The Chinese University of Hong Kong

ECON5170 Computational Methods in Economics
Spring, 2018-2019

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Lecture Hours and Location

Time: January 10th - April 18th, every Thursday 9:30 - 12:15
Venue: Esther Lee Bldg 304
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 three problems (micro, macro, or metrics). Present the results on April 18th or later (TBA). Hand in the final codes by May 6th.

Class Schedule

Date	Content
10 Jan	Basic R
17 Jan	Advanced R
24 Jan	Numerical Integration
31 Jan	Numerical Optimization
7 Feb	No class (Lunar New Year)
14 Feb	Basic Stata (in Undergraduate Computer Lab ELB 916)
21 Feb	Advanced Stata (in Undergraduate Computer Lab ELB 916)
28 Feb	Machine Learning I
7 Mar	Machine Learning II
14 Mar	Linear Equations
21 Mar	Nonlinear Equations
28 Mar	Approximation methods
4 Apr	Dynamic programming
11 Apr	Office hour
18 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)
- Wickham, Hadley and Grolemund, Garrett. (2016). R for Data Science: Import, Tidy, Transform, Visualize, and Model Data. O'Reilly Media, Inc. (Open access at author's page https://r4ds.had.co.nz/)

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.
- Gourieroux, C., Monfort, A., & Renault, E. (1993). Indirect inference. Journal of applied econometrics, 8(S1), S85-S118.

- 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), 380–89.
- 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
- Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. Neural networks, 2(5), 359-366.
- 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/.