inference: Algorithms, Evidence, and Data Science, Cambridge University Press (Freely downloadable at author's page <https://web.stanford.edu/~hastie/CASI/index.html>)

Recommended Readings

- Altonji, J. G., & Segal, L. M. (1996). Small-sample bias in GMM estimation of covariance structures. *Journal of Business and Economic Statistics*, 14(3), 353-366.
- Athey, S. (2018). The impact of machine learning on economics. In *The Economics of Artificial Intelligence: An Agenda*. University of Chicago Press.
- Chernozhukov, V., & Hong, H. (2003). An MCMC approach to classical estimation. *Journal of Econometrics*, 115(2), 293-346.
- Fan, J., & Li, R. (2001). Variable selection via nonconcave penalized likelihood and its oracle properties. *Journal of the American statistical Association*, 96(456), 1348-1360.
- Gentzkow, M., Kelly, B., & Taddy, M., (2017). *Text as Data*. National Bureau of Economic Research.
- Hansen, L. P., Heaton, J., & Yaron, A. (1996). Finite-sample properties of some alternative GMM estimators. *Journal of Business and Economic Statistics*, 14(3), 262-280.
- Tibshirani, R. (1996) Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B*, 267-288.

- Li, Q., Cheng, G., Fan, J. & Wang, Y., (2018). Embracing the Blessing of Dimensionality in Factor Models. *Journal of the American Statistical Association* 113 (521), 38089.
- Mullainathan, S., & Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, 31(2), 87-106.
- Pakes, A., & Pollard, D. (1989). Simulation and the asymptotics of optimization estimators. *Econometrica*, 1027-1057.
- Shi, Z., (2016). Econometric Estimation with High-Dimensional Moment Equalities. *Journal of Econometrics*, 195, 104-119
- Su, C. L., & Judd, K. L. (2012). Constrained optimization approaches to estimation of structural models. *Econometrica*, 80(5), 2213-2230.
- Su, L., Shi, Z., & Phillips, P. C. B. (2016). Identifying Latent Structures in Panel Data. *Econometrica*, 84(6), 2215-2264
- Taddy, M., (2018). The Technological Elements of Artificial Intelligence. National Bureau of Economic Research
- Wickham, H., & Grolemund, G. (2016). *R for Data Science: Import, Tidy, Transform, Visualize, and Model Data*. OReilly Media, Inc.
- Zou, H. (2006). The adaptive lasso and its oracle properties. *Journal of the American statistical association*, 101(476), 1418-1429.

Late Add/Drop Policy

Students are advised to strictly observe the official deadline for add/drop. The department, not the course teacher, will handle every late add/drop application. Late add/drop application is rarely approved; in those rare approvals, they will be based on extremely special reasons beyond students' control. Objective and substantial proofs are required. Failure to observe the deadline or negligence in checking the official course enrollment systems will not be accepted as reasons for late drop.

Academic Honesty

Attention is drawn to University policy and regulations on honesty in academic work, and to the disciplinary guidelines and procedures applicable to breaches of such policy and regulations. Details may be found at <http://www.cuhk.edu.hk/policy/academichonesty/>.